Real-World or Hypothetical Person? Building a Pipeline for Analyzing Gendered Person Mentions in Educational Text

UW EE 517, Spring 2021 Doruk Arisoy, Yuling Gu



Motivation & Task

- Motivation: Analyzing gender bias in educational textbooks
 - On the authors introduce gender bias to the text through hypothetical person mentions?
- Task: Identify real-world and hypothetical person-mentions and the genders associated with them.
- Biggest challenges
 - The same person can be mentioned multiple times
 - Identifying a real-world person can be difficult
- Our solution to address these challenges
 - Count all mentions of the same person as one person
 - Use a database to check person names

Data

Textbook data

Science textbooks:	Non-Science texts:	
Elementary school 10 textbooks	Grade K-8 9 textbooks (history)	
Middle School 23 textbooks	High school 2 textbooks (history	
High School 8 textbooks	and economics)	

Total number of items: 33,575

Example of an item:

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Critical Thinking 9. A baby girl sees a toy and reaches out to grab it. Describe the path of messages through

Person1

The baby's nervous system, from her eyes to her hand. 10. Assume you are so startled by a sudden loud noise that your heart starts pounding fast. Explain what controls your reaction to the loud sound.
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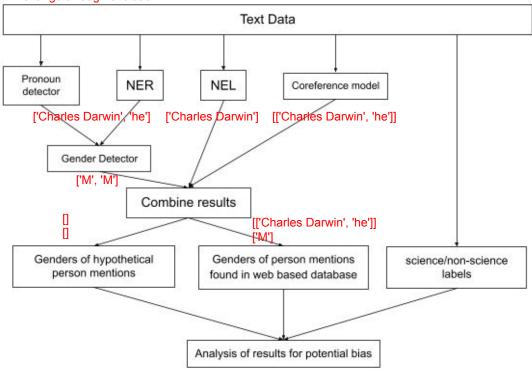
Overview of the approach: Pipeline

Text passes through five models:

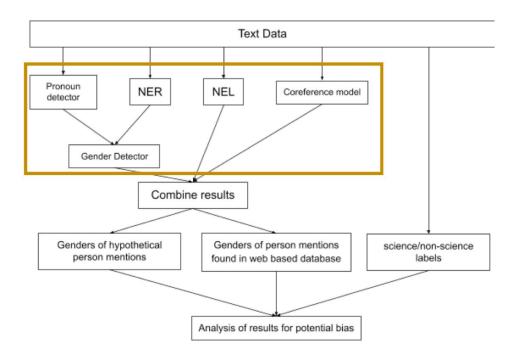
- Pronoun detector
- NER (entity recognition)
 - Looking for person labels
- NEL (entity linking)
 - Looking for person labels
- Coreference model
- Gender detector

Results are combined with the science/non-science labels to generate final analysis.

Check Your Understanding Where did Charles Darwin collect evidence of evolution and what kinds of evidence did he find? What is natural selection? What kinds of traits change through evolution?



Evaluation

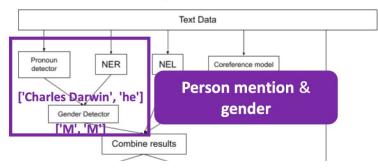


Evaluation (part1)

> Overall* performance (on detecting person mention)

	Previous work (baseline)		Our pipeline
Precision	78.71%	<	84.16%
Recall	83.56%	<	92.81%
F-score	81.06%	<	88.27%

What we are evaluating:



For male mentions

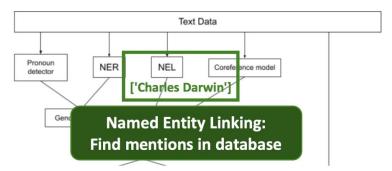
	Previous work (baseline)		Our pipeline 👍
Precision	84.00%	<	85.71%
Recall	65.62%	<	75.00%
F-score	73.68%	<	80.00%

> For <u>female</u> mentions

	Previous work (baseline)		Our pipeline
Precision	73.33%	<	80.00%
Recall	64.71%	<	94.12%
F-score	68.75%	<	86.49%

Evaluation (part2)

What we are evaluating:

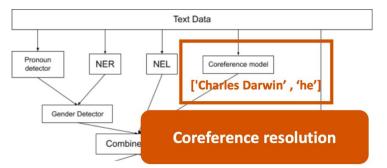


> Hyperparamter: threshold for similarity score

Threshold Metric	0.7	0.8	0.9
Precision	83.71%	87.60%	89.39%
Recall	68.42%	67.80%	67.80%
F-score	75.38%	76.44%	77.11%

Evaluation (part3)

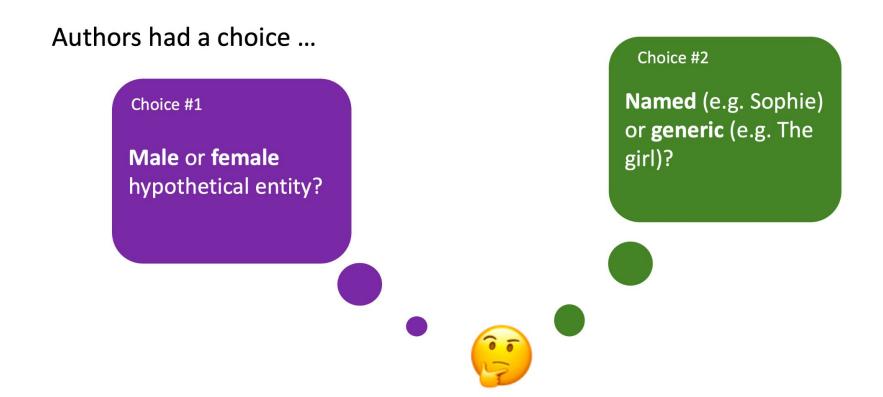
What we are evaluating:



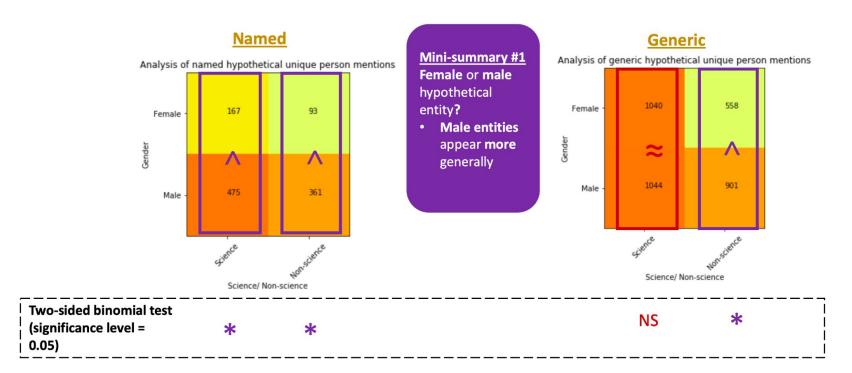
> Evaluating clusters: B-cubed, mention-based approach

	NeuralCoref*	AllenNLP
Precision	74.46%	64.95%
Recall	62.31%	65.24%
F-score	67.85%	65.09%
Compute time	1.6s/item (faster)	9.0s/item (slower)

Results and analysis: for hypothetical entities

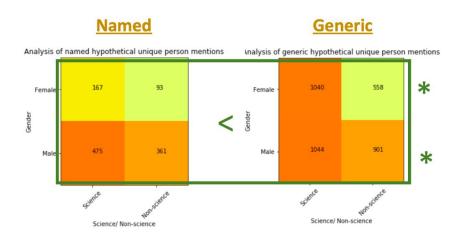


Results and analysis: for hypothetical entities



* Statistically significant

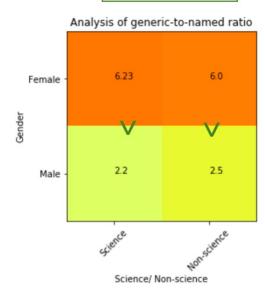
Results and analysis: for hypothetical entities



Two-sided binomial test (significance level = 0.05)

* Statistically significant





Mini-summary #2

Named or generic?

• Female more often portrayed as generic entity

Results summary for hypothetical entities

Bia reflected in ...

Mini-summary #1
Female or male
hypothetical entity?

Male entities appear more generally

Type of of entities (M>F)

Mini-summary #2
Named or generic?

 Female more often portrayed as generic entity

How the entities appear