

# SML ASS 4

Kaustubh Raykar </FONT>  
PRN : 21070126048  
AIML A3

## RIDGE AND LASSO

### Importing Librarires

In [ ]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

### Dataset

- X1 Relative Compactness
- X2 Surface Area
- X3 Wall Area
- X4 Roof Area
- X5 Overall Height
- X6 Orientation
- X7 Glazing Area
- X8 Glazing Area Distribution
- y1 Heating Load
- y2 Cooling Load

In [ ]:

```
df = pd.read_excel('/content/ENB2012_data.xlsx')
df
```

Out[ ]:

	X1	X2	X3	X4	X5	X6	X7	X8	Y1	Y2
0	0.98	514.5	294.0	110.25	7.0	2	0.0	0	15.55	21.33
1	0.98	514.5	294.0	110.25	7.0	3	0.0	0	15.55	21.33
2	0.98	514.5	294.0	110.25	7.0	4	0.0	0	15.55	21.33
3	0.98	514.5	294.0	110.25	7.0	5	0.0	0	15.55	21.33
4	0.90	563.5	318.5	122.50	7.0	2	0.0	0	20.84	28.28
...	...	...	...	...	...	...	...	...	...	...
763	0.64	784.0	343.0	220.50	3.5	5	0.4	5	17.88	21.40
764	0.62	808.5	367.5	220.50	3.5	2	0.4	5	16.54	16.88
765	0.62	808.5	367.5	220.50	3.5	3	0.4	5	16.44	17.11
766	0.62	808.5	367.5	220.50	3.5	4	0.4	5	16.48	16.61
767	0.62	808.5	367.5	220.50	3.5	5	0.4	5	16.64	16.03

768 rows × 10 columns

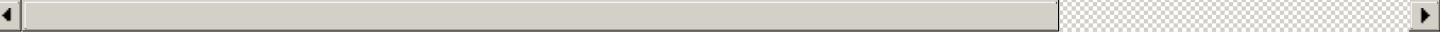
In [ ]:

```
#renaming some columns
df = df.rename(columns={'X1': 'Relative_Compactness', 'X2': 'Surface_Area', 'X3': 'Wall_Area', 'X4': 'Roof_Area', 'X5': 'Overall_Height', 'X6': 'Orientation', 'X7': 'Glazing_Area', 'X8': 'Glazing_Area_Distribution', 'Y1': 'Heating_Load', 'Y2': 'Cooling_Load'})
df
```

Out[ ]:

	Relative_Compactness	Surface_Area	Wall_Area	Roof_Area	Overall_Height	Orientation	Glazing_Area	Glazing_Area_Distr
0	0.98	514.5	294.0	110.25	7.0	2	0.0	
1	0.98	514.5	294.0	110.25	7.0	3	0.0	
2	0.98	514.5	294.0	110.25	7.0	4	0.0	
3	0.98	514.5	294.0	110.25	7.0	5	0.0	
4	0.90	563.5	318.5	122.50	7.0	2	0.0	
...	...	...	...	...	...	...	...	...
763	0.64	784.0	343.0	220.50	3.5	5	0.4	
764	0.62	808.5	367.5	220.50	3.5	2	0.4	
765	0.62	808.5	367.5	220.50	3.5	3	0.4	
766	0.62	808.5	367.5	220.50	3.5	4	0.4	
767	0.62	808.5	367.5	220.50	3.5	5	0.4	

768 rows x 10 columns



In [ ]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 10 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   Relative_Compactness                  768 non-null    float64
1   Surface_Area                         768 non-null    float64
2   Wall_Area                           768 non-null    float64
3   Roof_Area                           768 non-null    float64
4   Overall_Height                       768 non-null    float64
5   Orientation                          768 non-null    int64
6   Glazing_Area                        768 non-null    float64
7   Glazing_Area_Distribution             768 non-null    int64
8   Heating_Load                        768 non-null    float64
9   Cooling_Load                        768 non-null    float64
dtypes: float64(8), int64(2)
memory usage: 60.1 KB
```

In [ ]:

