

Sample

May 12, 2021

```
[1]: import pandas as pd
from copy import deepcopy
import matplotlib.pyplot as plt
import re
import numpy as np
from matplotlib import gridspec
import matplotlib
```

1 Helper functions

These are borrowed from the `Convert.ipynb` file.

```
[2]: headings = ['Building Identifier',
                 'Country',
                 'City',
                 'Quality / Stage of Data',
                 'Construction Date',
                 'Building Type',
                 'Gross Floor Area']
```

```
[3]: df = pd.read_excel('../Dataset/dataset.xlsx',header=1).drop('Unnamed: 0',axis=1)
```

```
[4]: df
```

```
[4]:
```

	Building Identifier	Country	City	Quality / Stage of Data	\
0	1	CA	TOR	00IFC	
1	2	CA	TOR	00IFC	
2	3	CA	TOR	00IFC	
3	4	CA	TOR	00IFC	
4	5	CA	TOR	00IFC	
5	6	CA	TOR	00IFC	
6	7	CA	TOR	00IFC	
7	8	CA	TOR	00IFC	
8	9	CA	TOR	00IFC	
9	10	CA	TOR	00IFC	
10	11	CA	TOR	00IFC	
11	12	CA	TOR	00IFC	

12	13	CA	TOR	00IFC
13	14	CA	TOR	00IFC
14	15	CA	TOR	00IFC
15	16	CA	TOR	00IFC
16	17	CA	TOR	00IFC
17	18	CA	TOR	00IFC
18	19	CA	TOR	00IFC
19	20	CA	TOR	00IFC
20	21	CA	TOR	00IFC
21	22	CA	TOR	00IFC
22	23	CA	TOR	00IFC
23	24	CA	TOR	00IFC
24	25	CA	TOR	00IFC
25	26	CA	TOR	00IFC
26	27	CA	WIN	00IFC
27	28	CA	TOR	00IFC
28	29	CA	TOR	00IFC
29	30	CA	TOR	00IFC
30	31	CA	TOR	00IFC
31	32	CA	TOR	00IFC
32	33	CA	TOR	00IFC
33	34	CA	TOR	00IFC
34	35	CA	TOR	00IFC
35	36	CA	TOR	00IFC
36	37	CA	TOR	00IFC
37	38	CA	TOR	00IFC
38	39	CA	TOR	00IFC
39	40	US	NEW	00IFC
40	41	CA	TOR	00IFC
41	42	CA	TOR	00IFC
42	43	CA	TOR	00IFC
43	44	CA	TOR	00IFC
44	45	CA	TOR	00IFC
45	46	CA	TOR	00IFC
46	47	CA	TOR	00IFC
47	48	CA	RIC	0IARC
48	49	CA	TOR	00IFC
49	50	CA	TOR	00IFC
50	51	CA	TOR	00IFC
51	52	CA	TOR	00IFC
52	53	CA	TOR	00IFC
53	54	CA	TOR	00IFC
54	55	CA	TOR	00IFC
55	56	CA	TOR	00IFC
56	57	CA	TOR	00IFC
57	58	CA	TOR	00IFC
58	59	CA	TOR	0IFBP

59

60

CA TOR

OIFBP

	Construction Date	Building Type	Gross Floor Area \
0	2021	SND	521.18
1	2021	SND	389.24
2	2021	SND	411.64
3	2021	SND	269.56
4	2011	OFF	11248.00
5	2011	APB	11317.00
6	2021	SND	445.99
7	2021	SND	438.45
8	2021	SND	714.07
9	2021	SND	343.24
10	2009	OFF	73083.00
11	1917	SMR	199.93
12	2021	SND	226.89
13	2021	SND	611.73
14	2021	SND	343.44
15	2021	SND	613.38
16	1969	SNR	413.72
17	1969	SNR	333.49
18	2021	SND	178.38
19	2021	SND	323.80
20	2020	SND	837.56
21	2021	SND	587.86
22	2021	SND	568.21
23	2021	SMD	234.73
24	2021	SND	294.84
25	2021	SND	496.77
26	2007	OFF	73600.00
27	2021	SND	643.30
28	2021	SND	701.61
29	2021	SMD	257.75
30	2021	SND	378.70
31	2021	SND	324.16
32	2020	SND	533.53
33	2020	SMD	254.05
34	2021	SND	423.03
35	2021	SND	328.16
36	2021	SND	421.59
37	2020	SND	628.59
38	2021	SND	464.51
39	2017	EDU	8983.00
40	2021	SND	346.14
41	1913	SNR	161.08
42	2021	SND	891.97
43	2021	SND	525.61

44	2021	SND	502.87
45	2021	SND	379.18
46	2021	SND	549.65
47	2016	EDU	6819.00
48	2020	SND	393.82
49	2021	SND	648.14
50	1988	INS	21934.00
51	2018	APB	53146.02
52	2018	MIX	33975.25
53	2017	APB	69784.00
54	2017	APB	39409.04
55	2016	APB	53871.00
56	2020	LNW	137.23
57	2020	LNW	144.92
58	2019	LNW	83.10
59	2021	LNW	234.79

	000_G2010.20.000_03 00 00.00_kg_1	000_B1010.20.000_03 00 00.00_kg_1 \
0	NaN	NaN
1	NaN	NaN
2	NaN	NaN
3	NaN	NaN
4	13704.0	1.776816e+06
5	NaN	1.514400e+06
6	NaN	NaN
7	NaN	NaN
8	NaN	NaN
9	NaN	NaN
10	58008.0	4.029264e+06
11	NaN	NaN
12	NaN	NaN
13	NaN	NaN
14	NaN	NaN
15	NaN	NaN
16	NaN	NaN
17	NaN	NaN
18	NaN	NaN
19	NaN	NaN
20	NaN	NaN
21	NaN	NaN
22	NaN	NaN
23	NaN	NaN
24	NaN	NaN
25	NaN	NaN
26	NaN	4.480680e+06
27	NaN	NaN
28	NaN	NaN

29	NaN	NaN
30	NaN	NaN
31	NaN	NaN
32	NaN	NaN
33	NaN	NaN
34	NaN	NaN
35	NaN	NaN
36	NaN	NaN
37	NaN	NaN
38	NaN	NaN
39	NaN	2.191431e+04
40	NaN	NaN
41	NaN	NaN
42	NaN	NaN
43	NaN	NaN
44	NaN	NaN
45	NaN	NaN
46	NaN	NaN
47	NaN	3.756000e+04
48	NaN	NaN
49	NaN	NaN
50	NaN	NaN
51	NaN	NaN
52	NaN	NaN
53	NaN	NaN
54	NaN	NaN
55	NaN	NaN
56	NaN	NaN
57	NaN	NaN
58	NaN	NaN
59	NaN	NaN

	000_C1010.10.000_04	22	00.00_kg_1	...	2_B2010.80.000_07	26	13.00_kg_2.1	\
0			NaN	...			NaN	
1			NaN	...			NaN	
2			NaN	...			NaN	
3			NaN	...			NaN	
4			19397.560000	...			NaN	
5			53877.650000	...			NaN	
6			NaN	...			NaN	
7			NaN	...			NaN	
8			NaN	...			NaN	
9			NaN	...			NaN	
10			562574.500000	...			NaN	
11			NaN	...			NaN	
12			NaN	...			NaN	
13			NaN	...			NaN	

14		NaN ...	NaN
15		NaN ...	NaN
16		NaN ...	NaN
17		NaN ...	NaN
18		NaN ...	NaN
19		NaN ...	NaN
20		NaN ...	NaN
21		NaN ...	NaN
22		NaN ...	NaN
23		NaN ...	NaN
24		NaN ...	NaN
25		NaN ...	NaN
26	354208.227500	NaN ...	NaN
27		NaN ...	NaN
28		NaN ...	NaN
29		NaN ...	NaN
30		NaN ...	NaN
31		NaN ...	NaN
32		NaN ...	NaN
33		NaN ...	NaN
34		NaN ...	NaN
35		NaN ...	NaN
36		NaN ...	NaN
37		NaN ...	NaN
38		NaN ...	NaN
39	8666.292723	NaN ...	NaN
40		NaN ...	NaN
41		NaN ...	NaN
42		NaN ...	NaN
43		NaN ...	NaN
44		NaN ...	NaN
45		NaN ...	NaN
46		NaN ...	NaN
47		NaN ...	NaN
48		NaN ...	NaN
49		NaN ...	NaN
50		NaN ...	NaN
51	8194.250000	NaN ...	NaN
52	191988.905000	NaN ...	NaN
53	82694.400000	NaN ...	NaN
54	46298.790000	NaN ...	NaN
55	422839.793489	NaN ...	NaN
56		NaN ...	NaN
57		NaN ...	NaN
58		NaN ...	NaN
59		NaN ...	3.93

	2_B2010.80.000_07 27 00.00_kg_2.1	2_B2010.80.000_07 21 13.00_kg_2.1 \
0	NaN	NaN
1	NaN	NaN
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN
5	NaN	NaN
6	NaN	NaN
7	NaN	NaN
8	NaN	NaN
9	NaN	NaN
10	NaN	NaN
11	NaN	NaN
12	NaN	NaN
13	NaN	NaN
14	NaN	NaN
15	NaN	NaN
16	NaN	NaN
17	NaN	NaN
18	NaN	NaN
19	NaN	NaN
20	NaN	NaN
21	NaN	NaN
22	NaN	NaN
23	NaN	NaN
24	NaN	NaN
25	NaN	NaN
26	NaN	NaN
27	NaN	NaN
28	NaN	NaN
29	NaN	NaN
30	NaN	NaN
31	NaN	NaN
32	NaN	NaN
33	NaN	NaN
34	NaN	NaN
35	NaN	NaN
36	NaN	NaN
37	NaN	NaN
38	NaN	NaN
39	NaN	NaN
40	NaN	NaN
41	NaN	NaN
42	NaN	NaN
43	NaN	NaN
44	NaN	NaN
45	NaN	NaN

46	NaN	NaN
47	NaN	NaN
48	NaN	NaN
49	NaN	NaN
50	NaN	NaN
51	NaN	NaN
52	NaN	NaN
53	NaN	NaN
54	NaN	NaN
55	NaN	NaN
56	NaN	NaN
57	NaN	NaN
58	NaN	NaN
59	37.3	112.67

	2_B2010.10.000_09 24 23.00_kg_2.1	OB1_A5020.10.000_06 11 00.00_kg_2.1 \
0	NaN	NaN
1	NaN	NaN
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN
5	NaN	NaN
6	NaN	NaN
7	NaN	NaN
8	NaN	NaN
9	NaN	NaN
10	NaN	NaN
11	NaN	NaN
12	NaN	NaN
13	NaN	NaN
14	NaN	NaN
15	NaN	NaN
16	NaN	NaN
17	NaN	NaN
18	NaN	NaN
19	NaN	NaN
20	NaN	NaN
21	NaN	NaN
22	NaN	NaN
23	NaN	NaN
24	NaN	NaN
25	NaN	NaN
26	NaN	NaN
27	NaN	NaN
28	NaN	NaN
29	NaN	NaN
30	NaN	NaN

31	NaN	NaN
32	NaN	NaN
33	NaN	NaN
34	NaN	NaN
35	NaN	NaN
36	NaN	NaN
37	NaN	NaN
38	NaN	NaN
39	NaN	NaN
40	NaN	NaN
41	NaN	NaN
42	NaN	NaN
43	NaN	NaN
44	NaN	NaN
45	NaN	NaN
46	NaN	NaN
47	NaN	NaN
48	NaN	NaN
49	NaN	NaN
50	NaN	NaN
51	NaN	NaN
52	NaN	NaN
53	NaN	NaN
54	NaN	NaN
55	NaN	NaN
56	NaN	NaN
57	NaN	NaN
58	NaN	NaN
59	2655.54	277.59

	OB1_A5020.10.000_06 11 00.00_kg_1.1	OB1_A5020.10.000_09 21 16.00_kg_1.1	\
0	NaN	NaN	
1	NaN	NaN	
2	NaN	NaN	
3	NaN	NaN	
4	NaN	NaN	
5	NaN	NaN	
6	NaN	NaN	
7	NaN	NaN	
8	NaN	NaN	
9	NaN	NaN	
10	NaN	NaN	
11	NaN	NaN	
12	NaN	NaN	
13	NaN	NaN	
14	NaN	NaN	
15	NaN	NaN	

16	NaN	NaN
17	NaN	NaN
18	NaN	NaN
19	NaN	NaN
20	NaN	NaN
21	NaN	NaN
22	NaN	NaN
23	NaN	NaN
24	NaN	NaN
25	NaN	NaN
26	NaN	NaN
27	NaN	NaN
28	NaN	NaN
29	NaN	NaN
30	NaN	NaN
31	NaN	NaN
32	NaN	NaN
33	NaN	NaN
34	NaN	NaN
35	NaN	NaN
36	NaN	NaN
37	NaN	NaN
38	NaN	NaN
39	NaN	NaN
40	NaN	NaN
41	NaN	NaN
42	NaN	NaN
43	NaN	NaN
44	NaN	NaN
45	NaN	NaN
46	NaN	NaN
47	NaN	NaN
48	NaN	NaN
49	NaN	NaN
50	NaN	NaN
51	NaN	NaN
52	NaN	NaN
53	NaN	NaN
54	NaN	NaN
55	NaN	NaN
56	NaN	NaN
57	NaN	NaN
58	NaN	NaN
59	889.66	854.98

000_C1010.10.000_07 21 13.00_kg_1.1	00R_B3010.90.000_07 21 13.00_kg_1.1	\
NaN	NaN	

1	NaN	NaN
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN
5	NaN	NaN
6	NaN	NaN
7	NaN	NaN
8	NaN	NaN
9	NaN	NaN
10	NaN	NaN
11	NaN	NaN
12	NaN	NaN
13	NaN	NaN
14	NaN	NaN
15	NaN	NaN
16	NaN	NaN
17	NaN	NaN
18	NaN	NaN
19	NaN	NaN
20	NaN	NaN
21	NaN	NaN
22	NaN	NaN
23	NaN	NaN
24	NaN	NaN
25	NaN	NaN
26	NaN	NaN
27	NaN	NaN
28	NaN	NaN
29	NaN	NaN
30	NaN	NaN
31	NaN	NaN
32	NaN	NaN
33	NaN	NaN
34	NaN	NaN
35	NaN	NaN
36	NaN	NaN
37	NaN	NaN
38	NaN	NaN
39	NaN	NaN
40	NaN	NaN
41	NaN	NaN
42	NaN	NaN
43	NaN	NaN
44	NaN	NaN
45	NaN	NaN
46	NaN	NaN
47	NaN	NaN

48	NaN	NaN
49	NaN	NaN
50	NaN	NaN
51	NaN	NaN
52	NaN	NaN
53	NaN	NaN
54	NaN	NaN
55	NaN	NaN
56	NaN	NaN
57	NaN	NaN
58	NaN	NaN
59	127.47	420.29

00R_B1020.20.000_07 51 13.00_kg_1.1

0	NaN
1	NaN
2	NaN
3	NaN
4	NaN
5	NaN
6	NaN
7	NaN
8	NaN
9	NaN
10	NaN
11	NaN
12	NaN
13	NaN
14	NaN
15	NaN
16	NaN
17	NaN
18	NaN
19	NaN
20	NaN
21	NaN
22	NaN
23	NaN
24	NaN
25	NaN
26	NaN
27	NaN
28	NaN
29	NaN
30	NaN
31	NaN
32	NaN

33	NaN
34	NaN
35	NaN
36	NaN
37	NaN
38	NaN
39	NaN
40	NaN
41	NaN
42	NaN
43	NaN
44	NaN
45	NaN
46	NaN
47	NaN
48	NaN
49	NaN
50	NaN
51	NaN
52	NaN
53	NaN
54	NaN
55	NaN
56	NaN
57	NaN
58	NaN
59	315.22

[60 rows x 4369 columns]

```
[5]: name_conversion = pd.read_csv('name_conversion.csv')
      building_name_conversion = pd.read_csv('building_type_name_conversion.csv')
```

```
[6]: building_name_map = {k['Building Code']:k['Building Type'] for _,k in
      ↪building_name_conversion.iterrows() }
```

```
[7]: name_map = {k.Code:k.Category for _,k in name_conversion.iterrows() }
```

```
[8]: additional_categories_map = {v:k for k,v in {
      'Continuous Footings':'OCF',
      'Foundation Walls':'OFW',
      'Spread Footings':'OSF',
      'Column Piers':'OCP',
      'Columns Supporting Floors':'CSF',
      'Floor Girders and Beams':'FGB',
      'Floor Trusses':'OFT',
      'Floor Joists':'OFJ',
```

```

'Columns Supporting Roofs':'CSR',
'Roof Girders and Beams':'RGB',
'Roof Trusses':'ORT',
'Roof Joists':'ORJ',
'Parking Bumpers':'OPB',
'Precast Concrete Stair Treads':'PCS',
'Roof Curbs':'ORC',
'Exterior Wall Construction':'EWC',
'Composite Decking':'CPD',
'Cast-in-Place concrete':'CIC',
'Floor Structural Frame':'FSF',
'Associated Metal Fabrications':'AMF',
'Floor Construction Supplementary Components':'FCS',
'Roof Construction Supplementary Components':'RCS',
'Residential Elevators':'ORE',
'Vegetated Low-Slope Roofing':'VLR',
'Swimming Pools':'SWP',
'Excavation Soil Anchors':'ESA',
'Floor Trusses':'FTS',
'Roof Window and Skylight Performance':'RWS',
'Rainwater Storage Tanks':'RST',
'Gray Water Tanks':'GWT'}.items()
}

additional_categories_map['OFT'] = 'Floor Trusses'

```

2 1. Plot sample figures

Here we plot building material mass.

```

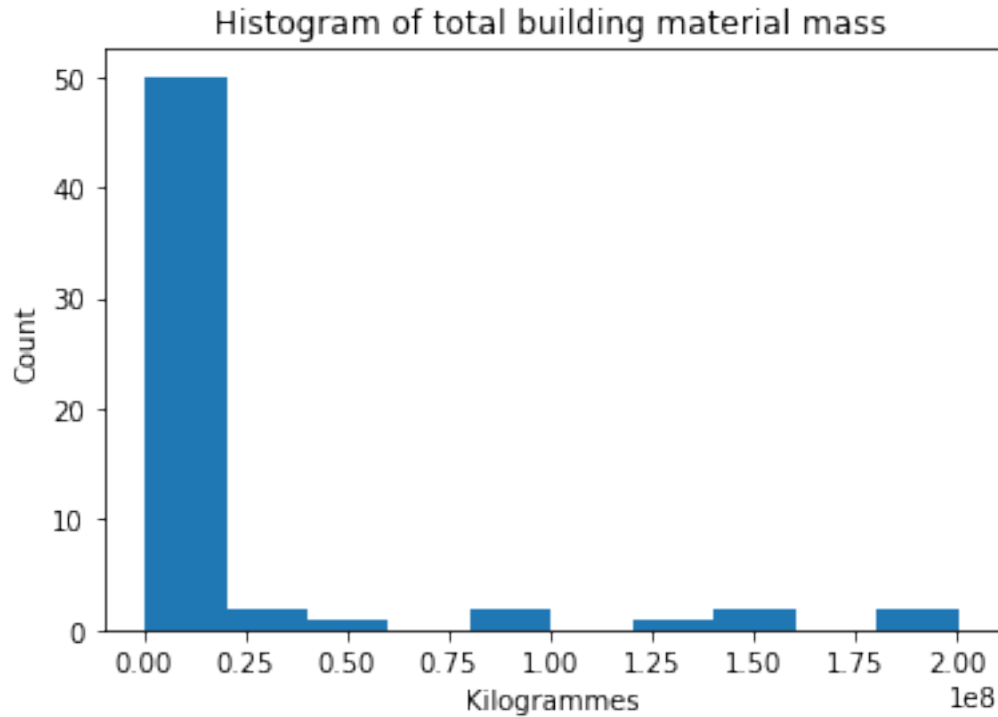
[9]: plt.hist(df[[c for c in df.columns if 'kg' in c]].sum(axis=1));
plt.title('Histogram of total building material mass')
plt.xlabel('Kilogrammes')
plt.ylabel('Count');

```

```

[9]: Text(0, 0.5, 'Count')

```



3 2. Investigate a specific material

In this example, we select only columns that match the MasterFormat code for Structural Concrete. Then, we aggregate based on Level 2 UniFormat code.

```
[10]: cols = [d for d in df.columns if '03 31 00' in d]
```

```
[11]: f = lambda x: re.split('[_\\.\\ ]',x)[1][0:3]
concrete_df = pd.concat([df[headings],df[cols].groupby(f,axis=1).sum()],axis=1).
    ↪rename(columns=name_map)
```

```
[12]: concrete_df
```

```
[12]: Building Identifier Country City Quality / Stage of Data \
0          1          CA  TOR          00IFC
1          2          CA  TOR          00IFC
2          3          CA  TOR          00IFC
3          4          CA  TOR          00IFC
4          5          CA  TOR          00IFC
5          6          CA  TOR          00IFC
6          7          CA  TOR          00IFC
7          8          CA  TOR          00IFC
8          9          CA  TOR          00IFC
```

9	10	CA	TOR	00IFC
10	11	CA	TOR	00IFC
11	12	CA	TOR	00IFC
12	13	CA	TOR	00IFC
13	14	CA	TOR	00IFC
14	15	CA	TOR	00IFC
15	16	CA	TOR	00IFC
16	17	CA	TOR	00IFC
17	18	CA	TOR	00IFC
18	19	CA	TOR	00IFC
19	20	CA	TOR	00IFC
20	21	CA	TOR	00IFC
21	22	CA	TOR	00IFC
22	23	CA	TOR	00IFC
23	24	CA	TOR	00IFC
24	25	CA	TOR	00IFC
25	26	CA	TOR	00IFC
26	27	CA	WIN	00IFC
27	28	CA	TOR	00IFC
28	29	CA	TOR	00IFC
29	30	CA	TOR	00IFC
30	31	CA	TOR	00IFC
31	32	CA	TOR	00IFC
32	33	CA	TOR	00IFC
33	34	CA	TOR	00IFC
34	35	CA	TOR	00IFC
35	36	CA	TOR	00IFC
36	37	CA	TOR	00IFC
37	38	CA	TOR	00IFC
38	39	CA	TOR	00IFC
39	40	US	NEW	00IFC
40	41	CA	TOR	00IFC
41	42	CA	TOR	00IFC
42	43	CA	TOR	00IFC
43	44	CA	TOR	00IFC
44	45	CA	TOR	00IFC
45	46	CA	TOR	00IFC
46	47	CA	TOR	00IFC
47	48	CA	RIC	0IARC
48	49	CA	TOR	00IFC
49	50	CA	TOR	00IFC
50	51	CA	TOR	00IFC
51	52	CA	TOR	00IFC
52	53	CA	TOR	00IFC
53	54	CA	TOR	00IFC
54	55	CA	TOR	00IFC
55	56	CA	TOR	00IFC

56	57	CA	TOR	00IFC
57	58	CA	TOR	00IFC
58	59	CA	TOR	0IFBP
59	60	CA	TOR	0IFBP

	Construction Date	Building Type	Gross Floor Area	Foundations \
0	2021	SND	521.18	3.418472e+05
1	2021	SND	389.24	2.165723e+05
2	2021	SND	411.64	3.818598e+05
3	2021	SND	269.56	1.347385e+05
4	2011	OFF	11248.00	0.000000e+00
5	2011	APB	11317.00	0.000000e+00
6	2021	SND	445.99	2.590405e+05
7	2021	SND	438.45	2.348862e+05
8	2021	SND	714.07	3.855360e+05
9	2021	SND	343.24	1.912945e+05
10	2009	OFF	73083.00	0.000000e+00
11	1917	SMR	199.93	1.985463e+05
12	2021	SND	226.89	1.167094e+05
13	2021	SND	611.73	4.122563e+05
14	2021	SND	343.44	2.873628e+05
15	2021	SND	613.38	3.579554e+05
16	1969	SNR	413.72	1.858717e+05
17	1969	SNR	333.49	2.372760e+05
18	2021	SND	178.38	1.281646e+05
19	2021	SND	323.80	9.466877e+04
20	2020	SND	837.56	5.211311e+05
21	2021	SND	587.86	4.910742e+05
22	2021	SND	568.21	2.830367e+05
23	2021	SMD	234.73	1.712043e+05
24	2021	SND	294.84	1.516173e+05
25	2021	SND	496.77	2.410672e+05
26	2007	OFF	73600.00	0.000000e+00
27	2021	SND	643.30	1.943771e+05
28	2021	SND	701.61	3.621866e+05
29	2021	SMD	257.75	1.636661e+05
30	2021	SND	378.70	2.954456e+05
31	2021	SND	324.16	2.377269e+05
32	2020	SND	533.53	3.254092e+05
33	2020	SMD	254.05	1.776420e+05
34	2021	SND	423.03	1.996054e+05
35	2021	SND	328.16	2.477087e+05
36	2021	SND	421.59	3.520846e+05
37	2020	SND	628.59	4.597656e+05
38	2021	SND	464.51	3.772762e+05
39	2017	EDU	8983.00	0.000000e+00
40	2021	SND	346.14	1.949726e+05

41	1913	SNR	161.08	1.072460e+05
42	2021	SND	891.97	4.315217e+05
43	2021	SND	525.61	5.135450e+05
44	2021	SND	502.87	2.744804e+05
45	2021	SND	379.18	2.874772e+05
46	2021	SND	549.65	2.871788e+05
47	2016	EDU	6819.00	0.000000e+00
48	2020	SND	393.82	1.458941e+05
49	2021	SND	648.14	4.432662e+05
50	1988	INS	21934.00	0.000000e+00
51	2018	APB	53146.02	2.231645e+07
52	2018	MIX	33975.25	8.440080e+06
53	2017	APB	69784.00	1.582589e+07
54	2017	APB	39409.04	1.870147e+07
55	2016	APB	53871.00	3.255024e+06
56	2020	LNW	137.23	6.222788e+04
57	2020	LNW	144.92	6.482345e+04
58	2019	LNW	83.10	6.695447e+04
59	2021	LNW	234.79	1.680143e+05

	Subgrade	Enclosures	Slabs-On-Grade	Substructure	Interior	\
0		0.0	1.344244e+05			0.0
1		0.0	7.152085e+04			0.0
2		0.0	6.492922e+04			0.0
3		0.0	3.190422e+04			0.0
4		0.0	0.000000e+00			0.0
5		0.0	0.000000e+00			0.0
6		0.0	7.043836e+04			0.0
7		0.0	8.578114e+04			0.0
8		0.0	1.689375e+05		22614.4	
9		0.0	4.066228e+04			0.0
10		0.0	0.000000e+00			0.0
11		0.0	3.943520e+04			0.0
12		0.0	2.871974e+04			0.0
13		0.0	8.280078e+04			0.0
14		0.0	4.493672e+04			0.0
15		0.0	8.438890e+04			0.0
16		0.0	6.753628e+04			0.0
17		0.0	5.244732e+04			0.0
18		0.0	4.687724e+04			0.0
19		0.0	4.736970e+04			0.0
20		0.0	1.268970e+05			0.0
21		0.0	1.373142e+05			0.0
22		0.0	1.336938e+05			0.0
23		0.0	2.588720e+04			0.0
24		0.0	3.583642e+04			0.0
25		0.0	1.027599e+05			0.0

26	0.0	0.000000e+00	0.0
27	0.0	1.046046e+05	0.0
28	0.0	1.246644e+05	0.0
29	0.0	2.423771e+04	0.0
30	0.0	7.029444e+04	0.0
31	0.0	4.023936e+04	0.0
32	0.0	7.349277e+04	0.0
33	0.0	2.320773e+04	0.0
34	0.0	6.658572e+04	0.0
35	0.0	3.862318e+04	0.0
36	0.0	6.608874e+04	0.0
37	0.0	1.105763e+05	0.0
38	0.0	5.733554e+04	0.0
39	0.0	0.000000e+00	0.0
40	0.0	4.474196e+04	0.0
41	0.0	2.471316e+04	0.0
42	0.0	1.189866e+05	0.0
43	0.0	6.757370e+04	0.0
44	0.0	7.902094e+04	0.0
45	0.0	5.827598e+04	0.0
46	0.0	7.012780e+04	0.0
47	0.0	0.000000e+00	0.0
48	0.0	6.728550e+04	0.0
49	0.0	1.219806e+05	0.0
50	0.0	0.000000e+00	0.0
51	5456016.0	7.295040e+05	22066896.0
52	3411360.0	7.669440e+05	10800576.0
53	6492336.0	2.814000e+06	28104000.0
54	7135440.0	1.809168e+06	15214560.0
55	6876336.0	1.434960e+06	45814368.0
56	0.0	2.879696e+04	0.0
57	0.0	4.000507e+04	0.0
58	0.0	1.082552e+04	0.0
59	0.0	3.925598e+04	0.0

	Substructure Related Activities	Superstructure \
0	0.0	3.877620e+03
1	0.0	2.795220e+03
2	0.0	3.057420e+02
3	0.0	2.424180e+01
4	0.0	0.000000e+00
5	0.0	0.000000e+00
6	0.0	1.066518e+03
7	0.0	3.941580e+03
8	0.0	8.099340e+03
9	0.0	1.888034e+03
10	0.0	0.000000e+00

11	0.0	0.000000e+00
12	0.0	1.957166e+03
13	0.0	1.076300e+03
14	0.0	0.000000e+00
15	0.0	0.000000e+00
16	0.0	0.000000e+00
17	0.0	1.502968e+04
18	0.0	0.000000e+00
19	0.0	4.223600e+03
20	0.0	6.541620e+03
21	0.0	5.067160e+03
22	0.0	1.203268e+03
23	0.0	3.655220e+03
24	0.0	1.195496e+03
25	0.0	5.081800e+03
26	0.0	0.000000e+00
27	0.0	1.437894e+03
28	0.0	4.552840e+02
29	0.0	3.175800e+03
30	0.0	2.193020e+04
31	0.0	1.106080e+04
32	0.0	2.721960e+03
33	0.0	4.354580e+03
34	0.0	1.304862e+03
35	0.0	7.888300e+03
36	0.0	8.802460e+02
37	0.0	1.703748e+03
38	0.0	5.186320e+03
39	0.0	0.000000e+00
40	0.0	4.721620e+02
41	0.0	0.000000e+00
42	0.0	1.719932e+03
43	0.0	2.077620e+03
44	0.0	9.763680e+02
45	0.0	2.535020e+03
46	0.0	2.309780e+03
47	0.0	0.000000e+00
48	0.0	3.670240e+02
49	0.0	2.082640e+03
50	0.0	0.000000e+00
51	266928.0	5.560013e+07
52	225744.0	4.453070e+07
53	339792.0	6.409243e+07
54	552528.0	2.967154e+07
55	186096.0	6.478267e+07
56	0.0	0.000000e+00
57	0.0	0.000000e+00

58	0.0	0.000000e+00
59	0.0	0.000000e+00

	Exterior Vertical Enclosures	Exterior Horizontal Enclosures \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0
5	0.0	0.0
6	0.0	0.0
7	0.0	0.0
8	0.0	0.0
9	0.0	0.0
10	0.0	0.0
11	0.0	0.0
12	0.0	0.0
13	0.0	0.0
14	0.0	0.0
15	0.0	0.0
16	0.0	0.0
17	0.0	0.0
18	0.0	0.0
19	0.0	0.0
20	0.0	0.0
21	0.0	0.0
22	0.0	0.0
23	0.0	0.0
24	0.0	0.0
25	0.0	0.0
26	0.0	0.0
27	0.0	0.0
28	0.0	0.0
29	0.0	0.0
30	0.0	0.0
31	0.0	0.0
32	0.0	0.0
33	0.0	0.0
34	0.0	0.0
35	0.0	0.0
36	0.0	0.0
37	0.0	0.0
38	0.0	0.0
39	0.0	0.0
40	0.0	0.0
41	0.0	0.0
42	0.0	0.0

43	0.0	0.0
44	0.0	0.0
45	0.0	0.0
46	0.0	0.0
47	0.0	0.0
48	0.0	0.0
49	0.0	0.0
50	0.0	0.0
51	1455792.0	1075968.0
52	810816.0	784800.0
53	656064.0	1599744.0
54	238176.0	0.0
55	318672.0	0.0
56	0.0	0.0
57	0.0	0.0
58	0.0	0.0
59	0.0	0.0

	Interior Construction	Conveying	Plumbing	Special Construction \
0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0
5	0.0	0.0	0.0	0.0
6	0.0	0.0	0.0	0.0
7	0.0	0.0	0.0	0.0
8	0.0	0.0	0.0	0.0
9	0.0	0.0	0.0	0.0
10	0.0	0.0	0.0	0.0
11	0.0	0.0	0.0	0.0
12	0.0	0.0	0.0	0.0
13	0.0	0.0	0.0	0.0
14	0.0	0.0	0.0	0.0
15	0.0	0.0	0.0	0.0
16	0.0	0.0	0.0	0.0
17	0.0	0.0	0.0	0.0
18	0.0	0.0	0.0	0.0
19	0.0	0.0	0.0	0.0
20	0.0	0.0	0.0	0.0
21	0.0	0.0	0.0	0.0
22	0.0	0.0	0.0	0.0
23	0.0	0.0	0.0	0.0
24	0.0	0.0	0.0	0.0
25	0.0	0.0	0.0	0.0
26	0.0	0.0	0.0	0.0
27	0.0	0.0	0.0	0.0

28	0.0	0.0	0.0	0.0
29	0.0	0.0	0.0	0.0
30	0.0	0.0	0.0	0.0
31	0.0	0.0	0.0	0.0
32	0.0	0.0	0.0	0.0
33	0.0	0.0	0.0	0.0
34	0.0	0.0	0.0	0.0
35	0.0	0.0	0.0	0.0
36	0.0	0.0	0.0	0.0
37	0.0	0.0	0.0	0.0
38	0.0	0.0	0.0	0.0
39	0.0	0.0	0.0	0.0
40	0.0	0.0	0.0	0.0
41	0.0	0.0	0.0	0.0
42	0.0	0.0	0.0	0.0
43	0.0	0.0	0.0	0.0
44	0.0	0.0	0.0	0.0
45	0.0	0.0	0.0	0.0
46	0.0	0.0	0.0	0.0
47	0.0	0.0	0.0	0.0
48	0.0	0.0	0.0	0.0
49	0.0	0.0	0.0	0.0
50	0.0	0.0	0.0	0.0
51	13633392.0	4989120.0	0.0	161184.0
52	11786352.0	3658656.0	97632.0	124560.0
53	18101184.0	4608960.0	344064.0	0.0
54	10361952.0	1723776.0	260304.0	0.0
55	11209920.0	3328896.0	0.0	441984.0
56	0.0	0.0	0.0	0.0
57	0.0	0.0	0.0	0.0
58	0.0	0.0	0.0	0.0
59	0.0	0.0	0.0	0.0

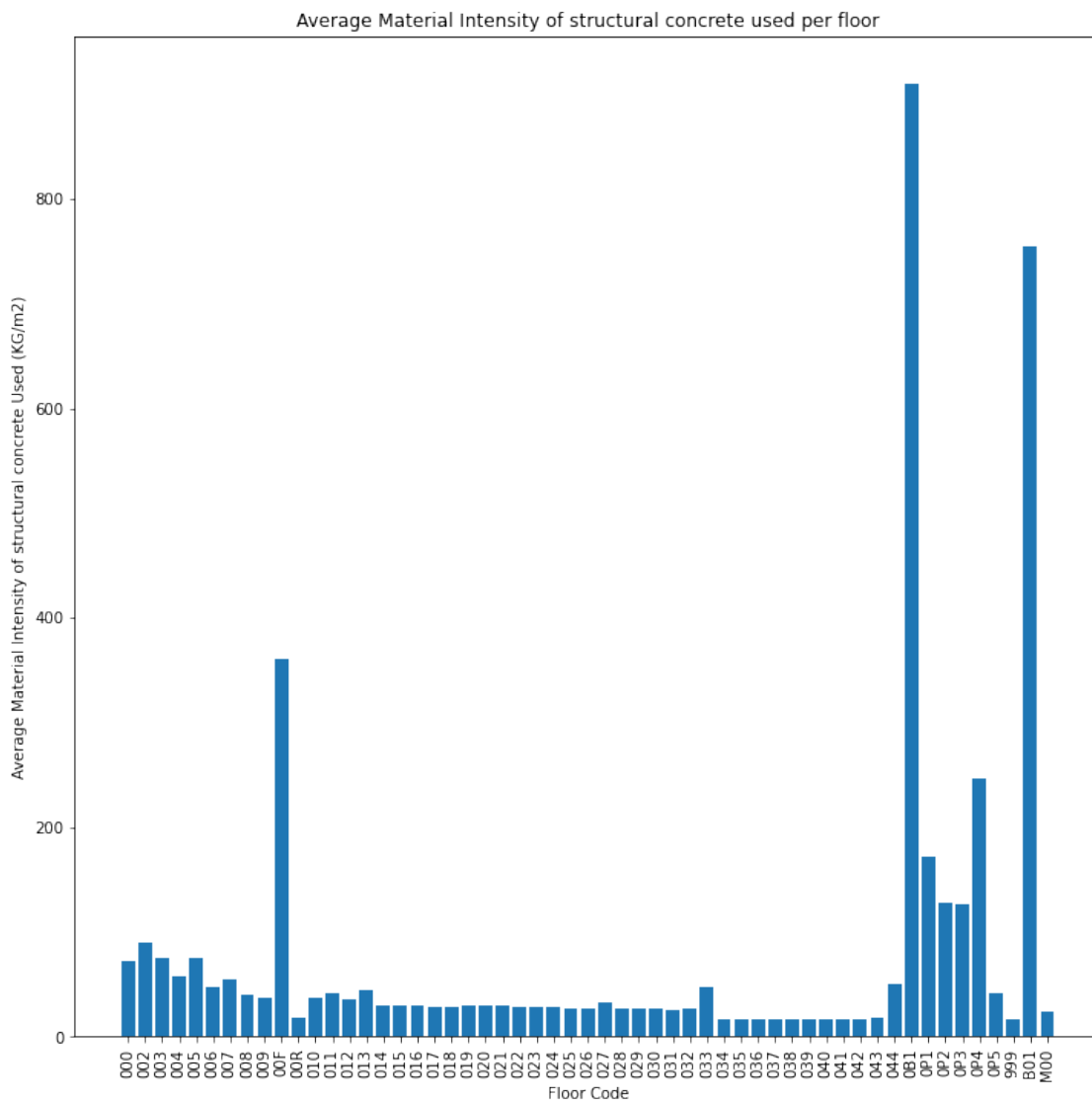
Site Improvements

0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
5	0.0
6	0.0
7	0.0
8	0.0
9	0.0
10	0.0
11	0.0
12	0.0

13	0.0
14	0.0
15	0.0
16	0.0
17	0.0
18	0.0
19	0.0
20	0.0
21	0.0
22	0.0
23	0.0
24	0.0
25	0.0
26	0.0
27	0.0
28	0.0
29	0.0
30	0.0
31	0.0
32	0.0
33	0.0
34	0.0
35	0.0
36	0.0
37	0.0
38	0.0
39	0.0
40	0.0
41	0.0
42	0.0
43	0.0
44	0.0
45	0.0
46	0.0
47	0.0
48	0.0
49	0.0
50	0.0
51	0.0
52	0.0
53	36768.0
54	195120.0
55	0.0
56	0.0
57	0.0
58	0.0
59	0.0


```
[13]: grouping_function = lambda x: x.split('_')[0] #This function takes in a full
      ↪ column name, like "000_G2010.20.000_03 00 00.00_m3_1", and returns only the
      ↪ floor.
      to_draw = df[cols].groupby(grouping_function,axis=1).sum().replace(0,np.NaN).
      ↪ div(df['Gross Floor Area'],axis='rows').mean()
      plt.figure(figsize=(12,12))
      plt.bar(to_draw.keys(), to_draw.values)
      plt.xticks(rotation=90)
      plt.title('Average Material Intensity of structural concrete used per floor')
      plt.ylabel('Average Material Intensity of structural concrete Used (KG/m2)')
      plt.xlabel('Floor Code');
```

```
[13]: Text(0.5, 0, 'Floor Code')
```



Now, we will aggregate to Level 3 MasterFormat codes, and display these values for the first three entries.

```
[14]: f = lambda x: name_map[re.split('_\.\ ',x)[1][0:3]] #This function takes in a
      ↪full column name and returns only the Level 3 MasterFormat code.
      concrete_df = df[cols].groupby(f,axis=1).sum()
```

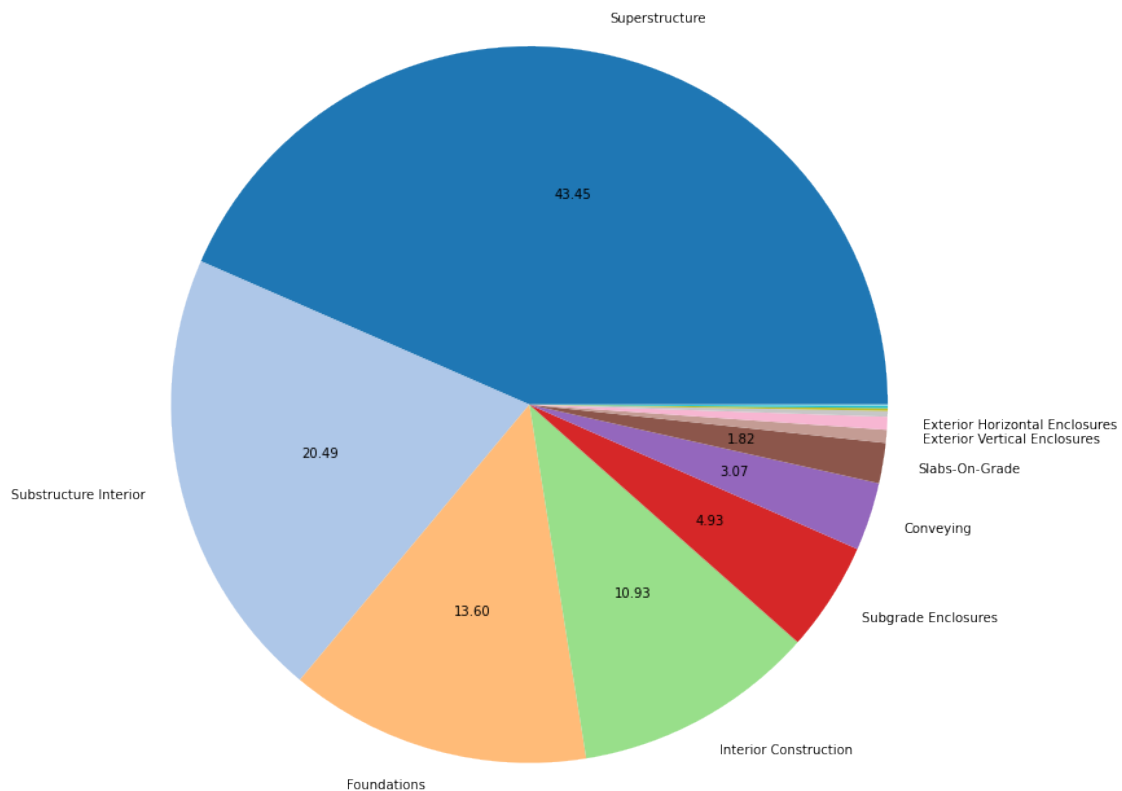
```
[15]: concrete_df.mean().sort_values(ascending=False)
```

```
[15]: Superstructure          4.313652e+06
      Substructure Interior    2.033717e+06
      Foundations             1.350052e+06
      Interior Construction    1.084880e+06
      Subgrade Enclosures      4.895248e+05
      Conveying                3.051568e+05
      Slabs-On-Grade           1.808602e+05
      Exterior Vertical Enclosures 5.799200e+04
      Exterior Horizontal Enclosures 5.767520e+04
      Substructure Related Activities 2.618480e+04
      Special Construction      1.212880e+04
      Plumbing                 1.170000e+04
      Site Improvements        3.864800e+03
      dtype: float64
```

3.1 Pie chart version A: on-pie chart labels for all > 1%

```
[16]: def my_autopct(pct):
      ↪return ('%.2f' % pct) if pct > 1 else ''
      to_plot = concrete_df.mean().sort_values(ascending=False)
      to_plot.plot.pie(figsize=(12,12),colormap='tab20',autopct=my_autopct,labels=[k_
      ↪if v > 30000 else '' for k,v in to_plot.items()])
      plt.ylabel('')
      plt.title('Percentage of total steel (e.g. Reinforcement bars, structural steel_
      ↪framing, steel decking) used in each building element category');
      # plt.legend(loc='center left',bbox_to_anchor=(-0.20, 0.75));
      plt.tight_layout();
```

Percentage of total steel (e.g. Reinforcement bars, structural steel framing, steel decking) used in each building element category



3.2 Pie version B: external legend with slice labels

```
[17]: fig = plt.figure(figsize=(16,12))
gs = gridspec.GridSpec(2, 2, width_ratios=[3, 1])
ax0 = plt.subplot(gs[:,0])

def my_autopct(pct):
    return ('%.2f' % pct) if pct > 1 else ''
to_plot = concrete_df.mean().sort_values(ascending=False)
to_plot.plot.pie(ax=ax0,colormap='tab20',autopct=my_autopct,labeldistance=None)
plt.ylabel('')
plt.legend(loc='center left',bbox_to_anchor=(-0.20, 0.75));
plt.tight_layout();

ax1 = plt.subplot(gs[0,1])
f = lambda x: \
    additional_categories_map[re.split('[_\\.\\ ]',x)[3]] \
    if \
```

```

re.split('[_\\.\\ ]',x)[3] != '000' \
else \
name_map['.'].join(re.split('[_\\.\\ ]',x)[1:3]))

superstructure_df = df[[c for c in cols if 'B10' in c]].groupby(f,axis=1).sum()
to_plot = superstructure_df.mean().sort_values(ascending=False)
def my_autopct(pct):
    return ('%.2f' % ((pct * 0.4335))) if pct > 1 else ''
to_plot.plot.pie(ax=ax1,colormap='Paired',autopct=my_autopct,labeldistance=None)
plt.ylabel('')
plt.legend(loc='center right',bbox_to_anchor=(1, -0.65));
plt.tight_layout();

transFigure = fig.transFigure.inverted()

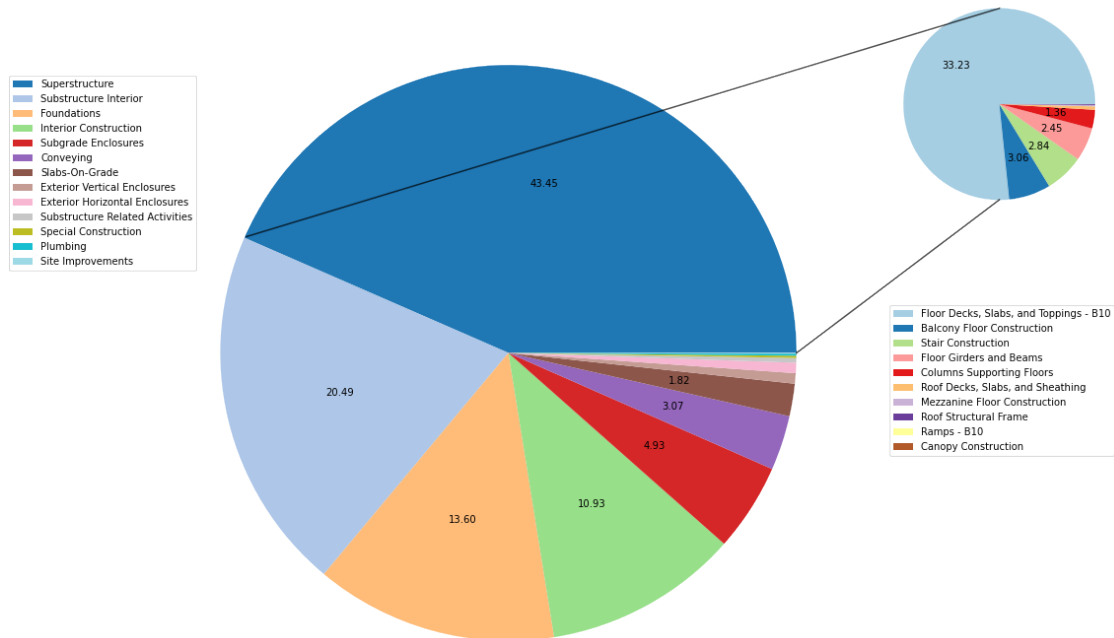
coord1a = transFigure.transform(ax0.transData.transform([1,0]))
coord2a = transFigure.transform(ax1.transData.transform([0,-0.72]))

coord1b = transFigure.transform(ax0.transData.transform([-0.91,0.35]))
coord2b = transFigure.transform(ax1.transData.transform([0,0.72]))

linea = matplotlib.lines.Line2D((coord1a[0],coord2a[0]),(coord1a[1],coord2a[1]),
                                transform=fig.transFigure,c='black',alpha=0.7)
lineb = matplotlib.lines.Line2D((coord1b[0],coord2b[0]),(coord1b[1],coord2b[1]),
                                transform=fig.transFigure,c='black',alpha=0.7)
fig.lines = linea,lineb,

plt.savefig('concrete_breakdown_pie.pdf')

```



We can produce a pie chart for a single building, also.

```
[18]: mf_codes = pd.read_csv('mf_name_conversion.csv')
```

```
[19]: tofind = [
    'Plain Steel Reinforcement Bars',
    'Reinforcement Bars',
    'Structural Steel Framing',
    'Fabric and Grid Reinforcing',
    'Metal Doors',
    'Metal Roof Panel',
    'Metal Stairs',
    'Metal Railings',
    'Steel Decking',
    'Steel Joist Framing',
    'Steel'
] #List of terms we are looking to identify in column names.

tokeep = [
    c for c in mf_codes.Title.values if any(t in c for t in tofind)
] #For each codes' corresponding in MasterFormat

steel_codes = mf_codes[mf_codes.Title.isin(tokeep)]
```

```
[20]: columns_to_keep = []
      for column in df.columns:
          if 'kg' in column:
              code = re.split('_',column)[2]
              for k,c in steel_codes.values:
                  if c in code:
                      columns_to_keep.append(column)
```

```
[21]: f = lambda x: mf_codes[mf_codes.Code == str.replace(re.split('_',x)[2],'00','').
      ↪strip('.').values[0][0]
      steel_df = df[columns_to_keep].groupby(f,axis=1).sum()
```

```
[22]: (steel_df>0).sum(axis=1).sort_values()
```

```
[22]: 15      1
      42      1
      22      1
      36      1
      7       1
      34      1
      31      1
      35      1
      55      2
      58      2
      40      2
      41      2
      1       2
      43      2
      24      2
      23      2
      21      2
      20      2
      54      2
      44      2
      17      2
      16      2
      30      2
      14      2
      45      2
      12      2
      11      2
      32      2
      9       2
      33      2
      3       2
      18      2
      0       3
```

```

52     3
53     3
56     3
46     3
39     3
29     3
37     3
28     3
27     3
26     3
25     3
13     3
10     3
2      3
38     3
5      3
6      3
8      3
57     4
4      4
49     4
50     4
48     4
47     4
19     4
51     4
59     4
dtype: int64

```

```

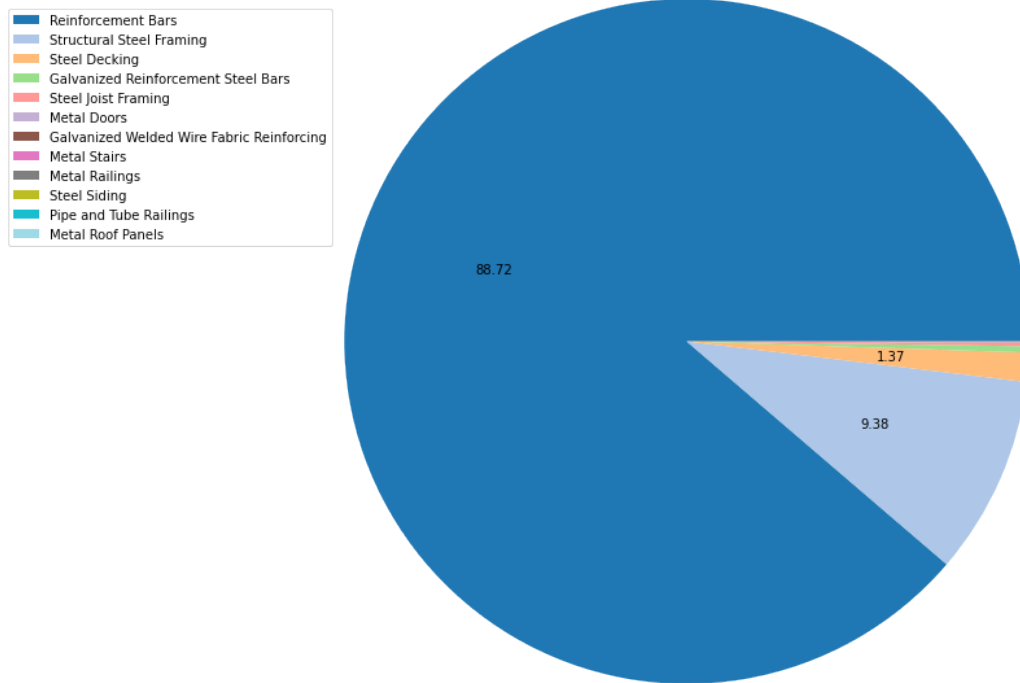
[23]: def my_autopct(pct):
        return ('%.2f' % (pct)) if pct > 1 else ''
to_plot = steel_df.sum().sort_values(ascending=False)
to_plot.plot.
    ↳ pie(figsize=(12,12),colormap='tab20',autopct=my_autopct,labeldistance=None)
plt.legend(loc='center left',bbox_to_anchor=(-0.30, 0.75));

plt.ylabel('')
plt.title(f'Types of steel use in all buildings in terms of MasterFormat_
    ↳ categories');
plt.tight_layout();

plt.savefig('steel_composition_pie.pdf')

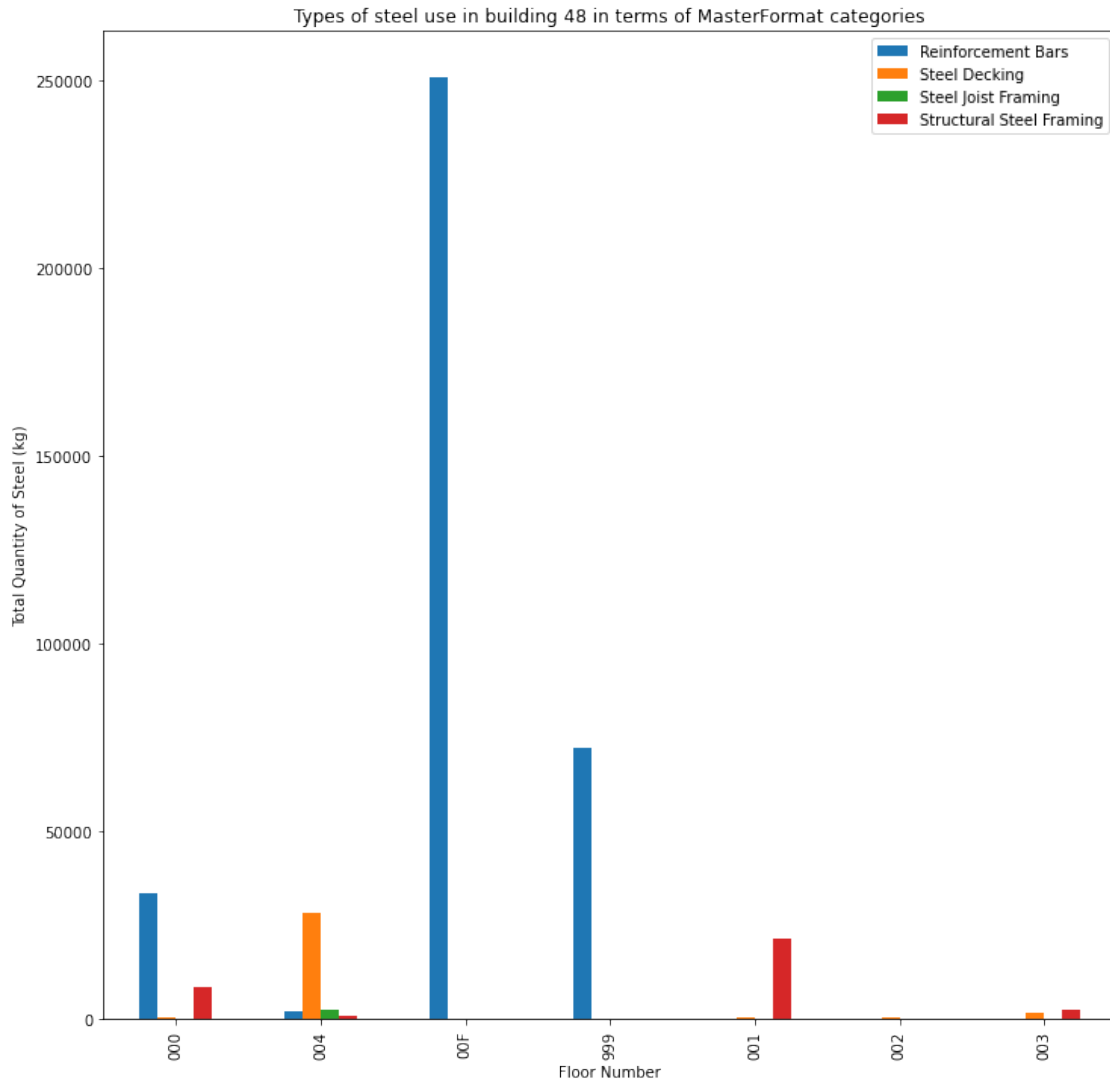
```

Types of steel use in all buildings in terms of MasterFormat categories



```
[24]: f = lambda x: mf_codes[mf_codes.Code == str.replace(re.split('_',x)[2],'00','').
    ↳strip('.')].values[0][0] + '/' + x.split('_')[0]
tdf = df[colums_to_keep].groupby(f,axis=1).sum().iloc[47,:]
tdf = tdf[tdf>0]
```

```
[25]: from collections import defaultdict
todf = defaultdict(dict)
for (a,b),c in zip(tdf.keys().str.split('/'),tdf.values):
    todf[a][b] = c
toplot = pd.DataFrame(todf)
toplot.plot.bar(figsize=(12,12));
plt.xlabel('Floor Number')
plt.ylabel('Total Quantity of Steel (kg)')
plt.title('Types of steel use in building 48 in terms of MasterFormat_
    ↳categories')
plt.savefig('bar_steel_onebuildingtype_byfloor.pdf')
```

We can also calculate the average for each Level 3 MasterFormat code by year of construction:

```
[26]: concrete_df = pd.concat([df[headings[1:]], df[cols].groupby(f,axis=1).
    ↳sum()),axis=1)
    concrete_df.groupby('Construction Date').mean()
```

```
[26]:
```

Construction Date	Gross Floor Area	Structural Concrete/000 \
1913	161.080000	3.888760e+03
1917	199.930000	9.944600e+03
1969	373.605000	1.452444e+04
1988	21934.000000	0.000000e+00
2007	73600.000000	0.000000e+00
2009	73083.000000	0.000000e+00

2011	11282.500000	0.000000e+00
2016	30345.000000	7.191312e+06
2017	39392.013333	8.168704e+06
2018	43560.635000	1.178736e+07
2019	83.100000	0.000000e+00
2020	418.528571	1.967624e+04
2021	445.404444	2.288333e+04

	Structural Concrete/002	Structural Concrete/003 \
Construction Date		
1913	0.0	0.0
1917	0.0	0.0
1969	0.0	0.0
1988	0.0	0.0
2007	0.0	0.0
2009	0.0	0.0
2011	0.0	0.0
2016	5361024.0	3372456.0
2017	1978560.0	2464672.0
2018	3023784.0	2695872.0
2019	0.0	0.0
2020	0.0	0.0
2021	0.0	0.0

	Structural Concrete/004	Structural Concrete/005 \
Construction Date		
1913	0.0	0.0
1917	0.0	0.0
1969	0.0	0.0
1988	0.0	0.0
2007	0.0	0.0
2009	0.0	0.0
2011	0.0	0.0
2016	2114064.0	2113560.0
2017	1556960.0	1366992.0
2018	2646264.0	4329624.0
2019	0.0	0.0
2020	0.0	0.0
2021	0.0	0.0

	Structural Concrete/006	Structural Concrete/007 \
Construction Date		
1913	0.0	0.0
1917	0.0	0.0
1969	0.0	0.0
1988	0.0	0.0
2007	0.0	0.0

2009	0.0	0.0
2011	0.0	0.0
2016	2259360.0	3619704.0
2017	1358752.0	1265040.0
2018	1938120.0	1504416.0
2019	0.0	0.0
2020	0.0	0.0
2021	0.0	0.0

	Structural Concrete/008	Structural Concrete/009	...	\
Construction Date			...	
1913	0.0	0.0	...	
1917	0.0	0.0	...	
1969	0.0	0.0	...	
1988	0.0	0.0	...	
2007	0.0	0.0	...	
2009	0.0	0.0	...	
2011	0.0	0.0	...	
2016	1715952.0	1715688.0	...	
2017	1302160.0	851088.0	...	
2018	1469376.0	1469376.0	...	
2019	0.0	0.0	...	
2020	0.0	0.0	...	
2021	0.0	0.0	...	

	Structural Concrete/044	Structural Concrete/0B1	\
Construction Date			
1913	0.0	0.000000	
1917	0.0	0.000000	
1969	0.0	0.000000	
1988	0.0	0.000000	
2007	0.0	0.000000	
2009	0.0	0.000000	
2011	0.0	0.000000	
2016	0.0	0.000000	
2017	1156064.0	0.000000	
2018	0.0	0.000000	
2019	0.0	77779.984332	
2020	0.0	0.000000	
2021	0.0	5757.507222	

	Structural Concrete/0P1	Structural Concrete/0P2	\
Construction Date			
1913	0.0	0.0	
1917	0.0	0.0	
1969	0.0	0.0	
1988	0.0	0.0	

2007	0.0	0.0
2009	0.0	0.0
2011	0.0	0.0
2016	4413336.0	3430056.0
2017	6719360.0	4959520.0
2018	7421040.0	5274120.0
2019	0.0	0.0
2020	0.0	0.0
2021	0.0	0.0

	Structural Concrete/OP3	Structural Concrete/OP4 \
Construction Date		
1913	0.0	0.0
1917	0.0	0.0
1969	0.0	0.0
1988	0.0	0.0
2007	0.0	0.0
2009	0.0	0.0
2011	0.0	0.0
2016	3192888.0	18263952.0
2017	4881280.0	3730944.0
2018	5513832.0	8186568.0
2019	0.0	0.0
2020	0.0	0.0
2021	0.0	0.0

	Structural Concrete/OP5	Structural Concrete/999 \
Construction Date		
1913	0.0	0.0
1917	0.0	0.0
1969	0.0	0.0
1988	0.0	0.0
2007	0.0	0.0
2009	0.0	0.0
2011	0.0	0.0
2016	0.0	310152.0
2017	979872.0	324016.0
2018	0.0	1123824.0
2019	0.0	0.0
2020	0.0	0.0
2021	0.0	0.0

	Structural Concrete/B01	Structural Concrete/M00
Construction Date		
1913	128070.380000	0.0
1917	228036.920000	0.0
1969	264556.030000	0.0

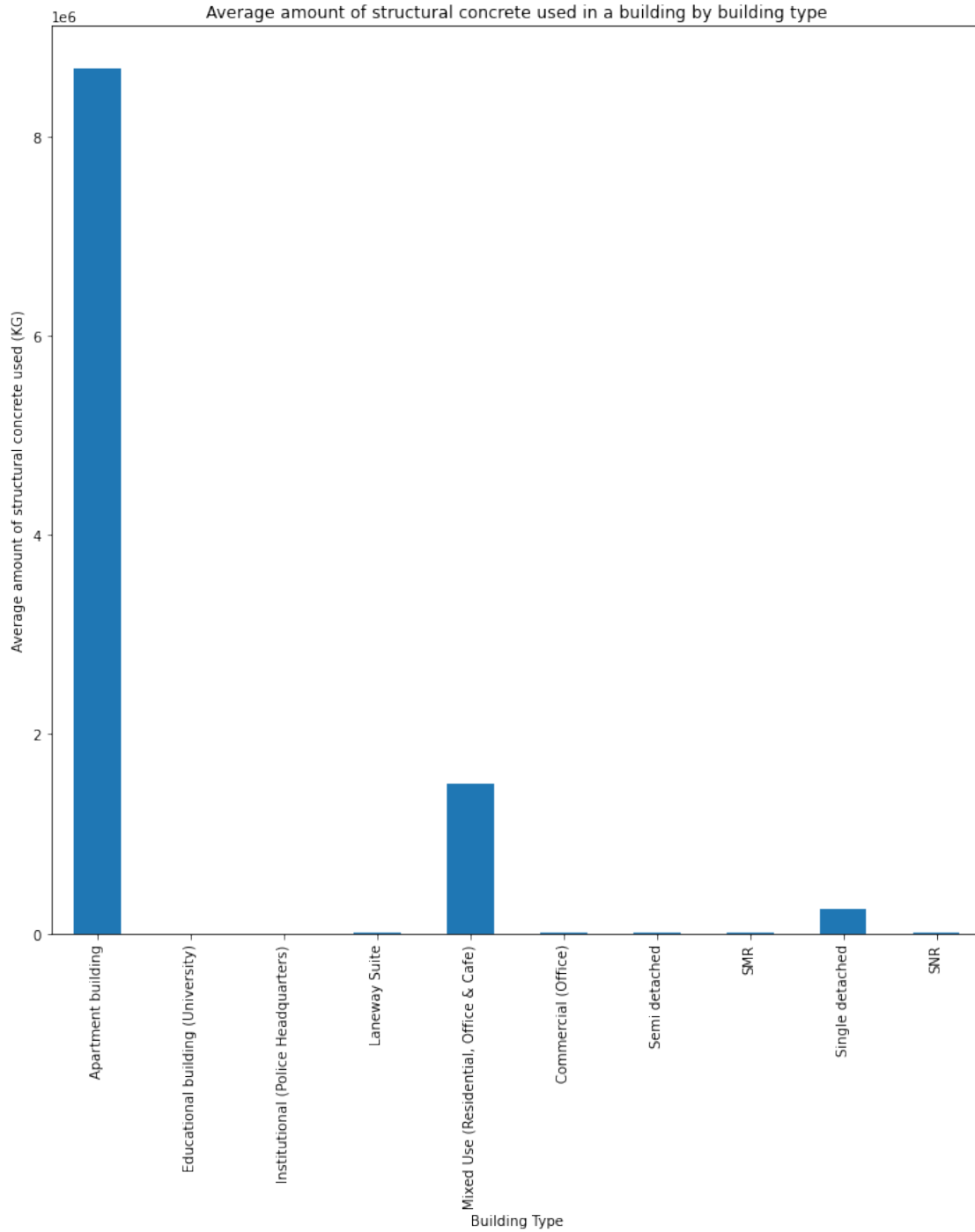
1988	0.000000	0.0
2007	0.000000	0.0
2009	0.000000	0.0
2011	0.000000	0.0
2016	0.000000	164112.0
2017	0.000000	0.0
2018	0.000000	1195248.0
2019	0.000000	0.0
2020	282579.811429	0.0
2021	323452.856389	0.0

[13 rows x 56 columns]

We can get the average amount of steel in KG used per building type:

```
[27]: concrete_df.groupby('Building Type').sum().mean(axis=1).
      ↪ rename(index=building_name_map).plot(kind='bar',figsize=(12,12))
plt.ylabel('Average amount of structural concrete used (KG)')
plt.title('Average amount of structural concrete used in a building by building_
      ↪ type');
```

```
[27]: Text(0.5, 1.0, 'Average amount of structural concrete used in a building by
building type')
```



4 3. Uncertainty by Building Type

In this section, we look at the uncertainty score associated with each material takeoff. We collect these by building type and then report the number of each value per type of building.

```
[28]: uncertainty_level = {}
      for k,v in df.iterrows():
          #Initialise empty lists for each building type as they occur
          if v['Building Type'] not in uncertainty_level.keys():
              uncertainty_level[v['Building Type']] = []
          #Append the uncertainty value for each column that is non-NaN
          for key in v[~v.isna()].keys()[7:]:
              uncertainty_level[v['Building Type']].append(key.split('_')[-1])

[29]: from collections import Counter

[30]: for k,v in uncertainty_level.items():
      uncertainty_level[k] = Counter(v) #Construct a Counter object per building_
      ↪ type

[31]: uncertainty_level

[31]: {'SND': Counter({'1': 1619,
                     '2': 626,
                     '4': 284,
                     '1.1': 1619,
                     '2.1': 626,
                     '4.1': 284}),
      'OFF': Counter({'1': 494, '3': 307, '1.1': 494, '3.1': 307}),
      'APB': Counter({'1': 1149,
                     '2': 1,
                     '3': 970,
                     '1.1': 1149,
                     '2.1': 1,
                     '3.1': 970}),
      'SMR': Counter({'1': 21, '2': 26, '4': 8, '1.1': 21, '2.1': 26, '4.1': 8}),
      'SNR': Counter({'1': 58, '2': 70, '4': 52, '1.1': 58, '2.1': 70, '4.1': 52}),
      'SMD': Counter({'1': 170,
                     '2': 34,
                     '4': 19,
                     '1.1': 170,
                     '2.1': 34,
                     '4.1': 19}),
      'EDU': Counter({'1': 93, '3': 24, '1.1': 93, '3.1': 24, '2': 6, '2.1': 6}),
      'INS': Counter({'1': 90, '3': 77, '2': 1, '1.1': 90, '3.1': 77, '2.1': 1}),
      'MIX': Counter({'1': 363, '3': 276, '1.1': 363, '3.1': 276}),
      'LNW': Counter({'2': 46,
                     '1': 142,
                     '4': 18,
                     '2.1': 46,
                     '1.1': 142,
                     '4.1': 18})}
```

Next, we aggregate columns by the purpose of the material and uncertainty combined, and report the average by building type.

```
[32]: f = lambda x: name_map[re.split('[_\\.\\ ]',x)[1][0]] + '/' + x.split('_')[-1].
      ↪split('.')[0] #From a full code, return only the use code and uncertainty
      ↪score.
by_function_df = pd.concat([df[headings[1:]],df[cols].groupby(f,axis=1).
      ↪sum()],axis=1)
```

```
[33]: by_function_df.groupby('Building Type').mean().rename(index=building_name_map).
      ↪drop(['Construction Date'],axis=1).round(2)
```

```
[33]:
```

	Gross Floor Area	Interiors/1	\
Building Type			
Apartment building	45505.41	10661289.6	
Educational building (University)	7901.00	0.0	
Institutional (Police Headquarters)	21934.00	0.0	
Laneway Suite	150.01	0.0	
Mixed Use (Residential, Office & Cafe)	33975.25	11786352.0	
Commercial (Office)	52643.67	0.0	
Semi detached	248.84	0.0	
SMR	199.93	0.0	
Single detached	478.40	0.0	
SNR	302.76	0.0	

	Services/1	Shell/1	Shell/2	\
Building Type				
Apartment building	3051024.0	43898236.80	0.00	
Educational building (University)	0.0	0.00	0.00	
Institutional (Police Headquarters)	0.0	0.00	0.00	
Laneway Suite	0.0	0.00	0.00	
Mixed Use (Residential, Office & Cafe)	3756288.0	46126320.00	0.00	
Commercial (Office)	0.0	0.00	0.00	
Semi detached	0.0	3728.53	0.00	
SMR	0.0	0.00	0.00	
Single detached	0.0	3094.01	26.39	
SNR	0.0	5009.89	0.00	

	Sitework/1	\
Building Type		
Apartment building	46377.6	
Educational building (University)	0.0	
Institutional (Police Headquarters)	0.0	
Laneway Suite	0.0	
Mixed Use (Residential, Office & Cafe)	0.0	
Commercial (Office)	0.0	
Semi detached	0.0	

SMR	0.0
Single detached	0.0
SNR	0.0

Special Construction And Demolition/1 \

Building Type	
Apartment building	120633.6
Educational building (University)	0.0
Institutional (Police Headquarters)	0.0
Laneway Suite	0.0
Mixed Use (Residential, Office & Cafe)	124560.0
Commercial (Office)	0.0
Semi detached	0.0
SMR	0.0
Single detached	0.0
SNR	0.0

Substructure/1 Substructure/2

Building Type		
Apartment building	41078352.00	0.00
Educational building (University)	0.00	0.00
Institutional (Police Headquarters)	0.00	0.00
Laneway Suite	120136.29	89.61
Mixed Use (Residential, Office & Cafe)	23644704.00	0.00
Commercial (Office)	0.00	0.00
Semi detached	195281.69	0.00
SMR	220179.80	17801.72
Single detached	362386.57	10695.74
SNR	186361.58	38668.55

Next, we report the total amount of material falling under each uncertainty score by year of construction.

```
[34]: f = lambda x: x.split('_')[-1].split('.')[0] #Select only the uncertainty score.
print('Average amount of material used per building, by year and uncertainty_
      ↳score (%)')
result = pd.concat([df['Construction Date'],df[[c for c in df.columns if 'kg'_
      ↳in c]].groupby(f,axis=1).sum()],axis=1).groupby('Construction Date').mean()
for k,v in result.iterrows():
    result.loc[k,:] = v/v.sum()
display(result.round(2))
```

Average amount of material used per building, by year and uncertainty score (%)

	1	2	3	4
Construction Date				
1913	0.85	0.08	0.00	0.07
1917	0.75	0.14	0.00	0.11

1969	0.50	0.37	0.00	0.13
1988	0.97	0.00	0.03	0.00
2007	0.97	0.00	0.03	0.00
2009	0.97	0.00	0.03	0.00
2011	0.94	0.03	0.03	0.00
2016	0.95	0.02	0.03	0.00
2017	0.97	0.00	0.03	0.00
2018	0.97	0.00	0.03	0.00
2019	0.96	0.04	0.00	0.00
2020	0.80	0.10	0.00	0.10
2021	0.78	0.09	0.00	0.13

5 4. Material Intensity

We can easily calculate material intensity by dividing takeoffs which are measured in kilograms by the Gross Floor Area:

```
[35]: kilogram_columns = [d for d in df.columns if 'kg' in d]
df_mi = df[kilogram_columns].div(df['Gross Floor Area'],axis=0)
```

```
[36]: kilogram_columns = [d for d in df.columns if 'kg' in d]
df_mi = df[kilogram_columns].div(df['Gross Floor Area'],axis=0)
f = lambda x: name_map[re.split('_\.\. ',x)[1][0:3]]
pd.concat([df[headings[1:]],df_mi[kilogram_columns].groupby(f,axis=1).
    ↪sum()),axis=1][df['Building Type'] == 'SND']
```

```
[36]: Country City Quality / Stage of Data Construction Date Building Type \
0 CA TOR 00IFC 2021 SND
1 CA TOR 00IFC 2021 SND
2 CA TOR 00IFC 2021 SND
3 CA TOR 00IFC 2021 SND
6 CA TOR 00IFC 2021 SND
7 CA TOR 00IFC 2021 SND
8 CA TOR 00IFC 2021 SND
9 CA TOR 00IFC 2021 SND
12 CA TOR 00IFC 2021 SND
13 CA TOR 00IFC 2021 SND
14 CA TOR 00IFC 2021 SND
15 CA TOR 00IFC 2021 SND
18 CA TOR 00IFC 2021 SND
19 CA TOR 00IFC 2021 SND
20 CA TOR 00IFC 2020 SND
21 CA TOR 00IFC 2021 SND
22 CA TOR 00IFC 2021 SND
24 CA TOR 00IFC 2021 SND
25 CA TOR 00IFC 2021 SND
27 CA TOR 00IFC 2021 SND
```

28	CA	TOR	00IFC	2021	SND
30	CA	TOR	00IFC	2021	SND
31	CA	TOR	00IFC	2021	SND
32	CA	TOR	00IFC	2020	SND
34	CA	TOR	00IFC	2021	SND
35	CA	TOR	00IFC	2021	SND
36	CA	TOR	00IFC	2021	SND
37	CA	TOR	00IFC	2020	SND
38	CA	TOR	00IFC	2021	SND
40	CA	TOR	00IFC	2021	SND
42	CA	TOR	00IFC	2021	SND
43	CA	TOR	00IFC	2021	SND
44	CA	TOR	00IFC	2021	SND
45	CA	TOR	00IFC	2021	SND
46	CA	TOR	00IFC	2021	SND
48	CA	TOR	00IFC	2020	SND
49	CA	TOR	00IFC	2021	SND

	Gross Floor Area	Conveying	Exterior Horizontal Enclosures \
0	521.18	0.0	22.275983
1	389.24	0.0	10.923878
2	411.64	0.0	7.572148
3	269.56	0.0	13.006958
6	445.99	0.0	23.867021
7	438.45	0.0	25.414390
8	714.07	0.0	25.731860
9	343.24	0.0	8.601238
12	226.89	0.0	24.848490
13	611.73	0.0	10.280399
14	343.44	0.0	12.988933
15	613.38	0.0	26.181048
18	178.38	0.0	19.564876
19	323.80	0.0	19.649137
20	837.56	0.0	27.043696
21	587.86	0.0	13.899565
22	568.21	0.0	25.508574
24	294.84	0.0	7.301085
25	496.77	0.0	10.705970
27	643.30	0.0	23.538085
28	701.61	0.0	23.598185
30	378.70	0.0	11.045477
31	324.16	0.0	10.722348
32	533.53	0.0	16.989813
34	423.03	0.0	22.204039
35	328.16	0.0	20.469873
36	421.59	0.0	24.446345
37	628.59	0.0	20.817516

38	464.51	0.0	8.237491
40	346.14	0.0	23.574161
42	891.97	0.0	21.420624
43	525.61	0.0	37.836980
44	502.87	0.0	12.029172
45	379.18	0.0	12.338604
46	549.65	0.0	22.621422
48	393.82	0.0	32.233722
49	648.14	0.0	19.369512

	Exterior Vertical	Enclosures	Foundations	...	Interior Finishes \
0		273.879246	671.298734	...	12.404160
1		138.036505	562.637396	...	8.982520
2		202.900740	928.924390	...	6.060738
3		376.430391	510.718271	...	5.840963
6		122.651951	590.233336	...	9.079800
7		261.105842	538.936925	...	9.535021
8		208.621020	553.834246	...	9.796603
9		421.264481	567.787700	...	13.507767
12		373.336551	523.749852	...	8.309207
13		204.664017	687.428497	...	11.155739
14		294.208560	848.199220	...	11.459760
15		313.973141	597.075425	...	11.527797
18		225.047421	742.299832	...	15.099686
19		373.141002	297.539422	...	6.768110
20		183.378773	635.166981	...	10.035389
21		189.114111	856.370643	...	9.421087
22		167.579773	510.025951	...	11.428838
24		255.713013	522.549251	...	7.202727
25		179.766287	503.451674	...	8.643960
27		167.899386	312.730496	...	11.530390
28		106.836046	532.328709	...	11.457562
30		328.429793	807.205178	...	14.442118
31		381.025836	755.707082	...	9.812179
32		137.036860	618.125391	...	9.942594
34		308.145095	487.215328	...	6.455055
35		368.404312	777.488705	...	3.530982
36		317.433015	848.887006	...	6.494623
37		272.153180	739.489718	...	8.361186
38		302.136065	825.690409	...	10.930098
40		292.958678	575.128514	...	11.529474
42		427.354429	490.411613	...	10.388085
43		219.059867	996.020597	...	11.670402
44		182.962148	557.359516	...	5.957241
45		344.836007	782.607723	...	8.646680
46		255.732337	532.936473	...	9.638352
48		280.139019	377.960490	...	15.602610

49

262.237167 694.374981 ...

7.410405

	Plumbing	Site Improvements	Slabs-On-Grade	Special Construction \
0	0.0	0.0	547.944803	0.0
1	0.0	0.0	385.748930	0.0
2	0.0	0.0	341.466712	0.0
3	0.0	0.0	248.373052	0.0
6	0.0	0.0	306.123236	0.0
7	0.0	0.0	423.820216	0.0
8	0.0	0.0	533.419152	0.0
9	0.0	0.0	277.020456	0.0
12	0.0	0.0	258.527086	0.0
13	0.0	0.0	331.026308	0.0
14	0.0	0.0	259.064497	0.0
15	0.0	0.0	332.828674	0.0
18	0.0	0.0	446.797277	0.0
19	0.0	0.0	316.356228	0.0
20	0.0	0.0	286.564536	0.0
21	0.0	0.0	475.837937	0.0
22	0.0	0.0	398.728694	0.0
24	0.0	0.0	262.348369	0.0
25	0.0	0.0	484.569517	0.0
27	0.0	0.0	304.815828	0.0
28	0.0	0.0	338.839280	0.0
30	0.0	0.0	359.737791	0.0
31	0.0	0.0	265.392494	0.0
32	0.0	0.0	270.780577	0.0
34	0.0	0.0	294.917900	0.0
35	0.0	0.0	257.775680	0.0
36	0.0	0.0	294.450482	0.0
37	0.0	0.0	372.669095	0.0
38	0.0	0.0	290.546806	0.0
40	0.0	0.0	279.642162	0.0
42	0.0	0.0	277.989207	0.0
43	0.0	0.0	279.292555	0.0
44	0.0	0.0	364.118658	0.0
45	0.0	0.0	316.892098	0.0
46	0.0	0.0	309.611427	0.0
48	0.0	0.0	397.721411	0.0
49	0.0	0.0	398.418928	0.0

	Subgrade Enclosures	Substructure Interior \
0	19.305806	15.043095
1	13.703909	23.742083
2	22.597144	16.554577
3	8.702931	40.140549
6	18.957284	11.151017

7	8.437842	3.634540
8	17.805246	50.385374
9	19.202489	15.489518
12	7.636806	19.065649
13	15.445508	12.336325
14	18.271059	11.202481
15	9.737016	18.008305
18	0.000000	17.516618
19	9.234013	23.892872
20	14.262339	17.750821
21	15.919505	18.196305
22	12.679302	22.419774
24	14.938095	7.790171
25	18.897377	8.309313
27	0.000000	23.013564
28	23.838920	17.579196
30	15.018237	21.150599
31	10.147984	16.619200
32	17.735736	26.870688
34	0.000000	20.026831
35	9.525678	38.173994
36	19.077879	25.667714
37	12.078412	14.286084
38	18.142034	24.971676
40	15.137569	24.023355
42	9.081839	21.450482
43	13.440870	16.550560
44	12.185477	21.757373
45	18.978312	27.501326
46	12.084458	16.691920
48	12.114254	11.723814
49	14.442444	16.480613

	Substructure Related Activities	Superstructure	Water And Gas Mitigation
0	0.0	60.456007	0.0
1	0.0	52.543045	0.0
2	0.0	47.512572	0.0
3	0.0	60.793441	0.0
6	0.0	79.813025	0.0
7	0.0	79.814947	0.0
8	0.0	76.583183	0.0
9	0.0	70.741076	0.0
12	0.0	70.710629	0.0
13	0.0	66.776008	0.0
14	0.0	78.740032	0.0
15	0.0	81.917127	0.0
18	0.0	126.012088	0.0

19	0.0	73.194094	0.0
20	0.0	57.468451	0.0
21	0.0	74.915166	0.0
22	0.0	72.531075	0.0
24	0.0	60.778949	0.0
25	0.0	87.457857	0.0
27	0.0	70.786828	0.0
28	0.0	78.816226	0.0
30	0.0	164.784471	0.0
31	0.0	92.761405	0.0
32	0.0	50.939741	0.0
34	0.0	71.332214	0.0
35	0.0	98.568923	0.0
36	0.0	68.070763	0.0
37	0.0	94.130050	0.0
38	0.0	75.842867	0.0
40	0.0	55.480441	0.0
42	0.0	58.091063	0.0
43	0.0	66.530978	0.0
44	0.0	74.530550	0.0
45	0.0	93.720893	0.0
46	0.0	62.305655	0.0
48	0.0	99.798839	0.0
49	0.0	76.042092	0.0

[37 rows x 21 columns]

```
[37]: master_format_convert = {v:k for k,v in {
    'Concrete':'03',
    'Masonry':'04',
    'Metals':'05',
    'WoodPlasticsAndComposites':'06',
    'ThermalAndMoistureProtection':'07',
    'Finishes':'09',
    'Openings':'08',
    'Earthwork':'31',
    'ExteriorImprovements':'32'
}.items() }
```

```
[38]: f = lambda x: master_format_convert[re.split('[_\\.\\ ]',x)[4]]
toplot = pd.concat([df[headings[1:]],df_mi[kilogram_columns].groupby(f,axis=1).
    ↪sum()),axis=1).sort_values(['Building Type'])
```

```
[39]: building_type_map = {
    'APB':'Mid to high-rise buildings',
    'EDU':'Mid to high-rise buildings',
    'INS':'Mid to high-rise buildings',
```

```

    'MIX': 'Mid to high-rise buildings',
    'OFF': 'Mid to high-rise buildings',
    'SND': 'Newly Constructed Single family dwellings',
    'SNR': 'Renovated Single family dwellings',
    'SMD': 'Newly Constructed Single family dwellings',
    'SMR': 'Renovated Single family dwellings',
    'ADU': 'Newly Constructed Single family dwellings',
    'SEC': 'Newly Constructed Single family dwellings',
    'ROW': 'Newly Constructed Single family dwellings',
    'LNW': 'Laneway Houses'
}

topplot['Building Type'] = topplot['Building Type'].replace(building_type_map)
topplot = topplot.sort_values('Building Type')

```

```
[40]: set(df['Building Type'].values)
```

```
[40]: {'APB', 'EDU', 'INS', 'LNW', 'MIX', 'OFF', 'SMD', 'SMR', 'SND', 'SNR'}
```

```
[41]: fig, ax = plt.subplots(figsize=(10,7))

cols = topplot.columns[6:]
margin_bottom = np.zeros(len(topplot))

cmap = plt.get_cmap('tab10')

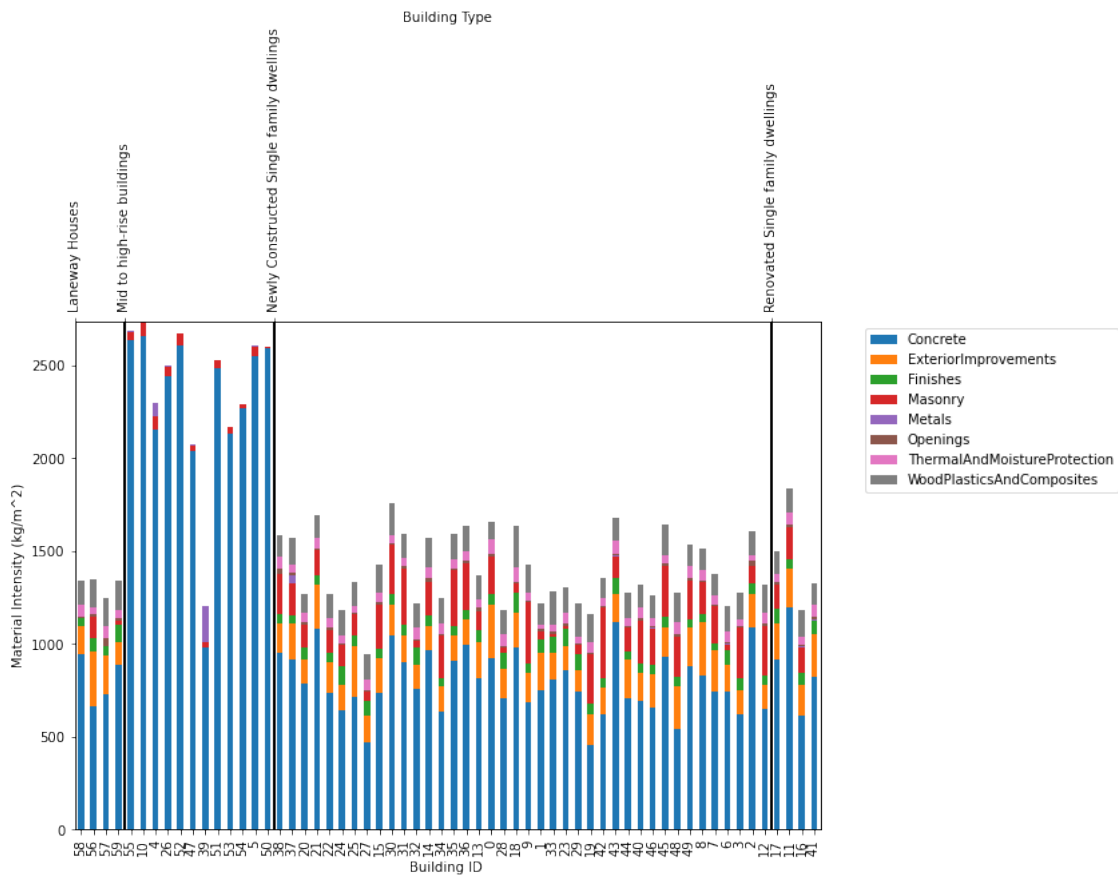
for num, col in enumerate(cols):
    values = topplot[col].values

    topplot[col].plot.bar(x='Year', y='Value', ax=ax, stacked=True,
                        bottom = margin_bottom, color=cmap(num),
                        label=col)
    margin_bottom += values
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.ylabel('Material Intensity (kg/m^2)')
plt.xlabel('Building ID ')
ax2 = ax.twinx()
ax2.set_xlim(0, len(topplot))
ax2.set_xticks([k for k,v in enumerate(topplot['Building Type'].values) if v !=
    topplot['Building Type'].values[k-1] or k==0])
for tick in ax2.get_xticklabels():
    tick.set_rotation(90)
ax2.set_xticklabels([v for k,v in enumerate(topplot['Building Type'].values) if
    v != topplot['Building Type'].values[k-1] or k==0])
ax2.set_xlabel("Building Type")
plt.grid(color='black', linewidth=2)

```



```
plt.show()
```



```
[42]: toplot['Total MI'] = toplot.iloc[:,6:].sum(axis=1)
```

```
[43]: print('Mean Material Intensity:')
display(toplot.groupby('Building Type').mean().iloc[:,1:].round(2))
print('Std Dev Material Intensity:')
display(toplot.groupby('Building Type').std().iloc[:,1:].round(2))
```

Mean Material Intensity:

	Gross Floor Area	Concrete	\
Building Type			
Laneway Houses	150.01	804.14	
Mid to high-rise buildings	38097.44	2296.10	
Newly Constructed Single family dwellings	461.18	793.42	
Renovated Single family dwellings	277.06	885.94	

	ExteriorImprovements	Finishes	\
Building Type			

Laneway Houses	194.18	64.80
Mid to high-rise buildings	0.00	0.00
Newly Constructed Single family dwellings	172.32	62.34
Renovated Single family dwellings	200.60	67.28

	Masonry	Metals	Openings	\
Building Type				
Laneway Houses	35.65	0.26	19.24	
Mid to high-rise buildings	41.80	25.53	0.00	
Newly Constructed Single family dwellings	167.55	1.92	11.98	
Renovated Single family dwellings	110.62	1.48	11.67	

	ThermalAndMoistureProtection	\
Building Type		
Laneway Houses	51.76	
Mid to high-rise buildings	0.00	
Newly Constructed Single family dwellings	51.26	
Renovated Single family dwellings	53.96	

	WoodPlasticsAndComposites	Total	MI
Building Type			
Laneway Houses	149.97	1320.01	
Mid to high-rise buildings	0.00	2363.42	
Newly Constructed Single family dwellings	137.64	1398.44	
Renovated Single family dwellings	129.17	1460.71	

Std Dev Material Intensity:

	Gross Floor Area	Concrete	\
Building Type			
Laneway Houses	62.86	130.35	
Mid to high-rise buildings	26125.17	466.31	
Newly Constructed Single family dwellings	168.17	164.27	
Renovated Single family dwellings	117.28	240.52	

	ExteriorImprovements	Finishes	\
Building Type			
Laneway Houses	74.50	20.17	
Mid to high-rise buildings	0.00	0.00	
Newly Constructed Single family dwellings	44.59	18.80	
Renovated Single family dwellings	25.87	12.77	

	Masonry	Metals	Openings	\
Building Type				
Laneway Houses	55.08	0.52	18.17	
Mid to high-rise buildings	19.83	56.15	0.00	
Newly Constructed Single family dwellings	98.51	6.70	4.41	
Renovated Single family dwellings	75.76	1.72	2.85	

	ThermalAndMoistureProtection \	
Building Type		
Laneway Houses		15.44
Mid to high-rise buildings		0.00
Newly Constructed Single family dwellings		12.27
Renovated Single family dwellings		10.87
	WoodPlasticsAndComposites	Total MI
Building Type		
Laneway Houses	10.83	47.15
Mid to high-rise buildings	0.00	424.77
Newly Constructed Single family dwellings	23.16	191.92
Renovated Single family dwellings	13.09	280.04

```
[44]: df_mi = df[kilogram_columns].div(df['Gross Floor Area'],axis=0)
```

```
[45]: df_mi = df[kilogram_columns].div(df['Gross Floor Area'],axis=0)
df_mi = df_mi.div(df_mi.sum(axis=1),axis=0) * 100
f = lambda x: name_map[re.split('[\\.\\ ]',x)[1][0]]
topplot = pd.concat([df[headings[1:]],df_mi[kilogram_columns].groupby(f,axis=1).
    ↳sum()),axis=1].sort_values('Building Type')
topplot['Building Type'] = topplot['Building Type'].replace(building_type_map)
topplot = topplot.sort_values('Building Type')
fig, ax = plt.subplots(figsize=(10,7))

cols = topplot.columns[6:]
margin_bottom = np.zeros(len(topplot))

cmap = plt.get_cmap('tab10')

for num, col in enumerate(cols):
    values = topplot[col].values

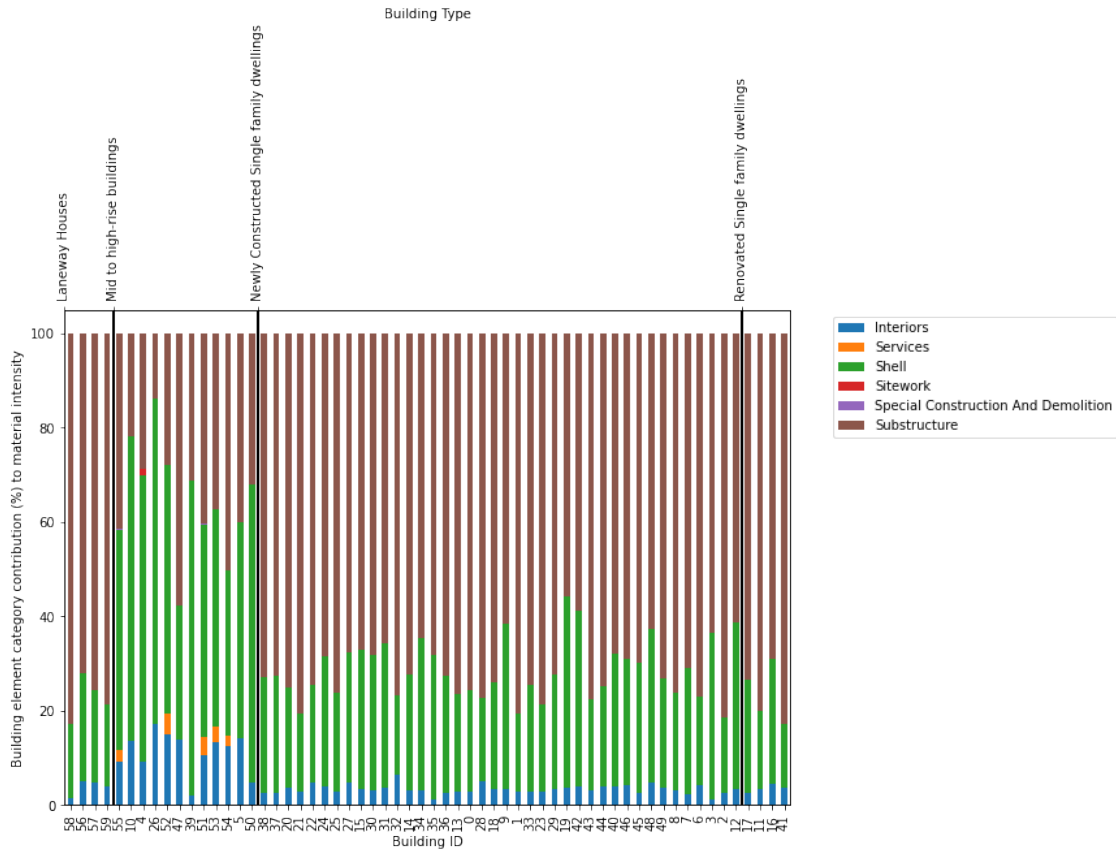
    topplot[col].plot.bar(x='Year',y='Value', ax=ax, stacked=True,
        bottom = margin_bottom, color=cmap(num),
        ↳label=col)
    margin_bottom += values
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.xlabel('Building ID')
plt.ylabel('Building element category contribution (%) to material intensity')

ax2 = ax.twinx()
ax2.set_xlim(0, len(topplot))
ax2.set_xticks([k for k,v in enumerate(topplot['Building Type'].values) if v !=
    ↳topplot['Building Type'].values[k-1] or k==0])
for tick in ax2.get_xticklabels():
    tick.set_rotation(90)
```

```

ax2.set_xticklabels([v for k,v in enumerate(toplot['Building Type'].values) if
↳ v != toplot['Building Type'].values[k-1] or k==0])
ax2.set_xlabel("Building Type")
plt.grid(color='black',linewidth=2)
plt.show()

```



```

[46]: f = lambda x: name_map[re.split('_\.\\ ',x)[1][0]] + '/' + re.split('_\.\\ 
↳ ',x)[-1]
toplot = df_mi[kilogram_columns].groupby(f,axis=1).sum()

```

```

[47]: df_mi = df[kilogram_columns].div(df['Gross Floor Area'],axis=0)
df_mi = df_mi.div(df_mi.sum(axis=1),axis=0)
f = lambda x: name_map[re.split('_\.\\ ',x)[1][0]] + '/' + re.split('_\.\\ 
↳ ',x)[-1]
toplot = df_mi[kilogram_columns].groupby(f,axis=1).sum()
for i in range(1,5):
    toplot[f'Total/{i}'] = 0
for k,v in toplot.iteritems():
    toplot[f'Total/{k.split("/")[-1]}'] += v
toplot_out = deepcopy(toplot)

```

```

for k,v in toplot.iteritems():
    toplot_out[k] = (v/toplot[[c for c in toplot.columns if k.split('/')[0] in_
    ↪c]].sum(axis=1)) * int(k.split('/')[1])
f = lambda x: x.split('/')[0]
toplot_out = pd.concat([df['Building Type'], toplot_out.groupby(f,axis=1).
    ↪sum()],axis=1).sort_values('Building Type')
toplot_out = toplot_out.reset_index()
toplot_out['index'] += 1
toplot_out['index'] = toplot_out['index'].astype('str')

```

```

[48]: # toplot_out = toplot_out[toplot_out['Building Type'].isin(types_to_keep)]
toplot_out['Building Type'] = toplot_out['Building Type'].
    ↪replace(building_type_map)
toplot_out = toplot_out.sort_values('Building Type')

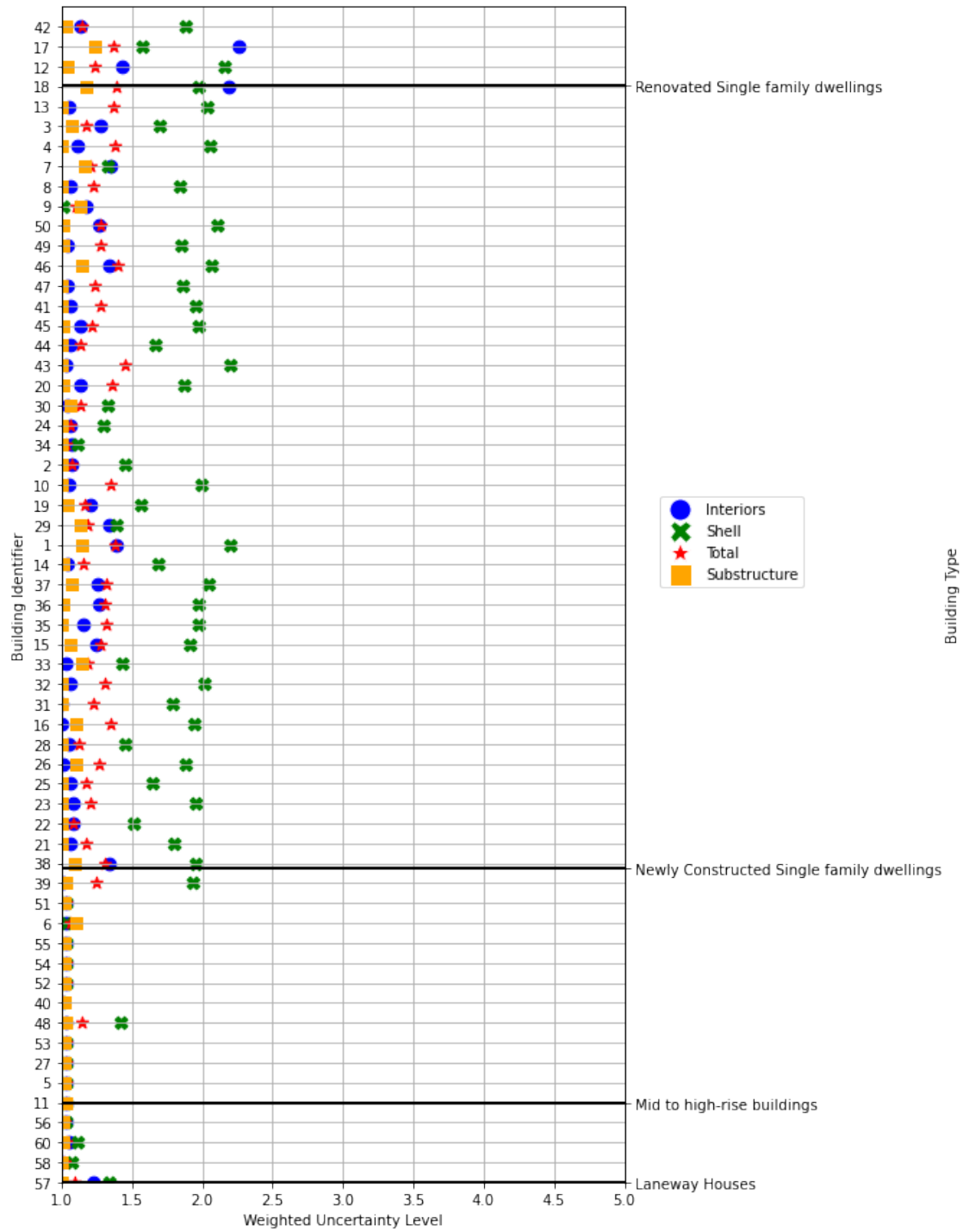
```

```

[49]: from matplotlib.lines import Line2D
fig, ax = plt.subplots(figsize=(7,15))
ax.set_xlim(1,5)
ax.set_ylim(1,len(toplot_out))
# ax.set_yticks(toplot_out['index'])
handles = []
for v,m,c in_
    ↪[('Interiors','o','blue'),('Shell','X','green'),('Total','*','red'),('Substructure','s','or
    ↪
        ax.scatter(x=toplot_out[v].values,y=toplot_out['index'].values, marker=m,_
        ↪color=c, s=75)
        handles.append(
            Line2D([0], [0], marker=m, color='w', label=v,
                    markerfacecolor=c, markersize=15)
        )
plt.legend(handles=handles,bbox_to_anchor=(1.05, 0.5), loc='lower left')
plt.ylabel('Building Identifier')
plt.xlabel('Weighted Uncertainty Level')
plt.grid()
ax2 = ax.twinx()
ax2.set_ylim(0, len(toplot_out))
ax2.set_yticks([k for k,v in enumerate(toplot_out['Building Type'].values) if v_
    ↪!= toplot_out['Building Type'].values[k-1] or k==0])
# for tick in ax2.get_yticklabels():
#     tick.set_rotation(90)
ax2.set_yticklabels([v for k,v in enumerate(toplot_out['Building Type'].values)_
    ↪if v != toplot_out['Building Type'].values[k-1] or k==0])
ax2.set_ylabel("Building Type")

plt.grid(color='black',linewidth=2)

```



[]: