

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

M.Sc. Thesis Defense

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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 arguments for research into XAI; for example [Danilevsky et al. \(2020\)](#) and [Arrieta et al. \(2020\)](#)
- [Schwartz et al. \(2018\)](#) approach XAI in NLP by proposing an explainable hybridized neural architecture called **Soft Patterns** (SoPa; Figure 2)
- SoPa provides localized and indirect explainability despite being suited for **globalized and direct** explanations by simplification

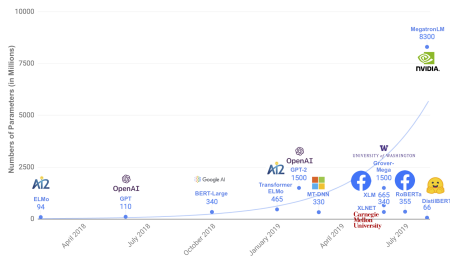


Figure 1: Parameter counts of recently released pre-trained language models; figure taken from [Sanh et al. \(2019\)](#)

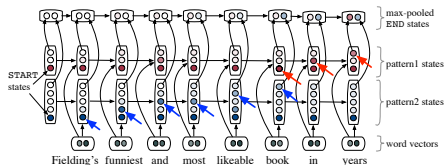


Figure 2: SoPa's partial computational graph; figure taken from [Schwartz et al. \(2018\)](#)

Objective and research questions

Objective:

- 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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Explainability

- Transparency is a passive feature that a model exhibits
- Explainability is an active feature that involves target audiences (Figure 3)
- [Arrieta et al. \(2020\)](#) explore a taxonomy of explainability techniques
- Prominent explainability techniques include local explanations, feature relevance and **explanations by simplification**
- Explainability techniques can provide meaningful insights into decision boundaries within black-box models (Figure 4)

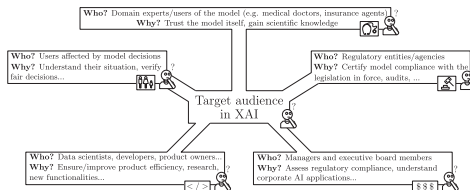
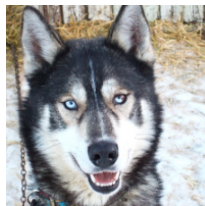
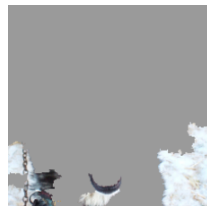


Figure 3: Examples of various target audiences in XAI; figure taken from [Arrieta et al. \(2020\)](#)



(a) Husky classified as wolf



(b) Explanation

Figure 4: Local explanation for “Wolf” classification decision, figure taken from [Ribeiro et al. \(2016\)](#)

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