Interpretable Structure Induction **Via Sparse Attention**

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→ Vlad Niculae

André Martins IT & Unbabel

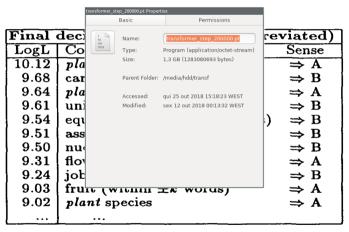




Sparse linear models are more interpretable...

Final decision list for plant (abbreviated)		
LogL	Collocation	Sense
10.12		\Rightarrow A
9.68	car (within $\pm k$ words)	⇒ B
9.64	plant height	\Rightarrow A
9.61	union (within $\pm k$ words)	\Rightarrow B
9.54	equipment (within $\pm k$ words)	⇒ B
9.51	assembly plant	⇒B
9.50	nuclear plant	⇒ B
9.31	flower (within $\pm k$ words)	\Rightarrow A
9.24	job (within $\pm k$ words)	⇒ B
9.03	fruit (within $\pm k$ words)	⇒A
9.02	plant species	⇒ A
	<u> </u>	

Sparse linear models are more interpretable... but we use bigger models today!



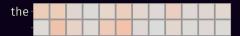
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codition out l'ade de lait le lie lection



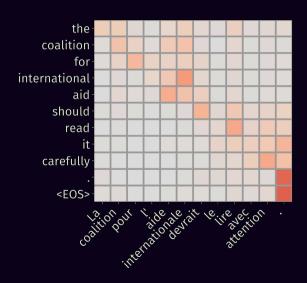
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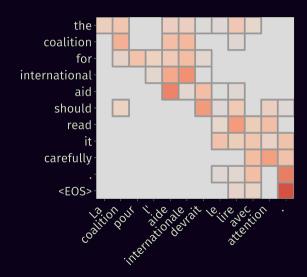
international site of the steerior

the coalition

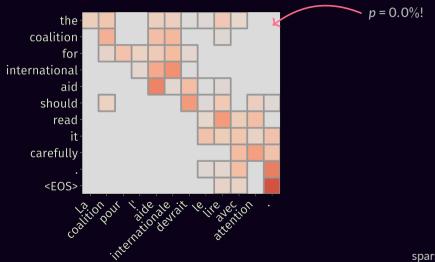
Cogition out side design less exterior



Sparse Neural Attention

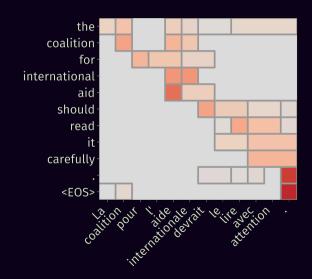


Sparse Neural Attention



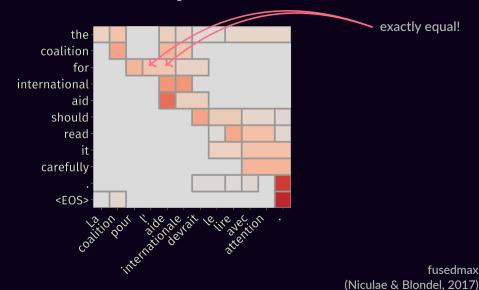
sparsemax (Martins & Astudillo, 2016)

Structured & Sparse Attention

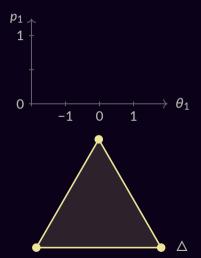


fusedmax (Niculae & Blondel, 2017)

Structured & Sparse Attention

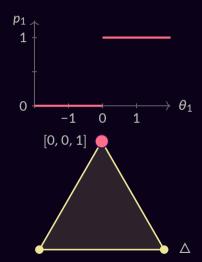


$$\Pi_{\Omega}(\boldsymbol{\theta}) = \underset{\boldsymbol{p} \in \Delta}{\operatorname{arg max}} \boldsymbol{p}^{\mathsf{T}} \boldsymbol{\theta} - \Omega(\boldsymbol{p})$$



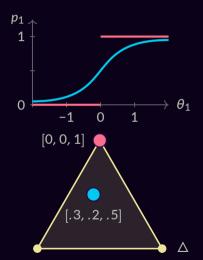
$$\Pi_{\Omega}(\boldsymbol{\theta}) = \arg \max_{\boldsymbol{p} \in \Delta} \boldsymbol{p}^{\top} \boldsymbol{\theta} - \Omega(\boldsymbol{p})$$

• argmax: $\Omega(\mathbf{p}) = 0$



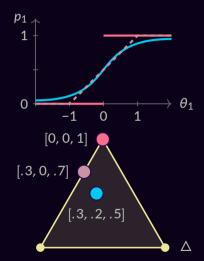
$$\Pi_{\Omega}(\boldsymbol{\theta}) = \underset{\boldsymbol{p} \in \Delta}{\operatorname{arg max}} \boldsymbol{p}^{\top} \boldsymbol{\theta} - \Omega(\boldsymbol{p})$$

- argmax: $\Omega(\mathbf{p}) = 0$
- softmax: $\Omega(\mathbf{p}) = \sum_{j} p_{j} \log p_{j}$



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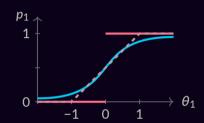
- argmax: $\Omega(\mathbf{p}) = 0$
- softmax: $\Omega(\mathbf{p}) = \sum_{i} p_{i} \log p_{i}$
- sparsemax: $\Omega(\mathbf{p}) = 1/2 ||\mathbf{p}||_2^2$



$$\Pi_{\Omega}(\boldsymbol{\theta}) = \arg \max_{\boldsymbol{p} \in \Delta} \boldsymbol{p}^{\top} \boldsymbol{\theta} - \Omega(\boldsymbol{p})$$

- argmax: $\Omega(\mathbf{p}) = 0$
- softmax: $\Omega(\mathbf{p}) = \sum_{i} p_{i} \log p_{i}$
- sparsemax: $\Omega(\mathbf{p}) =$

Unlike lasso, $\partial \Pi$ sparse attention needs





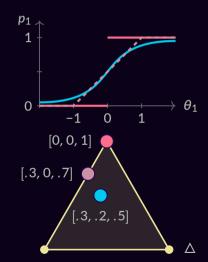
[0, 0, 1]

$$\Pi_{\Omega}(\boldsymbol{\theta}) = \underset{\boldsymbol{p} \in \Delta}{\operatorname{arg max}} \boldsymbol{p}^{\top} \boldsymbol{\theta} - \Omega(\boldsymbol{p})$$

- argmax: $\Omega(\mathbf{p}) = 0$
- softmax: $\Omega(\mathbf{p}) = \sum_{i} p_{i} \log p_{i}$
- sparsemax: $\Omega(p) = 1/2 ||p||_2^2$

fusedmax:
$$\Omega(\mathbf{p}) = 1/2 ||\mathbf{p}||_2^2 + \sum_j |p_j - p_{j-1}|$$

oscarmax: $\Omega(\mathbf{p}) = 1/2 ||\mathbf{p}||_2^2 + \sum_{i,j} \max(p_i, p_j)$

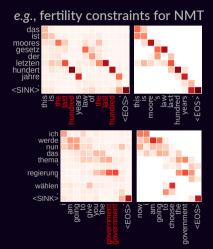


Constrained Attention

$$\underset{\boldsymbol{p} \in \Delta}{\operatorname{arg max}} \boldsymbol{p}^{\mathsf{T}} \boldsymbol{\theta} - \Omega_{1}(\boldsymbol{p})$$

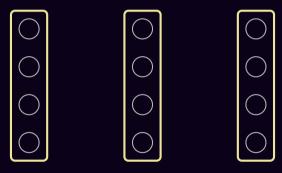
$$\underset{\boldsymbol{a} \leq \boldsymbol{p} \leq \boldsymbol{b}}{a \leq \boldsymbol{p} \leq \boldsymbol{b}}$$

$$= \underset{\boldsymbol{p} \in \Delta}{\operatorname{arg max}} \boldsymbol{p}^{\mathsf{T}} \boldsymbol{\theta} - \underbrace{\Omega(\boldsymbol{p})}_{:=\Omega_{1} + \operatorname{Id}_{[a,b]}}$$

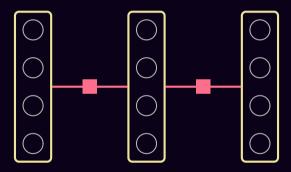


(Kreutzer & Martins, 18) (Malaviya et al, 18)

Structured Attention & Graphical Models



Structured Attention & Graphical Models



- **argmax** $\operatorname{arg\,max} \boldsymbol{p}^{\mathsf{T}} \boldsymbol{\theta}$
- softmax $\arg \max \boldsymbol{p}^{\top} \boldsymbol{\theta} + H(\boldsymbol{p})$
- sparsemax $\arg \max_{\boldsymbol{p} \in \Delta} \boldsymbol{p}^{\mathsf{T}} \boldsymbol{\theta} 1/2 ||\boldsymbol{p}||^2$

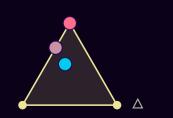


- **argmax** $\operatorname{arg\,max} \boldsymbol{p}^{\mathsf{T}} \boldsymbol{\theta}$
- softmax $\arg \max \mathbf{p}^{\mathsf{T}} \boldsymbol{\theta} + \mathsf{H}(\mathbf{p})$ $\mathbf{p} \in \Delta$
- sparsemax $\arg \max p^{\top} \theta \frac{1}{2} ||p||^2$

MAP
$$\arg \max \mu^{\mathsf{T}} \eta$$
 $\mu \in \mathcal{M}$

marginals $\arg \max_{\boldsymbol{\mu} \in \mathcal{M}} \mathbf{\Pi} + \widetilde{\mathbf{H}}(\boldsymbol{\mu})$

SparseMAP $\arg \max_{\mu \in \mathcal{M}} \frac{1}{2} - \frac{1}{2} \|\mu\|^2 \bullet$



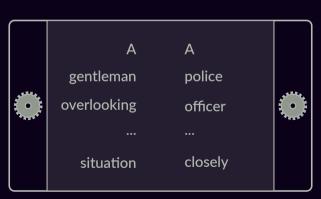


NLI premise: A gentleman overlooking a neighborhood situation.

hypothesis: A police officer watches a situation closely.

input

(P, H)



output



entails

contradicts

neutral

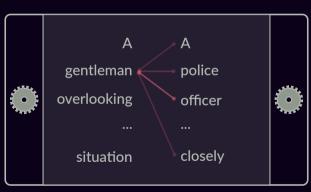
(Model: ESIM)

NLI premise: A gentleman overlooking a neighborhood situation.

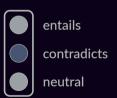
hypothesis: A police officer watches a situation closely.

input

(P, H)



output



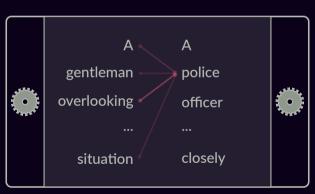
(Model: ESIM)

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output



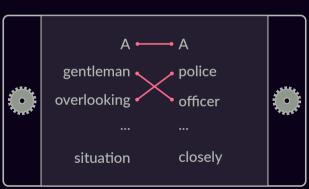
(Model: ESIM)

NLI premise: A gentleman overlooking a neighborhood situation.

hypothesis: A police officer watches a situation closely.

input

(P, H)



(Proposed model: global matching)

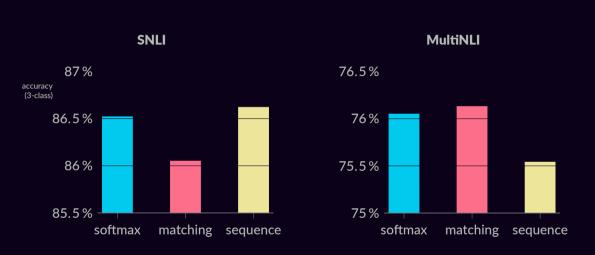
output

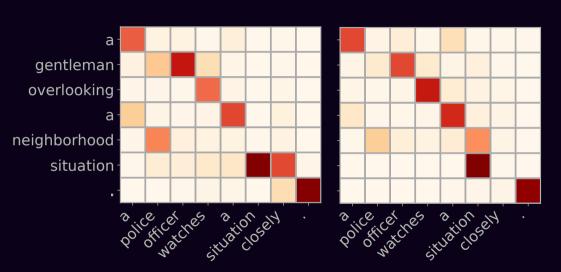


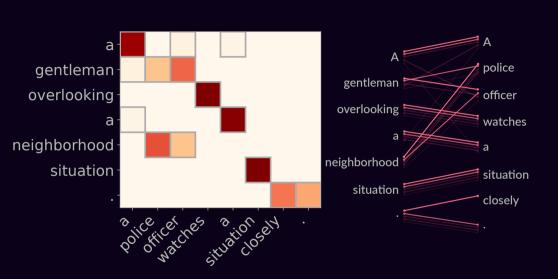
entails

contradicts

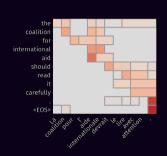
neutral



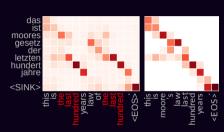




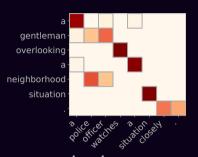
Summary: Neural attention with...



structured sparsity (e.g. fusedmax)



constraints (e.g. csparsemax — fertility)



structure (e.g. SparseMAP alignments)

and dynamic computation graphs with structured latent variables! (Friday 15:36 in 3B)

Acknowledgements



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Some icons by Dave Gandy and Freepik via flaticon.com.



Extra slides

