Phrase-BERT: Improved Phrase Embeddings from BERT with an Application to Corpus Exploration



Shufan Wang

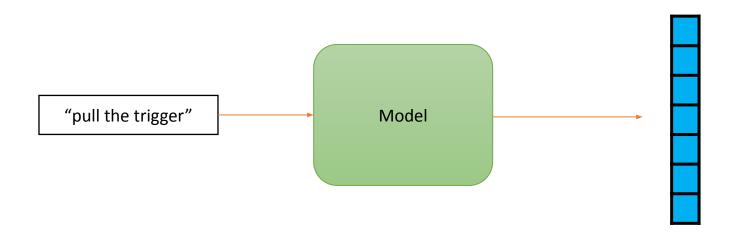


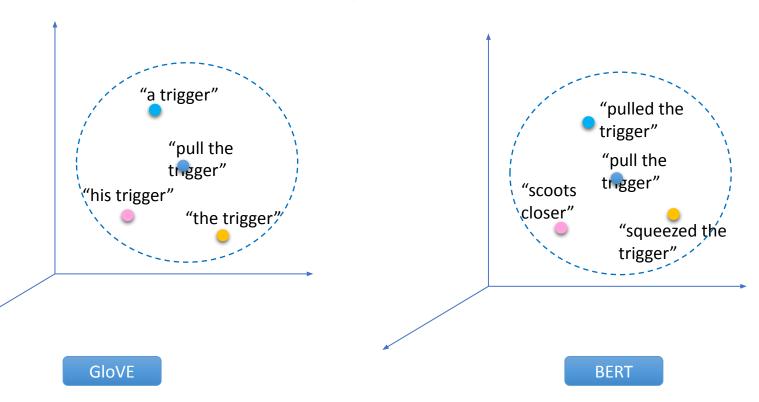
Laure Thompson

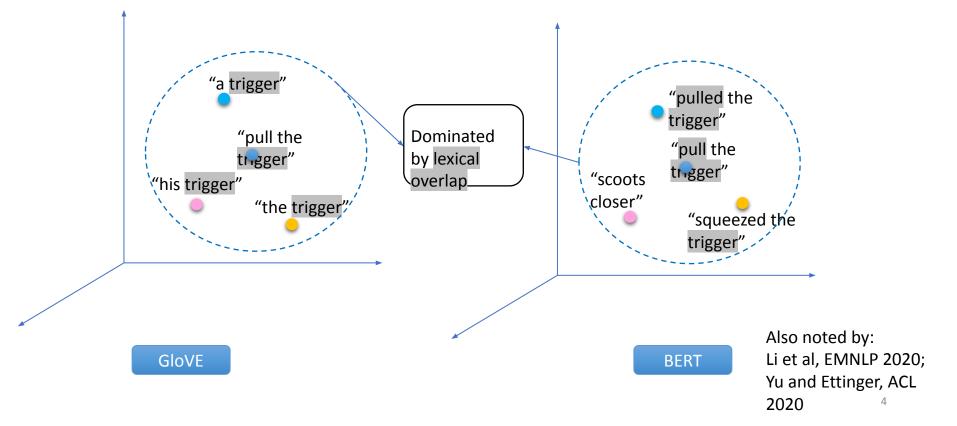


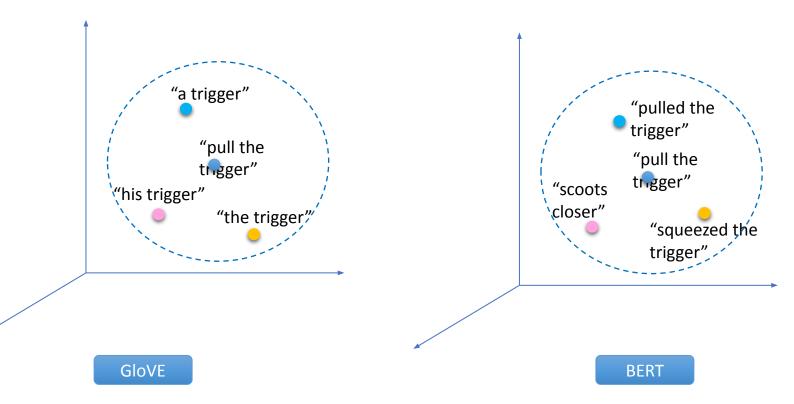
Mohit Iyyer

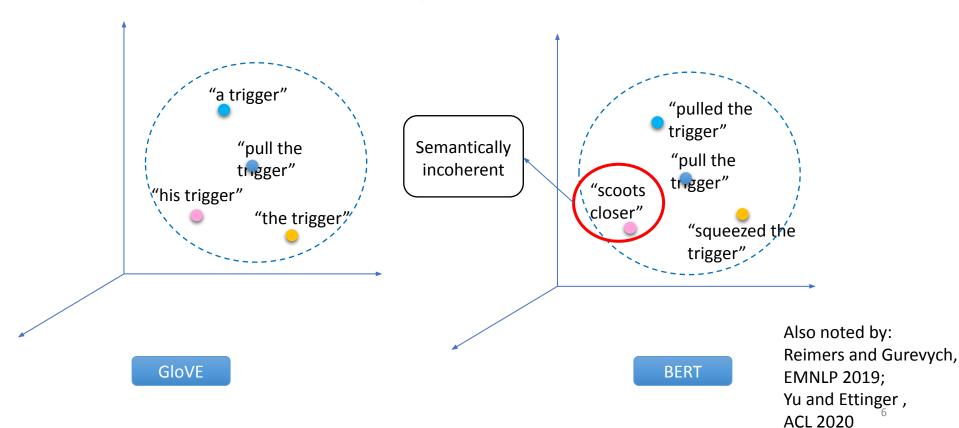
A general-purpose phrase embedding

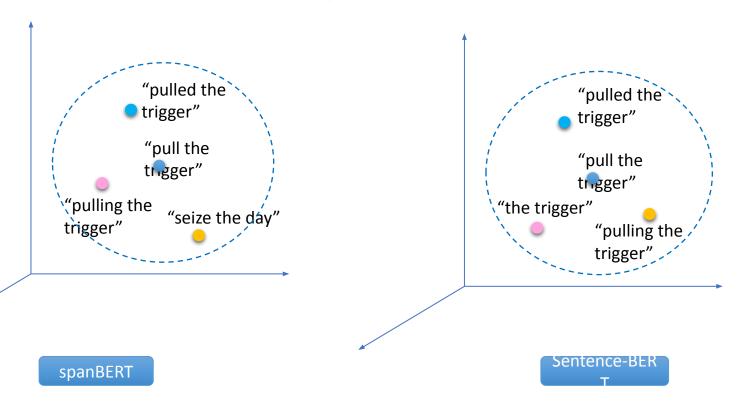


