Default Credit Card Prediction

Week 1:- Identify DataSet and UseCase

Use Case

This research aimed at the case of customers default payments in Taiwan and compares the predictive accuracy of probability of default among various data mining methods.

From the perspective of risk management, the result of predictive accuracy of the estimated probability of default will be more valuable than the binary result of classification - credible or not credible clients. In this tutorial we will look at how to predict defaulting, using Machine and Deep Learning techniques.

Data Source

Attribute Information

This study uses 25 variables as explanatory variables, extracted/interpreted from :

```
--------------------------------------------------------------------------
------------------
   Name                    Explantion
   --------------------
---------------------------------------------------------------------------
   limit_bal               Amount of the given credit (NT dollar):
                           it includes both the individual consumer
credit
                           and his/her family (supplementary) credit.

   sex                     Gender
                           (1 = male; 2 = female)

   education               Education
                           (1 = graduate school; 2 = university; 3 = high
school; 4 = others)

   marriage                Marital status
                           (1 = married; 2 = single; 3 = others)

   age                     Age (years)

   pay_1 - pay_6           History of past payment. Past monthly payment
records
                           From April to September, 2005 as follows:
```

```
                        pay_1 = the repayment status in September,
2005
                        pay_2 = the repayment status in August, 2005
                        ...
                        pay_6 = the repayment status in April, 2005

                        The measurement scale for the repayment status
is:
                        -1 = pay duly;
                        1 = payment delay for one month
                        2 = payment delay for two months
                        ...
                        8 = payment delay for eight months
                        9 = payment delay for nine months and above

   bill_amt1-bill_amt5  Amount of bill statement (NT dollar).
                        bill_amt1 = amount of bill statement in
September, 2005
                        bill_amt2 = amount of bill statement in
August, 2005
                        ...
                        bill_amt6= amount of bill statement in April,
2005

   pay_amt1-pay_amt6    Amount of previous payment (NT dollar)
                        pay_amt1 = amount paid in September, 2005
                        pay_amt2 = amount paid in August, 2005
                        ...
                        pay_amt6 = amount paid in April, 2005

----------------------------------------------------------------------
------------------
```

Import Required Libraries

```
import pandas as pd
import numpy as np
import seaborn as sns
import urllib
import wget
import xlrd
import shutil
import os
import re
from math import log


%matplotlib inline
import matplotlib.pyplot as plt
```

```
from sklearn.neighbors.kde import KernelDensity
from patsy import dmatrices
import itertools
from sklearn.metrics import roc_curve, auc, roc_auc_score, log_loss,
accuracy_score, confusion_matrix
import warnings
warnings.filterwarnings("ignore")
#warnings.simplefilter(action='ignore',
category=(UserWarning,RuntimeWarning))

from sklearn.feature_selection import SelectKBest, f_classif
from sklearn import preprocessing
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split
from sklearn.dummy import DummyClassifier
from sklearn import linear_model
from sklearn.ensemble import RandomForestClassifier
import xgboost as xgb
from keras.models import Sequential
from keras.layers.core import Dense, Activation, Dropout
from keras.callbacks import Callback

Using TensorFlow backend.
```

Plot default settings

```
plt.rcParams['figure.figsize'] = (20.0, 20.0)
plt.rcParams.update({'font.size': 10})
plt.rcParams['xtick.major.pad']='5'
plt.rcParams['ytick.major.pad']='5'

plt.style.use('ggplot')
```

Donwload and Read Data

```
data_dir = './data'
if not os.path.exists(data_dir):
    os.makedirs(data_dir)

url =
'https://archive.ics.uci.edu/ml/machine-learning-databases/00350/defau
lt of credit card clients.xls'
file_name = os.path.join(data_dir, 'default of credit card
clients.xls')

if not os.path.isfile(filename):
    wget.download(url, out=file_name)

file_name = 'default of credit card clients.xls'
os.chdir(r'C:\Srinu\AdvancedDataSciencewithIBM\
```

```
AdvancedDataScienceCapstone')
data = pd.read_excel(file_name, header=1)

data.head()

   ID  LIMIT_BAL  SEX  EDUCATION  MARRIAGE  AGE  PAY_0  PAY_2  PAY_3
PAY_4  \
0   1      20000    2          2         1   24      2      2     -1
-1
1   2     120000    2          2         2   26     -1      2      0
0
2   3      90000    2          2         2   34      0      0      0
0
3   4      50000    2          2         1   37      0      0      0
0
4   5      50000    1          2         1   57     -1      0     -1
0

              ...              BILL_AMT4  BILL_AMT5  BILL_AMT6
PAY_AMT1  \
0             ...                      0          0          0
0
1             ...                   3272       3455       3261
0
2             ...                  14331      14948      15549
1518
3             ...                  28314      28959      29547
2000
4             ...                  20940      19146      19131
2000

   PAY_AMT2  PAY_AMT3  PAY_AMT4  PAY_AMT5  PAY_AMT6  \
0       689         0         0         0         0
1      1000      1000      1000         0      2000
2      1500      1000      1000      1000      5000
3      2019      1200      1100      1069      1000
4     36681     10000      9000       689       679

   default payment next month
0                           1
1                           1
2                           0
3                           0
4                           0

[5 rows x 25 columns]

data.shape

(30000, 25)
```

Preprocessing or Data Cleansing

The following preprocessing and data cleansing activities performed

- Lower cased the columns
- Renamed the feature Pay_0 in to Pay_1
- ID attribute was dropped as its not required for this modeling
- Converted the attribute default payment next month type to category and stored the values in default which our target variable

```
data.columns = [x.lower() for x in data.columns]
data = data.rename(index=str, columns={"pay_0": "pay_1"})
data = data.drop('id', axis=1)
data.columns
```

```
Index(['limit_bal', 'sex', 'education', 'marriage', 'age', 'pay_1', 
'pay_2',
       'pay_3', 'pay_4', 'pay_5', 'pay_6', 'bill_amt1', 'bill_amt2',
       'bill_amt3', 'bill_amt4', 'bill_amt5', 'bill_amt6', 'pay_amt1',
       'pay_amt2', 'pay_amt3', 'pay_amt4', 'pay_amt5', 'pay_amt6',
       'default payment next month'],
      dtype='object')
```

```
# Rename the lable to default
data['default'] = data['default payment next 
month'].astype('category')
```

Descriptive Analysis

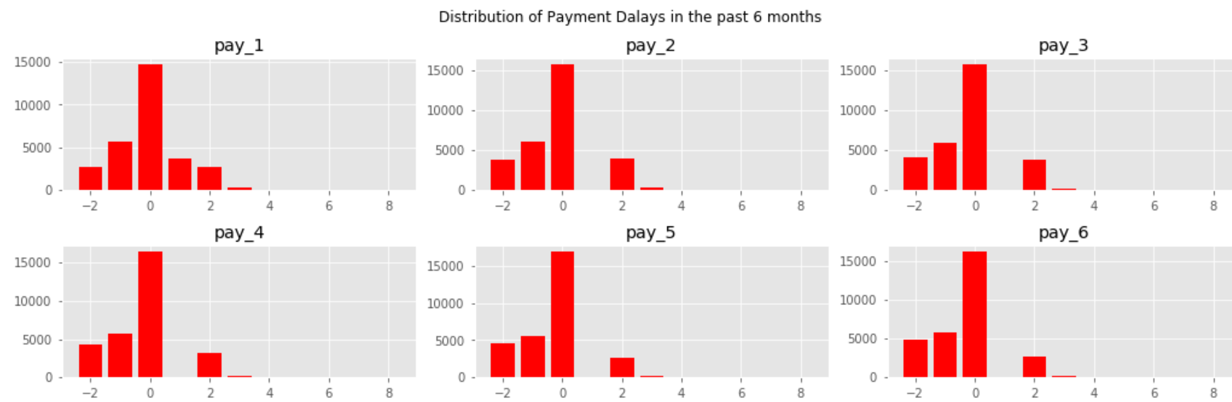
Analyse the **payment delay** features and understand them

```
pattern = re.compile("^pay_[0-9]+$")
pay_status_columns = [ x for x in data.columns if (pattern.match(x))]
data[pay_status_columns].head(10)
```

