Cold Calls: Data Mining and Model Selection

Python notebook using data from Car Insurance Cold Calls · 4,753 views · 2y ago

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Version 4
4 commits

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, ExtraTreesClassif
ier,GradientBoostingClassifier, VotingClassifier
from sklearn.naive_bayes import GaussianNB
```

```
/opt/conda/lib/python3.6/site-packages/sklearn/cross_validation.py:41:
DeprecationWarning: This module was deprecated in version 0.18 in favo
r of the model_selection module into which all the refactored classes
and functions are moved. Also note that the interface of the new CV it
erators are different from that of this module. This module will be re
moved in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/grid_search.py:42: Depr
ecationWarning: This module was deprecated in version 0.18 in favor of
the model_selection module into which all the refactored classes and f
unctions 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 features' % (train
.shape[0], train.shape[1]))
print('The test dataset has %d observations and %d features' % (test.s
hape[0], test.shape[1]))
```

```
The train dataset has 4000 observations and 19 features
The test dataset has 1000 observations and 19 features
```

Data Exploration & Visualization

In [4]:

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

Out[4]:

	Id	Age	Default	Balance	HHInsurance	CarLoan	LastC
count	4000.000000	4000.000000	4000.000000	4000.000000	4000.00000	4000.000000	4000.
mean	2000.500000	41.214750	0.014500	1532.937250	0.49275	0.133000	15.72
std	1154.844867	11.550194	0.119555	3511.452489	0.50001	0.339617	8.425
min	1.000000	18.000000	0.000000	-3058.000000	0.00000	0.000000	1.000
25%	1000.750000	32.000000	0.000000	111.000000	0.00000	0.000000	8.000
50%	2000.500000	39.000000	0.000000	551.500000	0.00000	0.000000	16.00
75%	3000.250000	49.000000	0.000000	1619.000000	1.00000	0.000000	22.00
max	4000.000000	95.000000	1.000000	98417.000000	1.00000	1.000000	31.00

In [5]:

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

Out[5]:

	Job	Marital	Education	Communication	LastContactMonth	Outcome	CallStart
count	3981	4000	3831	3098	4000	958	4000
unique	11	3	3	2	12	3	3777
top	management	married	secondary	cellular	may	failure	15:48:27
freq	893	2304	1988	2831	1049	437	3

In [6]:

```
train.head()
```

Out[6]:

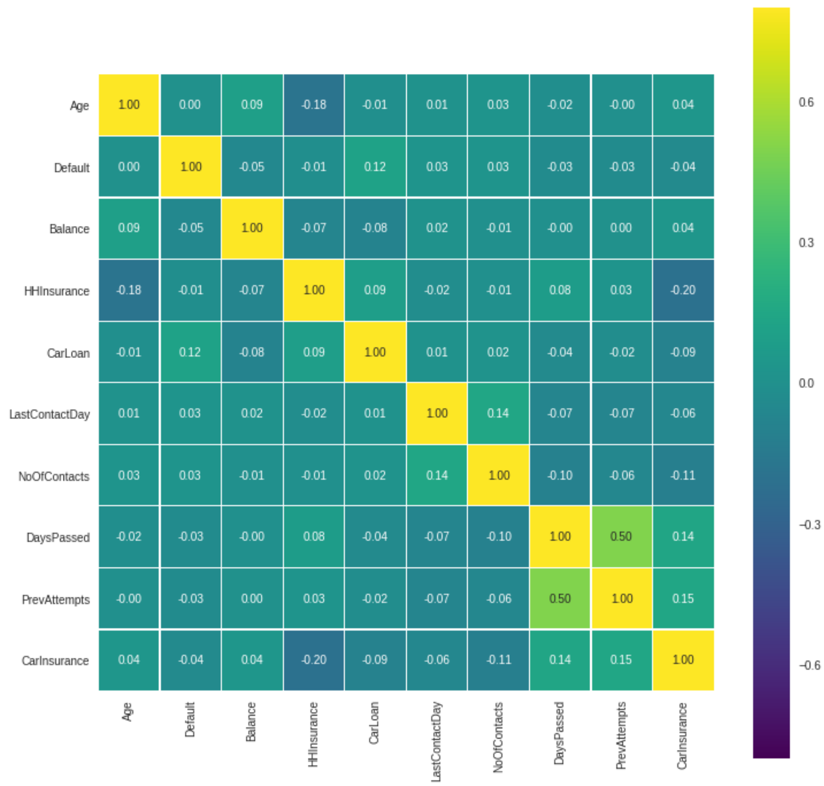
	Id	Age	Job	Marital	Education	Default	Balance	HHInsurance	CarLoan	Comm
0	1	32	management	single	tertiary	0	1218	1	0	telepho
1	2	32	blue-collar	married	primary	0	1156	1	0	NaN
2	3	29	management	single	tertiary	0	637	1	0	cellula
3	4	25	student	single	primary	0	373	1	0	cellula
4	5	30	management	married	tertiary	0	2694	0	0	cellula

In [7]:

```
# First check out correlations among numeric features
# Heatmap is a useful tool to get a quick understanding of which variabl
es 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=Tru
e,annot_kws={'size':10},linecolor='white',linewidths=0.1)
```

Out[7]:

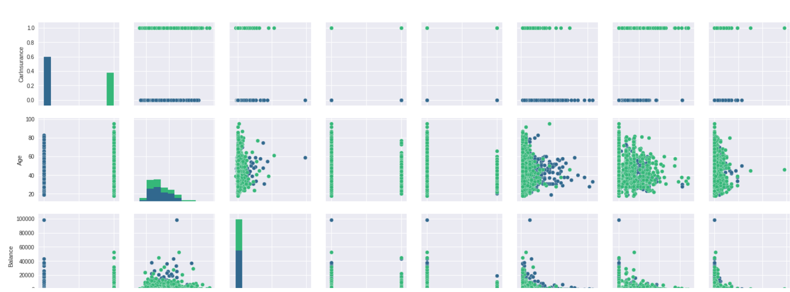
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb054a96978>
```



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','HHInsurance', 'CarLoan',
'NoOfContacts','DaysPassed','PrevAttempts']
sns.pairplot(train[imp_feats],hue='CarInsurance',palette='viridis',siz
e=2.5)
plt.show()
```



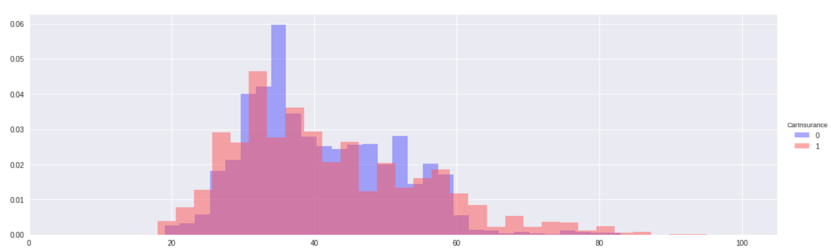
Age: It's interesting to see that seniors are more likely to buy car insurance.
Balance: For balance, the data point at the upper right corner might be an outlier
HHInsurance: Households insured are less likely to buy car insurance
CarLoan: People with car loan are less likely to buy
NoOfContacts: Too 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,palett
e='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]:

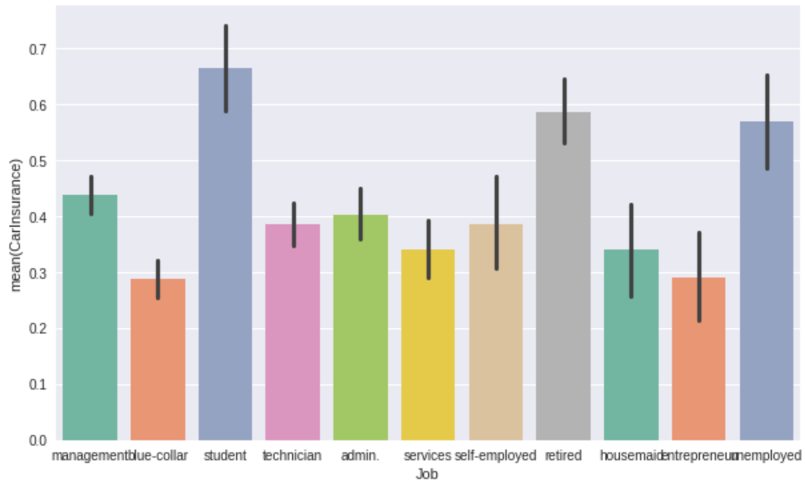
```
<seaborn.axisgrid.FacetGrid at 0x7fb0489efe10>
```

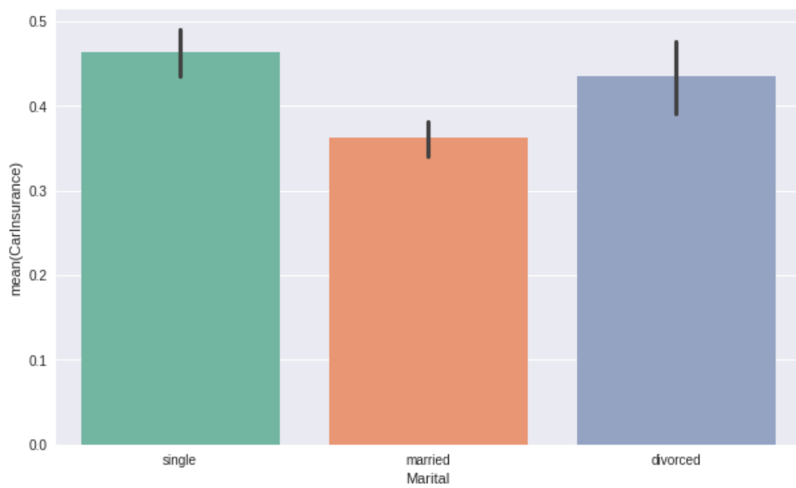


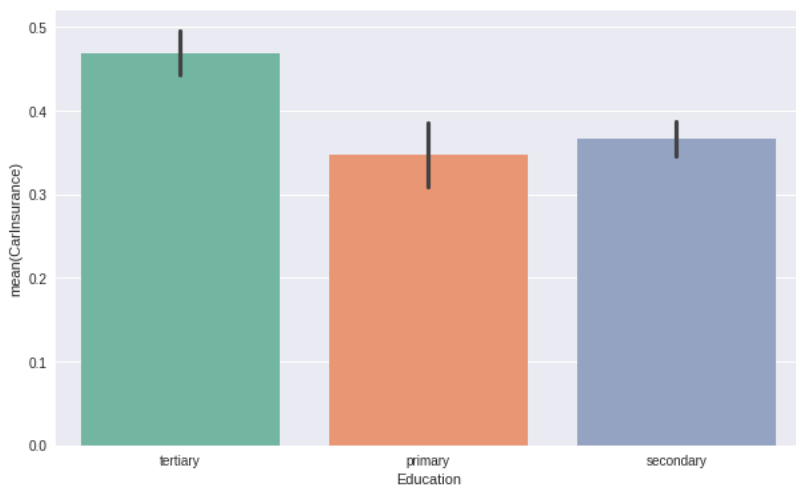
It looks like young people(<=30 years) and seniors are more likely to buy car insurance from this bank

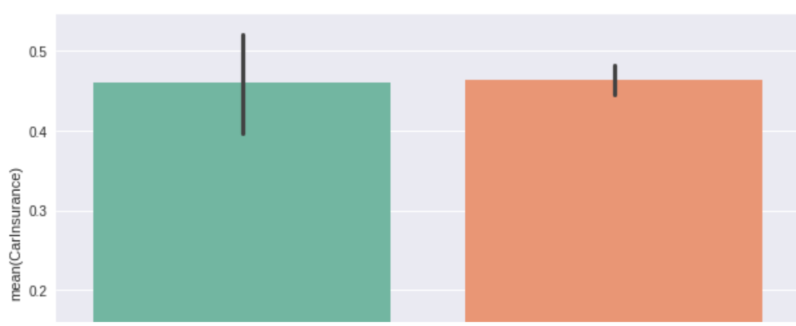
In [10]:

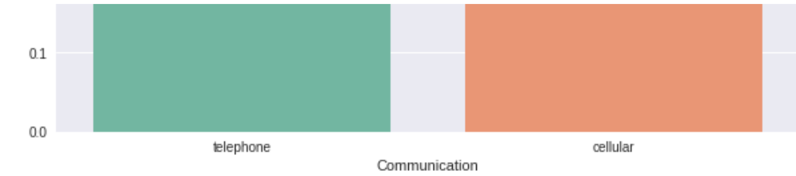
```
# Next check out categorical features
cat_feats = train.select_dtypes(include=['object']).columns
plt_feats = cat_feats[(cat_feats!= 'CallStart') & (cat_feats!='CallEn
d')]

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

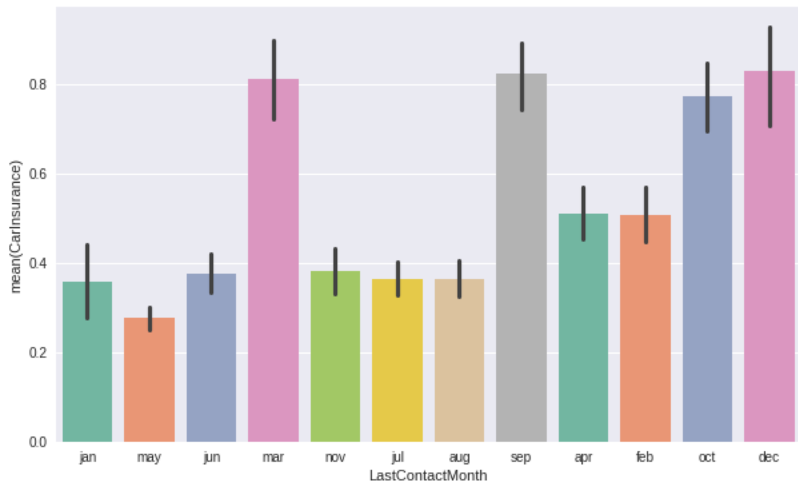

mean(CarInsurance)
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
management
blue-collar
student
technician
admin.
services
self-employed
retired
housemaid
entrepreneur
unemployed
Job

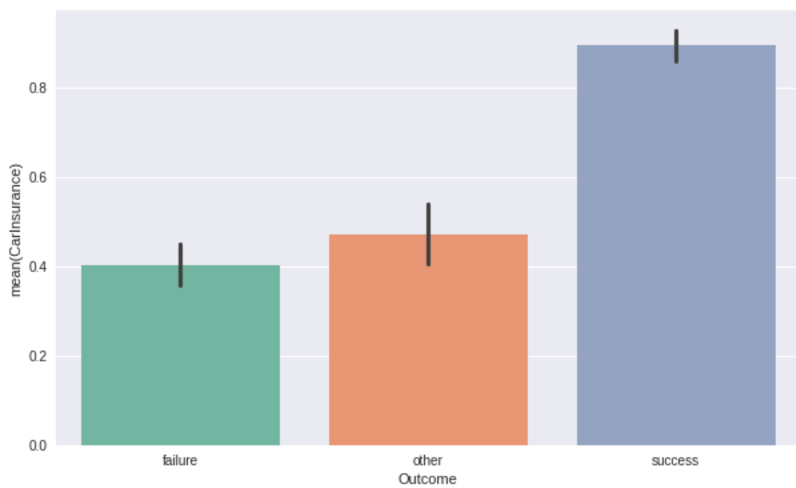

mean(CarInsurance)
0.0
0.1
0.2
0.3
0.4
0.5
single
married
divorced
Marital


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


mean(CarInsurance)
0.2
0.3
0.4
0.5







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 with extreme high ba
lance. 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 missing values all a
t 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=False)
```

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']='NoPrev'

# 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 typ
e
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().nlarges
t(1).index
    edu_mode = np.append(edu_mode,mode)
edu_map=pd.Series(edu_mode,index=all_df.Job.value_counts().index)

# Apply the mapping to missing eductaion obs
for j in job_types:
    all_df.loc[(all_df['Education'].isnull()) & (all_df['Job']==j),'Ed
ucation'] = 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),'AgeBin'] = 1
all_df.loc[(all_df['Age']>=34) & (all_df['Age']<49),'AgeBin'] = 2
all_df.loc[(all_df['Age']>=49) & (all_df['Age']<65),'AgeBin'] = 3
all_df.loc[(all_df['Age']>=65) & (all_df['Age']<80),'AgeBin'] = 4
all_df.loc[(all_df['Age']>=80) & (all_df['Age']<96),'AgeBin'] = 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['Balance']<17237),'Bal
anceBin'] = 1
all_df.loc[(all_df['Balance']>=17237) & (all_df['Balance']<37532),'Bal
anceBin'] = 2
all_df.loc[(all_df['Balance']>=37532) & (all_df['Balance']<57827),'Bal
anceBin'] = 3
all_df.loc[(all_df['Balance']>=57827) & (all_df['Balance']<78122),'Bal
anceBin'] = 4
all_df.loc[(all_df['Balance']>=78122) & (all_df['Balance']<98418),'Bal
anceBin'] = 5
all_df['BalanceBin'] = all_df['BalanceBin'].astype(int)

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

# Convert education level to numeric
all_df['Education'] = all_df['Education'].replace({'None':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
```

```
(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['CallStart'])
all_df['CallLength'] = ((all_df['CallEnd'] - all_df['CallStart'])/np.t
imedelta64(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['CallLength']<11),'Cal
lLengthBin'] = 1
all_df.loc[(all_df['CallLength']>=11) & (all_df['CallLength']<22),'Cal
lLengthBin'] = 2
all_df.loc[(all_df['CallLength']>=22) & (all_df['CallLength']<33),'Cal
lLengthBin'] = 3
all_df.loc[(all_df['CallLength']>=33) & (all_df['CallLength']<44),'Cal
lLengthBin'] = 4
all_df.loc[(all_df['CallLength']>=44) & (all_df['CallLength']<55),'Cal
lLengthBin'] = 5
all_df['CallLengthBin'] = all_df['CallLengthBin'].astype(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','CallStartHour']].hea
d())

# Get workday of last contact based on call day and month, assuming the
 year is 2016
all_df['LastContactDate'] = all_df.apply(lambda x:datetime.datetime.st
rptime("%s %s %s" %(2016,x['LastContactMonth'],x['LastContactDay']),"%
Y %b %d"),axis=1)
all_df['LastContactWkd'] = all_df['LastContactDate'].dt.weekday
all_df['LastContactWkd'].value_counts()
all_df['LastContactMon'] = all_df['LastContactDate'].dt.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 ways to do this, I w
ill keep exploring.
MonWk = all_df.groupby(['LastContactWk','LastContactMon'])['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:
            k=k+1
            row['LastContactWkNum']=k

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

```
            return row['LastContactWkNum']

all_df['LastContactWkNum'] = all_df.apply(lambda x: get_num_of_week(x
),axis=1)
print(all_df[['LastContactWkNum','LastContactWk','LastContactMon']].he
ad(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             CallEnd  CallLength  CallStart
Hour
train 0 2017-07-20 13:45:20 2017-07-20 13:46:30    1.166667
13
      1 2017-07-20 14:49:03 2017-07-20 14:52:08    3.083333
14
      2 2017-07-20 16:30:24 2017-07-20 16:36:04    5.666667
16
      3 2017-07-20 12:06:43 2017-07-20 12:20:22   13.650000
12
      4 2017-07-20 14:35:44 2017-07-20 14:38:56    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 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']).columns
num_feats = all_df.select_dtypes(include=['float64','int64']).columns
num_df = all_df[num_feats]
cat_df = all_df[cat_feats]
print('There are %d numeric features and %d categorical 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 categorical features

Numeric features:
 ['Education' 'Default' 'HHInsurance' 'CarLoan' 'LastContactDay'
 'NoOfContacts' 'DaysPassed' 'PrevAttempts' 'AgeBin' 'BalanceBin'
```

```
 'CallLength' 'CallLengthBin' 'CallStartHour' 'LastContactWkd'
 'LastContactMon' 'LastContactWk' 'LastContactWkNum']
Categorical features:
 ['Job' 'Marital' 'Communication' 'Outcome']
```

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(train_df,train_lab
el,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_grid = params_gri
d,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, title='Confusion ma
trix')

    print('\n--- Train Set -----------------------------')
    print('Accuracy: %.5f +/- %.4f' % (np.mean(cross_val_score(clf,x_t
rain,y_train,cv=cv)),np.std(cross_val_score(clf,x_train,y_train,cv=cv
))))
    print('AUC: %.5f +/- %.4f' % (np.mean(cross_val_score(clf,x_train,
y_train,cv=cv,scoring='roc_auc')),np.std(cross_val_score(clf,x_train,y
_train,cv=cv,scoring='roc_auc'))))
    print('\n--- Validation Set -----------------------------')
    print('Accuracy: %.5f +/- %.4f' % (np.mean(cross_val_score(clf,x_t
est,y_test,cv=cv)),np.std(cross_val_score(clf,x_test,y_test,cv=cv))))
    print('AUC: %.5f +/- %.4f' % (np.mean(cross_val_score(clf,x_test,y
_test,cv=cv,scoring='roc_auc')),np.std(cross_val_score(clf,x_test,y_te
st,cv=cv,scoring='roc_auc'))))
    print('-----------------------------------------------')

    # feature importance
    if feature_imp:
        feat_imp = pd.Series(clf.feature_importances_,index=all_data.c
olumns)
        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 sklearn documentati
on below:
# http://scikit-learn.org/stable/auto_examples/model_selection/plot_conf
usion_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 matrix.
    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 else "black")

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

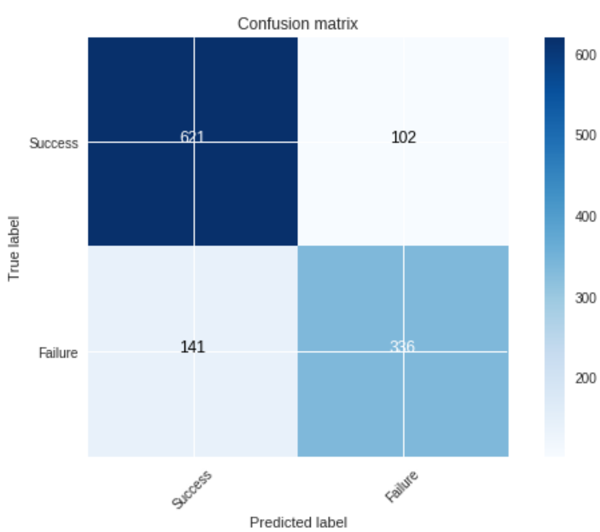
```
class_names = ['Success','Failure']
```

k-Nearest Neighbors (KNN)

In [25]:

```
# Let's start with KNN. An accuracy of 0.76 is not very impressive. I wi
ll just take this as the model benchmark.
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': 'distance'}

--- Best Model -----------------------------
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowsk
i',
           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
-----------------------------------------------
```



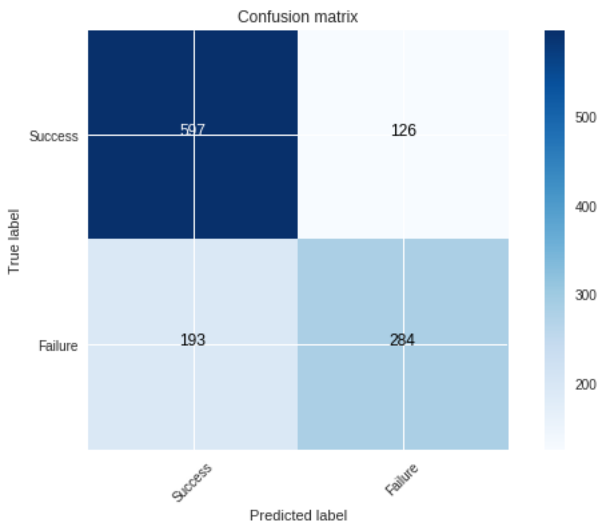
Naive Bayes Classifier

In [26]:

```
# As expected, Naive Bayes classifier doesn't perform well here.
# There are multiple reasons. Some of the numeric features are not norma
lly distributed, which is a strong assemption 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
----------------------------------------------
```

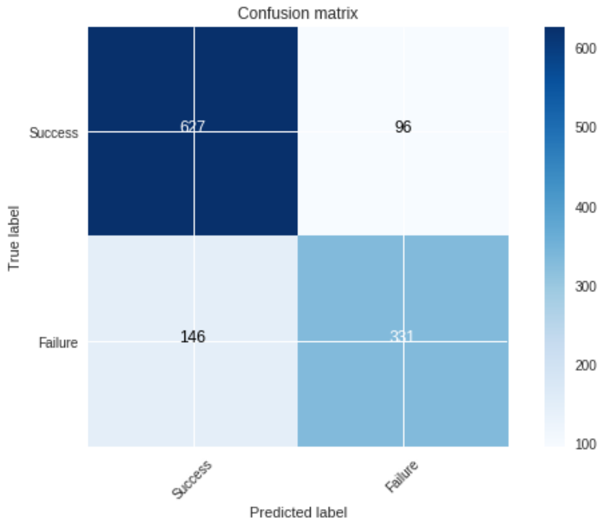


Logistic Regression

In [27]:
```
# We're making progress here. Logistic regression performs better than K
NN.
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=None, dual=False, fit_intercept
=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs
=1,
          penalty='l1', random_state=3, solver='liblinear', tol=0.000
1,
          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
-----------------------------------------------
```

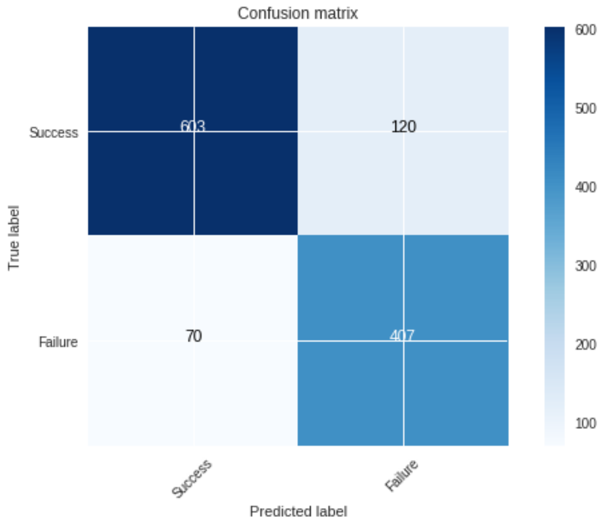


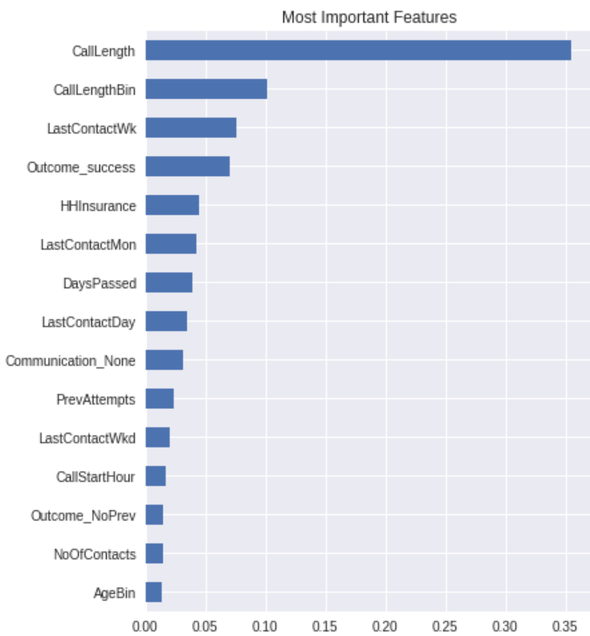
Random Forest

In [28]:

```
# I did some manual parameter tuning here. This is the best model so fa
r.
# Based on the feature importance report, call length, last contact wee
k, and previous success are strong predictors 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, 'min_samples_split': 11, 'n_esti
mators': 100}

--- Best Model -----------------------------
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='g
ini',
            max_depth=10, max_features=13, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=11,
            min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=1,
            oob_score=False, random_state=3, verbose=0, warm_start=Fal
se)

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

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





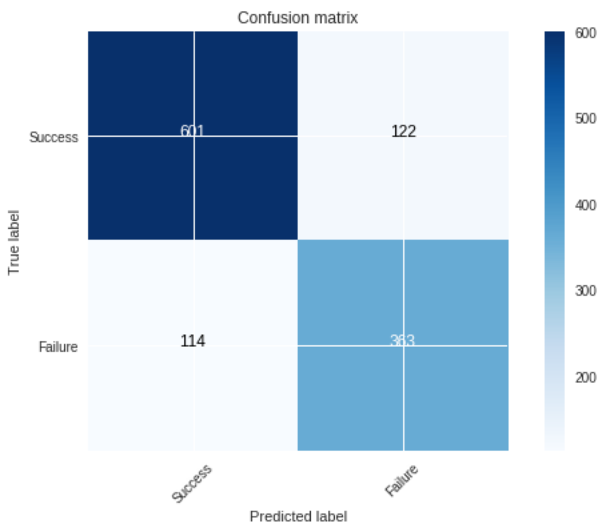
Support Vector Machines

In [29]:

```
# try a SVM RBF model
svc = svm.SVC(kernel='rbf', probability=True, random_state=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=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma=0.01, kernel='rbf',
  max_iter=-1, probability=True, random_state=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
-----------------------------------------------
```



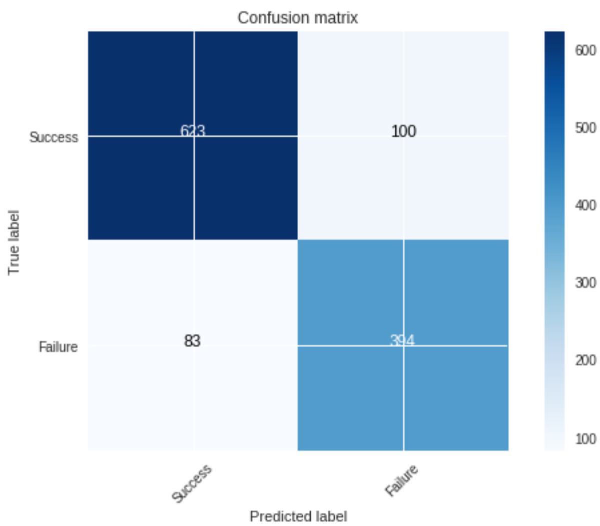
XGBoost

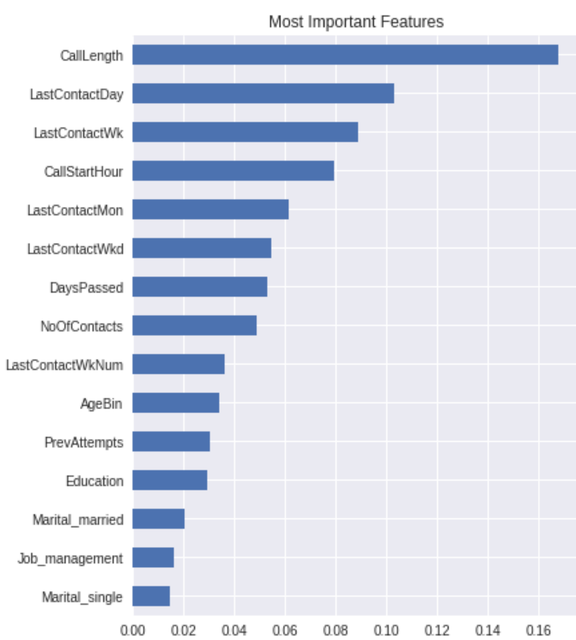
In [30]:

```
# Finally let's try out XBGoost. As expected, it outperforms all other a
lgorithms.
# Also, based on feature importances, some of the newly created features
such as call start hour, last contact week and weekday
# have been picked as top features.

import xgboost as xgb
xgb = xgb.XGBClassifier()
parameters={'n_estimators':[900,1000,1100],
            'learning_rate':[0.01],
            'max_depth':[8],
            'min_child_weight':[1],
            'subsample':[0.8],
            'colsample_bytree':[0.3,0.4,0.5]}
clf_xgb= get_best_model(xgb,parameters)
model_fit(model=clf_xgb, feature_imp=True)
```

```
--- Best Parameters -----------------------------
{'colsample_bytree': 0.3, 'learning_rate': 0.01, 'max_depth': 8, 'min_
child_weight': 1, 'n_estimators': 1000, 'subsample': 0.8}

--- Best Model -----------------------------
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=0.3, gamma=0, learning_rate=0.01, max_delta_st
ep=0,
       max_depth=8, min_child_weight=1, missing=None, n_estimators=100
0,
       n_jobs=1, nthread=None, objective='binary:logistic', random_sta
te=0,
```

```
te=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=True, subsample=0.8)

--- Train Set ----------------------------
Accuracy: 0.85424 +/- 0.0052
AUC: 0.93485 +/- 0.0070

--- Validation Set ----------------------------
Accuracy: 0.82995 +/- 0.0263
AUC: 0.91539 +/- 0.0144
----------------------------------------------
```





Model Evaluation

In [31]:

```
# Compare model performance
clfs= [clf_knn, clf_nb, clf_lg, clf_rf, clf_svc, clf_xgb]
index =['K-Nearest Neighbors','Naive Bayes','Logistic Regression','Ran
dom Forest','Support Vector Machines','XGBoost']
```

```
dom Forest', 'Support Vector Machines', 'XGBoost']
scores=[]
for clf in clfs:
    score = np.mean(cross_val_score(clf,x_test,y_test,cv=5,scoring =
'accuracy'))
    scores = np.append(scores,score)
models = pd.Series(scores,index=index)
models.sort_values(ascending=False)
```

Out[31]:

```
XGBoost                    0.829952
Random Forest              0.820813
Logistic Regression        0.804129
Support Vector Machines    0.782417
K-Nearest Neighbors        0.764906
Naive Bayes                0.733312
dtype: float64
```

Ensemble Voting

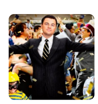
In [32]:

```
# XGBoost and Random Forest show different important features, implying
 that those models are capturing different aspects of the data
# To get the final model, I ensembled different classifiers based on maj
ority voting.
# XGBoost and Random Forest are given larger weights due to their better
performance.

clf_vc = VotingClassifier(estimators=[('xgb', clf_xgb),
```


Data

Data Sources

- Car Insurance Cold Calls
  - carInsurance_test.csv 19 columns
  - carInsurance_train.csv 19 columns
  - DSS_DMC_Description.pdf



Car Insurance Cold Calls

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

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 from a real world company and making it available to be shared

Comments (5)

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geher • Posted on Latest Version • 2 years ago — 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 — 0

Simple and high profile analysis
thank you Emma

Eugene Ivanin • Posted on Latest Version • a year ago — 0

Thanks for your kernel, really useful !

Samuel Reuther • Posted on Latest Version • 2 years ago — 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 — 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.