Cold Calls: Data Mining and Model Selection

Python notebook using data from Car Insurance Cold Calls · 4,773 views · 2y ago

Version 4

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Cold Calls: Data Mining and Model Selection

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This kernel aims to predict car insurance cold call success. It shows data exploration and visualization, along with feature engineering and model selection. Any comments/suggestions are welcome.

In [1]:

```
%matplotlib inline
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import datetime
from scipy import stats
from scipy.stats import skew
from scipy.stats import mode
from scipy.optimize import minimize
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split,
cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.grid_search import GridSearchCV
from sklearn import svm
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, E
xtraTreesClassifier,GradientBoostingClassifier, Voting
Classifier
from sklearn.naive_bayes import GaussianNB
```

```
/opt/conda/lib/python3.6/site-packages/sk
learn/cross_validation.py:41: Deprecation
Warning: This module was deprecated in ve
rsion 0.18 in favor of the model_selectio
n module into which all the refactored cl
asses and functions are moved. Also note
that the interface of the new CV iterator
s are different from that of this module
```

```
s are different from that of this module.
This module will be removed in 0.20.
  "This module will be removed in 0.20.",
DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sk
learn/grid_search.py:42: DeprecationWarni
ng: This module was deprecated in version
0.18 in favor of the model_selection modu
le into which all the refactored classes
and functions are moved. This module will
be removed in 0.20.
  DeprecationWarning)
```

In [2]:

```
# Read-in train and test datasets
train = pd.read_csv('../input/carInsurance_train.csv')
test = pd.read_csv('../input/carInsurance_test.csv')
```

In [3]:

```
print('The train dataset has %d observations and %d fe
atures' % (train.shape[0], train.shape[1]))
print('The test dataset has %d observations and %d fea
tures' % (test.shape[0], test.shape[1]))
```

```
The train dataset has 4000 observations a
nd 19 features
The test dataset has 1000 observations an
d 19 features
```

Data Exploration & Visualization

In [4]:

```
# Take a peak at the data
train.describe()
```

Out[4]:

	Id	Age	Default	Balan
count	4000.000000	4000.000000	4000.000000	4000.00000
mean	2000.500000	41.214750	0.014500	1532.93725
std	1154.844867	11.550194	0.119555	3511.45248
min	1.000000	18.000000	0.000000	-3058.0000(
25%	1000.750000	32.000000	0.000000	111.000000
50%	2000.500000	39.000000	0.000000	551.500000
75%	3000.250000	49.000000	0.000000	1619.00000
max	4000.000000	95.000000	1.000000	98417.0000

In [5]:

```
train.describe(include=['O'])
```

Out[5]:

	Job	Marital	Education	Communication
count	3981	4000	3831	3098
unique	11	3	3	2
top	management	married	secondary	cellular
freq	893	2304	1988	2831

In [6]:

```
train.head()
```

Out[6]:

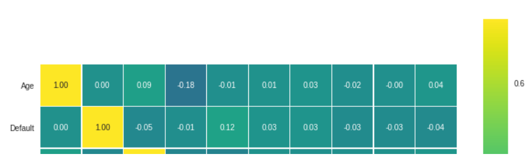
	Id	Age	Job	Marital	Education	Default	Ba
0	1	32	management	single	tertiary	0	12
1	2	32	blue-collar	married	primary	0	11
2	3	29	management	single	tertiary	0	63
3	4	25	student	single	primary	0	37
4	5	30	management	married	tertiary	0	26

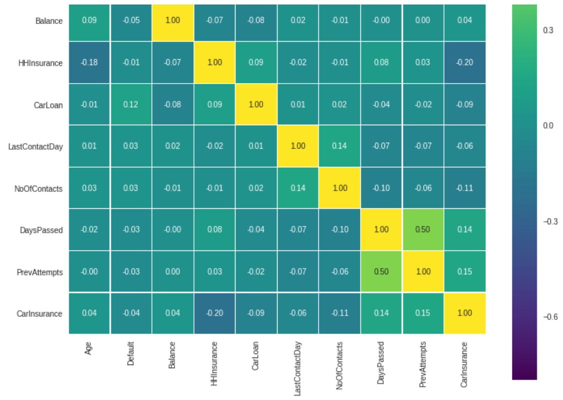
In [7]:

```
# First check out correlations among numeric features
# Heatmap is a useful tool to get a quick understanding of which variables are important
colormap = plt.cm.viridis
cor = train.corr()
cor = cor.drop(['Id'],axis=1).drop(['Id'],axis=0)
plt.figure(figsize=(12,12))
sns.heatmap(cor,vmax=0.8,cmap=colormap,annot=True,fmt='.2f',square=True,annot_kws={'size':10},linecolor='white',linewidths=0.1)
```

Out[7]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb054a96978>
```

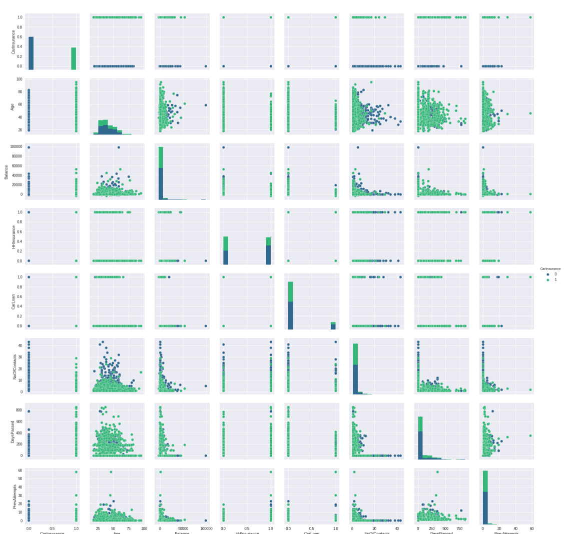




Features are fairly independent, except DaysPassed and PreAttempts. Cold call success is positively correlated with PreAttemps,DaysPassed,Age and Balance, and negatively correlated with default, HHInsurance, CarLoan, LastContactDay and NoOfContacts.

In [8]:

```
# Next, pair plot some important features
imp_feats = ['CarInsurance','Age','Balance','HHInsuran
ce', 'CarLoan','NoOfContacts','DaysPassed','PrevAttemp
ts']
sns.pairplot(train[imp_feats],hue='CarInsurance',palet
te='viridis',size=2.5)
plt.show()
```



Age: It's interesting to see that seniors are more likely to buy car insurance.
Balance: For balance, the data point at the upper right corner might be an outlier
HHInsurance: Households insured are less likely to buy car insurance
CarLoan: People with car loan are less likely to buy
NoOfContacts: Too many contacts causes customer attrition
DaysPassed: It looks like the more day passed since the last contact, the better

PrevAttempts: Also, more previous attempts, less likely to buy. There is a potential outlier here

In [9]:

```
# Take a further look at Age
facet = sns.FacetGrid(train, hue='CarInsurance',size=5
,aspect=3,palette='seismic')
facet.map(plt.hist,'Age',bins=30,alpha=0.5,normed=True
)
facet.set(xlim=(0,train.Age.max()+10))
facet.add_legend()
```

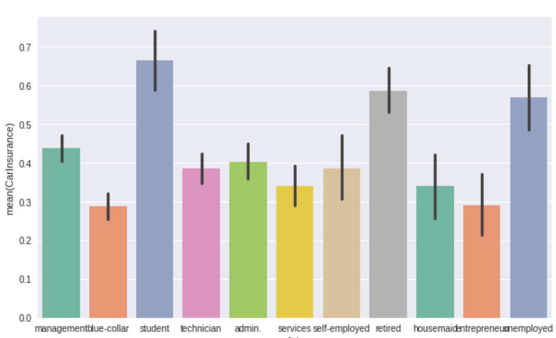
Out[9]:

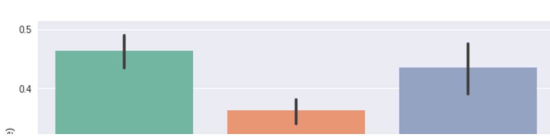
```
<seaborn.axisgrid.FacetGrid at 0x7fb0489e
fe10>
```

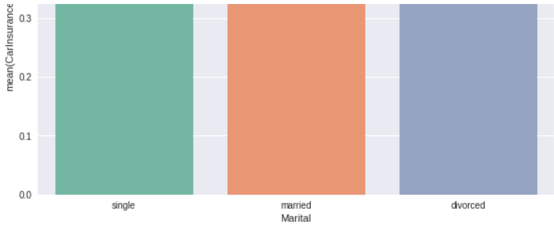
It looks like young people(<=30 years) and seniors are more likely to buy car insurance from this bank

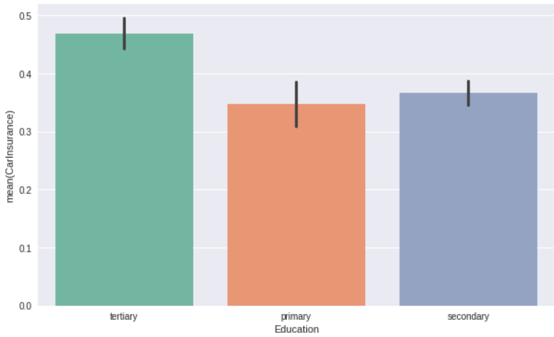
In [10]:

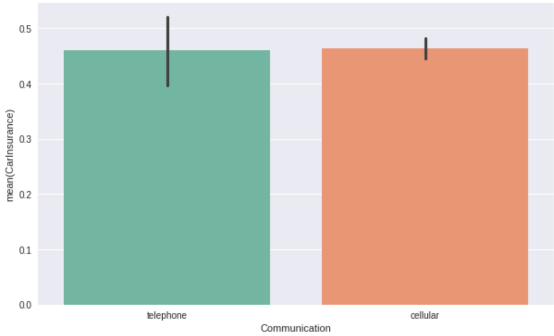
```
# Next check out categorical features
cat_feats = train.select_dtypes(include=['object']).co
lumns
plt_feats = cat_feats[(cat_feats!= 'CallStart') & (cat
_feats!='CallEnd')]

for feature in plt_feats:
    plt.figure(figsize=(10,6))
    sns.barplot(feature,'CarInsurance', data=train,pal
ette='Set2')
```

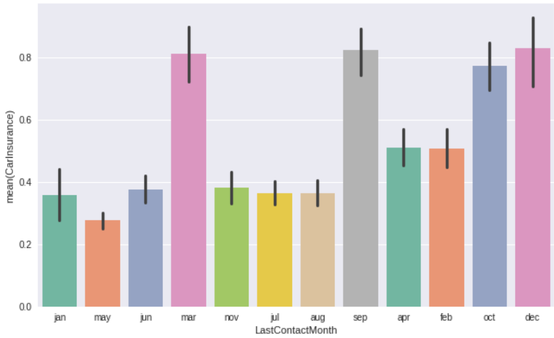


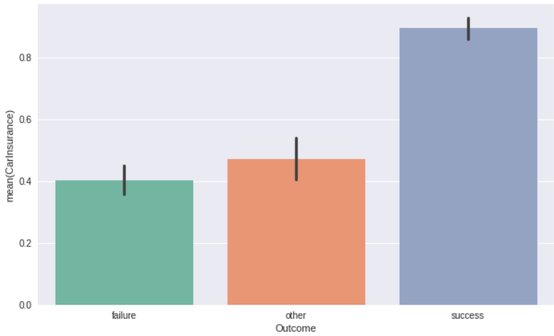



mean(CarInsurance
0.3
0.2
0.1
0.0
single
married
divorced
Marital


mean(CarInsurance)
0.5
0.4
0.3
0.2
0.1
0.0
tertiary
primary
secondary
Education


mean(CarInsurance)
0.5
0.4
0.3
0.2
0.1
0.0
telephone
cellular
Communication


mean(CarInsurance)
0.8
0.6
0.4
0.2
0.0
jan
may
jun
mar
nov
jul
aug
sep
apr
feb
oct
dec
LastContactMonth


mean(CarInsurance)
0.8
0.6
0.4
0.2
0.0
failure
other
success
Outcome

Job: Student are most likely to buy insurance, followed by retired and unemployed folks.This is aligned with the age distribution. There might be some promotion targeting students?
Marital status: Married people are least likely to buy car insurance. Opportunities for developing family insurance business
Education: People with higher education are more likely to buy
Communication: No big difference between cellular and telephone
Outcome in previous campaign: Success in previous marketing campaign is largely associated with success in this campaign
Contact Month: Mar, Sep, Oct, and Dec are the hot months. It might be associated with school season?

In [11]:

```
# Check outliers
# From the pairplot, we can see there is an outlier wit
h extreme high balance. Drop that obs here.
train[train['Balance']>80000]
train = train.drop(train[train.index==1742].index)
```

Handling Miss Data

In [12]:

```
# merge train and test data here in order to impute mis
sing values all at once
all=pd.concat([train,test],keys=('train','test'))
all.drop(['CarInsurance','Id'],axis=1,inplace=True)
print(all.shape)
```

```
(4999, 17)
```

In [13]:

```
total = all.isnull().sum()
pct = total/all.isnull().count()
NAs = pd.concat([total,pct],axis=1,keys=('Total','Pct'
))
NAs[NAs.Total>0].sort_values(by='Total',ascending=Fals
e)
```

Out[13]:

	Total	Pct
Outcome	3798	0.759752
Communication	1123	0.224645
Education	216	0.043209
Job	24	0.004801

In [14]:

```
all_df = all.copy()

# Fill missing outcome as not in previous campaign
all_df[all_df['DaysPassed']==-1].count()
all_df.loc[all_df['DaysPassed']==-1,'Outcome']='NoPre
v'

# Fill missing communication with none
all_df['Communication'].value_counts()
all_df['Communication'].fillna('None',inplace=True)

# Fill missing education with the most common education
level by job type
all_df['Education'].value_counts()

# Create job-education level mode mapping
edu_mode=[]
job_types = all_df.Job.value_counts().index
for job in job_types:
    mode = all_df[all_df.Job==job]['Education'].value_
counts().nlargest(1).index
    edu_mode = np.append(edu_mode,mode)
edu_map=pd.Series(edu_mode,index=all_df.Job.value_coun
ts().index)

# Apply the mapping to missing eductaion obs
for j in job_types:
    all_df.loc[(all_df['Education'].isnull()) & (all_d
f['Job']==j),'Education'] = edu_map.loc[edu_map.index=
=j][0]
all_df['Education'].fillna('None',inplace=True)

# Fill missing job with none
all_df['Job'].fillna('None',inplace=True)

# Double check if there is still any missing value
all_df.isnull().sum().sum()
```

Out[14]:

```
0
```

Feature Engineering

There are three types of features:
Client features: Age, Job, Marital, Education, Default, Balance, HHInsurance, CarLoan
Communication features: LastContactDay, LastContactMonth, CallStart, CallEnd, Communication, NoOfContacts, DaysPassed
Previous campaign features: PrevAttempts, Outcome

In [15]:

```
# First simplify some client features

# Create age group based on age bands
all_df['AgeBand']=pd.cut(all_df['Age'],5)
print(all_df['AgeBand'].value_counts())

all_df.loc[(all_df['Age']>=17) & (all_df['Age']<34),'A
geBin'] = 1
all_df.loc[(all_df['Age']>=34) & (all_df['Age']<49),'A
geBin'] = 2
all_df.loc[(all_df['Age']>=49) & (all_df['Age']<65),'A
geBin'] = 3
all_df.loc[(all_df['Age']>=65) & (all_df['Age']<80),'A
geBin'] = 4
all_df.loc[(all_df['Age']>=80) & (all_df['Age']<96),'A
geBin'] = 5
all_df['AgeBin'] = all_df['AgeBin'].astype(int)

# Create balance groups
all_df['BalanceBand']=pd.cut(all_df['Balance'],5)
print(all_df['BalanceBand'].value_counts())
all_df.loc[(all_df['Balance']>=-3200) & (all_df['Balan
ce']<17237),'BalanceBin'] = 1
all_df.loc[(all_df['Balance']>=17237) & (all_df['Balan
ce']<37532),'BalanceBin'] = 2
all_df.loc[(all_df['Balance']>=37532) & (all_df['Balan
ce']<57827),'BalanceBin'] = 3
all_df.loc[(all_df['Balance']>=57827) & (all_df['Balan
ce']<78122),'BalanceBin'] = 4
all_df.loc[(all_df['Balance']>=78122) & (all_df['Balan
ce']<98418),'BalanceBin'] = 5
all_df['BalanceBin'] = all_df['BalanceBin'].astype(int
)

all_df = all_df.drop(['AgeBand','BalanceBand','Age','B
alance'],axis=1)

# Convert education level to numeric
all_df['Education'] = all_df['Education'].replace({'No
ne':0,'primary':1,'secondary':2,'tertiary':3})
```

```
(33.4, 48.8]      2184
(17.923, 33.4]    1508
(48.8, 64.2]      1147
(64.2, 79.6]       133
(79.6, 95.0]        27
Name: AgeBand, dtype: int64
(-3113.645, 8071.0]    4847
(8071.0, 19200.0]       123
(19200.0, 30329.0]       20
(30329.0, 41458.0]        5
(41458.0, 52587.0]        4
Name: BalanceBand, dtype: int64
```

In [16]:

```
# Next create some new communication Features. This is
 the place feature engineering coming into play

# Get call length
all_df['CallEnd'] = pd.to_datetime(all_df['CallEnd'])
all_df['CallStart'] = pd.to_datetime(all_df['CallStar
t'])
all_df['CallLength'] = ((all_df['CallEnd'] - all_df['C
allStart'])/np.timedelta64(1,'m')).astype(float)
all_df['CallLenBand']=pd.cut(all_df['CallLength'],5)
print(all_df['CallLenBand'].value_counts())

# Create call length bins
all_df.loc[(all_df['CallLength']>= 0) & (all_df['CallL
ength']<11),'CallLengthBin'] = 1
all_df.loc[(all_df['CallLength']>=11) & (all_df['CallL
ength']<22),'CallLengthBin'] = 2
all_df.loc[(all_df['CallLength']>=22) & (all_df['CallL
ength']<33),'CallLengthBin'] = 3
all_df.loc[(all_df['CallLength']>=33) & (all_df['CallL
ength']<44),'CallLengthBin'] = 4
all_df.loc[(all_df['CallLength']>=44) & (all_df['CallL
ength']<55),'CallLengthBin'] = 5
all_df['CallLengthBin'] = all_df['CallLengthBin'].asty
pe(int)
all_df = all_df.drop('CallLenBand',axis=1)

# Get call start hour
all_df['CallStartHour'] = all_df['CallStart'].dt.hour
print(all_df[['CallStart','CallEnd','CallLength','Call
StartHour']].head())

# Get workday of last contact based on call day and mon
th, assuming the year is 2016
all_df['LastContactDate'] = all_df.apply(lambda x:date
time.datetime.strptime("%s %s %s" %(2016,x['LastContac
tMonth'],x['LastContactDay']),"%Y %b %d"),axis=1)
all_df['LastContactWkd'] = all_df['LastContactDate'].d
t.weekday
all_df['LastContactWkd'].value_counts()
all_df['LastContactMon'] = all_df['LastContactDate'].d
t.month
all_df = all_df.drop('LastContactMonth',axis=1)

# Get week of last contact
all_df['LastContactWk'] = all_df['LastContactDate'].dt
.week

# Get num of week in a month. There might be easier way
s to do this, I will keep exploring.
MonWk = all_df.groupby(['LastContactWk','LastContactMo
n'])['Education'].count().reset_index()
MonWk = MonWk.drop('Education',axis=1)
MonWk['LastContactWkNum']=0
for m in range(1,13):
    k=0
    for i,row in MonWk.iterrows():
        if row['LastContactMon']== m:
```

```
        if row['LastContactMon']== m:
            k=k+1
            row['LastContactWkNum']=k

def get_num_of_week(df):
    for i,row in MonWk.iterrows():
        if (df['LastContactWk']== row['LastContactWk'
]) & (df['LastContactMon']== row['LastContactMon']):
            return row['LastContactWkNum']

all_df['LastContactWkNum'] = all_df.apply(lambda x: ge
t_num_of_week(x),axis=1)
print(all_df[['LastContactWkNum','LastContactWk','Last
ContactMon']].head(10))
```

```
(0.0292, 10.91]     4274
(10.91, 21.737]      601
(21.737, 32.563]     104
(32.563, 43.39]       15
(43.39, 54.217]        5
Name: CallLenBand, dtype: int64
                  CallStart             C
allEnd  CallLength  CallStartHour
train 0 2017-07-20 13:45:20 2017-07-20 1
3:46:30    1.166667            13
      1 2017-07-20 14:49:03 2017-07-20 1
4:52:08    3.083333            14
      2 2017-07-20 16:30:24 2017-07-20 1
6:36:04    5.666667            16
      3 2017-07-20 12:06:43 2017-07-20 1
2:20:22   13.650000            12
      4 2017-07-20 14:35:44 2017-07-20 1
4:38:56    3.200000            14
         LastContactWkNum  LastContactWk
LastContactMon
train 0                 4             4
1
      1                 4            21
5
      2                 1            22
6
      3                 2            19
5
      4                 1            22
6
      5                 3            20
5
      6                 3            11
3
      7                 2            19
5
      8                 3            46
11
      9                 2            19
5
```

The two previous campaign features are good to go, no cleaning needed. I

The two previous campaign features are good to go, no cleaning needed. I also tried to add some interactions and polynomial features, but none of them seems helpful. I am planning to explore more on this.

Assembling Final Datasets

In [17]:

```
# Spilt numeric and categorical features
cat_feats = all_df.select_dtypes(include=['object']).c
olumns
num_feats = all_df.select_dtypes(include=['float64','i
nt64']).columns
num_df = all_df[num_feats]
cat_df = all_df[cat_feats]
print('There are %d numeric features and %d categorica
l features\n' %(len(num_feats),len(cat_feats)))
print('Numeric features:\n',num_feats.values)
print('Categorical features:\n',cat_feats.values)
```

```
There are 17 numeric features and 4 categ
orical features

Numeric features:
 ['Education' 'Default' 'HHInsurance' 'Ca
rLoan' 'LastContactDay'
 'NoOfContacts' 'DaysPassed' 'PrevAttempt
s' 'AgeBin' 'BalanceBin'
 'CallLength' 'CallLengthBin' 'CallStartH
our' 'LastContactWkd'
 'LastContactMon' 'LastContactWk' 'LastCo
ntactWkNum']
Categorical features:
 ['Job' 'Marital' 'Communication' 'Outcom
e']
```

In [18]:

```
# One hot encoding
cat_df = pd.get_dummies(cat_df)
```

In [19]:

```
# Merge all features
all_data = pd.concat([num_df,cat_df],axis=1)
```

In [20]:

```
# Split train and test
idx=pd.IndexSlice
train_df=all_data.loc[idx[['train',],:]]
test_df=all_data.loc[idx[['test',],:]]
```

```
train_label=train['CarInsurance']
print(train_df.shape)
print(len(train_label))
print(test_df.shape)
```

```
(3999, 39)
3999
(1000, 39)
```

In [21]:

```
# Train test split
x_train, x_test, y_train, y_test = train_test_split(tr
ain_df,train_label,test_size = 0.3,random_state=3)
```

Modeling

In [22]:

```
# Create a cross validation function
def get_best_model(estimator, params_grid={}):

    model = GridSearchCV(estimator = estimator,param_g
rid = params_grid,cv=3, scoring="accuracy", n_jobs= -1
)
    model.fit(x_train,y_train)
    print('\n--- Best Parameters ---------------------
--------')
    print(model.best_params_)
    print('\n--- Best Model --------------------------
---')
    best_model = model.best_estimator_
    print(best_model)
    return best_model
```

In [23]:

```
# Create a model fitting function
def model_fit(model,feature_imp=True,cv=5):

    # model fit
    clf = model.fit(x_train,y_train)

    # model prediction
    y_pred = clf.predict(x_test)

    # model report
    cm = confusion_matrix(y_test,y_pred)
    plot_confusion_matrix(cm, classes=class_names, tit
le='Confusion matrix')

    print('\n--- Train Set ---------------------------
```

```
--')
    print('Accuracy: %.5f +/- %.4f' % (np.mean(cross_v
al_score(clf,x_train,y_train,cv=cv)),np.std(cross_val_
score(clf,x_train,y_train,cv=cv))))
    print('AUC: %.5f +/- %.4f' % (np.mean(cross_val_sc
ore(clf,x_train,y_train,cv=cv,scoring='roc_auc')),np.s
td(cross_val_score(clf,x_train,y_train,cv=cv,scoring=
'roc_auc'))))
    print('\n--- Validation Set ----------------------
-------')
    print('Accuracy: %.5f +/- %.4f' % (np.mean(cross_v
al_score(clf,x_test,y_test,cv=cv)),np.std(cross_val_sc
ore(clf,x_test,y_test,cv=cv))))
    print('AUC: %.5f +/- %.4f' % (np.mean(cross_val_sc
ore(clf,x_test,y_test,cv=cv,scoring='roc_auc')),np.std
(cross_val_score(clf,x_test,y_test,cv=cv,scoring='roc_
auc'))))
    print('-------------------------------------------
----')

    # feature importance
    if feature_imp:
        feat_imp = pd.Series(clf.feature_importances_,
index=all_data.columns)
        feat_imp = feat_imp.nlargest(15).sort_values()
        plt.figure()
        feat_imp.plot(kind="barh",figsize=(6,8),title=
"Most Important Features")
```

In [24]:

```
# The confusion matrix plotting function is from the sk
learn documentation below:
# http://scikit-learn.org/stable/auto_examples/model_se
lection/plot_confusion_matrix.html
import itertools
def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matri
x.
    Normalization can be applied by setting `normalize=
True`.
    """
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np
.newaxis]

    thresh = cm.max() / 2.
```

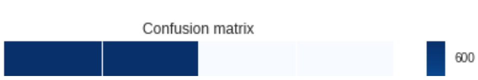
```
    for i, j in itertools.product(range(cm.shape[0]),
range(cm.shape[1])):
        plt.text(j, i, cm[i, j],
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh el
se "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')

class_names = ['Success','Failure']
```

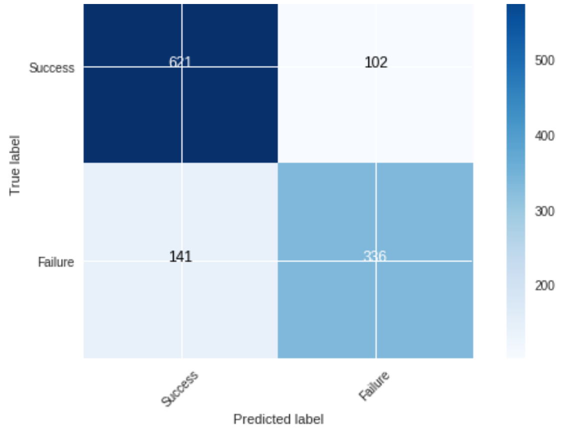
k-Nearest Neighbors (KNN)

In [25]:

```
# Let's start with KNN. An accuracy of 0.76 is not very
impressive. I will just take this as the model benchmar
k.
knn = KNeighborsClassifier()
parameters = {'n_neighbors':[5,6,7],
              'p':[1,2],
              'weights':['uniform','distance']}
clf_knn = get_best_model(knn,parameters)
model_fit(model=clf_knn, feature_imp=False)
```

```
--- Best Parameters ---------------------
--------
{'n_neighbors': 6, 'p': 2, 'weights': 'di
stance'}

--- Best Model --------------------------
---
KNeighborsClassifier(algorithm='auto', le
af_size=30, metric='minkowski',
           metric_params=None, n_jobs=1,
n_neighbors=6, p=2,
           weights='distance')

--- Train Set ---------------------------
--
Accuracy: 0.81854 +/- 0.0222
AUC: 0.88925 +/- 0.0154

--- Validation Set ----------------------
-------
Accuracy: 0.76491 +/- 0.0254
AUC: 0.84183 +/- 0.0121
----------------------------------------
------
```



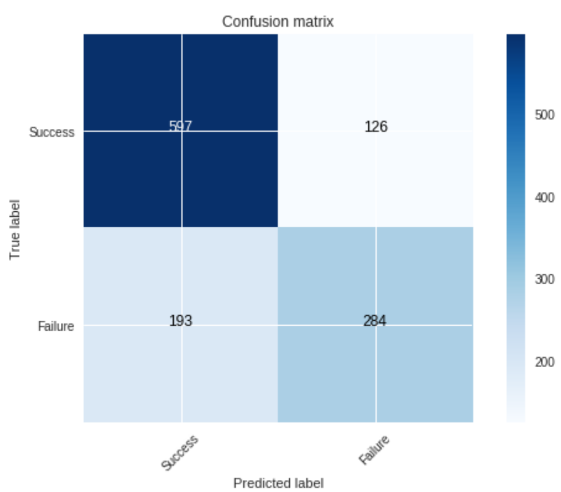


Naive Bayes Classifier

In [26]:

```
# As expected, Naive Bayes classifier doesn't perform w
ell here.
# There are multiple reasons. Some of the numeric featu
res are not normally distributed, which is a strong ass
emption hold by Naive Bayes.
# Also, features are definitely not independent.
clf_nb = GaussianNB()
model_fit(model=clf_nb,feature_imp=False)
```

```
--- Train Set ---------------------------
--
Accuracy: 0.75849 +/- 0.0148
AUC: 0.81460 +/- 0.0092

--- Validation Set ----------------------
-------
Accuracy: 0.73331 +/- 0.0122
AUC: 0.79530 +/- 0.0341
-----------------------------------------
------
```

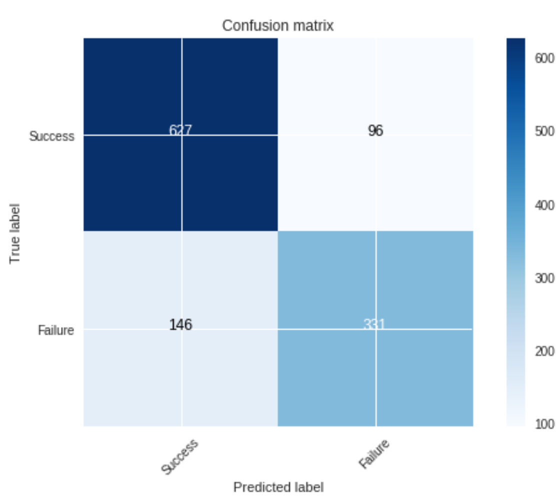


Logistic Regression

In [27]:

```
# We're making progress here. Logistic regression perfo
rms better than KNN.
lg = LogisticRegression(random_state=3)
parameters = {'C':[0.8,0.9,1],
              'penalty':['l1','l2']}
clf_lg = get_best_model(lg,parameters)
model_fit(model=clf_lg, feature_imp=False)
```

```
--- Best Parameters ---------------------
--------
{'C': 0.9, 'penalty': 'l1'}

--- Best Model --------------------------
---
LogisticRegression(C=0.9, class_weight=No
ne, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=1
00, multi_class='ovr', n_jobs=1,
          penalty='l1', random_state=3, s
olver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)

--- Train Set ---------------------------
--
Accuracy: 0.81923 +/- 0.0112
AUC: 0.89938 +/- 0.0132

--- Validation Set ----------------------
-------
Accuracy: 0.80413 +/- 0.0109
AUC: 0.88579 +/- 0.0133
-----------------------------------------
------
```

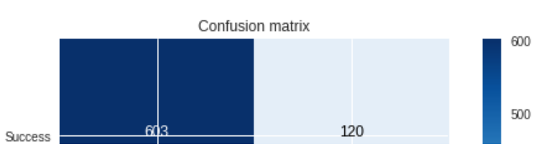


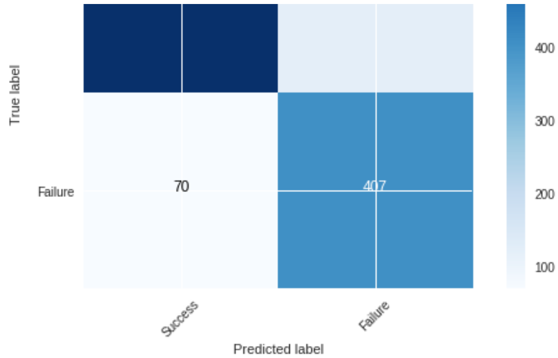
Random Forest

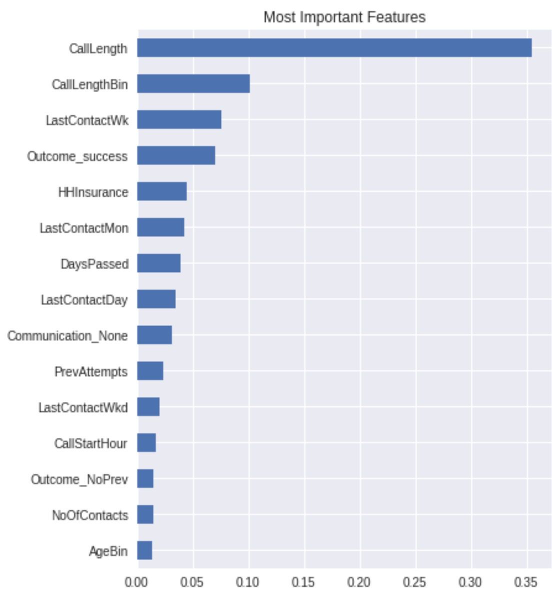
In [28]:

```
# I did some manual parameter tuning here. This is the
 best model so far.
# Based on the feature importance report, call length,
 last contact week, and previous success are strong pre
dictors of cold call success
rf = RandomForestClassifier(random_state=3)
parameters={'n_estimators':[100],
            'max_depth':[10],
            'max_features':[13,14],
            'min_samples_split':[11]}
clf_rf= get_best_model(rf,parameters)
model_fit(model=clf_rf, feature_imp=True)
```

```
--- Best Parameters ---------------------
--------
{'max_depth': 10, 'max_features': 13, 'mi
n_samples_split': 11, 'n_estimators': 10
0}

--- Best Model -------------------------
---
RandomForestClassifier(bootstrap=True, cl
ass_weight=None, criterion='gini',
            max_depth=10, max_features=1
3, max_leaf_nodes=None,
            min_impurity_decrease=0.0, mi
n_impurity_split=None,
            min_samples_leaf=1, min_sampl
es_split=11,
            min_weight_fraction_leaf=0.0,
n_estimators=100, n_jobs=1,
            oob_score=False, random_state
=3, verbose=0, warm_start=False)

--- Train Set ---------------------------
--
Accuracy: 0.84495 +/- 0.0074
AUC: 0.92308 +/- 0.0078

--- Validation Set ----------------------
-------
Accuracy: 0.82081 +/- 0.0115
AUC: 0.90453 +/- 0.0081
-----------------------------------------
------
```







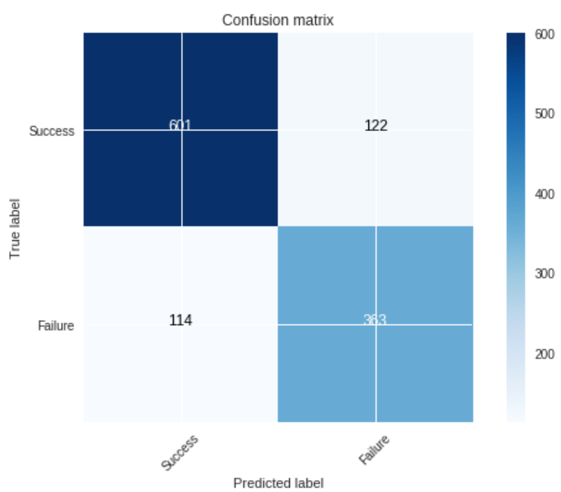
Support Vector Machines

In [29]:

```
# try a SVM RBF model
svc = svm.SVC(kernel='rbf', probability=True, random_s
tate=3)
parameters = {'gamma': [0.005,0.01,0.02],
              'C': [0.5,1,5]}
clf_svc = get_best_model(svc, parameters)
model_fit(model=clf_svc,feature_imp=False)
```

```
--- Best Parameters ---------------------
--------
{'C': 1, 'gamma': 0.01}

--- Best Model -------------------------
---
SVC(C=1, cache_size=200, class_weight=Non
e, coef0=0.0,
  decision_function_shape='ovr', degree=
3, gamma=0.01, kernel='rbf',
  max_iter=-1, probability=True, random_s
```

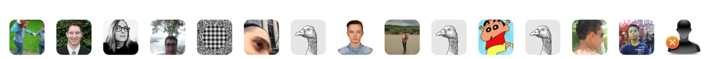
```
  max_iter=-1, probability=True, random_s
tate=3, shrinking=True, tol=0.001,
  verbose=False)

--- Train Set ---------------------------
--
Accuracy: 0.83569 +/- 0.0215
AUC: 0.90523 +/- 0.0149

--- Validation Set ----------------------
-------
Accuracy: 0.78242 +/- 0.0253
AUC: 0.86055 +/- 0.0155
-----------------------------------------
------
```



XGBoost

In [30]:

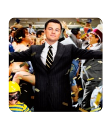
```
# Finally let's try out XBGoost. As expected, it outper
forms all other algorithms.
# Also, based on feature importances, some of the newly
```

Data

Data Sources

Car Insurance Cold Calls



Car Insurance Cold Calls

We help the guys and girls at the front to get out of Cold Call Hell

carInsurance_test.csv 19 columns
carInsurance_train.csv 19 columns
DSS_DMC_Description.pdf

Last Updated: 2 years ago (Version 1)

About this Dataset

Introduction

Here you find a very simple, beginner-friendly data set. No sparse matrices, no fancy tools needed to understand what's going on. Just a couple of rows and columns. Super simple stuff. As explained below, this data set is used for a competition. As it turns out, this competition tends to reveal a common truth in data science: KISS - Keep It Simple Stupid

What is so special about this data set is, given it's simplicity, it pays off to use "simple" classifiers as well. This year's competition was won by a C5.0 . Can you do better?

Description

We are looking at cold call results. Turns out, same salespeople called existing insurance customers up and tried to sell car insurance. What you have are details about the called customers. Their age, job, marital status, whether the have home insurance, a car loan, etc. As I said, super simple.

What I would love to see is some of you applying some crazy XGBoost classifiers, which we can square off against some logistic regressions. It would be curious to see what comes out on top. Thank you for your time, I hope you enjoy using the data set.

Acknowledgements

Thanks goes to the Decision Science and Systems Chair of Technical University of Munich (TUM) for getting the data set

Comments (5)

All Comments | Sort by Hotness

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geher • Posted on Latest Version • 2 years ago • Options • Reply 1

I'd infer that call length is such a highly predictive feature as a call naturally takes longer if a customer decides to purchase a policy on the phone. In terms of using this model to choose which customers to contact, I suppose this would need to be excluded as a feature. Very interesting kernel, thanks a lot.

abolfazl lotfabadi • Posted on Latest Version • 10 months ago • Options • Reply 0

Simple and high profile analysis
thank you Emma

Eugene Ivanin • Posted on Latest Version • a year ago • Options • Reply 0

Thanks for your kernel, really useful !

Samuel Reuther • Posted on Latest Version • 2 years ago • Options • Reply 0

Nice kernel.
I had the same thought as geher that "CallLength" could be a bad feature, because it might be target leakage (contain information, that would not be available when you would use that model in reality).
I read in the documentation, that CallStart and CallEnd refere to the last call. So I think, there is no problem at all if the last contact has been during a previous marketing campaign.
And if the client has been contacted for the actual marketing campaign before, the amount of time a customer has taken to listen to the offering is very telling. The question that your model is answering is: "Should the company call that customer (again)?" And it seams CallLength is the best indicator for answering that question.
So in any case CallLength is a great derived feature of yours.

GregKondla • Posted on Version 3 of 4 • 2 years ago • Options • Reply 0

That is a fantastic kernel, thank you Emma!
Also, thank you for the next step suggestions, I learned a lot from just reading your code.