Static Mortality Categorisation

Benjamin Frost 2022

In [ ]:

```
import pandas as pd
import numpy as np
import torch.multiprocessing as mp
from sklearn.preprocessing import KBinsDiscretizer, OneHotEncoder, MinMaxScaler
from Categorization import Categorizer
from matplotlib import pyplot as plt
from sklearn.cluster import AgglomerativeClustering
from sklearn.metrics import silhouette_score
from sklearn.cluster import KMeans
from tqdm import tqdm
from concurrent.futures import ThreadPoolExecutor, as_completed
import torch
import copy
from torch.nn.functional import one_hot
from torch.utils.data import DataLoader, TensorDataset, random_split
import imblearn
from collections import Counter
from importlib import reload
```

Loading in the data

In [ ]:

```
mimicDF = pd.read_csv('../LEN_Test/data/StaticData.csv')
targetDF = mimicDF[['deathperiod']]

ids = mimicDF['PatientID']

mimicDF = mimicDF.drop(columns=['PatientID', 'deathperiod'])

categorisationTypes = {}
```

In [ ]:

```
mimicDF.head()
```

Out[ ]:

	los	gender	age	comorbidity	sofa	respiration	coagulation	liver	renal	cardiovascular	cns
0	9	1	74.19	7	7	0.0	1.0	NaN	0.0	3.0	3.0
1	2	0	75.00	4	2	NaN	0.0	0.0	1.0	NaN	1.0
2	16	0	51.92	4	2	NaN	0.0	NaN	0.0	NaN	2.0
3	12	0	51.73	-13	4	2.0	2.0	NaN	0.0	NaN	0.0
4	7	0	62.07	0	3	0.0	2.0	NaN	1.0	NaN	0.0

Finding values in need of cleaning

In [ ]:

```
mimicDF.describe()
```

Out[ ]:

	los	gender	age	comorbidity	sofa	respiration	coagulation	liver	renal	cardiovascula
count	5262.000000	5262.000000	5262.000000	5262.000000	5262.000000	3311.000000	5227.000000	2254.000000	5261.000000	1294.00000
mean	14.668757	0.382554	75.049002	9.801026	4.794185	1.987315	0.674957	0.696983	1.017297	3.238022
std	14.101457	0.486057	50.553676	9.671438	2.694694	1.374066	0.892066	1.051290	1.263514	0.70611
min	1.000000	0.000000	16.010000	-16.000000	2.000000	0.000000	0.000000	0.000000	0.000000	0.00000
25%	6.000000	0.000000	55.410000	2.000000	3.000000	0.000000	0.000000	0.000000	0.000000	3.00000
50%	10.000000	0.000000	68.300000	9.000000	4.000000	2.000000	0.000000	0.000000	1.000000	3.00000
75%	18.000000	1.000000	78.525000	16.000000	6.000000	3.000000	1.000000	1.000000	2.000000	4.00000
max	202.000000	1.000000	306.880000	47.000000	22.000000	4.000000	4.000000	4.000000	4.000000	4.00000

In [ ]:

```
rowsWithNaN = sum(mimicDF.isnull().any(axis=1))
print(f"{mimicDF.shape[0]} rows in df, {rowsWithNaN} containing NaN values")
```

```
5262 rows in df, 4778 containing NaN values
```

Missing values dealt with by filling with the mode.

In [ ]:
```
mimicDF['age'] = mimicDF['age'].fillna(mimicDF['age'].mean())

for col in mimicDF:
    mimicDF[col] = mimicDF[col].fillna(mimicDF[col].mode()[0])

mimicDF['comorbidity'][mimicDF['comorbidity'] < 0] = mimicDF['comorbidity'][mimicDF['comorbidity'] < 0] * -1
```

```
C:\Users\benma\AppData\Local\Temp/ipykernel_27088/4017263199.py:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-
a-view-versus-a-copy
  mimicDF['comorbidity'][mimicDF['comorbidity'] < 0] = mimicDF['comorbidity'][mimicDF['comorbidity'] < 0] * -1
```

In [ ]:
```
mimicDF.describe()
```

Out[ ]:

	los	gender	age	comorbidity	sofa	respiration	coagulation	liver	renal	cardiovascular
count	5262.000000	5262.000000	5262.000000	5262.000000	5262.000000	5262.00000	5262.000000	5262.000000	5262.000000	5262.000000
mean	14.668757	0.382554	75.049002	10.553972	4.794185	2.36279	0.670468	0.298556	1.017104	3.058533
std	14.101457	0.486057	50.553676	8.843506	2.694694	1.19465	0.890785	0.769595	1.263472	0.364759
min	1.000000	0.000000	16.010000	0.000000	2.000000	0.00000	0.000000	0.000000	0.000000	0.000000
25%	6.000000	0.000000	55.410000	3.000000	3.000000	2.00000	0.000000	0.000000	0.000000	3.000000
50%	10.000000	0.000000	68.300000	9.000000	4.000000	3.00000	0.000000	0.000000	1.000000	3.000000
75%	18.000000	1.000000	78.525000	16.000000	6.000000	3.00000	1.000000	0.000000	2.000000	3.000000
max	202.000000	1.000000	306.880000	47.000000	22.000000	4.00000	4.000000	4.000000	4.000000	4.000000

All missing values filled

In [ ]:
```
rowsWithNaN = sum(mimicDF.isnull().any(axis=1))
print(f"{mimicDF.shape[0]} rows in df, {rowsWithNaN} containing NaN values")
```

```
5262 rows in df, 0 containing NaN values
```

In [ ]:
```
targetDF.describe()
```

Out[ ]:

	deathperiod
count	5262.000000
mean	0.896047
std	7.338713
min	-29.000000
25%	-1.000000
50%	-1.000000
75%	-1.000000
max	107.000000

In [ ]:
```
targetDF
```

Out[ ]:

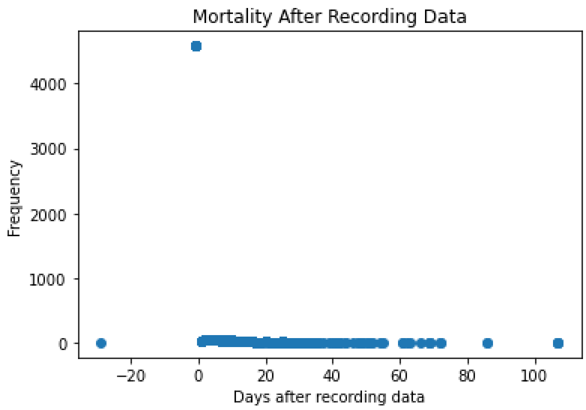
	deathperiod
0	-1
1	2
2	-1
3	-1
4	-1
...	...
5257	-1
5258	-1

	deathperiod
5259	-1
5260	-1
5261	-1

5262 rows × 1 columns

Exploring raw target data

In [ ]:
```
plt.scatter(targetDF['deathperiod'], targetDF['deathperiod'].map(targetDF['deathperiod'].value_counts()))
plt.xlabel("Days after recording data")
plt.ylabel("Frequency")
plt.title("Mortality After Recording Data")
plt.show()
```



In [ ]:
```
targetDF['deathperiod'] = targetDF['deathperiod'].apply(lambda x: x if x > -1 else -1)

targetDiedDF = targetDF[targetDF['deathperiod'] > -1]
targetNoDeathDF = targetDF[targetDF['deathperiod'] == -1].apply(lambda x: x+1.0)
```

Sanity Checks

In [ ]:
```
targetDiedDF.shape
```

Out[ ]: (678, 1)

In [ ]:
```
targetNoDeathDF.shape
```

Out[ ]: (4584, 1)

Categorising target data

In [ ]:
```
bins = 3

cat = Categorizer(targetDiedDF)
targetCategorisedDF = cat.kBins(bins=bins, strategy='quantile')

targetCategorisedDF['deathperiod'] = targetCategorisedDF['deathperiod'].apply(lambda x: x + 1)

targetCategorisedDF.set_index(targetDiedDF.index, inplace=True)

targetCategorisedDF.head()
```

Out[ ]:

	deathperiod
1	1.0
7	3.0
16	2.0
36	3.0
40	2.0

In [ ]:
```
targetNoDeathDF.head()
```

Out[ ]:

	deathperiod
0	0.0
2	0.0
3	0.0
4	0.0
5	0.0

Combining death and no death target data

In [ ]:

```
combinedTargetDF = targetCategorisedDF.merge(targetNoDeathDF, how='outer', left_index=True, right_index=True).rename(c

withDeath = combinedTargetDF.iloc[:,0]
noDeath = combinedTargetDF.iloc[:,1]

newTargetDF = withDeath.fillna(noDeath)

newTargetDF = newTargetDF.astype(np.int64)

newTargetDF
```

Out[ ]:

```
0       0
1       1
2       0
3       0
4       0
       ..
5257    0
5258    0
5259    0
5260    0
5261    0
Name: deathperiod, Length: 5262, dtype: int64
```

Simple version of target data (Used in the final dataset)

In [ ]:

```
simpleNewTargetDF = targetDF['deathperiod'].apply(lambda x: 0 if x < 0 else 1)

simpleNewTargetDF
```

Out[ ]:

```
0       0
1       1
2       0
3       0
4       0
       ..
5257    0
5258    0
5259    0
5260    0
5261    0
Name: deathperiod, Length: 5262, dtype: int64
```

In [ ]:

```
plt.scatter(targetDF['deathperiod'], targetDF['deathperiod'].map(targetDF['deathperiod'].value_counts()), c=simpleNewT
plt.xlabel("Days after recording data")
plt.ylabel("Frequency")
plt.title("Mortality Categorised Simple")
plt.show()
```

In [ ]:
```
simpleNewTargetDF.value_counts()
```

Out[ ]:
```
0    4584
1     678
Name: deathperiod, dtype: int64
```

Starting data categorization

In [ ]:
```
dataNeedingEncodingDF = mimicDF[['los', 'age', 'comorbidity', 'sofa']]
```

Fixing high age range

In [ ]:
```
ageWithoutOutliers = dataNeedingEncodingDF['age'][dataNeedingEncodingDF['age'] < 200]

dataNeedingEncodingDF['age'] = dataNeedingEncodingDF['age'].apply(lambda x: x if x < 200 else int(ageWithoutOutliers.s

dataNeedingEncodingDF.head()
```

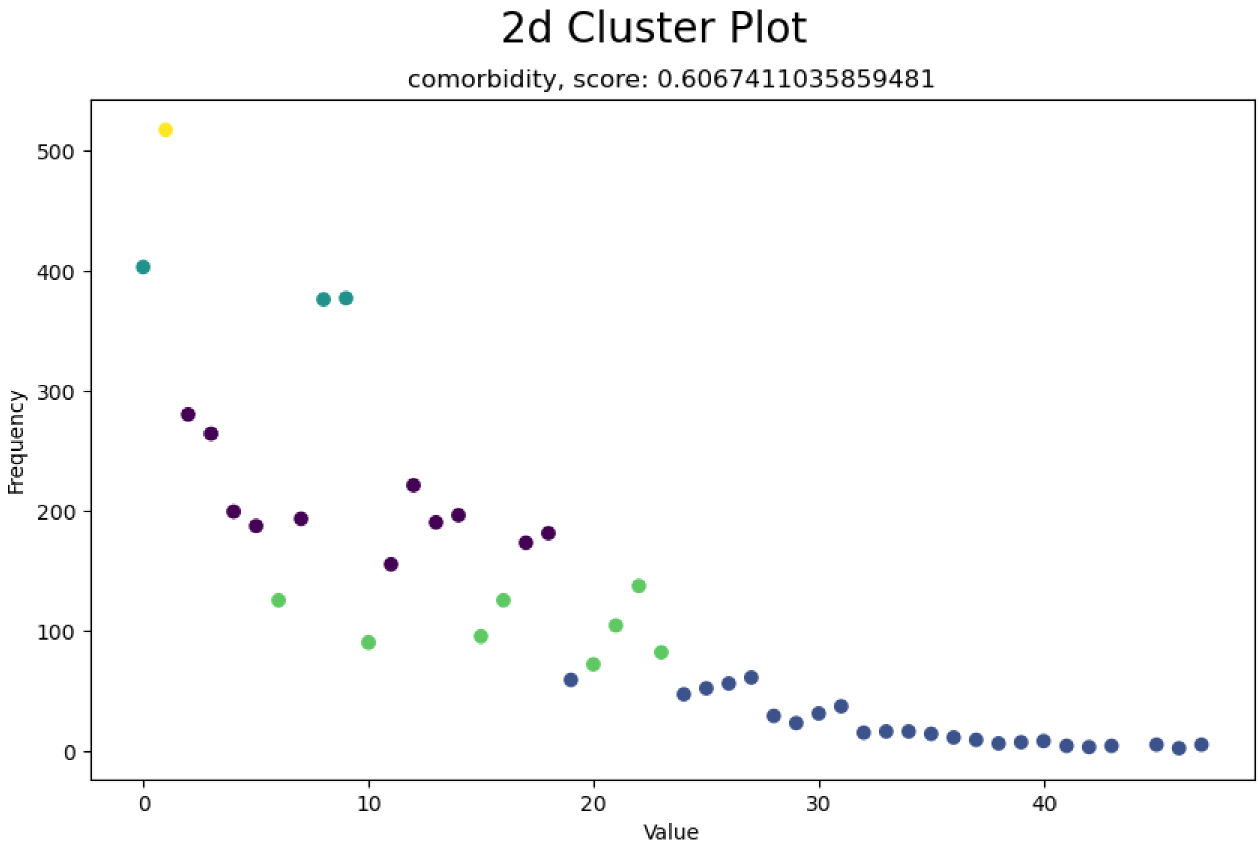
```
C:\Users\benma\AppData\Local\Temp/ipykernel_27088/2166811324.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  dataNeedingEncodingDF['age'] = dataNeedingEncodingDF['age'].apply(lambda x: x if x < 200 else int(ageWithoutOutliers.sample()))
```

Out[ ]:

	los	age	comorbidity	sofa
0	9	74.19	7	7
1	2	75.00	4	2
2	16	51.92	4	2
3	12	51.73	13	4
4	7	62.07	0	3

Exploring clustering in 2d here, wasn't used in the final dataset

In [ ]:
```
comorbidity = dataNeedingEncodingDF[['comorbidity']]

comorbidity = pd.DataFrame(data=list(zip(comorbidity.value_counts().index, comorbidity.value_counts().values)), columr

comorbidity['comorbidity'] = comorbidity['comorbidity'].astype(str).apply(lambda x: x[1:-2]).astype(np.int64)

comorbidityDF = AgglomerativeClustering(n_clusters=5).fit_predict(np.asarray(comorbidity))

sil_x = np.dstack((comorbidity['comorbidity'], comorbidity['count']))[0]

score = silhouette_score(sil_x, comorbidityDF)

fig = plt.figure(figsize=(10,6), dpi=100)
fig.suptitle("2d Cluster Plot", fontsize=20)

plt.scatter(comorbidity['comorbidity'], comorbidity['count'], c=comorbidityDF)
plt.xlabel("Value")
plt.ylabel("Frequency")
plt.title(f"comorbidity, score: {score}")
plt.show()
```



In [ ]:

```
dataNeedingEncodingDF
```

Out[ ]:

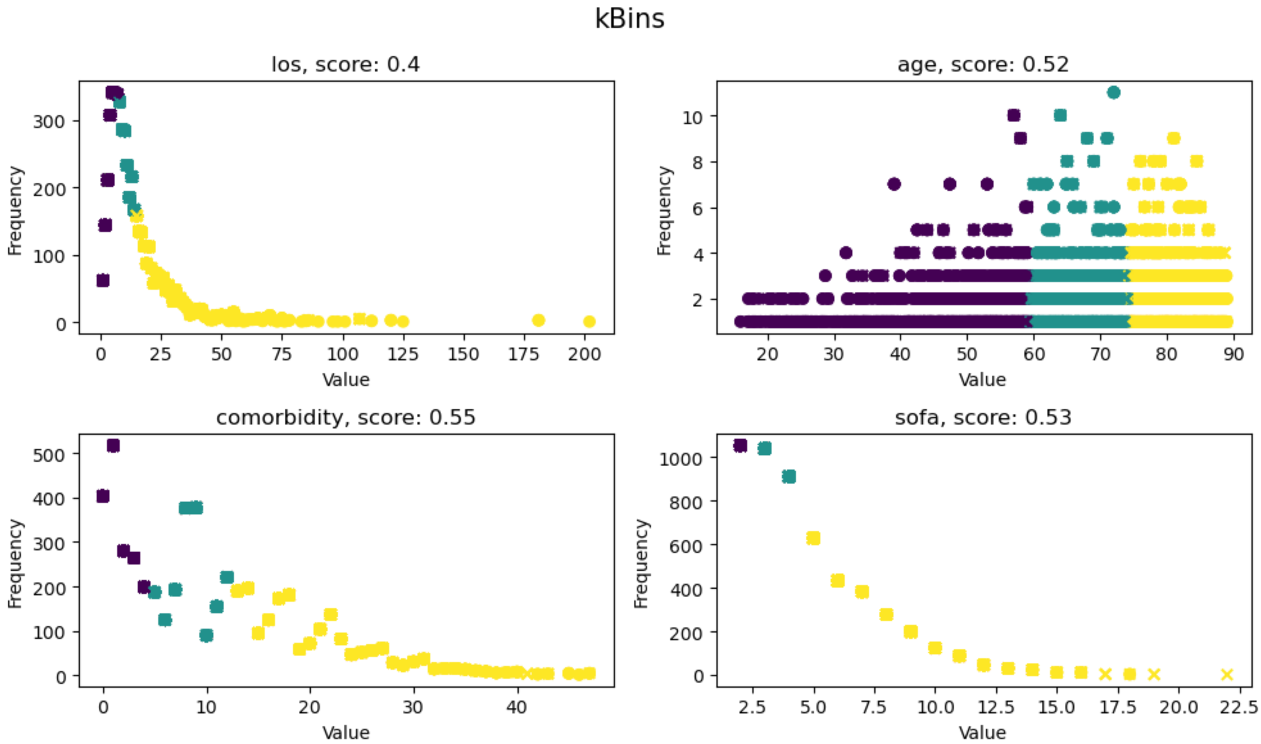
	los	age	comorbidity	sofa
0	9	74.19	7	7
1	2	75.00	4	2
2	16	51.92	4	2
3	12	51.73	13	4
4	7	62.07	0	3
...	...	...	...	...
5257	120	36.61	5	10
5258	13	53.90	12	4
5259	4	58.93	18	5
5260	16	68.98	4	3
5261	2	26.15	4	2

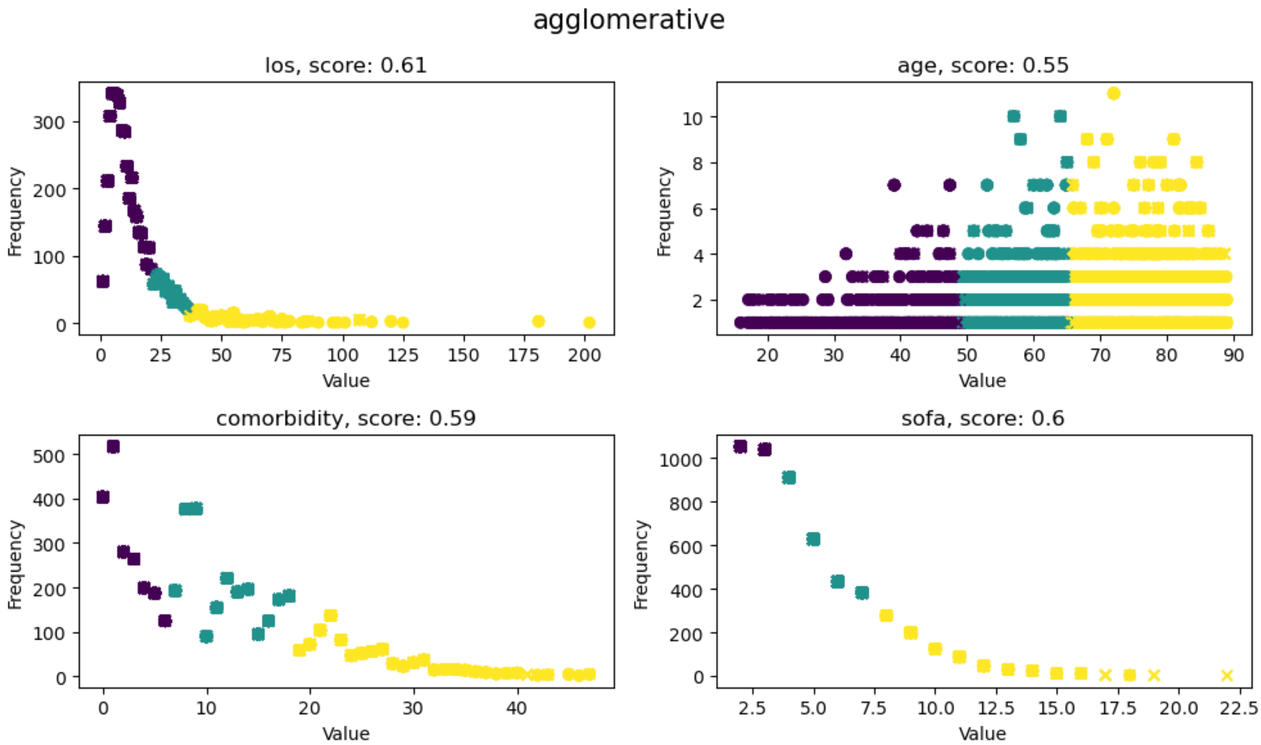
5262 rows × 4 columns

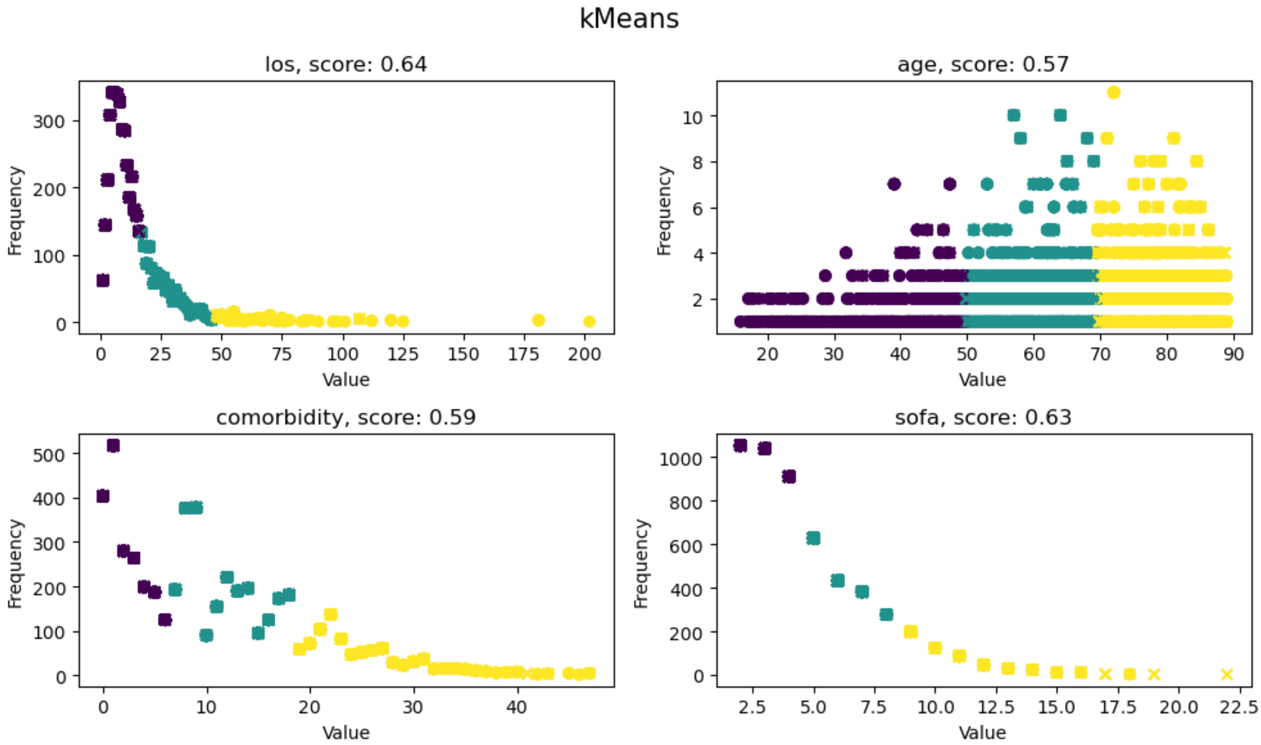
Graphically representing the categorisation

In [ ]:

```
cat = Categorizer(dataNeedingEncodingDF)

clusters = 3

kBinsDF = cat.kBins(bins=clusters, strategy='quantile')
aggDF = cat.agglomerative(n_clusters=clusters)
kMeansDF = cat.kMeans(n_clusters=clusters)

cat.display(target=simpleNewTargetDF)
```


kBins
los, score: 0.4
age, score: 0.52
comorbidity, score: 0.55
sofa, score: 0.53
Frequency
Value


agglomerative
los, score: 0.61
age, score: 0.55
comorbidity, score: 0.59
sofa, score: 0.6
Frequency
Value



Computing the boundaries of the categorised data.

In [ ]:

```
boundaries = cat.getBoundaries()
for type in boundaries:
    print(f"{type}: {boundaries[type]}")
```

```
kBins: {'los': [8.0, 15.0], 'age': [59.24, 74.28], 'comorbidity': [5.0, 13.0], 'sofa': [3.0, 5.0]}
agglomerative: {'los': [22, 37], 'age': [49.12, 65.2], 'comorbidity': [7, 19], 'sofa': [4, 8]}
kMeans: {'los': [17, 47], 'age': [49.76, 69.53], 'comorbidity': [7, 19], 'sofa': [5, 9]}
```

Labelling categorised data

In [ ]:

```
categories = {0: 'low', 1: 'medium', 2: 'high'}

mapped = cat.map_types(data={'agg': cat.categorizationTypes['agglomerative']}, mapping=categories)['agg']

mapped
```

Out[ ]:

	los_high	los_low	los_medium	age_high	age_low	age_medium	comorbidity_high	comorbidity_low	comorbidity_medium	sofa_high
0	0	1	0	1	0	0	0	0	1	0
1	0	1	0	1	0	0	0	1	0	0
2	0	1	0	0	0	1	0	1	0	0
3	0	1	0	0	0	1	0	0	1	0
4	0	1	0	0	0	1	0	1	0	0
...	...	...	...	...	...	...	...	...	...	...
5257	1	0	0	0	1	0	0	1	0	1
5258	0	1	0	0	0	1	0	0	1	0
5259	0	1	0	0	0	1	0	0	1	0
5260	0	1	0	1	0	0	0	1	0	0
5261	0	1	0	0	1	0	0	1	0	0

5262 rows × 12 columns

In [ ]:

```
mapped['Mortality14Days'] = simpleNewTargetDF

mapped['PatientID'] = ids

mapped = mapped.set_index('PatientID')
```

```
mapped
```

Out[ ]:

PatientID	los_high	los_low	los_medium	age_high	age_low	age_medium	comorbidity_high	comorbidity_low	comorbidity_medium	sofa_l
181199	0	1	0	1	0	0	0	0	1	
167020	0	1	0	1	0	0	0	1	0	
169463	0	1	0	0	0	1	0	1	0	
183338	0	1	0	0	0	1	0	0	1	
192665	0	1	0	0	0	1	0	1	0	
...	...	...	...	...	...	...	...	...	...	
106017	1	0	0	0	1	0	0	1	0	
186511	0	1	0	0	0	1	0	0	1	
188867	0	1	0	0	0	1	0	0	1	
115153	0	1	0	1	0	0	0	1	0	
131831	0	1	0	0	1	0	0	1	0	

5262 rows × 13 columns

In [ ]:

```
dataname = "staticData.csv"

mapped.to_csv(f"./categorisedData/{dataname}")
```