Australian National University

DWRank: Learning concept ranking for ontology search

In Semantic Web Journal, vol. 7, no. 4, Pages 447-461, May 2016

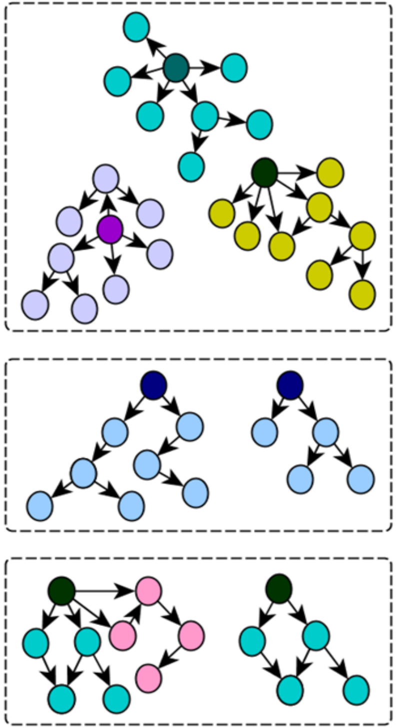
Anila Sahar Butt, ***Armin Haller***, and Lexing Xie
The Australian National University

CONCEPT SEARCH AND RANKING

Concept Search and Ranking

- Concept Search
  - Matching a search term with a more expressive class description

- Matching terms are defined with differing
  - Perspectives
  - Levels of detail
  - Reuse and Extensions



How to rank similar concepts with different levels of modelling details?

Relationship based Concept Retrieval Framework

- The framework retrieves and rank concepts for keyword query
  - DWRank Ranking Model
  - Top-k Filters

DWRank – Dual Walk Ranking Model

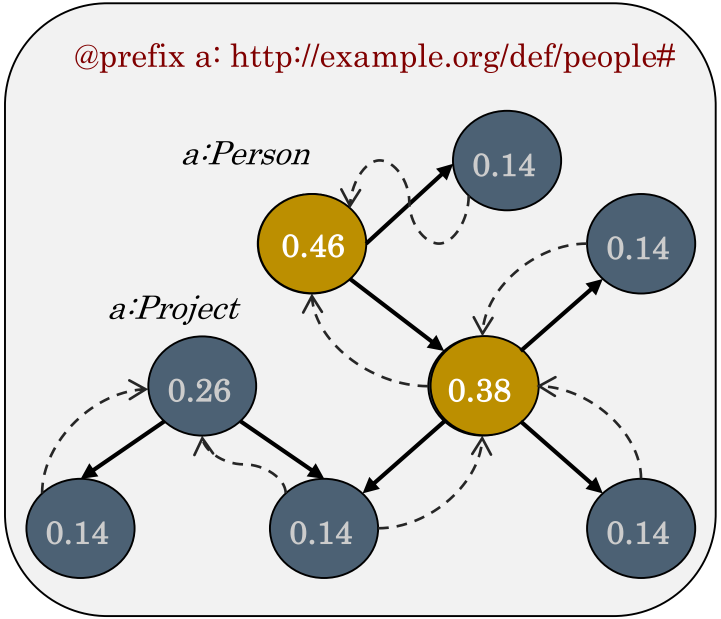
- Query independent scores for each concept of ontologies based on their importance
  - **HubScore:** Centrality of the concept
  - **AuthScore:** Authoritativeness of the Ontology

- Relevance score of a concept to a query:
  - **DWRank Function:** Linear model combines
    - Text relevancy of the concept label to a query
    - HubScore and AuthScore

Australian National University

HubScore – Centrality of a Concept

- **Connectivity:**
  - Relations starting from the concept
- **Neighbourhood:**
  - Relations starting from the concept to another central concept

