

Characterizing Chronic Disease and Polymedication Prescription Patterns from Electronic Health Records

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Context

Catalan Institute of Health - ICS

- ▶ Provides primary healthcare for 80% of 7.5M people
- ▶ Hospitalary healthcare for about 20%
- ▶ Electronic Health Records almost fully digital since 2009

Context

The concerns:

- ▶ 5% of patients use 50% resources
- ▶ Aging
- ▶ Complex, chronic disease
- ▶ Polymedication
- ▶ Increasingly heterogeneous population

The Project and Intended Users

Health managers and planners at ICS:

1. Understand “the landscape” of **complex, chronic disease**
2. and **polymedication** - prescription patterns
3. Rationalize prescription patterns - costs and patient safety
4. Analyze **diversity**, find **outliers**
 - ▶ geography, demography, among healthcare centers . . .
5. **Plan**: Define indicators and policies, assess costs, allocate resources, make projections to future scenarios

The Project and Intended Users

Healthcare researchers:

1. Support **hypothesis generation** and intuition
2. Discover and explore **subpopulations** of interest
3. Mine interesting **rules** and interactions among variables
4. Create predictive and explanatory **models**

The Project and Intended Users

First-line clinicians and prescribers:

1. **Alert** of unusual diagnostic/prescription combinations
2. Support case-based reasoning
 - ▶ Retrieve patients similar to this one
 - ▶ Get recommendations for diagnostic & treatment

The Dataset

- ▶ ICS primary care visits, Barcelona, 2013
- ▶ 3 tables: patient basic info, health annotations, prescriptions
- ▶ 1.6M potential patients, 0.5M actually present
- ▶ 12M health annotations (diagnostics, tests, findings)
- ▶ 7M medication prescriptions

Limitations:

- ▶ Only primary care, no hospital data
- ▶ Only public network, no private care
- ▶ Only one year
- ▶ Potential inconsistencies - e.g. open episodes

The Project. Novelty

- ▶ Unfocused, exploratory. Many studies focus on one research problem
 - ▶ predicting one disease, cluster patients for one goal, find drug side-effects, ...
- ▶ Tripartite graph patients - diagnostics - medications
 - ▶ other studies used e.g. diagnostics and genes
- ▶ k -ary, not binary, associations – Hypergraphs, not graphs
- ▶ Hierarchical itemsets - diagnostic codes and medications
- ▶ Detection of *open episodes*

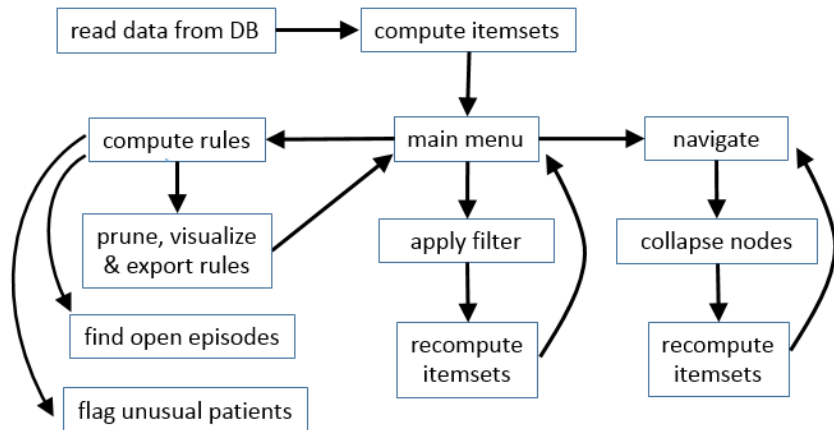
The Prototype so Far

- ▶ Generate k -ary diagnostic combinations
- ▶ Generate rules diagnostics - prescriptions
- ▶ Flag patients with unusual (alarming?) combinations
- ▶ Flag open episodes or prescription errors
- ▶ Navigate hypergraph of diagnostics and prescriptions
- ▶ First try at automatic predictor building

The Prototype - Workflow

Itemset = Subset of diagnostics \cup Prescriptions

Maintain **frequent itemsets of current subpopulation**



Exploring the Hypergraph

Nodes: **Sets** of diagnostics and medications

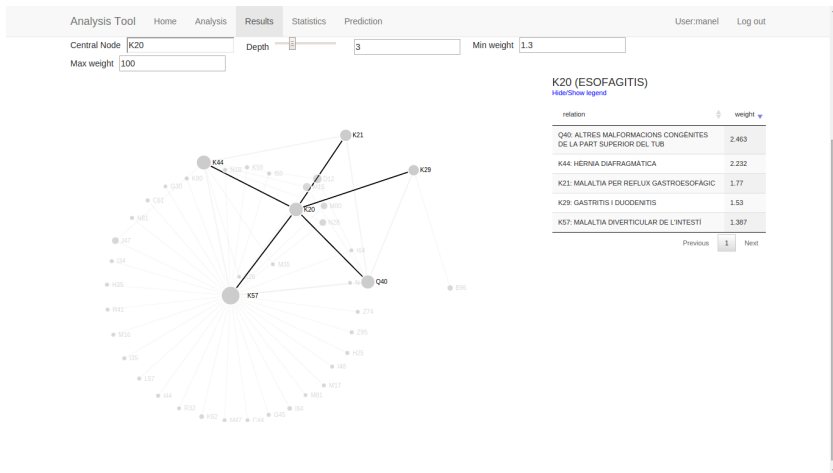
Edges: Strength of association; Pointwise Mutual Information

$$\text{PMI}(A, B) = \log_{10} \frac{\Pr(A \wedge B)}{\Pr(A)\Pr(B)}$$

Nodes can be collapsed (set union)

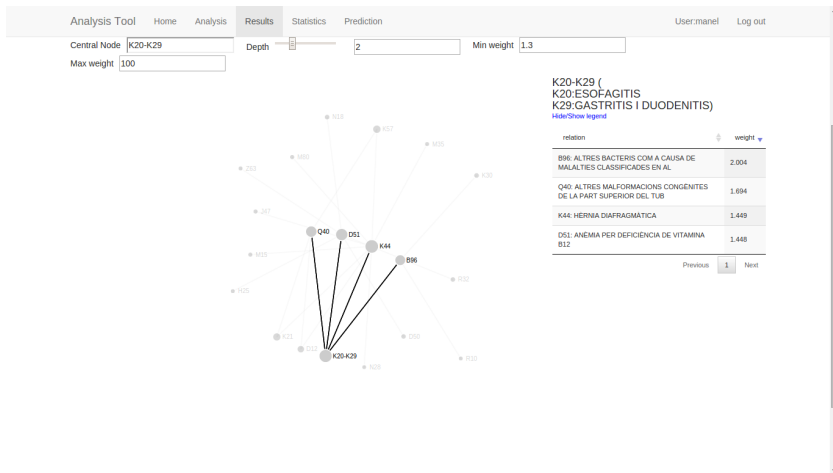
Exploring the Hypergraph

Graph around K20 (Esophagitis)



Exploring the Hypergraph

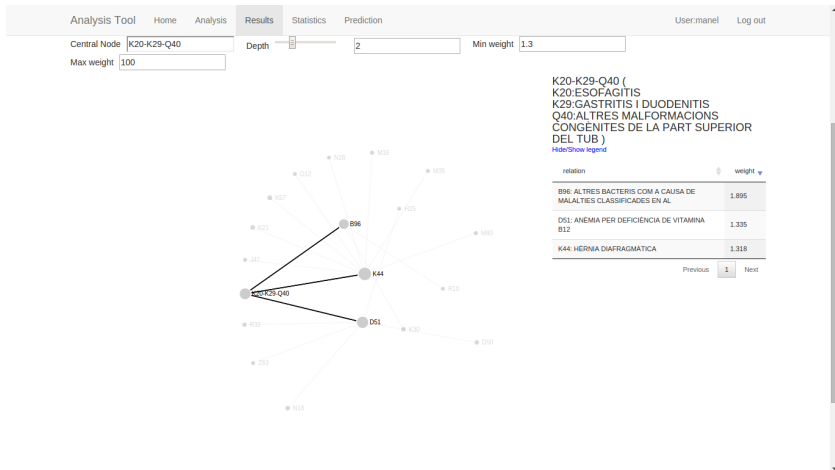
Graph around K20-K29 (Esophagitis + Gastritis/Duodenitis)



Exploring the Hypergraph

Graph around K20-K29-Q40

(Esophagitis + Gastritis/Duodenitis +
Other malformations of upper GI tract)



Implementation

- ▶ Client - server
- ▶ Borgelt's Apriori to find itemsets
- ▶ Custom association rule finder on top
- ▶ Two implementations of patient/diagnostic/prescription DB
 - ▶ RAM
 - ▶ Sparksee graph database
- ▶ But itemsets and hypergraph always in RAM

Some Results

With support $0.05\% \simeq 800$ patients, confidence 0.1 ,

- ▶ Hypergraph with 918 diagnostics and 268 medications
- ▶ 4051 diagnostic-to-medication rules
- ▶ 2253 medication-to-diagnostic rules
- ▶ Prescriptions without diagnostics for about 10% of patients
 - ▶ Lower than expected: application does not require diagnostic for prescription
- ▶ Diagnostics without usual medications for about 16% patients
 - ▶ Many are indeed open episodes

Clinical Significance

Under evaluation. 3 types of “discoveries”

- ▶ Well known, not surprising, but reassuring the program found them
 - (Diabetes ↔ retinopathy)
 - (Omeprazol for most everything)
- ▶ Unnoticed before, but believable
 - (Bedsore for advanced Alzheimer)
- ▶ Unnoticed and surprising
 - (Retinopathy more strongly associated to hypertension than to diabetes)

First Prediction Trial

(not in proceedings)

Factors that predict Hip Fracture

- ▶ Linear regression and odds ratio
- ▶ 7 out of 10 highest scorers reported in specialized literature

Conclusions

- ▶ System is well able to interactively find associations
diagnostics / medications
- ▶ Clinicians satisfied with initial interactions
- ▶ Detailed clinical study in course

- ▶ There's no such thing as “user-friendly enough”

Future Work (lots!)

- ▶ Improve rule pruning
- ▶ Improve interpretation of rule exceptions
- ▶ Taxonomies of diagnostics and medications
- ▶ Temporal evolution. Trajectories
- ▶ Predictive model building
- ▶ Patient clustering
- ▶ Differential analysis (geographic, demographic)
- ▶ Retrieve similar cases
- ▶ Suggest diagnostic/treatment
- ▶ Privacy, information sharing

Advertising

Looking for:

- ▶ Research partners
- ▶ Data partners
- ▶ Project partners

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Rule Mining

Find all rules

$$A_1 \dots A_k \rightarrow B_1 \dots B_\ell$$

with given support and confidence

Heuristics to purge rules (improvable):

- ▶ Low lift: remove $AB \rightarrow C$ if $A \rightarrow C$ same confidence
- ▶ Implied by transitivity:
remove $A \rightarrow C / (\sigma_1 \cdot \sigma_2)$ if $A \rightarrow B / \sigma_1$ and $B \rightarrow C / \sigma_2$
- ▶ Removals make sense to clinicians

Open Episodes and Unusual Patients

From the rules we find patients with:

- ▶ Medication not justified by recorded diagnostics
- ▶ Diagnostics without any of its usual medication

- ▶ Open episode?
Recording error?
Clinician error?
Conscious clinician decision?
- ▶ More heuristics and larger timespan data to decide