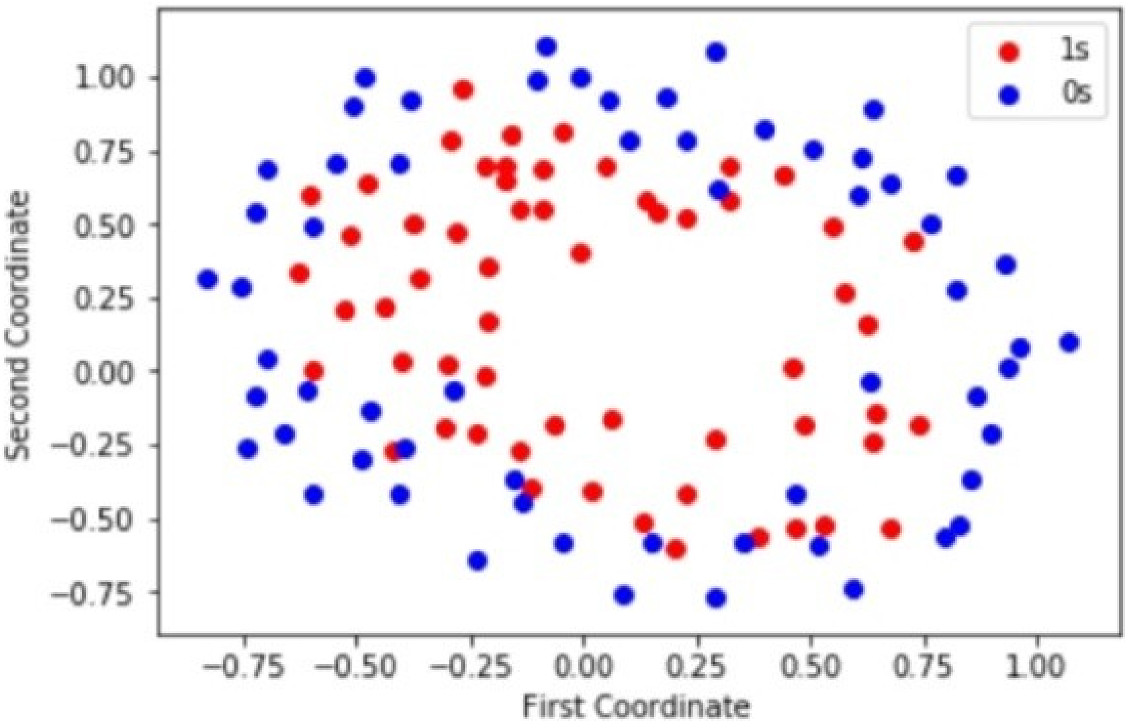
1. Определяю входные данные и задаю точки с распределением их по классам + отображаю это на графике точек

[9]:

```
import numpy as np
import matplotlib.pyplot as plt

# load data
data = np.loadtxt('chips.txt', delimiter=',')
X = data[:,0:2]   # 2D points
y = data[:, 2]    # classes (0 or 1)

# look into the data
print('Numer of Samples:', len(data))
print('Number of 1s:    ', len(np.where(y == 1)[0]))
print('Number of 0s:    ', len(np.where(y == 0)[0]))
print("Data Head Preview\n", data[0:3], "\n...\n", "Data Tail Preview\n", data[-3:])

# visualize the data
inds_one = np.where(y == 1)
inds_zero = np.where(y == 0)
plt.scatter(X[inds_one][:,0], X[inds_one][:,1], c='red', label='1s')
plt.scatter(X[inds_zero][:,0], X[inds_zero][:,1], c='blue', label='0s')
plt.xlabel('First Coordinate')
plt.ylabel('Second Coordinate')
plt.legend()
plt.show()
```

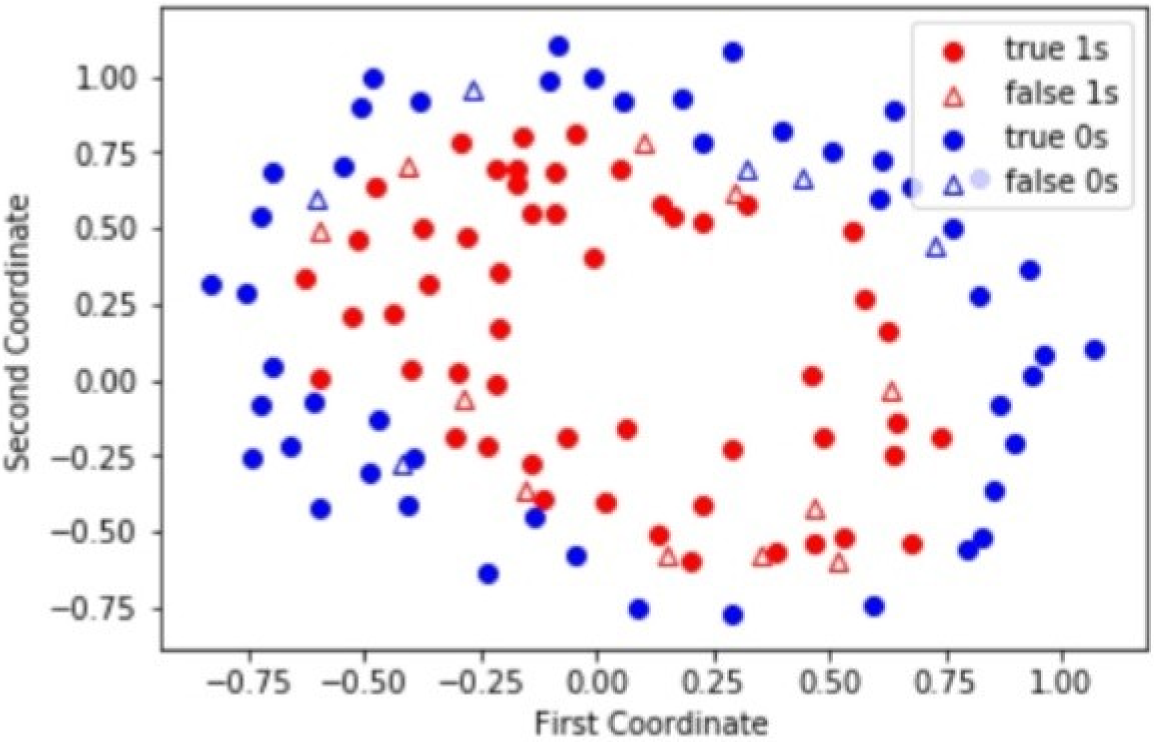
2.Результат:



3. Действую по алгоритму SVM, определяя для него лучшие показатели при выполнении и сравниваю с оригиналом и отображаю результат на плоскости, обозначая несовпадения треугольниками.

```python
###########################
# Support Vector Machine #
###########################

from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV

# support vector classifier
svc = SVC()

# parameter tuner for 'svc'
params = {'kernel':('linear', 'poly', 'rbf', 'sigmoid'),
          'C': np.linspace(0.1, 10, 100),
          'degree': np.linspace(1, 10, 10),
          'coef0': np.linspace(-2, 2, 5)}
clf = GridSearchCV(svc, params)
clf.fit(X, y)
print('Best Estimator\n', clf.best_estimator_)

pred_y_svc = clf.predict(X)
pred_inds_one = np.where(pred_y_svc == 1)
pred_inds_zero = np.where(pred_y_svc == 0)

def get_true_false_pred_inds_pair(pred_inds, inds):
    """Get pair of (<true prediction>, <false prediction>)"""
    false_pred = np.setdiff1d(pred_inds, inds)
    true_pred = np.setdiff1d(pred_inds, false_pred)
    return true_pred, false_pred

true_pred_inds_one, false_pred_inds_one = get_true_false_pred_inds_pair(pred_inds_one, i
true_pred_inds_zero, false_pred_inds_zero = get_true_false_pred_inds_pair(pred_inds_zero

# correctly classified 1s
plt.scatter(X[true_pred_inds_one][:,0],
            X[true_pred_inds_one][:,1],
            c='red', marker='o', label='true 1s')

# incorrectly classified 1s
plt.scatter(X[false_pred_inds_one][:,0],
            X[false_pred_inds_one][:,1],
            c='white', marker='^', edgecolors='red', label='false 1s')

# correctly classified 0s
plt.scatter(X[true_pred_inds_zero][:,0],
            X[true_pred_inds_zero][:,1],
            c='blue', marker='o', label='true 0s')

# incorrectly classified 0s
plt.scatter(X[false_pred_inds_zero][:,0],
            X[false_pred_inds_zero][:,1],
            c='white', marker='^', edgecolors='blue', label='false 0s')

plt.xlabel('First Coordinate')
plt.ylabel('Second Coordinate')
plt.legend()
plt.show()
```

4.Результат

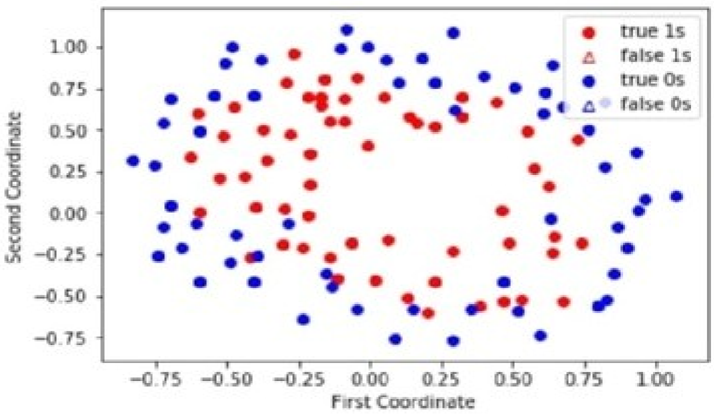


true 1s
false 1s
true 0s
false 0s
Second Coordinate
First Coordinate
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00

5. Проделываю ту же операцию с knn

```
#########################
# k-Nearest Neighbors #
#########################

from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV

# k-nearest neighbors classifier
knn = KNeighborsClassifier()

# parameter tuner for 'knn'
params = {'n_neighbors': np.arange(1, 50),
          'p': np.arange(1, 10),
          'algorithm': ['ball_tree', 'kd_tree', 'brute'],
          'weights': ['uniform', 'distance']}
clf = GridSearchCV(knn, params)
clf.fit(X, y)
print('Best Estimator\n', clf.best_estimator_)

pred_y_knn = clf.predict(X)
pred_inds_one = np.where(pred_y_knn == 1)
pred_inds_zero = np.where(pred_y_knn == 0)

true_pred_inds_one, false_pred_inds_one = get_true_false_pred_inds_pair(pred_inds_one, i
true_pred_inds_zero, false_pred_inds_zero = get_true_false_pred_inds_pair(pred_inds_zero

# correctly classified 1s
plt.scatter(X[true_pred_inds_one][:,0],
            X[true_pred_inds_one][:,1],
            c='red', marker='o', label='true 1s')

# incorrectly classified 1s
plt.scatter(X[false_pred_inds_one][:,0],
            X[false_pred_inds_one][:,1],
            c='white', marker='^', edgecolors='red', label='false 1s')

# correctly classified 0s
plt.scatter(X[true_pred_inds_zero][:,0],
            X[true_pred_inds_zero][:,1],
            c='blue', marker='o', label='true 0s')

# incorrectly classified 0s
plt.scatter(X[false_pred_inds_zero][:,0],
            X[false_pred_inds_zero][:,1],
            c='white', marker='^', edgecolors='blue', label='false 0s')

plt.xlabel('First Coordinate')
plt.ylabel('Second Coordinate')
plt.legend()
plt.show()
```

```
Best Estimator
 KNeighborsClassifier(algorithm='ball_tree', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=3, p=8,
           weights='distance')
```



6. Сравниваю неточность показаний в таблице и делаю вывод, что для данного датасета алгоритм knn работает точнее.

20]:
```
###################################################
# Support Vector Machine vs k-Nearest Neighbors #
###################################################

from sklearn.metrics import classification_report

target_names = ['1s', '0s']
report_svc = classification_report(y, pred_y_svc, target_names=target_names)
report_knn = classification_report(y, pred_y_knn, target_names=target_names)
print('classification_report')
print('SVC\n', report_svc)
print('kNN\n', report_knn)
print()
```

```
classification_report
SVC
              precision    recall  f1-score   support

         1s       0.89      0.82      0.85        60
         0s       0.83      0.90      0.86        58

avg / total       0.86      0.86      0.86       118

kNN
              precision    recall  f1-score   support

         1s       1.00      1.00      1.00        60
         0s       1.00      1.00      1.00        58

avg / total       1.00      1.00      1.00       118
```