



CONCEPT-BASED AND MULTIMODAL METHODS FOR MEDICAL CASE RETRIEVAL

PhD Defense
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OUTLINE 1

1. Introduction

- Medical Case Retrieval (MCR)
- Problem Statement
- Contributions

2. Biomedical Concept Mapping

3. Multimodal MCR

4. Further Work

5. Conclusion



MEDICAL CASE RETRIEVAL (MCR)

Problem statement

XML metadata for a medical case report:

```

<TOPIC>
  <ID>1</ID>
  <CTYPE>Case-Data</CTYPE>
  <SHORT-DESCRIPTION>
    A 43 year old man with painless, gross hematuria. Abdominal CT scan revealed a large left renal mass with extension into the retrorenal pelvis and ureter.
  </SHORT-DESCRIPTION>
  <IMAGE-Case-QueryImages201211_3.jpg</IMAGE>
  <Image-Case-QueryImages201211_2.jpg</IMAGE>
  <Image-Case-QueryImages201211_3.jpg</IMAGE>
</TOPIC>
  
```

The image shows a grid of CT scan slices of a kidney, with a large mass visible in the left renal pelvis.

Patient's symptoms

How to
find



relevant
documents?

XML metadata for a medical publication:

```

<article pmid="101267" pmid="11914125" doi="10.1188/071-0121-3-7" pmc-article-
url="http://www.ncbi.nlm.nih.gov/pmc/articles/PMC101267" original-article-
url="http://www.ncbi.nlm.nih.gov/pmc/articles/PMC101267">
  <title>
    The new anti-actin agent dihydrohalichondramide reveals filament-forming centers in hepatic
    endothelial cells
  </title>
  <authors><authors>
  </authors>
  <abstract></abstract>
  <fulltext></fulltext>
  </article>
  <figure Id="1471-2021-3-7-3">
    <caption>
      Fluorescence micrographs showing the effects of HALI and di-HALI on actin organization in
      LLCs, monitored with rhodamine-actin (R-actin) (red) and fluorescently-labeled F-actin
      (G-actin) (green). Blue color represents the nucleus stained with DAPI. (A) F-actin distribution in
    </caption>
  </figure>
  
```

The image shows a scientific figure with three panels: (A) Fluorescence micrographs of cells, (B) A line graph showing the number of filaments per cell over time, and (C) Fluorescence micrographs of cells.

Medical publications / health records

- Major component of **medical decision support systems** based on **case-based reasoning**
- Solution may help to generate datasets for **medical education and research**



PROBLEM STATEMENT

- **State of the art** for MCR on general datasets:
 - Best systems employ purely textual techniques
- **Main research problem:**
 - How to improve MCR methods using textual and visual information?
- **Hypothesis:**
 - **Biomedical concepts** may help – with techniques:
 - Query or document expansion for text retrieval
 - Concept-based retrieval
 - Fusion of text and concept-based retrieval



CONTRIBUTIONS OF PHD THESIS

- Novel automatic methods for **compound figure** classification and separation
- Evaluation of **concept mapping** techniques:
 - New and existing methods of mapping text or images to biomedical concepts
- Comparison of **query and document expansion** by biomedical concepts for text-based MCR
- Novel framework **combining text and concept-based retrieval**, improving over state of the art



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OUTLINE 2

1. Introduction
2. Biomedical Concept Mapping
 - Medical Subject Headings (MeSH)
 - Text-to-Concept Mapping
3. Multimodal MCR
4. Further Work
5. Conclusion



MEDICAL SUBJECT HEADINGS

- Controlled vocabulary of biomedical concepts:
 - ~27k primary terms, ~161k synonyms
 - “More general than” relations between primary terms impose 16 tree structures (maximal depth 11)
- Used to annotate biomedical publications

<i>Primary MeSH Term</i>	<i>Node Identifier</i>	<i>Specialty</i>
Eye Neoplasms	C04.588.364	2
Neoplasms by Site	C04.588	1
Neoplasms	C04	0
Eye Neoplasms	C11.319	1
Eye Diseases	C11	0



TEXT-TO-CONCEPT MAPPING 1

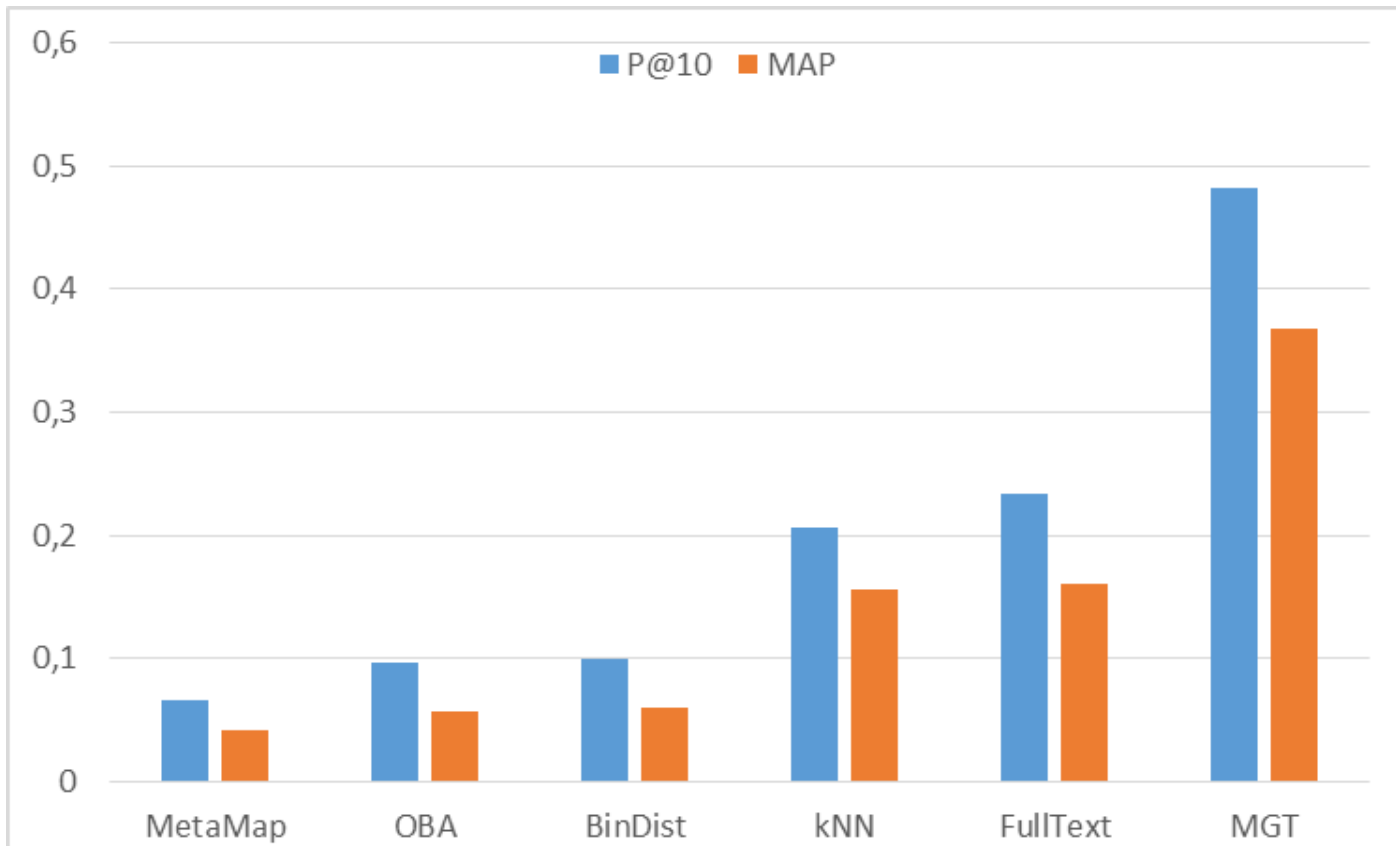
- Existing systems:
 - MetaMap, Open Biomedical Annotator: slow
 - Whatizit MeshUp: **kNN classifier**, short text input only
- Novel, more efficient **string matching** approach:
 - based on inverted index of MeSH terms
 - finds (partial) occurrences of MeSH terms in single pass through text document
- Effectiveness evaluated for two objectives:
 - **classification**: reproducing manual MeSH annotations
 - **concept-based retrieval** on MCR dataset (~75k docs)



TEXT-TO-CONCEPT MAPPING 2

Concept-based retrieval on MCR dataset

MGT: “ideal” concept mapping using ground-truth MeSH terms



35 queries
75k docs
BinDist index

Algorithms
used for
query
mapping

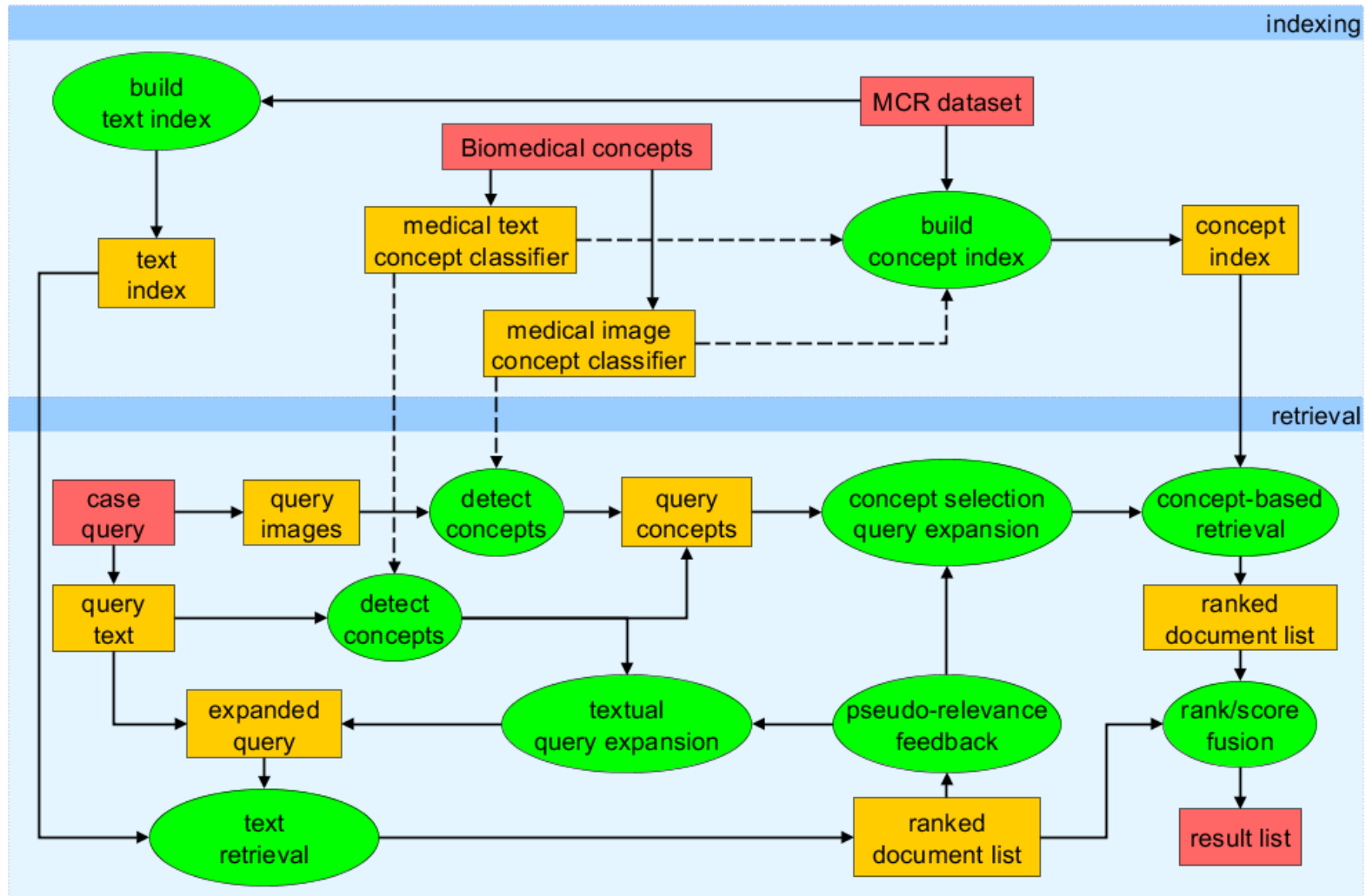


OUTLINE 3

1. Introduction
2. Biomedical Concept Mapping
3. Multimodal MCR
 - Framework for Text- and Concept-Based Retrieval
 - Fusion Methods
 - Results
4. Further Work
5. Conclusion



RETRIEVAL FRAMEWORK





FUSION METHODS

- Fuse result lists of retrieval methods A and B
- **Linear fusion:** $s = \beta * s_A + (1 - \beta) * s_B$
 - Combine retrieval scores with **fixed weight** β
 - s_A, s_B : logistic score normalization from rank positions
- **Query-adaptive fusion (QAF):**
 - For each query q , choose **weight** β depending on q
 - E.g. by estimating performance of A and B for q
$$\beta = p_A^2 / (p_A^2 + p_B^2)$$
 - **“Ideal” QAF:** use an oracle returning true average precision for q , used as p_A and p_B



FUSION RESULTS ON MCR DATASET

F: fulltext retrieval (R)

T: text-based R (query expansion)

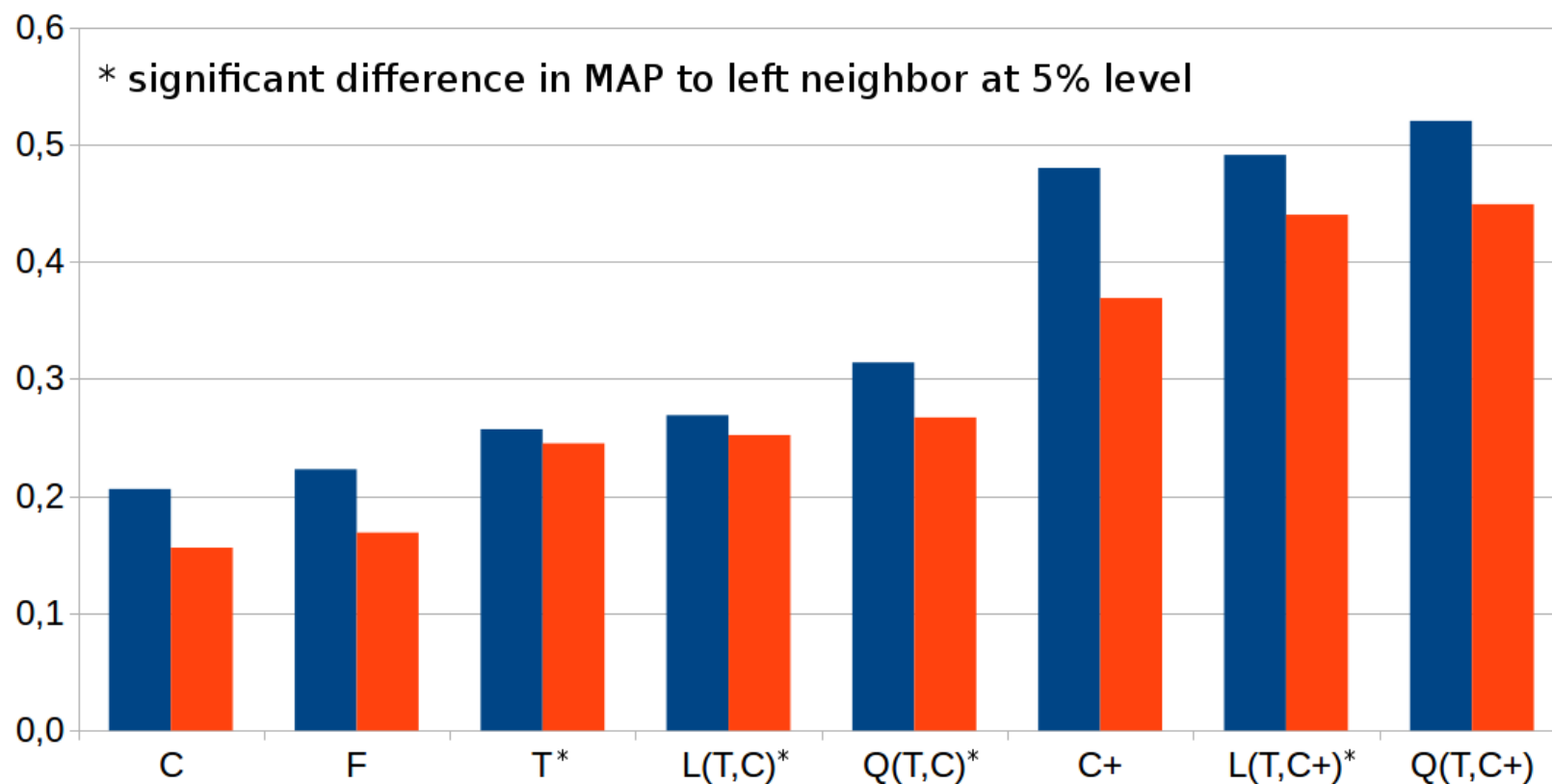
L: linear fusion

C: practical concept-based R

C+: ideal concept-based R

Q: ideal query-adaptive fusion

■ P@10 ■ MAP





OUTLINE 4

1. Introduction
2. Biomedical Concept Mapping
3. Multimodal MCR
4. Further Work
 - Concept Mapping
 - Retrieval in Multi-View Latent Space
5. Conclusion



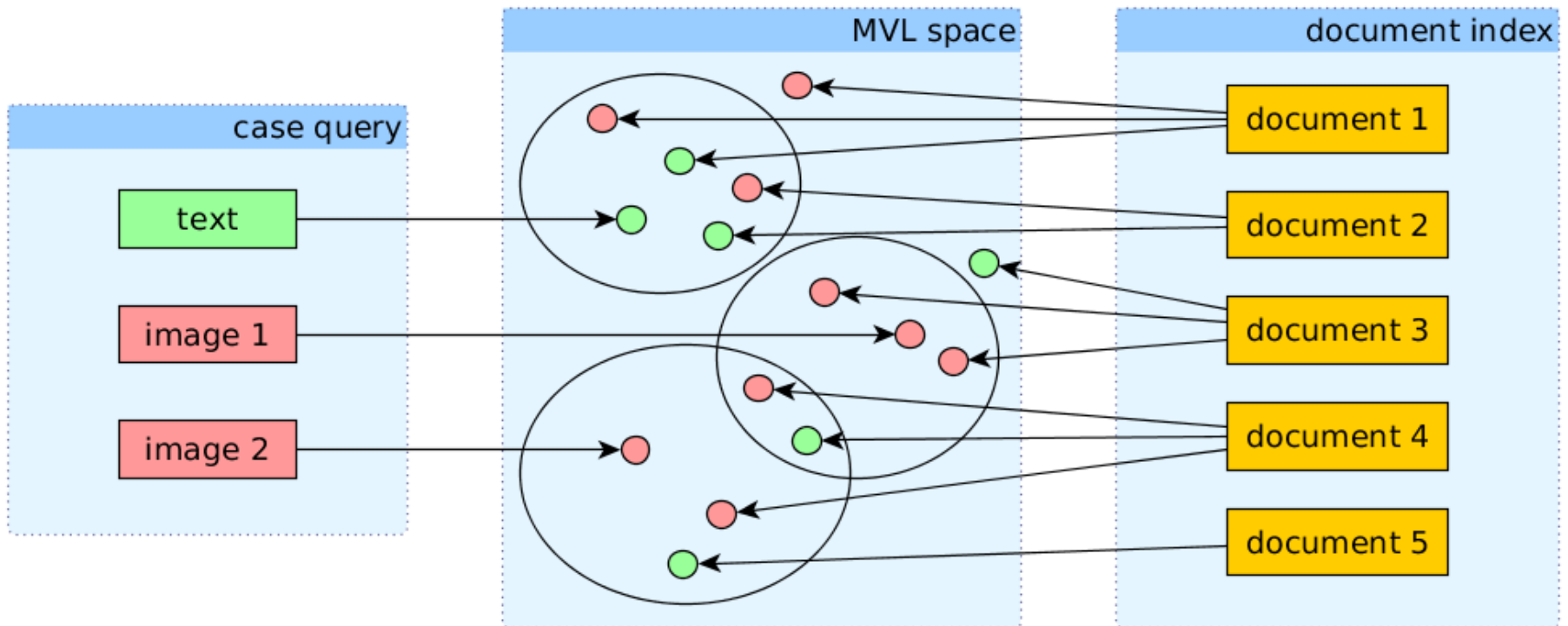
FURTHER WORK 1

- Concept mapping:
 - Apply **multi-view learning**
 - Textual and visual modalities can be used as views and non-linearly mapped to a shared latent space
 - Concept mapping is learned by linear projections or kNN techniques in latent space
 - Conceptual and experimental work partly done
 - Apply **deep learning** to concept mapping
 - Recent advances in image caption generation may provide a starting point



FURTHER WORK 2

- Retrieval in multi-view latent (MVL) space:
 - Assumption: nearby points in latent space represent semantically similar cases





CONCLUSION

- **Biomedical concepts can help** to improve MCR over fulltext retrieval
 - Text-based query expansion increased MAP by 45%
 - Multimodal fusion with practical concept-based retrieval added another 13%
- There is **room for future improvements** of concept-based and multimodal techniques
 - Ideal concept-based retrieval and fusion improved MAP by 161% w.r.t. fulltext retrieval