The purpose of the project is to build a model that could satisfactorily predict the energy consumption using historical data, with Linear Regression (Random Forest Tree)

In [87]:
```python
import pandas as pd
import os as o # creating the working directory
from matplotlib import pyplot as plt#For Visuals and chat
import numpy as np #numpy is used for making numpy array
import seaborn as sns#For visuals and chart
from sklearn.ensemble import RandomForestRegressor#Machine learning model
from sklearn.model_selection import train_test_split#to splitt the dataset to train and test
from sklearn import metrics#for accuracy score
#To remove warnings
import warnings
warnings.filterwarnings('ignore')
```

In [125…
```python
path = 'C:\\Users\\user\Desktop\Data Analytics\\Python\Machine Learning\\Energy Consumption Project\\'
```

In [126…
```python
##path = 'C:\\Users\\FEMI.OLUNUGA\\OneDrive - Landsec\\Desktop\\P.Project'
```

In [127…
```python
o.chdir(path) #to activate the path
```

In [128…
```python
o.getcwd()# to confirm the working path
```

Out[128…
```
'C:\\Users\\FEMI.OLUNUGA\\OneDrive - Landsec\\Desktop\\P.Project'
```

Loading and Preview of Data

In [129…
```python
df=pd.read_csv('Full_Energy.csv')
```

In [130…
```python
df2 = df # creating a duplicate data
```

In [131…
```python
df.shape
```

Out[131…
```
(1048575, 16)
```

In [132…
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1048575 entries, 0 to 1048574
Data columns (total 16 columns):
 #   Column              Non-Null Count    Dtype  
---  ------              --------------    -----  
 0   site_id             1048575 non-null  int64  
 1   building_id         1048575 non-null  int64  
 2   primary_use         1048575 non-null  object 
 3   square_feet         1048575 non-null  int64  
 4   year_built          1048575 non-null  int64  
 5   floor_count         0 non-null        float64
 6   timestamp           1048575 non-null  object 
 7   air_temperature     1048272 non-null  float64
 8   cloud_coverage      593261 non-null   float64
 9   dew_temperature     1048272 non-null  float64
 10  precip_depth_1_hr   1048474 non-null  float64
 11  sea_level_pressure  1038535 non-null  float64
 12  wind_direction      1018126 non-null  float64
 13  wind_speed          1048575 non-null  float64
 14  meter               1048575 non-null  int64  
 15  meter_reading       1048575 non-null  float64
dtypes: float64(9), int64(5), object(2)
memory usage: 128.0+ MB
```

In [133…
```python
#df['Date'] = pd.to_datetime(df['timestamp']).dt.date # create seperate date and time table
#df['time'] = pd.to_datetime(df['timestamp']).dt.time
```

In [134…
```python
df.isna().sum()/len(df) #checking for the percentage of null values
```

Out[134…
```
site_id               0.000000
building_id           0.000000
primary_use           0.000000
square_feet           0.000000
year_built            0.000000
floor_count           1.000000
timestamp             0.000000
air_temperature       0.000289
cloud_coverage        0.434222
dew_temperature       0.000289
precip_depth_1_hr     0.000096
sea_level_pressure    0.009575
wind_direction        0.029038
wind_speed            0.000000
meter                 0.000000
meter_reading         0.000000
dtype: float64
```

In [135…
```python
df= df.drop(columns = "floor_count", axis = 1) # dropping because all values are null
```

In [136…
```python
df.describe()
```

Out[136…

	site_id	building_id	square_feet	year_built	air_temperature	cloud_coverage	dew_temperature	precip_depth_1_hr	sea_level_p
count	1048575.0	1.048575e+06	1.048575e+06	1.048575e+06	1.048272e+06	593261.000000	1.048272e+06	1.048474e+06	1.0385
mean	0.0	5.148789e+01	8.796601e+04	1.995995e+03	2.306250e+01	3.048882	1.704932e+01	1.390079e+00	1.0179
std	0.0	3.022867e+01	1.028270e+05	1.427211e+01	5.917130e+00	2.103824	6.371691e+00	1.308847e+01	3.9900
min	0.0	0.000000e+00	2.830000e+02	1.968000e+03	1.700000e+00	0.000000	-9.400000e+00	-1.000000e+00	9.9200
25%	0.0	2.500000e+01	2.445600e+04	1.985000e+03	1.940000e+01	2.000000	1.330000e+01	0.000000e+00	1.0155
50%	0.0	5.100000e+01	5.464400e+04	2.001000e+03	2.390000e+01	2.000000	1.830000e+01	0.000000e+00	1.0180
75%	0.0	7.800000e+01	1.055450e+05	2.007000e+03	2.720000e+01	4.000000	2.220000e+01	0.000000e+00	1.0205
max	0.0	1.020000e+02	4.874330e+05	2.016000e+03	3.610000e+01	9.000000	2.560000e+01	3.430000e+02	1.0302

Exploratory Analysis

In [137…
```python
print("Number of Years:", df.year_built.nunique())
print("Number of unique Site:", df.site_id.nunique())
print("Number of unique Buildings:", df.building_id.nunique())
print("Number of unique Meters:", df.meter.nunique())
print("Unique uses of Buildings:", df.primary_use.nunique())
```

```
Number of Years: 36
Number of unique Site: 1
Number of unique Buildings: 103
Number of unique Meters: 2
Unique uses of Buildings: 7
```

In [138…
```python
df= df.drop(columns = "site_id", axis = 1) # dropping because there is only one uniquessite id, hence, it isn't
```

In [139…
```python
df.head()
```

Out[139…

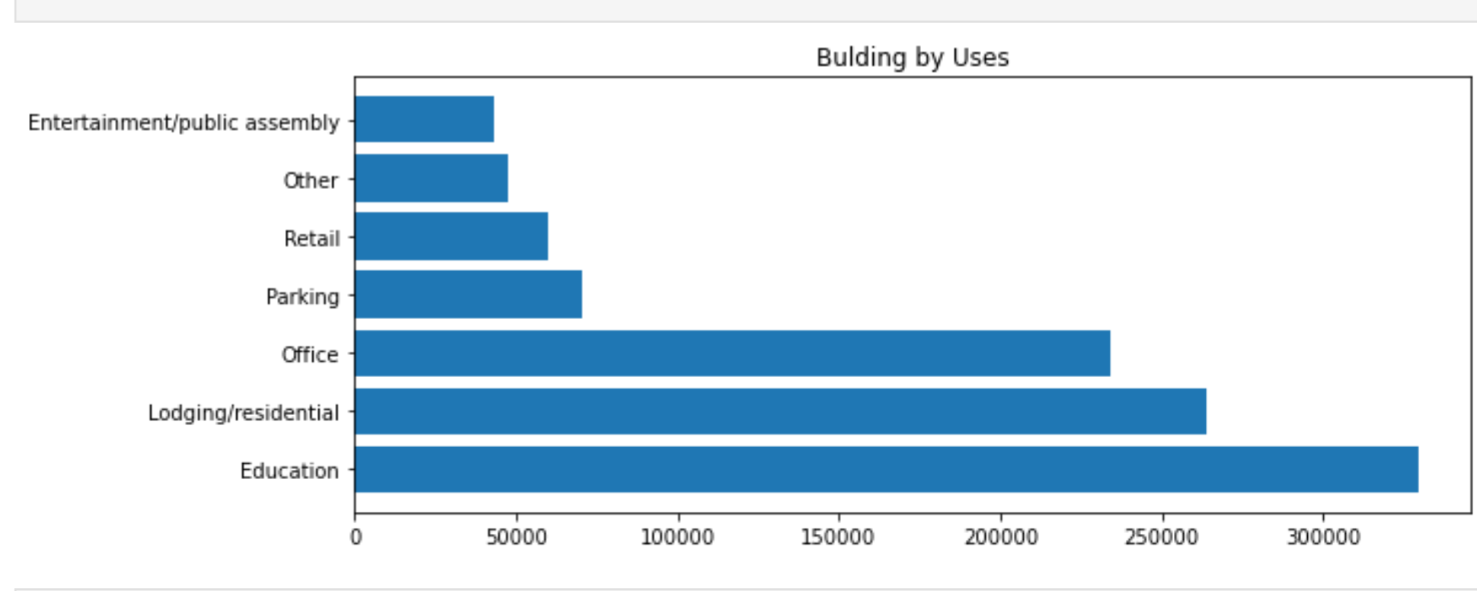
	building_id	primary_use	square_feet	year_built	timestamp	air_temperature	cloud_coverage	dew_temperature	precip_depth_1_hr	sea_leve
0	0	Education	7432	2008	01/01/2016 00:00	25.0	6.0	20.0	NaN	
1	0	Education	7432	2008	01/01/2016 01:00	24.4	NaN	21.1	-1.0	
2	0	Education	7432	2008	01/01/2016 02:00	22.8	2.0	21.1	0.0	
3	0	Education	7432	2008	01/01/2016 03:00	21.1	2.0	20.6	0.0	
4	0	Education	7432	2008	01/01/2016 04:00	20.0	2.0	20.0	-1.0	

In [140…
```python
buildinguse = df[["primary_use", "building_id"]].groupby("primary_use", as_index = False).count()
buildinguse.rename(columns = {'building_id': 'no_of_buildings'}, inplace = True)
buildinguse = buildinguse.sort_values(by = ["no_of_buildings"], ascending = False, inplace=False)
buildinguse
```

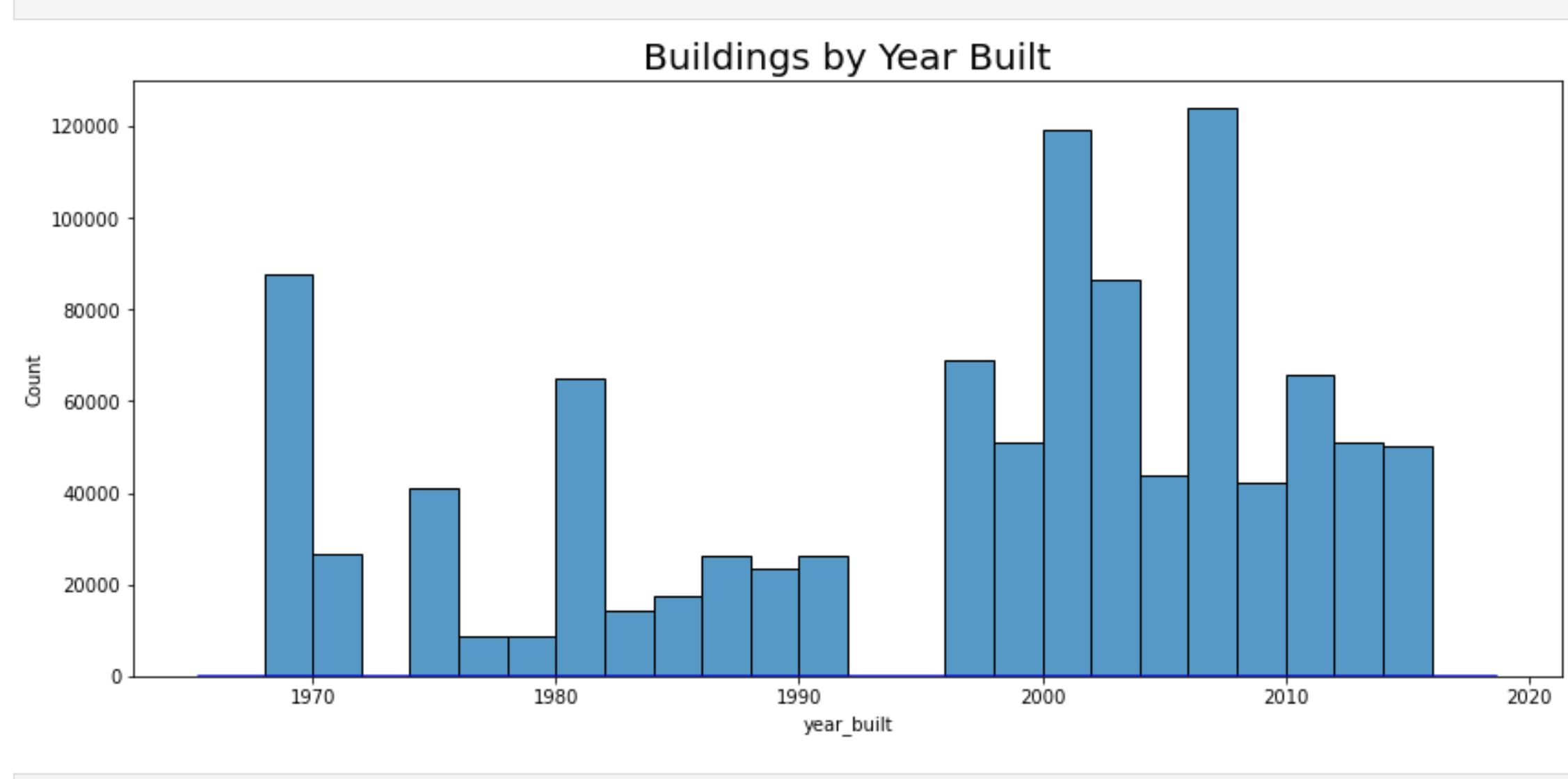
Out[140…

	primary_use	no_of_buildings
0	Education	329346
2	Lodging/residential	263621
3	Office	234160
5	Parking	70272
6	Retail	59958
4	Other	47654
1	Entertainment/public assembly	43564

In [141…
```python
plt.figure(figsize = (10, 4))
plt.barh(buildinguse.primary_use, buildinguse.no_of_buildings,  align='center', data=buildinguse)
#plt.tick_params(axis='x', rotation=90)
plt.title("Bulding by Uses")
plt.show()
```



In [142…
```python
plt.figure (figsize = (14,6))
penguins = sns.load_dataset("penguins")
sns.histplot(data=df, x="year_built", binwidth=2, bins = 50)
sns.distplot(df['year_built'], color = 'blue')
plt.title('Buildings by Year Built', size = 20)
plt.show()
```



In [145…
```python
annualenergy = df.groupby("year_built", as_index  = False)["meter_reading"].sum()
annualenergy = annualenergy.sort_values(["meter_reading"], ascending = False)
annualenergy.rename(columns = {'meter_reading': 'Energy_Used'}, inplace = True)
annualenergy.head(10)
```

Out[145…

	year_built	Energy_Used
27	2006	8.804346e+07
30	2009	7.319258e+07
28	2007	5.807715e+07
22	2001	4.774478e+07
33	2013	2.856542e+07
20	1999	2.804741e+07
17	1996	2.614427e+07
14	1989	2.610596e+07
31	2010	2.212682e+07
24	2003	2.201843e+07

In [146…
```python
#plt.bar("year_built", "Energy_Used", width=0.8,  data=df)
#plt.show()
```

Energy rate by building

Energy by year

Energy by types of building

In [147…
```python
Energybybuilding = pd.DataFrame(df2.groupby(['primary_use'])['meter_reading'].agg(['sum','count']).reset_index(
Energybybuilding.rename(columns = {'sum': 'Energy_Used','count': 'No_of_Buildings'}, inplace = True)
Energybybuilding = Energybybuilding.sort_values('Energy_Used', ascending = False).head()
Energybybuilding["avg_per_building"] = Energybybuilding.Energy_Used/Energybybuilding.No_of_Buildings
Energybybuilding
```

Out[147…

	primary_use	Energy_Used	No_of_Buildings	avg_per_building
0	Education	3.385265e+08	329346	1027.875001
2	Lodging/residential	1.242663e+08	263621	471.382389
3	Office	6.785761e+07	234160	289.791626
4	Other	2.169883e+07	47654	455.341276
1	Entertainment/public assembly	1.600554e+07	43564	367.402987

In [148…
```python
df.groupby(['primary_use', 'building_id'])['square_feet'].sum() # trying to get the sqft of each unique buildi
```

Out[148…
```
primary_use  building_id
Education    0                65282688
             1                23892480
             2                47222784
             3               208049040
             4              1024275888
                               ...    
Retail       44                2485872
             45              134415032
             46               79451280
             47              278122478
             89             1420855920
Name: square_feet, Length: 103, dtype: int64
```

In [149…
```python
Energybysqft = pd.DataFrame(df2.groupby(['primary_use'])['meter_reading','square_feet']
                            .agg({'meter_reading':'sum', 'square_feet':"sum" }).reset_index())
Energybysqft.rename(columns = {'meter_reading': 'Energy_Used','square_feet': 'square_feet'}, inplace = True)
#Energybysqft = Energybysqft.sort_values('Energy_Used', ascending = False).head()
Energybysqft["avg_energy_per_sqft"] = Energybysqft.Energy_Used/Energybysqft.square_feet
Energybysqft
```

Out[149…

	primary_use	Energy_Used	square_feet	avg_energy_per_sqft
0	Education	3.385265e+08	23948380908	0.014136
1	Entertainment/public assembly	1.600554e+07	4926954448	0.003249
2	Lodging/residential	1.242663e+08	21152910635	0.005875
3	Office	6.785761e+07	9060821238	0.007489
4	Other	2.169883e+07	2170364121	0.009998
5	Parking	4.564820e+06	28116696816	0.000162
6	Retail	1.251398e+07	2862829422	0.004371

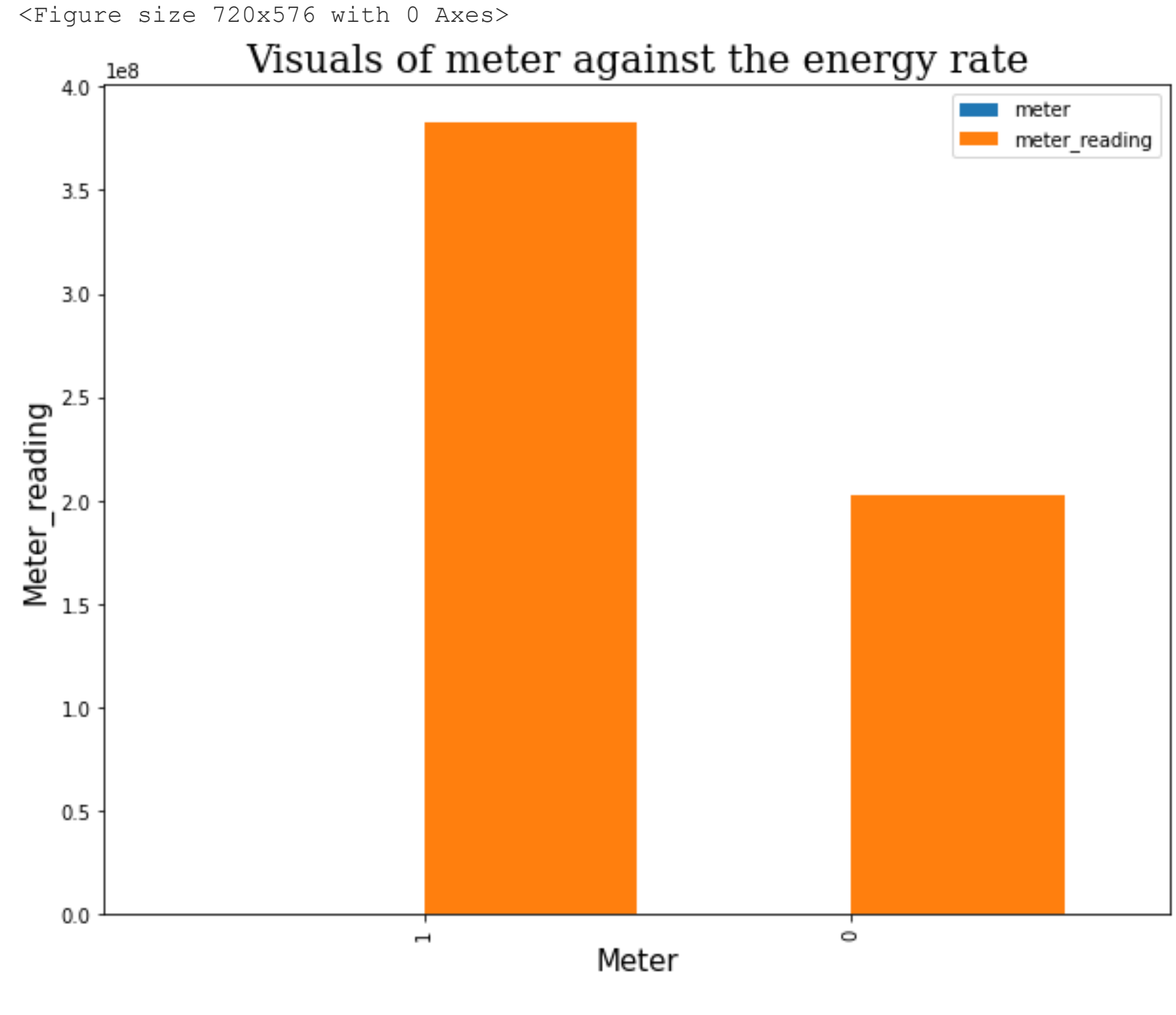
In [113…
```python
meter = df.groupby("meter", as_index  = False)["meter_reading"].sum() #Checking for the meter type and how they
meter = meter.sort_values(by = ["meter_reading"], ascending = False)
meter
```

Out[113…

	meter	meter_reading
1	1	3.825509e+08
0	0	2.028827e+08

In [114…
```python
plt.figure(figsize = (10,8))
meter.plot.bar(figsize = (10,8), width = 1)
plt.xlabel('Meter', size = 15)
plt.title("Visuals of meter against the energy rate",size = 20, family = 'serif')
plt.ylabel("Meter_reading", size = 15)
#plt.xticks(rotation = 90)
plt.show()
```

```
<Figure size 720x576 with 0 Axes>
```

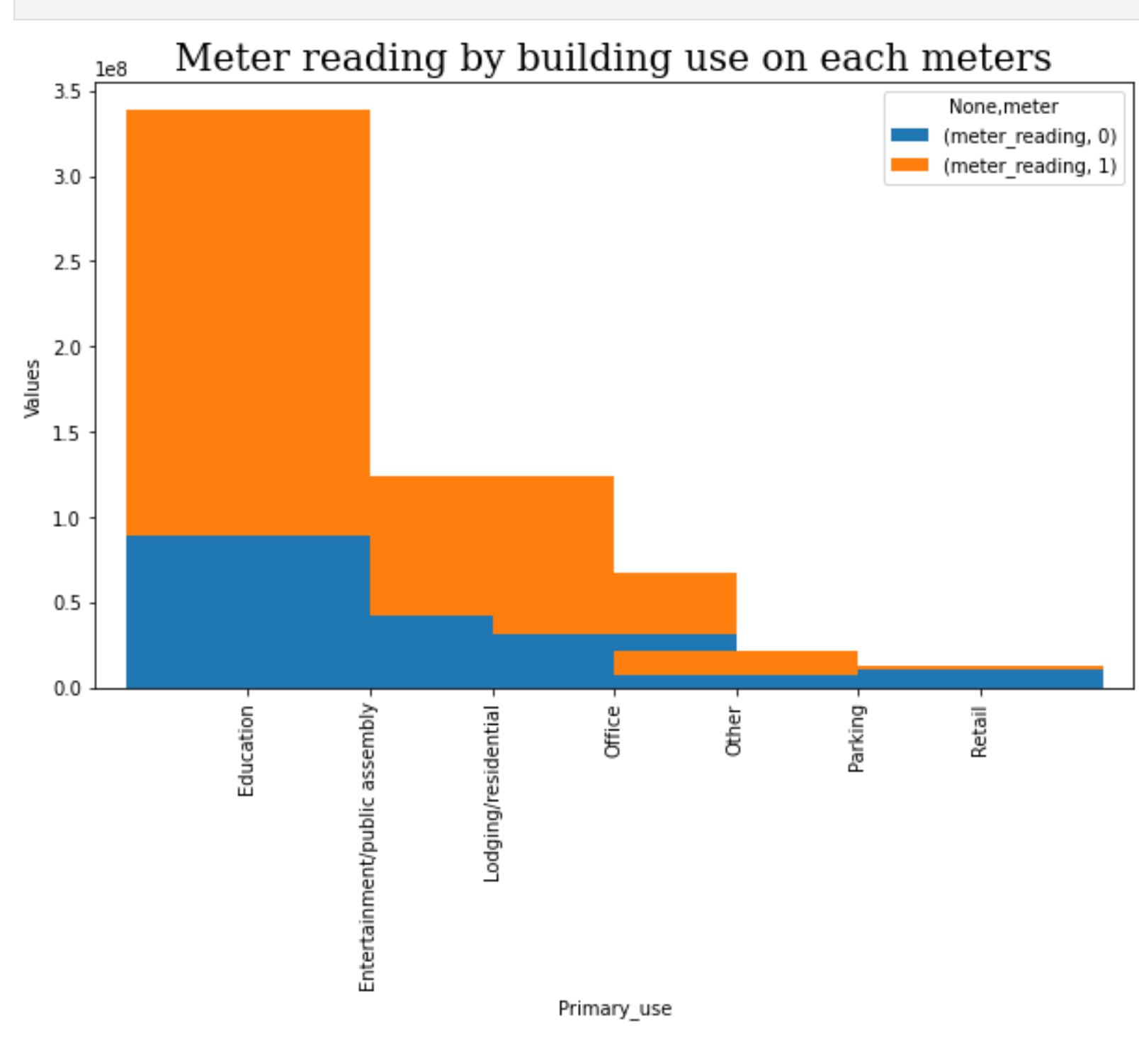


In [115…
```python
meterbrkdwn = pd.pivot_table(df, index = ["primary_use"], columns = ['meter'], values  = ['meter_reading'], agg
meterbrkdwn #Energy Consumption by primary use of building base on meter type
```

Out[115…

	meter_reading	
meter	**0**	**1**
primary_use		
Education	8.960344e+07	2.489231e+08
Entertainment/public assembly	1.600554e+07	NaN
Lodging/residential	4.245677e+07	8.180952e+07
Office	3.146556e+07	3.639205e+07
Other	7.730486e+06	1.396835e+07
Parking	4.564820e+06	NaN
Retail	1.105612e+07	1.457858e+06

In [116…
```python
meterbrkdwn.plot.bar(figsize = (10,6), width = 2, stacked = True)
plt.title("Meter reading by building use on each meters", family = 'serif', size = 20)
plt.xlabel("Primary_use", size = 10)
plt.ylabel("Values", size = 10)
plt.show()
```



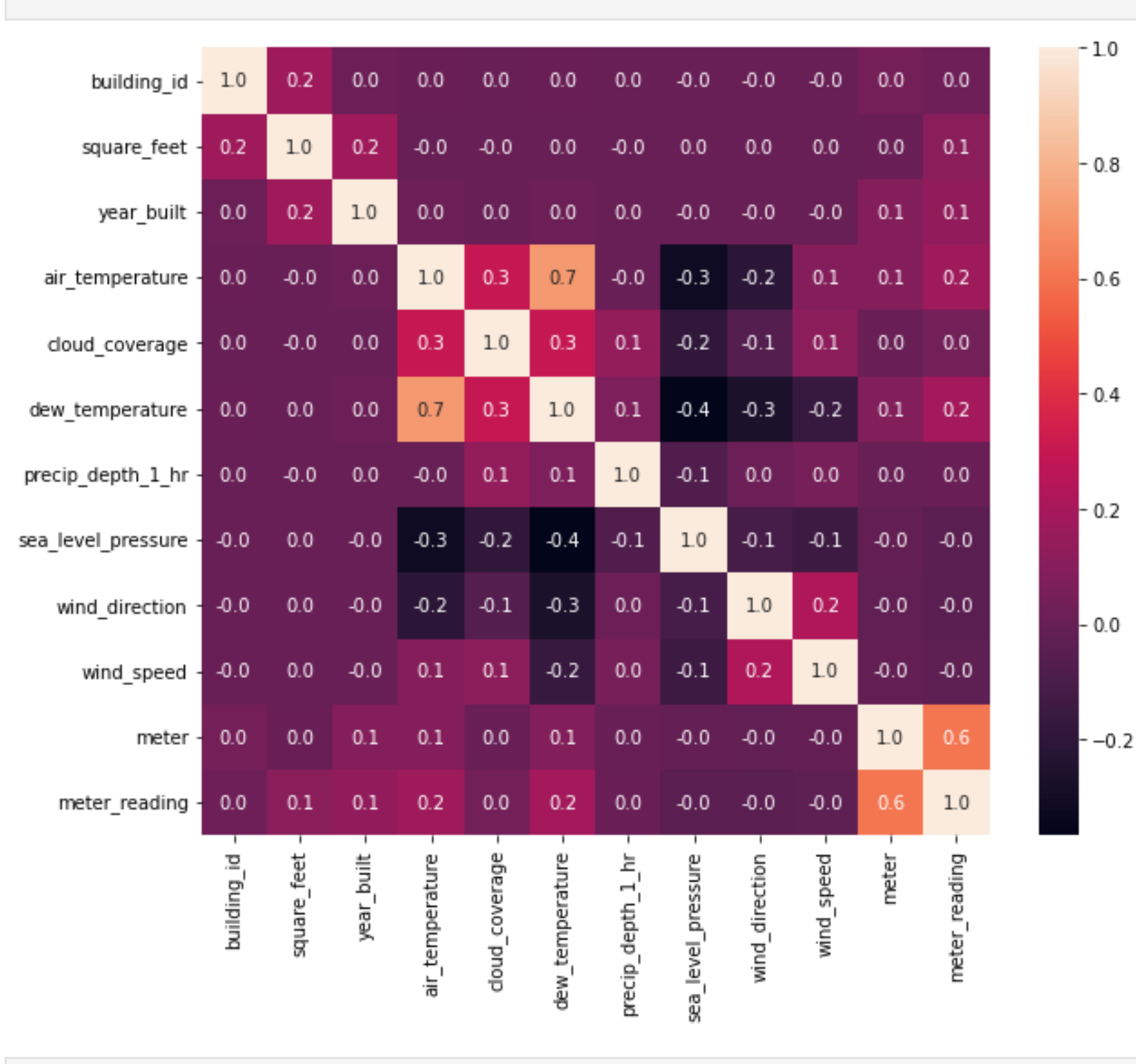
Checking for correlation in the variables in the data

In [150…
```python
correlatn = df[['building_id', 'square_feet', 'year_built',  'air_temperature', 'cloud_coverage',
                'dew_temperature', 'precip_depth_1_hr','sea_level_pressure','wind_direction','wind_speed',
                'meter', 'meter_reading']].corr()
correlatn
```

Out[150…

	building_id	square_feet	year_built	air_temperature	cloud_coverage	dew_temperature	precip_depth_1_hr	sea_level_pressure
building_id	1.000000	0.169070	0.010482	0.002845	0.000445	0.001965	0.000184	-0.000398
square_feet	0.169070	1.000000	0.172601	-0.000166	-0.000560	0.000331	-0.000035	0.000404
year_built	0.010482	0.172601	1.000000	0.010999	0.000265	0.012111	0.000110	-0.002110
air_temperature	0.002845	-0.000166	0.010999	1.000000	0.295912	0.717020	-0.000688	-0.315214
cloud_coverage	0.000445	-0.000560	0.000265	0.295912	1.000000	0.296416	0.138508	-0.187190
dew_temperature	0.001965	0.000331	0.012111	0.717020	0.296416	1.000000	0.066802	-0.366631
precip_depth_1_hr	0.000184	-0.000035	0.000110	-0.000688	0.138508	0.066802	1.000000	-0.080515
sea_level_pressure	-0.000398	0.000404	-0.002110	-0.315214	-0.187190	-0.366631	-0.080515	1.000000
wind_direction	-0.000378	0.000020	-0.003272	-0.211292	-0.062456	-0.265391	0.011444	-0.112328
wind_speed	-0.001063	0.000412	-0.002177	0.091966	0.115347	-0.168157	0.045101	-0.145828
meter	0.043674	0.006368	0.088126	0.088819	0.004831	0.084714	0.001323	-0.016235
meter_reading	0.022832	0.106520	0.130023	0.171254	0.037039	0.183738	0.002696	-0.045407

In [151…
```python
plt.figure (figsize = (10,8)) #Visuals of how variables correlate
sns.heatmap(correlatn, cbar = True , square = True, fmt = '.1f', annot = True, annot_kws = { 'size' : 10}) ##,
plt.show()
```



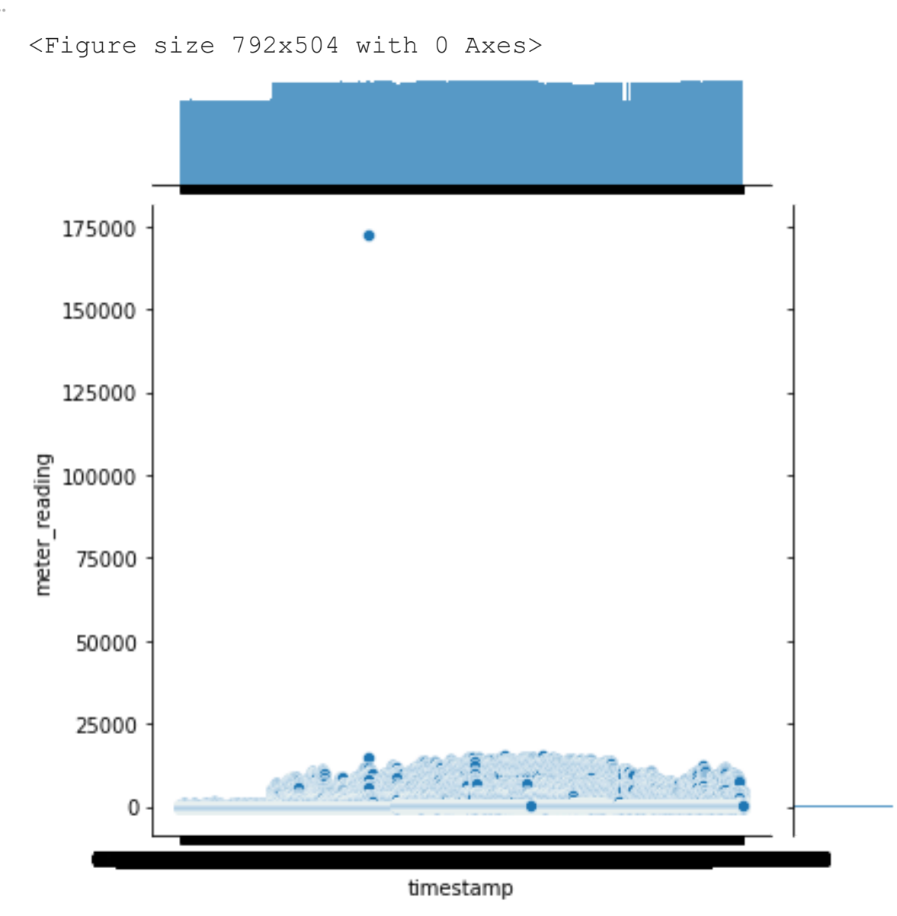
In [152…
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1048575 entries, 0 to 1048574
Data columns (total 14 columns):
 #   Column              Non-Null Count    Dtype  
---  ------              --------------    -----  
 0   building_id         1048575 non-null  int64  
 1   primary_use         1048575 non-null  object 
 2   square_feet         1048575 non-null  int64  
 3   year_built          1048575 non-null  int64  
 4   timestamp           1048575 non-null  object 
 5   air_temperature     1048272 non-null  float64
 6   cloud_coverage      593261 non-null   float64
 7   dew_temperature     1048272 non-null  float64
 8   precip_depth_1_hr   1048474 non-null  float64
 9   sea_level_pressure  1038535 non-null  float64
 10  wind_direction      1018126 non-null  float64
 11  wind_speed          1048575 non-null  float64
 12  meter               1048575 non-null  int64  
 13  meter_reading       1048575 non-null  float64
dtypes: float64(8), int64(4), object(2)
memory usage: 112.0+ MB
```

In [154…
```python
plt.figure(figsize=(11,7))
sns.jointplot(x='timestamp',y='meter_reading',data=df)
```

Out[154…
```
<seaborn.axisgrid.JointGrid at 0x2552c402910>

<Figure size 792x504 with 0 Axes>
```



Data Preprocessing

In [156…
```python
df.isna().sum()
```

Out[156…
```
building_id                0
primary_use                0
square_feet                0
year_built                 0
timestamp                  0
air_temperature          303
cloud_coverage        455314
dew_temperature          303
precip_depth_1_hr        101
sea_level_pressure     10040
wind_direction         30449
wind_speed                 0
meter                      0
meter_reading              0
dtype: int64
```

In [242…
```python
df[['wind_direction', 'sea_level_pressure', 'precip_depth_1_hr', 'dew_temperature', 'cloud_coverage', 'air_temp
```

In [243…
```python
df.isnull().sum()
```

Out[243…
```
building_id           0
primary_use           0
square_feet           0
year_built            0
timestamp             0
air_temperature       0
cloud_coverage        0
dew_temperature       0
precip_depth_1_hr     0
sea_level_pressure    0
wind_direction        0
wind_speed            0
meter                 0
meter_reading         0
dtype: int64
```

In [244…
```python
df = df.dropna()
```

In [245…
```python
df['year_built'] = df['year_built'].astype(int) #converting to int so it can be readable for ML
df['timestamp'] = pd.to_datetime(df['timestamp']).astype(np.int64)
```

In [246…
```python
df.replace({'primary_use' : {'Education' : 1, 'Lodging/residential' : 2,
                             'Office' : 3, 'Entertainment/public assembly' : 4, 'Retail' : 5,
                             'Parking' : 6, 'Other' : 7,}}, inplace = True) #Encoding primary use variable
```

In [247…
```python
df.primary_use.unique()
```

Out[247…
```
array([1, 2, 3, 4, 7, 5, 6], dtype=int64)
```

Building The Model

In [248…
```python
X = df.drop(columns = ['meter_reading'], axis = 1) #all columns except meter reading
y = df['meter_reading'] # meter reding column - the dependent variable
```

In [249…
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.30, random_state = 101)
```

In [250…
```python
print(X_train.shape)
print(y_train.shape)
```

```
(734001, 13)
(734001,)
```

In [251…
```python
model = RandomForestRegressor(n_estimators = 3) #calling a random regressor model
```

In [252…
```python
model = model.fit(X_train, y_train) #Fitting the variables into the model
```

Evaluating Model Accuracy

In [253…
```python
predictions = model.predict(X_test) #Evaluating the model accuracy
```

In [254…
```python
error_score = metrics.r2_score(predictions,  y_test)
```

In [256…
```python
error_score
```

Out[256…
```
0.8568052963014118
```

Predicting the Model

In [257…
```python
train_predict = model.predict(X_train)
```

In [258…
```python
error_score_train = metrics.r2_score(train_predict,  y_train)
```

In [259…
```python
error_score
```

Out[259…
```
0.8568052963014118
```

Conclusion

Considering the rapid changes in technology in the energy sector over the years that has disrupted the traditional ways of using energy with the override principle of renewable energy and sustainability, a model with 85% accuracy is score is usable to preidict furture energy consumtption