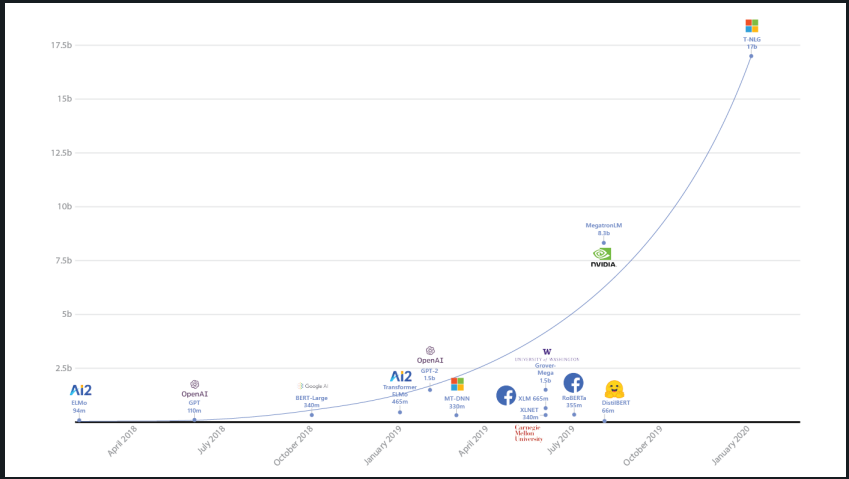
Thesis Proposal:

Neural Machine Translation with Latent Context

Gonçalo Correia

Committee: André Martins, Mário Figueiredo, Vlad Niculae, Wilker Aziz

Neural networks: big, uninterpretable, and powerful black-boxes?



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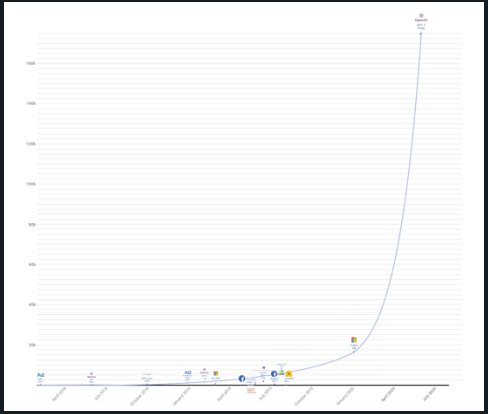

Key concepts of this thesis

- Transparency

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- Transparency
- Sparsity

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- Compactness

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- Data efficiency

(Brown et al., 1993)

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Neural Machine Translation (NMT)

- Advances in optimization → ditch structure in favour of direct decomposition

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- Advances in optimization → ditch structure in favour of direct decomposition
- Good for high-resource language, fails in low-resource settings

(Bahdanau et al., 2015)

A bit of context... On Seq2Seq

United Nations elections end today

Slide Credit: Vlad Niculae

(Bahdanau et al., 2015)

A bit of context… On Seq2Seq

Encoder

Slide Credit: Vlad Niculae

(Bahdanau et al., 2015)

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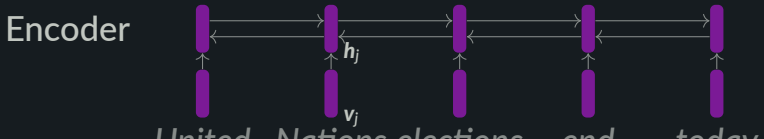

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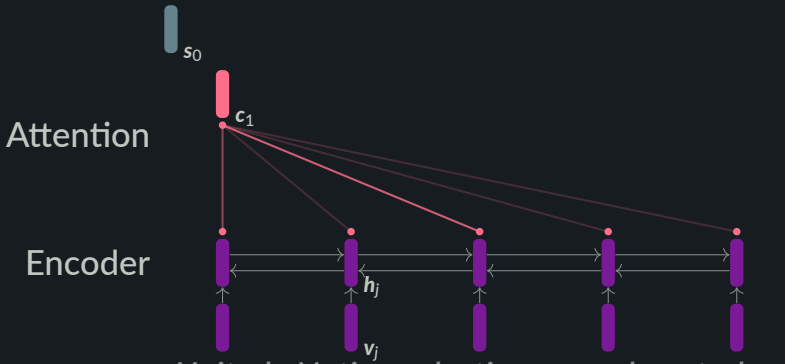

attention weights computed with *softmax*:

for some decoder state s_t, compute contextually weighted average of input c_t:

$$z_j = s_t^\top W^{(a)} h_j$$

$$\pi_j = \text{softmax}_j(z)$$

$$c_t = \sum_j \pi_j h_j$$

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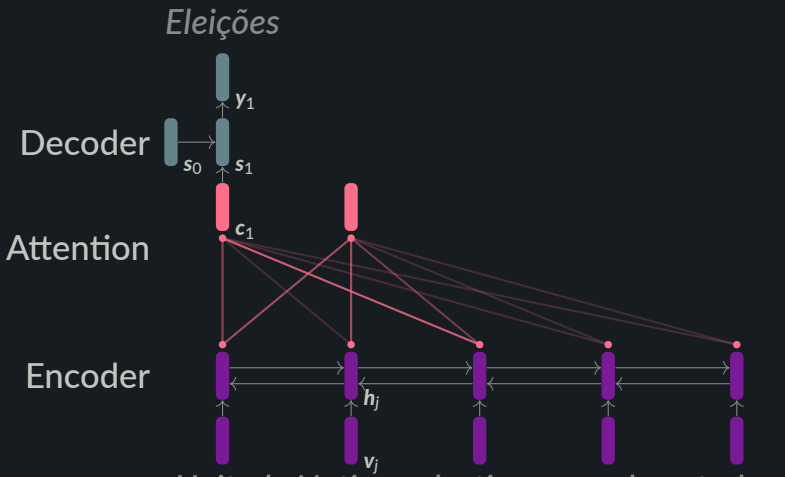

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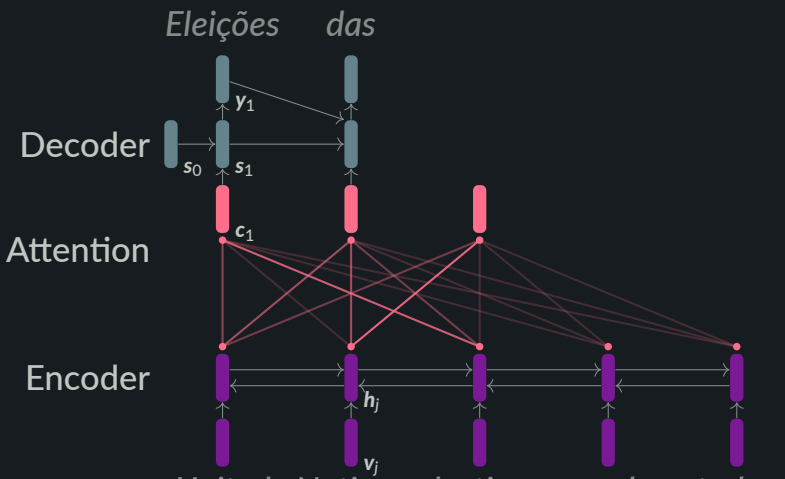

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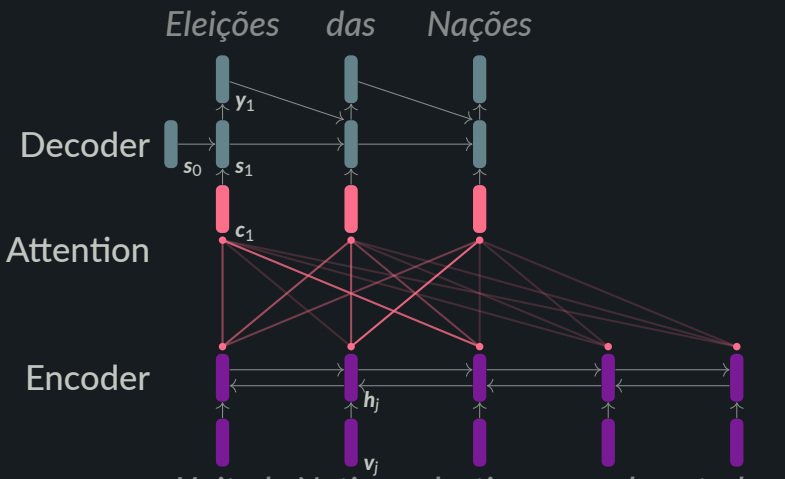

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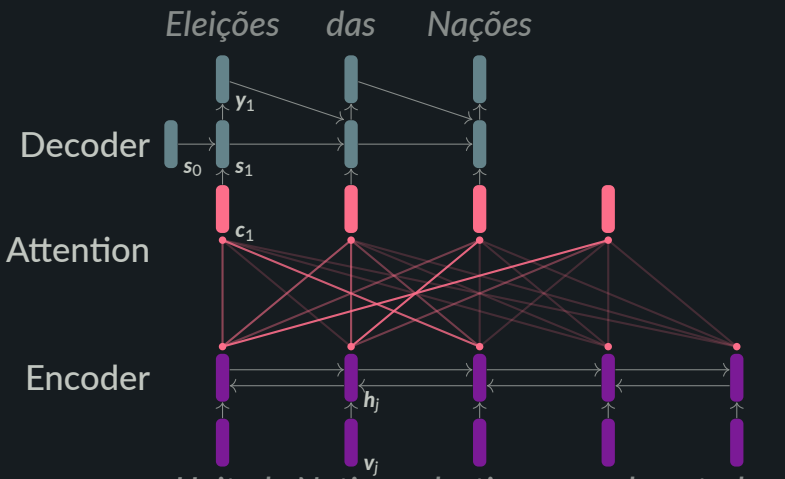

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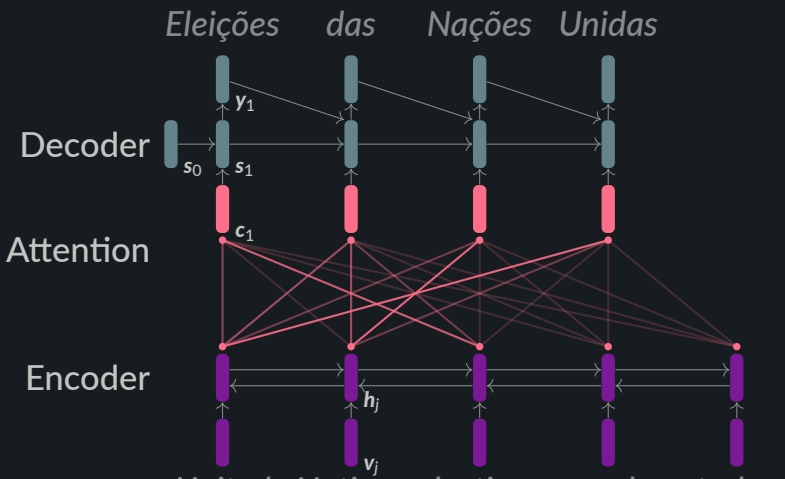

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A bit of context... on Transformers

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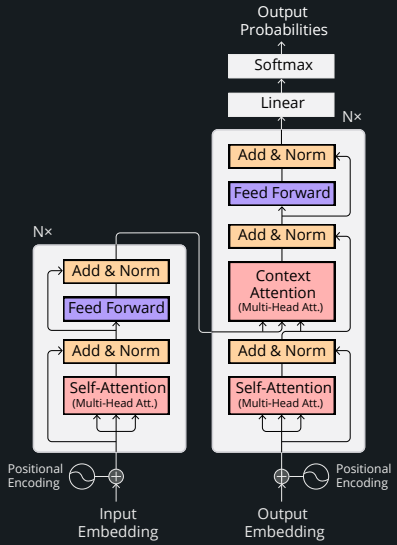

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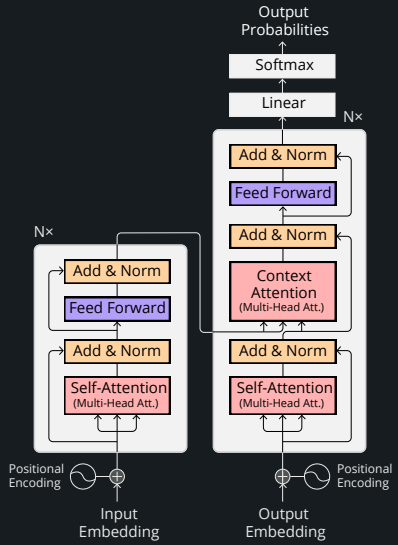
Key idea: Instead of Recurrent Neural Networks (RNNs), let's use attention mechanisms!



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Key idea: Instead of Recurrent Neural Networks (RNNs), let's use attention mechanisms!

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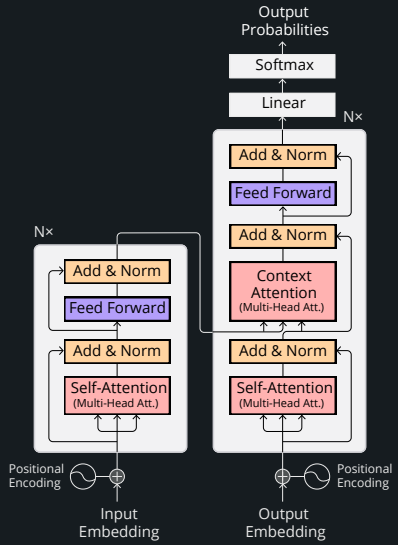

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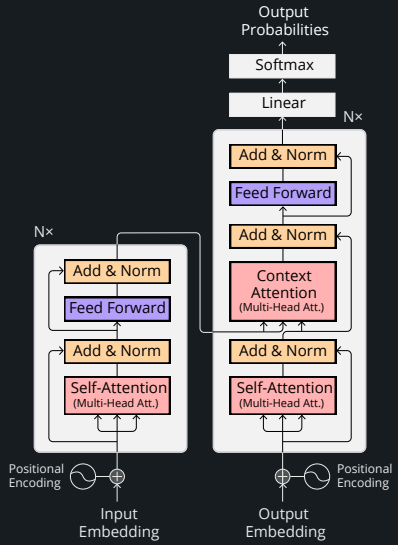

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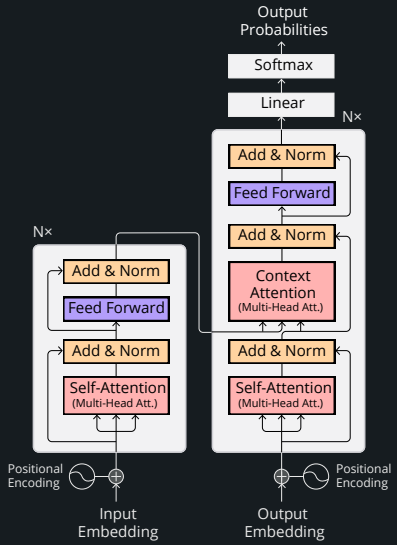
- ... and do it through several layers



(Devlin et al., 2019)

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What if... Attention is all you need?

Key idea: Instead of Recurrent Neural Networks (RNNs), let's use attention mechanisms!

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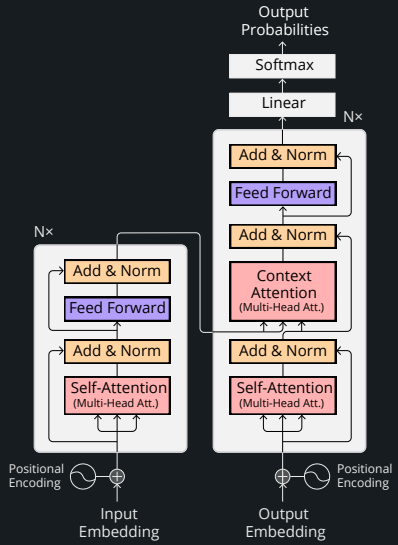
- ... and do it through several layers
- Inspiration for big general-purpose models like BERT!



Outline

(Correia and Martins, 2019)

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- Automatic Post-Editing (APE) using BERT (ACL 2019)

(Correia, Niculae, and Martins, 2019)

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- Letting Transformer learn how sparse it wants its attention (EMNLP 2019)

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- Future work: powerful structured latent variable models for NMT

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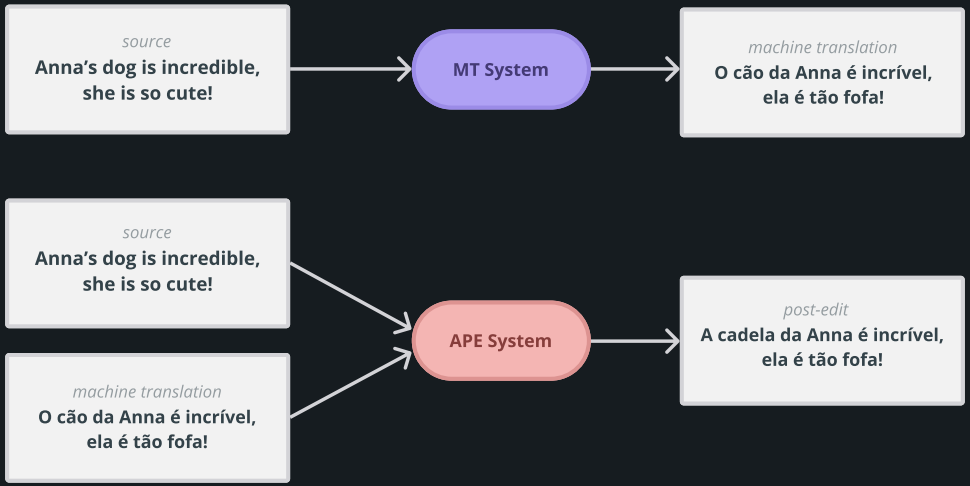
What is APE?


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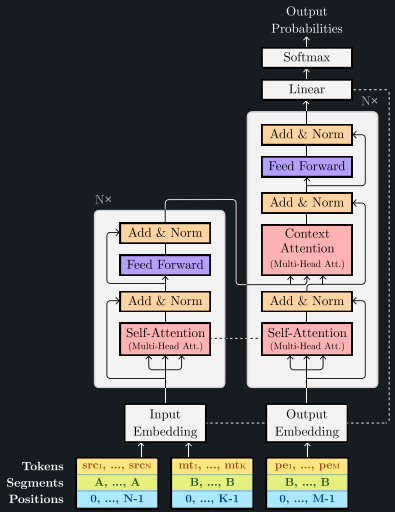
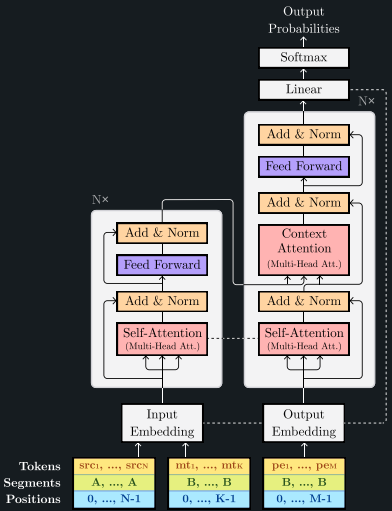
APE System
post-edit
A cadela da Anna é incrível, ela é tão fofa!

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

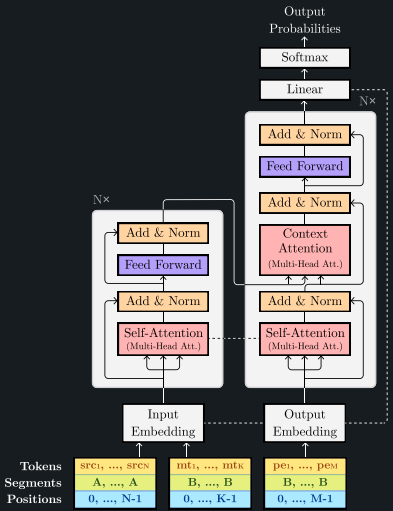
Key idea: Use BERT to do APE



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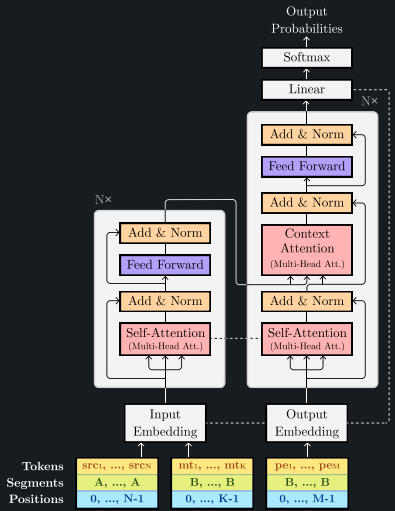
- We introduced an effective method to use BERT in a generation task (APE)



BERT for APE

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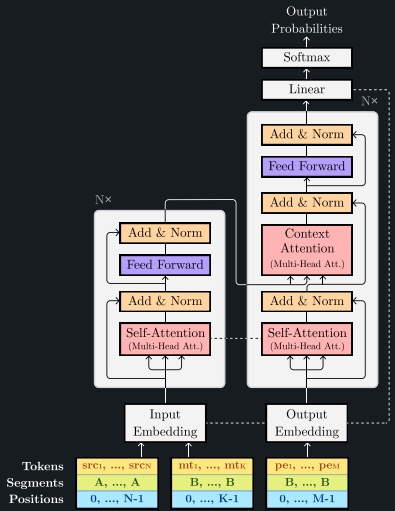
- Prior to this work, BERT was mainly used for simple classification tasks
- We introduced an effective method to use BERT in a generation task (APE)
- Smart parameter sharing between encoder and decoder



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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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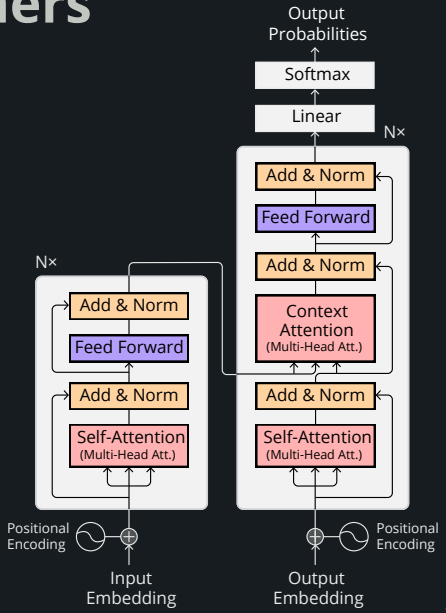
- for efficiency

(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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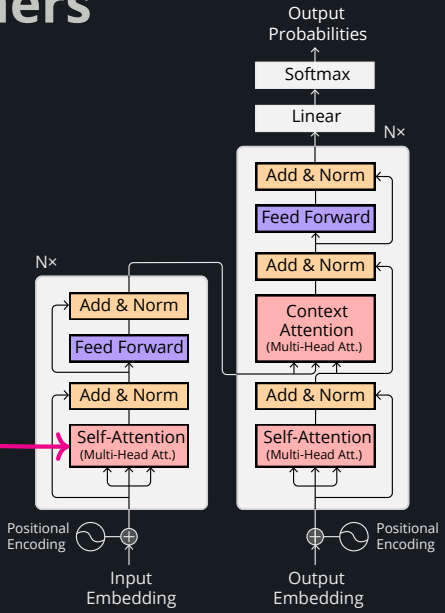
Attention in three places:

- Self-attention in the encoder



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In each attention head:

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Attention in three places:

- Self-attention in the encoder
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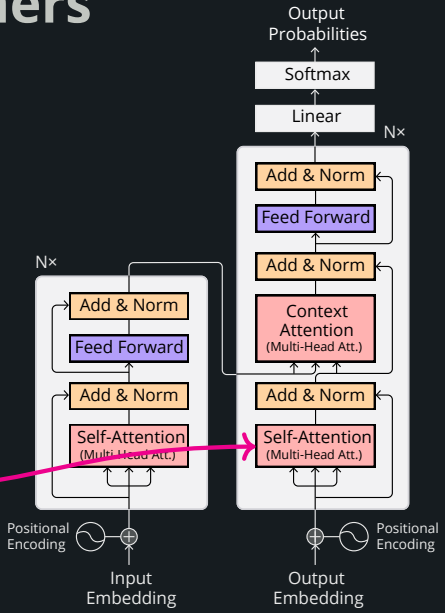

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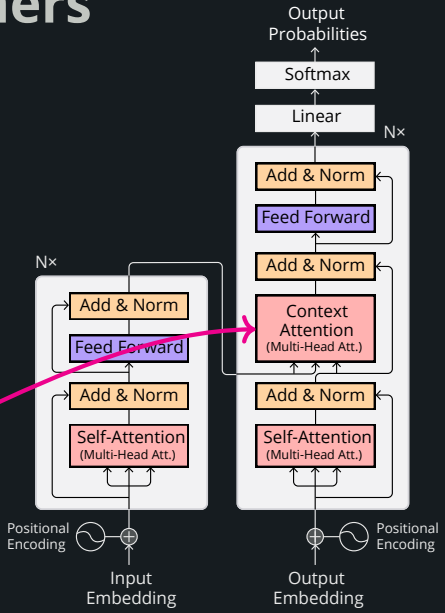
Attention in three places:

- 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: $\textbf{softmax}(\boldsymbol{z}) > \mathbf{0}$

(Peters et al., 2019)

α-Entmax

Parametrized by $\alpha \geq 0$:

(Peters et al., 2019)

α-Entmax

Parametrized by $\alpha \geq 0$:

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

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α-Entmax

Parametrized by $\alpha \geq 0$:

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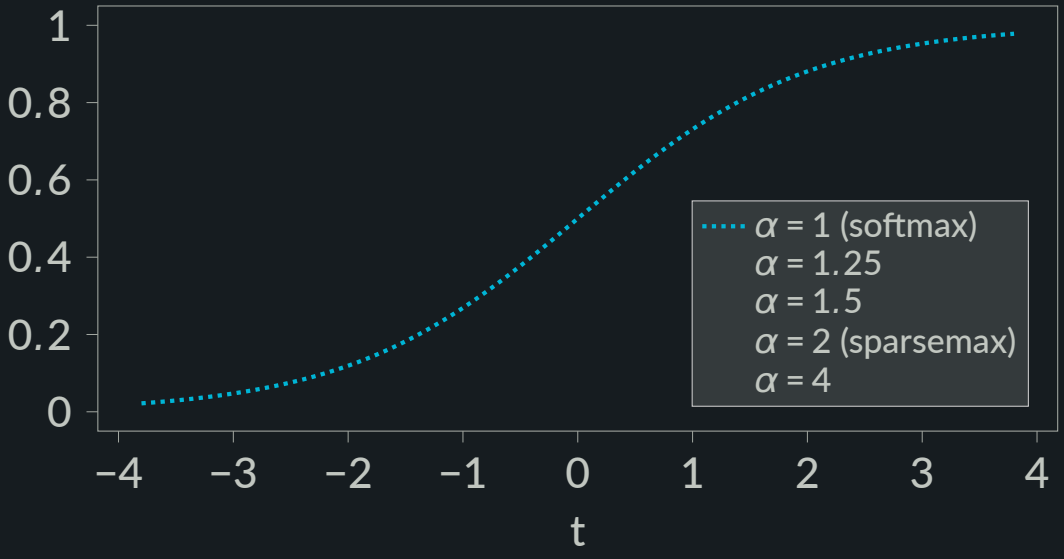
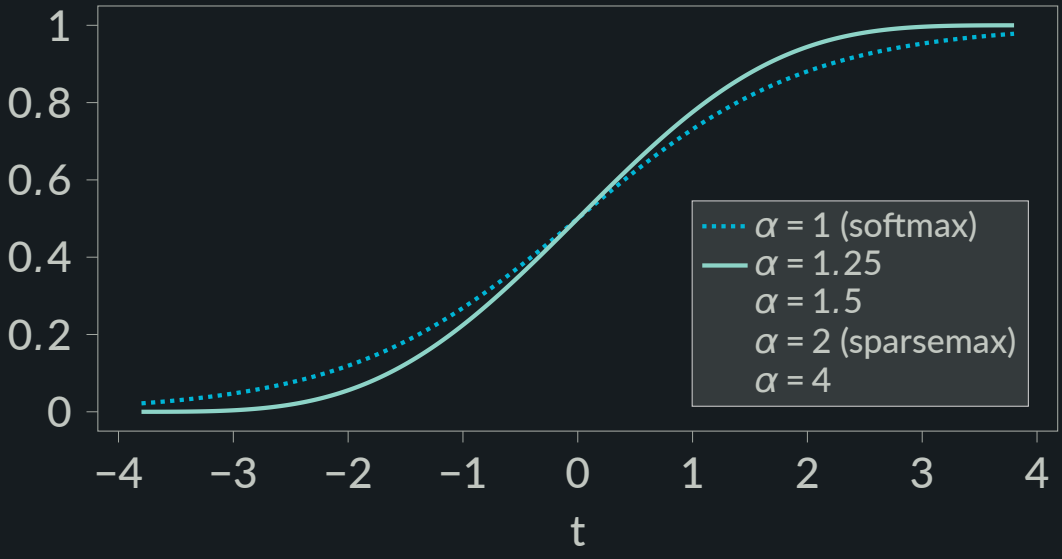
Key result: **can be sparse for** $\alpha > 1$, propensity for sparsity increases with α.


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


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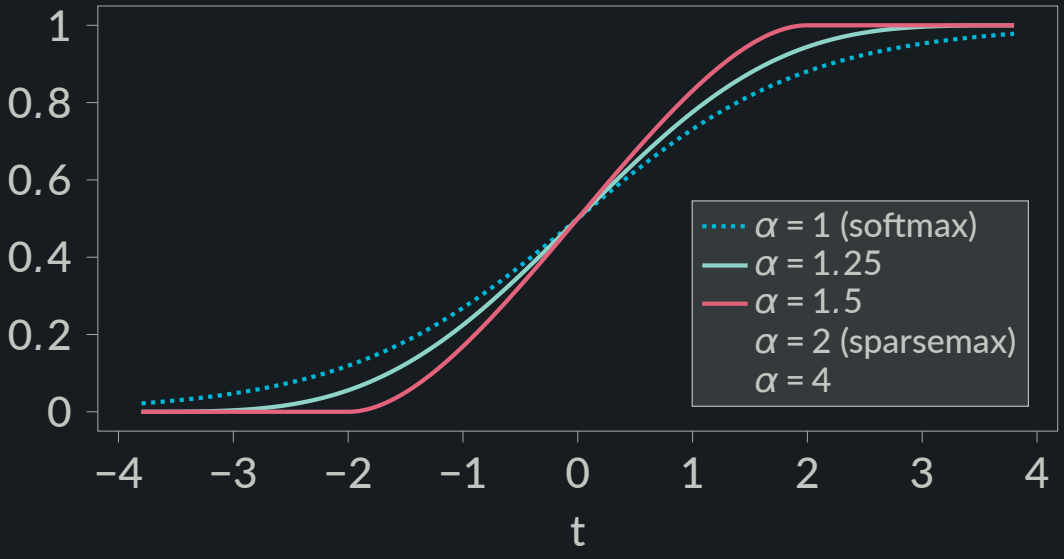
1
0.8
0.6
0.4
0.2
0
−4
−3
−2
−1
0
1
2
3
4
t
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α = 1.25
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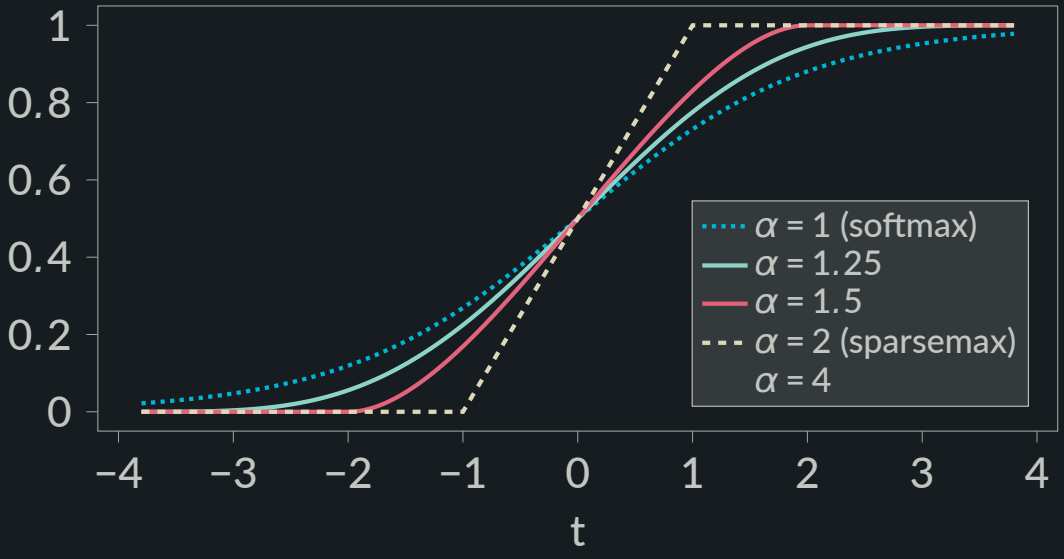
1
0.8
0.6
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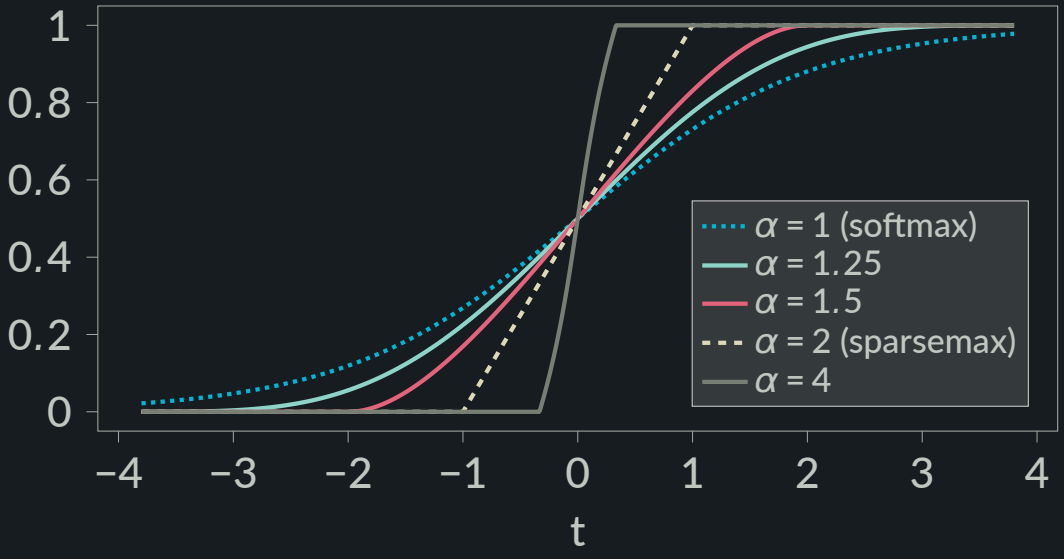
t
α = 1 (softmax)
α = 1.25
α = 1.5
α = 2 (sparsemax)
α = 4


1
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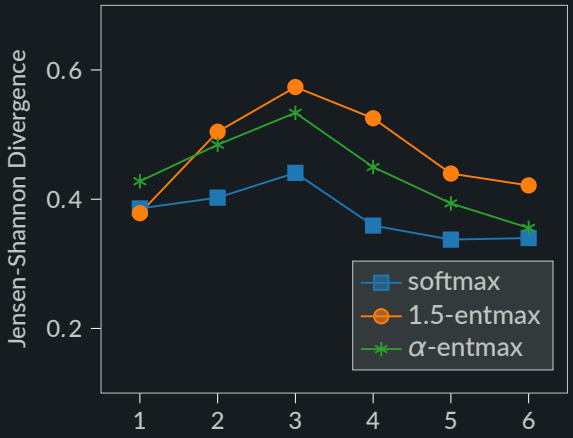
Learning α

Learning α

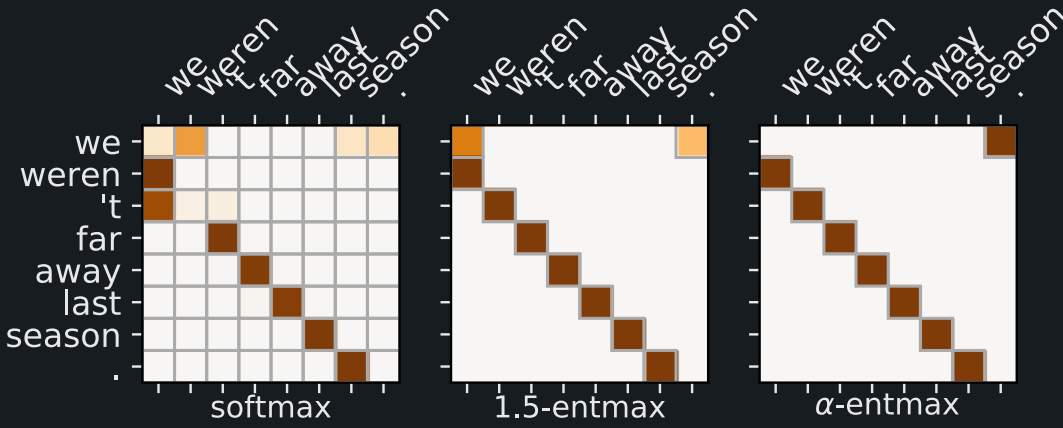
Key contribution:

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

Head Diversity per Layer

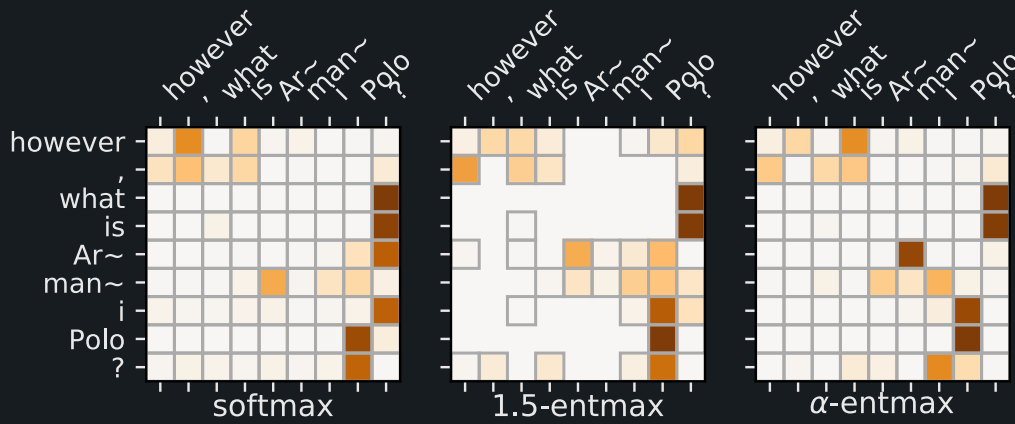


Previous Position Head



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

Interrogation-Detecting Head



Learned $\alpha = 1.05$.

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

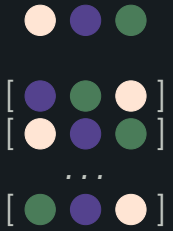
Latent variable z can be

Training Discrete or Structured Latent Variable Models

Latent variable z can be discrete

Training Discrete or Structured Latent Variable Models

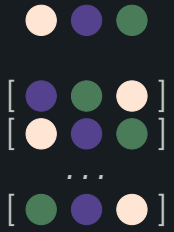
Latent variable z can be discrete or structured



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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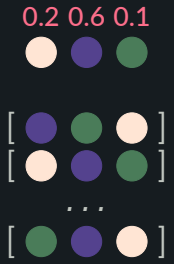

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If $\mathcal{Z}$ is large, this sum can get very expensive due to $\ell(x, z; \theta)$! 😱

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

Current Solutions

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

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no need for sampling → no variance
no relaxation into the continuous space

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 et al., 2018)

Sparse normalizers

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

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

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

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

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,

Results

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- Semi-Supervised VAE

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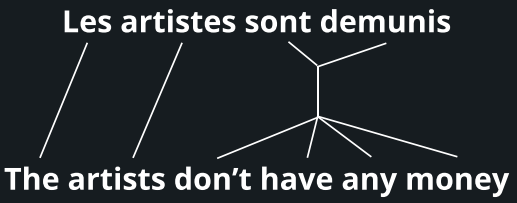
Our methods are top-performers and efficient!

Table of Contents

Proposed work: key concepts of this thesis

- Transparency
- Sparsity
- Compactness
- Data efficiency



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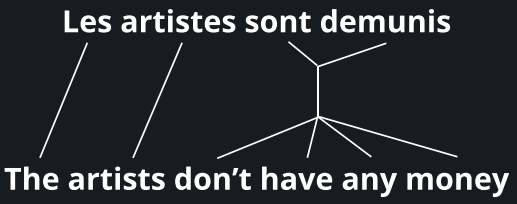

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- Inspired by, and data efficient like APE
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- Compact thanks to latent variables
- Using sparsity as a training method

Idea: create a latent, draft translation

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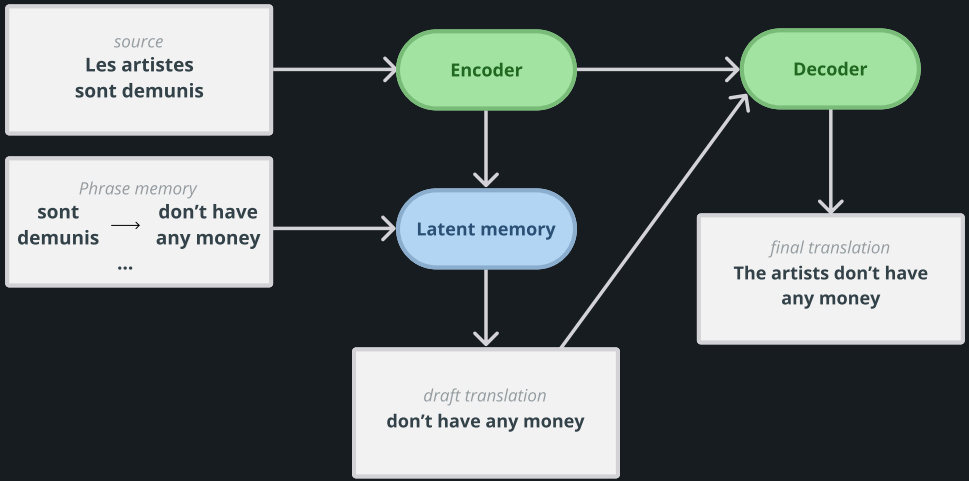

Another Idea: using latent summaries in NMT

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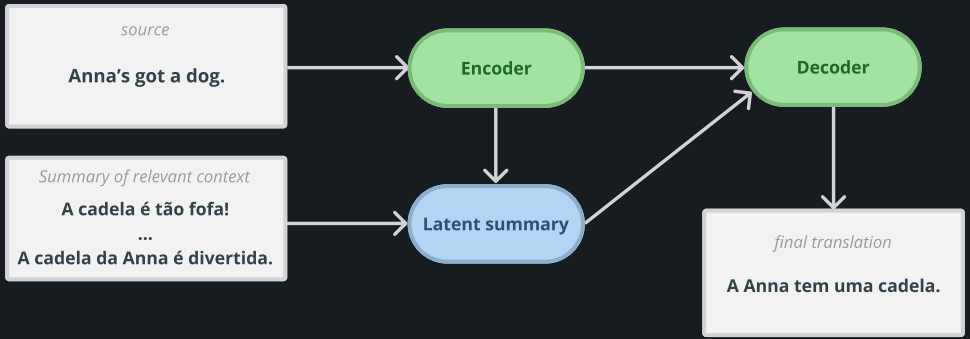

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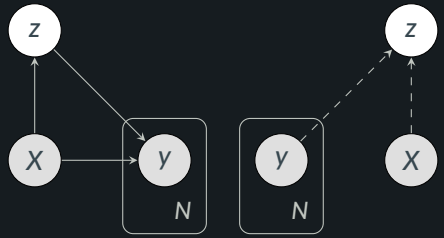
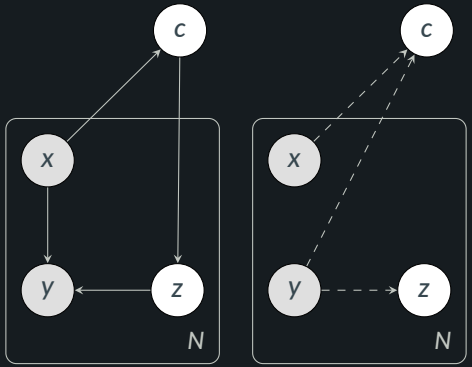
Using latent summaries in NMT



Multi-domain NMT



Document-level NMT