credit_analysis_notebook

March 3, 2019

In [1]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```python
#

companies_data = pd.read_excel(io='companies.xls', sheet_name=0)
```

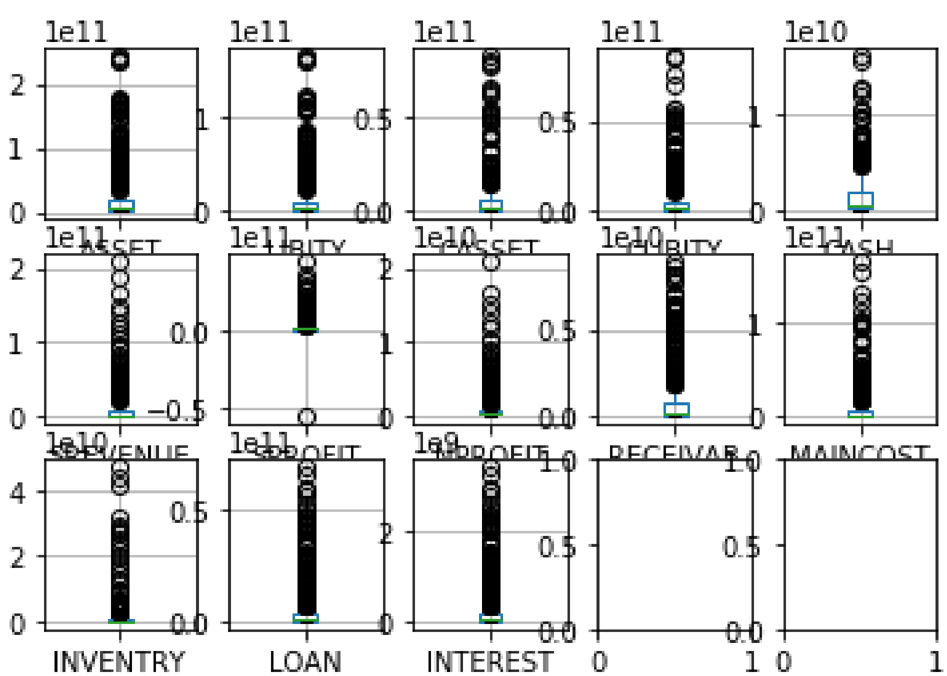
In [3]:
```python
companies_data.head(10)
```

Out[3]:
```
          ASSET        LIBITY        CASSET       CLIBITY          CASH  \
0  1.547336e+10  1.059925e+10  6.835456e+09  3.197114e+09  2.039102e+09
1  5.680612e+10  3.970748e+10  2.085414e+10  1.668331e+10  1.289789e+10
2  8.345341e+09  5.833393e+09  8.047869e+08  6.438295e+08  7.675127e+08
3  7.926957e+09  4.439096e+09  1.679505e+09  2.362389e+09  4.172194e+08
4  9.596428e+10  6.573553e+10  3.248151e+10  3.089705e+10  3.929240e+09
5  6.329863e+10  4.335956e+10  8.042116e+09  1.461258e+10  1.901062e+09
6  7.873401e+09  5.393280e+09  5.699675e+08  2.341210e+09  5.593455e+08
7  2.432424e+10  1.666210e+10  1.041738e+10  7.579921e+09  2.737957e+09
8  8.137729e+08  2.909524e+08  4.783448e+08  2.907972e+08  8.418496e+07
9  1.707652e+10  1.169742e+10  2.196964e+09  1.447596e+09  7.088404e+08

       SREVENUE       SPROFIT       NPROFIT      RECEIVAB      MAINCOST  \
0  1.641898e+10  4.895354e+09  7.454865e+08  8.873680e+07  1.152363e+10
1  3.511169e+09  1.814890e+09  7.598296e+08  2.265957e+09  1.696280e+09
2  2.031876e+09  1.407197e+09  8.709336e+08  0.000000e+00  6.246784e+08
3  1.187910e+09  5.533089e+08  1.284279e+08  1.136382e+09  6.346015e+08
4  2.166234e+10  2.408890e+09  9.145913e+08  2.869013e+09  1.925345e+10
5  2.683185e+10  5.915800e+09  3.175083e+09  3.269928e+09  2.091605e+10
6  8.910332e+08  5.780460e+08  3.555754e+08  0.000000e+00  3.129872e+08
7  1.753313e+10  1.162659e+09  7.667492e+08  5.307126e+07  1.637047e+10
8  5.963979e+08  4.163151e+07  7.056628e+06  6.136065e+07  2.442264e+08
9  1.102394e+09  6.967291e+08  5.776337e+08  1.136930e+09  4.056649e+08

       INVENTRY          LOAN      INTEREST  RATING
```

0	2.860091e+09	3.636876e+09	1.852834e+08	1
1	8.692615e+08	1.561541e+09	7.700409e+07	1
2	2.157535e+08	4.623853e+08	2.280155e+07	1
3	2.667839e+07	2.764960e+09	1.363481e+08	1
4	6.586292e+09	1.765877e+10	8.996395e+08	1
5	1.540905e+09	2.362876e+10	1.203785e+09	1
6	2.616537e+07	1.211009e+09	6.169577e+07	1
7	4.213021e+09	4.756771e+09	2.423373e+08	1
8	1.442264e+08	7.091970e+07	2.873910e+06	3
9	2.384750e+07	8.292707e+08	4.089373e+07	1

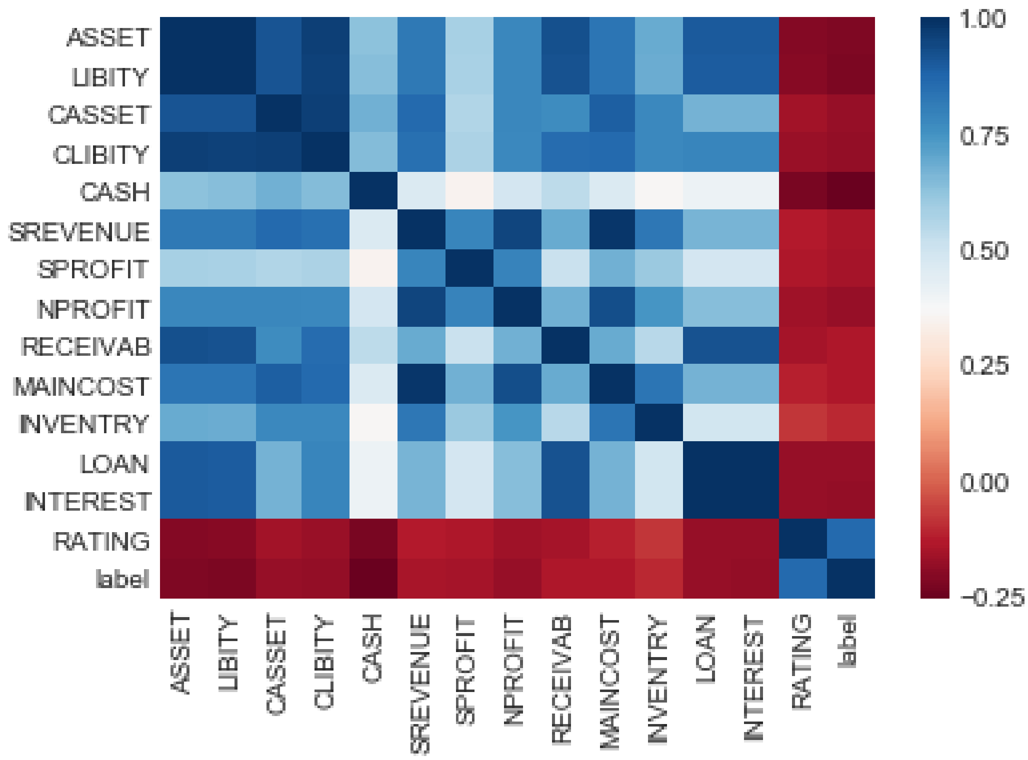
In [4]:
```
# RATING512345
#

companies_data['label'] = 1
companies_data['label'][companies_data['RATING']==1] = 0
companies_data['label'][companies_data['RATING']==2] = 0
data_label = companies_data['label']
data_features = companies_data.drop(labels=['RATING', 'label'], axis=1)
```

In [5]:
```
#

fig, axe = plt.subplots(nrows=3, ncols=5)
i = 0
for col_name in data_features.columns:
    data_features.boxplot(column=col_name, ax=axe[i//5][i%5], figsize=(10,10))
    i += 1


#
```



In [6]:
```
sns.set_style('whitegrid')
sns.heatmap(data=companies_data.corr(), cmap=sns.color_palette('RdBu', n_colors=200))

