

Selective Labeling and Incomplete Label Mitigation for Low-Cost Evaluation

Kai Hui, Klaus Berberich

Max Planck Institute for Informatics

khui@mpi-inf.mpg.de

kberberi@mpi-inf.mpg.de

Sep. 01, 2015



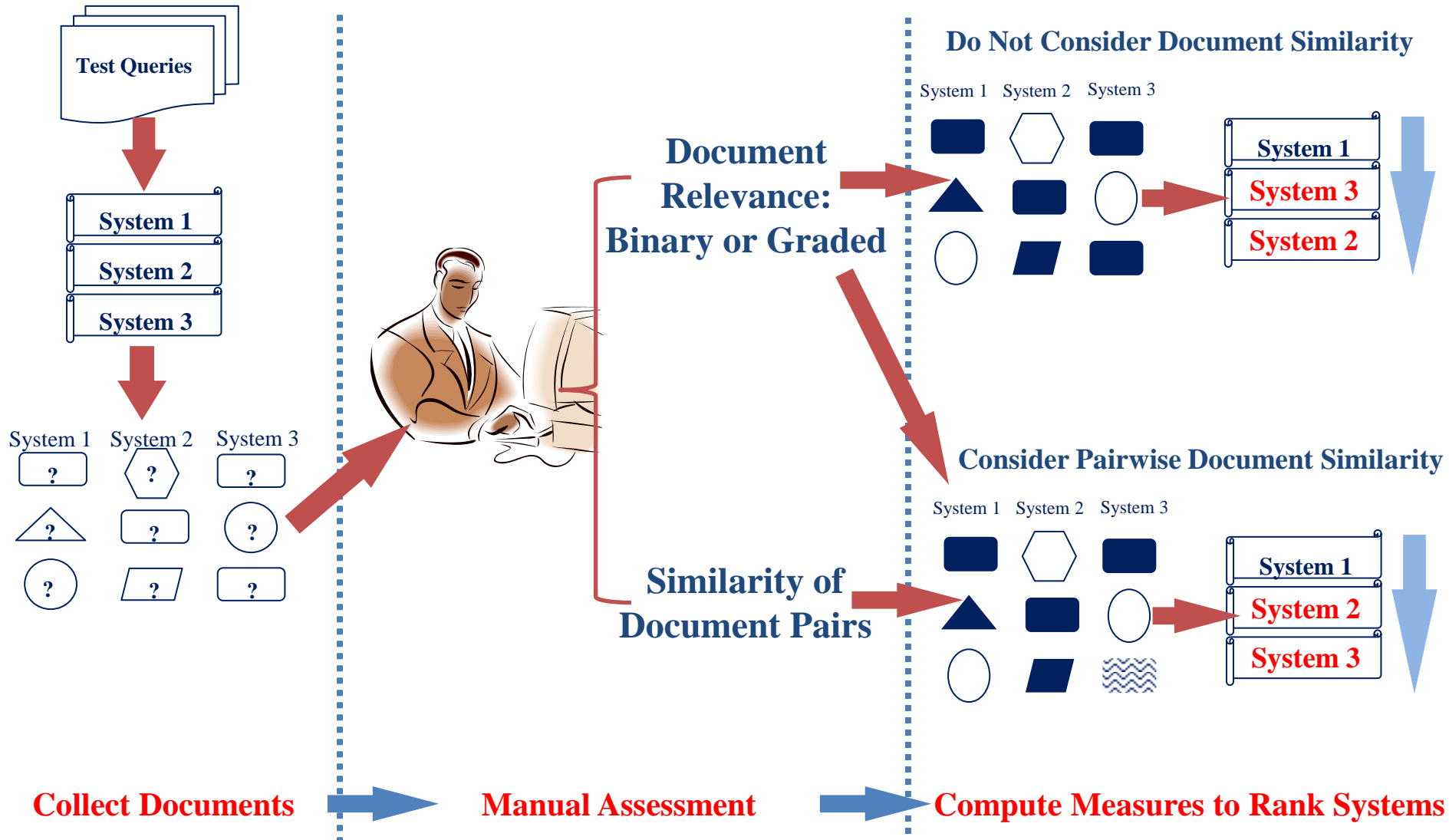
Overview

- Background: IR Evaluation
- Objectives & Related Work
- MaxRep Selective Labeling
- Experimental Results
- Conclusion

