Practical Guide

Alexander Guschin

Practical guide: intro

Before you enter a competition

Define your goals. What you can get out of your participation?

1. To learn more about an interesting problem
2. To get acquainted with new software tools
3. To hunt for a medal

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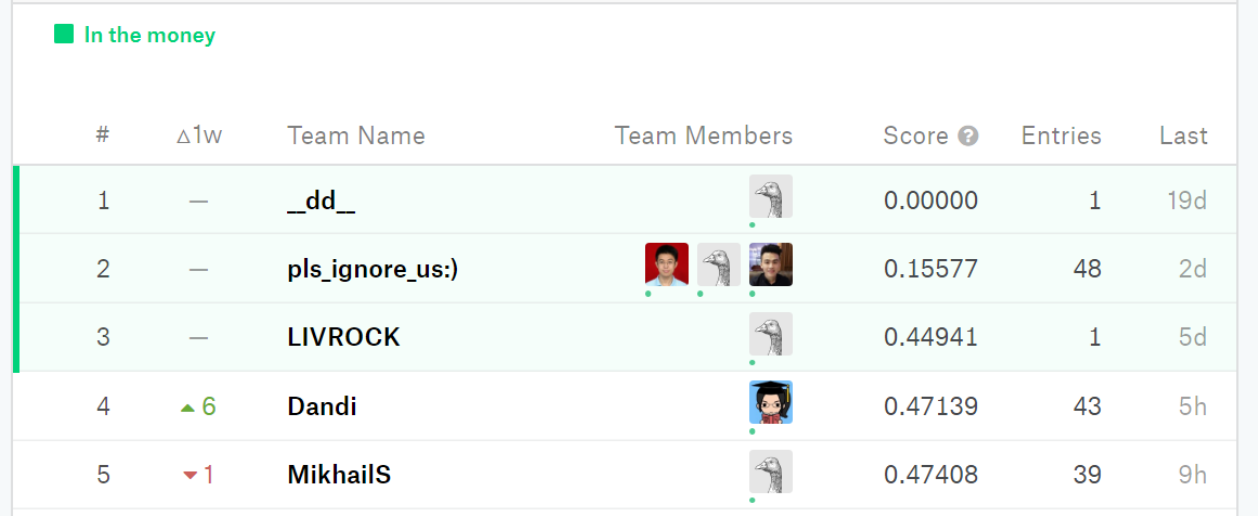


After you enter a competition: Working with ideas

1. Organize ideas in some structure
2. Select the most important and promising ideas
3. Try to understand the reasons why something does/doesn't work

After you enter a competition: Everything is a hyperparameter

Sort all parameters by these principles:

1. Importance
2. Feasibility
3. Understanding

Note: changing one parameter can affect the whole pipeline

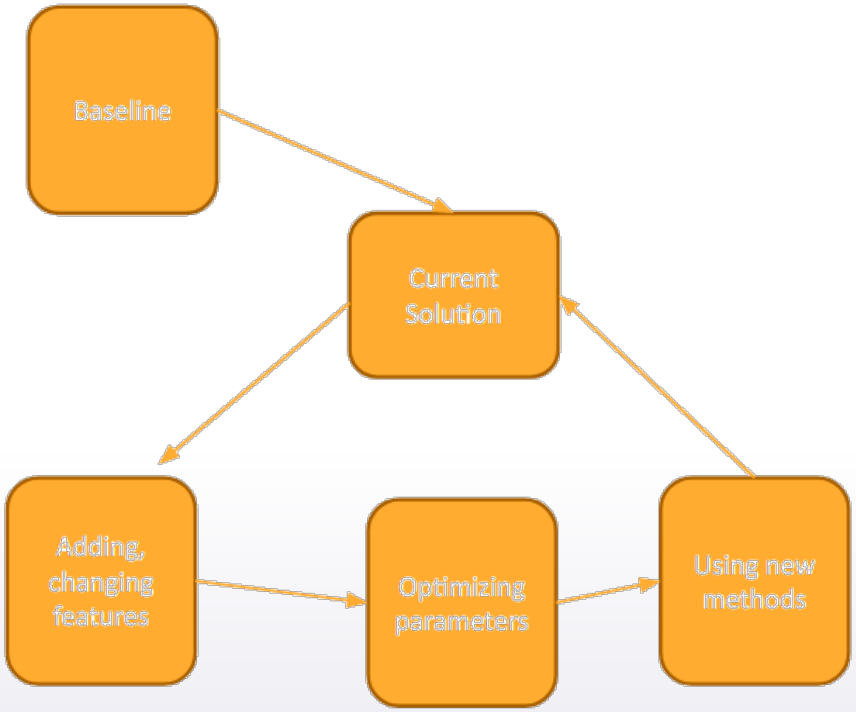
Dmitry Altukhov

Data loading

- Do basic preprocessing and convert csv/txt files into hdf5/npy for much faster loading
- Do not forget that by default data is stored in 64-bit arrays, most of the times you can safely downcast it to 32-bits
- Large datasets can be processed in chunks

Performance evaluation

- Extensive validation is not always needed
- Start with fastest models - LightGBM



Fast and dirty always better

- Don’t pay too much attention to code quality
- Keep things simple: save only important things
- If you feel uncomfortable with given computational resources - rent a larger server

Mikhail Trofimov

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- “From simple to complex”
  - I prefer to start with Random Forest rather than Gradient Boosted Decision Trees

Best Practices from Software Development

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- Keep your research reproducible
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  - Write down exactly how any features were generated
  - Use Version Control Systems (VCS, for example, git)
- Reuse code
  - Especially important to use same code for train and test stages

Read papers

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  - For example, how to optimize AUC
- Way to get familiar with problem domain
  - Especially useful for feature generation

Dmitry Ulyanov

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- **I add features in bulks**
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- **Hyperparameters optimization**
  - First find the parameters to overfit train dataset
  - And then try to trim model

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Out[521]: 0.042878536778555423
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Code organization: keeping it clean

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- **Your notebooks can become a total mess**

```
s = qq.sum(1)
ss = s[:,3]/qq.var()
sss = ss[0]
```

Code organization: keeping it clean

- **One notebook per submission** (and use git)

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- **Before creating a submission restart the kernel**
  - Use “Restart and run all” button

Code organization: test/val

- Split *train.csv* into *train* and *val* with structure of *train.csv* and *test.csv*

1.
```
train = pd.read_csv('data/train.csv')
test = pd.read_csv('data/test.csv')
```

2.
```
from sklearn.model_selection import train_test_split

# train set into new train and validation
train_train, train_val = train_test_split(train, random_state=660)

# save to disk
train_train.to_csv('data/val/train.csv')
train_val.to_csv('data/val/val.csv')
```

Code organization: test/val

- When validating, set it at the top of the notebook

```
train_path = 'data/val/train.csv'
test_path = 'data/val/val.csv'
```

- To retrain models on the whole dataset and get predictions for test set just change

```
train_path = 'data/train.csv'
test_path = 'data/test.csv'
```

Code organization: macros

I use macros for a frequent code

```
In [2]: __imp
```

```
In [5]: __fsmall
```

Code organization: macros

In [3]:
```
print __imp
```

```
import os
PYTHON_UTILS_PATH = os.environ['PYTHON_UTILS_PATH']

import numpy as np
import pandas as pd
from tqdm import tqdm_notebook

import matplotlib.pyplot as plt
get_ipython().magic(u'matplotlib inline')
plt.rcParams['figure.figsize'] = (14, 14)

# This will populate `globs_to_run`
get_ipython().magic(u'run {PYTHON_UTILS_PATH}/config.py')

for g in globs_to_run:
    files_to_run = get_ipython().getoutput(u'ls {os.path.join(PYTHON_UTILS_PATH,g)}')

    for f in files_to_run:
        if 'Macro.py' not in f:
            get_ipython().magic(u'run {f}')

import matplotlib as mpl

mpl.rcParams['axes.color_cycle'] =['#ff0000', '#0000ff',   '#00ffff','#ffA300', '#00ff00',
     '#ff00ff', '#990000', '#009999', '#999900', '#009900', '#009999']
from matplotlib import rc
rc('font', size=16)
rc('font',**{'family':'serif','serif':['Computer Modern']})
rc('text', usetex=False)
rc('figure', figsize=(16, 14))
rc('axes', linewidth=.5)
rc('lines', linewidth=1.75)
```

Code organization: custom library

- **I use a library with frequent operations implemented**
  - Out-of-fold predictions
  - Averaging
  - I can specify a classifier by it's name

```
param = {
    'C':1.2,
}
res = trylib(train_2lv, y_train,
             'lsvc', param,
             one = False, skf_seed = 660, skf = 4,
             test_mode='whole', X_test=test_2lv).res
```