Winning on Kaggle: Becoming a better data scientist

Data Science Retreat
March 18th, 2019

About me

- Undergraduate in Computer Science and Biology (U. of British Columbia)
- Master's in Machine learning (U. College London)
- Master's in Management (INSEAD)
- Ph.D. in Data Science and Business Analytics (U. of Amsterdam)
- Serious competitor on **Kaggle** (and other platforms) from 2015-2018
- Worked as a commercial data scientist on a variety of projects since 2015

Qingchen

Researcher and lecturer at University of Amsterdam
Amsterdam, Netherlands
Joined 7 years ago · last seen in the past day
https://www.qingchenwang.info/

Followers 164

Competitions Grandmaster

Competitions Summary

Competitions Grandmaster

Current Rank 157 of 102,312

Highest Rank 14

9 10 6

Competitions: 34
Solo: 19 (56%)
Team: 15 (44%)

Goals for today

1. Demystify **Kaggle** competitions
   - Why should you compete?

2. Provide a **framework** for excellent performance (top 10%) with minimal effort (5-10 hours per competition)
   - How to compete efficiently?

3. Provide some tips to **excel** in competitions
   - How to win?

4. Real life **experience** of a competition
   - I’ve set up a competition for you

Demystifying Kaggle competitions: Why you should compete

What do you think of Kaggle?

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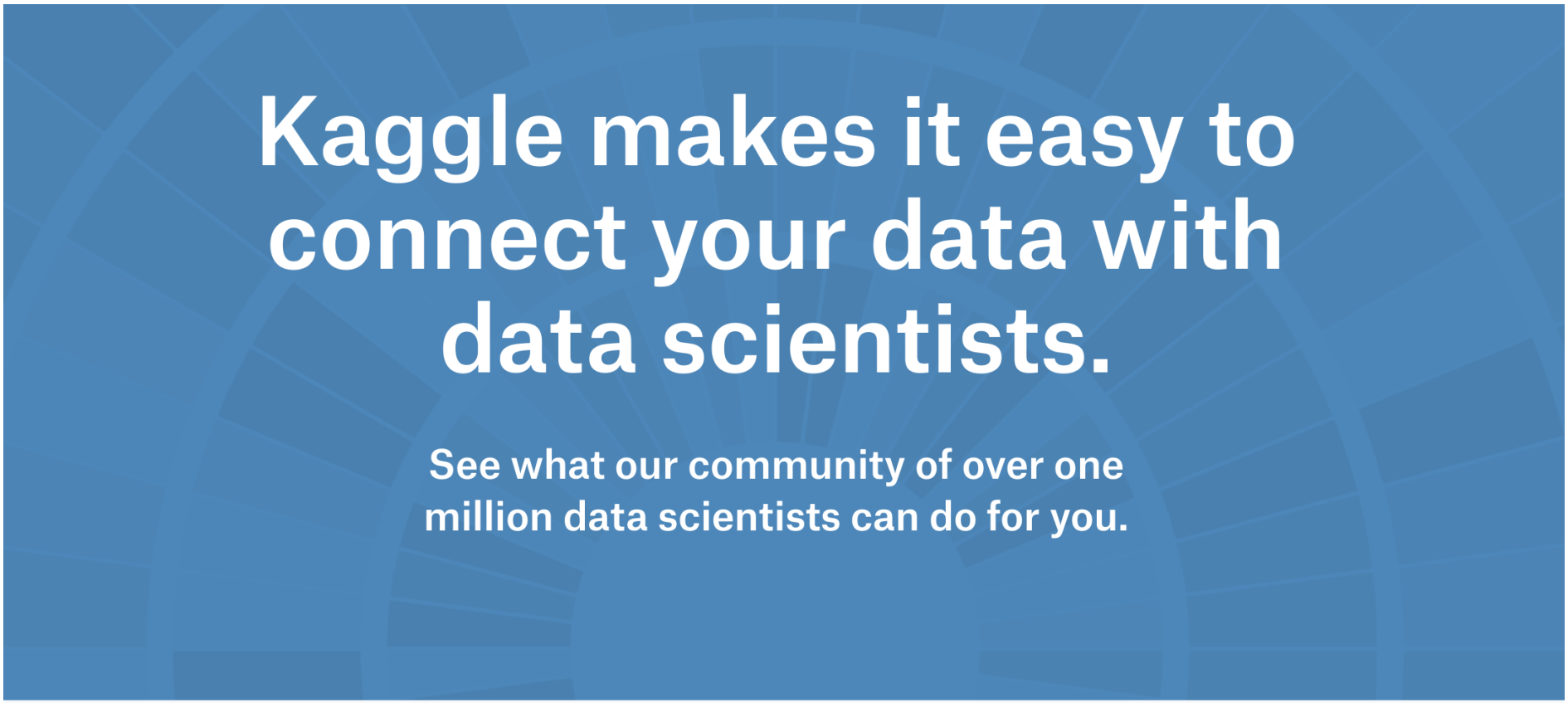

Kaggle is a platform for data science competitions.
We help you solve difficult problems, recruit strong teams, and amplify the power of your data science talent.

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The truth is...

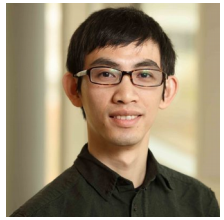
- Kaggle is a grind, but you learn and gain in real life from it!
- People are really nice!
- Kaggle will definitely make you a great data scientist!

Where are they now?









Giba – Lead Data Scientist at Ople.ai
Marios – Data Scientist at H2O.ai (London)
Xiaozhou (Little Boat) – Chief Data Scientist at Quartic.ai (Canada)
Mattias (Faron) – Data Scientist at H2O.ai (SV)
Abhishek Thakur – Chief Data Scientist at Boost.ai (Norway)
Carlos (NxGTR) – Senior Machine Learning Engineer at Instacart (SV)
Bojan – Data Scientist at H2O.ai (SV)
Jiwei – Data Scientist at Nvidia
Shize – Data/Applied Scientist at Microsoft
Vladamir – Computer Vision Engineer at Lyft
SRK – Data Scientist at H2O.ai (Chennai)
Jeong-Yoon – Senior Data Scientist Manager at Uber
Chenglong – Algorithm expert at Alibaba
Tom – Research engineer at DeepMind
Li – Research scientist at Google
Owen – Hedge fund something :) (Formerly Chief Product Officer at DataRobot

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– Rebuttal: This has to do with the trade-off between model complexity and correctness

- Is it better to have a model that is easy to explain, but wrongly accepts/rejects applications 5% more often?

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- Rebuttal: How many companies have properly deployed data science commercially?
  - I have worked in data science for 4 years, nothing has been commercially deployed. This has nothing to do with data science and everything to do with a company’s strategy, management, and capability.
  - The 2nd largest publisher in the Netherlands spent five years building an excellent data lake but has no data science to show for.

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– Rebuttal: Many Kaggle competitions require cleaning and manipulating data.

- Data science is hard, don’t force yourself to be a unicorn. Work with what you have. If you don’t have an opportunity to extract data and develop an interesting independent project, be coming a Kaggle rockstar is the next best thing.

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- Rebuttal: Most Kaggle competitions are highly relevant, data science problems are highly applicable to all industries.
  - Why would Facebook/Google/Microsoft/Amazon/Walmart etc host irrelevant competitions?

Other potential arguments

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- Rebuttal: It's because so many people are working on the same problem that you can learn from each other. Your own competition does not allow you to learn from others.

Don’t try to be a unicorn!

1) Can you write code in a timely manner that works?
2) Can you write code to process raw data?
3) Can you train/validate/test models from known packages with reasonable performance?
4) Do you understand conceptually how some prediction or statistical models work?

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Then you’re more useful than most data scientists I’ve met or worked with!

- Everything else is a matter of experience.

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- What about unobserved seasonality? Sales spikes in Nov. and Dec.

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Where does my model make mistakes?

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What are the chances that this will improve performance?

