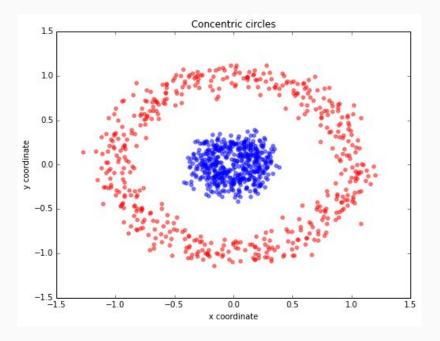
Продвинутые фичи, а также знания полезные в конкурсах на Kaggle и не только

Дмитрий Ульянов

Features based on nearest neighbors

- It is beneficial to add features, that describe geometry of the manifold
 - O Density:



Features based on nearest neighbors

- Mean target of nearest 5, 10, 15, 500, 2000 neighbors (KNN)
 - Optionally use a weighting scheme
- Mean distance to 5, 10, ... closest neighbors
- Mean distance to 10 closest neighbors with target 1
- Mean distance to 10 closest neighbors with target 0
- How many objects are there in a ball of radius 5, 10, ...
- Mean distance to the objects in a ball of radius 5, 10, ...
- How many of closest objects have the same label
- How many different labels are there among nearest neighbors
- ..
- ...

Different distributions in test and train

Different distributions in test and train

- We usually assume the train data is similar to test data.
- It does not always hold true.

Data:

- y -- label
- x -- a feature with 2 levels

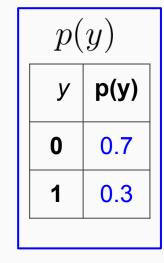
Bayes rule:

$$p(y|x) = \frac{p(x|y)p(y)}{p(x)} \propto p(x|y)p(y)$$

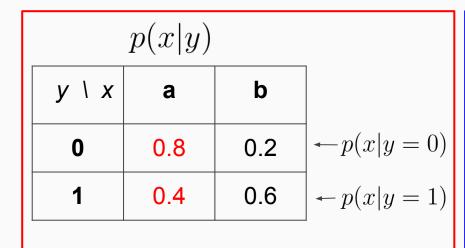
x	у
а	1
b	0
а	0
а	0
b	1

Bayes rule:
$$p(y|x) = \frac{p(x|y)p(y)}{p(x)} \propto p(x|y)p(y)$$

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p(y)		
У	p(y)	
0	0.7	
1	0.3	

Bayes rule:
$$p(y|x) = \frac{p(x|y)p(y)}{p(x)} \propto p(x|y)p(y)$$

p(y x)			
y \ x	а	b	
0	0.83	0.43	
1	0.17	0.57	
p(y x=a) p(y x=b)			

	p(x y)		
y \ x	а	b	
0	8.0	0.2	-p(x y=0)
1	0.4	0.6	-p(x y=1)

p(y)		
У	p(y)	
0	0.7	
1	0.3	

Classifier:
$$p(y = 1 | x = a) = \frac{0.4 \cdot 0.3}{0.8 \cdot 0.7 + 0.4 \cdot 0.3}$$

What if p(y) are different in test?

Bayes rule:
$$p(y|x) = \frac{p(x|y)p(y)}{p(x)} \propto p(x|y)p(y)$$

p(y x)				
ylx	а	b		
0	0.83	0.43		
1	0.17	0.57		
	p(y x=a) p(y x=b)			

	p(x y)		
ylx	а	b	
0	8.0	0.2	-p(x y=0)
1	0.4	0.6	-p(x y=1)

Classifier:
$$p(y = 1 | x = a) = 0.17 \neq \frac{0.4 \cdot 0}{0.8 \cdot 1 + 0.4 \cdot 0} = 0$$

Efficiency

Learn to implement everything efficiently.

- Learn to implement everything efficiently.
 - Joblib

```
# Simple loop
for i in range(1000):
    b[i] = a[i] ** 2
# The same, but using a closure
def f(x):
    return x ** 2
for i in range(1000):
    b[i] = f(a[i])
# Parallel version
Parallel(n_jobs=32)(delayed(f)(a[i]) for i in range(1000))
```

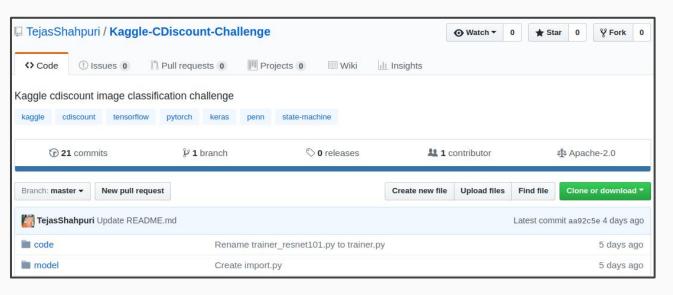
Numba

- Learn to implement everything efficiently.
 - Numba

```
from numba import jit
# Pure python
def sum python(arr):
    s = 0.0
    for i in xrange(arr.shape[0]):
        s += arr[i]
    return s
%timeit sum python(a) # 138 ms
# Numba
sum numba = jit(sum python)
%timeit sum numba(a) # 1 ms
# >100x boost
```

Github

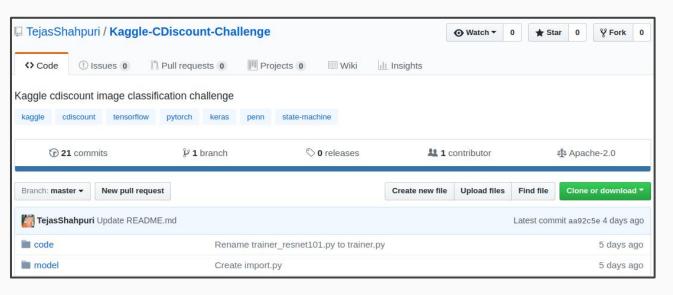
- Learn to implement everything efficiently.
- Search github for solutions and inspiration





Github

- Learn to implement everything efficiently.
- Search github for solutions and inspiration



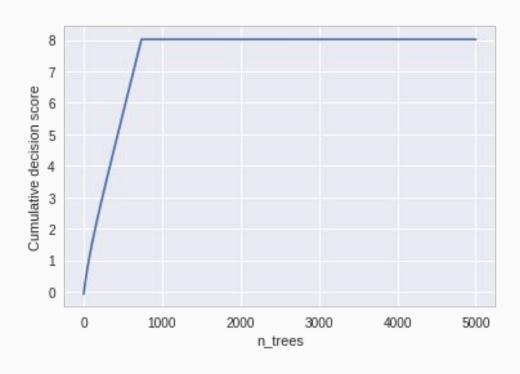


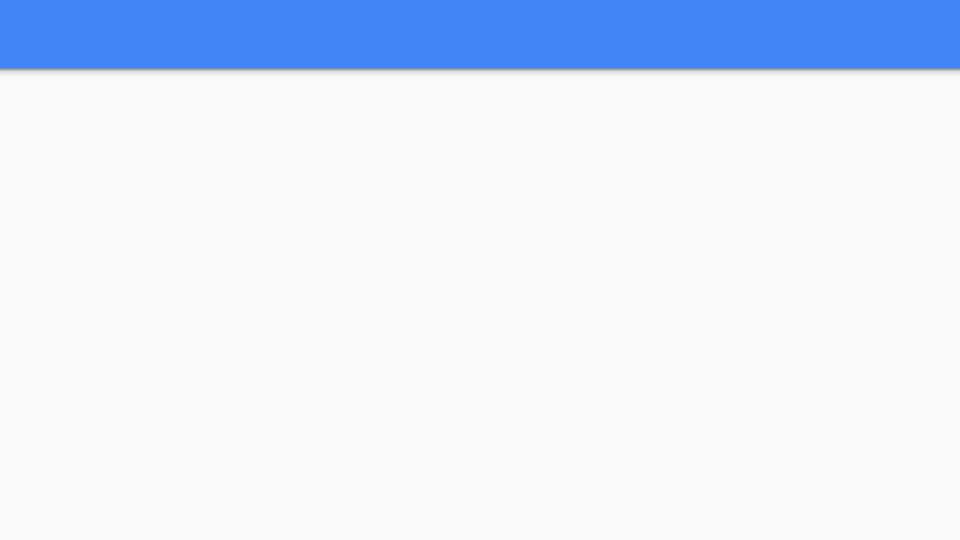
- Что будет, если из обученной GBDT модели (например XGboost) выкинуть первое дерево?
 - **a.** Все сломается к чертям (почти рандом)
 - **b.** Качество упадет, но не сильно
 - с. Качество не изменится
 - **d.** Качество улучшится, но не сильно
 - е. Качество станет 146

```
X_{all} = np.random.randn(5000, 1)
y_all = (X_{all}[:, 0] > 0)*2 - 1
```

```
clf = GradientBoostingClassifier(n_estimators=5000, learning_rate=0.01, max_depth=3,
clf.fit(X_train, y_train)
```

Logloss using all trees: 0.0003135802484425486
Logloss using all trees but last: 0.00031358024844265755
Logloss using all trees but first: 0.00032053682522239753





```
clf = GradientBoostingClassifier(n_estimators=5000, learning_rate=8, max_depth=3,
clf.fit(X train, y train)
```

```
Logloss using all trees: 3.03310165292726e-06
Logloss using all trees but last: 2.846209929270204e-06
Logloss using all trees but first: 2.3463091271266125
```

$$F(x) = const + \sum_{i=1}^{n} \gamma_i h_i(x)$$

Ad time

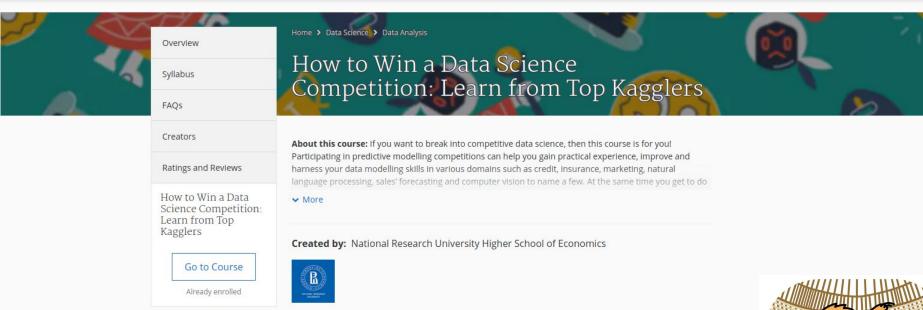


Yandex.Research (https://research.yandex.com/) ищет research interns. Это уникальная возможность присоединиться к нашей команде, заняться исследованиями мирового уровня, опубликовать результаты на ведущих конференциях (https://research.yandex.com/lib/publications) и внести вклад в наукоемкие сервисы Яндекса. Например, в технологии компьютерного зрения, диалоговые системы (Алиса), нейросетевой Перевод, алгоритмы Поиска на нейронных сетях (Королев), алгоритмы обучения на ансамблях деревьев (CatBoost), и не только.

Если вы интересуетесь глубинным обучением, алгоритмами, следите за последними статьями, хорошо знаете математику и питон, а также верите в себя как исследователя, мы будем рады пообщаться. С нашей стороны — внимание к вашим идеям, комфортный офис на Парке Культуры, продуктивная среда, дружелюбная и демократичная рабочая атмосфера. Присылайте ваши резюме и короткий рассказ о научных интересах на pavser@yandex-team.ru.

Ad time II

Financial Aid is available for learners





PAGOTAEM!

What the course is about?

Week1

- Intro to competitions & Recap
- Feature preprocessing & extraction

Week2

- o EDA
- Validation
- Data leaks

Week3

- Metrics
- Mean-encodings

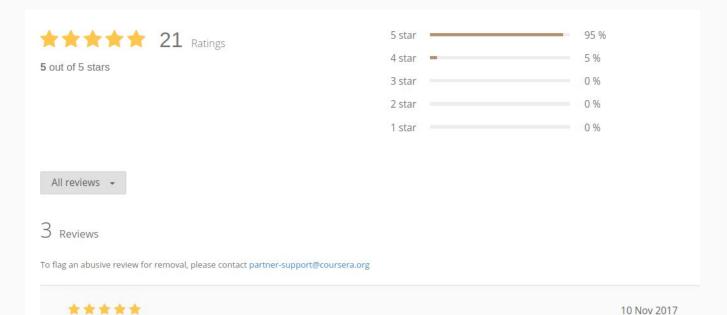
Week4

- Advanced features
- Hyperparameter optimization
- o Ensembles

Week5

- Final project
- Winning solutions

How it goes?



This course is fantastic. It's chock full of practical information that is presented clearly and concisely. I would like to thank the team for

sharing their knowledge so generously.

Reply

The last slide

Thank you!

