

# RMIT at the NTCIR-12 MobileClick-2: iUnit Ranking and Summarization Subtasks

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# Introduction

- Learning-to-Rank (LTR) framework<sup>1</sup>
- Enhance iUnit ranking using feature-based approach
- Extend existing QSum<sup>2</sup> feature set

<sup>1</sup> Yang et al. (2016)

<sup>2</sup> Metzler & Kanungo. (2008)

# Aim

- Maximise the score for ranking by exploring different novel features
  - 5 classes (BL, QSum, Semantic, QT, Ctx)
- Test our features on the summarisation subtask
- Check if LTR can deal with this level of homogeneity

# Methods (1)

5 different classes

Class		Type
Baseline	BL	Language Model
Lexical / Synonymy	QSum	Metzler and Kanungo (2008)
Semantic Relatedness	Sem	Yang et al. (2016)

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Question / Entity	QT	New
Document Context	Ctx	New

# Features

## **Base (BL)**

OddsRatio

## **QSum<sup>1</sup>**

ExactMatch

TermOverlap

SynonymOverlap

LanguageModel

iUnitLength

## **Sem<sup>2</sup>**

ESA

Word2Vec

Tagme

## **Question type and entities (QT)**

Leading5W1H

TopRankedWikiPage

WikipediaRR

WikipediaPassage

## **Contexts (Ctx)**

CollectionFrequency

AverageSentencePos

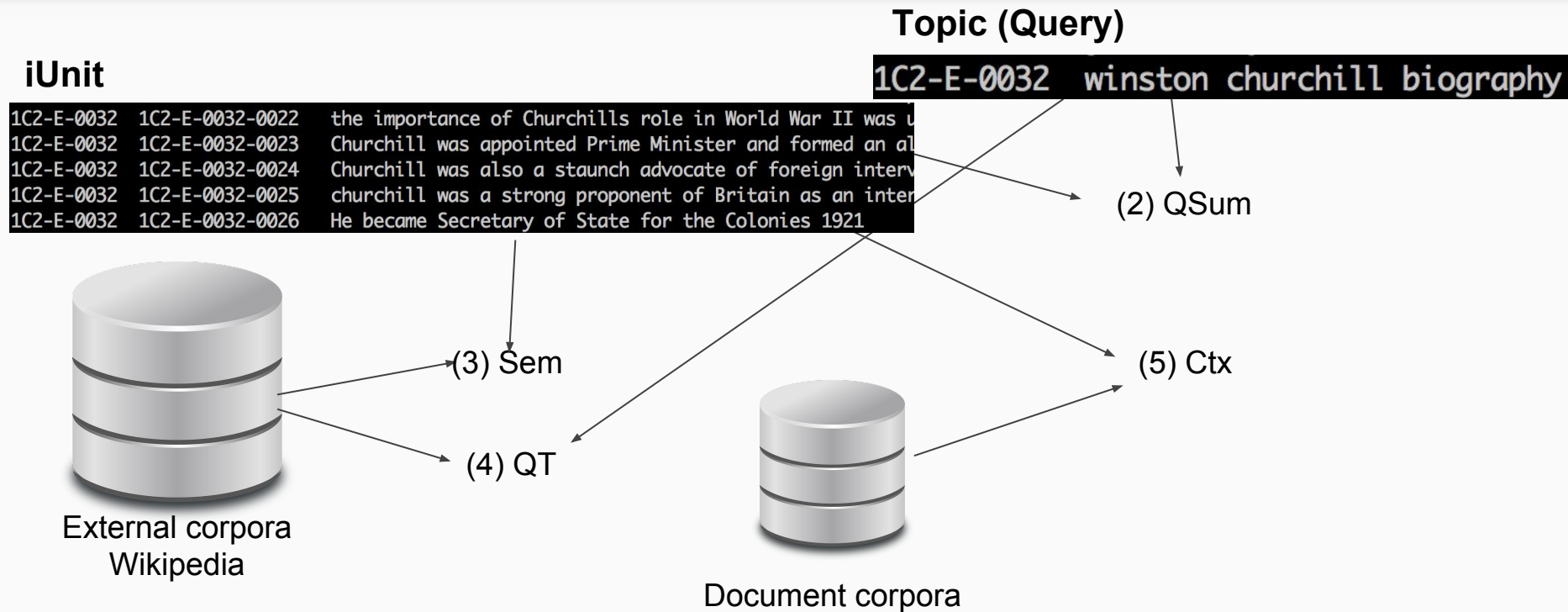
AverageDocumentRR



<sup>1</sup> Metzler & Kanungo. (2008)

<sup>2</sup> Yang et al. (2016)

# Methods (2)



# Results

## English iUnit Ranking (Training)

Rank	Group ID	Score
1	RISAR	0.8878
2	UHYG	0.8788
3	ORG	0.8772
4	ALICA	0.8621

## English iUnit Ranking (Test)

Rank	Group ID	Score
1	TITEC	0.9003
2	UHYG	0.8994
3	ORG	0.8975
4	RISAR	0.8972

## English iUnit Summarization (Test)

Rank	Group ID	Score
1	TITEC	18.2596
2	ORG	16.8975
3	RISAR	16.047

# Results - English iUnit Ranking (1)

Method	Algorithm	nDCG@3	nDCG@5	nDCG@10	nDCG@20	Q
Base ( <b>BL</b> )		0.7438	0.7643	0.7961	0.8325	0.8772
Base+QSum ( <b>BQ</b> )	Coordinate Ascent	0.7669*	<b>0.7821</b>	<b>0.8137*</b>	<b>0.8504**</b>	<b>0.8882**</b>
Base+QSum+Sem	LambdaMART	<b>0.7686*</b>	0.7759	0.8085*	0.8422*	0.8848**
Base+QSum+Sem+QT	LambdaMART	0.7674*	0.7788	0.8070*	0.8453**	0.8875**
Base+QSum+Sem+QT+Ctx ( <b>BQP</b> )	LambdaMART	0.7668*	0.7801*	0.8067	0.8435*	0.8819

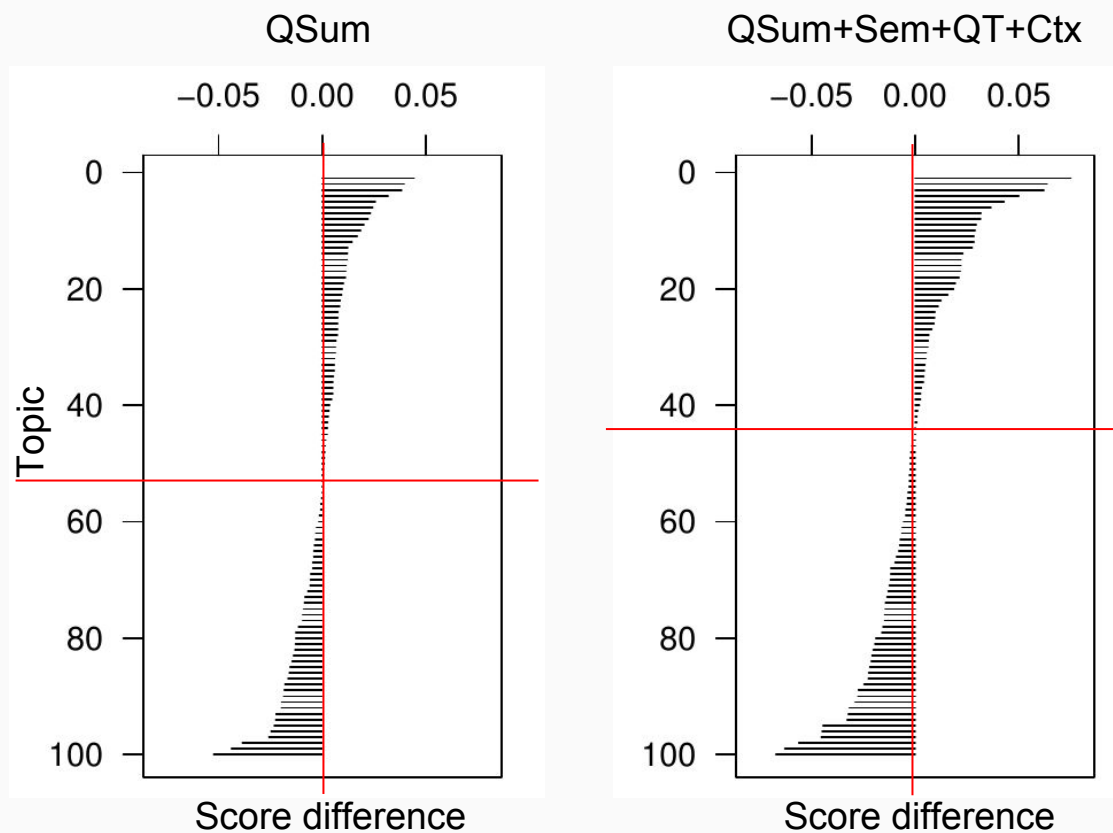
**Table 2: Performance results on the training set for English iUnit Ranking. Significant improvements are indicated by \* and \*\* (Two-tailed t-test;  $p < 0.05$  and  $p < 0.01$  respectively).**

Method	Algorithm	nDCG@3	nDCG@5	nDCG@10	nDCG@20	Q
Base ( <b>BL</b> )		<b>0.7460</b>	<b>0.7596</b>	<b>0.8033</b>	0.8689	<b>0.8975</b>
Base+QSum ( <b>BQ</b> )	Coordinate Ascent	0.7354	0.7557	0.8015	<b>0.8690</b>	0.8972
Base+QSum+Sem+QT+Ctx ( <b>BQP</b> )	LambdaMART	0.7352	0.7532	0.8002	0.8666	0.8962

**Table 3: Performance results on the test set for English iUnit Ranking.**



# Results - English iUnit Ranking (2)

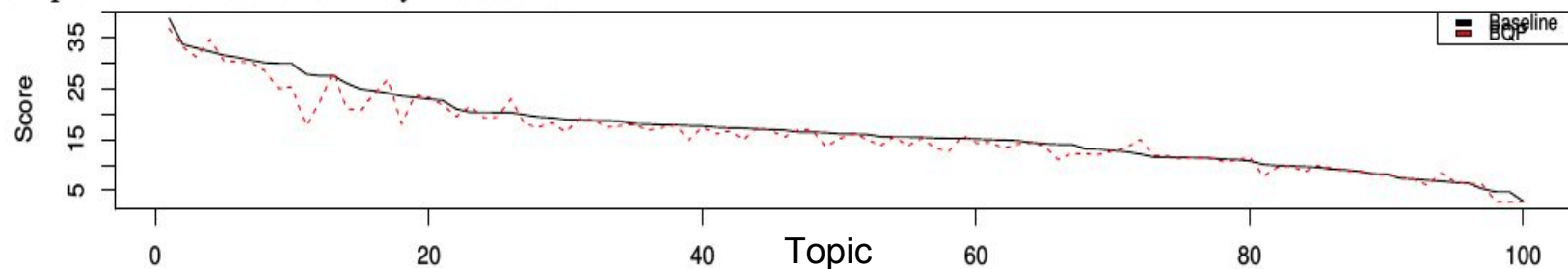


# Results - English iUnit Summarisation

Method	M
Base ( <b>BL</b> ), 2-layer	<b>16.8975</b>
Base+QSum+Sem+QT+Ctx ( <b>BQP</b> ), 2-layer	16.047

**Table 4: Results for English iUnit Summarization.**

Figure 2: Distribution of score for summarization subtask between Baseline and *BQP*. Baseline is observed to perform better than *BQP* features



# Conclusion

## For iUnit ranking

BL+QSum features outperformed newer features for training dataset

BL+QSum+Sem+QT+Ctx has a higher variance for gain/loss

## For iUnit Summarisation

1 simple run submitted

Interesting to find LTR score better than BL occasionally

## Generally

LTR may be useful to generate 2-layer summaries

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