Decide_if_a_bank_should_grant_a_loan

March 21, 2017

Contents

Chapter 1

Background

We are given a bank's loan records with information of individuals who have applied for loans. Some of the loans are approved and some are rejected. Out of the approved loans, some were repaid, and others were defaulted. The goal is to investigate if we could build a better model for the bank by examinig its loan data.

We take the approach of building a model that predicts whether an individual, if granted a loan, will repay the loan or not. With this model, we then predict how many of those who've been denied loans could have been good customers who repay their loans fully. The percentage of individuals who should've been granted loans could translate to an increase of financial returns for the bank for not denying good business.

Chapter 2

Import libraries

```
In [1]: import zipfile
        import os
        import random
        import collections

        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns

        from sklearn.neighbors import KNeighborsClassifier, KNeighborsRegressor
        from sklearn.preprocessing import LabelEncoder, MinMaxScaler
        from sklearn import model_selection
        from sklearn import cross_validation
        from sklearn import preprocessing
        from sklearn import svm
        from sklearn import linear_model
        from sklearn import tree
        from sklearn import ensemble # RandomForestClassifier
        from sklearn.naive_bayes import GaussianNB
        from sklearn import metrics
        from sklearn.feature_selection import SelectFromModel
        %matplotlib inline
```

```
/Users/yingjiang/miniconda2/lib/python2.7/site-packages/sklearn/cross_validation.py:44: DeprecationWarni
  "This module will be removed in 0.20.", DeprecationWarning)
```

Chapter 3

User defined functions

In [96]:
```
def fill_na_KNN(df, column, model):
    """Treat missing values as a classification / regresion problem
    df = original dataframe with NA cols
    column = col you want to impute
    model = the classification or regression model used to fill in the NAs
    Returns imputed column.
    """
    ## Remove all cols containing NAs, except for the col we want to impute.
    # Split the cols with and without missing values
    colNAs = df.loc[:, df.isnull().any()]
    df = df.dropna(axis=1)
    # Join back the col we want to impute
    ndf = pd.concat([df, colNAs.loc[:, column]], axis=1)

    ## Split into rows with known (train) and missing values (test)
    # Get a row-wise boolean for the rows containing the NAs (in the specified col)
    nullmask = ndf[column].isnull()
    # The rows containing NAs are the testing data; otherwise the training data
    train, test  = ndf[~nullmask], ndf[nullmask]
    train_x, train_y = train.drop(column, axis=1), train[column]
    test_x, test_y = test.drop(column, axis=1), test[column]

    ## Fit KNN model
    model.fit(train_x, train_y)
    pred_y = model.predict(test_x)

    ## Stitch together the NA-filled dataset.
    # Arrange the rows in the original order to prepare for next imputation.
    # Converted the predicted array (np array) into a Series object with the orignal index
    pred_y = pd.Series(pred_y, index = test_y.index)
    new_y = new_y = pd.concat([train_y, pred_y]).sort_index()

    return new_y


def performCV(X_train, Y_train, cv, model):
    Y_pred = []
    Y_true = []
    for trainIdx, cvIdx in cv.split(X_train):
```

```
        Y_pred.append(model.fit(X_train.iloc[trainIdx],
                                Y_train.iloc[trainIdx]).predict_proba(X_train.iloc[cvIdx]))
        Y_true.append(Y_train.iloc[cvIdx])
    return Y_pred, Y_true

def unpackCVResults(Y_pred, Y_true):
    Y_pred_unpack = []
    Y_true_unpack = []
    for yp, yt in zip(Y_pred, Y_true):
        Y_pred_unpack.append([pred_val.argmax() for pred_val in yp])
        Y_true_unpack.append(list(yt.values))
    return Y_pred_unpack, Y_true_unpack

def getCVScores(Y_pred_unpack, Y_true_unpack):
    cvScore_Acc = []
    cvScore_Sens = []
    cvScore_Spec = []
    cvScore_Prec = []
    for yp, yt in zip(Y_pred_unpack, Y_true_unpack):
        cm = metrics.confusion_matrix(y_true = yt, y_pred = yp, labels=None)
        accuracy, sensitivity, specificity, precision = evalModel(cm)
        ## Alternative way of calculating accuracy instead of through cm:
        # match = [i for i, j in zip(Y_pred0, Y_true0) if i == j]
        # len(match) / float(len(Y_pred0))
        cvScore_Acc.append(accuracy)
        cvScore_Sens.append(sensitivity)
        cvScore_Spec.append(specificity)
        cvScore_Prec.append(precision)
    cvScore = pd.DataFrame({
            'accuracy': cvScore_Acc,
            'sensitivity': cvScore_Sens,
            'specificity': cvScore_Spec,
            'precision': cvScore_Prec,
            'recall': cvScore_Sens
        })
    return cvScore

def evalModel(cm):
    TN = cm[0][0]
    FP = cm[0][1]
    FN = cm[1][0]
    TP = cm[1][1]
    P = FN + TP
    N = TN + FP
    Acc = (TN + TP) / float(P + N)
    sensitivity = TP / float(P)
    specificity = TN / float(N)
    precision = TP / float(TP+FP)
    NPV = TN / float(TN+FN)
    FPR = FP / float(FP+TN)
    FDR = FP / float(FP+TP)
    F1 = 2*TP / float(2*TP + FP + FN)
    return Acc, sensitivity, specificity, precision
```

Chapter 4

Load data

```
In [2]: os.listdir(os.getcwd())

Out[2]: ['.ipynb_checkpoints',
         'borrower_table.csv',
         'Loan_granting.ipynb',
         'Loan_granting.zip',
         'loan_table.csv']

In [3]: borrower = pd.read_csv('borrower_table.csv')
        loan = pd.read_csv('loan_table.csv')

In [4]: borrower.head()

Out[4]:    loan_id  is_first_loan  fully_repaid_previous_loans  \
        0   289774              1                          NaN
        1   482590              0                          1.0
        2   135565              1                          NaN
        3   207797              0                          1.0
        4   828078              0                          0.0

           currently_repaying_other_loans  total_credit_card_limit  \
        0                             NaN                     8000
        1                             0.0                     4500
        2                             NaN                     6900
        3                             0.0                     1200
        4                             0.0                     6900

           avg_percentage_credit_card_limit_used_last_year  saving_amount  \
        0                                             0.49           3285
        1                                             1.03            636
        2                                             0.82           2085
        3                                             0.82            358
        4                                             0.80           2138

           checking_amount  is_employed  yearly_salary  age  dependent_number
        0             1073            0              0   47                 3
        1             5299            1          13500   33                 1
        2             3422            1          24500   38                 8
        3             3388            0              0   24                 1
        4             4282            1          18100   36                 1
```

In [5]: loan.head()

Out[5]:

	loan_id	loan_purpose	date	loan_granted	loan_repaid
0	19454	investment	2012-03-15	0	NaN
1	496811	investment	2012-01-17	0	NaN
2	929493	other	2012-02-09	0	NaN
3	580653	other	2012-06-27	1	1.0
4	172419	business	2012-05-21	1	0.0

Chapter 5

Clean data

5.1 1. Merge data

Overall goal here is to predict if a loan should be granted to an individual or not. We therefore use the individuals who've been granted loans (loan_granted = 1) to train our model. We then use the denied rows (loan_granted = 0) as the test set, to see how many of these denied folks are actually predicted to honestly return their loans. This will be the money the bank lost.

```
In [6]: print borrower.columns
        print borrower.shape
        print loan.columns
        print loan.shape
```

```
Index([u'loan_id', u'is_first_loan', u'fully_repaid_previous_loans',
       u'currently_repaying_other_loans', u'total_credit_card_limit',
       u'avg_percentage_credit_card_limit_used_last_year', u'saving_amount',
       u'checking_amount', u'is_employed', u'yearly_salary', u'age',
       u'dependent_number'],
      dtype='object')
(101100, 12)
Index([u'loan_id', u'loan_purpose', u'date', u'loan_granted', u'loan_repaid'], dtype='object')
(101100, 5)
```

```
In [7]: loanData = pd.merge(borrower, loan, how='inner', on='loan_id')
```

```
In [8]: print loanData.columns
        print loanData.shape
```

```
Index([u'loan_id', u'is_first_loan', u'fully_repaid_previous_loans',
       u'currently_repaying_other_loans', u'total_credit_card_limit',
       u'avg_percentage_credit_card_limit_used_last_year', u'saving_amount',
       u'checking_amount', u'is_employed', u'yearly_salary', u'age',
       u'dependent_number', u'loan_purpose', u'date', u'loan_granted',
       u'loan_repaid'],
      dtype='object')
(101100, 16)
```

```
In [9]: granted = loanData[loanData.loan_granted == 1]
        granted.drop('loan_granted', axis=1, inplace=True)
        print granted.shape
```

```
(47654, 15)
```

```
/Users/yingjiang/miniconda2/lib/python2.7/site-packages/ipykernel/__main__.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing
  from ipykernel import kernelapp as app
```

In [10]:
```
granted.describe()
```

Out[10]:

```
             loan_id  is_first_loan  fully_repaid_previous_loans  \
count   47654.000000   47654.000000                 21865.000000
mean   500187.775402       0.541172                     0.902493
std    288925.682009       0.498307                     0.296654
min        37.000000       0.000000                     0.000000
25%    248669.250000       0.000000                     1.000000
50%    500013.500000       1.000000                     1.000000
75%    750413.250000       1.000000                     1.000000
max    999968.000000       1.000000                     1.000000

       currently_repaying_other_loans  total_credit_card_limit  \
count                    21865.000000             47654.000000
mean                         0.297736              4527.848659
std                          0.457273              1975.127016
min                          0.000000                 0.000000
25%                          0.000000              3100.000000
50%                          0.000000              4400.000000
75%                          1.000000              5800.000000
max                          1.000000             13500.000000

       avg_percentage_credit_card_limit_used_last_year  saving_amount  \
count                                     46751.000000   47654.000000
mean                                          0.700091    2022.366580
std                                           0.177729    1493.410303
min                                           0.000000       0.000000
25%                                           0.580000     914.000000
50%                                           0.710000    1553.000000
75%                                           0.830000    2878.000000
max                                           1.090000   10641.000000

       checking_amount   is_employed  yearly_salary           age  \
count     47654.000000  47654.000000   47654.000000  47654.000000
mean       3499.160595      0.909829   29245.991942     41.524657
std        2155.128304      0.286429   16286.512395     12.817587
min           0.000000      0.000000       0.000000     18.000000
25%        1873.000000      1.000000   18900.000000     32.000000
50%        3024.500000      1.000000   29400.000000     41.000000
75%        4842.000000      1.000000   40200.000000     50.000000
max       13165.000000      1.000000   97200.000000     79.000000

       dependent_number   loan_repaid
count      47654.000000  47654.000000
mean           3.752445      0.644353
std            2.621351      0.478714
min            0.000000      0.000000
25%            2.000000      0.000000
50%            3.000000      1.000000
```

```
75%             6.000000      1.000000
max             8.000000      1.000000
```

5.2 2. Drop 'date' column

We can drop the date feature first to see if a good enough model can be built. If date features can offer further insight, e.g. default is more likely when the grant is applied in certain months, the column can be considered in future.

```
In [11]: granted.drop('date', axis=1, inplace=True)
```

```
/Users/yingjiang/miniconda2/lib/python2.7/site-packages/ipykernel/__main__.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing
  if __name__ == '__main__':
```

5.3 3. Convert categorical variable into numeric

```
In [12]: granted.dtypes
```

```
Out[12]: loan_id                                          int64
         is_first_loan                                    int64
         fully_repaid_previous_loans                    float64
         currently_repaying_other_loans                 float64
         total_credit_card_limit                          int64
         avg_percentage_credit_card_limit_used_last_year    float64
         saving_amount                                    int64
         checking_amount                                  int64
         is_employed                                      int64
         yearly_salary                                    int64
         age                                              int64
         dependent_number                                 int64
         loan_purpose                                    object
         loan_repaid                                    float64
         dtype: object
```

```
In [13]: granted.select_dtypes(include=['O']).columns
```

```
Out[13]: Index([u'loan_purpose'], dtype='object')
```

```
In [14]: granted.loan_purpose.unique()
```

```
Out[14]: array(['other', 'business', 'emergency_funds', 'investment', 'home'], dtype=object)
```

There are five types of loan purposes. If one uses LabelEncoder, which generates ordinal labels -

```
In [15]: purpose_encoder = LabelEncoder()
         purpose_encoder.fit(granted.loan_purpose)
         print purpose_encoder.transform(granted.loan_purpose)[:20]
         print granted.loan_purpose[:20]
```

```
[4 4 0 1 0 0 0 1 0 3 2 0 2 0 1 0 3 0 1 2]
2               other
5               other
```

```
7             business
8      emergency_funds
9             business
10            business
11            business
13     emergency_funds
16            business
17          investment
21                home
22            business
23                home
31            business
35     emergency_funds
39            business
40          investment
42            business
45     emergency_funds
47                home
Name: loan_purpose, dtype: object
```

Since loan purposes don't have an ordinal relationship, one-hot encoding is more desirable. It retains more info by creating only four more columns.

```
In [16]: for purpose in granted.loan_purpose.unique():
             granted['purpose_'+purpose] = granted.loan_purpose.str.contains(purpose).astype(int)
         granted.drop('loan_purpose',axis=1, inplace=True)
```

```
/Users/yingjiang/miniconda2/lib/python2.7/site-packages/ipykernel/__main__.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexin
  from ipykernel import kernelapp as app
/Users/yingjiang/miniconda2/lib/python2.7/site-packages/ipykernel/__main__.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexin
  app.launch_new_instance()
```

```
In [17]: granted.head()
```

```
Out[17]:    loan_id  is_first_loan  fully_repaid_previous_loans  \
        2   135565              1                          NaN
        5   423171              1                          NaN
        7   200139              1                          NaN
        8   991294              0                          1.0
        9   875332              0                          1.0

           currently_repaying_other_loans  total_credit_card_limit  \
        2                             NaN                     6900
        5                             NaN                     6100
        7                             NaN                     4000
        8                             0.0                     7000
        9                             0.0                     4300
```

```
   avg_percentage_credit_card_limit_used_last_year  saving_amount  \
2                                             0.82           2085
5                                             0.53           6163
7                                             0.57            602
8                                             0.52           2575
9                                             0.83            722

   checking_amount  is_employed  yearly_salary  age  dependent_number  \
2             3422            1          24500   38                 8
5             5298            1          29500   24                 1
7             2757            1          31700   36                 8
8             2917            1          58900   33                 3
9              892            1           5400   32                 7

   loan_repaid  purpose_other  purpose_business  purpose_emergency_funds  \
2          1.0              1                 0                        0
5          1.0              1                 0                        0
7          0.0              0                 1                        0
8          1.0              0                 0                        1
9          1.0              0                 1                        0

   purpose_investment  purpose_home
2                   0             0
5                   0             0
7                   0             0
8                   0             0
9                   0             0
```

5.4 4. Deal with missing values

Three columns have a large number of missing values. The strategy is to build models without these columns, or after imputing the missing values by k-nearest neighbor regression. Then compare the model performance.

In [18]:
```
loanData.isnull().sum()
```

Out[18]:
```
loan_id                                                0
is_first_loan                                          0
fully_repaid_previous_loans                        54947
currently_repaying_other_loans                     54947
total_credit_card_limit                                0
avg_percentage_credit_card_limit_used_last_year     6972
saving_amount                                          0
checking_amount                                        0
is_employed                                            0
yearly_salary                                          0
age                                                    0
dependent_number                                       0
loan_purpose                                           0
date                                                   0
loan_granted                                           0
loan_repaid                                        53446
dtype: int64
```

In [19]:
```
granted.isnull().sum()
```

```
Out[19]: loan_id                                           0
         is_first_loan                                     0
         fully_repaid_previous_loans                   25789
         currently_repaying_other_loans                25789
         total_credit_card_limit                           0
         avg_percentage_credit_card_limit_used_last_year  903
         saving_amount                                     0
         checking_amount                                   0
         is_employed                                       0
         yearly_salary                                     0
         age                                               0
         dependent_number                                  0
         loan_repaid                                       0
         purpose_other                                     0
         purpose_business                                  0
         purpose_emergency_funds                           0
         purpose_investment                                0
         purpose_home                                      0
         dtype: int64
```

```
In [20]: print 'Percentage of loans granted:', granted.shape[0]/float(loanData.shape[0])
         print 'Percentage of individuals with payment history missing granted loans:', granted.isnull(
         print 'Percentage of individuals with credit-limit-use missing granted loans:', granted.isnull
```

```
Percentage of loans granted: 0.471355093966
Percentage of individuals with payment history missing granted loans: 0.469343185251
Percentage of individuals with credit-limit-use missing granted loans: 0.129518072289
```

It seems that the bank doesn't discriminate against people who've missing payment history when granting loans. But they do grant loans more to people whose credit limit use information is declared / known.

```
In [21]: for key, group in granted.groupby('loan_repaid'):
             print 'Repaid loan?', key
             print 'Number of cases:', group.shape
             print '% of individuals with previous payment history missing:', group.fully_repaid_previou
             print '% of individuals with current payment history missing:', group.currently_repaying_o
             print '% of individuals with credit-limit-use missing:', group.avg_percentage_credit_card_l
```

```
Repaid loan? 0.0
Number of cases: (16948, 18)
% of individuals with previous payment history missing: 0.532570214775
% of individuals with current payment history missing: 0.532570214775
% of individuals with credit-limit-use missing: 0.0440759971678
Repaid loan? 1.0
Number of cases: (30706, 18)
% of individuals with previous payment history missing: 0.545919364294
% of individuals with current payment history missing: 0.545919364294
% of individuals with credit-limit-use missing: 0.00508044030483
```

```
In [22]: granted.corr()
```

```
Out[22]:
                                                  loan_id  is_first_loan  \
         loan_id                                 1.000000       0.002246
         is_first_loan                           0.002246       1.000000
         fully_repaid_previous_loans             0.001710            NaN
         currently_repaying_other_loans          0.005651            NaN
```

```
total_credit_card_limit                      -0.000655       0.003657
avg_percentage_credit_card_limit_used_last_year  0.001768      -0.004016
saving_amount                                 -0.004482       0.009611
checking_amount                               -0.000531       0.010356
is_employed                                    0.012130      -0.000380
yearly_salary                                  0.006602      -0.002121
age                                            0.011177       0.002591
dependent_number                              -0.000816      -0.005861
loan_repaid                                   -0.002704       0.012824
purpose_other                                 -0.003571      -0.001679
purpose_business                               0.006619       0.006942
purpose_emergency_funds                       -0.006748      -0.013316
purpose_investment                             0.003740       0.002527
purpose_home                                  -0.001342       0.003613

                                               fully_repaid_previous_loans  \
loan_id                                                           0.001710
is_first_loan                                                          NaN
fully_repaid_previous_loans                                       1.000000
currently_repaying_other_loans                                   -0.015923
total_credit_card_limit                                           0.031333
avg_percentage_credit_card_limit_used_last_year                 -0.001759
saving_amount                                                     0.014028
checking_amount                                                   0.020963
is_employed                                                       0.002697
yearly_salary                                                     0.008098
age                                                               0.009527
dependent_number                                                  0.001105
loan_repaid                                                       0.038665
purpose_other                                                    -0.014614
purpose_business                                                 -0.006204
purpose_emergency_funds                                          -0.002374
purpose_investment                                                0.021886
purpose_home                                                     -0.001077

                                               currently_repaying_other_loans  \
loan_id                                                              0.005651
is_first_loan                                                             NaN
fully_repaid_previous_loans                                         -0.015923
currently_repaying_other_loans                                       1.000000
total_credit_card_limit                                             -0.198214
avg_percentage_credit_card_limit_used_last_year                     0.094812
saving_amount                                                       -0.251634
checking_amount                                                     -0.248012
is_employed                                                         -0.154352
yearly_salary                                                       -0.215739
age                                                                 -0.008255
dependent_number                                                     0.075054
loan_repaid                                                         -0.496350
purpose_other                                                        0.023734
purpose_business                                                    -0.043297
purpose_emergency_funds                                              0.074131
purpose_investment                                                  -0.039280
purpose_home                                                        -0.004114
```

```
                                           total_credit_card_limit  \
loan_id                                                  -0.000655
is_first_loan                                             0.003657
fully_repaid_previous_loans                               0.031333
currently_repaying_other_loans                           -0.198214
total_credit_card_limit                                   1.000000
avg_percentage_credit_card_limit_used_last_year          -0.076596
saving_amount                                             0.194137
checking_amount                                           0.203409
is_employed                                               0.156715
yearly_salary                                             0.186868
age                                                       0.000168
dependent_number                                         -0.059254
loan_repaid                                               0.401911
purpose_other                                            -0.029167
purpose_business                                          0.043437
purpose_emergency_funds                                  -0.057069
purpose_investment                                        0.032787
purpose_home                                             -0.001100

                                           avg_percentage_credit_card_limit_used_last_year
loan_id                                                                            0.00176
is_first_loan                                                                     -0.00401
fully_repaid_previous_loans                                                       -0.00175
currently_repaying_other_loans                                                     0.09481
total_credit_card_limit                                                           -0.07659
avg_percentage_credit_card_limit_used_last_year                                   1.000000
saving_amount                                                                     -0.09804
checking_amount                                                                   -0.10126
is_employed                                                                       -0.08972
yearly_salary                                                                     -0.10218
age                                                                                0.0031
dependent_number                                                                   0.02680
loan_repaid                                                                       -0.20987
purpose_other                                                                      0.02263
purpose_business                                                                  -0.02253
purpose_emergency_funds                                                            0.03095
purpose_investment                                                                -0.00763
purpose_home                                                                      -0.01572

                                           saving_amount  \
loan_id                                        -0.004482
is_first_loan                                   0.009611
fully_repaid_previous_loans                     0.014028
currently_repaying_other_loans                 -0.251634
total_credit_card_limit                         0.194137
avg_percentage_credit_card_limit_used_last_year -0.098045
saving_amount                                   1.000000
checking_amount                                 0.238092
is_employed                                     0.148637
yearly_salary                                   0.210556
age                                            -0.004327
dependent_number                               -0.064931
```

```
loan_repaid                                          0.493699
purpose_other                                       -0.037777
purpose_business                                     0.041576
purpose_emergency_funds                             -0.073808
purpose_investment                                   0.042976
purpose_home                                         0.012296

                                               checking_amount  is_employed  \
loan_id                                              -0.000531     0.012130
is_first_loan                                         0.010356    -0.000380
fully_repaid_previous_loans                           0.020963     0.002697
currently_repaying_other_loans                       -0.248012    -0.154352
total_credit_card_limit                               0.203409     0.156715
avg_percentage_credit_card_limit_used_last_year      -0.101262    -0.089726
saving_amount                                         0.238092     0.148637
checking_amount                                       1.000000     0.151237
is_employed                                           0.151237     1.000000
yearly_salary                                         0.210244     0.565322
age                                                   0.005039     0.005004
dependent_number                                     -0.071816    -0.042867
loan_repaid                                           0.494341     0.305749
purpose_other                                        -0.036413    -0.040120
purpose_business                                      0.040610     0.025119
purpose_emergency_funds                              -0.070055    -0.040674
purpose_investment                                    0.039581     0.034891
purpose_home                                          0.012180     0.009598

                                               yearly_salary       age  \
loan_id                                             0.006602  0.011177
is_first_loan                                      -0.002121  0.002591
fully_repaid_previous_loans                         0.008098  0.009527
currently_repaying_other_loans                     -0.215739 -0.008255
total_credit_card_limit                             0.186868  0.000168
avg_percentage_credit_card_limit_used_last_year    -0.102187  0.003110
saving_amount                                       0.210556 -0.004327
checking_amount                                     0.210244  0.005039
is_employed                                         0.565322  0.005004
yearly_salary                                       1.000000  0.009329
age                                                 0.009329  1.000000
dependent_number                                   -0.063628 -0.001281
loan_repaid                                         0.426648  0.000947
purpose_other                                      -0.038530  0.005612
purpose_business                                    0.039910  0.009843
purpose_emergency_funds                            -0.058598 -0.014166
purpose_investment                                  0.037036 -0.000665
purpose_home                                        0.007215 -0.001370

                                               dependent_number  \
loan_id                                               -0.000816
is_first_loan                                         -0.005861
fully_repaid_previous_loans                            0.001105
currently_repaying_other_loans                         0.075054
total_credit_card_limit                               -0.059254
avg_percentage_credit_card_limit_used_last_year        0.026807
```

```
saving_amount                                              -0.064931
checking_amount                                            -0.071816
is_employed                                                -0.042867
yearly_salary                                              -0.063628
age                                                        -0.001281
dependent_number                                            1.000000
loan_repaid                                                -0.136384
purpose_other                                               0.018753
purpose_business                                           -0.003657
purpose_emergency_funds                                     0.011459
purpose_investment                                         -0.005931
purpose_home                                               -0.015922

                                                 loan_repaid  purpose_other  \
loan_id                                            -0.002704      -0.003571
is_first_loan                                       0.012824      -0.001679
fully_repaid_previous_loans                         0.038665      -0.014614
currently_repaying_other_loans                     -0.496350       0.023734
total_credit_card_limit                             0.401911      -0.029167
avg_percentage_credit_card_limit_used_last_year    -0.209870       0.022634
saving_amount                                       0.493699      -0.037777
checking_amount                                     0.494341      -0.036413
is_employed                                         0.305749      -0.040120
yearly_salary                                       0.426648      -0.038530
age                                                 0.000947       0.005612
dependent_number                                   -0.136384       0.018753
loan_repaid                                         1.000000      -0.079813
purpose_other                                      -0.079813       1.000000
purpose_business                                    0.088177      -0.222593
purpose_emergency_funds                            -0.142721      -0.181546
purpose_investment                                  0.079986      -0.220322
purpose_home                                        0.024759      -0.233799

                                                 purpose_business  \
loan_id                                                  0.006619
is_first_loan                                            0.006942
fully_repaid_previous_loans                             -0.006204
currently_repaying_other_loans                          -0.043297
total_credit_card_limit                                  0.043437
avg_percentage_credit_card_limit_used_last_year         -0.022539
saving_amount                                            0.041576
checking_amount                                          0.040610
is_employed                                              0.025119
yearly_salary                                            0.039910
age                                                      0.009843
dependent_number                                        -0.003657
loan_repaid                                              0.088177
purpose_other                                           -0.222593
purpose_business                                         1.000000
purpose_emergency_funds                                 -0.238237
purpose_investment                                      -0.289122
purpose_home                                            -0.306807

                                                 purpose_emergency_funds  \
```

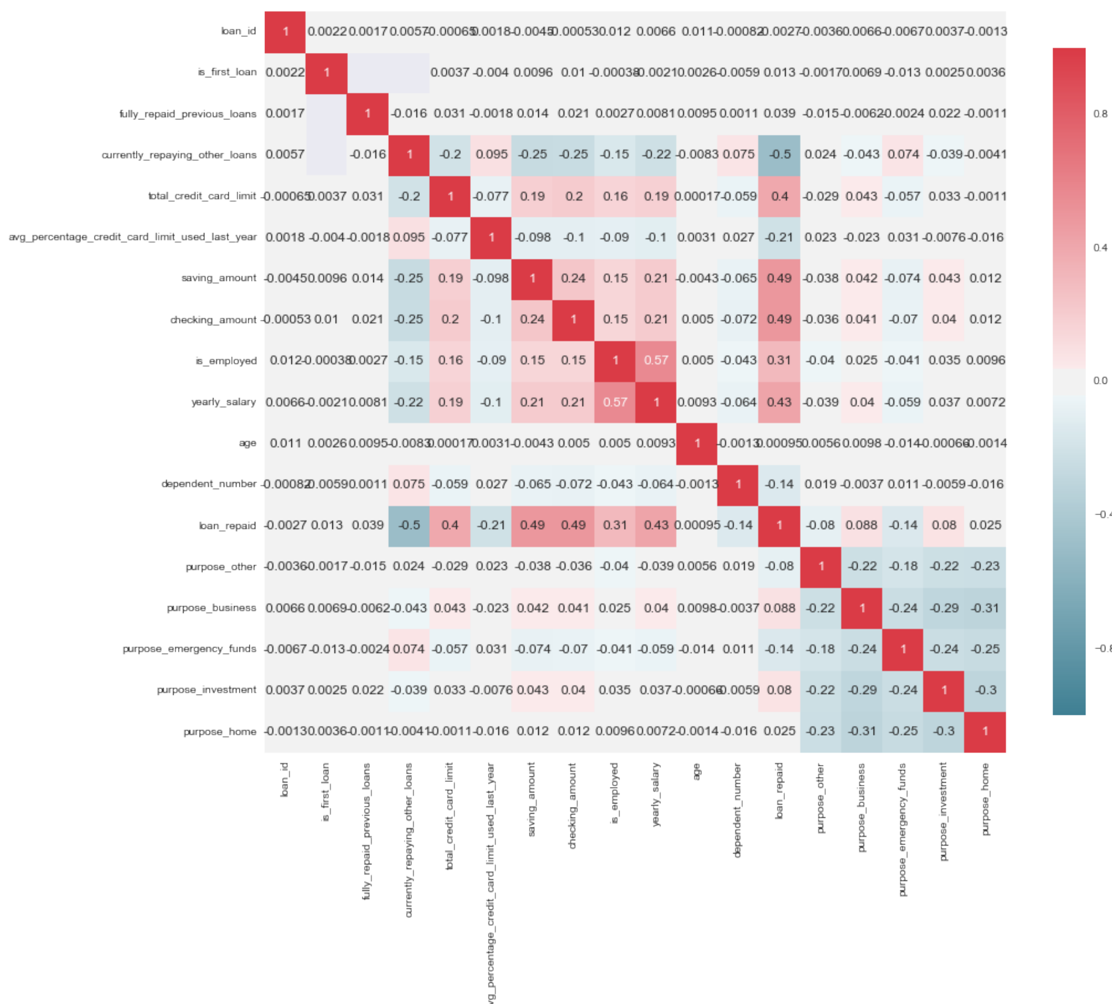
```
loan_id                                          -0.006748
is_first_loan                                    -0.013316
fully_repaid_previous_loans                      -0.002374
currently_repaying_other_loans                    0.074131
total_credit_card_limit                          -0.057069
avg_percentage_credit_card_limit_used_last_year   0.030959
saving_amount                                    -0.073808
checking_amount                                  -0.070055
is_employed                                      -0.040674
yearly_salary                                    -0.058598
age                                              -0.014166
dependent_number                                  0.011459
loan_repaid                                      -0.142721
purpose_other                                    -0.181546
purpose_business                                 -0.238237
purpose_emergency_funds                           1.000000
purpose_investment                               -0.235807
purpose_home                                     -0.250231

                                                 purpose_investment  \
loan_id                                                    0.003740
is_first_loan                                              0.002527
fully_repaid_previous_loans                                0.021886
currently_repaying_other_loans                            -0.039280
total_credit_card_limit                                    0.032787
avg_percentage_credit_card_limit_used_last_year           -0.007637
saving_amount                                              0.042976
checking_amount                                            0.039581
is_employed                                                0.034891
yearly_salary                                              0.037036
age                                                       -0.000665
dependent_number                                          -0.005931
loan_repaid                                                0.079986
purpose_other                                             -0.220322
purpose_business                                          -0.289122
purpose_emergency_funds                                   -0.235807
purpose_investment                                         1.000000
purpose_home                                              -0.303678

                                                 purpose_home
loan_id                                             -0.001342
is_first_loan                                        0.003613
fully_repaid_previous_loans                         -0.001077
currently_repaying_other_loans                      -0.004114
total_credit_card_limit                             -0.001100
avg_percentage_credit_card_limit_used_last_year     -0.015720
saving_amount                                        0.012296
checking_amount                                      0.012180
is_employed                                          0.009598
yearly_salary                                        0.007215
age                                                 -0.001370
dependent_number                                    -0.015922
loan_repaid                                          0.024759
purpose_other                                       -0.233799
```

```
purpose_business                                          -0.306807
purpose_emergency_funds                                   -0.250231
purpose_investment                                        -0.303678
purpose_home                                               1.000000
```

In [23]:
```python
_, ax = plt.subplots(figsize = (15,12))
cmap = sns.diverging_palette(220, 10, as_cmap=True)
_ = sns.heatmap(granted.corr(),
                cmap = cmap,
                square = True,
                cbar_kws = {'shrink': .9},
                ax = ax,
                annot = True,
                annot_kws = {'fontsize': 12})
```



The correlation plot illustrates several things relevant to missing values:

It appears that knowing loan payment history does not play a role in an individual's ability to repay loans. However, more than 75% of the individuals actually repaid their previous loans. Therefore it's a skewed dataset and mean imputation may not be accurate. Mode imputation (mode = 1.0) is more reasonable, but still dangerous to use. Considering the huge number of NAs, making them all 1.0 will skew the distribution heavily.

```
In [28]: print granted.fully_repaid_previous_loans.unique()
         print len(granted.fully_repaid_previous_loans)
         print sum(granted.fully_repaid_previous_loans == 1)
```

```
[ nan   1.   0.]
47654
19733
```

The other two NA cols, disclosure of loan payment current status and credit limit, are more (positively) correlated with loan repayment. Altering the NA values may have a high influence on data. Considering these factors, we decide to fill in the missing values for three cols through regression.

5.4.1 A. Ignore missing values

```
In [29]: granted_noNA = granted.dropna(axis=1)

         # or:
         # granted_noNA = granted.drop(['fully_repaid_previous_loans',
         #                             'currently_repaying_other_loans',
         #                             'avg_percentage_credit_card_limit_used_last_year'], axis = 1)

         print granted_noNA.shape
         print granted_noNA.isnull().sum()
```

```
(47654, 15)
loan_id                      0
is_first_loan                0
total_credit_card_limit      0
saving_amount                0
checking_amount              0
is_employed                  0
yearly_salary                0
age                          0
dependent_number             0
loan_repaid                  0
purpose_other                0
purpose_business             0
purpose_emergency_funds      0
purpose_investment           0
purpose_home                 0
dtype: int64
```

```
In [31]: granted_noNA.dtypes
```

```
Out[31]: loan_id                      int64
         is_first_loan                int64
         total_credit_card_limit      int64
         saving_amount                int64
         checking_amount              int64
         is_employed                  int64
         yearly_salary                int64
         age                          int64
         dependent_number             int64
         loan_repaid                float64
         purpose_other                int64
```

```
purpose_business             int64
purpose_emergency_funds     int64
purpose_investment           int64
purpose_home                 int64
dtype: object
```

5.4.2 B. Impute missing values

“Predict” missing values with k-nearest-neighbor regression or classification. Before doing this, it’s crucial to scale the data because an uneven data space will mess up the KNN algorithm.

The following columns are on a different order of magnitude than the rest:

‘total_credit_card_limit’, ‘saving_amount’, ‘checking_amount’, ‘yearly_salary’, ‘age’, ‘dependent_number’

These are all positive values with an actual siginificance in their positivity. Therefore a standard scaler ((x-mean)/std) is less appropriate than a min-max scaler ((x-min)/(max-min)).

In [73]:
```
granted_impNA = granted.copy()
# granted_impNA['fully_repaid_previous_loans'].fillna(granted_impNA['fully_repaid_previous_loa
```

In [74]:
```
r, c = KNeighborsRegressor(), KNeighborsClassifier(n_neighbors=5)
cols_to_impute = [('fully_repaid_previous_loans', c),
                  ('currently_repaying_other_loans', c),
                  ('avg_percentage_credit_card_limit_used_last_year', r)]
cols_to_scale = ['total_credit_card_limit',
                 'saving_amount',
                 'checking_amount',
                 'yearly_salary',
                 'age',
                 'dependent_number']
```

In [75]:
```
granted_impNA[cols_to_scale] = MinMaxScaler().fit_transform(granted_impNA[cols_to_scale])
```

In [76]:
```
granted_impNA.head()
```

Out[76]:
```
   loan_id  is_first_loan  fully_repaid_previous_loans  \
2   135565              1                          NaN
5   423171              1                          NaN
7   200139              1                          NaN
8   991294              0                          1.0
9   875332              0                          1.0

   currently_repaying_other_loans  total_credit_card_limit  \
2                             NaN                 0.511111
5                             NaN                 0.451852
7                             NaN                 0.296296
8                             0.0                 0.518519
9                             0.0                 0.318519

   avg_percentage_credit_card_limit_used_last_year  saving_amount  \
2                                             0.82       0.195940
5                                             0.53       0.579175
7                                             0.57       0.056574
8                                             0.52       0.241989
9                                             0.83       0.067851

   checking_amount  is_employed  yearly_salary       age  dependent_number  \
```

```
2         0.259932            1       0.252058  0.327869               1.000
5         0.402431            1       0.303498  0.098361               0.125
7         0.209419            1       0.326132  0.295082               1.000
8         0.221572            1       0.605967  0.245902               0.375
9         0.067755            1       0.055556  0.229508               0.875

   loan_repaid  purpose_other  purpose_business  purpose_emergency_funds  \
2          1.0              1                 0                        0
5          1.0              1                 0                        0
7          0.0              0                 1                        0
8          1.0              0                 0                        1
9          1.0              0                 1                        0

   purpose_investment  purpose_home
2                   0             0
5                   0             0
7                   0             0
8                   0             0
9                   0             0
```

```
In [77]: for col, model in cols_to_impute:
             colImputed = fill_na_KNN(granted_impNA, col, model)
             granted_impNA[col] = colImputed
             print granted_impNA.isnull().sum()
```

```
loan_id                                             0
is_first_loan                                       0
fully_repaid_previous_loans                         0
currently_repaying_other_loans                  25789
total_credit_card_limit                             0
avg_percentage_credit_card_limit_used_last_year   903
saving_amount                                       0
checking_amount                                     0
is_employed                                         0
yearly_salary                                       0
age                                                 0
dependent_number                                    0
loan_repaid                                         0
purpose_other                                       0
purpose_business                                    0
purpose_emergency_funds                             0
purpose_investment                                  0
purpose_home                                        0
dtype: int64
loan_id                                           0
is_first_loan                                     0
fully_repaid_previous_loans                       0
currently_repaying_other_loans                    0
total_credit_card_limit                           0
avg_percentage_credit_card_limit_used_last_year 903
saving_amount                                     0
checking_amount                                   0
is_employed                                       0
yearly_salary                                     0
age                                               0
```

```
dependent_number                                    0
loan_repaid                                         0
purpose_other                                       0
purpose_business                                    0
purpose_emergency_funds                             0
purpose_investment                                  0
purpose_home                                        0
dtype: int64
loan_id                                           0
is_first_loan                                     0
fully_repaid_previous_loans                       0
currently_repaying_other_loans                    0
total_credit_card_limit                           0
avg_percentage_credit_card_limit_used_last_year    0
saving_amount                                     0
checking_amount                                   0
is_employed                                       0
yearly_salary                                     0
age                                               0
dependent_number                                  0
loan_repaid                                       0
purpose_other                                     0
purpose_business                                  0
purpose_emergency_funds                           0
purpose_investment                                0
purpose_home                                      0
dtype: int64
```

```
In [78]: print granted_impNA.shape
         granted_impNA.head()
```

```
(47654, 18)
```

```
Out[78]:    loan_id  is_first_loan  fully_repaid_previous_loans  \
         2   135565              1                          1.0
         5   423171              1                          1.0
         7   200139              1                          1.0
         8   991294              0                          1.0
         9   875332              0                          1.0

            currently_repaying_other_loans  total_credit_card_limit  \
         2                             0.0                 0.511111
         5                             0.0                 0.451852
         7                             0.0                 0.296296
         8                             0.0                 0.518519
         9                             0.0                 0.318519

            avg_percentage_credit_card_limit_used_last_year  saving_amount  \
         2                                             0.82       0.195940
         5                                             0.53       0.579175
         7                                             0.57       0.056574
         8                                             0.52       0.241989
         9                                             0.83       0.067851

            checking_amount  is_employed  yearly_salary       age  dependent_number  \
```

```
2        0.259932            1      0.252058  0.327869              1.000
5        0.402431            1      0.303498  0.098361              0.125
7        0.209419            1      0.326132  0.295082              1.000
8        0.221572            1      0.605967  0.245902              0.375
9        0.067755            1      0.055556  0.229508              0.875

   loan_repaid  purpose_other  purpose_business  purpose_emergency_funds  \
2          1.0              1                 0                        0
5          1.0              1                 0                        0
7          0.0              0                 1                        0
8          1.0              0                 0                        1
9          1.0              0                 1                        0

   purpose_investment  purpose_home
2                   0             0
5                   0             0
7                   0             0
8                   0             0
9                   0             0
```

5.5 5. Drop 'loan_id' column

In [79]:
```
granted_noNA.drop('loan_id', axis=1, inplace = True)
granted_impNA.drop('loan_id', axis=1, inplace = True)
```

In [80]:
```
print granted_noNA.shape
print granted_impNA.shape
```

```
(47654, 14)
(47654, 17)
```

5.6 6. Scaling continued...

Lastly, bring back the non-scaled version of both 'noNA' and 'impNA' datasets.

In [81]:
```
granted_noNA_sca = granted_noNA.copy()
granted_noNA_sca[cols_to_scale] = MinMaxScaler().fit_transform(granted_noNA_sca[cols_to_scale])
```

In [82]:
```
granted_impNA_sca = granted_impNA.copy()
granted_impNA[cols_to_scale] = granted_noNA[cols_to_scale]
```

In [83]:
```
print granted_noNA.shape
print granted_impNA.shape

print granted_noNA_sca.shape
print granted_impNA_sca.shape
```

```
(47654, 14)
(47654, 17)
(47654, 14)
(47654, 17)
```

Chapter 6

Build models to predict grant repayment

```
In [87]: dfs = [granted_noNA, granted_impNA, granted_noNA_sca, granted_impNA_sca]
```

6.1 Dataset 1: Ignored NAs, not scaled

6.1.1 1. Make training and testing data

```
In [106]: Y = dfs[0].loan_repaid
          X = dfs[0].drop('loan_repaid', axis = 1)
          X_train, X_test, Y_train, Y_test = model_selection.train_test_split(X, Y, test_size=0.3, rand

          print X_train.shape
          print X_test.shape
          print Y_train.shape
          print Y_test.shape
```

```
(33357, 13)
(14297, 13)
(33357,)
(14297,)
```

6.1.2 2. Set up model and cross-validation

Note a bias-variance tradeoff in choosing k - - Small k: Low variance in predicted results, but high bias in models. (e.g. split into half; validate twice; one model may not be too different from the other, but they may not generalize well because they haven't seen too much data) - Large k: High variance in predicted results, but low bias in models. (e.g. leave-one-out; validate n times; the final model capture the characteristics of a lot of models, but may be overfitted - n times! - to existing data)

```
In [131]: key_value_pairs = [('naive Bayes', GaussianNB()),
                             ('logistic regression', linear_model.LogisticRegression()),
                             ('SVM', svm.SVC(degree=0.5)),
                             ('random forest', ensemble.RandomForestClassifier(n_estimators=100))
                            ]
          models = collections.OrderedDict(key_value_pairs)

          cv10 = model_selection.KFold(n_splits=10)
```

6.1.3 3. Perform cross-validation

In [107]:
```
model = models.get('random forest')
Y_pred, Y_true = performCV(X_train, Y_train, cv=cv10, model = model)
Y_pred_unpack, Y_true_unpack = unpackCVResults(Y_pred, Y_true)
cvScore = getCVScores(Y_pred_unpack, Y_true_unpack)

cvScore
```

Out[107]:

	accuracy	precision	recall	sensitivity	specificity
0	0.905276	0.942391	0.909217	0.909217	0.898046
1	0.909173	0.937739	0.918817	0.918817	0.892116
2	0.907974	0.941948	0.916629	0.916629	0.891323
3	0.910671	0.932921	0.925873	0.925873	0.884236
4	0.921163	0.946190	0.929808	0.929808	0.905755
5	0.911571	0.949707	0.910154	0.910154	0.914095
6	0.912470	0.947814	0.917615	0.917615	0.902546
7	0.914843	0.943765	0.919485	0.919485	0.906958
8	0.909445	0.933715	0.923149	0.923149	0.885502
9	0.914243	0.948850	0.919509	0.919509	0.904049

Simply throwing away the NA cols, predicts us the probability of users repaying / defaulting on their loans pretty darn well. (Note that RFs are rather tolerant to no scaling.)

6.1.4 4. Apply on unseen (test) data

In [98]:
```
Y_test_pred = model.fit(X_train, Y_train).predict_proba(X_test)
Y_test_pred_unpack = [pred_val.argmax() for pred_val in Y_test_pred]

cm_test = metrics.confusion_matrix(y_true = Y_test, y_pred = Y_test_pred_unpack, labels=None)
accuracy, sensitivity, specificity, precision = evalModel(cm_test)
print 'Model: ', model
print 'Testing accuracy: ', accuracy
print 'Testing precision: ', precision
print 'Testing recall: ', sensitivity
```

```
Model:  RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_split=1e-07, min_samples_leaf=1,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            n_estimators=100, n_jobs=1, oob_score=False, random_state=None,
            verbose=0, warm_start=False)
Testing accuracy:  0.915506749668
Testing precision:  0.94496942746
Testing recall:  0.922609356344
```

6.1.5 5. Insights from model

In [99]:
```
Y_test_pred_featImp = model.fit(X_train, Y_train)

importances = model.feature_importances_
std = np.std([indivTree.feature_importances_ for indivTree in model.estimators_],
             axis=0)
indices = np.argsort(importances)[::-1]
```

```
print("Feature ranking:")

for f in range(X_train.shape[1]):
    print("%d. %s (%f)" % (f + 1, X_train.columns[indices[f]], importances[indices[f]]))
```

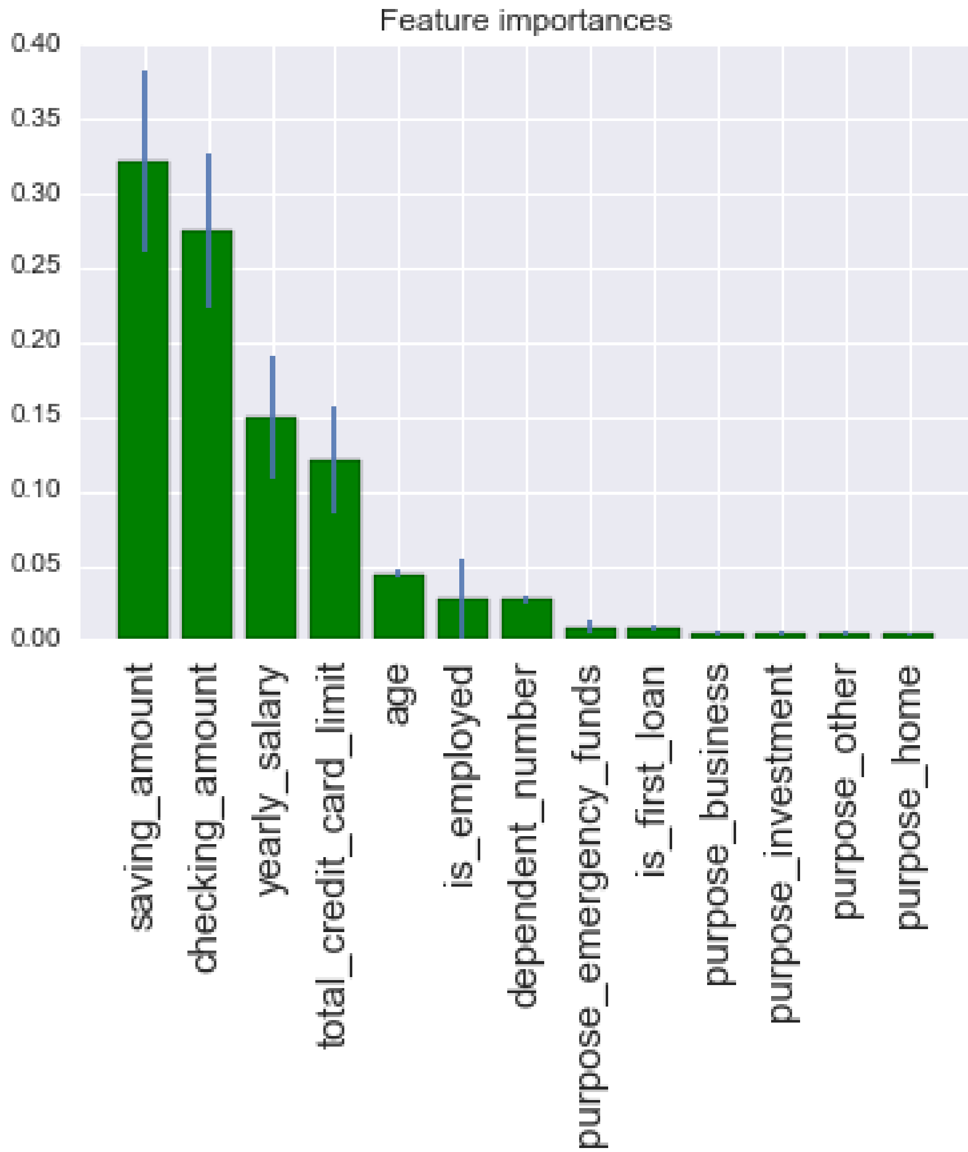
```
Feature ranking:
1. saving_amount (0.321948)
2. checking_amount (0.275183)
3. yearly_salary (0.149150)
4. total_credit_card_limit (0.120505)
5. age (0.044307)
6. is_employed (0.027806)
7. dependent_number (0.027349)
8. purpose_emergency_funds (0.008484)
9. is_first_loan (0.007772)
10. purpose_business (0.004682)
11. purpose_investment (0.004497)
12. purpose_other (0.004294)
13. purpose_home (0.004023)
```

Several things checked out against the simple correlation run earlier: - Cash positions such as back account, salary matter highly - Loan purpose for emergency matters more than the other purposes

Age, interestingly, matters moderately highly.

Now plot the feature importances of the forest.

```
In [100]: fig, ax = plt.subplots()
          # plt.figure() # If this line is included, an empty plot appears.
          plt.title("Feature importances")
          plt.bar(range(X_train.shape[1]), importances[indices],
                 color="g", yerr=std[indices], align="center")
          plt.xticks(range(X_train.shape[1]), indices, rotation=90)
          plt.xlim([-1, X_train.shape[1]])
          ax.set_xticklabels(X_train.columns[indices], rotation=90, size=15)
          plt.show() # If this line is not included, a bunch of msgs appear
```



While one can try a different model or do grid-search to tune the RF parameters, priority of this action is low since default params performed pretty well in this case. It would be more interesting to compare with a model built from the dataset with features containing guessed NA values.

6.2 Dataset 2: Imputed NAs, not scaled

6.2.1 1. Make training and testing data

```
In [108]: Y = dfs[1].loan_repaid
          X = dfs[1].drop('loan_repaid', axis = 1)
          X_train, X_test, Y_train, Y_test = model_selection.train_test_split(X, Y, test_size=0.3, rando

          print X_train.shape
          print X_test.shape
```

```
print Y_train.shape
print Y_test.shape
```

```
(33357, 16)
(14297, 16)
(33357,)
(14297,)
```

6.2.2 2. Set up model and cross-validation

```
In [95]: key_value_pairs = [('naive Bayes', GaussianNB()),
                            ('logistic regression', linear_model.LogisticRegression()),
                            ('SVM', svm.SVC(degree=0.5)),
                            ('decision tree', tree.DecisionTreeClassifier()),
                            ('random forest', ensemble.RandomForestClassifier(n_estimators=100))
                           ]
         models = collections.OrderedDict(key_value_pairs)

         cv10 = model_selection.KFold(n_splits=10)
```

6.2.3 3. Perform cross-validation

```
In [103]: model = models.get('random forest')
          Y_pred, Y_true = performCV(X_train, Y_train, cv=cv10, model = model)
          Y_pred_unpack, Y_true_unpack = unpackCVResults(Y_pred, Y_true)
          cvScore = getCVScores(Y_pred_unpack, Y_true_unpack)

          cvScore
```

Out[103]:

	accuracy	precision	recall	sensitivity	specificity
0	0.915168	0.944972	0.922649	0.922649	0.901444
1	0.914269	0.943296	0.921164	0.921164	0.902075
2	0.913369	0.944496	0.922551	0.922551	0.895706
3	0.921163	0.940199	0.935316	0.935316	0.896552
4	0.925959	0.947867	0.935891	0.935891	0.908257
5	0.917566	0.952821	0.916706	0.916706	0.919099
6	0.920264	0.950537	0.927173	0.927173	0.906936
7	0.922339	0.947907	0.927585	0.927585	0.913430
8	0.914843	0.934690	0.931165	0.931165	0.886326
9	0.918141	0.948324	0.926330	0.926330	0.902289

Is this better? Can't quite tell. Let's go onto testing.

6.2.4 4. Apply on unseen (test) data

```
In [104]: Y_test_pred = model.fit(X_train, Y_train).predict_proba(X_test)
          Y_test_pred_unpack = [pred_val.argmax() for pred_val in Y_test_pred]

          cm_test = metrics.confusion_matrix(y_true = Y_test, y_pred = Y_test_pred_unpack, labels=None)
          accuracy, sensitivity, specificity, precision = evalModel(cm_test)
          print 'Model: ', model
          print 'Testing accuracy: ', accuracy
          print 'Testing precision: ', precision
          print 'Testing recall: ', sensitivity
```

```
Model:  RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_split=1e-07, min_samples_leaf=1,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            n_estimators=100, n_jobs=1, oob_score=False, random_state=None,
            verbose=0, warm_start=False)
Testing accuracy:  0.922011610827
Testing precision:  0.947601149679
Testing recall:  0.930424400304
```

Slightly better testing performance, from **91.5%** to **92.2%** accuracy.

6.2.5 5. Insights from model

```
In [136]: Y_test_pred_featImp = model.fit(X_train, Y_train)

          importances = model.feature_importances_
          std = np.std([indivTree.feature_importances_ for indivTree in model.estimators_],
                       axis=0)
          indices = np.argsort(importances)[::-1]

          print("Feature ranking:")

          for f in range(X_train.shape[1]):
              print("%d. %s (%f)" % (f + 1, X_train.columns[indices[f]], importances[indices[f]]))
```

```
Feature ranking:
1. saving_amount (0.313070)
2. checking_amount (0.260543)
3. yearly_salary (0.127130)
4. total_credit_card_limit (0.103917)
5. avg_percentage_credit_card_limit_used_last_year (0.046815)
6. age (0.033202)
7. is_employed (0.030637)
8. currently_repaying_other_loans (0.023752)
9. dependent_number (0.022118)
10. is_first_loan (0.011961)
11. purpose_emergency_funds (0.006753)
12. purpose_business (0.004955)
13. purpose_investment (0.004498)
14. purpose_home (0.004279)
15. purpose_other (0.004154)
16. fully_repaid_previous_loans (0.002215)
```

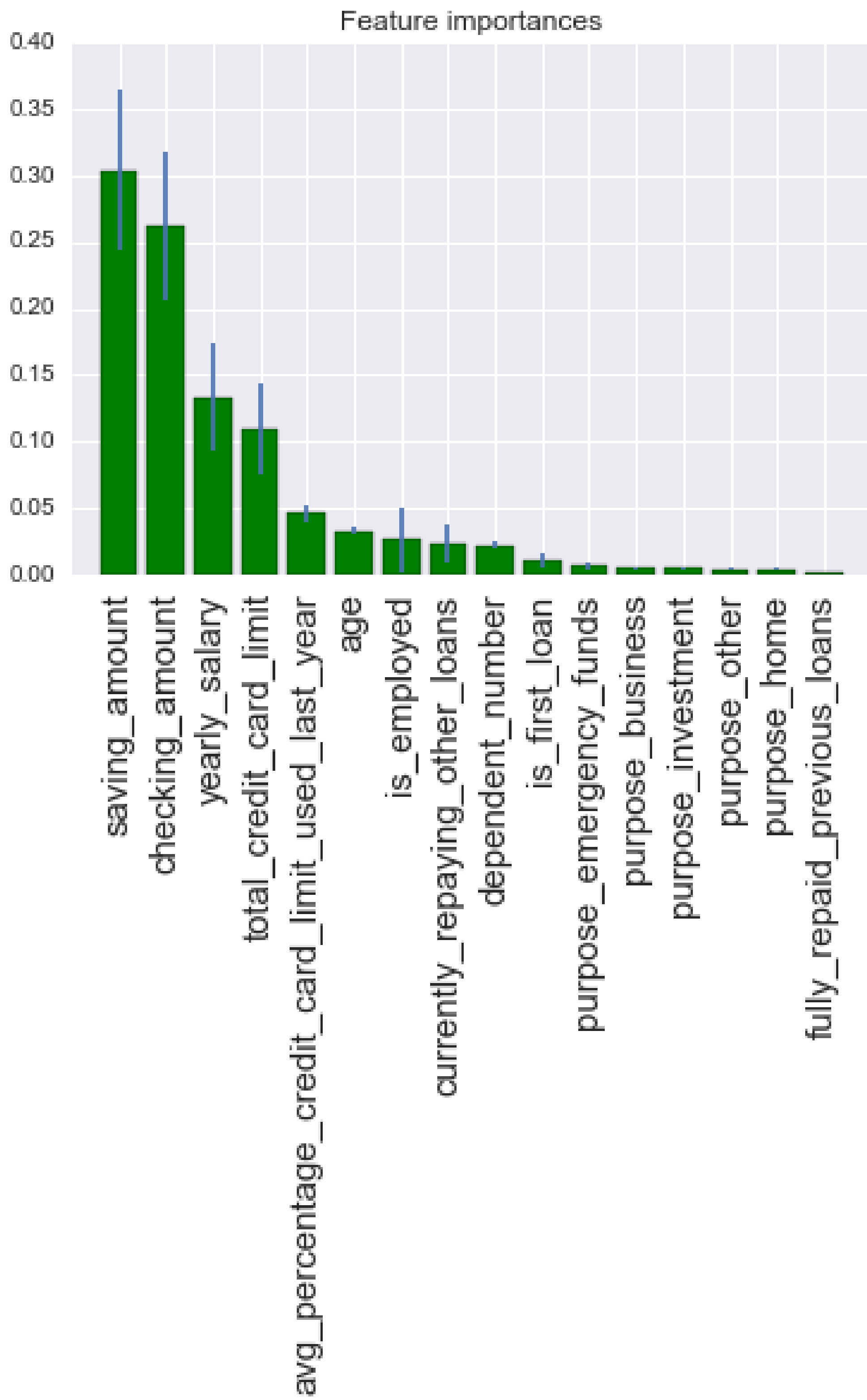
The presence of several moderately high-ranking features improved the model accuracy, especially 'avg_percentage_credit_card_limit_used_last_year'.

Whether or not previous loans have been fully repaid matters the least. It explains why leaving it out previously didn't impact the accuracy all that much.

Now plot the feature importances of the forest.

```
In [110]: fig, ax = plt.subplots()
          # plt.figure() # If this line is included, an empty plot appears.
          plt.title("Feature importances")
          plt.bar(range(X_train.shape[1]), importances[indices],
                 color="g", yerr=std[indices], align="center")
```

```
plt.xticks(range(X_train.shape[1]), indices, rotation=90)
plt.xlim([-1, X_train.shape[1]])
ax.set_xticklabels(X_train.columns[indices], rotation=90, size=15)
plt.show() # If this line is not included, a bunch of msgs appear
```



Chapter 7

Predict repayment in those denied the loan

Now, to see how many cases the bank missed out on.

First we need to take the "loans denied" data through the same cleaning. Then use the granted data with imputed missing values for prediction.

Here it would be interesting to note if a better model can be built by imputing missing values from the entire loanData, not just from the granted dataset. Let's take the imputation of the granted dataset as what we've done for now.