	pay_1	pay_2	pay_3	pay_4	pay_5	pay_6
0	2	2	-1	-1	-2	-2
1	-1	2	0	0	0	2
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	-1	0	-1	0	0	0
5	0	0	0	0	0	0
6	0	0	0	0	0	0
7	0	-1	-1	0	0	-1
8	0	0	2	0	0	0
9	-2	-2	-2	-2	-1	-1

```
fig, ax = plt.subplots(2,3)
fig.set_size_inches(15,5)
fig.suptitle('Distribution of Payment Dalays in the past 6 months')
```

```
for i in range(len(pay_status_columns)):
    row,col = int(i/3), i%3

    d  = data[pay_status_columns[i]].value_counts()
    ax[row,col].bar(d.index, d, align='center', color='r')
    ax[row,col].set_title(pay_status_columns[i])

plt.tight_layout(pad=3.0, w_pad=0.5, h_pad=1.0)
plt.show()
```



From the above graphs we can interpreted that some people pay 2 month upfront, others one month upfront, most of them are on par. a few are running behind payments.

Now, let's look now at how the debts/credit is accumulating over the months, credit to be repaid is a positive number here.

```
# bill columns
pattern = re.compile("^bill_amt[0-9]+$")
bill_columns = [ x for x in data.columns if (pattern.match(x))]
data[bill_columns].head()
```

	bill_amt1	bill_amt2	bill_amt3	bill_amt4	bill_amt5	bill_amt6
0	3913	3102	689	0	0	0
1	2682	1725	2682	3272	3455	3261
2	29239	14027	13559	14331	14948	15549
3	46990	48233	49291	28314	28959	29547
4	8617	5670	35835	20940	19146	19131

```
data[bill_columns].describe()
```

	bill_amt1	bill_amt2	bill_amt3	bill_amt4 \
count	30000.000000	30000.000000	3.000000e+04	30000.000000
mean	51223.330900	49179.075167	4.701315e+04	43262.948967
std	73635.860576	71173.768783	6.934939e+04	64332.856134
min	-165580.000000	-69777.000000	-1.572640e+05	-170000.000000
25%	3558.750000	2984.750000	2.666250e+03	2326.750000
50%	22381.500000	21200.000000	2.008850e+04	19052.000000

```
75%     67091.000000   64006.250000  6.016475e+04   54506.000000
max    964511.000000  983931.000000  1.664089e+06  891586.000000

           bill_amt5      bill_amt6
count   30000.000000   30000.000000
mean    40311.400967   38871.760400
std     60797.155770   59554.107537
min    -81334.000000 -339603.000000
25%      1763.000000    1256.000000
50%     18104.500000   17071.000000
75%     50190.500000   49198.250000
max    927171.000000  961664.000000
```

Previous months payments

Look at how the payments are performed in the previous month.

```
# pay status columns
pattern = re.compile("^pay_amt[0-9]+$")
pay_amount_columns = [ x for x in data.columns if (pattern.match(x))]
data[pay_amount_columns].head()
```

```
   pay_amt1  pay_amt2  pay_amt3  pay_amt4  pay_amt5  pay_amt6
0         0       689         0         0         0         0
1         0      1000      1000      1000         0      2000
2      1518      1500      1000      1000      1000      5000
3      2000      2019      1200      1100      1069      1000
4      2000     36681     10000      9000       689       679
```

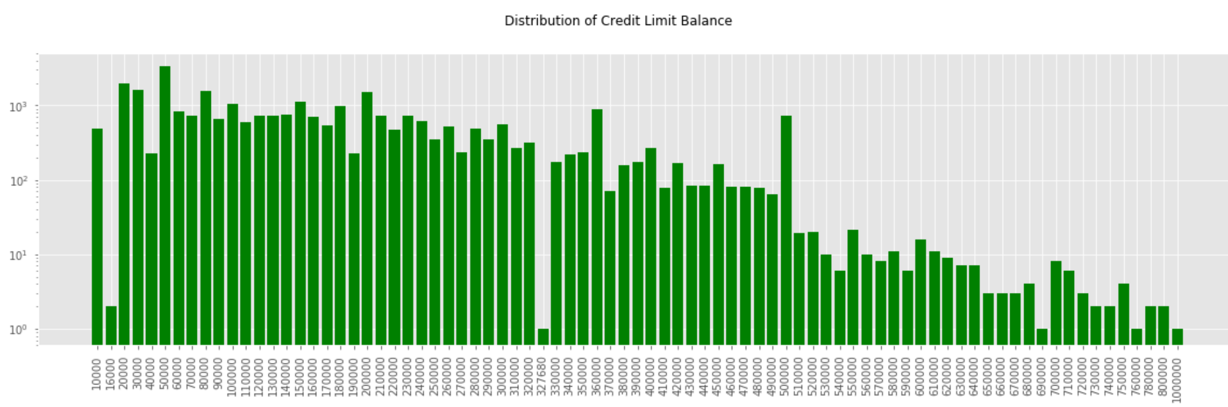
```
data[pay_amount_columns].describe()
```

```
            pay_amt1      pay_amt2      pay_amt3       pay_amt4  \
count   30000.000000  3.000000e+04   30000.00000   30000.000000
mean     5663.580500  5.921163e+03    5225.68150    4826.076867
std     16563.280354  2.304087e+04   17606.96147   15666.159744
min         0.000000  0.000000e+00       0.00000       0.000000
25%      1000.000000  8.330000e+02     390.00000     296.000000
50%      2100.000000  2.009000e+03    1800.00000    1500.000000
75%      5006.000000  5.000000e+03    4505.00000    4013.250000
max    873552.000000  1.684259e+06  896040.00000  621000.000000

            pay_amt5       pay_amt6
count   30000.000000   30000.000000
mean     4799.387633    5215.502567
std     15278.305679   17777.465775
min         0.000000       0.000000
25%       252.500000     117.750000
50%      1500.000000    1500.000000
75%      4031.500000    4000.000000
max    426529.000000  528666.000000
```

```
data['limit_bal'].describe()
```

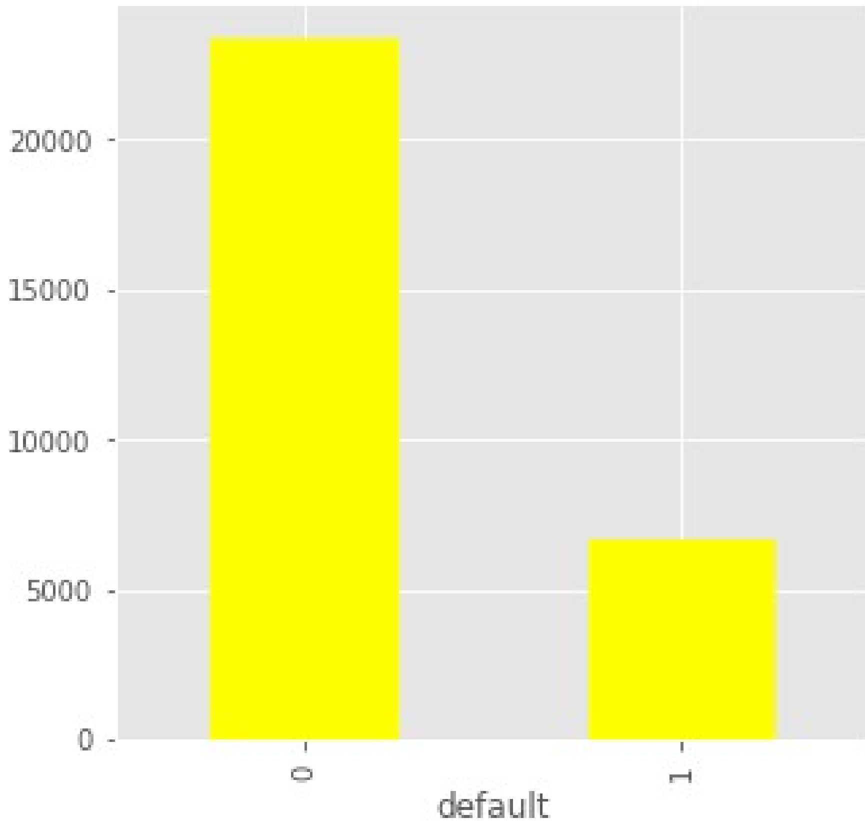
```
count      30000.000000
mean      167484.322667
std       129747.661567
min        10000.000000
25%        50000.000000
50%       140000.000000
75%       240000.000000
max      1000000.000000
Name: limit_bal, dtype: float64
```

```
# limit balance
fig = plt.figure()
fig.set_size_inches(20,5)
fig.suptitle('Distribution of Credit Limit Balance')
ax = fig.add_subplot(111)

d = data.groupby(['limit_bal']).size()
ax.set_yscale("log")
ax.set_xticks(np.arange(len(d)))
ax.set_xticklabels(['%d' % i for i in d.index], rotation='vertical')
p = ax.bar(np.arange(len(d)), d, color='green')
```



Now lets explore the **default** label

```
fig = plt.figure()
fig.set_size_inches(5,5)
d = data.groupby(['default']).size()
p = d.plot(kind='bar', stacked=True, color='yellow')
#p = d.plot(kind='barh', color='orange') #horizontal bar plot
```

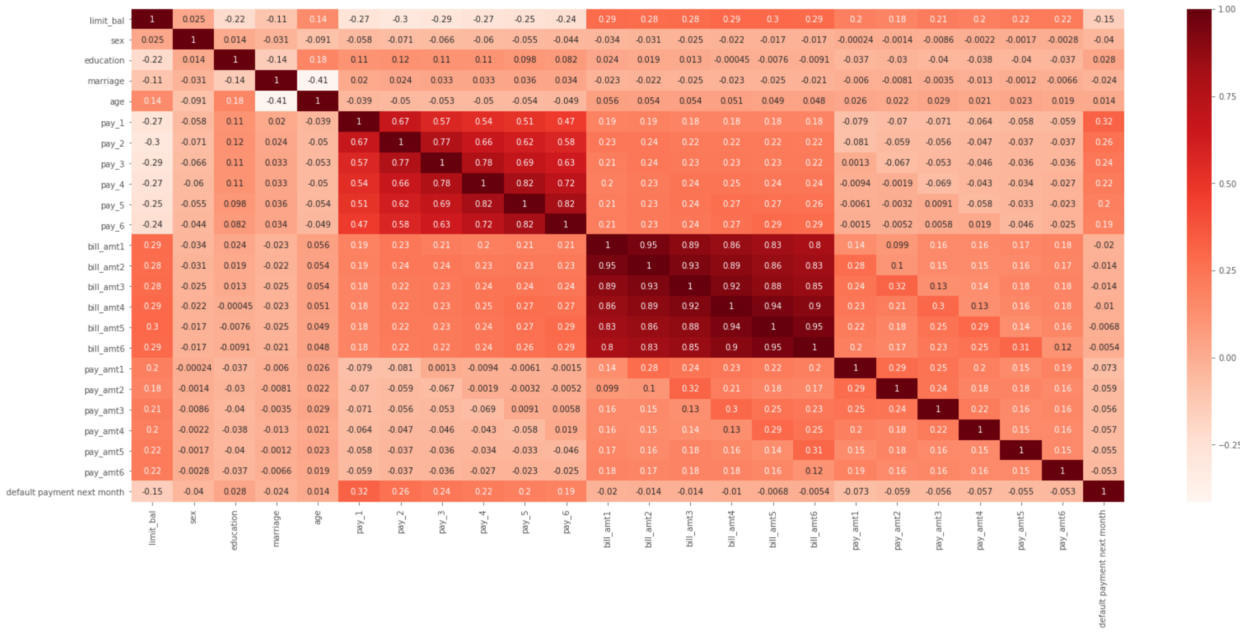



```
print('Distribution of default values:\n',
data.default.value_counts()/data.shape[0])
```

```
Distribution of default values:
 0    0.7788
1    0.2212
Name: default, dtype: float64
```

Correlation coefficient of attributes

```
#Using Pearson Correlation
plt.figure(figsize=(27,11))
cor = data.corr()
sns.heatmap(cor, annot=True, cmap=plt.cm.Reds)
plt.show()
```



The above correlation matrix represents how attributes correlated among each other and their strength of relationship. Pay_1 to Pay_6 features are reasonably positive correlation with the default.

Explore statistical analysis of the categorical variables

Look at a number of histograms to see how defaulting correlated with the categorical variables available, before that let's make use of categorical features of pandas, by converting target, sex, marriage, education, age and the pay_* columns to categories

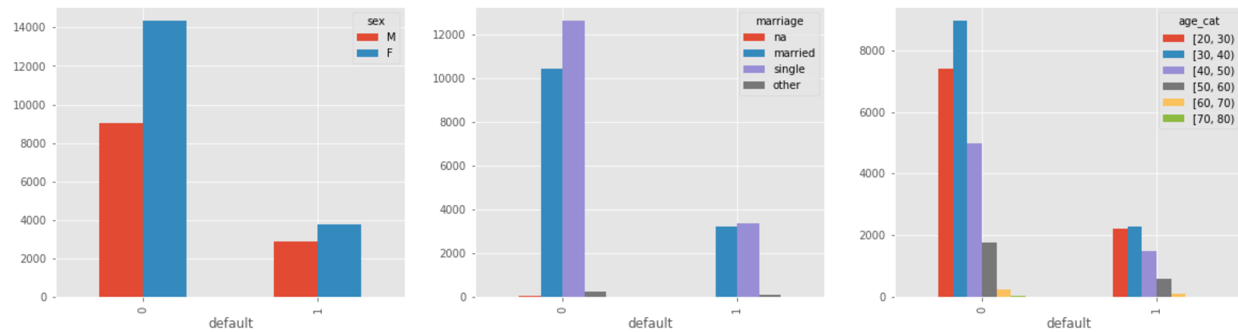
```
data['sex'] =
data['sex'].astype('category').cat.rename_categories(['M', 'F'])
data['marriage'] =
data['marriage'].astype('category').cat.rename_categories(['na',
'married', 'single', 'other'])

data['age_cat'] = pd.cut(data['age'], range(0, 100, 10), right=False)

pattern = re.compile("^pay_[0-9]+$")
pay_status_columns = [ x for x in data.columns if (pattern.match(x))]
for i in pay_status_columns:
    data[i] = data[i].astype('category')
```

Absolute statistics

```
fig, ax = plt.subplots(1,3)
fig.set_size_inches(20,5)
fig.suptitle('Defaulting by absolute numbers, for various
demographics')

d = data.groupby(['default', 'sex']).size()
p = d.unstack(level=1).plot(kind='bar', ax=ax[0])
```

```
d = data.groupby(['default', 'marriage']).size()
p = d.unstack(level=1).plot(kind='bar', ax=ax[1])

d = data.groupby(['default', 'age_cat']).size()
p = d.unstack(level=1).plot(kind='bar', ax=ax[2])
```

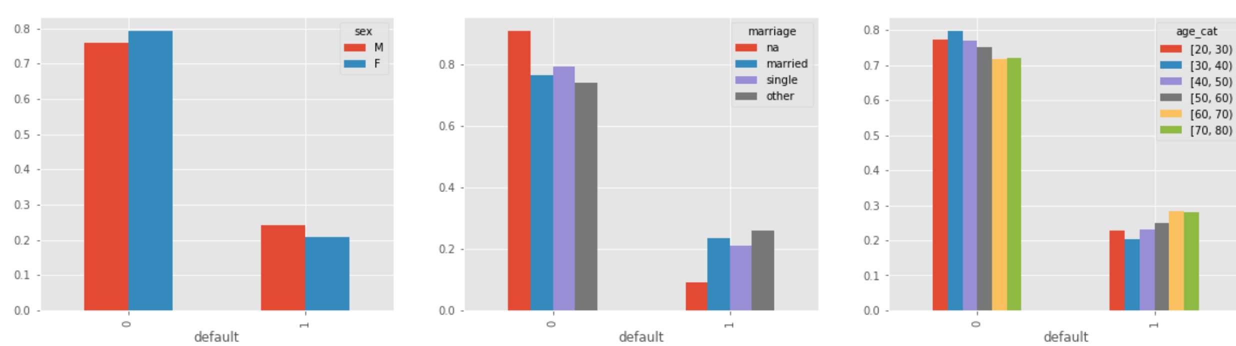
Defaulting by absolute numbers, for various demographics



Statistics relative to the population

```
fig, ax = plt.subplots(1,3)
fig.set_size_inches(20,5)
fig.suptitle('Defaulting by relative numbers given each class, for various demographics')

d = data.groupby(['default', 'sex']).size().unstack(level=1)
d = d / d.sum()
p = d.plot(kind='bar', ax=ax[0])

d = data.groupby(['default', 'marriage']).size().unstack(level=1)
d = d / d.sum()
p = d.plot(kind='bar', ax=ax[1])

d = data.groupby(['default', 'age_cat']).size().unstack(level=1)
d = d / d.sum()
p = d.plot(kind='bar', ax=ax[2])
```

Defaulting by relative numbers given each class, for various demographics



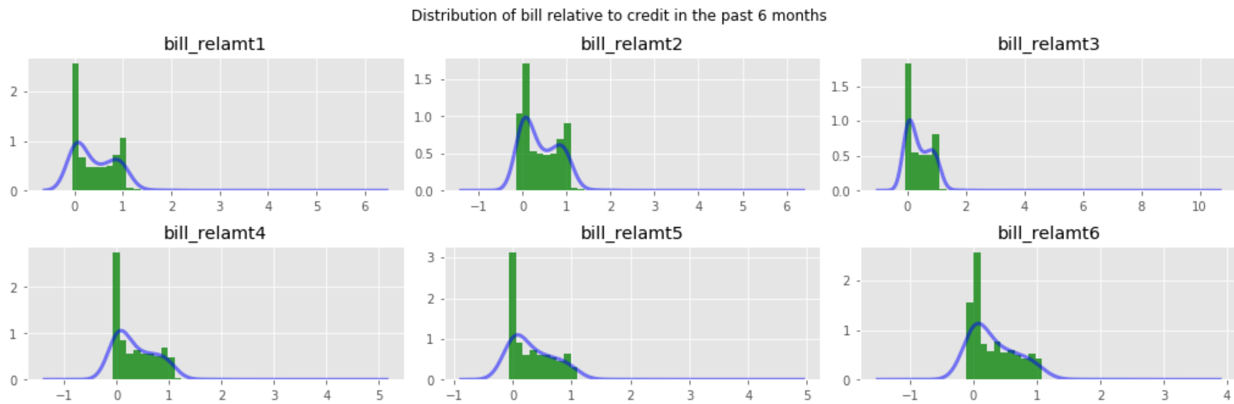
Week 2:- ETL and Feature Creation

Feature engineering

Extracted few new features by applying transformation techniques such as mean, standard deviation and logs etc.

```
# help func
def selcols(prefix, a=1, b=6):
    return [prefix+str(i) for i in np.arange(a,b+1)]

# average and standard deviation payment status
data['pay_avg'] = data[selcols('pay_')].mean(axis=1)
data['pay_std'] = data[selcols('pay_')].std(axis=1)

# average payment
data['pay_amt_avg']     = data[selcols('pay_amt')].mean(axis=1)

# log of average
data['pay_amt_avg_log'] = data['pay_amt_avg'].apply(lambda x:
log(x+1))

#amounts relative to the average payment
for i in np.arange(1,7):
    data['pay_relamt'+str(i)] =
data['pay_amt'+str(i)]/data['pay_amt_avg']

# log of payments
for i in np.arange(1,7):
    data['pay_amt_log'+str(i)] = data['pay_amt'+str(i)].apply(lambda
x: log(x+1))

# average bill
data['bill_amt_avg'] = data[selcols('bill_amt')].mean(axis=1)
data['bill_amt_avg_log'] = data['bill_amt_avg'].apply(lambda x:
log(x+1) if x>0 else 0)

# bill sign as a separate feature
for i in np.arange(1,7):
    data['bill_amt_sign'+str(i)] =
data['bill_amt'+str(i)].apply(lambda x: float(x>0))

# bill log as a separate feature (0 if bill is negative)
for i in np.arange(1,7):
    data['bill_amt_log'+str(i)] = data['bill_amt'+str(i)].apply(lambda
x: log(x+1) if x>0 else 0)

#bill amounts relative to the limit
for i in np.arange(1,7):
```

```
    data['bill_relamt'+str(i)] =
data['bill_amt'+str(i)]/data['limit_bal']

#log of credit limit
data['limit_bal_log'] = data['limit_bal'].apply(lambda x: log(x+1))
data['limit_bal_cat'] = pd.cut(data['limit_bal'], range(0, int(1e6),
10000), right=False)

warnings.filterwarnings("ignore")
pattern = re.compile("^bill_relamt[0-9]+$")
columns = [ x for x in data.columns if (pattern.match(x))]

fig, ax = plt.subplots(2,3)
fig.set_size_inches(15,5)
fig.suptitle('Distribution of bill relative to credit in the past 6
months')

for i in range(len(columns)):
    row,col = int(i/3), i%3

    d = data[columns[i]]
    # the histogram of the data
    n, bins, patches = ax[row,col].hist(d, 50, normed=1,
facecolor='green', alpha=0.75)

    # kernel density estimation
    kde = KernelDensity(kernel='gaussian',
bandwidth=0.2).fit(d.values.reshape(-1, 1))
    x_grid = np.linspace(d.min(), d.max(), 1000)
    log_pdf = kde.score_samples(x_grid.reshape(-1, 1))

    # add the density line
    ax[row,col].plot(x_grid, np.exp(log_pdf), color='blue', alpha=0.5,
lw=3)
    ax[row,col].set_title(columns[i])

plt.tight_layout(pad=3.0, w_pad=0.5, h_pad=1.0)
plt.show()
```



Generate Train and Test Matrix from the attributes

```
formula  = 'default ~ '

# original features
formula += 'C(sex) + C(marriage) +  C(education) + age'
formula += '+' + '+'.join(selcols('pay_'))

#### engineered / normalized features

# categorical age and credit limit (binned)
formula += '+' + 'C(age_cat)'
formula += '+' + 'C(limit_bal_cat) + limit_bal_log'

#pay delays
formula += '+' + 'pay_avg + pay_std'

#pay_amt
formula += '+' + 'pay_amt_avg_log'
formula += '+' + '+'.join(selcols('pay_relamt'))
formula += '+' + '+'.join(selcols('pay_amt_log'))

# bill amounts
formula += '+' + 'bill_amt_avg_log'
formula += '+' + '+'.join(selcols('bill_relamt'))
formula += '+' + '+'.join(selcols('bill_amt_sign'))
formula += '+' + '+'.join(selcols('bill_amt_log'))

y, X = dmatrices(formula, data=data, return_type='dataframe')
y = y.iloc[:, 1]

X.head()

   Intercept  C(sex)[T.F]  C(marriage)[T.married]  C(marriage)
[T.single]  \
0        1.0          1.0                     1.0
0.0
1        1.0          1.0                     0.0
```

```
1.0
2        1.0         1.0                     0.0
1.0
3        1.0         1.0                     1.0
0.0
4        1.0         0.0                     1.0
0.0

   C(marriage)[T.other]  C(education)[T.1]  C(education)[T.2]  \
0                   0.0                0.0                1.0
1                   0.0                0.0                1.0
2                   0.0                0.0                1.0
3                   0.0                0.0                1.0
4                   0.0                0.0                1.0

   C(education)[T.3]  C(education)[T.4]  C(education)[T.5]      ...
\
0                0.0                0.0                0.0      ...

1                0.0                0.0                0.0      ...

2                0.0                0.0                0.0      ...

3                0.0                0.0                0.0      ...

4                0.0                0.0                0.0      ...


   bill_amt_sign3  bill_amt_sign4  bill_amt_sign5  bill_amt_sign6  \
0             1.0             0.0             0.0             0.0
1             1.0             1.0             1.0             1.0
2             1.0             1.0             1.0             1.0
3             1.0             1.0             1.0             1.0
4             1.0             1.0             1.0             1.0

   bill_amt_log1  bill_amt_log2  bill_amt_log3  bill_amt_log4
bill_amt_log5  \
0       8.272315       8.040125       6.536692       0.000000
0.000000
1       7.894691       7.453562       7.894691       8.093462
8.147867
2      10.283293       9.548811       9.514880       9.570250
9.612400
3      10.757711      10.783819      10.805517      10.251147
10.273671
4       9.061608       8.643121      10.486708       9.949464
9.859901

   bill_amt_log6
0       0.000000
```

```
1       8.090096
2       9.651816
3      10.293771
4       9.859118

[5 rows x 211 columns]
```

Visualization: Confusion matrices and AUC curves

```
def plot_cm(ax, y_true, y_pred, classes, title, th=0.5,
cmap=plt.cm.Blues):
    # Returns Confusion Matrix
    y_pred_labels = (y_pred>th).astype(int)

    cm = confusion_matrix(y_true, y_pred_labels)

    im = ax.imshow(cm, interpolation='nearest', cmap=cmap)
    ax.set_title(title)

    tick_marks = np.arange(len(classes))
    ax.set_xticks(tick_marks)
    ax.set_yticks(tick_marks)
    ax.set_xticklabels(classes)
    ax.set_yticklabels(classes)

    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]),
range(cm.shape[1])):
        ax.text(j, i, cm[i, j],
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")
    ax.set_ylabel('True label')
    ax.set_xlabel('Predicted label')


def plot_auc(ax, y_train, y_train_pred, y_test, y_test_pred, th=0.5):
    # Retunrs AUC Curves
    y_train_pred_labels = (y_train_pred>th).astype(int)
    y_test_pred_labels  = (y_test_pred>th).astype(int)

    fpr_train, tpr_train, _ = roc_curve(y_train,y_train_pred)
    roc_auc_train = auc(fpr_train, tpr_train)
    acc_train = accuracy_score(y_train, y_train_pred_labels)

    fpr_test, tpr_test, _ = roc_curve(y_test,y_test_pred)
    roc_auc_test = auc(fpr_test, tpr_test)
    acc_test = accuracy_score(y_test, y_test_pred_labels)

    ax.plot(fpr_train, tpr_train)
    ax.plot(fpr_test, tpr_test)
```

```
    ax.plot([0, 1], [0, 1], 'k--')

    ax.set_xlim([0.0, 1.0])
    ax.set_ylim([0.0, 1.05])
    ax.set_xlabel('False Positive Rate')
    ax.set_ylabel('True Positive Rate')
    ax.set_title('ROC curve')

    train_text = 'train acc = {:.3f}, auc = {:.2f}'.format(acc_train,
roc_auc_train)
    test_text = 'test acc = {:.3f}, auc = {:.2f}'.format(acc_test,
roc_auc_test)
    ax.legend([train_text, test_text])
```

Feature selection

Feature selection is a technique where we choose those features in our data that contribute most to the target variable. In other words we choose the best predictors for the target variable.

The classes in the **sklearn.feature_selection** module can be used for feature selection/dimensionality reduction on sample sets, either to improve estimators' accuracy scores or to boost their performance on very high-dimensional datasets. We can get the following benefits by using this module:

- Reduces Overfitting: Less redundant data means less possibility of making decisions based on redundant data/noise.
- Improves Accuracy: Less misleading data means modeling accuracy improves.
- Reduces Training Time: Less data means that algorithms train faster.

```
# Take best 25 features/predictors
selector = SelectKBest(f_classif, 25)
selector.fit(X, y)

SelectKBest(k=25, score_func=<function f_classif at
0x0000027EF58FED90>)
```

We got the following best 25 features from the method

```
top_indices = np.nan_to_num(selector.scores_).argsort()[-25:][::-1]
selector.scores_[top_indices]
list(X.columns[top_indices])

['pay_1[T.2]',
 'pay_2[T.2]',
 'pay_avg',
 'pay_3[T.2]',
 'pay_4[T.2]',
 'pay_5[T.2]',
 'pay_std',
 'pay_6[T.2]',
```

```
 'pay_1[T.0]',
 'limit_bal_log',
 'pay_amt_log1',
 'pay_amt_avg_log',
 'bill_relamt6',
 'pay_2[T.0]',
 'bill_relamt5',
 'bill_relamt4',
 'pay_amt_log2',
 'bill_relamt3',
 'bill_relamt2',
 'pay_amt_log3',
 'pay_1[T.3]',
 'bill_relamt1',
 'pay_2[T.3]',
 'pay_3[T.0]',
 'pay_amt_log4']
```

Feature scaling

Many machine learning algorithms perform better when numerical input variables are scaled to a standard range. This includes algorithms that use a weighted sum of the input, like linear regression, and algorithms that use distance measures, like k-nearest neighbors. The two most popular techniques for scaling numerical data prior to modeling are normalization and standardization. **Normalization** scales each input variable separately to the range 0-1, which is the range for floating-point values where we have the most precision. **Standardization** scales each input variable separately by subtracting the mean (called centering) and dividing by the standard deviation to shift the distribution to have a mean of zero and a standard deviation of one.

We can apply the **MinMaxScaler** to the dataset directly to normalize the input variables.

```
scaler = preprocessing.MinMaxScaler()
scaler.fit(X)

MinMaxScaler(copy=True, feature_range=(0, 1))

preprocess = Pipeline([('anova', selector), ('scale', scaler)])
preprocess.fit(X,y)

X_scaled = preprocess.transform(X)
```

Model selection and validation

```
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y,
test_size=0.2, random_state=42)

def CMatrix(CM, labels=['Not Default','Default']):
    df = pd.DataFrame(data=CM, index=labels, columns=labels)
    df.index.name='TRUE'
```

```
    df.columns.name='Prediction'
    df.loc['Total'] = df.sum()
    df['Total'] = df.sum(axis=1)
    return df
```

Week 3 & 4:- Model Definition and Training, Model Evaluation, Tuning, Deployment and Documentation

Logistic Regression

- Used for Binary classification and Based on Probability
- Outputs have a probabilistic interpretation, and the algorithm can be regularized to avoid over fitting
- The conditional probability p of class belongs to 1 if probability >= threshold (default 0.5) else it belongs to class 0

Random Forest

- It is an ensembled model built on decision trees
- It builds multiple decision trees and merges them together to get a more accurate and stable prediction

Artificial Neural Network

- Neural Network is used with backpropagation algorithm to select optimum weights of predictors. The following architecture and hyper parameters used.

1. Input Layer 26 Hidden Layer 26 Output Layer 1
2. Epochs 10 Optimizer ADAM Activation function ReLU and Sigmoid Loss function Binary cross entropy

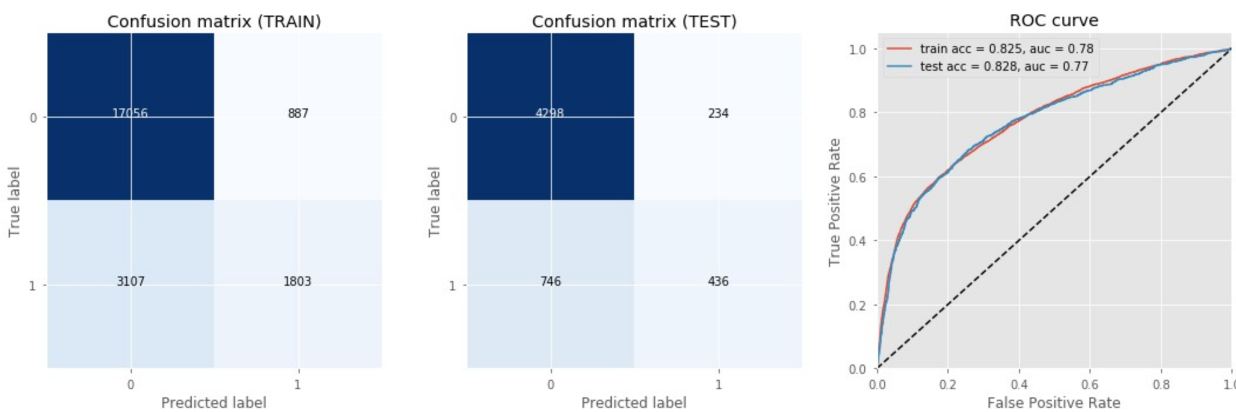
Dummy Classifier

```
dummy_clf = DummyClassifier(strategy="most_frequent")
dummy_clf.fit(X_train, y_train)

DummyClassifier(constant=None, random_state=None,
strategy='most_frequent')

print("Accuracy of the dummy classifier: ", dummy_clf.score(X_test,
y_test))

Accuracy of the dummy classifier:  0.7931396569828492
```

Logistic regression

```
# Create logistic regression object
LR_clf = linear_model.LogisticRegression()

# Train the model using the training sets
LR_clf.fit(X_train, y_train)
```

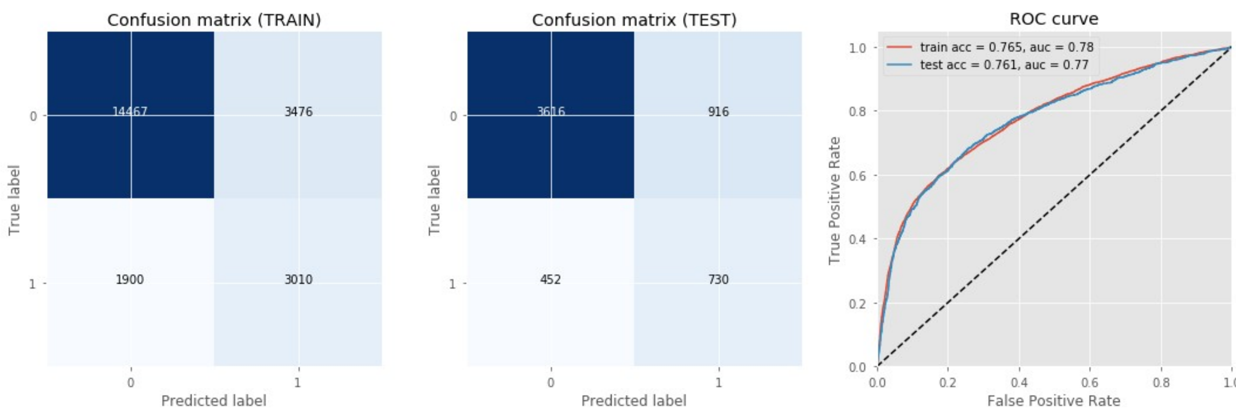
```
LogisticRegression(C=1.0, class_weight=None, dual=False,
fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)

y_train_pred = LR_clf.predict_proba(X_train)[:,1]
y_test_pred = LR_clf.predict_proba(X_test)[:,1]

threshold = 0.5

fig,ax = plt.subplots(1,3)
fig.set_size_inches(15,5)

plot_cm(ax[0],  y_train, y_train_pred, [0,1], 'Confusion matrix
(TRAIN)', threshold)
plot_cm(ax[1],  y_test, y_test_pred,   [0,1], 'Confusion matrix
(TEST)', threshold)
plot_auc(ax[2], y_train, y_train_pred, y_test, y_test_pred, threshold)

plt.tight_layout()
plt.show()
```



Logistic Regression with Threshold 0.2

```
y_train_pred = LR_clf.predict_proba(X_train)[:,1]
y_test_pred = LR_clf.predict_proba(X_test)[:,1]

threshold = 0.2

fig,ax = plt.subplots(1,3)
fig.set_size_inches(15,5)

plot_cm(ax[0],  y_train, y_train_pred, [0,1], 'Confusion matrix
(TRAIN)', threshold)
plot_cm(ax[1],  y_test, y_test_pred,   [0,1], 'Confusion matrix
(TEST)', threshold)
plot_auc(ax[2], y_train, y_train_pred, y_test, y_test_pred, threshold)
```

```
plt.tight_layout()
plt.show()
```



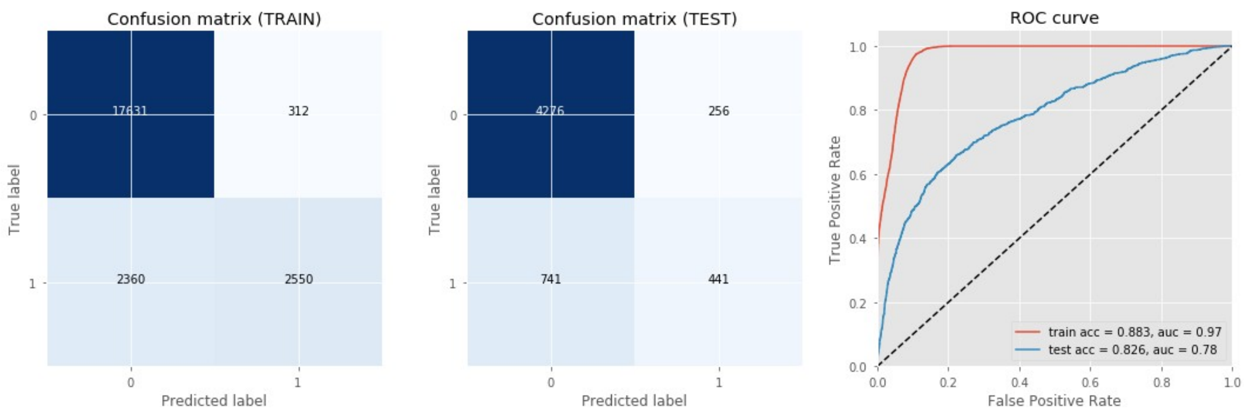

```
CMatrix(confusion_matrix(y_pred=[1 if i > threshold else 0 for i in
y_test_pred], y_true=y_test))
```

Prediction	Not Default	Default	Total
TRUE			
Not Default	3616	916	4532
Default	452	730	1182
Total	4068	1646	5714

Random Forest

```
RF_clf = RandomForestClassifier(n_estimators=500, min_samples_leaf=5)
RF_clf.fit(X_train,y_train)

RandomForestClassifier(bootstrap=True, class_weight=None,
criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=5, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=500,
n_jobs=None,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)

threshold = 0.5
y_train_pred = RF_clf.predict_proba(X_train)[:,1]
y_test_pred = RF_clf.predict_proba(X_test)[:,1]

fig,ax = plt.subplots(1,3)
fig.set_size_inches(15,5)

plot_cm(ax[0],  y_train, y_train_pred, [0,1], 'Confusion matrix
(TRAIN)', threshold)
```

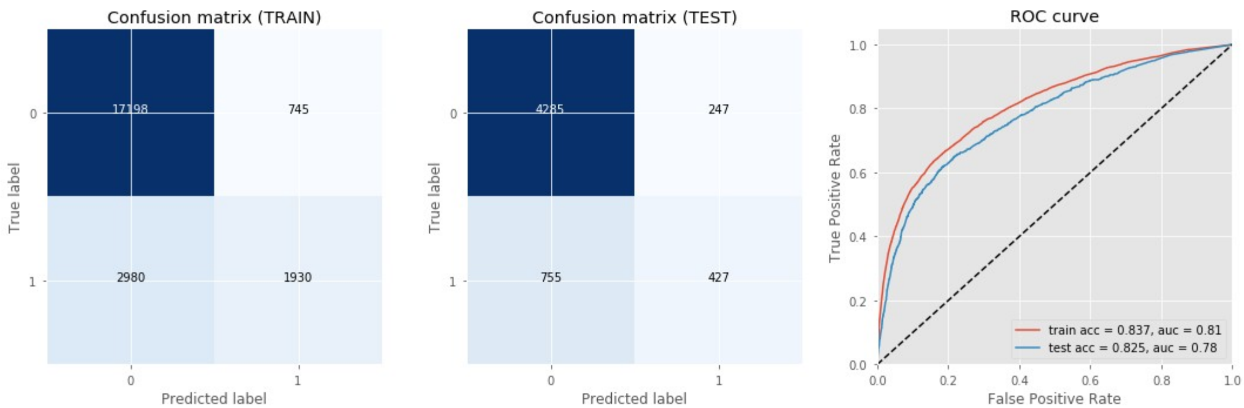
```
plot_cm(ax[1],  y_test, y_test_pred,   [0,1], 'Confusion matrix (TEST)', threshold)
plot_auc(ax[2], y_train, y_train_pred, y_test, y_test_pred, threshold)

plt.tight_layout()
plt.show()
```



Boosting

```
dtrain = xgb.DMatrix(X_train, label=y_train)
dtest = xgb.DMatrix(X_test, label=y_test)

num_round = 5
evallist  = [(dtest,'eval'), (dtrain,'train')]
param = {'objective':'binary:logistic', 'silent':1, 'eval_metric':
['error', 'logloss']}

bst = xgb.train( param, dtrain, num_round, evallist )

[0]	eval-error:0.178159	eval-logloss:0.572755	train-error:0.167505
	train-logloss:0.568834
[1]	eval-error:0.178509	eval-logloss:0.508294	train-error:0.165624
	train-logloss:0.501548
[2]	eval-error:0.176234	eval-logloss:0.471332	train-error:0.165011
	train-logloss:0.461776
[3]	eval-error:0.175884	eval-logloss:0.449392	train-error:0.164617
	train-logloss:0.437177
[4]	eval-error:0.175359	eval-logloss:0.435512	train-error:0.162998
	train-logloss:0.421064

threshold = 0.5
y_train_pred = bst.predict(dtrain)
y_test_pred = bst.predict(dtest)

fig,ax = plt.subplots(1,3)
fig.set_size_inches(15,5)

plot_cm(ax[0],  y_train, y_train_pred, [0,1], 'Confusion matrix
```

```
(TRAIN)', threshold)
plot_cm(ax[1],  y_test, y_test_pred,   [0,1], 'Confusion matrix
(TEST)', threshold)
plot_auc(ax[2], y_train, y_train_pred, y_test, y_test_pred, threshold)

plt.tight_layout()
plt.show()
```

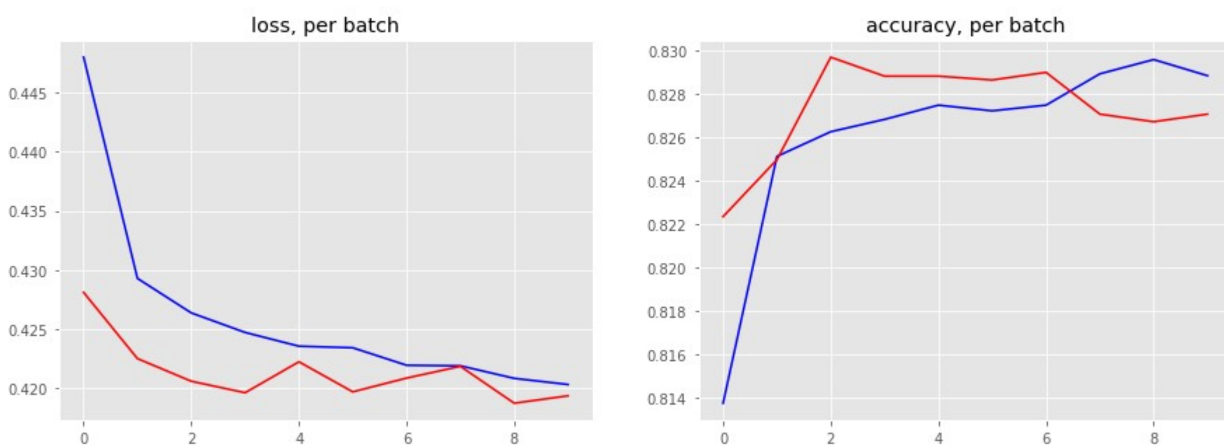


Feed forward deep neural nets

```
input_dim = X_train.shape[1]

model = Sequential()
model.add(Dense(256, input_shape=(input_dim,), activation='relu'))
model.add(Dense(256, activation='relu'))
model.add(Dense(64, activation='relu'))
model.add(Dense(64, activation='relu'))
model.add(Dense(10, activation='relu'))
model.add(Dense(10, activation='sigmoid'))
model.add(Dense(1,  activation='sigmoid'))

WARNING:tensorflow:From C:\Users\s.x.parimi\AppData\Local\Continuum\
anaconda3\lib\site-packages\tensorflow\python\framework\
op_def_library.py:263: colocate_with (from
tensorflow.python.framework.ops) is deprecated and will be removed in
a future version.
Instructions for updating:
Colocations handled automatically by placer.

model.compile(optimizer='adam', loss='binary_crossentropy',
metrics=['accuracy'])

from keras.callbacks import Callback

class BatchLogger(Callback):
    def on_train_begin(self, epoch, logs={}):
        self.log_values = {}
        for k in self.params['metrics']:
```

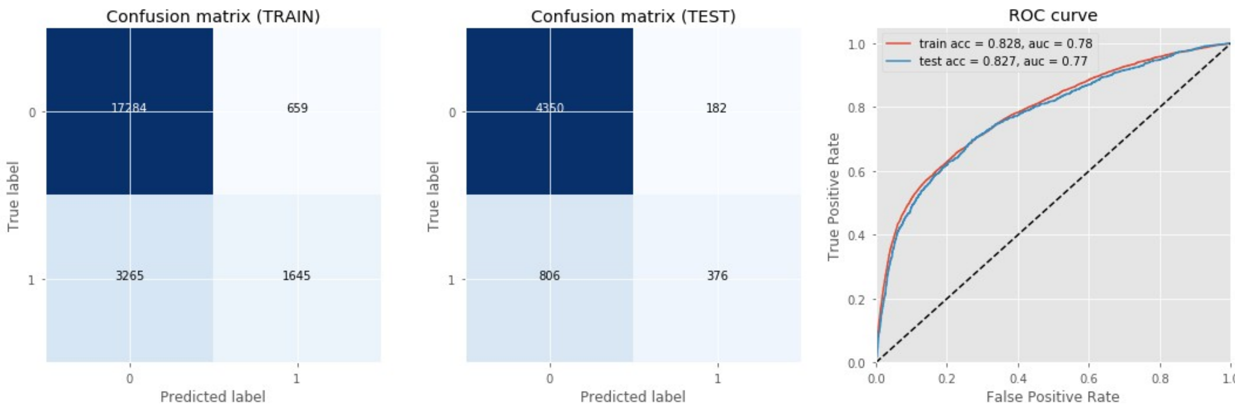
```
            self.log_values[k] = []

    def on_epoch_end(self, batch, logs={}):
        for k in self.params['metrics']:
            if k in logs:
                self.log_values[k].append(logs[k])

    def get_values(self, metric_name, window):
        d =  pd.Series(self.log_values[metric_name])
        return d.rolling(window,center=False).mean()

bl = BatchLogger()

history = model.fit(
              np.array(X_train), np.array(y_train),
              batch_size=25, epochs=10, verbose=1, callbacks=[bl],
              validation_data=(np.array(X_test), np.array(y_test)))

WARNING:tensorflow:From C:\Users\s.x.parimi\AppData\Local\Continuum\
anaconda3\lib\site-packages\tensorflow\python\ops\math_ops.py:3066:
to_int32 (from tensorflow.python.ops.math_ops) is deprecated and will
be removed in a future version.
Instructions for updating:
Use tf.cast instead.
Train on 22853 samples, validate on 5714 samples
Epoch 1/10
22853/22853 [==============================] - 5s 230us/step - loss:
0.4480 - acc: 0.8138 - val_loss: 0.4281 - val_acc: 0.8224
Epoch 2/10
22853/22853 [==============================] - 4s 156us/step - loss:
0.4293 - acc: 0.8251 - val_loss: 0.4225 - val_acc: 0.8250
Epoch 3/10
22853/22853 [==============================] - 3s 146us/step - loss:
0.4264 - acc: 0.8263 - val_loss: 0.4206 - val_acc: 0.8297
Epoch 4/10
22853/22853 [==============================] - 3s 146us/step - loss:
0.4247 - acc: 0.8268 - val_loss: 0.4196 - val_acc: 0.8288
Epoch 5/10
22853/22853 [==============================] - 3s 151us/step - loss:
0.4236 - acc: 0.8275 - val_loss: 0.4222 - val_acc: 0.8288
Epoch 6/10
22853/22853 [==============================] - 4s 170us/step - loss:
0.4234 - acc: 0.8272 - val_loss: 0.4197 - val_acc: 0.8287
Epoch 7/10
22853/22853 [==============================] - 3s 139us/step - loss:
0.4220 - acc: 0.8275 - val_loss: 0.4209 - val_acc: 0.8290
Epoch 8/10
22853/22853 [==============================] - 3s 150us/step - loss:
0.4219 - acc: 0.8290 - val_loss: 0.4219 - val_acc: 0.8271
Epoch 9/10
```

```
22853/22853 [==============================] - 3s 151us/step - loss:
0.4208 - acc: 0.8296 - val_loss: 0.4187 - val_acc: 0.8267
Epoch 10/10
22853/22853 [==============================] - 4s 179us/step - loss:
0.4203 - acc: 0.8289 - val_loss: 0.4194 - val_acc: 0.8271

score = model.evaluate(np.array(X_test), np.array(y_test), verbose=0)
print('Test log loss:', score[0])
print('Test accuracy:', score[1])

Test log loss: 0.4193731993697597
Test accuracy: 0.8270913545051404

plt.figure(figsize=(15,5))

plt.subplot(1, 2, 1)
plt.title('loss, per batch')
plt.plot(bl.get_values('loss',1), 'b-', label='train');
plt.plot(bl.get_values('val_loss',1), 'r-', label='test');

plt.subplot(1, 2, 2)
plt.title('accuracy, per batch')
plt.plot(bl.get_values('acc',1), 'b-', label='train');
plt.plot(bl.get_values('val_acc',1), 'r-', label='test');
plt.show()
```




```
y_train_pred = model.predict_on_batch(np.array(X_train))[:,0]
y_test_pred = model.predict_on_batch(np.array(X_test))[:,0]

fig,ax = plt.subplots(1,3)
fig.set_size_inches(15,5)

plot_cm(ax[0], y_train, y_train_pred, [0,1], 'Confusion matrix
(TRAIN)')
plot_cm(ax[1], y_test, y_test_pred, [0,1], 'Confusion matrix (TEST)')
```

```
plot_auc(ax[2], y_train, y_train_pred, y_test, y_test_pred)

plt.tight_layout()
plt.show()
```



Model Deployment

Model deployment comes in many shapes. The key to everything is that the business insights that result from the model are made available to stakeholders. This can happen in various ways. At the simplest level a PDF report is generated (e.g. using a jupyter notebook) and handed over to business stakeholders.