Assignment 3: Evaluating Classification Models

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https://github.com/clboetticher/practicalML/blob/master/Boetticher_MSDS%20Assignment%203_Evaluating%20Classification%20Models.ipynb

Study objective

This study employs data from a Portuguese bank marketing campaign, with variables on client characteristics such as demographic factors (age, job type, marital status, and education), previous use of banking services, and call details. In efforts to get clients to invest in term deposits, classification models are evaluated to help the bank identify potential factors that will positively affect client responses to future marketing campaigns.

Initial data inspection and exploratory data analysis

Of the 4521 study observations, 11.5 percent responded yes to a term deposit; 88.4 percent responded no. Further inspection of responses across the selected variables of interest (housing, loan, and default) shows a relative balance of response values for housing, but not for loan or default, suggesting the potential for housing as a meaningful feature in the classification modeling effort. None of the selected features appear to be discriminators in particular for response values, seen in the consistent pattern of no versus yes response ratios (Figure 2). For numerical features, neither balance nor age provide useful discrimination for response values. Participant demographics show a slight positive skew in age, with median values around 40 (Figure 1), with age shifting slightly higher for yes responses (Figure 3, 4). Examining feature correlations (Figure 8), pdays (number of days that passed since the client was last contacted from a previous campaign) and previous (number of contacts performed before this campaign for this client) show a strong positive correlation; duration and response do as well, though duration would be considered a leaky variable and not included as a potential predictor. Housing shows a slightly strong negative correlation with response, as does housing and age.

Data preparation

Four features are used in this study: three binary predictor features (default, loan, and housing) and one binary target feature (response). The binary features' values are converted from 'yes' and 'no' to '1' and '0' to facilitate numerical operations and model training and testing. Due to the imbalance between the yes and no response values in the training data (521 yes/4000 no), training classifiers on the data as is would result in a high likelihood of predicting accurately on only one class. While accuracy would be high, this would be a misleading indicator of the classifier's strength. Up-sampling is employed to randomly duplicate observations from the minority class (the 'yes' response values) to reinforce the signal. The resulting training data is then used to enable a more reliable assessment of model performance.

Study design and findings

Initially, multiple classification techniques are evaluated for performance across a 10-fold cross-validation design to make the most of the small sample size. While none of the models perform much better than random chance (50 percent accuracy), Logistic Regression, Naïve Bayes (Bernoulli), and Support Vector Classification (SVC) techniques are selected for comparison for the learning phase to predict the likelihood of a client responding positively to the campaign and enrolling in a term deposit. Accuracy provides a baseline measure of correct predictions; the f1 weighted metric is also used to evaluate the models during learning to get a better sense of the relationship of precision and recall in the classifiers across folds (Figure 9). Grid search is then used to identify ideal hyperparameters (C and alpha, particularly) for model performance and parameters for those three techniques are adjusted accordingly. Multiple indices of prediction error give perspective to model performance in this study. The AUC (area under the curve) scores for training each classifier are as follows:

Metric	LR (Train)	LR (Test)	NB (Train)	NB (Train)	SVC (Train)	SVC (Test)
AUC	62.44%	60.98%	61.35%	60.64%	63.66%	58.17%
PPV	65.8%	59.48%	65.8%	59.48%	73.85%	62.07%
NPV	58.33%	62.07%	58.33%	62.07%	54.6%	56.9%

The ROC curves for the three classifiers (Figures 14-16) on the training set show model performance not much better than random chance using the three predictor variables for response. On the test set (Figures 17-19), results are similar. This suggests these classifiers do not provide a clear path for selecting the optimal classification threshold; additionally, the similarity of AUC scores does not reliably favor one technique over another.

Recommendation

I do not recommend any of these modeling techniques as is from this study's particular design, rather they would serve as a useful baseline for further comparison with other classification models since they did generalize relatively well. Naïve Bayes methods, in particular, should not be relied upon as a single method since we have not yet established that all the predictor features are completely independent of each other. Although there is no guarantee of improved performance, the following steps may improve the odds of reliably identifying a useful target population of customers using these features: collecting more data (i.e., a larger number of quality observations), including additional meaningful predictor features beyond the three binary ones selected for this study, and/or the use of ensemble methods. If these steps contributed to improved performance in a reliably generalized manner, they could be used to target clients for direct marketing efforts for term deposits.

A Portuguese bank wants its clients to invest in term deposits, which are an investment such as a certificate of deposit. The interest rate and duration of the deposit are set in advance. A term deposit is distinct from a demand deposit. The bank is interested in identifying factors that affect client responses to new term deposit offerings, which are the focus of the marketing campaigns. Regarding the management problem, imagine that you are advising the bank about machine learning methods to guide telephone marketing campaigns. Which of the two modeling methods would you recommend and why? And, given the results of your research, which group of banking clients appears to be the best target for direct marketing efforts (similar to those used with previous telephone campaigns)?

Use three binary explanatory variables relating to client banking history: default, housing, and loan. Predict the binary response variable: Has the client subscribed to a term deposit? Use all banking client observations with complete data for these study variables. Employ two classification methods: (1) logistic regression as described in Chapter 4 of the Géron (2017) textbook and (2) naïve Bayes classification. Evaluate these methods within a cross-validation design, using the area under the receiver operating characteristic (ROC) curve as an index of classification performance. Python scikit-learn should be your primary environment for conducting this research.

Summay of data

Categorical Variables:

- job : admin,technician, services, management, retired, blue-collar, unemployed, entrepreneur, housemaid, unknown, self-employed, student
- marital : married, single, divorced
- education: secondary, tertiary, primary, unknown
- default : yes, no
- housing : yes, no
- loan : yes, no
- response : yes, no (target feature)
- contact : unknown, cellular, telephone
- month : jan, feb, mar, apr, may, jun, jul, aug, sep, oct, nov, dec
- poutcome: unknown, other, failure, success

Numerical Variables:

- age
- balance
- day
- duration
- campaign
- pdays
- previous

In [4]:
```
# Import dependencies

# Data preparation and analysis
import numpy as np
import pandas as pd
import os
from math import sqrt  # for root mean-squared error calculation
import itertools
from scipy import stats as st
import random

# Modeling routines from Scikit Learn packages
from sklearn.metrics import accuracy_score, confusion_matrix, precision_recall_curve, classification_report, recall_sc
ore, f1_score, roc_curve, auc, roc_auc_score
from sklearn.base import clone
import sklearn.utils.validation as val
from sklearn.utils import resample
from sklearn import preprocessing  # feature transformations
from sklearn.compose import ColumnTransformer   # for scaling particular features
from sklearn.linear_model import LogisticRegression, SGDClassifier
from sklearn.svm import LinearSVC, SVC
from sklearn.naive_bayes import GaussianNB, BernoulliNB, MultinomialNB
from sklearn.model_selection import KFold, StratifiedKFold, StratifiedShuffleSplit, train_test_split, cross_val_score,
cross_val_predict, GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn import tree
from sklearn.neural_network import MLPClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.gaussian_process.kernels import RBF
from sklearn.ensemble import RandomForestClassifier

# Plotting and visualization
from yellowbrick.model_selection import CVScores
from yellowbrick.classifier import ClassificationReport
from yellowbrick.features import Rank2D
import matplotlib.pyplot as plt  # static plotting
import seaborn as sns  # pretty plotting, including heat map
%matplotlib inline
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/utils/deprecation.py:144: FutureWarning: The sklearn.metrics.classific
ation module is  deprecated in version 0.22 and will be removed in version 0.24. The corresponding classes / function
s should instead be imported from sklearn.metrics. Anything that cannot be imported from sklearn.metrics is now part
of the private API.
  warnings.warn(message, FutureWarning)
```

In [5]:
```
# Seed value for random number generators to obtain reproducible results
RANDOM_SEED = 1
```

Data preparation and initial inspection

In [6]:
```
# Initial work with the smaller data set
bank = pd.read_csv('bank.csv', sep = ';')  # start with smaller data set

# Examine the shape of original input data
print(bank.shape)
```

```
(4521, 17)
```

In [7]:
```
# Drop observations with missing data, if any
bank.dropna()

# Examine the shape of input data after dropping missing data
print(bank.shape)

# Examine at the list of column names, note that y is the response
list(bank.columns.values)

# Examine the beginning of the DataFrame
bank.head()
```

```
(4521, 17)
```

Out[7]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	response
0	30	unemployed	married	primary	no	1787	no	no	cellular	19	oct	79	1	-1	0	unknown	no
1	33	services	married	secondary	no	4789	yes	yes	cellular	11	may	220	1	339	4	failure	no
2	35	management	single	tertiary	no	1350	yes	no	cellular	16	apr	185	1	330	1	failure	no
3	30	management	married	tertiary	no	1476	yes	yes	unknown	3	jun	199	4	-1	0	unknown	no
4	59	blue-collar	married	secondary	no	0	yes	no	unknown	5	may	226	1	-1	0	unknown	no

Predictor variables relating to client banking history:

- Default: Has credit in default? (yes/no)
- Housing: Has housing loan? (yes/no)
- Loan: Has personal loan? (yes/no)

Target variable:

- Response: Has the client subscribed to a term deposit? (yes/no)

