Understanding COPD patients in the hospital system via administrative data

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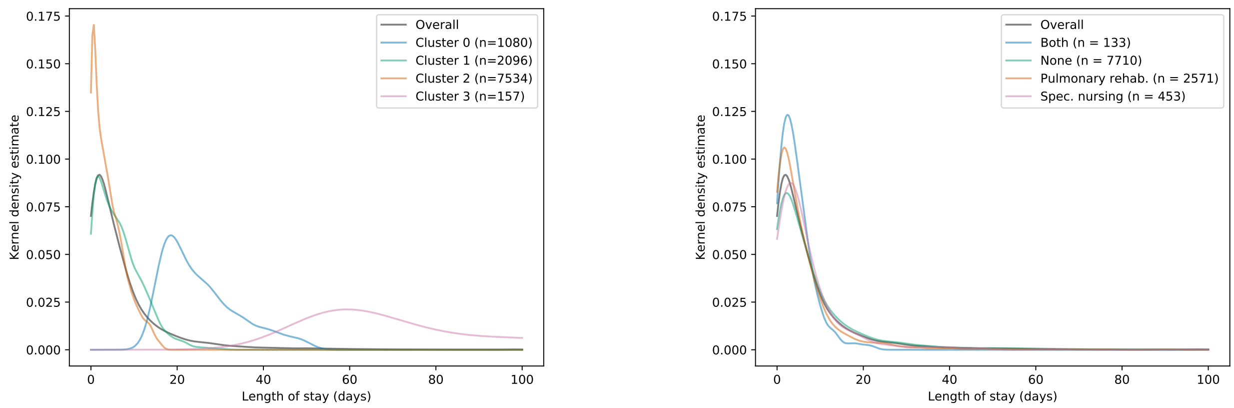
Abstract

This work presents an analysis of how patients with chronic obstructive pulmonary disorder (COPD) interact with the hospital system in South Wales.

1 Introduction

Population health research is becoming increasingly based on data-driven methods (as opposed to those designed solely by clinical experts) for patient-centred care through the advent of accessible software and a relative abundance of electronic data. To better understand the needs and behaviours of a population, it can be helpful to find an appropriate segmentation of that population; such a segmentation allows for finer-grained analysis of groups in the population that share some form of homogeneity. One commonly used method for such patient-centred analysis is that of patient flow and their interaction with the healthcare system.

However, this process relies heavily on detailed data — about both the system and the population within that system — which may limit research where sophisticated data pipelines are not yet in place. This work demonstrates how this issue may be overcome using administrative, spell-level hospital data to build a patient clustering that feeds into a multi-class queuing model. Specifically, this work examines patient records from the NHS Wales Cwm Taf Morgannwg University Health Board (UHB) that present chronic obstructive pulmonary disease (COPD). COPD is of particular interest to Cwm Taf Morgannwg as it was found that they had the highest prevalence of the condition across all the Welsh health boards in an internal report by NHS Wales.



(a)

(b)

Figure 1: Kernel density estimate plots for length of stay by (a) cluster and (b) intervention

1.1 Literature review

Clustering is the process of separating the instances of a dataset into distinct parts to maximise homogeneity within each cluster and heterogeneity between each cluster. Within healthcare, and particularly population health, this concept has many applications. When applying this to a population, some form of patient corpus is considered the *de facto* dataset but the choice of characteristics with which to describe a patient or record remains open. The review for this work identified three groups of characteristics used to cluster a patient population: a patient's system utilisation metrics, their clinical attributes and their pathway. The first two encompass a method known as segmentation analysis wherein a population is segmented in a straightforward sense. The latter, however, does not strictly segment the patients directly but rather groups their movements through a healthcare system via process mining. [1] and [2] demonstrate how this technique can help to improve the efficiency of a hospital system rather than tackling the issue of patient-centred care as is the focus of this work.

1.2 Cluster analysis

2 Estimating queuing parameters

Reiterate the objective of the paper — to model a COPD ward within a hospital — and draw attention to lack of fine-grain data. Lead into how this can be overcome with the Wasserstein distance (a lot of this has been written up in `nbs/wasserstein.ipynb`). A brief summary of how the parameter set is chosen and a nice image of the queue we are building. Close out the section with best and worst case parameter set plots.

		Cluster				Population (mean)
		0	1	2	3	
Characteristics	**COPD admissions last year**	1.91	1.51	1.31	1.98	1.29
	Min. LOS	12.82	0.01	-0.02	48.82	5.41
	Mean LOS	25.33	6.46	3.79	74.65	7.48
	Max. LOS	51.36	30.86	16.94	224.93	10.40
	No. of LTCs	2.05	3.10	1.47	2.70	2.00
	Median no. ICDs	9.00	8.00	5.00	11.00	6.58
	Median CCI	9.00	20.00	4.00	18.00	9.72
LTC Prevalence	**Acute myocardial infection, %**	14.27	23.42	10.84	16.56	14.26
	Cerebrovascular accident, %	9.67	15.01	1.19	19.21	5.84
	Congestive heart failure, %	14.50	54.55	0.00	27.15	14.82
	Connective tissue disorder, %	5.19	5.07	4.01	4.64	4.42
	Dementia, %	7.55	20.08	0.00	25.17	6.11
	Diabetes, %	20.17	28.70	16.72	25.83	20.08
	Liver disease, %	0.35	0.56	0.33	0.00	0.37
	Peptic ulcer, %	1.77	1.04	0.38	1.32	0.73
	Peripheral vascualar disease, %	5.07	8.90	3.18	5.96	4.78
	Pulmonary disease, %	100.00	100.00	100.00	100.00	100.00
	Cancer, %	8.02	13.76	4.11	10.60	6.95
	Diabetic complications, %	0.24	0.69	0.33	1.99	0.44
	Paraplegia, %	1.30	3.96	0.25	0.66	1.23
	Renal disease, %	8.61	22.52	3.03	18.54	8.51
	Metastatic cancer, %	1.77	5.77	0.00	0.66	1.55
	Severe liver disease, %	0.24	0.63	0.00	0.00	0.17
	HIV, %	0.00	0.00	0.03	0.00	0.02
	C. diff, %	0.83	0.14	0.03	0.66	0.17
	MRSA, %	0.35	0.07	0.05	1.32	0.12
	Obesity, %	2.83	3.75	2.22	7.95	2.78
	Sepsis, %	2.12	1.25	0.25	1.99	0.77

Table 1: A summary of patient-level clinical attributes and disease prevalence by cluster and by population

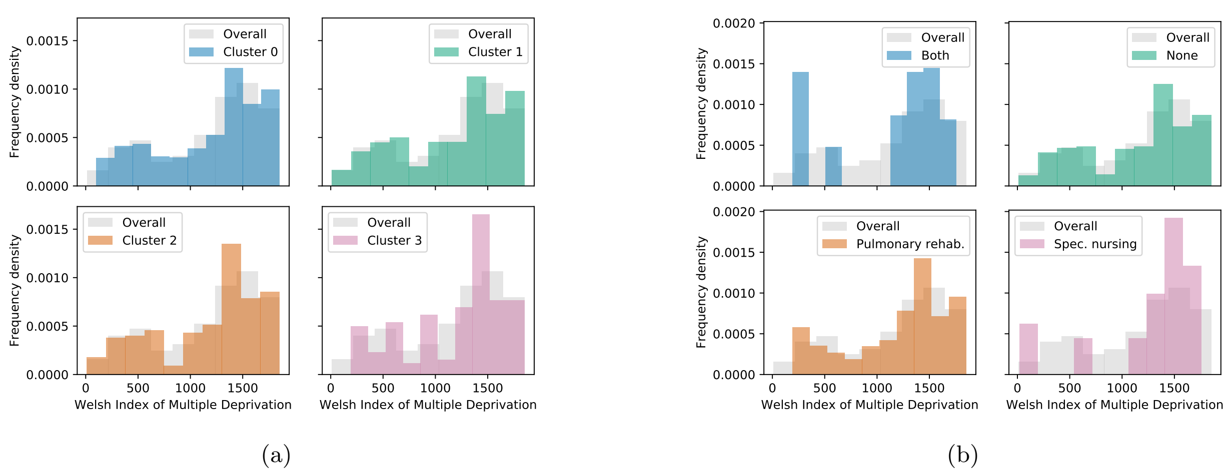
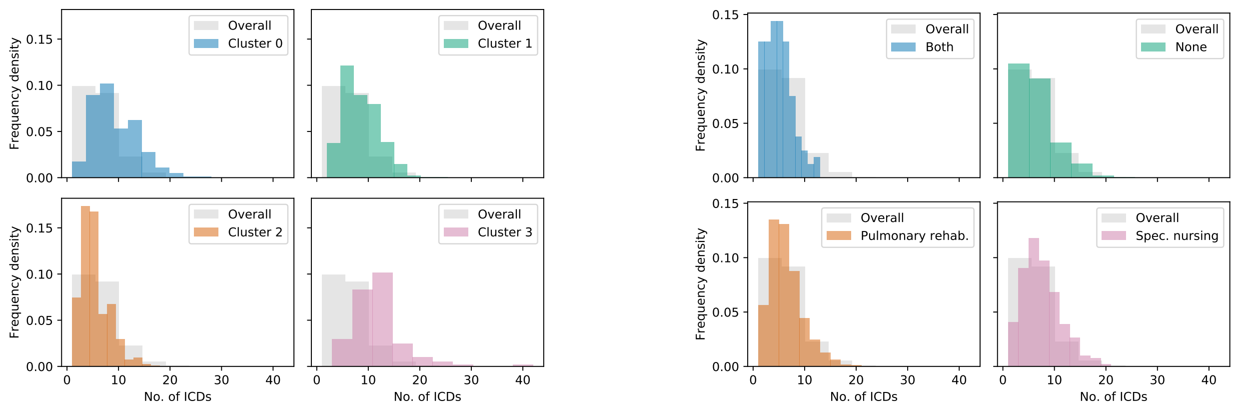
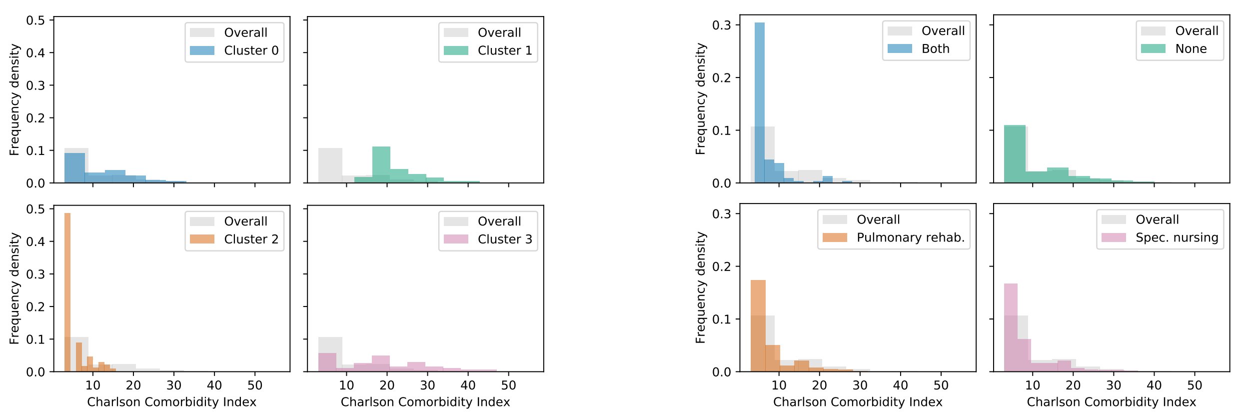


Figure 2: Histograms for WIMD by (a) cluster and (b) intervention



(a) (b)

Figure 3: Histograms for number of ICDs by (a) cluster and (b) intervention



(a) (b)

Figure 4: Histograms for CCI by (a) cluster and (b) intervention

3 Adjusting the queuing model

Body of the writing and plots come here. What can we see in the what-if scenarios? The main scenarios are:

- How would server utilisation (i.e. resource consumption) be affected by an increase in overall patient arrivals?
- How is the system affected by certain types of patients (e.g. short-stay, low-impact) arriving less frequently?
- What are the sensitivities of mean system times and server utilisation based on a change in c?

4 Conclusion

Summarise the findings and novelty of the paper: sensitivity analysis and queuing models are within reach despite a lack of data. The chosen modelling discipline for service times is very simplistic but can return good results (refer back to best-case parameter plot).

References

[1] I. V. Arnolds and D. Gartner. Improving hospital layout planning through clinical pathway mining. *Annals of Operations Research*, 263:453 – 477, 2018. doi: https://doi.org/10.1007/s10479-017-2485-4.

[2] P. Delias, M. Doumpos, E. Grigoroudis, P. Manolitzas, and N. Matsatsinis. Supporting healthcare management decisions via robust clustering of event logs. *Knowledge-Based Systems*, 84:203 – 213, 2015. doi: https://doi.org/10.1016/j.knosys.2015.04.012.