Second Classifier Prediction Model(s)

The original README file says:

> Often, more than one contact to the same client was required, **in order to access if the product (bank term deposit) would be (or not) subscribed**

This notebook builds off the previous *First Classifier Prediction Model* notebook through additional feature engineering, mainly by dropping additional features which seem unimportant based on extracted feature importances, or which would be unavailable ahead of time in a real business setting.

In [1]:
```python
#import the right libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, GradientBoostingClassifier
from sklearn.naive_bayes import GaussianNB, BernoulliNB, MultinomialNB
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis, QuadraticDiscriminantAnalysis
from sklearn.metrics import f1_score, confusion_matrix, classification_report, accuracy_score, log_loss, roc_au
from sklearn.model_selection import cross_val_predict, cross_val_score, learning_curve, GridSearchCV, Randomize
from sklearn.metrics import classification_report, accuracy_score, precision_recall_fscore_support
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import StandardScaler, Normalizer, LabelEncoder, RobustScaler, MinMaxScaler
from sklearn.svm import SVC, LinearSVC, NuSVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer, KNNImputer
from sklearn import metrics
plt.rcParams["figure.figsize"] = (9,9)
```

In [2]:
```python
#this option just allwos us to see every column in the notebook
pd.set_option('display.max_columns', None)

#pd.get_option("display.max_columns")
```

In [3]:
```python
#pull in the dataset and turn into a DataFrame
bank_main_df = pd.read_csv('./Dataset_1_Bank Marketing/bank_marketing.csv',delimiter=';')
bank_main_df
```

Out[3]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous
0	58.0	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0
1	44.0	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	0
2	33.0	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1	0
3	47.0	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	0
4	33.0	unknown	single	unknown	no	1	no	no	NaN	5	may	198	1	-1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
45206	51.0	technician	married	tertiary	no	825	no	no	cellular	17	nov	977	3	-1	0
45207	71.0	retired	divorced	primary	no	1729	no	no	cellular	17	nov	456	2	-1	0
45208	72.0	retired	married	secondary	no	5715	no	no	cellular	17	nov	1127	5	184	3
45209	57.0	blue-collar	married	secondary	no	668	no	no	telephone	17	nov	508	4	-1	0
45210	37.0	entrepreneur	married	secondary	no	2971	no	no	cellular	17	nov	361	2	188	11

45211 rows × 17 columns

In [4]:
```python
bank_main_df.describe()
```

Out[4]:

	age	balance	day	duration	campaign	pdays	previous
count	43872.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000
mean	40.924781	1362.272058	15.806419	258.163080	2.763841	40.197828	0.580323
std	10.610835	3044.765829	8.322476	257.527812	3.098021	100.128746	2.303441
min	18.000000	-8019.000000	1.000000	0.000000	1.000000	-1.000000	0.000000
25%	33.000000	72.000000	8.000000	103.000000	1.000000	-1.000000	0.000000
50%	39.000000	448.000000	16.000000	180.000000	2.000000	-1.000000	0.000000
75%	48.000000	1428.000000	21.000000	319.000000	3.000000	-1.000000	0.000000
max	95.000000	102127.000000	31.000000	4918.000000	63.000000	871.000000	275.000000

In [5]:
```python
#creating a field that determines whether or not the customer was ever previously contacted
bank_main_df['prior_contact'] = [ 0 if bank_main_df['pdays'][i] == -1 else 1 for i in range(len(bank_main_df))]

#replacing the yes/no categorical values with 1/0 binary digits
bank_main_df['deposit'] = [0 if (bank_main_df['deposit'][i] == 'yes') else 1 for i in range(len(bank_main_df))

#convert the "day" field to a categorical variable
bank_main_df['day'] = pd.Categorical(bank_main_df['day'])

#dropping pdays and previous, because the important information is captured in prior_contact
bank_main_df.drop(columns=['pdays','previous','job','marital','education','default','housing','loan','contact',
```

In [6]:
```python
#because we have so many cateogrical variables, we should one-hot encode them (i.e. create dummy categorical va
#we also use drop_first=True to reduce the redundant column count
bank_main_df = pd.get_dummies(bank_main_df, drop_first=False)

# bank_main_df
```

In [7]:
```python
#note that only the "age" category has null values

# pd.isnull(bank_main_df).sum()
```

Imputing the missing values in "Age" variable

- **Iterative Imputer:** Multivariate imputer that estimates each feature from all the others. A strategy for imputing missing values by modeling each feature with missing values as a function of other features in a round-robin fashion.

https://scikit-learn.org/stable/modules/generated/sklearn.impute.IterativeImputer.html

In [8]:
```python
# Use multivariate imputer that estimates and imputes null values based on all the others.

imp = IterativeImputer(max_iter=10, verbose=0) # values passed are defaults, but added them because they seem i
imp.fit(bank_main_df)
imputed_df = imp.transform(bank_main_df)
imputed_df = pd.DataFrame(imputed_df, columns=bank_main_df.columns)
```

In [9]:
```python
# pd.isnull(imputed_df).sum()
```

MinMaxScaler

In [10]:
```python
# StandardScaler, MinMaxScaler, RobustScaler
#scaler = RobustScaler()
#X_scaled = scaler.fit_transform(imputed_df)

X = imputed_df.drop(columns='deposit')
y = imputed_df['deposit']

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3, shuffle=True)

scaler = MinMaxScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

R-Forest Feature Importance

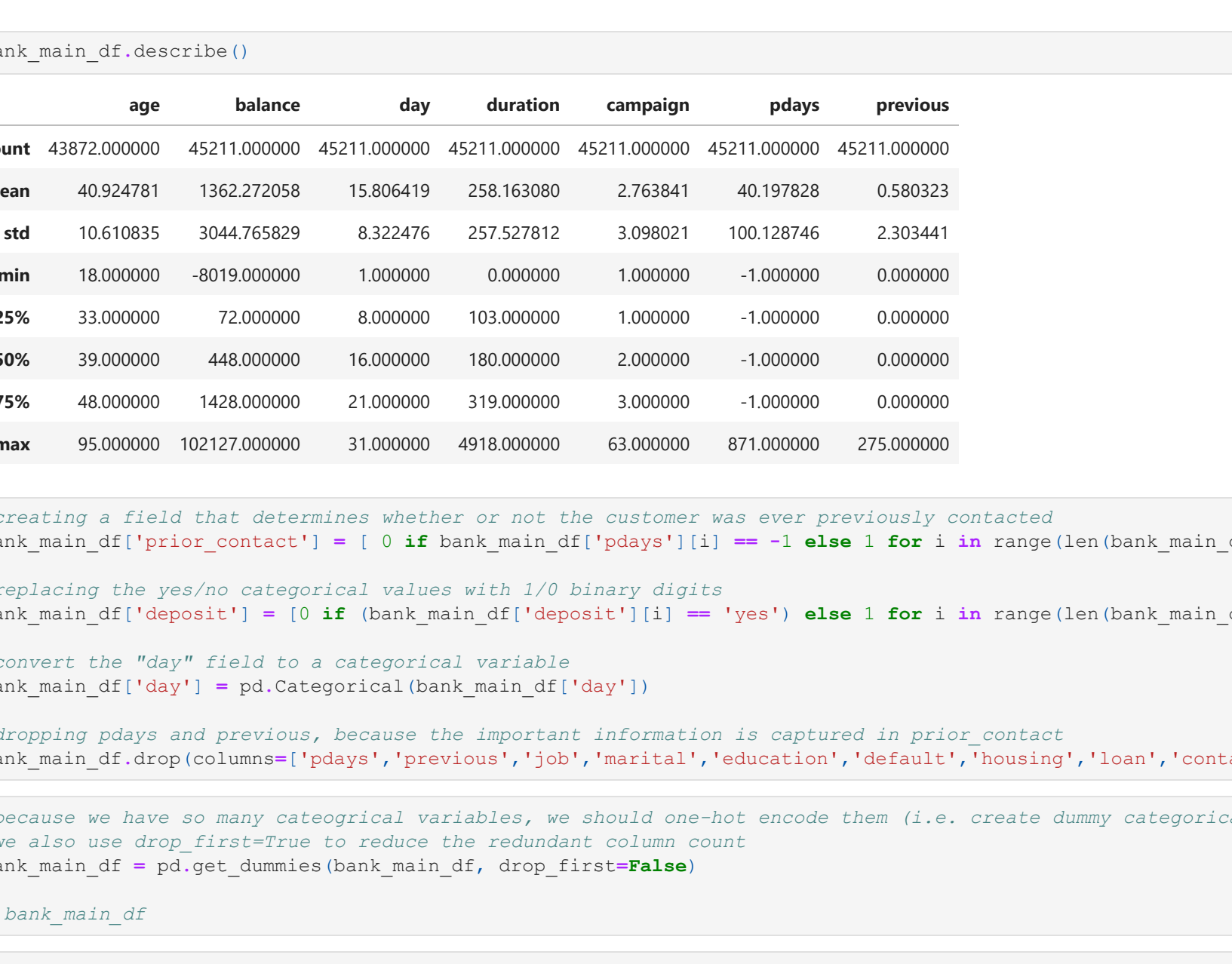
In [11]:
```python
clf = RandomForestClassifier()
# fit the classifier to the training set
clf.fit(X_train, y_train)
# predict on the test set
y_pred = clf.predict(X_test)
acc_ = accuracy_score(y_test, y_pred)
print(acc_)

#for feature in zip(X.columns, clf.feature_importances_.round(3)):
#    print(feature)

plt.figure(figsize=(12,12))
sns.barplot(y=X.columns, x=clf.feature_importances_,orient = 'h');
#plt.xticks(rotation=90);
# visualize feature importance
#with plt.style.context('ggplot', ):
#    sns.set(font_scale=1)
#    plt.figure(num=None, figsize=(14,10), dpi=80, facecolor='w')
plt.title("Random Forest Feature Importance Weighting", size=18)
plt.ylabel('Features', size = 14)
plt.xlabel('Feature Importance', size=14)
#    feat_importances = pd.Series(clf.feature_importances_, index= X.columns)
```

```
0.877838395753465
```

Out[11]:
```
Text(0.5, 0, 'Feature Importance')
```



In [12]:
```python
classifiers = [
    KNeighborsClassifier(3),
    DecisionTreeClassifier(),
#     RandomForestClassifier(),
#     AdaBoostClassifier(),
#     GradientBoostingClassifier(),
#     GaussianNB(),
#     BernoulliNB(),
#     MLPClassifier(),
#     MLPClassifier(hidden_layer_sizes=[100, 100]),
#     LinearDiscriminantAnalysis(),
#     LogisticRegression(),
#     QuadraticDiscriminantAnalysis(),
]

log_cols=["Classifier", "Accuracy", "F1 Score", "ROC", "Precision", "Recall", "Log Loss", "Sensitivity", "Speci
log = pd.DataFrame(columns=log_cols)

for clf in classifiers:
    clf.fit(X_train, y_train)
    name = clf.__class__.__name__

    print("="*60)
    print(name)
    print('****Results****')

    train_predictions = clf.predict(X_test)
    acc_ = accuracy_score(y_test, train_predictions)
    acc = acc_.round(3)
    print("Accuracy: {:.4%}".format(acc))

#     coef_scores = X_scaled
#     coef_scores = clf.coef_
#     print(coef_scores)

    fbeta_ = fbeta_score(y_test, train_predictions, beta=1)
    fbeta = fbeta_.round(3)
    print("F1 Score: {}".format(fbeta))

    roc_ = roc_auc_score(y_test, train_predictions)
    roc = roc_.round(3)
    print("AUC (ROC) Score: {}".format(roc))

    precision_ = precision_score(y_test, train_predictions, average='binary')
    precision = precision_.round(3)
    print("Precision Score: {}".format(precision))

    recall_ = recall_score(y_test, train_predictions)
    recall = recall_.round(3)
    print("Recall Score: {}".format(recall))

    TP = confusion_matrix(y_test,train_predictions).ravel()[0]
    FN = confusion_matrix(y_test,train_predictions).ravel()[1]
    sensitivity_ = TP / (TP + FN)
    sensitivity = sensitivity_.round(3)
    print("Sensitivty Score: {}".format(sensitivity))

    TN = confusion_matrix(y_test,train_predictions).ravel()[3]
    FP = confusion_matrix(y_test,train_predictions).ravel()[2]
    specificity_ = TN / (TN + FP)
    specificity = specificity_.round(3)
    print("Specificity Score: {}".format(specificity))

    true_positives = confusion_matrix(y_test,train_predictions).ravel()[0]

    print(f"\nClassic train score: {np.round(clf.score(X_train, y_train),4)}")
    print(f"Classic test score: {np.round(clf.score(X_test, y_test),4)}")
    confusion_matrix_ = confusion_matrix(y_test, train_predictions)
    print(f"Confusion matrix: \n{confusion_matrix_}\n")

    ll_ = log_loss(y_test, train_predictions)
    ll = ll_.round(3)

    log_entry = pd.DataFrame([[name, acc*100, fbeta, roc, precision, recall, ll, sensitivity, specificity, true_
    log = pd.concat([log,log_entry])

# type(coef_scores)
# print(index)
# print(log_entry)
# type(log)
```

```
============================================================
KNeighborsClassifier
****Results****
Accuracy: 86.7000%
F1 Score: 0.927
AUC (ROC) Score: 0.575
Precision Score: 0.9
Recall Score: 0.955
Sensitivty Score: 0.194
Specificity Score: 0.955

Classic train score: 0.9116
Classic test score: 0.867
Confusion matrix:
[[  305  1268]
 [  536 11455]]

============================================================
DecisionTreeClassifier
****Results****
Accuracy: 81.5000%
F1 Score: 0.895
AUC (ROC) Score: 0.573
Precision Score: 0.901
Recall Score: 0.888
Sensitivty Score: 0.258
Specificity Score: 0.888

Classic train score: 0.9986
Classic test score: 0.8154
Confusion matrix:
[[  406  1167]
 [ 1337 10654]]
```

In [13]:
```python
# Save DF as PNG
def render_mpl_table(imputed_df, col_width=6.0, row_height=0.625, font_size=10,
                     header_color='red', row_colors=['#f1f1f2', 'w'], edge_color='w',
                     bbox=[0, 0, 1, 1], header_columns=0,
                     ax=None, **kwargs):
    if ax is None:
        size = (np.array(imputed_df.shape[::-1]) + np.array([0, 1])) * np.array([col_width, row_height])
        fig, ax = plt.subplots(figsize=size)
        ax.axis('off')
    mpl_table = ax.table(cellText=imputed_df.values, bbox=bbox, colLabels=imputed_df.columns, **kwargs)
    mpl_table.auto_set_font_size(False)
    mpl_table.set_fontsize(font_size)

    for k, cell in mpl_table._cells.items():
        cell.set_edgecolor(edge_color)
        if k[0] == 0 or k[1] < header_columns:
            cell.set_text_props(weight='bold', color='w')
            cell.set_facecolor(header_color)
        else:
            cell.set_facecolor(row_colors[k[0]%len(row_colors) ])
    return ax.get_figure(), ax

fig,ax = render_mpl_table(log, header_columns=0, col_width=3.0)
fig.savefig("Images/table_mpl_minmax2.png")
```

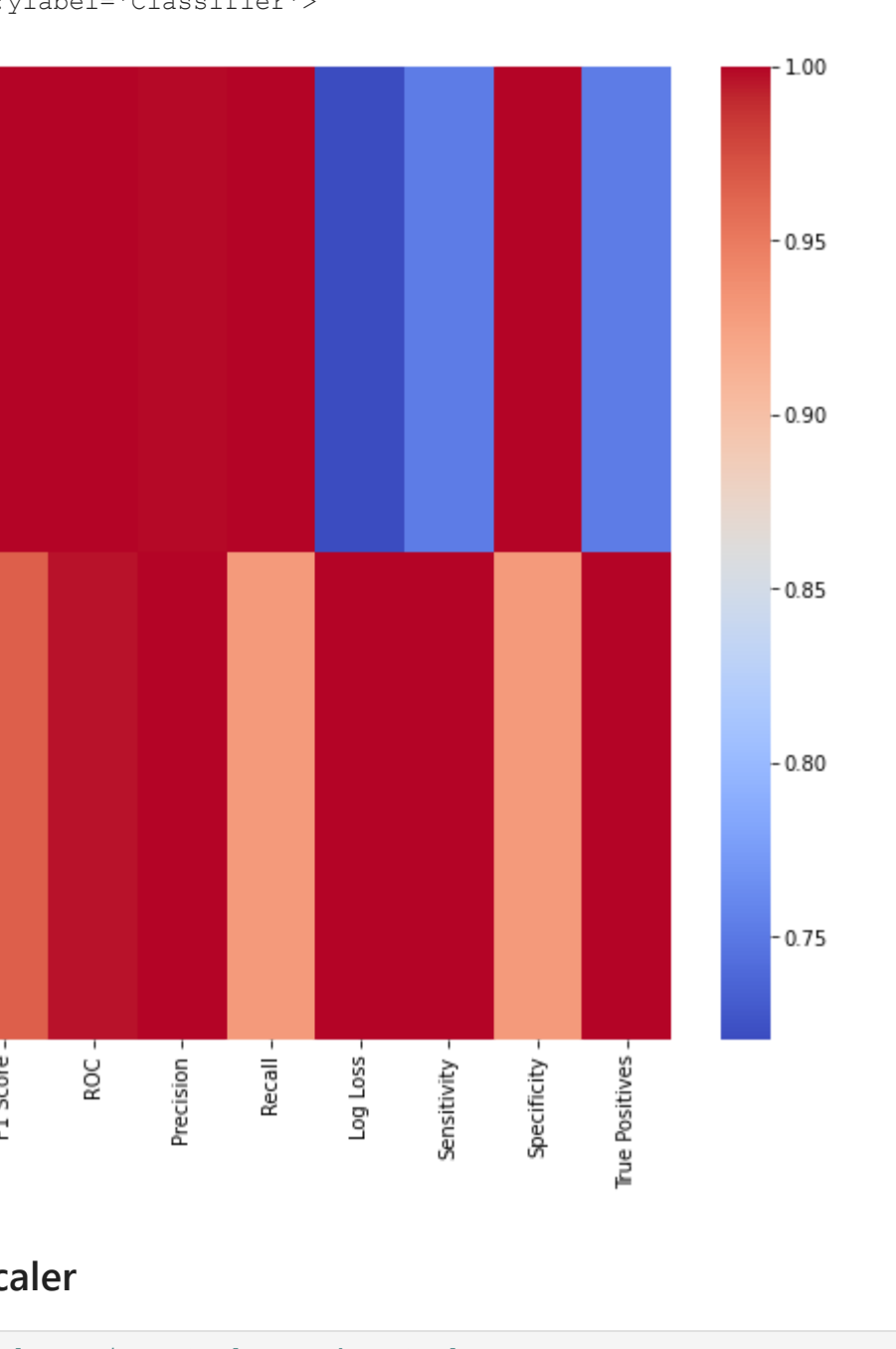
Classifier	Accuracy	F1 Score	ROC	Precision	Recall	Log Loss	Sensitivity	Specificity	True Positives
KNeighborsClassifier	86.7	0.927	0.575	0.9	0.955	4.594	0.194	0.955	305
DecisionTreeClassifier	81.5	0.895	0.573	0.901	0.888	6.376	0.258	0.888	406

In [14]:
```python
log1 = log.set_index('Classifier')

norm1_df = log1 / log1.max(0)

sns.heatmap(norm1_df.astype('float'),cmap='coolwarm')
```

Out[14]:
```
<AxesSubplot:ylabel='Classifier'>
```



StandardScaler

In [15]:
```python
# StandardScaler, MinMaxScaler, RobustScaler
#scaler = RobustScaler()
#X_scaled = scaler.fit_transform(imputed_df)

X = imputed_df.drop(columns='deposit')
y = imputed_df['deposit']

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3, shuffle=True)

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [16]:
```python
classifiers = [
#     MultinomialNB(), # doesn't work
    KNeighborsClassifier(3), # works
#     SVC(kernel="rbf", C=0.001, probability=True), # took a long time... need to refresh memory
#     SVC(kernel='linear'), # took a long time... need to refresh memory
#     NuSVC(probability=True, nu=0.1), # took a long time... need to refresh memory
    DecisionTreeClassifier(), # works
    RandomForestClassifier(), # works
    AdaBoostClassifier(), # works
    GradientBoostingClassifier(), # works
    GaussianNB(), # works
    BernoulliNB(), # works
    MLPClassifier(), # works
    MLPClassifier(hidden_layer_sizes=[100, 100]), # works
    LinearDiscriminantAnalysis(), # works
    LogisticRegression(), # works
    QuadraticDiscriminantAnalysis(), # works
]

log_cols=["Classifier", "Accuracy", "F1 Score", "ROC", "Precision", "Recall", "Log Loss", "Sensitivity", "Speci
log = pd.DataFrame(columns=log_cols)

for clf in classifiers:
    clf.fit(X_train, y_train)
#     y_pred = clf.predict(X)
    name = clf.__class__.__name__

    print("="*60)
    print(name)
    print('****Results****')

    train_predictions = clf.predict(X_test)
    acc_ = accuracy_score(y_test, train_predictions)
    acc = acc_.round(3)
    print("Accuracy: {:.4%}".format(acc))

#     coef_scores = X_scaled
#     coef_scores = clf.coef_
#     print(coef_scores)

    fbeta_ = fbeta_score(y_test, train_predictions, beta=1)
    fbeta = fbeta_.round(3)
    print("F1 Score: {}".format(fbeta))

    roc_ = roc_auc_score(y_test, train_predictions)
    roc = roc_.round(3)
    print("AUC (ROC) Score: {}".format(roc))

    precision_ = precision_score(y_test, train_predictions, average='binary')
    precision = precision_.round(3)
    print("Precision Score: {}".format(precision))

    recall_ = recall_score(y_test, train_predictions)
    recall = recall_.round(3)
    print("Recall Score: {}".format(recall))

    TP = confusion_matrix(y_test,train_predictions).ravel()[0]
    FN = confusion_matrix(y_test,train_predictions).ravel()[1]
    sensitivity_ = TP / (TP + FN)
    sensitivity = sensitivity_.round(3)
    print("Sensitivty Score: {}".format(sensitivity))

    TN = confusion_matrix(y_test,train_predictions).ravel()[3]
    FP = confusion_matrix(y_test,train_predictions).ravel()[2]
    specificity_ = TN / (TN + FP)
    specificity = specificity_.round(3)
    print("Specificity Score: {}".format(specificity))

    true_positives = confusion_matrix(y_test,train_predictions).ravel()[0]

    print(f"\nClassic train score: {np.round(clf.score(X_train, y_train),4)}")
    print(f"Classic test score: {np.round(clf.score(X_test, y_test),4)}")
    confusion_matrix_ = confusion_matrix(y_test, train_predictions)
    print(f"Confusion matrix: \n{confusion_matrix_}\n")

#     train_predictions = clf.predict_proba(X_test)
    ll_ = log_loss(y_test, train_predictions)
    ll = ll_.round(3)
#     print("Log Loss: {}".format(ll))

    log_entry = pd.DataFrame([[name, acc*100, fbeta, roc, precision, recall, ll, sensitivity, specificity, true_
    log = pd.concat([log,log_entry])

# print("="*30)
# type(coef_scores)
# print(index)
# print(log_entry)
# type(log)
```

```
============================================================
KNeighborsClassifier
****Results****
Accuracy: 87.3000%
F1 Score: 0.93
AUC (ROC) Score: 0.586
Precision Score: 0.901
Recall Score: 0.962
Sensitivty Score: 0.211
Specificity Score: 0.962

Classic train score: 0.9096
Classic test score: 0.873
Confusion matrix:
[[  338  1266]
 [  456 11504]]

============================================================
DecisionTreeClassifier
****Results****
Accuracy: 82.5000%
F1 Score: 0.9
AUC (ROC) Score: 0.583
Precision Score: 0.901
Recall Score: 0.9
Sensitivty Score: 0.266
Specificity Score: 0.9

Classic train score: 0.9987
Classic test score: 0.8247
Confusion matrix:
[[  427  1177]
 [ 1201 10759]]

============================================================
RandomForestClassifier
****Results****
Accuracy: 88.0000%
F1 Score: 0.935
AUC (ROC) Score: 0.583
Precision Score: 0.9
Recall Score: 0.972
Sensitivty Score: 0.193
Specificity Score: 0.972

Classic train score: 0.9986
Classic test score: 0.8803
Confusion matrix:
[[  310  1294]
 [  330 11630]]

============================================================
AdaBoostClassifier
****Results****
Accuracy: 89.3000%
F1 Score: 0.942
AUC (ROC) Score: 0.582
Precision Score: 0.899
Recall Score: 0.989
Sensitivty Score: 0.174
Specificity Score: 0.989

Classic train score: 0.8904
Classic test score: 0.893
Confusion matrix:
[[  279  1325]
 [  126 11834]]

============================================================
GradientBoostingClassifier
****Results****
Accuracy: 89.6000%
F1 Score: 0.944
AUC (ROC) Score: 0.594
Precision Score: 0.902
Recall Score: 0.989
Sensitivty Score: 0.198
Specificity Score: 0.989

Classic train score: 0.8939
Classic test score: 0.8956
Confusion matrix:
[[  318  1286]
 [  130 11830]]

============================================================
GaussianNB
****Results****
Accuracy: 77.0000%
F1 Score: 0.862
AUC (ROC) Score: 0.623
Precision Score: 0.914
Recall Score: 0.815
Sensitivty Score: 0.43
Specificity Score: 0.815

Classic train score: 0.7629
Classic test score: 0.7696
Confusion matrix:
[[ 690  914]
 [2211 9749]]

============================================================
BernoulliNB
****Results****
Accuracy: 88.3000%
F1 Score: 0.936
AUC (ROC) Score: 0.611
Precision Score: 0.906
Recall Score: 0.968
Sensitivty Score: 0.254
Specificity Score: 0.968

Classic train score: 0.8785
Classic test score: 0.8834
Confusion matrix:
[[  408  1196]
 [  386 11574]]

C:\Users\reagins\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.10_qbz5n2kfra8p0\LocalCache\local-packages\Python310\site-packages\sklearn\neural_network\_multilayer_perceptron.py:692: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the optimization hasn't converged yet.
  warnings.warn(
============================================================
MLPClassifier
****Results****
Accuracy: 89.3000%
F1 Score: 0.942
AUC (ROC) Score: 0.596
Precision Score: 0.903
Recall Score: 0.985
Sensitivty Score: 0.207
Specificity Score: 0.985

Classic train score: 0.8963
Classic test score: 0.893
Confusion matrix:
[[  332  1272]
 [  179 11781]]

C:\Users\reagins\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.10_qbz5n2kfra8p0\LocalCache\local-packages\Python310\site-packages\sklearn\neural_network\_multilayer_perceptron.py:692: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the optimization hasn't converged yet.
  warnings.warn(
============================================================
MLPClassifier
****Results****
Accuracy: 88.0000%
F1 Score: 0.934
AUC (ROC) Score: 0.59
Precision Score: 0.902
Recall Score: 0.97
Sensitivty Score: 0.21
Specificity Score: 0.97

Classic train score: 0.9114
Classic test score: 0.88
Confusion matrix:
[[  337  1267]
 [  361 11599]]

============================================================
LinearDiscriminantAnalysis
****Results****
Accuracy: 89.6000%
F1 Score: 0.943
AUC (ROC) Score: 0.597
Precision Score: 0.903
Recall Score: 0.988
Sensitivty Score: 0.206
Specificity Score: 0.988

Classic train score: 0.8914
Classic test score: 0.8955
Confusion matrix:
[[  330  1274]
 [  143 11817]]

============================================================
LogisticRegression
****Results****
Accuracy: 89.5000%
F1 Score: 0.943
AUC (ROC) Score: 0.589
Precision Score: 0.901
Recall Score: 0.989
Sensitivty Score: 0.19
Specificity Score: 0.989

Classic train score: 0.8917
Classic test score: 0.8949
Confusion matrix:
[[  304  1300]
 [  126 11834]]

============================================================
QuadraticDiscriminantAnalysis
****Results****
Accuracy: 76.6000%
F1 Score: 0.86
AUC (ROC) Score: 0.616
Precision Score: 0.913
Recall Score: 0.813
Sensitivty Score: 0.419
Specificity Score: 0.813

Classic train score: 0.7565
Classic test score: 0.7664
Confusion matrix:
[[ 672  932]
 [2237 9723]]

C:\Users\reagins\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.10_qbz5n2kfra8p0\LocalCache\local-packages\Python310\site-packages\sklearn\discriminant_analysis.py:878: UserWarning: Variables are collinear
  warnings.warn("Variables are collinear")
```

In [17]:
```python
# Save DF as PNG
def render_mpl_table(imputed_df, col_width=6.0, row_height=0.625, font_size=10,
                     header_color='#40466e', row_colors=['#f1f1f2', 'w'], edge_color='w',
                     bbox=[0, 0, 1, 1], header_columns=0,
                     ax=None, **kwargs):
    if ax is None:
        size = (np.array(imputed_df.shape[::-1]) + np.array([0, 1])) * np.array([col_width, row_height])
        fig, ax = plt.subplots(figsize=size)
        ax.axis('off')
    mpl_table = ax.table(cellText=imputed_df.values, bbox=bbox, colLabels=imputed_df.columns, **kwargs)
    mpl_table.auto_set_font_size(False)
    mpl_table.set_fontsize(font_size)

    for k, cell in mpl_table._cells.items():
        cell.set_edgecolor(edge_color)
        if k[0] == 0 or k[1] < header_columns:
            cell.set_text_props(weight='bold', color='w')
            cell.set_facecolor(header_color)
        else:
            cell.set_facecolor(row_colors[k[0]%len(row_colors) ])
    return ax.get_figure(), ax

fig,ax = render_mpl_table(log, header_columns=0, col_width=3.0)
fig.savefig("Images/table_mpl_standard2.png")
```

Classifier	Accuracy	F1 Score	ROC	Precision	Recall	Log Loss	Sensitivity	Specificity	True Positives
KNeighborsClassifier	87.3	0.93	0.586	0.901	0.962	4.385	0.211	0.962	338
DecisionTreeClassifier	82.5	0.9	0.583	0.901	0.9	6.055	0.266	0.9	427
RandomForestClassifier	88.0	0.935	0.583	0.9	0.972	4.135	0.193	0.972	310
AdaBoostClassifier	89.3	0.942	0.582	0.899	0.989	3.695	0.174	0.989	279
GradientBoostingClassifier	89.60000000000001	0.944	0.594	0.902	0.989	3.606	0.198	0.989	318
GaussianNB	77.0	0.862	0.623	0.914	0.815	7.957	0.43	0.815	690
BernoulliNB	88.3	0.936	0.611	0.906	0.968	4.028	0.254	0.968	408
MLPClassifier	89.3	0.942	0.596	0.903	0.985	3.695	0.207	0.985	332
MLPClassifier	88.0	0.934	0.59	0.902	0.97	4.146	0.21	0.97	337
LinearDiscriminantAnalysis	89.60000000000001	0.943	0.597	0.903	0.988	3.608	0.206	0.988	330
LogisticRegression	89.5	0.943	0.589	0.901	0.989	3.631	0.19	0.989	304
QuadraticDiscriminantAnalysis	76.6	0.86	0.616	0.913	0.813	8.069	0.419	0.813	672

In [18]:
```python
log2 = log.set_index('Classifier')

norm2_df = log2 / log2.max(0)

sns.heatmap(norm2_df.astype('float'),cmap='coolwarm')
```

Out[18]:
```
<AxesSubplot:ylabel='Classifier'>
```

RobustScaler

In [19]:
```python
# StandardScaler, MinMaxScaler, RobustScaler
#scaler = RobustScaler()
#X_scaled = scaler.fit_transform(imputed_df)

X = imputed_df.drop(columns='deposit')
y = imputed_df['deposit']

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3, shuffle=True)

scaler = RobustScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [20]:
```python
classifiers = [
#     MultinomialNB(), # doesn't work
    KNeighborsClassifier(3), # works
#     SVC(kernel="rbf", C=0.001, probability=True), # took a long time... need to refresh memory
#     SVC(kernel='linear'), # took a long time... need to refresh memory
#     NuSVC(probability=True, nu=0.1), # took a long time... need to refresh memory
    DecisionTreeClassifier(), # works
    RandomForestClassifier(), # works
    AdaBoostClassifier(), # works
    GradientBoostingClassifier(), # works
    GaussianNB(), # works
    BernoulliNB(), # works
    MLPClassifier(), # works
    MLPClassifier(hidden_layer_sizes=[100, 100]), # works
    LinearDiscriminantAnalysis(), # works
    LogisticRegression(), # works
    QuadraticDiscriminantAnalysis(), # works
]

log_cols=["Classifier", "Accuracy", "F1 Score", "ROC", "Precision", "Recall", "Log Loss", "Sensitivity", "Speci
log = pd.DataFrame(columns=log_cols)

for clf in classifiers:
    clf.fit(X_train, y_train)
#     y_pred = clf.predict(X)
    name = clf.__class__.__name__

    print("="*60)
    print(name)
    print('****Results****')

    train_predictions = clf.predict(X_test)
    acc_ = accuracy_score(y_test, train_predictions)
    acc = acc_.round(3)
    print("Accuracy: {:.4%}".format(acc))

#     coef_scores = X_scaled
#     coef_scores = clf.coef_
#     print(coef_scores)

    fbeta_ = fbeta_score(y_test, train_predictions, beta=1)
    fbeta = fbeta_.round(3)
    print("F1 Score: {}".format(fbeta))

    roc_ = roc_auc_score(y_test, train_predictions)
    roc = roc_.round(3)
    print("AUC (ROC) Score: {}".format(roc))

    precision_ = precision_score(y_test, train_predictions, average='binary')
    precision = precision_.round(3)
    print("Precision Score: {}".format(precision))

    recall_ = recall_score(y_test, train_predictions)
    recall = recall_.round(3)
    print("Recall Score: {}".format(recall))

    TP = confusion_matrix(y_test,train_predictions).ravel()[0]
    FN = confusion_matrix(y_test,train_predictions).ravel()[1]
    sensitivity_ = TP / (TP + FN)
    sensitivity = sensitivity_.round(3)
    print("Sensitivty Score: {}".format(sensitivity))

    TN = confusion_matrix(y_test,train_predictions).ravel()[3]
    FP = confusion_matrix(y_test,train_predictions).ravel()[2]
    specificity_ = TN / (TN + FP)
    specificity = specificity_.round(3)
    print("Specificity Score: {}".format(specificity))

    true_positives = confusion_matrix(y_test,train_predictions).ravel()[0]

    print(f"\nClassic train score: {np.round(clf.score(X_train, y_train),4)}")
    print(f"Classic test score: {np.round(clf.score(X_test, y_test),4)}")
    confusion_matrix_ = confusion_matrix(y_test, train_predictions)
    print(f"Confusion matrix: \n{confusion_matrix_}\n")

#     train_predictions = clf.predict_proba(X_test)
    ll_ = log_loss(y_test, train_predictions)
    ll = ll_.round(3)
#     print("Log Loss: {}".format(ll))

    log_entry = pd.DataFrame([[name, acc*100, fbeta, roc, precision, recall, ll, sensitivity, specificity, true_
    log = pd.concat([log,log_entry])

# print("="*30)
# type(coef_scores)
# print(index)
# print(log_entry)
# type(log)
```

```
============================================================
KNeighborsClassifier
****Results****
Accuracy: 87.0000%
F1 Score: 0.929
AUC (ROC) Score: 0.568
Precision Score: 0.9
Recall Score: 0.96
Sensitivty Score: 0.177
Specificity Score: 0.96

Classic train score: 0.9107
Classic test score: 0.8699
Confusion matrix:
[[  276  1287]
 [  478 11523]]

============================================================
DecisionTreeClassifier
****Results****
Accuracy: 81.8000%
F1 Score: 0.897
AUC (ROC) Score: 0.57
Precision Score: 0.901
Recall Score: 0.893
Sensitivty Score: 0.248
Specificity Score: 0.893

Classic train score: 0.9987
Classic test score: 0.8185
Confusion matrix:
[[  387  1176]
 [ 1286 10715]]

============================================================
RandomForestClassifier
****Results****
Accuracy: 87.8000%
F1 Score: 0.933
AUC (ROC) Score: 0.576
Precision Score: 0.901
Recall Score: 0.968
Sensitivty Score: 0.184
Specificity Score: 0.968

Classic train score: 0.9986
Classic test score: 0.8775
Confusion matrix:
[[  288  1275]
 [  386 11615]]

============================================================
AdaBoostClassifier
****Results****
Accuracy: 89.3000%
F1 Score: 0.942
AUC (ROC) Score: 0.578
Precision Score: 0.901
Recall Score: 0.988
Sensitivty Score: 0.168
Specificity Score: 0.988

Classic train score: 0.8912
Classic test score: 0.893
Confusion matrix:
[[  262  1301]
 [  150 11851]]

============================================================
GradientBoostingClassifier
****Results****
Accuracy: 89.4000%
F1 Score: 0.943
AUC (ROC) Score: 0.585
Precision Score: 0.903
Recall Score: 0.986
Sensitivty Score: 0.184
Specificity Score: 0.986

Classic train score: 0.8945
Classic test score: 0.8937
Confusion matrix:
[[  288  1275]
 [  167 11834]]

============================================================
GaussianNB
****Results****
Accuracy: 77.0000%
F1 Score: 0.863
AUC (ROC) Score: 0.623
Precision Score: 0.917
Recall Score: 0.815
Sensitivty Score: 0.431
Specificity Score: 0.815

Classic train score: 0.7708
Classic test score: 0.7705
Confusion matrix:
[[ 673  890]
 [2223 9778]]

============================================================
BernoulliNB
****Results****
Accuracy: 89.4000%
F1 Score: 0.943
AUC (ROC) Score: 0.59
Precision Score: 0.904
Recall Score: 0.985
Sensitivty Score: 0.196
Specificity Score: 0.985

Classic train score: 0.8912
Classic test score: 0.8942
Confusion matrix:
[[  306  1257]
 [  178 11823]]

C:\Users\reagins\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.10_qbz5n2kfra8p0\LocalCache\local-packages\Python310\site-packages\sklearn\neural_network\_multilayer_perceptron.py:692: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the optimization hasn't converged yet.
  warnings.warn(
============================================================
MLPClassifier
****Results****
Accuracy: 88.9000%
F1 Score: 0.94
AUC (ROC) Score: 0.589
Precision Score: 0.904
Recall Score: 0.979
Sensitivty Score: 0.198
Specificity Score: 0.979

Classic train score: 0.8981
Classic test score: 0.8893
Confusion matrix:
[[  310  1253]
 [  249 11752]]

C:\Users\reagins\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.10_qbz5n2kfra8p0\LocalCache\local-packages\Python310\site-packages\sklearn\neural_network\_multilayer_perceptron.py:692: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the optimization hasn't converged yet.
  warnings.warn(
============================================================
MLPClassifier
****Results****
Accuracy: 86.9000%
F1 Score: 0.928
AUC (ROC) Score: 0.58
Precision Score: 0.902
Recall Score: 0.956
Sensitivty Score: 0.204
Specificity Score: 0.956

Classic train score: 0.9171
Classic test score: 0.8691
Confusion matrix:
[[  319  1244]
 [  532 11469]]

============================================================
LinearDiscriminantAnalysis
****Results****
Accuracy: 89.5000%
F1 Score: 0.943
AUC (ROC) Score: 0.589
Precision Score: 0.904
Recall Score: 0.986
Sensitivty Score: 0.192
Specificity Score: 0.986

Classic train score: 0.8919
Classic test score: 0.8946
Confusion matrix:
[[  300  1263]
 [  167 11834]]

============================================================
LogisticRegression
****Results****
Accuracy: 89.5000%
F1 Score: 0.943
AUC (ROC) Score: 0.587
Precision Score: 0.903
Recall Score: 0.987
Sensitivty Score: 0.186
Specificity Score: 0.987

Classic train score: 0.8917
Classic test score: 0.8946
Confusion matrix:
[[  291  1272]
 [  157 11844]]

============================================================
QuadraticDiscriminantAnalysis
****Results****
Accuracy: 71.5000%
F1 Score: 0.822
AUC (ROC) Score: 0.615
Precision Score: 0.917
Recall Score: 0.745
Sensitivty Score: 0.486
Specificity Score: 0.745

Classic train score: 0.7184
Classic test score: 0.7149
Confusion matrix:
[[ 759  804]
 [3063 8938]]

C:\Users\reagins\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.10_qbz5n2kfra8p0\LocalCache\local-packages\Python310\site-packages\sklearn\discriminant_analysis.py:878: UserWarning: Variables are collinear
  warnings.warn("Variables are collinear")
```

In [21]:
```python
# Save DF as PNG
def render_mpl_table(imputed_df, col_width=6.0, row_height=0.625, font_size=10,
                     header_color='blue', row_colors=['#f1f1f2', 'w'], edge_color='w',
                     bbox=[0, 0, 1, 1], header_columns=0,
                     ax=None, **kwargs):
    if ax is None:
        size = (np.array(imputed_df.shape[::-1]) + np.array([0, 1])) * np.array([col_width, row_height])
        fig, ax = plt.subplots(figsize=size)
        ax.axis('off')
    mpl_table = ax.table(cellText=imputed_df.values, bbox=bbox, colLabels=imputed_df.columns, **kwargs)
    mpl_table.auto_set_font_size(False)
    mpl_table.set_fontsize(font_size)

    for k, cell in mpl_table._cells.items():
        cell.set_edgecolor(edge_color)
        if k[0] == 0 or k[1] < header_columns:
            cell.set_text_props(weight='bold', color='w')
            cell.set_facecolor(header_color)
        else:
            cell.set_facecolor(row_colors[k[0]%len(row_colors) ])
    return ax.get_figure(), ax

fig,ax = render_mpl_table(log, header_columns=0, col_width=3.0)
fig.savefig("Images/table_mpl_robust2.png")
```

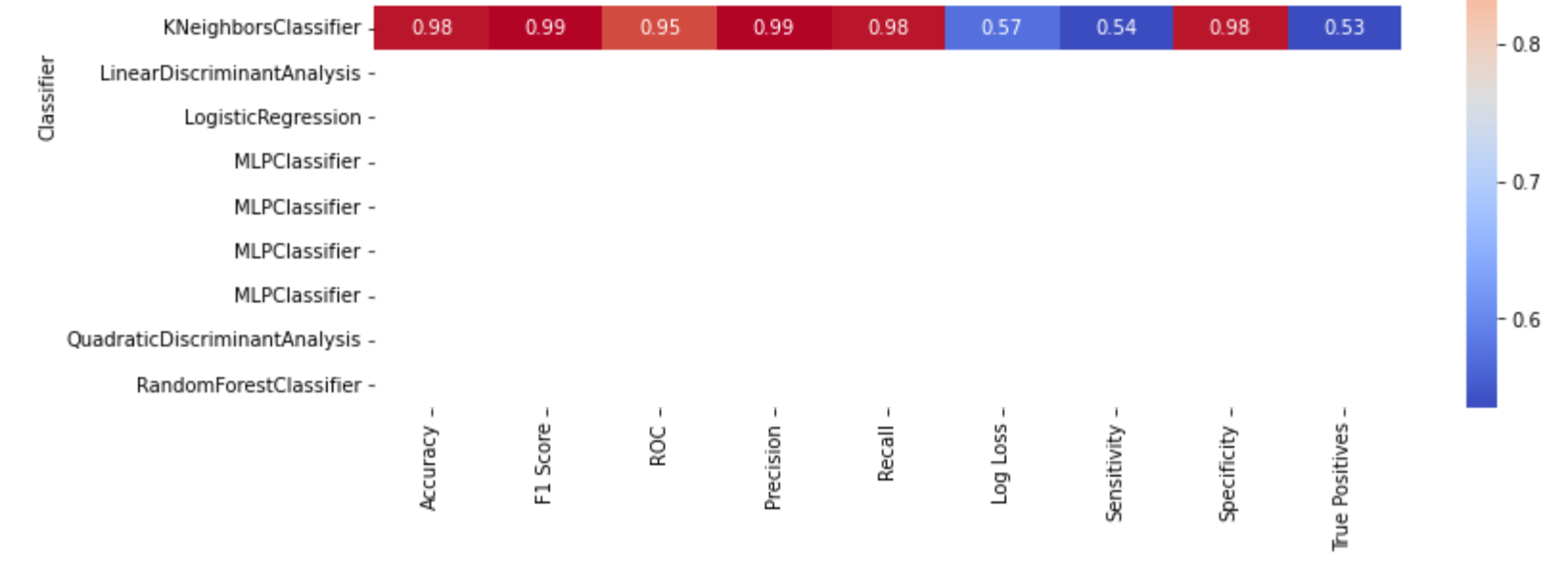
Classifier	Accuracy	F1 Score	ROC	Precision	Recall	Log Loss	Sensitivity	Specificity	True Positives
KNeighborsClassifier	87.0	0.929	0.568	0.9	0.96	4.494	0.177	0.96	276
DecisionTreeClassifier	81.8	0.897	0.57	0.901	0.893	6.269	0.248	0.893	387
RandomForestClassifier	87.8	0.933	0.576	0.901	0.968	4.23	0.184	0.968	288
AdaBoostClassifier	89.3	0.942	0.578	0.901	0.988	3.695	0.168	0.988	262
GradientBoostingClassifier	89.4	0.943	0.585	0.903	0.986	3.672	0.184	0.986	288
GaussianNB	77.0	0.863	0.623	0.917	0.815	7.927	0.431	0.815	673
BernoulliNB	89.4	0.943	0.59	0.904	0.985	3.654	0.196	0.985	306
MLPClassifier	88.9	0.94	0.589	0.904	0.979	3.825	0.198	0.979	310
MLPClassifier	86.9	0.928	0.58	0.902	0.956	4.522	0.204	0.956	319
LinearDiscriminantAnalysis	89.5	0.943	0.589	0.904	0.986	3.641	0.192	0.986	300
LogisticRegression	89.5	0.943	0.587	0.903	0.987	3.639	0.186	0.987	291
QuadraticDiscriminantAnalysis	71.5	0.822	0.615	0.917	0.745	9.847	0.486	0.745	759

In [22]:
```python
log3 = log.set_index('Classifier')

norm3_df = log3 / log3.max(0)

plt.figure(figsize=(12,6))
sns.heatmap(norm2_df.astype('float'),cmap='coolwarm',annot=True)
```

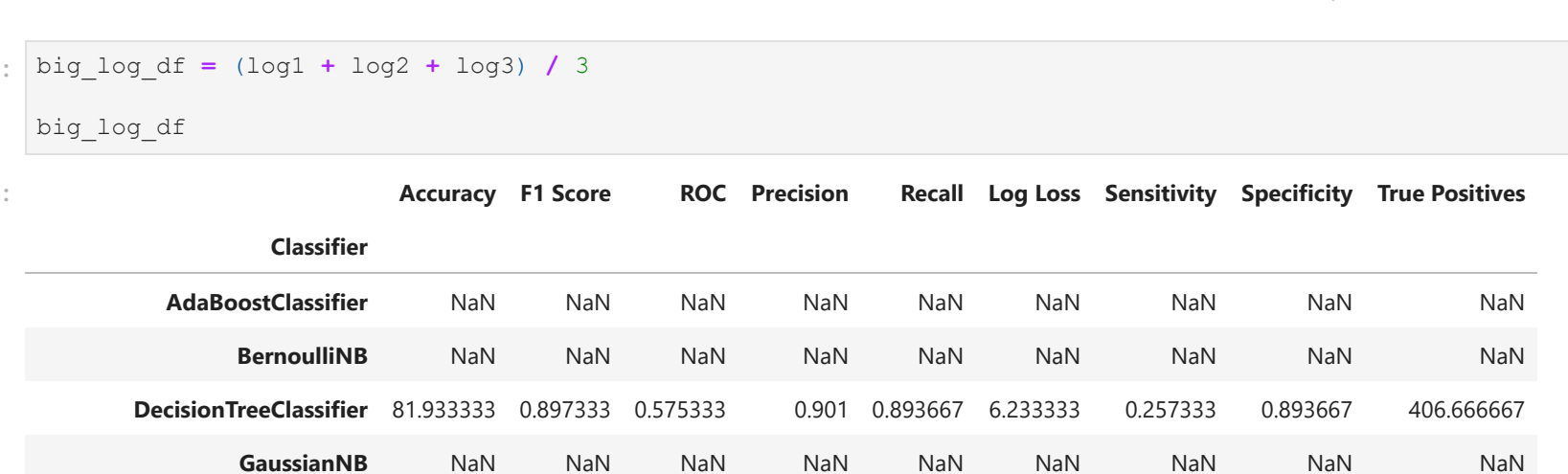
Out[22]: `<AxesSubplot:ylabel='Classifier'>`



In [23]:
```python
big_norm_df = (norm1_df + norm2_df + norm3_df) / 3

plt.figure(figsize=(12,6))
sns.heatmap(big_norm_df.astype('float'),cmap='coolwarm',annot=True)
```

Out[23]: `<AxesSubplot:ylabel='Classifier'>`



In [24]:
```python
big_log_df = (log1 + log2 + log3) / 3

big_log_df
```

Out[24]:

Classifier	Accuracy	F1 Score	ROC	Precision	Recall	Log Loss	Sensitivity	Specificity	True Positives
AdaBoostClassifier	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
BernoulliNB	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
DecisionTreeClassifier	81.933333	0.897333	0.575333	0.901	0.893667	6.233333	0.257333	0.893667	406.666667
GaussianNB	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
GradientBoostingClassifier	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
KNeighborsClassifier	87.0	0.928667	0.576333	0.900333	0.959	4.491	0.194	0.959	306.333333
LinearDiscriminantAnalysis	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
LogisticRegression	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
MLPClassifier	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
MLPClassifier	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
MLPClassifier	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
MLPClassifier	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
QuadraticDiscriminantAnalysis	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
RandomForestClassifier	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [ ]:

In [25]:
```python
#plt.figure(figsize=(24,3))
#sns.barplot(X.columns,logreg.coef_[0])
#plt.xticks(rotation=60)
#plt.title("Extracting the Feature Importance");
```

Further discussion for the group

- **What further refinements to the dataset should we make as part of the EDA / cleanup?**
  - Removing the *pdays* variable, for example
  - Dropping outliers
- **How might the use of other classification algorithms and scalers affect the final predictions?**
  - ~Algorithms like LogisticRegression, DecisionTree, RandomForest, Kneighbors, NaiveBayes, neural net, etc.~
  - Scalers like StandardScaler, MinMaxScaler, RobustScaler
  - PCA (principal component analysis) to reduce dimensions
- **Playing with parameters, pipelines, gridsearches to maximize True Negatives and minimize False Negatives**
  - That is, maximize deposit==1 correct predictions and reducing deposit==0 wrong predictions
  - Even if that means accidentally overpredicting the number of true deposits, better to try a bad path than miss a potential business opportunity
- **Extending this to other predictions**
  - e.g. predicting the "default" variable, or some other classification
  - e.g. predicting a range for continuous values based on categorical values
- **Best ways to impute missing data?** *

In [ ]:

In [ ]:

In [ ]: