Predictive and Similarity Analytics for Healthcare

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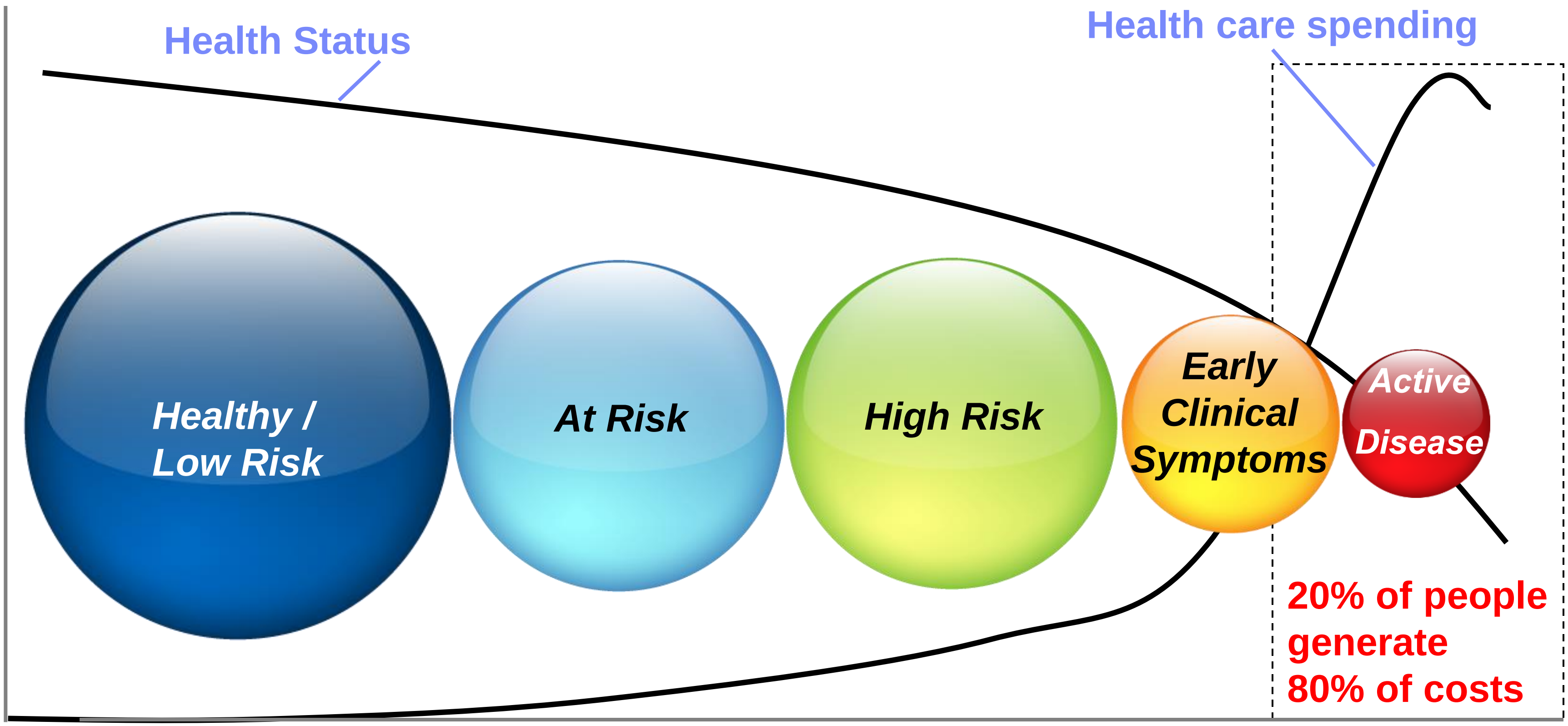
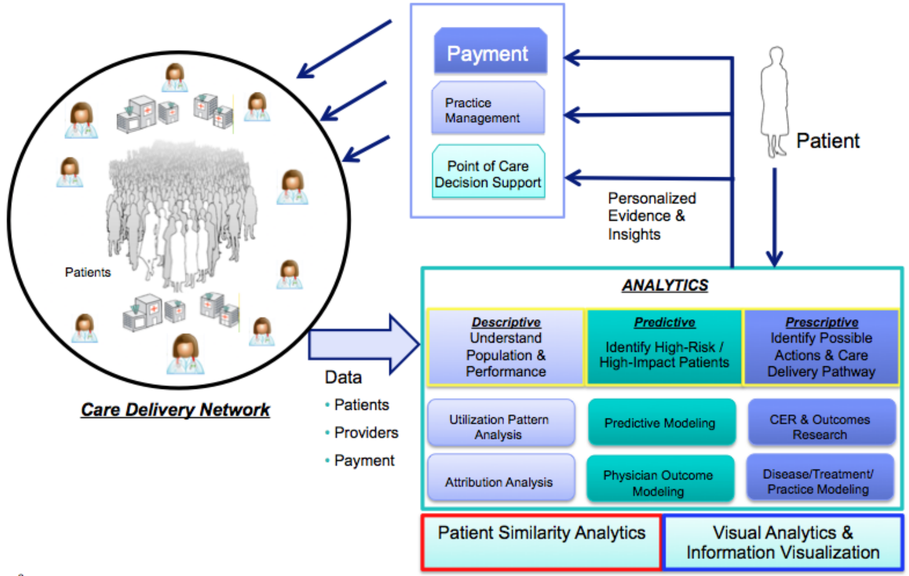
IBM Smarter Care Analytics

Disease Progression & Cost of Care

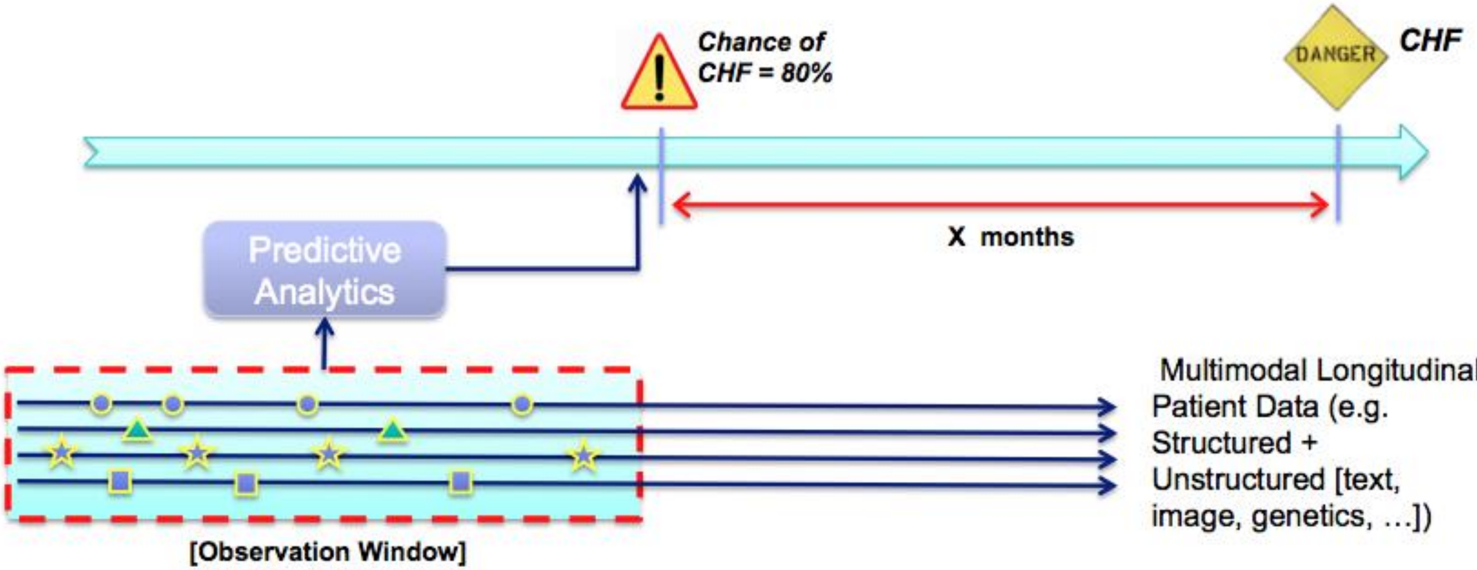




PREDICTIVE MODELING

Problem Definition: Early Detection of Heart Failure (HF)

- Goal:
  - How to build a model for predicting HF onset x months before the HF diagnosis?
- Data: Longitudinal patient records
  - Structured data:
    - Demographics, Outpatient diagnoses, Problem List , Vitals, Medication, Labs
  - Unstructured text : encounter notes



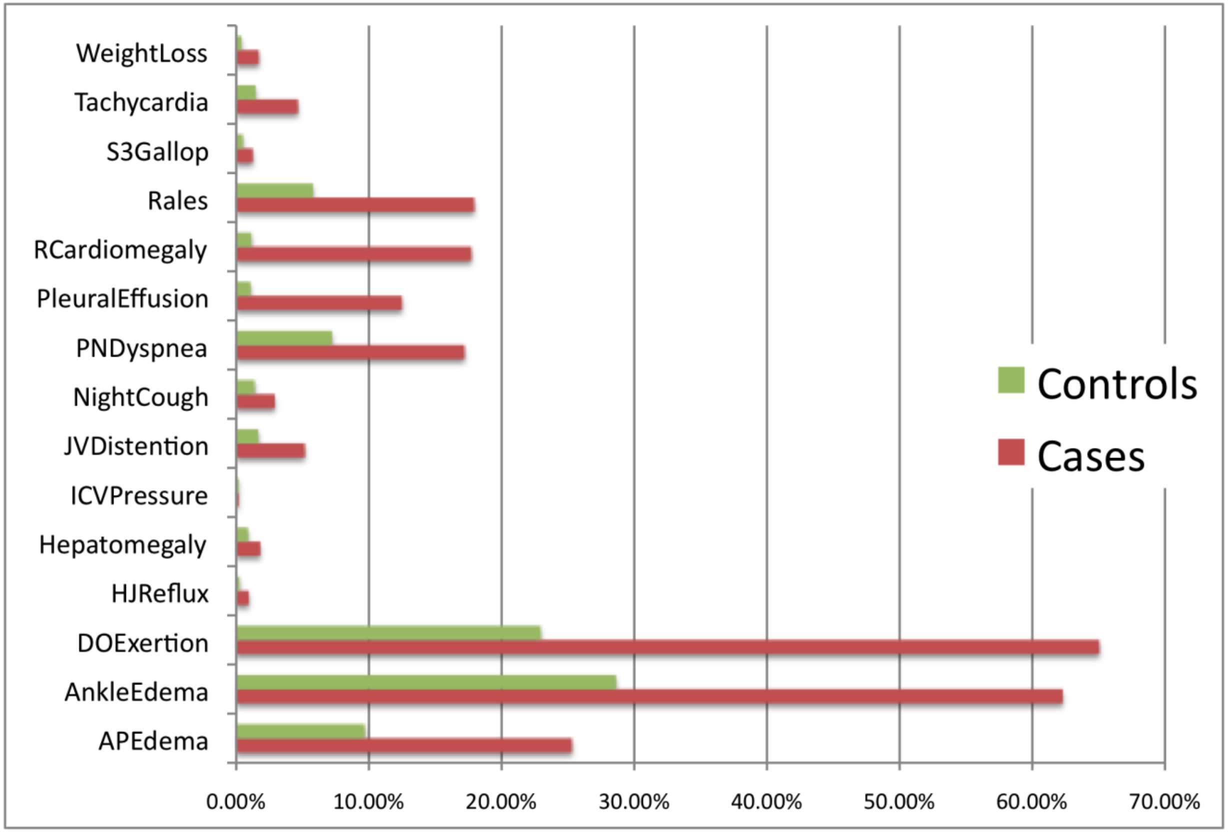
What are the known signs and symptoms of HF?

Framingham Risk Criteria for Heart Failure	
Major Criteria	**Extracted Criteria Code Names**
Paroxysmal nocturnal dyspnea or orthopnea	PNDyspnea (PND)
Neck vein distention	JVDistention (JVD)
Rales	Rales (RALE)
Radiographic cardiomegaly	RCardiomegaly (RC)
Acute pulmonary edema	APEdema (APED)
S3 gallop	S3Gallop (S3G)
Central venous pressure > 16 cm of H_2O	ICVPressure (ICV)
Circulation time of 25 seconds	*(not extracted)*
Hepatojugular reflux	HJReflux (HJR)
Weight loss of 4.5 kg in 5 days, in response to Rx	WeightLoss (WTL)
Minor Criteria	
Bilateral ankle edema	AnkleEdema (ANKED)
Nocturnal cough	NightCough (NC)
Dyspnea on ordinary exertion	DOExertion (DOE)
Hepatomegaly	Hepatomegaly (HEP)
Pleural effusion	PleuralEffusion (PLE)
A decrease in vital capacity by 1/3 of max	*(not extracted)*
Tachycardia (rate of ≥ 120/min)	Tachycardia (TACH)

- Framingham criteria for HF* are common signs and symptoms that are documented even at primary care visits

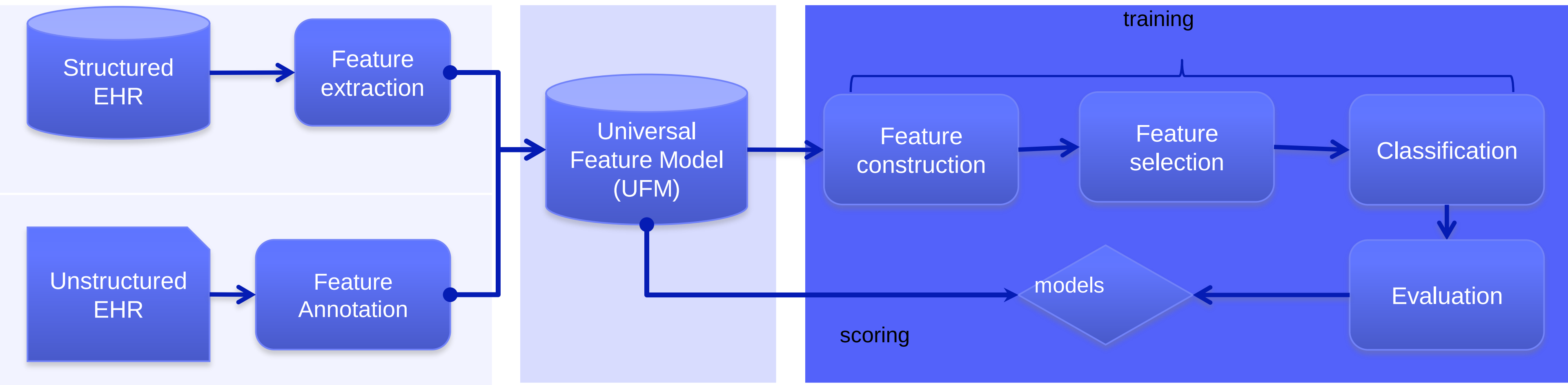
* McKee PA, Castelli WP, McNamara PM, Kannel WB. The natural history of congestive heart failure: the Framingham study. N Engl J Med. 1971;**285**(26):1441-6.

How predictive are Framingham criteria?

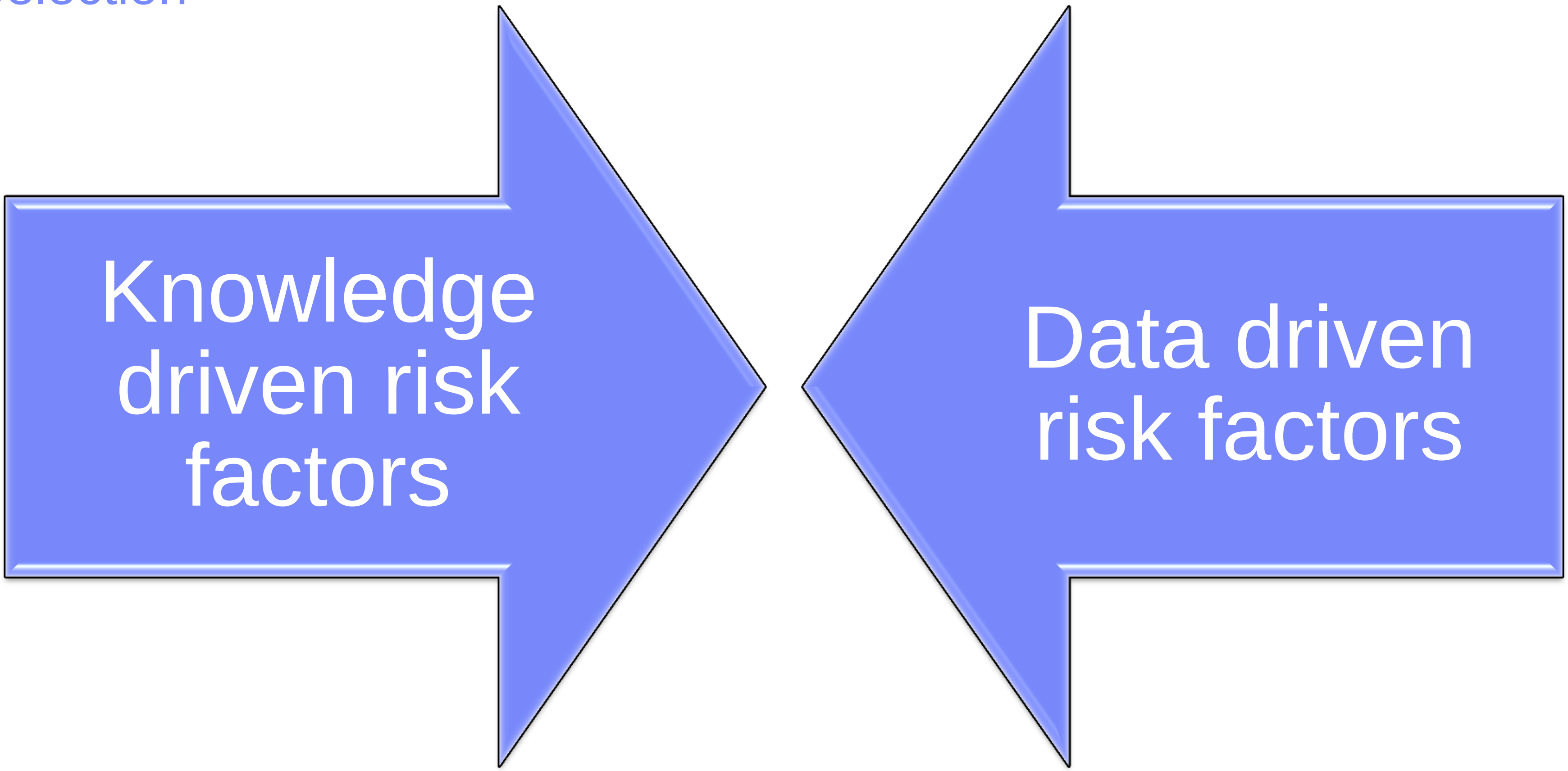


- The prevalence of Framingham criteria varied widely between cases (<1% - 65%) and controls (<1% - 28%)
- The most common Framingham criteria of HF were ankle edema and DOE, but these were also the most common findings in controls, albeit with ~half the prevalence.

Predictive Modeling Pipeline



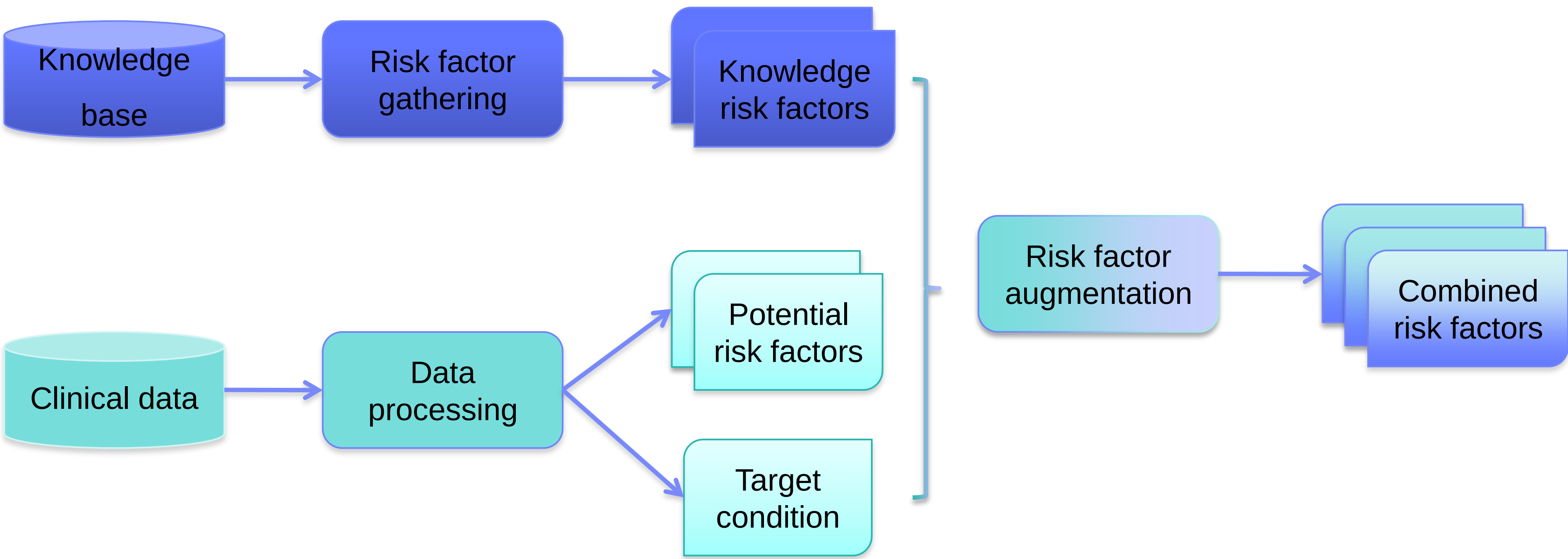
Combining Knowledge and Data Driven Insights for Feature Selection[1,2]



[1] Dijun Luo, Fie Wang, Jimeng Sun, Marianthi Markatou, Jianying Hu,Shahram Ebadollahi, SOR: ScalableOrthogonal Regression for Low-Redundancy Feature Selection and its Healthcare Applications. SDM'12

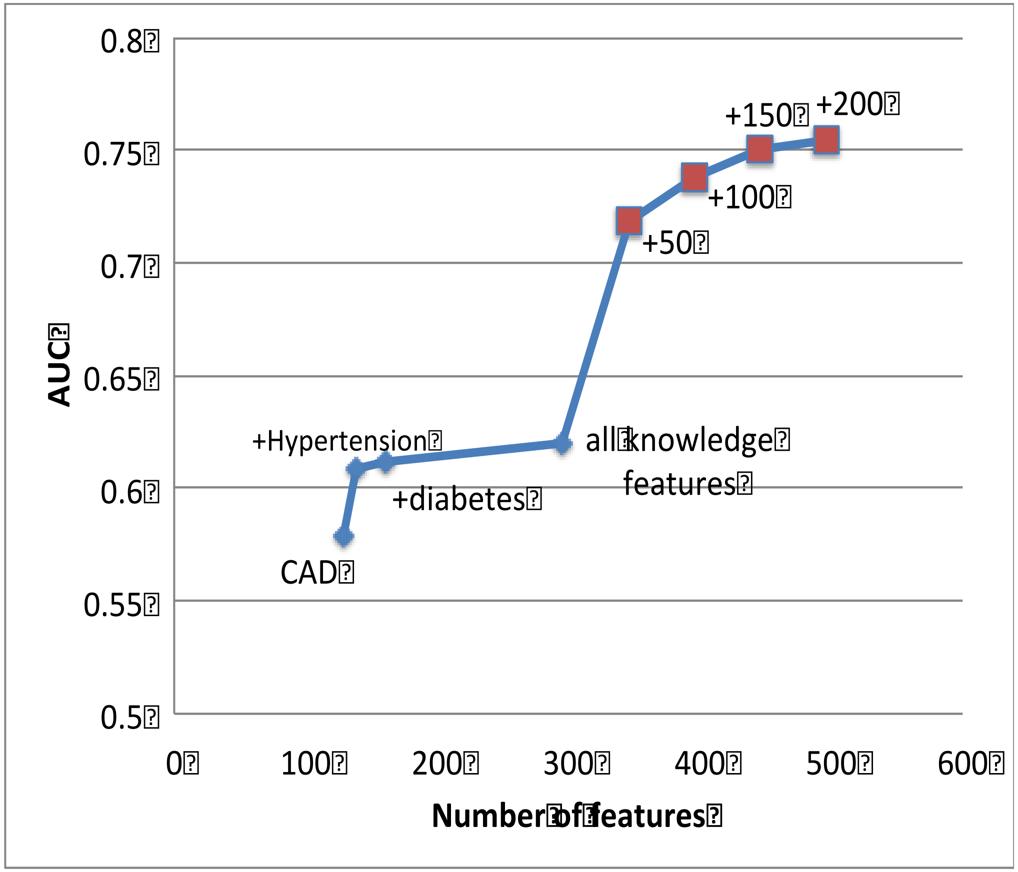
[2] Jimeng Sun, Jianying Hu, Dijun Luo, Marianthi Markatou, Fei Wang, Shahram Edabollahi, Steven E. Steinhubl, Zahra Daar, Walter F. Stewart. Combining Knowledge and Data Driven Insights for Identifying Risk Factors using Electronic Health Records. AMIA'12 (to appear)

Method for combining knowledge- and data- driven risk factors[1]



[1] Jimeng Sun, Jianying Hu, Dijun Luo, Marianthi Markatou, Fei Wang, Shahram Edabollahi, Steven E. Steinhubl, Zahra Daar, Walter F. Stewart. Combining Knowledge and Data Driven Insights for Identifying Risk Factors using Electronic Health Records. AMIA'12 (to appear)

Prediction Results of Knowledge-driven Features plus Data-driven Features



- AUC significantly improves as complementary data driven risk factors are added into existing knowledge based risk factors.
- A significant AUC increase occurs when we add first 50 data driven features

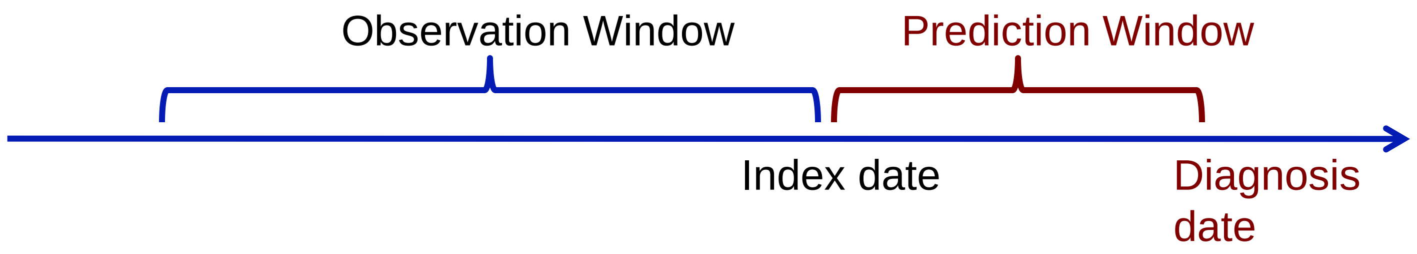
Clinical Validation of Data-driven Feature Enhancement

Table 1: Top 10 data driven features among Cases and Controls

Feature type	Feature name	Relevancy to HF
Diagnosis	DYSLIPIDEMIA	Yes
Medication	Thiazides and Thiazide-Like Diuretics	Yes
Medication	Antihypertensive Combinations	Yes
Medication	Aminopenicillins	Yes
Medication	Bone Density Regulators	Possible side effect, or maybe a surrogate for elderly women
Medication	NATRIURETIC PEPTIDE	Yes
Symptoms	Denial Rales	Yes
Medication	Diuretic Combinations	Yes
Symptoms	Denial S3Gallop	Yes
Medication	Nonsteroidal Anti-inflammatory Agents (NSAIDs)	Yes, contribute to fluid retention due to renal effects

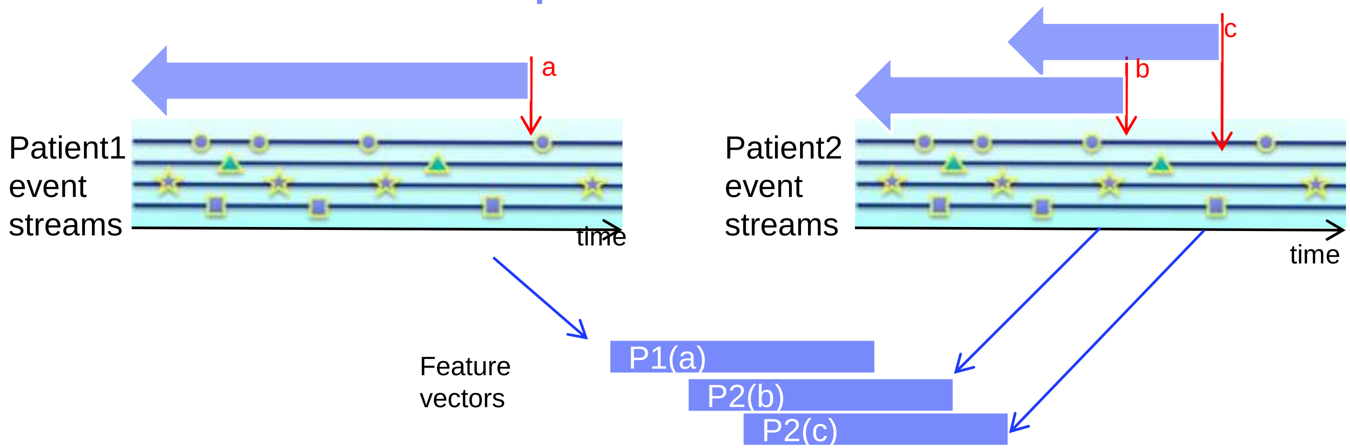
- 9 out of 10 are considered relevant to HF, and one possibly relevant, which confirm the interpretability of the proposed method for expanding knowledge driven risk factors.
- The additional features are mostly from medications and symptoms which are complementary to the existing diagnosis (knowledge-driven) features

Evaluation Design for Predictive Modeling



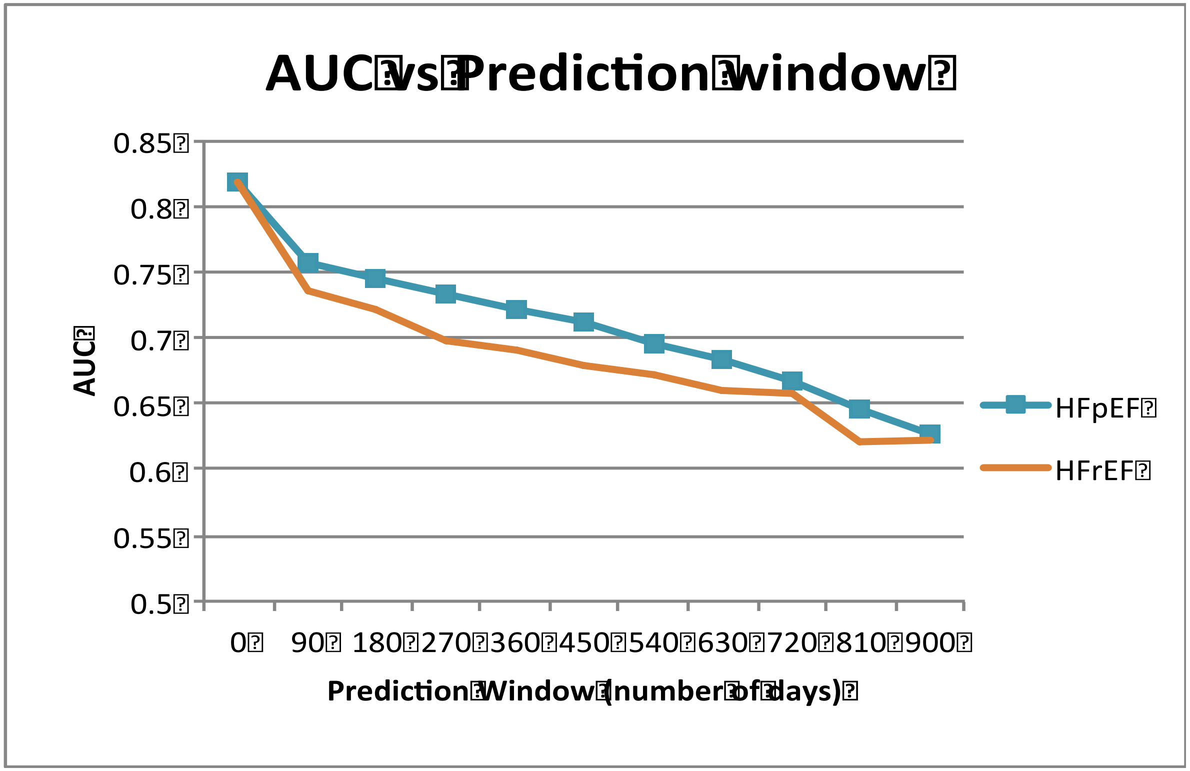
- Diagnosis date: the day that patient x has been diagnosed with HF
- Index date: the day that we want to predict the risk of HF for a given patient x
- Prediction window: the time interval between diagnosis date and index date
- Observation window: a fixed time interval prior to index date
- Metric: Area under the ROC curve (AUC)

Feature-based Patient Representation



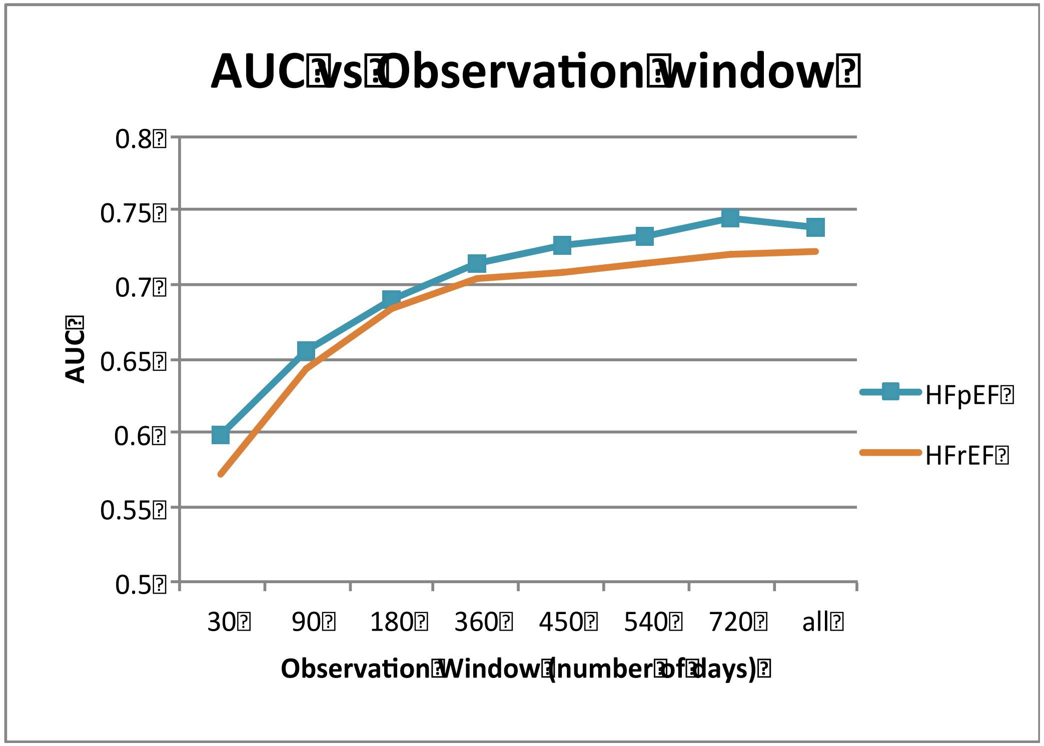
- Patients are modeled as longitudinal streams
- At any time T (indicated by red arrows) for a patient P, we can construct a feature vector to represent the characteristics of P at T.
- Remarks
  - Absolute time is patient specific. It is not meaningful to compare across patients based on the absolute time.
    - E.g. It does not make sense to compare two patients on their condition at 1/1/2011 in general.
  - Relative time is meaningful across patients.
    - E.g. We can compare patients with respect to multiple sequential events, such as a certain medication followed by certain lab results within a month.
  - Feature vectors are global. i.e., we can compare and build models on the feature vectors across patients.

Area under the ROC curve (AUC) measure on different prediction windows

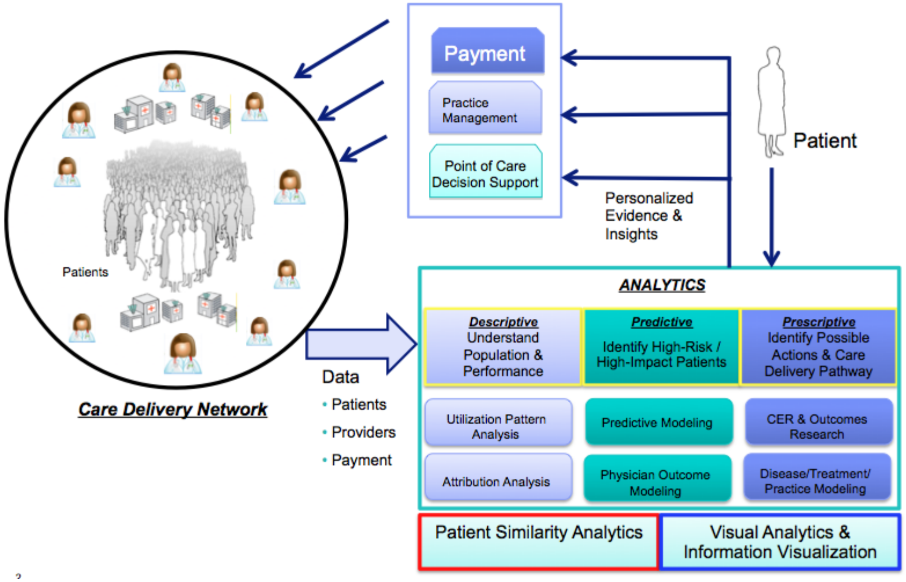


- Setting: observation window=12months, classifiers={random forest, logistic regression}, evaluation mechanism = 10-fold cross-validation
- Observation:
  - AUC slowly decreases as the prediction window increases

AUC measure on different observation windows



- Setting: prediction window= 180 days, classifiers= {random forest, logistic regression}, evaluation mechanism =10-fold cross-validation
- Observation:
  - AUC increases as the observation window increases. i.e., more data for a longer period of time will lead to better performance of the predictive model
  - Combined features performed the best at .85 AUC for observation window= 24 months



PATIENT SIMILARITY

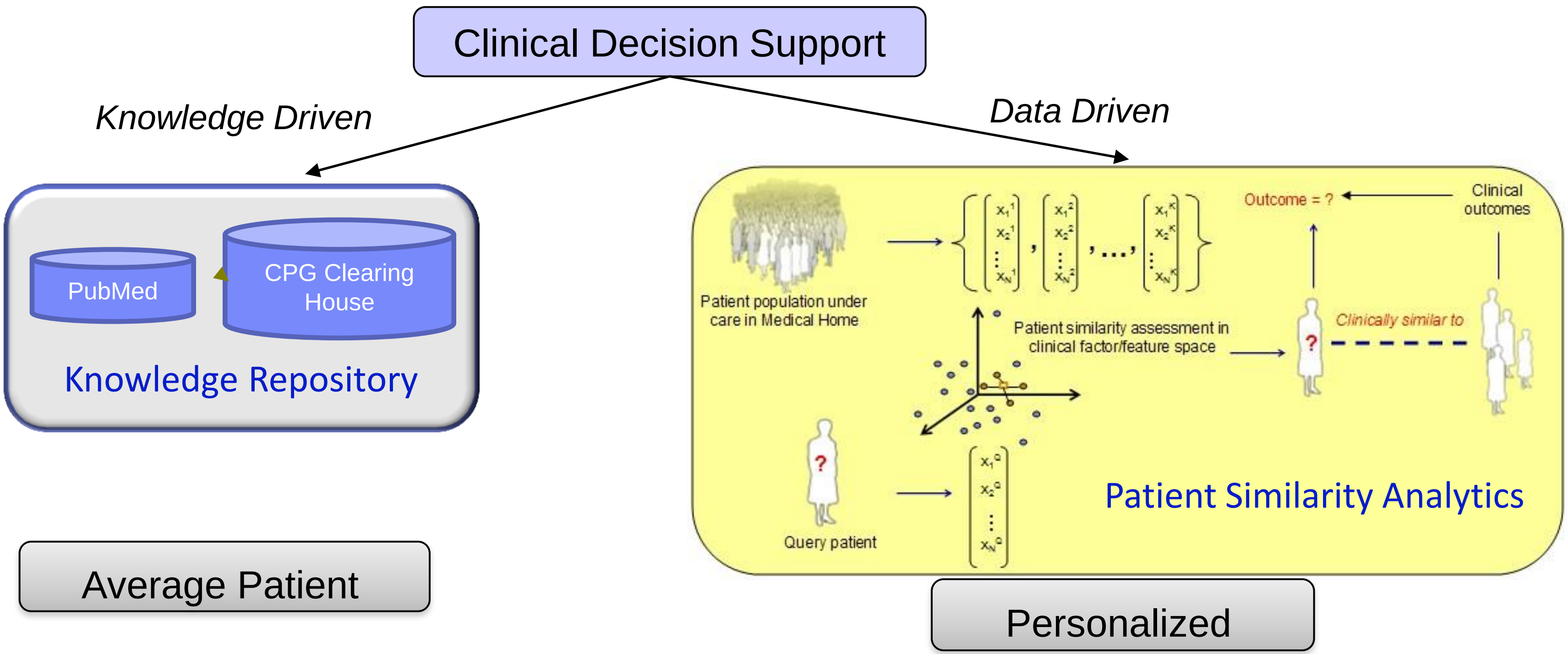
Patient Similarity Analytics

Objective

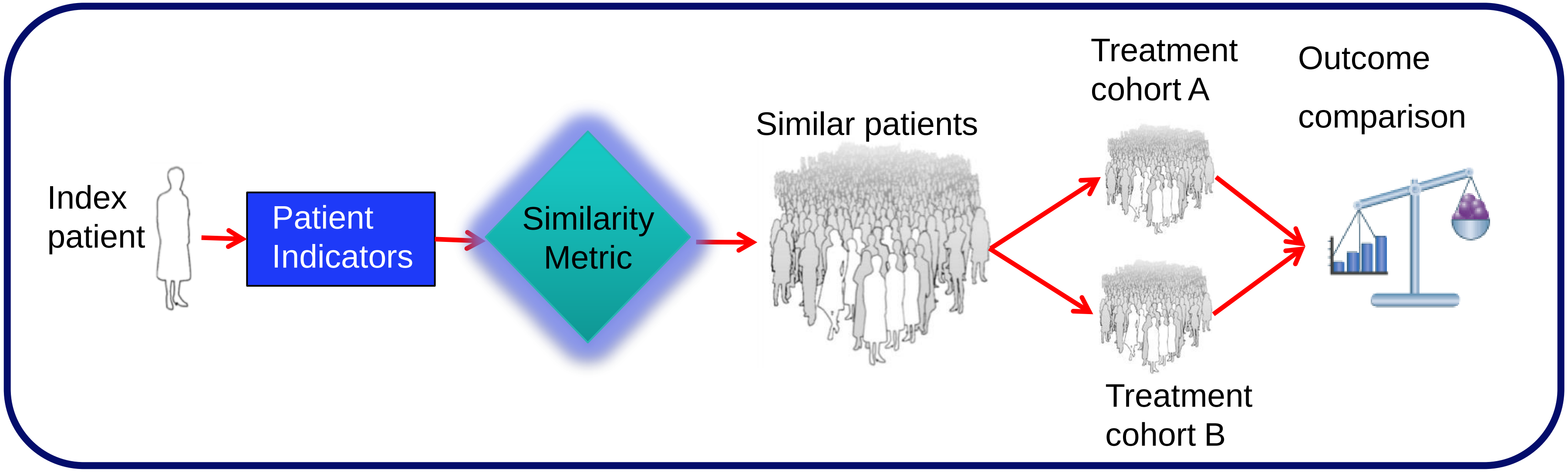
Given an index patient, find clinically similar patients for decision support and Comparative Effectiveness

Highlights

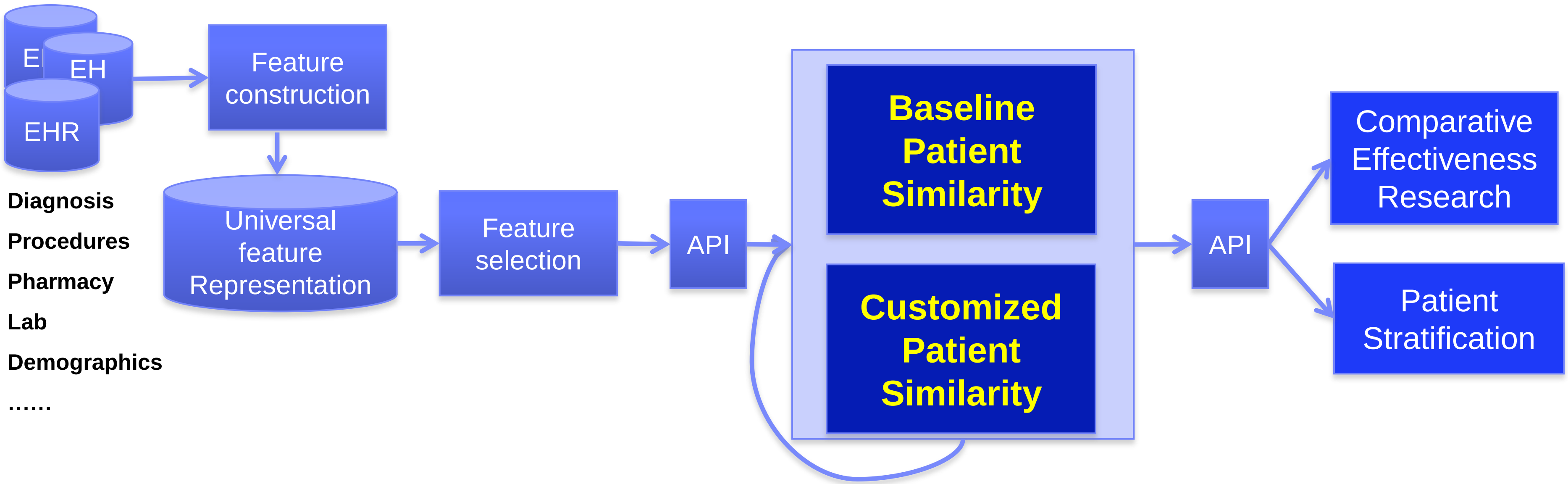
- Analytics pipeline for similarity that allows flexible combination of information from heterogeneous data sources
- Data driven customization to fine tune similarity metric to specific investigation



Patient Similarity for Treatment Comparison



Analytics Pipeline for Patient Similarity



Baseline Similarity

Factors combined using expert defined weights

Customized Similarity

Learned context and end point specific distance metric tailored to a specific purpose (outcome, diagnosis, utilization etc.)

Customized Patient Similarity

- **Localized Supervised Metric Learning**
- **Composite Distance Integration**
- **Interactive Metric Learning**

Published at: AMIA'10, ICPR'10, ICDM'10, SDM'11a, SDM'11b

Physician Outcome Model

Objective
Predict the likely outcome of a (patient, physician) pair based on population data and past outcomes

Highlights
- Patient and physician characterization using records of past practices and outcomes
- Prediction by analyzing how index patient relates to past success and failure cases of particular physician
- Provides individualized insight vs. population level averages

Physician Assessment and Selection

Population Based

Individual Outcome Based

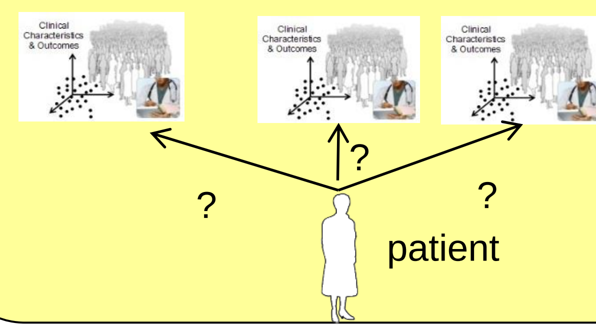
Comprehensive Diabetes Care (CDC)

- Born HEDIS 1999
- Percentage of members 18-75 with diabetes (type 1 and 2) who had:
  - Hemoglobin A1c (HbA1c) testing
  - HbA1c poorly controlled (greater than 9%)
  - Retinal eye exam
  - LDL-C screening performed
  - LDL-C controlled (below 130 mg/dL)
  - LDL-C controlled (below 100 mg/dL)
  - Kidney disease (nephropathy) monitored

Assessment at Population Level

Physician Outcome Model

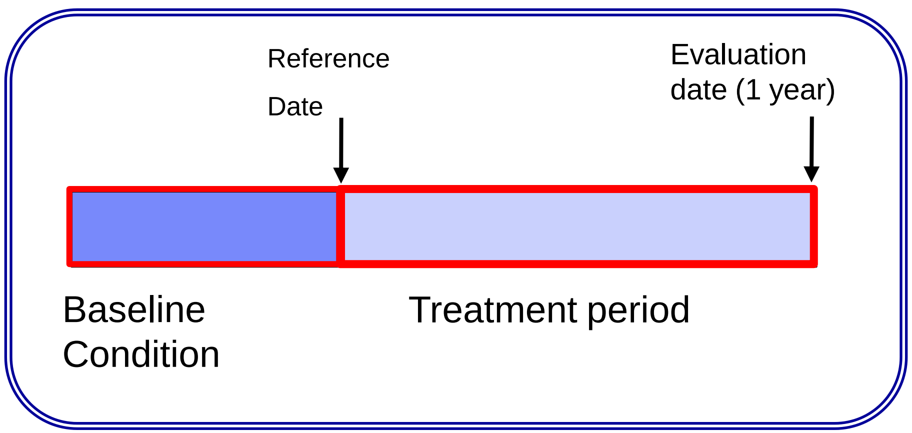
Predict likely outcome based on patient characteristic, provider characteristics and care history



Personalized Matching

Problem Formulation

- Data
  - Diabetic patient's longitudinal data and their PCPs
  - Segmented by patient into baseline condition assessment period and treatment evaluation period
  - Used to train and validate models



- Reference date: one day after the first abnormal HbA1C lab test

HbA1C:

Normal	Well Controlled	Moderately Controlled	Poorly Controlled

6.4 7 9

- Samples
  - Patients having at least one abnormal HbA1C test result (baseline)
- Outcomes
  - HbA1C range change between reference and evaluation date (1 year ± 2 months)

↓ **Positive outcome**:

- range change closer to normal, or remain in "well controlled" range

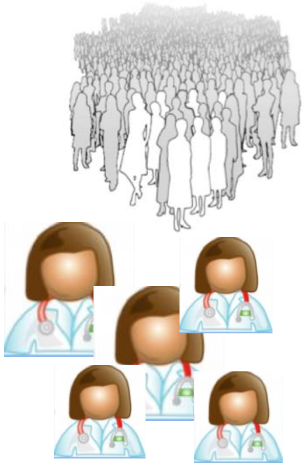
↑ **Negative outcome**:

- range change further away from normal, or remain in moderately or sub-optimally controlled

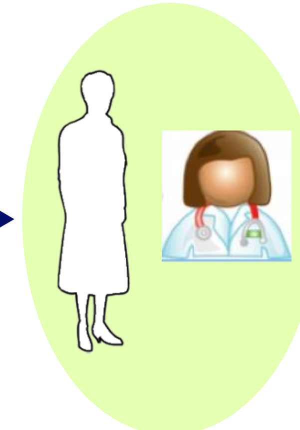
Outcome Prediction Process

Total: 195, positive: 81, negative: 114; 80 physicians

Physician related features improves prediction for challenging patients



Identifying Challenging Patients → Differentiating Physicians →

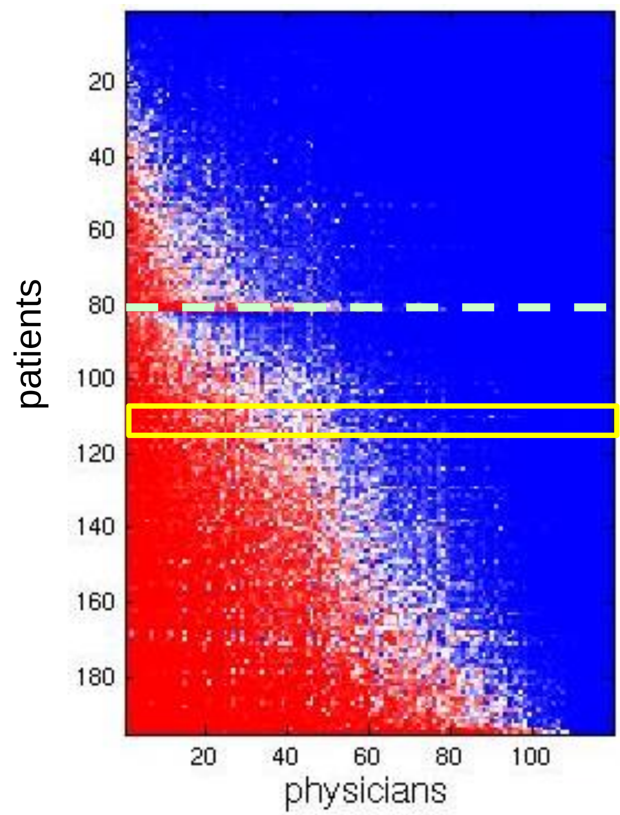


Well managed

Patients (Positive)

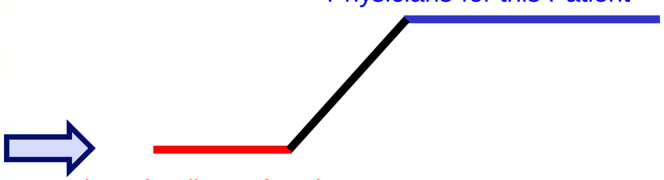
Poorly managed

Patients (Negative)



Optimally Performing

Physicians for this Patient



Sub-optimally Performing

Physicians for this Patient

Experiments confirmed that choice of physician has statistically significant impact on challenging patients' likely outcome

Utilization Pattern Analysis through Patient Segmentation

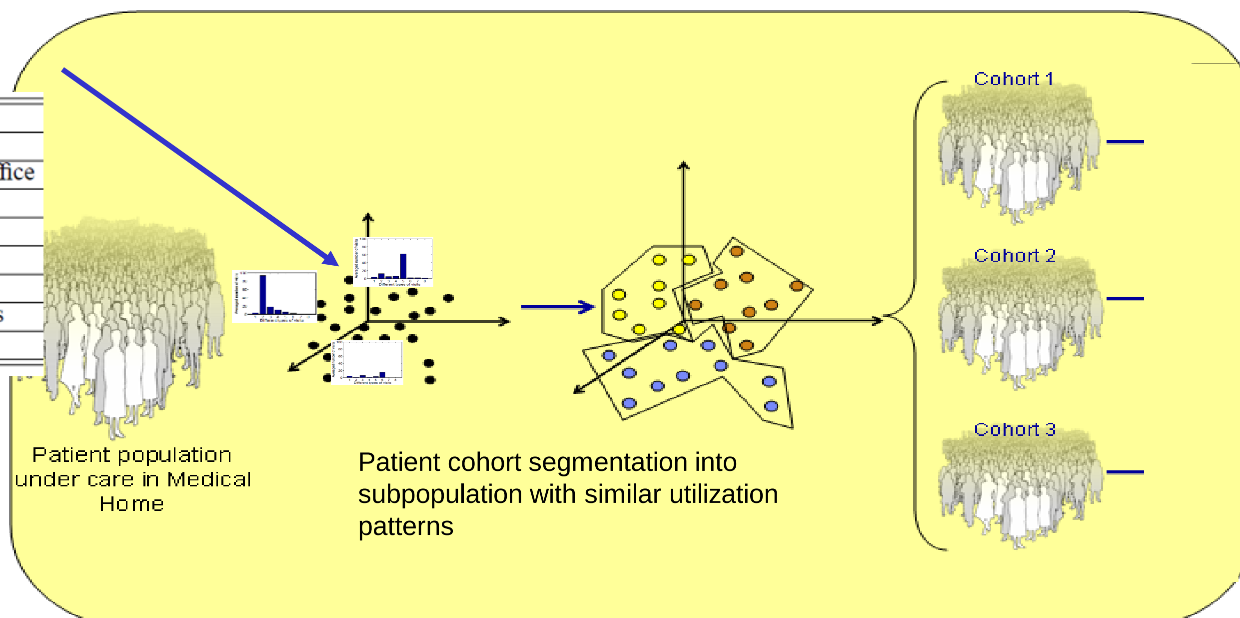
IBM

Objectives
Continuously assess salient utilization patterns within patient population and how they relate to clinical characteristics; Identify patients with abnormal utilization

Highlights
- Identification of dominant utilization groups through patient segmentation
- Specialized predictive modeling methodology linking clinical characteristics to expected utilization
- Identification of unexpected cases via comparison between expected and actual utilization groups for each patient

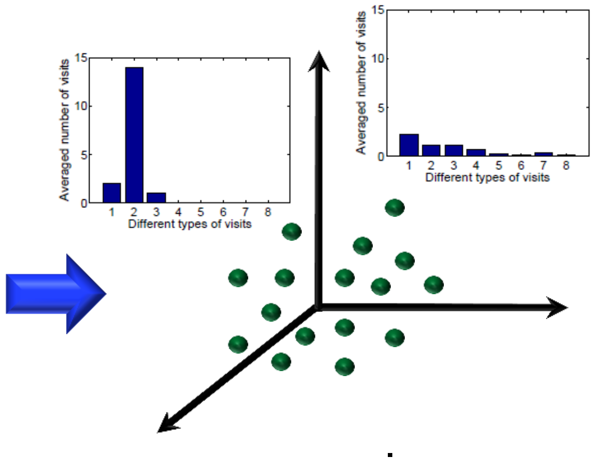
Utilization Profiles

Visit Type	Description
1	PCP visit in Doctor's office
2	Other (Specialist) visits in doctor's office
3	Independent lab visits
4	Outpatient hospital visits
5	Inpatient hospital visits
6	Patient's home
7	Emergency room & Urgent care visits
8	Other visits

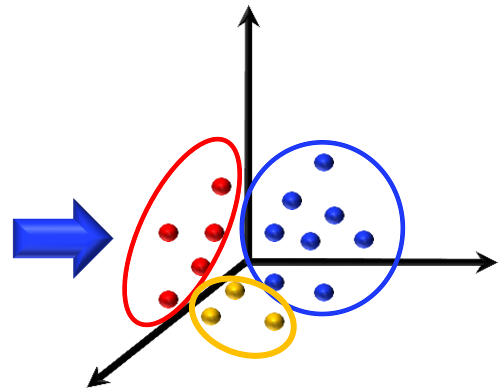


Utilization Pattern Analysis

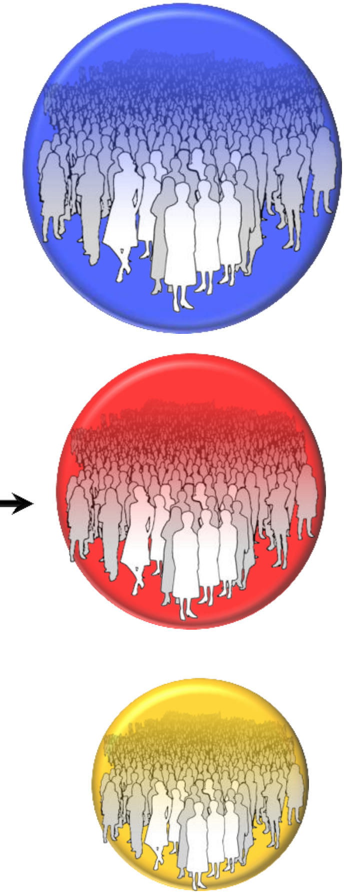
Patient population under care in medical home



Patient utilization profiling

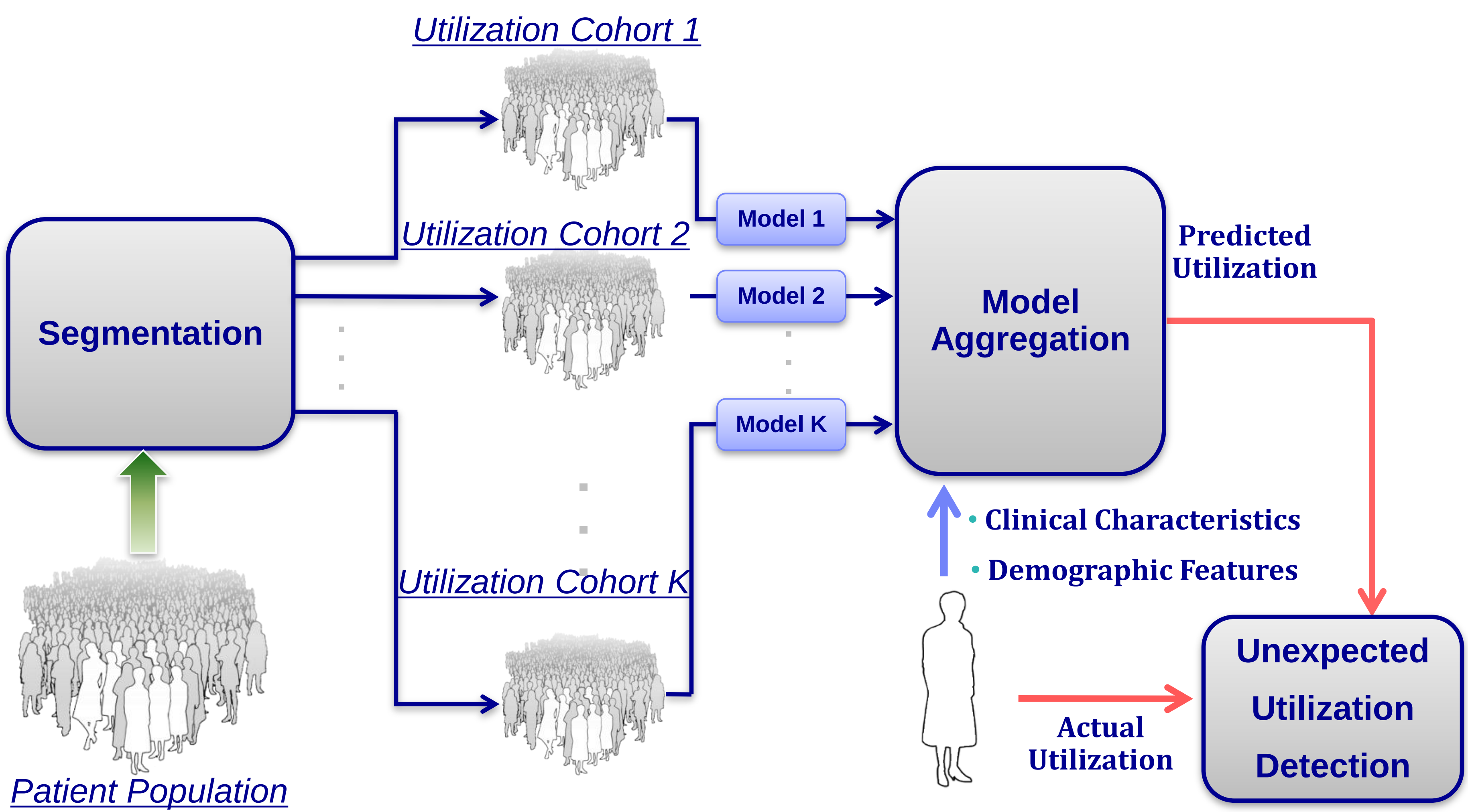


Patient cohort segmentation



Identify patient cohorts with similar utilizations

Unexpected Utilization Detection



Detected Unexpected Utilizations

Example 1: unexpectedly high utilization

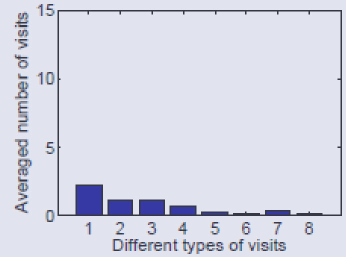
27 year old female

Diagnoses:

HCC127 (Other Ear, Nose, Throat and Mouth Disorders)

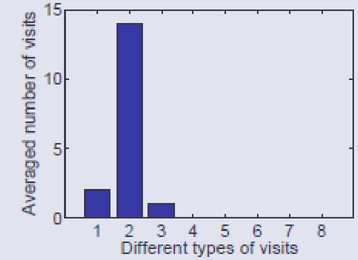
HCC183 (Screening/Observation/Special Exams)

Expected Utilization



(Cohort 1)

Actual Utilization



(Cohort 2)

Example 2: unexpectedly low utilization

73 year old male

Diagnoses:

HCC080 (Congestive Heart Failure)

HCC166 (Major Symptoms, Abnormalities)

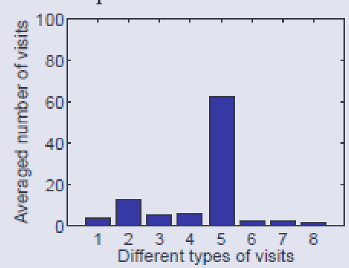
HCC091 (Hypertension)

HCC179 (Post-Surgical States/Aftercare/Elective)

HCC019 (Diabetes with No or Unspecified Complications)

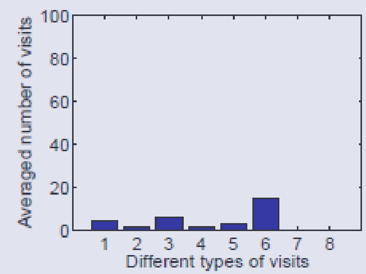
……

Expected Utilization



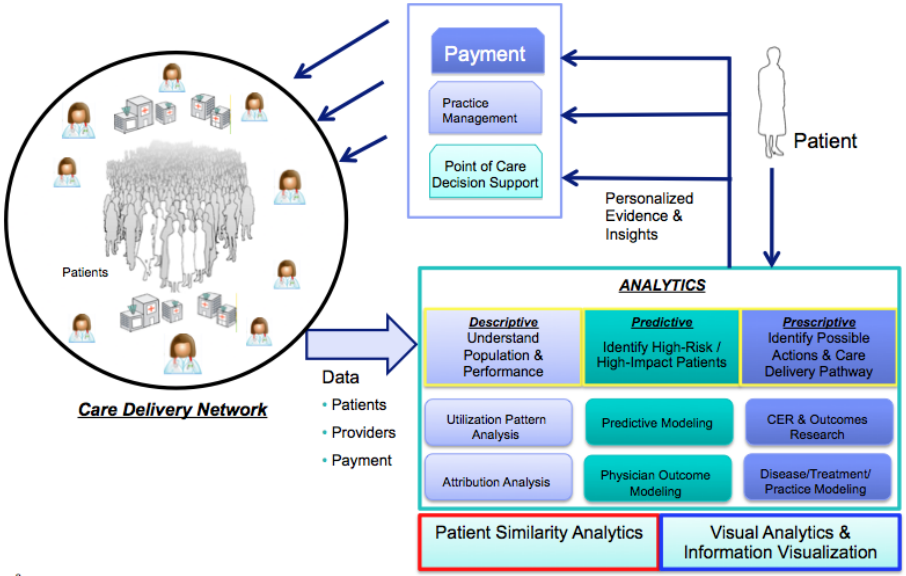
(Cohort 3)

Actual Utilization



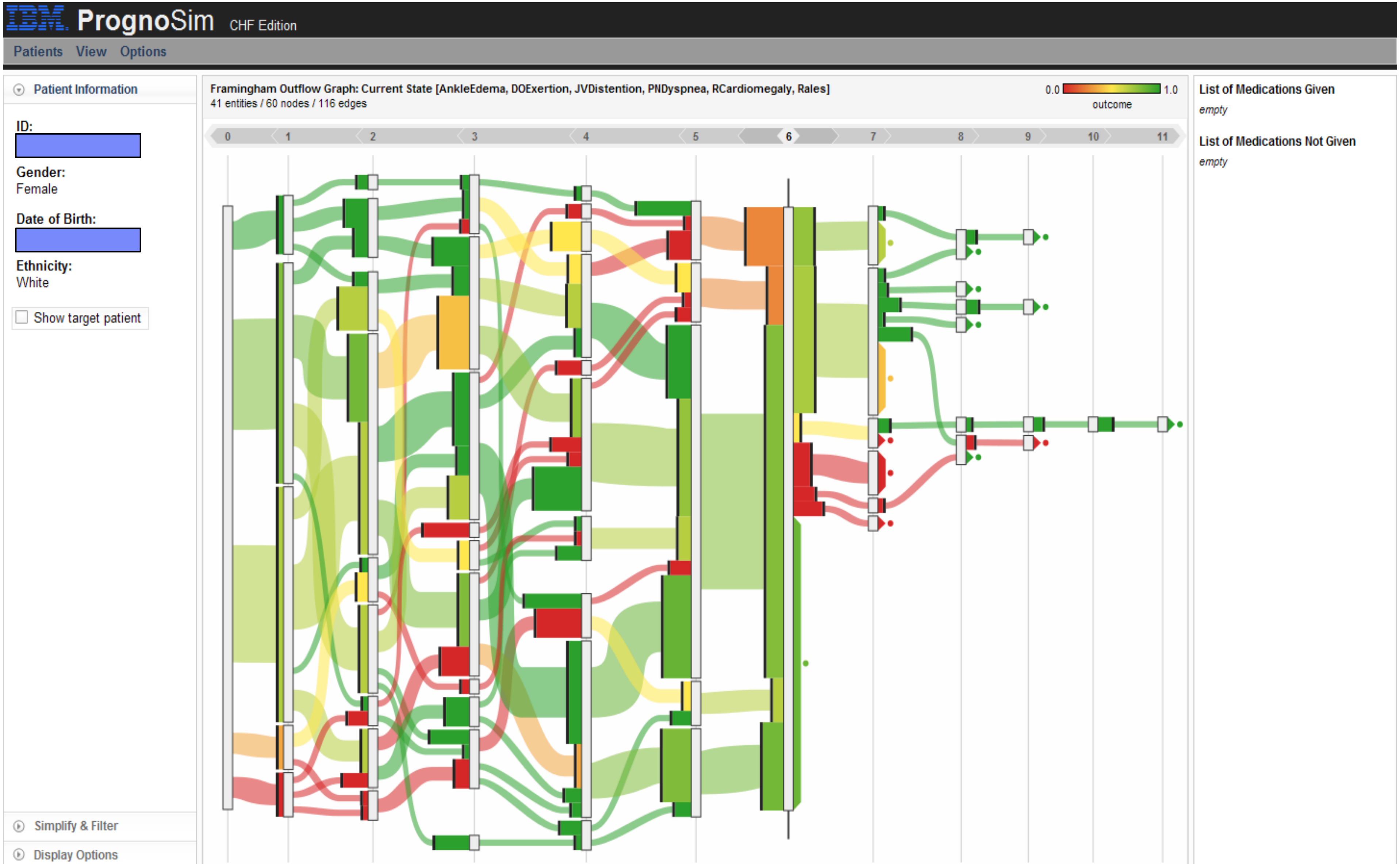
(Cohort 1)

Jianying Hu, Fei Wang, Jimeng Sun, Robert Sorrentino, Shahram Ebadollahi. *A Healthcare Utilization Analysis Framework for Hot Spotting and Contextual Anomaly Detection*. *AMIA* 2012 (to appear)

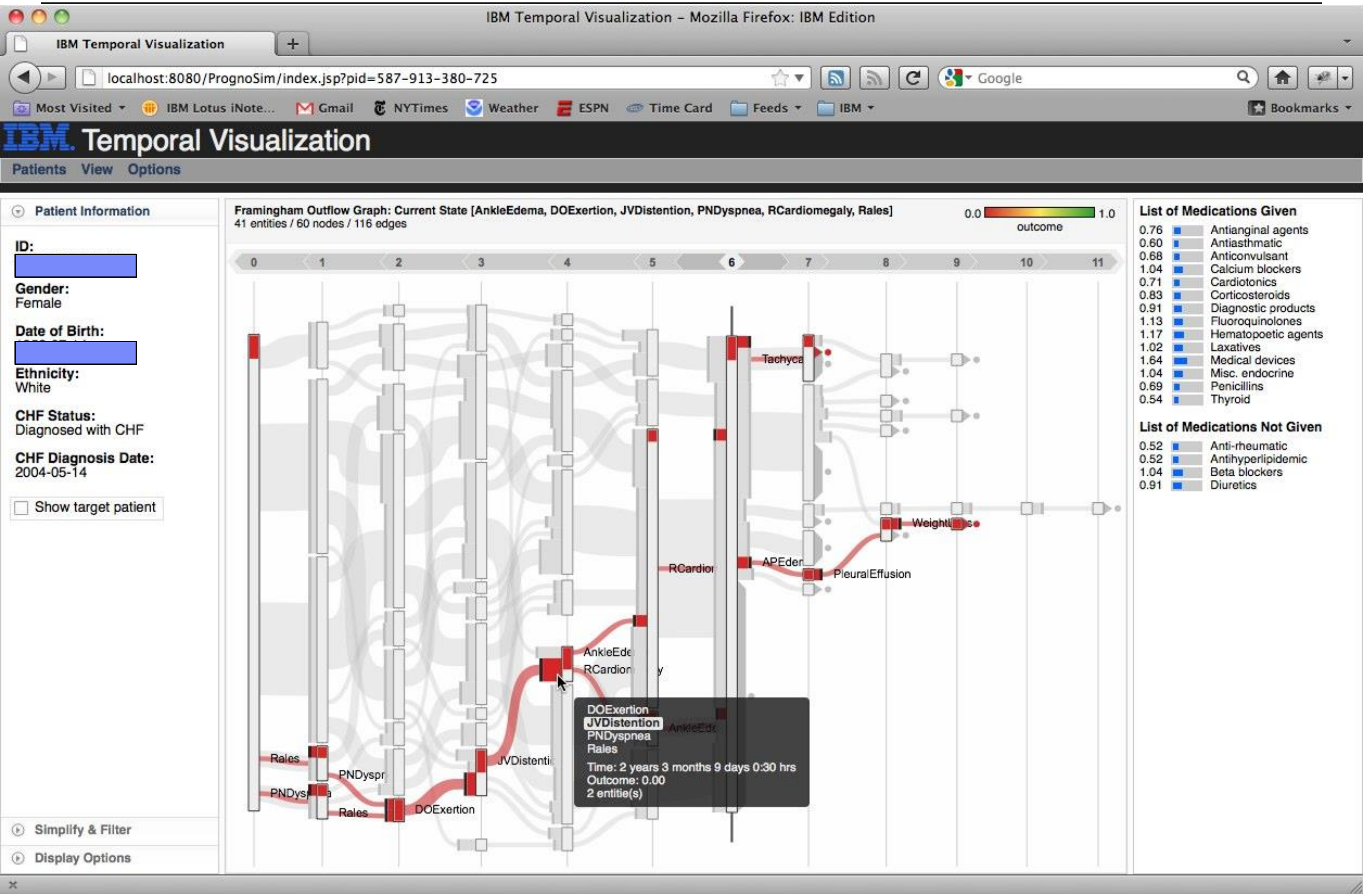


ADVANCED VISUALIZATION

Outflow Temporal Analysis



Outflow Temporal Analysis



Outflow's Visual Encoding