

Project 5 : Great Energy Predictor

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```
In [1]: #load libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import category_encoders
from sklearn.model_selection import train_test_split
from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler
from sklearn import linear_model
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.ensemble import RandomForestRegressor
from math import sqrt
from sklearn.metrics import mean_squared_error

import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)
```

```
In [2]: # get building metadata
building_metadata = pd.read_csv("building_metadata.csv")
print(building_metadata.shape)
building_metadata.head(10)
```

(1449, 6)

Out[2]:

| | site_id | building_id | primary_use | square_feet | year_built | floor_count |
|---|---------|-------------|---------------------|-------------|------------|-------------|
| 0 | 0 | 0 | Education | 7432 | 2008.0 | NaN |
| 1 | 0 | 1 | Education | 2720 | 2004.0 | NaN |
| 2 | 0 | 2 | Education | 5376 | 1991.0 | NaN |
| 3 | 0 | 3 | Education | 23685 | 2002.0 | NaN |
| 4 | 0 | 4 | Education | 116607 | 1975.0 | NaN |
| 5 | 0 | 5 | Education | 8000 | 2000.0 | NaN |
| 6 | 0 | 6 | Lodging/residential | 27926 | 1981.0 | NaN |
| 7 | 0 | 7 | Education | 121074 | 1989.0 | NaN |
| 8 | 0 | 8 | Education | 60809 | 2003.0 | NaN |
| 9 | 0 | 9 | Office | 27000 | 2010.0 | NaN |

```
In [3]: # get train data
train_data = pd.read_csv("train.csv")
print(train_data.shape)
train_data["timestamp"] = pd.to_datetime(train_data["timestamp"])
train_data.head(10)
```

(20216100, 4)

Out[3]:

| | building_id | meter | timestamp | meter_reading |
|---|-------------|-------|------------|---------------|
| 0 | 0 | 0 | 2016-01-01 | 0.0 |
| 1 | 1 | 0 | 2016-01-01 | 0.0 |
| 2 | 2 | 0 | 2016-01-01 | 0.0 |
| 3 | 3 | 0 | 2016-01-01 | 0.0 |
| 4 | 4 | 0 | 2016-01-01 | 0.0 |
| 5 | 5 | 0 | 2016-01-01 | 0.0 |
| 6 | 6 | 0 | 2016-01-01 | 0.0 |
| 7 | 7 | 0 | 2016-01-01 | 0.0 |
| 8 | 8 | 0 | 2016-01-01 | 0.0 |
| 9 | 9 | 0 | 2016-01-01 | 0.0 |

```
In [4]: # get weather train data
weather_train_data = pd.read_csv("weather_train.csv")
print(weather_train_data.shape)
weather_train_data["timestamp"] = pd.to_datetime(weather_train_data["timestamp"])
weather_train_data.head(10)
```

(139773, 9)

Out[4]:

| | site_id | timestamp | air_temperature | cloud_coverage | dew_temperature | precip_depth_1_hr | sea |
|---|---------|---------------------|-----------------|----------------|-----------------|-------------------|-----|
| 0 | 0 | 2016-01-01 00:00:00 | 25.0 | 6.0 | 20.0 | NaN | |
| 1 | 0 | 2016-01-01 01:00:00 | 24.4 | NaN | 21.1 | -1.0 | |
| 2 | 0 | 2016-01-01 02:00:00 | 22.8 | 2.0 | 21.1 | 0.0 | |
| 3 | 0 | 2016-01-01 03:00:00 | 21.1 | 2.0 | 20.6 | 0.0 | |
| 4 | 0 | 2016-01-01 04:00:00 | 20.0 | 2.0 | 20.0 | -1.0 | |
| 5 | 0 | 2016-01-01 05:00:00 | 19.4 | NaN | 19.4 | 0.0 | |
| 6 | 0 | 2016-01-01 06:00:00 | 21.1 | 6.0 | 21.1 | -1.0 | |
| 7 | 0 | 2016-01-01 07:00:00 | 21.1 | NaN | 21.1 | 0.0 | |
| 8 | 0 | 2016-01-01 08:00:00 | 20.6 | NaN | 20.0 | 0.0 | |
| 9 | 0 | 2016-01-01 09:00:00 | 21.1 | NaN | 20.6 | 0.0 | |

```
In [5]: # merge building_metadata and train data
building_train_merged = pd.merge(building_metadata, train_data, how = 'inner', on = ['building_id'], sort = True)
print(building_train_merged.shape)
building_train_merged.head(10)
```

(20216100, 9)

Out[5]:

| | site_id | building_id | primary_use | square_feet | year_built | floor_count | meter | timestamp | meter |
|---|---------|-------------|-------------|-------------|------------|-------------|-------|---------------------|-------|
| 0 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 0 | 2016-01-01 00:00:00 | |
| 1 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 0 | 2016-01-01 01:00:00 | |
| 2 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 0 | 2016-01-01 02:00:00 | |
| 3 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 0 | 2016-01-01 03:00:00 | |
| 4 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 0 | 2016-01-01 04:00:00 | |
| 5 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 0 | 2016-01-01 05:00:00 | |
| 6 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 0 | 2016-01-01 06:00:00 | |
| 7 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 0 | 2016-01-01 07:00:00 | |
| 8 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 0 | 2016-01-01 08:00:00 | |
| 9 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 0 | 2016-01-01 09:00:00 | |

```
In [6]: # merge weather_train with merged building_metadata and train data
data_merged = pd.merge(building_train_merged, weather_train_data, how =
'left', on = ['site_id', 'timestamp'], sort = True)
print(data_merged.shape)
data_merged.head(10)
```

(20216100, 16)

Out[6]:

| | site_id | building_id | primary_use | square_feet | year_built | floor_count | meter | timestamp |
|---|---------|-------------|---------------------|-------------|------------|-------------|-------|------------|
| 0 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 0 | 2016-01-01 |
| 1 | 0 | 1 | Education | 2720 | 2004.0 | NaN | 0 | 2016-01-01 |
| 2 | 0 | 2 | Education | 5376 | 1991.0 | NaN | 0 | 2016-01-01 |
| 3 | 0 | 3 | Education | 23685 | 2002.0 | NaN | 0 | 2016-01-01 |
| 4 | 0 | 4 | Education | 116607 | 1975.0 | NaN | 0 | 2016-01-01 |
| 5 | 0 | 5 | Education | 8000 | 2000.0 | NaN | 0 | 2016-01-01 |
| 6 | 0 | 6 | Lodging/residential | 27926 | 1981.0 | NaN | 0 | 2016-01-01 |
| 7 | 0 | 7 | Education | 121074 | 1989.0 | NaN | 0 | 2016-01-01 |
| 8 | 0 | 8 | Education | 60809 | 2003.0 | NaN | 0 | 2016-01-01 |
| 9 | 0 | 9 | Office | 27000 | 2010.0 | NaN | 0 | 2016-01-01 |

```
In [7]: # extract hour, day, weekday, month from timestamp attribute in data_mer
ged
data_merged['hour'] = data_merged['timestamp'].dt.hour
data_merged['day'] = data_merged['timestamp'].dt.day
data_merged['weekday'] = data_merged['timestamp'].dt.weekday
data_merged['month'] = data_merged['timestamp'].dt.month
del data_merged['timestamp']
data_merged.head(10)
```

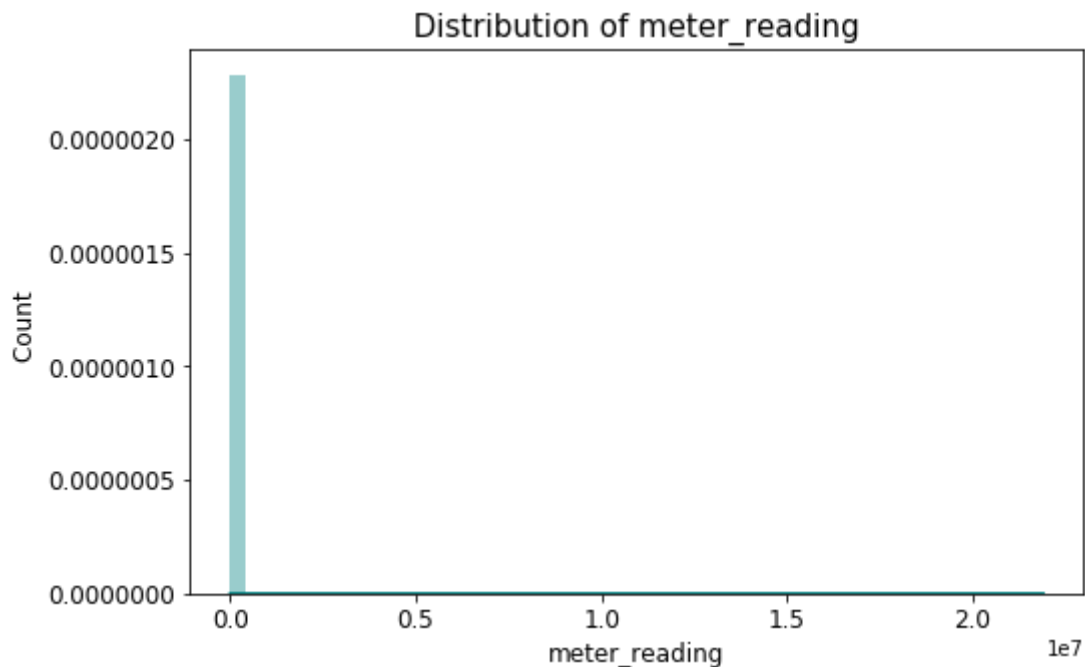
Out[7]:

| | site_id | building_id | primary_use | square_feet | year_built | floor_count | meter | meter_readin |
|---|---------|-------------|---------------------|-------------|------------|-------------|-------|--------------|
| 0 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 0 | C |
| 1 | 0 | 1 | Education | 2720 | 2004.0 | NaN | 0 | C |
| 2 | 0 | 2 | Education | 5376 | 1991.0 | NaN | 0 | C |
| 3 | 0 | 3 | Education | 23685 | 2002.0 | NaN | 0 | C |
| 4 | 0 | 4 | Education | 116607 | 1975.0 | NaN | 0 | C |
| 5 | 0 | 5 | Education | 8000 | 2000.0 | NaN | 0 | C |
| 6 | 0 | 6 | Lodging/residential | 27926 | 1981.0 | NaN | 0 | C |
| 7 | 0 | 7 | Education | 121074 | 1989.0 | NaN | 0 | C |
| 8 | 0 | 8 | Education | 60809 | 2003.0 | NaN | 0 | C |
| 9 | 0 | 9 | Office | 27000 | 2010.0 | NaN | 0 | C |

```
In [8]: # replace numerical values of meter with categorical values
data_merged['meter'].replace({0:"Electricity",1:"ChilledWater",2:"Steam"
,3:"HotWater"},inplace=True)
```

```
In [9]: # plot for distribution of meter reading
plt.rcParams['figure.figsize'] = (8, 5)
ax = sns.distplot(data_merged['meter_reading'], color = 'teal')
plt.xlabel('meter_reading', fontsize = 12)
plt.ylabel('Count ', fontsize = 12)
plt.xticks(fontsize = 12)
plt.yticks(fontsize = 12)
plt.title(' Distribution of meter_reading ', fontsize = 15)
plt.show()
```

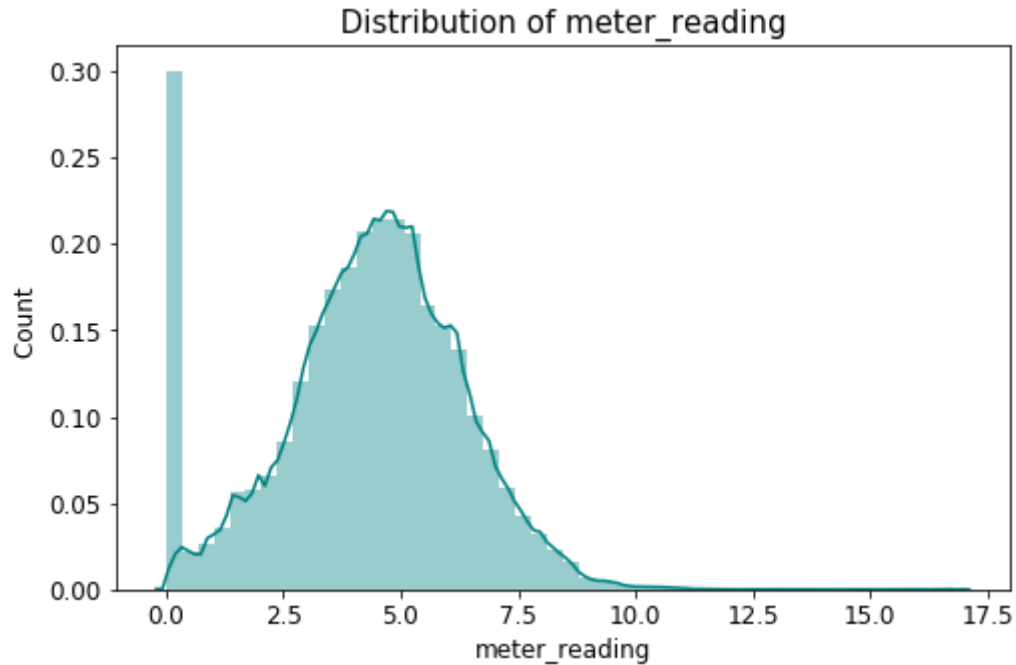
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-packages/seaborn/distributions.py:218: MatplotlibDeprecationWarning: The 'normed' kwarg was deprecated in Matplotlib 2.1 and will be removed in 3.1. Use 'density' instead.
color=hist_color, **hist_kws)



```
In [10]: # descriptive statistics of meter_reading
data_merged['meter_reading'].describe()
```

```
Out[10]: count      2.021610e+07
mean        2.117121e+03
std         1.532356e+05
min         0.000000e+00
25%         1.830000e+01
50%         7.877500e+01
75%         2.679840e+02
max         2.190470e+07
Name: meter_reading, dtype: float64
```

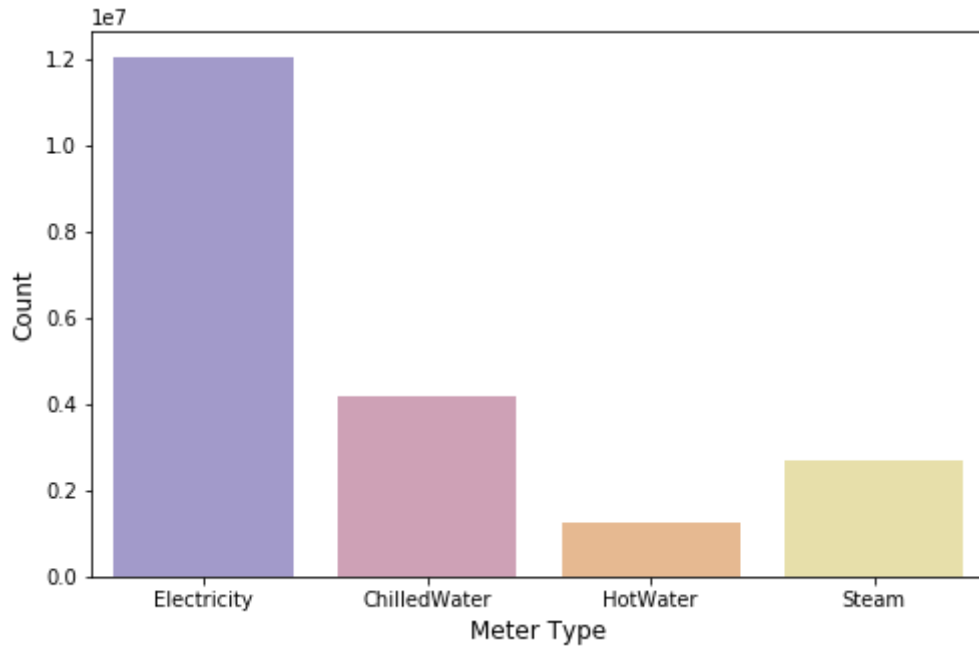
```
In [11]: # log transformation of meter_reading and distribution of meter reading
         # after transformation
data_merged['meter_reading'] = np.log1p(data_merged['meter_reading'])
plt.rcParams['figure.figsize'] = (8,5)
ax = sns.distplot(data_merged['meter_reading'], color = 'teal')
plt.xlabel('meter_reading', fontsize = 12)
plt.ylabel('Count ', fontsize = 12)
plt.xticks(fontsize = 12)
plt.yticks(fontsize = 12)
plt.title(' Distribution of meter_reading ', fontsize = 15)
plt.show()
```



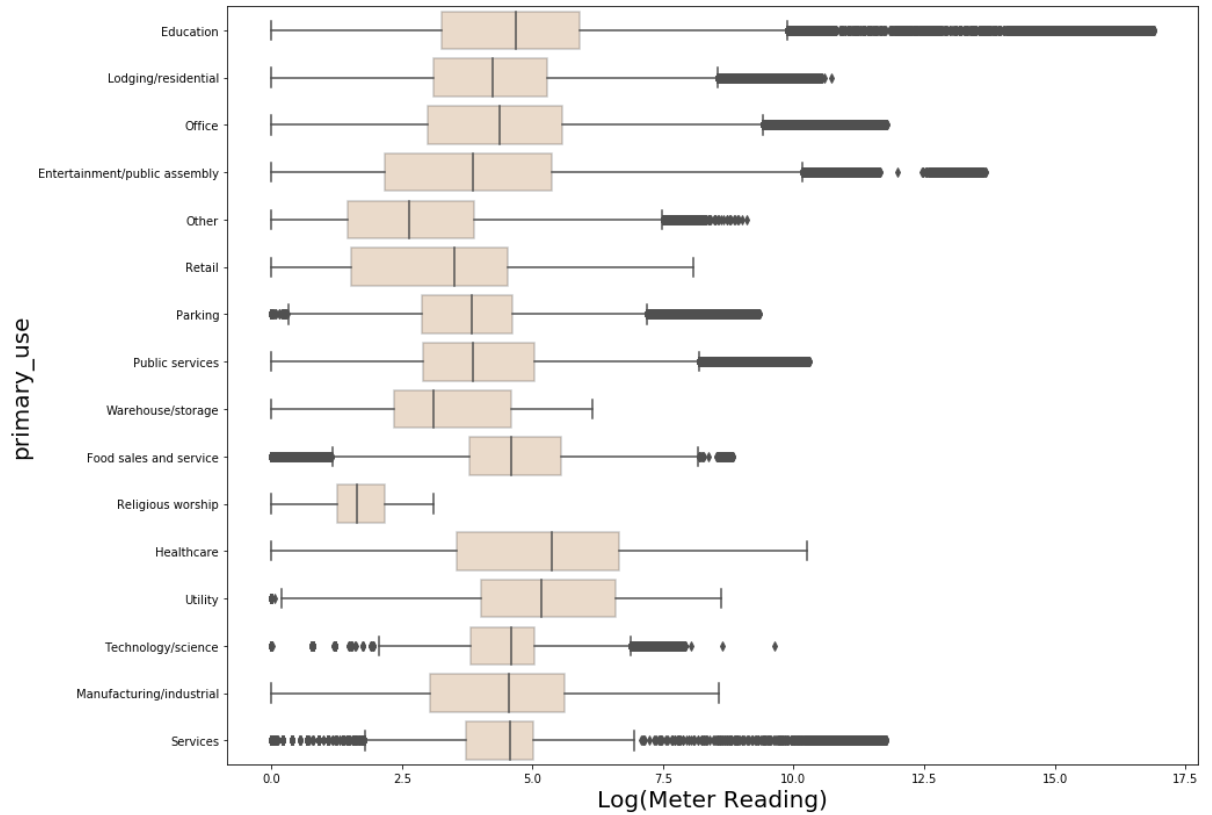
```
In [12]: # check the maximum and minimum values of meter_reading in training set
print("Max: ",data_merged['meter_reading'].max())
print("Min: ",data_merged['meter_reading'].min())
```

Max: 16.902211829285342
Min: 0.0


