Learnable Sparsity and Weak Supervision for Data-efficient, Transparent, and Compact Neural Models

Gonçalo M. Correia

Jury: André Martins, Mário Figueiredo, Ivan Titov, Wilker Aziz, Isabel Trancoso

Deep learning successes

Deep learning successes

- Subset of machine learning that uses **neural networks**

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- Powerful tool for learning representations of any data

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- Remarkable results

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GPT-3

The Guardian

News website of the year

Deep learning successes

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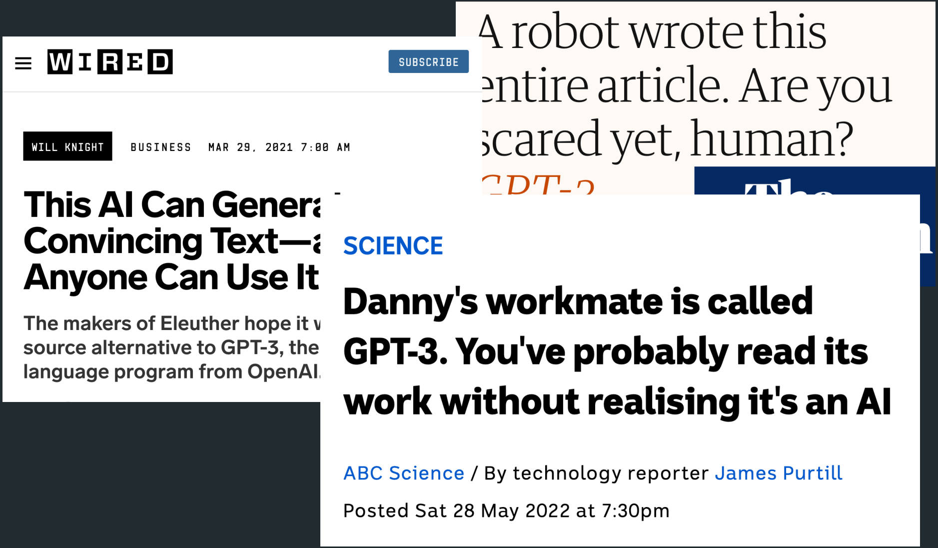

Deep learning successes

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Posted Sat 28 May 2022 at 7:30pm

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AI 'outperforms' doctors diagnosing breast cancer

Fergus Walsh
Medical correspondent
@BBCFergusWalsh

INNOVATION

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Deep learning limitations and drawbacks

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- Requires a lot of data

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AI

Overcoming AI's Transparency Paradox

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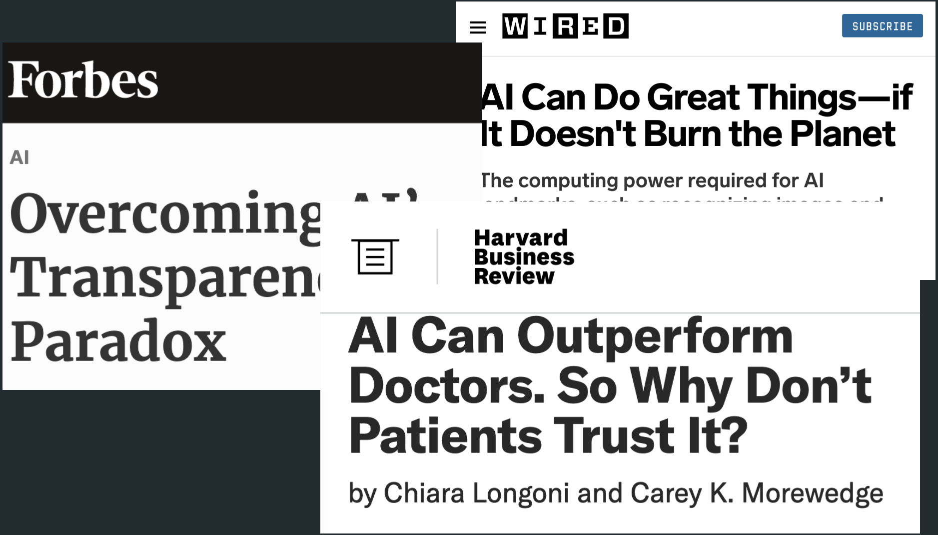
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AI

Overcoming
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Paradox

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The computing power required for AI

Harvard Business Review

AI Can Outperform Doctors. So Why Don't Patients Trust It?

by Chiara Longoni and Carey K. Morewedge

Key concepts of this thesis

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Learnable Sparsity and **Weak Supervision**

for **Data-efficient**, **Transparent**, and **Compact**

Neural Models

Published work

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- A Simple and Effective Approach to APE with Transfer Learning
  - weak supervision
  - data-efficiency
  - Poster at ACL 2019

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  - learnable sparsity
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  - Spotlight paper at NeurIPS 2020

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A bit of context on Transformers

What if... Attention is all you need?

(Vaswani et al., 2017)

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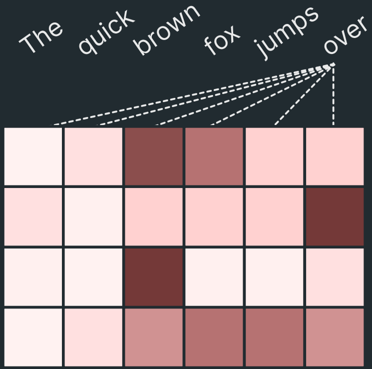

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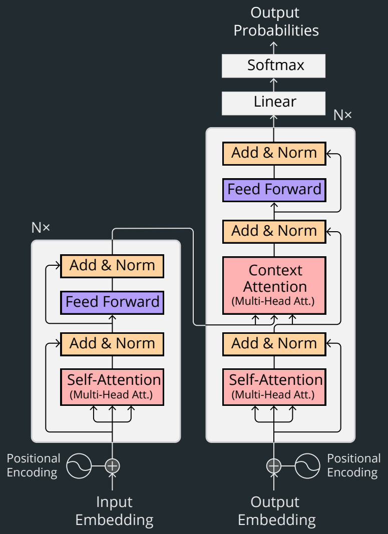

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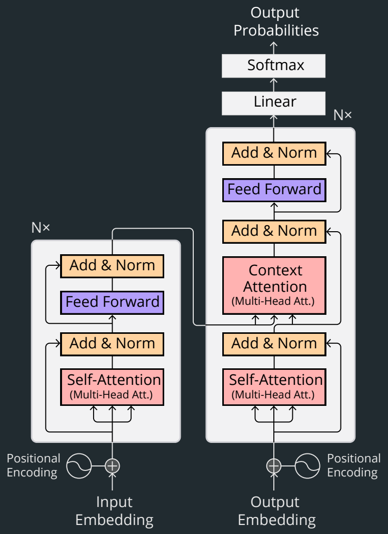

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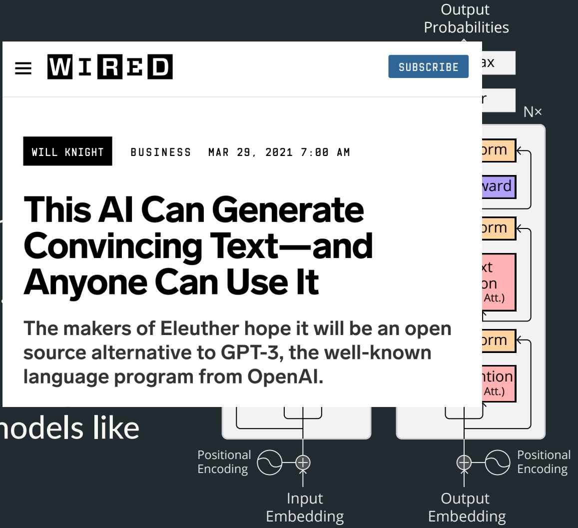

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What is APE?

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Anna’s dog is incredible, she is so cute!
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O cão da Anna é incrível, ela é tão fofa!

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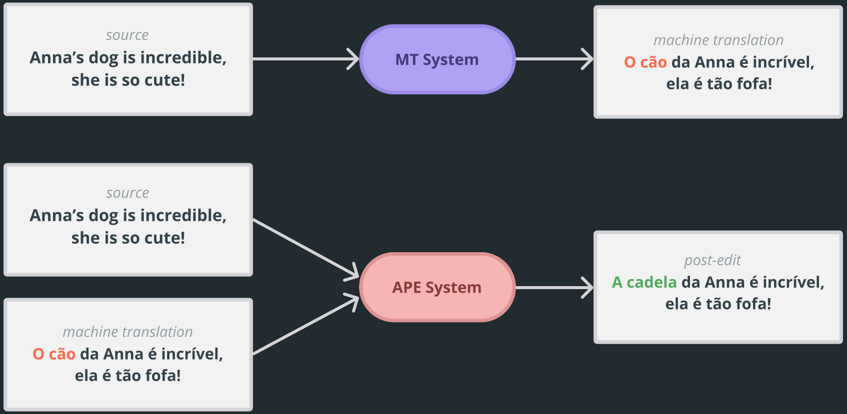
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APE System
post-edit
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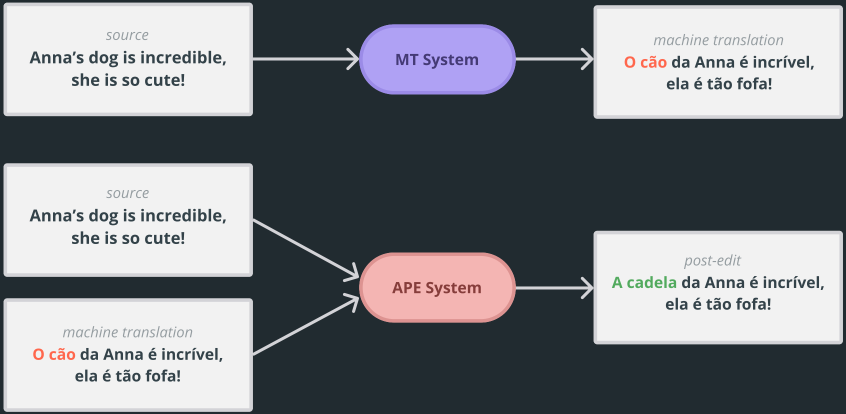
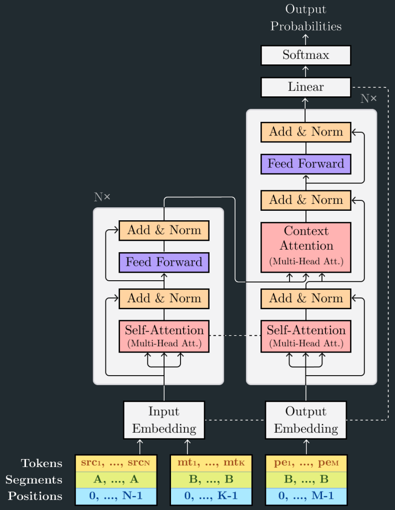
What is APE?



Challenge: APE data is very scarce! Need to create artificial data.

BERT for APE


Output
Probabilities
Softmax
Linear
N×
Add & Norm
Feed Forward
Add & Norm
Context
Attention
(Multi-Head Att.)
Add & Norm
Self-Attention
(Multi-Head Att.)
N×
Add & Norm
Feed Forward
Add & Norm
Self-Attention
(Multi-Head Att.)
Input
Embedding
Output
Embedding
Tokens
Segments
Positions
src1, ..., srcN
A, ..., A
0, ..., N-1
mt1, ..., mtK
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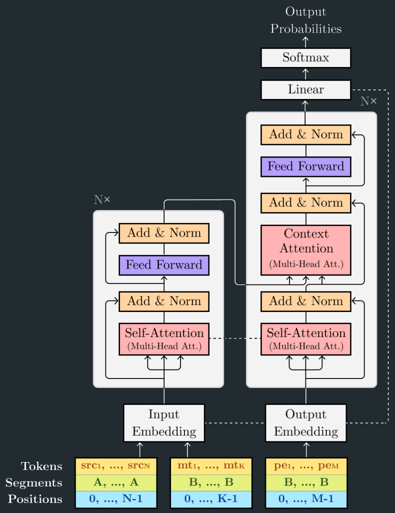
BERT for APE

Key idea: Use BERT to do APE 🙌



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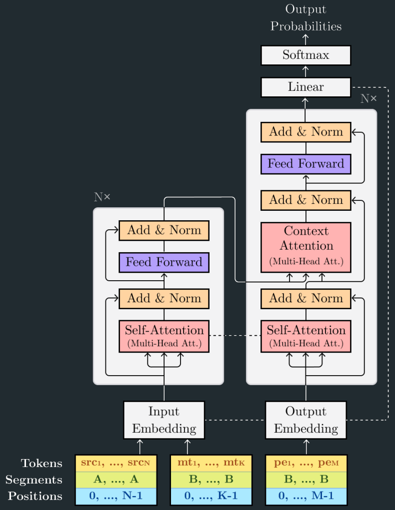

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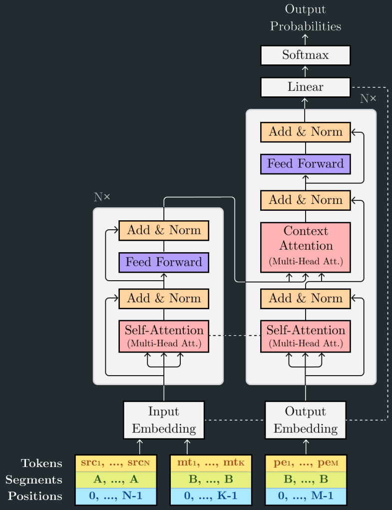
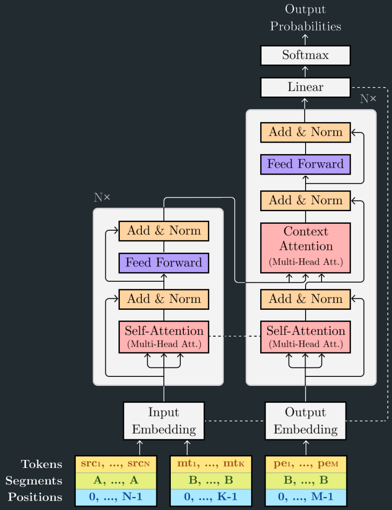


BERT for APE

Key idea: Use BERT to do APE 🙌

- Prior to this work, BERT was mainly used for simple classification tasks
- We introduced an effective method to use BERT in a generation task (APE)
- Smart parameter sharing between encoder and decoder



Key results

model (data size)	TER↓	BLEU↑
mt baseline	24.48	62.49

(Junczys-Dowmunt and Grundkiewicz, 2018)

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Key takeaways

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- Massive improvement in low-resource scenario (data-efficiency)
- Steered SOTA of APE towards using weak supervision through pre-trained models

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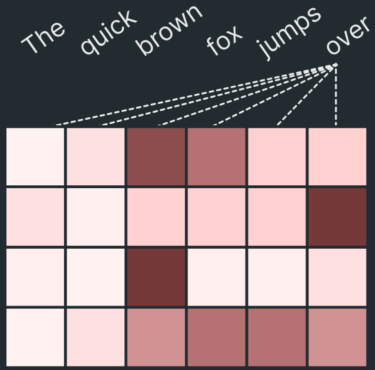
Getting to know attention heads better

Attention heads may aid visualization but they are completely dense.



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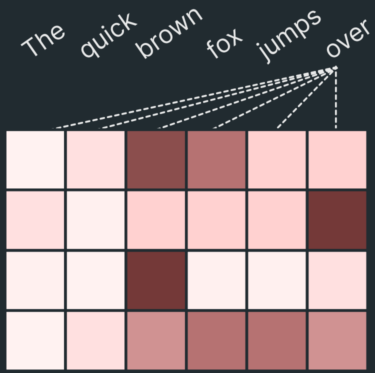
Our solution is to bet on sparsity:

- for interpretability
- for discovering linguistic structure
- for efficiency



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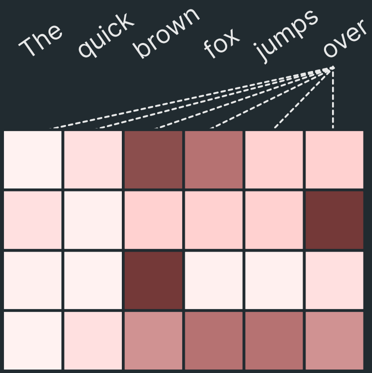
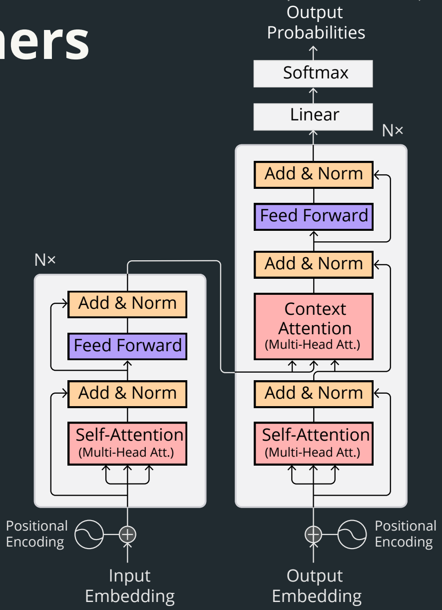


Transformers

In each attention head:

$$\bar{V} = \mathrm{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V.$$

(Vaswani et al., 2017)



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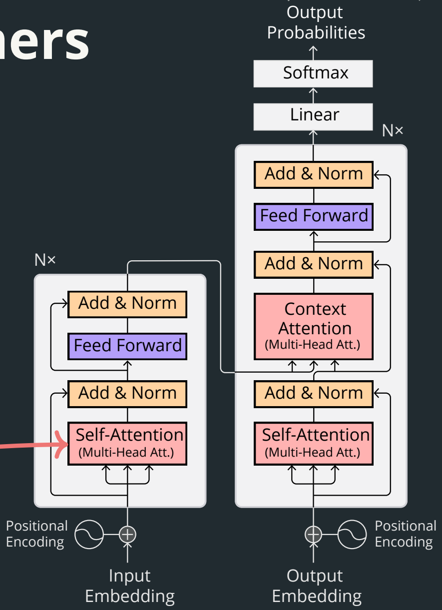

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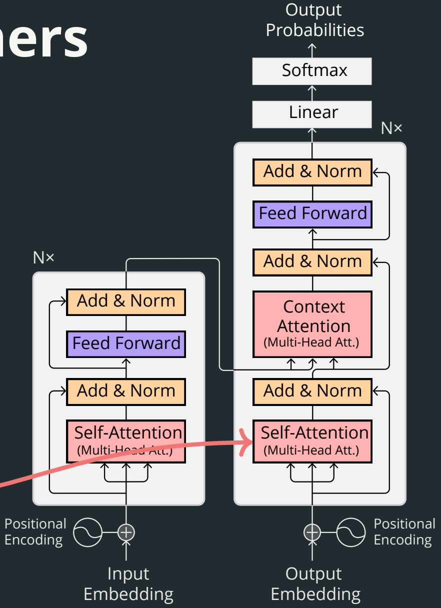

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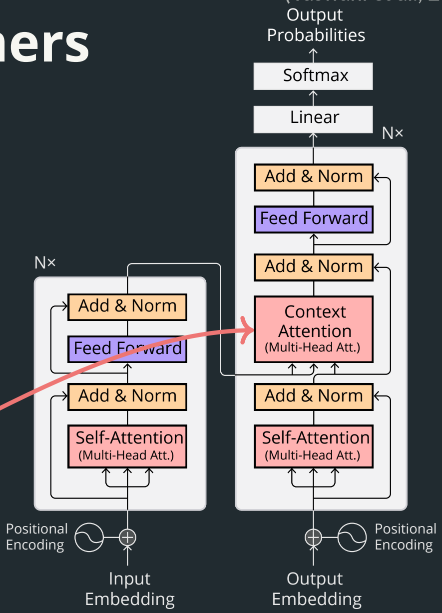

Sparse Transformers

Sparse Transformers

Key idea: replace softmax in attention heads by a sparse normalizing function! 🙌

Adaptively Sparse Transformers

Key idea: replace softmax in attention heads by a sparse normalizing function! 🙌

Another key idea: use a normalizing function that is adaptively sparse via a learnable α! 🙌 🙌 🙌

What is softmax?

Softmax exponentiates and normalizes:

$$[\mathbf{softmax}(z)]_i := \frac{\exp(z_i)}{\sum_j \exp(z_j)}$$

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$$[\textbf{softmax}(z)]_i := \frac{\exp(z_i)}{\sum_j \exp(z_j)}$$

It's fully dense: $\textbf{softmax}(\boldsymbol{z}) > \mathbf{0}$

α-entmax

Parametrized by $\alpha \geq 0$:

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- **Argmax** corresponds to $\alpha \to \infty$

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α-entmax

Parametrized by $\alpha \geq 0$:

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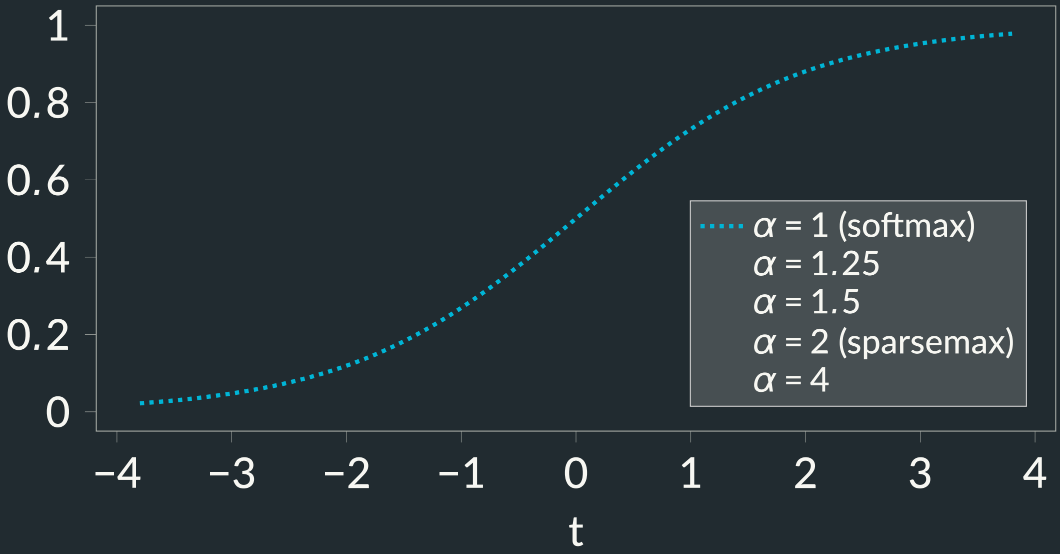
- **Softmax** amounts to $\alpha \to 1$

Key result: **can be sparse for** $\alpha > 1$, propensity for sparsity increases with α.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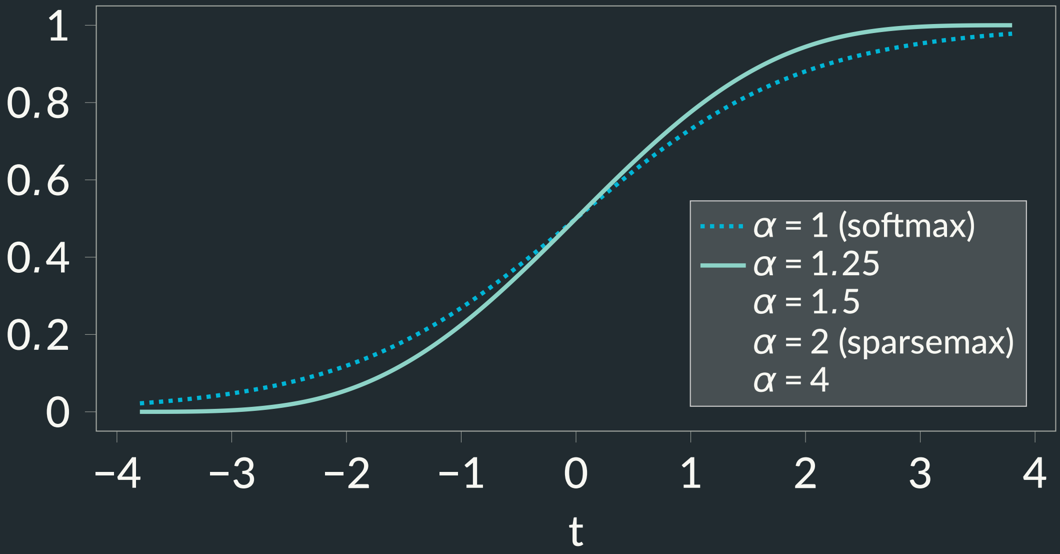
α = 1 (softmax)
α = 1.25
α = 1.5
α = 2 (sparsemax)
α = 4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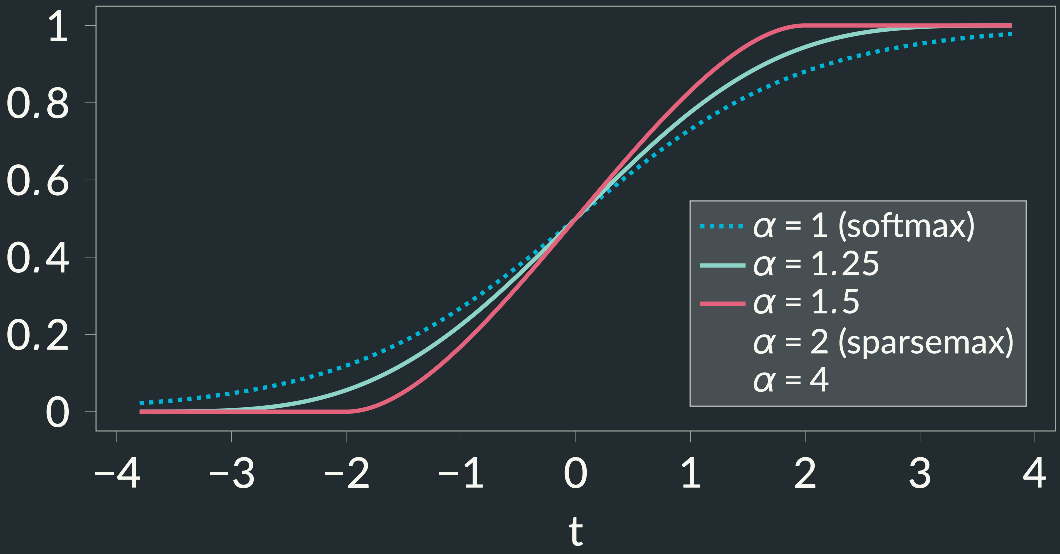
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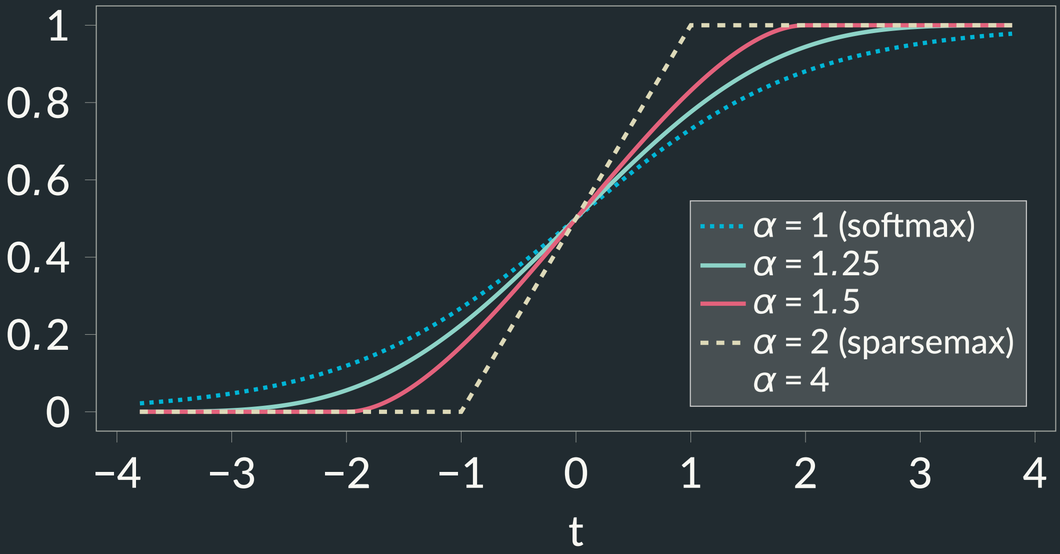
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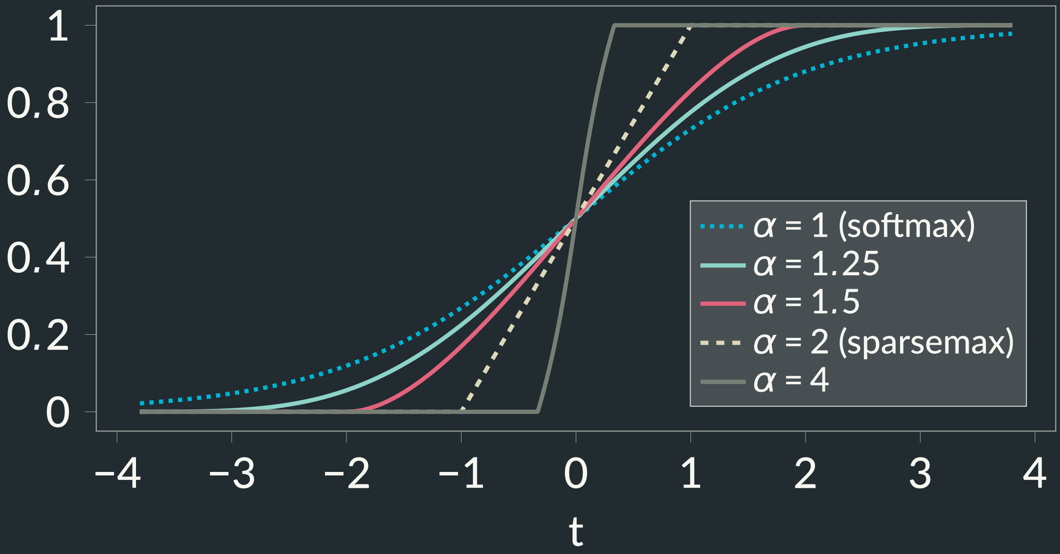
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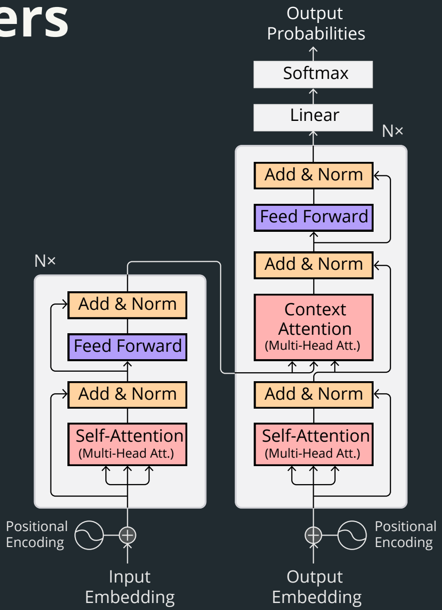
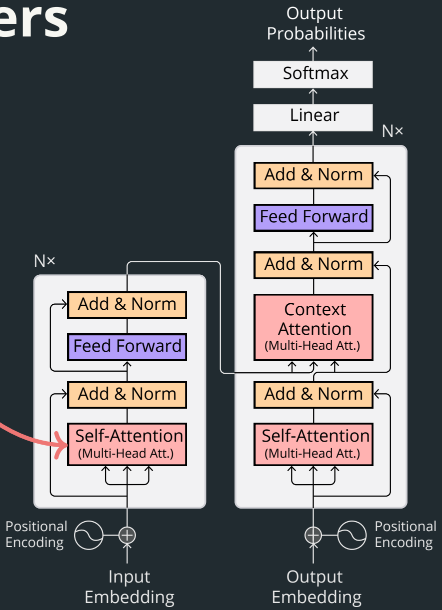


Transformers

Attention in three places:

- Self-attention in the encoder

6 layers × 8 attention heads = 48



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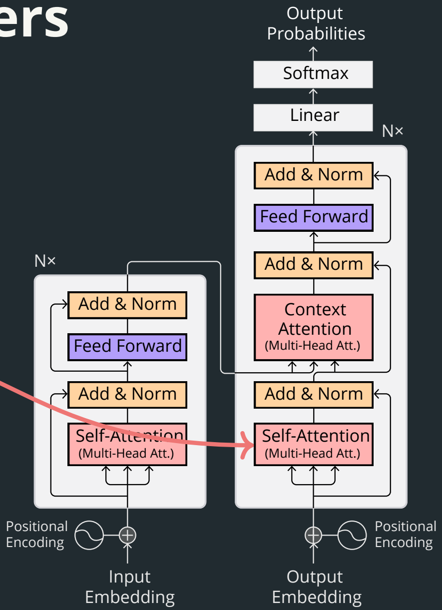
+ 48

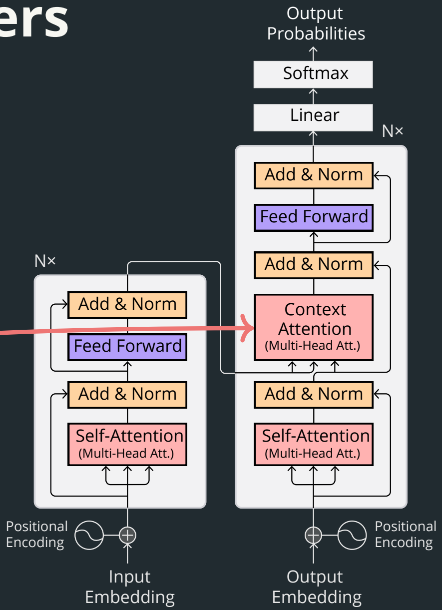


Transformers

Attention in three places:

- Self-attention in the encoder
- Self-attention in the decoder
- Contextual attention

6 layers × 8 attention heads = 48
+ 48
+ 48 = 144



Learning α

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Key contribution:

a closed-form expression for $\dfrac{\partial\, \alpha\text{-entmax}(\boldsymbol{z})}{\partial \alpha}$ 😱

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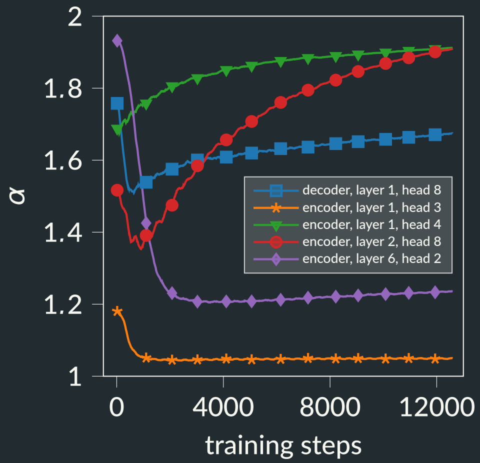
Not trivial! Requires implicit differentiation

Trajectories of α during training



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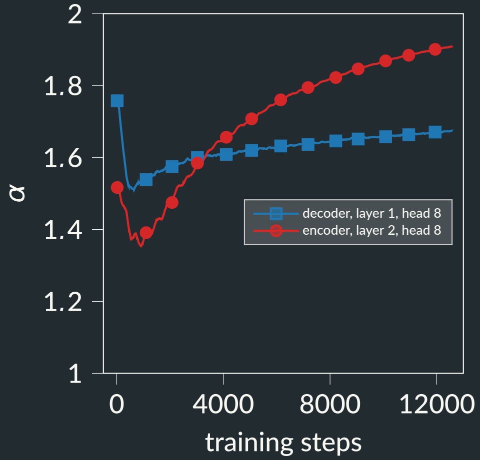
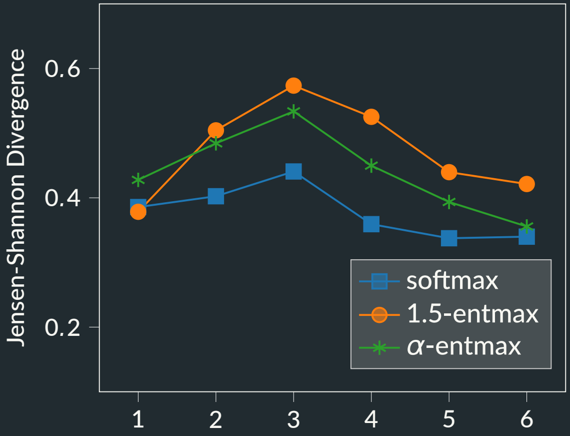


Some heads choose to start dense before becoming sparse.

Head Diversity per Layer



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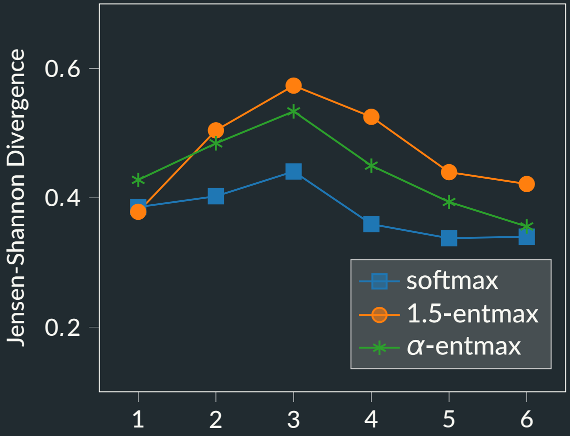
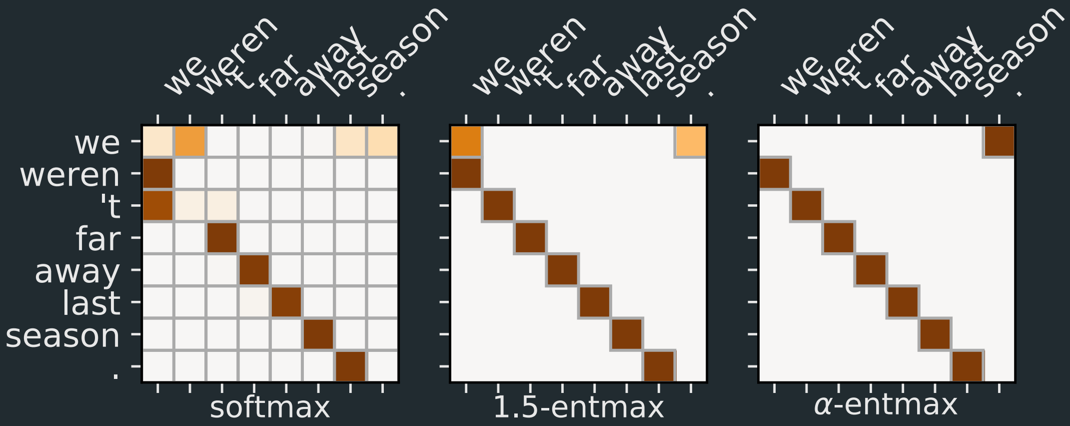


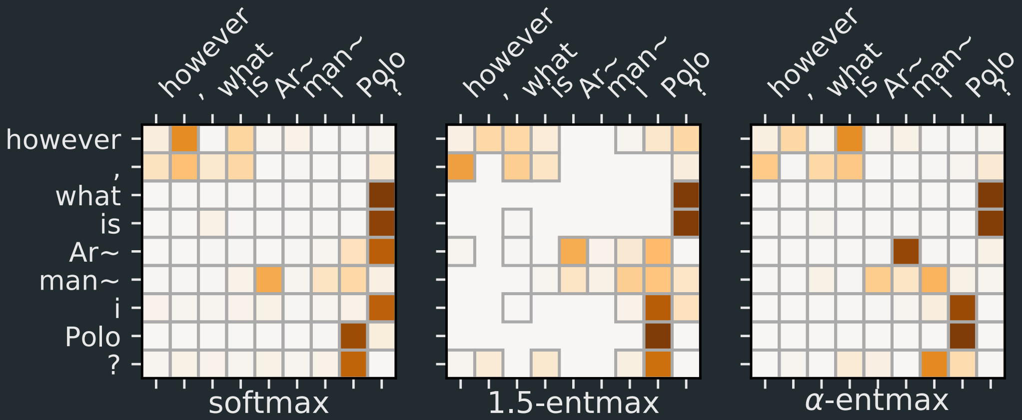
Specialized heads are important as seen in Voita et al. (2019)!

Previous position head



This head role was also found in Voita et al. (2019)! Learned $\alpha = 1.91$.

Interrogation-detecting head



Learned $\alpha = 1.05$.

Key takeaways

Introduce adaptive sparsity
for Transformers via α-entmax with a gradient learnable α,
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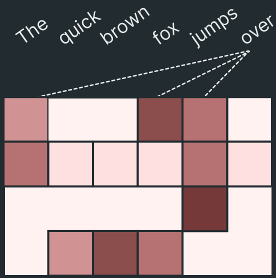

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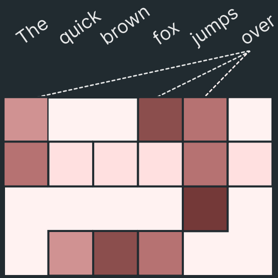
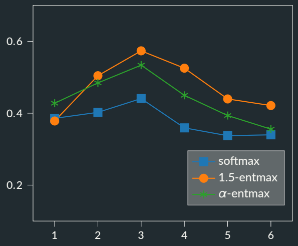


reduced head redundancy



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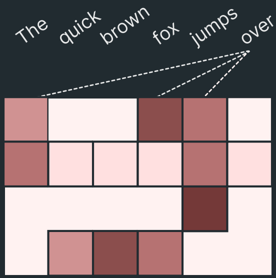

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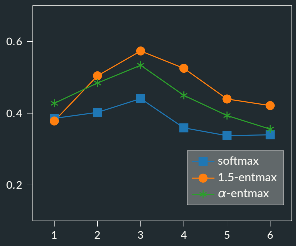


clearer head roles

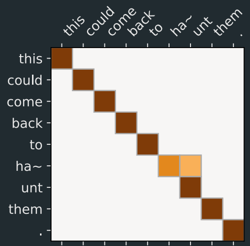


Table of Contents

Latent variable models

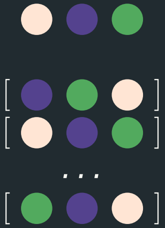
We focus on latent variables z that are

Latent variable models

We focus on latent variables z that are discrete

Latent variable models

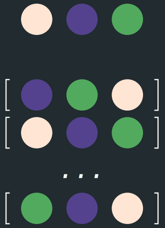
We focus on latent variables z that are discrete or structured



Latent variable models

We focus on latent variables z that are discrete or structured

$\pi(z|x, \theta)$: distribution over possible z



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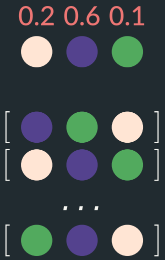

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If $\mathcal{Z}$ is large, this sum can get very expensive due to $\ell(x,z;\theta)$! 😱

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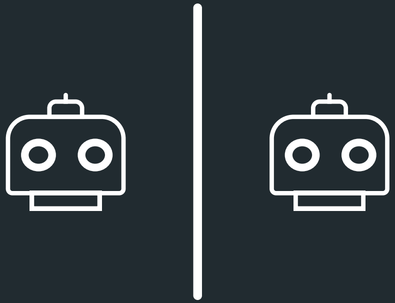
If $\mathcal{Z}$ is combinatorial, this can be intractable to compute! 😱 😱 😱

Current solutions

Using emergent communication as example



Method	success (%)	# messages
Monte Carlo		
Marginalization		

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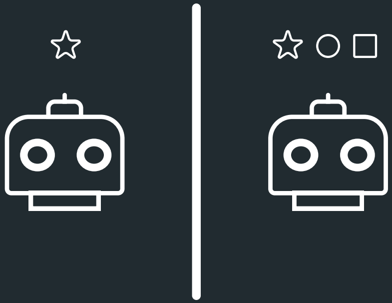

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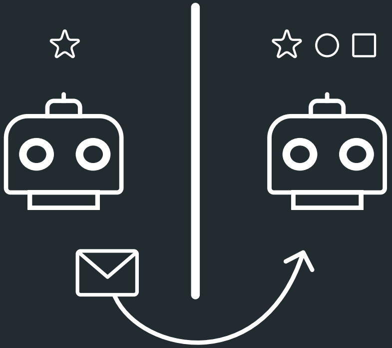

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Dense	93.37 ±0.42	256

Current solutions

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Method	success (%)	# messages
Monte Carlo		
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Gumbel	23.51 ±16.19	1
Marginalization		
Dense	93.37 ±0.42	256
Sparse	93.35 ±0.50	3.13±0.48

Our solution

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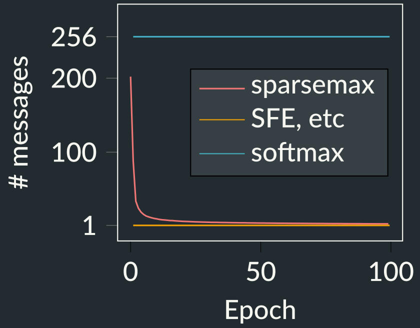

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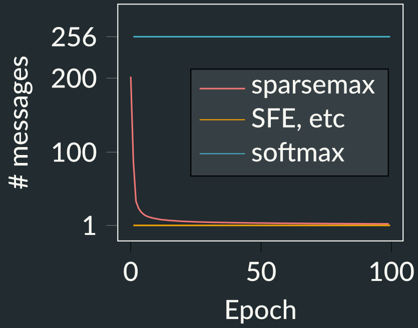

We use sparsemax, top-*k* sparsemax and SparseMAP to allow efficient marginalization

Results

We test our methods for models with discrete latent variables,

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Our methods are top-performers and efficient!

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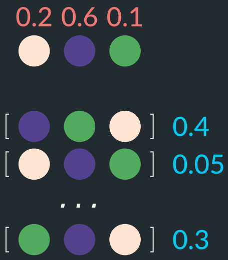

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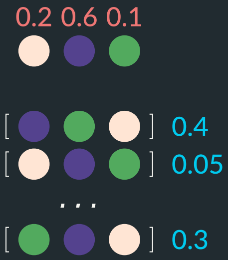

deterministic, yet efficient

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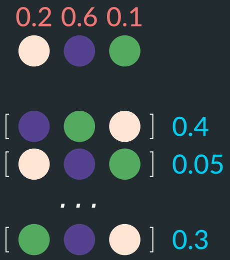

deterministic, yet efficient

sparse, as needed

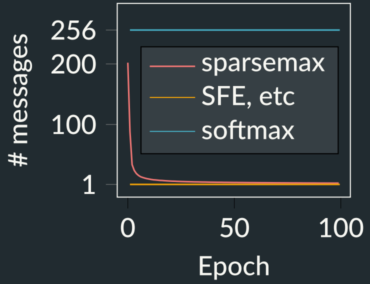

Table of Contents

Future directions

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- Semi-supervised learning: data-efficiency and compactness

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- Learning $\pi(z|x)$ without learning $\ell(x, z)$: compactness

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- Latent draft translations: transparency and compactness

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Using learned sparsity and weak supervision
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data-efficiency

model (data size)	BLEU↑
dual-source transformer (8M)	71.72
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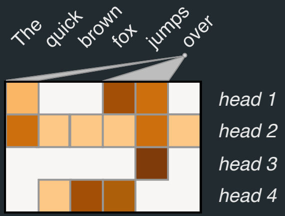

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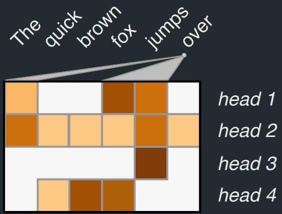

better & efficient compactness

github.com/deep-spin goncalomcorreia.com

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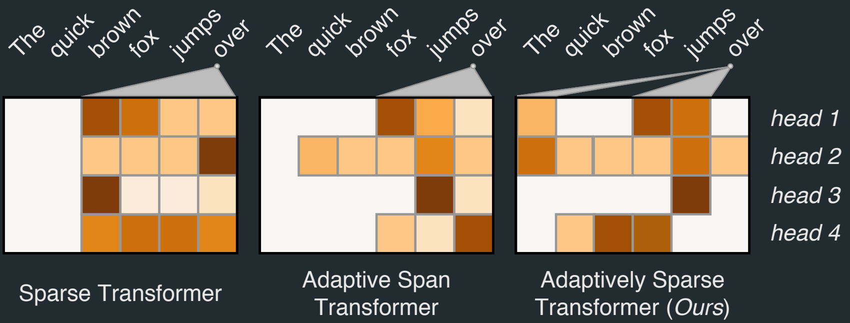
Parameter sharing analysis

	TER↓	BLEU↑
MT Baseline	24.76	62.11
Transformer	27.80	60.76
Transformer decoder	20.33	69.31
Pre-trained BERT	20.83	69.11
with CA ← SA	18.91	71.81
and SA ⟷ Encoder SA	**18.44**	**72.25**
and CA ⟷ SA	18.75	71.83
and FF ⟷ Encoder FF	19.04	71.53

(Child et al., 2019; Sukhbaatar et al., 2019)

Related Work: Other Sparse Transformers



Our model allows non-contiguous attention for each head.

(Niculae and Blondel, 2017)

Ω-Regularized Argmax

For convex Ω, define the Ω**-regularized argmax transformation:**

$$\mathbf{argmax}_{\Omega}(\boldsymbol{z}) := \arg\max_{\boldsymbol{p}\in\triangle} \boldsymbol{z}^\top \boldsymbol{p} - \Omega(\boldsymbol{p})$$

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(Martins and Astudillo, 2016)

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Is there something in-between?

BLEU Scores

activation	de→en	ja→en	ro→en	en→de
softmax	29.79	21.57	32.70	26.02
1.5-entmax	29.83	22.13	33.10	25.89
α-entmax	29.90	21.74	32.89	26.93

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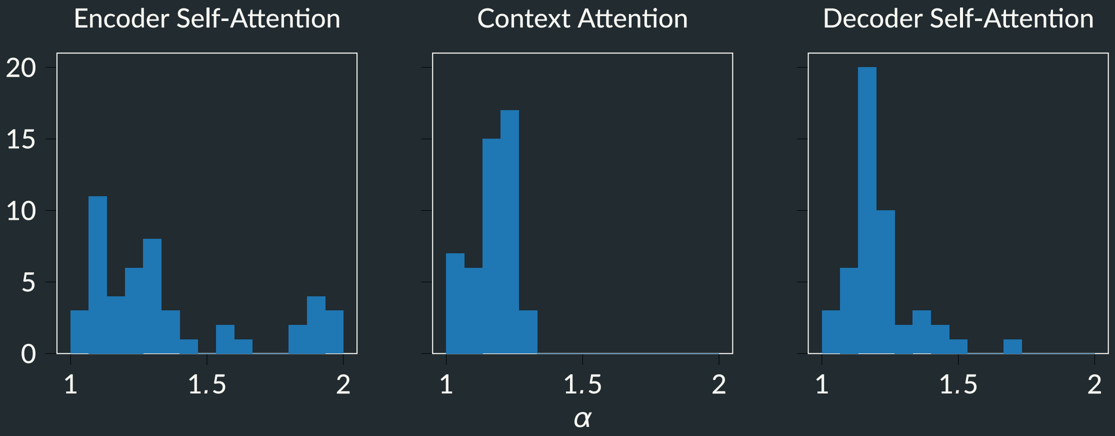
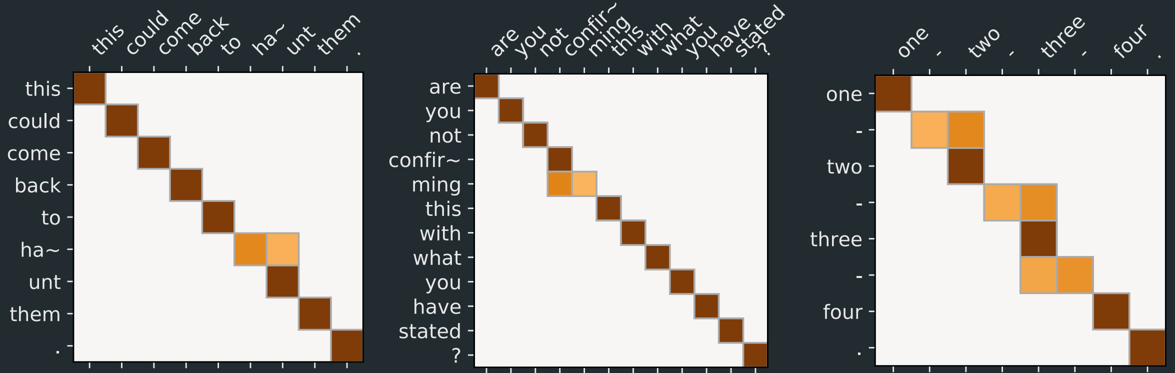
For analysis for other language pairs, see Appendix A.

Learned α



Bimodal for the encoder, mostly unimodal for the decoder.

Subword-Merging Head



Learned $\alpha = 1.91$.

Semi-Supervised VAE

$$\mathcal{L}_x(\theta) = \sum_{z \in \mathcal{Z}} \pi(z|x)\, \ell(x, z)$$
$$= \mathbb{E}_{z \sim \pi(z|x)}\, \ell(x, z)$$

- Semi-Supervised VAE on MNIST: z is one of 10 categories

Semi-Supervised VAE

Gaussian VAE

$$\mathcal{L}_x(\theta) = \sum_{z \in \mathcal{Z}} \pi(z|x)\, \ell(x, z)$$

classification network

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- Semi-Supervised VAE on MNIST: z is one of 10 categories
- Train this with 10% labeled data

Semi-Supervised VAE

Method	Accuracy (%)	Dec. calls
Monte Carlo		
SFE	$94.75_{\pm.002}$	1
SFE+	$96.53_{\pm.001}$	2
NVIL	$96.01_{\pm.002}$	1
Gumbel	$95.46_{\pm.001}$	1
Marginalization		
Dense	$96.93_{\pm.001}$	10

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Sparse	96.87 $\pm .001$	1.01 ± 0.01

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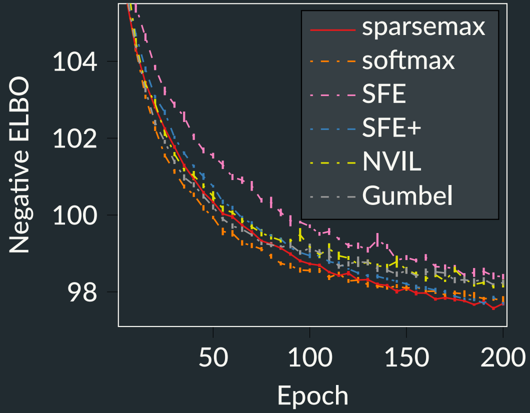
Gumbel	95.46±.001	1
Marginalization		
Dense	96.93±.001	10
Sparse	96.87±.001	1.01±0.01



Emergent communication

$$\mathcal{L}_x(\theta) = \sum_{z \in \mathcal{Z}} \pi(z|x)\, \ell(x, z)$$

$$= \mathbb{E}_{z \sim \pi(z|x)}\, \ell(x, z)$$

Emergent communication

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- receiver picks image from a set $\mathcal{V}$ based on message

Emergent communication

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sum over
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- receiver picks image from a set $\mathcal{V}$ based on message
- images come from ImageNet

(Lazaridou et al., 2017; Correia et al., 2020)

Emergent Communication

... but make it harder: $|\mathcal{Z}| = 256$, $|\mathcal{V}| = 16$

Method	success (%)	Dec. calls
Monte Carlo		
SFE	33.05 ±2.84	1
SFE+	44.32 ±2.72	2
NVIL	37.04 ±1.61	1
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ST Gumbel	27.42 ±13.36	1
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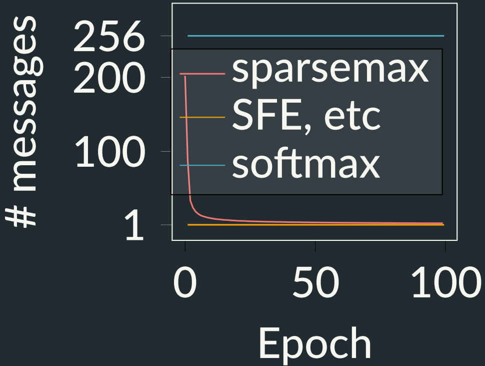

Limitations

- Mostly (and eventually) very sparse.
  But fully dense worst case.
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$$k\text{-sparsemax}(\boldsymbol{s}) = \underset{\boldsymbol{p}\in\triangle,\, \|\boldsymbol{p}\|_0 \le k}{\arg\min} \|\boldsymbol{p} - \boldsymbol{s}\|_2^2$$

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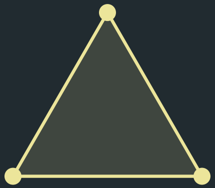
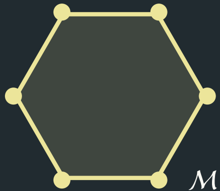
- Non-convex but easy: sparsemax over the k highest scores (Kyrillidis et al., 2013).
- Top-k oracle available for some structured problems.
- Certificate: if at least one of the top-k z gets $p(z) = 0$, **k-sparsemax = sparsemax**!
  thus, biased early on, but it goes away.

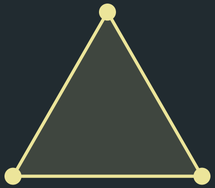


$\triangle$



$\mathcal{M}$

$$
\begin{aligned}
\mathcal{M} := \operatorname{conv}\left\{\boldsymbol{a}_z : z \in \mathcal{Z}\right\} \\
= \left\{\boldsymbol{A}\boldsymbol{p} : \boldsymbol{p} \in \Delta\right\} \\
= \left\{\mathbb{E}_{Z \sim \boldsymbol{p}}\, \boldsymbol{a}_Z : \boldsymbol{p} \in \Delta\right\}
\end{aligned}
$$



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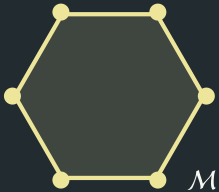
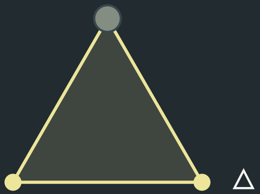
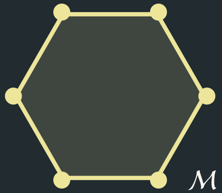


$\mathcal{M}$

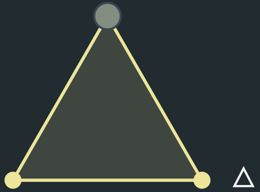
- **argmax** $\arg\max_{\boldsymbol{p}\in\triangle} \boldsymbol{p}^\top \boldsymbol{s}$

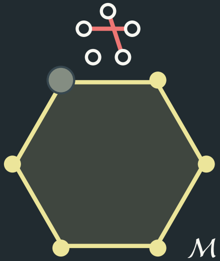




argmax $\arg\max_{\boldsymbol{p}\in\triangle} \boldsymbol{p}^\top \boldsymbol{s}$

MAP $\arg\max_{\boldsymbol{\mu}\in\mathcal{M}} \boldsymbol{\mu}^\top \boldsymbol{t}$





- **argmax** $\arg\max_{\boldsymbol{p}\in\triangle} \boldsymbol{p}^\top \boldsymbol{s}$
- **softmax** $\arg\max_{\boldsymbol{p}\in\triangle} \boldsymbol{p}^\top \boldsymbol{s} + \mathrm{H}(\boldsymbol{p})$

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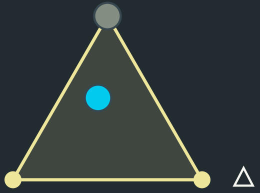

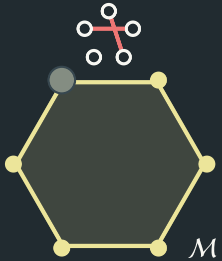

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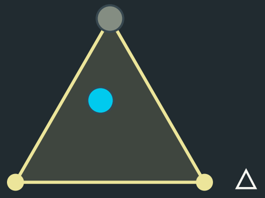

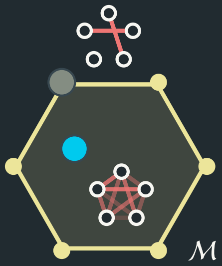

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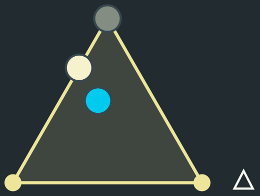

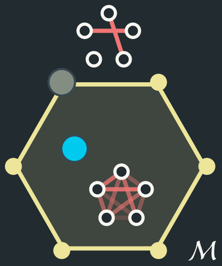

(Niculae, Martins, Blondel, and Cardie, 2018)

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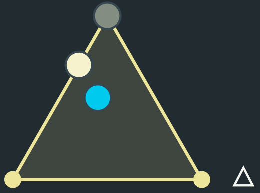

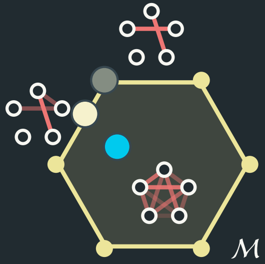

Bit-vector VAE

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Bit-vector VAE

sum over
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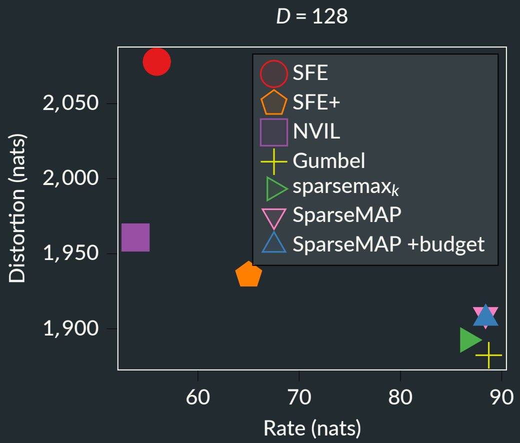

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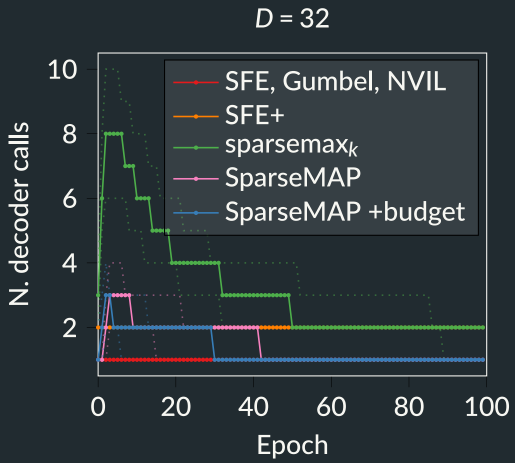

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