# Identification of Corporate Competitiveness Factors – Comparing Different Approaches

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**Abstract:** The methodology and current results of identifying factors of corporate competitiveness in the Czech Republic are discussed. The task is to investigate what is the mutual dependency between the corporate competitiveness (characterized here by the corporate financial performance (hereinafter called 'CFP) and selected characteristics describing these companies. Such characteristics can be regarded as the factors of competitiveness. The task of determining these factors has to be solved in multidimensional space. Therefore, the feature selection methodology from statistical pattern recognition, selecting a group of the most informative characteristics appears to be a suitable and promising approach. As opposed to our recent paper based on the classification approach, an alternative approach based on non-linear statistical regression is presented here. The paper presents a brief introduction to both the approaches and the results achieved when using them.

**Keywords**: factors of corporate competitiveness, corporate financial performance, empirical research, non-linear regression, feature selection, statistical pattern recognition

## 1. Introduction

The topic of automated search for factors of corporate competitiveness is important both for corporate economics theory and for the management theory. It has been also a subject of research of The Research Centre for Competitiveness of the Czech Economy (RCCCE). As the competitiveness of companies can be characterized by their financial performance, a hypothesis that there exists a significant mutual dependency between the CFP and selected characteristics describing these companies can be formulated. Then the task is to find a smaller subset of these characteristics that has a good informative power for discrimination between competitive and non-competitive companies. The characteristics (variables) belonging to this subset may be regarded as the factors of competitiveness.

Concerning research focused on corporate competitiveness, studies using correlations (cf. Andrews, R., 2010, Liu, P. L., 2004), t-tests (cf. Artiach, T., 2010) or other methods based on examining associations between two or a very small number of variables were published. The authors believe that corporate competitiveness, even if narrowed down to CFP, depends on many factors and that the influence of these factors needs to be examined as mutual associations between a number of interconnected variables and CFP. Our view is in accordance with empirical studies of corporate competitiveness using advanced statistical methods such as multiple regression (cf. Cagwin, D., 2006), logistic regression (cf. Kessler, A., 2007), structural modelling (cf. Yilmaz, C., 2005) or decision trees (cf. Molina, M. A., 2004). However, each of these methods has its limitations, requirements and drawbacks. Similarly, though the first results of the Centre (cf. Blazek et al. 2008) were based mainly on bivariate analysis of these variables, the fact that they are generally not mutually independent resulted in using methods of multivariate analysis. The authors aim to show that the methodology of feature selection in statistical pattern reduction, rarely used in this context to date (cf. Pudil et al. 2002), is a well-developed methodology fulfilling this task. This prompted the inter-disciplinary cooperation between the RCCCE and researchers in the field of statistical pattern recognition and machine learning. The results stemming from this cooperation are briefly presented in the following.

In order to verify the above-specified hypothesis, two approaches have been investigated, differing in the way the factors group is selected and moreover, also how the CFP is defined:

- "Pattern classification approach" - by means of the informativeness for classification into a pre-defined set of mutually exclusive classes of companies;
- "Regression approach" - by means of the non-linear regression model accuracy.

The first approach has been the primary focus of our paper at 8th European Conference on Management Leadership and Governance (cf. Pudil et al. 2012). The current paper is more focused on the second approach; however, it also presents a comparison of both the approaches.

## 2. Corporate data set properties and definition of corporate financial performance

It is obvious that owing to vast differences among various types of companies, our research had to focus on a more homogenous selection of companies. Taking into consideration the availability of needed information, the primary set of researched companies was defined by:

- territorial aspect – companies located in the Czech Republic, further divided by regions
- business sectors (industry segment) aspect – sector D Manufacturing industry and sector F Construction business (according to the sector classification of economic activities)
- size aspect – companies with more than 50 employees
- legal form of business – limited liability companies, and joint-stock companies.

The set of companies that would satisfy the given criteria, after excluding companies in liquidation proceedings, bankruptcy, or under court execution, totalled 4483 subjects at the time of empirical survey carried out by the RCCCE. For the experiments, a representative sample of 396 companies located in the Czech Republic were utilized. The information from 'Albertina Data' database provided economic data of individual companies compiled from their financial statements. The characteristics representing potential competitiveness factors were drawn from questionnaires filled out during an empirical survey by researchers in cooperation with the respondents. After pre-processing, each company was characterized in this way by 36 variables (cf. Blazek at al. 2008).

To enable the evaluation of the relation between selected company characteristics and the overall CFP, it is first necessary to define how CFP is expressed within our investigation. Considering Kaplan and Norton`s (2004) proposal of two possible strategies to achieve a company's financial goals (Revenue Growth and Productivity), two indicators were used: Assets Growth (GA) and Return on Assets (ROA). The authors consider this as more complex approach than the use of a single indicator (as used in Bottazzi, G., 2008 or Abor, J., 2007) but still better operationalizable than the 9 indicators used by Yilmaz (2005) or the 14 used by Molina (2004). A long-term situation of the companies was characterized by the mean of six-year time series for the chosen indicators.

For the purpose of classification, (cf. Pudil et al. 2012) companies were grouped into three classes on the two-indicator space. The companies with the above average value of the CFP coefficient were denoted as having a good CFP, thus 'successful' (group A, included 165 companies). On the other hand, the companies having a negative assets growth or/and with a negative ROA were denoted as 'unsuccessful' (group C, included 82 companies). The remaining companies became the 'intermediate' group B.
For regression analysis, we do not need the class information but a single continuous value expressing the overall CFP. For this purpose, we use the sum $2^{GA} + 2^{ROA}$.

## 3. Feature selection based evaluation of competitiveness factors

As stated above, the multivariate analysis has to be used for the investigated task. In the context of machine learning, however, multivariate analysis is common and the available analysis frameworks have been considered vital in various recognition tasks (credibility scoring, image analysis, automated medical diagnostics (cf. Theodoridis and Koutroumbas 2006)). One of the key approaches to multi-variate analysis is feature selection (FS).

### 3.1 Feature Selection Methodology

The methodology of feature selection or more generally dimensionality reduction in machine learning is very extensive and its detailed description is beyond the scope of this paper. The principal goal of FS is to select a small subset of given problem characteristics to optimize a model, typically with the aim to discriminate among classes of observations, or to optimize any suitably defined criterion function. We utilize the FS methodology in two ways1/ to search for a subset of characteristics which discriminate best between companies of groups A, B and C as much as possible; 2/ to search for a subset of characteristics that minimizes the regression error.

It should be noted that the resulting optimized subsets of these two different tasks may be different.

The main advantage of non-trivial FS methods is their ability to evaluate characteristics in context, possibly extracting more information than is customary with commonly used ranking methods. In machine learning it is well known that "the two individually best features may not be the best pair". Very often either the two individually best might prove redundant (each of them provides almost exactly the same information despite their seemingly different nature), or none of the features proves sufficient to reveal the true structure in data (see Figure 1 for illustration of a two-dimensional case, note that the same effects can take place in multiple-dimensional subspaces).

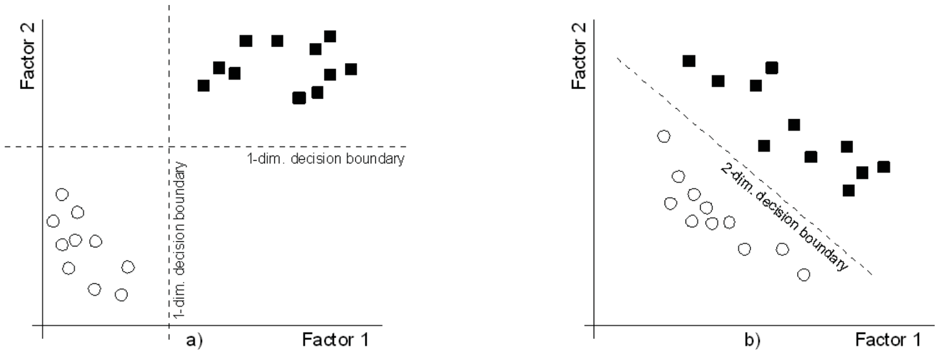


**Figure 1:** Cases of possible univariate analysis failure (illustrative example). Let green dots represent the companies of poor CFP and blue rectangles represent the well performing companies. Univariate analysis is not capable of revealing a) competitiveness factor redundancy, b) multi-variate factor dependency leading to crucial model accuracy improvement in higher than one-dimensional subspace.

In order to find the most informative subset of features, we need:

- an efficient strategy of traversing the space of possible subsets towards the optimum
- a criterion to evaluate the quality of arbitrary subsets of features.

A wealth of search strategies and criteria exists. There is no single strategy, nor a single criterion function known to be best in all cases. Moreover, our data had the limitation of a relatively high dimensionality and a low sample size which is rather typical in this type of analyses – the more characteristics we try to collect, the less companies we have available. With respect to this fact, we decided to first apply two conceptually different FS methods and to evaluate their performance not only in terms of achieved results, but also in terms of their stability (cf. Somol and Novovovicova 2010). Further analysis (Section 4) will then be performed using the more stable (robust) method identified in the following Section 3.2.

## 4. Evaluating stability of feature selection methods

To evaluate candidate feature subsets in the stability test, we estimated the accuracy of the well-known *k*-Nearest Neighbour classifier (cf. Theodoridis and Koutroumbas 2006)). The advantage here is the simplicity, non-linearity (high descriptive power), adjustability of sensitivity to outliers through the *k* value, and most important, the possibility to redefine *k*-NN to support a mix of feature types: numerical and nominal. This was achieved by normalizing all numerical feature values to <0,1>, and defining the distance between nominal values as 0 in case of equality and 1 otherwise.

As a search strategy, we chose a) Sequential Forward Floating Search (SFFS) (cf. Pudil et al. 1994), generally known for its good optimization performance but also good search speed, and b) Dependency-Aware Feature Ranking (DAF) (cf. Somol et al. 2011) known to be very robust against over-fitting. We evaluated and compared

both of these methods with respect to achieved *k*-NN accuracy, and stability of results, evaluated by means of several stability measures (cf. Somol and Novovovicova 2010).
Based on the stability evaluation published in Pudil et al. (2012) we decided to perform all further analyses using the more stable DAF method.

## 5. Introducing the modified feature selection methodology

In order to perform a feature selection process (analysis of the dependency between particular competitiveness factors and overall CFP over the available training data) using the chosen feature selection method in our particular case, we first need to impose a suitable model on the data that would describe the underlying data structure as accurately as possible. A good model can then be used to evaluate the quality of candidate subsets of characteristics in the process of feature selection. In the following, we consider the two principally different approaches – classification and regression. The difference is in the measure of accuracy to be optimized. In the case of classification, we aim to identify such a subset of competitiveness factors, for which the model proves most accurate in distinguishing among the company groups A, B, and C (cf. Section 1). In the case of regression, we avoid the grouping and aim at minimizing the prediction error of a dependent variable expressing the overall CFP.

### 5.1 Non-parametric model

From the vast battery of existing models (cf. Theodoridis and Koutroumbas 2006) our choices are limited due to two specifics of our problem: the data is incomplete (roughly 5% of values are missing for various companies and various characteristics) and some of the available characteristics are non-numeric, i.e., their values are impossible to order. Another concern is the sample-size vs. dimensionality ratio, which in this case prevents application of models requiring large numbers of samples (mixture models or other multi-dimensional models, cf. Theodoridis and Koutroumbas 2006, where curse of dimensionality would quickly lead to over-training).

As reported in (Pudil et al. 2012) a suitable approach is the application of k-Nearest Neighbor idea (Cover, Hart 1967). k-NN is the non-parametric classifier that imposes a non-linear model taking direct use of existing samples in the training data set. Its known disadvantage – the necessity to store permanently the complete data set – is not a disadvantage in our case due to limited data size and off-line nature of our search process. On the other hand its advantage – good model fit and accuracy in case of limited data size – makes it a good choice for our purpose. The only additional tool needed is a suitably defined distance function capable of expressing the distance between any two samples (companies) in the 36-dimensional space of our data set. The commonly used distance is the Euclidean distance. A modification of standard Euclidean distance is the basis of our handling of missing values and non-numeric values.

### 5.2 Handling missing values and non-numeric values

The accuracy of the model is affected not only by its fundamental principle but also by its possible parameters or other setup details. In our case, the handling of missing values and non-numeric values proves important. Both of these concerns are reflected in the definition of distance function used within the applied models.

We considered two approaches of missing value handling, as expressed by the definition of pseudo-Euclidean distance.

- "standard" one-time substitution of each unknown value by the mean value over all known values for the respective feature in case of numeric features, or substitution by the most frequent value in case of non-numeric values
- "pessimistic" handling of unknown values when computing distance; missing values are always interpreted as if the distance was maximum with respect to the respective feature.

### 5.3 Pattern classification approach

In the classification approach, the DAF feature selection method (cf. Section 3.2) is applied to maximize the estimated prediction accuracy of k-NN classifier. In the course of the search, the DAF method generates candidate feature subsets, evaluates each of them and collects the results to obtain final feature ranking. Each candidate subset is evaluated as follows. The k-NN classifier is used to classify each single known company to one of the groups A, B, C purely based on the characteristics in the current subset. The result of classification is in each case compared to the known assignment of the respective company to one of the classes. Eventually, the percentage of companies classified correctly (predicted to belong to the same group where they actually belong) is used as the measure of subset quality.

### 5.4 Regression approach

Applying regression instead of classification has the potential benefit of preventing the impact of possible inaccuracies introduced when pre-processing data (at the moment of initial assignment of companies to classes).
We consider two regression models following an analogous idea as discussed in Sect. 4.1:

- 1-NN, where the dependent value for any point in the 36-dimensional space is predicted to be equal to that of such existing sample that is the nearest to the point in question.
- “Kernel” regressor, where the dependent value is predicted as a linear combination over dependent values of existing samples, where more distant samples get a lower weight. “Kernel” in this context is the weighing function dependent on distance among the point in question and existing samples (companies).

The idea of “kernel” regression can be viewed as analogous to the idea of k-NN classifier (cf. Sect. 4.1). Similar to k-NN, our kernel regressor imposes a non-parametric non-linear model that directly uses information from the available data. When compared to the original kernel regression idea (cf. Nadaraya 1964, Simonoff 1996) we apply a slight modification. In order to accommodate the solutions to problems described in Sect 4.2, we apply only 1-dimensional Gaussian kernels on the space of sample distances. Kernel width is then optimized, starting initially from the estimated average distance between any two samples in the available data.

In the regression approach, the DAF feature selection method (cf. Section 3.2) is applied to minimize the estimated error of predicted dependent values for each known company. The feature selection procedure is analogous to that described in Section 4.4.

## 6. Experiments and results

In our key experiments we primarily considered four different regression models, obtained by combining two types of regression models (1-Nearest Neighbour and Kernel Regressor) and two types of missing value substitution (substitution by mean value, and pessimistic treatment of each missing value as indicator of maximum distance). Feature ranking by DAF (Somol et al. 2011) has been computed in every of the four cases so as to minimize the average model error. The DAF method produced for each feature a weight, mirroring roughly the average feature ability to improve the criterion value on addition to a subset, evaluated over a large number and variety of contexts (various subsets). Additionally, we performed classification based experiments for comparison purposes.

### 6.1 Regression-based analysis results

The best-achieved models of the four types as described in Section 5 are illustrated in Figure 3.

The single best model identified in our survey – Kernel Regressor with pessimistic missing value substitution – achieved the average error of $e= 0.0268903$ and determination coefficient $Dc= 0.781963$. The fact that 1-dimensional kernel instead of 36-dimensional kernel is used proved advantageous as it prevented over-fitting issues. Kernel regression thus proved more accurate in our experiments than simple 1-NN regression.

The highest accuracy was achieved with the set all features. Removal of any feature led to degradation of results. The result of feature ranking is thus of interest to compare the importance of various company characteristics though it has not lead to any decrease of dimensionality.

The DAF method (cf. Somol et al. 2011) produced for each feature a weight, mirroring roughly the average feature ability to improve the criterion value on addition to a subset, evaluated over a large number and variety of contexts (various subsets). Figure 4 shows the obtained weights in regression case ordered in descending order. Note that the obtained DAF weights provide only the information about the relative quality of features when compared to other features. It can be seen that there is roughly up to 8 features that tend to improve criterion value considerably more than the others.

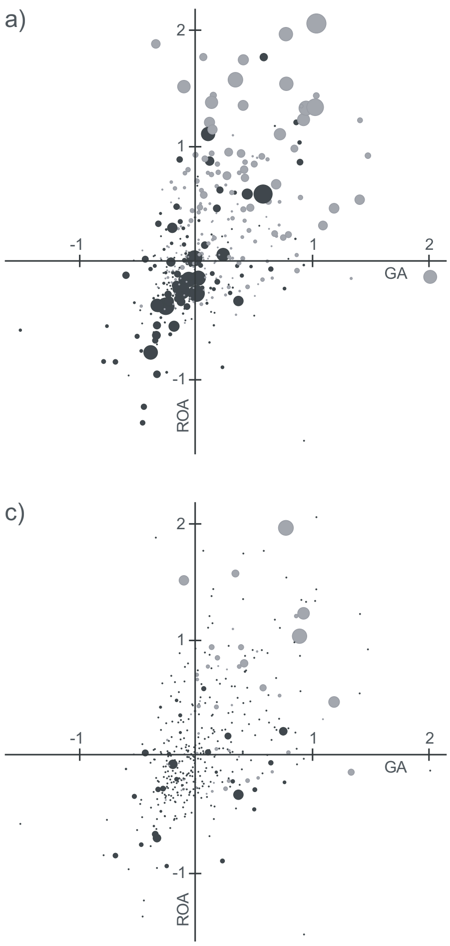


**Figure 3:** Errors of four regression models – each dot represents a company, positioned according to its Assets Growth (GA) and Return on Assets (ROA) values, higher dot diameter depicts higher regression error; black and grey colours depict its positive or negative value, respectively: a) 1-Nearest Neighbour with missing values substituted by mean values, b) Kernel Regressor with missing values substituted by mean values, c) 1-Nearest Neighbour with missing values treated pessimistically, d) (best) Kernel Regressor with missing values treated pessimistically.

The best 8 factors (regression based) in decreasing order:
Region
DAF1 coefficient 1.11868, regressor error on single feature not computable due to missing values)
*Share of technical-economic employees*
DAF1 coefficient 1.10539, regressor error on 2 best features 0.104015
*Strategy*
DAF1 coefficient 0.782508, regressor error on 3 best features 0.101098
*Business entity type (legal form of the company)*
DAF1 coefficient 0.710418, regressor error on 4 best features 0.0983053
*Ownership type (5 types of ownership)*
DAF1 coefficient 0.652801, regressor error on 5 best features 0.0920556
*Owners' origin (domestic owner, foreign, both)*
DAF1 coefficient 0.483909, regressor error on 6 best features 0.085747
Share of foreign customers
DAF1 coefficient 0.462479, regressor error on 7 best features 0.0698314
Participation of owners in top management (yes/no)
DAF1 coefficient 0.408192, regressor error on 8 best features 0.0653676

Regarded as factors of competitiveness within the framework of this pilot study, 5 out of 8 these features (denoted in italic) correspond with the previous results of Spalek and Castek (2010) based on different analyses on the same data.

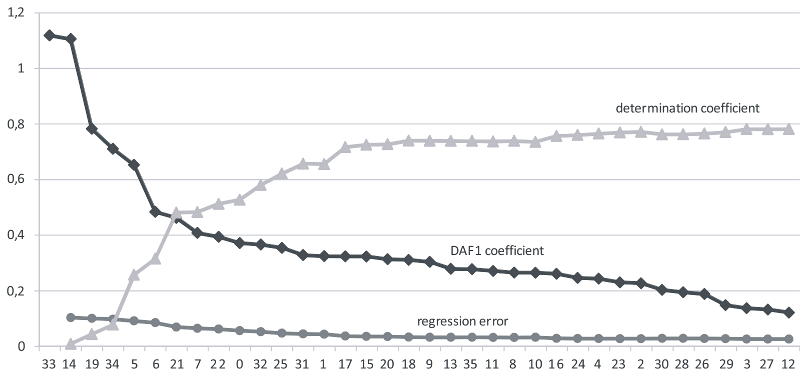


**Figure 4:** Importance of single company characteristics according to best achieved regression model. Graph represents growing subsets of features, features added according to highest DAF1 coefficients. Note that model accuracy notably improves after adding the first 8 features, and then after adding roughly next 7 features.

## 6.2 Classification-based analysis results

We performed a series of k-NN classifier based experiments for the values of k=1, 2, 3, 5, and two types of missing value substitution (substitution by mean value, and pessimistic treatment of each missing value as indicator of maximum distance).

The single best classifier identified in our survey – 1-NN classifier with pessimistic missing value substitution – achieved the estimated classification accuracy of 0.873737 for the subset of 32 features out of the complete set of 36. With the complete set, the accuracy is 0.866162. However, as illustrated in Figure 5, roughly half of all features are enough to achieve classification accuracy only negligibly worse than the best achieved. k-NN classifiers for k>1 tend to smooth out the decision boundary, i.e., reduce the influence of outliers at the cost of reducing sensitivity to detail. In our case this effect proved disadvantageous.

The DAF method (cf. Somol et al. 2011) produced for each feature a weight, mirroring roughly the average feature ability to improve criterion value on addition to a subset, evaluated over a large number and variety of contexts (various subsets). Figure 5 shows the obtained weights in classification case ordered in descending order. Note that the obtained DAF weights provide only the information about the relative quality of features when compared to other features. It can be seen that there are roughly up to 8 features that tend to improve the criterion value considerably more than the others.

The best 8 factors (classification based) in decreasing order:
Share of technical-economic employees
DAF1 coefficient 1.1404, 1-NN accuracy on the single feature 0.472222
Business entity type (legal form of the company)
DAF1 coefficient 0.574625, 1-NN accuracy on best 2 features 0.472222
ISO 14000 certificate holding (yes/no)
DAF1 coefficient 0.42274, 1-NN accuracy on best 3 features 0.472222
The quality of important assets
DAF1 coefficient 0.284363, 1-NN accuracy on best 4 features 0.494949
Participation of owners in top management (yes/no)
DAF1 coefficient 0.242903, 1-NN accuracy on best 5 features 0.494949
Software applications – SCM module (yes/no)
DAF1 coefficient 0.206311, 1-NN accuracy on best 6 features 0.525253
Ethical code adoption (yes/no)
DAF1 coefficient 0.177655, 1-NN accuracy on best 7 features 0.563131
Share of performance-related pay

DAF1 coefficient 0.164487, 1-NN accuracy on best 8 features 0.739899

Regarded as factors of competitiveness within the framework of this pilot study, 4 out of 8 these features (denoted in italic) correspond with the previous results of Spalek and Castek (2010) based on different analyses on the same data.

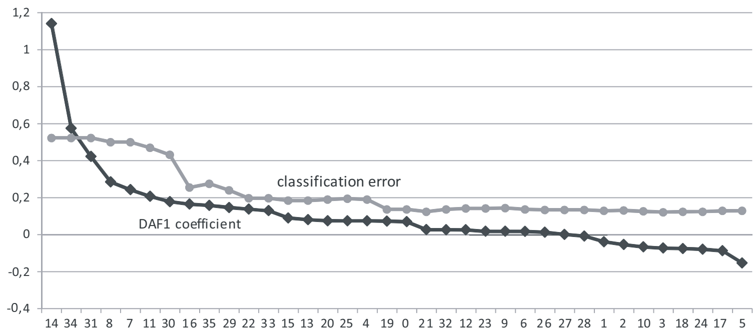


**Figure 5:** Importance of single company characteristics according to best-achieved classification using 1-NN classifier and 3-class data. Graph represents growing subsets of features, features added according to highest DAF1 coefficients. Note that model accuracy notably improves notably after adding the first 8 features, and then after adding roughly next 10 features.

### 6.3 Comparing Regression-based and Classification-based analysis results

When comparing the results achieved by both the discussed approaches, we should bear in mind that our goal is not prediction but identification of "informative" factors. Thus, the error in predicting the CFP or in classifying a company is not critically important; what matters more is which factors are assigned to the group of key factors influencing the CFP and thus the corporate competitiveness. In this context, we should not be too surprised that the regression approach and the classification one yield somewhat different results. We should keep in mind that the tasks solved by respective approaches are not absolutely the same. The way of defining the CFP, implicitly hidden in these tasks, is different. In the regression approach the CFP is defined by a combination of GA and ROA and attains continuous values. On the other hand, in the classification approach the CFP is discretized by means of clustering the companies into distinct classes.

Clearly, the classification approach does not utilize "fine" information about the value of CFP as the regression. On the other hand, as a generally accepted unique definition of CFP does not exist, clustering its values into distinct classes can also be a reasonable solution. This clustering certainly represents a simplification, representing a certain loss of information but at the same time having the potential benefit of giving more comprehensible information to the observer: the financial performance of a given company (and thus its competitiveness) is a good, average or bad one. However, from experiments we have carried out, it seems that the regression approach is less sensitive to modifications in defining the CFP and thus we can consider its results as preferable.

In any case, by comparing these different approaches and analysing the results, we can get a more robust insight into the task.

## 7. Conclusions and further directions of research

The necessity to use multivariate methods in search for factors of corporate competitiveness is undisputable. Though the methods of machine learning and feature selection (FS) in particular are related to statistical methods, they are less strict with respect to assumptions about the analysed data compared to multivariate methods of classical statistical analysis. As they have been successfully used in a number of various disciplines, the authors aimed to apply them also in the field of management.

The comparison of classification and regression-based FS approaches used in our research points at higher regression-based FS accuracy. This is understandable due to the fact that the data does not naturally imply a strict separation of samples into classes. Analysing imposed class information is thus affected by the artificially

added inaccuracy. The ranking of company characteristics obtained by optimizing the regression model can thus be considered more valuable than that obtained by optimizing a classifier (cf. Pudil et al. 2012).
The applied DAF feature selection method has been shown capable of ranking competitiveness factors according to their ability to explain the overall CFP. Several factors have been identified in the current data set as considerably more important than others, with a weight given to each evaluated factor.

Various potential problems of feature selection based analysis have been taken into account and pointed out. The important problem of possible over-fitting has been addressed and prevention measures have been taken to improve the robustness of the eventual analysis results.

The achieved results demonstrate the potential of using machine-learning methods in the field of management. Further research will be focused on refining the model selection, setup, data pre-processing and modifications in defining the CFP with the overall aim of increasing overall accuracy and stability of results.

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