# Towards Conversational Data Annotation: Personalized Annotation Explanation Generation via Large Language Models Thesis Proposal

Mark Nagengast Porro

# Contents

- 1. Thesis Proposal
- 1.1 Motivation
- 1.2 Problem
- 1.3 Research Questions
- 1.4 Thesis Goals and Tasks to Tackle Each Goal
- 1.5 Outline

▶ Data annotation often done by multiple annotators

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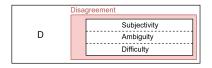
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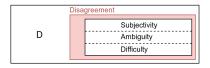
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- Provide annotators with explanations that
  - address subjectiveness (objectify)
  - elaborate on issue (disambiguate, simplify)

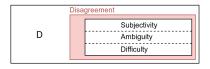
#### Overview



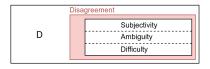
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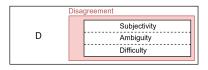
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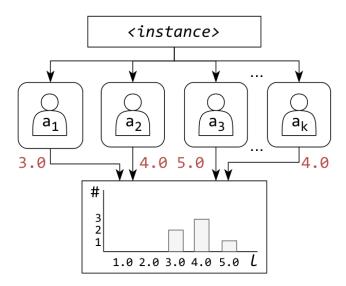


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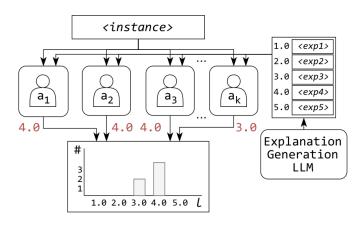


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- Quantify helpfulness based on change in agreement

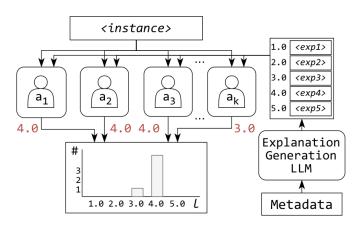
#### Default



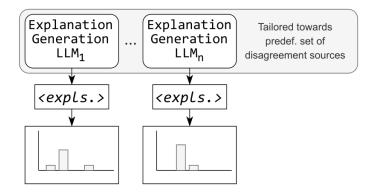
#### Basic Explanations



#### Inclusion of Metadata



#### Tailored Models



# Research Questions

- How does providing explanations for each labeling option in a data annotation task affect the agreement between annotators?
- ► How can metadata such as sociodemographic information about annotators and existing annotations be used to improve explanation generation?

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- Multiple runs of annotations
- Analyze how annotations change as a result

# ► POPQUORN (Pei & Jurgens, 2023)

Task	Description	Data	Total Annotations	Number of Annotators	Instances	Average Labels per Instance
Offensiveness rating	Rate comment offensive-	Ruddit	13,036	262	1,500	8.7
	ness using a 1-5 scale					
Question Answering	Read a passage and an-	SQuAD	4,576	459	1,000	4.6
	swer a question through					
	highlighting the text					
Text rewriting / Style transfer	Read an email and revise	Enron	2,346	257	1,429	1.6
	it to make it sound more					
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Politeness Rating	Rate the politeness of an	Enron	25,042	506	3,718	6.7
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- Given annotators' backgrounds (gender, race, age, occupation, education)
- Example:

635, 0, Don't tell them just let them and their liniage die out so we can be free of humans without brain cells, 3.0, Man, White, 35-39, Unemployed, High school diploma or equivalent

# Outline

- Introduction
- Related work
  - Human-LLM collaboration
    - Data annotation
  - Annotator Disagreement
  - Explanation generation
  - LLM personalization
- Datasets
  - POPQUORN
- Approach
  - Sources of disagreement
  - Fine-tuning LLMs
    - Predicting disagreement source
    - Generating tailored explanations
- Annotation Experiments
- Evaluation
  - ► Inter-annotator agreement
  - Impact of disagreement type
- Conclusion