Beyond Spell-checking: Word-checking

An attention based Transformer approach

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Abstract

This work attempts to address some of the shortcomings of spell-checkers. Indeed, spell-checkers help us to correct typos and other errors due to a lack of attentiveness. Besides these obvious faults, there are also faults we make when we mistake between homophones. Homophones are words that are pronounced the same, but they have different writings and different meanings. Therefore, to choose the right form among several homophones, we must use other sources of information such as the semantic or grammatical contexts. In addition to that, since homophones are words that actually exist, most errors will go unnoticed, neither by ourselves nor by most of the autocorrect systems and spell-checkers. To solve this problem, we propose to go beyond spell-checker and use a word-checker instead.

For this purpose, we use the Transformer, an artificial neural network equipped with attention mechanism [1]. The Transformer has revolutionized Natural Language Processing and Deep Learning, with now well-known models such as BERT [2] and GPT-3 [3] capable of startling achievements. Furthermore, to assess the relevance of our trained model, we compare its performance with that of humans on the homophone correction task.

Moreover, throughout this work, we tackle the issue of homophone correction using the French language.

Contents

CHAPTER 1

Introduction

This report is intended to present and discuss the work accomplished during the TER. In this chapter we outline the key ideas of this TER and introduce some of the concepts needed to understand the reminder of this report.

1.1 The general framework

Let's begin by presenting the issue we will try to solve throughout this report. As we grow up, we are able to make less and less mistakes when writing a sentence or a long text. However, some words are more difficult to spell correctly than others. Especially, words called *homophones* can be quite challenging. What are homophones ? **Homophones** are words that are pronounced the same, but they have different writings and different meanings. For instance, in the French language - the language used for all of the studies in this TER - the words "leur" and "leurs" are homophones. To spell properly these homophones, we must use information such as the context in which they occur. To make matters worse, when humans make mistakes, they are very confident that they have chosen the right word (see section 3.2). Then we can wonder, how can we avoid these pitfalls ?

We can certainly treat such a question by leveraging knowledge from many different fields of study. For instance, we can use knowledge and concepts from linguistics to help us address the issue of choosing the right homophone. We can further use brain imaging techniques to spot any differences between the condition where we choose the right form and the condition we don't. The latter methods could be, broadly speaking, categorized as the cognitive science approach. While cognitive science is arguably well suited for this task, we won't take this approach. Instead, we will take a more computer science oriented approach and tackle the issue of homophones by using **deep learning** (commonly abbreviated as **DL**) and the latest breakthrough in **natural language processing** (commonly abbreviated as **NLP**) known as the *Transformer* [1]. The Transformer has democratized and brought to a new level the use of *attention* mechanisms in NLP and sequential problems in general. More precisely, we wil try to answer the following question: **can we implement an effective attention based Transformer model for homophone correction ?**

We discuss what we mean by the term *effective*, and the terms *homophone correction* in chapter 3. Throughout this chapter, we will have a glimpse of what *attention* and *Tranformer model* mean, but their in-depth explanation is left for the next chapter.

1.2 DL and NLP prerequisites

In this section we will review basic concepts of DL and NLP needed to understand the material present in chapter 2 and chapter 3. Throughout this report, we won't get into too much details when it comes to mathematical theory or more technical methods usually employed in DL. Indeed, this is not the objective here and is beyond the scope of this report, in addition to the fact that many great resources on these topics already exist (see [4] and [5]). However, we will always try to give an intuitive explanation, enough to understand what the different components are used for. Also, additional explanations are given in the appendices. Most of the pages are dedicated to explain the in-depth functioning of the Transformer model and its building blocks, along with the experiment that have been done.

1.2.1 Deep Learning prerequisites

In deep learning we use terms like loss function, gradient, optimizer, true label, parameters, layers, units, activation function, etc. For an exhaustive survey see [4], [6] and [7]. We will mainly focus on the components used to implement the Transformer.

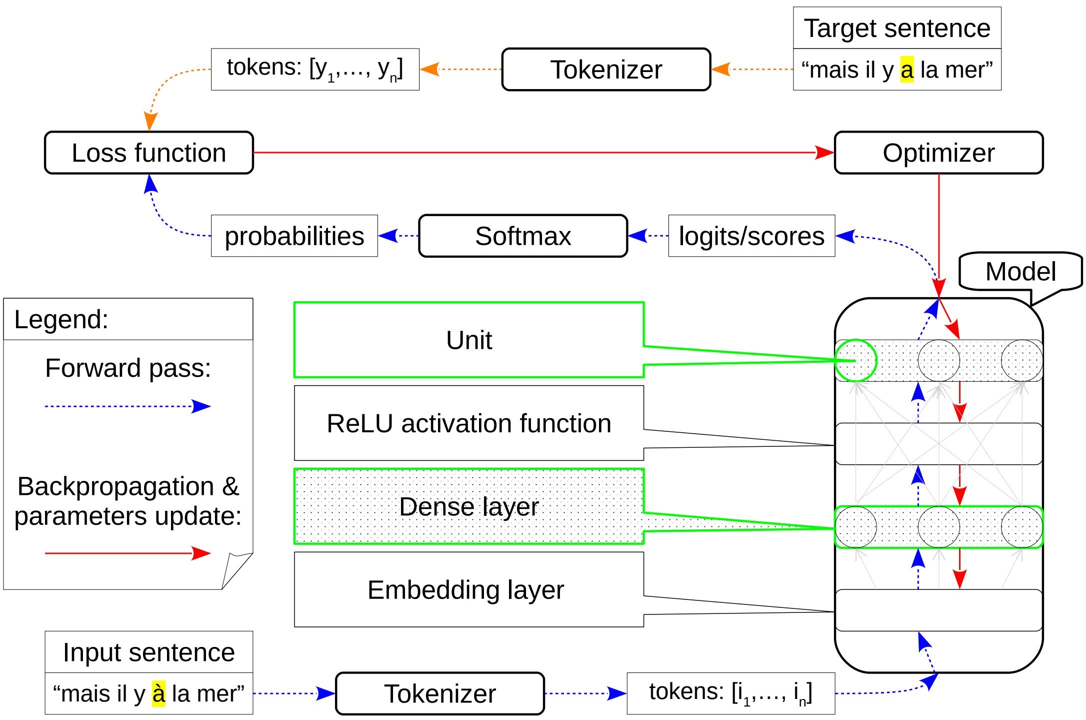


Figure 1.1: How different DL components can be related to each other during training. The model shown here is not the Transformer, and serves only as an illustration.

In the example in figure 1.1, we give the tokenized input (see section 1.2.2 for more details) to the model, and then compare what the model outputs with the correct sentence i.e. target sentence. Target sentence is employed here to emphasize that, for each input sentence, we have the corresponding correct sentence (itself if it's already correct or the corresponding corrected sentence). Thus, the model is trained in a supervised setting. We want the model to correct the errors present - if any - in the input sentence, and output the corrected sentence. For instance in figure 1.1, the input contains an error whereas target sentence doesn't (see the highlighted terms "à" and "a"). That being said, let's review what each component in figure 1.1 does. First, the list of tokens (each token is a number) of length l goes through the **Embedding layer**, where each token is transformed into a vector of a given fixed dimension d called *embedding dimension*. Indeed, for every token in the vocabulary (see section 1.2.2), the embedding layer has an associated vector of dimension d. For instance if $l = 11$ (there are 11 tokens) and $d = 64$, then the list of tokens is transformed into a matrix X having 11 rows and 64 columns ($X \in \mathbb{R}^{11\times 64}$). This newly created matrix is then fed to a **Dense layer**. Moreover, a dense layer consists of **units** and those *units* determine the shape of the weight matrix W representing the layer. What happens at the dense layer boils down to a matrix multiplication. Indeed, if we omit the bias term, and the number of units is equal to 16, then the following matrix multiplication occurs: $X \times W$ with $X \in \mathbb{R}^{11\times 64}$ and $W \in \mathbb{R}^{64\times 16}$ resulting in a matrix $X_{\text{new}} \in \mathbb{R}^{11\times 16}$. Oftentimes an activation function is applied to a layer's output. The activation function used in figure 1.1 - and also by the Transformer - is called **ReLU** activation function. For every real number x, $\text{ReLU}(x) = x$ if $x \geq 0$ and $\text{ReLU}(x) = 0$ if $x < 0$. ReLU is applied *element-wise* to the previous matrix $X_{\text{new}} \in \mathbb{R}^{11\times 16}$. Activation functions serve to inject non-linearity into our models. Finally, in figure 1.1, the output of the ReLU goes through a second Densely connected layer. If this second layer has $|V|$ units, then we get a new matrix $S \in \mathbb{R}^{11\times|V|}$ ($S = X_{\text{new}} \times W_2$ with $X_{\text{new}} \in \mathbb{R}^{11\times 16}$ and $W_2 \in \mathbb{R}^{16\times|V|}$). As we will see in section 1.2.2, $|V|$ denotes the size of the vocabulary, i.e. the total number of tokens that make up the vocabulary being used by the Model. Notice that this time we didn't use an activation function after the dense layer. Thus, elements of S can be any real number, we call these numbers *logits*. Next, we use the **Softmax** function to get *probabilities*. We apply softmax along the columns of S and obtain the probability matrix P:

$$P = softmax_j(S) \quad \text{i.e.} \quad P_{ij} = \frac{\exp(S_{ij})}{\sum_{j=1}^{|V|} \exp(S_{ij})} \tag{1.1}$$

P_{ij} gives for the i^{th} output token, the probability that this token is the j^{th} token of the vocabulary. In our example (figure 1.1), $P \in \mathbb{R}^{11\times|V|}$, hence the model outputs probabilities for 11 tokens (corresponding to 11 rows in P). Intuitively, we can consider that the i^{th} output of the model, is the j^{th} token of the vocabulary, such that P_{ij} is the maximum i.e. $j = argmax_j(P_{i,.})$, for those who are familiar with this notation.

Furthermore, as we have the correct sentence i.e. target sentence, we also have the correct tokens i.e. target tokens, we tokeize the target sentence to get them. The same tokenizer is used to tokenize both the input sentence and the target sentence. Consequently, we can compare how well the model is doing for the task of correcting incorrect sentences. We compare the model's output - the probability matrix P - with the target tokens from the target sentence. This is accomplished by the **Loss function**, it takes as input both the list of target tokens and the probability matrix P, and it calculates the *loss*, which is a measure of how different the model's output is from what is expected i.e. target sentence. We want this loss to be as low as possible. If we denote the loss function by L, and all the trainable parameters by θ, then parameters update is given by:

$$\theta_{\text{new}} = \theta_{\text{old}} - \epsilon \times \nabla_\theta L \quad \text{where} \quad \nabla_\theta L \text{ is the gradient of } L \text{ w.r.t } \theta \tag{1.2}$$

We notice that, $\nabla_\theta L$ - obtained via the *backpropagation algorithm* - indicates the direction in which θ is moved, and ϵ specifies by how much it is moved. Additional update options can be configured and the **Optimizer** handles their implementation. This ends the quick review of the basic DL concepts needed to get the big picture of the problem. Next, we review some concepts related to NLP and the loss function in detail.

1.2.2 Natural Language Processing prerequisites

In order to train and evaluate a model, we have to first define a vocabulary. This vocabulary is linked to the way we *tokenize* textual data. Indeed, when we encode textual data using a **Tokeinzer**, the resulting token representation depends on the tokens the tokenizer is able to handle. For instance, a character-level tokenizer encodes each character separately, while a world-level tokenizer encodes each word separately. However, we will use for the Transformer a *subword-level* tokenizer. The subword tokenizer is first trained on a text corpus, then *the most frequent chunks* [see 5, for more details] of text are each associated with a number between 1 and $|V|$. Here, $|V|$ indicates the maximum number the tokenizer can emit. Moreover, at the beginning (respectively end) of a sentence, we add the $<SOS>$ token (respectively the $<EOS>$ token), see figure 1.2 for an example.

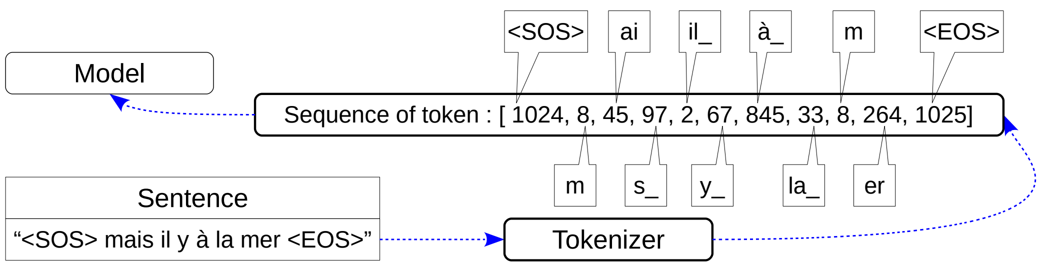


Figure 1.2: How Subword Tokenizer encodes sentences.

Finally, we describe the loss function L used in figure 1.1, and also used by the Transformer. More precisely, L is the *Sparse Categorical Cross-Entropy Loss*. We saw in section 1.2.1, that this loss function takes as input the list of target tokens, and the probability matrix P from the model. Let's denote by y the list of target tokens, and $y_i \in \{1, ..., |V|\}$ the i^{th} token in the list. Moreover, l is both the length of y and the number of rows in P (in figure 1.1, $l = 11$). L is given by formula 1.3, and measures the loss for a pair input sentence/target sentence:

$$L(y, P) = -\sum_{i=1}^{l} \log(P_{i,y_i}) \tag{1.3}$$

We notice that, both the length of y and the number of rows in P must be equal (it's the same number l), we will see in the next section how it is ensured for the Transformer model. Additionally, if P_{i,y_i} tends to 1, then $\log(P_{i,y_i})$ tends to 0, and if P_{i,y_i} tends to 0, then $\log(P_{i,y_i})$ tends to $-\infty$ (then L tends to $+\infty$). Consequently, minimizing L forces P_{i,y_i} to be close to 1, i.e. the model gives a high probability for the i^{th} output token to be the i^{th} token in the target token list. Thus, the model *learns* to output what we expect it to output (the target tokens) given a certain input.

1.3 High-level picture of the problem setup

In this section, we look at the elements surrounding the training of the Tranfsormer. To begin with, the set-up used to train the Transformer is similar to the setting in figure 1.1, with changes only occurring at the model level. Indeed, as shown in figure 1.3, the Transformer is composed of two main blocks - an **Encoder** block and a **Decoder** block - along with a dense i.e. linear layer. Within these blocks, is implemented the *attention* mechanism. Moreover, *the Transformer takes as input two sequences*, one entering through the encoder and the other through the decoder. The encoder takes as input the list of tokens from the input sentence. However, the decoder takes as input the list of tokens from a truncated version of the target sentence. Indeed, from the entire target sentence, we extract two truncated sentences, one without the "<EOS>" token, the other without the "<SOS>" token. Both have the same length after tokenization, it's mandatory to use the loss function 1.3. For instance, in figure 1.3, from the target sentence "<SOS> mais il y a la mer <EOS>", we extract "mais il y a la mer <EOS>" and "<SOS> mais il y a la mer". The one without the "<EOS>" token is given as input to the decoder. The other one, without the "<SOS>" token is considered as the target sentence, and the resulting list of tokens (after tokenization) is given to the loss function.

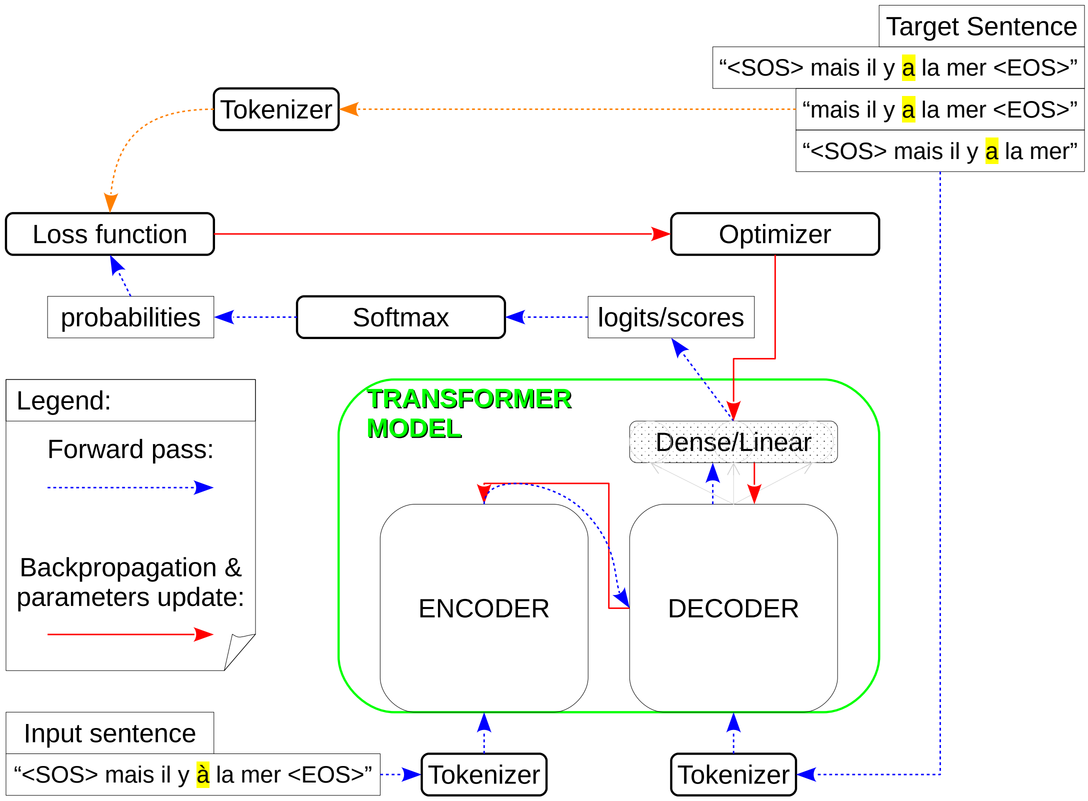


Figure 1.3: How the Transformer model fits into the big picture, with its Encoder and Decoder blocks along with a final linear layer. This figure illustrates the setting during the training phase.

We can also observe that the sequence given as input to the decoder is the sequence used as the target, but shifted by one token to the right. Since, the 1st token/word in the target sequence (for instance "mais" in figure 1.3) is the 2nd token/word in the sequence given as input to the decoder, and this observation applies to all following tokens/words in the target sequence. This is indicated in figure 2.1 in chapter 2 by "*Outputs (shifted right)*".

In the next chapter, we unpack the encoder and the decoder to see the building blocks that make them up. We also present how the Transformer is used during the evaluation/test phase. Moreover, we can notice that the underlined sentences in figure 2.2 are the ones used as the Decoder input and the target sentence in figure 1.3. This is how we can better understand the training configuration in light of the evaluation configuration and vice versa.

CHAPTER 2

The Transformer Explained

In this chapter, we will see how the inputs are transformed within the Transformer model, and how the *attention* mechanism works. As we have seen in figure 1.3, there isn't one input but two. Indeed, the model takes as input the input sentence (at the encoder level), for instance "<SOS> mais il y à la mer <EOS>", and what we call *the decoder input*, for instance "<SOS> mais il y a la mer". At training time, from these two inputs, the model is trained to output "mais il y a la mer <EOS>", which is the target i.e. true label. We will illustrate the inner working of the Transformer by following what happens to our sentence from the previous chapter, from the moment it enters the model at the encoder level and the moment the model outputs probabilities for each output token. See section 1.3 for a refresher and the explanation of the meaning of "*Outputs (shifted right)*" at the decoder level in figure 2.1. Throughout this chapter we will describe in detail each component shown in figure 2.1, therefore you should refer to it as many times as necessary.

2.1 The Encoder Input

We first tokenize the sentence "<SOS> mais il y à la mer <EOS>", which gives us a list (or a vector) of tokens. Moreover, suppose that after tokenization the sentence is $l = 11$ tokens long as in figure 1.2. Recall that tokens are just numbers, each one representing a specific subword (see section 1.2.2 for more details). This list of tokens is represented by

"**Inputs**" and this is what goes into the encoder.

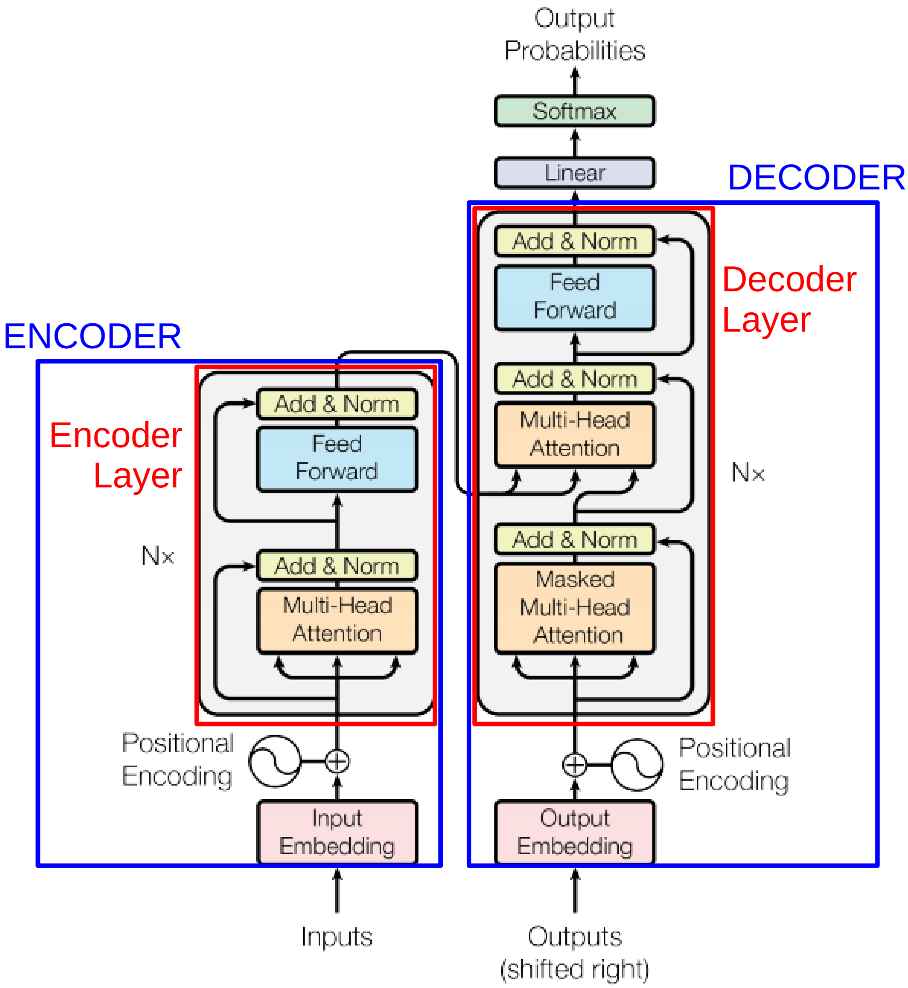


Figure 2.1: The Transformer - model architecture adapted from the original paper [1].

2.1.1 Input Embedding and Positional Encoding

The list of tokens goes through the *Embedding layer* (see section 1.2.1 for the details) and we get a matrix $X \in \mathbb{R}^{l \times d_{model}}$. Here, d_{model} represents the dimension of the vectors representing each input token. If we set $d_{model} = 64$, then we get an "**Input Embedding**" matrix $X \in \mathbb{R}^{11 \times 64}$. Though we have encoded the information about words identity until now, we didn't encode the information about words position in the sentence. To inject the information about the position, we add X and a *sinusoidal* matrix R, with R having the same dimension as X. If $R \in \mathbb{R}^{l \times d_{model}}$, then each element of R is given by:

$$\forall i \in \{1, ..., l\}, \forall j \in \{1, ..., d_{model}\}, R_{ij} = \begin{cases} \sin(i/10000^{2j/d_{model}}) & \text{if } j \text{ is an even integer} \\ \cos(i/10000^{2j/d_{model}}) & \text{if } j \text{ is an odd integer} \end{cases}$$

R represents the "**Positional Encoding**". Let's call the resulting matrix $X_E \in \mathbb{R}^{l \times d_{model}}$, $X_E \in \mathbb{R}^{11 \times 64}$ in our example, encoding both the identity of the words and their position within the sentence. Then X_E enters the *Encoder Layer*. All the computations occurring within the latter can be repeated N times as indicated in figure 2.1.

2.1.2 Multi-Head Attention

First of all, **Multi-Head Attention** is made of multiple *Single-Head Attention*. Lets denote by *Attention* the calculations performed in a Single-Head Attention module and by h the number of Single-Head Attention composing the Multi-Head Attention module. The Attention module (and hence the Single-Head Attention) takes as input three matrices denoted by $Q \in \mathbb{R}^{l_q \times d_q}$, $K \in \mathbb{R}^{l_k \times d_k}$ and $V \in \mathbb{R}^{l_v \times d_v}$. We usually refer to these matrices by "Query" matrix, "Key" matrix and "Value" matrix respectively. In the encoder we obtain these matrices as follows:

$$Q = X_E W_Q \ , \quad K = X_E W_K \ , \quad V = X_E W_V \ , \quad \text{with } X_E \in \mathbb{R}^{l \times d_{model}} \tag{2.1}$$

with $W_Q \in \mathbb{R}^{d_{model} \times d_q}$, $W_K \in \mathbb{R}^{d_{model} \times d_k}$ and $W_V \in \mathbb{R}^{d_{model} \times d_v}$. Moreover, we have $depth = d_q = d_k = d_v = d_{model}/h$. If there is $h = 4$ heads (as in our implementation in chapter 3) then we have $depth = d_q = d_k = d_v = 64/4 = 16$. Single-Head Attention is then given by:

$$\text{Attention}(Q, K, V) = softmax_j(\frac{QK^T}{\sqrt{d_k}})V = AV, \quad \text{with } A = softmax_j(\frac{QK^T}{\sqrt{d_k}}) \tag{2.2}$$

More precisely, matrix $A \in \mathbb{R}^{l_q \times l_k}$ contains the **attention** weights. By using the softmax function along the columns we get, for each row of A, weights between 0 and 1. Afterwards, the matrix multiplication AV calculates a linear combination of the rows of $V \in \mathbb{R}^{l_v \times d_v}$ weighted by the attention weights found in A. Thus, if we denote by $AV_{i,.}$ the i^{th} row in AV and $V_{j,.}$ the j^{th} row in V then we have:

$$AV_{i,.} = \sum_{j=1}^{l_k} A_{ij} V_{j,.} \quad \forall i \in \{1, ..., l_q\} \tag{2.3}$$

In other words, as each row in V represents a token in the token list, AV contains a new representation for each token that takes into account the information about the other tokens in the sentence. Therefore, the representation of a token or word is not fixed, it changes depending on the context (surrounding words) where it occurs. Attention weights dictate how much each of the surrounding words/tokens should contribute for the new representation of a given word/token. Notice also that, $l_q = l_k = l_v = l = 11$ here. To summarize each Single-Head outputs a matrix that contains a new representation for each token and the matrices W_Q, W_K, and W_V are learned by the model during training.

As we have h heads, we also have h sets of matrices $\{W_Q^i, W_K^i, W_V^i\}$ for $i \in \{1, ..h\}$ that are learned by the model during training for a Multi-Head Attention layer. Each head outputs a matrix, we then concatenate all these matrices along the columns to get a single matrix that we finally multiply by another matrix $W_O \in \mathbb{R}^{hd_v \times d_{model}}$. At the end of the Multi-Head Attention layer we have a matrix $X_{MHA} \in \mathbb{R}^{l_q \times d_{model}}$. With our numeric example we have $X_{MHA} \in \mathbb{R}^{11 \times 64}$.

2.1.3 Add & Norm

Each **Add & Norm** layer, takes as input, both the input and the output of the previous layer. It adds up both and then normalizes the result. The normalization used is *Layer Normalization*, which standardizes the output along the columns for each row of the matrix obtained after the aforementioned addition.

2.1.4 Feed Forward

Feed Forward layer consists of two Dense layers with a ReLU activation in between. See section 1.2.1 for a refresher on Dense layers and ReLU activation function. The first Dense layer outputs a matrix $X_{FF1} \in \mathbb{R}^{l \times dff}$ (we use $dff = 256$ in chapter 3) and the second Dense layer outputs a matrix $X_{FF2} \in \mathbb{R}^{l \times d_{model}}$. The weight matrices associated with both of the Dense layer are trainable weights learned during training. After the Add & Norm layer following the Feed Forward layer in the Encoder we can either repeat once again the Encoder layer (the output will be fed anew as X_E) or we take the output as the Encoder's output. For convenience we will denote the Encoder's output by $H \in \mathbb{R}^{l \times d_{model}}$. We usually refer to it as the Encoder's *Hidden states*. H is then employed by the Decoder's Multi-Head Attention layer (see figure 2.1). More precisely H is used to calculate the key matrix K and value matrix V as we will see in section 2.2.3. Now lets see how the Decoder processes its input.

2.2 The Decoder Input

The Decoder takes as input the target sentence without the <EOS> token. In our example (figure 1.3) it takes as input "<SOS> mais il y a la mer". Suppose that after tokenization, the length of the input tokens list is $m = 10$ (recall that l indicates the length of the Encoder input and $l = 11$ in our example). This list of tokens is represented by "**Outputs (shifted right)**" in figure 2.1.

2.2.1 Output Embedding and Positional Encoding

As with the Encoder input, the vector of tokens is first transformed into a matrix. We then add to it the positional encoding matrix $R \in \mathbb{R}^{m \times d_{model}}$. We denote the resulting matrix by $X_D \in \mathbb{R}^{m \times d_{model}}$. X_D then enters the *Decoder Layer*. As with the Encoder Layer, all the computation occurring inside the Decoder Layer can be repeated N times.

2.2.2 Masked Multi-Head Attention

Everything is the same as the Multi-Head Attention in the Encoder except that we use X_D instead of X_E in equation 2.1 and $l_q = l_k = l_v = m = 10$ here. What is new is the "**Masked**" part. As we give to the Decoder what it has to output but shifted by one token, it can just learn to output what it takes as input but shifted by one token. Thus, it won't learn anything interesting but to shift a sequence. To prevent the model from "cheating", we apply a **mask** to the matrix A containing the attention weights in equation 2.2. This mask zeroes out all the coefficients above the main diagonal i.e. $A_{ij} = 0$, if $j > i$. See appendix A for an illustration. Therefore, in order to output the i^{th} token, the model can't look ahead and can only attend to tokens that come before it in the Decoder input. For our example, we get a final matrix $X_{MMHA} \in \mathbb{R}^{10 \times 64}$.

2.2.3 Add & Norm, Multi-Head Attention and Feed Forward

The Add & Norm layer is the same as the one in the Encoder. We continue to denote by X_{MMHA} the output of this layer. What is new in the next Multi-Head Attention layer, is that $H \in \mathbb{R}^{l \times d_{model}}$ from the Encoder get involved in the computations along with $X_{MMHA} \in \mathbb{R}^{m \times d_{model}}$. Indeed, H is used to calculate K and V and formula 2.1 becomes:

$$Q = X_{MMHA} W_Q \ , \quad K = H W_K \ , \quad V = H W_V \tag{2.4}$$

with $Q \in \mathbb{R}^{m \times d_q}$, $K \in \mathbb{R}^{l \times d_k}$ and $V \in \mathbb{R}^{l \times d_v}$. As in the Encoder we have $depth = d_q = d_k = d_v = d_{model}/h = 64/4 = 16$ for our example. Everything else (equation 2.2 and 2.3) remain the same. Finally the output of the Multi-Head Attention goes through an Add & Norm layer and a Feed Forward layer. The latter outputs a matrix $D \in \mathbb{R}^{m \times d_{model}}$, see figure 2.1. We can either repeat the Decoder Layer one more time (D will be given as input to the Masked Multi-Head Attention layer) or we can pass D to a final Linear layer.

2.3 From the Decoder Output to Probabilities

Matrix D goes through a final Linear layer which has $|V|$ units. Thus, it outputs a matrix $S \in \mathbb{R}^{m \times |V|}$ containing the *scores*, see figure 2.1. Then S is softmaxed along the columns and we get a matrix $P \in \mathbb{R}^{m \times |V|}$ that contains probabilities, see equation 1.1. For the bigger picture of the problem setup see figure 1.3.

2.4 The Transformer at Evaluation Time

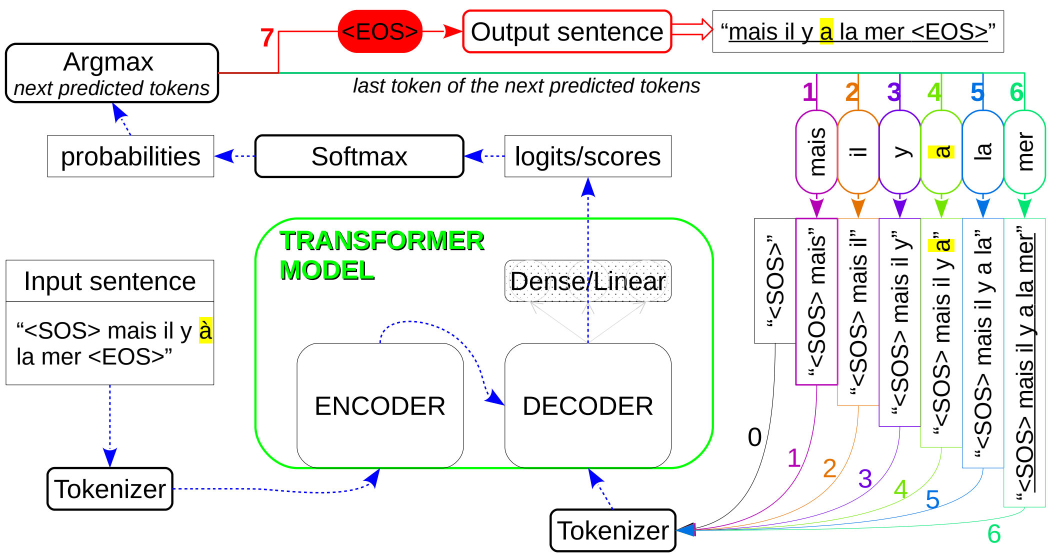


Figure 2.2: The Transformer at evaluation time. For the sake of simplicity, this illustration uses word-level tokens. First, the Encoder takes as input the sentence to be evaluated, and outputs a new representation used by the Decoder afterwards. Second, the Decoder takes as input successively sentence 0 to sentence 6. Each time, we append the last predicted token (from the output sequence) to the next Decoder input. We stop when either the <EOS> token is predicted or a given maximum sentence length is reached.

CHAPTER 3

Homophone Correction using The Transformer

The first two chapters set the stage for this last chapter of the report. Indeed, we will use the knowledge and expertise gained from the study of DL and the Transformer architecture to implement a homophone corrector. Therefore we will have an answer to the question stated in the introduction: **can we implement an effective attention based Transformer model for homophone correction ?**.

One of the criticisms often voiced about deep learning (DL) models is that they need to train on a large amount of data and therefore also require a lot of computing power. To give you an idea, the models in DL, and especially those in NLP, that make headlines with their exploits, are often trained for several weeks in a row on powerful machines, with data ranging from a few gigabytes to several hundred gigabytes, and these models have a number of parameters ranging from a few tens of millions to several hundreds of millions, some even reaching tens of billions of parameters !. Consequently, the trained model is deemed as ***effective*** because it is a relatively small model that does not need a large amount of data or computing power. The performances you will see were obtained with a model that took only *half an hour* to converge (i.e. it has learned the maximum it could learn with the data it was given) on a PC with GPU. Furthermore, the model was trained on *100,000 sentences* in total, the file containing these sentences requires *6 MB* on disk - the size of about 2 photos taken with a smartphone, which is remarkably small.

Also, the model has *431,490 parameters*, and takes up only *5 MB* on the disk.

Finally, the model was trained with 10 pairs of french homophones: (a, à), (est, et), (ces, ses), (ce, se), (ou, où), (la, là), (tout, tous), (leur, leurs), (ceux, ce), (cette, cet). Henceforth we will refer to the two homophones of a given pair as h_1 and h_2. The aim was to train ***an attention based Transformer model*** that correct sentences in which the wrong homophone is employed. For instance in figure 1.3 the input sentence contains "à" but it's incorrect because the right form here is "a". In the latter case, the model is expected to output the sentence by replacing "à" by "a". Thus, the model will take as input a sentence containing an incorrect homophone (h_1 or h_2) and output the sentence by correcting it and replacing the wrong homophone with the correct one (respectively h_2 or h_1). Thus we employ the model for ***homophone correction***. Of course if the sentence is already error-free i.e. the correct homophone is employed, then the model is expected to output exactly the same sentence as the one received as input.

3.1 Methodology

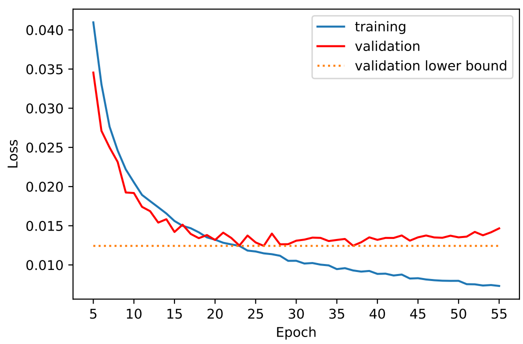
To assess the relevance of such a model, we compare the model's performance with human performance on the homophone correction task. The comparison metrics used are **Precision**, **Recall** and **Accuracy** derived from the counts of *true positive* (**TP**), *false positive* (**FP**), *true negative* (**TN**) and *false negative* (**FN**). For each pair of homophone (h_1, h_2), we have 4 possibilities. Among these 4 possibilities, there are 2 possibilities where one of the two homophones (say h_1) is present in the input sentence, and 2 possibilities where the other one (say h_2) is present. Indeed, h_1 (respectively h_2) can be present in the sentence and either the sentence is correct or the sentence is incorrect because it should have been written h_2 (respectively h_1) instead of h_1 (respectively h_2).

For each pair of homophone the model was trained on $10,000$ sentences; $2,500$ sentences for each of the 4 aforementioned possibilities. Then for each pair the model was tested on $2,000$ sentences; 500 sentences for each possibility. During training, a validation set comprising the same number of sentences as the test set was used to monitor model convergence. Additionally, notice that if the model is given a sentence where h_1 is present and the sentence is correct, it can either keep h_1 (TN) or replace h_1 with h_2 (FP). Now, if the model is given a sentence where h_1 is present and the sentence is incorrect, it can either keep h_1 (FN) or replace h_1 with h_2 (TP). The same reasoning applies to h_2.

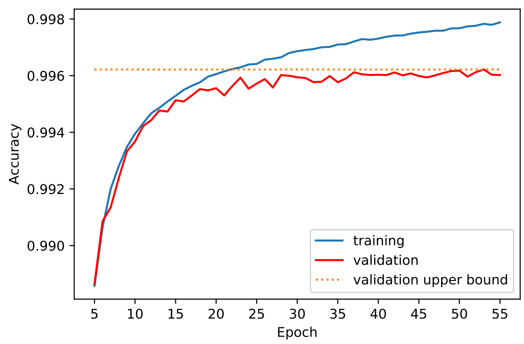
See the online *Github repository* for all source code and detailed information on data selection and data preprocessing [8]. Besides, the trained Transformer have $N = 2$ (Encoder/Decoder) layers, $d_{model} = 64$, $dff = 256$ and number of heads $h = 4$. Moreover, human performance was measured through an *online form* [9]. They were also asked, for each question, to rate the level of confidence they had in their answer, on a scale ranging from 1 (not confident at all) to 10 (very confident). Subsequently, **exact binomial test** was performed to determine statistically significant differences between the model and human performance. See appendix B for a refresher on the metrics used and statistical hypothesis testing.

3.2 Results

First of all, the Transformer converged (the model learned as much as it could from the training data without overfitting) after 25 epochs, and 1 epoch took about 1 minute. Indeed, as we can see in figure 3.1a, at the beginning, both the training loss and the validation loss decrease. Then around epoch 25, the validation loss starts to increase and the training loss continues to decrease. Therefore, after epoch 25 the loss curves diverge. Notice that, the loss and the accuracy are calculated at the token level. As the model learns to output almost the exact same sentence that it takes as input - indeed only a small fraction of the tokens need to be changed - even if it learns nothing it can possibly be wrong for a very small proportion of the tokens. As a consequence, the accuracy on the training set and on the validation set in figure 3.1b are quite high.



(a) Training and Validation Loss curves.



(b) Training and Validation Accuracy curves.

Figure 3.1: The Transformer converges after 25 training epochs.

	Precision		Recall		Accuracy	
	Humans	Transformer	Humans	Transformer	Humans	Transformer
a/à	.9176	**.9831**	**.9398**	.8239	.9277	.8960
à/a	.9405	**.9953**	**.9518**	.8717	.9458	.9210
est/et	.9620	.9229	**.9157**	.8161	**.9398**	.8590
et/est	.9186	**.9870**	**.9518**	.6235	**.9337**	.7980
ces/ses	.8202	.8741	**.8795**	.7434	.8434	.8080
ses/ces	**.9859**	.9000	**.8434**	.6207	**.9157**	.7620
ce/se	.9625	**.9954**	.9277	.8810	.9458	.9250
se/ce	.9625	**.9930**	.9277	.8730	.9458	.9230
ou/où	.9474	.9440	.8675	**.9267**	.9096	.9230
où/ou	.9302	.9312	**.9639**	.8958	.9458	.9110
la/là	.9634	**.9978**	.9518	.9268	.9578	.9470
là/la	.9870	.9740	.9157	**.9819**	.9518	.9710
tout/tous	.9286	.9504	.7831	**.8909**	.8614	**.9120**
tous/tout	.8617	**.9430**	**.9759**	.9067	.9096	.9140
leur/leurs	.8657	**.9645**	.6988	**.9333**	.7952	**.9420**
leurs/leur	.9091	.9482	.8434	**.9597**	.8795	**.9480**
ceux/ce	.9753	.9350	.9518	.9819	.9639	.9500
ce/ceux	.9867	.9830	.8916	**.9448**	.9398	.9450
cette/cet	.9157	**.9757**	.9157	**.9679**	.9157	**.9660**
cet/cette	.9651	.9818	1.	.9739	.9819	.9750
Average	.9353	.9590	.9048	.8772	.9205	.9098
Advantage	1	9	8	7	3	4

Table 3.1: Comparison of Transformer performance with those of all respondents. The bold word at the beginning of each line indicates the homophone whose measurements are reported on the line, and the associated form is indicated after the slash. Statistically significant results (p-value < 0.05) are in bold.

Next, 83 people completed the online form, with an average age of 28 years (standard deviation is 15 years). For a detailed presentation of the respondents' profile see appendix C. In addition, *when respondents made an error (FP and FN), the average confidence level* *was **8***, while when the answer was correct (TP and TN), the average confidence level was 9.5. Thus, even when they were wrong, they were very confident.

Finally, Table 3.1 compares the model's performance with human performance on the homophone correction task. Table 3.1 reads as follows: on the first line, for example, "***a***/*à*" means that the sentence proposed to the model or human contains the letter "*a*". The *Precision* on this line indicates then, the probability that the model or the human is right (the confidence that one can have on the modification made) when it changes the "*a*" into "*à*". The *Recall* indicates, among all the times when "*a*" had to be changed into "*à*" (because the sentence is not correct), the probability that the model or the human detects the error. Finally, the *Accuracy* indicates the probability that the model or the human gives the right answer, when "*a*" is present in the proposed sentence (all situations combined). For the second line, we are interested in the results when it is "*à*" that is proposed to the model or to the human. More generally on each line, the results are given in relation to the homophone in bold at the beginning of the line. The homophone after the slash indicates the word with which the model or human replaces the word in bold (when it replaces it, which is not always the case).

3.3 Discussion

For the comparison of results, one could only compare the average performance. However, comparing the model and the human for each condition of a pair of homophones, gives a more refined measure. Each pair (h_1, h_2) has two conditions, h_1/h_2 (for instance ***a***/*à*) and h_2/h_1 (for instance ***à***/*a*). Therefore, for the 10 pairs there are a total of 20 conditions corresponding to the 20 rows in Table 3.1.

The performance taken condition by condition (each row in Table 3.1) indicates that, for Precision, the model performs better than humans in 9 conditions, the human performs better than the model in 1 condition, and the difference is not statistically significant in 10 conditions. For Recall, the model performs better than humans in 7 conditions, the human performs better than the model in 8 conditions, and the difference is not statistically significant in 5 conditions. Finally, for Accuracy, the model performs better than humans in 4 conditions, the human performs better than the model in 3 conditions, and the difference is not statistically significant in 13 conditions.

Using this way of comparing, we have 60 points of comparison. What emerges from these results is a clear advantage (9-1) for the model for Precision, tight results for Recall (7-8) and Accuracy (4-3). Overall, *the model scores more points (20) than the humans (12), and "wins" against the humans on a score of 20-28-12*, with 28 indicating the number of points that could not be awarded to either because the difference was not statistically significant. We can add a further argument for the relevance of the model: *time.* Indeed, to evaluate the 40 sentences of the questionnaire, the Transformer took only 38 seconds (a little less than 1 second per sentence) - with a score of 37/40. In contrast, humans take much longer, with some respondents reporting 10 to 15 minutes to complete the questionnaire (the exact time taken by the respondents was not measured) - that is, 15 to 20 times longer than the Transformer.

Additionally, we must discuss the limitations of the present study. In particular, *human performance was biased.* Indeed, the main bias is the way the answers were collected through the online questionnaire. When we make a mistake, we do so by writing it down the first time, then if we check again we may not detect the mistake (or change a word that was actually good), and thus leave the mistake (or introduce a new mistake) after checking. The questionnaire simulated more the 2^{nd} condition i.e. a review of what we have already written, since a sentence was presented and the respondent had to judge if it was correct or not. This led to better performance, since all the attention was focused on error detection. All the more so since, in the context of the questionnaire, *the respondents knew there would be errors* (this was explicitly indicated in the presentation of the questionnaire) and were therefore even more watchful. On the other hand, error checking was made even easier, as humans had only two response options, "oui, la phrase est correcte" (yes, the sentence is correct) and "non, la phrase n'est pas correcte, *il faut remplacer x par y*" (no, the sentence is not correct, *we should replace x with y*) where x is a homophone present in the sentence and y its associated homophone. Thus, thanks to the hint, the humans knew exactly where to focus their attention in the sentence, which is far from the real conditions of error correction during a rereading. *This may explain the good performance of humans on the Recall measure* which indicates the ability to detect an error when it is present. While the model, received as input only the sentence without any other indication, and had to output the sentence with correction if necessary. These biases are related to the way human performance was evaluated.

A second, but equally important, bias stems from the composition of the sample of respondents. Indeed, among the respondents, 48% have a level of education higher than BAC+2 (and 10% even have a level of education higher than BAC+5) see figure C.2b, while according to INSEE [10, data for 2020], only 25% of the French people have a level of education higher than BAC+2. Moreover, it is also indicated that 18.5% of French people between 25 and 64 years old have no diploma (maximum the "Brevet des collèges"), whereas in the sample of respondents, all the people between 25 and 64 years old have at least the BAC. These two elements combined suggest that the sample is biased toward highly educated individuals. This bias arguably favored human performance.

Last but not least, we discuss ideas for further studies extending what has been done here. We used only 10 pairs of homophone, so we could train a model on a much bigger number of pairs. We could also use the same approach but using pairs constituted of subword level units. For instance we can use pairs made of verb endings such as (-*ais*/-*ait*) that would simulate conjugation errors: ("je voul*ais*", "il voul*ait*") $\longmapsto$ ("je voul*ait*", "il voul*ais*"). At the time of writing these lines, a database referencing common mistakes in French doesn't exist. Therefore we could conduct studies in order to constitute a comprehensive database of typical errors that are made. Then we could train a model to corrupt correct sentences by introducing errors inspired by this database instead of injecting errors at random. Thus, we can get an even larger database which can be used to train efficient spell or word checkers, as it has been done for this TER.

3.4 Conclusion

The Transformer introduced by Vaswani et al. was a major breakthrough in Natural Language Processing. Since then, it has been successfully employed in other fields of Artificial Intelligence but also in problems that were not traditionally solved using Deep Learning. In addition to analyzing the Transformer in detail, we also used it to implement an effective word checker, which tackles the problem of homophone correction by leveraging the Transformer's attention mechanism. We then compared its performance with that of humans. Overall, the Transformer performs better and takes considerably less time than humans, even under conditions where humans have a significant advantage over the model in correcting homophone-related errors.

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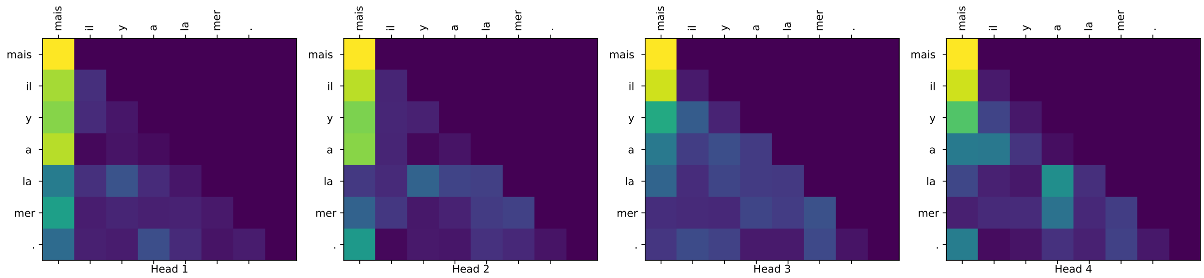
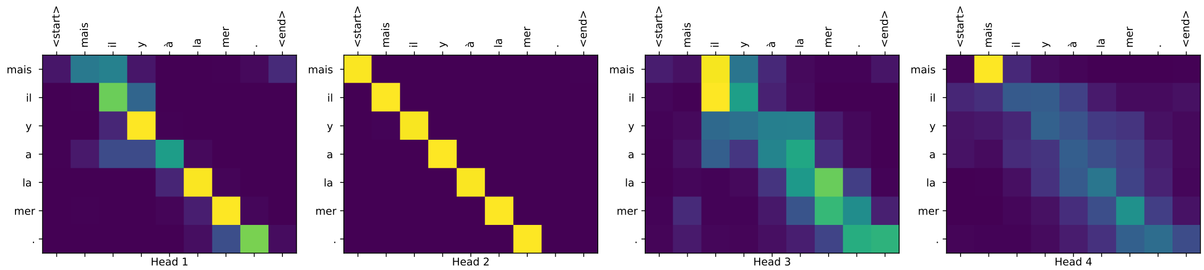
APPENDIX A

Attention Weights Visualization

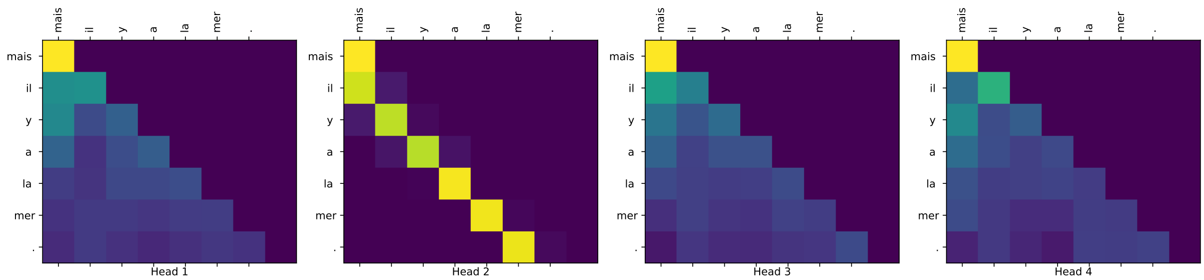
In figure A.1 we can visualize the attention weights. In this example, the Transformer takes as input the incorrect sentence “mais il y **à** la mer.”, and outputs a corrected version of this sentence - “mais il y **a** la mer.” - by replacing “à” with “a”. The incorrect sentence is also what the Encoder takes as input as mentioned in chapter 2.



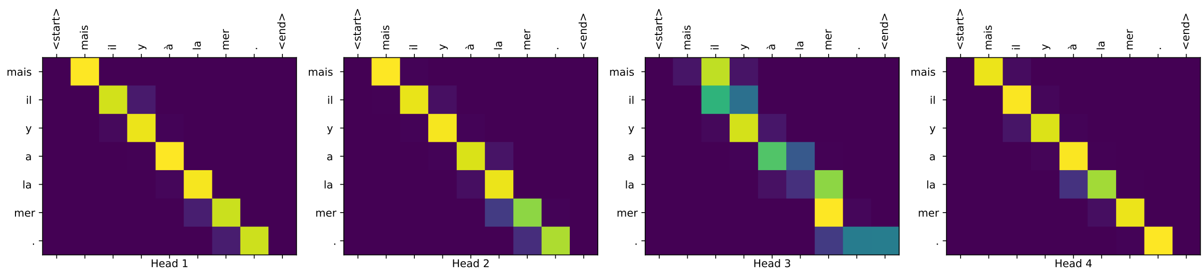
(a) Decoder Layer 1 Block 1 (Masked Multi-Head Attention).



(b) Decoder Layer 1 Block 2 (Multi-Head Attention).



(c) Decoder Layer 2 Block 1 (Masked Multi-Head Attention).



(d) Decoder Layer 2 Block 2 (Multi-Head Attention).

Figure A.1: Example of attention weights that can be found within the Transformer. The model's output tokens are shown along the y-axis (vertically). Along the x-axis (horizontally) are shown the Decoder's input for the Masked Multi-Head Attention Block (sub-figure a and c), and the Encoder's input for the Multi-Head Attention Block (sub-figure b and d). Moreover, the yellower the cell, the higher the attention weight - i.e. close to 1. The darker the cell, the lower the attention weight - i.e. close to 0.

APPENDIX B

Metrics and Statistical Hypothesis Testing

To assess and compare the performance of humans with the Transformer model, we will use 3 metrics/probabilities (Precision, Recall and Accuracy), which are deduced from 4 other measures (TP, FP, TN, FN). Let's first look at these 4 measures.

B.1 The 4 potential situations: TP, FP, TN, FN

We will see the reasoning with one pair of homophones in particular. The reasoning will then be generalized to all other pairs. Let's take the pair (a, à). Here the goal for the human and the model is to detect an error if there is one. First of all, there are 2 possibilities: either the sentence proposed to the human or to the model contains an error on a homophone, or the sentence does not contain any error. Then there are again 2 possibilities, the human or the model will either choose to change or not to change the homophone present in the proposed sentence.

For example, we can propose the sentence "Il *a* fait valoir que les tarifs du câble ont été réglementés aux États-Unis" (1). This sentence is correct because it is "a" that should be used, not "à". This sentence is what the human or model takes as input. However, even if the input sentence is correct, the human or the model may change the homophone (here "a") and replace it by its associated form (here "à"), and therefore be wrong. When the input sentence is correct and the model or the human modifies the sentence, and thus is wrong, we call it a false positive, since an error is detected (hence the term positive) where there is none (hence the term false). The abbreviation **FP** is used to designate this situation. Moreover, if the human or the model does not change the correct sentence that it was given (here "Il *a* fait valoir que les tarifs du câble ont été réglementés aux États-Unis"), then it does not make an error and we call it a true negative, since no error is detected (hence the term negative) and there was really no error (hence the term true). In this case, the abbreviation **TN** is used to designate this situation. Here we have seen the 2 possibilities when the presented sentence is correct. Let's now look at what happens if the sentence presented to the human or to the model contains a wrong homophone.

We can take a sentence and voluntarily introduce an error into it (this is how the training data was created to train the Transformer model). We propose to the human or to the model, for example, the sentence "Mais quand t'es embarqué dans l'engrenage, tu ne penses même pas *a* ça" (2). This sentence is incorrect because it is "à" that should have been used, not "a". The goal for the human or the model is to detect this error and to replace "a" by "à" in order to output the correct sentence: "Mais quand t'es embarqué dans l'engrenage, tu ne penses même pas *à* ça". However, the human or the model may fail to detect this error, and so will not modify the sentence and leave the incorrect form "a". When the input sentence is incorrect, and the human or the model fails to detect the error (does not correct the error and thus makes a mistake by leaving the incorrect form), we call it a *false negative*, since an error is not detected (hence the term *negative*) whereas there is really an error (hence the term *false*). We use the abbreviation **FN** to designate this situation. Furthermore, if the human or the model succeed in detecting the error and replace "a" by the correct form "à" (and thus outputs "Mais quand t'es embarqué dans l'engrenage, tu ne penses même pas *à* ça"), we call it a true positive, since an error is detected (hence the term *positive*) and there really was an error (hence the term *true*). The abbreviation **TP** is used to designate this situation. These 2 possibilities add to the 2 possibilities seen in the last paragraph, which makes 4 possible situations, namely TP, FP, TN and FN. Table B.1 summarizes the 4 possibilities.

Hence, with the example sentences (1) and (2) we have just seen the 4 possible cases when we propose to the model or to the human a sentence containing the homophone "a". Each sentence leads to two possibilities, TN/FP for one, and TP/FN for the other. Moreover, each homophone is associated with another homophone, forming a pair of homo-

	Correct output	Incorrect output
Incorrect input	TP	FN
Correct input	TN	FP

Table B.1: The 4 possible situations when a sentence contains a homophone.

phones. The associated homophone is then what the model or the human puts, if he decides to modify the given input sentence. Similarly, we can give as input a sentence containing "à" that is correct, and a sentence containing "à" that is incorrect (the model or human will then have to change the "à" into "a"). Therefore, for the pair of homophones (a, à), we need 4 different sentences to cover all possible cases.

More generally, we need 4 sentences to represent all possible cases for the input for each pair of homophones. Consequently, to have all the possible cases for all the pairs (we have 10 in this study) we need 40 sentences. This is why in the online questionnaire there were 40 questions. Using these 4 measures for each homophone, we construct 3 other metrics that can be interpreted as probabilities.

B.2 Precision, Recall and Accuracy

In this section we will see how to calculate these 3 metrics.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{B.1}$$

The measure of **Precision** takes into account all the times when the homophone present in the sentence proposed to the model or the human was changed into its associated form by the latter. Either he changed it and there was really an error (TP), or he changed it but there was no error (FP). The *Precision* gives the probability that the model or the human was right if he changes the homophone present in the sentence. In other words, if the model or the human changes the homophone in the sentence and puts the associated form instead, the probability that it is correct is given by the precision.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{B.2}$$

The measure of **Recall** takes into account all the times when the homophone present in the sentence proposed to the model or human should be changed into its associated form by the latter. All the sentences presented to measure this criterion therefore contain an error. For example, the sentence “Mais quand t’es embarqué dans l’engrenage, tu ne penses même pas *a* ça” can be used to calculate the *Recall* for the homophone “a”. Afterwards, either the human or the model changes the homophone and replaces it with its associated form and we know that there was really an error (TP), or it does not detect the error and does not change anything (FN, it made a mistake by leaving the incorrect form i.e. failed to detect the error). The *Recall* gives the probability, for a given homophone, that the model or the human will detect the error if there is one. In other words, if the homophone present in the sentence is not of the correct form (and therefore must be replaced by its associated form), the probability that the model or the human will manage to detect the error is given by the *Recall*.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{B.3}$$

The **Accuracy** measure takes into account all 4 possible situations for each homophone when it is present in a sentence. This is the measure that we intuitively think of when we measure a score for example. We count all the times when the model or the human gave the right answer ($TP + TN$). Then we deduce all the times when the model or the human gave the wrong answer ($FP + FN$). Then we divide the number of correct answers by the total number of sentences that were presented ($TP + TN + FP + FN$). The *Accuracy* gives an overall measure of performance in all situations. However, when there is an imbalance between the frequency of incorrect sentences and the frequency of correct sentences, the *Accuracy* measure is less informative. Indeed, let’s imagine a situation where an error occurs only in 5% of the cases, and we wish to detect the error when it occurs. A simple rule would be to decide that there is no error every time, and in this case we will give the right answer in 95% of the cases since 95% of the cases are error-free. We will then have an accuracy of 0.95 (95%) and we could say that we have a good system. However, the Recall (which measures the probability of detecting an error) will be 0 (0%), since we will never take the decision, with the simple rule, to say that there is an error - and thus when there is really an error (in 5% of the cases) we will not detect it - while the goal of our system is, above all, to detect errors !

B.3 Statistical Hypothesis Testing

This section briefly explains the statistical tests used to evaluate the differences between human and Transformer performance. First, it is necessary to explain how the measures are obtained. Human performance was obtained through an online questionnaire. The answers to the 40 questions given by the respondents were used to count the TP, FP, TN and FN and then calculate Precision, Recall and Accuracy. The performance of the Transformer was obtained after testing it on 20,000 sentences. For each pair of homophones there were 2,000 sentences. Within these 2,000 sentences, each homophone in the pair was present in 1,000 sentences. Among these 1,000 sentences, in 500 sentences its form was the correct form (thus measuring the number of FP and TN). In the other 500 sentences, its associated homophone should have been written instead, thus the model had to detect it and replace it by its associated form (thus measuring the number of TP and FN).

To get an idea of the relevance of the model, we compare its performance with human performance. However, we need to know when the difference between the performances can be considered *statistically* significant. We use the **exact binomial test**. Moreover, the Precision, the Recall, and the Accuracy are measures between 0 and 1 since they represent probabilities.

In a statistical test we have 2 hypotheses. Let us note, the model precision by p_0 and the human precision by p_h. The first hypothesis, called the *null hypothesis* and noted H_0, is the hypothesis that we consider true by default. Here, H_0 is the hypothesis that the Precision of the model is equal to the Precision of the humans i.e. "$H_0 : p_0 = p_h$". The second hypothesis, called the *alternative hypothesis* and noted H_1, is the hypothesis against which we test H_0. The goal of the test is to see if we can reject or not the hypothesis H_0 in favor of H_1. Nevertheless, it is important to understand that if we cannot reject H_0 in favor of H_1, it does not mean that we have shown that H_0 is true. All the test allows us to say is that we can reject H_0 in favor of H_1. The test does not allow to prove that H_0 is true. This being said, for each test, we can never be 100% sure of taking the right decision. There is always a risk of being wrong. This risk is given by the *p-value*. The **p-value** indicates, if H_0 is true, then what is the probability of observing outcomes that are at least as extreme or more extreme than the observed outcome. Thus, the smaller the p-value, the smaller the probability that H_0 is true with respect to our data. We then - arbitrarily - decide on a threshold for the p-value, below which we decide to reject H_0. For example, if we set the threshold at p-value = 0.05, then if a test has a smaller p-value, 0.02 for example, then we will reject H_0, and we will say that we reject H_0 and we decide H_1 with a risk (i.e. a probability) of being wrong of 0.02 .

In general, we can note p_0 the performance of the Transformer for a given measure, and p_h the performance of humans for this same measure. Finally, for all comparisons, the alternative hypothesis will be $H_1 : p_0 < p_h$ when testing whether humans are significantly better than the Transformer (when the performance gap is in favor of humans), and $H_1 : p_0 > p_h$ when testing whether humans are significantly worse than the Transformer (when the performance gap is in favor of the Transformer). If a test has a p-value higher than the threshold value, then we can neither reject H_0 nor accept H_0, we will say that the test is not statistically significant, or not conclusive. In our case, if a test is not statistically significant, we will say that we are undecided between the Transformer and the humans. Indeed, intuitively, if the difference in performance is very small, then we need a large sample of respondents to be able to conclude, and our sample size is limited by the number of people who answered the online questionnaire.

APPENDIX C

Additional Characteristics of Human Respondents

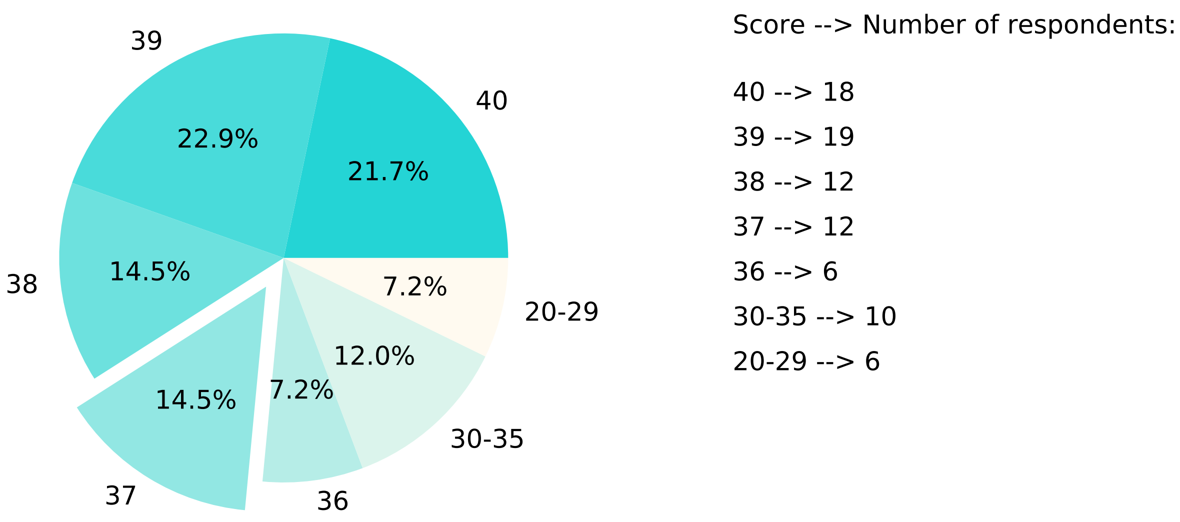
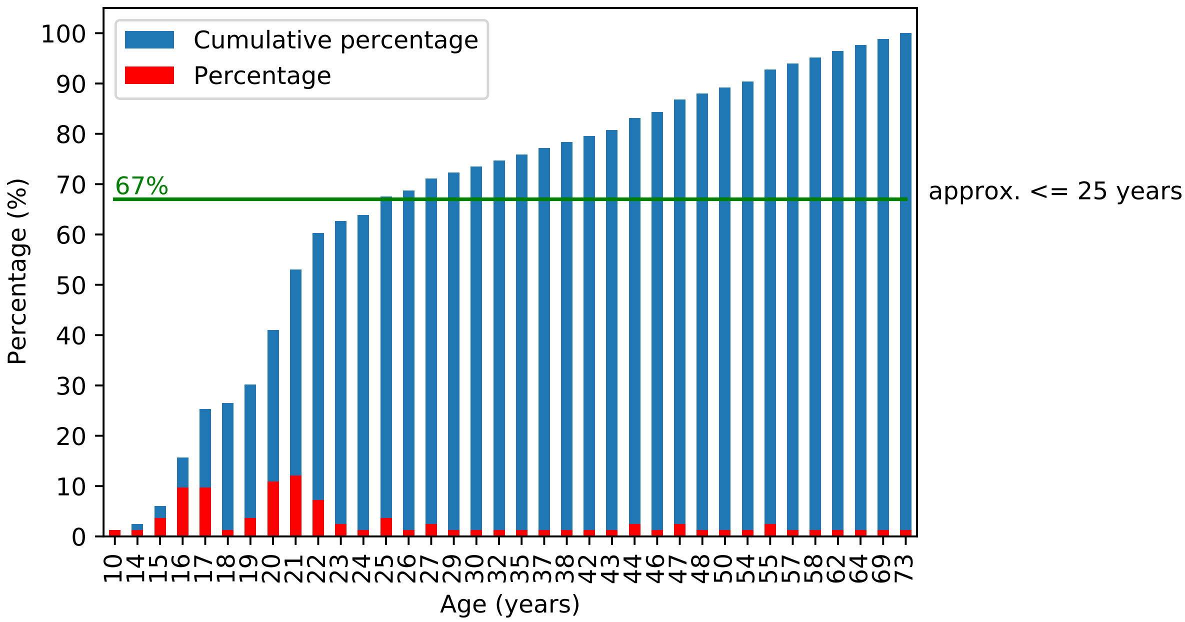
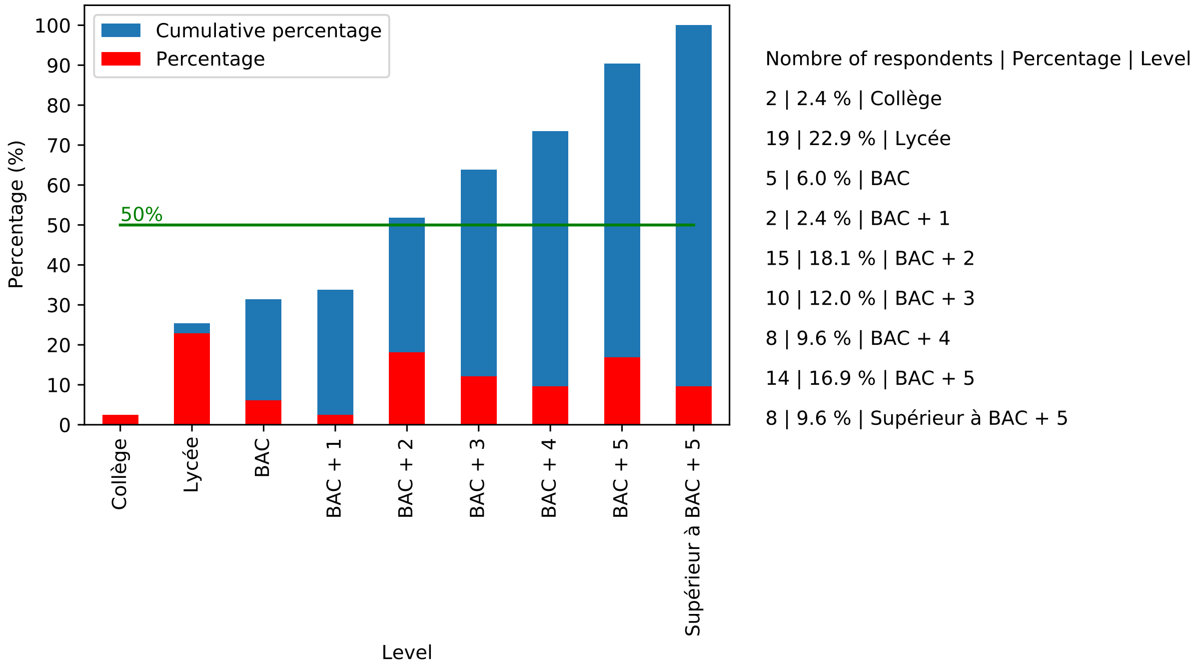


Figure C.1: Scores of all 83 respondents on the online questionnaire. The Transformer obtained 37 points.



(a) Percentage of respondents by age across all 83 respondents.



(b) Study level across all 83 respondents.

Figure C.2: Age and Study level distribution of the 83 human participants who responded to the online questionnaire.