Chapter 5: Classification Problems

5.1 Classification Overview

5.3 Credit Classification

```
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
import numpy as np

credit_df = pd.read_csv( "German Credit Data.csv" )
credit_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 14 columns):
checkin_acc         1000 non-null object
duration            1000 non-null int64
credit_history      1000 non-null object
amount              1000 non-null int64
savings_acc         1000 non-null object
present_emp_since   1000 non-null object
inst_rate           1000 non-null int64
personal_status     1000 non-null object
residing_since      1000 non-null int64
age                 1000 non-null int64
inst_plans          1000 non-null object
num_credits         1000 non-null int64
job                 1000 non-null object
status              1000 non-null int64
dtypes: int64(7), object(7)
memory usage: 109.5+ KB
```

```
credit_df.iloc[0:5,1:7]
```

	duration	credit_history	amount	savings_acc	present_emp_since	inst_rate
0	6	A34	1169	A65	A75	4
1	48	A32	5951	A61	A73	2
2	12	A34	2096	A61	A74	2
3	42	A32	7882	A61	A74	2
4	24	A33	4870	A61	A73	3

```
credit_df.iloc[0:5,7:]
```

	personal_status	residing_since	age	inst_plans	num_credits	job	status
0	A93	4	67	A143	2	A173	0
1	A92	2	22	A143	1	A173	1
2	A93	3	49	A143	1	A172	0
3	A93	4	45	A143	1	A173	0
4	A93	4	53	A143	2	A173	1

```
credit_df.status.value_counts()
```

```
0    700
1    300
Name: status, dtype: int64
```

```
X_features = list( credit_df.columns )
X_features.remove( 'status' )
X_features
```

```
['checkin_acc',
 'duration',
 'credit_history',
 'amount',
 'savings_acc',
 'present_emp_since',
 'inst_rate',
 'personal_status',
 'residing_since',
 'age',
 'inst_plans',
 'num_credits',
 'job']
```

5.3.1 Encoding Categorical Features

```
encoded_credit_df = pd.get_dummies( credit_df[X_features],
                                    drop_first = True )
```

```
list(encoded_credit_df.columns)
```

```
['duration',
 'amount',
 'inst_rate',
 'residing_since',
 'age',
 'num_credits',
 'checkin_acc_A12',
 'checkin_acc_A13',
 'checkin_acc_A14',
 'credit_history_A31',
 'credit_history_A32',
 'credit_history_A33',
 'credit_history_A34',
 'savings_acc_A62',
 'savings_acc_A63',
 'savings_acc_A64',
 'savings_acc_A65',
 'present_emp_since_A72',
 'present_emp_since_A73',
 'present_emp_since_A74',
 'present_emp_since_A75',
 'personal_status_A92',
 'personal_status_A93',
 'personal_status_A94',
 'inst_plans_A142',
 'inst_plans_A143',
 'job_A172',
 'job_A173',
 'job_A174']
```

```
encoded_credit_df[['checkin_acc_A12',
                   'checkin_acc_A13',
                   'checkin_acc_A14']].head(5)
```

	checkin_acc_A12	checkin_acc_A13	checkin_acc_A14
0	0	0	0
1	1	0	0
2	0	0	1
3	0	0	0
4	0	0	0

```
import statsmodels.api as sm

Y = credit_df.status
X = sm.add_constant( encoded_credit_df )
```

5.3.2 Splitting into Train and Validation Sets

```
from sklearn.model_selection import train_test_split


X_train, X_test, y_train, y_test = train_test_split(X,
                                                     Y,
                                                     test_size = 0.3,
                                                     random_state = 42)
```

5.3.3 Building Logistic Regression Model

```
import statsmodels.api as sm

logit = sm.Logit(y_train, X_train)
logit_model = logit.fit()
```

```
Optimization terminated successfully.
         Current function value: 0.488938
         Iterations 6
```

5.3.4 Printing Model Summary

```
logit_model.summary2()
```

Model:	Logit	Pseudo R-squared:	0.198
Dependent Variable:	status	AIC:	744.5132
Date:	2019-04-23 21:07	BIC:	881.0456
No. Observations:	700	Log-Likelihood:	-342.26
Df Model:	29	LL-Null:	-426.75
Df Residuals:	670	LLR p-value:	1.0630e-21
Converged:	1.0000	Scale:	1.0000
No. Iterations:	6.0000		

