A Data Mining Framework for the Analysis of Patient Arrivals into Healthcare Centers

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Outline

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- **Healthcare Operations**
- **Performance Measure: Lateness**
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- **Results**
- **Conclusions**
- **Optimization Model**
- **Acknowledgement**

Demand for Healthcare

- **Growing world population**
- **Growing demand for healthcare** services
- Healthcare **spending to increase**
  - 2.4-7.5% per year until 2020 in various countries
- Increase in costs

- **Real-world project**
- Conducted in the **United Arab Emirates (U.A.E.)**
- Data from **large public hospital**

Demand for Healthcare

- **Middle East and North Africa (MENA)** region
- **Shortage** in MENA by 2020:
  - 150,000 physicians
  - 326,000 dentists
  - 1.8 million nurses and midwifery personnel
- **U.A.E. healthcare** market to **grow 12.7% per year** until 2020.
- May grow even further due to **medical tourism**
  - an economic priority for U.A.E.'s tourism sector.
- Increasing demand resulting in **higher staff costs.**

http://www.un.org/sustainabledevelopment/sustainable-development-goals/
http://bit.ly/1Kjkn0B

Healthcare Operations

- **“Improving operational efficiencies”**
  - to cope with increased competition and rising staff costs.

- Adoption of **information technologies (IT)**
- **Analytical tools**
  - data mining
  - optimization
- Can greatly contribute to achieving such operational efficiencies.

- **Growth of 15.9% per year in healthcare IT** market until 2021.

Healthcare Operations

- **First step** in the service process
  - Patient contacting the provider to **schedule an appointment** and **arriving** around the scheduled time.
    OR
  - **Arrival of walk-in patients**, who directly show up.
- Patient admitted into the system
- Vitals checked
- Doctor appointment
- Other steps

- **This study:**
  - **Patient arrivals.**
  - Quantifying and analyzing the timing of patient arrivals.
- Ultimate **goal:**
  - **Improving the patient admission process step.**
  - Through elimination of wasted time.

Performance Measure: Lateness

- **Lateness = (Arrival Time) – (Appointment Time)**
- Main performance measure in our study.

- Arrival at exact appointment time:
  - **Lateness = 0**
- Arrival later than appointment time:
  - **Lateness > 0**
- Arrival earlier than appointment time:
  - **Lateness < 0**

Contributions

- A **data mining framework** for **analyzing patient arrival data.**

- Unique data mining study
- **Real world application:**
  - applicability
  - possible benefits.

- **Data size:**
  - 110,608 rows for 14 hospital units.
  - **At least 10-fold larger** compared to similar research.

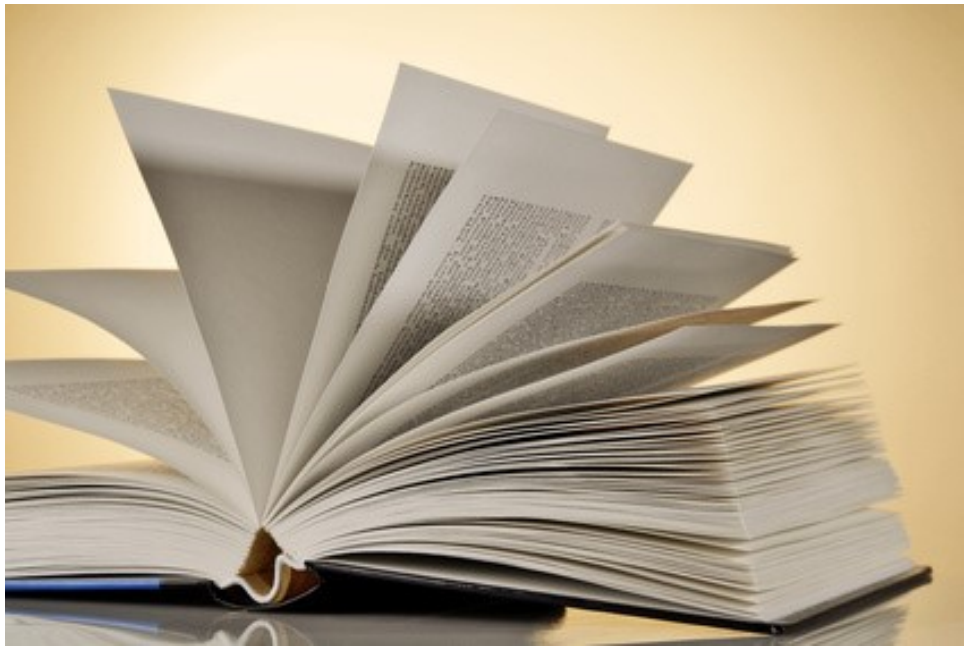
- We also present in this paper, **a subsequent optimization model for**
  - **scheduling appointments** for
  - direct improvement in operational efficiency.

Literature (1 of 3)

- **Patient flow modeling [7]**
  - Patient arrival and service time distributions are used **to compute waiting times.**

- **Our focus**
  - **Lateness**
  - **Association of Lateness with various factors.**

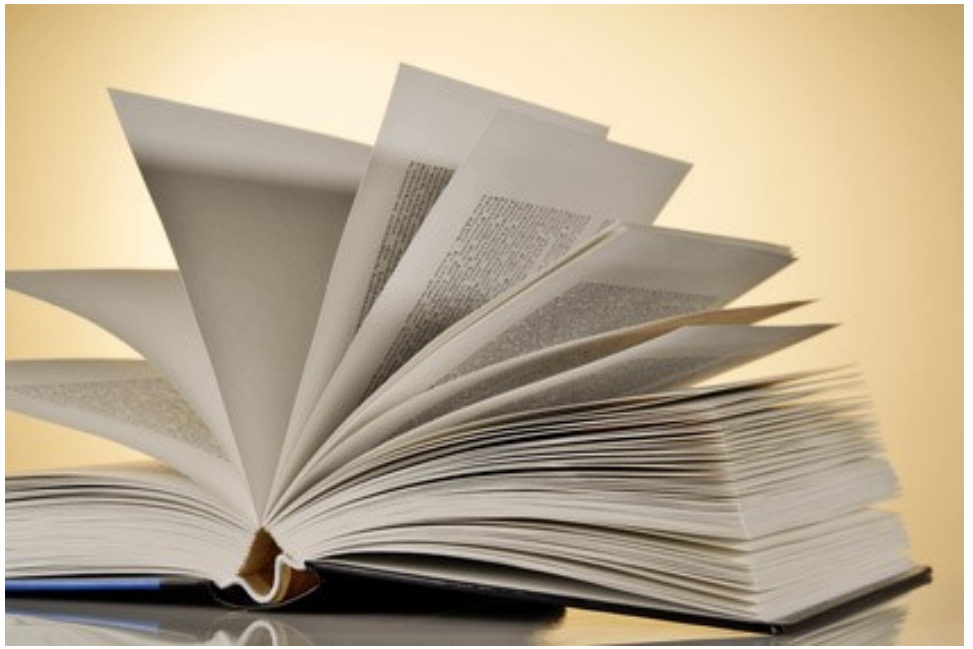
- **Our dataset**
  - No attributes pertaining to the resources (number of doctors, nurses, rooms, etc. over time).



Literature (2 of 3)

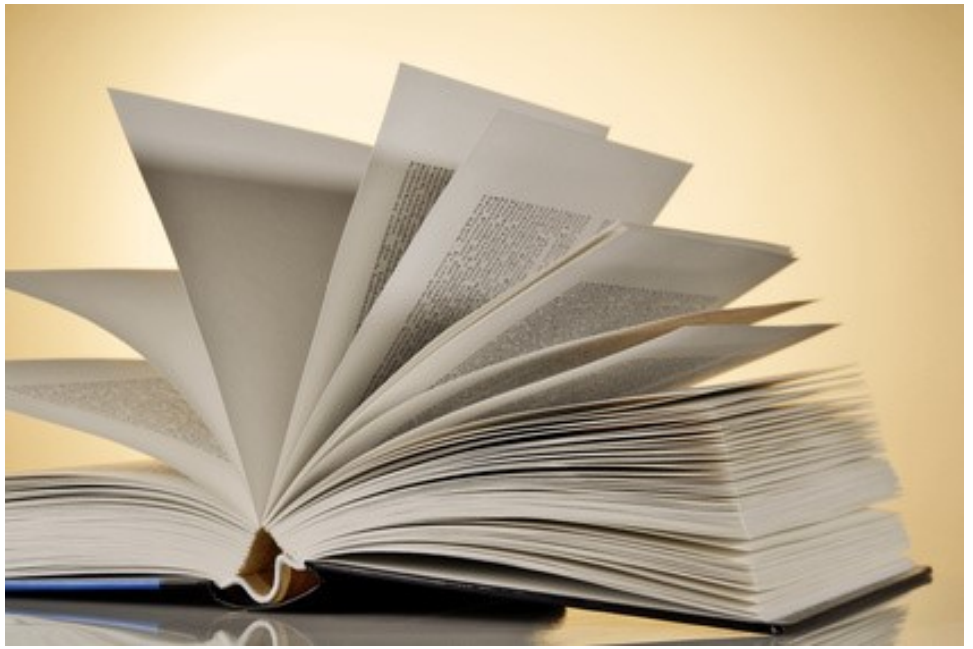
- Analysis of **patient-related factors behind delays/no-shows** in seeking care **[8][9][10].**

- **[11] applies lean principles**,
  - specifically root cause analysis,
  - to identify sources of operational inefficiency.
- **[13] derives statistical distributions** that characterize lateness,
  - [13] assumes that the population of patients is uniform.
  - We, on the contrary, accept that Lateness is very much dependent on the attributes of each patient, and focus on coming up with a predictive regression model for characterizing this dependency relation.
- **[14] predicts arrival time and no shows** in outpatient clinics, as we do.
  - However, [14] employs a very different set of independent variables than we do.



Literature (3 of 3)

- **[15] applies association mining to predict no-shows**
  - [15] applies data mining, specifically association mining, and optimization together, the objective is not to optimize appointment assignments.
- **[16] develops an appointment scheduling algorithm.**
  - Our study and the optimization model we propose (as future work), on the other hand, assume that Lateness is dependent on the scheduled time, rather than being independent of it.
- **[17] predicts the duration of an appointment,** and identifies late arrival of the surgeon as the most important factor.
  - We, on the other hand, do not consider any resource-related factors, and predict Lateness using other variables.



Research Gap

- **No academic studies** on **predicting Lateness as a function of schedule day and time.**

- **Significant gap of knowledge and insights** with regards to the **understanding of Lateness and the factors underlying Lateness** in healthcare centres.

Research Topic

- **<u>Predicting Lateness</u> as a function of schedule day and time** (as well as other factors)**.**

- **Developing an optimization model**
  - for **scheduling appointments,**
  - to **minimize average lateness.**

Research Questions

1. **How can** the **patient arrivals** into healtcare centres **be analyzed** to come up with insights into Lateness?

2. **Which factors** are **associated with Lateness**?

3. **How can patient appoinments be scheduled** to minimize Lateness?

Research Methods (1 of 6)

- **Data Mining**
  - growing field of computer science and informatics
  - aims at **discovering new and useful information and knowledge** from data.
  - multitude of analytical methods (and algorithms)
  - each method or combination of methods are most suitable for a given data with unique characteristics.

Research Methods (2 of 6)

- **Association Mining**
  - data mining method for
  - identifying **associations between**
    - **elements (items)** of a set (set of items),
  - based on **how these elements appear in**
    - multiple subsets **(transactions)** of the set.
  - gives as output
    - list of **itemsets appearing together frequently** in transactions (frequent itemsets), and
    - **rules** that describe how these associations affect each other (association rules).

- An **association rule** is a rule in the form **"IF [Antecedent A] THEN [Consequent B]"** (or simply as **"A⇒B"**).

Research Methods (3 of 6)

- **Text Cloud Analysis**
  - **visualization of frequent textual terms** in a document, where
  - the **size of each term reflects its frequency** of appearance in the document

- **Our Study**
  - we used text cloud visualization
  - **for analyzing the association rules** obtained from association mining.
  - using **Wordle.net online service**.

Research Methods (4 of 6)

- **Pareto Analysis**
  - "Majority of effects are due to a minority of factors."
  - Suggested by Italian economist Vilfredo Pareto in 1896
  - Globally applicable in any applied field of knowledge.
  - One can prioritize identifying these most influential factors, rather than all factors.

- **Cross-Tabular Analysis**
  - Contingency tables or cross tabs
  - Quantitative method for analyzing the relations between multiple variables of interest
  - Using MS Excel's Pivot Table functionality.

Research Methods (5 of 6)

- **Regression Analysis**
  - Technique for estimating **the relation between one or more independent variables and a dependent variable**.
  - Our study, **for each hospital unit,**
    - **best linear regression model** and the regression function (including confounding effects)
    - obtained through extensive **search using genetic algorithm (GA).**

Research Methods (6 of 6)

- **Optimization**
  - Selection of best element from among a set of alternatives, based on one or more objectives to be optimized (maximized or minimized).
- **Linear programming**
  - an optimization method
  - single linear objective function to be optimized under a set of linear constraints.

Developed Framework

- **Step 0.** Data Cleaning
- **Step 1.** Association Mining
- **Step 2.** Text Cloud Analysis
- **Step 3.** Pareto Analysis
- **Step 4.** Cross-Tabular Analysis
- **Step 5.** Regression Analysis
- **Step 6.** Optimization

Results: **Association Mining**

- Coming up with cut-off values
- Cut-off values were selected as -60 and +60 minutes
- **Lateness < -60** and **Lateness > 60** were identified as values of interest.

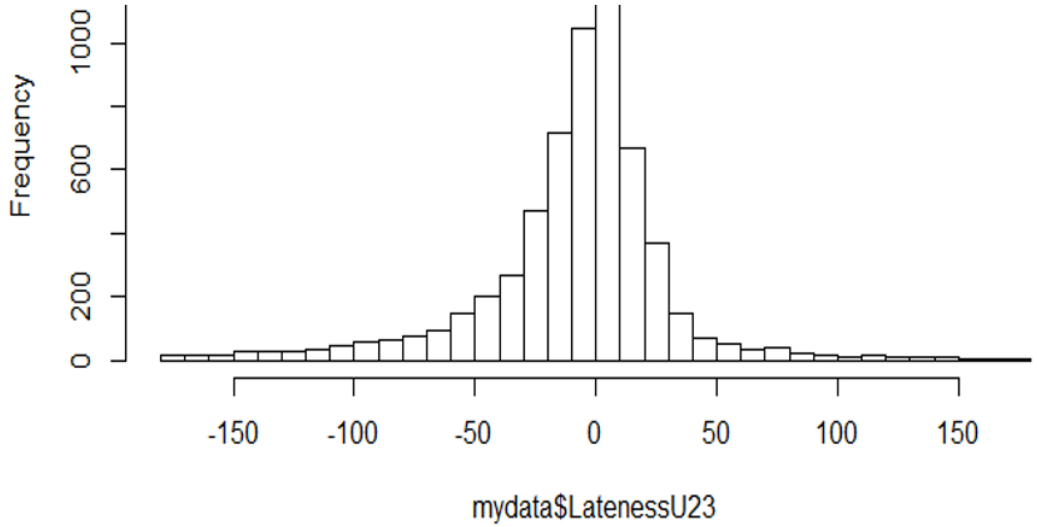


Figure 1. Histogram of **Lateness** for hospital unit **U23**.

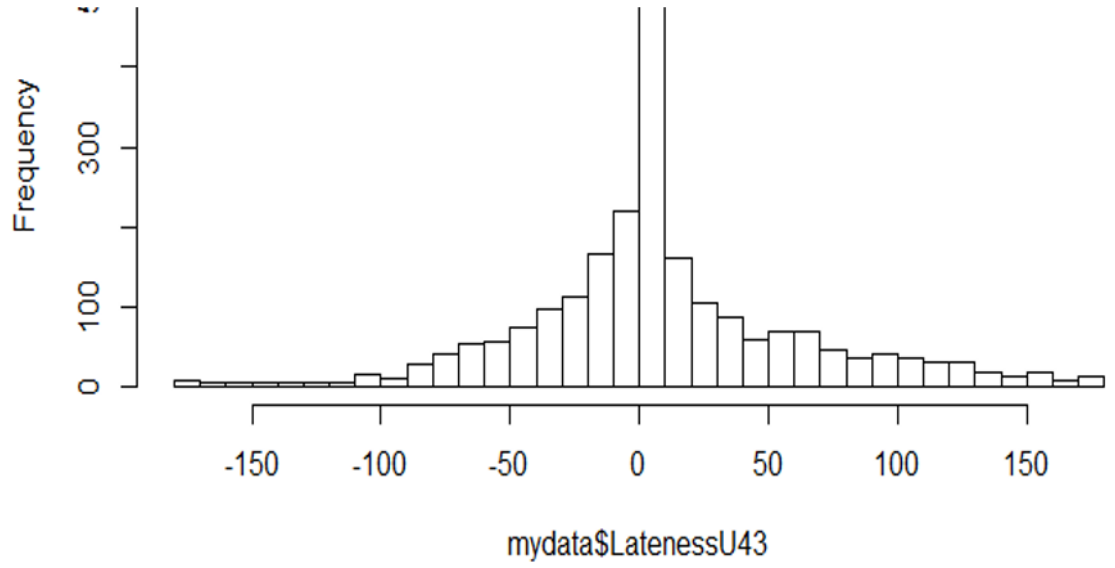


Figure 2. Histogram of **Lateness** for hospital unit **U43**

Results: Association Mining

- **“IF Antecedent THEN Consequent”**
  - minimum support of 0.1%
  - minimum confidence of 40%
  - at most 4 items in each rule

- Rules with a value of
  - **E_60_INF** (early at least 1 hour) and
  - **L_60_INF** (late at least 1 hour
- in the consequent were filtered out
- Goal: identify which attribute values are associated with
  - **very early arrivals** or
  - **very late arrivals.**

Results: Text Cloud Analysis

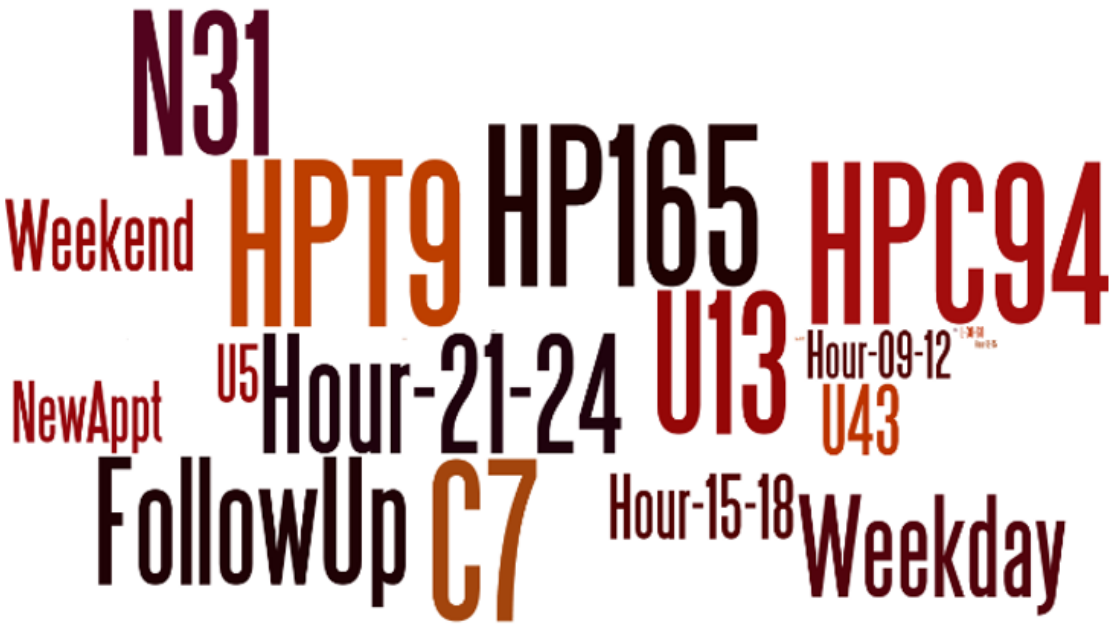


Figure 3. Attribute values when the patients are **early** at least 60 minutes, with a confidence of at least 40%.

Figure 4. Attribute values when the patients are **late** at least 60 minutes, with a confidence of at least 40%.

Lateness < -60

Lateness > 60

Results: Pareto Analysis

- Conducted ***before*** **cross-tabular analysis.**
  - Identify the significant few values for each attribute.
  - Cross-tabular analysis will include **the few most significant attribute values.**

- Pareto analysis **threshold values ~ 90%**

- Out of the 46 hospital units, 17 account for >90% of rows.
- Out of 110 different nationalities, 9 account for > 92% of rows.
- Week days account for > 97% of rows
  - Only week days were considered in further analysis.

Results: **Cross-Tabular Analysis**

- Average lateness differs considerably
  - among **health plan categories**
  - among **different hospital units.**

HealthPlanCategory	Hour_06_09	Hour_09_12	Hour_12_15	Hour_15_18	Hour_18_21	Hour_21_24	Average for Lateness
HPC3	22.48	3.66	-3.60	-13.15		-14.90	**-2.18**
HPC35	12.03	-6.72	1.94	-8.33	7.44	3.31	**-0.56**
HPC8	10.44	3.73	5.80	-8.18	61.00	11.75	**1.71**
HPC94	11.62	-2.92	-5.13	-11.42	16.37	-1.05	**-1.80**
Average for Lateness	**11.69**	**-2.85**	**-4.06**	**-11.06**	**16.50**	**-1.04**	**-1.67**

Figure 6. Cross-tabular analysis of **Lateness** with respect to **health plan category**.

Results: **Cross-Tabular Analysis**

Units	Hour_06_09	Hour_09_12	Hour_12_15	Hour_15_18	Hour_18_21	Hour_21_24	Average for Lateness
U8	8.66	-5.32	-5.23	-12.68		-2.71	**-3.94**
U9	6.68	-8.96	-6.63	-16.75		-0.53	**-5.99**
U14	15.11	-1.43	-1.90	-12.81	-19.62	-1.60	**-0.95**
U19	14.28	-5.42	-8.05	-17.70	-5.60	-2.57	**-3.95**
U20	6.78	-9.04	-6.54	-11.89		0.88	**-5.61**
U21	7.06	-5.90	-5.00	-13.32	-31.00	-1.55	**-4.83**
U23	8.18	-7.20	-7.40	-31.42		0.09	**-7.65**
U25	26.15	-5.20	-19.45	-35.91		-13.51	**-7.27**
U26	8.94	-2.76	-3.79	-17.66		-0.74	**-2.02**
U27	5.52	-6.16	-7.23	-13.10	-14.70	-2.14	**-6.03**
U29	10.94	-0.14	-1.80	-8.97	-4.33	1.34	**0.13**
U31	17.20	12.03	6.06	1.34		1.24	**8.26**
U41	23.98	0.48	-1.10	-12.29		6.50	**4.40**
U43	12.99	-5.93	-9.75	11.24	35.24	-10.71	**9.53**
Average for Lateness	**11.69**	**-2.85**	**-4.06**	**-11.06**	**16.50**	**-1.04**	**-1.67**

Figure 5. Cross-tabular analysis of **Lateness** with respect to **hospital units**.

Results: **Regression Analysis**

- **R** statistical language and system
- **RStudio** , an open-source integrated development environment (IDE) for R
- **glmulti** R package for automatically conducting regression analysis and systematically trying out different models.
  - genetic algorithm (GA) built into glmulti package
  - extensively searching for the best model for each hospital unit.

Unit	Intercept	Hour	DayOfWeek	NewOrFollowUp	HealthPlanCategory	HealthPlanType	InsuranceCompany	HealthPlan	Nationality	HealthPlanType:Hour	HealthPlanType:NewOrFollowUp	InsuranceCompany:HealthPlanCategory	HealthPlan:HealthPlanCategory	HealthPlanType:HealthPlanCategory	InsuranceCompany:HealthPlan	NewOrFollowUp:DayOfWeek	InsuranceCompany:HealthPlanType	DayOfWeek:Hour	HealthPlanType:DayOfWeek	HealthPlanType:Nationality	NewOrFollowUp:Hour	HealthPlanCategory:NewOrFollowUp
U8	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	0	0	0	0	0	0	0
U9	1	1	0	1	1	0	1	1	0	0	0	1	0	0	1	0	0	0	0	0	0	0
U14	1	1	1	0	1	1	1	1	0	1	0	1	1	1	1	0	0	0	0	0	0	0
U19	1	1	1	1	1	1	1	1	0	1	0	1	0	1	1	1	1	0	0	0	0	0
U20	1	1	1	1	1	1	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0
U21	1	1	0	0	1	1	1	1	0	1	0	0	0	1	0	0	0	0	0	0	0	0
U23	1	1	1	1	1	1	1	1	0	0	1	1	0	1	1	0	0	1	1	0	0	0
U25	1	1	1	1	1	1	0	1	1	0	0	0	0	1	0	0	0	0	0	1	0	0
U26	1	1	0	0	1	1	1	1	1	0	0	1	0	1	1	0	0	0	0	0	0	0
U27	1	1	1	1	1	1	1	1	0	1	0	1	0	0	1	0	1	0	0	0	1	1
U29	1	1	1	0	1	1	0	1	0	1	0	0	0	1	0	0	0	0	0	0	0	0
U31	1	1	1	1	1	1	0	1	1	1	1	0	0	0	0	1	0	0	0	0	1	0
U41	1	1	1	0	1	1	1	1	0	0	0	0	0	1	1	0	1	0	0	0	0	0
U43	1	1	1	1	1	1	1	1	0	0	0	1	0	1	1	1	0	1	0	0	1	0
∑□	**14**	**14**	**11**	**9**	**14**	**13**	**10**	**14**	**3**	**7**	**3**	**8**	**1**	**10**	**9**	**3**	**3**	**2**	**1**	**1**	**3**	**1**

Table 2. The best regression model obtained for Hospital Unit U23.

Number of GA Generations: 830

Lateness ~ 1 + Hour + DayOfWeek + NewOrFollowUp + HealthPlanCategory + HealthPlanType + InsuranceCompany + DayOfWeek:Hour + HealthPlanType:DayOfWeek + HealthPlanType:NewOrFollowUp + HealthPlanType:HealthPlanCategory + InsuranceCompany:HealthPlanCategory

	Estimate	Std. Error	df
(Intercept)	3.3791639	5.117549	6119
HourHour_09_12	-15.9692562	3.504481	6119
HourHour_12_15	-14.430737	3.490735	6119
HourHour_15_18	-41.4217847	3.902486	6119
HourHour_21_24	-7.0373843	4.235951	6119
DayOfWeekSaturday	2.2369168	6.748343	6119
DayOfWeekSunday	-2.8651697	4.691285	6119
DayOfWeekThursday	-1.5603118	5.196154	6119
DayOfWeekTuesday	0.2219676	4.377265	6119
DayOfWeekWednesday	0.1872806	4.282621	6119
NewOrFollowUpN	4.3659576	1.066314	6119
HealthPlanCategoryHPC8	-11.948427	37.658373	6119
HealthPlanCategoryHPC94	4.0305095	4.101377	6119
HourHour_09_12:DayOfWeekSaturday	-2.2177596	7.680761	6119

• • •

Conclusions

- Data mining framework:
  - **reveals hidden patterns.**
  - **generates insights** into patient arrival patterns.
  - **identifies significant factors** (independent variables) that affect Lateness
  - **determines**
    - form and
    - parameters of the

  “best” regression function

Conclusions

- Our framework can **serve as an engine**
  - for **determining the parameters of** a subsequent **optimization** model,
  - which can **optimize appointment day and time.**

- Regression model
  - considers **Lateness as a function of various factors,**
  - including **Hour** and **DayOfWeek** in which the patient arrived.

- **None of the considered factors, except Hour and DayOfWeek, can be controlled by the healthcare provider,** as these factors depend on the attributes or the medical condition of the patient.
- **Healthcare provider can minimize the Lateness of the patient by selecting the "best" DayOfWeek-Hour combination.**

Optimization Model

Let

$\mathcal{P}$: set of patients who will visit the selected hospital unit, p= $1 \cdots P$

$\mathcal{D}$: set of days (DayOfWeek) $d = 1 \cdots 5$

$\mathcal{T}$: set of time periods (Hour) $t = 1 \cdots 5$

be the *sets* of the optimization model.

Next, let

$C_{d,t}$: capacity of the hospital unit for time period (Hour) t on day (DayOfWeek) d

be the *parameters* of the optimization model.

Let the *decision variables* of the optimization model be

$$Z_{p,d,t} = \begin{cases} 1 & \text{if patient } p \text{ is scheduled to time period } t \text{ on day } d \\ 0 & \text{o/w} \end{cases}$$

Optimization Model

The *optimization model* designed to *minimize average Lateness*, is as follows:

$$\min_{p,d,t} \Lambda = \frac{1}{P} \sum_{p=1}^{P} \hat{L}(Z_{p,d,t})$$

fitted regression function for that hospital unit

$$\sum_p Z_{p,d,t} = C_{d,t} \qquad \forall (d,t)$$

$$\sum_{d,t} Z_{p,d,t} = 1 \qquad \forall p$$

$$Z_{p,d,t} \quad \text{binary}$$

Research Questions

1. **How can** the **patient arrivals** into healtcare centres **be analyzed** to come up with insights into Lateness?

2. **Which factors** are **associated with Lateness**?

3. **How can patient appoinments be scheduled** to minimize Lateness?

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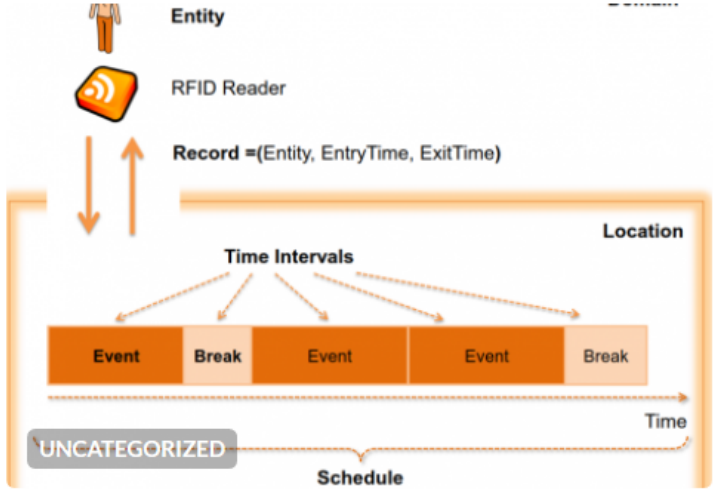

A Framework for Mining RFID Data From Schedule-Based Systems

Dr. Gurdal Ertek

Wind Turbine Accidents: A Data Mining Study

Dr. Gurdal Ertek

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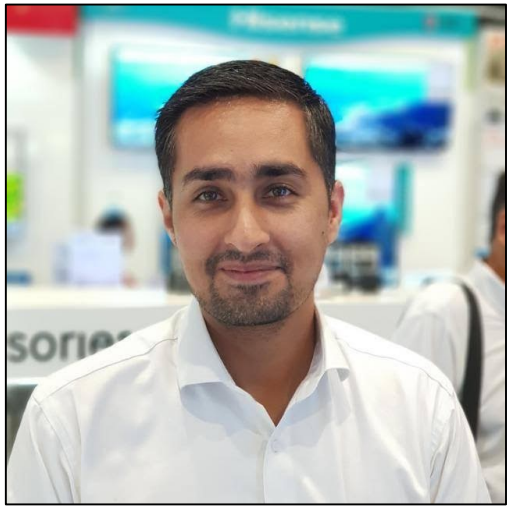

Thank you. Your Questions?