

SoPa++: Leveraging explainability from hybridized RNN, CNN and weighted finite-state neural architectures

M.Sc. Thesis Defense

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Cognitive Systems: Language, Learning, and Reasoning (M.Sc.)

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Overview

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Motivation

- Trend of increasingly complex deep learning models achieving SOTA performance on ML and NLP tasks (Figure 1)
- To address emerging concerns such as inductive biases, several studies make argument for research into XAI ([Danilevsky et al., 2020](#); [Arrieta et al., 2020](#))
- [Schwartz et al. \(2018\)](#) approach XAI in NLP by proposing an explainable hybridized RNN, CNN and WFA neural architecture called **Soft Patterns (SoPa)**
- SoPa provides localized and indirect explainability despite being suited for **globalized and direct** explanations by simplification

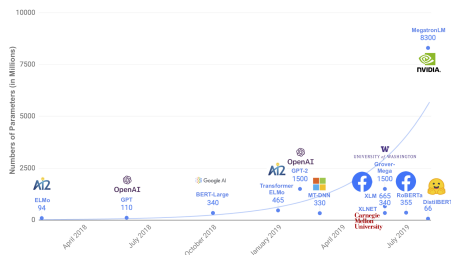


Figure 1: Parameter counts of recently released pre-trained language models; figure taken from [Sanh et al. \(2019\)](#)

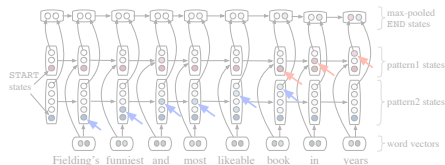


Figure 2: SoPa's partial computational graph; figure taken from [Schwartz et al. \(2018\)](#)

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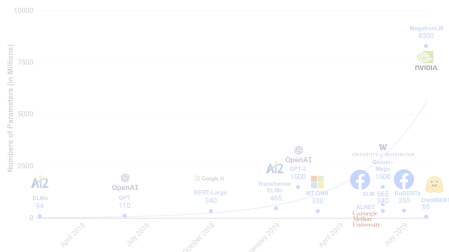


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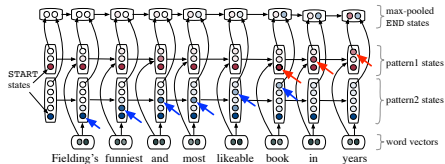


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Objective and research questions

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- Address limitations of SoPa by proposing **SoPa++**, which could allow for effective explanations by simplification.

Process:

- We study the performance and explanations by simplification of SoPa++ on the **FMTOD** data set from [Schuster et al. \(2019\)](#); focusing on the English-language intent classification task.

Research questions:

- 1 Does SoPa++ provide **competitive** performance?
- 2 To what extent does SoPa++ contribute to **effective** explanations by simplification?
- 3 What **interesting and relevant** explanations can SoPa++ provide?

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Bibliography I

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CONCLUSIONS

1. *Journal of the American Medical Association*, 1997; 277: 1001-1005.