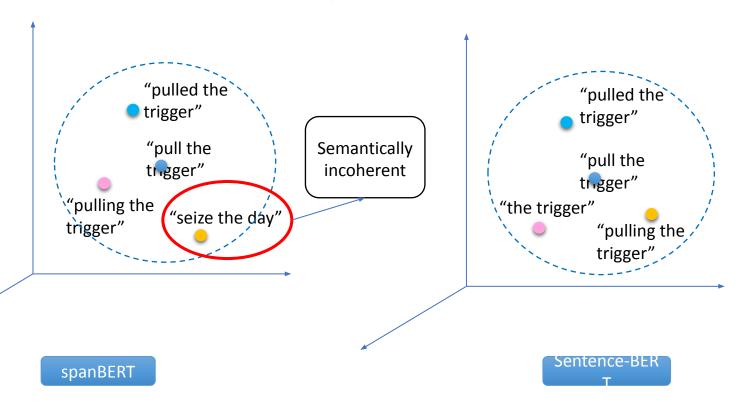


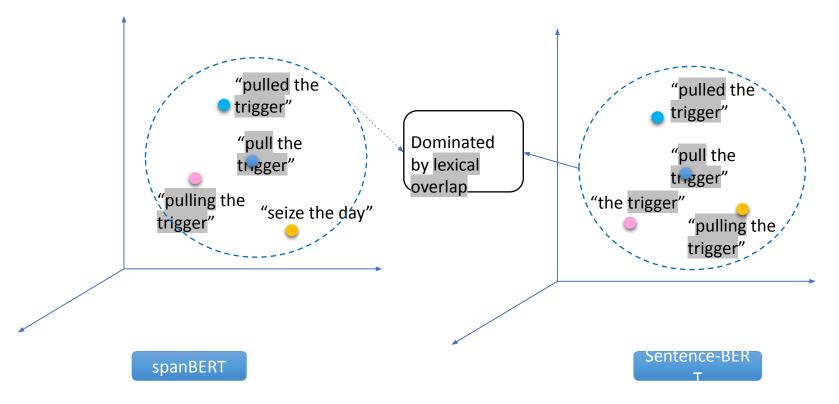




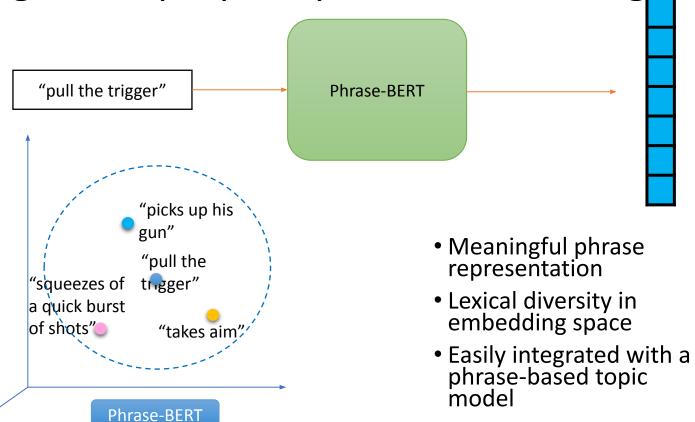




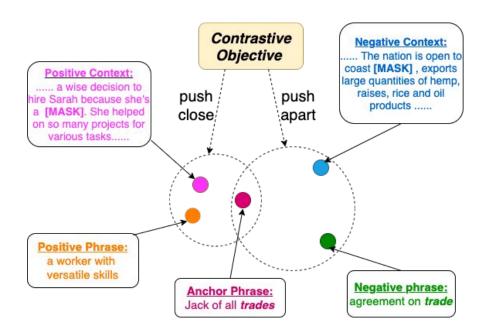




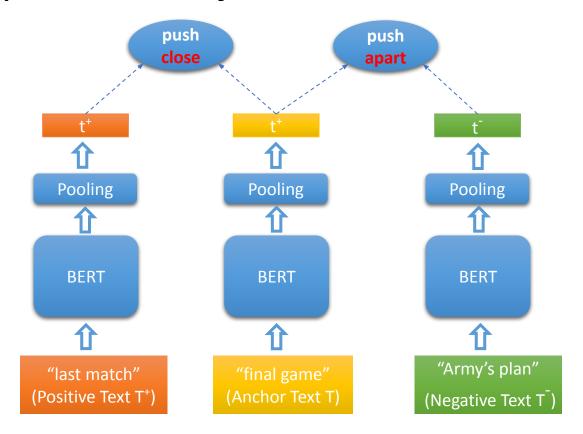
A general-purpose phrase embedding



A Contrastive Learning approach

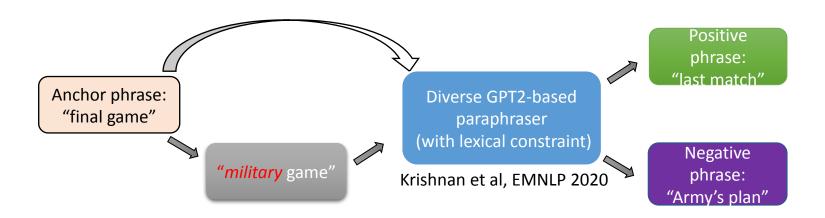


A Triplet Loss Objective



A dataset of diverse paraphrases

Construct diverse paraphrases to remove lexical cues:



A dataset of phrase-in-context

 Context are from Books 3 Corpus (a large scale 100 GB collection of books from various genres)

Positive Context: The current legal education consists of a 5-year-long course after which the scholar is granted a bachelor's degree

- Negative contexts are randomly sampled
- Mask off the actual occurrence of the anchor phrase

Turney: unigram-bigram concept match

BiRD: bi-gram Relatedness

PPDB: paraphrase detection

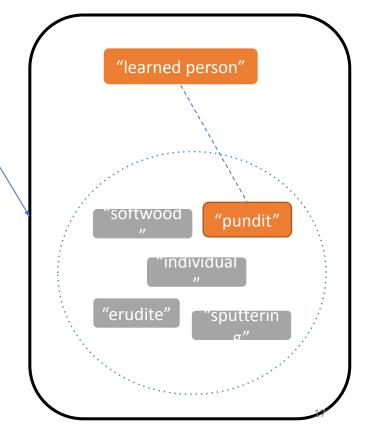
PPDB-filtered: paraphrase detection

Turney: unigram-bigram concept match

BiRD: bi-gram Relatedness

PPDB: paraphrase detection

PPDB-filtered: paraphrase detection

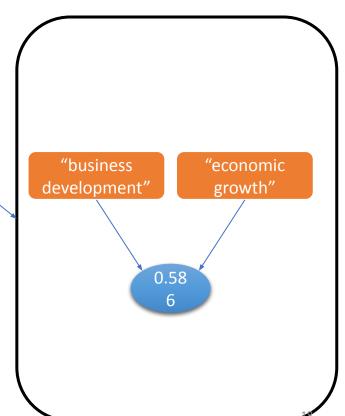


Turney: unigram-bigram concept match

BiRD: bi-gram Relatedness

PPDB: paraphrase detection

PPDB-filtered: paraphrase detection

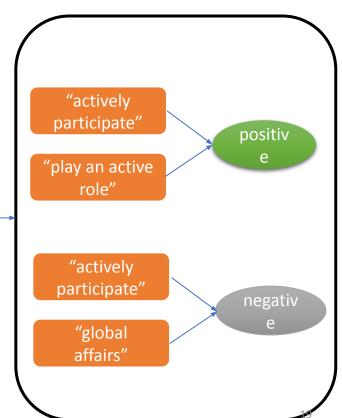


Turney: unigram-bigram concept match

BiRD: bi-gram Relatedness

PPDB: paraphrase detection

PPDB-filtered: paraphrase detection

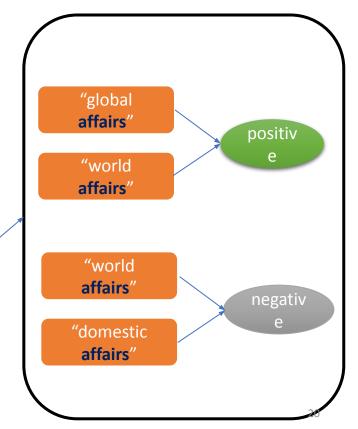


Turney: unigram-bigram concept match

BiRD: bi-gram Relatedness

PPDB: paraphrase detection

PPDB-filtered*: paraphrase detection



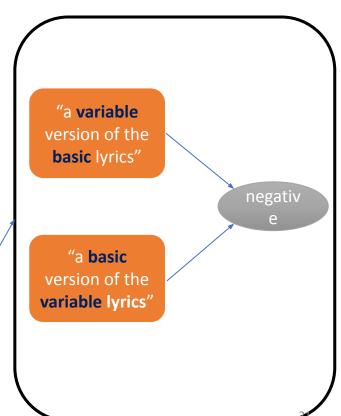
^{*} Yu and Ettinger, ACL 2020

Turney: unigram-bigram concept match

BiRD: bi-gram Relatedness

PPDB: paraphrase detection

PPDB-filtered: paraphrase detection



Model	Turney	BiRD	PPDB-filt ered	PPDB	PAWS-sh ort
Glove	37.8	0.560	44.2	47.2	50.0
BERT	42.6	0.444	60.1	86.2	50.0
SpanBERT	38.7	0.258	57.3	95.1	50.1
Sentence- BERT	51.8	0.687	64.2	95.8	50.0
Phrase-BE RT	57.2	0.688	68.0	97.6	58.9

Model	Turney	BiRD	PPDB-filt ered	PPDB	PAWS-sh ort
Glove	37.8	0.560	44.2	47.2	50.0
BERT	42.6	0.444	60.1	86.2	50.0
SpanBERT	38.7	0.258	57.3	95.1	50.1
Sentence- BERT	51.8	0.687	64.2	95.8	50.0
Phrase-BE RT	57.2	0.688	68.0	97.6	58.9

Phrase-BERT consistently outperforms baselines across all tasks

Model	Turney	BiRD	PPDB-filt ered	PPDB	PAWS-sh ort
Glove	37.8	0.560	44.2	47.2	50.0
BERT	42.6	0.444	60.1	86.2	50.0
SpanBERT	38.7	0.258	57.3	95.1	50.1
Sentence- BERT	51.8	0.687	64.2	95.8	50.0
Phrase-BE RT	57.2	0.688	68.0	97.6	58.9

BERT sometimes underperforms un-contextualized baselines

Model	Turney	BiRD	PPDB-filt ered	PPDB	PAWS-sh ort
Glove	37.8	0.560	44.2	47.2	50.0
BERT	42.6	0.444	60.1	86.2	50.0
SpanBERT	38.7	0.258	57.3	95.1	50.1
Sentence- BERT	51.8	0.687	64.2	95.8	50.0
Phrase-BE RT	57.2	0.688	68.0	97.6	58.9

SpanBERT is not the solution for phrases representation

Model	Turney	BiRD	PPDB-filt ered	PPDB	PAWS-sh ort
Glove	37.8	0.560	44.2	47.2	50.0
BERT	42.6	0.444	60.1	86.2	50.0
SpanBERT	38.7	0.258	57.3	95.1	50.1
Sentence- BERT	51.8	0.687	64.2	95.8	50.0
Phrase-BE RT	57.2	0.688	68.0	97.6	58.9

Sentence-BERT (contrastively fine-tuned) offers closer performance to Phrase-BERT

Model	Turney	BiRD	PPDB-filt ered	PPDB	PAWS-sh ort
Glove	37.8	0.560	44.2	47.2	50.0
BERT	42.6	0.444	60.1	86.2	50.0
SpanBERT	38.7	0.258	57.3	95.1	50.1
Sentence- BERT	51.8	0.687	64.2	95.8	50.0
Phrase-BE RT	57.2	0.688	68.0	97.6	58.9

BERT-based baselines are great at taking lexical cues

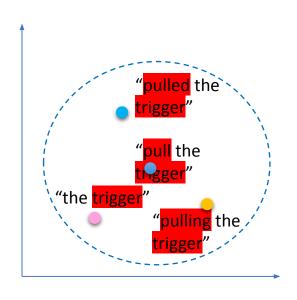
Model	Turney	BiRD	PPDB-filt ered	PPDB	PAWS-sh ort
Glove	37.8	0.560	44.2	47.2	50.0
BERT	42.6	0.444	60.1	86.2	50.0
SpanBERT	38.7	0.258	57.3	95.1	50.1
Sentence- BERT	51.8	0.687	64.2	95.8	50.0
Phrase-BE RT	57.2	0.688	68.0	97.6	58.9

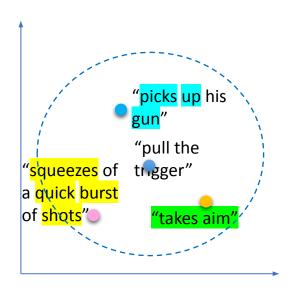
But over-reliance on lexical overlaps hurts phrase semantics understanding

Model	Turney	BiRD	PPDB-filt ered	PPDB	PAWS-sh ort
Glove	37.8	0.560	44.2	47.2	50.0
BERT	42.6	0.444	60.1	86.2	50.0
SpanBERT	38.7	0.258	57.3	95.1	50.1
Sentence- BERT	51.8	0.687	64.2	95.8	50.0
Phrase-BE RT	57.2	0.688	68.0	97.6	58.9

Compositionality is hard to capture for all models

Lexical diversity





Sentence-BER

Phrase-BERT

Lexical diversity

Model	percentage of new tokens (↑= more diverse)	LCS- Precision (↓= more diverse)	Levenshtein distance (↑= more diverse)
Sentence-BERT	5.0	51.1	8.5
Phrase-BERT	5.3	47.6	8.7

Phrase-based topic model: a case study

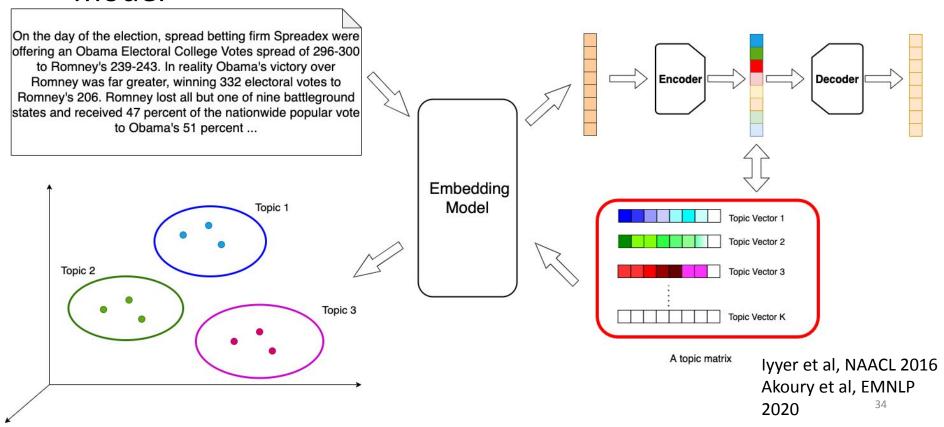
Baseline model: LDA

• LDA = latent dirichlet allocation

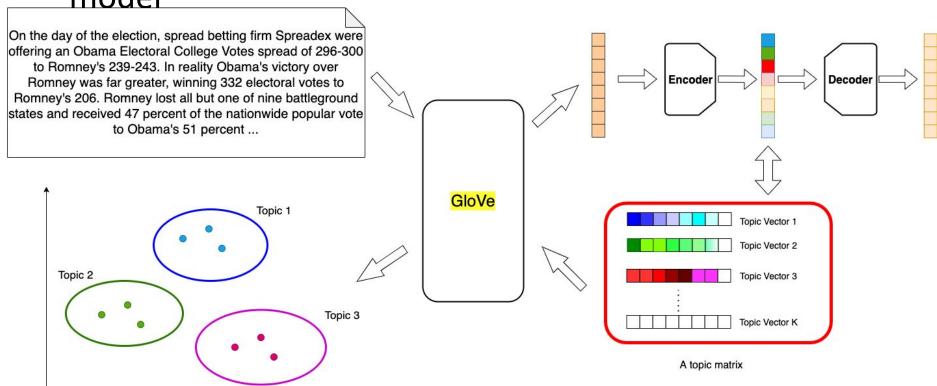
The dominant approach for corpus exploration

Each topic is represented by a list of unigrams.

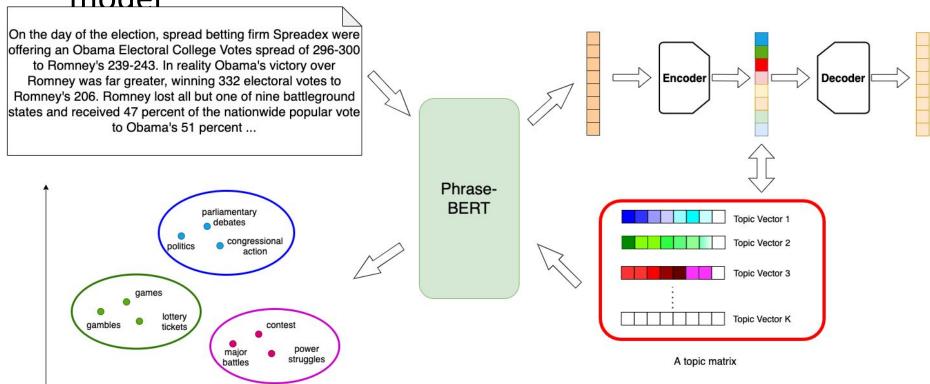
Autoencoder + phrase-BERT = Phrase-based topic model



Autoencoder + phrase-BERT = Phrase-based topic model



Autoencoder + phrase-BERT = Phrase-based topic model



Human Evaluation on Topic Coherence

Model	Wiki	Story	Reviews	Average
Phrase-BERT based topic model (PNTM)	83.3	76.7	77.3	79.1
Phrase-LDA (pLDA)	55.3	48.7	50.7	51.6
Topical N-Gram (TNG)	37.3	58.7	60.0	52.1
Unigram (GloVe) based topic model (UNTM)	76.9	70.0	62.0	69.6
Latent Dirichlet Allocation (LDA)	48.7	48.0	52.7	49.8

Word Intrusion Test for Topic Coherence (↑= more coherent)

Human Evaluation on Topic-to-document relatedness

Model	Accuracy
Phrase-BERT based topic model (PNTM)	89.3
Phrase-LDA (pLDA)	89.3
Topical N-Gram (TNG)	78.7
Unigram (GloVe) based topic model (UNTM)	80.7
Latent Dirichlet Allocation (LDA)	90.0

Topic Intrusion Test for Topic Assignment (\(\gamma=\) more agreement with humans in assigning topics to documents)

Phrase-BERT enables meaningful topic by reducing lexical overlap

Topic on "sports"

winning, semifinalist, finisher, a race, raceme, race, the race, the race's, side rowing competition, formula one

```
the semifinal, Olympic,
marathon, raceme, bicyclist,
semifinalist, side rowing race,
race, place finish, side rowing
competition
```

Topic on "music"

the Beatles, his album, the album, discography, the album, an album, Beatles, this album, the Beatles', their album

musician, his music, musical, concerto, chorale, liver performance, a concert, accompaniment, pianistic, antiphonal

Conclusion and Future work

Our contributions:

- Phrase-BERT, a more powerful phrase embedding models
- ↑ capture phrase semantics, ↓ lexical overlap
- Easily integrated into a phrase-based topic model

Future directions:

- Towards a benchmark of holistic phrase-evaluation
- Multi-lingual phrase embeddings,
- Other downstream tasks involving phrases

Thank you!