Fraudulent Firm Classification: A Case Study of an External Audit

Project description:

Please read the Data Set Information section to learn about this dataset. Data description is also provided for thi dataset. Read data into Jupyter notebook, use pandas to import data into a data frame Preprocess data: Explore data, check for missing data and apply data scaling. Justify the type of scaling used.

Objectives of the project

1)Used Linear Regression, Polynomial Regression and KNN Regressor to determine the Risk Audit Score for 777 target firms. 2)Built a classification model to predict the Risk Audit Class (Fraud or Not-Fraud) of the firms with 97% accuracy on test score. 3)Trained several machine learning algorithms for classification (Decision Tree, KNN, Logistic Regression and SVC) to find the best model based on accuracy and performance.

Regression Task:

We used several regression models to find the predict the audot score on the test set and used Grid Search to find the best scaling parameter. Also used plots and graphs to get a better glimpse of the results. Finally we reported the best regressor for our dataset.

Classification task:

We used several classification models: KNN classifcation, Logistic Regression, Linear Supprt Vector Machine, Kerenilzed Support Vector Machine, Decision Tree ,to classify whether a company is indulging in fraudulent practises or not and reported the best model bsaed on scores

Data Set Information:

This dataset is taken from a research explained here.

The goal of the research is to help the auditors by building a classification model that can predict the fraudulent firm on the basis the present and historical risk factors. The information about the sectors and the counts of firms are listed respectively as Irrigation (114), Public Health (77), Buildings and Roads (82), Forest (70), Corporate (47), Animal Husbandry (95), Communication (1), Electrical (4), Land (5), Science and Technology (3), Tourism (1), Fisheries (41), Industries (37), Agriculture (200).

There are two csv files to present data. Please merge these two datasets into one dataframe.

The main objective of this project is to perform the audit risk analysis using 776 target firm's historical data. Our main foucs is on determining the Rish Audit Score and preddiction of Risk Class. We used several supervised techniques (Regression, Classification) to determine the Risk Audit Score and Predict the Risk Class which will be discussed below.

We followed a sequence of steps starting with with importing required libraries, data merging, data pre-processing, data vizualization, etc. So let's get started

Importing Libraries

In [15]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

Importing Datasets

In [16]:
```
audit = pd.read_csv('audit_risk.csv')
trial = pd.read_csv('trial.csv')
```

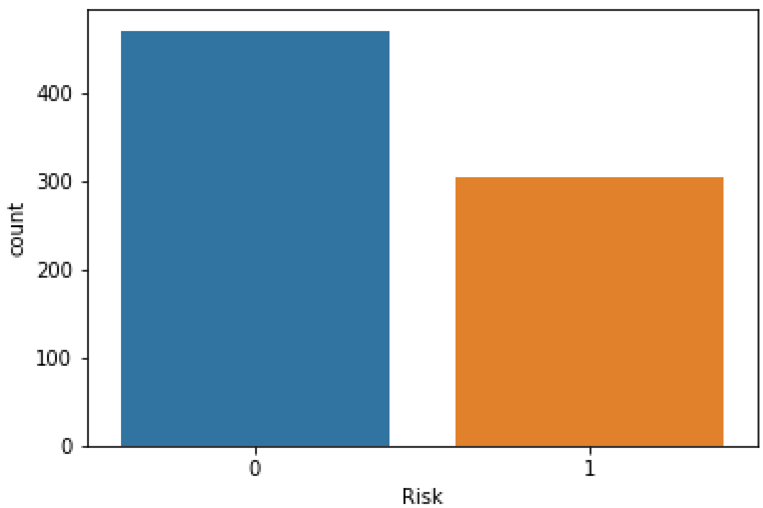
Data Distribution

In [17]:
```
sns.countplot(audit['Risk'])
audit.groupby('Risk').count()
```

Out[17]:

	Sector_score	LOCATION_ID	PARA_A	Score_A	Risk_A	PARA_B	Score_B	Risk_B	TOTA
Risk									
0	471	471	471	471	471	471	471	471	47
1	305	305	305	305	305	305	305	305	30

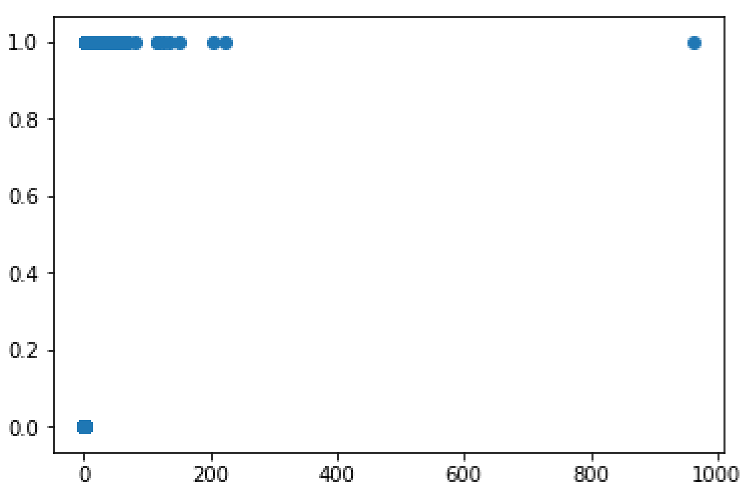
2 rows × 26 columns



Audit_Risk Vs Risk

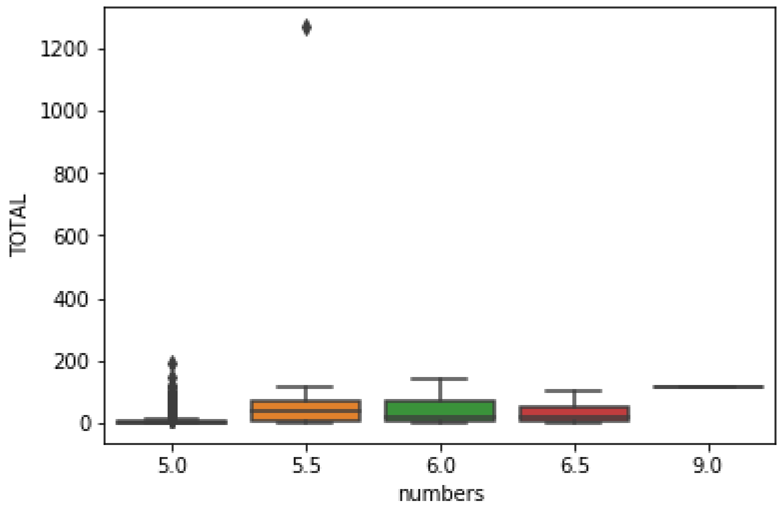
In [18]:
```
plt.scatter(audit['Audit_Risk'],audit['Risk'])

## We can see an outlier that screws can screw out analysis. We will handle th
is outlier in data pre-processing.
```

Out[18]: <matplotlib.collections.PathCollection at 0x1e46a13cd68>



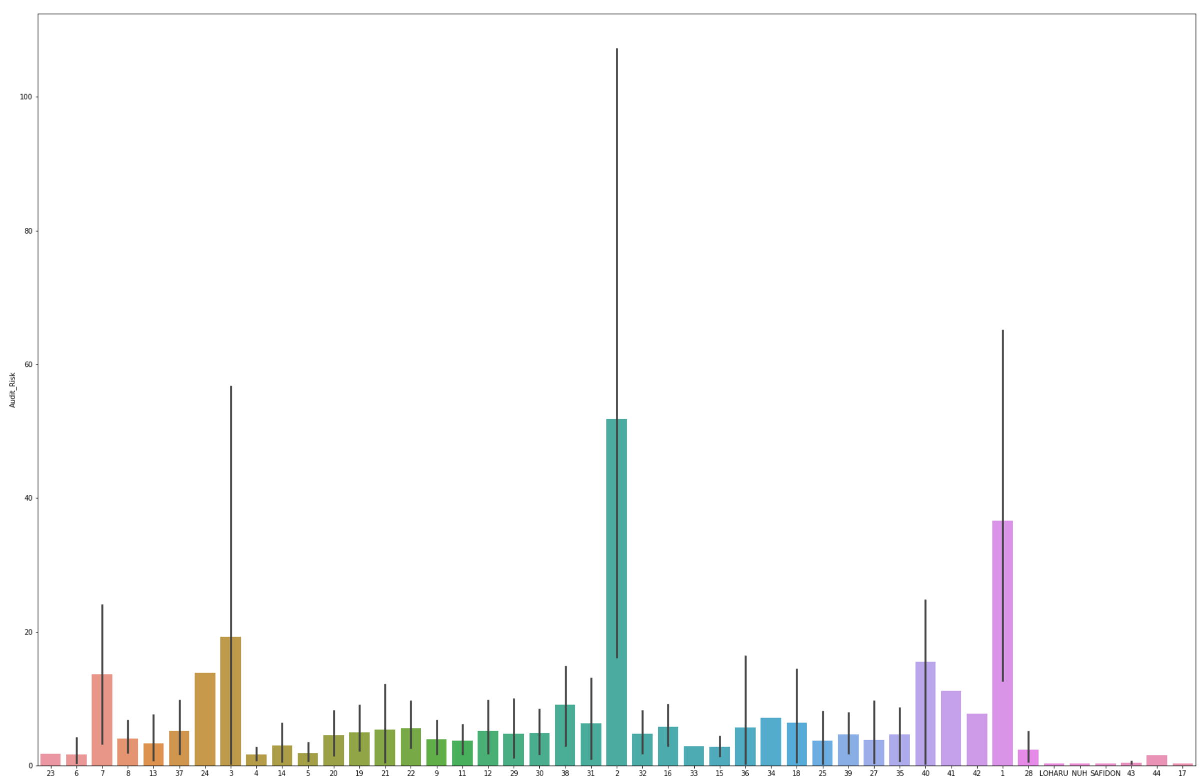
In [19]:
```
sns.boxplot(audit['numbers'],audit['TOTAL'])
```

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x1e46a0c5898>



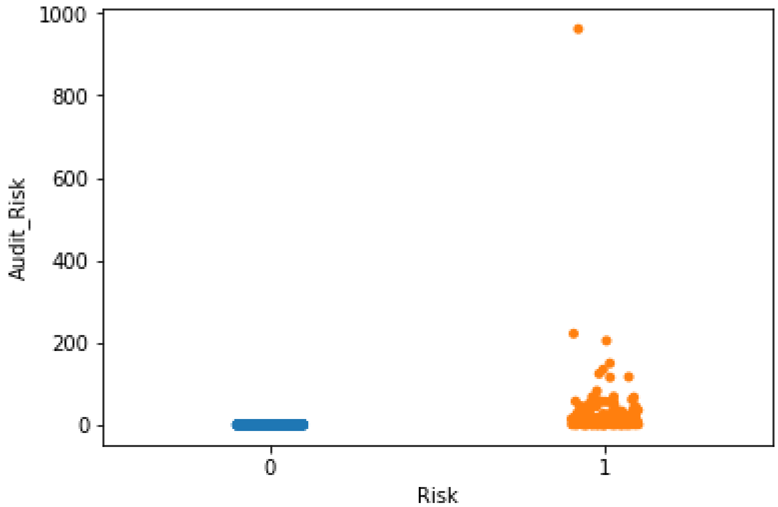
In [20]:
```
plt.figure(figsize=(30,20))
sns.barplot(x='LOCATION_ID',y='Audit_Risk',data= audit,estimator=np.mean)
```

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x1e46a16cb70>



In [21]:
```
#loooking for outliers in the audit's risk colum
sns.stripplot(x='Risk',y='Audit_Risk',data=audit)
```

Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x1e46a383c88>



Data Pre-processing

1. Imputing Missing values
2. Merging Data
3. Checking for outliers

1. Imputing Missing Values

In [22]:
```
audit['Money_Value'].unique()
```

Out[22]:
```
array([3.3800e+00, 9.4000e-01, 0.0000e+00, 1.1750e+01, 2.9500e+00,
       4.4950e+01, 7.7900e+00, 7.3400e+00, 1.9300e+00, 4.4200e+00,
       9.6000e-01, 1.0430e+01, 7.0000e-03, 9.0000e+00, 4.1280e+01,
       1.4030e+01, 6.3180e+01, 3.4240e+01, 1.0000e-02, 2.0519e+02,
       1.0000e-01, 1.1160e+01, 1.2500e+00, 1.4600e+00, 6.7800e+00,
       1.1600e+00, 1.5241e+02, 1.0800e+00, 2.8400e+00, 9.0000e-01,
       9.6700e+00, 3.2680e+01, 9.3503e+02, 2.9630e+01, 1.1000e-01,
       2.6200e+00, 6.0000e-02, 2.4300e+00, 1.2613e+02, 2.0790e+01,
       1.5692e+02, 1.2290e+01, 2.2900e+00, 7.7800e+00, 2.5100e+00,
       8.3100e+00, 1.6000e-01, 4.7900e+01, 8.9100e+00, 4.9500e+00,
       1.7500e+00, 6.8000e-01, 1.5820e+01, 5.8000e-01, 2.1531e+02,
       5.0000e-02, 5.3340e+01, 1.0690e+01, 5.6900e+00, 1.3500e+00,
       1.1690e+01, 1.4600e+01, 2.0780e+01, 1.0222e+02, 7.4000e-01,
       8.7337e+02, 1.4000e+00, 4.2000e-01, 3.6520e+01, 6.0200e+00,
       1.7160e+01, 1.2910e+01, 1.0790e+01, 3.4600e+00, 2.3300e+00,
       5.5800e+00, 7.6000e-01, 2.5270e+01, 2.0000e-01, 7.5600e+00,
       6.7030e+01, 1.9400e+01, 3.4830e+01, 9.8750e+01, 3.6000e-01,
       3.5210e+01, 8.2000e+00, 2.0330e+01, 3.5130e+01, 6.3700e+01,
       2.8000e-01, 2.7130e+01, 1.0270e+01, 1.3050e+01, 1.8790e+01,
       1.6820e+01, 1.0030e+01, 1.2670e+01, 1.3790e+01, 1.0160e+01,
       9.7300e+00, 2.6950e+01, 2.9070e+01, 9.7600e+00, 1.3310e+01,
       7.7000e+00, 1.0400e+01, 2.0620e+01, 4.4020e+01, 4.3530e+01,
       1.2030e+01, 1.1880e+01, 6.9600e+00, 2.1070e+01, 5.7160e+01,
       1.0650e+01, 5.3600e+00, 2.4500e+00, 3.1610e+01, 3.4320e+01,
       4.2400e+00, 8.3800e+00, 2.2100e+01, 5.4070e+01, 2.7680e+01,
       2.1450e+01, 1.1090e+01, 1.0140e+01, 5.2130e+01, 1.7020e+01,
       1.8000e+01, 6.9760e+01, 1.3880e+01, 4.0300e+00, 2.4400e+00,
       7.8980e+01, 6.8800e+00, 5.4900e+00, 3.7790e+01, 6.0880e+01,
       1.8320e+02, 1.0020e+01, 3.2000e-01, 1.8000e-01, 4.8560e+01,
       1.8450e+01, 8.4400e+00, 3.9650e+01, 9.5300e+00, 4.4670e+01,
       3.4200e+00, 2.6640e+01, 1.6910e+01, 1.2900e+01, 6.7900e+00,
       8.7600e+00, 2.1000e-01, 1.9680e+01, 1.4270e+01, 1.6190e+01,
       5.0300e+00, 1.4100e+01, 1.0239e+02, 4.2600e+00, 2.7230e+01,
       5.9180e+01, 1.3350e+01, 8.9640e+01, 8.0800e+01, 8.9500e+00,
       1.2459e+02, 5.8000e+00, 2.1600e+01, 1.4597e+02, 7.6470e+01,
       4.7600e+01, 2.8400e+01, 2.5970e+01, 8.5810e+01, 4.5370e+01,
       1.4300e+00, 1.5900e+00, 8.2990e+01, 8.6700e+01, 1.5140e+01,
       3.1380e+01, 7.1700e+00, 1.8240e+01, 5.8860e+01, 6.0600e+00,
       2.2800e+01, 5.3700e+00, 7.7470e+01, 1.5200e+01, 6.8014e+02,
       7.1000e-01, 1.4400e+00, 2.0000e-02, 4.6000e+00, 3.0850e+01,
       8.2100e+00, 4.9310e+01, 3.6900e+00, 1.1250e+01, 3.0800e+00,
       1.6030e+01, 3.4300e+00, 8.9000e-01, 1.2800e+00, 5.4200e+00,
       5.4100e+00, 7.2700e+00, 8.6000e+00, 3.6600e+00, 3.2500e+00,
       2.6280e+01, 2.2000e-01, 1.8200e+00, 8.2000e-01, 2.7990e+01,
       2.4700e+00, 7.5400e+00, 2.7100e+01, 4.0000e-02, 6.7000e-01,
       7.2000e-01, 8.4000e-01, 7.0000e-02, 1.2000e-01, 6.7300e+00,
       5.7000e-01, 6.1400e+00, 1.1500e+00, 3.6290e+01, 3.1000e-01,
       1.2200e+00, 2.3000e-01, 8.4437e+02, 1.9500e+00, 9.0000e-02,
       7.4800e+00, 9.4500e+00, 2.7700e+00, 2.7280e+01, 7.3000e-01,
       4.7000e-01, 1.7590e+02, 1.3540e+01, 4.1820e+01, 2.9760e+01,
       3.0000e-02, 8.5130e+01, 1.0980e+01, 1.7302e+02, 5.2000e-01,
       1.2400e+00, 1.1900e+00, 1.3000e-01, 1.0530e+01, 5.1000e-01,
       1.5000e-01, 4.9000e-01, 7.9000e-01, 1.9450e+01, 4.4000e-01,
       3.5000e-01, 3.5300e+00, 8.0000e-02, 4.3000e-01, 6.4000e-01,
       3.7000e-01, 9.7000e-01, 1.9000e-01, 1.4000e-01, 3.5400e+00,
       3.9200e+00, 3.3000e-01, 8.8400e+01, 2.0890e+01, 9.4750e+01,
       8.3960e+01, 3.9731e+02, 1.6041e+02, 2.3970e+01, 7.0560e+01,
```

```
       1.1330e+01, 1.3200e+00, 2.4000e-01, 6.5000e-01, 8.0000e-01,
       3.9000e-01, 1.3300e+01, 2.9000e-01, 3.3000e+00, 1.6090e+01,
       1.6600e+00, 7.0000e-01, 6.3000e-01, 9.3000e-01, 1.2000e+00,
       1.0300e+00, 2.8600e+00, 1.5500e+00, 2.3900e+00, 1.3000e+00,
       6.0000e-01, 1.7000e-01, 4.0000e-01, 3.6800e+00, 8.5050e+01,
       8.4700e+00, 2.5312e+02, 4.5000e-01, 6.4100e+00, 5.9000e-01,
       2.5000e-01, 6.5000e+00, 6.3100e+00, 1.6500e+00, 5.6100e+00,
       6.9000e-01, 9.9000e-01, 9.4300e+00,        nan, 8.8340e+01,
       3.5700e+00, 1.8000e+00, 1.9100e+00, 2.4000e+00])
```

In [23]:
```
trial['Money_Value'].unique()
```

```
Out[23]: array([3.3800e+00, 9.4000e-01, 0.0000e+00, 1.1750e+01, 2.9500e+00,
                4.4950e+01, 7.7900e+00, 7.3400e+00, 1.9300e+00, 4.4200e+00,
                9.6000e-01, 1.0430e+01, 7.0000e-03, 9.0000e+00, 4.1280e+01,
                1.4030e+01, 6.3180e+01, 3.4240e+01, 1.0000e-02, 2.0519e+02,
                1.0000e-01, 1.1160e+01, 1.2500e+00, 1.4600e+00, 6.7800e+00,
                1.1600e+00, 1.5241e+02, 1.0800e+00, 2.8400e+00, 9.0000e-01,
                9.6700e+00, 3.2680e+01, 9.3503e+02, 2.9630e+01, 1.1000e-01,
                2.6200e+00, 6.0000e-02, 2.4300e+00, 1.2613e+02, 2.0790e+01,
                1.5692e+02, 1.2290e+01, 2.2900e+00, 7.7800e+00, 2.5100e+00,
                8.3100e+00, 1.6000e-01, 4.7900e+01, 8.9100e+00, 4.9500e+00,
                1.7500e+00, 6.8000e-01, 1.5820e+01, 5.8000e-01, 2.1531e+02,
                5.0000e-02, 5.3340e+01, 1.0690e+01, 5.6900e+00, 1.3500e+00,
                1.1690e+01, 1.4600e+01, 2.0780e+01, 1.0222e+02, 7.4000e-01,
                8.7337e+02, 1.4000e+00, 4.2000e-01, 3.6520e+01, 6.0200e+00,
                1.7160e+01, 1.2910e+01, 1.0790e+01, 3.4600e+00, 2.3300e+00,
                5.5800e+00, 7.6000e-01, 2.5270e+01, 2.0000e-01, 7.5600e+00,
                6.7030e+01, 1.9400e+01, 3.4830e+01, 9.8750e+01, 3.6000e-01,
                3.5210e+01, 8.2000e+00, 2.0330e+01, 3.5130e+01, 6.3700e+01,
                2.8000e-01, 2.7130e+01, 1.0270e+01, 1.3050e+01, 1.8790e+01,
                1.6820e+01, 1.0030e+01, 1.2670e+01, 1.3790e+01, 1.0160e+01,
                9.7300e+00, 2.6950e+01, 2.9070e+01, 9.7600e+00, 1.3310e+01,
                7.7000e+00, 1.0400e+01, 2.0620e+01, 4.4020e+01, 4.3530e+01,
                1.2030e+01, 1.1880e+01, 6.9600e+00, 2.1070e+01, 5.7160e+01,
                1.0650e+01, 5.3600e+00, 2.4500e+00, 3.1610e+01, 3.4320e+01,
                4.2400e+00, 8.3800e+00, 2.2100e+01, 5.4070e+01, 2.7680e+01,
                2.1450e+01, 1.1090e+01, 1.0140e+01, 5.2130e+01, 1.7020e+01,
                1.8000e+01, 6.9760e+01, 1.3880e+01, 4.0300e+00, 2.4400e+00,
                7.8980e+01, 6.8800e+00, 5.4900e+00, 3.7790e+01, 6.0880e+01,
                1.8320e+02, 1.0020e+01, 3.2000e-01, 1.8000e-01, 4.8560e+01,
                1.8450e+01, 8.4400e+00, 3.9650e+01, 9.5300e+00, 4.4670e+01,
                3.4200e+00, 2.6640e+01, 1.6910e+01, 1.2900e+01, 6.7900e+00,
                8.7600e+00, 2.1000e-01, 1.9680e+01, 1.4270e+01, 1.6190e+01,
                5.0300e+00, 1.4100e+01, 1.0239e+02, 4.2600e+00, 2.7230e+01,
                5.9180e+01, 1.3350e+01, 8.9640e+01, 8.0800e+01, 8.9500e+00,
                1.2459e+02, 5.8000e+00, 2.1600e+01, 1.4597e+02, 7.6470e+01,
                4.7600e+01, 2.8400e+01, 2.5970e+01, 8.5810e+01, 4.5370e+01,
                1.4300e+00, 1.5900e+00, 8.2990e+01, 8.6700e+01, 1.5140e+01,
                3.1380e+01, 7.1700e+00, 1.8240e+01, 5.8860e+01, 6.0600e+00,
                2.2800e+01, 5.3700e+00, 7.7470e+01, 1.5200e+01, 6.8014e+02,
                7.1000e-01, 1.4400e+00, 2.0000e-02, 4.6000e+00, 3.0850e+01,
                8.2100e+00, 4.9310e+01, 3.6900e+00, 1.1250e+01, 3.0800e+00,
                1.6030e+01, 3.4300e+00, 8.9000e-01, 1.2800e+00, 5.4200e+00,
                5.4100e+00, 7.2700e+00, 8.6000e+00, 3.6600e+00, 3.2500e+00,
                2.6280e+01, 2.2000e-01, 1.8200e+00, 8.2000e-01, 2.7990e+01,
                2.4700e+00, 7.5400e+00, 2.7100e+01, 4.0000e-02, 6.7000e-01,
                7.2000e-01, 8.4000e-01, 7.0000e-02, 1.2000e-01, 6.7300e+00,
                5.7000e-01, 6.1400e+00, 1.1500e+00, 3.6290e+01, 3.1000e-01,
                1.2200e+00, 2.3000e-01, 8.4437e+02, 1.9500e+00, 9.0000e-02,
                7.4800e+00, 9.4500e+00, 2.7700e+00, 2.7280e+01, 7.3000e-01,
                4.7000e-01, 1.7590e+02, 1.3540e+01, 4.1820e+01, 2.9760e+01,
                3.0000e-02, 8.5130e+01, 1.0980e+01, 1.7302e+02, 5.2000e-01,
                1.2400e+00, 1.1900e+00, 1.3000e-01, 1.0530e+01, 5.1000e-01,
                1.5000e-01, 4.9000e-01, 7.9000e-01, 1.9450e+01, 4.4000e-01,
                3.5000e-01, 3.5300e+00, 8.0000e-02, 4.3000e-01, 6.4000e-01,
                3.7000e-01, 9.7000e-01, 1.9000e-01, 1.4000e-01, 3.5400e+00,
                3.9200e+00, 3.3000e-01, 8.8400e+01, 2.0890e+01, 9.4750e+01,
                8.3960e+01, 3.9731e+02, 1.6041e+02, 2.3970e+01, 7.0560e+01,
```

```
1.1330e+01, 1.3200e+00, 2.4000e-01, 6.5000e-01, 8.0000e-01,
3.9000e-01, 1.3300e+01, 2.9000e-01, 3.3000e+00, 1.6090e+01,
1.6600e+00, 7.0000e-01, 6.3000e-01, 9.3000e-01, 1.2000e+00,
1.0300e+00, 2.8600e+00, 1.5500e+00, 2.3900e+00, 1.3000e+00,
6.0000e-01, 1.7000e-01, 4.0000e-01, 3.6800e+00, 8.5050e+01,
8.4700e+00, 2.5312e+02, 4.5000e-01, 6.4100e+00, 5.9000e-01,
2.5000e-01, 6.5000e+00, 6.3100e+00, 1.6500e+00, 5.6100e+00,
6.9000e-01, 9.9000e-01, 9.4300e+00,        nan, 8.8340e+01,
3.5700e+00, 1.8000e+00, 1.9100e+00, 2.4000e+00])
```

Both audit & trail have one missing value. Since dataset is small its better to impute the missing value rather than removing missing values. So let's impute the missing Money_Value with it's mean grouped by 'numbers' column

In [24]:
```
audit[audit['Money_Value'].isnull()]
```

Out[24]:

	Sector_score	LOCATION_ID	PARA_A	Score_A	Risk_A	PARA_B	Score_B	Risk_B	TOTAl
642	55.57	4	0.23	0.2	0.046	0.0	0.2	0.0	0.2:

1 rows × 27 columns

In [25]:
```
audit['Sector_score'].value_counts()
```

Out[25]:
```
55.57    200
3.89     114
1.85      95
2.72      82
3.41      76
2.37      74
1.99      47
21.61     41
59.85     37
2.34       5
15.56      3
2.36       1
17.68      1
Name: Sector_score, dtype: int64
```

In [26]:
```
audit[['Sector_score','Money_Value']].groupby('Sector_score').mean()
```

Out[26]:

Sector_score	Money_Value
1.85	2.401579
1.99	26.892340
2.34	16.792000
2.36	88.400000
2.37	5.569189
2.72	30.059512
3.41	18.294737
3.89	33.157842
15.56	193.896667
17.68	70.560000
21.61	0.449024
55.57	2.574221
59.85	1.672703

In [27]:
```
audit[['Sector_score','Money_Value']].groupby('Sector_score').median()
```

Out[27]:

Sector_score	Money_Value
1.85	0.020
1.99	0.050
2.34	0.000
2.36	88.400
2.37	0.575
2.72	8.325
3.41	10.215
3.89	2.565
15.56	160.410
17.68	70.560
21.61	0.000
55.57	0.000
59.85	0.290

Sector_Score - Is the score of each firm mentioned above in Data Description

Missing value is in 'Money_Value' that falls under Sector_Score = 55.57.

Impute the missing value with median of Money_Value under Sector_score = 55.57

In [28]:
```
audit['Money_Value'].fillna(0,inplace=True)
trial['Money_Value'].fillna(0,inplace=True)
```

2. Merging Datasets

Both dataframes (audit, trial) have similar columns that hold similar value

First sort by common columns and concatenate later

So selecting only unique column from trial data frame and concatenating to audit for analysis

Removing the column ('LOCATION_ID') on which analysis is not done

In [29]:
```
# Sorting the data frames
audit = audit.sort_values(by=['LOCATION_ID','TOTAL'])
trial = trial.sort_values(by=['LOCATION_ID','TOTAL'])

#Concatinate data frames
data = pd.concat([audit,trial[['Loss','History_score','LOSS_SCORE','MONEY_Mark
s']]],axis=1)

#Removing LOCATION_ID
data.drop('LOCATION_ID',axis=1,inplace=True)
```

3. Handling Outliers

In data distribution section we can across an outlier with large Audit_Risk, TOTAL value. We can handle this enither by imputing with a mean value or removing the outlier value.

Let's remove the outlier observation from data

In [30]:
```
data['TOTAL'].max()
# 1268.91
```

Out[30]: 1268.91

In [31]:
```
data[data['TOTAL'] == 1268.91]
```

Out[31]:

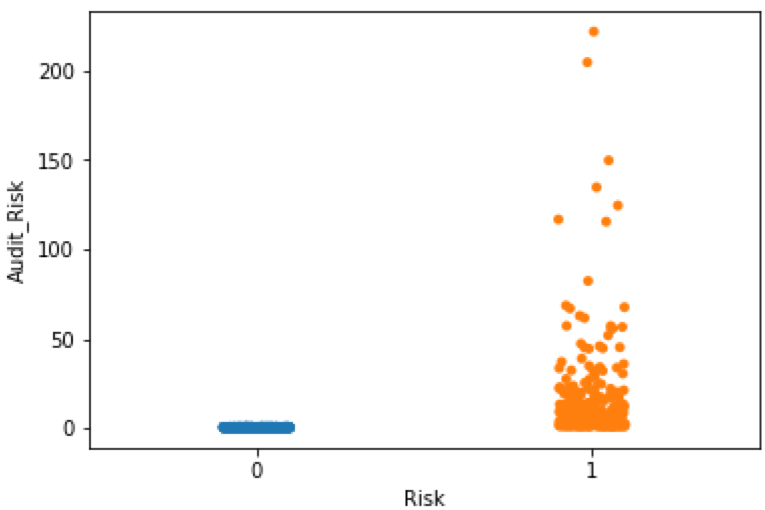
	Sector_score	PARA_A	Score_A	Risk_A	PARA_B	Score_B	Risk_B	TOTAL	numbers	S
241	2.72	4.28	0.6	2.568	1264.63	0.6	758.778	1268.91	5.5	

1 rows × 30 columns

In [32]:
```
# index = 241
data.drop(241,inplace=True)
```

In [33]:
```
#loooking for outliers in the risk colum after removing outlier
sns.stripplot(x='Risk',y='Audit_Risk',data=data)
```

Out[33]: <matplotlib.axes._subplots.AxesSubplot at 0x1e46aba3b00>



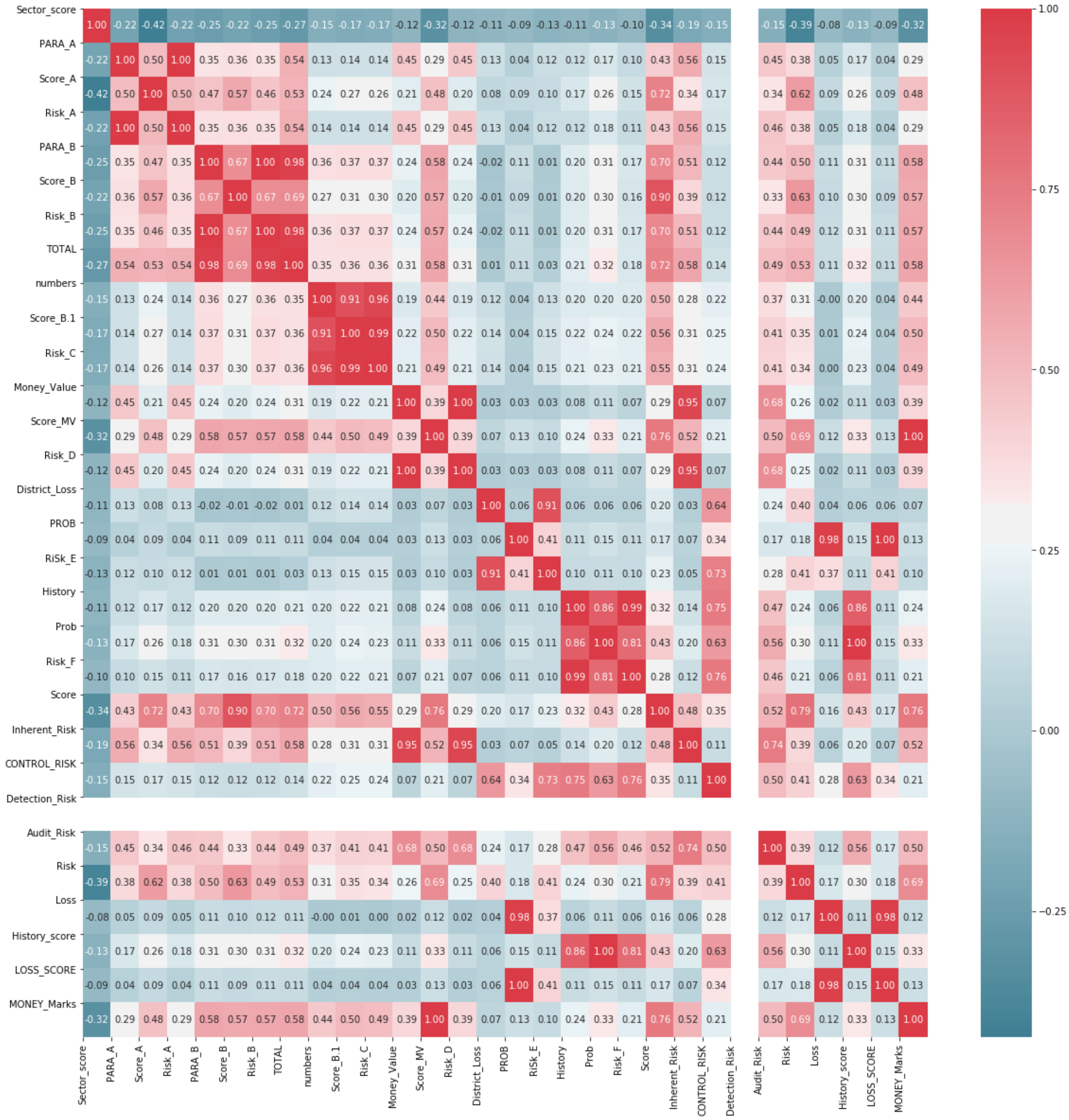
Feature Selection

In [34]:
```
data.columns
```

Out[34]:
```
Index(['Sector_score', 'PARA_A', 'Score_A', 'Risk_A', 'PARA_B', 'Score_B',
       'Risk_B', 'TOTAL', 'numbers', 'Score_B.1', 'Risk_C', 'Money_Value',
       'Score_MV', 'Risk_D', 'District_Loss', 'PROB', 'RiSk_E', 'History',
       'Prob', 'Risk_F', 'Score', 'Inherent_Risk', 'CONTROL_RISK',
       'Detection_Risk', 'Audit_Risk', 'Risk', 'Loss', 'History_score',
       'LOSS_SCORE', 'MONEY_Marks'],
      dtype='object')
```

In [35]:
```
fig, ax = plt.subplots(figsize=(20, 20))
corr = data.corr()
colormap = sns.diverging_palette(220, 10, as_cmap=True)
sns.heatmap(corr, cmap=colormap, annot=True, fmt=".2f")
plt.xticks(range(len(corr.columns)), corr.columns)
plt.yticks(range(len(corr.columns)), corr.columns)
```

Out[35]:
```
([<matplotlib.axis.YTick at 0x1e46abfab70>,
  <matplotlib.axis.YTick at 0x1e46abfa438>,
  <matplotlib.axis.YTick at 0x1e46abf9390>,
  <matplotlib.axis.YTick at 0x1e46b4c3978>,
  <matplotlib.axis.YTick at 0x1e46b4c3e48>,
  <matplotlib.axis.YTick at 0x1e46b4cd358>,
  <matplotlib.axis.YTick at 0x1e46b4cd828>,
  <matplotlib.axis.YTick at 0x1e46b4cdcf8>,
  <matplotlib.axis.YTick at 0x1e46b4d7208>,
  <matplotlib.axis.YTick at 0x1e46b4d7710>,
  <matplotlib.axis.YTick at 0x1e46b4d7c18>,
  <matplotlib.axis.YTick at 0x1e46b4d7cf8>,
  <matplotlib.axis.YTick at 0x1e46b4cd780>,
  <matplotlib.axis.YTick at 0x1e46b4de160>,
  <matplotlib.axis.YTick at 0x1e46b4de5f8>,
  <matplotlib.axis.YTick at 0x1e46b4deb00>,
  <matplotlib.axis.YTick at 0x1e46b4e70b8>,
  <matplotlib.axis.YTick at 0x1e46b4e7550>,
  <matplotlib.axis.YTick at 0x1e46b4e7a58>,
  <matplotlib.axis.YTick at 0x1e46b4e7f60>,
  <matplotlib.axis.YTick at 0x1e46b4e75f8>,
  <matplotlib.axis.YTick at 0x1e46b4deac8>,
  <matplotlib.axis.YTick at 0x1e46b4f04a8>,
  <matplotlib.axis.YTick at 0x1e46b4f08d0>,
  <matplotlib.axis.YTick at 0x1e46b4f0dd8>,
  <matplotlib.axis.YTick at 0x1e46b4f7320>,
  <matplotlib.axis.YTick at 0x1e46b4f7828>,
  <matplotlib.axis.YTick at 0x1e46b4f7d30>,
  <matplotlib.axis.YTick at 0x1e46b4fe278>,
  <matplotlib.axis.YTick at 0x1e46b4f77f0>],
 <a list of 30 Text yticklabel objects>)
```



Highly correlated variables deflects model's accuracy. So it's better to remove variables that are highly correlated. Choosing correlation = 0.7 as threshold and removing variables that have correlation greater than 0.7

Below are the columns that that are considered for analysis which are less correlated

Removing Risk column since it's formed due to Audit_Risk score. Being Risk(1/0) is due to Audit_Risk.

In [36]:
```
data = data[['Sector_score', 'PARA_A', 'Score_A','PARA_B', 'Score_B','numbers'
,'Money_Value','Score_MV','District_Loss','LOSS_SCORE','History_score','Audit_
Risk']]
```

In [37]:
```
data.columns
```

Out[37]:
```
Index(['Sector_score', 'PARA_A', 'Score_A', 'PARA_B', 'Score_B', 'numbers',
       'Money_Value', 'Score_MV', 'District_Loss', 'LOSS_SCORE',
       'History_score', 'Audit_Risk'],
      dtype='object')
```

Data Scaling

Since the variables we considered for analysis are not in same range we need to scale them before analysis.

In [38]:
```
X = data.drop('Audit_Risk',axis=1)
y = data['Audit_Risk']

from sklearn.model_selection import train_test_split
X_train_org, X_test_org, y_train, y_test = train_test_split(X, y, test_size=0.
2, random_state=0)

from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
X_train = scaler.fit_transform(X_train_org)
X_test = scaler.transform(X_test_org)
```

```
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:32
3: DataConversionWarning: Data with input dtype int64, float64 were all conve
rted to float64 by MinMaxScaler.
  return self.partial_fit(X, y)
```

Supervised Learning - Regression

1. Linear Regression
2. KNN Regressor
3. Ridge Regression
4. Lasso Regression
5. Polynomial Regression
6. SVM (simple & kernal)

1.Linear Regression

In [111]:
```
#Linear Regression
from sklearn import metrics
from sklearn.linear_model import LinearRegression
from sklearn.metrics import accuracy_score
lr = LinearRegression()
lr.fit(X_train,y_train)
print("Train:%.4f"%lr.score(X_train,y_train))
print("Test:%.4f"%lr.score(X_test,y_test))
pred = lr.predict(X_test)

print("Mean Squared Error Test:", metrics.mean_squared_error(y_test,pred))
```

```
Train:0.7544
Test:0.7233
Mean Squared Error Test: 0.06791434815183471
```

In [40]:
```
# Using GridSearch
from sklearn.model_selection import GridSearchCV
model = LinearRegression()
parameters = {'fit_intercept':[True,False], 'normalize':[True,False], 'copy_X'
:[True, False]}
grid = GridSearchCV(model,param_grid=parameters,cv=5)
grid.fit(X_train,y_train)
print("Train:%.4f"%grid.score(X_train,y_train))
print("Test:%.4f"%grid.score(X_test,y_test))
print("Best Parameters:{}",format(grid.best_params_))
```

```
Train:0.8002
Test:0.6659
Best Parameters:{} {'copy_X': True, 'fit_intercept': False, 'normalize': Tru
e}
```

In [41]:
```
#cross validation
from sklearn.model_selection import cross_val_score
lr = LinearRegression()
train_score = cross_val_score(lr,X_train,y_train,cv=10)
test_score = cross_val_score(lr,X_test,y_test,cv=10)

print("Avg Train Score:%.4f"%train_score.mean())
print("Avg Test Score:%.4f"%test_score.mean())
```

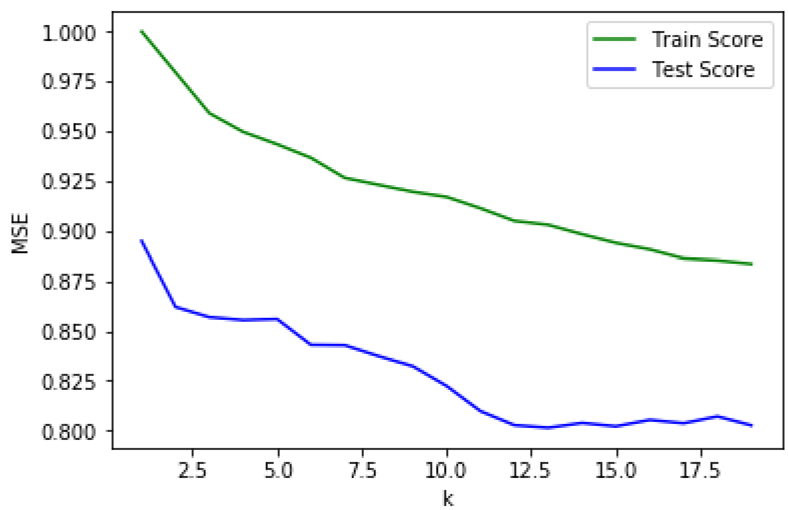
```
Avg Train Score:0.7300
Avg Test Score:-0.0222
```

2. KNN Regression

In [113]:
```
from sklearn.neighbors import KNeighborsRegressor
from sklearn.preprocessing import StandardScaler

X_train_org, X_test_org, y_train, y_test = train_test_split(X,y,test_size=0.2,
random_state = 0)

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train_org)
X_test = scaler.transform(X_test_org)

train_score_array = []
test_score_array = []

for k in range(1,20):
    knn_reg = KNeighborsRegressor(k)
    knn_reg.fit(X_train, y_train)
    train_score_array.append(knn_reg.score(X_train, y_train))
    test_score_array.append(knn_reg.score(X_test, y_test))

print("Train score: {}",format(train_score_array))
print("Test score: {}",format(test_score_array))
x_axis = range(1,20)
plt.plot(x_axis, train_score_array, c = 'g', label = 'Train Score')
plt.plot(x_axis, test_score_array, c = 'b', label = 'Test Score')
plt.legend()
plt.xlabel('k')
plt.ylabel('MSE')
```

```
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:62
5: DataConversionWarning: Data with input dtype int64, float64 were all conve
rted to float64 by StandardScaler.
  return self.partial_fit(X, y)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\base.py:462: DataConversi
onWarning: Data with input dtype int64, float64 were all converted to float64
by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
C:\Users\Tanmay\Anaconda3\lib\site-packages\ipykernel_launcher.py:8: DataConv
ersionWarning: Data with input dtype int64, float64 were all converted to flo
at64 by StandardScaler.


Train score: {} [1.0, 0.979508873979575, 0.95901774795915, 0.949625981866455
1, 0.9434444921836269, 0.9366292954553522, 0.9265386162397008, 0.923051552808
7164, 0.9195533571049981, 0.9169426358638773, 0.9112615699611347, 0.904943943
1830284, 0.902960170463431, 0.8982761958271758, 0.8939318602735332, 0.8906873
134040607, 0.8862234363756331, 0.8852328291613231, 0.8835241257786367]
Test score: {} [0.8948439620081411, 0.8619827001356852, 0.8568709482888588,
0.855410447761194, 0.8559362279511534, 0.842996193276044, 0.8428024534101292,
0.8373367537313433, 0.8322047171549659, 0.8222862957937584, 0.809676261816387
6, 0.8026498661993064, 0.8013546442076867, 0.8037713219616205, 0.802072968490
879, 0.8052970234056988, 0.8036056349269695, 0.8070516525118515, 0.8025775491
71794]
```

Out[113]: Text(0, 0.5, 'MSE')



In [114]:
```python
knn = KNeighborsRegressor(3)
knn.fit(X_train,y_train)
print(knn.score(X_train,y_train))
print(knn.score(X_test,y_test))
```

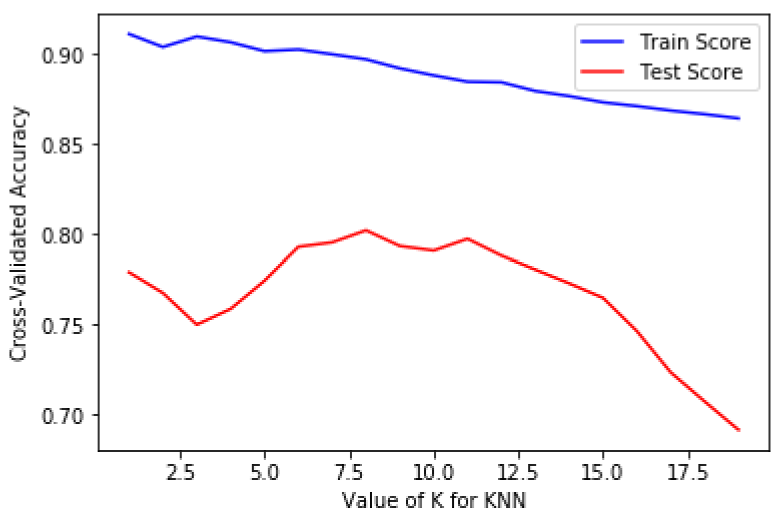
```
0.95901774795915
0.8568709482888588
```

In [115]:
```
# Using Cross Validation
from sklearn.model_selection import cross_val_score
knn_reg = KNeighborsRegressor(n_neighbors=3)
train_score = cross_val_score(knn_reg,X_train,y_train,cv=10)
test_score = cross_val_score(knn_reg,X_test,y_test,cv=10)

print("Avg Train Score:%.4f"%train_score.mean())
print("Avg Test Score:%.4f"%test_score.mean())
pred = knn.predict(X_test)
print("Mean Squared Error Test:", metrics.mean_squared_error(y_test,pred))
```

```
Avg Train Score:0.9100
Avg Test Score:0.7501
Mean Squared Error Test: 0.035125448028673840
```

In [116]:
```
k_range = range(1, 20)
# list of scores from k_range
k_train_scores = []
k_test_scores = []

# 1. we will loop through reasonable values of k
for k in k_range:
    # 2. run KNeighborsRegressor with k neighbours
    knn = KNeighborsRegressor(n_neighbors=k)
    # 3. obtain cross_val_score for KNeighborsRegressor with k neighbours
    scores1 = cross_val_score(knn, X_train, y_train, cv=10)
    scores2 = cross_val_score(knn, X_test, y_test, cv=10)
    # 4. append mean of scores for k neighbors to k_scores list
    k_train_scores.append(scores1.mean())
    k_test_scores.append(scores2.mean())

# plot the value of K for KNN (x-axis) versus the cross-validated accuracy (y-
axis)
plt.plot(k_range, k_train_scores,'b',label='Train Score')
plt.plot(k_range, k_test_scores,'r',label='Test Score')
plt.legend()
plt.xlabel('Value of K for KNN')
plt.ylabel('Cross-Validated Accuracy')
```

Out[116]: Text(0, 0.5, 'Cross-Validated Accuracy')



In [118]:
```
#Most efficient parameter using GridSearch()
from sklearn.model_selection import GridSearchCV
k_range = list(range(1, 31))
param_grid = dict(n_neighbors=k_range)
grid = GridSearchCV(knn, param_grid, cv=10)
grid.fit(X_train,y_train)
grid.best_score_
grid.best_estimator_

print("Best parameters: {}".format(grid.best_params_))
print("Best cross-validation score: {:.2f}".format(grid.best_score_))

results = pd.DataFrame(grid.cv_results_)
# show the first 5 rows
display(results.head())
```

```
Best parameters: {'n_neighbors': 1}
Best cross-validation score: 0.91
```

```
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:125:
FutureWarning: You are accessing a training score ('split0_train_score'), whi
ch will not be available by default any more in 0.21. If you need training sc
ores, please set return_train_score=True
  warnings.warn(*warn_args, **warn_kwargs)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:125:
FutureWarning: You are accessing a training score ('split1_train_score'), whi
ch will not be available by default any more in 0.21. If you need training sc
ores, please set return_train_score=True
  warnings.warn(*warn_args, **warn_kwargs)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:125:
FutureWarning: You are accessing a training score ('split2_train_score'), whi
ch will not be available by default any more in 0.21. If you need training sc
ores, please set return_train_score=True
  warnings.warn(*warn_args, **warn_kwargs)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:125:
FutureWarning: You are accessing a training score ('split3_train_score'), whi
ch will not be available by default any more in 0.21. If you need training sc
ores, please set return_train_score=True
  warnings.warn(*warn_args, **warn_kwargs)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:125:
FutureWarning: You are accessing a training score ('split4_train_score'), whi
ch will not be available by default any more in 0.21. If you need training sc
ores, please set return_train_score=True
  warnings.warn(*warn_args, **warn_kwargs)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:125:
FutureWarning: You are accessing a training score ('split5_train_score'), whi
ch will not be available by default any more in 0.21. If you need training sc
ores, please set return_train_score=True
  warnings.warn(*warn_args, **warn_kwargs)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:125:
FutureWarning: You are accessing a training score ('split6_train_score'), whi
ch will not be available by default any more in 0.21. If you need training sc
ores, please set return_train_score=True
  warnings.warn(*warn_args, **warn_kwargs)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:125:
FutureWarning: You are accessing a training score ('split7_train_score'), whi
ch will not be available by default any more in 0.21. If you need training sc
ores, please set return_train_score=True
  warnings.warn(*warn_args, **warn_kwargs)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:125:
FutureWarning: You are accessing a training score ('split8_train_score'), whi
ch will not be available by default any more in 0.21. If you need training sc
ores, please set return_train_score=True
  warnings.warn(*warn_args, **warn_kwargs)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:125:
FutureWarning: You are accessing a training score ('split9_train_score'), whi
ch will not be available by default any more in 0.21. If you need training sc
ores, please set return_train_score=True
  warnings.warn(*warn_args, **warn_kwargs)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:125:
FutureWarning: You are accessing a training score ('mean_train_score'), which
will not be available by default any more in 0.21. If you need training score
s, please set return_train_score=True
  warnings.warn(*warn_args, **warn_kwargs)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:125:
FutureWarning: You are accessing a training score ('std_train_score'), which
```

```
will not be available by default any more in 0.21. If you need training score
s, please set return_train_score=True
  warnings.warn(*warn_args, **warn_kwargs)
```

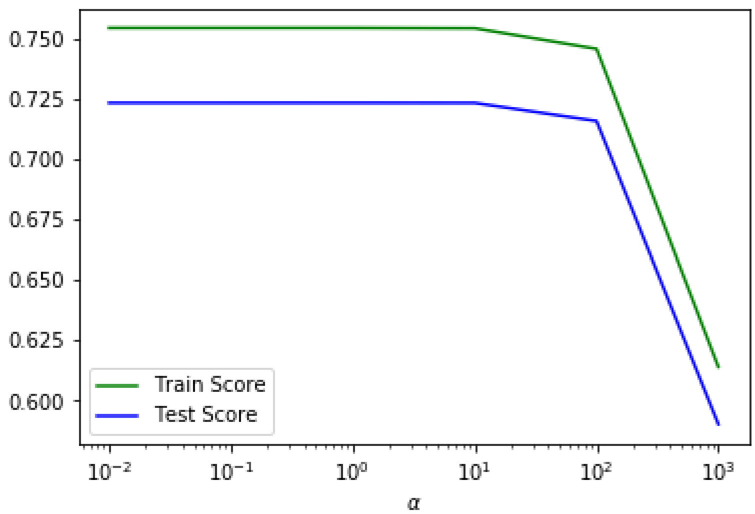
	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_n_neighbors	parar
0	0.000997	0.000446	0.001297	0.000457	1	{'n_neighbor
1	0.000898	0.000299	0.001097	0.000299	2	{'n_neighbor
2	0.000997	0.000446	0.001097	0.000299	3	{'n_neighbor
3	0.001094	0.000538	0.001299	0.000455	4	{'n_neighbor
4	0.000693	0.000454	0.001388	0.000481	5	{'n_neighbor

5 rows × 31 columns

3.Ridge Regression

In [120]:
```
from  sklearn.linear_model import Ridge

x_range = [0.01, 0.1, 1, 10, 100,1000]
train_score_list = []
test_score_list = []

for alpha in x_range:
    ridge = Ridge(alpha)
    ridge.fit(X_train,y_train)
    train_score_list.append(ridge.score(X_train,y_train))
    test_score_list.append(ridge.score(X_test, y_test))

plt.plot(x_range, train_score_list, c = 'g', label = 'Train Score')
plt.plot(x_range, test_score_list, c = 'b', label = 'Test Score')
plt.xscale('log')
plt.legend(loc = 3)
plt.xlabel(r'$\alpha$')
```

Out[120]:
```
Text(0.5, 0, '$\\alpha$')
```

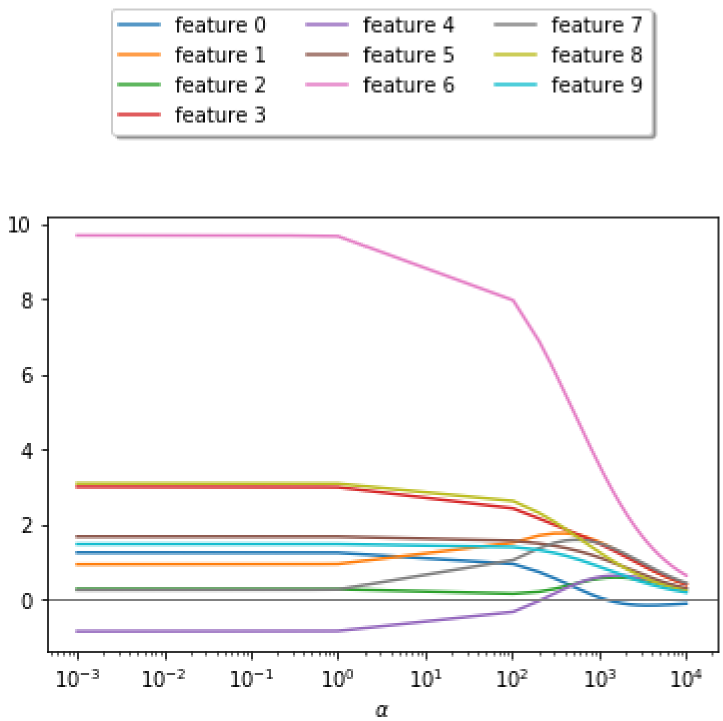


In [121]:
```
ridge = Ridge(alpha = 0.01)
ridge.fit(X_train,y_train)
print('Train score: {:.4f}'.format(ridge.score(X_train,y_train)))
print('Test score: {:.4f}'.format(ridge.score(X_test, y_test)))
pred = ridge.predict(X_test)
print("Mean Squared Error Test:", metrics.mean_squared_error(y_test,pred))
```

```
Train score: 0.7544
Test score: 0.7233
Mean Squared Error Test: 0.0679143177607114
```

In [49]:
```
x_range1 = np.linspace(0.001, 1, 100).reshape(-1,1)
x_range2 = np.linspace(1, 10000, 100).reshape(-1,1)

x_range = np.append(x_range1, x_range2)
coeff = []

for alpha in x_range:
    ridge = Ridge(alpha)
    ridge.fit(X_train,y_train)
    coeff.append(ridge.coef_ )

coeff = np.array(coeff)

for i in range(0,10):
    plt.plot(x_range, coeff[:,i], label = 'feature {:d}'.format(i))

plt.axhline(y=0, xmin=0.001, xmax=9999, linewidth=1, c ='gray')
plt.xlabel(r'$\alpha$')
plt.xscale('log')
plt.legend(loc='upper center', bbox_to_anchor=(0.5, 1.5),
          ncol=3, fancybox=True, shadow=True)
```

Out[49]: <matplotlib.legend.Legend at 0x1e46c262e10>

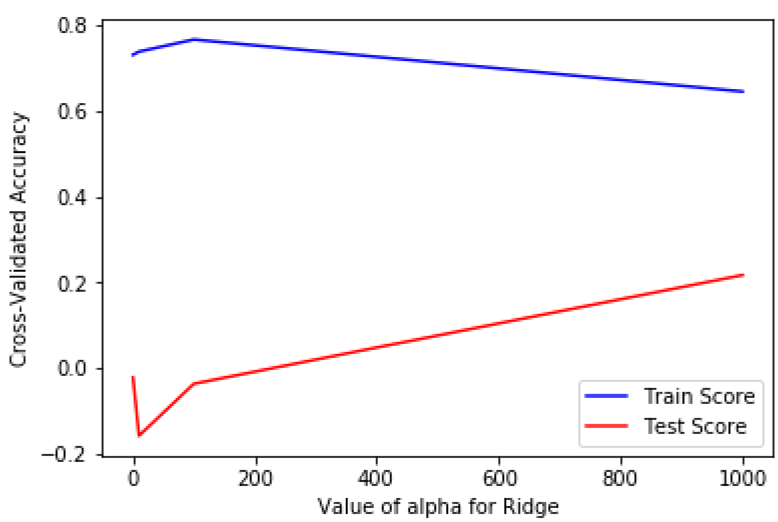


In [125]:
```
#cross validation
ridge = Ridge(alpha = 1000)
train_score = cross_val_score(ridge,X_train,y_train,cv=5)
test_score = cross_val_score(ridge,X_test,y_test,cv=5)
print("Avg Train Score:%.4f"%train_score.mean())
print("Avg Test Score:%.4f"%test_score.mean())
```

```
Avg Train Score:0.5754
Avg Test Score:0.3051
```

