Informatics in Out of Hours Service Delivery: Methods and Applications to Inform Health Care Policy and Management

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Abstract

Secondary healthcare systems around the world are facing ever increasing pressures and governments frequently revise the provision of important services, often without available data or studies necessary to understand the demand placed on clinical teams. The situation is particularly severe during Out of Hours (OoH) settings, which account for over 75% of the working week. Here, doctors work in a stressful environment, performing complex tasks and making difficult prioritisation decisions.

In this work, we discuss methodology and applications demonstrating the potential of data science and machine learning, in order to design intelligent systems capable of informing, supporting and driving improvements in health care policy and management. For that matter, we introduce the use of combined location and tasking informatics, sourcing diverse data allowing for the study of clinical behaviour and workload patterns in OoH secondary care settings; and we review example applications and ongoing work on Bayesian statistics, graphical models and queueing networks.

Specifically, we exploit comprehensive data for the purposes of location identification and evaluation of task demand and workload. And we show it is possible to gain valuable information for the purposes of rota scheduling, task prioritisation or resource allocation, among other things.

Keywords— Healthcare Management; Out of Hours; Time Series; Indoor Positioning; Graphical Models.

1 Introduction

Secondary healthcare systems around the world are in need to undergo major changes and optimise the use of limited resources. The number of patient admissions is on the rise (Royal College of Physicians, 2012) and the complexity of conditions and treatments is increasing (Cornwell et al., 2012). However, global trends in clinical practice tend to impose limits on the number of hours doctors may work (Clarke et al., 2014), and diminished budgets (Reeves et al., 2014) are tied to reductions of available beds and working teams (Ham et al., 2011).

The situation is particularly severe during Out of Hours (OoH) settings, outside standard 9am-5pm Monday to Friday working shifts. This setting involves a reduced number of doctors covering a very large number of patients (Larkin et al., 2014). During OoH shifts doctors work in a stressful environment, performing complex tasks and making difficult prioritisation decisions; in addition, they must navigate large and often unfamiliar sites in order to locate wards, patients, other staff and equipment (Brown et al., 2015). Thus, the provision of this service is often revised in order to deliver safe healthcare of a consistently high quality (Grol et al. (2006)); yet, this often occurs without underlying comprehensive data or understanding of the work demand placed on clinical teams.

There is hence a need to design modern management technologies for the development of effective decision support systems (cf. Sharples et al. (2015)), aiming to drive improvements in health care policy and management. In this paper we discuss the use of combined location and tasking

informatics, and we demonstrate the potential of quantitative data-driven methods in order to study clinical behaviour and workload patterns in OoH secondary care settings. Thus, we present intelligent systems that can drive improvements in efficiency and provide clinicians and service managers with high quality information for managing processes such as task allocation, clinical training and people management.

2 Location and Tasking Informatics

The informatics system presented relies on web and mobile device interfaces, and replaces the traditional *pager* system employed by nurses and doctors in most hospitals during OoH shifts. Doctors, nurses and clinical support workers are all equipped with portable devices connected to a local network; and the distribution of workload is centralized and managed by a *senior nurse coordinator* (see Figure 1). Additionally, each doctor or nurse benefits from a different level of access to information regarding patients or current task-demand in the system.

Figure 1: Simplified diagram for a centralized task-managment system.

With this electronic tool, a coordinator can quickly triage requests for clinical review and intervention in a simplified manner; and data including the type, timing and location of activities is captured without the need of direct observation. Traditional task allocation relying on pagers and phone calls is noticeably inefficient (see Figure 2), in that phones may constantly be engaged, and doctors are likely to reject incoming requests due to high workload. With an electronic alternative, a coordinator can observe and make informed judgements regarding the current workload of doctors and nurses on duty.

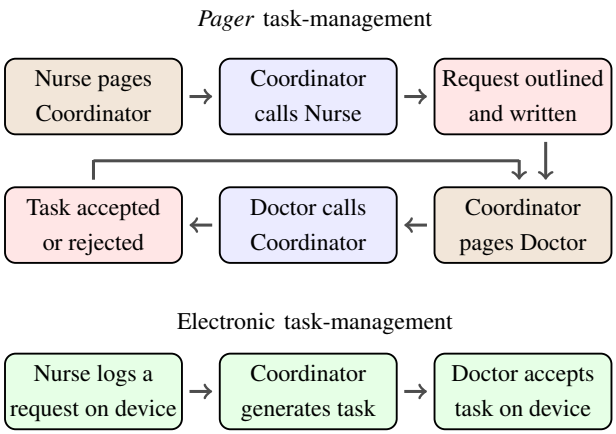

Figure 2: On top, a traditional *pager* management system. At the bottom, a the electronic alternative.

The tasking information collected can thus be linked with datasets including details on ward arrangements within a hospital, bed occupancy numbers, speciality allocations and wireless network radio-signal scans obtained from mobile devices carried by doctors (cf. Pinchin et al. (2014)). Therefore, it is possible to generate a comprehensive dataset enabling the study of data-driven support systems for healthcare management; in the following, we summarize example applications and ongoing work on graphical models, bayesian statistics and queueing networks.

2.1 Data-Driven Location Identification and Clinical Behaviour Evaluation

The understanding of behaviour patterns employed by experienced staff is key for the design of improved work systems. In addition, the training of clinical workers within complex workplaces requires studying human performance. Experienced doctors are more likely to efficiently transit long distances in order to visit patients, and they often take breaks for personal resting purposes. On the other hand, junior doctors noticeably struggle within often unfamiliar environments; thus, they rarely depart from pre-set routes during ward rounds, and are less efficient when prioritising patients needs (Brown et al., 2014).

Traditional methods for drawing such conclusions have required shadowing or interviewing of staff members (Pinchin et al., 2013); however, these are expensive, intrusive and time-consuming approaches usually performed on a limited scale, thus lacking generalisability. Mathematical methodology relying on sequential labelling techniques (Perez et al., 2016) has the ability to establish links between positioning and activity information of doctors, in a com-

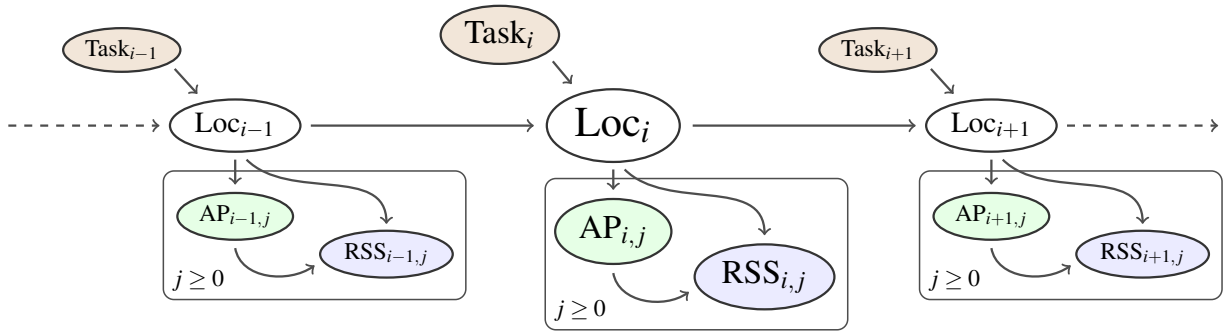

Figure 3: Graphical model representing a partial structure of dependencies within tasks/activity, wireless signal observations and the location of doctors/nurses. AP denotes access point observations, and RSS referes to the received signal strength.

pletely automated and unsupervised manner; thus, it enables the processing of vast amounts of performance data with the potential to address many of the above issues.

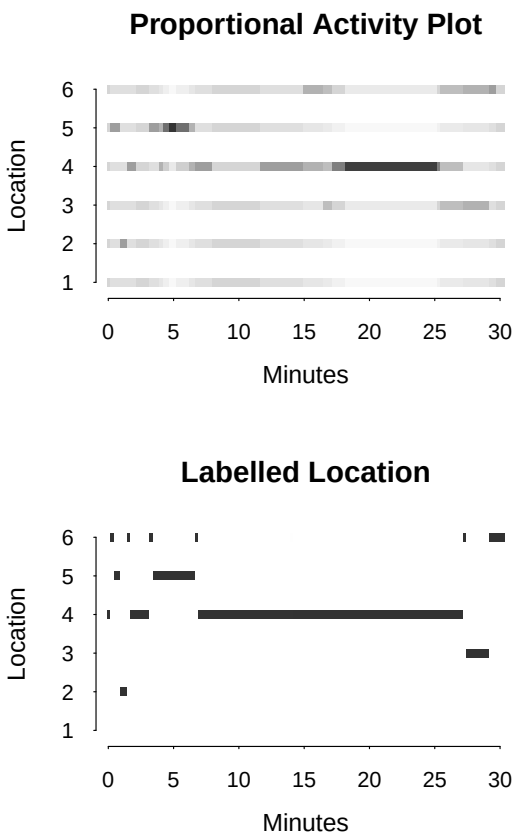

Figure 4: On top, proportional location likelihoods (in gray-scale) in relation to tasking information; in the bottom, inferred location sequences.

Relating tasking and WiFi signal observations through a sequence of latent location nodes on a graphical model (such as in Figure 3), it is possible to assign location labels to doctors in a spatially informative manner; irrespective of the layout of the hospital. In Figure 4 we observe how we can infer a temporal sequence of locations for a device carrier, from a total of 6 whereabouts of interest within a certain ward. Hence, it is now feasible to quantify certain behavioural patterns that vary across groups of experienced and inexperienced specialists, and draw inference supported by large and temporally-structured data sets.

2.2 Care Fragmentation and the Study of Patterns in Work Demand

Extensive research has to-date been concerned with the estimation of service demand in healthcare; for instance, it is known that seasonal patterns and serial correlation structures play important roles in understanding demand loads (e.g. Jones et al. (2008)). There also exist common characteristics of variation in workload across groups of medical and surgical disciplines; and the relative importance of short-term scheduling is a subject of interest. However, previous work has been centred on patient volumes (consultation and admission counts) and is thus insufficient in order to quantify all aspects of work demand, or to inform local staff management and policy.

Data on task creation and completion counts allows for a superior representation of workload, and can be specific to each healthcare facility, medical speciality or working group; however, sources for such information have so far been non-existent. With an electronic task-management alternative such as the one discussed in this work, the collection of such statistics is automated. Hence, it is possible to design support systems for managing the delivery of care. A Bayesian approach to the study of multivariate series of counts can enable drawing probabilistic inference on seasonal patterns of work demand, along with contemporary and serial correlations over different medical and surgical specialities.

For instance, in Figure 5 we observe %90 credible inter-

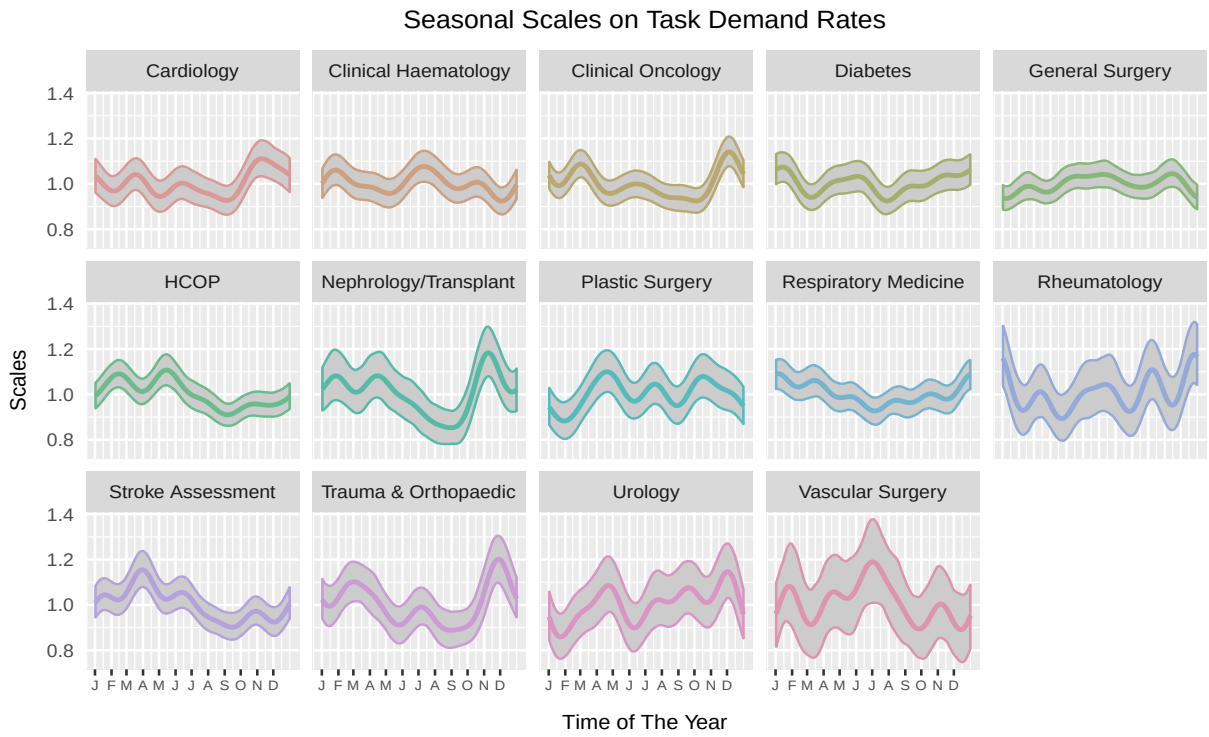

Figure 5: Credible intervals on year-round variation of demand accross different specialties.

vals for seasonal variation on task demand, across different groups of medical and surgical specialities. In addition, Table 1 shows mean absolute deviations in both year-round and weekly variations. These results are obtained by means of a state-space model for multivariate count data (cf. Jung et al. (2011); Chib and Winkelmann (2001)), and cover a 4 year period of OoH work within 2 major university hospitals in the UK, jointly servicing over 2.5 million residents.

	Year Deviation	Week Deviation
Cardiology	0.054 (0.011)	0.11 (0.009)
Clinical Haematology	0.044 (0.009)	0.09 (0.008)
Clinical Oncology	0.055 (0.008)	0.12 (0.009)
Diabetes	0.046 (0.010)	0.34 (0.009)
General Surgery	0.036 (0.008)	0.17 (0.006)
Care for the Older People	0.056 (0.009)	0.36 (0.008)
Nephrology and Transplants	0.088 (0.017)	0.06 (0.009)
Plastic Surgery	0.063 (0.013)	0.08 (0.011)
Respiratory Medicine	0.046 (0.009)	0.21 (0.007)
Rheumatology	0.079 (0.015)	0.38 (0.014)
Stroke Assessment	0.067 (0.011)	0.15 (0.009)
Trauma and Orthopaedic	0.084 (0.014)	0.12 (0.009)
Urology	0.082 (0.017)	0.06 (0.011)
Vascular Surgery	0.117 (0.025)	0.09 (0.012)

Table 1: Mean absolute deviations in seasonality. Values in parenthesis denote standard deviations.

There, we observe a split between surgical and medical disciplines. Medical disciplines are subject to high variations in weekly demand, while surgical ones are mostly influenced by year-round patterns. We thus notice that there exist quantifiable workload patterns, indicating local staffing would benefit from data-driven support methods.

2.3 Prioritisation Policies and Assessing the Optimality of Task Allocations

Finally, the estimation of workload pressures generated by different kinds of tasks is of special relevance for the purposes of prioritisation. We note that different duties may create varying loads of work over different specialist groups of doctors and nurses. Thus, it is important to understand the routing of complex medical procedures, over smaller groups of activities that it links to.

For instance, in Figure 6 we observe a simplified routing network where a patient alternates between visits to the doctor and nurse, until a doctor determines no further intervention is required. There, we notice that each network *node* (i.e. doctor or nurse) may be engaged in further activities in relation to additional patients. Thus, for an appropriate task allocation and prioritisation scheme, it is key to understand the expected delivery times of multiple service nodes, jointly offering services to patients with non-identical needs.

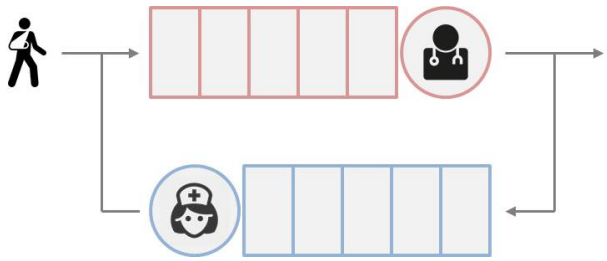

Figure 6: Sample network of two queues for task service delivery.

Electronic task-management can capture the required information in order to address the above issues. By means of queueing networks (cf. Kleinrock (1975)) it is possible to draw inference on expected service loads and delivery times; for instance, employing sampling alternatives relying on Markov Chain Monte Carlo methods (see Sutton and Jordan (2011))

3 Discussion

This paper has discussed results and ongoing work within an interdisciplinary research project with the collaboration of medical consultants, engineers, human factors researchers and mathematicians; and has displayed various benefits of adopting electronic task-management alternatives within local health care facilities.

We recall that services such as OoH are constantly revised with aims to optimise the use of increasingly limited resources. Here, we have provided evidence regarding the usefulness of data-driven studies in order to gain a better understanding of the work demand placed on clinical teams. Such approaches can yield future improvements in health care policy and management within local facilities. Additionally, the use of statistical and machine learning methodologies have the potential to design expert systems capable of supporting improvements in task scheduling and prioritisation, resource allocation or rota scheduling, to name a few.

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