Combining Word Embedding Interactions and LETOR Feature Evidences for Supervised QPP

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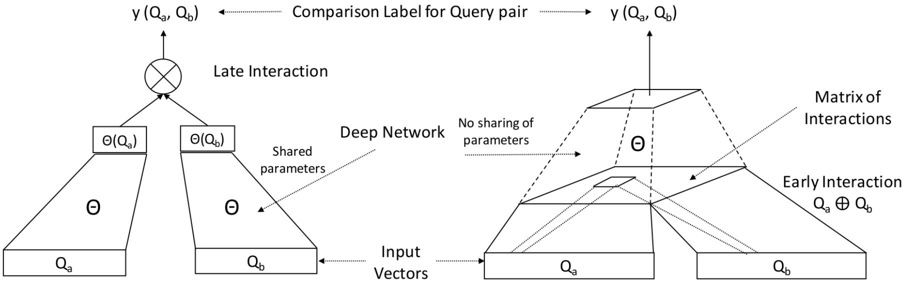
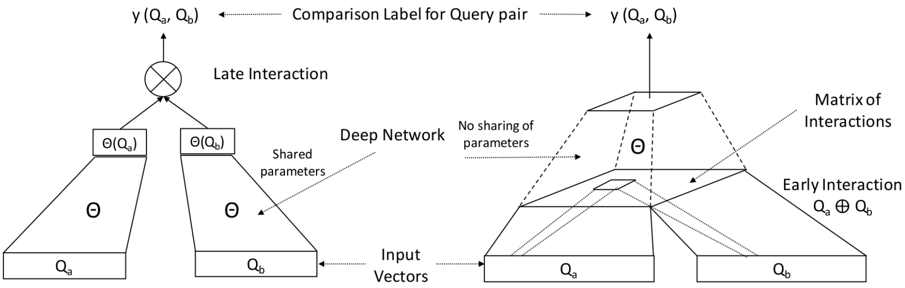
We proposed in WSDM'22

- An end-to-end supervised QPP model.
- Early interactions between query-document pairs.

QPP with Neural Models

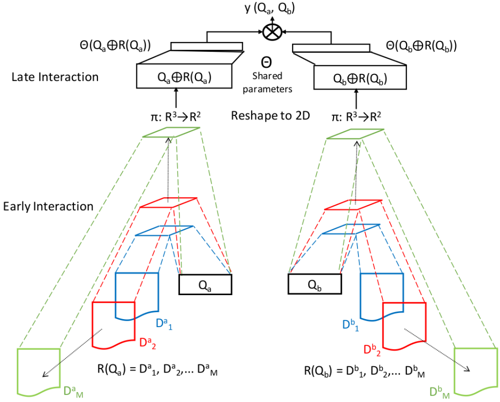


QPP with Neural Models



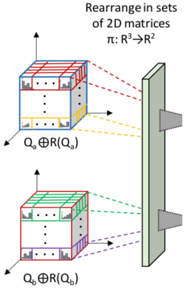
- Representation-based models rely on *late interaction* involving shared parameters (left).
- Interaction-based models make use of *early interactions* transforming paired instances into a single input (right).

What did we propose? - Deep-QPP

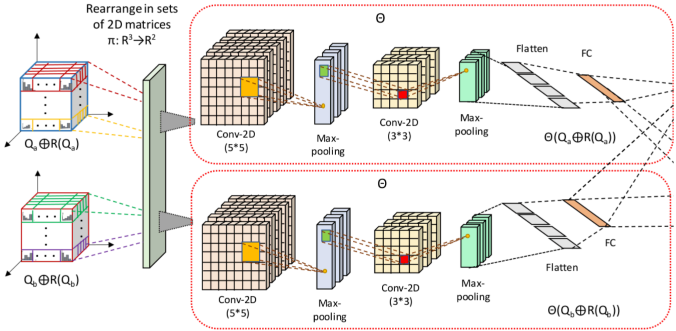


- Combines the benefits of both early and late interactions.
- Includes interaction of the terms in the top-retrieved documents of a query with the constituent terms of the query.
- Incorporates the characteristic pattern of these interactions to estimate the comparison function $y(Q_a, Q_b)$ between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

Deep-QPP - A Pairwise Interaction-based QPP Model

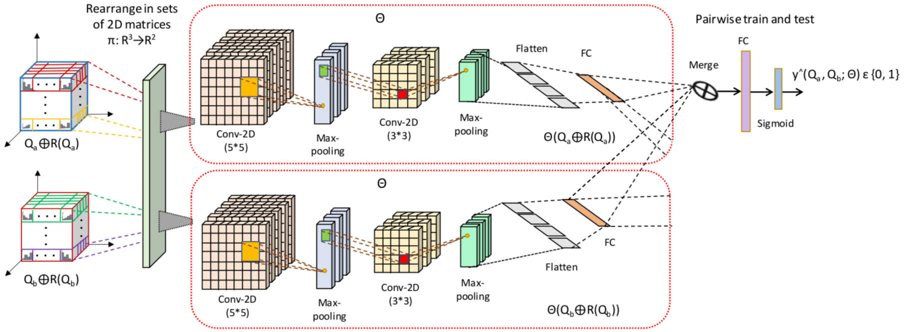


Deep-QPP



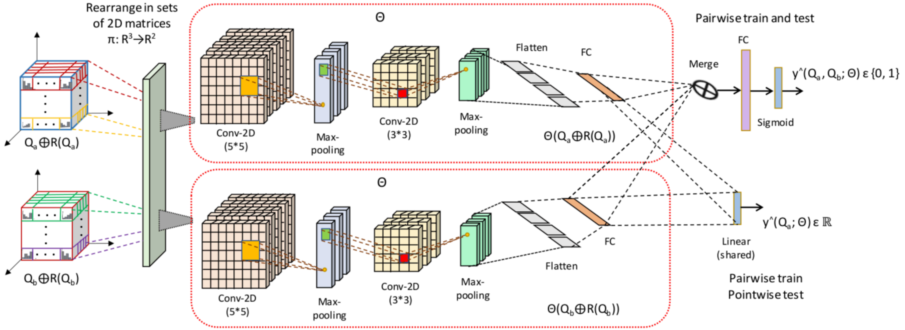
Rearrange in sets of 2D matrices
π: R³→R²
$Q_a \oplus R(Q_a)$
$Q_b \oplus R(Q_b)$
Θ
Conv-2D (5*5)
Max-pooling
Conv-2D (3*3)
Max-pooling
Flatten
FC
$\Theta(Q_a \oplus R(Q_a))$
Θ
Conv-2D (5*5)
Max-pooling
Conv-2D (3*3)
Max-pooling
FC
Flatten
$\Theta(Q_b \oplus R(Q_b))$

Deep-QPP



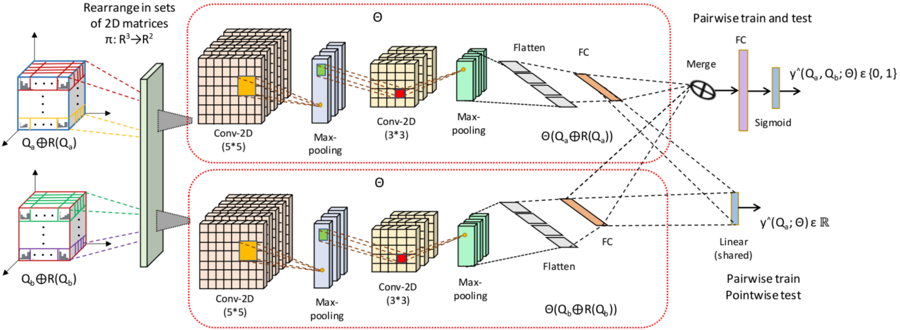
Rearrange in sets of 2D matrices
π: R³→R²
Θ
Conv-2D (5*5)
Max-pooling
Conv-2D (3*3)
Max-pooling
Flatten
FC
Θ(Qa⊕R(Qa))
Qa⊕R(Qa)
Qb⊕R(Qb)
Θ
Conv-2D (5*5)
Max-pooling
Conv-2D (3*3)
Max-pooling
Flatten
FC
Θ(Qb⊕R(Qb))
Pairwise train and test
Merge
FC
Sigmoid
y^(Qa, Qb; Θ) ε {0, 1}

Deep-QPP



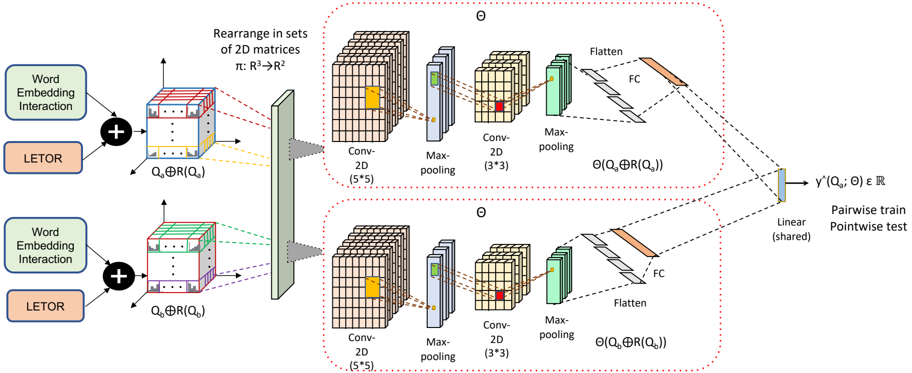
Rearrange in sets
of 2D matrices
π: R³→R²
Θ
Pairwise train and test
Flatten
FC
Merge
FC
y^(Qa, Qb; Θ) ε {0, 1}
Sigmoid
Conv-2D
(5*5)
Max-
pooling
Conv-2D
(3*3)
Max-
pooling
Θ(Qa⊕R(Qa))
Qa⊕R(Qa)
Θ
Qb⊕R(Qb)
y^(Qa; Θ) ε ℝ
Linear
(shared)
FC
Flatten
Pairwise train
Pointwise test
Θ(Qb⊕R(Qb))

Deep-QPP



Suchana Datta, Debasis Ganguly, Derek Greene, and Mandar Mitra. 2022. **Deep-QPP: A Pairwise Interaction-based Deep Learning Model for Supervised Query Performance Prediction.** In Proceedings of the Fifteenth ACM International Conference on Web Search and Data Mining (WSDM '22). Association for Computing Machinery, New York, NY, USA, 201–209. https://doi.org/10.1145/3488560.3498491

Combining LETOR features with Deep-QPP



LETOR features

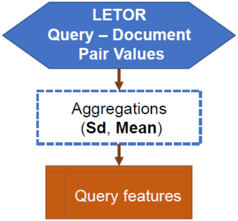
- Use **query-document pairs** to compute query features (as **aggregation** of the pair values)

Examples of **LETOR Features**

- BM25
- TF
- TF-IDF
- Divergence From Randomness
- Language Model with Dirichlet Smoothing (LMDS)

Examples of **Query Features**

- BM25_{STD}
- $\text{TF-IDF}_{\text{MEAN}}$
- LMDS_{STD}



Deveaud et al. [2018]
Mothe and Ullah [2021]
Chifu et al. [2018]

1. Deveaud, R., Mothe, J., Ullah, M. Z., & Nie, J. Y., Learning to adaptively rank document retrieval system configurations. ACM TOIS, 37(1), 2018
2. Mothe, J., & Ullah, M. Z.., Defining an Optimal Configuration Set for Selective Search Strategy-A Risk-Sensitive Approach. CIKM 2021
3. Chifu, A., Laporte, L., Mothe, J., and Ullah, M. Z., Query Performance Prediction Focused on Summarized Letor Features, SIGIR 2018

LETOR features

- Initial documents retrieved using the **BM25 model**
- Extracted the following **19** query-document based features as LETOR features[2] using **Terrier IR**

- WMODEL:Tf
- WMODEL:TF_IDF
- WMODEL:LemurTF_IDF
- WMODEL:BM25
- WMODEL:Js_KLs
- WMODEL:In_expC2
- WMODEL:InB2
- WMODEL:DLH
- WMODEL:ML2
- WMODEL:BB2
- WMODEL:DFIC
- WMODEL:IFB2
- WMODEL:InL2
- WMODEL:PL2
- WMODEL:LGD
- WMODEL:MDL2
- WMODEL:DirichletLM
- WMODEL:DFRee,
- WMODEL:Hiemstra_LM

1. C. Macdonald, R.L. Santos, I. Ounis, and B. He, About learning models with multiple query-dependent features. ACM Transactions on Information Systems, 31 (3), 2013
2. http://terrier.org/docs/v5.2/javadoc/org/terrier/matching/models/WeightingModel.html

Experiments and Evaluation

- Test collection
  - TREC-6-7-8 and Robust collections (250 topics)
- Train-test splits
  - Train set: TREC-6-8 and Robust (200 topics)
  - Test set: TREC-7 (50 topics)
- Pairwise instances
  - Training: 39 402
  - Testing: 2 450
- Metrics
  - AP@100 and nDCG@20
  - Training accuracy, Pearson's r, and Kendall's tau

Preliminary Results

Training on TREC6-8 and Robust (200 topics)

Testing on TREC-7 (50 topics)

	Methods	TREC-7					
		Metric : AP@100			Metric : nDCG@20		
		Pairwise	Pointwise		Pairwise	Pointwise	
		Accuracy	P-r	K-τ	Accuracy	P-r	K-τ
Baselines	NQC	.3110	.2197	.3463	.2971	.2140	**.3420**
	WIG	.3355	.2675	.2751	.3347	.3075	.2931
	UEF (WIG)	.3355	.2743	.2522	.3347	.3110	.2702
Deep-QPP	LETOR	.6669	.4620	.3358	.5522	.1645	.1045
	SDMQ	.6841	.5356	.3668	.5996	.3044	.2025
	SDMQ + LETOR	**.7041**	**.5815**	**.4060**	**.6065**	**.3080**	**.2123**

Concluding Remarks

- We suggest the combination of two approaches that have been developed in two different IR groups.
- We presented the model as well as the way it could be evaluated.
- Our preliminary results show that the combination could be effective.
- We would like to complete the evaluation and analyse the results deeper.

Thank you for your attention!!

LETOR features (know more)

- Extracted the following query-document based features as LETOR features[2]
- Initial documents retrieved using the BM25 model

Feature Names	Definitions
WMODEL:Tf	Tf weighting model
WMODEL:TF_IDF	TF_IDF weighting model
WMODEL:LemurTF_IDF	TF_IDF weighting model as it is implemented in Lemur
WMODEL:BM25	Okapi BM25 weighting model
WMODEL:Js_KLs	Jefrreys' divergence with the Kullback Leibler's divergence
WMODEL:In_expC2	Inverse Expected Document Frequency model with Bernoulli after-effect and normalization
WMODEL:InB2	Inverse Document Frequency model with Bernoulli after-effect and normalisation 2
WMODEL:DLH	A parameter-free weighting model
WMODEL:ML2	ML2 field-based weighting model
WMODEL:BB2	BB2 weighting model

1. C. Macdonald, R.L. Santos, I. Ounis, and B. He, About learning models with multiple query-dependent features. ACM Transactions on Information Systems, 31 (3), 2013
2. http://terrier.org/docs/v5.2/javadoc/org/terrier/matching/models/WeightingModel.html

LETOR features (know more)

- Extracted the following query-document based features as LETOR features[2]
- Initial documents retrieved using the BM25 model

Feature Names	**Definitions**
WMODEL:DFIC	Divergence From Independence model based on Chi-square statistics
WMODEL:IFB2	IFB2 weighting model
WMODEL:InL2	InL2 weighting model
WMODEL:PL2	PL2 weighting model
WMODEL:LGD	LGD weighting model (Bridging LM and DFR models)
WMODEL:MDL2	MDL2 field-based weighting model
WMODEL:DirichletLM	Language model with Dirichlet Prior
WMODEL:DFRee	DFR free from parameters
WMODEL:Hiemstra_LM	Hiemstra LM weighting model

1. C. Macdonald, R.L. Santos, I. Ounis, and B. He, About learning models with multiple query-dependent features. ACM Transactions on Information Systems, 31 (3), 2013
2. http://terrier.org/docs/v5.2/javadoc/org/terrier/matching/models/WeightingModel.html