Passage Retrieval & Re-ranking

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NLP Systems & Applications
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Roadmap

- Passage retrieval vs passage ranking
  - Comparisons of
    - Passage unit size
    - Passage type
- Passage re-ranking
  - Exploiting deeper processing
    - Dependency matching
    - Answer types

Units of Retrieval

- *Simple is Best: Experiments with Different Document Segmentation Strategies for Passage Retrieval*
  - Tiedemann and Mur, 2008

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- *Simple is Best: Experiments with Different Document Segmentation Strategies for Passage Retrieval*
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  - Comparison of units for retrieval in QA
    - Documents
    - Paragraphs
    - Sentences
    - Semantically-based units (discourse segments)
    - Spans

Motivation

- Passage units necessary for QA
  - Focused sources for answers
  - Typically > 20 passage candidates yield poor QA

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  - Typically > 20 passage candidates yield poor QA
- Retrieval fundamentally crucial
- Re-ranking passages is hard
  - Tellex et al experiments
    - Improvements for passage reranking, but
    - Still dramatically lower than oracle retrieval rates

	Strict				
	Lucene		PRISE		TREC
Algorithm	MRR	% Inc.	MRR	% Inc.	% Inc.
IBM	0.326	49.20%	0.331	39.60%	44.3%
ISI	0.329	48.80%	0.287	41.80%	41.7%
SiteQ	0.323	48.00%	0.358	40.40%	56.1%
MultiText	0.354	46.40%	0.325	41.60%	43.1%
Alicante	0.296	50.00%	0.321	42.60%	60.4%
bm25	0.312	48.80%	0.252	46.00%	n/a
stemmed MITRE	0.250	52.60%	0.242	58.60%	n/a

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ISI	37	8.56%	0.852
Alicante	39	9.03%	0.816
MultiText	44	10.19%	0.845
bm25	45	10.42%	0.810
MITRE	45	10.42%	0.800
stemmed MITRE	63	14.58%	0.762

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  - Documents vary in
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      - across type
  - Passages can be less variable
    - Effectively normalizing for length

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        - Not always available

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    - In words/chars or sentences/paragraphs
    - Overlapping?
    - Can be determined empirically
- All experiments use Zettair retrieval engine

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1. [Jim McClements en Susan Sandvig-Shobe]$_i$ hebben een onrechtmatig argument gebruikt.
2. [De Nederlandse scheidsrechter]$_j$ [Jacques de Koning]$_j$ bevestigt dit.
3. [Kuipers]$_k$ versloeg zondag in een rechtstreeks duel [Shani Davis]$_m$.
4. Toch werd [hij]$_k$ in de rangschikking achter [de Amerikaan]$_m$ geklasseerd.
5. [De twee hoofdarbiters]$_i$ verklaarden dat [Kuipers']$_k$ voorste schaats niet op de grond stond.

Cluster i (1,5): [Jim McClements en Susan Sandvig-Shobe]
[De twee hoofdarbiters]

Cluster j (2): [De Nederlandse scheidsrechter]
[Jacques de Koning]

Cluster k (3-5): [Kuipers] [hij] [Kuipers']

Cluster m (3,4): [Shani Davis] [de Amerikaan]

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  - Existing implementations

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    - Sentences required for downstream deep processing
  - Overlap? No overlap?
    - No overlap is simple, but
      - Not guaranteed to line up with natural boundaries
        - Including document boundaries

Evaluation

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  - CLEF Dutch QA track
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  - MAP
- Focus on MRR for prediction of end-to-end QA

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- MRR-IR; MRR-QA (top 5); CLEF: end-to-end score
- Surprisingly good sentence results in top-5 and CLEF
  - Sensitive to exact retrieval weighting

	#sent	cov	red	*MRR* IR	*MRR* QA	CLEF
sent	16,737	0.784	2.95	0.490	**0.487**	**0.430**
par	80,046	0.842	4.17	0.565	0.483	0.416
doc	618,865	0.877	6.13	0.666	0.457	0.387

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  - Paragraphs and coref chains (bounded)
  - TextTiling (CPAN) – Best : beats baseline

	#sent	MRR IR	MRR QA	CLEF
sent/coref	490,968	**0.604**	0.469	0.405
sent/coref (200-1000)	76,865	0.535	0.462	0.395
par+coref (200-1000)	82,378	0.560	**0.493**	0.426
par+coref (200-400)	67,580	0.555	**0.489**	0.422
TextTiling	107,879	**0.586**	△ **0.503**	**0.434**

Fixed Size Windows

- Different lengths: non-overlapping
- 2-, 4-sentence units improve over semantic units

	#sent	MRR IR	MRR QA	CLEF
2 sentences	33468	0.545	△ **0.506**	**0.443**
3 sentences	50190	0.554	**0.504**	**0.436**
4 sentences	66800	**0.581**	△ **0.512**	**0.447**
5 sentences	83575	**0.588**	**0.493**	0.422
6 sentences	100110	**0.583**	**0.489**	0.423

Sliding Windows

- Fixed length windows, overlapping
- Best MRR-QA values
  - Small units with overlap
  - Other settings weaker

	#sent	MRR IR	MRR QA	CLEF
2 sent (sliding)	29095	0.548	△ **0.516**	**0.456**
3 sent (sliding)	36415	0.549	**0.484**	0.411
4 sent (sliding)	41565	0.546	0.476	0.409
5 sent (sliding)	45737	0.534	0.465	0.403
6 sent (sliding)	49091	0.528	0.454	0.390

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- Competing retrieval demands:
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- Competing retrieval demands:
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  - QA performance
- MRR at 5 favors:
  - Small, fixed width units
    - Advantageous for downstream processing too
  - Any benefit of more sophisticated segments
    - Outweighed by increased processing

Reranking with Deep Processing

- Passage Reranking for Question Answering Using Syntactic Structures and Answer Types
  - Atkolga et al, 2011
- Reranking of retrieved passages
  - Integrates
    - Syntactic alignment
    - Answer type
    - Named Entity information

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    - Question implies particular relations
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  - Joint strategy required
    - Checking syntactic parallelism when no answer, useless
- Current approach incorporates all (plus NER)

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- Question analysis + Wordnet: QuAn-Wnet
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- Best performance: QuAn-Wnet (baseline)

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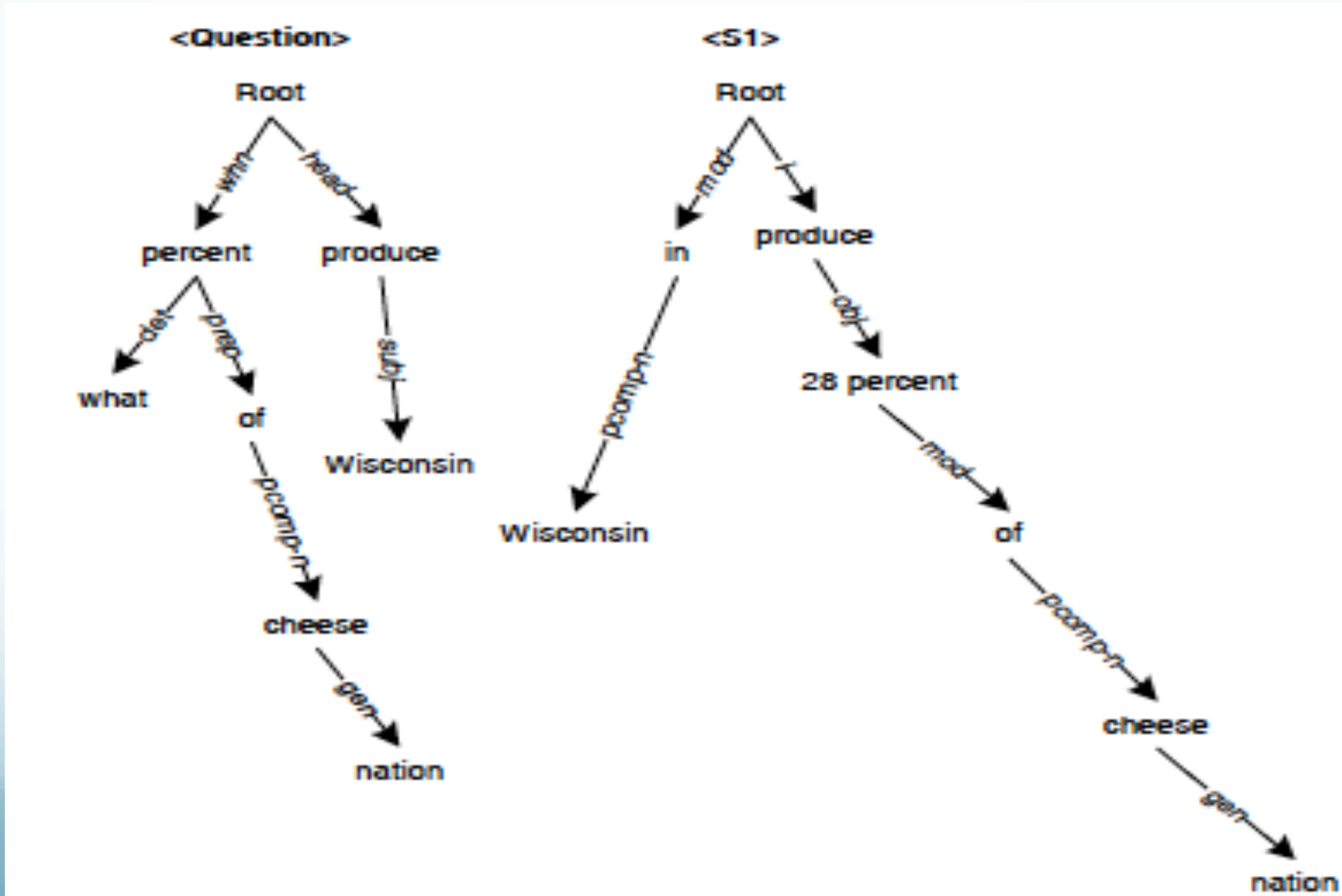
- Train path 'translation pair' probabilities
  - Use true Q/A pairs, $<path_q,path_a>$
  - GIZA++, IBM model 1
    - Yields $Pr(label_a,label_q)$

Dependency Path Similarity



Dependency Path Similarity

Figure 2. Dependency trees for the sample question and sentence S1 in Figure 1 generated by Minipar. Some nodes are omitted due to lack of space.

Question:

Path_ID	Node1	Path	Node2
<P_{Q1}>	Wisconsin	*<subj>*	produce
<P_{Q2}>	produce	*<head, whn, prep, pcomp-n>*	cheese
<P_{Q3}>	nation	<gen>	cheese

S1:

Path_ID	Node1	Path	Node2
<P_{S1}>	Wisconsin	*<pcomp-n, mod, i>*	produce
<P_{S2}>	produce	*<obj, mod, pcomp-n>*	cheese
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- Approaches have employed
  - Exact match
  - Fuzzy match
  - Both can improve over baseline retrieval, fuzzy more

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$$\frac{1}{|path_a|} \prod_{label_{a_j}} \sum_{label_{q_t}} \Pr(label_{a_j} \mid label_{q_t})$$

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$$\max_i \sum_{path_q, path_a \in Paths_{ACand_i}} scorePair(path_q, path_a)$$

Comparisons

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- QuAn-Elim:
  - Acts a passage answer-type filter
  - Excludes any passage w/o correct answer type

Results

- Atype-DP-IP best

Table 2. Evaluation of Reranking Techniques. All results are averages from the testing datasets TREC 2000 and TREC 2001, evaluated on the top 100 retrieved passages.

Model	*MRR@1*	*MRR@5*	*MRR@10*	*MRR@20*	*MRR@50*	*MRR@100*
Q-BOW	0.168	0.266	0.286	0.293	0.299	0.301
QuAn-Wnet	0.193	0.289	0.308	0.319	0.324	0.325
Cui	0.202	0.307	0.325	0.335	0.339	0.341
Atype-DP	0.148	0.24	0.26	0.273	0.279	0.28
Atype-DP-IP	**0.261***	**0.363***	**0.38***	**0.389***	**0.393***	**0.394***
% Improvement over Cui	**+29.2**	+18.24	+16.9	+16.12	+15.9	+15.54
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  - Employ explicit rank learner
    - E.g. RankBoost

Shallow Features & Ranking

- Is Question Answering an Acquired Skill?
  - Ramakrishnan et al, 2004
- Full QA system described
  - Shallow processing techniques
  - Integration of Off-the-shelf components
  - Focus on rule-learning vs hand-crafting
  - Perspective: questions as noisy SQL queries

Architecture

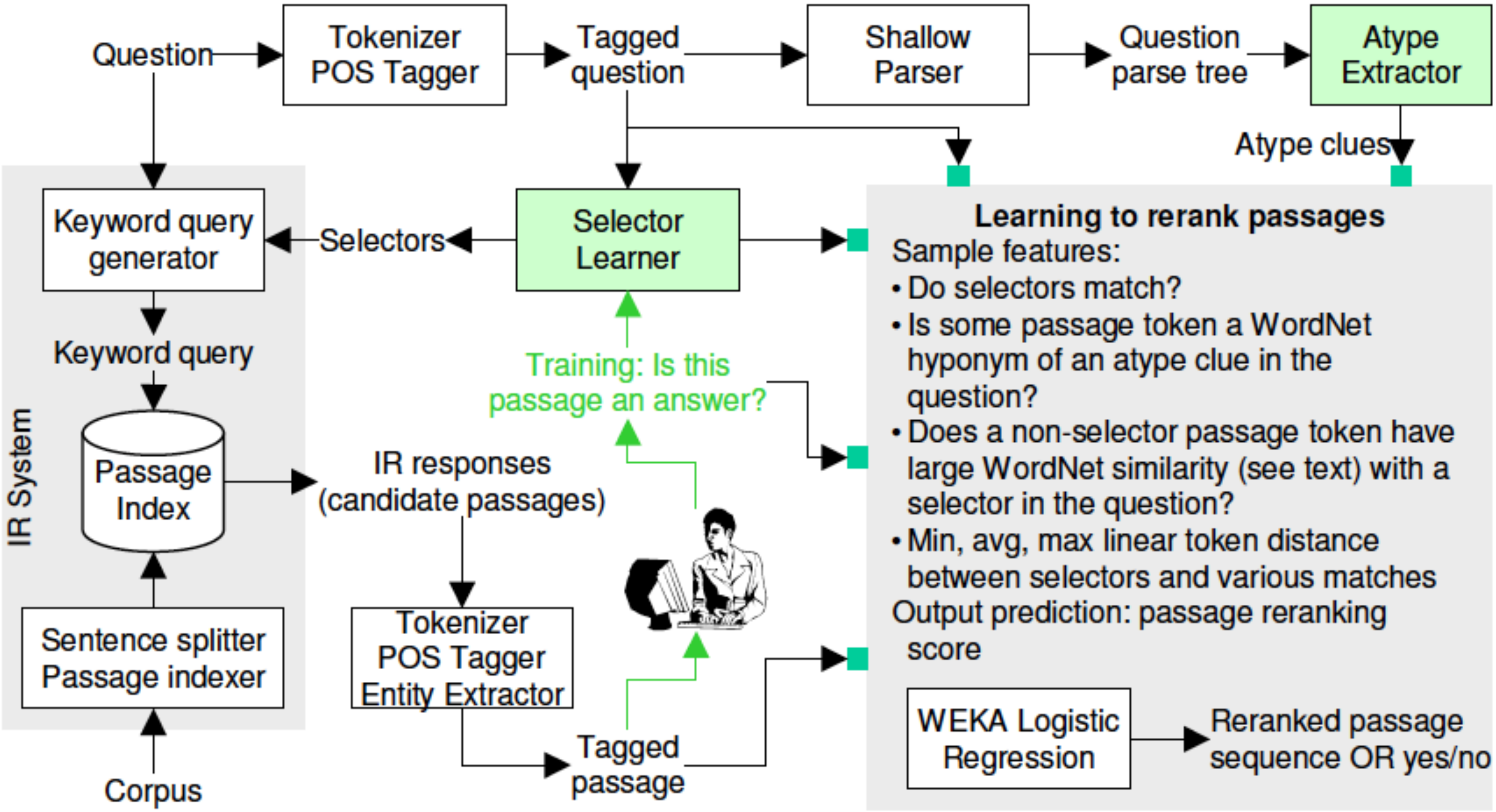

Figure 2: Overall architecture of our trainable QA system.

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- Question-type classification
  - Based on shallow parsing
  - Synsets or surface patterns

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      - Tokyo+++
      - Capital+
      - Country?

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    - Measures of word specificity/ambiguity
- Train Decision Tree classifier on gold answers: +/-S

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Passage Ranking

- For question q and passage r, in a good passage:
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  - Distances b/t selectors and answer zone A are small
  - A has high similarity with question type
  - Relationship b/t Qtype, A's POS and NE tag (if any)

Passage Ranking Features

- Find candidate answer zone A* as follows for (q.r)
  - Remove all matching q selectors in r
  - For each word (or compound in r) A
    - Compute Hyperpath distance b/t Qtype & A
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- Compute L as set of distances from selectors to A*
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  - IR passage rank; HD score; max, mean, min of L
  - POS tag of A*; NE tag of A*; Qwords in q

Passage Ranking

- Train logistic regression classifier
  - Positive example:

Passage Ranking

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  - Positive example: question + passage with answer
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  - Negative example: question w/any other passage
- Classification:
  - Hard decision: 80% accurate, but
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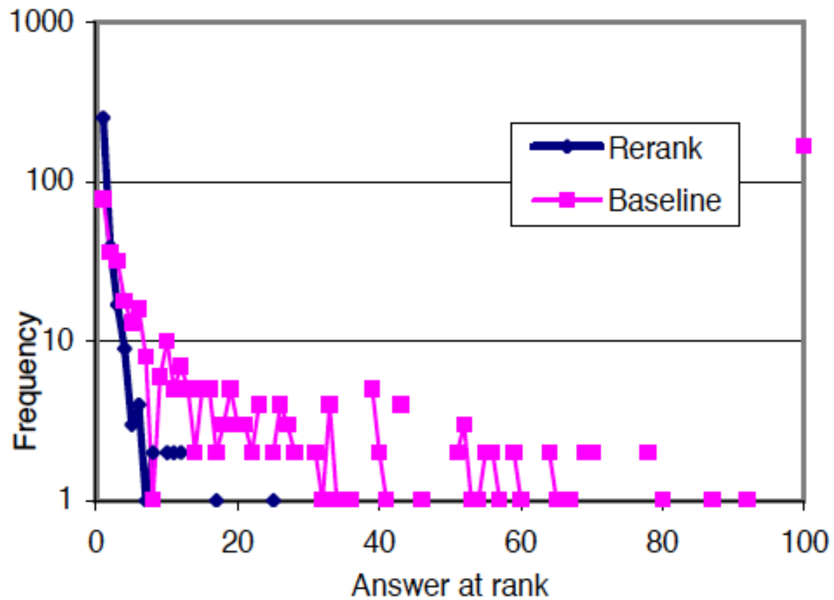
- Use regression scores directly to rank

Passage Ranking



igure 9: Reranking significantly improves the rank
f correct passages. The x-axis is the rank at which

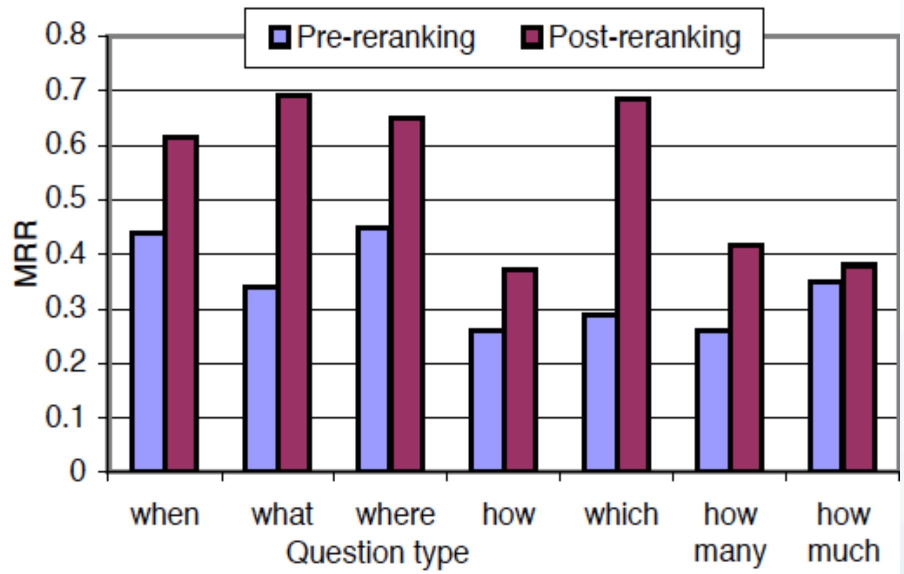


Figure 12: Sample MRR improvement via reranking separated into question categories.