- 100s of ideas to try, start with what you think is most likely to work.
- 100s of models to try, you should already know what works.

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The power of teamwork

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Don't be afraid to ask for help

- Because less accomplished teammates are still valuable, you can add value.
- Home Depot Product Search – I was new to NLP problems and got stuck at 40th position, then joined a 6th ranked team, we finished 2nd.
- Quora Question Pairs – I was ranked 1st for a long time, then two others teamed up with me. I soon ran out of ideas, and my teammates were able to secure us a 5th place finish.

What I learned from Kaggle

Determination and grit is most important

- Many of the top Kagglers did not start strongly.
- It can be very daunting at first, but focus on one step at a time.
- After two or three competitions you'll all be experts.
- Some people took many years before finally getting their first gold medal.

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Data science is your career, think of everything you do now as an investment for the next 20-30 years.

Pick one or two things you're passionate about, and really do it!

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Help my friend get a job

- He did a Kaggle competition with me and we got a gold medal. His employer was very impressed during the interview

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Most fun 2 years of my life!

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- Mine used to be Bayesian probabilistic models (e.g., HMM, LDA).

What did I learn in school?

- Linear regression + regularization, SVM + Kernels, Perceptron, Adaboost, Probabilistic modeling.

What was my takeaway from school?

- Should try different methods for a given prediction problem because you don't know what might work.

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All of this is wrong!

- Most prediction models are developed and published based on academic novelty and mathematical elegance.
- Academics traditionally did not care how well a model predicts as long as it beats a benchmark.

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- To predict well is to minimize some error between the predicted and true values.
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- Over-fitting happens – all the time!

Everything I learned was useful

- Machine learning is for one purpose and one purpose only – prediction.
- To predict well is to minimize some error between the predicted and true values.
- A model needs to be evaluated by how well it predicts.
- Over-fitting happens – all the time!
- Under-fitting happens – even more often!

How to achieve excellent performance with minimal effort

Getting started

1) Understanding the prediction problem.
2) Understanding the data.
3) Read the discussion forums.
4) Start with a public kernel.
5) Develop your own solution.

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Follow the developments in discussions and public kernels and continue to work on your own solution.

If your own solution can surpass the best public kernel, you will finish in the top 10%, most likely earn a silver medal.

Understanding the prediction problem

Using high-resolution lung scans to determine when lesions in the lungs are cancerous

Predicting how expensive a car insurance claim will be

Predicting faulty products from manufacturing lines

Predicting the relevance of search results

Predicting telecommunication network faults

Identifying who are likely to get cervical cancer

Predicting whether two questions are the same

Predicting stock returns

Forecasting sales at retail stores

Predicting prices of products on p2p markets

Answering exam questions

Understanding the data

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Data in a single file, M-by-N table, anonymized columns.

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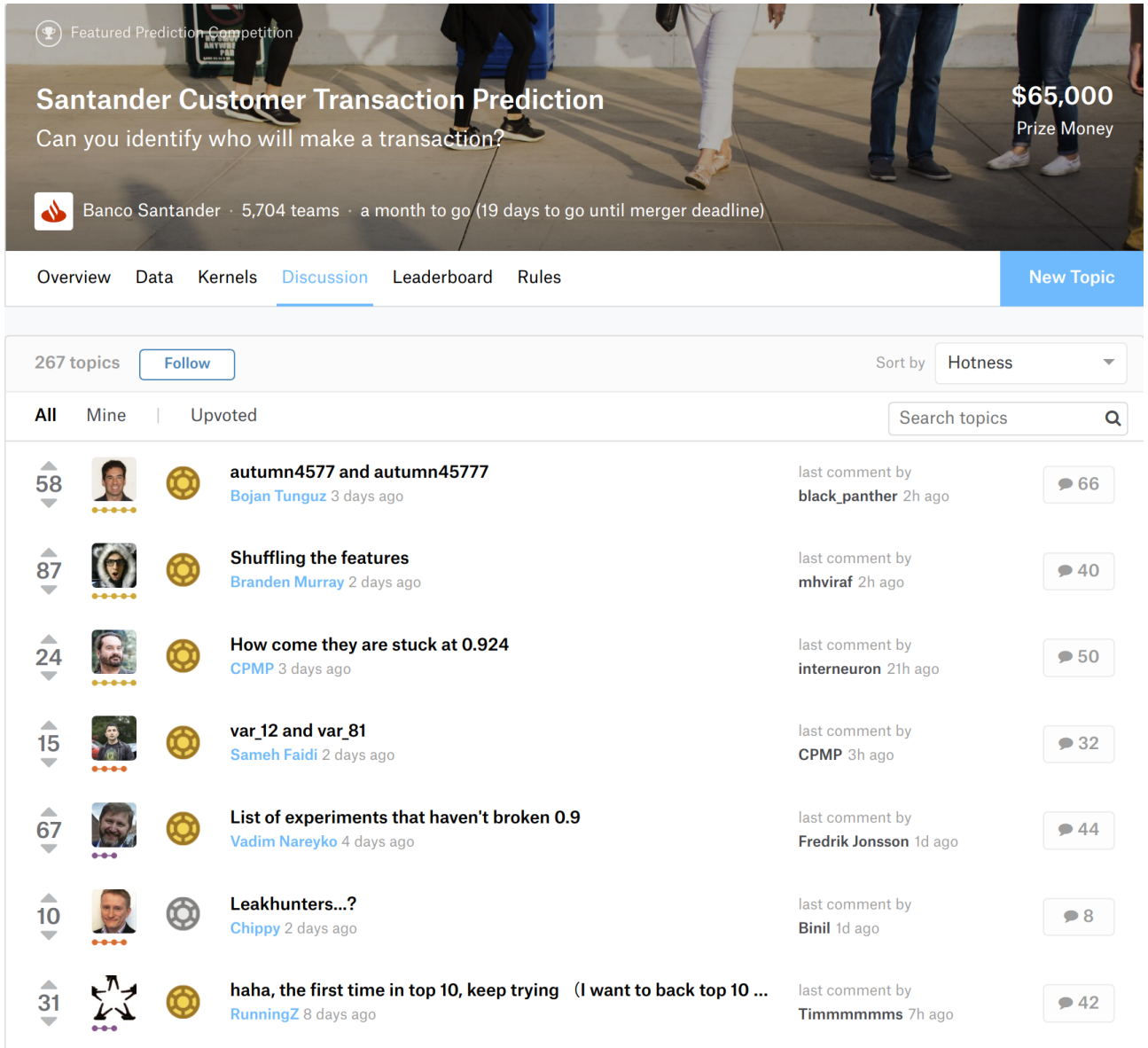
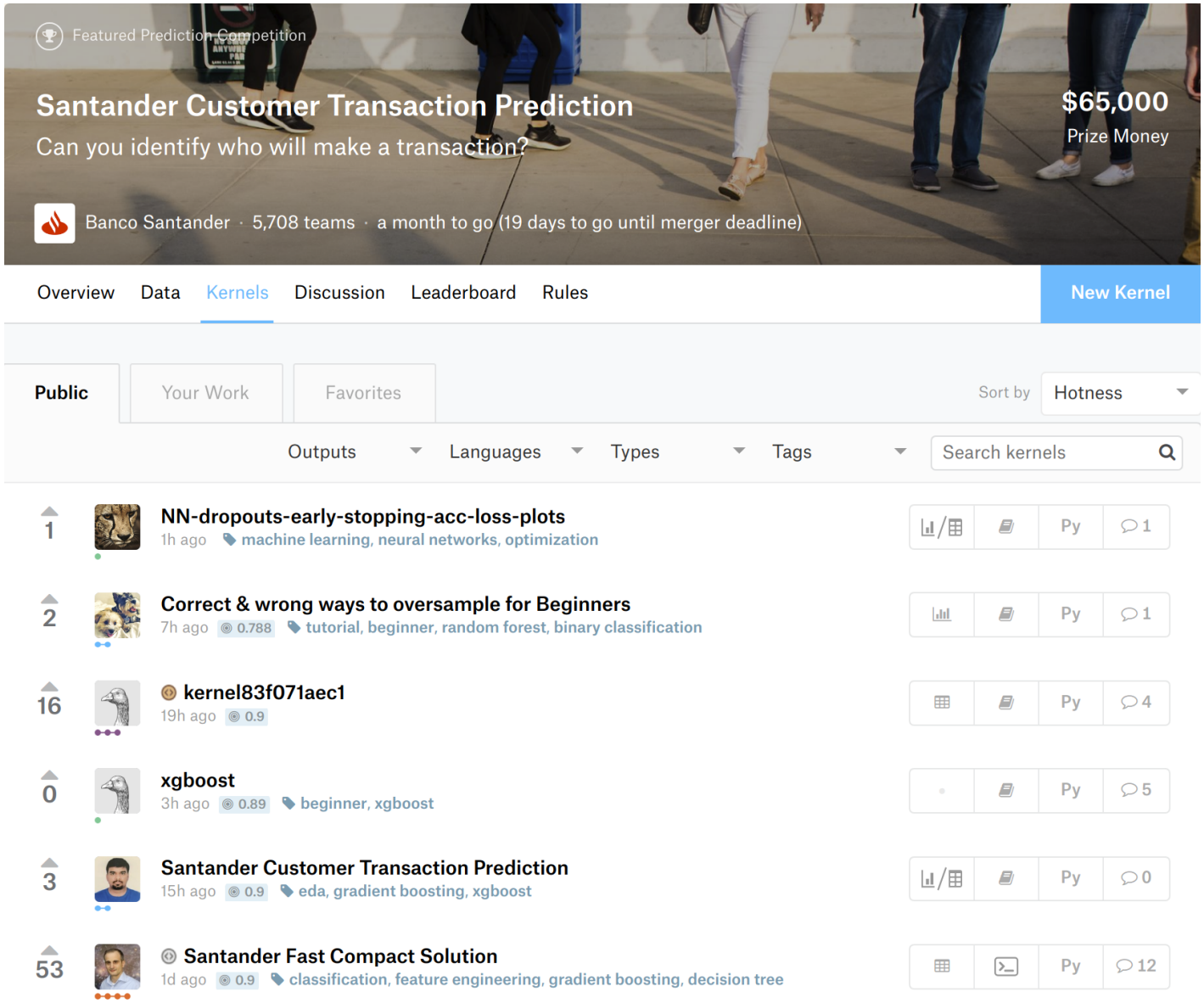
Data in unstructured format (e.g., images, unstructured text)

- Advantage: Freedom in how to put the data together. Weak competition
- Disadvantage: High entry barrier to get started.

Read the discussion forums



Start with the public kernel



Start with the public kernel

```
import numpy as np
import pandas as pd
import lightgbm as lgb
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import StratifiedKFold
import warnings
warnings.filterwarnings('ignore')
train_df = pd.read_csv('../input/train.csv')
test_df = pd.read_csv('../input/test.csv')
features = [c for c in train_df.columns if c not in ['ID_code', 'target']]
target = train_df['target']
param = {
    'bagging_freq': 5,
    'bagging_fraction': 0.331,   'boost_from_average':'false',
    'boost': 'gbdt',             'feature_fraction': 0.0405,     'learning_rate': 0.0083,
    'max_depth': -1,             'metric':'auc',                 'min_data_in_leaf': 80,     'min_sum_hessian_in_lea
    'num_leaves': 13,            'num_threads': 8,               'tree_learner': 'serial',   'objective': 'binary',
}
folds = StratifiedKFold(n_splits=15, shuffle=False, random_state=2319)
oof = np.zeros(len(train_df))
predictions = np.zeros(len(test_df))
for fold_, (trn_idx, val_idx) in enumerate(folds.split(train_df.values, target.values)):
    print("Fold {}".format(fold_))
    trn_data = lgb.Dataset(train_df.iloc[trn_idx][features], label=target.iloc[trn_idx])
    val_data = lgb.Dataset(train_df.iloc[val_idx][features], label=target.iloc[val_idx])
    clf = lgb.train(param, trn_data, 1000000, valid_sets = [trn_data, val_data], verbose_eval=5000, early_stopping_
    oof[val_idx] = clf.predict(train_df.iloc[val_idx][features], num_iteration=clf.best_iteration)
    predictions += clf.predict(test_df[features], num_iteration=clf.best_iteration) / folds.n_splits
print("CV score: {:<8.5f}".format(roc_auc_score(target, oof)))
sub = pd.DataFrame({"ID_code": test_df.ID_code.values})
sub["target"] = predictions
sub.to_csv("submission.csv", index=False)
```

Liberty Mutual Group: Property Inspection Prediction

Competition background

A Fortune 100 company, Liberty Mutual Insurance has provided a wide range of insurance products and services designed to meet their customers' ever-changing needs for over 100 years.

To ensure that Liberty Mutual's portfolio of home insurance policies aligns with their business goals, many newly insured properties receive a home inspection. These inspections review the condition of key attributes of the property, including things like the foundation, roof, windows and siding. The results of an inspection help Liberty Mutual determine if the property is one they want to insure.

In this challenge, your task is to predict a transformed count of hazards or pre-existing damages using a dataset of property information. This will enable Liberty Mutual to more accurately identify high risk homes that require additional examination to confirm their insurability.

Liberty Mutual is interested in hiring predictive modelers like you to work on one of many growing analytics teams within our company. As a member of Liberty Mutual's advanced analytics community, you will have the opportunity to apply sophisticated, cutting-edge techniques, similar to those used in this competition, to large data sets in departments such as Actuarial, Product, Claims, Marketing, Distribution, Human Resources, and Finance. Click to view available positions.

This could have been you: Top 4%

70	▼ 56	STR	0.39302	174	4y
71	▼ 19	SummerRightnow	0.39302	22	4y
72	▲ 329	Sandro	0.39301	26	4y
73	▼ 25	Sad&PqiNNN	0.39301	122	4y
74	▼ 70	nrg	0.39300	228	4y
75	▼ 31	NxGTR	0.39300	154	4y
76	▼ 14	Daniel Chin	0.39297	81	4y
77	▼ 14	UNH Analytics	0.39294	56	4y
78	▼ 48	Hazardous ☠	0.39292	240	4y
79	▲ 384	Vincent Firmansyah	0.39291	34	4y
80	▲ 218	pi_informatics	0.39290	23	4y
81	▼ 8	Miner's Brain	0.39289	112	4y
82	▲ 153	YaTa	0.39289	6	4y
83	▲ 608	BlackMagic	0.39289	134	4y

General Takeaways

Best machine learning algorithms

- Logistic regression
  - Easy to understand and describe, performs reasonably well
- Gradient boosted decision trees
  - XGBoost, LightGBM
  - Great for everything, easy to use
- Feed-forward Neural Networks
  - Can give you great performance, but difficult to tune
- Convolutional Neural Networks
  - Best for images, can work well for text-based problems as well
- Recurrent Neural Networks
  - Seems to be good for text/speech problems
- Factorization Machines
  - LibFFM
  - Kills problems with high cardinality categorical variables

What to do for prediction problems

- Standard tabular problems
- Time series problems
- Text problems
- Image problems

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Standard tabular data format

- Think about how to handle categorical variables
  - Cardinality: high cardinality requires smart encoding
- Think about the distribution of numeric variables
- Is it really a standard tabular data?
  - Maybe dates are involved? (Springleaf)
    - Differences in date values within row (start date, email date)
  - Maybe time series is involved? (Santander, Telstra)
    - Multiple rows for the same user implies sequence or time is involved

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  - Trends, patterns
- Combine predictions of individual entities and across entities
  - Rossmann

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- Combine predictions of many different prediction algorithms
  - GBDT, FFM, CNN, RNN

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  - Do things like flip and rotate the images to enhance the training sample
- Ensemble a lot!