energy-efficiency-data

November 7, 2022

0.1 Libraries we used for the report

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

0.2 Dataframe

Scottish Energy Performance Certificate Register Publication of Energy Performance Data for Domestic Buildings Dataset – Q4 2012 to Q1 2022 – March 2022 https://market.oceanprotocol.com/asset/did:op:2c586b710625b6ef2899b0c690d2a350a1c6c428669c35fd75400f01de

[2]:
```
dataframe = pd.read_csv("/kaggle/input/energy-efficiency-data-challenge/
↪Scotland EPC Dataset.csv")
```

[3]:
```
dataframe.head()
```

[3]:
```
   Property_UPRN Postcode   POST_TOWN Date of Assessment  \
0   1.001101e+09  EH4 5EZ  EDINBURGH         01/01/2021
1   1.001951e+09  EH7 4HE  EDINBURGH         01/01/2021
2   1.000996e+09  EH4 2DL  EDINBURGH         02/01/2021
3   1.001257e+09  PH1 1SA      PERTH         02/01/2021
4   1.235709e+09  G78 1QN    Glasgow         02/01/2021

   Primary Energy Indicator (kWh/m²/year)  Total floor area (m²)  \
0                                   375.0                   94.0
1                                   250.0                  175.0
2                                   403.0                   72.0
3                                   174.0                   96.0
4                                   145.0                   58.0

   Current energy efficiency rating Current energy efficiency rating band  \
0                              53.0                                     E
1                              66.0                                     D
2                              61.0                                     D
3                              76.0                                     C
4                              79.0                                     C
```

```
   Potential Energy Efficiency Rating Potential energy efficiency rating band  \
0                              85.0                                        B
1                              80.0                                        C
2                              78.0                                        C
3                              87.0                                        B
4                              79.0                                        C

   …  Total current energy costs over 3 years (£)  \
0  …                                       3789.0
1  …                                       4635.0
2  …                                       3570.0
3  …                                       2049.0
4  …                                       1212.0

  Current heating costs over 3 years (£)  \
0                                 2922.0
1                                 4068.0
2                                 2226.0
3                                 1554.0
4                                  828.0

   Potential heating costs over 3 years (£)  \
0                                    1548.0
1                                    3015.0
2                                    1191.0
3                                    1554.0
4                                     828.0

  Current hot water costs over 3 years (£)  \
0                                    645.0
1                                    246.0
2                                   1038.0
3                                    258.0
4                                    216.0

   Potential hot water costs over 3 years (£)  \
0                                       219.0
1                                       246.0
2                                       564.0
3                                       177.0
4                                       216.0

  Current lighting costs over 3 years (£)  \
0                                   222.0
1                                   321.0
2                                   306.0
```

```
3                                  237.0
4                                  168.0

  Potential lighting costs over 3 years (£) Part 1 Construction Age Band  \
0                                      222.0                    1930-1949
1                                      321.0                    1919-1929
2                                      207.0                    1965-1975
3                                      237.0                    1999-2002
4                                      168.0                  before 1919

      Built Form Property Type
0  Semi-Detached         House
1    End-Terrace         House
2  Semi-Detached          Flat
3    Mid-Terrace         House
4    Mid-Terrace          Flat

[5 rows x 48 columns]
```

Next, we cleane the dataset from extraspaces and removed spelling errors in town names

[4]:
```
dataframe.POST_TOWN = dataframe.POST_TOWN.str.strip()
dataframe.POST_TOWN = dataframe.POST_TOWN.str.upper()
dataframe.POST_TOWN = dataframe.POST_TOWN.replace("ACHARCLE", "ACHARACLE").
 ↪replace("ARGYLL &AMP; BUTE","ARGYLL AND BUTE").replace("BRECHIN,␣
 ↪ANGUS","BRECHIN").replace("CAMPBE;TOWN","CAMPBELTOWN").replace("CASLTE␣
 ↪DOUGLAS","CASTLE DOUGLAS").replace("STORNAWAY","STORNOWAY").replace("SOUTH␣
 ↪ARYSHIRE","SOUTH AYRSHIRE").replace("SHETLAND ISLANDS","SHETLAND").
 ↪replace("ROYBRIDGE","ROY BRIDGE").replace("PERTH &AMP; KINROSS", "PERTH").
 ↪replace("ORMITSTON", "ORMISTON").replace("NORTH ARYSHIRE","NORTH AYRSHIRE").
 ↪replace("NEWTON MERANS","NEWTON MEARNS").replace("NEWPORT-ON-TAY","NEWPORT␣
 ↪ON TAY").replace("MUSSLEBURGH","MUSSELBURGH").replace("LEVEN, FIFE",␣
 ↪"LEVEN").replace("ISLE OF SCALPY", "ISLE OF SCALPAY").replace("GRANTOWN ON␣
 ↪SPEY","GRANTOWN-ON-SPEY").replace("GRANTON-ON-SPEY","GRANTOWN-ON-SPEY").
 ↪replace("GRANTON ON SPEY","GRANTOWN-ON-SPEY").replace("EDINGBURGH",␣
 ↪"EDINBURGH")
```

0.3 Descriptive statistics of the dataset

[5]:
```
dataframe.describe()
```

[5]:
```
        Property_UPRN  Primary Energy Indicator (kWh/m²/year)  \
count    1.850390e+05                            185039.000000
mean     1.053923e+09                               248.665157
std      9.780732e+07                               144.397097
min      1.000002e+09                              -858.000000
25%      1.000734e+09                               160.000000
```

```
50%     1.001543e+09                                227.000000
75%     1.002494e+09                                303.000000
max     1.235956e+09                               3378.000000

       Total floor area (m²)  Current energy efficiency rating  \
count          185039.000000                     185039.000000
mean               88.522128                         69.191797
std                49.246079                         13.578025
min                15.000000                          1.000000
25%                62.000000                         63.000000
50%                77.000000                         71.000000
75%                99.000000                         78.000000
max              1498.000000                        268.000000

       Potential Energy Efficiency Rating  \
count                       185039.000000
mean                            82.189511
std                              7.987645
min                              2.000000
25%                             78.000000
50%                             82.000000
75%                             87.000000
max                            291.000000

       Current Environmental Impact Rating  \
count                        185039.000000
mean                             67.137128
std                              16.173906
min                               1.000000
25%                              58.000000
50%                              69.000000
75%                              78.000000
max                             262.000000

       Potential Environmental Impact Rating  \
count                          185039.000000
mean                               80.458914
std                                10.408101
min                                13.000000
25%                                76.000000
50%                                82.000000
75%                                87.000000
max                               282.000000

       CO2 Emissions Current Per Floor Area (kg.CO2/m²/yr)  \
count                                      185039.000000
mean                                           44.384972
```

```
std                                                       26.192351
min                                                     -159.000000
25%                                                       28.000000
50%                                                       40.000000
75%                                                       55.000000
max                                                      585.000000

       Current Emissions (T.CO2/yr)  \
count                 185039.000000
mean                       3.799927
std                        3.369697
min                      -22.700000
25%                        2.000000
50%                        3.000000
75%                        4.500000
max                      410.000000

       Potential Reduction in Emissions (T.CO2/yr)  \
count                                185039.000000
mean                                      1.565072
std                                       2.246415
min                                      -0.600000
25%                                       0.300000
50%                                       1.100000
75%                                       1.900000
max                                     402.700000

       Total current energy costs over 3 years (£)  \
count                                185039.000000
mean                                   2691.063084
std                                    2076.714794
min                                     312.000000
25%                                    1557.000000
50%                                    2151.000000
75%                                    3093.000000
max                                  180036.000000

       Current heating costs over 3 years (£)  \
count                           185039.000000
mean                              2033.206416
std                               1886.857082
min                                 57.000000
25%                               1047.000000
50%                               1557.000000
75%                               2346.000000
max                             176205.000000
```

```
       Potential heating costs over 3 years (£)  \
count                               185039.000000
mean                                  1480.955393
std                                   1066.420023
min                                     57.000000
25%                                    870.000000
50%                                   1221.000000
75%                                   1738.500000
max                                  50484.000000

       Current hot water costs over 3 years (£)  \
count                               185039.000000
mean                                   404.849691
std                                    289.961225
min                                      0.000000
25%                                    246.000000
50%                                    291.000000
75%                                    441.000000
max                                   4071.000000

       Potential hot water costs over 3 years (£)  \
count                                 185039.000000
mean                                     281.331692
std                                      151.211792
min                                        0.000000
25%                                      198.000000
50%                                      237.000000
75%                                      300.000000
max                                     2532.000000

       Current lighting costs over 3 years (£)  \
count                              185039.000000
mean                                  253.006977
std                                   100.134687
min                                    57.000000
25%                                   186.000000
50%                                   234.000000
75%                                   300.000000
max                                  2220.000000

       Potential lighting costs over 3 years (£)
count                                185039.000000
mean                                   215.394711
std                                     71.690024
min                                     57.000000
25%                                    171.000000
50%                                    207.000000
```

```
75%                                   249.000000
max                                  2526.000000
```

0.3.1 The top 25 Post Towns by occurences are:

[6]:
```
dataframe["POST_TOWN"].value_counts().head(25)
```

[6]:
```
GLASGOW          37529
EDINBURGH        19276
ABERDEEN          9226
DUNDEE            5782
PAISLEY           3136
DUNFERMLINE       3011
PERTH             2965
INVERNESS         2877
STIRLING          2548
FALKIRK           2387
KILMARNOCK        2227
AYR               2137
HAMILTON          1995
MOTHERWELL        1939
LIVINGSTON        1922
KIRKCALDY         1775
GREENOCK          1709
AIRDRIE           1701
DUMFRIES          1692
COATBRIDGE        1536
BATHGATE          1507
ELGIN             1373
PETERHEAD         1321
WISHAW            1247
CLYDEBANK         1212
Name: POST_TOWN, dtype: int64
```

On average a post town has 286 occurences in the data:

[7]:
```
dataframe["POST_TOWN"].value_counts().mean()
```

[7]:
```
286.06366459627327
```

While a median town has 8 occurences

[8]:
```
dataframe["POST_TOWN"].value_counts().median()
```

[8]:
```
8.0
```

We also find that there is a large amount of single town occurences in the data, for instance, at least 25% of observations belong to unique postal towns

[9]:
```python
np.quantile(dataframe["POST_TOWN"].value_counts(), 0.25)
```

[9]: 1.0

Hence, we decided to report multiple statistics: average observation for all postal towns(which favors unique exteme values), sum of all data (which favors agglomerates), as well as statistics dedicated to postal towns with observations equal or higher than 8, which should provide the less bias findings.

1. Rank Towns by current efficiency rating - (2 points)

[10]:
```python
current_efficiency_dict = {
    'Current energy efficiency rating': [np.median, np.mean, 'count', 'sum'],
}

df_current_efficiency = dataframe.groupby(['POST_TOWN']).
 ↪agg(current_efficiency_dict).sort_values(ascending=False, by=[('Current␣
 ↪energy efficiency rating',   'mean')])
df_current_efficiency.head(5)
```

[10]:

	Current energy efficiency rating			
	median	mean	count	sum
POST_TOWN				
GARTOCHARN	115.0	115.000000	1	115.0
BANNOCKBURN	114.5	111.750000	4	447.0
GATEHOUSE OF FLEET	101.0	101.000000	1	101.0
NORTH LANARKSHIRE	97.0	97.117647	17	1651.0
AULDEARN	96.0	96.000000	1	96.0

[11]:
```python
df_current_efficiency.sort_values(ascending=False, by=[('Current energy␣
 ↪efficiency rating',   'sum')]).head(5)
```

[11]:

	Current energy efficiency rating			
	median	mean	count	sum
POST_TOWN				
GLASGOW	73.0	71.073863	37529	2667331.0
EDINBURGH	72.0	70.927682	19276	1367202.0
ABERDEEN	71.0	69.753089	9226	643542.0
DUNDEE	71.0	69.004151	5782	398982.0
PAISLEY	73.0	71.469707	3136	224129.0

[12]:
```python
df_current_efficiency.loc[(df_current_efficiency[('Current energy efficiency␣
 ↪rating','count')] >= 8)].sort_values(ascending=False, by=[('Current energy␣
 ↪efficiency rating',   'mean')]).head(5)
```

[12]:

	Current energy efficiency rating			
	median	mean	count	sum
POST_TOWN				

```
NORTH LANARKSHIRE                              97.0   97.117647    17   1651.0
WALLYFORD                                      91.0   89.826087    23   2066.0
GLENMAVIS                                      90.0   89.521739    23   2059.0
METHIL                                         89.0   89.437500    16   1431.0
WINCHBURGH                                     91.0   89.419355    31   2772.0
```

2. Rank Towns by potential energy efficiency rating - (2 points)

[13]:
```
potential_efficiency_dict = {
    'Potential Environmental Impact Rating': [np.median, np.std, np.mean,␣
 ↪'count', 'sum'],
}


df_potential_efficiency = dataframe.groupby(['POST_TOWN']).
 ↪agg(potential_efficiency_dict).sort_values(ascending=False, by=[('Potential␣
 ↪Environmental Impact Rating',   'mean')])
df_potential_efficiency.head(5)
```

[13]:
```
           Potential Environmental Impact Rating
                                          median std   mean count    sum
POST_TOWN
WEST PLEAN                                 126.0 NaN  126.0     1  126.0
MEIGLE                                     122.0 NaN  122.0     1  122.0
COMRIE                                     121.0 NaN  121.0     1  121.0
GARTOCHARN                                 117.0 NaN  117.0     1  117.0
SANDAY                                     117.0 NaN  117.0     1  117.0
```

[14]:
```
df_potential_efficiency.sort_values(ascending=False, by=[('Potential␣
 ↪Environmental Impact Rating',   'sum')]).head(5)
```

[14]:
```
          Potential Environmental Impact Rating                              \
                                         median        std       mean  count
POST_TOWN
GLASGOW                                    81.0   9.443690  79.705055  37529
EDINBURGH                                  81.0   9.536754  79.502023  19276
ABERDEEN                                   81.0   9.379837  79.722957   9226
DUNDEE                                     81.0  10.152283  78.899862   5782
PAISLEY                                    81.0   9.423686  80.338648   3136


                 sum
POST_TOWN
GLASGOW    2991251.0
EDINBURGH  1532481.0
ABERDEEN    735524.0
DUNDEE      456199.0
```

```
PAISLEY     251942.0
```

[15]:
```python
df_potential_efficiency.loc[(df_potential_efficiency[('Potential Environmental Impact Rating','count')] >= 8)].sort_values(ascending=False, by=[('Potential Environmental Impact Rating',   'mean')]).head(5)
```