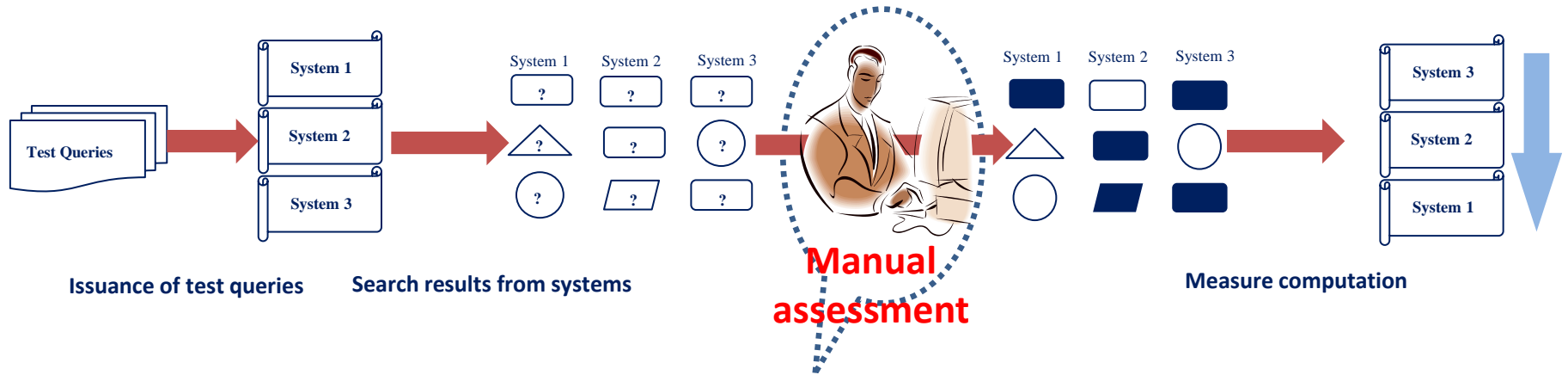
Overview

- Background: IR Evaluation**
- Objectives & Related Work
- MaxRep Selective Labeling
- Experimental Results
- Conclusion

Background: IR Evaluation Pipeline



Expensive Cost of Evaluation



Statistics of Labels from TREC Web Track

Year	#Systems	Pooling depth	#Total labeled doc
2011	62	25	19,344
2012	48	20/30	16,036
2013	61	10/20	14,336
2014	42	25	14,429

Overview

- Background: IR Evaluation
- Objectives & Related Work**
- MaxRep Selective Labeling
- Experimental Results
- Conclusion

Objective:

Evaluation with Fewer Labels

Evaluation based on complete judgment

Low-cost evaluation with fewer labels

Collect Documents



Select Subset of Documents

How to select the subset?



Manual Assessment



Mitigate Missing Labels

How to mitigate the unlabeled documents?

Measures Computation

Related Work

Evaluation based on complete judgment

Collect Documents

Manual Assessment

Measures Computation

Low-cost evaluation with fewer labels

Select Subset of Documents

Different selection strategies:

- **Sampling:** uniformly sampling, statAP
- **Pooling:** incremental pooling
- **Active selection:** MTC, RTC

Mitigate Missing Labels

Different mitigation methods:

- **Regard missing labels as non-relevant or non-existing:** default in TREC, indAP & condensed list
- **Distinct labeled non-relevant documents:** bpref
- **As random variables:** infAP, eMAP (MTC)
- **Predict missing labels**

Overview

- Background: IR Evaluation
- Objectives & Related Work
- MaxRep Selective Labeling**
- Experimental Results
- Conclusion

Framework:

Selective Labeling & Label Prediction

Observations

- ❑ **Cluster Hypothesis:** relevant documents are clustered
- ❑ **Label Bias:** there exist more non-relevant documents than relevant documents

Selective Labeling Strategies

Cluster Hypothesis → representative documents

Label Bias → documents are more likely to be relevant

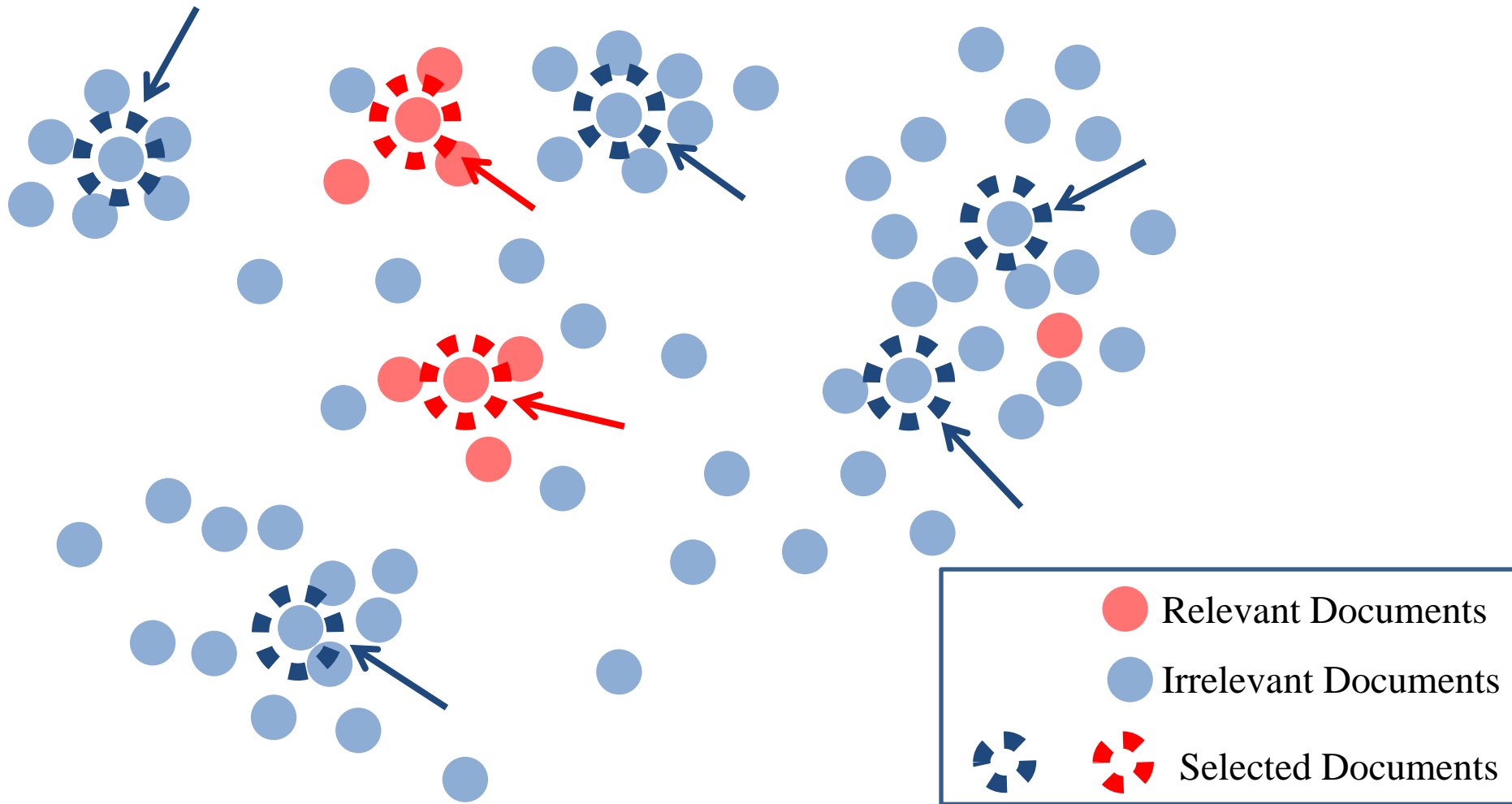
General Framework

Selective Labeling + Label Prediction

Label Prediction

Standard text classification method: SVM with linear kernel

MaxRep Example: Document Vector Space for A Given Query



MaxRep Method: Representative Documents

Representativeness of Document Subset

- Document subset L with t documents from document collection D
- Representativeness of L is the aggregating maximum coverage of the remaining documents D

$$f(L) = \sum_{d_i \in D_q} \max_{d_j \in L} \text{sim}(d_i, d_j)$$

MaxRep Method: Encode Document Relevance

Encode Document Relevance in Selection

- AP-Prior: documents ranked higher by rivaling systems are more likely to be relevant. n denotes length of ranking, r is the rank

$$P[r] \approx \frac{1}{2n} \log \frac{n}{r}$$

- Allocate aggregated AP-Prior weight w to document

$$f(L) = \sum_{d_i \in D_q} \max_{d_j \in L} w_i \text{sim}(d_i, d_j)$$

Optimization Target: $L_k^* = \operatorname{argmax}_{L_k} f(L) \quad \text{s.t.} \quad |L| = k$

Overview

- Background: IR Evaluation
- Objectives & Related Work
- MaxRep Selective Labeling
- Experimental Results**
- Conclusion

Experimental Setting

❑ Dataset

TREC Web Track 2011–2014 on ClueWeb 09 & 12, 64 k labeled documents, 200 queries

❑ Ground truth measure

Mean Average Precision (MAP)

❑ Benchmark

➤ Kendall's τ correlation:

Approximation to the system ranking

➤ Root Mean Square Error (RMSE):

Approximation to the MAP values

Methods in Comparison

Different alternatives in two building blocks:

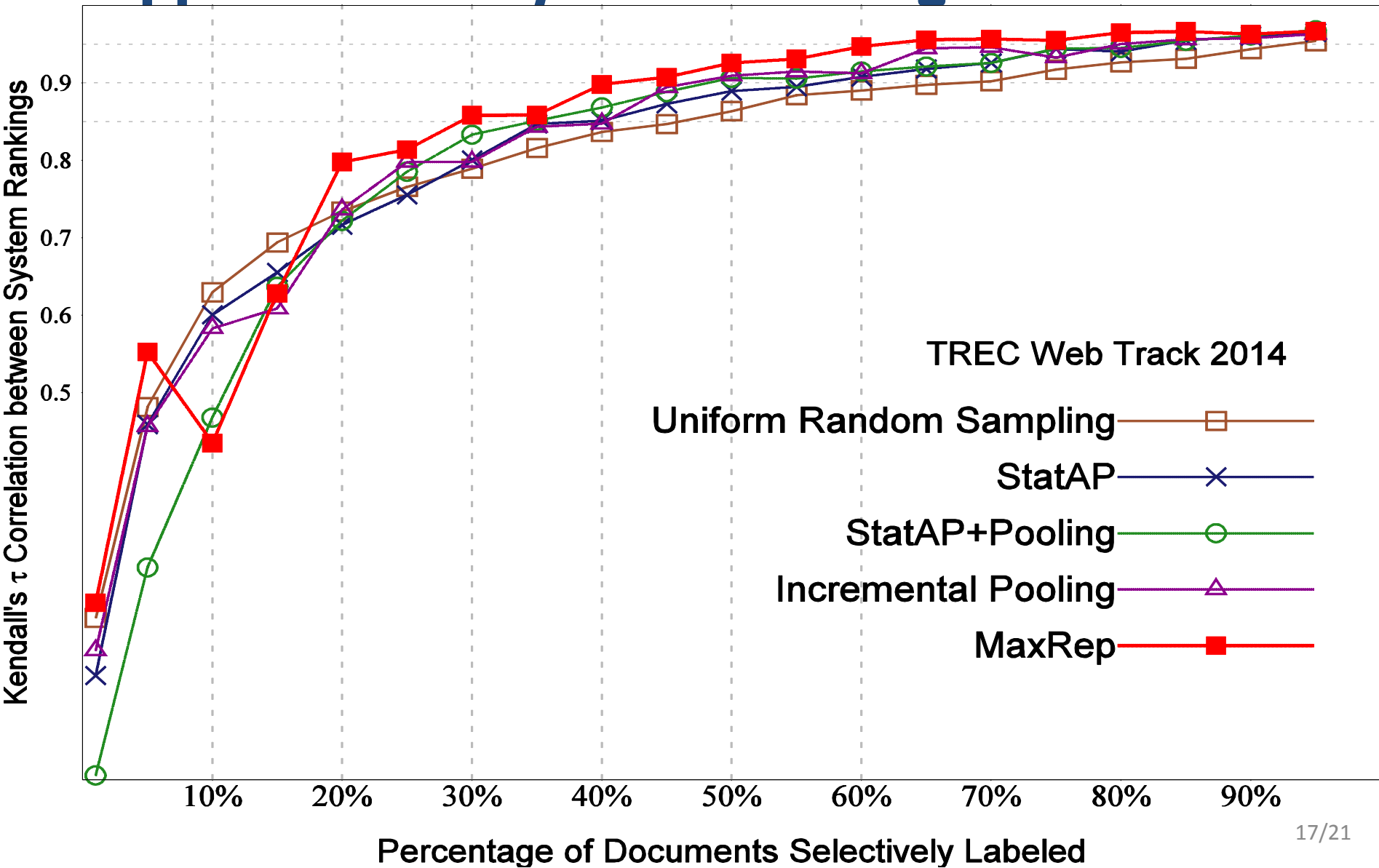
Select Subset of Documents

