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

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- 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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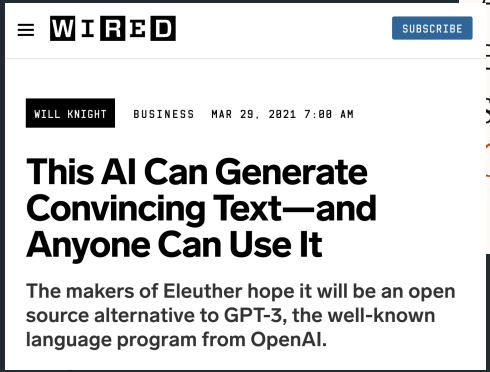
A robot wrote this entire article. Are you scared yet, human?

GPT-3

The Guardian
News website of the year

Deep learning successes



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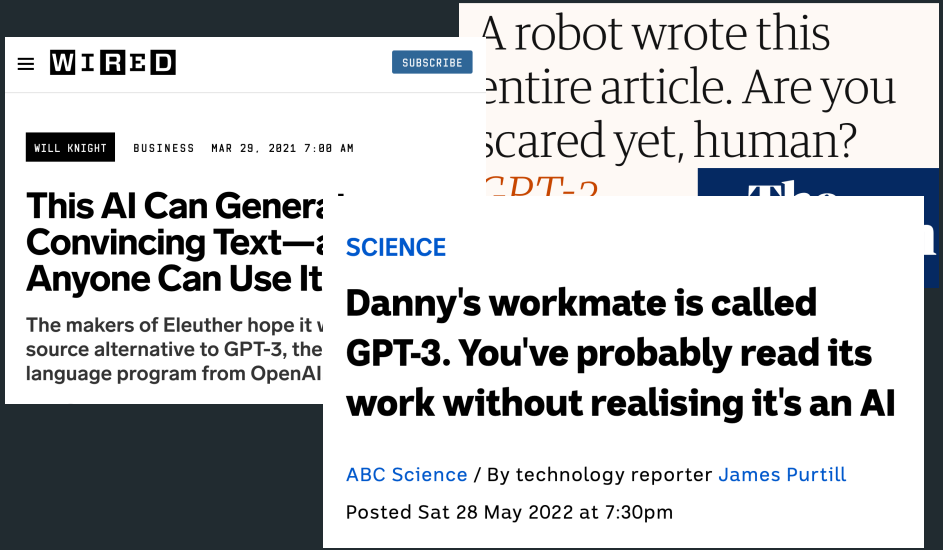

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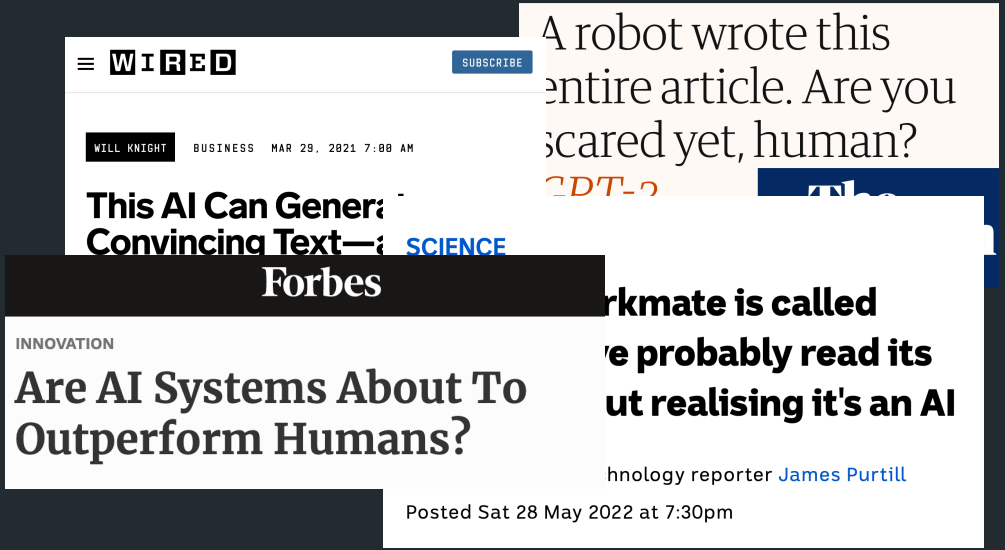

Deep learning successes

Artificial intelligence beats eight world champions at bridge

Victory marks milestone for AI as bridge requires more human skills than other strategy games

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PT-2

INNOVATION

Are AI Systems About To Outperform Humans?

rkmate is called
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ut realising it's an AI

hnology reporter James Purtill

Posted Sat 28 May 2022 at 7:30pm

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AI 'outperforms' doctors diagnosing breast cancer

Fergus Walsh
Medical correspondent
@BBCFergusWalsh

Deep learning limitations and drawbacks

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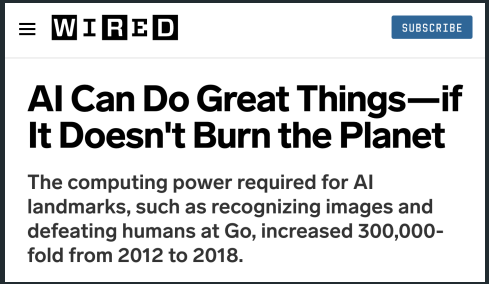

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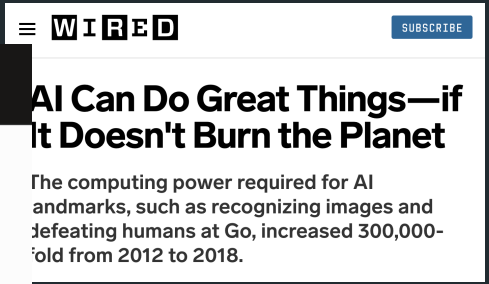

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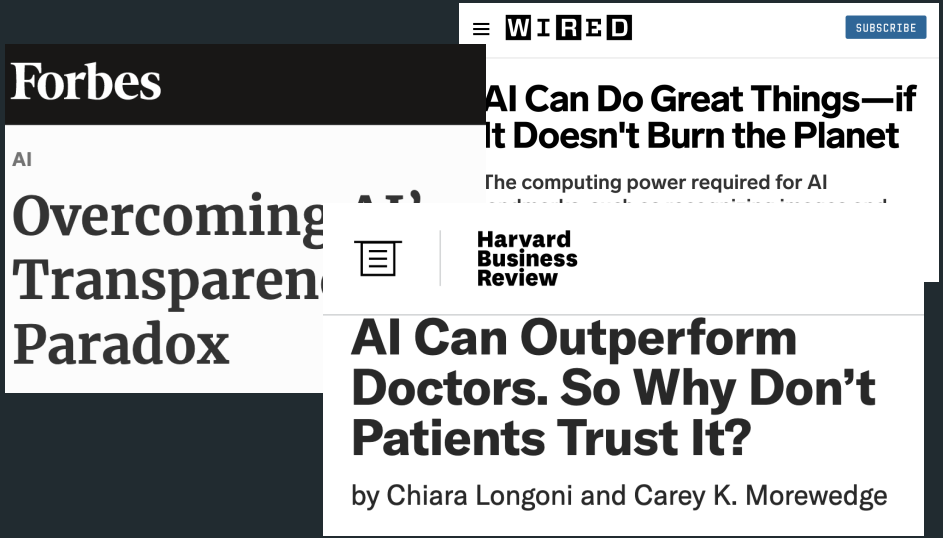

Key concepts of this thesis

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Neural Models

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Efficient Marg. of Discrete Latent Variables via Sparsity

Conclusions

(Vaswani et al., 2017)

A bit of context on transformers

What if... Attention is all you need?

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Key idea: Let's mainly use attention mechanisms!

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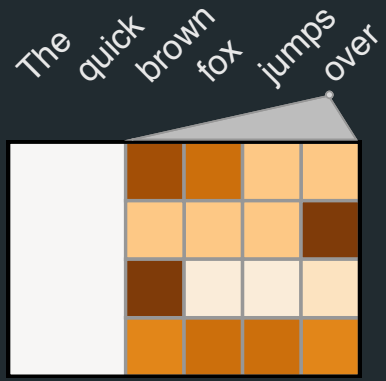

(Vaswani et al., 2017)

A bit of context on transformers

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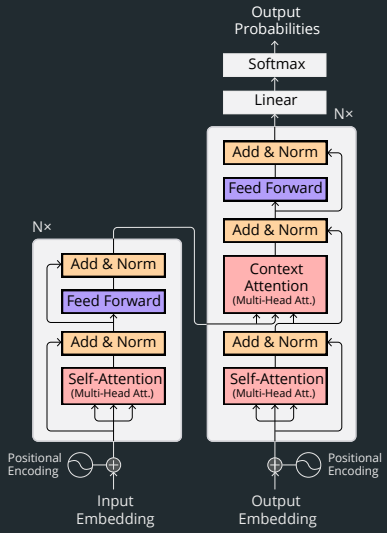

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What if... Attention is all you need?

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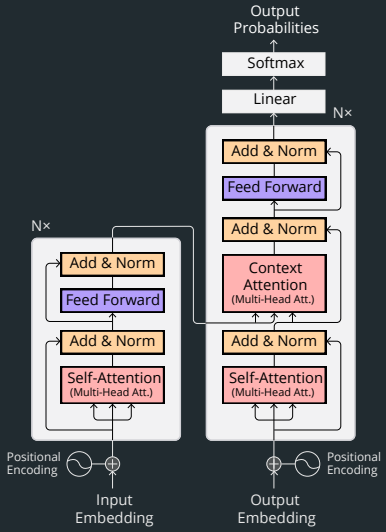
- Inspiration for big general-purpose models like BERT and GPT-3!



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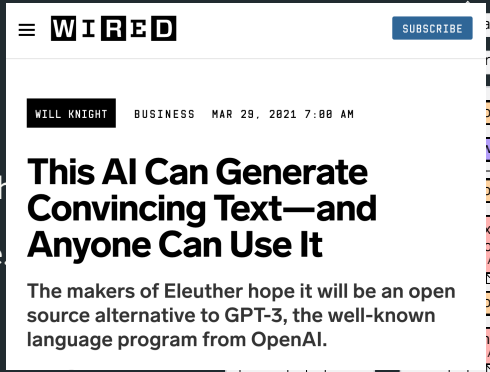
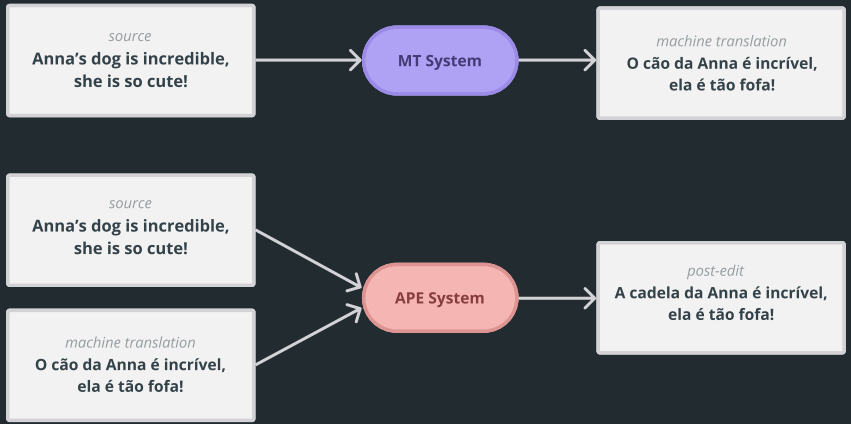


What is APE?


source
Anna's dog is incredible, she is so cute!
MT System
machine translation
O cão da Anna é incrível, ela é tão fofa!
source
Anna's dog is incredible, she is so cute!
machine translation
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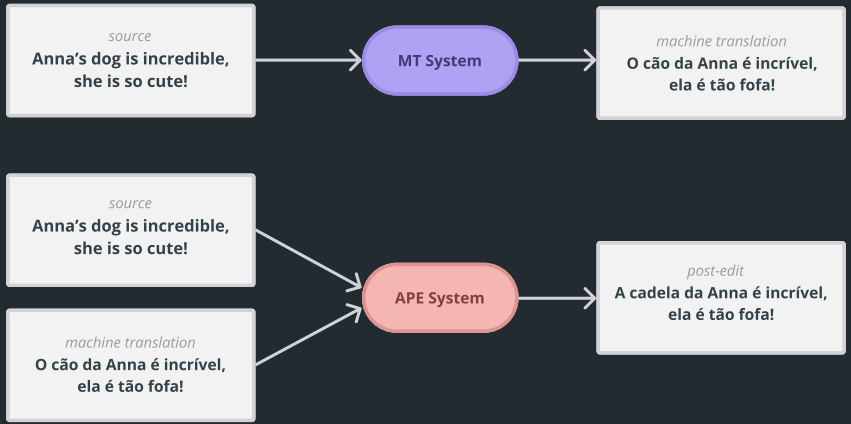
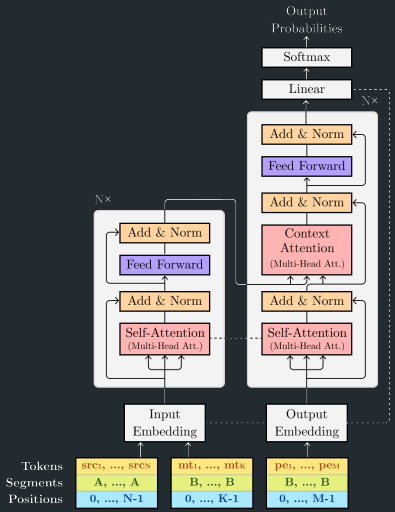
APE System
post-edit
A cadela da Anna é incrível, ela é tão fofa!

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
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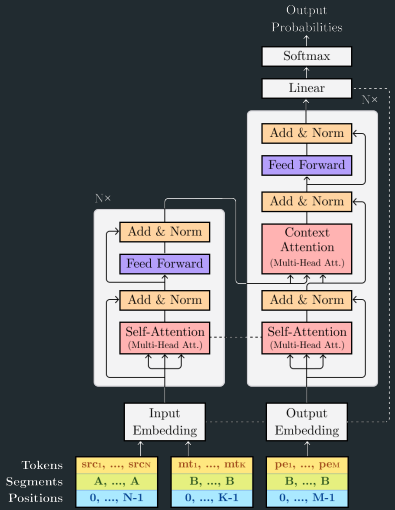
Self-Attention
(Multi-Head Att.)
Input Embedding
Output Embedding
Tokens
Segments
Positions
src1, ..., srcN
A, ..., A
0, ..., N-1
mt1, ..., mtK
B, ..., B
0, ..., K-1
pe1, ..., peM
B, ..., B
0, ..., M-1

BERT for APE

Key idea: Use BERT to do APE



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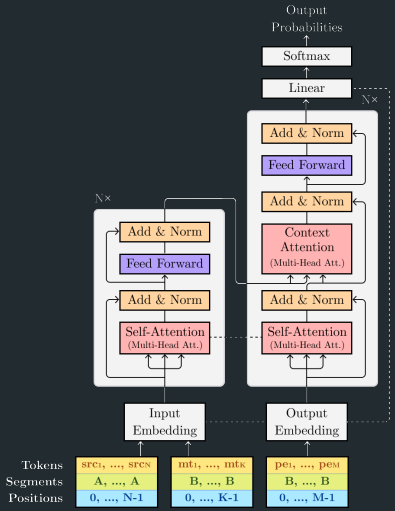

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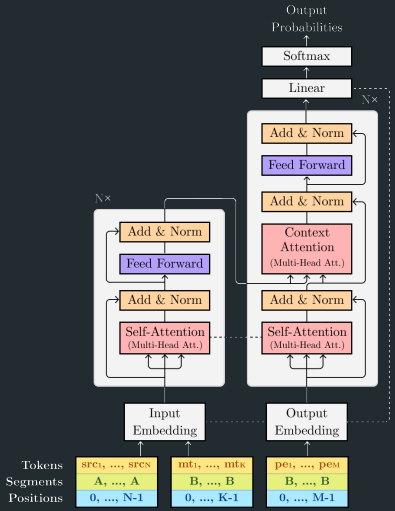
- We introduced an effective method to use BERT in a generation task (APE)



BERT for APE

Key idea: Use BERT to do APE

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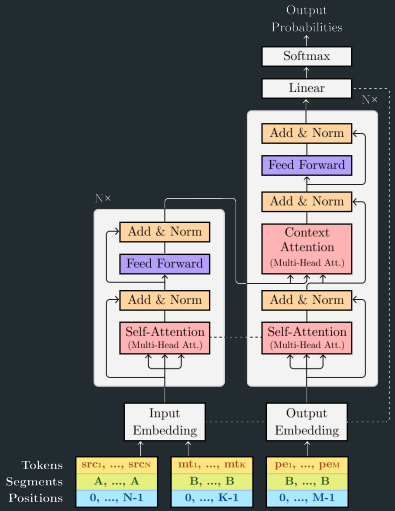
- We introduced an effective method to use BERT in a generation task (APE)
- Smart parameter sharing between encoder and decoder



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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(Lee et al., 2020)

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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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- for interpretability
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- for efficiency

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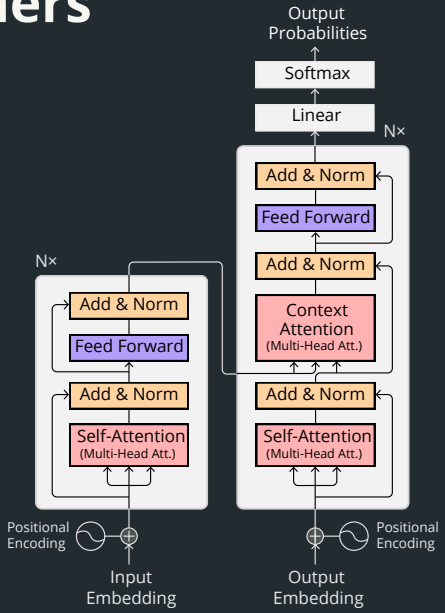
(Vaswani et al., 2017)

Transformers

In each attention head:

$$\bar{\mathbf{V}} = \mathbf{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{d_k}}\right)\mathbf{V}.$$



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Attention in three places:

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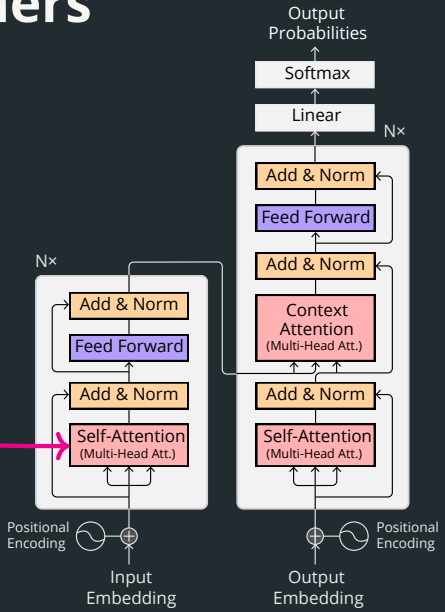

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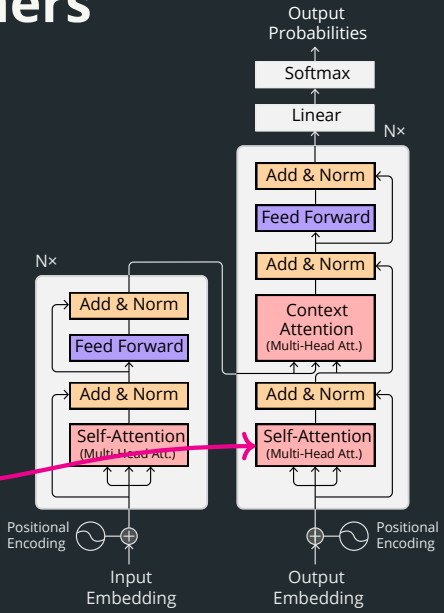

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Transformers

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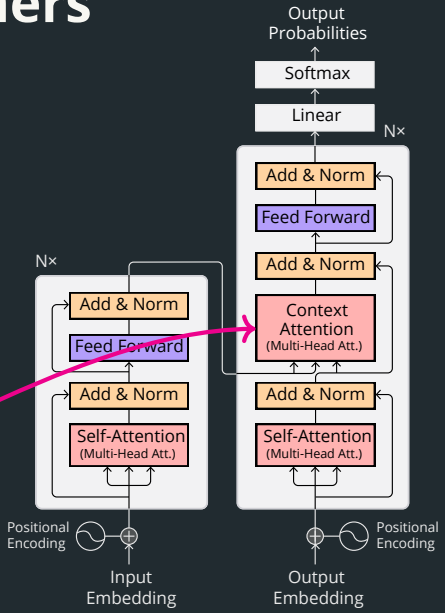
Attention in three places:

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



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

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

(Peters et al., 2019)

α-entmax

Parametrized by $\alpha \geq 0$:

(Peters et al., 2019)

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

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α-entmax

Parametrized by $\alpha \geq 0$:

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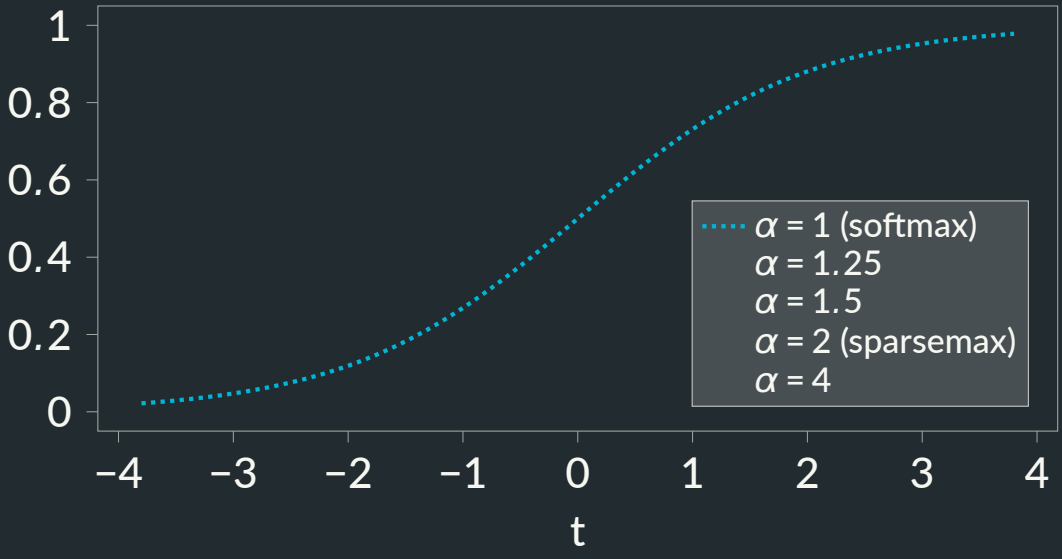
Key result: **can be sparse for** $\alpha > 1$, propensity for sparsity increases with α.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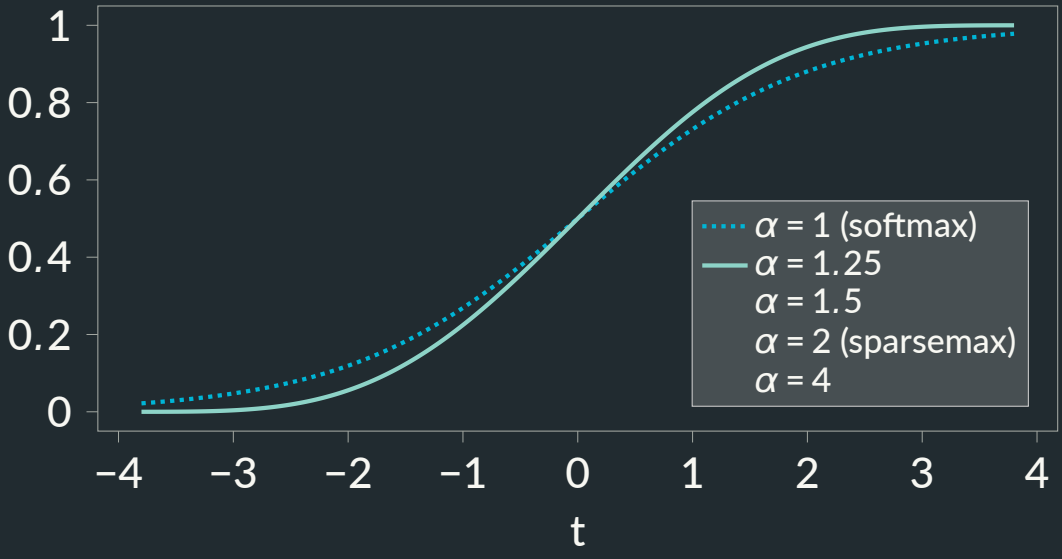
α = 1 (softmax)
α = 1.25
α = 1.5
α = 2 (sparsemax)
α = 4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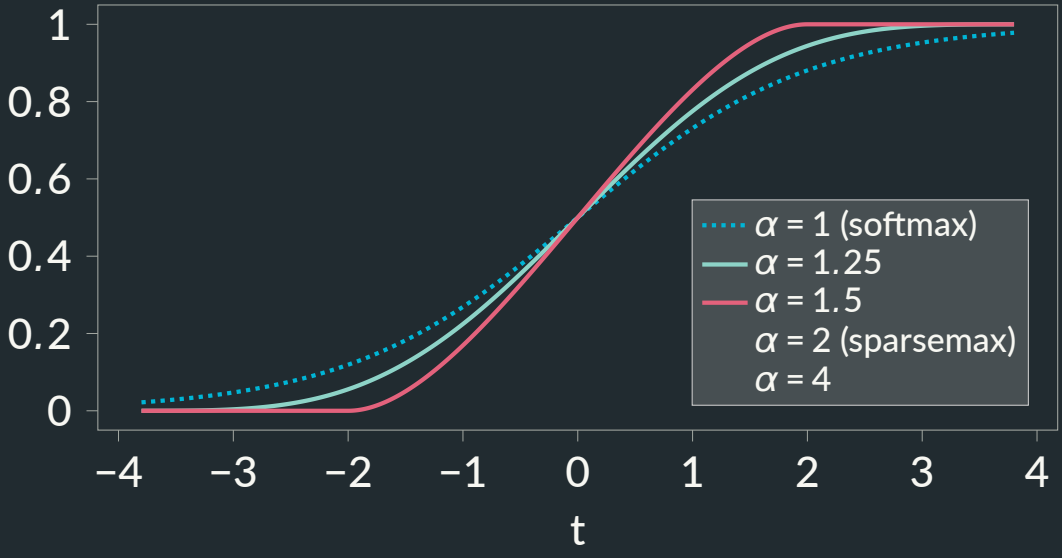
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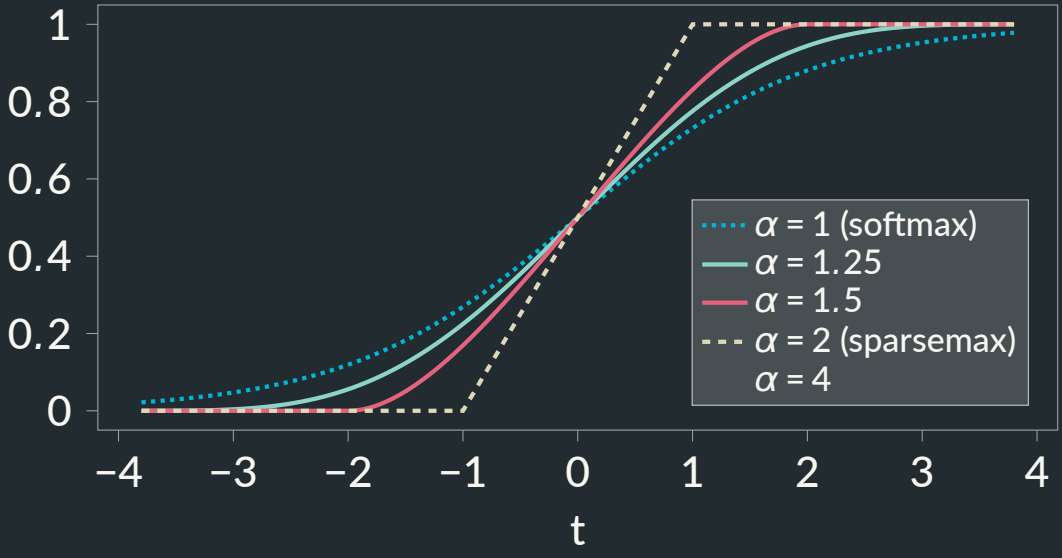
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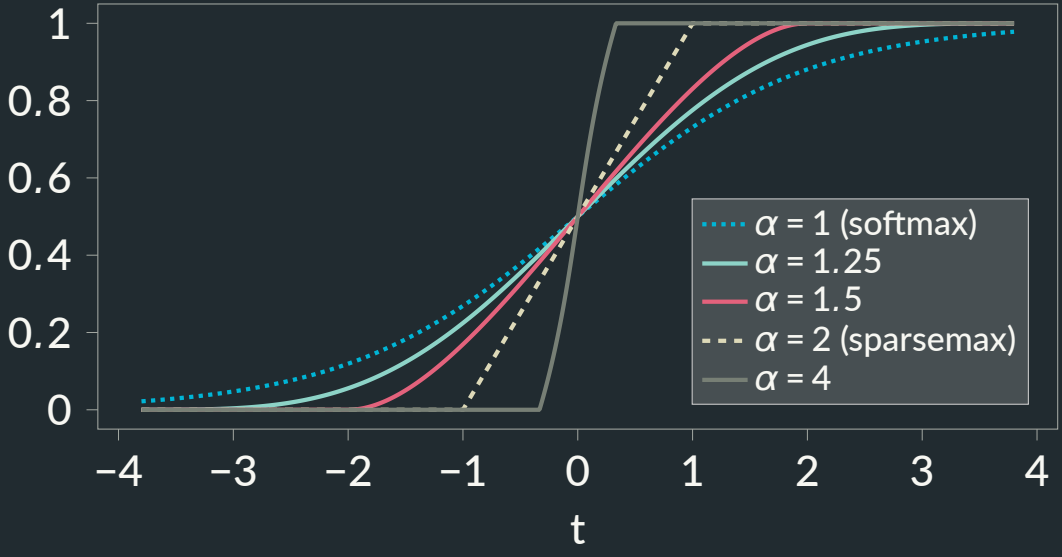
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Learning α

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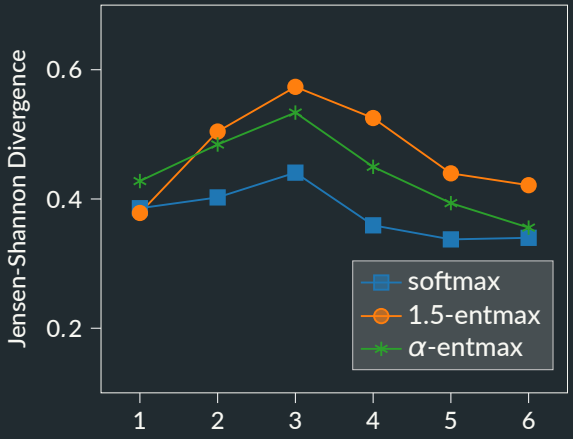
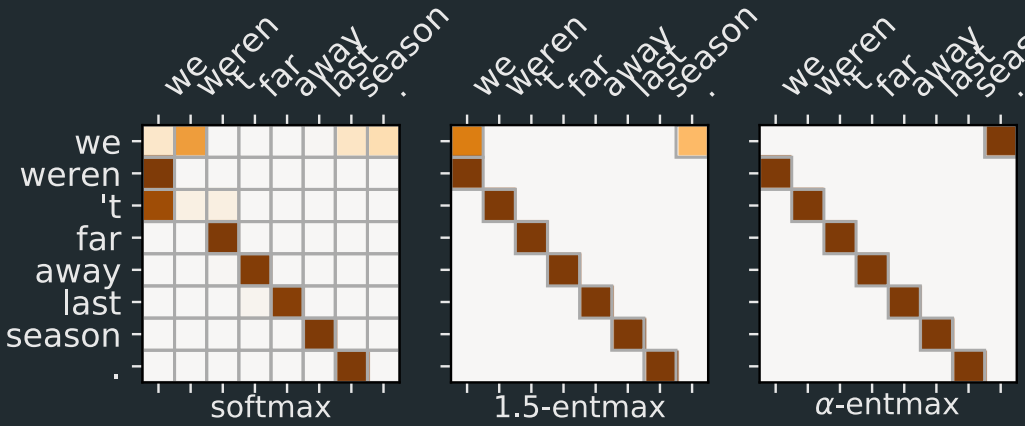
Key contribution:

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

Head diversity per layer

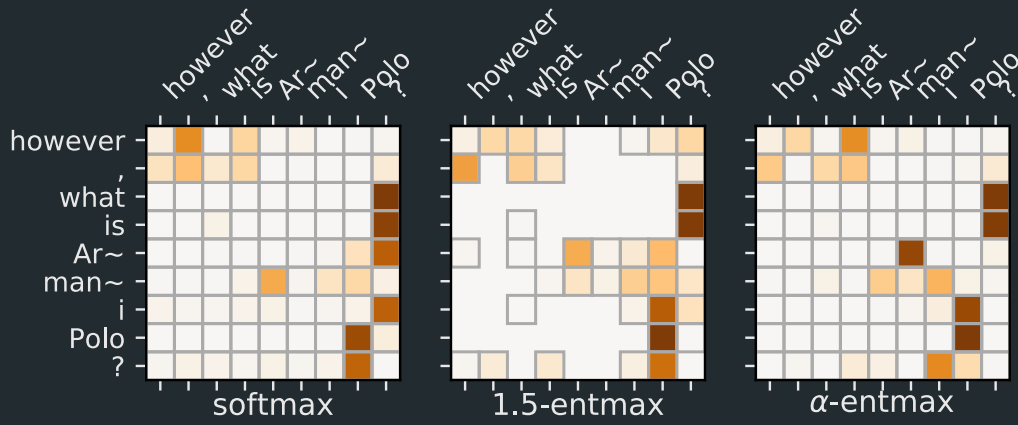


Previous position head



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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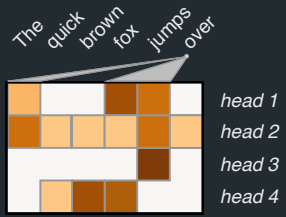
adaptive sparsity



Key takeaways

Introduce adaptive sparsity
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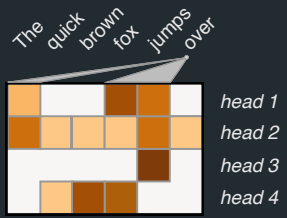
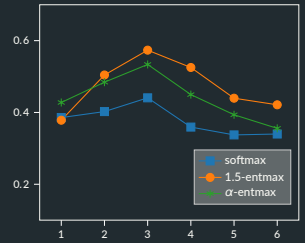


reduced head redundancy



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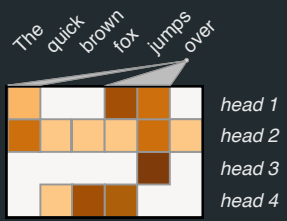

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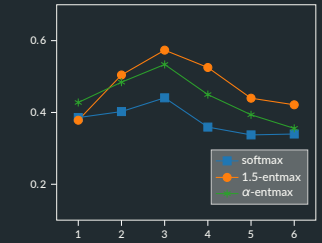
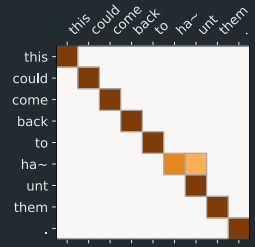


clearer head roles



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Latent variable models

Latent variable z can be

Latent variable models

Latent variable z can be continuous

Source: Bouges et al., 2013

Latent variable models

Latent variable z can be continuous, discrete

Source: valleyeyecareaz.com

Latent variable models

Latent variable z can be continuous, discrete, or structured

Source: Liu et al., 2015

Training discrete or structured latent variable models

Latent variable z can be

Training discrete or structured latent variable models

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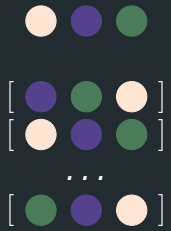
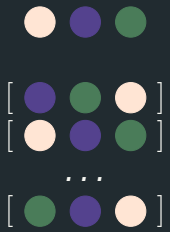
Latent variable z can be discrete or structured



Training discrete or structured latent variable models

Latent variable z can be discrete or structured

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



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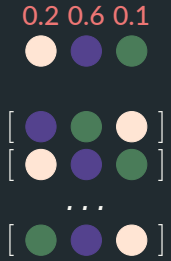

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If $\mathcal{Z}$ is large, this sum can get very expensive due to $\ell(x, z; \theta)$! 😱

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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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(Martins and Astudillo, 2016; Niculae, Martins, et al., 2018)

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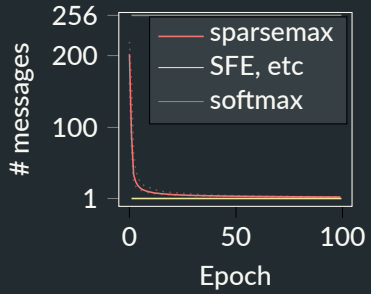

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Results

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Our methods are top-performers and efficient!

Key takeaways

We introduce a new method
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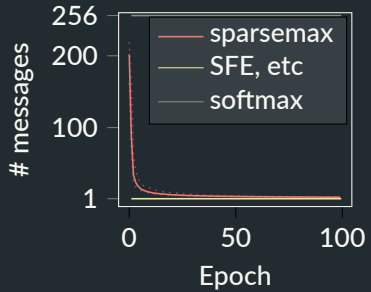

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dual-source transformer (8M)	71.72
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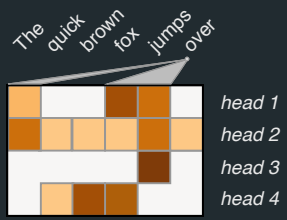

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better & efficient compactness

References I

- Bouges, Pierre, Thierry Chateau, Christophe Blanc, and Gaëlle Loosli (Dec. 2013). “Handling missing weak classifiers in boosted cascade: application to multiview and occluded face detection”. In: *EURASIP Journal on Image and Video Processing* 2013, p. 55. DOI: 10.1186/1687-5281-2013-55.
- Correia, Gonçalo M., Vlad Niculae, Wilker Aziz, and André F. T. Martins (2020). “Efficient Marginalization of Discrete and Structured Latent Variables via Sparsity”. In: *Proc. NeurIPS*. URL: https://arxiv.org/abs/2007.01919.
- Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2019). “BERT: Pre-training of deep bidirectional transformers for language understanding”. In: *Proc. NAACL-HLT*.
- Junczys-Dowmunt, Marcin and Roman Grundkiewicz (2018). “MS-UEdin Submission to the WMT2018 APE Shared Task: Dual-Source Transformer for Automatic Post-Editing”. In: *Proceedings of WMT18*.
- Lazaridou, Angeliki, Alexander Peysakhovich, and Marco Baroni (2017). “Multi-agent cooperation and the emergence of (natural) language”. In: *Proc. ICLR*.
- Lee, Jihyung, WonKee Lee, Jaehun Shin, Baikjin Jung, Young-Kil Kim, and Jong-Hyeok Lee (2020). “POSTECH-ETRI’s Submission to the WMT2020 APE Shared Task: Automatic Post-Editing with Cross-lingual Language Model”. In: *Proceedings of WMT*.
- Liu, Ziwei, Ping Luo, Xiaogang Wang, and Xiaoou Tang (Dec. 2015). “Deep Learning Face Attributes in the Wild”. In: *Proceedings of International Conference on Computer Vision (ICCV)*.

References II

- Martins, André FT and Ramón Fernandez Astudillo (2016). “From softmax to sparsemax: A sparse model of attention and multi-label classification”. In: *Proc. of ICML*.
- Niculae, Vlad and Mathieu Blondel (2017). “A Regularized Framework for Sparse and Structured Neural Attention”. In: *arXiv preprint arXiv:1705.07704*.
- Niculae, Vlad, André FT Martins, Mathieu Blondel, and Claire Cardie (2018). “SparseMAP: Differentiable sparse structured inference”. In: *Proc. of ICML*.
- Peters, Ben, Vlad Niculae, and André F. T. Martins (2019). “Sparse Sequence-to-Sequence Models”. In: *Proceedings of the Annual Meeting of the Association for Computational Linguistics*.
- Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin (2017). “Attention Is All You Need”. In: *Proc. of NeurIPS*.
- Voita, Elena, David Talbot, Fedor Moiseev, Rico Sennrich, and Ivan Titov (2019). “Analyzing multi-head self-attention: Specialized heads do the heavy lifting, the rest can be pruned”. In: *Proc. ACL*.

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

(Niculae and Blondel, 2017)

Ω-Regularized Argmax

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

$$\textbf{argmax}_{\Omega}(\boldsymbol{z}) := \operatorname*{arg\,max}_{\boldsymbol{p} \in \triangle} \boldsymbol{z}^\top \boldsymbol{p} - \Omega(\boldsymbol{p})$$

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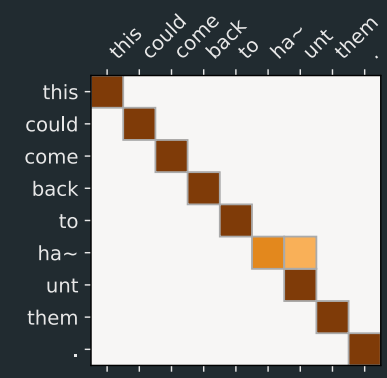
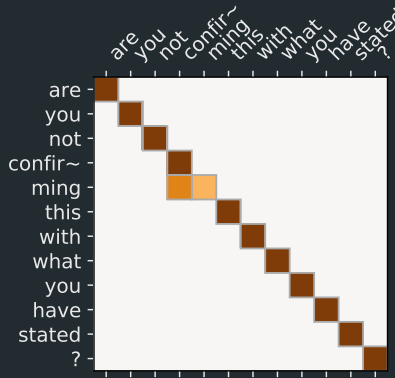
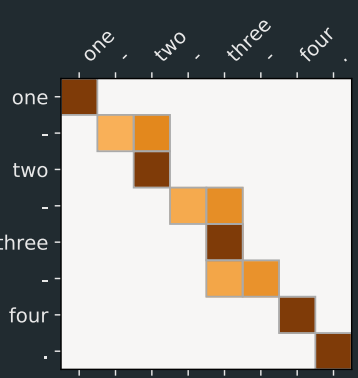
Is there something in-between?

Subword-Merging Head







Learned $\alpha = 1.91$.

Semi-Supervised VAE

$$\mathcal{L}_x(\theta) = \sum_{z \in \mathcal{Z}} \pi(z|x)\, \ell(x, z)$$
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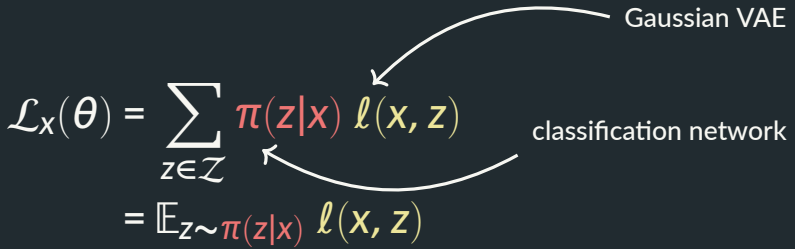
- Semi-Supervised VAE on MNIST: z is one of 10 categories

Semi-Supervised VAE



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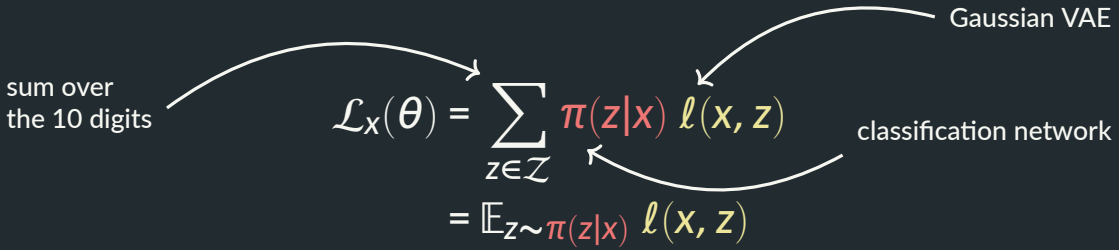

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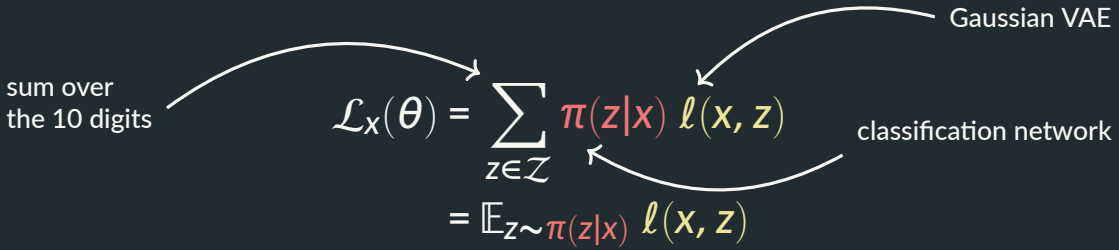

- Semi-Supervised VAE on MNIST: z is one of 10 categories
- Train this with 10% labeled data

Semi-Supervised VAE

Method	Accuracy (%)	Dec. calls
Monte Carlo		
SFE	94.75±.002	1
SFE+	96.53±.001	2
NVIL	96.01±.002	1
Gumbel	95.46±.001	1
Marginalization		
Dense	96.93±.001	10

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Dense	96.93±.001	10
Sparse	96.87±.001	1.01±0.01

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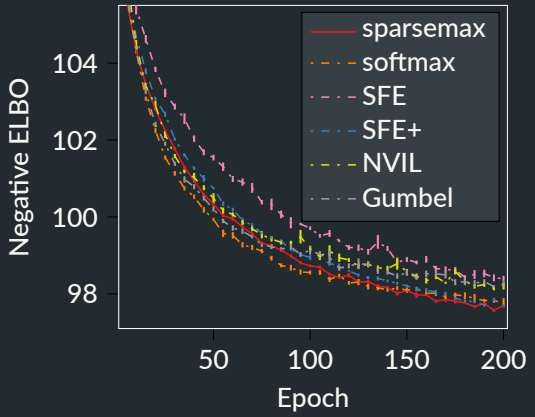

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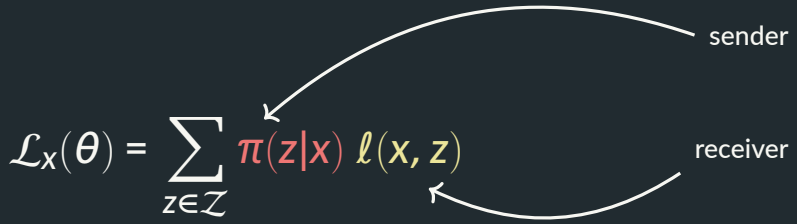

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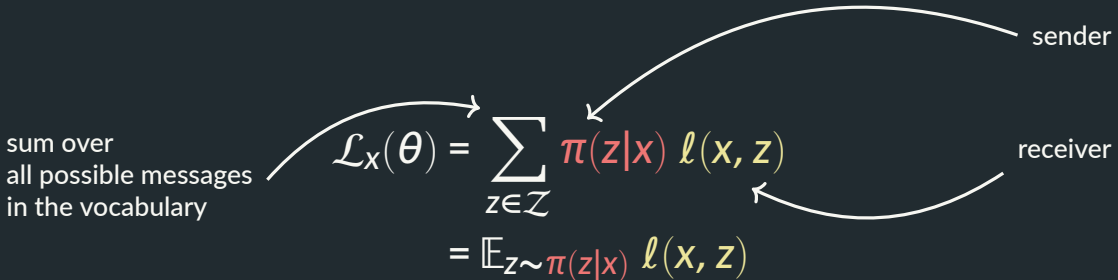

- receiver picks image from a set $\mathcal{V}$ based on message
- images come from ImageNet

(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
Gumbel	23.51 ±16.19	1
ST Gumbel	27.42 ±13.36	1
Marginalization		

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

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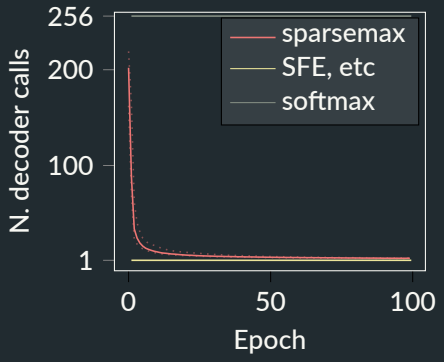
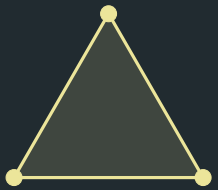
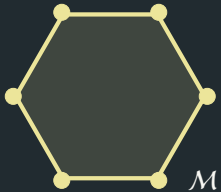


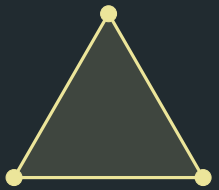


Δ

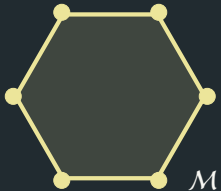


$\mathcal{M}$

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

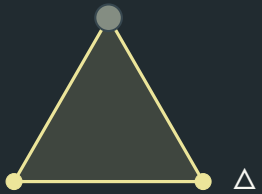


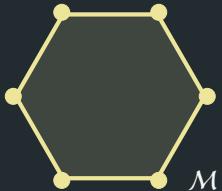
Δ



$\mathcal{M}$

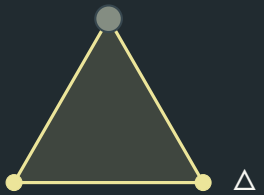
- **argmax** $\arg\max_{p \in \Delta} p^\top s$

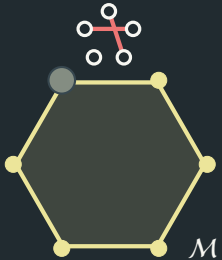




argmax $\arg\max_{\boldsymbol{p} \in \triangle} \boldsymbol{p}^\top \boldsymbol{s}$

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





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

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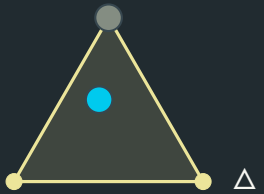

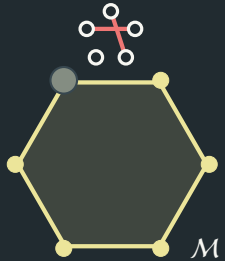

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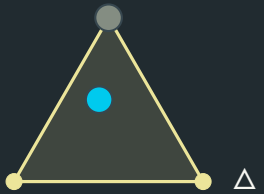
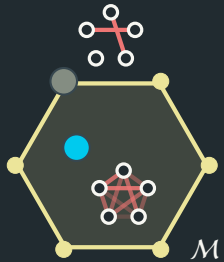


- **MAP** $\arg\max_{\boldsymbol{\mu} \in \mathcal{M}} \boldsymbol{\mu}^\top \boldsymbol{t}$
- **marginals** $\arg\max_{\boldsymbol{\mu} \in \mathcal{M}} \boldsymbol{\mu}^\top \boldsymbol{t} + \widetilde{\mathrm{H}}(\boldsymbol{\mu})$



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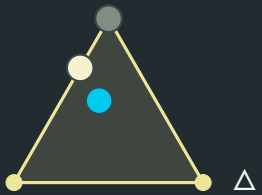

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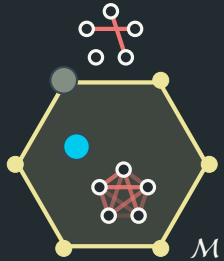

(Niculae, Martins, Blondel, and Cardie, 2018)

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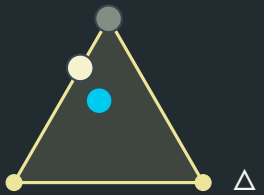
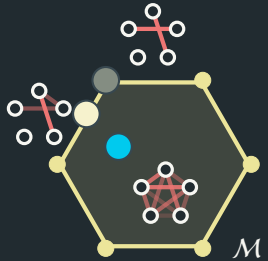
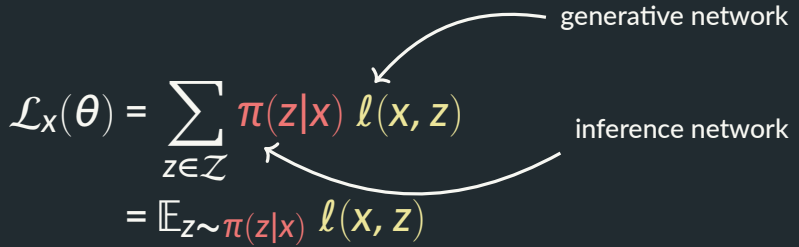




Bit-vector VAE

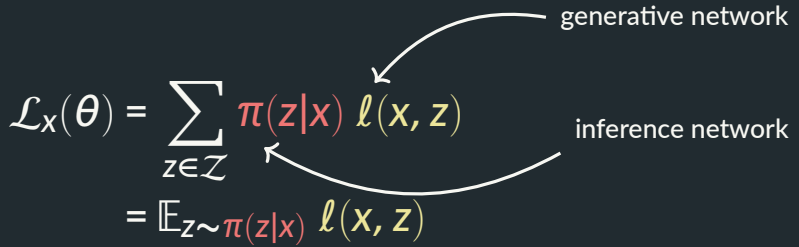
$$\mathcal{L}_x(\theta) = \sum_{z \in \mathcal{Z}} \pi(z|x)\, \ell(x, z)$$
$$= \mathbb{E}_{z \sim \pi(z|x)}\, \ell(x, z)$$

Bit-vector VAE



- VAE where z is a collection of D bits

Bit-vector VAE



- VAE where z is a collection of D bits
- Minimize the negative ELBO

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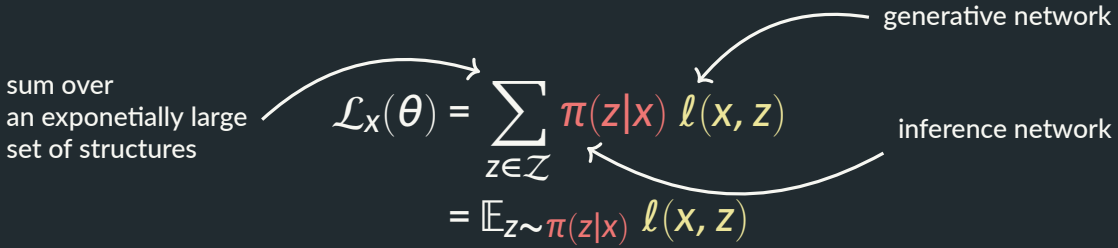

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Bit-vector VAE

Method	$D = 32$	$D = 128$
Monte Carlo		
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SFE+	3.61	3.59
NVIL	3.65	3.60
Gumbel	3.57	3.49
Marginalization		
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SparseMAP	3.72	3.67
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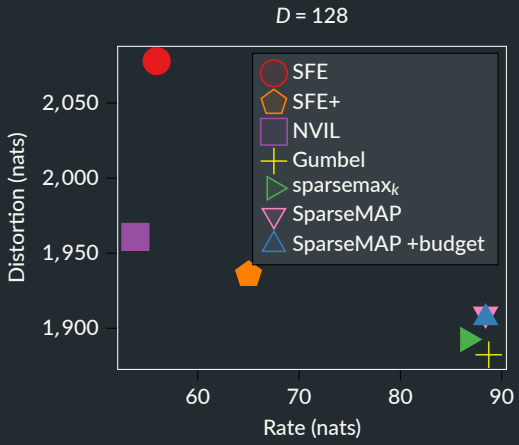

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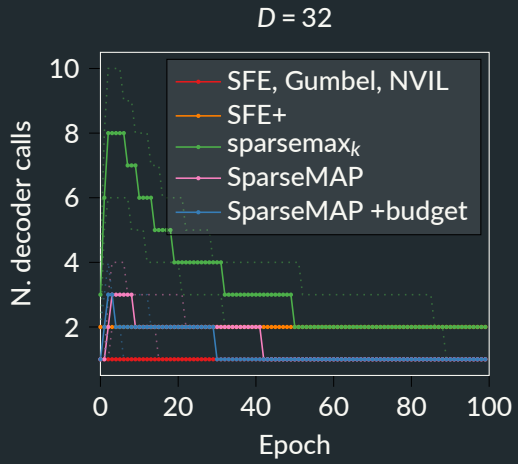

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