Import Libraries

In [41]:
```
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_sco
from sklearn.model_selection import train_test_split, cross_validate, Shuff
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error
import matplotlib.pyplot as plt
import seaborn as sns
import xgboost as XGBRegressor
from sklearn.model_selection import GridSearchCV
from numpy import absolute
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import RepeatedKFold
from xgboost import XGBRegressor
from sklearn.pipeline import Pipeline
from sklearn.pipeline import make_pipeline
from sklearn.impute import SimpleImputer
import pickle
import category_encoders as ce
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import RandomForestRegressor
```

Functions

In [42]:
```
# R-squared and RMSE Function
def performance(y_true, y_predict):
    """
    Calculates and returns the two performance scores between
    true and predicted values - first R-Squared, then RMSE
    """

    # Calculate the r2 score between 'y_true' and 'y_predict'
    r2 = r2_score(y_true, y_predict)

    # Calculate the root mean squared error between 'y_true' and 'y_predict
    rmse = mean_squared_error(y_true, y_predict, squared=False)

    # Return the score
    return [r2, rmse]
```

Importing Semi-Cleaned Data

In [43]:
```
df = pd.read_pickle('df_model')
```

Final clean to get ready for modeling

In [44]:
```
df = df.dropna(subset =['final_years', 'final_make'])
df =df.drop(['make','make_title', 'year', 'years', 'title_lower', 'URL', 'b
df = df[df['final_years'].astype(str).str.isdigit()]
df['odometer'] = df.odometer.str.extract('(^\d*)')
df[["final_years"]] = df[['final_years']].apply(pd.to_numeric)
df['Price']= df['Price'].apply(lambda x: x.replace('$',''))
df['Price']= df['Price'].apply(lambda x: x.replace(',',''))
df[['Price']] = df[['Price']].apply(pd.to_numeric)
df[['odometer']] = df[['odometer']].apply(pd.to_numeric)
df =df.reset_index(drop=True)
df = df[df['Price']<50000]
df=df[df['Price']>600]
df = df[df['odometer']<100000]
df = df[df['final_years']>1960]
df = df[df['final_years']<2022]
df.drop("VIN", inplace =True, axis =1)
df =df.reset_index(drop=True)
df['condition'] = df['condition'].str.replace('excellentcryptocurrency ok',
df['condition'] = df['condition'].str.replace('like newcryptocurrency ok',
df['condition'] = df['condition'].str.replace('goodcryptocurrency ok', 'goo
df['condition'] = df['condition'].str.replace('faircryptocurrency ok', 'fai
df['condition'] = df['condition'].str.replace('newcryptocurrency ok', 'new'
df['fuel'] = df['fuel'].fillna(value='other')
df['paint color'] = df['paint color'].fillna(value='other')
df['title status'] = df['title status'].fillna(value='other')
df['transmission'] = df['transmission'].fillna(value='other')
df['condition'] = df['condition'].fillna(value='other')
df['engine displacement (CC)'] = df['engine displacement (CC)'].fillna(valu
df['type'] = df['type'].fillna(value='other')
df = df[df['engine displacement (CC)']!='other']
df['engine displacement (CC)']= df['engine displacement (CC)'].astype(float
bins = [0,250,500,750,1000,1250,1500,1750,2000, np.inf]
names =['0-250', '251-500', '501-750', '751-1000', '1001- 1250', '1251-1500

df['engine_displacement'] = pd.cut(df['engine displacement (CC)'], bins, la
df=df.drop('engine displacement (CC)',axis=1)
```

