

# Predicting Heart Rates Of Sport Activities Using Machine Learning

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## ABSTRACT

Predicting heart rates for cycling exercise is useful for a more efficient planning workout and estimating nutrition intake. This is a difficult problem that is influenced by both internal factors such as the persons physical condition and external factors such as the weather. The goal of the research is to predict heart rate zones for new users for bicycle rides. Two problems are defined. The first problem is to find an optimal regression model trained on a set of bicycle rides and their average features. The best performing model was a random forest regressor with feature selection through random feature elimination. The second problem is to predict the heart rate on the time sequence data of these bicycle rides, where each sequence or segment denotes 100 meters. This is done by training a LSTM. The LSTM was capable of predicting heart rate averages for segments, but struggled with peaks and under- and overestimation.

## Keywords

Machine Learning, Exercise, Heart Rate, LSTM, Regression Models, Random Forest, Feature Selection

## 1. INTRODUCTION

EatMyRide is a food plan application that helps cyclists determine what nutritions they need[6]. This is done based on both user variables and ride circumstances. The goal for this research is to estimate the intensity of a workout when there is little data available for a user, for example in the case that this user just signed up and did not complete any rides. The intensity of a workout will be defined by an estimated heart rate or heart rate category. This can later be used to develop a personalized nutrition plan.

There are some difficulties with the prediction of a heart rate. There are many personal circumstances that might influence the heart rate of someone during a ride. Daniel Boulosa et al [3] state that differences in the genetic predisposition for endurance running, the time available for training, and physical, psychological, and physiological characteristics can all influence an athlete's performance. This paper will use basic user information, sequential information of the ride and ride-averages to tackle this prob-

lem as best as possible.

We can define two problems. The first is problem the general ride and its heart rate zone prediction. The second is the prediction of heart rates for ride segments, which can be used to estimate heart rate zones. This is supervised learning task that can be solved through regression learning. In order to find an optimal regression model, we will also perform feature selection.

The second problem involves sequential data, where each segment denotes 100 meters of a ride. This can thus be seen as a multivariate time series problem. Because of this, we will use recurrent neural networks (RNNs) to find a solution to this problem. The dependent variables we are interested in are the average heart rate zone of a ride and heart rates per 100 meters of a ride. The variables consist of both internal variables, such as the weight of the user, and external variables such as wind speed and average slope of a ride or ride segment.

First, there will be an exploration of background information and related works. After this the methodology is defined. This is followed by the experiments and their analysis. Finally, there is a discussion of the applications and limitations and finally a conclusion.

There was no research found that uses regression models to estimate the average heart rate category or heart rate for a bicycle or long cardio exercise in the same way as this paper. Some related works are discussed in the background section. However, Jianmo Ni et al [12] published a paper using a 2-layered Long-short term memory (LSTM) to estimate heart rates using wearables. There are two key differences with this study. The first is that this study uses historical data of a user to predict heart rates, whereas this study predicts the heart rate zones for new users where this data is not available. The second is that this study takes a wider range of external variables of ride segments into account whereas the previous study only uses internal variables, besides speed and sport activity type. Thus, this paper will aid in the field of heart rate estimation using regression models and a RNN.

### 1.1 Research Questions

There are 3 parts to our research. RQ 1.1 needs to be investigated first. Afterwards, RQ 1.2 can be answered. Following this, we move to the second problem and answer RQ 2.

**RQ 1.1** Which variables from the database contribute to estimating the average heart rate zone for a ride?

**RQ 1.2** Can we estimate the average heart rate zone for a ride using a regression model and how does it perform?

**RQ 2** Can we estimate heart rate zone averages for ride segments using a LSTM and how does it perform?

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## 2. BACKGROUND

This section first explores regression analysis, as this is important for RQ 1. Secondly, as shown in objectives, we are dealing with a problem that involves temporal data so we then explore the use of a LSTM. This is a type of architecture used for RNNs that deals with the vanishing gradient problem and is relevant for answering RQ 2.

### 2.1 Regression Analysis

Regression Analysis is a statistical method used for prediction, forecasting and finding relationships between independent and dependent variables. In this paper, we will use different regression models to predict the average heart rate category for a bicycle ride. Multiple linear regression is, as the name suggests, an extension on linear regression [2]. Linear regression is a simple regression model where an optimally fitting linear model is made for a dataset in order to estimate future outcomes. Whilst simple linear regression has a one-to-one relationship between independent and dependent variables, multiple linear regression has a many-to-one relationship. Thus, the model has a similar form to simple linear regression in multiple dimensions.

We will also look into non-linear regression models, the most important being the random forest regressor. A random forest regressor is a collection of decision trees used to predict the outcome for continuous values [4].

There are some problems that might occur with any regression model. Such problems include multicollinearity, where independent variables have a correlation, and overfitting, where a model performs well on training data but not on testing data. Both can be avoided by doing proper exploratory data analysis on the dataset and performing feature selection. For multicollinearity one has to keep in mind whether or not input variables are independent. In order to prevent overfitting, one has to ensure that only statistically significant variables are used and models are validated with cross validation. Proper feature selection also makes the model simpler and allows for faster training.

### 2.2 Related Works

In 1994 Mary Sue Fairbairn et al. used simple linear regression to estimate the heart rate and oxygen uptake for intense physical activity [8]. They found age to be the most important factor for both males and females. Roger G. Eston et al also used multiple simple regressions for the purpose of predicting the energy cost of physical activities for children and came to the conclusion that heart rate is an adequate method of measurement, though oxygen intake and accelerometry proved to be better [7].

Both studies relied strongly on measurement of the maximum oxygen uptake of the participants in the study. This information is not available for new EatMyRide users.

There are also regression studies that proved more useful. Gary E. Larsen et al used gender, body weight and elapsed exercise time to estimate the oxygen uptake of participants with minimal statistical loss [11]. Paulo Lopes-Silva et al. researched physical fitness for judokas and found that HR contributed most to the Special Judo Fitness Test performance using multiple linear regression [13]. Last but not least, Yichen Wu et al. found that Multiple Linear Regression proved better at determining exercise intensity than other regression and deep learning methods and performed equally to ridge regression [17].

From this literature review it remains unclear which vari-

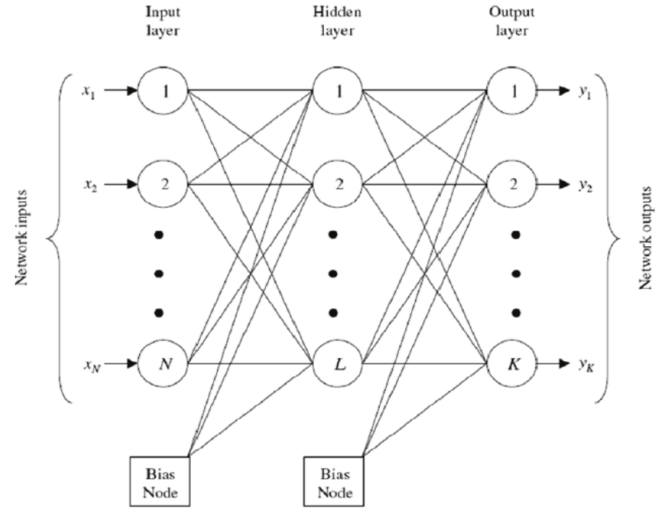


Figure 1. Schematic overview of a simple neural network.

ables weight most heavily in a regression model that attempts to predict exercise activity, so this will be covered later in the Experiments and Results section.

### 2.3 Recurrent Neural Networks and LSTMs

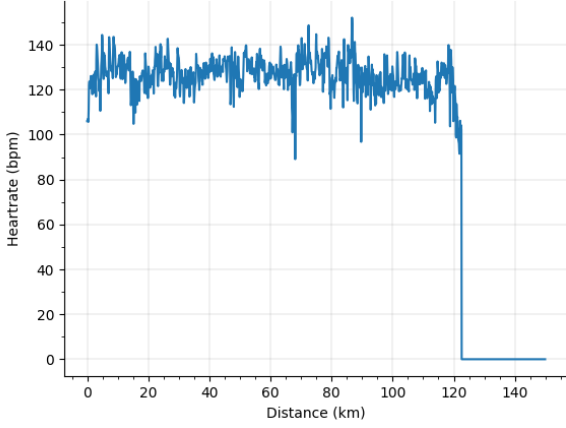
A neural network (NN) is a machine learning model that takes resemblance after biological neural networks [16]. A NN consists of multiple connected neurons in a layer structure. It consists of an input and output layer with potentially hidden layers in between. An example can be found in 1[10]. It is important to select the right input values for a NN. A model that is too big can cause overfitting and slow learning. It is also important to consider whether the dataset is broad enough for the NN to not only succeed in training, but to also succeed with never-seen testing data.

Recurrent Neural Networks, based on a paper by David Rumelhart, are NNs based on the principle that it remains in a state that is able to keep track of information from previous sequences [15]. This gives the advantage that a RNN can deal with temporal sequences that have dependencies.

RNNs have a problem with vanishing gradients however. A solution proposed by Hochreiter and Schmidhuber in 1997 involves Long Short-Term Memory, also known as LSTM [9]. This solution implements more complex memory cells with multiple gates. Another proposed solution is called GRU proposed by Kyunghyun Cho et al. in 2014 [5]. It is similar to an LSTM in that it has gates, but it lacks an output gate thus giving it fewer parameters. It has been shown that both LSTMs and GRUs have very similar performance. GRUs tend to converge faster on smaller and less regular datasets, though LSTMs tend to perform better on longer sequences. Since the length of segments in our rides are of irregular length and quite long we will settle on an LSTM.

### 2.4 Related Works

The field of using LSTMs to estimate workout intensity has little prior research. In 2019 Jianmo Ni et al. published a paper where they proposed FitRec, a 2-layered stacked LSTM model that uses information gathered by wearables, such as smartwatches [12]. The gathered data is used to model heart rate and activity data of the wearer. This is then used to make a personalized fitness recommendation. The result for heart rate prediction was sig-



**Figure 2.** Heart rate plotted per 100m segment for a padded ride.

nificantly better than other models from prior research ( $p < 0.05$ ). This suggests an LSTM can be used for our research, although their data is time and not distance related.

### 3. METHOD

#### 3.1 Data

The dataset was provided by Eatmyride. It consisted of 21834 bicycle rides which were gathered from 133 different users, where each ride has a length of at least 50km. There were 20 female and 103 male users. The data was split into three sets. The first contains the averages of all features collected over the ride and was used to help answer RQ1. The second contains features collected per ride segment of each ride, where each ride segment spans 100 meters of this ride. It was used to answer RQ2. The first set is described by 45 different features and the second set by 37 features. The third dataset contains features on the 133 users and was used in combination with the first and second dataset. Numpy and Pandas were used for the preparation of the data.

The data first has its redundant features removed. After this, the remaining data was normalized using z-score normalization. The equation for this is as follows:

$$z = \frac{x_i - \mu}{\sigma} \quad (1)$$

The ride segments dataset is split into three different sets containing 107, 13 and 13 users for the training, validation and testing sets respectively. Each set has the same male/female ratio. The maximum ride distance has been set at 300km as the size of a numpy arrays would become a problem when it comes to memory usage, as well as unrealistic distances influencing the models. The ride segment dataset is then merged with the user dataset. The features are then normalized through z-score normalization and converted to a numpy 3D array. The array is padded to ensure that every sequence of ride segments has the same length. An example of a ride per segment from the training set can be seen in figure 2, where the flat line indicates the padding.

#### 3.2 Predicting heart rate categories

In order to apply regression models on the dataset containing rides, scikit-learn was used. First, a feature selec-

tion step was applied consisting of two phases: through selection from models and recursive feature elimination (RFE). Selection by model uses importance weights to select a range of features, whereas RFE recursively removes features to find an optimal set. A multitude of models is tested with both sets of selected features and the most optimal one was the random forest model resulting from a hyperparameter random grid search. It has 321 estimators, a minimum of 5 samples per split, a minimum of 2 samples per leaf and a depth of 100. The predicted values and metrics are discussed in more detail in the next section.

#### 3.3 Predicting heart rate sequences

Keras and Tensorflow are used to build the NN [1]. Google Colab is used for the training infrastructure. In order to find the best performing model, multiple experiments are conducted. These experiments cover the depth and amount of LSTM units. The mean squared error (MAE) loss function is used due to outliers in the dataset. Adam is used as the optimizer, with a maximum learning rate per weight of 0.001. Each LSTM has a masking layer to deal with the padding that makes all rides of equal length, as otherwise it is only possible to perform online learning with a batch size of one. Each LSTM is also followed by a dense output layer with just one weight, in order to process the output. Each LSTM layer in the NN has a dropout of 20% to prevent overfitting.

### 4. EXPERIMENTS

#### 4.1 Performance Evaluation

Both the first and second problem are evaluated using multiple metrics that help us understand the correctness of the models.

Firstly, in order to evaluate the random forest model for RQ1.2 we look into the mean absolute error (MAE), root mean squared error (RMSE) and R-squared metrics. Finally, we also evaluate the mean error (ME) to determine whether the model under- or overestimates the heart rate category.

Secondly, in order to evaluate the LSTMs used to answer RQ2 we use the MAE and RMSE to determine the correctness of the models.

The equations used to calculate the mentioned metrics are as follows, where  $\hat{y}$  denotes the predicted output and  $y$  denotes the expected output:

$$ME = \frac{\sum_{i=1}^n (\hat{y}_i - y_i)}{n} \quad (2)$$

$$MAE = \frac{\sum_{i=1}^n |\hat{y}_i - y_i|}{n} \quad (3)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (\hat{y}_t - y_t)^2} \quad (4)$$

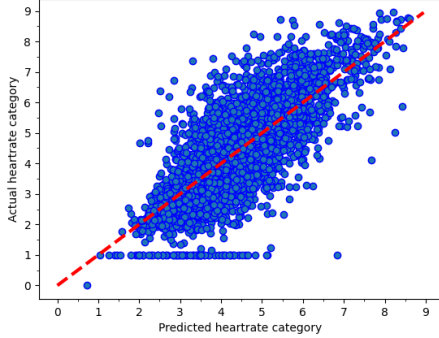
$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2} \quad (5)$$

#### 4.2 Predicting heart rate categories

Scikit-learn is used to apply regression models on the dataset containing rides. [14]. For feature selection RFE and selection by model are used. Both used a Random Forest Regressor. The results of this feature selection can be found in table 1.

**Table 1. RF features**

Feature	RFE	model-based
user weight	yes	yes
user age	yes	yes
user length	yes	yes
average speed	yes	yes
maximum elevation	yes	no
minimum elevation	yes	no
estimated energy	yes	no
estimated power	yes	yes
normalized estimated	yes	yes
total time	yes	yes

**Figure 3. Predicted heart rate categories plotted against the actual heart rate categories for the training set.**

In table 3 in the Appendices, we can see the results from the multitude of models that are tested with both selected features. The results are found using 10-fold cross validation. For the random forest regressors, the name is formatted as random-forest-n-m-o where: n denotes the number of estimators, m denotes the maximum depth and o either denotes the maximum features or maximum leaf nodes. The latter two are tested as they make a model simpler but might decrease correctness.

Multiple models are tested, where the optimal model is the random forest model resulting from a hyperparameter random grid search. It has 410 estimators, a minimum of 2 samples per split, a minimum of 2 samples per leaf and a depth of 90. The maximum features used per tree is the square root of the amount of features available. The MSE is used as a criterion.

The predicted values for this model are visualized and plotted against the expected values in figure 3. The red line indicates the perfect prediction. One can see that the predictions are quite spread out. This is also reflected by the R-squared value and RMSE, shown in table 2. Despite this, a RMSE and MAE under 1 indicate that the model can be used to get a good indication of overall intensity of a bicycle ride. The difference between the MAE and RMSE also indicate that there is some variance between individual errors, though not that big. In addition, a ME of -0.005 was found for this random forest. This indicated that the model does not over or underestimate strongly.

Additionally, we can see that other random forest models performed relatively well compared to other models. We can also see that a depth over 15 has very little impact on the performance of the random forest regressors. The amount of estimators has a bigger impact. The maximum amount of leaf nodes also seems to have quite an impact,

**Table 2. LSTM results**

Model	MAE	RMSE
Model-1-128 (1)	15.480	22.567
Model-2-128 (2)	15.785	23.431
Model-3-128 (3)	15.784	23.460
Model-3-256 (4)	15.263	22.641
Model-1-256 (5)	15.831	23.475
Model-3-256-128-64 (6)	15.533	23.548
Model-1-128-agecat (7)	15.430	23.529
Model-3-128-agecat (8)	15.445	23.495

so it is better left untouched and set to unlimited. The amount of features used per estimator does not seem to strongly affect the results. The above explains why the grid search found an optimal tree with 410 estimators, though it only has a limited increase from the tree with only 150 estimators and a depth of 15.

### 4.3 Predicting heart rate sequences

Multiple experiments are conducted on the impact of depth and number of LSTM units in order to try and optimize the model described in the methodology. Additionally an experiment is conducted where the age of users is categorized into 5 categories.

#### 4.3.1 Impact of depth

For this experiment, three models are compared. Each model had either one, two or three LSTM layers. Each layer has 128 LSTM units. From table X, we can see that the models (1), (2) and (3) do not have any significant changes in the metrics. The MAE and RMSE of (1) are slightly lower than the metrics of other models however.

#### 4.3.2 Impact of width

For this experiment we compare five models with a different amount of LSTM units. The first three that are compared have 3 layers. Model 3 has 128 LSTM units per layer, model 4 has 256 and model 6 has 256, 128 and 64 LSTM units per layer.

There is a small improvement between (3) and (4) found, but it is not a significant change. For model (6) we see that the metrics are comparable to the other models.

Models (1) and (5) both have one layer with 128 and 256 units respectively. It seems that (1) performs slightly better than (5), but there is no significant difference here either.

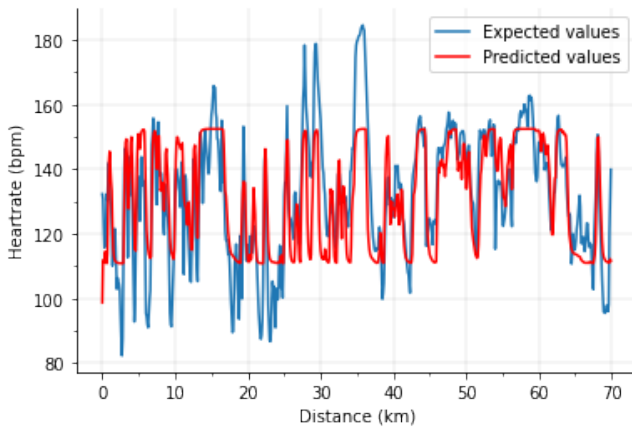
#### 4.3.3 Impact of categorized age

In this experiment the age of users is categorized. Models (7) and (8) are trained on this data set. However, there was no significant difference between these models and the others.

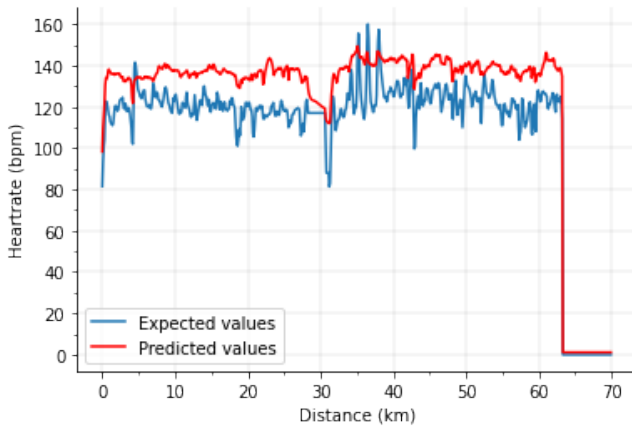
## 5. DISCUSSION

Different regression models have been looked into for the average heart rate category prediction and they perform quite well. Additionally, the LSTM models can be used to estimate an approximate intensity of a bicycle ride and to approximate where more heart rate intensive parts of a bicycle route may lie. However, there are also limitations. The dataset only features 133 people, of which 20 were female. This could lead to underfitting of the models for this group. This could also partially explain why the MAE and RMSE are not decreasing with different models being used. This can also be seen in the difference between the results of the validation and testing set, where the RMSE





**Figure 4. Predicted heart rate plotted next to the actual heart rate.**



**Figure 5. Predicted heart rate plotted next to the actual heart rate.**

was quite a bit lower for the validation set. These results can be found in the appendices.

Additionally, the prediction of the heart rate seems to have difficulties with high and low spikes despite the use of MAE as a loss function for the LSTMs. An example of this is figure 5. Here, the predicted heart rate is plotted against the actual heart rate. It seems that the model tends to stay within a minimum and maximum prediction range. There is also the fact that there is no feature available indicating the endurance levels for a user which can cause over- and underestimations. This can be seen in 5. This is likely why papers such as shown in Eston et al. [7] included the VO2 max for their models.

There is also future work related to this research to be done. It is unclear what each feature exactly contributed to the prediction results, researching this could lead to a better understanding of the models and might allow for improvements. Additionally it could be looked into whether or not the techniques of this paper can be applied to different forms of cardio exercise where heart-rates are less likely to spike, such as marathon running or long distance ice skating.

## 6. CONCLUSION

Finally, we will address the answers to the research questions.

For RQ1.1 we researched the variables that could con-

tribute to estimating the average heart rate zone for a ride. We found that the features selected using RFE performed slightly better on the better performing models than the features selected using importance weights, through scikit learns selection by model. The selected features can be found in table 1.

For RQ1.2 we researched whether or not we could use regression models to estimate the average heart rate zone for a ride. The random forest regressor found through a random grid search performed best. Although the R-squared metric indicates that the results are off, the metrics still show that it can be used to make an adequate estimation of the average heart rate zone for a ride.

In RQ2 we used LSTMs to predicted the average heart rate over 100 meter segments for a ride. The results give a good indication of an over-all ride, as explained in the discussion section. The metrics point out that it is not precise enough to estimate the actual average heart rate well enough though, as it struggles with high and low peaks. .

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## 8. APPENDICES

### 8.1 Appendix A.

found on next page.

**Table 3. Regression results**

Model	MAE model-based	MAE RFE	R2 model-based	R2 RFE	RMSE model-based	RMSE RFE
linear-regression	1,1085	1,103	0,1438	0,133	1,3986	1,4067
poly-2nd	1,0779	1,4293	0,1849	-467,0497	1,3646	20,2975
lasso	1,1369	1,1369	0,1164	0,1164	1,4208	1,4208
ridge-regression	1,1085	1,103	0,1438	0,133	1,3986	1,4067
random-forest-50-5	0,9945	0,9935	0,3005	0,3014	1,2641	1,2633
random-forest-50-10	0,7833	0,7801	0,5424	0,546	1,0224	1,0184
random-forest-50-15	0,7208	0,7076	0,5958	0,6115	0,9609	0,942
random-forest-50-30	0,7195	0,6937	0,5924	0,6202	0,965	0,9315
random-forest-100-5	0,9943	0,9933	0,3009	0,3018	1,2637	1,2629
random-forest-100-10	0,7824	0,7791	0,5435	0,5475	1,0211	1,0167
random-forest-100-15	0,719	0,7055	0,598	0,6144	0,9583	0,9385
random-forest-100-30	0,7163	0,6905	0,5959	0,624	0,9608	0,9268
random-forest-150-5	0,9941	0,9932	0,3011	0,302	1,2636	1,2628
random-forest-150-10	0,7821	0,7788	0,5437	0,5479	1,0209	1,0162
random-forest-150-15	0,7184	0,7046	0,5985	0,6155	0,9576	0,9372
random-forest-150-30	0,7154	0,6896	0,5969	0,625	0,9596	0,9256
random-forest-50-15-10mlf	1,0352	1,0352	0,257	0,2571	1,3028	1,3027
random-forest-50-15-20mlf	0,9583	0,9587	0,3566	0,356	1,2123	1,2129
random-forest-50-15-30mlf	0,9122	0,9115	0,4113	0,4111	1,1596	1,1598
random-forest-50-15-40mlf	0,8814	0,8777	0,4466	0,4474	1,1243	1,1235
random-forest-50-15-50mlf	0,8584	0,8552	0,4725	0,4733	1,0977	1,0969
random-forest-50-15-2mf	0,7416	0,8094	0,5861	0,5213	0,9724	1,0457
random-forest-50-15-4mf	0,7175	0,7393	0,6024	0,5891	0,953	0,9688
random-forest-50-15-6mf	0,7195	0,7183	0,5983	0,6065	0,9579	0,9481
random-forest-gridsearch	0,713	0,687	0,6011	0,6276	0,9546	0,9224
gradient-boosting	0,8897	0,8864	0,4342	0,4371	1,1369	1,134
decision-tree-5	1,012	1,0116	0,2757	0,2761	1,2864	1,286
decision-tree-10	0,8347	0,8415	0,4653	0,453	1,1051	1,1178
decision-tree-15	0,8382	0,8371	0,4165	0,4108	1,1545	1,1601