

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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Foundations of Computational Linguistics

Department of Linguistics

University of Potsdam, SoSe 2021

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Overview

1 Introduction

2 Background concepts

3 Data and methodologies

4 Results

5 Discussion

6 Conclusions

7 Further work

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**

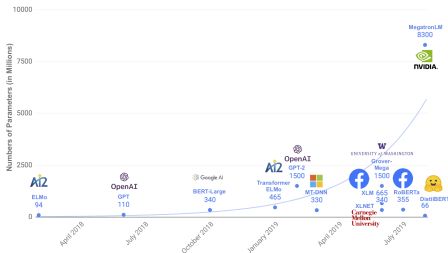


Figure 1: Parameter counts of recently released pre-trained language models; figure taken from [Sanh et al. \(2019\)](#)

SoPa: Bridging CNNs, RNNs, and Weighted Finite-State Machines

Roy Schwartz*♦♦ Sam Thomson*♣ Noah A. Smith♦

♦Paul G. Allen School of Computer Science & Engineering, University of Washington

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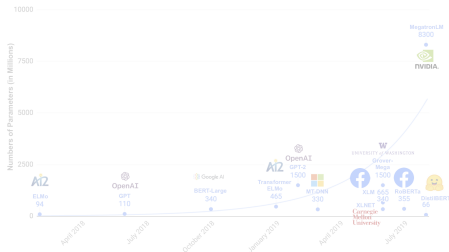


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Objective and research questions

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 Facebook Multilingual Task Oriented Dialog (**FMTOD**) data set from [Schuster et al. \(2019\)](#); focusing on the English-language intent classification task.

Research questions:

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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 post-hoc explainability techniques
- Explainability techniques can provide meaningful insights into decision boundaries within black-box models (Figure 4)
- Prominent explainability techniques include local explanations, feature relevance and **explanations by simplification**

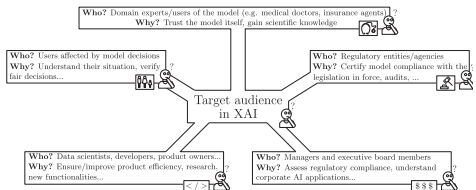
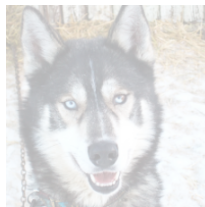


Figure 3: Examples of various target audiences in XAI; figure taken from [Arrieta et al. \(2020\)](#)



(a) Husky classified as wolf

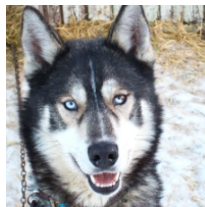


(b) Explanation

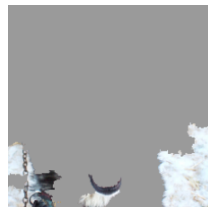
Figure 4: Local explanation for "Wolf" classification decision, figure taken from [Ribeiro et al. \(2016\)](#)

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SoPa: Weighted Finite-State Automaton (WFA)

Definition 1 (Semiring; Kuich and Salomaa 1986)

A semiring is a set \mathbb{K} along with two binary associative operations \oplus (addition) and \otimes (multiplication) and two identity elements: $\bar{0}$ for addition and $\bar{1}$ for multiplication. Semirings require that addition is commutative, multiplication distributes over addition, and that multiplication by $\bar{0}$ annihilates, i.e., $\bar{0} \otimes a = a \otimes \bar{0} = \bar{0}$.

- Semirings follow the following generic notation: $\langle \mathbb{K}, \oplus, \otimes, \bar{0}, \bar{1} \rangle$.
- **Max-sum** semiring: $\langle \mathbb{R} \cup \{-\infty\}, \max, +, -\infty, 0 \rangle$
- **Max-product** semiring: $\langle \mathbb{R}_{>0} \cup \{-\infty\}, \max, \times, -\infty, 1 \rangle$

Definition 2 (Weighted finite-state automaton; Peng et al. 2018)

A weighted finite-state automaton over a semiring \mathbb{K} is a 5-tuple $\mathcal{A} = \langle \Sigma, \mathcal{Q}, \Gamma, \lambda, \rho \rangle$, with:

- a finite input alphabet Σ ;
- a finite state set \mathcal{Q} ;
- transition matrix $\Gamma : \mathcal{Q} \times \mathcal{Q} \times (\Sigma \cup \{\epsilon\}) \rightarrow \mathbb{K}$;
- initial vector $\lambda : \mathcal{Q} \rightarrow \mathbb{K}$;
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SoPa: Computational graph

