Portfolio_code

December 13, 2021

[1]:
```
import pandas as pd
#pd.set_option('display.max_columns', None)#, 'display.max_rows', None)
from pandas.api.types import CategoricalDtype
import numpy as np
import matplotlib.pyplot as plt

import sklearn
from sklearn import preprocessing
from sklearn.svm import SVC
from sklearn.model_selection import KFold
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import train_test_split
from scipy.stats import uniform, randint
from sklearn.impute import SimpleImputer
from sklearn.ensemble import AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
import xgboost as xgb
from sklearn.metrics import log_loss
from sklearn.metrics import hinge_loss

from sklearn.calibration import CalibratedClassifierCV
import random
random.seed(1995)

import datetime
import time
import pickle

import warnings
warnings.filterwarnings('ignore') # Used for a deprecation warning on XGBoost

import json
```

1 Loading and processing data

[2]:
```python
# Read in data, and display first 5 rows
coupon = pd.read_csv('Coupon_data/train.csv')
coupon.head()
```

[2]:
```
   id  Decision       Driving_to Passanger Weather  Temperature Time  \
0   1         1  No Urgent Place   Partner   Sunny           80  6PM
1   2         0             Work     Alone   Sunny           80  7AM
2   3         1  No Urgent Place   Partner   Sunny           80  6PM
3   4         1             Work     Alone   Sunny           55  7AM
4   5         1             Home     Alone   Sunny           30  6PM

                  Coupon Coupon_validity  Gender  …  \
0                    Bar              1d    Male  …
1      Restaurant(20-50)              1d  Female  …
2        Restaurant(<20)              1d    Male  …
3        Restaurant(<20)              1d    Male  …
4  Carry out & Take away              2h    Male  …

                  Education                               Occupation  \
0  Some college - no degree               Construction & Extraction
1  Some college - no degree                              Unemployed
2         Associates degree                              Unemployed
3  Some college - no degree               Construction & Extraction
4  Some college - no degree  Arts Design Entertainment Sports & Media

             Income  Bar Coffeehouse Carryaway  Restaurantlessthan20  \
0  $100000 or More  2.0         0.0       3.0                   2.0
1  $62500 - $74999  0.0         1.0       4.0                   3.0
2  $37500 - $49999  1.0         1.0       1.0                   3.0
3  $100000 or More  2.0         0.0       3.0                   2.0
4  $12500 - $24999  0.0         0.0       2.0                   2.0

   Restaurant20to50  Direction_same  Distance
0               2.0               0         2
1               0.0               0         2
2               1.0               0         1
3               2.0               0         1
4               0.0               1         2

[5 rows x 23 columns]
```

[3]:
```python
# View original data types
coupon.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10184 entries, 0 to 10183
```

```
Data columns (total 23 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   id                    10184 non-null  int64
 1   Decision              10184 non-null  int64
 2   Driving_to            10184 non-null  object
 3   Passanger             10184 non-null  object
 4   Weather               10184 non-null  object
 5   Temperature           10184 non-null  int64
 6   Time                  10184 non-null  object
 7   Coupon                10184 non-null  object
 8   Coupon_validity       10184 non-null  object
 9   Gender                10184 non-null  object
 10  Age                   10184 non-null  object
 11  Maritalstatus         10184 non-null  object
 12  Children              10184 non-null  int64
 13  Education             10184 non-null  object
 14  Occupation            10184 non-null  object
 15  Income                10184 non-null  object
 16  Bar                   10091 non-null  float64
 17  Coffeehouse           10002 non-null  float64
 18  Carryaway             10059 non-null  float64
 19  Restaurantlessthan20  10079 non-null  float64
 20  Restaurant20to50      10033 non-null  float64
 21  Direction_same        10184 non-null  int64
 22  Distance              10184 non-null  int64
dtypes: float64(5), int64(6), object(12)
memory usage: 1.8+ MB
```

The following function produces the dataset that was ultimately used for analysis and modeling. As discussed in the "Exploratory Analysis" portion of the report, variants of this process were also attempted. For brevity and the sake of providing clean code, only the final version is shown here.

[4]:
```python
def process_data(df):

    """Creates single pipeline for transforming training and testing data into␣
 ↪format used for modeling.
    Modifications include (1) changing data types, (2) dropping the 'id'␣
 ↪column, and (3) performing
    minimal feature engineering"""

    # Fill NA values with text 'NA', which will create a new category. There␣
 ↪were previously 495 observations
    # with at least one NA value
    df = df.fillna('NA')

    # Convert all columns to category type
    df = df.astype('category')
```

```
# Apply ordering to select columns
temp_type = CategoricalDtype(categories=[30, 55, 80], ordered=True)
coupon_val_type = CategoricalDtype(categories=["2h", "1d"], ordered=True)
age_type = CategoricalDtype(categories=["below21", "21", "26", "31", "36",␣
↪"41", "46", "50plus"], \
                             ordered=True)
education_type = CategoricalDtype(categories=["Some High School", "High␣
↪School Graduate", \
                                              "Some college - no degree",␣
↪"Associates degree", \
                                              "Bachelors degree", "Graduate␣
↪degree (Masters or Doctorate)"], \
                                   ordered=True)
income_type = CategoricalDtype(categories=["Less than $12500", "$12500 -␣
↪$24999", "$25000 - $37499", \
                                          "$37500 - $49999", "$50000 -␣
↪$62499", \
                                          "$62500 - $74999", "$75000 -␣
↪$87499", \
                                          "$87500 - $99999", "$100000 or␣
↪More"], ordered=True)
freq_type = CategoricalDtype(categories=['NA', 0.0, 1.0, 2.0, 3.0, 4.0],␣
↪ordered=True)
distance_type = CategoricalDtype(categories=[1, 2, 3], ordered=True)
df = df.astype({'Temperature': temp_type, 'Coupon_validity':␣
↪coupon_val_type, 'Age': age_type, \
                           'Education': education_type, 'Income': income_type,␣
↪'Bar': freq_type, \
                           'Coffeehouse': freq_type, 'Carryaway': freq_type,␣
↪'Restaurantlessthan20': freq_type, \
                           'Restaurant20to50': freq_type, 'Distance':␣
↪distance_type})

# Remove id column
df = df.drop(columns = 'id')

# Add Coupon_category_rating feature
conditions = [df['Coupon'] == 'Bar', \
              df['Coupon'] == 'Carry out & Take away', \
              df['Coupon'] == 'Coffee House', \
              df['Coupon'] == 'Restaurant(20-50)', \
              df['Coupon'] == 'Restaurant(<20)']
outputs = [df['Bar'], df['Carryaway'], df['Coffeehouse'],␣
↪df['Restaurant20to50'], \
           df['Restaurantlessthan20']]
```

```
    df['Coupon_category_rating'] = np.select(conditions, outputs, 'Other')

    # Return processed df
    return df
```

[5]:
```
# Pre-process the training data
coupon1 = process_data(coupon)
coupon1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10184 entries, 0 to 10183
Data columns (total 23 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Decision                10184 non-null  category
 1   Driving_to              10184 non-null  category
 2   Passanger               10184 non-null  category
 3   Weather                 10184 non-null  category
 4   Temperature             10184 non-null  category
 5   Time                    10184 non-null  category
 6   Coupon                  10184 non-null  category
 7   Coupon_validity         10184 non-null  category
 8   Gender                  10184 non-null  category
 9   Age                     10184 non-null  category
 10  Maritalstatus           10184 non-null  category
 11  Children                10184 non-null  category
 12  Education               10184 non-null  category
 13  Occupation              10184 non-null  category
 14  Income                  10184 non-null  category
 15  Bar                     10184 non-null  category
 16  Coffeehouse             10184 non-null  category
 17  Carryaway               10184 non-null  category
 18  Restaurantlessthan20    10184 non-null  category
 19  Restaurant20to50        10184 non-null  category
 20  Direction_same          10184 non-null  category
 21  Distance                10184 non-null  category
 22  Coupon_category_rating  10184 non-null  object
dtypes: category(22), object(1)
memory usage: 303.2+ KB
```

[6]:
```
# Show counts and observed incidence of Decision = 1 for each category within␣
↪each variable
for col in coupon1.columns[1:]:
    print(coupon1[[col, 'Decision']].groupby(col).agg(['count', np.average]))
    print('')
```

```
                Decision
                   count    average
```

Driving_to	Decision count	Decision average
Home	2595	0.502890
No Urgent Place	5085	0.635988
Work	2504	0.505192

	Decision	
	count	average
Passanger		
Alone	5834	0.525540
Friend(s)	2678	0.677745
Kid(s)	802	0.508728
Partner	870	0.591954

	Decision	
	count	average
Weather		
Rainy	988	0.461538
Snowy	1125	0.451556
Sunny	8071	0.599678

	Decision	
	count	average
Temperature		
30	1850	0.522162
55	3078	0.538661
80	5256	0.605023

	Decision	
	count	average
Time		
10AM	1851	0.601297
10PM	1609	0.502797
2PM	1595	0.672727
6PM	2625	0.588190
7AM	2504	0.505192

	Decision	
	count	average
Coupon		
Bar	1628	0.404177
Carry out & Take away	1897	0.738007
Coffee House	3220	0.506832
Restaurant(20-50)	1198	0.445743
Restaurant(<20)	2241	0.705042

	Decision	
	count	average
Coupon_validity		

2h	4525	0.500110
1d	5659	0.625729

	Decision	
	count	average
Gender		
Female	5200	0.549808
Male	4984	0.590891

	Decision	
	count	average
Age		
below21	442	0.628959
21	2136	0.599719
26	2014	0.599801
31	1609	0.549410
36	1104	0.545290
41	865	0.565318
46	563	0.580817
50plus	1451	0.506547

	Decision	
	count	average
Maritalstatus		
Divorced	420	0.528571
Married partner	4130	0.546731
Single	3794	0.603321
Unmarried partner	1736	0.569124
Widowed	104	0.451923

	Decision	
	count	average
Children		
0	5965	0.591282
1	4219	0.539701

	Decision	
	count	average
Education		
Some High School	70	0.714286
High School Graduate	715	0.604196
Some college - no degree	3509	0.597036
Associates degree	934	0.555675
Bachelors degree	3465	0.557864
Graduate degree (Masters or Doctorate)	1491	0.519785

	Decision	
	count	average

Occupation		
Architecture & Engineering	141	0.624113
Arts Design Entertainment Sports & Media	516	0.525194
Building & Grounds Cleaning & Maintenance	39	0.589744
Business & Financial	436	0.555046
Community & Social Services	193	0.497409
Computer & Mathematical	1148	0.567944
Construction & Extraction	115	0.730435
Education&Training&Library	770	0.524675
Farming Fishing & Forestry	34	0.558824
Food Preparation & Serving Related	242	0.570248
Healthcare Practitioners & Technical	202	0.673267
Healthcare Support	195	0.676923
Installation Maintenance & Repair	110	0.563636
Legal	169	0.461538
Life Physical Social Science	133	0.578947
Management	646	0.589783
Office & Administrative Support	514	0.607004
Personal Care & Service	145	0.551724
Production Occupations	87	0.620690
Protective Service	136	0.647059
Retired	408	0.458333
Sales & Related	879	0.569966
Student	1272	0.610063
Transportation & Material Moving	172	0.610465
Unemployed	1482	0.551957

	Decision	
	count	average
Income		
Less than $12500	833	0.588235
$12500 - $24999	1503	0.577512
$25000 - $37499	1603	0.598253
$37500 - $49999	1406	0.567568
$50000 - $62499	1349	0.595997
$62500 - $74999	678	0.541298
$75000 - $87499	692	0.484104
$87500 - $99999	719	0.531293
$100000 or More	1401	0.571734

	Decision	
	count	average
Bar		
NA	93	0.537634
0.0	4161	0.530161
1.0	2802	0.568879
2.0	1983	0.622794
3.0	865	0.641618

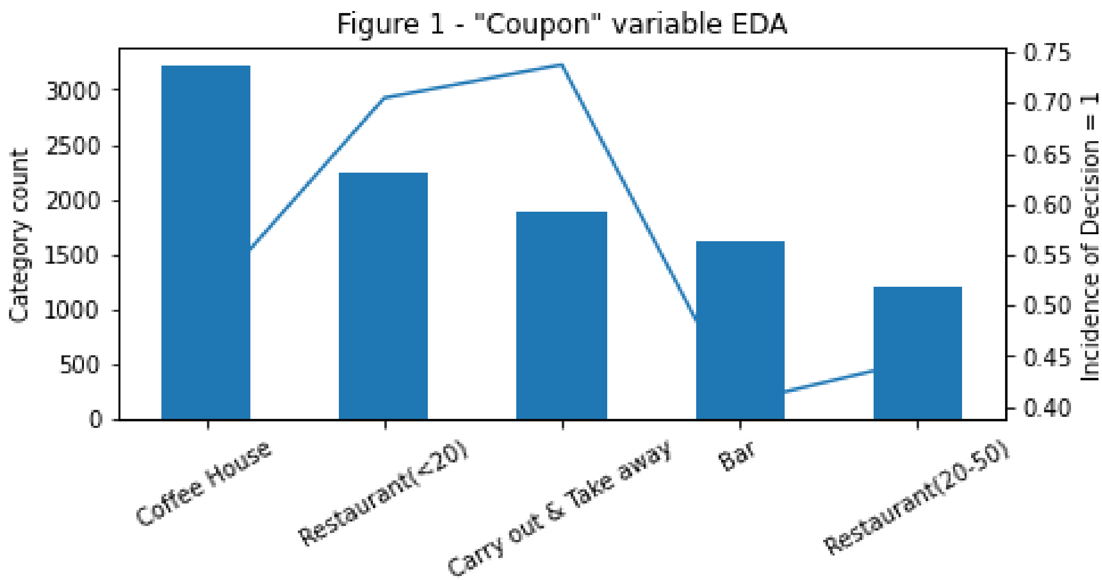
```
4.0       280  0.585714

            Decision
               count   average
Coffeehouse
NA               182  0.521978
0.0             2363  0.468472
1.0             2729  0.544155
2.0             2596  0.653698
3.0             1431  0.635220
4.0              883  0.578709

          Decision
             count   average
Carryaway
NA             125  0.672000
0.0            113  0.530973
1.0           1521  0.502301
2.0           3753  0.583800
3.0           3405  0.582379
4.0           1267  0.569850

                     Decision
                        count   average
Restaurantlessthan20
NA                        105  0.695238
0.0                       181  0.563536
1.0                      1694  0.528926
2.0                      4300  0.564419
3.0                      2899  0.588824
4.0                      1005  0.596020

                 Decision
                    count   average
Restaurant20to50
NA                    151  0.556291
0.0                  1720  0.517442
1.0                  4879  0.557696
2.0                  2643  0.600832
3.0                   588  0.659864
4.0                   203  0.655172

               Decision
                  count   average
Direction_same
0                  8034  0.565596
1                  2150  0.586047
```

```
         Decision
            count   average
Distance
1            4437  0.617534
2            4525  0.563757
3            1222  0.419804

                      Decision
                         count   average
Coupon_category_rating
0.0                       1652  0.214286
1.0                       2602  0.508455
2.0                       3102  0.679239
3.0                       1894  0.724921
4.0                        802  0.709476
NA                         132  0.590909
```

[7]:
```python
# Find overall incidence of Decision = 1 to assess class balance / imbalance
np.average(coupon1.Decision)
```

[7]: 0.5699135899450117

[8]:
```python
### Produce plot used in report
# Create plotting dataframe
plot_df = coupon1[['Coupon', \
                   'Decision']].groupby('Coupon').agg(['count', \
                                                       np.average])['Decision'].
 ↪sort_values('count', ascending = False)

# Generate plot
figure = plt.gcf()
ax = plot_df['count'].plot(kind = 'bar')
ax2 = plot_df['average'].plot(secondary_y=True, ax=ax)
ax.set_ylabel('Category count')
ax2.set_ylabel('Incidence of Decision = 1')
x_axis = ax.axes.get_xaxis()
x_axis.set_label_text('')
plt.title('Figure 1 - "Coupon" variable EDA')
for tick in ax.get_xticklabels():
    tick.set_rotation(30)

# Save plot
figure.set_size_inches(7, 3)
plt.savefig('Images/coupon_EDA.png', bbox_inches = 'tight')
```



2 Fitting models / results

Data preparation, cross-validation function definition

[9]:
```
# Create cross-validation folds, which will be used for all algorithms
kf = KFold(n_splits = 10, shuffle = True, random_state = 0)

# Split X and y... Also create X_dummy for SVM
def split_vars(df):
    return df.iloc[:, 1:], df.iloc[:, 0], pd.get_dummies(df.iloc[:, 1:])
X, y, X_dummy = split_vars(coupon1) # All data categorical

# Fix column name that XGBoost cannot handle
X_dummy_new = X_dummy.rename(columns = {'Coupon_Restaurant(<20)':␣
↪'Coupon_Restaurant_lt_20'})
```

[10]:
```
def cross_val(X, y, model):
    """Perform cross-validation using given data and model

    INPUTS:
    X - Data to be used for training and validation
    y - Labels to be used for training and validation
    model - Model object to be trained on data

    OUTPUTS:
    accuracy - List of prediction accuracy values from each fold

    NOTE: CV folds should be created outside of this function and called kf
```

```
    """

    accuracy = []
    for train_index, test_index in kf.split(X):
        X_train, X_test = X.iloc[train_index, :], X.iloc[test_index, :]
        y_train, y_test = y[train_index], y[test_index]
        model.fit(X_train, y_train)
        preds = model.predict(X_test)
        accuracy.append(np.average(preds == y_test))
    return accuracy
```

[11]:
```
# Load test data
coupon_test = pd.read_csv('Coupon_data/test.csv')
ids = coupon_test.iloc[:, 0]

# Load test labels
test_labels = pd.read_csv('Test_labels.csv')

# Prepare data for modeling
coupon_test = process_data(coupon_test)
coupon_test_dummy = pd.get_dummies(coupon_test)

# Modify test dataset for XGBoost
coupon_test_dummy_new = coupon_test_dummy.rename(columns = \
                                                 {'Coupon_Restaurant(<20)':␣
 ↪'Coupon_Restaurant_lt_20'})
```

SVM

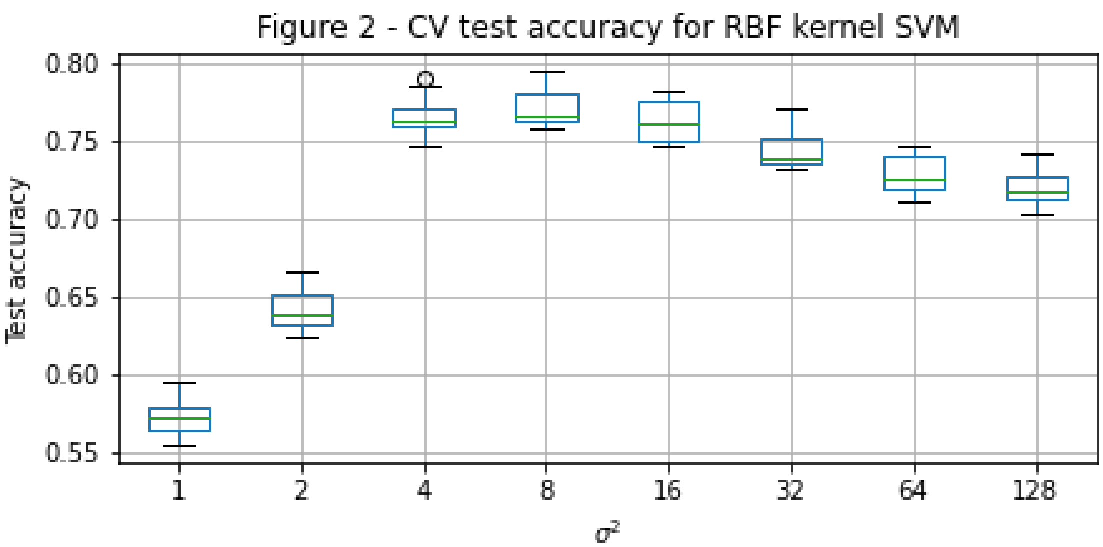
[12]:
```
# Define sigma_squared values to test
sigma_sq = np.array([1, 2, 4, 8, 16, 32, 64, 128])
gamma = 1 / sigma_sq

# Initialize matrix of accuracy values
accuracy_svm = np.zeros((kf.get_n_splits(X_dummy_new), len(gamma)))

# Loop through different sigma_sq values and perform CV for each
for idx, val in enumerate(gamma):
    print('Gamma =', val)
    start = time.time()
    model = SVC(kernel = 'rbf', gamma = val)
    accuracy_svm[:, idx] = cross_val(X_dummy_new, y, model)
    stop = time.time()
    print("Iteration duration:", (stop - start))
```

```
Gamma = 1.0
Iteration duration: 156.42913007736206
Gamma = 0.5
Iteration duration: 153.482581615448
```

```
Gamma = 0.25
Iteration duration: 135.5385718345642
Gamma = 0.125
Iteration duration: 75.63980293273926
Gamma = 0.0625
Iteration duration: 68.22620272636414
Gamma = 0.03125
Iteration duration: 68.90236115455627
Gamma = 0.015625
Iteration duration: 69.41631293296814
Gamma = 0.0078125
Iteration duration: 72.44565510749817
```

[13]:

```
# Plot cross-validation results
pd.DataFrame(accuracy_svm, columns = sigma_sq).boxplot(figsize = (7, 3));
plt.xlabel('$\sigma^2$');
plt.ylabel('Test accuracy');
plt.title('Figure 2 - CV test accuracy for RBF kernel SVM');

# Save plot
plt.savefig('Images/SVM_cv.png', bbox_inches = 'tight');
```



[62]:

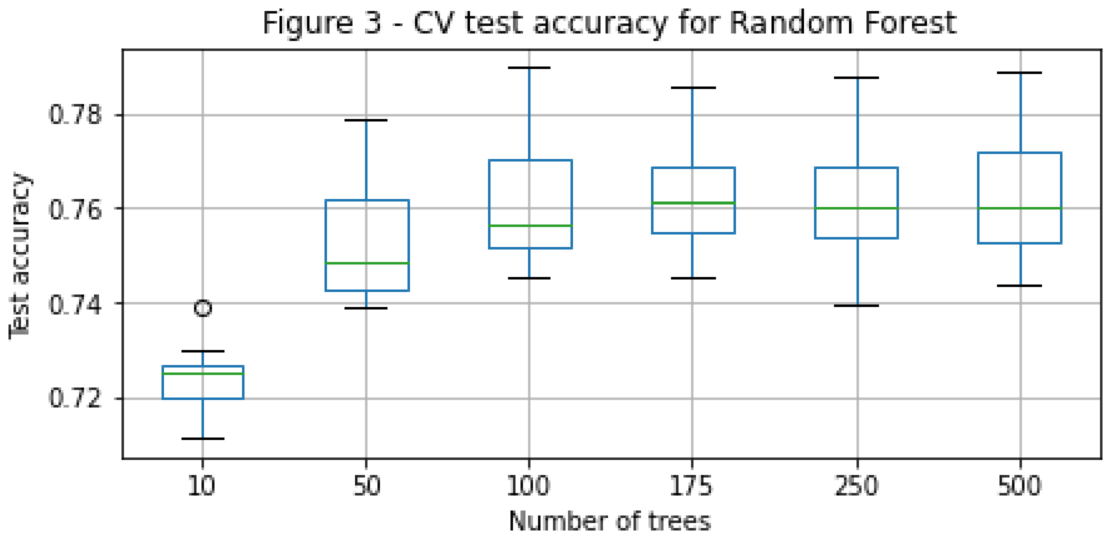
```
# Fit best model
model_svm = SVC(kernel = 'rbf', gamma = 1/8, probability = True)
model_svm.fit(X_dummy_new, y);
```

Random Forest

[19]:
```python
# Define n_trees values to test
n_trees = [10, 50, 100, 175, 250, 500]

# Initialize matrix of accuracy values
accuracy_rf = np.zeros((kf.get_n_splits(X_dummy_new), len(n_trees)))

# Loop through different sigma_sq values and perform CV for each
for idx, val in enumerate(n_trees):
    print('Number of trees =', val)
    start = time.time()
    model = RandomForestClassifier(n_estimators = val)
    accuracy_rf[:, idx] = cross_val(X_dummy_new, y, model)
    stop = time.time()
    print("Iteration duration:", (stop - start))
```

```
Number of trees = 10
Iteration duration: 0.9421980381011963
Number of trees = 50
Iteration duration: 4.342059135437012
Number of trees = 100
Iteration duration: 8.579497814178467
Number of trees = 175
Iteration duration: 14.89770793914795
Number of trees = 250
Iteration duration: 21.138985872268677
Number of trees = 500
Iteration duration: 42.814404010772705
```

[20]:
```python
# Plot cross-validation results
pd.DataFrame(accuracy_rf, columns = n_trees).boxplot(figsize = (7, 3));
plt.xlabel('Number of trees');
plt.ylabel('Test accuracy');
plt.title('Figure 3 - CV test accuracy for Random Forest');

# Save plot
plt.savefig('Images/RF_cv.png', bbox_inches = 'tight');
```



[21]:
```
# Fit best model
model_rf = RandomForestClassifier(n_estimators = 175)
model_rf.fit(X_dummy_new, y);
```

AdaBoost

[22]:
```
# Set grid of n_trees and depth values to search
n_trees = [10, 50, 100, 175, 250, 500]
depth = range(1, 9)

# Initialize DataFrame of accuracy values
folds = kf.get_n_splits(X_dummy_new)
accuracy_ada = pd.DataFrame({'n_trees' : np.repeat(n_trees, folds *␣
 ↪len(depth)), \
                             'depth' : np.tile(np.repeat(depth, folds),␣
 ↪len(n_trees)),
                             'accuracy' : np.zeros(10 * len(depth) *␣
 ↪len(n_trees))})

# Loop through different n_trees, depth values and perform CV for each
for idx, val in enumerate(n_trees):
    for idx2, val2 in enumerate(depth):
        print('Number of trees =', val, "... Max depth =", val2)
        start = time.time()
        model = AdaBoostClassifier(n_estimators = val, \
                                   base_estimator =␣
 ↪DecisionTreeClassifier(max_depth = val2))
        start_index = idx * folds * len(depth) + idx2 * folds
```

```
        end_index = idx * folds * len(depth) + idx2 * folds + kf.
↪get_n_splits(X_dummy_new) - 1
        accuracy_ada.loc[start_index:end_index, 'accuracy'] =␣
↪cross_val(X_dummy_new, y, model)
        stop = time.time()
        print("Iteration duration:", (stop - start))
```

```
Number of trees = 10 … Max depth = 1
Iteration duration: 0.8513829708099365
Number of trees = 10 … Max depth = 2
Iteration duration: 1.3323688507080078
Number of trees = 10 … Max depth = 3
Iteration duration: 1.8363170623779297
Number of trees = 10 … Max depth = 4
Iteration duration: 2.30936598777771
Number of trees = 10 … Max depth = 5
Iteration duration: 2.776823043823242
Number of trees = 10 … Max depth = 6
Iteration duration: 3.2513551712036133
Number of trees = 10 … Max depth = 7
Iteration duration: 3.7509829998016357
Number of trees = 10 … Max depth = 8
Iteration duration: 4.259921073913574
Number of trees = 50 … Max depth = 1
Iteration duration: 3.897386312484741
Number of trees = 50 … Max depth = 2
Iteration duration: 6.484836101531982
Number of trees = 50 … Max depth = 3
Iteration duration: 8.798183917999268
Number of trees = 50 … Max depth = 4
Iteration duration: 11.240533113479614
Number of trees = 50 … Max depth = 5
Iteration duration: 13.717737913131714
Number of trees = 50 … Max depth = 6
Iteration duration: 16.033516883850098
Number of trees = 50 … Max depth = 7
Iteration duration: 19.29244899749756
Number of trees = 50 … Max depth = 8
Iteration duration: 21.241236925125122
Number of trees = 100 … Max depth = 1
Iteration duration: 7.764058828353882
Number of trees = 100 … Max depth = 2
Iteration duration: 12.759939193725586
Number of trees = 100 … Max depth = 3
Iteration duration: 17.455379962921143
Number of trees = 100 … Max depth = 4
Iteration duration: 22.313122987747192
```

```
Number of trees = 100 … Max depth = 5
Iteration duration: 27.224900007247925
Number of trees = 100 … Max depth = 6
Iteration duration: 32.17254900932312
Number of trees = 100 … Max depth = 7
Iteration duration: 37.60603404045105
Number of trees = 100 … Max depth = 8
Iteration duration: 41.079185009002686
Number of trees = 175 … Max depth = 1
Iteration duration: 13.67704701423645
Number of trees = 175 … Max depth = 2
Iteration duration: 22.684147119522095
Number of trees = 175 … Max depth = 3
Iteration duration: 31.243494987487793
Number of trees = 175 … Max depth = 4
Iteration duration: 39.03135800361633
Number of trees = 175 … Max depth = 5
Iteration duration: 48.431777000427246
Number of trees = 175 … Max depth = 6
Iteration duration: 56.524218797683716
Number of trees = 175 … Max depth = 7
Iteration duration: 64.21632528305054
Number of trees = 175 … Max depth = 8
Iteration duration: 62.58631896972656
Number of trees = 250 … Max depth = 1
Iteration duration: 19.093611001968384
Number of trees = 250 … Max depth = 2
Iteration duration: 31.761607885360718
Number of trees = 250 … Max depth = 3
Iteration duration: 44.81095910072327
Number of trees = 250 … Max depth = 4
Iteration duration: 56.95619583129883
Number of trees = 250 … Max depth = 5
Iteration duration: 72.90487504005432
Number of trees = 250 … Max depth = 6
Iteration duration: 83.16201496124268
Number of trees = 250 … Max depth = 7
Iteration duration: 82.23913502693176
Number of trees = 250 … Max depth = 8
Iteration duration: 87.45231986045837
Number of trees = 500 … Max depth = 1
Iteration duration: 38.94234800338745
Number of trees = 500 … Max depth = 2
Iteration duration: 62.87963104248047
Number of trees = 500 … Max depth = 3
Iteration duration: 87.16763496398926
Number of trees = 500 … Max depth = 4
Iteration duration: 113.2155978679657
```

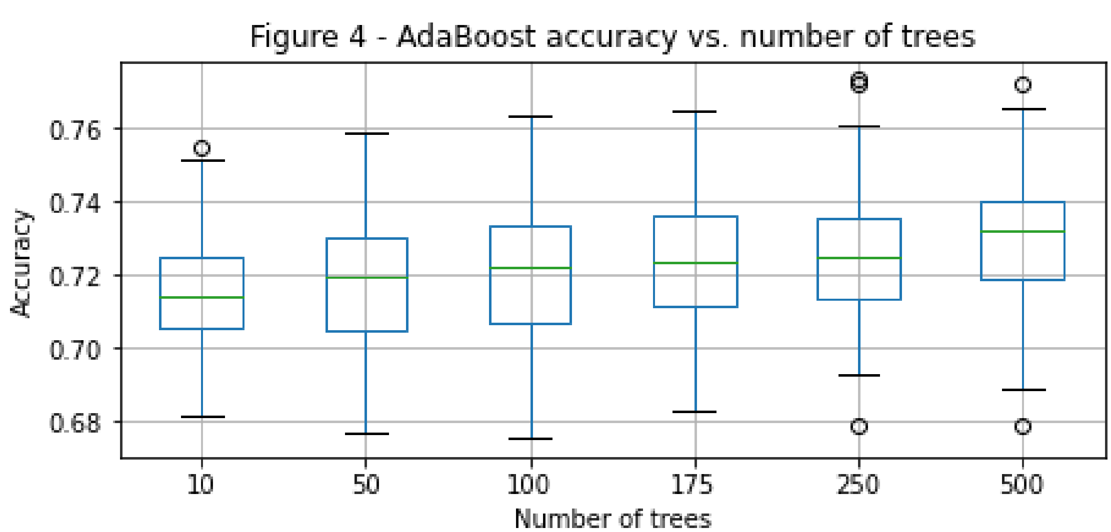
```
Number of trees = 500 … Max depth = 5
Iteration duration: 140.2541778087616
Number of trees = 500 … Max depth = 6
Iteration duration: 145.0643880367279
Number of trees = 500 … Max depth = 7
Iteration duration: 150.91491198539734
Number of trees = 500 … Max depth = 8
Iteration duration: 177.58576107025146
```

[23]:
```
# Summarize results, and find hyperparameters that yield best results
avg_df = accuracy_ada.groupby(['n_trees', 'depth']).agg(np.average).
↪reset_index()
avg_df.nlargest(5, 'accuracy').reset_index(drop = True)
```

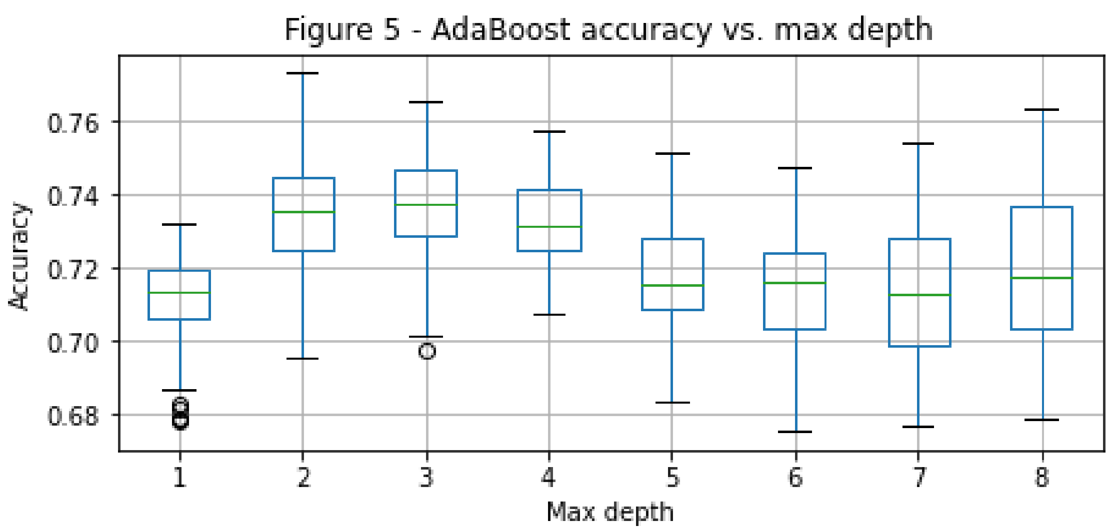
[23]:

	n_trees	depth	accuracy
0	250	2	0.748133
1	500	8	0.746858
2	100	3	0.745972
3	500	2	0.743323
4	175	2	0.742244

[24]:
```
# Plot univariate relationships - Number of trees
accuracy_ada[['n_trees', 'accuracy']].boxplot(by = 'n_trees', figsize = (7, 3));
plt.suptitle('');
plt.xlabel('Number of trees');
plt.ylabel('Accuracy');
plt.title('Figure 4 - AdaBoost accuracy vs. number of trees');

# Save plot
plt.savefig('Images/Ada_accuracy_vs_trees.png', bbox_inches = 'tight');
```



```
[25]: # Plot univariate relationships - Max depth
accuracy_ada[['depth', 'accuracy']].boxplot(by = 'depth', figsize = (7, 3));
plt.suptitle('');
plt.xlabel('Max depth');
plt.ylabel('Accuracy');
plt.title('Figure 5 - AdaBoost accuracy vs. max depth');

# Save plot
plt.savefig('Images/Ada_accuracy_vs_depth.png', bbox_inches = 'tight')
```




```
[26]: # Fit best model
model_ada = AdaBoostClassifier(n_estimators = 250, \
                               base_estimator =␣
 ↪DecisionTreeClassifier(max_depth = 2))
model_ada.fit(X_dummy_new, y);
```

XGBoost

```
[27]: # Define model
model = xgb.XGBClassifier(objective = 'binary:logistic', random_state = 0,␣
 ↪eval_metric = 'logloss')

# Define valid hyperparameters
params = {'learning_rate': uniform(0.1, 0.5), 'max_depth': randint(1, 8), \
          'n_estimators': randint(50, 300)}

# Perform Randomized Search CV
```

```
search = RandomizedSearchCV(model, param_distributions = params, random_state =␣
↪0, n_iter = 500, \
                            scoring = 'accuracy', cv = 5, n_jobs = 1)
search.fit(X_dummy_new, y)
```

[27]:
```
RandomizedSearchCV(cv=5,
                   estimator=XGBClassifier(base_score=None, booster=None,
                                           colsample_bylevel=None,
                                           colsample_bynode=None,
                                           colsample_bytree=None,
                                           enable_categorical=False,
                                           eval_metric='logloss', gamma=None,
                                           gpu_id=None, importance_type=None,
                                           interaction_constraints=None,
                                           learning_rate=None,
                                           max_delta_step=None, max_depth=None,
                                           min_child_weight=None, missing=na…
                                           validate_parameters=None,
                                           verbosity=None),
                   n_iter=500, n_jobs=1,
                   param_distributions={'learning_rate':
<scipy.stats._distn_infrastructure.rv_frozen object at 0x7fdb49775dc0>,
                                        'max_depth':
<scipy.stats._distn_infrastructure.rv_frozen object at 0x7fdb48f9f730>,
                                        'n_estimators':
<scipy.stats._distn_infrastructure.rv_frozen object at 0x7fdb48b71940>},
                   random_state=0, scoring='accuracy')
```

[28]:
```
# Visualize results
xgb_cv = pd.DataFrame(search.cv_results_).sort_values('rank_test_score').
↪reset_index(drop = True)
xgb_cv[['param_learning_rate', 'param_max_depth', 'param_n_estimators',␣
↪'mean_test_score']].head()
```

[28]:

	param_learning_rate	param_max_depth	param_n_estimators	mean_test_score
0	0.238814	6	189	0.765711
1	0.266982	7	188	0.764827
2	0.115118	7	216	0.764239
3	0.274391	5	284	0.763846
4	0.200182	7	298	0.763747

[29]:
```
# Fit best model
model_xgb = search.best_estimator_
model_xgb.fit(X_dummy_new, y);
```

Prediction aggregation

[32]:
```
# Notice that all AdaBoost probabilities are approximately 50%, rendering these␣
↪predictions useless
# for an ensemble model. We need to calibrate these probabilities
model_ada.predict_proba(X_dummy_new)[:,0][0:10]
```

[32]:
```
array([0.49700957, 0.50270805, 0.49710198, 0.49821534, 0.49834462,
       0.49398802, 0.49811995, 0.49836173, 0.49892323, 0.49948693])
```

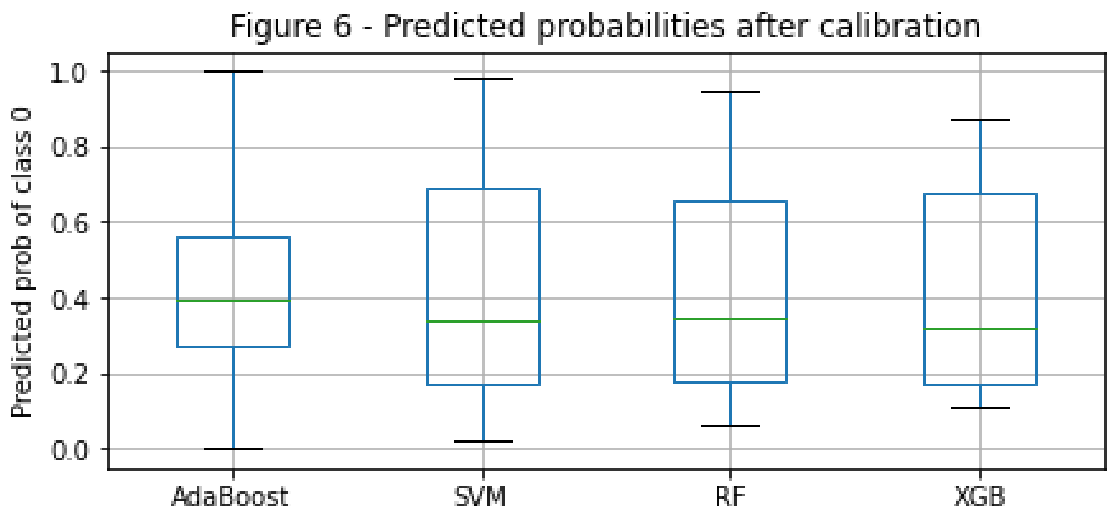
[33]:
```
# Create separate training and validation sets
X_train2, X_val, y_train2, y_val = train_test_split(X_dummy_new, y, test_size =␣
↪0.2, random_state = 5)
```

[34]:
```
# Calibrate AdaBoost
calibrated_ada = CalibratedClassifierCV(base_estimator = model_ada, cv = kf);
calibrated_ada.fit(X_train2, y_train2);

# Calibrate SVM
calibrated_svm = CalibratedClassifierCV(base_estimator = model_svm, cv = kf);
calibrated_svm.fit(X_train2, y_train2);

# Calibrate RF
calibrated_rf = CalibratedClassifierCV(base_estimator = model_rf, cv = kf);
calibrated_rf.fit(X_train2, y_train2);

# Calibrate XGBoost
calibrated_xgb = CalibratedClassifierCV(base_estimator = model_xgb, cv = kf);
calibrated_xgb.fit(X_train2, y_train2);
```

[35]:
```
# Initialize results dataframe
result_df = pd.DataFrame(columns = ['Fold', 'AdaBoost', 'SVM', 'RF', 'XGB',␣
↪'Label'])

# Store predicted probabilities and labels
for fold, (train_index, test_index) in enumerate(kf.split(X_val)):

    # Test / train split
    X_train, X_test = X_val.iloc[train_index, :], X_val.iloc[test_index, :]
    y_train, y_test = y_val.iloc[train_index], y_val.iloc[test_index]

    # Predict probabilities for each model
    ada_proba = calibrated_ada.predict_proba(X_test)[:,0]
    svm_proba = calibrated_svm.predict_proba(X_test)[:,0]
    rf_proba = calibrated_rf.predict_proba(X_test)[:,0]
    xgb_proba = calibrated_xgb.predict_proba(X_test)[:,0]

    # Create intermediate dataframe
    iter_df = pd.DataFrame({'Fold': np.repeat(fold, len(test_index)), \
```

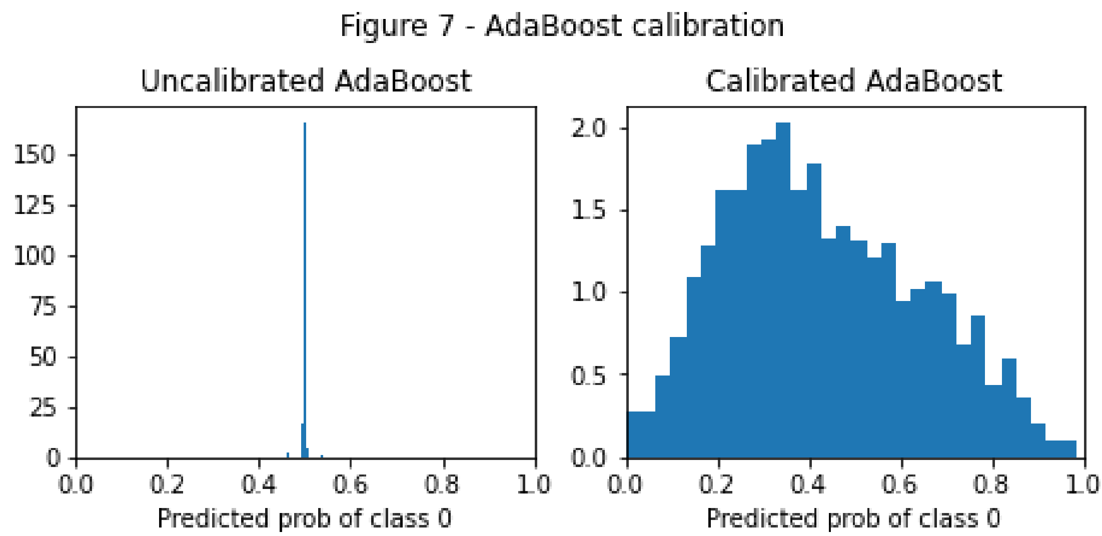
```
                              'AdaBoost': ada_proba, 'SVM': svm_proba, 'RF':␣
↪rf_proba, \
                              'XGB': xgb_proba, 'Label': y_test})

    # Concatenate df
    result_df = result_df.append(iter_df, ignore_index = True)
```

[36]:
```
# Plot calibrated probabilities to visualize result of calibration
result_df[['AdaBoost', 'SVM', 'RF', 'XGB']].boxplot(figsize = (7, 3));
plt.ylabel('Predicted prob of class 0');
plt.title('Figure 6 - Predicted probabilities after calibration');
plt.savefig('Images/Calibration.png', bbox_inches = 'tight');
```



[60]:
```
# Show dramatic effect of calibration on AdaBoost predicted probabilities
fig, (ax1, ax2) = plt.subplots(1, 2, figsize = (7.5, 3))

# Subplot 1
test = model_ada.predict_proba(coupon_test_dummy_new)[:, 0]
ax1.hist(test, density = True, bins = 30);
ax1.set(xlabel = 'Predicted prob of class 0');
ax1.set_title('Uncalibrated AdaBoost');
ax1.set_xlim(0, 1);

# Subplot 2
test2 = calibrated_ada.predict_proba(coupon_test_dummy_new)[:, 0]
ax2.hist(test2, density = True, bins = 30);
ax2.set(xlabel = 'Predicted prob of class 0');
ax2.set_title('Calibrated AdaBoost');
ax2.set_xlim(0, 1);
```

```
# Overall title
plt.suptitle('Figure 7 - AdaBoost calibration')
plt.subplots_adjust(top = 0.8)

# Save plot
plt.savefig('Images/AdaBoost_calibration.png', bbox_inches = 'tight')
```




```
[38]: # Create df to track results of using different coefficients
ensemble_df = pd.DataFrame(columns = ['AdaBoost', 'SVM', 'RF', 'XGB', 'Avg'])

# Try out many different combinations of models
for i in range(1000):

    # Random draw of contributions
    ada_coef = random.uniform(0, 1)
    svm_coef = random.uniform(0, 1)
    rf_coef = random.uniform(0, 1)
    xgb_coef = random.uniform(0, 1)
    total = ada_coef + svm_coef + rf_coef + xgb_coef

    accuracy = np.zeros(10)
    for fold in range(10):
        filter_df = result_df[result_df.Fold == fold]
        combined_probs = (ada_coef * filter_df.iloc[:, 1] + svm_coef *␣
↪filter_df.iloc[:, 2] + \
        rf_coef * filter_df.iloc[:, 3] + xgb_coef * filter_df.iloc[:, 4]) /␣
↪total
```

```
        preds = [0 if prob >= 0.5 else 1 for prob in combined_probs]
        accuracy[fold] = np.average(preds == filter_df.iloc[:, 5])
    ensemble_df.loc[len(ensemble_df.index)] = [ada_coef / total, svm_coef /␣
↪total, rf_coef / total, \
                                               xgb_coef / total, np.
↪average(accuracy)]

# Display results
ensemble_df.sort_values('Avg', ascending = False).reset_index(drop = True).
↪head(5)
```

[38]:

	AdaBoost	SVM	RF	XGB	Avg
0	0.170078	0.467426	0.280440	0.082055	0.784966
1	0.030555	0.569299	0.233043	0.167103	0.784483
2	0.197595	0.472985	0.287395	0.042024	0.783983
3	0.144471	0.483611	0.303343	0.068575	0.783500
4	0.206534	0.457703	0.239741	0.096023	0.783490

[39]:

```
# Recalibrate with full training data
# Calibrate AdaBoost
calibrated_ada = CalibratedClassifierCV(base_estimator = model_ada, cv = kf);
calibrated_ada.fit(X_dummy, y);

# Calibrate SVM
calibrated_svm = CalibratedClassifierCV(base_estimator = model_svm, cv = kf);
calibrated_svm.fit(X_dummy, y);

# Calibrate RF
calibrated_rf = CalibratedClassifierCV(base_estimator = model_rf, cv = kf);
calibrated_rf.fit(X_dummy, y);

# Calibrate XGBoost
calibrated_xgb = CalibratedClassifierCV(base_estimator = model_xgb, cv = kf);
calibrated_xgb.fit(X_dummy, y);
```

[40]:

```
# Try out best result on test data
ada_proba_test = ensemble_df.iloc[0, 0] * calibrated_ada.
↪predict_proba(coupon_test_dummy_new)[:,0]
svm_proba_test = ensemble_df.iloc[0, 1] * calibrated_svm.
↪predict_proba(coupon_test_dummy_new)[:,0]
rf_proba_test = ensemble_df.iloc[0, 2] * calibrated_rf.
↪predict_proba(coupon_test_dummy_new)[:,0]
xgb_proba_test = ensemble_df.iloc[0, 3] * calibrated_xgb.
↪predict_proba(coupon_test_dummy_new)[:,0]
combined_probs_test = (ada_proba_test + svm_proba_test + rf_proba_test +␣
↪xgb_proba_test)
test_preds = [0 if prob >= 0.5 else 1 for prob in combined_probs_test]
```

```python
np.average(test_preds == test_labels.iloc[:, 1])
```

[40]: 0.7724

We'll ultimately compare this test error value with some simpler ensembles later.

Last thing we can try is simple majority vote.

[41]:
```python
# Predictions
labels_svm = model_svm.predict(coupon_test_dummy_new)
labels_rf = model_rf.predict(coupon_test_dummy_new)
labels_xgb = model_xgb.predict(coupon_test_dummy_new)
labels_ada = model_ada.predict(coupon_test_dummy_new)

# Create predictions
avg = (labels_svm + labels_rf + labels_xgb + labels_ada) / 4
preds = [1 if pred >= 0.5 else 0 for pred in avg]

# Compute accuracy
np.average(preds == test_labels.iloc[:, 1])
```

[41]: 0.7724

Show training accuracy for all final models (based on 10-fold CV).

[42]:
```python
# AdaBoost
print('AdaBoost:', np.average(cross_val(X_dummy_new, y, model_ada)))
print('')

# SVM
print('SVM:', np.average(cross_val(X_dummy_new, y, model_svm)))
print('')

# RF
print('Random Forest:', np.average(cross_val(X_dummy_new, y, model_rf)))
print('')

# XGBoost
print('XGBoost:', np.average(cross_val(X_dummy_new, y, model_xgb)))
```

```
AdaBoost: 0.7481326312826435

SVM: 0.7713069556616815

Random Forest: 0.7634513978996319

XGBoost: 0.7653201162201088
```

Show test accuracy for all of our final models (including ensembles)

```
[63]: # Ensemble: RF + XGB (calibrated)
combined_probs_test = (calibrated_rf.predict_proba(coupon_test_dummy_new)[:, 0]␣
 ↪+ \
                      calibrated_xgb.predict_proba(coupon_test_dummy_new)[:,␣
 ↪0]) / 2
test_preds = [0 if prob >= 0.5 else 1 for prob in combined_probs_test]
print('Calibrated ensemble (XGB, RF):', np.average(test_preds == test_labels.
 ↪iloc[:, 1]))
print('')

# Ensemble: SVM + XGB (calibrated)
combined_probs_test = (calibrated_svm.predict_proba(coupon_test_dummy_new)[:,␣
 ↪0] + \
                      calibrated_xgb.predict_proba(coupon_test_dummy_new)[:,␣
 ↪0]) / 2
test_preds = [0 if prob >= 0.5 else 1 for prob in combined_probs_test]
print('Calibrated ensemble (XGB, SVM):', np.average(test_preds == test_labels.
 ↪iloc[:, 1]))
print('')

# Ensemble: RF + XGB + SVM (calibrated)
combined_probs_test = (calibrated_rf.predict_proba(coupon_test_dummy_new)[:, 0]␣
 ↪+ \
                      calibrated_xgb.predict_proba(coupon_test_dummy_new)[:,␣
 ↪0] + \
                     calibrated_svm.predict_proba(coupon_test_dummy_new)[:,␣
 ↪0]) / 3
test_preds = [0 if prob >= 0.5 else 1 for prob in combined_probs_test]
print('Calibrated ensemble (XGB, RF, SVM):', np.average(test_preds ==␣
 ↪test_labels.iloc[:, 1]))
print('')

# Ensemble: RF + XGB
combined_probs_test = (model_rf.predict_proba(coupon_test_dummy_new)[:, 0] + \
                      model_xgb.predict_proba(coupon_test_dummy_new)[:, 0]) / 2
test_preds = [0 if prob >= 0.5 else 1 for prob in combined_probs_test]
print('Ensemble (XGB, RF):', np.average(test_preds == test_labels.iloc[:, 1]))
print('')

# Ensemble: SVM + XGB
combined_probs_test = (model_svm.predict_proba(coupon_test_dummy_new)[:, 0] + \
                      model_xgb.predict_proba(coupon_test_dummy_new)[:, 0]) / 2
test_preds = [0 if prob >= 0.5 else 1 for prob in combined_probs_test]
print('Ensemble (XGB, SVM):', np.average(test_preds == test_labels.iloc[:, 1]))
print('')
```

```
# Ensemble: RF + XGB + SVM
combined_probs_test = (model_rf.predict_proba(coupon_test_dummy_new)[:, 0] + \
                       model_xgb.predict_proba(coupon_test_dummy_new)[:, 0] + \
                      model_svm.predict_proba(coupon_test_dummy_new)[:, 0]) / 3
test_preds = [0 if prob >= 0.5 else 1 for prob in combined_probs_test]
print('Ensemble (XGB, RF, SVM):', np.average(test_preds == test_labels.iloc[:,␣
 ↪1]))
print('')

# AdaBoost
print('AdaBoost:', np.average(model_ada.predict(coupon_test_dummy_new) ==␣
 ↪test_labels.iloc[:, 1]))
print('')

# SVM
print('SVM:', np.average(model_svm.predict(coupon_test_dummy_new) ==␣
 ↪test_labels.iloc[:, 1]))
print('')

# RF
print('Random Forest:', np.average(model_rf.predict(coupon_test_dummy_new) ==␣
 ↪test_labels.iloc[:, 1]))
print('')

# XGBoost
print('XGBoost:', np.average(model_xgb.predict(coupon_test_dummy_new) ==␣
 ↪test_labels.iloc[:, 1]))
```

```
Calibrated ensemble (XGB, RF): 0.7776

Calibrated ensemble (XGB, SVM): 0.7792

Calibrated ensemble (XGB, RF, SVM): 0.7772

Ensemble (XGB, RF): 0.774

Ensemble (XGB, SVM): 0.7744

Ensemble (XGB, RF, SVM): 0.7784

AdaBoost: 0.7424

SVM: 0.7668

Random Forest: 0.7556

XGBoost: 0.7628
```

3 Model reliance

[64]:
```
def model_reliance_dummy(X_train, y_train, X_test, y_test, X_orig, model, loss):

    """Compute model reliance for dummy variable formulation of original data.␣
↪Rather than treating
    each column of binary variables as independent, we create groupings that␣
↪resemble the original 22
    covariates before they were one-hot encoded. The chosen loss function
    is (1 - Accuracy) to allow for easy use with other algorithms.

    INPUTS:
    X_train, X_test - Covariate matrix, which is output of pd.get_dummies()␣
↪function on original data
    y_train, y_test - Accompanying labels for covariate matrices
    X_orig - Original data before transformation with pd.get_dummies() function
    model - A model object to use for fitting and predicting
    loss - Loss function to be used in calculation

    OUTPUTS:
    imp_df - Data frame with variable grouping identifiers, error, and model␣
↪reliance ratio
    """

    # Initialize dataframe to store results
    imp_df = pd.DataFrame({'Variable' : X_orig.columns, 'Error': np.
↪zeros(len(X_orig.columns))})
    imp_df.loc[-1] = ['All variables', 0.0]
    imp_df = imp_df.sort_index().reset_index(drop = True)

    # Define column groupings
    column_groups = [X_train.columns[0:3].values, X_train.columns[3:7].values,␣
↪X_train.columns[7:10].values, \
                X_train.columns[10:13].values, X_train.columns[13:18].values,␣
↪X_train.columns[18:23].values, \
                X_train.columns[23:25].values, X_train.columns[25:27].values, \
                X_train.columns[27:35].values, X_train.columns[35:40].values, \
                X_train.columns[40:42].values, X_train.columns[42:48].values, \
                X_train.columns[48:73].values, X_train.columns[73:82].values, \
                X_train.columns[82:88].values, X_train.columns[88:94].values, \
                X_train.columns[94:100].values, X_train.columns[100:106].
↪values, \
                X_train.columns[106:112].values, X_train.columns[112:114].
↪values, \
                X_train.columns[114:117].values, X_train.columns[117:123].
↪values]
```

```
    # Fit full model
    model.fit(X_train, y_train)
    preds = model.predict(X_test)
    if loss == hinge_loss:
        preds[np.where(preds == 0)] = -1
    imp_df.iloc[0, 1] = loss(y_test, preds)

    # Compute model reliance values
    for idx, group in enumerate(column_groups):
        X_test_new = X_test.copy()
        for col in group:
            X_test_new.loc[:, col] = np.random.permutation(X_test.loc[:, col])
        preds = model.predict(X_test_new)
        if loss == hinge_loss:
            preds[np.where(preds == 0)] = -1
        imp_df.iloc[idx + 1, 1] = loss(y_test, preds)

    # Create column for model reliance ratio
    imp_df['Importance'] = imp_df['Error'] / imp_df.iloc[0, 1]

    return imp_df
```

[65]:
```
# SVM model reliance
svm_mi = model_reliance_dummy(X_dummy_new, y, coupon_test_dummy_new,␣
 ↪test_labels.iloc[:, 1], \
                              X, model_svm, hinge_loss)
svm_mi.sort_values('Error', ascending = False).reset_index(drop = True)
```

[65]:

	Variable	Error	Importance
0	Coupon_category_rating	0.5792	1.241852
1	Coupon_validity	0.5264	1.128645
2	Coupon	0.5184	1.111492
3	Income	0.4976	1.066895
4	Occupation	0.4920	1.054889
5	Restaurantlessthan20	0.4872	1.044597
6	Age	0.4856	1.041166
7	Passanger	0.4824	1.034305
8	Gender	0.4808	1.030875
9	Driving_to	0.4800	1.029160
10	Education	0.4800	1.029160
11	Distance	0.4784	1.025729
12	Maritalstatus	0.4776	1.024014
13	Time	0.4768	1.022298
14	Bar	0.4768	1.022298
15	Coffeehouse	0.4768	1.022298
16	Direction_same	0.4752	1.018868
17	Carryaway	0.4744	1.017153

```
18                 Children  0.4720    1.012007
19         Restaurant20to50  0.4704    1.008576
20            All variables  0.4664    1.000000
21              Temperature  0.4624    0.991424
22                  Weather  0.4552    0.975986
```

[66]:
```
# Random Forest model reliance
rf_mi = model_reliance_dummy(X_dummy_new, y, coupon_test_dummy_new, test_labels.
 ↪iloc[:, 1], \
                              X, model_rf, log_loss)
rf_mi.sort_values('Error', ascending = False).reset_index(drop = True)
```

[66]:
```
                  Variable      Error  Importance
0   Coupon_category_rating  10.845347    1.362848
1                   Coupon   9.436145    1.185765
2          Coupon_validity   9.146007    1.149305
3               Occupation   8.676269    1.090277
4     Restaurantlessthan20   8.662455    1.088541
5                Education   8.634826    1.085069
6                   Income   8.579563    1.078125
7                      Age   8.579562    1.078125
8              Coffeehouse   8.538114    1.072916
9                      Bar   8.469037    1.064236
10              Driving_to   8.358512    1.050347
11               Carryaway   8.344695    1.048611
12                  Gender   8.330879    1.046875
13           Maritalstatus   8.317063    1.045139
14        Restaurant20to50   8.261800    1.038194
15               Passanger   8.247988    1.036459
16                Children   8.220350    1.032986
17                 Weather   8.192724    1.029514
18                    Time   8.178908    1.027778
19                Distance   8.123644    1.020833
20          Direction_same   8.026929    1.008680
21             Temperature   7.957858    1.000000
22           All variables   7.957856    1.000000
```

[67]:
```
# AdaBoost model reliance
ada_mi = model_reliance_dummy(X_dummy_new, y, coupon_test_dummy_new,␣
 ↪test_labels.iloc[:, 1], \
                              X, model_ada, log_loss)
ada_mi.sort_values('Error', ascending = False).reset_index(drop = True)
```

[67]:
```
                  Variable      Error  Importance
0   Coupon_category_rating  12.102557    1.394905
1                   Coupon  10.085463    1.162421
2               Occupation  10.002562    1.152866
```

3	Income	9.947303	1.146497
4	Driving_to	9.560458	1.101910
5	Coupon_validity	9.505202	1.095541
6	Time	9.367043	1.079618
7	Direction_same	9.242696	1.065286
8	Coffeehouse	9.104547	1.049363
9	Temperature	9.076914	1.046178
10	Gender	9.021651	1.039809
11	Age	9.007841	1.038217
12	Passanger	8.994022	1.036624
13	Restaurant20to50	8.980209	1.035032
14	Restaurantlessthan20	8.966389	1.033439
15	Carryaway	8.924942	1.028662
16	Bar	8.924940	1.028662
17	Children	8.897314	1.025478
18	Maritalstatus	8.869676	1.022293
19	Weather	8.814417	1.015924
20	Education	8.800599	1.014331
21	Distance	8.731523	1.006370
22	All variables	8.676260	1.000000

[68]:

```
# XGBoost model reliance
xgb_mi = model_reliance_dummy(X_dummy_new, y, coupon_test_dummy_new,␣
↪test_labels.iloc[:, 1], \
                              X, model_xgb, log_loss)
xgb_mi.sort_values('Error', ascending = False).reset_index(drop = True)
```

[68]:

	Variable	Error	Importance
0	Coupon_category_rating	10.983482	1.407080
1	Coupon	9.546650	1.223009
2	Coupon_validity	9.297961	1.191150
3	Occupation	8.745335	1.120354
4	Maritalstatus	8.496647	1.088495
5	Age	8.482840	1.086726
6	Restaurant20to50	8.455208	1.083186
7	Education	8.455205	1.083185
8	Driving_to	8.427575	1.079646
9	Income	8.413762	1.077876
10	Time	8.261789	1.058407
11	Distance	8.261786	1.058407
12	Coffeehouse	8.178895	1.047788
13	Temperature	8.165080	1.046018
14	Passanger	8.151263	1.044248
15	Bar	8.082184	1.035398
16	Gender	8.082184	1.035398
17	Direction_same	7.985470	1.023008
18	Children	7.971660	1.021239

19	Restaurantlessthan20	7.971658	1.021239
20	Carryaway	7.930214	1.015930
21	Weather	7.861133	1.007080
22	All variables	7.805870	1.000000