Зотов Алексей

In [16]:
```
import pandas as pd
import numpy as np
from tqdm import tqdm

from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
```

In [17]:
```
!ls
```

```
README.md       solution.ipynb
```

Используем набор данных партий игр в крестики нолики (tic-tac-toe). Целью является показать победил ли игрок ходивший первым.

In [19]:
```
df = pd.read_csv("data/tic-tac-toe.csv", sep=',', names = list(range(9)) + ['target'])
df.head()
```

Out[19]:

	0	1	2	3	4	5	6	7	8	target
0	x	x	x	x	o	o	x	o	o	positive
1	x	x	x	x	o	o	o	x	o	positive
2	x	x	x	x	o	o	o	o	x	positive
3	x	x	x	x	o	o	o	b	b	positive
4	x	x	x	x	o	o	b	o	b	positive

Проведем бинаризацию признаков.

In [20]:
```
import copy
def dummy_encode_categorical_columns(data):
    result_data = copy.deepcopy(data)
    for column in data.columns.values:
        result_data = pd.concat(
            [result_data, pd.get_dummies(result_data[column],
                                         prefix = column, prefix_sep = '_')], axis = 1)
        del result_data[column]
    return result_data
df = dummy_encode_categorical_columns(df)
df['target'] = df['target_positive']
df = df.drop(['target_positive', 'target_negative'], axis=1)
df.head()
```

Out[20]:

	0_b	0_o	0_x	1_b	1_o	1_x	2_b	2_o	2_x	3_b	...	6_b	6_o	6_x	7_b	7_o	7_x	8_b	8_o	8_x	target
0	0	0	1	0	0	1	0	0	1	0	...	0	0	1	0	1	0	0	1	0	1
1	0	0	1	0	0	1	0	0	1	0	...	0	1	0	0	0	1	0	1	0	1
2	0	0	1	0	0	1	0	0	1	0	...	0	1	0	0	1	0	0	0	1	1
3	0	0	1	0	0	1	0	0	1	0	...	0	1	0	1	0	0	1	0	0	1
4	0	0	1	0	0	1	0	0	1	0	...	1	0	0	0	1	0	1	0	0	1

5 rows × 28 columns

Разделим исходные данные на обучающую и контрольную подвыборки в отношении 7:3.

In [21]:
```
from sklearn.model_selection import train_test_split
df_train, df_test = train_test_split(df, test_size=0.3)
len(df_train), len(df_test)
```

Out[21]: (670, 288)

In [22]:
```
X_train, y_train = df_train.drop(['target'], axis=1), df_train['target']
X_test, y_test = df_test.drop(['target'], axis=1), df_test['target']
```

В предложенной реализации удобно разделить объекты из негативного и позитивного контекстовю

In [23]:
```
X_train_pos = np.array(X_train[y_train == 1])
X_train_neg = np.array(X_train[y_train == 0])
```

Для настройки уровня влияния поддержки и достоверности введем вспомогательный коэффициент.

In [50]:
```
RECALL_RATIO = 0.35
```

Реализуем предложенный простой вариант алгоритма.

In [51]:
```
def print_apc(metrics) :
    print('accuracy {}'.format(metrics[0]))
    print('precision {}'.format(metrics[1]))
    print('recall {}'.format(metrics[2]))

def get_impact_baseline(obj, X):
    impact = 0
    for x in X:
        common_ids = (obj == x)
        closure_power = np.sum(np.all(obj[common_ids] == X[:, common_ids], axis=1)) - 1
        assert(closure_power >= 0)
        impact += closure_power
    return impact

def apply_baseline():
    y_pred = np.zeros(len(X_test), dtype=np.int32)
    for i, test_obj in tqdm(enumerate(np.array(X_test)), position=0):
        positive_impact = get_impact_baseline(test_obj, X_train_pos)
        negative_impact = get_impact_baseline(test_obj, X_train_neg)
        y_pred[i] = (positive_impact * RECALL_RATIO > negative_impact)
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    return accuracy, precision, recall
```

In [52]:
```
print_apc(apply_baseline())
```

```
288it [00:03, 83.02it/s]

accuracy 0.7326388888888888
precision 0.7389380530973452
recall 0.9027027027027027
```

Усовершенствуем алгоритм.

Нормализуем величину поддержки/влияния на размер контекста.

Положим вес(weight) каждого замыкания пропорционально размеру пересечения.

Введем параметр weight_power.

Итоговый вес будет вычисляться как степенная функция от веса(weight) с показателем weight_power.

In [55]:
```
RECALL_RATIO = 0.8

def get_impact(obj, X, weight_power):
    impact = 0
    for x in X:
        common_ids = (obj == x)
        weight = np.sum(common_ids) / len(common_ids)
        closure_power = np.sum(np.all(obj[common_ids] == X[:, common_ids], axis=1)) - 1
        assert(closure_power >= 0)
        impact += closure_power * (weight**weight_power)
    impact /= len(X)
    return impact

def apply(weight_power):
    y_pred = np.zeros(len(X_test), dtype=np.int32)
    for i, test_obj in tqdm(enumerate(np.array(X_test)), position=0):
        positive_impact = get_impact(test_obj, X_train_pos, weight_power)
        negative_impact = get_impact(test_obj, X_train_neg, weight_power)
        y_pred[i] = (positive_impact * RECALL_RATIO > negative_impact)
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    return accuracy, precision, recall
```

In [56]:
```
accuracy, precision, recall = apply(5)
print("acc : {}, precision : {}, recall : {}".format(accuracy, precision, recall))
```

```
288it [00:05, 50.62it/s]

acc : 0.8333333333333334, precision : 0.8071748878923767, recall : 0.972972972972973
```

Результат заметно лучше по всем метрикам.

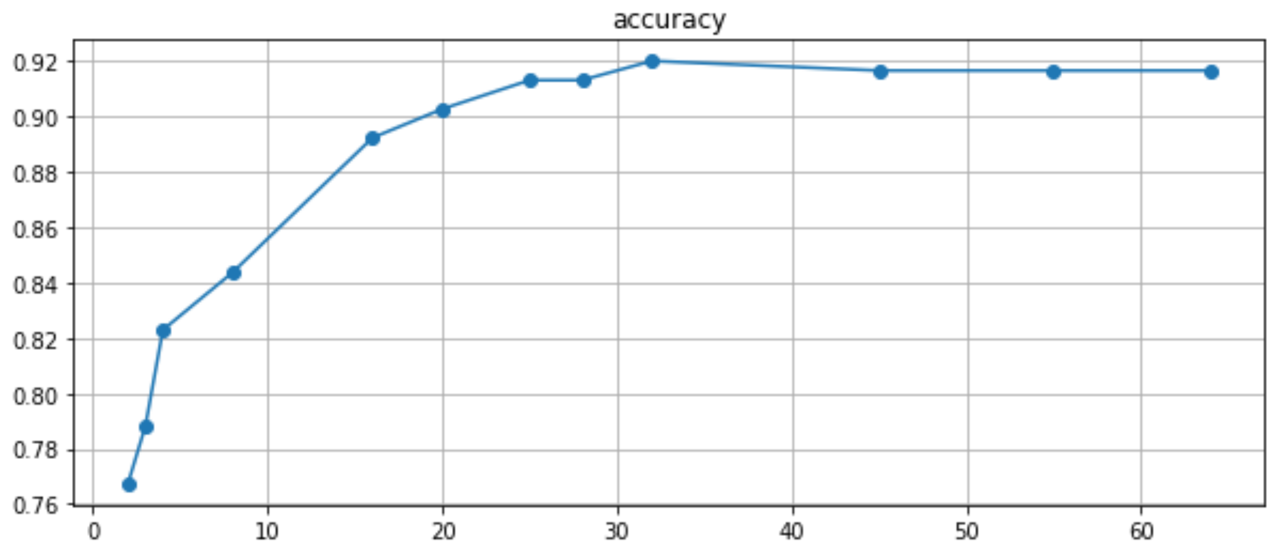
Подберем оптимальный параметр weight_power.

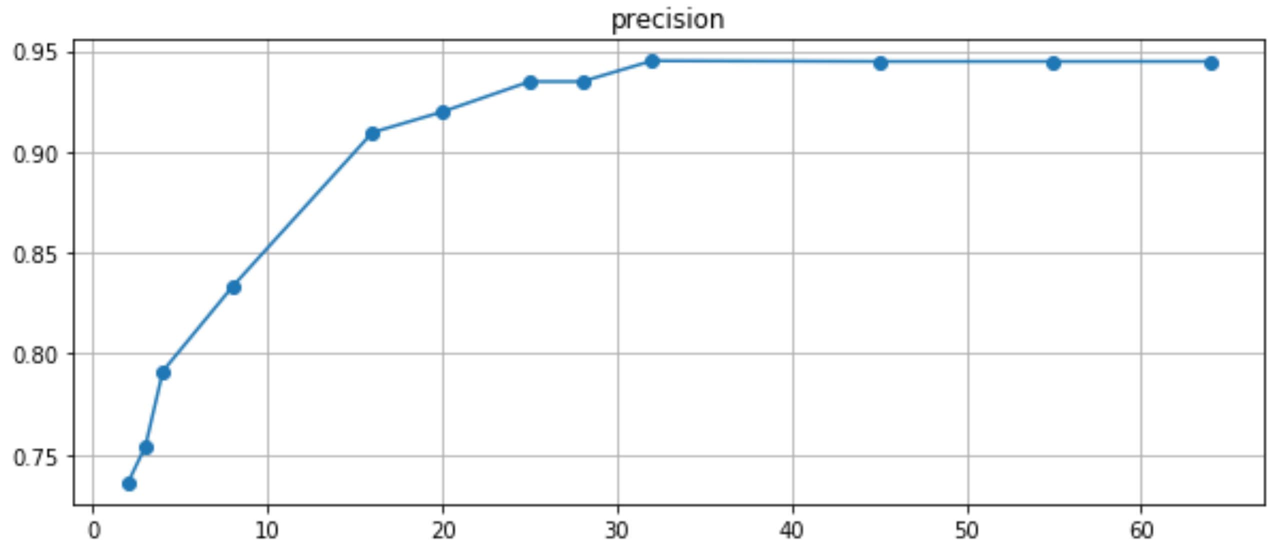
In [57]:
```
weight_power_range = [2, 3, 4, 8, 16, 20, 25, 28, 32, 45, 55, 64]
accuracy_all, precision_all, recall_all = [], [], []
for weight_power in weight_power_range:
    accuracy, precision, recall = apply(weight_power)
    accuracy_all.append(accuracy)
    precision_all.append(precision)
    recall_all.append(recall)
```

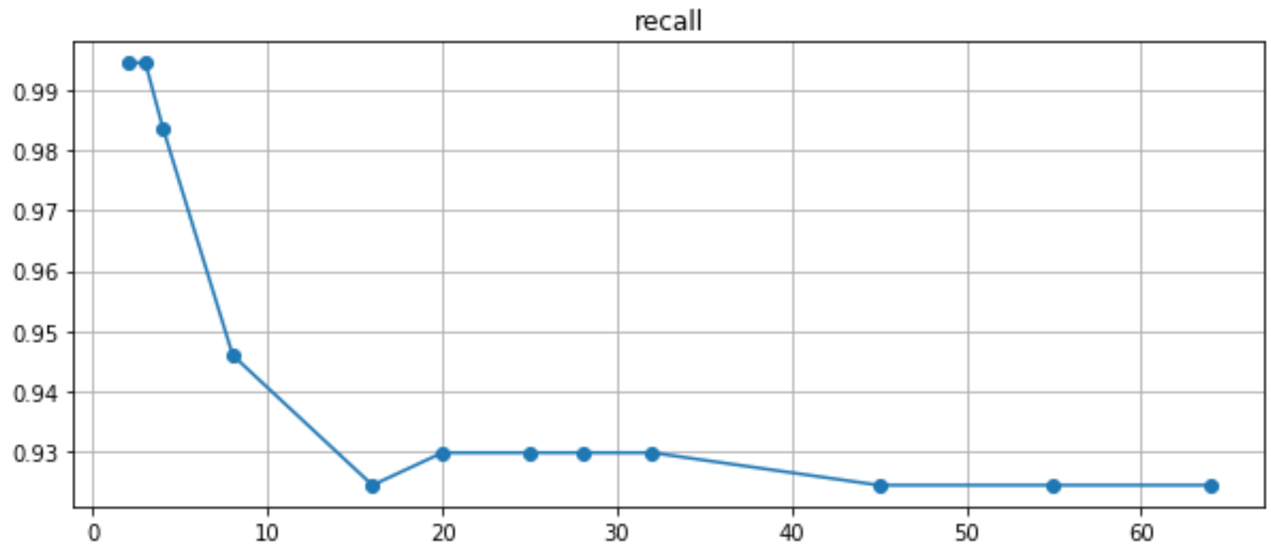
```
288it [00:05, 48.93it/s]
288it [00:05, 50.57it/s]
288it [00:05, 53.08it/s]
288it [00:05, 53.61it/s]
288it [00:05, 51.93it/s]
288it [00:05, 54.33it/s]
288it [00:05, 51.56it/s]
288it [00:05, 52.48it/s]
288it [00:05, 50.89it/s]
288it [00:05, 51.51it/s]
288it [00:05, 52.76it/s]
288it [00:05, 52.55it/s]
```

In [61]:
```
import matplotlib.pyplot as plt
%matplotlib inline
```

In [62]:
```
metrics = (accuracy_all, precision_all, recall_all)
names = ("accuracy", "precision", "recall")
for name, metric in zip(names, metrics):
    plt.figure(figsize=(10,4))
    plt.grid(True)
    plt.title(name)
    plt.plot(weight_power_range, metric, '-o')
    plt.show()
```







При данной точности измерений, оптимальной точкой примем weight_power=32

In [64]:
```
accuracy, precision, recall = apply(32)
print("acc : {}, precision : {}, recall : {}".format(accuracy, precision, recall))
```

```
288it [00:05, 53.27it/s]

acc : 0.9201388888888888, precision : 0.945054945054945, recall : 0.9297297297297298
```