A Genetic Algorithm to Ensemble Feature Selection

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1. Introduction

It has been shown in several studies that an ensemble of diverse classifiers is generally more accurate than a single model. One way to obtain an ensemble of classifiers is selecting different feature subsets from the original dataset and creating for each subset a base classifier. This approach is known as an ensemble feature selection.

Nowadays we may use large dataset where each instance can have more than 2000 features. To find the attributes to be selected in order to get the best subsets collection we should try more than 2^{2000} possible combinations of features**.** In order not to do that necessarily, we suggest the use of Genetic Search which has been obtaining good results in optimisation problems. *Tsymbal et al* [1] had also proposed a genetic algorithm to solve this problem. In this paper, based on their work, we are going to implement their algorithm, GA-SEFS, and analyse experimentally its performance depending on the classifier algorithms used in the fitness function. Three classifier algorithms are going to be used, Naïve Baies (NB) [13], Nearest Neighbour with generalization (NNge) [10] and Sequential Minimal Optimization (SMO) [11]. We are also going to study the effect of adding to the fitness function, a measure to control the complexity of the base classifiers.

2. An ensemble of classifiers.

There are some reasons to choose an ensemble of classifiers in order to face up the challenging problem of classification. One of the main reasons is that an ensemble is generally able to obtain higher accuracy than one single model, because of the reduction of *variance* and *bias*. *Variance* expects the error made by a learning method due to the training set, and the fact that different training sets are used to build the ensemble makes the obtained results less dependent on peculiarities of a single training set. The error rate for a particular learning algorithm is called its *bias* for a learning problem and measures how well the learning method matches the problem.

A lot of studies have proved that in order to obtain a good ensemble, the base classifiers in the ensemble not only must have high accuracy, but they have to make their errors in different parts of the input space and this production of errors should be independent. So the main objective when creating an ensemble of models is to obtain a good coverage of the data, that is, the percentage of the instances that at least one base classifier can classify correctly. To obtain a good coverage of the data is essential to have diversity among the base classifiers. There are different measures to quantify ensemble diversity and we decided to use fail/non-fail disagreement which is going to be explained in section 3.1.1.

There are several techniques to build an ensemble of classifiers. One of them is using learning algorithms with heterogeneous representations and search biases, such as decision trees, instance-based leaning, etc. Another way of generating ensembles is using models with an homogeneous representation that differ in their method of search or in the data which they are trained. The most well-known techniques of this type are bagging and boosting [12]. When bagging, the original training data is altered by deleting some instances and replicating others randomly, so new training sets of the same size are created. This subsets generated by resampling, are different from one another but not really independent from the original dataset. Then, after building the base classifiers using this training sets, its predictions are combined with some kind of integration method (often Simple Voting).

In boosting, the learning algorithm must handle weighted instances, so instance weights are used to build the different base classifiers. The presence of instance weights changes the way in which a classifier’s error is calculated: addition of the misclassified instances weights divided by the total weight of all instances. By weighting instances, the learning algorithm can be forced to concentrate on a particular set of instances which have high weight.

2.1 Ensemble feature selection.

Bagging and boosting, that have been overviewed before, build ensembles basing its approach on finding instance subspaces in the dataset. Instead of that, ensemble feature selection makes an ensemble of models by using different feature subsets for each base classifier [1][4][6][9]. So, the task of ensemble feature selection has the goal of finding a set of feature subsets that not only will have high accuracy but also will promote diversity among the base classifiers.

Random Subspace Method or simply Random Subspacing (RS) is a good method for ensemble feature selection. This method takes some features at random creating thus different subspaces which may not be accurate but this lack of accuracy is compensated by their diversity. RS has much in common with bagging, but instead of sampling instances, it samples features. This method is a parallel learning algorithm, so each generation of base classifiers is independent and it is possible to run it in parallel. Like bagging, accuracy could be only increased with the addition of new base classifiers.

Hill Climbing (HC), Ensemble Forward Sequential Selection (EFSS) and Ensemble Backward Sequential Selection (EBSS) are other more sophisticated techniques that has been used to ensemble feature selection [7]. HC starts with an initial population created by Random Subspacing, then some mutations are applied over this population iteratively in order to improve the accuracy and diversity of the base classifiers. For all the feature subsets, an attempt is applied to include or delete each feature. If the subset obtained is better according to the fitness function, then the changes will kept. This process is repeated until no improvements are achieved.

EFSS and EBSS apply iteratively FSS or BSS to each base classifiers. FSS and BSS are techniques to select single feature subsets. FSS starts with zero attributes and it evaluates all features subsets with exactly one feature. Then, the selected feature that obtain the best subset is kept to evaluate the subsets of the next larger size. This procedure is repeated until no improvement is obtained from extending the current subset. BSS, instead of that, begins with all features and repeatedly removes a feature until no improvement is obtained. Note that the cost of these two techniques are polynomial.

3. GA for Sequential Ensemble Feature Selection

Genetic Algorithms have shown to be effective in global optimisation techniques and it has been an important direction in feature selection research. In *Tsymbal et al* [1] they proposed the GA-SEFS for sequential ensemble feature selection which consist in adding sequentially to the ensemble the best base classifiers selected in each run of the Genetic Algorithm. They used in the fitness function, as Kuncheva and Jain, the accuracy of each base classifier instead of ensemble accuracy. This genetic search has some other peculiarities as the use of log(1+fitness) in selecting the individuals used in crossover operator and the prohibition of this operator to create offspring equal to their parents. Moreover, mutation operator was not allowed to create full feature subsets. On this work, this peculiarities have been kept.

The Genetic Algorithm for ensemble feature selection begins with creating an initial population with RS and calculating its fitness. The representation of each individual is a constant-length string of bits, where each bit corresponds to a particular feature.

Then, new candidate classifiers are produced by crossover and mutation. The crossover operator selects at random individuals from the initial population with a probability proportional to log(1+fitness) (roulette-wheel selection). Then each feature of a children takes randomly a value from one of the parents. After that, half of the offspring created are mutated by the two mutation operators. These operators changes at random a number of bits in an individual.

After producing a determined number of individuals, the process continues with selecting a new subset of candidates according to fitness which they will become the initial population for the next generation. The process of creating new classifiers and selecting a subset of them (a generation) continues a predefined number of times. After a predefined number of generations, the individual with the highest fitness is selected and is added into the ensemble sequentially.

Pseudo-code for this GA-SEFS is given in Figure 1. After each genetic process, one base classifier is selected into the ensemble. In the fitness function, the diversity is calculated with the base classifiers already formed by previous genetic processes, so in the first GA process, the fitness function has to use accuracy only.

```
for (i=0; i<ensembleSize; i++){
        for (j=0; j<10; j++){
                population[j]=new Individual(numFeatures, rand); //random
                population[j].CalculateFitness();
        }
        for (j=0; j<numGenerations; j++){
                for (k=0; k<40; k++){
                        //randomly proportional to log(1+fitness)
                        Select2(rand);
                        offsprings[k].CrossOver(selected1,selected2,rand);
                }
                for (k=0; k<10; k++){
                        offsprings[20+k].Mutate1_0(rand);
                        offsprings[30+k].Mutate0_1(rand);
                }
                for (k=0; k<40; k++){
                        offsprings[k].CalculateFitness();
                }
                Select10(50,10);
        }
        //according to fitness
        BaseClassifier[i]=Select1(10, i);
}
```

Figure 1 Code details for GA

As it has told, full feature sets are not allowed in RS. Individuals for uniform crossover are selected randomly proportional to log(1+*fitness*), which adds more diversity into the new population and the generation of children identical to their parents is prohibited.

To provide a better diversity in the length of feature subsets, two different mutation operators are used (*Mutate1_0* and *Mutate0_1*), one of which deletes some features randomly, and the other adds features. The mutation operator *Mutate0_1* is not allowed to produce full feature subsets neither the mutation operator *Mutate1_0* produce an empty feature subset. This operators changes at random a number of bits proportional to the number of features selected as we can see in the following rules. The fist-one (1) is applied in Mutate1_0 and the second-one (2) in Mutate0_1:

$$NumBits1\_0 = 1 + random\left(1 + \left\lfloor i \cdot \frac{NFS}{NF} \cdot 0.5 \right\rfloor\right) \quad (1)$$

$$NumBits0\_1 = 1 + random\left(1 + \left\lfloor i \cdot \left(1 - \frac{NFS}{NF}\right) \cdot 0.5 \right\rfloor\right) \quad (2)$$

where, *NumBits* is the number of bits (features) to change, *i* is the total number of bits that can be changed (the number of features selected in *Mutate1_0* and the number of features not selected in *Mutate0_1*). *NFS* is the number of features selected and *NF* is the total number of features. The function *random(n)* returns a random number between 0 and *n*-1 and the constant 0,5 is used in order not to change more than the half of the total number of bits that are able to.

In order to avoid having repeated individuals in one generation, if one of the operators (*RS*, *Crossover* or *Mutate*) produce an existing subset of features, it is called again until it produces a not existing feature subset. The maximum number of times that an operator can be called when this happens is ten. If after 10 runs no different subsets are obtained, the last generated subset is taken.

Parameter settings for our implementation of GA include an initial population size of 10 obtained by RS in the first generation, a search length of 40 feature subsets, where 20 of them are the offspring created by crossover from the current population, and the other 20 are mutated offsprings (10 with each mutation operator). When a generation ends, the 10-best individuals are selected from the total population of 50 to obtain the initial population for the next generation.

The complexity of this GA-SEFS does not depend on the number of features, which is $O(S \cdot S' \cdot N_{gen})$ where S is the number of base classifiers, S' is the number of individuals in one generation and N_{gen} is the number of generations. In our experiments GA-SEFS look through 4000 feature subsets, so the number of base classifiers is 10, the number of individuals in a generation is 40, and the number of generations is 10.

3.1. Measures used in the fitness function

3.1.1 Diversity: The fail/non-fail disagreement measure.

As it has been explained, an ensemble of classifiers must have diversity among the base classifiers. There are a number of ways to quantify ensemble diversity [7], such as plain disagreement, the Q statistic, the correlation coefficient and kappa statistic.

These measures are pairwise, that means they are able to measure diversity of a pair of classifiers. Then the total ensemble diversity is the average of all the classifier pairs in the ensemble. There are also non-pairwise measures which measures diversity of the whole ensemble only, such as entropy or ambiguity.

The fail/non-fail disagreement is another pairwise measure of diversity and it is the guiding diversity measure used in our experiments. It is defined as the percentage of test instances for which the classifiers make different predictions but that for one of them is correct:

$$div\_dis_{ij} = \frac{N^{01} + N^{10}}{N^{11} + N^{10} + N^{01} + N^{00}} \qquad (3)$$

where N^{ab} is the number of instances in the data set, classified correctly (a=1) or incorrectly (a=0) by the classifier *i*, and correctly (b=1) or incorrectly (b=0) by the classifier *j*. The denominator in this function is equal to the total number of instances *N*. The fail/non-fail disagreement varies from 0 to 1. This measure is equal to 0, when the classifiers return the same classes for each instance, or different but incorrect classes, and it is equal to 1 when the predictions are always different and one of them is correct.

3.1.2 Number of features

It was shown in [7] that the subsets created by genetic search have more features than the subsets created by other search strategies, even more than EBSS. This measure was taken averaging the number of features selected on each base classifier in the ensemble. It was also shown in [1] than the number of features in the last subsets, added sequentially in the ensemble, falls as the *alpha* value grows, so they concluded that less features in the subsets are needed to increase diversity as the number of base classifiers grows. So it seems to be a relationship between the number of features and the diversity of the ensemble. For that reason, we thought that could be a good choice to add in the fitness function a control measure for this.

In order to do that, we have used two opposite measures to control the number of features selected. One of them, gives more fitness at the subsets with less number of features (4) and the other gives more fitness at the subsets with more number of features (5). The first one (4) could also help to prevent overfitting. We have used these two opposite measures so that we could have a positive number to add in the numeric fitness evaluation.

$$num\_feat\_\beta + = e^{\left(\frac{FS}{F}-1\right)} \quad (4)$$

$$num\_feat\_\beta - = e^{-\frac{FS}{F}} \quad (5)$$

where FS is the number of features selected and F is the total number of features. We use a factor (*beta*) in the fitness function which reflects the influence of this term.

3.2. Fitness function

We could say that fitness function is one of the most important part in genetic search. This function have to evaluate the goodness of each individual in a population, so it has an individual as an input and it returns a numerical evaluation that must represent the goodness of the feature subset. The search strategy's goal is to find a feature subset maximizing this function.

In order to evaluate a subset of features, a model is build using this feature subset and the accuracy is obtained testing it in the test set. It is reasonable to include both accuracy and diversity in the fitness function in order to obtain an ensemble of diverse models. Then, diversity is calculated using a determinate measure, in our case fail/non-fail disagreement.

One measure of fitness, defines fitness $Fitness_i$ of classifier i corresponding to feature subset i to be proportional to classification accuracy acc_i and diversity div_i of the classifier:

$$Fitness_i = acc_i + \alpha \cdot div_i \quad (6)$$

where α reflects the influence of diversity.

However, we have added to the fitness function one measure to control the model's complexity getting a numeric evaluation that depends on the number of features selected. This measure is added in the fitness function so that we can change *beta* value, which reflect the influence of this complexity measure in the final fitness value. Finally, the fitness function is:

$$Fitness_i = acc_i + \alpha \cdot div\_dis_i + \beta \cdot num\_feat_i \qquad (7)$$

Diversity div_dis_i is the average pairwise diversity for all the pairs of classifiers that include *i*. This measure reflect the contribution of classifier *i* to the total ensemble diversity.

Num_feat_i is calculated using the formulas proposed before (4) (5). When *beta* is negative (5) is used and *beta*'s absolute value is used in the fitness function (7). When *beta* is positive we use (4). We could understand that a negative value of *beta* means that is a negative thing having more features in the base classifiers, so it gives more fitness at the individuals that have less number of features selected. The opposite happens for the positive values of *beta*. Finally, the value added in the fitness function is calculated as it follows:

$$num\_feat_i = num\_feat_i \cdot \log\left(1 + \frac{AES}{ES}\right) \qquad (8)$$

where *AES* is the actual ensemble size and *ES* is the total number of base classifiers in the ensemble. By this way, this measure has more weight as the ensemble size grows. Looking for the first base classifier, this measure have no effect so it is interesting to obtain a feature subset with high accuracy.

Accuracy acc_i is the accuracy of the base classifier *i* in the test set. Using accuracy of the base classifiers instead of the ensemble accuracy has been shown to be a good choice. When taking ensemble accuracy, one kind of integration method have to be chosen and often SV is used. But there is a problem with this design because it suffer from bias. For that reason, accuracy of each individual has been taken in the fitness function.

4. Integration methods

The challenging problem of integration is to decide which of the classifiers to select or how to combine the results produced by the base classifiers. This is one of the most important part in ensemble's construction. Even when the coverage of the data is 100%, selecting the base classifier which can correctly classify one given instance is a problem difficult to solve.

A number of selection and combination approaches have been proposed. There are two kinds of approaches to solve this problem: *static* and *dynamic*. The *static* methods select one model for the whole data space or combine the models uniformly. Simple Voting, Weighted voting and Static Selection are some examples of this kind of methods. In *dynamic* integration, each new instance to be classified is taken into account. Usually, better results can be achieved if integration is dynamic. There are other integration methods that can work better than the ones used in this paper for example the dynamic integration method in [3], but this is not the main goal of this work and we have only implemented the methods explained here below.

4.1 Simple Voting

One of the most popular and simplest techniques used to combine the results of the base classifiers, is simple voting (also called majority voting). In the voting, the output of each base classifier is considered as a vote for a particular class value. The class value that receives the biggest number of votes is selected as the final classification.

4.2 Weighted Voting

This technique uses the probability given by each base classifier for a particular predicted class. In the same manner as in SV, the output of each base classifier is considered as a vote but on this case the vote have the weight of the probability given by the base classifier. Then the class that have higher value of votes is selected as the final prediction. This technique usually works slightly better than SV. Another way to obtain the weight assigned to each base classifier is using cross validation. Then, the weight given to a base classifier's prediction is its expected accuracy in cross validation. We have used the first option explained in our experiments.

4.3 Staking

One of the oldest and practical dynamic integration method is Staking or Class-Combiner Meta-learning, that combines the result of the classifiers in a non-linear way. The combining task (meta-learning) integrates the computed base classifiers into a higher level classifier, called meta-classifier, by learning over a meta-level training set [2].

This approach contains two phases. In the learning phase, the training set is partitioned into a couple of folds. Then, cross-validation technique [12] is used to estimate the error of the base classifiers and the meta-level training set is formed. In cross-validation technique we must decide the number of folds, for example k. Then, the training set is divided into a k equal partitions F_k. One of this partitions is used as a test set and the remaining data as a training set. So then, each base classifier B_i (where the subindex i means the total number of base classifiers) is trained with the new training set and tested with F_k, taking into the meta-level training set, the predictions made by each base classifier for each instance in the test set F_k. This process is repeated for all F_k subsets. In our experiment we decided to take k=10. When k=*NumInstances*, cross-validation is called *leave-one-out*. That's because each fold F_k is formed for only one instance.

In Staking [12], each instance in the meta-level training set contains, as attributes, the class predicted by each base classifier and the true class as a target. In order to obtain high accuracy, StakingC [12], used in this work, takes the probability given by each base classifier for each class instead of only the class value. So each instance in the meta-level training set contains, as attributes, the probability's distribution for each class given by each base classifier for a given instance, and the true class as a target. So, if we have N possible classes and i base classifiers, each instance in the meta-level training set will have $(N \cdot i)$ numeric attributes and a nominal attribute which is the true class. Note that the meta-level training set will have the same number of instances as the training set.

From these predictions, the meta-learner learns the characteristics and performance of the base classifiers and computes a meta-classifier which is a model of the "global" data set. In the second phase, the meta-classifier is build using the meta-level training set formed before and all the base classifiers are trained with the original training set.

To classify an unlabeled instance, the base classifiers present their own predictions to the meta-classifier which makes the final classification.

4.4 Dynamic Voting with Selection

Dynamic voting with selection (DVS) is another dynamic integration method. It consists in calculating the estimated error that have each base classifier for a given instance using cross validation technique. Then the base classifiers with the least estimated accuracy are discarded and WV applied in the remaining base classifier using the estimated accuracy as a weight [6].

In order to implement this method, we build a meta-classifier for each base classifier. The training set to build each meta-classifier is also obtained using cross validation. Then, each instance in this training set contains the same attributes than the original training set (with all features) and the correctness of each base classifier for that instance as a class value. That means that an instance in the meta level training set can have as a class two different values corresponding to *correct* or *incorrect* depending on the prediction of the base classifier. Then, for classifying a new instance, the error of each base classifier is calculated using their own meta-level classifier and the base classifiers that are predicted to obtain a correct classification are integrated using WV. The weight that have the prediction made by a base classifier is the probability given for their meta-level classifier for the class correct, that is the estimated accuracy for this instance.

5. Experimental Investigations

5.1 Experimental settings.

The experiments has been conducted on 8 datasets taken from the UCI machine learning repository. These datasets, varied in characteristics, were previously investigated by other researchers. The main characteristics of the datasets are presented in Table 1.

Relation	*Instances*	*Classes*	*Features*
Zoo	*101*	*7*	*18*
Wine	*178*	*3*	*14*
Tic-tac-toe	*958*	*2*	*10*
Glass	*214*	*6*	*10*
Horse colic	*368*	*2*	*23*
Hepatitis-domain	*155*	*2*	*20*
Breast cancer	*286*	*2*	*10*
Auto-mpg	*240*	*3*	*8*

Table 1: Datasets used

Eight different values had been used for *alpha* coefficient in our experiments, 0, 0.125, 0.25, 0.5, 1, 2, 4 and 8. For *beta*, it has been taken –0.5, -0.25, 0, 0.25 and 0.5 as it has been explained in sections 3.1.2 and 3.2.

In order to determine the best values for *alpha* and *beta* coefficients, GA has been submitted to cross validation technique. Each dataset has been randomised and partitioned into 10 folds, where one of them has been left as a validation set and the remaining data has been partitioned into 2 parts: one of them, with approximately 66% of the data, has been used as a training set and the rest as a test set. This procedure has been made using NB and NNge in genetic search and NNge as a meta-level classifier in StakingC and DVS. We can see the results obtained from this experiments in the Annex.

After that, we have selected the best *alpha* and *beta* values, that is, the values for which the GA-SEFS has obtained the highest accuracy in the validation set. Then these values have been used to make de final validation experiments presented in the next section. After selecting the best *alpha* and *beta* values, 40 runs have been made for each selected *alpha-beta* combination. In each run, the datasets has been partitioned into three subsets, taking randomly instances from the original dataset. One of the subsets, with approximately 66% of the instances, has been used as a training set and the remaining data has been partitioned into 2 subsets of equal size, using one of them as a test set and the other as a validation set.

Naïve Bayes (NB) and Nearest Neighbour with generalization (NNge) has been the classification algorithms used in GA fitness function to determine accuracy value for an individual. NB has advantatges in terms of simplicity, learnin speed and classification speed. NNge, which often is able to obtain high accuracy, spend more time on computing. No experiments has been made using SMO in the fitness function due to computational limitations but were seeing in our preliminary experiments that no improvements were achieved. So the results than we can see in the next section for SMO, have been obtained building the base classifiers with the subsets obtained using NB and NNge in the genetic search.

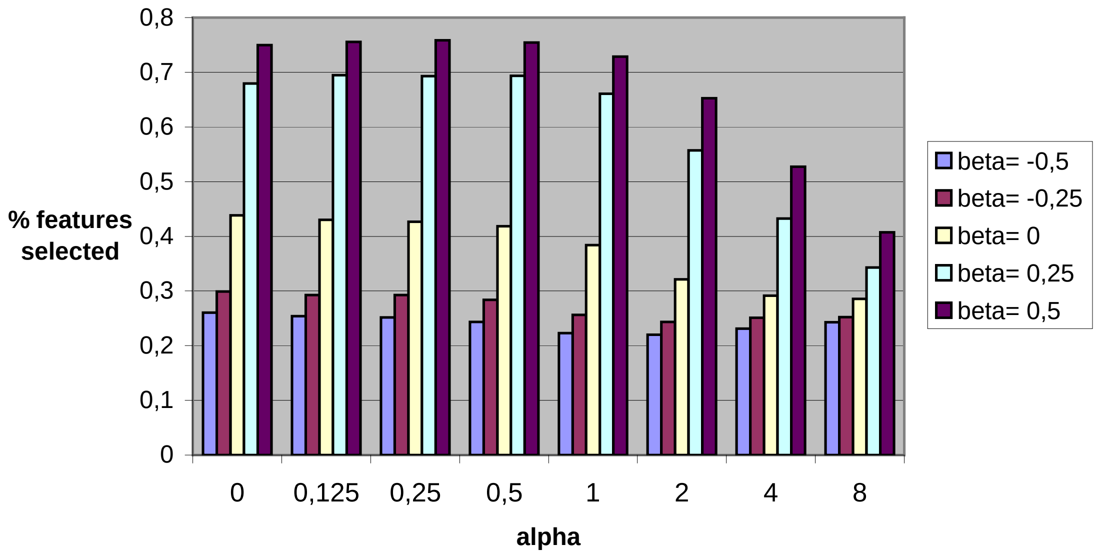
After each run of the GA, the base classifiers obtained have been build using the three classifier algoritms (NB, NNge and SMO). Also the results of StakingC and DVS using this three algorithms have been collected.

The test environment has been implemented with Weka, the machine learning library in java. The default settings have been used in SMO algorithm; this means that the complexity constant C was 1 and the exponent for the polynomial kernel was also 1. In NNge, the number of attempts of generalisation is 5.

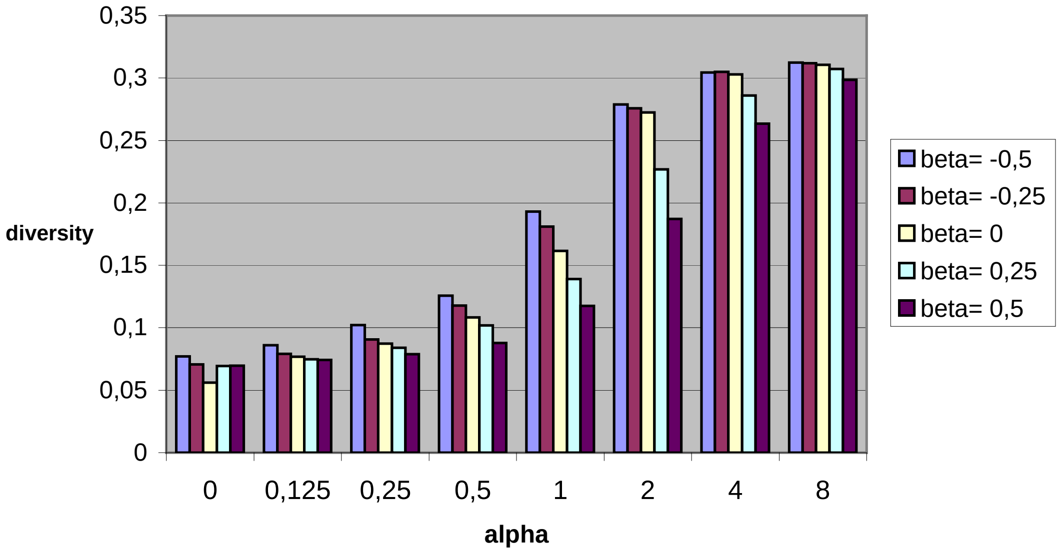
5.2 Experimental results

We are going to start this section explaining the results obtained in cross validation. After that, we are going to see the general results obtained in the validation experiments and two datasets are going to be showed thoughtfully.

