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

M.Sc. Thesis Defense

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Overview

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**

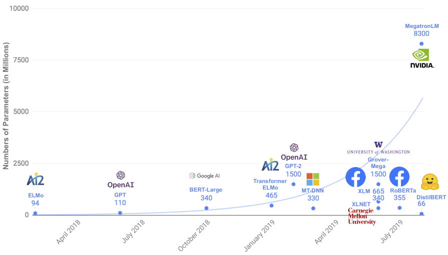

Figure 1: Parameter counts of recently released pre-trained language models; figure taken from Sanh et al. (2019)

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

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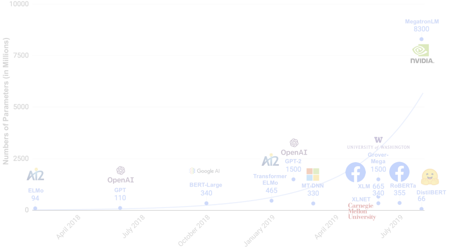

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Objective and research questions

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:

1. Does SoPa++ provide **competitive** performance?
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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**

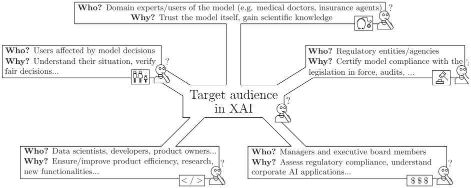

Figure 3: Examples of various target audiences in XAI; figure taken from Arrieta et al. (2020)

(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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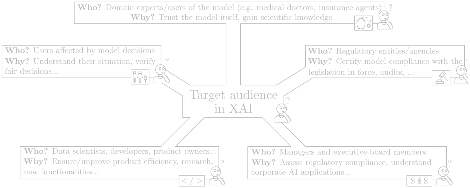

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SoPa: Weighted Finite-State Automaton (WFA)

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 $\mathcal{A} = \langle \Sigma, \mathcal{Q}, \boldsymbol{\Gamma}, \boldsymbol{\lambda}, \boldsymbol{\rho} \rangle$, with:

- a finite input alphabet Σ;
- a finite state set $\mathcal{Q}$;
- transition matrix $\boldsymbol{\Gamma} : \mathcal{Q} \times \mathcal{Q} \times (\Sigma \cup \{\epsilon\}) \to \mathbb{K}$;
- initial vector $\boldsymbol{\lambda} : \mathcal{Q} \to \mathbb{K}$;
- and final vector $\boldsymbol{\rho} : \mathcal{Q} \to \mathbb{K}$.

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SoPa: Computational graph

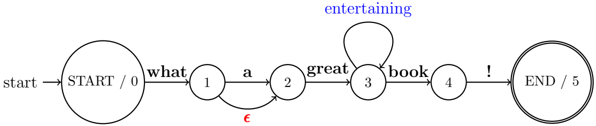

Figure 5: WFA slice: linear-chain FA with self-loop (blue), ϵ (red) and main-path (black) transitions; figure adapted from Schwartz et al. (2018)

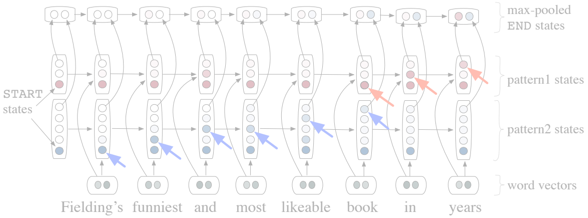

Figure 6: SoPa's partial computational graph; figure taken from Schwartz et al. (2018)

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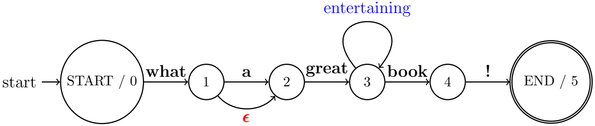

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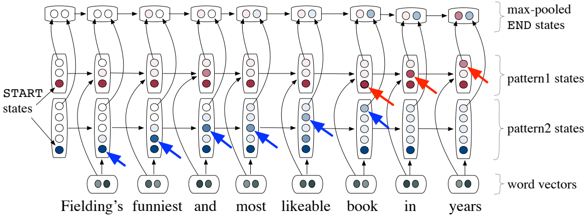

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SoPa: Post-hoc explainability techniques

- 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	,	reverent	portrait	of
	and	astonishingly	articulate	cast	of
	entertaining	,	thought-provoking	film	with
	gentle	,	mesmerizing	portrait	of
	poignant	and	uplifting	story	in
Patt. 2	's	ϵ	uninspired	story	.
	this	ϵ	bad	on	purpose
	this	ϵ	leaden	comedy	.
	a	ϵ	half-assed	film	.
	is	ϵ	clumsy $,_{SL}$	the	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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Overview

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 ± 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

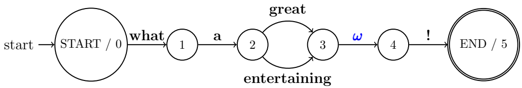

Figure 9: WFA-ω slice: strict linear-chain FA with ω (blue) and main-path (black) transitions

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

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

- $\text{TauSTE}'(x)$ 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)

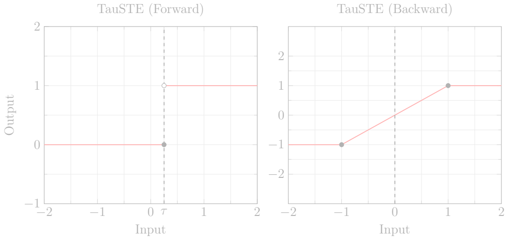

Figure 10: TauSTE's forward and backward passes

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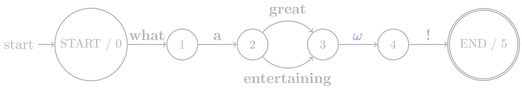

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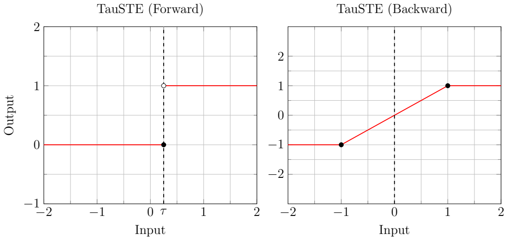

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SoPa++: Computational graph

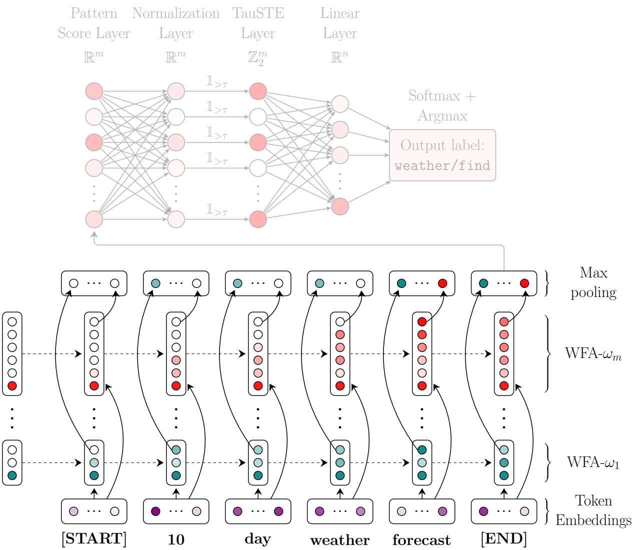

Figure 11: SoPa++ computational graph; flow of graph is from bottom to top and left to right

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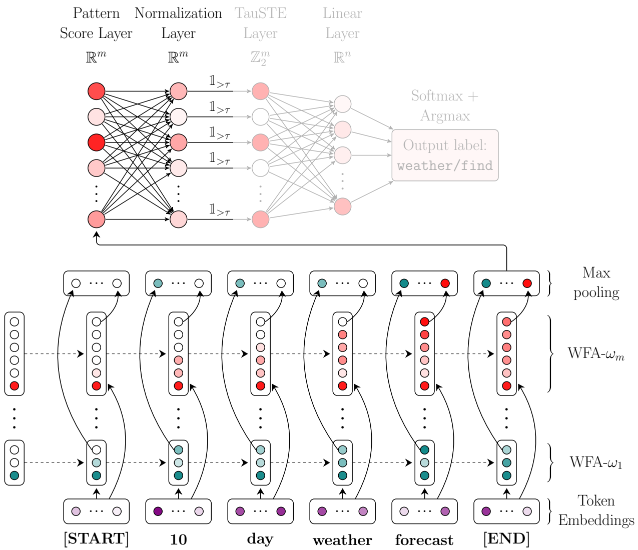

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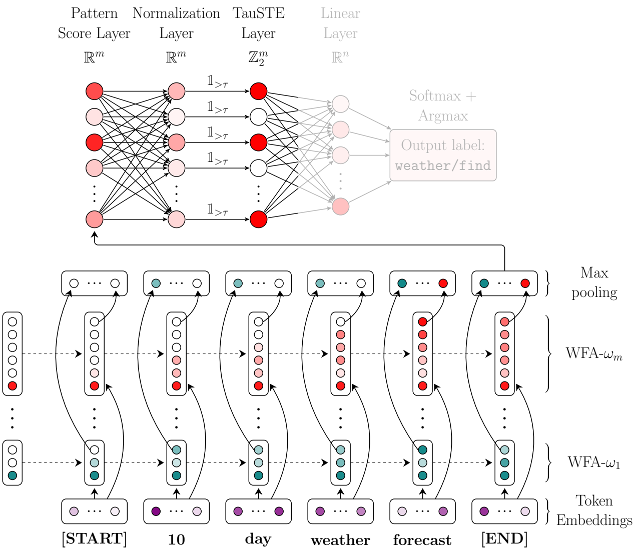

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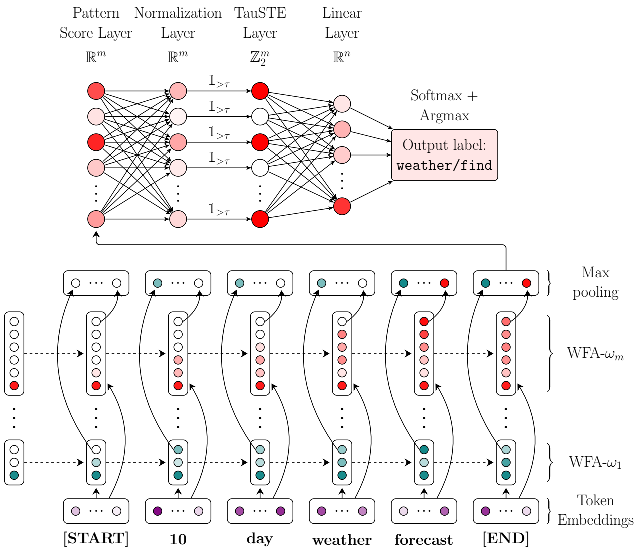

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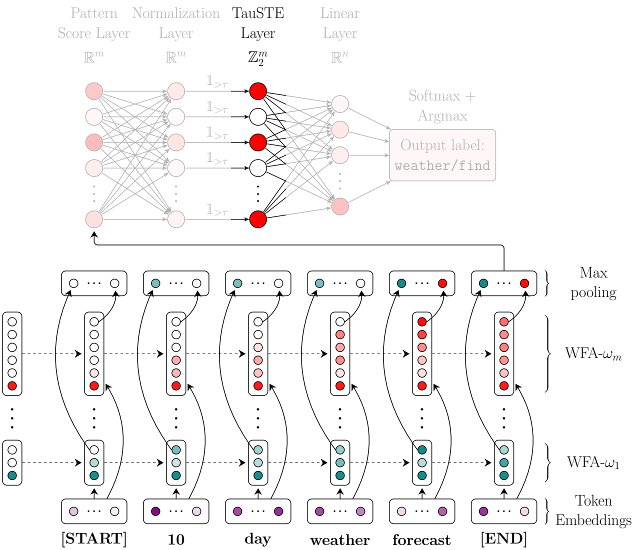

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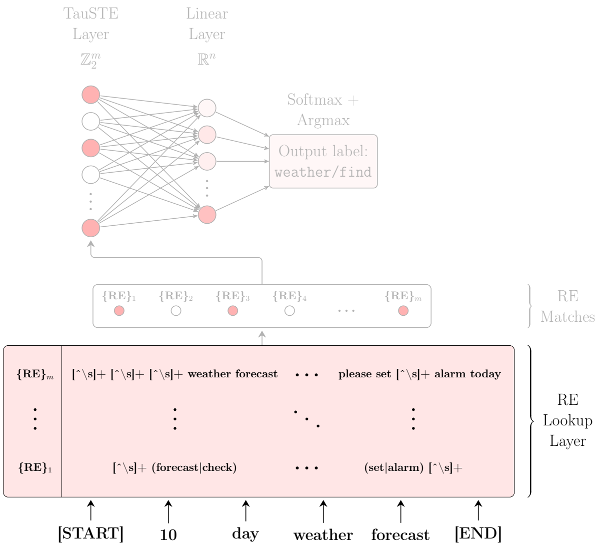

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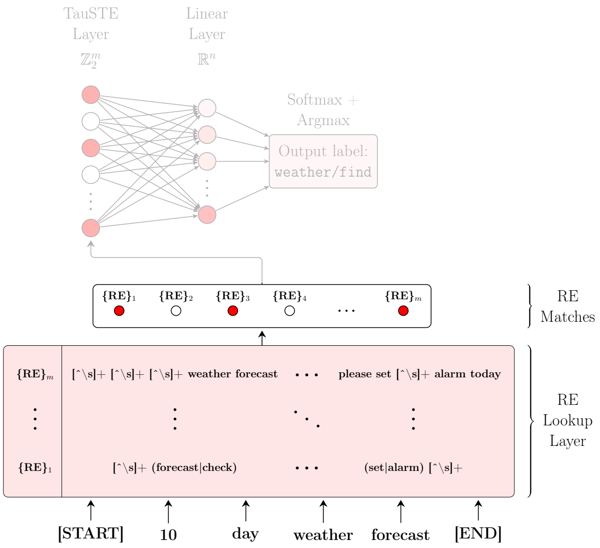

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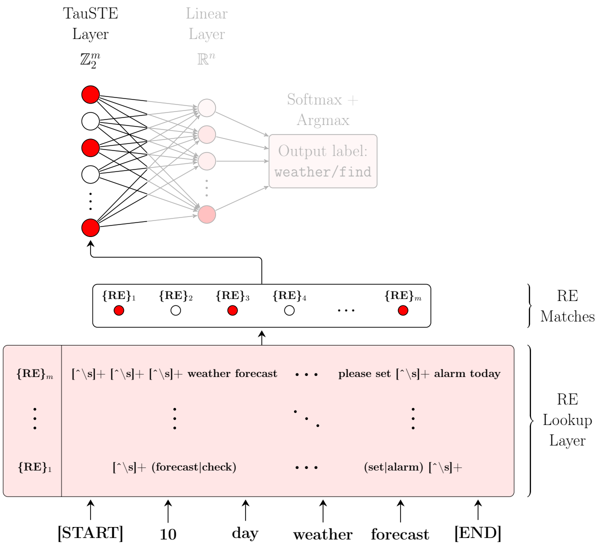

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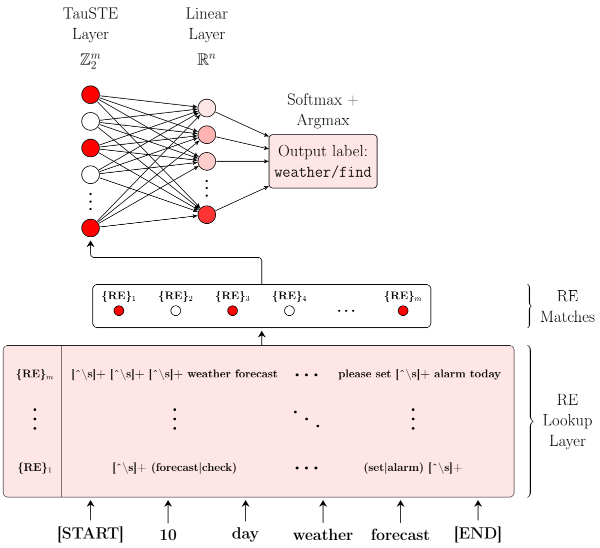

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SoPa vs. SoPa++

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:

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

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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
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Overview

Research Question 1: Competitive performance

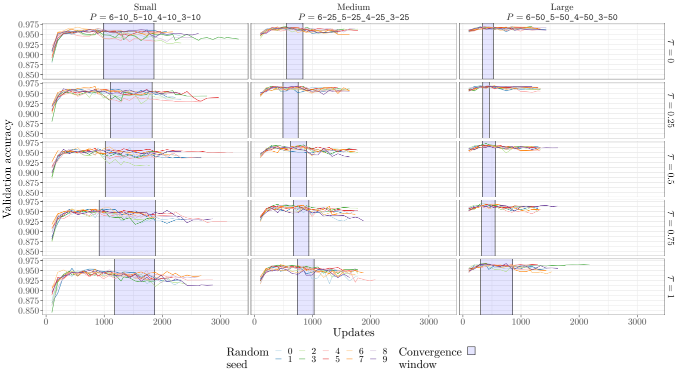

Figure 13: Validation accuracies of SoPa++ models against training updates

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

Table 4: Test accuracies of SoPa++ models

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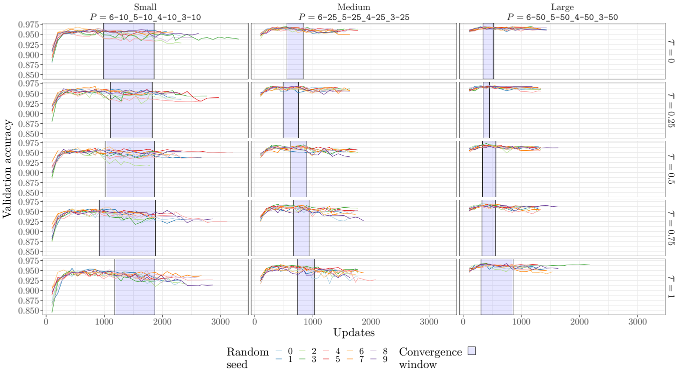

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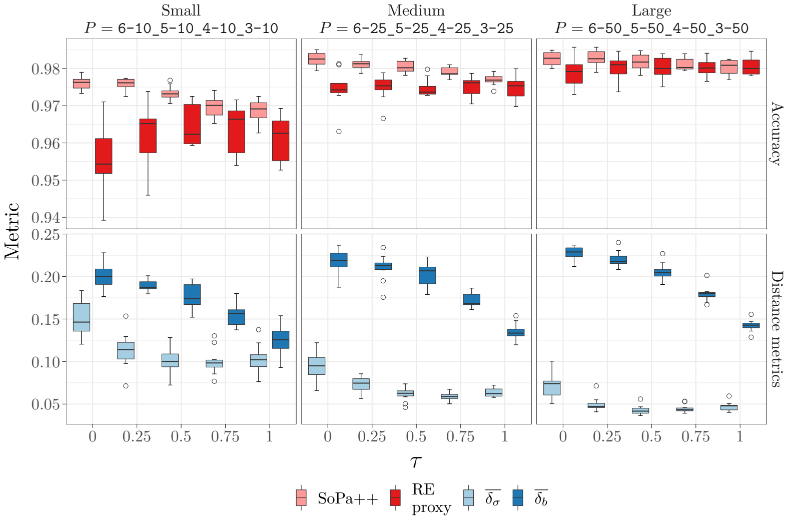

Figure 14: Visualization of model-pair accuracies and distance metrics

Research Question 3: Relevant explanations

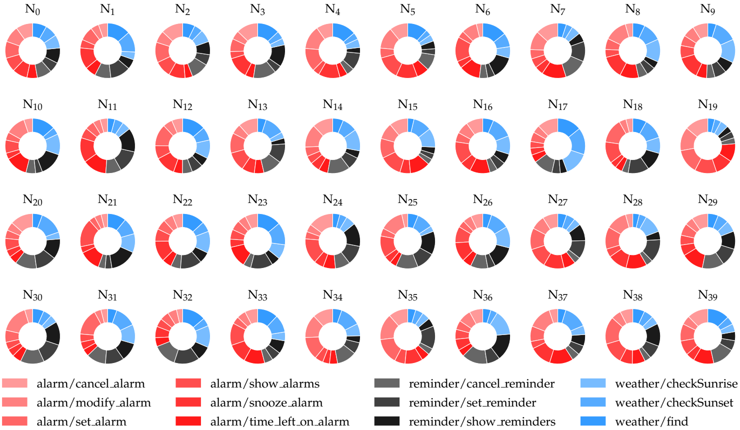

Figure 15: Relative linear layer weights applied to TauSTE neurons for the best performing small RE proxy model with a test accuracy of 97.4%

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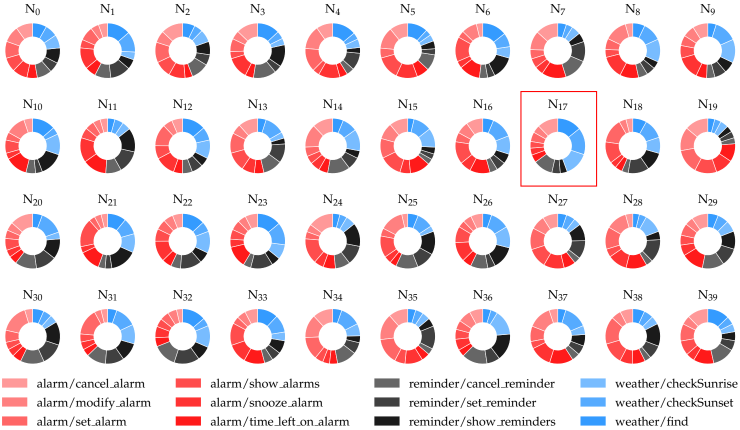

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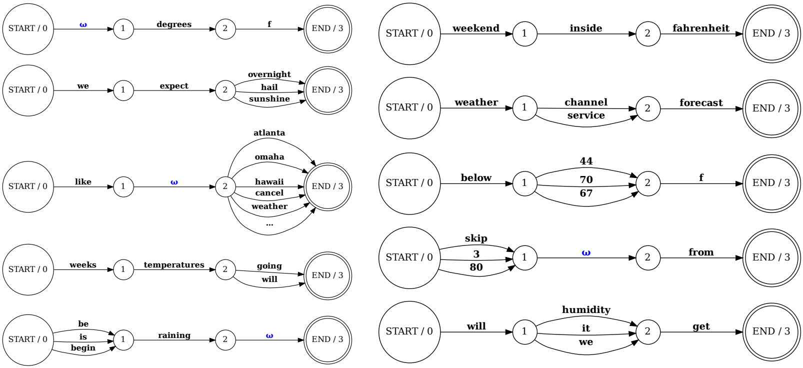

Figure 16: Ten sampled regular expressions from the RE lookup layer corresponding to TauSTE neuron 17 for the best performing small RE proxy model

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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 $\mathbf{0.1 - 0.7\%}$ and softmax distance norms ranging from $\mathbf{4.3 - 10.0\%}$
- Most effective for medium-large sized models with $\tau \in [0.50, 1.00]$

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- 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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- Similar lexical properties in branches
- USA-centric inductive biases
- Pronoun-level inductive biases

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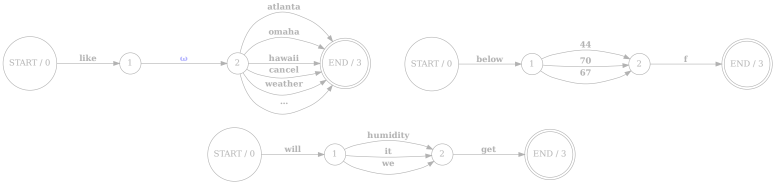

Figure 17: Sampled regular expressions from the RE lookup layer corresponding to TauSTE neuron 17 for the best performing small RE proxy model

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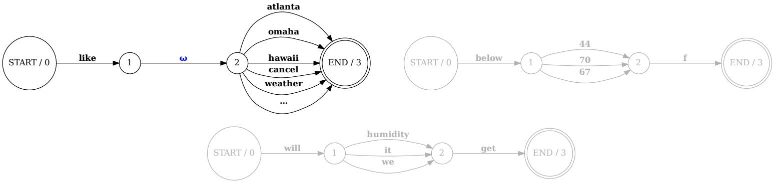

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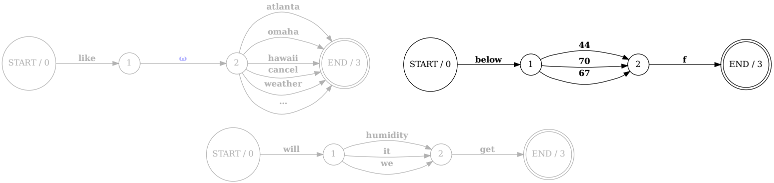

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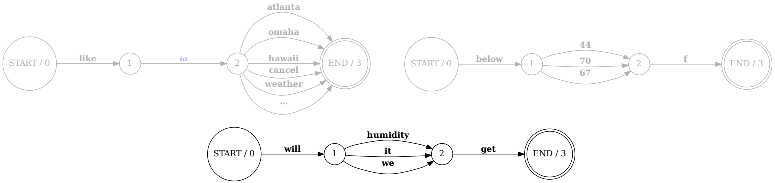

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Conclusions

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 ✓
   - Linguistic features and inductive biases ✓
   - Small sample size ✗

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Further work

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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