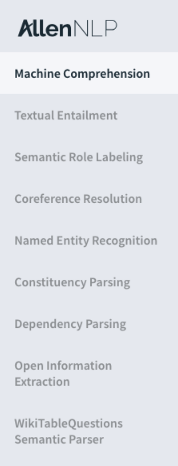
Towards Interpretable Deep Learning for Natural Language Processing

Roy Schwartz

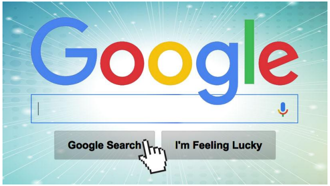
University of Washington & Allen Institute for Artificial Intelligence

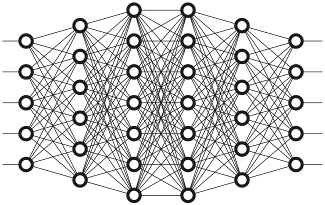
December 2018

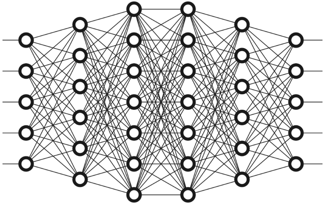
(Deep-Learning-Based) AI Today



Microsoft Translator

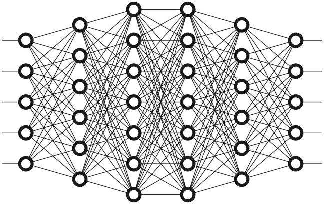






Deep Learning

- backpropagation
- stochastic gradient descent
- PyTorch, TensorFlow, AllenNLP
- **state-of-the-art**

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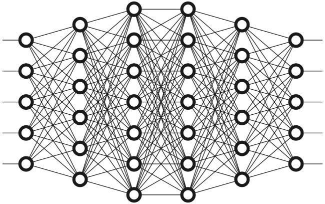

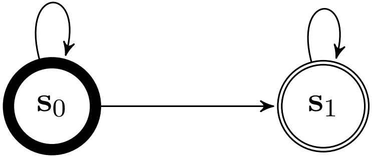

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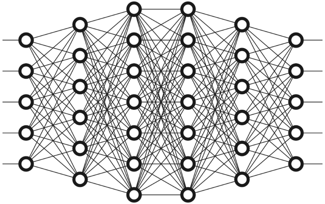

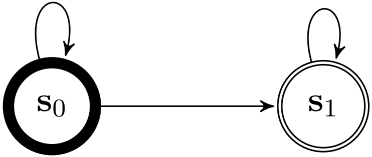

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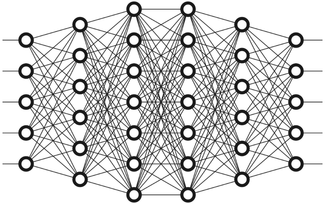
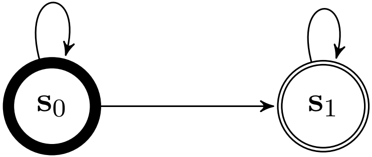
Weighted Finite-State Automata

- widely studied
- understandable
- interpretable
- **informed model development**





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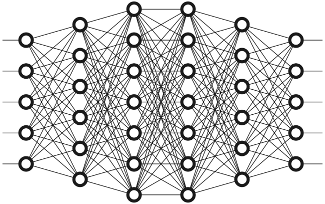

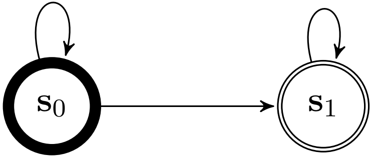

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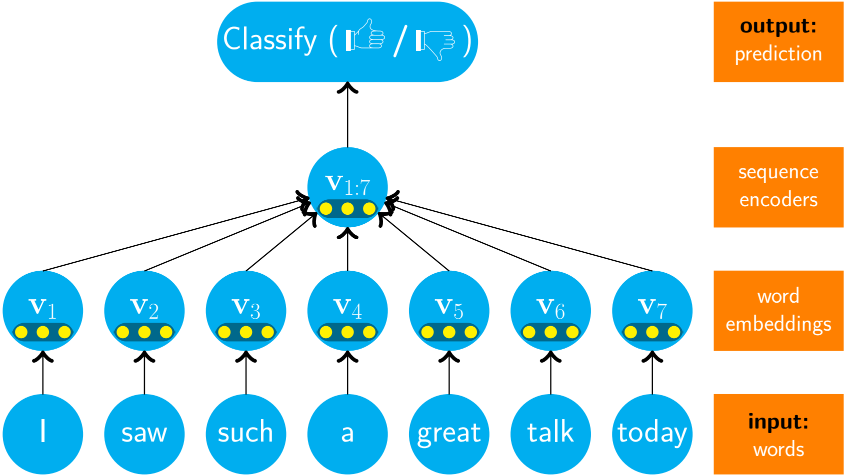
Deep Learning Models for NLP: Overview

Case Study: Sentiment Analysis



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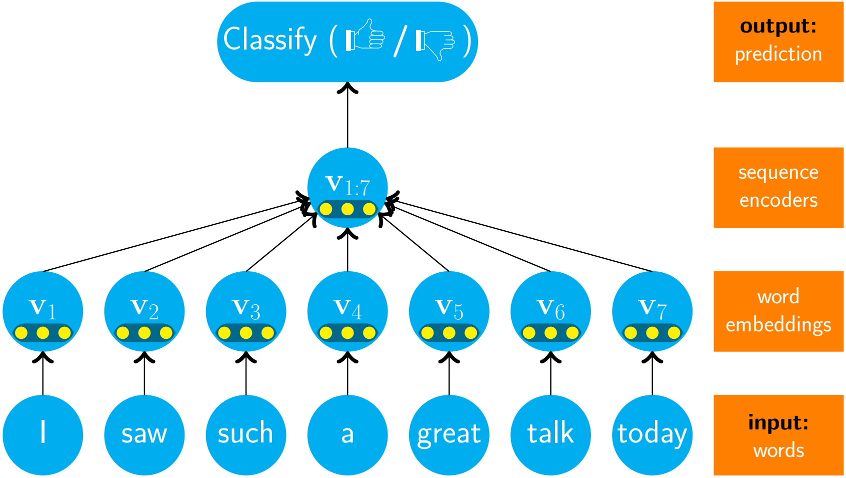

Main component in

- Machine translation
- Question answering
- Text summarization
- Sentiment analysis
- Information extraction
- ...

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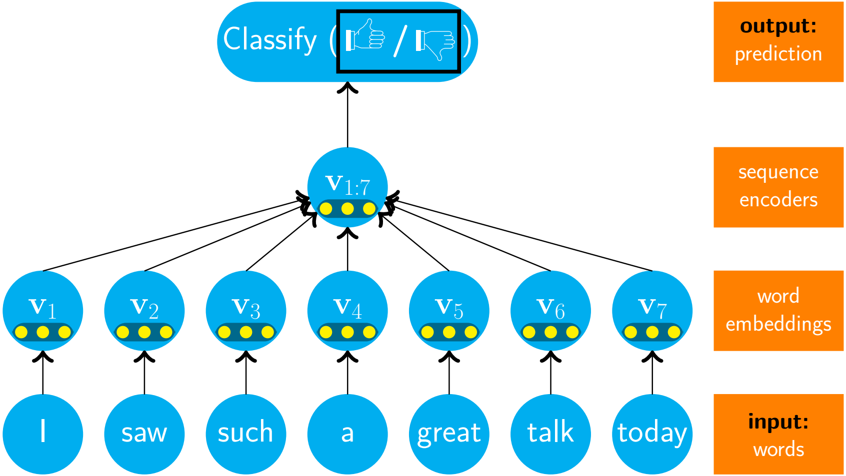

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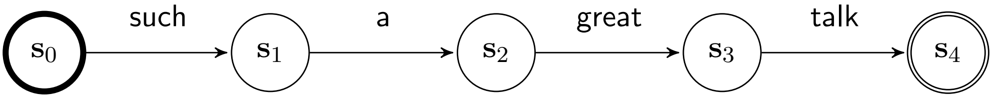
Background: Finite-State Automata

Regular Expressions (Patterns)



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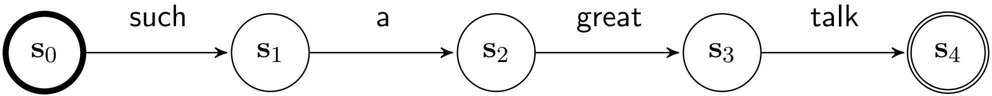
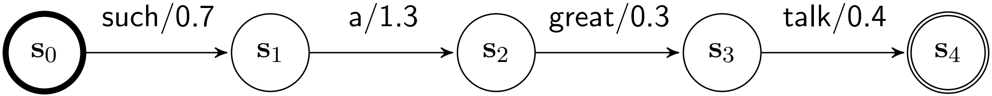


Pattern: *such a great talk*

Background: **Weighted** Finite-State Automata (WFSA)

Each Transition Defines a Weight Function



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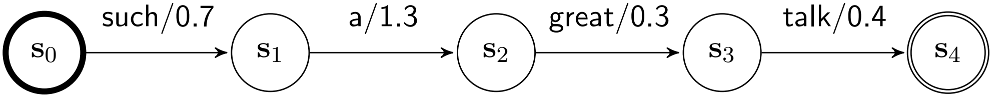

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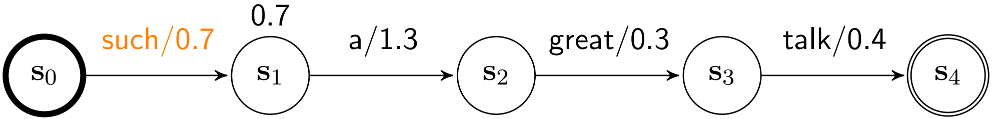

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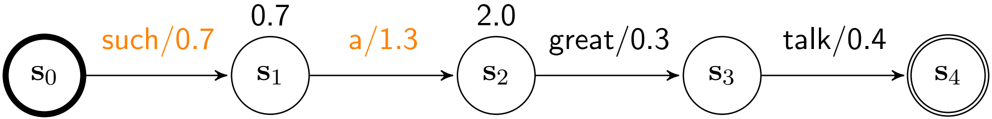

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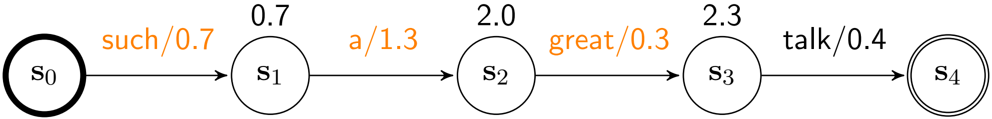

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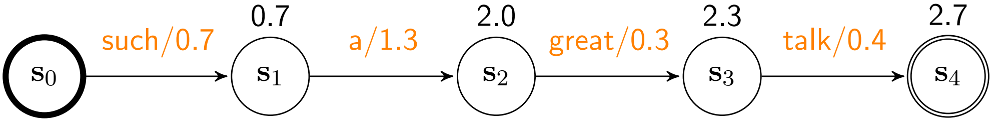

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Motivation: **Soft** Pattern Matching

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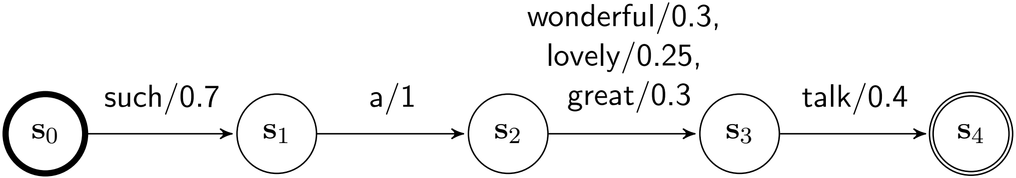

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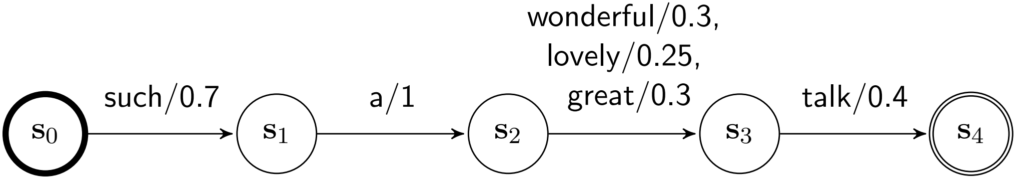

- Problem: **not scalable**
  - *what* a great talk, such *an awesome* talk

Solution: **Neural** Transitions

Schwartz et al., ACL 2018

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- Step 3: weights: $\mathbf{f}_\theta : \mathbb{R}^d \to \mathbb{R}$
  - These functions **favor** specific words
  - θ parameters are learned

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- Neural transitions **accept** all words,
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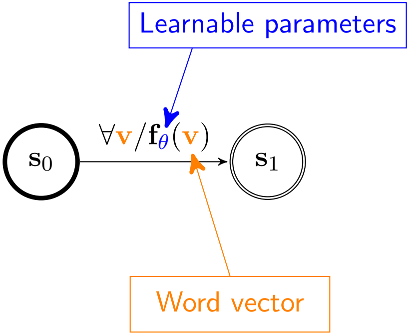

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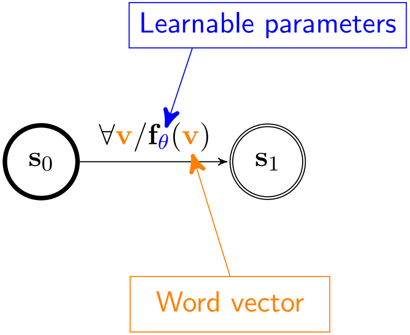

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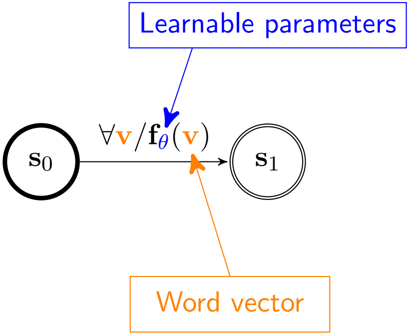
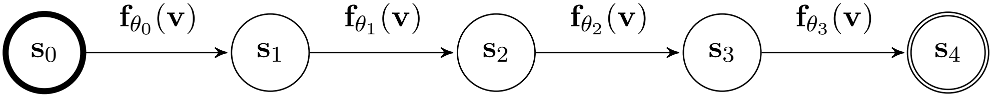
  - low score: car, love, well



Neural Weighted Finite-State Automata

Schwartz et al., ACL 2018

v – word vectors
$\theta = (\theta_0, \theta_1, \theta_2, \theta_3)$ – learned parameters



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[1] Pending length constraints

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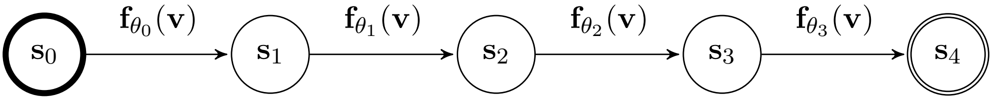

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- Example 2: *is not very exciting*
  - high score: is not **particularly** exciting, **are** not very **inspiring**

[1] Pending length constraints

Training Procedure

Formally

End-to-end training:

- Input
  - $\mathbf{s}_0 \xrightarrow{\mathbf{f}_{\theta_0}(\mathbf{v})} \mathbf{s}_1 \xrightarrow{\mathbf{f}_{\theta_1}(\mathbf{v})} \mathbf{s}_2 \xrightarrow{\mathbf{f}_{\theta_2}(\mathbf{v})} \mathbf{s}_3 \xrightarrow{\mathbf{f}_{\theta_3}(\mathbf{v})} \mathbf{s}_4$
  - Word embeddings: word $\rightarrow \mathbb{R}^d$
  - Training data: pairs of $<$document, sentiment label$>$
- Output
  - Parameter values: θ

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Test:

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- Standard training procedure
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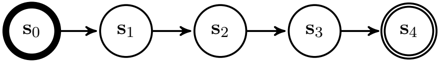
  - Stochastic gradient descent

Benefits of Neural WFSAs 1:

Informed Model Development



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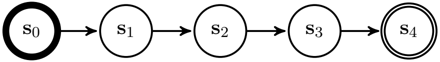

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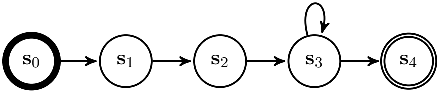

Self loops:
such a great, wonderful, funny talk

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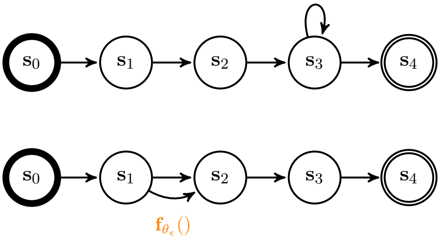

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Epsilon transitions:
such ___ *great shoes*

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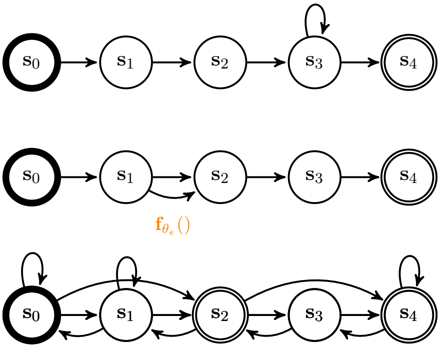

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- Coming up:
  - Many deep models are **mathematically equivalent** to neural WFSAs
    - A (new) joint framework
    - Allows extension of these models

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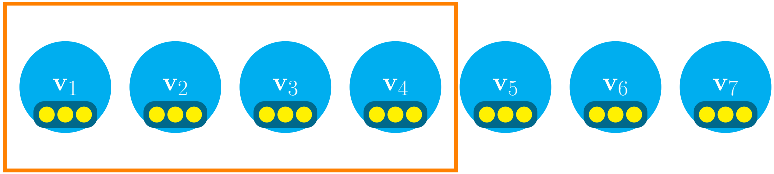
Case Study: Convolutional Neural Networks (ConvNets)

A Linear-Kernel Filter with Max-Pooling



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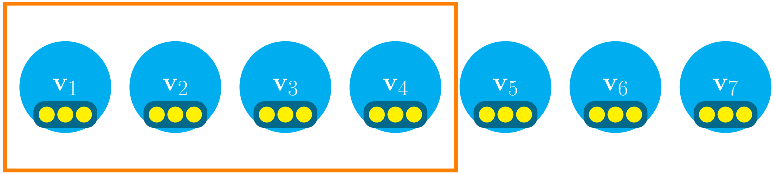


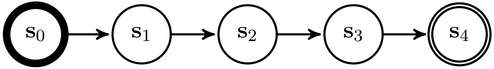
$$\boxed{S_\theta(\mathbf{v}_1 : \mathbf{v}_4) = \sum_{j=1:4} \theta_j \cdot \mathbf{v}_j}$$

Learnable parameters

Word vectors

Proposition 1: ConvNet Filters are Computing WFSA scores

Schwartz et al., ACL 2018



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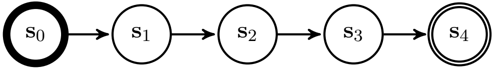

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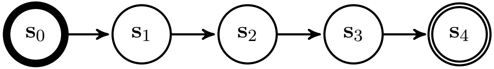
- $\mathbf{f}_{\theta_j}(\mathbf{v}) = \theta_j \cdot \mathbf{v}$
- $s_\theta(\mathbf{v}_1 : \mathbf{v}_4) = \sum_{j=1:4} \mathbf{f}_{\theta_j}(\mathbf{v}_j) = \sum_{j=1:4} (\theta_j \cdot \mathbf{v}_j)$



ConvNets are (**Implicitly**) Computing WFSA Scores!

$$\text{ConvNet} : S_\theta(\mathbf{v}_1 : \mathbf{v}_d) = \sum_{j=1:d} (\theta_j \cdot \mathbf{v}_j) \tag{1}$$

$$\text{Neural WFSA} : s_\theta(\mathbf{v}_1 : \mathbf{v}_d) = \sum_{j=1:d} (\theta_j \cdot \mathbf{v}_j) \tag{2}$$

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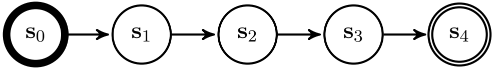
Benefits:

- ✓ **Interpret** ConvNets
- ✓ **Improve** ConvNets

A ConvNet Learns a Fixed-Length *Soft*-Pattern!

Schwartz et al., ACL 2018



- E.g., *"such a great talk"*
  - <u>*what*</u> a great <u>*song*</u>
  - such <u>*an*</u> <u>*awesome*</u> <u>*movie*</u>

Improving ConvNets: **SoPa** (Soft-Patterns)

Schwartz et al., ACL 2018

- Language pattern are often flexible-length
- *such a great talk*
  - such a great, *funny, interesting* talk
  - such __ great *shoes*

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Schwartz et al., ACL 2018

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Convolutional Neural Network:

$$S_\theta(\mathbf{v}_1 : \mathbf{v}_d) = \sum_{j=1:d} (\theta_j \cdot \mathbf{v}_j)$$

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Schwartz et al., ACL 2018

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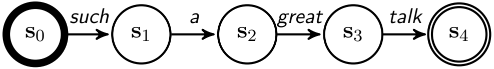
Weighted Finite-State Automaton:



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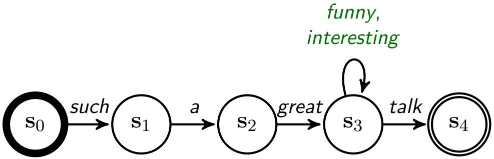

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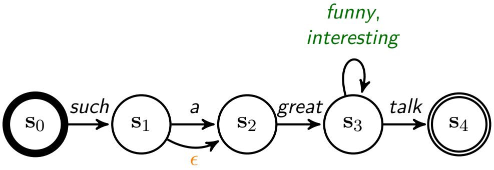

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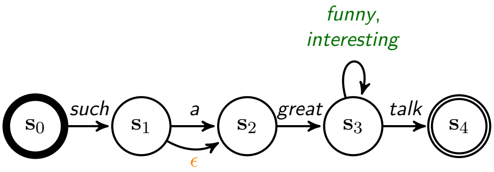
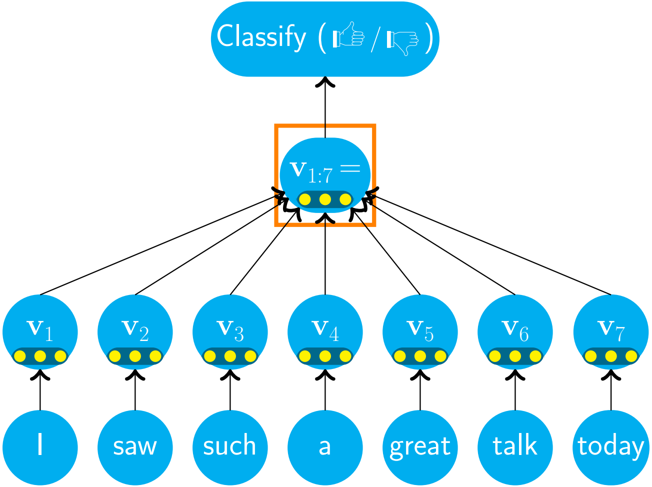


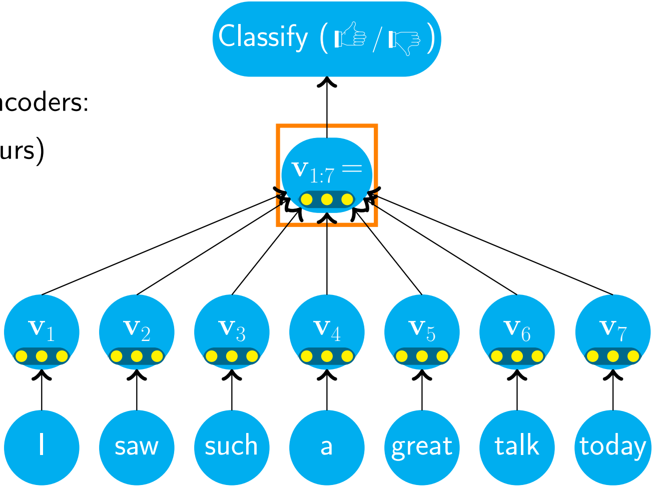
Sentiment Analysis Experiments



Sentiment Analysis Experiments

Sequence encoders:

- **SoPa** (ours)
- ConvNet



Sentiment Analysis Experiments

Sequence encoders:

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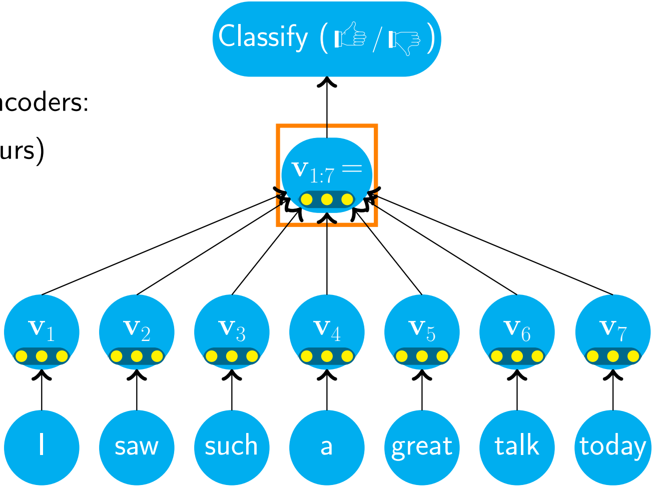
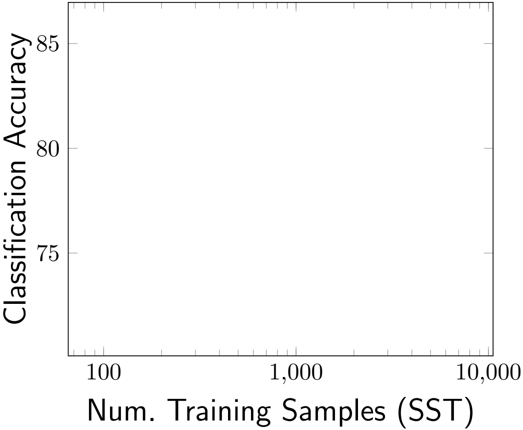
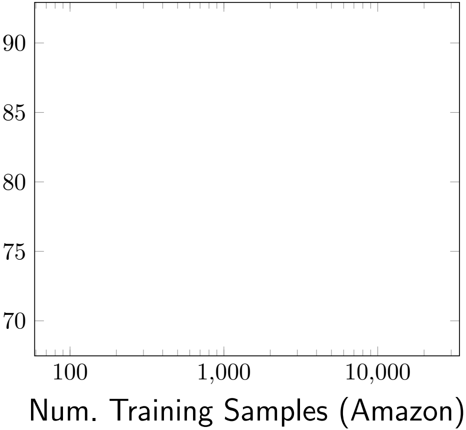
LSTM



Sentiment Analysis Results

Schwartz et al., ACL 2018





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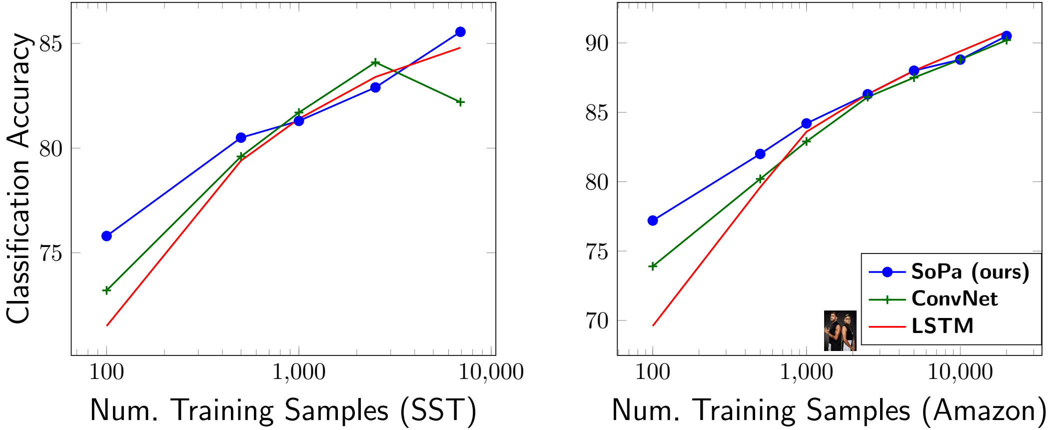
Schwartz et al., ACL 2018



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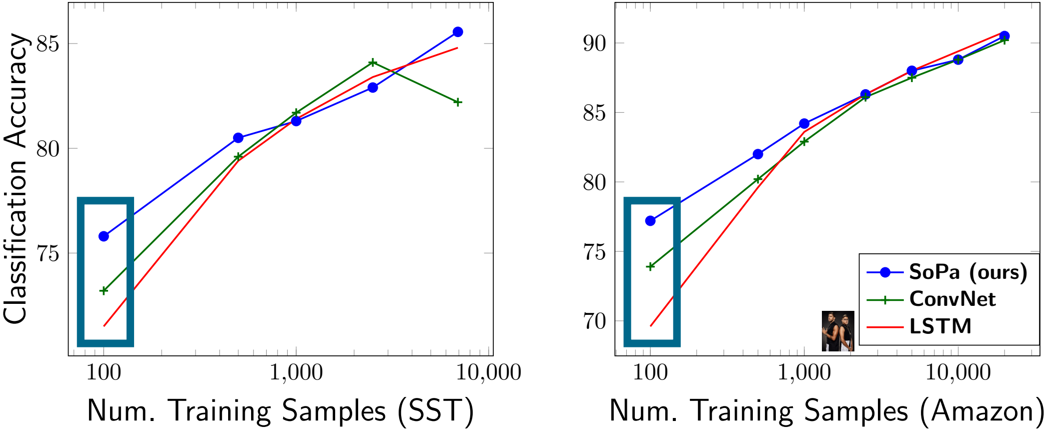
Schwartz et al., ACL 2018



Interpreting SoPa

Soft Patterns!

- For each learned pattern, extract the 4 top scoring phrases in the training set

Interpreting SoPa

Soft Patterns!

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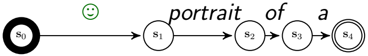
	Highest Scoring Phrases	
Patt. 1	mesmerizing	portrait of a
	engrossing	portrait of a
	clear-eyed	portrait of an
	fascinating	portrait of a



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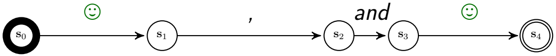
	Highest Scoring Phrases		
Patt. 2	honest	,	and enjoyable
	forceful	,	and beautifully
	energetic	,	and surprisingly



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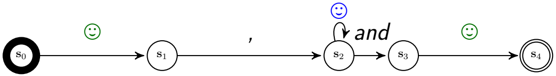
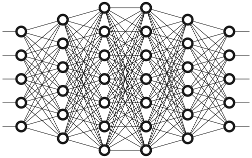
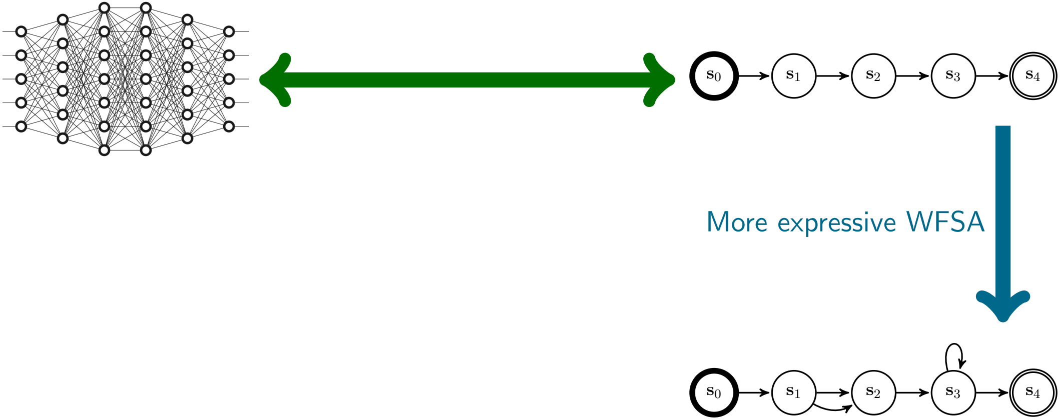
	Highest Scoring Phrases			
Patt. 1	mesmerizing	portrait	of	a
	engrossing	portrait	of	a
	clear-eyed	portrait	of	an
	fascinating	portrait	of	a

	Highest Scoring Phrases				
Patt. 2	honest	,		and	enjoyable
	forceful	,		and	beautifully
	energetic	,		and	surprisingly
	unpretentious	,	charming$_{SL}$	,	quirky

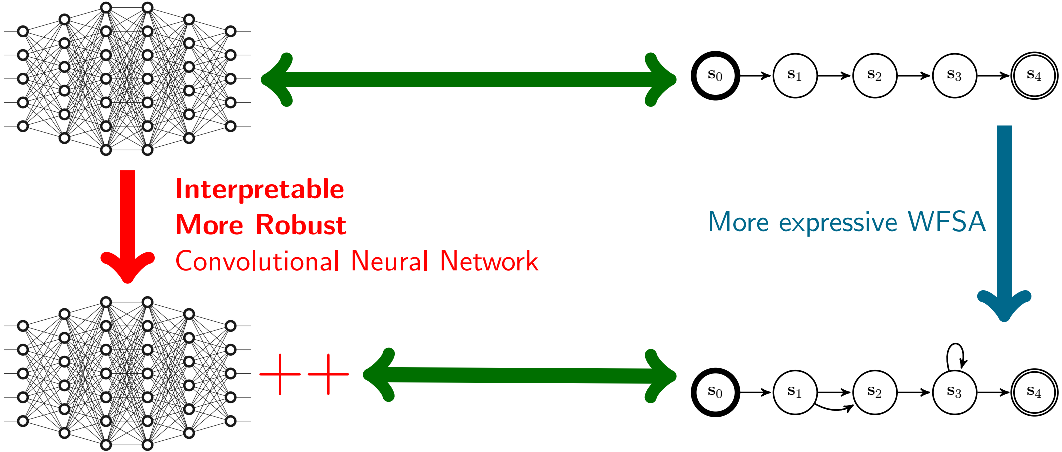





$\mathbf{s}_0$
$\mathbf{s}_1$
$\mathbf{s}_2$
$\mathbf{s}_3$
$\mathbf{s}_4$



$\mathbf{s}_0$ $\mathbf{s}_1$ $\mathbf{s}_2$ $\mathbf{s}_3$ $\mathbf{s}_4$
More expressive WFSA
$\mathbf{s}_0$ $\mathbf{s}_1$ $\mathbf{s}_2$ $\mathbf{s}_3$ $\mathbf{s}_4$


Interpretable
More Robust
Convolutional Neural Network
More expressive WFSA
++
s_0
s_1
s_2
s_3
s_4

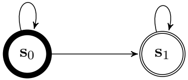
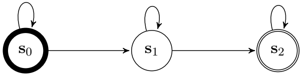
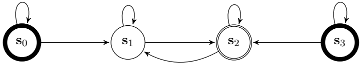
Many Existing Deep Models are Neural WFSAs!

Peng, **Schwartz** et al., EMNLP 2018

Mikolov et al. Balduzzi and Ghifary Bradbury et al. Lei et al.	arXiv 2014 ICML 2016 ICLR 2017 EMNLP 2018	
Lei et al.	NAACL 2016	
Foerster et al.	ICML 2017	

Many Existing Deep Models are Neural WFSAs!

Peng, **Schwartz** et al., EMNLP 2018

<table>
<tr><td>Mikolov et al.
Balduzzi and Ghifary
Bradbury et al.
Lei et al.</td><td>arXiv 2014
ICML 2016
ICLR 2017
EMNLP 2018</td><td></td></tr>
<tr><td>Lei et al.</td><td>NAACL 2016</td><td></td></tr>
<tr><td>Foerster et al.</td><td>ICML 2017</td><td></td></tr>
</table>

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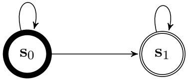
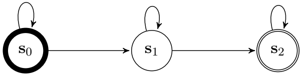
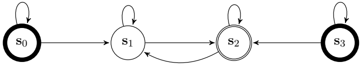
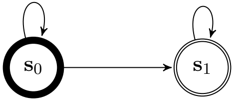
Mikolov et al. Balduzzi and Ghifary Bradbury et al. Lei et al.	arXiv 2014 ICML 2016 ICLR 2017 EMNLP 2018	
Lei et al.	NAACL 2016	
Foerster et al.	ICML 2017	

- Six recent recurrent neural networks (RNN) models are also **implicitly** computing WFSA scores

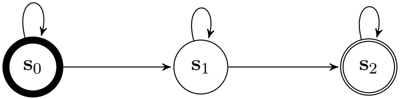
Developing more Robust WFSA Models

$\mathcal{S}_2$:



Mikolov et al. (2014)
Balduzzi and Ghifary (2016)
Bradbury et al. (2017)
Lei et al. (2018)

$\mathcal{S}_3$:



Lei et al. (2016)

Developing more Robust WFSA Models

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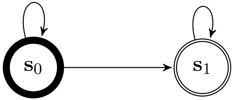

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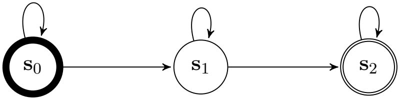
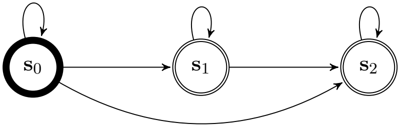


Lei et al. (2016)

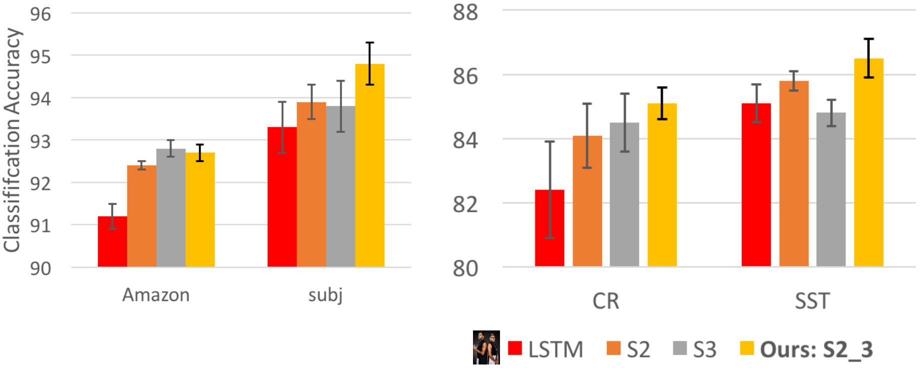
$\mathcal{S}_{2\_3}$:



Peng, **Schwartz** et al. (2018)

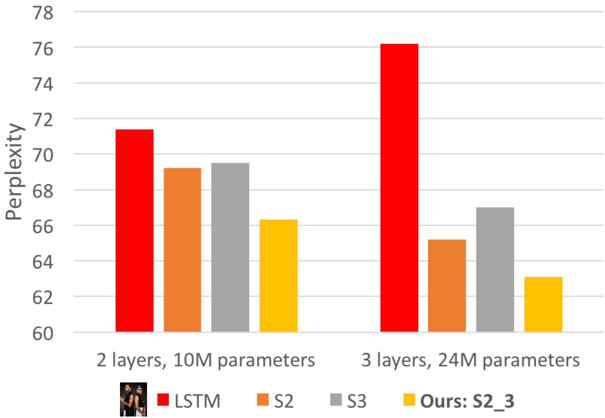
Sentiment Analysis Results

Peng, **Schwartz** et al., EMNLP 2018

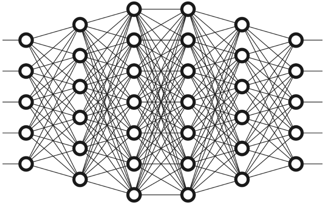
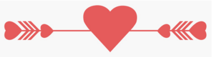
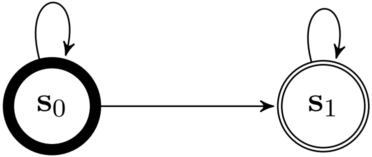


Language Modeling Results

Peng, **Schwartz** et al., EMNLP 2018



lower is better

Deep Learning

- backpropagation
- stochastic gradient descent
- PyTorch, TensorFlow, AllenNLP
- **state-of-the-art**
- ~~architecture engineering~~

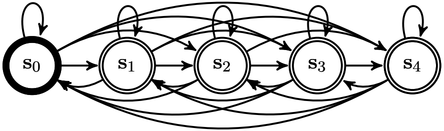
Weighted Finite-State Automata

- widely studied
- understandable
- interpretable
- **informed model development**
- ~~low performance~~

Work in Progress 1: Are All Deep Models for NLP Equivalent to WFSAs?

- Elman RNN: $\mathbf{h}_i = \sigma(\mathbf{W}\mathbf{h}_{i-1} + \mathbf{U}\mathbf{v}_i + \mathbf{b})$
- The interaction between $\mathbf{h}_i$ and $\mathbf{h}_{i-1}$ is via affine transformations followed by nonlinearities
  - Same for LSTM 
- Most probably **not** equivalent to a WFSA

Work in Progress 2: **Automatic** Model Development



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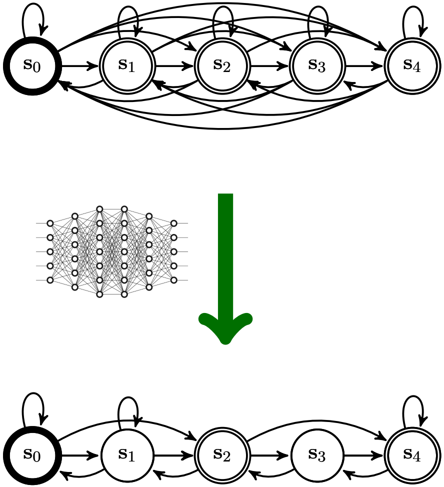
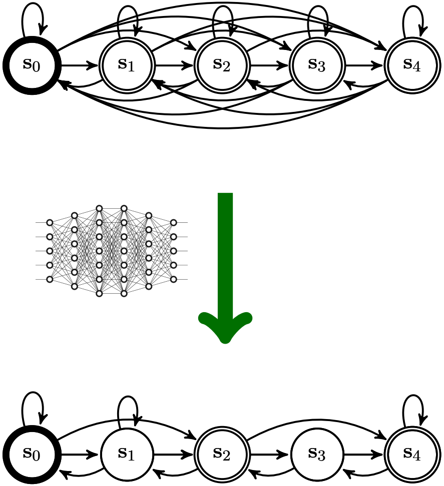


Work in Progress 2: **Automatic** Model Development

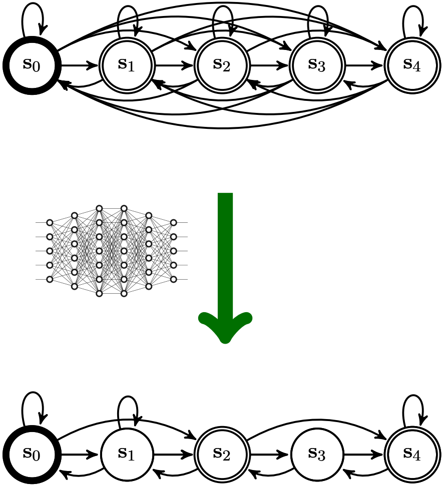
Deep learning: model engineering



Work in Progress 2: **Automatic** Model Development

Deep learning: model engineering

SoPa: *informed* model development

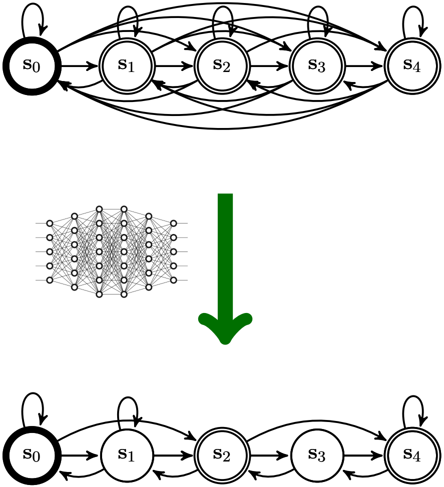


Work in Progress 2: **Automatic** Model Development

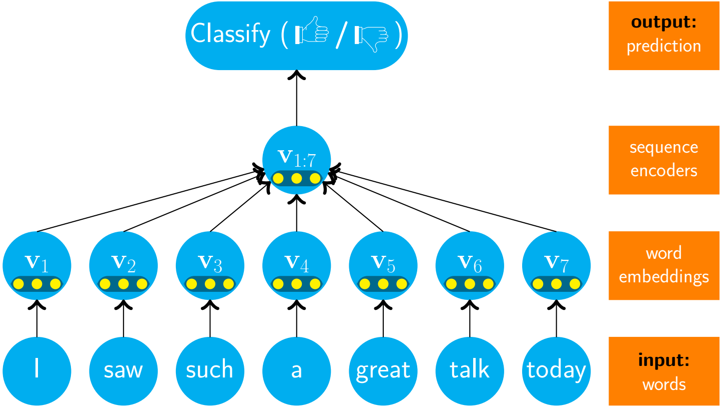
Deep learning: model engineering

SoPa: *informed* model development

New: **Automatic** model development



Other Projects



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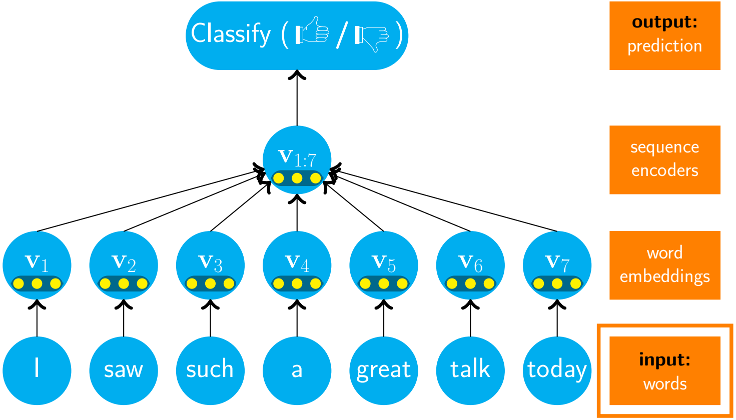
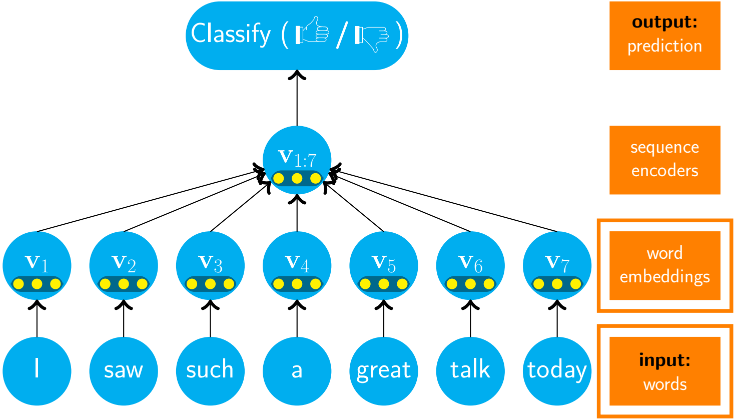


Schwartz et al., EMNLP 2013
Schwartz et al., COLING 2014

Other Projects



Schwartz et al., CoNLL 2015
Rubinstein et al., ACL 2015
Schwartz et al., NAACL 2016
Vulić et al., CoNLL 2017
Peters et al., 2018

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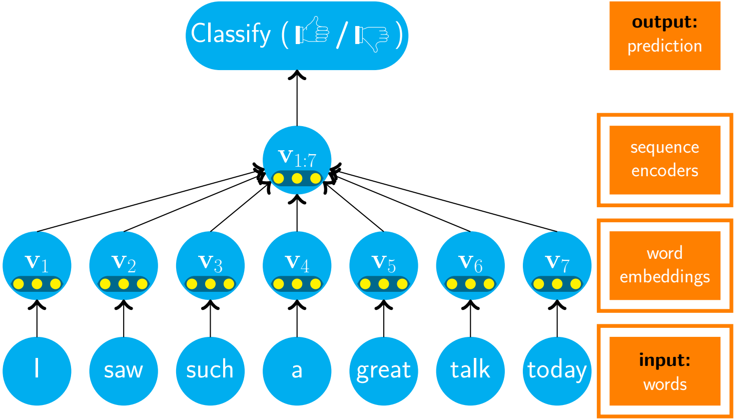

Schwartz et al., ACL 2018
Peng et al., EMNLP 2018
Liu et al., RepL4NLP 2018
best paper award

Schwartz et al., CoNLL 2015
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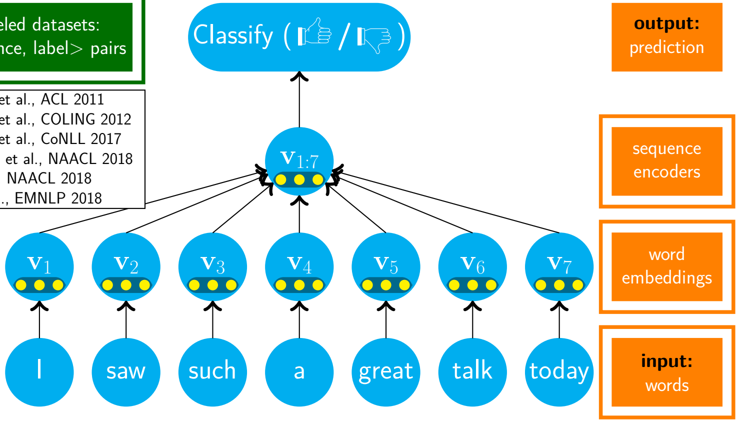
Vulić et al., CoNLL 2017
Peters et al., 2018

Schwartz et al., EMNLP 2013
Schwartz et al., COLING 2014

Other Projects

Labeled datasets:
<sentence, label> pairs

Schwartz et al., ACL 2011
Schwartz et al., COLING 2012
Schwartz et al., CoNLL 2017
Gururangan et al., NAACL 2018
Kang et al., NAACL 2018
Zellers et al., EMNLP 2018



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Schwartz et al., COLING 2014

Annotation Artifacts in NLP Datasets

Schwartz et al., CoNLL 2017; Gururangan, Swayamdipta, Levy, **Schwartz** et al., NAACL 2018

Premise	A person is running on the beach	
Hypothesis	The person is sleeping	

Textual Entailment (state-of-the-art ~90% accuracy)

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AllenNLP Demo!

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Textual Entailment (state-of-the-art ∼90% accuracy)

- The word "sleeping" is over-represented in the training data with **contradiction** label
  - **annotation artifact**
- State-of-the-art models focus on this word rather than *understanding* the text

Annotation Artifacts in NLP Datasets

Schwartz et al., CoNLL 2017; Gururangan, Swayamdipta, Levy, **Schwartz** et al., NAACL 2018

Premise	A person is running on the beach	
Hypothesis	The person is sleeping	? entailment ? **contradiction** ? neutral

Textual Entailment (state-of-the-art ∼90% accuracy)

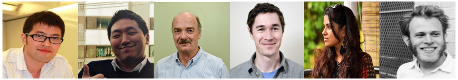
- The word "sleeping" is over-represented in the training data with **contradiction** label
  - **annotation artifact**
- State-of-the-art models focus on this word rather than *understanding* the text
- Models are **not as strong** as we think they are

Long Term Vision

Long Term Vision

- **Explainable** models
- **Unbiased** models

Special Thanks to...



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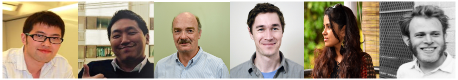

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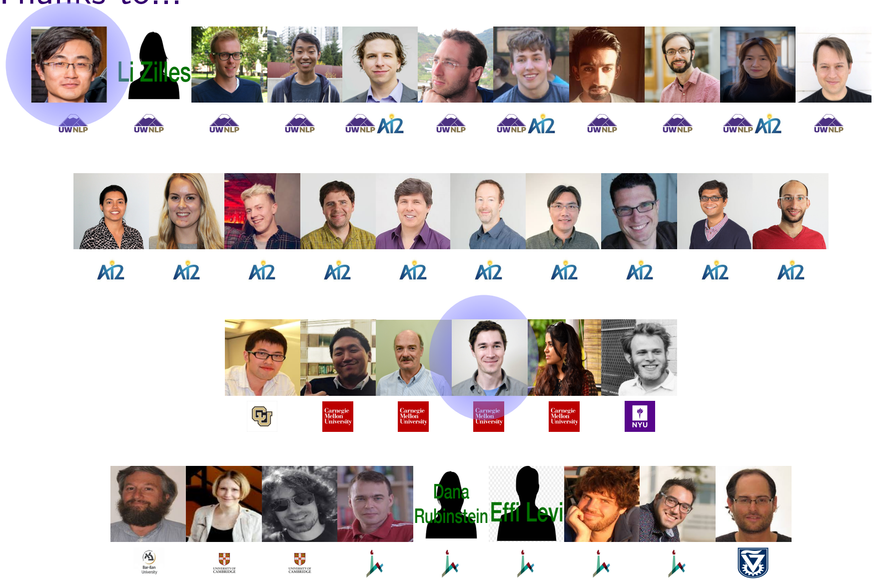
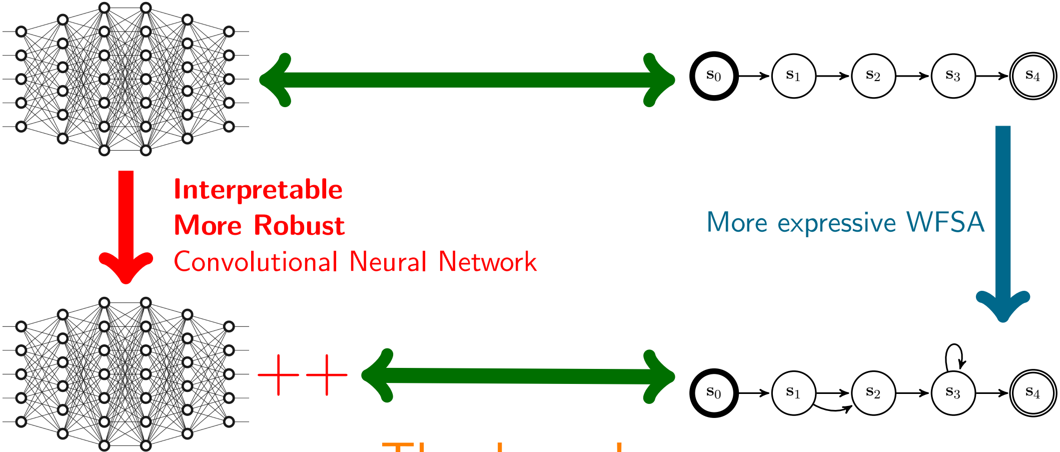
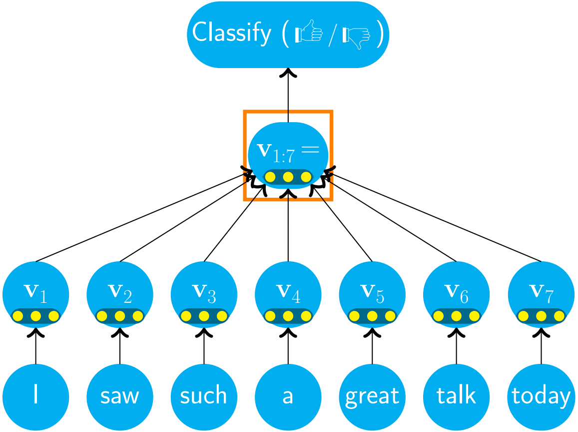




Thank you!

Roy Schwartz
homes.cs.washington.edu/~roysch/ roysch@cs.washington.edu

Neural WFSAs as Sequence Encoders



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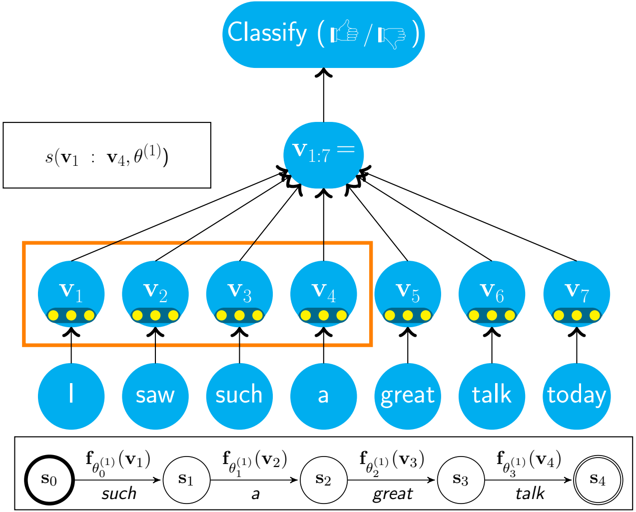
Neural WFSAs as Sequence Encoders



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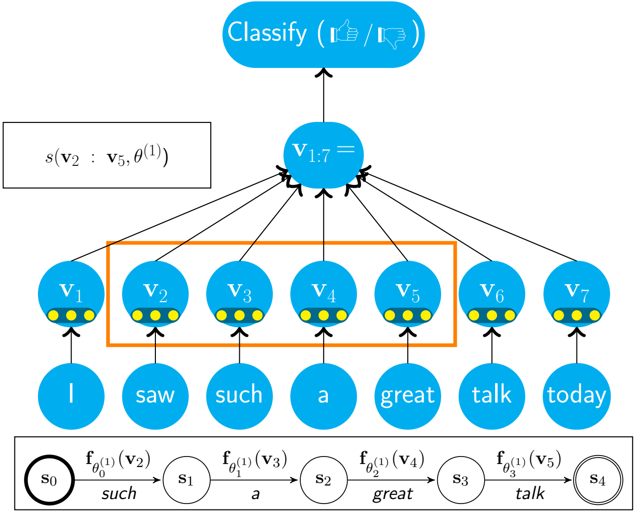
Neural WFSAs as Sequence Encoders



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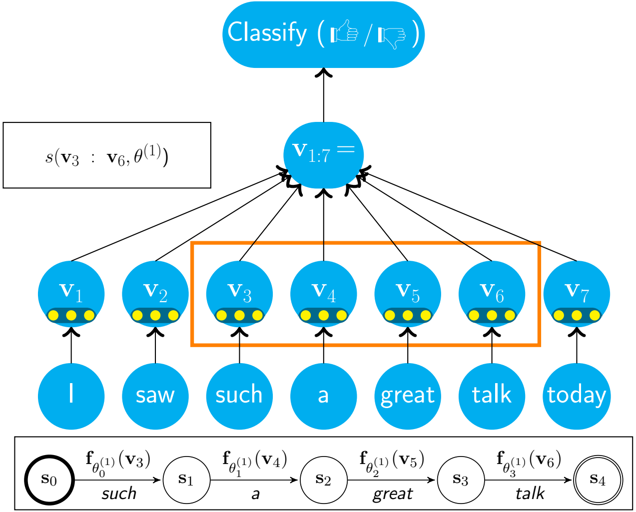

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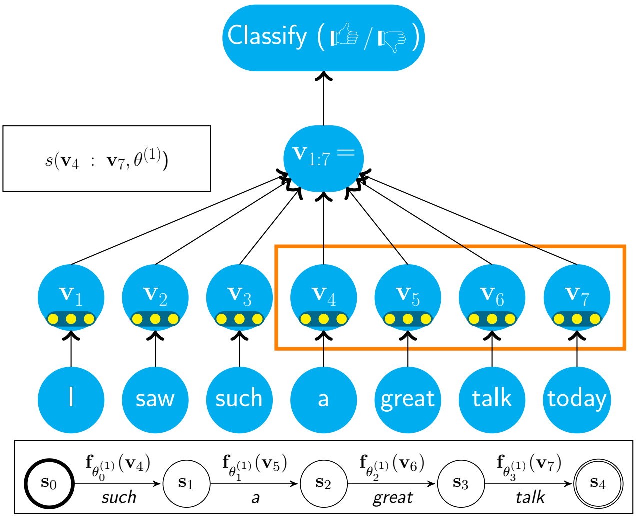

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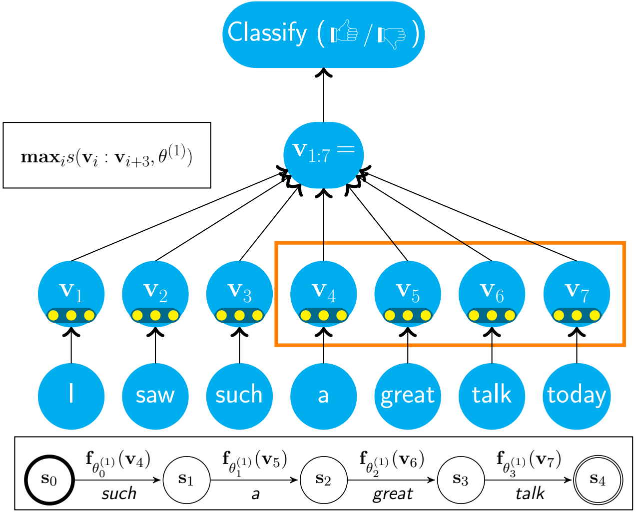

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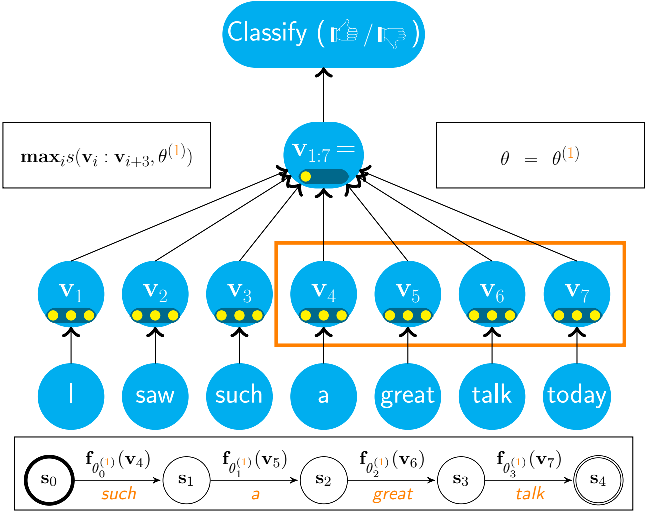

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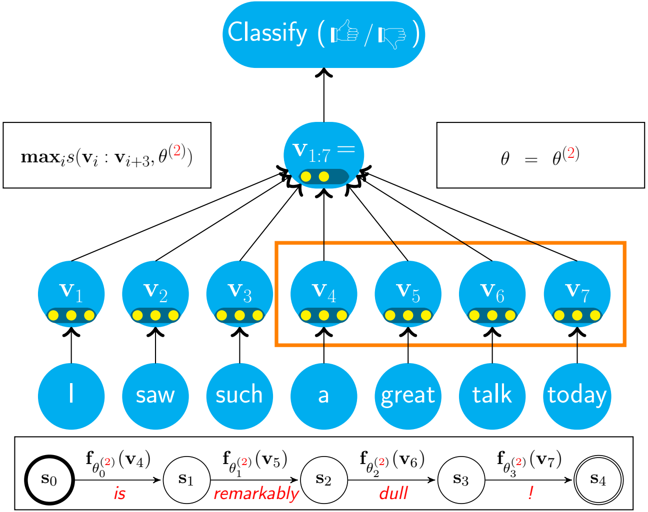

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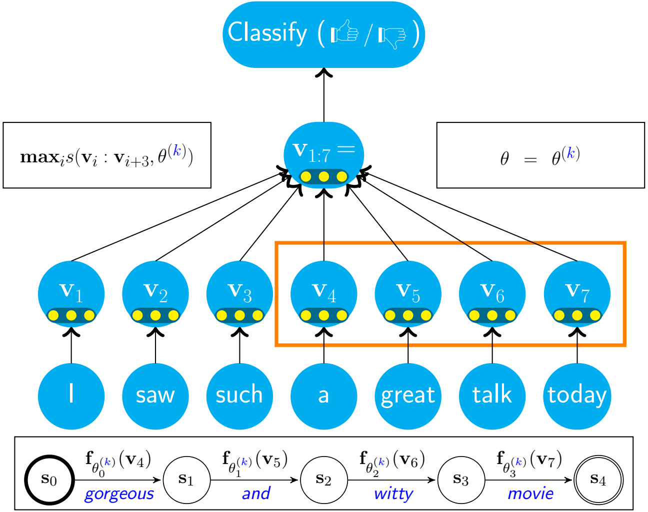
Neural WFSAs as Sequence Encoders



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SoPa Complexity

- Running the Viterbi (1967) algorithm on a sequence of n tokens and a WFSA of d states typically takes $O(d^3 + d^2(n))$
- We only allow zero or one ϵ-transition at a time $\Rightarrow O(d^2(n))$
- We only allow self-loop and main path transitions $\Rightarrow O(dn)$
- Scores on all patterns can be computed in parallel
  - GPU optimization further reduces the observed runtime to be **sublinear** in d

back to main

Interpreting SoPa

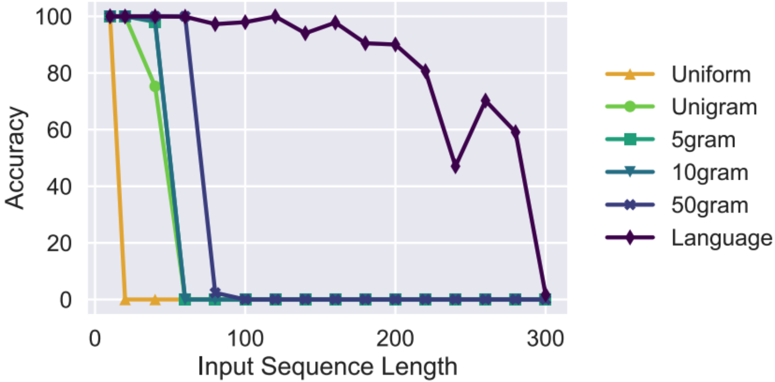
Visualizing Sentiment Predictions

- Leave-one-out method on all patterns
- Visualize the spans with the largest (**positive**) and (*negative*) contribution

Analyzed Documents
it's dumb, **but more importantly**, *it's just not scary*
While **its careful pace and** seemingly *opaque story* may not satisfy every movie-goer's appetite, the film's final scene is **soaringly, transparently moving**

LSTMs Exploit Linguistic Attributes of Data

Liu, Levy, **Schwartz** et al., RepL4NLP 2018, best paper award



- Non-linguistic task

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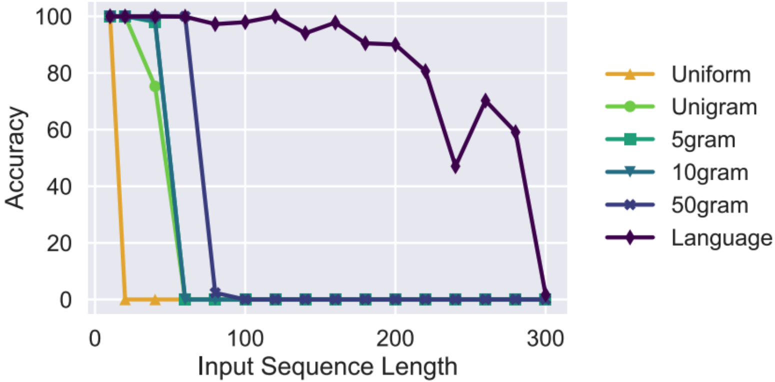
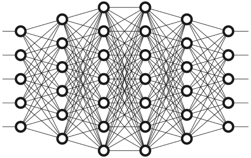
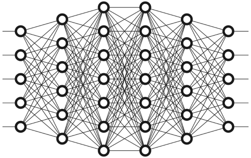


- Non-linguistic task
- Although they weren't designed that way, LSTMs do much better when trained on **language data**

Case Study 2: Recurrent Neural Networks (RNN)



Interpretable
More robust
RNNs



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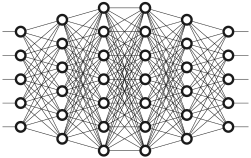

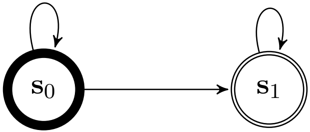

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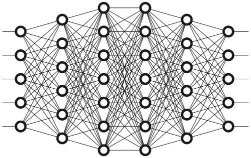

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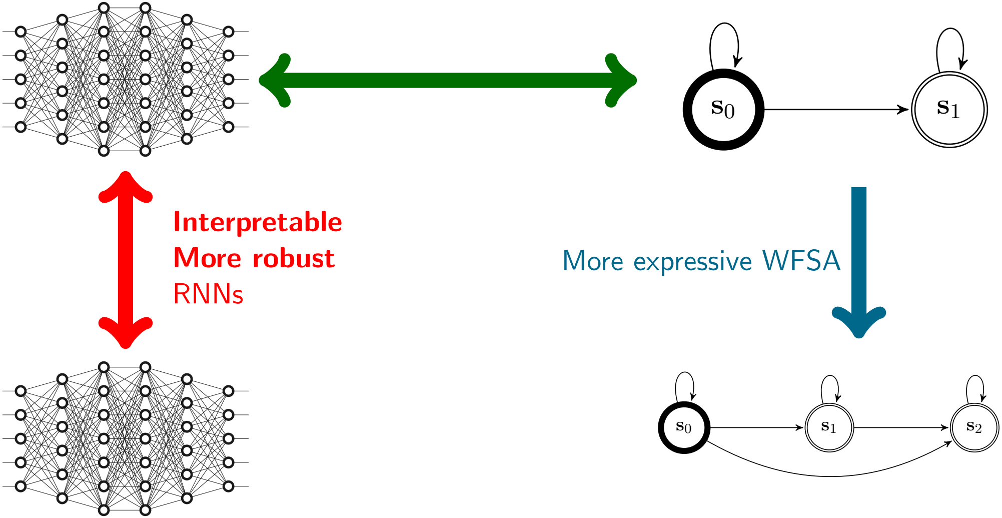

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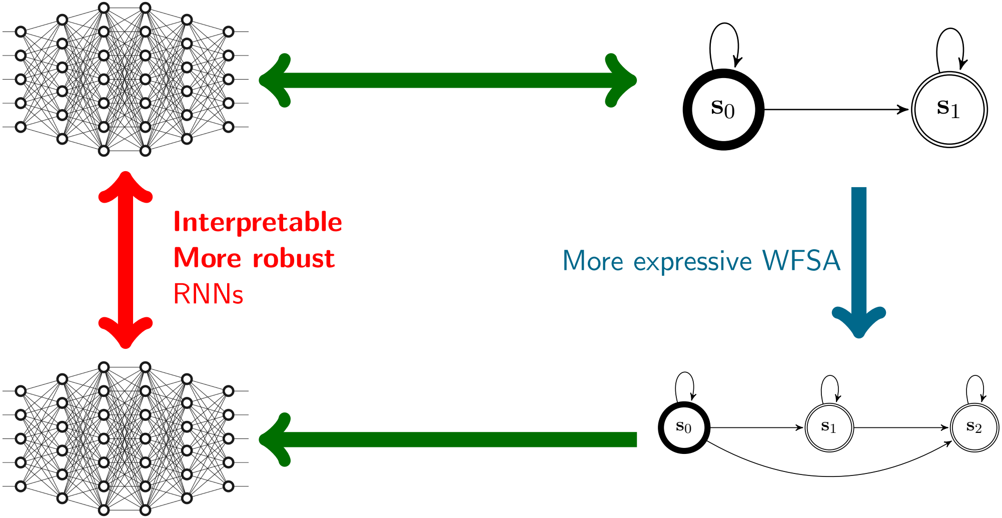
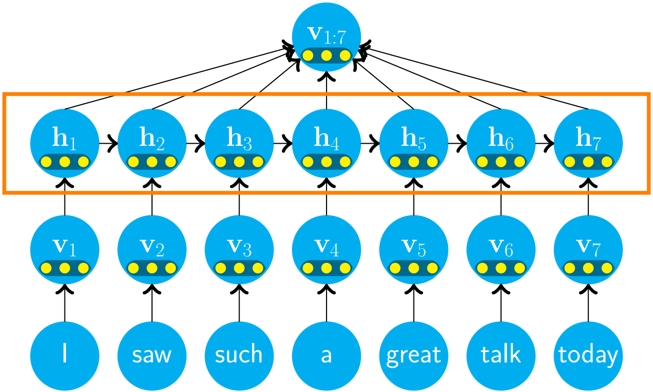
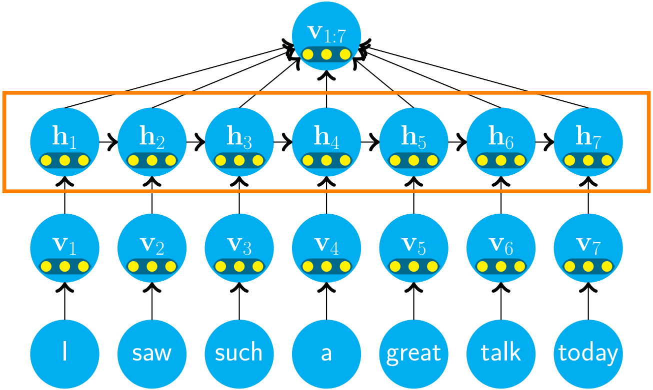


Recurrent Neural Networks: Hidden States



Recurrent Neural Networks: Hidden States



Recurrent function: $\boxed{\mathbf{h_i = f(h_{i-1}, v_i)}}$

Multiple Variants of Recurrent Neural Networks

- Elman (1990)
-  LSTM (Hochreiter and Schmidhuber, 1997)
- GRU (Cho et al., 2014)
- SGU (Gao and Glowacka, 2016)
- RAN (Lee et al., 2017)
- SCRN (Mikolov et al., 2014)
- T-RNN (Balduzzi and Ghifary, 2016)
- RCNN (Lei et al., 2016)
- Q-RNN (Bradbury et al., 2017)
- ISAN (Foerster et al., 2017)
- SoPa (Schwartz et al., 2018)
- SRU (Lei et al., 2018)

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- *What do different RNN variants have in common?*
- *What are they learning?*
- *Can we improve them?*

Example: Strongly-Typed Recurrent Neural Networks

Balduzzi and Ghifary (2016)

- A simple, competitive RNN
  - Draws inspiration from physics and functional programming
- $\mathbf{h}_i = \mathbf{z}_i \cdot \mathbf{h}_{i-1} + \mathbf{u}_i$
  - $\mathbf{z}_i, \mathbf{u}_i$ are non-linear parameterized functions of $\mathbf{v}_i$

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$$\mathbf{h}_n = \mathbf{z}_n \cdot \mathbf{h}_{n-1} + \mathbf{u}_n$$

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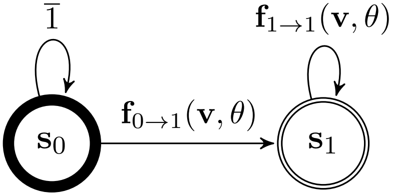
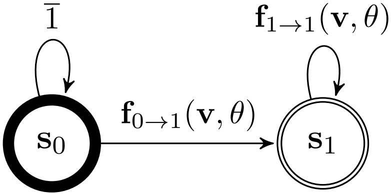
&= \mathbf{z}_n \cdot (\mathbf{z}_{n-1} \cdot (\mathbf{z}_{n-2} \cdot \mathbf{h}_{n-3} + \mathbf{u}_{n-2}) + \mathbf{u}_{n-1}) + \mathbf{u}_n \\
&= \dots \\
&= \sum_{i=1}^{n-1} \left(\mathbf{u}_i \prod_{j=i+1}^{n} \mathbf{z}_j \right) + \mathbf{u}_n
\end{aligned}
$$

Weighted Finite-State Automata!

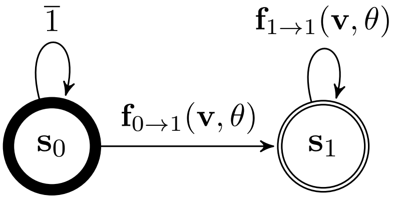


Weighted Finite-State Automata!



- Soft Pattern: W
  - Ignore the self-loops for simplicity

Weighted Finite-State Automata!



- Soft Pattern: W
  - Ignore the self-loops for simplicity
- $\mathcal{S}_2\ (\mathbf{v}_1 : \mathbf{v}_n) = \sum_{i=1}^{n-1} \left(\mathbf{f}_{0\to 1}(\mathbf{v}_i,\theta) \prod_{j=i+1}^{n} \mathbf{f}_{1\to 1}(\mathbf{v}_j,\theta) \right) + \mathbf{f}_{0\to 1}(\mathbf{v}_n,\theta)$

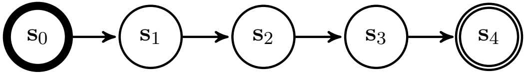
Strongly-Typed RNNs are Rational!

Can Be Computed Using a Set of WFSAs

$$\mathbf{h}_n = \sum_{i=1}^{n-1} \left(\mathbf{u}_i \prod_{j=i+1}^{n} \mathbf{z}_j \right) + \mathbf{u}_n$$

$$\mathcal{S}_2(\mathbf{v}_1 : \mathbf{v}_n) = \sum_{i=1}^{n-1} \left(\mathbf{f}_{0 \to 1}(\mathbf{v}_i, \theta) \prod_{j=i+1}^{n} \mathbf{f}_{1 \to 1}(\mathbf{v}_j, \theta) \right) + \mathbf{f}_{0 \to 1}(\mathbf{v}_n, \theta)$$

Work in Progress 3: Make your own Deep Model!



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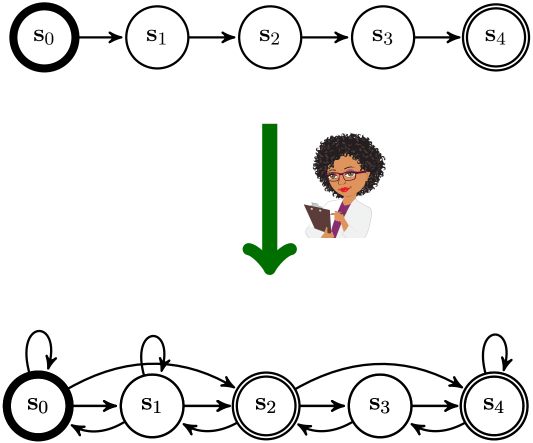

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