# Classification of Calendar Events

Machine Learning Course Project

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**Abstract**

The initial goal of this project was to explore a collection of events recorded in my personal Google calendar and to categorize them.

Based on keywords in the event descriptions we semi-manually labeled a subset of events and then used SVMs and random forests (and marginally tree boosting and multilayer perceptrons) to solve a classification task: prediction of the event category based on its start time, duration. In the final stage of the project we also created PCA-based word vectors of short event descriptions and achieved 80% classification accuracy.

## 1 Introduction

In the period between November 2014 and March 2017 I have been recording most of my daily activities (sleep, learning, leisure activities, ...) in a Google calendar which resulted in approximately 6000 calendar events. As my project I chose to analyze this data.

My initial idea was to discover some behavioral patterns and try to predict the next action I would do based on historic data. However to be able to do this, I would need some categorization of the activities So I postponed the event prediction, and focused mainly on event categorization and classification. Thus the main goals of this project were to prepare and explore the dataset and to try to categorize events.

I ended up with a semi-manual categorization (I categorized events based on manually selected keywords in summaries), but as a machine learning exercise I also trained multiple classifiers to validate the categorization (to check whether ML models can distinguish these categories) and used these classifiers to categorize uncategorized events.

In this project we first prepare the dataset of 6075 events – we process calendar `.ics` files and for each event we extract its start timestamp, duration and a short summary text.

To gain a bit of insight we visualize the dataset and train simple classification models which use numeric attributes (date, time, duration) to map each event to one of three categories – sleep, school, personal. During the data collection period we separated events into three calendars so these labels are based on calendar names. We achieve 70% accuracy.

Based on event summaries we semi-manually label a subset of 4243 events into six categories and then we train classifiers from numeric attributes into these six categories. Here we achieve only 50% accuracy, since multiple categories were indistinguishable only with use of numeric attributes.

Finally we construct word vectors from summary texts with use of PCA on bag of words. We use these vectors as additional event attributes in six-category classification task. With use of word vectors we achieved 78% accuracy and we eventually used these models in an attempt to categorize uncategorized events.

As the calendar information are personal, we do not include them in the repository.

# 2 Dataset Preparation

Our first task was to convert three calendar files `sleep.ics`, `school.ics` and `personal.ics` into a usable dataset in form of table of all events. From each event we extracted its start timestamp, end timestamp and a short summary text and preprocessed them.

## 2.1 Attribute Preprocessing

We decided to use the following attributes to represent a start timestamp:

- `minutes_of_day` (integer in range $0 - 24 \times 60$). Since people live in a daily cycle, the time of the day is very important attribute as it enables to associate events that occur in the same part of the day.
- `weekday` (integer in range $0 - 6$, 0 is Sunday). The weekly cycle and most importantly weekends influence the human behaviour and so should be considered.
- `day_number` – number of days since Jan 1st 2014. We added this attribute so that events which happened in a similar time period would have something similar and also so that events which happened on different days would be distinguishable. Thanks to this attribute it might be possible to observe long term trends.

Instead of using start and end timestamps, we use start time and duration. An event may start and end on different days (e.g. sleep) and as we use multiple attributes to represent a timestamp, it might be almost impossible for a model to reconstruct duration from start and end attributes.
We represent duration with one integer in minutes `duration_minutes`.

As the summaries are mostly in Slovak language, we first removed diacritics. Since the upper case is used inconsistently (as the first character of summary or as a person's name), we lower-cased the summaries. Finally we replaced all characters except `a-z0-9_` with a space and we removed repeated, leading and trailing spaces. Although we decided to keep the numbers to allow detection of some university room names (e.g. t2, f1), we later discarded most of them (at removal of short words in word vector preprocessing).

For each event we also included a name of the source calendar file (sleep, school or personal) that can be used as a simple classification label.

Applying this procedure we produced a single file with 6075 events where each event is characterized by `summary`, `day_number`, `weekday`, `minutes_of_day`, `duration_minutes` and `label`. There are 10 randomly selected data points shown in the following table:

| summary | day_number | weekday | minutes_of_day | duration_minutes | label |
|---:|---:|---:|---:|---:|---:|
| cvicenie | 714 | 2 | 1410 | 30.0 | personal |
| neurodrogy stavba mozgu neuronu | 778 | 3 | 1290 | 90.0 | personal |
| citanie o meditacii | 670 | 0 | 780 | 60.0 | personal |
| riad | 1084 | 1 | 1110 | 30.0 | personal |
| cesta do ba ucenie sa sieti | 823 | 6 | 600 | 120.0 | school |
| libetov experiment s rp a vedomim | 689 | 5 | 900 | 90.0 | school |
| bakalarsky seminar 1 | 1050 | 2 | 690 | 60.0 | school |
| skolemov normalny tvar | 724 | 5 | 690 | 60.0 | school |
| spanok | 413 | 2 | 0 | 480.0 | sleep |
| spanok | 1017 | 4 | 60 | 270.0 | sleep |

# 3 Three-class Classification

At first we didn't use the summaries and we tried to solve the classification task where the inputs $X$ consisted of numeric attributes: $X_i =$ (`day_number`, `weekday`, `minutes_of_day`, `duration_minutes`) and the labels $y$ were the calendar names: $y_i :=$ `label`.

4172 events were from personal calendar, 985 were from school calendar, and 917 events from sleep calendar.

## 3.1 Dataset Visualization

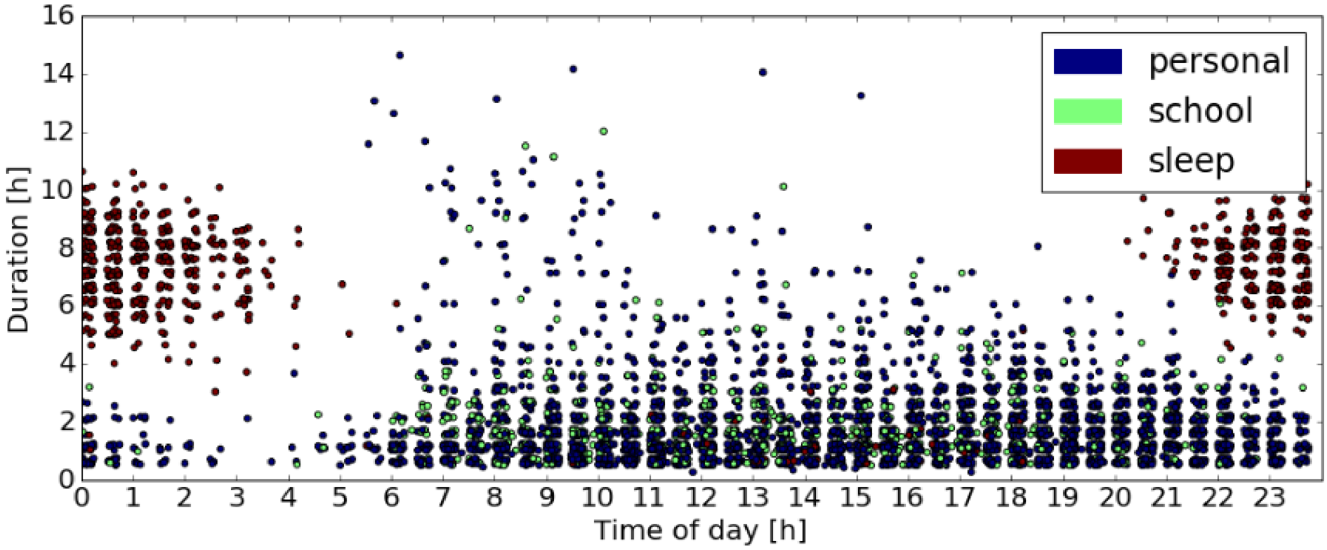



Figure 1: The distribution of events of different durations and at different times of day. As most events have their start times and durations rounded to 15 minutes (XX:00, XX:15, XX:30, XX:45), to visualize multiple points per (t.o.d. $\times$ duration) we add small random noise to points.

In Figure 1 we can see that most of the sleep events are easily distinguishable because of their long duration and night time, but a few sleep events also occur during the day after lunch. The school and personal events don't seem to be separable, although there is considerably fewer school events after 19:00.

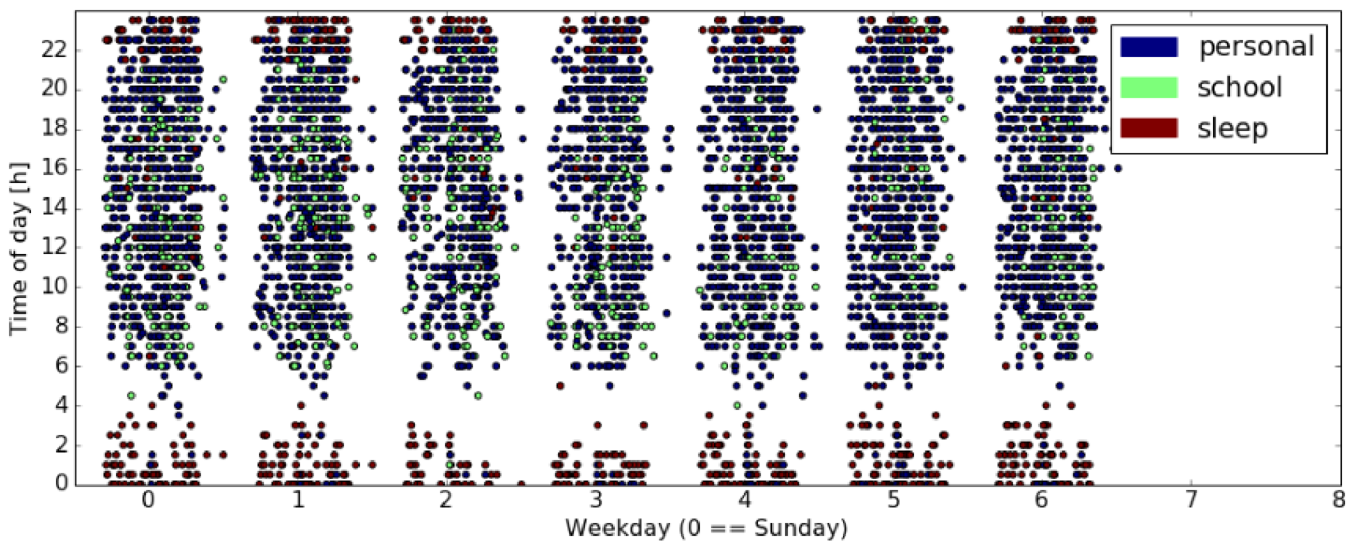



Figure 2: The distribution of events at different different times of day on different weekdays. Here we add randomness only in $x$ coordinate. The data in this projection shows similar patterns as in Fig.1.

Although we might expect fewer school events during the weekends in Figure 2, we did not include the lecture (repeated) events and so all school events correspond to homeworks and learning which is spread throughout the whole week. The students can never truly rest.

The same patterns were also observable via 2D PCA – distinguishable sleep, indistinguishable school and personal and area without much school.

### 3.2 Classification

We tried to train a Support Vector Machine (SVM) with gaussian kernel and a Random Forest Classifier (RFC).

To indicate overfitting we split the data into training and testing in 80:20 ratio. To minimize the effect of variance we have also used 5-fold cross validation and we observed the mean and standard deviation of accuracies of 5 trained instances per one setting of parameters.

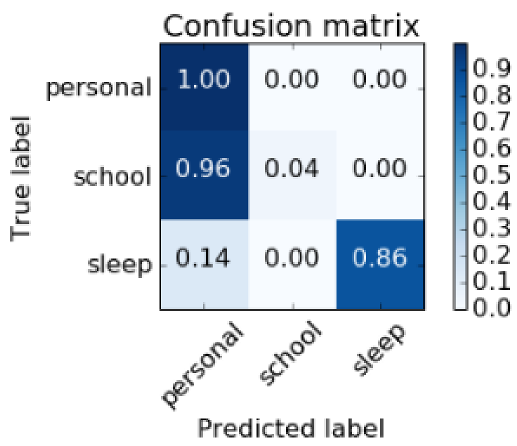
We have manually tuned the parameters to achieve the highest testing accuracy. we also tried to achieve the smallest gap between training and testing data as it is an indicator of low variance and thus minimal overfitting.

For SVMs we changed two parameters: $C$ – the penalty for crossing the margin and $\gamma$ – inverse of the width of gaussian. We fought the overfitting by decreasing $\gamma$ and thus increasing SVM's generalization ability. Modifying $C$ usually only led to overfitting (larger gap between training and testing accuracy) or to underfitting (drastic drop in both accuracies).

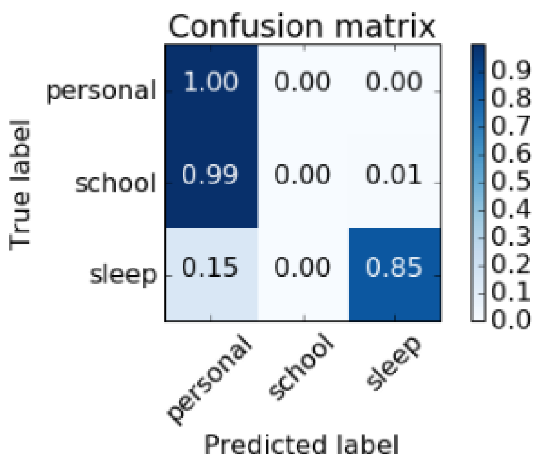
For RFCs we changed $n$ – the number of trees and $d$ – max. depth of a tree. Since we only used 4-dimensional examples $X_i$, for any $d < 4$ the RFC underfitted and so we only minimized the number of trees to avoid overfitting and to increase the efficiency.

After the training we obtained the following results:

| model | training accuracy | testing accuracy |
|---|---|---|
| SVM ($C = 1, \gamma = 0.0001$) | 0.823 +/- 0.003 | 0.815 +/- 0.013 |
| RFC ($n = 20, d = 4$) | 0.813 +/- 0.003 | 0.813 +/- 0.013 |




(a) A confusion matrix for SVM.




(b) A confusion matrix for RFC.

A look at the confusion matrix revealed that we have a problem with imbalanced classes (as there are 4 times more personal events than sleep or school events) and so the accuracy is not the only metric we would want to optimize.

As the sleep events are easily separable, both models are able to successfully categorize sleep events but fail to separate school and personal events.

### 3.3 Dealing With Imbalanced Classes

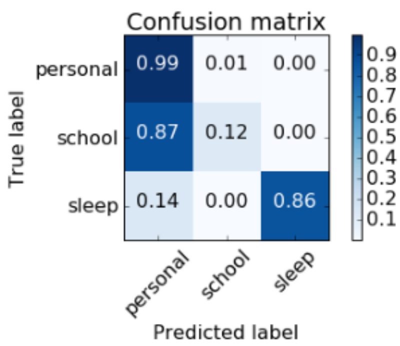
We started to use macro-F1 score as metric which would consider classes as equally important. F1 score allows to compare classification methods in both specificity (precision, true positives /

classified positives) and selectivity (recall, true positives / all positives). For macro-F1, F1 score is first computed for each class and then the average of scores is taken, thus assigning the same importance to each class.

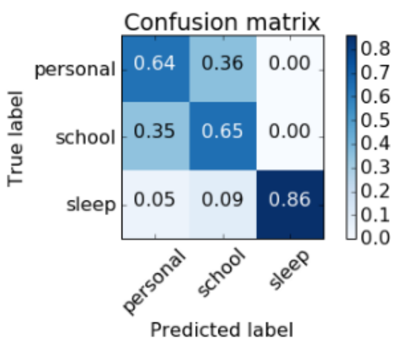
The first thing which we tried was to use boosting as it should train some classifiers on wrongly classified examples. As the base classifier we used RFC from the previous section. We minimized the number of RFC instances to 10 (higer number led to overfitting, lower had small effect) but we only achieved a slight change in confusion matrix (12% of school events were now successfully categorized).

As our final solution we decided to subsample training data so it would contain approximately 1000 events from each class (we have randomly sampled 1/4 of the personal events, shrinking the dataset from 6000 total examples to 3000) and we summarize the achieved results in the following table and confusion matrices.

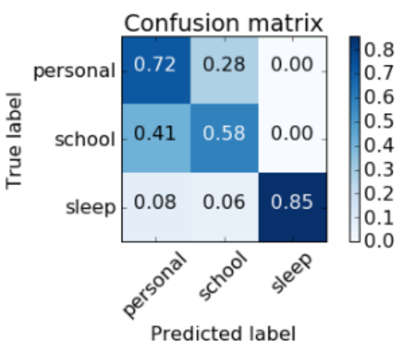
| model | training acc. | testing acc. | training mac-F1 | testing mac-F1 |
|---|---|---|---|---|
| SVM ($C = 1, \gamma = 0.0001$) | 0.823 +/- 0.003 | 0.815 +/- 0.013 | 0.632 +/- 0.006 | 0.610 +/- 0.008 |
| RFC ($n = 20, d = 4$) | 0.813 +/- 0.003 | 0.813 +/- 0.013 | 0.595 +/- 0.004 | 0.594 +/- 0.007 |
| Boosted 10× RFC | 0.833 +/- 0.002 | 0.822 +/- 0.012 | 0.685 +/- 0.006 | 0.659 +/- 0.015 |
| Subsampled SVM | 0.713 +/- 0.004 | 0.696 +/- 0.025 | 0.726 +/- 0.003 | 0.710 +/- 0.021 |
| Subsampled RFC | 0.723 +/- 0.008 | 0.699 +/- 0.021 | 0.731 +/- 0.007 | 0.707 +/- 0.018 |



(a) Boosted RFC.



(b) Subsampled SVM.



(c) Subsampled RFC.

Although with the subsampling the deviation of scores increased and the accuracies dropped to 70%, the macro-F1 scores increased and we can see from the confusion matrix that these models are much better in distinguishing school and personal events (approximately 65% 2-class accuracy).

Accuracies and scores were evaluated using the subsampled dataset, but even when we trained the models on subsampled dataset and evaluated them on the whole dataset, the confusion matrix remained almost identical and the accuracies dropped to 66% (effect of more personal data).

One remark for the end of section: sleep events can be discriminated with 96% accuracy if we treat school and personal events as one category.

# 4 Six-class Classification

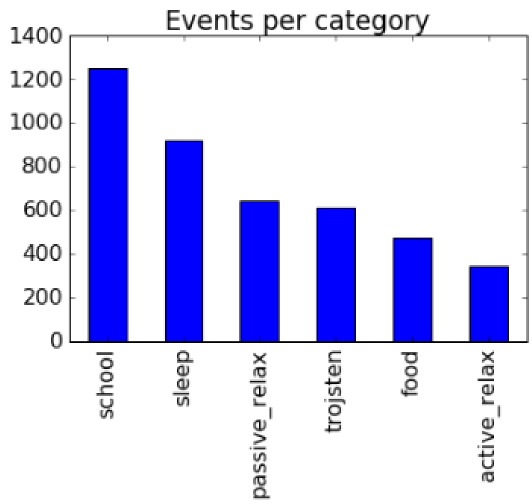
The personal calendar holds events of many different types. To come closer to our goal, we would like to identify some more fine-grained categories of events in the personal calendar.

This should be possible to do with use of summary texts. Although clustering of data-points could be done with unsupervised methods such as k-means, we first opted for a simpler solution: semi-manual categorization based on keywords.

### 4.1 Semi-manual Categorization

To categorize events we have printed out 200 of the most frequent words and manually created categories (trojsten[1], chores, school[2], work, active_relax, workout, passive_relax, food, with_people) and a list of keywords for each category, e.g. `'food': ['obed', 'vecera', 'ranajky', 'pizza']`.

Afterwards we created a list of categories for each summary – if a summary contained a keyword belonging to a category, this category was added to the list. Some summaries were associated with multiple categories and this problem had to be resolved.




It turned out that many of the summaries contained a comma separated list of activities, since each activity was too short to deserve its own event. The best solution would probably be to split each of these compound events into more shorter events. We, however, opted for a simpler solution – discarding the events that have been assigned to multiple categories.

To minimize the losses caused by multiple-category-conflicts we reduced the number of different categories. We discarded categories chores and work since they contained less than 100 events. Furthermore we discarded categories workout and with_people since they had a lot of conflicts with food events (morning workout + breakfast, lunch with a person). This process has left us with five categories: trojsten, school, food, active_relax, passive_relax.

When we also added the data from school and sleep calendars, we got a set of 4243 categorized events with the distribution shown in the barplot.

### 4.2 Dataset Visualization

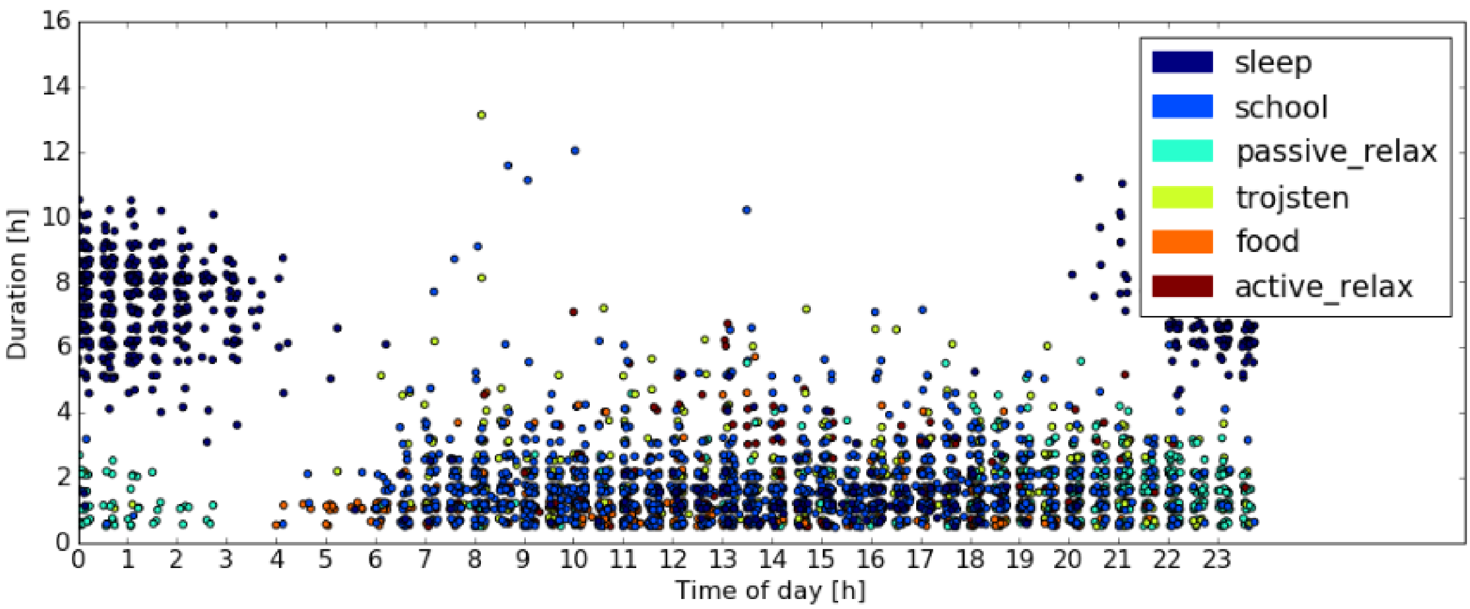



Figure 5: The distribution of events of different durations and at different times of day with small random noise.

[1]A volunteer activity: organizing programming competitions and camps for high-school students. Check www.trojsten.org.

[2]A closer look on data revealed that also some school events were recorded in the personal calendar (in the period when the school calendar did not exist yet). This might have caused some difficulties in the 3-class classification, although only 300 out of 4000 personal events were categorized as school.

With use of Figure 5 we can do some new observations. Almost all non-sleep events that start after midnight fall into passive_relax category (watching a movie, reading a book, ...). The periods of time from 20:00 are filled with passive_relax, but also some school and trojsten activities occur. The longer events are mostly categorized as school and trojsten. Food events are usually short and occur mostly in ranges 4:00 - 7:00, 10:00 - 15:00 and 18:00 - 20:00. No shocking news, but it is nice what can be seen from such a simple plot.

### 4.3 Classification

We used the same methods for classification here as in case of three classes. The only changes in parameters that led to better models were $\gamma = 0.00005$ (half of the previous value = wider gaussians) for SVMs and we only used 5 copies of RFC at boosting.

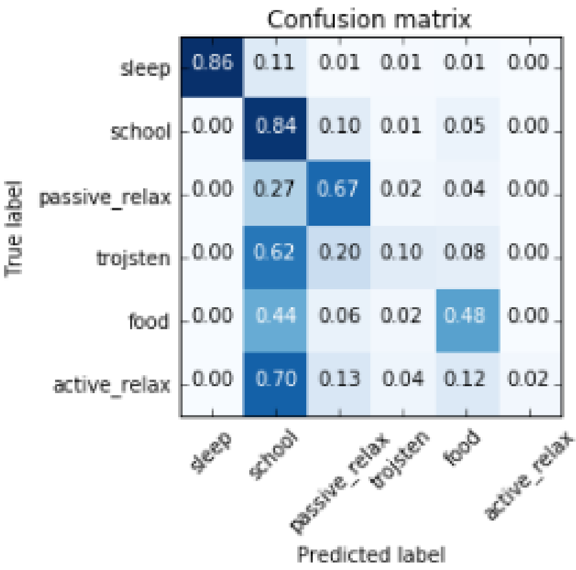
The problem of imbalanced classes again came into play so the SVM and RFC trained on all data were unable to distinguish trojsten, food and active_relax (the least frequented categories) from the most frequented one – school. The RFC scored significantly worse here than SVM, most probably because the SVM can formulate more sophisticated hypotheses (decision trees only cut the space with hyperplanes that are perpendicular to the main axes).

Boosted RFC reached the same accuracy and scores as SVM – here was boosting used on the purpose for which it was designed, to decrease bias. The fact that boosted RFC and SVM reached the same results (accuracy of 58%, F1 score of 0.45) can hint us that this is probably the best result which we can get with all data.

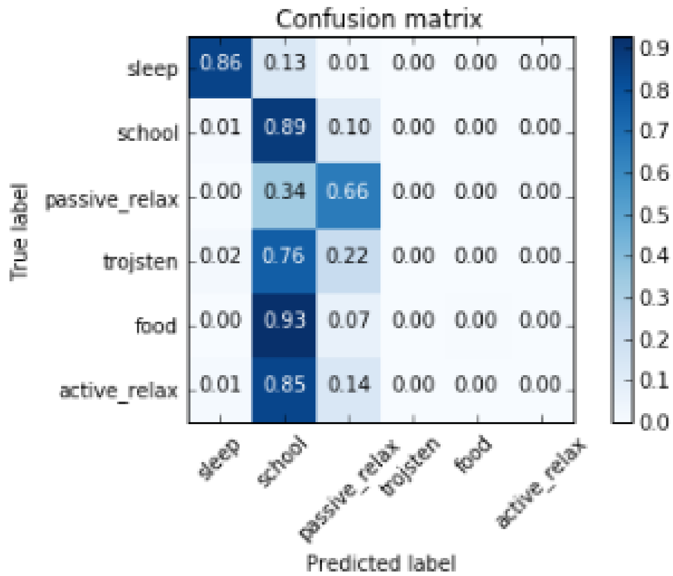
To decrease bias towards frequent categories, we again subsampled data, so approximately 400 datapoints are present in each category (2400 out of total 4243 events). The best trained model was SVM with testing accuracy of 50% and F1 score 0.49. The change in F1 score wasn't so high as in 3-class case (now only 0.05 points instead of 0.1), but as the macro F1 score is the average of F1 scores for each class and here we have two times more classes, the change is quite comparable. Still, the accuracies of trojsten and active_relax classification are insufficient.

From these observations we can conclude that it is very hard to distinguish active_relax and trojsten activities from school and food only by using the time and duration of events.

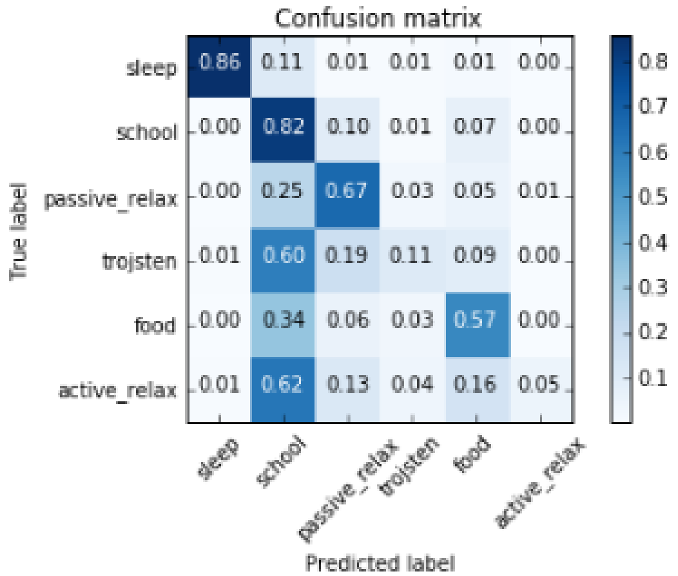
| model | training acc. | testing acc. | training mac-F1 | testing mac-F1 |
|---|---|---|---|---|
| SVM ($C = 1, \gamma = 0.00005$) | 0.606 +/- 0.003 | 0.580 +/- 0.011 | 0.482 +/- 0.004 | 0.447 +/- 0.009 |
| RFC ($n = 20, d = 4$) | 0.547 +/- 0.002 | 0.541 +/- 0.014 | 0.354 +/- 0.011 | 0.347 +/- 0.017 |
| Boosted 5× RFC | 0.613 +/- 0.005 | 0.583 +/- 0.014 | 0.500 +/- 0.006 | 0.451 +/- 0.014 |
| Subsampled SVM | 0.579 +/- 0.002 | 0.508 +/- 0.017 | 0.566 +/- 0.003 | 0.491 +/- 0.018 |
| Subsampled RFC | 0.509 +/- 0.002 | 0.503 +/- 0.012 | 0.441 +/- 0.012 | 0.434 +/- 0.014 |



