Secondary Use of Clinical Data from Electronic Health Records: The TREC Medical Records Track

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Overview

- Motivations for secondary use of clinical data
- Challenges for secondary use of clinical data
- Primer on information retrieval and related topics
- TREC Medical Records Track
- Conclusions and future directions

Motivations for secondary use of clinical data

- Many "secondary uses" or re-uses of electronic health record (EHR) data, including (Safran, 2007)
  - Personal health records (PHRs)
  - Clinical and translational research – generating hypotheses and facilitating research
  - Health information exchange (HIE)
  - Public health surveillance for emerging threats
  - Healthcare quality measurement and improvement
- Opportunities facilitated by growing incentives for "meaningful use" of EHRs in the HITECH Act (Blumenthal, 2011; Blumenthal, 2011), aiming toward the "learning healthcare system" (Friedman, 2010)

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Challenges for secondary use of clinical data

- EHR data does not automatically lead to knowledge
  - Data quality and accuracy is not a top priority for busy clinicians
- Little research, but problems identified
  - EHR data is inaccurate and incomplete, especially for longitudinal assessment (Berlin, 2011)
  - Many steps in process of ICD-9 assignment can lead to inaccuracy (O'Malley, 2005)
- There are also important "provocations" about use of "big data" for research (Boyd, 2011)

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Challenges (cont.)

- Many data idiosyncrasies (Weiner, 2011)
  - "Left censoring": First instance of disease in record may not be when first manifested
  - "Right censoring": Data source may not cover long enough time interval
  - Data might not be captured from other clinical (other hospitals or health systems) or non-clinical (OTC drugs) settings
  - Bias in testing or treatment
  - Institutional or personal variation in practice or documentation styles
  - Inconsistent use of coding or standards

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Data in EHRs is incomplete

- Claims data failed to identify more than half of patients with prognostically important cardiac conditions prior to admission for catheterization (Jollis, 1993)
- Various approaches generated variable rate of retrieval of cases for quality measurement (Benin, 2005; Rhodes, 2007); algorithmic methods can lead to improvement (Benin, 2011)
- At Columbia University Medical Center, 48.9% of patients with ICD-9 code for pancreatic cancers did not have corresponding disease documentation in pathology reports, with many data elements incompletely documented (Botsis, 2010)

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Data incomplete (cont.)

- In Texas academic hospital, billing data alone only identified 22.7% and 52.2% respectively of patients with breast and endometrial cancer, increasing to 59.1% and 88.6% with a machine learning algorithm (Bernstam, 2010)
- Alerting system to add 17 problems to patient problem lists accepted 41% of time (Wright, 2012)
- Data from two medical centers in a Minnesota were found to better predict Type 2 diabetes mellitus than single center (Wei, 2012)

Patients get care in multiple places

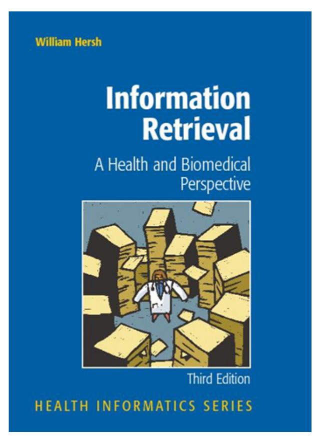
- Study of 3.7M patients in Massachusetts found 31% visited 2 or more hospitals over 5 years (57% of all visits) and 1% visited 5 or more hospitals (10% of all visits) (Bourgeois, 2010)
- Study of 2.8M emergency department (ED) patients in Indiana found 40% of patients had data at multiple institutions, with all 81 EDs sharing patients in common (Finnell, 2011)

Primer on information retrieval (IR) and related topics

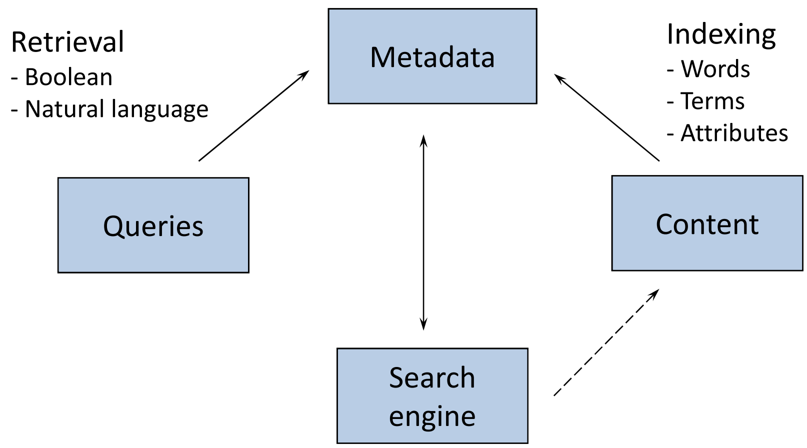
- Information retrieval
- Evaluation
- Challenge evaluations

