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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- Powerful tool for learning representations of any data
- Remarkable results

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Deep learning successes

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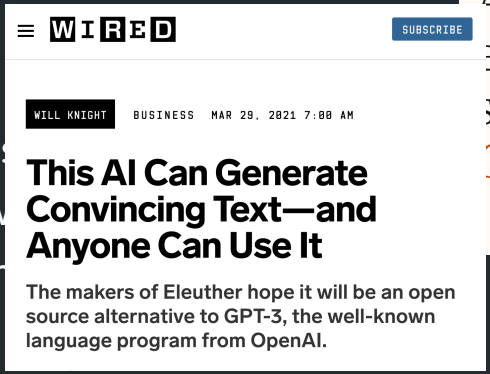
- Pow
- Rem



Deep learning successes

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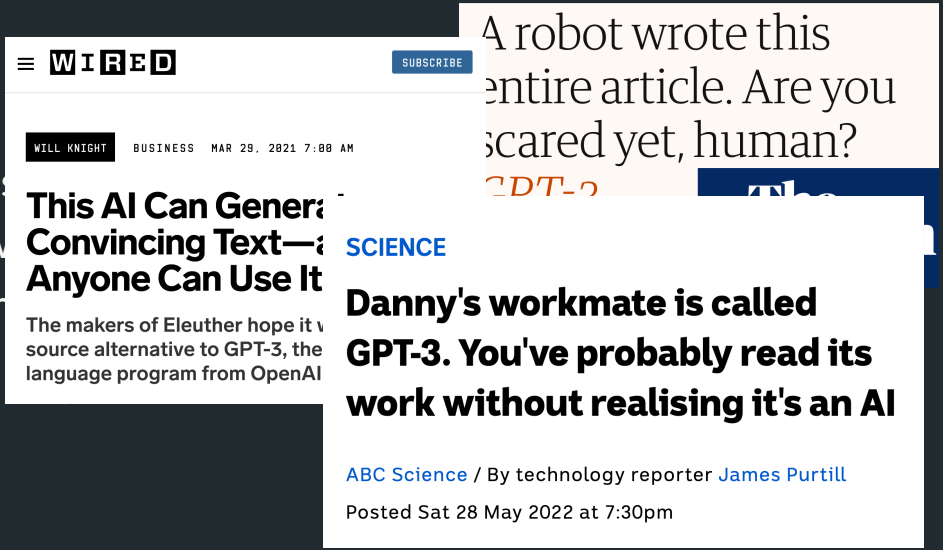
- Pow
- Rem



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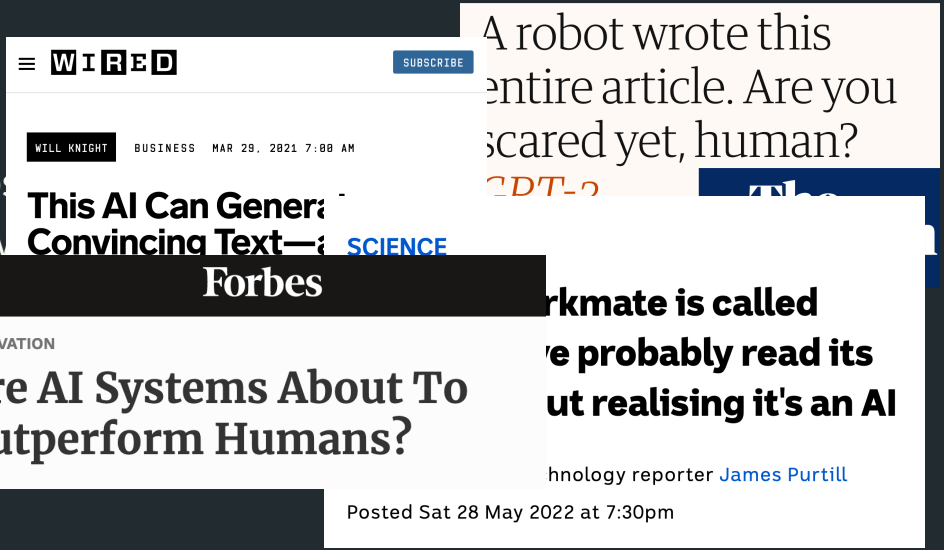

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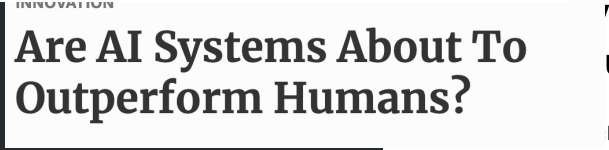

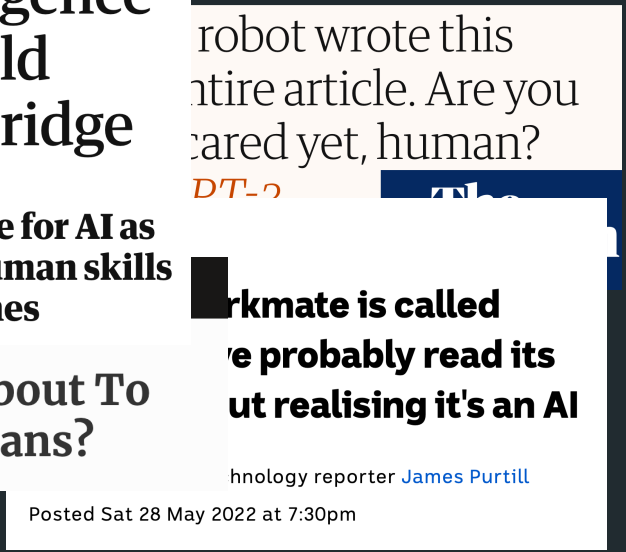

Deep learning successes

Artificial intelligence beats eight world champions at bridge

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

INNOVATION

Are AI Systems About T Outperform Humans?

Posted Sa

robot wrote this

AI 'outperforms' doctors diagnosing breast cancer

Fergus Walsh
Medical correspondent
@BBCFergusWalsh

Deep learning limitations and drawbacks

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- Requires a lot of data

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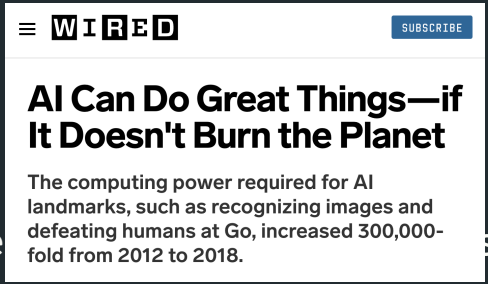
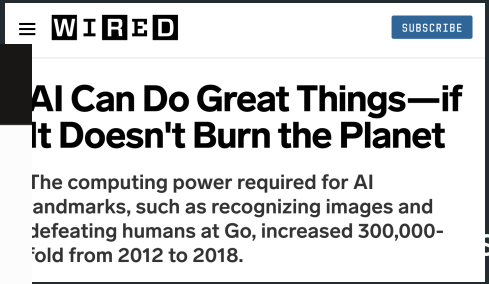


Deep learning limitations and drawbacks

- Req
- Har
- Req



sions

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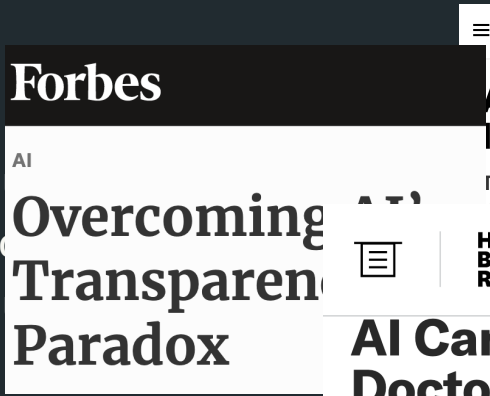

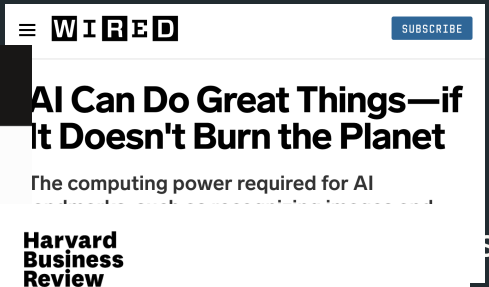

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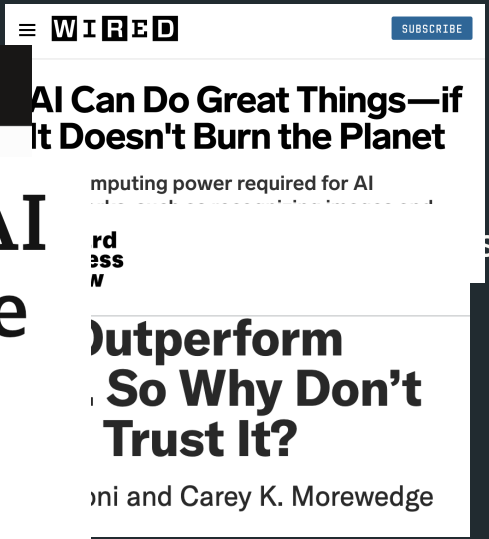

- R
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sions

Key concepts of this thesis

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Learnable Sparsity and **Weak Supervision**
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Neural Models

Published work of this thesis

(Correia and Martins, 2019)

Published work of this thesis

- Automatic Post-Editing using weak supervision for data-efficiency (ACL)

(Correia, Niculae, and Martins, 2019)

Published work of this thesis

- Automatic Post-Editing using weak supervision for data-efficiency (ACL)
- Letting transformer learn sparsity of its attentions for transparency (EMNLP)

(Correia, Niculae, Aziz, and Martins, 2020a)

Published work of this thesis

- Automatic Post-Editing using weak supervision for data-efficiency (ACL)
- Letting transformer learn sparsity of its attentions for transparency (EMNLP)
- General strategy for efficiently training discrete latent variable models, to have compactness (NeurIPS)

Table of Contents

(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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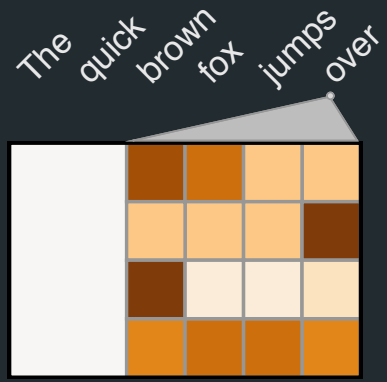

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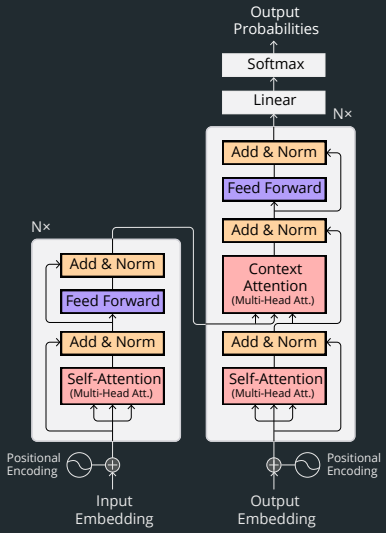

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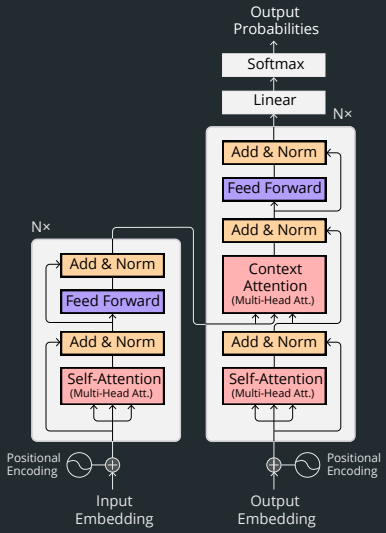
- Inspiration for big general-purpose models like BERT and GPT-3!



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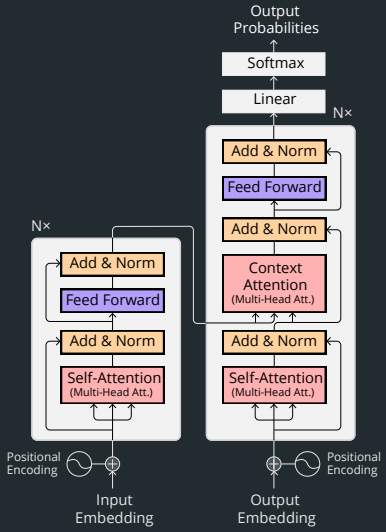

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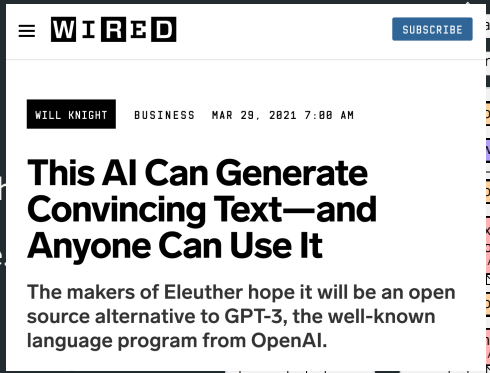
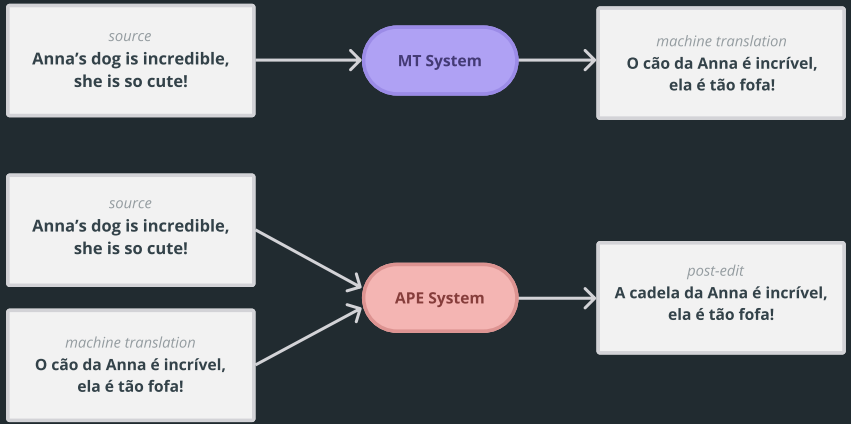


What is APE?


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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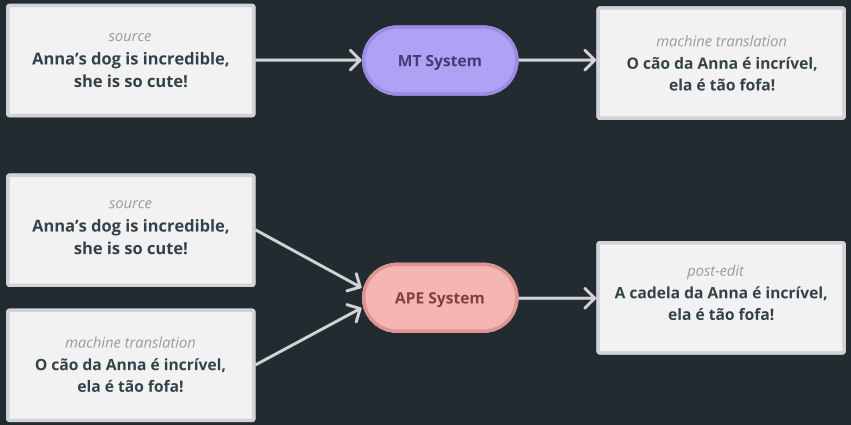
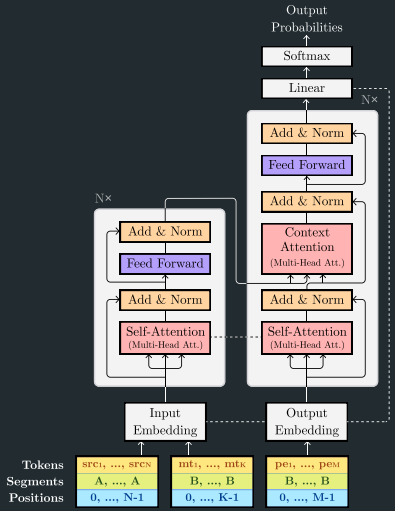
APE System
post-edit
A cadela da Anna é incrível, ela é tão fofa!

What is APE?



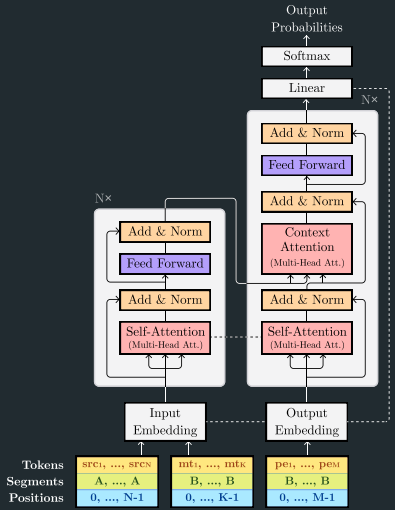
Challenge: APE data is very scarce! Need to create artificial data.

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
Add & Norm
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

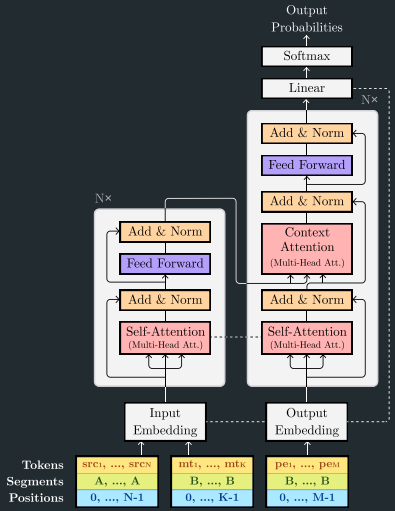
Key idea: Use BERT to do APE



BERT for APE

Key idea: Use BERT to do APE

- Prior to this work, BERT was mainly used for simple classification tasks



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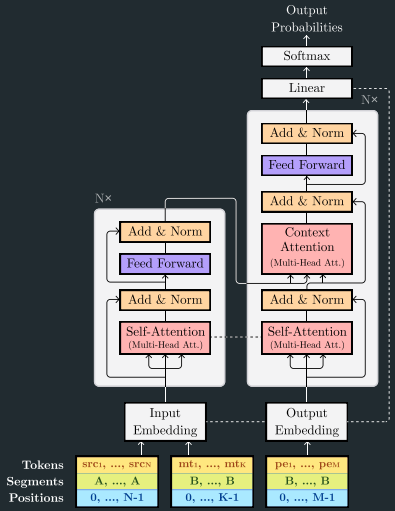
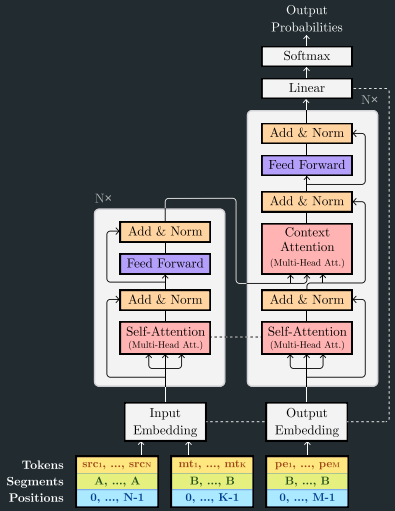
- We introduced an effective method to use BERT in a generation task (APE)



BERT for APE

Key idea: Use BERT to do APE

- 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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(Junczys-Dowmunt and Grundkiewicz, 2018)

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dual-source transformer (23K)	27.73	59.78

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ours (23K)	19.03	70.66

Key results

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ours (23K)	19.03	70.66
ours (8M)	17.26	73.42

(Lee et al., 2020; Kodama et al., 2020)

Conclusions and impact

(Lee et al., 2020; Kodama et al., 2020)

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- One of pioneers in using pre-trained transformer encoders for a generation task

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Conclusions and impact

- One of pioneers in using pre-trained transformer encoders for a generation task
- Massive improvement in low-resource scenario (data-efficiency)
- Steered SOTA of APE towards using weak supervision through pre-trained models
- Inspired other works that use scarse data (*e.g.*, dialogue with metadata)

Table of Contents

Getting to know attention heads better

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Our solution is to bet on sparsity:

- for interpretability
- for discovering linguistic structure
- for efficiency

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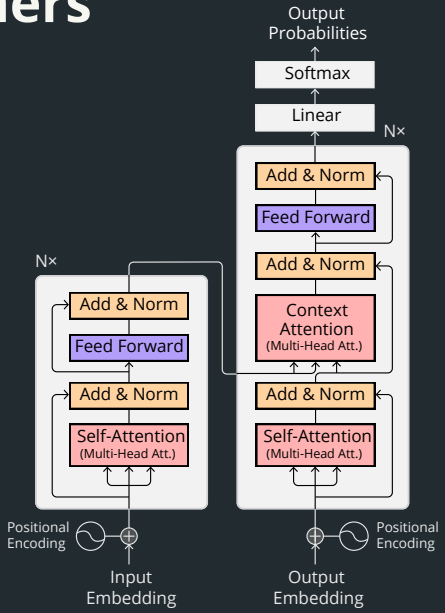
(Vaswani et al., 2017)

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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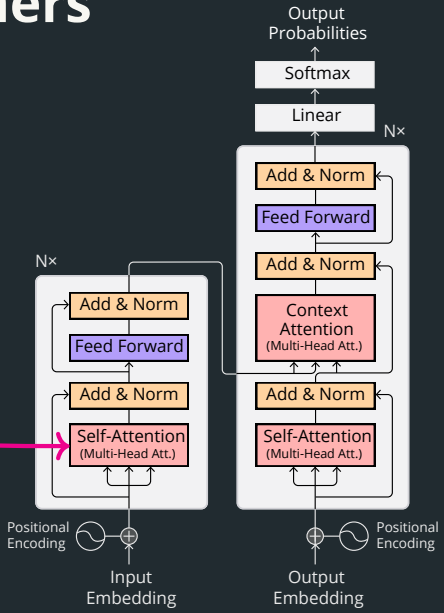

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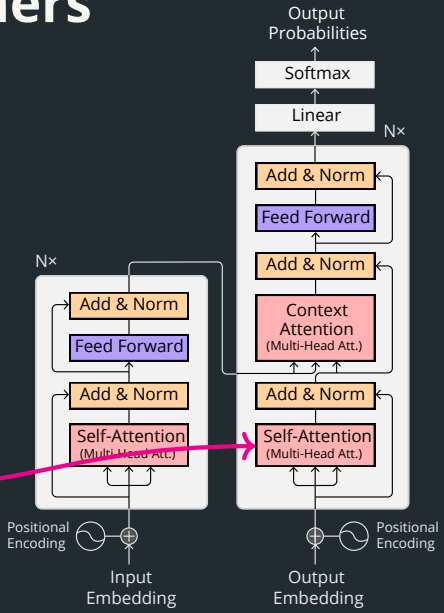

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Transformers

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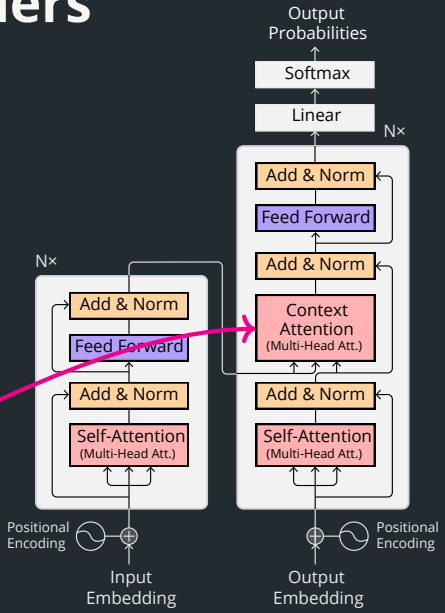
Attention in three places:

- 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:

$$\textbf{softmax}(z_i) := \frac{\exp(z_i)}{\sum_j \exp(z_j)}$$

What is softmax?

Softmax exponentiates and normalizes:

$$\textbf{softmax}(z_i) := \frac{\exp(z_i)}{\sum_j \exp(z_j)}$$

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

(Peters et al., 2019)

α-entmax

Parametrized by $\alpha \geq 0$:

(Peters et al., 2019)

α-entmax

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

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Parametrized by $\alpha \geq 0$:

- **Argmax** corresponds to $\alpha \to \infty$
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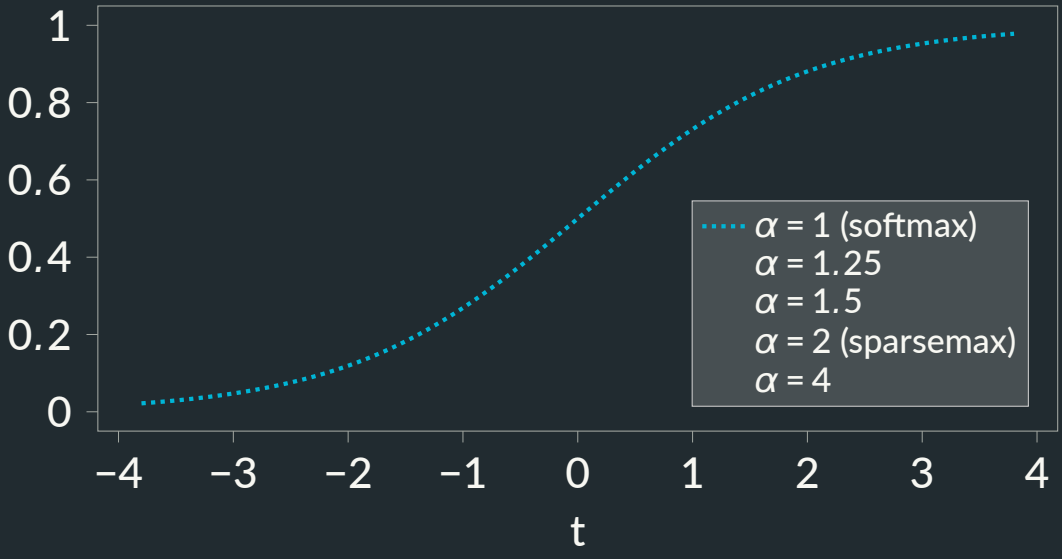
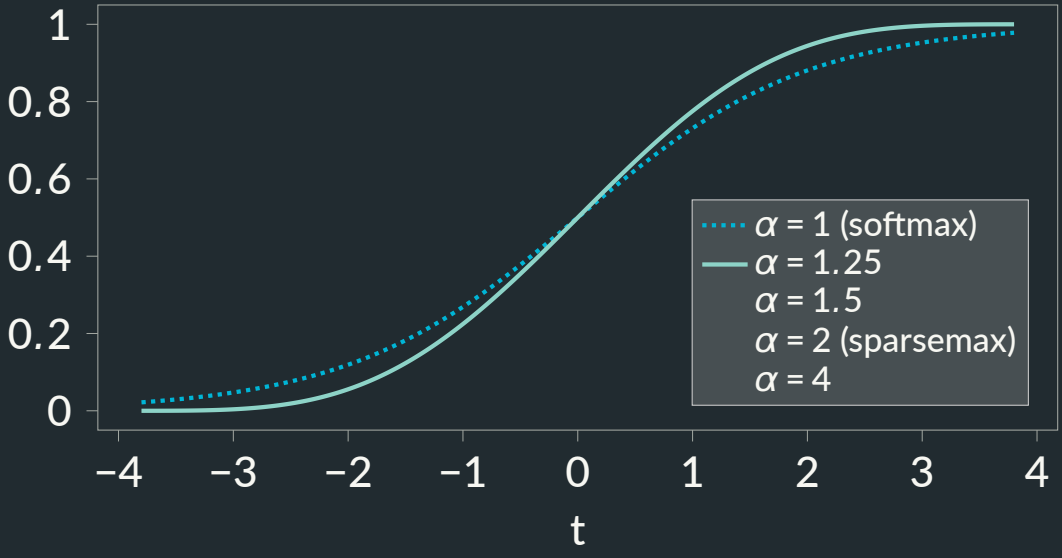
Key result: **can be sparse for** $\alpha > 1$, propensity for sparsity increases with α.


1
0.8
0.6
0.4
0.2
0
−4
−3
−2
−1
0
1
2
3
4
t
α = 1 (softmax)
α = 1.25
α = 1.5
α = 2 (sparsemax)
α = 4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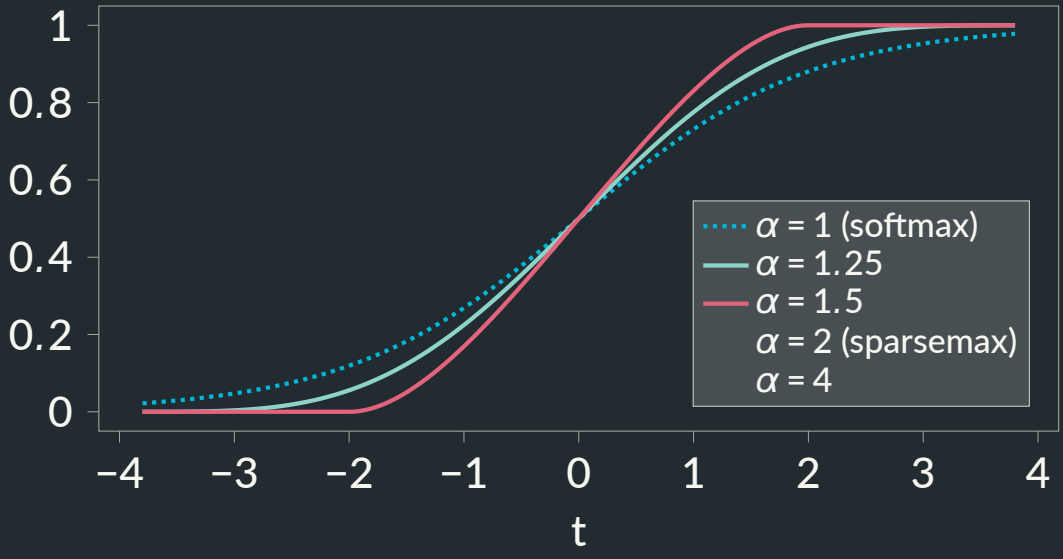
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t
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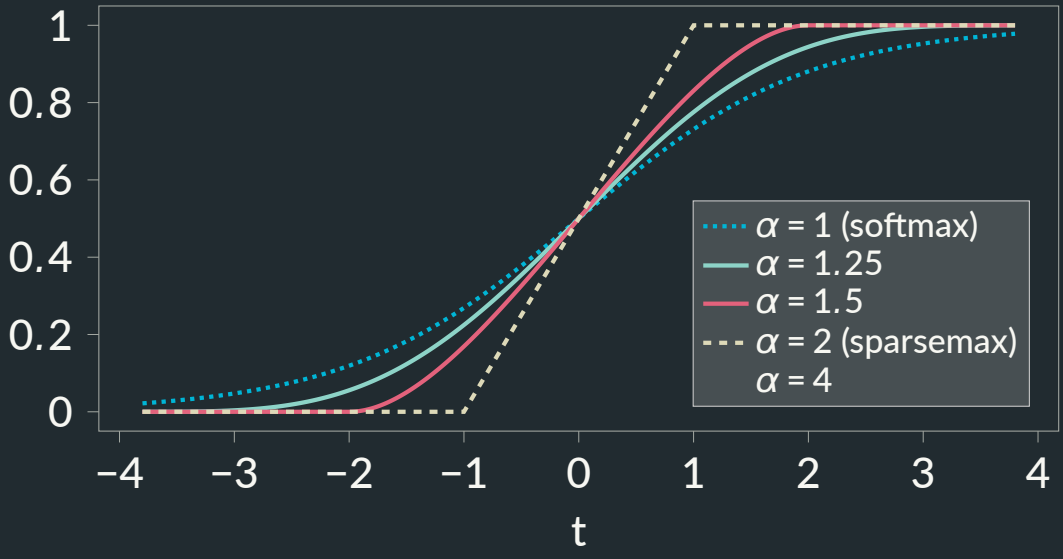
α = 1.25
α = 1.5
α = 2 (sparsemax)
α = 4


1
0.8
0.6
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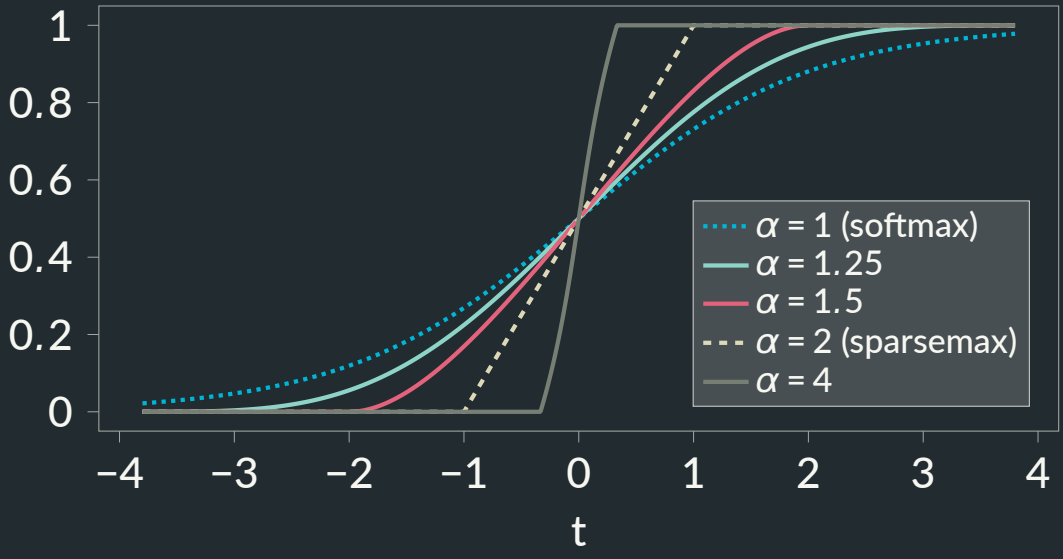
t
α = 1 (softmax)
α = 1.25
α = 1.5
α = 2 (sparsemax)
α = 4


1
0.8
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−1
0
1
2
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4
t
α = 1 (softmax)
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α = 4

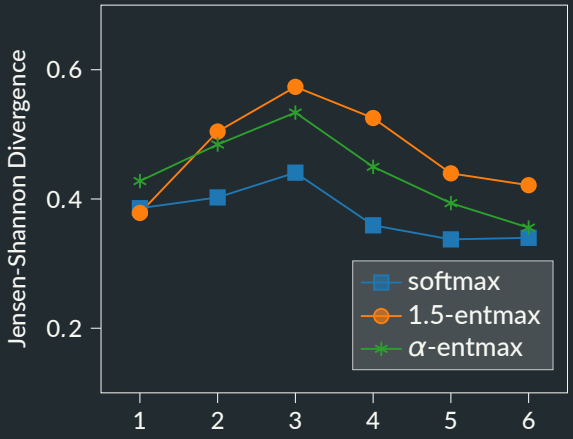
Learning α

Learning α

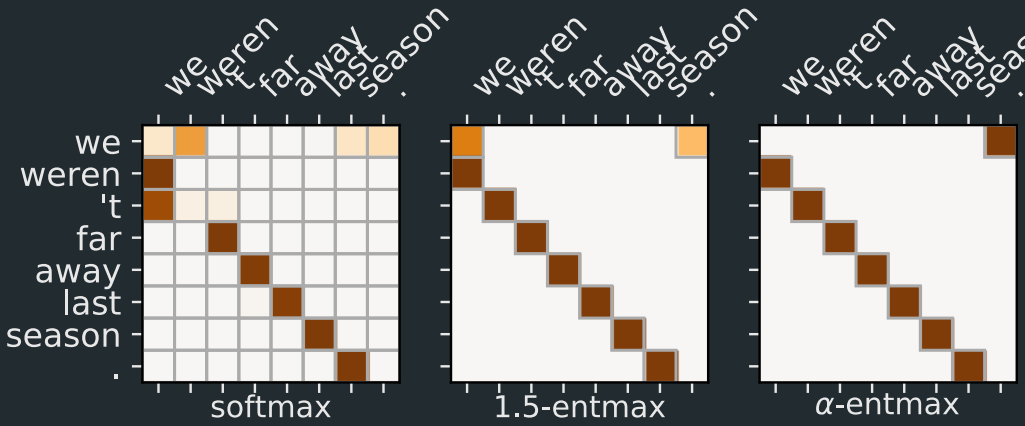
Key contribution:

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

Head diversity per layer

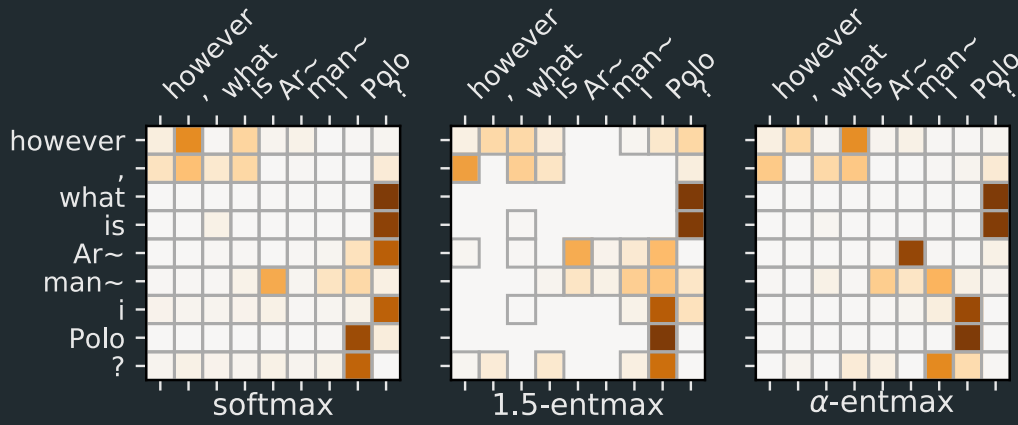


Previous position head



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

Interrogation-detecting head



Learned $\alpha = 1.05$.

Conclusions and impact

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

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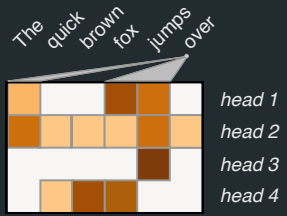

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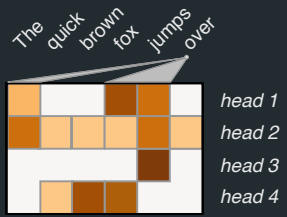
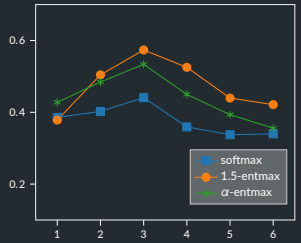


reduced head redundancy



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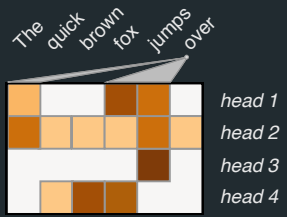

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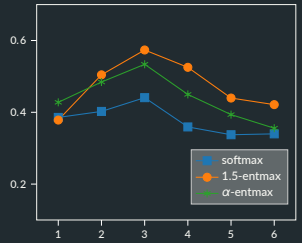
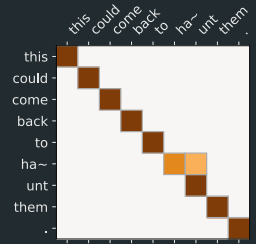


clearer head roles



(Treviso et al., 2022; Zhang et al., 2021; Raganato et al., 2020)

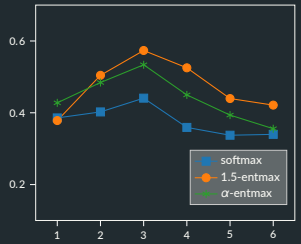
Conclusions and impact

Subsequent work has:

- focused on taking computational advantage of sparsity
- proposed other sparse activations (*e.g.*, ReLU)
- incorporated fixed attention patterns that we found.

adaptive sparsity

reduced head redundancy



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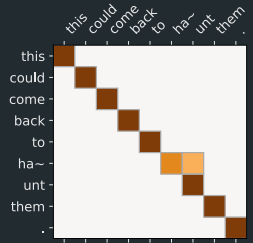


Table of Contents

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

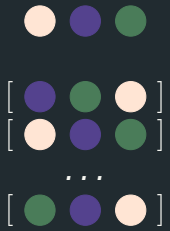
Latent variable z can be

Training Discrete or Structured Latent Variable Models

Latent variable z can be discrete

Training Discrete or Structured Latent Variable Models

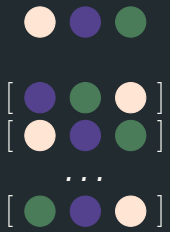
Latent variable z can be discrete or structured



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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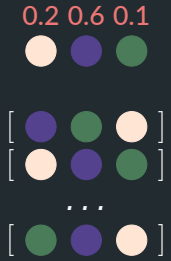

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If $\mathcal{Z}$ is large, this sum can get very expensive due to $\ell(x, z; \theta)$! 😱

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

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If $\mathcal{Z}$ is large, exact gradient computation is prohibitive

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Taking a step back...

Does the expectation over possible z need to be expensive?

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$$\begin{aligned}\mathcal{L}_x(\theta) &= \sum_{z \in \mathcal{Z}} \pi(z|x, \theta)\, \ell(x, z; \theta) \\ &= \pi(z_1|x, \theta)\, \ell(x, z_1; \theta) + \pi(z_2|x, \theta)\, \ell(x, z_2; \theta) + \ldots \\ &+ \pi(z_i|x, \theta)\, \ell(x, z_i; \theta) + \ldots + \pi(z_N|x, \theta)\, \ell(x, z_N; \theta)\end{aligned}$$

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Usually we normalize π with softmax $\propto \exp(s) \Rightarrow \pi(z_i\,|x, \theta) > 0$

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

Sparse normalizers

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

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

$$= \pi(z_1|x, \theta)\, \ell(x, z_1; \theta) + \underbrace{\pi(z_2|x, \theta)}_{=0}\, \cancel{\ell(x, z_2; \theta)} + \ldots$$

$$+ \pi(z_i|x, \theta)\, \ell(x, z_i; \theta) + \ldots + \underbrace{\pi(z_N|x, \theta)}_{=0}\, \cancel{\ell(x, z_N; \theta)}$$

No need for computing $\ell(x, z; \theta)$ for all $z \in \mathcal{Z}$!

Results

We test our methods for models with discrete latent variables,

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- Semi-Supervised VAE

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Our methods are top-performers and efficient!

Key Takeaways

We introduce a new method
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$$\mathcal{L}_x(\theta) = \pi(z_1|x,\theta)\,\ell(x, z_1; \theta) + \pi(z_2|x,\theta)\,\ell(x, z_2; \theta) + \ldots + \pi(z_i|x,\theta)\,\ell(x, z_i; \theta) + \ldots + \pi(z_N|x,\theta)\,\ell(x, z_N; \theta)$$

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sparse, as needed

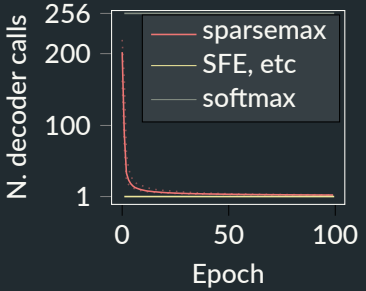

Table of Contents

References I

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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

(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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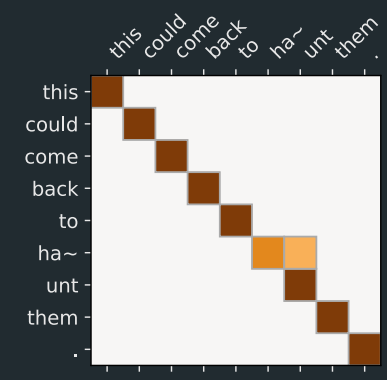
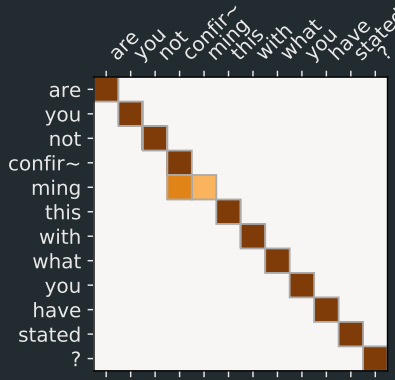
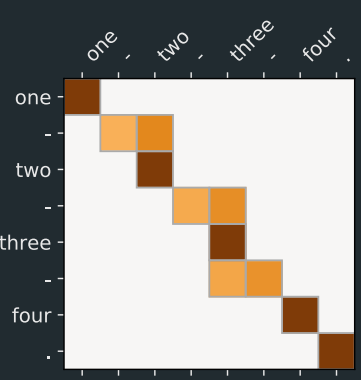
Is there something in-between?

Subword-Merging Head







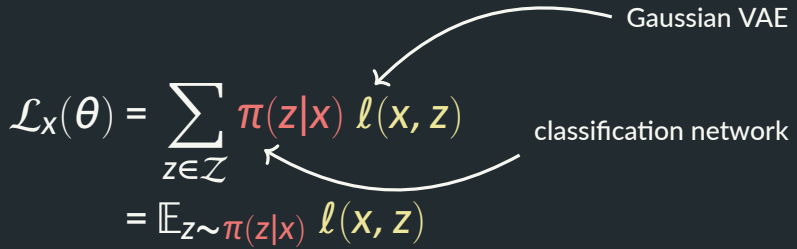
Learned $\alpha = 1.91$.

Semi-Supervised VAE

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

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

Semi-Supervised VAE



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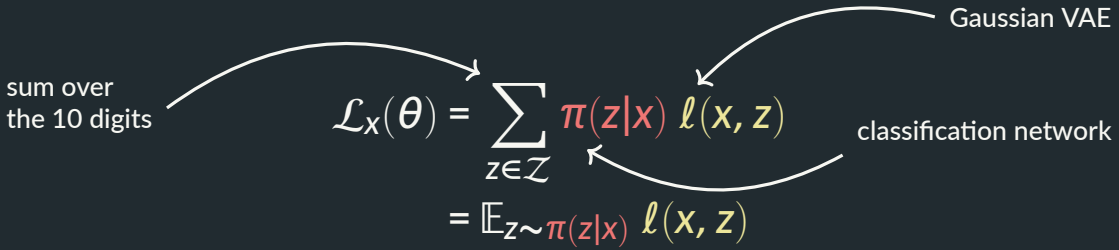
Semi-Supervised VAE



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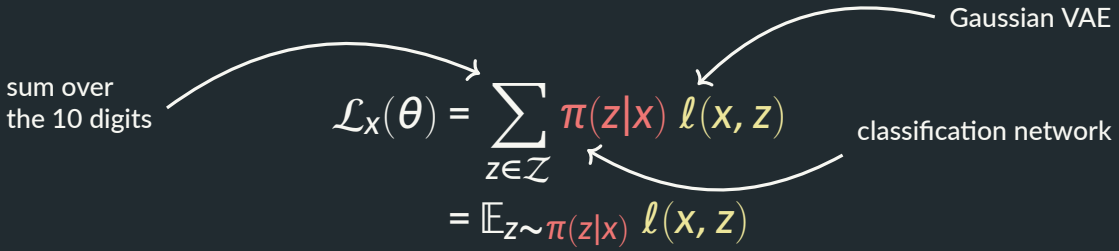
Semi-Supervised VAE



- 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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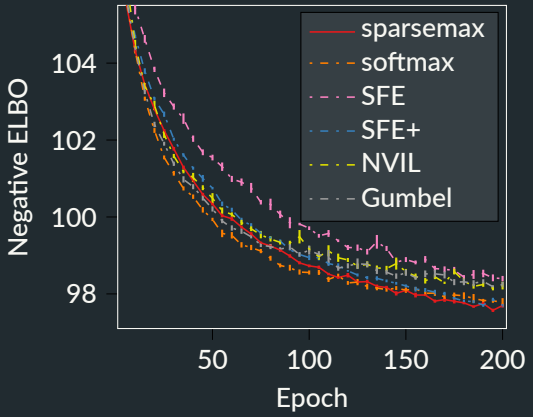

Emergent communication

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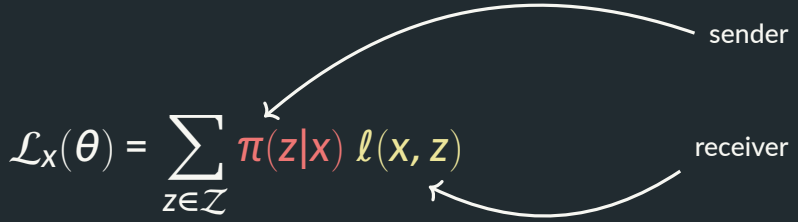
Emergent communication



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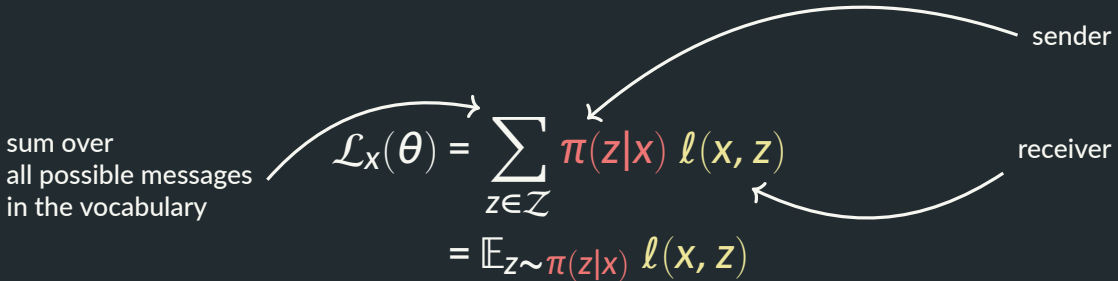
- receiver picks image from a set $\mathcal{V}$ based on message

Emergent communication



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

(Lazaridou et al., 2017; Correia, Niculae, Aziz, et al., 2020b)

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, Niculae, Aziz, et al., 2020b)

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Marginalization		
Dense	93.37 ±0.42	256

(Lazaridou et al., 2017; Correia, Niculae, Aziz, et al., 2020b)

Emergent Communication

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Marginalization		
Dense	93.37 ±0.42	256
Sparse	93.35 ±0.50	3.13 ±0.48

(Lazaridou et al., 2017; Correia, Niculae, Aziz, et al., 2020b)

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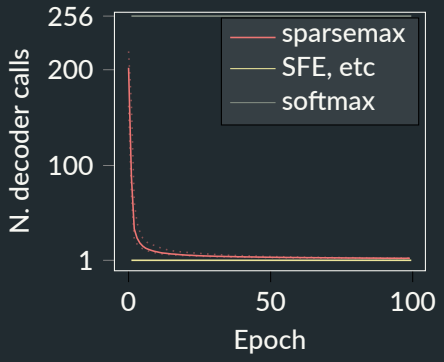
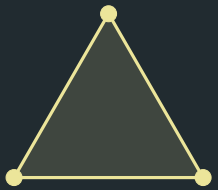
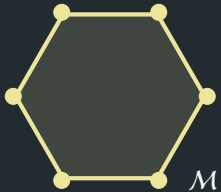


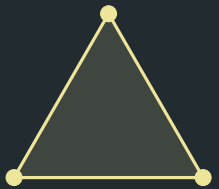


Δ

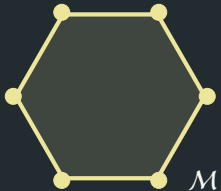


$\mathcal{M}$

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

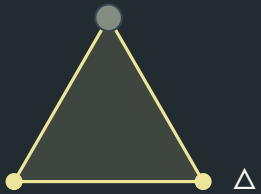


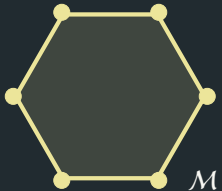
Δ



$\mathcal{M}$

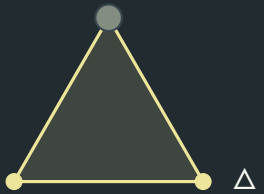
- **argmax** $\arg\max_{p \in \Delta} p^\top s$

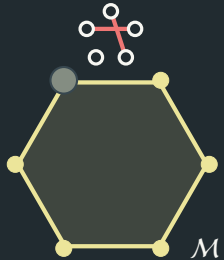




argmax $\arg\max_{\boldsymbol{p} \in \Delta} \boldsymbol{p}^\top \boldsymbol{s}$

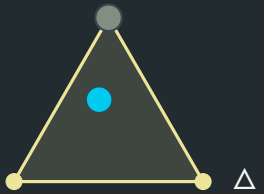
MAP $\arg\max_{\boldsymbol{\mu} \in \mathcal{M}} \boldsymbol{\mu}^\top \boldsymbol{t}$

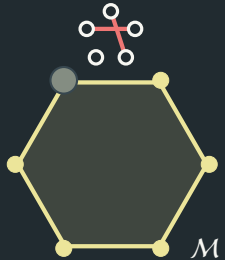




- **argmax** $\arg\max_{\boldsymbol{p} \in \Delta} \boldsymbol{p}^\top \boldsymbol{s}$
- **softmax** $\arg\max_{\boldsymbol{p} \in \Delta} \boldsymbol{p}^\top \boldsymbol{s} + \mathrm{H}(\boldsymbol{p})$

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





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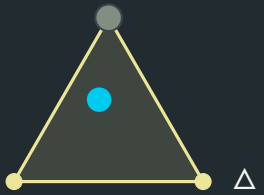
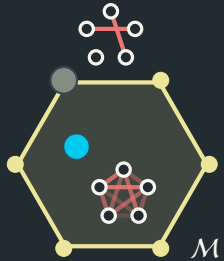
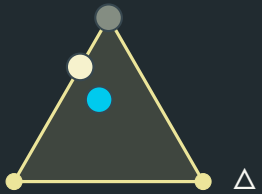


- **MAP** $\arg\max_{\boldsymbol{\mu} \in \mathcal{M}} \boldsymbol{\mu}^\top \boldsymbol{t}$
- **marginals** $\arg\max_{\boldsymbol{\mu} \in \mathcal{M}} \boldsymbol{\mu}^\top \boldsymbol{t} + \widetilde{\mathrm{H}}(\boldsymbol{\mu})$



- **argmax** $\arg\max_{p \in \triangle} p^\top s$
- **softmax** $\arg\max_{p \in \triangle} p^\top s + \mathrm{H}(p)$
- **sparsemax** $\arg\max_{p \in \triangle} p^\top s - \frac{1}{2}\|p\|^2$



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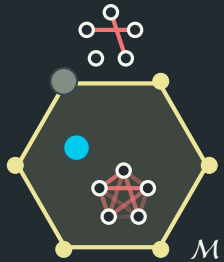

(Niculae, Martins, Blondel, and Cardie, 2018)

- **argmax** $\arg\max_{p \in \triangle} p^\top s$
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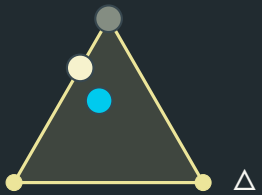
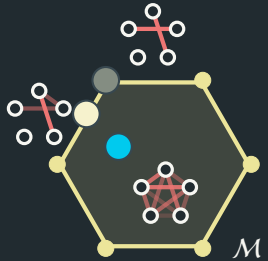
- **MAP** $\arg\max_{\mu \in \mathcal{M}} \mu^\top t$
- **marginals** $\arg\max_{\mu \in \mathcal{M}} \mu^\top t + \widetilde{\mathrm{H}}(\mu)$
- **SparseMAP** $\arg\max_{\mu \in \mathcal{M}} \mu^\top t - \frac{1}{2}\|\mu\|^2$





Bit-vector VAE

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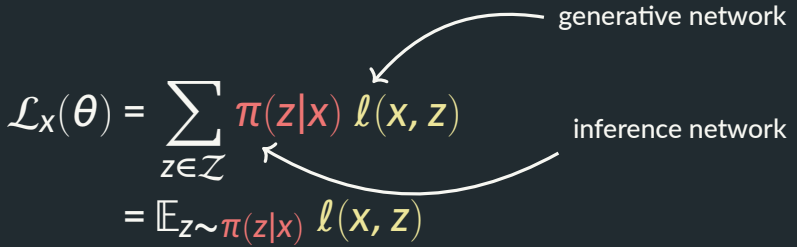
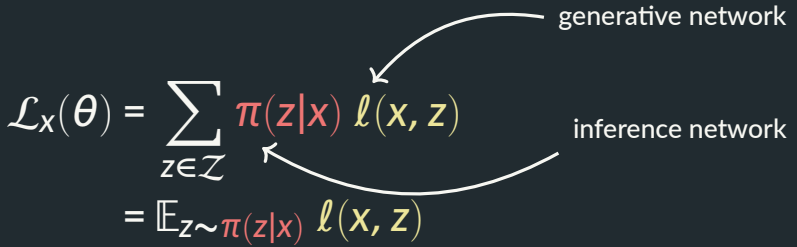
Bit-vector VAE



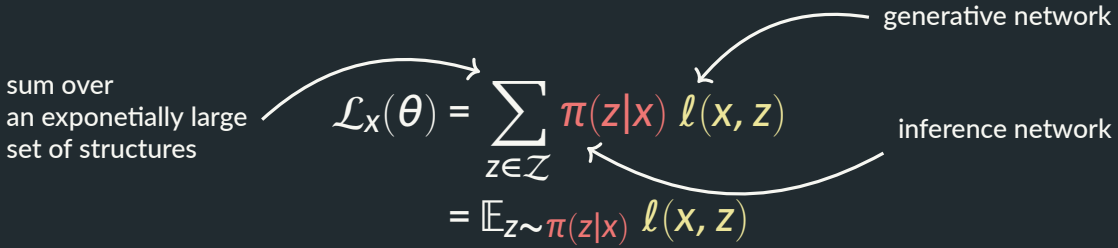
- VAE where z is a collection of D bits

Bit-vector VAE



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

Bit-vector VAE



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

Bit-vector VAE

Method	$D = 32$	$D = 128$
Monte Carlo		
SFE	3.74	3.77
SFE+	3.61	3.59
NVIL	3.65	3.60
Gumbel	3.57	3.49
Marginalization		
Top-k sparsemax	3.62	3.61
SparseMAP	3.72	3.67
SparseMAP (w/ budget)	3.64	3.66

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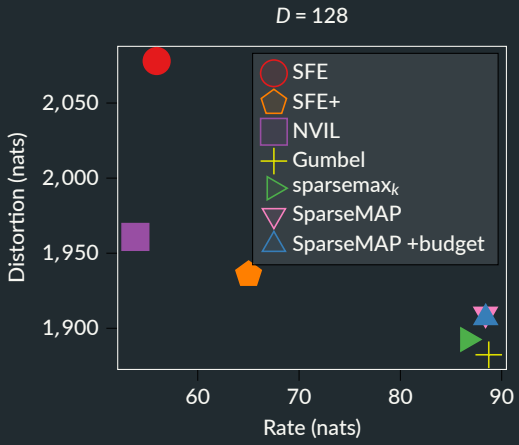

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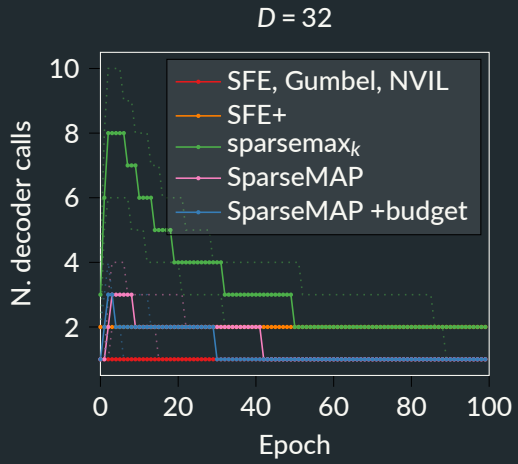

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