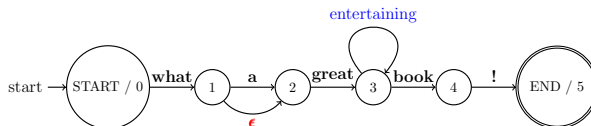
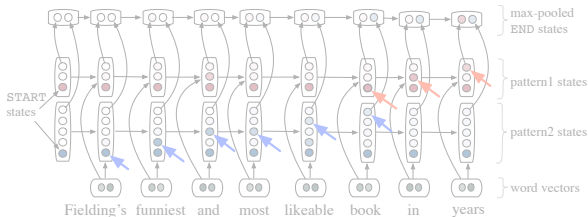


Figure 5: WFA slice: linear-chain FA with self-loop (blue), ϵ (red) and main-path (black) transitions; figure adapted from [Schwartz et al. \(2018\)](#)



SoPa: Post-hoc explainability techniques

- SoPa provides two post-hoc explainability techniques; namely **local explanations** and **feature relevance**
- Local explanations gather highest scoring phrases across the training data (Figure 7)
- Feature relevance perturbs inputs using an occlusion technique to determine the highest impact phrases for a classification decision (Figure 8)
- Overall, both techniques are **localized** and **indirect**
- WFAs have a rich theoretical background which can be exploited for more direct and globalized explanations

	Highest Scoring Phrases				
Patt. 1	thoughtful and entertaining gentle poignant	, astonishingly , , and	reverent articulate thought-provoking mesmerizing uplifting	portrait cast film portrait story	of of with of in
Patt. 2	's this this a is	€ € € € €	uninspired bad leaden half-assed clumsy <i>.SL</i>	story on comedy film the	. purpose . . writing

Figure 7: Ranked local explanations from SoPa; table taken from [Schwartz et al. \(2018\)](#)

Analyzed Documents

it 's dumb , but more importantly , it 's just not scary

though moonlight mile is replete with **acclaimed actors and actresses** and tackles a subject that 's **potentially moving** , the movie is *too predictable* and *too self-conscious to reach* a level of **high drama**

While **its careful pace and** seemingly *opaque story* may not satisfy every moviegoer 's appetite, the film 's final scene is **soaringly , transparently moving**

Figure 8: Feature relevance outputs from SoPa; table taken from [Schwartz et al. \(2018\)](#)

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FMTOD: Summary statistics

Class and description	Frequency	Utterance length [†]	Example [‡]
0: alarm/cancel_alarm	1791	5.6 ± 1.9	cancel weekly alarm
1: alarm/modify_alarm	566	7.1 ± 2.5	change alarm time
2: alarm/set_alarm	5416	7.5 ± 2.5	please set the new alarm
3: alarm/show_alarms	914	6.9 ± 2.2	check my alarms.
4: alarm/snooze_alarm	366	6.1 ± 2.1	pause alarm please
5: alarm/time_left_on_alarm	344	8.6 ± 2.1	minutes left on my alarm
6: reminder/cancel_reminder	1060	6.6 ± 2.2	clear all reminders.
7: reminder/set_reminder	5549	8.9 ± 2.5	birthday reminders
8: reminder/show_reminders	773	6.8 ± 2.2	list all reminders
9: weather/check_sunrise	101	6.7 ± 1.7	when is sunrise
10: weather/check_sunset	136	6.7 ± 1.7	when is dusk
11: weather/find	14338	7.8 ± 2.3	jacket needed?
Σ/μ	31354	7.7 ± 2.5	—

[†] Summary statistics follow the mean \pm standard-deviation format

[‡] Short and simple examples were chosen for brevity and formatting purposes

Table 1: Summary statistics and examples for the preprocessed FMTOD data set

SoPa++: WFA- ω and TauSTE

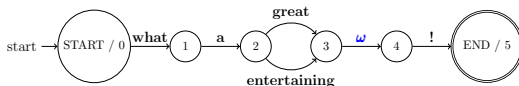


Figure 9: WFA- ω slice: strict linear-chain FA with ω (blue) and main-path (black) transitions

$$\text{TauSTE}(x) = \begin{cases} 1 & x \in (\tau, +\infty) \\ 0 & x \in (-\infty, \tau] \end{cases}$$

$$\text{TauSTE}'(x) = \begin{cases} 1 & x \in (1, +\infty) \\ x & x \in [-1, 1] \\ -1 & x \in (-\infty, -1) \end{cases}$$

- $\text{TauSTE}'(x)$ implies the backward pass and **not** the gradient in this context
- Flavors of STEs are being extensively researched, such as in Yin et al. (2019)

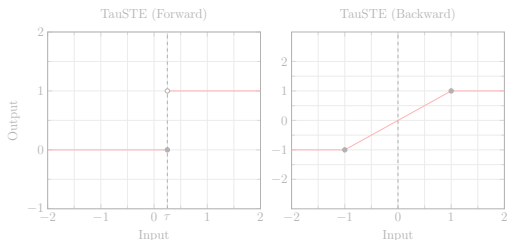


Figure 10: TauSTE's forward and backward passes

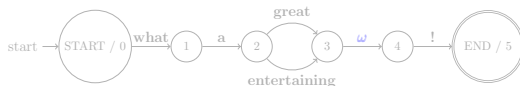
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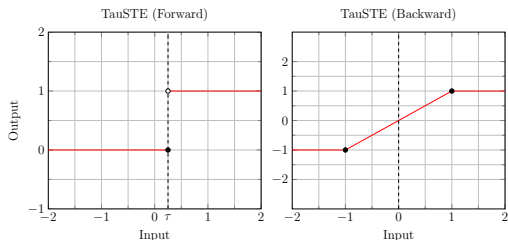


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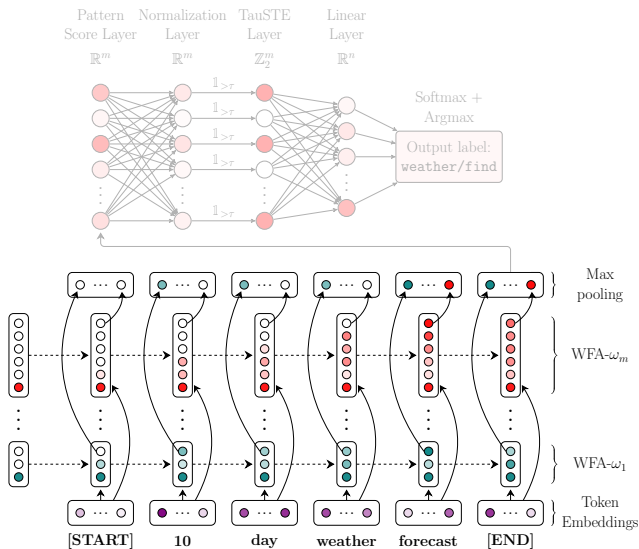


Figure 11: SoPa++ computational graph; flow of graph is from bottom to top and left to right

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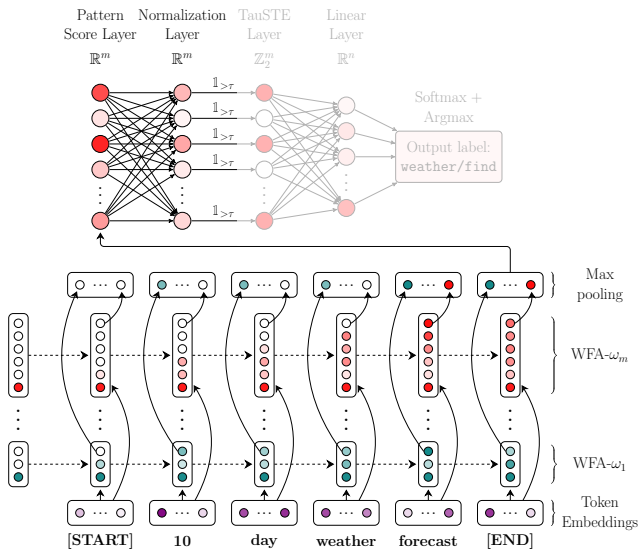


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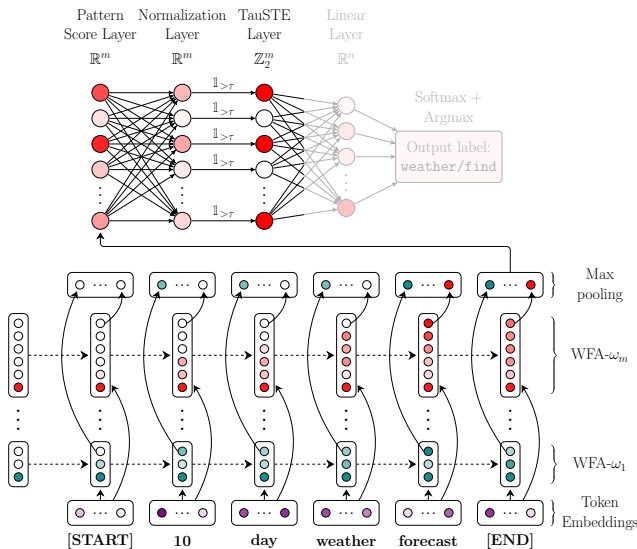


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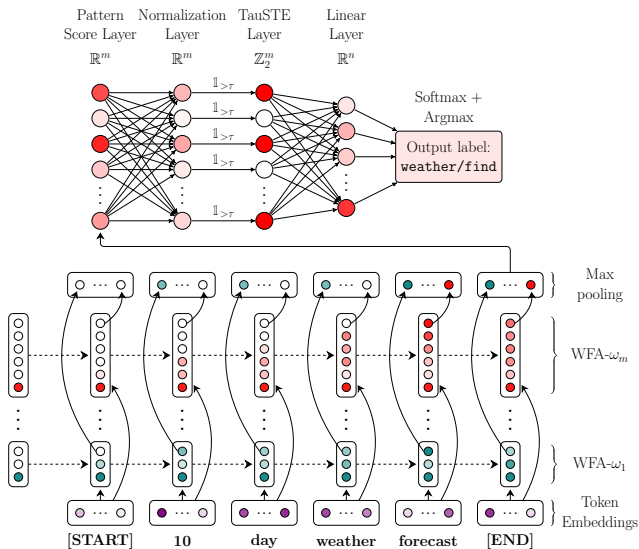


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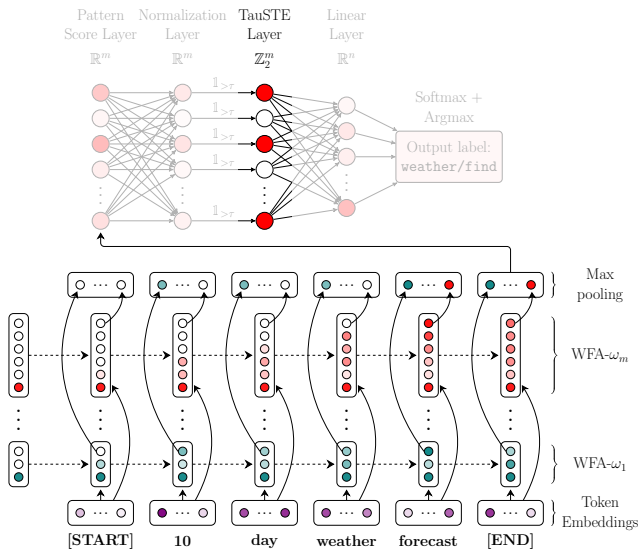


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SoPa++: Regular Expression (RE) proxy

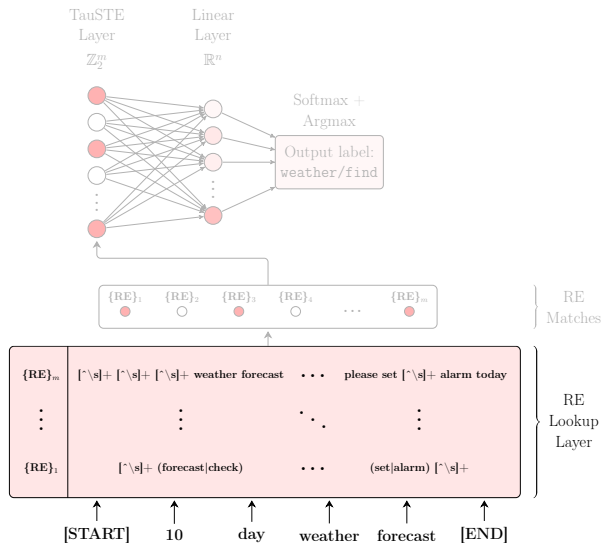


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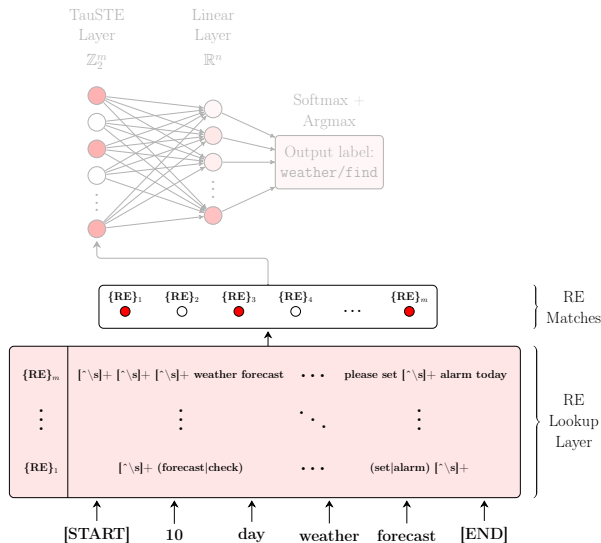


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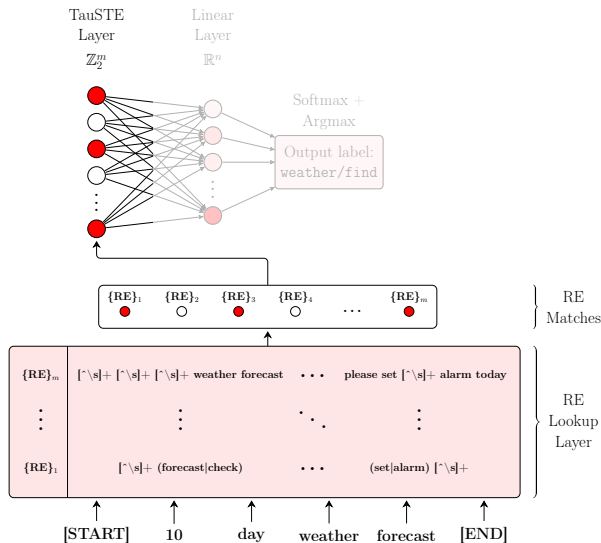


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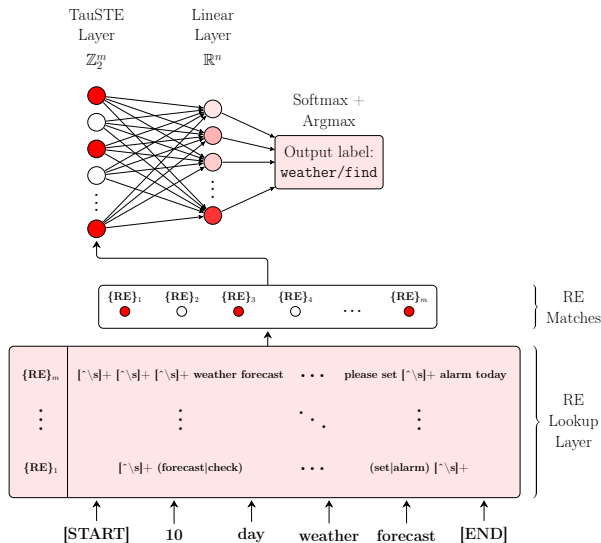


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SoPa vs. SoPa++

Characteristic	SoPa	SoPa++
Text casing	True-cased	Lower-cased
Token embeddings	GloVe 840B 300-dimensions	GloVe 6B 300-dimensions
WFAs	Linear-chain WFA's with ϵ , self-loop and main-path transitions	Strict linear-chain WFA- ω 's with ω and main-path transitions
Hidden layers	Multi-layer perceptron after max-pooling	Layer normalization, TauSTE and linear transformation after max-pooling
Post-hoc explainability technique(s)	Local explanations, feature relevance	Explanations by simplification

Table 2: Summarized differences for SoPa vs. SoPa++

Research Question 1: Competitive performance

Model size	Patterns hyperparameter P	Parameter count
Small	6-10_5-10_4-10_3-10	1,260,292
Medium	6-25_5-25_4-25_3-25	1,351,612
Large	6-50_5-50_4-50_3-50	1,503,812

Table 3: Three different SoPa++ model sizes used during training

- RQ 1: Does SoPa++ provide **competitive** performance?
- Competitive accuracy range: **96.6 — 99.5%** (Schuster et al., 2019; Zhang et al., 2019; Zhang et al., 2020)
- Upsampling minority classes to mitigate data imbalance
- Grid-search with three model sizes, varying τ -thresholds: $\{0.00, 0.25, 0.50, 0.75, 1.00\}$ and 10 random seed iterations
- $3 \times 5 \times 10 = 150$ model runs
- Evaluation and comparison on the test set

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Research Question 2: Effective explanations

- RQ 2: To what extent does SoPa++ contribute to **effective** explanations by simplification?
- Effective explanations by simplification require **simpler model**, **similar performance** and **maximizing resemblance** to antecedent
- Similar performance \Rightarrow compare test set evaluations
- Maximum resemblance \Rightarrow minimum distances over test set
- Softmax distance norm:

$$\delta_{\sigma}(\mathbf{y}) = \|\sigma_{\mathcal{S}}(\mathbf{y}) - \sigma_{\mathcal{R}}(\mathbf{y})\|_2 = \sqrt{\sum_{i=1}^n (\sigma_{\mathcal{S}_i}(\mathbf{y}) - \sigma_{\mathcal{R}_i}(\mathbf{y}))^2}$$

- Binary-misalignment rate:

$$\delta_b(\mathbf{y}) = \frac{\|\mathbf{b}_{\mathcal{S}}(\mathbf{y}) - \mathbf{b}_{\mathcal{R}}(\mathbf{y})\|_1}{\dim(\mathbf{b}_{\mathcal{S}}(\mathbf{y}) - \mathbf{b}_{\mathcal{R}}(\mathbf{y}))} = \frac{\sum_{i=1}^n |b_{\mathcal{S}_i}(\mathbf{y}) - b_{\mathcal{R}_i}(\mathbf{y})|}{\dim(\mathbf{b}_{\mathcal{S}}(\mathbf{y}) - \mathbf{b}_{\mathcal{R}}(\mathbf{y}))}$$

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Research Question 3: Relevant explanations

- RQ 3: What **interesting and relevant** explanations can SoPa++ provide?
- Open-ended question, can answer in different ways
- Capitalize on the new linear layer \Rightarrow allows for direct analysis of relative linear weights
- Sample REs from RE lookup layer corresponding to salient TauSTE neurons
- Analyze REs for interesting linguistic features and inductive biases

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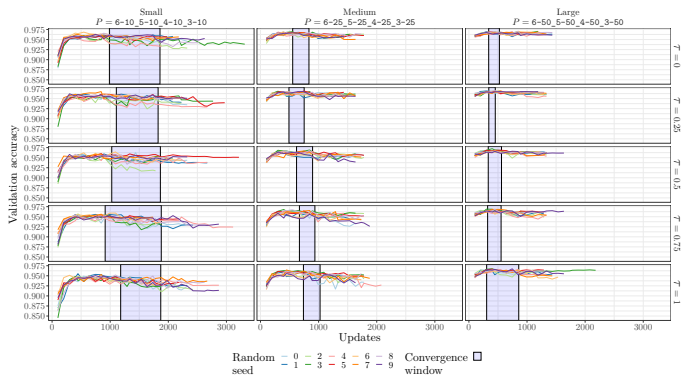


Figure 13: Validation accuracies of SoPa++ models against training updates

Size	Parameters	Accuracy in % with mean \pm standard-deviation				
		$\tau=0.00$	$\tau=0.25$	$\tau=0.50$	$\tau=0.75$	$\tau=1.00$
Small	1,260,292	97.6 \pm 0.2	97.6 \pm 0.2	97.3 \pm 0.2	97.0 \pm 0.3	96.9 \pm 0.3
Medium	1,351,612	98.3 \pm 0.2	98.1 \pm 0.1	98.0 \pm 0.2	97.9 \pm 0.1	97.7 \pm 0.1
Large	1,503,812	98.3 \pm 0.2	98.3 \pm 0.2	98.2 \pm 0.2	98.1 \pm 0.2	98.0 \pm 0.2

Table 4: Test accuracies of SoPa++ models

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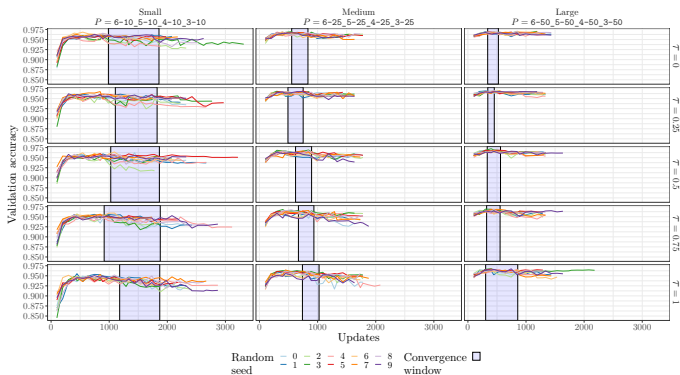


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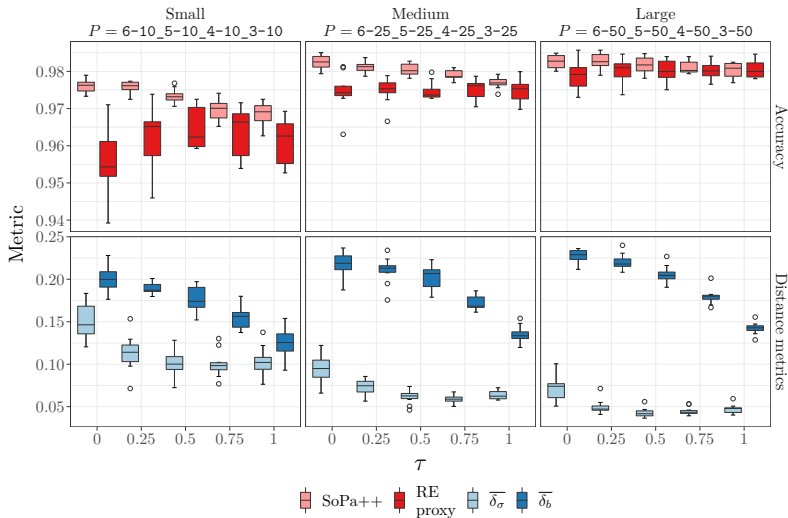


Figure 14: Visualization of model-pair accuracies and distance metrics

Research Question 3: Relevant explanations

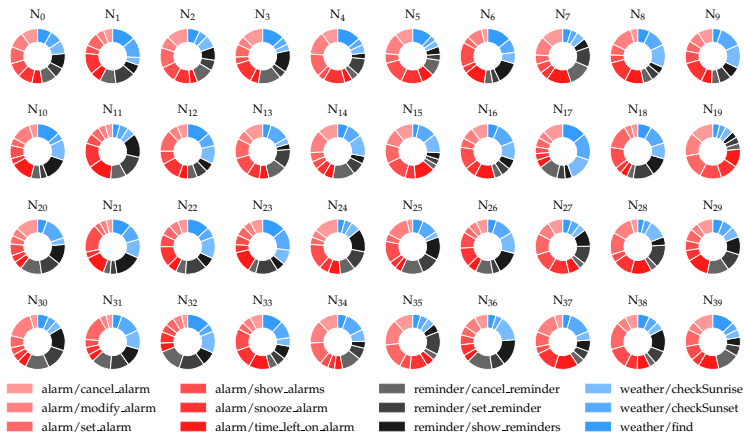


Figure 15: Relative linear layer weights applied to TauSTE neurons for the best performing small RE proxy model with a test accuracy of 97.4%

Research Question 3: Relevant explanations

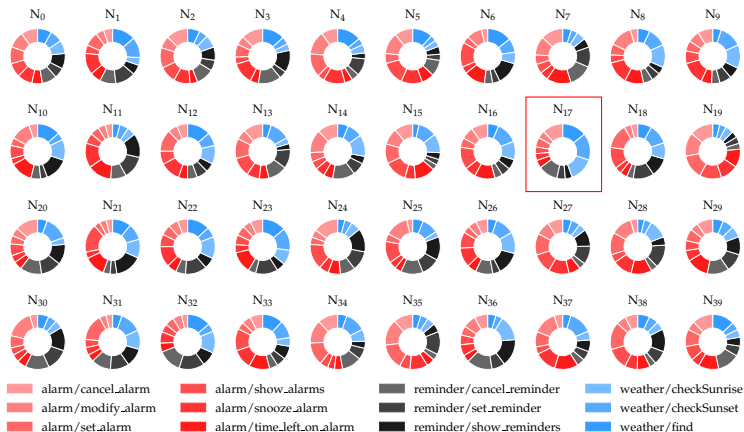


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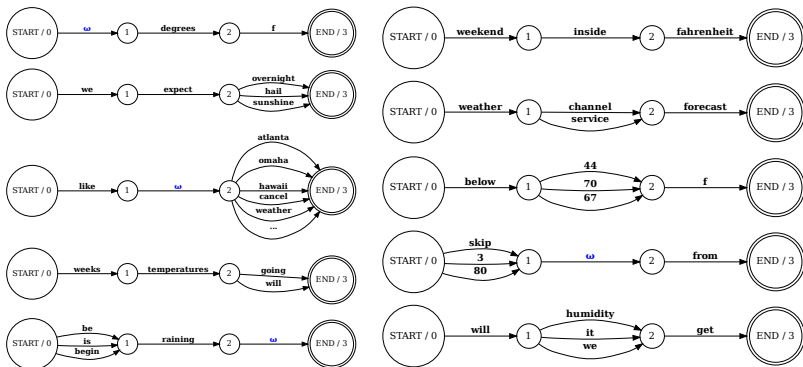


Figure 16: Ten sampled regular expressions from the RE lookup layer corresponding to TauSTE neuron 17 for the best performing small RE proxy model

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Research Question 1: Competitive performance

Overview:

- RQ 1: Does SoPa++ provide **competitive** performance?
- Competitive accuracy range: 96.6 – 99.5% ([Schuster et al., 2019](#); [Zhang et al., 2019](#); [Zhang et al., 2020](#))
- Observed best accuracy range for $\tau = 0.00$: **97.6 – 98.3%**
- SoPa++ offers **competitive** performance on FMTOD's English language intent detection task

Discussion:

- Other studies worked with true-cased text
- Observed performance is in the middle of competitive range
- Worth noting the sizes of competitive BERT-derived models with external data

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- RQ 2: To what extent does SoPa++ contribute to **effective** explanations by simplification?
- Effective explanations by simplification require simpler model, similar performance and maximizing resemblance to antecedent
- **Effective** to the extent of: lowest accuracy differences ranging from **0.1 – 0.7%** and softmax distance norms ranging from **4.3 – 10.0%**
- Most effective for medium-large sized models with $\tau \in [0.50, 1.00]$

Discussion:

- No benchmark for effective explanations by simplification
- RE proxy may not necessarily always be transparent given size of RE lookup layer
- Target audience was omitted in this analysis

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Research Question 3: Relevant explanations

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- RQ 3: What **interesting and relevant** explanations can SoPa++ provide?
- Similar lexical properties in branches
- USA-centric inductive biases
- Pronoun-level inductive biases

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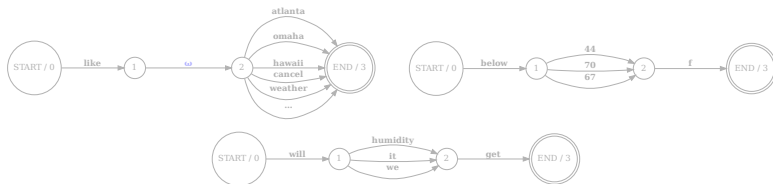


Figure 17: Sampled regular expressions from the RE lookup layer corresponding to TauSTE neuron 17 for the best performing small RE proxy model

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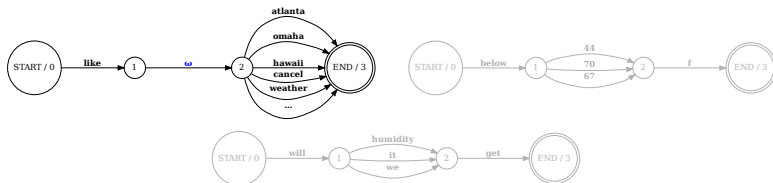


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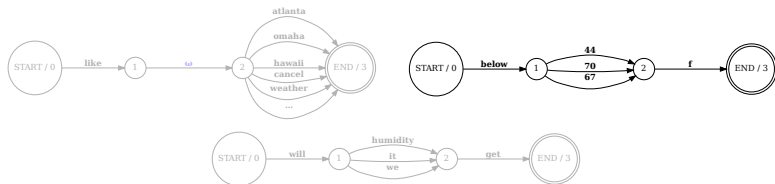


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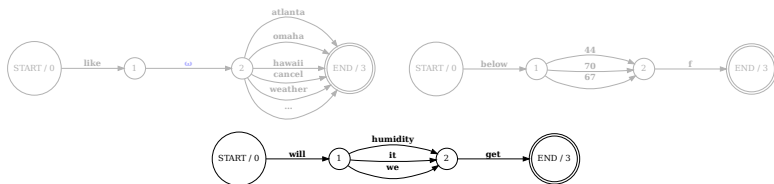


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Objective:

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

Research questions:

- 1 Does SoPa++ provide **competitive** performance?
 - Best accuracy range: 97.6 – 98.3% ✓
- 2 To what extent does SoPa++ contribute to **effective** explanations by simplification?
 - Lowest accuracy differences ranging from 0.1 – 0.7% and softmax distance norms ranging from 4.3 – 10.0% ✓
 - Target audience analysis omitted ✗
- 3 What **interesting and relevant** explanations can SoPa++ provide?
 - Regular expression samples from salient TauSTE neurons analyzed ✓
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 - Small sample size ✗

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Explainability:

- Are SoPa++'s explanations **useful** for its target audience?

Bias correction:

- Manual bias corrections through large-scale analysis of RE lookup layer
- Mitigate **ethical** issues of using black-box models?

Generalization:

- Possible to generalize branches with broad categories like locations and numbers
- For example, replace digital tokens with `\-?[\d]+\.[\d]*`
- **Robustness** on unseen data?

Efficiency:

- **Parallelize** RE lookup layer
- Utilize GPU-based regular expression matching algorithms (Wang et al., 2011; Zu et al., 2012; Yu and Becchi, 2013)

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Thank you for your time and attention ♥

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