Mitigate Missing Labels

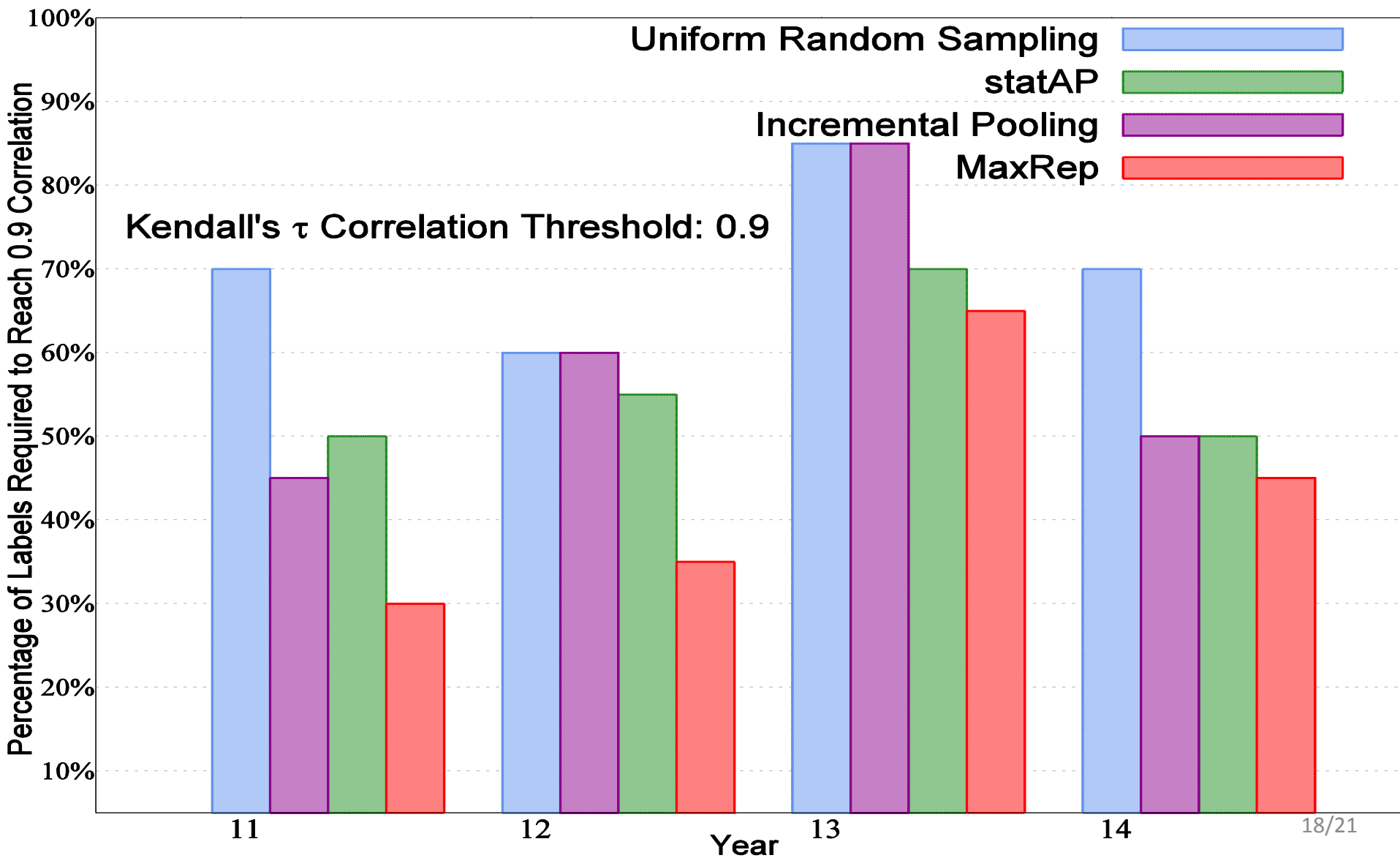
- Uniform random sampling
- Incremental pooling
- Non-uniform random sampling: statAP
- MaxRep**: maximum representative

- trec-map: missing labels as non-relevance
- bpref: separates labeled non-relevance
- indAP: missing labels as non-exist
- infAP: estimator of precision at rank r
- statAP: adjusts inclusion probability
- Predict-map**: SVM based label prediction

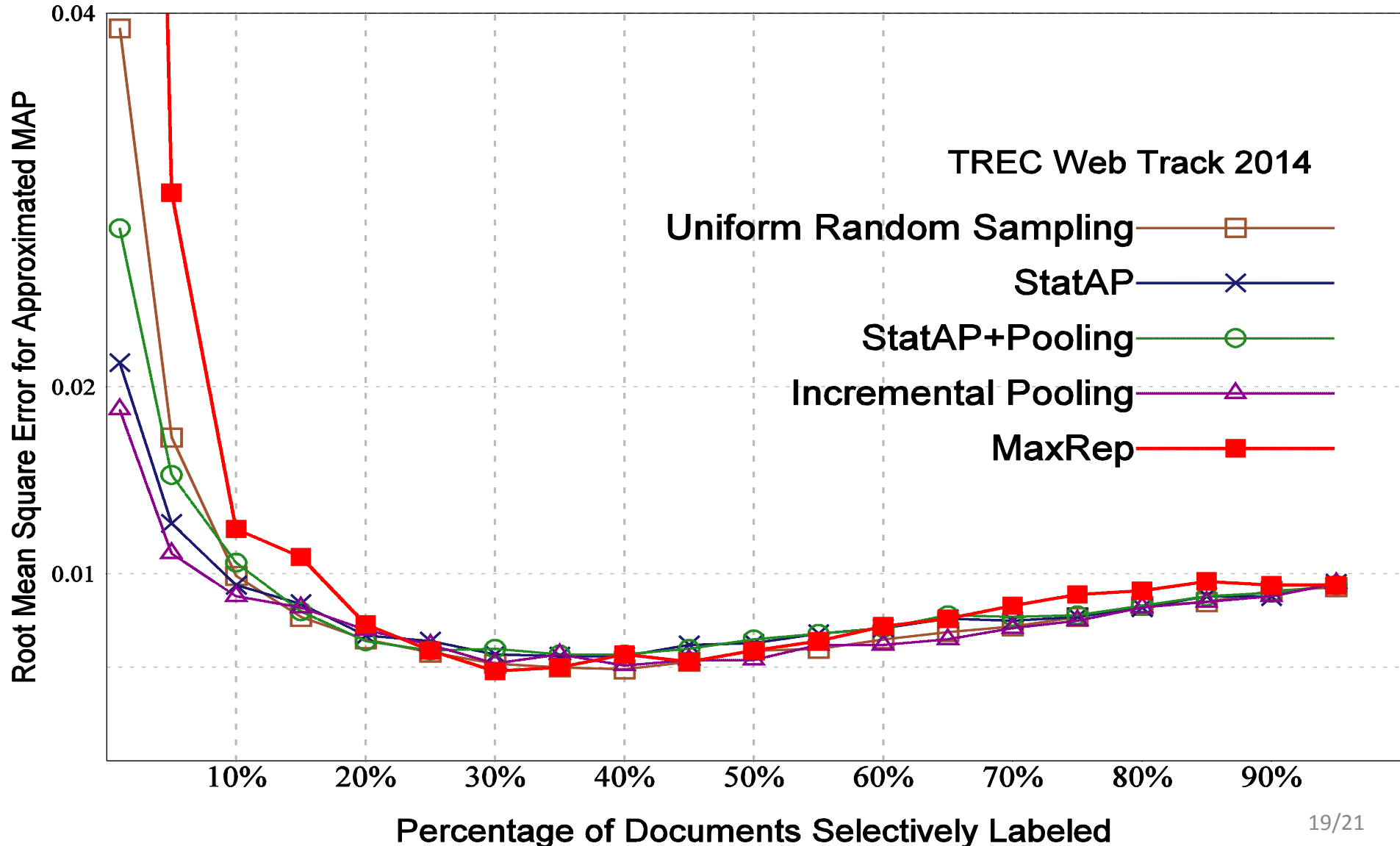
Approximate System Ranking: Kendall's τ



Summarization of Kendall's τ



Approximate MAP Score: RMSE



Overview

- Background: IR Evaluation
- Objectives & Related Work
- MaxRep Selective Labeling
- Experimental Results
- Conclusion**

Conclusion

- ❑ **Label prediction is a robust and viable** strategy to mitigate incomplete labels, with at least 20% of documents as training data
- ❑ **A novel strategy MaxRep is proposed**, considering both ranking information and document contents and seeking to select a representative subset of documents to label
- ❑ **Large scale experiments on TREC Web Track** data confirmed MapRep outperforms other strategies when label prediction is used
- ❑ For future works, **novelty & diversity will be considered**, and corresponding measures, like ERR-IA, will be approximated

Thanks!