	Coef.	**Std.Err.**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-0.1511	1.1349	-0.1331	0.8941	-2.3754	2.0733
duration	0.0206	0.0104	1.9927	0.0463	0.0003	0.0409
amount	0.0001	0.0000	2.3765	0.0175	0.0000	0.0002
inst_rate	0.3064	0.0986	3.1083	0.0019	0.1132	0.4996
residing_since	0.0967	0.0920	1.0511	0.2932	-0.0836	0.2771
age	-0.0227	0.0103	-2.2131	0.0269	-0.0428	-0.0026
num_credits	0.2854	0.2139	1.3342	0.1821	-0.1338	0.7045
checkin_acc_A12	-0.4126	0.2391	-1.7260	0.0843	-0.8812	0.0559
checkin_acc_A13	-0.9053	0.4338	-2.0868	0.0369	-1.7556	-0.0550
checkin_acc_A14	-1.6052	0.2586	-6.2073	0.0000	-2.1120	-1.0983
credit_history_A31	0.1532	0.5795	0.2643	0.7916	-0.9827	1.2890
credit_history_A32	-0.4960	0.4411	-1.1245	0.2608	-1.3604	0.3685
credit_history_A33	-0.8881	0.5022	-1.7683	0.0770	-1.8724	0.0962
credit_history_A34	-1.4124	0.4528	-3.1190	0.0018	-2.2999	-0.5249
savings_acc_A62	-0.0496	0.3208	-0.1545	0.8772	-0.6782	0.5791
savings_acc_A63	-0.6640	0.4818	-1.3779	0.1682	-1.6084	0.2804
savings_acc_A64	-1.1099	0.6019	-1.8439	0.0652	-2.2896	0.0699
savings_acc_A65	-0.6061	0.2745	-2.2080	0.0272	-1.1441	-0.0681
present_emp_since_A72	0.0855	0.4722	0.1810	0.8564	-0.8401	1.0110
present_emp_since_A73	-0.0339	0.4492	-0.0754	0.9399	-0.9142	0.8465
present_emp_since_A74	-0.3789	0.4790	-0.7910	0.4289	-1.3178	0.5600
present_emp_since_A75	-0.2605	0.4554	-0.5721	0.5673	-1.1532	0.6321
personal_status_A92	-0.0069	0.4841	-0.0142	0.9887	-0.9557	0.9419
personal_status_A93	-0.4426	0.4764	-0.9291	0.3528	-1.3762	0.4911
personal_status_A94	-0.3080	0.5554	-0.5546	0.5792	-1.3967	0.7806
inst_plans_A142	-0.2976	0.5157	-0.5772	0.5638	-1.3084	0.7131

inst_plans_A143	-0.4458	0.2771	-1.6086	0.1077	-0.9889	0.0974
job_A172	-0.0955	0.7681	-0.1243	0.9011	-1.6009	1.4100
job_A173	-0.0198	0.7378	-0.0269	0.9786	-1.4658	1.4262
job_A174	-0.0428	0.7371	-0.0581	0.9537	-1.4876	1.4019

5.3.5 Model Dignostics

```
def get_significant_vars( lm ):
    var_p_vals_df = pd.DataFrame( lm.pvalues )
    var_p_vals_df['vars'] = var_p_vals_df.index
    var_p_vals_df.columns = ['pvals', 'vars']
    return list( var_p_vals_df[var_p_vals_df.pvals <= 0.05]['vars'] )
```

```
significant_vars = get_significant_vars( logit_model )

significant_vars
```

```
['duration',
 'amount',
 'inst_rate',
 'age',
 'checkin_acc_A13',
 'checkin_acc_A14',
 'credit_history_A34',
 'savings_acc_A65']
```

```
final_logit = sm.Logit( y_train,
            sm.add_constant( X_train[significant_vars] ) ).fit()
```

```
Optimization terminated successfully.
         Current function value: 0.511350
         Iterations 6
```

```
final_logit.summary2()
```

Model:	Logit	Pseudo R-squared:	0.161
Dependent Variable:	status	AIC:	733.8898
Date:	2019-04-23 21:07	BIC:	774.8495
No. Observations:	700	Log-Likelihood:	-357.94
Df Model:	8	LL-Null:	-426.75
Df Residuals:	691	LLR p-value:	7.4185e-26
Converged:	1.0000	Scale:	1.0000
No. Iterations:	6.0000		

	Coef.	**Std.Err.**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-0.8969	0.4364	-2.0551	0.0399	-1.7523	-0.0415
duration	0.0197	0.0098	2.0033	0.0451	0.0004	0.0390
amount	0.0001	0.0000	2.3205	0.0203	0.0000	0.0002
inst_rate	0.2811	0.0929	3.0264	0.0025	0.0991	0.4632
age	-0.0216	0.0089	-2.4207	0.0155	-0.0392	-0.0041
checkin_acc_A13	-0.8038	0.4081	-1.9697	0.0489	-1.6037	-0.0040
checkin_acc_A14	-1.5452	0.2187	-7.0649	0.0000	-1.9738	-1.1165
credit_history_A34	-0.8781	0.2319	-3.7858	0.0002	-1.3327	-0.4235
savings_acc_A65	-0.5448	0.2581	-2.1108	0.0348	-1.0507	-0.0389