Information retrieval (Hersh, 2009)

- Focus on indexing and retrieval of knowledge-based information
- Historically centered on text in knowledge-based documents, but increasingly associated with many types of content
- www.irbook.info



Elements of IR systems



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Evaluation of IR systems

- System-oriented – how well system performs
  - Historically focused on relevance-based measures
    - Recall and precision – proportions of relevant documents retrieved
  - When documents ranked, can combine both in a single measures
    - Mean average precision (MAP) – mean of average precision across topics
    - Bpref – takes into account retrieved but unjudged documents
- User-oriented – how well user performs with system
  - e.g., performing task, user satisfaction, etc.

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System-oriented IR evaluation

- Historically assessed with *test collections*, which consist of
  - Content – fixed yet realistic collections of documents, images, etc.
  - Topics – statements of information need that can be fashioned into queries entered into retrieval systems
  - Relevance judgments – by expert humans for which content items should be retrieved for which topics
- Evaluation consists of *runs* using a specific IR approach with output for each topic measured and averaged across topics

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Recall and precision

- Recall

$$R = \frac{\#\,retrieved\ and\ relevant\ documents}{\#\,relevant\ documents\ in\ collection}$$

  - Usually use *relative recall* when not all relevant documents known, where denominator is number of known relevant documents in collection
- Precision

$$P = \frac{\#\,retrieved\ and\ relevant\ documents}{\#\,retrieved\ documents}$$

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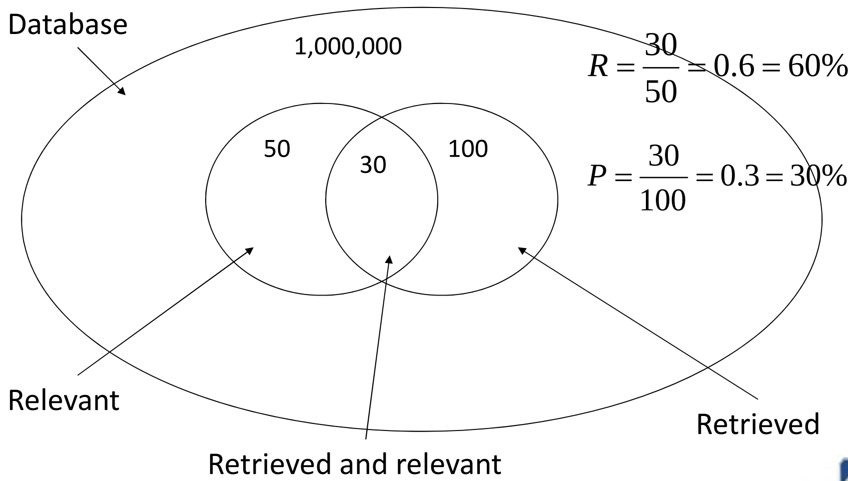
Example of recall and precision



$$R = \frac{30}{50} = 0.6 = 60\%$$

$$P = \frac{30}{100} = 0.3 = 30\%$$

Some measures can be combined into a single aggregated measure

- Mean average precision (MAP) is mean of average precision for each topic (Harman, 2005)
  - Average precision is average of precision at each point of recall (relevant document retrieved)
  - Despite name, emphasizes recall
- Bpref accounts for when relevance information is significantly incomplete (Buckley, 2004)

Challenge evaluations

- A common approach in computer science, not limited to IR
- Develop a common task, data set, evaluation metrics, etc., ideally aiming for real-world size and representation for data, tasks, etc.
- In case of IR, this usually means
  - Test collection of content items
  - Topics of items to be retrieved – usually want 25-30 for "stability" (Buckley, 2000)
  - Runs from participating groups with retrieval for each topic
  - Relevance judgments of which content items are relevant to which topics – judged items derived from submitted runs

Challenge evaluations (cont.)

- Typical flow of events in an IR challenge evaluation

Release of document collection to participating groups → Experimental runs and submission of results → Relevance judgments → Analysis of results

- In IR, challenge evaluation results usually show wide variation between topics and between systems
  - Should be viewed as relative, not absolute performance
  - Averages can obscure variations

Some well-known challenge evaluations in IR

- Text Retrieval Conference (TREC, trec.nist.gov; Voorhees, 2005) – sponsored by National Institute for Standards and Technology (NIST)
  - Many "tracks" of interest, such as routing/filtering, Web searching, question-answering, etc.
  - Non-medical, with exception of Genomics Track (Hersh, 2009)
- Cross-Language Evaluation Forum (CLEF, www.clef-campaign.org)
  - Focus on retrieval across languages, European-based
  - Additional focus on image retrieval, which includes medical image retrieval tasks (Hersh, 2009; Müller, 2010)
- Both operate on annual cycle of test collection release, experiments, and analysis of results

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TREC Medical Records Track

- Appealing task given societal value and leveraging HITECH investment
  - NIST involved in HITECH in various ways
- Has always been easier with knowledge-based content than patient-specific data due to a variety of reasons
  - Privacy issues
  - Task issues
- Facilitated with development of large-scale, de-identified data set from University of Pittsburgh Medical Center (UPMC)

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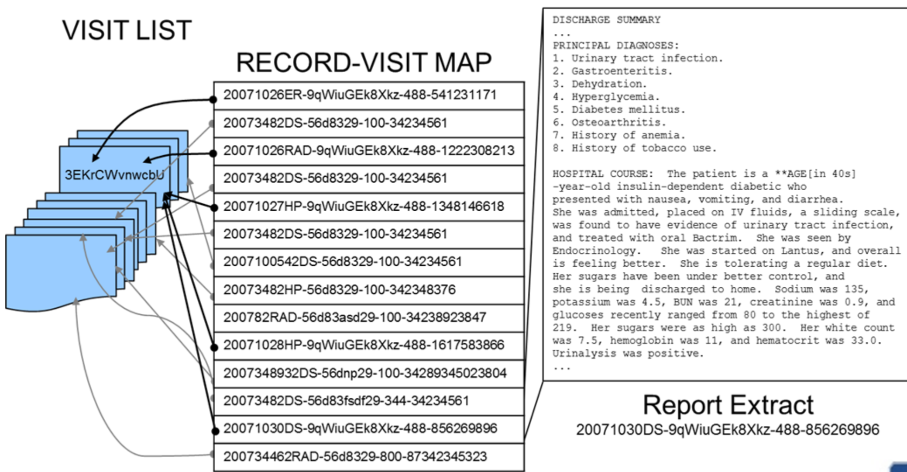
Test collection



17,265 visits

101,712 reports (93,552 mapped to visits)

(Courtesy, Ellen Voorhees, NIST)

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Some issues for test collection

- De-identified to remove protected health information (PHI), e.g., age number → range
- De-identification precludes linkage of same patient across different visits (encounters)
- UPMC only authorized use for TREC 2011 and nothing else, including TREC 2012 or any other research

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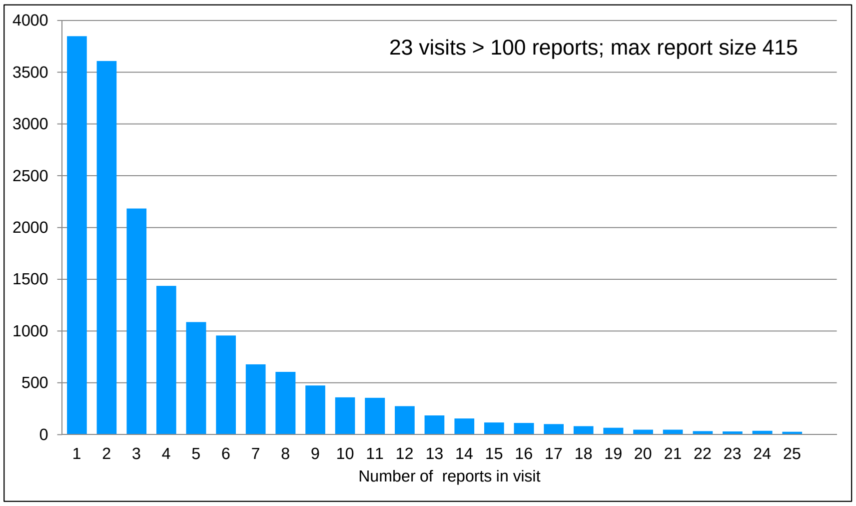
Wide variations in number of documents per visit



(Courtesy, Ellen Voorhees, NIST)

Topic development and relevance assessments

- Task – Identify patients who are possible candidates for clinical studies/trials
  - Had to be done at "visit" level due to de-identification of records
- Topics derived from 100 top critical medical research priorities in comparative effectiveness research (IOM, 2009)
- Topic development done as IR course student project
  - Selected topics appropriate for data and with at least some relevant "visits"
- Relevance judgments by OHSU BMI students who were physicians

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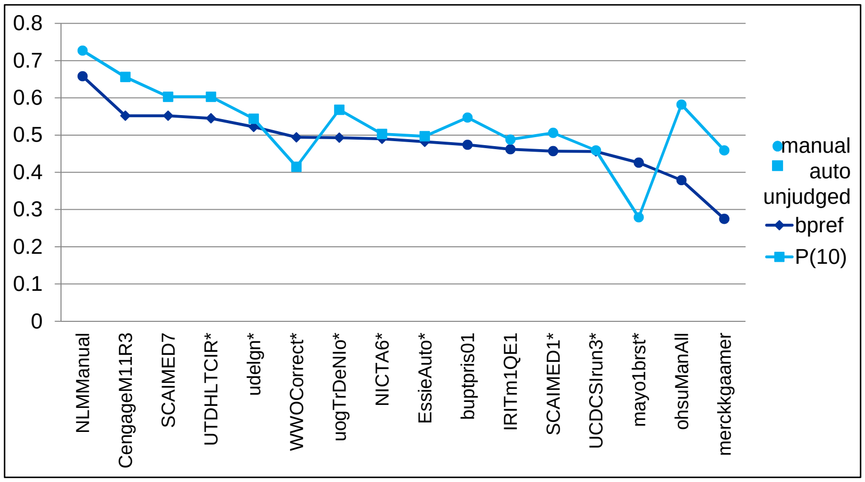
Sample topics

- Patients taking atypical antipsychotics without a diagnosis of schizophrenia or bipolar depression
- Patients treated for lower extremity chronic wound
- Patients with atrial fibrillation treated with ablation
- Elderly patients with ventilator-associated pneumonia

Participation

- Runs consisted of ranked list of up to 1000 visits per topic for each of 35 topics
  - Automatic – no human intervention from input of topic statement to output of ranked list
  - Manual – everything else
- Up to 8 runs per participating group
- Subset of retrieved visits contributed to judgment sets
  - Because resources for judging limited, could not do complete judgments, necessitating use of BPref for 1˚ evaluation measure
- 127 runs submitted from 29 groups
  - 109 automatic
  - 18 manual

Evaluation results for top runs …



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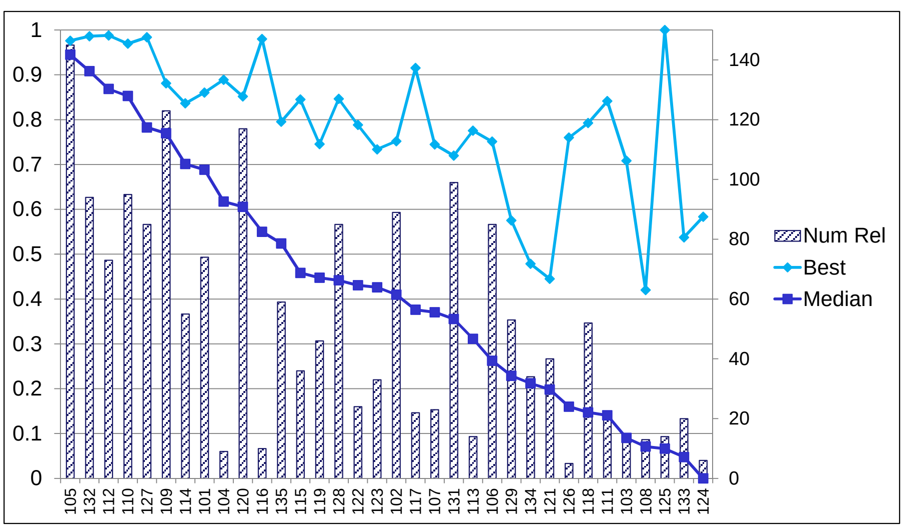
… BUT, wide variation among topics



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Easy and hard topics

- Easiest – best median bpref
  - 105: Patients with dementia
  - 132: Patients admitted for surgery of the cervical spine for fusion or discectomy
- Hardest – worst best bpref and worst median bpref
  - 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 bpref
  - 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

What approaches did (and did not) work?

- Best results obtained from NLM group (Demner-Fushman, 2011)
  - Top results from manually constructed queries using Essie domain-specific search engine (Ide, 2007) – BPref = 0.658
  - Other automated processes fared less well, e.g., creation of PICO frames, negation, term expansion, etc. – BPref = 0.4822
- Best automated results also obtained by Cengage (King, 2011)
  - Filtered by age, race, gender, admission status; terms expanded by UMLS Metathesaurus – BPref = 0.552
- Benefits of approaches commonly successful in IR did provided small or inconsistent value for this task
  - Document focusing, term expansion, etc.

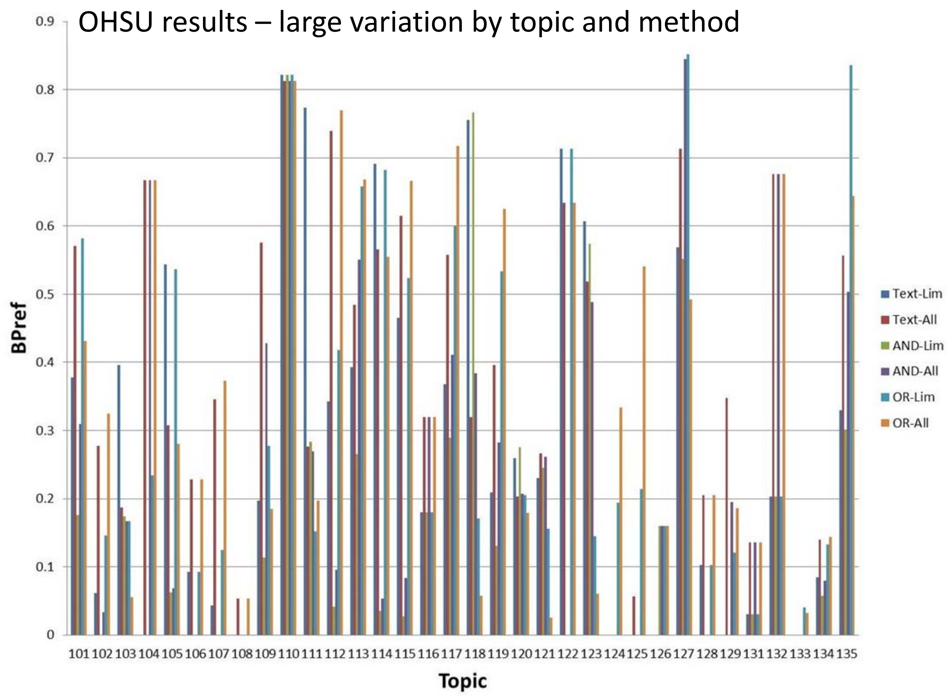
OHSU approach (Bedrick, 2011)

- Manually constructed queries of text and ICD-9 codes, run against all and high-yield (discharge summary, emergency department) documents
- Visits ranked by top-ranking documents
- Text and ICD-9 combined by Boolean operators

Run	BPref	P@10
Text-only – All	0.3751	0.5853
Text-only – High	0.2894	0.4824
Text AND ICD-9 – All	0.2497	0.4471
Text AND ICD-9 – High	0.1695	0.3235
Text OR ICD-9 – All	0.3657	0.4618
Text OR ICD-9 – High	0.3238	0.4206

Example query (topic #127)
Text: (diabetes mellitus) OR diabetic OR DM OR hypertension AND (morbid obesity)
ICD-9: 278.01 AND (250.* OR 401.* OR 405.*)

OHSU results – large variation by topic and method



Conclusions and future directions

- Growing amount of EHR data provides potential benefit for learning healthcare system
  - Many challenges to use of EHR data exist
  - One potentially beneficial technique is understanding of data in clinical narrative text
- TREC Medical Records Track extended IR challenge evaluation approach to a patient selection triage task
  - Initial results show mixed success for different methods – common with a new IR task
- Future work can hopefully proceed from this and other data sets – if there is continued access to the test collection allowed

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