[15]:
```
                   Potential Environmental Impact Rating                      \
                                                  median       std       mean
POST_TOWN
NORTH LANARKSHIRE                                  100.0  1.477777  99.941176
MACHLINE                                            97.0  1.327368  96.809524
SOUTH AYRSHIRE                                      95.0  7.510707  95.125000
LUGAR                                               97.0  6.008328  95.100000
ARDERSIER                                           98.0  6.196862  94.357143


                   count     sum
POST_TOWN
NORTH LANARKSHIRE     17  1699.0
MACHLINE              21  2033.0
SOUTH AYRSHIRE         8   761.0
LUGAR                 10   951.0
ARDERSIER             14  1321.0
```

Here we find that NORTH LANARKSHIRE is a clear leader in both current efficiency rating and potential energy efficiency

3. Rank Towns by current environmental impact rating and note if there have been periods where houses were more or less environmentally friendly- (2 points)

[16]:
```python
current_env_dict = {
    'Current Environmental Impact Rating': [np.median, np.std, np.mean, 'count', 'sum'],
}

df_current_env = dataframe.groupby(['POST_TOWN']).agg(current_env_dict).sort_values(ascending=False, by=[('Current Environmental Impact Rating',   'mean')])
df_current_env.head(5)
```

[16]:
```
                   Current Environmental Impact Rating                     \
                                                median       std        mean
POST_TOWN
GARTOCHARN                                       113.0       NaN  113.000000
BANNOCKBURN                                      112.0  6.130525  109.750000
NORTH LANARKSHIRE                                 99.0  2.468925   98.705882
AULDEARN                                          96.0       NaN   96.000000
WESTERN ISLES                                     96.0       NaN   96.000000
```

```
                  count     sum
POST_TOWN
GARTOCHARN            1   113.0
BANNOCKBURN           4   439.0
NORTH LANARKSHIRE    17  1678.0
AULDEARN              1    96.0
WESTERN ISLES         1    96.0
```

[17]:
```
df_current_env.sort_values(ascending=False, by=[('Current Environmental Impact␣
↪Rating',   'sum')]).head(5)
```

[17]:
```
          Current Environmental Impact Rating                              \
                                       median        std       mean  count
POST_TOWN
GLASGOW                                  71.0  13.970218  69.543153  37529
EDINBURGH                                71.0  14.814219  69.462855  19276
ABERDEEN                                 70.0  14.384589  68.005636   9226
DUNDEE                                   68.0  14.635000  66.440678   5782
PAISLEY                                  71.0  14.047345  70.311862   3136


                 sum
POST_TOWN
GLASGOW    2609885.0
EDINBURGH  1338966.0
ABERDEEN    627420.0
DUNDEE      384160.0
PAISLEY     220498.0
```

[18]:
```
df_current_env.loc[(df_current_env[('Current Environmental Impact␣
↪Rating','count')] >= 8)].sort_values(ascending=False, by=[('Current␣
↪Environmental Impact Rating',   'mean')]).head(5)
```

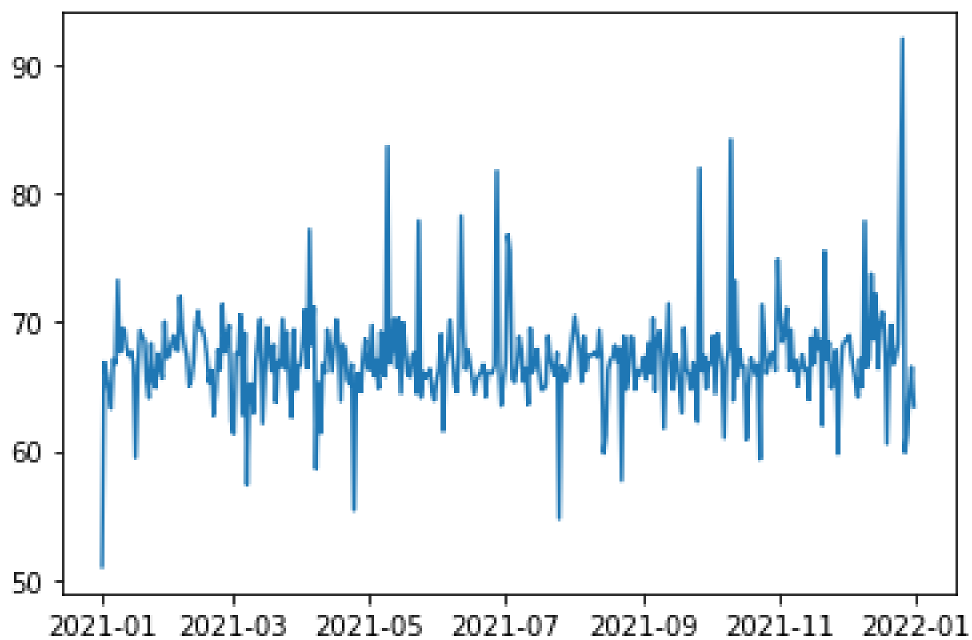
[18]:
```
                  Current Environmental Impact Rating                      \
                                               median       std       mean
POST_TOWN
NORTH LANARKSHIRE                                99.0  2.468925  98.705882
WALLYFORD                                        92.0  2.295381  91.217391
METHIL                                           91.0  0.442531  91.062500
ROXBURGHSHIRE                                    91.0  0.597001  90.950000
GLENMAVIS                                        90.0  0.792754  90.086957


                  count     sum
POST_TOWN
```

```
NORTH LANARKSHIRE    17  1678.0
WALLYFORD            23  2098.0
METHIL               16  1457.0
ROXBURGHSHIRE        40  3638.0
GLENMAVIS            23  2072.0
```

We find NORTH LANARKSHIRE as a clear Leader

[19]:
```
dataframe['Date of Assessment'] = pd.to_datetime(dataframe['Date of␣
↪Assessment'])
plt.plot(dataframe.groupby(['Date of Assessment'])["Current Environmental␣
↪Impact Rating"].mean())
```

[19]:
```
[<matplotlib.lines.Line2D at 0x7f4b02fe6050>]
```



In terms of date there are noticeable spikes in average rating, however the average observation data is somewhat stable across time.

4. Rank Towns by potential environmental impact rating - (2 points)

[20]:
```
potential_env_dict = {
    'Potential Environmental Impact Rating': [np.median, np.std, np.mean,␣
↪'count', 'sum'],
}
```

```
df_potential_env = dataframe.groupby(['POST_TOWN']).agg(potential_env_dict).
 ↪sort_values(ascending=False, by=[('Potential Environmental Impact Rating', ␣
 ↪'mean')])
df_potential_env.head(5)
```

[20]:

```
           Potential Environmental Impact Rating
                                          median std   mean count    sum
POST_TOWN
WEST PLEAN                                 126.0 NaN  126.0     1  126.0
MEIGLE                                     122.0 NaN  122.0     1  122.0
COMRIE                                     121.0 NaN  121.0     1  121.0
GARTOCHARN                                 117.0 NaN  117.0     1  117.0
SANDAY                                     117.0 NaN  117.0     1  117.0
```

[21]:

```
df_potential_env.sort_values(ascending=False, by=[('Potential Environmental␣
 ↪Impact Rating',   'sum')]).head(5)
```

[21]:

```
          Potential Environmental Impact Rating                              \
                                         median        std       mean  count
POST_TOWN
GLASGOW                                    81.0   9.443690  79.705055  37529
EDINBURGH                                  81.0   9.536754  79.502023  19276
ABERDEEN                                   81.0   9.379837  79.722957   9226
DUNDEE                                     81.0  10.152283  78.899862   5782
PAISLEY                                    81.0   9.423686  80.338648   3136


                 sum
POST_TOWN
GLASGOW    2991251.0
EDINBURGH  1532481.0
ABERDEEN    735524.0
DUNDEE      456199.0
PAISLEY     251942.0
```

[22]:

```
df_potential_env.loc[(df_potential_env[('Potential Environmental Impact␣
 ↪Rating','count')] >= 8)].sort_values(ascending=False, by=[('Potential␣
 ↪Environmental Impact Rating',   'mean')]).head(5)
```

[22]:

```
                 Potential Environmental Impact Rating                       \
                                                median       std       mean
POST_TOWN
NORTH LANARKSHIRE                                100.0  1.477777  99.941176
MACHLINE                                          97.0  1.327368  96.809524
SOUTH AYRSHIRE                                    95.0  7.510707  95.125000
LUGAR                                             97.0  6.008328  95.100000
ARDERSIER                                         98.0  6.196862  94.357143
```

```
                    count     sum
POST_TOWN
NORTH LANARKSHIRE      17  1699.0
MACHLINE               21  2033.0
SOUTH AYRSHIRE          8   761.0
LUGAR                  10   951.0
ARDERSIER              14  1321.0
```

5. Rank Towns by Current Emissions (T.CO2/yr) - (2 points)

[23]:
```
current_emissions_dict = {
    'Current Emissions (T.CO2/yr)': [np.median, np.std, np.mean, 'count',␣
 ↪'sum'],
}

df_current_em = dataframe.groupby(['POST_TOWN']).agg(current_emissions_dict).
 ↪sort_values(ascending=False, by=[('Current Emissions (T.CO2/yr)','mean')])
df_current_em.head(5)
```

[23]:
```
           Current Emissions (T.CO2/yr)
                                 median std  mean count   sum
POST_TOWN
BONAWE                             37.0 NaN  37.0     1  37.0
MORVERN                            31.0 NaN  31.0     1  31.0
FINDHORN                           26.0 NaN  26.0     1  26.0
KINCARDINE                         20.0 NaN  20.0     1  20.0
BY MAYBOLE                         19.0 NaN  19.0     1  19.0
```

[24]:
```
df_current_em.sort_values(ascending=False, by=[('Current Emissions (T.CO2/
 ↪yr)','sum')]).head(5)
```

[24]:
```
          Current Emissions (T.CO2/yr)
                                median       std      mean  count       sum
POST_TOWN
GLASGOW                            2.6  2.261893  3.134392  37529  117630.6
EDINBURGH                          2.6  2.540780  3.153294  19276   60782.9
ABERDEEN                           2.8  2.733995  3.533059   9226   32596.0
DUNDEE                             3.0  2.494935  3.591612   5782   20766.7
PERTH                              3.1  3.073072  3.955784   2965   11728.9
```

[25]:
```
df_current_em.loc[(df_current_em[('Current Emissions (T.CO2/yr)','count')] >=␣
 ↪8)].sort_values(ascending=False, by=[('Current Emissions (T.CO2/yr)',  ␣
 ↪'mean')]).head(5)
```

[25]:

```
                Current Emissions (T.CO2/yr)
                                      median        std       mean count    sum
POST_TOWN
CARRBRIDGE                             12.00   7.075298  12.256522    23  281.9
LOCHAILORT                              8.50  10.512902  11.488889     9  103.4
CRIANLARICH                             6.45  11.699348  10.795455    22  237.5
HELMSDALE                              11.00   4.955106  10.500000    27  283.5
KINGUSSIE                               8.50   6.595212   9.694366    71  688.3
```

In this category we notice that NORTH LANARKSHIRE is not on the top 5 list.

6. Rank Towns by Potential Reduction in Emissions (T.CO2/yr) - (2 points)

[26]:

```python
potential_emissions_dict = {
    'Potential Reduction in Emissions (T.CO2/yr)': [np.median, np.std, np.mean,
 ↪'count', 'sum'],
}

df_potential_em = dataframe.groupby(['POST_TOWN']).
 ↪agg(potential_emissions_dict).sort_values(ascending=False, by=[('Potential
 ↪Reduction in Emissions (T.CO2/yr)','mean')])
df_potential_em.head(5)
```

[26]:

```
               Potential Reduction in Emissions (T.CO2/yr)
                                                    median std  mean count   sum
POST_TOWN
BONAWE                                                24.0 NaN  24.0     1  24.0
MORVERN                                               16.0 NaN  16.0     1  16.0
FINDHORN                                              15.0 NaN  15.0     1  15.0
BY MAYBOLE                                            14.5 NaN  14.5     1  14.5
PORTSOY                                               10.9 NaN  10.9     1  10.9
```

[27]:

```python
df_potential_em.sort_values(ascending=False, by=[('Potential Reduction in
 ↪Emissions (T.CO2/yr)','sum')]).head(5)
```

[27]:

```
              Potential Reduction in Emissions (T.CO2/yr)                    \
                                                   median       std      mean
POST_TOWN
GLASGOW                                               0.8  1.291082  1.070551
EDINBURGH                                             0.7  1.428905  1.084981
ABERDEEN                                              1.0  1.635308  1.332517
DUNDEE                                                1.1  1.496025  1.351799
PERTH                                                 1.1  1.991694  1.600641


           count      sum
POST_TOWN
GLASGOW    37529  40176.7
```

```
EDINBURGH  19276  20914.1
ABERDEEN    9226  12293.8
DUNDEE      5782   7816.1
PERTH       2965   4745.9
```

[28]:
```
df_potential_em.loc[(df_potential_em[('Potential Reduction in Emissions (T.CO2/
↪yr)','count')] >= 8)].sort_values(ascending=False, by=[('Potential Reduction␣
↪in Emissions (T.CO2/yr)','mean')]).head(5)
```

[28]:
```
            Potential Reduction in Emissions (T.CO2/yr)                       \
                                                  median        std      mean
POST_TOWN
LOCHAILORT                                          4.50   7.332879  7.288889
CRIANLARICH                                         2.80   9.023020  6.818182
TARBERT                                             2.70  35.108361  6.642308
ROGART                                              4.45   4.799939  6.431818
COLINTRAIVE                                         3.90   6.053395  5.623077


            count    sum
POST_TOWN
LOCHAILORT      9   65.6
CRIANLARICH    22  150.0
TARBERT       130  863.5
ROGART         22  141.5
COLINTRAIVE    13   73.1
```

We find that LOCHAILORT is a clear favourite in reducing T.CO2 per average house and currently undertakes great effort.

7. Rank Towns by potential savings in heating costs (£) over three years - (2 points)

[29]:
```
potential_heating_costs_dict = {
    "Potential heating costs over 3 years (£)": [np.median, np.std, np.mean,␣
↪'count', 'sum'],
}

df_potential_heating_costs = dataframe.groupby(['POST_TOWN']).
↪agg(potential_heating_costs_dict).sort_values(ascending=False,␣
↪by=[('Potential heating costs over 3 years (£)','mean')])
df_potential_heating_costs.head(5)
```

[29]:
```
            Potential heating costs over 3 years (£)                        \
                                                median           std     mean
POST_TOWN
MEIKLEOUR                                      15069.0  16363.865130  15069.0
NEW CUMNOCK                                     9883.5    935.502272   9883.5
EAGLESHAM                                       9858.0           NaN   9858.0
```

```
TEALING                                               9717.0          NaN   9717.0
ST OLA                                                8859.0          NaN   8859.0


            count      sum
POST_TOWN
MEIKLEOUR       2  30138.0
NEW CUMNOCK     2  19767.0
EAGLESHAM       1   9858.0
TEALING         1   9717.0
ST OLA          1   8859.0
```

[30]:
```python
df_potential_heating_costs.sort_values(ascending=False, by=[('Potential heating costs over 3 years (£)','sum')]).head(5)
```

[30]:
```
          Potential heating costs over 3 years (£)                          \
                                            median         std         mean
POST_TOWN
GLASGOW                                     1032.0  780.235624  1233.052200
EDINBURGH                                    939.0  836.650612  1156.244138
ABERDEEN                                    1116.0  859.447195  1352.490137
DUNDEE                                      1134.0  854.064169  1354.216188
PERTH                                       1242.0  974.042108  1510.952782



           count         sum
POST_TOWN
GLASGOW    37529  46275216.0
EDINBURGH  19276  22287762.0
ABERDEEN    9226  12478074.0
DUNDEE      5782   7830078.0
PERTH       2965   4479975.0
```

[31]:
```python
df_potential_heating_costs.loc[(df_potential_heating_costs[('Potential heating costs over 3 years (£)','count')] >= 8)].sort_values(ascending=False, by=[('Potential heating costs over 3 years (£)','mean')]).head(5)
```

[31]:
```
             Potential heating costs over 3 years (£)              \
                                               median          std
POST_TOWN
ARISAIG                                        4011.0  2206.179184
NETHY BRIDGE                                   3223.5  3030.858790
CARRBRIDGE                                     3921.0  2420.224776
KILLIN                                         3177.0  4926.316916
DALWHINNIE                                     3588.0  1979.605415
```

```
                    mean  count       sum
POST_TOWN
ARISAIG       4565.375000    24  109569.0
NETHY BRIDGE  4444.730769    26  115563.0
CARRBRIDGE    4394.347826    23  101070.0
KILLIN        4203.439024    41  172341.0
DALWHINNIE    3993.600000    10   39936.0
```

potential savings in heating costs over the next 3 years includes a unique sequence of towns.

8. Rank Towns by potential savings in hot water costs (£) over three years - (2 points)

[32]:
```python
potential_hot_water_costs_dict = {
    "Potential hot water costs over 3 years (£)": [np.median, np.std, np.mean,
 ↪'count', 'sum'],
}

df_potential_heating_costs = dataframe.groupby(['POST_TOWN']).
 ↪agg(potential_hot_water_costs_dict).sort_values(ascending=False,
 ↪by=[('Potential hot water costs over 3 years (£)','mean')])
df_potential_heating_costs.head(5)
```

[32]:
```
           Potential hot water costs over 3 years (£)                   \
                                                   median std    mean count
POST_TOWN
EAGLESHAM                                          1281.0 NaN  1281.0     1
TEALING                                             987.0 NaN   987.0     1
BURRAY                                              930.0 NaN   930.0     1
KNOYDART                                            906.0 NaN   906.0     1
GLENTROMIE                                          843.0 NaN   843.0     1


                 sum
POST_TOWN
EAGLESHAM   1281.0
TEALING      987.0
BURRAY       930.0
KNOYDART     906.0
GLENTROMIE   843.0
```

[33]:
```python
df_potential_heating_costs.sort_values(ascending=False, by=[('Potential hot
 ↪water costs over 3 years (£)','sum')]).head(5)
```

[33]:
```
          Potential hot water costs over 3 years (£)                          \
                                                  median         std        mean
POST_TOWN
GLASGOW                                            243.0  143.313996  275.811985
EDINBURGH                                          252.0  138.370361  289.023293
```

```
ABERDEEN                                                237.0  153.088675  281.094732
DUNDEE                                                  240.0  161.438816  290.520062
PERTH                                                   246.0  169.717870  306.850927


           count         sum
POST_TOWN
GLASGOW    37529  10350948.0
EDINBURGH  19276   5571213.0
ABERDEEN    9226   2593380.0
DUNDEE      5782   1679787.0
PERTH       2965    909813.0
```

[34]:
```
df_potential_heating_costs.loc[(df_potential_heating_costs[('Potential hot␣
↪water costs over 3 years (£)','count')] >= 8)].sort_values(ascending=False,␣
↪by=[('Potential hot water costs over 3 years (£)','mean')]).head(5)
```

[34]:
```
             Potential hot water costs over 3 years (£)              \
                                                  median        std
POST_TOWN
NEWCASTLETON                                       462.0  222.894209
MILLPORT                                           508.5  215.605439
PERTHSHIRE                                         528.0   54.933776
LOCHGILPHEAD                                       489.0  167.786217
TARBERT                                            477.0  188.435523


                    mean count       sum
POST_TOWN
NEWCASTLETON  549.823529    51   28041.0
MILLPORT      524.863636    88   46188.0
PERTHSHIRE    501.214286    14    7017.0
LOCHGILPHEAD  499.158501   347  173208.0
TARBERT       494.769231   130   64320.0
```

9. Rank the top 5 wall descriptions (wall materials) by CO_2 emissions current per floor area and wall energy efficiency (create a single rating combining CO_2 emissions and wall energy efficiency) - (2 points)

The number of unique values in Wall description column

[35]:
```
dataframe["WALL_DESCRIPTION"].nunique()
```

[35]: 1519

First we transform the data

[36]:
```
dataframe.WALL_DESCRIPTION = dataframe.WALL_DESCRIPTION.str.strip()
```

[37]:
```python
def calculate_rating(values):
    length = len(values)
    total = 0
    for x in values:
        if x == "Very Poor":
            total += 1
        elif x == "Poor":
            total += 2
        elif x == "Average":
            total += 3
        elif x == "Good":
            total += 4
        elif x == "Very Good":
            total += 5
    return total/length

dataframe.WALL_ENERGY_EFF = dataframe.WALL_ENERGY_EFF.str.strip()
dataframe.WALL_ENERGY_EFF = dataframe.WALL_ENERGY_EFF.apply(lambda x:␣
↪calculate_rating(x.split(' | ')))
```

We scale the wall energy efficiency column to create an equally weighted index

[38]:
```python
dataframe.WALL_ENERGY_EFF.mean()
```

[38]: 3.348927793600269

[39]:
```python
dataframe["CO2 Emissions Current Per Floor Area (kg.CO2/m²/yr)"].mean()
```

[39]: 44.38497181675214

[40]:
```python
dataframe["CO2 Emissions Current Per Floor Area (kg.CO2/m²/yr)"].mean() /␣
↪dataframe.WALL_ENERGY_EFF.mean()
```

[40]: 13.253487250925772

[41]:
```python
dataframe['index9'] =  dataframe["CO2 Emissions Current Per Floor Area (kg.CO2/
↪m²/yr)"] / 13.25 + dataframe.WALL_ENERGY_EFF
```

[42]:
```python
wall_dict = {
    "index9": [np.median, np.std, np.mean, 'count', 'sum', np.min, np.max],
}

df_wall = dataframe.groupby(['WALL_DESCRIPTION']).agg(wall_dict)
df_wall.sort_values(ascending=False,by=[('index9',   'mean')]).head(5)
```

[42]:
```
                                              index9                      \
                                              median   std         mean
```

```
WALL_DESCRIPTION
Cavity wall, as built, insulated (assumed) | Ca…  18.836478  NaN  18.836478
Cavity wall, as built, partial insulation (assu…  17.698113  NaN  17.698113
Timber frame, as built, no insulation (assumed)…  16.518868  NaN  16.518868
Sandstone or limestone, with internal insulatio…  16.194969  NaN  16.194969
Granite or whinstone, as built, no insulation (…  16.037736  0.0  16.037736

                                                                       \
                                                   count        sum
WALL_DESCRIPTION
Cavity wall, as built, insulated (assumed) | Ca…      1  18.836478
Cavity wall, as built, partial insulation (assu…      1  17.698113
Timber frame, as built, no insulation (assumed)…      1  16.518868
Sandstone or limestone, with internal insulatio…      1  16.194969
Granite or whinstone, as built, no insulation (…      2  32.075472


                                                       amin       amax
WALL_DESCRIPTION
Cavity wall, as built, insulated (assumed) | Ca…  18.836478  18.836478
Cavity wall, as built, partial insulation (assu…  17.698113  17.698113
Timber frame, as built, no insulation (assumed)…  16.518868  16.518868
Sandstone or limestone, with internal insulatio…  16.194969  16.194969
Granite or whinstone, as built, no insulation (…  16.037736  16.037736
```

10. Rank the top 5 roof descriptions by CO2 emissions current per floor area and wall energy efficiency (create a single rating combining CO2 emissions and wall energy efficiency) - (2 points)

[43]:
```python
dataframe.ROOF_ENERGY_EFF = dataframe.ROOF_ENERGY_EFF.str.strip()
```

[44]:
```python
roof_df = dataframe[dataframe.ROOF_ENERGY_EFF!="N/A"]
roof_df = roof_df[roof_df.ROOF_ENERGY_EFF!="nan"]
roof_df.ROOF_ENERGY_EFF.value_counts()
```

[44]:
```
Good                                 51723
Very Good                            33936
Very Poor                             9991
Average                               9120
Good | Good                           4940
                                   …
Average | Average | Very Good            1
Very Good | Poor | Very Good             1
N/A | Poor | Good                        1
Very Good | Very Poor | Average          1
N/A | Good | Poor                        1
Name: ROOF_ENERGY_EFF, Length: 167, dtype: int64
```

[45]:
```
def calculate_rating_2(values):
    try:
        values = values.split(' | ')
        length = len(values)
        total = 0
        for x in values:
            if x == "Very Poor":
                total += 1
            elif x == "Poor":
                total += 2
            elif x == "Average":
                total += 3
            elif x == "Good":
                total += 4
            elif x == "Very Good":
                total += 5
            elif x == "N/A":
                length -=1
        if total==length:
            return 0
        return total/length
    except:
        return -10


roof_df.ROOF_ENERGY_EFF = roof_df.ROOF_ENERGY_EFF.apply(lambda x:␣
 ↪calculate_rating_2(x))
roof_df = roof_df[roof_df.ROOF_ENERGY_EFF>=0]
```

[46]:
```
roof_df.ROOF_ENERGY_EFF.count()
```

[46]: 133875

[47]:
```
roof_df["CO2 Emissions Current Per Floor Area (kg.CO2/m²/yr)"].mean() / roof_df.
 ↪ROOF_ENERGY_EFF.mean()
```

[47]: 12.71590827830652

[48]:
```
roof_df['index10'] =  roof_df["CO2 Emissions Current Per Floor Area (kg.CO2/m²/
 ↪yr)"] / 12.71 + roof_df.ROOF_ENERGY_EFF
```

[49]:
```
roof_dict = {
    "index10": [np.median, np.std, np.mean, 'count', 'sum', np.min, np.max],
}

df_roof = roof_df.groupby(['ROOF_DESCRIPTION']).agg(roof_dict)
```

```python
df_roof.sort_values(ascending=False,by=[('index10',   'mean')]).head(5)
```

[49]:
```
                                                         index10              \
                                                          median std       mean
ROOF_DESCRIPTION
Pitched, 250 mm loft insulation | Pitched, insu…  21.961448 NaN  21.961448
Pitched, 50 mm loft insulation | Pitched, no in…  21.396276 NaN  21.396276
Pitched, 25 mm loft insulation | Pitched, 50 mm…  17.166273 NaN  17.166273
Pitched, 100 mm loft insulation | Pitched, 200 …  16.828744 NaN  16.828744
Pitched, insulated at rafters | Pitched, no ins…  16.240755 NaN  16.240755

                                                                       \
                                                  count         sum
ROOF_DESCRIPTION
Pitched, 250 mm loft insulation | Pitched, insu…      1   21.961448
Pitched, 50 mm loft insulation | Pitched, no in…      1   21.396276
Pitched, 25 mm loft insulation | Pitched, 50 mm…      1   17.166273
Pitched, 100 mm loft insulation | Pitched, 200 …      1   16.828744
Pitched, insulated at rafters | Pitched, no ins…      1   16.240755


                                                        amin       amax
ROOF_DESCRIPTION
Pitched, 250 mm loft insulation | Pitched, insu…  21.961448  21.961448
Pitched, 50 mm loft insulation | Pitched, no in…  21.396276  21.396276
Pitched, 25 mm loft insulation | Pitched, 50 mm…  17.166273  17.166273
Pitched, 100 mm loft insulation | Pitched, 200 …  16.828744  16.828744
Pitched, insulated at rafters | Pitched, no ins…  16.240755  16.240755
```

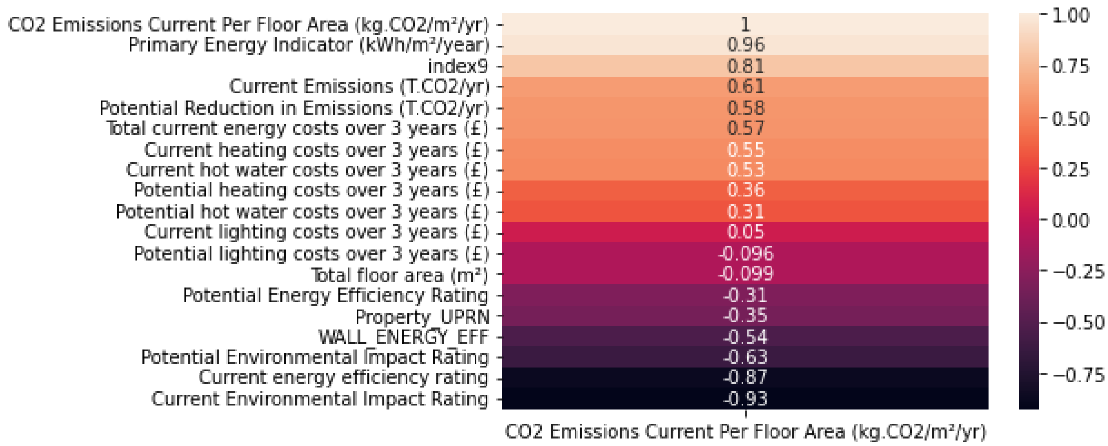
1 2

https://stackabuse.com/bytes/calculate-correlation-of-dataframe-featurescolumns-with-pandas/

1. Build and algorithm to find correlations between CO2 emissions current per floor area vs wall description and wall energy efficiency - (5 points)

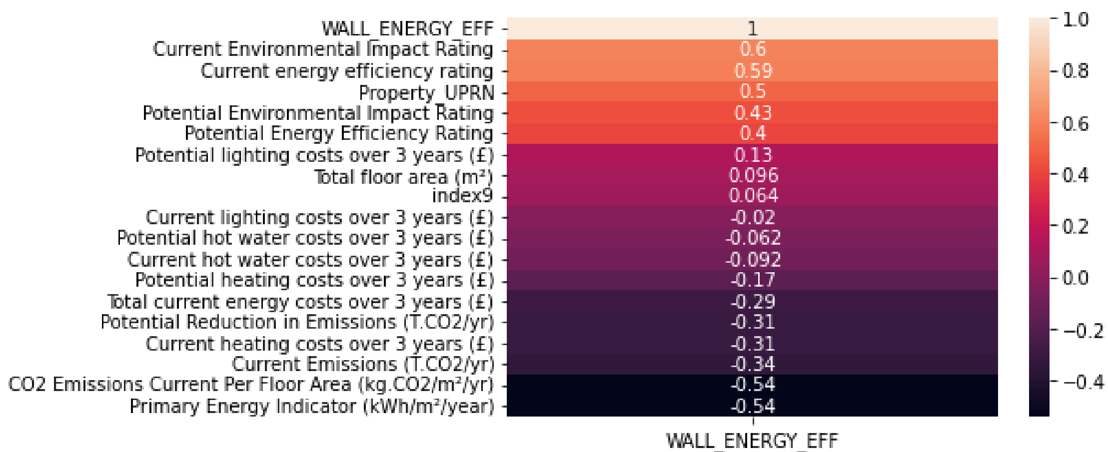
[50]:
```python
corrCO2 = dataframe.corr()[["CO2 Emissions Current Per Floor Area (kg.CO2/m²/
↪yr)"]].sort_values(by='CO2 Emissions Current Per Floor Area (kg.CO2/m²/yr)',␣
↪ascending=False)
sns.heatmap(corrCO2, annot=True)
```

[50]: <AxesSubplot:>




```
[51]: corrWallEff = dataframe.corr()[["WALL_ENERGY_EFF"]].
        ↪sort_values(by='WALL_ENERGY_EFF', ascending=False)
      sns.heatmap(corrWallEff, annot=True)
```

[51]: <AxesSubplot:>




```
[52]: df_algo_1 = dataframe[["CO2 Emissions Current Per Floor Area (kg.CO2/m²/yr)",␣
        ↪"WALL_ENERGY_EFF","WALL_DESCRIPTION"]]
```

```
[53]: df_algo_1 = pd.get_dummies(df_algo_1, columns=['WALL_DESCRIPTION'])
```

```
[54]: corr_algo_1 = df_algo_1.corr()[["CO2 Emissions Current Per Floor Area (kg.CO2/
        ↪m²/yr)"]].sort_values(by='CO2 Emissions Current Per Floor Area (kg.CO2/m²/
        ↪yr)', ascending=False)
      corr_algo_1.head(25)
```

```
[54]:                                               CO2 Emissions Current Per
Floor Area (kg.CO2/m²/yr)
CO2 Emissions Current Per Floor Area (kg.CO2/m²…
1.000000
WALL_DESCRIPTION_Sandstone or limestone, as bui…
0.147565
WALL_DESCRIPTION_Granite or whinstone, as built…
0.147330
WALL_DESCRIPTION_Cavity wall, as built, no insu…
0.133198
WALL_DESCRIPTION_Cavity wall, as built, no insu…
0.098835
WALL_DESCRIPTION_Sandstone or limestone, as bui…
0.095882
WALL_DESCRIPTION_Cavity wall, as built, no insu…
0.084978
WALL_DESCRIPTION_System built, as built, no ins…
0.084660
WALL_DESCRIPTION_Granite or whinstone, as built…
0.080292
WALL_DESCRIPTION_Solid brick, as built, no insu…
0.075816
WALL_DESCRIPTION_Timber frame, as built, no ins…
0.061895
WALL_DESCRIPTION_Granite or whinstone, as built…
0.056654
WALL_DESCRIPTION_Granite or whinstone, as built…
0.042642
WALL_DESCRIPTION_Timber frame, as built, partia…
0.042063
WALL_DESCRIPTION_Solid brick, as built, no insu…
0.040726
WALL_DESCRIPTION_Granite or whinstone, as built…
0.040162
WALL_DESCRIPTION_Cavity wall, as built, partial…
0.039709
WALL_DESCRIPTION_Cavity wall, as built, no insu…
0.038955
WALL_DESCRIPTION_Cavity wall, as built, partial…
0.038843
WALL_DESCRIPTION_Sandstone or limestone, as bui…
0.037483
WALL_DESCRIPTION_Cavity wall, as built, insulat…
0.036280
WALL_DESCRIPTION_Cavity wall, as built, no insu…
0.036153
WALL_DESCRIPTION_Granite or whinstone, as built…
```

```
0.036105
WALL_DESCRIPTION_Cavity wall, as built, partial…
0.036011
WALL_DESCRIPTION_Cavity wall, as built, insulat…
0.034387
```

[55]:
```
corr_algo_1.tail(25)
```

[55]:
```
                                                    CO2 Emissions Current Per
Floor Area (kg.CO2/m²/yr)
WALL_DESCRIPTION_Cavity wall, as built, insulat…
-0.024844
WALL_DESCRIPTION_Average thermal transmittance …
-0.024912
WALL_DESCRIPTION_System built, as built, no ins…
-0.024974
WALL_DESCRIPTION_Cavity wall, as built, insulat…
-0.025952
WALL_DESCRIPTION_Average thermal transmittance …
-0.026359
WALL_DESCRIPTION_Average thermal transmittance …
-0.027116
WALL_DESCRIPTION_Average thermal transmittance …
-0.030017
WALL_DESCRIPTION_Average thermal transmittance …
-0.030343
WALL_DESCRIPTION_Average thermal transmittance …
-0.039062
WALL_DESCRIPTION_Average thermal transmittance …
-0.043661
WALL_DESCRIPTION_Solid brick, as built, insulat…
-0.044190
WALL_DESCRIPTION_Cavity wall, as built, insulat…
-0.044379
WALL_DESCRIPTION_Solid brick, as built, insulat…
-0.046284
WALL_DESCRIPTION_Average thermal transmittance …
-0.067553
WALL_DESCRIPTION_System built, as built, insula…
-0.070615
WALL_DESCRIPTION_Average thermal transmittance …
-0.087900
WALL_DESCRIPTION_Average thermal transmittance …
-0.089966
WALL_DESCRIPTION_Average thermal transmittance …
-0.091865
WALL_DESCRIPTION_Average thermal transmittance …
```

```
-0.102216
WALL_DESCRIPTION_Average thermal transmittance …
-0.124610
WALL_DESCRIPTION_Timber frame, as built, insula…
-0.145286
WALL_DESCRIPTION_Average thermal transmittance …
-0.166051
WALL_DESCRIPTION_Average thermal transmittance …
-0.184010
WALL_DESCRIPTION_Average thermal transmittance …
-0.220240
WALL_ENERGY_EFF
-0.539478
```

2 Build and algorithm to find correlations between CO2 emissions current per floor area vs roof description and roof energy efficiency - (5 points)

[56]:
```
df_algo_2 = dataframe[["CO2 Emissions Current Per Floor Area (kg.CO2/m²/yr)",␣
↪"ROOF_ENERGY_EFF","ROOF_DESCRIPTION"]]
df_algo_2 = pd.get_dummies(df_algo_2, columns=['ROOF_DESCRIPTION'])
corr_algo_2 = df_algo_2.corr()[["CO2 Emissions Current Per Floor Area (kg.CO2/
↪m²/yr)"]].sort_values(by='CO2 Emissions Current Per Floor Area (kg.CO2/m²/
↪yr)', ascending=False)
corr_algo_2.head(25)
```

[56]:
```
                                                    CO2 Emissions Current Per
Floor Area (kg.CO2/m²/yr)
CO2 Emissions Current Per Floor Area (kg.CO2/m²…
1.000000
ROOF_DESCRIPTION_Pitched, no insulation (assumed)
0.170423
ROOF_DESCRIPTION_Pitched, no insulation (assume…
0.109249
ROOF_DESCRIPTION_Roof room(s), no insulation (a…
0.096822
ROOF_DESCRIPTION_Pitched, no insulation (assumed)
0.090895
ROOF_DESCRIPTION_Pitched, no insulation
0.089627
ROOF_DESCRIPTION_Flat, no insulation (assumed)
0.061669
ROOF_DESCRIPTION_Pitched, 100 mm loft insulation
0.059501
ROOF_DESCRIPTION_Roof room(s), ceiling insulated
0.057374
ROOF_DESCRIPTION_Pitched, limited insulation (a…
0.057124
```

```
ROOF_DESCRIPTION_Pitched, no insulation (assume…
0.056380
ROOF_DESCRIPTION_Pitched, no insulation | Roof …
0.055006
ROOF_DESCRIPTION_Pitched, no insulation (assume…
0.054743
ROOF_DESCRIPTION_Pitched, no insulation
0.052219
ROOF_DESCRIPTION_Pitched, 100 mm loft insulatio…
0.046286
ROOF_DESCRIPTION_Roof room(s), no insulation (a…
0.044902
ROOF_DESCRIPTION_Pitched, 50 mm loft insulation
0.043280
ROOF_DESCRIPTION_Flat, limited insulation (assu…
0.042721
ROOF_DESCRIPTION_Flat, no insulation (assumed) …
0.041753
ROOF_DESCRIPTION_Pitched, 200 mm loft insulatio…
0.037325
ROOF_DESCRIPTION_Flat, limited insulation (assu…
0.035895
ROOF_DESCRIPTION_Pitched, 150 mm loft insulatio…
0.035728
ROOF_DESCRIPTION_Pitched, 100 mm loft insulation
0.035596
ROOF_DESCRIPTION_Flat, no insulation (assumed) …
0.033131
ROOF_DESCRIPTION_Pitched, 150 mm loft insulation
0.032498
```

[57]:
```
corr_algo_2.tail(25)
```

[57]:
```
                                                     CO2 Emissions Current Per
Floor Area (kg.CO2/m²/yr)
ROOF_DESCRIPTION_Average thermal transmittance …
-0.020449
ROOF_DESCRIPTION_Average thermal transmittance …
-0.021004
ROOF_DESCRIPTION_Flat, insulated (assumed)
-0.022001
ROOF_DESCRIPTION_Average thermal transmittance …
-0.023086
ROOF_DESCRIPTION_Average thermal transmittance …
-0.027601
ROOF_DESCRIPTION_Pitched, 400+ mm loft insulation
-0.028157
```

```
ROOF_DESCRIPTION_(another dwelling above)
-0.030751
ROOF_DESCRIPTION_Average thermal transmittance …
-0.035884
ROOF_DESCRIPTION_Average thermal transmittance …
-0.037202
ROOF_DESCRIPTION_Average thermal transmittance …
-0.037888
ROOF_DESCRIPTION_Average thermal transmittance …
-0.040976
ROOF_DESCRIPTION_Average thermal transmittance …
-0.042605
ROOF_DESCRIPTION_Average thermal transmittance …
-0.055881
ROOF_DESCRIPTION_Average thermal transmittance …
-0.058787
ROOF_DESCRIPTION_Average thermal transmittance …
-0.073677
ROOF_DESCRIPTION_Average thermal transmittance …
-0.076650
ROOF_DESCRIPTION_Average thermal transmittance …
-0.077936
ROOF_DESCRIPTION_Average thermal transmittance …
-0.078285
ROOF_DESCRIPTION_(other premises above)
-0.089748
ROOF_DESCRIPTION_Average thermal transmittance …
-0.090455
ROOF_DESCRIPTION_Average thermal transmittance …
-0.100062
ROOF_DESCRIPTION_Average thermal transmittance …
-0.127215
ROOF_DESCRIPTION_(other premises above)
-0.158682
ROOF_DESCRIPTION_Average thermal transmittance …
-0.164210
ROOF_DESCRIPTION_Average thermal transmittance …
-0.190300
```

3 Build and algorithm to find correlations between construction age band vs current energy efficiency and current emissions (T.CO2/yr) - (5 points)

[58]:
```
df_algo_3 = dataframe[["Current Emissions (T.CO2/yr)", "Current energy␣
↪efficiency rating","Part 1 Construction Age Band"]]
df_algo_3 = pd.get_dummies(df_algo_3, columns=['Part 1 Construction Age Band'])
corr_algo_3 = df_algo_3.corr()[["Current Emissions (T.CO2/yr)"]].
↪sort_values(by='Current Emissions (T.CO2/yr)', ascending=False)
```

```
corr_algo_3.head(25)
```

[58]:

	Current Emissions (T.CO2/yr)
Current Emissions (T.CO2/yr)	1.000000
Part 1 Construction Age Band_before 1919	0.269476
Part 1 Construction Age Band_1919-1929	0.043787
Part 1 Construction Age Band_1930-1949	0.039775
Part 1 Construction Age Band_1965-1975	0.032173
Part 1 Construction Age Band_1950-1964	0.021660
Part 1 Construction Age Band_1976-1983	0.003980
Part 1 Construction Age Band_1999-2002	-0.021283
Part 1 Construction Age Band_1992-1998	-0.022020
Part 1 Construction Age Band_1984-1991	-0.022652
Part 1 Construction Age Band_2008 onwards	-0.059909
Part 1 Construction Age Band_2003-2007	-0.062239
Current energy efficiency rating	-0.675123

[59]:
```
corr_algo_3.tail(25)
```

[59]:

	Current Emissions (T.CO2/yr)
Current Emissions (T.CO2/yr)	1.000000
Part 1 Construction Age Band_before 1919	0.269476
Part 1 Construction Age Band_1919-1929	0.043787
Part 1 Construction Age Band_1930-1949	0.039775
Part 1 Construction Age Band_1965-1975	0.032173
Part 1 Construction Age Band_1950-1964	0.021660
Part 1 Construction Age Band_1976-1983	0.003980
Part 1 Construction Age Band_1999-2002	-0.021283
Part 1 Construction Age Band_1992-1998	-0.022020
Part 1 Construction Age Band_1984-1991	-0.022652
Part 1 Construction Age Band_2008 onwards	-0.059909
Part 1 Construction Age Band_2003-2007	-0.062239
Current energy efficiency rating	-0.675123