5.3.6 Predicting on Test Data

```
y_pred_df = pd.DataFrame( { "actual": y_test,
                            "predicted_prob": final_logit.predict(
                        sm.add_constant( X_test[significant_vars] ) ) } )
```

```
y_pred_df.sample(10, random_state = 42)
```

	actual	predicted_prob
557	1	0.080493
798	0	0.076653
977	0	0.345979
136	0	0.249919
575	0	0.062264
544	0	0.040768
332	1	0.833093
917	1	0.370667
678	0	0.388392
363	0	0.088952

```
y_pred_df['predicted'] = y_pred_df.predicted_prob.map(
                            lambda x: 1 if x > 0.5 else 0)

y_pred_df.sample(10, random_state = 42)
```

	actual	predicted_prob	predicted
557	1	0.080493	0
798	0	0.076653	0
977	0	0.345979	0
136	0	0.249919	0
575	0	0.062264	0
544	0	0.040768	0
332	1	0.833093	1
917	1	0.370667	0
678	0	0.388392	0
363	0	0.088952	0

5.3.7 Creating a Confusion Matrix

```
import matplotlib.pyplot as plt
import seaborn as sn
%matplotlib inline
from sklearn import metrics
```

```
def draw_cm( actual, predicted ):
    ## Cret
    cm = metrics.confusion_matrix( actual, predicted, [1,0] )
    sn.heatmap(cm, annot=True,  fmt='.2f',
                xticklabels = ["Bad credit", "Good Credit"] ,
                yticklabels = ["Bad credit", "Good Credit"] )
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.show()
```

```
draw_cm( y_pred_df.actual,
        y_pred_df.predicted )
```

5.3.8 Measuring Accuracies

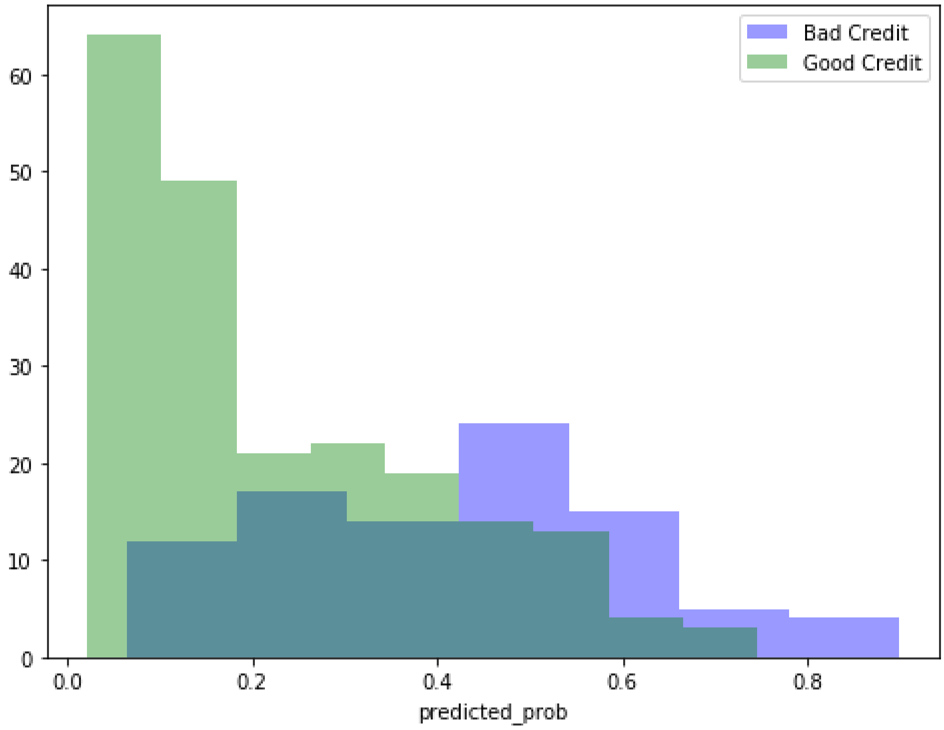
```
print( metrics.classification_report( y_pred_df.actual,
                                      y_pred_df.predicted ) )
```

```
              precision    recall  f1-score   support

           0       0.76      0.90      0.82       209
           1       0.59      0.33      0.42        91

   micro avg       0.73      0.73      0.73       300
   macro avg       0.67      0.61      0.62       300
weighted avg       0.70      0.73      0.70       300
```

```
plt.figure( figsize = (8,6) )
sn.distplot( y_pred_df[y_pred_df.actual == 1]["predicted_prob"],
            kde=False, color = 'b',
            label = 'Bad Credit' )
sn.distplot( y_pred_df[y_pred_df.actual == 0]["predicted_prob"],
            kde=False, color = 'g',
            label = 'Good Credit' )
plt.legend()
plt.show()
```



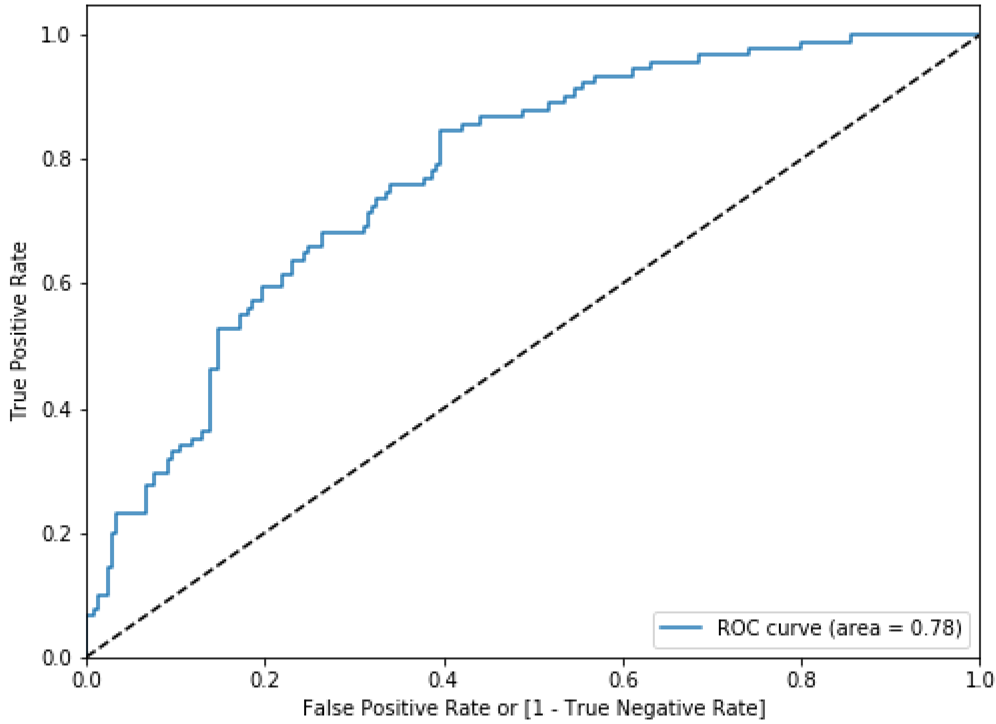
5.3.9 ROC & AUC

```
def draw_roc( actual, probs ):
    fpr, \
    tpr, \
    thresholds = metrics.roc_curve( actual,
                                    probs,
                                    drop_intermediate = False )
    auc_score = metrics.roc_auc_score( actual, probs )
    plt.figure(figsize=(8, 6))
    plt.plot( fpr, tpr, label='ROC curve (area = %0.2f)' % auc_score )
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
    plt.ylabel('True Positive Rate')
    plt.legend(loc="lower right")
    plt.show()

    return fpr, tpr, thresholds
```



```
fpr, tpr, thresholds = draw_roc( y_pred_df.actual,
                                 y_pred_df.predicted_prob)
```




```
auc_score = metrics.roc_auc_score( y_pred_df.actual,
                                   y_pred_df.predicted_prob   )
round( float( auc_score ), 2 )
```

```
0.78
```

5.3.10 Finding Optimal Cutoff

5.3.10.1 Youden's index

```
tpr_fpr = pd.DataFrame( { 'tpr': tpr,
                          'fpr': fpr,
                          'thresholds': thresholds } )

tpr_fpr['diff'] = tpr_fpr.tpr - tpr_fpr.fpr
tpr_fpr.sort_values( 'diff', ascending = False )[0:5]
```

	fpr	thresholds	tpr	diff
160	0.397129	0.221534	0.846154	0.449025
161	0.401914	0.216531	0.846154	0.444240
162	0.406699	0.215591	0.846154	0.439455
159	0.397129	0.223980	0.835165	0.438036
166	0.421053	0.207107	0.857143	0.436090

```
y_pred_df['predicted_new'] = y_pred_df.predicted_prob.map(
                                lambda x: 1 if x > 0.22 else 0)
```

```
draw_cm( y_pred_df.actual,
        y_pred_df.predicted_new)
```


```
print(metrics.classification_report( y_pred_df.actual,
                                     y_pred_df.predicted_new ))
```

```
              precision    recall  f1-score   support

           0       0.90      0.60      0.72       209
           1       0.48      0.85      0.61        91

   micro avg       0.68      0.68      0.68       300
   macro avg       0.69      0.72      0.67       300
weighted avg       0.77      0.68      0.69       300
```

5.3.10.2 Cost Based Approach

```
def get_total_cost( actual, predicted, cost_FPs, cost_FNs ):
    cm = metrics.confusion_matrix( actual, predicted, [1,0] )
    cm_mat = np.array( cm )
    return cm_mat[0,1] * cost_FNs + cm_mat[1,0] * cost_FPs
```

```
cost_df = pd.DataFrame( columns = ['prob', 'cost'])
```

```
idx = 0

## iterate cut-off probability values between 0.1 and 0.5
for each_prob in range( 10, 50):
    cost = get_total_cost( y_pred_df.actual,
                          y_pred_df.predicted_prob.map(
            lambda x: 1 if x > (each_prob/100)  else 0), 1, 5 )
    cost_df.loc[idx] = [(each_prob/100), cost]
    idx += 1
```

```
cost_df.sort_values( 'cost', ascending = True )[0:5]
```

	prob	cost
4	0.14	150.0
12	0.22	153.0
2	0.12	154.0
10	0.20	154.0
9	0.19	156.0

```
y_pred_df['predicted_using_cost'] = y_pred_df.predicted_prob.map(
    lambda x: 1 if x > 0.14 else 0)
```

```
draw_cm( y_pred_df.actual,
        y_pred_df.predicted_using_cost )
```

