# Team Classified

Sberbank Russian Housing Market*

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## 1 Introduction

The *Classified* team worked on the *Sberbank Russian Housing Market* competition. The competition ran roughly from the start of May until the end of June, which may shift our final position on the leaderboard. This report gives insight in the competition, our approach and our results. We discuss our findings and put forward some critical notes regarding the competition.

## 2 Problem description

Sberbank is the largest, state-owned bank in Russia. They are involved in financing and brokering deals in the Russian realty market. Therefore, they heavily rely on models to predict the value of property. Although the Russian house market remains fairly stable, Russia's economy relies on natural resources and is often subject to volatile changes. This makes predicting property value, and correcting for the economy, a non-trivial task.

The goal of the Kaggle competition is to predict realty prices. The dataset contains training data of 30 000 properties (e.g. apartments) from 2011 until 2015. The test set is based on details from 2015 and 2016. Furthermore, a highly-detailed macro-economic dataset is provided. The true prices of the test set are not known, and the public leaderboard is based on 35% of the test data.

The metric used for the leaderboard is the *Root Mean Squared Logarithmic Error* (RMSLE). We could submit our predictions five times per day.

## 3 Approach

We used Apache Spark[1] and Python plots to do some early data exploration and visualization. The JavaScript library "Leaflet" was used for plotting data on a map. This method provided a good feel of the data as well as early identification of outliers and missing data.

### 3.1 Exploratory analysis

The training data was supplied as numerical and categorical data. In order to work with e.g. a Random Forest Regressor (sklearn) this needed to be one-hot encoded. For validation purposes, the training set was split in a new training set containing all entries before 2015, and a validation set consisting of all entries in 2015. We used internal validation to preliminarily test various methods. These methods include Linear Regression, Random Forests, AdaBoost, kNN, XGBoost, Deep Learning and Stochastic Gradient Descent. These methods are easy to use, readily available, and have been proven to work decently.

It quickly became clear that eXtreme Gradient Boosting, or XGBoost, outperformed all other methods. XGBoost outperforms other methods, most likely, by its inherent ensemble property and by being able to robustly handle different categories of data. The boosting of weak learners might emphasize the vari-

[*] https://www.kaggle.com/c/sberbank-russian-housing-market

[1] https://rubigdata.github.io/bigdata-blog-2017-jeffluppes/2017/05/04/Give-me-a-spark/

ables that are useful for prediction, while it de-emphasizes variables that indicate fraud.

There was little correlation between internal validation and validation done by the Kaggle submission platform. It is likely that this is caused by the presence of fraud in data, which is influential in validation, and may be less present in the test set. Another explanation might be that there are some discrepancies in the time-price trend correction, which causes an offset in the evaluation error. Various forms of validation, including K-fold Cross Validation, provided no improvement, greatly decreasing the usefulness of validation. The dataset was far from complete, and many entries were missing data. It was particularly viable to improve the performance by focusing on pre-processing.

### 3.2 Imputing data

Various methods of imputing, such as kNN- and SVD-based methods, have been tested. Matrix Factorization methods, like those used in the famous Netflix competition, were not readily available, and were too costly to develop internally. kNN- and SVD-based methods rely on the construction of large matrices of *sample* $\times$ *sample* size. Those were unfeasible to construct, because they have an estimated size of over 90 GB. More memory-efficient implementations were, again, not available. More simple methods, such as the mean, modus or median offered no improvement over not replacing the `NaN` values in the data. Not replacing the `NaN` values means some numerical variables cannot be used for prediction. For categorical variables, `NaN` values are treated as a separate category.

### 3.3 Regression using XGBoost and Keras

In the early part of the competition, single models using XGBoost performed reasonably well, yielding results in the top 20%. Deep Learning methods using Keras were not able to compete, and, regardless of network complexity, did not come close to the performance of single XGBoost models. Deep Learning might suffer more from a lack of appropriate regularization and an overemphasis of non-important features. This might be alleviated with more experimentation with other activation layers or a better batch selection procedure.

Near the end of the competition (and near our project deadline), a modestly successful kernel was published. This kernel was an ensemble of three XGBoost models, which, when combined, were able to hit top 5% at the date of publication. The bulk of further work was based on these models, being mostly based on ensemble weighting tweaking. Using linear regression to optimize ensemble weighting was briefly tested, but was hindered by the little correlation between validation and testing sets. A graphical representation of the final model, including the XGBoost parameter settings and other weightings can be found in appendix A.

## 4 Results

The results of some key submissions and models are illustrated in table 1. These may not reflect the final position at the end of the competition. For each implementation, we list details regarding the error returned by Kaggle. A lower RMSLE score indicates a better performing model. These results are discussed in depth in the next section.

## 5 Discussion

The ensemble of three XGBoost models performed better than any other method, including previous XGBoost models individually. Early on in the competition, these performed with modest success, as they ended up in the middle of the Kaggle ranking.

The performance of many classic regression methods were poor. The high complexity and sparsity of the dataset were particularly difficult for these models, as there are many patterns not identified by linear methods. Still, we thought these methods could be included in the ensemble, but intermediate results were not affirming any potential in this approach.

The best method was an XGBoost ensemble

| Classifier | Method | RMSLE | Kaggle Rank (of 3077) |
|---|---|---|---|
| XGBoost | Ensemble with 3 models, readjustment of submission | 0.31038 | 146 |
| XGBoost | Ensemble with 3 models | 0.31062 | 266 |
| XGBoost | Single | 0.32575 | 1856 |
| Gradientboosting Regressor | Complete dataset, only 2015 | 0.41384 | 2767 |
| Deep Learning | Dense and Dropout | 0.46745 | 2870 |
| Linear Regression | Complete dataset, only 2015 | 0.49689 | 2897 |
| Decision Tree | Complete dataset, only 2015 | 0.58460 | 3020 |
| SGD Regressor | Naive | 0.59560 | 3021 |
| Benchmark Submission | Naive XGBoost | 0.67333 | 3034 |
| Random Forests | Removing outliers, only 2015 | 0.75239 | 3040 |
| k-Nearest Neighbours | $k = 6$, removing outliers, only 2015 | 0.93122 | 2050 |
| Random Forest | Naive | 6.12138 | 3072 |

Table 1: Overview of key submissions with their models, result and rank

based on a published kernel by Kaggle user and econometrist Andy Harless[2], which included work from other Kaggle contributors. This model was improved upon, and outperformed the original kernel which, on its own, quickly saw wide adaption within the community.

Sadly, the Keras approach (see 'Deep Learning' in table 1), a 10-layer deep neural network could not compete with the success of XGBoost implementations

In this competition, Kaggle kernels were used with good success, unlike our experience in the previous competition. This was very useful as starting point and inspiration for our own approach(es). We were keeping a close eye on what the community was coming up with. Some of our code was also published on Kaggle in the form of kernels.

As we explained earlier, the in-house evaluation method based on the training data proved to have no correlation with success on the leaderboard. This was the experience of other Kaggle users as well, as we could tell from a lot of disgruntled posts on the forum.

At the moment of writing (20 June 2017) the highest score achieved was 0.31038 with (currently) the rank of 150/3222. This places us in the top 5 percent (4.65%, to be exact). The all-time highest placement was rank 49 (top 1.5%) with 0.31062 obtained on June 5. Overall, our team made over 50 submissions. If the competition would end today, we would be awarded silver.

# 6 Criticism

The competition is not without flaws. The test set was very different (both in balance, and quality) from the training set. This made the evaluation of candidate submissions hard to do. Without a proper method of model validation, we were left in the dark. A lot of data was missing and fraud was suspected in a significant amount of objects[3].

Some major issues were published very late in the competition. Various details, such as the distance of properties to schools, hospitals and such, were actually based on the distance to the *housing agencies* instead of the properties themselves.

[2] `https://www.kaggle.com/aharless/latest-iteration-in-this-silly-game`

[3] `https://www.kaggle.com/c/sberbank-russian-housing-market/discussion/32608`

# 7 Individual contributions

We started our project with an exploration of the data, in which we all analyzed the data, generated images and reported our findings in our group meetings. This free-form allowed us to explore a lot of ideas. After this we decided how we would tackle the problem: Jordi and Roel looked at pre-processing, Gerdriaan and Thijs tried different classifiers to see what worked well, and Jeffrey looked at constructing an ensemble in addition to standard regression models.

Gerdriaan tested stochastic gradient descent (SGD) and Thijs looked at Keras Deep Neural Networks, both of which had results that did not look promising enough to improve on. After discovering the Magic Numbers kernel on Kaggle, mostly Jordi, Roel and Jeffrey worked at improving this script and making submissions.

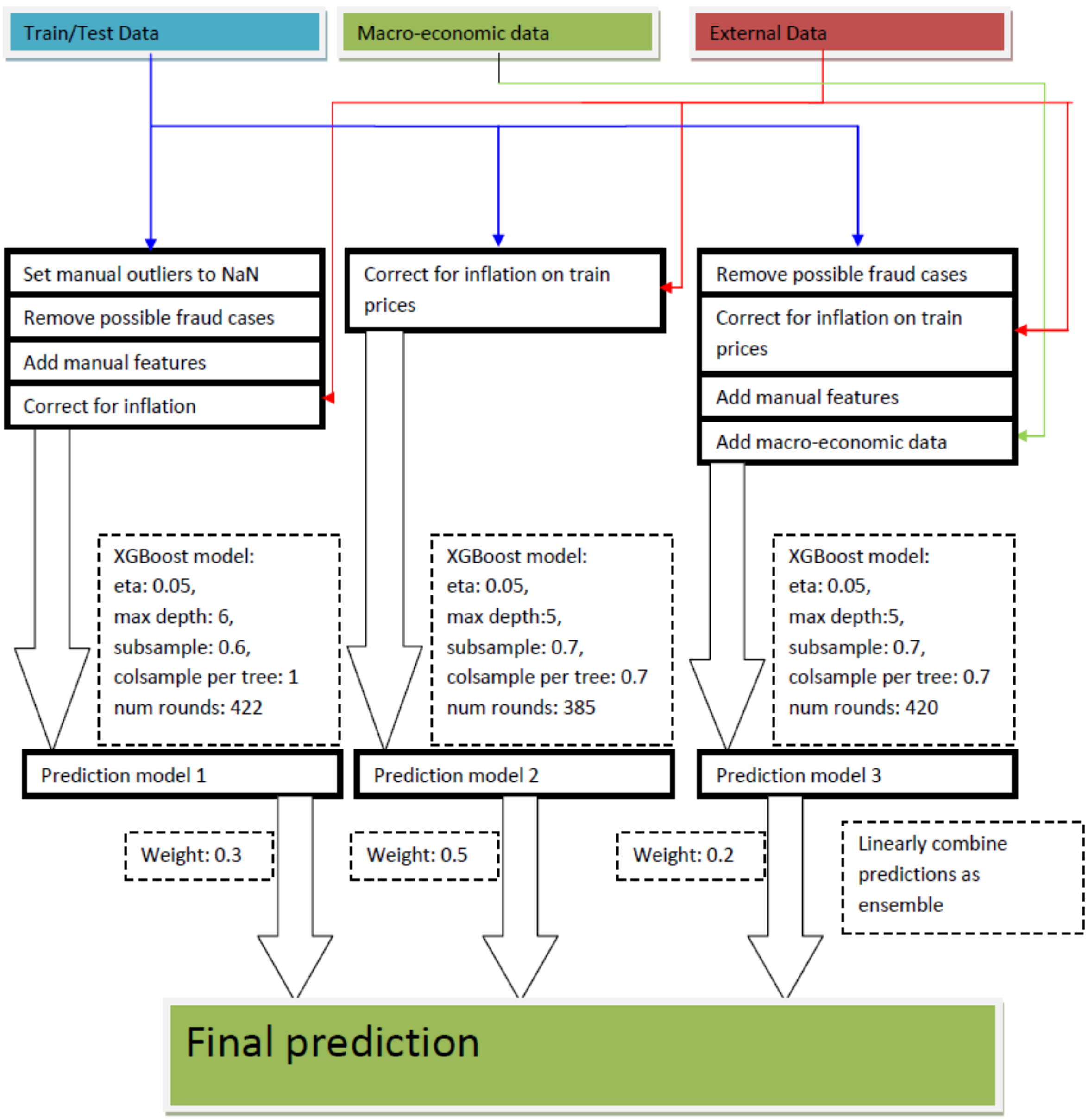
Notes taken at our meetings were written by Jordi. The flash talk was presented by Jeffrey. To finish the project, we wrote the report together, with editing in the hands of Jeffrey and Gerdriaan. Gerdriaan worked on the code delivery[4]. Thijs and Jeffrey made and presented the final presentation.

### Previous competition

Flashback of the first competition. Pre-processing was done by Jordi and Gerdriaan. The XGBoost implementation was made by Jeffrey and Jordi. Roel made the classification pipeline and worked on the Random Forests implementation. Thijs focused on Deep Learning. Jeffrey wrote the report with input from the group. Gerdriaan worked on the code delivery and installed the project on the lilo servers. The first flash talk was done by Roel and the final presentation was made and presented by Gerdriaan and Jordi.

[4]See our Github repository at `https://github.com/mrngm/Classified` and, more specifically, our final code (release) at `https://github.com/mrngm/Classified/releases/tag/second_competition`

# A The final ensemble method




The train, test and macro-economic data can be found in train.csv, test.csv and macro.csv respectively.

Manual outlier detection consisted of detection of data that was incorrect based on simple logic heuristics. This covers cases such as “the sum of the area of the kitchen and living room is larger than the total area”, as well as possible typo’s in for example room number, such as 100 square meter apartments contained 126 rooms.

Some further fraud detection was done by removing extremely high prices from the training set. A manual selection was made by some Kagglers, based on apartments selling for 2-5 times the price of regular (identical) apartments.