Predicting electricity consumption

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Estimate electricity consumption in the residential sector in the US

0.1 Summary of Study

This study develops two models to predict the electricity consumption per year (KWh/yr) of a residential hosehold. The models employ the RECS dataset, which consists of 5686 instances and 756 features. The first model employs one featrue (building area (sqft)) as an independant variable. The second model employs several categorical and numerical features to predict the yearly electricity consumption, including avg household income, location, climate, house size (sqft), and number of bedrooms.

[169]:
```
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn import linear_model
from sklearn import metrics
```

1 Load data

Dataset is from micro sample of the Residental Electricity Consumption Survey v. 2015.

[136]:
```
electricity = pd.read_csv('recs2015_public_v4.csv')
```

[137]:
```
print('dataset size: ', electricity.shape)
```

```
dataset size:  (5686, 759)
```

2 Extract and Exploring the data

The electricity consumption is correlated with the size of a house (square-feet of living space).

[170]:
```
plt.scatter(electricity.TOTSQFT_EN,electricity.KWH )
plt.title("RECS- 2015")
plt.xlabel('Sqf')
plt.ylabel('electricity consumption (KWh/yr)')
plt.show()
```


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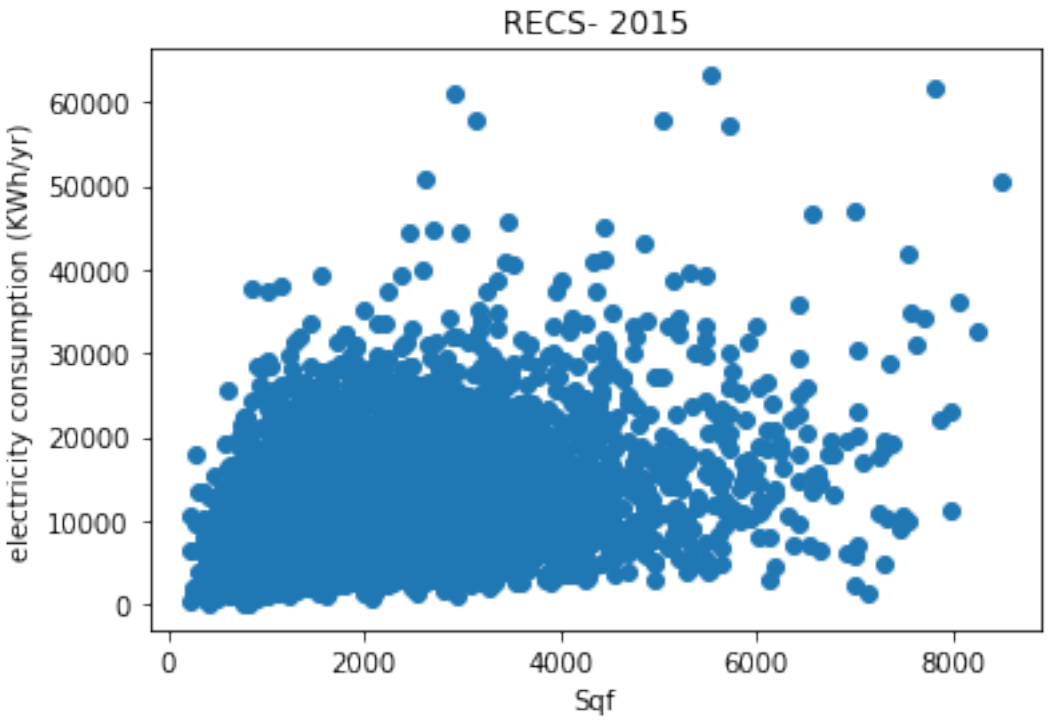


3 Create a simple regression model of sqft to electricity consumption

[146]:
```
df = pd.DataFrame(electricity)
```

3.0.1 check for missing data

[148]:
```
if df.isnull().values.any():
    print ("Some missing data are found!")
else: print ("No missing data is found.")
```

```
Some missing data are found!
```

3.0.2 replace missing data with average values of the data in the same column

[149]:
```
df = df.fillna(df.mean())
```

[150]:
```
if df.isnull().values.any():
    print ("Some missing data are found!")
else: print ("No missing data is found.")
```

```
No missing data is found.
```

[151]:
```
X=df['TOTSQFT_EN']
Y=df['KWH']
```

[152]:
```
print ('independant variable: SQF')
X.describe()
```

```
independant variable: SQF
```

[152]:
```
count    5686.000000
mean     2081.443546
std      1282.660286
min       221.000000
25%      1100.500000
50%      1773.500000
75%      2766.000000
max      8501.000000
Name: TOTSQFT_EN, dtype: float64
```

[153]:
```
print ('dependant variable: KWH')
Y.describe()
```

```
dependant variable: KWH
```

[153]:
```
count     5686.000000
mean     11028.934872
std       7049.727589
min         59.078000
25%       5926.525750
50%       9549.351000
75%      14557.606750
max      63216.806000
Name: KWH, dtype: float64
```

3.1 Split data into train (70%) and test set (30%) with seed =42

[154]:
```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.30,␣
↪random_state=42)
```

[155]:
```
print ('dataset size: ', X.size,'\ntrianing dataset', X_train.size,'\ntest␣
↪dataset size:',X_test.size)
```

```
dataset size:  5686
trianing dataset 3980
test dataset size: 1706
```

3.2 Build the regression model using only sqft as a feature

Packege: Skit-Learn

[156]:
```
regressor = linear_model.LinearRegression()
```

[157]:
```
model1 = regressor.fit(X_train.values.reshape(-1, 1),y_train.values.reshape(-1,␣
↪1))
```

[158]:
```
print ('intercept:',int(model1.intercept_),'\ncoefficinet: ', int(model1.coef_))
```

```
intercept: 6793
coefficinet:  2
```

The smallest house in this dataset (221 sqf.) consume 6793 KWh/yr electricty, and each additional sqf results in increase consumption of 2 KWh/yr.

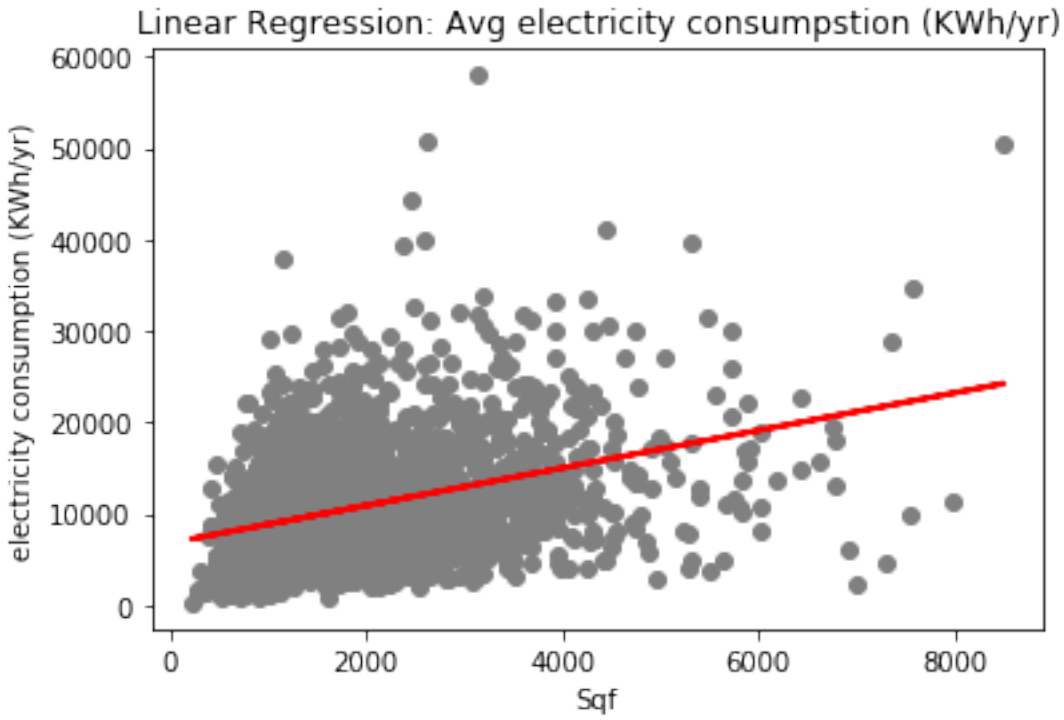
3.3 Evaluate the quality of fit: RMSE

[167]:
```
y_pred = regressor.predict(X_test.values.reshape(-1,1))
```

[168]:
```
print('Root Mean Squared Error:', int(np.sqrt(metrics.mean_squared_error(y_test.
↪values.reshape(-1,1), y_pred))))
```

```
Root Mean Squared Error: 6413
```

[161]:
```
plt.scatter(X_test, y_test,  color='gray')
plt.plot(X_test, y_pred, color='red', linewidth=2)
plt.title('Linear Regression: Avg electricity consumpstion (KWh/yr)')
plt.xlabel('Sqf')
plt.ylabel('electricity consumption (KWh/yr)')
plt.show()
```



Considering the range of average electricity consumption is aobut 63000 (KWh/yr), the RMSE is about 10%. While it is not low, by looking at the scatter plot we can observe the dataset is not concentrate along a linear line.

4 Add more features

The next step is adding more feautre and examining if it increases the accuracy of the prediction (lower the RMSE). This step adds the following features: 1. Average Households' Income (catgorical) 2. Location type (categorical) 3. No. of Bedrooms 4. Climate (CDD) 5. Climate (HDD)

[162]:
```
print('Average Households Income data type:', df['MONEYPY'].dtypes)
print('Location-type data type:', df['UATYP10'].dtypes)
print('No. of Bedrooms data type:', df['BEDROOMS'].dtypes)
print('CDD data type:', df['CDD65'].dtypes)
print('HDD data type:', df['HDD65'].dtypes)
```

```
Average Households Income data type: int64
Location-type data type: object
No. of Bedrooms data type: int64
CDD data type: int64
HDD data type: int64
```

[220]:
```
df2 = df[['TOTSQFT_EN','MONEYPY','UATYP10','BEDROOMS','CDD65','HDD65']]
```

[221]:
```
df2.describe()
```

[221]:

	TOTSQFT_EN	MONEYPY	BEDROOMS	CDD65	HDD65
count	5686.000000	5686.000000	5686.000000	5686.00000	5686.000000
mean	2081.443546	3.669891	2.832923	1719.20612	3707.848751
std	1282.660286	2.228755	1.106412	1193.56296	2149.272713
min	221.000000	1.000000	0.000000	0.00000	0.000000
25%	1100.500000	2.000000	2.000000	793.00000	1881.000000
50%	1773.500000	3.000000	3.000000	1378.00000	3877.500000
75%	2766.000000	5.000000	3.000000	2231.00000	5467.000000
max	8501.000000	8.000000	10.000000	6607.00000	9843.000000

4.0.1 Dummy Coding for categorical feature: Location-type

Convert location-type categories (Urban Area: U, Urban Cluster: C, Rural: R) to urban:0, urban cluster:1, and rural 2

[279]:
```
df2_1 = pd.concat([df2, pd.get_dummies(df2['UATYP10']),pd.
↪get_dummies(df2['MONEYPY'])], axis=1)
```

[280]:
```
df2_1.shape
```

[280]:
```
(5686, 17)
```

Check the dummy-coding

[281]:
```
df2_1.head(10)
```

[281]:

	TOTSQFT_EN	MONEYPY	UATYP10	BEDROOMS	CDD65	HDD65	C	R	U	1	2	3	4	5	6	7	8
0	1808	8	U	3	1768	2031	0	0	1	0	0	0	0	0	0	0	1
1	759	2	R	2	2795	1915	0	1	0	0	1	0	0	0	0	0	0
2	2288	2	U	4	2235	2263	0	0	1	0	1	0	0	0	0	0	0
3	2573	3	C	3	1374	3754	1	0	0	0	0	1	0	0	0	0	0
4	1024	3	U	3	993	5401	0	0	1	0	0	1	0	0	0	0	0
5	623	1	C	0	408	7597	1	0	0	1	0	0	0	0	0	0	0
6	832	4	U	2	2582	1579	0	0	1	0	0	0	1	0	0	0	0
7	2682	3	R	3	673	6560	0	1	0	0	0	1	0	0	0	0	0
8	1900	5	U	4	1083	5301	0	0	1	0	0	0	0	1	0	0	0
9	1230	6	U	3	3390	1400	0	0	1	0	0	0	0	0	1	0	0

Remove the categorical feature that was dummy-coded

[282]:
```
df2_1 = df2_1.drop(['UATYP10','MONEYPY'], axis=1)
```

[283]:
```
df2_1.shape
```

[283]:
```
(5686, 15)
```

[284]:
```
df2_1.head(10)
```

[284]:

	TOTSQFT_EN	BEDROOMS	CDD65	HDD65	C	R	U	1	2	3	4	5	6	7	8
0	1808	3	1768	2031	0	0	1	0	0	0	0	0	0	0	1
1	759	2	2795	1915	0	1	0	0	1	0	0	0	0	0	0
2	2288	4	2235	2263	0	0	1	0	1	0	0	0	0	0	0
3	2573	3	1374	3754	1	0	0	0	0	1	0	0	0	0	0
4	1024	3	993	5401	0	0	1	0	0	1	0	0	0	0	0
5	623	0	408	7597	1	0	0	1	0	0	0	0	0	0	0
6	832	2	2582	1579	0	0	1	0	0	0	1	0	0	0	0
7	2682	3	673	6560	0	1	0	0	0	1	0	0	0	0	0
8	1900	4	1083	5301	0	0	1	0	0	0	0	1	0	0	0
9	1230	3	3390	1400	0	0	1	0	0	0	0	0	1	0	0

Drop one column of each categorical features

[285]:
```
X2 = df2_1.drop(['C',1], axis=1)
```

[274]:
```
X2.head(10)
```

[274]:

	TOTSQFT_EN	BEDROOMS	CDD65	HDD65	R	U	2	3	4	5	6	7	8
0	1808	3	1768	2031	0	1	0	0	0	0	0	0	1
1	759	2	2795	1915	1	0	1	0	0	0	0	0	0
2	2288	4	2235	2263	0	1	1	0	0	0	0	0	0
3	2573	3	1374	3754	0	0	0	1	0	0	0	0	0
4	1024	3	993	5401	0	1	0	1	0	0	0	0	0
5	623	0	408	7597	0	0	0	0	0	0	0	0	0
6	832	2	2582	1579	0	1	0	0	1	0	0	0	0
7	2682	3	673	6560	1	0	0	1	0	0	0	0	0
8	1900	4	1083	5301	0	1	0	0	0	1	0	0	0
9	1230	3	3390	1400	0	1	0	0	0	0	1	0	0

[286]:
```
X2.shape
```

[286]:
```
(5686, 13)
```

4.1 Split new dataframe into Test (70%) and Train (30%) and develop a new regression model

[287]:
```
X2_train, X2_test, y2_train, y2_test = train_test_split(X2, Y, test_size=0.30,␣
↪random_state=42)
```

[288]:
```
print ('dataset size: ', X2.shape,'\ntrianing dataset', X2_train.shape,'\ntest␣
↪dataset size:',X2_test.shape)
```

```
dataset size:  (5686, 13)
trianing dataset (3980, 13)
test dataset size: (1706, 13)
```

4.1.1 Develop a new regression model

[296]:
```
regressor_normalize = linear_model.LinearRegression(normalize=True)
```

[297]:
```
model2 = regressor_normalize.fit(X2_train,y2_train)
```

4.2 Evaluate the quality of the second model: RMSE

[300]:
```
y2_pred = regressor.predict(X2_test)
```

[301]:
```
print('Root Mean Squared Error for the second model:', int(np.sqrt(metrics.
↪mean_squared_error(y2_test, y2_pred))))
```

```
Root Mean Squared Error for the second model: 5660
```

The RMSE drops from 6413 to 5660

[302]:
```
coefficients=pd.DataFrame({'name':list(X2),'value':model2.coef_})
intercept = model2.intercept_
```

[307]:
```
coefficients
```

[307]:

	name	value
0	TOTSQFT_EN	1.208580
1	BEDROOMS	1496.008120
2	CDD65	1.650074
3	HDD65	-0.029184
4	R	2523.639515
5	U	-1711.396588
6	2	213.997398
7	3	450.338610
8	4	485.528723
9	5	924.361981
10	6	617.218248
11	7	1555.668549
12	8	1522.404199

[306]:
```
print ('Intercept:', int(intercept))
```

```
Intercept: 1714
```

The second model shows size and number of bedrooms both have positive impact on increasing the electricity cinsumption. The electricity consumption of houses in rural areas is higher than urban areas. Finally, the households with a higher income tend to consume higher electricty, with an exception of income bracket representing avg. yearly income between \$ 100,000 and \$120,000 .