In [51]:
```
alpha = [0.001,0.01, 0.1,1,10,100,1000]

ridge_train_scores = []
ridge_test_scores = []

# 1. we will loop through reasonable values of k
for i in alpha:
    # 2. run KNeighborsClassifier with k neighbours
    ridge = Ridge(i)
    # 3. obtain cross_val_score for KNeighborsClassifier with k neighbours
    scores1 = cross_val_score(ridge, X_train, y_train, cv=10)
    scores2 = cross_val_score(ridge, X_test, y_test, cv=10)
    # 4. append mean of scores for k neighbors to k_scores list
    ridge_train_scores.append(scores1.mean())
    ridge_test_scores.append(scores2.mean())

# plot the value of K for KNN (x-axis) versus the cross-validated accuracy (y-axis)
plt.plot(alpha, ridge_train_scores,'b',label='Train Score')
plt.plot(alpha, ridge_test_scores,'r',label='Test Score')
plt.legend()
plt.xlabel('Value of alpha for Ridge')
plt.ylabel('Cross-Validated Accuracy')
```

Out[51]:
```
Text(0, 0.5, 'Cross-Validated Accuracy')
```



In [52]:
```
# GridSearch()
from sklearn.model_selection import GridSearchCV
alphas = np.array([1000,100,10,1,0.1,0.01,0.001])
model = Ridge()
grid = GridSearchCV(estimator=model, param_grid=dict(alpha=alphas))
grid.fit(X_train,y_train)

print("Best parameters: {}".format(grid.best_params_))
print("Best cross-validation score: {:.2f}".format(grid.best_score_))

results = pd.DataFrame(grid.cv_results_)
# show the first 5 rows
display(results.head())
```

```
Best parameters: {'alpha': 100.0}
Best cross-validation score: 0.75
```

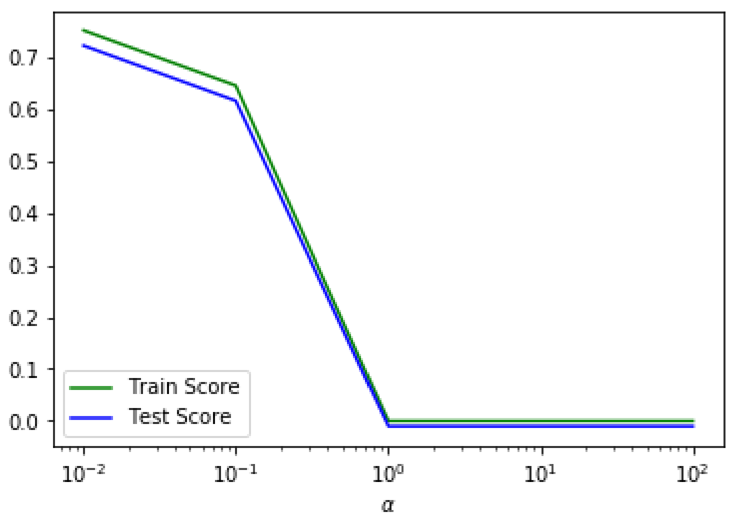
```
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\model_selection\_split.p
y:2053: FutureWarning: You should specify a value for 'cv' instead of relying
on the default value. The default value will change from 3 to 5 in version 0.
22.
  warnings.warn(CV_WARNING, FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\model_selection\_search.p
y:841: DeprecationWarning: The default of the `iid` parameter will change fro
m True to False in version 0.22 and will be removed in 0.24. This will change
numeric results when test-set sizes are unequal.
  DeprecationWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:125:
FutureWarning: You are accessing a training score ('split0_train_score'), whi
ch will not be available by default any more in 0.21. If you need training sc
ores, please set return_train_score=True
  warnings.warn(*warn_args, **warn_kwargs)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:125:
FutureWarning: You are accessing a training score ('split1_train_score'), whi
ch will not be available by default any more in 0.21. If you need training sc
ores, please set return_train_score=True
  warnings.warn(*warn_args, **warn_kwargs)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:125:
FutureWarning: You are accessing a training score ('split2_train_score'), whi
ch will not be available by default any more in 0.21. If you need training sc
ores, please set return_train_score=True
  warnings.warn(*warn_args, **warn_kwargs)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:125:
FutureWarning: You are accessing a training score ('mean_train_score'), which
will not be available by default any more in 0.21. If you need training score
s, please set return_train_score=True
  warnings.warn(*warn_args, **warn_kwargs)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:125:
FutureWarning: You are accessing a training score ('std_train_score'), which
will not be available by default any more in 0.21. If you need training score
s, please set return_train_score=True
  warnings.warn(*warn_args, **warn_kwargs)
```

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_alpha	params	split0_te
0	0.000665	4.703589e-04	0.000332	0.00047	1000	{'alpha': 1000.0}	
1	0.000665	4.701341e-04	0.000332	0.00047	100	{'alpha': 100.0}	
2	0.000665	4.703027e-04	0.000332	0.00047	10	{'alpha': 10.0}	
3	0.000997	6.257699e-07	0.000000	0.00000	1	{'alpha': 1.0}	
4	0.000665	4.701903e-04	0.000332	0.00047	0.1	{'alpha': 0.1}	

4.Lasso

In [126]:
```
from sklearn.linear_model import Lasso
x_range = [0.01, 0.1, 1, 10, 100]
train_score_list = []
test_score_list = []

for alpha in x_range:
    lasso = Lasso(alpha)
    lasso.fit(X_train,y_train)
    train_score_list.append(lasso.score(X_train,y_train))
    test_score_list.append(lasso.score(X_test, y_test))

plt.plot(x_range, train_score_list, c = 'g', label = 'Train Score')
plt.plot(x_range, test_score_list, c = 'b', label = 'Test Score')
plt.xscale('log')
plt.legend(loc = 3)
plt.xlabel(r'$\alpha$')
```

Out[126]:
```
Text(0.5, 0, '$\\alpha$')
```

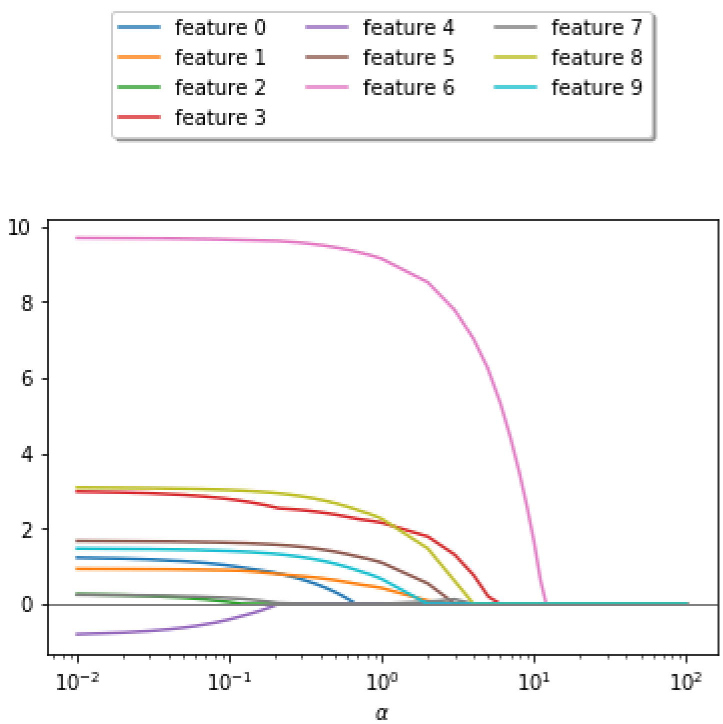


In [128]:
```
lasso = Lasso(alpha=0.01)
lasso.fit(X_train,y_train)
print('Train score: {:.4f}'.format(lasso.score(X_train,y_train)))
print('Test score: {:.4f}'.format(lasso.score(X_test, y_test)))
pred = lasso.predict(X_test)
print("Mean Squared Error Test:", metrics.mean_squared_error(y_test,pred))
```

```
Train score: 0.7507
Test score: 0.7214
Mean Squared Error Test: 0.06837231408835201
```

In [55]:
```
x_range1 = np.linspace(0.01, 1, 100).reshape(-1,1)
x_range2 = np.linspace(1, 100, 100).reshape(-1,1)

x_range = np.append(x_range1, x_range2)
coeff = []

for alpha in x_range:
    lasso = Lasso(alpha)
    lasso.fit(X_train,y_train)
    coeff.append(lasso.coef_ )

coeff = np.array(coeff)

for i in range(0,10):
    plt.plot(x_range, coeff[:,i], label = 'feature {:d}'.format(i))

plt.axhline(y=0, xmin=0.001, xmax=9999, linewidth=1, c ='gray')
plt.xlabel(r'$\alpha$')
plt.xscale('log')
plt.legend(loc='upper center', bbox_to_anchor=(0.5, 1.5),
          ncol=3, fancybox=True, shadow=True)
```

Out[55]: <matplotlib.legend.Legend at 0x1e46d8dbcf8>



In [56]:
```
#Grid_Search
param_grid = {'alpha':[0.001, 0.01, 0.1, 1, 10, 100]}
grid_search = GridSearchCV(Lasso(),param_grid,cv=5,return_train_score=True)
grid_search.fit(X_train,y_train)

print("Best parameters: {}".format(grid_search.best_params_))
print("Best cross-validation score: {:.2f}".format(grid_search.best_score_))

results = pd.DataFrame(grid_search.cv_results_)
# show the first 5 rows
display(results.head())
```

```
Best parameters: {'alpha': 1}
Best cross-validation score: 0.78
```

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_alpha	params	split0_te
0	0.001197	0.000399	0.000599	0.000489	0.001	{'alpha': 0.001}	
1	0.000598	0.000488	0.000200	0.000399	0.01	{'alpha': 0.01}	
2	0.000798	0.000399	0.000200	0.000399	0.1	{'alpha': 0.1}	
3	0.000399	0.000489	0.000399	0.000489	1	{'alpha': 1}	
4	0.000399	0.000489	0.000199	0.000399	10	{'alpha': 10}	-

5 rows × 21 columns

In [57]:
```
#cross validation
lasso = Lasso(alpha =0.001)
train_score = cross_val_score(lasso,X_train,y_train,cv=5)
test_score = cross_val_score(lasso,X_test,y_test,cv=5)
print("Avg Train Score:%.4f"%train_score.mean())
print("Avg Test Score:%.4f"%test_score.mean())
```

```
Avg Train Score:0.7572
Avg Test Score:-0.1782
```

5. Polynomial

In [138]:
```
from sklearn.preprocessing import PolynomialFeatures

train_score_list = []
test_score_list = []

for n in range(1,3):
    poly = PolynomialFeatures(n)
    X_train_poly = poly.fit_transform(X_train)
    X_test_poly = poly.transform(X_test)
    lr.fit(X_train_poly, y_train)
    train_score_list.append(lr.score(X_train_poly, y_train))
    test_score_list.append(lr.score(X_test_poly, y_test))

print(train_score_list)
print(test_score_list)
pred = lr.predict(X_test_poly)
print("Mean Squared Error Test:", metrics.mean_squared_error(y_test,pred))
```

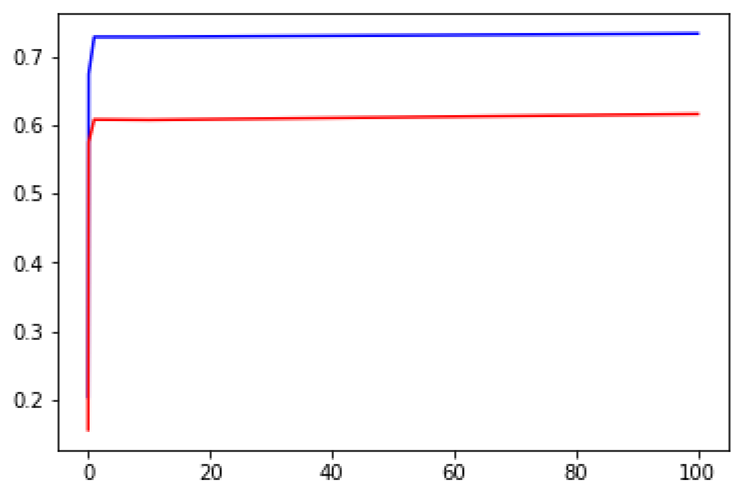
```
[0.7543570677111144, 0.9052075426722959]
[0.723262853740192, 0.692590358908533]
Mean Squared Error Test: 0.0754417167065677
```

6. SVM(simple)

In [59]:
```
from sklearn.svm import LinearSVR
train_score = []
test_score = []
C = [0.01,0.1,1,10,100]

for i in C:
    svr = LinearSVR(C=i)
    svr.fit(X_train,y_train)
    train_score.append(svr.score(X_train,y_train))
    test_score.append(svr.score(X_test,y_test))

plt.plot(C,train_score,'b')
plt.plot(C,test_score,'r')
```

```
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
```

Out[59]:
```
[<matplotlib.lines.Line2D at 0x1e46d97d9e8>]
```



In [60]:
```
svr = LinearSVR(C=10)
svr.fit(X_train,y_train)
print('Train score: {:.4f}'.format(svr.score(X_train,y_train)))
print('Test score: {:.4f}'.format(svr.score(X_test, y_test)))
```

```
Train score: 0.7283
Test score: 0.6079

C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
```

In [61]:
```
# Grid_Search
from sklearn.model_selection import GridSearchCV
param_grid ={'C':[0.001, 0.01, 0.1, 1, 10]}
grid_search = GridSearchCV(LinearSVR(),param_grid,cv=5,return_train_score=True
)

grid_search.fit(X_train,y_train)

print("Best parameters: {}".format(grid_search.best_params_))
print("Best cross-validation score: {:.2f}".format(grid_search.best_score_))

results = pd.DataFrame(grid_search.cv_results_)
# show the first 5 rows
display(results.head())
```

```
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
```

```
Best parameters: {'C': 10}
Best cross-validation score: 0.77
```

```
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
```

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_C	params	split0_test_s
0	0.000599	0.000489	0.000399	0.000488	0.001	{'C': 0.001}	-0.09
1	0.001005	0.000016	0.000000	0.000000	0.01	{'C': 0.01}	0.08
2	0.001590	0.000483	0.000199	0.000399	0.1	{'C': 0.1}	0.51
3	0.015167	0.003713	0.000399	0.000489	1	{'C': 1}	0.62
4	0.023535	0.001493	0.000199	0.000399	10	{'C': 10}	0.62

5 rows × 21 columns

In [62]:
```
#cross validation
svr = LinearSVR(C=10)
train_score = cross_val_score(svr,X_train,y_train,cv=5)
test_score = cross_val_score(svr,X_test,y_test,cv=5)
print("Avg Train Score:%.4f"%train_score.mean())
print("Avg Test Score:%.4f"%test_score.mean())
```

```
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)

Avg Train Score:0.7734
Avg Test Score:0.5096

C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
```

Supervised Learning - Classification

1. KNN Classification
2. Logistic Regression
3. Linear SVM
4. Kernalized SVM
5. Decision Tree

In [63]:
```
audit = pd.read_csv('audit_risk.csv')
trial = pd.read_csv('trial.csv')
audit['Money_Value'].fillna(0,inplace=True)
trial['Money_Value'].fillna(0,inplace=True)
# Sorting the data frames
audit = audit.sort_values(by=['LOCATION_ID','TOTAL'])
trial = trial.sort_values(by=['LOCATION_ID','TOTAL'])

#Concatinate data frames
data = pd.concat([audit,trial[['Loss','History_score','LOSS_SCORE','MONEY_Mark
s']]],axis=1)

#Removing LOCATION_ID
data.drop('LOCATION_ID',axis=1,inplace=True)

data['TOTAL'].max()
# 1268.91
data[data['TOTAL'] == 1268.91]
# index = 241
data.drop(241,inplace=True)
```

Repeating the same Data pre-processing, exploratory analysis, and feature selection.

Only difference is for classification we consider Risk variable.

So we drop the Audit_Risk and include Risk variable for analysis.

In [64]:
```
data = data[['Sector_score', 'PARA_A', 'Score_A','PARA_B', 'Score_B','numbers'
,'Money_Value','Score_MV','District_Loss','LOSS_SCORE','History_score','Risk'
]]
```

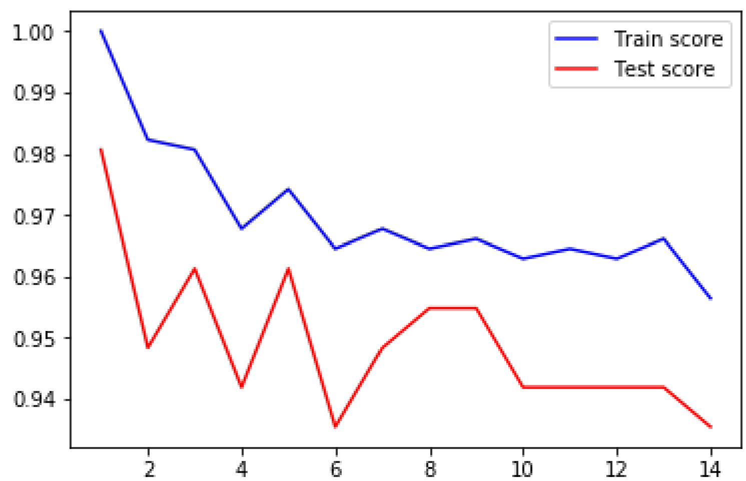
In [65]:
```
from sklearn.model_selection import train_test_split
X = data.drop('Risk',axis=1)
y = data['Risk']

X_train_org, X_test_org, y_train, y_test = train_test_split(X, y, test_size=0.
2, random_state=0)

from sklearn.preprocessing import MinMaxScaler
scale = MinMaxScaler()
X_train = scale.fit_transform(X_train_org)
X_test = scale.transform(X_test_org)
```

```
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:32
3: DataConversionWarning: Data with input dtype int64, float64 were all conve
rted to float64 by MinMaxScaler.
  return self.partial_fit(X, y)
```

1. KNN Classification

In [66]:
```
from sklearn.neighbors import KNeighborsClassifier
train_score = []
test_score = []

n = range(1,15)
for i in n:
    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(X_train,y_train)
    train_score.append(knn.score(X_train,y_train))
    test_score.append(knn.score(X_test,y_test))

plt.plot(n,train_score,'b',label='Train score')
plt.plot(n,test_score,'r',label = 'Test score')
plt.legend()
```

Out[66]:
```
<matplotlib.legend.Legend at 0x1e46da092b0>
```



In [67]:
```
knn = KNeighborsClassifier(5)
knn.fit(X_train, y_train)
print('Train score: {:.4f}'.format(knn.score(X_train, y_train)))
print('Test score: {:.4f}'.format(knn.score(X_test, y_test)))
```

```
Train score: 0.9742
Test score: 0.9613
```

In [68]:
```
from sklearn.metrics import classification_report,confusion_matrix
predictions = knn.predict(X_test)
print(confusion_matrix(y_test,predictions))
print(classification_report(y_test,predictions))
```

```
[[87  1]
 [ 5 62]]
              precision    recall  f1-score   support

           0       0.95      0.99      0.97        88
           1       0.98      0.93      0.95        67

   micro avg       0.96      0.96      0.96       155
   macro avg       0.96      0.96      0.96       155
weighted avg       0.96      0.96      0.96       155
```

In [69]:
```
#Cross validation
knn = KNeighborsClassifier(n_neighbors=5)
scores = cross_val_score(knn, X_train, y_train, cv=5, scoring='accuracy')
scores1= cross_val_score(knn, X_test, y_test, cv=5, scoring='accuracy')

print('Avg train score: {:.4f}'.format(scores.mean()))
print('Avg train score: {:.4f}'.format(scores1.mean()))
```

```
Avg train score: 0.9629
Avg train score: 0.9348
```

In [70]:
```
#Grid Search
from sklearn.model_selection import GridSearchCV
k_range = list(range(1, 21))
param_grid = dict(n_neighbors=k_range)
grid = GridSearchCV(knn, param_grid, cv=10, scoring='accuracy')
grid.fit(X_train, y_train)
print('Best Score: {:.4f}'.format(grid.best_score_))
print('Best Paramater: {:}'.format(grid.best_params_))
```

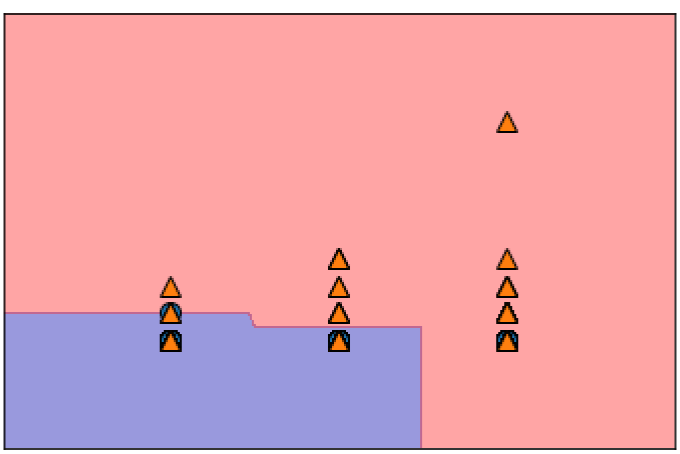
```
Best Score: 0.9710
Best Paramater: {'n_neighbors': 1}
```

In [71]:
```
cvres = grid.cv_results_
for mean_score, params in zip(cvres["mean_test_score"], cvres["params"]):
    print(np.sqrt(mean_score), params)
```

```
0.9853769542340047 {'n_neighbors': 1}
0.9796312670361429 {'n_neighbors': 2}
0.981276324898574 {'n_neighbors': 3}
0.981276324898574 {'n_neighbors': 4}
0.9804541409880654 {'n_neighbors': 5}
0.9788077013024735 {'n_neighbors': 6}
0.981276324898574 {'n_neighbors': 7}
0.9771584874918804 {'n_neighbors': 8}
0.9796312670361429 {'n_neighbors': 9}
0.9779834420393966 {'n_neighbors': 10}
0.9788077013024735 {'n_neighbors': 11}
0.9763328358974787 {'n_neighbors': 12}
0.9771584874918804 {'n_neighbors': 13}
0.9755064854862865 {'n_neighbors': 14}
0.9746794344808963 {'n_neighbors': 15}
0.9738516810963533 {'n_neighbors': 16}
0.9746794344808963 {'n_neighbors': 17}
0.9730232235401101 {'n_neighbors': 18}
0.9730232235401101 {'n_neighbors': 19}
0.9713641887040999 {'n_neighbors': 20}
```

In [72]:
```
import mglearn
x_b = X_train[0:774,[2,5]]
y_b = y_train[0:774]

knn = KNeighborsClassifier(7)
knn.fit(x_b, y_b)

mglearn.plots.plot_2d_separator(knn, x_b, fill=True, eps=0.5, alpha=.4)
mglearn.discrete_scatter(x_b[:, 0], x_b[:, 1], y_b)
```

Out[72]:
```
[<matplotlib.lines.Line2D at 0x1e4718b6da0>,
 <matplotlib.lines.Line2D at 0x1e471605198>]
```

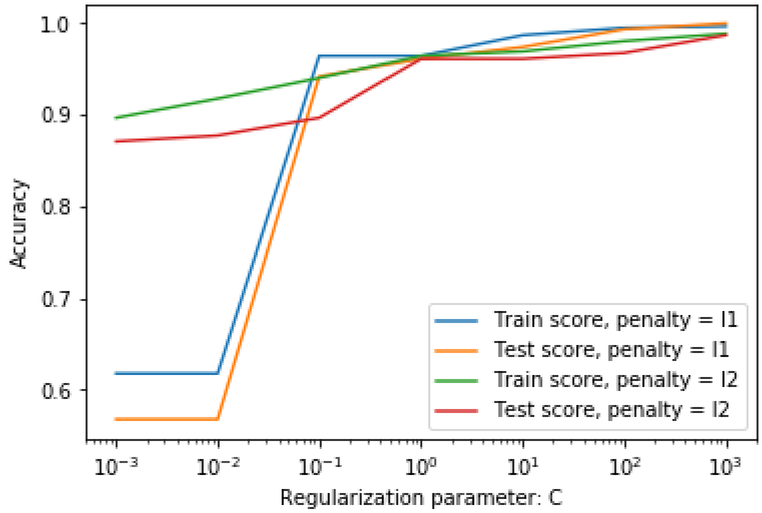


2. Logistic Regression

In [73]:
```
from sklearn.linear_model import LogisticRegression

c_range = [0.001, 0.01, 0.1, 1, 10, 100, 1000]
train_score_l1 = []
train_score_l2 = []
test_score_l1 = []
test_score_l2 = []

for c in c_range:
    log_l1 = LogisticRegression(penalty = 'l1', C = c)
    log_l2 = LogisticRegression(penalty = 'l2', C = c)
    log_l1.fit(X_train, y_train)
    log_l2.fit(X_train, y_train)
    train_score_l1.append(log_l1.score(X_train, y_train))
    train_score_l2.append(log_l2.score(X_train, y_train))
    test_score_l1.append(log_l1.score(X_test, y_test))
    test_score_l2.append(log_l2.score(X_test, y_test))

import matplotlib.pyplot as plt
%matplotlib inline

plt.plot(c_range, train_score_l1, label = 'Train score, penalty = l1')
plt.plot(c_range, test_score_l1, label = 'Test score, penalty = l1')
plt.plot(c_range, train_score_l2, label = 'Train score, penalty = l2')
plt.plot(c_range, test_score_l2, label = 'Test score, penalty = l2')
plt.legend()
plt.xlabel('Regularization parameter: C')
plt.ylabel('Accuracy')
plt.xscale('log')
```

```
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: Converge
nceWarning: Liblinear failed to converge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
```

```
y a solver to silence this warning.
  FutureWarning)
```



In [74]:
```
log_l1 = LogisticRegression(penalty = 'l1', C = 0.1)
log_l2 = LogisticRegression(penalty = 'l2', C = 1)
log_l1.fit(X_train,y_train)
log_l2.fit(X_train,y_train)
print("Penality: l1")
print("Train_score:{:.4f}".format(log_l1.score(X_train, y_train)))
print("Test_score:{:.4f}".format(log_l1.score(X_test, y_test)))
print("Penality: l2")
print("Train_score:{:.4f}".format(log_l2.score(X_train, y_train)))
print("Test_score:{:.4f}".format(log_l2.score(X_test, y_test)))
```

```
Penality: l1
Train_score:0.9645
Test_score:0.9419
Penality: l2
Train_score:0.9645
Test_score:0.9613

C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
```

In [75]:
```
#Confusion Matrix
from sklearn.metrics import classification_report, confusion_matrix
pred = log_l2.predict(X_test)
print(confusion_matrix(y_test, pred))
print(classification_report(y_test, pred))
```

```
[[87  1]
 [ 5 62]]
              precision    recall  f1-score   support

           0       0.95      0.99      0.97        88
           1       0.98      0.93      0.95        67

   micro avg       0.96      0.96      0.96       155
   macro avg       0.96      0.96      0.96       155
weighted avg       0.96      0.96      0.96       155
```

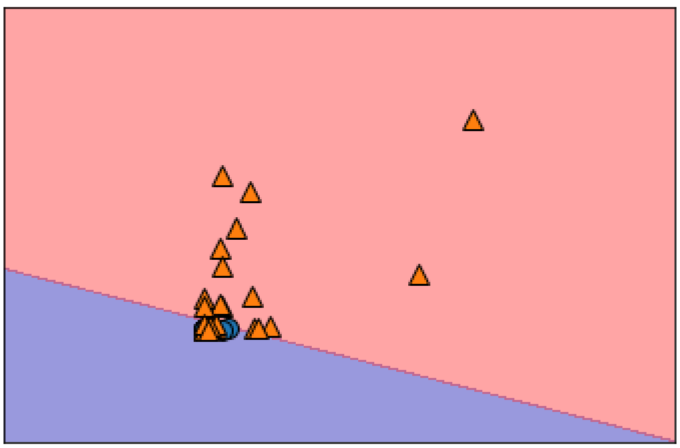
In [76]:
```
#Cross validation
log_l2 = LogisticRegression(penalty = 'l2', C = 1)
scores = cross_val_score(log_l2, X_train, y_train, cv=5, scoring='accuracy')
scores1= cross_val_score(log_l2, X_test, y_test, cv=5, scoring='accuracy')

print('Avg train score: {:.4f}'.format(scores.mean()))
print('Avg train score: {:.4f}'.format(scores1.mean()))
```

```
Avg train score: 0.9612
Avg train score: 0.9477

C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
```