In [8]:
```
# Transform data
bank1 = pd.read_csv('bank.csv', sep = ';')

print([[bank1.columns],[bank1.dtypes]])
print(pd.DataFrame.head(bank1))

bank = pd.get_dummies(bank1)
print([[bank.columns],[bank.dtypes]])
```

```
[[Index(['age', 'job', 'marital', 'education', 'default', 'balance', 'housing',
       'loan', 'contact', 'day', 'month', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'response'],
      dtype='object')], [age           int64
job          object
marital      object
education    object
default      object
balance       int64
housing      object
loan         object
contact      object
day           int64
month        object
duration      int64
campaign      int64
pdays         int64
previous      int64
poutcome     object
response     object
dtype: object]]
   age          job  marital  education default  balance housing loan  \
0   30   unemployed  married    primary      no     1787      no   no
1   33     services  married  secondary      no     4789     yes  yes
2   35   management   single   tertiary      no     1350     yes   no
3   30   management  married   tertiary      no     1476     yes  yes
4   59  blue-collar  married  secondary      no        0     yes   no

    contact  day month  duration  campaign  pdays  previous poutcome response
0  cellular   19   oct        79         1     -1         0  unknown       no
1  cellular   11   may       220         1    339         4  failure       no
2  cellular   16   apr       185         1    330         1  failure       no
3   unknown    3   jun       199         4     -1         0  unknown       no
4   unknown    5   may       226         1     -1         0  unknown       no
[[Index(['age', 'balance', 'day', 'duration', 'campaign', 'pdays', 'previous',
       'job_admin.', 'job_blue-collar', 'job_entrepreneur', 'job_housemaid',
       'job_management', 'job_retired', 'job_self-employed', 'job_services',
       'job_student', 'job_technician', 'job_unemployed', 'job_unknown',
       'marital_divorced', 'marital_married', 'marital_single',
       'education_primary', 'education_secondary', 'education_tertiary',
       'education_unknown', 'default_no', 'default_yes', 'housing_no',
       'housing_yes', 'loan_no', 'loan_yes', 'contact_cellular',
       'contact_telephone', 'contact_unknown', 'month_apr', 'month_aug',
       'month_dec', 'month_feb', 'month_jan', 'month_jul', 'month_jun',
       'month_mar', 'month_may', 'month_nov', 'month_oct', 'month_sep',
       'poutcome_failure', 'poutcome_other', 'poutcome_success',
       'poutcome_unknown', 'response_no', 'response_yes'],
      dtype='object')], [age                    int64
balance                int64
day                    int64
duration               int64
campaign               int64
pdays                  int64
previous               int64
job_admin.             uint8
job_blue-collar        uint8
job_entrepreneur       uint8
job_housemaid          uint8
job_management         uint8
job_retired            uint8
job_self-employed      uint8
job_services           uint8
job_student            uint8
job_technician         uint8
job_unemployed         uint8
job_unknown            uint8
marital_divorced       uint8
marital_married        uint8
marital_single         uint8
education_primary      uint8
education_secondary    uint8
education_tertiary     uint8
education_unknown      uint8
default_no             uint8
default_yes            uint8
housing_no             uint8
housing_yes            uint8
loan_no                uint8
loan_yes               uint8
contact_cellular       uint8
contact_telephone      uint8
contact_unknown        uint8
month_apr              uint8
month_aug              uint8
month_dec              uint8
```

Descriptive statistics and exploratory data analysis

- crosstabs and descriptive statistics
- demographics of participants
- class balance across all categorical variables, especially response variable skew
- distributions of all features
- pair plots and correlation matrix

In [9]:
```
# Crosstabs for initial analysis
a = pd.crosstab(bank.response_yes,
                bank.housing_yes,
                rownames=['Response'], colnames=['Housing'])

b = pd.crosstab(bank.response_yes,
                bank.loan_yes,
                rownames=['Response'], colnames=['Loan'])

c = pd.crosstab(bank.response_yes,
                bank.default_yes,
                rownames=['Response'], colnames=['Default'])

print(a,"\n")
print(b,"\n")
print(c,"\n")

def myor(a):
        myv=round((a.loc[1,1]/a.loc[0,1])/(a.loc[1,0]/a.loc[0,0]),3)
        logmyv = np.log(myv)
        se = np.sqrt(1/(a.loc[1,1]+1/a.loc[0,1]+a.loc[1,0]+a.loc[0,0]))
        lower = round(np.exp(logmyv-1.96*se),3)
        upper = round(np.exp(logmyv+1.96*se),3)
        return [myv, lower, upper]

print("Odds for Response Yes for Each Variable with 95% CI")
print("If housing = yes, odds for response = yes:", myor(a))
print("If loan = yes, odds for response = yes:", myor(b))
print("If default = yes, odds for response = yes:", myor(c))

print(bank1.groupby('response').mean())
```

```
Housing      0     1
Response
0         1661  2339
1          301   220

Loan         0    1
Response
0         3352  648
1          478   43

Default      0   1
Response
0         3933  67
1          512   9

Odds for Response Yes for Each Variable with 95% CI
If housing = yes, odds for response = yes: [0.519, 0.498, 0.541]
If loan = yes, odds for response = yes: [0.465, 0.451, 0.48]
If default = yes, odds for response = yes: [1.032, 1.002, 1.063]
                age      balance        day    duration  campaign      pdays  \
response
no        40.998000  1403.211750  15.948750  226.347500  2.862250  36.006000
yes       42.491363  1571.955854  15.658349  552.742802  2.266795  68.639155

          previous
response
no        0.471250
yes       1.090211
```

In [10]:
```
# Define binary variable for yes/no responses and map to original DataFrame columns
bank1['default'] = bank1['default'].map({'yes': 1, 'no': 0})
bank1['housing'] = bank1['housing'].map({'yes': 1, 'no': 0})
bank1['loan'] = bank1['loan'].map({'yes': 1, 'no': 0})
bank1['response'] = bank1['response'].map({'yes': 1, 'no': 0})
```

In [11]:
```
bank1.head()
```

Out[11]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	response
0	30	unemployed	married	primary	0	1787	0	0	cellular	19	oct	79	1	-1	0	unknown	0
1	33	services	married	secondary	0	4789	1	1	cellular	11	may	220	1	339	4	failure	0
2	35	management	single	tertiary	0	1350	1	0	cellular	16	apr	185	1	330	1	failure	0
3	30	management	married	tertiary	0	1476	1	1	unknown	3	jun	199	4	-1	0	unknown	0
4	59	blue-collar	married	secondary	0	0	1	0	unknown	5	may	226	1	-1	0	unknown	0

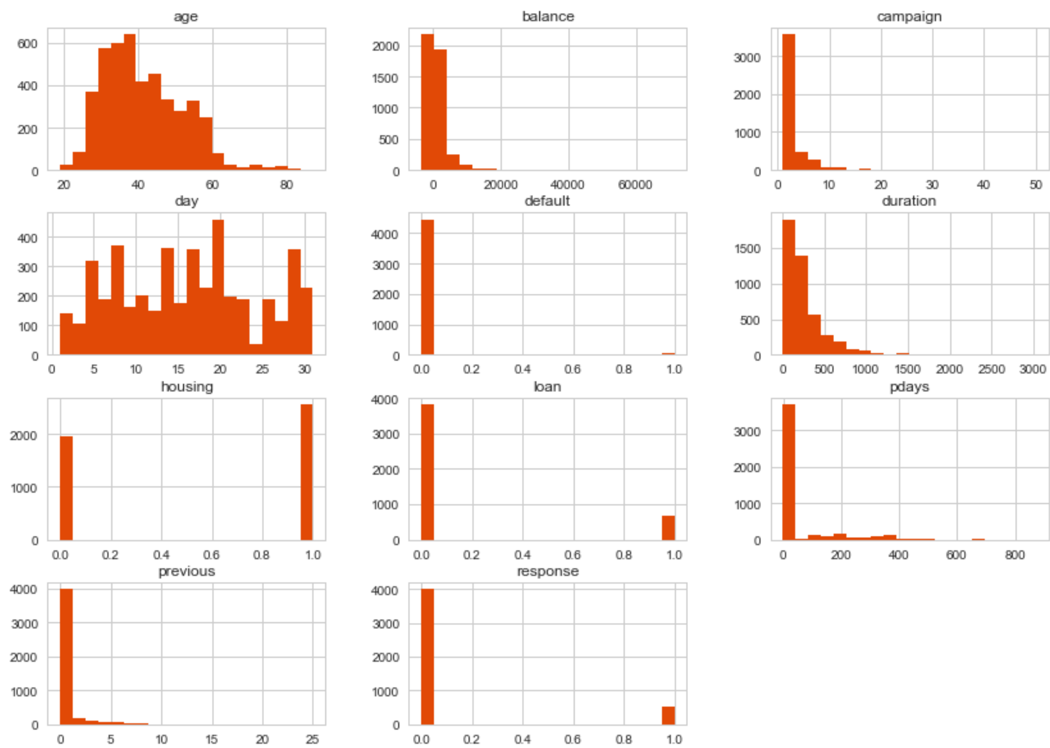
In [12]:
```
bank1.describe()
```

Out[12]:

	age	default	balance	housing	loan	day	duration	campaign	pdays	previous	response
count	4521.000000	4521.000000	4521.000000	4521.000000	4521.000000	4521.000000	4521.000000	4521.000000	4521.000000	4521.000000	4521.000000
mean	41.170095	0.016810	1422.657819	0.566025	0.152842	15.915284	263.961292	2.793630	39.766645	0.542579	0.115240
std	10.576211	0.128575	3009.638142	0.495676	0.359875	8.247667	259.856633	3.109807	100.121124	1.693562	0.319347
min	19.000000	0.000000	-3313.000000	0.000000	0.000000	1.000000	4.000000	1.000000	-1.000000	0.000000	0.000000
25%	33.000000	0.000000	69.000000	0.000000	0.000000	9.000000	104.000000	1.000000	-1.000000	0.000000	0.000000
50%	39.000000	0.000000	444.000000	1.000000	0.000000	16.000000	185.000000	2.000000	-1.000000	0.000000	0.000000
75%	49.000000	0.000000	1480.000000	1.000000	0.000000	21.000000	329.000000	3.000000	-1.000000	0.000000	0.000000
max	87.000000	1.000000	71188.000000	1.000000	1.000000	31.000000	3025.000000	50.000000	871.000000	25.000000	1.000000

Figure 1: Feature Distributions

In [15]:
```
# Distributions of features
plt.style.use('seaborn-whitegrid')
bank1.hist(bins=20, figsize=(14,10), color='#E14906')
plt.show()
```



Class balances

In [16]:
```
# Value counts: total and relative - response
# Yes = 1, No = 1
print(bank1['response'].value_counts(ascending=False))
print('------------------------')
print(bank1['response'].value_counts(normalize=True))
```

```
0    4000
1     521
Name: response, dtype: int64
------------------------
0    0.88476
1    0.11524
Name: response, dtype: float64
```

In [67]:
```
# Value counts: total and relative - default
print(bank1['default'].value_counts(ascending=False))
print('------------------------')
print(bank1['default'].value_counts(normalize=True))
```

```
0    4445
1      76
Name: default, dtype: int64
------------------------
0    0.98319
1    0.01681
Name: default, dtype: float64
```

