

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

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Introduction

- Learning-to-Rank (LTR) framework¹
- Enhance iUnit ranking using feature-based approach
- Extend existing QSum² feature set

¹ Yang et al. (2016)

² 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)

Question / Entity	QT	New
Document Context	Ctx	New

Features

Base (BL)

OddsRatio

QSum¹

ExactMatch

TermOverlap

SynonymOverlap

LanguageModel

iUnitLength

Sem²

ESA

Word2Vec

Tagme

Question type and entities (QT)

Leading5W1H

TopRankedWikiPage

WikipediaRR

WikipediaPassage

Contexts (Ctx)

CollectionFrequency

AverageSentencePos

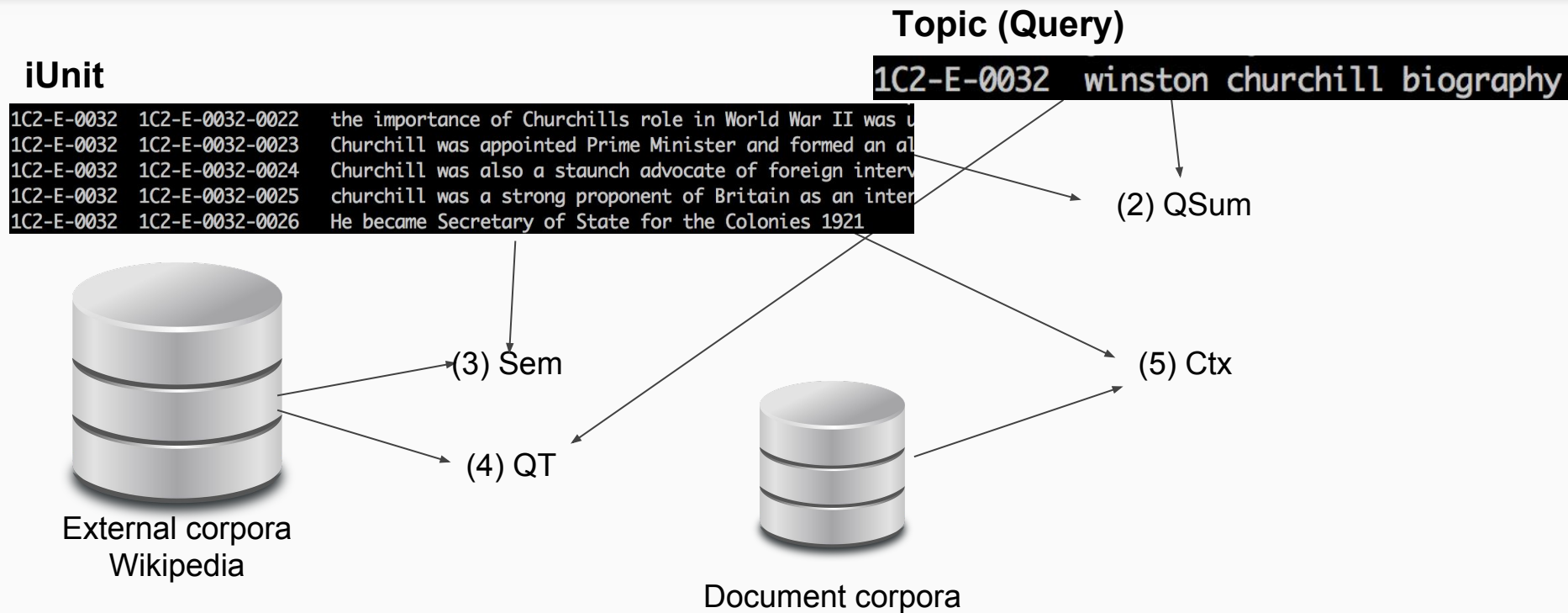
AverageDocumentRR



¹ Metzler & Kanungo. (2008)

² 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)

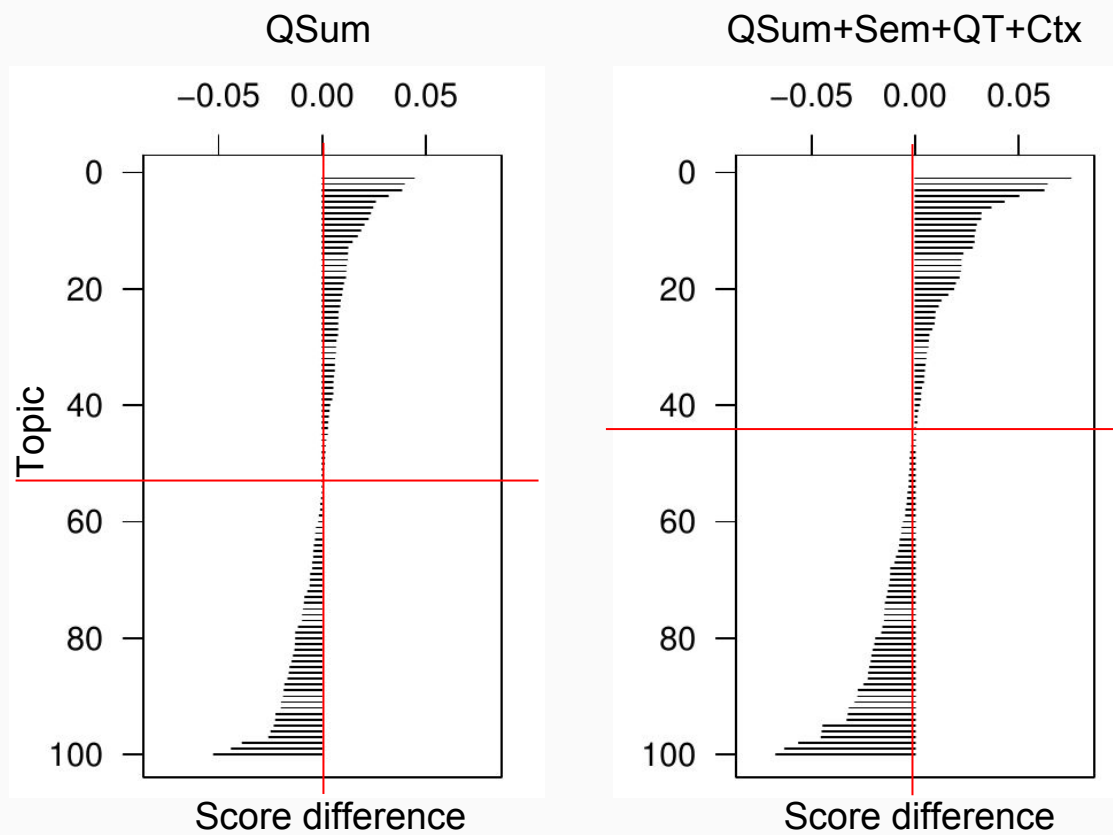
Method	Algorithm	nDCG@3	nDCG@5	nDCG@10	nDCG@20	Q
Base (BL)		0.7438	0.7643	0.7961	0.8325	0.8772
Base+QSum (BQ)	Coordinate Ascent	0.7669*	0.7821	0.8137*	0.8504**	0.8882**
Base+QSum+Sem	LambdaMART	0.7686*	0.7759	0.8085*	0.8422*	0.8848**
Base+QSum+Sem+QT	LambdaMART	0.7674*	0.7788	0.8070*	0.8453**	0.8875**
Base+QSum+Sem+QT+Ctx (BQP)	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 (BL)		0.7460	0.7596	0.8033	0.8689	0.8975
Base+QSum (BQ)	Coordinate Ascent	0.7354	0.7557	0.8015	0.8690	0.8972
Base+QSum+Sem+QT+Ctx (BQP)	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)

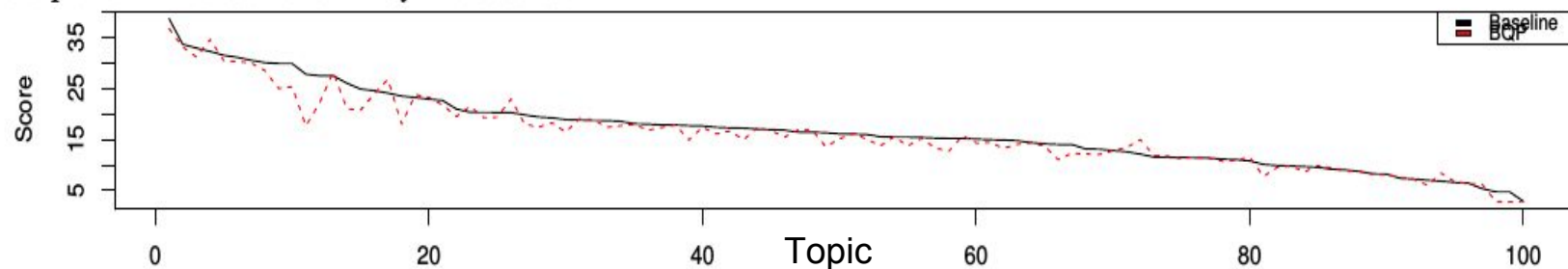


Results - English iUnit Summarisation

Method	M
Base (BL), 2-layer	16.8975
Base+QSum+Sem+QT+Ctx (BQP), 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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