In [45]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5045 entries, 3 to 12483
Data columns (total 12 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Price                5045 non-null   int64
 1   title                5045 non-null   object
 2   fuel                 5045 non-null   object
 3   odometer             5045 non-null   float64
 4   paint color          5045 non-null   object
 5   title status         5045 non-null   object
 6   transmission         5045 non-null   object
 7   condition            5045 non-null   object
 8   type                 5045 non-null   object
 9   final_make           5045 non-null   object
 10  final_years          5045 non-null   int64
 11  engine_displacement  4999 non-null   category
dtypes: category(1), float64(1), int64(2), object(8)
memory usage: 478.3+ KB
```

Train Test Split

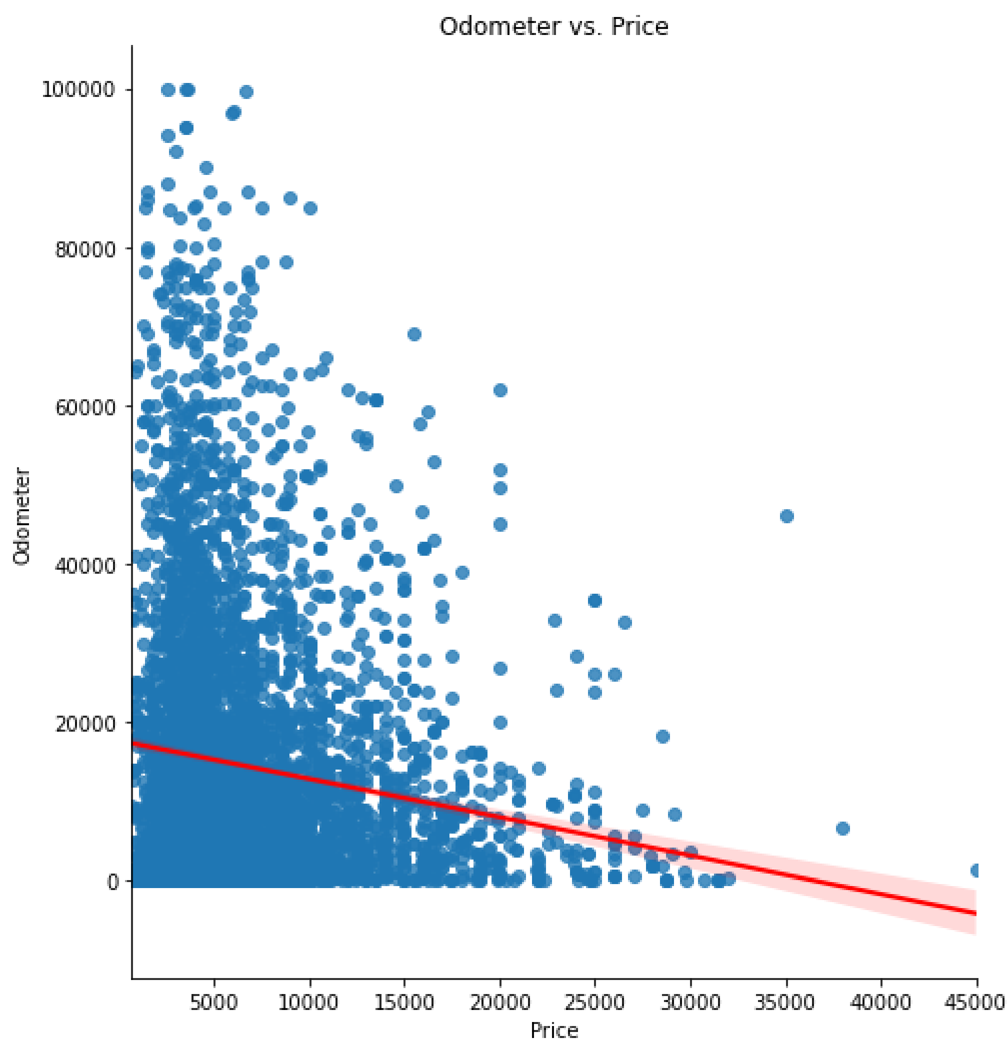
In [46]:
```
# Use train_test_split to create training data and testing data
X = df.drop(['Price', 'title'], axis=1)
y = df['Price']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, r
```

Baseline Model

Using just odometer vs the price

In [47]:
```
sns.lmplot(data=df, x='Price', y='odometer', size=7,line_kws={'color':'red'
plt.xlabel('Price')
plt.ylabel('Odometer')
plt.title('Odometer vs. Price');
```

```
/Users/avijames/anaconda3/lib/python3.8/site-packages/seaborn/regression.
py:580: UserWarning: The `size` parameter has been renamed to `height`; p
lease update your code.
  warnings.warn(msg, UserWarning)
```



The graph above shows that there is a negative linear line between price and mileage.

Now we will get the r-squared values for this model

In [48]:
```
# We are going to perform 3 separate train-test splits within our X_train a
# then we will find both the train and the test scores for each
baseline_model = LinearRegression()

splitter = ShuffleSplit(n_splits=3, test_size=0.25, random_state=0)

baseline_scores = cross_validate(
    estimator=baseline_model,
    X=X_train[['odometer']],
    y=y_train,
    return_train_score=True,
    cv=splitter
)

print("Train score:     ", baseline_scores["train_score"].mean())
print("Validation score:", baseline_scores["test_score"].mean())
```

```
Train score:      0.0189343081282702
Validation score: 0.02125667383241821
```

Our baseline model showed that our R-Squared is about .02

We can now try adding in dummy classifiers and one hot encoding to make our models better

Decision Tree Models with Dummies

In [49]:
```
# Get categoricals
categoricals = ['fuel','paint color','title status', 'transmission', 'condi

train_dummies = X_train[categoricals]
test_dummies = X_test[categoricals]

# Create OneHotEncoder object to create dummies
ohe = OneHotEncoder(handle_unknown='ignore')

# Transform the dataset into dummies matrix
enc = ohe.fit(train_dummies)

train_dummies_trans = enc.transform(train_dummies)
test_dummies_trans = enc.transform(test_dummies)

# Dummies values in matrix form
train_data = train_dummies_trans.todense()
test_data = test_dummies_trans.todense()

# New dummy column names
names = ohe.get_feature_names(categoricals)

# Make them into Dataframe
train_dummies_trans_df = pd.DataFrame(train_data, columns=names)
test_dummies_trans_df = pd.DataFrame(test_data, columns=names)
```

In [50]:
```
#dropping the other columns
train_dummies_trans_df = train_dummies_trans_df[train_dummies_trans_df.colu
test_dummies_trans_df = test_dummies_trans_df[test_dummies_trans_df.columns
```

In [51]:
```
train_dummies_trans_df.reset_index(drop=True, inplace=True)


test_dummies_trans_df.reset_index(drop=True, inplace=True)

X_train =X_train.drop(categoricals, axis=1)
X_test = X_test.drop(categoricals, axis=1)

X_train.reset_index(drop=True, inplace=True)
X_test.reset_index(drop=True, inplace=True)

X_train_comb = pd.concat([X_train, train_dummies_trans_df], axis=1)
X_test_comb = pd.concat([X_test, test_dummies_trans_df], axis=1)
```

In [52]:
```
# X_train_comb = X_train_comb.drop(['engine displacement (CC)'],axis=1)
# X_test_comb = X_test_comb.drop(['engine displacement (CC)'], axis=1)
```

In [53]:
```
regressor = DecisionTreeRegressor(random_state=42)
regressor.fit(X_train_comb, y_train)
```

Out[53]:
```
DecisionTreeRegressor(random_state=42)
```

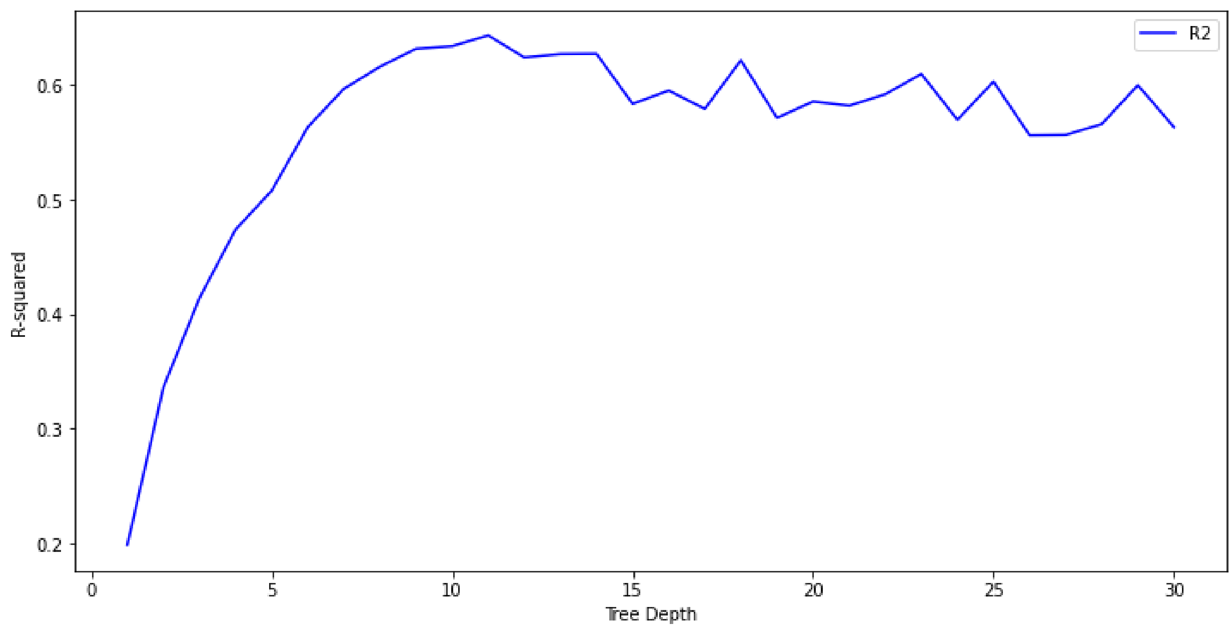
In [54]:
```
# Make predictions on the test set
y_pred = regressor.predict(X_test_comb)
score = performance(y_test, y_pred)
score
```

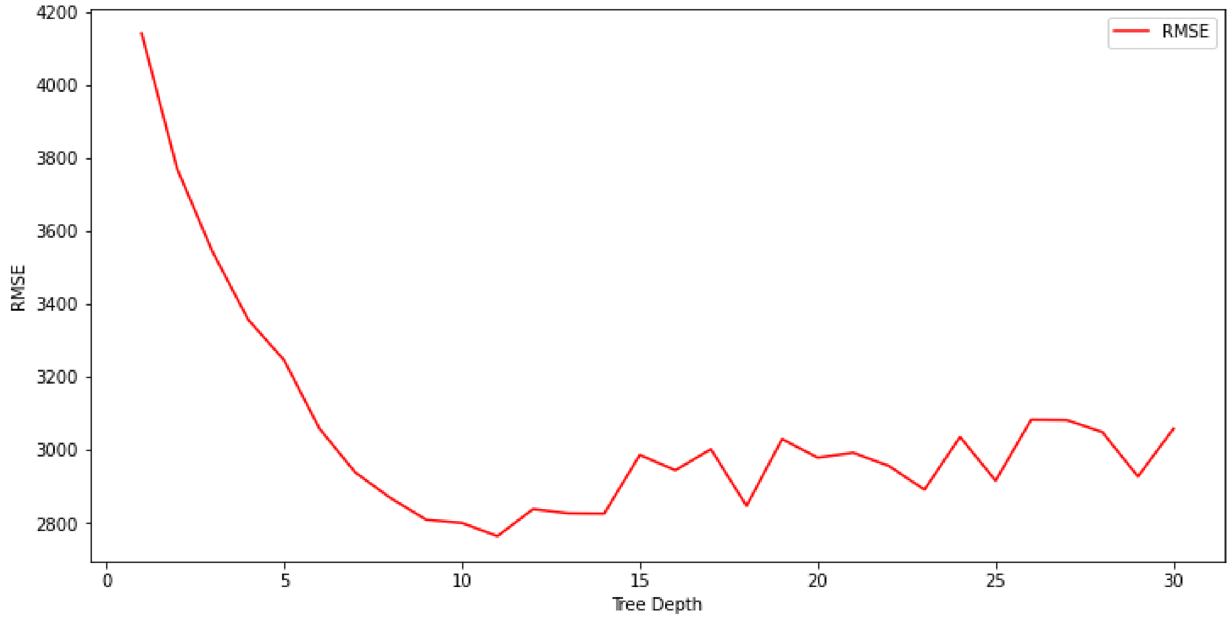
Out[54]:
```
[0.5629593777534452, 3058.3100249964295]
```

Showing a .56 for R-Squared and $3,058 for RMSE

Let's try and fine tune our Decision Tree Model

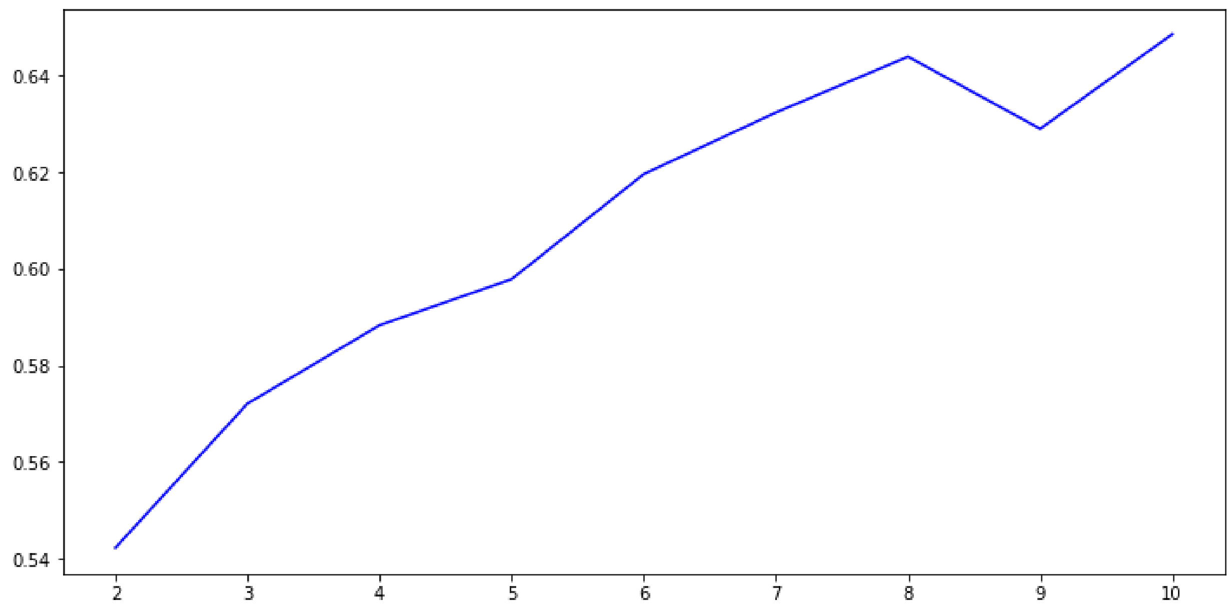
In [55]:
```
# Identify the optimal tree depth for given data
max_depths = np.linspace(1, 30, 30, endpoint=True)
mse_results = []
r2_results = []

