# Week 02 - Duke Tickets Example

This example loads the Duke Tickets A data example and performs regression in Python.

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### To Do (Future Versions):

Use machine-learning pipeline functionality for training to illustrate a production process

In [1]:
```
import pandas as pd
from sklearn.linear_model import LinearRegression, Ridge
from sklearn import metrics
import datetime
```

## Prepare the Data

In [2]:
```
dfDuke = pd.read_excel(r'W2 - DukeTixA.xlsx')
```

In [3]:
```
dfDuke.head(5)
```

Out[3]:

| | Observation | Price | Date | Quantity | Row | Deck | UNC rank | Duke rank |
|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 1400 | 2011-11-01 | 2 | t | L | 1 | 6 |
| 1 | 2 | 665 | 2011-11-01 | 4 | g | U | 1 | 6 |
| 2 | 3 | 565 | 2011-11-03 | 2 | w | U | 1 | 6 |
| 3 | 4 | 590 | 2011-11-03 | 2 | q | U | 1 | 6 |
| 4 | 5 | 750 | 2011-11-06 | 2 | o | U | 1 | 6 |

In [4]:
```
dfDuke.describe()
```

Out[4]:

| | Observation | Price | Quantity | UNC rank | Duke rank |
|---|---|---|---|---|---|
| count | 203.000000 | 203.000000 | 203.000000 | 203.000000 | 203.000000 |
| mean | 102.000000 | 649.492611 | 2.275862 | 4.753695 | 7.546798 |
| std | 58.745213 | 557.724509 | 0.753052 | 1.658588 | 1.760830 |
| min | 1.000000 | 55.000000 | 1.000000 | 1.000000 | 3.000000 |
| 25% | 51.500000 | 300.000000 | 2.000000 | 5.000000 | 7.000000 |
| 50% | 102.000000 | 495.000000 | 2.000000 | 5.000000 | 7.000000 |
| 75% | 152.500000 | 750.000000 | 2.000000 | 5.000000 | 9.000000 |
| max | 203.000000 | 4785.000000 | 4.000000 | 8.000000 | 10.000000 |

Check for missing/null values

In [5]:
```
dfDuke.isnull().sum()
```

Out[5]:
```
Observation    0
Price          0
Date           0
Quantity       0
Row            0
Deck           0
UNC rank       0
Duke rank      0
dtype: int64
```

Check datatypes for regression

In [6]:
```
dfDuke.dtypes
```

Out[6]:
```
Observation             int64
Price                   int64
Date           datetime64[ns]
Quantity                int64
Row                    object
Deck                   object
UNC rank                int64
Duke rank               int64
dtype: object
```

### Clean Data

1. Fix Dates
2. One-Hot-Encode the Quantity
3. Apply lambda to "Row"
4. One-Hot-Encode "Deck"
5. Prepare Calculated Fields from UNC and Duke Rank

In [7]:
```
# 1. Fix Dates
game_day = dfDuke['Date'].max()
dfDuke['Days to Game'] = (game_day - dfDuke['Date']) / datetime.timedelta(days=1)
```

In [8]:
```
# 2. One-Hot Encode the Quantity
dfQ = pd.get_dummies(dfDuke['Quantity'], drop_first=True, prefix='Quantity')
dfDuke = dfDuke.join(dfQ)
```

In [9]:
```
# 3. Apply Lambda to "Row"
dfDuke['Row (Clean)'] = dfDuke['Row'].str.strip()
dfDuke['Row Number'] = dfDuke['Row (Clean)'].apply ( \
        lambda x: ord(x) - 96 if len(x) == 1 else ord(x[0]) - 96)
```

In [10]:
```
# 4. One-Hot Encode Deck
dfDuke['Upper Deck'] = pd.get_dummies(dfDuke['Deck'], drop_first=True)
```

In [11]:
```
#5. Prepare calculated fields from UNC and Duke Rank
dfDuke['RankSum'] = dfDuke['UNC rank'] + dfDuke['Duke rank']
dfDuke['RankDif'] = abs(dfDuke['UNC rank'] - dfDuke['Duke rank'])
```

Drop extra columns and split the data into X and y:

In [12]:
```
y = dfDuke['Price']
X = dfDuke.drop(columns=['Price','Observation','Row','Row (Clean)', 'Date', 'Deck',
'UNC rank', 'Duke rank', 'Quantity'])
```

In [13]:
```
# Check our X data frame
X.head()
```

Out[13]:

| | Days to Game | Quantity_2 | Quantity_3 | Quantity_4 | Row Number | Upper Deck | RankSum | RankDif |
|---|---|---|---|---|---|---|---|---|
| 0 | 99.0 | 1 | 0 | 0 | 20 | 0 | 7 | 5 |
| 1 | 99.0 | 0 | 0 | 1 | 7 | 1 | 7 | 5 |
| 2 | 97.0 | 1 | 0 | 0 | 23 | 1 | 7 | 5 |
| 3 | 97.0 | 1 | 0 | 0 | 17 | 1 | 7 | 5 |
| 4 | 94.0 | 1 | 0 | 0 | 15 | 1 | 7 | 5 |

## Prepare the Regressions

### Specify Hyperparameters

Normally we would calibrate the regularization parameter using a grid-search or cross-validation; however, for simplicity we are just using $\lambda = 10.0$.

In [14]:
```
regLambda = 10.0 # Note that lambda is a protected word in python
```

Given hyperparameters, initialize the models - no hyperparameters for classical linear regression.

In [15]:
```
classicLR = LinearRegression()
ridgeLR = Ridge(alpha = regLambda)
```

### Fit the models

In [16]:
```
model_CLR = classicLR.fit(X, y)
```

In [17]:
```
model_RLR = ridgeLR.fit(X, y)
```

### Build predictions (in-sample)

In [18]:
```
yp = model_CLR.predict(X)
ypr = model_RLR.predict(X)
```

### Simple performance metrics

We are not using a validation/holdout set this week. Typically cross-validation or train/validate/test splits would apply when evaluating machine learning models.

In [19]:
```
print("Classical: ")
print("R2:   %10.3f" % metrics.r2_score(y, yp))
print("RMSE: %10.4f" % metrics.mean_squared_error(y, yp) ** 0.5)
print("")
print("Ridge:")
print("R2:   %10.3f" % metrics.r2_score(y, ypr))
print("RMSE: %10.4f" % metrics.mean_squared_error(y, ypr) ** 0.5)
```

```
Classical:
R2:        0.429
RMSE:   420.2544

Ridge:
R2:        0.418
RMSE:   424.4176
```

#### Output intercepts and coefficients for comparison

In [20]:
```
#  Simple vs. Regularized (Ridge)
cols= len(X.columns)
coeffs = [model_CLR.coef_, model_RLR.coef_]

print ("%14s" % "VAR", "%11s" % "SIMPLE", "%11s" % "RIDGE", "%11s" % "Delta")
print ("%14s" % "Intecept", "%11.4f" % model_CLR.intercept_, "%11.4f" % model_RLR.i
ntercept_, "%11.4f" % (model_CLR.intercept_ - model_RLR.intercept_))
for i in range(0,cols):
    print("%14s" % X.columns[i], "%11.4f" % coeffs[0][i], "%11.4f" % coeffs[1][i],
"%11.4f" % (coeffs[0][i] - coeffs[1][i]))
```

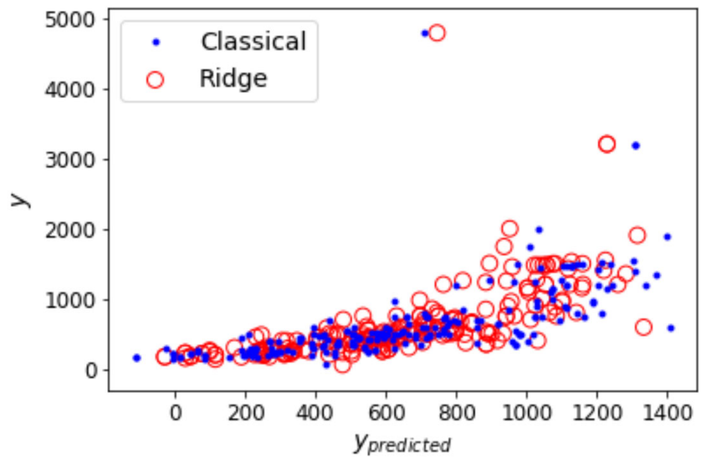
```
           VAR      SIMPLE       RIDGE       Delta
      Intecept   1250.7322   1268.4101    -17.6779
  Days to Game      5.9223      5.6874      0.2350
    Quantity_2    109.4939     58.3309     51.1630
    Quantity_3   -165.9811    -56.6931   -109.2879
    Quantity_4     40.9764     -2.2518     43.2282
    Row Number    -15.8415    -15.9277      0.0862
    Upper Deck   -641.0195   -521.1882   -119.8313
       RankSum     -1.2886     -3.9505      2.6619
       RankDif    -62.5887    -64.7643      2.1756
```

## Plots and visualizations

In [21]:
```
%matplotlib inline
import matplotlib as mpl
import matplotlib.pyplot as plt
mpl.rc('axes', labelsize=14)
mpl.rc('xtick', labelsize=12)
mpl.rc('ytick', labelsize=12)
```

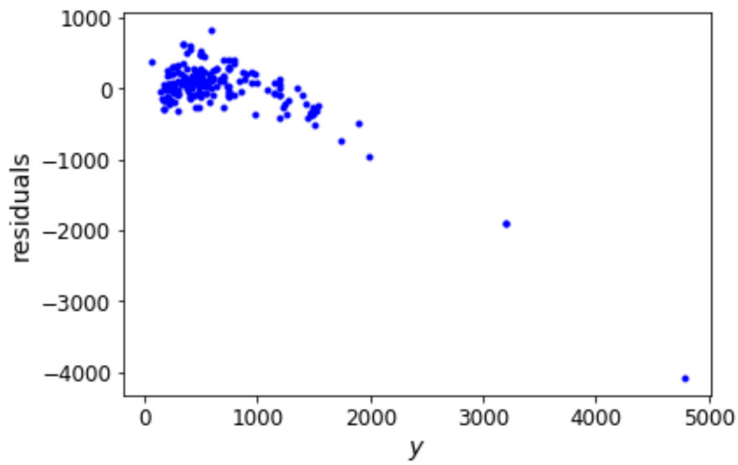
Plot Y vs. Prediction using Classical and Ridge

In [22]:
```
plt.plot(yp, y, "b.", label="Classical")
plt.scatter(ypr, y, s=80, facecolors='none', edgecolors='r', label="Ridge")
plt.xlabel("$y_{predicted}$")
plt.ylabel("$y$")
plt.legend(loc="upper left", fontsize=14)
plt.show()
```

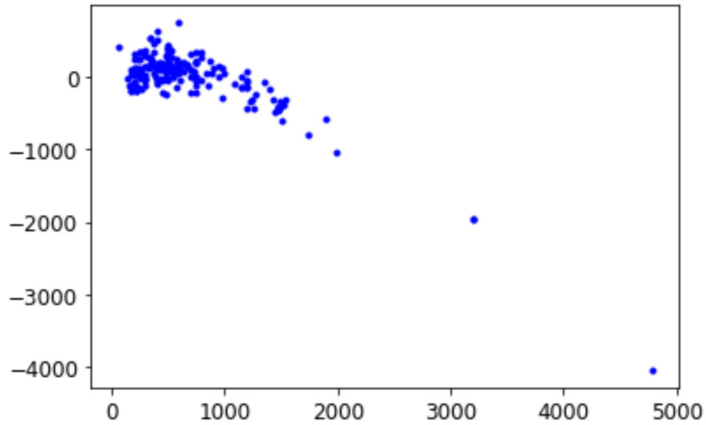



Plot residuals for classical and ridge

In [23]:
```
plt.plot(y, (yp - y), "b.")
plt.xlabel("$y$")
plt.ylabel("residuals")
plt.show()
```



In [24]:
```
plt.plot(y,(ypr-y), "b.")
plt.show()
```




**End of Notebook!**