#
```

Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x21c3ce93f28>



In [7]:
```
#

#
#

data = pd.DataFrame(columns=['x%s' % i for i in range(1,19)])
data['x1'] = data_features['LIBITY'] / data_features['ASSET'] # /
data['x2'] = data_features['SREVENUE'] / data_features['INTEREST'] # /
data['x3'] = data_features['CASSET'] / data_features['CLIBITY'] # /
data['x4'] = data_features['NPROFIT'] / (data_features['ASSET'] - data_features['LIBIT
data['x5'] = data_features['SREVENUE'] / data_features['CASH'] # /
data['x6'] = np.log(data_features['ASSET']) #
data['x7'] = data_features['SREVENUE'] / data_features['ASSET'] # /
```

```
data['x8'] = data_features['SPROFIT'] / data_features['ASSET'] # /
data['x9'] = (data_features['SREVENUE'] - data_features['SPROFIT']) / data_features['SI
data['x10'] = (data_features['RECEIVAB'] + data_features['INVENTRY']) / (data_features
data['x11'] = data_features['INVENTRY'] / (data_features['ASSET'] - data_features['LIBI
data['x12'] = data_features['SREVENUE'] / data_features['LIBITY'] # /
data['x13'] = data_features['CASSET'] / (data_features['ASSET'] - data_features['LIBITY
data['x14'] = data_features['SPROFIT'] / data_features['INTEREST'] # /
data['x15'] = data_features['SREVENUE'] / data_features['CASSET'] # /
data['x16'] = data_features['SREVENUE'] / (data_features['ASSET'] - data_features['LIBI
data['x17'] = data_features['CASSET'] / data_features['INTEREST'] # /
data['x18'] = data_features['MAINCOST'] / data_features['SREVENUE'] # /
y = data_label
```

In [8]:
```
data.head(10)
```

Out[8]:

	x1	x2	x3	x4	x5	x6	x7 \
0	0.685000	88.615529	2.138008	0.152948	8.052067	23.462385	1.061113
1	0.699000	45.597179	1.250000	0.044438	0.272228	24.762910	0.061810
2	0.699000	89.111301	1.250000	0.346716	2.647351	22.844969	0.243474
3	0.560000	8.712333	0.710935	0.036821	2.847208	22.793535	0.149857
4	0.685000	24.078909	1.051282	0.030256	5.513112	25.287242	0.225733
5	0.685000	22.289575	0.550356	0.159239	14.114138	24.871129	0.423893
6	0.685000	14.442370	0.243450	0.143370	1.592992	22.786756	0.113170
7	0.685000	72.350120	1.374338	0.100070	6.403729	23.914739	0.720809
8	0.357535	207.521430	1.644943	0.013497	7.084376	20.517192	0.732880
9	0.685000	26.957534	1.517664	0.107385	1.555208	23.560970	0.064556

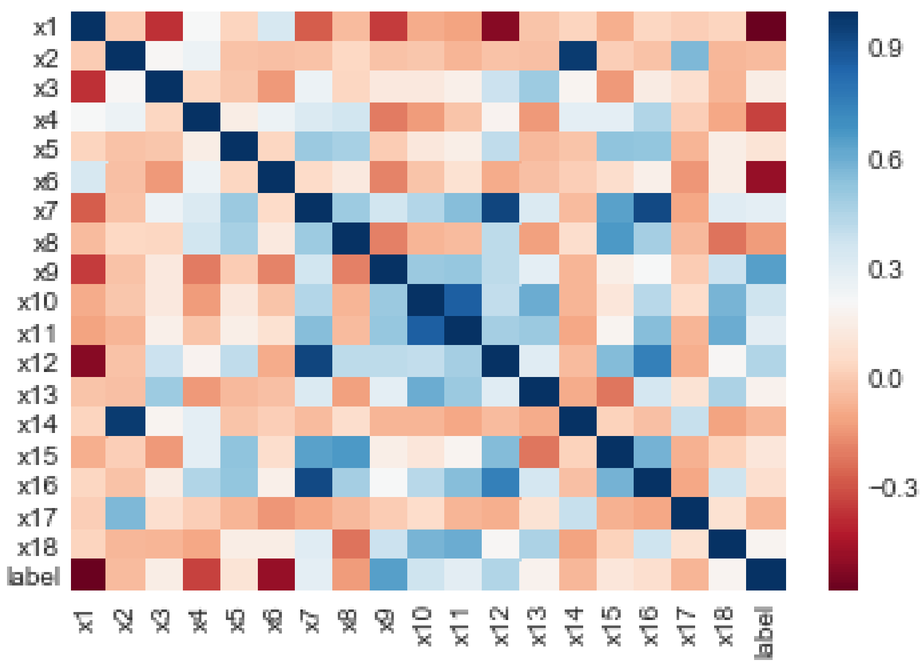
	x8	x9	x10	x11	x12	x13	x14 \
0	0.316373	2.353993	0.604998	0.586793	1.549070	1.402402	26.420905
1	0.031949	0.934646	0.183361	0.050838	0.088426	1.219637	23.568743
2	0.168621	0.443917	0.085891	0.085891	0.348318	0.320384	61.714986
3	0.069801	1.146921	0.333459	0.007649	0.267602	0.481528	4.058060
4	0.025102	7.992666	0.312792	0.217882	0.329538	1.074524	2.677616
5	0.093459	3.535625	0.241277	0.077281	0.618822	0.403335	4.914334
6	0.073418	0.541457	0.010550	0.010550	0.165212	0.229814	9.369297
7	0.047798	14.080204	0.556776	0.549850	1.052276	1.359592	4.797688
8	0.051159	13.325637	0.393227	0.275862	2.049813	0.914931	14.486017
9	0.040800	0.582242	0.215794	0.004433	0.094243	0.408426	17.037555

	x15	x16	x17	x18
0	2.402032	3.368613	36.891905	0.701848
1	0.168368	0.205348	270.818555	0.483110
2	2.524738	0.808885	35.295269	0.307439
3	0.707298	0.340584	12.317767	0.534217
4	0.666913	0.716614	36.105030	0.888798
5	3.336417	1.345692	6.680693	0.779523
6	1.563305	0.359270	9.238355	0.351263
7	1.683066	2.288283	42.987096	0.933688

```
8  1.246795  1.140732  166.443914  0.409502
9  0.501781  0.204940   53.723747  0.367985
```

```
In [9]: #

        from sklearn.model_selection import train_test_split

        train_temp, test_temp, y_train, y_test = train_test_split(data, y, test_size=0.3, rando
        X_train = train_temp.copy()
        X_test = test_temp.copy()
        train = train_temp.copy()
        test = test_temp.copy()
        train['label'] = y_train
        test['label'] = y_test
```

```
In [10]: #
         #
         # 1.

         sns.set_style('whitegrid')
         sns.heatmap(data=train.corr(), cmap=sns.color_palette('RdBu', n_colors=200)) #

         train_corr = train.corr()
         train_corr1 = train_corr[train_corr['label'] <= 0.25][train_corr['label'] >= -0.25]
         col_keep = train_corr1.index.tolist()
         X_train_keep = X_train[col_keep]
         X_test_keep = X_test[col_keep]
```



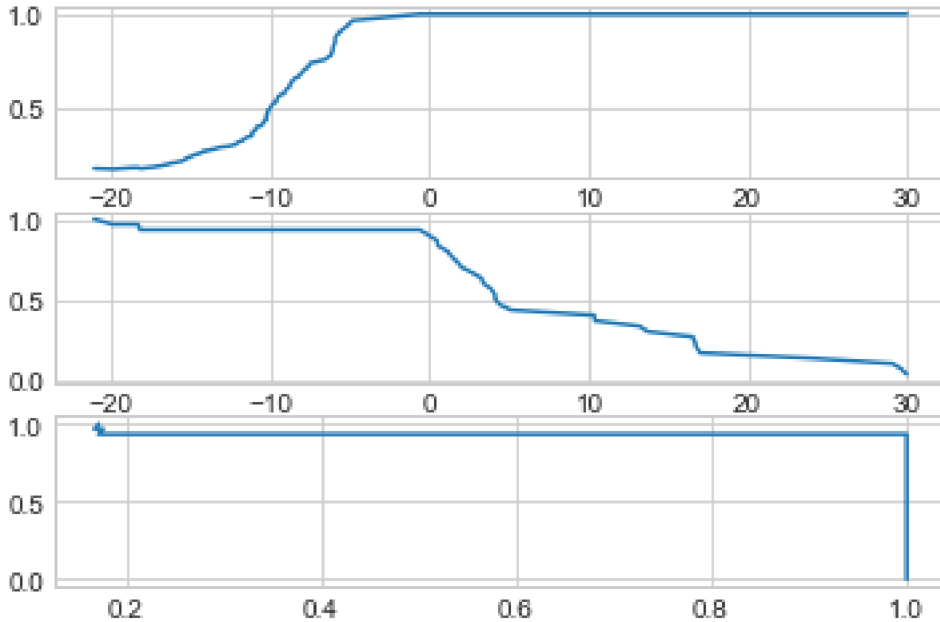
In [11]:
```
# 2.LDA
# PCAPCA
# from sklearn.decomposition import PCA
# pca_test = PCA(n_components=data.shape[1])
# pca_test.fit(X_train)
# a = pca_test.explained_variance_ratio_
# plt.plot([i for i in range(data.shape[1])], [np.sum(a[:i+1]) for i in range(data.sh

# LDA

from sklearn.discriminant_analysis import LinearDiscriminantAnalysis

lda = LinearDiscriminantAnalysis(n_components=data.shape[1])
lda.fit(X_train, y_train)
lda_score = lda.score(X_test, y_test)
lda_c_score = lda.decision_function(X_test)
```

In [12]:
```
lda_score
```

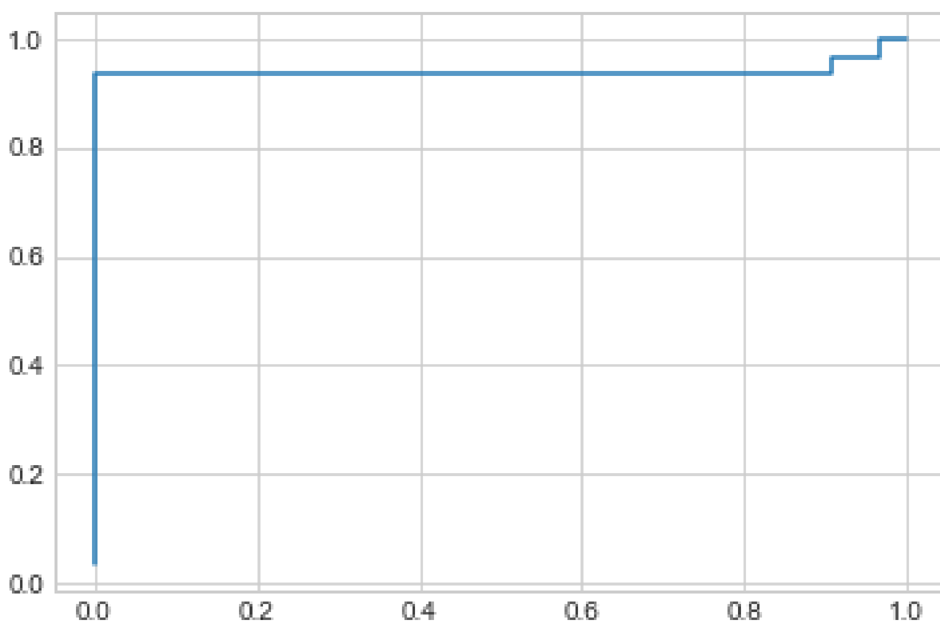
Out[12]: 0.9776536312849162

In [13]:
```
#

from sklearn.metrics import confusion_matrix, precision_score, recall_score, f1_score

lda_y_pred = lda.predict(X_test)
lda_c_m = confusion_matrix(y_test, lda_y_pred)
lda_p_score = precision_score(y_test, lda_y_pred)
lda_r_score = recall_score(y_test, lda_y_pred)
lda_f1_score = f1_score(y_test, lda_y_pred)
lda_p, lda_r, lda_th = precision_recall_curve(y_test, lda_c_score)

#

fig, axe = plt.subplots(3, 1)
axe[0].plot(lda_th, lda_p[:-1])
axe[1].plot(lda_th, lda_r[:-1])
axe[2].plot(lda_p, lda_r)
```

Out[13]: [<matplotlib.lines.Line2D at 0x21c3d8cf898>]




```
In [14]: # ROC

         lda_fpr, lda_tpr, lda_th = roc_curve(y_test, lda_c_score)
         plt.plot(lda_fpr, lda_tpr)
         lda_res = roc_auc_score(y_test, lda_c_score)
```

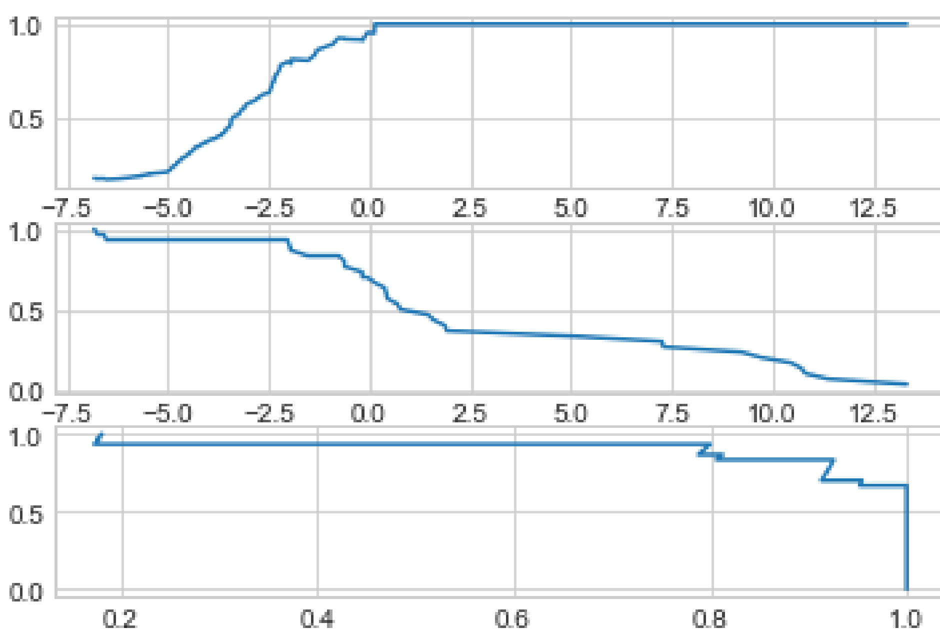


In [15]:
```python
lda_res
```

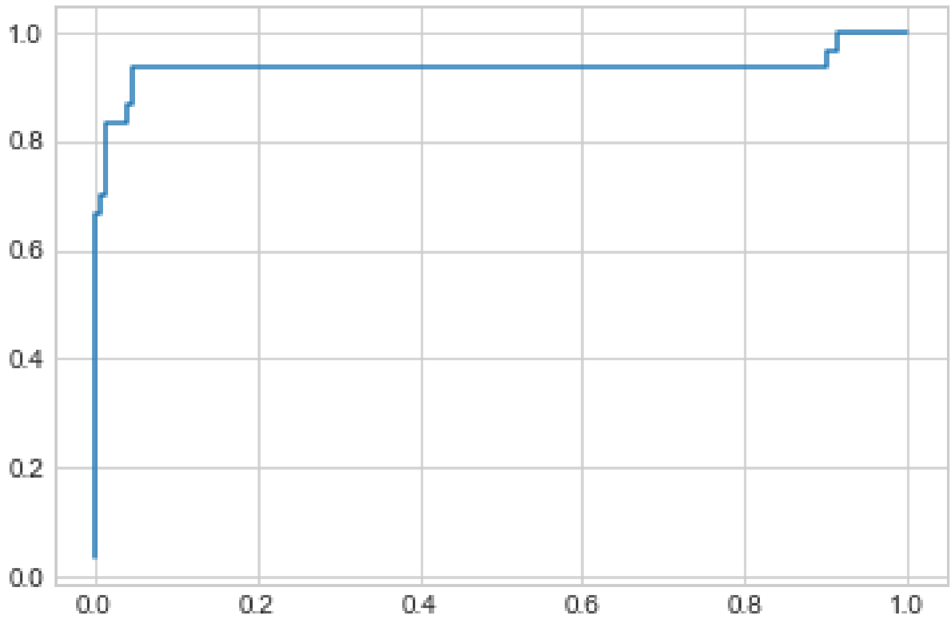
Out[15]: 0.9375838926174497

In [16]:
```python
# kNN
# 1.+()

from sklearn.linear_model import LogisticRegression

lr = LogisticRegression()
lr.fit(X_train, y_train)
lr_y_pred = lr.predict(X_test)
lr_score = lr.score(X_test, y_test)
lr_c_score = lr.decision_function(X_test)

lr_c_m = confusion_matrix(y_test, lr_y_pred)
lr_p_score = precision_score(y_test, lr_y_pred)
lr_r_score = recall_score(y_test, lr_y_pred)
lr_f1_score = f1_score(y_test, lr_y_pred)
lr_p, lr_r, lr_th = precision_recall_curve(y_test, lr_c_score)

#

fig, axe = plt.subplots(3, 1)
axe[0].plot(lr_th, lr_p[:-1])
axe[1].plot(lr_th, lr_r[:-1])
axe[2].plot(lr_p, lr_r)
```

Out[16]: [<matplotlib.lines.Line2D at 0x21c3cd59048>]



In [17]:
```
# ROC

lr_fpr, lr_tpr, lr_th = roc_curve(y_test, lr_c_score)
plt.plot(lr_fpr, lr_tpr)
lr_res = roc_auc_score(y_test, lr_c_score)
```



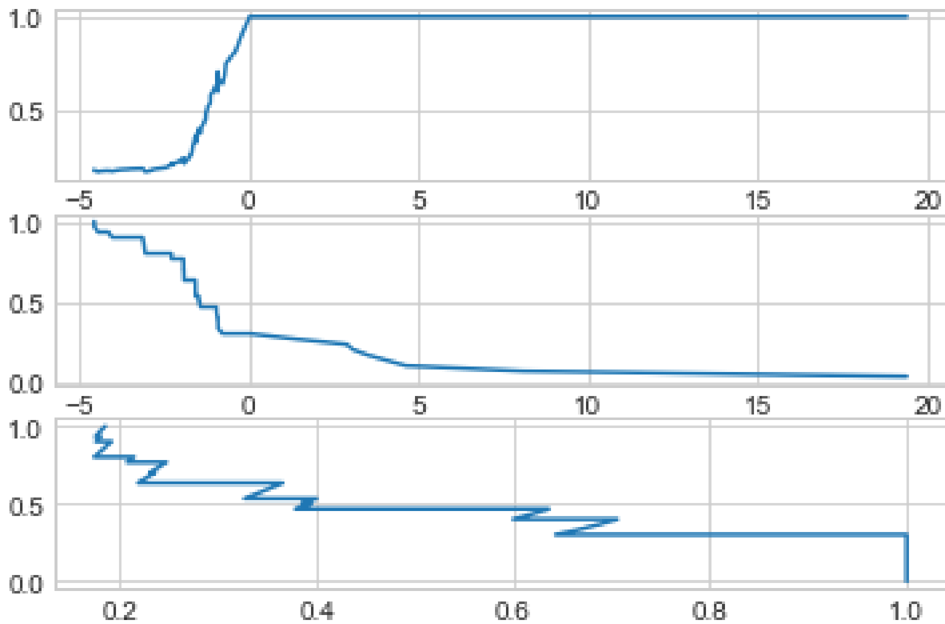
In [18]:
```
lr_res
```

Out[18]: 0.9331096196868008

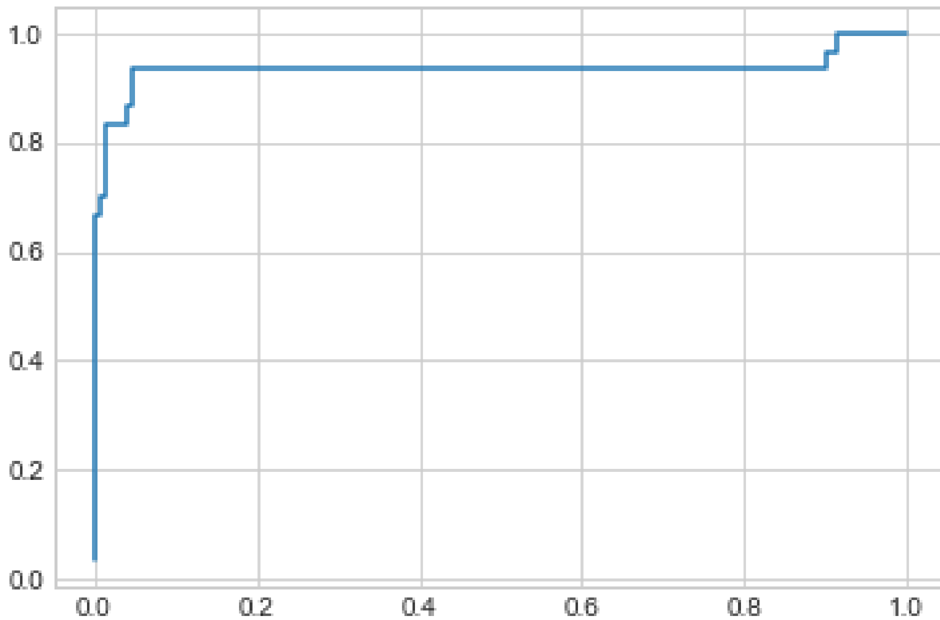
In [19]:
```
# ()

from sklearn.linear_model import LogisticRegression
lr2 = LogisticRegression()
lr2.fit(X_train_keep, y_train)
lr2_y_pred = lr2.predict(X_test_keep)
lr2_score = lr2.score(X_test_keep, y_test)
lr2_c_score = lr2.decision_function(X_test_keep)

lr2_c_m = confusion_matrix(y_test, lr2_y_pred)
lr2_p_score = precision_score(y_test, lr2_y_pred)
lr2_r_score = recall_score(y_test, lr2_y_pred)
lr2_f1_score = f1_score(y_test, lr2_y_pred)
lr2_p, lr2_r, lr2_th = precision_recall_curve(y_test, lr2_c_score)
```

```
fig, axe = plt.subplots(3, 1)
axe[0].plot(lr2_th, lr2_p[:-1])
axe[1].plot(lr2_th, lr2_r[:-1])
axe[2].plot(lr2_p, lr2_r)
```

Out[19]: [<matplotlib.lines.Line2D at 0x21c3b6fafd0>]



In [20]:
```
lr2_fpr, lr2_tpr, lr2_th = roc_curve(y_test, lr2_c_score)
plt.plot(lr_fpr, lr_tpr)
lr2_res = roc_auc_score(y_test, lr2_c_score)
```



In [21]:
```
lr2_res

#
```

Out[21]: 0.7149888143176734

In [22]:
```
# 2.kNN+
# ()

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

knn = KNeighborsClassifier()
grid_param = [
    {
        "weights": ["uniform"],
        "n_neighbors": [i for i in range(1, 20)]},
    {
        "weights": ["distance"],
        "n_neighbors": [i for i in range(1, 20)],
        "p": [i for i in range(1, 10)]
    }
]
gridcv_knn = GridSearchCV(knn, grid_param, n_jobs=-1, verbose=10)
gridcv_knn.fit(X_train, y_train)
best_est = gridcv_knn.best_estimator_
```

```
        beat_pred = best_est.predict(X_test)
        best_score_model = gridcv_knn.best_score_
        knn_cof = confusion_matrix(y_test, beat_pred)
        best_param = gridcv_knn.best_params_
        best_c_m = confusion_matrix(y_test, beat_pred)
```

```
Fitting 3 folds for each of 190 candidates, totalling 570 fits


[Parallel(n_jobs=-1)]: Done   5 tasks      | elapsed:   13.5s
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:   13.5s
[Parallel(n_jobs=-1)]: Done  17 tasks      | elapsed:   13.6s
[Parallel(n_jobs=-1)]: Done  24 tasks      | elapsed:   13.6s
[Parallel(n_jobs=-1)]: Batch computation too fast (0.1947s.) Setting batch_size=2.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:   13.8s
[Parallel(n_jobs=-1)]: Batch computation too fast (0.0987s.) Setting batch_size=8.
[Parallel(n_jobs=-1)]: Done  48 tasks      | elapsed:   13.9s
[Parallel(n_jobs=-1)]: Done 130 tasks      | elapsed:   15.1s
[Parallel(n_jobs=-1)]: Done 218 tasks      | elapsed:   17.9s
[Parallel(n_jobs=-1)]: Batch computation too slow (2.0362s.) Setting batch_size=4.
[Parallel(n_jobs=-1)]: Done 310 tasks      | elapsed:   20.4s
[Parallel(n_jobs=-1)]: Done 362 tasks      | elapsed:   21.7s
[Parallel(n_jobs=-1)]: Done 422 tasks      | elapsed:   23.5s
[Parallel(n_jobs=-1)]: Done 482 tasks      | elapsed:   26.6s
[Parallel(n_jobs=-1)]: Done 570 out of 570 | elapsed:   29.1s finished
```

```
In [23]: #

         best_est
```

```
Out[23]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                    metric_params=None, n_jobs=1, n_neighbors=1, p=1,
                    weights='distance')
```

```
In [24]: #

         best_param
```

```
Out[24]: {'n_neighbors': 1, 'p': 1, 'weights': 'distance'}
```

```
In [25]: #

         best_score_model
```

```
Out[25]: 0.9951807228915662
```

```
In [26]: #

         best_c_m
```

```
Out[26]: array([[149,   0],
                [  4,  26]], dtype=int64)
```