Project for Machine Learning 2022/2023

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1 Introduction

One of the biggest headaches of the project managers is accurate effort estimates. Good estimates allow to organize project work more efficiently and plan budget more precisely, thus, saving money. While an experienced project manager is able to render an estimate from the task parameters with no issues, it might be hard for employees from other roles to do the same. In this document I describe my attempts to produce a model, which is able to give an estimation of time required to resolve a work item based on its parameters. Though the initial was not achieved, my experiments included several iterations of trials with different tools, libraries and techniques, which might be worth documenting.

2 Dataset

My dataset is, basically, an export file from the project management system. It consists of **28791** work items and each of them has a few poperties, which in my opinion might influence he time spent on the task. Here is an example of one work item:

Name	Description	Example
timeSpent	The time spent on the task in milliseconds	144000000
summary	Short summary of the work item	FST-4320 - Falscher Ablauf beim Versand XJustiz Nachricht
description	Multiline description of the work item	Es existiert ein FAM VA Verfahren mit Auskunftsersuchen. Eine XJustiz Nachricht nachricht.vag.fehler Version 3.3.1 mit Signaturstatus unknown, mit fehlerhafte Schematronprüfung und erfolgreiche Plausibilitätsprüfung wurde an Postfach gesendet. Es läuft der AF002 Normalablauf (Schritte 1-9). Im Schritt 10. stellt System fest, dass Regelverstöße bei der Schematronprüfung vorliegen.
priority	Priority assigned to the work item. Ranged from 1 to 5	Prio 2
severity	The severity of the work item. Blocker, Normal, Minor, Major, Critical are some of the values. (fixed collection of values)	Blocker
category	Category of the work item. Might be Release-Test, KM, Maintenance, etc. (fixed collection of values)	Release-Test
type	Type of the work item. Internal Defect/Issue/Action/etc. (fixed collection of values)	Issue

3 Data pre-processing

Since the raw data is in the **XML** format, I decided to parse it into the common format, where the samples are separated by the line breaks and the features are separated by the spaces. This stage also includes encoding the text data into the vector form.

3.1 Feature encoding

Since most of the features are represented by a static set of values, I have enumerated those values in such way, that unassigned values are turned to zeroes. Here I have experimented with feature scaling. Three methods were tested: no feature scaling, normalization and standardization. Normalization (scaling between 0 and 1) was obtained by using the following equation:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

However, normalization gave slightly worse results compared to the model without any feature scaling applied. Standardization of features has been computed with the equation below:

$$x' = \frac{x - \bar{x}}{\sigma}$$

Here σ is a standard deviation, which is calculated as

$$\sigma = \sqrt{\frac{\sum(x_i - \mu)^2}{N}}$$

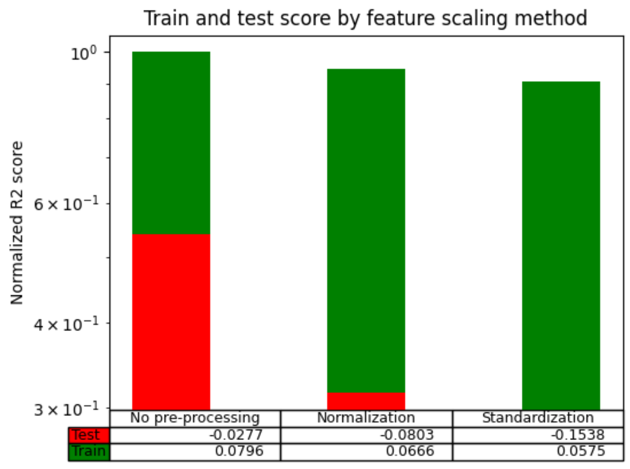
Standardization has shown even worse results as it also has scaled some features into infinity. The results are plotted as bar chart (see Figure 1). It is clear that no feature scaling is required for this dataset, so all further experiments are conducted without feature scaling.

3.2 Text encoding

Before vectorizing the text it is important to deprive it of every undesired details. Therefore, I am removing all special characters and numbers from the text prior to vectorizing it. The following function is designed to do so:

```
def clean(text):
    return re.sub("[^a-zA-Z0-9 ]+", '', text)
```

I have conducted experiments with two modules: the `sklearn.feature_extraction.text`, from which I am using `CountVectorizer` class, and the `fasttext`, which is developed and maintained by Facebook. The former (as suggested by its name) encodes the text into a vector with the number of features equal to the vocabulary size found by analyzing the data, and each feature is a count of occurences of the word in the input text. The latter obtains the vector

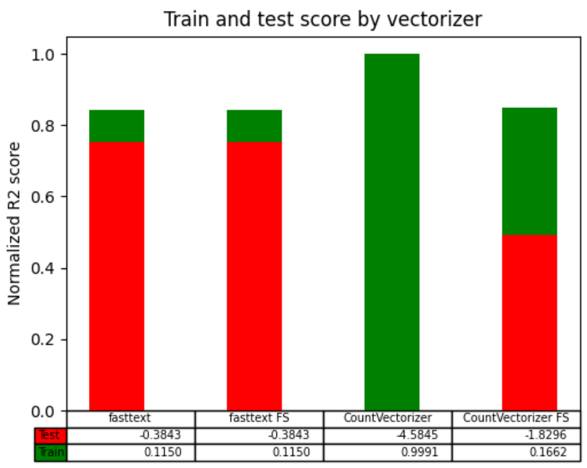


	No pre-processing	Normalization	Standardization
🟥 Test	-0.0277	-0.0803	-0.1538
🟩 Train	0.0796	0.0666	0.0575

Figure 1: Comparison of feature scaling techniques in terms of $R2$ score. Y axis has normalized $R2$ score, whereas the bottom table presents raw values.

reprezentation using either unsupervised or supervised learning. When using `CountVectorizer` we have two options: either feed it a precomposed vocabulary to work with or let it learn the vocabulary of the whole text input. The first option should, in theory, yield better results, but it requires some method of extracting words, which have the most influence on the outcome. I did not manage to find a way to compose a good vocabulary and had to utilize the second option instead. Thus, I ended up with almost $300k$ features, most of which were zeroes. That is when I came up with idea to reduce the dimensionality of the input using feature selection methods (I describe them in the next section).

Another big advantage of `fasttext` is its perfomance. `CountVectorizer` does not have an option to save and reuse model and, therefore, we have to retrain it every time we want to render an input file.`fasttext`, on the other hand, does offer this option, allowing to generate a binary file with pretrained model, which is then loaded from the script. So in this test we are comparing the results of the four models: model using `fasttext` without the feature selection, model using `fasttext` with feature selection, model using `CountVectorizer` without the feature selection and `CountVectorizer` with feature selection (see Figure 2). The test had to be perfomed on 100 samples only (instead of the common 1000) as anything above lead my laptop to freezing. According to the plot, both variants of `fasttext` have the same perfomance score. This is caused by feature selection not changing the feature vector on such small sample size. However, when considering `CountVectorizer` we can see a big perfomance improvment in terms of test score when feature selection is applied. Interestingly, when using `CountVectorizer` without the feature selection, score on the training set greatly bigger than on the test set, which means huge overfit. With feature selection, though, those $300k$ features are reduced to around 20 with $C = 0.1$. Nevertheless, `fasttext` still outperforms `CountVectorizer` and is better in multiple ways described before, thus, we will be using it in all our forthmentioned experiments.



	fasttext	fasttext FS	CountVectorizer	CountVectorizer FS
🟥 Test	-0.3843	-0.3843	-4.5845	-1.8296
🟩 Train	0.1150	0.1150	0.9991	0.1662

Figure 2: Comparison of text vectorizing techniques in terms of $R2$ score. Y axis has normalized $R2$ score, whereas the bottom table presents raw values.

4 Feature selection

I am using `sklearn.svm.LinearSVC` with $l1$ penalty as a feature selection method. This is a piece of code, which performs feature selection:

```python
def feature_selection(X, y, C=0.01, max_iter=1000):
    lsvc = LinearSVC(C=C, penalty="l1", dual=False,
   max_iter=max_iter).fit(X, y)
    model = SelectFromModel(lsvc, prefit=True)
    return model.transform(X)
```

Here we are tweaking `C` parameter to find the best results. Feature selection doesn't really influence the perfomance when using `fasttext`, so these experiments were conducted using the `CountVectorizer` instead. Increasing C corresponds to less regularization and vice versa. The graph below (see Figure 3) depicts the results of experiments with different values of C. It looks like the value of 0.3 has the best scores. Everything below 0.25 does not leave enough features for the regression, and after 1.2 we have too much features left.

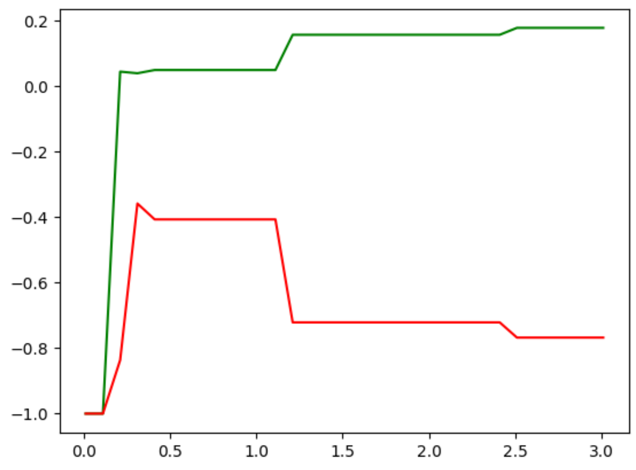
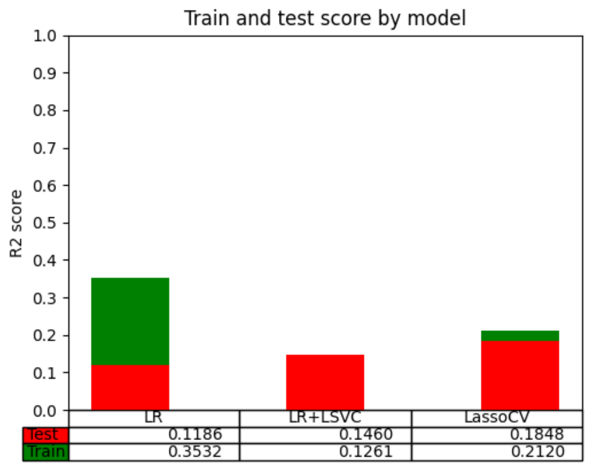


Figure 3: Comparison of different regularization values in feature selection. The red curve is test score and the green one is the train score.

There is no point tweaking `max_iter` since `LinearSVC` converges before it reaches 1000 iterations, so it yields the same results for every other number of iterations above that value. And decreasing the number of iterations leads to non-convergence, which is not exactly what we want.

5 Model tuning

Now that we have chosen a text vectorizer we can compare different models. `Sckit-learn` library has a few linear models implemented. Some of them, like for instance `Lasso`, already include variable selection in them. There is also `LassoCV` with k-fold cross validation, which we can use to find optimal model for us. In this section we are comparing different models, such as `LinearRegression`, `LinearRegression+LinearSVC`, `LassoCV`. According to the Figure 4, the overall best results were achieved when using `LassoCV`. Bare linear regression is very exposed to overfitting on the undesired features. When using `LinearSVC` to select features, and then feeding reduced feature vector to the `LinearRegression` we get interesting results: ahieved test score is bigger than the train score.



	LR	LR+LSVC	LassoCV
🟥 Test	0.1186	0.1460	0.1848
🟩 Train	0.3532	0.1261	0.2120

Figure 4: Comparison of different models.

`LassoCV` is actually yielding some adequate results, though, of course I was aiming for more initially. To better understand how good is it performing, here are a few sample results:

```
got: 68864.5, expected: 59400.0
got: 38284.0, expected: 7200.0
got: 20963.4, expected: 1800.0
got: 186710.0, expected: 144000.0
got: 54440.0, expected: 10800.0
```

6 Conclusion

All in all, after multiple iterations and experiments I can conclude, that it is very hard to predict the time estimate based on this (real-world) dataset. After all, the time spent on the task does not only depend on its priority, severity, description or other parameters, but also on the person, who was the task assigned to. Moreover, complexity of the task can vary depending on different other conditions not possible to include in the dataset.

However, I think there is still a lot of space for research. Firstly, I believe that by generating the right vocabulary for the `CountVectorizer` we can get some satisfiable results from the model. Secondly, the dataset is not very clean, so it will surely improve the results if we prune it of outliers and exceptions. Lastly, other linear regression models can be researched like `Ridge` and `SGDRegressor` offered by *scikit-learn* library.

Personally, I was really pleased, when I got a test score of 0.18, but, unfortunately, this is the maximum I could squeeze out of my models. Additionally, this is the first time I am facing data pre-preprocessing, this project made me realize how important and how hard it is to clean and prepare your dataset before feeding it to the model.

7 Appendix

Source code and other related files can be found in this repository. Unfortunately, I did not receive a permission to share the dataset itself as it holds too much corporate data. However, I think it is rather safe to share the input files, which are created with `parse` function. Repository also contains *model.vec* and *model.bin* files, which hold the `fasttext` model. The *poject.py* is the main script, where I did all my experiments. It is rather messy and has a lot of commented code, I am attaching it mainly to prove that everything above was computed and generated with the script.