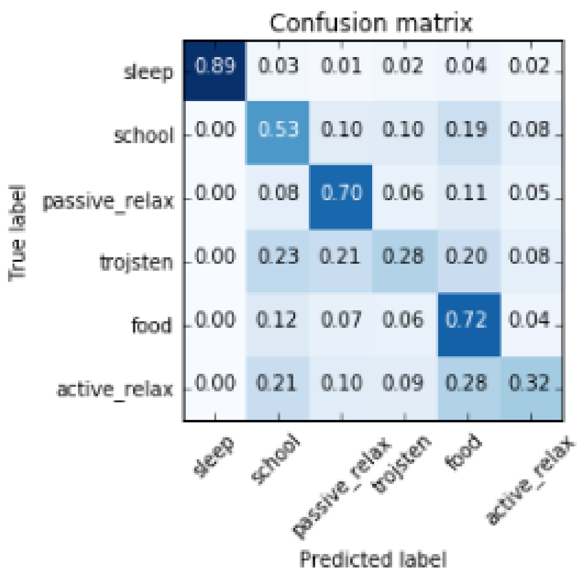

(a) SVM.



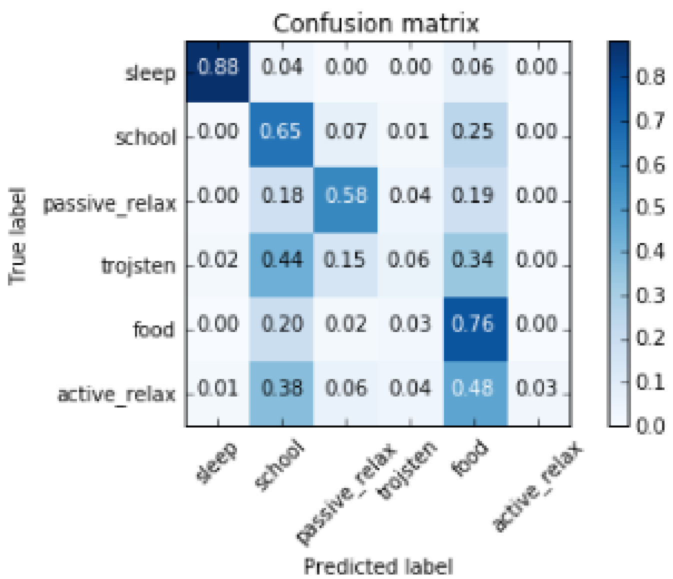

(b) RFC.




(c) Boosted RFC.




(d) Subsampled SVM.




(e) Subsampled RFC.

# 5 Word vectors

In this section we finally use methods of machine learning on the summaries.

We were incrementally improving the word vectors and we tried to evaluate their quality in each stage with PCA. When the vectors were computed, we looked at the explained variance ration in the first 2 and 100 components, we printed out the 5 most important words (words which had the highest absolute value in the principal component) in the 5 most important components and we also plotted the PCA projection to 2D.

## 5.1 Gradual Improvement of Word Vectors

We started with creating a bag of words with use of all 4701 distinct words. Although the conjunctions and prepositions were considered as most important words, the first 100 components already captured 47% of all variance (of all information). In the 2D projection most of sleep events and also a lot of trojsten events are easily separable and other events create some clusters.

```
Explained variance ratio in    2 components 0.079192669504
Explained variance ration in 100 components 0.471266889902
5 most important words in first 5 components:
['spanok', 'a', 's', 'obed', 'o']
['a', 's', 'spanok', 'obed', 'vecera']
['s', 'ksp', 'a', 'obed', 'o']
['s', 'a', 'o', 'ranajky', 'cvicenie']
['o', 'ranajky', 'cvicenie', 'sprcha', 'ksp']
```

In the second step we tried to remove stop words – unimportant words, usually those that often repeat in text. When we removed all short words (with lengths 1, 2) and all words with less than three occurrences, we were left with 855 words and now the first 100 components captured almost 60% of variance. In 2D projection clear clusters of food events and passive_relax events were formed.

```
Explained variance ratio in   2 components 0.116129541457
Explained variance ratio in 100 components 0.597728010393
5 most important words in first 5 components:
['spanok', 'ksp', 'obed', 'gitara', '9gag']
['ranajky', 'sprcha', 'cvicenie', 'ksp', 'proofread']
['ksp', 'ranajky', 'cvicenie', 'sprcha', 'obed']
['gitara', 'obed', '9gag', 'ksp', 'film']
['gitara', 'film', 'obed', 'the', 'ksp']
```

Finally we used a Slovak stemmer from `https://github.com/mrshu/stemm-sk` to first stem all words, and then we removed all short and infrequent words. This approach led to 80% of explained variance in the first 100 components.

```
Explained variance ratio in   2 components 0.234588594894
Explained variance ratio in 100 components 0.808329433367
5 most important words in first 5 components:
['spanok', 'ksp', 'obed', '9gag', 'film']
['ksp', 'proofread', 'obed', '9gag', 'film']
['obed', '9gag', 'film', 'ksp', 'the']
['9gag', 'obed', 'film', 'the', 'ksp']
['film', '9gag', 'the', 'ksp', 'obed']
```

## 5.2 Classification

Eventually we trained SVM, RFC and Multilayer Perceptron (with ReLu units, 100 and 50 neurons on hidden layers and optimized with Adam) on word vectors (v) and then on word wectors combined with numeric data (v + n) and finally on subsampled data (v + n sumsampled). All methods achieved approximately 80% accuracy and F1 score in range of 0.75 to 0.8.

| model | training acc. | testing acc. | training mac-F1 | testing mac-F1 |
|---|---|---|---|---|
| v SVM | 0.818 +/- 0.002 | 0.808 +/- 0.010 | 0.760 +/- 0.001 | 0.748 +/- 0.009 |
| v RFC | 0.815 +/- 0.003 | 0.804 +/- 0.007 | 0.755 +/- 0.003 | 0.743 +/- 0.010 |
| v MLP | 0.823 +/- 0.002 | 0.811 +/- 0.009 | 0.767 +/- 0.001 | 0.752 +/- 0.008 |
| v + n SVM | 0.860 +/- 0.002 | 0.802 +/- 0.012 | 0.818 +/- 0.003 | 0.756 +/- 0.010 |
| v + n RFC | 0.833 +/- 0.002 | 0.818 +/- 0.013 | 0.781 +/- 0.005 | 0.761 +/- 0.014 |
| v + n MLP | 0.868 +/- 0.004 | 0.825 +/- 0.022 | 0.856 +/- 0.004 | 0.811 +/- 0.019 |
| v + n subsampled SVM | 0.810 +/- 0.004 | 0.743 +/- 0.022 | 0.820 +/- 0.003 | 0.758 +/- 0.019 |
| v + n subsampled RFC | 0.826 +/- 0.004 | 0.784 +/- 0.017 | 0.837 +/- 0.003 | 0.797 +/- 0.016 |
| v + n subsampled MLP | 0.842 +/- 0.003 | 0.785 +/- 0.019 | 0.842 +/- 0.004 | 0.786 +/- 0.021 |

## 5.3 Labeling of unlabeled data

The classification models could be used for labeling of uncategorized data. Here we only show a few examples. Also, because of time pressure we did not evaluate this labeling in any way (apart from marking with * the labels which we consider as correct).

| summaries | categories SVM | categories RF | categories MLP |
|---|---|---|---|
| zapis stipendium diplomy na gjh | school* | trojsten | sleep |
| prve 2 kapitoly z algebry | school* | school* | school* |
| gjh ocenovanie | trojsten | trojsten | trojsten |
| trojstenovy pondeok kvizy | school | school | school |
| d u programko | school* | school* | school* |
| riad | food | food | active_relax |
| 55 vyrocie gjh | trojsten | trojsten | trojsten |
| vysavanie | school | school | school |
| aj uloha | school* | school* | school* |
| cvicenia z matalyzy | school* | school* | school* |
| heno | school | school | school |
| ... | ... | ... | ... |
| kapustnica | school | school | school |
| pomoc na akademii veci do skoly ak nebude treba | school* | school* | school* |
| vub | school | school | passive_relax |
| webstretko | active_relax | school | trojsten* |
| aupark | active_relax* | school | trojsten |
| party byrokratov | active_relax* | school | trojsten* |
| organizacia | school | school | school |
| ml engineer s look at insurance | active_relax | school | trojsten |
| posedenie s janom a petou | active_relax* | school | trojsten* |
| matfyzacka kapustnica | school* | school* | trojsten |

# 6 Ideas For Improvement

## 6.1 Format of Time-denoting Attributes

Instead of coding Sunday, ..., Saturday as 0, ..., 6 it would have been probably better to code Monday as 0 and Sunday as 6, since Saturday and Sunday are similar days (they are both free) and so they should be denoted with similar values.

It might also be helpful to add `month_of_year`, but since the data cover only a period of two years, characteristics of each month are probably not observable or the trends can be expressed with use of `day_number`. People usually don't even realize which `day_of_year` is today and don't make decisions only based on `day_of_month` so we considered these attributes as uninformative (although we didn't experimentally prove it).

## 6.2 Unused Calendar Information

All calendar events also contain timestamp of its creation and last modification. For simplicity we decided to not to take these timestamps into account, but it might be interesting to also consider the creation timestamp in relationship to start time, since it might help to distinguish planned and unplanned events.

Since only very few ($< 20$) of the calendar events include the location information and a longer description, these information were discarded.

Google calendar allows creation of repeated events (e.g. lectures). To consider such events, one record would have to be transformed into multiple records (one calendar event per occurrence). As this would require a bit more engineering and also it might cause our models to overfit repeated events, we decided to not implement this feature and we did not process repeated events. If we would include these events to the dataset we would add a binary attribute denoting whether an event is repeated and maybe the number of occurrences. Since almost all repeated events occur weekly, we would not include frequency.

The dataset could be further enhanced by other relevant information such as the times of sunrise and sunset (which might influence the sleep) or the weather during the day (which might influence in-door and out-door activities).