# Queue Mining: Queueing Theory meets Process Mining

**AIS Group Meeting** 

Arik Senderovich 10/11/2016

### **Short Bio**

Postdoc @







- BSc in IE&M (Knowledge Systems)
- MSc in STAT (Service Engineering)
- PhD in Data Science (Queue Mining)

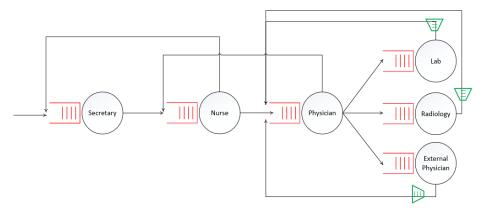
### Favorites: Service Processes

Processes where (efficient and effective) service is the

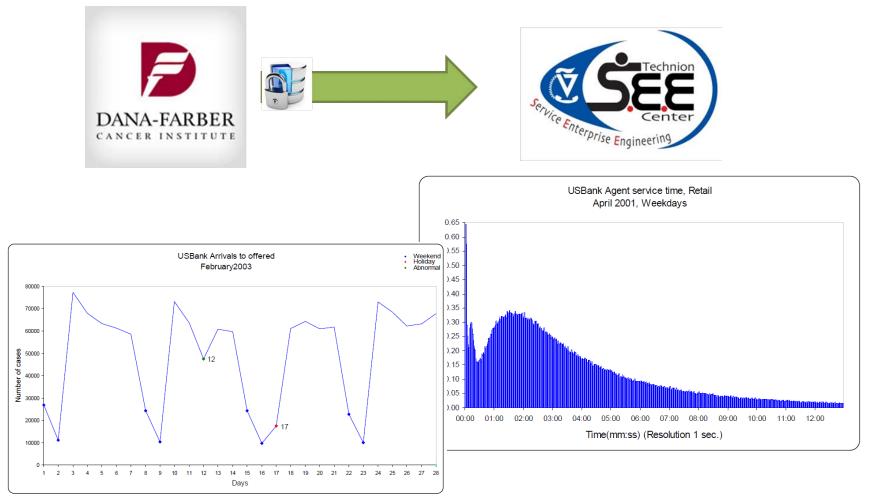
desired business outcome:

- Call centers
- Hospitals
- Transportation

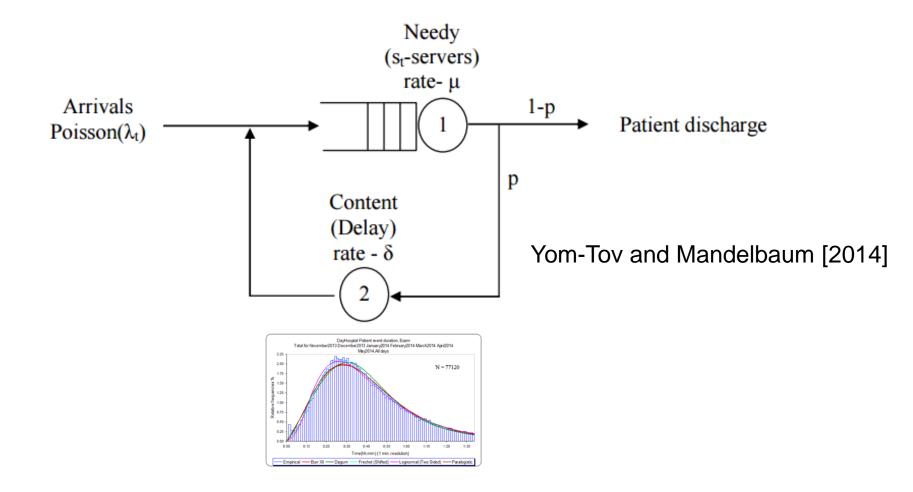


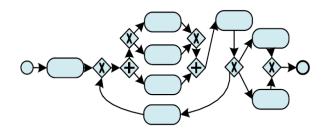


### SEELab and SEEData



# Hand-made Performance Modeling







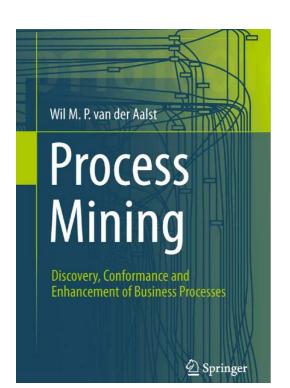
# Automated process modeling based on data = Process mining



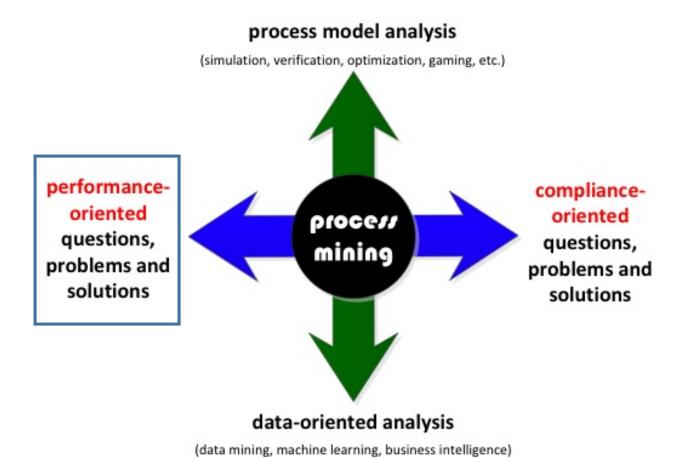


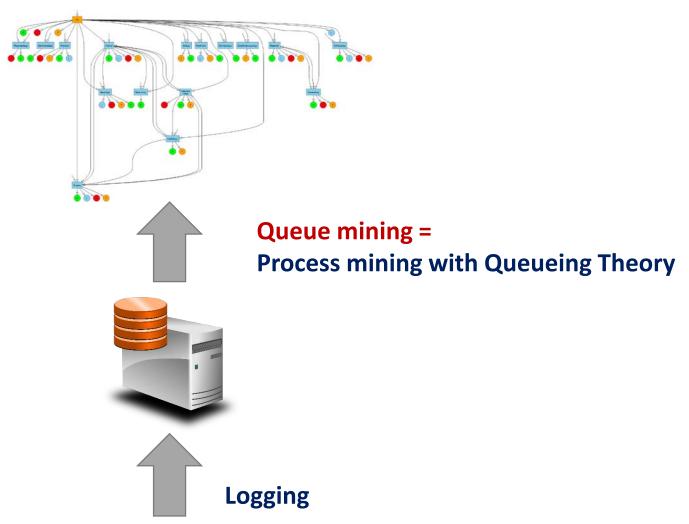
Logging





# Focus: Performance Analysis

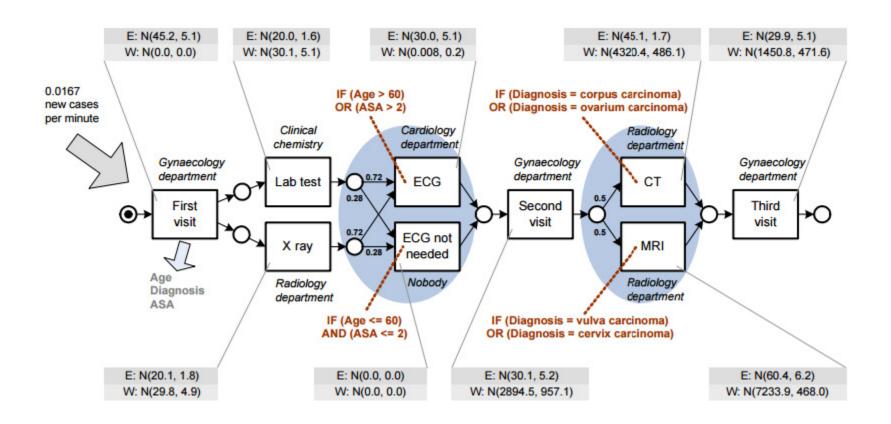






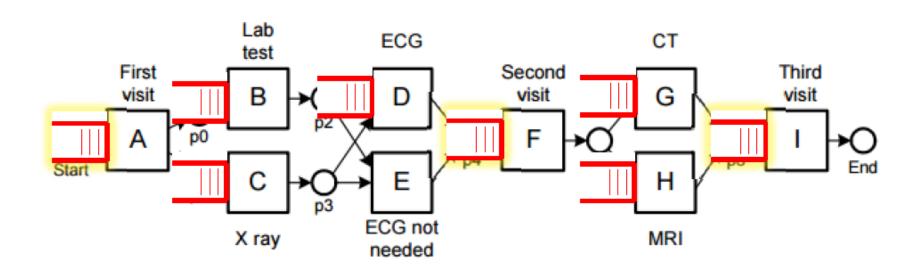
S. A., Weidlich M., Gal A., Mandelbaum A., in Information Systems 2014

## State-of-the-art: Approach I



From Rozinat et al. [2009]; Rogge-Solti et al. [2013]

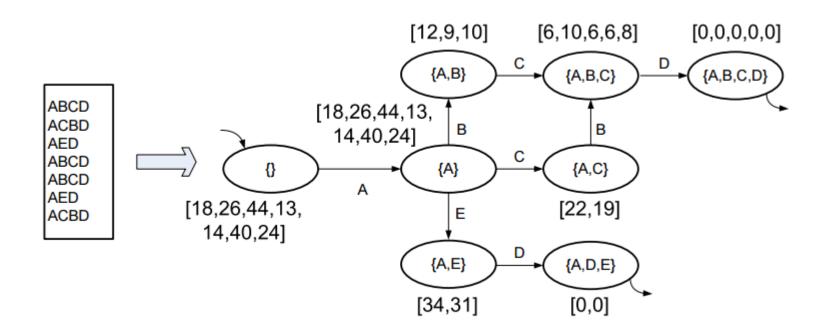
## Queue Mining: Approach I



### Queueing models:

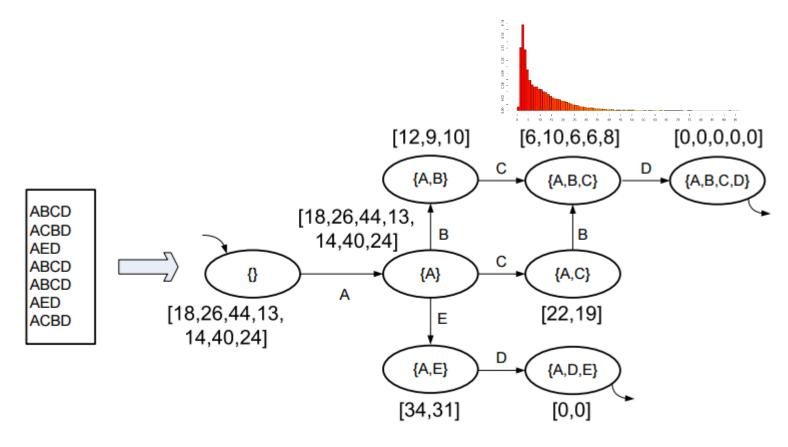
- Analytically simple models (efficiency) no need for simulation
- (Often) accurate performance analysis w.r.t. data (robust/generalize well)

## State-of-the-art: Approach II



From van der Aalst et al. [2011]

## Queue Mining: Approach II



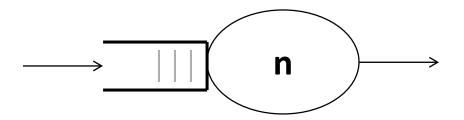
### Queueing features added to state:

- > Examples: queue-lengths, delays, classes
- Input for machine learning techniques

### Outline

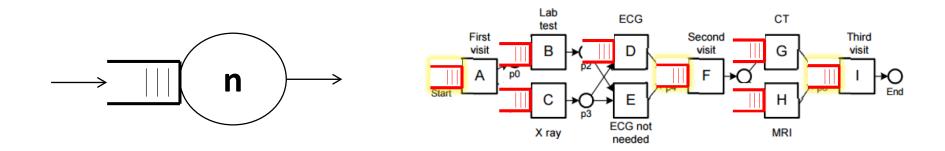
- > Background
- Single-station queueing models
  - Single-class
  - Multi-class
- Queueing networks
  - Pre-defined routing
  - Random routing
- Conformance checking with queueing networks

### Single-Station Single-Class Queues



Are these useful models?

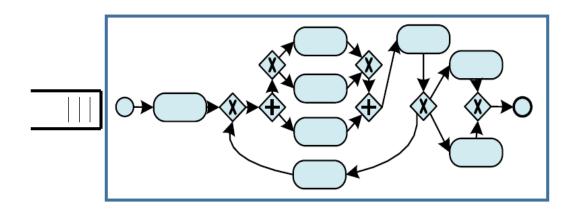
## Single-Station Queues



Are these useful models?

Building block of networks

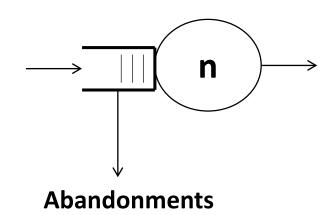
### Single-Station Queues



#### Are these useful models?

- Building block of networks
- Single-resource type processes
  - Total time is <u>delay</u> (queueing) and process time

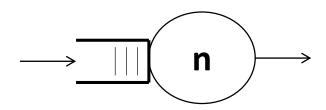
### Queueing Model: Building Blocks



### Kendall's notation – A/B/C/Y/Z+X:

- ➤ A arrivals, B service times
- C static server capacity (n servers); Y queue size
- Z service policy (FCFS, LCFS, Processor Sharing...)
- ➤ X (Im)patience

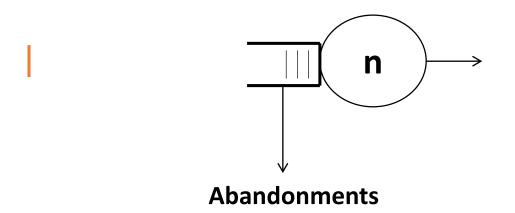
### Example: M/M/n



### Assumptions (A/B/C/Y/Z+X):

- Dropped notation Y,Z,X (defaults are taken): infinite queue size, FCFS policy, no abandonments
- M Poisson arrivals (completely random, one at a time, constant rate)
- M Exponentially distributed service times
- Easy to analyze when parameters are known (data)

### Problem: Delay Prediction



CAiSE2014 paper with Weidlich, Gal, Mandelbaum

### How long will the target customer wait?

- Online prediction problem
- Approach I fit q-model (&parameters) from the log
- Approach II transition system + learning

## Notation and Accuracy Measure

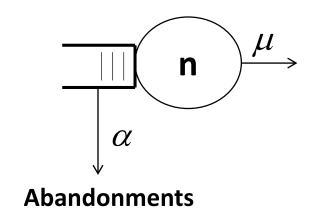
- $\succ$  The actual waiting time of a customer:  $W_i$
- $\succ$  Delay predictor from a certain method:  $heta_{method}$
- Accuracy via the root of average squared-error (RASE):

$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(W_{i}-\theta^{i}_{method})^{2}}$$

> Systemic errors in assumptions- avg. absolute bias:

$$\left|\frac{1}{n}\sum_{i=1}^{n}\left(W_{i}-\theta^{i}_{method}\right)\right|$$

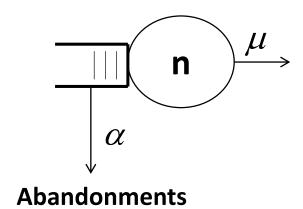
## Approach I: Queueing Model is Fitted



### G/M/n+M model:

- Exponential service times and (im)patience
- > General arrival rates, FCFS policy, unlimited queue

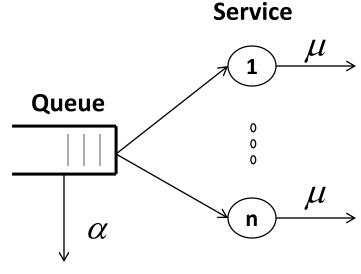
# Approach I: Analysis



### Two families of delay predictors:

- Queue-length (state based)
- Snapshot principle (history based)

### Queue-Length Predictors



**Abandonments** 

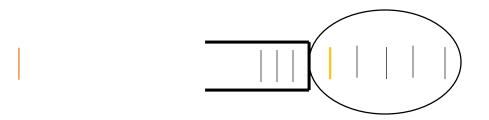
$$\theta_{QLM-NA} = \frac{QL+1}{n\mu}$$

$$\theta_{QLM} = \sum_{i=0}^{QL} \frac{1}{n\mu + i\alpha}$$

Whitt [1999]

## Snapshot Prediction: Last-to-Enter-Service

(Armony et al., 2009; Ibrahim and Whitt, 2009)

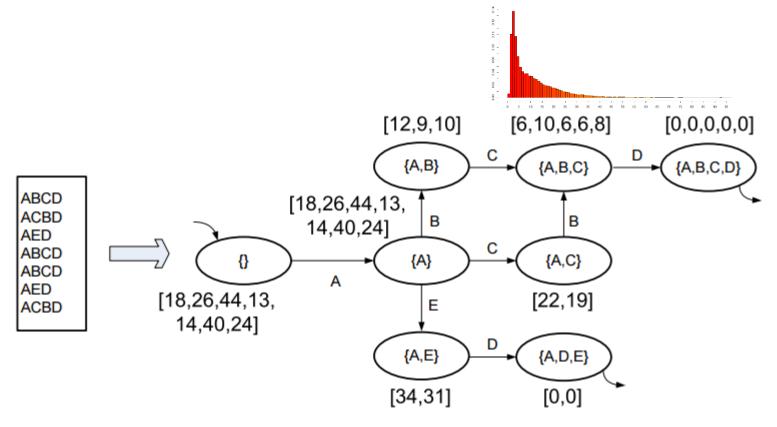


#### **Prediction:**

The last customer to enter service waited w in queue

$$\theta_{LES} = w$$

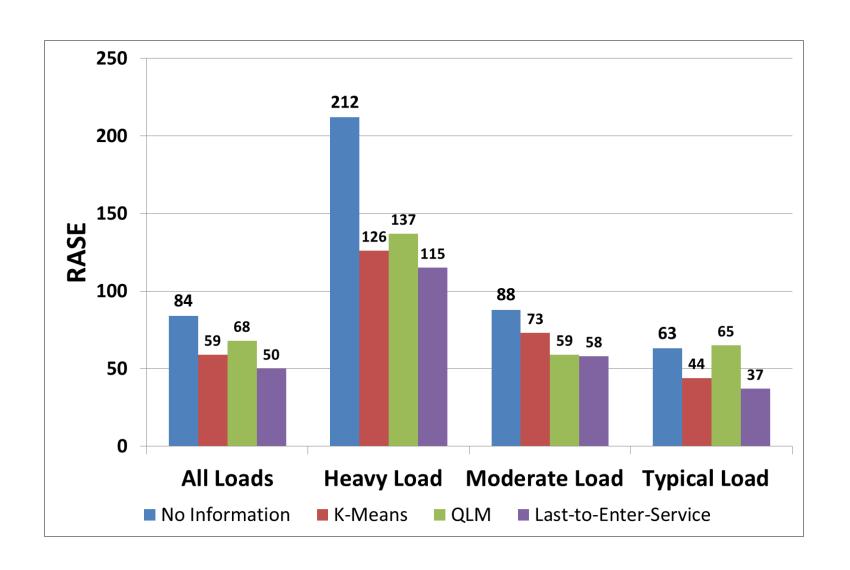
### Approach II: Transition System Based



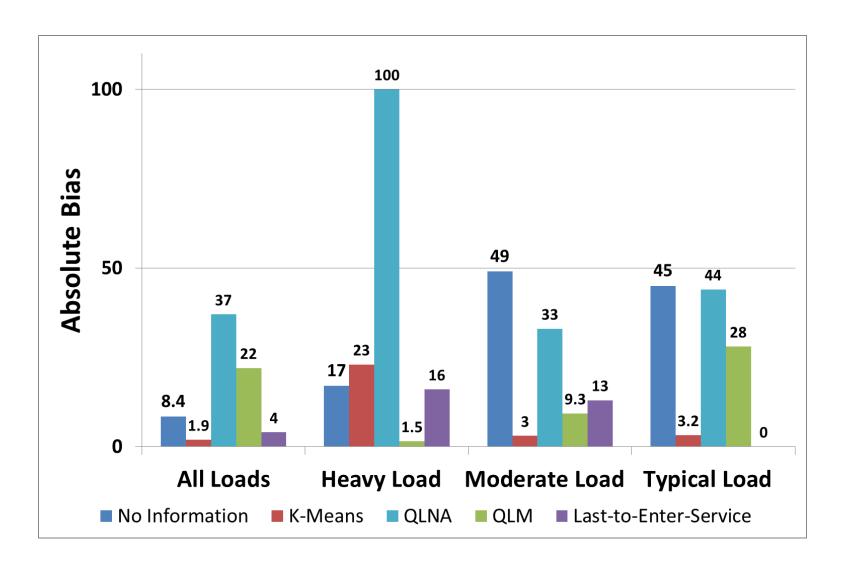
Transition system with queueing features:

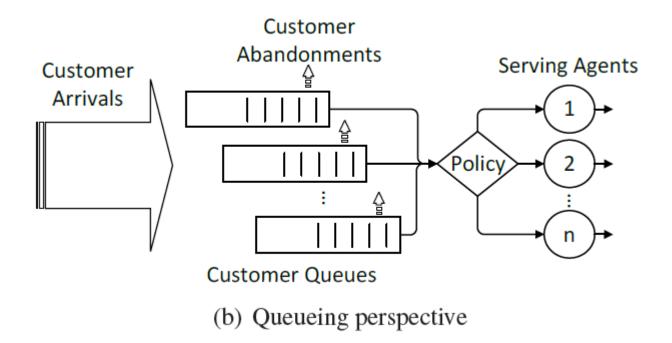
- Queue lengths are clustered (heavy, moderate, typ.)
- Prediction is based on QL cluster + progress

### Results I: Bank's Call Center Data

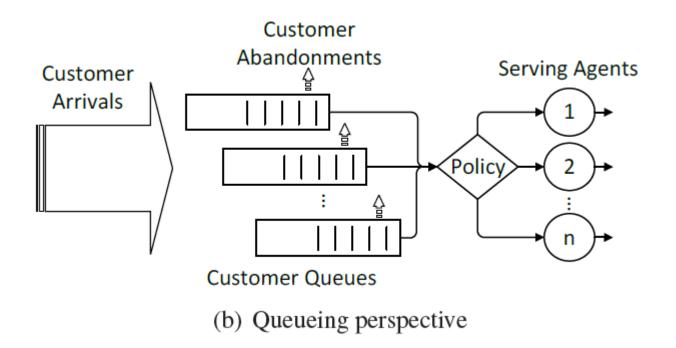


### Results II: Bank's Call Center Data



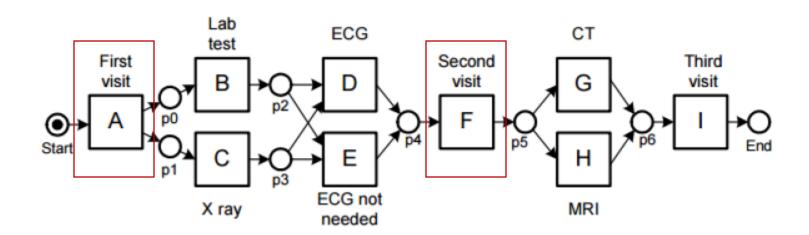


Useful?