```
#basic statics of the dataset
df.describe()
```

Out[ ]:

	Relative_Compactness	Surface_Area	Wall_Area	Roof_Area	Overall_Height	Orientation	Glazing_Area	Glazing_Area_I
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	
mean	0.764167	671.708333	318.500000	176.604167	5.250000	3.500000	0.234375	
std	0.105777	88.086116	43.626481	45.165950	1.75114	1.118763	0.133221	
min	0.620000	514.500000	245.000000	110.250000	3.500000	2.000000	0.000000	
25%	0.682500	606.375000	294.000000	140.875000	3.500000	2.750000	0.100000	

50%	Relative_Compactness	Surface_Area	Wall_Area	Roof_Area	Overall_Height	Orientation	Glazing_Area	Glazing_Area_I
	0.750000	673.750000	318.500000	183.750000	5.250000	3.500000	0.250000	
75%	0.830000	741.125000	343.000000	220.500000	7.000000	4.250000	0.400000	
max	0.980000	808.500000	416.500000	220.500000	7.000000	5.000000	0.400000	

In [ ]:

```
#checking null values in the dataset
df.isnull().sum()
```

Out[ ]:

```
Relative_Compactness      0
Surface_Area              0
Wall_Area                 0
Roof_Area                 0
Overall_Height            0
Orientation                0
Glazing_Area              0
Glazing_Area_Distribution  0
Heating_Load              0
Cooling_Load              0
dtype: int64
```

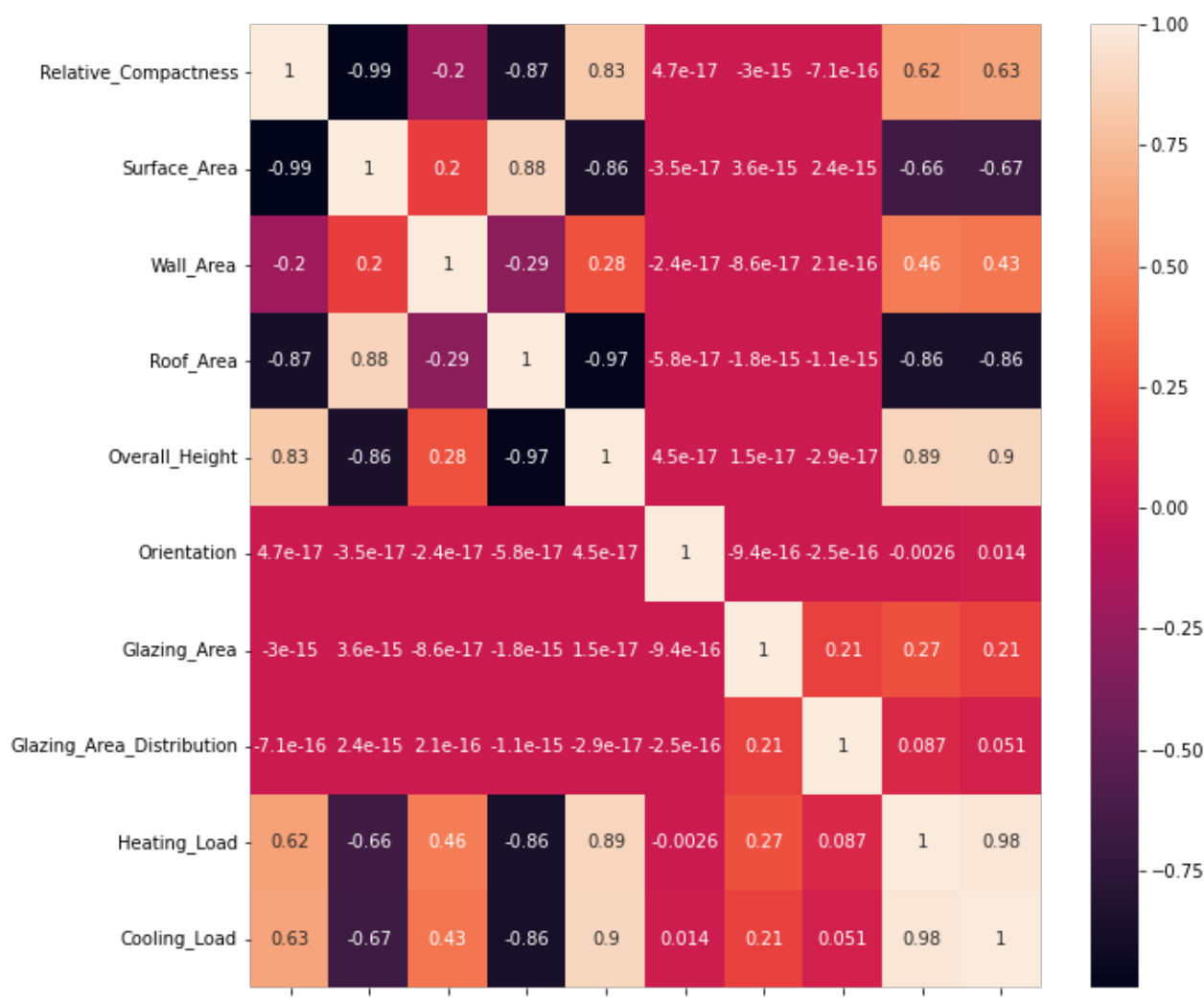
## EDA

In [ ]:

```
fig, ax = plt.subplots(figsize=(10,10))
sns.heatmap(df.corr(),annot = True)
```

Out[ ]:

<matplotlib.axes.\_subplots.AxesSubplot at 0x7fdacae20a90>



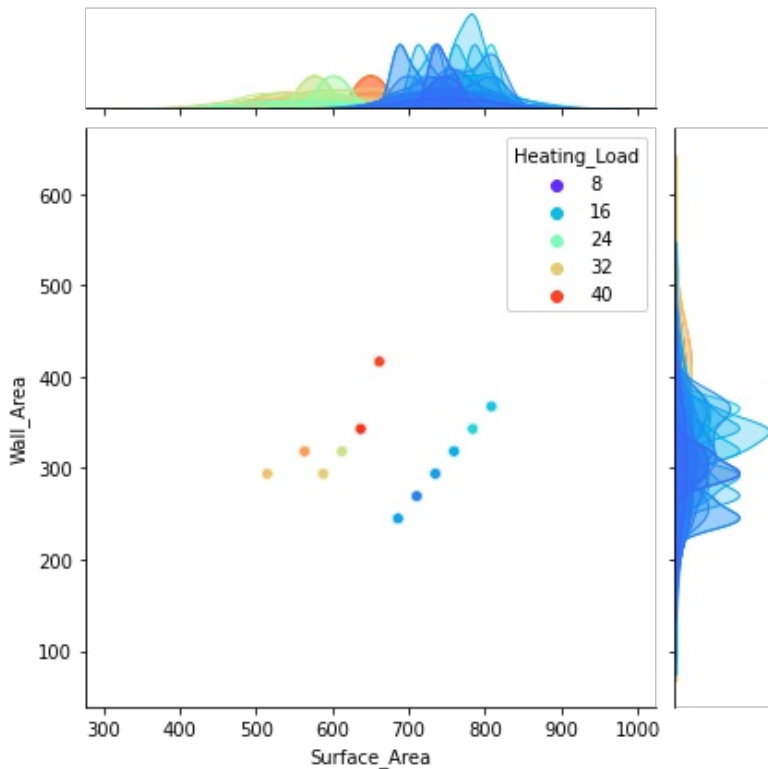
Relative\_Compactness  
Surface\_Area  
Wall\_Area  
Roof\_Area  
Overall\_Height  
Orientation  
Glazing\_Area  
Glazing\_Area\_Distribution  
Heating\_Load  
Cooling\_Load

In [ ]:

```
sns.jointplot(data=df, x="Surface_Area", y="Wall_Area", hue="Heating_Load", palette = 'rainbow')
```

Out[ ]:

<seaborn.axisgrid.JointGrid at 0x7fdac7cfa820>

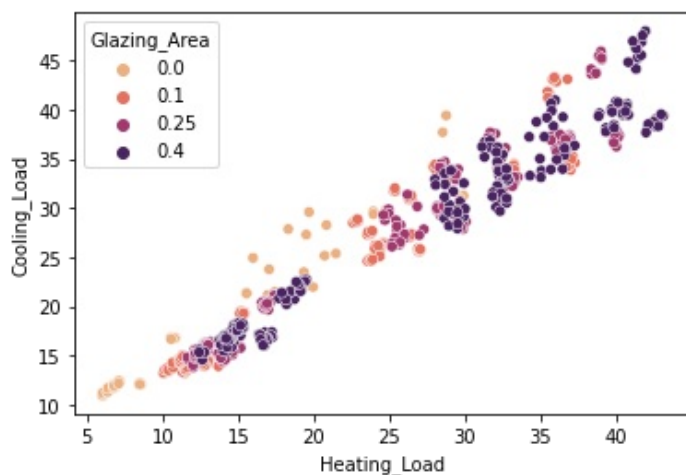


In [ ]:

```
sns.scatterplot(df["Heating_Load"], df["Cooling_Load"], hue=df["Glazing_Area"], palette = "flare")
plt.show()
```

/usr/local/lib/python3.8/dist-packages/seaborn/\_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

warnings.warn(

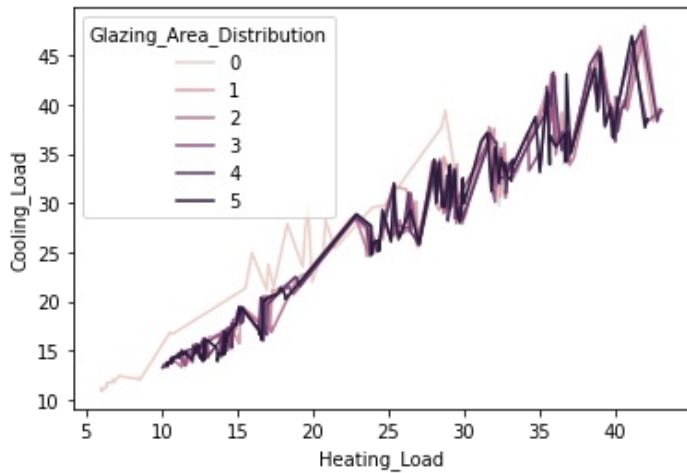


```
In [ ]:
```

```
sns.lineplot(data=df, x="Heating_Load", y="Cooling_Load", hue="Glazing_Area_Distribution")
```

```
Out[ ]:
```

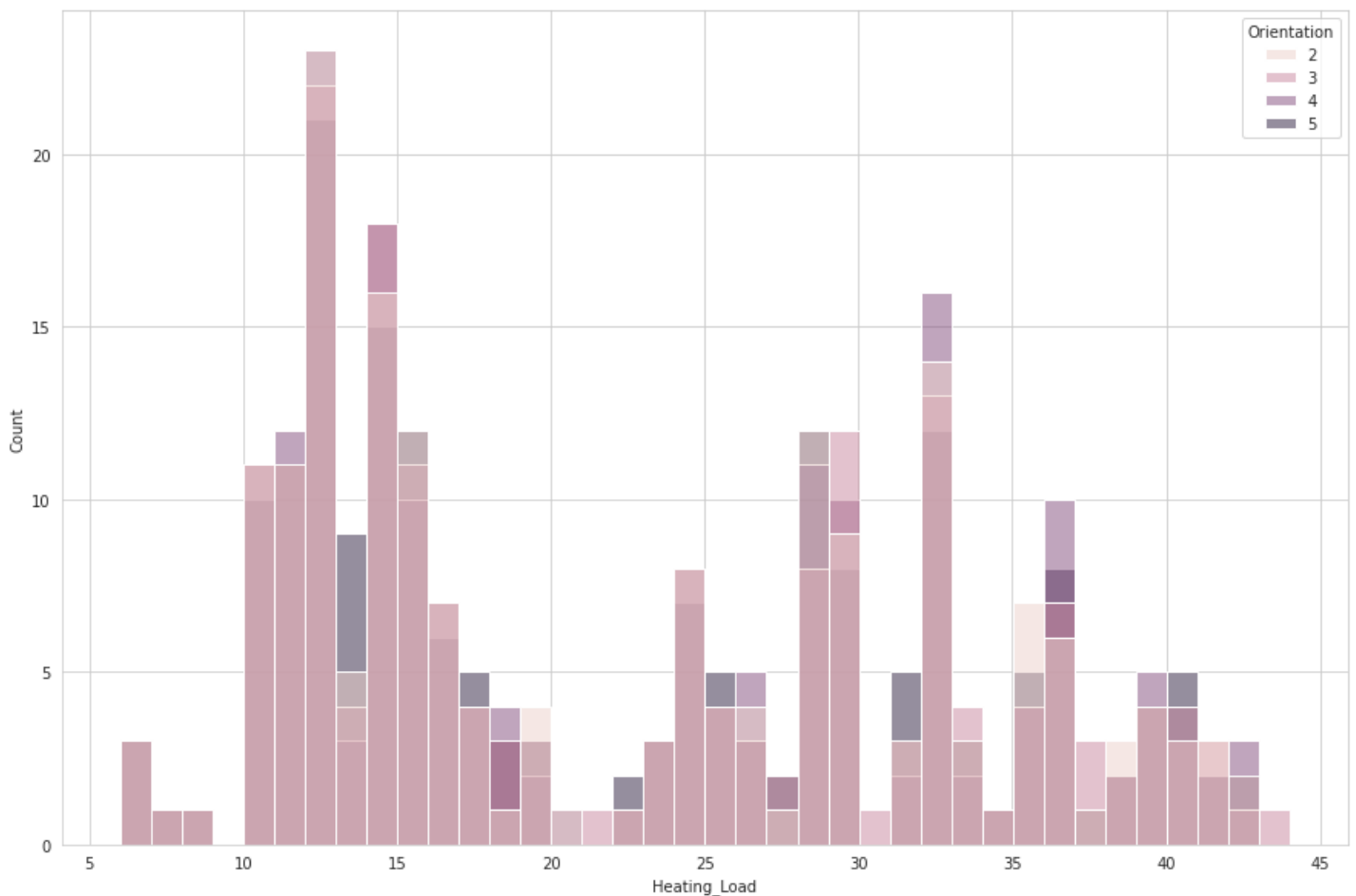
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fdabff95940>
```



```
In [ ]:
```

```
fig, ax = plt.subplots(figsize=(15, 10))
sns.histplot(data=df, x="Heating_Load", binwidth=1, hue="Orientation", ax=ax)

plt.show()
```



```
In [ ]:
```

```
# Set the column name to use for the pie chart
column_name = 'Surface_Area'

# Get the unique values in the column and count them
unique_values = df[column_name].unique()
```

```

num_slices = len(unique_values)

custom_palette = sns.color_palette('pastel', len(grouped))

fig = plt.figure(figsize=(6, 6))

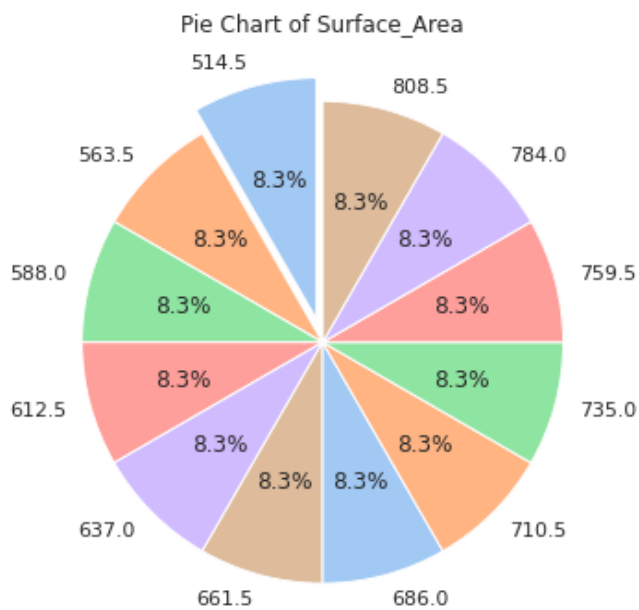
# Set up the explode parameter to make each slice of the pie chart stand out
explode = np.zeros(num_slices)
explode[0] = 0.1 # the first slice is moved out by 0.1

# Create the pie chart
plt.pie(df.groupby(column_name).size(), labels=unique_values, explode=explode, autopct='%1.1f%%', startangle=90, colors=custom_palette)

# Add a title
plt.title('Pie Chart of ' + column_name)

# Show the chart
plt.show()

```



In [ ]:

```

# Set the column name to use for the pie chart
column_name = 'Wall_Area'

# Get the unique values in the column and count them
unique_values = df[column_name].unique()
num_slices = len(unique_values)

custom_palette = sns.color_palette('pastel', len(grouped))

fig = plt.figure(figsize=(6, 6))

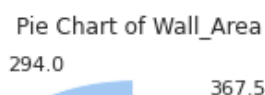
# Set up the explode parameter to make each slice of the pie chart stand out
explode = np.zeros(num_slices)
explode[0] = 0.1 # the first slice is moved out by 0.1

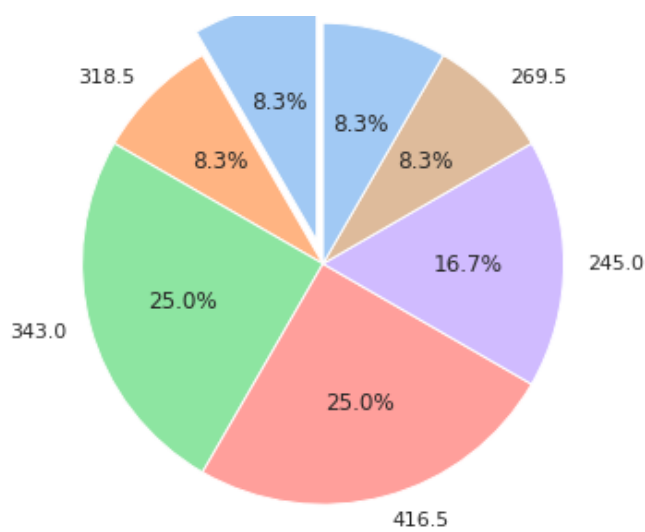
# Create the pie chart
plt.pie(df.groupby(column_name).size(), labels=unique_values, explode=explode, autopct='%1.1f%%', startangle=90, colors=custom_palette)

# Add a title
plt.title('Pie Chart of ' + column_name)

# Show the chart
plt.show()

```



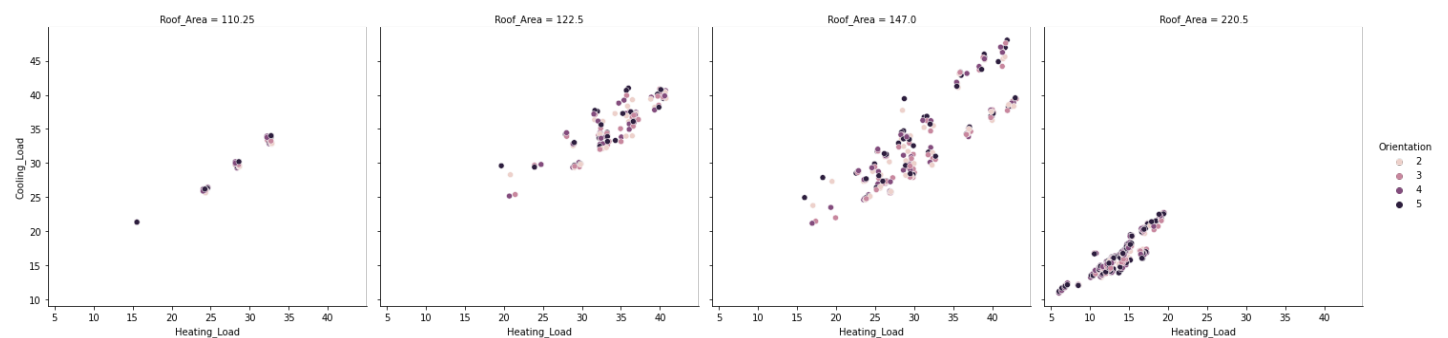


In [ ]:

```
sns.relplot(
    data=df, x="Heating_Load", y="Cooling_Load",
    col="Roof_Area", hue="Orientation",
    kind="scatter"
)
```

Out[ ]:

<seaborn.axisgrid.FacetGrid at 0x7fdabff6e2e0>

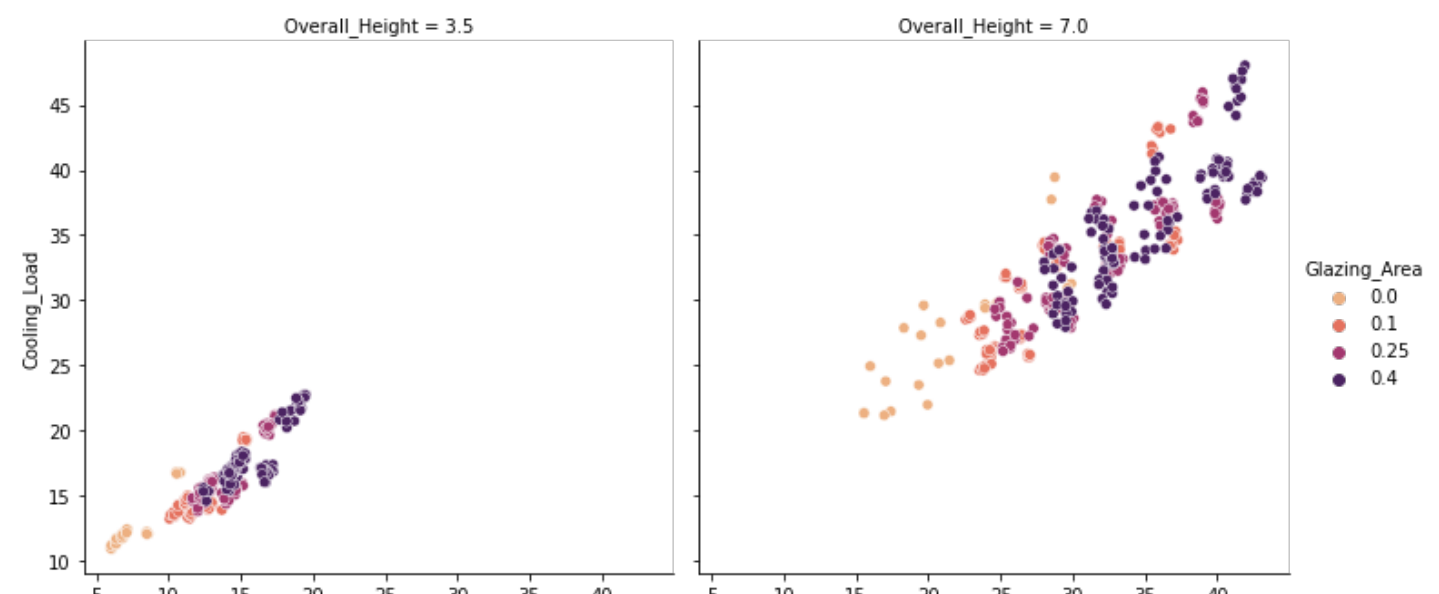


In [ ]:

```
sns.relplot(
    data=df, x="Heating_Load", y="Cooling_Load",
    col="Overall_Height", hue="Glazing_Area", palette = "flare", kind = "scatter"
)
```

Out[ ]:

<seaborn.axisgrid.FacetGrid at 0x7fdac818e130>



# Ridge Regression

In [ ]:

```
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge, RidgeCV, Lasso
from sklearn.preprocessing import StandardScaler
```

## Data splitting and scaling

In [ ]:

```
features = df.columns[0:7]
target = df.columns[8:9]

#X and y values
X = df[features].values
y = df[target].values

from sklearn.model_selection import train_test_split
#split
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.3, random_state =
17)

print("The dimension of X_train is {}".format(X_train.shape))
print("The dimension of X_test is {}".format(X_test.shape))

#scale features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

The dimension of X\_train is (537, 7)  
The dimension of X\_test is (231, 7)

In [ ]:

```
#Ridge Regression Model
ridgeReg = Ridge(alpha = 8) #alpha can be canged (we can optimize to reduce error)

ridgeReg.fit(X_train,y_train)

#train and test scorefor rridge regression
train_score_ridge = ridgeReg.score(X_train, y_train)
test_score_ridge = ridgeReg.score(X_test, y_test)

print("\n\nRidge Model \n")
print("The train score for ridge model is {}".format(train_score_ridge))
print("The test score for ridge model is {}".format(test_score_ridge))
```

Ridge Model

The train score for ridge model is 0.9122234728492367  
The test score for ridge model is 0.9125914393039551

## Lasso Regression

In [ ]:

```
#lasso regression model (l1 regularization)

lasso = Lasso(alpha = 0)
```



```
lasso.fit(X_train,y_train)
train_score_ls = lasso.score(X_train, y_train)
test_score_ls = lasso.score(X_test,y_test)

print("\nLasso model\n")
print("The train score for ls model is {}".format(train_score_ls))
print("The test score for ls model is {}".format(test_score_ls))
```

Lasso model

The train score for ls model is 0.9146081536479443  
The test score for ls model is 0.915441034217831

```
<ipython-input-16-0e787a5f3ba2>:4: UserWarning: With alpha=0, this algorithm does not converge well. You are advised to use the LinearRegression estimator
    lasso.fit(X_train,y_train)
/usr/local/lib/python3.8/dist-packages/sklearn/linear_model/_coordinate_descent.py:647: UserWarning: Coordinate descent with no regularization may lead to unexpected results and is discouraged.
    model = cd_fast.enet_coordinate_descent(
/usr/local/lib/python3.8/dist-packages/sklearn/linear_model/_coordinate_descent.py:647: ConvergenceWarning: Objective did not converge. You might want to increase the number of iterations, check the scale of the features or consider increasing regularisation. Duality gap: 2.346e+03, tolerance: 5.495e+00 Linear regression models with null weight for the l1 regularization term are more efficiently fitted using one of the solvers implemented in sklearn.linear_model.Ridge/RidgeCV instead.
    model = cd_fast.enet_coordinate_descent(
```

In [ ]: