# Siamese recurrent networks can learn first-order logic reasoning and exhibit zero-shot generalization to novel expressions

Mathijs Mul  Jelle Zuidema

May 3, 2019

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  - In particular: the recursive neural networks used by Bowman e.a. in 'Recursive neural networks can learn logical semantics' (2015)
- Do they apply compositional generalization, or just memorization?

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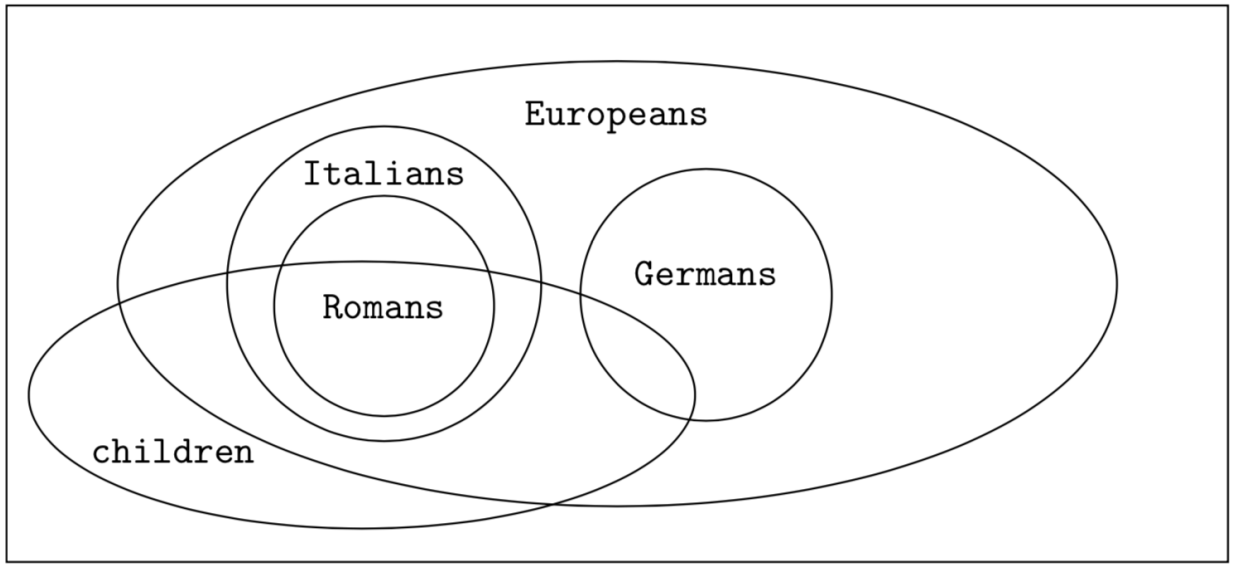
3. Test the models on the data thus generated

# Language $\mathcal{L}$

- Asymmetric taxonomy of nouns:



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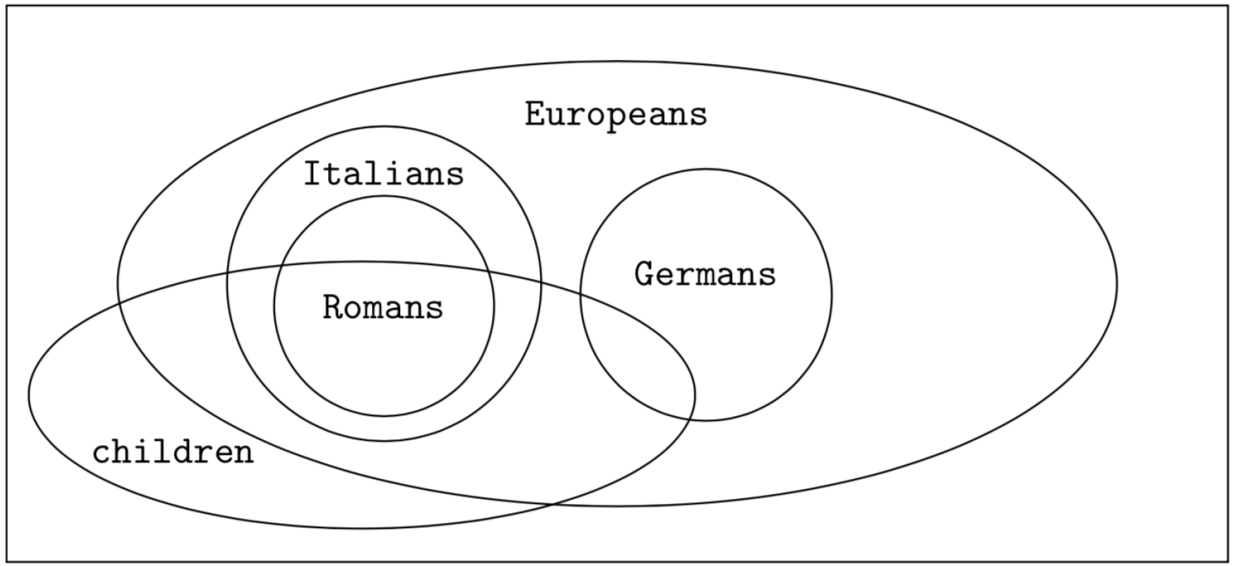
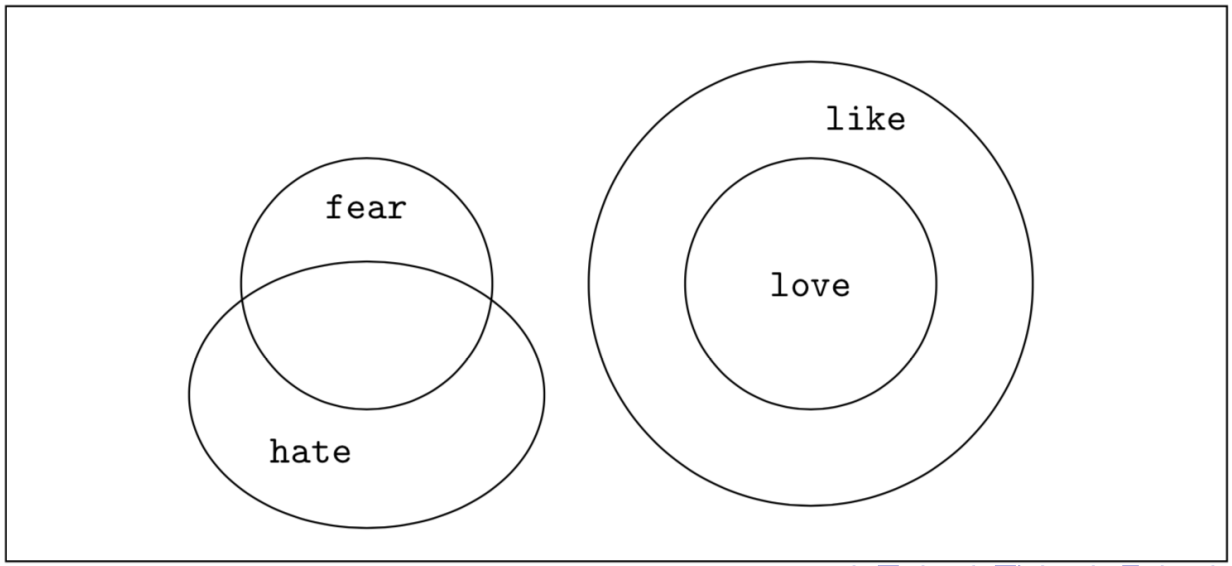



- Binary predicates:



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- Adverbs: $\{\texttt{not}, \epsilon\}$

# Data sample

```
< ( ( all Europeans ) ( hate ( all Germans ) ) )
      ( ( all Romans ) ( hate ( some Europeans ) ) )
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# Data sample

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< ( ( all Europeans ) ( hate ( all Germans ) ) )
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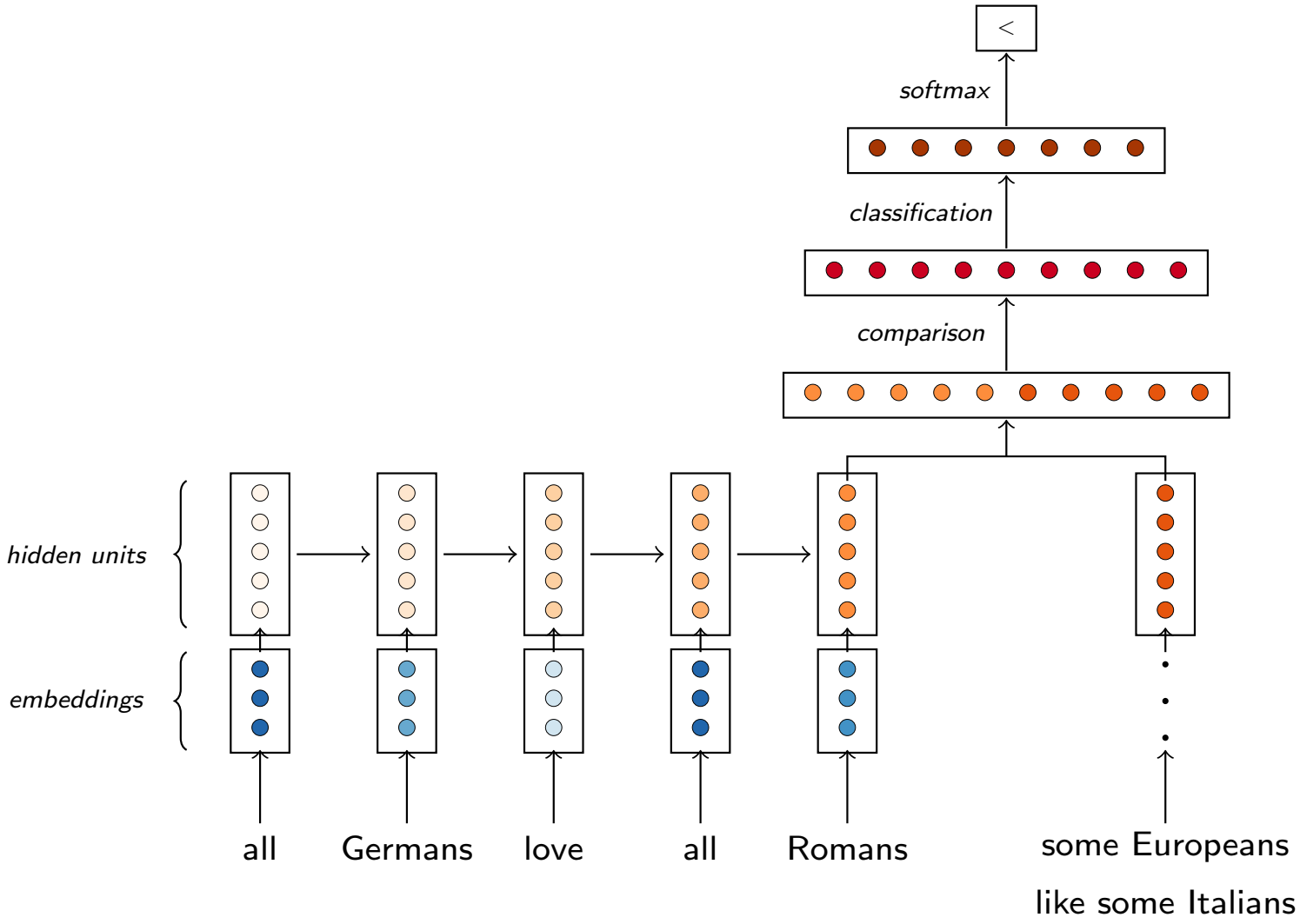
*Only 0.07% of the data space is seen during training.*

# Models

- Recurrent network



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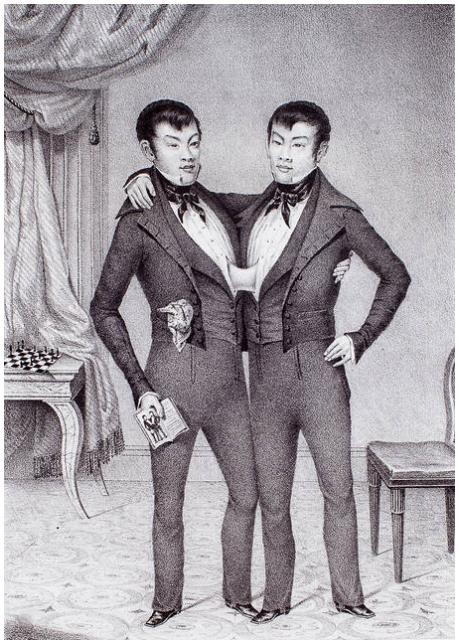
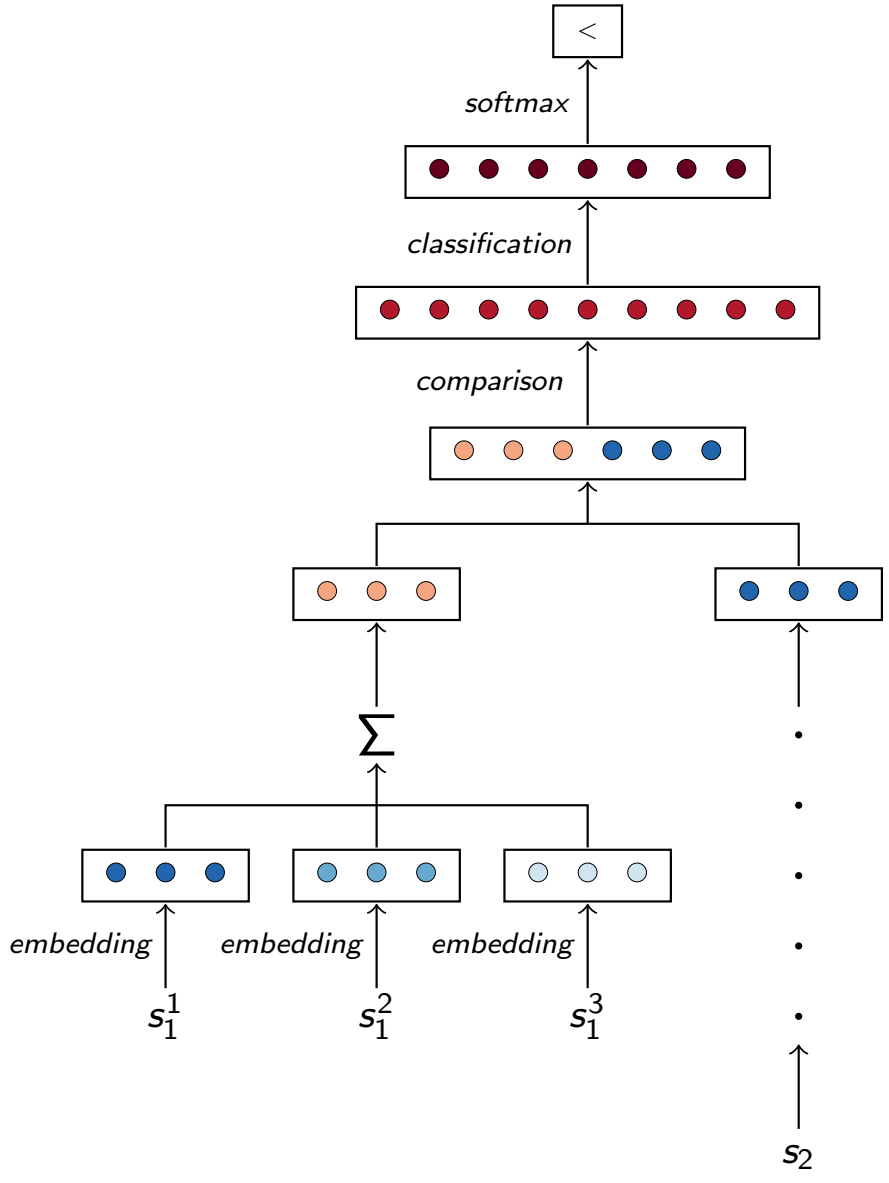


# Models

- Recurrent network
- Three types:
  - Simple Recurrent Network (SRN)
  - Gated Recurrent Unit (GRU)
  - Long Short-Term Memory (LSTM)

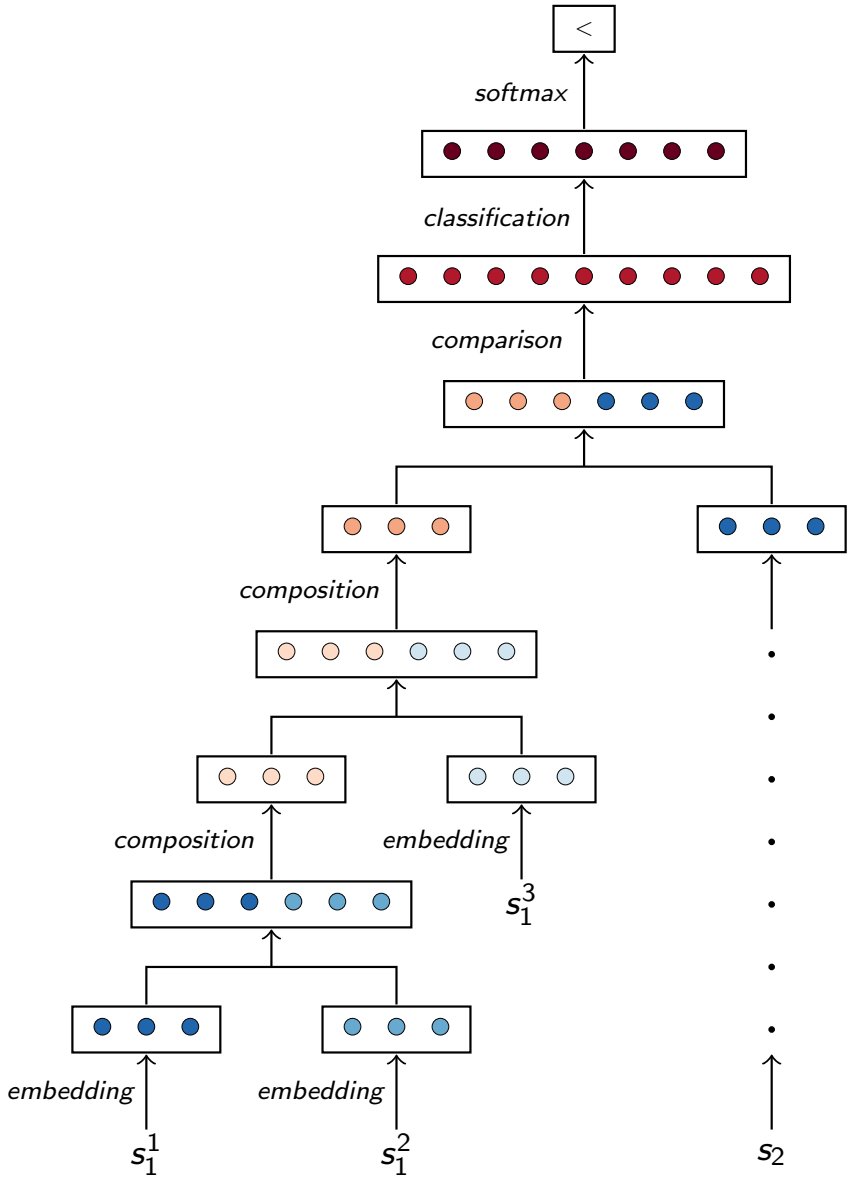
# Models

- Baseline 1: Summing Neural Network (sumNN)



# Models

- Baseline 2: Tree-Shaped Neural (Matrix) Networks (tRNN)



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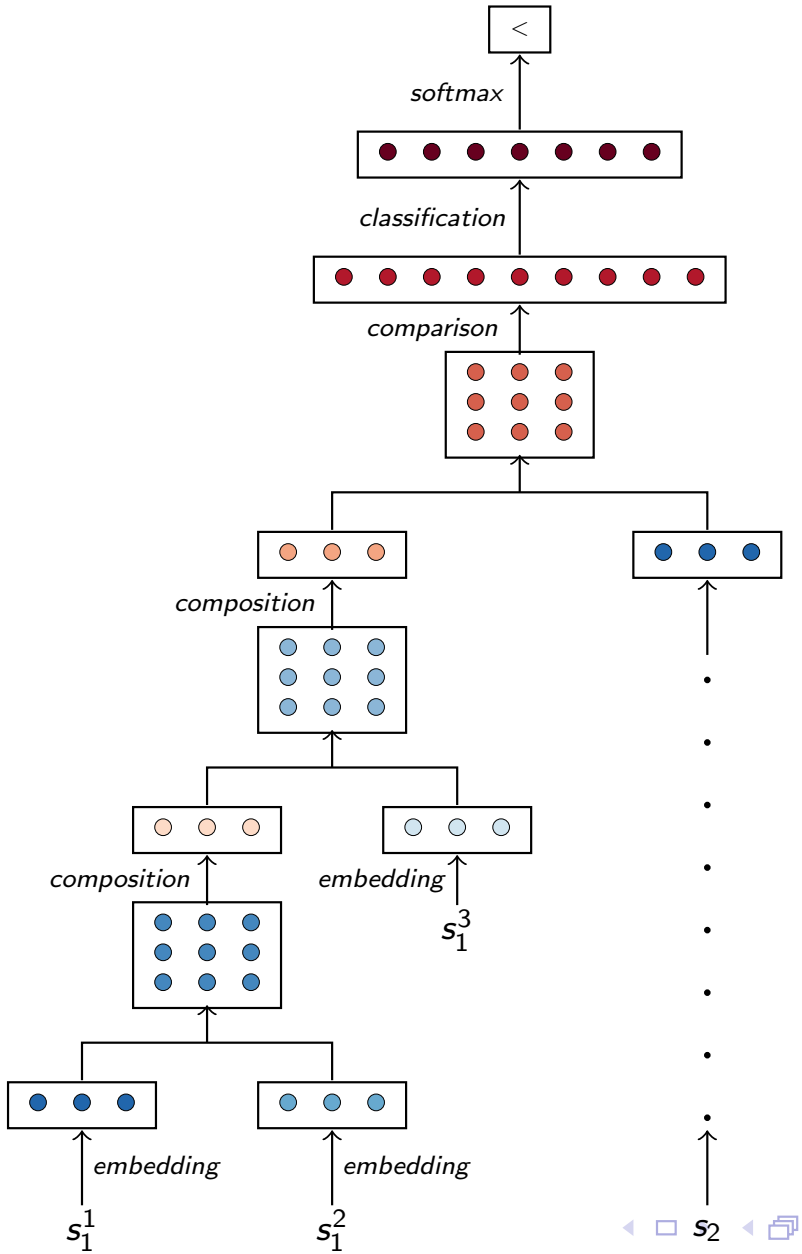
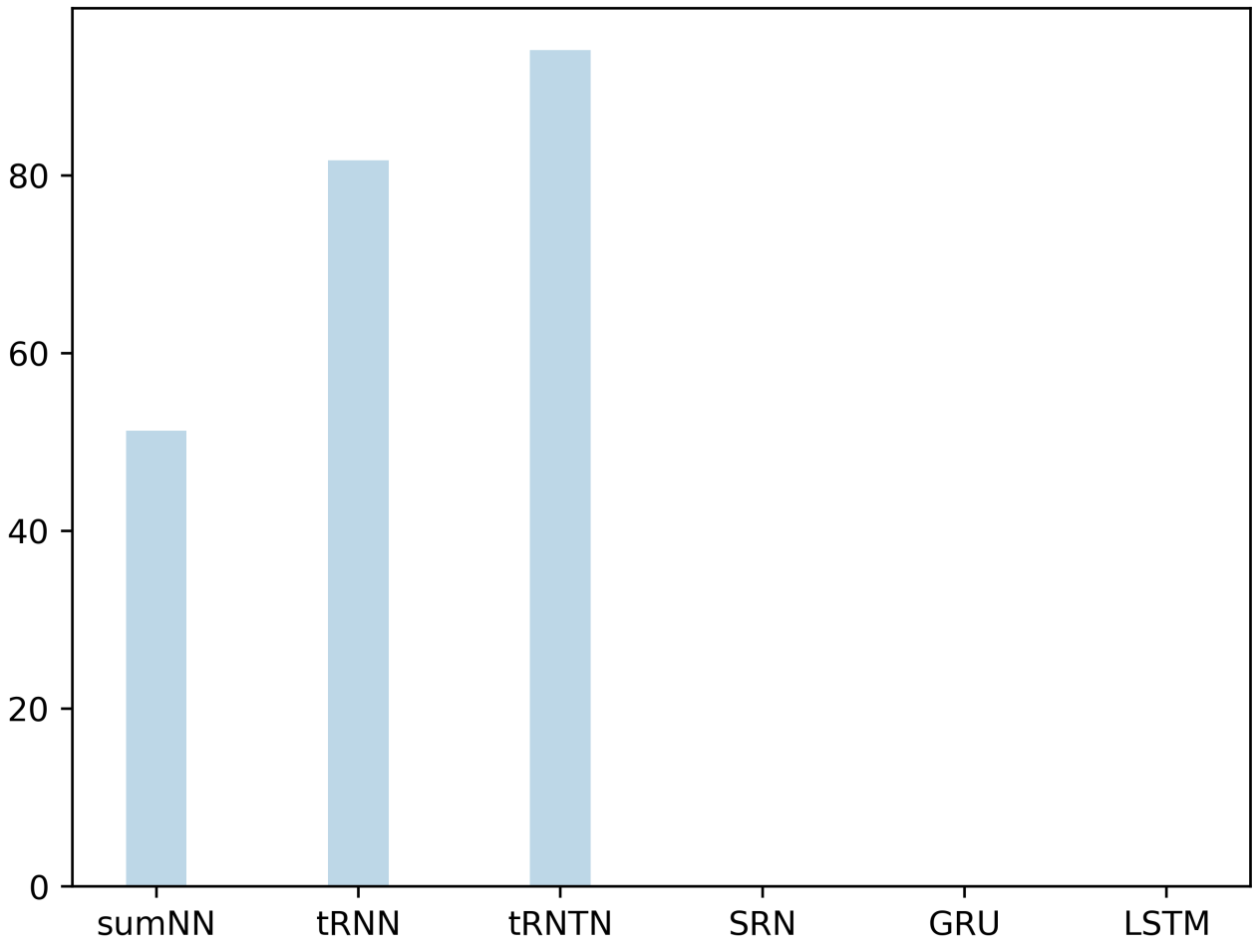
- Baseline 3: Tree-Shaped Neural Tensor Networks (tRNTN)



# Testing accuracy



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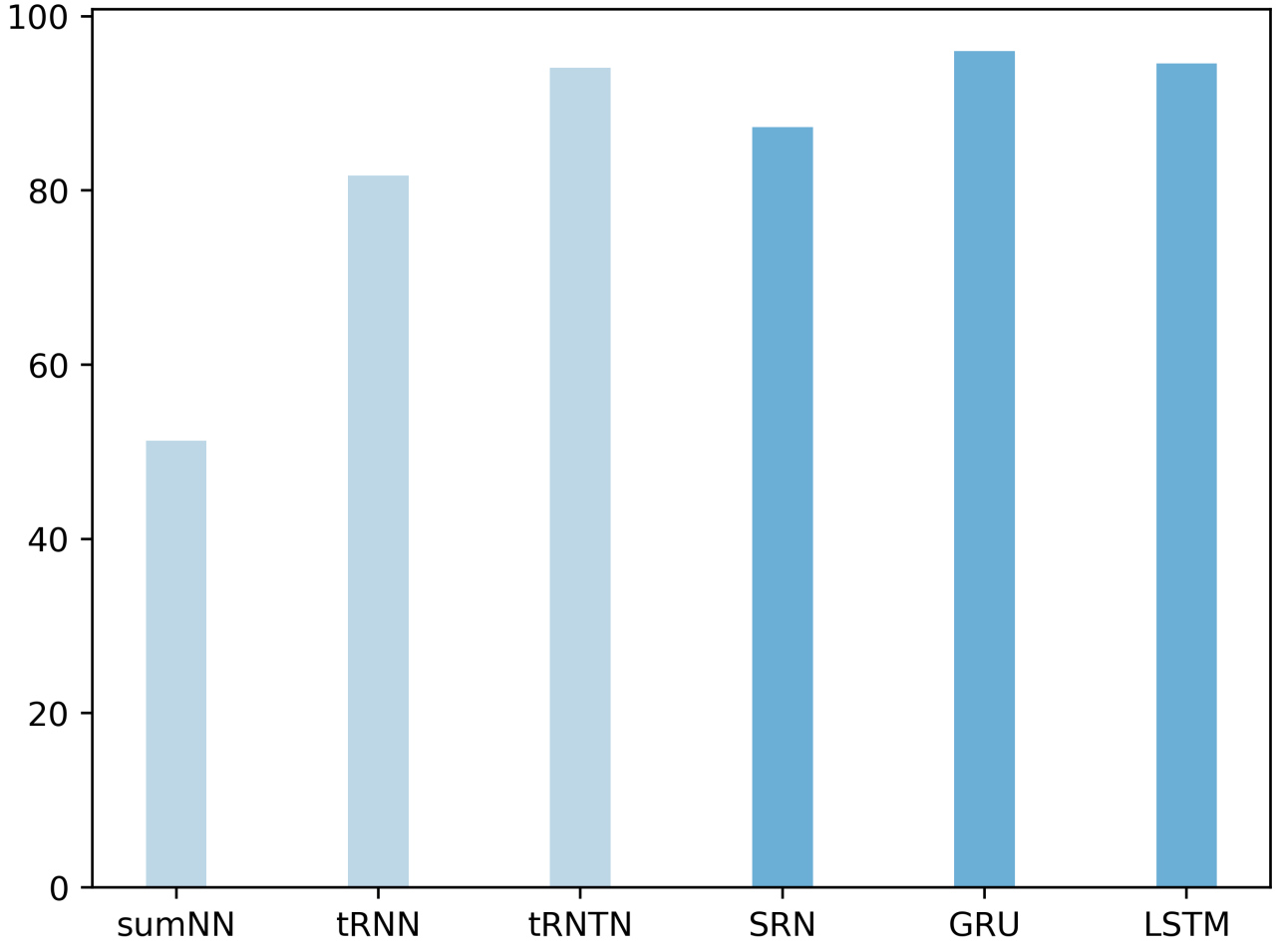

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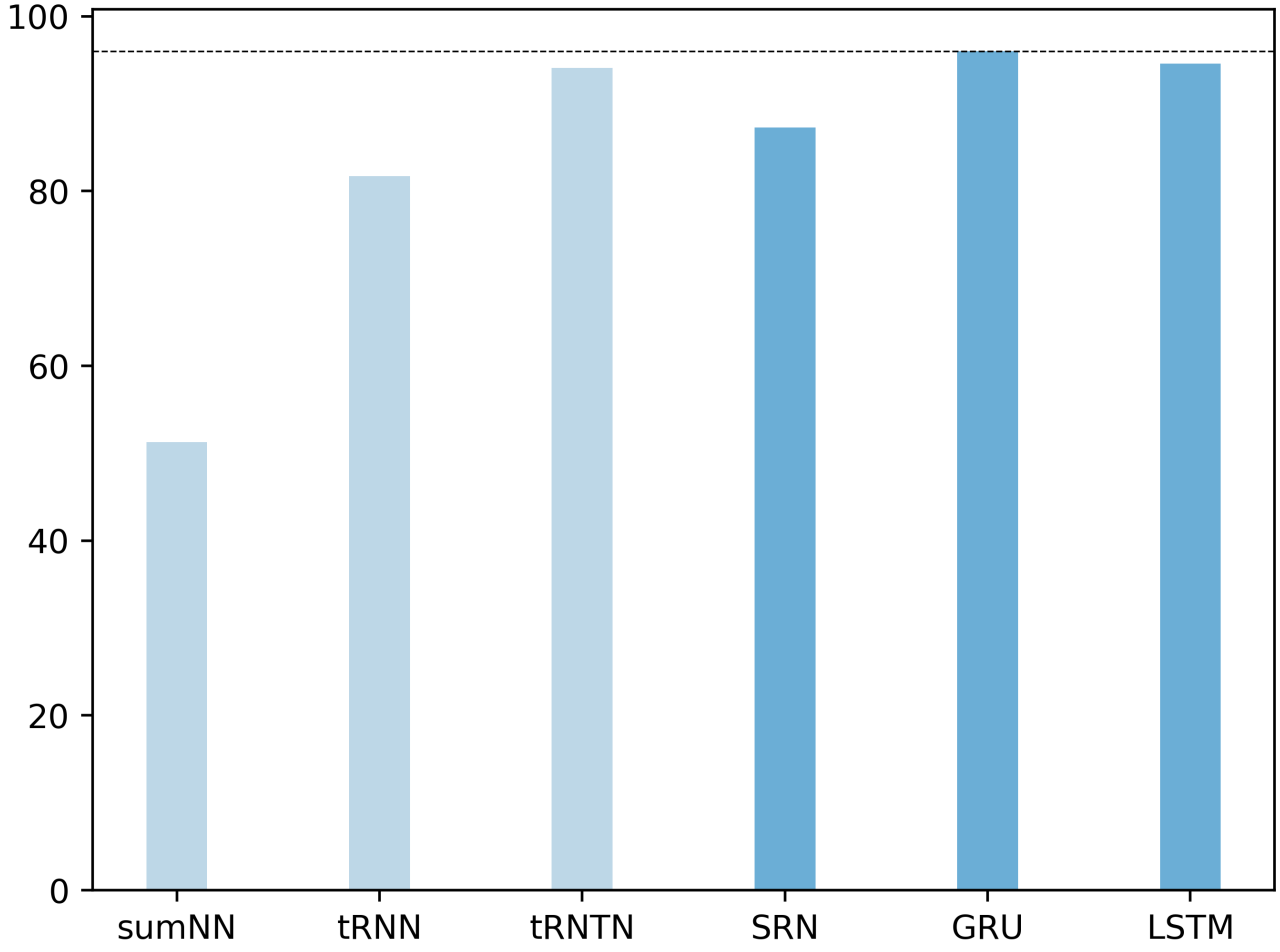
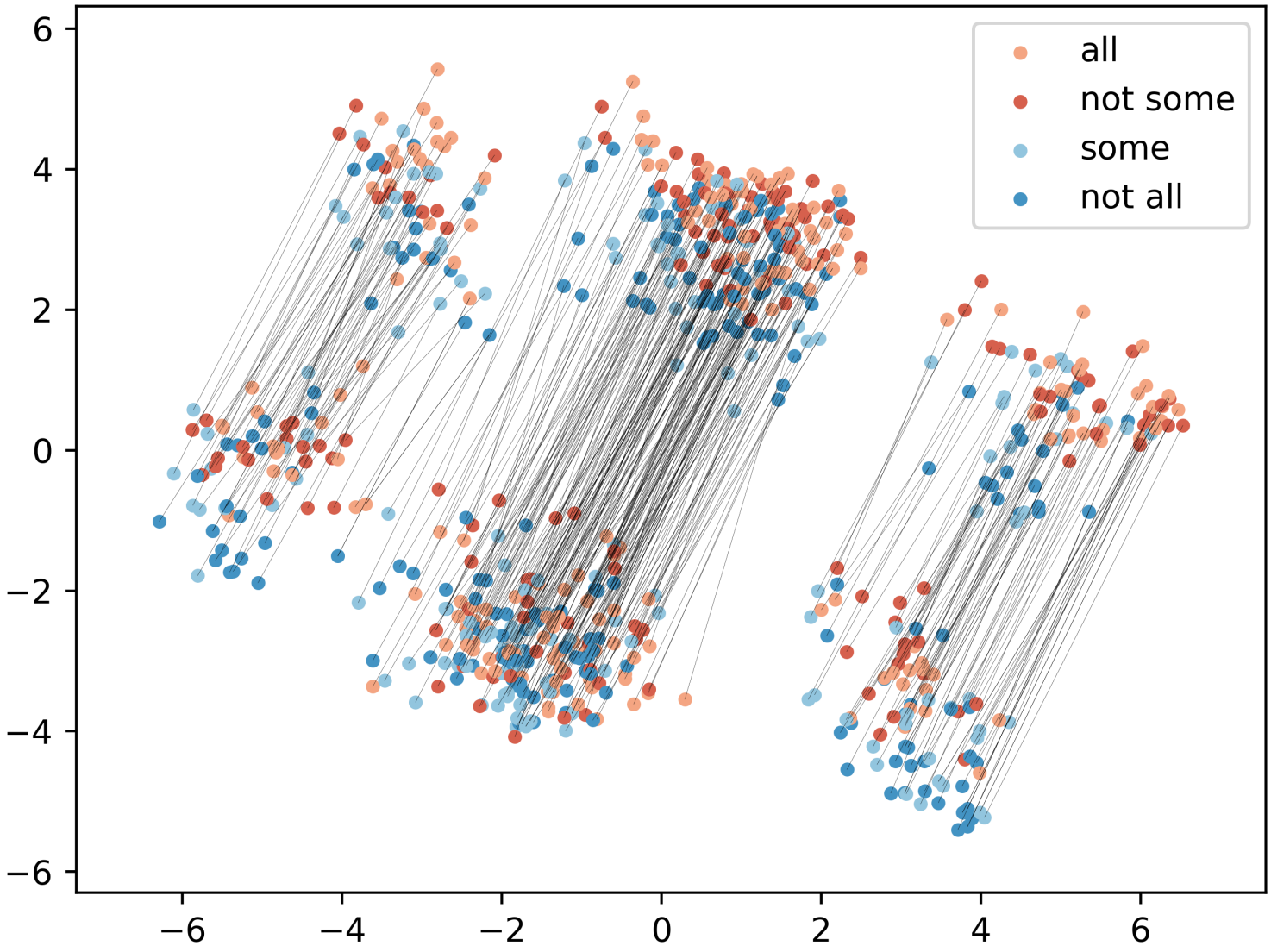
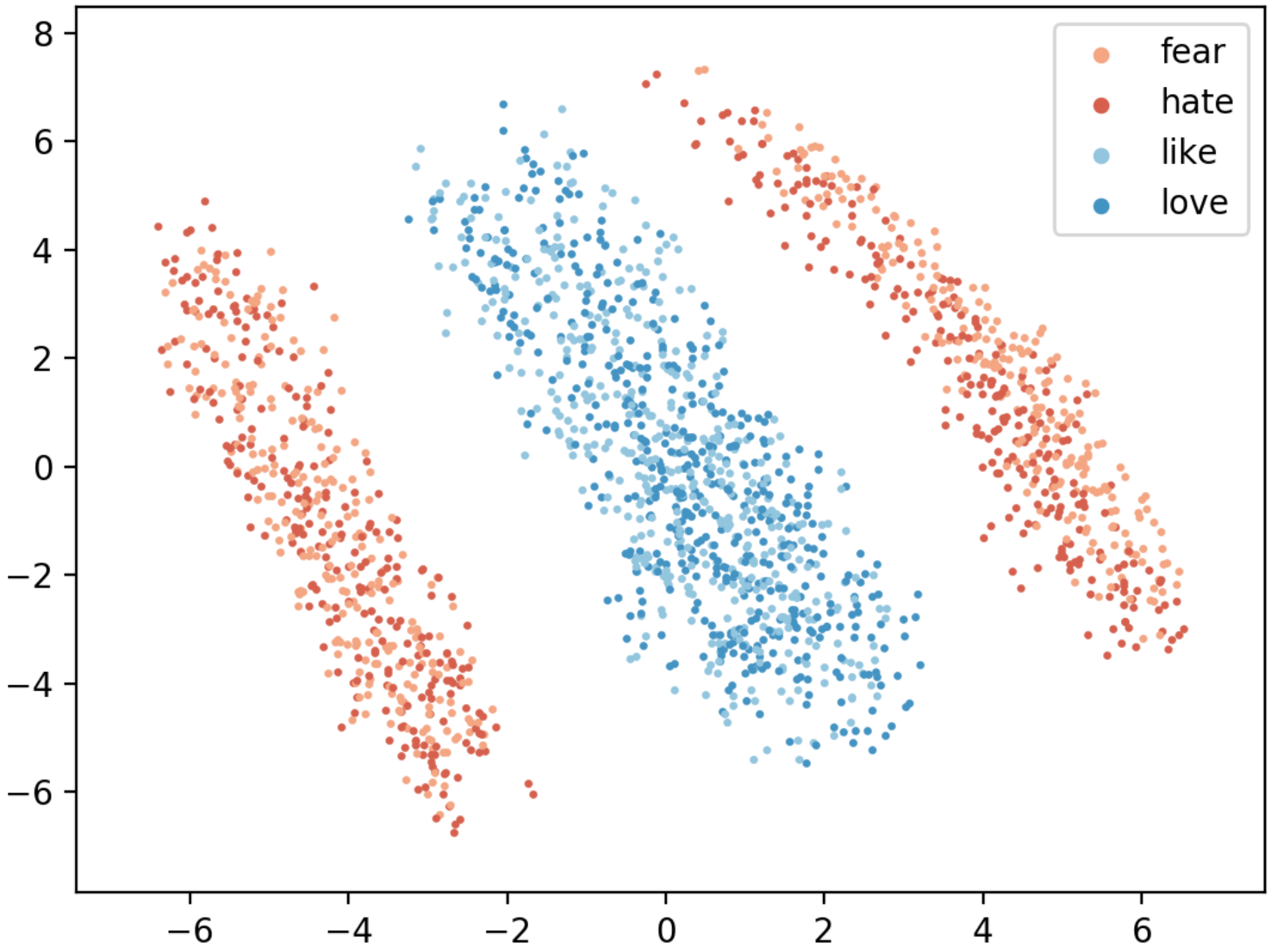


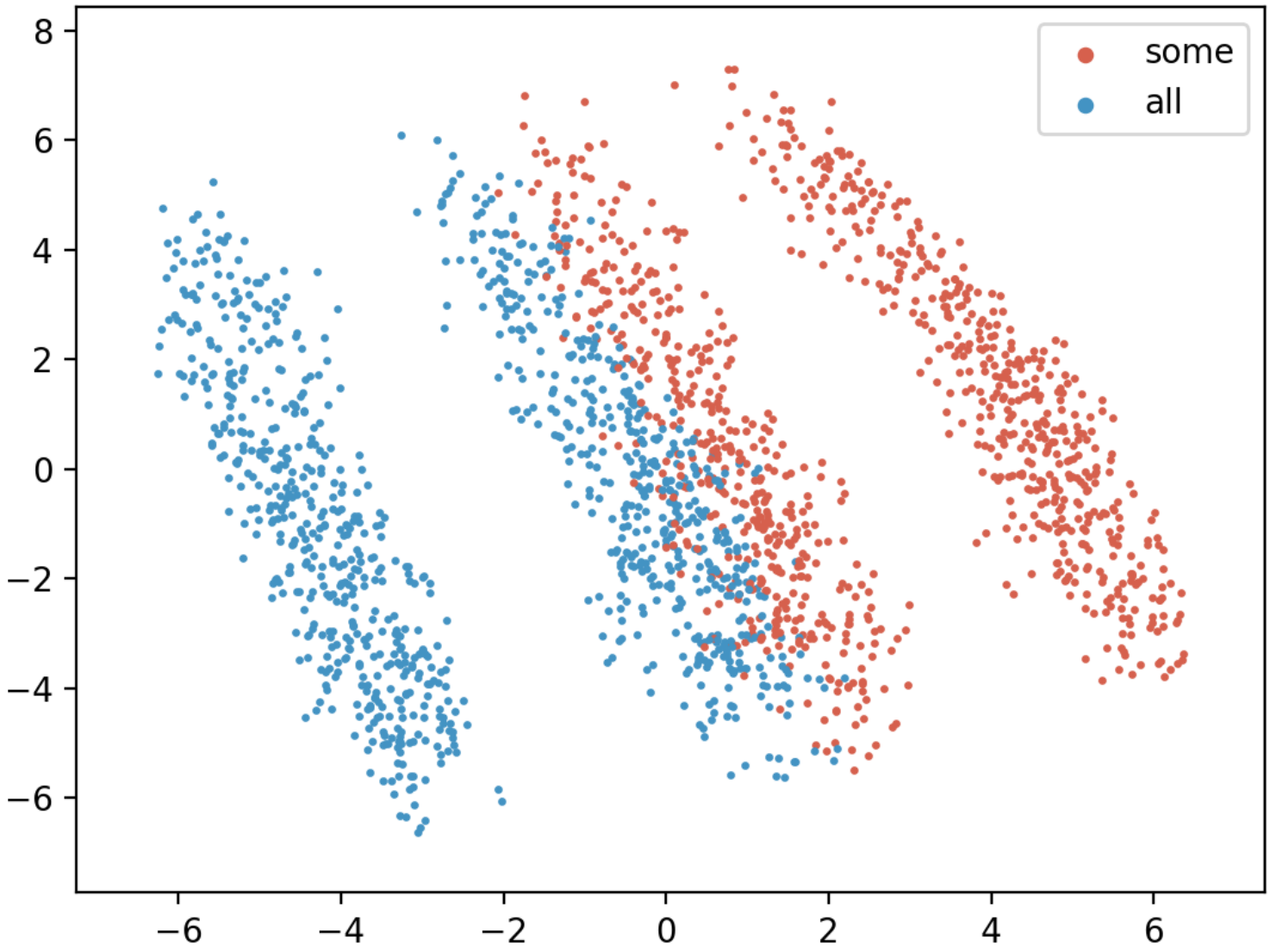
# Negated sentence vectors (GRU)



# Sentence vectors cluster according to verb...



# ... and second quantifier



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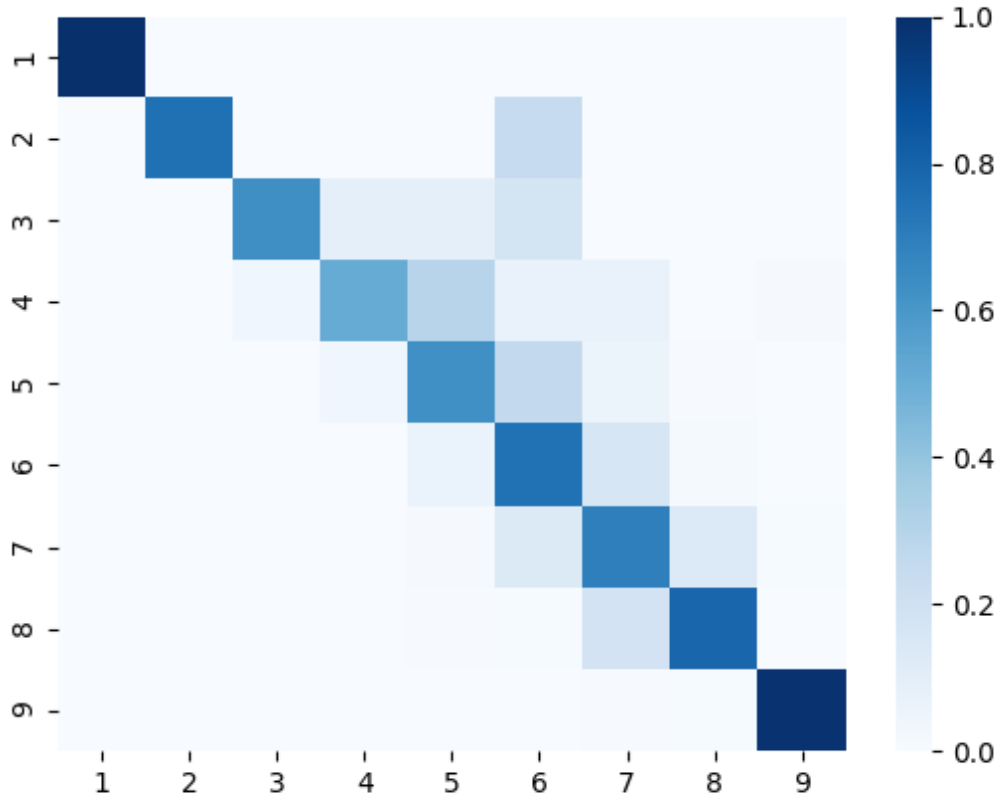

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- Generalization to unseen lengths
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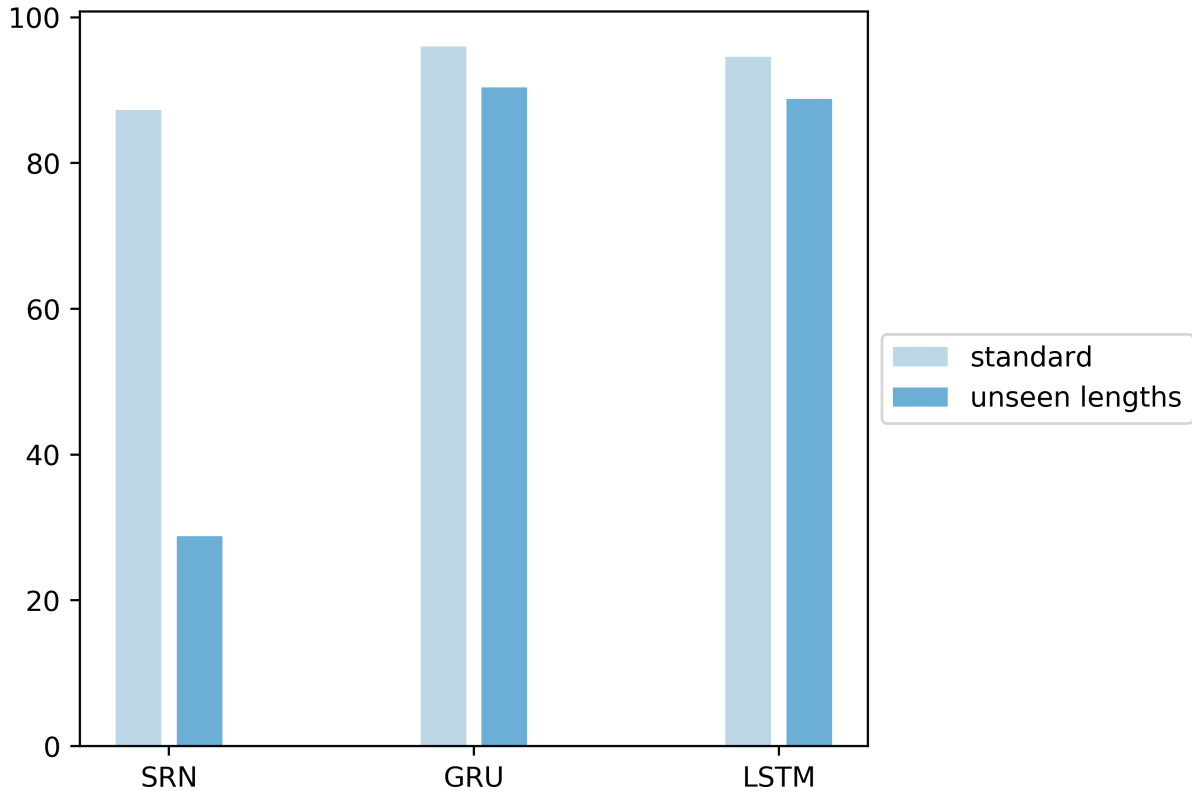

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- One-shot learning
  - Train GRU with fixed GloVe embeddings
  - At testing time, replace words in data with unseen ones, and add corresponding word embeddings to models

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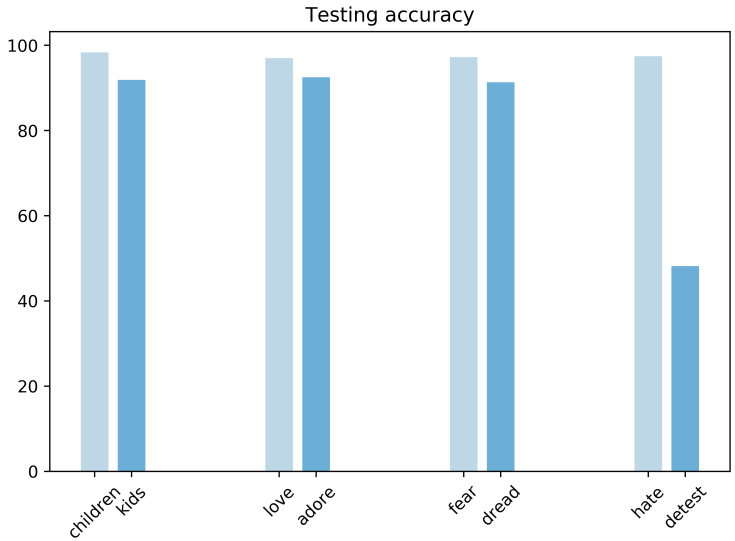
Testing accuracy
100
80
60
40
20
0
children
kids
love
adore
fear
dread
hate
detest

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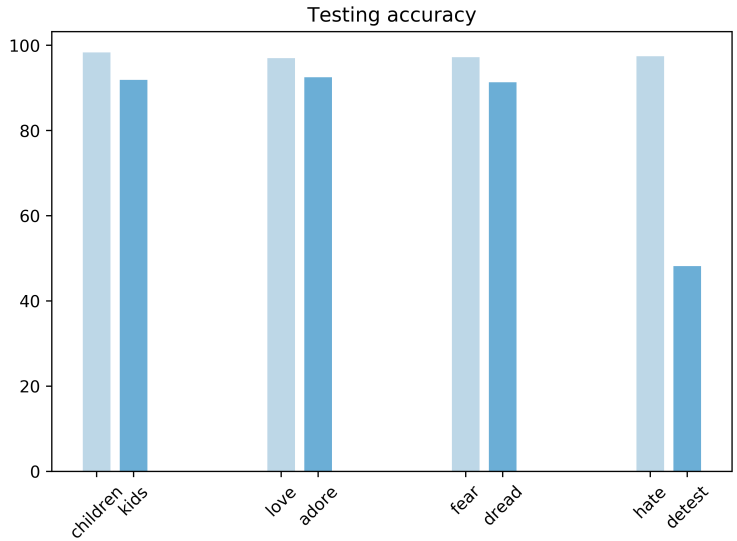
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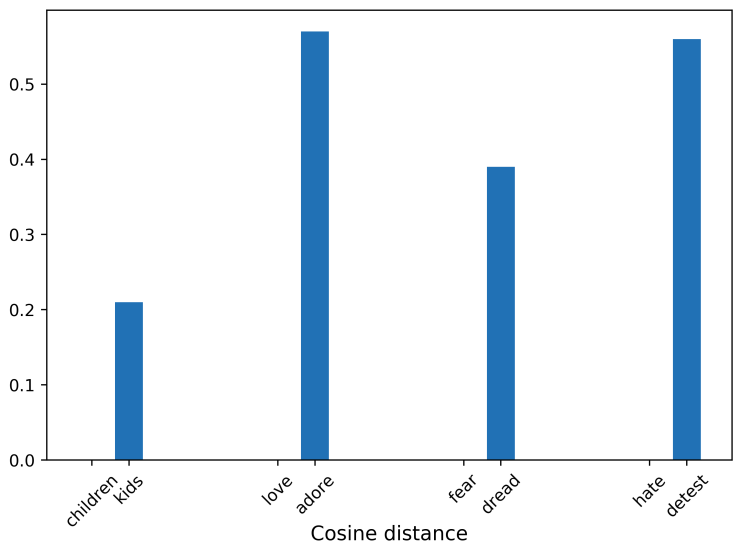
0.5
0.4
0.3
0.2
0.1
0.0
children
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love
adore
fear
dread
hate
detest
Cosine distance

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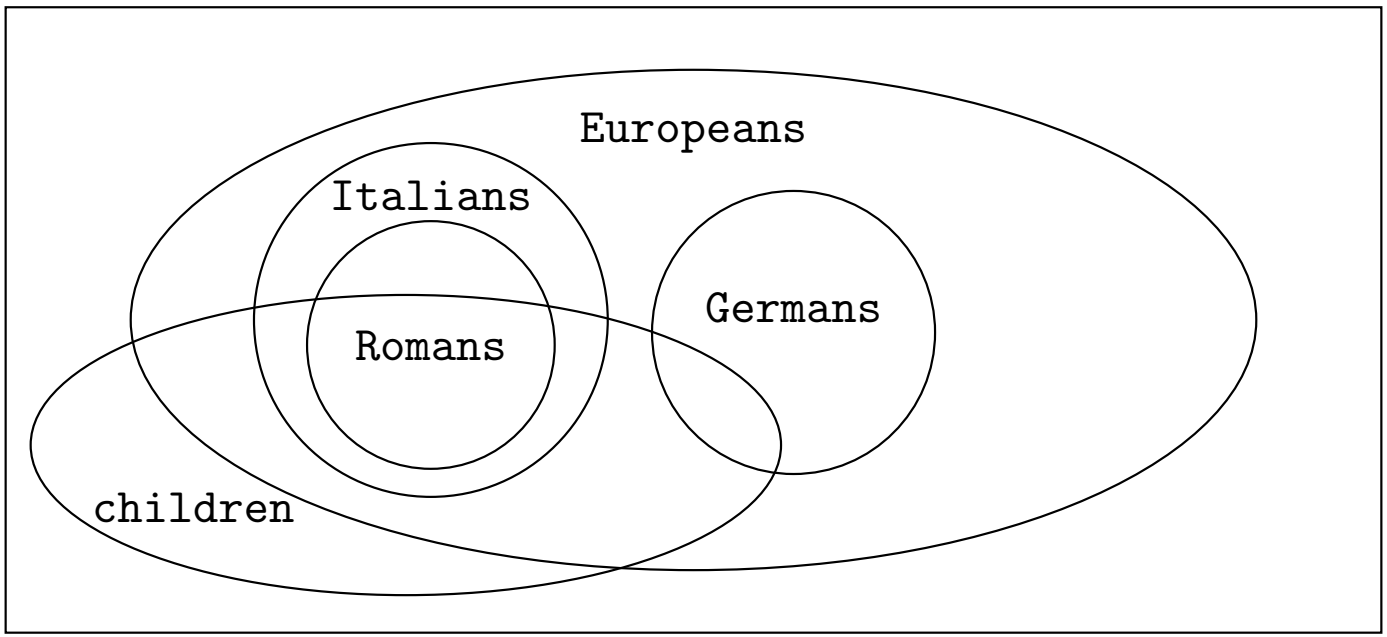

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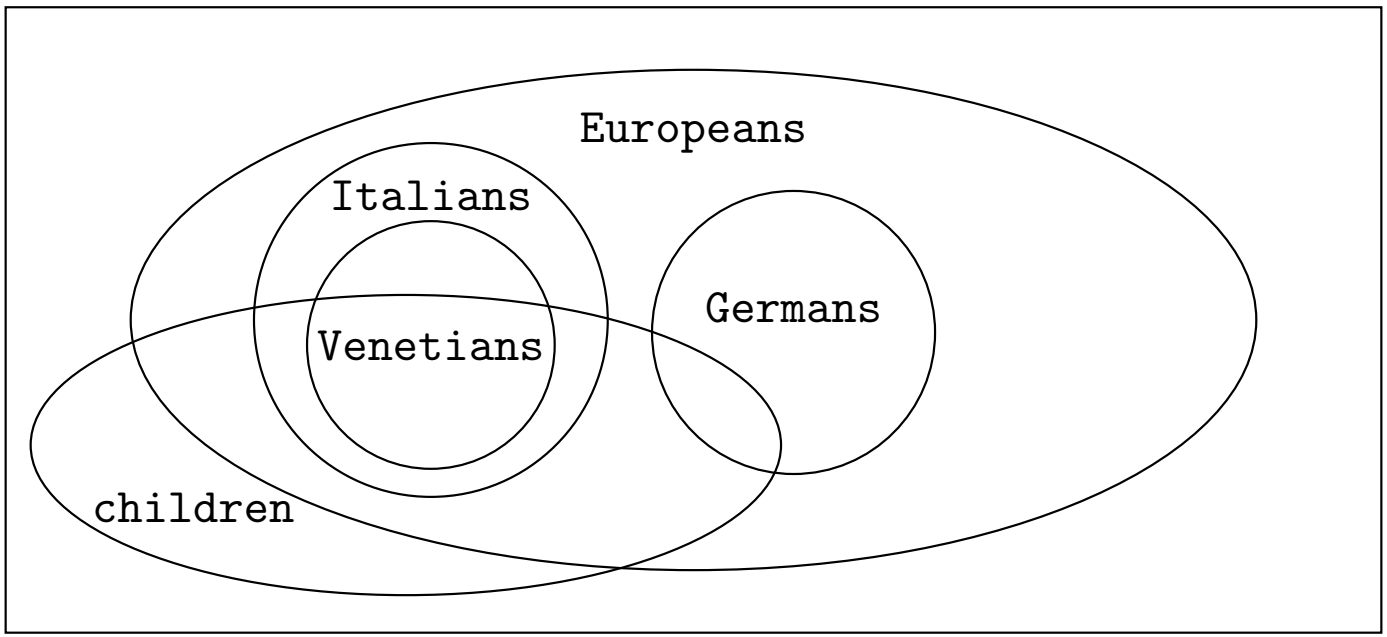

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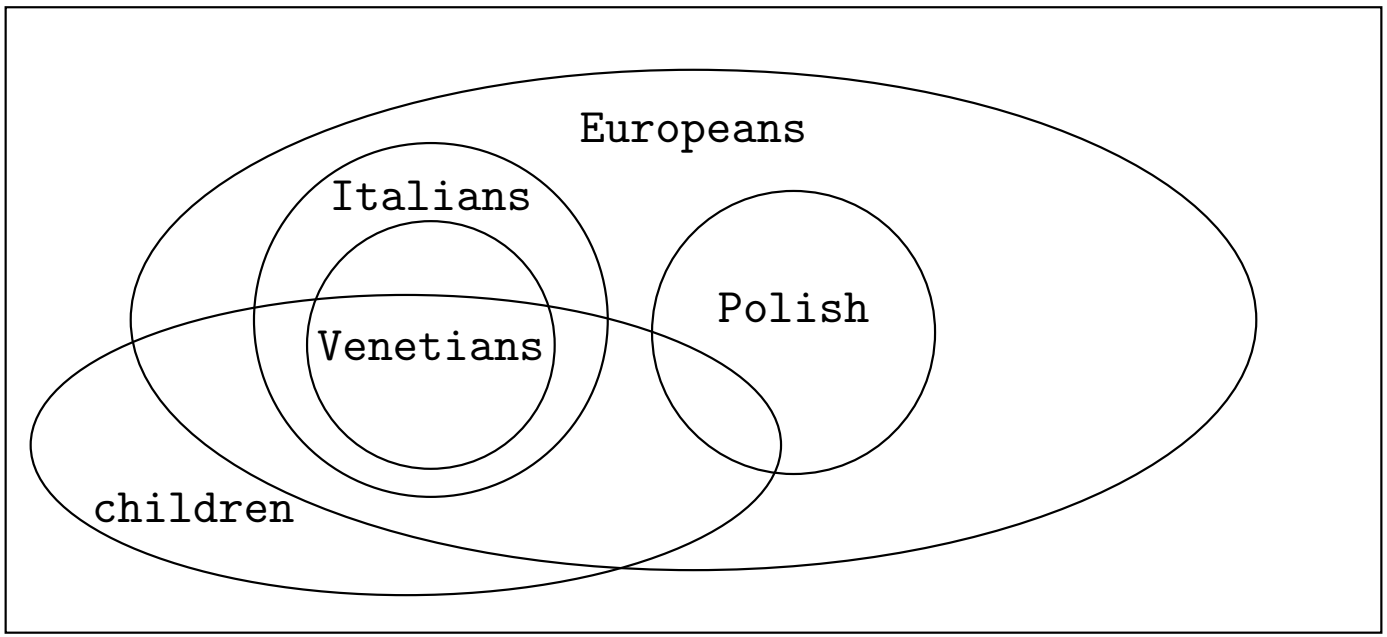

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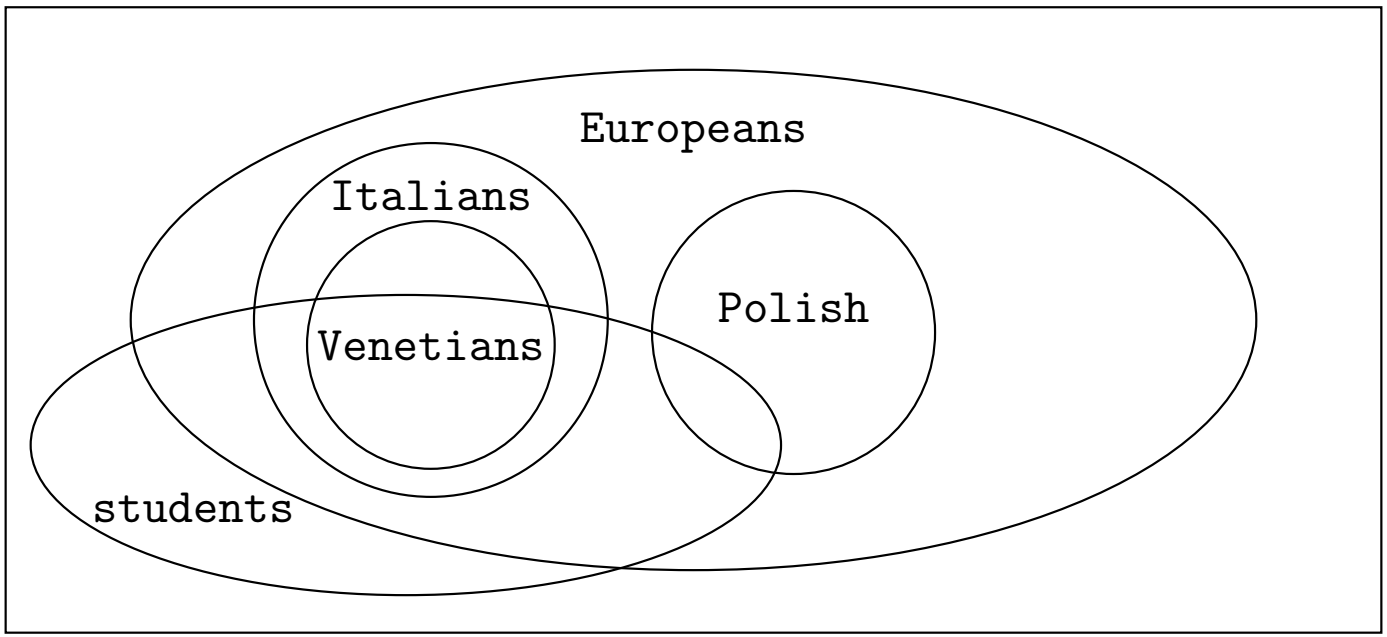

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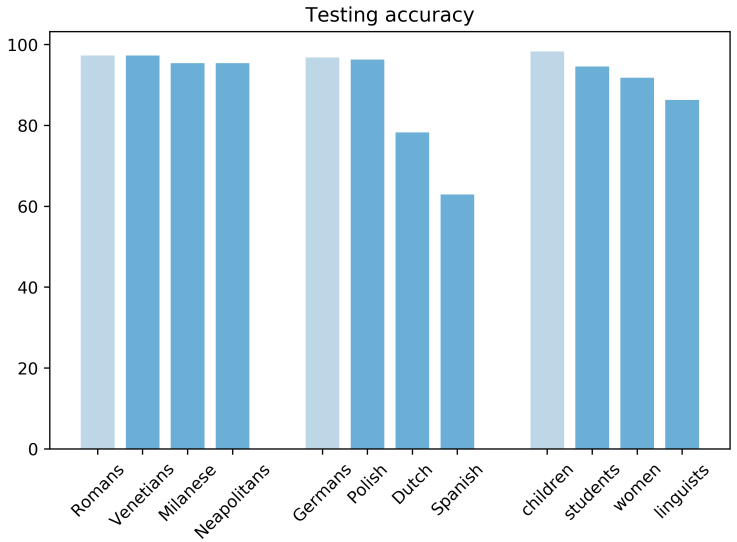

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