In [63]:
```
# Value counts: total and relative - housing
# Balance of responses suggests this may be a more meaningful feature
print(bank1['housing'].value_counts(ascending=False))
print('------------------------')
print(bank1['housing'].value_counts(normalize=True))
```

```
1    2559
0    1962
Name: housing, dtype: int64
------------------------
1    0.566025
0    0.433975
Name: housing, dtype: float64
```

In [64]:
```
# Value counts: total and relative - loan
print(bank1['loan'].value_counts(ascending=False))
print('------------------------')
print(bank1['loan'].value_counts(normalize=True))
```

```
0    3830
1     691
Name: loan, dtype: int64
------------------------
0    0.847158
1    0.152842
Name: loan, dtype: float64
```

Participant demographics

In [13]:
```
# Value counts: total and relative - age
print(bank1['age'].value_counts(ascending=False))
print('------------------------')
print(bank1['age'].value_counts(normalize=True))
```

```
34    231
32    224
31    199
36    188
33    186
     ...
76      2
84      1
81      1
86      1
87      1
Name: age, Length: 67, dtype: int64
------------------------
34    0.051095
32    0.049547
31    0.044017
36    0.041584
33    0.041141
        ...
76    0.000442
84    0.000221
81    0.000221
86    0.000221
87    0.000221
Name: age, Length: 67, dtype: float64
```

In [14]:
```
# Value counts: total and relative - marital
print(bank1['marital'].value_counts(ascending=False))
print('------------------------')
print(bank1['marital'].value_counts(normalize=True))
```

```
married     2797
single      1196
divorced     528
Name: marital, dtype: int64
------------------------
married     0.618668
single      0.264543
divorced    0.116788
Name: marital, dtype: float64
```

In [15]:
```
# Value counts: total and relative - education
print(bank1['education'].value_counts(ascending=False))
print('------------------------')
print(bank1['education'].value_counts(normalize=True))
```

```
secondary    2306
tertiary     1350
primary       678
unknown       187
Name: education, dtype: int64
------------------------
secondary    0.510064
tertiary     0.298607
primary      0.149967
unknown      0.041363
Name: education, dtype: float64
```

In [16]:
```
# Value counts: total and relative - job
print(bank1['job'].value_counts(ascending=False))
print('------------------------')
print(bank1['job'].value_counts(normalize=True))
```

```
management       969
blue-collar      946
technician       768
admin.           478
services         417
retired          230
self-employed    183
entrepreneur     168
unemployed       128
housemaid        112
student           84
unknown           38
Name: job, dtype: int64
------------------------
management       0.214333
blue-collar      0.209246
technician       0.169874
admin.           0.105729
services         0.092236
retired          0.050874
self-employed    0.040478
entrepreneur     0.037160
unemployed       0.028312
housemaid        0.024773
student          0.018580
unknown          0.008405
Name: job, dtype: float64
```

Feature relationships

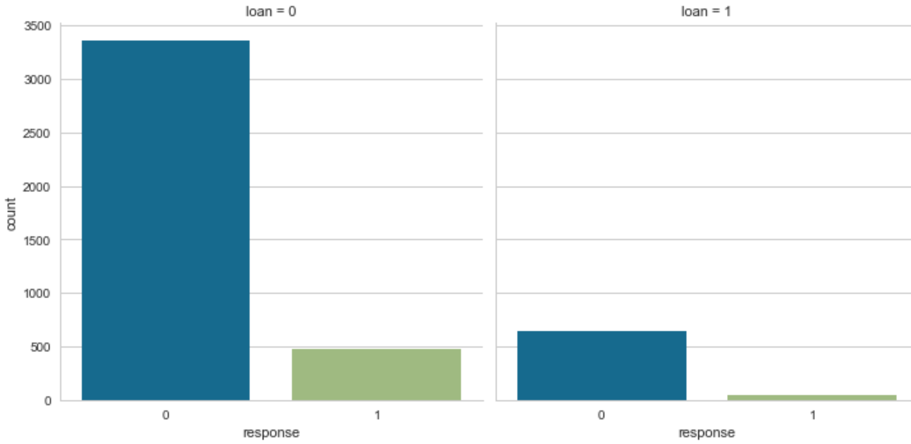
In [72]:
```
bank1.head()
```

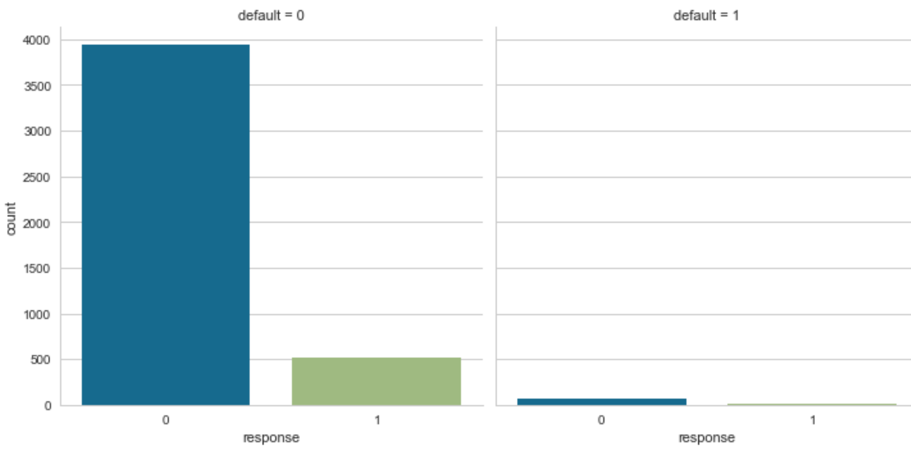
Out[72]:

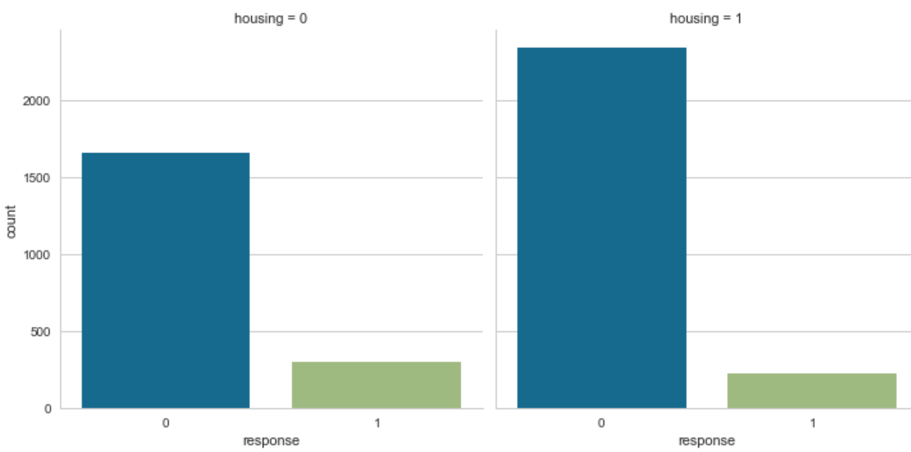
	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	response
0	30	unemployed	married	primary	0	1787	0	0	cellular	19	oct	79	1	-1	0	unknown	0
1	33	services	married	secondary	0	4789	1	1	cellular	11	may	220	1	339	4	failure	0
2	35	management	single	tertiary	0	1350	1	0	cellular	16	apr	185	1	330	1	failure	0
3	30	management	married	tertiary	0	1476	1	1	unknown	3	jun	199	4	-1	0	unknown	0
4	59	blue-collar	married	secondary	0	0	1	0	unknown	5	may	226	1	-1	0	unknown	0

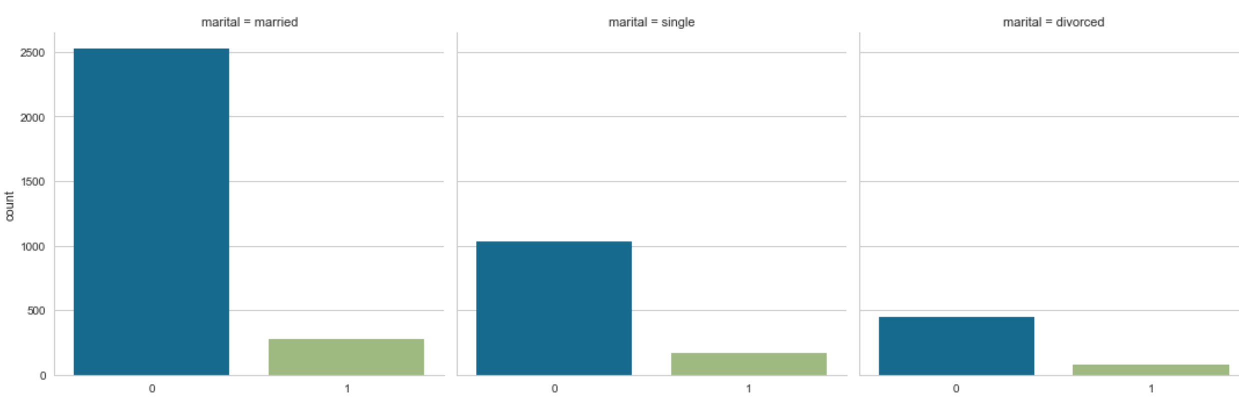
Figure 2: Feature Counts by Target and Predictor Features

In [14]:
```
# Plot feature counts by response - loan
fig1 = sns.catplot(x="response", col="loan", data=bank1, kind="count")

# Plot feature counts by response - default
fig1 = sns.catplot(x="response", col="default", data=bank1, kind="count")

# Plot feature counts by response - housing
fig1 = sns.catplot(x="response", col="housing", data=bank1, kind="count")

# Plot feature counts by response - marital
fig1 = sns.catplot(x="response", col="marital", data=bank1, kind="count")

# Plot feature counts by response - education
fig1 = sns.catplot(x="response", col="education", data=bank1, kind="count")
```


loan = 0
loan = 1
count
response
0
1
3500
3000
2500
2000
1500
1000
500


default = 0
default = 1
count
response
0
1
4000
3500
3000
2500
2000
1500
1000
500


housing = 0
housing = 1
count
response
0
1
2000
1500
1000
500


marital = married
marital = single
marital = divorced
count
response
0
1
2500
2000
1500
1000
500

