In [2]:

```
import pandas as pd
import matplotlib as mpl
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import datetime
from numpy import mean
from numpy import std
from numpy import absolute
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import RepeatedKFold
from sklearn.linear_model import RidgeCV
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LassoCV
from sklearn.linear_model import ElasticNetCV
import sklearn.metrics as metrics
from statistics import mean
from matplotlib.axes._axes import _log as matplotlib_axes_logger
matplotlib_axes_logger.setLevel('ERROR')
from yellowbrick.regressor import ResidualsPlot
from yellowbrick.regressor import residuals_plot
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import SGDRegressor
from scipy import stats
from sklearn.ensemble import RandomForestRegressor
```

PA04

Jeremy Waibel and London Kasper

This project is an exploration of feature selection and different dimensionality reduction techniques (option 1 of program handout). We are using a dataset provided by Trinity Industries and are performing an analysis of the dataset according to the instructions provided:

> Problem: Shopping cars (maintenance events) is a large logistical problem for rail car owners and managers. One pain point is not knowing how long a car will be out of service while in a repair facility (shop). Attached is a list of shopping events from 2018 to 2019 for various shops. These cars are in shop for the same reason but some cars may require additional attention.
>
> Goal: Create a regressor to predict how long a car will be in shop (Cycle Time). Use cars completed 1/1/2018 to 5/31/2019 as your training set and provide performance metrics (Mean Absolute Error & Root Mean Square Error) for cars completed 6/1/2019 to 12/31/2019. Compare your performance metrics with a baseline (Avg Shop Cycle Time).
>
> Hint: CycleTimedays = DateCompleted − ArrivalDate

Data Dictionary:

(Dataset: problem_dataset.csv -> '|' delimited file)

- ArrivalDate, DateCompleted – Datetime
- Age – Years since car was built
- ShopRecordID – Shopping event Identifier
- ShopID – Shop location identifier
- CarModelID – Car model identifier
- CommodityID – Commodity Type Identifier
- IsHeavy – Heavy work for repair event identifier

What is dimensionality reduction?

In machine learning, features are attributes (or columns) of data that can be used to contribute toward a prediction. You would think that more features would help to produce a more accurate prediction. However, there exists a 'curse of dimentionality' that states that too many features can actually harm a model rather than make it more accurate. Having too many features slows training to halt, but also makes it more difficult to visualize your data.

So how would we fix this issue? The simplest answer seems to be to delete columns of data that seem insignificant. However, how do you determine what data is insignificant? Other than flat-out incorrect data, all data points offer information to the overall picture. Sometimes there are components to the dataset that are less significant to the question we're asking.

For example, if we wanted to predict the weather forecast for the next week based on the previous week's data, we wouldn't want to factor in what day of the week had the most rain (Saturday, Monday, etc). The day of the week is a categorical variable that has nothing to do with the weather conditions that were present that particular week. If we did make a prediction using day of the week as a feature, we would likely end up with a prediction mirroring the conditions of the last week. The day of the week is irrelevant to the conditions of the prediction, so we can discard the information for the model.

There is a difference between dimensionality reduction and feature selection that should be noted before we continue. Dimensionality reduction takes multiple features and attempts to condense them into a few features while still preserving the dataset's variance. On the other hand, feature selection is a decision to take data out of the equation, and does not necessarily mean that the variance of the dataset will still be preserved (unless specifically calculated to do so). Bottom line is, don't throw away data unless you're absolutely sure it's okay to do so.

Our process

We will first focus on exploratory data analysis, as there is much more information that can be gathered from the dataset before modeling. After an adequite analysis of the data, we will build an initial regression model to gather a baseline prediction. We will then build a second version of the model, this time using a dataset that has the dimensionality reduced and finally compare the results of the varying models.

EDA

In [3]:

```
rawData = pd.read_csv('problem_dataset.csv', delimiter='|',index_col=0,parse_dates=[1,7
print(rawData.head())
print(rawData.info())
print(rawData.isnull().sum())
```

```
             ArrivalDate    Age  ShopID  IsHeavy  CarModelID  CommodityID  \
ShopRecordID
1             2017-06-27   8.49  471553     True      292204       477991
2             2017-10-10   7.86  471554     True      292205       477992
3             2017-10-10   4.32  471555    False      292206       477993
4             2017-10-04  10.10  471556    False      292207       477994
5             2017-10-18   9.64  471556     True      292207       477995

             DateCompleted
ShopRecordID
1               2018-01-02
2               2018-02-24
3               2018-01-24
4               2018-06-15
5               2018-02-16
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7264 entries, 1 to 7264
Data columns (total 7 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   ArrivalDate    7264 non-null   datetime64[ns]
 1   Age            7264 non-null   float64
 2   ShopID         7264 non-null   int64
 3   IsHeavy        7264 non-null   bool
 4   CarModelID     7264 non-null   int64
 5   CommodityID    7264 non-null   int64
 6   DateCompleted  7264 non-null   datetime64[ns]
dtypes: bool(1), datetime64[ns](2), float64(1), int64(3)
memory usage: 404.3 KB
None
ArrivalDate      0
Age              0
ShopID           0
IsHeavy          0
CarModelID       0
CommodityID      0
DateCompleted    0
dtype: int64
```

In [4]:

```
rawData['CycleTime'] = (rawData['DateCompleted'] - rawData['ArrivalDate']).dt.days
print(rawData['CycleTime'])
```

```
ShopRecordID
1       189
2       137
3       106
```

```
4       254
5       121
       ...
7260     63
7261     29
7262     52
7263     34
7264     20
Name: CycleTime, Length: 7264, dtype: int64
```

In [5]:

```
#convert to categorical variable datatype
rawData['ShopID'] = pd.Categorical(rawData.ShopID)
rawData['CarModelID'] = pd.Categorical(rawData.CarModelID)
rawData['CommodityID'] = pd.Categorical(rawData.CommodityID)
```

In [6]:

```
rawData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7264 entries, 1 to 7264
Data columns (total 8 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   ArrivalDate    7264 non-null   datetime64[ns]
 1   Age            7264 non-null   float64
 2   ShopID         7264 non-null   category
 3   IsHeavy        7264 non-null   bool
 4   CarModelID     7264 non-null   category
 5   CommodityID    7264 non-null   category
 6   DateCompleted  7264 non-null   datetime64[ns]
 7   CycleTime      7264 non-null   int64
dtypes: bool(1), category(3), datetime64[ns](2), float64(1), int64(1)
memory usage: 332.5 KB
```

- All records are valid
- Data is in tidy format
- Categorical/Factor: ShopID, IsHeavy, CarModelID, CommodityID
- Numeric: Age, CycleTime
- Dates: ArrivalDate, DateCompleted

"Use cars completed 1/1/2018 to 5/31/2019 as your training set"

In [7]:

```
rawData['DateCompleted'].min()
```

Out[7]:

```
Timestamp('2018-01-01 00:00:00')
```

In [8]:

```
trainingData = rawData[(rawData['DateCompleted'] <= pd.to_datetime("2019-05-31"))].copy
trainingData.head()
```

Out[8]:

	ArrivalDate	Age	ShopID	IsHeavy	CarModelID	CommodityID	DateCompleted	CycleT
ShopRecordID								
1	2017-06-27	8.49	471553	True	292204	477991	2018-01-02	

	ArrivalDate	Age	ShopID	IsHeavy	CarModelID	CommodityID	DateCompleted	CycleT
ShopRecordID								
2	2017-10-10	7.86	471554	True	292205	477992	2018-02-24	
3	2017-10-10	4.32	471555	False	292206	477993	2018-01-24	
4	2017-10-04	10.10	471556	False	292207	477994	2018-06-15	
5	2017-10-18	9.64	471556	True	292207	477995	2018-02-16	

Analysis Plots

Now's a good time to take a step back and look at our data. What is it doing, and are there any patterns we can notice right off of the bat?

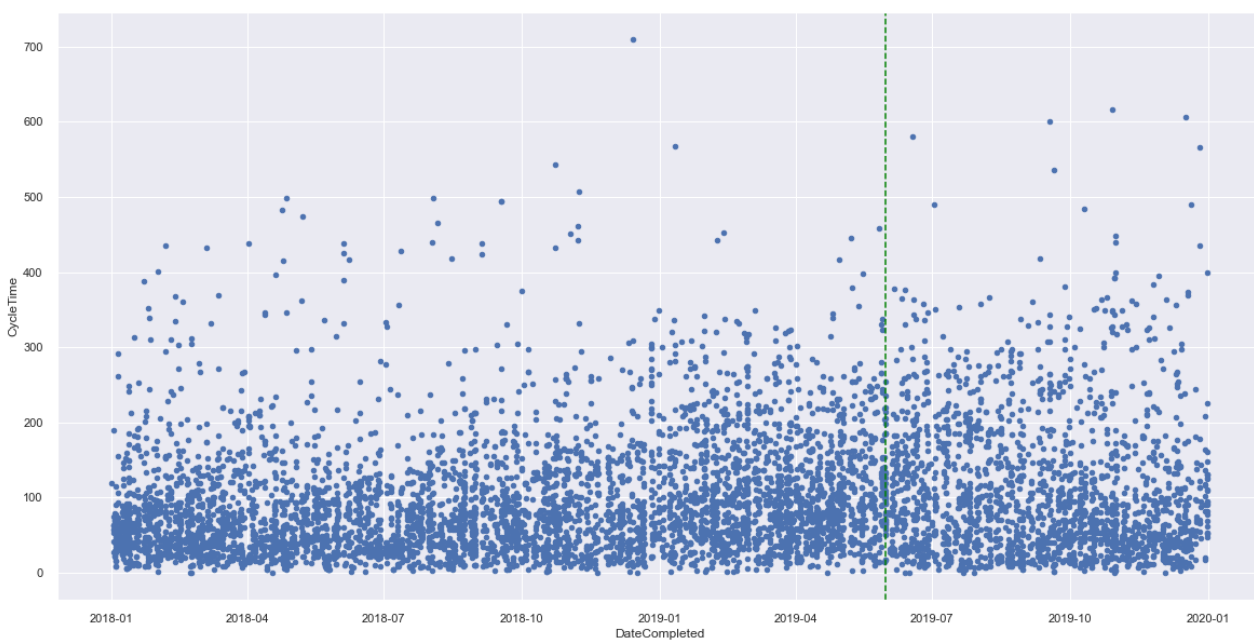
In [9]:

```
mpl.rcParams['figure.figsize'] = (20, 10)
sns.set(rc = {'figure.figsize':(20,10)})
```

Complete Data

In [10]:

```
ax = rawData.plot.scatter(x = 'DateCompleted', y = 'CycleTime');
ax.axvline(pd.to_datetime("2019-05-31"), color="green", linestyle="dashed");
```



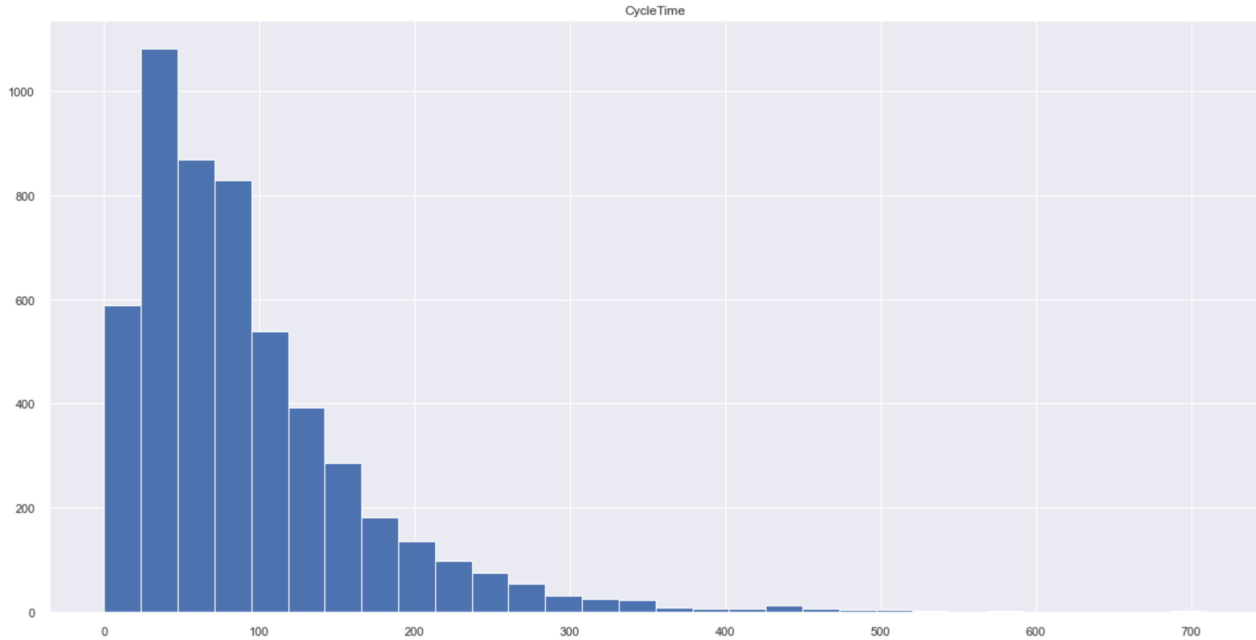
- CycleTime seem to be fairly consistent in the training/testing split

CycleTime

In [11]:

```
trainingData.hist('CycleTime', bins = 30)
```

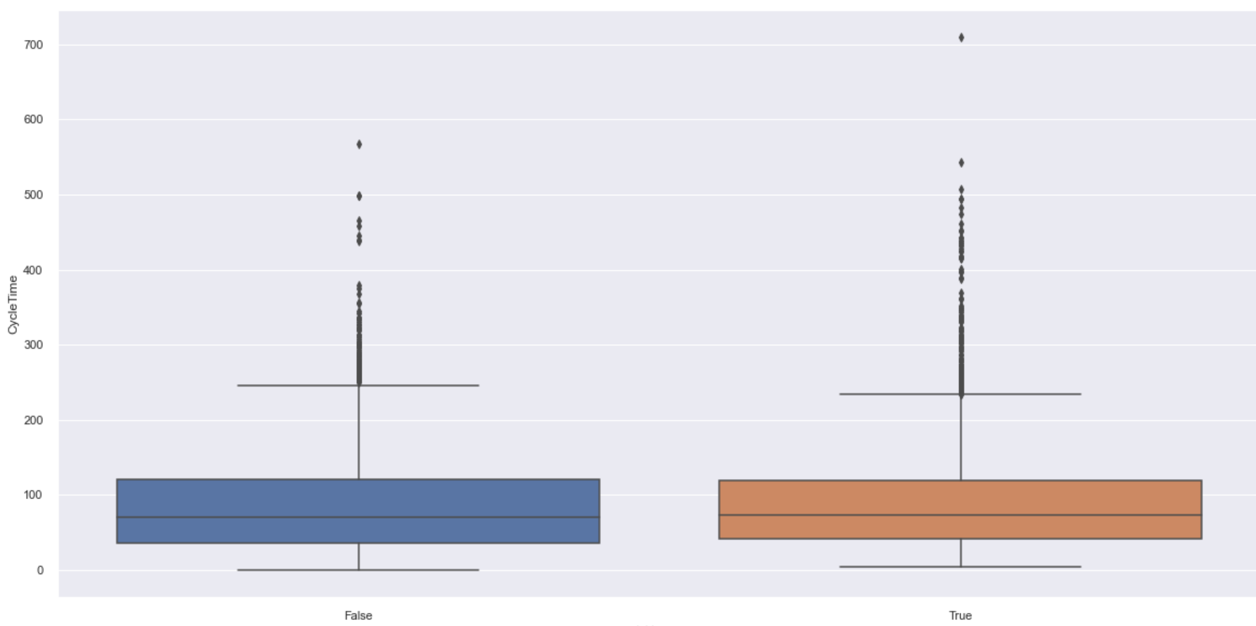
Out[11]: array([[<AxesSubplot:title={'center':'CycleTime'}>]], dtype=object)



- CycleTime is skewed right, however scaling the target variable is not normally required

IsHeavy

In [12]:
```
sns.boxplot(x = "IsHeavy", y = "CycleTime", data = trainingData);
```



In [13]:
```
trainingData.groupby('IsHeavy')['CycleTime'].describe().round(2)
```

Out[13]:

	count	mean	std	min	25%	50%	75%	max
IsHeavy								
False	1764.0	90.59	74.68	0.0	36.0	71.0	121.0	568.0

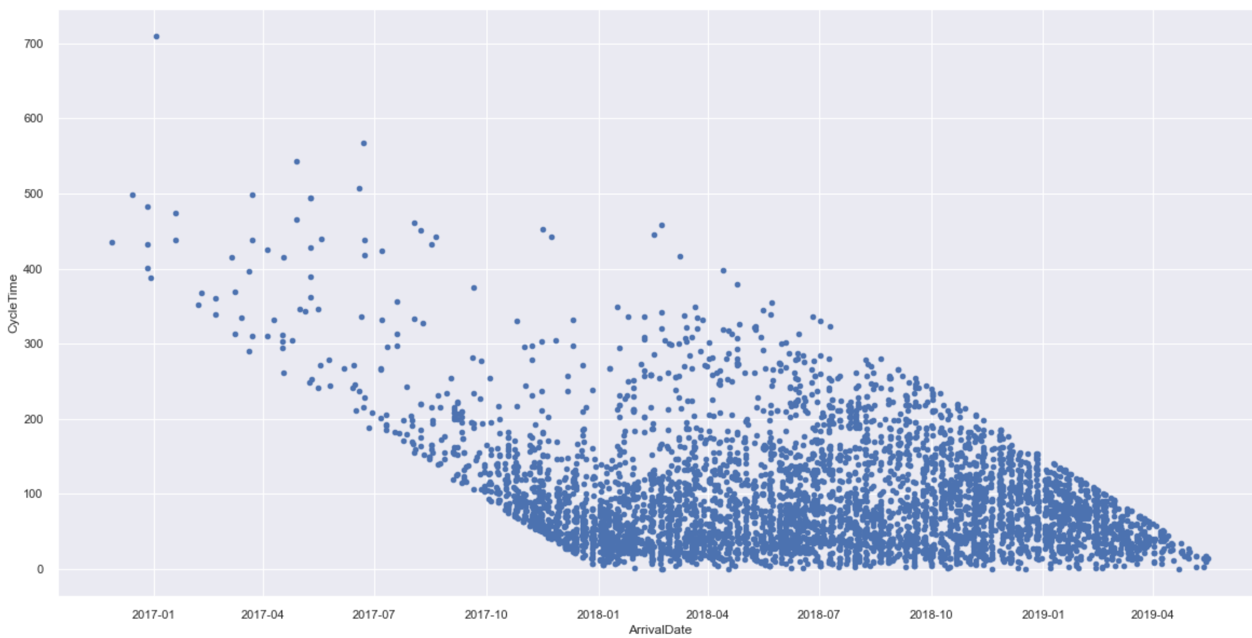
	count	mean	std	min	25%	50%	75%	max
IsHeavy								
True	3488.0	90.91	71.33	4.0	42.0	74.0	119.0	710.0

- Quite a few outiers
- High standard deviation
- While IsHeavy does not seem to affect CycleTime on its own, it may have an interaction with other variables

ArrivalDate

In [14]:

```
trainingData.plot.scatter('ArrivalDate','CycleTime');
```

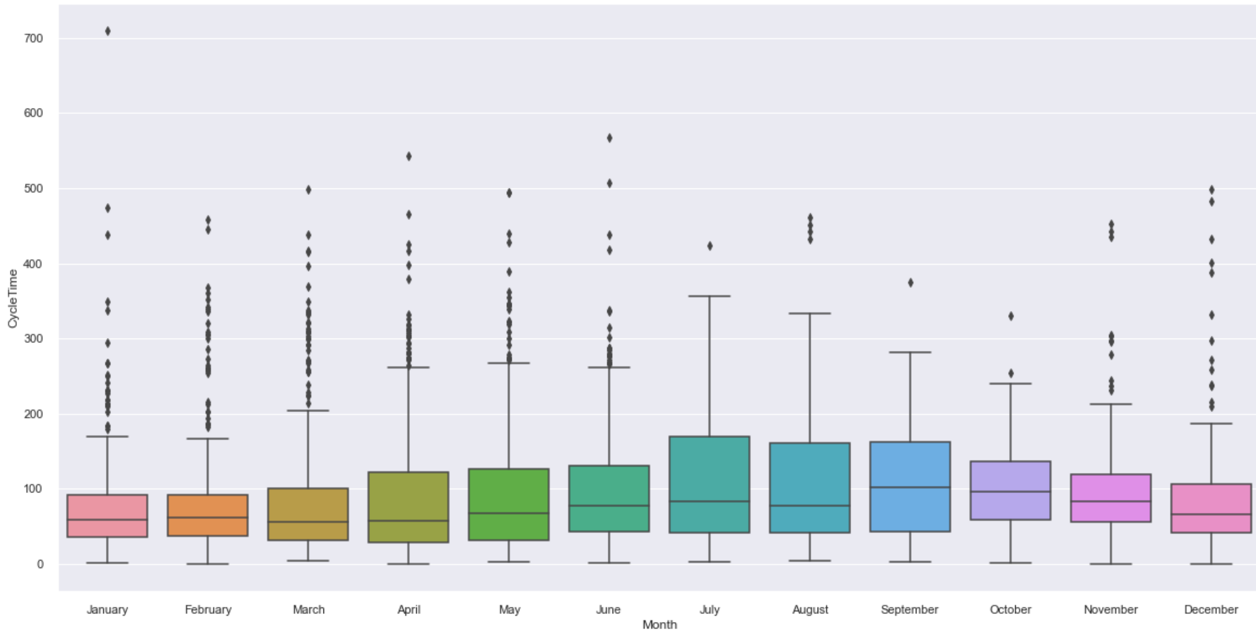


- The shape of the plot indicates that there is a ceiling and floor effect because of the way the data was partitioned
- The CycleTime of the car can only be at most max(DateCompleted) - ArrivalDate
- The CycleTime of the car can only be at least min(DateCompleted) - ArrivalDate
- Instead of just throwing away this data, we can break down ArrivalDate into Months/Days to see if they can provide information

ArrivalDate - Month

In [15]:

```
trainingData['Month'] = trainingData['ArrivalDate'].dt.month_name()
months = ["January", "February", "March", "April", "May", "June", "July", "August", "Se
trainingData['Month'] = pd.Categorical(trainingData['Month'], categories=months, ordere
trainingData.sort_values(by = 'Month')
sns.boxplot(x = "Month", y = "CycleTime", data = trainingData);
```



- Months may still possess the same ceiling and floor effect that ArrivalDate shows so we decided to break it down further into days of the week

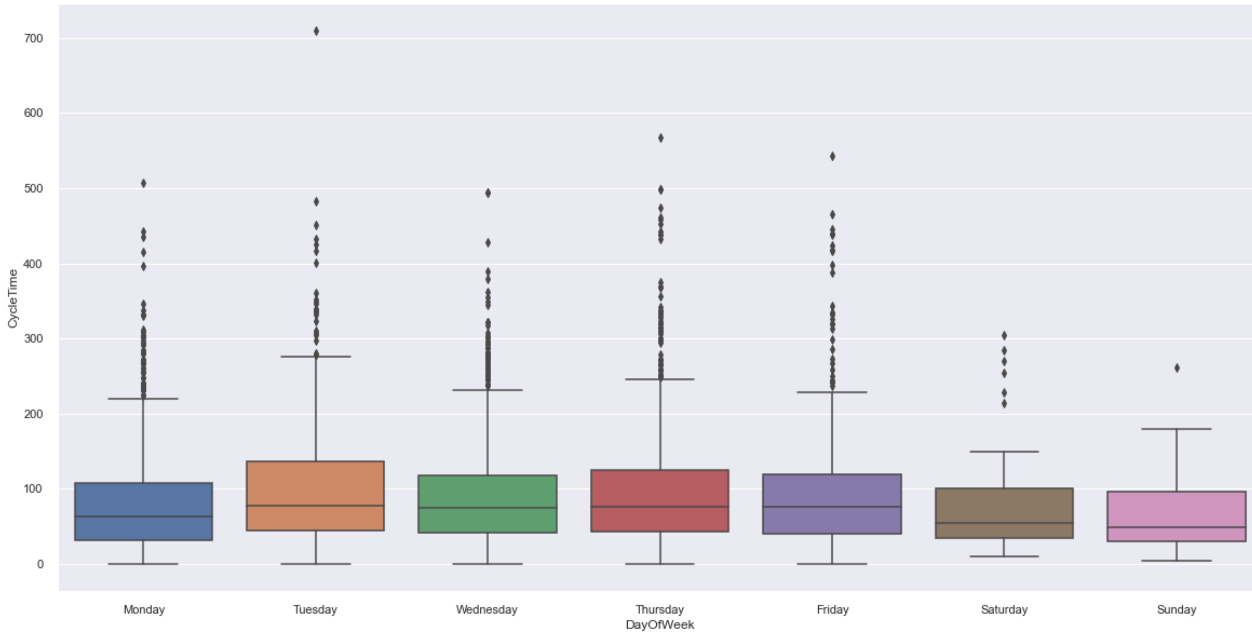
ArrivalDate - DayOfWeek

In [16]:

```
trainingData['DayOfWeek'] = trainingData['ArrivalDate'].dt.day_name()
dayofweek = ['Monday','Tuesday','Wednesday','Thursday','Friday','Saturday','Sunday']
trainingData['DayOfWeek'] = pd.Categorical(trainingData['DayOfWeek'], categories=dayofw
#trainingData.sort_values(by = 'DayOfWeek')
sns.boxplot(x = "DayOfWeek", y = "CycleTime", data = trainingData);
trainingData.groupby('DayOfWeek')['CycleTime'].describe().round(2)
```

Out[16]:

DayOfWeek	count	mean	std	min	25%	50%	75%	max
Monday	1143.0	81.02	67.80	0.0	32.00	63.0	108.00	507.0
Tuesday	1109.0	98.72	75.82	0.0	44.00	77.0	137.00	710.0
Wednesday	1052.0	90.00	68.36	0.0	42.00	75.0	118.00	495.0
Thursday	1165.0	95.54	75.48	0.0	43.00	76.0	125.00	568.0
Friday	630.0	91.86	76.13	0.0	40.00	75.5	118.75	543.0
Saturday	69.0	78.94	66.19	10.0	34.00	54.0	101.00	305.0
Sunday	84.0	65.75	48.72	4.0	29.75	48.5	97.00	262.0

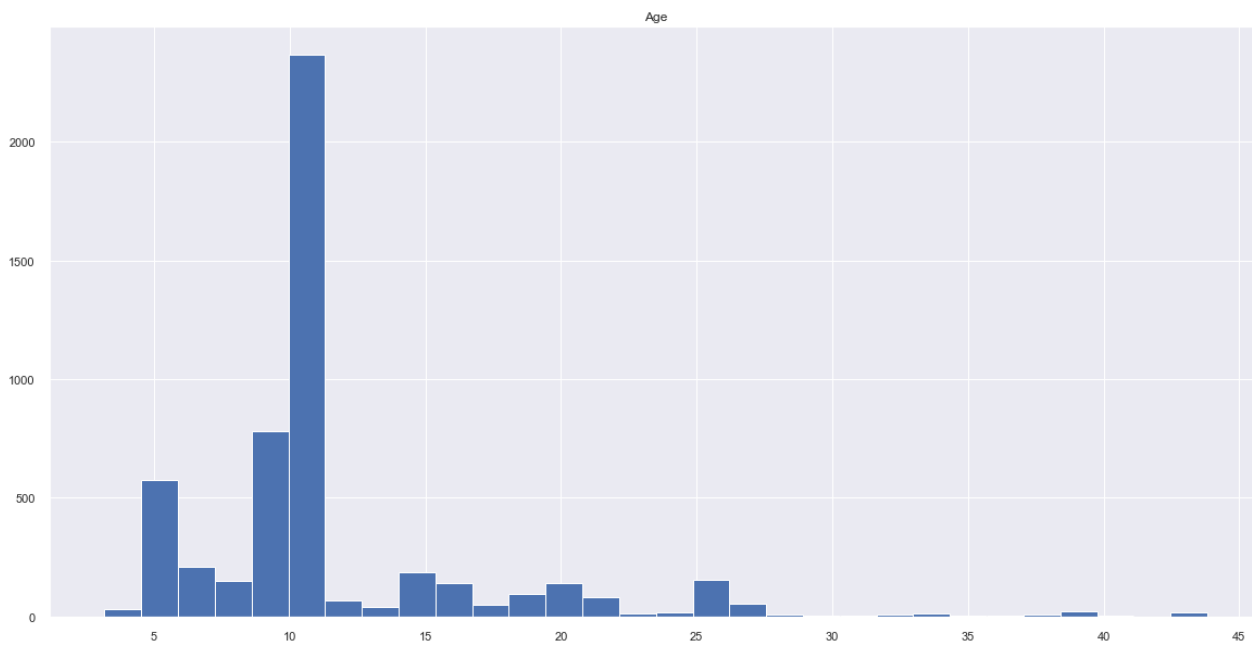


- DayOfWeek seems to have an effect on CycleTime
- There is no ceiling or floor effect using this metric

Age

In [17]:

```
trainingData.hist('Age', bins = 30);
```

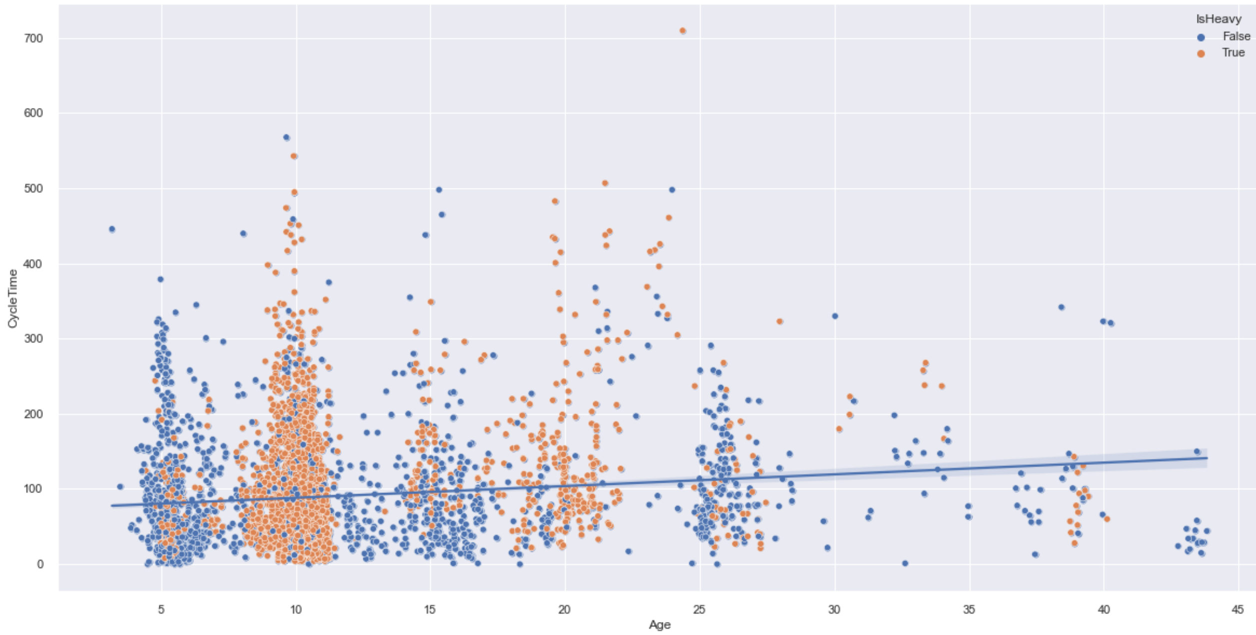


In [18]:

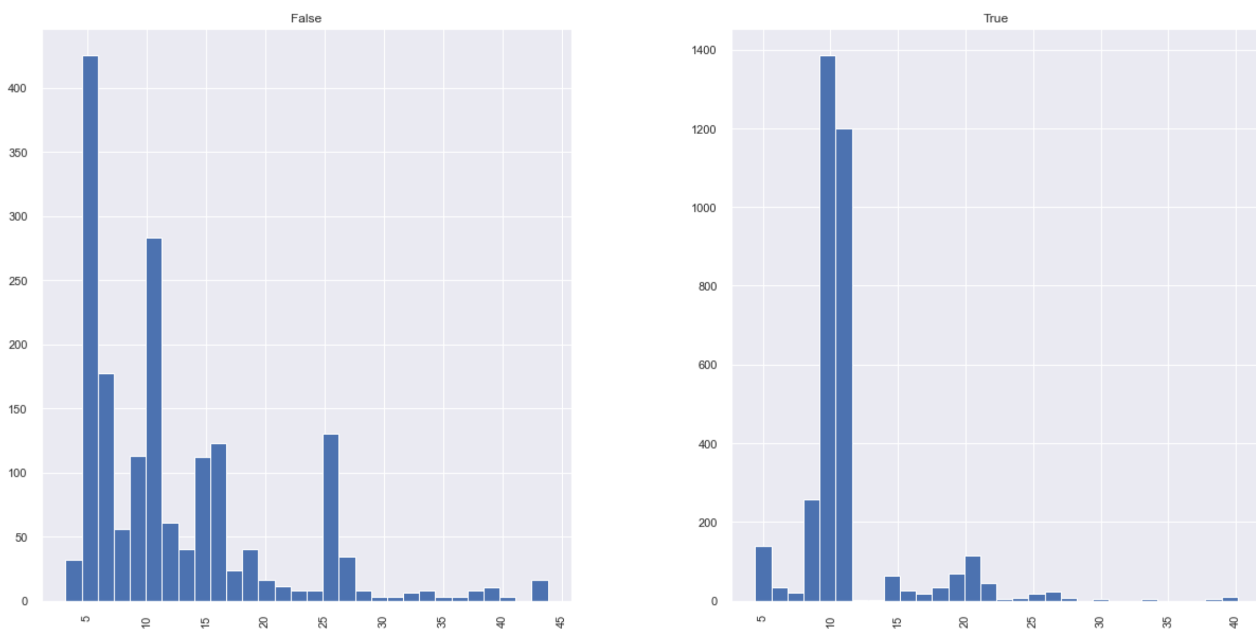
```
sns.regplot(x = 'Age', y = 'CycleTime', data = trainingData);
sns.scatterplot(x = 'Age', y = 'CycleTime', hue = 'IsHeavy', data = trainingData)
```

Out[18]:

```
<AxesSubplot:xlabel='Age', ylabel='CycleTime'>
```



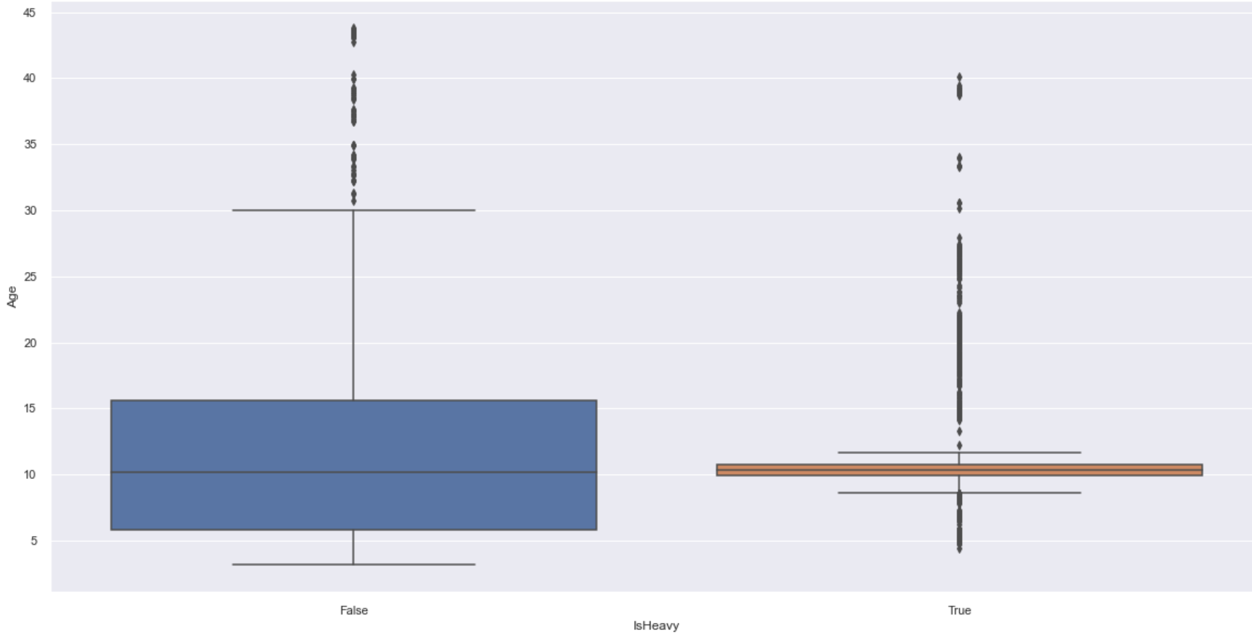
In [19]:
```
trainingData.hist('Age', by = 'IsHeavy', bins = 30);
```



In [20]:
```
sns.boxplot(x = "IsHeavy", y = "Age", data = trainingData);
trainingData.groupby('IsHeavy')['Age'].describe().round(2)
```

Out[20]:

IsHeavy	count	mean	std	min	25%	50%	75%	max
False	1764.0	12.35	8.05	3.18	5.79	10.20	15.62	43.82
True	3488.0	11.27	4.15	4.44	9.90	10.34	10.78	40.12



- Age seems to be a factor in determining CycleTime
- Intresting interaction between IsHeavy and Age
- It seems that cars go into the shop at different ages depending on if they are heavy or not
- Heavy cars seem to go in every 10 years, perhaps for inspections?
- Heavy cars do not typically have as long of a life as non-heavy cars
- A transformation into the Age varible may be explored as the kurtosis is high (Leptokurtic)

Categorical Variables (ShopID, CarModelID, CommodityID)

In [21]:

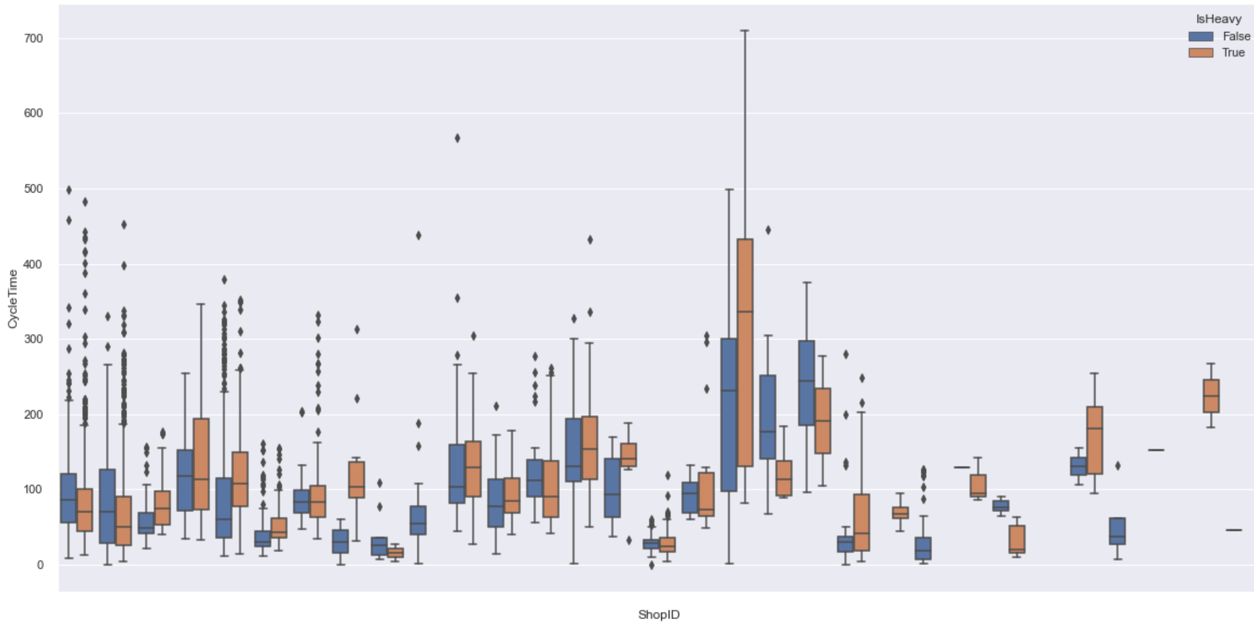
```
print("Unique Shops:", pd.unique(trainingData['ShopID']).shape[0])
print("Unique Cars:",pd.unique(trainingData['CarModelID']).shape[0])
print("Unique Commodities:",pd.unique(trainingData['CommodityID']).shape[0])
```

```
Unique Shops: 30
Unique Cars: 26
Unique Commodities: 294
```

ShopID

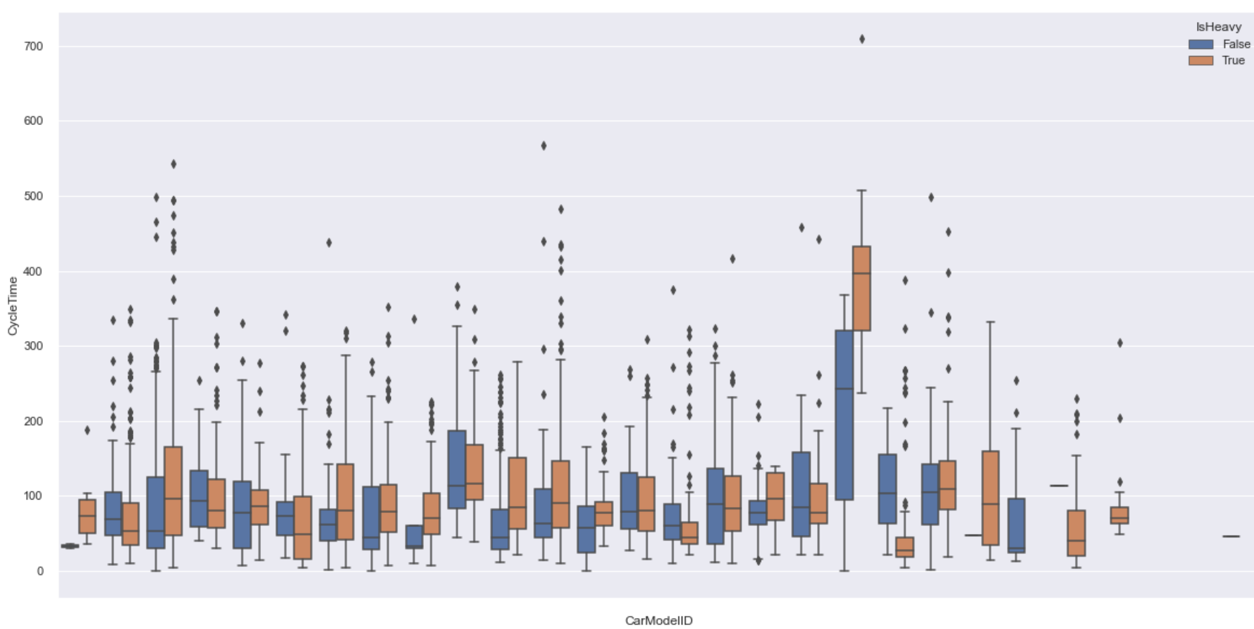
In [22]:

```
ax = sns.boxplot(x = "ShopID", y = "CycleTime", hue = "IsHeavy", data = trainingData).s
```



- ShopID seems to be a factor in determining CycleTime
- An interaction between ShopID and IsHeavy could be explored

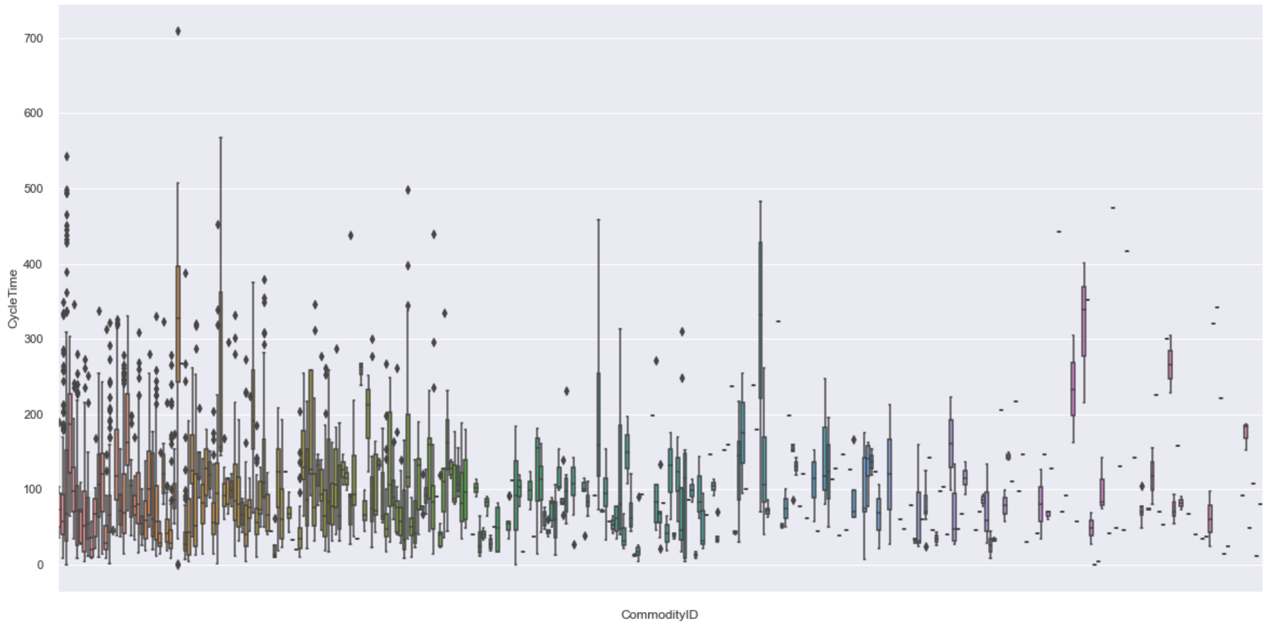
In [23]:
```
ax = sns.boxplot(x = "CarModelID", y = "CycleTime", hue = "IsHeavy", data = trainingDat
```



- CarModelID seems to be a factor in determining CycleTime
- An interaction between CarModelID and IsHeavy could be explored

CommodityID

In [24]:
```
ax = sns.boxplot(x = "CommodityID", y = "CycleTime", data = trainingData).set(xticklabe
```



- CommodityID seems to be a factor in determining CycleTime

Initial Model Building

- DateCompleted should not be used to build a model as it is directly correlated with the target variable (CycleTime)
- ShopID, CarModelID, CommodityID, and Age should be considered in the model
- ArrivalDate should not be used to build the model, instead use DayOfWeek

Set Up Dummy Variables (One-Hot-Encoding)

In [25]:

```
rawData['DayOfWeek'] = rawData['ArrivalDate'].dt.day_name()
dummyData = pd.get_dummies(rawData,prefix=['ShopID', 'CarModelID','CommodityID','DayOfW
                           columns= ['ShopID', 'CarModelID','CommodityID','DayOfWeek'])
```

In [72]:

```
trainDF = dummyData[(dummyData['DateCompleted'] >= pd.to_datetime("2018-01-01")) & (dum
trainDF['ArrivalDate'] = trainDF['ArrivalDate'].values.astype('float')
trainDF.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5252 entries, 1 to 7230
Columns: 406 entries, ArrivalDate to DayOfWeek_Wednesday
dtypes: bool(1), datetime64[ns](1), float64(2), int64(1), uint8(401)
memory usage: 2.2 MB
```

In [73]:

```
X_train = trainDF.copy()
X_train = X_train.drop(['CycleTime'],axis=1)
X_train = X_train.drop(['DateCompleted'],axis=1)
X_train = X_train.drop(['ArrivalDate'],axis=1)
y_train = trainDF['CycleTime'].copy()
cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)
#interaction = PolynomialFeatures(include_bias=False, interaction_only=True)
#X_inter = interaction.fit_transform(X)
```

RandomForestRegressor

In [28]:
```
forest_reg = RandomForestRegressor()
forest_reg.fit(X_train, y_train)
```

Out[28]:
```
RandomForestRegressor()
```

Dimensionality Reduction

The dataset provided only has one numeric datatype (Age), but multiple categorical variables. In the initial model above, the categorical variables selected (DayofWeek, ShopID, CarModelID, CommodityID) were one-hot encoded, resulting in 402 additional columns. This will be the focus of our dimensionality reduction - reducing how many columns there are in the dataset.

One thing we didn't anticipate was the difference between dimensionality reduction techniques for categorical variables (like most of our variables are) and numerical variables. There are fewer ways to reduce dimensionality with categorical variables as most dimensionality reduction techniques depend on calculating the variance of the variables.

We wanted to implement the Principal Component Analysis algorithm into our dimensionality reduction, but found that we could not apply PCA to categorical data. We pivoted toward using feature selection methods rather than dimensionality reduction methods.

More on feature selection

Feature selection is important to do before modeling data. There are a few benefits that can come from this practice, such as a faster training phase. Additionally, there's usually less overfitting because there is less redundant data. This lack of overfitting also contributes to a model with a higher accuracy.

In [ ]:
```
testDF = dummyData[(dummyData['DateCompleted'] >= pd.to_datetime("2019-06-01")) & (dumm
```

Feature Selection - Dropping CommodityID

Lets first test a simple approach at dimensionalty reduction by dropping the CommodityID column entirely. This will reduce the number of columns by 294. Note that this is arbitrary and not best practice.

In [108…
```
x_train_drop = trainDF.loc[:, ~trainDF.columns.str.startswith('CommodityID')].copy()
x_test_drop = testDF.loc[:, ~testDF.columns.str.startswith('CommodityID')].copy()
x_test_drop.drop(columns = ['CycleTime','DateCompleted','ArrivalDate'],inplace = True)
x_train_drop.drop(columns = ['CycleTime','DateCompleted','ArrivalDate'],inplace = True)
y_train = trainDF['CycleTime'].copy()
#x_train_drop.info()
```

In [115…

```
#Now we build a model with the new x attributes
forest_reg_drop = RandomForestRegressor()
forest_reg_drop.fit(x_train_drop, y_train)
```

Out[115…

```
RandomForestRegressor()
```

Feature Selection using SelectKBest

In [83]:

```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import mutual_info_classif
from matplotlib import pyplot
```

In [40]:

```
#trainingData = rawData[(rawData['DateCompleted'] <= pd.to_datetime("2019-05-31"))].cop
testingData = rawData[(rawData['DateCompleted'] >= pd.to_datetime("2019-06-01")) & (raw
testingData['DayOfWeek'] = testingData['ArrivalDate'].dt.day_name()
testingData['DayOfWeek'] = pd.Categorical(testingData['DayOfWeek'], categories=dayofwee
```

In [74]:

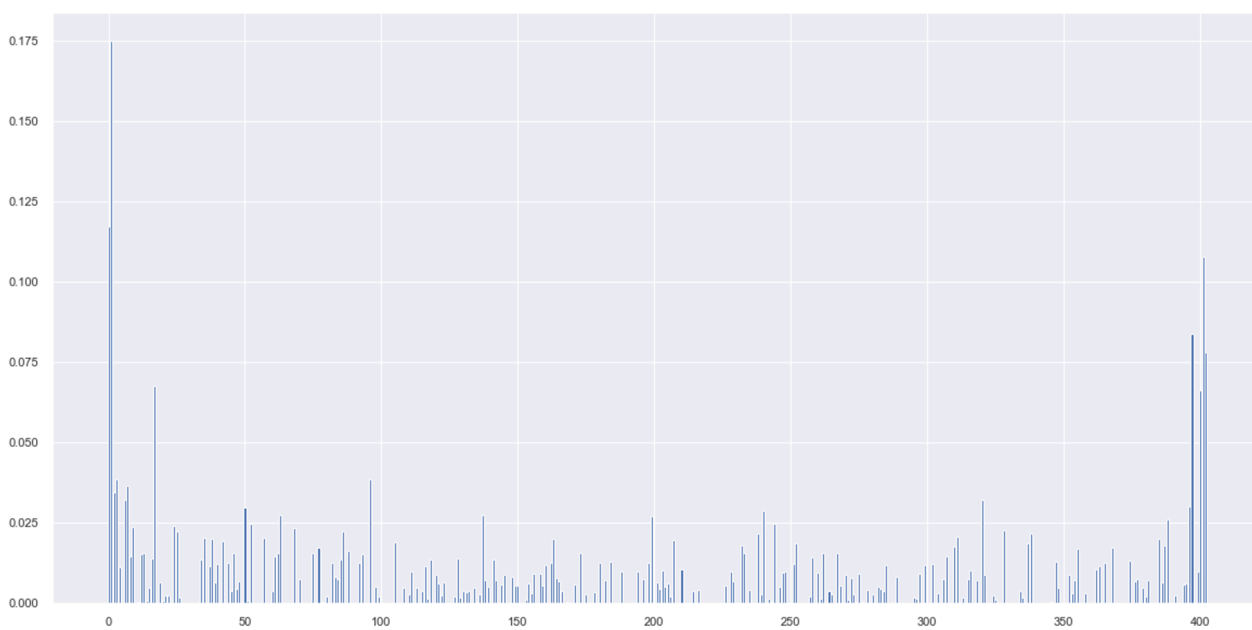
```
xtrain = trainDF.copy()
xtest = testDF.copy()
xtest.drop(columns = ['CycleTime','DateCompleted','ArrivalDate'],inplace = True)
xtrain.drop(columns = ['CycleTime','DateCompleted','ArrivalDate'],inplace = True)

ytrain = trainDF['CycleTime'].copy()
```

In [82]:

```
fsall = SelectKBest(score_func=mutual_info_classif, k='all')
fsall.fit(xtrain, ytrain)
X_train_fsall = fs.transform(xtrain)
X_test_fsall = fs.transform(xtest)
```

In [85]:

```
pyplot.bar([i for i in range(len(fsall.scores_))], fsall.scores_)
pyplot.show()
```



In [117…

```
#Selecting num features > .025, This is an arbitrary number based off of the above grap
numk = len(np.where( fsall.scores_ > .025 )[0])
numk
```

Out[117…

```
20
```

In [111…

```
fs = SelectKBest(score_func=mutual_info_classif, k=numk)
fs.fit(xtrain, ytrain)
X_train_fs = fs.transform(xtrain)
X_test_fs = fs.transform(xtest)
```

In [112…

```
forest_reg_kbest = RandomForestRegressor()
forest_reg_kbest.fit(X_train_fs, ytrain)
```

Out[112…

```
RandomForestRegressor()
```

Model Comparison and Analysis

"Provide performance metrics (Mean Absolute Error & Root Mean Square Error) for cars completed 6/1/2019 to 12/31/2019."

In [113…

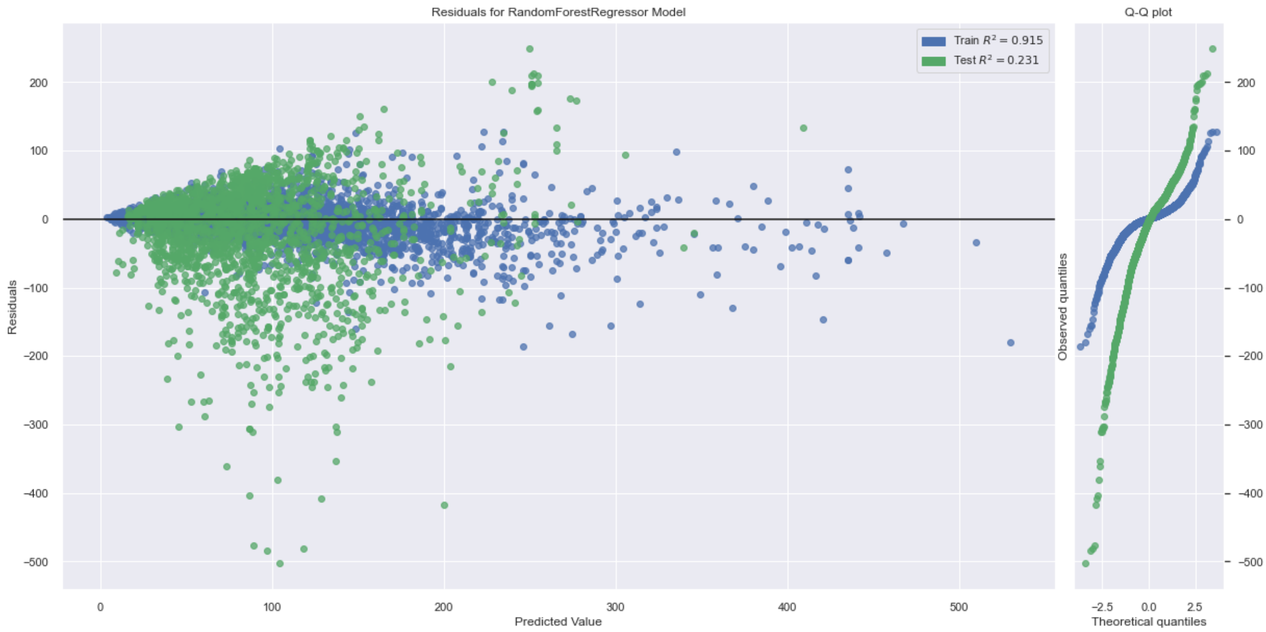
```
testDF = dummyData[(dummyData['DateCompleted'] >= pd.to_datetime("2019-06-01")) & (dumm
X_test = testDF
X_test = X_test.drop(['CycleTime'],axis=1)
X_test = X_test.drop(['DateCompleted'],axis=1)
X_test = X_test.drop(['ArrivalDate'],axis=1)
y_test = testDF['CycleTime'].copy()
```

Initial Random Forest (No Dimensionality Reduction)

In [101…

```
forestYHat = forest_reg.predict(X_test)
forestMAE = metrics.mean_absolute_error(y_test, forestYHat)
forestMSE = metrics.mean_squared_error(y_test, forestYHat)
forestRMSE = np.sqrt(forestMSE)
print("MAE: ", forestMAE)
print("RMSE: ", forestRMSE)
visualizer = residuals_plot(RandomForestRegressor(), X_train, y_train, X_test, y_test,
```

```
MAE:  53.912826501580575
RMSE:  79.55062546237937
```

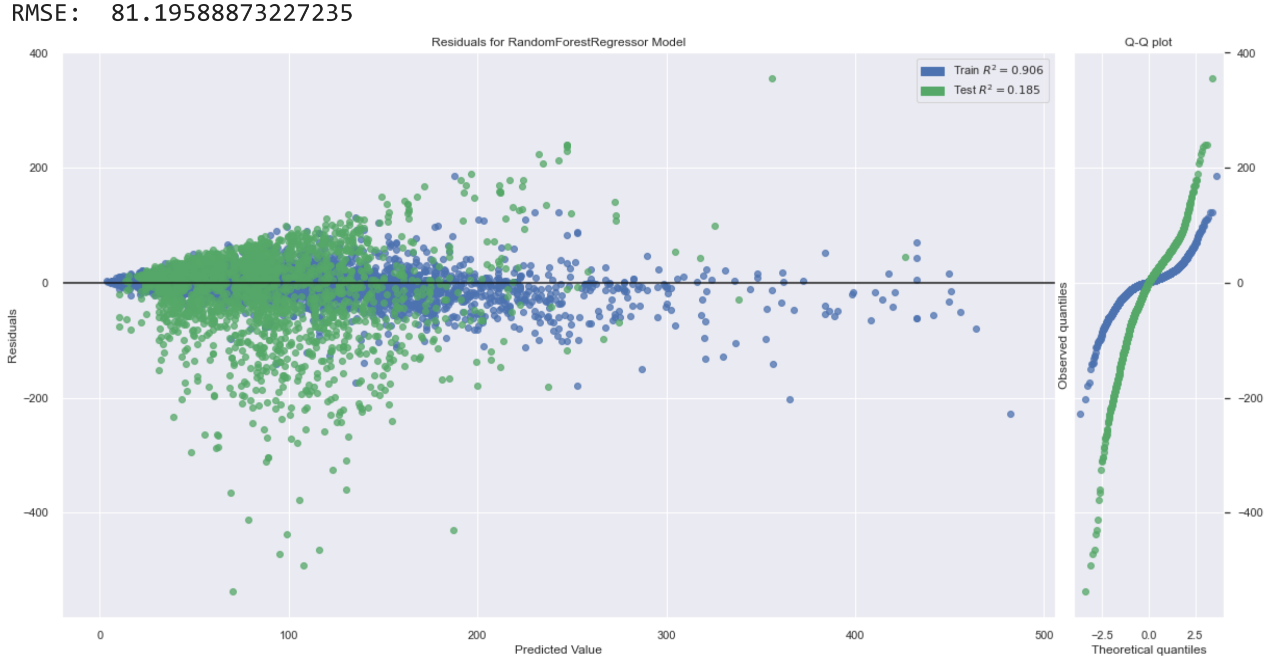


Random Forest with CommodityID dropped

In [118…

```
forest_drop_YHat = forest_reg_drop.predict(x_test_drop)
forest_drop_MAE = metrics.mean_absolute_error(y_test, forest_drop_YHat)
forest_drop_MSE = metrics.mean_squared_error(y_test, forest_drop_YHat)
forest_drop_RMSE = np.sqrt(forest_drop_MSE)
print("MAE: ", forest_drop_MAE)
print("RMSE: ", forest_drop_RMSE)
visualizer = residuals_plot(RandomForestRegressor(), x_train_drop, y_train, x_test_drop
```

```
MAE:  55.85547721122759
RMSE:  81.19588873227235
```



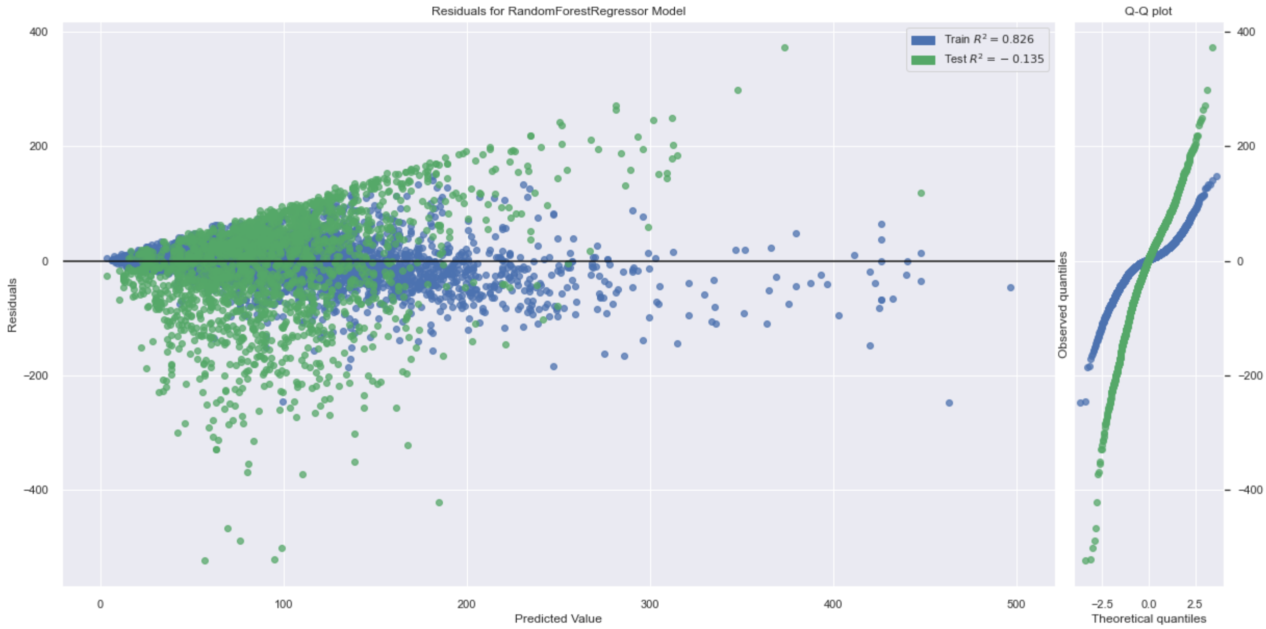
Random Forest with K Best Feature Selection

In [121…

```
forest_kbest_YHat = forest_reg_kbest.predict(X_test_fs)
forest_kbest_MAE = metrics.mean_absolute_error(y_test, forest_kbest_YHat)
forest_kbest_MSE = metrics.mean_squared_error(y_test, forest_kbest_YHat)
```

```
forest_kbest_RMSE = np.sqrt(forest_kbest_MSE)
print("MAE: ", forest_kbest_MAE)
print("RMSE: ", forest_kbest_RMSE)
visualizer = residuals_plot(RandomForestRegressor(), X_train_fs, y_train, X_test_fs, y_
```

```
MAE:  71.15369240348726
RMSE:  96.43430020888682
```



Thoughts and Conclusions

In the end it seems like the methods of dimensionality reduction did not resut with a more accurrate prediction. The reason why this might be the case is that the variables that we dropped may have more impact than we realize. In future tests, we can look into more complex clustering algorithms such as k-means to group variables together, rather than to get rid of them as a whole. This will allow us to use more information than our current methods.