for max_depth in max_depths:
    regressor = DecisionTreeRegressor(max_depth=max_depth,
                                      random_state=42)
    regressor.fit(X_train_comb, y_train)
    y_pred = regressor.predict(X_test_comb)
    score = performance(y_test, y_pred)
    r2_results.append(score[0])
    mse_results.append(score[1])

plt.figure(figsize=(12, 6))
plt.plot(max_depths, r2_results, 'b', label='R2')
plt.xlabel('Tree Depth')
plt.ylabel('R-squared')
plt.legend()
plt.show()
plt.figure(figsize=(12, 6))
plt.plot(max_depths, mse_results, 'r', label='RMSE')
plt.xlabel('Tree Depth')
plt.ylabel('RMSE')
plt.legend()
plt.show()
```

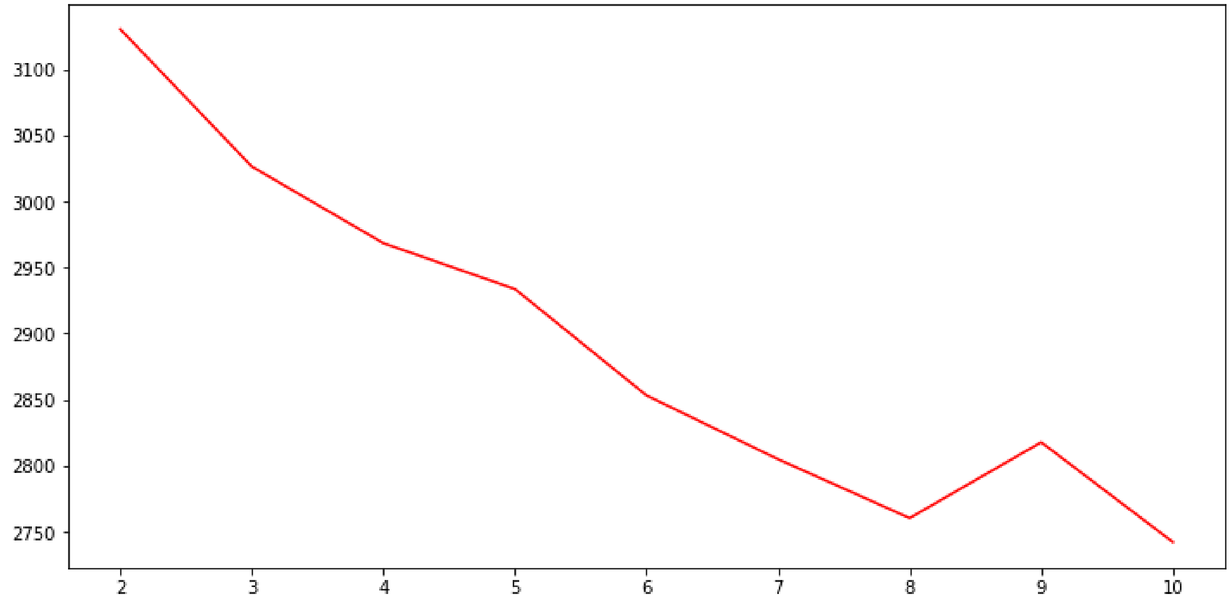



RMSE
4200
4000
3800
3600
3400
3200
3000
2800
0
5
10
15
20
25
30
Tree Depth
RMSE

In [56]:

```
# Identify the optimal minimum split size for given data
min_samples_splits = np.arange(2, 11)
mse_results = []
r2_results = []

for min_samples_split in min_samples_splits:
    regressor = DecisionTreeRegressor(min_samples_split=int(min_samples_spl
                                      random_state=45)
    regressor.fit(X_train_comb, y_train)
    y_pred = regressor.predict(X_test_comb)
    score = performance(y_test, y_pred)
    r2_results.append(score[0])
    mse_results.append(score[1])

plt.figure(figsize=(12, 6))
plt.plot(min_samples_splits, r2_results, 'b', label='R2')
plt.show()
plt.figure(figsize=(12, 6))
plt.plot(min_samples_splits, mse_results, 'r', label='RMSE')
plt.show()
```





In [57]:
```
regressor = DecisionTreeRegressor(min_samples_split=2, max_depth=11, random
regressor.fit(X_train_comb, y_train)
y_pred = regressor.predict(X_test_comb)
score = performance(y_test, y_pred)
score[0], score[1], regressor
```

Out[57]:
```
(0.6432248651271761,
 2763.235469098934,
 DecisionTreeRegressor(max_depth=11, random_state=42))
```

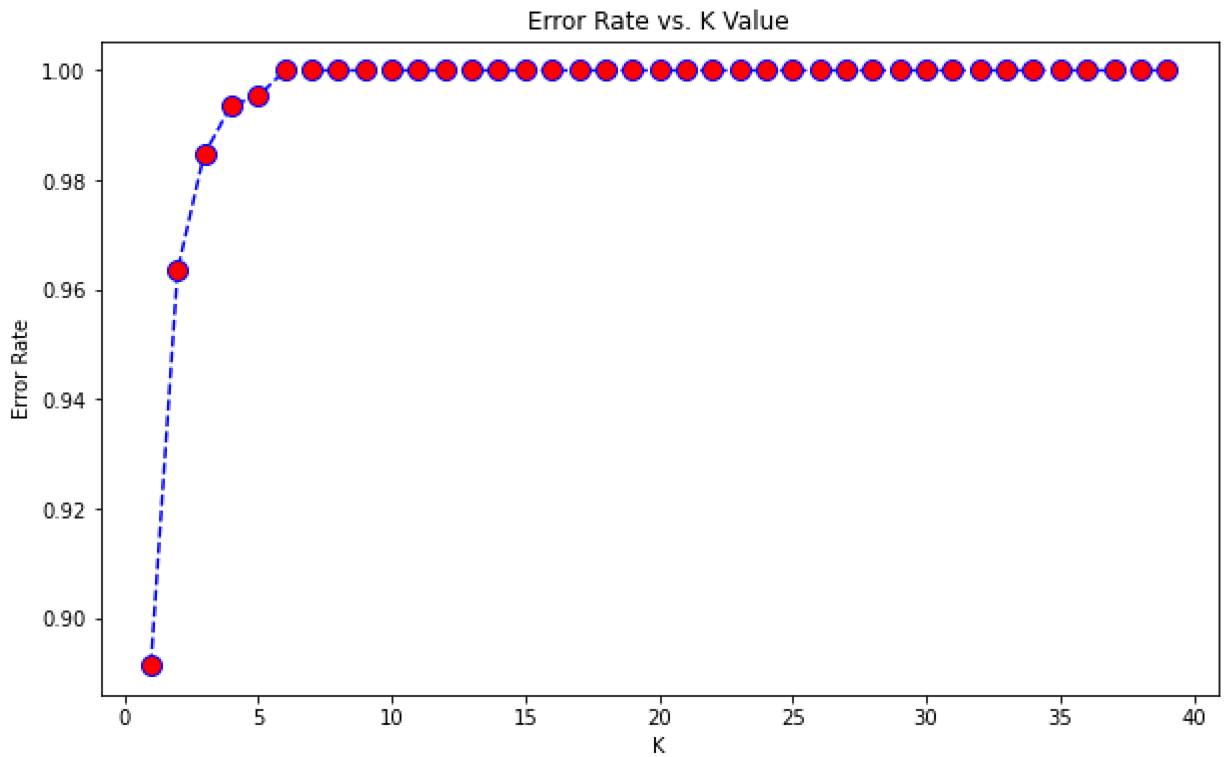
And we see significant improvement with the optimal parameters

Maybe a KNN Model can do better?

In [58]:
```
error_rate = []

for i in range(1,40):

    knn = KNeighborsRegressor(n_neighbors=i)
    knn.fit(X_train_comb,y_train)
    pred_i = knn.predict(X_test_comb)
    error_rate.append(np.mean(pred_i != y_test))
```

In [59]:
```
plt.figure(figsize=(10,6))
plt.plot(range(1,40),error_rate,color='blue', linestyle='dashed', marker='o
         markerfacecolor='red', markersize=10)
plt.title('Error Rate vs. K Value')
plt.xlabel('K')
plt.ylabel('Error Rate')
```

Out[59]:
```
Text(0, 0.5, 'Error Rate')
```



In [60]:
```
knn = KNeighborsRegressor(n_neighbors=10)
knn.fit(X_train_comb,y_train)
y_pred = knn.predict(X_test_comb)
score = performance(y_test, y_pred)
score[0], score[1], knn
```

Out[60]:
```
(0.05089714443802407, 4506.892979257636, KNeighborsRegressor(n_neighbors=
10))
```

That did not do better at all, let's try a random forest pipeline

Random Forest PipeLine

In [61]:
```
pipeline1 = make_pipeline(
    ce.TargetEncoder(),
    SimpleImputer(strategy='median'),
    RandomForestRegressor(max_depth=30,
                                  n_estimators=50, n_jobs=-3,
                                    random_state=30)
)
pipeline1.fit(X_train_comb, y_train)

y_pred = pipeline1.predict(X_test_comb)
print('MAE:', mean_absolute_error(y_test, y_pred))
print('R^2:', r2_score(y_test, y_pred))
print('RMSE:', mean_squared_error(y_test, y_pred, squared=False))
```

```
MAE: 1485.9391843736646
R^2: 0.7675847500209521
RMSE: 2230.2467537052116
```

GridSearch and Cross Validate for our Random Forest PipeLine

In [62]:
```
param_grid = {
    'randomforestregressor__max_depth': [2,5,6,10,30,50],
    'randomforestregressor__n_jobs': [10,-5,-3,-1, 0,1, 3,5,10],
    'randomforestregressor__n_estimators': [10, 50, 100, 500 ],
}
```

In [63]:
```
rfr =RandomForestRegressor()
```

In [64]:
```
pipeline1 = make_pipeline(
    ce.TargetEncoder(),
    SimpleImputer(strategy='median'),
    rfr)
```

In [65]:
```
grid_rfr = GridSearchCV(pipeline1, param_grid, cv=5, n_jobs=1, return_train
```

In [66]:
```
results_rfr = grid_rfr.fit(X_train_comb, y_train)
```

```
/Users/avijames/anaconda3/lib/python3.8/site-packages/sklearn/model_selec
tion/_validation.py:610: FitFailedWarning: Estimator fit failed. The scor
e on this train-test partition for these parameters will be set to nan. D
etails:
Traceback (most recent call last):
  File "/Users/avijames/anaconda3/lib/python3.8/site-packages/sklearn/mod
el_selection/_validation.py", line 593, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/Users/avijames/anaconda3/lib/python3.8/site-packages/sklearn/pip
eline.py", line 346, in fit
    self._final_estimator.fit(Xt, y, **fit_params_last_step)
  File "/Users/avijames/anaconda3/lib/python3.8/site-packages/sklearn/ens
emble/_forest.py", line 387, in fit
    trees = Parallel(n_jobs=self.n_jobs, verbose=self.verbose,
  File "/Users/avijames/anaconda3/lib/python3.8/site-packages/joblib/para
llel.py", line 966, in __call__
    n_jobs = self._initialize_backend()
  File "/Users/avijames/anaconda3/lib/python3.8/site-packages/joblib/para
llel.py", line 733, in _initialize_backend
```

In [67]:
```
results_rfr.best_params_
```

Out[67]:
```
{'randomforestregressor__max_depth': 30,
 'randomforestregressor__n_estimators': 100,
 'randomforestregressor__n_jobs': -5}
```

Using the best parameters to make the finished pipeline

In [68]:
```
pipeline2 = make_pipeline(
    ce.TargetEncoder(),
    SimpleImputer(strategy='median'),
    RandomForestRegressor(max_depth=30,
                                      n_estimators=100, n_jobs=-5,
                                        random_state=30))
```

In [69]:
```
pipeline2.fit(X_train_comb, y_train)

y_pred = pipeline2.predict(X_test_comb)
print('MAE:', mean_absolute_error(y_test, y_pred))
print('R^2:', r2_score(y_test, y_pred))
print('RMSE:', mean_squared_error(y_test, y_pred, squared=False))
```

```
MAE: 1481.0566153584805
R^2: 0.7691879284355592
RMSE: 2222.541427463498
```

Realy Solid with a 77% R-Squared and RMSE of $2,222

XGBoost Regression with Pipeline

In [70]:
```
pipeline4 = make_pipeline(
    ce.TargetEncoder(),
    SimpleImputer(strategy='median'),
    XGBRegressor(learning_rate=0.1,
                 max_depth=6,
                 min_child_weight=2,
                 n_estimators =100,
                 subsample=0.9))

pipeline4.fit(X_train_comb, y_train)
y_pred = pipeline4.predict(X_test_comb)
print('MAE:', mean_absolute_error(y_test, y_pred))
print('R^2:', r2_score(y_test, y_pred))
print('RMSE:', mean_squared_error(y_test, y_pred, squared=False))
```

```
MAE: 1481.042324253572
R^2: 0.7906198932981898
RMSE: 2116.8413667604714
```

Very solid results, let's try with a grid search and cross validation

Let's try with a Grid Search Cross Validate

In [71]:
```
param_grid = {
    'xgbregressor__learning_rate': [0.1, 0.5, 1],
    'xgbregressor__max_depth': [2,5,6,10],
    'xgbregressor__min_child_weight': [1, 2, 3],
    'xgbregressor__subsample': [0.5, 0.7, .9],
    'xgbregressor__n_estimators': [10, 50, 100, 500 ],
}
```

In [72]:
```
xgb =XGBRegressor()
```

In [73]:
```
pipeline5 = make_pipeline(
    ce.TargetEncoder(),
    SimpleImputer(strategy='median'),
    xgb)
```

In [74]:
```
grid_clf = GridSearchCV(pipeline5, param_grid, cv=5, n_jobs=1, return_train
```

In [75]:
```
results = grid_clf.fit(X_train_comb, y_train)
```

In [76]:
```
results.best_params_
```

Out[76]:
```
{'xgbregressor__learning_rate': 0.1,
 'xgbregressor__max_depth': 6,
 'xgbregressor__min_child_weight': 1,
 'xgbregressor__n_estimators': 100,
 'xgbregressor__subsample': 0.9}
```

Using the best parameters to make the finished

pipeline

In [78]:
```
pipeline6 = make_pipeline(
    ce.TargetEncoder(),
    SimpleImputer(strategy='median'),
    XGBRegressor(learning_rate=0.1,
                max_depth=6,
                min_child_weight=1,
                n_estimators =100,
                subsample=0.9))

pipeline6.fit(X_train_comb, y_train)
y_pred = pipeline6.predict(X_test_comb)
print('MAE:', mean_absolute_error(y_test, y_pred))
print('R^2:', r2_score(y_test, y_pred))
print('RMSE:', mean_squared_error(y_test, y_pred, squared=False))
```

```
MAE: 1484.6020720613362
R^2: 0.7861867404483275
RMSE: 2139.133665010211
```

In [ ]: