Models

In [38]:
```
import pandas as pd
import numpy as np
import matplotlib
import matplotlib.pyplot as plt
import itertools
from imblearn.over_sampling import SMOTE

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

import statsmodels.api as sm
from statsmodels.api import OLS
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LogisticRegressionCV
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier

from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score

from sklearn.metrics import precision_recall_fscore_support
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import auc, roc_curve

import warnings
warnings.filterwarnings('ignore')

import keras
from keras.models import Sequential
from keras.layers import Dense
from keras.utils import to_categorical

import seaborn as sns
pd.set_option('display.width', 500)
pd.set_option('display.max_columns', 500)

% matplotlib inline
```

Data Preparation

There are too many observations in the dataset, which will take hours or even days to fit for some sophisticated algorithms. Thus, we decided to take a stratified sample on year of raw dataset in the model fitting stage.

In [2]:
```
df_fe = pd.read_csv("data/output_fe.csv")
print("Shape of the raw input file: {}".format(df_fe.shape))
```

```
Shape of the raw input file: (95765, 196)
```

In [3]:
```
df_clean = df_fe.copy(deep=True)
df_clean = df_fe.groupby('year', group_keys=False).apply(lambda x: x.sample(f
df_clean.drop(['year'], axis=1, inplace=True)

print("Shape of the clean input file: {}".format(df_clean.shape))
```

```
Shape of the clean input file: (4789, 195)
```

Stratified Sampling

We split training and test dataset by stratifing on the response variable.

In [4]:
```
df_train, df_test = train_test_split(df_clean,
                                     test_size = .5,
                                     stratify = df_clean['response'],
                                     random_state=90)

print("Shape of the training set: {}".format(df_train.shape))
print("Shape of the test set: {}".format(df_test.shape))
```

```
Shape of the training set: (2394, 195)
Shape of the test set: (2395, 195)
```

In [5]:
```
def split_columns(df, target_col, drop_columns):
    # Get the response variable
    y_train = df[[target_col]]

    # Drop the required columns
    X_train = df.drop(drop_columns, axis=1)

    return X_train, y_train
```

In [6]:
```
X_train, y_train = split_columns(df_train, target_col='response', drop_column
X_test, y_test = split_columns(df_test, target_col='response', drop_columns=[
```

Standardization

We standardize all the predictors that are not dummy variables.

In [7]:
```python
def scale_datasets(train_data, test_data, cols_to_scale):
    train = train_data.copy()
    test = test_data.copy()

    # Fit the scaler on the training data
    scaler = StandardScaler().fit(train[cols_to_scale])

    # Scale both the test and training data.
    train[cols_to_scale] = scaler.transform(train[cols_to_scale])
    test[cols_to_scale] = scaler.transform(test[cols_to_scale])

    return train, test
```

In [8]:
```python
X_train, X_test = scale_datasets(X_train, X_test, list(X_train.columns))
```

Custom Functions

In [9]:
```python
def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues,
                          fontsize=16):
    """
    This function plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title, fontsize=fontsize)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, fontsize=fontsize)
    plt.yticks(tick_marks, classes, fontsize=fontsize)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black",
                 fontsize=fontsize)

    plt.ylabel('True label', fontsize=fontsize)
    plt.xlabel('Predicted label', fontsize=fontsize)
    plt.tight_layout()
```

Classification of Good and Bad Loans

Baseline Model

For classification, a simple baseline is always predicting the most common class, which is good loans in our dataset.

In [10]:
```
base_train_acc = y_train.response.value_counts()[0] / len(y_train)
base_test_acc = y_test.response.value_counts()[0] / len(y_test)
print("Baseline model accuracy in training set: {:.2%}".format(base_train_acc
print("Baseline model accuracy in test set: {:.2%}".format(base_test_acc))
```

```
Baseline model accuracy in training set: 84.17%
Baseline model accuracy in test set: 84.18%
```

Oversampling

As we can see from the baseline model accuracy, the lending club dataset is an imbalanced one with 84% of majority class and only 16% minority class. A common problem with imbalanced dataset is that the model will simply predict the majority class with a high accuracy score and ignore the minority class. However, accuracy or precision may not be the only concern we have as data scientists.

For example, if we were building a model for cancer detection, we would want to capture all the patients that do have cancer, even at the cost of some misclassification of heathy people, as these people can be examined futher by doctors. As investors on lending club, what we really care about is the default risk. The key question we need to ask ourselves is that among all the bad loans, how many of them we can predict correctly? This is the so called recall rate.

Oversampling is a technique that can deal with this imbalanced dataset. The basic idea is to over sample the minority class, so that the model can achieve higher recall at the cost of precision, and that's exactly what we want. In the modeling stage, We used Synthetic Minority Oversampling Technique (SMOTE) to oversample the training set.

In [11]:
```
sm = SMOTE(random_state=12, ratio = 1.0)
X_train_sm, y_train_sm = sm.fit_sample(X_train, y_train)
print("Oversampled Training Set:\nNumber of bad loans: {}\nNumber of good loa
    np.count_nonzero(y_train_sm == 1), np.count_nonzero(y_train_sm == 0))
)
```

```
Oversampled Training Set:
Number of bad loans: 2015
Number of good loans: 2015
```

Logistic Regression

Raw training set

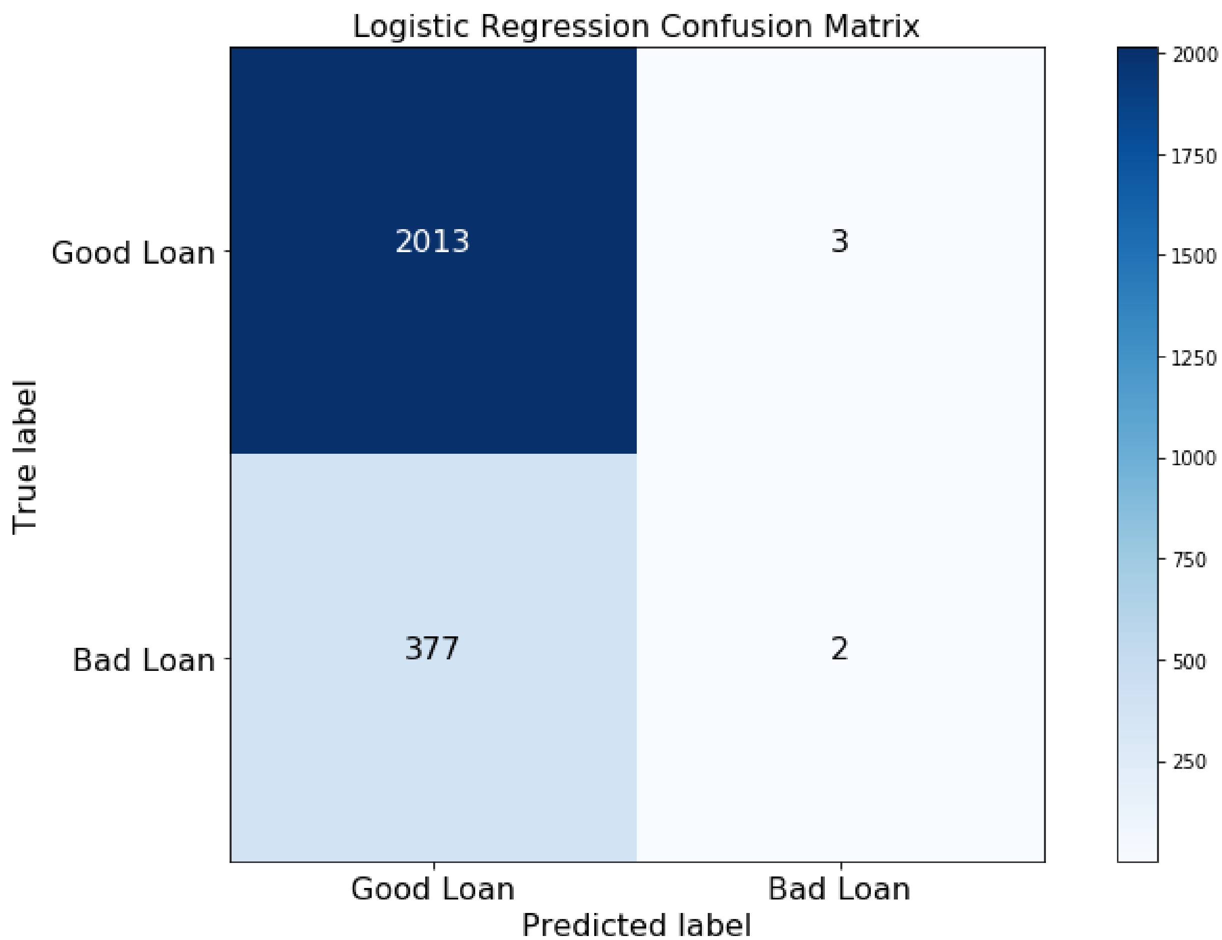
In [12]:

```
# Raw training set
logit = LogisticRegressionCV(cv=5, random_state=0, penalty='l2').fit(X_train,

train_acc = logit.score(X_train, y_train)
test_acc = logit.score(X_test, y_test)
report_lr = precision_recall_fscore_support(y_test, logit.predict(X_test), av

logit_results = {
    'model': 'Logistic',
    'train_acc': train_acc,
    'test_acc': test_acc,
    'precision': report_lr[0],
    'recall': report_lr[1],
    'F1': report_lr[2]
}

print('Logistic Regression: accuracy on train={:.2%}, test={:.2%}, precision=
      format(logit_results['train_acc'],
             logit_results['test_acc'],
             logit_results['precision'],
             logit_results['recall'],
             logit_results['F1']))
```

```
Logistic Regression: accuracy on train=84.34%, test=84.13%, precision=0.40, rec
all=0.01, F1=0.01
```

In [13]:

```
# Plot confusion matrix
cnf_matrix = confusion_matrix(y_test, logit.predict(X_test))
np.set_printoptions(precision=2)

plt.figure(figsize=(11,7))
plot_confusion_matrix(cnf_matrix, classes=["Good Loan", "Bad Loan"], normaliz
                      title='Logistic Regression Confusion Matrix')

plt.show()
```



Oversampled Training set

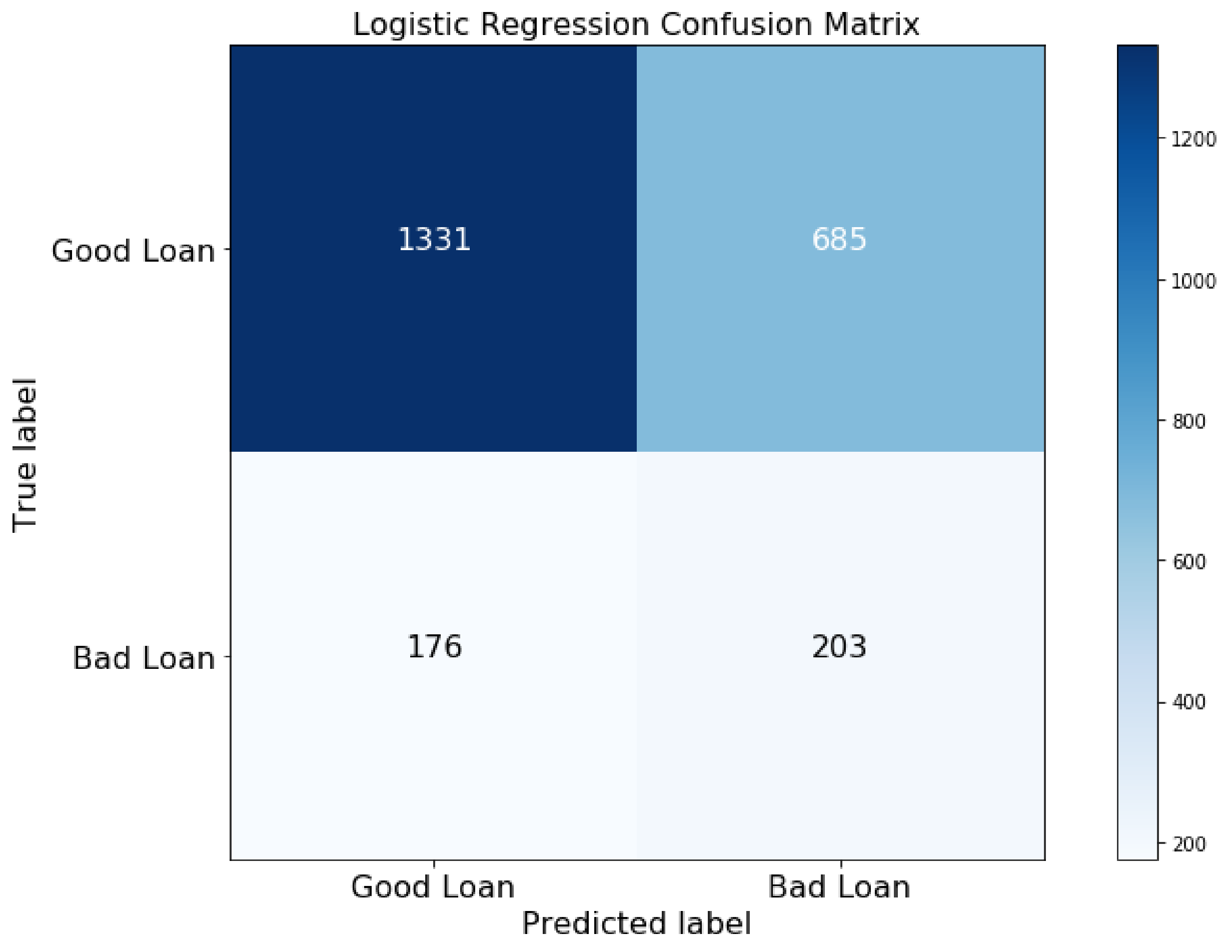
In [33]:

```
# SMOTE training set
logit_sm = LogisticRegressionCV(cv=5, random_state=0, penalty='l2').fit(X_tra

train_acc, test_acc = logit_sm.score(X_train_sm, y_train_sm), logit_sm.score(
report_lr = precision_recall_fscore_support(y_test, logit_sm.predict(X_test),

logit_sm_results = {
    'model': 'Logistic',
    'train_acc': train_acc,
    'test_acc': test_acc,
    'precision': report_lr[0],
    'recall': report_lr[1],
    'F1': report_lr[2]
}

print('Logistic Regression: accuracy on train={:.2%}, test={:.2%}, precision=
      format(logit_sm_results['train_acc'],
             logit_sm_results['test_acc'],
             logit_sm_results['precision'],
             logit_sm_results['recall'],
             logit_sm_results['F1']))
```

```
Logistic Regression: accuracy on train=73.05%, test=64.05%, precision=0.23, rec
all=0.54, F1=0.32
```

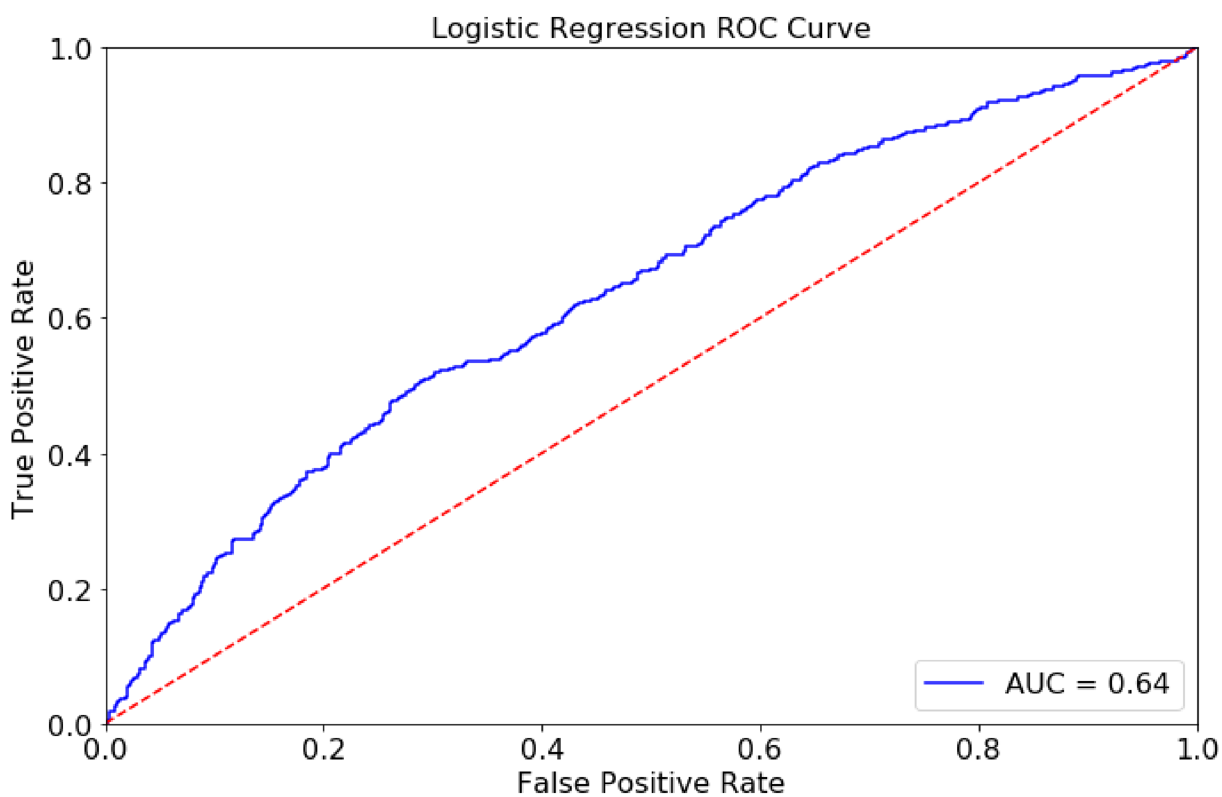
In [34]:

```
# Plot confusion matrix
cnf_matrix = confusion_matrix(y_test, logit_sm.predict(X_test))
np.set_printoptions(precision=2)

plt.figure(figsize=(11,7))
plot_confusion_matrix(cnf_matrix, classes=["Good Loan", "Bad Loan"], normaliz
                      title='Logistic Regression Confusion Matrix')

plt.show()
```



In [48]:

```
# Plot ROC curve
probs = logit_sm.predict_proba(X_test)
preds = probs[:,1]
fpr, tpr, threshold = roc_curve(y_test, preds)
roc_auc = auc(fpr, tpr)

f, ax = plt.subplots(figsize=(11,7))
plt.title('Logistic Regression ROC Curve', fontsize=16)
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right', fontsize=16)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate', fontsize=16)
plt.xlabel('False Positive Rate', fontsize=16)
plt.tick_params(labelsize=16)
plt.show()
```

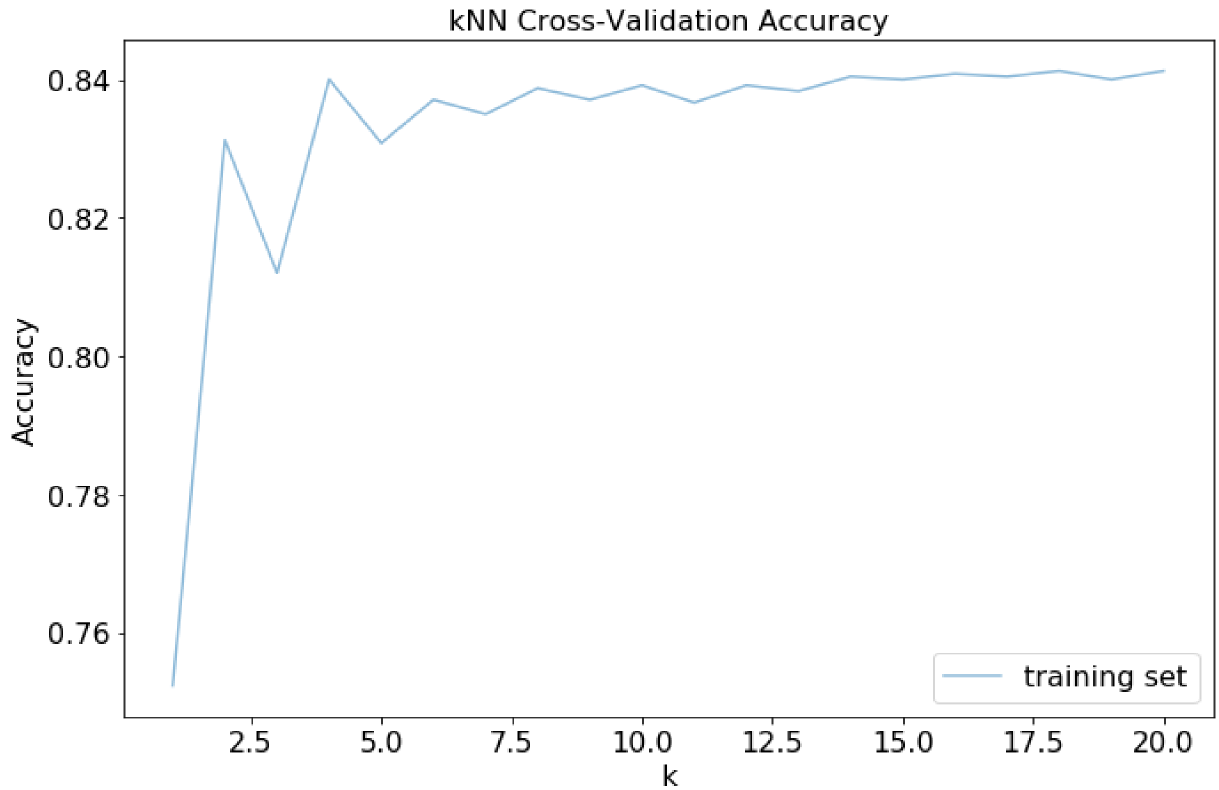


kNN

Raw training set

In [16]:
```
max_score = 0
max_k = 0
scores = []

for k in range(1, 21):
    knn = KNeighborsClassifier(n_neighbors = k)
    score = cross_val_score(knn, X_train, y_train, cv=5).mean()

    scores.append(score)
    if score > max_score:
        max_k = k
        max_score = score

scores = pd.DataFrame({'k': range(1, 21), 'accuracy': scores})
```

In [17]:
```
fig, ax = plt.subplots(1, 1, figsize=(11, 7))
ax.plot(scores['k'], scores['accuracy'], alpha=0.5, label='training set')
ax.set_title('kNN Cross-Validation Accuracy', fontsize=16)
ax.set_xlabel('k', fontsize=16)
ax.set_ylabel('Accuracy', fontsize=16)
ax.legend(fontsize=16)
ax.tick_params(labelsize=16)
plt.show()
```

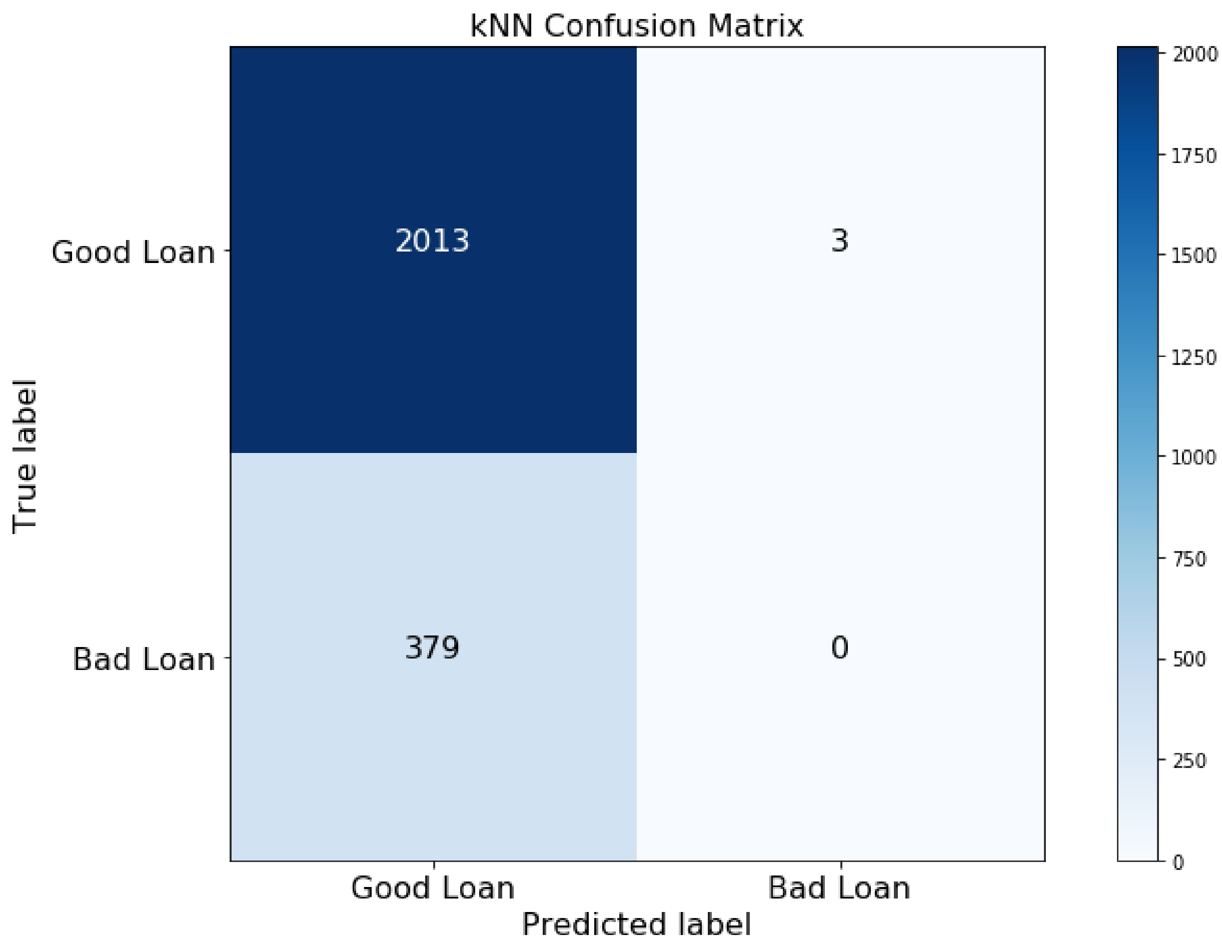


In [18]:

```
knn = KNeighborsClassifier(n_neighbors = max_k)
knn.fit(X_train, y_train)

train_acc, test_acc = knn.score(X_train, y_train), knn.score(X_test, y_test)

print('kNN: Optimal k={}'.format(max_k))

report_lr = precision_recall_fscore_support(y_test, knn.predict(X_test), aver

knn_results = {
    'model': 'kNN',
    'train_acc': train_acc,
    'test_acc': test_acc,
    'precision': report_lr[0],
    'recall': report_lr[1],
    'F1': report_lr[2]
}

print('kNN: accuracy on train={:.2%}, test={:.2%}, precision={:.2f}, recall={
      format(knn_results['train_acc'],
             knn_results['test_acc'],
             knn_results['precision'],
             knn_results['recall'],
             knn_results['F1']))
```

```
kNN: Optimal k=18
kNN: accuracy on train=84.21%, test=84.05%, precision=0.00, recall=0.00, F1=0.0
0
```

In [19]:
```
cnf_matrix = confusion_matrix(y_test, knn.predict(X_test))
np.set_printoptions(precision=2)

plt.figure(figsize=(11,7))
plot_confusion_matrix(cnf_matrix, classes=["Good Loan", "Bad Loan"], normaliz
                      title='kNN Confusion Matrix')

plt.show()
```

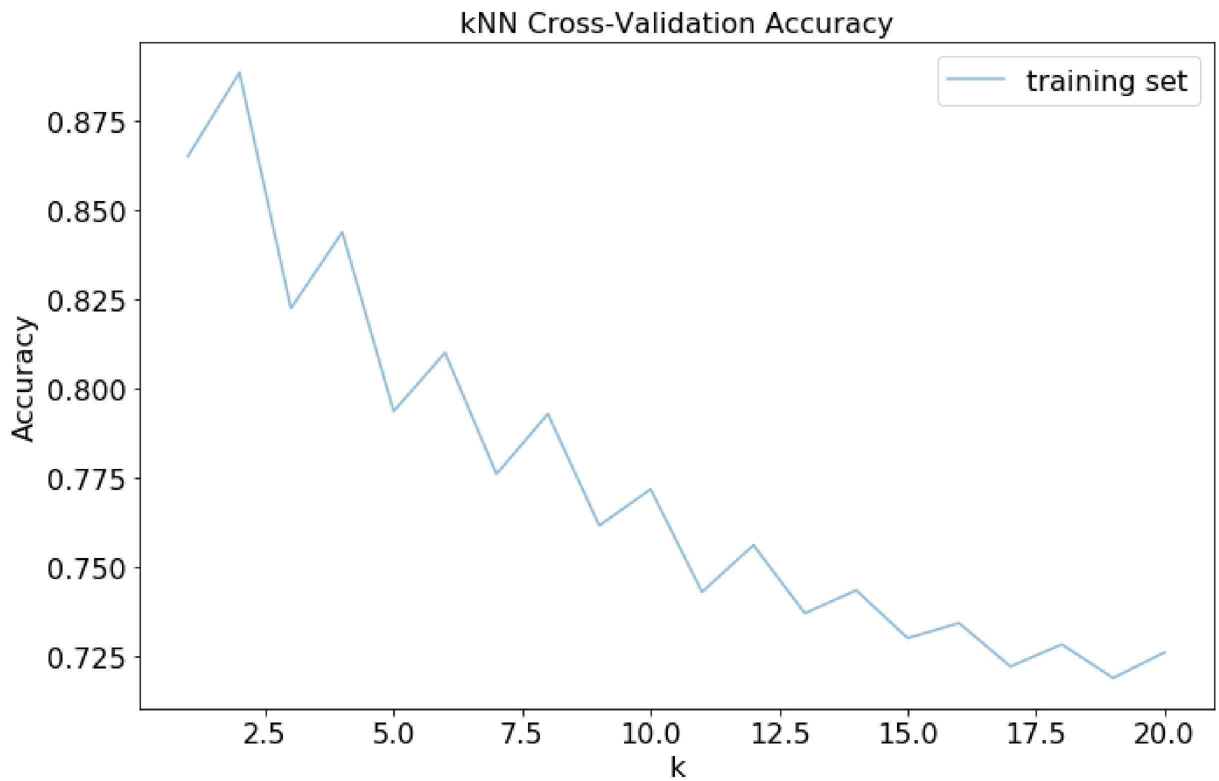


Oversampled Training set

In [20]:
```
max_score = 0
max_k = 0
scores = []

for k in range(1, 21):
    knn = KNeighborsClassifier(n_neighbors = k)
    score = cross_val_score(knn, X_train_sm, y_train_sm, cv=5).mean()

    scores.append(score)
    if score > max_score:
        max_k = k
        max_score = score

scores = pd.DataFrame({'k': range(1, 21), 'accuracy': scores})
```

In [21]:

```
fig, ax = plt.subplots(1, 1, figsize=(11, 7))
ax.plot(scores['k'], scores['accuracy'], alpha=0.5, label='training set')
ax.set_title('kNN Cross-Validation Accuracy', fontsize=16)
ax.set_xlabel('k', fontsize=16)
ax.set_ylabel('Accuracy', fontsize=16)
ax.legend(fontsize=16)
ax.tick_params(labelsize=16)
plt.show()
```

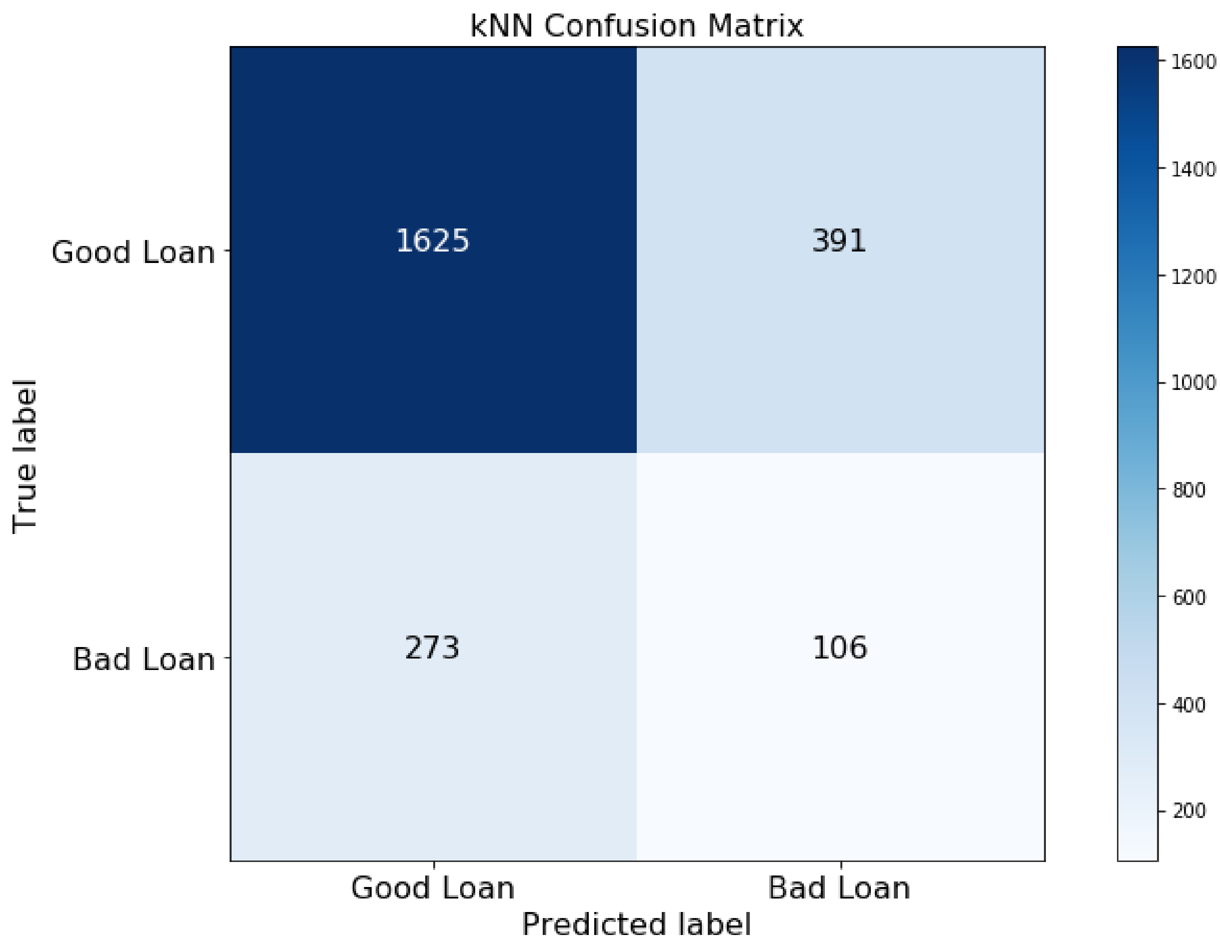


In [22]:

```
knn_sm = KNeighborsClassifier(n_neighbors = max_k)
knn_sm.fit(X_train_sm, y_train_sm)

train_acc, test_acc = knn_sm.score(X_train_sm, y_train_sm), knn_sm.score(X_te

print('kNN: Optimal k={}'.format(max_k))

report_lr = precision_recall_fscore_support(y_test, knn_sm.predict(X_test), a

knn_sm_results = {
    'model': 'kNN',
    'train_acc': train_acc,
    'test_acc': test_acc,
    'precision': report_lr[0],
    'recall': report_lr[1],
    'F1': report_lr[2]
}

print('kNN: accuracy on train={:.2%}, test={:.2%}, precision={:.2f}, recall={
      format(knn_sm_results['train_acc'],
             knn_sm_results['test_acc'],
             knn_sm_results['precision'],
             knn_sm_results['recall'],
             knn_sm_results['F1']))
```

```
kNN: Optimal k=2
kNN: accuracy on train=99.80%, test=72.28%, precision=0.21, recall=0.28, F1=0.2
4
```

In [23]:
```
cnf_matrix = confusion_matrix(y_test, knn_sm.predict(X_test))
np.set_printoptions(precision=2)

plt.figure(figsize=(11,7))
plot_confusion_matrix(cnf_matrix, classes=["Good Loan", "Bad Loan"], normaliz
                      title='kNN Confusion Matrix')

plt.show()
```



LDA

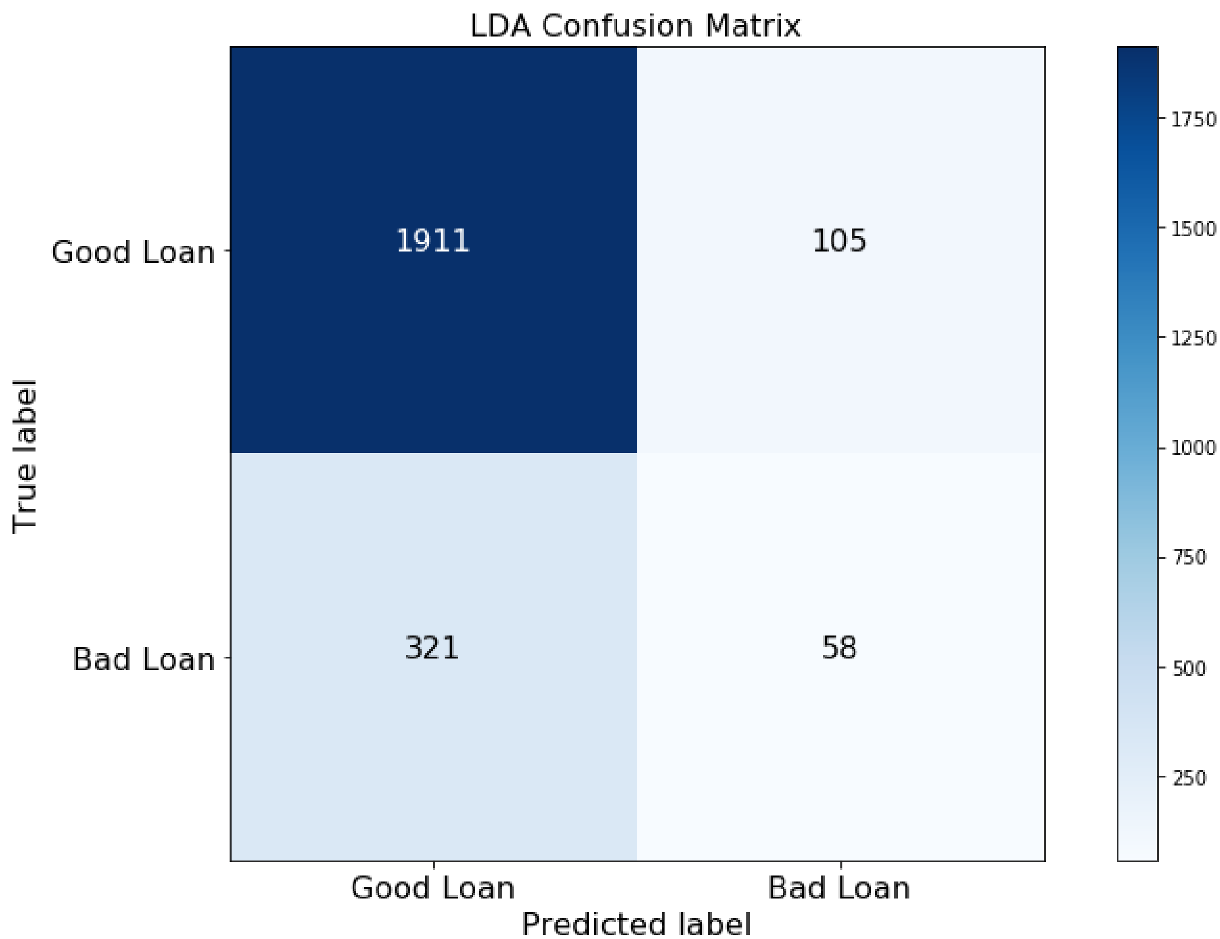
Raw training set

In [24]:
```
lda = LinearDiscriminantAnalysis()
lda.fit(X_train, y_train)

train_acc, test_acc = lda.score(X_train, y_train), lda.score(X_test, y_test)
report_lr = precision_recall_fscore_support(y_test, lda.predict(X_test), aver

lda_results = {
    'model': 'LDA',
    'train_acc': train_acc,
    'test_acc': test_acc,
    'precision': report_lr[0],
    'recall': report_lr[1],
    'F1': report_lr[2]
}

print('LDA: accuracy on train={:.2%}, test={:.2%}, precision={:.2f}, recall={
      format(lda_results['train_acc'],
             lda_results['test_acc'],
             lda_results['precision'],
             lda_results['recall'],
             lda_results['F1']))
```

```
LDA: accuracy on train=85.13%, test=82.21%, precision=0.36, recall=0.15, F1=0.2
1
```

In [25]:

```
cnf_matrix = confusion_matrix(y_test, lda.predict(X_test))
np.set_printoptions(precision=2)

plt.figure(figsize=(11,7))
plot_confusion_matrix(cnf_matrix, classes=["Good Loan", "Bad Loan"], normaliz
                      title='LDA Confusion Matrix')

plt.show()
```

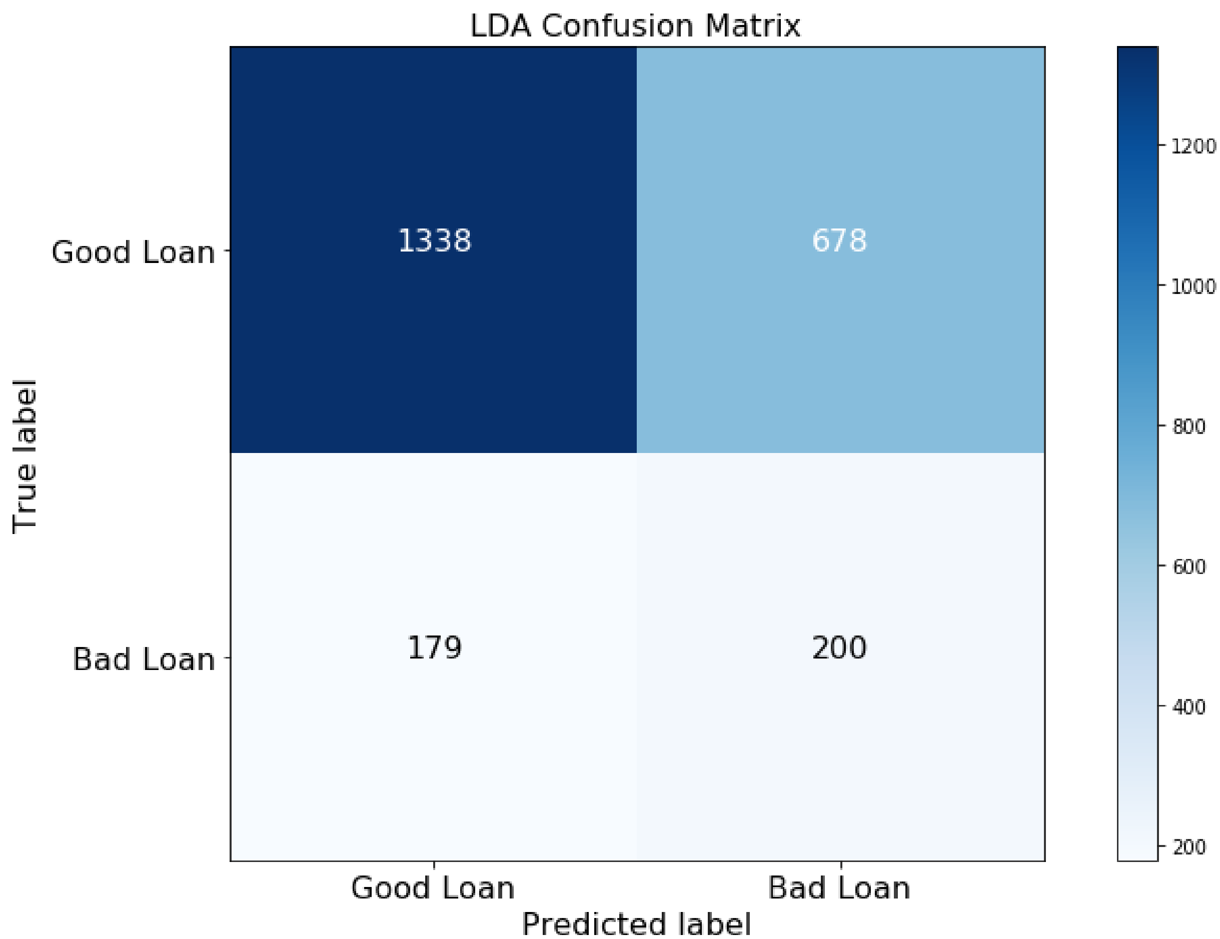


Oversampled Training set

In [26]:
```
lda_sm = LinearDiscriminantAnalysis()
lda_sm.fit(X_train_sm, y_train_sm)

train_acc, test_acc = lda_sm.score(X_train_sm, y_train_sm), lda_sm.score(X_te
report_lr = precision_recall_fscore_support(y_test, lda_sm.predict(X_test), a

lda_sm_results = {
    'model': 'LDA',
    'train_acc': train_acc,
    'test_acc': test_acc,
    'precision': report_lr[0],
    'recall': report_lr[1],
    'F1': report_lr[2]
}

print('LDA: accuracy on train={:.2%}, test={:.2%}, precision={:.2f}, recall={
      format(lda_sm_results['train_acc'],
             lda_sm_results['test_acc'],
             lda_sm_results['precision'],
             lda_sm_results['recall'],
             lda_sm_results['F1']))
```

```
LDA: accuracy on train=72.61%, test=64.22%, precision=0.23, recall=0.53, F1=0.3
2
```

In [27]:
```
cnf_matrix = confusion_matrix(y_test, lda_sm.predict(X_test))
np.set_printoptions(precision=2)

plt.figure(figsize=(11,7))
plot_confusion_matrix(cnf_matrix, classes=["Good Loan", "Bad Loan"], normaliz
                      title='LDA Confusion Matrix')

plt.show()
```



QDA

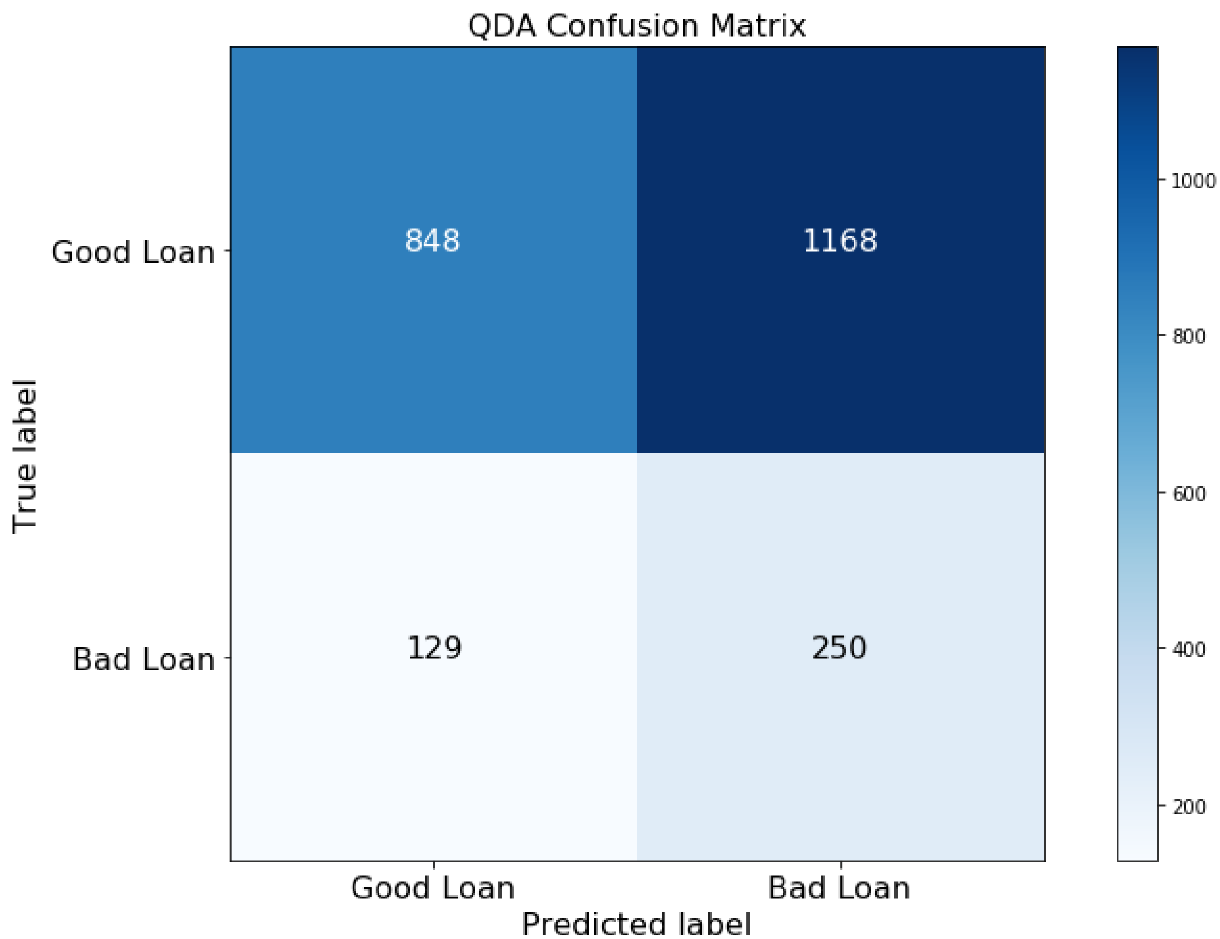
Raw training set

In [28]:
```
qda = QuadraticDiscriminantAnalysis()
qda.fit(X_train, y_train)

train_acc, test_acc = qda.score(X_train, y_train), qda.score(X_test, y_test)
report_lr = precision_recall_fscore_support(y_test, qda.predict(X_test), aver

qda_results = {
    'model': 'QDA',
    'train_acc': train_acc,
    'test_acc': test_acc,
    'precision': report_lr[0],
    'recall': report_lr[1],
    'F1': report_lr[2]
}

print('LDA: accuracy on train={:.2%}, test={:.2%}, precision={:.2f}, recall={
      format(qda_results['train_acc'],
             qda_results['test_acc'],
             qda_results['precision'],
             qda_results['recall'],
             qda_results['F1']))
```

```
LDA: accuracy on train=53.63%, test=45.85%, precision=0.18, recall=0.66, F1=0.2
8
```

In [29]:

```
cnf_matrix = confusion_matrix(y_test, qda.predict(X_test))
np.set_printoptions(precision=2)

plt.figure(figsize=(11,7))
plot_confusion_matrix(cnf_matrix, classes=["Good Loan", "Bad Loan"], normaliz
                      title='QDA Confusion Matrix')

plt.show()
```



Oversampled Training set

In [30]:
```
qda_sm = QuadraticDiscriminantAnalysis()
qda_sm.fit(X_train_sm, y_train_sm)

train_acc, test_acc = qda_sm.score(X_train_sm, y_train_sm), qda_sm.score(X_te
report_lr = precision_recall_fscore_support(y_test, qda_sm.predict(X_test), a

qda_sm_results = {
    'model': 'QDA',
    'train_acc': train_acc,
    'test_acc': test_acc,
    'precision': report_lr[0],
    'recall': report_lr[1],
    'F1': report_lr[2]
}

print('LDA: accuracy on train={:.2%}, test={:.2%}, precision={:.2f}, recall={
      format(qda_sm_results['train_acc'],
             qda_sm_results['test_acc'],
             qda_sm_results['precision'],
             qda_sm_results['recall'],
             qda_sm_results['F1']))
```

```
LDA: accuracy on train=76.72%, test=53.32%, precision=0.17, recall=0.51, F1=0.2
6
```

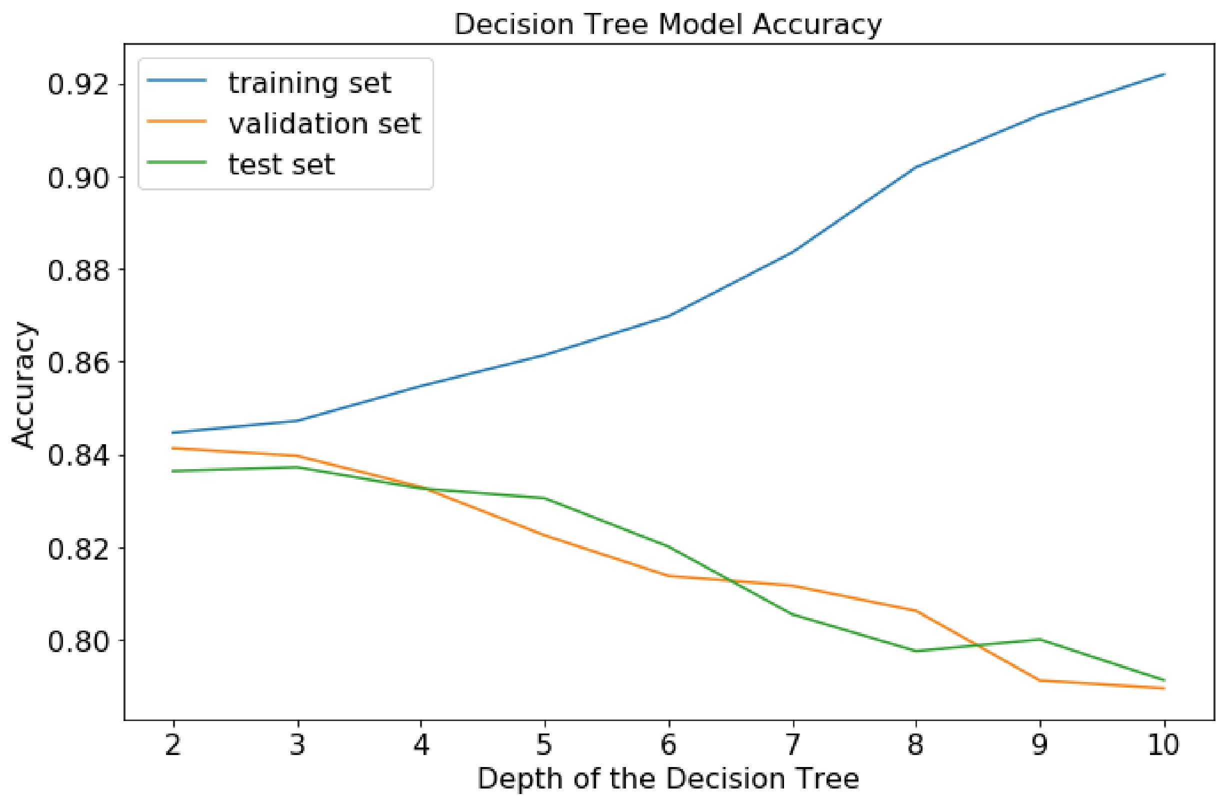
Single Decision Tree

Raw training set

In [31]:
```
train_scores = []
validation_scores = []
test_scores = []

best_score = 0
best_depth = 0

depths = [i for i in range(2, 11)]

for depth in depths:
    tree = DecisionTreeClassifier(max_depth = depth)
    tree.fit(X_train, y_train)

    train_scores.append(tree.score(X_train, y_train))
    test_scores.append(tree.score(X_test, y_test))

    val_score = cross_val_score(estimator=tree, X=X_train, y=y_train, cv=5).m
    validation_scores.append(val_score)

    if val_score > best_score:
        best_depth = depth
        best_score = score
```

In [32]:

```
fig, ax = plt.subplots(1, 1, figsize=(11, 7))
ax.plot(depths, train_scores, label='training set')
ax.plot(depths, validation_scores, label='validation set')
ax.plot(depths, test_scores, label='test set')
ax.tick_params(labelsize=16)
ax.set_title('Decision Tree Model Accuracy', fontsize=16)
ax.set_xlabel('Depth of the Decision Tree', fontsize=16)
ax.set_ylabel('Accuracy', fontsize=16)
ax.legend(fontsize=16)
plt.show()
```

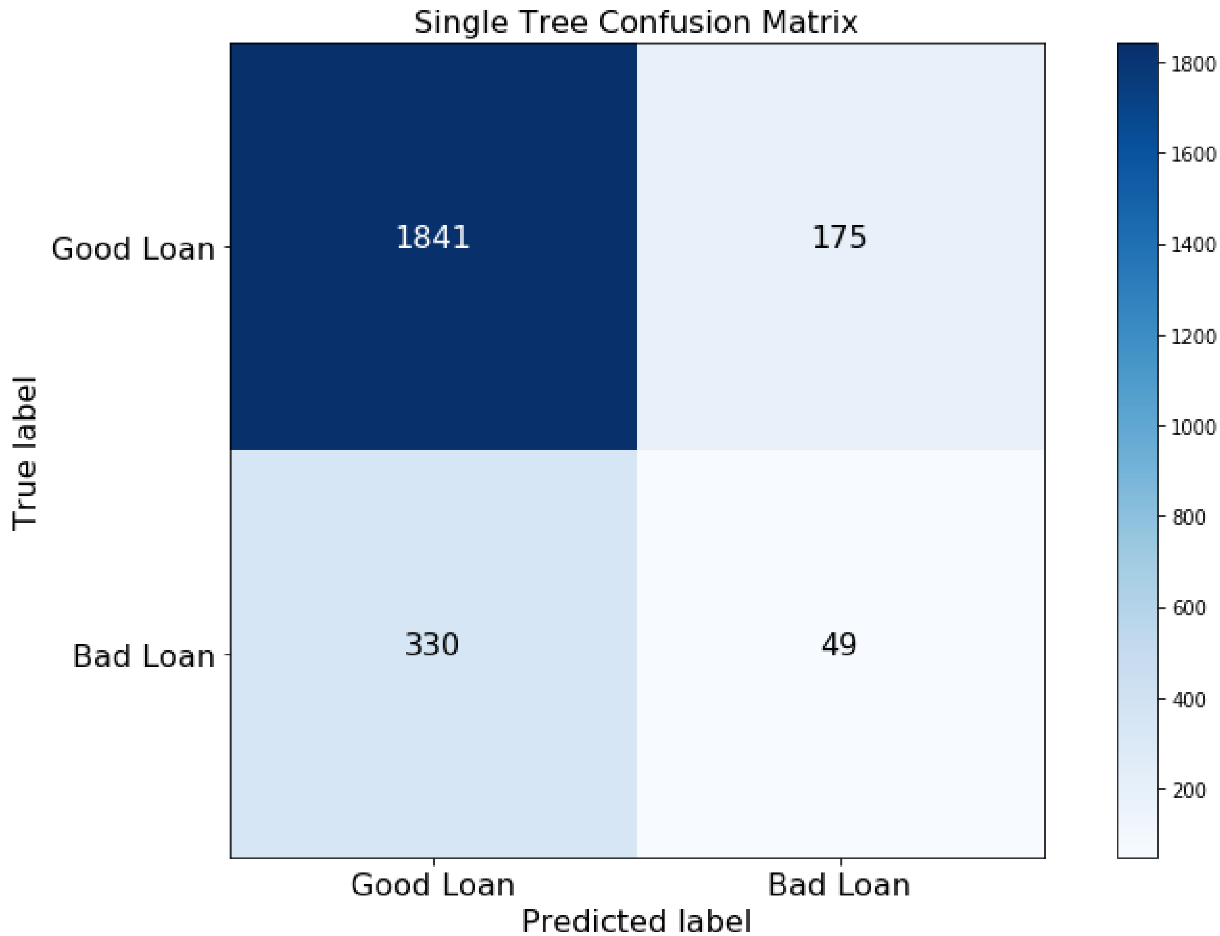


In [33]:

```
tree = DecisionTreeClassifier(max_depth = best_depth)
tree.fit(X_train, y_train)

train_acc, test_acc = tree.score(X_train, y_train), tree.score(X_test, y_test

print('Single Tree: Optimal depth={}'.format(best_depth))

report_lr = precision_recall_fscore_support(y_test, tree.predict(X_test), ave

tree_results = {
    'model': 'Single Tree',
    'train_acc': train_acc,
    'test_acc': test_acc,
    'precision': report_lr[0],
    'recall': report_lr[1],
    'F1': report_lr[2]
}

print('Signle Tree: accuracy on train={:.2%}, test={:.2%}, precision={:.2f},
      format(tree_results['train_acc'],
             tree_results['test_acc'],
             tree_results['precision'],
             tree_results['recall'],
             tree_results['F1']))
```

```
Single Tree: Optimal depth=10
Signle Tree: accuracy on train=92.19%, test=78.91%, precision=0.22, recall=0.1
3, F1=0.16
```

In [34]:
```
# Plot confusion matrix
y_pred = tree.predict(X_test)

cnf_matrix = confusion_matrix(y_test, y_pred)
np.set_printoptions(precision=2)

plt.figure(figsize=(11,7))
plot_confusion_matrix(cnf_matrix, classes=["Good Loan", "Bad Loan"], normaliz
                      title='Single Tree Confusion Matrix')

plt.show()
```

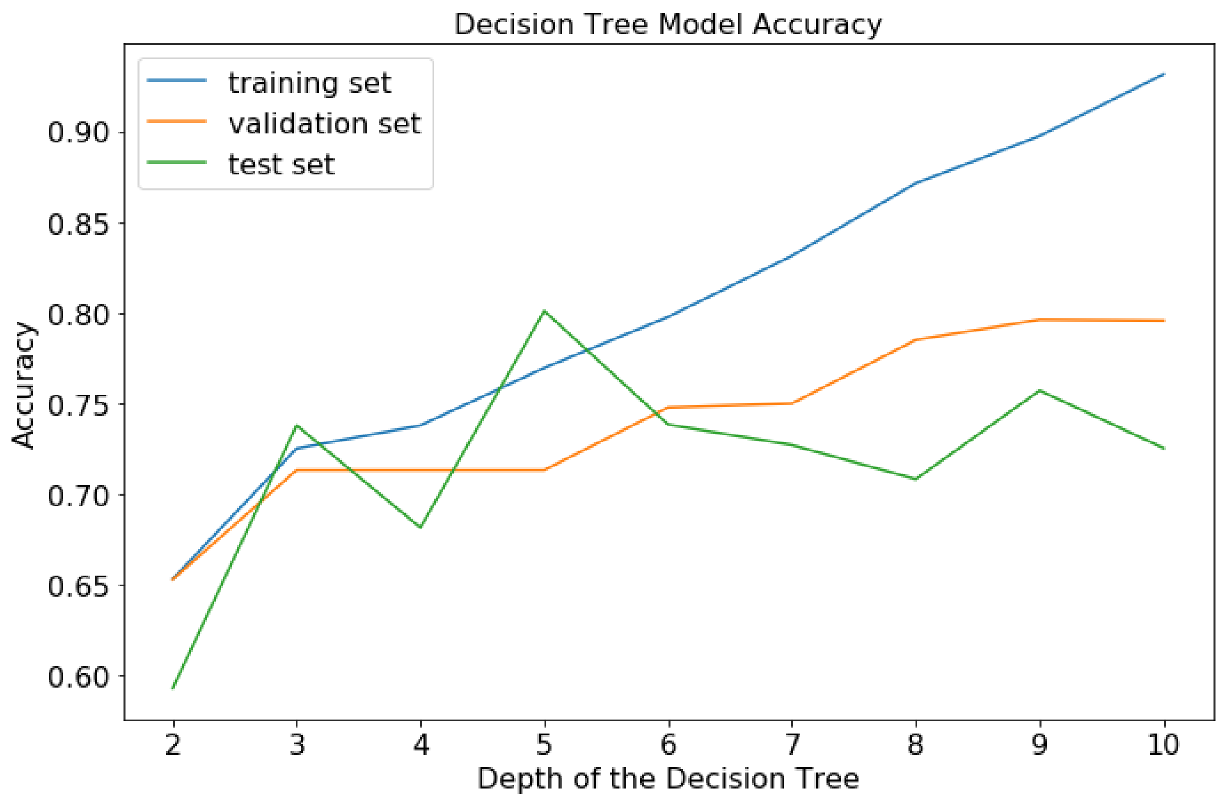


Oversampled Training set

In [35]:

```
train_scores = []
validation_scores = []
test_scores = []

best_score = 0
best_depth = 0

depths = [i for i in range(2, 11)]

for depth in depths:
    tree = DecisionTreeClassifier(max_depth = depth)
    tree.fit(X_train_sm, y_train_sm)

    train_scores.append(tree.score(X_train_sm, y_train_sm))
    test_scores.append(tree.score(X_test, y_test))

    val_score = cross_val_score(estimator=tree, X=X_train_sm, y=y_train_sm, c
    validation_scores.append(val_score)

    if val_score > best_score:
        best_depth = depth
        best_score = score
```

In [36]:
```
fig, ax = plt.subplots(1, 1, figsize=(11, 7))
ax.plot(depths, train_scores, label='training set')
ax.plot(depths, validation_scores, label='validation set')
ax.plot(depths, test_scores, label='test set')
ax.tick_params(labelsize=16)
ax.set_title('Decision Tree Model Accuracy', fontsize=16)
ax.set_xlabel('Depth of the Decision Tree', fontsize=16)
ax.set_ylabel('Accuracy', fontsize=16)
ax.legend(fontsize=16)
plt.show()
```



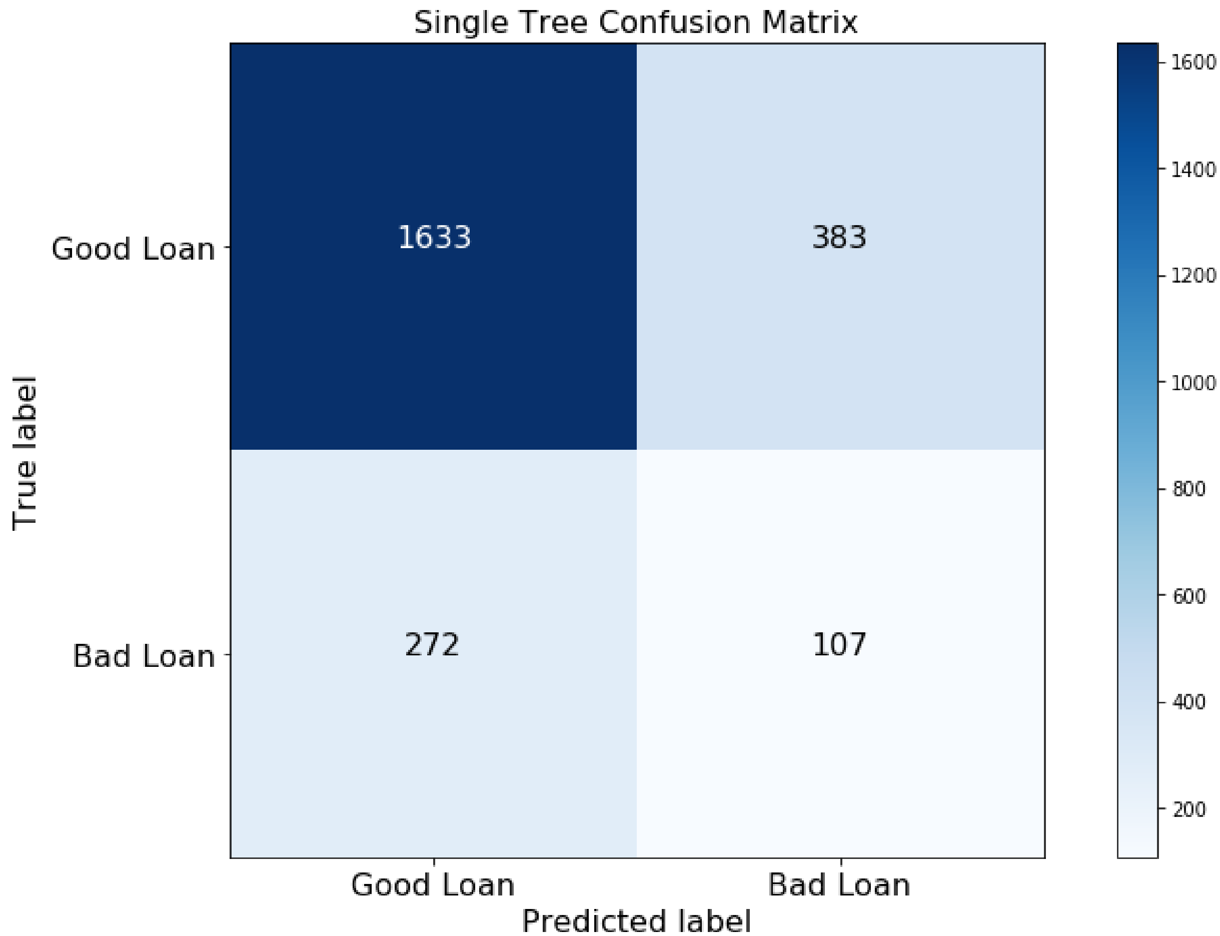
In [37]:

```
tree_sm = DecisionTreeClassifier(max_depth = best_depth)
tree_sm.fit(X_train_sm, y_train_sm)

train_acc, test_acc = tree_sm.score(X_train_sm, y_train_sm), tree_sm.score(X_

print('Single Tree: Optimal depth={}'.format(best_depth))

report_lr = precision_recall_fscore_support(y_test, tree_sm.predict(X_test),

tree_sm_results = {
    'model': 'Single Tree',
    'train_acc': train_acc,
    'test_acc': test_acc,
    'precision': report_lr[0],
    'recall': report_lr[1],
    'F1': report_lr[2]
}

print('Single Tree: accuracy on train={:.2%}, test={:.2%}, precision={:.2f},
      format(tree_sm_results['train_acc'],
             tree_sm_results['test_acc'],
             tree_sm_results['precision'],
             tree_sm_results['recall'],
             tree_sm_results['F1']))
```

```
Single Tree: Optimal depth=10
Single Tree: accuracy on train=93.08%, test=72.65%, precision=0.22, recall=0.2
8, F1=0.25
```

In [38]:

```
# Plot confusion matrix
y_pred = tree_sm.predict(X_test)

cnf_matrix = confusion_matrix(y_test, y_pred)
np.set_printoptions(precision=2)

plt.figure(figsize=(11,7))
plot_confusion_matrix(cnf_matrix, classes=["Good Loan", "Bad Loan"], normaliz
                      title='Single Tree Confusion Matrix')

plt.show()
```



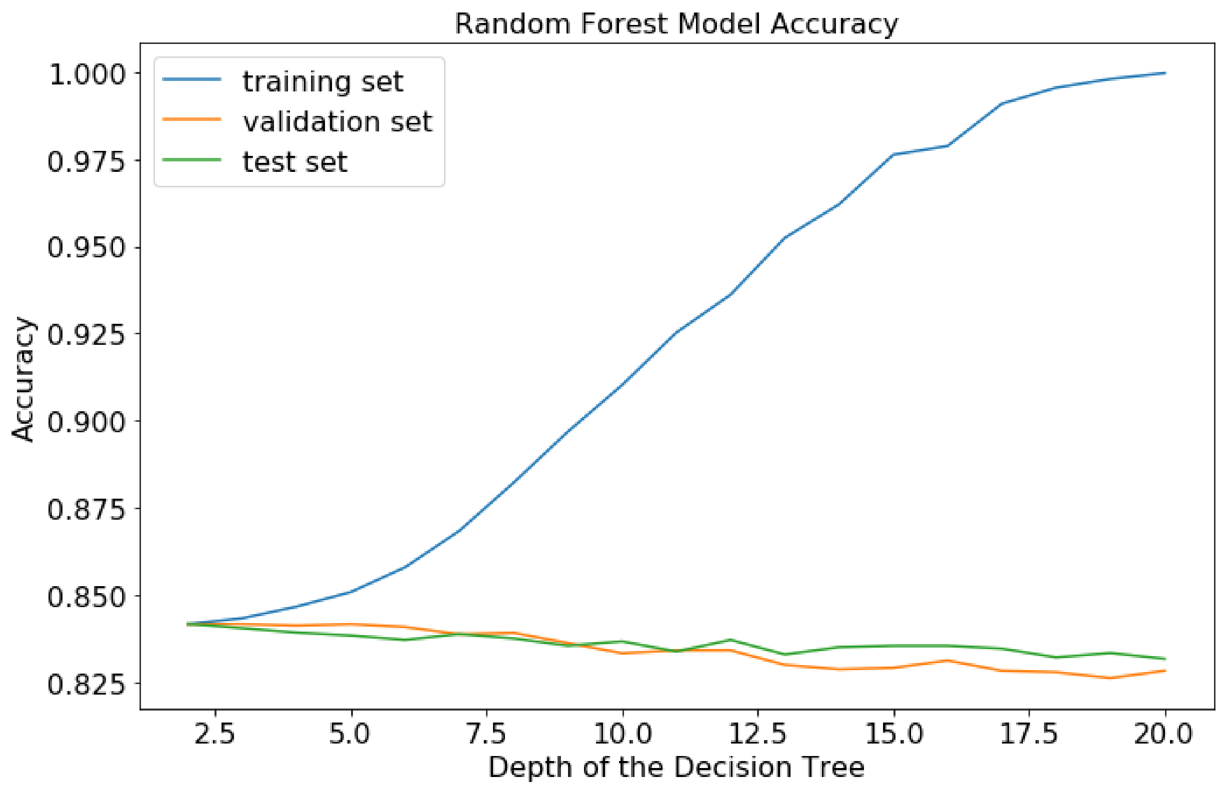
Random Forest

Raw training set

In [39]:

```
train_scores = []
validation_scores = []
test_scores = []

best_score = 0
best_depth = 0

n_trees = 100
depths = [i for i in range(2, 21)]

for depth in depths:
    rf = RandomForestClassifier(n_estimators=n_trees, max_depth=depth, n_jobs
    rf.fit(X_train, y_train)

    train_scores.append(rf.score(X_train, y_train))
    test_scores.append(rf.score(X_test, y_test))

    val_score = cross_val_score(estimator=rf, X=X_train, y=y_train, cv=5).mea
    validation_scores.append(val_score)

    if val_score > best_score:
        best_depth = depth
        best_score = val_score
```

In [40]:
```
fig, ax = plt.subplots(1, 1, figsize=(11, 7))
ax.plot(depths, train_scores, label='training set')
ax.plot(depths, validation_scores, label='validation set')
ax.plot(depths, test_scores, label='test set')
ax.tick_params(labelsize=16)
ax.set_title('Random Forest Model Accuracy', fontsize=16)
ax.set_xlabel('Depth of the Decision Tree', fontsize=16)
ax.set_ylabel('Accuracy', fontsize=16)
ax.legend(fontsize=16)
plt.show()
```



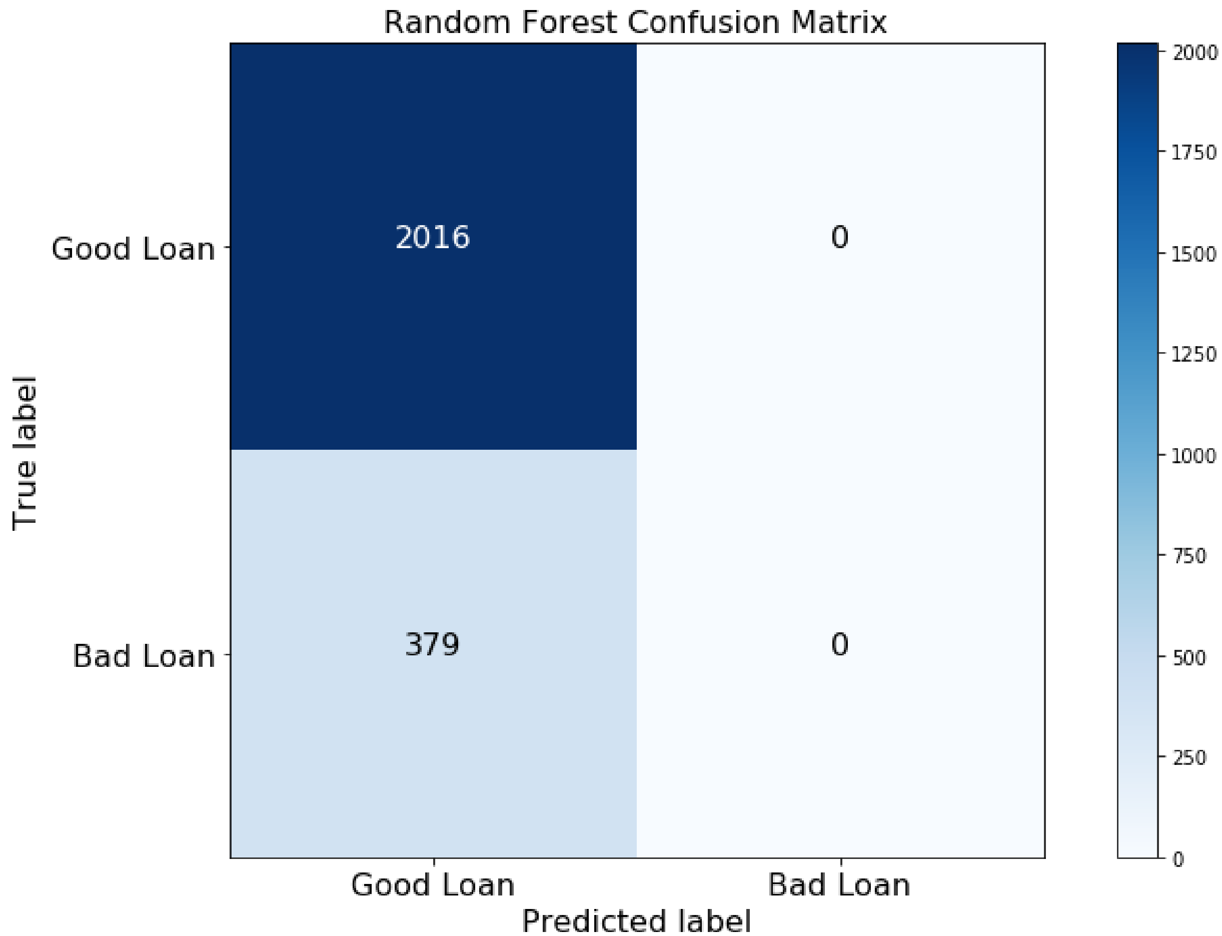
In [41]:

```
rf = RandomForestClassifier(n_estimators=n_trees, max_depth=best_depth, n_job
rf.fit(X_train, y_train)

train_acc, test_acc = rf.score(X_train, y_train), rf.score(X_test, y_test)

print('Random Forest: Optimal depth={}'.format(best_depth))

report_lr = precision_recall_fscore_support(y_test, rf.predict(X_test), avera

rf_results = {
    'model': 'Random Forest',
    'train_acc': train_acc,
    'test_acc': test_acc,
    'precision': report_lr[0],
    'recall': report_lr[1],
    'F1': report_lr[2]
}

print('Random Forest: accuracy on train={:.2%}, test={:.2%}, precision={:.2f}
      format(rf_results['train_acc'],
             rf_results['test_acc'],
             rf_results['precision'],
             rf_results['recall'],
             rf_results['F1']))
```

```
Random Forest: Optimal depth=2
Random Forest: accuracy on train=84.17%, test=84.18%, precision=0.00, recall=0.
00, F1=0.00
```

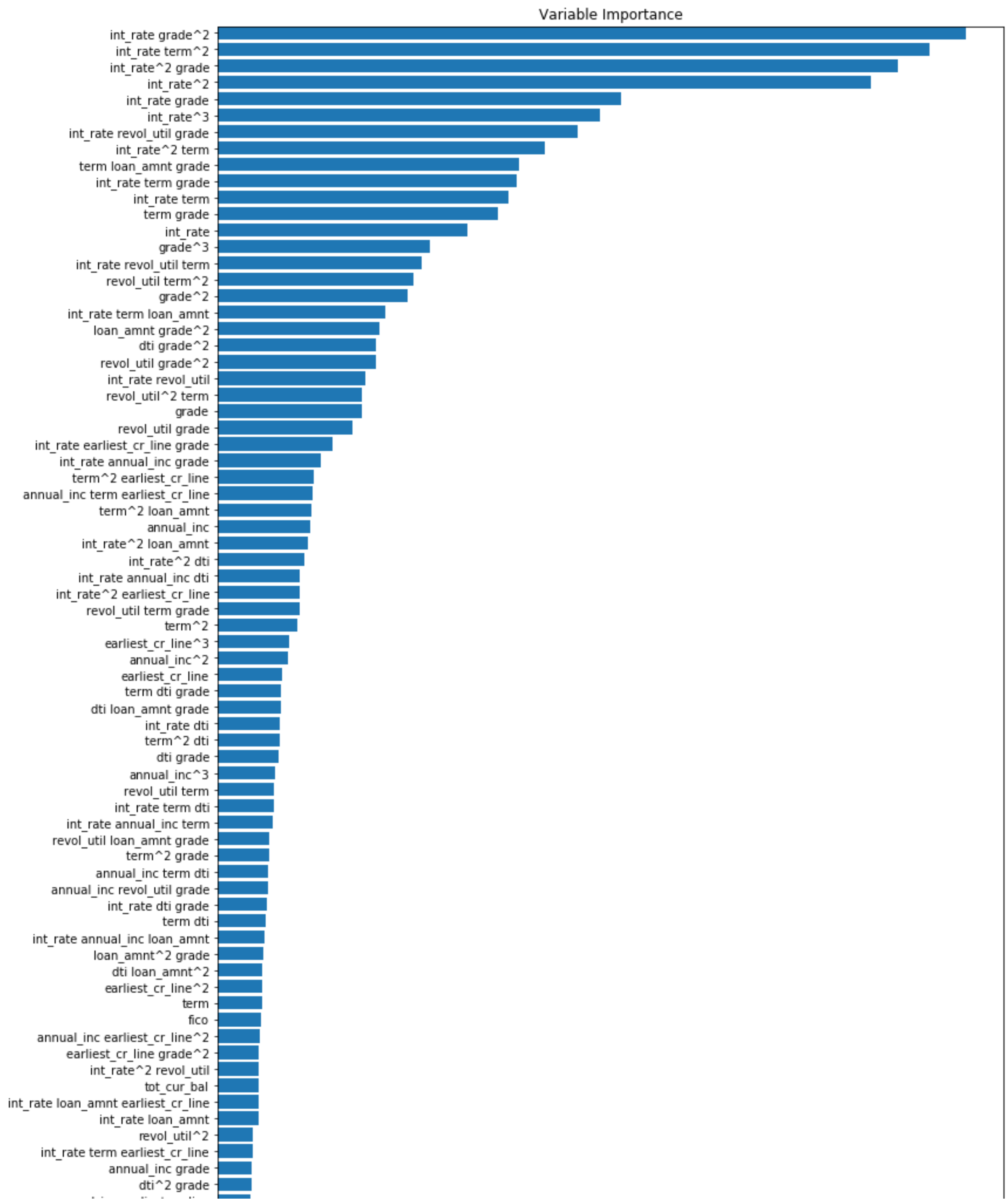
In [42]:

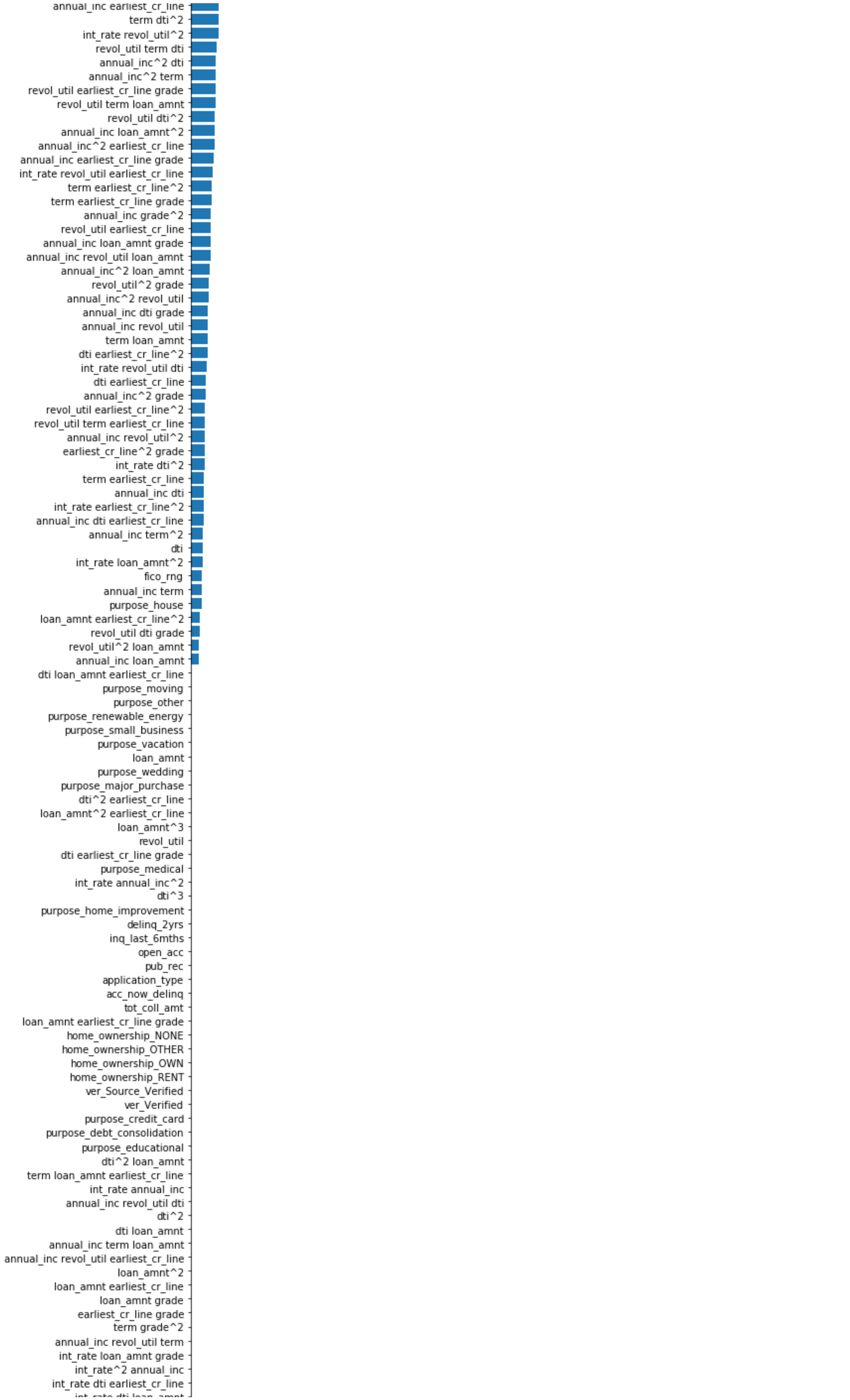
```
# Plot confusion matrix
y_pred = rf.predict(X_test)

cnf_matrix = confusion_matrix(y_test, y_pred)
np.set_printoptions(precision=2)

plt.figure(figsize=(11,7))
plot_confusion_matrix(cnf_matrix, classes=["Good Loan", "Bad Loan"], normaliz
                      title='Random Forest Confusion Matrix')

plt.show()
```

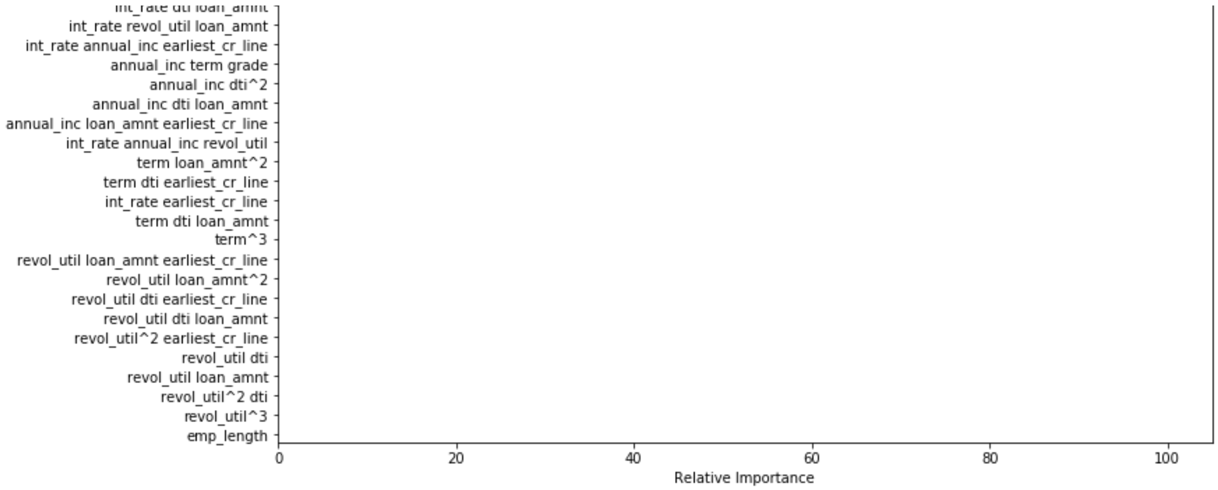


In [43]:

```
# Random Forest Feature Importance
feature_importance = rf.feature_importances_
feature_importance = 100.0 * (feature_importance / feature_importance.max())
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0])

# Plot
plt.figure(figsize=(12,50))
plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, X_train.columns[sorted_idx])
plt.xlabel('Relative Importance')
plt.title('Variable Importance')
plt.margins(y=0)
plt.show()
```



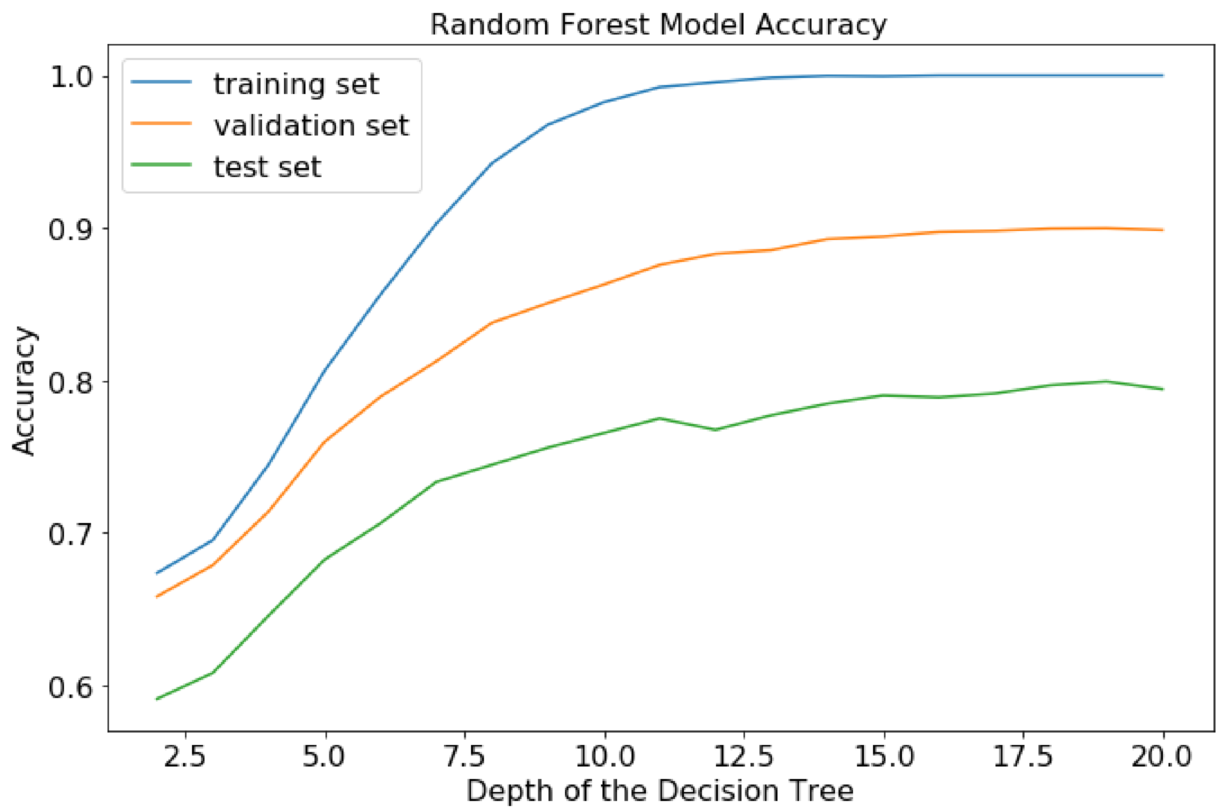

annual_inc earliest_cr_line
term dti^2
int_rate revol_util^2
revol_util term dti
annual_inc^2 dti
annual_inc^2 term
revol_util earliest_cr_line grade
revol_util term loan_amnt
revol_util dti^2
annual_inc loan_amnt^2
annual_inc^2 earliest_cr_line
annual_inc earliest_cr_line grade
int_rate revol_util earliest_cr_line
term earliest_cr_line^2
term earliest_cr_line grade
annual_inc grade^2
revol_util earliest_cr_line
annual_inc loan_amnt grade
annual_inc revol_util loan_amnt
annual_inc^2 loan_amnt
revol_util^2 grade
annual_inc^2 revol_util
annual_inc dti grade
annual_inc revol_util
term loan_amnt
dti earliest_cr_line^2
int_rate revol_util dti
dti earliest_cr_line
annual_inc^2 grade
revol_util earliest_cr_line^2
revol_util term earliest_cr_line
annual_inc revol_util^2
earliest_cr_line^2 grade
int_rate dti^2
term earliest_cr_line
annual_inc dti
int_rate earliest_cr_line^2
annual_inc dti earliest_cr_line
annual_inc term^2
dti
int_rate loan_amnt^2
fico_rng
annual_inc term
purpose_house
loan_amnt earliest_cr_line^2
revol_util dti grade
revol_util^2 loan_amnt
annual_inc loan_amnt
dti loan_amnt earliest_cr_line
purpose_moving
purpose_other
purpose_renewable_energy
purpose_small_business
purpose_vacation
loan_amnt
purpose_wedding
purpose_major_purchase
dti^2 earliest_cr_line
loan_amnt^2 earliest_cr_line
loan_amnt^3
revol_util
dti earliest_cr_line grade
purpose_medical
int_rate annual_inc^2
dti^3
purpose_home_improvement
delinq_2yrs
inq_last_6mths
open_acc
pub_rec
application_type
acc_now_delinq
tot_coll_amt
loan_amnt earliest_cr_line grade
home_ownership_NONE
home_ownership_OTHER
home_ownership_OWN
home_ownership_RENT
ver_Source_Verified
ver_Verified
purpose_credit_card
purpose_debt_consolidation
purpose_educational
dti^2 loan_amnt
term loan_amnt earliest_cr_line
int_rate annual_inc
annual_inc revol_util dti
dti^2
dti loan_amnt
annual_inc term loan_amnt
annual_inc revol_util earliest_cr_line
loan_amnt^2
loan_amnt earliest_cr_line
loan_amnt grade
earliest_cr_line grade
term grade^2
annual_inc revol_util term
int_rate loan_amnt grade
int_rate^2 annual_inc
int_rate dti earliest_cr_line



Oversampled Training set

In [44]:
```
train_scores = []
validation_scores = []
test_scores = []

best_score = 0
best_depth = 0

n_trees = 100
depths = [i for i in range(2, 21)]

for depth in depths:
    rf = RandomForestClassifier(n_estimators=n_trees, max_depth=depth, n_jobs
    rf.fit(X_train_sm, y_train_sm)

    train_scores.append(rf.score(X_train_sm, y_train_sm))
    test_scores.append(rf.score(X_test, y_test))

    val_score = cross_val_score(estimator=rf, X=X_train_sm, y=y_train_sm, cv=
    validation_scores.append(val_score)

    if val_score > best_score:
        best_depth = depth
        best_score = val_score
```

In [45]:
```
fig, ax = plt.subplots(1, 1, figsize=(11, 7))
ax.plot(depths, train_scores, label='training set')
ax.plot(depths, validation_scores, label='validation set')
ax.plot(depths, test_scores, label='test set')
ax.tick_params(labelsize=16)
ax.set_title('Random Forest Model Accuracy', fontsize=16)
ax.set_xlabel('Depth of the Decision Tree', fontsize=16)
ax.set_ylabel('Accuracy', fontsize=16)
ax.legend(fontsize=16)
plt.show()
```

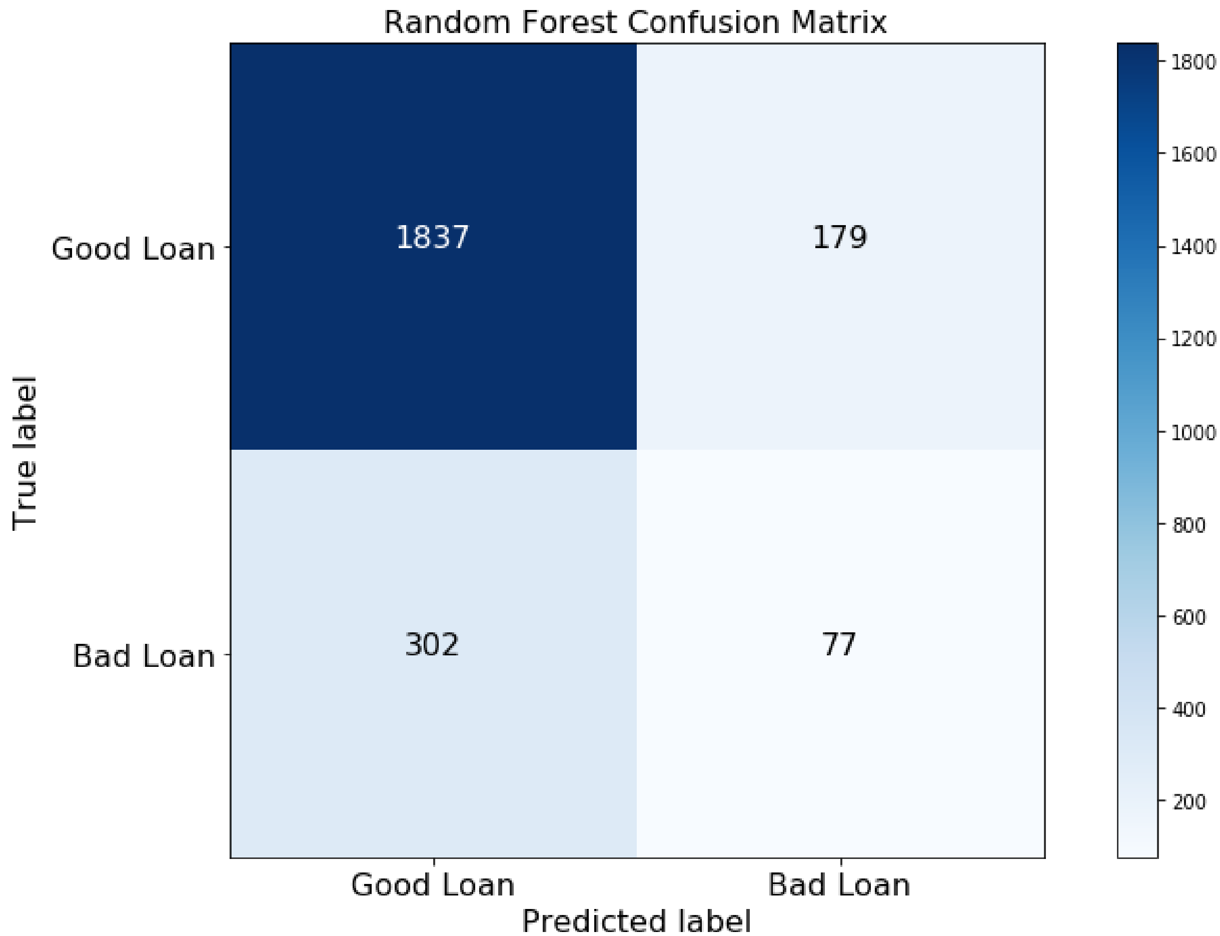


In [46]:
```
rf_sm = RandomForestClassifier(n_estimators=n_trees, max_depth=best_depth, n_
rf_sm.fit(X_train_sm, y_train_sm)

train_acc, test_acc = rf_sm.score(X_train_sm, y_train_sm), rf_sm.score(X_test

print('Random Forest: Optimal depth={}'.format(best_depth))

report_lr = precision_recall_fscore_support(y_test, rf_sm.predict(X_test), av

rf_sm_results = {
    'model': 'Random Forest',
    'train_acc': train_acc,
    'test_acc': test_acc,
    'precision': report_lr[0],
    'recall': report_lr[1],
    'F1': report_lr[2]
}

print('Random Forest: accuracy on train={:.2%}, test={:.2%}, precision={:.2f}
      format(rf_sm_results['train_acc'],
             rf_sm_results['test_acc'],
             rf_sm_results['precision'],
             rf_sm_results['recall'],
             rf_sm_results['F1']))
```

```
Random Forest: Optimal depth=19
Random Forest: accuracy on train=100.00%, test=79.92%, precision=0.30, recall=
0.20, F1=0.24
```

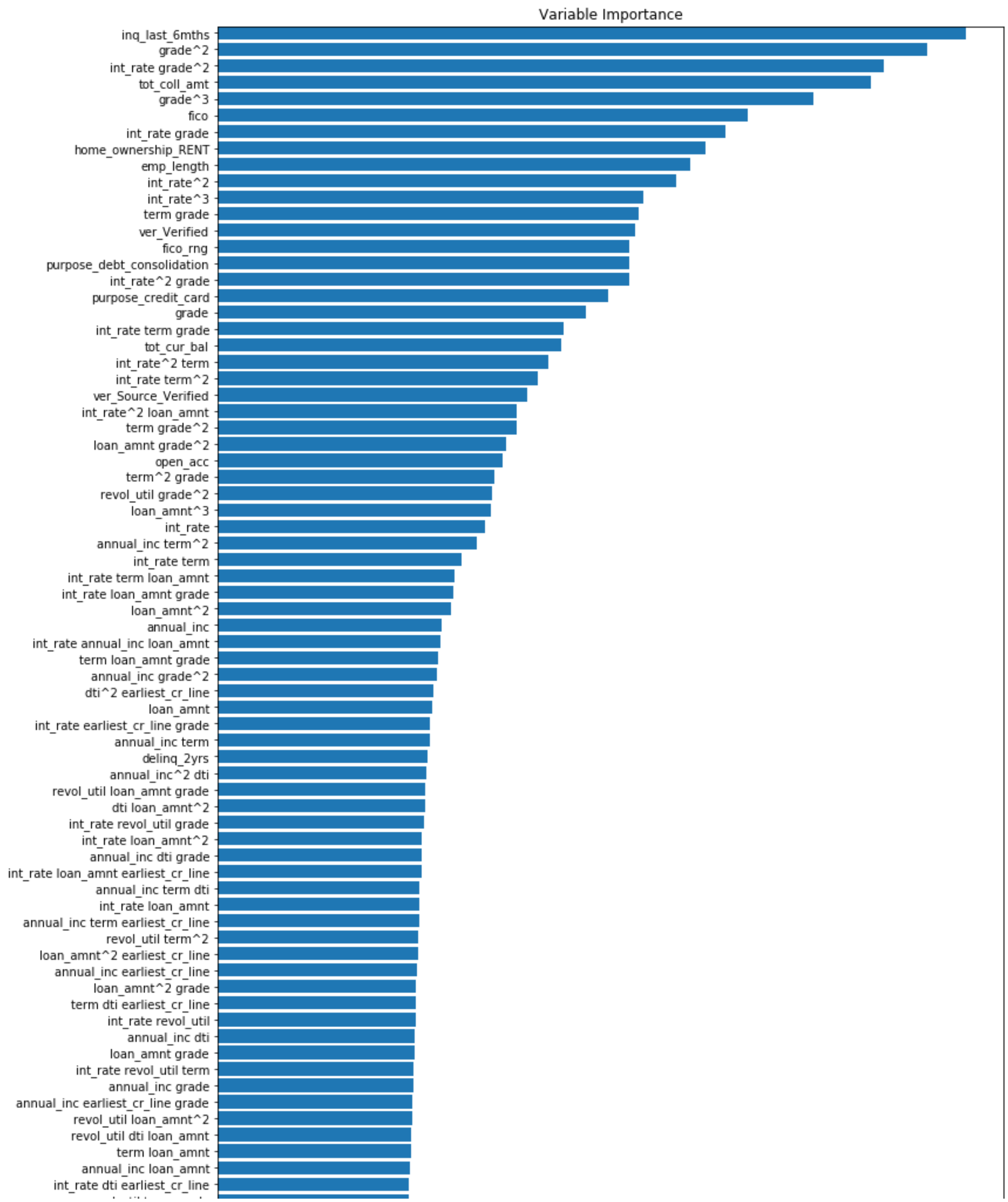
In [47]:

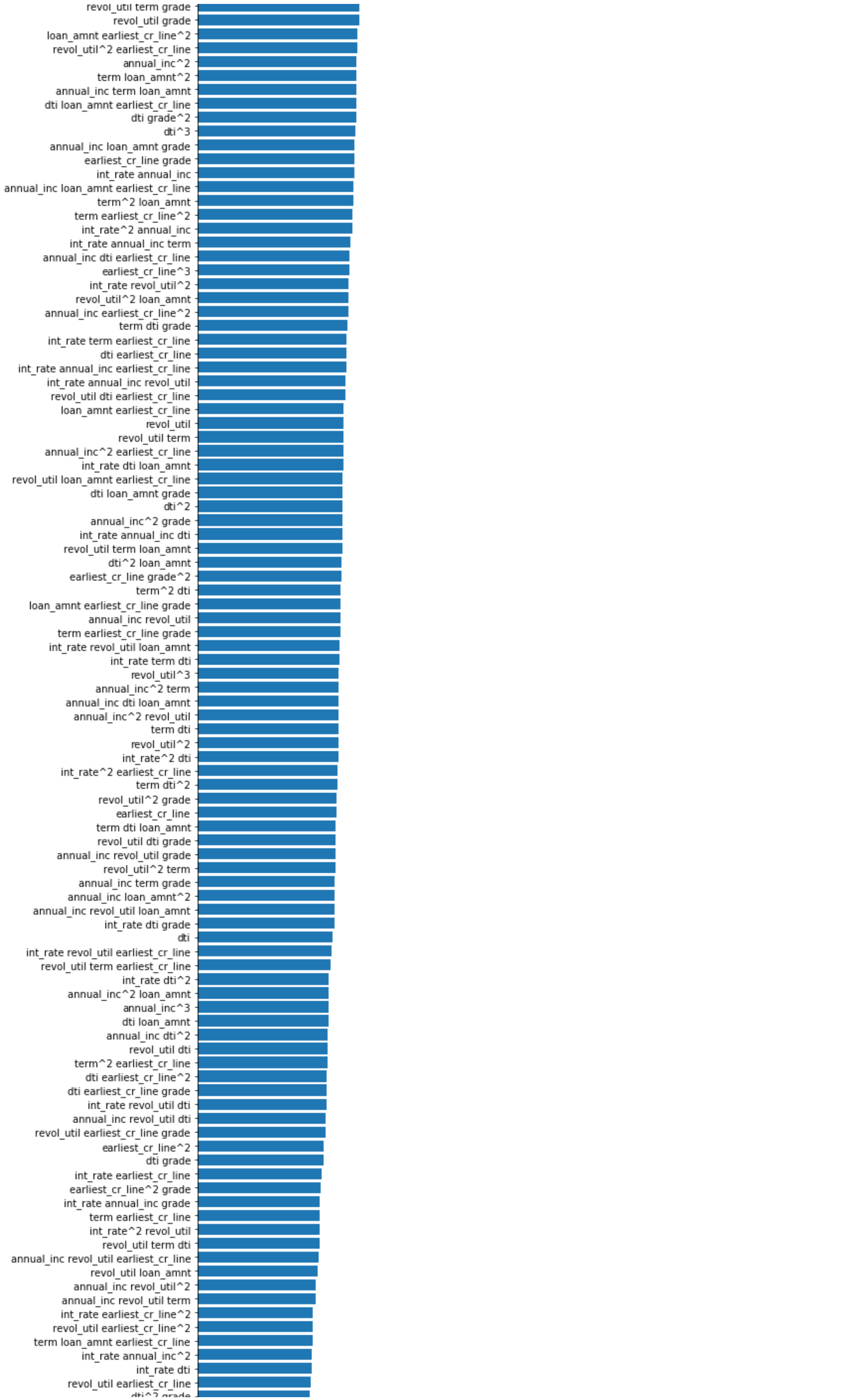
```
# Plot confusion matrix
y_pred = rf_sm.predict(X_test)

cnf_matrix = confusion_matrix(y_test, y_pred)
np.set_printoptions(precision=2)

plt.figure(figsize=(11,7))
plot_confusion_matrix(cnf_matrix, classes=["Good Loan", "Bad Loan"], normaliz
                      title='Random Forest Confusion Matrix')

plt.show()
```

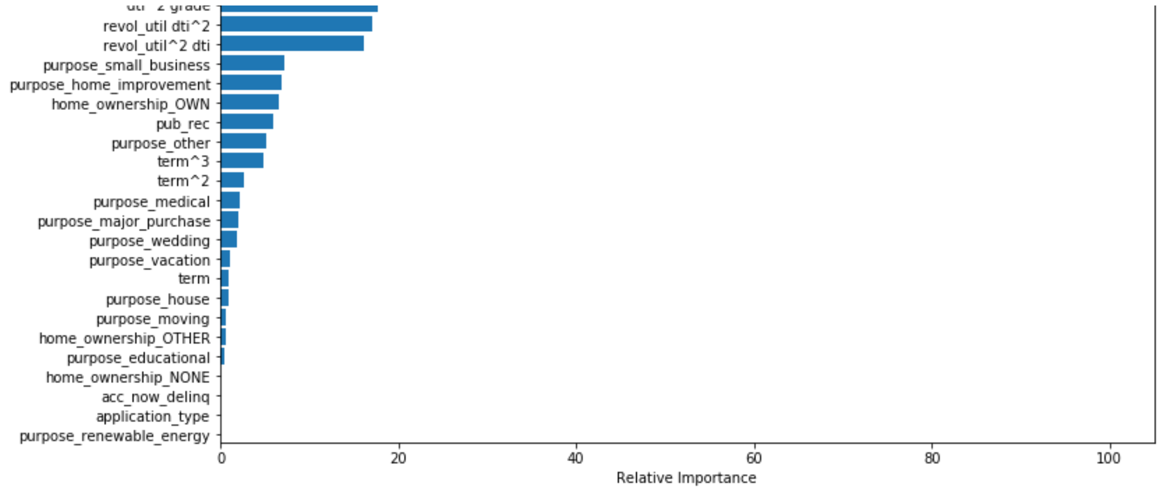


In [48]:

```python
# Random Forest Feature Importance
feature_importance = rf_sm.feature_importances_
feature_importance = 100.0 * (feature_importance / feature_importance.max())
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0])

# Plot
plt.figure(figsize=(12,50))
plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, X_train.columns[sorted_idx])
plt.xlabel('Relative Importance')
plt.title('Variable Importance')
plt.margins(y=0)
plt.show()
```




revol_util term grade
revol_util grade
loan_amnt earliest_cr_line^2
revol_util^2 earliest_cr_line
annual_inc^2
term loan_amnt^2
annual_inc term loan_amnt
dti loan_amnt earliest_cr_line
dti grade^2
dti^3
annual_inc loan_amnt grade
earliest_cr_line grade
int_rate annual_inc
annual_inc loan_amnt earliest_cr_line
term^2 loan_amnt
term earliest_cr_line^2
int_rate^2 annual_inc
int_rate annual_inc term
annual_inc dti earliest_cr_line
earliest_cr_line^3
int_rate revol_util^2
revol_util^2 loan_amnt
annual_inc earliest_cr_line^2
term dti grade
int_rate term earliest_cr_line
dti earliest_cr_line
int_rate annual_inc earliest_cr_line
int_rate annual_inc revol_util
revol_util dti earliest_cr_line
loan_amnt earliest_cr_line
revol_util
revol_util term
annual_inc^2 earliest_cr_line
int_rate dti loan_amnt
revol_util loan_amnt earliest_cr_line
dti loan_amnt grade
dti^2
annual_inc^2 grade
int_rate annual_inc dti
revol_util term loan_amnt
dti^2 loan_amnt
earliest_cr_line grade^2
term^2 dti
loan_amnt earliest_cr_line grade
annual_inc revol_util
term earliest_cr_line grade
int_rate revol_util loan_amnt
int_rate term dti
revol_util^3
annual_inc^2 term
annual_inc dti loan_amnt
annual_inc^2 revol_util
term dti
revol_util^2
int_rate^2 dti
int_rate^2 earliest_cr_line
term dti^2
revol_util^2 grade
earliest_cr_line
term dti loan_amnt
revol_util dti grade
annual_inc revol_util grade
revol_util^2 term
annual_inc term grade
annual_inc loan_amnt^2
annual_inc revol_util loan_amnt
int_rate dti grade
dti
int_rate revol_util earliest_cr_line
revol_util term earliest_cr_line
int_rate dti^2
annual_inc^2 loan_amnt
annual_inc^3
dti loan_amnt
annual_inc dti^2
revol_util dti
term^2 earliest_cr_line
dti earliest_cr_line^2
dti earliest_cr_line grade
int_rate revol_util dti
annual_inc revol_util dti
revol_util earliest_cr_line grade
earliest_cr_line^2
dti grade
int_rate earliest_cr_line
earliest_cr_line^2 grade
int_rate annual_inc grade
term earliest_cr_line
int_rate^2 revol_util
revol_util term dti
annual_inc revol_util earliest_cr_line
revol_util loan_amnt
annual_inc revol_util^2
annual_inc revol_util term
int_rate earliest_cr_line^2
revol_util earliest_cr_line^2
term loan_amnt earliest_cr_line
int_rate annual_inc^2
int_rate dti
revol_util earliest_cr_line



AddBoost

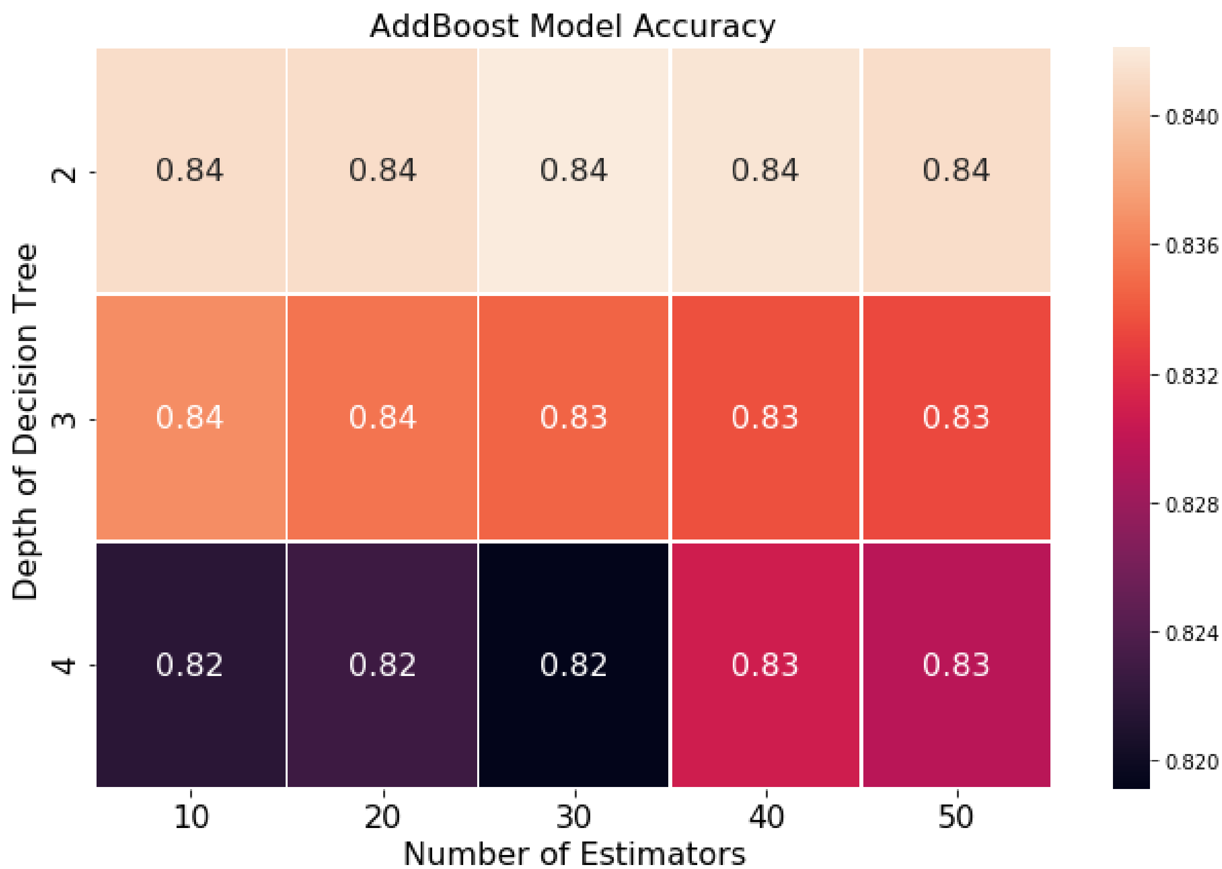
Raw training set

In [49]:

```
estimators = [10, 20, 30, 40, 50]
depths = list(range(2, 5))

train_scores = pd.DataFrame(index=depths, columns=estimators)
validation_scores = pd.DataFrame(index=depths, columns=estimators)
test_scores = pd.DataFrame(index=depths, columns=estimators)

best_score = 0
best_depth = 0
best_estimator = 0

for e in estimators:
    for d in depths:
        ab = AdaBoostClassifier(base_estimator=DecisionTreeClassifier(max_dep
                                n_estimators=e, learning_rate=0.05)
        ab.fit(X_train, y_train)

        train_scores.loc[d, e] = ab.score(X_train, y_train)
        test_scores.loc[d, e] = ab.score(X_test, y_test)

        val_score = cross_val_score(estimator=ab, X=X_train, y=y_train, cv=5)
        validation_scores.loc[d, e] = val_score

        if val_score > best_score:
            best_depth = d
            best_estimator = e
            best_score = val_score
```

In [50]:

```
validation_scores = validation_scores.astype(float)

f, ax = plt.subplots(figsize=(11, 7))
sns.heatmap(validation_scores, annot=True, linewidths=.5, ax=ax, annot_kws={"
ax.set_ylabel('Depth of Decision Tree', fontsize=16)
ax.set_xlabel('Number of Estimators', fontsize=16)
ax.set_title('AddBoost Model Accuracy', fontsize=16)
ax.tick_params(labelsize=16)
```

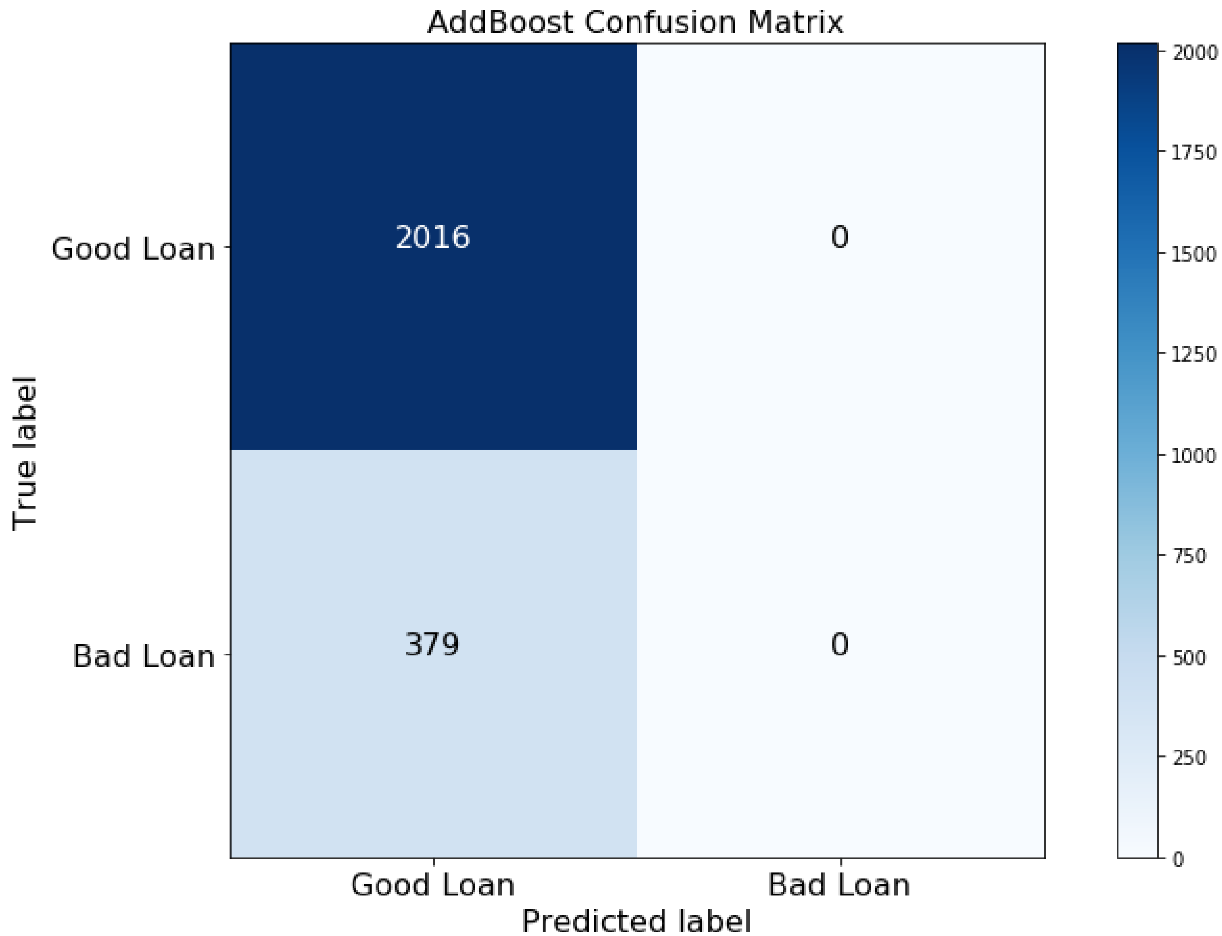


In [51]:

```
print('AddBoost: Optimal depth={}'.format(best_depth))
print('AddBoost: Optimal number of estimators={}'.format(best_estimator))

ab = AdaBoostClassifier(base_estimator=DecisionTreeClassifier(max_depth=best_
                        n_estimators=best_estimator, learning_rate=0.05)
ab.fit(X_train, y_train)

train_acc, test_acc = ab.score(X_train, y_train), ab.score(X_test, y_test)

report_lr = precision_recall_fscore_support(y_test, ab.predict(X_test), avera

ab_results = {
    'model': 'AddBoost',
    'train_acc': train_acc,
    'test_acc': test_acc,
    'precision': report_lr[0],
    'recall': report_lr[1],
    'F1': report_lr[2]
}

print('Random Forest: accuracy on train={:.2%}, test={:.2%}, precision={:.2f}
      format(ab_results['train_acc'],
             ab_results['test_acc'],
             ab_results['precision'],
             ab_results['recall'],
             ab_results['F1']))
```

```
AddBoost: Optimal depth=2
AddBoost: Optimal number of estimators=30
Random Forest: accuracy on train=84.17%, test=84.18%, precision=0.00, recall=0.
00, F1=0.00
```

In [52]:
```
# Plot confusion matrix
y_pred = ab.predict(X_test)

cnf_matrix = confusion_matrix(y_test, y_pred)
np.set_printoptions(precision=2)

plt.figure(figsize=(11,7))
plot_confusion_matrix(cnf_matrix, classes=["Good Loan", "Bad Loan"], normaliz
                      title='AddBoost Confusion Matrix')

plt.show()
```

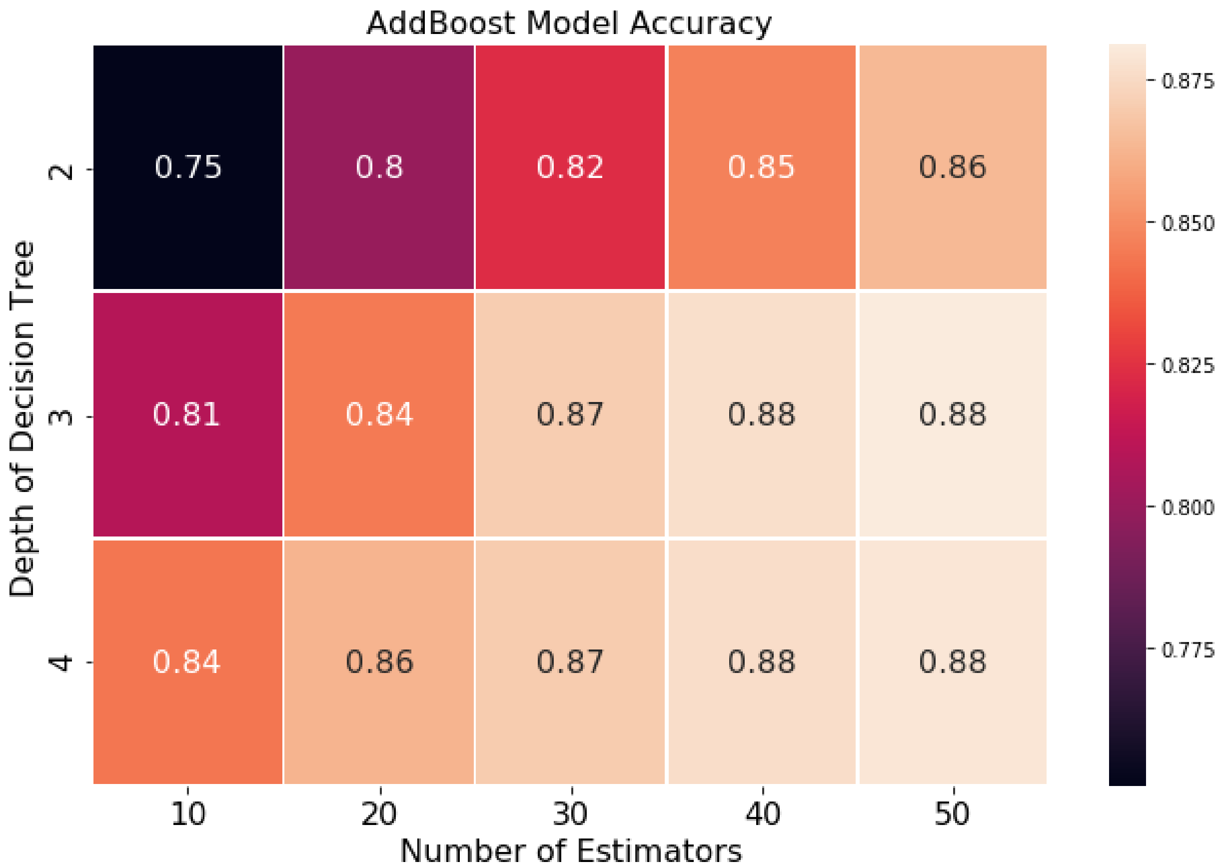


Oversampled Training set

In [53]:

```
estimators = [10, 20, 30, 40, 50]
depths = list(range(2, 5))

train_scores = pd.DataFrame(index=depths, columns=estimators)
validation_scores = pd.DataFrame(index=depths, columns=estimators)
test_scores = pd.DataFrame(index=depths, columns=estimators)

best_score = 0
best_depth = 0
best_estimator = 0

for e in estimators:
    for d in depths:
        ab = AdaBoostClassifier(base_estimator=DecisionTreeClassifier(max_dep
                                n_estimators=e, learning_rate=0.05)
        ab.fit(X_train_sm, y_train_sm)

        train_scores.loc[d, e] = ab.score(X_train_sm, y_train_sm)
        test_scores.loc[d, e] = ab.score(X_test, y_test)

        val_score = cross_val_score(estimator=ab, X=X_train_sm, y=y_train_sm,
        validation_scores.loc[d, e] = val_score

        if val_score > best_score:
            best_depth = d
            best_estimator = e
            best_score = val_score
```

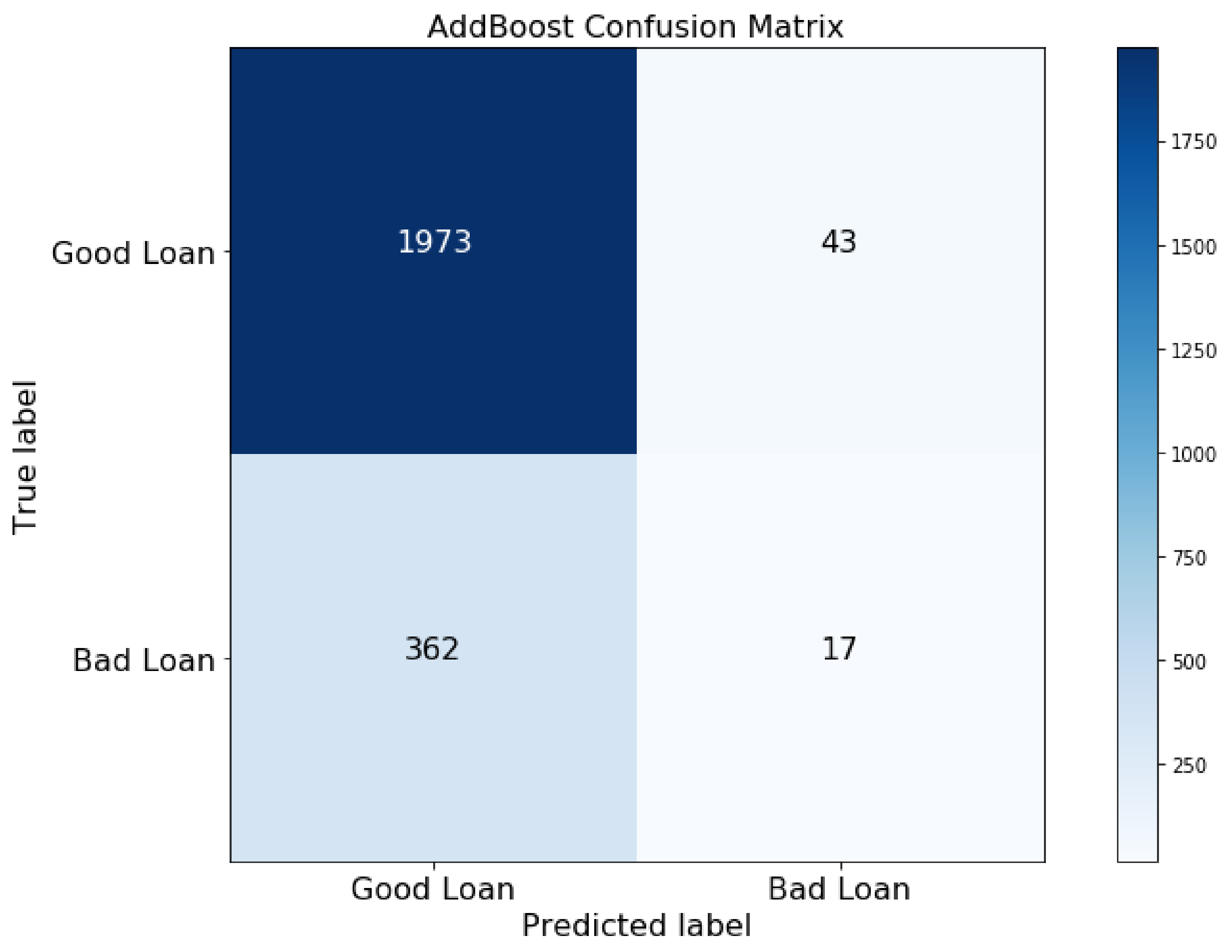
In [54]:
```
validation_scores = validation_scores.astype(float)

f, ax = plt.subplots(figsize=(11, 7))
sns.heatmap(validation_scores, annot=True, linewidths=.5, ax=ax, annot_kws={"
ax.set_ylabel('Depth of Decision Tree', fontsize=16)
ax.set_xlabel('Number of Estimators', fontsize=16)
ax.set_title('AddBoost Model Accuracy', fontsize=16)
ax.tick_params(labelsize=16)
```



In [55]:
```
print('AddBoost: Optimal depth={}'.format(best_depth))
print('AddBoost: Optimal number of estimators={}'.format(best_estimator))

ab_sm = AdaBoostClassifier(base_estimator=DecisionTreeClassifier(max_depth=be
                          n_estimators=best_estimator, learning_rate=0.05)
ab_sm.fit(X_train_sm, y_train_sm)

train_acc, test_acc = ab_sm.score(X_train_sm, y_train_sm), ab.score(X_test, y

report_lr = precision_recall_fscore_support(y_test, ab_sm.predict(X_test), av

ab_sm_results = {
    'model': 'AddBoost',
    'train_acc': train_acc,
    'test_acc': test_acc,
    'precision': report_lr[0],
    'recall': report_lr[1],
    'F1': report_lr[2]
}

print('Random Forest: accuracy on train={:.2%}, test={:.2%}, precision={:.2f}
      format(ab_sm_results['train_acc'],
             ab_sm_results['test_acc'],
             ab_sm_results['precision'],
             ab_sm_results['recall'],
             ab_sm_results['F1']))
```

```
AddBoost: Optimal depth=3
AddBoost: Optimal number of estimators=50
Random Forest: accuracy on train=90.79%, test=82.13%, precision=0.28, recall=0.
04, F1=0.08
```

In [56]:
```
# Plot confusion matrix
y_pred = ab_sm.predict(X_test)

cnf_matrix = confusion_matrix(y_test, y_pred)
np.set_printoptions(precision=2)

plt.figure(figsize=(11,7))
plot_confusion_matrix(cnf_matrix, classes=["Good Loan", "Bad Loan"], normaliz
                      title='AddBoost Confusion Matrix')

plt.show()
```



Neural Network

Raw training set

In [12]:
```
X_train_arr = X_train.values
y_train_arr = to_categorical(y_train.values)
X_test_arr = X_test.values
y_test_arr = to_categorical(y_test.values)
```

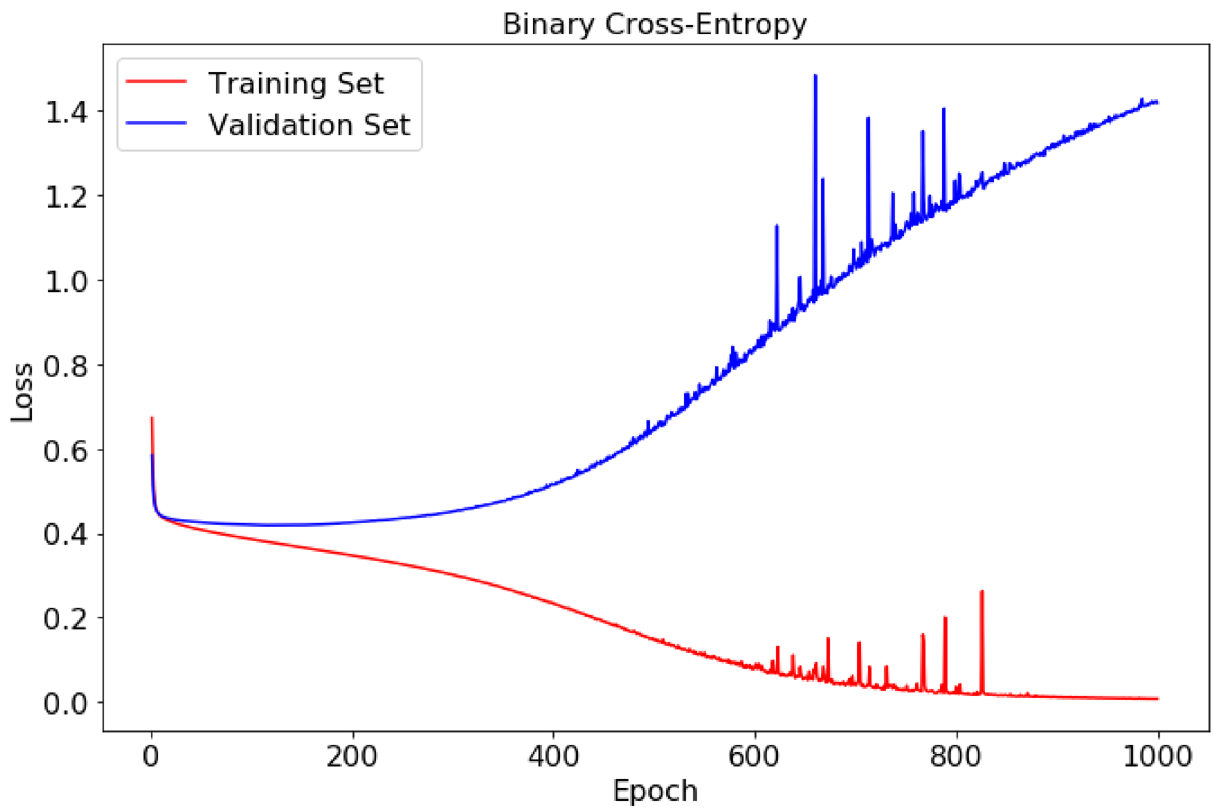
In [13]:

```
H = 100 # number of nodes in the layer
input_dim = X_train.shape[1] # input dimension
output_dim = 2 # output dimension

nn = Sequential() # create sequential multi-layer perceptron

# layer 0, our hidden layer
nn.add(Dense(H, input_dim=input_dim, activation='relu'))

# layer 1, our hidden layer
nn.add(Dense(H, activation='relu'))

# layer 2, our hidden layer
nn.add(Dense(H, activation='relu'))

# layer 3
nn.add(Dense(output_dim, activation='sigmoid'))

# compile the model
nn.compile(loss='binary_crossentropy', optimizer='sgd')
nn.summary()

epochs = 1000
batch_size = 128
validation_split = 0.5

nn_history = nn.fit(X_train_arr, y_train_arr,
                    batch_size=batch_size,
                    epochs=epochs, verbose=False,
                    shuffle = True, validation_data = (X_test_arr, y_test_arr
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_1 (Dense)              (None, 100)               19500     
_________________________________________________________________
dense_2 (Dense)              (None, 100)               10100     
_________________________________________________________________
dense_3 (Dense)              (None, 100)               10100     
_________________________________________________________________
dense_4 (Dense)              (None, 2)                 202       
=================================================================
Total params: 39,902
Trainable params: 39,902
Non-trainable params: 0
_________________________________________________________________
```

In [14]:

```
fig, ax = plt.subplots(1, 1, figsize=(11,7))
ax.plot(range(1, epochs + 1), nn_history.history['loss'], 'r', label='Trainin
ax.plot(range(1, epochs + 1), nn_history.history['val_loss'], 'b', label='Val
ax.set_title('Binary Cross-Entropy', fontsize=16)
ax.set_xlabel('Epoch', fontsize=16)
ax.set_ylabel('Loss', fontsize=16)
ax.legend(fontsize=16)
ax.tick_params(labelsize=16)
```



In [15]:

```
H = 100 # number of nodes in the layer
input_dim = X_train.shape[1] # input dimension
output_dim = 2 # output dimension

nn = Sequential() # create sequential multi-layer perceptron

# layer 0, our hidden layer
nn.add(Dense(H, input_dim=input_dim, activation='relu'))

# layer 1, our hidden layer
nn.add(Dense(H, activation='relu'))

# layer 2, our hidden layer
nn.add(Dense(H, activation='relu'))

# layer 3
nn.add(Dense(output_dim, activation='sigmoid'))

# compile the model
nn.compile(loss='binary_crossentropy', optimizer='sgd')
nn.summary()

epochs = 160
batch_size = 128

nn_history = nn.fit(X_train_arr, y_train_arr,
                    batch_size=batch_size,
                    epochs=epochs, verbose=False,
                    shuffle = True, validation_data = (X_test_arr, y_test_arr
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_5 (Dense)              (None, 100)               19500     
_________________________________________________________________
dense_6 (Dense)              (None, 100)               10100     
_________________________________________________________________
dense_7 (Dense)              (None, 100)               10100     
_________________________________________________________________
dense_8 (Dense)              (None, 2)                 202       
=================================================================
Total params: 39,902
Trainable params: 39,902
Non-trainable params: 0
_________________________________________________________________
```

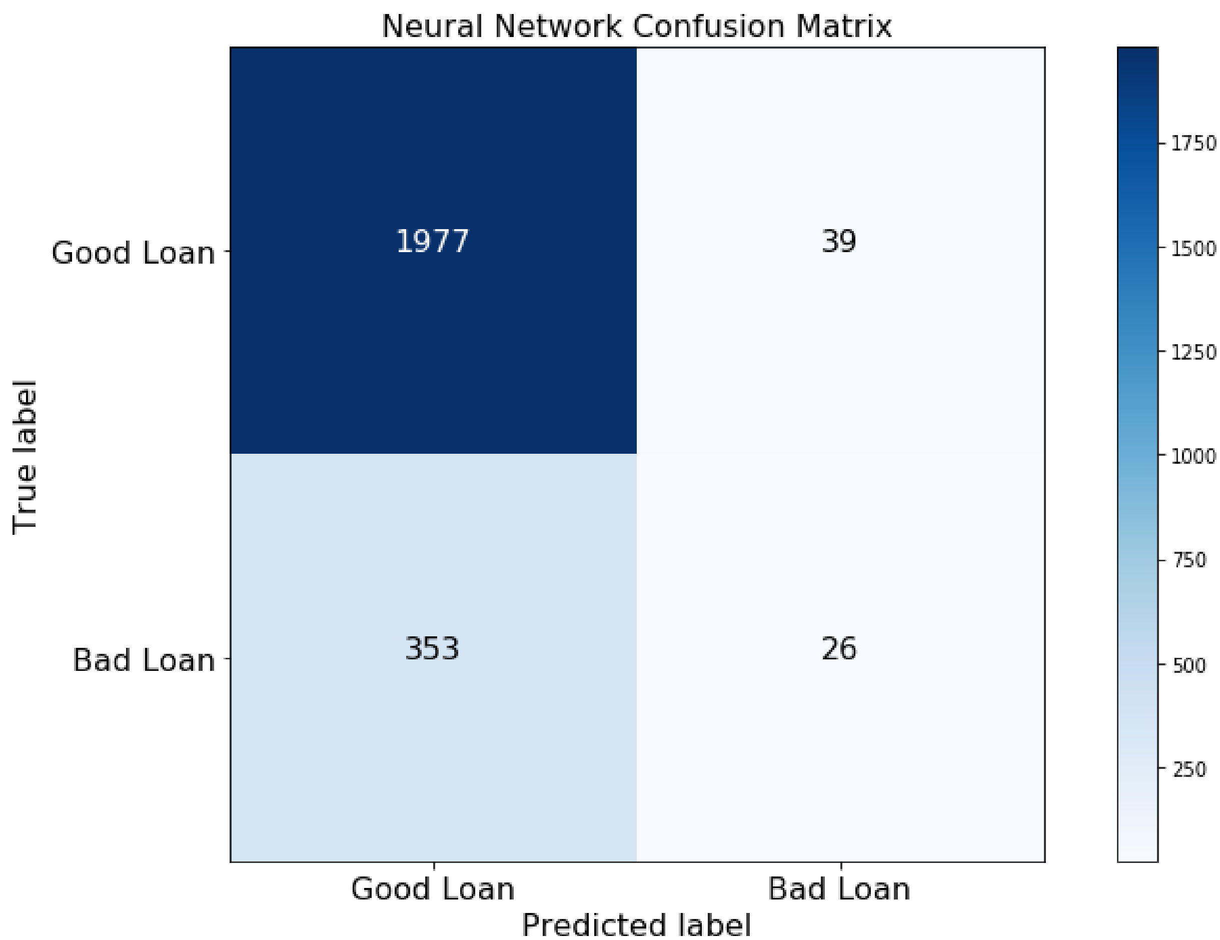
In [16]:

```
nn_train_df = pd.DataFrame(nn.predict(X_train_arr))
nn_train_df['pred'] = nn_train_df.apply(lambda x: 1 if x[0] < x[1] else 0, ax
nn_train_acc = accuracy_score(y_train, nn_train_df['pred'].values)

nn_test_df = pd.DataFrame(nn.predict(X_test_arr))
nn_test_df['pred'] = nn_test_df.apply(lambda x: 1 if x[0] < x[1] else 0, axis
nn_test_acc = accuracy_score(y_test, nn_test_df['pred'].values)

report_lr = precision_recall_fscore_support(y_test, nn_test_df['pred'], avera

nn_results = {
    'model': 'Neural Network',
    'train_acc': nn_train_acc,
    'test_acc': nn_test_acc,
    'precision': report_lr[0],
    'recall': report_lr[1],
    'F1': report_lr[2]
}

print('Neural Network: accuracy on train={:.2%}, test={:.2%}, precision={:.2f
      format(nn_results['train_acc'],
             nn_results['test_acc'],
             nn_results['precision'],
             nn_results['recall'],
             nn_results['F1']))
```

```
Neural Network: accuracy on train=85.96%, test=83.63%, precision=0.40, recall=
0.07, F1=0.12
```

In [17]:

```
# Plot confusion matrix
cnf_matrix = confusion_matrix(y_test, nn_test_df['pred'].values)
np.set_printoptions(precision=2)

plt.figure(figsize=(11,7))
plot_confusion_matrix(cnf_matrix, classes=["Good Loan", "Bad Loan"], normaliz
                      title='Neural Network Confusion Matrix')

plt.show()
```



Oversampled Training set

In [18]:

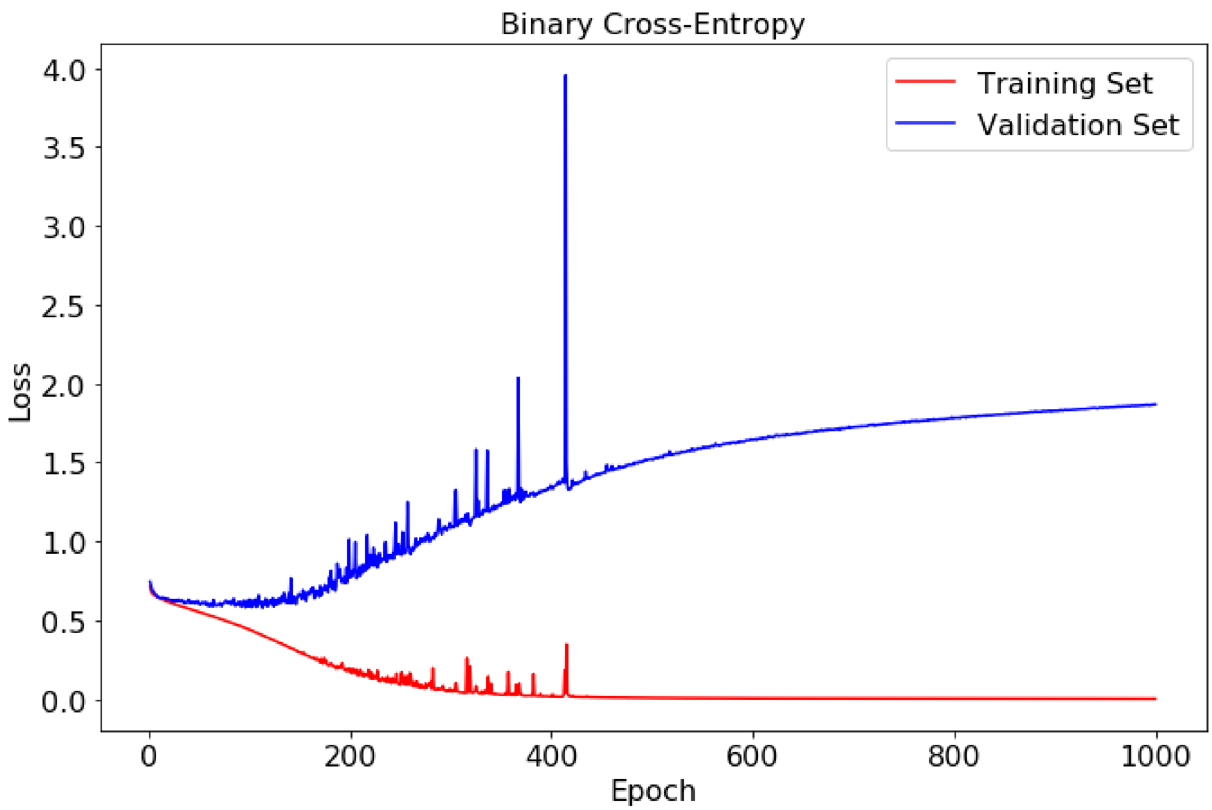
```
X_train_arr = X_train_sm
y_train_arr = to_categorical(y_train_sm)
X_test_arr = X_test.values
y_test_arr = to_categorical(y_test.values)
```

In [19]:
```
H = 100 # number of nodes in the layer
input_dim = X_train_sm.shape[1] # input dimension
output_dim = 2 # output dimension

nn = Sequential() # create sequential multi-layer perceptron

# layer 0, our hidden layer
nn.add(Dense(H, input_dim=input_dim, activation='relu'))

# layer 1, our hidden layer
nn.add(Dense(H, activation='relu'))

# layer 2, our hidden layer
nn.add(Dense(H, activation='relu'))

# layer 3
nn.add(Dense(output_dim, activation='sigmoid'))

# compile the model
nn.compile(loss='binary_crossentropy', optimizer='sgd')
nn.summary()

epochs = 1000
batch_size = 128
validation_split = 0.5

nn_history = nn.fit(X_train_arr, y_train_arr,
                    batch_size=batch_size,
                    epochs=epochs, verbose=False,
                    shuffle = True, validation_data = (X_test_arr, y_test_arr
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_9 (Dense)              (None, 100)               19500     
_________________________________________________________________
dense_10 (Dense)             (None, 100)               10100     
_________________________________________________________________
dense_11 (Dense)             (None, 100)               10100     
_________________________________________________________________
dense_12 (Dense)             (None, 2)                 202       
=================================================================
Total params: 39,902
Trainable params: 39,902
Non-trainable params: 0
_________________________________________________________________
```

In [20]:

```
fig, ax = plt.subplots(1, 1, figsize=(11,7))
ax.plot(range(1, epochs + 1), nn_history.history['loss'], 'r', label='Trainin
ax.plot(range(1, epochs + 1), nn_history.history['val_loss'], 'b', label='Val
ax.set_title('Binary Cross-Entropy', fontsize=16)
ax.set_xlabel('Epoch', fontsize=16)
ax.set_ylabel('Loss', fontsize=16)
ax.legend(fontsize=16)
ax.tick_params(labelsize=16)
```



In [21]:

```
H = 100 # number of nodes in the layer
input_dim = X_train_sm.shape[1] # input dimension
output_dim = 2 # output dimension

nn_sm = Sequential() # create sequential multi-layer perceptron

# layer 0, our hidden layer
nn_sm.add(Dense(H, input_dim=input_dim, activation='relu'))

# layer 1, our hidden layer
nn_sm.add(Dense(H, activation='relu'))

# layer 2, our hidden layer
nn_sm.add(Dense(H, activation='relu'))

# layer 3
nn_sm.add(Dense(output_dim, activation='sigmoid'))

# compile the model
nn_sm.compile(loss='binary_crossentropy', optimizer='sgd')
nn_sm.summary()

epochs = 100
batch_size = 128

nn_sm_history = nn_sm.fit(X_train_arr, y_train_arr,
                          batch_size=batch_size,
                          epochs=epochs, verbose=False,
                          shuffle = True, validation_data = (X_test_arr, y_te
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_13 (Dense)             (None, 100)               19500
_________________________________________________________________
dense_14 (Dense)             (None, 100)               10100
_________________________________________________________________
dense_15 (Dense)             (None, 100)               10100
_________________________________________________________________
dense_16 (Dense)             (None, 2)                 202
=================================================================
Total params: 39,902
Trainable params: 39,902
Non-trainable params: 0
_________________________________________________________________
```

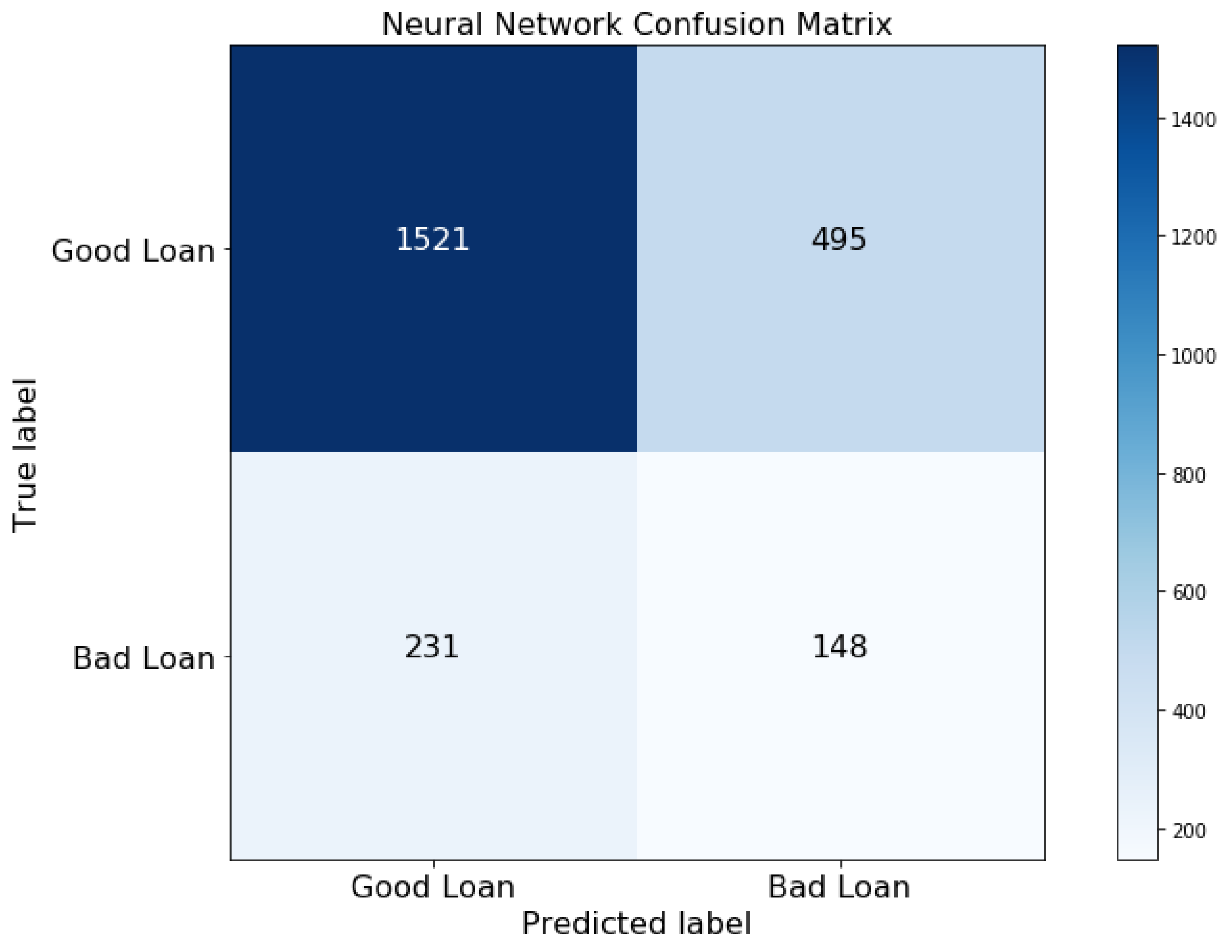
In [22]:

```
nn_train_df = pd.DataFrame(nn_sm.predict(X_train_arr))
nn_train_df['pred'] = nn_train_df.apply(lambda x: 1 if x[0] < x[1] else 0, ax
nn_train_acc = accuracy_score(y_train_sm, nn_train_df['pred'].values)

nn_test_df = pd.DataFrame(nn_sm.predict(X_test_arr))
nn_test_df['pred'] = nn_test_df.apply(lambda x: 1 if x[0] < x[1] else 0, axis
nn_test_acc = accuracy_score(y_test, nn_test_df['pred'].values)

report_lr = precision_recall_fscore_support(y_test, nn_test_df['pred'], avera

nn_sm_results = {
    'model': 'Neural Network',
    'train_acc': nn_train_acc,
    'test_acc': nn_test_acc,
    'precision': report_lr[0],
    'recall': report_lr[1],
    'F1': report_lr[2]
}

print('Neural Network: accuracy on train={:.2%}, test={:.2%}, precision={:.2f
      format(nn_sm_results['train_acc'],
             nn_sm_results['test_acc'],
             nn_sm_results['precision'],
             nn_sm_results['recall'],
             nn_sm_results['F1']))
```

```
Neural Network: accuracy on train=84.74%, test=69.69%, precision=0.23, recall=
0.39, F1=0.29
```

In [23]:

```
# Plot confusion matrix
cnf_matrix = confusion_matrix(y_test, nn_test_df['pred'].values)
np.set_printoptions(precision=2)

plt.figure(figsize=(11,7))
plot_confusion_matrix(cnf_matrix, classes=["Good Loan", "Bad Loan"], normaliz
                      title='Neural Network Confusion Matrix')

plt.show()
```



Output Model Results

In [25]:

```
# Output results
results = pd.DataFrame([logit_results,
                        knn_results,
                        lda_results,
                        qda_results,
                        tree_results,
                        rf_results,
                        ab_results,
                        nn_results])
results.set_index('model', inplace=True)
results.to_csv("data/results.csv", index=True)
```

In [70]:

```
# Output results
results_sm = pd.DataFrame([logit_sm_results,
                           knn_sm_results,
                           lda_sm_results,
                           qda_sm_results,
                           tree_sm_results,
                           rf_sm_results,
                           ab_sm_results,
                           nn_sm_results])
results_sm.set_index('model', inplace=True)
results_sm.to_csv("data/results_sm.csv", index=True)
```

In [ ]:

```

```