# Have We Solved The *Hard* Problem? It's Not *Easy*! Contextual Lexical Contrast as a Means to Probe Neural Coherence

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## Full Slides

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https://cont2lex.github.io/

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# 1. Task Introduction — Contextual Lexical Contrast

# Contextual Lexical Contrast (CLC)

Example: positive vs negative:

(Ex. 1 Positive CLC): A **positive** attitude helps you relax and ace the exams, and a **negative** mental status will however make you nervous and sleepless.

(Ex. 2 Negative CLC): The reviewers are rather **positive** about this paper. They are nominating it for the Best Paper for its discovery of a **negative** finding that dispels conventional wisdom.

Definition of CLC (a new NLP task):

- Two words are understood as contrast in order to understand the coherence of context.

# 2. Motivation and Background

# Motivation and Background
## — Why CLC is important.

- Cohesion Modeling
  - Entity-based
  - Lexical-based
- Lexical Contrast and Lexical Relation
- Interpretations of Semantic Representations

# Cohesion Modeling
## — Lexical-based approach is overlooked.

### Entity-based Approach

**BERT** (Bidirectional Encoder Representations from Transformers; Devlin et al., 2019) is also based on the transformer, but it is bidirectional as opposed to left-to-right as in the OpenAI GPT, and the directions are dependent as opposed to ELMo's independently trained left-to-right and right-to-left LSTMs. It also introduces a somewhat different objective called ''masked language model'': during training, some tokens are randomly masked, and the objective is to restore them from the context.

Excerpted from Shwartz & Dagan, TACL2019

✅ Entity grid method (Barzilay and Lapata)

### Lexical-based Approach

**BERT** (Bidirectional Encoder Representations from Transformers; Devlin et al., 2019) is also based on the transformer, but it is bidirectional as opposed to left-to-right as in the OpenAI GPT, and the directions are dependent as opposed to ELMo's independently trained left-to-right and right-to-left LSTMs. It also introduces a somewhat different objective called ''masked language model'': during training, some tokens are randomly masked, and the objective is to restore them from the context.

Excerpted from Shwartz & Dagan, TACL2019

❓
- Being Largely Ignored
- Need to put into context

# Lexical Contrast

## — Context is critical for downstream applications.

**Computing Lexical Contrast**

Saif M. Mohammad*
National Research Council Canada

Bonnie J. Dorr**
University of Maryland

Graeme Hirst†
University of Toronto

Peter D. Turney‡
National Research Council Canada

Computational Linguistic, 2013

**Applications**

- Discourse relation.

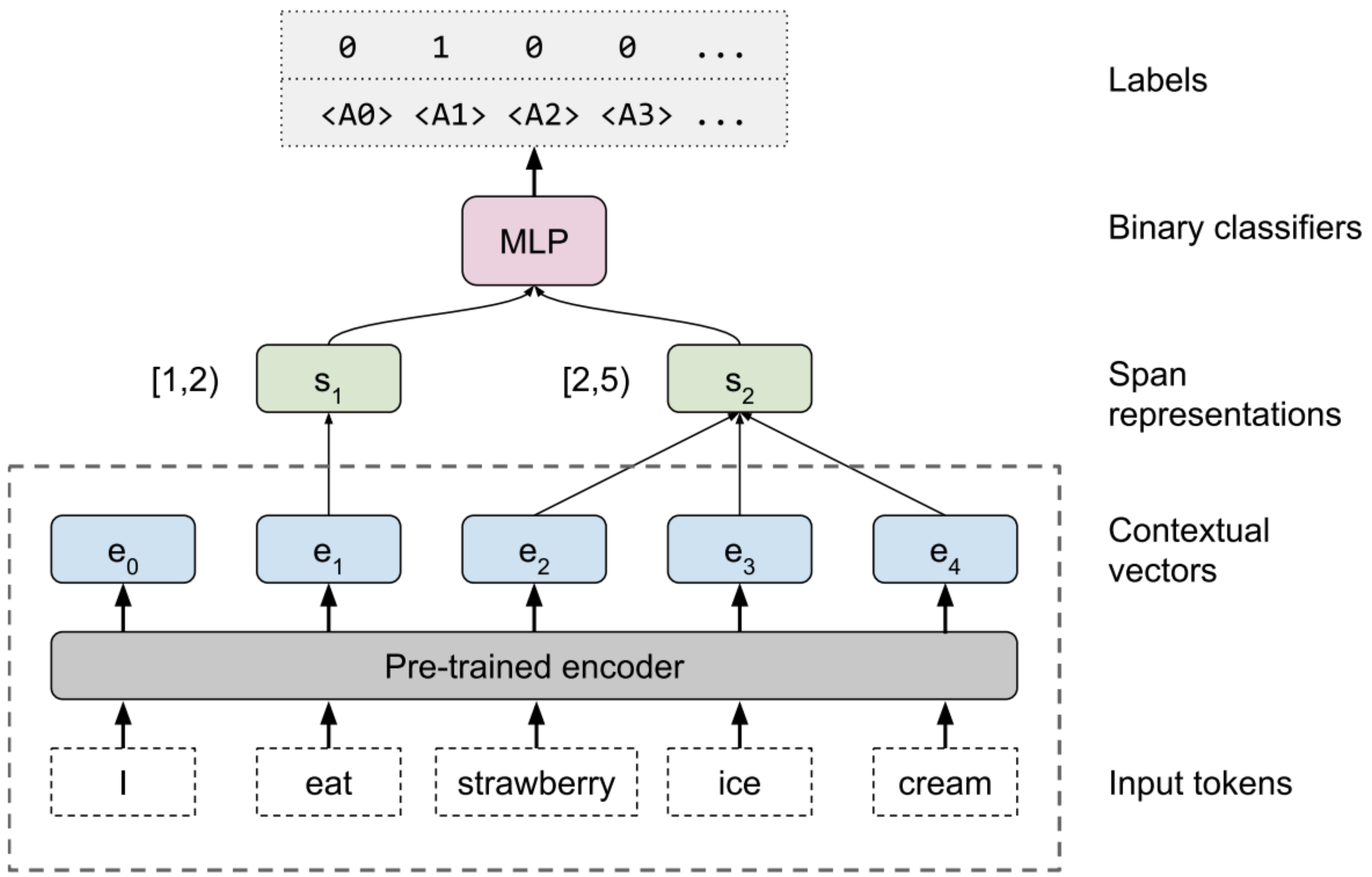
"Tokyo is ***cold***. Beijing is ***hot***."

- Contradiction detection.

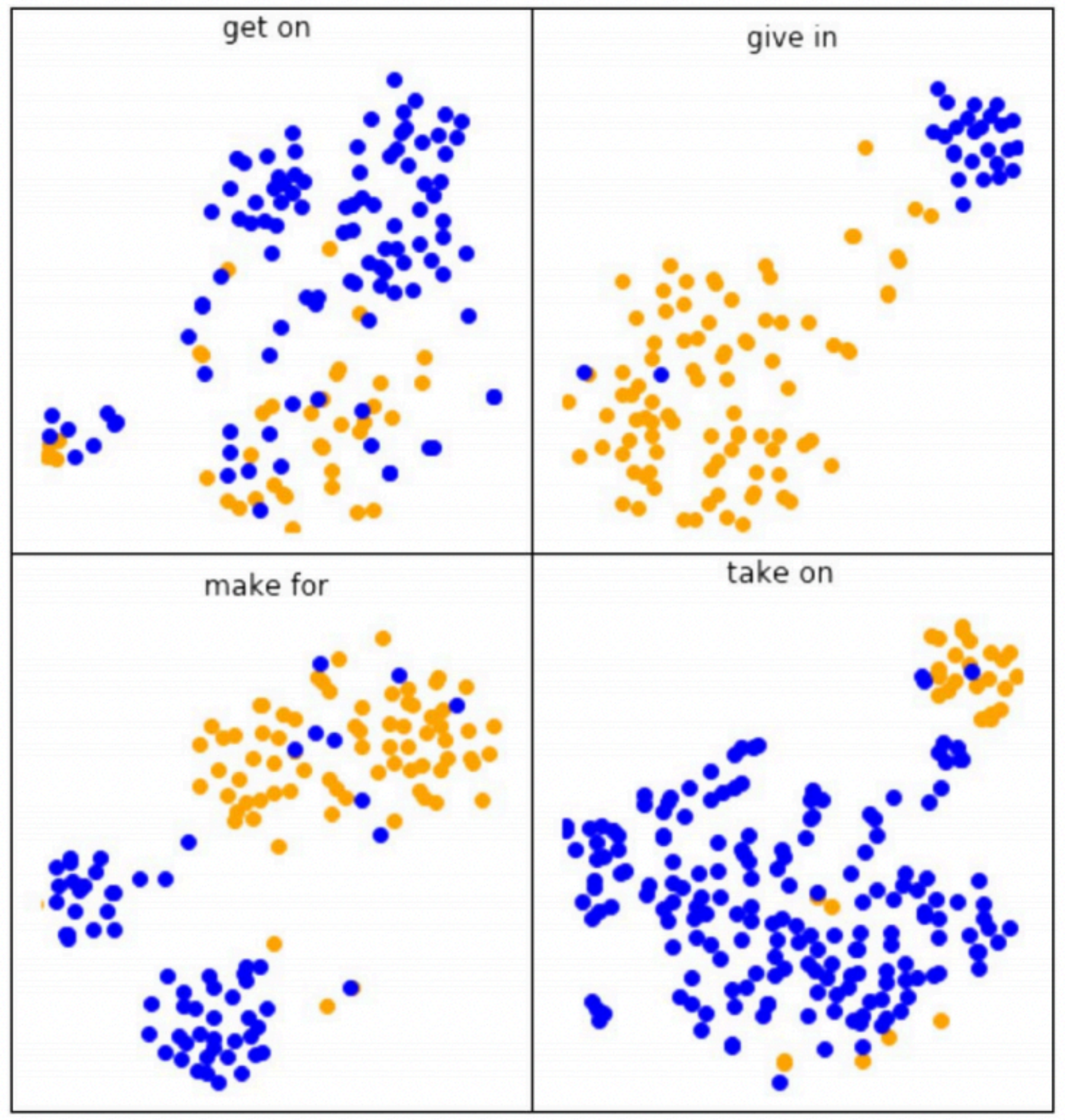
"Kyoto has a predominantly ***wet*** climate" / "It is mostly ***dry*** in Kyoto"

- Humour detection.

# Interpretations of Semantic Representations
## — Right timing to do CLC.




Probing Contextual LMs (Tenney et.al. ICLR '19)




Probing Contextual Lexical Composition (Shwartz and Dagan TACL '19)

- Syntactic tasks: POS, Constituents, Dependencies
- Semantic tasks: SRL, OntoNotes coref, Semantic proto-role

- Light Verb Construction (LVC): *make* a decision
- Verb-Particle Construction (VPC): carry on vs carry

# 3. Cont$^2$Lex Corpus

# Problem Formalization

Problem Formalization:

Given $w^+$ and $w^-$ in context $c$ (a sequence of words $w_1, w_2, \ldots w_n$), a human (or a machine) needs to indicate a binary $tag$ for CLC.

# Instance Preparation

ConceptNet
An open, multilingual knowledge graph

Wikipedia
The Free Encyclopedia

WSJ

- Constraint 1: Contrasting degree in ConceptNet
- Constraint 2: Distance between $w^+$ and $w^-$ (Adjacent sentence or difference clause in same sentence.)
- Constraint 3: Appearance of the same pair of $w^+$ and $w^-$

6,316 instances to be annotated.

# Human Annotation

(Ex. 1 Positive CLC): A **positive** attitude helps you relax and ace the exams, and a **negative** mental status will however make you nervous and sleepless.

(Ex. 2 Negative CLC): The reviewers are rather **positive** about this paper. They are nominating it for the Best Paper for its discovery of a **negative** finding that dispels conventional wisdom.

- Quality Control 1: Predict $w^-$, given only $w^+$ and $c$
- Quality Control 2: Hard-to-decide Option.

# Corpus Statistics

Inter-Annotator Agreement (IAA):
We calculate IAA using the consensus of our 5 annotators, reaching 75.3%.

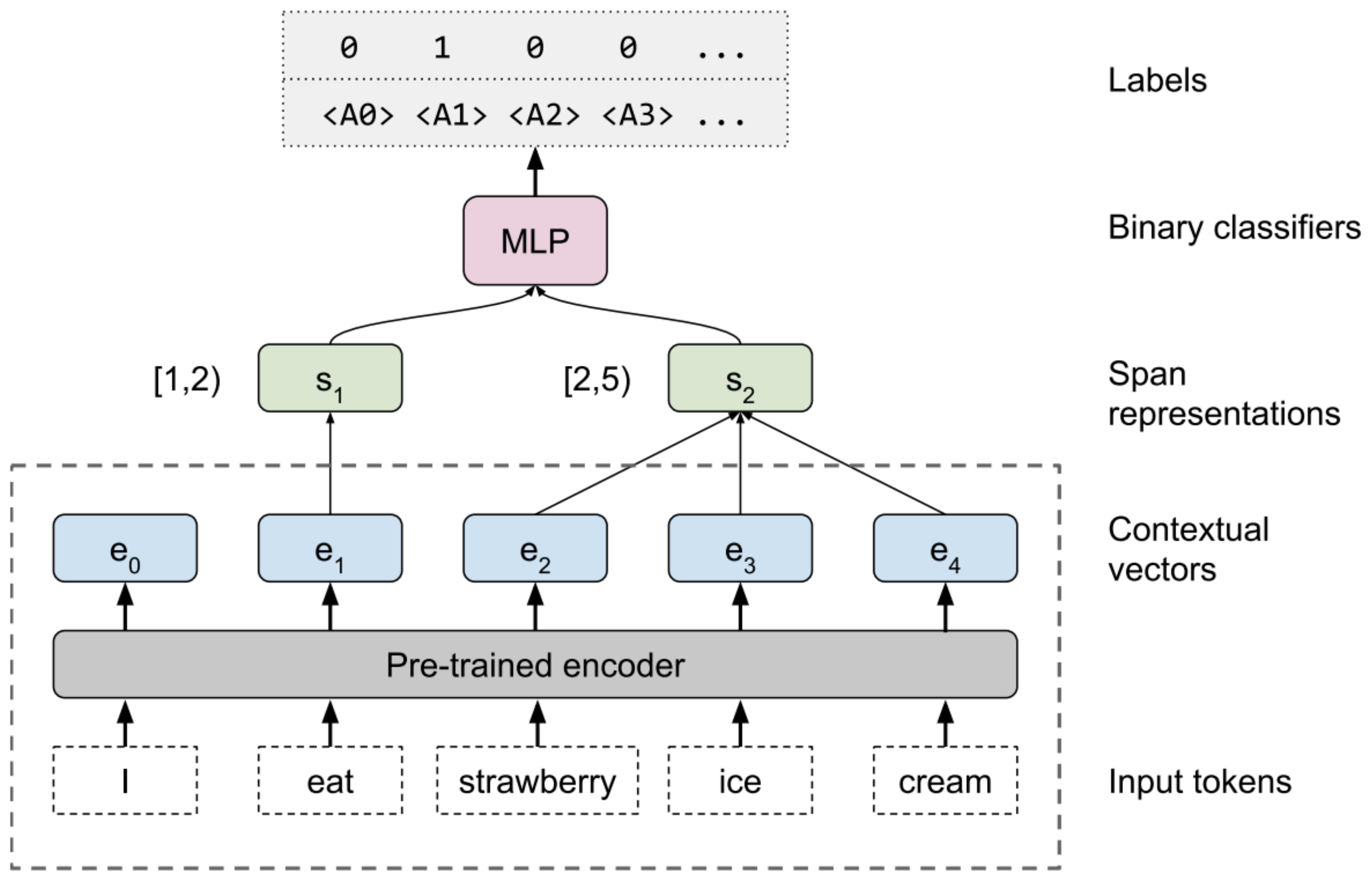
| Part-of-Speech | # | Positive Ratio |
|---|---|---|
| Noun | 2,413 | 33.2% |
| Verb | 1,568 | 27.9% |
| Adj | 2,081 | 43.7% |
| Adv | 254 | 40.9% |
| Total | 6,316 | 35.7% |

Possible reason: Adj and Adv has purer semantic dimensions.

# 4. Benchmark

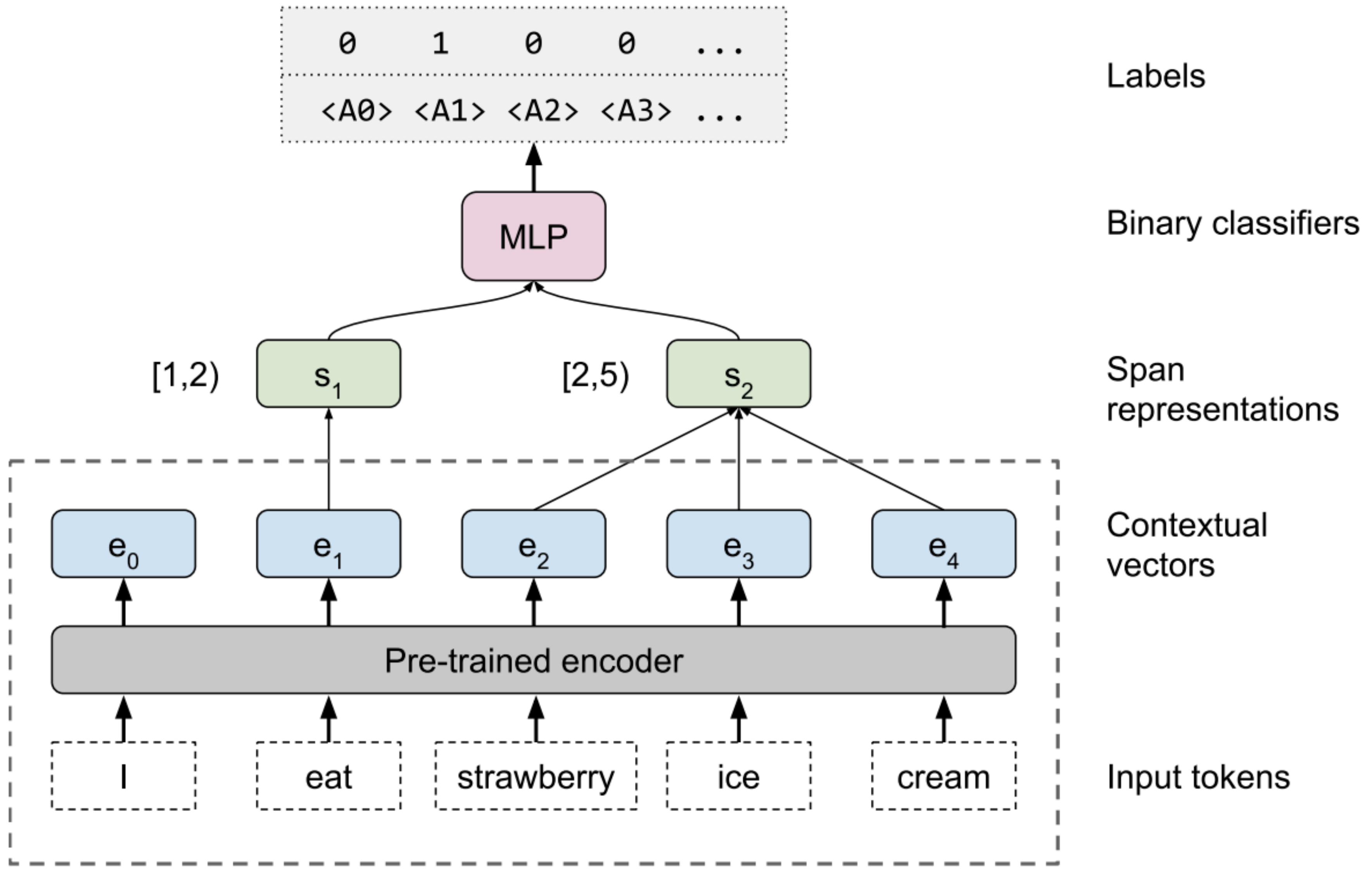
# Evaluation Framework

- 6,316 instances enable us to do supervised learning, for the binary classification.
- Similar approach as Tenney et.al, and “Embed — Encode — Predict” framework (Shwartz and Dagan)
- We didn’t fine-tune BERT. Why?




Probing Contextual LMs (Tenney et.al. ICLR ’19)

# Evaluated Embeddings




Probing Contextual LMs (Tenney et.al. ICLR ’19)

- Static embeddings: Glove, Word2Vec, fastText
- Contextual Embeddings: ELMo, OpenAI GPT, BERT
- The “Lex” version of GPT and BERT. Why?

# 5. Experiments and Conclusion

# Research Questions

- RQ1: How do models perform on the CLC recognition?
- RQ2: Are models able to recognize lexical contrast out-of-context?
- RQ3: What are the capabilities and limitations of current models?

# Main Experiment (RQ1)

| | BiLSTM | Attention | None |
|---|---|---|---|
| **Glove** | 65.3 | 64.9 | 65.3 |
| **Word2Vec** | 65 | 65.7 | 64.7 |
| **FastText** | 66.2 | 65.5 | 66.3 |
| **ELMo** | 65.6 | 65.6 | 65.7 |
| **GPT.Lex** | 65.8 | 64.8 | 64.8 |
| **GPT** | 66.8 | 67.0 | 66.9 |
| **BERT.Lex** | 66.4 | 66.2 | 66.4 |
| **BERT** | 70.0 | 69.2 | 69.1 |
| **Majority** | 64.3 | | |

BERT and GPT are better than their Lex version.

Acc scores show that CLC is a challenging task!

# Out-of-context Lexical Contrast (RQ2)

(Ex. 2 Negative CLC): The reviewers are rather **positive** about this paper. They are nominating it for the Best Paper for its discovery of a **negative** finding that dispels ***conventional*** wisdom.

👆

| Embeddings | Glove | Word2Vec | fastText | ELMo | GPT | BERT |
|---|---|---|---|---|---|---|
| acc. | 79.7 | 82.6 | 84.1 | 83.5 | 81.2 | 79.5 |

Acc scores of out-of-context lexical contrast recognition, which is much more easier than CLC.

# Model Characteristics (RQ3)

S: CLC Word Pairs Occurring in the Same Sentence.

R: Word Repetitions Co-Occurring with CLC Pairs.

(Ex. 3 Repetition): ...is considered spurious **by** Hefele questionable by Haddan and Stubbs, and genuine **by** JaffA Regest.

(Ex. 4 Repetition): They had many children who **lived in the** darkness between them. The children wished to **live in the** light and so separated their unwilling parents.

# Model Characteristics (RQ3)

| | S | ¬S | R | ¬R |
|---|---|---|---|---|
| Glove+None | 61.3 (+4.2) | 67.9 (-2.0) | 60.9 (+7.2) | 67.3 (-3.1) |
| W2V+Attention | 60.3 (+3.2) | 68.8 (-1.1) | 60.4 (+6.7) | 68.1 (-2.3) |
| FastText+None | 60.4 (+3.3) | 69.8 (-0.1) | 61.1 (+7.4) | 68.8 (-1.6) |
| ELMo+None | 63.6 (+6.5) | 68 (-1.9) | 63 (+9.4) | 68 (-2.5) |
| GPT.Lex+BiLSTM | 61.5 (+4.4) | 68.3 (-1.6) | 60.8 (+7.1) | 68.1 (-2.3) |
| GPT+Attention | 64 (+6.9) | 68.7 (-1.2) | 65.5 (+11.8) | 67.8 (-2.6) |
| BERT.Lex+BiLSTM | 60.7 (+3.6) | 69.8 (-0.1) | 58.7 (+5.0) | 69.9 (-0.4) |
| BERT+BiLSTM | 67.4 (+10.3) | 71.4 (+1.5) | 68.7 (+14.9) | 70.7 (+0.3) |
| Majority | 57.1 | 69.9 | 53.7 | 70.4 |

The delta over baseline are majorly achieved by S and R.

# Model Characteristics (RQ3)

## — Q: Besides Repetition, what other cohesive ties is BERT using?

Cohesive devices (M.A.K. Halliday):
- Collocation
- Substitution
- Coreference

T: All types of cohesive ties
R: Repetition
R is a subset of T.

| | ¬R | ¬T |
|---|---|---|
| ΔBERT+BiLSTM | 4.1 | 4.2 |
| ΔBERT+Attention | 3.6 | 3.5 |
| ΔBERT+None | 3.7 | 3.7 |

This table shows that models are no better handling T than R.

# Conclusion

- We propose a new NLP task as CLC for cohesion modelling. Our Cont$^2$Lex corpus makes CLC a computational feasible task.

- CLC is a challenging semantic representation task. Contextual embeddings are capable to capture part of contextual information.

- The advantage gained by BERT is largely due to modelling surface textual patterns.