```
In [13]: # Distribution of data with respect to meter type
plt.rcParams['figure.figsize'] = (8, 5)
ax = sns.countplot(data = data_merged, x='meter', palette = 'CMRmap', alpha = 0.5)
ax.set_ylabel('Count', fontsize = 12)
ax.set_xlabel('Meter Type', fontsize = 12)
plt.show()
```

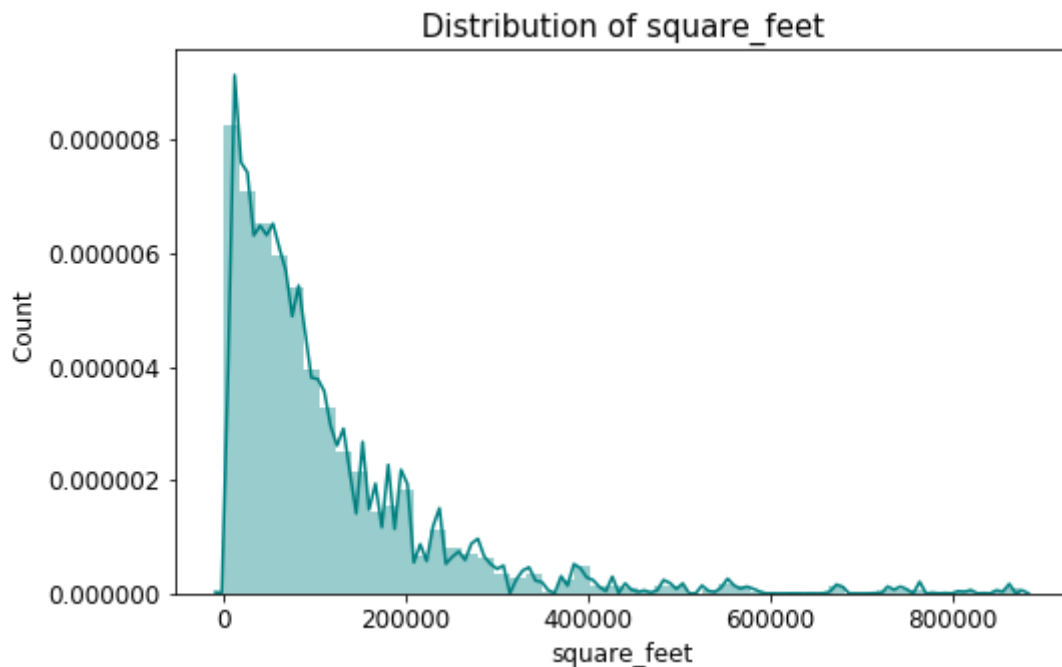


```
In [14]: # Distribution of data with respect to primary_use
plt.rcParams['figure.figsize'] = (15, 12)
ax = sns.boxplot(data = data_merged, y='primary_use', x = 'meter_reading', color = 'peru', boxprops=dict(alpha=.3))
ax.set_xlabel('Log(Meter Reading)', fontsize = 20)
ax.set_ylabel('primary_use', fontsize = 20)
plt.show()
```

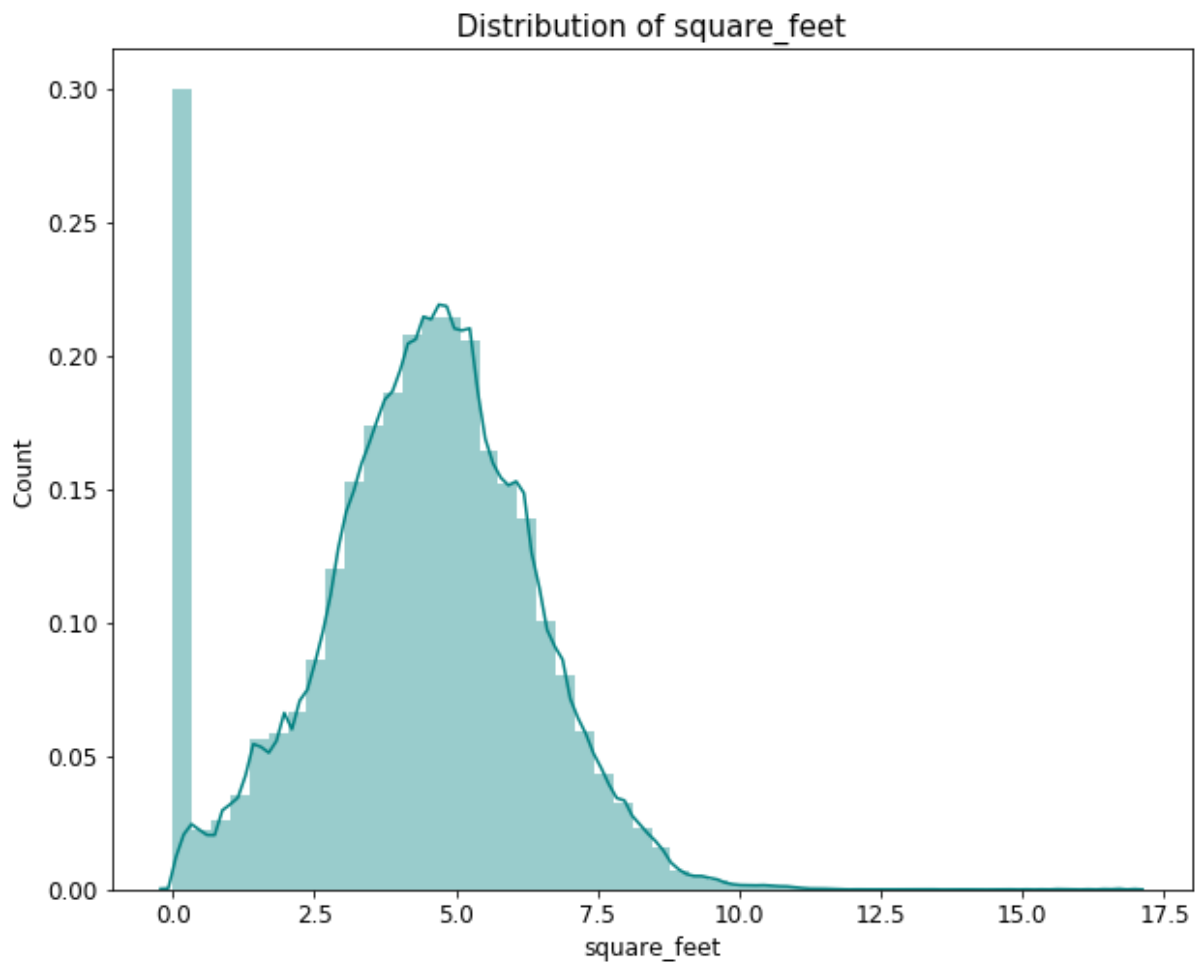


```
In [15]: # plot for distribution of square feet
plt.rcParams['figure.figsize'] = (8, 5)
ax = sns.distplot(data_merged['square_feet'], color = 'teal')
plt.xlabel('square_feet', fontsize = 12)
plt.ylabel('Count ', fontsize = 12)
plt.xticks(fontsize = 12)
plt.yticks(fontsize = 12)
plt.title(' Distribution of square_feet ', fontsize = 15)
plt.show()
```

/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-packages/seaborn/distributions.py:218: MatplotlibDeprecationWarning: The 'normed' kwarg was deprecated in Matplotlib 2.1 and will be removed in 3.1. Use 'density' instead.
color=hist_color, **hist_kws)



```
In [16]: # log transformation of square_feet and distribution of square_feet after
r transformation
data_merged['square_feet'] = np.log1p(data_merged['square_feet'])
plt.rcParams['figure.figsize'] = (10, 8)
ax = sns.distplot(data_merged['meter_reading'], color = 'teal')
plt.xlabel('square_feet', fontsize = 12)
plt.ylabel('Count ', fontsize = 12)
plt.xticks(fontsize = 12)
plt.yticks(fontsize = 12)
plt.title(' Distribution of square_feet ', fontsize = 15)
plt.show()
```



```
In [17]: # encode the categorical values of primary_use to numeric values
data_merged['primary_use']=data_merged.primary_use.map({'Education':1,'Lodging/residential':2,'Entertainment/public assembly':3,
                                                         'Public services':4,'Office':5,
                                                         'Technology/science':6,'Utility':7,
                                                         'Parking':8,'Other':9,'Health care':10,'Manufacturing/industrial':11})
data_merged.head()
```

```
Out[17]:
```

| | site_id | building_id | primary_use | square_feet | year_built | floor_count | meter | meter_reading |
|---|---------|-------------|-------------|-------------|------------|-------------|-------------|---------------|
| 0 | 0 | 0 | 1.0 | 8.913685 | 2008.0 | NaN | Electricity | 0.0 |
| 1 | 0 | 1 | 1.0 | 7.908755 | 2004.0 | NaN | Electricity | 0.0 |
| 2 | 0 | 2 | 1.0 | 8.589886 | 1991.0 | NaN | Electricity | 0.0 |
| 3 | 0 | 3 | 1.0 | 10.072639 | 2002.0 | NaN | Electricity | 0.0 |
| 4 | 0 | 4 | 1.0 | 11.666573 | 1975.0 | NaN | Electricity | 0.0 |

```
In [18]: # get dummies for the categorical attribute 'meter'
meter_dummies = pd.get_dummies(data_merged['meter'])
```

```
In [19]: # drop the actual attribute 'meter'
data_merged = data_merged.drop(columns=['meter'], axis = 1)
data_merged.head(10)
```

```
Out[19]:
```

| | site_id | building_id | primary_use | square_feet | year_built | floor_count | meter_reading | air_temperature |
|---|---------|-------------|-------------|-------------|------------|-------------|---------------|-----------------|
| 0 | 0 | 0 | 1.0 | 8.913685 | 2008.0 | NaN | 0.0 | |
| 1 | 0 | 1 | 1.0 | 7.908755 | 2004.0 | NaN | 0.0 | |
| 2 | 0 | 2 | 1.0 | 8.589886 | 1991.0 | NaN | 0.0 | |
| 3 | 0 | 3 | 1.0 | 10.072639 | 2002.0 | NaN | 0.0 | |
| 4 | 0 | 4 | 1.0 | 11.666573 | 1975.0 | NaN | 0.0 | |
| 5 | 0 | 5 | 1.0 | 8.987322 | 2000.0 | NaN | 0.0 | |
| 6 | 0 | 6 | 2.0 | 10.237349 | 1981.0 | NaN | 0.0 | |
| 7 | 0 | 7 | 1.0 | 11.704165 | 1989.0 | NaN | 0.0 | |
| 8 | 0 | 8 | 1.0 | 11.015510 | 2003.0 | NaN | 0.0 | |
| 9 | 0 | 9 | 5.0 | 10.203629 | 2010.0 | NaN | 0.0 | |

```
In [20]: # concatenate the data set with dummies of 'meter'
data_merged = pd.concat([meter_dummies, data_merged], axis = 1)
data_merged.head(10)
```

Out[20]:

| | ChilledWater | Electricity | HotWater | Steam | site_id | building_id | primary_use | square_feet | year |
|---|--------------|-------------|----------|-------|---------|-------------|-------------|-------------|------|
| 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1.0 | 8.913685 | 2 |
| 1 | 0 | 1 | 0 | 0 | 0 | 1 | 1.0 | 7.908755 | 2 |
| 2 | 0 | 1 | 0 | 0 | 0 | 2 | 1.0 | 8.589886 | 1 |
| 3 | 0 | 1 | 0 | 0 | 0 | 3 | 1.0 | 10.072639 | 2 |
| 4 | 0 | 1 | 0 | 0 | 0 | 4 | 1.0 | 11.666573 | 1 |
| 5 | 0 | 1 | 0 | 0 | 0 | 5 | 1.0 | 8.987322 | 2 |
| 6 | 0 | 1 | 0 | 0 | 0 | 6 | 2.0 | 10.237349 | 1 |
| 7 | 0 | 1 | 0 | 0 | 0 | 7 | 1.0 | 11.704165 | 1 |
| 8 | 0 | 1 | 0 | 0 | 0 | 8 | 1.0 | 11.015510 | 2 |
| 9 | 0 | 1 | 0 | 0 | 0 | 9 | 5.0 | 10.203629 | 2 |

10 rows × 22 columns

```
In [21]: # standardize year values
data_merged['year_built'] = np.uint8(data_merged['year_built']-1900, inplace = True)
```

```
In [22]: # encode categorical features
categorical_features = ['ChilledWater', 'Electricity', 'HotWater', 'Steam', "site_id", "building_id", "primary_use", "hour", "weekday", "wind_direction"]
ce = category_encoders.CountEncoder(cols=categorical_features)
ce.fit(data_merged)
data_merged = ce.transform(data_merged)
data_merged.head()
```

Out[22]:

| | ChilledWater | Electricity | HotWater | Steam | site_id | building_id | primary_use | square_feet |
|---|--------------|-------------|----------|----------|---------|-------------|-------------|-------------|
| 0 | 16033660 | 12060910 | 18952063 | 17507387 | 1076662 | 8784 | 8165504 | 8.913685 |
| 1 | 16033660 | 12060910 | 18952063 | 17507387 | 1076662 | 8784 | 8165504 | 7.908755 |
| 2 | 16033660 | 12060910 | 18952063 | 17507387 | 1076662 | 8784 | 8165504 | 8.589886 |
| 3 | 16033660 | 12060910 | 18952063 | 17507387 | 1076662 | 8784 | 8165504 | 10.072639 |
| 4 | 16033660 | 12060910 | 18952063 | 17507387 | 1076662 | 8784 | 8165504 | 11.666573 |

5 rows × 22 columns

```
In [23]: # find the number of missing values in each column
data_merged.isnull().sum(axis = 0)
```

```
Out[23]: ChilledWater          0
Electricity                   0
HotWater                      0
Steam                        0
site_id                      0
building_id                  0
primary_use                   0
square_feet                   0
year_built                    0
floor_count                   16709167
meter_reading                 0
air_temperature               96658
cloud_coverage                8825365
dew_temperature               100140
precip_depth_1_hr            3749023
sea_level_pressure            1231669
wind_direction                0
wind_speed                    143676
hour                          0
day                           0
weekday                       0
month                         0
dtype: int64
```

```
In [24]: # replace the missing values with 0
data_merged = data_merged.fillna(0)
```

```
In [25]: # get the valid rows from the data_merged which are non zero
data_merged = data_merged[(data_merged.square_feet>0) & (data_merged.yea
r_built>0) & (data_merged.floor_count >0)
& (data_merged.primary_use >0)]
```



```
In [28]: # Standardize(scale) the data
scalerX = StandardScaler()
columnsX = X_train.columns
scalerX.fit(X_train)
X_train_scaled = scalerX.transform(X_train)
X_val_scaled = scalerX.transform(X_val)
X_train_scaled_df = pd.DataFrame(X_train_scaled, columns=columnsX)
X_val_scaled_df = pd.DataFrame(X_val_scaled, columns=columnsX)
```

```
In [29]: #LINEAR REGRESSION model
LR_model = linear_model.LinearRegression().fit(X = X_train_scaled_df, y
= Y_train)

LR_predicted = LR_model.predict(X_val_scaled_df)

print('Linear Regression Model')

LR_R_square = LR_model.score(X = X_val_scaled_df, y = Y_val)
print()
print('R square')
print(LR_R_square)

LR_RootMeanSquareError = np.sqrt(mean_squared_error(Y_val, LR_predicted
))
print()
print('Root Mean Square Error')
print(LR_RootMeanSquareError)
```

Linear Regression Model

R square
0.43923074997777584

Root Mean Square Error
1.561774097294691

```
In [30]: #Ridge REGRESSION model
Ridge_model = linear_model.Ridge(alpha=.5).fit(X = X_train_scaled_df, y
= Y_train)

Ridge_predicted = Ridge_model.predict(X_val_scaled_df)

print('Ridge Regression Model')

Ridge_R_square = Ridge_model.score(X = X_val_scaled_df,y = Y_val)
print()
print('R square')
print(Ridge_R_square)

Ridge_RootMeanSquareError = np.sqrt(mean_squared_error(Y_val, Ridge_pred
icted))
print()
print('Root Mean Square Error')
print(Ridge_RootMeanSquareError)
```

Ridge Regression Model

R square
0.4392309491413351

Root Mean Square Error
1.5617738199537743

```
In [31]: #Bayesian Ridge REGRESSION model
Y_train = Y_train.values.ravel()
Bayesian_Ridge_model = linear_model.BayesianRidge().fit(X = X_train_scal
ed_df, y = Y_train)

Bayesian_Ridge_predicted = Bayesian_Ridge_model.predict(X_val_scaled_df)

print('Bayesian Ridge Regression Model')

Bayesian_Ridge_R_square = Bayesian_Ridge_model.score(X = X_val_scaled_df
,y = Y_val)
print()
print('R square')
print(Bayesian_Ridge_R_square)

Bayesian_Ridge_RootMeanSquareError = np.sqrt(mean_squared_error(Y_val, B
ayesian_Ridge_predicted))
print()
print('Root Mean Square Error')
print(Bayesian_Ridge_RootMeanSquareError)
```

Bayesian Ridge Regression Model

R square
0.43923087396057203

Root Mean Square Error
1.5617739246451292

```

In [32]: # Gradient Boosting REGRESSION model
GB_model = GradientBoostingRegressor(n_estimators=10, learning_rate=0.1,
                                     max_depth=1, random_state=0).fit(X = X_train_scaled_df, y = Y_train)

GB_predicted = GB_model.predict(X_val_scaled_df)

print('Gradient Boosting Regressor')

GB_R_square = GB_model.score(X = X_val_scaled_df, y = Y_val)
print()
print('R square')
print(GB_R_square)

GB_RootMeanSquareError = np.sqrt(mean_squared_error(Y_val, GB_predicted))
print()
print('Root Mean Square Error')
print(GB_RootMeanSquareError)

print()
print('Feature importances')
print(GB_model.feature_importances_)

```

Gradient Boosting Regressor

R square

0.3026301927146213

Root Mean Square Error

1.7416371924352358

Feature importances

```

[0.         0.         0.         0.         0.         0.
 0.         0.69540225 0.         0.30459775 0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         ]

```

```

In [33]: # Random Forest REGRESSION model
RF_model = RandomForestRegressor(n_estimators=10, random_state=42).fit(X
= X_train_scaled_df, y = Y_train)

RF_predicted = RF_model.predict(X_val_scaled_df)

print('Random Forest Regressor')

RF_R_square = RF_model.score(X = X_val_scaled_df,y = Y_val)
print()
print('R square')
print(RF_R_square)

RF_RootMeanSquareError = np.sqrt(mean_squared_error(Y_val, RF_predicted
))
print()
print('Root Mean Square Error')
print(RF_RootMeanSquareError)

print()
print('Feature importances')
print(RF_model.feature_importances_ )

```

Random Forest Regressor

R square

0.9655695882252688

Root Mean Square Error

0.3869877595712031

Feature importances

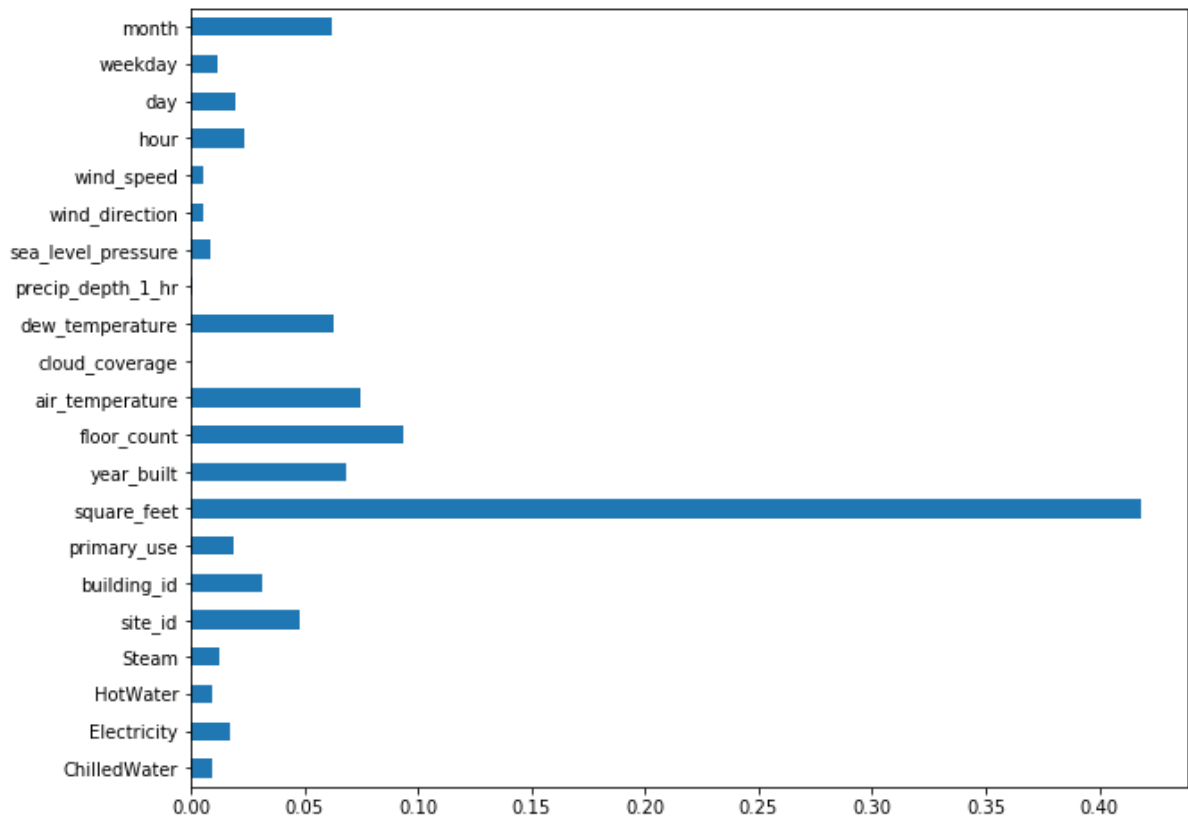
```

[9.55050710e-03 1.74860238e-02 9.59637762e-03 1.24279025e-02
 4.74667305e-02 3.11190941e-02 1.85284481e-02 4.18146707e-01
 6.84833133e-02 9.38473759e-02 7.43693295e-02 9.78923142e-05
 6.29277176e-02 3.60597681e-04 8.52371138e-03 5.09873214e-03
 5.26616847e-03 2.38243250e-02 1.91478862e-02 1.16321861e-02
 6.20989739e-02]

```

```
In [34]: # plot feature importances
imp_features = pd.Series(RF_model.feature_importances_, index = X_train.
columns)
imp_features.plot(kind = "barh")
```

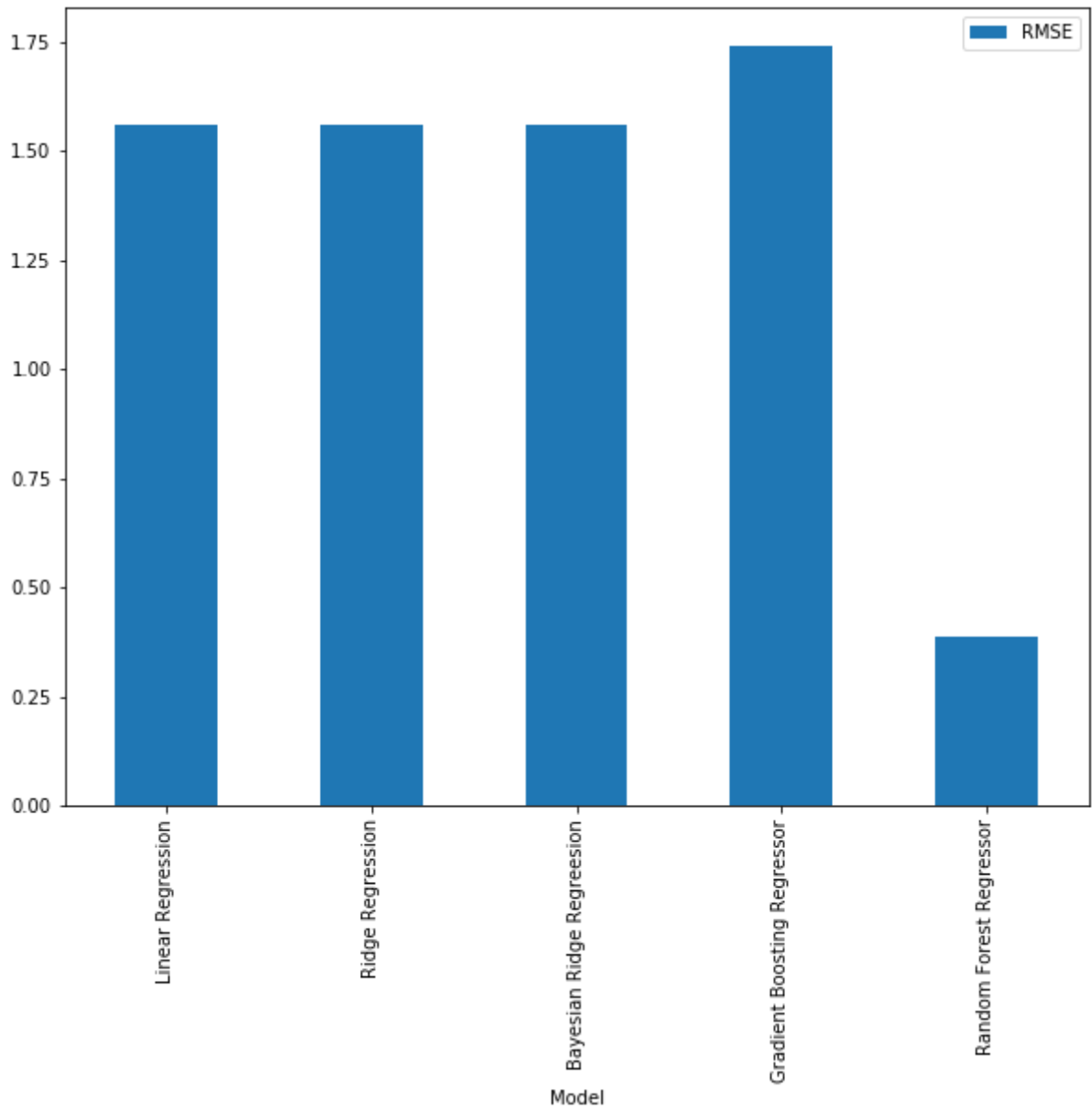
Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x128e4f320>



```
In [35]: # create a dataframe with models and corresponding RMSE
R2_RMSE = [ ['Linear Regression', LR_RootMeanSquareError, LR_R_square],
            [ 'Ridge Regression', Ridge_RootMeanSquareError, Ridge_R_squ
quare],
            [ 'Bayesian Ridge Regreesion', Bayesian_Ridge_RootMeanSquar
eError, Bayesian_Ridge_R_square],
            [ 'Gradient Boosting Regressor', GB_RootMeanSquareError, GB
_R_square],
            [ 'Random Forest Regressor', RF_RootMeanSquareError, RF_R_s
quare]]
ModelEvaluation = pd.DataFrame(R2_RMSE, columns = ['Model', 'RMSE', 'R_S
quare'])
```

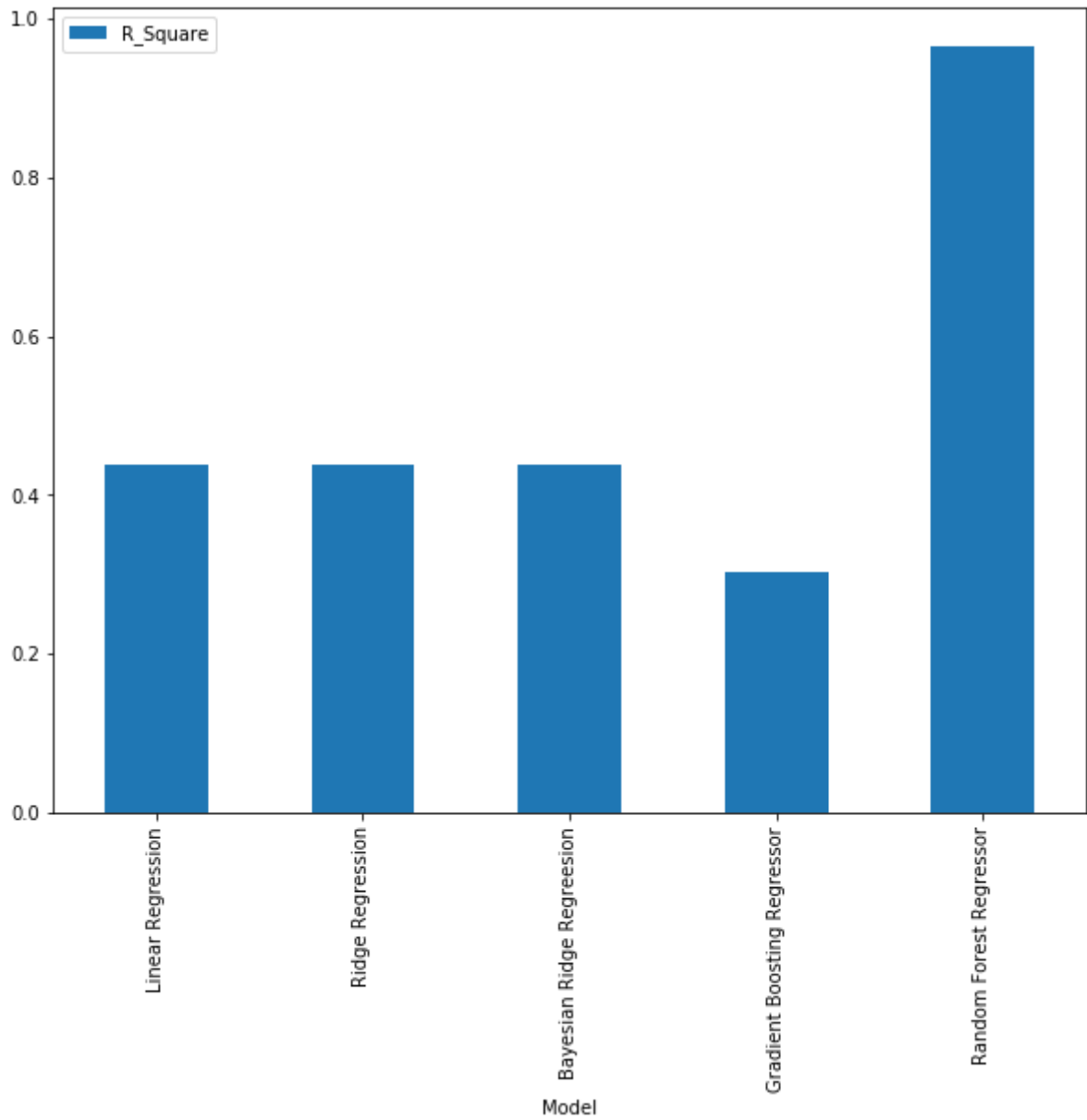
```
In [36]: # plot RMSE for the evaluation of models
plt.rcParams['figure.figsize'] = (10, 8)
ModelEvaluation.plot(kind='bar',x='Model',y='RMSE')
```

Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x1290a92b0>



```
In [37]: # plot R_Square for the evaluation of models
plt.rcParams['figure.figsize'] = (10, 8)
ModelEvaluation.plot(kind='bar',x='Model',y='R_Square')
```

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x128aa7048>



```
In [38]: # get test data
test_data = pd.read_csv("test.csv")
print(test_data.shape)
test_data["timestamp"] = pd.to_datetime(test_data["timestamp"])
test_data.head(10)
```

(41697600, 4)

Out[38]:

| | row_id | building_id | meter | timestamp |
|---|--------|-------------|-------|------------|
| 0 | 0 | 0 | 0 | 2017-01-01 |
| 1 | 1 | 1 | 0 | 2017-01-01 |
| 2 | 2 | 2 | 0 | 2017-01-01 |
| 3 | 3 | 3 | 0 | 2017-01-01 |
| 4 | 4 | 4 | 0 | 2017-01-01 |
| 5 | 5 | 5 | 0 | 2017-01-01 |
| 6 | 6 | 6 | 0 | 2017-01-01 |
| 7 | 7 | 7 | 0 | 2017-01-01 |
| 8 | 8 | 7 | 1 | 2017-01-01 |
| 9 | 9 | 8 | 0 | 2017-01-01 |


```
In [39]: # get weather test data
weather_test_data = pd.read_csv("weather_test.csv")
print(weather_test_data.shape)
weather_test_data["timestamp"] = pd.to_datetime(weather_test_data["timestamp"])
weather_test_data.head(10)
```

(277243, 9)

Out[39]:

| | site_id | timestamp | air_temperature | cloud_coverage | dew_temperature | precip_depth_1_hr | sea |
|---|---------|---------------------|-----------------|----------------|-----------------|-------------------|-----|
| 0 | 0 | 2017-01-01 00:00:00 | 17.8 | 4.0 | 11.7 | NaN | |
| 1 | 0 | 2017-01-01 01:00:00 | 17.8 | 2.0 | 12.8 | 0.0 | |
| 2 | 0 | 2017-01-01 02:00:00 | 16.1 | 0.0 | 12.8 | 0.0 | |
| 3 | 0 | 2017-01-01 03:00:00 | 17.2 | 0.0 | 13.3 | 0.0 | |
| 4 | 0 | 2017-01-01 04:00:00 | 16.7 | 2.0 | 13.3 | 0.0 | |
| 5 | 0 | 2017-01-01 05:00:00 | 15.6 | 2.0 | 12.8 | 0.0 | |
| 6 | 0 | 2017-01-01 06:00:00 | 15.0 | 0.0 | 12.8 | 0.0 | |
| 7 | 0 | 2017-01-01 07:00:00 | 15.0 | 2.0 | 13.3 | 0.0 | |
| 8 | 0 | 2017-01-01 08:00:00 | 13.3 | 0.0 | 12.2 | 0.0 | |
| 9 | 0 | 2017-01-01 09:00:00 | 12.2 | 4.0 | 11.7 | 0.0 | |

```
In [40]: # merge building_metadata and test data
building_test_merged = pd.merge(building_metadata, test_data, how = 'inner', on = ['building_id'], sort = True)
print(building_test_merged.shape)
building_test_merged.head(10)
```

(41697600, 9)

Out[40]:

| | site_id | building_id | primary_use | square_feet | year_built | floor_count | row_id | meter | timestamp |
|---|---------|-------------|-------------|-------------|------------|-------------|--------|-------|---------------------|
| 0 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 0 | 0 | 2017-01-01 00:00:00 |
| 1 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 129 | 0 | 2017-01-01 01:00:00 |
| 2 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 258 | 0 | 2017-01-01 02:00:00 |
| 3 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 387 | 0 | 2017-01-01 03:00:00 |
| 4 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 516 | 0 | 2017-01-01 04:00:00 |
| 5 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 645 | 0 | 2017-01-01 05:00:00 |
| 6 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 774 | 0 | 2017-01-01 06:00:00 |
| 7 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 903 | 0 | 2017-01-01 07:00:00 |
| 8 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 1032 | 0 | 2017-01-01 08:00:00 |
| 9 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 1161 | 0 | 2017-01-01 09:00:00 |

```
In [41]: # merge weather_train with merged building_metadata and test data
data_merged_test = pd.merge(building_test_merged, weather_test_data, how
= 'left', on = ['site_id', 'timestamp'], sort = True)
print(data_merged_test.shape)
data_merged_test.head(10)
```

(41697600, 16)

Out[41]:

| | site_id | building_id | primary_use | square_feet | year_built | floor_count | row_id | meter | time |
|---|---------|-------------|---------------------|-------------|------------|-------------|--------|-------|------|
| 0 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 0 | 0 | 20 |
| 1 | 0 | 1 | Education | 2720 | 2004.0 | NaN | 1 | 0 | 20 |
| 2 | 0 | 2 | Education | 5376 | 1991.0 | NaN | 2 | 0 | 20 |
| 3 | 0 | 3 | Education | 23685 | 2002.0 | NaN | 3 | 0 | 20 |
| 4 | 0 | 4 | Education | 116607 | 1975.0 | NaN | 4 | 0 | 20 |
| 5 | 0 | 5 | Education | 8000 | 2000.0 | NaN | 5 | 0 | 20 |
| 6 | 0 | 6 | Lodging/residential | 27926 | 1981.0 | NaN | 6 | 0 | 20 |
| 7 | 0 | 7 | Education | 121074 | 1989.0 | NaN | 7 | 0 | 20 |
| 8 | 0 | 7 | Education | 121074 | 1989.0 | NaN | 8 | 1 | 20 |
| 9 | 0 | 8 | Education | 60809 | 2003.0 | NaN | 9 | 0 | 20 |

```
In [42]: # extract hour, day, weekday, month from timestamp attribute in data_mer
ged
data_merged_test['hour'] = data_merged_test['timestamp'].dt.hour
data_merged_test['day'] = data_merged_test['timestamp'].dt.day
data_merged_test['weekday'] = data_merged_test['timestamp'].dt.weekday
data_merged_test['month'] = data_merged_test['timestamp'].dt.month
del data_merged_test['timestamp']
data_merged_test.head(10)
```

Out[42]:

| | site_id | building_id | primary_use | square_feet | year_built | floor_count | row_id | meter | air_ |
|---|---------|-------------|---------------------|-------------|------------|-------------|--------|-------|------|
| 0 | 0 | 0 | Education | 7432 | 2008.0 | NaN | 0 | 0 | |
| 1 | 0 | 1 | Education | 2720 | 2004.0 | NaN | 1 | 0 | |
| 2 | 0 | 2 | Education | 5376 | 1991.0 | NaN | 2 | 0 | |
| 3 | 0 | 3 | Education | 23685 | 2002.0 | NaN | 3 | 0 | |
| 4 | 0 | 4 | Education | 116607 | 1975.0 | NaN | 4 | 0 | |
| 5 | 0 | 5 | Education | 8000 | 2000.0 | NaN | 5 | 0 | |
| 6 | 0 | 6 | Lodging/residential | 27926 | 1981.0 | NaN | 6 | 0 | |
| 7 | 0 | 7 | Education | 121074 | 1989.0 | NaN | 7 | 0 | |
| 8 | 0 | 7 | Education | 121074 | 1989.0 | NaN | 8 | 1 | |
| 9 | 0 | 8 | Education | 60809 | 2003.0 | NaN | 9 | 0 | |

```
In [43]: # replace numerical values of meter with categorical values
data_merged_test['meter'].replace({0:"Electricity",1:"ChilledWater",2:"S
team",3:"HotWater"},inplace=True)
```

```
In [44]: # apply log transformation on square_feet
data_merged_test['square_feet'] = np.log1p(data_merged_test['square_fee
t'])
```

```
In [45]: # encode the categorical values of primary_use in data_merged_test to numeric values
data_merged_test['primary_use']=data_merged_test.primary_use.map({'Education':1,'Lodging/residential':2,'Entertainment/public assembly':3,
                                                                    'Public services':4,'Office':5,
                                                                    'Technology/science':6,'Utility':7,
                                                                    'Parking':8,'Other':9,'Health care':10,'Manufacturing/industrial':11})
data_merged_test.head()
```

```
Out[45]:
```

| | site_id | building_id | primary_use | square_feet | year_built | floor_count | row_id | meter | air_tem |
|---|---------|-------------|-------------|-------------|------------|-------------|--------|-------------|---------|
| 0 | 0 | 0 | 1.0 | 8.913685 | 2008.0 | NaN | 0 | Electricity | |
| 1 | 0 | 1 | 1.0 | 7.908755 | 2004.0 | NaN | 1 | Electricity | |
| 2 | 0 | 2 | 1.0 | 8.589886 | 1991.0 | NaN | 2 | Electricity | |
| 3 | 0 | 3 | 1.0 | 10.072639 | 2002.0 | NaN | 3 | Electricity | |
| 4 | 0 | 4 | 1.0 | 11.666573 | 1975.0 | NaN | 4 | Electricity | |

```
In [46]: # get the dummies of the attribute 'meter'
meter_dummies = pd.get_dummies(data_merged_test['meter'])
```

```
In [47]: # drop the actual attribute 'meter'
data_merged_test = data_merged_test.drop(columns=['meter'], axis = 1)
data_merged_test.head(10)
```

```
Out[47]:
```

| | site_id | building_id | primary_use | square_feet | year_built | floor_count | row_id | air_temperature |
|---|---------|-------------|-------------|-------------|------------|-------------|--------|-----------------|
| 0 | 0 | 0 | 1.0 | 8.913685 | 2008.0 | NaN | 0 | 17.8 |
| 1 | 0 | 1 | 1.0 | 7.908755 | 2004.0 | NaN | 1 | 17.8 |
| 2 | 0 | 2 | 1.0 | 8.589886 | 1991.0 | NaN | 2 | 17.8 |
| 3 | 0 | 3 | 1.0 | 10.072639 | 2002.0 | NaN | 3 | 17.8 |
| 4 | 0 | 4 | 1.0 | 11.666573 | 1975.0 | NaN | 4 | 17.8 |
| 5 | 0 | 5 | 1.0 | 8.987322 | 2000.0 | NaN | 5 | 17.8 |
| 6 | 0 | 6 | 2.0 | 10.237349 | 1981.0 | NaN | 6 | 17.8 |
| 7 | 0 | 7 | 1.0 | 11.704165 | 1989.0 | NaN | 7 | 17.8 |
| 8 | 0 | 7 | 1.0 | 11.704165 | 1989.0 | NaN | 8 | 17.8 |
| 9 | 0 | 8 | 1.0 | 11.015510 | 2003.0 | NaN | 9 | 17.8 |

```
In [48]: # concatenate the data set with dummies of 'meter'
data_merged_test = pd.concat([meter_dummies, data_merged_test], axis = 1)
data_merged_test.head(10)
```

Out[48]:

| | ChilledWater | Electricity | HotWater | Steam | site_id | building_id | primary_use | square_feet | year |
|---|--------------|-------------|----------|-------|---------|-------------|-------------|-------------|------|
| 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1.0 | 8.913685 | 2 |
| 1 | 0 | 1 | 0 | 0 | 0 | 1 | 1.0 | 7.908755 | 2 |
| 2 | 0 | 1 | 0 | 0 | 0 | 2 | 1.0 | 8.589886 | 1 |
| 3 | 0 | 1 | 0 | 0 | 0 | 3 | 1.0 | 10.072639 | 2 |
| 4 | 0 | 1 | 0 | 0 | 0 | 4 | 1.0 | 11.666573 | 1 |
| 5 | 0 | 1 | 0 | 0 | 0 | 5 | 1.0 | 8.987322 | 2 |
| 6 | 0 | 1 | 0 | 0 | 0 | 6 | 2.0 | 10.237349 | 1 |
| 7 | 0 | 1 | 0 | 0 | 0 | 7 | 1.0 | 11.704165 | 1 |
| 8 | 1 | 0 | 0 | 0 | 0 | 7 | 1.0 | 11.704165 | 1 |
| 9 | 0 | 1 | 0 | 0 | 0 | 8 | 1.0 | 11.015510 | 2 |

10 rows × 22 columns

```
In [49]: data_merged_test['year_built'] = np.uint8(data_merged_test['year_built']
-1900, inplace = True)
```

```
In [50]: categorical_features = ['ChilledWater', 'Electricity', 'HotWater', 'Steam',
"site_id", "building_id",
"primary_use", "hour", "weekday", "wind_direction"]
ce = category_encoders.CountEncoder(cols=categorical_features)
ce.fit(data_merged_test)
data_merged_test = ce.transform(data_merged_test)
data_merged_test.head()
```

Out[50]:

| | ChilledWater | Electricity | HotWater | Steam | site_id | building_id | primary_use | square_feet |
|---|--------------|-------------|----------|----------|---------|-------------|-------------|-------------|
| 0 | 32972640 | 24755760 | 39157200 | 36021120 | 2260080 | 17520 | 16801680 | 8.913685 |
| 1 | 32972640 | 24755760 | 39157200 | 36021120 | 2260080 | 17520 | 16801680 | 7.908755 |
| 2 | 32972640 | 24755760 | 39157200 | 36021120 | 2260080 | 17520 | 16801680 | 8.589886 |
| 3 | 32972640 | 24755760 | 39157200 | 36021120 | 2260080 | 17520 | 16801680 | 10.072639 |
| 4 | 32972640 | 24755760 | 39157200 | 36021120 | 2260080 | 17520 | 16801680 | 11.666573 |

5 rows × 22 columns

```
In [51]: # find the number of missing values in each column
data_merged_test.isnull().sum(axis = 0)
```

```
Out[51]: ChilledWater          0
Electricity          0
HotWater             0
Steam               0
site_id             0
building_id         0
primary_use         0
square_feet         0
year_built          0
floor_count        34444320
row_id              0
air_temperature     221901
cloud_coverage     19542180
dew_temperature     260799
precip_depth_1_hr   7801563
sea_level_pressure  2516826
wind_direction      0
wind_speed          302089
hour                0
day                 0
weekday             0
month               0
dtype: int64
```

```
In [52]: # replace the missing values with averages
avgs = data_merged_test.loc[:,data_merged_test.isnull().sum(axis = 0) >
0].mean()
avgs = avgs.astype(int)
data_merged_test = data_merged_test.fillna(avgs)
```

```
In [53]: # get the shape of the data_merged_test set
data_merged_test.shape
```

```
Out[53]: (41697600, 22)
```

```
In [54]: # get sample_submission to see the format of output
sample_submission = pd.read_csv("sample_submission.csv")
print(sample_submission.shape)
sample_submission.head(10)
```

```
(41697600, 2)
```

Out[54]:

| | row_id | meter_reading |
|---|--------|---------------|
| 0 | 0 | 0 |
| 1 | 1 | 0 |
| 2 | 2 | 0 |
| 3 | 3 | 0 |
| 4 | 4 | 0 |
| 5 | 5 | 0 |
| 6 | 6 | 0 |
| 7 | 7 | 0 |
| 8 | 8 | 0 |
| 9 | 9 | 0 |

```
In [55]: # get rowids from data_merged_test and then drop them
rowids = pd.DataFrame(data_merged_test['row_id'])
data_merged_test=data_merged_test.drop(["row_id"],axis=1)
```

```
In [56]: # standardize(scale) the test set
columnsX = data_merged_test.columns
X_test_scaled = scalerX.transform(data_merged_test)
X_test_scaled_df = pd.DataFrame(X_test_scaled, columns=columnsX)
```

```
In [57]: # Use the best model with least Root Mean Square Error (RandomForestRegressor) to predict the target on the test set
RF_test_predicted = RF_model.predict(X_test_scaled_df)
#test_pred = scalerY.inverse_transform(LR_test_predicted)
test_pred = RF_test_predicted
```

```
In [58]: # Build the output in the required format with rowids and predicted values on the test set
output = pd.DataFrame({'row_id':rowids["row_id"], 'meter_reading': test_pred})
```



```
In [59]: # check the output  
output
```

Out[59]:

| | row_id | meter_reading |
|----------|----------|---------------|
| | 0 | 1.533930 |
| | 1 | 0.557138 |
| | 2 | 1.755082 |
| | 3 | 2.412684 |
| | 4 | 3.958811 |
| | 5 | 1.473085 |
| | 6 | 2.728818 |
| | 7 | 3.958811 |
| | 8 | 3.958811 |
| | 9 | 2.135211 |
| | 10 | 2.343753 |
| | 11 | 2.343753 |
| | 12 | 6.158011 |
| | 13 | 3.495652 |
| | 14 | 4.168485 |
| | 15 | 3.336897 |
| | 16 | 3.336897 |
| | 17 | 2.695239 |
| | 18 | 2.695239 |
| | 19 | 2.695239 |
| | 20 | 2.695239 |
| | 21 | 4.158408 |
| | 22 | 2.250648 |
| | 23 | 3.958811 |
| | 24 | 2.203024 |
| | 25 | 3.958811 |
| | 26 | 1.533930 |
| | 27 | 0.557138 |
| | 28 | 3.958811 |
| | 29 | 3.426255 |
| | ... | ... |
| 41697570 | 41498533 | 4.575191 |
| 41697571 | 41498534 | 2.473921 |
| 41697572 | 41498535 | 0.694374 |

| | row_id | meter_reading |
|-----------------|----------|---------------|
| 41697573 | 41498536 | 4.161283 |
| 41697574 | 41498537 | 4.161283 |
| 41697575 | 41498538 | 4.187002 |
| 41697576 | 41498569 | 4.187002 |
| 41697577 | 41498539 | 4.575191 |
| 41697578 | 41498540 | 2.273064 |
| 41697579 | 41498541 | 2.273064 |
| 41697580 | 41498542 | 2.389645 |
| 41697581 | 41498543 | 2.389645 |
| 41697582 | 41498544 | 1.159257 |
| 41697583 | 41498545 | 2.421060 |
| 41697584 | 41498546 | 2.421060 |
| 41697585 | 41498547 | 4.304390 |
| 41697586 | 41498548 | 4.304390 |
| 41697587 | 41498549 | 3.923303 |
| 41697588 | 41498550 | 3.923303 |
| 41697589 | 41498551 | 4.092965 |
| 41697590 | 41498552 | 4.392161 |
| 41697591 | 41498553 | 2.330136 |
| 41697592 | 41498554 | 2.696598 |
| 41697593 | 41498555 | 2.696598 |
| 41697594 | 41498556 | 0.694374 |
| 41697595 | 41498557 | 2.559255 |
| 41697596 | 41498558 | 0.134225 |
| 41697597 | 41498559 | 2.749679 |
| 41697598 | 41498560 | 2.499639 |
| 41697599 | 41498570 | 3.485455 |

41697600 rows × 2 columns

```
In [60]: # check the maximum and minimum values for predicted meter reading
print("Max: ",output['meter_reading'].max())
print("Min: ",output['meter_reading'].min())
```

```
Max:  9.414237718580951
Min:  0.0
```

```
In [61]: # copy the output to Project5_submission_results.csv
output.to_csv('Project5_submission_results.csv', index=False)
```

```
In [62]: # check Project5_submission_results.csv
Project5_submission_results = pd.read_csv("Project5_submission_results.csv")
print(Project5_submission_results.shape)
Project5_submission_results.head(10)
```

```
(41697600, 2)
```

Out[62]:

| | row_id | meter_reading |
|---|--------|---------------|
| 0 | 0 | 1.533930 |
| 1 | 1 | 0.557138 |
| 2 | 2 | 1.755082 |
| 3 | 3 | 2.412684 |
| 4 | 4 | 3.958811 |
| 5 | 5 | 1.473085 |
| 6 | 6 | 2.728818 |
| 7 | 7 | 3.958811 |
| 8 | 8 | 3.958811 |
| 9 | 9 | 2.135211 |

```
In [ ]:
```