5.4 Gain Chart and Lift Chart

5.4.1 Loading and Preparing the Dataset

```
import pandas as pd
bank_df = pd.read_csv( 'bank.csv' )
bank_df.head( 5 )
```

	age	job	marital	education	default	balance	housing-loan	personal-loan	curre campai
0	30	unemployed	married	primary	no	1787	no	no	1
1	33	services	married	secondary	no	4789	yes	yes	1
2	35	management	single	tertiary	no	1350	yes	no	1
3	30	management	married	tertiary	no	1476	yes	yes	4
4	59	blue-collar	married	secondary	no	0	yes	no	1

```
bank_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4521 entries, 0 to 4520
Data columns (total 11 columns):
age                     4521 non-null int64
job                     4521 non-null object
marital                 4521 non-null object
education               4521 non-null object
default                 4521 non-null object
balance                 4521 non-null int64
housing-loan            4521 non-null object
personal-loan           4521 non-null object
current-campaign        4521 non-null int64
previous-campaign       4521 non-null int64
subscribed              4521 non-null object
dtypes: int64(4), object(7)
memory usage: 388.6+ KB
```

```
X_features = list( bank_df.columns )
X_features.remove( 'subscribed' )
X_features
```

```
['age',
 'job',
 'marital',
 'education',
 'default',
 'balance',
 'housing-loan',
 'personal-loan',
 'current-campaign',
 'previous-campaign']
```

```
encoded_bank_df = pd.get_dummies( bank_df[X_features],
                                  drop_first = True )
```

```
Y = bank_df.subscribed.map( lambda x: int( x == 'yes') )
X = encoded_bank_df
```

5.4.2 Building the Logistic Regression Model

```
logit_model = sm.Logit( Y, sm.add_constant( X ) ).fit()
```

```
Optimization terminated successfully.
         Current function value: 0.335572
         Iterations 7
```

```
logit_model.summary2()
```

Model:	Logit	Pseudo R-squared:	0.061
Dependent Variable:	subscribed	AIC:	3082.2384
Date:	2019-04-23 21:07	BIC:	3236.2341
No. Observations:	4521	Log-Likelihood:	-1517.1
Df Model:	23	LL-Null:	-1615.5
Df Residuals:	4497	LLR p-value:	1.4866e-29
Converged:	1.0000	Scale:	1.0000
No. Iterations:	7.0000		

	Coef.	**Std.Err.**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-1.7573	0.3799	-4.6251	0.0000	-2.5019	-1.0126
age	0.0078	0.0058	1.3395	0.1804	-0.0036	0.0191
balance	-0.0000	0.0000	-0.2236	0.8231	-0.0000	0.0000
current-campaign	-0.0905	0.0238	-3.8042	0.0001	-0.1371	-0.0439
previous-campaign	0.1414	0.0212	6.6569	0.0000	0.0998	0.1830
job_blue-collar	-0.3412	0.2000	-1.7060	0.0880	-0.7331	0.0508
job_entrepreneur	-0.2900	0.3161	-0.9175	0.3589	-0.9096	0.3295
job_housemaid	-0.0166	0.3339	-0.0497	0.9603	-0.6711	0.6379
job_management	-0.0487	0.1984	-0.2455	0.8061	-0.4375	0.3401
job_retired	0.5454	0.2503	2.1794	0.0293	0.0549	1.0360
job_self-employed	-0.2234	0.2895	-0.7715	0.4404	-0.7909	0.3441
job_services	-0.2248	0.2245	-1.0012	0.3167	-0.6648	0.2152
job_student	0.3888	0.3181	1.2223	0.2216	-0.2346	1.0122
job_technician	-0.2101	0.1874	-1.1213	0.2622	-0.5773	0.1571
job_unemployed	-0.3723	0.3336	-1.1162	0.2643	-1.0261	0.2815
job_unknown	0.3193	0.4620	0.6913	0.4894	-0.5861	1.2248
marital_married	-0.4012	0.1440	-2.7857	0.0053	-0.6835	-0.1189
marital_single	-0.0463	0.1676	-0.2763	0.7823	-0.3749	0.2822
education_secondary	0.2128	0.1680	1.2670	0.2052	-0.1164	0.5420
education_tertiary	0.3891	0.1935	2.0103	0.0444	0.0098	0.7684
education_unknown	-0.1956	0.2927	-0.6682	0.5040	-0.7693	0.3781
default_yes	0.2286	0.3670	0.6228	0.5334	-0.4908	0.9479
housing-loan_yes	-0.5355	0.1024	-5.2273	0.0000	-0.7362	-0.3347
personal-loan_yes	-0.7139	0.1689	-4.2268	0.0000	-1.0449	-0.3829

```
significant_vars = get_significant_vars( logit_model )

significant_vars
```

```
['const',
 'current-campaign',
 'previous-campaign',
 'job_retired',
 'marital_married',
 'education_tertiary',
 'housing-loan_yes',
 'personal-loan_yes']
```

```
X_features = ['current-campaign',
              'previous-campaign',
              'job_retired',
              'marital_married',
              'education_tertiary',
              'housing-loan_yes',
              'personal-loan_yes']
```

```
logit_model_2 = sm.Logit( Y, sm.add_constant( X[X_features] ) ).fit()
```

```
Optimization terminated successfully.
         Current function value: 0.337228
         Iterations 7
```

```
logit_model_2.summary2()
```

Model:	Logit	Pseudo R-squared:	0.056
Dependent Variable:	subscribed	AIC:	3065.2182
Date:	2019-04-23 21:07	BIC:	3116.5501
No. Observations:	4521	Log-Likelihood:	-1524.6
Df Model:	7	LL-Null:	-1615.5
Df Residuals:	4513	LLR p-value:	8.1892e-36
Converged:	1.0000	Scale:	1.0000
No. Iterations:	7.0000		

	Coef.	**Std.Err.**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-1.4754	0.1133	-13.0260	0.0000	-1.6974	-1.2534
current-campaign	-0.0893	0.0236	-3.7925	0.0001	-0.1355	-0.0432
previous-campaign	0.1419	0.0211	6.7097	0.0000	0.1004	0.1833
job_retired	0.8246	0.1731	4.7628	0.0000	0.4853	1.1639
marital_married	-0.3767	0.0969	-3.8878	0.0001	-0.5667	-0.1868
education_tertiary	0.2991	0.1014	2.9500	0.0032	0.1004	0.4978
housing-loan_yes	-0.5834	0.0986	-5.9179	0.0000	-0.7767	-0.3902
personal-loan_yes	-0.7025	0.1672	-4.2012	0.0000	-1.0302	-0.3748

```
y_pred_df = pd.DataFrame( { 'actual': Y,
                            'predicted_prob': logit_model_2.predict(
                            sm.add_constant( X[X_features] ) ) } )
```

```
sorted_predict_df = y_pred_df[['predicted_prob',
                               'actual']].sort_values( 'predicted_prob',
                                                      ascending = False )
```

```
num_per_decile = int( len( sorted_predict_df ) / 10 )
print( "Number of observations per decile: ", num_per_decile)
```

```
Number of observations per decile:  452
```

```
def get_deciles( df ):
    df['decile'] = 1

    idx = 0

    for each_d in range( 0, 10 ):
        df.iloc[idx:idx+num_per_decile, df.columns.get_loc('decile')] = each_d
        idx += num_per_decile

    df['decile'] = df['decile'] + 1

    return df
```

```
deciles_predict_df = get_deciles( sorted_predict_df )
```

```
deciles_predict_df[0:10]
```

	predicted_prob	actual	decile
3682	0.864769	0	1
97	0.828031	0	1
3426	0.706809	0	1
1312	0.642337	1	1
3930	0.631032	1	1
4397	0.619146	0	1
2070	0.609129	0	1
3023	0.573199	0	1
4080	0.572364	0	1
804	0.559350	0	1

```
gain_lift_df = pd.DataFrame(
    deciles_predict_df.groupby(
            'decile')['actual'].sum() ).reset_index()
gain_lift_df.columns = ['decile', 'gain']
```



```
gain_lift_df['gain_percentage'] = (100 *
                  gain_lift_df.gain.cumsum()/gain_lift_df.gain.sum())
```

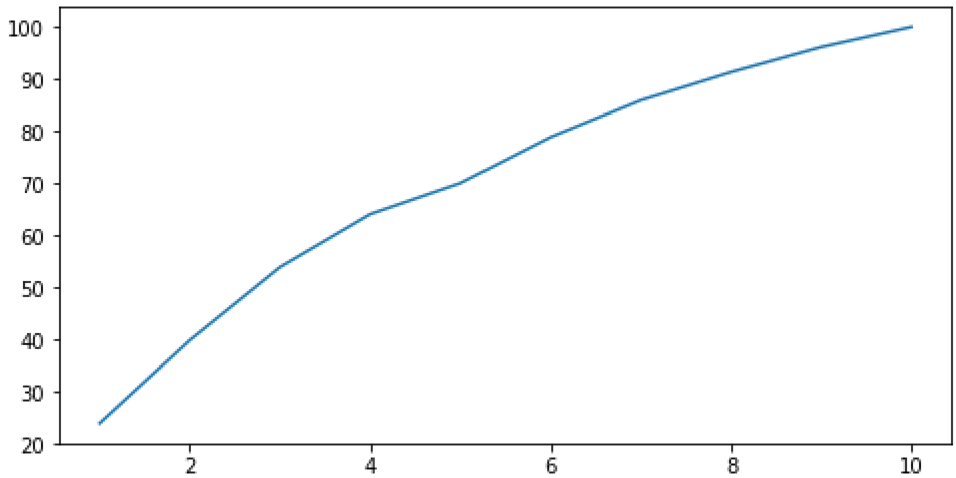
```
gain_lift_df
```

	decile	gain	gain_percentage
0	1	125	23.992322
1	2	83	39.923225
2	3	73	53.934741
3	4	53	64.107486
4	5	31	70.057582
5	6	46	78.886756
6	7	37	85.988484
7	8	28	91.362764
8	9	25	96.161228
9	10	20	100.000000

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

```
plt.figure( figsize = (8,4))
plt.plot( gain_lift_df['decile'],
         gain_lift_df['gain_percentage'], '-' )

plt.show()
```



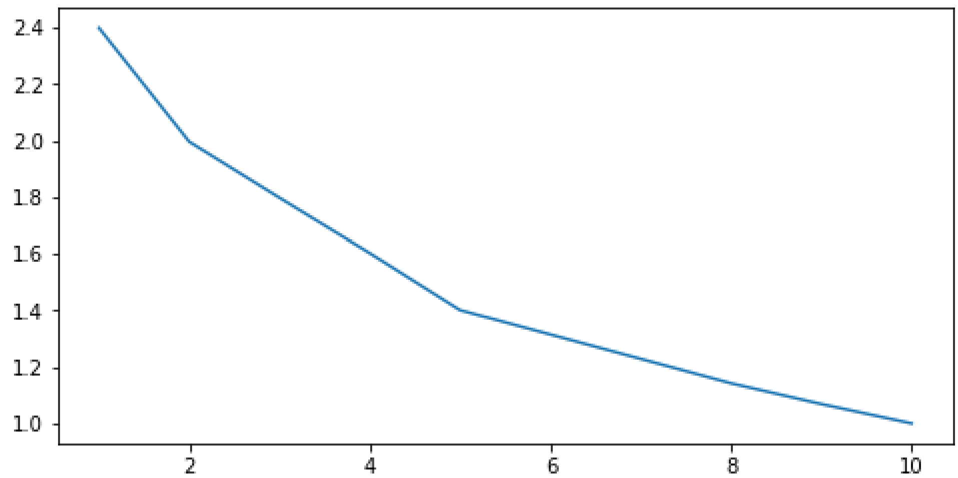
Calculating Lift

```
gain_lift_df['lift'] = ( gain_lift_df.gain_percentage
                        / ( gain_lift_df.decile * 10) )
```

```
gain_lift_df
```

	decile	gain	gain_percentage	lift
0	1	125	23.992322	2.399232
1	2	83	39.923225	1.996161
2	3	73	53.934741	1.797825
3	4	53	64.107486	1.602687
4	5	31	70.057582	1.401152
5	6	46	78.886756	1.314779
6	7	37	85.988484	1.228407
7	8	28	91.362764	1.142035
8	9	25	96.161228	1.068458
9	10	20	100.000000	1.000000

```
plt.figure( figsize = (8,4))
plt.plot( gain_lift_df['decile'], gain_lift_df['lift'], '-' )
plt.show()
```



5.5 Decision Trees

5.5.1 Split the dataset

```
Y = credit_df.status
X = encoded_credit_df

from sklearn.model_selection import train_test_split


X_train, X_test, y_train, y_test = train_test_split( X, Y,
                                                      test_size = 0.3,
                                                      random_state = 42)
```

5.5.2 Building Decision Tree classifier using Gini Criteria

```
from sklearn.tree import DecisionTreeClassifier

clf_tree = DecisionTreeClassifier(criterion = 'gini',
                                  max_depth = 3 )
```

```
clf_tree.fit( X_train, y_train )
```

```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_dept
h=3,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_stat
e=None,
            splitter='best')
```

5.5.3 Measuring Test Accuracy

```
tree_predict = clf_tree.predict( X_test )
metrics.roc_auc_score( y_test, tree_predict )
```

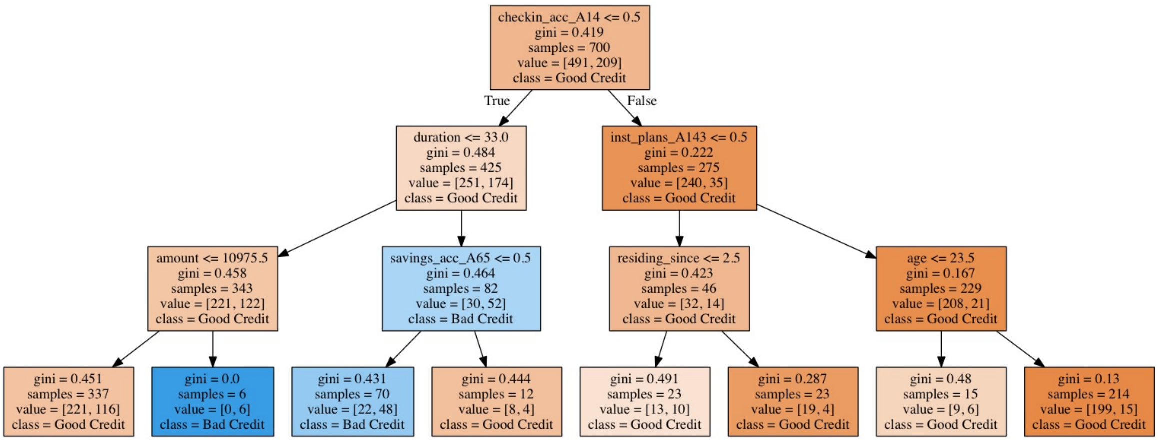
```
0.5835743204164258
```

5.5.4 Displaying the Tree

```
from sklearn.tree  import export_graphviz
import pydotplus as pdot
from IPython.display import Image

# Export the tree into odt file
export_graphviz( clf_tree,
              out_file = "chd_tree.odt",
              feature_names = X_train.columns,
              class_names= ['Good Credit', 'Bad Credit'],
              filled = True)

# Read the create the image file
chd_tree_graph = pdot.graphviz.graph_from_dot_file( 'chd_tree.odt' )
chd_tree_graph.write_jpg( 'chd_tree.png' )
# Render the png file
Image(filename='chd_tree.png')
```



5.5.5 Understanding Gini Impurity

```
gini_node_1 = 1 - pow(491/700, 2) - pow (209/700, 2)
print( round( gini_node_1, 4) )
```

```
0.4189
```

```
X_test.shape
```

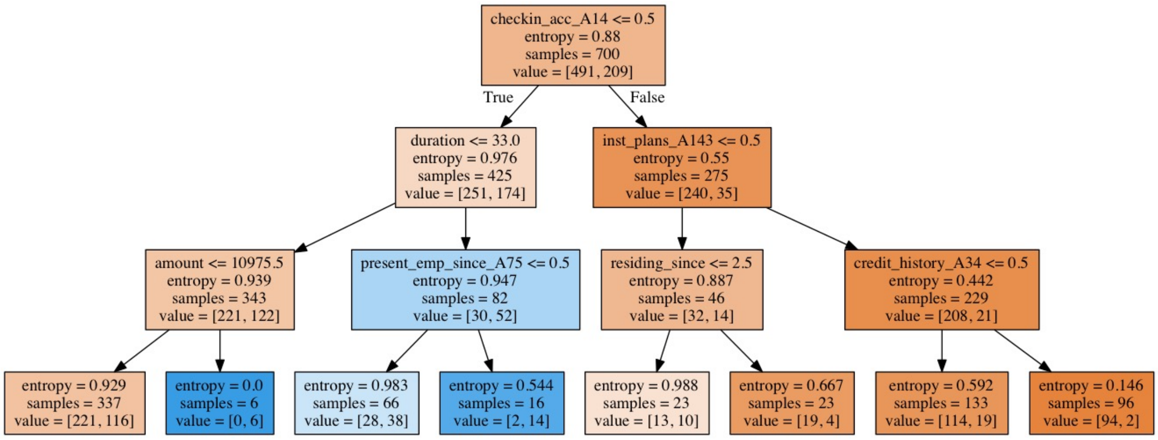
```
(300, 29)
```

5.5.6 Building Decision Tree using Entropy Criteria

```
clf_tree_entropy = DecisionTreeClassifier( criterion = 'entropy',
                                          max_depth = 3 )
clf_tree_entropy.fit( X_train, y_train )

# Export the tree into odt file
export_graphviz( clf_tree_entropy,
              out_file = "chd_tree_entropy.odt",
              feature_names = X_train.columns,
              filled = True )

# Read the create the image file
chd_tree_graph = pdot.graphviz.graph_from_dot_file( 'chd_tree_entropy.odt' )
chd_tree_graph.write_jpg( 'chd_tree_entropy.png' )
# Render the png file
Image(filename='chd_tree_entropy.png')
```



Calculating entropy impurity

```
import math

entropy_node_1 = - (491/700) * math.log2(491/700) - (209/700) * math.log2(209/70
0)
print( round( entropy_node_1, 2) )
```

```
0.88
```

Measuring test accuracy

```
tree_predict = clf_tree_entropy.predict( X_test )
metrics.roc_auc_score( y_test, tree_predict )
```

```
0.5763972869236027
```

5.5.7 Finding optimal criteria and max_depth

```
from sklearn.model_selection import GridSearchCV

tuned_parameters = [{'criterion': ['gini','entropy'],
                     'max_depth': range(2,10)}]



clf_tree = DecisionTreeClassifier()

clf = GridSearchCV(clf_tree,
                   tuned_parameters,
                   cv=10,
                   scoring='roc_auc')

clf.fit(X_train, y_train )
```

```
/Users/manaranjan/anaconda/lib/python3.5/site-packages/sklearn/model
_selection/_search.py:841: DeprecationWarning: The default of the `i
id` parameter will change from True to False in version 0.22 and wil
l be removed in 0.24. This will change numeric results when test-set
sizes are unequal.
  DeprecationWarning)
```

```
GridSearchCV(cv=10, error_score='raise-deprecating',
       estimator=DecisionTreeClassifier(class_weight=None, criterion
='gini', max_depth=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_stat
e=None,
            splitter='best'),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid=[{'max_depth': range(2, 10), 'criterion': ['gini',
'entropy']}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='war
n',
       scoring='roc_auc', verbose=0)
```

```
clf.best_score_
```

```
0.6824299319727891
```

```
clf.best_params_
```

```
{'criterion': 'gini', 'max_depth': 2}
```