With the results obtained in cross validation, we could see that the average of number of features selected in an ensemble decrease as the *alpha* value grows. It also changes in function of *beta* obtaining the results expected, so the number of features in an ensemble is lower for a negative value of *beta* and higher for a positive-one. The most interesting think to see is the fact that, in most of the cases, the diversity of the ensemble can be kept even when the total number of features selected in the ensemble is altered by a given value of *beta*. These results are shown on the next graphs made with the results obtained using NB in the GA-SEFS. The results obtained with NNge have almost been the same.



Graph 1: Average number of features selected in the ensembles.



Graph 2: Average of ensemble diversity.

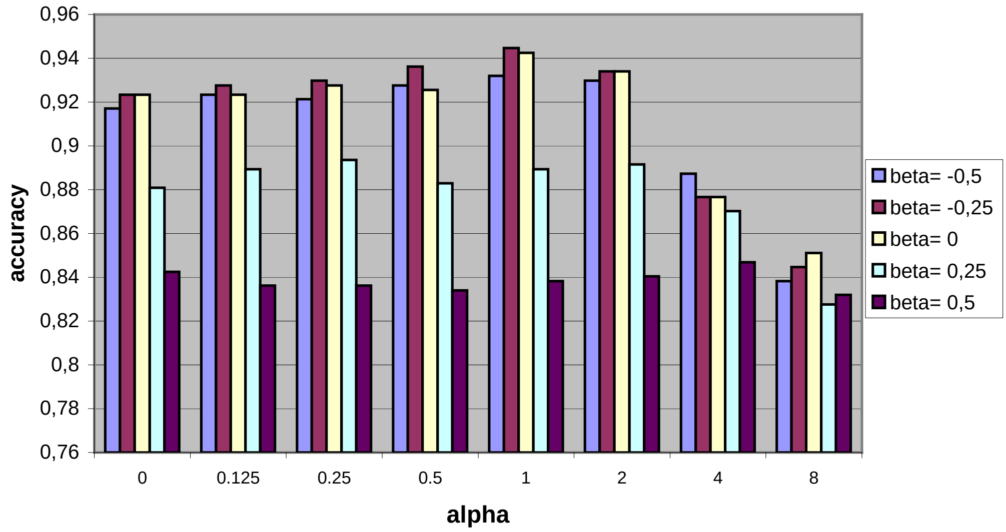
The relationship between *alpha-beta* and accuracy depends mostly on the datasets, integration method and the classifier algorithm. On average, high accuracy has been obtained with negative values of *beta*. In spite of that, for some datasets and integration methods, the highest value of this coefficient (0,5) has obtained the highest accuracy in cross validation.

Alpha also depends on the datasets, integration method and the classifier algorithm. In order to compare the difference between using or not the ensemble complexity measure, we have selected the best *alpha* values when *beta*=0 and the best combination of *alpha-beta* values. For this reason, we show the average of *alpha* values in two different tables depending on the use of *beta*. Looking to these tables we can say that *alpha* and *beta* are also dependent on each other**.**

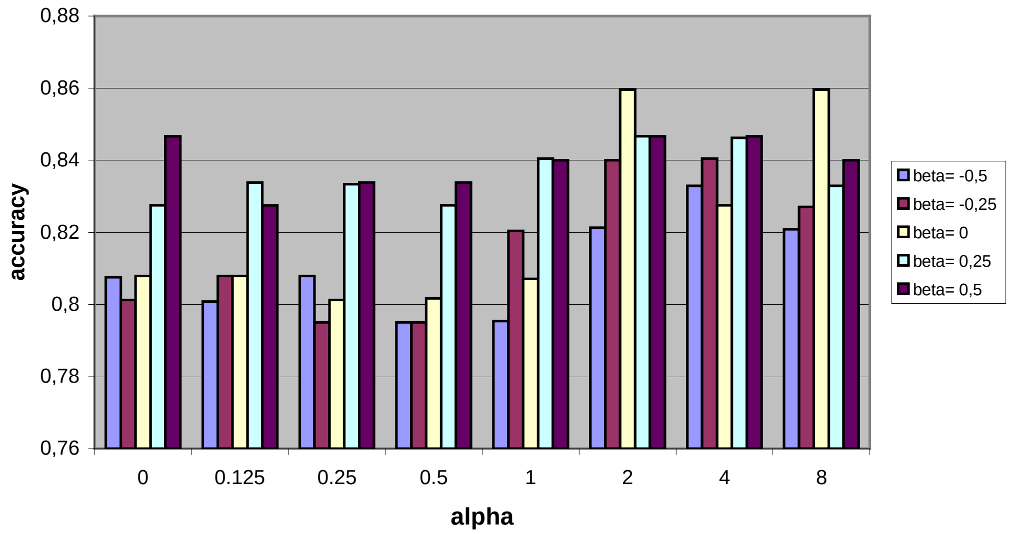
	Using beta		Without using beta	
	NB	NNge	NB	NNge
SV	1,03125	1,671875	1,40625	0,9375
WV	1,3125	1,671875	0,71875	0,9375
StakingC	2,015625	1,203125	1,0625	1,046875
DVS	2,15625	1,8125	3,3125	0,765625

Table 2: Averare of selected *alpha* values.

We have presented the accuracy obtained in two representative datasets in function of *alpha* and *beta* obtained in cross validation. In the following graphs we can observe that, in some cases, accuracy obtained in the test set is quite different than the one obtained in the validation set. This must be because of overfitting. Moreover, the test set has an important role building the ensemble due at the selection of feature subsets is done in function of the accuracy in the test set. Anyway, we think that results obtained in the validation set are more realistic and the best *alpha-beta* combination for this results has been selected to do the final experiments.

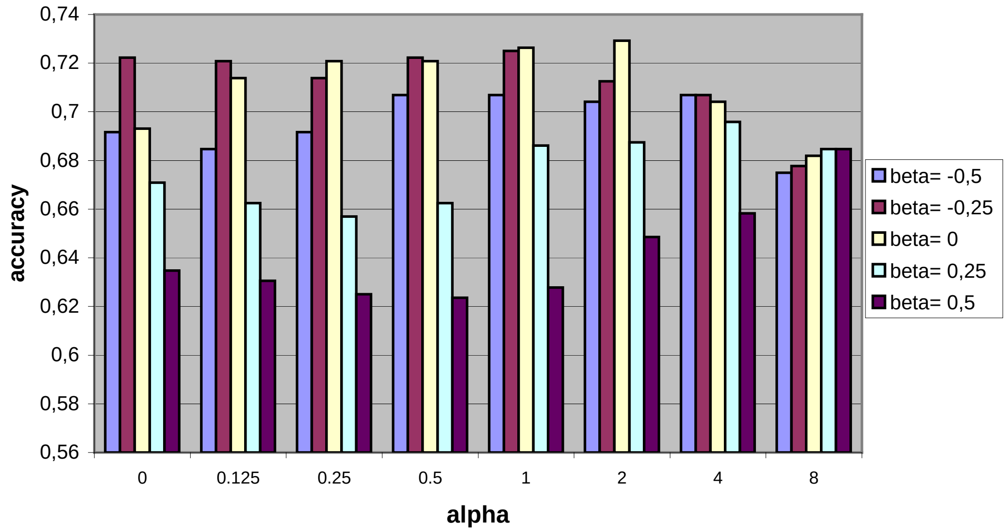


Graph 3: Average of accuracy in the test set with NB classifier and SV as a integration method in hepatitis-domain dataset.

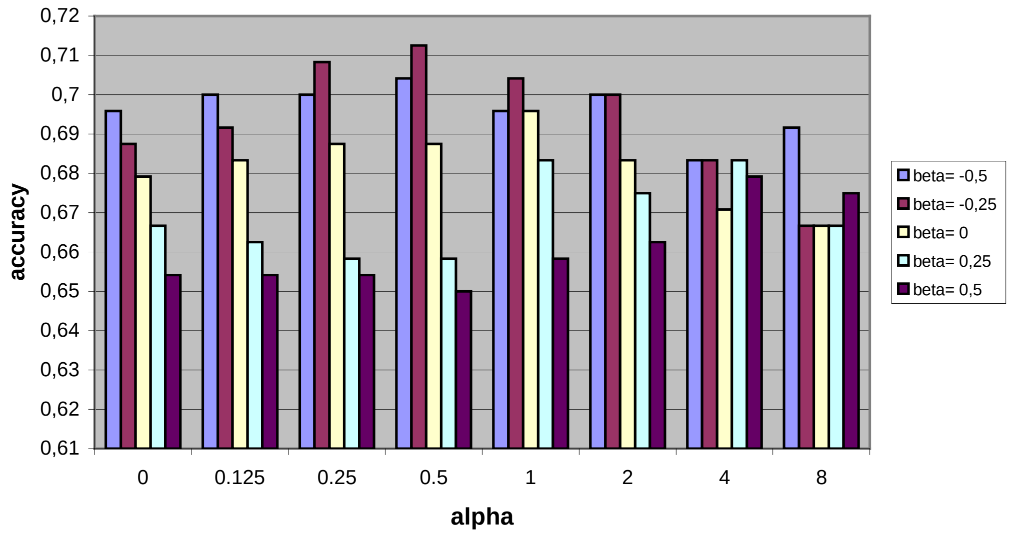


Graph 4: Average of accuracy in the validation set with NB classifier and SV as a integration method in hepatitis-domain dataset.

On this example, from hepatitis-domain dataset, we can see the difference between the results in the test set and the results in the validation set. In the test set the highest accuracy was achieved with the pair (1, -0.25) (*alpha*, *beta*). On the other hand, in the validation set the best results has obtained with (2, 0). We could also see that in the test set, the negative values of *beta* are clearly better than the positive-ones but this fact is the opposite with the validation set. In the next graphs, from auto-mpg dataset, we can see an opposite behaviour.

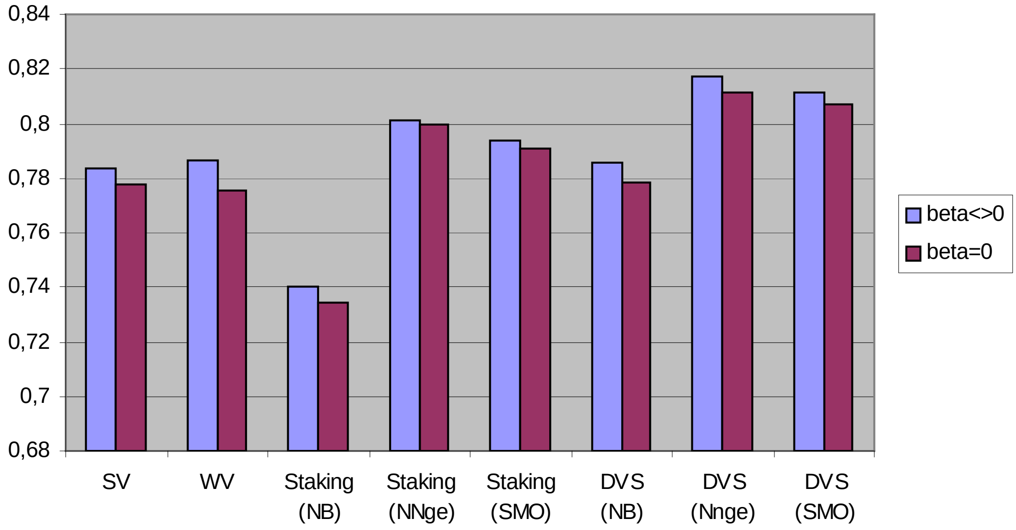


Graph 5: Average of accuracy in the test set with NB classifier and SV as a integration method in auto-mpg dataset.



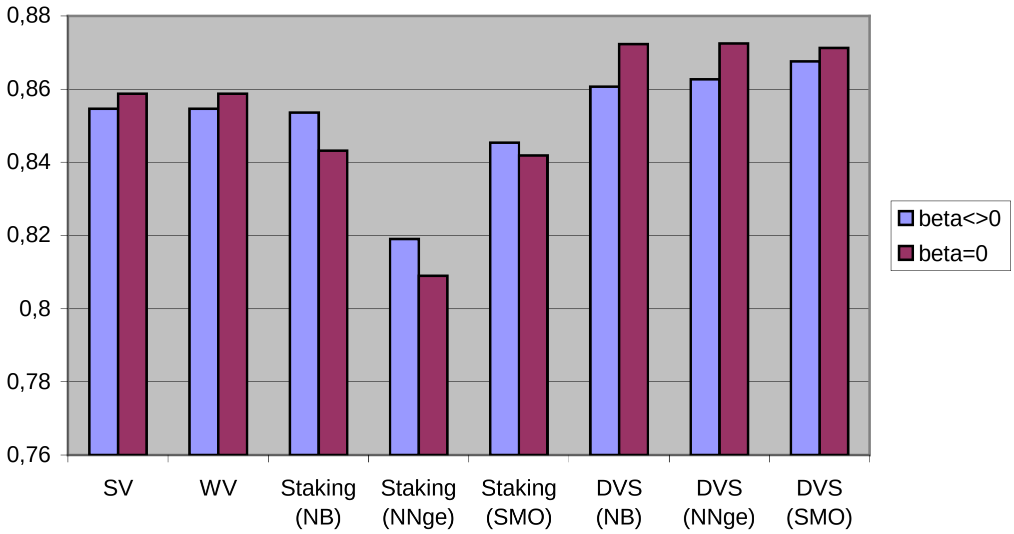
Graph 6: Average of accuracy in the validation set with NB classifier and SV as a integration method in auto-mpg dataset.

Now we are going to present the results obtained in the final validation experiments done as it has been explained in point 5.1. The average of accuracy depending on the integration methods are presented in the following graphs. The next graph shows the results using NB in genetic search.



Graph 7: Average of accuracy with the pre-selected *alpha-beta* values using NB in several datasets.

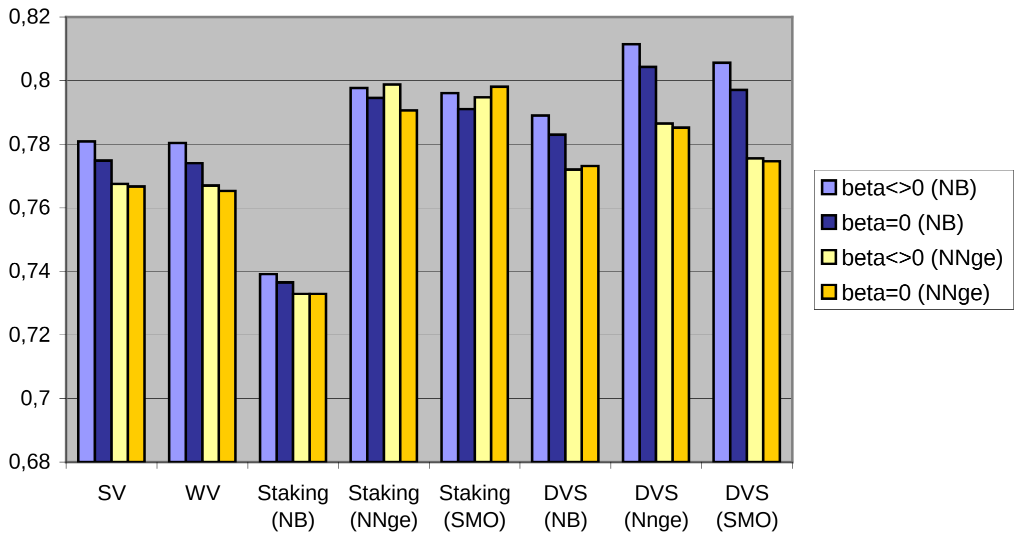
This graph has been made from the result obtained with the pre-selected *alpha-beta* values. Note that all this pre-selected values have been obtained using NNge in dynamic integration methods so the lower accuracy in the other dynamic methods could be due to that. The following graph shows the results using NNge in genetic search.



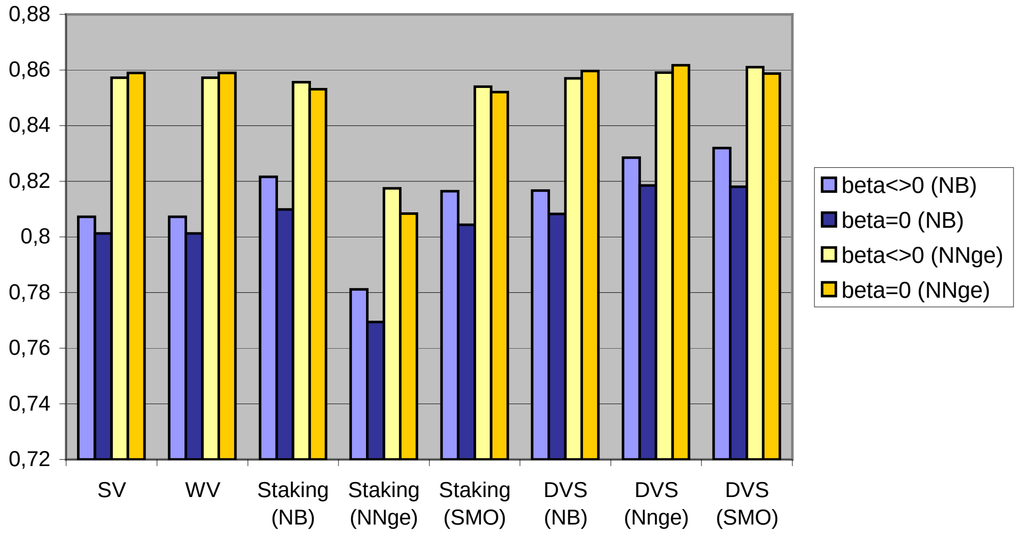
Graph 8: Average of accuracy with the pre-selected *alpha-beta* values using NNge in several datasets.

On this case, the use of *beta* does not obtain good results on average. That is because, surprisingly, in some datasets, the results obtained are not the expected-ones in cross validation and this has been reflected in the accuracy's average. A 10-time 10-fold cross validation can be done in order to obtain a more accurate behavior's prediction of the GA-SEFS.

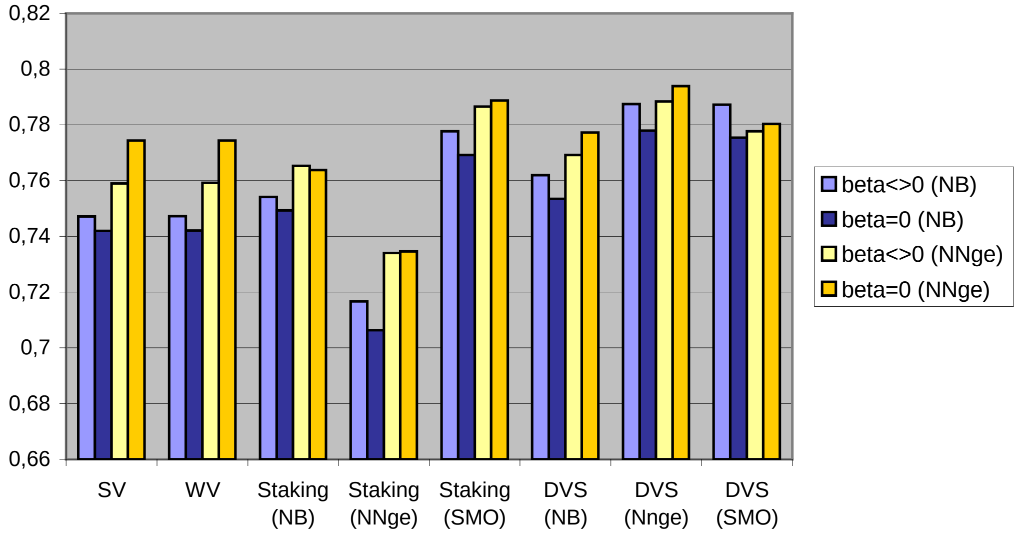
For each run of the GA, the base classifiers have been trained using the three classifier algorithms (NB, NNge, SMO) and its results have been integrated using all the integration methods, independently of the *alpha* and *beta* values so, in the following graphs, we can see the accuracy for several combination of *alpha-beta* and different datasets. From these results we could see that using NNge in genetic search (the series on yellow) GA-SEFS is able to obtain better results than using NB (series on blue). We could also see that the feature subsets created depends on the classifier algorithm used in genetic search and the highest accuracy for a given algorithm is obtained when the base classifiers are build with the same classifier algorithm used in the genetic search.



Graph 9: Average of accuracy obtained with NB from the subsets created by GA-SEFS using NB (on blue) and NNge (on yellow) for several values of *alpha* and *beta* and different datasets.

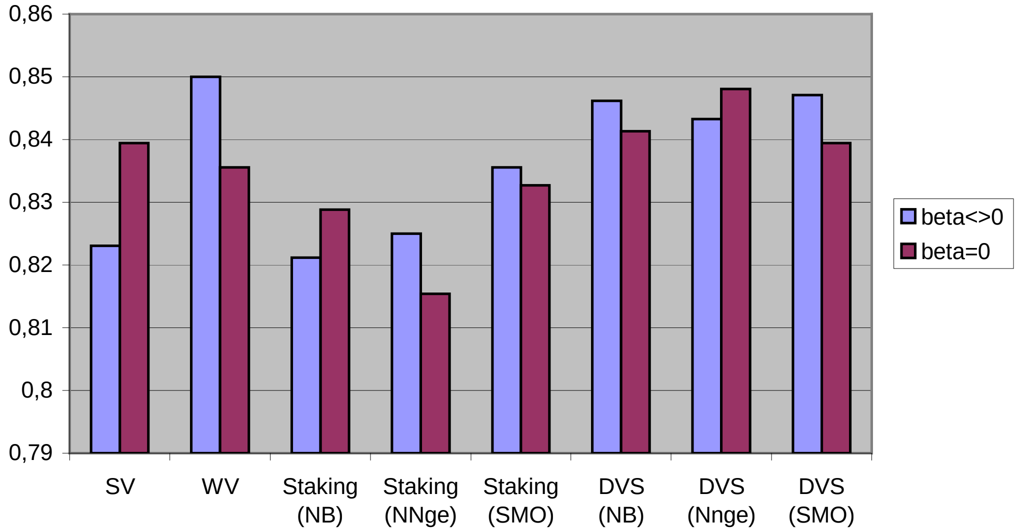


Graph 10: Average of accuracy obtained with NNge from the subsets created by GA-SEFS using NB (on blue) and NNge (on yellow) for several values of *alpha* and *beta* and different datasets.

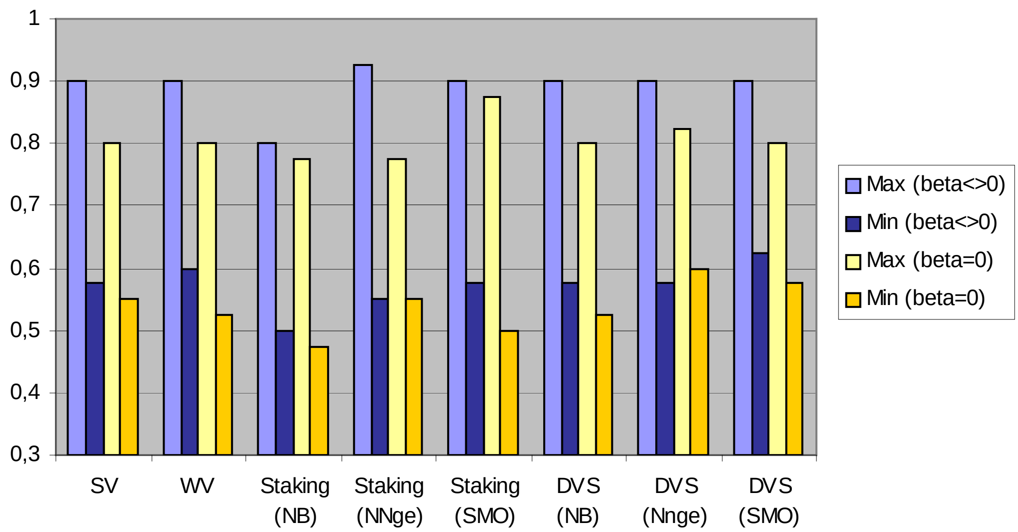


Graph 11: Average of accuracy obtained with SMO from the subsets created by GA-SEFS using NB (on blue) and NNge (on yellow) for several values of *alpha* and *beta* and different datasets.

We have seen the accuracy average for some *alpha-beta* combinations and all the datasets, getting an idea of the behaviour of the genetic search. Now we are going to analyse more thoughtfully the results from two different datasets that have been introduced before, hepatitis-domain and auto-mpg. The following graphs has been make from the results obtained with the pre-selected best combinations of *alpha-beta* for each classifier algorithm and integration method (with NNge in Staking and DVS).

