Daniel Lupercio HW4

Apply boosting, bagging, and random forests to the OJ data set - the data and a short description are attached. Be sure to fit all the models on a training set and to evaluate their performance on a test set.

In [1]:
```
%load_ext autoreload
%autoreload 2
import sys
```

In [2]:
```
# %load ../standard_import.txt
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Tree plotting
import pydot
from IPython.display import Image
import graphviz
#from sklearn.externals.six import StringIO
from io import StringIO

# Model selection
from sklearn.metrics import mean_squared_error, confusion_matrix, classification_report, accuracy_score
from sklearn.model_selection import train_test_split, cross_val_score

# Trees
from sklearn.tree import DecisionTreeRegressor, DecisionTreeClassifier, export_graphviz

%matplotlib inline
plt.style.use('seaborn-white')
```

In [3]:
```
oj_df = pd.read_csv("/Users/daniel421/Desktop/STAT_724/ISLR_data/OJ.csv", index_col = 0)
```

In [4]:
```
oj_df['Store7'] = oj_df['Store7'].map({'Yes':1, "No":0})
oj_df['Purchase'] = oj_df['Purchase'].map({'CH': 1, 'MM':0})
oj_df.head()
```

Out[4]:

	Purchase	WeekofPurchase	StoreID	PriceCH	PriceMM	DiscCH	DiscMM	SpecialCH	SpecialMM	LoyalCH	SalePriceMM	SalePriceCH	PriceDiff	Store7	PctDiscMM	PctDiscCH	ListPriceDiff	STORE
1	1	237	1	1.75	1.99	0.00	0.0	0	0	0.500000	1.99	1.75	0.24	0	0.000000	0.000000	0.24	1
2	1	239	1	1.75	1.99	0.00	0.3	0	1	0.600000	1.69	1.75	-0.06	0	0.150754	0.000000	0.24	1
3	1	245	1	1.86	2.09	0.17	0.0	0	0	0.680000	2.09	1.69	0.40	0	0.000000	0.091398	0.23	1
4	0	227	1	1.69	1.69	0.00	0.0	0	0	0.400000	1.69	1.69	0.00	0	0.000000	0.000000	0.00	1
5	1	228	7	1.69	1.69	0.00	0.0	0	0	0.956535	1.69	1.69	0.00	1	0.000000	0.000000	0.00	0

In [5]:
```
X = oj_df.drop('Purchase', axis = 1)
y = oj_df.Purchase
```

In [6]:
```
X.shape
```

Out[6]:
```
(1070, 17)
```

In [7]:
```
from sklearn.ensemble import BaggingClassifier, RandomForestClassifier, BaggingRegressor, RandomForestRegressor, GradientBoostingRegressor
```

In [8]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.5, random_state=0)

#X_train, X_test, y_train, y_test = train_test_split(oj_df.drop(['Purchase'], axis=1),
                                                     #oj_df[['Purchase']])
```

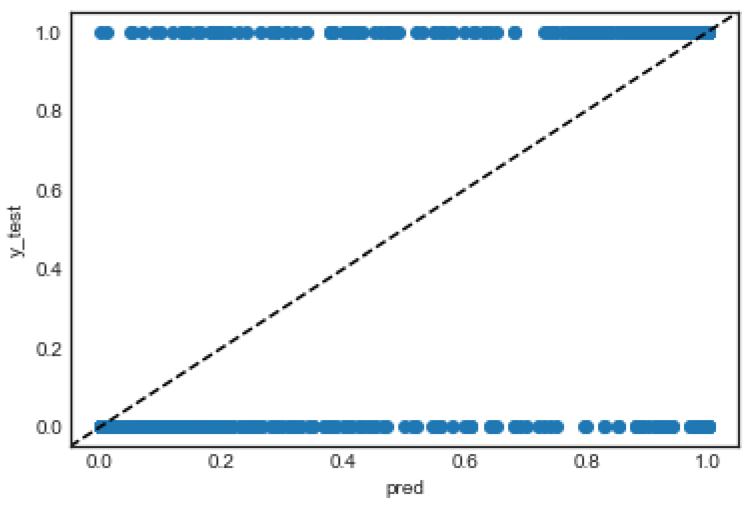
Random Forest: using all features

In [9]:
```
regr1 = RandomForestRegressor(max_features = 17, random_state = 1 )
regr1.fit(X_train, y_train)
```

Out[9]:
```
RandomForestRegressor(max_features=17, random_state=1)
```

In [10]:
```
pred = regr1.predict(X_test)
plt.scatter(pred, y_test, label = 'Purchase')
plt.plot([0, 1], [0, 1], '--k', transform=plt.gca().transAxes)
plt.xlabel('pred')
plt.ylabel('y_test')
```

Out[10]:
```
Text(0, 0.5, 'y_test')
```



In [11]:
```
print("Test MSE is: ", mean_squared_error(y_test, pred))
```

```
Test MSE is:  0.14918441017335282
```

Bagging: Using all features

In [12]:
```
from sklearn.ensemble import BaggingRegressor

bagging = BaggingRegressor(random_state=1)
bagging.fit(X=X_train, y=y_train.values.ravel())
p = bagging.predict(X_test)
print("Test MSE is: " + str(mean_squared_error(p, y_test)))
```

```
Test MSE is: 0.1625133644859813
```

Boosting: Using all features

In [13]:
```
regr2 = GradientBoostingRegressor(n_estimators=500, learning_rate=0.01, random_state=1)
regr2.fit(X_train, y_train)
```

Out[13]:
```
GradientBoostingRegressor(learning_rate=0.01, n_estimators=500, random_state=1)
```

In [14]:
```
p2 = regr2.predict(X_test)
print('Test MSE is: ' + str(mean_squared_error(p2, y_test)))
```

```
Test MSE is: 0.13162753964955742
```

How accurate are the results compared to simple methods like a single tree or a logistic regression (you need to fit one of these 2 models to compare to)? Which of the approaches yields the best performance?

In [15]:
```
from sklearn.linear_model import LogisticRegression
import statsmodels.api as sm
import statsmodels.formula.api as smf
```

In [16]:
```
lr = LogisticRegression()
```

In [17]:
```
import warnings
warnings.filterwarnings('ignore')
model_lr = lr.fit(X_train, y_train)
```

In [18]:
```
score = lr.score(X_test, y_test)
print(score)
```

```
0.8205607476635514
```

In [19]:
```
p3 = lr.predict(X_test)
print('Test MSE is: ' + str(mean_squared_error(p3, y_test)))
```

```
Test MSE is: 0.17943925233644858
```

The model with the lowest MSE on the testing observations, at approximately 0.13, is the boosting model with all features. When implementing a logistic regression, this model produced an MSE of approximately 0.18.