

# Sample

April 22, 2021

```
[1]: import pandas as pd
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	0IFBP

	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	SMD	199.93
12	2021	SND	226.89
13	2021	SND	611.73
14	2021	SND	343.44
15	2021	SND	613.38
16	1969	SND	413.72
17	1969	SND	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	SND	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 ...	000_B2010.10.000_07 46 16.00_kg_2 \
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
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
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
52	191988.905000		...	NaN
53	82694.400000		...	NaN
54	46298.790000		...	NaN
55	422839.793489		...	NaN
56		NaN	...	NaN
57		NaN	...	NaN
58		NaN	...	NaN
59		NaN	...	67.3

001\_B2010.80.000\_07 27 00.00\_kg\_2 001\_B2010.80.000\_07 21 13.00\_kg\_2 \

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

	001_B2010.10.000_09 24 23.00_kg_2	OB1_A5020.10.000_06 11 00.00_kg_2 \
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	OB1_A5020.10.000_09 21 16.00_kg_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 00R_B3010.90.000_07 21 13.00_kg_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	127.47	420.29

00R\_B1020.20.000\_07 51 13.00\_kg\_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 2090 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, and volume histograms.

```

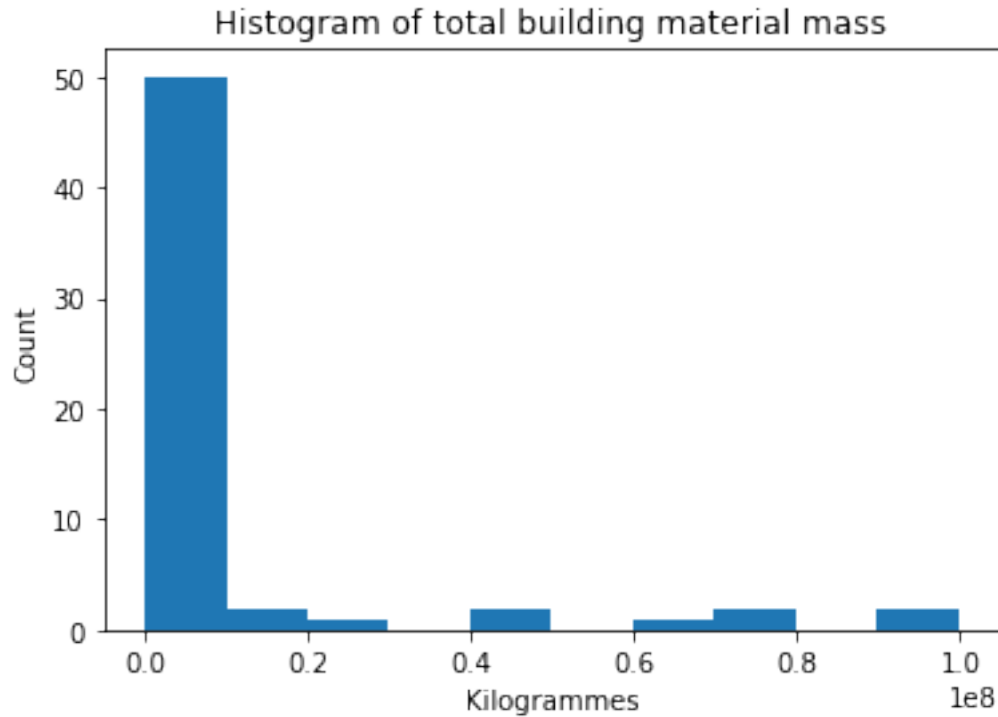
[9]: plt.hist(df[[c for c in df.columns if 'kg' in c]].sum(axis=1));
plt.title('Histogram of total building material mass')
plt.xlabel('Kilogrammes')
plt.ylabel('Count');

```

```

[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	1.709236e+05
1	2021	SND	389.24	1.082862e+05
2	2021	SND	411.64	1.909299e+05
3	2021	SND	269.56	6.736923e+04
4	2011	OFF	11248.00	0.000000e+00
5	2011	APB	11317.00	0.000000e+00
6	2021	SND	445.99	1.295202e+05
7	2021	SND	438.45	1.174431e+05
8	2021	SND	714.07	1.927680e+05
9	2021	SND	343.24	9.564723e+04
10	2009	OFF	73083.00	0.000000e+00
11	1917	SMD	199.93	9.927316e+04
12	2021	SND	226.89	5.835472e+04
13	2021	SND	611.73	2.061282e+05
14	2021	SND	343.44	1.436814e+05
15	2021	SND	613.38	1.789777e+05
16	1969	SND	413.72	9.293583e+04
17	1969	SND	333.49	1.186380e+05
18	2021	SND	178.38	6.408230e+04
19	2021	SND	323.80	4.733438e+04
20	2020	SND	837.56	2.605656e+05
21	2021	SND	587.86	2.455371e+05
22	2021	SND	568.21	1.415184e+05
23	2021	SMD	234.73	8.560216e+04
24	2021	SND	294.84	7.580863e+04
25	2021	SND	496.77	1.205336e+05
26	2007	OFF	73600.00	0.000000e+00
27	2021	SND	643.30	9.718853e+04
28	2021	SND	701.61	1.810933e+05
29	2021	SMD	257.75	8.183304e+04
30	2021	SND	378.70	1.477228e+05
31	2021	SND	324.16	1.188635e+05
32	2020	SND	533.53	1.627046e+05
33	2020	SMD	254.05	8.882102e+04
34	2021	SND	423.03	9.980270e+04
35	2021	SND	328.16	1.238544e+05
36	2021	SND	421.59	1.760423e+05
37	2020	SND	628.59	2.298828e+05
38	2021	SND	464.51	1.886381e+05
39	2017	EDU	8983.00	0.000000e+00
40	2021	SND	346.14	9.748630e+04

41	1913	SND	161.08	5.362299e+04
42	2021	SND	891.97	2.157609e+05
43	2021	SND	525.61	2.567725e+05
44	2021	SND	502.87	1.372402e+05
45	2021	SND	379.18	1.437386e+05
46	2021	SND	549.65	1.435894e+05
47	2016	EDU	6819.00	0.000000e+00
48	2020	SND	393.82	7.294707e+04
49	2021	SND	648.14	2.216331e+05
50	1988	INS	21934.00	0.000000e+00
51	2018	APB	53146.02	1.115822e+07
52	2018	MIX	33975.25	4.220040e+06
53	2017	APB	69784.00	7.912944e+06
54	2017	APB	39409.04	9.350736e+06
55	2016	APB	53871.00	1.627512e+06
56	2020	LNW	137.23	3.111394e+04
57	2020	LNW	144.92	3.241172e+04
58	2019	LNW	83.10	3.347723e+04
59	2021	LNW	234.79	8.400714e+04

	Subgrade	Enclosures	Slabs-On-Grade	Substructure	Interior	\
0		0.0	6.721219e+04		0.0	
1		0.0	3.576043e+04		0.0	
2		0.0	3.246461e+04		0.0	
3		0.0	1.595211e+04		0.0	
4		0.0	0.000000e+00		0.0	
5		0.0	0.000000e+00		0.0	
6		0.0	3.521918e+04		0.0	
7		0.0	4.289057e+04		0.0	
8		0.0	8.446873e+04		0.0	
9		0.0	2.033114e+04		0.0	
10		0.0	0.000000e+00		0.0	
11		0.0	1.971760e+04		0.0	
12		0.0	1.435987e+04		0.0	
13		0.0	4.140039e+04		0.0	
14		0.0	2.246836e+04		0.0	
15		0.0	4.219445e+04		0.0	
16		0.0	3.376814e+04		0.0	
17		0.0	2.622366e+04		0.0	
18		0.0	2.343862e+04		0.0	
19		0.0	2.368485e+04		0.0	
20		0.0	6.344851e+04		0.0	
21		0.0	6.865710e+04		0.0	
22		0.0	6.684690e+04		0.0	
23		0.0	1.294360e+04		0.0	
24		0.0	1.791821e+04		0.0	
25		0.0	5.137996e+04		0.0	

26	0.0	0.000000e+00	0.0
27	0.0	5.230228e+04	0.0
28	0.0	6.233222e+04	0.0
29	0.0	1.211886e+04	0.0
30	0.0	3.514722e+04	0.0
31	0.0	2.011968e+04	0.0
32	0.0	3.674638e+04	0.0
33	0.0	1.160387e+04	0.0
34	0.0	3.329286e+04	0.0
35	0.0	1.931159e+04	0.0
36	0.0	3.304437e+04	0.0
37	0.0	5.528816e+04	0.0
38	0.0	2.866777e+04	0.0
39	0.0	0.000000e+00	0.0
40	0.0	2.237098e+04	0.0
41	0.0	1.235658e+04	0.0
42	0.0	5.949332e+04	0.0
43	0.0	3.378685e+04	0.0
44	0.0	3.951047e+04	0.0
45	0.0	2.913799e+04	0.0
46	0.0	3.506390e+04	0.0
47	0.0	0.000000e+00	0.0
48	0.0	3.364275e+04	0.0
49	0.0	6.099032e+04	0.0
50	0.0	0.000000e+00	0.0
51	2728008.0	3.647520e+05	11033448.0
52	1705680.0	3.834720e+05	5400288.0
53	3246168.0	1.407000e+06	14052000.0
54	3567720.0	9.045840e+05	7607280.0
55	3438168.0	7.174800e+05	22907184.0
56	0.0	1.439848e+04	0.0
57	0.0	2.000253e+04	0.0
58	0.0	5.412759e+03	0.0
59	0.0	1.962799e+04	0.0

	Substructure Related Activities	Superstructure \
0	0.0	1.938810e+03
1	0.0	1.397610e+03
2	0.0	1.528710e+02
3	0.0	1.212090e+01
4	0.0	0.000000e+00
5	0.0	0.000000e+00
6	0.0	5.332590e+02
7	0.0	1.970790e+03
8	0.0	4.049670e+03
9	0.0	9.440170e+02
10	0.0	0.000000e+00

11	0.0	0.000000e+00
12	0.0	9.785830e+02
13	0.0	5.381500e+02
14	0.0	0.000000e+00
15	0.0	0.000000e+00
16	0.0	0.000000e+00
17	0.0	7.514840e+03
18	0.0	0.000000e+00
19	0.0	2.111800e+03
20	0.0	3.270810e+03
21	0.0	2.533580e+03
22	0.0	6.016340e+02
23	0.0	1.827610e+03
24	0.0	5.977480e+02
25	0.0	2.540900e+03
26	0.0	0.000000e+00
27	0.0	7.189470e+02
28	0.0	2.276420e+02
29	0.0	1.587900e+03
30	0.0	1.096510e+04
31	0.0	5.530400e+03
32	0.0	1.360980e+03
33	0.0	2.177290e+03
34	0.0	6.524310e+02
35	0.0	3.944150e+03
36	0.0	4.401230e+02
37	0.0	8.518740e+02
38	0.0	2.593160e+03
39	0.0	0.000000e+00
40	0.0	2.360810e+02
41	0.0	0.000000e+00
42	0.0	8.599660e+02
43	0.0	1.038810e+03
44	0.0	4.881840e+02
45	0.0	1.267510e+03
46	0.0	1.154890e+03
47	0.0	0.000000e+00
48	0.0	1.835120e+02
49	0.0	1.041320e+03
50	0.0	0.000000e+00
51	133464.0	2.780006e+07
52	112872.0	2.226535e+07
53	169896.0	3.204622e+07
54	276264.0	1.483577e+07
55	93048.0	3.239134e+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	727896.0	537984.0
52	405408.0	392400.0
53	328032.0	799872.0
54	119088.0	0.0
55	159336.0	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	11307.2	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	6816696.0	2494560.0	0.0	80592.0
52	5893176.0	1829328.0	48816.0	62280.0
53	9050592.0	2304480.0	172032.0	0.0
54	5180976.0	861888.0	130152.0	0.0
55	5604960.0	1664448.0	0.0	220992.0
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

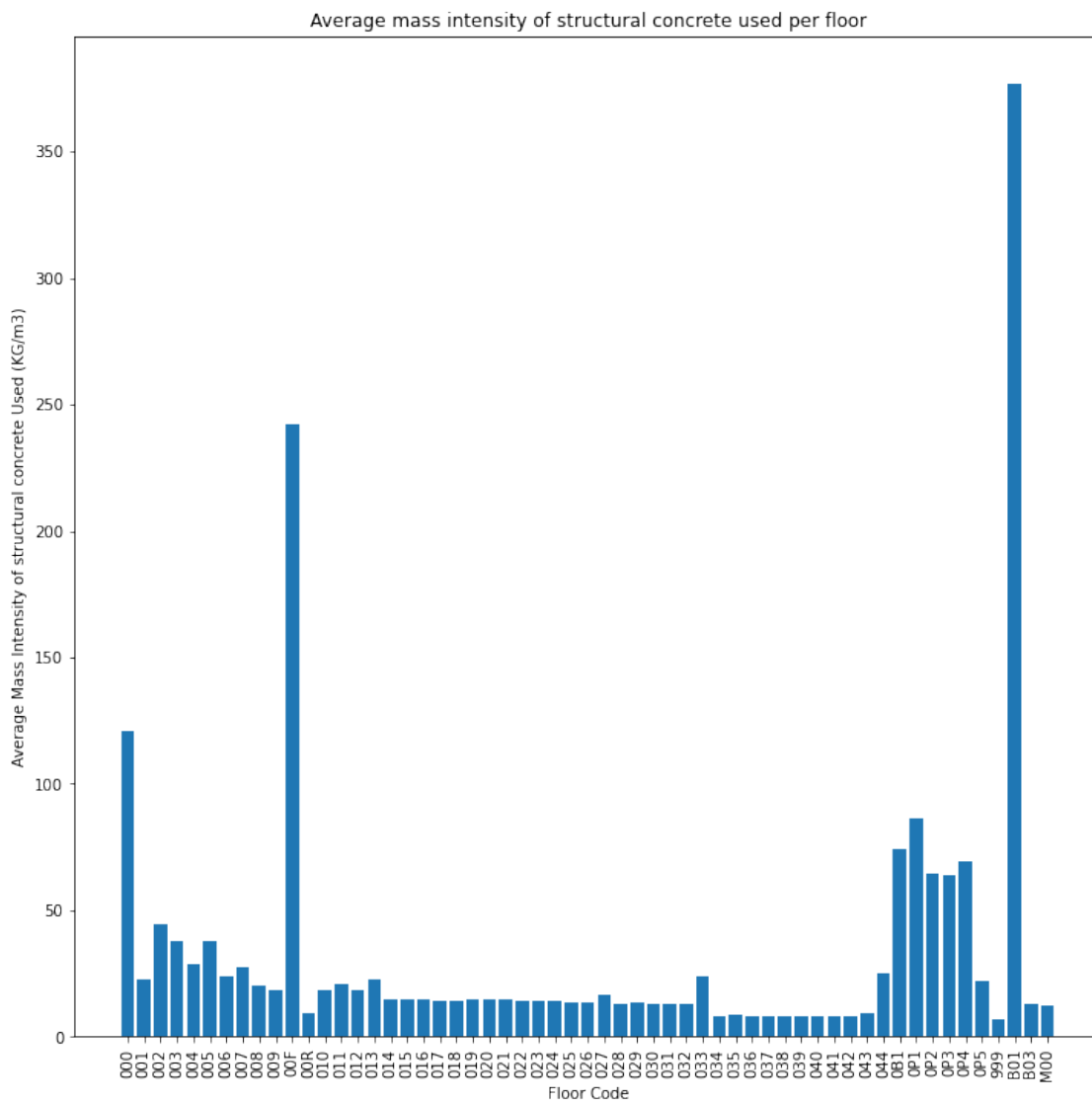
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0
5	0.0
6	0.0
7	0.0
8	0.0
9	0.0
10	0.0
11	0.0
12	0.0

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	18384.0
54	97560.0
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 mass intensity of structural concrete used per floor')
plt.ylabel('Average Mass Intensity of structural concrete Used (KG/m3)')
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.

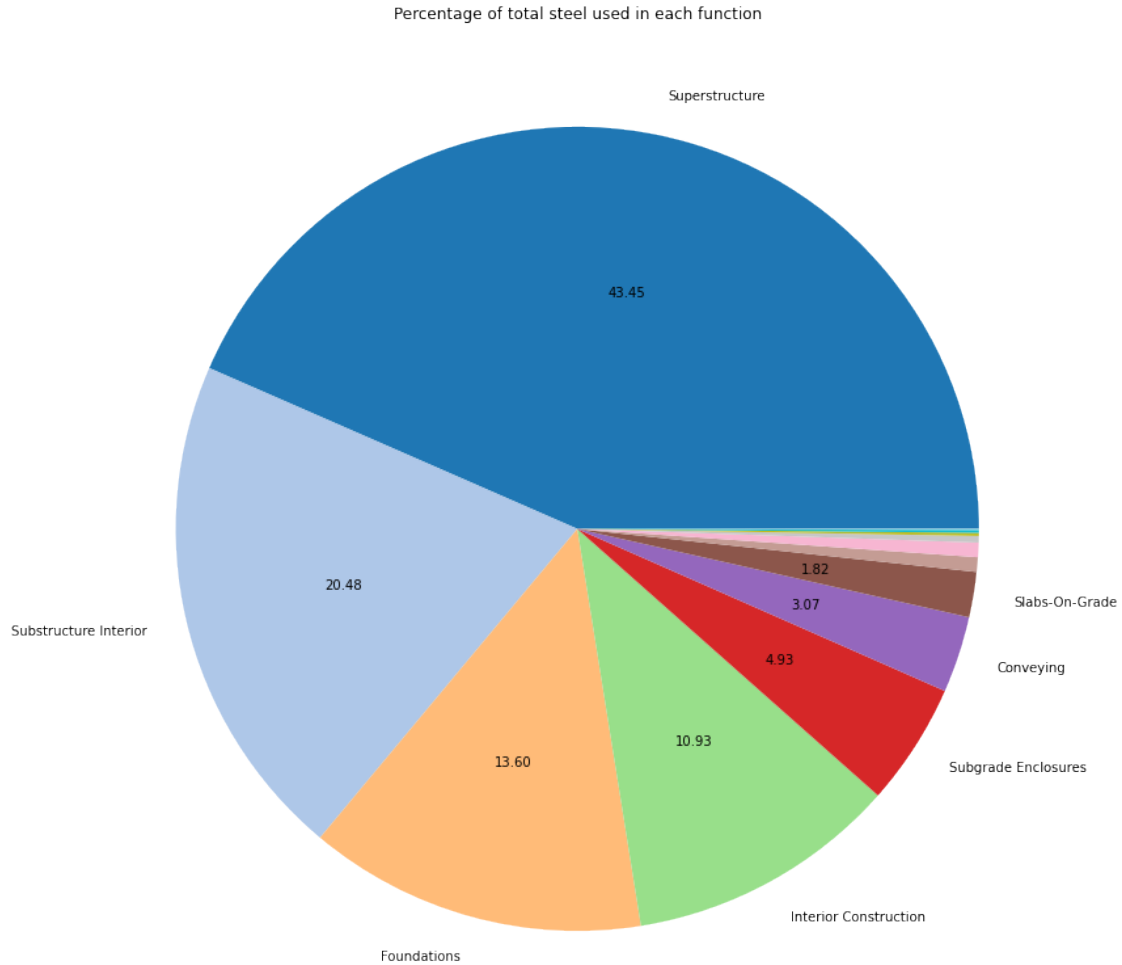
```
[14]: f = lambda x: name_map[re.split('_\.\\ ',x)[1][0:3]] #This function takes in a  
      ↪ full column name and returns only the Level 3 MasterFormat code.  
      concrete_df = df[cols].groupby(f,axis=1).sum()
```

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

```
[15]: Superstructure                2.156826e+06  
      Substructure Interior         1.016670e+06  
      Foundations                  6.750260e+05  
      Interior Construction         5.426285e+05  
      Subgrade Enclosures           2.447624e+05  
      Conveying                     1.525784e+05  
      Slabs-On-Grade                9.043012e+04  
      Exterior Vertical Enclosures  2.899600e+04  
      Exterior Horizontal Enclosures 2.883760e+04  
      Substructure Related Activities 1.309240e+04  
      Special Construction           6.064400e+03  
      Plumbing                      5.850000e+03  
      Site Improvements              1.932400e+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 used in each function');  
      # plt.legend(loc='center left',bbox_to_anchor=(-0.20, 0.75));  
      plt.tight_layout();
```



### 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()

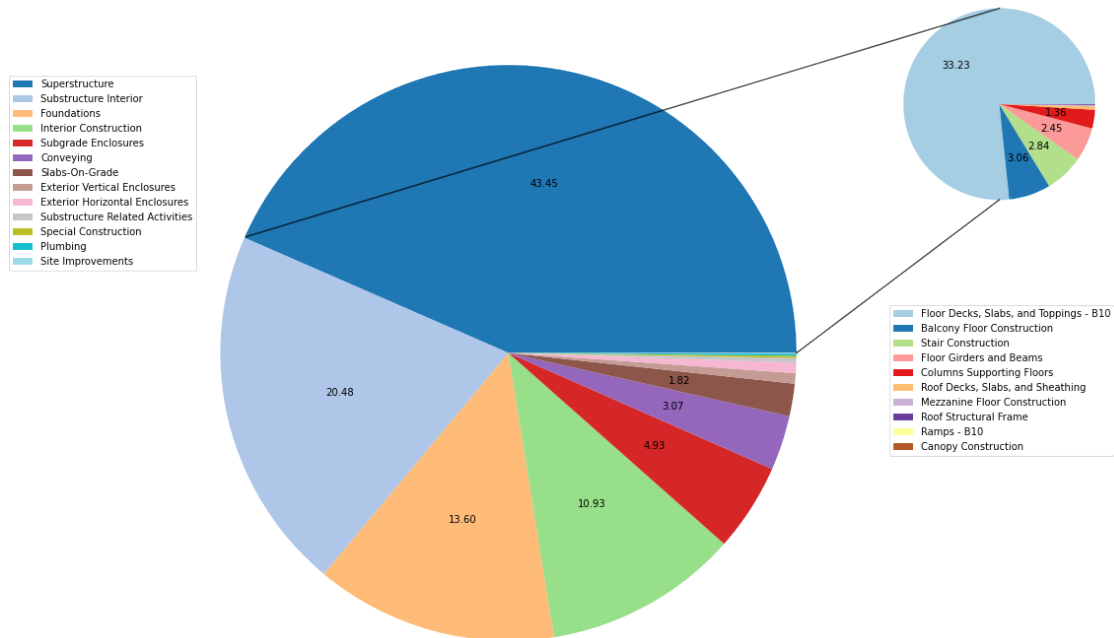
coord1a = transFigure.transform(ax0.transData.transform([1,0]))
coord2a = transFigure.transform(ax1.transData.transform([0,-0.72]))

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]: steel_codes = mf_codes[mf_codes.Title.str.lower().str.contains('steel')].Code.  
      ↪ values
```

```
[20]: f = lambda x: mf_codes[mf_codes.Code == str.replace(re.split('_',x)[2],'00','')].  
      ↪ strip('.').values[0][0]  
      steel_df = df[[c for c in df.columns if any('_'+code in c for code in_  
      ↪ steel_codes)]] .groupby(f,axis=1).sum()  
      # concrete_df = pd.concat([df[headings],df[cols].groupby(f,axis=1).  
      ↪ sum()],axis=1).rename(columns=name_map)
```

