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Silesian University of Technology
Faculty of Transport and Aviation Engineering

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Keywords: transport management; economic of transport, road transport, machine learning

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THE USE OF MACHINE LEARNING TO IMPROVE ROAD TRANSPORT MANAGEMENT PROCESSES

Summary. The article deals with the problem of road freight transport. The issues of the price of the transport of goods are presented. What features and how much affect the price were examined. The feature engineering process was discussed. The methods of using the Python programming language to solve the problem, conducting experiments in Jupyter Notebook, data processing in Pandas, performing calculations in NumPy and implementing machine learning models with Scikit-Learn were presented. A machine learning model was trained to compare its predictions with those of humans. Students and experts were asked to quote five free market transport offers. The results were compared with the predictions of the model. The thesis was confirmed that the model performs the forecast with a smaller error on average. The materials used for this article are available in open access on the GitHub repository.

WYKORZYSTANIE UCZENIA MASZYNOWEGO DO USPRAWNIENIA PROCESÓW ZARZĄDZANIA TRANSPORTEM DROGOWYM

Streszczenie. Artykuł porusza problematykę drogowego transportu towaru. Przedstawiono zagadnienia wyceny transportu towarów. Zbadano jakie cechy i w jakim stopniu wpływają na cenę. Omówiono proces feature engineering. Przedstawiono metody wykorzystania do rozwiązania problemu języka programowania Python, prowadzenia eksperymentów w Jupyter Notebook, przetwarzania danych w Pandas, wykonywania obliczeń w NumPy oraz implementacji modeli uczenia maszynowego z Scikit-Learn. Model uczenia maszynowego został przeszkolony w celu porównania jego predykcji z predykcjami ludzi. Studenci i eksperci zostali poproszeni o wycenę 5 ofert transportu na wolnym rynku. Wyniki porównano z przewidywaniami modelu. Potwierdzono tezę, ż model wykonuje prognozę średnio z mniejszym błędem. Materiały wykorzystane do tego artykułu są udostępnione w otwartym dostępie w repozytorium GitHub.

1. INTRODUCTION

Due to technological progress, humans are being replaced by machines in an increasing number of activities. Machine learning was defined in [1] by Tom Mitchel as the science of computer algorithms that improve automatically through experience. Applications range from data mining programs that discover general principles in large data sets to information filtering systems that automatically learn about user interests. In [2] described is the possibility of learning a machine to play checkers, which is an example of how a machine can perform certain tasks better than a human. Prediction projects based on machine learning on transport are found in the literature. In [3] the consumption of diesel fuel for 40 tons of vehicles in international transportation was presented. In [4], the prediction of demand in the freight exchange was presented based on machine learning solutions.

Transport exchange is a place where the subject of exchange is a transport service. Freight exchanges [5] are described as one of the promising solutions to transport logistics problems. The price depends on many factors. The impact of the gross domestic product on the price is presented in [6]. The publication [7] presents more complex dependencies that affect the price.

The Jupyter Notebook [8] is an editor for programming code. Pandas [9] is a data processing programming library. NumPy [10] is the programming library for calculation analysis, Scikit-Learn [11] is the machine learning programming library. Matplotlib [12] and Seaborn [13] are visualization programming libraries. GitHub [14] is a repository for programming projects. The above methods are shown in the fig. 1. Each method was assigned the number of citations in the Scopus and Researchgate database as of May 15, 2022. It was decided to also quote from Researchgate as not all articles are indexed in Scopus.

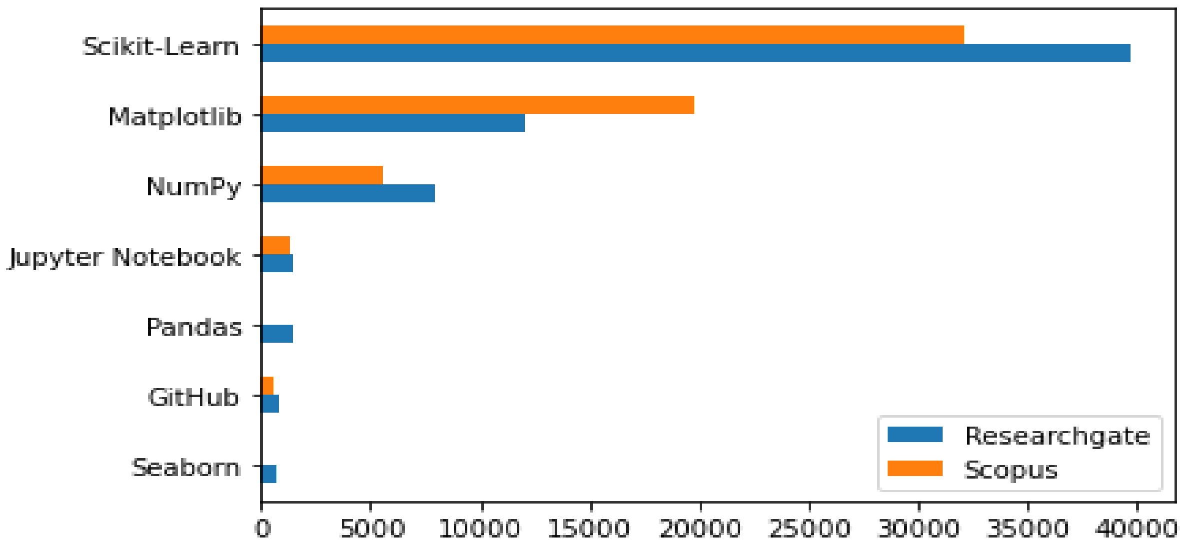

Fig. 1. Barh the number of method citations in Scopus and Researchgate databases
Rys. 1. Barh ilości cytowań metod w bazach Scopus i Researchgate

Kaggle is a platform where competitions are held for the best prediction model. The above methods are commonly used in competitions. Some examples are described below. In [15] the topic was car price forecasting in Poland using machine learning. In [16], the topic was to predict energy demand using machine learning. In [17], the topic was sales prediction with the help of machine learning. In [18] the theme was home value prediction. In [19] the topic was forecasting tram delays in Kraków. In [20] the topic was the prediction of the company bankruptcy.

With reference to the question whether machines can think in [21], it is proposed to consider the question whether machines can perform certain activities better than humans. When analyzing the literature and the situation in the free market, it can be said that the price of road transport of goods depends on many factors. The impact of the gross domestic product on transport on the number of tons of kilometers was investigated in [22]. In [23] the influence of relationships is described. The [24] shows the dependence of the price on seasonality, for example in Slovakia. In [25] the problems of pallet exchange are described. The price depends on the type of goods that will be transported. Different goods require different methods of securing [26]. In [27] the problems of food transport, in [28] temperature-controlled, and in [29] oversized ones are described. In [30] the method is presented to predict the risk and cost of cargo theft in road transport. It is important for an entrepreneur performing a transport service to know who is the payer, what the form and date of payment is.

Payment terms can be long and the customer's financial situation can be a concern for the transport company. Effective cash flow management in transport companies is described in [31]. The issue of cash flow also affects container transport [32]. The above factors are not all that can affect the price. Features can turn into a non-obvious linear trend. Seasonality can change differently in each relationship. Analysis of large data sets is also a problem, which can be difficult for a human being.

All this is the basis for the hypothesis that machine learning will become a viable method for this task. The advancement of technology and computing power is contributing to machine learning. It is proposed to consider the experiment of comparing human and machine learning in prediction. The aim of such a study is to demonstrate that machine learning is a method of improving work efficiency for people managing road freight transport.

2. METHODOLOGY

The method of many years of observation allows for hypotheses regarding the features that affect the price of transport. The statistical method, including regression and correlation analysis, is used in the project. The experimental method is used in the project. Experiments consist of checking how the model behaves with various combinations of input data. Data processing and model training were performed in the Jupyter Notebook editor and the Python programming language. The experiment is to check how human calculates the price and how the machine learning model. Programming libraries: Pandas for data processing, NumPy for calculation analysis, Scikit-Learn for machine learning, Matplolib and Seaborn for visualization are used to complete the project. The code to execute the project has been made available to the public in open access on the GitHub repository. This project is available at [33]. The methods of using Python are described in [34] The import system, the Python code in one module, accesses the code in another module through the import process. ELI5 is a Python library that allows visualization and debugging of various machine learning models using a unified API. It has built-in support for several ML frameworks and provides a way to explain black box models. ELI5 is a Python library that allows to visualize and check which features have influenced the model.

2.1. Pandas

The methods for working with data using the Pandas [35] library are presented below:

- pandas.read_csv - read a comma-separated csv file in DataFrame
- pandas.DataFrame.shape - return a tuple representing the dimensionality of the DataFrame
- pandas.DataFrame.info - give information about a DataFrame
- pandas.DataFrame.agg - an aggregation method that uses at least one operation, for example: mean, median, minimum, maximum, standard deviation
- pandas.DatetimeIndex - method to get valuable date and time data
- pandas.DataFrame.corr - method to compute pairwise correlation of columns
- pandas.DataFrame.fillna - empty values fill method
- pandas.factorize - method to obtain a numeric representation

2.2. NumPy

The calculation methods that use Numpy [36] are shown below:

- numpy.mean - method for the arithmetic mean along the specified axis
- numpy.median - method to compute the median along the specified axis
- numpy.ndarray.max - method to return the maximum along a given axis
- numpy.ndarray.min - method to return the minimum along a given axis
- numpy.ndarray.std - method to return the standard deviation along a given axis
- numpy.corrcoef - method to return Pearson product-moment correlation coefficients

2.3. Scikit-Learn

Methods with the use of Scikit-Learn [37] are presented below:

- sklearn.tree.DecisionTreeRegressor - method based on decision tree regressor
- sklearn.ensemble.RandomForestRegressor - method based on random forest which is a metaestimator that fits a number of classification decision trees on various subsamples of the dataset and uses averaging to improve predictive accuracy and control overfitting
- sklearn.ensemble.ExtraTreesRegressor - method implements a metaestimator that fits a number of randomised decision trees
- sklearn.ensemble.GradientBoostingRegressor - method of gradient boosting for regression
- sklearn.metrics.mean_squared_error - mean squared error regression loss.

2.3. Method for describe transport offer

Data should be save in a way that will be useful to analyze or train predictive models. The following is a suggestion of how each feature should be written. There are data that are necessary. The distance should be saved in kilometers and divided by country. This is important due to the differences in fees between countries. Price is necessary because that is the target variable. These are data that are useful. The gaps can be filled, for example, with the term "other". The vehicle type should be recorded according to these terms and in this order: Rigid truck, Articulated truck, Vehicle up to 12 t, Vehicle up to 7.5 t, Vehicle up to 3.5 t. The body type should be recorded according to these terms and in this order: Skip loader, Silo trailer, Box, Thermo, Tank trailer , Tipper, Container chassis, Special truck, Jumbo, Coil trough, Tautliner, Walking floor, Walking floor (Bulk material), Panel van, Car transporter, Inloader, Mega, Semi-trailer with inclined table, Extendable trailer, Low loader, Swap body truck, Roll-on roll-off tipper, Refrigerator, Tractor, Curtain, Flatbed truck, Drop side. The method of loading and unloading should be recorded according to these terms and in this order: Side, Back, Top. The payment term expressed in days determines the date on which the transport will be paid. A payment term equal to 0 means payment at the unloading point.

3. TABLES, FIGURES

Every table should have its own title. The dataset contains information on 262 free-market freight offers. All offers are for full truck loads (FTL). Each order is assigned a quantity with a price in euros. The most expensive price is 4300€ and the cheapest 20€. The average price is 811.98€ and the median is 690€. The standard deviation was 527.16 €. The prices are varied. The price is variable for prediction.

The number of kilometers is assigned to each order. The longest route is 2045.4 km and the shortest is 20.7 km. The mean load would be transported over a distance of 817.66 km and the median is 747 km. The standard deviation was 422.78 km. The distances are varied.

Each load is assigned a weight in tons. The heaviest is 25.7t. and the lightest 1.52t. The average is 21.24t and the median is 24t. It is common practice for transport seekers to expose a maximum weight of about 24 tons for the tautliner or curtain body type. The standard deviation is 5.13t.

The Pearson correlation of distance and price is 0.77. The highest rate was 6.72 [€/km] and the lowest was 0.46 [€/km]. The average cost is 1.02 [€/km] and the median is 0.92[€/ km]. The standard deviation is 0.52 [€/km]. The price of [€/km] of the route is a feature that allows analysis to compare all offers with each other.

The correlation between weight in tons and rate [€/km] is negative and is -0.04. The histogram presented in the fig. 2 is helpful in understanding this phenomenon. This is a phenomenon that may seem illogical. A decidedly uneven distribution is visible. This is due to the fact that the most common practice in offers for full truck loads is to include the maximum weight in the offer. The most common weight is 24 or 25 tons for standard loads or 22 tons for refrigerated loads. This is also because non-standard loads, which are more expensive to transport, are low. This shows that it is better to choose the rate in [€/km] than in [€/tonne-kilometre].

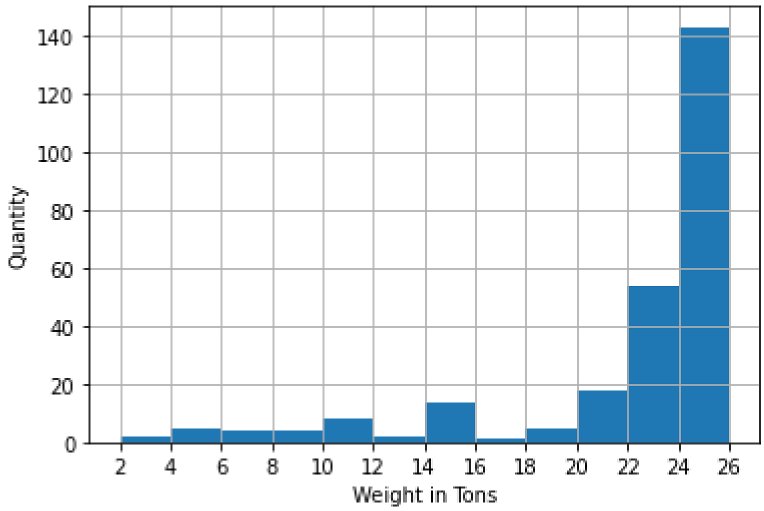

Fig. 2. Weight distribution histogram in [tons]
Rys. 2. Histogram rozkładu masy w [tony]

The price dependence on the loading and unloading place is shown in the Fig. 3. For transports in relation to and from Sweden, for better visualization, prices are given after deducting the costs of ferries. Poland is a country in which all exports are higher than import prices. Sweden is a country where all exports are cheaper than imports. The model presented in the article covers 9 countries of the European Union. This is because data are available to train a valuable model. Further coverage expansion is planned. The planned area is an area of the European Union. The European Union is an area of free exchange of goods and services. On the basis of this, it can be concluded that modelling for such an area makes sense. Modelling transport with countries outside the European Union is riskier for political and formal reasons. A weak positive correlation is demonstrated with: the number of pallets for exchange 0.03, the number of loading places 0.01, and the payment term 0.04. A weak positive correlation of 0.1 was shown between the TimoID number and the price. TimoID is assigned to the company in chronological order, which means that longer-running companies have a lower number. The correlation between the rate in [€/km] and the distance was -0.13, which means that longer routes have a lower rate. This is understandable because the time required for the loading and unloading operations is greater with short distances.

3.1. Modelling

The first challenge is to process the data in a way that is useful to the model. Then experiments are performed to improve the quality of the model or reduce the error. The process of creating new features is called feature engineering. The methods of implementing features into the model can be divided into 4 categories: introducing without changes; factorize; processing the date; presenting statistics for a feature or unique combination of features. Fig. 4 shows the 20 most important features of the model.

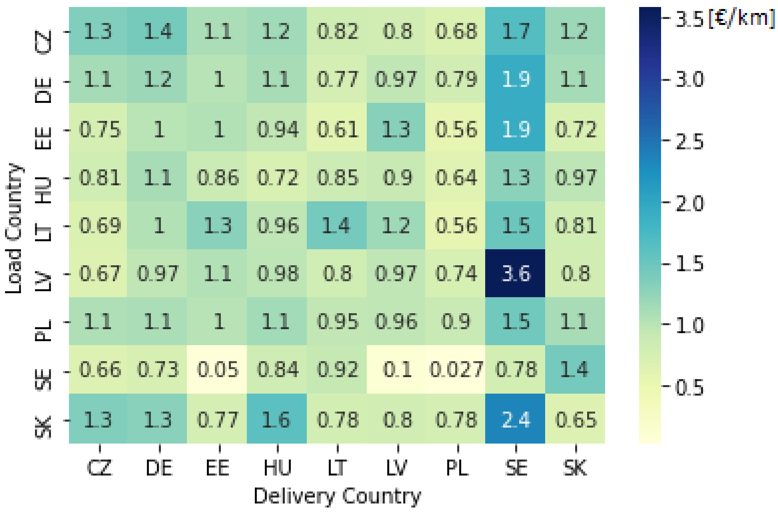

Fig. 3. Average freight price in the transport of goods between countries in [€/km]
Rys. 3. Średnia cena frachtu w transporcie towarów między krajami w [€/km]

The first method is to present a feature as it occurs or using simple actions. The PL_KM feature is the number of kilometers in Poland, DE_KM is the number of kilometers in Germany. The distance [km] is the sum of all the kilometers on the route.

Factorize encodes the object as an enumerated type or categorical variable. In the most important features, COUNTRY_DELIVERY_PLACE presents a unique id for each country of unloading. VEHICLE_TYPE shows a unique id for each vehicle type configuration.

By presenting a characteristic in a statistical form, it is understood that the model obtains the following: mean, median, standard deviation, or size. Such data can be provided for a single feature or group. The median price by country represents the median per km for each of nine unique countries. The mean price from country to country represents the average rate per kilometer for each of 9 unique countries. The median price for vehicle type is the median for each of the 3 unique vehicle type combinations. The mean price for vehicle type is the mean for each of the 3 unique vehicle type combinations. The mean price on the start load data day represents the average for each of the 31 unique days of the month. The mean price in relation means the average for each of the 81 unique relationships. The median price in relation is the median for each of the 81 unique relationships. The mean price for the start-load data day in the relationship is the average price for each of the unique 81 relationships in one unique 31 days. this gives 2511 unique possibilities. The mean price for the start-load data day in the relationship is the average price for each of the unique 81 relationships in one unique 31 days. this gives 2511 unique possibilities. The median price for the start load data day in the relationship is the median for each of the unique 81 relationships in one unique 31 days. this gives 2511 unique possibilities. The median price for the start delivery weekday in the relationship is the median for each of the unique 81 relationships on one unique 7 days of the week. This gives 567 unique possibilities. The median price for the vehicle type in relation is the median for each of the unique 81 relationships for 3 unique vehicle types, giving 243 unique possibilities. The mean price for the vehicle type in relation is the average for each of the unique 81 relationships for 3 unique vehicle types, which gives 243 unique possibilities. The mean price for the start of delivery weekday in relation is the average for each of the unique 81 relationships for 7 unique days of the week, which gives 567 unique opportunities. The mean price for the start of the load day in the country is the average for each of the 9 unique unloading countries for 31 unique days of the week, which gives 279 unique opportunities.

Weight	Feature
0.4125 ± 0.2128	Distance [km]
0.0897 ± 0.2006	Median Price to Country
0.0472 ± 0.1640	Mean Price to Country
0.0322 ± 0.1366	Mean Price in Relation
0.0301 ± 0.0898	Mean Price for start load data day in Relation
0.0285 ± 0.1121	Median Price for start start delivery weekday in Relation
0.0273 ± 0.0814	Median Price for start load data day in Relation
0.0245 ± 0.1057	Median Price for Vehicle Type in Relation
0.0240 ± 0.1007	Mean Price for Vehicle Type in Relation
0.0235 ± 0.0885	Mean Price for start delivery weekday in Relation
0.0233 ± 0.1053	Median Price in Relation
0.0222 ± 0.1061	COUNTRY_DELIVERY_PLACE
0.0203 ± 0.0824	Median Price for Vehicle Type
0.0202 ± 0.0828	Mean Price for start load day to Country
0.0163 ± 0.0644	PL_KM
0.0153 ± 0.0757	Mean Price for Vehicle Type
0.0144 ± 0.0689	Median Price start load day to Country
0.0119 ± 0.0651	VEHICLE_TYPE
0.0104 ± 0.0598	Mean Price in start load data day
0.0090 ± 0.0414	DE_KM
	… 58 more …

Fig. 4. Top 20 most important features for model
Rys. 4. Najważniejsze 20 cech dla modelu

3.2. Compare machine learning and human prediction

The experiment aims to compare the model and human predictions according to the MAE metric. 19 people participated in the study, including 11 experts and 8 students. The participants' task was to provide the price for 5 transports according to the given specification. 96 unique valuations were obtained and compared with the model's predictions. The comparison of experts, students, and the model according to the mean absolute error (MAE) metric is presented in the fig. 5. This confirms that the model performs better on the task because it makes fewer errors. The error in prediction made by students and experts was similar. The important thing is that the execution of the prediction, apart from the lower accuracy of the human factor, also takes time. When using the model, the employee can carry out other activities. The employee may then have more time for activities that require emotional intelligence, such as building a relationship with the client.

4. CONCLUSIONS

Road transport of goods is a process described by many features. The feature with the strongest impact on price is distance. The impact depends on the proportions of the occurrence in individual countries. The place of loading and unloading affects the price. The seasonality in road transport was found to be in the annual and weekly range. The dependence of the price on the type of vehicle required was shown. ExtraTreeRegressor is the machine learning model with the least error. It was shown that the machine learning model is better in prediction than the human in the studied group. Students and experts participated in the study. Experts predicted better on average, but the difference is small. Machine learning methods are used to work with large data sets. The management of transport processes has been shown to be an area in which machine learning can be successfully applied. It is proposed to extend the scope of the model's operation to the area of the entire European Union in future studies. The expected effect of applying the research results is a more effective work of operational personnel in transport. As a result of the application of research results, operational transport employees work more efficiently. Employees can spend the time saved on other tasks or leisure activities. The possible effect is the reduction in the number of people necessary to manage the transport processes in the company. The project discussed in this article is available on GitHub in open access.

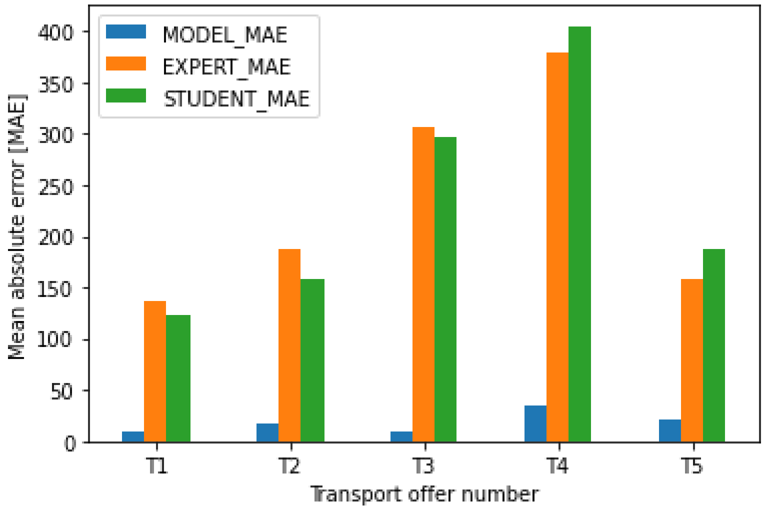

Fig. 5. Compare human and model prediction error
Rys. 5. Porównanie błędu przy predykcji przez człowieka i model

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