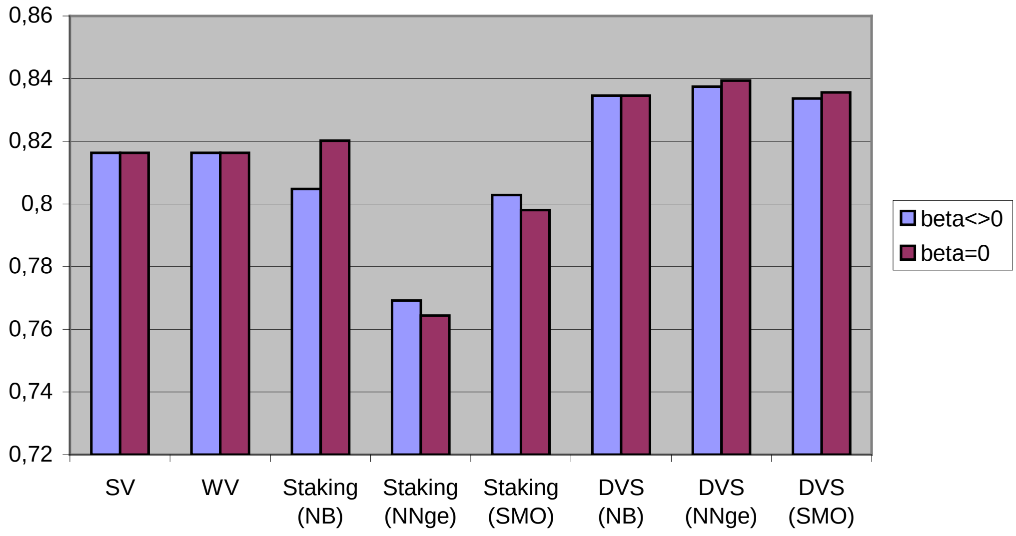


Graph 12: Average of accuracy for the best pre-selected *alpha* and *beta* values in hepatitis-domain dataset for some integration methods using NB.



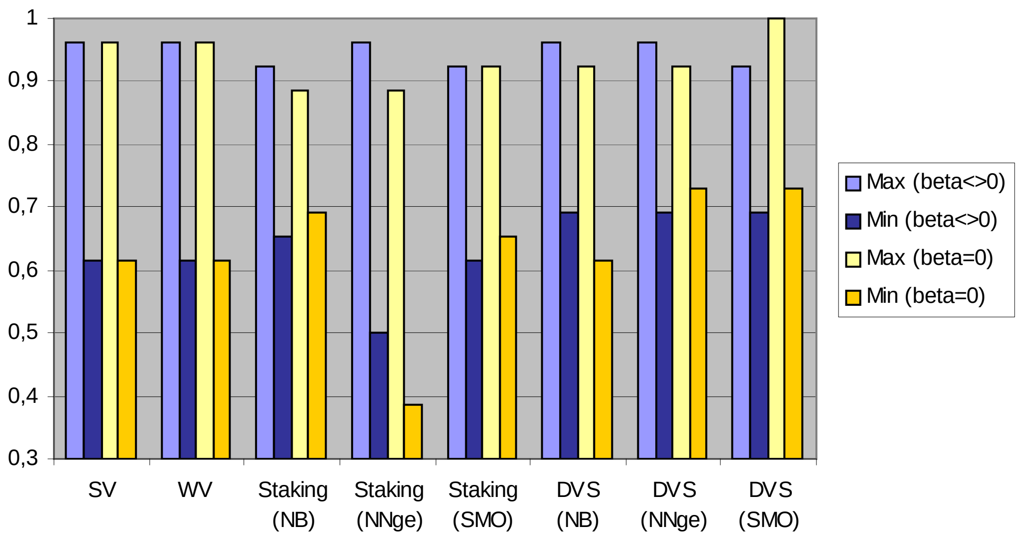
Graph 13: Accuracy's maximum and minimum for the best pre-selected *alpha* and *beta* values in hepatitis-domain dataset for some integration methods using NB.

We can see in the last graph that the maximum and the minimum are in the most of cases higher using the ensemble's complexity measure. However, we also can observe in the average accuracy graph, that this fact do not imply a higher accuracy.



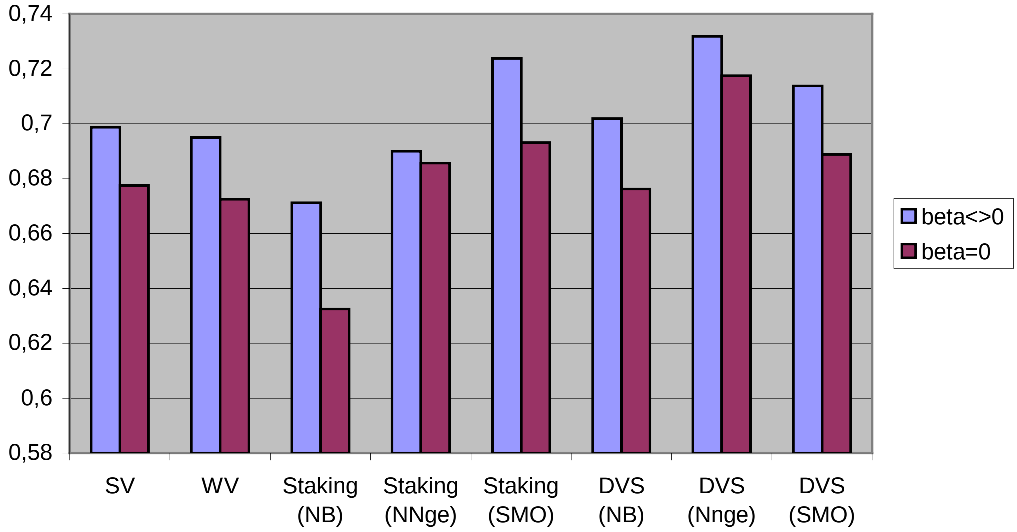
Graph 14: Average of accuracy for the best pre-selected *alpha* and *beta* values in hepatitis-domain dataset for some integration methods using NNge.

On this graph we can observe than SV or WV has the same accuracy both using and not using *beta*. This is because the selected *beta* value has been 0. We can also see that in some cases, such as in Staking with NB, we obtain higher accuracy without using *beta*, against the expected in cross validation. In the next graph we can see the maximum and minimum obtained with the same settings.

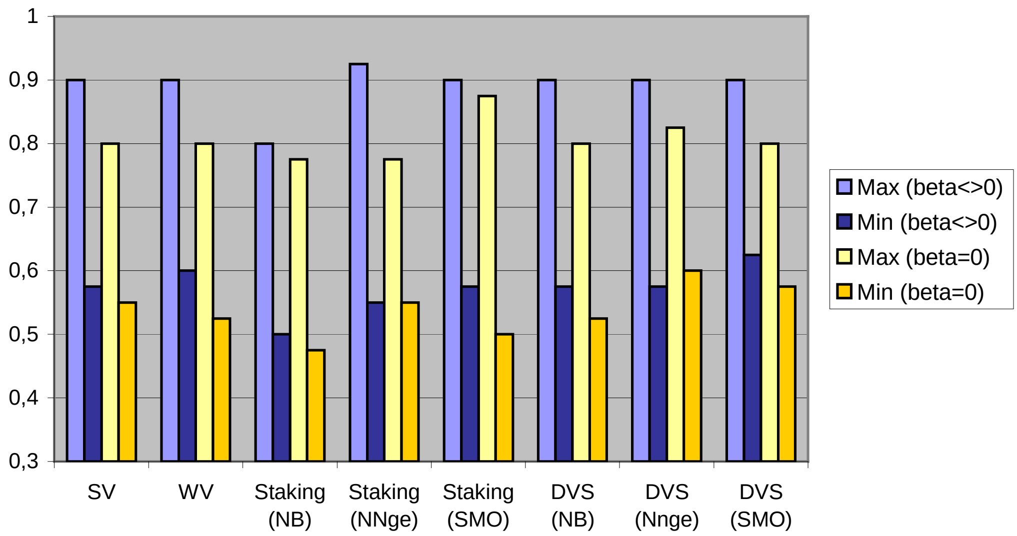


Graph 15: Accuracy's maximum and minimum for the best pre-selected *alpha* and *beta* values in hepatitis-domain dataset for some integration methods using NNge.

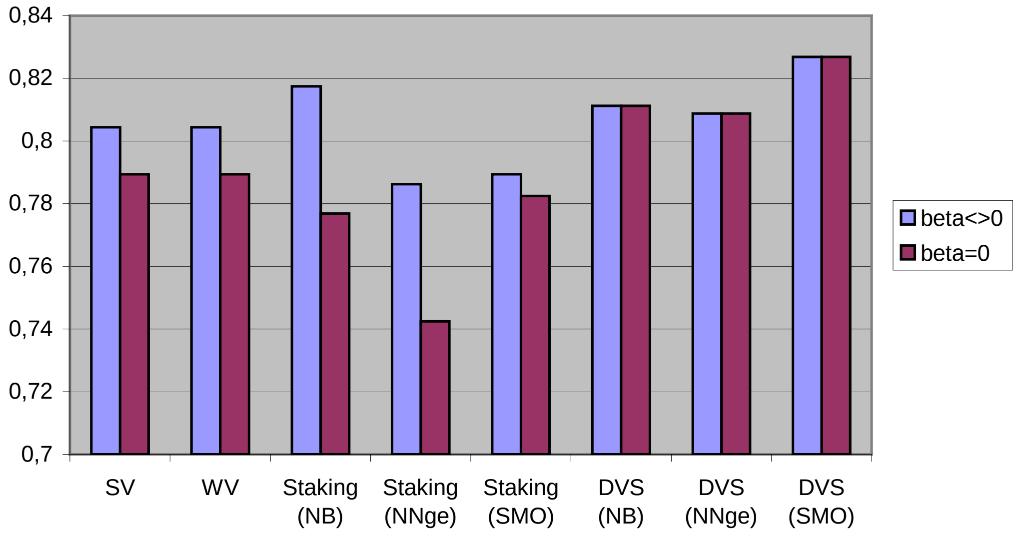
Finally, in the following graph from auto-mpg dataset, we can see that, the use of the complexity measure is clearly better when NB is used in genetic search. When NNge is used in the fitness function (the last graphs) the pre-selected *beta* value has been 0 in DVS, but with the other integration methods, better results have been obtained using different values of *beta*.



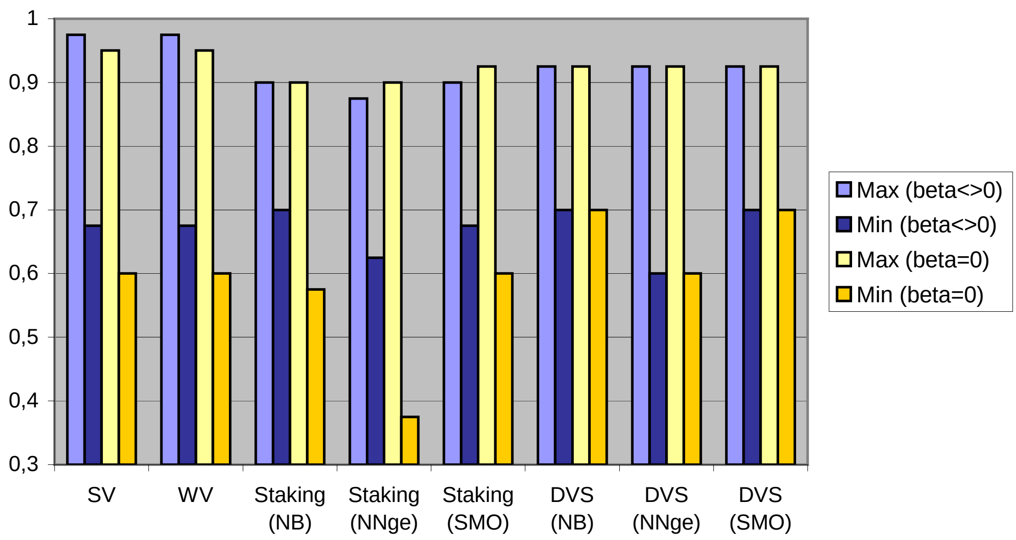
Graph 16: Average of accuracy for the best pre-selected *alpha* and *beta* values in auto-mpg dataset for some integration methods using NB.



Graph 17: The accuracy's maxim and minim for the best pre-selected *alpha* and *beta* values in auto-mpg dataset for some integration methods using NB.



Graph 18: Average of accuracy for the best pre-selected *alpha* and *beta* values in auto-mpg dataset for some integration methods using NNge.



Graph 19: The accuracy's maxim and minim for the best pre-selected *alpha* and *beta* values in auto-mpg dataset for some integration methods using NNge.

6. Conclusions

The good results obtained with GA-SEFS can be due to the fact that it starts with a base classifier with high accuracy and the other base classifiers are added sequentially to increase diversity. These base classifiers have also high accuracy so the accuracy of each base classifier is taken instead of the accuracy of the ensemble in the fitness function, making by this way an ensemble of diverse and accurate base classifiers.

It has been shown that ensembles build by GA-SEFS depend on the classifier algorithm and the integration method. This dependency on the classifier algorithm could be due at the peculiarities of each algorithm, such as variance and bias. On the same manner, the values of *alpha* and *beta*, which play an important role building the ensembles, also are dependent on these parameters and the datasets. This implies that before using this search method, we must find the *alpha-beta* values for which GA-SEFS is able to obtain the best results for the given dataset. The classifier algorithm to use in the fitness function can be chosen a priori, trying to find a balance between accuracy and speed. We can see in the experimental results that NNge can be a good candidate, so it is more accurate than NB and, in spite of spend more time on computing this can be supported in a practical situation. Not less important is the choice of a good integration method to obtain a good accuracy.

As we have seen in the last section, in most of the cases better results are achieved by controlling the number of features in the base classifiers. However, this fact depends mostly on the datasets and in some cases no improvements are achieved by using this control method. In any case, the fact that we can obtain ensembles with less features makes the ensemble simpler with the advantages that it has in terms of classification speed. The effect of using this measure of control, generally, is more deeply reflected in the simpler integration methods as SV or WV than in DVS which is the strongest method that has been implemented here.

The use of this measure to control the complexity of the ensemble has positive effects in most of the cases. This could be because controlling the number of features selected in the base classifiers we are also controlling the overfitting of the ensemble as we have seen in point 5.2. Moreover, the way this measure has been applied, weighting more as the ensemble size grows, allow us to control the overfitting of the whole ensemble by controlling the overfitting of each base classifier on a different way in function of the ensemble size. This has a positive effect so, as it has been shown in several studies, the overfitting at the level of base classifiers is more desirable than overfitting at the ensemble itself.

7. Acknowledgements

Primarily thanks to my family.

I would like to take this opportunity to thank my supervisor, Elena Marchiori for both giving me the opportunity to undertake this assignment an her help and guidance throughout the development of the project.

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My most sincere gratitude to everyone.

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Annex

In the following tables we can see the results obtained in cross validation for each dataset depending on the integration method and the classifier algorithm used in the fitness function. The results in validation set (ACC) and the ones in the test set (ACC test) has been collected so that we can see the different behaviours. The accuracy values which are higher than the average are highlighted in green for each table. The maximum of each table are in **bold** and the maximum obtained in the column where *beta*=0 are also highlighted on blue. The average of each line and column has been calculated and its maximums highlighted on red. We can see in the last tables the coverage of the data obtained, that is, if one of the base classifier can classify correctly a given instance from the test set. The average diversity and number of features selected, are also collected in two different tables.

Using NB in Genetic Search

Tic-tac-toe dataset

ACC SV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,714046	0,721327	0,731798	0,730768	0,727632	0,725114
0,125	0,712982	0,716118	0,723465	0,731798	0,730779	0,723029
0,25	0,718191	0,714024	0,720296	0,730757	0,728673	0,722388
0,5	0,721327	0,711952	0,722368	0,737018	0,730779	0,724689
1	0,703629	0,720274	0,709825	0,741195	0,740143	0,723013
2	0,685768	0,690987	0,692072	0,734879	0,733893	0,70752
4	0,674309	0,67534	0,674342	0,696239	0,711919	0,68643
8	0,673246	0,676404	0,681645	0,679561	0,687917	0,679754
	0,700437	0,703303	0,706976	0,722777	0,723967	

ACC test SV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,735764	0,738889	0,742014	0,7375	0,732986	0,737431
0,125	0,735069	0,739236	0,743403	0,735417	0,734028	0,737431
0,25	0,738194	0,737847	0,742014	0,735417	0,734028	0,7375
0,5	0,738194	0,739236	0,743403	0,739236	0,736111	0,739236
1	0,727083	0,726042	0,732639	0,739236	0,736111	0,732222
2	0,698264	0,696875	0,691319	0,728472	0,732639	0,709514
4	0,676736	0,675	0,670833	0,690278	0,713542	0,685278
8	0,674306	0,672569	0,675694	0,672917	0,684375	0,675972
	0,715451	0,715712	0,717665	0,722309	0,725477	

ACC WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,712982	0,714035	0,727621	0,732851	0,732851	0,724068
0,125	0,716129	0,714035	0,72136	0,732851	0,732851	0,723445
0,25	0,711941	0,714035	0,719265	0,732851	0,732851	0,722189
0,5	0,718202	0,71091	0,723421	0,735976	0,731798	0,724061
1	0,706765	0,722357	0,710866	0,740143	0,737007	0,723428
2	0,685768	0,692029	0,693114	0,733849	0,734956	0,707943
4	0,675351	0,676393	0,675384	0,705647	0,724463	0,691447
8	0,674298	0,676404	0,681645	0,682686	0,691053	0,681217
	0,70018	0,702525	0,706584	0,724607	0,727229	

ACC test WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,730903	0,731597	0,739236	0,734028	0,728819	0,732917
0,125	0,730556	0,733681	0,739236	0,732986	0,73125	0,733542
0,25	0,732292	0,735764	0,738194	0,733333	0,731944	0,734306
0,5	0,736111	0,737847	0,740972	0,7375	0,734375	0,737361
1	0,728472	0,726042	0,732639	0,737847	0,735417	0,732083
2	0,701042	0,697917	0,693056	0,728125	0,732292	0,710486
4	0,677431	0,676042	0,673958	0,698264	0,715625	0,688264
8	0,675347	0,674653	0,678125	0,676736	0,691667	0,679306
	0,714019	0,714193	0,716927	0,722352	0,725174	

ACC Staking

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,794485	0,766272	0,769331	0,744189	0,743136	0,763482
0,125	0,780822	0,779803	0,771425	0,734792	0,756776	0,764724
0,25	0,797511	0,800647	0,766151	0,7525	0,761974	0,775757
0,5	0,800768	0,766184	0,781798	0,768257	0,765219	0,776445
1	0,792226	0,765143	0,786042	0,7808	0,783893	0,781621
2	0,782873	0,782763	0,771338	0,783947	0,771447	0,778474
4	0,780746	0,775581	0,794419	0,788103	0,788202	0,78541
8	0,807873	0,787018	0,792281	0,794419	0,799529	0,796224
	0,792163	0,777926	0,779098	0,768376	0,771272	

ACC test SK

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,7875	0,771181	0,770139	0,741667	0,747222	0,763542
0,125	0,786111	0,782986	0,775	0,748264	0,76875	0,772222
0,25	0,795486	0,790625	0,785069	0,755208	0,776736	0,780625
0,5	0,780208	0,783681	0,798958	0,778819	0,778125	0,783958
1	0,798611	0,784375	0,789236	0,775347	0,770139	0,783542
2	0,786458	0,79375	0,796875	0,784375	0,776736	0,787639
4	0,790278	0,797222	0,8	0,786111	0,793403	0,793403
8	0,799653	0,810069	0,805208	0,796875	0,806597	0,803681
	0,790538	0,789236	0,790061	0,770833	0,777214	

ACC DVS

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,767281	0,748509	0,751612	0,742237	0,743279	0,750583
0,125	0,76625	0,752664	0,752664	0,743268	0,749529	0,752875
0,25	0,772478	0,770406	0,757895	0,743268	0,749529	0,758715
0,5	0,7808	0,781875	0,772489	0,753706	0,751623	0,768099
1	0,798575	0,784978	0,778783	0,756842	0,757884	0,775412
2	0,789145	0,786086	0,776634	0,777697	0,770395	0,779991
4	0,775614	0,781941	0,779781	0,773586	0,767237	0,775632
8	0,781908	0,779781	0,774572	0,773498	0,774572	0,776866
	0,779006	0,77328	0,768054	0,758013	0,758006	

ACC test DV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,76875	0,767708	0,755903	0,748611	0,744792	0,757153
0,125	0,767361	0,772222	0,757292	0,749653	0,745486	0,758403
0,25	0,78125	0,779514	0,764583	0,751042	0,746181	0,764514
0,5	0,782986	0,786111	0,775694	0,754514	0,746875	0,769236
1	0,783681	0,785069	0,7875	0,758333	0,752778	0,773472
2	0,782986	0,781944	0,771181	0,766667	0,766667	0,773889
4	0,768403	0,769792	0,772569	0,767708	0,761458	0,767986
8	0,764931	0,765625	0,764583	0,763194	0,765972	0,764861
	0,775043	0,775998	0,768663	0,757465	0,753776	

Diversity

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,095868	0,079299	0,053104	0,054542	0,057035	0,067969
0,125	0,099681	0,08759	0,060361	0,056819	0,069076	0,074706
0,25	0,124771	0,105701	0,074396	0,060042	0,072403	0,087462
0,5	0,150653	0,151965	0,122326	0,091535	0,080028	0,119301
1	0,19	0,191722	0,183264	0,126667	0,105868	0,159504
2	0,206993	0,206896	0,208319	0,171833	0,146771	0,188163
4	0,212278	0,213507	0,213076	0,202396	0,181042	0,20446
8	0,213653	0,213938	0,213618	0,212563	0,207042	0,212163
	0,161737	0,156327	0,141058	0,122049	0,114908	

Coverage

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,836806	0,840972	0,815972	0,793403	0,792014	0,815833
0,125	0,838889	0,844097	0,826042	0,795486	0,804514	0,821806
0,25	0,872917	0,869097	0,844792	0,804167	0,808681	0,839931
0,5	0,900694	0,906597	0,898958	0,844792	0,821875	0,874583
1	0,941667	0,944792	0,944792	0,89375	0,853472	0,915694
2	0,967014	0,962153	0,969444	0,933681	0,908333	0,948125
4	0,965972	0,969444	0,968403	0,957639	0,941319	0,960556
8	0,963889	0,968056	0,964931	0,964236	0,957292	0,963681
	0,910981	0,913151	0,904167	0,873394	0,860938	

% num feat

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,301	0,376	0,571	0,76	0,771	0,5558
0,125	0,296	0,36	0,561	0,76	0,777	0,5508
0,25	0,288	0,356	0,538	0,749	0,776	0,5414
0,5	0,268	0,319	0,472	0,735	0,768	0,5124
1	0,276	0,308	0,395	0,679	0,739	0,4794
2	0,289	0,301	0,342	0,588	0,657	0,4354
4	0,29	0,313	0,335	0,462	0,571	0,3942
8	0,312	0,322	0,335	0,372	0,441	0,3564
	0,29	0,331875	0,443625	0,638125	0,6875	

Using NB in Genetic Search

Glass dataset

ACC SV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,59026	0,595238	0,581169	0,595671	0,529221	0,578312
0,125	0,595238	0,59026	0,580952	0,581385	0,524459	0,574459
0,25	0,595022	0,599567	0,590476	0,571645	0,533983	0,578139
0,5	0,622078	0,585498	0,571429	0,59026	0,538745	0,581602
1	0,612771	0,6	0,594589	0,575758	0,54329	0,585974
2	0,616883	0,626407	0,608225	0,571212	0,557792	0,596104
4	0,603896	0,583983	0,570779	0,608225	0,571212	0,587619
8	0,574892	0,574675	0,603247	0,556061	0,533333	0,568442
	0,60138	0,594886	0,587608	0,581277	0,541504	

ACC test SV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,637596	0,642212	0,640649	0,603654	0,533918	0,611606
0,125	0,639231	0,648438	0,643798	0,594375	0,530817	0,611332
0,25	0,64226	0,649976	0,642236	0,588125	0,535457	0,611611
0,5	0,660817	0,64851	0,654663	0,59899	0,532428	0,619082
1	0,668702	0,66863	0,668678	0,606683	0,552428	0,633024
2	0,674856	0,671707	0,663942	0,637668	0,580264	0,645688
4	0,650072	0,651731	0,65012	0,64226	0,622236	0,643284
8	0,647043	0,628582	0,637716	0,613101	0,612933	0,627875
	0,652572	0,651223	0,650225	0,610607	0,56256	

ACC WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,590476	0,590693	0,590476	0,576623	0,54329	0,578312
0,125	0,6	0,595238	0,585714	0,562554	0,533983	0,575498
0,25	0,581169	0,599784	0,599784	0,566883	0,54329	0,578182
0,5	0,608009	0,59026	0,585498	0,580952	0,54329	0,581602
1	0,599567	0,575758	0,571429	0,552381	0,538528	0,567532
2	0,575541	0,599134	0,561905	0,561905	0,547835	0,569264
4	0,575758	0,580303	0,557359	0,580303	0,548052	0,568355
8	0,556926	0,556926	0,580087	0,551948	0,542424	0,557662
	0,585931	0,586012	0,579031	0,566694	0,542587	