```
[21]: steel_df
```

```
[21]: Galvanized Reinforcement Steel Bars  Steel Decking  Steel Joist Framing  \  
0      404.82300      0.00000      0.00000  
1      39.11950      0.00000      0.00000  
2      279.76886      0.00000      0.00000  
3      268.61530      0.00000      0.00000  
4           0.00000     36463.77000     32390.637801  
5           0.00000     1065.40000      0.00000
```

6	38.46761	0.000000	0.000000
7	44.00918	0.000000	0.000000
8	1571.63651	0.000000	0.000000
9	46.05571	0.000000	0.000000
10	0.00000	20121.360000	0.000000
11	60.92610	0.000000	0.000000
12	19.15980	0.000000	0.000000
13	75.60890	0.000000	0.000000
14	0.00000	0.000000	0.000000
15	3279.60820	0.000000	0.000000
16	13.82180	0.000000	0.000000
17	202.99950	0.000000	0.000000
18	0.00000	0.000000	0.000000
19	54.21826	0.000000	0.000000
20	86.47600	0.000000	0.000000
21	1453.94520	0.000000	0.000000
22	145.83870	0.000000	0.000000
23	29.07493	0.000000	0.000000
24	46.33040	0.000000	0.000000
25	2315.14960	0.000000	0.000000
26	0.00000	119243.083000	0.000000
27	305.86314	0.000000	0.000000
28	2608.80655	0.000000	0.000000
29	186.48870	0.000000	0.000000
30	3631.90365	0.000000	0.000000
31	1876.27340	0.000000	0.000000
32	65.21890	0.000000	0.000000
33	179.64820	0.000000	0.000000
34	54.73736	0.000000	0.000000
35	1898.51116	0.000000	0.000000
36	87.26520	0.000000	0.000000
37	2358.28100	0.000000	0.000000
38	110.96350	0.000000	0.000000
39	0.00000	91742.730862	0.000000
40	18.11669	0.000000	0.000000
41	342.79680	0.000000	0.000000
42	166.77610	0.000000	0.000000
43	1672.16739	0.000000	0.000000
44	726.32664	0.000000	0.000000
45	1908.83810	0.000000	0.000000
46	57.80600	0.000000	0.000000
47	0.00000	15013.230000	1080.899186
48	49.97006	0.000000	0.000000
49	956.68180	0.000000	0.000000
50	0.00000	2134.201117	645.920732
51	0.00000	169.830000	0.000000
52	0.00000	0.000000	143.934000

53	0.00000	0.000000	0.000000
54	0.00000	0.000000	0.000000
55	0.00000	0.000000	0.000000
56	0.00000	0.000000	0.000000
57	0.00000	0.000000	0.000000
58	0.00000	0.000000	0.000000
59	0.00000	0.000000	0.000000

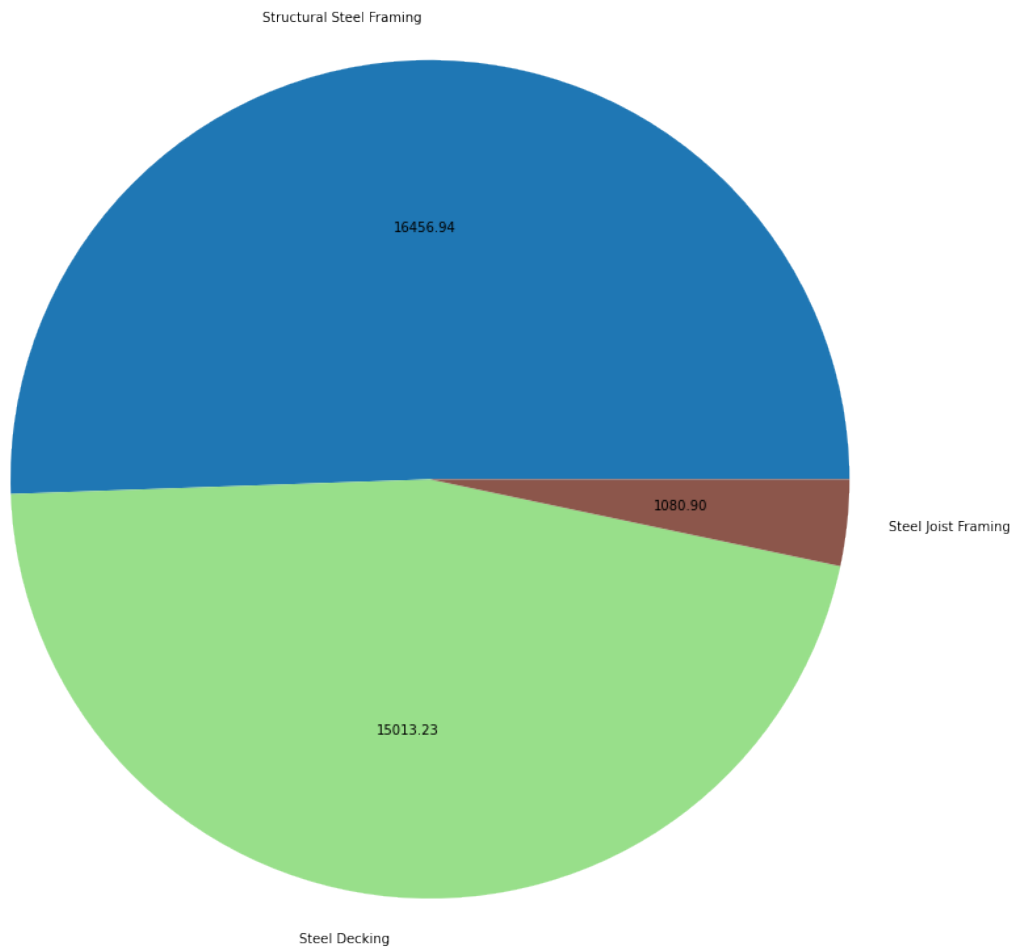
	Steel Siding	Structural Steel Framing
0	0.000000	833.719844
1	0.000000	86.750700
2	0.000000	77.569800
3	0.000000	16.902960
4	0.000000	355263.964465
5	0.000000	13137.294500
6	0.000000	882.529100
7	0.000000	0.000000
8	0.000000	0.000000
9	0.000000	0.000000
10	0.000000	468399.372253
11	0.000000	0.000000
12	0.000000	0.000000
13	0.000000	216.126000
14	0.000000	8.212260
15	0.000000	0.000000
16	0.000000	165.249000
17	0.000000	195.051000
18	0.000000	119.592000
19	0.000000	18.239000
20	0.000000	203.157000
21	0.000000	0.000000
22	0.000000	0.000000
23	0.000000	124.000000
24	0.000000	215.085000
25	0.000000	111.731000
26	0.000000	178012.680000
27	0.000000	307.121000
28	0.000000	309.208000
29	0.000000	125.600000
30	0.000000	125.036000
31	0.000000	0.000000
32	0.000000	277.451000
33	0.000000	147.359000
34	0.000000	0.000000
35	0.000000	0.000000
36	0.000000	0.000000
37	0.000000	12784.293000

38	0.000000	63.017700
39	0.000000	765899.330235
40	0.000000	0.000000
41	0.000000	318.008000
42	0.000000	0.000000
43	0.000000	266.210000
44	0.000000	0.000000
45	0.000000	0.000000
46	0.000000	1047.606600
47	0.000000	16456.940000
48	0.000000	900.873980
49	0.000000	1749.015000
50	0.000000	11709.756098
51	0.000000	39205.071773
52	0.000000	12684.312817
53	0.000000	6532.207000
54	0.000000	2600.046000
55	0.000000	65443.840000
56	373.820000	0.000000
57	761.226866	0.000000
58	0.000000	0.000000
59	0.000000	122.850000

```
[22]: BUILDING_ID = 47
total_steel = steel_df.loc[BUILDING_ID,:].sum()
def my_autopct(pct):
    return ('%.2f' % (pct * total_steel/100)) if pct > 1 else ''
to_plot = steel_df.loc[BUILDING_ID,:].sort_values(ascending=False)
to_plot.plot.pie(figsize=(12,12),colormap='tab20',autopct=my_autopct)
plt.ylabel('')
plt.title(f'Amount of total steel used in each function for building_
→{BUILDING_ID} (kg)');
plt.tight_layout();
```



Amount of total steel used in each function for building 47 (kg)



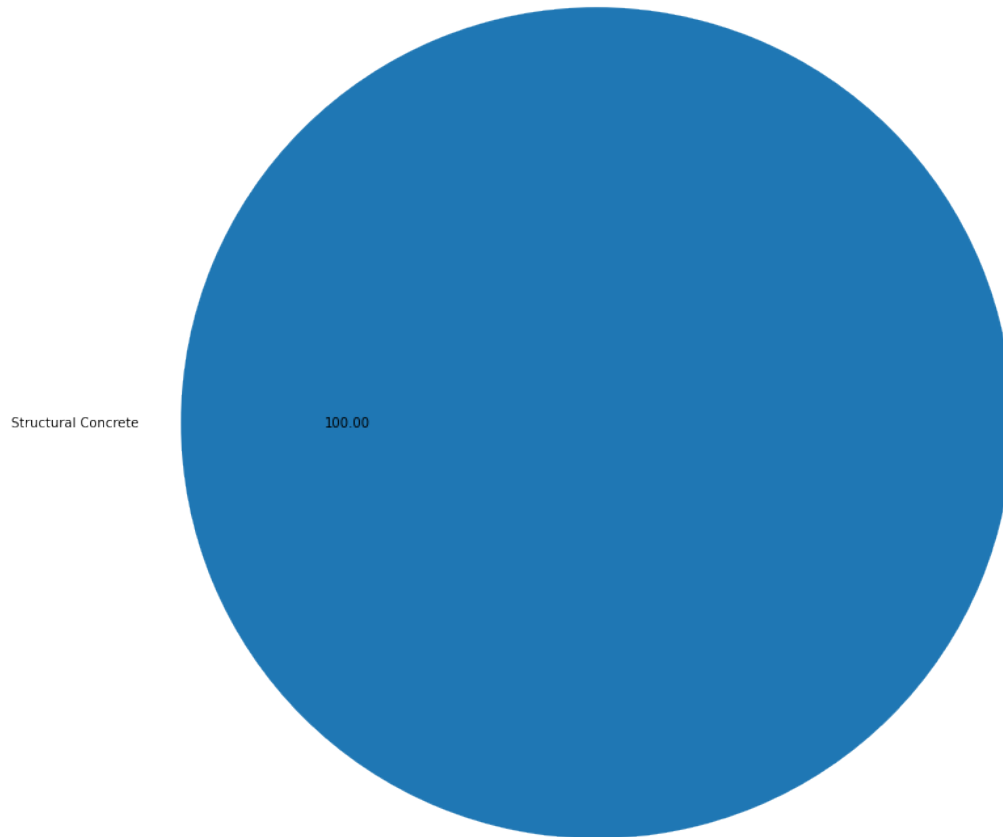
Or an entire class of building:

```
[23]: concrete_df = pd.concat([df['Building Type'],df[cols].groupby(f,axis=1).
    ↳sum()],axis=1)
BUILDING_TYPE = 'LNW'

def my_autopct(pct):
    return ('%.2f' % pct) if pct > 1 else ''
to_plot = concrete_df[concrete_df['Building Type'] == BUILDING_TYPE][concrete_df.columns[1:]].mean().sort_values(ascending=False)
to_plot.plot.pie(figsize=(12,12),colormap='tab20',autopct=my_autopct)
plt.ylabel('')
plt.title(f'Percentage of total structural concrete used in each function for building type {BUILDING_TYPE}');
```

```
plt.tight_layout();
```

Percentage of total structural concrete used in each function for building type LNW



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

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

```
[24]:
```

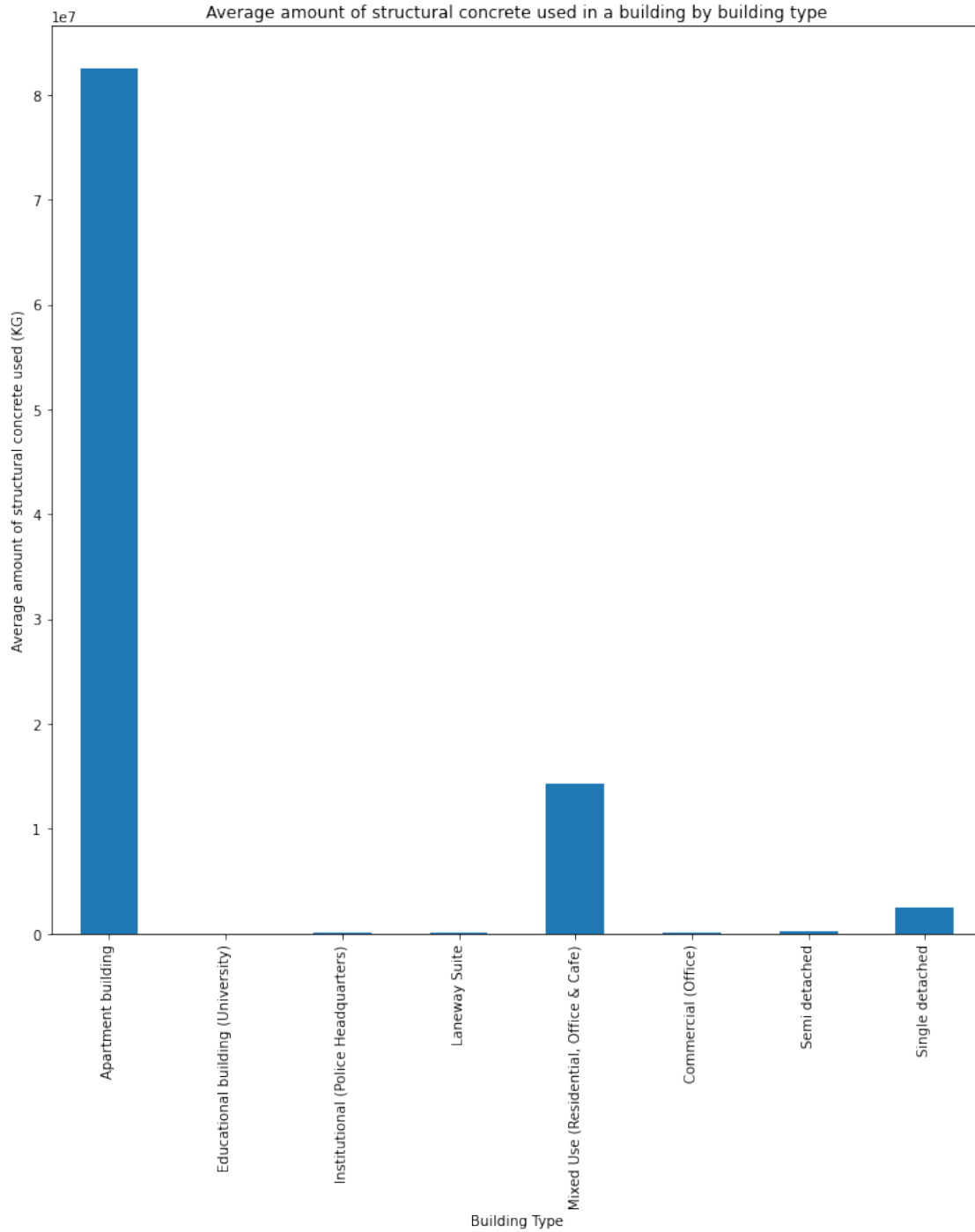
Construction Date	Gross Floor Area	Structural Concrete
1913	161.080000	6.597957e+04
1917	199.930000	1.189908e+05
1969	373.605000	1.395402e+05
1988	21934.000000	0.000000e+00

2007	73600.000000	0.000000e+00
2009	73083.000000	0.000000e+00
2011	11282.500000	0.000000e+00
2016	30345.000000	3.441223e+07
2017	39392.013333	3.814654e+07
2018	43560.635000	5.329740e+07
2019	83.100000	3.888999e+04
2020	418.528571	1.602031e+05
2021	445.404444	1.760668e+05

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

```
[25]: 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');
```

```
[25]: 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 code associated with each column. We collect these by building type and then report the number of each value per type of building.

```
[26]: 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])

[27]: from collections import Counter

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

[29]: uncertainty_level

[29]: {'SND': Counter({'1': 1720, '2': 711, '4': 349}),
      'OFF': Counter({'1': 494, '3': 307}),
      'APB': Counter({'1': 1171, '2': 1, '3': 971}),
      'SMD': Counter({'1': 191, '2': 61, '4': 27}),
      'EDU': Counter({'1': 93, '3': 24, '2': 6}),
      'INS': Counter({'1': 90, '3': 77, '2': 1}),
      'MIX': Counter({'1': 363, '3': 276}),
      'LNW': Counter({'2': 46, '1': 142, '4': 19})}
```

Next, we aggregate columns by use code and uncertainty combined, and report the average by building type.

```
[30]: 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_
      ↪code.
      by_function_df = pd.concat([df[headings[1:]],df[cols].groupby(f,axis=1).
      ↪sum()],axis=1)

[31]: by_function_df.groupby('Building Type').mean().rename(index=building_name_map)
```

```
[31]:
```

Building Type	Construction Date	Gross Floor Area \
Apartment building	2015.80	45505.412000
Educational building (University)	2016.50	7901.000000
Institutional (Police Headquarters)	1988.00	21934.000000
Laneway Suite	2020.00	150.010000
Mixed Use (Residential, Office & Cafe)	2018.00	33975.250000
Commercial (Office)	2009.00	52643.666667
Semi detached	1994.75	236.615000
Single detached	2015.60	465.227000

	Interiors/1	Services/1	Shell/1 \
Building Type			
Apartment building	5330644.80	1525512.0	2.194912e+07
Educational building (University)	0.00	0.0	0.000000e+00
Institutional (Police Headquarters)	0.00	0.0	0.000000e+00
Laneway Suite	0.00	0.0	0.000000e+00
Mixed Use (Residential, Office & Cafe)	5893176.00	1878144.0	2.306316e+07
Commercial (Office)	0.00	0.0	0.000000e+00
Semi detached	0.00	0.0	1.398200e+03
Single detached	282.68	0.0	1.618852e+03

	Shell/2	Sitework/1 \
Building Type		
Apartment building	0.0000	23188.8
Educational building (University)	0.0000	0.0
Institutional (Police Headquarters)	0.0000	0.0
Laneway Suite	0.0000	0.0
Mixed Use (Residential, Office & Cafe)	0.0000	0.0
Commercial (Office)	0.0000	0.0
Semi detached	0.0000	0.0
Single detached	12.2046	0.0

	Special Construction And Demolition/1 \
Building Type	
Apartment building	60316.8
Educational building (University)	0.0
Institutional (Police Headquarters)	0.0
Laneway Suite	0.0
Mixed Use (Residential, Office & Cafe)	62280.0
Commercial (Office)	0.0
Semi detached	0.0
Single detached	0.0

	Substructure/1	Substructure/2 \
Building Type		
Apartment building	2.053918e+07	0.000000
Educational building (University)	0.000000e+00	0.000000
Institutional (Police Headquarters)	0.000000e+00	0.000000
Laneway Suite	5.821718e+04	44.805527
Mixed Use (Residential, Office & Cafe)	1.182235e+07	0.000000
Commercial (Office)	0.000000e+00	0.000000
Semi detached	1.007531e+05	2225.215000
Single detached	1.743097e+05	6396.852125

	Substructure/4
Building Type	

Apartment building	0.0000
Educational building (University)	0.0000
Institutional (Police Headquarters)	0.0000
Laneway Suite	1850.9675
Mixed Use (Residential, Office & Cafe)	0.0000
Commercial (Office)	0.0000
Semi detached	0.0000
Single detached	0.0000

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

```
[32]: f = lambda x: x.split('_')[-1].split('.')[0] #Select only the uncertainty code.
pd.concat([df[headings[1:]],df[cols].groupby(f,axis=1).sum()],axis=1).
↳groupby('Construction Date').mean()
```

```
[32]:
```

	Gross Floor Area	1	2	4
Construction Date				
1913	161.080000	6.169728e+04	4282.290000	0.000000
1917	199.930000	1.100899e+05	8900.860000	0.000000
1969	373.605000	1.126800e+05	26860.270500	0.000000
1988	21934.000000	0.000000e+00	0.000000	0.000000
2007	73600.000000	0.000000e+00	0.000000	0.000000
2009	73083.000000	0.000000e+00	0.000000	0.000000
2011	11282.500000	0.000000e+00	0.000000	0.000000
2016	30345.000000	3.441223e+07	0.000000	0.000000
2017	39392.013333	3.814654e+07	0.000000	0.000000
2018	43560.635000	5.329740e+07	0.000000	0.000000
2019	83.100000	3.871077e+04	179.222109	0.000000
2020	418.528571	1.550909e+05	5112.262857	0.000000
2021	445.404444	1.713452e+05	4515.933278	205.663056

## 5 4. Material Intensity

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

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

```
[34]: 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']
```

[34]:	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	
16	CA	TOR	00IFC	1969	SND	
17	CA	TOR	00IFC	1969	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	
41	CA	TOR	00IFC	1913	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	11.137992	
1	389.24	0.0	5.461939	
2	411.64	0.0	3.786074	
3	269.56	0.0	6.503479	



6	445.99	0.0	11.933511
7	438.45	0.0	12.707195
8	714.07	0.0	12.865930
9	343.24	0.0	4.300619
12	226.89	0.0	12.424245
13	611.73	0.0	5.140200
14	343.44	0.0	6.494467
15	613.38	0.0	13.090524
16	413.72	0.0	6.437864
17	333.49	0.0	7.176775
18	178.38	0.0	9.782438
19	323.80	0.0	9.824569
20	837.56	0.0	13.521848
21	587.86	0.0	6.949783
22	568.21	0.0	12.754287
24	294.84	0.0	3.650542
25	496.77	0.0	5.352985
27	643.30	0.0	11.769043
28	701.61	0.0	11.799093
30	378.70	0.0	5.522739
31	324.16	0.0	5.361174
32	533.53	0.0	8.494907
34	423.03	0.0	11.102019
35	328.16	0.0	10.234937
36	421.59	0.0	12.223172
37	628.59	0.0	10.408758
38	464.51	0.0	4.118745
40	346.14	0.0	11.787081
41	161.08	0.0	8.266350
42	891.97	0.0	10.710312
43	525.61	0.0	18.918490
44	502.87	0.0	6.014586
45	379.18	0.0	6.169302
46	549.65	0.0	11.310711
48	393.82	0.0	16.116861
49	648.14	0.0	9.684756

	Exterior Vertical	Enclosures	Foundations	...	Interior Finishes \
0		136.939623	335.649367	...	8.309413
1		69.018253	281.318698	...	6.490936
2		101.450370	464.462195	...	4.574905
3		188.215196	255.359136	...	8.510443
6		61.325975	295.116668	...	6.391063
7		130.552921	269.468463	...	6.584780
8		104.310510	276.917123	...	6.563894
9		210.632241	283.893850	...	8.940907
12		186.668275	261.874926	...	6.134611

13	102.332008	343.714248	...	7.638991
14	147.104280	424.099610	...	7.860800
15	156.986570	298.537712	...	8.068881
16	104.759146	224.634608	...	5.373842
17	121.363560	355.746799	...	4.610513
18	112.523711	371.149916	...	9.551856
19	186.570501	148.769711	...	9.483653
20	91.689386	317.583491	...	7.152371
21	94.557055	428.185321	...	6.754074
22	83.789887	255.012975	...	7.860492
24	127.856507	261.274626	...	4.807604
25	89.883144	251.725837	...	5.921358
27	83.949693	156.365248	...	8.492430
28	53.418023	266.164355	...	7.952623
30	164.214896	403.602589	...	7.221059
31	190.512918	377.853541	...	6.597902
32	68.518430	309.062696	...	6.648595
34	154.072547	243.607664	...	4.717349
35	184.202156	388.744353	...	5.648226
36	158.716507	424.443503	...	5.625641
37	136.076590	369.744859	...	5.699975
38	151.068033	412.845205	...	7.621364
40	146.479339	287.564257	...	7.916204
41	58.430002	345.135557	...	4.455575
42	213.677214	245.205806	...	7.577250
43	109.529933	498.010299	...	7.954358
44	91.481074	278.679758	...	4.564488
45	172.418003	391.303861	...	6.339432
46	127.866168	266.468237	...	6.701647
48	140.069509	188.980245	...	10.629628
49	131.118584	347.187490	...	5.089382

	Plumbing	Site Improvements	Slabs-On-Grade	Special Construction	\
0	0.0	0.0	273.972401		0.0
1	0.0	0.0	192.874465		0.0
2	0.0	0.0	170.733356		0.0
3	0.0	0.0	124.186526		0.0
6	0.0	0.0	153.061618		0.0
7	0.0	0.0	211.910108		0.0
8	0.0	0.0	266.709576		0.0
9	0.0	0.0	138.510228		0.0
12	0.0	0.0	129.263543		0.0
13	0.0	0.0	165.513154		0.0
14	0.0	0.0	129.532248		0.0
15	0.0	0.0	166.414337		0.0
16	0.0	0.0	166.704176		0.0
17	0.0	0.0	177.790288		0.0