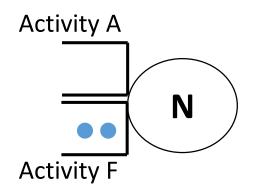
#### Useful?

Different types of customers (VIP vs. Regular; Urgent vs. Ambulatory)



#### Useful?

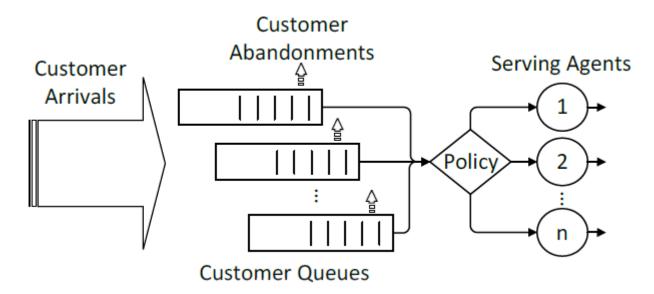
- Different types of customers (VIP vs. Regular; Urgent vs. Ambulatory)
- $\triangleright$  Classes = activities (A vs. F A gets priority)



#### Useful?

- Different classes/types of customers (VIP vs. Regular; Urgent vs. Ambulatory)
- $\triangleright$  Classes = activities (A vs. F A gets priority)

### Approach I for Multi-Class Queues

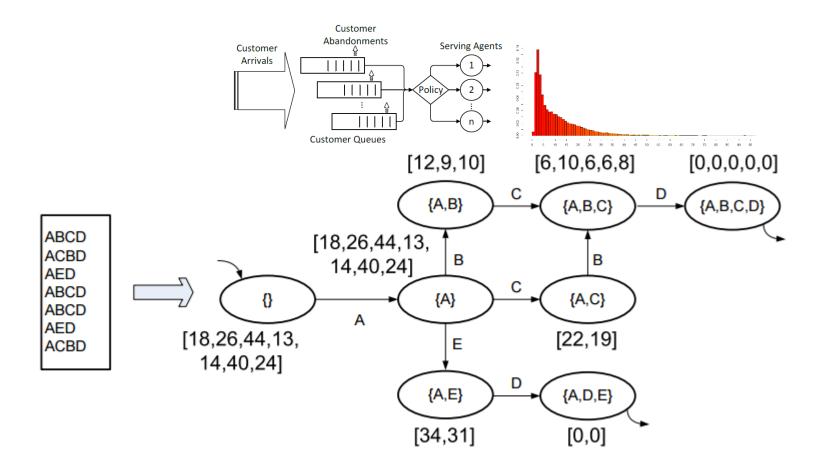


Information Systems [2014] with Weidlich, Gal, Mandelbaum

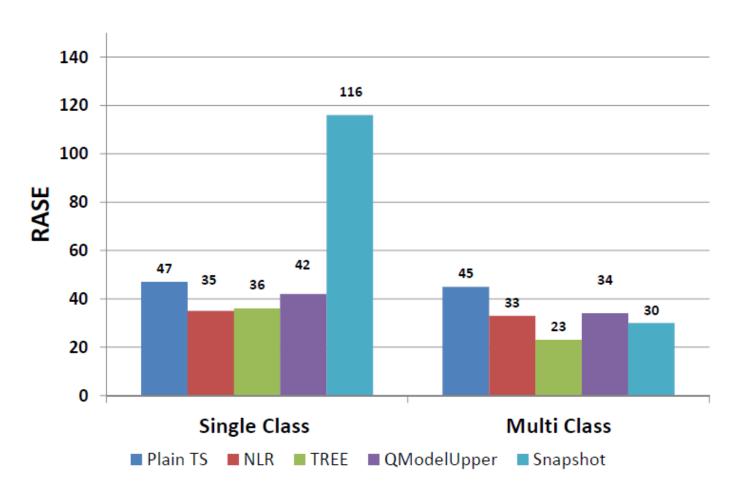
#### Assuming priority queues model:

- Queue length predictors derived upper and lower bounds
- Snapshot principle (based on Reiman and Simon [1990])

## Approach II for Multi-Class Queues

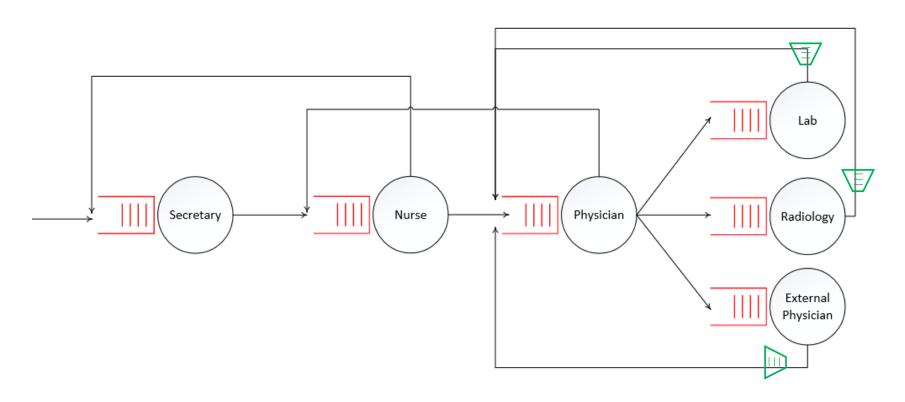


### Results: Telecom Call Center Data



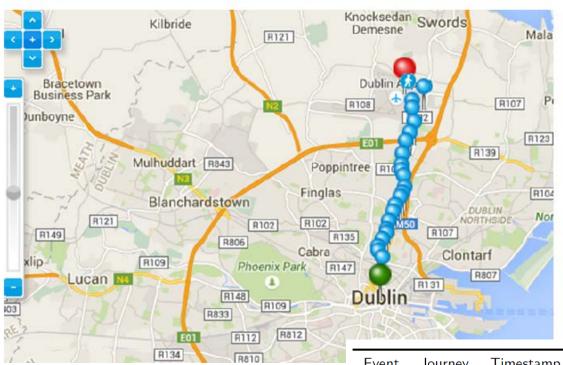
NLR, Tree – similar to De Leoni et al. [2014] (BPM14' best paper)

## What about networks of queues?



Snapshot principle holds in q-networks with **pre- defined routing:** public transport, outpatient clinics,...

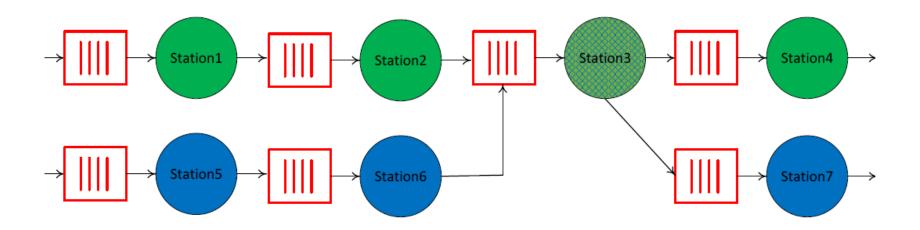
# Bus Traveling Time Prediction



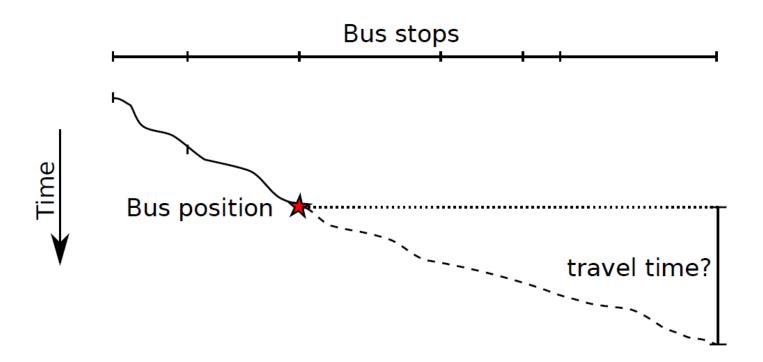
Information Systems [2015] with Weidlich, Schnitzler, Gal, Mandelbaum

Event Id	Journey Id	Timestamp	Bus Stop	Journey Pattern
1	36006	1415687360	Leeson Street Lower (846)	046 <i>A</i> 0001
2	36012	1415687365	North Circular Road (813)	046 <i>A</i> 0001
3	36009	1415687366	Parnell Square (264)	046 <i>A</i> 0001
4	36006	1415687381	Leeson Street Lower (846)	046 <i>A</i> 0001
5	36009	1415687386	O'Connell St (6059)	046 <i>A</i> 0001
6	36012	1415687386	North Circular Road (814)	046 <i>A</i> 0001
7	36006	1415687401	Leeson Street Upper (847)	046 <i>A</i> 0001
8	36009	1415687406	O'Connell St (6059)	046 <i>A</i> 0001

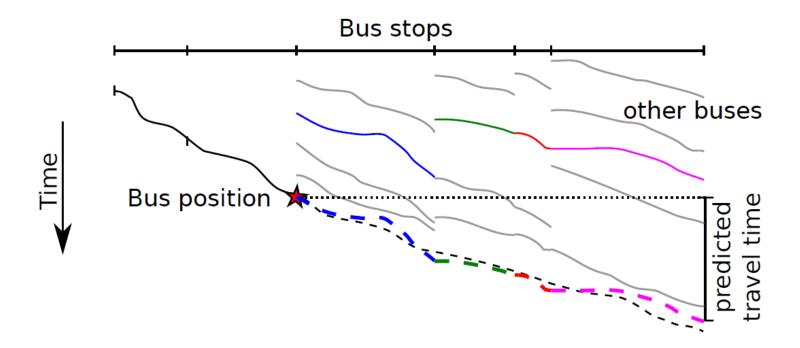
#### Bus Routes as Q-Networks



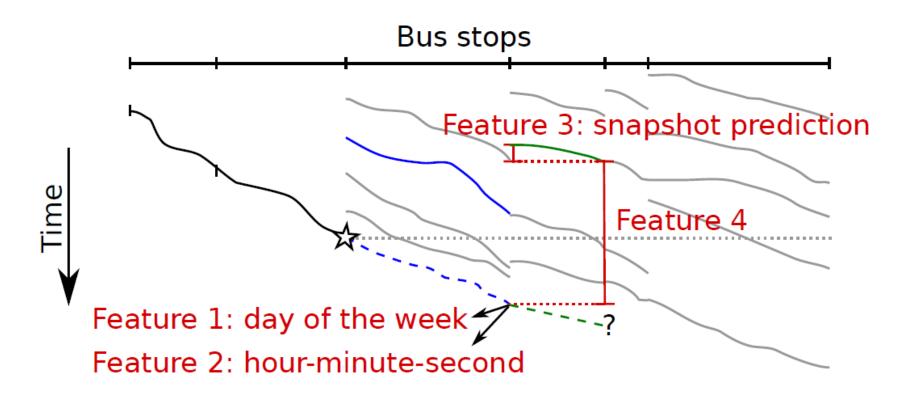
#### Prediction Problem



# Approach I: Snapshot Principle



# Approach II: Load-related + Snapshot Features



#### Ensemble of Regression Trees

RF random forests (bagging)

ET extremely randomized trees

Intuition:

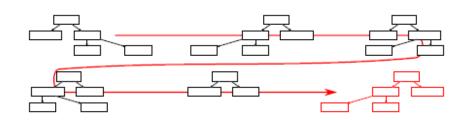
build each tree non-optimally and independently from the others

AB adaboost

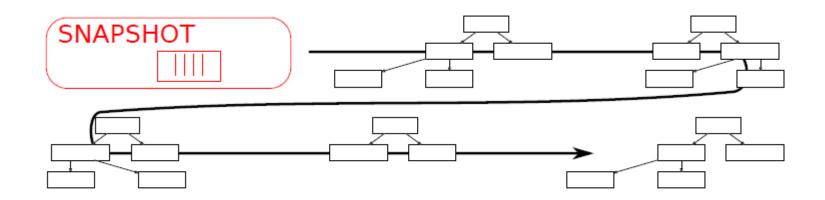
GB gradient tree boosting

GBLAD robust gradient tree boosting

build trees sequentially, trying to add a tree that correct the flaws of the current ensemble



# Boosting over the Snapshot Predictor

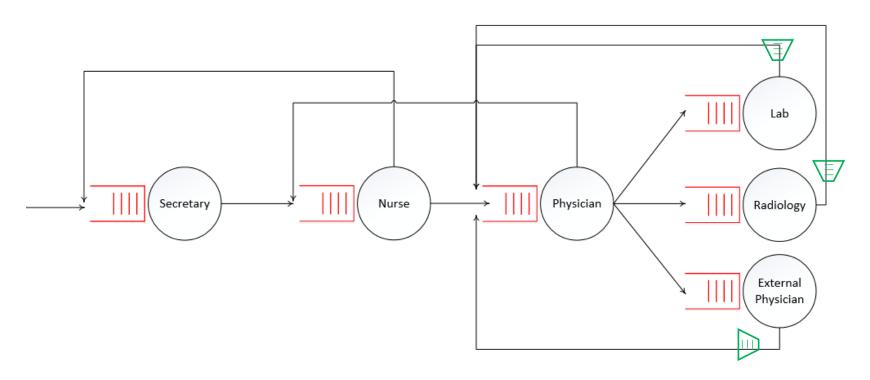


### Results: Dublin Buses (GPS data)

Accuracy of the prediction over all trips. Worse, Best, **Best of S+xx and xx** 

RMSE	MARE (%)	MdARE (%)
539	23.37	16.15
539	24.11	16.37
519	22.05	15.23
512	27.08	18.05
504	26.32	16.84
508	20.46	13.84
494	19.95	13.53
520	19.38	13.86
514	19.06	13.65
	539 539 519 512 <b>504</b> 508 <b>494</b> 520	539 23.37   539 24.11   519 22.05   512 27.08   504 26.32   508 20.46   494 19.95   520 19.38

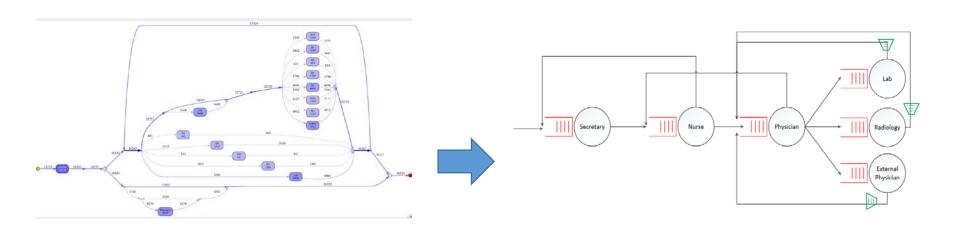
### What if routing is not pre-defined?



Approximation techniques, e.g. Queueing Network Analyzer (Whitt [1983]):

- Allows concurrency and non-exponential times
- Steady-state approx. (model per hour...)

#### Idea: PN->GSPN->QN Transformation

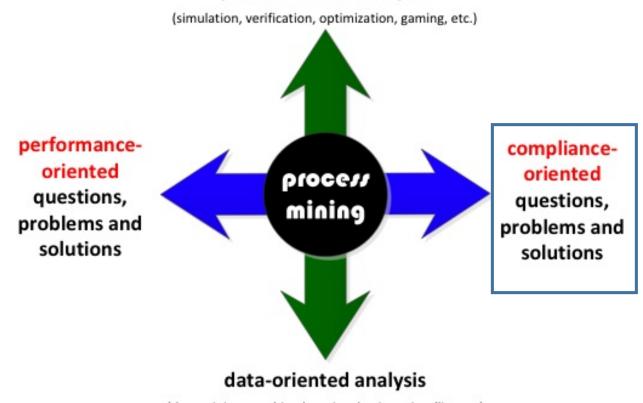


#### Four step approach:

- Control-flow discovery (e.g., IM)
- 2. Enrichment (firing times, arrivals, resources,...)
- 3. Simplification (helps to avoid over-fitting)
- Translation to QN for analysis (QNA)

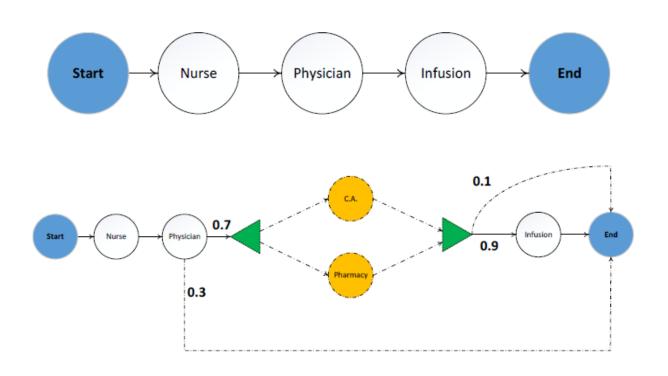
# Conformance checking: A Queueing Network Perspective

#### process model analysis



(data mining, machine learning, business intelligence)

# Conformance checking: A Queueing Network Perspective



Information systems [2015] with Yedidsion, Weidlich, Gal, Mandelbaum, Kadish, Bunnel

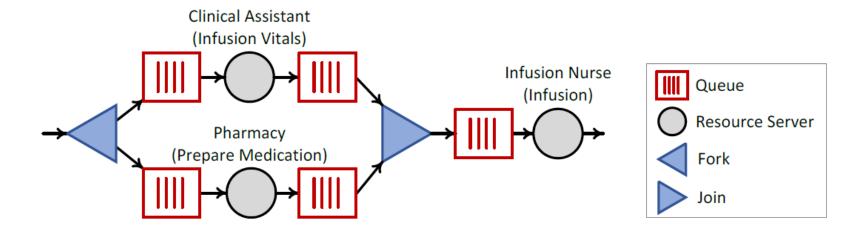
# Conformance checking: A Queueing Network Perspective

The two queueing networks are compared:

- Detect deviations between planned and actual performance measures
- 2. Root-cause analysis:
  - Compare structures (unscheduled activities)
  - Building blocks (arrivals, service times,...)

Root-cause of deviations can lead to performance improvement (example is coming up)

# Example: Fork-Join Construct



# Step I: Unexpected Queueing

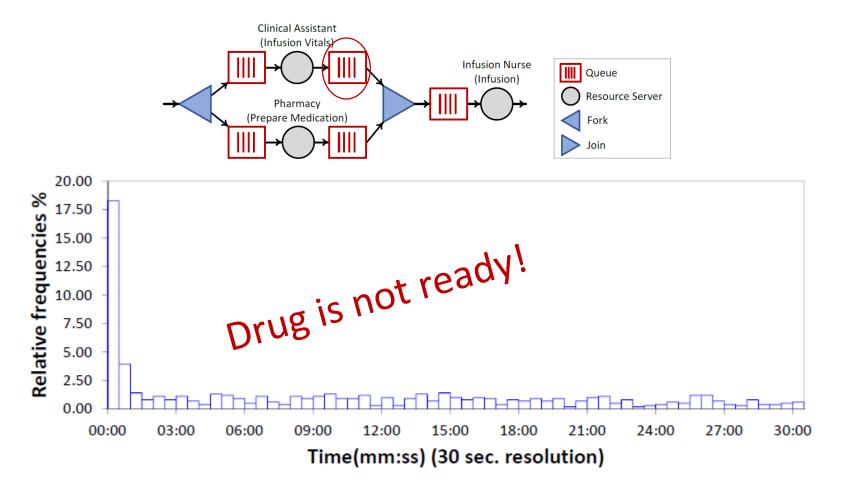


Figure 5: Waiting time for Infusion (after vitals); Sample size = 996, Mean = 25min, Stdev = 29min

# Step II: Production time is not the cause!

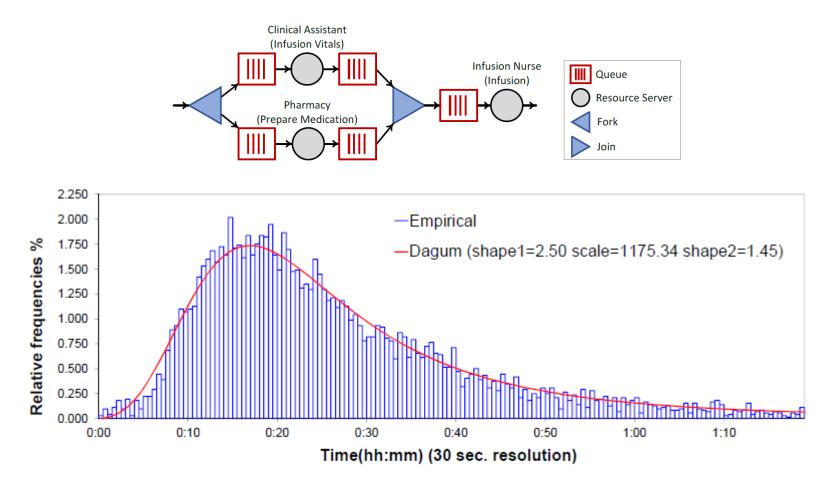
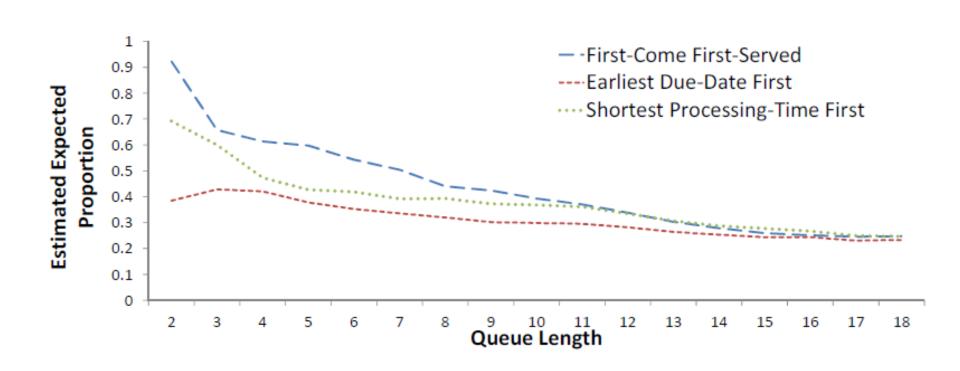
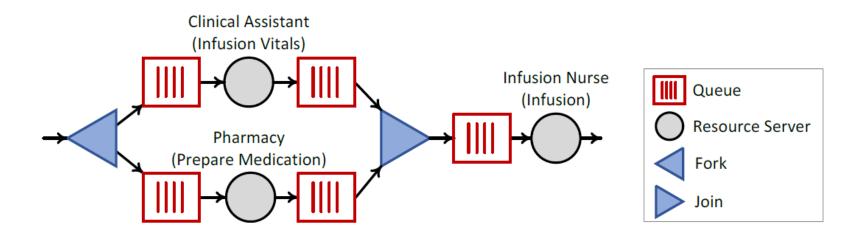


Figure 6: Medication production time; Sample size = 7187, Mean = 30min, Stdev = 24min.

# Step II: Production policy is...!



# Process Improvement: Idea



- New policy for sequencing "vitals" patients to reduce waiting and increase throughput
- Dominates the EDD policy proofs and experiments in the paper

#### Conclusion



- Queueing models are useful for process mining
- > Especially: in service processes with scarce resources
- Happy to collaborate on further integration of queueing theory into process mining

Thank you! sariks@tx.technion.ac.il