In [77]:
```
import mglearn
x_b = X_train[50:100, [1,3]]
y_b = y_train[50:100]

lreg = LogisticRegression()
lreg.fit(x_b, y_b)

mglearn.plots.plot_2d_separator(lreg, x_b, fill=True, eps=0.5, alpha=.4)
mglearn.discrete_scatter(x_b[:, 0], x_b[:, 1], y_b)
```

```
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
```

Out[77]:
```
[<matplotlib.lines.Line2D at 0x1e40012c5f8>,
 <matplotlib.lines.Line2D at 0x1e4001f4c50>]
```



3. Linear SVM

In [78]:
```
from sklearn.svm import LinearSVC
linear_svm = LinearSVC()
linear_svm.fit(X_train,y_train)
print('Train score: {:.4f}'.format(linear_svm.score(X_train,y_train)))
print('Test score: {:.4f}'.format(linear_svm.score(X_test,y_test)))
```

```
Train score: 0.9710
Test score: 0.9613
```

In [79]:
```
#Confusion Matrix
from sklearn.metrics import classification_report, confusion_matrix
pred = linear_svm.predict(X_test)
print(confusion_matrix(y_test, pred))
print(classification_report(y_test, pred))
```

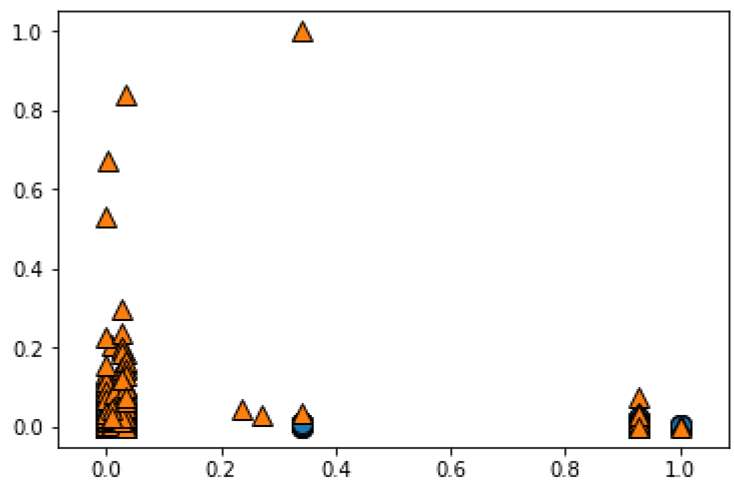
```
[[87  1]
 [ 5 62]]
              precision    recall  f1-score   support

           0       0.95      0.99      0.97        88
           1       0.98      0.93      0.95        67

   micro avg       0.96      0.96      0.96       155
   macro avg       0.96      0.96      0.96       155
weighted avg       0.96      0.96      0.96       155
```

In [80]:
```
#Cross validation
linear_svm = LinearSVC()
scores = cross_val_score(linear_svm, X_train, y_train, cv=5, scoring='accurac
y')
scores1= cross_val_score(linear_svm, X_test, y_test, cv=5, scoring='accuracy')

print('Avg train score: {:.4f}'.format(scores.mean()))
print('Avg train score: {:.4f}'.format(scores1.mean()))
```

```
Avg train score: 0.9629
Avg train score: 0.9540
```

In [81]:
```
mglearn.discrete_scatter(X_train[:, 0], X_train[:, 1], y_train)
line = np.linspace(-5, 5)
for coef, intercept, color in zip(linear_svm.coef_, linear_svm.intercept_,
                                  mglearn.cm3.colors):
    plt.plot(line, -(line * coef[0] + intercept) / coef[1], c=color)
plt.ylim(-2, 2)
plt.xlim(0, 1.5)
plt.xlabel("Feature 0")
plt.ylabel("Feature 1")
plt.legend(['Class 0', 'Class 1', 'Line class 0', 'Line class 1'], loc=(1.01,
0.3))
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
<ipython-input-81-28f5a8b24143> in <module>
      1 mglearn.discrete_scatter(X_train[:, 0], X_train[:, 1], y_train)
      2 line = np.linspace(-5, 5)
----> 3 for coef, intercept, color in zip(linear_svm.coef_, linear_svm.interc
ept_,
      4                                   mglearn.cm3.colors):
      5     plt.plot(line, -(line * coef[0] + intercept) / coef[1], c=color)

AttributeError: 'LinearSVC' object has no attribute 'coef_'
```



4. Kernalized SVM

RBF kernal

In [83]:

```
#kernal = 'rbf'
from sklearn.svm import SVC
C1 = [0.01,0.1,1,10]
gamma1 = [0.01,0.1,1,10]

for i in C1:
    for j in gamma1:
        svc = SVC(C=i,kernel='rbf',gamma=j)
        svc.fit(X_train,y_train)
        print('C:{},gamma:{}'.format(i,j))
        print('Train score: {:.4f},Test score: {:.4f}'.format(svc.score(X_trai
n,y_train),svc.score(X_test,y_test)))
```

```
C:0.01,gamma:0.01
Train score: 0.6177,Test score: 0.5677
C:0.01,gamma:0.1
Train score: 0.6177,Test score: 0.5677
C:0.01,gamma:1
Train score: 0.9000,Test score: 0.8387
C:0.01,gamma:10
Train score: 0.6177,Test score: 0.5677
C:0.1,gamma:0.01
Train score: 0.6177,Test score: 0.5677
C:0.1,gamma:0.1
Train score: 0.9194,Test score: 0.8774
C:0.1,gamma:1
Train score: 0.9661,Test score: 0.9484
C:0.1,gamma:10
Train score: 0.9339,Test score: 0.9355
C:1,gamma:0.01
Train score: 0.9161,Test score: 0.8774
C:1,gamma:0.1
Train score: 0.9710,Test score: 0.9613
C:1,gamma:1
Train score: 0.9694,Test score: 0.9484
C:1,gamma:10
Train score: 0.9774,Test score: 0.9548
C:10,gamma:0.01
Train score: 0.9710,Test score: 0.9613
C:10,gamma:0.1
Train score: 0.9726,Test score: 0.9548
C:10,gamma:1
Train score: 0.9774,Test score: 0.9677
C:10,gamma:10
Train score: 0.9855,Test score: 0.9677
```

In [84]:
```
#Cross validation
svc = SVC(C=0.1,kernel='rbf',gamma=1)
scores = cross_val_score(svc, X_train, y_train, cv=5, scoring='accuracy')
scores1= cross_val_score(svc, X_test, y_test, cv=5, scoring='accuracy')

print('Avg train score: {:.4f}'.format(scores.mean()))
print('Avg train score: {:.4f}'.format(scores1.mean()))
```

```
Avg train score: 0.9629
Avg train score: 0.9544
```

Best Parameters: C = 0.1, gamma=1

Linear Kernal

In [85]:
```
#kernal = Linear
C1 = [0.01,0.1,1,10]

for i in C1:
    svc = SVC(C=i,kernel='linear')
    svc.fit(X_train,y_train)
    print('C:{}'.format(i))
    print('Train score: {:.4f},Test score: {:.4f}'.format(svc.score(X_train,y_
train),svc.score(X_test,y_test)))
```

```
C:0.01
Train score: 0.8758,Test score: 0.8452
C:0.1
Train score: 0.9581,Test score: 0.9419
C:1
Train score: 0.9726,Test score: 0.9677
C:10
Train score: 0.9758,Test score: 0.9677
```

In [86]:
```
#Cross validation
svc = SVC(C=10,kernel='linear')
scores = cross_val_score(svc, X_train, y_train, cv=5, scoring='accuracy')
scores1= cross_val_score(svc, X_test, y_test, cv=5, scoring='accuracy')

print('Avg train score: {:.4f}'.format(scores.mean()))
print('Avg train score: {:.4f}'.format(scores1.mean()))
```

```
Avg train score: 0.9662
Avg train score: 0.9544
```

Best Paramter: C=1

polynomial kernal

In [87]:
```
#kernal = poly
C1 = [0.01,0.1,1,10]
gamma1 = [0.01,0.1,1,10]

for i in C1:
    for j in gamma1:
        svc = SVC(C=i,kernel='poly',gamma=j)
        svc.fit(X_train,y_train)
        print('C:{},gamma:{}'.format(i,j))
        print('Train score: {:.4f},Test score: {:.4f}'.format(svc.score(X_trai
n,y_train),svc.score(X_test,y_test)))
```

```
C:0.01,gamma:0.01
Train score: 0.6177,Test score: 0.5677
C:0.01,gamma:0.1
Train score: 0.6177,Test score: 0.5677
C:0.01,gamma:1
Train score: 0.8806,Test score: 0.8194
C:0.01,gamma:10
Train score: 0.9790,Test score: 0.9548
C:0.1,gamma:0.01
Train score: 0.6177,Test score: 0.5677
C:0.1,gamma:0.1
Train score: 0.6177,Test score: 0.5677
C:0.1,gamma:1
Train score: 0.9548,Test score: 0.9226
C:0.1,gamma:10
Train score: 0.9903,Test score: 0.9806
C:1,gamma:0.01
Train score: 0.6177,Test score: 0.5677
C:1,gamma:0.1
Train score: 0.7855,Test score: 0.7613
C:1,gamma:1
Train score: 0.9677,Test score: 0.9548
C:1,gamma:10
Train score: 0.9952,Test score: 1.0000
C:10,gamma:0.01
Train score: 0.6177,Test score: 0.5677
C:10,gamma:0.1
Train score: 0.8806,Test score: 0.8194
C:10,gamma:1
Train score: 0.9790,Test score: 0.9548
C:10,gamma:10
Train score: 0.9952,Test score: 1.0000
```

In [88]:
```
#Cross validation
svc = SVC(C=1,kernel='poly',gamma=10)
scores = cross_val_score(svc, X_train, y_train, cv=5, scoring='accuracy')
scores1= cross_val_score(svc, X_test, y_test, cv=5, scoring='accuracy')

print('Avg train score: {:.4f}'.format(scores.mean()))
print('Avg train score: {:.4f}'.format(scores1.mean()))
```

```
Avg train score: 0.9791
Avg train score: 0.9552
```

5. Decision Tree

In [89]:
```
from sklearn.tree import DecisionTreeClassifier
dtree = DecisionTreeClassifier(max_depth=3,random_state=0)
dtree.fit(X_train, y_train)

print("Accuracy on training set: {:.3f}".format(dtree.score(X_train, y_train
)))
print("Accuracy on test set: {:.3f}".format(dtree.score(X_test, y_test)))
```

```
Accuracy on training set: 0.956
Accuracy on test set: 0.961
```

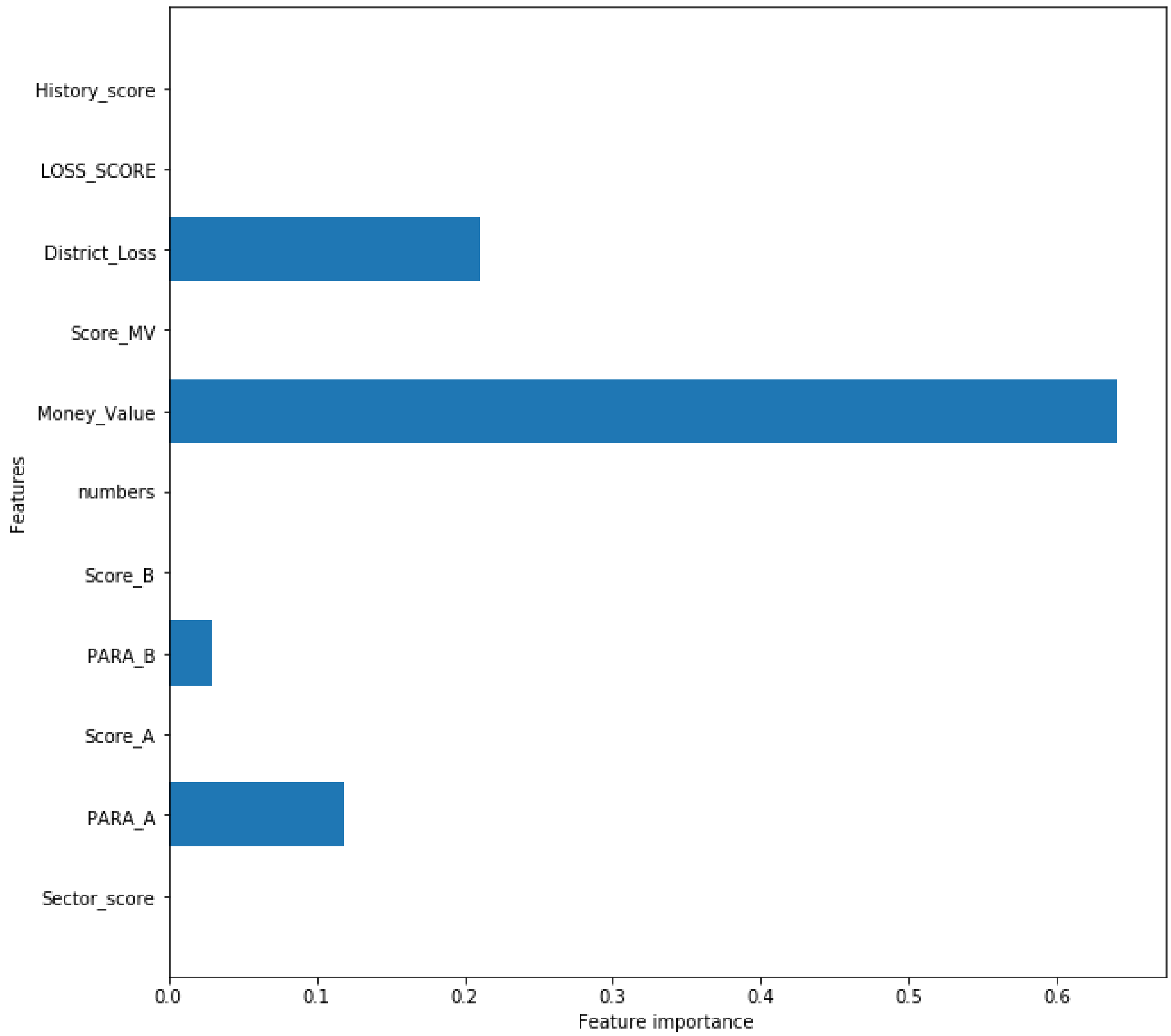
In [90]:
```
#Cross validation
from sklearn.model_selection import cross_val_score
dtree = DecisionTreeClassifier(random_state=0)
scores = cross_val_score(dtree, X_train, y_train, cv=5, scoring='accuracy')
scores1= cross_val_score(dtree, X_test, y_test, cv=5, scoring='accuracy')

print('Avg train score: {:.4f}'.format(scores.mean()))
print('Avg test score: {:.4f}'.format(scores1.mean()))
```

```
Avg train score: 0.9742
Avg test score: 0.9735
```

In [91]:
```
#Cross validation
dtree = DecisionTreeClassifier(max_depth=3,random_state=0)
scores = cross_val_score(dtree, X_train, y_train, cv=5, scoring='accuracy')
scores1= cross_val_score(dtree, X_test, y_test, cv=5, scoring='accuracy')

print('Avg train score: {:.4f}'.format(scores.mean()))
print('Avg test score: {:.4f}'.format(scores1.mean()))
```

```
Avg train score: 0.9371
Avg test score: 0.9544
```

In [92]:
```
from sklearn import tree
dtree.fit(X_train, y_train)
def plot_feature_importances_risk(model):
    n_features = X.shape[1]
    plt.barh(range(n_features), model.feature_importances_, align='center')
    plt.yticks(np.arange(n_features), list(X.columns))
    plt.xlabel("Feature importance")
    plt.ylabel("Features")
    plt.ylim(-1, n_features)
plt.figure(figsize=(10,10))
plot_feature_importances_risk(dtree)
```



In [93]:
```
import os
os.environ["PATH"] += os.pathsep + 'C:/Program Files (x86)/Graphviz2.38/bin/'
+ 'C:/Users/jmoha/AppData/Local/conda/conda/envs/fluffy/Lib/site-packages/grap
hviz' + 'C:/Users/jmoha/AppData/Local/conda/conda/envs/fluffy/Lib/site-package
s/PIL'

# Create DOT data
from sklearn.tree import export_graphviz
dot_data = export_graphviz(dtree, out_file=None, filled=True, rounded=True, sp
ecial_characters=True)

# Draw graph
import pydotplus
graph = pydotplus.graph_from_dot_data(dot_data)

# Show graph
from PIL import *
import graphviz
from IPython.display import Image
Image(graph.create_png())
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
<ipython-input-93-64e399046e3a> in <module>
      7 
      8 # Draw graph
----> 9 import pydotplus
     10 graph = pydotplus.graph_from_dot_data(dot_data)
     11 

ModuleNotFoundError: No module named 'pydotplus'
```

In [94]:
```
#Confusion Matrix
from sklearn.metrics import classification_report, confusion_matrix
pred = dtree.predict(X_test)
print(confusion_matrix(y_test, pred))
print(classification_report(y_test, pred))
```

```
[[88  0]
 [ 6 61]]
              precision    recall  f1-score   support

           0       0.94      1.00      0.97        88
           1       1.00      0.91      0.95        67

   micro avg       0.96      0.96      0.96       155
   macro avg       0.97      0.96      0.96       155
weighted avg       0.96      0.96      0.96       155
```

Overview of Regression scores

All the below scores are cross validation scores

In [95]:
```
Regression = {'Model':['Linear Regression','KNN Regression','Ridge Regression'
,'Lasso Regression','SVM Regression'],'Avg.Train Score':[0.7347,0.6872,0.6067,
0.7377,0.6581],'Avg_Test_Score':[0.6588,0.4047,0.227,0.6695,0.4419]}
Regression_score = pd.DataFrame(Regression)
Regression_score
```

Out[95]:

	Model	Avg.Train Score	Avg_Test_Score
0	Linear Regression	0.7347	0.6588
1	KNN Regression	0.6872	0.4047
2	Ridge Regression	0.6067	0.2270
3	Lasso Regression	0.7377	0.6695
4	SVM Regression	0.6581	0.4419

Overview of Classification scores

All the below scores are cross validation scores

In [96]:
```
Classification = {'Model':['KNN classification','Logistic Regerssion','Linear
SVM','SVC - rbf','SVC - linear','SVC - poly','Decision Tree'],'Avg.Train Scor
e':[0.9629,0.9612,0.9629,0.9629,0.9662,0.9791,0.9726],'Avg_Test_Score':[0.9348
,0.9477,0.9613,0.9544,0.9544,0.9552,0.9735]}
Classification_score = pd.DataFrame(Classification)
Classification_score
```

Out[96]:

	Model	Avg.Train Score	Avg_Test_Score
0	KNN classification	0.9629	0.9348
1	Logistic Regerssion	0.9612	0.9477
2	Linear SVM	0.9629	0.9613
3	SVC - rbf	0.9629	0.9544
4	SVC - linear	0.9662	0.9544
5	SVC - poly	0.9791	0.9552
6	Decision Tree	0.9726	0.9735

Result

The Best Regression model: Lasso Regression

Parameters: alpha = 0.001

The Best Classification model: Decision Tree

The important features in analysis : 'PARA_A', 'PARA_B','Score_MV', 'District_Loss', 'LOSS_SCORE'

In [ ]:

```
```

Let's run the above models with important features only

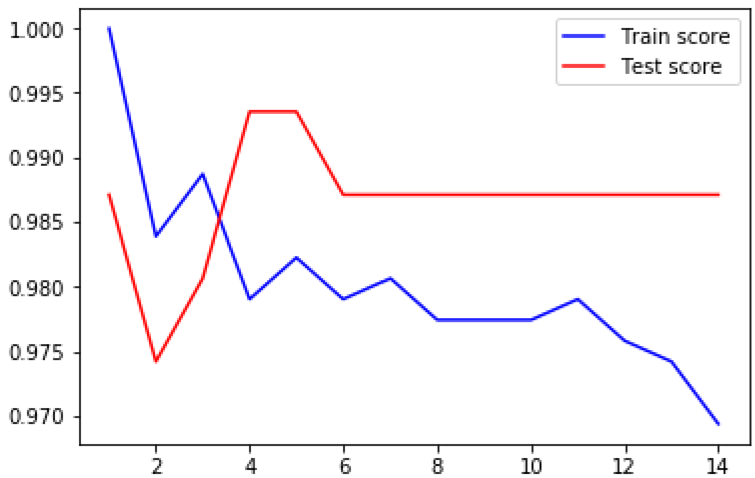
In [97]:

```
p = data[['PARA_A', 'PARA_B','Score_MV', 'District_Loss', 'LOSS_SCORE']]
q = data['Risk']

from sklearn.model_selection import train_test_split

p_train_org, p_test_org, q_train, q_test = train_test_split(p, q, test_size=0.
2, random_state=0)

from sklearn.preprocessing import MinMaxScaler
scale = MinMaxScaler()
p_train = scale.fit_transform(p_train_org)
p_test = scale.transform(p_test_org)
```

```
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:32
3: DataConversionWarning: Data with input dtype int64, float64 were all conve
rted to float64 by MinMaxScaler.
  return self.partial_fit(X, y)
```

In [98]:
```
# KNN Classifier
from sklearn.neighbors import KNeighborsClassifier
train_score = []
test_score = []

n = range(1,15)
for i in n:
    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(p_train,q_train)
    train_score.append(knn.score(p_train,q_train))
    test_score.append(knn.score(p_test,q_test))

plt.plot(n,train_score,'b',label='Train score')
plt.plot(n,test_score,'r',label = 'Test score')
plt.legend()
```

Out[98]: <matplotlib.legend.Legend at 0x1e4001184e0>



In [ ]:
```
knn = KNeighborsClassifier(3)
knn.fit(p_train, q_train)
print('Train score: {:.4f}'.format(knn.score(p_train,q_train)))
print('Test score: {:.4f}'.format(knn.score(p_test,q_test)))
predictions = knn.predict(p_test)
print(confusion_matrix(q_test,predictions))
print(classification_report(q_test,predictions))
```

In [100]:
```
#Logistic Regression
from sklearn.linear_model import LogisticRegression

c_range = [0.001, 0.01, 0.1, 1, 10, 100, 1000]
train_score_l1 = []
train_score_l2 = []
test_score_l1 = []
test_score_l2 = []

for c in c_range:
    log_l1 = LogisticRegression(penalty = 'l1', C = c)
    log_l2 = LogisticRegression(penalty = 'l2', C = c)
    log_l1.fit(p_train, q_train)
    log_l2.fit(p_train, q_train)
    train_score_l1.append(log_l1.score(p_train, q_train))
    train_score_l2.append(log_l2.score(p_train, q_train))
    test_score_l1.append(log_l1.score(p_test, q_test))
    test_score_l2.append(log_l2.score(p_test, q_test))

import matplotlib.pyplot as plt
%matplotlib inline

plt.plot(c_range, train_score_l1, label = 'Train score, penalty = l1')
plt.plot(c_range, test_score_l1, label = 'Test score, penalty = l1')
plt.plot(c_range, train_score_l2, label = 'Train score, penalty = l2')
plt.plot(c_range, test_score_l2, label = 'Test score, penalty = l2')
plt.legend()
plt.xlabel('Regularization parameter: C')
plt.ylabel('Accuracy')
plt.xscale('log')
```

```
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
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  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
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  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
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C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
```

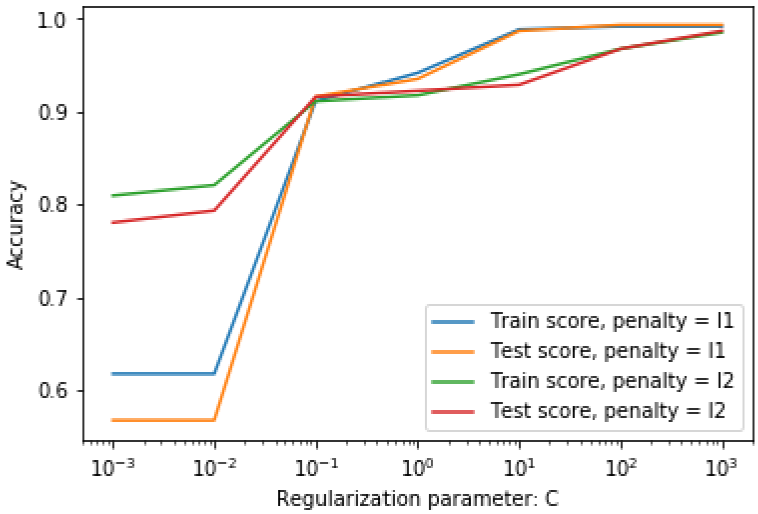
Accuracy
Regularization parameter: C
Train score, penalty = l1
Test score, penalty = l1
Train score, penalty = l2
Test score, penalty = l2
1.0
0.9
0.8
0.7
0.6
10^{-3}
10^{-2}
10^{-1}
10^{0}
10^{1}
10^{2}
10^{3}

In [101]:
```
log_l1 = LogisticRegression(penalty = 'l1', C = 0.1)
log_l2 = LogisticRegression(penalty = 'l2', C = 0.1)
log_l1.fit(p_train,q_train)
log_l2.fit(p_train,q_train)
print("Penality: l1")
print('Train score: {:.4f}'.format(log_l1.score(p_train,q_train)))
print('Test score: {:.4f}'.format(log_l1.score(p_test,q_test)))
predictions = log_l1.predict(p_test)
print(confusion_matrix(q_test,predictions))
print(classification_report(q_test,predictions))
print("Penality: l2")
print('Train score: {:.4f}'.format(log_l2.score(p_train,q_train)))
print('Test score: {:.4f}'.format(log_l2.score(p_test,q_test)))
predictions = log_l2.predict(p_test)
print(confusion_matrix(q_test,predictions))
print(classification_report(q_test,predictions))
```

```
Penality: l1
Train score: 0.9113
Test score: 0.9161
[[88  0]
 [13 54]]
              precision    recall  f1-score   support

           0       0.87      1.00      0.93        88
           1       1.00      0.81      0.89        67

   micro avg       0.92      0.92      0.92       155
   macro avg       0.94      0.90      0.91       155
weighted avg       0.93      0.92      0.91       155

Penality: l2
Train score: 0.9113
Test score: 0.9161
[[88  0]
 [13 54]]
              precision    recall  f1-score   support

           0       0.87      1.00      0.93        88
           1       1.00      0.81      0.89        67

   micro avg       0.92      0.92      0.92       155
   macro avg       0.94      0.90      0.91       155
weighted avg       0.93      0.92      0.91       155


C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
C:\Users\Tanmay\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:
433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specif
y a solver to silence this warning.
  FutureWarning)
```

In [102]:
```
# RBF SVM
#kernal = 'rbf'
C1 = [0.01,0.1,1,10]
gamma1 = [0.01,0.1,1,10]

for i in C1:
    for j in gamma1:
        svc = SVC(C=i,kernel='rbf',gamma=j)
        svc.fit(p_train,q_train)
        print('C:{},gamma:{}'.format(i,j))
        print('Train score: {:.4f},Test score: {:.4f}'.format(svc.score(p_trai
n,q_train),svc.score(p_test,q_test)))
```

```
C:0.01,gamma:0.01
Train score: 0.6177,Test score: 0.5677
C:0.01,gamma:0.1
Train score: 0.6177,Test score: 0.5677
C:0.01,gamma:1
Train score: 0.8823,Test score: 0.8774
C:0.01,gamma:10
Train score: 0.9032,Test score: 0.8903
C:0.1,gamma:0.01
Train score: 0.6177,Test score: 0.5677
C:0.1,gamma:0.1
Train score: 0.8290,Test score: 0.8065
C:0.1,gamma:1
Train score: 0.9145,Test score: 0.9161
C:0.1,gamma:10
Train score: 0.9274,Test score: 0.9097
C:1,gamma:0.01
Train score: 0.8290,Test score: 0.8065
C:1,gamma:0.1
Train score: 0.9210,Test score: 0.9161
C:1,gamma:1
Train score: 0.9274,Test score: 0.9097
C:1,gamma:10
Train score: 0.9548,Test score: 0.9355
C:10,gamma:0.01
Train score: 0.9242,Test score: 0.9226
C:10,gamma:0.1
Train score: 0.9306,Test score: 0.9097
C:10,gamma:1
Train score: 0.9581,Test score: 0.9548
C:10,gamma:10
Train score: 0.9742,Test score: 0.9742
```

In [103]:
```
#Decision Tree
from sklearn.tree import DecisionTreeClassifier
dtree = DecisionTreeClassifier(max_depth=3,random_state=0)
dtree.fit(p_train, q_train)

print("Accuracy on training set: {:.3f}".format(dtree.score(p_train, q_train
)))
print("Accuracy on test set: {:.3f}".format(dtree.score(p_test, q_test)))

predictions = dtree.predict(p_test)
print(confusion_matrix(q_test,predictions))
print(classification_report(q_test,predictions))
```

```
Accuracy on training set: 0.952
Accuracy on test set: 0.948
[[87  1]
 [ 7 60]]
              precision    recall  f1-score   support

           0       0.93      0.99      0.96        88
           1       0.98      0.90      0.94        67

   micro avg       0.95      0.95      0.95       155
   macro avg       0.95      0.94      0.95       155
weighted avg       0.95      0.95      0.95       155
```

In [ ]:
```

```