

Applying Information Retrieval to the Electronic Health Record for Cohort Discovery

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Overview

- Applying IR to the EHR
- Cohort discovery
- Challenges for EHR research
- This work funded by grant from
 - NLM 1R01LM011934
- With help from OHSU collaborators
 - Steven Bedrick
 - Jolie Kaner

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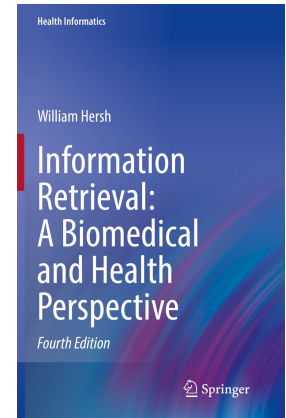
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Information retrieval (IR, aka, search)

- We all do it – Google, PubMed, etc.
- As academics, we evaluate it – personal journey from
 - Knowledge-based information (1990, 1994, 1998)
 - Studies of users (mostly physicians) (1996, 2002)
 - Participation/leadership of challenge evaluations, mainly Text Retrieval Conference (TREC) (<https://trec.nist.gov/>; Hersh, 2009; Voorhees, 2012; Roberts, 2016; Gupta, 2024)



(Hersh, 2020)



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Applying IR to the EHR

- Increased availability of data with incentives for electronic health record (EHR) adoption in HITECH Act of 2009
- With availability of EHR data, first effort was cohort discovery task of TREC Medical Records Track (Voorhees, 2012; Voorhees, 2013)
- Awarding in 2014 of NIH R01 to (former) OHSU faculty Stephen Wu to explore methods in parallel with Mayo Clinic (Wu, 2017; Wang, 2019; Chamberlin, 2020)



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IR system evaluation based on test collections of “documents”

- Recall $R = \frac{\# \text{retrieved and relevant documents}}{\# \text{relevant documents in collection}}$
- Precision $P = \frac{\# \text{retrieved and relevant documents}}{\# \text{retrieved documents}}$
- Aggregate measures
 - F – combining and (optional) weighting of R and P
 - For ranked output (Harman, 2011)
 - Mean average precision (MAP)
 - B-Pref – used when relevance judgments incomplete (Buckley, 2004)
 - Cumulative gain and other “inferred” measures (Järvelin, 2022)
- Usual approach in test collections is to average results across topics for each “run”

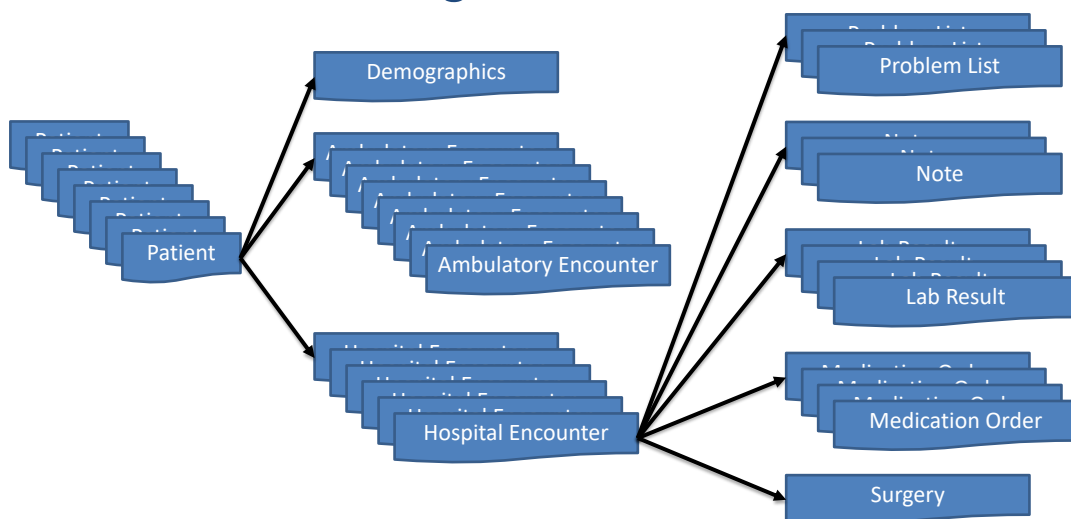
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Electronic health record (EHR) is (typically) not a single document



