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Heart Failure Hospitalization Prediction in Remote Patient Management Systems

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Project page: http://www.win.tue.nl/~mpechen/projects/rpm/
Supported by KWR MIP project

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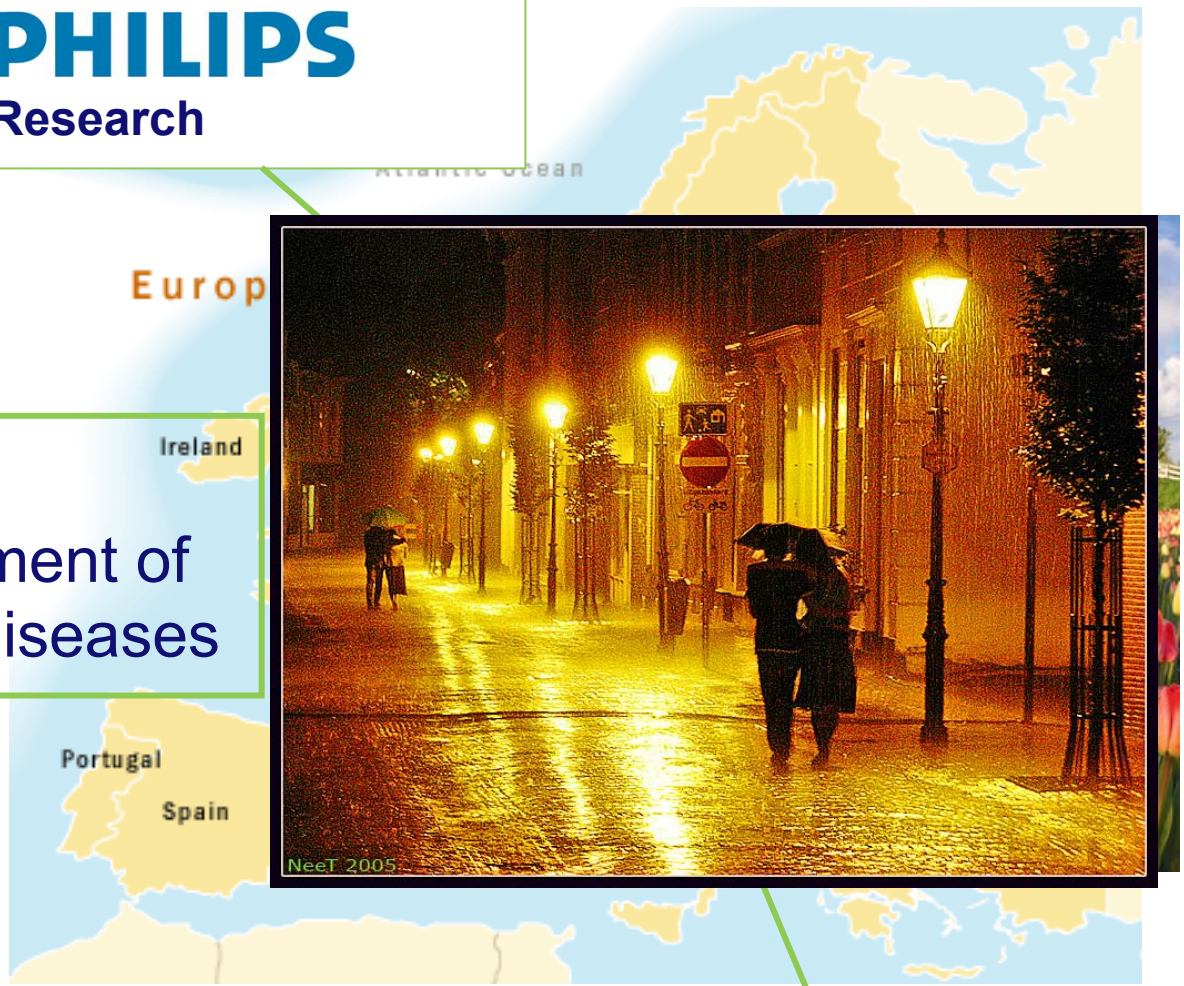
Research



Focus on Cardio:

- Treatment and management of chronic cardiovascular diseases

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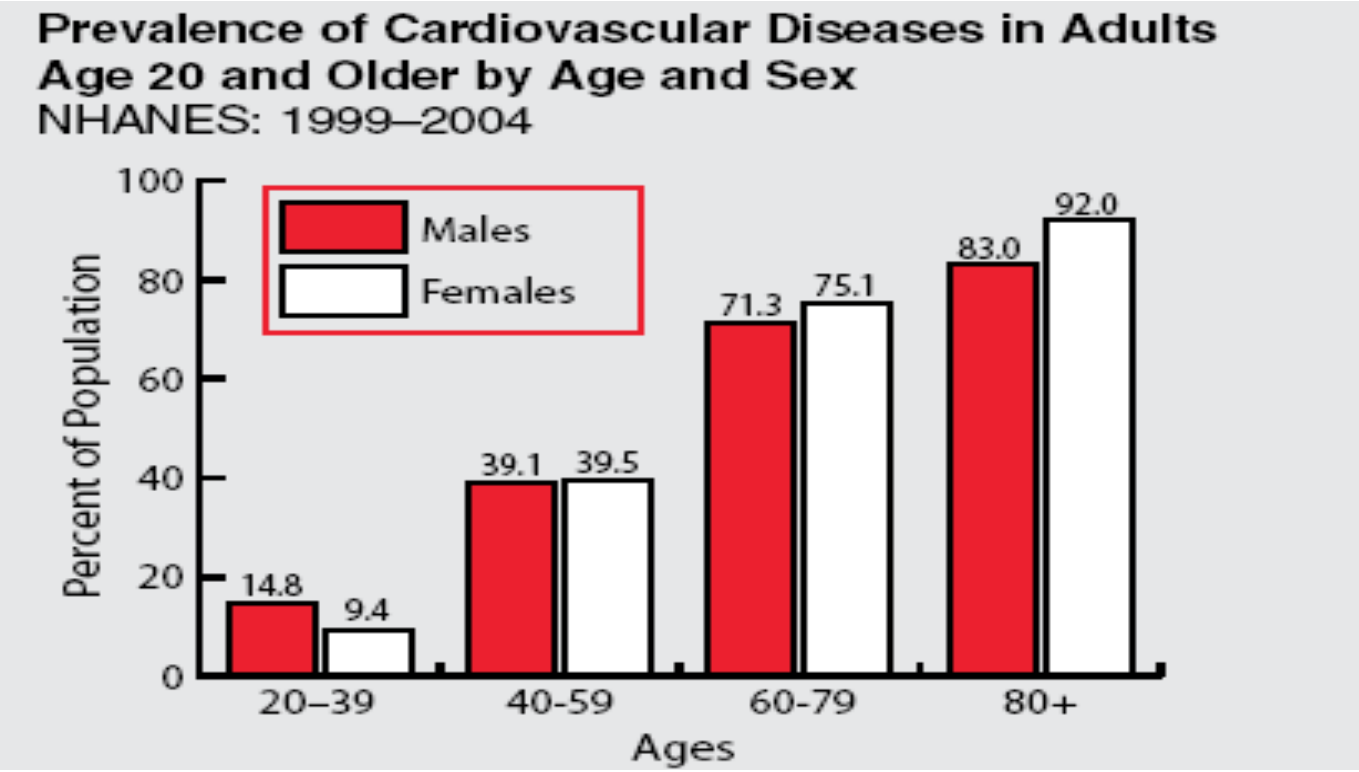
Outline

- Remote Patient Management (RPM)
- Patient modeling in RPM
- Heart Failure Hospitalization (HFH) Prediction
  - Problem formulation
  - Available data sources
- Our approach for HFH predicting modeling
  - Construction of positive and negative training instances
- Experimental results
- Conclusions and further work

Health and cost problem

- **Cardio-vascular diseases**
  - Major cause of death and health costs in EU and US
  - Affect 40% of overall population
  - After first event is chronic: heart failure, coronary artery disease,…
  - Shift from patient care in the hospital to care at home



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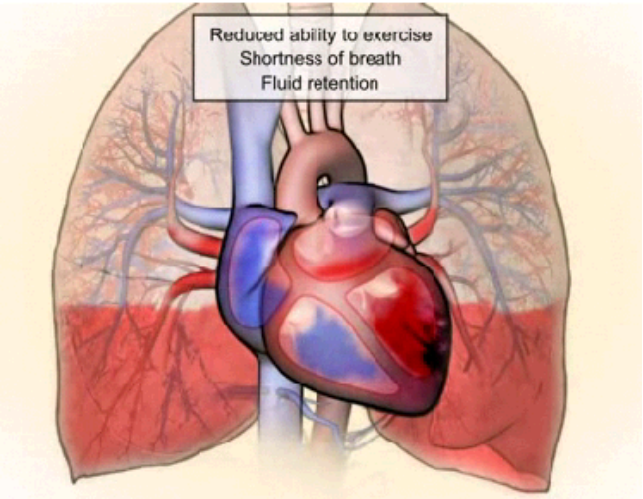
Chronic Heart Failure

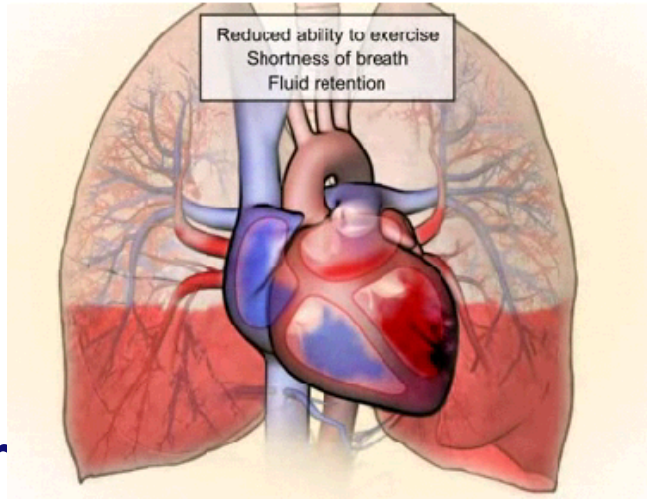
- Inability of the heart to pump blood adequately around the body
- Prevalence:
  - 5.7 million people in the US [1]
  - 14 million people in Europe [2]
  - will be doubled by 2020 [2].
- Patients are around 75 year [3] having several co-morbidities
- Prognostics:
  - 40 percent will die within one year [2]
  - 25 ~ 38 percent will survive more than five years [2]



[1] AHA Heart Disease and Stroke Statistics 2009
[2] Shape, study group on heart failure awareness and perception in Europe
[3] ESC Heart Failure Guidelines 2008

Chronic Heart Failure – Management

- **Costs :**
  - **38.4B$ annually in the US**
  - **Half of the cost is due to re-admissions**
    - **20%-30% patients readmitted within 30 days**
    - **56% patients readmitted within a year**



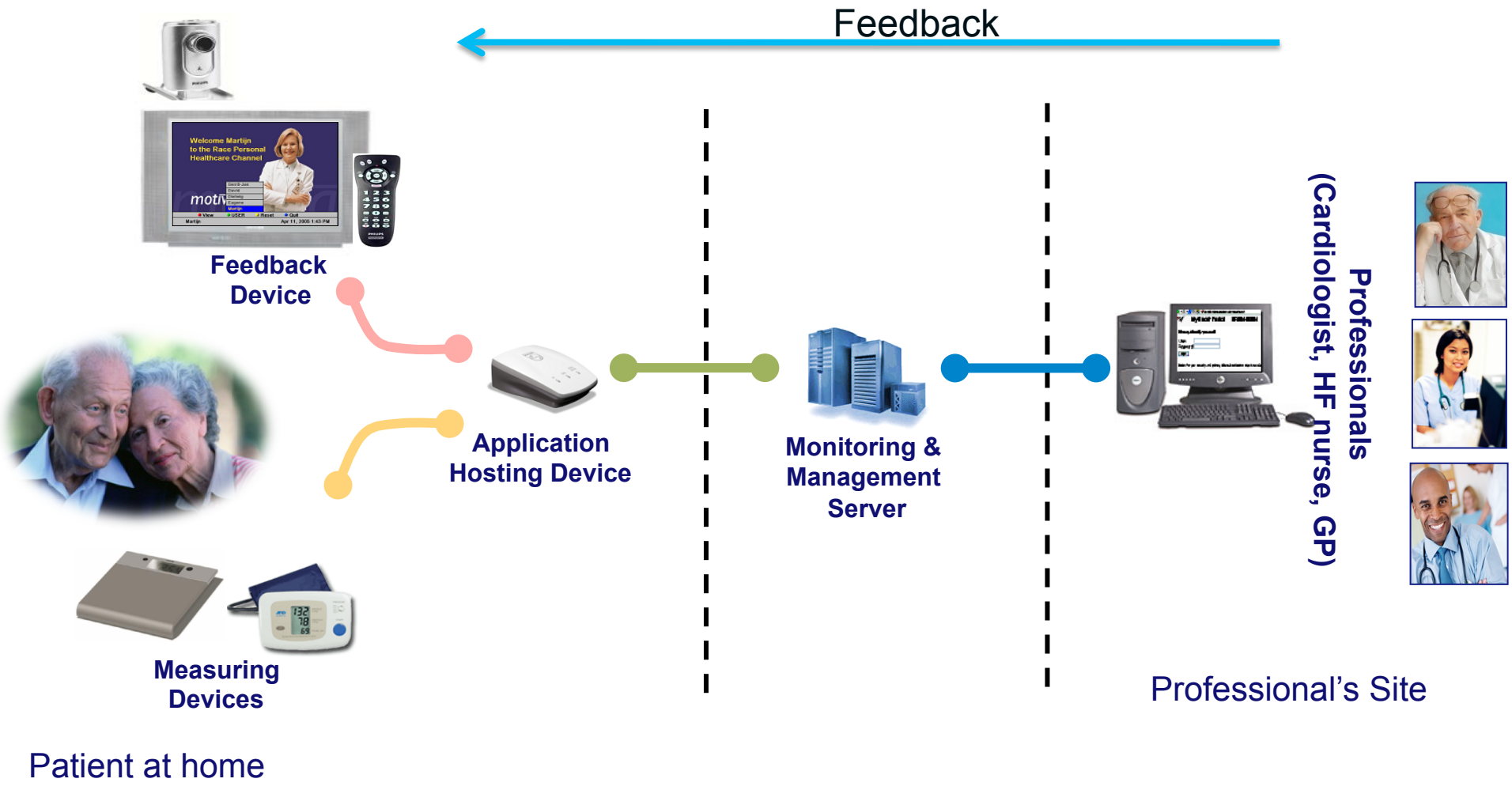
- **Guidelines for Management**
  - **Invasive: devices (implants) and surgery**
  - **Non-Invasive: pharmacological therapy**
  - **Non-pharmacological management**
    - **Nurse led Self Management programs**
    - **Telehealth and guidance**

ESC Heart Failure Guidelines 2008

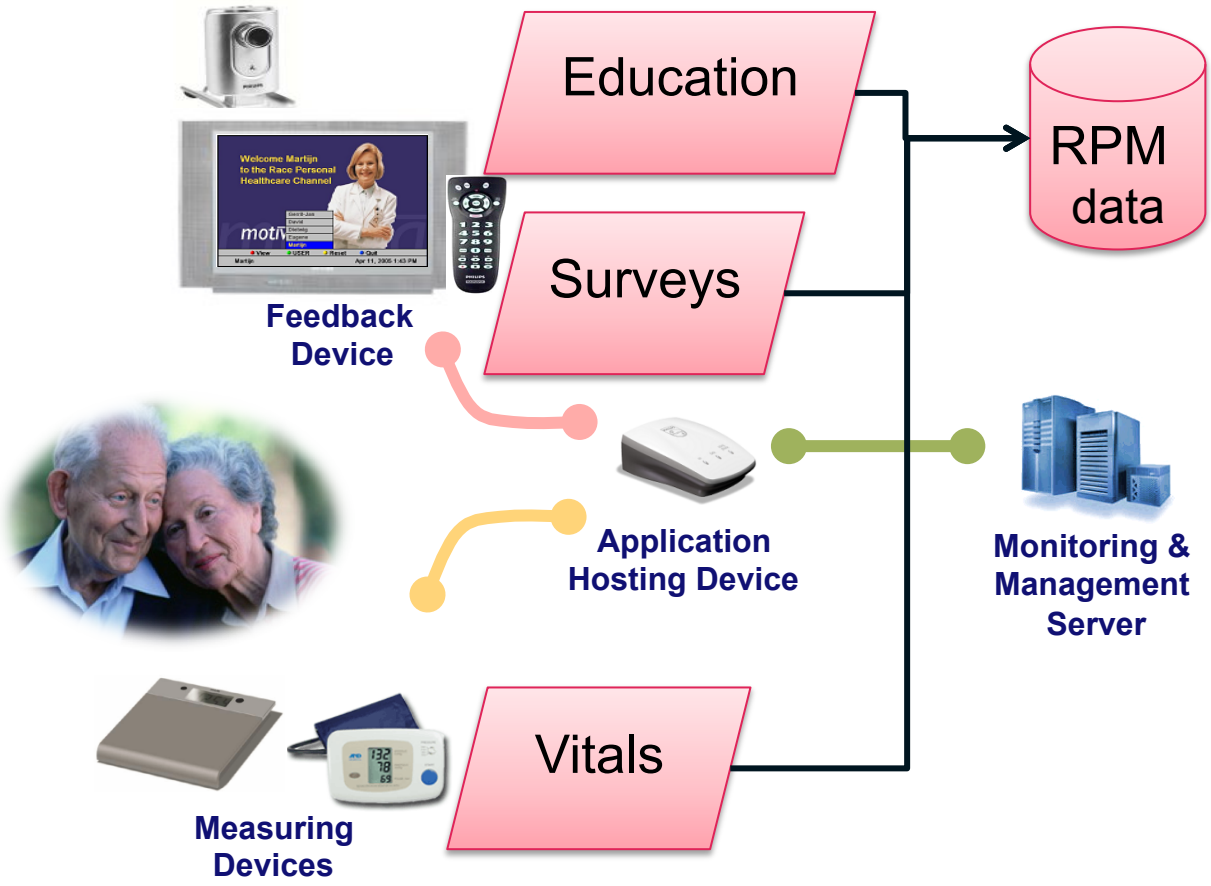
Current limitations

- Telehealth programs are not flexible
- Educational material is too generic
- Alerting power is limited
- Generally, it is not clear what the model of RPM technology acceptance is
- Follow presentation by Seppo Puuronen tomorrow

Telehealth and guidance



Example: Teleheath data



Patient at home

Data sources

- Cardiology information systems (IS)
  - Imaging, labs, medical history, medications, some vitals
  - Longitudinal data (multiple-years)
- Hospital IS and electronic patient records
  - Medical history, labs/biomarkers, other diseases, causes, vitals
  - Longitudinal data (multiple-years)
- Telehealth IS
  - Vitals, symptoms, education, medical history, medications
  - Logs of system usage
  - Operational data, one-two years per patient
- Clinical studies
  - Vitals, symptoms, medications, medical history
  - Average one and a half years per patient

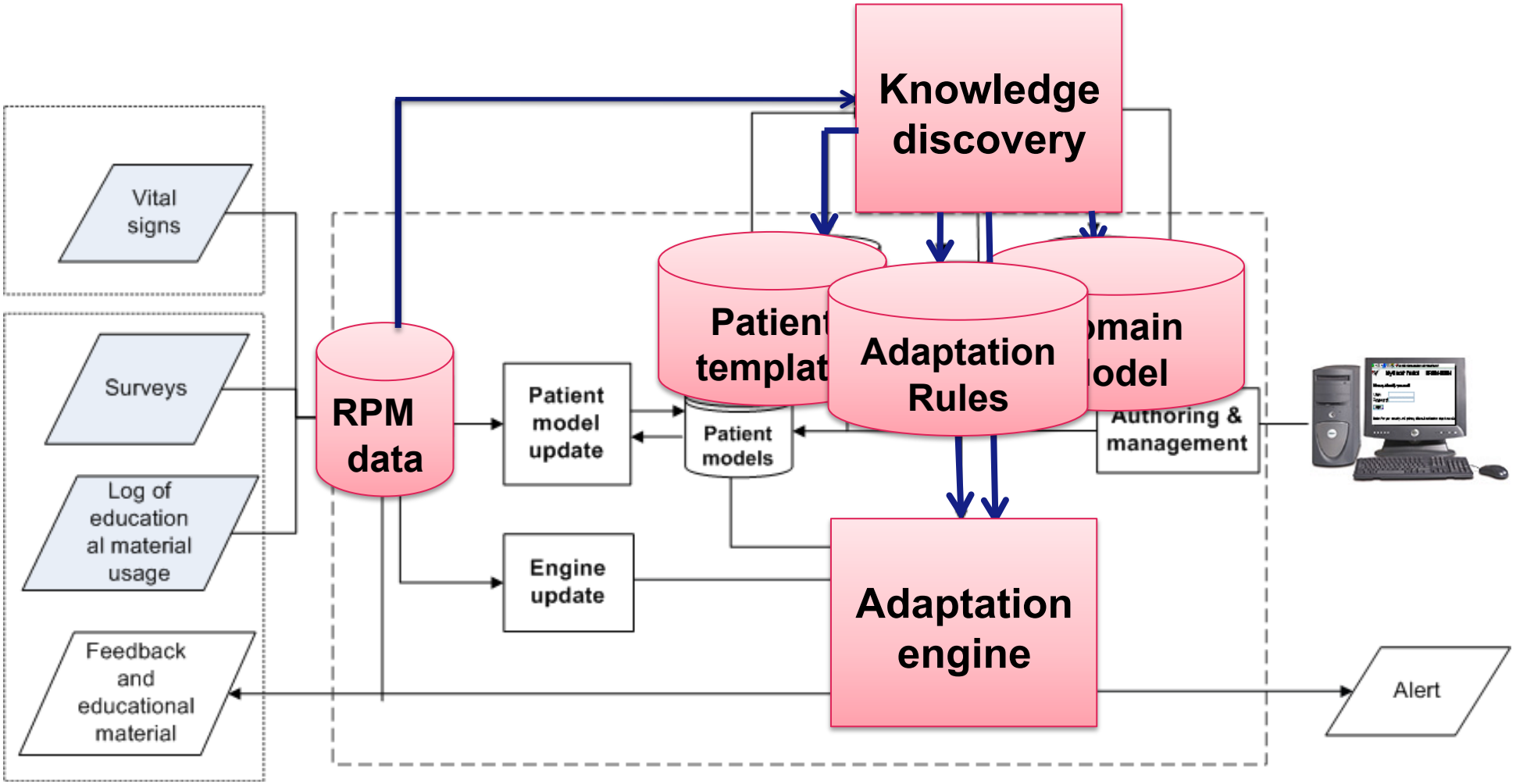
Clinical data – availability and reliability

Data classes		Collected via	(Typical) Frequency
Medical history	**Causes**	Face to face meeting at a medical professional's institution	Once, when diagnosis for chronic condition is made
	Co-mobidities		
	Prior hospitalizations		
	Implanted devices		
Vital signs	**Weight**	-Few months at office -Daily using the system at a patient's home	Daily
	Blood pressure		
	Pulse		
Bio-markers		Face to face meeting at a medical professional's institution	(Few) months
Medications	**Disease related drugs**	•Via a telephone contact by a medical professional •Via face to face meeting during regular checkups	Few weeks to few months
	Non-disease related drugs		

Clinical data – availability and reliability

Data classes		Collected via	(Typical) Frequency
Baseline data	**Vitals**	Face to face meeting at a medical professional's institution; before discharge or use of telehealth	Every few month, during regular follow-up
	Hight		
	Other diagnosis		
	Lab results		
Question-naires	**Symptoms**	Several alternatives: - A system at a patient's home, but also can be collected: - Via a telephone contact by a medical professional - Via face to face meeting during regular checkups at medical professional institution	Varies depending on the protocol of care and can be collected: - Daily (system) - Weekly (system/phone) - Monthly (phone) - Few months (face to face meetings)
	Depression		
	Anxiety		
	Overal health		
	Overal QoL		
	Stress		
	Sleep patterns		
	Fatique		
	Loneliness		

Next generation architecture



Tesanovic et al. CBMS 2009

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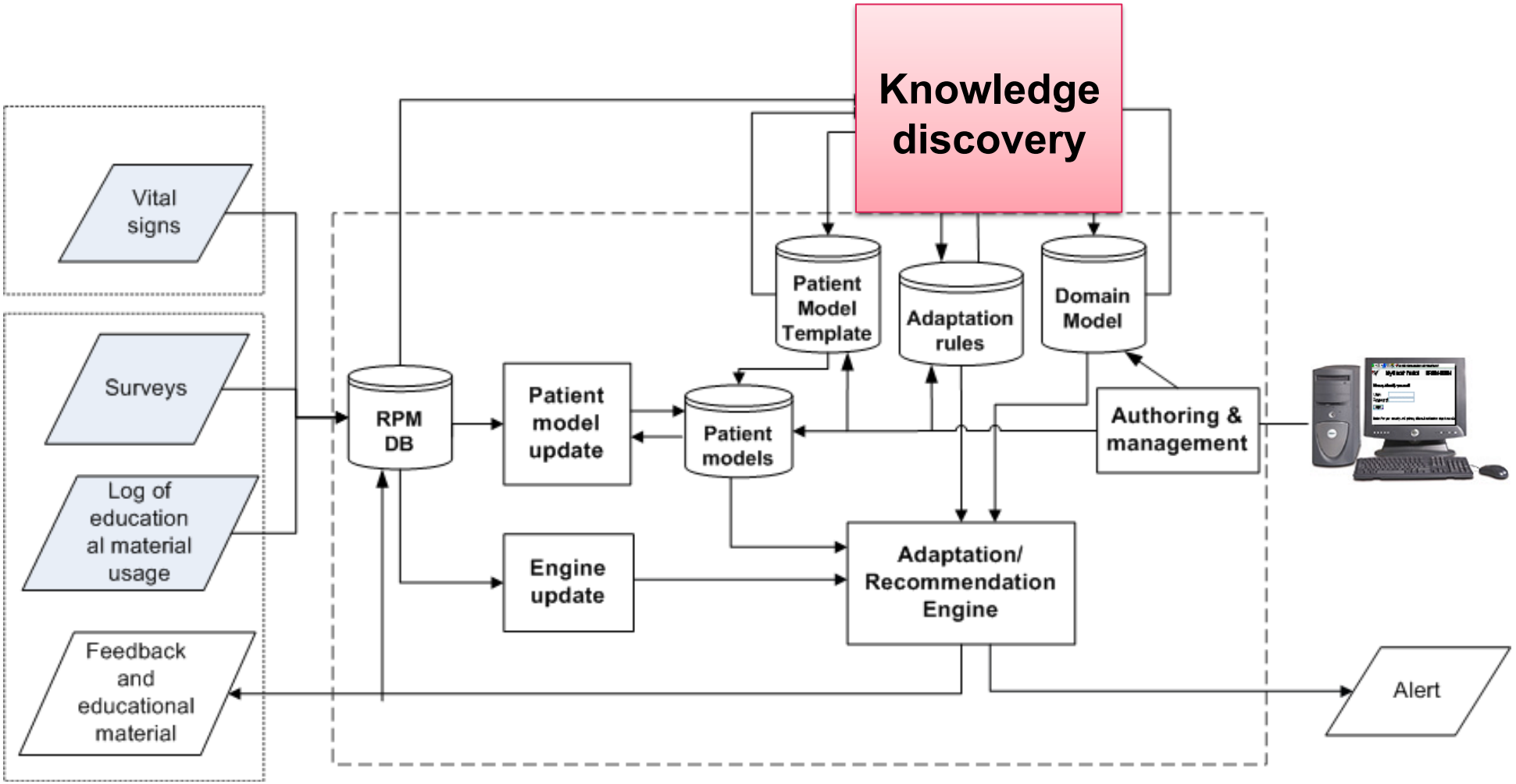
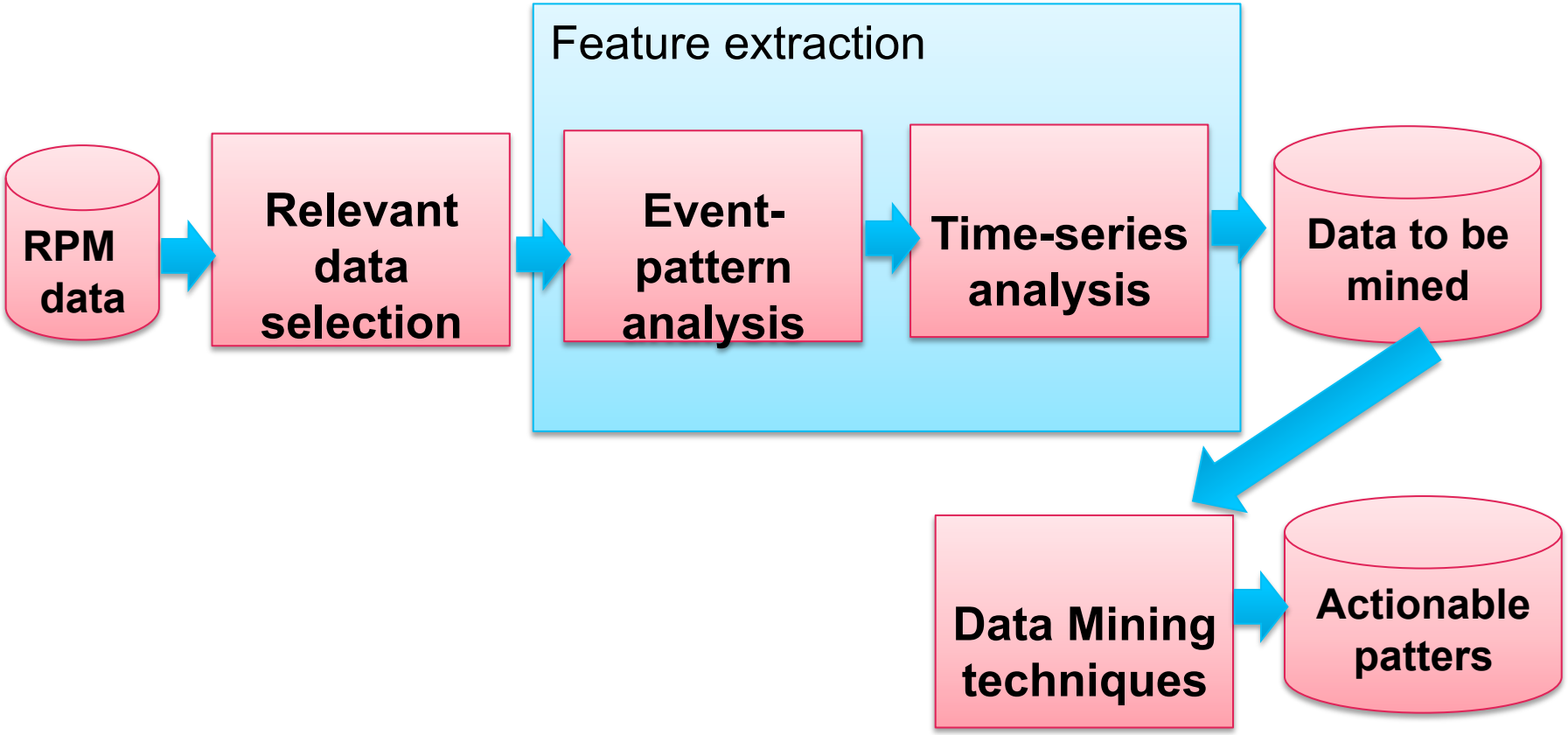
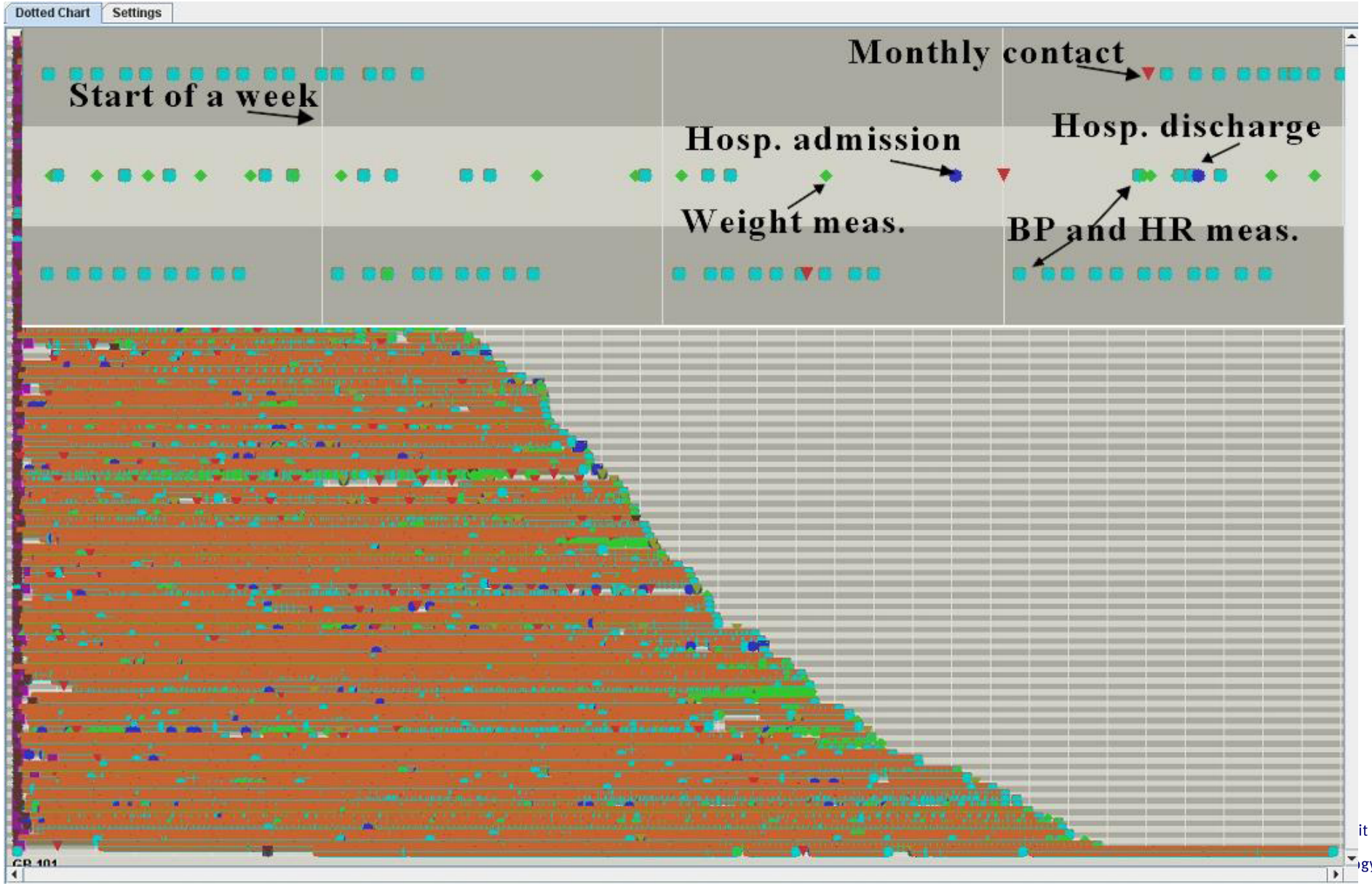
Next generation architecture



