Associating Chief Complaints with Electronic Health Record Activity to Decrease Provider Administrative Burden

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Introduction

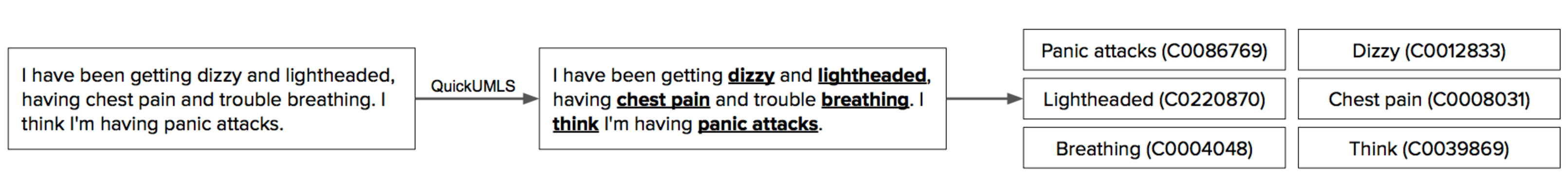
Physician burnout has become a widespread issue, with electronic health record (EHR) use known to be a major predictor of burnout[1]. The burden of EHRs has become so problematic that patients are now reluctant to engage in medical encounters due to the overuse of technology in the exam room[2]. The average physician spends almost six hours per day interacting with their EHR[3]. Machine learning and data mining create opportunities to decrease this administrative burden through smart shortcuts based on predicted user behavior.

This preliminary work seeks to demonstrate the feasibility of using patient data to predict which clinical activities will be performed in an ambulatory encounter. This is done with an eye towards building smart shortcuts in an EHR in order to allow clinicians to document and order in fewer clicks. Emphasis is intentionally placed on interpretability, as this may aid in clinician buy-in, ensure clinically appropriate suggestions, and enable future quality improvement activities.

Methods

Feature Extraction

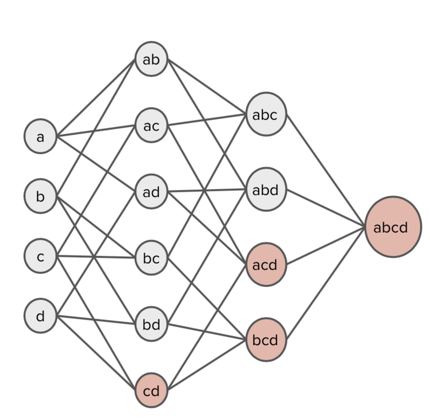
Clinical encounters were gathered from a large, national primary care clinic system. The reason for visit (rfv) was parsed into UMLS concepts using QuickUMLS[4], a clinical named entity recognition tool.



These parsed concepts were then combined with patient demographics (age, gender, insurance status). Clinical activities done during the encounter (lab orders, prescriptions, diagnoses, and referrals) were collected and attached to each record. Prescriptions were aggregated to their generic medication, and diagnoses were translated and aggregated from an internal vocabulary to ICD-10. Extracted UMLS concepts were converted to SNOMED-CT.

Rule Discovery

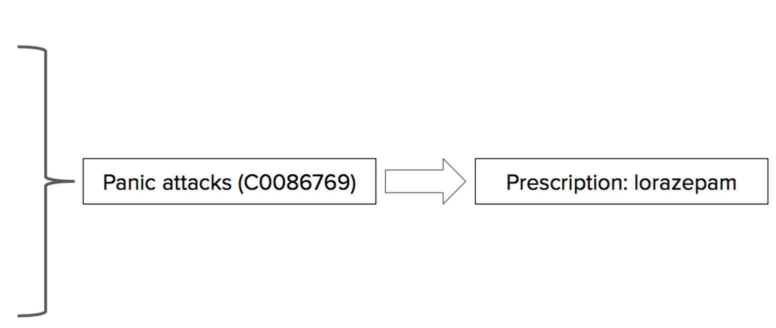
The apriori algorithm[5] was used for candidate generation for association rule discovery. This algorithm works by evaluating the conditional probability of one consequent concept given some set of antecedent concepts, and returning those whose confidence is above some preset threshold. This evaluation is executed only for candidates with support above some preset threshold. The existence of a support threshold substantially decreases the search space by allowing any further combinations of an under-supported item to be skipped (see inset, where itemset including c and d do not meet the support threshold).



The support threshold was chosen to represent approximately 10 patients, and a minimal confidence threshold of 0.1 was chosen. This low confidence threshold allows for evaluation and further pruning in future steps.

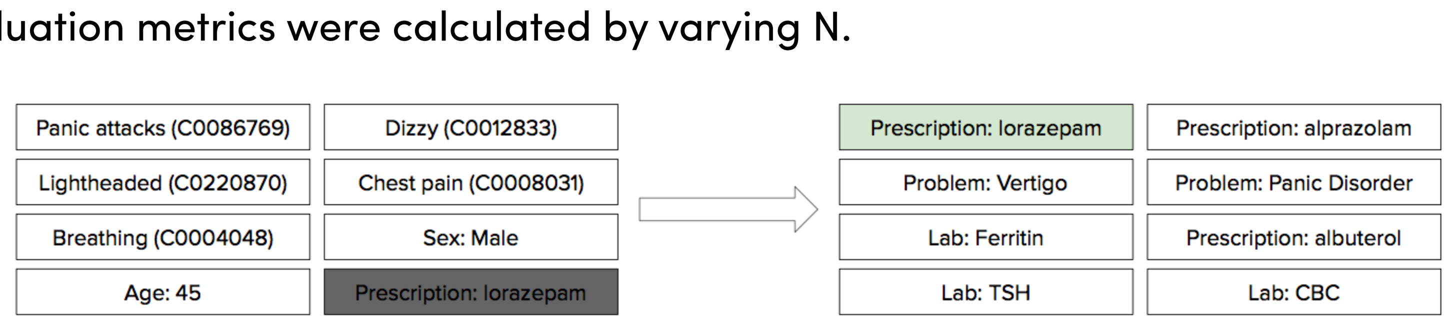
Rules predicting referrals, diagnoses, prescriptions, and lab orders were identified, and any feature (including clinical activity within the encounter) was allowed to be used. In a production setting, this would allow for real-time updating of suggested activities given actions performed by the clinician.

Panic Attacks	Dizzy	Chest Pain	Male	lorazepam
1	1	0	1	1
1	1	0	0	1
1	0	1	1	0
0	1	0	0	1
0	0	1	1	0
1	1	0	0	1



Evaluation & Impact Estimation

An evaluation dataset was created from a holdout portion of data. A random concept was removed from each encounter, and the discovered association rules were used to attempt to reidentify the removed concept. A control model was created by identifying the Top N most common diagnoses, prescriptions, and labs, and was similarly evaluated by looking for the removed concept in a Top N list. Evaluation metrics were calculated by varying N.



Impact on physician administrative burden was estimated using the sample's sensitivity and assuming one click reduction for medication and diagnosis, and two click reduction for lab orders.

Results

The resultant dataset included 5,655,811 encounters, and association rule mining discovered 3,019,661 rules.

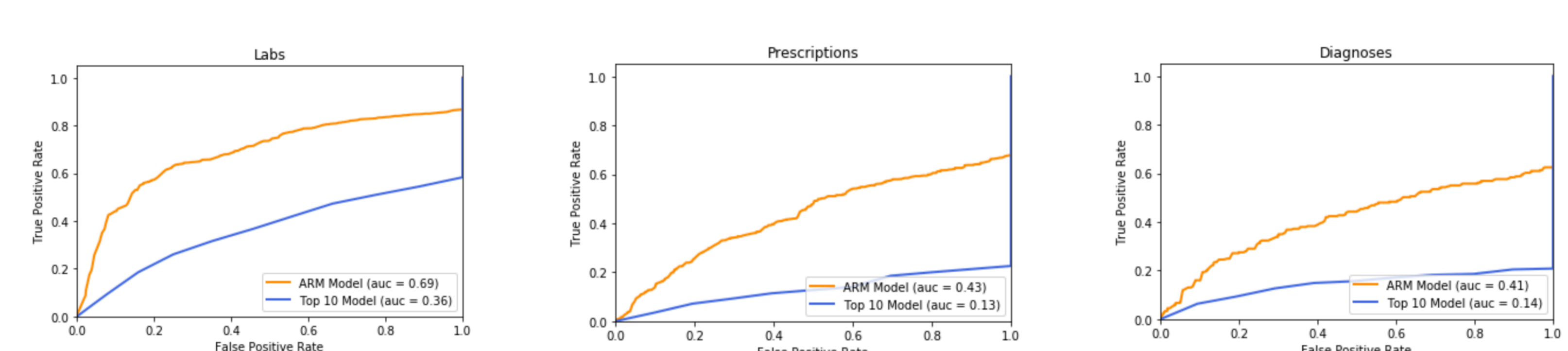
Model Results

A sample of discovered rules are shown below. Many of the highest confidence rules involved a direct correspondence between the chief complaint and the resultant activity. For example, patients mentioning finasteride in the reason for visit had a 71% chance of being prescribed finasteride during the encounter.

Antecedent	Consequent	Confidence	Lift
rfv: 386963006 (finasteride)	Prescription: finasteride oral	0.71	303
rfv: 18530007 (Sea Sickness)	Prescription: Scopolamine	0.75	1487
rfv: 193031009 (Cluster headache)	Prescription: sumatriptan nasal	0.29	1893
rfv: 42883007 (Alpine sickness)	Prescription: acetazolamide	0.69	1329
rfv: 248437004 (malaria)	Prescription: atovaquone-proguanil	0.58	246
rfv: 398909004 (Rosacea)	Prescription: metronidazole	0.34	557
rfv: 126084009 (polyestradiol phosphate)	Prescription: raltegravir	0.16	3739
rfv: 47367009 (Pancreatic exocrine insufficiency)	Prescription: epinephrine injection	0.78	519
Problem: J02.0 (strep throat), rfv: 405737000 (pharyngitis)	Prescription: penicillin V potassium	0.50	153
Lab: 144 (RPR), Lab: 168 (Creatinine), Lab: 775 (CT/GC NAAT swab)	Prescription: FTC-TDF	0.46	66
Prescription: blood sugar diagnostic, Prescription: blood-glucose meter	Prescription: lancets	0.72	2291
Problem: T75.3 (Motion Sickness)	Prescription: Scopolamine	0.62	1257
Problem: J02.0 (strep throat)	Prescription: penicillin V potassium	0.42	127
rfv: 706506000 (condom)	Lab: 767 (CT/GC NAAT swab)	0.34	19
Prescription: FTC-TDF, Lab: 767 (CT/GC NAAT) rfv: 20135006 (Screening)	Lab: 521 (HIV)	1.0	19
Lab: 212 (metabolic panel) rfv:90560007 (gout)	Lab: 330 (uric acid)	0.88	356
Lab: 100 (ALT)	Lab: 128 (AST)	0.64	3063
rfv: 698065002 (Acid Reflux)	Problem: K21 (GERD)	0.19	77
rfv: 4651008 (Burn)	Problem: T30.0 (Burn, unspecified location)	0.75	2281
rfv: 112625008 (skin rash)	Problem: R21 (Rash)	0.13	30
Prescription: valacyclovir, rfv: 112625008 (skin rash)	Problem: B02.9 (Zoster w/o complications)	0.35	406
Prescription: amoxicillin-potassium	Problem: J01.90 (Acute sinusitis)	0.27	54
Prescription: meclizine	Problem: R42 (vertigo)	0.20	112
Lab: 957 (Influenza A & B RT-PCR)	Problem: J11.1 (Influenza)	0.39	114
rfv: 2252308 (Vasectomy)	Referral: Urology	0.10	14
rfv: 126660000 (Deviated Nasal Septum)	Referral: ENT	0.12	9

Clusters of rules, and bidirectional rules, often existed: motion sickness diagnosis predicted scopolamine prescription and scopolamine prescription predicted motion sickness diagnosis; HIV screening, RPR, and CT/GC screening all predict each other. Some acronyms picked up by QuickUMLS had alternative meanings: "HIV PEP" was identified as polyestradiol phosphate, and "epi pen" was identified as pancreatic exocrine insufficiency. Despite not being the intended concept, correct relationships were identified (e.g., "HIV PEP" predicted raltegravir, and "epi pen" identified epinephrin)

Performance varied based on type of activity being predicted, with labs being the most performant (AUC = 0.69), followed by prescriptions (0.43) and diagnoses (0.41). The Top N models performed universally worse (labs: 0.36, prescriptions: 0.13, diagnoses: 0.14).



Impact

We estimate this approach would reduce the number of clicks by 3.2 per patient per year, or 3,625 clicks per provider per year.

Conclusions

This preliminary work suggests that association rule mining is a reasonably performant and easily auditable method of predicting clinician EHR activity given patient data. The use of named entity recognition to pre-process reason for visit appears to work in many cases, although sometimes through unintended intermediary concepts. The apriori algorithm appears effective in this clinical context, particularly when initially parameterized with low support and confidence thresholds.

This method shows promise as an approach to using machine learning and data mining to decrease clinician administrative burden (and clicks) through the smart suggestion of EHR activity given patient data.

References

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