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Cohort discovery

- Widely offered service by most academic medical centers to identify cohorts to retrieve for clinical study recruitment but little formal evaluation of approaches
- Early work – TREC Medical Records Track, 2011-2012
- Follow-on collaboration funded by NLM R01

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TREC Medical Records Track (Voorhees, 2012; Voorhees, 2013)

- Task – identify patients who are possible candidates for clinical studies/trials
- Documents – de-identified patient records from University of Pittsburgh Medical Center (UPMC)
- Topics – 35 clinical study topics from IOM key areas for comparative effectiveness research
- Relevance judgments – patients “relevant” to topics, judged by OHSU informatics students who were also physicians

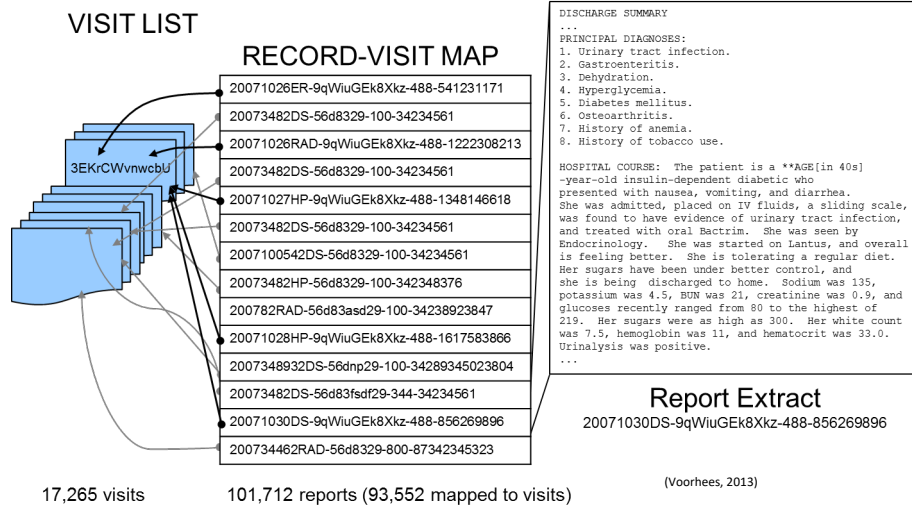
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Test collection structure

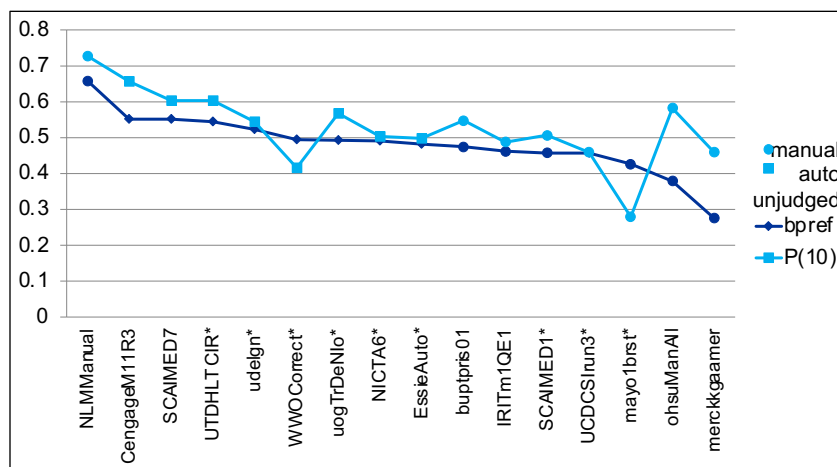


(Voorhees, 2013)



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Evaluation results for top runs – 2011



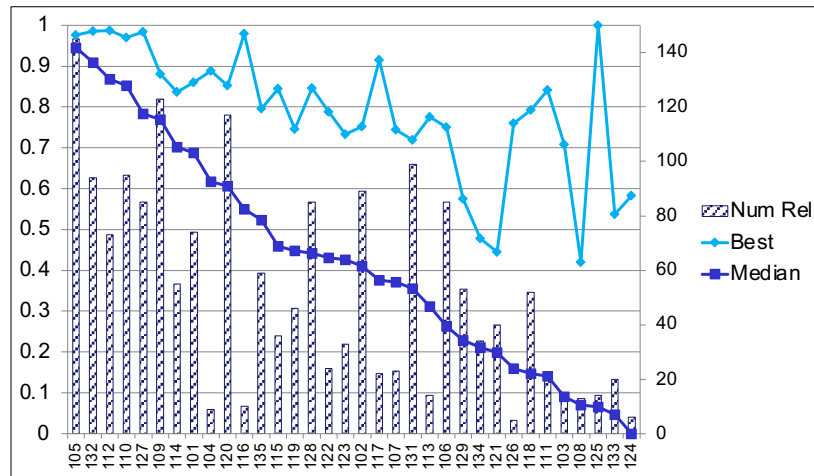
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But as commonly seen in IR, wide variation across topics



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“Easy” and “hard” topics

- Easiest – best median B-Pref
 - 105: Patients with dementia
 - 132: Patients admitted for surgery of the cervical spine for fusion or discectomy
- Hardest – worst best B-Pref and worst median B-Pref
 - 108: Patients treated for vascular claudication surgically
 - 124: Patients who present to the hospital with episodes of acute loss of vision secondary to glaucoma
- Large differences between best and median B-Pref
 - 125: Patients co-infected with Hepatitis C and HIV
 - 103: Hospitalized patients treated for methicillin-resistant Staphylococcus aureus (MRSA) endocarditis
 - 111: Patients with chronic back pain who receive an intraspinal pain-medicine pump

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Failure analysis for 2011 topics (Edinger, 2012)

Reasons for Incorrect Retrieval	Number of Visits	Number of Topics
Visits Judged Not Relevant		
Topic terms mentioned as future possibility	16	9
Topic symptom/condition/procedure done in the past	22	9
All topic criteria present but not in the time/sequence specified by the topic description	19	6
Most, but not all, required topic criteria present	17	8
Topic terms denied or ruled out	19	10
Notes contain very similar term confused with topic term	13	11
Non-relevant reference in record to topic terms	37	18
Topic terms not present—unclear why record was ranked highly	14	8
Topic present—record is relevant—disagree with expert judgment	25	11
Visits Judged Relevant		
Topic not present—record is not relevant—disagree with expert judgment	44	21
Topic present in record but overlooked in search	103	27
Visit notes used a synonym or lexical variant for topic terms	22	10
Topic terms not named in notes and must be inferred	3	2
Topic terms present in diagnosis list but not visit notes	5	5

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Extending cohort discovery work

- Multi-site collaboration of OHSU, Mayo Clinic, and University of Texas Houston Health Science Center
- Aimed to add natural language processing (NLP) and language modeling (LM) to base IR methods on large amounts of unmodified (not de-identified) text from EHR
- Initial methods (Wu, 2017) and results (Chamberlin, 2020)

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EHR data – 100K OHSU patients having ≥3 visits

Type	Patients	Encounters	Records	Average	Median	Max
Administered Meds	47,208	125,831	6,497,157	51.634	6	-
Ambulatory Encounters	99,965	3,760,205	3,760,205	-	-	-
Current Meds	92,783	-	31,997,402	344.863	64	20,102
Demographics	99,965	-	-	-	-	-
Encounter Attributes	99,965	6,273,137	6,273,137	-	-	-
Encounter Diagnoses	99,938	3,725,603	18,170,896	4.877	4	107
Notes	99,868	3,491,659	10,111,930	-	-	-
Hospital Encounters	73,303	466,252	466,252	-	-	-
Lab Results	83,435	733,461	20,186,748	27.523	12	19488
Microbiology Results	27,515	65,373	296,548	4.536	1	268
Medications Ordered	94,089	1,388,086	5,336,506	3.845	1	1551
Procedures Ordered	98,514	1,880,309	7,229,854	3.845	1	6681
Problem List	90,722	-	761,260	8.391	6	182
Result Comments	72,716	468,814	916,554	1.955	1	691
Surgeries	18,640	29,895	31,889	1.067	1	41
Vitals	99,098	1,362,431	6,647,115	4.879	2	6387

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Judgments from Patient Relevance Assessment Interface (PRAI)

Patient Evaluation William Hersh -

Topic Description: Women who had a pregnancy during which they had a 3rd trimester outpatient visit, didn't smoke, and didn't have intellectual disability, mood disorder, schizophrenia, autism, or ADHD.

Pool 2 / Topic 1 Basic Info

Patient ☐ Pre ☐ Maybe ☐ Con

Encounters

Ambulatory Encounters

Hospital Encounters

Encounter Diagnoses

Vitals

Lab Results

Result Comments

Microbiology Results

Administered Medications

Ordered Medications

Notes

Ordered Procedures

Surgeries

Demographics

Filter Results

Judge	OHSU_MRN	CURRENT_AGE_YRS	BIRTH_DATE	GENDER	PATIENT_ALIVE	DEATH_DATE	ADDRESS_STATE	ADDRESS_COUNTY	GEA
☐ Pre ☐ Maybe ☐ Con							OR	WASHINGTON	N

1/1

Problems

Filter Results

Judge	DX_START_DATE	DX_END_DATE	DX_ICD	DX_NAME	PROBLEM_LIST_DX_STATUS
☐ Pre ☐ Maybe ☐ Con	9999-12-31	314.00		ATTENTION DEFICIT DISORDER WITHOUT MENTION OF HYPERACTIVITY	ACTIVE
☐ Pre ☐ Maybe ☐ Con	9999-12-31	250.01		DIABETES MELLITUS TYPE I	ACTIVE
☐ Pre ☐ Maybe ☐ Con	9999-12-31	250.01		TYPE 1 DIABETES MELLITUS	ACTIVE
☐ Pre ☐ Maybe ☐ Con	9999-12-31	251.2		HYPOGLYCEMIA	ACTIVE

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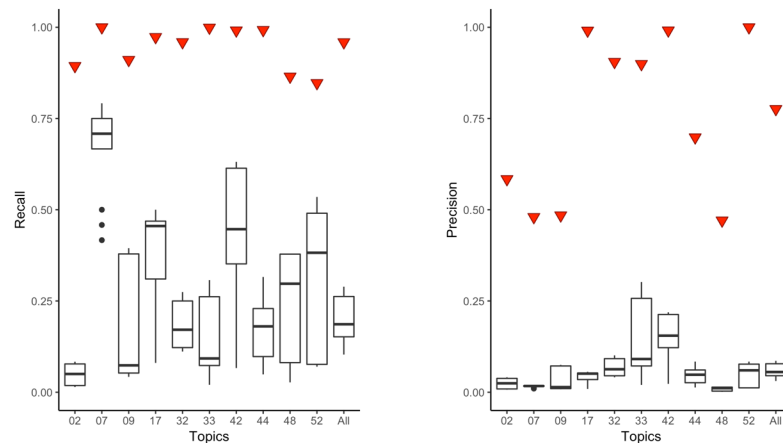
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Reformulating as Boolean queries with additional relevance judgments for 10 topics



Improved relative recall and precision

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Results and future work ...

- Focus on 13 topics due to resource constraints
- To facilitate comparative methods and results without sharing data, standardizing all data, code, and methods using Observational Medical Outcomes Partnership (OMOP) format
- Current results show some improvement over word-based methods with simple LLM methods but still inferior to Boolean
 - Benefit from state-of-art LLMs? Stay tuned

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Challenges for EHR retrieval work

- Need for large and realistic data sets
 - Scalability of methods
 - More generalizable to real world
- Big challenge is patient privacy
 - Data not readily sharable
 - Leading to concerns about reproducibility
- Can we solve privacy problems?
 - Exhaustive de-identification, including of notes – is it possible?
 - Controlled access to identified data (Guerrero, 2019)
 - Evaluation as a service (Roegiest, 2016; Hopfgartner, 2018; Fröbe, 2023)

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Questions?

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