DiscoGeM: A Crowdsourced Corpus of Genre-Mixed Implicit Discourse Relations

Merel Scholman, Tianai Dong, Frances Yung, & Vera Demberg
Saarland University, Germany

LREC 2022
Discourse relations (DRs): logical links between segments of text

Can be *explicit* (connectives) or *implicit*

Implicit relations difficult to classify (automatic & manually)

Example:

1. I’m a feminist **because** I believe in gender equality.
2. I’m a feminist; **in other words**, I believe in gender equality.
3. I’m a feminist. I believe in gender equality.
Introduction

- Parsers perform poorly on implicit relations (and out-of-domain text) → need for implicit relation annotations in different genres
- Obtaining manually annotated data is costly and time-consuming
- Crowdsourcing can provide solution
- Additional benefit: multiple observations per relation → Derive a distribution of relation senses per relation that might better represent the ambiguity of the relation
Goals of current contribution:

▸ Collect large, multi-genre, reliable discourse-annotated resource
▸ Provide distribution of relation senses; examine optimal aggregation method
▸ Compare distributions of implicit relations between genres
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DiscoGeM: PDTB3-style crowdsourced corpus of 6,505 implicit discourse relations
1 Method
   ■ Data
   ■ Task design
   ■ Crowd annotators

2 Results
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   ■ Data
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2 Results
Method: Data

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Table: Corpus size in number of discourse relations per genre and in total.
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Wikipedia

- Informative text; explains known facts about common topics
- Texts taken from first section of 69 Wikipedia entries
- Reference annotations available for this genre (3 expert annotators)
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Crowdsourced annotations using **Two-step Discourse Connective (DC) Method**
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1. Freely insert connective to express relation

I merely repeat, remember always your duty of enmity towards Man and all his ways. [type here]

Whatever goes upon two legs is an enemy. Whatever goes upon four legs, or has wings, is a friend.
Method: Task design

Crowdsourced annotations using **Two-step Discourse Connective (DC) Method**

1. Freely insert connective to express relation

   ![Example Text](I merely repeat, remember always your duty of enmity towards Man and all his ways. **type here**. Whatever goes upon two legs is an enemy. Whatever goes upon four legs, or has wings, is a friend.)

2. Choose from automatically provided list to disambiguate

   ![Example Text](I merely repeat, remember always your duty of enmity towards Man and all his ways. **the reason(s) is/are that**. Whatever goes upon two legs is an enemy. Whatever goes upon four legs, or has wings, is a friend.)

Yung, Scholman & Demberg (2019), *LAW*. 
Method: Connective bank

Created a connective bank for DC method to map connectives and labels

Contains >2,000 entries, including:

- typical connectives (e.g., because)
- variations (largely because)
- combinations (and because)
- frequent typos (becuase)
- “alternative lexicalizations” (the reason is that)
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Method: Selecting crowdsourced annotators

Participant qualification through recruitment task:

- Obtain annotations that allowed us to evaluate annotator potential
- Significantly improves quality of annotations (Scholman et al., 2022 LREC)

- 310 Prolific workers
- Native English speakers
- At least undergrad degree

- 199 qualified workers
Method
- Data
- Task design
- Crowd annotators

Results
Results: Label aggregation

- Majority-single: sense with majority agreement
- IRT-single: highest probability sense, based on Dawid-Skene model (Passonneau & Carpenter, 2014)
- CrowdTruth-distribution: all senses that reached threshold of 20% probability based on CrowdTruth 2.0 (Dumitrache et al., 2018)
- Doesn't enforce agreement between annotators
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Agreement good for implicit DR annotation
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PDTB & RST-DT on implicits: 37% (Demberg et al., 2019)
2 experts on implicits spoken text: 66%, κ = .58 (Hoek et al., 2021)

Distribution measure better captures the reference label senses
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Example:

1. Cities are home to 80% of the EU inhabitants. // It is in cities that the great majority of jobs and companies are located.

- Conjunction – 4 annotators; Result – 5 annotators
Results: Genre comparison

Clear differences in relational distribution between genres:

Highlights the importance of taking genre effects into consideration
Results: Genre comparison

Clear differences in relational distribution between genres:

- **Conjunction** most prevalent in Wikipedia
- **Result** relations occur more in Europarl
- Most **Precedence** relations in literature

Highlights the importance of taking genre effects into consideration
We created an awesome corpus! Go ahead and use it!
Conclusion

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- Many implicit DRs can express multiple relation senses. This is the first large resource that provides sense distributions → valuable for downstream tasks
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Thank you for your attention!

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