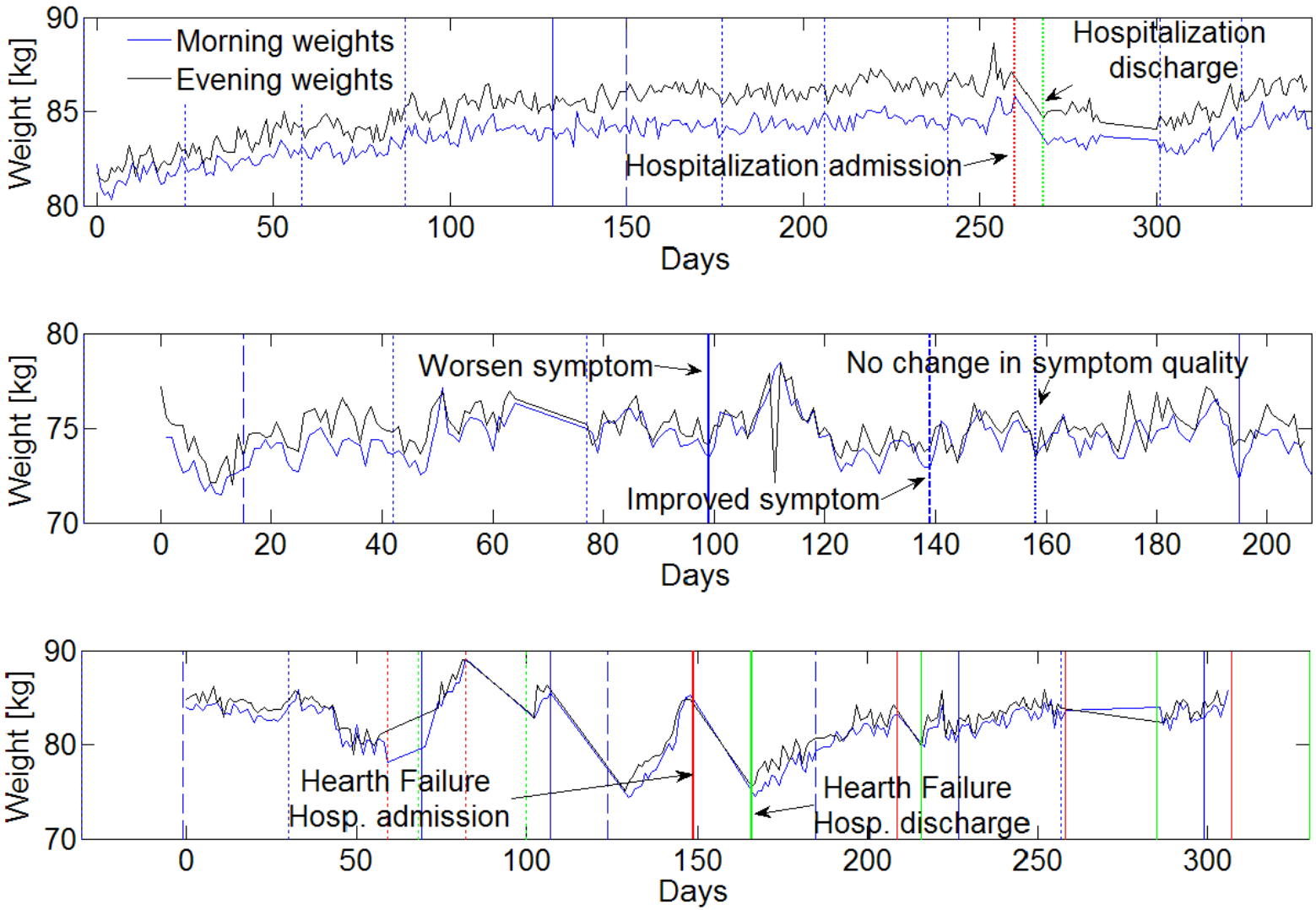
Knowledge discovery process



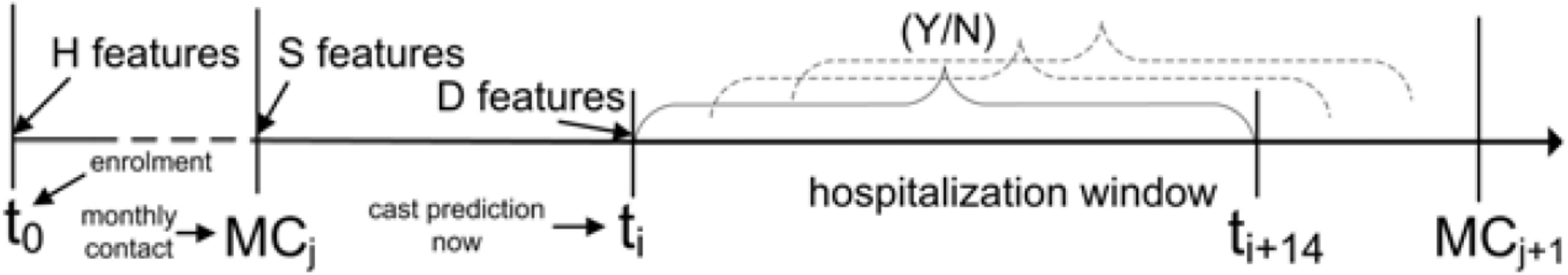
Event analysis



Facilitating feature extraction

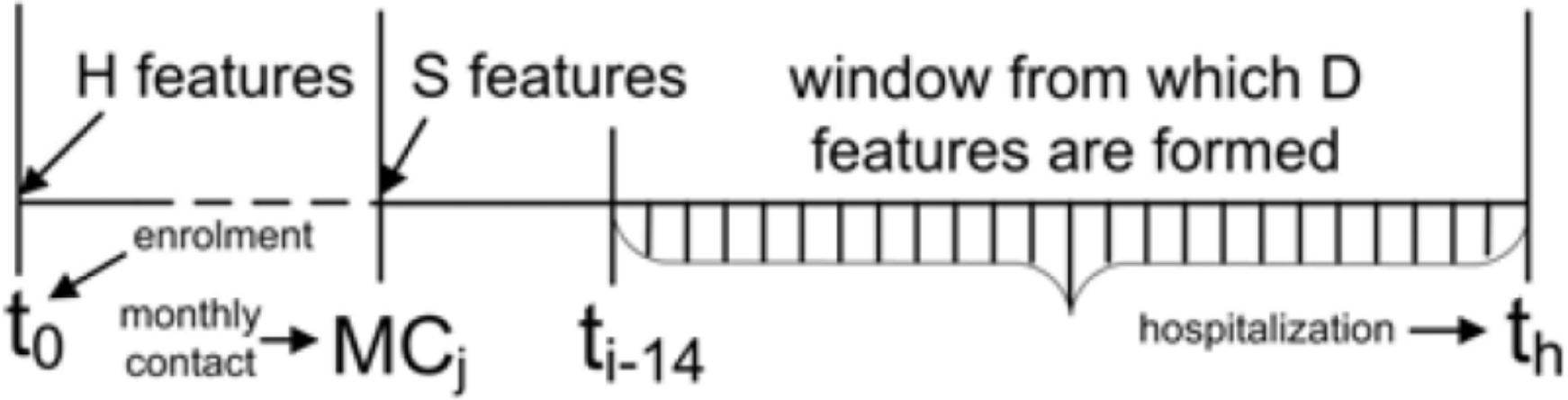


HFH Prediction Problem Formulation



- **Based on the available data about a patient at moment t_i cast a prediction (alert /no alert) whether the hospitalization for this patient is likely within next 14 days period, $(t_i ; t_{i+14}]$**
- **Predictions are casted on the daily basis**

How do we form positive training instances?



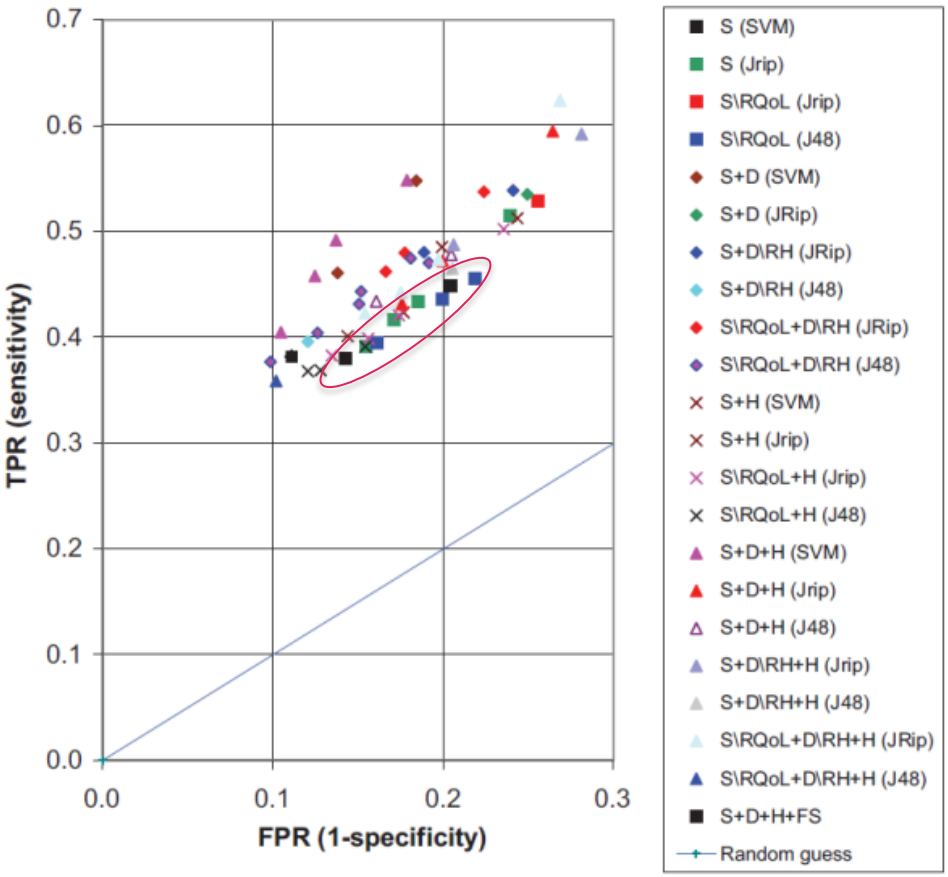
- **For negative examples we choose two MC between which no hospitalization happened and select an arbitrary reference point "no hospitalization"**

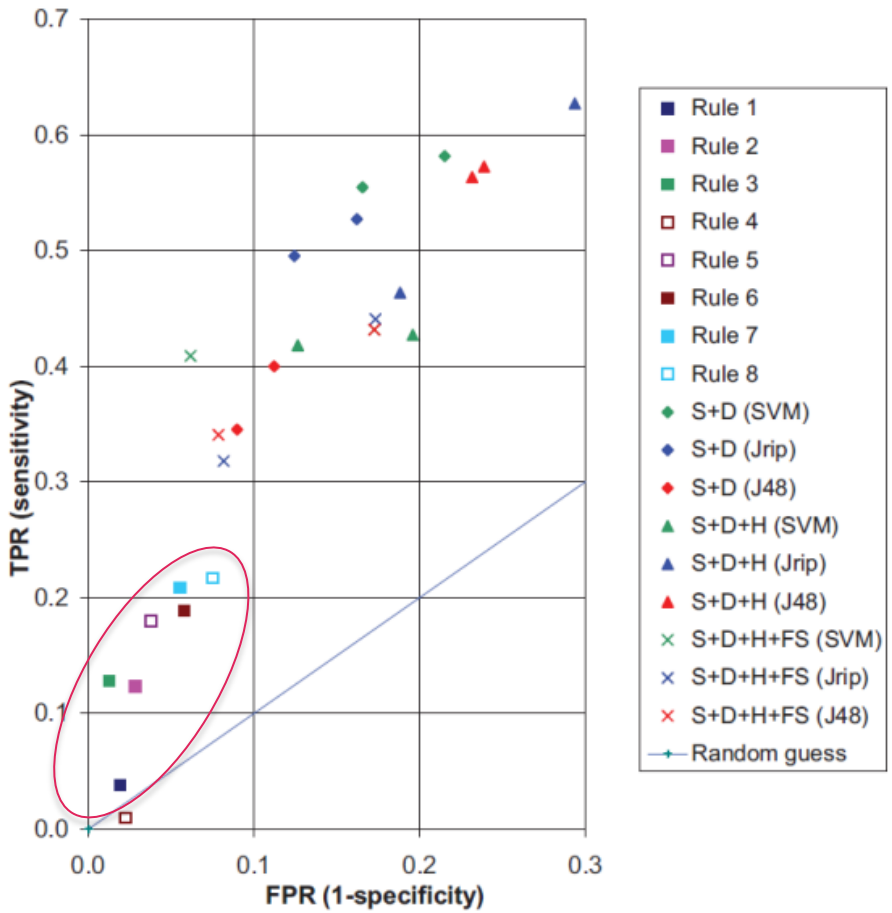
- **Some tricks for dealing with missing data, noise, outliers, etc**

Experiment design: TEN-HMS database

- 426 patients with cardiovascular diseases
- 143 patients of which were HF patients home tele-monitored during
- 2 years, 92 hospitalizations, 43 patients hospitalized at least once due to HF
- SVN, J48, JRip and other popular approaches (WEKA)
- Train/test random split with classifier/parameter/ feature subset selection by CV on the training data
  - Test: 29 patients (9/20)
  - Training: 114 patients (34/80)
- We do not relearn the models every day to keep the setup simple but prequential testing could be used as well

TPR-FPR trade-off





Parameter and algorithm selection on training data

Final estimates with the test set

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Our approach performs consistently better

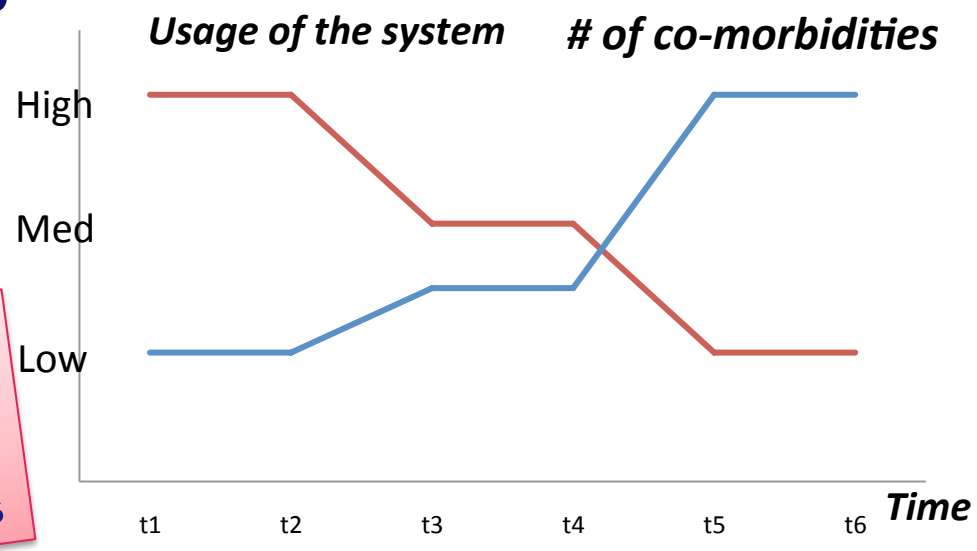
Classification model		TPR	FPR	YIndex	HRate
Rule 1		0.038	0.019	0.019	0.316
Rule 2		0.123	0.028	0.095	0.211
Rule 3		0.128	0.012	0.115	0.211
Rule 4		0.010	0.022	-0.012	0.053
Rule 5		0.180	0.038	0.143	0.263
Rule 6		0.189	0.058	0.131	0.316
Rule 7		0.209	0.055	0.153	0.421
Rule 8		0.217	0.075	0.142	0.474
S+D	max TPR	0.582	0.215	0.367	0.526
(SVM)	min FPR	0.555	0.124	0.371	0.474
S+D	max TPR	0.527	0.162	0.365	0.684
(JRip)	min FPR	0.495	0.124	0.371	0.579
S+D	max TPR	0.400	0.112	0.288	0.526
(J48)	min FPR	0.345	0.090	0.256	0.579
S+D+H	max TPR	0.427	0.196	0.232	0.474
(SVM)	min FPR	0.418	0.126	0.292	0.727
S+D+H	max TPR	0.627	0.293	0.334	0.737
(JRip)	min FPR	0.464	0.188	0.276	0.579
S+D+H	max TPR	0.573	0.239	0.334	0.632
(J48)	min FPR	0.564	0.231	0.332	0.632
S+D+H+FS	max TPR	0.432	0.172	0.259	0.632
(SVM)	min FPR	0.409	0.062	0.348	0.579
S+D+H+FS	max TPR	0.441	0.173	0.268	0.632
(JRip)	min FPR	0.318	0.082	0.237	0.368
S+D+H+FS	max TPR	0.432	0.172	0.259	0.632
(J48)	min FPR	0.341	0.078	0.263	0.474

Conclusions and Further work

- HFH prediction is difficult
- Automated classification works better than any individual trigger suggested by experts
- The challenge is in combing data of different types (with different availability and reliability)
- It is important to model availability and reliability explicitly
- Context-awareness in time and space
- Can we improve the accuracy of models if we take educational (usage) data, and feedback patients receive into account

What if…

- … the patient's condition deteriorates
- … the patient's habits change
- … the seasons changes
- …



Challenges
- discover the hidden context
- adapt rules (second-order adaptation)
- incorporate new knowledge as it appears

Handling changes in the data

- **Expected yet not directly observable**
  - **Number of co-morbidities**
- **Unforeseen**
  - **Changes in hidden contexts**

- **Handling Concept Drift in Medical Applications**
  - **3rd Tutorial on October 14**

  - **Welcome!**

Questions?

- **Thank you!**

References

- **Puuronen et al., CBMS 2010**
  - **Puuronen, S., Pechenizkiy, M., Vasilyeva, E. & Tesanovic, A. (2010) A Holistic Framework for Understanding Acceptance of Remote Patient Management (RPM) Systems by Non-Professional Users, In Proceedings of IEEE Conference on Computer-Based Medical Systems**
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- **Tesanovic et al., CBMS 2009**
  - **Aleksandra Tesanovic, Goran Manev, Mykola Pechenizkiy, Ekaterina Vasilyeva: eHealth personalization in the next generation RPM systems. CBMS 2009: 1-8**

- **preprints available at www.win.tue.nl/~mpechen/publications/**