18	0.0	0.0	223.398638	0.0
19	0.0	0.0	158.178114	0.0
20	0.0	0.0	143.282268	0.0
21	0.0	0.0	237.918968	0.0
22	0.0	0.0	199.364347	0.0
24	0.0	0.0	131.174185	0.0
25	0.0	0.0	242.284758	0.0
27	0.0	0.0	152.407914	0.0
28	0.0	0.0	169.419640	0.0
30	0.0	0.0	179.868896	0.0
31	0.0	0.0	132.696247	0.0
32	0.0	0.0	135.390288	0.0
34	0.0	0.0	147.458950	0.0
35	0.0	0.0	128.887840	0.0
36	0.0	0.0	147.225241	0.0
37	0.0	0.0	186.334547	0.0
38	0.0	0.0	145.273403	0.0
40	0.0	0.0	139.821081	0.0
41	0.0	0.0	191.028748	0.0
42	0.0	0.0	138.994603	0.0
43	0.0	0.0	139.646277	0.0
44	0.0	0.0	182.059329	0.0
45	0.0	0.0	158.446049	0.0
46	0.0	0.0	154.805714	0.0
48	0.0	0.0	198.860705	0.0
49	0.0	0.0	199.209464	0.0

	Subgrade Enclosures	Substructure Interior \
0	9.652903	0.000000
1	6.851955	0.000000
2	11.298572	0.000000
3	4.351465	0.000000
6	9.478642	0.054452
7	4.218921	0.000000
8	8.902623	0.000000
9	9.601245	0.000000
12	3.818403	0.935612
13	7.722754	0.000000
14	9.135529	0.000000
15	4.868508	0.467438
16	9.729092	0.000000
17	11.222919	0.000000
18	0.000000	0.000000
19	4.617006	0.000000
20	7.131170	0.000000
21	7.959752	0.000000
22	6.339651	0.000000

24	7.469048	0.000000
25	9.448689	0.078017
27	0.000000	0.096759
28	11.919460	0.000000
30	7.509119	0.330172
31	5.073992	0.000000
32	8.867868	0.000000
34	0.000000	0.000000
35	4.762839	0.000000
36	9.538939	0.000000
37	6.039206	1.461249
38	9.071017	0.000000
40	7.568785	0.394416
41	5.419045	0.000000
42	4.540919	0.371810
43	6.720435	0.000000
44	6.092739	0.000000
45	9.489156	0.195110
46	6.042229	0.499896
48	6.057127	1.647329
49	7.221222	1.208104

	Substructure Related Activities	Superstructure	Water And Gas Mitigation
0	0.0	30.228003	0.0
1	0.0	26.271523	0.0
2	0.0	23.756286	0.0
3	0.0	30.517748	0.0
6	0.0	39.906513	0.0
7	0.0	39.907474	0.0
8	0.0	38.291591	0.0
9	0.0	35.370538	0.0
12	0.0	35.355314	0.0
13	0.0	33.388004	0.0
14	0.0	39.370016	0.0
15	0.0	40.958564	0.0
16	0.0	46.688433	0.0
17	0.0	51.425780	0.0
18	0.0	63.006044	0.0
19	0.0	36.597047	0.0
20	0.0	28.734226	0.0
21	0.0	37.457583	0.0
22	0.0	36.265538	0.0
24	0.0	30.389475	0.0
25	0.0	43.728928	0.0
27	0.0	35.393414	0.0
28	0.0	39.408113	0.0
30	0.0	82.392236	0.0

31	0.0	46.380703	0.0
32	0.0	25.469871	0.0
34	0.0	35.666107	0.0
35	0.0	49.404111	0.0
36	0.0	34.035382	0.0
37	0.0	47.065025	0.0
38	0.0	37.921434	0.0
40	0.0	27.740220	0.0
41	0.0	22.962391	0.0
42	0.0	29.045531	0.0
43	0.0	33.265489	0.0
44	0.0	37.265275	0.0
45	0.0	46.860447	0.0
46	0.0	31.152827	0.0
48	0.0	49.899420	0.0
49	0.0	38.021046	0.0

[40 rows x 21 columns]

[ ]:

```
[35]: 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() }
```

```
[36]: 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'])
```

```
[37]: types_to_keep = ['APB','SND','SMD','ADU','SEC','ROW','LNW']
toplot = toplot[toplot['Building Type'].isin(types_to_keep)]

building_type_map = {
    'APB':'Mid to high-rise buildings',
    'SND':'Single family dwellings',
    'SMD':'Single family dwellings',
    'ADU':'Single family dwellings',
    'SEC':'Single family dwellings',
    'ROW':'Single family dwellings',
```

```

    'LNW': 'Laneway Houses'
}

```

```

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

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

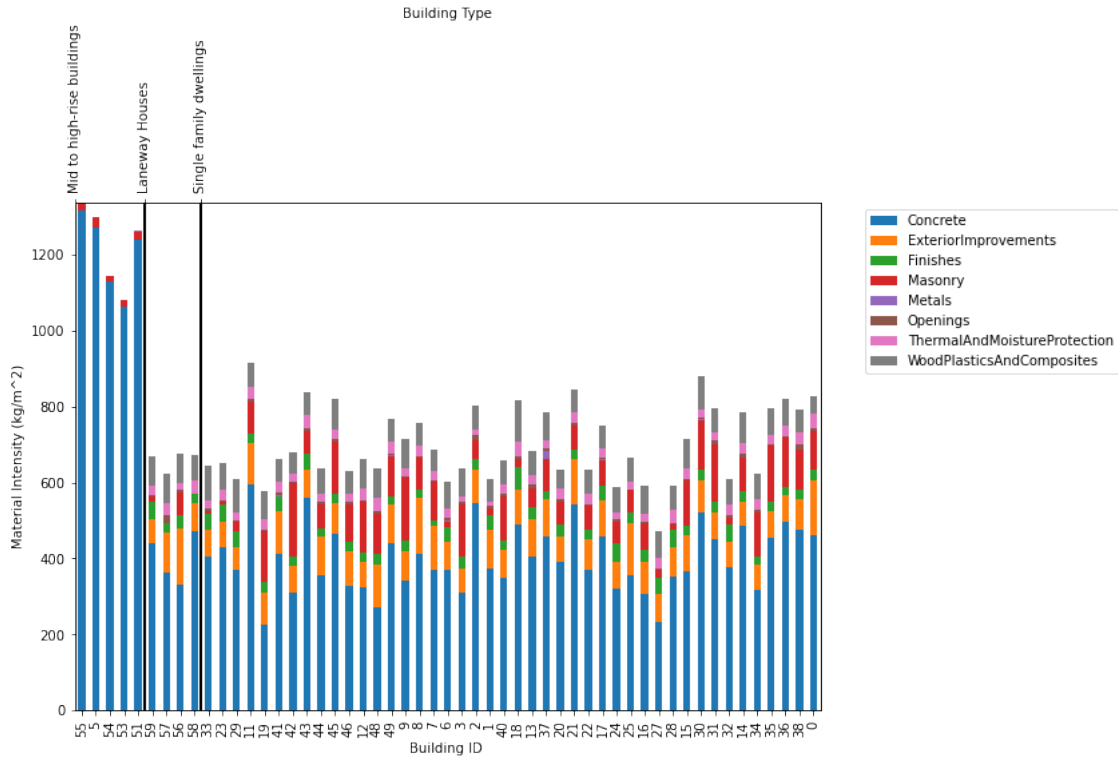
cmap = plt.get_cmap('tab10')

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

    toplot[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(toplot))
ax2.set_xticks([k for k,v in enumerate(toplot['Building Type'].values) if
    ↪building_type_map[v] != building_type_map[toplot['Building Type'].
    ↪values[k-1]] or k==0])
for tick in ax2.get_xticklabels():
    tick.set_rotation(90)
ax2.set_xticklabels([building_type_map[v] for k,v in enumerate(toplot['Building_
    ↪Type'].values) if building_type_map[v] != building_type_map[toplot['Building_
    ↪Type'].values[k-1]] or k==0])
ax2.set_xlabel("Building Type")
plt.grid(color='black', linewidth=2)

plt.show()

```



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

```
[40]: 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 = topplot[topplot['Building Type'].isin(types_to_keep)]

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

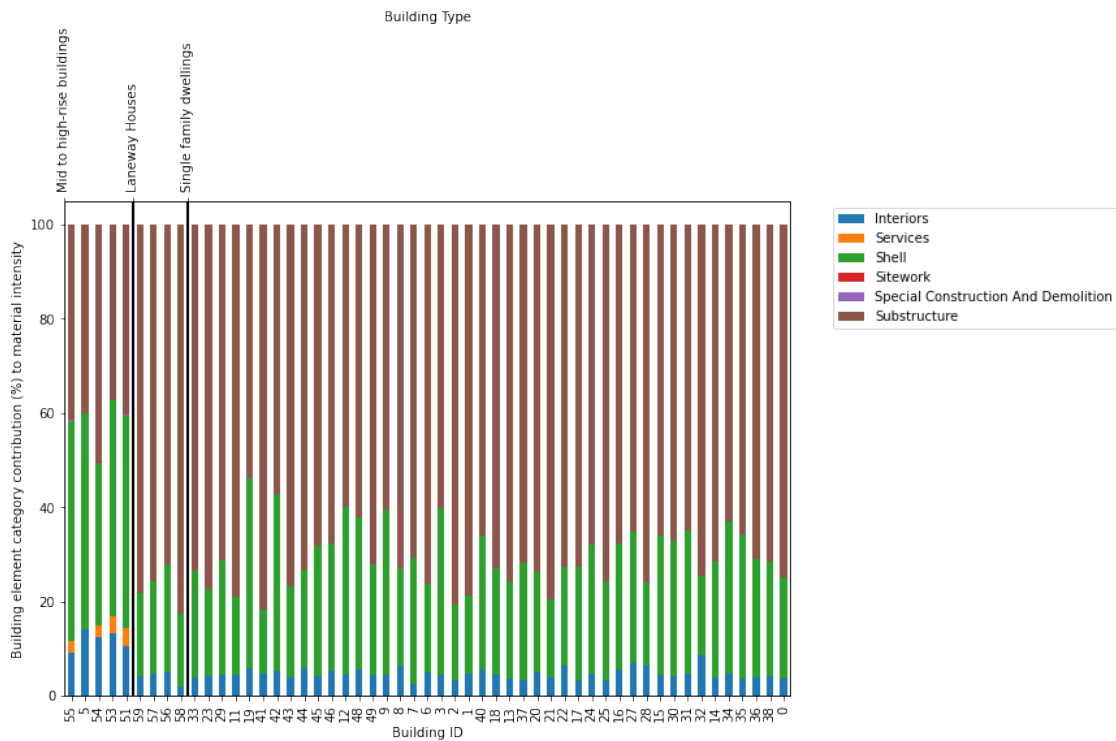
    topplot[col].plot.bar(x='Year',y='Value', ax=ax, stacked=True,
        bottom = margin_bottom, color=cmap(num),
        ↳label=col)
    margin_bottom += values
```

```

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(toplot))
ax2.set_xticks([k for k,v in enumerate(toplot['Building Type'].values) if
    ↳building_type_map[v] != building_type_map[toplot['Building Type'].
    ↳values[k-1]] or k==0])
for tick in ax2.get_xticklabels():
    tick.set_rotation(90)
ax2.set_xticklabels([building_type_map[v] for k,v in enumerate(toplot['Building_
    ↳Type'].values) if building_type_map[v] != building_type_map[toplot['Building_
    ↳Type'].values[k-1]] or k==0])
ax2.set_xlabel("Building Type")
plt.grid(color='black',linewidth=2)
plt.show()

```



```

[41]: 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 k,v in toplot.iteritems():
    toplot[k] = v * int(k.split('/')[1])
f = lambda x: x.split('/')[0]
toplot = pd.concat([df['Building Type'], toplot.groupby(f,axis=1).sum()],axis=1).
    ↳sort_values('Building Type')
# toplot['index'] = toplot['index'].astype('str')

```

```

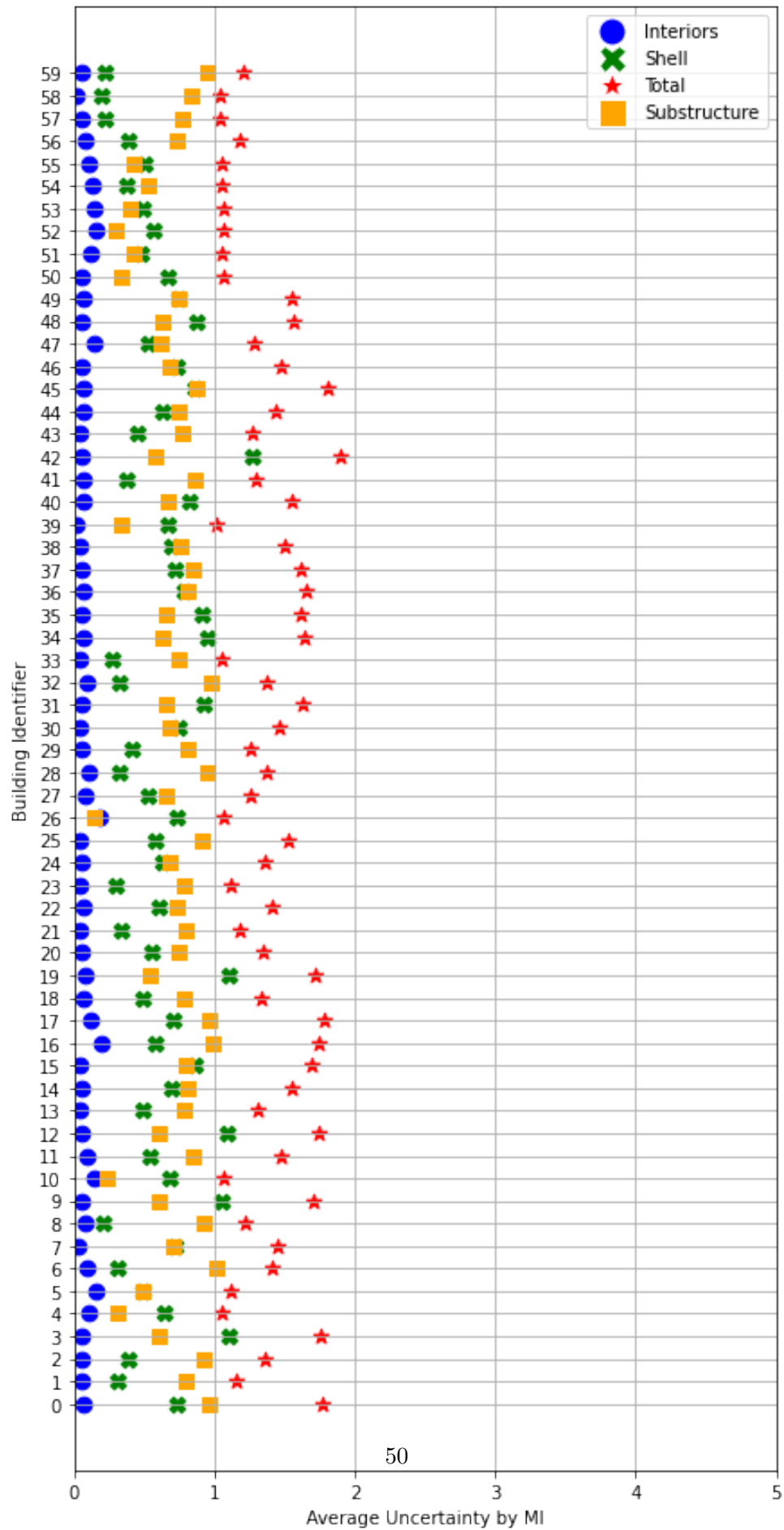
[42]: toplot['Total'] = toplot[['Interiors','Services','Shell','Sitework','Special_
    ↳Construction And Demolition','Substructure']].sum(axis=1)
toplot = toplot[['Interiors','Shell','Substructure','Total']].reset_index()

```

```

[43]: from matplotlib.lines import Line2D
fig, ax = plt.subplots(figsize=(7,15))
ax.set_xlim(0,5)
ax.set_yticks(toplot.index)
handles = []
for v,m,c in
    ↳[(('Interiors','o','blue'),('Shell','X','green'),('Total','*','red'),('Substructure','s','or
    ↳
        toplot.plot.scatter(x=v,y='index', ax=ax, 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)
plt.ylabel('Building Identifier')
plt.xlabel('Average Uncertainty by MI')
plt.grid()

```



[ ]: