Table of Contents

In [1]:
```
import pandas as pd
import numpy as np
from sklearn.svm import SVC
import matplotlib.pyplot as plt
import time

import sys
sys.path.append('../metrics/')
import metrics
import importlib

plt.rcParams['font.family']=['Songti SC']
plt.rcParams['axes.unicode_minus'] = False
pd.set_option('display.float_format', lambda x: '%.5f' % x)
pd.options.display.max_rows = 200
np.set_printoptions(threshold=np.inf)
np.set_printoptions(linewidth=100, suppress=True)    # 打印numpy时设置显示宽度，并且不用科学计数法显示
```

这个文件是用来测试sklearn.svm中的SVC的linear核和rbf核在recall, precision, ks上的区别

In [2]:
```
def test_SVC(df,X,y,kernel,THRESHOLD):
    """测试sklearn.svm中的SVC

    这部分使用sklearn的SVM，并可调整预测的概率值用于分类时的阈值（不调整情况下的官方默认实现是0.5），
    计算量模型得分recall、precision和ks，并绘制ks曲线

    """
    start = time.time()
    clf = SVC(gamma='auto',random_state=1, probability=True,kernel=kernel)
    clf.fit(X,y)
    y_predict = (clf.predict_proba(X)[:,1] >= THRESHOLD).astype(int)#自己设定阈值，Label=1的概率>=0.4就判为1
    end = time.time()
    print(f"{kernel} time: {end - start} s")
    dff = df.drop(df.columns[[0,1]], axis=1)
    dff.insert(0, 'y_predict', y_predict)
    dff.insert(0, 'y', df["Label"])
    dff.insert(0, 'prob_predict', clf.predict_proba(X)[:,1])
    recall, precision = metrics.recall_and_precision(dff,metrics.metricStruct(0,1))
    ks = metrics.plot_ks_curve(dff,metrics.metricStruct(0,1))
    print(f"recall: {recall}, \nprecision: {precision}, \nks: {ks}")
    return clf, recall, precision, ks, end-start, dff
```

In [3]:
```
def get_table1d(t, j):
    linear = []
    rbf = []
    for i in range(len(t)):
        if i%2 == 0:
            linear.append(t[i][j])
        else:
            rbf.append(t[i][j])
    return linear, rbf
```

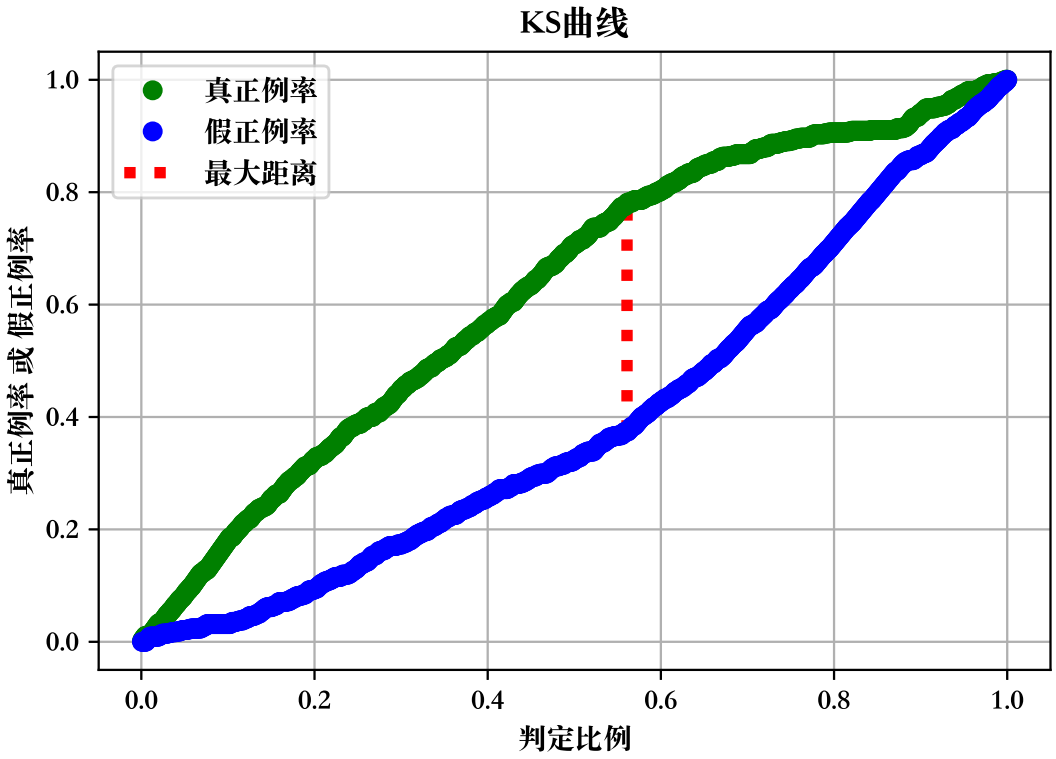
In [4]:
```
def get_table2d(t):
    linear = []
    rbf = []
    for i in [1,2,3,4]: #依次是recall, precision, ks, end - start
        linear_i,rbf_i = get_table1d(t, i)
        linear.append(linear_i)
        rbf.append(rbf_i)
    return linear,rbf
```

In [5]:
```
def plot_score(t,type,h=1):
    """绘制在不同阈值和内核下的得分柱状图"""
    linear, rbf = get_table2d(t)
    if type == "Recall":
        x = 0
    elif type == "Precision":
        x = 1
    elif type == "KS":
        x = 2
    elif type == "Time(s)":
        x = 3

    labels = ['0.4', '0.5', '0.55']
    linear_score = [linear[x][0], linear[x][1], linear[x][2]]
    rbf_score = [rbf[x][0], rbf[x][1], rbf[x][2]]

    x = np.arange(len(labels))  # the label locations
    width = 0.3  # the width of the bars

    fig, ax = plt.subplots()
    rects1 = ax.bar(x - width/2, linear_score, width, label='linear
')
    rects2 = ax.bar(x + width/2, rbf_score, width, label='rbf')

    # Add some text for labels, title and custom x-axis tick labels
, etc.
    ax.set_ylabel(f"{type}")
    ax.set_xlabel("Threshold")
    ax.set_title(f'{type} by threshold and kernel')
    ax.set_xticks(x)
    ax.set_xticklabels(labels)
    ax.legend()
    ax.set_ylim([0, h])

    def autolabel(rects):
        """Attach a text label above each bar in *rects*, displayin
g its height."""
        for rect in rects:
            height = rect.get_height()
            ax.annotate('{:.3}'.format(height),
                        xy=(rect.get_x() + rect.get_width() / 2, he
ight),
                        xytext=(0, 3),  # 3 points vertical offset
                        textcoords="offset points",
                        ha='center', va='bottom')

    autolabel(rects1)
    autolabel(rects2)
    plt.show()
```

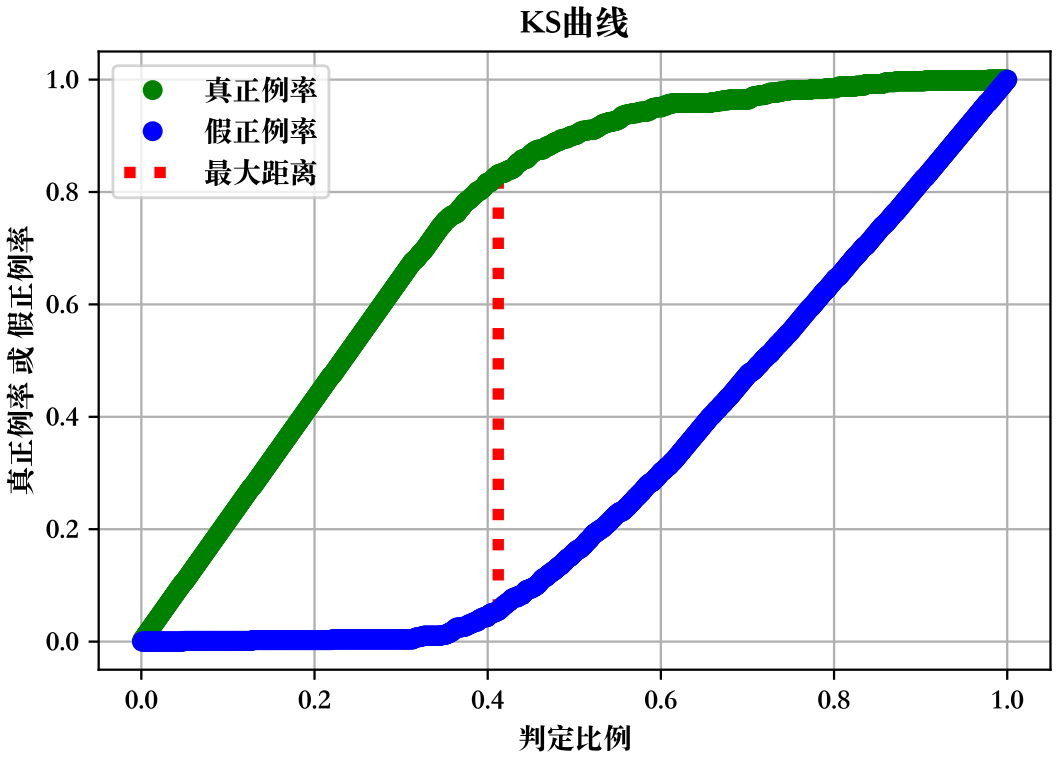
两个类别0、1，设置不同的阈值和内核进行试验

In [6]:
```
if __name__ == '__main__':
    df = pd.read_csv("../data/preprocess.csv")
    X,y = df.drop(df.columns[[0,1]], axis=1), df["Label"]
    t = []

    # 计算阈值=0.4时，即预测的概率大于0.4就将类别判为1时，linear核与rbf核的效果
    t.append(test_SVC(df,X,y,"linear",0.4))
    t.append(test_SVC(df,X,y,"rbf",0.4))
```

```
linear time: 0.1878359317779541 s
```



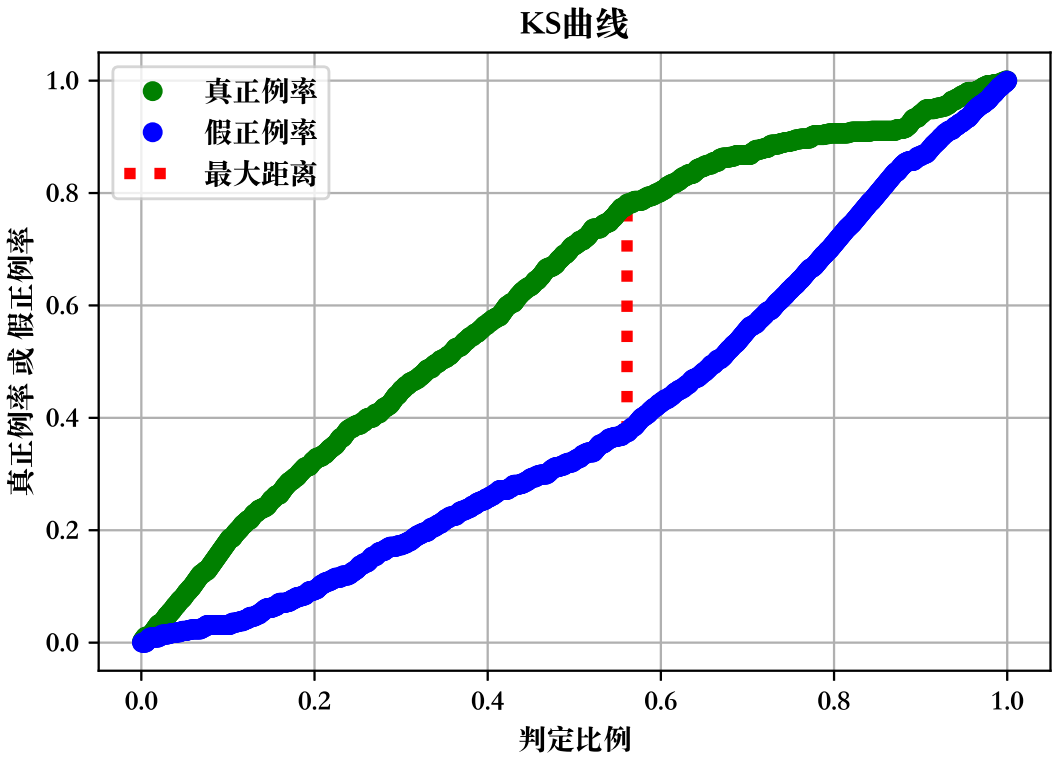

```
recall: 0.7307692307692307,
precision: 0.6480218281036835,
ks: 0.40752271350696545
rbf time: 0.2313683032989502 s
```



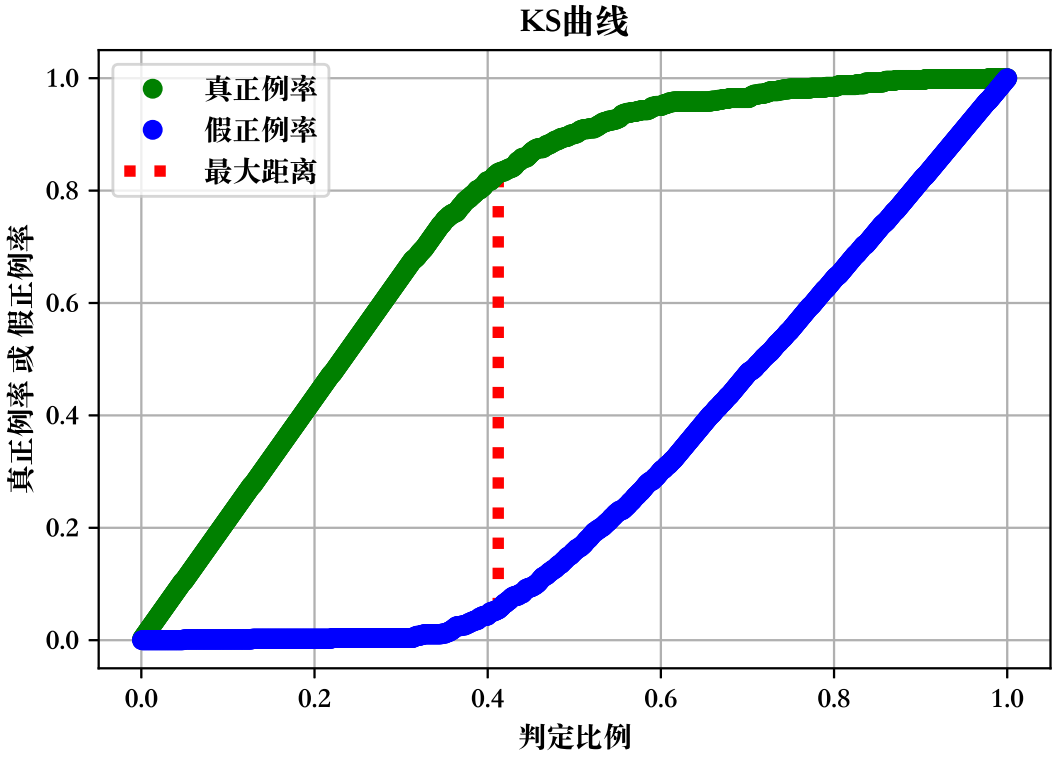

```
recall: 0.8015384615384615,
precision: 0.9489981785063752,
ks: 0.7771895820714718
```

In [7]:
```
    # 计算阈值=0.5时，即预测的概率大于0.5就将类别判为1时，linear核与rbf核的效果

    t.append(test_SVC(df,X,y,"linear",0.5))
    t.append(test_SVC(df,X,y,"rbf",0.5))
```

```
linear time: 0.18386578559875488 s
```




```
recall: 0.7307692307692307,
precision: 0.6480218281036835,
ks: 0.40752271350696545
rbf time: 0.1952371597290039 s
```

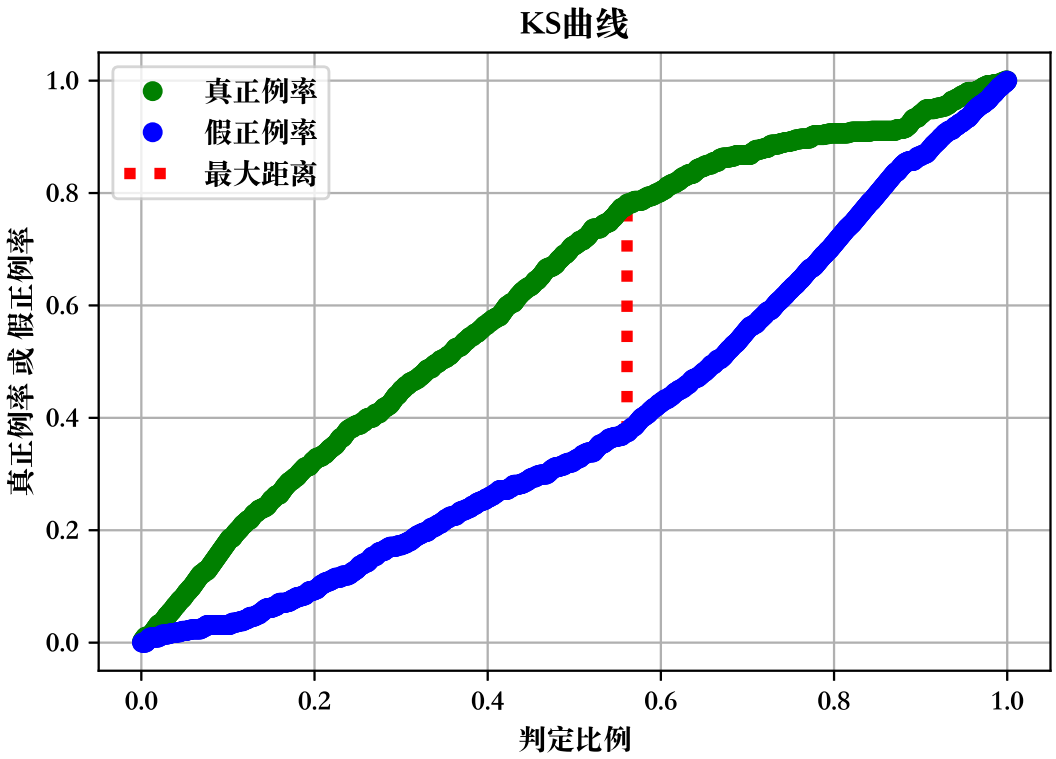



```
recall: 0.78,
precision: 0.9620493358633776,
ks: 0.7771895820714718
```

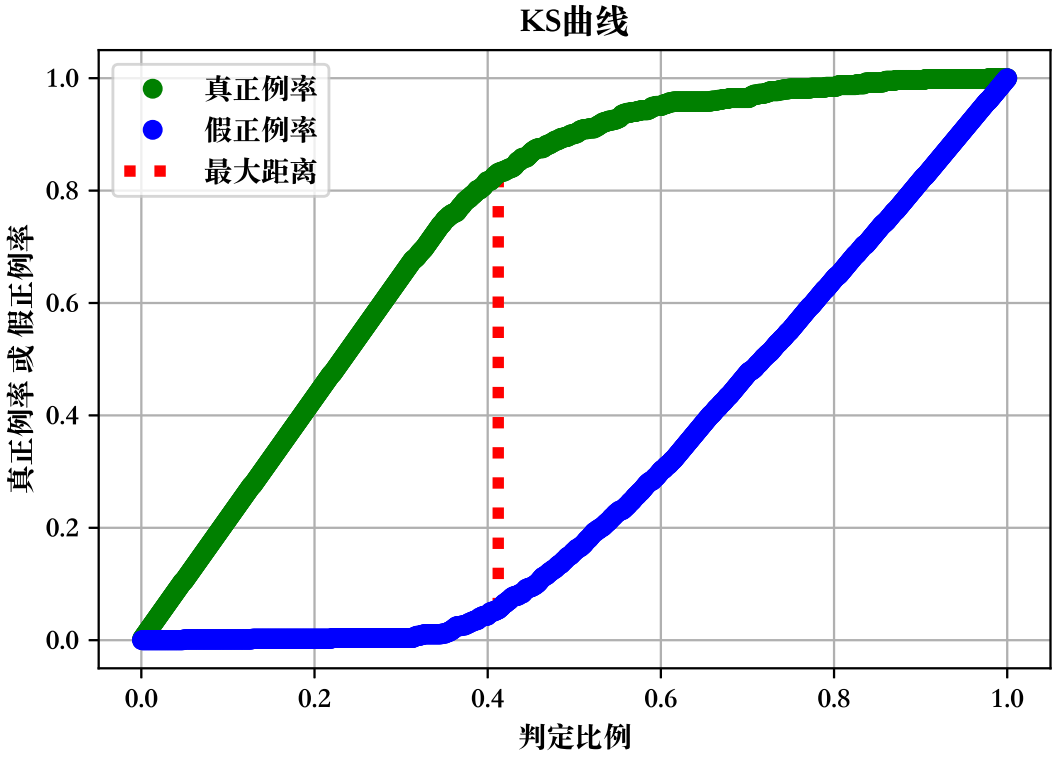
In [8]:

```
    # 计算阈值=0.55时，即预测的概率大于0.55就将类别判为1时，linear核与rbf核的效果
    t.append(test_SVC(df,X,y,"linear",0.55))
    t.append(test_SVC(df,X,y,"rbf",0.55))
```

```
linear time: 0.1898200511932373 s
```




```
recall: 0.7307692307692307,
precision: 0.6480218281036835,
ks: 0.40752271350696545
rbf time: 0.20151209831237793 s
```



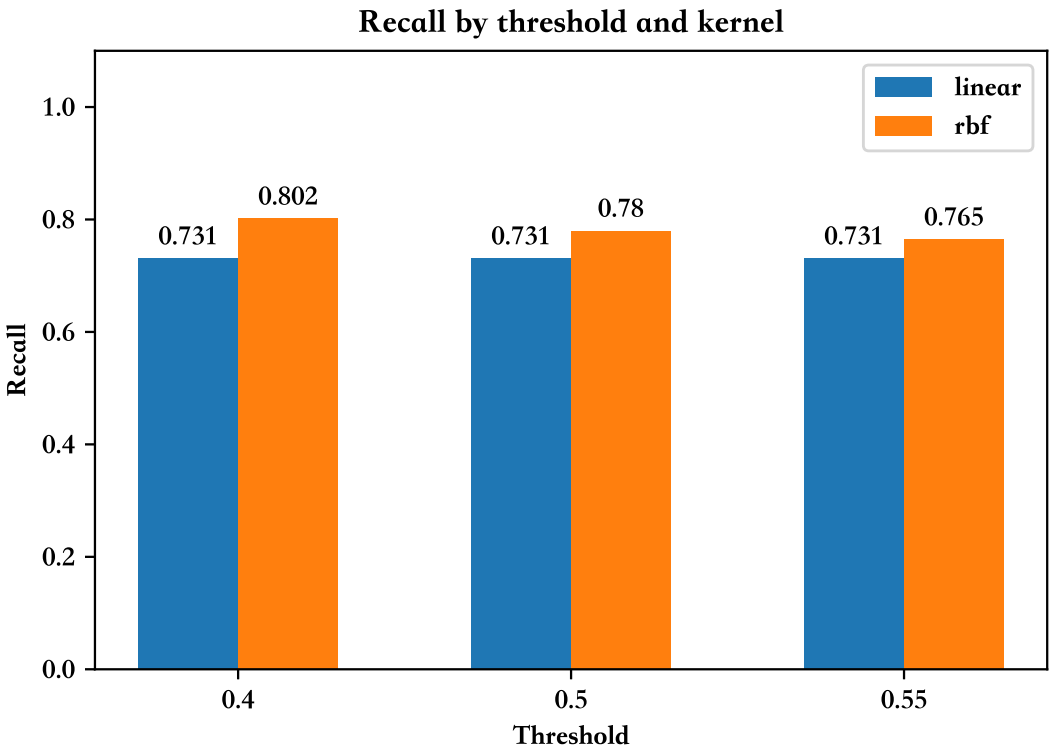

```
recall: 0.7646153846153846,
precision: 0.9631782945736435,
ks: 0.7771895820714718
```

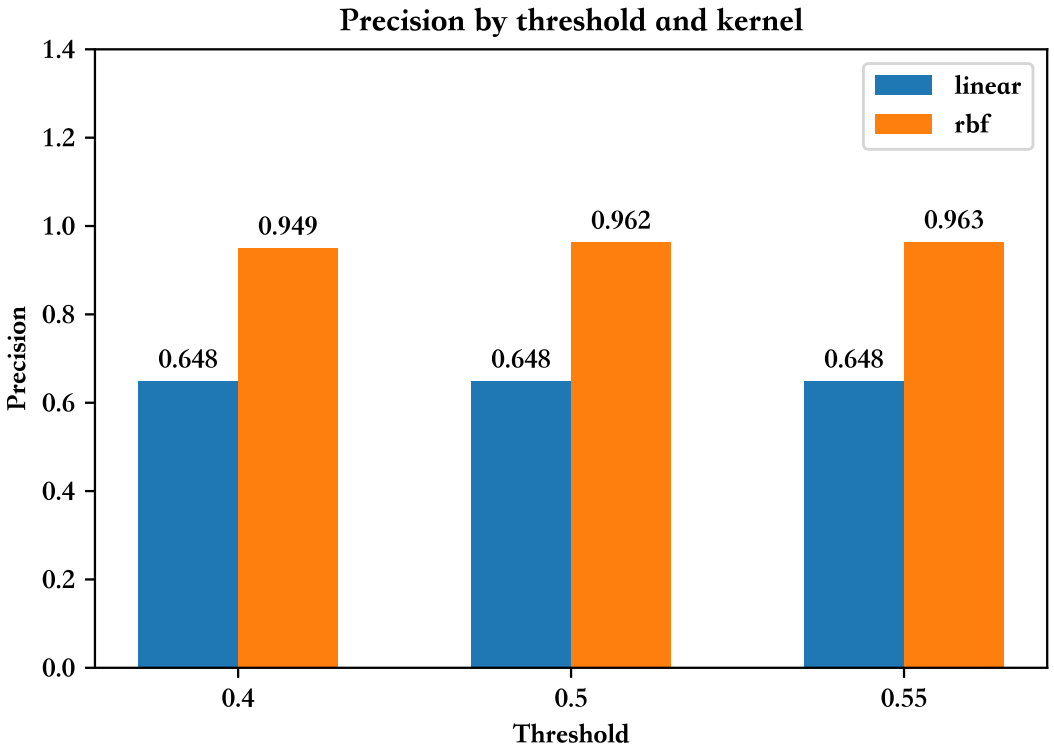
下图是将各个指标得分进行比较：

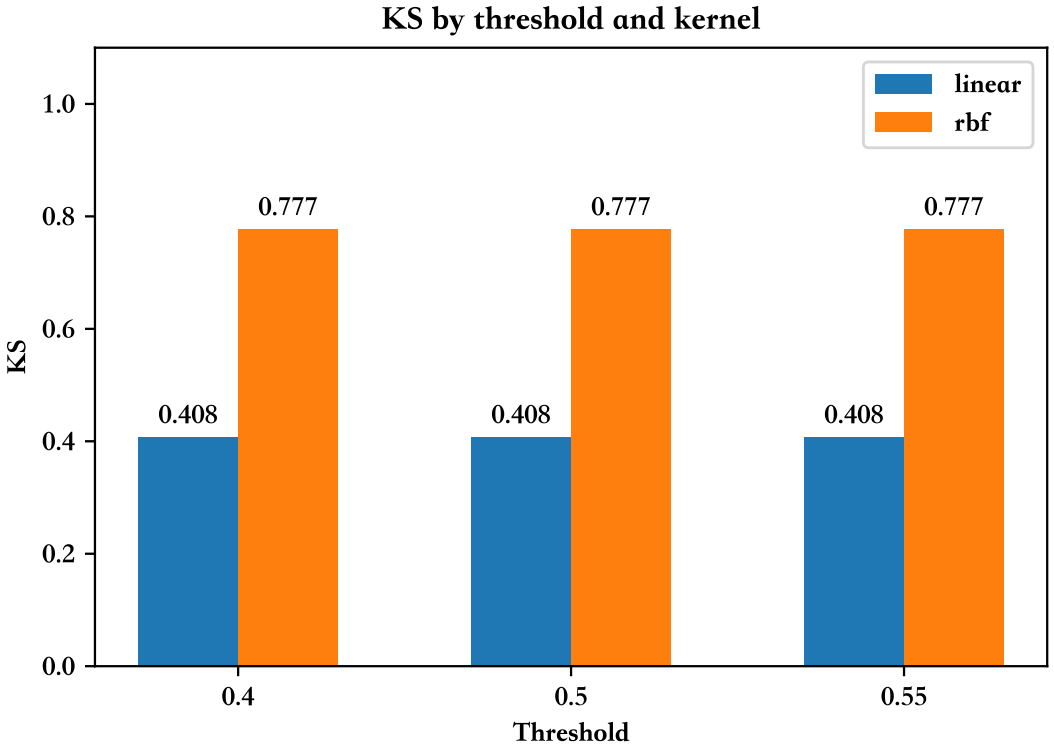
- recall：rbf和linear核得分都在0.75左右，但rbf核得分稍微更高些
  不同阈值对linear核得分几乎没有影响，但是rbf的低阈值得分更高
- precision：rbf核的得分比linear核的高得多，高于0.9
  不同阈值对linear核得分几乎没有影响，但是rbf的高阈值得分更高
- KS：rbf核的得分比linear核的高得多，0.77
  不同阈值对rbf和linear核得分几乎没有影响
- time：不同阈值、不同内核时间都接近0.2s

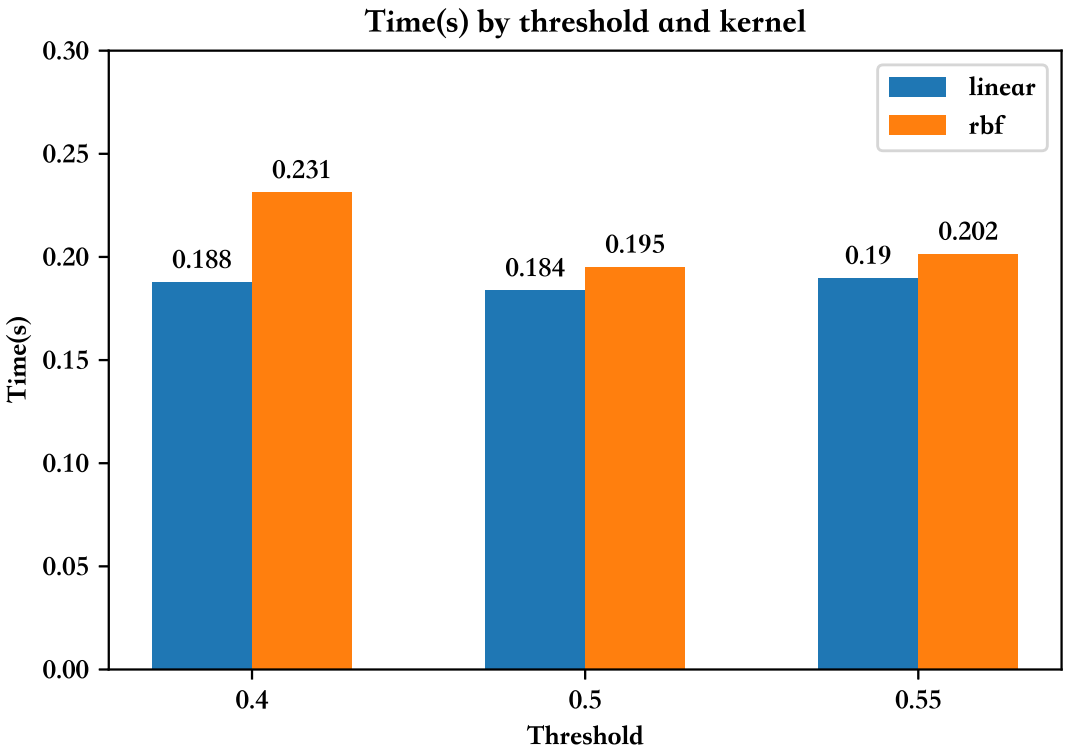
总之，根据precision和KS的显著得分差异，我们觉得rbf核在这个数据集上分类效果好。
rbf核下，低阈值的recall值更高，高阈值的precision值更高

In [9]:
```
plot_score(t,"Recall",1.1)
plot_score(t,"Precision",1.4)
plot_score(t,"KS",1.1)
plot_score(t,"Time(s)",0.3)
```




Precision by threshold and kernel
linear
rbf
Precision
Threshold
0.4
0.5
0.55
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
0.648
0.949
0.648
0.962
0.648
0.963


KS by threshold and kernel
linear
rbf
KS
Threshold
0.4
0.5
0.55
0.0
0.2
0.4
0.6
0.8
1.0
0.408
0.777
0.408
0.777
0.408
0.777



在信用评分，我们认为应该查全率最重要，所以将查全率最高的对应预测结果进行保存，rbf、阈值0.4。

In [10]:
```
t[1][5].to_csv('../result/sklearn_rbf_0.4.csv',index=False)
```