ACC test WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,64226	0,639135	0,639063	0,572764	0,530841	0,604813
0,125	0,639207	0,646875	0,639135	0,569567	0,530841	0,605125
0,25	0,643774	0,654591	0,639135	0,566442	0,53238	0,607264
0,5	0,649928	0,659255	0,651514	0,569591	0,523101	0,610678
1	0,659255	0,659231	0,642332	0,569543	0,533918	0,612856
2	0,659279	0,637548	0,633101	0,588053	0,546274	0,612851
4	0,612788	0,629904	0,611298	0,575649	0,571034	0,600135
8	0,640817	0,619159	0,612885	0,591226	0,567764	0,60637
	0,643413	0,643212	0,633558	0,575355	0,542019	

ACC Staking

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,584199	0,561472	0,557143	0,599567	0,551948	0,570866
0,125	0,622078	0,584632	0,533333	0,5671	0,533766	0,568182
0,25	0,603463	0,565584	0,594156	0,565368	0,55671	0,577056
0,5	0,618182	0,570996	0,612338	0,570346	0,598052	0,593983
1	0,631602	0,607359	0,645238	0,644589	0,616667	0,629091
2	0,603247	0,612987	0,641126	0,612338	0,583983	0,610736
4	0,579437	0,622078	0,570346	0,612554	0,622078	0,601299
8	0,580087	0,589177	0,608225	0,556494	0,571645	0,581126
	0,602787	0,589286	0,595238	0,591044	0,579356	

ACC test SK

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,606827	0,580337	0,588053	0,581755	0,595865	0,590567
0,125	0,608149	0,609808	0,586514	0,592668	0,569639	0,593356
0,25	0,632957	0,59274	0,60649	0,581923	0,56488	0,595798
0,5	0,609567	0,606538	0,620481	0,583462	0,566418	0,597293
1	0,623389	0,618846	0,604952	0,623846	0,583702	0,610947
2	0,592716	0,606587	0,601923	0,622067	0,608317	0,606322
4	0,615865	0,608221	0,60649	0,617596	0,594399	0,608514
8	0,603678	0,587933	0,598846	0,595745	0,569519	0,591144
	0,611644	0,601376	0,601719	0,599883	0,581593	

ACC DVS

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,584848	0,575758	0,608442	0,609091	0,571645	0,589957
0,125	0,593939	0,593723	0,593939	0,613203	0,580736	0,595108
0,25	0,579654	0,593939	0,612554	0,612771	0,580519	0,595887
0,5	0,60368	0,598701	0,6171	0,603463	0,594805	0,60355
1	0,621645	0,635714	0,62619	0,594372	0,594372	0,614459
2	0,663636	0,663636	0,616883	0,603247	0,594156	0,628312
4	0,668398	0,630952	0,635498	0,62619	0,608009	0,63381
8	0,62619	0,616667	0,612121	0,617316	0,635281	0,621515
	0,617749	0,613636	0,615341	0,609957	0,59494	

ACC test DV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,632981	0,643918	0,647019	0,648534	0,60363	0,635216
0,125	0,637644	0,646995	0,65012	0,64238	0,60363	0,636154
0,25	0,640745	0,650072	0,648534	0,643822	0,606707	0,637976
0,5	0,665409	0,653125	0,66387	0,656226	0,611346	0,649995
1	0,671635	0,666875	0,659375	0,665553	0,642284	0,661144
2	0,680913	0,684038	0,665457	0,68875	0,657764	0,675385
4	0,697933	0,685553	0,679519	0,677909	0,66238	0,680659
8	0,68101	0,679519	0,667019	0,674784	0,676298	0,675726
	0,663534	0,663762	0,660114	0,662245	0,633005	

Diversity

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,147669	0,145949	0,139089	0,170521	0,164279	0,153502
0,125	0,175225	0,162196	0,158501	0,176307	0,167071	0,16786
0,25	0,208175	0,184015	0,180541	0,190599	0,171057	0,186878
0,5	0,286627	0,254517	0,229792	0,215801	0,188592	0,235066
1	0,350244	0,337918	0,33234	0,299422	0,265254	0,317036
2	0,392167	0,393012	0,383961	0,36567	0,336839	0,37433
4	0,407948	0,404963	0,406529	0,39751	0,389348	0,401259
8	0,413493	0,411952	0,413435	0,412631	0,407578	0,411818
	0,297694	0,286815	0,280523	0,278558	0,261252	

Coverage

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,76762	0,773798	0,770745	0,79387	0,784399	0,778087
0,125	0,803413	0,796995	0,792284	0,801563	0,793774	0,797606
0,25	0,834279	0,815697	0,810938	0,810889	0,80625	0,815611
0,5	0,875986	0,86363	0,840409	0,829495	0,824832	0,84687
1	0,897596	0,894495	0,892957	0,893029	0,880673	0,89175
2	0,908341	0,90988	0,909928	0,908389	0,900721	0,907452
4	0,909928	0,909928	0,913005	0,920793	0,914615	0,913654
8	0,906851	0,911466	0,913005	0,917692	0,917716	0,913346
	0,863002	0,859486	0,855409	0,859465	0,852873	

% num feat

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,33	0,358	0,39	0,561	0,663	0,4604
0,125	0,32	0,354	0,387	0,579	0,679	0,4638
0,25	0,308	0,347	0,39	0,58	0,681	0,4612
0,5	0,286	0,331	0,381	0,56	0,67	0,4456
1	0,26	0,291	0,334	0,505	0,605	0,399
2	0,242	0,267	0,3	0,417	0,524	0,35
4	0,247	0,256	0,273	0,351	0,402	0,3058
8	0,241	0,249	0,259	0,278	0,332	0,2718
	0,27925	0,306625	0,33925	0,478875	0,5695	

Using NB in Genetic Search

Hepatitis-domain dataset

ACC SV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,8075	0,80125	0,80791667	0,8275	0,84666667	0,81816667
0,125	0,80083333	0,80791667	0,80791667	0,83375	0,8275	0,81558333
0,25	0,80791667	0,795	0,80125	0,83333333	0,83375	0,81425
0,5	0,795	0,795	0,80166667	0,8275	0,83375	0,81058333
1	0,79541667	0,82041667	0,80708333	0,84041667	0,84	0,82066667
2	0,82125	0,84	0,85958333	0,84666667	0,84666667	0,84283333
4	0,83291667	0,84041667	0,8275	0,84625	0,84666667	0,83875
8	0,82083333	0,82708333	0,85958333	0,83291667	0,84	0,83608333
	0,81020833	0,81588542	0,8215625	0,83604167	0,839375	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,91702128	0,92340426	0,92340426	0,88085106	0,84255319	0,89744681
0,125	0,92340426	0,92765957	0,92340426	0,8893617	0,83617021	0,9
0,25	0,9212766	0,92978723	0,92765957	0,89361702	0,83617021	0,90170213
0,5	0,92765957	0,93617021	0,92553191	0,88297872	0,83404255	0,9012766
1	0,93191489	0,94468085	0,94255319	0,8893617	0,83829787	0,9093617
2	0,92978723	0,93404255	0,93404255	0,89148936	0,84042553	0,90595745
4	0,88723404	0,87659574	0,87659574	0,87021277	0,84680851	0,87148936
8	0,83829787	0,84468085	0,85106383	0,82765957	0,83191489	0,8387234
	0,90957447	0,91462766	0,91303191	0,87819149	0,83829787	

ACC WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,80125	0,80791667	0,80791667	0,82125	0,85291667	0,81825
0,125	0,82041667	0,81458333	0,80791667	0,83375	0,83375	0,82208333
0,25	0,80791667	0,80166667	0,80791667	0,8275	0,84	0,817
0,5	0,81416667	0,795	0,80166667	0,8275	0,83375	0,81441667
1	0,80166667	0,81416667	0,81375	0,85333333	0,84	0,82458333
2	0,82125	0,84	0,85333333	0,84666667	0,85333333	0,84291667
4	0,82708333	0,82791667	0,84083333	0,85958333	0,84666667	0,84041667
8	0,82791667	0,84041667	0,84666667	0,84	0,84041667	0,83908333
	0,81520833	0,81770833	0,8225	0,83869792	0,84260417	

ACC test WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,90425532	0,91914894	0,91914894	0,88297872	0,83617021	0,89234043
0,125	0,9106383	0,91702128	0,92340426	0,88085106	0,82765957	0,89191489
0,25	0,91276596	0,9212766	0,92340426	0,88510638	0,82765957	0,89404255
0,5	0,91489362	0,92340426	0,9212766	0,87234043	0,82553191	0,89148936
1	0,91702128	0,92978723	0,92340426	0,86382979	0,8212766	0,89106383
2	0,90638298	0,90425532	0,90638298	0,87021277	0,8212766	0,88170213
4	0,86382979	0,85531915	0,85106383	0,84893617	0,83617021	0,85106383
8	0,82340426	0,82340426	0,83191489	0,81914894	0,83404255	0,82638298
	0,89414894	0,89920213	0,9	0,86542553	0,8287234	

ACC

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,80833333	0,78916667	0,82041667	0,81375	0,80666667	0,80766667
0,125	0,80833333	0,81333333	0,81958333	0,82708333	0,8075	0,81516667
0,25	0,78208333	0,76958333	0,75041667	0,84625	0,79375	0,78841667
0,5	0,81416667	0,80166667	0,75458333	0,79458333	0,80166667	0,79333333
1	0,84625	0,79416667	0,83333333	0,79541667	0,815	0,81683333
2	0,80791667	0,8125	0,82666667	0,81291667	0,83291667	0,81858333
4	0,82083333	0,80125	0,80166667	0,82	0,80208333	0,80916667
8	0,78125	0,75625	0,81958333	0,83916667	0,80791667	0,80083333
	0,80864583	0,79223958	0,80328125	0,81864583	0,8084375	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,78297872	0,82553191	0,84255319	0,79148936	0,7893617	0,80638298
0,125	0,82340426	0,81702128	0,83191489	0,80212766	0,78297872	0,81148936
0,25	0,8	0,81914894	0,81276596	0,80638298	0,78085106	0,80382979
0,5	0,79148936	0,80638298	0,80638298	0,75957447	0,76382979	0,78553191
1	0,77659574	0,80425532	0,82765957	0,75957447	0,78297872	0,79021277
2	0,80851064	0,7893617	0,77659574	0,77234043	0,8	0,7893617
4	0,78510638	0,79787234	0,77021277	0,76808511	0,80425532	0,78510638
8	0,78510638	0,7893617	0,81276596	0,76170213	0,76808511	0,78340426
	0,79414894	0,80611702	0,81010638	0,77765957	0,78404255	

ACC DVS

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,80166667	0,80125	0,81416667	0,81458333	0,85291667	0,81691667
0,125	0,8075	0,81416667	0,81416667	0,84666667	0,84041667	0,82458333
0,25	0,8075	0,80791667	0,81416667	0,83333333	0,84	0,82058333
0,5	0,795	0,79458333	0,81458333	0,8275	0,83375	0,81308333
1	0,80125	0,81375	0,82041667	0,84	0,84	0,82308333
2	0,83375	0,86583333	0,84583333	0,83333333	0,8525	0,84625
4	0,82	0,83333333	0,84708333	0,83333333	0,84666667	0,83608333
8	0,82666667	0,83291667	0,8525	0,83375	0,84625	0,83841667
	0,81166667	0,82046875	0,82786458	0,8328125	0,8440625	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,9106383	0,9212766	0,91914894	0,88297872	0,84042553	0,89489362
0,125	0,91914894	0,9212766	0,92553191	0,89148936	0,83829787	0,89914894
0,25	0,93191489	0,92340426	0,92553191	0,9	0,84042553	0,90425532
0,5	0,92765957	0,92978723	0,92978723	0,88297872	0,84468085	0,90297872
1	0,9106383	0,92765957	0,93191489	0,88085106	0,84042553	0,89829787
2	0,89787234	0,93404255	0,90212766	0,87234043	0,83617021	0,88851064
4	0,87234043	0,86170213	0,86595745	0,87446809	0,84893617	0,86468085
8	0,84042553	0,84468085	0,85319149	0,82553191	0,83617021	0,84
	0,90132979	0,90797872	0,90664894	0,87632979	0,84069149	

Diversity

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,06246809	0,05697872	0,0613617	0,06710638	0,06923404	0,06342979
0,125	0,0666383	0,06514894	0,07714894	0,07940426	0,07570213	0,07280851
0,25	0,07242553	0,07378723	0,07710638	0,08421277	0,07468085	0,07644255
0,5	0,10012766	0,09191489	0,09242553	0,09859574	0,08225532	0,09306383
1	0,15982979	0,15348936	0,15319149	0,12957447	0,11055319	0,14132766
2	0,22965957	0,22829787	0,23187234	0,20089362	0,16493617	0,21113191
4	0,26523404	0,26787234	0,26587234	0,2547234	0,23	0,25674043
8	0,27621277	0,27685106	0,27361702	0,27514894	0,26855319	0,2740766
	0,15407447	0,15179255	0,15407447	0,14870745	0,13448936	

Coverage

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,97021277	0,97021277	0,9787234	0,96808511	0,96382979	0,97021277
0,125	0,9787234	0,9787234	0,98297872	0,97659574	0,96808511	0,97702128
0,25	0,97659574	0,9787234	0,98297872	0,97659574	0,96595745	0,97617021
0,5	0,9893617	0,9893617	0,99148936	0,98510638	0,97021277	0,98510638
1	0,99787234	0,99787234	0,99787234	0,99574468	0,98723404	0,99531915
2	0,99787234	0,99787234	0,99787234	0,99787234	0,99574468	0,99744681
4	0,99787234	0,99787234	0,99787234	0,99787234	0,99361702	0,99702128
8	0,99574468	0,99787234	0,99574468	0,99787234	0,99787234	0,99702128
	0,98803191	0,98856383	0,99069149	0,98696809	0,98031915	

% num feat

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,2225	0,268	0,3925	0,691	0,7855	0,4719
0,125	0,2375	0,2735	0,384	0,703	0,7945	0,4785
0,25	0,227	0,276	0,385	0,7045	0,791	0,4767
0,5	0,211	0,2715	0,387	0,7275	0,7975	0,4789
1	0,203	0,249	0,384	0,711	0,782	0,4658
2	0,221	0,2685	0,3785	0,603	0,7195	0,4381
4	0,2595	0,283	0,347	0,4975	0,6085	0,3991
8	0,285	0,295	0,354	0,4245	0,473	0,3663
	0,2333125	0,2730625	0,3765	0,63275	0,7189375	

Using NB in Genetic Search

Auto-mpg dataset

ACC SV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,695833	0,6875	0,679167	0,666667	0,654167	0,676667
0,125	0,7	0,691667	0,683333	0,6625	0,654167	0,678333
0,25	0,7	0,708333	0,6875	0,658333	0,654167	0,681667
0,5	0,704167	0,7125	0,6875	0,658333	0,65	0,6825
1	0,695833	0,704167	0,695833	0,683333	0,658333	0,6875
2	0,7	0,7	0,683333	0,675	0,6625	0,684167
4	0,683333	0,683333	0,670833	0,683333	0,679167	0,68
8	0,691667	0,666667	0,666667	0,666667	0,675	0,673333
	0,696354	0,694271	0,681771	0,669271	0,660938	

ACC test SV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,691667	0,722222	0,693056	0,670833	0,634722	0,6825
0,125	0,684722	0,720833	0,713889	0,6625	0,630556	0,6825
0,25	0,691667	0,713889	0,720833	0,656944	0,625	0,681667
0,5	0,706944	0,722222	0,720833	0,6625	0,623611	0,687222
1	0,706944	0,725	0,726389	0,686111	0,627778	0,694444
2	0,704167	0,7125	0,729167	0,6875	0,648611	0,696389
4	0,706944	0,706944	0,704167	0,695833	0,658333	0,694444
8	0,675	0,677778	0,681944	0,684722	0,684722	0,680833
	0,696007	0,712674	0,711285	0,675868	0,641667	

ACC WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,695833	0,683333	0,670833	0,666667	0,658333	0,675
0,125	0,695833	0,6875	0,683333	0,658333	0,658333	0,676667
0,25	0,695833	0,695833	0,6875	0,654167	0,658333	0,678333
0,5	0,7	0,704167	0,6875	0,658333	0,654167	0,680833
1	0,6875	0,6875	0,679167	0,675	0,658333	0,6775
2	0,691667	0,691667	0,683333	0,670833	0,6625	0,68
4	0,679167	0,6625	0,666667	0,6625	0,683333	0,670833
8	0,666667	0,658333	0,658333	0,654167	0,675	0,6625
	0,689063	0,683854	0,677083	0,6625	0,663542	

ACC test WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,684722	0,708333	0,693056	0,656944	0,625	0,673611
0,125	0,677778	0,705556	0,711111	0,654167	0,623611	0,674444
0,25	0,681944	0,698611	0,7125	0,647222	0,622222	0,6725
0,5	0,6875	0,709722	0,713889	0,65	0,623611	0,676944
1	0,690278	0,709722	0,713889	0,663889	0,625	0,680556
2	0,695833	0,702778	0,713889	0,6625	0,638889	0,682778
4	0,694444	0,690278	0,693056	0,666667	0,644444	0,677778
8	0,679167	0,688889	0,688889	0,676389	0,654167	0,6775
	0,686458	0,701736	0,705035	0,659722	0,632118	

ACC Staking

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,6625	0,679167	0,7	0,679167	0,675	0,679167
0,125	0,708333	0,683333	0,7	0,704167	0,6875	0,696667
0,25	0,6875	0,708333	0,708333	0,704167	0,6875	0,699167
0,5	0,725	0,691667	0,704167	0,720833	0,7375	0,715833
1	0,691667	0,7125	0,695833	0,658333	0,729167	0,6975
2	0,7	0,675	0,6875	0,675	0,708333	0,689167
4	0,679167	0,725	0,708333	0,7125	0,6875	0,7025
8	0,7125	0,720833	0,691667	0,7	0,7125	0,7075
	0,695833	0,699479	0,699479	0,694271	0,703125	

ACC test SK

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,672222	0,636111	0,652778	0,651389	0,6625	0,655
0,125	0,6625	0,655556	0,656944	0,651389	0,645833	0,654444
0,25	0,647222	0,659722	0,643056	0,651389	0,6625	0,652778
0,5	0,647222	0,631944	0,665278	0,661111	0,647222	0,650556
1	0,65	0,65	0,658333	0,656944	0,6625	0,655556
2	0,663889	0,651389	0,65	0,672222	0,648611	0,657222
4	0,665278	0,640278	0,6375	0,654167	0,656944	0,650833
8	0,655556	0,668056	0,645833	0,65	0,645833	0,653056
	0,657986	0,649132	0,651215	0,656076	0,653993	

ACC DVS

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,720833	0,720833	0,7	0,675	0,704167	0,704167
0,125	0,716667	0,720833	0,695833	0,683333	0,6625	0,695833
0,25	0,729167	0,7375	0,7375	0,725	0,7	0,725833
0,5	0,7125	0,758333	0,7	0,695833	0,6875	0,710833
1	0,716667	0,729167	0,733333	0,708333	0,729167	0,723333
2	0,720833	0,720833	0,729167	0,720833	0,733333	0,725
4	0,729167	0,720833	0,716667	0,7125	0,725	0,720833
8	0,720833	0,729167	0,704167	0,716667	0,725	0,719167
	0,720833	0,729688	0,714583	0,704688	0,708333	

ACC test DV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,672222	0,690278	0,698611	0,694444	0,6625	0,683611
0,125	0,684722	0,7	0,706944	0,695833	0,672222	0,691944
0,25	0,693056	0,698611	0,711111	0,686111	0,690278	0,695833
0,5	0,683333	0,709722	0,709722	0,690278	0,668056	0,692222
1	0,695833	0,672222	0,702778	0,688889	0,691667	0,690278
2	0,694444	0,709722	0,693056	0,693056	0,711111	0,700278
4	0,694444	0,683333	0,694444	0,713889	0,698611	0,696944
8	0,6875	0,665278	0,702778	0,675	0,690278	0,684167
	0,688194	0,691146	0,702431	0,692188	0,68559	

Diversity

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,167111	0,161806	0,093167	0,078417	0,0735	0,1148
0,125	0,172306	0,172222	0,158694	0,085611	0,074806	0,132728
0,25	0,175472	0,178389	0,17975	0,119528	0,104556	0,151539
0,5	0,180694	0,182167	0,183278	0,147278	0,1195	0,162583
1	0,192139	0,194028	0,193972	0,19525	0,154167	0,185911
2	0,204	0,205889	0,2055	0,199639	0,188778	0,200761
4	0,212778	0,213667	0,213611	0,210222	0,200778	0,210211
8	0,217389	0,217306	0,217417	0,215389	0,21075	0,21565
	0,190236	0,190684	0,180674	0,156417	0,140854	

Coverage

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,895833	0,895833	0,818056	0,777778	0,772222	0,831944
0,125	0,895833	0,897222	0,897222	0,790278	0,773611	0,850833
0,25	0,895833	0,895833	0,897222	0,870833	0,854167	0,882778
0,5	0,895833	0,897222	0,897222	0,891667	0,8875	0,893889
1	0,901389	0,9	0,9	0,891667	0,8875	0,896111
2	0,905556	0,906944	0,902778	0,894444	0,888889	0,899722
4	0,906944	0,906944	0,906944	0,901389	0,897222	0,903889
8	0,906944	0,906944	0,906944	0,905556	0,901389	0,905556
	0,900521	0,900868	0,890799	0,865451	0,857812	

% num feat

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,225	0,26375	0,37375	0,57	0,6525	0,417
0,125	0,22	0,25	0,3125	0,58375	0,6525	0,40375
0,25	0,22375	0,25625	0,3025	0,56375	0,64125	0,3975
0,5	0,2275	0,25875	0,305	0,55625	0,635	0,3965
1	0,23625	0,2675	0,30375	0,48375	0,59	0,37625
2	0,2525	0,27875	0,32125	0,4625	0,52625	0,36825
4	0,28	0,2975	0,32	0,41875	0,48125	0,3595
8	0,29125	0,30375	0,32375	0,375	0,4225	0,34325
	0,244531	0,272031	0,320313	0,501719	0,575156	

Using NB in Genetic Search

Zoo dataset

ACC SV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,88181818	0,88181818	0,91181818	0,93181818	0,94181818	0,90981818
0,125	0,88181818	0,89181818	0,92181818	0,95181818	0,94181818	0,91781818
0,25	0,89181818	0,87181818	0,90181818	0,93181818	0,94181818	0,90781818
0,5	0,88181818	0,89181818	0,91181818	0,96181818	0,97181818	0,92381818
1	0,90181818	0,89181818	0,96181818	0,95181818	0,94181818	0,92981818
2	0,91181818	0,91181818	0,94181818	0,94181818	0,96181818	0,93381818
4	0,90181818	0,90181818	0,86181818	0,92181818	0,94181818	0,90581818
8	0,87181818	0,86363636	0,86181818	0,88181818	0,88181818	0,87218182
	0,89056818	0,88829545	0,90931818	0,93431818	0,94056818	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,94505376	0,94182796	0,94182796	0,94182796	0,93215054	0,94053763
0,125	0,94182796	0,94182796	0,95150538	0,93537634	0,93215054	0,94053763
0,25	0,94182796	0,95150538	0,95150538	0,93860215	0,92892473	0,94247312
0,5	0,94827957	0,94505376	0,95150538	0,94182796	0,91924731	0,9411828
1	0,95150538	0,9611828	0,9644086	0,94182796	0,92569892	0,94892473
2	0,94827957	0,95473118	0,9644086	0,94827957	0,94182796	0,95150538
4	0,92236559	0,9255914	0,92892473	0,94505376	0,94505376	0,93339785
8	0,88043011	0,90301075	0,89978495	0,90623656	0,9255914	0,90301075
	0,93494624	0,9405914	0,94423387	0,93737903	0,93133065	

ACC WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,88181818	0,88181818	0,91181818	0,93181818	0,94181818	0,90981818
0,125	0,88181818	0,89181818	0,93181818	0,93181818	0,94181818	0,91581818
0,25	0,88181818	0,87181818	0,91181818	0,93181818	0,93181818	0,90581818
0,5	0,90181818	0,88181818	0,89181818	0,94181818	0,96181818	0,91581818
1	0,88181818	0,90181818	0,95181818	0,93181818	0,94181818	0,92181818
2	0,94181818	0,89181818	0,93181818	0,92181818	0,95181818	0,92781818
4	0,89181818	0,91181818	0,91181818	0,93181818	0,94181818	0,91781818
8	0,91181818	0,89181818	0,91181818	0,93181818	0,93181818	0,91581818
	0,89681818	0,89056818	0,91931818	0,93181818	0,94306818	

ACC test WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,93860215	0,93860215	0,93537634	0,93537634	0,93215054	0,93602151
0,125	0,94182796	0,93537634	0,94182796	0,93215054	0,92892473	0,93602151
0,25	0,93860215	0,93860215	0,94182796	0,93215054	0,91913978	0,93406452
0,5	0,93860215	0,94182796	0,94505376	0,92892473	0,91602151	0,93408602
1	0,93860215	0,93860215	0,94505376	0,92892473	0,91924731	0,93408602
2	0,93860215	0,94505376	0,94505376	0,93215054	0,92569892	0,93731183
4	0,91924731	0,94182796	0,92892473	0,93537634	0,93215054	0,93150538
8	0,9127957	0,91913978	0,93215054	0,93215054	0,92236559	0,92372043
	0,93336022	0,93737903	0,9394086	0,93215054	0,92446237	

ACC

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,88181818	0,88272727	0,91181818	0,94090909	0,93181818	0,90981818
0,125	0,87181818	0,88181818	0,92090909	0,93181818	0,93181818	0,90763636
0,25	0,89181818	0,91181818	0,90181818	0,93181818	0,93181818	0,91381818
0,5	0,88181818	0,88181818	0,90181818	0,94090909	0,93181818	0,90763636
1	0,91181818	0,90181818	0,89272727	0,91272727	0,93181818	0,91018182
2	0,91181818	0,87181818	0,88181818	0,91272727	0,94181818	0,904
4	0,86272727	0,87272727	0,88272727	0,86272727	0,89272727	0,87472727
8	0,89272727	0,84272727	0,88272727	0,87272727	0,89272727	0,87672727
	0,88829545	0,88090909	0,89704545	0,91329545	0,92329545	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,86752688	0,86741935	0,88688172	0,89655914	0,89655914	0,88298925
0,125	0,84172043	0,88688172	0,88043011	0,89333333	0,88365591	0,8772043
0,25	0,85784946	0,86430108	0,89010753	0,89333333	0,90623656	0,88236559
0,5	0,85451613	0,86107527	0,86096774	0,90301075	0,90946237	0,87780645
1	0,85795699	0,86419355	0,88688172	0,90301075	0,90623656	0,88365591
2	0,87387097	0,85129032	0,87709677	0,90623656	0,90946237	0,8835914
4	0,86096774	0,85451613	0,87709677	0,86096774	0,89322581	0,86935484
8	0,85129032	0,8283871	0,84806452	0,84806452	0,88032258	0,85122581
	0,85821237	0,85975806	0,87594086	0,88806452	0,89814516	

ACC DVS

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,91181818	0,88181818	0,91181818	0,93181818	0,94181818	0,91581818
0,125	0,88181818	0,89181818	0,92181818	0,95181818	0,94181818	0,91781818
0,25	0,89181818	0,88181818	0,89181818	0,93181818	0,93181818	0,90581818
0,5	0,88181818	0,90181818	0,91181818	0,96181818	0,97181818	0,92581818
1	0,91181818	0,89181818	0,96181818	0,93181818	0,94181818	0,92781818
2	0,90181818	0,90181818	0,94181818	0,93181818	0,96181818	0,92781818
4	0,89181818	0,90181818	0,94181818	0,92181818	0,94181818	0,91981818
8	0,89181818	0,85272727	0,91181818	0,90181818	0,91181818	0,894
	0,89556818	0,88818182	0,92431818	0,93306818	0,94306818	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,94505376	0,94182796	0,93860215	0,94182796	0,93215054	0,93989247
0,125	0,94182796	0,94182796	0,95150538	0,93537634	0,92892473	0,93989247
0,25	0,94182796	0,94505376	0,94827957	0,93860215	0,92892473	0,94053763
0,5	0,94827957	0,94505376	0,94505376	0,93860215	0,91924731	0,93924731
1	0,95150538	0,96763441	0,9611828	0,93860215	0,92247312	0,94827957
2	0,95473118	0,9611828	0,97408602	0,94827957	0,94182796	0,95602151
4	0,93537634	0,9644086	0,94827957	0,94817204	0,94505376	0,94825806
8	0,93860215	0,94172043	0,93215054	0,93860215	0,94172043	0,93855914
	0,94465054	0,95108871	0,94989247	0,94100806	0,93254032	

Diversity

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,00896774	0,00948387	0,00787097	0,01070968	0,01933548	0,01127355
0,125	0,01363226	0,01367742	0,02703226	0,01580645	0,02779355	0,01958839
0,25	0,02679355	0,02225806	0,03058065	0,01993548	0,03076344	0,02606624
0,5	0,04532903	0,0356129	0,0363871	0,03822796	0,03718925	0,03854925
1	0,13070968	0,09762151	0,07699355	0,05847097	0,05170538	0,08310022
2	0,32464086	0,30356129	0,30273118	0,22877634	0,18069892	0,26808172
4	0,36377419	0,36187957	0,36076559	0,33669677	0,3139914	0,34742151
8	0,3760172	0,37663871	0,37441075	0,36890753	0,35727097	0,37064903
	0,16123306	0,15259167	0,15209651	0,1346914	0,12734355	

Coverage

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,9611828	0,95795699	0,95473118	0,95473118	0,94827957	0,95537634
0,125	0,95795699	0,9644086	0,97408602	0,9611828	0,9644086	0,9644086
0,25	0,97731183	0,97731183	0,98376344	0,9644086	0,96763441	0,97408602
0,5	0,98698925	0,98698925	0,98698925	0,97731183	0,97731183	0,98311828
1	0,98698925	0,98698925	0,98698925	0,98698925	0,98376344	0,98634409
2	0,98698925	0,98698925	0,98698925	0,98698925	0,98698925	0,98698925
4	0,98376344	0,98698925	0,98698925	0,98698925	0,98698925	0,98634409
8	0,98698925	0,98376344	0,98376344	0,98698925	0,98698925	0,98569892
	0,97852151	0,97892473	0,98053763	0,97569892	0,9752957	

% num feat

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,33277778	0,32333333	0,59833333	0,80888889	0,83555556	0,57977778
0,125	0,32	0,33055556	0,58666667	0,81277778	0,84055556	0,57811111
0,25	0,32833333	0,34222222	0,58388889	0,81111111	0,84166667	0,58144444
0,5	0,33222222	0,35333333	0,58888889	0,80888889	0,84	0,58466667
1	0,28111111	0,325	0,555	0,8	0,83277778	0,55877778
2	0,24944444	0,28555556	0,44111111	0,68722222	0,75666667	0,484
4	0,25333333	0,28222222	0,35277778	0,54777778	0,62611111	0,41244444
8	0,25055556	0,25277778	0,35055556	0,44555556	0,50388889	0,36066667
	0,29347222	0,311875	0,50715278	0,71527778	0,75965278	

Using NB in Genetic Search

Horse-colic dataset

ACC SV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,84279279	0,83738739	0,8454955	0,82912913	0,79624625	0,83021021
0,125	0,83738739	0,84557057	0,84557057	0,81546547	0,80165165	0,82912913
0,25	0,84279279	0,84286787	0,85112613	0,79632132	0,79624625	0,82587087
0,5	0,8454955	0,84286787	0,85097598	0,81238739	0,80157658	0,83066066
1	0,84016517	0,84016517	0,82387387	0,80705706	0,79084084	0,82042042
2	0,8265015	0,83198198	0,82942943	0,82357357	0,80157658	0,82261261
4	0,80195195	0,80983483	0,81554054	0,7966967	0,80720721	0,80624625
8	0,76126126	0,79361862	0,77454955	0,78265766	0,78303303	0,77902402
	0,82479354	0,83053679	0,8295702	0,80791104	0,7972973	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,91261261	0,91441441	0,91621622	0,89099099	0,81081081	0,88900901
0,125	0,91261261	0,91891892	0,92072072	0,87477477	0,81261261	0,88792793
0,25	0,91441441	0,91531532	0,92522523	0,86576577	0,80540541	0,88522523
0,5	0,91711712	0,92252252	0,92522523	0,83963964	0,8	0,8809009
1	0,92162162	0,91981982	0,92072072	0,84954955	0,8027027	0,88288288
2	0,88378378	0,89189189	0,8972973	0,84684685	0,80990991	0,86594595
4	0,84234234	0,85675676	0,85135135	0,83063063	0,81171171	0,83855856
8	0,79009009	0,81441441	0,7954955	0,79099099	0,81171171	0,80054054
	0,88682432	0,89425676	0,89403153	0,84864865	0,80810811	

ACC WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,8454955	0,8454955	0,8454955	0,82642643	0,79354354	0,83129129
0,125	0,83738739	0,84286787	0,84016517	0,80720721	0,79354354	0,82423423
0,25	0,8481982	0,84557057	0,84834835	0,79894895	0,79346847	0,82690691
0,5	0,84286787	0,84834835	0,84557057	0,80698198	0,79887387	0,82852853
1	0,83746246	0,84557057	0,82665165	0,80705706	0,79084084	0,82151652
2	0,83183183	0,85382883	0,84016517	0,8234985	0,79624625	0,82911411
4	0,81291291	0,8289039	0,83460961	0,80202703	0,80165165	0,81602102
8	0,79121622	0,81253754	0,79632132	0,78798799	0,7963964	0,79689189
	0,83092155	0,84039039	0,83466592	0,80751689	0,79557057	

ACC test WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,90990991	0,91261261	0,91711712	0,87837838	0,80630631	0,88486486
0,125	0,91351351	0,91891892	0,91891892	0,85135135	0,80810811	0,88216216
0,25	0,91261261	0,91261261	0,92252252	0,84504505	0,7990991	0,87837838
0,5	0,91621622	0,91711712	0,91891892	0,83153153	0,7981982	0,8763964
1	0,91441441	0,91261261	0,91441441	0,83243243	0,79369369	0,87351351
2	0,88648649	0,8963964	0,89459459	0,82522523	0,8	0,86054054
4	0,86666667	0,86576577	0,86216216	0,81891892	0,8027027	0,84324324
8	0,83063063	0,83873874	0,81801802	0,81891892	0,80810811	0,82288288
	0,89380631	0,89684685	0,89583333	0,83772523	0,80202703	

ACC

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,82935435	0,82657658	0,80465465	0,8265015	0,83168168	0,82375375
0,125	0,83753754	0,81306306	0,80998498	0,82117117	0,7771021	0,81177177
0,25	0,78596096	0,84812312	0,82372372	0,79917417	0,78768769	0,80893393
0,5	0,82094595	0,82094595	0,82124625	0,81794294	0,81261261	0,81873874
1	0,8207958	0,84001502	0,82897898	0,80172673	0,82372372	0,82304805
2	0,83460961	0,81539039	0,80765766	0,79331832	0,83168168	0,81653153
4	0,82912913	0,81531532	0,8210961	0,81824324	0,81283784	0,81932432
8	0,81546547	0,80472973	0,82057057	0,82342342	0,81576577	0,81599099
	0,82172485	0,82301989	0,81723911	0,81268769	0,81163664	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,85675676	0,86936937	0,85495495	0,82702703	0,84054054	0,84972973
0,125	0,85315315	0,85585586	0,85945946	0,83063063	0,84684685	0,84918919
0,25	0,86666667	0,87927928	0,87567568	0,82882883	0,82432432	0,85495495
0,5	0,85765766	0,86396396	0,86756757	0,84954955	0,83333333	0,85441441
1	0,85315315	0,86756757	0,86306306	0,85045045	0,83243243	0,85333333
2	0,84144144	0,86666667	0,84504505	0,83963964	0,82522523	0,8436036
4	0,86306306	0,83963964	0,84414414	0,82342342	0,82072072	0,8381982
8	0,82702703	0,84414414	0,84144144	0,82612613	0,83423423	0,83459459
	0,85236486	0,86081081	0,85641892	0,83445946	0,83220721	

ACC DVS

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,84279279	0,83738739	0,8536036	0,83716216	0,79902402	0,83399399
0,125	0,84279279	0,84557057	0,84827327	0,81546547	0,79346847	0,82911411
0,25	0,84279279	0,84286787	0,86463964	0,80442943	0,80165165	0,83127628
0,5	0,85105105	0,8454955	0,8454955	0,80157658	0,80975976	0,83067568
1	0,83738739	0,8481982	0,83468468	0,80975976	0,79354354	0,82471471
2	0,84264264	0,84024024	0,82935435	0,80720721	0,79887387	0,82366366
4	0,82372372	0,84804805	0,8292042	0,82387387	0,81261261	0,82749249
8	0,82357357	0,82094595	0,80187688	0,82357357	0,80195195	0,81438438
	0,83834459	0,84109422	0,83839152	0,81538101	0,80136074	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,91351351	0,91441441	0,91531532	0,89279279	0,81531532	0,89027027
0,125	0,91351351	0,92162162	0,92432432	0,87477477	0,81801802	0,89045045
0,25	0,91531532	0,91981982	0,92522523	0,86216216	0,80990991	0,88648649
0,5	0,91621622	0,92522523	0,92882883	0,83783784	0,80900901	0,88342342
1	0,91801802	0,91981982	0,92522523	0,84774775	0,80720721	0,8836036
2	0,88288288	0,89369369	0,89369369	0,84324324	0,81801802	0,86630631
4	0,85405405	0,86486486	0,85315315	0,84324324	0,81801802	0,84666667
8	0,83063063	0,84054054	0,83603604	0,82792793	0,81711712	0,83045045
	0,89301802	0,9	0,90022523	0,85371622	0,81407658	

Diversity

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,03421622	0,03798198	0,03378378	0,07681081	0,07317117	0,05119279
0,125	0,0410991	0,03967568	0,04072072	0,07981982	0,07825225	0,05591351
0,25	0,04717117	0,04	0,04522523	0,08443243	0,07099099	0,05756396
0,5	0,06115315	0,05917117	0,05527928	0,088	0,07416216	0,06755315
1	0,1898018	0,17118919	0,14052252	0,12403604	0,09834234	0,14477838
2	0,31697297	0,31742342	0,30526126	0,23983784	0,17252252	0,2704036
4	0,34922523	0,35122523	0,34578378	0,32718919	0,28124324	0,33093333
8	0,35846847	0,35661261	0,35371171	0,35091892	0,33547748	0,35103784
	0,17476351	0,17165991	0,16503604	0,17138063	0,14802027	

Coverage

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,94594595	0,95225225	0,95225225	0,95855856	0,94864865	0,95153153
0,125	0,95135135	0,95405405	0,95315315	0,95855856	0,95225225	0,95387387
0,25	0,95225225	0,95315315	0,95495495	0,95765766	0,95405405	0,95441441
0,5	0,95585586	0,95855856	0,95765766	0,95945946	0,95675676	0,95765766
1	0,97837838	0,97837838	0,97837838	0,97567568	0,97117117	0,9763964
2	0,97837838	0,97927928	0,97927928	0,97747748	0,97747748	0,97837838
4	0,97837838	0,97927928	0,97837838	0,97927928	0,97657658	0,97837838
8	0,97837838	0,97927928	0,97927928	0,97927928	0,97747748	0,97873874
	0,96486486	0,96677928	0,96666667	0,96824324	0,9643018	

% num feat

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,16782609	0,20869565	0,28695652	0,57173913	0,75608696	0,39826087
0,125	0,16652174	0,20130435	0,28304348	0,62913043	0,75478261	0,40695652
0,25	0,16782609	0,20347826	0,29	0,64521739	0,78173913	0,41765217
0,5	0,16391304	0,20347826	0,30434783	0,68782609	0,78565217	0,42904348
1	0,12913043	0,16173913	0,28043478	0,65478261	0,77	0,39921739
2	0,1226087	0,14	0,19913043	0,53217391	0,67826087	0,33443478
4	0,1273913	0,14608696	0,17478261	0,33565217	0,4926087	0,25530435
8	0,14304348	0,15956522	0,17521739	0,23	0,32	0,20556522
	0,14853261	0,17804348	0,24923913	0,53581522	0,6673913	

Using NB in Genetic Search

Breast cancer dataset

ACC SV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,7135468	0,70972906	0,70652709	0,73805419	0,72758621	0,71908867
0,125	0,70652709	0,70985222	0,71009852	0,72770936	0,72770936	0,71637931
0,25	0,72068966	0,71330049	0,71366995	0,74150246	0,72758621	0,72334975
0,5	0,73091133	0,73103448	0,7137931	0,74507389	0,73460591	0,73108374
1	0,74864532	0,72438424	0,72758621	0,73472906	0,73115764	0,73330049
2	0,72795567	0,72783251	0,72081281	0,73805419	0,73472906	0,72987685
4	0,72795567	0,71736453	0,73128079	0,72783251	0,73115764	0,72711823
8	0,72783251	0,72081281	0,72450739	0,72770936	0,72783251	0,72573892
	0,725508	0,71928879	0,71853448	0,73508313	0,73029557	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,7755814	0,7755814	0,77325581	0,74883721	0,73255814	0,76116279
0,125	0,77209302	0,7744186	0,77906977	0,74418605	0,73372093	0,76069767
0,25	0,77674419	0,7744186	0,78139535	0,74418605	0,73488372	0,76232558
0,5	0,7744186	0,77790698	0,78023256	0,74767442	0,73953488	0,76395349
1	0,76511628	0,77674419	0,77093023	0,75348837	0,73953488	0,76116279
2	0,75465116	0,75581395	0,76162791	0,74069767	0,73604651	0,74976744
4	0,74302326	0,74418605	0,74302326	0,72906977	0,72790698	0,73744186
8	0,73255814	0,73488372	0,73255814	0,73837209	0,72790698	0,73325581
	0,76177326	0,76424419	0,76526163	0,74331395	0,73401163	

ACC WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,71009852	0,70628079	0,70652709	0,73448276	0,72758621	0,71699507
0,125	0,70665025	0,70972906	0,7137931	0,72758621	0,72758621	0,71706897
0,25	0,72413793	0,71342365	0,7067734	0,73103448	0,72758621	0,72059113
0,5	0,73435961	0,73115764	0,71022167	0,73805419	0,73103448	0,72896552
1	0,75221675	0,72795567	0,73448276	0,73817734	0,72770936	0,73610837
2	0,72795567	0,72783251	0,72426108	0,73460591	0,73472906	0,72987685
4	0,72450739	0,72081281	0,73128079	0,73128079	0,73128079	0,72783251
8	0,73128079	0,72081281	0,72783251	0,72426108	0,72426108	0,72568966
	0,72640086	0,71975062	0,71939655	0,73243534	0,72897167	

ACC test WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,77093023	0,77093023	0,76860465	0,75	0,73139535	0,75837209
0,125	0,77093023	0,77093023	0,76511628	0,74418605	0,73139535	0,75651163
0,25	0,76976744	0,76860465	0,76976744	0,74069767	0,73139535	0,75604651
0,5	0,77093023	0,76976744	0,76976744	0,74069767	0,73604651	0,75744186
1	0,75930233	0,76860465	0,75465116	0,74534884	0,73488372	0,75255814
2	0,75232558	0,74883721	0,75116279	0,72790698	0,73139535	0,74232558
4	0,74186047	0,73953488	0,73837209	0,72209302	0,72906977	0,73418605
8	0,73139535	0,73139535	0,72790698	0,73023256	0,72209302	0,72860465
	0,75843023	0,75857558	0,7556686	0,73764535	0,7309593	

ACC

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,71699507	0,7023399	0,64593596	0,71662562	0,62229064	0,68083744
0,125	0,67536946	0,64310345	0,66761084	0,68940887	0,61884236	0,658867
0,25	0,67857143	0,68238916	0,66465517	0,64778325	0,67820197	0,6703202
0,5	0,69236453	0,68953202	0,66083744	0,65812808	0,67475369	0,67512315
1	0,69889163	0,68226601	0,69211823	0,68534483	0,66428571	0,68458128
2	0,68214286	0,67438424	0,67820197	0,64729064	0,65763547	0,66793103
4	0,66403941	0,66416256	0,66108374	0,71724138	0,6682266	0,67495074
8	0,65369458	0,67179803	0,65751232	0,67906404	0,63669951	0,65975369
	0,68275862	0,67624692	0,66599446	0,68011084	0,652617	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,63604651	0,68023256	0,68604651	0,66511628	0,69767442	0,67302326
0,125	0,70465116	0,68372093	0,69302326	0,70348837	0,68023256	0,69302326
0,25	0,70581395	0,69302326	0,68023256	0,70581395	0,71046512	0,69906977
0,5	0,70813953	0,69186047	0,70581395	0,70697674	0,69767442	0,70209302
1	0,70930233	0,69302326	0,71744186	0,68488372	0,68023256	0,69697674
2	0,66627907	0,67674419	0,72093023	0,68139535	0,69883721	0,68883721
4	0,71046512	0,70930233	0,72325581	0,68023256	0,67325581	0,69930233
8	0,68837209	0,69418605	0,71395349	0,70232558	0,69883721	0,69953488
	0,69113372	0,69026163	0,70508721	0,69127907	0,69215116	

ACC DVS

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,70652709	0,70640394	0,71699507	0,74137931	0,72746305	0,71975369
0,125	0,70665025	0,72007389	0,71366995	0,71724138	0,74137931	0,71980296
0,25	0,72770936	0,72376847	0,73448276	0,72758621	0,72401478	0,72751232
0,5	0,74852217	0,74839901	0,7203202	0,74150246	0,73435961	0,73862069
1	0,73460591	0,74162562	0,73091133	0,73091133	0,72746305	0,73310345
2	0,73460591	0,74174877	0,72758621	0,74827586	0,71711823	0,733867
4	0,74839901	0,74864532	0,74150246	0,72438424	0,69963054	0,73251232
8	0,7520936	0,74864532	0,74495074	0,74519704	0,72068966	0,74231527
	0,73238916	0,73491379	0,72880234	0,73455973	0,72401478	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,7744186	0,77325581	0,77674419	0,75232558	0,73604651	0,76255814
0,125	0,7627907	0,77674419	0,77906977	0,75232558	0,73488372	0,76116279
0,25	0,75813953	0,77790698	0,76744186	0,75465116	0,72906977	0,75744186
0,5	0,75930233	0,76744186	0,77209302	0,75	0,7372093	0,7572093
1	0,74651163	0,75930233	0,76860465	0,75	0,74186047	0,75325581
2	0,74767442	0,75348837	0,75581395	0,74767442	0,74302326	0,74953488
4	0,74186047	0,74534884	0,73837209	0,73372093	0,72906977	0,73767442
8	0,74418605	0,72674419	0,74418605	0,73255814	0,72325581	0,73418605
	0,75436047	0,76002907	0,7627907	0,74665698	0,73430233	

Diversity

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,091	0,07167442	0,05951163	0,08490698	0,08702326	0,07882326
0,125	0,10327907	0,087	0,09290698	0,0925814	0,08702326	0,09255814
0,25	0,1415814	0,11406977	0,11118605	0,09986047	0,09251163	0,11184186
0,5	0,15374419	0,15602326	0,14772093	0,12234884	0,106	0,13716744
1	0,19111628	0,18616279	0,17906977	0,15148837	0,13053488	0,16767442
2	0,21009302	0,20872093	0,20944186	0,19027907	0,16869767	0,19744651
4	0,21760465	0,2205814	0,22102326	0,21183721	0,19323256	0,21285581
8	0,22153488	0,22248837	0,22190698	0,22088372	0,21432558	0,22022791
	0,16624419	0,15834012	0,15534593	0,14677326	0,1349186	

Coverage

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,8744186	0,87093023	0,85930233	0,88023256	0,87325581	0,87162791
0,125	0,88255814	0,88372093	0,89883721	0,88372093	0,8755814	0,88488372
0,25	0,93023256	0,91627907	0,91511628	0,89186047	0,88255814	0,9072093
0,5	0,93488372	0,93488372	0,93255814	0,91627907	0,89883721	0,92348837
1	0,94418605	0,94186047	0,93837209	0,9255814	0,91511628	0,93302326
2	0,94651163	0,94534884	0,94418605	0,93953488	0,93488372	0,94209302
4	0,94651163	0,94534884	0,94534884	0,94302326	0,94186047	0,9444186
8	0,94418605	0,94534884	0,94418605	0,94186047	0,94186047	0,94348837
	0,92543605	0,92296512	0,92223837	0,91526163	0,90799419	

% num feat

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,209	0,265	0,371	0,677	0,725	0,4494
0,125	0,202	0,253	0,399	0,698	0,73	0,4564
0,25	0,205	0,255	0,396	0,69	0,73	0,4552
0,5	0,202	0,246	0,381	0,667	0,716	0,4424
1	0,204	0,224	0,348	0,637	0,691	0,4208
2	0,205	0,228	0,313	0,555	0,624	0,385
4	0,24	0,266	0,329	0,458	0,561	0,3708
8	0,271	0,285	0,325	0,388	0,453	0,3444
	0,21725	0,25275	0,35775	0,59625	0,65375	

Using NB in Genetic Search

Wine dataset

ACC SV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,96111111	0,97222222	0,96111111	0,95	0,96111111	**0,96111111**
0,125	0,96078431	0,96666667	0,96666667	0,96111111	0,96111111	**0,96326797**
0,25	0,95522876	0,96666667	0,96111111	0,96111111	0,96111111	**0,96104575**
0,5	0,96666667	0,95555556	0,96111111	0,96111111	0,96111111	**0,96111111**
1	0,96078431	0,94411765	**0,98333333**	0,95555556	0,96111111	**0,96098039**
2	0,95555556	0,94411765	0,96666667	0,95555556	0,95555556	**0,9554902**
4	0,91666667	0,88888889	0,89411765	0,96111111	0,96111111	**0,92437908**
8	0,84379085	0,88333333	0,87712418	0,91078431	0,92777778	**0,88856209**
	0,94007353	**0,94019608**	**0,94640523**	**0,95204248**	**0,95625**	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	1	1	1	0,98888889	0,97592593	**0,99296296**
0,125	1	1	1	0,98518519	0,97592593	**0,99222222**
0,25	1	1	1	0,98148148	0,97592593	**0,99148148**
0,5	1	1	1	0,97592593	0,97592593	**0,99037037**
1	1	1	1	0,97777778	0,97592593	**0,99074074**
2	0,99444444	0,99814815	0,99814815	0,98333333	0,97592593	**0,99**
4	0,91481481	0,92592593	0,93888889	0,97037037	0,97962963	**0,94592593**
8	0,87592593	0,86851852	0,88703704	0,89814815	0,90555556	**0,88703704**
	0,97314815	**0,97407407**	**0,97800926**	**0,97013889**	**0,96759259**	

ACC WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,96111111	0,97222222	0,96111111	0,95	0,96111111	**0,96111111**
0,125	0,96078431	0,96666667	0,96666667	0,96111111	0,96111111	**0,96326797**
0,25	0,95522876	0,96666667	0,96666667	0,96111111	0,96111111	**0,96215686**
0,5	0,97222222	0,95555556	0,96111111	0,96111111	0,96111111	**0,96222222**
1	0,97189542	0,9496732	**0,97777778**	0,95555556	0,96111111	**0,96320261**
2	0,96666667	0,96078431	0,96666667	0,96111111	0,96111111	**0,96326797**
4	0,94444444	0,94444444	0,95	0,96666667	0,96666667	**0,95444444**
8	0,94411765	0,92222222	0,93300654	0,95	0,96111111	**0,9420915**
	0,95955882	**0,95477941**	**0,96037582**	**0,95833333**	**0,96180556**	

ACC test WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	1	1	1	0,98518519	0,97777778	**0,99259259**
0,125	1	1	1	0,98333333	0,97962963	**0,99259259**
0,25	1	1	1	0,97962963	0,97592593	**0,99111111**
0,5	1	1	1	0,97592593	0,97592593	**0,99037037**
1	1	1	1	0,98148148	0,97592593	**0,99148148**
2	1	1	1	0,98333333	0,97592593	**0,99185185**
4	0,96666667	0,98148148	0,98148148	0,98148148	0,98333333	**0,97888889**
8	0,9537037	0,95555556	0,95555556	0,97407407	0,97592593	**0,96296296**
	0,9900463	**0,99212963**	**0,99212963**	**0,98055556**	**0,9775463**	

ACC

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,96045752	0,97745098	0,95522876	0,95555556	0,96633987	**0,96300654**
0,125	0,95522876	0,96078431	**0,97777778**	0,95522876	0,97189542	**0,96418301**
0,25	0,94934641	0,96666667	0,96633987	0,97745098	0,9496732	**0,96189542**
0,5	0,95522876	0,96045752	0,96666667	0,96666667	0,9496732	**0,95973856**
1	0,9496732	0,95	0,97745098	0,96078431	0,96111111	**0,95980392**
2	0,96666667	0,9496732	0,96078431	0,96078431	0,93300654	**0,95418301**
4	0,92156863	0,97222222	0,95555556	0,94444444	0,9496732	**0,94869281**
8	0,96078431	0,96633987	0,94346405	0,95	0,91633987	**0,94738562**
	0,95236928	**0,96294935**	**0,9629085**	**0,95886438**	**0,94971405**	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	1	1	0,99444444	0,95925926	0,94259259	**0,97925926**
0,125	0,9962963	1	0,98888889	0,98703704	0,96851852	**0,98814815**
0,25	0,99444444	0,99814815	0,9962963	0,96481481	0,9462963	**0,98**
0,5	0,99814815	1	0,98518519	0,96666667	0,97407407	**0,98481481**
1	0,98518519	0,98518519	0,98888889	0,96111111	0,9462963	**0,97333333**
2	0,97777778	0,97222222	0,99259259	0,96851852	0,95555556	**0,97333333**
4	0,97222222	0,97407407	0,97962963	0,97037037	0,95185185	**0,96962963**
8	0,94259259	0,96851852	0,97222222	0,95740741	0,96666667	**0,96148148**
	0,98333333	**0,98726852**	**0,98726852**	**0,96689815**	**0,95648148**	

ACC DVS

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,96111111	0,97222222	0,96111111	0,95	0,96111111	**0,96111111**
0,125	0,96078431	0,96666667	0,96666667	0,96111111	0,96111111	**0,96326797**
0,25	0,95522876	0,96666667	0,96111111	0,96111111	0,96111111	**0,96104575**
0,5	0,96111111	0,96111111	0,96111111	0,96111111	0,96111111	**0,96111111**
1	0,97189542	0,9496732	**0,98333333**	0,95555556	0,96111111	**0,96431373**
2	0,95555556	0,96111111	0,96666667	0,96111111	0,96111111	**0,96111111**
4	0,94444444	0,93300654	0,92777778	0,95555556	0,96666667	**0,9454902**
8	0,9496732	0,91568627	0,93300654	0,92745098	0,92222222	**0,92960784**
	0,95747549	**0,95326797**	**0,95759804**	**0,95412582**	**0,95694444**	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	1	1	1	0,98888889	0,97592593	**0,99296296**
0,125	1	1	1	0,98518519	0,97592593	**0,99222222**
0,25	1	1	1	0,98148148	0,97592593	**0,99148148**
0,5	1	1	1	0,97592593	0,97592593	**0,99037037**
1	1	1	1	0,97777778	0,97592593	**0,99074074**
2	1	1	0,9962963	0,98518519	0,97777778	**0,99185185**
4	0,97592593	0,96481481	0,98148148	0,99259259	0,98333333	**0,97962963**
8	0,95	0,92962963	0,95740741	0,96481481	0,96296296	**0,95296296**
	0,99074074	**0,98680556**	**0,99189815**	**0,98148148**	**0,97546296**	

Diversity

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,00977778	0,002	0	0,01185185	0,01325926	**0,00737778**
0,125	0,01688889	0,00451852	0	0,01274074	0,01392593	**0,00961481**
0,25	0,02103704	0,00774074	0,00033333	0,01274074	0,01381481	**0,01113333**
0,5	0,02792593	0,01155556	0	0,01344444	0,01459259	**0,0135037**
1	0,13966667	0,11544444	0,033	0,02733333	0,02385185	**0,06785926**
2	0,346	0,34214815	0,33307407	0,21866667	0,13755556	**0,27548889**
4	0,40588889	0,40596296	0,39603704	0,34677778	0,31748148	**0,37442963**
8	0,42148148	0,42003704	0,41607407	0,40133333	0,38711111	**0,40920741**
	0,17358333	**0,16367593**	**0,14731481**	**0,13061111**	**0,11519907**	

Coverage

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	1	1	1	1	1	**1**
0,125	1	1	1	1	1	**1**
0,25	1	1	1	1	1	**1**
0,5	1	1	1	1	1	**1**
1	1	1	1	1	1	**1**
2	1	1	1	1	1	**1**
4	1	1	1	1	1	**1**
8	1	1	1	1	1	**1**
	1	**1**	**1**	**1**	**1**	

% num feat

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,295	0,33	0,52357143	0,79428571	0,81071429	**0,55071429**
0,125	0,27214286	0,32071429	0,53	0,78928571	0,815	**0,54542857**
0,25	0,26642857	0,30285714	0,52642857	0,80142857	0,82357143	**0,54414286**
0,5	0,255	0,28785714	0,52928571	0,805	0,82357143	**0,54014286**
1	0,19642857	0,22285714	0,47142857	0,81357143	0,81857143	**0,50457143**
2	0,17785714	0,17714286	0,27714286	0,61142857	0,735	**0,39571429**
4	0,15357143	0,16642857	0,19928571	0,38928571	0,475	**0,27671429**
8	0,14785714	0,15142857	0,16071429	0,23214286	0,31142857	**0,20071429**
	0,22053571	**0,24491071**	**0,40223214**	**0,65455357**	**0,70160714**	

Using NNge in Genetic Search

Tic-tac-toe dataset

ACC SV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,864287	0,879901	0,89136	0,894583	0,891393	0,884305
0,125	0,876787	0,877818	0,887182	0,897708	0,890428	0,885985
0,25	0,886217	0,889331	0,901831	0,909189	0,890362	0,895386
0,5	0,877895	0,892489	0,898794	0,890384	0,892445	0,890401
1	0,844463	0,913322	0,894572	0,906053	0,892489	0,89018
2	0,767204	0,81841	0,815263	0,879956	0,882061	0,832579
4	0,722379	0,721327	0,73591	0,786053	0,817314	0,756596
8	0,704583	0,685768	0,711908	0,73273	0,744254	0,715849
	0,817977	0,834796	0,842103	0,862082	0,862593	

ACC test SV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,907986	0,905208	0,897917	0,892361	0,883333	0,897361
0,125	0,912847	0,911806	0,904514	0,895486	0,8875	0,902431
0,25	0,916319	0,91875	0,910417	0,892361	0,890278	0,905625
0,5	0,917361	0,927083	0,921181	0,901736	0,893403	0,912153
1	0,904861	0,949653	0,946875	0,911806	0,901389	0,922917
2	0,872917	0,909722	0,93125	0,919792	0,901042	0,906944
4	0,779514	0,816319	0,829861	0,857986	0,873264	0,831389
8	0,736458	0,732639	0,745486	0,784722	0,804861	0,760833
	0,868533	0,883898	0,885938	0,882031	0,879384	

ACC WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,864287	0,879901	0,89136	0,894583	0,891393	0,884305
0,125	0,876787	0,877818	0,887182	0,897708	0,890428	0,885985
0,25	0,886217	0,889331	0,901831	0,909189	0,890362	0,895386
0,5	0,877895	0,892489	0,898794	0,890384	0,892445	0,890401
1	0,844463	0,913322	0,894572	0,906053	0,892489	0,89018
2	0,767204	0,81841	0,815263	0,879956	0,882061	0,832579
4	0,722379	0,721327	0,73591	0,786053	0,817314	0,756596
8	0,704583	0,685768	0,711908	0,73273	0,744254	0,715849
	0,817977	0,834796	0,842103	0,862082	0,862593	

ACC test WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,907986	0,905208	0,897917	0,892361	0,883333	0,897361
0,125	0,912847	0,911806	0,904514	0,895486	0,8875	0,902431
0,25	0,916319	0,91875	0,910417	0,892361	0,890278	0,905625
0,5	0,917361	0,927083	0,921181	0,901736	0,893403	0,912153
1	0,904861	0,949653	0,946875	0,911806	0,901389	0,922917
2	0,872917	0,909722	0,93125	0,919792	0,901042	0,906944
4	0,779514	0,816319	0,829861	0,857986	0,873264	0,831389
8	0,736458	0,732639	0,745486	0,784722	0,804861	0,760833
	0,868533	0,883898	0,885938	0,882031	0,879384	

ACC Staking

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,852763	0,863224	0,875746	0,864232	0,88307	0,867807
0,125	0,86534	0,846458	0,847522	0,867325	0,858015	0,856932
0,25	0,852752	0,853849	0,885154	0,858037	0,868509	0,86366
0,5	0,88409	0,880987	0,874737	0,833794	0,8767	0,870061
1	0,894649	0,885219	0,879879	0,896689	0,863246	0,883936
2	0,842434	0,858125	0,873739	0,866349	0,885055	0,86514
4	0,82352	0,795329	0,819419	0,833015	0,868509	0,827958
8	0,808925	0,792314	0,793213	0,841305	0,8225	0,811651
	0,853059	0,846938	0,856176	0,857593	0,8657	

ACC test SK

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,877431	0,837847	0,859722	0,872917	0,874306	0,864444
0,125	0,873611	0,863889	0,86875	0,877083	0,886806	0,874028
0,25	0,882986	0,894097	0,876042	0,886111	0,881944	0,884236
0,5	0,875694	0,885417	0,886458	0,878819	0,878819	0,881042
1	0,898264	0,890972	0,904167	0,880208	0,874306	0,889583
2	0,870833	0,881597	0,877778	0,890278	0,878472	0,879792
4	0,818403	0,838542	0,840625	0,859722	0,873264	0,846111
8	0,812153	0,801042	0,794444	0,811458	0,826389	0,809097
	0,863672	0,861675	0,863498	0,869575	0,871788	

ACC DVS

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,894419	0,914397	0,899759	0,903893	0,89455	0,901404
0,125	0,900779	0,902928	0,898706	0,896634	0,904002	0,90061
0,25	0,899726	0,908114	0,915461	0,912237	0,911261	0,90936
0,5	0,922741	0,922708	0,923827	0,914419	0,901853	0,91711
1	0,903969	0,923783	0,934211	0,904035	0,907061	0,914612
2	0,868575	0,889419	0,900943	0,917566	0,909189	0,897138
4	0,83	0,862281	0,855899	0,878914	0,884167	0,862252
8	0,830811	0,799627	0,824682	0,845559	0,851831	0,830502
	0,881377	0,890407	0,894186	0,896657	0,895489	

ACC test DV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,905556	0,906944	0,916319	0,907639	0,9	0,907292
0,125	0,917361	0,907986	0,917014	0,917014	0,905903	0,913056
0,25	0,911111	0,919097	0,921875	0,911458	0,909722	0,914653
0,5	0,915278	0,923958	0,925694	0,9125	0,902431	0,915972
1	0,918403	0,929861	0,938889	0,924306	0,917361	0,925764
2	0,889236	0,900347	0,912847	0,919097	0,912153	0,906736
4	0,84375	0,857986	0,852778	0,880208	0,883333	0,863611
8	0,836806	0,825694	0,847222	0,854167	0,869792	0,846736
	0,892188	0,896484	0,90408	0,903299	0,900087	

Diversity

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,206222	0,198153	0,193521	0,200715	0,207243	0,201171
0,125	0,213382	0,205458	0,200813	0,202347	0,212174	0,206835
0,25	0,222979	0,21375	0,206535	0,206688	0,214847	0,21296
0,5	0,244944	0,229313	0,223368	0,217007	0,22741	0,228408
1	0,321875	0,281569	0,264375	0,251701	0,256139	0,275132
2	0,412743	0,400278	0,381833	0,341688	0,329715	0,373251
4	0,447437	0,443785	0,438965	0,421958	0,395743	0,429578
8	0,453743	0,455049	0,45259	0,44809	0,4395	0,449794
	0,315416	0,303419	0,29525	0,286274	0,285346	

Coverage

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,999306	0,998958	0,997222	0,997917	0,998958	0,998472
0,125	0,999306	0,999306	0,998958	0,997569	0,998958	0,998819
0,25	0,999653	0,999653	0,999653	0,999306	0,998264	0,999306
0,5	0,999653	0,999653	1	0,999306	1	0,999722
1	1	1	1	1	1	1
2	1	1	1	1	1	1
4	1	1	1	1	1	1
8	1	1	1	1	1	1
	0,99974	0,999696	0,999479	0,999262	0,999523	

% num feat

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,627	0,658	0,687	0,746	0,763	0,6962
0,125	0,625	0,653	0,679	0,744	0,764	0,693
0,25	0,611	0,644	0,676	0,748	0,765	0,6888
0,5	0,573	0,627	0,664	0,746	0,767	0,6754
1	0,454	0,585	0,637	0,737	0,759	0,6344
2	0,383	0,448	0,505	0,662	0,698	0,5392
4	0,325	0,374	0,395	0,504	0,573	0,4342
8	0,32	0,321	0,338	0,398	0,443	0,364
	0,48975	0,53875	0,572625	0,660625	0,6915	

Glass dataset

ACC SV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,671212	0,686147	0,685714	0,677056	0,695887	0,683203
0,125	0,695238	0,667316	0,699567	0,652814	0,677273	0,678442
0,25	0,682468	0,67684	0,648268	0,658225	0,708874	0,674935
0,5	0,66342	0,704978	0,657576	0,681602	0,691342	0,679784
1	0,691342	0,699567	0,728571	0,648701	0,662338	0,686104
2	0,709957	0,760823	0,704978	0,690043	0,704762	0,714113
4	0,657359	0,714286	0,68658	0,69026	0,703463	0,69039
8	0,677056	0,667316	0,709091	0,727922	0,657792	0,687835
	0,681006	0,697159	0,690043	0,678328	0,687716	

ACC test SV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,832837	0,832885	0,825168	0,786322	0,772404	0,809923
0,125	0,840577	0,842188	0,832933	0,786298	0,772404	0,81488
0,25	0,857692	0,84988	0,843822	0,801803	0,764663	0,823572
0,5	0,86851	0,860793	0,856082	0,815793	0,772428	0,834721
1	0,882428	0,896442	0,887091	0,84375	0,792572	0,860457
2	0,891707	0,901034	0,899495	0,851538	0,825096	0,873774
4	0,854543	0,877716	0,863918	0,859183	0,842236	0,859519
8	0,837572	0,834495	0,83774	0,848365	0,833005	0,838236
	0,858233	0,861929	0,855781	0,824132	0,796851	

ACC WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,671212	0,686147	0,685714	0,677056	0,695887	0,683203
0,125	0,695238	0,667316	0,699567	0,652814	0,677273	0,678442
0,25	0,682468	0,67684	0,648268	0,658225	0,708874	0,674935
0,5	0,66342	0,704978	0,657576	0,681602	0,691342	0,679784
1	0,691342	0,699567	0,728571	0,648701	0,662338	0,686104
2	0,709957	0,760823	0,704978	0,690043	0,704762	0,714113
4	0,657359	0,714286	0,68658	0,69026	0,703463	0,69039
8	0,677056	0,667316	0,709091	0,727922	0,657792	0,687835
	0,681006	0,697159	0,690043	0,678328	0,687716	

ACC test WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,832837	0,832885	0,825168	0,786322	0,772404	0,809923
0,125	0,840577	0,842188	0,832933	0,786298	0,772404	0,81488
0,25	0,857692	0,84988	0,843822	0,801803	0,764663	0,823572
0,5	0,86851	0,860793	0,856082	0,815793	0,772428	0,834721
1	0,882428	0,896442	0,887091	0,84375	0,792572	0,860457
2	0,891707	0,901034	0,899495	0,851538	0,825096	0,873774
4	0,854543	0,877716	0,863918	0,859183	0,842236	0,859519
8	0,837572	0,834495	0,83774	0,848365	0,833005	0,838236
	0,858233	0,861929	0,855781	0,824132	0,796851	

ACC Staking

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,620346	0,55	0,522511	0,554762	0,569481	0,56342
0,125	0,621645	0,5829	0,535931	0,587879	0,584632	0,582597
0,25	0,546537	0,535931	0,544805	0,527706	0,587879	0,548571
0,5	0,582684	0,577706	0,541558	0,574242	0,583333	0,571905
1	0,615152	0,611472	0,587229	0,611472	0,601948	0,605455
2	0,602381	0,589177	0,582035	0,62987	0,533117	0,587316
4	0,596753	0,615152	0,612554	0,596753	0,570346	0,598312
8	0,607143	0,620346	0,584416	0,55974	0,583983	0,591126
	0,59908	0,585335	0,56388	0,580303	0,57684	

ACC test SK

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,656226	0,623678	0,631851	0,647067	0,643846	0,640534
0,125	0,647332	0,664303	0,658029	0,609976	0,586346	0,633197
0,25	0,656394	0,614952	0,607019	0,636154	0,588269	0,620558
0,5	0,695144	0,664183	0,599183	0,639375	0,592716	0,63812
1	0,671875	0,656322	0,656322	0,628462	0,636274	0,649851
2	0,636178	0,634639	0,63137	0,658101	0,597308	0,631519
4	0,597332	0,650192	0,643966	0,662644	0,648389	0,640505
8	0,622188	0,620913	0,613029	0,630264	0,623798	0,622038
	0,647834	0,641148	0,630096	0,639005	0,614618	

ACC DVS

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,672727	0,672727	0,672078	0,68658	0,677922	0,676407
0,125	0,691126	0,7	0,681602	0,67316	0,686364	0,68645
0,25	0,648485	0,681169	0,705195	0,667532	0,675974	0,675671
0,5	0,662987	0,705844	0,648918	0,666883	0,629654	0,662857
1	0,719264	0,704762	0,719264	0,667965	0,67316	0,696883
2	0,70974	0,70974	0,681818	0,708874	0,643939	0,690823
4	0,667749	0,708874	0,686147	0,648268	0,676407	0,677489
8	0,662771	0,672294	0,659307	0,691126	0,680519	0,673203
	0,679356	0,694426	0,681791	0,676299	0,667992	

ACC test DV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,753918	0,761611	0,763101	0,744591	0,696418	0,743928
0,125	0,767668	0,781635	0,730745	0,735216	0,735216	0,750096
0,25	0,760072	0,787909	0,727764	0,718173	0,73363	0,74551
0,5	0,746106	0,76637	0,752284	0,724423	0,711995	0,740236
1	0,780337	0,775625	0,761731	0,738389	0,701082	0,751433
2	0,732091	0,750889	0,752284	0,741731	0,718125	0,739024
4	0,729063	0,756947	0,744663	0,772524	0,736899	0,748019
8	0,716803	0,693438	0,721418	0,720096	0,712356	0,712822
	0,748257	0,759303	0,744249	0,736893	0,718215	

Diversity

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,177223	0,167138	0,159686	0,155361	0,166937	0,165269
0,125	0,205621	0,185488	0,18018	0,169099	0,181069	0,184291
0,25	0,221562	0,206025	0,191108	0,188538	0,188358	0,199118
0,5	0,256175	0,233498	0,226043	0,208976	0,201859	0,22531
1	0,316365	0,310615	0,294435	0,265259	0,245713	0,286477
2	0,408706	0,401699	0,397032	0,365183	0,325106	0,379545
4	0,444794	0,444231	0,438726	0,426307	0,408211	0,432454
8	0,45345	0,453104	0,45359	0,450972	0,443472	0,450918
	0,310487	0,300225	0,2926	0,278712	0,270091	

Coverage

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,958365	0,958365	0,95988	0,950577	0,947452	0,954928
0,125	0,976875	0,966082	0,969159	0,961394	0,959832	0,966668
0,25	0,983053	0,979952	0,978438	0,970673	0,962933	0,97501
0,5	0,992284	0,990721	0,98613	0,978389	0,970673	0,983639
1	0,998462	0,998438	0,998462	0,995385	0,992284	0,996606
2	0,998438	1	1	0,998462	0,992284	0,997837
4	0,998462	0,996899	1	0,998462	0,998462	0,998457
8	0,998438	0,998438	0,998438	0,996899	0,998462	0,998135
	0,988047	0,986112	0,986313	0,98128	0,977797	

% num feat

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,442	0,486	0,544	0,672	0,723	0,5734
0,125	0,426	0,476	0,531	0,672	0,724	0,5658
0,25	0,421	0,469	0,532	0,671	0,727	0,564
0,5	0,393	0,454	0,516	0,654	0,718	0,547
1	0,37	0,4	0,473	0,613	0,692	0,5096
2	0,322	0,358	0,394	0,515	0,616	0,441
4	0,298	0,317	0,341	0,408	0,472	0,3672
8	0,301	0,312	0,311	0,343	0,376	0,3286
	0,371625	0,409	0,45525	0,5685	0,631	

Using NNge in Genetic Search

Hepatitis-domain dataset

ACC SV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,81208333	0,825	0,84375	0,81208333	0,85166667	**0,82891667**
0,125	0,81208333	0,81958333	**0,85833333**	0,81791667	0,85708333	**0,833**
0,25	0,83125	0,83166667	0,79916667	0,79333333	0,80625	**0,81233333**
0,5	0,80583333	0,83208333	0,83791667	0,83125	0,83291667	**0,828**
1	0,8125	0,85041667	0,80583333	0,81416667	0,83208333	**0,823**
2	0,77208333	0,8125	0,82541667	0,84458333	0,8375	**0,81841667**
4	0,74916667	0,78666667	0,79333333	0,85041667	0,81958333	**0,79983333**
8	0,78625	0,78833333	0,81958333	0,79291667	0,79291667	**0,796**
	0,79765625	**0,81828125**	**0,82291667**	**0,81958333**	**0,82875**	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,96170213	0,96382979	0,95319149	0,9106383	0,8787234	**0,93361702**
0,125	0,97021277	0,96808511	0,96808511	0,91489362	0,88510638	**0,9412766**
0,25	0,97021277	0,97021277	0,97021277	0,9106383	0,88723404	**0,94170213**
0,5	0,97021277	0,97234043	0,97021277	0,92340426	0,88723404	**0,94468085**
1	0,97234043	**0,98085106**	0,97659574	0,92978723	0,89574468	**0,95106383**
2	0,97234043	0,97234043	0,97234043	0,93404255	0,8893617	**0,94808511**
4	0,84893617	0,87021277	0,91276596	0,90212766	0,88723404	**0,88425532**
8	0,74680851	0,75957447	0,7787234	0,82340426	0,84893617	**0,79148936**
	0,92659574	**0,93218085**	**0,93776596**	**0,90611702**	**0,88244681**	

ACC WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,81208333	0,825	0,84375	0,81208333	0,85166667	**0,82891667**
0,125	0,81208333	0,81958333	**0,85833333**	0,81791667	0,85708333	**0,833**
0,25	0,83125	0,83166667	0,79916667	0,79333333	0,80625	**0,81233333**
0,5	0,80583333	0,83208333	0,83791667	0,83125	0,83291667	**0,828**
1	0,8125	0,85041667	0,80583333	0,81416667	0,83208333	**0,823**
2	0,77208333	0,8125	0,82541667	0,84458333	0,8375	**0,81841667**
4	0,74916667	0,78666667	0,79333333	0,85041667	0,81958333	**0,79983333**
8	0,78625	0,78833333	0,81958333	0,79291667	0,79291667	**0,796**
	0,79765625	**0,81828125**	**0,82291667**	**0,81958333**	**0,82875**	

ACC test WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,96170213	0,96382979	0,95319149	0,9106383	0,8787234	**0,93361702**
0,125	0,97021277	0,96808511	0,96808511	0,91489362	0,88510638	**0,9412766**
0,25	0,97021277	0,97021277	0,97021277	0,9106383	0,88723404	**0,94170213**
0,5	0,97021277	0,97234043	0,97021277	0,92340426	0,88723404	**0,94468085**
1	0,97234043	**0,98085106**	0,97659574	0,92978723	0,89574468	**0,95106383**
2	0,97234043	0,97234043	0,97234043	0,93404255	0,8893617	**0,94808511**
4	0,84893617	0,87021277	0,91276596	0,90212766	0,88723404	**0,88425532**
8	0,74680851	0,75957447	0,7787234	0,82340426	0,84893617	**0,79148936**
	0,92659574	**0,93218085**	**0,93776596**	**0,90611702**	**0,88244681**	

ACC

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,71208333	0,74291667	0,8325	0,71916667	0,73291667	**0,74791667**
0,125	0,78708333	0,77541667	0,73875	0,73916667	0,76083333	**0,76025**
0,25	0,75958333	0,73916667	0,80125	0,7325	0,78125	**0,76275**
0,5	0,755	0,76583333	0,66	0,725	0,71291667	**0,72375**
1	0,7625	0,74916667	0,75541667	0,78625	0,73625	**0,75791667**
2	**0,84458333**	0,73375	0,77416667	0,77458333	0,74875	**0,77516667**
4	0,77583333	0,7225	0,77375	0,74166667	0,72791667	**0,74833333**
8	0,78708333	0,74958333	0,78625	0,59958333	0,78	**0,7405**
	0,77296875	**0,74729167**	**0,76526042**	**0,72723958**	**0,74760417**	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,79787234	0,82765957	0,76382979	0,80212766	0,78085106	**0,79446809**
0,125	0,81489362	0,82553191	0,79787234	0,67234043	0,80425532	**0,78297872**
0,25	0,75744681	0,74680851	0,77446809	0,73617021	0,7893617	**0,76085106**
0,5	0,80425532	0,75531915	0,77234043	0,68510638	0,75744681	**0,75489362**
1	0,81914894	**0,82978723**	0,80425532	0,81276596	0,80212766	**0,81361702**
2	0,8	0,76170213	0,75531915	0,77234043	0,81489362	**0,78085106**
4	0,75531915	0,76808511	0,67659574	0,72978723	0,75106383	**0,73617021**
8	0,75106383	0,73829787	0,71489362	0,7787234	0,75106383	**0,74680851**
	0,7875	**0,78164894**	**0,75744681**	**0,74867021**	**0,78138298**	

ACC DVS

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,8125	0,805	0,85083333	0,80041667	0,84458333	**0,82266667**
0,125	0,805	0,80625	0,81208333	0,845	0,82	**0,81766667**
0,25	0,82458333	0,78583333	0,81875	0,82583333	0,81791667	**0,81458333**
0,5	0,81958333	0,83833333	0,79333333	0,83791667	0,81833333	**0,8215**
1	0,81916667	0,86333333	0,83833333	0,82541667	0,85166667	**0,83958333**
2	0,81291667	0,79958333	0,81833333	0,83291667	0,84458333	**0,82166667**
4	0,81125	0,83791667	0,81291667	0,83125	0,81875	**0,82241667**
8	0,84541667	0,80625	0,79291667	0,83083333	**0,865**	**0,82808333**
	0,81880208	**0,8178125**	**0,8171875**	**0,82869792**	**0,83510417**	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,85744681	0,87234043	0,85957447	0,84468085	0,82765957	**0,85234043**
0,125	0,85319149	**0,88723404**	0,84680851	0,83404255	0,82553191	**0,8493617**
0,25	0,85531915	0,85319149	0,86808511	0,82978723	0,83829787	**0,84893617**
0,5	0,85744681	0,86595745	0,84893617	0,83404255	0,82553191	**0,84638298**
1	0,85531915	0,86170213	0,85957447	0,8212766	0,84680851	**0,84893617**
2	0,83191489	0,82978723	0,81702128	0,84255319	0,83617021	**0,83148936**
4	0,83191489	0,81702128	0,8212766	0,82978723	0,82765957	**0,82553191**
8	0,80851064	0,81914894	0,80212766	0,82553191	0,83404255	**0,81787234**
	0,84388298	**0,85079787**	**0,84042553**	**0,83271277**	**0,83271277**	

Diversity

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,07923404	0,06497872	0,06238298	0,05353191	0,06161702	**0,06434894**
0,125	0,08434043	0,07161702	0,06748936	0,06280851	0,06961702	**0,07117447**
0,25	0,09225532	0,07919149	0,07374468	0,06995745	0,06978723	**0,07698723**
0,5	0,11310638	0,10144681	0,08493617	0,08276596	0,08931915	**0,09431489**
1	0,21417021	0,20740426	0,17378723	0,12544681	0,12834043	**0,16982979**
2	0,38544681	0,38348936	0,35578723	0,27302128	0,20978723	**0,32150638**
4	0,43770213	0,43348936	0,41923404	0,37931915	0,32553191	**0,39905532**
8	0,44348936	**0,446**	0,44280851	0,42357447	0,40821277	**0,43281702**
	0,23121809	**0,22345213**	**0,21002128**	**0,18380319**	**0,1702766**	

Coverage

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,98085106	0,98510638	0,9787234	0,97234043	0,97234043	**0,97787234**
0,125	0,9893617	0,98723404	0,98723404	0,96595745	0,96595745	**0,97914894**
0,25	0,99148936	0,99148936	0,98510638	0,9787234	0,96382979	**0,98212766**
0,5	0,99787234	0,99787234	0,99574468	0,98297872	0,97659574	**0,99021277**
1	1	1	1	0,99574468	0,99148936	**0,99744681**
2	1	1	1	1	0,99361702	**0,9987234**
4	1	1	1	1	0,99787234	**0,99957447**
8	1	1	1	1	1	**1**
	0,99494681	**0,99521277**	**0,99335106**	**0,98696809**	**0,98271277**	

% num feat

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,3085	0,3645	0,514	0,725	0,7895	**0,5403**
0,125	0,301	0,369	0,4715	0,7385	0,799	**0,5358**
0,25	0,298	0,344	0,462	0,7415	0,809	**0,5309**
0,5	0,2505	0,3315	0,456	0,7415	0,8135	**0,5186**
1	0,2015	0,252	0,397	0,7255	0,79	**0,4732**
2	0,198	0,22	0,3015	0,6095	0,724	**0,4106**
4	0,1975	0,202	0,2735	0,4515	0,5295	**0,3308**
8	0,192	0,213	0,2355	0,3235	0,4015	**0,2731**
	0,243375	**0,287**	**0,388875**	**0,6320625**	**0,707**	

Auto-mpg dataset

ACC SV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,825	0,8125	0,783333	0,733333	0,775	0,785833
0,125	0,833333	0,829167	0,8125	0,758333	0,733333	0,793333
0,25	0,85	0,816667	0,8125	0,745833	0,725	0,79
0,5	0,8125	0,833333	0,825	0,741667	0,741667	0,790833
1	0,804167	0,804167	0,795833	0,7375	0,75	0,778333
2	0,775	0,7875	0,779167	0,758333	0,7625	0,7725
4	0,75	0,716667	0,7375	0,7375	0,7375	0,735833
8	0,708333	0,708333	0,733333	0,775	0,729167	0,730833
	0,794792	0,788542	0,784896	0,748438	0,744271	

ACC test SV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,847222	0,845833	0,845833	0,811111	0,795833	0,829167
0,125	0,848611	0,85	0,85	0,806944	0,788889	0,828889
0,25	0,85	0,851389	0,845833	0,805556	0,784722	0,8275
0,5	0,854167	0,858333	0,854167	0,813889	0,783333	0,832778
1	0,848611	0,858333	0,873611	0,819444	0,776389	0,835278
2	0,843056	0,856944	0,854167	0,844444	0,788889	0,8375
4	0,823611	0,816667	0,830556	0,829167	0,795833	0,819167
8	0,801389	0,788889	0,793056	0,8	0,783333	0,793333
	0,839583	0,840799	0,843403	0,816319	0,787153	

ACC WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,825	0,8125	0,783333	0,733333	0,775	0,785833
0,125	0,833333	0,829167	0,8125	0,758333	0,733333	0,793333
0,25	0,85	0,816667	0,8125	0,745833	0,725	0,79
0,5	0,8125	0,833333	0,825	0,741667	0,741667	0,790833
1	0,804167	0,804167	0,795833	0,7375	0,75	0,778333
2	0,775	0,7875	0,779167	0,758333	0,7625	0,7725
4	0,75	0,716667	0,7375	0,7375	0,7375	0,735833
8	0,708333	0,708333	0,733333	0,775	0,729167	0,730833
	0,794792	0,788542	0,784896	0,748438	0,744271	

ACC test WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,847222	0,845833	0,845833	0,811111	0,795833	0,829167
0,125	0,848611	0,85	0,85	0,806944	0,788889	0,828889
0,25	0,85	0,851389	0,845833	0,805556	0,784722	0,8275
0,5	0,854167	0,858333	0,854167	0,813889	0,783333	0,832778
1	0,848611	0,858333	0,873611	0,819444	0,776389	0,835278
2	0,843056	0,856944	0,854167	0,844444	0,788889	0,8375
4	0,823611	0,816667	0,830556	0,829167	0,795833	0,819167
8	0,801389	0,788889	0,793056	0,8	0,783333	0,793333
	0,839583	0,840799	0,843403	0,816319	0,787153	

ACC Staking

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,7625	0,8125	0,770833	0,679167	0,745833	0,754167
0,125	0,708333	0,720833	0,641667	0,7625	0,708333	0,708333
0,25	0,775	0,791667	0,741667	0,770833	0,754167	0,766667
0,5	0,6875	0,770833	0,75	0,783333	0,720833	0,7425
1	0,766667	0,745833	0,754167	0,7875	0,779167	0,766667
2	0,7875	0,754167	0,775	0,766667	0,708333	0,758333
4	0,783333	0,725	0,741667	0,75	0,758333	0,751667
8	0,704167	0,733333	0,745833	0,766667	0,770833	0,744167
	0,746875	0,756771	0,740104	0,758333	0,743229	

ACC test SK

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,758333	0,748611	0,765278	0,790278	0,730556	0,758611
0,125	0,752778	0,7625	0,765278	0,761111	0,772222	0,762778
0,25	0,766667	0,779167	0,751389	0,745833	0,772222	0,763056
0,5	0,761111	0,769444	0,738889	0,752778	0,713889	0,747222
1	0,766667	0,758333	0,736111	0,768056	0,765278	0,758889
2	0,770833	0,734722	0,7375	0,788889	0,768056	0,76
4	0,761111	0,769444	0,754167	0,727778	0,716667	0,745833
8	0,743056	0,738889	0,756944	0,770833	0,758333	0,753611
	0,760069	0,757639	0,750694	0,763194	0,749653	

ACC DVS

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,795833	0,791667	0,8125	0,770833	0,770833	0,788333
0,125	0,820833	0,783333	0,795833	0,754167	0,779167	0,786667
0,25	0,825	0,820833	0,8	0,7625	0,7625	0,794167
0,5	0,804167	0,795833	0,7875	0,745833	0,795833	0,785833
1	0,783333	0,7875	0,833333	0,7875	0,75	0,788333
2	0,770833	0,7875	0,775	0,741667	0,758333	0,766667
4	0,7875	0,745833	0,758333	0,75	0,741667	0,756667
8	0,7625	0,779167	0,754167	0,741667	0,766667	0,760833
	0,79375	0,786458	0,789583	0,756771	0,765625	

ACC test DV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,808333	0,8125	0,797222	0,777778	0,772222	0,793611
0,125	0,808333	0,806944	0,806944	0,784722	0,773611	0,796111
0,25	0,795833	0,808333	0,804167	0,793056	0,770833	0,794444
0,5	0,818056	0,813889	0,816667	0,783333	0,763889	0,799167
1	0,791667	0,786111	0,797222	0,784722	0,770833	0,786111
2	0,806944	0,791667	0,797222	0,791667	0,777778	0,793056
4	0,784722	0,784722	0,784722	0,769444	0,754167	0,775556
8	0,758333	0,779167	0,769444	0,783333	0,743056	0,766667
	0,796528	0,797917	0,796701	0,783507	0,765799	

Diversity

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,18475	0,175694	0,157111	0,151556	0,157417	0,165306
0,125	0,191472	0,180528	0,162917	0,1565	0,158444	0,169972
0,25	0,199917	0,181611	0,168889	0,157722	0,158556	0,173339
0,5	0,213583	0,1975	0,178528	0,166194	0,162056	0,183572
1	0,250972	0,24575	0,225917	0,186361	0,176444	0,217089
2	0,303583	0,301278	0,300861	0,2805	0,240167	0,285278
4	0,320528	0,320167	0,319028	0,310028	0,295139	0,312978
8	0,326972	0,327222	0,326583	0,325139	0,321056	0,325394
	0,248972	0,241219	0,229979	0,21675	0,20866	

Coverage

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,981944	0,981944	0,972222	0,965278	0,965278	0,973333
0,125	0,983333	0,981944	0,975	0,968056	0,965278	0,974722
0,25	0,9875	0,981944	0,979167	0,968056	0,965278	0,976389
0,5	0,995833	0,988889	0,983333	0,970833	0,968056	0,981389
1	0,997222	0,998611	0,997222	0,9875	0,981944	0,9925
2	0,998611	0,998611	0,998611	0,997222	0,9875	0,996111
4	1	0,998611	0,998611	0,995833	0,995833	0,997778
8	1	1	1	0,998611	0,995833	0,998889
	0,993056	0,991319	0,988021	0,981424	0,978125	

% num feat

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,29125	0,34875	0,415	0,55	0,6	0,441
0,125	0,27875	0,33	0,40375	0,55375	0,615	0,43625
0,25	0,2675	0,3275	0,39125	0,5575	0,62125	0,433
0,5	0,255	0,30375	0,3775	0,5575	0,62	0,42275
1	0,225	0,265	0,3275	0,5275	0,60375	0,38975
2	0,20125	0,23	0,2725	0,4075	0,525	0,32725
4	0,205	0,2275	0,2475	0,3325	0,425	0,2875
8	0,21375	0,23	0,2375	0,2775	0,325	0,25675
	0,242188	0,282813	0,334063	0,470469	0,541875	

Using NNge in Genetic Search

Zoo dataset

ACC SV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,95090909	0,94181818	0,95090909	0,95090909	0,96090909	0,95109091
0,125	0,94181818	0,93181818	0,95090909	0,95090909	0,95090909	0,94527273
0,25	0,93181818	0,93181818	0,95090909	0,95090909	0,94090909	0,94127273
0,5	0,96090909	0,95090909	0,95090909	0,95090909	0,94090909	0,95090909
1	0,95181818	0,94181818	0,95090909	0,95090909	0,94090909	0,94727273
2	0,95181818	0,95181818	0,95090909	0,95090909	0,93090909	0,94727273
4	0,92090909	0,92090909	0,93090909	0,93090909	0,95090909	0,93090909
8	0,85272727	0,92090909	0,92090909	0,94090909	0,93181818	0,91345455
	0,93284091	0,93647727	0,94465909	0,94715909	0,94352273	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,99354839	0,99354839	0,99354839	0,99354839	0,97408602	0,98965591
0,125	0,99354839	0,99354839	0,99354839	0,99354839	0,9644086	0,98772043
0,25	0,99354839	0,99354839	0,99354839	0,99032258	0,95462366	0,98511828
0,5	0,99354839	0,99354839	0,99354839	0,99032258	0,92569892	0,97933333
1	0,99354839	0,99677419	0,99354839	0,98698925	0,9288172	0,97993548
2	0,99677419	0,99677419	0,99354839	0,99021505	0,9611828	0,98769892
4	0,98387097	0,97075269	0,98709677	0,98709677	0,98376344	0,98251613
8	0,92548387	0,9516129	0,9544086	0,97075269	0,98688172	0,95782796
	0,98423387	0,98626344	0,98784946	0,98784946	0,9599328	

ACC WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,95090909	0,94181818	0,95090909	0,95090909	0,96090909	0,95109091
0,125	0,94181818	0,93181818	0,95090909	0,95090909	0,95090909	0,94527273
0,25	0,93181818	0,93181818	0,95090909	0,95090909	0,94090909	0,94127273
0,5	0,96090909	0,95090909	0,95090909	0,95090909	0,94090909	0,95090909
1	0,95181818	0,94181818	0,95090909	0,95090909	0,94090909	0,94727273
2	0,95181818	0,95181818	0,95090909	0,95090909	0,93090909	0,94727273
4	0,92090909	0,92090909	0,93090909	0,93090909	0,95090909	0,93090909
8	0,85272727	0,92090909	0,92090909	0,94090909	0,93181818	0,91345455
	0,93284091	0,93647727	0,94465909	0,94715909	0,94352273	

ACC test WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,99354839	0,99354839	0,99354839	0,99354839	0,97408602	0,98965591
0,125	0,99354839	0,99354839	0,99354839	0,99354839	0,9644086	0,98772043
0,25	0,99354839	0,99354839	0,99354839	0,99032258	0,95462366	0,98511828
0,5	0,99354839	0,99354839	0,99354839	0,99032258	0,92569892	0,97933333
1	0,99354839	0,99677419	0,99354839	0,98698925	0,9288172	0,97993548
2	0,99677419	0,99677419	0,99354839	0,99021505	0,9611828	0,98769892
4	0,98387097	0,97075269	0,98709677	0,98709677	0,98376344	0,98251613
8	0,92548387	0,9516129	0,9544086	0,97075269	0,98688172	0,95782796
	0,98423387	0,98626344	0,98784946	0,98784946	0,9599328	

ACC

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,91181818	0,91181818	0,88181818	0,89181818	0,90090909	0,89963636
0,125	0,90181818	0,90181818	0,88181818	0,89090909	0,91090909	0,89745455
0,25	0,87272727	0,89181818	0,89181818	0,87181818	0,89090909	0,88381818
0,5	0,88181818	0,91181818	0,92	0,90181818	0,89090909	0,90127273
1	0,90181818	0,91181818	0,90181818	0,88090909	0,87090909	0,89345455
2	0,91181818	0,91090909	0,89090909	0,88090909	0,89090909	0,89709091
4	0,91181818	0,87181818	0,91090909	0,88181818	0,89090909	0,89345455
8	0,90181818	0,85181818	0,88181818	0,89181818	0,88181818	0,88181818
	0,89943182	0,89545455	0,89511364	0,88647727	0,89102273	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,87376344	0,88645161	0,87376344	0,89967742	0,87053763	0,88083871
0,125	0,88655914	0,88344086	0,87043011	0,86677419	0,88978495	0,87939785
0,25	0,90623656	0,87698925	0,87698925	0,87698925	0,87688172	0,8828172
0,5	0,88021505	0,87376344	0,88344086	0,87365591	0,85763441	0,87374194
1	0,8672043	0,86731183	0,87376344	0,87698925	0,88021505	0,87309677
2	0,86376344	0,87344086	0,87064516	0,87698925	0,9027957	0,87752688
4	0,84795699	0,85408602	0,83150538	0,83817204	0,86086022	0,84651613
8	0,86731183	0,89634409	0,82505376	0,84451613	0,81215054	0,84907527
	0,87412634	0,87647849	0,86319892	0,86922043	0,86885753	

ACC DVS

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,96090909	0,94181818	0,95090909	0,95090909	0,96090909	0,95309091
0,125	0,94181818	0,95090909	0,94090909	0,95090909	0,95090909	0,94709091
0,25	0,95090909	0,94090909	0,95090909	0,95090909	0,94090909	0,94690909
0,5	0,94090909	0,95181818	0,95090909	0,95090909	0,94090909	0,94709091
1	0,94090909	0,95181818	0,95090909	0,95090909	0,94090909	0,94709091
2	0,93181818	0,96090909	0,95090909	0,95090909	0,95090909	0,94909091
4	0,93090909	0,95090909	0,95090909	0,96090909	0,94090909	0,94690909
8	0,94181818	0,96090909	0,95090909	0,94090909	0,93090909	0,94509091
	0,9425	0,95125	0,94965909	0,95090909	0,94465909	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,99032258	0,99032258	0,99032258	0,99354839	0,97408602	0,98772043
0,125	0,98043011	0,99354839	0,99032258	0,99354839	0,95795699	0,98316129
0,25	0,99354839	0,99354839	0,99354839	0,99032258	0,95139785	0,98447312
0,5	0,99032258	0,99354839	0,99354839	0,99032258	0,92236559	0,97802151
1	0,99354839	0,98064516	0,98709677	0,98376344	0,9288172	0,97477419
2	0,99032258	0,99032258	0,99032258	0,99021505	0,96774194	0,98578495
4	0,98709677	0,98387097	0,98064516	0,99032258	0,98709677	0,98580645
8	0,97096774	0,93849462	0,95483871	0,98387097	0,98387097	0,9664086
	0,98706989	0,98303763	0,98508065	0,98948925	0,95916667	

Diversity

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,00509677	0,00234194	0,00232258	0,01935484	0,03878925	0,01358108
0,125	0,00956774	0,00279355	0,00406452	0,02463441	0,04275484	0,01676301
0,25	0,01563226	0,00393548	0,00058065	0,02718065	0,04346882	0,01815957
0,5	0,02646022	0,01324516	0,00774194	0,03406882	0,04264301	0,02483183
1	0,16552473	0,14212258	0,07487097	0,05323441	0,05901935	0,09895441
2	0,38044301	0,38095269	0,3652129	0,31968172	0,25713763	0,34068559
4	0,44164301	0,44475699	0,44224301	0,4194172	0,39961075	0,42953419
8	0,46258925	0,46675484	0,4634172	0,45428817	0,44653978	0,45871785
	0,18836962	0,1821129	0,17005672	0,16898253	0,16624543	

Coverage

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,99354839	0,99354839	0,99354839	0,99354839	0,99354839	0,99354839
0,125	0,99354839	0,99354839	0,99354839	0,99354839	0,99354839	0,99354839
0,25	0,99677419	0,99354839	0,99354839	0,99354839	0,99354839	0,99419355
0,5	1	1	1	0,99354839	0,99354839	0,99741935
1	1	1	1	1	1	1
2	1	1	1	1	0,99677419	0,99935484
4	1	1	1	1	1	1
8	1	1	1	1	1	1
	0,99798387	0,99758065	0,99758065	0,99677419	0,99637097	

% num feat

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,37833333	0,39166667	0,56666667	0,75111111	0,80555556	0,57866667
0,125	0,36611111	0,38833333	0,56222222	0,75944444	0,81777778	0,57877778
0,25	0,35111111	0,38944444	0,57222222	0,76833333	0,81944444	0,58011111
0,5	0,34555556	0,37722222	0,56111111	0,77944444	0,82944444	0,57855556
1	0,28555556	0,32277778	0,53222222	0,79777778	0,82833333	0,55333333
2	0,25833333	0,26444444	0,41944444	0,66444444	0,73166667	0,46766667
4	0,23888889	0,24833333	0,35555556	0,51666667	0,59333333	0,39055556
8	0,22777778	0,245	0,33	0,45055556	0,49166667	0,349
	0,30645833	0,32840278	0,48743056	0,68597222	0,73965278	

Using NNge in Genetic Search

Horse colic dataset

ACC SV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,83400901	0,82575075	0,83408408	0,79842342	0,78190691	0,81483483
0,125	0,83400901	0,82304805	0,83408408	0,80638138	0,82567568	0,82463964
0,25	0,83130631	0,83130631	0,8231982	0,82867868	0,78490991	0,81987988
0,5	0,84211712	0,83956456	0,8286036	0,81771772	0,80135135	0,82587087
1	0,81486486	0,83933934	0,84481982	0,80397898	0,77665165	0,81593093
2	0,74692192	0,7740991	0,75262763	0,81216216	0,79324324	0,77581081
4	0,72792793	0,74984985	0,71456456	0,76591592	0,78521021	0,74869369
8	0,71734234	0,70915916	0,69827327	0,72807808	0,72522523	0,71561562
	0,79356231	0,79901464	0,79128191	0,79516704	0,78427177	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,9	0,8990991	0,9018018	0,87117117	0,85315315	0,88504505
0,125	0,8972973	0,9045045	0,90630631	0,87207207	0,85585586	0,88720721
0,25	0,90720721	0,90720721	0,9036036	0,87027027	0,85675676	0,88900901
0,5	0,91621622	0,91891892	0,91261261	0,87567568	0,85225225	0,89513514
1	0,92702703	0,93423423	0,92252252	0,88108108	0,85945946	0,90486486
2	0,91081081	0,92432432	0,91081081	0,87837838	0,85765766	0,8963964
4	0,84054054	0,82612613	0,83783784	0,85405405	0,84954955	0,84162162
8	0,75135135	0,76126126	0,76576577	0,78558559	0,8	0,77279279
	0,88130631	0,88445946	0,88265766	0,86103604	0,84808559	

ACC WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,83400901	0,82575075	0,83408408	0,79842342	0,78190691	0,81483483
0,125	0,83400901	0,82304805	0,83408408	0,80638138	0,82567568	0,82463964
0,25	0,83130631	0,83130631	0,8231982	0,82867868	0,78490991	0,81987988
0,5	0,84211712	0,83956456	0,8286036	0,81771772	0,80135135	0,82587087
1	0,81486486	0,83933934	0,84481982	0,80397898	0,77665165	0,81593093
2	0,74692192	0,7740991	0,75262763	0,81216216	0,79324324	0,77581081
4	0,72792793	0,74984985	0,71456456	0,76591592	0,78521021	0,74869369
8	0,71734234	0,70915916	0,69827327	0,72807808	0,72522523	0,71561562
	0,79356231	0,79901464	0,79128191	0,79516704	0,78427177	

ACC test WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,9	0,8990991	0,9018018	0,87117117	0,85315315	0,88504505
0,125	0,8972973	0,9045045	0,90630631	0,87207207	0,85585586	0,88720721
0,25	0,90720721	0,90720721	0,9036036	0,87027027	0,85675676	0,88900901
0,5	0,91621622	0,91891892	0,91261261	0,87567568	0,85225225	0,89513514
1	0,92702703	0,93423423	0,92252252	0,88108108	0,85945946	0,90486486
2	0,91081081	0,92432432	0,91081081	0,87837838	0,85765766	0,8963964
4	0,84054054	0,82612613	0,83783784	0,85405405	0,84954955	0,84162162
8	0,75135135	0,76126126	0,76576577	0,78558559	0,8	0,77279279
	0,88130631	0,88445946	0,88265766	0,86103604	0,84808559	

ACC

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,63280781	0,72507508	0,71936937	0,70367868	0,7960961	0,71540541
0,125	0,7771021	0,8262012	0,78798799	0,67965465	0,75818318	0,76582583
0,25	0,70608108	0,7015015	0,71426426	0,77432432	0,71591592	0,72241742
0,5	0,76651652	0,78551051	0,79594595	0,6957958	0,73100601	0,75495495
1	0,71659159	0,74737237	0,73866366	0,75803303	0,75037538	0,74220721
2	0,69857357	0,71463964	0,74474474	0,74714715	0,73843844	0,72870871
4	0,73340841	0,6768018	0,71704204	0,70653153	0,73355856	0,71346847
8	0,69587087	0,70375375	0,6737988	0,72267267	0,71441441	0,7021021
	0,71586899	0,73510698	0,7364771	0,72347973	0,7422485	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,7981982	0,74864865	0,81711712	0,77567568	0,80900901	0,78972973
0,125	0,78198198	0,83243243	0,82612613	0,7972973	0,74504505	0,79657658
0,25	0,82162162	0,73783784	0,71981982	0,74414414	0,58198198	0,72108108
0,5	0,8027027	0,79009009	0,78918919	0,71891892	0,65585586	0,75135135
1	0,78018018	0,77207207	0,81711712	0,71081081	0,81081081	0,7781982
2	0,78828829	0,75945946	0,77747748	0,75855856	0,74864865	0,76648649
4	0,73243243	0,6981982	0,72432432	0,74684685	0,73873874	0,72810811
8	0,70540541	0,72342342	0,73063063	0,73423423	0,75585586	0,72990991
	0,77635135	0,75777027	0,77522523	0,74831081	0,73074324	

ACC DVS

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,83956456	0,83115616	0,84211712	0,78753754	0,8015015	0,82037538
0,125	0,82852853	0,83941441	0,83385886	0,8259009	0,81493994	0,82852853
0,25	0,84767267	0,8259009	0,83663664	0,81771772	0,77995495	0,82157658
0,5	0,85555556	0,83956456	0,83400901	0,82582583	0,83138138	0,83726727
1	0,81741742	0,81764264	0,85578078	0,81208709	0,80112613	0,82081081
2	0,79054054	0,7798048	0,79572072	0,80653153	0,80660661	0,79584084
4	0,78543544	0,77927928	0,75795796	0,79872372	0,79564565	0,78340841
8	0,7225976	0,73603604	0,75765766	0,746997	0,76066066	0,74478979
	0,81091404	0,80609985	0,81421734	0,80266517	0,7989771	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,86756757	0,86756757	0,85945946	0,80990991	0,8027027	0,84144144
0,125	0,87207207	0,87297297	0,86126126	0,80630631	0,81891892	0,84630631
0,25	0,87297297	0,86306306	0,85135135	0,83423423	0,81531532	0,84738739
0,5	0,87747748	0,86126126	0,85045045	0,81531532	0,81621622	0,84414414
1	0,86396396	0,87207207	0,84864865	0,82522523	0,81621622	0,84522523
2	0,82162162	0,83963964	0,82792793	0,82792793	0,82342342	0,82810811
4	0,8027027	0,81621622	0,77837838	0,79189189	0,80990991	0,79981982
8	0,77747748	0,77477477	0,75045045	0,77477477	0,79009009	0,77351351
	0,84448198	0,84594595	0,82849099	0,8106982	0,8115991	

Diversity

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,09241441	0,08472072	0,0770991	0,06441441	0,07576577	0,07888288
0,125	0,10374775	0,09331532	0,08300901	0,07542342	0,0841982	0,08793874
0,25	0,11618018	0,10010811	0,0894955	0,08594595	0,09165766	0,09667748
0,5	0,14027027	0,12985586	0,11221622	0,10295495	0,09899099	0,11685766
1	0,27054054	0,24223423	0,21063063	0,16023423	0,14333333	0,20539459
2	0,40556757	0,39609009	0,39005405	0,30362162	0,2627027	0,35160721
4	0,45081081	0,45036036	0,44753153	0,42288288	0,38596396	0,43150991
8	0,46659459	0,46369369	0,46302703	0,45430631	0,44511712	0,45854775
	0,25576577	0,2450473	0,23413288	0,20872297	0,19846622	

Coverage

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,98558559	0,98468468	0,98018018	0,95315315	0,94684685	0,97009009
0,125	0,98828829	0,99189189	0,97927928	0,95405405	0,95225225	0,97315315
0,25	0,99369369	0,98558559	0,98288288	0,96396396	0,95495495	0,97621622
0,5	0,9981982	0,9972973	0,99189189	0,96846847	0,96036036	0,98324324
1	1	1	1	0,98738739	0,97207207	0,99189189
2	1	1	1	0,9981982	0,9981982	0,99927928
4	1	1	0,9990991	1	0,9981982	0,99945946
8	1	1	0,9990991	0,9990991	0,9981982	0,99927928
	0,99572072	0,99493243	0,99155405	0,97804054	0,97263514	

% num feat

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,30695652	0,3573913	0,48913043	0,77391304	0,82869565	0,55121739
0,125	0,2826087	0,35217391	0,47391304	0,77565217	0,82652174	0,54217391
0,25	0,28478261	0,33869565	0,46	0,77956522	0,83347826	0,53930435
0,5	0,24	0,31695652	0,44173913	0,78695652	0,83217391	0,52356522
1	0,20434783	0,27043478	0,40130435	0,76913043	0,82173913	0,4933913
2	0,19130435	0,23695652	0,29826087	0,63086957	0,7326087	0,418
4	0,19695652	0,2273913	0,27043478	0,43130435	0,56826087	0,33886957
8	0,19869565	0,22826087	0,2473913	0,31217391	0,38478261	0,27426087
	0,23820652	0,29103261	0,38527174	0,65744565	0,72853261	

Using NNge in Genetic Search

Breast cancer dataset

ACC SV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,65812808	0,73128079	0,70307882	0,68842365	0,69199507	**0,69458128**
0,125	0,67524631	0,70332512	0,71699507	0,70640394	0,69950739	**0,70029557**
0,25	0,66071429	0,69236453	0,71366995	0,69605911	0,67475369	**0,68751232**
0,5	0,6817734	0,6570197	0,71403941	0,70344828	0,70640394	**0,69253695**
1	0,72376847	0,69605911	0,69630542	0,70665025	0,68891626	**0,7023399**
2	0,71022167	0,72044335	0,6820197	0,69987685	0,70307882	**0,70312808**
4	0,6820197	0,69975369	0,72376847	0,69876847	0,71366995	**0,70359606**
8	0,63953202	0,69926108	0,69926108	**0,73793103**	0,69913793	**0,69502463**
	0,67892549	**0,69993842**	**0,70614224**	**0,7046952**	**0,69718288**	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,70232558	0,71976744	0,73023256	0,70813953	0,6872093	**0,70953488**
0,125	0,70697674	0,72209302	0,73604651	0,70348837	0,69186047	**0,71209302**
0,25	0,70581395	0,72209302	0,7372093	0,70813953	0,69418605	**0,71348837**
0,5	0,71627907	0,73953488	0,73953488	0,71046512	0,69651163	**0,72046512**
1	0,72093023	0,7372093	**0,74418605**	0,71046512	0,69651163	**0,72186047**
2	0,70697674	0,70465116	0,71395349	0,71046512	0,70581395	**0,70837209**
4	0,68139535	0,68255814	0,69302326	0,68953488	0,6872093	**0,68674419**
8	0,65813953	0,65232558	0,65581395	0,66744186	0,67906977	**0,66255814**
	0,69985465	**0,71002907**	**0,71875**	**0,70101744**	**0,69229651**	

ACC WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,65812808	0,73128079	0,70307882	0,68842365	0,69199507	**0,69458128**
0,125	0,67524631	0,70332512	0,71699507	0,70640394	0,69950739	**0,70029557**
0,25	0,66071429	0,69236453	0,71366995	0,69605911	0,67475369	**0,68751232**
0,5	0,6817734	0,6570197	0,71403941	0,70344828	0,70640394	**0,69253695**
1	0,72376847	0,69605911	0,69630542	0,70665025	0,68891626	**0,7023399**
2	0,71022167	0,72044335	0,6820197	0,69987685	0,70307882	**0,70312808**
4	0,6820197	0,69975369	0,72376847	0,69876847	0,71366995	**0,70359606**
8	0,63953202	0,69926108	0,69926108	**0,73793103**	0,69913793	**0,69502463**
	0,67892549	**0,69993842**	**0,70614224**	**0,7046952**	**0,69718288**	

ACC test WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,70232558	0,71976744	0,73023256	0,70813953	0,6872093	**0,70953488**
0,125	0,70697674	0,72209302	0,73604651	0,70348837	0,69186047	**0,71209302**
0,25	0,70581395	0,72209302	0,7372093	0,70813953	0,69418605	**0,71348837**
0,5	0,71627907	0,73953488	0,73953488	0,71046512	0,69651163	**0,72046512**
1	0,72093023	0,7372093	**0,74418605**	0,71046512	0,69651163	**0,72186047**
2	0,70697674	0,70465116	0,71395349	0,71046512	0,70581395	**0,70837209**
4	0,68139535	0,68255814	0,69302326	0,68953488	0,6872093	**0,68674419**
8	0,65813953	0,65232558	0,65581395	0,66744186	0,67906977	**0,66255814**
	0,69985465	**0,71002907**	**0,71875**	**0,70101744**	**0,69229651**	

ACC

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,63953202	0,59753695	0,63633005	0,65024631	**0,70689655**	**0,64610837**
0,125	0,67438424	0,62142857	0,62241379	0,65763547	0,61945813	**0,63906404**
0,25	0,6682266	0,61564039	0,65049261	0,59371921	0,62573892	**0,63076355**
0,5	0,66182266	0,67487685	0,608867	0,67807882	0,59248768	**0,6432266**
1	0,675	0,57044335	0,68214286	0,65775862	0,54187192	**0,62544335**
2	0,60160099	0,62931034	0,64421182	0,63682266	0,62647783	**0,62768473**
4	0,59519704	0,64064039	0,58756158	0,63066502	0,59408867	**0,60963054**
8	0,58694581	0,6044335	0,61022167	0,58485222	0,62573892	**0,60243842**
	0,63783867	**0,61928879**	**0,63028017**	**0,63622229**	**0,61659483**	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,57790698	0,59651163	0,60116279	0,59883721	0,60581395	**0,59604651**
0,125	0,61627907	0,60232558	0,61395349	0,62674419	0,59069767	**0,61**
0,25	**0,64651163**	0,59418605	**0,64651163**	0,6	0,63023256	**0,62348837**
0,5	0,62209302	0,61744186	0,58953488	0,5744186	0,59418605	**0,59953488**
1	0,63255814	0,59069767	0,56046512	0,62325581	0,6244186	**0,60627907**
2	0,57674419	0,63023256	0,56860465	0,57209302	0,59069767	**0,58767442**
4	0,59767442	0,59767442	0,57674419	0,60813953	0,59069767	**0,59418605**
8	0,5872093	0,58372093	0,58837209	0,60348837	0,59186047	**0,59093023**
	0,60712209	**0,60159884**	**0,5931686**	**0,60087209**	**0,60232558**	

ACC DVS

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,72746305	0,73066502	0,69273399	0,69224138	0,70246305	**0,7091133**
0,125	0,65024631	0,72364532	0,71687192	0,7023399	0,68214286	**0,69504926**
0,25	0,69926108	0,70615764	0,69248768	0,67487685	0,67844828	**0,69024631**
0,5	0,73091133	0,70628079	0,68559113	0,69938424	0,70640394	**0,70571429**
1	0,70985222	0,69211823	0,68571429	0,67869458	0,69593596	**0,69246305**
2	0,70295567	**0,73448276**	0,69248768	0,70307882	0,72389163	**0,71137931**
4	0,68214286	0,70640394	0,6955665	0,7203202	0,67475369	**0,69583744**
8	0,69593596	0,70972906	0,69593596	0,70997537	0,70283251	**0,70288177**
	0,69984606	**0,71368534**	**0,69467365**	**0,69761392**	**0,69585899**	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,6372093	0,68488372	0,68488372	0,68488372	0,66860465	**0,67209302**
0,125	0,68372093	0,69186047	0,68953488	0,67209302	0,67906977	**0,68325581**
0,25	0,65697674	0,68372093	**0,70465116**	0,66860465	0,68837209	**0,68046512**
0,5	0,68604651	0,68953488	0,69534884	0,67674419	0,66395349	**0,68232558**
1	0,67674419	0,67906977	0,69302326	0,66511628	0,66744186	**0,67627907**
2	0,69418605	0,68255814	0,66162791	0,68488372	0,67674419	**0,68**
4	0,64651163	0,6744186	0,6627907	0,67093023	0,66162791	**0,66325581**
8	0,63372093	0,65	0,65813953	0,6627907	0,66162791	**0,65325581**
	0,66438953	**0,67950581**	**0,68125**	**0,67325581**	**0,67093023**	

Diversity

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,15830233	0,16225581	0,161	0,16506977	0,172	**0,16372558**
0,125	0,17248837	0,17269767	0,18127907	0,18039535	0,17465116	**0,17630233**
0,25	0,193	0,19753488	0,20353488	0,19083721	0,18751163	**0,19448372**
0,5	0,24186047	0,24434884	0,24265116	0,21446512	0,19834884	**0,22833488**
1	0,29765116	0,30172093	0,2987907	0,26823256	0,24402326	**0,28208372**
2	0,3574186	0,36137209	0,3582093	0,3334186	0,30597674	**0,34327907**
4	0,38372093	0,38218605	0,38239535	0,37434884	0,35988372	**0,37650698**
8	**0,38948837**	0,3875814	0,38937209	0,38732558	0,38446512	**0,38764651**
	0,27424128	**0,27621221**	**0,27715407**	**0,26426163**	**0,25335756**	

Coverage

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,89186047	0,89651163	0,89883721	0,89069767	0,88604651	**0,8927907**
0,125	0,90465116	0,90581395	0,9255814	0,90697674	0,8872093	**0,90604651**
0,25	0,9244186	0,93255814	0,9372093	0,91511628	0,91162791	**0,92418605**
0,5	0,95465116	0,95813953	0,96162791	0,93837209	0,92209302	**0,94697674**
1	0,96860465	0,97325581	0,97209302	0,96511628	0,95232558	**0,96627907**
2	0,97325581	0,9755814	0,97674419	0,9755814	0,96976744	**0,97418605**
4	0,97325581	0,97790698	0,9755814	0,9744186	0,97325581	**0,97488372**
8	0,97325581	0,97790698	0,9744186	0,97674419	0,97674419	**0,97581395**
	0,94549419	**0,9497093**	**0,95276163**	**0,94287791**	**0,93488372**	

% num feat

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,284	0,349	0,457	0,676	0,731	**0,4994**
0,125	0,278	0,347	0,458	0,686	0,736	**0,501**
0,25	0,295	0,357	0,475	0,681	0,732	**0,508**
0,5	0,306	0,357	0,463	0,667	0,717	**0,502**
1	0,313	0,369	0,454	0,606	0,691	**0,4866**
2	0,319	0,37	0,403	0,534	0,615	**0,4482**
4	0,354	0,365	0,375	0,454	0,519	**0,4134**
8	0,365	0,375	0,377	0,402	0,411	**0,386**
	0,31425	**0,361125**	**0,43275**	**0,58825**	**0,644**	

Using NNge in Genetic Search

Wine dataset

ACC SV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,94346405	0,92679739	0,93267974	0,95522876	0,94934641	0,94150327
0,125	0,95522876	0,93823529	0,95490196	0,96078431	0,95490196	0,95281046
0,25	0,95522876	0,95490196	0,93823529	0,9496732	0,96078431	0,95176471
0,5	0,95490196	0,95490196	0,92091503	0,98267974	0,96045752	0,95477124
1	0,97745098	0,93823529	0,93823529	0,95490196	0,96045752	0,95385621
2	0,9496732	0,95555556	0,94411765	0,96078431	0,96601307	0,95522876
4	0,89281046	0,8879085	0,93856209	0,94379085	0,96633987	0,92588235
8	0,88137255	0,88823529	0,87712418	0,91013072	0,92156863	0,89568627
	0,93876634	0,93059641	0,93059641	0,95224673	0,95498366	

ACC WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,94346405	0,92679739	0,93267974	0,95522876	0,94934641	0,94150327
0,125	0,95522876	0,93823529	0,95490196	0,96078431	0,95490196	0,95281046
0,25	0,95522876	0,95490196	0,93823529	0,9496732	0,96078431	0,95176471
0,5	0,95490196	0,95490196	0,92091503	0,98267974	0,96045752	0,95477124
1	0,97745098	0,93823529	0,93823529	0,95490196	0,96045752	0,95385621
2	0,9496732	0,95555556	0,94411765	0,96078431	0,96601307	0,95522876
4	0,89281046	0,8879085	0,93856209	0,94379085	0,96633987	0,92588235
8	0,88137255	0,88823529	0,87712418	0,91013072	0,92156863	0,89568627
	0,93876634	0,93059641	0,93059641	0,95224673	0,95498366	

ACC

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,93267974	0,87679739	0,91568627	0,89901961	0,94901961	0,91464052
0,125	0,94934641	0,92156863	0,95490196	0,94183007	0,97156863	0,94784314
0,25	0,93823529	0,96601307	0,9369281	0,92124183	0,93267974	0,93901961
0,5	0,96633987	0,92679739	0,93823529	0,94379085	0,8996732	0,93496732
1	0,93823529	0,96633987	0,94379085	0,94379085	0,96045752	0,95052288
2	0,92124183	0,93235294	0,93235294	0,96013072	0,93267974	0,93575163
4	0,94379085	0,95457516	0,93267974	0,97189542	0,93267974	0,94712418
8	0,94379085	0,92712418	0,93823529	0,89313725	0,93823529	0,92810458
	0,94170752	0,93394608	0,93660131	0,93435458	0,93962418	

ACC DVS

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,95457516	0,90392157	0,9379085	0,96078431	0,95490196	0,9424183
0,125	0,93267974	0,92679739	0,94346405	0,96078431	0,96045752	0,9448366
0,25	0,94411765	0,93300654	0,96045752	0,96601307	0,96601307	0,95392157
0,5	0,96078431	0,9496732	0,94934641	0,95490196	0,97189542	0,95732026
1	0,96633987	0,94379085	0,93823529	0,96601307	0,96601307	0,95607843
2	0,96111111	0,95522876	0,96633987	0,95522876	0,96601307	0,96078431
4	0,94411765	0,91013072	0,93300654	0,96045752	0,96633987	0,94281046
8	0,92091503	0,92647059	0,91633987	0,92124183	0,94934641	0,92686275
	0,94808007	0,93112745	0,94313725	0,9556781	0,96262255	

Diversity

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,01622222	0,00944444	0,00477778	0,01614815	0,01455556	0,01222963
0,125	0,02992593	0,01507407	0,01511111	0,01681481	0,01481481	0,01834815
0,25	0,03244444	0,02044444	0,0147037	0,0177037	0,01407407	0,01987407
0,5	0,0472963	0,02585185	0,01792593	0,0197037	0,01644444	0,02544444
1	0,15844444	0,15118519	0,06948148	0,03748148	0,03203704	0,08972593
2	0,37677778	0,38059259	0,36522222	0,27025926	0,18937037	0,31644444
4	0,44522222	0,44425926	0,44040741	0,40144444	0,35514815	0,4172963
8	0,46077778	0,4617037	0,4567037	0,44877778	0,43840741	0,45327407
	0,19588889	0,18856944	0,17304167	0,15354167	0,13435648	

% num feat

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,30357143	0,34785714	0,55357143	0,79285714	0,815	0,56257143
0,125	0,28714286	0,32428571	0,51071429	0,79857143	0,82357143	0,54885714
0,25	0,27214286	0,32071429	0,50214286	0,79642857	0,80857143	0,54
0,5	0,25	0,31	0,51714286	0,79214286	0,81714286	0,53728571
1	0,20214286	0,23714286	0,45428571	0,80714286	0,81857143	0,50385714
2	0,19071429	0,20642857	0,255	0,59714286	0,70214286	0,39028571
4	0,17214286	0,17428571	0,20571429	0,37642857	0,49571429	0,28485714
8	0,16142857	0,16357143	0,17571429	0,23571429	0,29	0,20528571
	0,22991071	0,26053571	0,39678571	0,64955357	0,69633929	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,98888889	0,98703704	0,98703704	0,97592593	0,95925926	0,97962963
0,125	0,98888889	0,98888889	0,99259259	0,96851852	0,95925926	0,97962963
0,25	0,98703704	0,99074074	0,9962963	0,96481481	0,95925926	0,97962963
0,5	0,99444444	0,9962963	0,99814815	0,95925926	0,95925926	0,98148148
1	0,99814815	1	1	0,96481481	0,96296296	0,98518519
2	1	1	1	0,97407407	0,96481481	0,98777778
4	0,97407407	0,98148148	0,98518519	0,98888889	0,96851852	0,97962963
8	0,9462963	0,94814815	0,96481481	0,96851852	0,95185185	0,95592593
	0,98472222	0,98657407	0,99050926	0,97060185	0,96064815	

ACC test WV

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,98888889	0,98703704	0,98703704	0,97592593	0,95925926	0,97962963
0,125	0,98888889	0,98888889	0,99259259	0,96851852	0,95925926	0,97962963
0,25	0,98703704	0,99074074	0,9962963	0,96481481	0,95925926	0,97962963
0,5	0,99444444	0,9962963	0,99814815	0,95925926	0,95925926	0,98148148
1	0,99814815	1	1	0,96481481	0,96296296	0,98518519
2	1	1	1	0,97407407	0,96481481	0,98777778
4	0,97407407	0,98148148	0,98518519	0,98888889	0,96851852	0,97962963
8	0,9462963	0,94814815	0,96481481	0,96851852	0,95185185	0,95592593
	0,98472222	0,98657407	0,99050926	0,97060185	0,96064815	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,94259259	0,96296296	0,96481481	0,97592593	0,96851852	0,96296296
0,125	0,96851852	0,98148148	0,96851852	0,96296296	0,93703704	0,9637037
0,25	0,97407407	0,97407407	0,97592593	0,97222222	0,94074074	0,96740741
0,5	0,97777778	0,96851852	0,97962963	0,96851852	0,96296296	0,97148148
1	0,97037037	0,96851852	0,97407407	0,96296296	0,94074074	0,96333333
2	0,97407407	0,94814815	0,96296296	0,95925926	0,9037037	0,94962963
4	0,9537037	0,95185185	0,9462963	0,9462963	0,95555556	0,95074074
8	0,94074074	0,93333333	0,94074074	0,94259259	0,9537037	0,94222222
	0,96273148	0,96111111	0,96412037	0,96134259	0,94537037	

ACC test

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,98703704	0,97592593	0,95555556	0,96851852	0,96666667	0,97074074
0,125	0,97962963	0,98333333	0,97222222	0,96296296	0,96851852	0,97333333
0,25	0,97962963	0,98148148	0,97592593	0,95925926	0,96851852	0,97296296
0,5	0,98703704	0,98148148	0,96666667	0,95740741	0,96851852	0,97222222
1	0,98703704	0,98703704	0,97962963	0,96481481	0,96851852	0,97740741
2	0,98703704	0,98703704	0,98333333	0,96666667	0,96481481	0,97777778
4	0,9462963	0,95185185	0,96296296	0,95555556	0,98333333	0,96
8	0,94074074	0,93703704	0,96851852	0,93888889	0,95740741	0,94851852
	0,97430556	0,97314815	0,97060185	0,95925926	0,96828704	

Coverage

alpha \ beta	-0,5	-0,25	0	0,25	0,5	
0	0,9962963	0,9962963	0,9962963	0,99074074	0,99074074	0,99407407
0,125	1	0,99814815	0,99814815	0,99074074	0,99074074	0,99555556
0,25	1	1	1	0,99444444	0,99259259	0,99740741
0,5	1	1	1	0,99814815	0,99444444	0,99851852
1	1	1	1	1	1	1
2	1	1	1	1	1	1
4	1	1	1	1	1	1
8	1	1	1	1	1	1
	0,99953704	0,99930556	0,99930556	0,99675926	0,99606481	