HW1

28 февраля 2017 г.

1 Домашнее задание 1

1.1 Гаркавый Андрей, 494 группа

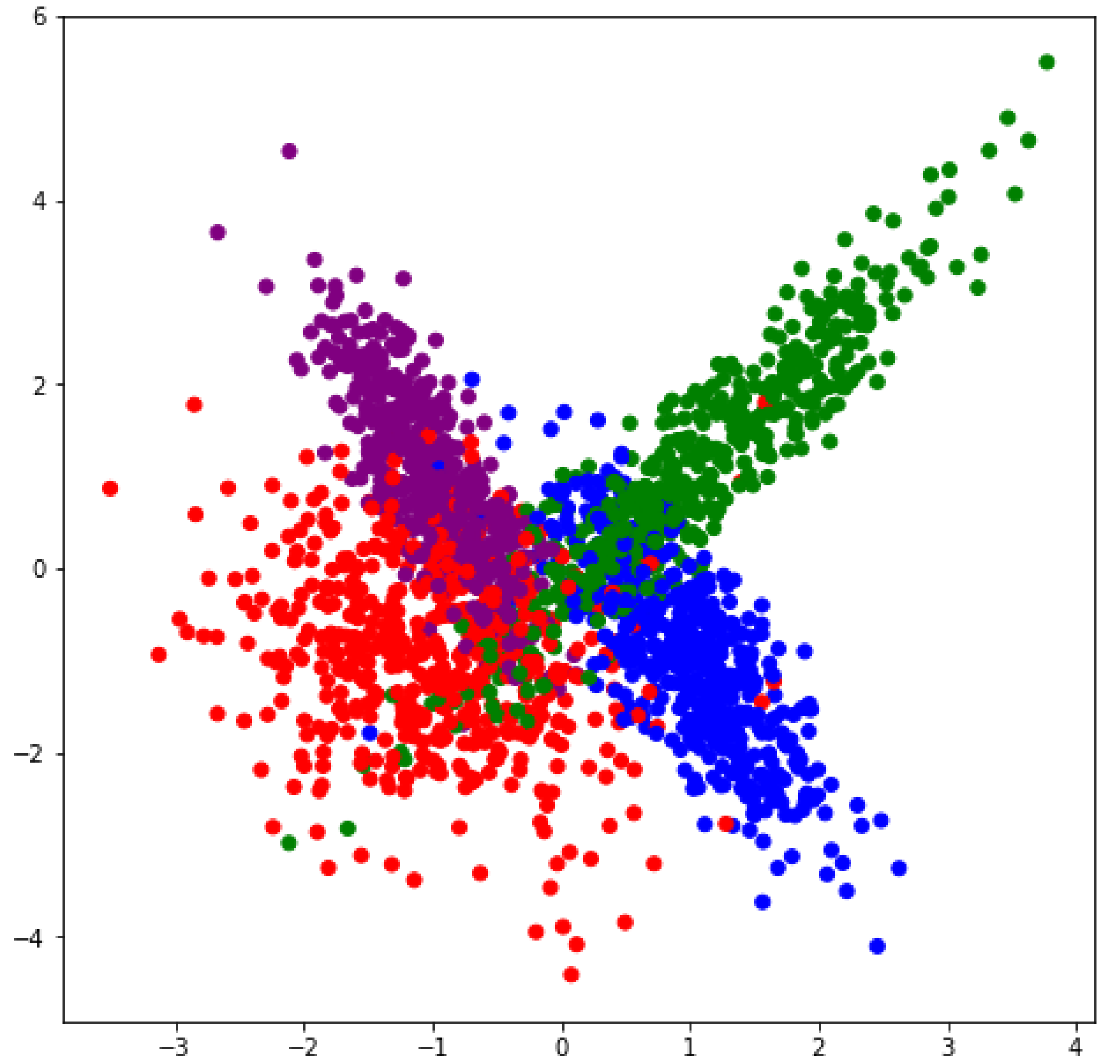
1.1.1 1. Метод k ближайших соседей

In [4]:
```
from sklearn import cross_validation, datasets, metrics, neighbors, model_selection
from matplotlib.colors import ListedColormap
import numpy as np
%pylab inline
```

```
/usr/local/lib/python3.5/dist-packages/sklearn/cross_validation.py:44: DeprecationWarning: This
  "This module will be removed in 0.20.", DeprecationWarning)


Populating the interactive namespace from numpy and matplotlib
```

In [5]:
```
colors = ListedColormap(['red', 'blue', 'purple', 'green'])
light_colors = ListedColormap(['lightcoral', 'lightblue', 'pink', 'lightgreen'])

def plot_2d_dataset(data, colors):
    pyplot.figure(figsize(8, 8))
    pyplot.scatter(list(map(lambda x: x[0], data[0])), list(map(lambda x: x[1], data[0])
```

In [6]:
```
classification_problem = datasets.make_classification(n_samples=2000, n_features=2, n_in
                                                      n_classes=4, n_redundant=0, n_clus
                                                      random_state=1)
plot_2d_dataset(classification_problem, colors)
```



In [7]:
```
train_data, test_data, train_labels, test_labels = cross_validation.train_test_split(cla
                                                                                     cla
                                                                                     tes
                                                                                     ran
```

In [8]:
```
estimator = neighbors.KNeighborsClassifier()
estimator.fit(train_data, train_labels)
```

Out[8]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
```

In [9]:
```
predictions = estimator.predict(test_data)
metrics.accuracy_score(test_labels, predictions)
```

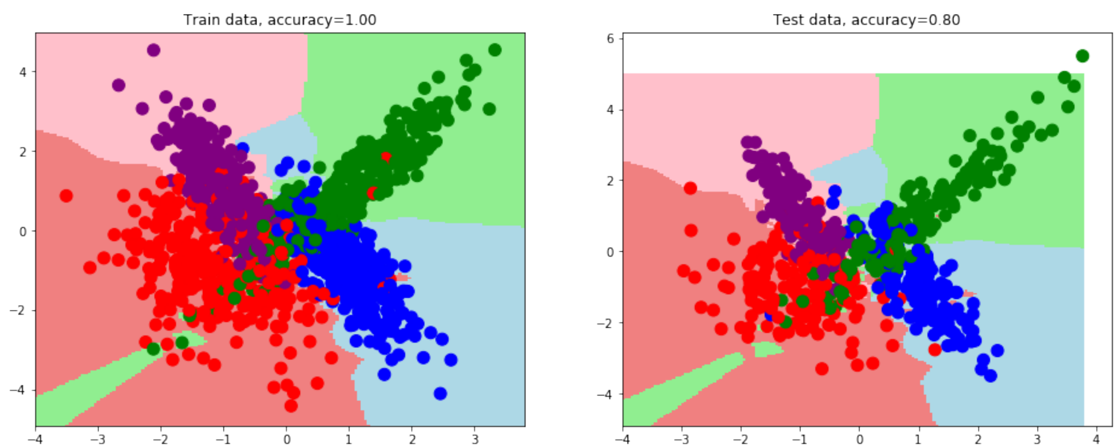
Out[9]: 0.83499999999999996

```
In [10]: def get_meshgrid(data, step=.05, border=.5,):
             x_min, x_max = data[:, 0].min() - border, data[:, 0].max() + border
             y_min, y_max = data[:, 1].min() - border, data[:, 1].max() + border
             return np.meshgrid(np.arange(x_min, x_max, step), np.arange(y_min, y_max, step))
```

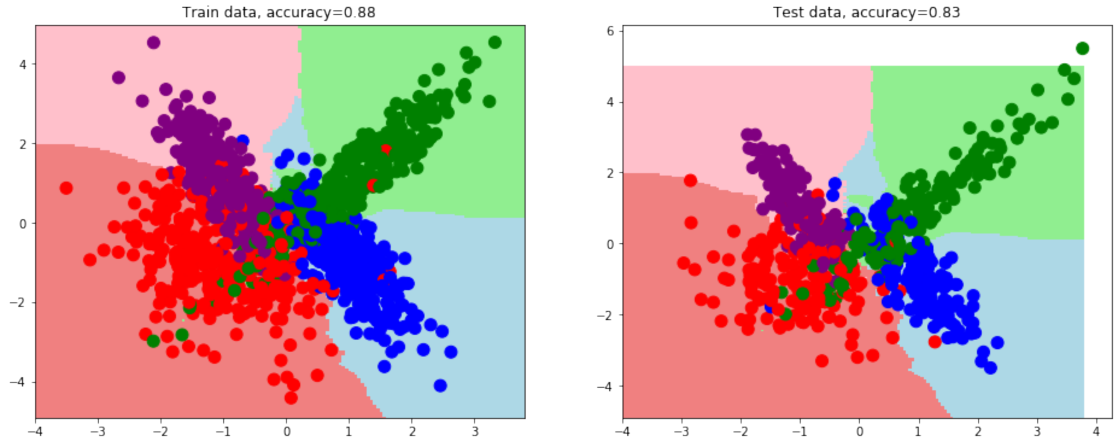
```
In [11]: def plot_decision_surface(estimator, train_data, train_labels, test_data, test_labels,
                                   colors = colors, light_colors = light_colors):
             #fit model
             estimator.fit(train_data, train_labels)

             #set figure size
             pyplot.figure(figsize = (16, 6))

             #plot decision surface on the train data
             pyplot.subplot(1,2,1)
             xx, yy = get_meshgrid(train_data)
             mesh_predictions = np.array(estimator.predict(np.c_[xx.ravel(), yy.ravel()])).resha
             pyplot.pcolormesh(xx, yy, mesh_predictions, cmap = light_colors)
             pyplot.scatter(train_data[:, 0], train_data[:, 1], c = train_labels, s = 100, cmap
             pyplot.title('Train data, accuracy={:.2f}'.format(metrics.accuracy_score(train_labe

             #plot decision surface on the test data
             pyplot.subplot(1,2,2)
             pyplot.pcolormesh(xx, yy, mesh_predictions, cmap = light_colors)
             pyplot.scatter(test_data[:, 0], test_data[:, 1], c = test_labels, s = 100, cmap = c
             pyplot.title('Test data, accuracy={:.2f}'.format(metrics.accuracy_score(test_labels
```

```
In [12]: def plot_decision_surface_neighbors(k):
             estimator = neighbors.KNeighborsClassifier(n_neighbors=k)
             plot_decision_surface(estimator, train_data, train_labels, test_data, test_labels)
```

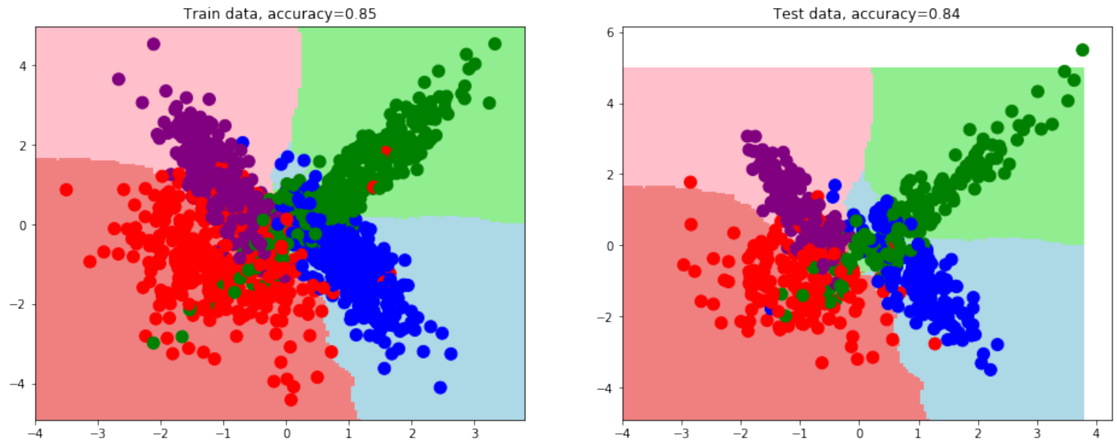
```
In [13]: plot_decision_surface_neighbors(1)
```



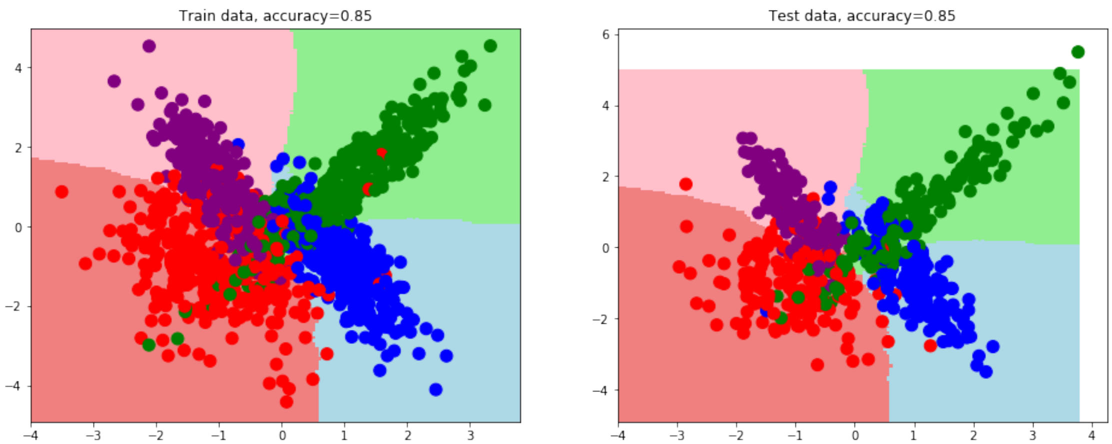
```
In [14]: plot_decision_surface_neighbors(5)
```



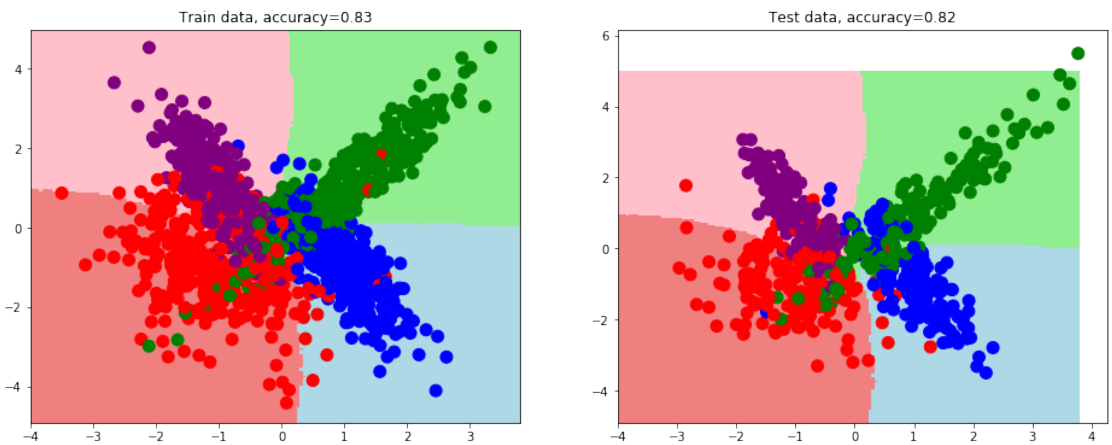

```
In [15]: plot_decision_surface_neighbors(15)
```



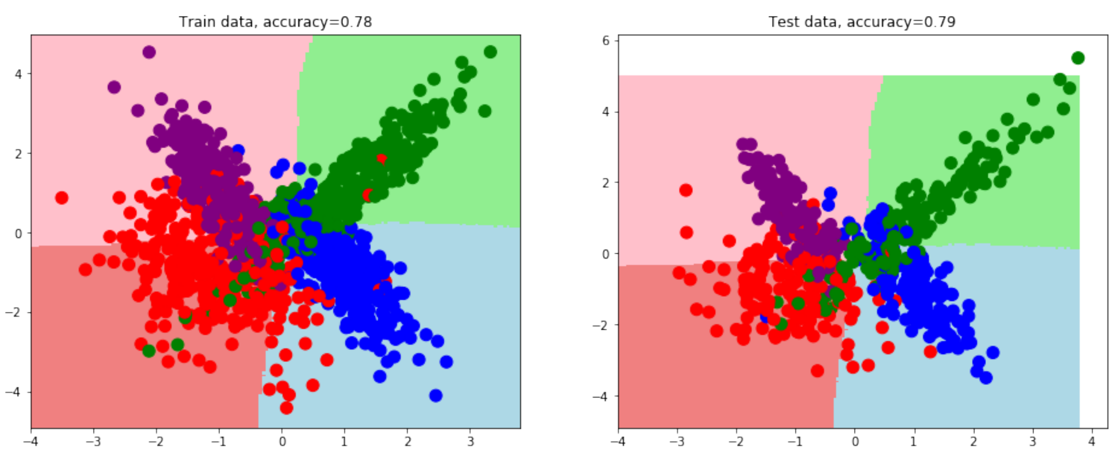

```
In [16]: plot_decision_surface_neighbors(32)
```




```
In [17]: plot_decision_surface_neighbors(120)
```

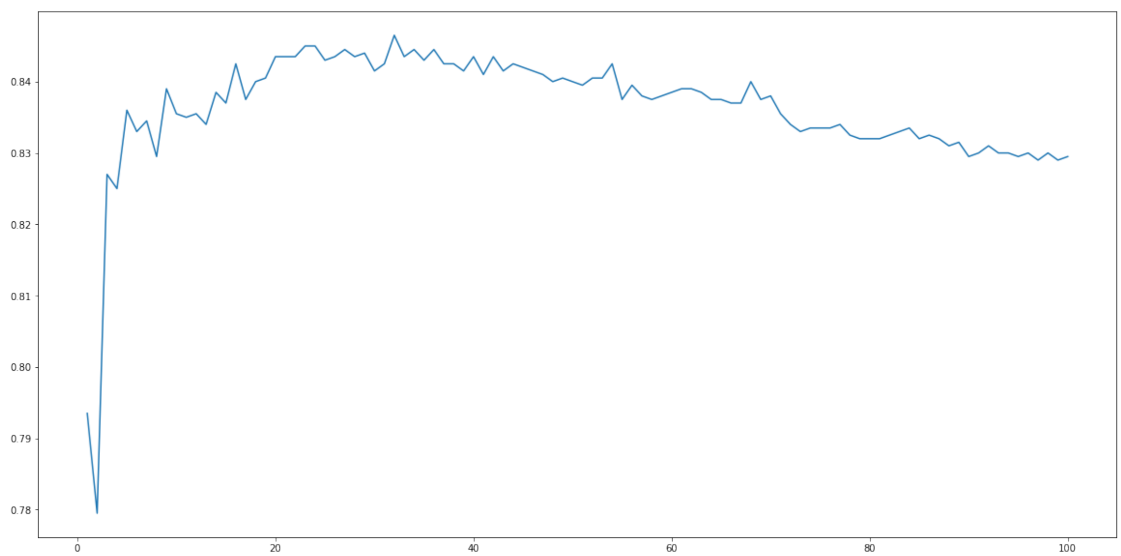



```
In [18]: plot_decision_surface_neighbors(500)
```



```
In [19]: MAX_NEIGHBORS = 100
         accuracy = []
         for k in range(1, MAX_NEIGHBORS + 1):
             scores = []
             for train_indices, test_indices in model_selection.KFold(n_splits=5).split(classifi
                 train_data = classification_problem[0][train_indices]
                 train_labels = classification_problem[1][train_indices]
                 test_data = classification_problem[0][test_indices]
                 test_labels = classification_problem[1][test_indices]

                 estimator = neighbors.KNeighborsClassifier(n_neighbors=k)
                 estimator.fit(train_data, train_labels)
                 predictions = estimator.predict(test_data)
                 scores.append(metrics.accuracy_score(test_labels, predictions))
             accuracy.append(np.mean(scores))
```

```
In [20]: plt.figure(figsize=(20, 10))
         plt.plot(np.arange(1, MAX_NEIGHBORS + 1), accuracy)
         plt.show()

         print("the best K is", 1 + argmax(accuracy))
```




```
the best K is 32
```

1.1.2 2. Наивный байесовский классификатор

```
In [23]: from sklearn.model_selection import cross_val_score
         from sklearn.naive_bayes import BernoulliNB, MultinomialNB, GaussianNB
```

```
In [24]: data_digits = datasets.load_digits()
         data_breast_cancer = datasets.load_breast_cancer()
```

```
In [25]: print(data_digits['data'])
         print(data_breast_cancer['data'])
```

```
[[  0.   0.   5. ...,   0.   0.   0.]
 [  0.   0.   0. ...,  10.   0.   0.]
 [  0.   0.   0. ...,  16.   9.   0.]
 ...,
 [  0.   0.   1. ...,   6.   0.   0.]
 [  0.   0.   2. ...,  12.   0.   0.]
 [  0.   0.  10. ...,  12.   1.   0.]]
[[  1.79900000e+01   1.03800000e+01   1.22800000e+02 ...,   2.65400000e-01
    4.60100000e-01   1.18900000e-01]
 [  2.05700000e+01   1.77700000e+01   1.32900000e+02 ...,   1.86000000e-01
    2.75000000e-01   8.90200000e-02]
 [  1.96900000e+01   2.12500000e+01   1.30000000e+02 ...,   2.43000000e-01
    3.61300000e-01   8.75800000e-02]
 ...,
 [  1.66000000e+01   2.80800000e+01   1.08300000e+02 ...,   1.41800000e-01
    2.21800000e-01   7.82000000e-02]
 [  2.06000000e+01   2.93300000e+01   1.40100000e+02 ...,   2.65000000e-01
    4.08700000e-01   1.24000000e-01]
 [  7.76000000e+00   2.45400000e+01   4.79200000e+01 ...,   0.00000000e+00
    2.87100000e-01   7.03900000e-02]]
```

digits - целые неотрицательные признаки
breast_cancer - вещественные признаки

```
In [26]: for data in (data_digits, data_breast_cancer):
             for estimator in (BernoulliNB(), MultinomialNB(), GaussianNB()):
                 print(cross_val_score(estimator=estimator, X=data.data, y=data.target).mean())
             print()
```

```
0.825823650778
0.870877148974
0.818600380355

0.627420402859
0.894579040193
0.936749280609
```

1. Каким получилось максимальное качество классификации на датасете breast_cancer?

   94%

2. Каким получилось максимальное качество классификации на датасете digits?

   87%

3. Какие утверждения из приведенных ниже верны?

   (a) На вещественных признаках лучше всего сработал наивный байесовский классификатор с распределением Бернулли

   Нет, хуже

   (b) На вещественных признаках лучше всего сработал наивный байесовский классификатор с мультиномиальным распределением

   Нет, с Гауссовым распределением

   (c) Мультиномиальное распределение лучше показало себя на выборке с целыми неотрицательными значениями признаков

   Да, лучше, чем Гауссово и Бернулли. Нет, хуже чем с вещественными признаками

   (d) На вещественных признаках лучше всего сработало нормальное распределение

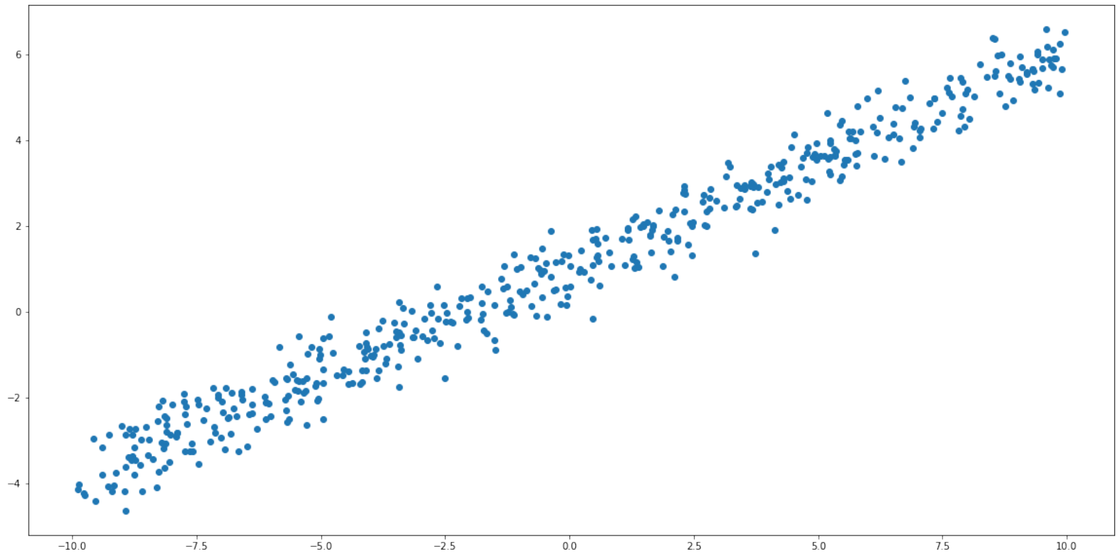
   Да

1.1.3 3. Метрики в задаче регрессии

In [62]:
```
from scipy import stats as sps
from scipy.optimize import minimize
```

In [74]:
```
MIN = -10
MAX = 10

x = sps.uniform.rvs(MIN, MAX - MIN, size=500)
y = 0.5 * x + 1 + sps.norm.rvs(scale=0.2 ** 0.5, size=500)
```

In [75]:
```
plt.figure(figsize=(20, 10))
plt.scatter(x, y)
plt.show()
```



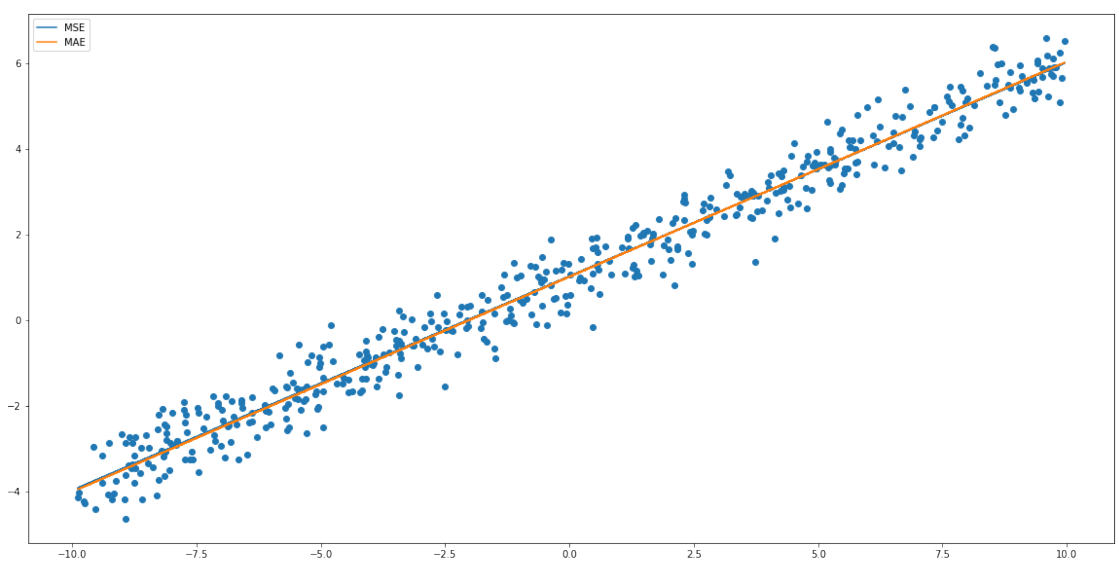

```
In [76]: def function_mse(args):
             k, b = args
             return ((k * x + b - y) ** 2).mean()

         def function_mae(args):
             k, b = args
             return np.abs(k * x + b - y).mean()
```

```
In [77]: mse = minimize(function_mse, [0, 0])
         mae = minimize(function_mae, [0, 0])
         print(mse)
         print()
         print(mae)
```

```
      fun: 0.22413098492403824
 hess_inv: array([[ 0.01555316,  0.00479266],
       [ 0.00479266,  1.00393264]])
      jac: array([  1.63912773e-07,   2.42143869e-08])
  message: 'Optimization terminated successfully.'
     nfev: 20
      nit: 2
     njev: 5
   status: 0
  success: True
        x: array([ 0.4999781 ,  1.02264583])

      fun: 0.37848766814651036
 hess_inv: array([[  5.98041558e-06,   5.36401568e-05],
       [  5.36401568e-05,   3.24649297e-01]])
```

```
      jac: array([ 0.00247844,  0.        ])
  message: 'Desired error not necessarily achieved due to precision loss.'
     nfev: 451
      nit: 10
     njev: 110
   status: 2
  success: False
        x: array([ 0.50240869,  1.01370381])
```

```
In [78]: k_mse, b_mse = mse.x
         k_mae, b_mae = mae.x

         plt.figure(figsize=(20, 10))
         plt.scatter(x, y)
         plt.plot(x, k_mse * x + b_mse, label="MSE")
         plt.plot(x, k_mae * x + b_mae, label="MAE")
         plt.legend()
         plt.show()
```



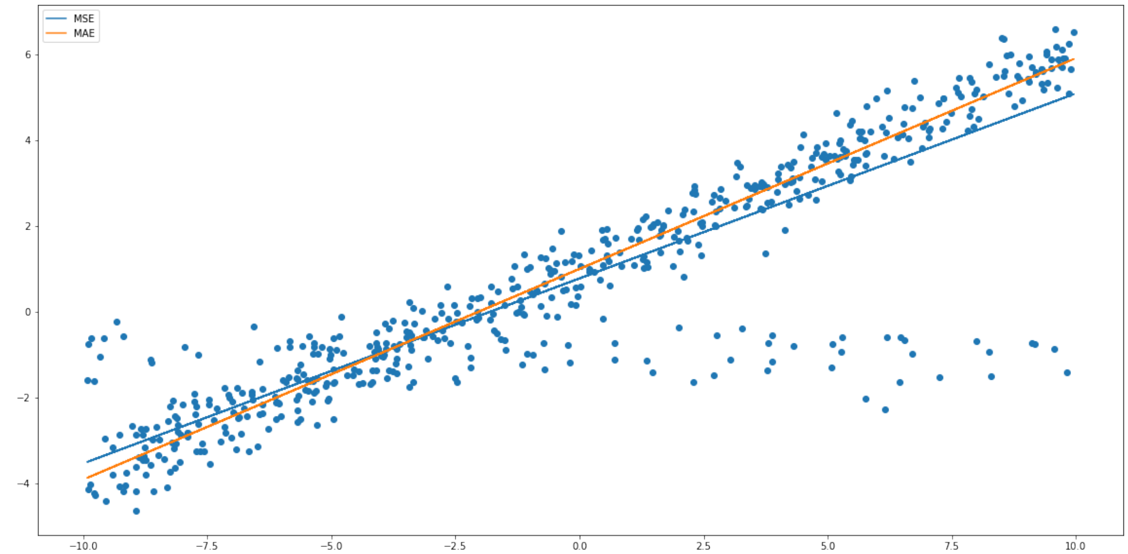

```
In [80]: new_x = np.append(x, sps.uniform.rvs(MIN, MAX - MIN, size=75))
         new_y = np.append(y, -1 + sps.norm.rvs(scale=0.2 ** 0.5, size=75))
```

```
In [81]: def function_mse(args):
             k, b = args
             return ((k * new_x + b - new_y) ** 2).mean()

         def function_mae(args):
             k, b = args
             return np.abs(k * new_x + b - new_y).mean()
```

In [82]:
```
mse = minimize(function_mse, [0, 0])
mae = minimize(function_mae, [0, 0])
print(mse)
print()
print(mae)
```

```
      fun: 1.5886404915855898
 hess_inv: array([[ 0.01538811,  0.00626163],
       [ 0.00626163,  1.00294681]])
      jac: array([  1.93715096e-07,  -1.49011612e-08])
  message: 'Optimization terminated successfully.'
     nfev: 20
      nit: 2
     njev: 5
   status: 0
  success: True
        x: array([ 0.43142489,  0.77433421])

      fun: 0.7068464887415729
 hess_inv: array([[ 0.00054595, -0.00166921],
       [-0.00166921,  0.00764435]])
      jac: array([ 0.00183568,  0.00104306])
  message: 'Desired error not necessarily achieved due to precision loss.'
     nfev: 384
      nit: 9
     njev: 93
   status: 2
  success: False
        x: array([ 0.49134287,  0.99685401])
```

In [83]:
```
k_mse, b_mse = mse.x
k_mae, b_mae = mae.x

plt.figure(figsize=(20, 10))
plt.scatter(new_x, new_y)
plt.plot(new_x, k_mse * new_x + b_mse, label="MSE")
plt.plot(new_x, k_mae * new_x + b_mae, label="MAE")
plt.legend()
plt.show()
```



Видим, что MAE более устойчива к выбросам.

```
In [ ]:
```