Probing for Referential Information in Language Models

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Introduction

Background

Language models: computational models that learn to predict the next word considering the past context.

These models develop representations that encode different types of linguistic information.

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These models develop representations that encode different types of linguistic information.

Goal

We want to understand to what extent they capture referential information.

Mary went with John. She → She / She

Hypothesis

Language models encode:

- ☺ **grammatical** properties of anaphora
- ☹ **semantico-referential** information

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Method

Probe model: small classifier to predict a feature of interest, in this case anaphoric coreference, given the model's hidden representations as input.

Resources

Pretrained Models

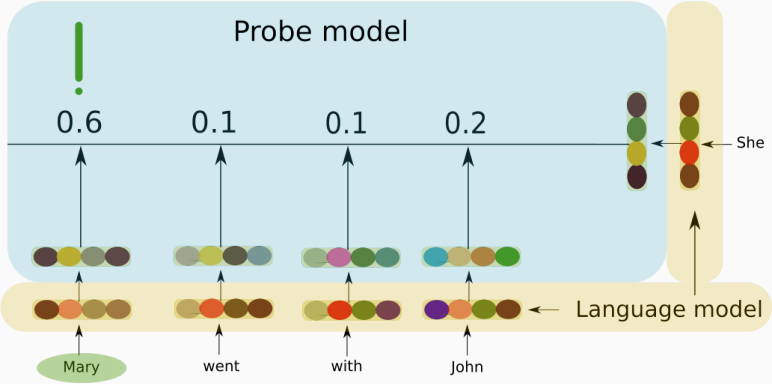
- AWD-LSTM
- Transformer-XL

Both models are trained on the same corpus with a comparable vocabulary.

Dataset: Ontonotes

he$_1$ was elected to be president of the People's Republic of China, and chairman of the Central Military Commission$_2$. Yeping Wang$_3$ was born in Shanghai in 1926. She$_3$ studied in Shanghai Foreign Language College, and started working in 1949. For a long time, she$_3$

Model



- Task: predict which element the target (**she**) refers to
- Correct if it points to any element in the coreference chain

Results

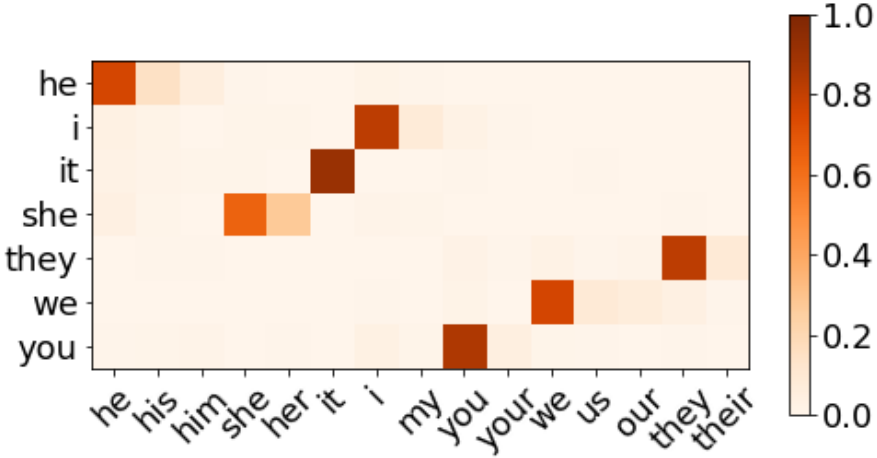
Model	Accuracy
closest gold entity	56.1
closest same-form token	61.3
LSTM	64.8
Transformer	**75.9**

Morphosyntactic factors: Noun phrases

Syntax

- Pronouns refer to nominal elements
  - Refers to element in a chain: 92.6%
  - Even when it doesn't, refers to a nominal element 82% of the time
- Pronouns agree in gender and number
- Across sentences

Morphosyntactic factors: Gender tendencies



Current findings

Findings
Language models encode:

- ☺ **grammatical** properties of anaphora

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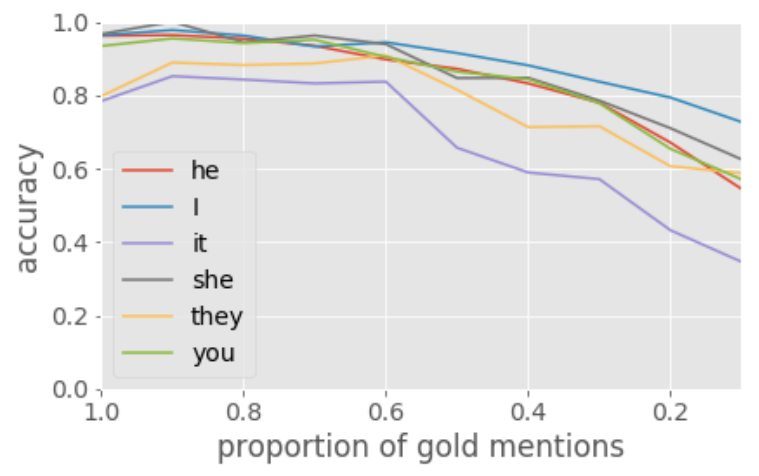
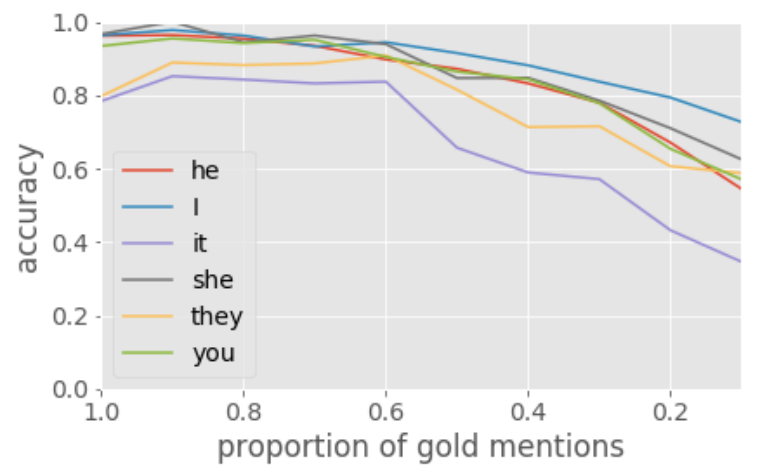
Semantic factors: Distractors



Semantic factors: Distractors



DISTRACTORS CONFUSE THE MODEL, BUT THEY DO NOT FOOL IT COMPLETELY

Semantic features: Distractor types

Type	T Acc.
No distractor	**81.8**
Distractor(s)	73.8
= number	65.3
= gender	48.6
= pron.	49.1

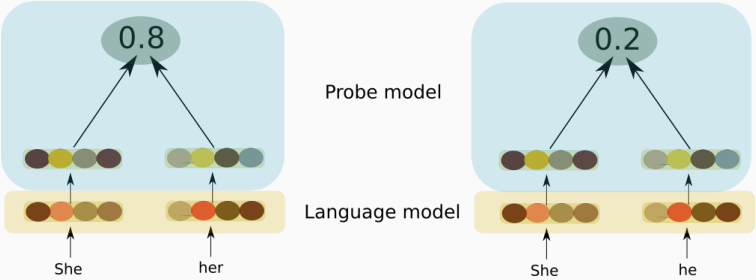
Accuracy of the model with different types of distractors

Semantic features: Distractor types

Type	T Acc.	Baseline
No distractor	81.8	100
Distractor(s)	73.8	32.0
= number	65.3	26.6
= gender	48.6	15.7
= pron.	49.1	20.3

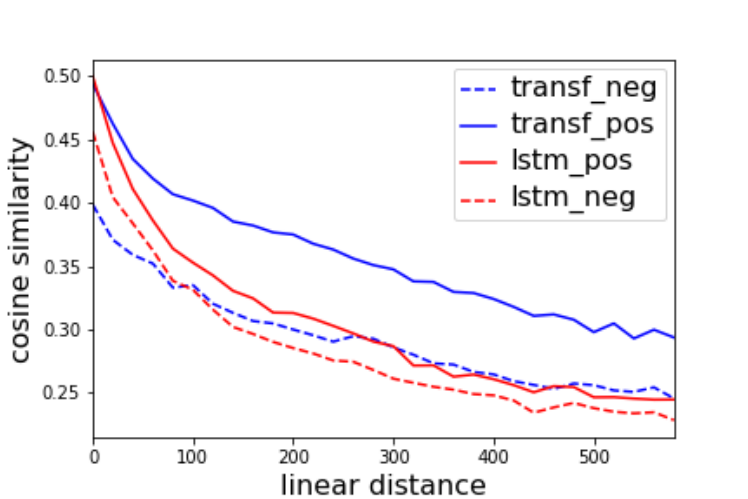
Accuracy of the model with different types of distractors

Document level: Model



- Take all pronominal mentions in a document
- Task: distinguish those that refer to the same entity from those that refer to different entities

Semantic features: Linear distance vs cosine distance



Conclusions

Hypothesis

Language models encode:

☺ **grammatical** properties of anaphora

- Gender
- Number
- Part of speech

😐 **semantico-referential** information

- Confusion when there are other mentions in the context
- But limited ability to distinguish mentions that have the same form but are in different chains

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