Sample

April 22, 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 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	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	…	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	0B1_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

	0B1_A5020.10.000_06 11 00.00_kg_1	0B1_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':'0CF',
    'Foundation Walls':'0FW',
    'Spread Footings':'0SF',
    'Column Piers':'0CP',
    'Columns Supporting Floors':'CSF',
    'Floor Girders and Beams':'FGB',
    'Floor Trusses':'0FT',
    'Floor Joists':'0FJ',
```

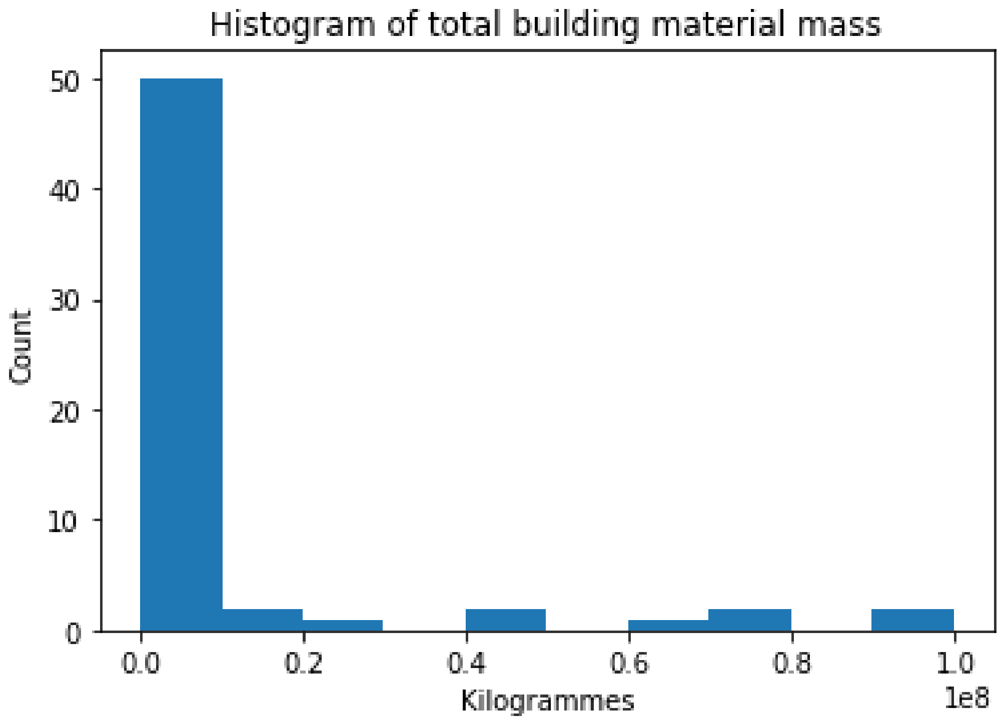
```
    'Columns Supporting Roofs':'CSR',
    'Roof Girders and Beams':'RGB',
    'Roof Trusses':'ORT',
    'Roof Joists':'ORJ',
    'Parking Bumpers':'OPB',
    'Precast Concrete Stair Treads':'PCS',
    'Roof Curbs':'ORC',
    'Exterior Wall Construction':'EWC',
    'Composite Decking':'CPD',
    'Cast-in-Place 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	SMR	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	SNR	413.72	9.293583e+04
17	1969	SNR	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	SNR	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	

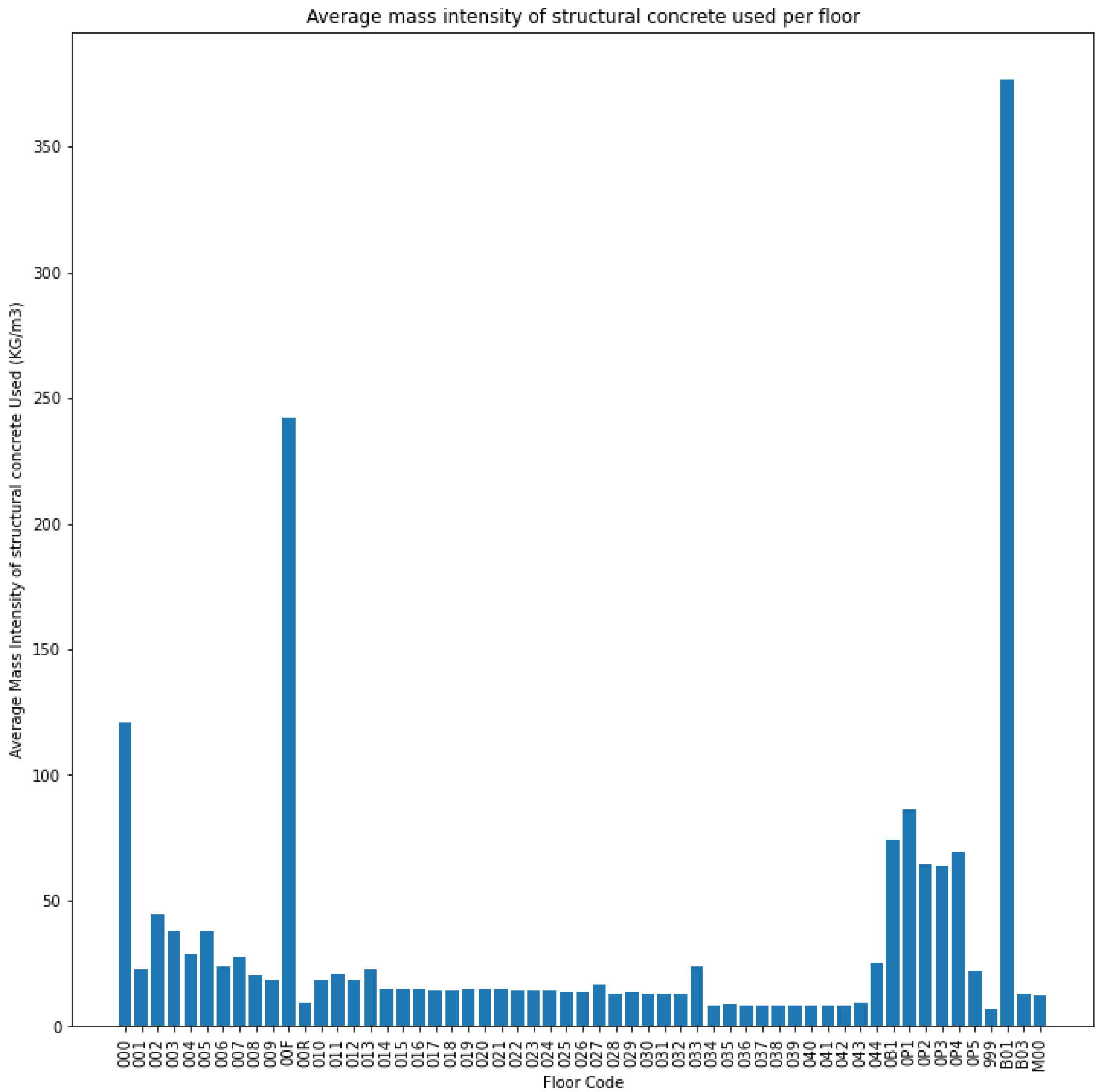
28	0.0	0.0	0.0	0.0
29	0.0	0.0	0.0	0.0
30	0.0	0.0	0.0	0.0
31	0.0	0.0	0.0	0.0
32	0.0	0.0	0.0	0.0
33	0.0	0.0	0.0	0.0
34	0.0	0.0	0.0	0.0
35	0.0	0.0	0.0	0.0
36	0.0	0.0	0.0	0.0
37	0.0	0.0	0.0	0.0
38	0.0	0.0	0.0	0.0
39	0.0	0.0	0.0	0.0
40	0.0	0.0	0.0	0.0
41	0.0	0.0	0.0	0.0
42	0.0	0.0	0.0	0.0
43	0.0	0.0	0.0	0.0
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]:
```python
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.

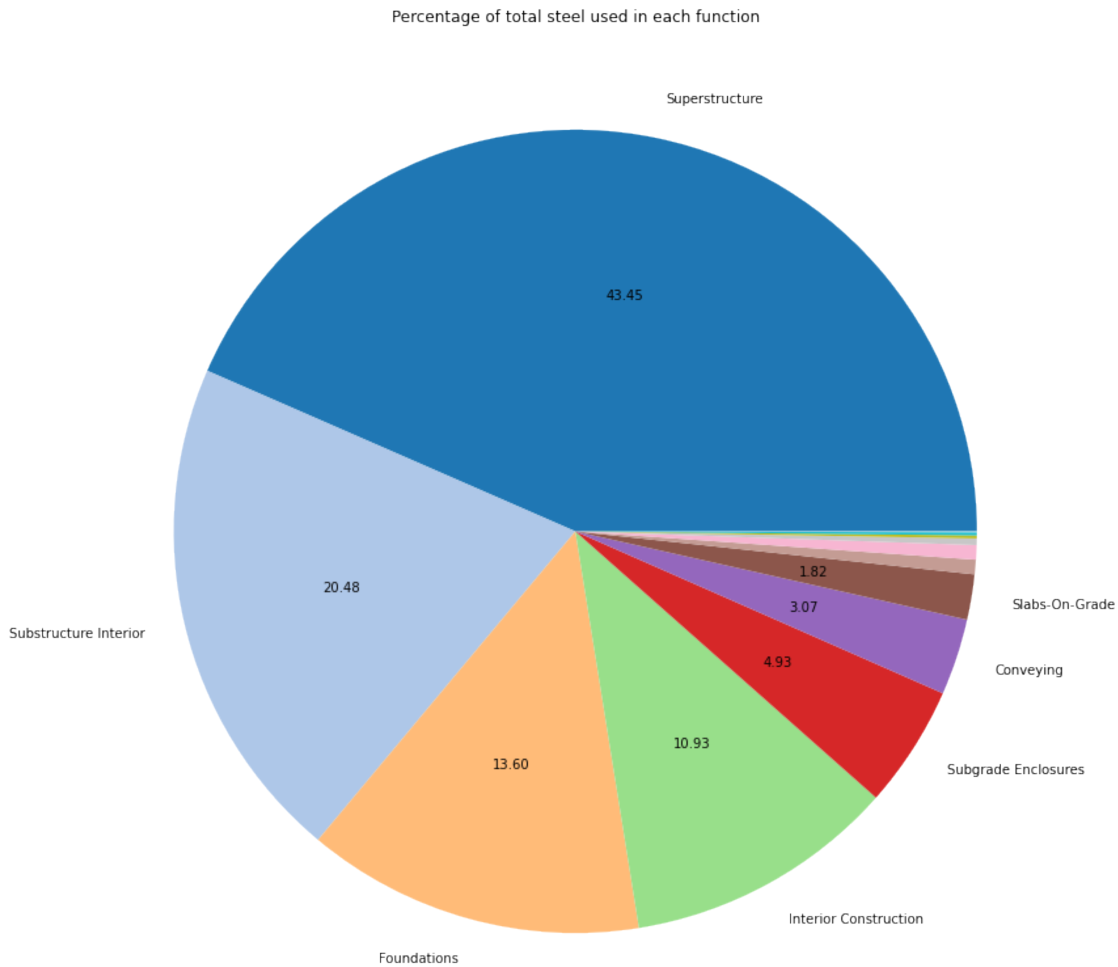
[14]:
```
f = lambda x: name_map[re.split('[_\.\ ]',x)[1][0:3]] #This function takes in a␣
↪full column name and returns only the Level 3 MasterFormat code.
concrete_df = df[cols].groupby(f,axis=1).sum()
```

[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%

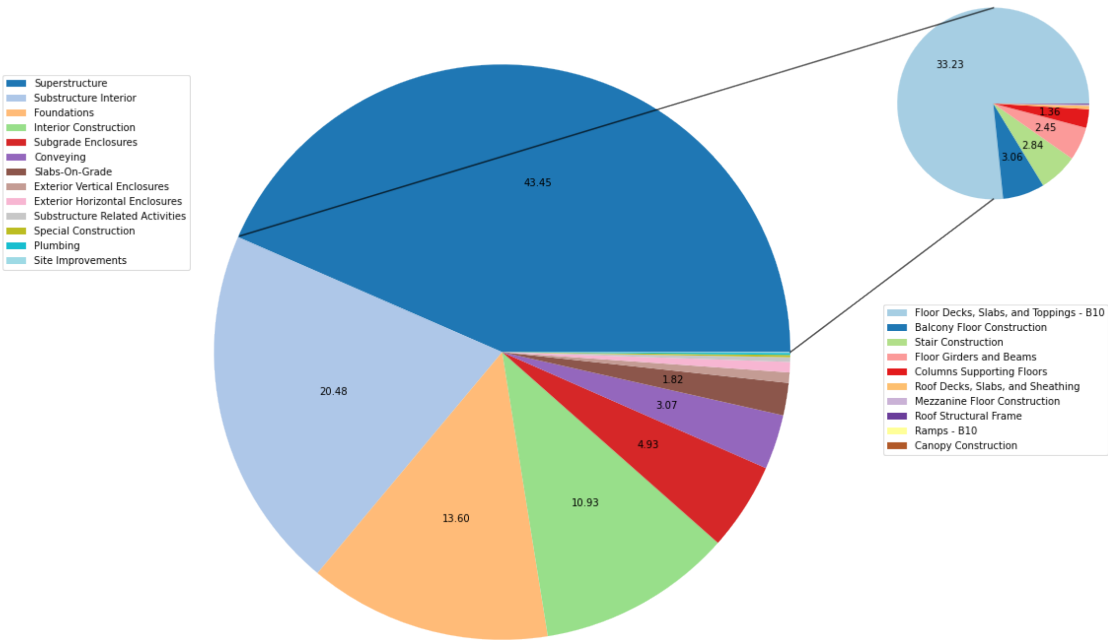
[16]:
```
def my_autopct(pct):
    return ('%.2f' % pct) if pct > 1 else ''
to_plot = concrete_df.mean().sort_values(ascending=False)
to_plot.plot.pie(figsize=(12,12),colormap='tab20',autopct=my_autopct,labels=[k␣
↪if v > 30000 else '' for k,v in to_plot.items()])
plt.ylabel('')
plt.title('Percentage 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]:
```
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)
```

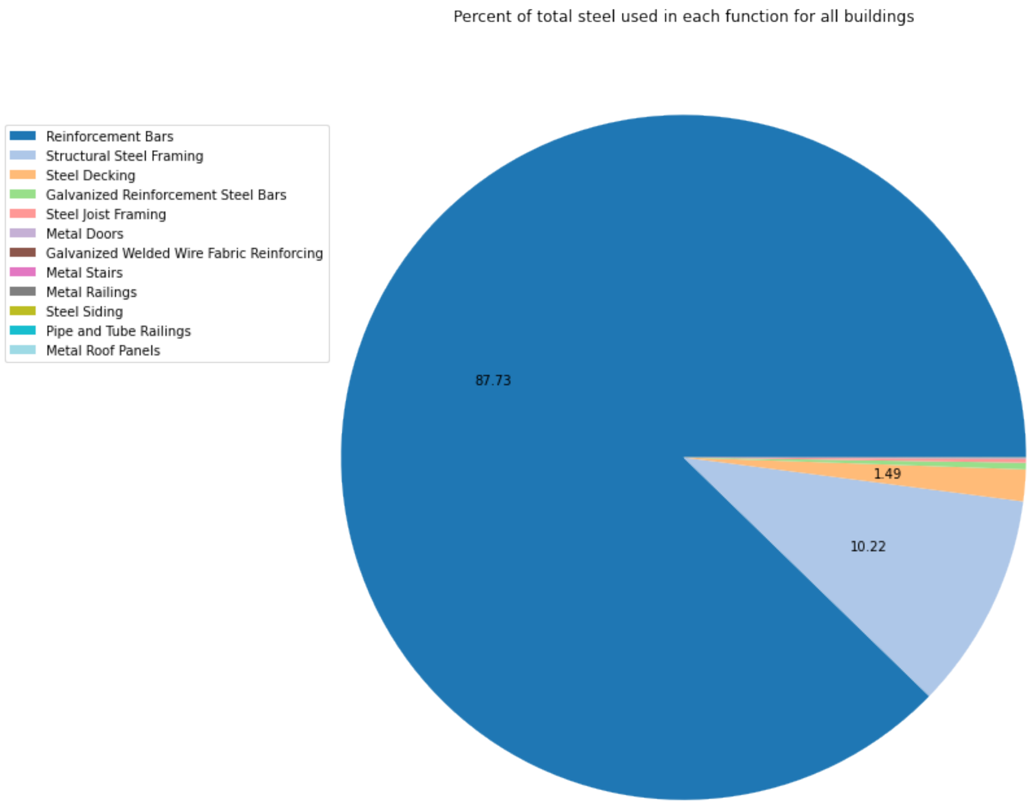
[21]:
```
f = lambda x: mf_codes[mf_codes.Code == str.replace(re.split('_',x)[2],'00','').
 ↪strip('.')].values[0][0]
steel_df = df[columns_to_keep].groupby(f,axis=1).sum()
```

[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
```

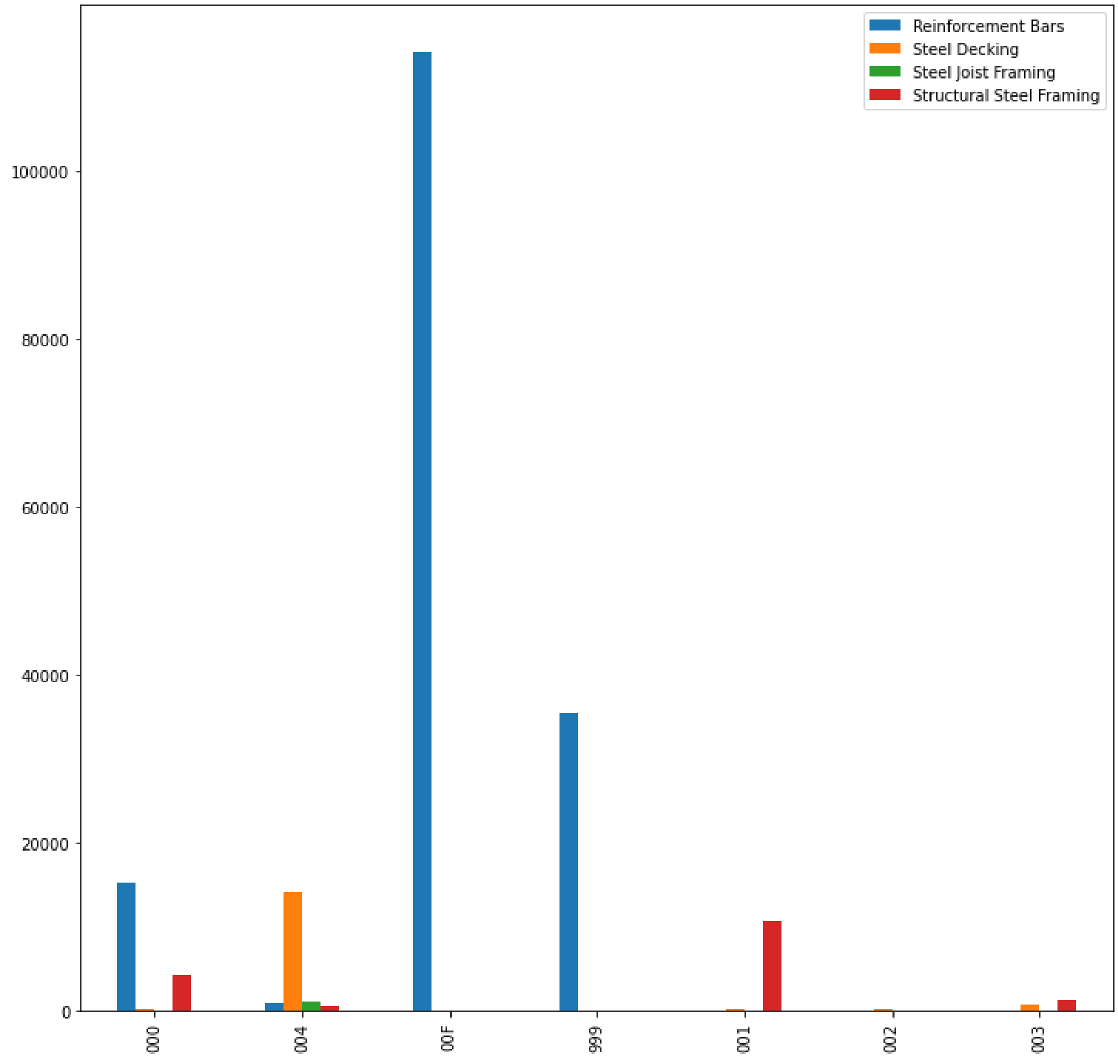
```
52    3
53    3
56    3
46    3
39    3
29    3
37    3
28    3
27    3
26    3
25    3
13    3
10    3
2     3
38    3
5     3
6     3
8     3
57    4
4     4
49    4
50    4
48    4
47    4
19    4
51    4
59    4
dtype: int64
```

[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'Percent of total steel used in each function for all buildings');
plt.tight_layout();

plt.savefig('steel_composition_pie.pdf')
```



[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[columns_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.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]:
```
                   Gross Floor Area  Structural Concrete/000  \
Construction Date
1913                     161.080000             0.000000e+00
1917                     199.930000             0.000000e+00
1969                     373.605000             0.000000e+00
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	3.595656e+06
2017	39392.013333	4.084352e+06
2018	43560.635000	5.893680e+06
2019	83.100000	0.000000e+00
2020	418.528571	4.914431e+03
2021	445.404444	0.000000e+00

	Structural Concrete/001	Structural Concrete/002 \
Construction Date		
1913	1944.380000	0.0
1917	4972.300000	0.0
1969	7262.220500	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	2680512.0
2017	0.000000	989280.0
2018	0.000000	1511892.0
2019	0.000000	0.0
2020	4923.690714	0.0
2021	11399.123858	0.0

	Structural Concrete/003	Structural Concrete/004 \
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	1686228.0	1057032.0
2017	1232336.0	778480.0
2018	1347936.0	1323132.0
2019	0.0	0.0
2020	0.0	0.0
2021	0.0	0.0

	Structural Concrete/005	Structural Concrete/006 \
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                               1056780.0                 1129680.0
2017                                683496.0                  679376.0
2018                               2164812.0                  969060.0
2019                                     0.0                       0.0
2020                                     0.0                       0.0
2021                                     0.0                       0.0

                   Structural Concrete/007  Structural Concrete/008  …  \
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                             1809852.0                 857976.0  …
2017                              632520.0                 651080.0  …
2018                              752208.0                 734688.0  …
2019                                   0.0                      0.0  …
2020                                   0.0                      0.0  …
2021                                   0.0                      0.0  …

                   Structural Concrete/0B1  Structural Concrete/0P1  \
Construction Date
1913                              0.000000                      0.0
1917                              0.000000                      0.0
1969                              0.000000                      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                2206668.0
2017                              0.000000                3402456.0
2018                              0.000000                3713916.0
2019                           5412.758585                      0.0
2020                              0.000000                      0.0
2021                            545.221944                      0.0

                   Structural Concrete/0P2  Structural Concrete/0P3  \
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	1715028.0	1596444.0
2017	2513320.0	2469984.0
2018	2637060.0	2756916.0
2019	0.0	0.0
2020	0.0	0.0
2021	0.0	0.0

	Structural Concrete/0P4	Structural Concrete/0P5 \
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	0.0
2017	1895672.0	508328.0
2018	4093284.0	0.0
2019	0.0	0.0
2020	0.0	0.0
2021	0.0	0.0

	Structural Concrete/999	Structural Concrete/B01 \
Construction Date		
1913	0.0	64035.190000
1917	0.0	114018.460000
1969	0.0	132278.015000
1988	0.0	0.000000
2007	0.0	0.000000
2009	0.0	0.000000
2011	0.0	0.000000
2016	155076.0	0.000000
2017	7736.0	0.000000
2018	558516.0	0.000000
2019	0.0	0.000000
2020	0.0	140301.728571
2021	0.0	161741.376806

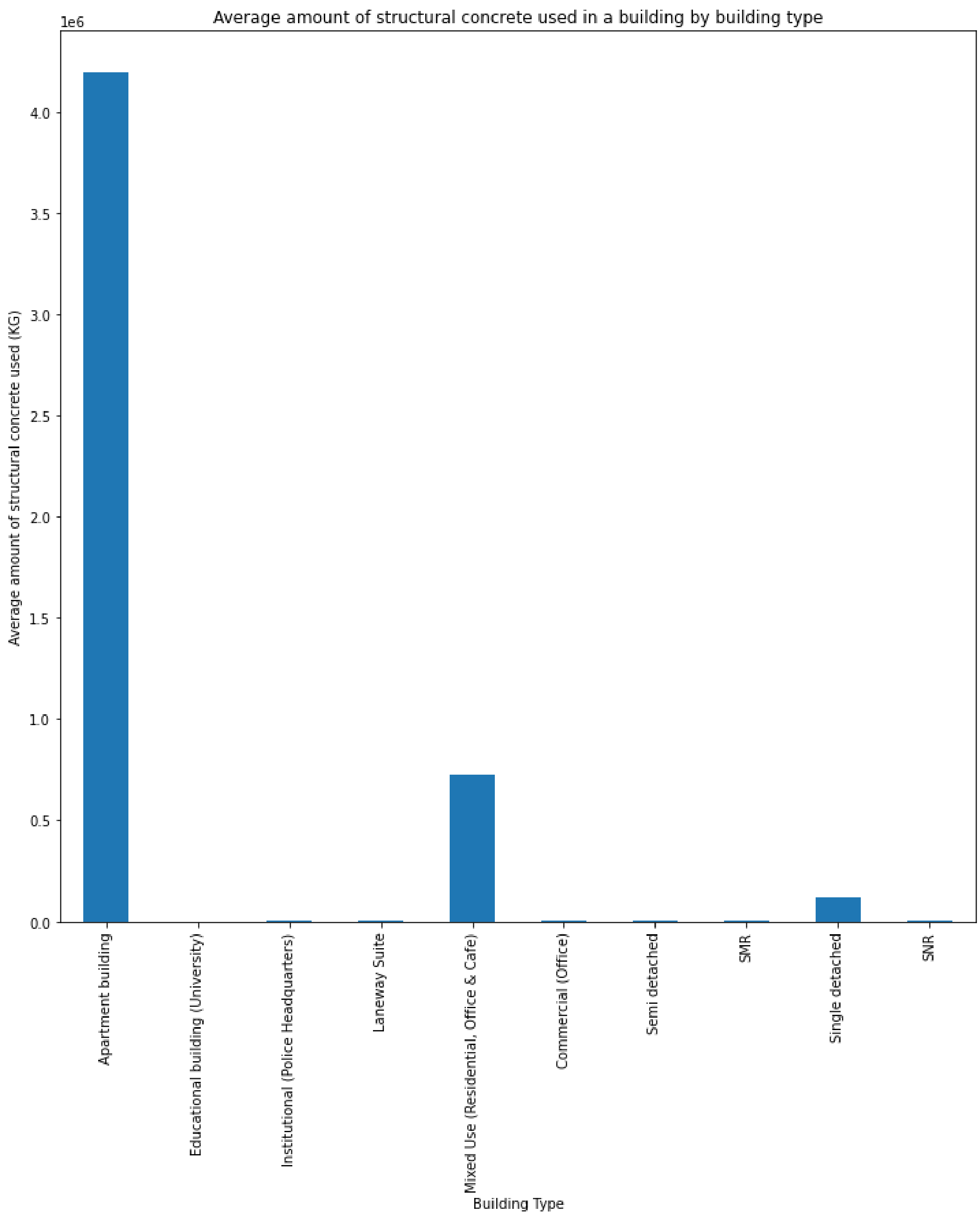
	Structural Concrete/B03	Structural Concrete/M00
Construction Date		
1913	0.000000	0.0
1917	0.000000	0.0
1969	0.000000	0.0
1988	0.000000	0.0

```
2007                                    0.000000               0.0
2009                                    0.000000               0.0
2011                                    0.000000               0.0
2016                                    0.000000           82056.0
2017                                    0.000000               0.0
2018                                    0.000000          597624.0
2019                                    0.000000               0.0
2020                                  988.177143               0.0
2021                                    0.000000               0.0

[13 rows x 58 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 code associated with each column. 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': 1662, '2': 641, '4': 293}),
 'OFF': Counter({'1': 494, '3': 307}),
 'APB': Counter({'1': 1171, '2': 1, '3': 971}),
 'SMR': Counter({'1': 21, '2': 27, '4': 8}),
 'SNR': Counter({'1': 58, '2': 70, '4': 56}),
 'SMD': Counter({'1': 170, '2': 34, '4': 19}),
 '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.

[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␣
↪code.
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)
```

[33]:
```
                                        Construction Date  Gross Floor Area  \
Building Type
Apartment building                            2015.800000      45505.412000
Educational building (University)             2016.500000       7901.000000
Institutional (Police Headquarters)           1988.000000      21934.000000
Laneway Suite                                 2020.000000        150.010000
Mixed Use (Residential, Office & Cafe)        2018.000000      33975.250000
Commercial (Office)                           2009.000000      52643.666667
```

```
Semi detached                                 2020.666667       248.843333
SMR                                           1917.000000       199.930000
Single detached                               2020.891892       478.399730
SNR                                           1950.333333       302.763333

                                        Interiors/1  Services/1       Shell/1  \
Building Type
Apartment building                        5330644.8   1525512.0  2.194912e+07
Educational building (University)               0.0         0.0  0.000000e+00
Institutional (Police Headquarters)             0.0         0.0  0.000000e+00
Laneway Suite                                   0.0         0.0  0.000000e+00
Mixed Use (Residential, Office & Cafe)    5893176.0   1878144.0  2.306316e+07
Commercial (Office)                             0.0         0.0  0.000000e+00
Semi detached                                   0.0         0.0  1.864267e+03
SMR                                             0.0         0.0  0.000000e+00
Single detached                               305.6         0.0  1.547007e+03
SNR                                             0.0         0.0  2.504947e+03

                                          Shell/2  Sitework/1  \
Building Type
Apartment building                       0.000000     23188.8
Educational building (University)        0.000000         0.0
Institutional (Police Headquarters)      0.000000         0.0
Laneway Suite                            0.000000         0.0
Mixed Use (Residential, Office & Cafe)   0.000000         0.0
Commercial (Office)                      0.000000         0.0
Semi detached                            0.000000         0.0
SMR                                      0.000000         0.0
Single detached                         13.194162         0.0
SNR                                      0.000000         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
SMR                                                                       0.0
Single detached                                                           0.0
SNR                                                                       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                             9.764084e+04        0.000000
SMR                                       1.100899e+05     8900.860000
Single detached                           1.808877e+05     5347.871730
SNR                                       9.318079e+04    19334.277000

                                        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
SMR                                             0.0000
Single detached                                 0.0000
SNR                                             0.0000
```

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

[34]:
```
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()
```

[34]:
```
                   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`:

[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	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	
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	
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
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
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
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
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	
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
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
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
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

[37 rows x 21 columns]
```

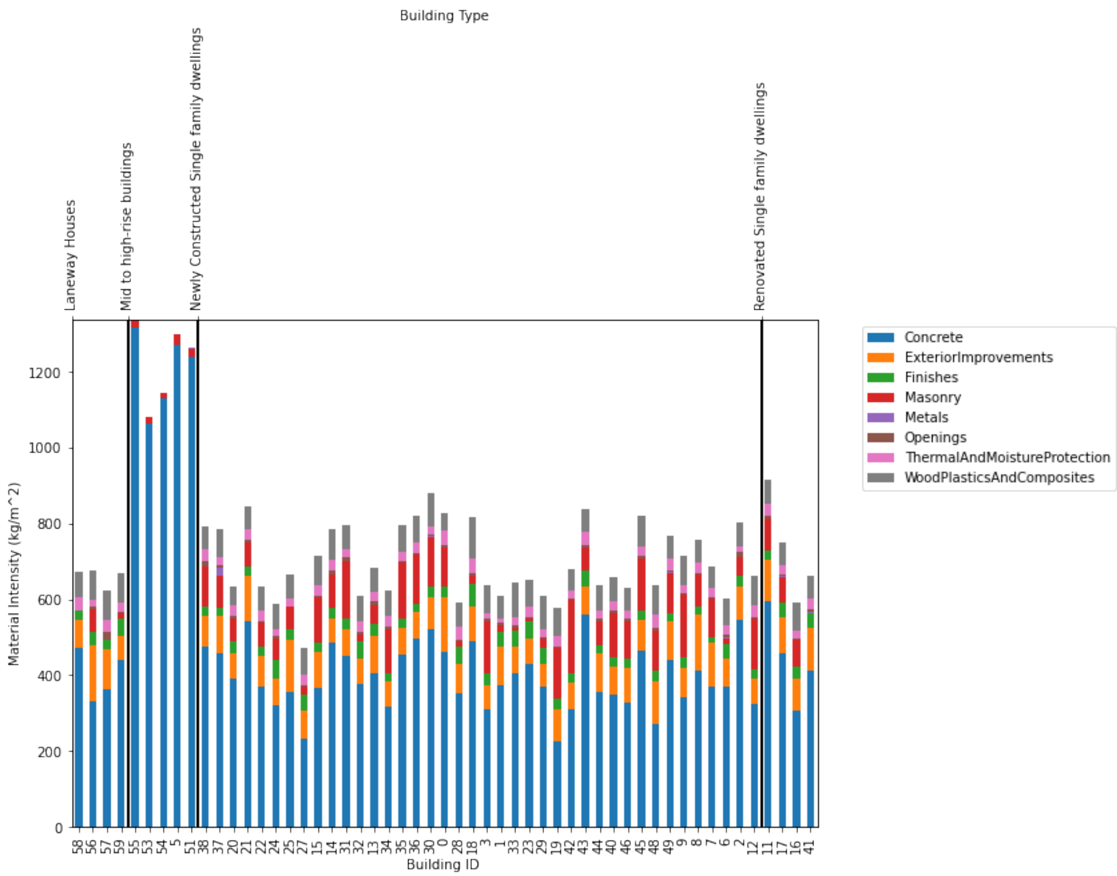
[37]:
```
master_format_convert = {v:k for k,v in {
    'Concrete':'03',
    'Masonry':'04',
    'Metals':'05',
    'WoodPlasticsAndComposites':'06',
    'ThermalAndMoistureProtection':'07',
    'Finishes':'09',
    'Openings':'08',
    'Earthwork':'31',
    'ExteriorImprovements':'32'
}.items() }
```

[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]:
```
types_to_keep = ['APB','SND','SNR','SMR','SMD','ADU','SEC','ROW','LNW']
toplot = toplot[toplot['Building Type'].isin(types_to_keep)]
building_type_map = {
    'APB':'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'
}

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

[40]:

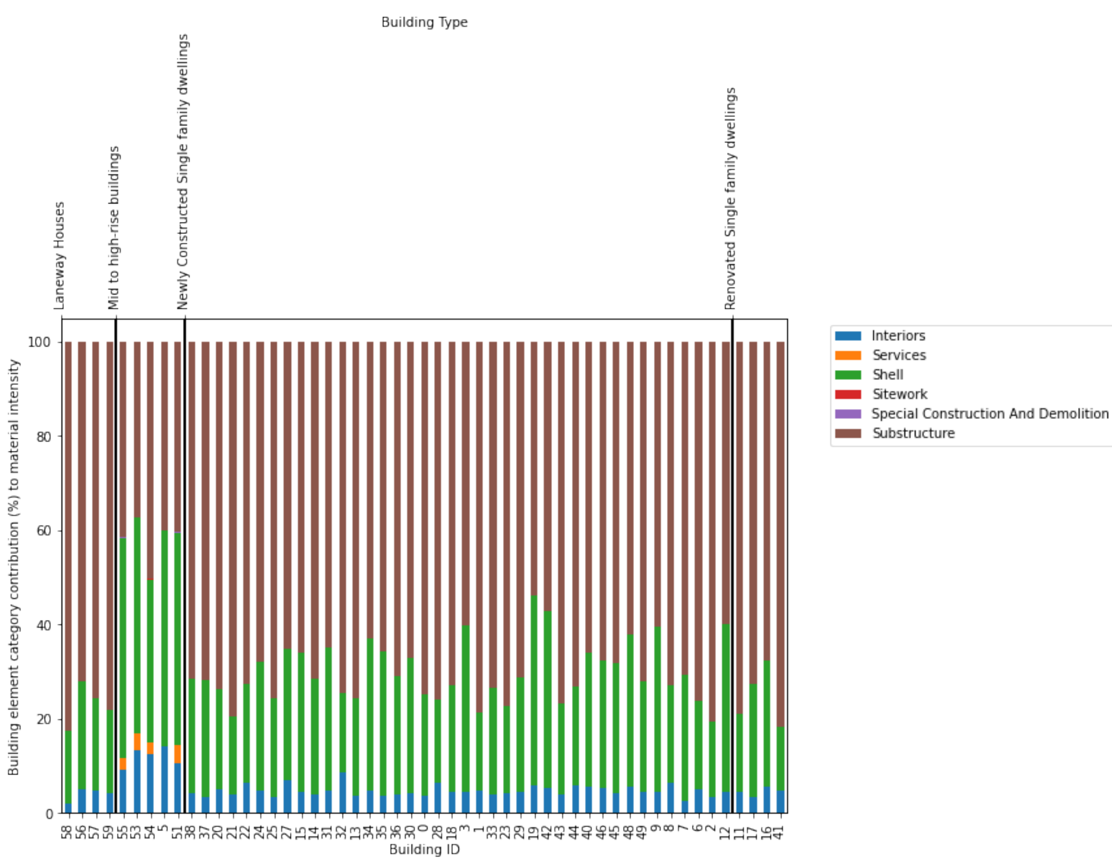
```python
fig, ax = plt.subplots(figsize=(10,7))

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.twiny()
ax2.set_xlim(0, len(toplot))
ax2.set_xticks([k for k,v in enumerate(toplot['Building Type'].values) if v != toplot['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()
```



[41]:
```
df_mi = df[kilogram_columns].div(df['Gross Floor Area'],axis=0)
```

[42]:
```
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]]
toplot = pd.concat([df[headings[1:]],df_mi[kilogram_columns].groupby(f,axis=1).
 ↪sum()],axis=1).sort_values('Building Type')
toplot = toplot[toplot['Building Type'].isin(types_to_keep)]
toplot['Building Type'] = toplot['Building Type'].replace(building_type_map)
toplot = toplot.sort_values('Building Type')
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.xlabel('Building ID')
plt.ylabel('Building element category contribution (%) to material intensity')

ax2 = ax.twiny()
ax2.set_xlim(0, len(toplot))
ax2.set_xticks([k for k,v in enumerate(toplot['Building Type'].values) if v != toplot['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()
```



[43]:
```
f = lambda x: name_map[re.split('[_\.\ ]',x)[1][0]] + '/' + re.split('[_\.\␣
↪]',x)[-1]
toplot = df_mi[kilogram_columns].groupby(f,axis=1).sum()
```

[44]:
```
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')
```

[45]:
```
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')
```

[46]:
```
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('Average Uncertainty by MI')
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)
```

Renovated Single family dwellings
Newly Constructed Single family dwellings
Mid to high-rise buildings
Laneway Houses
Interiors
Shell
Total
Substructure
Building Type
Building Identifier
Average Uncertainty by MI
42
17
18
12
13
3
7
8
9
10
50
49
46
47
41
45
44
43
20
30
24
34
2
4
19
29
1
31
37
36
35
14
33
32
15
16
28
26
25
23
22
21
38
39
52
6
55
54
56
60
58
57
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0

[ ]:

[ ]: