Credit_Card_Clients_Interpretability

April 27, 2018

In [1]:
```
# h2o Python API with specific classes
import h2o
from h2o.estimators.glm import H2OGeneralizedLinearEstimator # for LIME
from h2o.estimators.gbm import H2OGradientBoostingEstimator  # for GBM

import operator # for sorting dictionaries

import numpy as np   # array, vector, matrix calculations
import pandas as pd  # DataFrame handling

# display plots in notebook
%matplotlib inline
```

In [2]:
```
h2o.init(max_mem_size='2G')       # start h2o
h2o.remove_all()                  # remove any existing data structures from h2o memory
```

```
Checking whether there is an H2O instance running at http://localhost:54321... not found.
Attempting to start a local H2O server...
  Java Version: java version "1.8.0_161"; Java(TM) SE Runtime Environment (build 1.8.0_161-b12);
  Starting server from /home/acmankit/anaconda3/envs/py35/lib/python3.5/site-packages/h2o/backen
  Ice root: /tmp/tmpgd7q09xc
  JVM stdout: /tmp/tmpgd7q09xc/h2o_acmankit_started_from_python.out
  JVM stderr: /tmp/tmpgd7q09xc/h2o_acmankit_started_from_python.err
  Server is running at http://127.0.0.1:54321
Connecting to H2O server at http://127.0.0.1:54321... successful.


--------------------------  ----------------------------------------
H2O cluster uptime:         06 secs
H2O cluster timezone:       Europe/Madrid
H2O data parsing timezone:  UTC
H2O cluster version:        3.18.0.8
H2O cluster version age:    8 days
H2O cluster name:           H2O_from_python_acmankit_qy0xym
H2O cluster total nodes:    1
H2O cluster free memory:    1.778 Gb
H2O cluster total cores:    4
H2O cluster allowed cores:  4
```

```
H2O cluster status:         accepting new members, healthy
H2O connection url:         http://127.0.0.1:54321
H2O connection proxy:
H2O internal security:      False
H2O API Extensions:         XGBoost, Algos, AutoML, Core V3, Core V4
Python version:             3.5.4 final
--------------------------  ----------------------------------------
```

In [5]:
```
# import XLS file
path = 'default_of_credit_card_clients.xls'
data = pd.read_excel(path,skiprows=1)

# remove spaces from target column name
data = data.rename(columns={'default payment next month': 'DEFAULT_NEXT_MONTH'})
```

In [6]:
```
# assign target and inputs for GBM
y = 'DEFAULT_NEXT_MONTH'
X = [name for name in data.columns if name not in [y, 'ID']]
print('y =', y)
print('X =', X)
```

```
y = DEFAULT_NEXT_MONTH
X = ['LIMIT_BAL', 'SEX', 'EDUCATION', 'MARRIAGE', 'AGE', 'PAY_0', 'PAY_2', 'PAY_3', 'PAY_4', 'PA
```

In [7]:
```
def recode_cc_data(frame):

    """ Recodes numeric categorical variables into categorical character variables
    with more transparent values.

    Args:
        frame: Pandas DataFrame version of UCI credit card default data.

    Returns:
        H2OFrame with recoded values.

    """

    # define recoded values
    sex_dict = {1:'male', 2:'female'}
    education_dict = {0:'other', 1:'graduate school', 2:'university', 3:'high school',
                      4:'other', 5:'other', 6:'other'}
    marriage_dict = {0:'other', 1:'married', 2:'single', 3:'divorced'}
    pay_dict = {-2:'no consumption', -1:'pay duly', 0:'use of revolving credit', 1:'1 mo
                2:'2 month delay', 3:'3 month delay', 4:'4 month delay', 5:'5 month dela
                7:'7 month delay', 8:'8 month delay', 9:'9+ month delay'}

    # recode values using Pandas apply() and anonymous function
```

```
        frame['SEX'] = frame['SEX'].apply(lambda i: sex_dict[i])
        frame['EDUCATION'] = frame['EDUCATION'].apply(lambda i: education_dict[i])
        frame['MARRIAGE'] = frame['MARRIAGE'].apply(lambda i: marriage_dict[i])
        for name in frame.columns:
            if name in ['PAY_0', 'PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6']:
                frame[name] = frame[name].apply(lambda i: pay_dict[i])

        return h2o.H2OFrame(frame)

    data = recode_cc_data(data)
```

```
Parse progress: || 100%
```

In [8]:
```
data[y] = data[y].asfactor()
```

In [9]:
```
# split into training and validation
train, test = data.split_frame([0.7], seed=12345)

# summarize split
print('Train data rows = %d, columns = %d' % (train.shape[0], train.shape[1]))
print('Test data rows = %d, columns = %d' % (test.shape[0], test.shape[1]))
```

```
Train data rows = 21060, columns = 25
Test data rows = 8940, columns = 25
```

In [10]:
```
# initialize GBM model
model = H2OGradientBoostingEstimator(ntrees=150,            # maximum 150 trees in GBM
                                     max_depth=4,           # trees can have maximum de
                                     sample_rate=0.9,       # use 90% of rows in each i
                                     col_sample_rate=0.9,   # use 90% of variables in e
                                     stopping_rounds=5,     # stop if validation error
                                     score_tree_interval=1, # for reproducibility, set
                                     seed=12345)            # random seed for reproduci

# train a GBM model
model.train(y=y, x=X, training_frame=train, validation_frame=test)

# print AUC
print('GBM Test AUC = %.2f' % model.auc(valid=True))
```

```
gbm Model Build progress: || 100%
GBM Test AUC = 0.78
```

In [11]:
```
row = test[test['ID'] == 29116]
row
```

Out[11]:

In [12]:
```
def generate_local_sample(row, frame, X, N=1000):

    """ Generates a perturbed sample around a row of interest.

    Args:
        row: Row of H2OFrame to be explained.
        frame: H2OFrame in which row is stored.
        X: List of model input variables.
        N: Number of samples to generate.

    Returns:
        Pandas DataFrame containing perturbed sample.

    """

    # initialize Pandas DataFrame
    sample_frame = pd.DataFrame(data=np.zeros(shape=(N, len(X))), columns=X)

    # generate column vectors of
    # randomly drawn levels for categorical variables
    # normally distributed numeric values around mean of column for numeric variables
    for key, val in frame[X].types.items():
        if val == 'enum': # 'enum' means categorical
            rs = np.random.RandomState(11111) # random seed for reproducibility
            draw = rs.choice(frame[key].levels()[0], size=(1, N))[0]
        else:
            rs = np.random.RandomState(11111) # random seed for reproducibility
            loc = row[key][0, 0]
            sd = frame[key].sd()
            draw = rs.normal(loc, sd, (N, 1))
            draw[draw < 0] = loc # prevents unrealistic values when std. dev. is large

        sample_frame[key] = draw

    return sample_frame

# run and display results
perturbed_sample = generate_local_sample(row, test, X)
perturbed_sample.head(n=3)
```

Out[12]:
```
     LIMIT_BAL     SEX        EDUCATION  MARRIAGE        AGE          PAY_0  \
0    9988.454213  female  graduate school  divorced  58.287510  5 month delay
1  181039.642122    male      high school   married  70.460689       pay duly
2   20000.000000    male       university    single  43.284233  7 month delay

          PAY_2          PAY_3          PAY_4                    PAY_5  \
0  5 month delay  5 month delay  5 month delay            6 month delay
1       pay duly       pay duly       pay duly  use of revolving credit
```

```
2  7 month delay  7 month delay  7 month delay           8 month delay

       ...          BILL_AMT3     BILL_AMT4     BILL_AMT5     BILL_AMT6  \
0      ...        5433.340804   6276.576876   8055.530587   7347.467911
1      ...       94937.888614  90412.278099  87766.906051  85915.192926
2      ...       10672.000000  11201.000000  12721.000000  11946.000000

       PAY_AMT1      PAY_AMT2      PAY_AMT3      PAY_AMT4      PAY_AMT5  \
0   1597.834490      0.000000   1000.000000    823.253257      0.000000
1  22137.303918  25583.930273  21802.010398  20928.433066  19123.775929
2   2800.000000      0.000000   1000.000000   2000.000000      0.000000

       PAY_AMT6
0      0.000000
1  22563.515833
2      0.000000

[3 rows x 23 columns]
```

In [13]:
```python
# scaling and one-hot encoding for calculating Euclidian distance
# for the row of interest

# scale numeric
numeric = list(set(X) - set(['ID', 'SEX', 'EDUCATION', 'MARRIAGE', 'PAY_0', 'PAY_2',
                             'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6', 'DEFAULT_NEXT_MONTH']))

scaled_test = test.as_data_frame()
scaled_test[numeric] = (scaled_test[numeric] - scaled_test[numeric].mean())/scaled_test

# encode categorical
row_df = scaled_test[scaled_test['ID'] == 22760]
row_dummies = pd.concat([row_df.drop(['ID', 'SEX', 'EDUCATION', 'MARRIAGE', 'PAY_0', 'P
                                      'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6', 'DEFAULT_NEXT
                        pd.get_dummies(row_df[['SEX', 'EDUCATION', 'MARRIAGE', 'PAY_0',
                                               'PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY
                        axis=1)

# convert to H2OFrame
row_dummies = h2o.H2OFrame(row_dummies)
row_dummies
```

Parse progress: || 100%

Out[13]:

In [14]:
```python
# scaling and one-hot encoding for calculating Euclidian distance
# for the simulated sample
```

```
# scale
scaled_perturbed_sample = perturbed_sample[numeric].copy(deep=True)
scaled_perturbed_sample = (scaled_perturbed_sample - scaled_perturbed_sample.mean())/sc

# encode
perturbed_sample_dummies = pd.concat([scaled_perturbed_sample,
                                      pd.get_dummies(perturbed_sample[['SEX', 'EDUCATIO
                                                                       'PAY_2', 'PAY_3'
                                     axis=1)

# convert to H2OFrame
perturbed_sample_dummies = h2o.H2OFrame(perturbed_sample_dummies[row_dummies.columns])
perturbed_sample_dummies.head(rows=3)
```

```
Parse progress: || 100%
```

Out[14]:

```
In [15]: # calculate distance using H2OFrame distance function
         distance = row_dummies.distance(perturbed_sample_dummies, measure='l2').transpose()
         distance.columns = ['distance']          # rename
         distance = distance.max() - distance     # lower distances, higher weight in LIME
         distance.head(rows=3)
```

Out[15]:

```
In [16]: perturbed_sample = h2o.H2OFrame(perturbed_sample).cbind(distance)
         perturbed_sample.head(rows=3)
```

```
Parse progress: || 100%
```

Out[16]:

```
In [17]: yhat = 'p_DEFAULT_NEXT_MONTH'
         preds1 = model.predict(perturbed_sample).drop(['predict', 'p0'])
         preds1.columns = [yhat]
         perturbed_sample = perturbed_sample.cbind(preds1)
         perturbed_sample.head(rows=3)
```

```
gbm prediction progress: || 100%
```

Out[17]:

```
In [18]: # initialize
         local_glm1 = H2OGeneralizedLinearEstimator(lambda_search=True,
                                                    weights_column='distance',
                                                    seed=12345)
```

```python
    # train
    local_glm1.train(x=X, y=yhat, training_frame=perturbed_sample)

    # coefs
    print('\nLocal Positive GLM Coefficients:')
    for c_name, c_val in sorted(local_glm1.coef().items(), key=operator.itemgetter(1)):
        if c_val > 0.0:
            print('%s %s' % (str(c_name + ':').ljust(25), c_val))

    # r2
    print('\nLocal GLM R-square:\n%.2f' % local_glm1.r2())
```

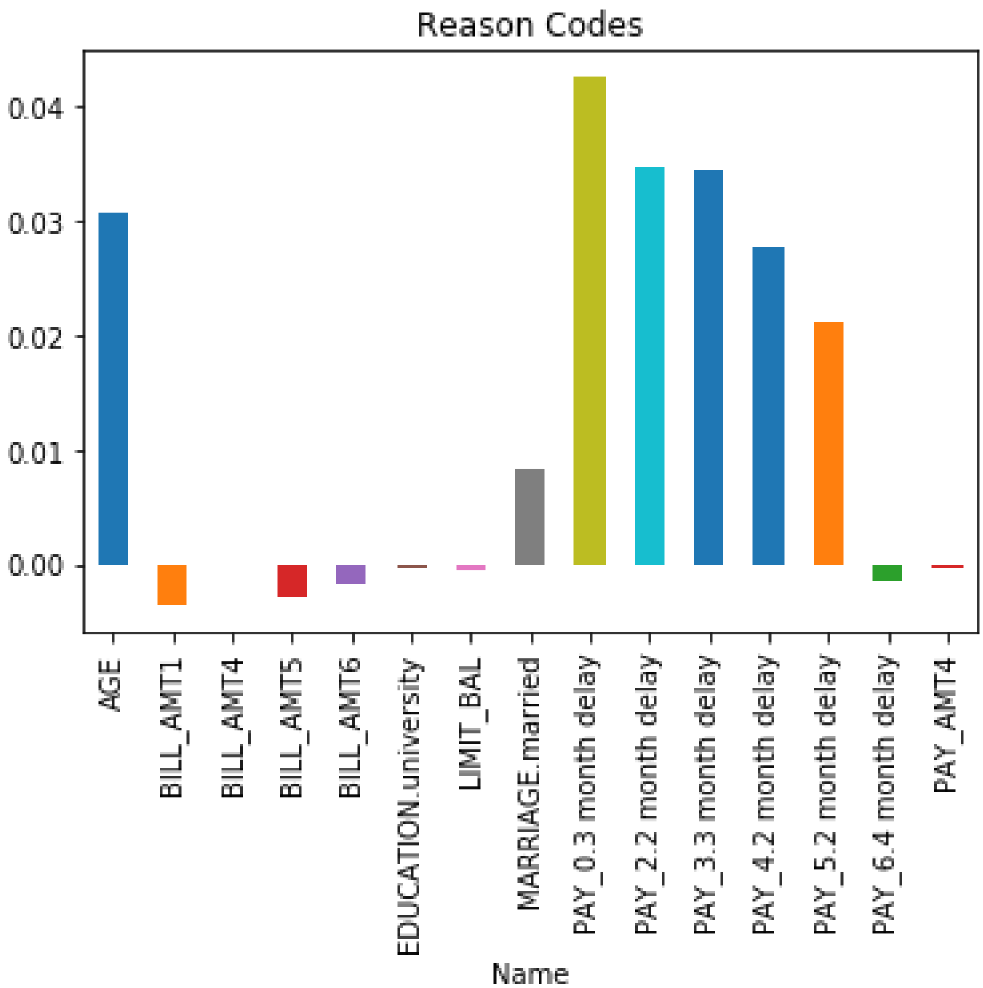
```
glm Model Build progress: || 100%

Local Positive GLM Coefficients:
PAY_6.5 month delay:      0.00012336828327697705
PAY_6.8 month delay:      0.00017180686755602562
AGE:                      0.0005214813169893759
MARRIAGE.divorced:        0.0009908636978089515
PAY_5.5 month delay:      0.0029210607400959312
PAY_5.8 month delay:      0.0034766652812617737
MARRIAGE.married:         0.00839449832911553
EDUCATION.graduate school: 0.0087785945155O6156
PAY_4.8 month delay:      0.009194057851981784
PAY_6.2 month delay:      0.010989810282326163
PAY_3.8 month delay:      0.011784255155206258
PAY_4.4 month delay:      0.013724839005152558
PAY_2.8 month delay:      0.015148689640095393
PAY_3.4 month delay:      0.015894167507824828
EDUCATION.high school:    0.017278858933894182
PAY_0.8 month delay:      0.01866577067319948
PAY_2.4 month delay:      0.01883620843956382
PAY_5.2 month delay:      0.021213743679622924
PAY_0.4 month delay:      0.02226790035088684
PAY_6.6 month delay:      0.02579847200811933
PAY_4.2 month delay:      0.02761803647343567
PAY_3.2 month delay:      0.03054379350100437
PAY_4.3 month delay:      0.031544128994333266
PAY_3.3 month delay:      0.03433816489254767
PAY_2.2 month delay:      0.03462878399791587
PAY_5.6 month delay:      0.0355329696935376
PAY_4.7 month delay:      0.037294721565890726
PAY_2.3 month delay:      0.03816134857629098
PAY_3.7 month delay:      0.03945791591841178
PAY_0.2 month delay:      0.039808994576340025
PAY_2.7 month delay:      0.042385398311322965
PAY_0.3 month delay:      0.04255010418495568
PAY_0.7 month delay:      0.04551379447400766
```

```
PAY_6.3 month delay:      0.05188952365736261
PAY_5.3 month delay:      0.06147834271742927
Intercept:                0.5056288963178366

Local GLM R-square:
0.88
```

```
In [21]: def plot_local_contrib(row, model, X):

             """ Plots reason codes in a bar chart.

             Args:

                 row: Row of H2OFrame to be explained.
                 model: H2O linear model used for generating reason codes.
                 X: List of model input variables.

             """

             # initialize Pandas DataFrame to store results
             local_contrib_frame = pd.DataFrame(columns=['Name', 'Local Contribution', 'Sign'])

             # multiply values in row by local glm coefficients
             for key, val in sorted(row[X].types.items()):
                 contrib = 0
                 name = ''
                 if val == 'enum':
                         level = row[key][0, 0]
                         name = '.'.join([str(key), str(level)])
                         if name in model.coef():
                             contrib = model.coef()[name]
                 else:
                     name = key
                     if name in model.coef():
                         contrib = row[name][0, 0]*model.coef()[name]

                 # save only non-zero values
                 if contrib != 0.0:
                     local_contrib_frame = local_contrib_frame.append({'Name': name,
                                                                       'Local Contribution': con
                                                                       'Sign': contrib > 0},
                                                                      ignore_index=True)

             # plot
             _ = local_contrib_frame.plot(x='Name',
                                          y='Local Contribution',
                                          kind='bar',
```

```
                                  title='Reason Codes',
                                  #color=''.join(local_contrib_frame.Sign.map({True:'b',
                                  legend=False)
```

In [22]:
```
plot_local_contrib(row, local_glm1, X)
```



In [23]:
```
preds2 = model.predict(test).drop(['predict', 'p0'])
preds2.columns = [yhat]
practical_sample = test.cbind(preds2)
practical_sample = practical_sample[practical_sample['SEX'] == 'female']
practical_sample.head(rows=3)
```

```
gbm prediction progress: || 100%
```

Out[23]:

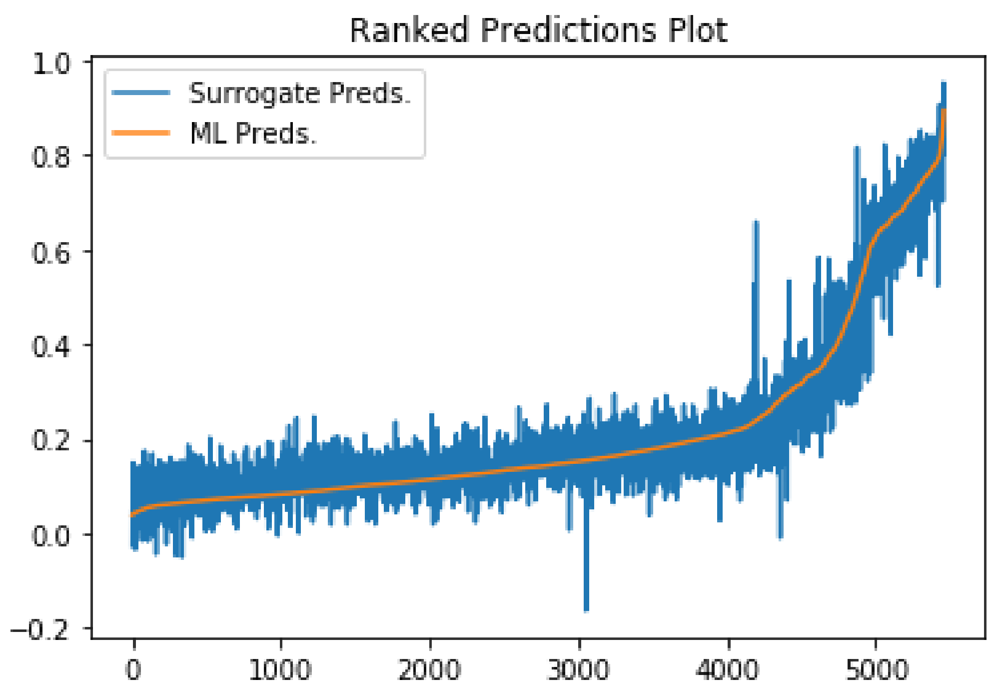
In [24]:
```
# initialize
local_glm2 = H2OGeneralizedLinearEstimator(lambda_search=True, seed=12345)

# train
local_glm2.train(x=X, y=yhat, training_frame=practical_sample)

# coefs
print('\nLocal Positive GLM Coefficients:')
for c_name, c_val in sorted(local_glm2.coef().items(), key=operator.itemgetter(1)):
    if c_val > 0.0:
        print('%s %s' % (str(c_name + ':').ljust(25), c_val))

# r2
print('\nLocal GLM R-square:\n%.2f' % local_glm2.r2())
```

```
glm Model Build progress: || 100%

Local Positive GLM Coefficients:
BILL_AMT5:                1.1826997991308345e-07
BILL_AMT2:                1.40866409117354e-07
PAY_2.use of revolving credit: 8.019899530507052e-05
PAY_5.no consumption:     0.0005253910928260071
AGE:                      0.0005358697742774277
EDUCATION.high school:    0.001738945706593454
PAY_6.5 month delay:      0.003746060705692238
EDUCATION.university:     0.0050869233726203505
MARRIAGE.divorced:        0.008137713429375004
PAY_3.2 month delay:      0.009655714764721601
PAY_6.7 month delay:      0.009949478307751001
MARRIAGE.married:         0.010783461117748264
PAY_6.2 month delay:      0.017777285984771147
PAY_4.4 month delay:      0.018246956356881238
PAY_0.5 month delay:      0.02282693801079417
PAY_5.3 month delay:      0.02513913532234654
PAY_2.2 month delay:      0.027053294000875572
PAY_2.3 month delay:      0.027735314903293225
PAY_3.3 month delay:      0.03306463224575794
PAY_4.2 month delay:      0.034888814725250496
PAY_5.2 month delay:      0.04227839273926825
PAY_3.6 month delay:      0.045744519066213275
PAY_5.7 month delay:      0.04899783921490372
PAY_4.7 month delay:      0.06621325735295537
PAY_2.7 month delay:      0.06967904222914757
PAY_2.5 month delay:      0.07827450156661904
PAY_0.8 month delay:      0.11612935759003508
PAY_6.3 month delay:      0.12335032934322444
PAY_2.6 month delay:      0.16221244593488762
PAY_0.4 month delay:      0.251408547348665
```

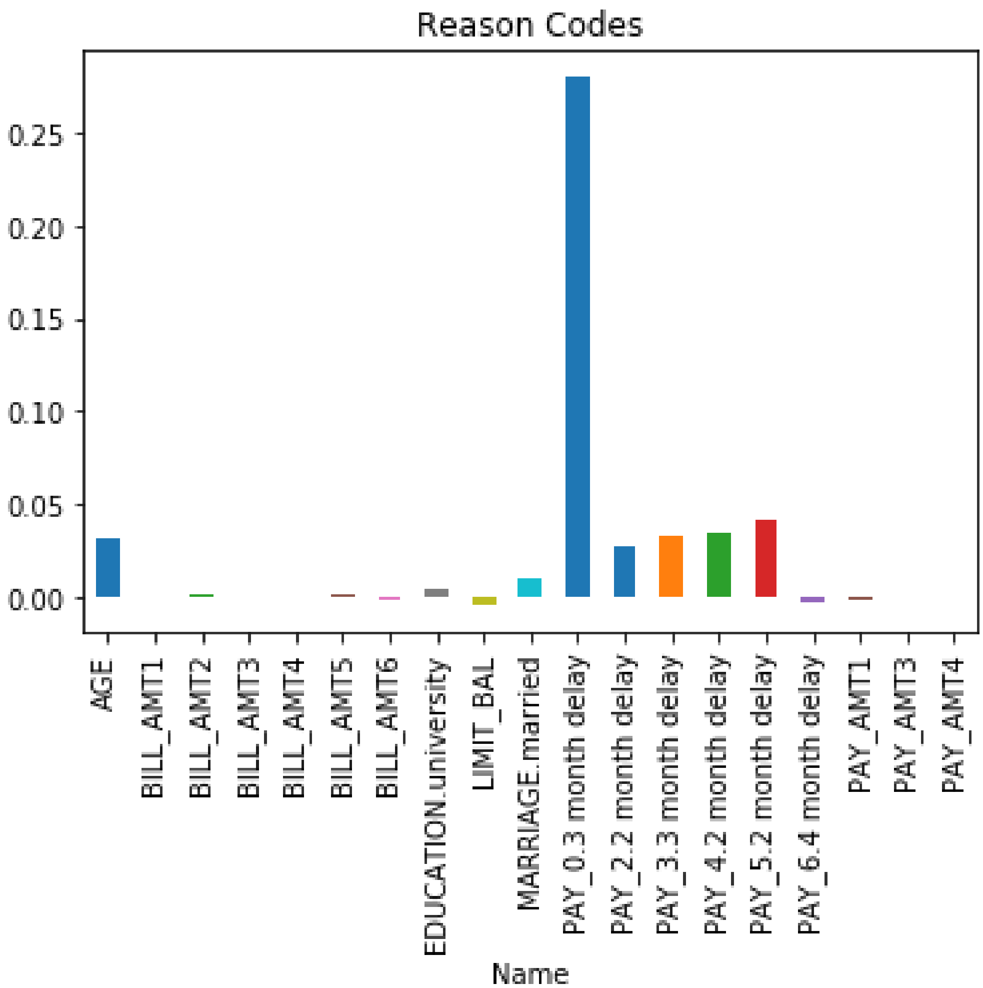
```
PAY_0.3 month delay:      0.2795924865330281
PAY_0.2 month delay:      0.28633293810272625
Intercept:                0.3907733223754482

Local GLM R-square:
0.93
```

```
In [25]: # ranked predictions plot
         pred_frame = local_glm2.predict(practical_sample).cbind(practical_sample)\
                                .as_data_frame()[['predict', yhat  ]]

         pred_frame.columns = ['Surrogate Preds.', 'ML Preds.']
         pred_frame.sort_values(by='ML Preds.', inplace=True)
         pred_frame.reset_index(inplace=True, drop=True)
         _ = pred_frame.plot(title='Ranked Predictions Plot')
```

```
glm prediction progress: || 100%
```




```
In [26]: plot_local_contrib(row, local_glm2, X)
```


Reason Codes
0.25
0.20
0.15
0.10
0.05
0.00
AGE
BILL_AMT1
BILL_AMT2
BILL_AMT3
BILL_AMT4
BILL_AMT5
BILL_AMT6
EDUCATION.university
LIMIT_BAL
MARRIAGE.married
PAY_0.3 month delay
PAY_2.2 month delay
PAY_3.3 month delay
PAY_4.2 month delay
PAY_5.2 month delay
PAY_6.4 month delay
PAY_AMT1
PAY_AMT3
PAY_AMT4
Name