

# Query Performance Prediction the Past, the Present, and the Future

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# Outline

- 1 A Brief Introduction to Query Performance Prediction (QPP)
- 2 A Pairwise Interaction-based Supervised QPP Model (WSDM'22)
- 3 A Pointwise-Query:Listwise-Document based QPP Approach (SIGIR'22)
- 4 Analyzing the Sensitivity of QPP Evaluation (ECIR'22)
- 5 Ongoing work (Submitted to WSDM'23)
- 6 Concluding Remarks

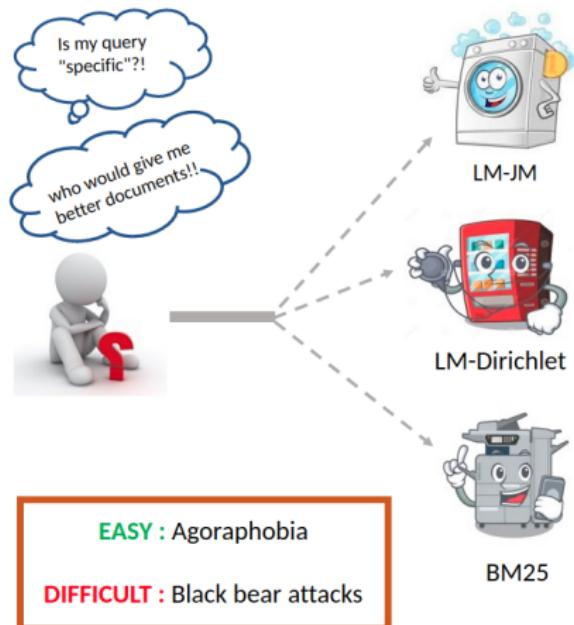
# A Brief Introduction to Query Performance Prediction (QPP)

# What is Query Performance Prediction (QPP)?

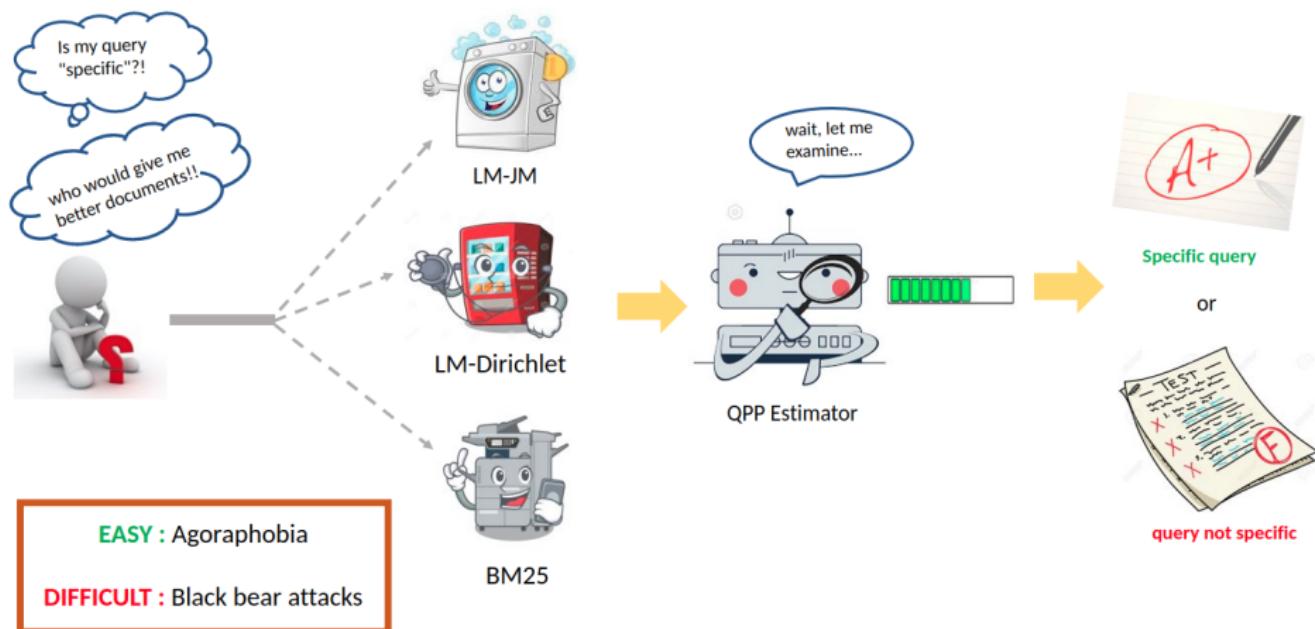
"If we could determine in advance which retrieval approach would work well for a given query, then hopefully, selecting the appropriate retrieval method on a [per] query basis could improve the retrieval effectiveness significantly."

– Carmel, D., Yom-Tov, E.: Estimating the query difficulty for information retrieval. *Synthesis Lectures on Information Concepts, Retrieval, and Services* 2(1), 1–89 (2010)

# What is Query Performance Prediction (QPP)?



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# Why do we need QPP?

- There are always a number of **difficult queries that cannot be effectively addressed**.

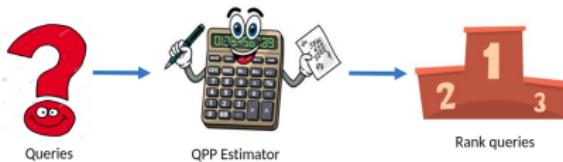
# Why do we need QPP?

- There are always a number of **difficult queries that cannot be effectively addressed**.
- Detecting hard/poor-performing queries is useful -
  - Query Reformulation
  - Feedback to system
  - Query Routing

# Why do we need QPP?

- There are always a number of **difficult queries that cannot be effectively addressed.**
- Detecting hard/poor-performing queries is useful -
  - Query Reformulation
  - Feedback to system
  - Query Routing
- **QPP** - Predicting the quality of retrieved documents to satisfy the information needs behind the query.

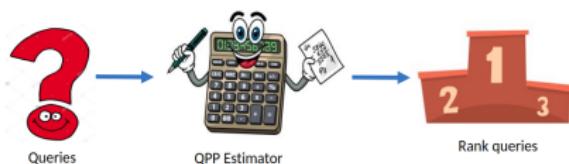
# Types of QPP estimators



## Pre-retrieval

- Predicts the performance of each query based on the content and the context of the query.
- Predictors are often derived from linguistic or statistical information.
- AvgIDF, MaxIDF.

# Types of QPP estimators



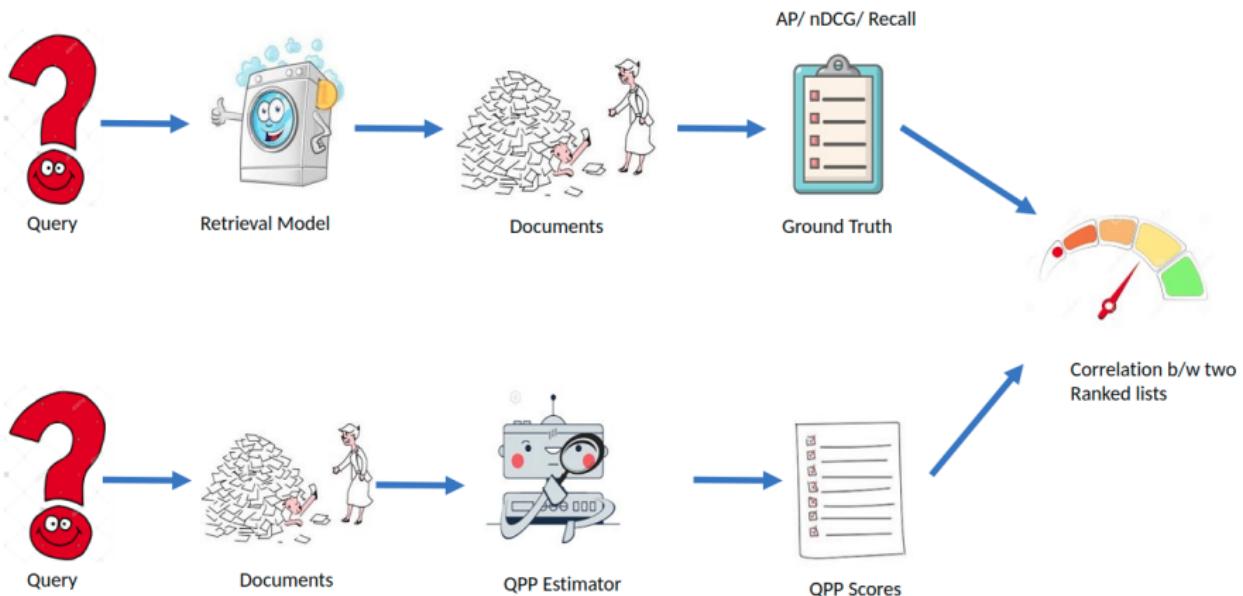
## Pre-retrieval

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## Post-retrieval

- Estimates the query performance by analyzing the result list returned by the retrieval engine.
- Clarity-based approaches - Clarity.
- Score-based approaches - WIG, NQC.
- Robustness-based approaches - UEF.

# Evaluating QPP Estimators



# A Pairwise Interaction-based Supervised QPP Model (WSDM'22)

# Deep-QPP: A data-driven Supervised QPP Model

A purely **data-driven supervised** QPP approach that leverages information from the semantic interactions between the terms of the query and those of the top-retrieved documents.

- Datta, S., Ganguly, D., Greene, D., and Mitra, M. Deep-QPP: A pairwise interaction-based deep learning model for supervised query performance prediction. In proceedings of WSDM (2022), ACM, pp. 201–209.



Suchana Datta  
University College Dublin

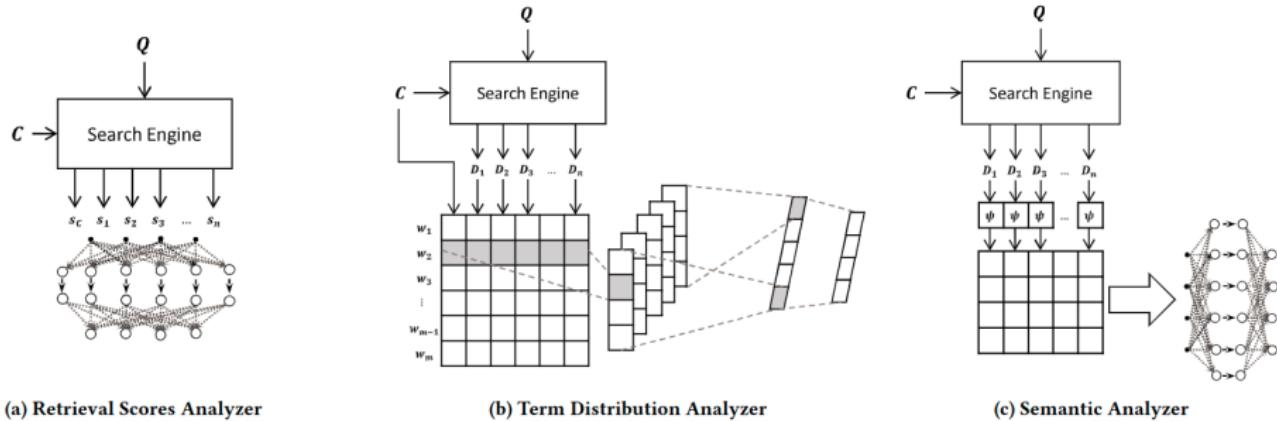


Derek Greene  
University College Dublin



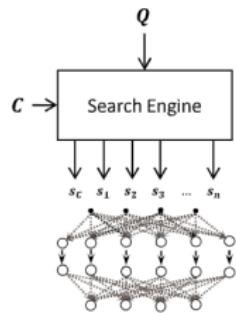
Mandar Mitra  
Indian Statistical Institute

# NeuralQPP - SIGIR'18

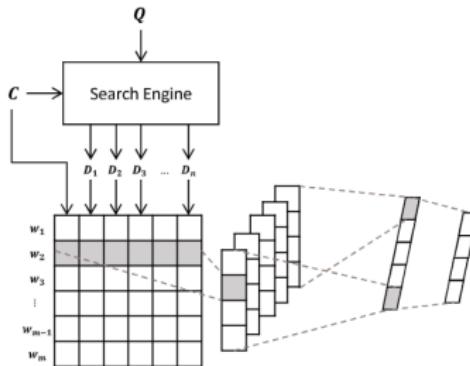


Hamed Zamani, W. Bruce Croft, and J. Shane Culpepper. 2018. Neural Query Performance Prediction Using Weak Supervision from Multiple Signals. In proceedings of SIGIR' 18. Association for Computing Machinery, 105–114.

