```
In [1]:
         import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         %matplotlib inline
         import seaborn as sns
         pd.set option("display.max columns",60)
         from IPython.core.pylabtools import figsize
         from sklearn.impute import SimpleImputer
         from sklearn.preprocessing import MinMaxScaler
         from sklearn.linear model import LinearRegression
         from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
         from sklearn.svm import SVR
         from sklearn.neighbors import KNeighborsRegressor
         from sklearn.model selection import RandomizedSearchCV, GridSearchCV
In [2]:
         train features = pd.read csv('F:/Dhrumil/r/Tableau/training features.csv')
         test features = pd.read csv('F:/Dhrumil/r/Tableau/testing features.csv')
         train labels = pd.read csv('F:/Dhrumil/r/Tableau/training labels.csv')
         test labels = pd.read csv('F:/Dhrumil/r/Tableau/testing labels.csv')
         print('Training Feature Size: ', train features.shape)
         print('Testing Feature Size: ', test features.shape)
         print('Training Labels Size: ', train labels.shape)
         print('Testing Labels Size: ', test labels.shape)
        Training Feature Size: (6322, 65)
        Testing Feature Size:
                                (2710, 65)
        Training Labels Size:
                                (6322, 1)
        Testing Labels Size:
                                (2710, 1)
In [3]:
         train features.head(12)
Out[3]:
```

	(Order	Property Id	DOF Gross Floor Area	Year Built	number	Occupancy	Site EUI (kBtu/ft²)	Weather Normalized Site Electricity Intensity (kWh/ft²)	Weather Normalized Site Natural Gas Intensity (therms/ft²)	Weather Normalized Site Natural Gas Use (therms)	Water Intensity (All Water Sources) (gal/ft²)	Latitude	Longitude	Commur Bo
	0	8749	2661595	69595.0	1964	1	100	95.4	5.6	NaN	NaN	NaN	40.882731	-73.903729	
	1 1	10643	4938575	67500.0	1940	1	100	58.9	3.2	0.5	34446.7	32.17	40.645814	-73.962376	1
	2	3605	2630626	85952.0	1927	1	100	76.6	13.9	0.0	390.3	40.71	40.757220	-73.979877	
	3	335	4994373	370814.0	1970	1	95	24.6	6.5	0.0	8217.0	59.90	40.815052	-73.935936	1
	4	6599	2795611	117080.0	1938	1	100	72.1	3.8	0.5	77304.6	NaN	40.833607	-73.918558	
	5	8815	3116754	78825.0	1950	1	100	73.3	3.1	0.1	4782.4	64.43	40.896786	-73.896854	
	6	2015	4949050	183168.0	1896	1	95	83.3	13.7	0.2	32817.6	NaN	40.743415	-73.989094	
	7	3661	4403231	58001.0	1970	1	100	46.5	6.8	NaN	NaN	NaN	40.763197	-73.974496	
	8 1	14500	4436800	85900.0	1965	1	70	108.7	15.6	0.6	48752.3	12027.41	NaN	NaN	N
	9 1	13369	2790338	76681.0	1929	1	100	76.6	3.2	0.7	51950.3	NaN	NaN	NaN	Ν
1	0	4349	4401486	88829.0	1927	1	100	59.4	1.9	0.1	9521.4	35.59	40.769466	-73.962891	
1	1	8913	4494218	123700.0	1914	1	90	49.6	7.6	0.3	31407.7	22.54	40.702307	-73.989627	

12 rows × 65 columns

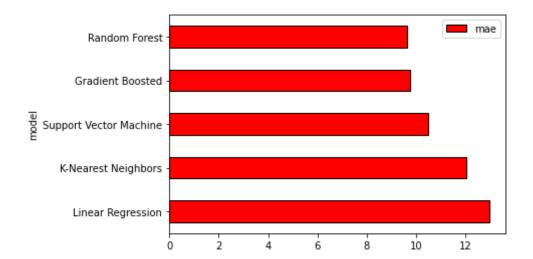
In [4]: train_features= train_features.drop(columns=['Borough','Largest Property Use Type'])

In [5]:	t	train_features.head()													
Out[5]:		Order	Property Id	DOF Gross Floor Area	Year Built	number	Occupancy	Site EUI (kBtu/ft²)	Weather Normalized Site Electricity Intensity (kWh/ft²)	Weather Normalized Site Natural Gas Intensity (therms/ft²)	Weather Normalized Site Natural Gas Use (therms)	Water Intensity (All Water Sources) (gal/ft²)	Latitude	Longitude	Communi Boa
	0	8749	2661595	69595.0	1964	1	100	95.4	5.6	NaN	NaN	NaN	40.882731	-73.903729	8
	1	10643	4938575	67500.0	1940	1	100	58.9	3.2	0.5	34446.7	32.17	40.645814	-73.962376	14
	2	3605	2630626	85952.0	1927	1	100	76.6	13.9	0.0	390.3	40.71	40.757220	-73.979877	5
	3	335	4994373	370814.0	1970	1	95	24.6	6.5	0.0	8217.0	59.90	40.815052	-73.935936	11
	4	6599	2795611	117080.0	1938	1	100	72.1	3.8	0.5	77304.6	NaN	40.833607	-73.918558	4
	5 r	ows × 6	3 columns	5											
	4														>
In [6]:	t	est_fe	atures=	test_fea	itures	.drop(c	olumns=['B	orough',	'Largest F	Property Us	se Type'])				
In [7]:	t	test_features.head()													
Out[7]:		Order	Property Id	DOF Gross Floor Area	Year Built	number	Occupancy	Site EUI (kBtu/ft²)	Weather Normalized Site Electricity Intensity (kWh/ft²)	Weather Normalized Site Natural Gas Intensity (therms/ft²)	Weather Normalized Site Natural Gas Use (therms)	Water Intensity (All Water Sources) (gal/ft²)	Latitude	Longitude	Communi Boa
	0	3848	1423551	345743.0	1980	1	100	61.1	14.4	NaN	NaN	16.12	40.756651	-73.972264	5

		Order	Property Id	DOF Gross Floor Area	Year Built	number	Occupancy	Site EUI (kBtu/ft²)	Weather Normalized Site Electricity Intensity (kWh/ft²)	Weather Normalized Site Natural Gas Intensity (therms/ft²)	Weather Normalized Site Natural Gas Use (therms)	Water Intensity (All Water Sources) (gal/ft²)	Latitude	Longitude	Communi Boa
	1	13331	5838686	148181.0	1932	1	100	54.4	3.7	0.4	60727.8	32.41	NaN	NaN	Na
	2	14865	3111579	195678.0	1983	1	100	79.1	NaN	NaN	NaN	55.80	40.581202	-74.162664	2
	3	8461	4859883	125891.0	1962	1	100	90.7	4.7	0.3	37674.2	50.57	40.858853	-73.868957	11
	4	9903	5848160	54698.0	2008	1	95	58.4	6.6	0.4	22174.9	22.10	40.716762	-73.964742	1
	5 rc	ows × 6	3 columns	1											
	4														•
<pre>imputer = SimpleImputer(strategy= 'median') imputer.fit(train_features) x = imputer.transform(train_features) x_test = imputer.transform(test_features)</pre>															
In [9]:	<pre>print('Missing values in training features: ', np.sum(np.isnan(x))) print('Missing values in testing features: ', np.sum(np.isnan(x_test)))</pre>														
Missing values in training features: 0 Missing values in testing features: 0															
In [10]:				∼np.isfi ∼np.isfi))								
							type=int64 type=int64								
In [12]:			= MinMax fit(x)	Scaler(f	eatur	e_range	=(0,1))								

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x = scaler.transform(x)
          x test = scaler.transform(x test)
In [14]:
          y= np.array(train labels).reshape((-1, ))
          y test= np.array(test labels).reshape((-1, ))
In [19]:
          def mae(y test,y pred):
              return np.mean(abs(y_test-y_pred))
          def model eval(model):
              model.fit(x,y)
              model pred = model.predict(x test)
              model mae = mae(y test, model pred)
              return model_mae
In [20]:
          lr= LinearRegression()
          lr mae = model eval(lr)
          lr mae
Out[20]: 12.988557015563204
In [21]:
          svm = SVR(C=1000, gamma=0.1)
          svm mae = model eval(svm)
In [22]:
          svm mae
Out[22]: 10.49089165674137
In [24]:
          random forest = RandomForestRegressor(random state=60)
          random forest mae = model eval(random forest)
          random_forest_mae
Out[24]: 9.623974169741699
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In [25]:
          gradient boost = GradientBoostingRegressor(random state=60)
          gradient boost mae = model eval(gradient boost)
In [26]:
          gradient boost mae
Out[26]: 9.773772232725227
In [27]:
          knn = KNeighborsRegressor(n neighbors= 10)
          knn mae = model eval(knn)
          knn mae
Out[27]: 12.04789667896679
In [29]:
          model_comparison = pd.DataFrame({'model': ['Linear Regression', 'Support Vector Machine',
                                                     'Random Forest', 'Gradient Boosted',
                                                      'K-Nearest Neighbors'],
                                           'mae': [lr mae, svm mae, random forest mae,
                                                   gradient boost mae, knn mae]})
          # Horizontal bar chart of test mae
          model comparison.sort values('mae', ascending = False).plot(x = 'model', y = 'mae', kind = 'barh',
                                                                     color = 'red', edgecolor = 'black')
Out[29]: <AxesSubplot:ylabel='model'>
```



In []: