# Advanced Text-As-Data - Winter School - Iesp UERJ

Day 3: Introduction to Transformers

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July 8, 2025

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# The Evolving Methods of NLP

# Evolving Methods

In the last couple of days we have learned about the different goals of NLP: measure some latent characteristic of a set of texts.

- Bag-of-Words: *Wordfish* (Slapin and Proksch, 2008).
- Embeddings: Party ideological placement, i.e., party-embeddings (Rheault and Cochrane, 2020).
- Transformers: Supervised models for text classification (Timoneda and Vallejo Vera, 2025*b*).

More recently, increased focus on Generative Large Language Models (LLM).

- Applied: latent dimensions, i.e., ideology (Kato and Cochrane, 2025; Wu et al., 2023); annotators (Timoneda and Vallejo Vera, 2025*c*)
- Limitations: biases from party cues (Vallejo Vera and Driggers, 2025); bias from language (Walker and Timoneda, 2024).
- Meta: effect of LLMs on respondents.

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# Transformers

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- We can think of Transformers as the engines that drive machine-learning models and improve (significantly) their performance.
- Transformers are the architecture behind most (all?) state-of-the-art language models: BERT, RoBERTa, Llama, etc.

# Do I Know Any Transformers?

Have I been exposed to this architecture before?

# You DO Know Some Transformers

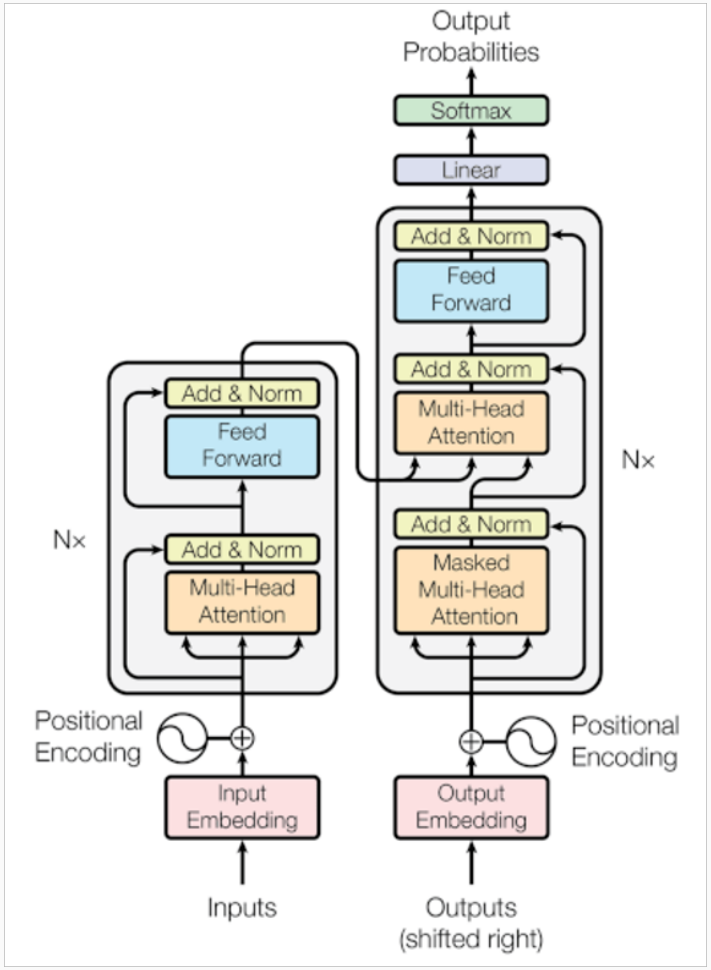
You have!

- Google Translate (and preditction).
- ChatGPT, Grok 😟, etc.
- GitHub Copilot.
- Automatic caption generation in social media.

GPT = Generative Pre-trained Transformers

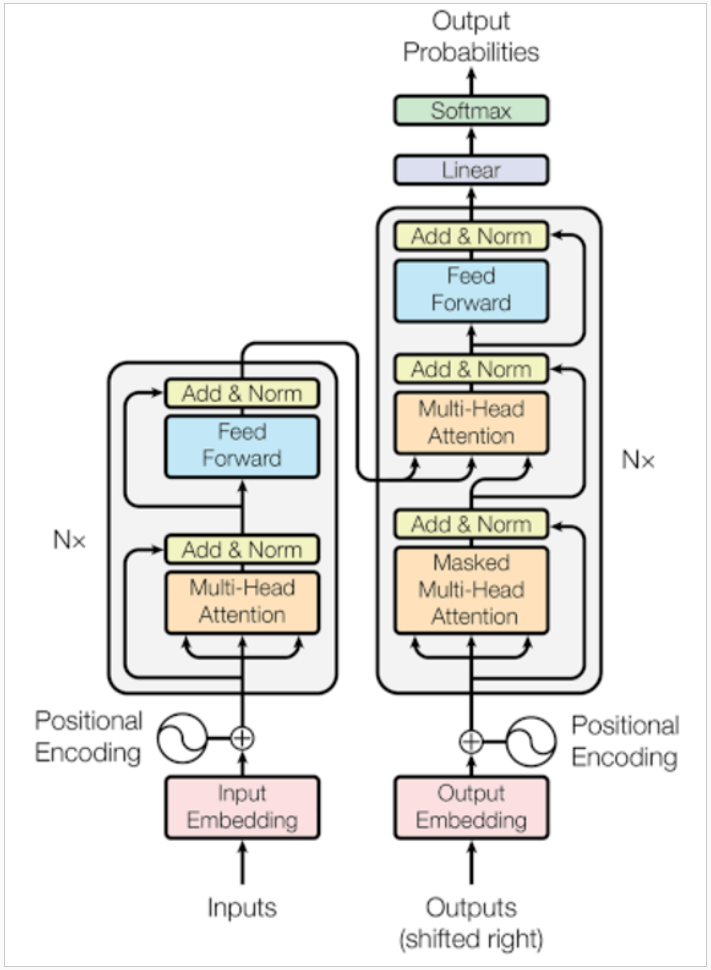
# How Do Transformers Work?

# The Encoder - Decoder Architecture




- It’s complicated...

# The Encoder - Decoder Architecture




- It's complicated... but we can break it down into parts.

# Encoder Mechanism

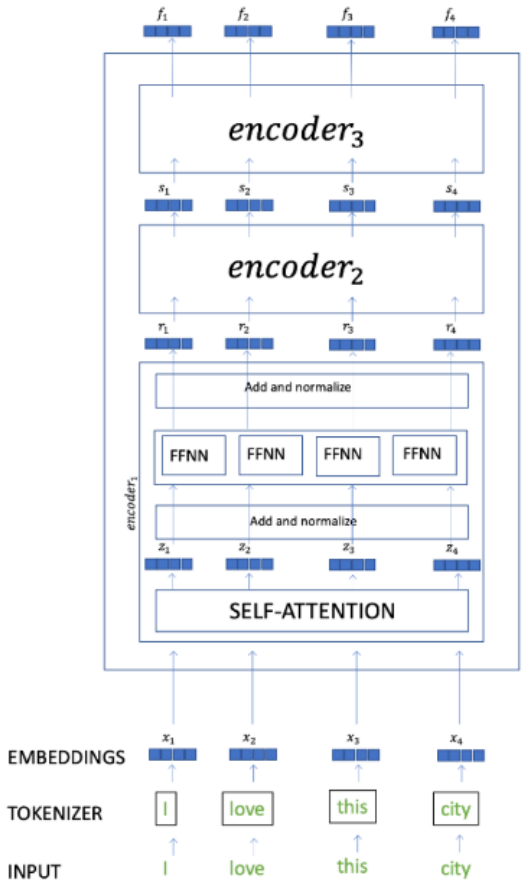



**Figure 1:** Diagram of a three-stack encoder of a Transformers model. Input text is tokenized and given an initial embedding (vectorized representation) simplified in our figure as $x_1$ through $x_4$. The initial embeddings are transformed as they enter the first $encoder_1$. In it, the self-attention mechanism updates the embeddings ($z_1$ through $z_4$), which are then passed through a feed-forward neural network. They exit the encoder as a more accurate set of embeddings ($r_1$ through $r_4$). The process is repeated for all encoders in the neural network. For example, pre-trained BERT-base models use 12 encoder layers.

# Masking

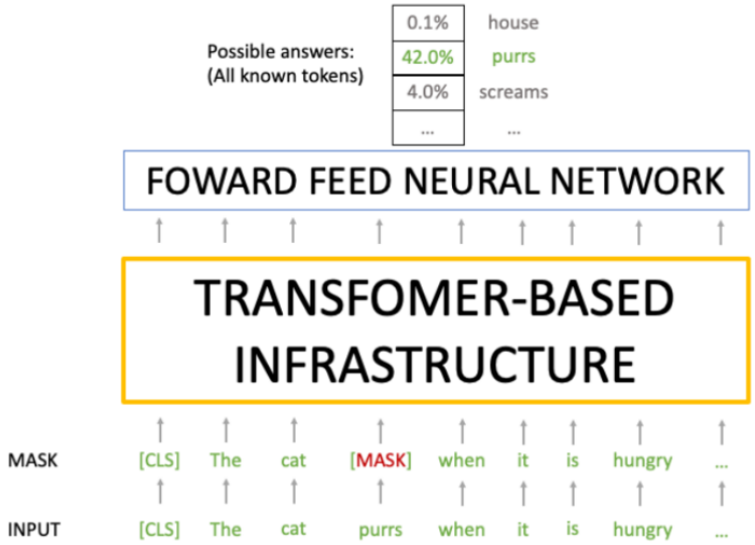
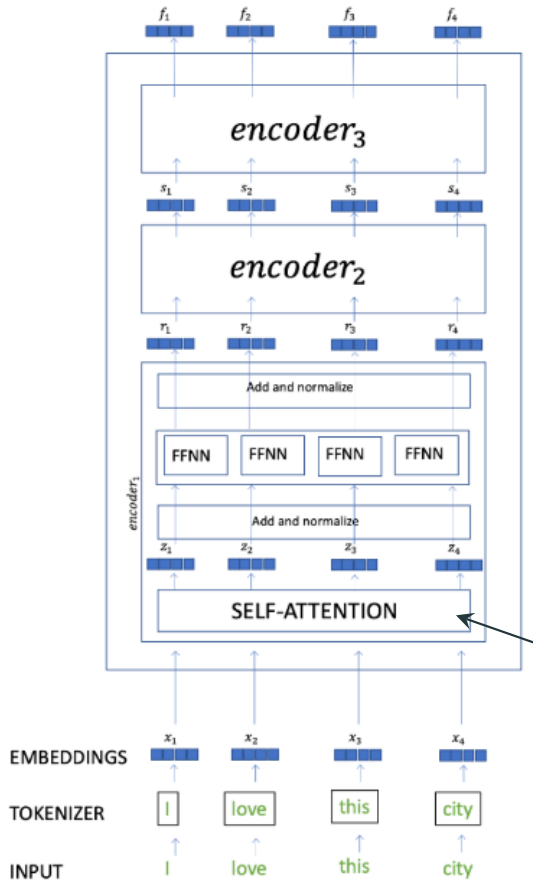



**Figure 2:** Representation of the Masked Language Modeling. Transformer models randomly mask 15% of tokens. After running the corpus through the Transformers and neural-network architecture, it asks the model to predict the masked word. Transformer models then calculate loss and the required gradient changes to optimize the model's weights and obtain better representations.

This is called a *cloze procedure*, developed in Taylor (1953)... the only non-CS paper cited in Vaswani et al. (2017).

# Encoder Mechanism




Attention Is All You Need

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# Self-Attention Mechanism

The self-attention mechanism ('Attention is All you Need') is the revolutionary component of the architecture (Vaswani et al., 2017).

- Each input consists of 'queries' and 'keys' matrices. In the sentence 'Mary likes books', to give meaning to the word 'Mary' (query) we look at the whole sentence, a find the word that is most related to it, in this case, 'likes' (key).

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- Note that, while the tokens can be the same, the representations will be different (as they come from previous layers).
- Mathematically, we obtain the dot product of *K*(eys) and *Q*(ueries) such that $Attention(Q, K, V) = softmax(QK^T)/\sqrt{d_k})V$ where $d$ is the dimension of $K$ and used as an scaling factor.

# Neural View of Self-Attention

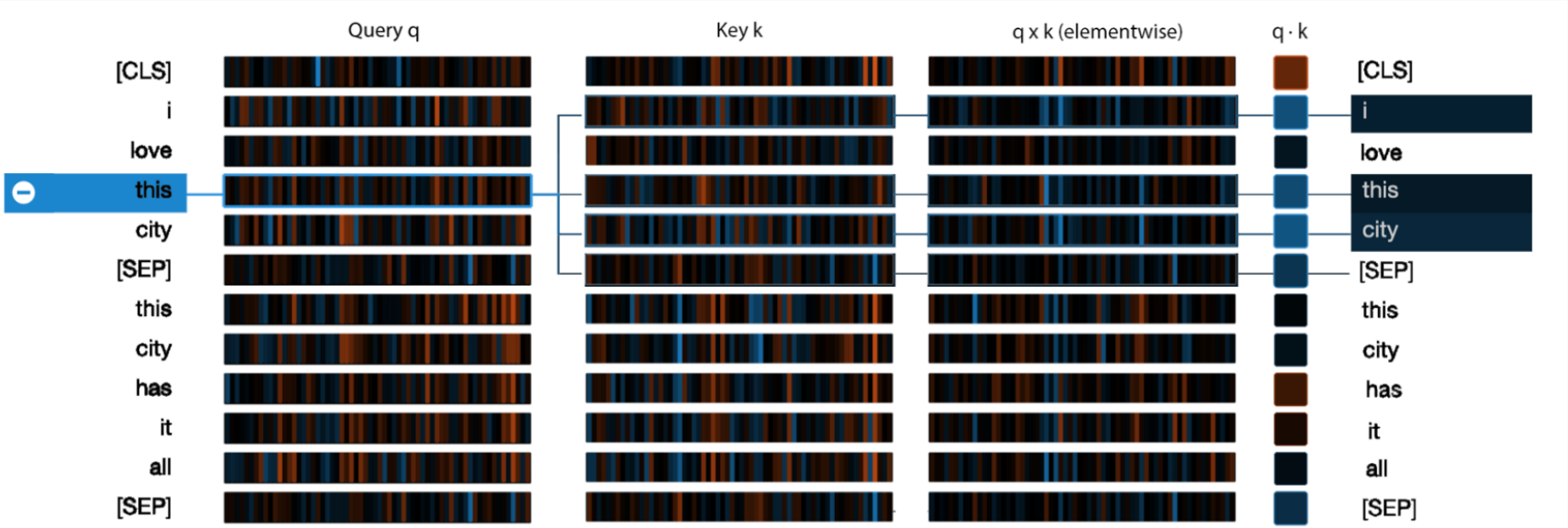


**Figure F.2:** Neuron view of the attention pattern at Layer 4, Head 1 of the BERT-base pretrained model. The neuron view visualizes the query and key vectors that are used to compute attention. Each color band represents a single neuron value, where color intensity indicates the magnitude and hue the sign (blue=positive, orange=negative).

# The Last Layer

One final note on self-attention is how embeddings for the same token will change according to the context. This is the truest nature of the “you shall know a word by the company it keeps” quote.

- Take the word ‘bear’: it can mean the animal *bear*, a teddy *bear*, or to *bear* fruit. These all have different meanings, so they should all have different embeddings.
- Since embeddings are numerical representations of words , the distance between two embeddings is an approximation of the relation between words.
- In the sentences: ‘The kid had to bear the loss of misplacing his teddy bear and his doll,’ the cosine similarity between (teddy) bear and doll should be higher than the cosine similarity between (teddy) bear and bear (the loss). Thanks to the attention mechanism, this is the case! (see Appendix H in Timoneda and Vallejo Vera, 2025*a*)

# Positioning Encoding i

- A large corpus cannot be fed in its entirety into the encoding process. Thus, it is broken down into a list of vectors of size 512.
- As the corpus is broken down, key elements of the structure are maintained: [CLS] and [SEP] represent the beginning and the of a sentence, respectively.
- It also adds a positional encoding to the list of vectors to maintain the order of each token in the sentence. Since embeddings flow independently through the FFNN, position encoding (a vector) helps maintain the order while also providing a relation between words.
- the position encoding ($PE$) adopts a sinusoidal form:

$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{model}})$$

$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{model}})$$

# Positioning Encoding ii

- The intuition behind it is that position encoding allows the model to easily find the position of each token in a batch. It also allows to count the number of steps between tokens: the farther the distance, the faster it decays (the weaker the relationship between these tokens).

Vaswani et al. (2017) writing about position encoding say that "we chose this function because we hypothesized it would allow the model to easily learn to attend by relative positions, since for any fixed offset $k$, $PE_{pos+k}$ can be represented as a linear function of $PE_{pos}$". While there is no formal proof on their paper of this assertion, it apparently works.

# What Does it All Mean? i

This is a lot! It can be a bit overwhelming as well. We will simplify it all when we implement it, but for now the most pressing question should be: what do we do with all of this?

- First, just like you learned with word embeddings, we can pre-train models. Well, not 'we'... people* with a lot of computer power. *For example, Google, Meta, and OpenAI.
- Pre-trained models are encoders: they create representations of tokens, *encoding* these with 'meaning'. These are SOTA understanding text: BERT, RoBERTa.
- We could also train models to generate text (i.e., GPT or LLM).

# What Does it All Mean? ii

- Generative Pre-Trained Transformers (GPT) or Generative Large Language Models (LLM) are decoders: they take some input (e.g., a question in a search query), interpret it (i.e., *decode it*), and produce some response that matches the input. These are SOTA producing text (next token prediction): Llama, OpenAI.
- Or we can combine both for sequential tasks, such as translation (e.g., T5 or BART). These tend to be slower and less efficient and for most tasks it is better to use BERT-based models or LLMs.

# Final Thoughts

# Next Steps

We have learned the basic mechanisms underlying the Transformers infrastracture. Yet, you still do not know what to do with it. Here is what we will do next:

1. Learn about BERT-based pre-trained models.
2. Learn how to implement the aforementioned BERT-based pre-trained models.
3. Learn about Large Language models (LLMs), their applications and limitations.
4. Learn how to implement LLMs.

Thank you!

Questions? Comments? Break?

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