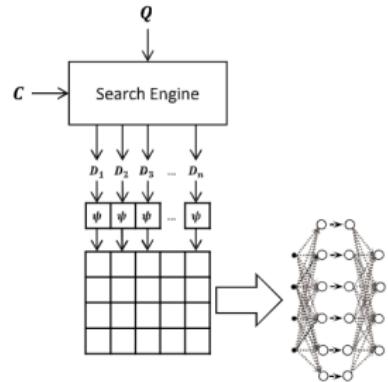
# NeuralQPP - SIGIR'18



(a) Retrieval Scores Analyzer



(b) Term Distribution Analyzer



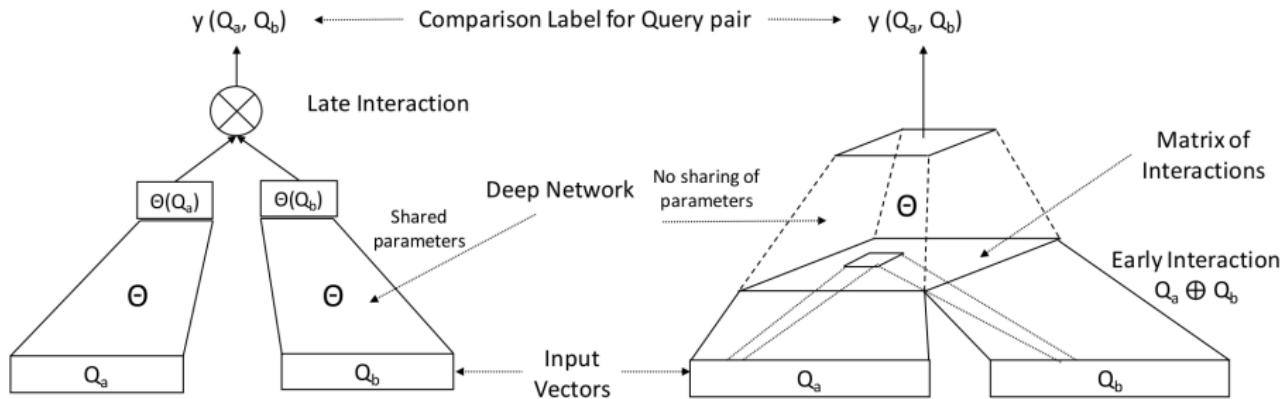
(c) Semantic Analyzer

- A weakly supervised model.
- Uses a combination of features (e.g. retrieval scores) and word embedded vectors to learn an optimal combination.
- A major limitation - training procedure involves weak supervision over a number of estimators.

# Advantages of our Proposed Method

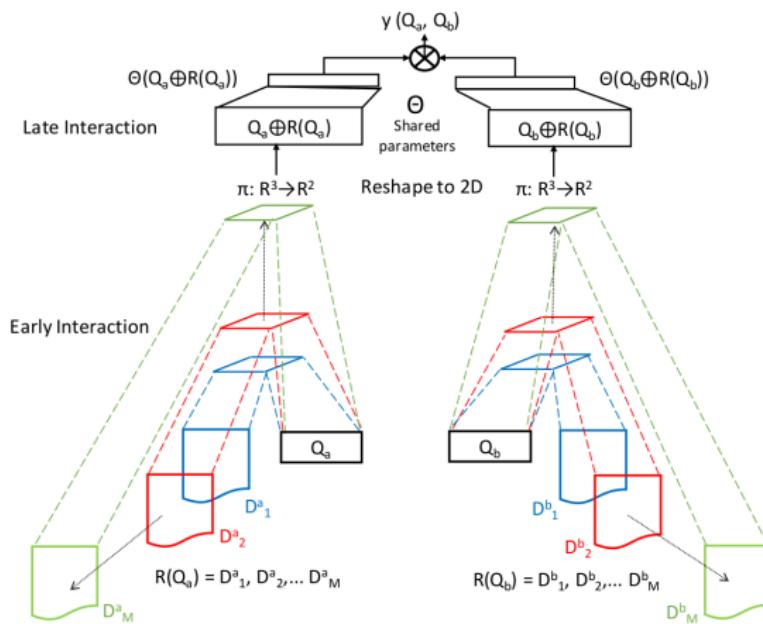
- An end-to-end **strictly supervised** QPP model.
- Solely **data-driven** because it does not rely on other estimators.
- Early interactions between query-document pairs.

# Types of Interactions in Pairwise Models



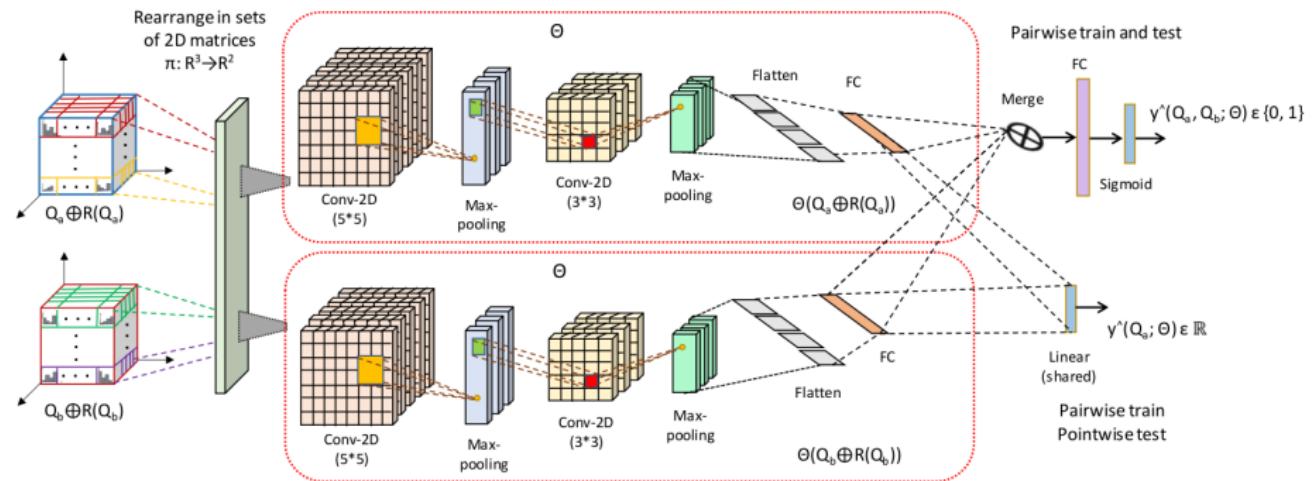
- Representation-based models rely on *late interaction* involving shared parameters (left).
- Interaction-based models make use of *early interactions* transforming paired instances into a single input (right).

# Interaction between Queries and Top-Docs

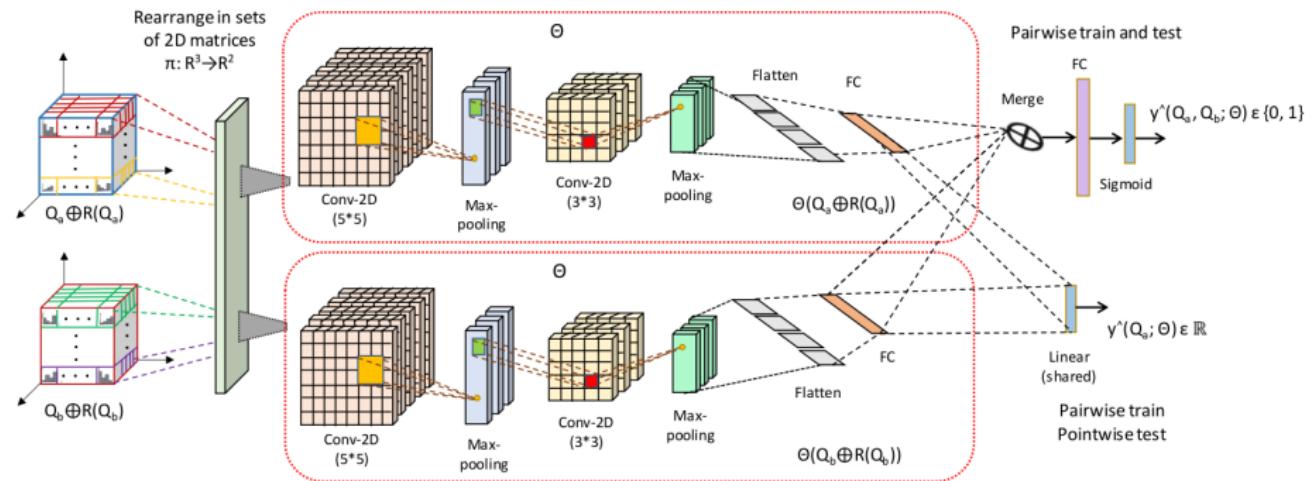


- Combines the benefits of both early and late interactions.
- Includes interaction of the terms in the top-retrieved documents of a query with the constituent terms of the query.
- Incorporates the characteristic pattern of these interactions to estimate the comparison function  $y(Q_a, Q_b)$  between a pair of queries.

# End-to-end Architecture of Deep-QPP



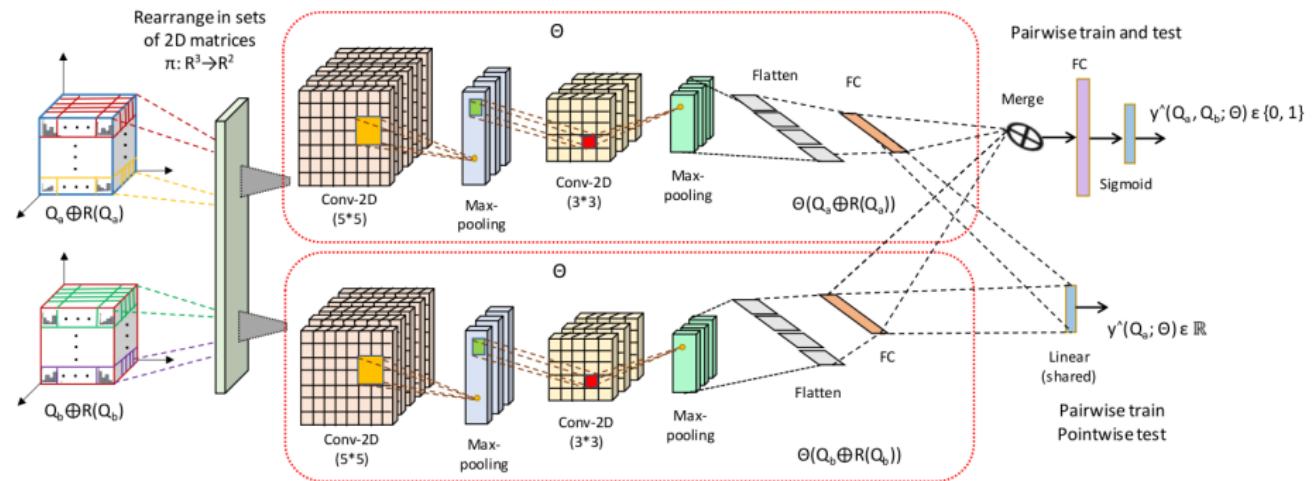
# End-to-end Architecture of Deep-QPP



$$\textbf{Pairwise: } \mathcal{L}(Q_a, Q_b) = (y(Q_a, Q_b) - \hat{y}(Q_a, Q_b; \Theta))^2$$

$$\textbf{Pointwise: } \mathcal{L}(Q_a, Q_b) = \max(0, 1 - \text{sgn}(y(Q_a, Q_b) \cdot (\hat{y}(Q_a; \Theta) - \hat{y}(Q_b; \Theta))))$$

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Available at: <https://github.com/suchanadatta/DeepQPP.git>

# A comparative evaluation of Deep-QPP

Methods	Metric : AP@100						Metric : nDCG@20					
	TREC-Robust			ClueWeb09B			TREC-Robust			ClueWeb09B		
	Pairwise		Pointwise	Pairwise		Pointwise	Pairwise		Pointwise	Pairwise		Pointwise
	Accuracy	P- $\rho$	K- $\tau$	Accuracy	P- $\rho$	K- $\tau$	Accuracy	P- $\rho$	K- $\tau$	Accuracy	P- $\rho$	K- $\tau$
Clarity	0.6251	0.4863	0.3140	0.6120	0.1911	0.0641	0.6118	0.3529	0.2462	0.6101	0.0923	0.0714
NQC	0.6720	0.5269	0.4041	0.7030	0.2654	0.1518	0.6689	0.4261	0.3017	0.6916	0.3105	0.1987
WIG	0.6613	0.5440	0.4279	0.6829	0.2492	0.1920	0.6629	0.3915	0.2407	0.6710	0.2780	0.1823
UEF	0.6941	0.5523	0.4154	0.7217	0.3162	0.1959	0.6792	0.5029	0.3510	0.6925	0.3320	0.1854
SN-BERT	0.6613	0.5208	0.4169	0.6902	0.2317	0.1441	0.6529	0.5023	0.3624	0.6724	0.2241	0.1334
SN-SG	0.6349	0.5112	0.3987	0.6273	0.2110	0.1154	0.6147	0.4736	0.3561	0.6231	0.2049	0.1283
DRMM	0.5871	0.4730	0.3710	0.6023	0.2014	0.1141	0.5629	0.4038	0.3119	0.6004	0.1927	0.1201
WS-NeurQPP	0.8123	0.7215	0.5090	0.7727	0.5192	0.2828	0.7973	0.5913	0.4126	0.7614	0.3928	0.2337
Deep-QPP (MDMQ)	0.7857	0.6988	0.4981	0.7414	0.4636	0.2495	0.7632	0.5649	0.3619	0.7189	0.3509	0.2185
Deep-QPP (SDSQ)	0.7210	0.6303	0.4018	0.6844	0.4208	0.2401	0.7284	0.5112	0.3065	0.6753	0.3124	0.2014
Deep-QPP (MDSQ)	0.8006	0.7203	0.4989	0.7426	0.4840	0.2575	0.7824	0.5601	0.3245	0.7037	0.3518	0.2100
Deep-QPP (SDMQ)	<b>0.8420</b>	<b>0.7404</b>	<b>0.5434</b>	<b>0.8045</b>	<b>0.5532</b>	<b>0.3130</b>	<b>0.8371</b>	<b>0.6315</b>	<b>0.4614</b>	<b>0.7903</b>	<b>0.4431</b>	<b>0.2554</b>

Weakly Supervised Method outperforms Unsupervised Baselines.

# Performance of Deep-QPP

Methods	Metric : AP@100						Metric : nDCG@20					
	TREC-Robust			ClueWeb09B			TREC-Robust			ClueWeb09B		
	Pairwise	Pointwise		Pairwise	Pointwise		Pairwise	Pointwise		Pairwise	Pointwise	
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Strictly supervised QPP model **Deep-QPP** outperforms the **Weakly Supervised QPP Model**.

# Performance of Deep-QPP

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Purely representation-based or purely interaction-based approaches perform worse than Deep-QPP.

# A Pointwise-Query:Listwise-Document based QPP Approach (SIGIR'22)

# A BERT-based End-to-end Model

An end-to-end neural cross-encoder-based approach - trained **pointwise** on individual queries, but **listwise** over the top ranked documents (split into chunks).

– **Datta, S., MacAvaney, S., Ganguly, D., Greene, D.** A ‘Pointwise-Query, Listwise-Document’ based Query Performance Prediction Approach (to appear in the proceedings of SIGIR'22).



**Suchana Datta**  
University College Dublin



**Sean MacAvaney**  
University of Glasgow

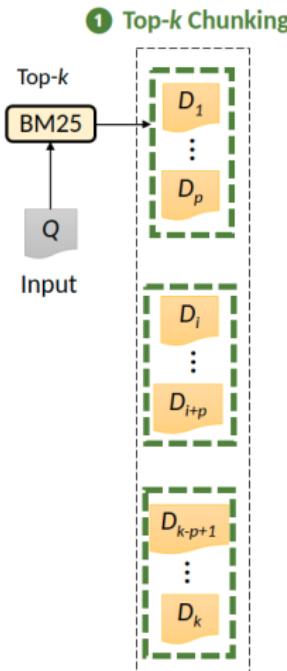


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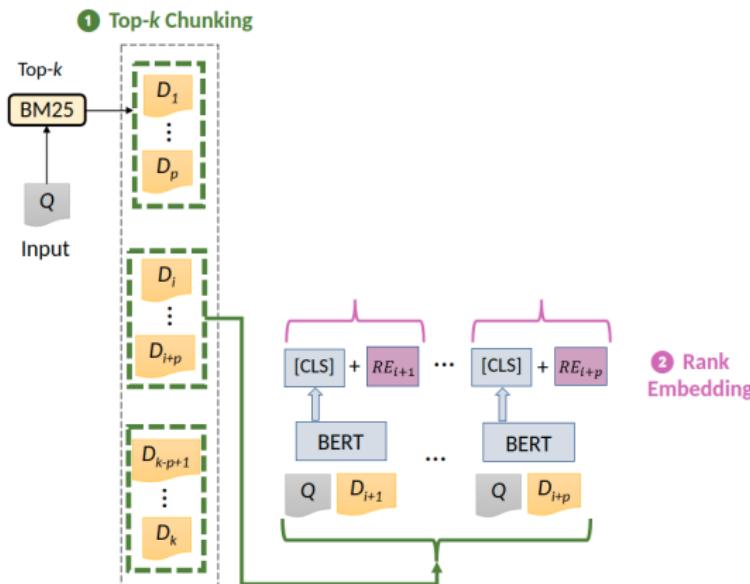
- A novel architecture and objective function for a **pointwise** neural QPP.
- Transformed the pointwise QPP objective into a **classification task**, not a regression model.
- Models the top-ranked documents as a **sequence of chunks (Listwise)**, not as a whole set.
- Incorporates the **relative Positions (or ranks)** of the top documents.

# End-to-end Architecture of qppBERT-PL



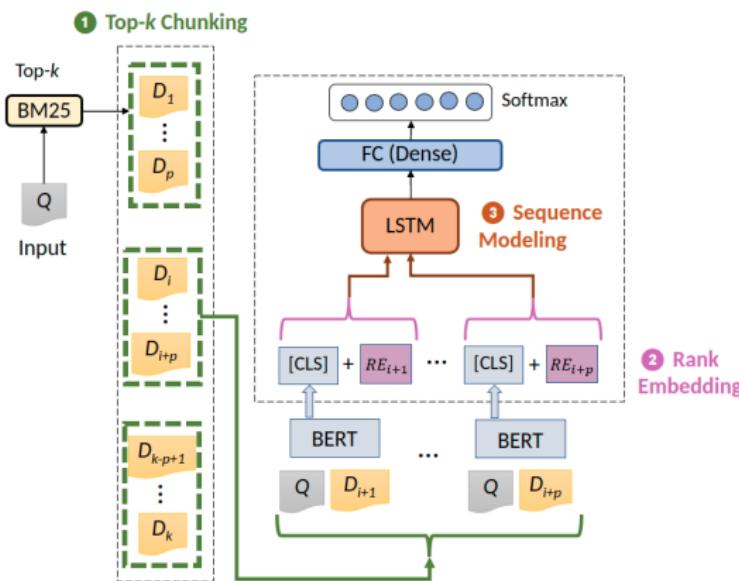
- Popular unsupervised QPP methods (e.g. NQC, WIG) work well when information used from the top-100 documents.
- Encoding long sequences of 100 documents is likely to be noisy.
- Top-ranked set is segmented into equal sized partitions (chunks).

# End-to-end Architecture of qppBERT-PL



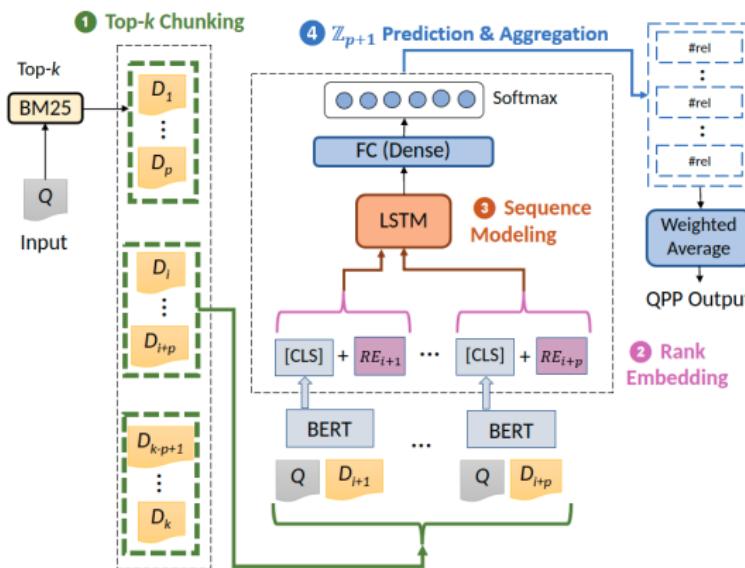
- BERT-based cross-encoder is used to model the interactions between the query and the document terms of each chunk.
- LSTM-encoded representation of this interaction sequence.
- Ranks are encoded via BERT positional embeddings.

# End-to-end Architecture of qppBERT-PL



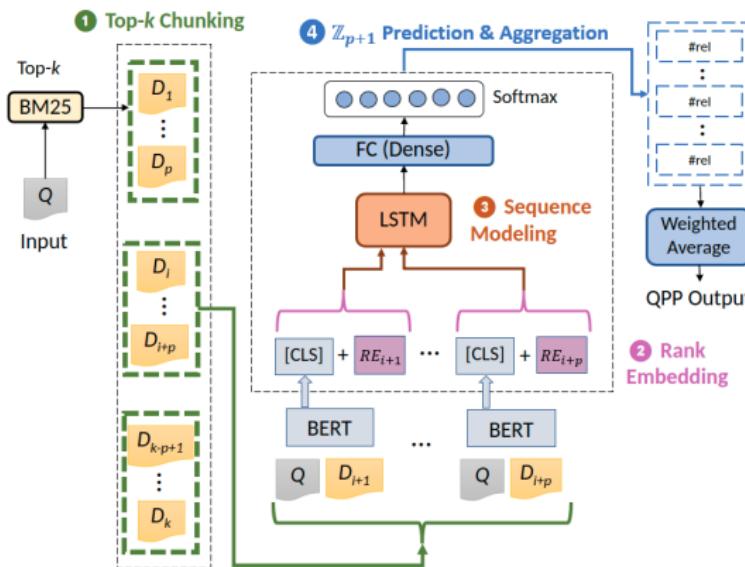
- Passed through a fully connected layer (FC).
- Terminates at a  $p + 1$  dimensional Softmax representing the probability of finding  $r$  relevant documents within this  $p$ -sized chunk  
 $(r \in \{0, 1, \dots, p\})$ .

# End-to-end Architecture of qppBERT-PL



- Compute a weighted average from the outputs of the network, predicted for each  $p$ -sized partition of the top documents.
  - Aggregated scores are used to sort the queries in descending order.

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Available at: <https://github.com/suchanadatta/qppBERT-PL.git>

# Performance of qppBERT-PL

Type	Models	MS MARCO Dev				TREC-DL'19				TREC-DL'20			
		MRR@10		AP@100		MRR@10		AP@100		MRR@10		AP@100	
		P-r	K- $\tau$										
Baselines	NQC	0.331	0.298	0.285	0.227	0.239	0.185	0.183	0.107	0.259	0.243	0.179	0.124
	Clarity	0.173	0.248	0.172	0.207	0.156	0.147	0.096	0.113	0.239	0.215	0.107	0.129
	WIG	0.193	0.215	0.215	0.203	0.192	0.133	0.133	0.089	0.260	0.241	0.143	0.096
	UEF(NQC)	0.347	0.313	0.294	0.227	0.254	0.235	0.189	0.112	0.275	0.291	0.200	0.126
	SCNQC	0.334	0.310	0.304	0.228	0.261	0.251	0.204	0.123	0.284	0.298	0.215	0.141
	NeuralQPP	0.215	0.197	0.173	0.193	0.156	0.126	0.129	0.133	0.271	0.253	0.133	0.112
	BERT-QPP	0.520	0.411	0.326	0.301	0.350	0.363	0.268	0.202	0.343	0.341	0.233	0.195
	+ Seq.	0.463	0.360	0.301	0.312	0.345	0.333	0.265	0.193	0.277	0.218	0.258	0.190
Ours	+ Seq. + RankEmb	0.473	0.370	0.328	0.285	0.323	0.332	0.253	0.167	0.303	0.236	0.252	0.172
	qppBERT-PL	<b>0.562</b>	<b>0.448</b>	<b>0.354</b>	<b>0.327</b>	<b>0.413</b>	<b>0.403</b>	<b>0.301</b>	<b>0.247</b>	<b>0.422</b>	<b>0.392</b>	<b>0.303</b>	<b>0.251</b>
	- Seq.	0.512	0.386	0.303	0.283	0.357	0.349	0.274	0.193	0.345	0.320	0.271	0.200
	- Chunked	0.520	0.413	0.331	0.274	0.373	0.326	0.290	0.225	0.370	0.333	0.297	0.231
	- RankEmb	0.519	0.392	0.320	0.267	0.361	0.328	0.285	0.232	0.352	0.331	0.293	0.215
	- Chunked - RankEmb	0.405	0.329	0.293	0.285	0.309	0.299	0.260	0.159	0.217	0.198	0.199	0.184

qppBERT-PL is more effective at predicting query performance than other supervised and unsupervised methods.

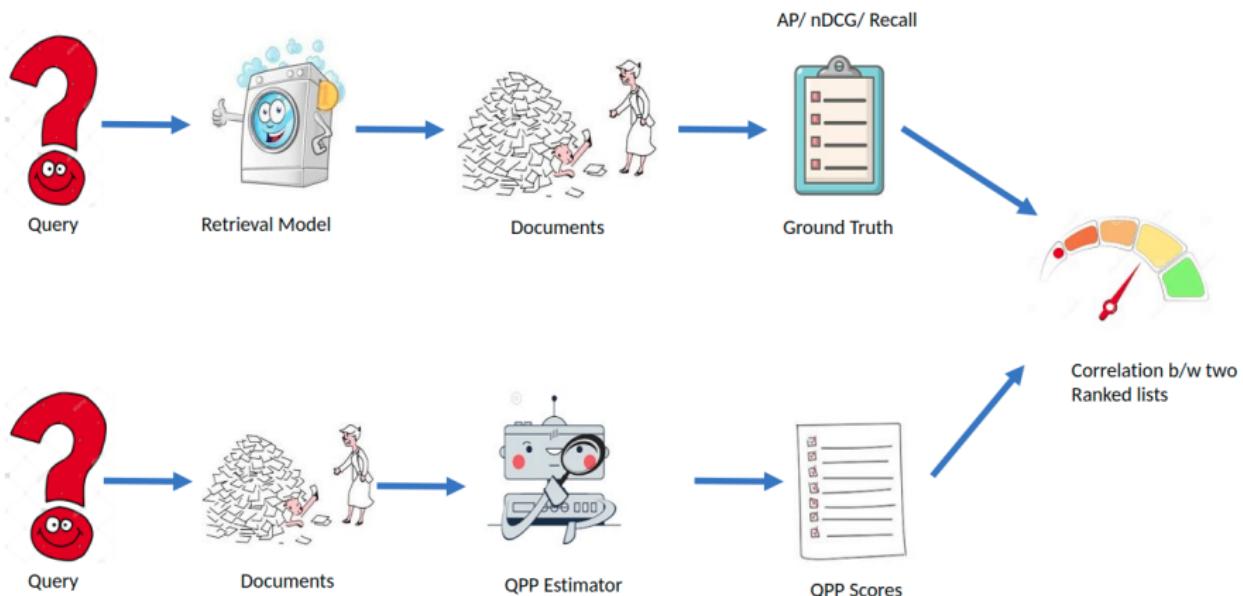
# Performance of qppBERT-PL

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	Clarity	0.173	0.248	0.172	0.207	0.156	0.147	0.096	0.113	0.239	0.215	0.107	0.129
	WIG	0.193	0.215	0.215	0.203	0.192	0.133	0.133	0.089	0.260	0.241	0.143	0.096
	UEF(NQC)	0.347	0.313	0.294	0.227	0.254	0.235	0.189	0.112	0.275	0.291	0.200	0.126
	SCNQC	0.334	0.310	0.304	0.228	0.261	0.251	0.204	0.123	0.284	0.298	0.215	0.141
	NeuralQPP	0.215	0.197	0.173	0.193	0.156	0.126	0.129	0.133	0.271	0.253	0.133	0.112
	BERT-QPP	0.520	0.411	0.326	0.301	0.350	0.363	0.268	0.202	0.343	0.341	0.233	0.195
	+ Seq.	0.463	0.360	0.301	0.312	0.345	0.333	0.265	0.193	0.277	0.218	0.258	0.190
Ours	+ Seq. + RankEmb	0.473	0.370	0.328	0.285	0.323	0.332	0.253	0.167	0.303	0.236	0.252	0.172
	qppBERT-PL	<b>0.562</b>	<b>0.448</b>	<b>0.354</b>	<b>0.327</b>	<b>0.413</b>	<b>0.403</b>	<b>0.301</b>	<b>0.247</b>	<b>0.422</b>	<b>0.392</b>	<b>0.303</b>	<b>0.251</b>
	- Seq.	0.512	0.386	0.303	0.283	0.357	0.349	0.274	0.193	0.345	0.320	0.271	0.200
	- Chunked	0.520	0.413	0.331	0.274	0.373	0.326	0.290	0.225	0.370	0.333	0.297	0.231
	- RankEmb	0.519	0.392	0.320	0.267	0.361	0.328	0.285	0.232	0.352	0.331	0.293	0.215
	- Chunked - RankEmb	0.405	0.329	0.293	0.285	0.309	0.299	0.260	0.159	0.217	0.198	0.199	0.184

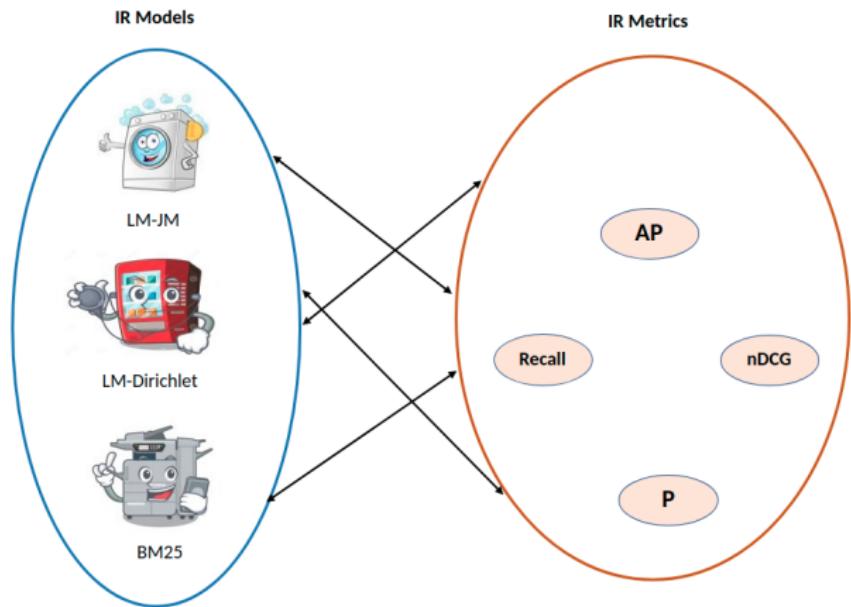
Sequence modeling, chunking and Rank Embeddings are critical components of qppBERT-PL.

# Analyzing the Sensitivity of QPP Evaluation (ECIR'22)

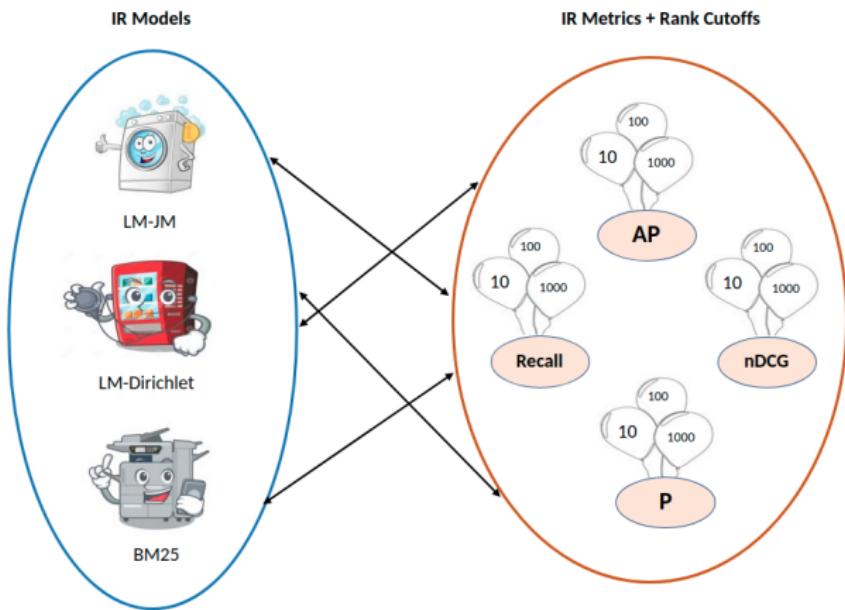
# How Do We Evaluate QPP Estimators?



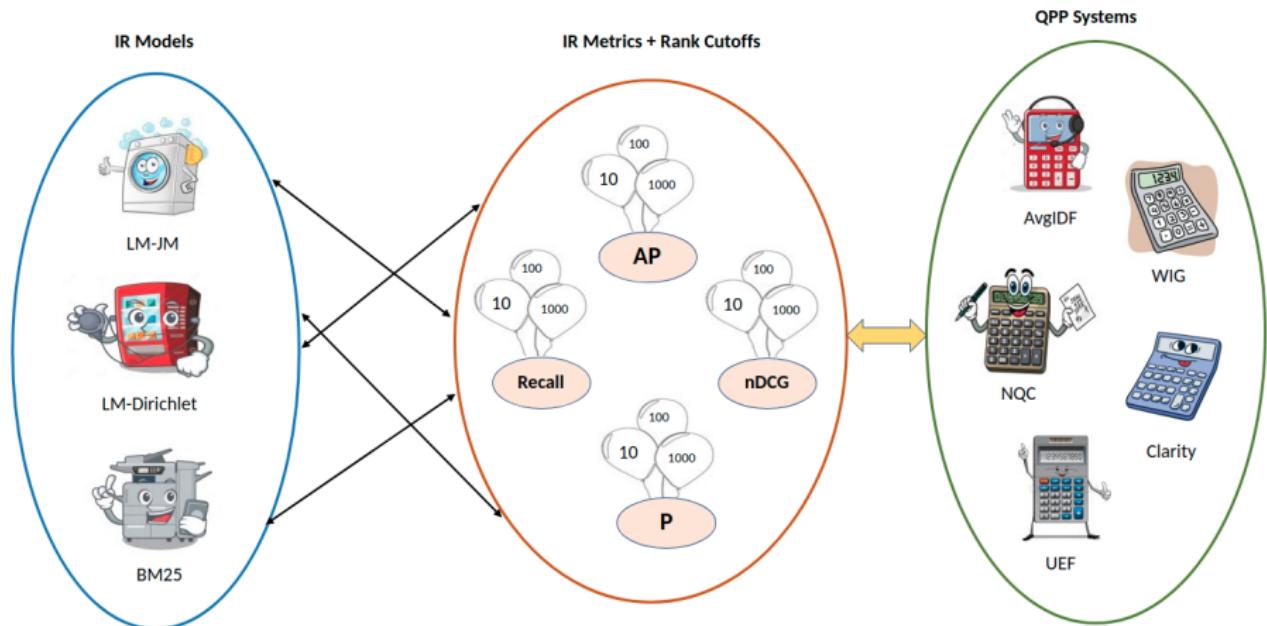
# There are too many combinations!



# There are too many combinations!



# There are too many combinations!



# Research Question

**RQ1:** Do variations in the QPP context, in terms of the **IR metric**, the **IR model**, and the **rank cut-off** used to construct the QPP evaluation ground-truth, lead to significant differences in outcome of a QPP method?

# Research Question

**RQ1:** Do variations in the QPP context, in terms of the **IR metric**, the **IR model**, and the **rank cut-off** used to construct the QPP evaluation ground-truth, lead to significant differences in outcome of a QPP method?

- We measure the sensitivity of QPP results with variations in the IR evaluation metric and the IR model for the QPP methods.
- We compute the *standard deviations* in the observed values for different QPP experiment setup.

# What Do We Observe?

IR Evaluation Metric ( $\theta$ )						IR Evaluation Metric ( $\theta$ )					
Model( $\mathcal{S}$ )	AP	nDCG	R	P@10	$\sigma(\theta)$	Model( $\mathcal{S}$ )	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.3795	0.3966	0.3869	0.3311	<b>0.0291</b>	LMJM	0.3652	0.4169	0.4503	0.2548	0.0855
	0.5006	0.4879	0.4813	0.2525	<b>0.1190</b>		0.3563	0.4118	0.4495	0.2707	<b>0.0777</b>
	0.5208	0.5062	0.4989	0.2851	0.1121		0.4354	0.4583	0.4854	0.2842	<b>0.0901</b>
$\sigma(\mathcal{S})$	<b>0.0764</b>	0.0587	0.0602	<b>0.0395</b>		$\sigma(\mathcal{S})$	<b>0.0433</b>	0.0255	0.0205	<b>0.0147</b>	
BM25	0.4553	0.4697	0.4663	0.3067	<b>0.0788</b>	BM25	0.4545	0.4843	0.5248	0.2918	<b>0.1022</b>
	0.4526	0.4700	0.4736	0.2842	<b>0.0911</b>		0.4618	0.4887	0.5137	0.3308	<b>0.0814</b>
	0.4695	0.4848	0.4893	0.3017	0.0902		0.5024	0.5260	0.5453	0.3340	0.0969
$\sigma(\mathcal{S})$	0.0091	<b>0.0086</b>	<b>0.0118</b>	0.0114		$\sigma(\mathcal{S})$	<b>0.0258</b>	0.0229	<b>0.0160</b>	0.0235	
LMDir	0.3175	0.3285	0.3278	0.2193	<b>0.0529</b>	LMDir	0.3100	0.3319	0.3657	0.2061	<b>0.0688</b>
	0.3144	0.3162	0.3319	0.2040	0.0589		0.3170	0.3370	0.3551	0.2374	<b>0.0519</b>
	0.3307	0.3407	0.3440	0.2155	<b>0.0617</b>		0.3539	0.3713	0.3828	0.2379	0.0668
$\sigma(\mathcal{S})$	0.0087	<b>0.0123</b>	<b>0.0084</b>	0.0120		$\sigma(\mathcal{S})$	<b>0.0236</b>	0.0214	<b>0.0140</b>	0.0182	

(a) AvgIDF

(b) NQC

IR Evaluation Metric ( $\theta$ )						IR Evaluation Metric ( $\theta$ )					
Model( $\mathcal{S}$ )	AP	nDCG	R	P@10	$\sigma(\theta)$	Model( $\mathcal{S}$ )	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.4056	0.4071	0.3971	0.3054	<b>0.0491</b>	LMJM	0.4746	0.4763	0.4646	0.3573	<b>0.0575</b>
	0.4484	0.4563	0.4386	0.3485	0.0502		0.5386	0.5476	0.5263	0.4182	0.0603
	0.4908	0.4798	0.4632	0.3423	<b>0.0688</b>		0.5693	0.5566	0.5373	0.3971	<b>0.0797</b>
$\sigma(\mathcal{S})$	<b>0.0426</b>	0.0371	0.0334	<b>0.0233</b>		$\sigma(\mathcal{S})$	<b>0.0483</b>	0.0440	0.0392	<b>0.0309</b>	
BM25	0.3716	0.3794	0.3790	0.3120	<b>0.0325</b>	BM25	0.4385	0.4477	0.4472	0.3682	<b>0.0384</b>
	0.4520	0.4601	0.4505	0.3586	0.0480		0.5334	0.5429	0.5316	0.4231	0.0567
	0.4582	0.4688	0.4667	0.3528	<b>0.0561</b>		0.5407	0.5532	0.5507	0.4163	<b>0.0662</b>
$\sigma(\mathcal{S})$	0.0483	<b>0.0493</b>	0.0467	<b>0.0254</b>		$\sigma(\mathcal{S})$	0.0570	<b>0.0582</b>	0.0551	<b>0.0300</b>	
LMDir	0.2514	0.2567	0.2607	0.2209	<b>0.0181</b>	LMDir	0.3017	0.3080	0.3128	0.2651	<b>0.0217</b>
	0.3116	0.3181	0.3125	0.2549	0.0297		0.3677	0.3754	0.3688	0.3008	0.0351
	0.3194	0.3267	0.3259	0.2493	<b>0.0375</b>		0.3833	0.3920	0.3911	0.2992	<b>0.0450</b>
$\sigma(\mathcal{S})$	0.0372	<b>0.0382</b>	0.0344	<b>0.0182</b>		$\sigma(\mathcal{S})$	0.0433	<b>0.0445</b>	0.0303	<b>0.0202</b>	

(c) WIG

(d) UEF(WIG)

# Variations due to IR Evaluation Metrics

Model( $\mathcal{S}$ )	IR Evaluation Metric ( $\theta$ )				
	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.3795	0.3966	0.3869	0.3311	<b>0.0291</b>
$r$ BM25	0.5006	0.4879	0.4813	0.2525	<b>0.1190</b>
LMDir	0.5208	0.5062	0.4989	0.2897	0.1121
$\sigma(\mathcal{S})$	<b>0.0764</b>	0.0587	0.0602	<b>0.0395</b>	
LMJM	0.4553	0.4697	0.4663	0.3067	<b>0.0784</b>
$\rho$ BM25	0.4526	0.4700	0.4736	0.2842	<b>0.0911</b>
LMDir	0.4695	0.4848	0.4893	0.3017	0.0902
$\sigma(\mathcal{S})$	0.0091	<b>0.0086</b>	<b>0.0118</b>	0.0114	
LMJM	0.3175	0.3285	0.3278	0.2193	<b>0.0529</b>
$\tau$ BM25	0.3144	0.3162	0.3319	0.2040	0.0589
LMDir	0.3307	0.3407	0.3440	0.2155	<b>0.0617</b>
$\sigma(\mathcal{S})$	0.0087	<b>0.0123</b>	<b>0.0084</b>	0.0120	

(a) AvgIDF

Model( $\mathcal{S}$ )	IR Evaluation Metric ( $\theta$ )				
	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.3652	0.4169	0.4503	0.2548	0.0855
$r$ BM25	0.3563	0.4118	0.4495	0.2707	<b>0.0777</b>
LMDir	0.4354	0.4583	0.4854	0.2842	<b>0.0901</b>
$\sigma(\mathcal{S})$	<b>0.0433</b>	0.0255	0.0205	<b>0.0147</b>	
LMJM	0.4545	0.4843	0.5248	0.2918	<b>0.1022</b>
$\rho$ BM25	0.4618	0.4887	0.5137	0.3308	<b>0.0814</b>
LMDir	0.5024	0.5260	0.5453	0.3340	0.0969
$\sigma(\mathcal{S})$	<b>0.0258</b>	0.0229	<b>0.0160</b>	0.0235	
LMJM	0.3100	0.3319	0.3657	0.2061	<b>0.0688</b>
$\tau$ BM25	0.3170	0.3370	0.3551	0.2374	<b>0.0519</b>
LMDir	0.3539	0.3713	0.3828	0.2379	0.0668
$\sigma(\mathcal{S})$	<b>0.0236</b>	0.0214	<b>0.0140</b>	0.0182	

(b) NQC

Model( $\mathcal{S}$ )	IR Evaluation Metric ( $\theta$ )				
	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.4056	0.4071	0.3971	0.3054	<b>0.0491</b>
$r$ BM25	0.4488	0.4563	0.4386	0.3485	0.0502
LMDir	0.4908	0.4798	0.4632	0.3423	<b>0.0688</b>
$\sigma(\mathcal{S})$	<b>0.0426</b>	0.0371	0.0334	<b>0.0233</b>	
LMJM	0.3716	0.3794	0.3790	0.3120	<b>0.0325</b>
$\rho$ BM25	0.4520	0.4601	0.4505	0.3586	0.0480
LMDir	0.4582	0.4688	0.4667	0.3528	<b>0.0561</b>
$\sigma(\mathcal{S})$	0.0483	<b>0.0493</b>	0.0467	<b>0.0254</b>	
LMJM	0.2514	0.2567	0.2607	0.2209	<b>0.0181</b>
$\tau$ BM25	0.3116	0.3181	0.3125	0.2549	0.0297
LMDir	0.3194	0.3267	0.3259	0.2493	<b>0.0375</b>
$\sigma(\mathcal{S})$	0.0372	<b>0.0382</b>	0.0344	<b>0.0182</b>	

(c) WIG

Model( $\mathcal{S}$ )	IR Evaluation Metric ( $\theta$ )				
	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.4746	0.4763	0.4646	0.3573	<b>0.0575</b>
$r$ BM25	0.5386	0.5476	0.5263	0.4182	0.0603
LMDir	0.5693	0.5564	0.5373	0.3971	<b>0.0797</b>
$\sigma(\mathcal{S})$	<b>0.0483</b>	0.0440	0.0392	<b>0.0309</b>	
LMJM	0.4385	0.4477	0.4472	0.3682	<b>0.0384</b>
$\rho$ BM25	0.5334	0.5429	0.5316	0.4231	0.0567
LMDir	0.5407	0.5532	0.5507	0.4163	<b>0.0662</b>
$\sigma(\mathcal{S})$	0.0570	<b>0.0582</b>	0.0551	<b>0.0300</b>	
LMJM	0.3017	0.3080	0.3128	0.2651	<b>0.0217</b>
$\tau$ BM25	0.3677	0.3754	0.3688	0.3008	0.0351
LMDir	0.3833	0.3920	0.3911	0.2992	<b>0.0450</b>
$\sigma(\mathcal{S})$	0.0433	<b>0.0445</b>	0.0303	<b>0.0202</b>	

(d) UEF(WIG)

- Substantial absolute differences in the QPP outcomes.

# Variations due to IR Evaluation Metrics

Model( $\mathcal{S}$ )	IR Evaluation Metric ( $\theta$ )				
	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.3795	0.3966	0.3869	0.3311	<b>0.0291</b>
$\tau$ BM25	0.5006	0.4879	0.4813	0.2525	<b>0.1190</b>
LMDir	0.5208	0.5062	0.4989	0.2851	0.1121
$\sigma(\mathcal{S})$	<b>0.0764</b>	0.0587	0.0602	<b>0.0395</b>	

$\rho$	IR Evaluation Metric ( $\theta$ )				
	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.4553	0.4697	0.4663	0.3067	<b>0.0788</b>
BM25	0.4526	0.4700	0.4736	0.2842	<b>0.0911</b>
LMDir	0.4695	0.4848	0.4893	0.3017	0.0902
$\sigma(\mathcal{S})$	0.0091	<b>0.0086</b>	<b>0.0118</b>	0.0114	

$\tau$	IR Evaluation Metric ( $\theta$ )				
	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.3175	0.3285	0.3278	0.2193	<b>0.0529</b>
BM25	0.3144	0.3162	0.3319	0.2040	0.0589
LMDir	0.3307	0.3407	0.3440	0.2155	<b>0.0617</b>
$\sigma(\mathcal{S})$	0.0087	<b>0.0123</b>	<b>0.0084</b>	0.0120	

(a) AvgIDF

Model( $\mathcal{S}$ )	IR Evaluation Metric ( $\theta$ )				
	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.3652	0.4169	0.4503	0.2548	0.0855
BM25	0.3563	0.4118	0.4495	0.2707	<b>0.0777</b>
LMDir	0.4354	0.4582	0.4854	0.2842	0.0901
$\sigma(\mathcal{S})$	<b>0.0433</b>	0.0255	0.0205	<b>0.0147</b>	

$\rho$	IR Evaluation Metric ( $\theta$ )				
	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.4545	0.4843	0.5248	0.2918	<b>0.1022</b>
BM25	0.4618	0.4887	0.5137	0.3308	<b>0.0814</b>
LMDir	0.5024	0.5266	0.5453	0.3340	0.0969
$\sigma(\mathcal{S})$	<b>0.0258</b>	0.0229	<b>0.0160</b>	0.0235	

$\tau$	IR Evaluation Metric ( $\theta$ )				
	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.3100	0.3319	0.3657	0.2061	<b>0.0688</b>
BM25	0.3170	0.3370	0.3551	0.2374	<b>0.0519</b>
LMDir	0.3539	0.3713	0.3828	0.2379	0.0668
$\sigma(\mathcal{S})$	0.0236	0.0214	<b>0.0140</b>	0.0182	

(b) NQC

Model( $\mathcal{S}$ )	IR Evaluation Metric ( $\theta$ )				
	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.4056	0.4071	0.3971	0.3054	<b>0.0491</b>
$\rho$ BM25	0.4488	0.4563	0.4386	0.3485	0.0802
LMDir	0.4908	0.4798	0.4632	0.3423	<b>0.0688</b>
$\sigma(\mathcal{S})$	<b>0.0426</b>	0.0371	0.0334	<b>0.0233</b>	

$\rho$	IR Evaluation Metric ( $\theta$ )				
	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.4746	0.4763	0.4646	0.3573	<b>0.0575</b>
BM25	0.5386	0.5476	0.5263	0.4182	0.0603
LMDir	0.5693	0.5566	0.5373	0.3971	<b>0.0797</b>
$\sigma(\mathcal{S})$	<b>0.0483</b>	0.0440	0.0392	<b>0.0309</b>	

$\tau$	IR Evaluation Metric ( $\theta$ )				
	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.4385	0.4477	0.4472	0.3682	<b>0.0384</b>
$\rho$ BM25	0.5334	0.5429	0.5316	0.4231	0.0567
LMDir	0.5407	0.5532	0.5507	0.4163	0.0662
$\sigma(\mathcal{S})$	0.0570	<b>0.0582</b>	0.0551	<b>0.0300</b>	

$\tau$	IR Evaluation Metric ( $\theta$ )				
	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.3017	0.3080	0.3128	0.2651	<b>0.0217</b>
BM25	0.3677	0.3754	0.3688	0.3008	0.0351
LMDir	0.3833	0.3920	0.3911	0.2992	<b>0.0450</b>
$\sigma(\mathcal{S})$	0.0433	<b>0.0445</b>	0.0303	<b>0.0202</b>	

(c) WIG

(d) UEF(WIG)

- Substantial absolute differences in the QPP outcomes.
- Lower variations with Kendall's  $\tau$ .

# Variations due to IR Evaluation Metrics

IR Evaluation Metric ( $\theta$ )												
Model( $\mathcal{S}$ )	AP	nDCG	R	P@10	$\sigma(\theta)$	Model( $\mathcal{S}$ )	AP	nDCG	R	P@10	$\sigma(\theta)$	
LMJM	0.3795	0.3966	0.3869	0.331	<b>0.0291</b>	$\tau$	LMJM	0.3652	0.4169	0.4503	0.254	<b>0.0855</b>
BM25	0.5006	0.4879	0.4813	0.2525	<b>0.1190</b>		BM25	0.3563	0.4118	0.4495	0.2707	<b>0.0777</b>
LMDir	0.5208	0.5062	0.4989	0.2851	0.1121		LMDir	0.4354	0.4583	0.4854	0.2842	0.0901
$\sigma(\mathcal{S})$	<b>0.0764</b>	0.0587	0.0602	<b>0.0395</b>			$\sigma(\mathcal{S})$	<b>0.0433</b>	0.0255	0.0205	<b>0.0147</b>	
LMJM	0.4553	0.4697	0.4663	0.306	<b>0.0788</b>	$\rho$	LMJM	0.4545	0.4843	0.5248	0.2918	<b>0.1022</b>
BM25	0.4526	0.4700	0.4736	0.2842	<b>0.0591</b>		BM25	0.4618	0.4887	0.5137	0.3308	<b>0.0814</b>
LMDir	0.4695	0.4848	0.4893	0.3017	0.0902		LMDir	0.5024	0.5260	0.5453	0.3340	0.0969
$\sigma(\mathcal{S})$	0.009	<b>0.0086</b>	<b>0.0118</b>	0.0114			$\sigma(\mathcal{S})$	<b>0.0258</b>	0.0229	<b>0.0160</b>	0.0235	
LMJM	0.3175	0.3285	0.3278	0.219	<b>0.0529</b>	$\tau$	LMJM	0.3100	0.3319	0.3657	0.2061	<b>0.0688</b>
BM25	0.3144	0.3162	0.3319	0.2040	<b>0.0589</b>		BM25	0.3170	0.3370	0.3551	0.2374	<b>0.0519</b>
LMDir	0.3307	0.3407	0.3440	0.2155	<b>0.0617</b>		LMDir	0.3539	0.3713	0.3828	0.2379	0.0668
$\sigma(\mathcal{S})$	0.0087	<b>0.0123</b>	<b>0.0084</b>	0.0120			$\sigma(\mathcal{S})$	<b>0.0236</b>	0.0214	<b>0.0140</b>	0.0182	

(a) AvgIDF

(b) NQC

IR Evaluation Metric ( $\theta$ )												
Model( $\mathcal{S}$ )	AP	nDCG	R	P@10	$\sigma(\theta)$	Model( $\mathcal{S}$ )	AP	nDCG	R	P@10	$\sigma(\theta)$	
LMJM	0.4056	0.4071	0.3971	0.305	<b>0.0491</b>	$\tau$	LMJM	0.4746	0.4763	0.4646	0.357	<b>0.0575</b>
BM25	0.4488	0.4563	0.4386	0.3485	<b>0.0502</b>		BM25	0.5386	0.5476	0.5263	0.4182	0.0603
LMDir	0.4908	0.4798	0.4632	0.3423	<b>0.0688</b>		LMDir	0.5693	0.5566	0.5373	0.3971	<b>0.0797</b>
$\sigma(\mathcal{S})$	<b>0.0426</b>	0.0371	0.0334	<b>0.0233</b>			$\sigma(\mathcal{S})$	<b>0.0483</b>	0.0440	0.0392	<b>0.0309</b>	
LMJM	0.3716	0.3794	0.3790	0.312	<b>0.0325</b>	$\rho$	LMJM	0.4385	0.4477	0.4472	0.3682	<b>0.0384</b>
BM25	0.4520	0.4601	0.4502	0.3586	<b>0.0480</b>		BM25	0.5334	0.5429	0.5316	0.4231	0.0567
LMDir	0.4582	0.4688	0.4667	0.3528	<b>0.0561</b>		LMDir	0.5407	0.5532	0.5507	0.4163	0.0662
$\sigma(\mathcal{S})$	0.0483	<b>0.0493</b>	0.0467	<b>0.0254</b>			$\sigma(\mathcal{S})$	0.0570	<b>0.0582</b>	0.0551	<b>0.0300</b>	
LMJM	0.2514	0.2567	0.2607	0.220	<b>0.0181</b>	$\tau$	LMJM	0.3017	0.3080	0.3128	0.265	<b>0.0217</b>
BM25	0.3116	0.3181	0.3125	0.2549	<b>0.0297</b>		BM25	0.3677	0.3754	0.3688	0.3008	0.0351
LMDir	0.3194	0.3267	0.3259	0.2493	<b>0.0375</b>		LMDir	0.3833	0.3920	0.3911	0.2992	0.0450
$\sigma(\mathcal{S})$	0.0372	<b>0.0382</b>	0.0344	<b>0.0182</b>			$\sigma(\mathcal{S})$	0.0433	<b>0.0445</b>	0.0303	<b>0.0202</b>	

(c) WIG

(d) UEF(WIG)

- Substantial absolute differences in the QPP outcomes.
- Lower variations with Kendall's  $\tau$ .
- Lower variances with LMJM.

# Variations due to IR Models

IR Evaluation Metric ( $\theta$ )					
Model( $\mathcal{S}$ )	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.3795	0.3966	0.3869	0.3311	<b>0.0291</b>
$r$ BM25	0.5006	0.4879	0.4813	0.2525	<b>0.1190</b>
LMDir	0.5208	0.5062	0.4989	0.2851	0.1121
$\sigma(\mathcal{S})$	<b>0.0764</b>	0.0587	0.0602	<b>0.0395</b>	

(a) AvgIDF

IR Evaluation Metric ( $\theta$ )					
Model( $\mathcal{S}$ )	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.3652	0.4169	0.4503	0.2548	0.0855
$r$ BM25	0.3563	0.4118	0.4495	0.2707	<b>0.0777</b>
LMDir	0.4354	0.4583	0.4854	0.2842	<b>0.0901</b>
$\sigma(\mathcal{S})$	<b>0.0433</b>	0.0255	0.0205	<b>0.0147</b>	

(b) NQC

IR Evaluation Metric ( $\theta$ )					
Model( $\mathcal{S}$ )	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.4056	0.4071	0.3971	0.3054	<b>0.0491</b>
$r$ BM25	0.4488	0.4563	0.4386	0.3485	0.0502
LMDir	0.4908	0.4798	0.4632	0.3423	<b>0.0688</b>
$\sigma(\mathcal{S})$	<b>0.0426</b>	0.0371	0.0334	<b>0.0233</b>	

(c) WIG

IR Evaluation Metric ( $\theta$ )					
Model( $\mathcal{S}$ )	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.4746	0.4763	0.4646	0.3573	<b>0.0575</b>
$r$ BM25	0.5386	0.5476	0.5263	0.4182	0.0603
LMDir	0.5693	0.5564	0.5373	0.3971	<b>0.0797</b>
$\sigma(\mathcal{S})$	<b>0.0483</b>	0.0440	0.0392	<b>0.0309</b>	

(d) UEF(WIG)

- Lower variations with Kendall's  $\tau$ .

# Variations due to IR Models

Model( $\mathcal{S}$ )	IR Evaluation Metric ( $\theta$ )				
	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.3795	0.3966	0.3869	0.3311	0.0291
$r$ BM25	0.5006	0.4879	0.4813	0.2520	0.1190
LMDir	0.5208	0.5062	0.4989	0.2851	0.1121
$\sigma(\mathcal{S})$	0.0764	0.0587	0.0602	0.0395	
LMJM	0.4553	0.4697	0.4663	0.3067	0.0788
$\rho$ BM25	0.4526	0.4700	0.4736	0.2842	0.0911
LMDir	0.4695	0.4848	0.4893	0.3017	0.0902
$\sigma(\mathcal{S})$	0.0091	0.0086	0.0118	0.0114	
LMJM	0.3175	0.3285	0.3278	0.2193	0.0529
$\tau$ BM25	0.3144	0.3162	0.3319	0.2040	0.0589
LMDir	0.3307	0.3407	0.3440	0.2155	0.0617
$\sigma(\mathcal{S})$	0.0087	0.0123	0.0084	0.0120	

(a) AvgIDF

Model( $\mathcal{S}$ )	IR Evaluation Metric ( $\theta$ )				
	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.3652	0.4169	0.4503	0.2548	0.0855
$r$ BM25	0.3563	0.4118	0.4495	0.2707	0.0777
LMDir	0.4354	0.4583	0.4854	0.2842	0.0901
$\sigma(\mathcal{S})$	0.0433	0.0255	0.0205	0.0147	
LMJM	0.4545	0.4843	0.5248	0.2918	0.1022
$\rho$ BM25	0.4618	0.4887	0.5137	0.3308	0.0814
LMDir	0.5024	0.5260	0.5454	0.3340	0.0969
$\sigma(\mathcal{S})$	0.0258	0.0229	0.0160	0.0235	
LMJM	0.3100	0.3319	0.3657	0.2061	0.0688
$\tau$ BM25	0.3170	0.3370	0.3551	0.2374	0.0519
LMDir	0.3539	0.3713	0.3828	0.2379	0.0668
$\sigma(\mathcal{S})$	0.0236	0.0214	0.0140	0.0182	

(b) NQC

Model( $\mathcal{S}$ )	IR Evaluation Metric ( $\theta$ )				
	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.4056	0.4071	0.3971	0.3054	0.0491
$r$ BM25	0.4488	0.4563	0.4386	0.3485	0.0502
LMDir	0.4908	0.4798	0.4632	0.3424	0.0688
$\sigma(\mathcal{S})$	0.0426	0.0371	0.0334	0.0233	
LMJM	0.3716	0.3794	0.3790	0.3120	0.0325
$\rho$ BM25	0.4520	0.4601	0.4505	0.3586	0.0480
LMDir	0.4582	0.4688	0.4667	0.3528	0.0561
$\sigma(\mathcal{S})$	0.0483	0.0493	0.0467	0.0254	
LMJM	0.2514	0.2567	0.2607	0.2209	0.0181
$\tau$ BM25	0.3116	0.3181	0.3125	0.2549	0.0297
LMDir	0.3194	0.3267	0.3259	0.2493	0.0375
$\sigma(\mathcal{S})$	0.0372	0.0382	0.0344	0.0182	

(c) WIG

Model( $\mathcal{S}$ )	IR Evaluation Metric ( $\theta$ )				
	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.4385	0.4477	0.4472	0.3682	0.0384
$r$ BM25	0.5334	0.5429	0.5316	0.4231	0.0567
LMDir	0.5407	0.5532	0.5507	0.4163	0.0662
$\sigma(\mathcal{S})$	0.0570	0.0582	0.0551	0.0300	
LMJM	0.3017	0.3080	0.3128	0.2651	0.0217
$\tau$ BM25	0.3677	0.3754	0.3688	0.3008	0.0351
LMDir	0.3833	0.3924	0.3911	0.2992	0.0450
$\sigma(\mathcal{S})$	0.0433	0.0445	0.0303	0.0202	

(d) UEF(WIG)

- Lower variations with Kendall's  $\tau$ .
- Lower variations across IR models than IR metrics.

# Variations due to IR Models

Model( $\mathcal{S}$ )	IR Evaluation Metric ( $\theta$ )				
	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.3795	0.3966	0.3869	0.3311	<b>0.0291</b>
$\tau$ BM25	0.5006	0.4879	0.4813	0.2525	<b>0.1190</b>
LMDir	0.5208	0.5062	0.4989	0.2851	0.1121
$\sigma(\mathcal{S})$	<b>0.0764</b>	0.0587	0.0602	<b>0.0395</b>	

(a) AvgIDF

Model( $\mathcal{S}$ )	IR Evaluation Metric ( $\theta$ )				
	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.3652	0.4169	0.4503	0.2548	0.0855
$\tau$ BM25	0.3563	0.4118	0.4495	0.2707	<b>0.0777</b>
LMDir	0.4354	0.4583	0.4854	0.2842	<b>0.0901</b>
$\sigma(\mathcal{S})$	<b>0.0433</b>	0.0255	0.0205	<b>0.0147</b>	

(b) NQC

Model( $\mathcal{S}$ )	IR Evaluation Metric ( $\theta$ )				
	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.4056	0.4071	0.3971	0.3054	<b>0.0491</b>
$\tau$ BM25	0.4488	0.4563	0.4386	0.3485	0.0502
LMDir	0.4908	0.4798	0.4632	0.3423	<b>0.0688</b>
$\sigma(\mathcal{S})$	<b>0.0426</b>	0.0371	0.0334	<b>0.0233</b>	

(c) WIG

Model( $\mathcal{S}$ )	IR Evaluation Metric ( $\theta$ )				
	AP	nDCG	R	P@10	$\sigma(\theta)$
LMJM	0.4746	0.4763	0.4646	0.3573	<b>0.0575</b>
$\tau$ BM25	0.5386	0.5476	0.5263	0.4182	<b>0.0603</b>
LMDir	0.5693	0.5566	0.5373	0.3971	<b>0.0797</b>
$\sigma(\mathcal{S})$	<b>0.0483</b>	0.0440	0.0392	<b>0.0309</b>	

(d) UEF(WIG)

- Lower variations with Kendall's  $\tau$ .
- Lower variations across IR models than IR metrics.
- Lack of consistency on which combination of QPP method with IR evaluation context yields the least variance.

# Research Question

**RQ2:** Do these variations lead to **significant differences in the relative ranks of different QPP methods?**

Model	Metric	AP@100	AP@1000	R@10	R@100	R@1000	nDCG@10	nDCG@100	nDCG@1000
LMJM		0.4286	0.3333	0.9048	0.2381	<b>-0.1429</b>	1.0000	0.2381	0.3333
BM25	AP@10	1.0000	0.9048	1.0000	0.9048	0.4286	1.0000	1.0000	0.7143
LMDir		1.0000	0.9048	1.0000	0.9048	0.4286	1.0000	1.0000	0.7143
LMJM			0.9048	0.5238	0.8095	<b>0.4286</b>	<b>0.4286</b>	0.8095	0.9048
BM25	AP@100		0.9048	1.0000	0.9048	<b>0.4286</b>	1.0000	1.0000	0.7143
LMDir			0.9048	1.0000	0.9048	<b>0.4286</b>	1.0000	1.0000	0.7143
LMJM				0.4286	0.8095	0.5238	<b>0.3333</b>	0.9048	1.0000
BM25	AP@1000			0.9048	0.8095	<b>0.3333</b>	0.9048	0.9048	0.8095
LMDir				0.9048	0.8095	0.5238	0.9048	0.9048	0.8095
LMJM					0.3333	<b>-0.0476</b>	0.9048	0.3333	0.4286
BM25	R@10				0.9048	0.4286	1.0000	1.0000	0.7143
LMDir					0.9048	0.4286	1.0000	1.0000	0.7143
LMJM						0.6190	<b>0.2381</b>	1.0000	0.9048
BM25	R@100					0.5238	0.9048	0.9048	0.6190
LMDir						0.5238	0.9048	0.9048	0.6190
LMJM							<b>-0.1429</b>	0.6190	0.5238
BM25	R@1000						0.4286	0.4286	0.5238
LMDir							0.4286	0.4286	0.5238
LMJM								<b>0.2381</b>	0.3333
BM25	nDCG@10							1.0000	0.7143
LMDir								1.0000	0.7143
LMJM									<b>0.9048</b>
BM25	nDCG@100								0.7143
LMDir									0.7143

- Each cell indicates the correlation (Kendall's  $\tau$ ) between QPP systems ranked in order by their evaluated effectiveness.
- A total of 7 QPP systems were used in these experiments - AvgIDF, Clarity, WIG, NQC, UEF(Clarity), UEF(WIG) and UEF(NQC).
- The lowest correlation for each group is in red and the lowest correlations, overall, are bold-faced.

# Variations due to IR Evaluation Metrics

Model	Metric	AP@100	AP@1000	R@10	R@100	R@1000	nDCG@10	nDCG@100	nDCG@1000
LMJM		0.4286	0.3333	0.9048	0.2386	-0.1429	1.0000	0.2381	0.3333
BM25	AP@10	1.0000	0.9048	1.0000	0.9048	0.4286	1.0000	1.0000	0.7143
LMDir		1.0000	0.9048	1.0000	0.9048	0.4286	1.0000	1.0000	0.7143
LMJM		0.9048	0.5238	0.8095	0.4286	0.4286	0.8095	0.9048	
BM25	AP@100		0.9048	1.0000	0.9048	0.4286	1.0000	1.0000	0.7143
LMDir		0.9048	1.0000	0.9048	0.4286	1.0000	1.0000	0.7143	
LMJM			0.4286	0.8095	0.5238	0.3333	0.9048	1.0000	
BM25	AP@1000			0.9048	0.8095	0.3333	0.9048	0.9048	0.8095
LMDir			0.9048	0.8095	0.5238	0.9048	0.9048	0.8095	
LMJM				0.3333	-0.0476	0.9048	0.3333	0.4286	
BM25	R@10				0.9048	0.4286	1.0000	1.0000	0.7143
LMDir					0.9048	0.4286	1.0000	1.0000	0.7143
LMJM					0.6190	0.2381	1.0000	0.9048	
BM25	R@100					0.5238	0.9048	0.9048	0.6190
LMDir						0.5238	0.9048	0.9048	0.6190
LMJM						-0.1429	0.6190	0.5238	
BM25	R@1000						0.4286	0.4286	0.5238
LMDir							0.4286	0.4286	0.5238
LMJM							0.2381	0.3333	
BM25	nDCG@10							1.0000	0.7143
LMDir								1.0000	0.7143
LMJM								0.9048	
BM25	nDCG@100								0.7143
LMDir									0.7143

- LMJM leads to the most instability in the relative ranks.

# Variations due to IR Evaluation Metrics

Model	Metric	AP@100	AP@1000	R@10	R@100	R@1000	DCG@10	nDCG@100	nDCG@1000
LMJM		0.4286	0.3333	0.9048	0.2381	<b>-0.1429</b>	1.0000	0.2381	0.3333
BM25	AP@10	1.0000	0.9048	1.0000	0.9048	0.4286	1.0000	1.0000	0.7143
LMDir		1.0000	0.9048	1.0000	0.9048	0.4286	1.0000	1.0000	0.7143
LMJM		0.9048	0.5238	0.8095	0.4286	0.4286	0.8095	0.9048	
BM25	AP@100		0.9048	1.0000	0.9048	0.4286	1.0000	1.0000	0.7143
LMDir		0.9048	1.0000	0.9048	0.4286	1.0000	1.0000	0.7143	
LMJM			0.4286	0.8095	0.5238	0.3333	0.9048	1.0000	
BM25	AP@1000			0.9048	0.8095	0.3333	0.9048	0.9048	0.8095
LMDir				0.9048	0.8095	0.5238	0.9048	0.9048	0.8095
LMJM				0.3333	<b>-0.0476</b>	0.9048	0.3333	0.4286	
BM25	R@10				0.9048	0.4286	1.0000	1.0000	0.7143
LMDir					0.9048	0.4286	1.0000	1.0000	0.7143
LMJM					0.6190	<b>0.2381</b>	1.0000	0.9048	
BM25	R@100					0.5238	0.9048	0.9048	0.6190
LMDir						0.5238	0.9048	0.9048	0.6190
LMJM						<b>-0.1429</b>	0.6190	0.5238	
BM25	R@1000						0.4286	0.4286	0.5238
LMDir							0.4286	0.4286	0.5238
LMJM							<b>0.2381</b>	0.3333	
BM25	nDCG@10						1.0000	0.7143	
LMDir							1.0000	0.7143	
LMJM							<b>0.9048</b>		
BM25	nDCG@100							0.7143	
LMDir								0.7143	

- LMJM leads to the most instability in the relative ranks.
- Some evaluation metrics are more sensitive to rank cut-off values.

Metric	Model	LMJM (0.6)	BM25 (0.7, 0.3)	BM25 (1.0, 1.0)	BM25 (0.3, 0.7)	LMDir (100)	LMDir (500)	LMDir (1000)
AP@100	LMJM (0.3)	1.0000	0.9048	1.0000	0.9048	0.9048	0.9048	0.9048
nDCG@100		1.0000	0.8095	0.9048	0.9048	0.9048	0.8095	0.8095
R@100		0.9048	0.8095	0.9048	1.0000	1.0000	0.9048	0.9048
P@10		1.0000	0.8095	1.0000	0.8095	<b>0.7143</b>	<b>0.7143</b>	1.0000
AP@100	LMJM (0.6)	0.9048	1.0000	0.9048	0.9048	0.9048	0.9048	0.9048
nDCG@100		0.8095	0.9048	0.9048	0.9048	0.8095	0.8095	0.8095
R@100		0.9048	1.0000	0.9048	0.9048	1.0000	1.0000	1.0000
P@10		0.8095	1.0000	0.8095	<b>0.7143</b>	<b>0.7143</b>	1.0000	1.0000
AP@100	BM25 (0.7, 0.3)	0.9048	0.9048	1.0000	1.0000	1.0000	1.0000	1.0000
nDCG@100		0.9048	0.9048	0.9048	1.0000	1.0000	1.0000	1.0000
R@100		0.9048	0.8095	0.8095	0.9048	0.9048	0.9048	0.9048
P@10		0.8095	1.0000	0.9048	0.9048	0.9048	<b>0.8095</b>	1.0000
AP@100	BM25 (1.0, 1.0)	0.9048	0.9048	0.9048	0.9048	0.9048	0.9048	0.9048
nDCG@100		1.0000	1.0000	0.9048	0.9048	0.9048	0.9048	0.9048
R@100		0.9048	0.9048	1.0000	1.0000	1.0000	1.0000	1.0000
P@10		0.8095	0.7143	<b>0.7143</b>	<b>0.7143</b>	1.0000	1.0000	1.0000
AP@100	LMDir (0.3, 0.7)	0.9048	0.9048	0.9048	1.0000	1.0000	1.0000	1.0000
nDCG@100		1.0000	1.0000	0.9048	0.9048	0.9048	0.9048	0.9048
R@100		1.0000	0.9048	0.9048	0.9048	0.9048	0.9048	0.9048
P@10		0.9048	0.9048	0.9048	0.8095	<b>0.7143</b>	1.0000	1.0000
AP@100	LMDir (100)	0.9048	0.9048	0.9048	0.9048	1.0000	1.0000	1.0000
nDCG@100		0.9048	0.9048	0.9048	0.9048	1.0000	1.0000	1.0000
R@100		0.9048	0.9048	0.9048	0.9048	1.0000	1.0000	1.0000
P@10		0.9048	0.9048	0.9048	0.8095	<b>0.7143</b>	1.0000	1.0000
AP@100	LMDir (500)	0.9048	0.9048	0.9048	0.9048	1.0000	1.0000	1.0000
nDCG@100		0.9048	0.9048	0.9048	0.9048	1.0000	1.0000	1.0000
R@100		0.9048	0.9048	0.9048	0.9048	1.0000	1.0000	1.0000
P@10		0.9048	0.9048	0.9048	0.9048	<b>0.7143</b>	1.0000	1.0000

- Each cell in the table indicates the correlation (Kendall's  $\tau$ ) between QPP systems ranked in order by their evaluated effectiveness.
- 7 QPP systems were used in these experiments.
- The lowest correlation for each group is in red and the lowest correlations, overall, are bold-faced.

# Variations due to IR Models

Metric	Model	LMJM (0.6)	BM25 (0.7, 0.3)	BM25 (1.0, 1.0)	BM25 (0.3, 0.7)	LMDir (100)	LMDir (500)	LMDir (1000)
AP@100		1.0000	0.9048	1.0000	0.9048	0.9048	0.9048	0.9048
nDCG@100	LMJM	1.0000	0.8095	0.9048	0.9048	0.9048	0.8095	0.8095
R@100	(0.3)	0.9048	0.8095	0.9048	1.0000	1.0000	0.9048	0.9048
P@10		1.0000	0.8095	1.0000	0.8095	<b>0.7143</b>	<b>0.7143</b>	1.0000
AP@100			0.9048	<b>1.0000</b>	0.9048	0.9048	0.9048	0.9048
nDCG@100	LMJM		0.8095	0.9048	0.9048	0.9048	0.8095	0.8095
R@100	(0.6)		0.9048	1.0000	0.9048	0.9048	1.0000	1.0000
P@10			0.8095	1.0000	0.8095	<b>0.7143</b>	<b>0.7143</b>	1.0000
AP@100				0.9048	0.9048	1.0000	1.0000	1.0000
nDCG@100	BM25			0.9048	0.9048	0.9048	1.0000	1.0000
R@100	(0.7, 0.3)			0.9048	<b>0.8095</b>	<b>0.8095</b>	0.9048	0.9048
P@10				0.8095	1.0000	0.9048	0.9048	0.8095
AP@100					0.9048	0.9048	0.9048	0.9048
nDCG@100	BM25				1.0000	1.0000	0.9048	0.9048
R@100	(1.0, 1.0)				0.9048	0.9048	1.0000	1.0000
P@10					0.8095	<b>0.7143</b>	<b>0.7143</b>	1.0000
AP@100						1.0000	1.0000	1.0000
nDCG@100	BM25					1.0000	0.9048	0.9048
R@100	(0.3, 0.7)					1.0000	0.9048	0.9048
P@10						0.9048	0.9048	<b>0.8095</b>
AP@100							1.0000	1.0000
nDCG@100	LMDir						0.9048	0.9048
R@100	(100)						0.9048	0.9048
P@10							0.8095	<b>0.7143</b>
AP@100								1.0000
nDCG@100	LMDir							1.0000
R@100	(500)							1.0000
P@10								<b>0.7143</b>

- Relative ranks of QPP systems are quite stable across IR models.

# Variations due to IR Models

Metric	Model	LMJM (0.6)	BM25 (0.7, 0.3)	BM25 (1.0, 1.0)	BM25 (0.3, 0.7)	LMDir (100)	LMDir (500)	LMDir (1000)
AP@100	LMJM (0.3)	1.0000	0.9048	1.0000	0.9048	0.9048	0.9048	0.9048
nDCG@100		1.0000	0.8095	0.9048	0.9048	0.9048	0.8095	0.8095
R@100		0.9048	0.8095	0.9048	1.0000	1.0000	0.9048	0.9048
P@10		1.0000	0.8095	1.0000	0.8095	<b>0.7143</b>	<b>0.7143</b>	1.0000
AP@100	LMJM (0.6)	0.9048	1.0000	0.9048	0.9048	0.9048	0.9048	0.9048
nDCG@100		0.8095	0.9048	0.9048	0.9048	0.8095	0.8095	0.8095
R@100		0.9048	1.0000	0.9048	0.9048	1.0000	1.0000	1.0000
P@10		0.8095	1.0000	0.8095	<b>0.7143</b>	<b>0.7143</b>	1.0000	1.0000
AP@100	BM25 (0.7, 0.3)	0.9048	0.9048	1.0000	1.0000	1.0000	1.0000	1.0000
nDCG@100		0.9048	0.9048	0.9048	1.0000	1.0000	1.0000	1.0000
R@100		0.9048	0.8095	0.8095	<b>0.7143</b>	0.9048	0.9048	0.9048
P@10		0.8095	1.0000	0.9048	0.9048	0.9048	0.8095	0.8095
AP@100	BM25 (1.0, 1.0)	0.9048	0.9048	0.9048	0.9048	0.9048	0.9048	0.9048
nDCG@100		1.0000	1.0000	0.9048	0.9048	0.9048	0.9048	0.9048
R@100		0.9048	0.9048	1.0000	1.0000	1.0000	1.0000	1.0000
P@10		0.8095	<b>0.7143</b>	<b>0.7143</b>	1.0000	0.9048	0.9048	0.8095
AP@100	BM25 (0.3, 0.7)	0.9048	0.9048	1.0000	1.0000	1.0000	1.0000	1.0000
nDCG@100		0.9048	0.9048	1.0000	0.9048	0.9048	0.9048	0.9048
R@100		0.9048	0.9048	1.0000	0.9048	0.9048	0.9048	0.9048
P@10		0.9048	0.9048	0.9048	0.9048	0.9048	0.9048	0.8095
AP@100	LMDir (100)	0.9048	0.9048	0.9048	0.9048	1.0000	1.0000	1.0000
nDCG@100		0.9048	0.9048	0.9048	0.9048	0.9048	0.9048	0.9048
R@100		0.9048	0.9048	0.9048	0.9048	0.9048	0.9048	0.9048
P@10		0.8095	0.8095	0.8095	<b>0.7143</b>	0.8095	<b>0.7143</b>	0.8095
AP@100	LMDir (500)	0.9048	0.9048	0.9048	0.9048	1.0000	1.0000	1.0000
nDCG@100		0.9048	0.9048	0.9048	0.9048	1.0000	1.0000	1.0000
R@100		0.9048	0.9048	0.9048	0.9048	1.0000	1.0000	1.0000
P@10		0.9048	0.9048	0.9048	0.9048	<b>0.7143</b>	0.9048	<b>0.7143</b>

- Relative ranks of QPP systems are quite stable across IR models.
- LMJM leads to more instability in the QPP outcomes.

# Variations due to IR Models

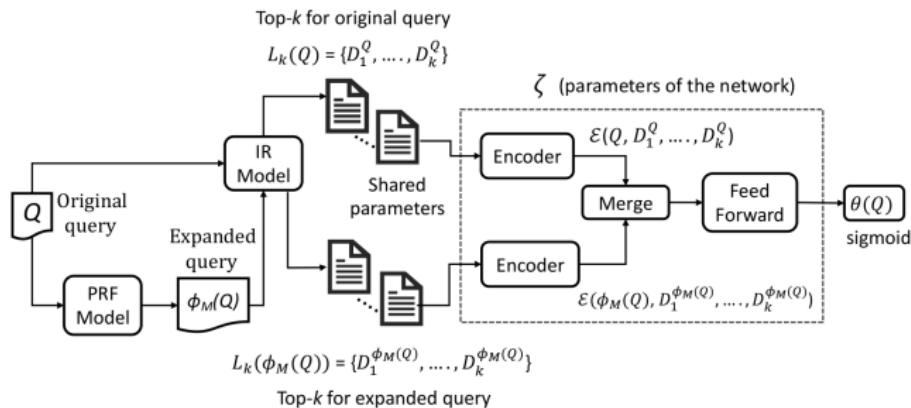
Metric	Model	LMJM	BM25 (0.6)	BM25 (0.7, 0.3)	BM25 (1.0, 1.0)	BM25 (0.3, 0.7)	LMDir (100)	LMDir (500)	LMDir (1000)
AP@100		1.0000	0.9048	1.0000	0.9048	0.9048	0.9048	0.9048	0.9048
nDCG@100	LMJM	1.0000	0.8095	0.9048	0.9048	0.9048	0.8095	0.8095	0.8095
R@100		(0.3)	0.9048	0.8095	0.9048	1.0000	1.0000	0.9048	0.9048
P@10		1.0000	0.8095	1.0000	0.8095	0.7143	0.7143	1.0000	
AP@100			0.9048	1.0000	0.9048	0.9048	0.9048	0.9048	0.9048
nDCG@100	LMJM		0.8095	0.9048	0.9048	0.9048	0.8095	0.8095	0.8095
R@100		(0.6)	0.9048	1.0000	0.9048	0.9048	1.0000	1.0000	1.0000
P@10			0.8095	1.0000	0.8095	0.7143	0.7143	1.0000	
AP@100				0.9048	0.9048	1.0000	1.0000	1.0000	1.0000
nDCG@100	BM25			0.9048	0.9048	0.9048	1.0000	1.0000	1.0000
R@100		(0.7, 0.3)		0.9048	0.8095	0.8095	0.9048	0.9048	
P@10				0.8095	1.0000	0.9048	0.9048	0.8095	
AP@100					0.9048	0.9048	0.9048	0.9048	0.9048
nDCG@100	BM25				1.0000	1.0000	0.9048	0.9048	0.9048
R@100		(1.0, 1.0)			0.9048	0.9048	1.0000	1.0000	
P@10					0.8095	0.7143	0.7143	1.0000	
AP@100						1.0000	1.0000	1.0000	1.0000
nDCG@100	BM25					1.0000	0.9048	0.9048	
R@100		(0.3, 0.7)				1.0000	0.9048	0.9048	
P@10						0.9048	0.9048	0.8095	
AP@100							1.0000	1.0000	1.0000
nDCG@100	LMDir						0.9048	0.9048	
R@100		(100)					0.9048	0.9048	
P@10							0.8095	0.7143	
AP@100								1.0000	
nDCG@100	LMDir							1.0000	
R@100		(500)						1.0000	
P@10								0.7143	

- Relative ranks of QPP systems are quite stable across IR models.
- LMJM leads to more instability in the QPP outcomes.
- Relative ranks of QPP systems are more stable with Kendall's  $\tau$ .

## Ongoing work (Submitted to WSDM'23)

# Adaptive Pseudo-relevance Feedback

- A supervised approach to QPP works quite well!
- QPP prediction can let us decide whether to apply PRF or not.



## Concluding Remarks

# Concluding Remarks

- Summary:

- QPP experiments are very sensitive to the metric used for evaluation, and the IR model which derives a ranked list.
- A purely data-driven early interaction-based model improves QPP.
- Transformer-based approach further improves results; however, training and inference slower compared to 2DCNN.
- Supervised QPP also useful for adaptive relevance feedback.

- Future Directions:

- QPP provides an estimate about the quality of a model's prediction.
- Can be used for recommender systems - because the output is a ranked list of top- $k$  items; Query  $\mapsto$  Context of a user.
- Can also be used for other prediction systems;  $\theta : \vec{x} \mapsto \mathbb{Z}$  could be transformed to  $\phi : \vec{x}, \vec{z} \mapsto \mathbb{R}$ .
- QPP can be extended to *sessions of queries*.

# Thank you!

For any questions you may have, please e-mail me at:

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