Лабораторная работа №11 “Реализация криптографических атак с помощью машинного обучения на физически неклонируемые функции”

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Физически неклонируемые функции (ФНФ) часто используются в качестве криптографических примитивов при реализации протоколов аутентификации.

Рассмотрим простейший из них, основанный на на запросах и ответах (challenge response).

В данном случае устройство А, содержащее реализацию ФНФ, может быть аутентифицировано с помощью набора запросов (challenge) и проверки ответов на них (response). При этом использованные пары запрос-ответ удаляются из базы данных устройства.

Более подробно о физически неклонируемых функциях можно прочесть:
https://habr.com/post/343386/ (https://habr.com/post/343386/)
https://www.researchgate.net/profile/Alexander_Ivaniuk/publication/322077869_Proektirovanie vstraivaemyh-cifrovyh-ustrojstv-i-sistem.pdf
(https://www.researchgate.net/profile/Alexander_Ivaniuk/publication/322077869_Proektirovanie vstraivaemyh-cifrovyh-ustrojstv-i-sistem.pdf) (глава 5, раздел 4)

Сформулируйте задачу в терминах машинного обучения.

Задача: Обучить модель машинного обучения таким образом, чтобы она смогла предсказывать выходное значение (Response, R) по запросу (Challenge, CH)

In [48]:

```
import pandas
import numpy as np
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier
import sklearn.cross_validation
from sklearn.metrics import accuracy_score, f1_score
from sklearn.metrics import log_loss, recall_score
import matplotlib.pyplot as pyplot
```

Обучите модель, которая могла бы предсказывать ответы по запросам, которых нет в обучающей выборке.

In [51]:

```
def getData(fileName, rowsCount=500):
    data = pandas.read_csv(fileName, sep=" ",
                           header=None, nrows=rowsCount)
    symbolsCount = int(fileName.replace("Base", "").replace(".txt"

    x = np.array(list(data[0].apply(str)
            .map(lambda x: np.array(map(int, (symbolsCount - len(
            .squeeze().values))

    y = data[1].values

    trainX, testX, trainY, testY = sklearn.cross_validation.train_

    return trainX, testX, trainY, testY

trainX, testX, trainY, testY = getData("Base128.txt")
print(trainX.shape, trainY.shape)
print(testX.shape, testY.shape)
```

```
((400, 128), (400,))
((100, 128), (100,))
```

Применить как минимум 3 различных алгоритма (например, метод опорных векторов, логистическая регрессия и градиентный бустинг).

In [3]:

```
def fitModel(algoritm, x, y):
    return algoritm.fit(x, y)

def getModels(x, y):
    algoritms = [KNeighborsClassifier(),
                 DecisionTreeClassifier(),
                 GradientBoostingClassifier()]
    models = []
    for algoritm in algoritms:
        model = fitModel(algoritm, x, y)
        models.append(model)
    return models

models = getModels(trainX, trainY)
```

In [4]:
```
print models
```

```
[KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkow
ski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform'), DecisionTreeClassifier(class_weight=N
one, criterion='gini', max_depth=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_stat
e=None,
            splitter='best'), GradientBoostingClassifier(criterion='
friedman_mse', init=None,
              learning_rate=0.1, loss='deviance', max_depth=3,
              max_features=None, max_leaf_nodes=None,
              min_impurity_decrease=0.0, min_impurity_split=None,
              min_samples_leaf=1, min_samples_split=2,
              min_weight_fraction_leaf=0.0, n_estimators=100,
              presort='auto', random_state=None, subsample=1.0, verb
ose=0,
              warm_start=False)]
```

Какая метрика наиболее подходит для оценки качества алгоритма?

Какой наибольшей доли правильных ответов (Accuracy) удалось достичь?

In [5]:
```
def getMetrics(models, testX, testY):
    metrics = [accuracy_score, f1_score, log_loss, recall_score]

    results = dict()

    for model in models:
        print "\n", type(model)
        predict = model.predict(testX)
        metricsValue = []
        for metric in metrics:
            print str(metric), "=========>", metric(testY, predict
            metricsValue.append(metric(testY, predict))
        results[str(type(model))] = metricsValue
    return results

metrics = getMetrics(models, testX, testY)
```

```
<class 'sklearn.neighbors.classification.KNeighborsClassifier'>
<function accuracy_score at 0x1a1597b5f0> =========> 0.55
<function f1_score at 0x1a1597b8c0> =========> 0.68085106383
<function log_loss at 0x1a1597bc80> =========> 15.5427212408
<function recall_score at 0x1a1597bb18> =========> 0.813559322034

<class 'sklearn.tree.tree.DecisionTreeClassifier'>
<function accuracy_score at 0x1a1597b5f0> =========> 0.58
<function f1_score at 0x1a1597b8c0> =========> 0.671875
<function log_loss at 0x1a1597bc80> =========> 14.5064939812
<function recall_score at 0x1a1597bb18> =========> 0.728813559322

<class 'sklearn.ensemble.gradient_boosting.GradientBoostingClassifie
r'>
<function accuracy_score at 0x1a1597b5f0> =========> 0.55
<function f1_score at 0x1a1597b8c0> =========> 0.676258992806
<function log_loss at 0x1a1597bc80> =========> 15.5427132449
<function recall_score at 0x1a1597bb18> =========> 0.796610169492
```

Какой размер обучающей выборки необходим, чтобы достигнуть доли правильных ответов минимум 0.95?

In [6]:
```
def investigation(rowsCount):
    trainX, testX, trainY, testY = getData("Base128.txt",
                                           rowsCount=rowsCount)
    models = getModels(trainX, trainY)
    metrics = getMetrics(models, testX, testY)
    return metrics
```

Как зависит доля правильных ответов от N?

In [7]:
```
history = dict()
nCounts = [100, 1000, 10000, 20000, 30000]
for n in nCounts:
    print "\n", n
    history[n] = investigation(n)
```

```
100

<class 'sklearn.neighbors.classification.KNeighborsClassifier'>
<function accuracy_score at 0x1a1597b5f0> =========> 0.65
<function f1_score at 0x1a1597b8c0> =========> 0.758620689655
<function log_loss at 0x1a1597bc80> =========> 12.0887316577
<function recall_score at 0x1a1597bb18> =========> 0.785714285714

<class 'sklearn.tree.tree.DecisionTreeClassifier'>
<function accuracy_score at 0x1a1597b5f0> =========> 0.7
<function f1_score at 0x1a1597b8c0> =========> 0.8125
<function log_loss at 0x1a1597bc80> =========> 10.3618328178
<function recall_score at 0x1a1597bb18> =========> 0.928571428571

<class 'sklearn.ensemble.gradient_boosting.GradientBoostingClassifie
r'>
<function accuracy_score at 0x1a1597b5f0> =========> 0.65
<function f1_score at 0x1a1597b8c0> =========> 0.774193548387
<function log_loss at 0x1a1597bc80> =========> 12.0887716376
<function recall_score at 0x1a1597bb18> =========> 0.857142857143

1000

<class 'sklearn.neighbors.classification.KNeighborsClassifier'>
<function accuracy_score at 0x1a1597b5f0> =========> 0.53
<function f1_score at 0x1a1597b8c0> =========> 0.654411764706
<function log_loss at 0x1a1597bc80> =========> 16.2334887728
<function recall_score at 0x1a1597bb18> =========> 0.760683760684

<class 'sklearn.tree.tree.DecisionTreeClassifier'>
<function accuracy_score at 0x1a1597b5f0> =========> 0.59
<function f1_score at 0x1a1597b8c0> =========> 0.655462184874
<function log_loss at 0x1a1597bc80> =========> 14.1610702354
<function recall_score at 0x1a1597bb18> =========> 0.666666666667

<class 'sklearn.ensemble.gradient_boosting.GradientBoostingClassifie
r'>
<function accuracy_score at 0x1a1597b5f0> =========> 0.555
<function f1_score at 0x1a1597b8c0> =========> 0.676363636364
<function log_loss at 0x1a1597bc80> =========> 15.3700153649
<function recall_score at 0x1a1597bb18> =========> 0.794871794872

10000
```

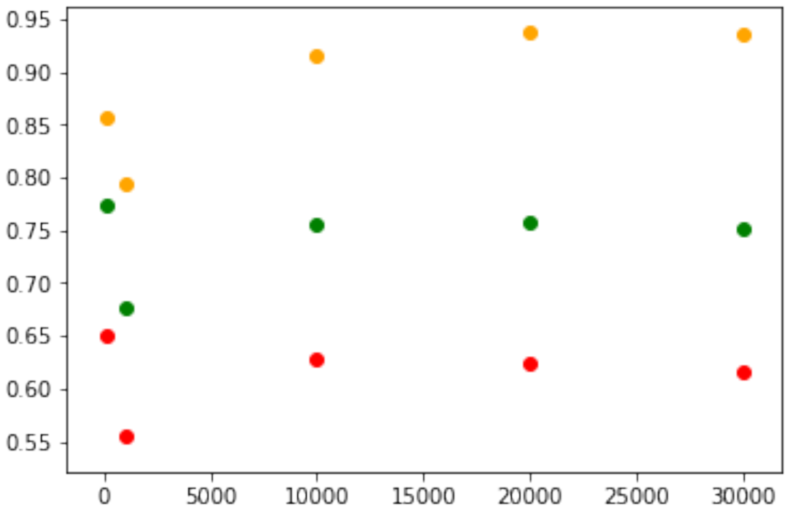
```
-----

<class 'sklearn.neighbors.classification.KNeighborsClassifier'>
<function accuracy_score at 0x1a1597b5f0> =========> 0.551
<function f1_score at 0x1a1597b8c0> =========> 0.666666666667
<function log_loss at 0x1a1597bc80> =========> 15.5081240938
<function recall_score at 0x1a1597bb18> =========> 0.711568938193


<class 'sklearn.tree.tree.DecisionTreeClassifier'>
<function accuracy_score at 0x1a1597b5f0> =========> 0.527
<function f1_score at 0x1a1597b8c0> =========> 0.612929623568
<function log_loss at 0x1a1597bc80> =========> 16.3370143476
<function recall_score at 0x1a1597bb18> =========> 0.593502377179

<class 'sklearn.ensemble.gradient_boosting.GradientBoostingClassifie
r'>
<function accuracy_score at 0x1a1597b5f0> =========> 0.6275
<function f1_score at 0x1a1597b8c0> =========> 0.756297023225
<function log_loss at 0x1a1597bc80> =========> 12.8659496785
<function recall_score at 0x1a1597bb18> =========> 0.916006339144

20000

<class 'sklearn.neighbors.classification.KNeighborsClassifier'>
<function accuracy_score at 0x1a1597b5f0> =========> 0.56525
<function f1_score at 0x1a1597b8c0> =========> 0.675982858208
<function log_loss at 0x1a1597bc80> =========> 15.0159441314
<function recall_score at 0x1a1597bb18> =========> 0.726471766119

<class 'sklearn.tree.tree.DecisionTreeClassifier'>
<function accuracy_score at 0x1a1597b5f0> =========> 0.52225
<function f1_score at 0x1a1597b8c0> =========> 0.609122519943
<function log_loss at 0x1a1597bc80> =========> 16.5010809318
<function recall_score at 0x1a1597bb18> =========> 0.596315578694

<class 'sklearn.ensemble.gradient_boosting.GradientBoostingClassifie
r'>
<function accuracy_score at 0x1a1597b5f0> =========> 0.6245
<function f1_score at 0x1a1597b8c0> =========> 0.757115135834
<function log_loss at 0x1a1597bc80> =========> 12.9695796008
<function recall_score at 0x1a1597bb18> =========> 0.937525030036

30000

<class 'sklearn.neighbors.classification.KNeighborsClassifier'>
<function accuracy_score at 0x1a1597b5f0> =========> 0.553
<function f1_score at 0x1a1597b8c0> =========> 0.662386706949
<function log_loss at 0x1a1597bc80> =========> 15.4390456082
<function recall_score at 0x1a1597bb18> =========> 0.707638515331

<class 'sklearn.tree.tree.DecisionTreeClassifier'>
<function accuracy_score at 0x1a1597b5f0> =========> 0.5265
<function f1_score at 0x1a1597b8c0> =========> 0.606890826069
<function log_loss at 0x1a1597bc80> =========> 16.3542860014
```

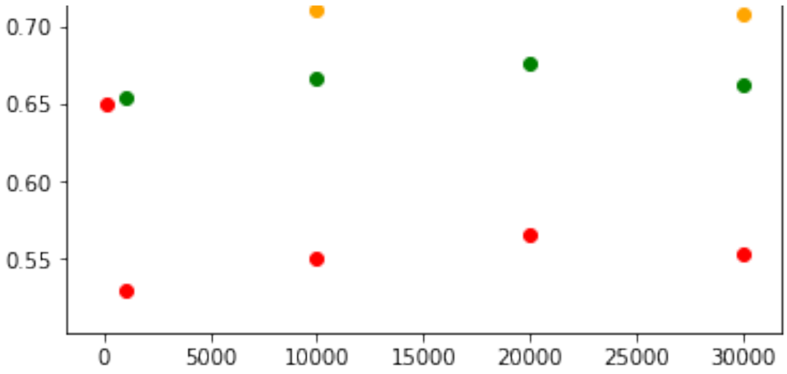
```
<function recall_score at 0x1a1597bb18> =========> 0.589833243679

<class 'sklearn.ensemble.gradient_boosting.GradientBoostingClassifie
r'>
<function accuracy_score at 0x1a1597b5f0> =========> 0.615333333333
<function f1_score at 0x1a1597b8c0> =========> 0.750809760311

<function log_loss at 0x1a1597bc80> =========> 13.2861914479
<function recall_score at 0x1a1597bb18> =========> 0.935180204411
```

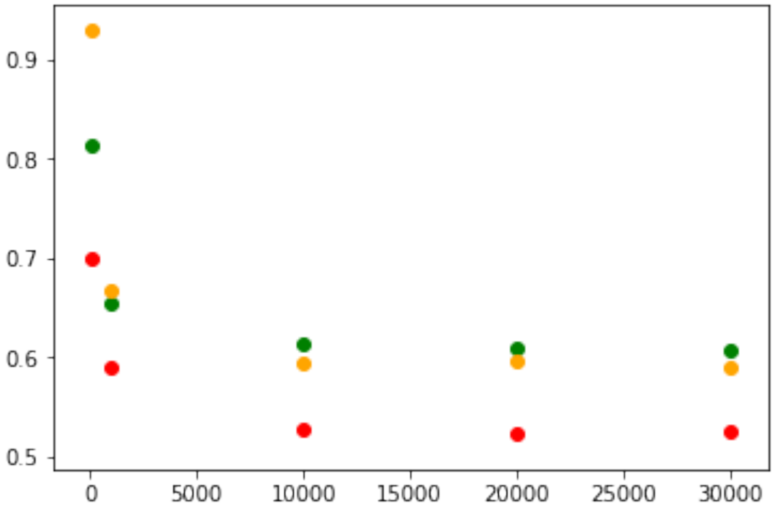
Ответы на вопросы представьте в виде графиков.

In [52]:

```python
originalKeys = history.values()[0].keys()

accuracy = dict()
f1 = dict()
recall = dict()

for key in originalKeys:
    for n in history:
        values = history[n][key]
        accuracy[n] = values[0]
        f1[n] = values[1]
        recall[n] = values[3]

    pyplot.scatter(accuracy.keys(), accuracy.values(), c="red")
    pyplot.scatter(f1.keys(), f1.values(), c="green")
    pyplot.scatter(recall.keys(), recall.values(), c="orange")
    pyplot.show()
```







Вывод

Наличие стабильности подвергает ФНФ риску криптографической атаки с помощью методов машинного обучения (построения точной математической модели ФНФ)