Hands on Camembert

Building a dialog act classification model for French

Benjamin Muller Roman Castagne Nathan Godey INRIA Paris

Hands on Camembert

Session 1 [lecture]: Dialog Act Classification with Camembert

Session 2 [coding]: Camembert Language Modeling

Session 3 [coding]: Building a supervised model for dialog act prediction for French with Camembert

Hands on Camembert: Session 1

1. Framework: Focus on Dialog Act Prediction

2. Task-Specific Modeling
    a. Segmentation
    b. The Transformers Architecture
    c. Training

3. The Camembert model

Acknowledgement

We built Camembert in 2019 as part of a collaboration between **INRIA Paris (ALMANACH** team) and **Facebook AI**

Work done by **Louis Martin, Pedro Ortiz, Benjamin Muller** with the guidance of Yoann Dupont, Laurent Romary, Éric Villemonte de la Clergerie, Djamé Seddah and Benoît Sagot

Camembert derived from **BERT** (released by Google in 2018) and **ROBERTa** (released by Facebook in 2019).

Framework

Given a sequence of tokens $(w_1, .., w_T)$ goal is to find the best model $model_\theta$ to predict a label or sequence of label *Y*

$$model_\theta : \quad \mathcal{V}^T \quad \rightarrow \quad \Omega = \mathcal{L},\ \mathcal{V}'^{T'}$$

$$(w_1, .., w_T) \mapsto \hat{Y}$$

We may want to

- ➔ assign a category to each word (*sequence labeling*)
- ➔ assign a category to each sentence (*sequence classification*)
- ➔ Generate a sequence (*sequence generation*)

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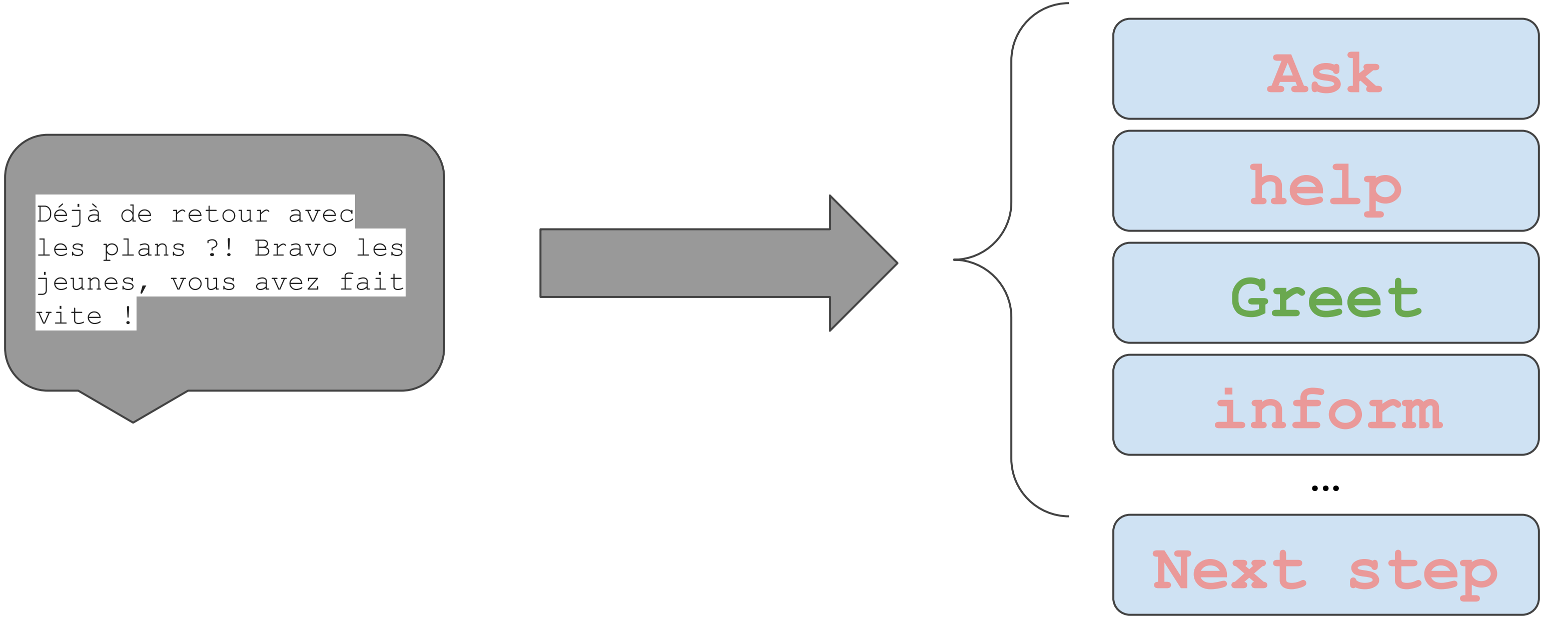
In this tutorial

We will build a **Dialog Act Classification model for French**

Dialog Act Classification Model

We build a **Dialog Act Classification model for French**



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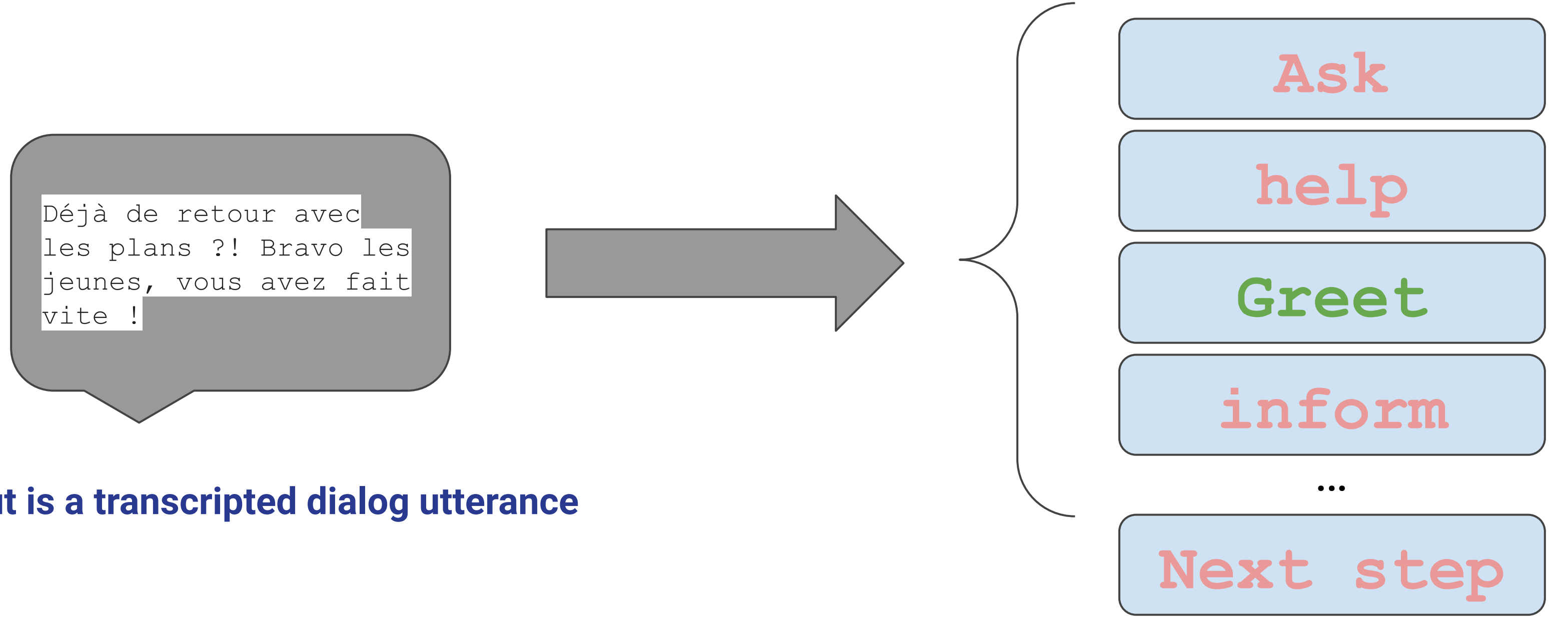

Input is a transcripted dialog utterance

Label is a dialog act [29 possible labels]

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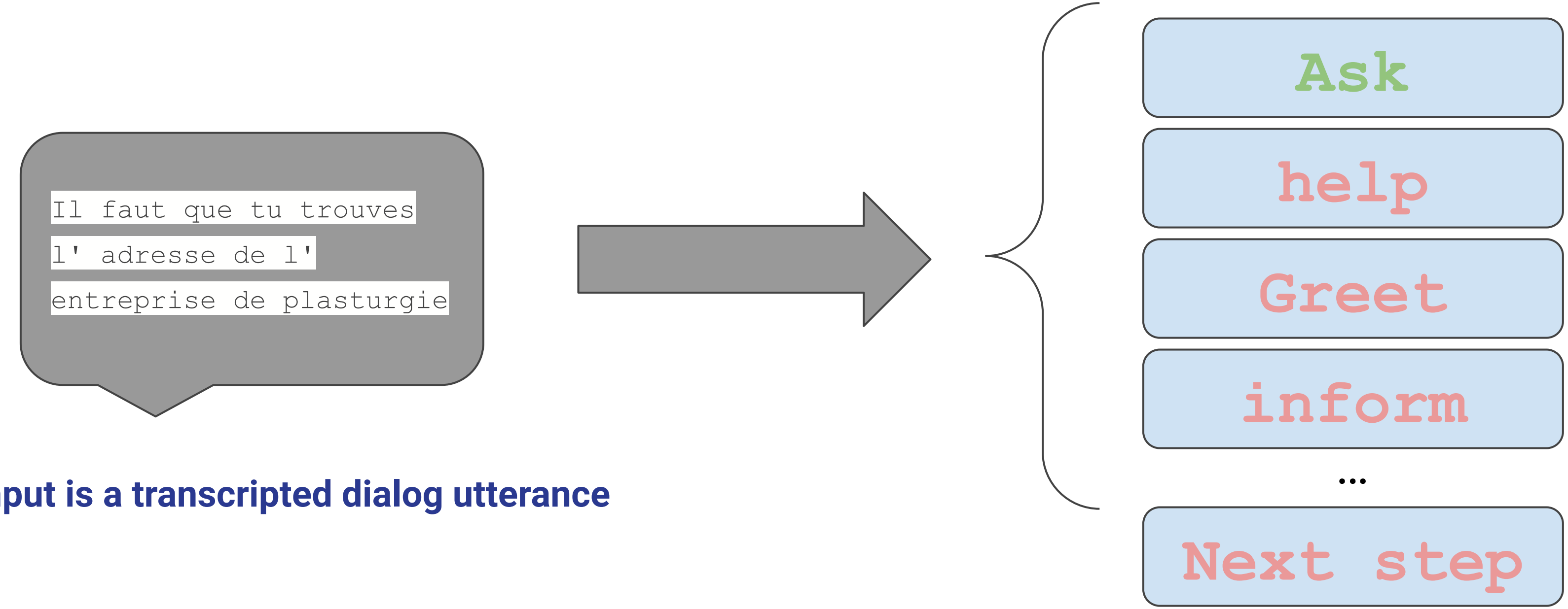

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Building a NLP Model

1. How do we segment the input text ?

2. How do we parametrize the *model*?

3. How do we train the model?

Building a NLP Model: In this Tutorial

1. **How do we segment the input text ?**

➔ We use **sentencepiece** tokenization which is a data-driven sub-word segmentation algorithm

2. How do we parametrize the *model*?

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Tokenization

Tokenization is the first step of everything we do in NLP

It consists in segmenting raw text to define **our modeling units (tokens)**

E.g.: `Il faut que tu trouves l' adresse de l' entreprise de plasturgie`

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E.g.: *`Il faut que tu trouves l' adresse de l' entreprise de plasturgie`*

★ Word level segmentation

➔ `['Il', 'faut', 'que', 'tu', 'trouves', "l'", 'adresse', 'de', "l'", 'entreprise', 'de', 'plasturgie']`

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What happens for an unknown word at test time?

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★ Word level segmentation → **Limit: Out-of-Vocabulary Problem**

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★ Character-Level Segmentation

`['I', 'l', ' ', 'f', 'a', 'u', 't', ' ', 'q', 'u', 'e', ' ', 't', 'u', ' ', 't',....`

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- ★ Word level segmentation → **Limit: Out-of-Vocabulary Problem**
- ★ Character-Level Segmentation → **Limit: Too Long Sequences**

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★ **Sentencepiece**
Segment at the word-level except for infrequent words that are segmented at the subword level

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★ Word level segmentation → **Limit: Out-of-Vocabulary Problem**

★ Character-Level Segmentation → **Limit: Too Long Sequences**

★ **Sentencepiece** → **Tradeoff between both approaches**
Segment at the word-level except for infrequent words that are segmented at the subword level
`['_Il','_faut','_que','_tu','_trouve','s','_l',"'",'_adresse','_de','_l',"'",'_entreprise','_de','_','plast','ur','gie']`

Building a NLP Model: In this Tutorial

1. How do we segment the input text ?

➔ We use sentencepiece tokenization which is a data-driven sub-word segmentation algorithm

2. **How do we parametrize the *model*?**

➔ **We use the transformer architecture**

3. How do we train the model?

Recall

Given a sequence of tokens $(w_1, .., w_T)$ goal is to find the best model $model_\theta$ to predict a label or sequence of label *Y*

$$model_\theta : \qquad \mathcal{V}^T \qquad \rightarrow \quad \Omega = \mathcal{L}, \ \mathcal{V}'^{T'}$$

$$(w_1, .., w_T) \mapsto \hat{Y}$$

We want to build a **Dialog Act Classification model for French**

How to parametrize the Model?

We parametrize the model with a **Transformer** architecture

- The Transformer is a deep-learning architecture
- It **can be used to parametrize any** sequence labelling, classification and generation **task**
- It is **the most popular and accurate architecture for most NLP tasks**

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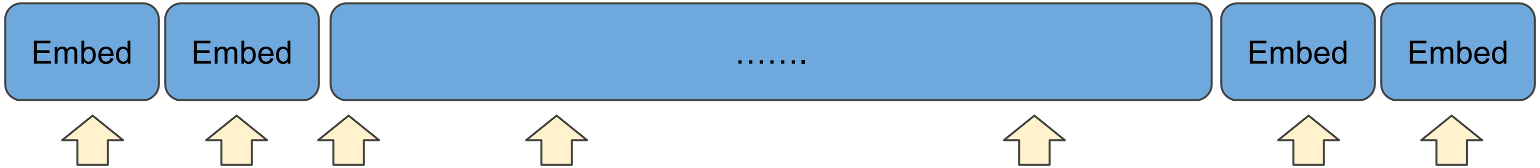
In a nutshell

- Transformers are *trainable functions* made of **the stack of multiple linear and non-linear functions**
- All the parameters are trained **to minimize a loss function for a given task**
- In this tutorial, we use **a Transformer (Camembert) to perform dialog act prediction**

Sequence Classification with a Transformer

```
[<s> '_Il',,"'",'_entreprise','_de','_','plast','ur','gie', </s>]
```

Sequence Classification with a Transformer



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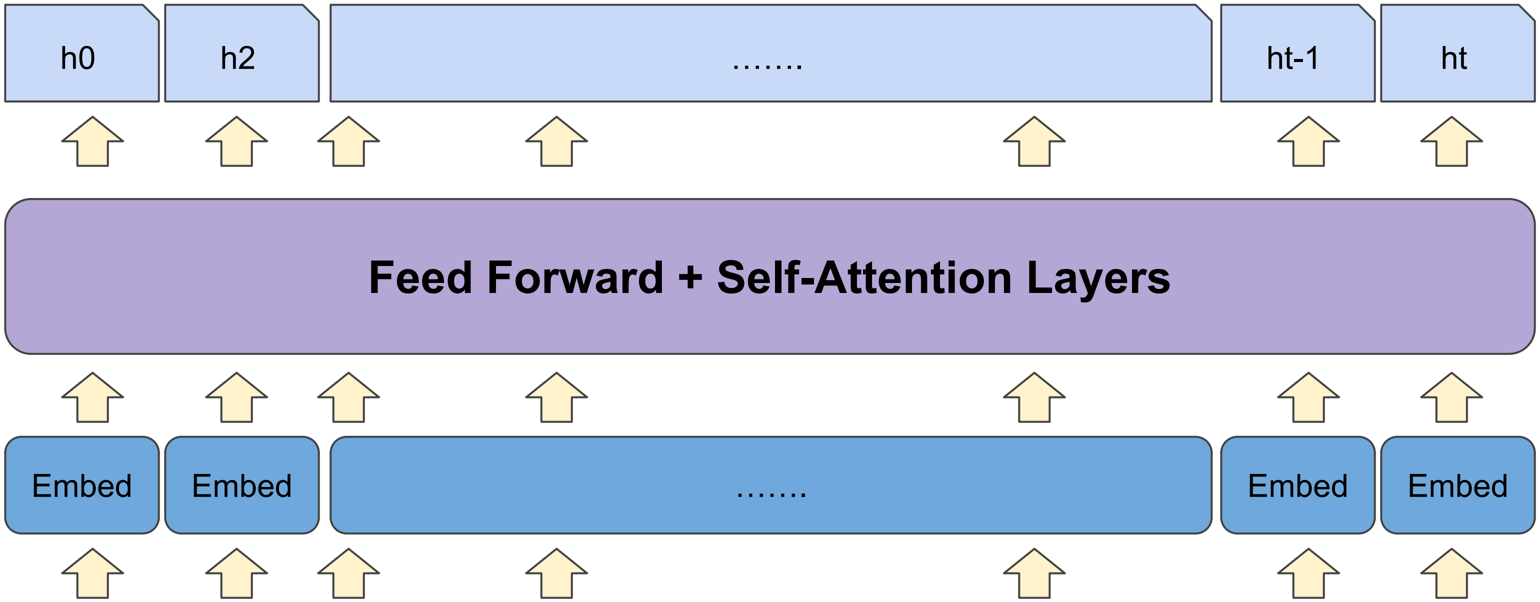

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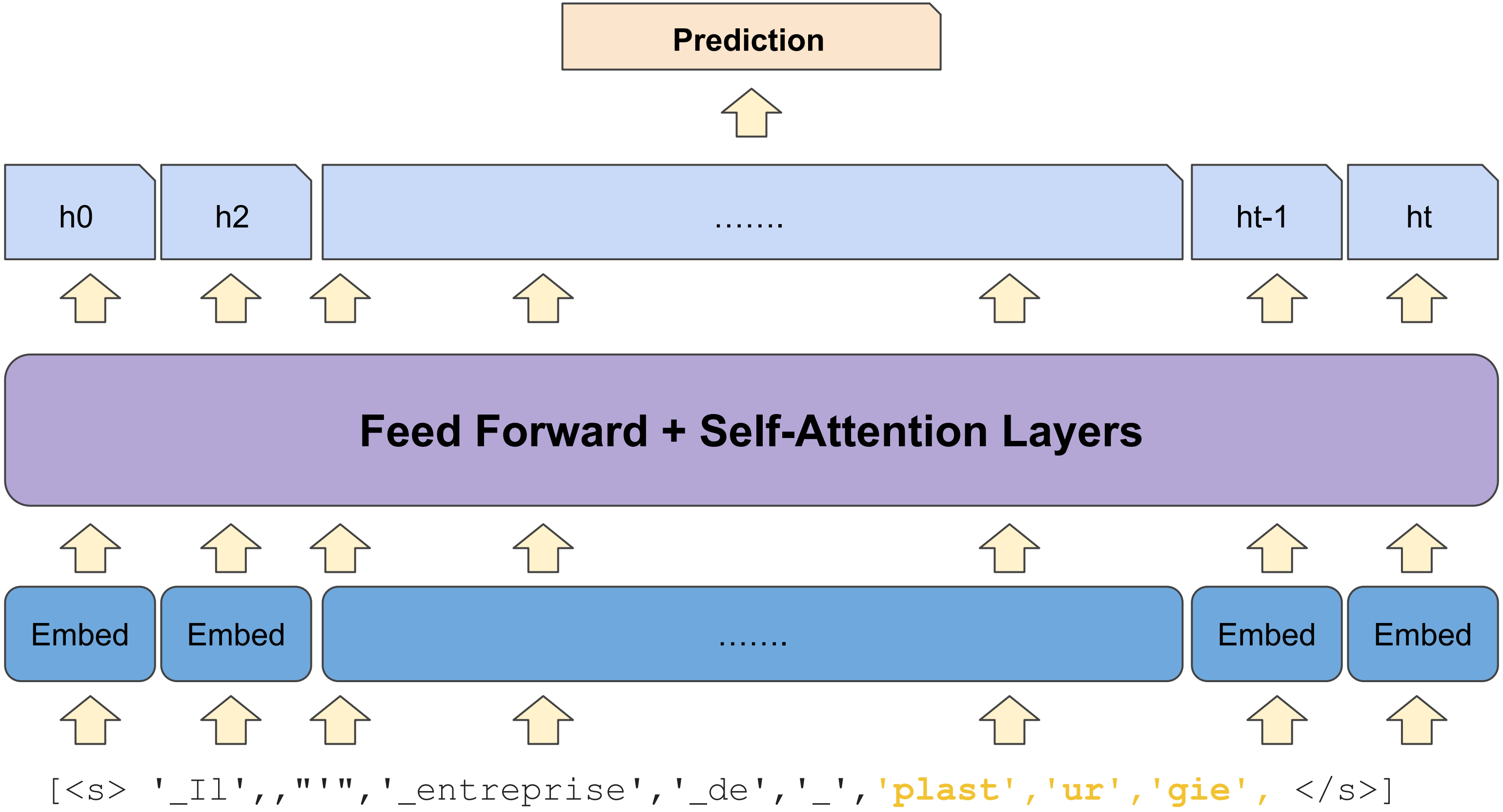
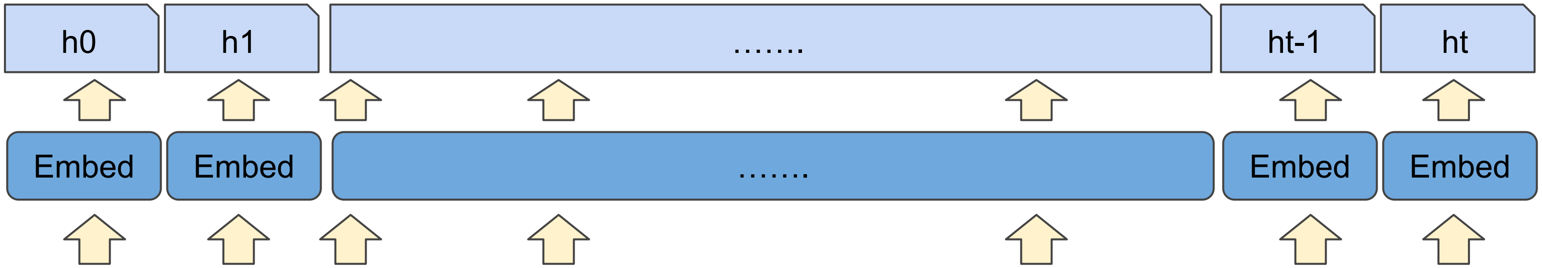


Self-Attention Layer



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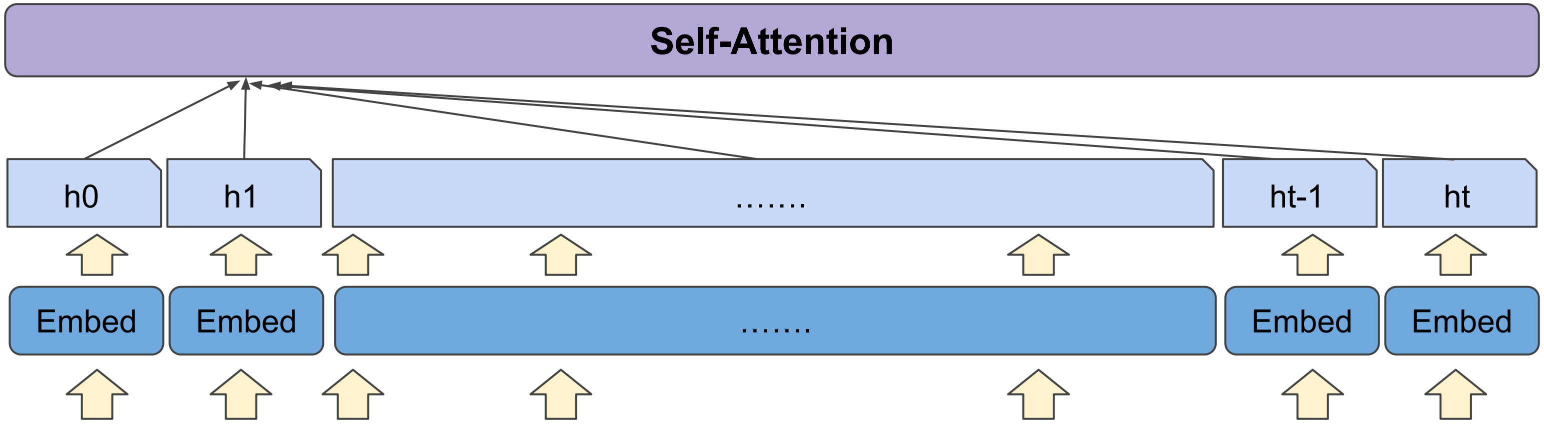

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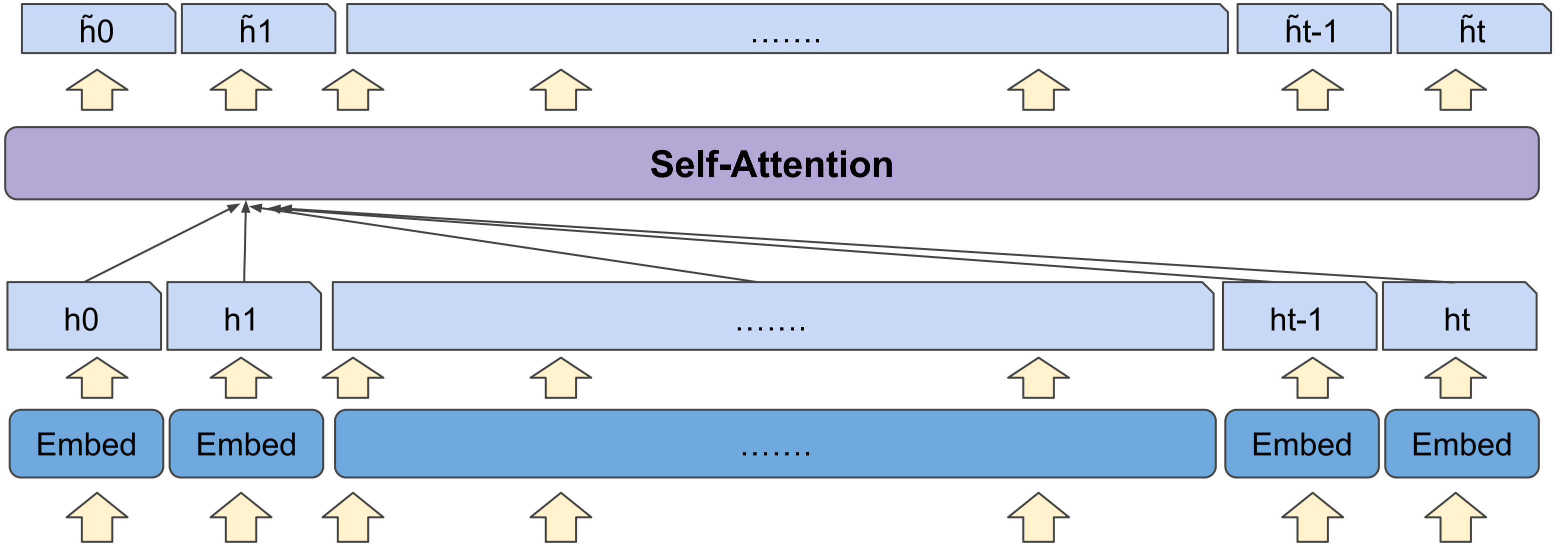

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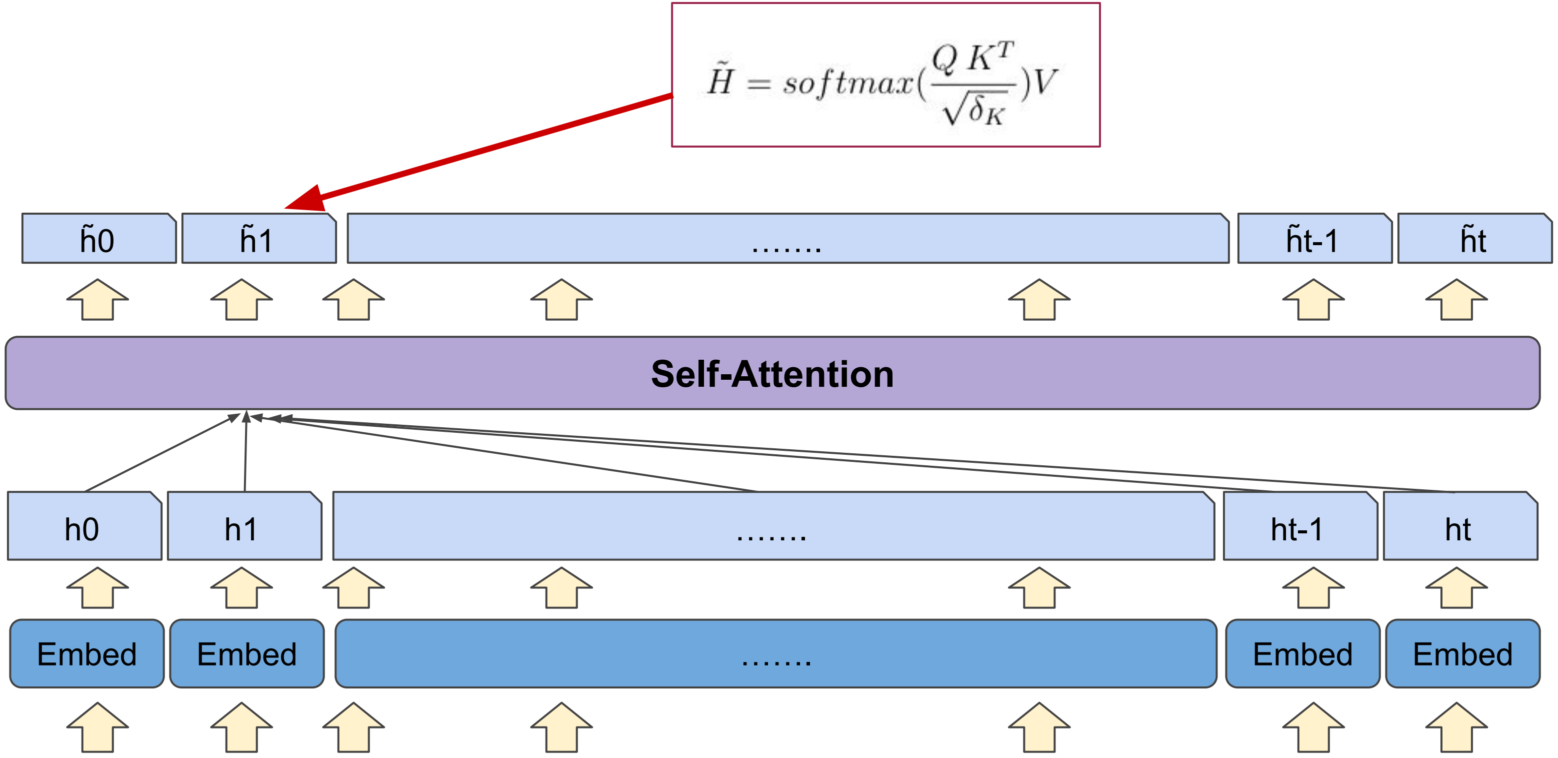


[<s> '_Il',,"'",'_entreprise','_de','_','plast','ur','gie', </s>]

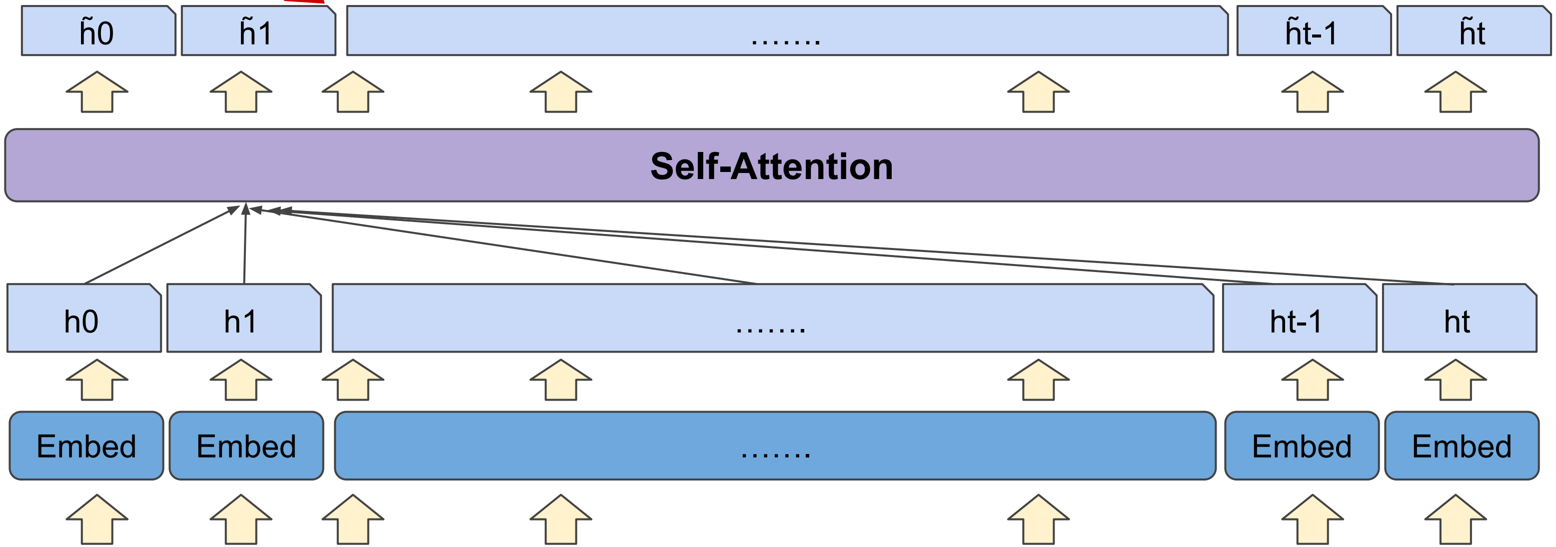
Self-Attention Layer

$$q_t = W_Q h_t \ , \forall\, t \in [|1, T|] \text{ with } W_Q \in \mathrm{R}^{\delta_q \times \delta}$$

$$k_t = W_K h_t \ , \forall\, t \in [|1, T|] \text{ with } W_K \in \mathrm{R}^{\delta_k \times \delta}$$

$$v_t = W_V h_t \ , \forall\, t \in [|1, T|] \text{ with } W_V \in \mathrm{R}^{\delta_v \times \delta}$$

$$\tilde{H} = softmax\left(\frac{Q\,K^T}{\sqrt{\delta_K}}\right)V$$

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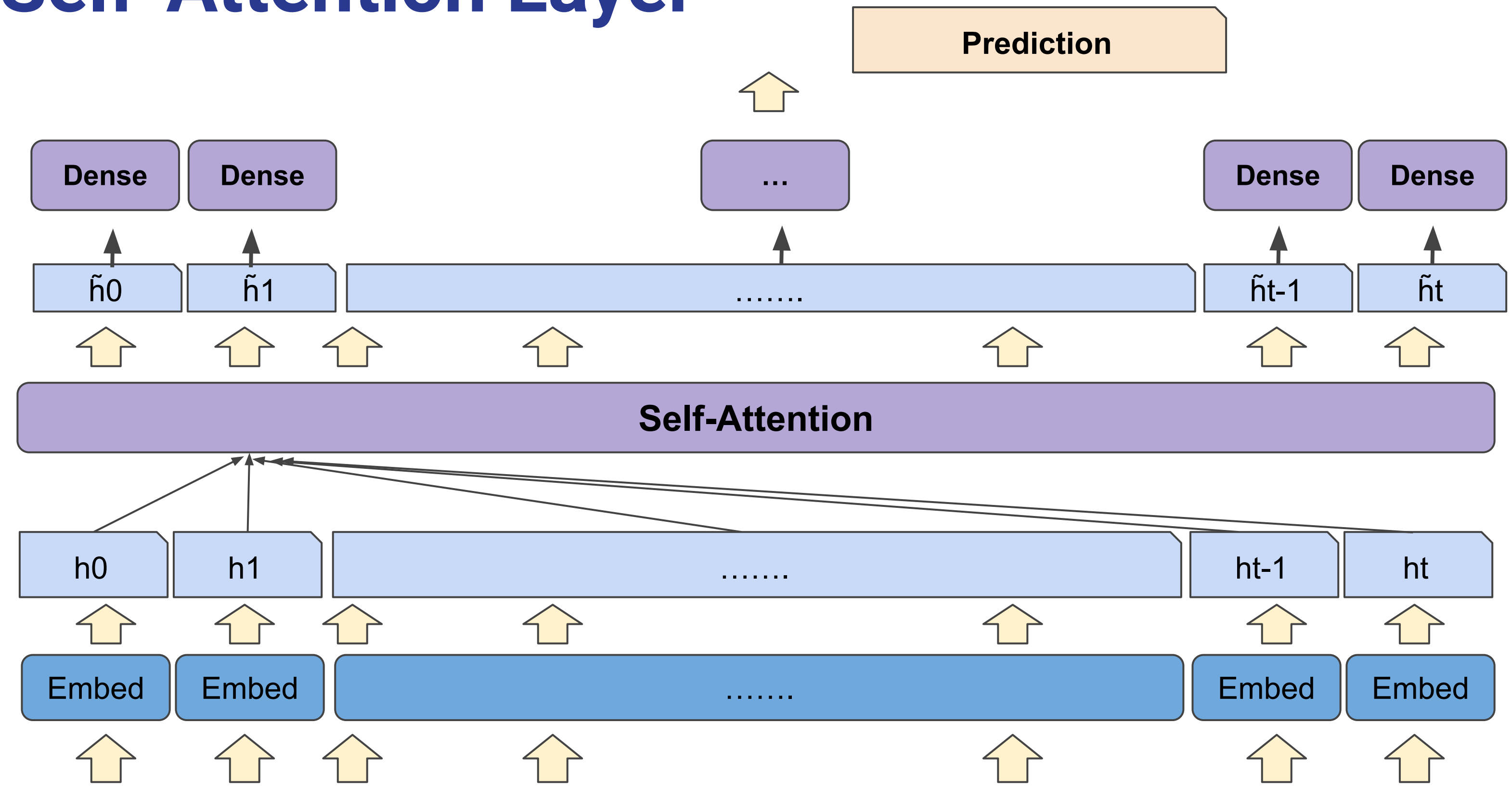

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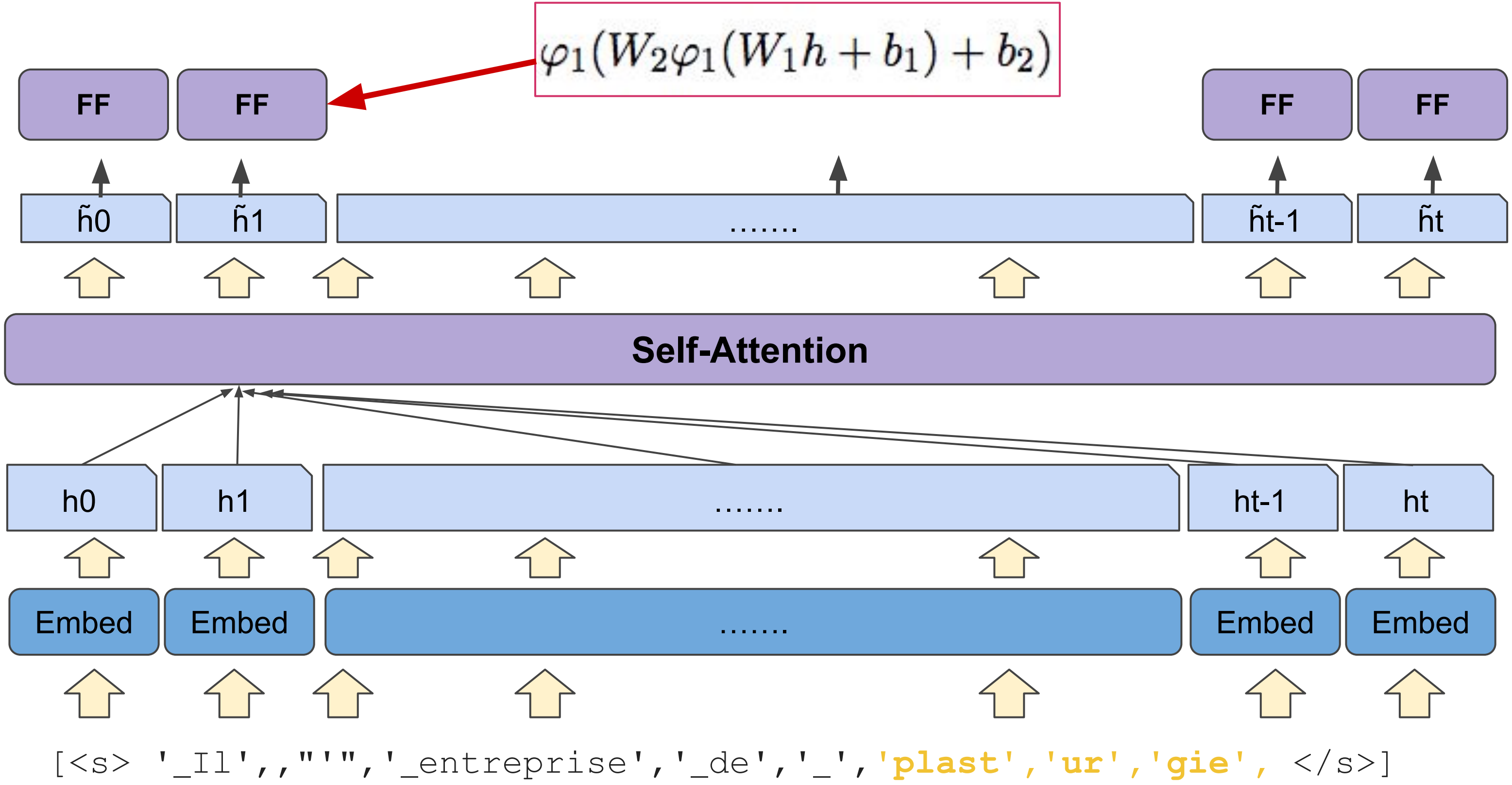
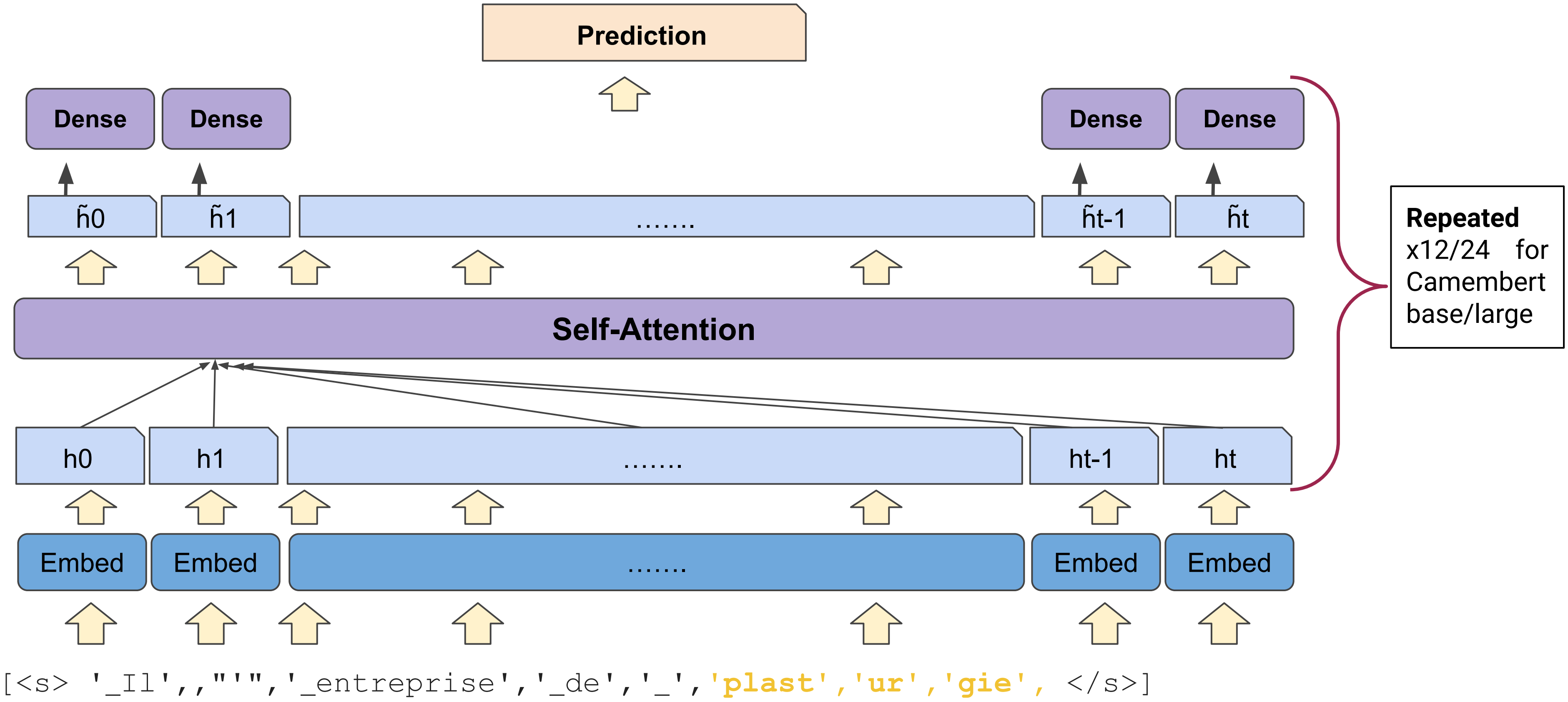
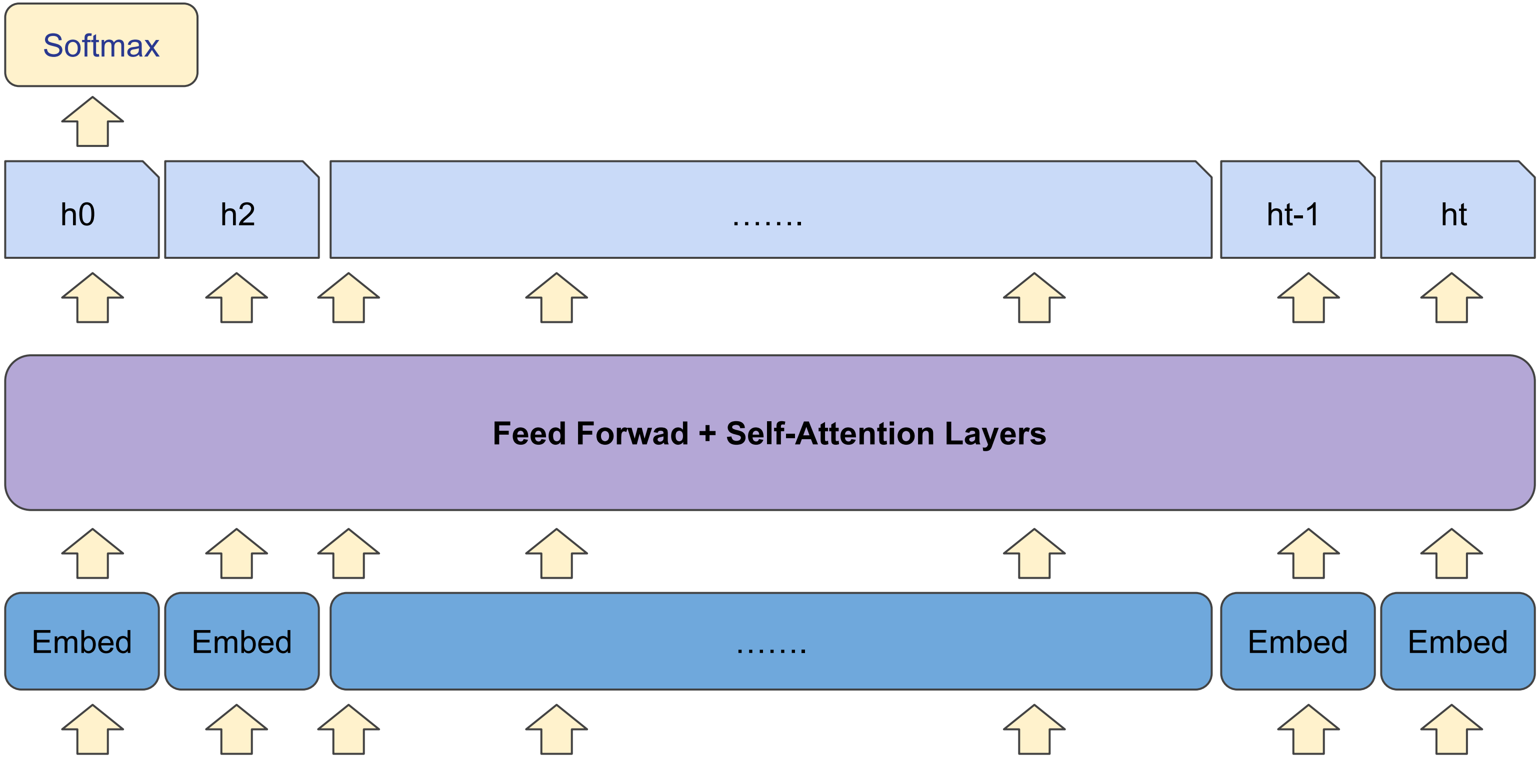
Dense Layer


$\varphi_1(W_2\varphi_1(W_1 h + b_1) + b_2)$
FF
FF
FF
FF
h̃0
h̃1
…….
h̃t-1
h̃t
Self-Attention
h0
h1
…….
ht-1
ht
Embed
Embed
…….
Embed
Embed
[<s> '_Il',,"'",'_entreprise','_de','_','plast','ur','gie', </s>]

Transformer



Sequence Classification



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Sequence Classification: Output Function

We compute a distribution over the labels using the softmax function.
We have K=31 **speech acts labels**

$$softmax(s) = \left(\frac{e^{s_i}}{\sum_k e^{s_k}}\right)_{i \in [|1,K|]}, \text{ for } s \in \mathbb{R}^K$$

*s is also referred to as the **logit** vector*

Sequence Classification: Output Function

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➔ At test time, we make predictions by picking the label that has the **maximum output likelihood** (argmax)

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3. **How do we train the model?**

➔ **Training the transformers on sequence classification**

Training for Sequence Classification

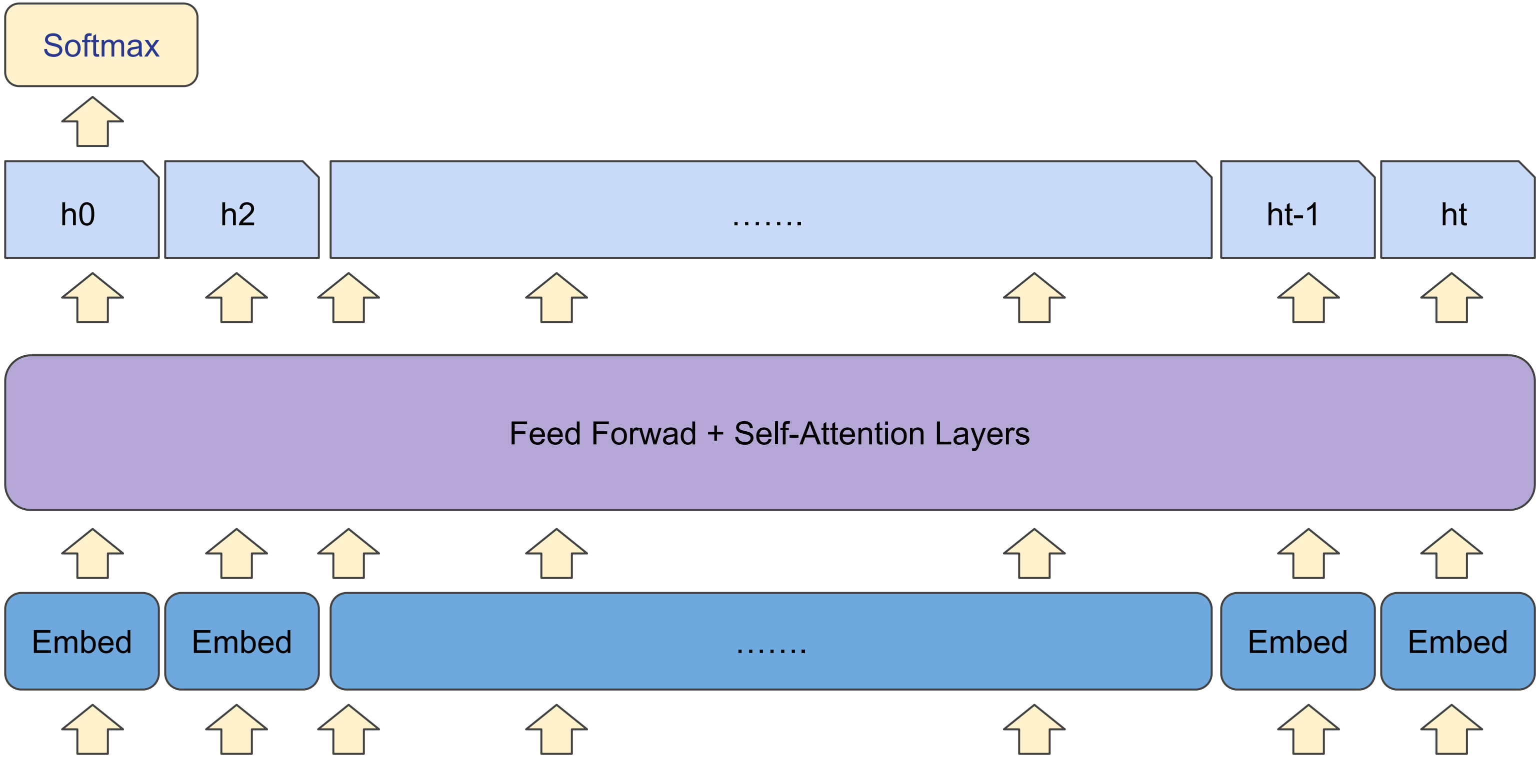
As most deep learning models, we train our model by:

1. **Initializing** all the parameters of the model

2. Defining **a loss function** **to compare the prediction of the model with observed labels**

3. Find the parameters of the model that minimize **the loss** **with Gradient Descent**
   NB: all the parameters are trained end-to-end

Sequence Classification



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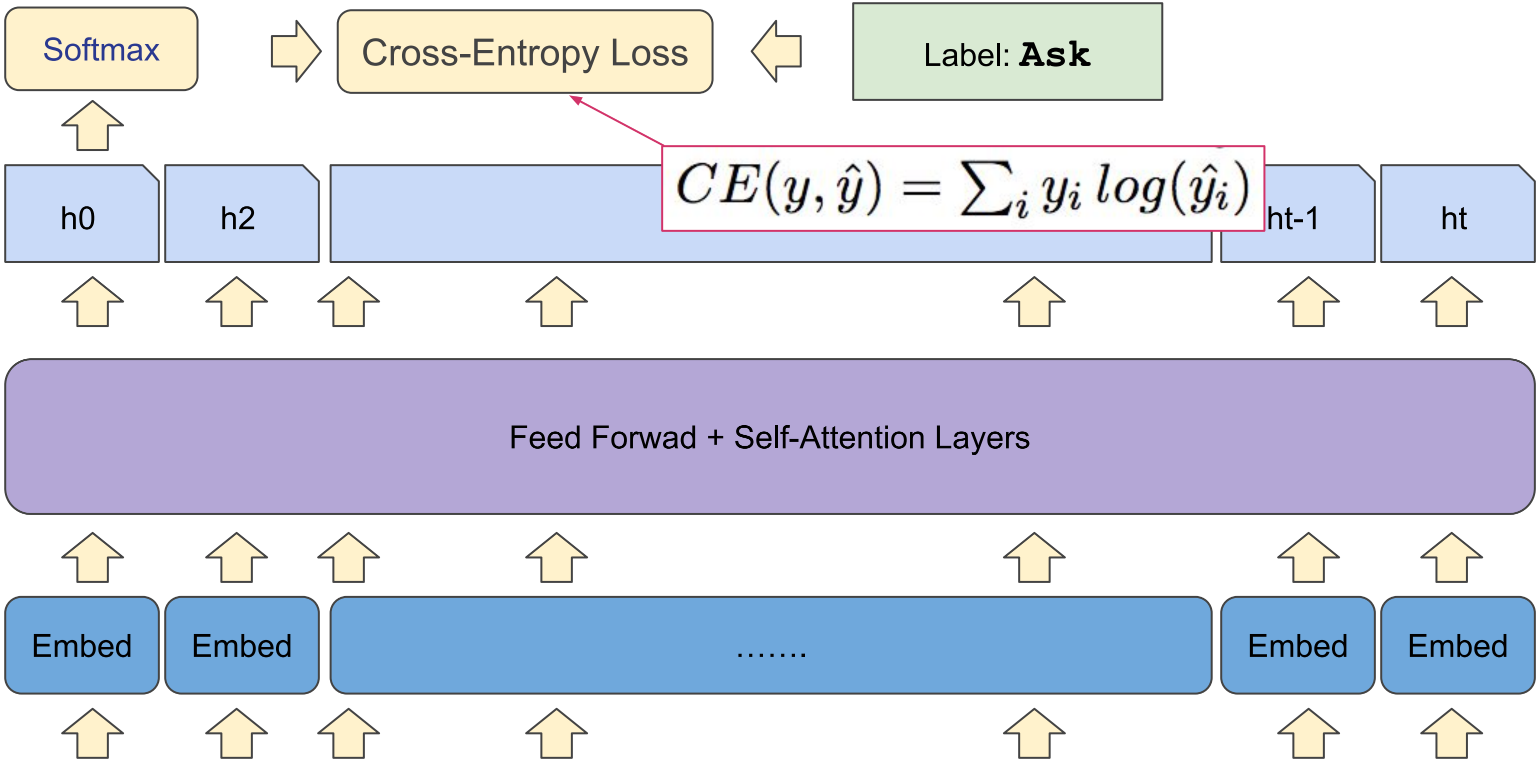

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Training with Stochastic Gradient Descent

Algorithm 2 Stochastic Gradient Descend

Given observations $((x_i), (y_i))$ of two variables (X, Y)
Given a loss function l. An architecture dnn_θ
The goal is to find the best θ **s.t.** $E(l(Y, dnn_\theta(X)))$ **is small.** Given a learning rate α
for *step* $<$ max **do**
  Sample (x, y)
  # Forward pass:
  $\hat{y} = dnn_\theta(x)$ and $l(y, \hat{y})$
  # Backward pass:
  $\nabla_\theta\, l(y, \hat{y})$ # compute gradients
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Stochastic Gradient Descent

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Training step

Learning rate

In this tutorial, you will use **Adam a variant of SGD** to train our model.

How to initialize our Transformer?

Randomly initialize all the parameters and train all the parameters from scratch for Speech Act Classification

Limits: Training Transformers this way is suboptimal

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➔ **Likely to overfit**

➔ **Poor Generalization**

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Limits: Training Transformers this way is suboptimal

Solution: **Pretrain** the transformer on **Masked-Language Modeling**

Finally: Camembert

Camembert is a large transformer model **(300M+ parameters)**

Pretrained with

- **a Masked-Language Modeling Objective**
- On **138 GB of Web-Crawled Data (32B tokens)** in French (OSCAR)

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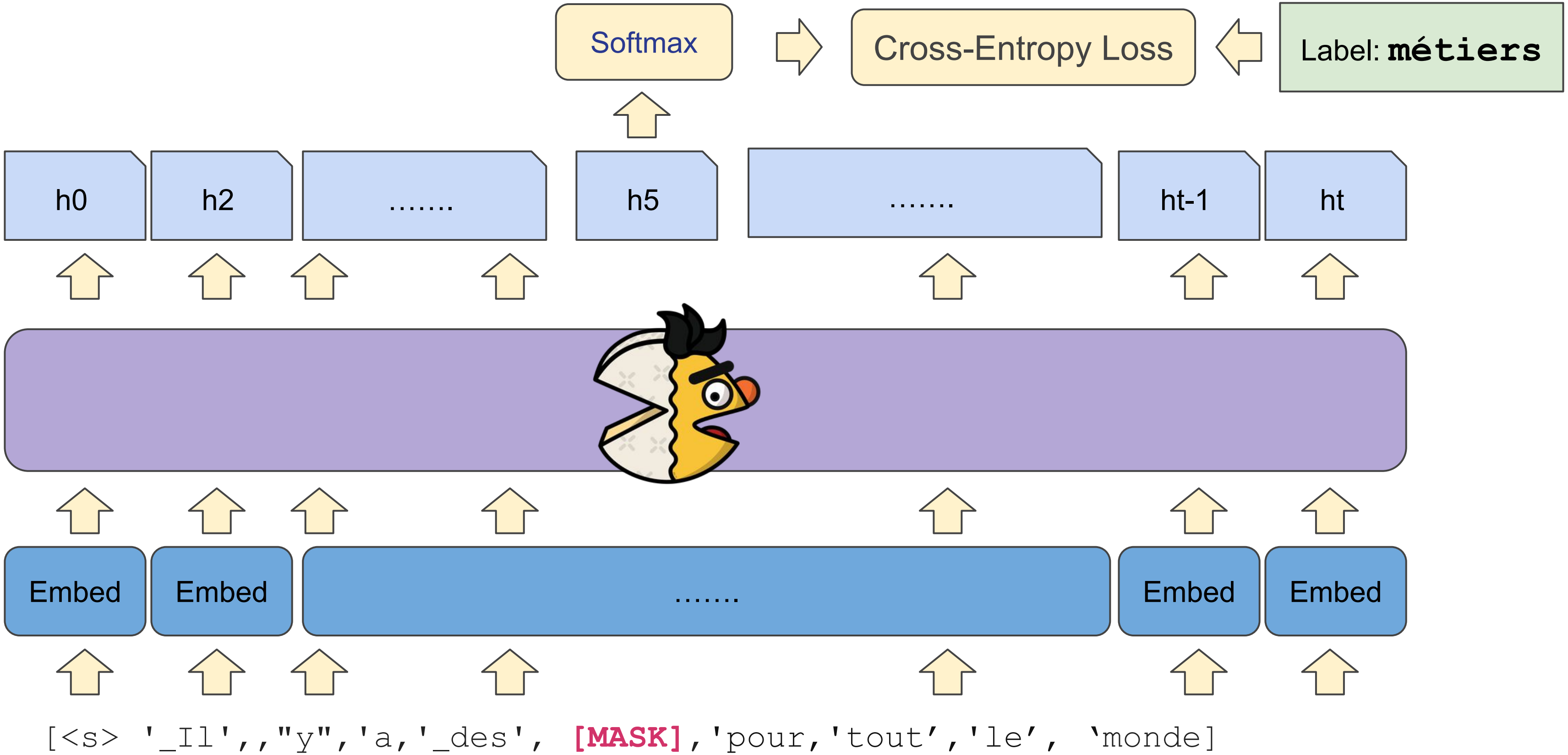
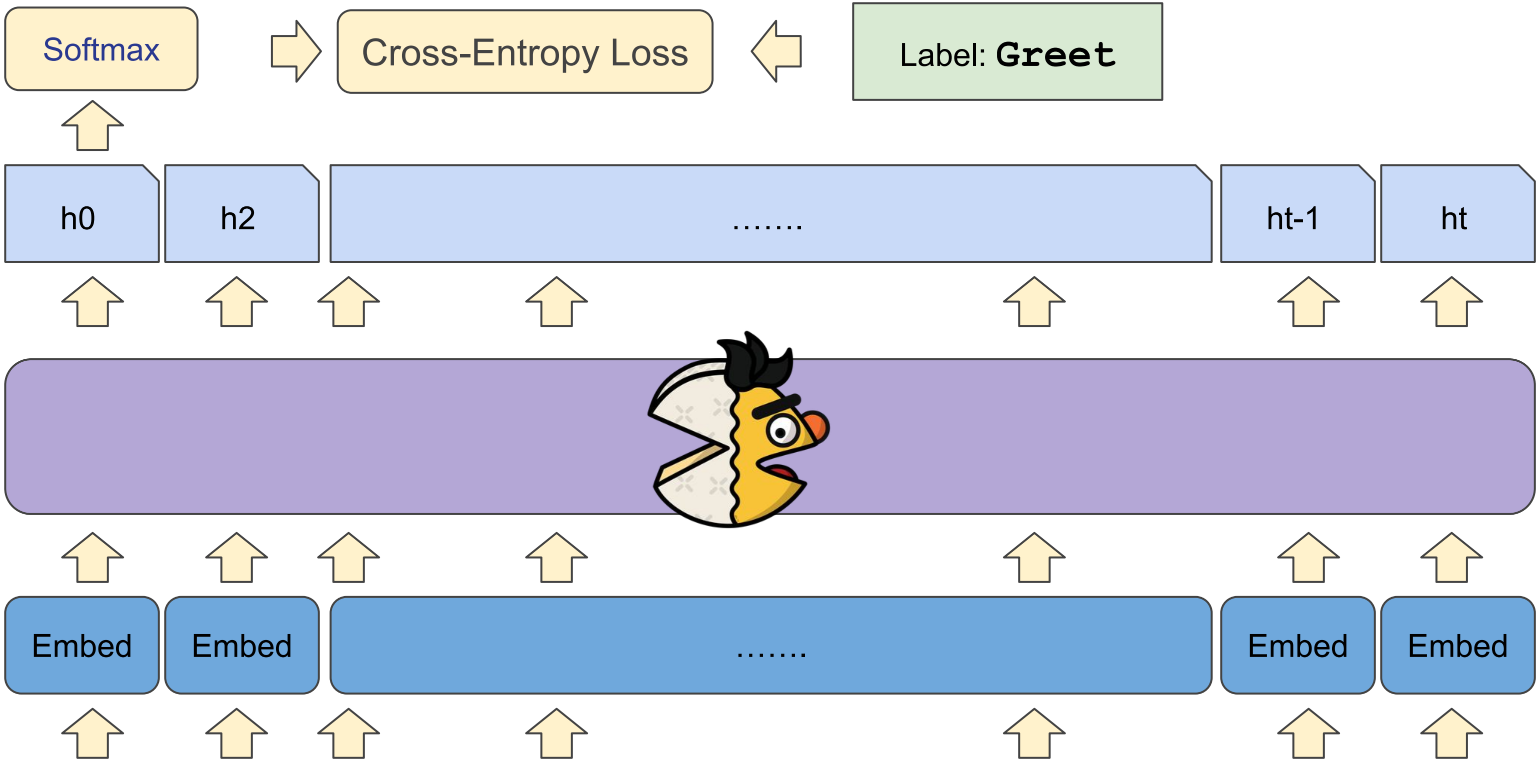
Camembert can be used as the initialization of any transformer architecture to build a model for French

In other words, **Camembert can be fine-tuned** (i.e. trained further) on any sequence labeling and sequence classification task

Pretraining of Camembert with MLM



Fine-tuning of Camembert



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Camembert **delivers state-of-the-art performance** on multiple NLP benchmark for French

Camembert Performance on standard tasks

After pretraining, we can reuse the entire camembert model and **fine-tune** it on our task

Model	F1
SEM (CRF) (Dupont, 2017)	85.02
LSTM-CRF (Dupont, 2017)	85.57
mBERT (fine-tuned)	87.35
CamemBERT (fine-tuned)	89.08
LSTM+CRF+CamemBERT (embeddings)	**89.55**

Named-Entity Recognition

	FQuAD1.1-test		FQuAD1.1-dev	
Model	F1	EM	F1	EM
Human Perf.	91.2	75.9	92.1	78.3
CamemBERT$_{\text{BASE}}$	88.4	78.4	88.1	78.1
CamemBERT$_{\text{LARGE}}$	**92.2**	**82.1**	**91.8**	**82.4**
FlauBERT$_{\text{BASE}}$	77.6	66.5	76.3	65.5
FlauBERT$_{\text{LARGE}}$	80.5	69.0	79.7	69.3
mBERT	86.0	75.4	86.2	75.5
XLM-R$_{\text{BASE}}$	85.9	75.3	85.5	74.9
XLM-R$_{\text{LARGE}}$	89.5	79.0	89.1	78.9

Question-Answering

In Summary

- **Camembert is a large transformers model**
- Pretrained with the Masked-Language Objective
- **That can be re-used for any sequence labelling or sequence prediction tasks**
- **And likely to deliver good downstream performance**

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In the next sessions of the tutorial

➔ you will use the **transformers library** 🤗 **to download** **and play with it!**
➔ We showcase camembert for dialog act classification but the same approach can be used for any sequence classification or labeling task