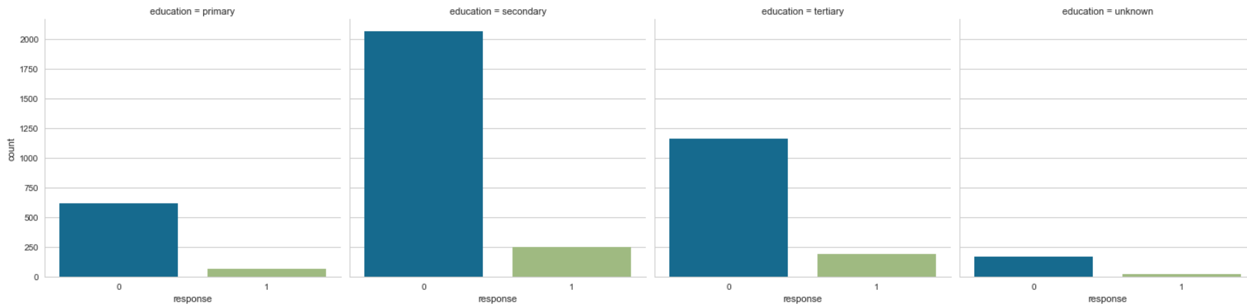
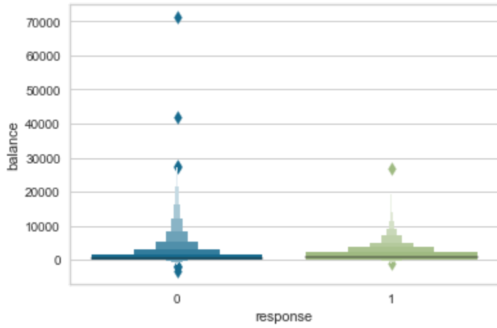
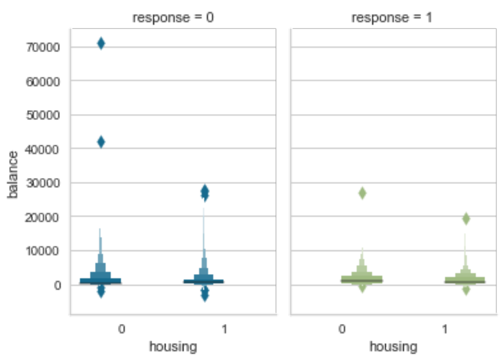
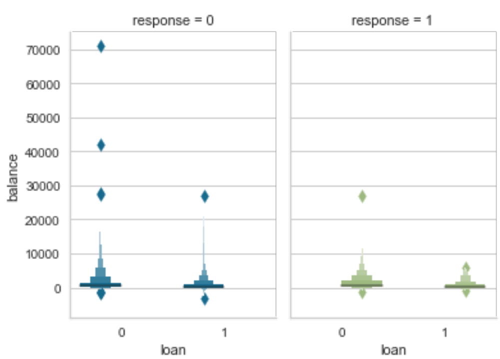


Figure 3: Balance Values by Predictor and Target Features

In [17]:
```
# Plot response values by balance
sns.boxenplot(x="response", y="balance", data=bank1, linewidth=2.5)

# Plot response values by balance and housing
g = sns.catplot(x="housing", y="balance", hue="response", col="response", data=bank1,
                kind="boxen",height=4, aspect=.7);

# Plot response values by balance and loan
g = sns.catplot(x="loan", y="balance", hue="response", col="response", data=bank1,
                kind="boxen",height=4, aspect=.7);

# Plot response values by balance and default
g = sns.catplot(x="default", y="balance", hue="response", col="response", data=bank1,
                kind="boxen",height=4, aspect=.7);
```







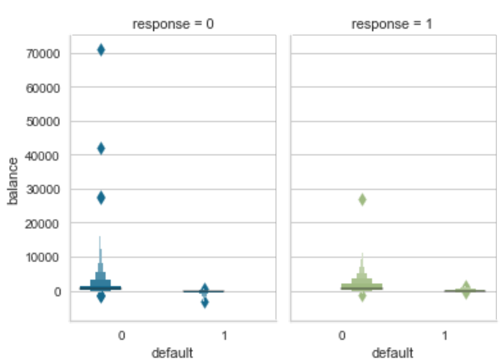
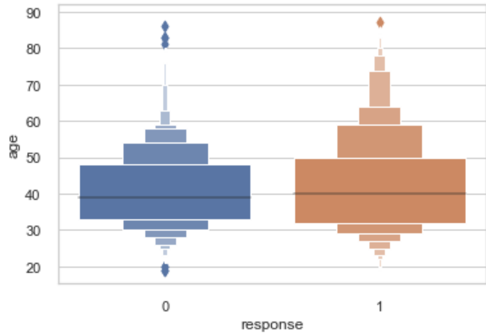
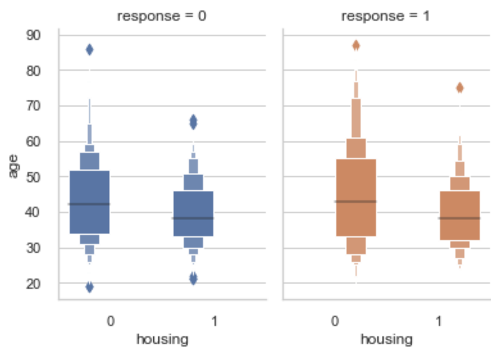
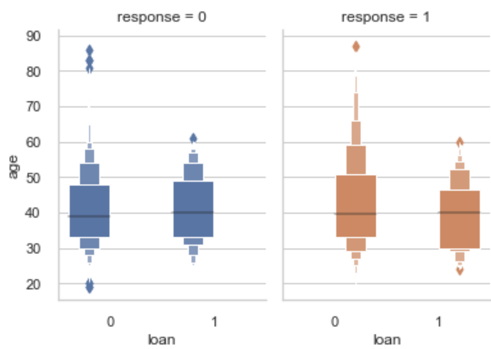


Figure 4: Age Values by Predictor and Target Features

In [25]:
```
# Plot response values by balance
sns.boxenplot(x="response", y="age", data=bank1, linewidth=2.5)

# Plot response values by balance and housing
g = sns.catplot(x="housing", y="age", hue="response", col="response", data=bank1,
                kind="boxen",height=4, aspect=.7);

# Plot response values by balance and loan
g = sns.catplot(x="loan", y="age", hue="response", col="response", data=bank1,
                kind="boxen",height=4, aspect=.7);

# Plot response values by balance and default
g = sns.catplot(x="default", y="age", hue="response", col="response", data=bank1,
                kind="boxen",height=4, aspect=.7);
```







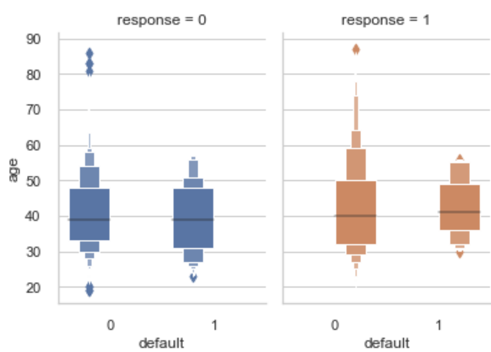
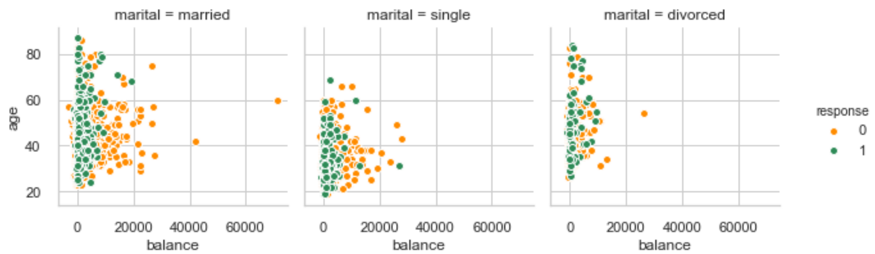


Figure 5: Balance Values by Target and Non-Predictor Features

In [22]:
```
# Plot Balance by Marital Status, Age, and Response
sns.set(style="whitegrid")
g = sns.FacetGrid(bank1, hue="response", col="marital", margin_titles=True,
                  palette={1:"seagreen", 0:"darkorange"})
g = g.map(plt.scatter, "balance", "age",edgecolor="w").add_legend();

# Plot Balance by Education, Age, and Response
g = sns.FacetGrid(bank1, hue="response", col="education", margin_titles=True,
                  palette={1:"seagreen", 0:"darkorange"})
g = g.map(plt.scatter, "balance", "age",edgecolor="w").add_legend();
```



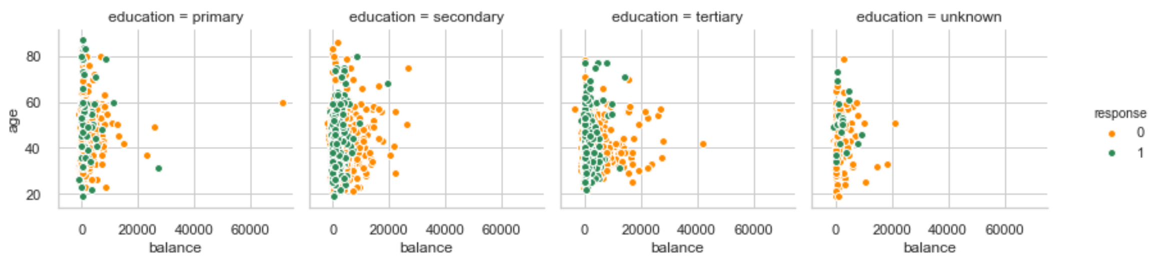


Figure 6: Age by Education

In [24]:
```
# Plot response values by balance and loan
ax = sns.boxenplot(x=bank1["age"])

# Median age by education
sns.boxenplot(x="age", y="education", data=bank1, linewidth=2.5)
```

```
'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have pre
cedence in case its length matches with 'x' & 'y'.  Please use a 2-D array with a single row if you really want to sp
ecify the same RGB or RGBA value for all points.
'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have pre
cedence in case its length matches with 'x' & 'y'.  Please use a 2-D array with a single row if you really want to sp
ecify the same RGB or RGBA value for all points.
'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have pre
cedence in case its length matches with 'x' & 'y'.  Please use a 2-D array with a single row if you really want to sp
ecify the same RGB or RGBA value for all points.
```

Out[24]: `<matplotlib.axes._subplots.AxesSubplot at 0x1c66250e80>`

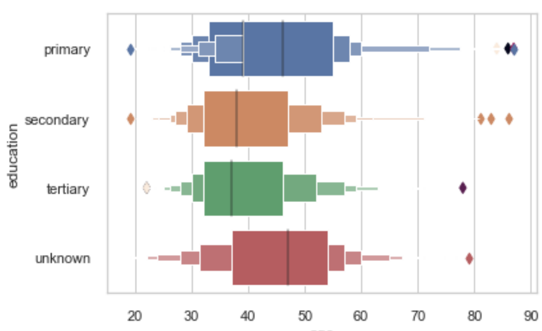


Figure 7: Feature Pair Plots

In [71]:
```
# Pair plots of selected features color-coded by response values
g = sns.pairplot(bank1, vars=["age", "marital", "education", "default", "balance", "housing", "loan"],
                 hue="response", palette="husl")
```

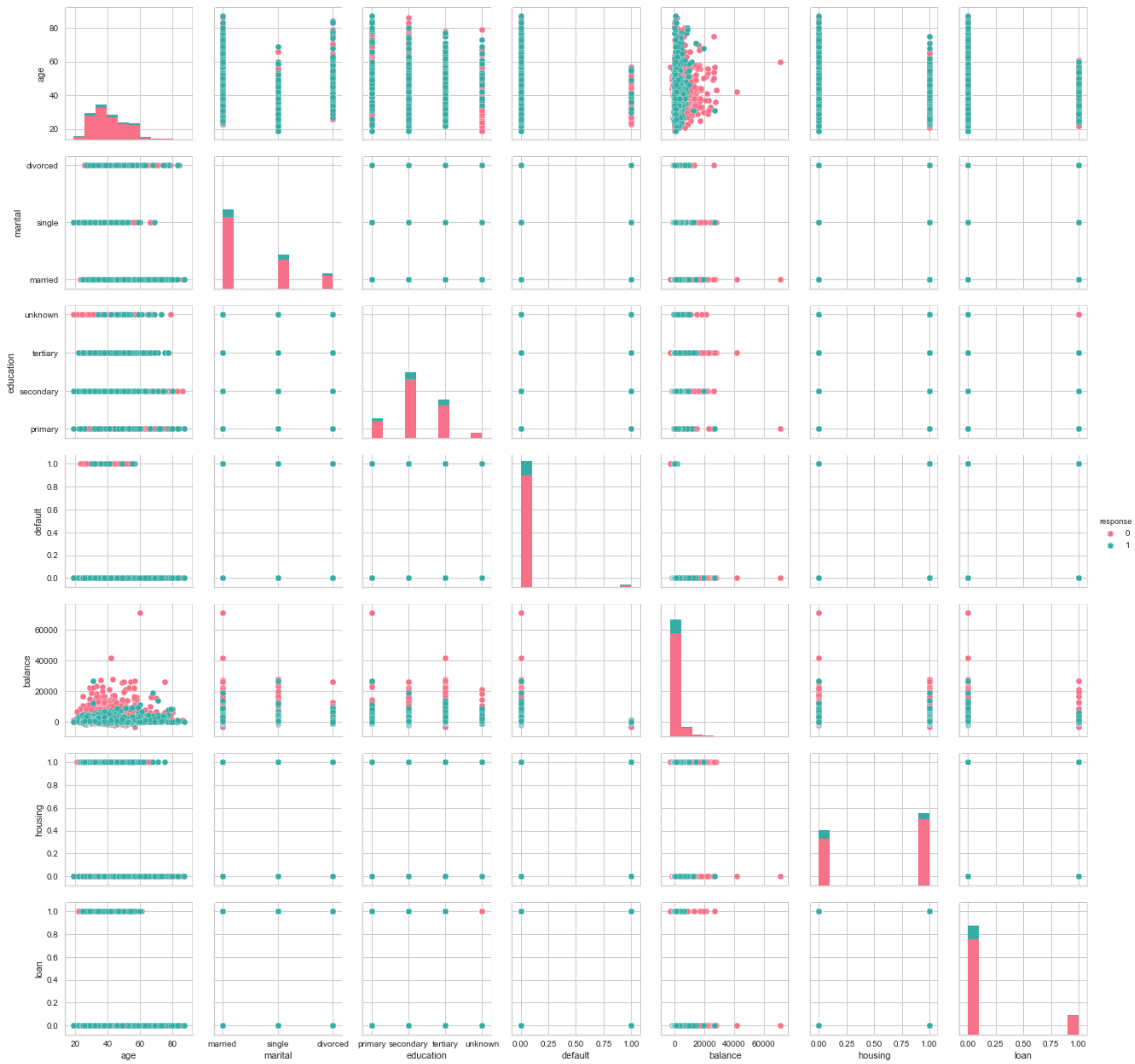
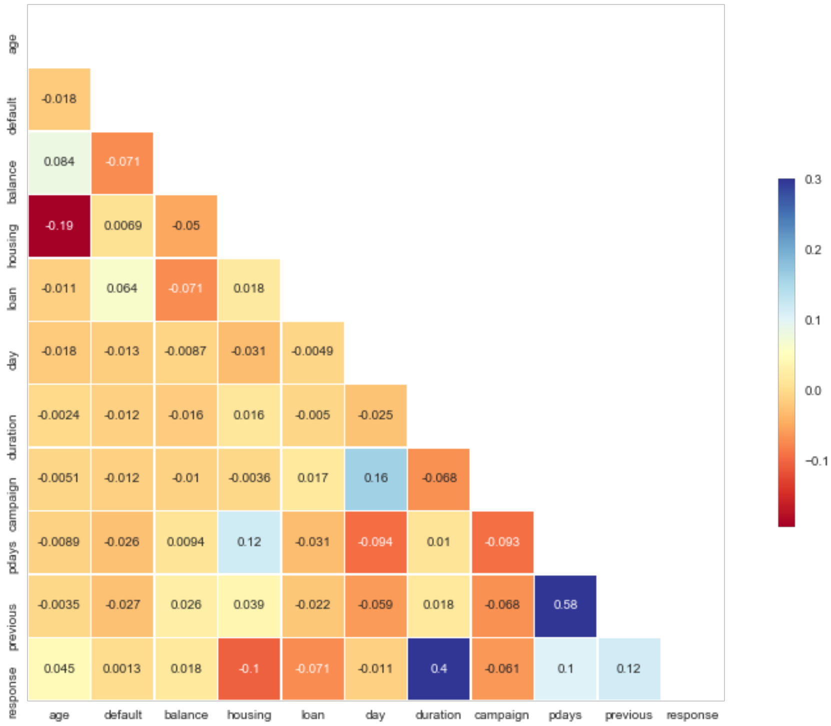


Figure 8: Correlation Matrix

In [68]:
```python
# Correlation matrix of all features
plt.figure(figsize=(15,10))
corr = bank1.corr(method='pearson')
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True
sns.heatmap(corr, mask=mask, annot=True, vmax=.3, cmap="RdYlBu", square=True, linewidths = .5,
            cbar_kws={"shrink": .5})
```

Out[68]: <matplotlib.axes._subplots.AxesSubplot at 0x116167cc0>



Data split strategy 1 - stratified train test split

In [21]:
```python
# Select subset of features
# Yes = 1, NO = 0
bank_model_df = bank1.loc[:, ['default','housing','loan','response']]
bank_model_df.head()
```

Out[21]:

	default	housing	loan	response
0	0	0	0	0
1	0	1	1	0
2	0	1	0	0
3	0	1	1	0
4	0	1	0	0

In [22]:
```
# Prepare data for train/test splitting
X = bank_model_df.iloc[:,0:3].values
y = bank_model_df.iloc[:,3].values

print('X shape: ', X.shape)
print('y shape: ', y.shape)

# Split into train and test sets and review
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, random_state=42)

print('X_train.shape: ', X_train.shape)
print('X_test.shape: ', X_test.shape)
print('y_train.shape: ', y_train.shape)
print('y_test.shape: ', y_test.shape)
```

```
X shape:  (4521, 3)
y shape:  (4521,)
X_train.shape:  (3390, 3)
X_test.shape:  (1131, 3)
y_train.shape:  (3390,)
y_test.shape:  (1131,)
```

Data split strategy 2 - upsampling

This intends to deal with the imbalance of Yes reponses (521) to No responses (4000) in the original data.

In [61]:
```
# Training set
X = pd.DataFrame(bank[['loan_yes', 'default_yes', 'housing_yes', 'response_yes']])
trainnum = random.sample(range(1,4521), 521)
train = X.loc[trainnum]
test = X.drop(X.index[trainnum])

X_train = train[['loan_yes', 'default_yes', 'housing_yes']]
y_train = val.column_or_1d(train[['response_yes']])

# Display proportion of Response = yes samples
print(np.mean(X['response_yes']))
```

```
0.11523999115239991
```

In [62]:
```
# Test set
X_test = np.array(test[['loan_yes', 'default_yes', 'housing_yes']])
y_test = np.array(val.column_or_1d(test[['response_yes']]))
```

In [63]:
```
# Upsampling to address imbalance of "no" responses

# Separate majority and minority classes
minority = train[train['response_yes']==1]
majority = train[train['response_yes']==0]

# Upsample minority class and create new DataFrame
upsampled = resample(minority, replace=True, n_samples=len(majority), random_state=123)
newbank = pd.concat([majority, upsampled])
newbank.response_yes.value_counts()
```

Out[63]:
```
1    464
0    464
Name: response_yes, dtype: int64
```

In [64]:
```
newbank.head()
# len(newbank)
```

Out[64]:

	loan_yes	default_yes	housing_yes	response_yes
4443	0	0	0	0
1305	1	0	1	0
1922	1	0	1	0
2167	0	0	0	0
1456	1	0	1	0

In [65]:
```
# Prepare upsampled data for train/test splitting
X = newbank.drop('response_yes', axis=1)
y = newbank.response_yes

print('X shape: ', X.shape)
print('y shape: ', y.shape)

# Split into train and test sets and review
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, random_state=42)

print('X_train.shape: ', X_train.shape)
print('X_test.shape: ', X_test.shape)
print('y_train.shape: ', y_train.shape)
print('y_test.shape: ', y_test.shape)
```

```
X shape:  (928, 3)
y shape:  (928,)
X_train.shape:  (696, 3)
X_test.shape:  (232, 3)
y_train.shape:  (696,)
y_test.shape:  (232,)
```

Learning phase

Employ cross-validation design to test out accuracy for multiple classification models on training set

In [66]:
```
# Use Cross-validation
nfolds = 10

# Logistic Regression
log_reg = LogisticRegression(solver="lbfgs")
log_scores = cross_val_score(log_reg, X_train, y_train, cv=nfolds)
log_reg_mean = log_scores.mean()

# Naives Bayes - Gaussian
nav_clf = GaussianNB()
nav_scores = cross_val_score(nav_clf, X_train, y_train, cv=nfolds)
nav_mean = nav_scores.mean()

# Naive Bayes - Bernoulli
bern_clf = BernoulliNB()
bern_scores = cross_val_score(bern_clf, X_train, y_train, cv=nfolds)
bern_mean = bern_scores.mean()

# SVC
svc_clf = SVC()
svc_scores = cross_val_score(svc_clf, X_train, y_train, cv=nfolds)
svc_mean = svc_scores.mean()

# KNearestNeighbors
knn_clf = KNeighborsClassifier(weights="distance")
knn_scores = cross_val_score(knn_clf, X_train, y_train, cv=nfolds)
knn_mean = knn_scores.mean()

# Decision Tree
tree_clf = tree.DecisionTreeClassifier()
tree_scores = cross_val_score(tree_clf, X_train, y_train, cv=nfolds)
tree_mean = tree_scores.mean()

# Gradient Boosting Classifier
grad_clf = GradientBoostingClassifier()
grad_scores = cross_val_score(grad_clf, X_train, y_train, cv=nfolds)
grad_mean = grad_scores.mean()

# Random Forest Classifier
rand_clf = RandomForestClassifier(n_estimators=18)
rand_scores = cross_val_score(rand_clf, X_train, y_train, cv=nfolds)
rand_mean = rand_scores.mean()

# NeuralNet Classifier
neural_clf = MLPClassifier(alpha=1)
neural_scores = cross_val_score(neural_clf, X_train, y_train, cv=nfolds)
neural_mean = neural_scores.mean()

# Stochastic Gradient Descent
sgd_clf = SGDClassifier(loss='log')
sgd_scores = cross_val_score(sgd_clf, X_train, y_train, cv=nfolds)
sgd_mean = sgd_scores.mean()

# Create a Dataframe with the results.
d = {'Classifiers': ['Logistic Reg.', 'Naives Bayes Gaussian', 'Naive Bayes Bernoulli', 'SVC', 'KNN', 'Dec Tree', 'Gra
d B CLF', 'Rand FC', 'Neural Classifier', 'SGD'],
    'Cross-validated Mean Scores': [log_reg_mean, svc_mean, knn_mean, tree_mean, grad_mean, rand_mean, neural_mean, na
v_mean, bern_mean, sgd_mean]}

result_df = pd.DataFrame(data=d)
```

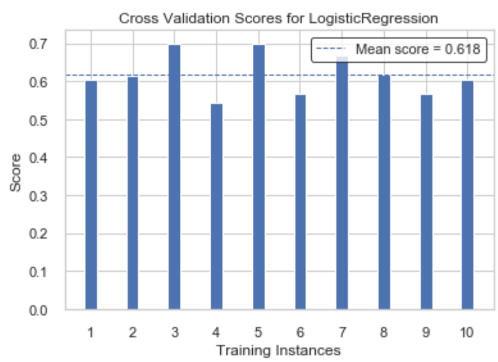
In [67]:
```
# Results DataFrame
result_df = result_df.sort_values(by=['Cross-validated Mean Scores'], ascending=False)
result_df
```

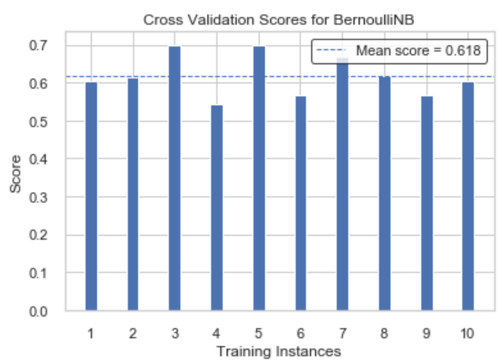
Out[67]:

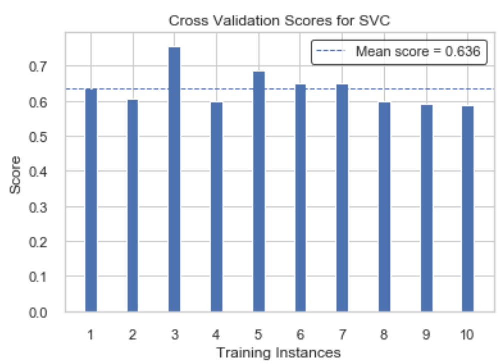
	Classifiers	Cross-validated Mean Scores
1	Naives Bayes Gaussian	0.642091
3	SVC	0.642091
4	KNN	0.642091
5	Dec Tree	0.642091
0	Logistic Reg.	0.620663
6	Grad B CLF	0.620663
8	Neural Classifier	0.620663
7	Rand FC	0.612050
2	Naive Bayes Bernoulli	0.555901
9	SGD	0.521781

Figure 9: Cross-Validated F1 Scores for Logistic Regression and Naive Bayes Models

In [68]:
```
# Use YellowBrick Cross Val visualization for alternate evaluation

# Load the classification dataset
X, y = X_train, y_train

# Create a cross-validation strategy
cv = StratifiedKFold(n_splits=10)

# Instantiate the classification model and visualizer - LR
model = LogisticRegression(solver="lbfgs")
visualizer = CVScores(model, cv=cv, scoring='f1_weighted')

visualizer.fit(X, y)        # Fit the data to the visualizer
visualizer.show()           # Finalize and render the figure

# Instantiate the classification model and visualizer - NB
model = BernoulliNB()
visualizer = CVScores(model, cv=cv, scoring='f1_weighted')

visualizer.fit(X, y)        # Fit the data to the visualizer
visualizer.show()           # Finalize and render the figure

# Instantiate the classification model and visualizer - SVC
model = SVC()
visualizer = CVScores(model, cv=cv, scoring='f1_weighted')

visualizer.fit(X, y)        # Fit the data to the visualizer
visualizer.show()           # Finalize and render the figure
```







Out[68]: `<matplotlib.axes._subplots.AxesSubplot at 0x1c6a7247f0>`

Figure 10: Scatterplot - Logistic Regression and Naive Bayes (Bernoulli) Models

In [69]:
```
# Scatterplot of two models - LogReg and Naive Bayes (Bernoulli)
# Two models produce same results as training set size approaches infinity (?)
# NB assumption holds that xi's are conditionally independent of each other given y
plt.scatter(log_scores, bern_scores)
```

Out[69]: <matplotlib.collections.PathCollection at 0x1c6a87ce10>

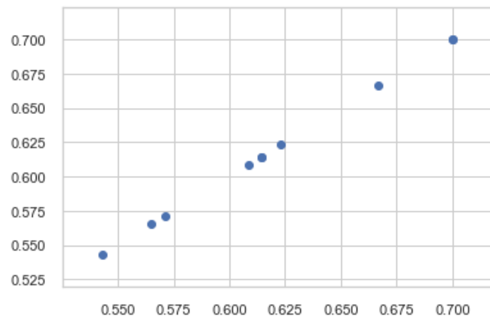
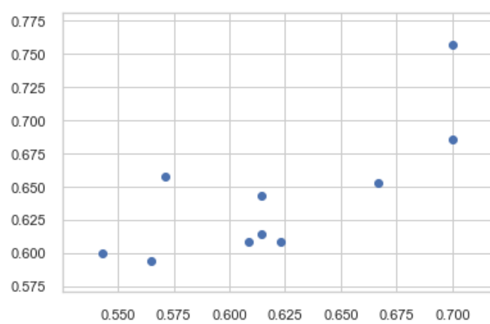


Figure 11: Scatterplot - Logistic Regression and SVC Models

In [70]:
```
# Scatterplot of two models - LogReg and SVC
# Two models produce same results as training set size approaches infinity (?)
# NB assumption holds that xi's are conditionally independent of each other given y
plt.scatter(log_scores, svc_scores)
```

Out[70]: <matplotlib.collections.PathCollection at 0x1c6a961160>



Grid search to fine-tune models

In [17]:
```
# Grid Search to fine-tune short list of models
# Try different C and alpha values
# Try L1 versus L2
```

In [71]:
```
# Classifier parameters
lr_param = {'C': [0.001, 0.01, 0.1, 1, 5, 10]}
nb_param = {'alpha': [0.001, 0.01, 0.1, 1, 5, 10]}
svc_param = {'C': [0.001, 0.01, 0.1, 1, 5, 10]}

print("Parameter grid:\n{}".format(lr_param))
print("Parameter grid:\n{}".format(nb_param))
print("Parameter grid:\n{}".format(svc_param))

# LR
gs_lr = GridSearchCV(LogisticRegression(), lr_param, cv=10, scoring="roc_auc", return_train_score=True)
gs_lr.fit(X_train, y_train)
print("Test set score: {:.2f}".format(gs_lr.score(X_test, y_test)))
print("Best parameters: {}".format(gs_lr.best_params_))
print("Best cross-validation score: {:.2f}".format(gs_lr.best_score_))
print("Best estimator:\n{}".format(gs_lr.best_estimator_))
```

```
Parameter grid:
{'C': [0.001, 0.01, 0.1, 1, 5, 10]}
Parameter grid:
{'alpha': [0.001, 0.01, 0.1, 1, 5, 10]}
Parameter grid:
{'C': [0.001, 0.01, 0.1, 1, 5, 10]}
Test set score: 0.61
Best parameters: {'C': 1}
Best cross-validation score: 0.62
Best estimator:
LogisticRegression(C=1, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

In [51]:
```
# NB
gs_nb = GridSearchCV(BernoulliNB(binarize=0.5, class_prior = [0.5, 0.5], fit_prior=False), nb_param, cv=10,
                    scoring="roc_auc", return_train_score=True)
gs_nb.fit(X_train, y_train)
print("Test set score: {:.2f}".format(gs_nb.score(X_test, y_test)))
print("Best parameters: {}".format(gs_nb.best_params_))
print("Best cross-validation score: {:.2f}".format(gs_nb.best_score_))
print("Best estimator:\n{}".format(gs_nb.best_estimator_))
```

```
Test set score: 0.66
Best parameters: {'alpha': 0.001}
Best cross-validation score: 0.63
Best estimator:
BernoulliNB(alpha=0.001, binarize=0.5, class_prior=[0.5, 0.5], fit_prior=False)
```

In [73]:
```
# SVC
gs_svc = GridSearchCV(SVC(), svc_param, cv=10, scoring="roc_auc", return_train_score=True)
gs_svc.fit(X_train, y_train)
print("Test set score: {:.2f}".format(gs_svc.score(X_test, y_test)))
print("Best parameters: {}".format(gs_svc.best_params_))
print("Best cross-validation score: {:.2f}".format(gs_svc.best_score_))
print("Best estimator:\n{}".format(gs_svc.best_estimator_))
```

```
Test set score: 0.58
Best parameters: {'C': 5}
Best cross-validation score: 0.65
Best estimator:
SVC(C=5, break_ties=False, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='scale', kernel='rbf',
    max_iter=-1, probability=False, random_state=None, shrinking=True,
    tol=0.001, verbose=False)
```

In [76]:
```
# Revise Logistic Regression and Naive Bayes parameters
log_reg = LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)

bern_clf = BernoulliNB(alpha=0.001, binarize=0.5, class_prior=[0.5, 0.5], fit_prior=False)

svc_clf = SVC(C=5, probability=True)
```

Fit training set

- log_reg
- bern_clf
- svc_clf

In [77]:
```
# Fit Logistic Regression model
log_reg.fit(X_train, y_train)
lr_pred = log_reg.predict_proba(X_train)
lr_pred = [p[1] for p in lr_pred]
lr_pred_class = log_reg.predict(X_train)
```

In [78]:
```
# Fit Naive Bayes model
bern_clf.fit(X_train, y_train)
bern_pred = bern_clf.predict_proba(X_train)
bern_pred = [p[1] for p in bern_pred]
bern_pred_class = bern_clf.predict(X_train)
```

In [79]:
```
# Fit SVC model
svc_clf.fit(X_train, y_train)
svc_pred = svc_clf.predict_proba(X_train)
svc_pred = [p[1] for p in svc_pred]
svc_pred_class = svc_clf.predict(X_train)
```

In [107]:

```
# Define function for model performance metrics
def metrics(y, pred, predclass):
    print("Area Under the Curve: ", roc_auc_score(y, pred))
    myconfusion = confusion_matrix(y, predclass)
    PPV = (myconfusion[1,1]/(myconfusion[1,0]+myconfusion[1,1]))
    NPV = (myconfusion[0,0]/(myconfusion[0,0]+myconfusion[0,1]))
    print("\n Confusion Matrix: \n", myconfusion)
    print("\n PPV, Correctly Classifies Response Yes: \n", PPV)
    print("\n NPV, Correctly Classifies Response No: \n", NPV)

print("Logistic Regression: \n")
metrics(y_train, lr_pred, lr_pred_class)
print('-------------------')
print("Naive Bayes (Bernoulli): \n")
metrics(y_train, bern_pred, bern_pred_class)
print('-------------------')
print("SVC: \n")
metrics(y_train, svc_pred, svc_pred_class)
print('-------------------')
```

```
Logistic Regression:

Area Under the Curve:  0.6244054696789537

 Confusion Matrix:
 [[203 145]
 [119 229]]

 PPV, Correctly Classifies Response Yes:
 0.6580459770114943

 NPV, Correctly Classifies Response No:
 0.5833333333333334
-------------------
Naive Bayes (Bernoulli):

Area Under the Curve:  0.6134974897608667

 Confusion Matrix:
 [[203 145]
 [119 229]]

 PPV, Correctly Classifies Response Yes:
 0.6580459770114943

 NPV, Correctly Classifies Response No:
 0.5833333333333334
-------------------
SVC:

Area Under the Curve:  0.6366015986259743

 Confusion Matrix:
 [[190 158]
 [ 91 257]]

 PPV, Correctly Classifies Response Yes:
 0.7385057471264368

 NPV, Correctly Classifies Response No:
 0.5459770114942529
-------------------
```

In [82]:

```
# Precision recall curve - Logistic Regression
precision, recall, thresholds = precision_recall_curve(y_train, lr_pred)
print('Precision: ',precision)
print('------------------------')
print('Recall: ', recall)
print('------------------------')
print('Thresholds: ', thresholds)
```

```
Precision:  [0.50144092 0.60090703 0.60364465 0.61229947 0.60821918 0.33333333
 0.34782609 1.        ]
------------------------
Recall:  [1.         0.76149425 0.76149425 0.65804598 0.63793103 0.02298851
 0.02298851 0.        ]
------------------------
Thresholds:  [0.46056888 0.46080384 0.46124149 0.53336308 0.53380142 0.53403676
 0.53447502]
```

In [83]:
```
# Precision recall curve - Naive Bayes
precision, recall, thresholds = precision_recall_curve(y_train, bern_pred)
print('Precision: ',precision)
print('------------------------')
print('Recall: ', recall)
print('------------------------')
print('Thresholds: ', thresholds)
```

```
Precision:  [0.5        0.49602544 0.60904255 0.61229947 0.63142857 0.62756598
 1.        ]
------------------------
Recall:  [1.         0.89655172 0.65804598 0.65804598 0.63505747 0.61494253
 0.        ]
------------------------
Thresholds:  [0.35433557 0.37187963 0.37187963 0.59653044 0.61465051 0.61465051]
```

In [84]:
```
# Precision recall curve - SVC
precision, recall, thresholds = precision_recall_curve(y_train, svc_pred)
print('Precision: ',precision)
print('------------------------')
print('Recall: ', recall)
print('------------------------')
print('Thresholds: ', thresholds)
```

```
Precision:  [0.5        0.59819413 0.59954751 0.61336516 0.61630695 0.61927711
 0.58108108 0.77777778 1.        ]
------------------------
Recall:  [1.         0.76149425 0.76149425 0.73850575 0.73850575 0.73850575
 0.12356322 0.02011494 0.        ]
------------------------
Thresholds:  [0.34273207 0.34273207 0.34275808 0.34279046 0.34280553 0.61694899
 0.61704054 0.61706307]
```

Figure 12: Logistic Regression Precision-Recall Curve

In [85]:
```
# Logistic Regression Precision Recall

# To decide on a threshold, look at decision scores
y_scores = cross_val_predict(log_reg, X_train, y_train, cv=3, method="decision_function")

# Compute precision and recall for all possible thresholds
precisions, recalls, thresholds = precision_recall_curve(y_train, y_scores)

# Plot ROC
def plot_precision_recall_vs_threshold(precisions, recalls, thresholds):
    plt.plot(thresholds, precisions[:-1], "b--", label="Precision", linewidth=2)
    plt.plot(thresholds, recalls[:-1], "g-", label="Recall", linewidth=2)
    plt.xlabel("Threshold", fontsize=16)
    plt.legend(loc="upper left", fontsize=16)
    plt.ylim([0, 1])

plt.figure(figsize=(8, 4))
plot_precision_recall_vs_threshold(precisions, recalls, thresholds)
# plt.xlim([-400000, 400000])
# save_fig("precision_recall_vs_threshold_plot")
plt.show()
```

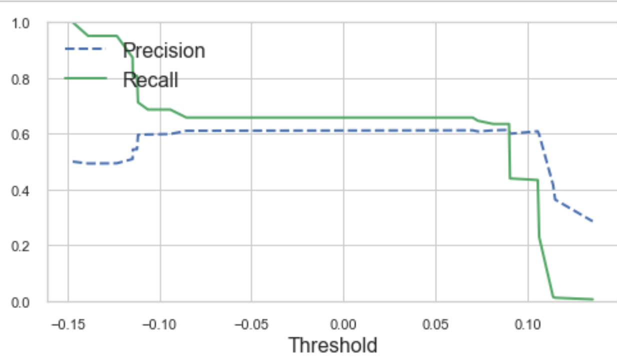


Figure 13: Logistic Regression Precision-Recall Plot

In [86]:
```
# Plot precision directly against recall for Logistic Regression

def plot_precision_vs_recall(precisions, recalls):
    plt.plot(recalls, precisions, "b-", linewidth=2)
    plt.xlabel("Recall", fontsize=16)
    plt.ylabel("Precision", fontsize=16)
    plt.axis([0, 1, 0, 1])

plt.figure(figsize=(8, 6))
plot_precision_vs_recall(precisions, recalls)
# save_fig("precision_vs_recall_plot")
plt.show()
```

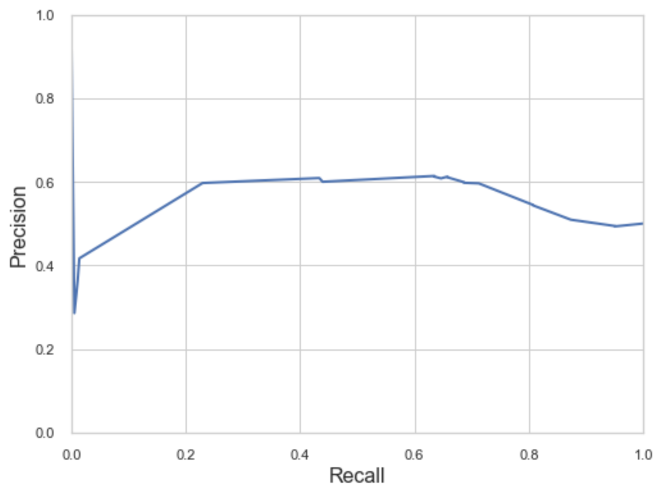


Figure 14: Logistic Regression ROC Curve - Train Set

In [87]:
```
# ROC curve for Logistic Regression

fpr, tpr, thresholds = roc_curve(y_train, y_scores)
roc_auc = auc(fpr, tpr)
y_scores = cross_val_predict(log_reg, X_train, y_train, cv=10)

def plot_roc_curve(fpr, tpr, label=None):
    plt.plot(fpr, tpr, linewidth=2, label=label)
    plt.plot([0, 1], [0, 1], 'k--')
    plt.axis([0, 1, 0, 1])
    plt.xlabel('False Positive Rate', fontsize=16)
    plt.ylabel('True Positive Rate', fontsize=16)
    plt.title('Receiver Operating Characteristic, Test Set, Logistic Regression\nROC curve (area = %0.2f)' % roc_auc)

plt.figure(figsize=(8, 6))
plot_roc_curve(fpr, tpr)
# save_fig("roc_curve_plot")
plt.show()
```

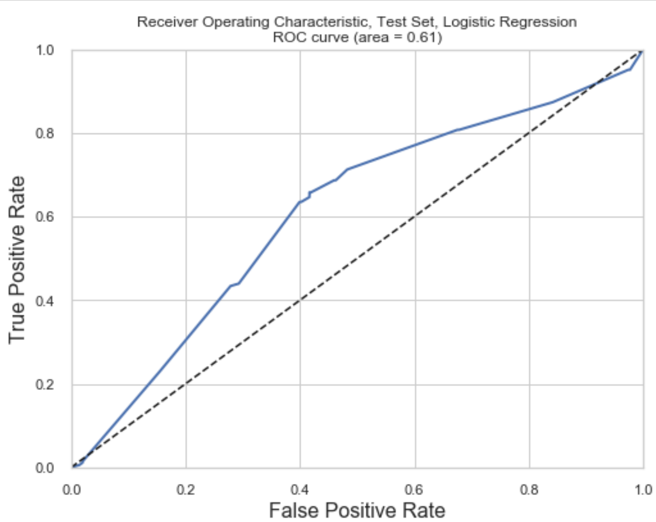


Figure 15: Naive Bayes (Bernoulli) ROC Curve - Train Set

In [88]:
```
# ROC curve for Naive Bayes
y_scores = cross_val_predict(bern_clf, X_train, y_train, cv=10)
fpr, tpr, thresholds = roc_curve(y_train, y_scores)
roc_auc = auc(fpr, tpr)

def plot_roc_curve(fpr, tpr, label=None):
    plt.plot(fpr, tpr, linewidth=2, label=label)
    plt.plot([0, 1], [0, 1], 'k--')
    plt.axis([0, 1, 0, 1])
    plt.xlabel('False Positive Rate', fontsize=16)
    plt.ylabel('True Positive Rate', fontsize=16)
    plt.title('Receiver Operating Characteristic, Test Set, Naive Bayes\nROC curve (area = %0.2f)' % roc_auc)

plt.figure(figsize=(8, 6))
plot_roc_curve(fpr, tpr)
# save_fig("roc_curve_plot")
plt.show()
```

Figure 16: SVC ROC Curve - Train Set

In [90]:
```
# ROC curve for SVC
y_scores = cross_val_predict(svc_clf, X_train, y_train, cv=10)
fpr, tpr, thresholds = roc_curve(y_train, y_scores)
roc_auc = auc(fpr, tpr)

def plot_roc_curve(fpr, tpr, label=None):
    plt.plot(fpr, tpr, linewidth=2, label=label)
    plt.plot([0, 1], [0, 1], 'k--')
    plt.axis([0, 1, 0, 1])
    plt.xlabel('False Positive Rate', fontsize=16)
    plt.ylabel('True Positive Rate', fontsize=16)
    plt.title('Receiver Operating Characteristic, Test Set, SVC\nROC curve (area = %0.2f)' % roc_auc)

plt.figure(figsize=(8, 6))
plot_roc_curve(fpr, tpr)
# save_fig("roc_curve_plot")
plt.show()
```

Evaluate models on test set

In [91]:
```
# Logistic Regression
lr_pred_test = log_reg.predict_proba(X_test)
lr_pred_test = [p[1] for p in lr_pred_test]
lr_pred_class_test = log_reg.predict(X_test)
```

In [92]:
```
# Naive Bayes
bern_pred_test = bern_clf.predict_proba(X_test)
bern_pred_test = [p[1] for p in bern_pred_test]
bern_pred_class_test = bern_clf.predict(X_test)
```

In [93]:
```
# SVC
svc_pred_test = svc_clf.predict_proba(X_test)
svc_pred_test = [p[1] for p in svc_pred_test]
svc_pred_class_test = svc_clf.predict(X_test)
```

In [94]:
```
# Evaluate
print("Logistic Regression: \n")
metrics(y_test, lr_pred_test, lr_pred_class_test)
print('-------------------')
print("Naive Bayes (Bernoulli): \n")
metrics(y_test, bern_pred_test, bern_pred_class_test)
print('-------------------')
print("SVC: \n")
metrics(y_test, svc_pred_test, svc_pred_class_test)
```

```
Logistic Regression:

Area Under the Curve:  0.6097651605231867

 Confusion Matrix:
 [[72 44]
 [47 69]]

 PPV, Correctly Classifies Response Yes:
 0.5948275862068966

 NPV, Correctly Classifies Response No:
 0.6206896551724138
-------------------
Naive Bayes (Bernoulli):

Area Under the Curve:  0.6064209274673009

 Confusion Matrix:
 [[72 44]
 [47 69]]

 PPV, Correctly Classifies Response Yes:
 0.5948275862068966

 NPV, Correctly Classifies Response No:
 0.6206896551724138
-------------------
SVC:

Area Under the Curve:  0.5816736028537455

 Confusion Matrix:
 [[66 50]
 [44 72]]

 PPV, Correctly Classifies Response Yes:
 0.6206896551724138

 NPV, Correctly Classifies Response No:
 0.5689655172413793
```

In [ ]:
```
# Model is a little better than random
```

Figure 17: Logistic Regression ROC Curve - Test Set

In [50]:
```
# ROC curve for Logistic Regression
fpr, tpr, thresholds = roc_curve(y_test, lr_pred_test)
roc_auc = auc(fpr, tpr)

# Plot curve

def plot_roc_curve(fpr, tpr, label=None):
    plt.plot(fpr, tpr, linewidth=2, label=label)
    plt.plot([0, 1], [0, 1], 'k--')
    plt.axis([0, 1, 0, 1])
    plt.xlabel('False Positive Rate', fontsize=16)
    plt.ylabel('True Positive Rate', fontsize=16)
    plt.title('Receiver Operating Characteristic, Test Set, Logistic\nROC curve (area = %0.2f)' % roc_auc)

plt.figure(figsize=(8, 6))
plot_roc_curve(fpr, tpr)
# save_fig("roc_curve_plot")
plt.show()
```

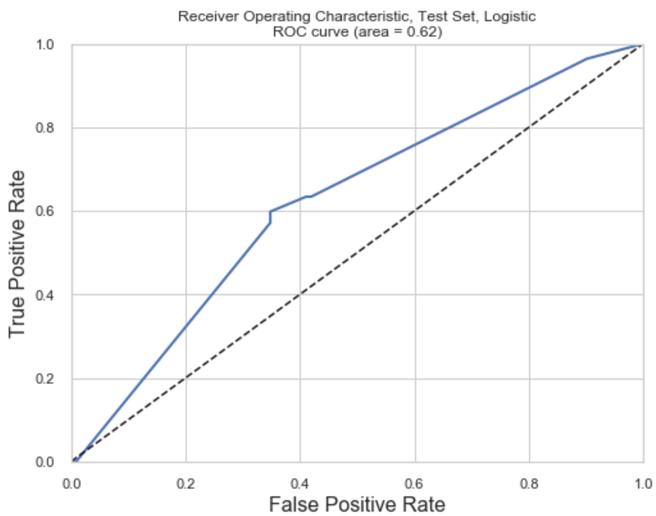


Figure 18: Naive Bayes (Bernoulli) ROC Curve - Test Set

In [51]:
```
# ROC curve for Naive Bayes
fpr, tpr, thresholds = roc_curve(y_test, bern_pred_test)
roc_auc = auc(fpr, tpr)

# Plot curve

def plot_roc_curve(fpr, tpr, label=None):
    plt.plot(fpr, tpr, linewidth=2, label=label)
    plt.plot([0, 1], [0, 1], 'k--')
    plt.axis([0, 1, 0, 1])
    plt.xlabel('False Positive Rate', fontsize=16)
    plt.ylabel('True Positive Rate', fontsize=16)
    plt.title('Receiver Operating Characteristic, Test Set, Naive Bayes\nROC curve (area = %0.2f)' % roc_auc)

plt.figure(figsize=(8, 6))
plot_roc_curve(fpr, tpr)
# save_fig("roc_curve_plot")
plt.show()
```

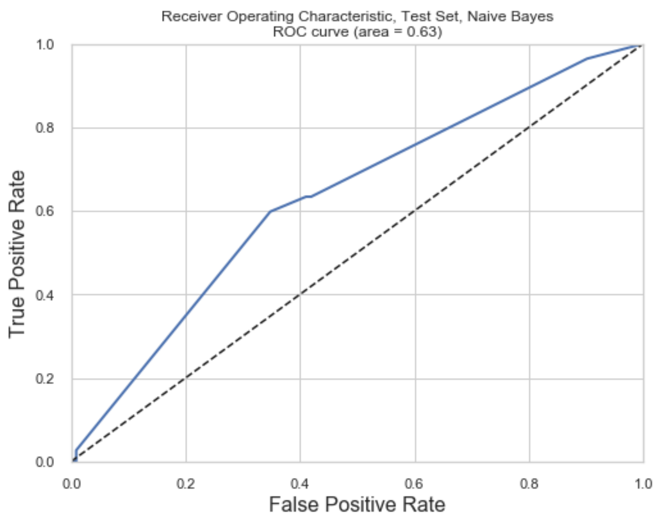


Figure 19: SVC ROC Curve - Test Set

In [95]:
```
# ROC curve for SVC
fpr, tpr, thresholds = roc_curve(y_test, svc_pred_test)
roc_auc = auc(fpr, tpr)

# Plot curve

def plot_roc_curve(fpr, tpr, label=None):
    plt.plot(fpr, tpr, linewidth=2, label=label)
    plt.plot([0, 1], [0, 1], 'k--')
    plt.axis([0, 1, 0, 1])
    plt.xlabel('False Positive Rate', fontsize=16)
    plt.ylabel('True Positive Rate', fontsize=16)
    plt.title('Receiver Operating Characteristic, Test Set, SVC\nROC curve (area = %0.2f)' % roc_auc)

plt.figure(figsize=(8, 6))
plot_roc_curve(fpr, tpr)
# save_fig("roc_curve_plot")
plt.show()
```