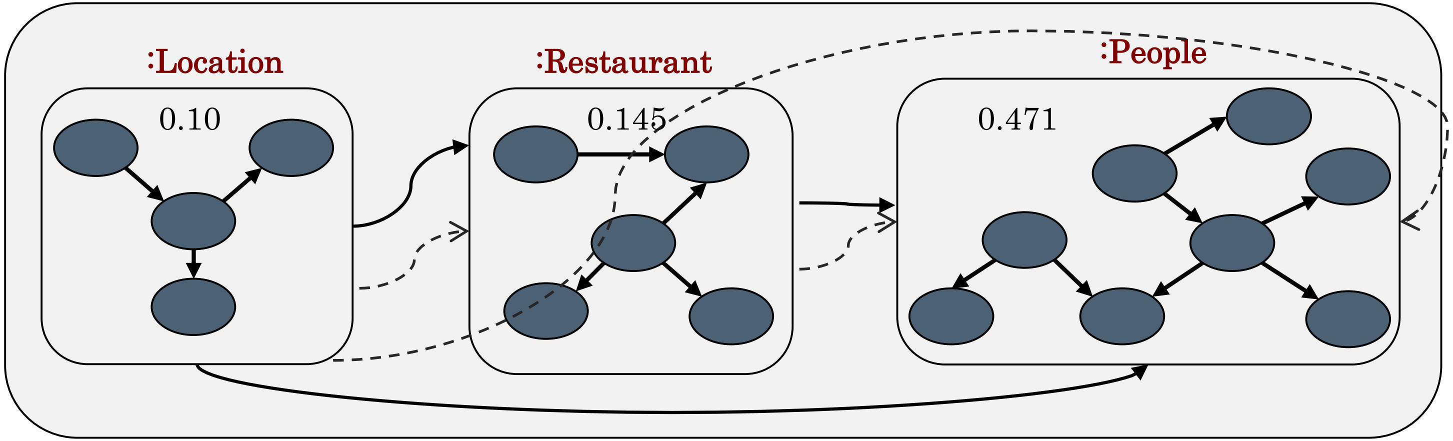


Reverse PageRank

AuthScore – Authoritativeness of an Ontology

- **Reuse** : Relations ending at the ontology
- **Neighbourhood** : Relations starting from another authoritative ontology to the ontology

PageRank



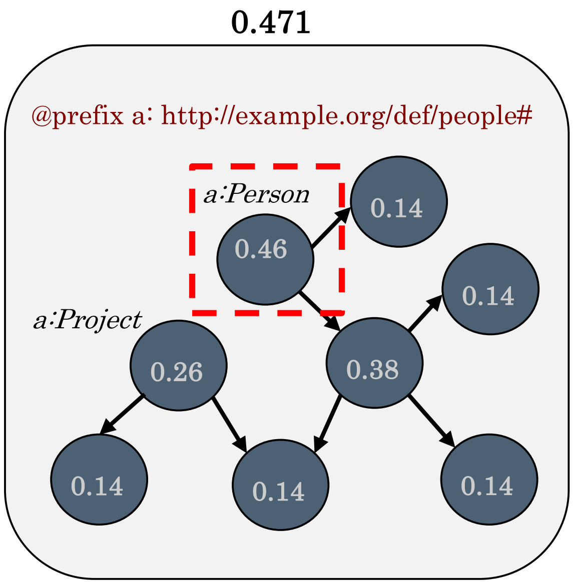
DWRank Function

- The ranking model is function of
  - Concept Relevancy: $F_v(v, Q) = \sum_{q \in Q} f(q, \varphi(q))$
  - Hub Score: $h(v, Q)$
  - Auth Score: $a(O)$

- $R(v, Q) = Fv(v, Q) * [\,\alpha\, h(v, Q) + (1 - \alpha)\, a(O)]$

  $= 1 * [0.5\ (0.46) + 0.5(0.471)]$

  $= 0.466$



DWRank vs. Linked-based Ranking Models

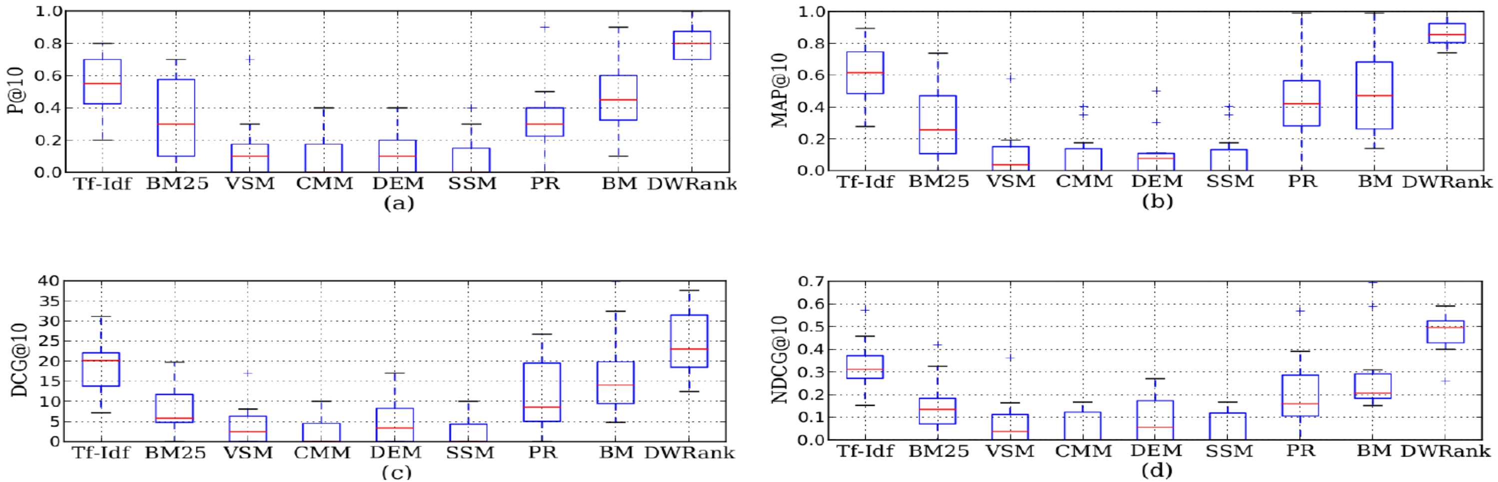
1. Direction of the walk varies based on the link type
   - Intra-ontology links: Reverse PageRank
   - Inter-ontology links: PageRank
2. Linked Analysis :
   - HubScore – Concept
     - Independently on each ontology
   - AuthScore – Ontology
     - Ontology Corpus

Top-K Filter

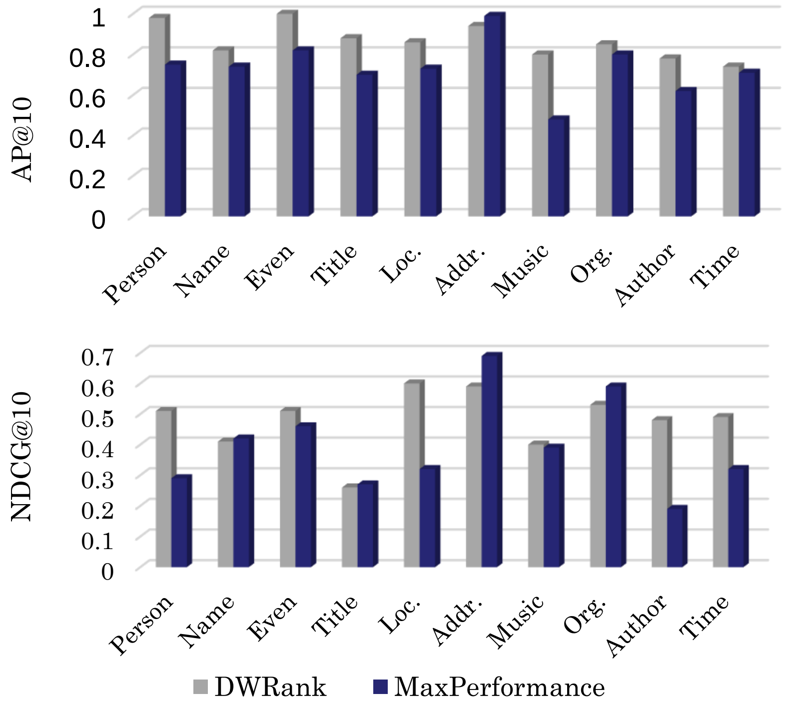
- Intended Type Filter
  - Intended Type vs. Context Resource
    - Name of the Person
      - Intended Type: Name
      - Context Resource: Person
- Distinct Resource Filter
  - Select Resources that are less overlapping

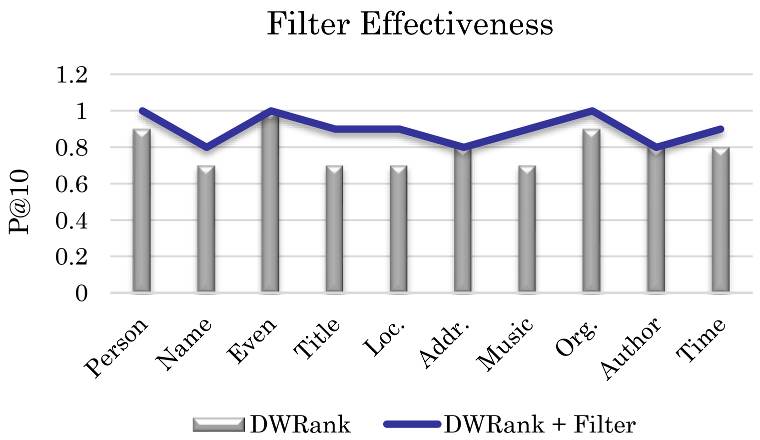
Evaluation

- Effectiveness of the approach
  - DWRank
  - DWRank + Filter
- CBRBench
  - Queries and Gold standard
  - Baseline Ranking models



DWRank and Filter Effectiveness





LEARNING CONCEPT RANKING

Need for LTR

- None of the commonly used evaluation algorithm performs adequately for all type of queries.

- So most of the proposed approaches used more than one ranking/evaluation metric to optimise the effectiveness of ranking models.
  - However for optimal performance of such algorithms the metrics' weights need to be reset for each user query.
    - Manually setting metrics' weights for each and every query is impractical
    - Solution: Learning to Rank

Learning Concept Ranking for DWRank

- Feature Set
  - HubScore, Max HubScore, Min HubScore, AuthScore, Text Relevancy
  - Target Feature: **Relevance Score**
- Training Data
  - CBRBench
    - <target> qid:<qid> <feature1>:<value> <feature2>:<value> … <featuren>:<value> #<info>
  - Data Set
    - Training Set,
    - Validation Set,
    - Test Set

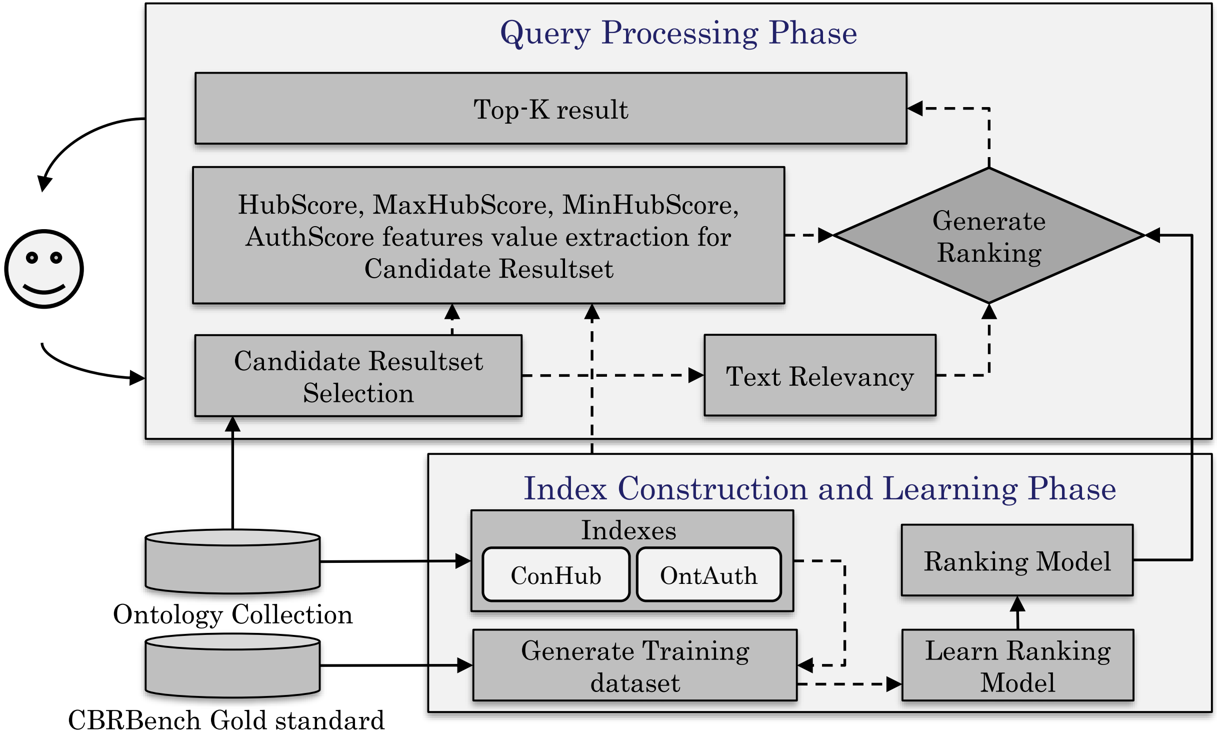
Australian National University

Learning Concept Ranking for DWRank (1/2)

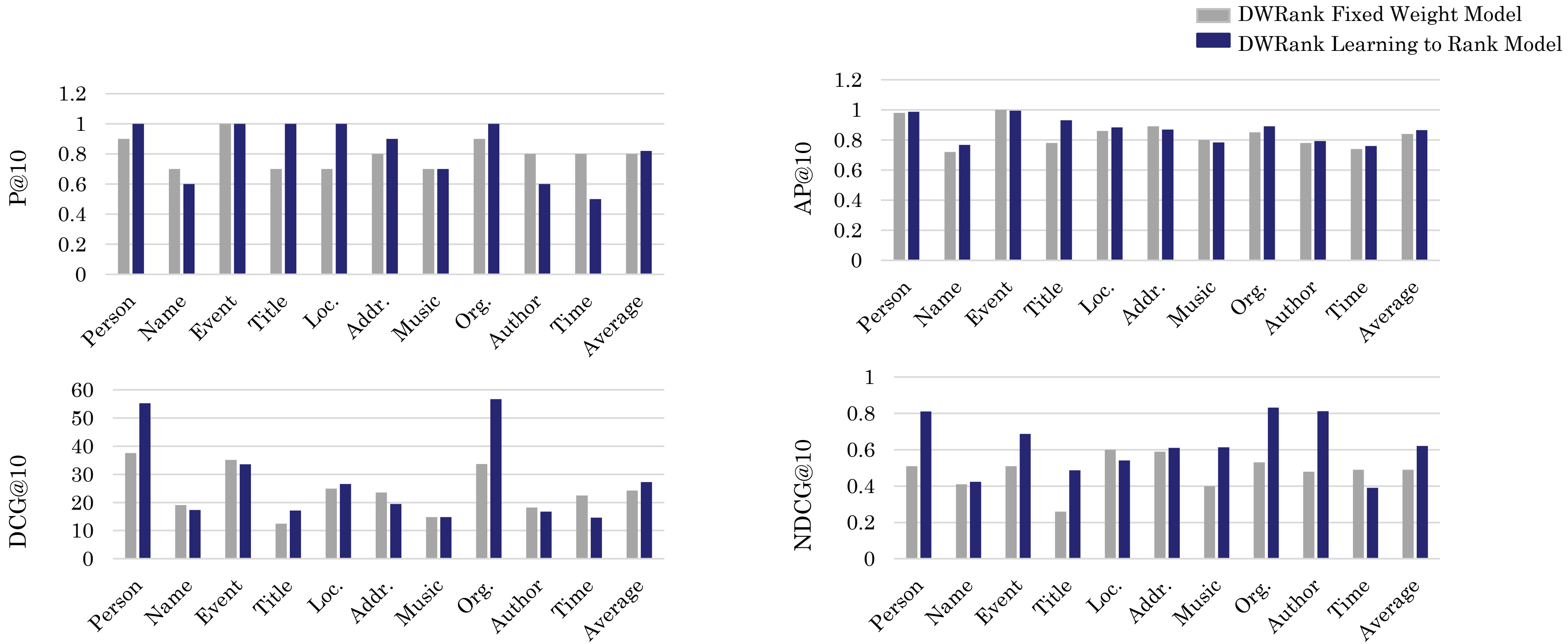
- Metrics
  - P@10, AP@10, DCG@10, NDCG@10

- Learning to Rank Algorithm
  - LambdaMART
    - RankLib: http://sourceforge.net/p/lemur/wiki/RankLib/
  - Leave-one-out Cross Validation (LOOCV)
  - Optimised NDCG and Tested DCG, AP, P

Framework Overview



Learning to Rank Model Effectiveness




time for questions
answer