Just to remind ourselves, the granted data has 16 features:

```
In [111]: granted_impNA.shape
```

```
Out[111]: (47654, 17)
```

7.1 Clean data

7.1.1 1. Drop unhelpful columns

```
In [114]: denied = loanData[loanData.loan_granted == 0]
          denied.drop(['loan_id', 'loan_granted', 'date', 'loan_granted', 'loan_repaid'], axis=1, inpla
          print denied.shape
```

```
(53446, 12)

/Users/yingjiang/miniconda2/lib/python2.7/site-packages/ipykernel/__main__.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexin
  from ipykernel import kernelapp as app
```

7.1.2 2. Convert categorical variable into numeric

```
In [115]: for purpose in denied.loan_purpose.unique():
              denied['purpose_'+purpose] = denied.loan_purpose.str.contains(purpose).astype(int)
          denied.drop('loan_purpose',axis=1, inplace=True)
```

```
/Users/yingjiang/miniconda2/lib/python2.7/site-packages/ipykernel/__main__.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexin
  from ipykernel import kernelapp as app
/Users/yingjiang/miniconda2/lib/python2.7/site-packages/ipykernel/__main__.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexin
  app.launch_new_instance()
```

In [116]:
```python
denied.head()
```

Out[116]:

	is_first_loan	fully_repaid_previous_loans	currently_repaying_other_loans
0	1	NaN	NaN
1	0	1.0	0.0
3	0	1.0	0.0
4	0	0.0	0.0
6	1	NaN	NaN

	total_credit_card_limit	avg_percentage_credit_card_limit_used_last_year
0	8000	0.49
1	4500	1.03
3	1200	0.82
4	6900	0.80
6	600	0.89

	saving_amount	checking_amount	is_employed	yearly_salary	age
0	3285	1073	0	0	47
1	636	5299	1	13500	33
3	358	3388	0	0	24
4	2138	4282	1	18100	36
6	305	1456	0	0	50

	dependent_number	purpose_business	purpose_investment
0	3	1	0
1	1	0	1
3	1	0	1
4	1	0	0
6	2	0	0

	purpose_emergency_funds	purpose_other	purpose_home
0	0	0	0
1	0	0	0
3	0	0	0
4	1	0	0
6	1	0	0

7.1.3 3. Deal with missing values

In [117]:
```python
denied_impNA = denied.copy()
```

In [118]:
```python
r, c = KNeighborsRegressor(), KNeighborsClassifier(n_neighbors=5)
cols_to_impute = [('fully_repaid_previous_loans', c),
                  ('currently_repaying_other_loans', c),
                  ('avg_percentage_credit_card_limit_used_last_year', r)]
cols_to_scale = ['total_credit_card_limit',
                 'saving_amount',
```

```
                         'checking_amount',
                         'yearly_salary',
                         'age',
                         'dependent_number']
```

```
In [119]: denied_impNA[cols_to_scale] = MinMaxScaler().fit_transform(denied_impNA[cols_to_scale])
```

```
In [121]: denied_impNA.head()
```

```
Out[121]:    is_first_loan  fully_repaid_previous_loans  currently_repaying_other_loans  \
          0              1                          NaN                             NaN
          1              0                          1.0                             0.0
          3              0                          1.0                             0.0
          4              0                          0.0                             0.0
          6              1                          NaN                             NaN

             total_credit_card_limit  avg_percentage_credit_card_limit_used_last_year  \
          0                 0.601504                                             0.49
          1                 0.338346                                             1.03
          3                 0.090226                                             0.82
          4                 0.518797                                             0.80
          6                 0.045113                                             0.89

             saving_amount  checking_amount  is_employed  yearly_salary       age  \
          0       0.340133         0.077095            0       0.000000  0.475410
          1       0.065852         0.381014            1       0.148842  0.245902
          3       0.037068         0.243581            0       0.000000  0.098361
          4       0.221371         0.307875            1       0.199559  0.295082
          6       0.031580         0.104639            0       0.000000  0.524590

             dependent_number  purpose_business  purpose_investment  \
          0             0.375                 1                   0
          1             0.125                 0                   1
          3             0.125                 0                   1
          4             0.125                 0                   0
          6             0.250                 0                   0

             purpose_emergency_funds  purpose_other  purpose_home
          0                        0              0             0
          1                        0              0             0
          3                        0              0             0
          4                        1              0             0
          6                        1              0             0
```

```
In [122]: for col, model in cols_to_impute:
              colImputed = fill_na_KNN(denied_impNA, col, model)
              denied_impNA[col] = colImputed
              print denied_impNA.isnull().sum()
```

```
is_first_loan                                          0
fully_repaid_previous_loans                            0
currently_repaying_other_loans                     29158
total_credit_card_limit                                0
avg_percentage_credit_card_limit_used_last_year     6069
saving_amount                                          0
```

```
checking_amount                                   0
is_employed                                       0
yearly_salary                                     0
age                                               0
dependent_number                                  0
purpose_business                                  0
purpose_investment                                0
purpose_emergency_funds                           0
purpose_other                                     0
purpose_home                                      0
dtype: int64
is_first_loan                                   0
fully_repaid_previous_loans                     0
currently_repaying_other_loans                  0
total_credit_card_limit                         0
avg_percentage_credit_card_limit_used_last_year    6069
saving_amount                                   0
checking_amount                                 0
is_employed                                     0
yearly_salary                                   0
age                                             0
dependent_number                                0
purpose_business                                0
purpose_investment                              0
purpose_emergency_funds                         0
purpose_other                                   0
purpose_home                                    0
dtype: int64
is_first_loan                                   0
fully_repaid_previous_loans                     0
currently_repaying_other_loans                  0
total_credit_card_limit                         0
avg_percentage_credit_card_limit_used_last_year    0
saving_amount                                   0
checking_amount                                 0
is_employed                                     0
yearly_salary                                   0
age                                             0
dependent_number                                0
purpose_business                                0
purpose_investment                              0
purpose_emergency_funds                         0
purpose_other                                   0
purpose_home                                    0
dtype: int64
```

```
In [123]: denied_impNA_sca = denied_impNA.copy()
          denied_impNA[cols_to_scale] = denied[cols_to_scale]
```

```
In [125]: print denied_impNA.shape
          denied_impNA.head()
```

```
(53446, 16)
```

```
Out[125]:    is_first_loan  fully_repaid_previous_loans  currently_repaying_other_loans  \
          0              1                          1.0                             0.0
```

```
1              0                      1.0                        0.0
3              0                      1.0                        0.0
4              0                      0.0                        0.0
6              1                      1.0                        0.0

   total_credit_card_limit  avg_percentage_credit_card_limit_used_last_year  \
0                     8000                                             0.49
1                     4500                                             1.03
3                     1200                                             0.82
4                     6900                                             0.80
6                      600                                             0.89

   saving_amount  checking_amount  is_employed  yearly_salary  age  \
0           3285             1073            0              0   47
1            636             5299            1          13500   33
3            358             3388            0              0   24
4           2138             4282            1          18100   36
6            305             1456            0              0   50

   dependent_number  purpose_business  purpose_investment  \
0                 3                 1                   0
1                 1                 0                   1
3                 1                 0                   1
4                 1                 0                   0
6                 2                 0                   0

   purpose_emergency_funds  purpose_other  purpose_home
0                        0              0             0
1                        0              0             0
3                        0              0             0
4                        1              0             0
6                        1              0             0
```

7.2 Use the RF model to predict how many cases would've repaid loans

7.2.1 1. Make training and testing data

In [126]:
```
Y_train = granted_impNA.loan_repaid
X_train = granted_impNA.drop('loan_repaid', axis = 1)

X_test = denied_impNA

print X_train.shape
print X_test.shape
print Y_train.shape
```

```
(47654, 16)
(53446, 16)
(47654,)
```

In [138]:
```
model = models.get('random forest')
Y_test_pred = model.fit(X_train, Y_train).predict_proba(X_test)
Y_test_pred_unpack = [pred_val.argmax() for pred_val in Y_test_pred]
```

```
# cm_test = metrics.confusion_matrix(y_true = Y_test, y_pred = Y_test_pred_unpack, labels=Non
# accuracy, sensitivity, specificity, precision = evalModel(cm_test)
print 'Model: ', model
print 'Number of cases denied loan:', X_test.shape[0]
print 'Number of cases predicted to repay loan had they been granted one: ', sum(Y_test_pred_u
print 'Percentage of potential revenue lost:', sum(Y_test_pred_unpack)/float(X_test.shape[0])
```

```
Model:  RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_split=1e-07, min_samples_leaf=1,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            n_estimators=100, n_jobs=1, oob_score=False, random_state=None,
            verbose=0, warm_start=False)
Number of cases denied loan: 53446
Number of cases predicted to repay loan had they been granted one:  18443
Percentage of potential revenue lost: 0.345077274258
```

The bank missed 35% of the business it could've done by granting a loan, which in turn could've yielded a return.

Chapter 8

Summary and conclusion

By analyzing the loan applications where loan has been granted, we built a model that predicts an individual's ability to repay a loan at 92% accuracy. We find that the following attributes of a person helps with prediction: 1. His/Her cash position (bank accounts, salary) 2. His/Her credit position (total credit card limit, previous limit use) 3. His/her age, employment status, other loan commitment and number of dependents 4. He/She is less likely to repay the loan if the purpose of borrowing had been for emergency needs

Applying the model on the cases that have been denied a loan, we find that up to 35% of these cases could have repaid the loan. Therefore our prediction would help the bank justify not to be too conservative on granting loans, which potentially causes non trivial losses.

```
In [ ]:
```