Interpretable Structure Induction **Via Sparse Attention**

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→ Vlad Niculae

André Martins IT & Unbabel

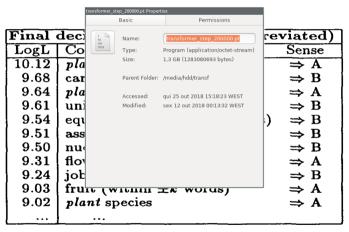




Sparse linear models are more interpretable...

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!



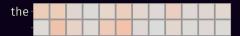
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codition out l'ade de lait le lie lection



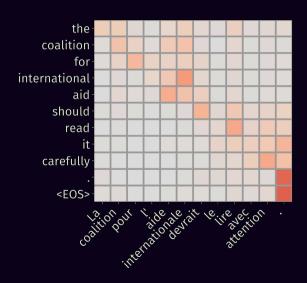
Codition out l'ide de loit le lie stertion



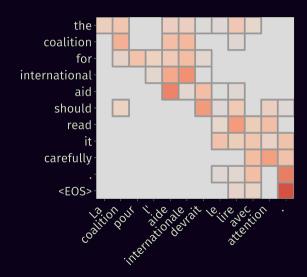
international site of the steerior

the coalition

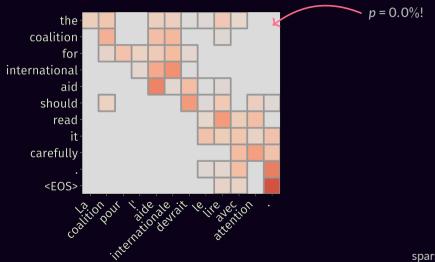
Cogition out side design less exterior



Sparse Neural Attention

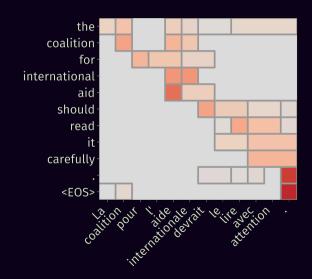


Sparse Neural Attention



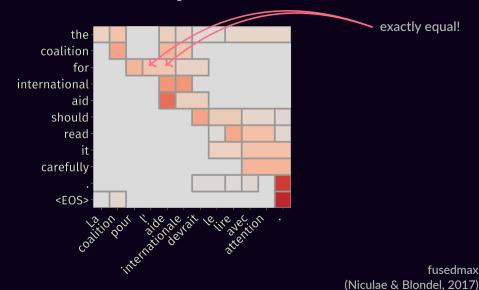
sparsemax (Martins & Astudillo, 2016)

Structured & Sparse Attention

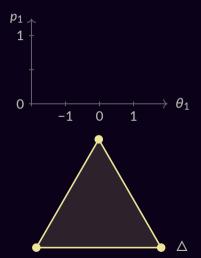


fusedmax (Niculae & Blondel, 2017)

Structured & Sparse Attention

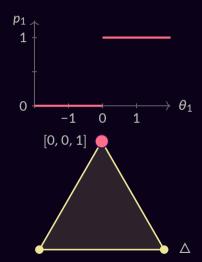


$$\Pi_{\Omega}(\boldsymbol{\theta}) = \underset{\boldsymbol{p} \in \Delta}{\operatorname{arg max}} \boldsymbol{p}^{\mathsf{T}} \boldsymbol{\theta} - \Omega(\boldsymbol{p})$$



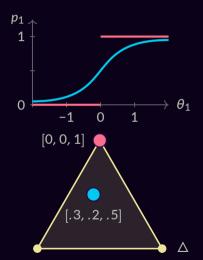
$$\Pi_{\Omega}(\boldsymbol{\theta}) = \arg \max_{\boldsymbol{p} \in \Delta} \boldsymbol{p}^{\top} \boldsymbol{\theta} - \Omega(\boldsymbol{p})$$

• argmax: $\Omega(\mathbf{p}) = 0$



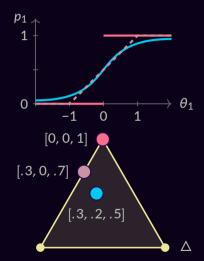
$$\Pi_{\Omega}(\boldsymbol{\theta}) = \underset{\boldsymbol{p} \in \Delta}{\operatorname{arg max}} \boldsymbol{p}^{\top} \boldsymbol{\theta} - \Omega(\boldsymbol{p})$$

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



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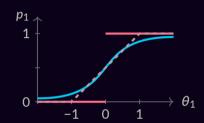
- argmax: $\Omega(\mathbf{p}) = 0$
- softmax: $\Omega(\mathbf{p}) = \sum_{i} p_{i} \log p_{i}$
- sparsemax: $\Omega(\mathbf{p}) = 1/2 ||\mathbf{p}||_2^2$



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- 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





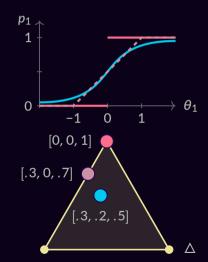
[0, 0, 1]

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

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

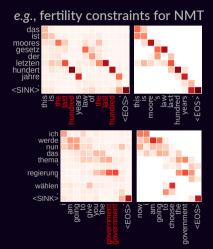


Constrained Attention

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

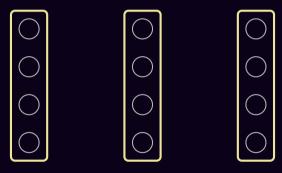
$$\underset{\boldsymbol{a} \leq \boldsymbol{p} \leq \boldsymbol{b}}{a \leq \boldsymbol{p} \leq \boldsymbol{b}}$$

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

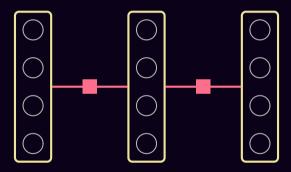


(Kreutzer & Martins, 18) (Malaviya et al, 18)

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 $\arg \max_{\boldsymbol{p} \in \Delta} \boldsymbol{p}^{\mathsf{T}} \boldsymbol{\theta} 1/2 ||\boldsymbol{p}||^2$

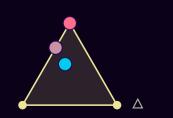


- **argmax** $\operatorname{arg\,max} \boldsymbol{p}^{\mathsf{T}} \boldsymbol{\theta}$
- softmax $\arg \max \mathbf{p}^{\mathsf{T}} \boldsymbol{\theta} + \mathsf{H}(\mathbf{p})$ $\mathbf{p} \in \Delta$
- sparsemax $\arg \max p^{\top} \theta \frac{1}{2} ||p||^2$

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



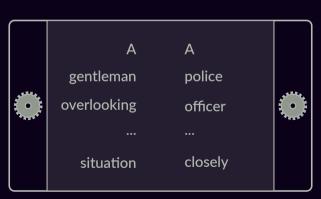


NLI premise: A gentleman overlooking a neighborhood situation.

hypothesis: A police officer watches a situation closely.

input

(P, H)



output



entails

contradicts

neutral

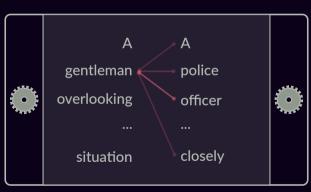
(Model: ESIM)

NLI premise: A gentleman overlooking a neighborhood situation.

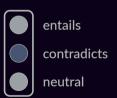
hypothesis: A police officer watches a situation closely.

input

(P, H)



output



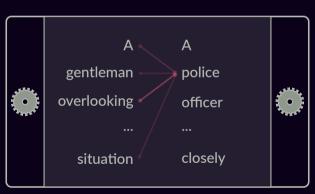
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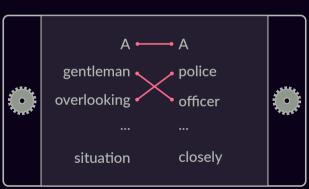
(Model: ESIM)

NLI premise: A gentleman overlooking a neighborhood situation.

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input

(P, H)



(Proposed model: global matching)

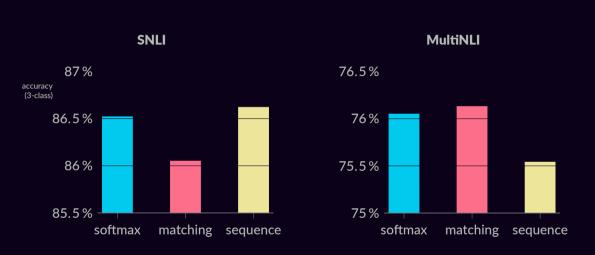
output

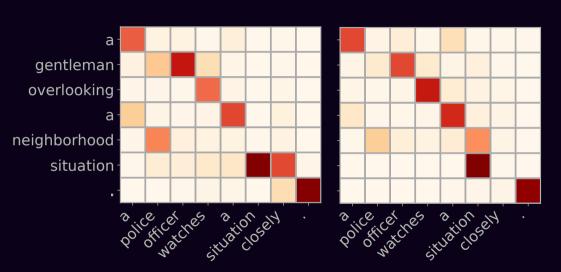


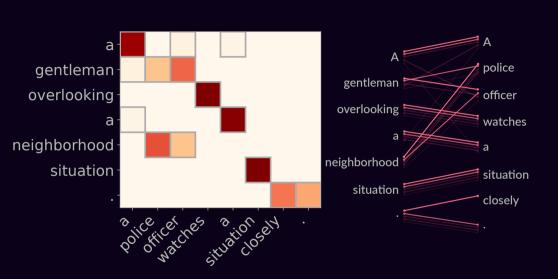
entails

contradicts

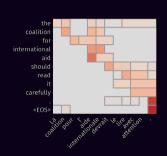
neutral



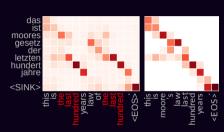




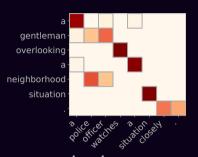
Summary: Neural attention with...



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)



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

