BENEFICIAL SEQUENTIAL COMBINATION OF DATA MINING ALGORITHMS

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Abstract: Depending on the goal of an instance of the Knowledge Discovery in Databases (*KDD*) process, there are instances that require more than a single data mining algorithm to determine a solution. Sequences of data mining algorithms offer room for improvement that are yet unexploited.
If it is known that an algorithm is the first of a sequence of algorithms and there will be future runs of other algorithms, the first algorithm can determine intermediate results that the succeeding algorithms need. The anteceding algorithm can also determine helpful statistics for succeeding algorithms. As the anteceding algorithm has to scan the data anyway, computing intermediate results happens as a by-product of computing the anteceding algorithm's result.
On the one hand, a succeeding algorithm can save time because several steps of that algorithm have already been pre-computed. On the other hand, additional information about the analysed data can improve the quality of results such as the accuracy of classification, as demonstrated in experiments with synthetical and real data.

1 INTRODUCTION

Sophisticated algorithms analyse large data sets for patterns in the data mining phase of the *KDD* process.

Depending on the goal the analyst is striving for when performing an analysis, he or she must apply a combination of data mining algorithms to achieve that goal.

We observed in a project with NCR Teradata Austria that the same data is analysed several times—yet, each time with different purpose. Typically, several pre-analyses antecede an analysis. In most of these analyses data mining algorithms are involved.

Clustering is often used to segment a data set of heterogenous objects into subsets of objects that are more homogenous than the unsegmented data set. Succeeding algorithms analyse these homogenous data sets for interesting patterns, for instance to find some kind of predictive model such as a churn model that can be used to predict the probability a customer will cancel one's contract in a given time frame. In other words, clustering and classification algorithms are used in combination to achieve a common goal—in this case to determine a churn model per segment.

A company can also use the combination of clustering and classification algorithms to determine segments that it can easily identify a customer's segment. Otherwise, there could be too many customers which are erroneously assigned to a segment.

When there is a sequence of data mining algorithms analysing data, the conventional way is to compute the results of each algorithm individually. We will call that kind of sequential computation of a combination of data mining algorithms *naïve combined data mining* because this proceeding lacks to exploit potential improvements the combination of algorithms offers.

Figure 1 illustrates (a) the conventional way of combining data mining algorithms and (b) our improved way of combining algorithms, which is sketched in the remainder of this section.

In a sequence of algorithms, each algorithm within that sequence has the role of antecessor or successor of another algorithm. Although algorithms in the middle of a sequence with more than two algorithms can have both roles, there is only one antecessor and one successor in each pair of algorithms.

The antecessor retrieves tuples and performs some operations on them such as determining groups of

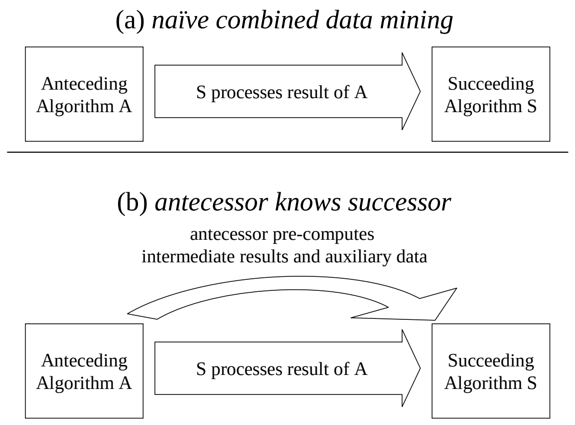


Figure 1: Conventional and improved way of sequences in algorithm combinations.

similar tuples or marking some tuples as relevant according to a given criterion. The successor needs the antecessor's result or the modifications the antecessor has applied to the data because otherwise both algorithms could have been run in parallel.

In this work we examine only sequences of data mining algorithms that are connected due to their results, i.e. the result of one algorithm is needed for another algorithm. Thus, parallelising unconnected data mining algorithms is no issue of this work.

If it is known that there will be a run of the successor, the antecessor can do more than processing its own task: During a scan of the data the antecessor can compute intermediate results the successor needs and auxiliary data the successor can profit of. As accessing tuples on a hard disk takes much more time than CPU operations do, additional computations are almost for free once a tuple is loaded into main memory.

Profiting of intermediate results and auxiliary data means that the succeeding algorithm is either faster or it returns results of higher quality than in the case of not-using intermediate results and auxiliary data.

We call the approach of the antecessor preprocessing items for the successor *antecessor knows successor* because the task of the successor must be known when starting the antecessor.

We demonstrate in a series of experiments that the approach *antecessor knows successor* is beneficial for succeeding data mining algorithms. As some results have been declared as corporate secret by our industrial partner only half of our tests shown in this paper are made with real data. Where free real data was unavailable we re-did tests with synthetical data having similar characteristics.

The remainder of this paper is organised as follows: Section 2 discusses related work in literature. Previous work concentrates on what we refer to as *naïve combined data mining* . Section 3 describes how an anteceding algorithm can pre-compute intermediate results for later usage by succeeding algorithms. The experimental results section, section 4, discusses the results of our experiments based on costs and benefits of our approach. It also concludes this paper.

2 RELATED WORK

This section surveys previous work on using combinations of data mining algorithms. Previous work can be classified in (a) work on solving a complex problem of knowledge discovery by combining a set of algorithms of different type and (b) work on solving a problem by using a combination of algorithms of the same type.

Our discussion of previous work below shows that especially combining algorithms of different type offers much room for improvement.

2.1 Using Different Types of Data Mining Algorithms to Solve Complex Problems

The combination of clustering and classification is the by far most used combination of different types of data mining algorithms we found in literature. Hence, this paper focusses on the combination of clustering and classification. However, we also present how to apply our concept on other combinations in short because the concept is not limited to clustering and classification.

Several approaches like (Kim et al., 2004) and (Genther and Glesner, 1994) use clustering to improve the accuracy of a succeeding classification algorithm when there are too many different attributes for classification. Having less attributes is desirable because there are less combinations of attributes possible. As a consequence of less combinations, the resulting trees are less vulnerable to over-fitting.

Approaches of text classification such as (Dhillon et al., 2002) pre-cluster words in groups of words before predicting the category of a document. Again, the accuracy of classification rises due to the decreasing number of different words.

However, all above-mentioned approaches combine clustering and classification without taking potential improvements in the algorithms. The algorithms are merely executed sequentially. Hence, we call such approaches naïve combined data mining.

Combinations of association rule analysis (*ARA*) and other data mining techniques include the combinations clustering succeeded by *ARA*, classification succeeded by *ARA*, and *ARA* succeeded by clustering.

There exist several approaches that reduce the number of found rules by clustering such as (Lent et al., 1997) and (Han et al., 1997). Unfortunately, the herein presented auxiliary data are unable to improve approaches of this kind. Thus, we omit this combination in further sections.

In web usage mining, an anteceding clustering of web sessions partitions user in groups having a different profile of accessing a web site. A succeeding association rule analysis examines patterns of navigation segment by segment, as shown in (Lai and Yang, 2000) or (Cooley, 2000). However, most papers focus on either *ARA* or clustering, as shown in (Facca and Lanzi, 2005).

Again in web usage mining, a classification algorithm can determine filter rules to distinguish accesses of human users and software agents which is needed as only user accesses represent user behaviour.

Both, a clustering algorithm and the scoring function of a classification algorithm, scan all data the succeeding *ARA* algorithm needs. Thus, they could efficiently pre-compute intermediate results for an association rule analysis.

However, all above-mentioned approaches are approaches of naïve combined data mining. Hence, they are candidates for being improved by our approach as shown in section 3.

There are data mining algorithms such as the approaches of (Kruengkrai and Jaruskulchai, 2002) and (Liu et al., 2000) that call other data mining algorithms during their run. Hereby, there is a strong coupling between both algorithms as the calling algorithm cannot exist on its own. The calling algorithm would become a different algorithm when removing the call of the other algorithm. Thus, we do not call this coupling of algorithms a sequence of algorithms because one cannot separate them. In contrast to that our approach uses loosely coupled algorithms where each algorithm can exist on its own.

2.2 Combining Data Mining Algorithms of the Same Type to Improve Results

Combining data mining algorithms of the same type to solve a problem is a good choice when there is a trade-off between speed and quality. Fast but inaccurate algorithms find initial solutions for succeeding algorithms that deliver better results but need more time. k-means (MacQueen, 1967) and EM (Dempster et al., 1977) is such a combination where k-means generates an initial solution for EM.

Some approaches that cluster streams use hierarchical clustering to compress the data in a dendrogram which a partitioning clustering algorithm uses as a replacement of tuples. Using this combination, only one scan of data is needed—which is a necessary condition to apply an algorithm on a data stream. Partitioning clustering algorithms typically need multiple scans of the data they analyse. (O'Callaghan et al., 2002), (Guha et al., 2003), (Zhang et al., 2003), and (Chiu et al., 2001) are approaches that use a dendrogram to compute a partitioning clustering.

An algorithm clustering streams must scan the data at least once. Thus, algorithms clustering data streams need a scan in any case.

As the above-mentioned approaches of clustering streams need only the minimum number of scans, there is not much room for improvement. (Bradley et al., 1998) have shown that quality of clustering remains high when using aggregated representations of data such as a dendrogram instead of the data itself. Thus, the approaches clustering streams mentioned above are not limited to streams.

As combining clustering algorithms of the same type is established in research community, the herein-presented approach focusses on combinations of data mining algorithms of different type.

3 ANTECESSOR KNOWS SUCCESSOR

This section describes the concept *antecessor knows successor* in detail. It is organised as follows: Subsection 3.1 introduces different types of intermediate results and auxiliary data. Subsection 3.2 shows their efficient computation during the antecessor's run. The subsequent subsections describe the beneficial usage of intermediate results and auxiliary data in runs of succeeding algorithms that are association rule algorithms in subsection 3.3, decision tree algorithms in subsection 3.4, and naïve bayes classification algorithms in subsection 3.5.

3.1 Intermediate Results and Auxiliary Data

The antecessor can compute intermediate results or auxiliary data for the successor.

We call an item an intermediate result for the successor if the successor would have to compute that item during its run if not already computed by the antecessor.

Further, we call a date an auxiliary date for the successor if that item is unnecessary for the successor to compute its result but either improves the quality of the result or simplifies the successor's computation.

Therefore, the type of the succeeding algorithm determines whether an item is an intermediate result or an auxiliary date. An item can be intermediate result in the one application and an auxiliary date in the other one. For instance, statistics of the distribution of tuples are intermediate results for naïve Bayes classification but are auxiliary data for decision tree classification.

Both, intermediate results and auxiliary data, are either tuples fulfilling some special condition or some statistics of the data. For instance, tuples that are modus, medoid, or outliers of the data set are tuples fulfilling a special condition—modus and medoid represent typical items of the data set, while outliers represent atypical items. Furthermore, all kind of statistics such as mean and deviation parameter are potential characteristics of the data.

We call a tuple fulfilling a special condition an *auxiliary tuple* while we denote an additionally computed statistic of the data an *auxiliary statistic*.

3.2 Requirements for Efficient Computation of Intermediate Results and Auxiliary Data

This section shows what is required to efficiently compute intermediate results and auxiliary data for the successor. It concentrates on the cost of computing and storing intermediate results and auxiliary data. Their beneficial usage depends on the type of the succeeding algorithm. Hence, the description of using intermediate results and auxiliary data is part of the following subsections 3.3, 3.4, and 3.5.

For computing the antecessor's result, intermediate results and auxiliary data in parallel, it must be possible to compute intermediate results and auxiliary data without additional scans of the data. Otherwise, pre-computing intermediate results and auxiliary data would decrease the antecessor's performance without guaranteeing that the successor's performance gain exceeds the successor's performance loss. Consequentially, our approach is limited to auxiliary data and intermediate results that can easily be determined.

Statistics such as mean and deviation are easy to compute as count, linear sum, and sum of squares of tuples is all that is needed to determine mean and deviation.

Hence, count, linear sum and sum of squares are easily-computed items that enable the computation of several auxiliary statistics.

If the antecessor is a clustering algorithm, auxiliary statistics can be statistics of a cluster or statistics of all tuples of the data set. As the number of clusters of a partitioning clustering algorithm is typically much smaller than the number of tuples, storing auxiliary statistics of all clusters is inexpensive. Thus, we suggest to store all of them. Our experiments show that cluster-specific statistics enable finding good split points when the successor is a decision tree algorithm.

Other statistics like the frequencies of attribute values and the frequencies of the k most frequent pairs of attribute values are also easy to compute as shown in subsections 3.3 and 3.5, respectively.

The cost of determining whether a tuple is an auxiliary tuple or not depends on the special condition which that tuple must fulfill. The mode of a data set is easy to determine. However, determining if a tuple is an outlier or a typical representative of the data set is difficult because one requires the tuple's vicinity to test the conditions "is outlier" and "is typical representative". Tuples in sparse areas are candidates for outliers. In analogy to that, tuples in dense areas are candidates for typical representatives.

However, if the anteceding algorithm is an iteratively optimising clustering algorithm such as EM or k-means, the task of determining whether a tuple is a typical representative or an outlier simplifies to the task of determining whether the tuple is within the vicinity of the cluster's centre, or far away of its cluster's centre.

Further, intermediate results must be independent of any of the successor's parameters because the specific value of a parameter of the successor might be unknown when starting the antecessor. For instance, it could be known there will be a succeeding classification but the analyst has not yet specified which attribute will be the class attribute.

Yet, if a parameter of the successor has a domain with a finite number of distinct values, the successor can pre-compute intermediate results for all potential values of this parameter. For instance, assume that the class attribute is unknown. Then, the class attribute must be one of the data set's attributes. To be more specific, it must be one of the ordinal or categorical attributes that are non-unique, as shown in section 4.2.2. Section 4.2.2 also shows that small buffers are sufficient to store auxiliary statistics for all potential class attributes.

3.3 Intermediate Results for Association Rule Analyses

If the succeeding algorithm is an algorithm which mines association rules such as apriori or FP-growth, the frequency of all item sets with one element is a parameter-independent intermediate result: Apriori (Agrawal and Srikant, 1994) can then determine the frequent item sets of length 1 without scanning the data. FP-growth (Han et al., 2000) can also then determine the item to start the FP-tree with—which is the most-frequent item—without scanning the data.

Therefore having pre-computed the frequencies of 1-itemsets as intermediate results during the antecessor's run saves exactly one scan. If the additional time is less than the time of a scan, we receive an improvement in runtime.

As the saving is constantly a scan and the results are identical with or without pre-computed frequencies, we omit presenting tests in the experimental results section.

If it is known which attribute represents the item of the succeeding association rule analysis, the antecessor can limit the number of potential 1-itemsets. Otherwise, the antecessor must compute the frequency of each attribute value for all ordinal and categorical attributes.

Even for large numbers of attributes and different attribute values per attribute, the space that is necessary to store the frequency of 1-itemsets is small enough to easily fit in the main memory of an up-to-date computer. We exclude attributes with unique values because they would significantly increase the number of 1-itemsets while using them in an association rule analysis makes no sense.

3.4 Auxiliary Data for Decision Tree Classification

Classification algorithms generating decision trees take a set of tuples where the class is known—the training set—to derive a tree where each path in the tree reflects a series of decisions and an assignment to a class. A decision tree algorithm iteratively identifies a split criterion using a single attribute and splits the training set in disjoint subsets according to the split criterion. For doing this, the algorithm tries to split the training set according to each attribute and finally uses that attribute for splitting that partitions the training set best to some kind of metric such as entropy loss.

Composing the training set and the way the training set is split influence the quality of the decision tree.

One can choose the training set randomly or one can choose tuples that fulfill a special condition as elements of the training set. Our experiments in subsection 4.2.1 show that accuracy of classification increases when choosing tuples fulfilling a special condition.

Splitting ordinal or continuous attributes is typically a binary split at a split point: Initially, the algorithm determines a split point. Then, tuples with an attribute value of the split attribute that is less than the split point become part of the one subset, tuples with greater values become part of the other subset.

Determining the split point is non-trivial if the split attribute is continuous because the number of potential split points is unlimited.

However, auxiliary statistics describing the distribution of attributes simplify finding good split points.

Assume that the anteceding algorithm is a partitioning clustering algorithm. Thus, the set of auxiliary statistics also includes a set of statistics of each cluster.

With the auxiliary statistics of each cluster one can determine a set of density functions for each continuous attribute the decision tree algorithm wants to test for splitting.

The experiments in section 4.2.1 show that the points of intersection of all pairs of density functions are good candidates of split points.

3.5 Intermediate Results and Auxiliary Data for Naive Bayes Classification

It is very easy to deduce a naive Bayes-classifier using only pre-computed frequencies. A naive Bayes-classifier classifies a tuple $t = (t_1, \ldots, t_d)$ as the class $c \in C$ of a set of classes C that has the highest posterior probability $P(c|t)$. The naive Bayes-classifier needs the prior probabilities $P(t_i|c)$ and the probability $P(c)$ of class c—which the successor can pre-compute—to determine the posterior probabilities according to the formula

$$P(c|t) = P(c) \prod_{i=1}^{d} P(t_i|c). \qquad (1)$$

Determining the probabilities on the right hand side of formula 1 requires the number of tuples, the total frequency of each attribute value of the class attribute, and the total frequencies of pairs of attribute values where one element of a pair is an attribute value of the class attribute, as the probabilities $P(c)$ and $P(t_i|c)$ are approximated by the total frequencies $F(c)$ and $F(c \cap t_i)$ as $P(c) = \frac{F(c)}{n}$ and $P(t_i|c) = \frac{F(c \cap t_i)}{F(c)}$, respectively.

Frequency $F(c)$ is also the frequency of the 1-itemset $\{c\}$, which is an intermediate result stored for an association rule analysis, as shown in subsection 3.3. As count n is the sum of all frequencies of the class attribute, the frequency of pairs of attribute values is the only remaining item to determine.

Storing all potential combinations of attribute values is very expensive when there is a reasonable number of attributes but storing the top frequent combinations is tolerable. As the Bayes classifier assigns a tuple to the class that maximises posterior probability, a class with infrequent combinations is rarely the most likely class because a low frequency in formula 1 influences the product more than several frequencies that represent the maximum probability of 1.

As a potential solution, one can store the top frequent pairs of attribute values in a buffer with fixed size and take the risk of having a small fraction of unclassified tuples.

Counting the frequency of attribute value pairs is only appropriate when the attributes to classify are ordinal or categorical because continuous attributes potentially have too many distinct attribute values.

If a continuous attribute shall be used for classification, the joint probability density function replaces the probabilities of pairs of attribute values in formula 1.

The parameters necessary to determine the joint probability density function such as the covariance matrix are auxiliary statistics for the succeeding Bayes classification.

Hence, pre-computed frequencies and a set of pre-computed parameters of probability density function are all that is needed to derive a naïve Bayes classifier. Subsection 4.2.2 shows that the resulting classifiers have high quality.

4 EXPERIMENTS

We exemplify our approach with a series of experiments organised in two scenarios: (a) Combining clustering with decision tree construction and (b) combining clustering with naïve Bayes classification.

k-means clustering is the antecessor in both scenarios. It pre-computes statistics and identifies specific tuples that could potentially be used as intermediate results and auxiliary data as mentioned in subsection 3.2. All intermediate results and auxiliary data needed by the successors in scenarios (a) and (b) are a subset of these items. We examine the costs for pre-computing all items.

In scenario (a) we adapt the classification algorithm Rainforest (Gehrke et al., 2000) to use auxiliary data consisting of auxiliary tuples and statistics. We investigate the improvement on classification accuracy by using these auxiliary data.

In scenario (b) we construct naïve Bayes classifiers using only pre-computed intermediate results consisting of frequent pairs of attribute values. We compare the classification accuracy using these pre-computed intermediate results with the conventional way to train a naïve Bayes classifier.

4.1 Cost of Anticipatory Computation of Intermediate Results and Auxiliary Data for the Succeeding Algorithm

The cost of computing intermediate results and auxiliary data are two-fold. On the one hand, storing intermediate results and auxiliary data requires space.

Table 1: Computational cost of k-means with and without pre-computing auxiliary data and intermediate results.

		time in seconds		overhead
tuples	iterations	without	with	in percent
100’000	4	655	710	8
200’000	3	676	780	15
300’000	7	2’123	2’144	1
400’000	3	1’266	1’500	18
500’000	4	1’654	2’064	25
600’000	6	2’636	3’296	25
700’000	6	2’968	3’740	26
800’000	5	3’137	3’720	19
900’000	5	3’506	4’284	22
1’000’000	2	2’297	2’928	27
2’000’000	6	8’492	10’352	22
3’000’000	2	6’209	6’999	13
4’000’000	5	13’745	16’824	22
5’000’000	5	18’925	22’165	17

This space should fit into the main memory to avoid additional write and read accesses to the hard disk—which would slow down the performance of computation. On the other hand, additional computations need time regardless there are additional disk accesses or not.

Table 1 shows the cost of runtime of k-means without and with pre-computing intermediate results and auxiliary data. The data set used in this table is the largest data set of our test series. It is the synthetical data set we used in the test series as described in section 4.2.1.

In the tests of table 1 we saved intermediate results and auxiliary data to disk such that we receive the maximum time of overhead.

Yet, the average percentage of additional time is 20 percent when saving intermediate results and auxiliary data. In a third of all tests this additional time is approximately the same amount of time as needed for an additional scan.

However, in a majority of cases the additionally needed time is a minor temporal overhead.

The space that is necessary to store intermediate results and auxiliary data significantly depends on the type of data mining algorithm that succeeds the current algorithm. Hence, we postpone the costs of space when we discuss the benefit for different types of data mining algorithms.

4.2 Benefit of Pre-Computed Intermediate Results

4.2.1 Benefit for Decision Tree Classification

For demonstrating the benefit of auxiliary data for decision tree classification we modified the Rainforest classification algorithm to use auxiliary data. The

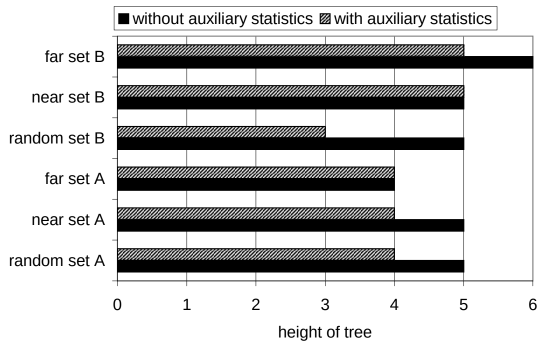


Figure 2: Height of decision tree.

data set used for testing is a synthetical data set having two dozens attributes of mixed type. The class attribute has five distinct values. Ten percent of the data is noisy to make the classification task harder. Additionally, classes overlap.

In a anteceding step we applied k-means to find the best-fitting partitioning of tuples. We use these partitions to select tuples that are typical representatives and outliers of the data set: We consider tuples that are near a cluster's centre as a typical representative. Analogically, we consider a tuple that is far away of a cluster's centre as an outlier. Yet, both are auxiliary tuples according to our definition in section 3.1. Due to their distance to their cluster's centre we call them *near* and *far*.

We tested using both kinds of auxiliary tuples as training set instead of selecting the training set randomly.

In addition to auxiliary tuples we stored auxiliary statistics such as mean and deviation of tuples of a cluster in each dimension.

We used these statistics for determining split points in a succeeding run of Rainforest. After each run we compared the results of these tests with the results of the same tests without using auxiliary statistics.

Compactness of tree and accuracy are the measures we examined. Compacter trees tend to be more resistant to over-fitting, e.g. (Freitas, 2002, p 49). Hence, we prefer smaller trees. We measure the height of a decision tree to indicate its compactness.

Using statistics of distribution for splitting returns a tree that is lower or at maximum as high as the tree of the decision tree algorithm that uses no auxiliary statistics, as indicated in figure 2.

The influence of using auxiliary statistics on accuracy is ambiguous, as shown in figure 3. Some tests show equal or slightly better accuracy, others show worse accuracy than using no auxiliary statistics.

However, using auxiliary tuples as training set significantly influences accuracy. Figure 3 shows that choosing tuples of the near set is superior to choosing tuples randomly.

Table 3: Classification accuracy of Bayes classifier with pre-computed frequencies.

test	S10%	S20%	S50%	aux400	aux1000
accuracy (%)	80.5	81.8	83.5	83.5	83.8
classified (%)	96.6	97.1	98.4	96.9	97.3
total accuracy (%)	77.8	79.4	82.2	80.9	81.2
buffer size				400	1000
pairs of class attribute *churn*				107	248

Considering each test series individually we observe that the number of tuples only slightly influences accuracy. Except for the test series foA and faA, accuracy is approximately constant within a test series.

Thus, selecting the training set from auxiliary tuples is more beneficial than increasing the number of tuples in the training set. We suppose that the chance that there are noisy data in the training set is smaller when we select less tuples or select tuples out of the near set.

Summarising, if one is interested in compact and accurate decision trees then selecting training data out of the near data set in combination with using statistics about distribution for splitting is a good option.

4.2.2 Benefit for Naïve Bayes Classification

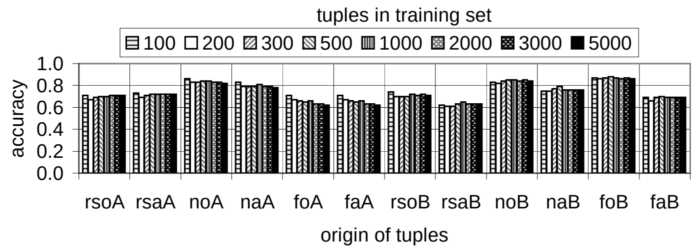
For demonstrating the benefit of pre-computing frequencies of frequent combinations for naïve Bayes classification, we compared naïve Bayes classifiers using a buffer of pre-computed frequencies with naïve using the traditional way of determining a naïve Bayes classifier.

We trained naïve Bayes classifiers on a real data set provided by a mobile phone company to us. We used data with demographical and usage data of mobil phone customers to predict whether a customer is about to churn or not. Most continuous and ordinal attributes such as age and sex have few distinct values. Yet, other attributes such as city have several hundreds of them. We used all non-unique categorical and ordinal attributes.

For checking the classifiers' accuracy, we reserved 20 % of available tuples or $9'999$ tuples as test data. Further, we used the remaining tuples to draw samples of different size and to store the frequencies of frequent combinations in a buffer.

For storing the top frequent pairs of attribute values, we reserved a buffer of different sizes. If the buffer is full when trying to insert a new pair an item with low frequency is removed from the buffer.

To ensure that a newly inserted element of the list is not removed at the next insertion, we guarantee a minimum lifetime t_L of each element in the list. Thus,



legend	without auxiliary statistics		with auxiliary statistics	
	data set A	data set B	data set A	data set B
random sample	rsoA	rsoB	rsaA	rsaB
near tuples	noA	noB	naA	naB
far tuples	foA	foB	faA	faB

Figure 3: Accuracy of decision tree classifier.

Table 2: Results of Naïve Bayes Classification in detail.

	sample 10 %		sample 20 %		sample 50 %		auxiliary buffer 400		auxiliary buffer 1000	
	actual class		actual class		actual class		actual class		actual class	
estimate	false	true	false	true	false	true	false	true	false	true
false	7683	1394	7885	1449	8195	1494	8054	1461	8124	1471
true	487	97	321	52	130	25	140	35	108	31

we remove the least frequent item that has survived at least t_L insertions.

Estimating the class of a tuple needs the frequency of all attribute values of that tuple in combination with all values of the class attribute. If a frequency is not present, classification of that tuple is impossible.

A frequency can be unavailable because either (a) it is not part of the training set or (b) it is not part of the frequent pairs of the buffer. While option (b) can be solved by increasing the buffer size, the problem of option (a) is an immanent problem of Bayes classification.

Therefore, we used variable buffer sizes and sampling rates in our test series. We tested with a buffer with space for 400 pairs and 1000 pairs of attribute values. As the buffer with capacity of 1000 pairs became not full, we left out tests with larger buffers.

Table 3 contains the results of tests with sampling S10%, S20%, and S50% and results of tests with buffers as auxiliary data aux400 and aux1000 in summarised form. Table 2 lists these results in detail.

Table 3 shows that small buffers are sufficient for generating Bayes classifiers with high accuracy.

Although the tests show that classification accuracy is very good when frequencies of combinations are kept in the buffer, there are few percent of tuples that cannot be classified. Thus, we split accuracy in table 3 in accuracy of tuples that could be classified and accuracy of all tuples. The tests show that the buffer size influences the number of classified tuples. They also show that small buffers have a high classification ratio.

Thus, small buffers are sufficient to generate naïve Bayes classifiers having high total accuracy using exclusively intermediate results.

4.3 Summary of Costs and Benefits

Our experiments have shown that the costs for computing intermediate results and auxiliary data are low—even, if one saves a broad range of different types of intermediate results such as the top frequent attribute value pairs and auxiliary data such as typical members of clusters to disk. In contrast to that, the benefit of intermediate results and auxiliary data is high.

In scenario (a) we examined the effect of using typical cluster members as auxiliary data on the accuracy of a decision tree classification that succeeds a k-means clustering. We observed that tuples which are near the clusters' centres are good candidates of the training set.

In scenario (b) we examined the accuracy of naïve Bayes classifiers that were generated only by using frequencies of attribute value pairs calculated as intermediate results for the naïve Bayes classifier by an anteceding k-means clustering. These classifiers had about the same accuracy as conventional classifiers using high sampling rates but could be quickly computed from the intermediate results.

Furthermore, the general principle of our approach is widely applicable. For instance, with regards to *ARA* we have shown that pre-computing frequencies of 1-itemsets saves exactly one scan of an association rule analysis without changing the result.

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