Sample

March 24, 2021

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import re
```

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',
             'Contributor']
```

[3]:
```
df = pd.read_excel('Dataset/dataset.xlsx',header=1,usecols='B:BKX')
```

[4]:
```
mapper = pd.read_excel('/Users/alex/Downloads/Mapping material names_20210324.
 ↪xlsx',header=2,usecols='B:U').replace(r'\n','', regex=True)
```

[5]:
```
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':'0RT',
    'Roof Joists':'0RJ',
    'Parking Bumpers':'0PB',
    'Precast Concrete Stair Treads':'PCS',
    'Roof Curbs':'0RC',
```

```
    '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'}.items()
}

additional_categories_map['OFT'] = 'Floor Trusses'

headings = ['Building Identifier',
            'Country',
 'City',
 'Quality / Stage of Data',
 'Construction Date',
 'Building Type',
 'Contributor']
```

[6]:
```
def get_material_name(l):
    split = re.split('[_\.\ ]',l) #Split up the code into its requisite parts
    result = mapper[mapper['Unnamed: 7'] == split[1]+'.'+split[2]] #Filter by␣
↪Level 4 Master Format
    if len(result) == 0:
        result = mapper #If that code does not exist in the table, reset
    if len(result) == 1:
        return result['Mapping Table'].values[0] #If it maps to exactly one␣
↪value, return that. We do this check after every step
    if split[3] != '000': #Check if there is an additional code, and if so␣
↪filter by that
        result = result[result['Level 5\n'] ==␣
↪additional_categories_map[split[3]]]
        if len(result) == 1:
            return result['Mapping Table'].values[0]

    #Now filter by UniFormat.
    #Filter only by the level of UniFormat present. If the code is XX 00 00,␣
↪for example, then we only have Level 1.
    if int(split[5]) == 0:
        result = result[result['Unnamed: 12'] == f'{split[4]} 00 00']
        if len(result) == 1:
```

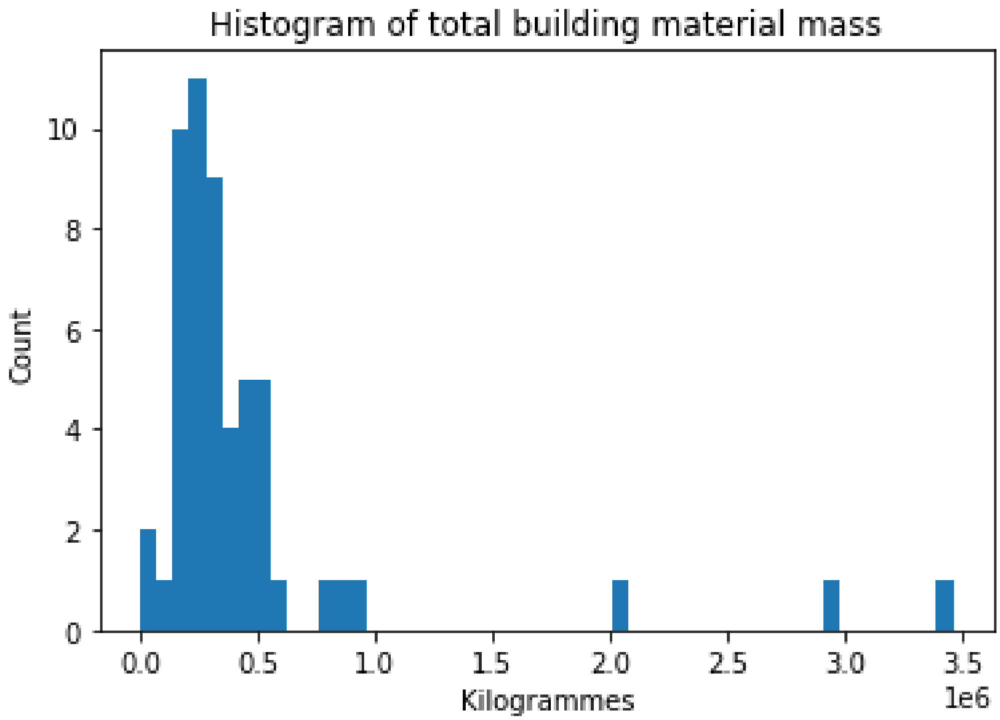
```
            return result['Mapping Table'].values[0]
    elif int(split[6]) == 0:
        result = result[(result['Unnamed: 14'] == f'{split[4]} {split[5]} 00')␣
↪| (result['Unnamed: 16'] == f'{split[4]} {split[5]} 00')]
        if len(result) == 1:
            return result['Mapping Table'].values[0]
    else:
        result = result[result['Unnamed: 18'] == f'{split[4]} {split[5]}␣
↪{split[6]}']
        if len(result) == 1:
            return result['Mapping Table'].values[0]

    #If we couldn't find it, or there is an unspecified edge case, return None.
    if len(result) == 0:
        return None

    #If there are multiple results but they all map to the same material,␣
↪return that material.
    if all(element == result['Mapping Table'].values[0] for element in␣
↪result['Mapping Table'].values):
        return result['Mapping Table'].values[0]
    else:
        return None
```

2 1. Plot sample figures

Here we plot building material mass, and volume histograms.

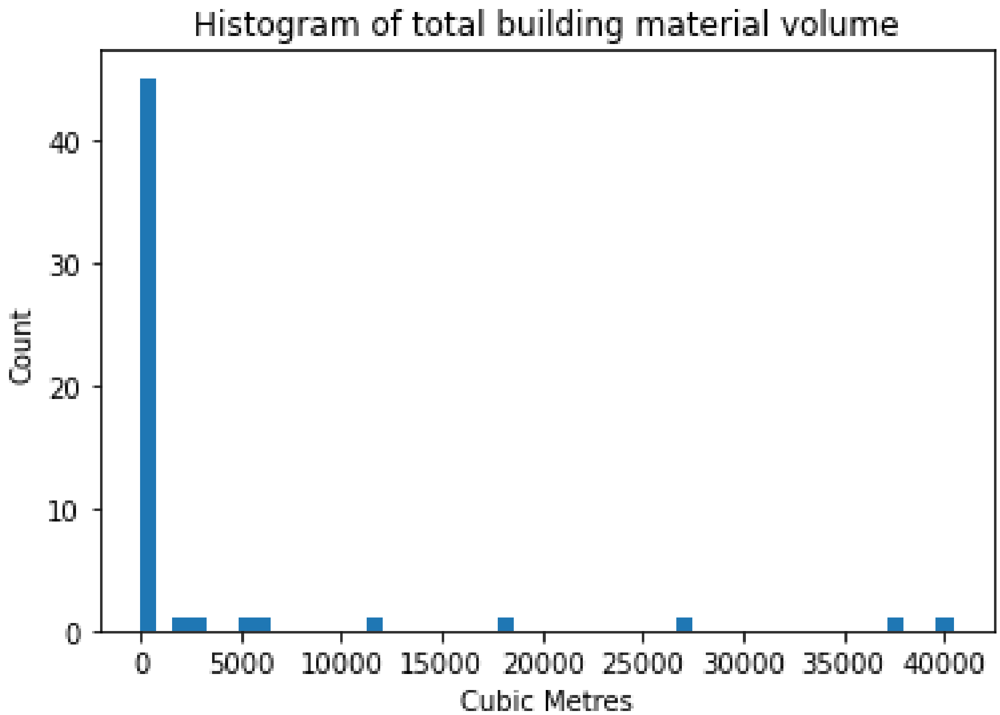
[7]:
```
plt.hist(df[[c for c in df.columns if 'kg' in c]].sum(axis=1),bins=50);
plt.title('Histogram of total building material mass')
plt.xlabel('Kilogrammes')
plt.ylabel('Count');
```

[7]:
```
Text(0, 0.5, 'Count')
```



[8]:
```
plt.hist(df[[c for c in df.columns if 'm3' in c]].sum(axis=1),bins=50);
plt.title('Histogram of total building material volume')
plt.xlabel('Cubic Metres')
plt.ylabel('Count');
```

[8]:
```
Text(0, 0.5, 'Count')
```



3 2. Investigate a specific material

In this example, we use the helper function `get_material_name()` to select columns which match `steel`. Then, we calculate the average amount of steel used by floor, produce a table of values by Level 3 MasterFormat only, and calculate the average values for these by year in the dataset.

[9]:
```
material = 'steel'
cols = []
for column in df.columns[7:]: #Iterate through columns that represent materials
    if get_material_name(column) == 'steel' and 'kg' in column: #If that column␣
↪represents steel and is a mass value:
        cols.append(column) #Append to cols
```

[10]:
```
steel_df = df[df.columns[1:7].to_list() + cols].fillna(0) #Select only the␣
↪heading columns and the columns related to steel
```

[11]:
```
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.
steel_df[cols].groupby(grouping_function,axis=1).sum().mean()
```

[11]:
```
000    4631.751063
001    3067.385626
```

```
002    2827.391277
003    1748.778503
004     484.167710
005     818.053124
006     822.260903
007    1488.697400
008    1015.103971
009     653.231968
00F    7948.405146
00R     129.413985
010     488.252782
011     515.548827
012      36.441030
013      50.939630
014      35.358148
015      30.791481
016      45.260000
017      39.808611
018      25.340093
019      39.808611
020      39.808611
021     216.558611
022      20.773426
023      20.773426
024      20.787963
025      20.817037
026      72.347685
027    1026.355741
028      27.751204
029      20.555370
030      20.555370
031      22.517870
032      25.774167
033     138.751963
0P1     188.160139
0P2      82.890185
0P3     379.685602
0P4    1439.617315
999    4045.162555
B01     515.030276
M00     121.837870
M01     119.556954
P01    2825.480285
P02      17.547222
P03    1476.614537
dtype: float64
```

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

[12]:
```
f = lambda x: re.split('[_\.\ ]',x)[1] #This function takes in a full column␣
↪name and returns only the Level 3 MasterFormat code.
steel_general_df = pd.concat([steel_df[headings[1:]],steel_df[cols].
↪groupby(f,axis=1).sum()],axis=1)
```

[13]:
```
steel_general_df.head(3)
```

[13]:
```
  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

                             Contributor     A1010  A1020     A4010  \
0  Saxe Research Group University of Toronto   91.4005    0.0  285.8086
1  Saxe Research Group University of Toronto    0.0000    0.0    0.0000
2  Saxe Research Group University of Toronto  261.3180    0.0    0.0000

     A4020  …  B2010  B2050  B2070    B3010  B3060  C1030  C1090  D1010  \
0  16.7488  …    0.0    0.0    0.0  81.7519    0.0    0.0    0.0    0.0
1  27.1446  …    0.0    0.0    0.0   0.0000    0.0    0.0    0.0    0.0
2  15.0979  …    0.0    0.0    0.0   0.0000    0.0    0.0    0.0    0.0

   G2010  G2060
0    0.0    0.0
1    0.0    0.0
2    0.0    0.0

[3 rows x 26 columns]
```

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

[14]:
```
steel_general_df.groupby('Construction Date').mean()
```

[14]:
```
                          A1010          A1020         A4010     A4020  \
Construction Date
1913                   0.000000       0.000000     48.162700   0.00000
1917                   0.000000       0.000000      0.000000  20.81880
1969                   0.000000       0.000000      0.000000  98.43640
1988               67016.749257       0.000000  24922.610789   0.00000
2007                   0.000000  122069.070000  68246.330000   0.00000
2009               92590.750000       0.000000  58354.545000   0.00000
2011               10048.588750   11019.437500  17521.985000   0.00000
2016                   0.000000  113531.410000  14850.630000   0.00000
2017                8946.288121    3728.788900   7498.122611   0.00000
2018               11373.210833   84343.296833   1988.405000   0.00000
```

2020	418.544600	0.000000	71.606600	41.67172
2021	495.281777	0.000000	168.656643	66.54690

Construction Date	A4040	A5010	A6010	B1010 \
1913	0.000000	0.000000	0.000000	0.000000
1917	0.000000	0.000000	0.000000	0.000000
1969	0.000000	0.000000	0.000000	0.000000
1988	0.000000	617.952711	0.000000	129.786585
2007	0.000000	0.000000	0.000000	32828.900000
2009	0.000000	0.000000	0.000000	77762.100000
2011	180.157500	815.260000	0.000000	92701.751675
2016	470.215000	0.000000	0.000000	16048.100000
2017	927.640379	0.000000	0.000000	426847.063700
2018	0.000000	6904.075000	98.648333	3853.024333
2020	0.000000	297.007000	0.000000	395.993400
2021	0.000000	28.811631	0.000000	91.699229

Construction Date	B1020	B1080	B2010	B2050 \
1913	0.000000	0.000000	0.000000	0.000000
1917	0.000000	0.000000	0.000000	0.000000
1969	0.000000	0.000000	0.000000	0.000000
1988	0.000000	5677.162679	5039.204304	0.000000
2007	2249.000000	86571.370000	0.000000	0.000000
2009	63740.722253	0.000000	1062.890000	0.000000
2011	0.000000	2180.730000	1425.050000	0.000000
2016	0.000000	6437.785000	0.000000	0.000000
2017	0.000000	0.000000	0.000000	0.000000
2018	867.198000	22870.451667	0.000000	0.000000
2020	0.000000	0.000000	0.000000	133.268600
2021	0.000000	0.000000	0.000000	26.285429

Construction Date	B2070	B3010	B3060	C1030	C1090 \
1913	0.000	0.000000	0.000	0.000000	0.000000
1917	0.000	0.000000	0.000	0.000000	0.000000
1969	0.000	0.000000	0.000	0.000000	0.000000
1988	0.000	0.000000	0.000	0.000000	0.000000
2007	0.000	0.000000	0.000	0.000000	16665.000000
2009	88591.000	0.000000	0.000	0.000000	0.000000
2011	0.000	0.000000	0.000	0.000000	0.000000
2016	0.000	0.000000	0.000	0.000000	0.000000
2017	0.000	0.000000	0.000	0.000000	0.000000
2018	237.372	0.000000	1798.362	0.000000	320.180758
2020	0.000	0.000000	0.000	0.000000	0.000000
2021	0.000	9.384283	0.000	19.758857	0.000000

```
                        D1010     G2010    G2060
Construction Date
1913                 0.000000     0.000     0.00
1917                 0.000000     0.000     0.00
1969                 0.000000     0.000     0.00
1988               334.146341     0.000     0.00
2007              7925.800000     0.000     0.00
2009              6959.600000  3242.050     0.00
2011                 0.000000   988.315  1698.74
2016                 0.000000     0.000     0.00
2017                 0.000000     0.000     0.00
2018                 0.000000     0.000     0.00
2020                 0.000000     0.000     0.00
2021                 0.000000     0.000     0.00
```

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.

[15]:
```
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])
```

[16]:
```
from collections import Counter
```

[17]:
```
for k,v in uncertainty_level.items():
    uncertainty_level[k] = Counter(v) #Construct a Counter object per building␣
↪type
```

[18]:
```
uncertainty_level
```

[18]:
```
{'SND': Counter({'1': 1720, '2': 711, '4': 349}),
 'OFF': Counter({'1': 494, '3': 307}),
 'APB': Counter({'1': 358, '2': 1, '3': 314}),
 'SMD': Counter({'1': 191, '2': 61, '4': 27}),
 'EDU': Counter({'1': 93, '3': 24, '2': 6}),
 'INS': Counter({'1': 90, '3': 77, '2': 1}),
 'ROW': Counter({'1': 15, '3': 5}),
 'MIX': Counter({'1': 315})}
```

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

[19]:
```
f = lambda x: re.split('[_\.\ ]',x)[1][0] + x.split('_')[-1] #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)
```

[20]:
```
by_function_df.groupby('Building Type').mean()
```

[20]:
```
               Construction Date             A1         A2             A3  \
Building Type
APB                      2014.50  101344.154000   0.000000   74241.767500
EDU                      2016.50       0.000000   0.000000   74976.547506
INS                      1988.00       0.000000   0.000000   92557.312757
MIX                      2018.00       0.000000   0.000000       0.000000
OFF                      2009.00       0.000000   0.000000  127794.205833
ROW                      2018.00       0.000000   0.000000       0.000000
SMD                      1994.75      82.653250  11.036450       0.000000
SND                      2015.60     676.023563  68.474865       0.000000

                      A4             B1       B2            B3        B4  \
Building Type
APB             0.000000    6090.412000   0.0000  38926.972500  0.000000
EDU             0.000000  221447.581850   0.0000   3218.892500  0.000000
INS             0.000000     129.786585   0.0000  10716.366983  0.000000
MIX             0.000000       0.000000   0.0000      0.000000  0.000000
OFF             0.000000  149228.155201   0.0000  29491.141667  0.000000
ROW             0.000000    7019.600000   0.0000   1088.010000  0.000000
SMD             4.246275       0.000000   0.0000      0.000000  0.000000
SND            20.342905     115.462900  55.4561      0.000000  6.686572

                        C1      C2           D1           G3
Building Type
APB             480.271137   0.000     0.000000     0.000000
EDU               0.000000   0.000     0.000000     0.000000
INS               0.000000   0.000   334.146341     0.000000
MIX               0.000000   0.000     0.000000     0.000000
OFF            5555.000000   0.000  4961.800000  2872.053333
ROW               0.000000   0.000     0.000000     0.000000
SMD               0.000000   0.000     0.000000     0.000000
SND               0.000000  17.289     0.000000     0.000000
```

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

[21]:
```
f = lambda x: x.split('_')[-1] #Select only the uncertainty code.
```

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

[21]:

	1	2	3	4
Construction Date				
1913	48.162700	0.000000	0.000000	0.000000
1917	0.000000	20.818800	0.000000	0.000000
1969	0.000000	98.436400	0.000000	0.000000
1988	463.932927	0.000000	103273.679739	0.000000
2007	59668.700000	0.000000	276886.770000	0.000000
2009	237053.422253	0.000000	155250.235000	0.000000
2011	93514.931675	0.000000	45065.083750	0.000000
2016	16048.100000	0.000000	135290.040000	0.000000
2017	426847.063700	0.000000	21100.840011	0.000000
2018	72777.384758	0.000000	61876.840000	0.000000
2020	1076.002180	157.941140	0.000000	124.148600
2021	758.911369	133.872774	0.000000	13.640606

[ ]: