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Hands-on Hugging Face for Natural Language Processing

Prerequisites

- Comfortable programming in Python
- Basic familiarity with machine learning and deep learning
- Basic familiarity with natural language processing

Poll Question

How comfortable are you building and training machine learning models in Python?

- Never worked with ML before
- Built traditional ML models using scikit-learn
- Built ML models using TensorFlow and PyTorch

Poll Question

Have you worked with Natural Language Processing before?

- Never worked with NLP before
- Built traditional NLP models with scikit-learn
- Built NLP models with TensorFlow, PyTorch

Hugging Face

A company known for its work in the field of artificial intelligence particularly in the field of natural language processing

Hugging Face

A machine learning and data science platform and community that helps users build, deploy, and train machine learning models

Natural Language Processing with Transformers

- The original transformer architecture was introduced in the 2017 paper "**Attention Is All You Need**"
- Introduced the novel concept of attention to focus on the right parts of the input
- Revolutionized the field of NLP, leading to the powerful LLMs that we work with today

Hugging Face Transformer Library

- Offer a wide range of **pre-trained** transformer models for different use cases
- Cross-framework compatibility – all models can be used with both PyTorch and TensorFlow
- Used in a variety of applications – chatbots, enhancing search, translation, and more

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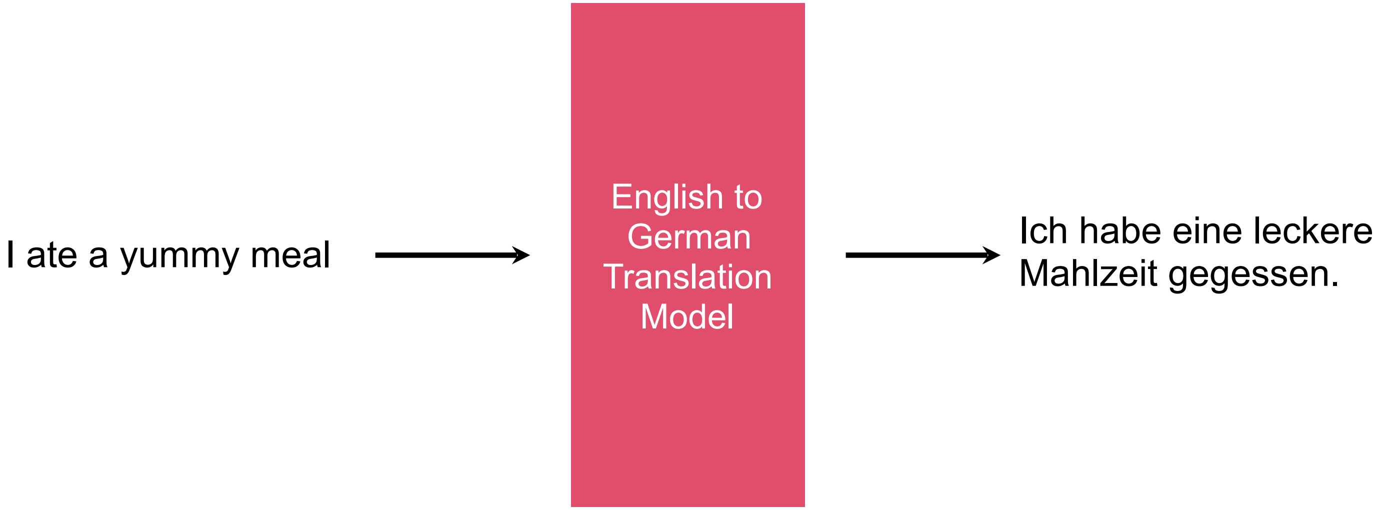
Attention and Transformer Models

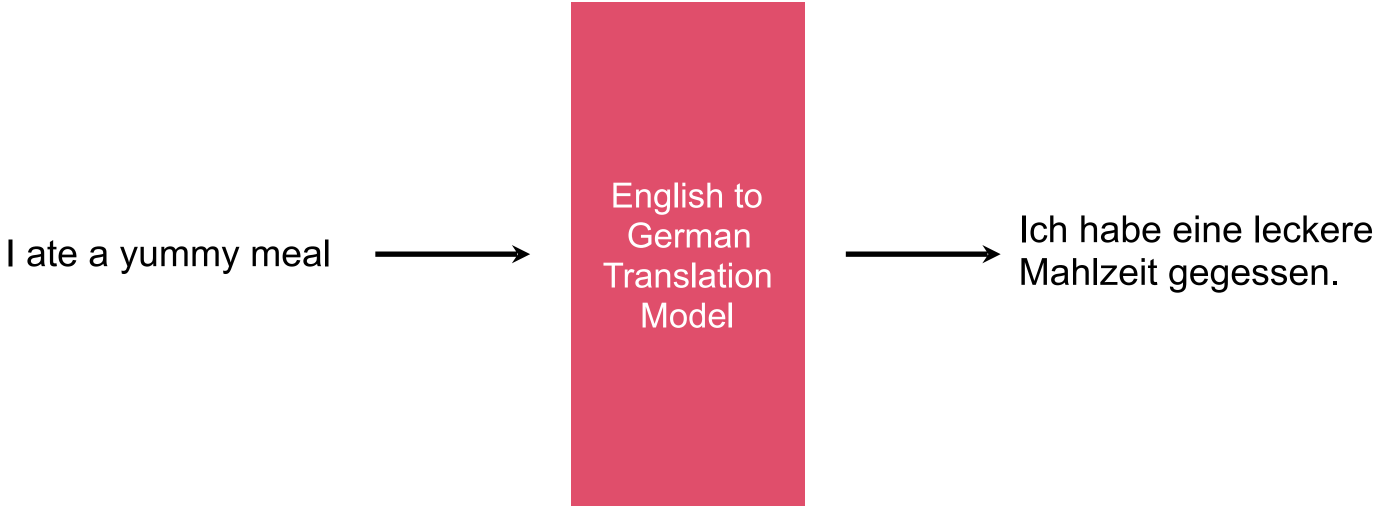
Attention in Neural Networks

Mechanism that allows the network to focus on specific parts of the input data while ignoring others

Language Translation Model



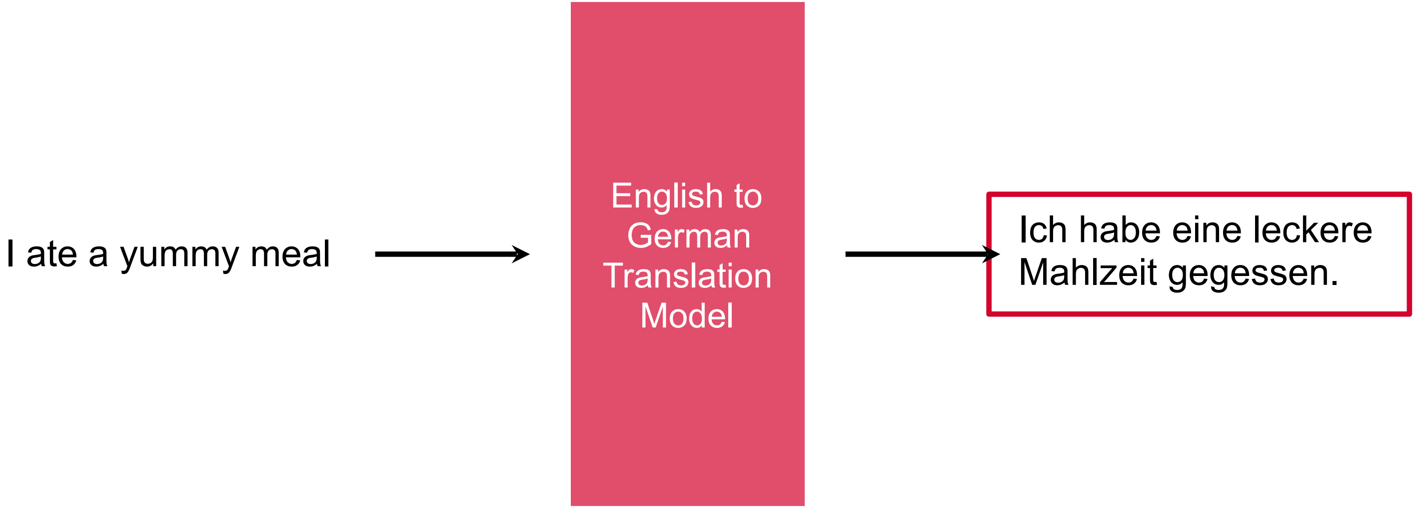
Model Without Attention



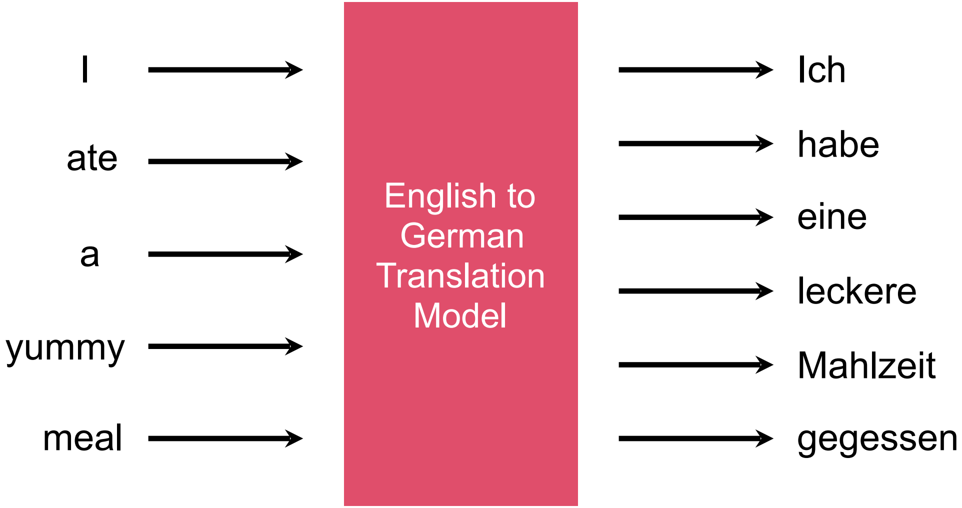
Parses the Entire Input

I ate a yummy meal → English to German Translation Model → Ich habe eine leckere Mahlzeit gegessen.

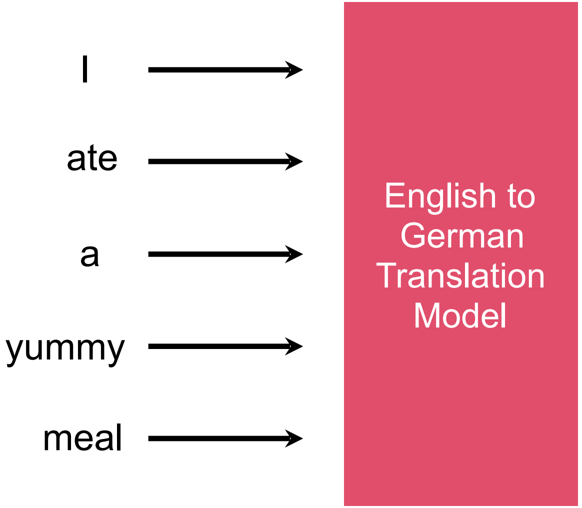
To Generate the Translation



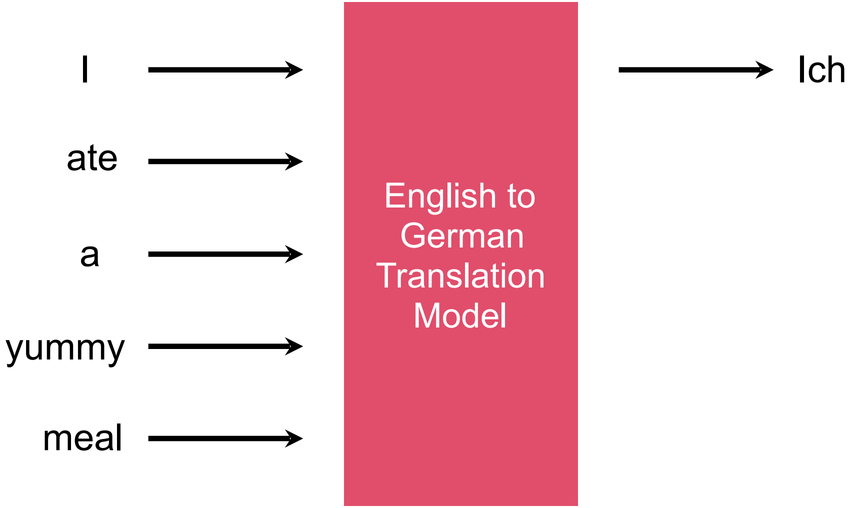
Input and Output are Sequences



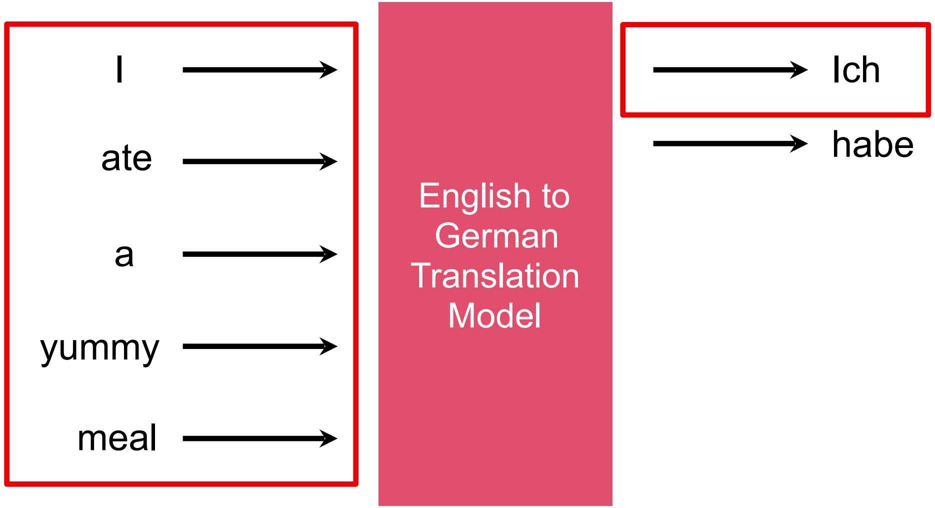
Input Sequence Fed In



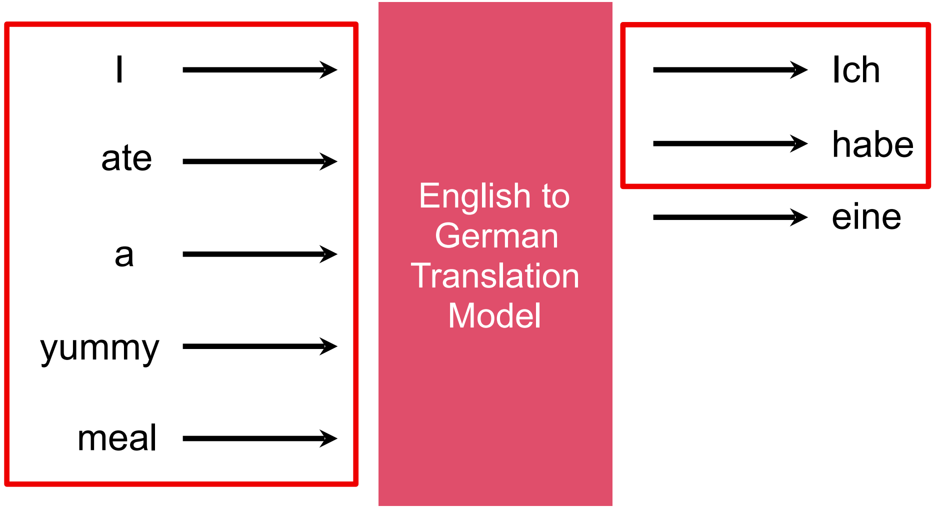
Output Sequence Produced one Word at a Time



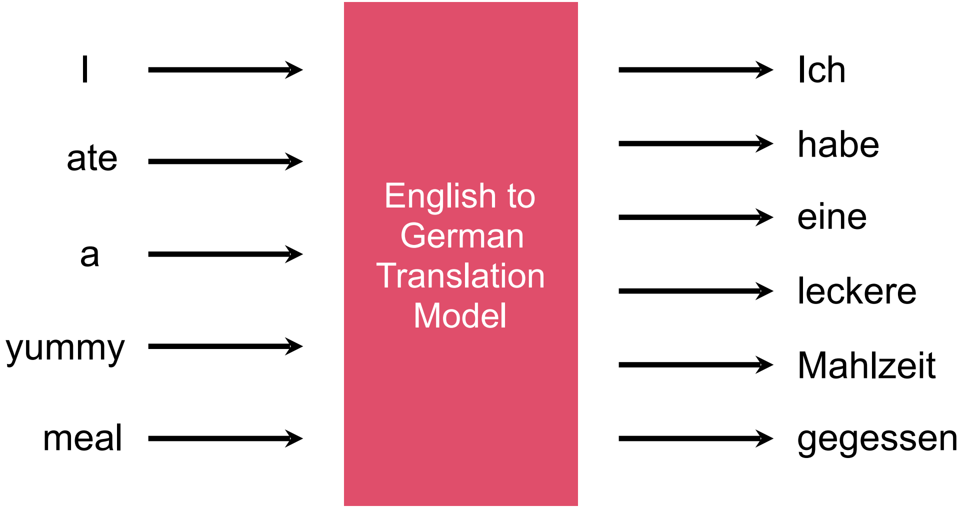
Complete Input + Words Produces So Far Used to Get Next Word in Sequence



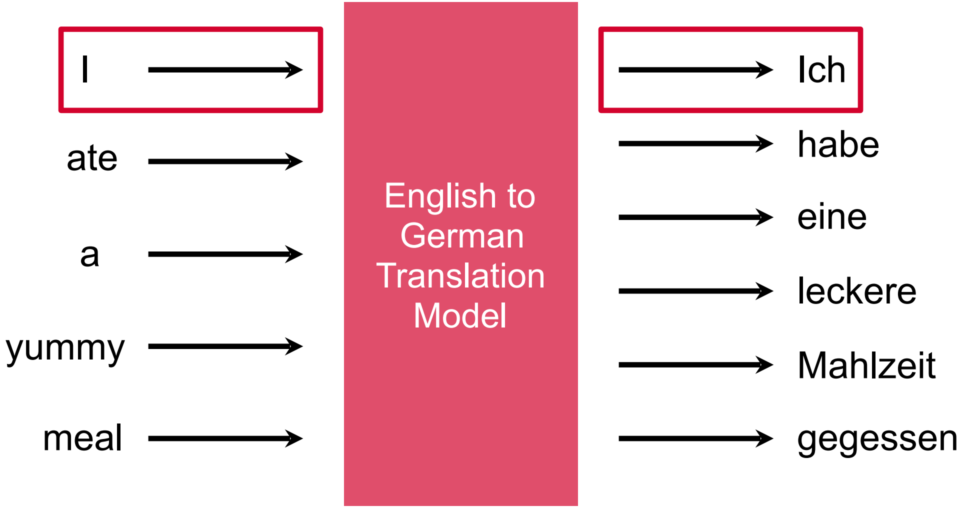
Predict One Word at a Time



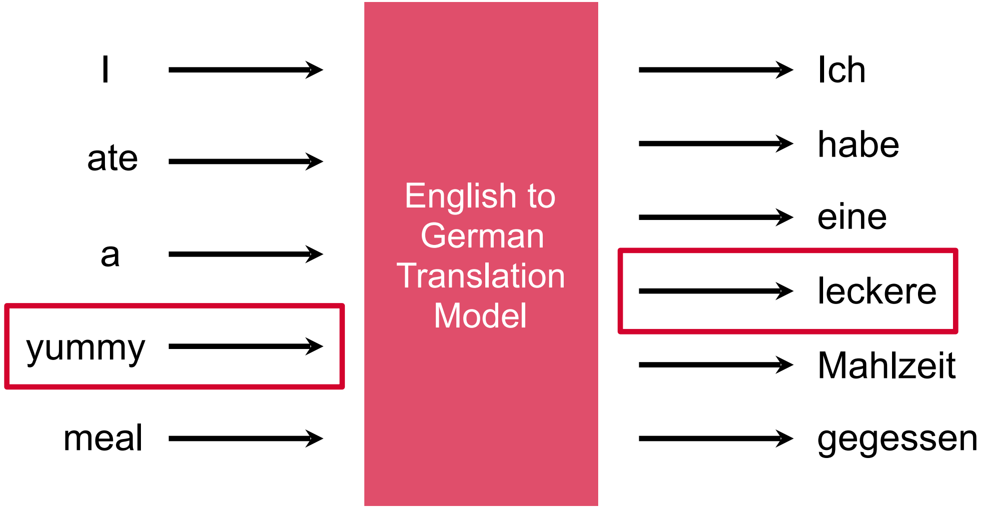
Better Predictions with Attention



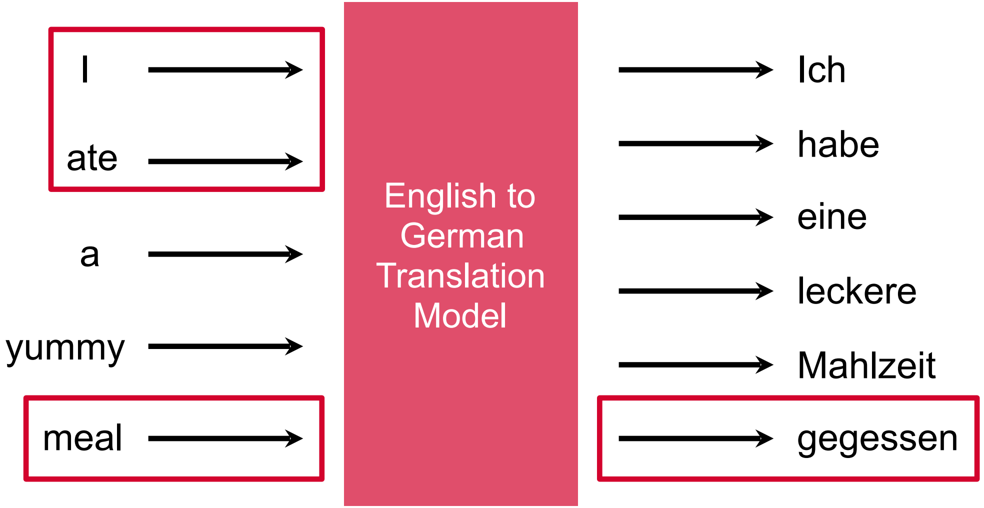
Better Predictions with Attention



Better Predictions with Attention



Better Predictions with Attention



Attention

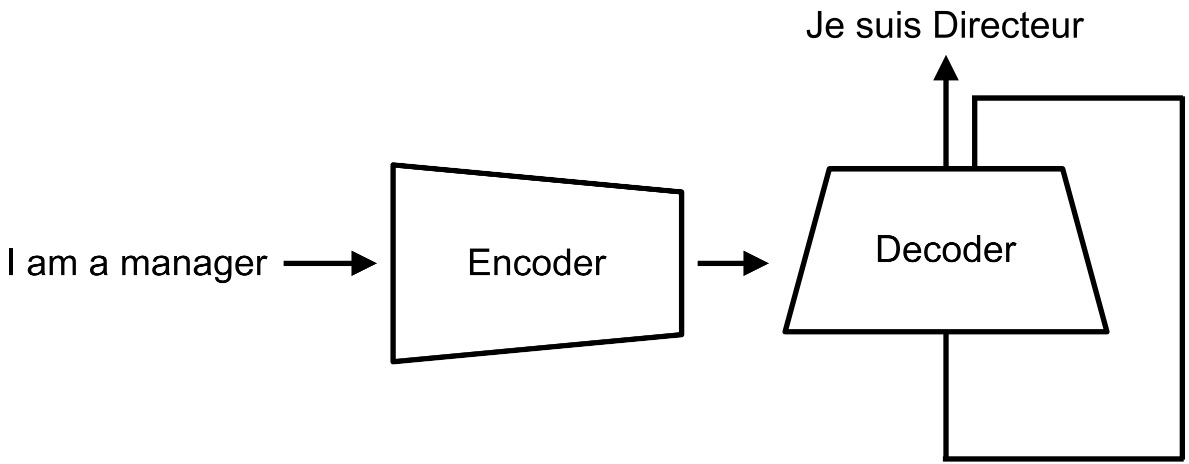
- Help models focus on the right parts of the input to generate the output
- The entire input along with attention generates better outputs
- Are the foundation of transformers used to power the large language models of today

The Transformer Architecture

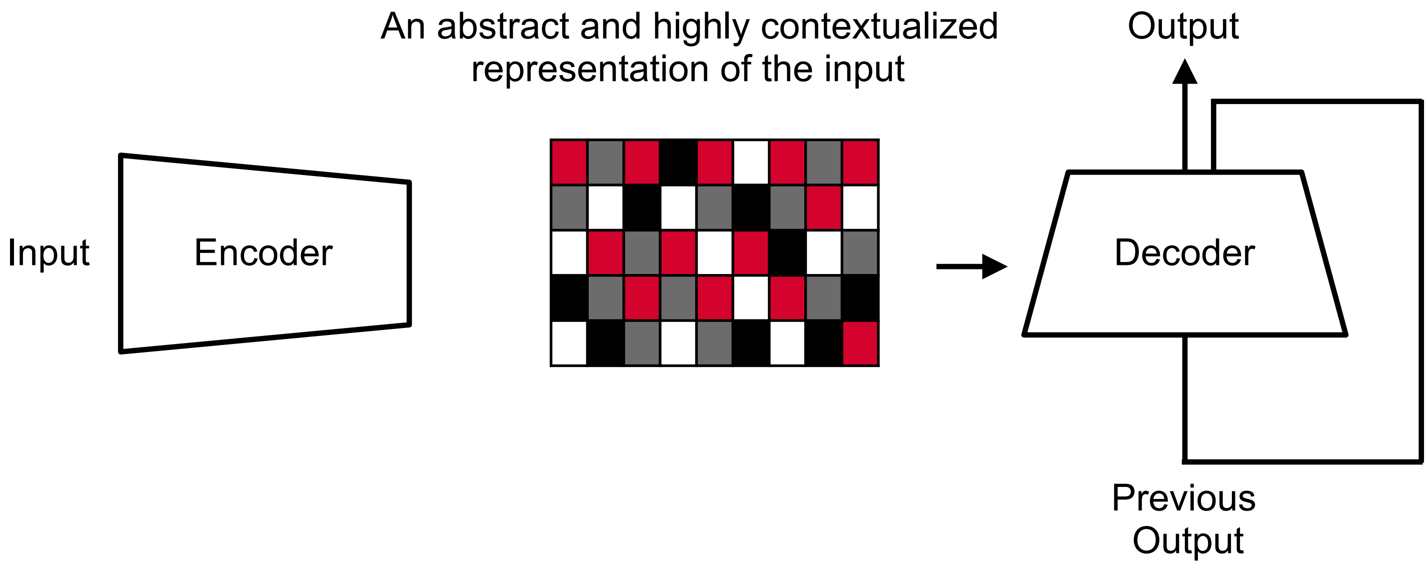
The Transformer Architecture

A model architecture primarily used in natural language processing that relies on self-attention mechanisms to process sequential data more effectively than previous models

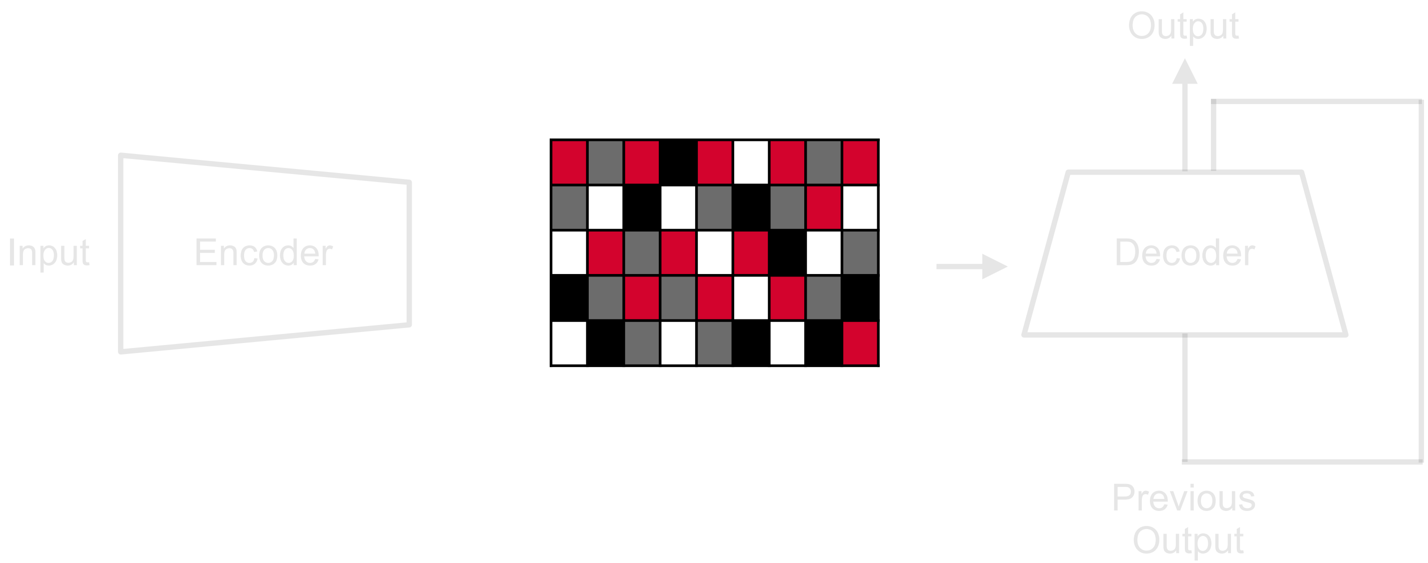
High-level Architecture of Transformers



Encoder Creates Abstract Representation Fed to the Decoder

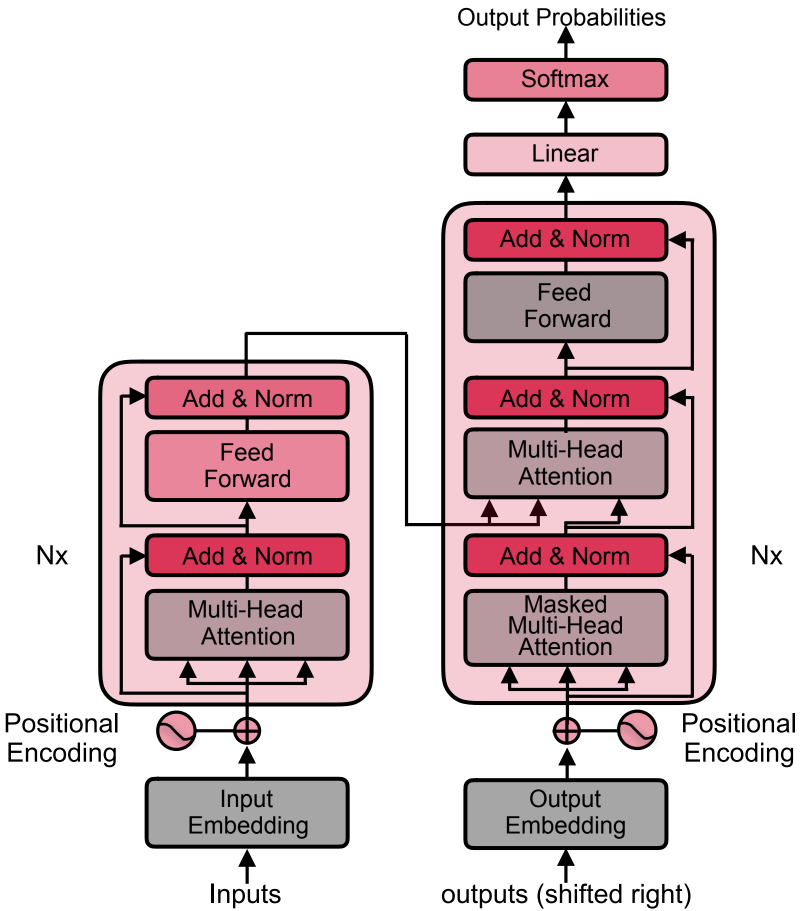


Encoder Creates Abstract Representation Fed to the Decoder

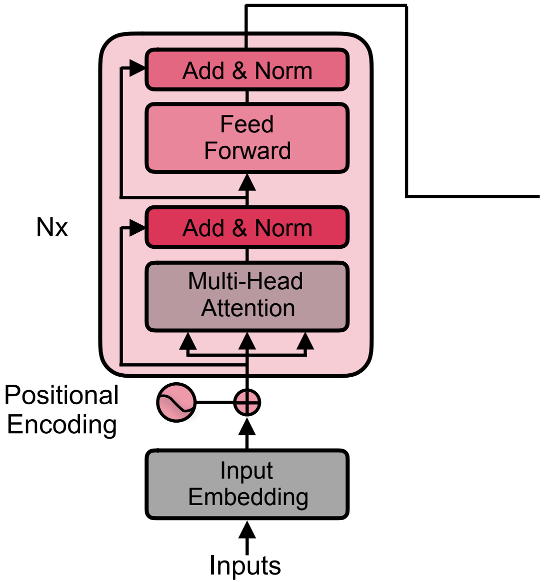


This representation encodes the importance of every word with respect to other words in the same input sequence

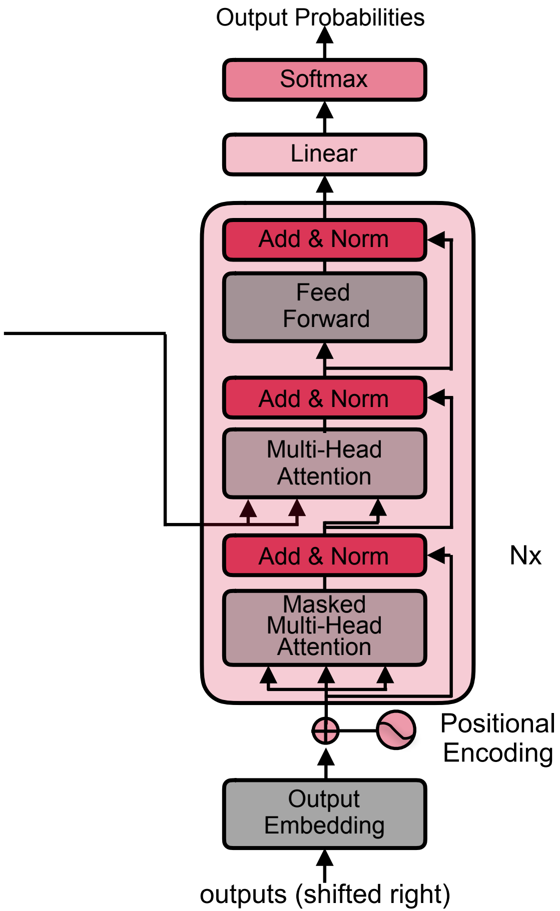
Transformer Architecture



Encoder


Add & Norm
Feed Forward
Nx
Add & Norm
Multi-Head Attention
Positional Encoding
Input Embedding
Inputs

Decoder


Output Probabilities
Softmax
Linear
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Add & Norm
Masked Multi-Head Attention
Nx
Positional Encoding
Output Embedding
outputs (shifted right)

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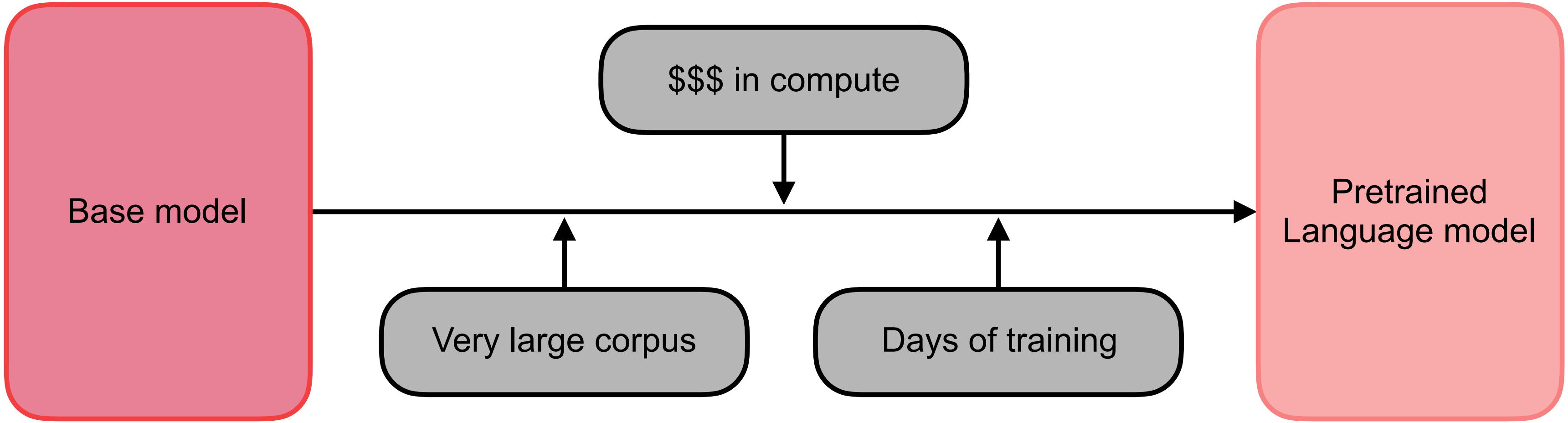
Transformers in Hugging Face

Pretrained Transformers in Hugging Face

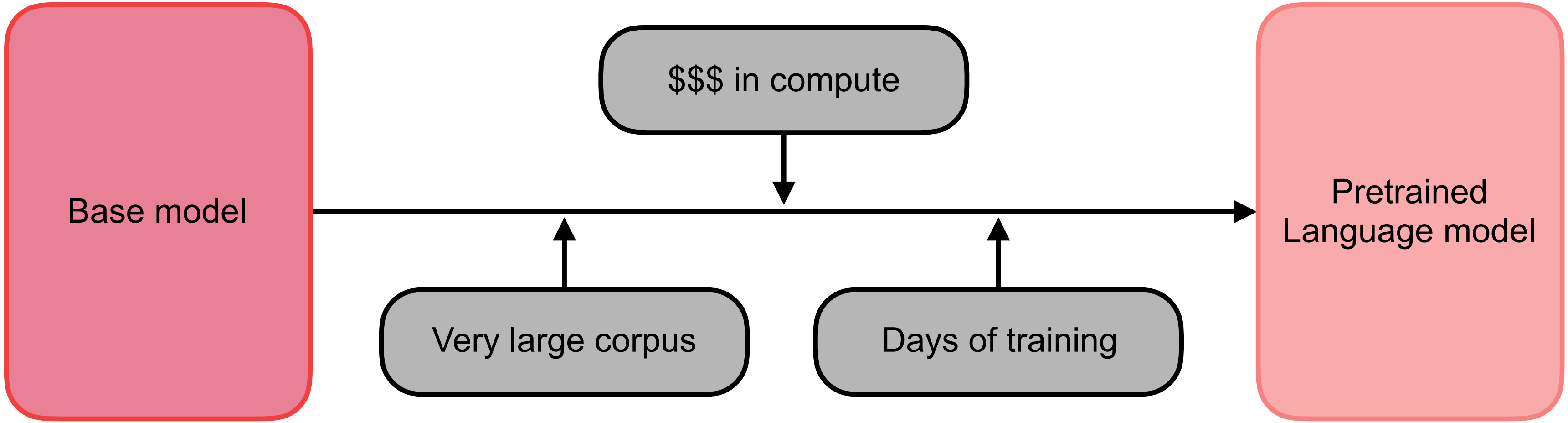
Transformers are very larger models and very expensive to train – in terms of data, time, and resources

Training Transformers from Scratch



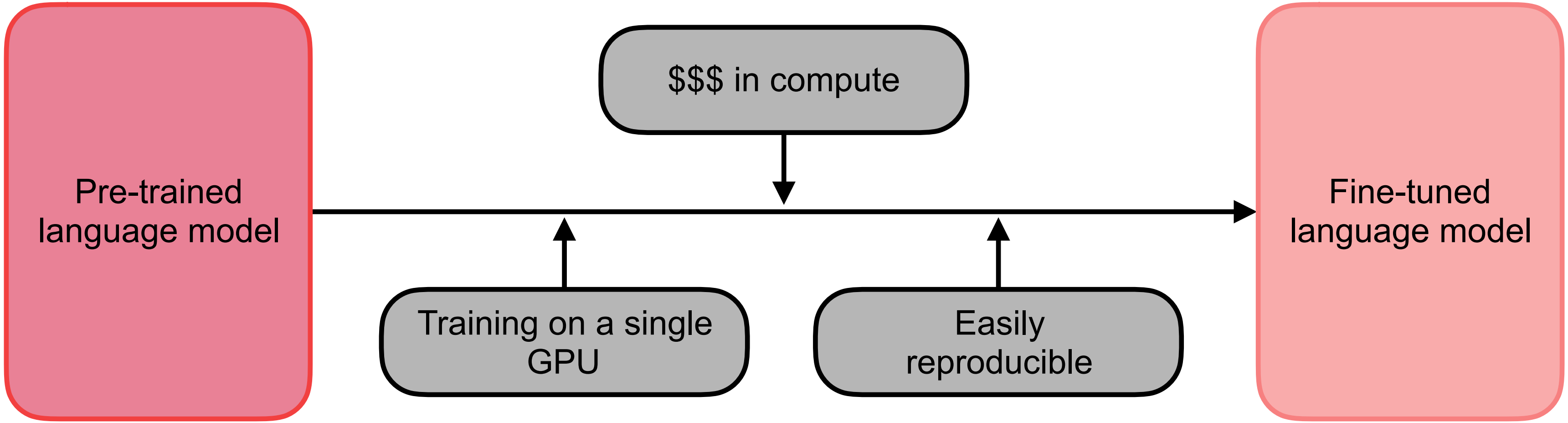
Training transformer models from scratch (pretraining) - model weights are initialized at random and the model has no prior knowledge embedded within it

Training Transformers from Scratch



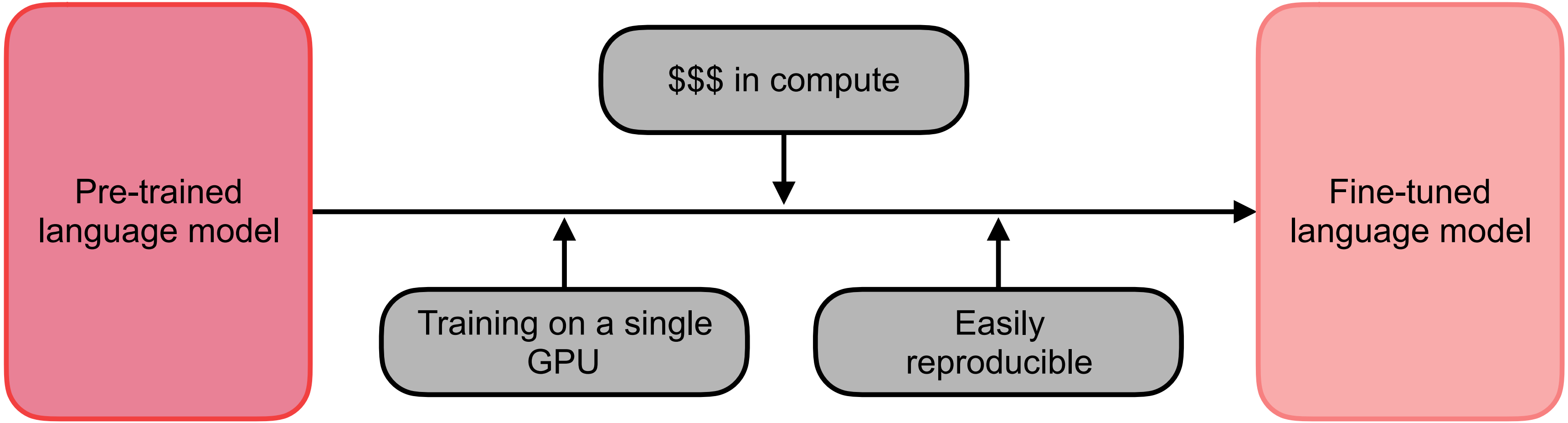
Needs huge amounts of data and compute resources - can be very expensive

Fine-tuning Transformers



Fine-tuning models involve additional training on an already pretrained model

Fine-tuning Transformers

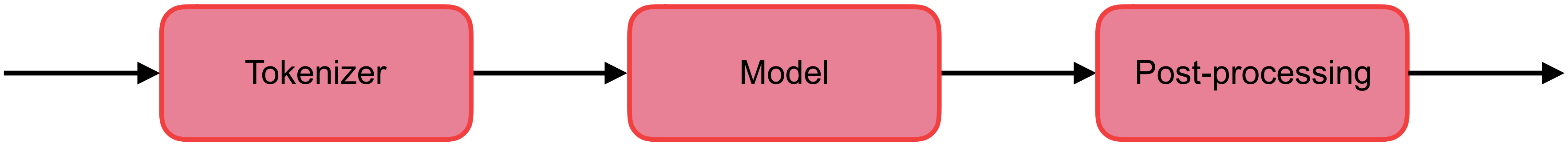


Use less data, time, and resources to get good results - overall costs and environment impact of training is much lower than training from scratch

Hugging Face Pipelines

A high-level abstraction that makes it easy for users to perform NLP tasks using pre-trained models

Pipeline Components



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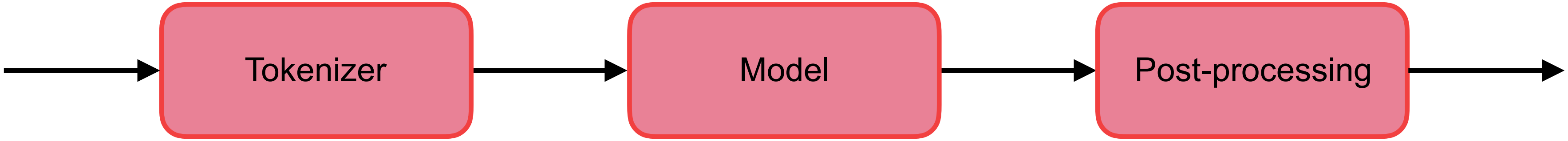
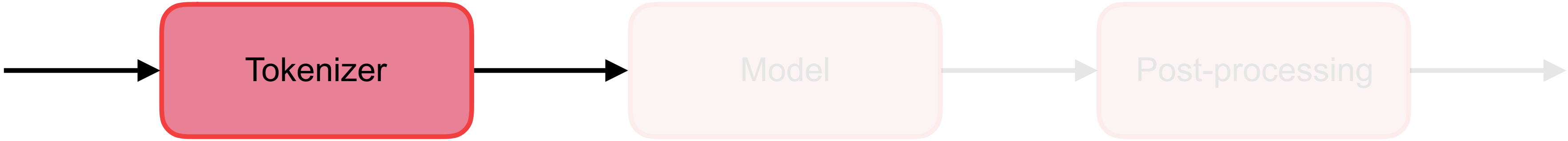
Hugging Face Tokenizers

Pipeline Components



Tokenizer



Tokenizing Text

Don’t you know what time it is?

Split by Spaces

[“Don’t”, “you”, “know”, “what”, “time”, “it”, “is?”]

Consider Punctuation

[“Don”, “‘”, “t”, “you”, “know”, “what”, “time”, “it”, “is”, “?”]

Split Words Like Won’t and Don’t

[“Do”, “n’t”, “you”, “know”, “what”, “time”, “it”, “is”, “?”]

Tokenizers

- Rule-based tokenizers with different rules split data in different ways
- Pretrained models only work well with **inputs tokenized in the same manner as its training data**

Categories of Tokenizers

Word Tokenizers

Character Tokenizers

Subword Tokenizers

Word and Character Tokenizers

- Split text into tokens in meaningful ways
- “swim” and “swimming” should be identified as related
- Reduce the number of unknown words
- Word tokenizers
  - Too large a vocabulary
  - Will not identify related words
- Character tokenizers
  - Large number of tokens for each sentence
  - Intuitively less meaningful

Subword Tokenization

- Relies on the principle that frequently used words should not be split but rare words should be split into subwords
- “emotionally” could be a rare word, split into “emotional” and “ly”
- Allow models to have a reasonable vocabulary size and yet learn meaningful context independent representations

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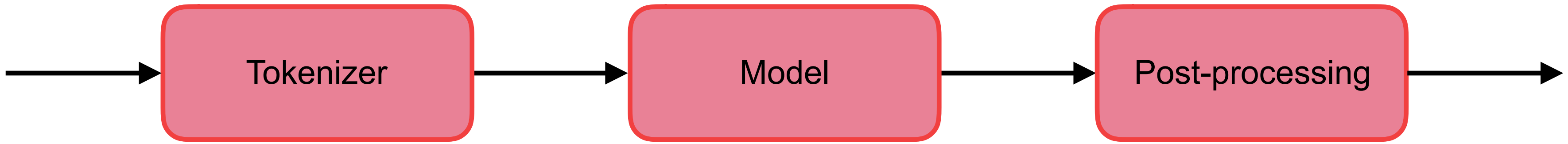
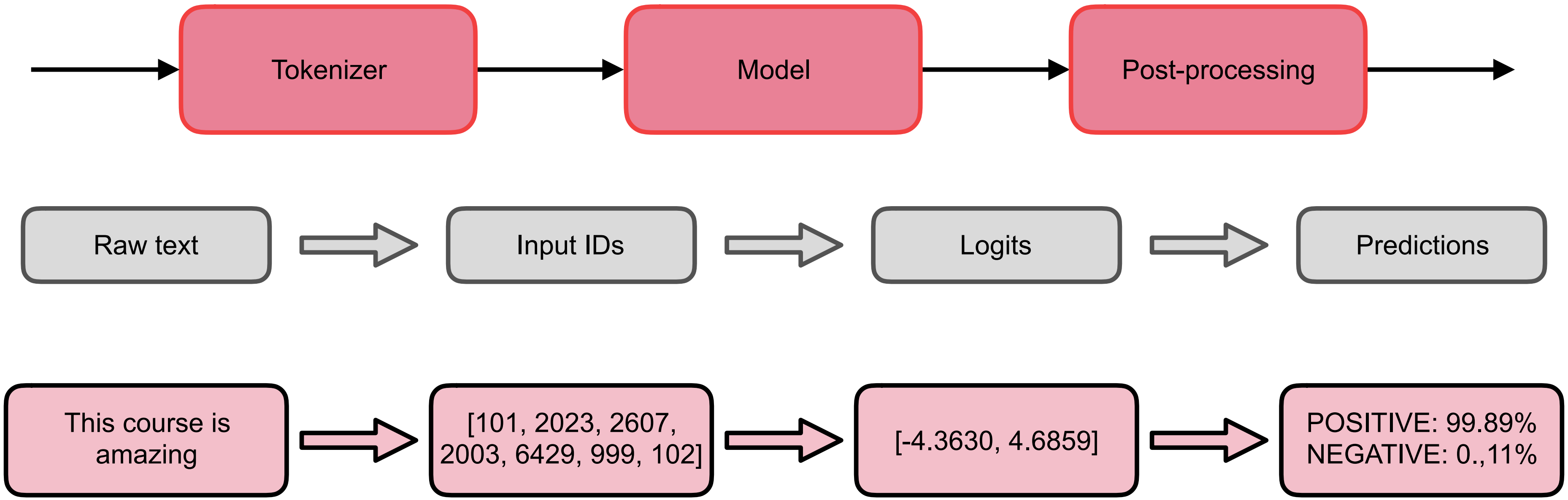
Hugging Face Pipelines

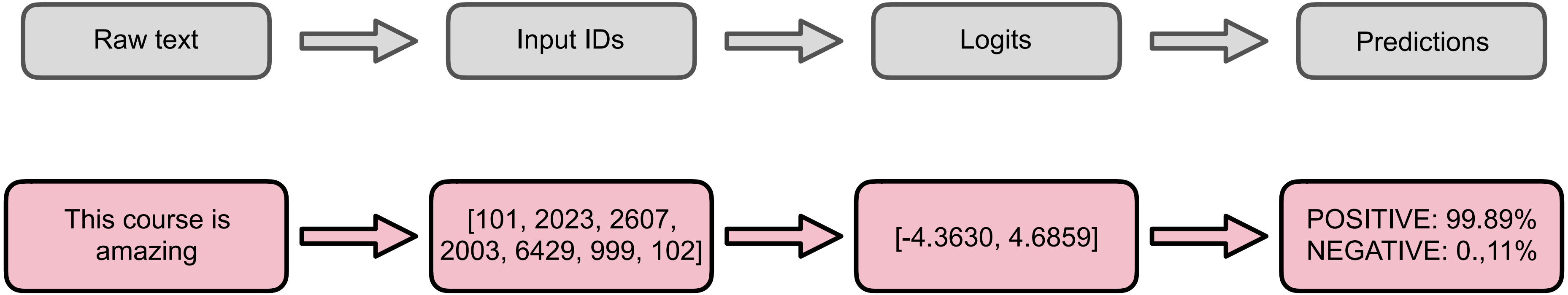
Pipeline Components



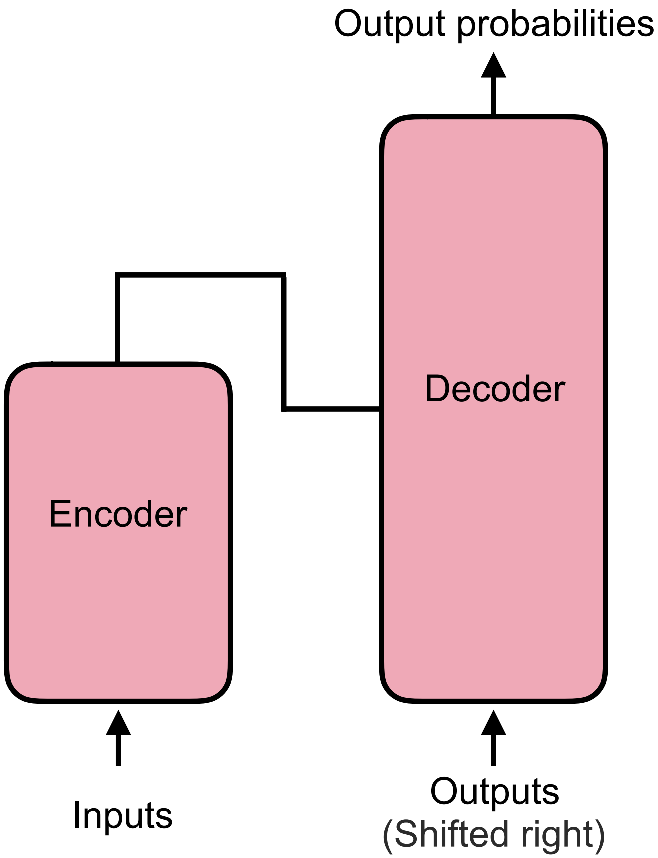
Hugging Face Transformer Pipeline



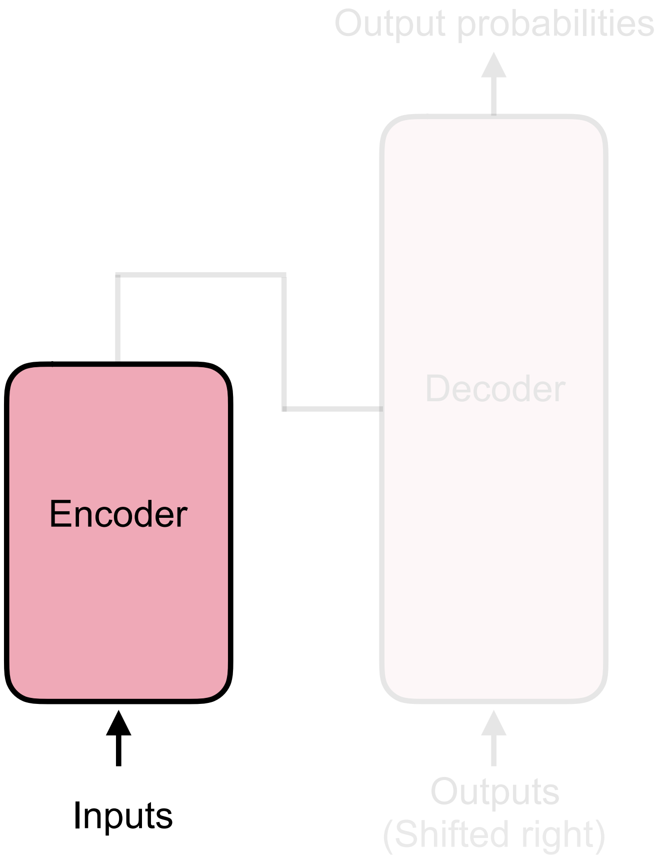
Hugging Face Transformer Pipeline



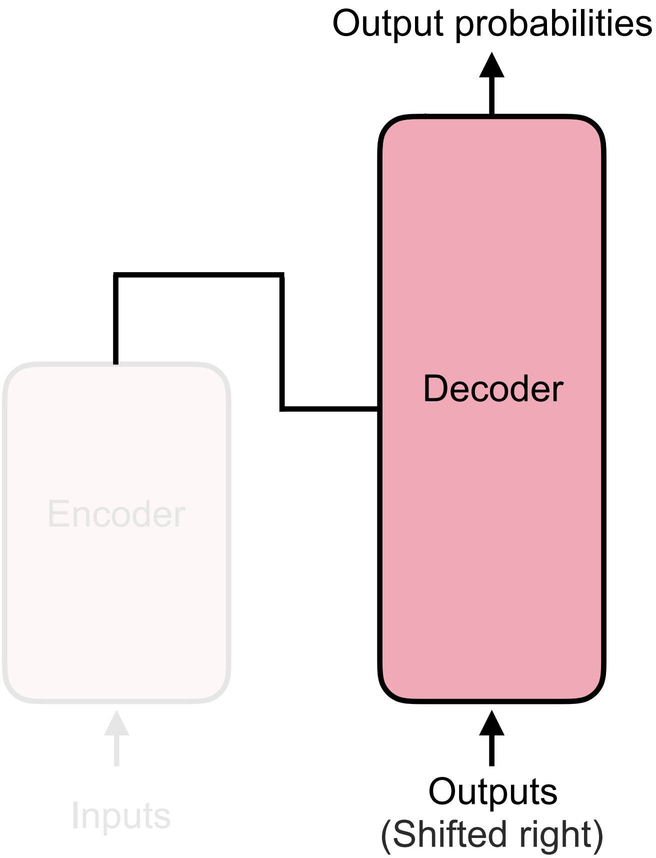
General Transformer Architecture



Encoder


Output probabilities
Decoder
Encoder
Inputs
Outputs
(Shifted right)

Decoder


Output probabilities
Encoder
Decoder
Inputs
Outputs
(Shifted right)

Encoder-only Models

- Attention layers in the encoder can access all the words in the input sentence called “bi-directional” or “auto-encoding” models
- Pre-training involves corrupting the initial sentence (masking) and having the model predict the masked word
- Suited for tasks such as **sentence classification, named entity recognition, and question answering**

Masked Word Prediction

Let’s have some fun doing ______ programming!

Python?
Java?
C++?

Decoder-only Models

- Attention layers in the decoder can only access words before the current word in the sentence – called “auto-regressive” models
- Pre-training of these models involve predicting the next word in the sentence, given all words seen so far
- Models are best suited for natural language tasks such as **text generation**

Next Word Prediction

It’s a nice sunny afternoon. Let’s go _____

outside
swimming
running
Dancing

Encoder-Decoder Models

- Called sequence-to-sequence models
- Attention layers in the encoder can access all parts of the input sentence,
- Attention in the decoder can only access words positioned before the given word
- Pre-training usually done using the objectives of the encoder and decoder (masked word prediction and next word prediction)
- Suited for tasks such as **summarization, translation, and generative question answering**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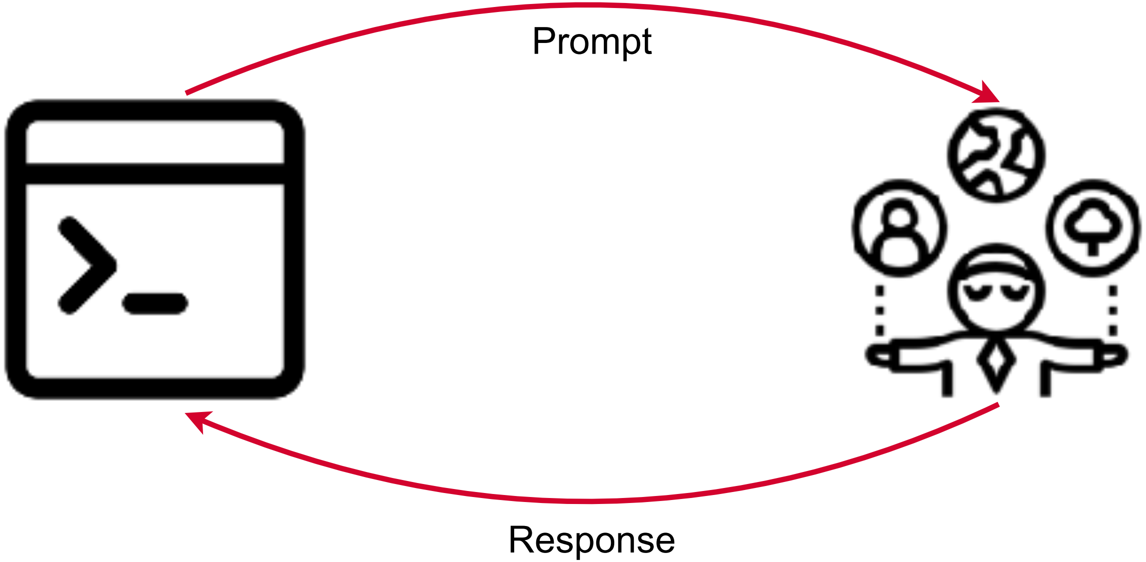
Text
Generation
by LLMs

Model Responses to Prompts



Response a Sequence of Words

She speaks French quite well

Model Generates One Word at a Time

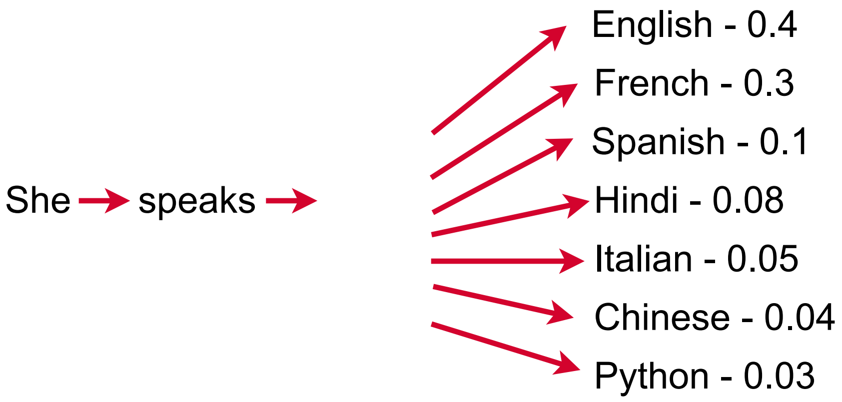
She → speaks → French → quite → well

Many Possible Words at Each Step

She → speaks →

- English
- French
- Spanish
- Hindi
- Italian
- Chinese
- Python

Each Possible Next Word is Assigned a Probability



The Model Picks One Word from Possible Next Words

She → speaks →

- English - 0.4
- French - 0.3
- Spanish - 0.1
- Hindi - 0.08
- Italian - 0.05
- Chinese - 0.04
- Python - 0.03

Higher Probability Words are More Likely to be Picked

She → speaks →

- English - 0.4
- French - 0.3
- Spanish - 0.1
- Hindi - 0.08
- Italian - 0.05
- Chinese - 0.04
- Python - 0.03

Response Generated by Picking Words at Each Step

She → speaks → French → quite → well

Model Settings for Tweaking Generated Text

Large language models offer settings that you can tweak to make the generated text **more creative and diverse or more predictable and deterministic**

Creativity vs. Predictability in Text Generation

- High creativity will produce more diverse and unexpected results making the text more engaging
- High predictability generates more consistent and reliable text – useful when you need precise responses
- Striking a balance can produce text that is both interesting and coherent

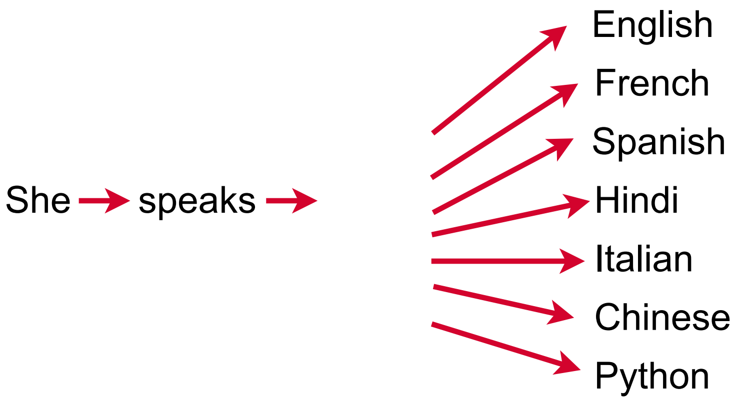
Model Settings to Control Creativity and Predictability

- Temperature
- Top-p (Nucleus Sampling)
- Top-k

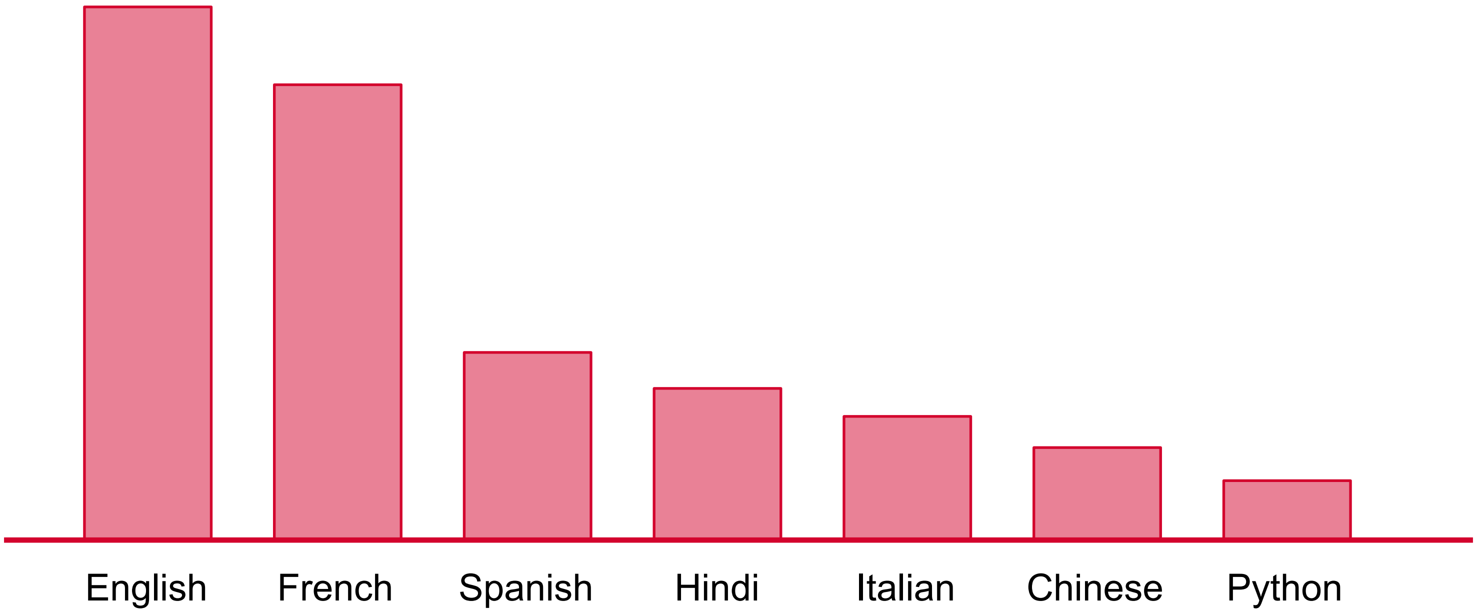
Temperature

- Values range between 0 and 1 (both inclusive)
- Higher values closer to 1 results in more creative output
- Lower values closer to 0 results in more predictable output

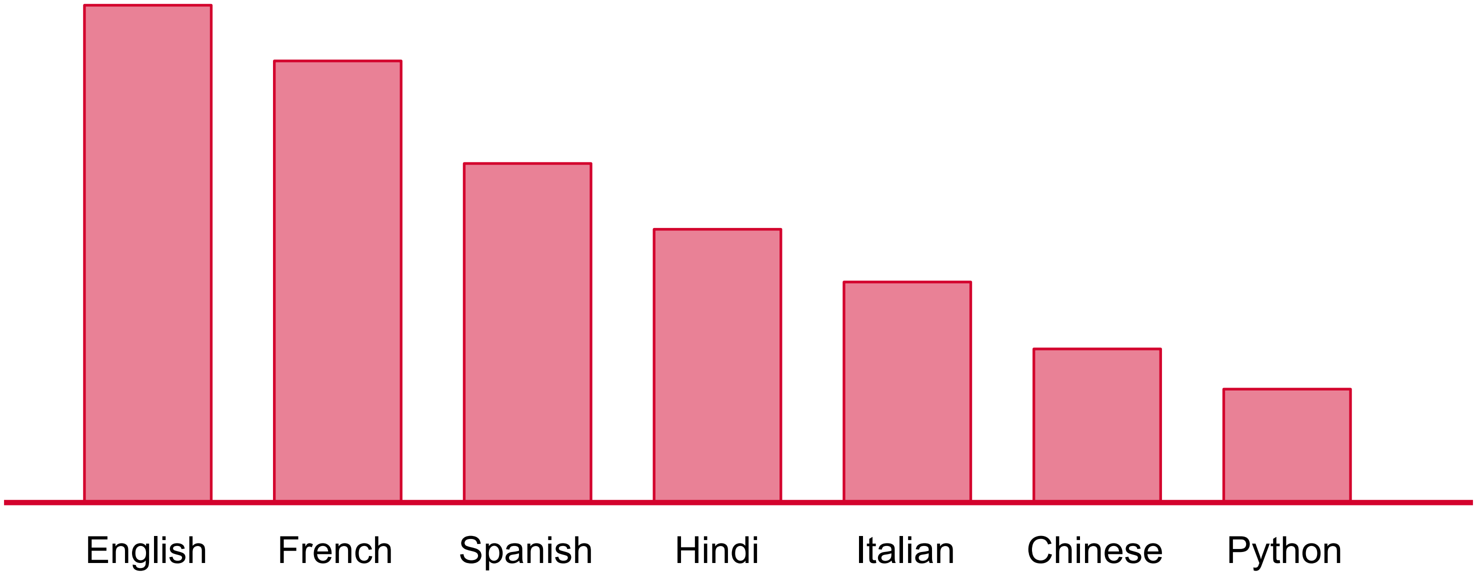
The Model Picks One Word from Possible Next Words



Original Probabilities of Possible Next Words

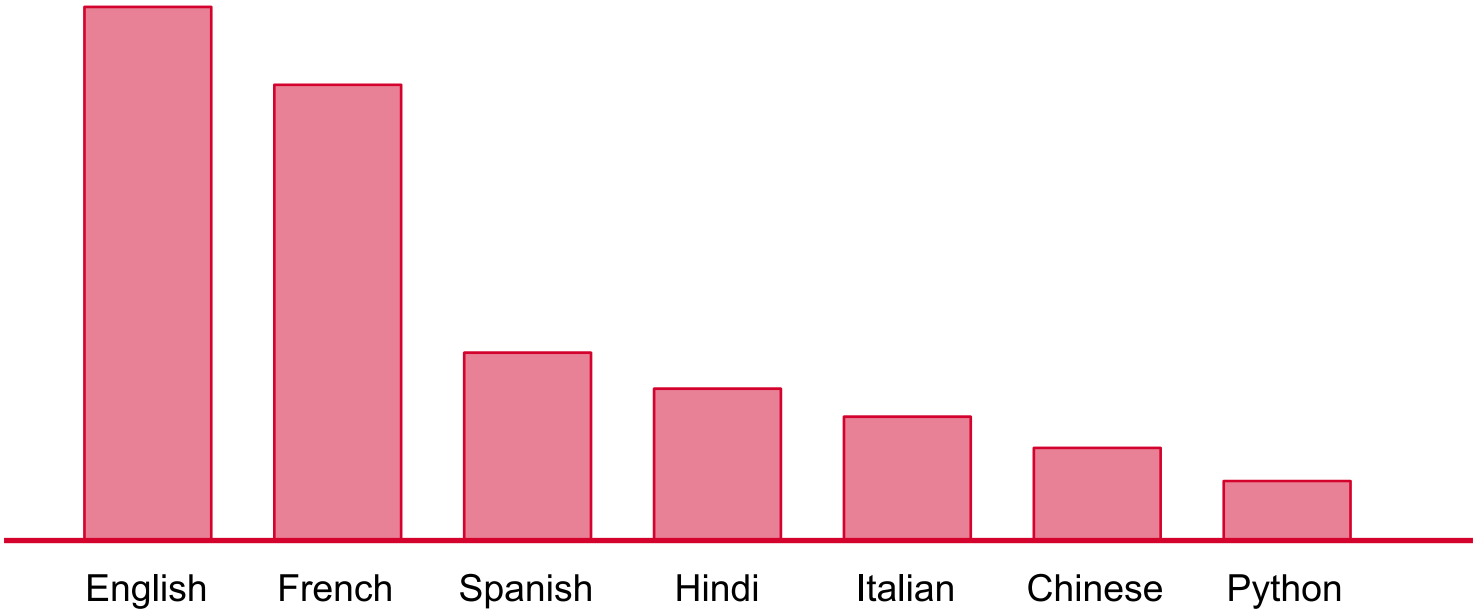


Higher Values of Temperature (Closer to 1)

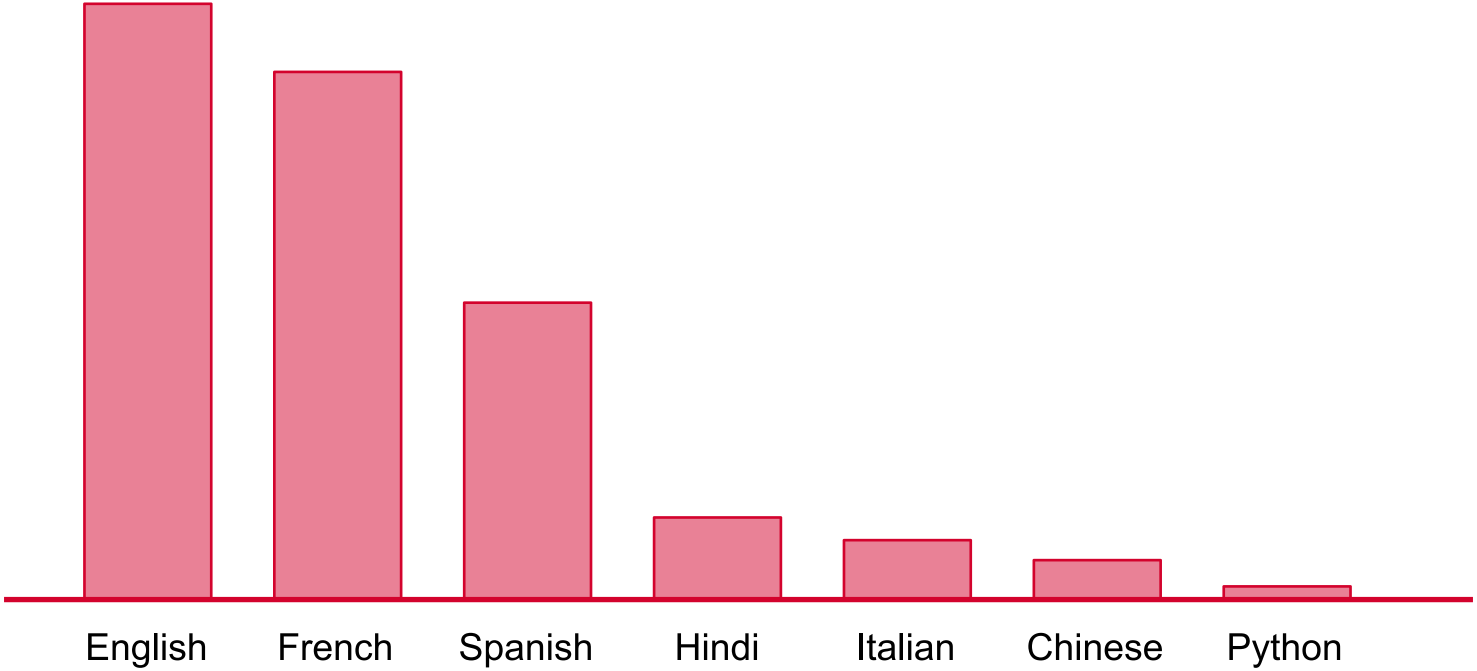


The probability distribution over the next possible word becomes **flatter.**

Original Probabilities of Possible Next Words



Lower Values of Temperature (Closer to 0)



The probability distribution over the next possible word becomes **sharper.**

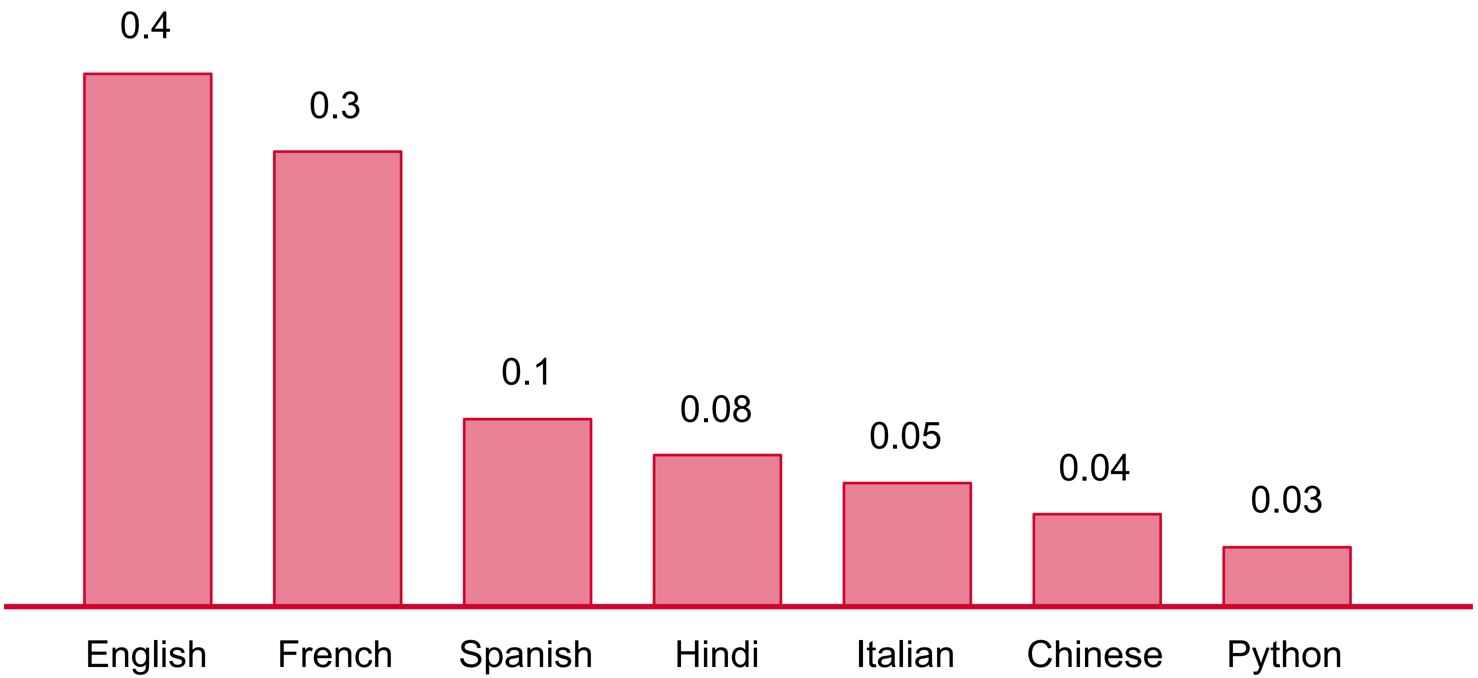
Top-p (Nucleus Sampling)

- Values range between 0 and 1 (both inclusive)
- Values close to 1 result in more diverse and creative output
- Values close to 0 result in more predictable output

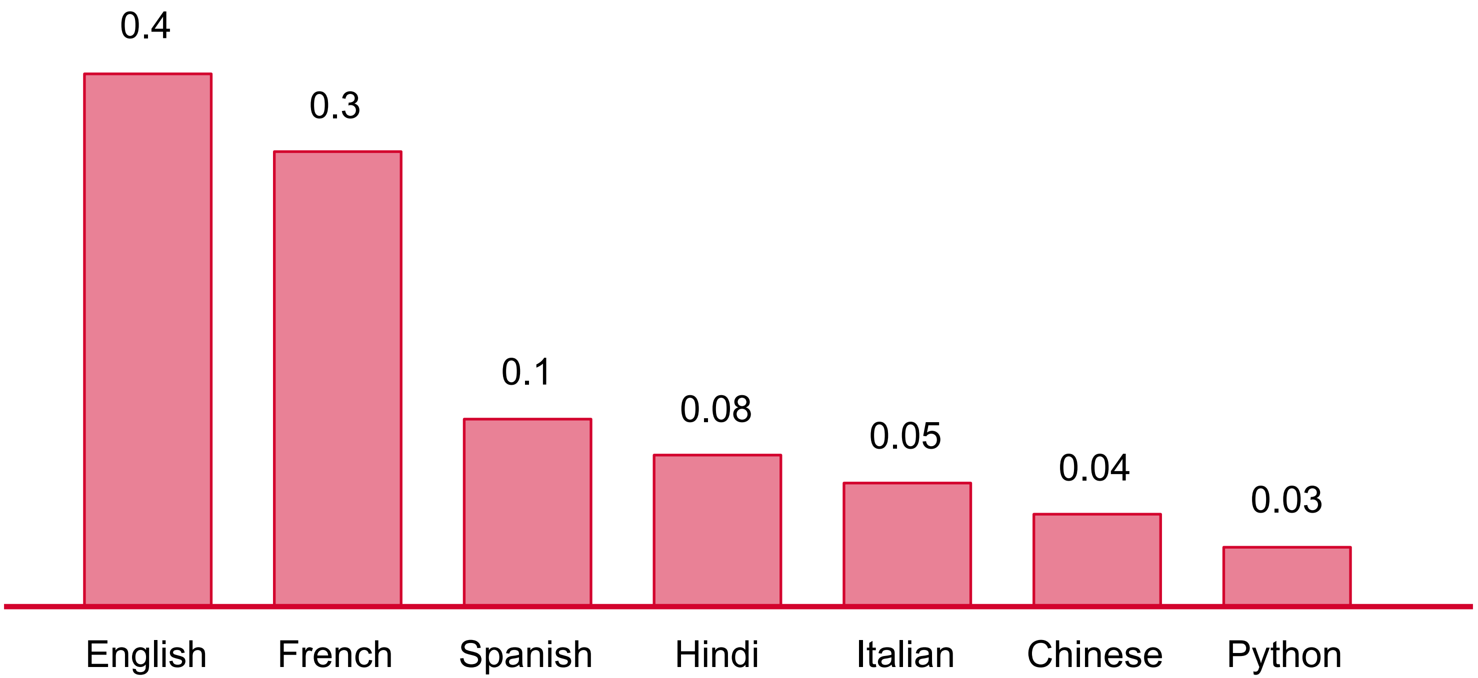
Top-p (Nucleus Sampling)

Top-p sampling, also known as nucleus sampling, works by selecting the **smallest set of top candidate words whose cumulative probability exceeds a given threshold p.**

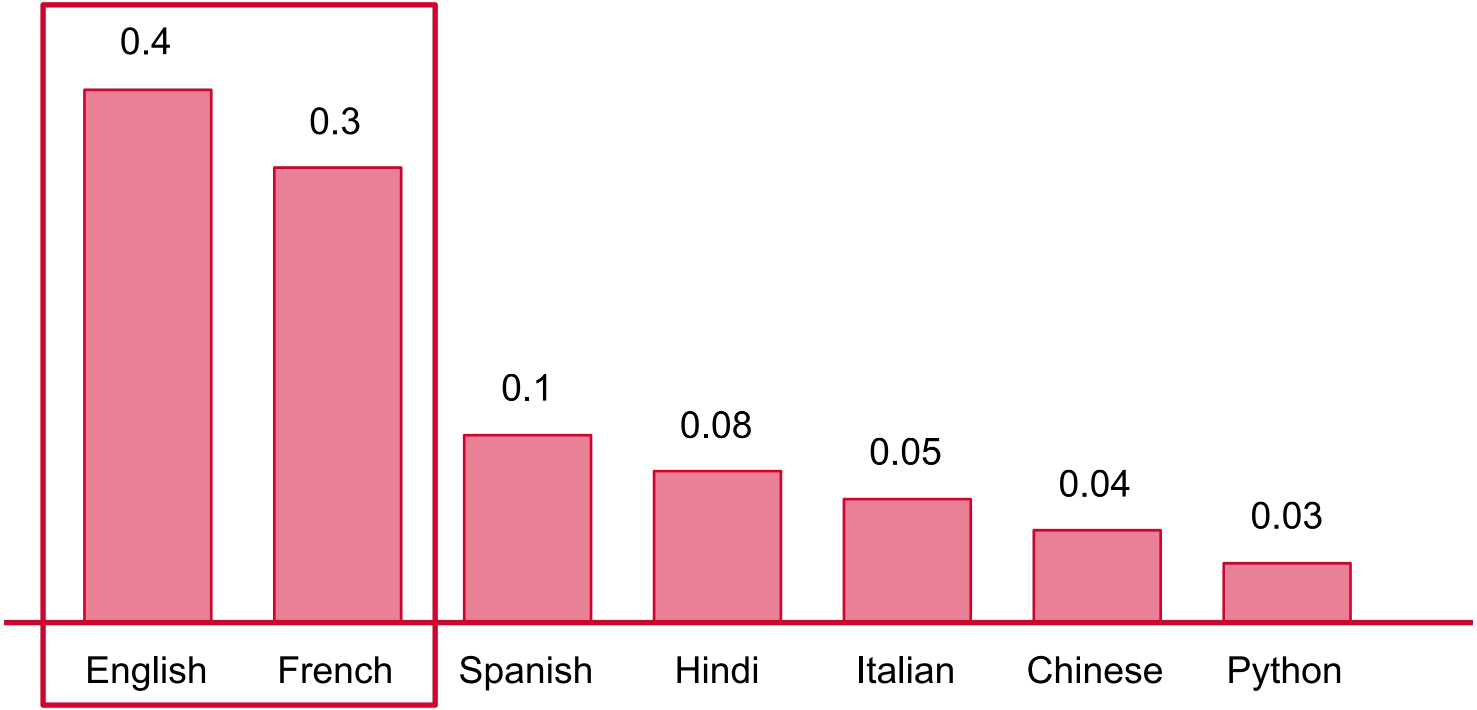
Probabilities of Possible Next Words



Sort All Words in Order of Probability

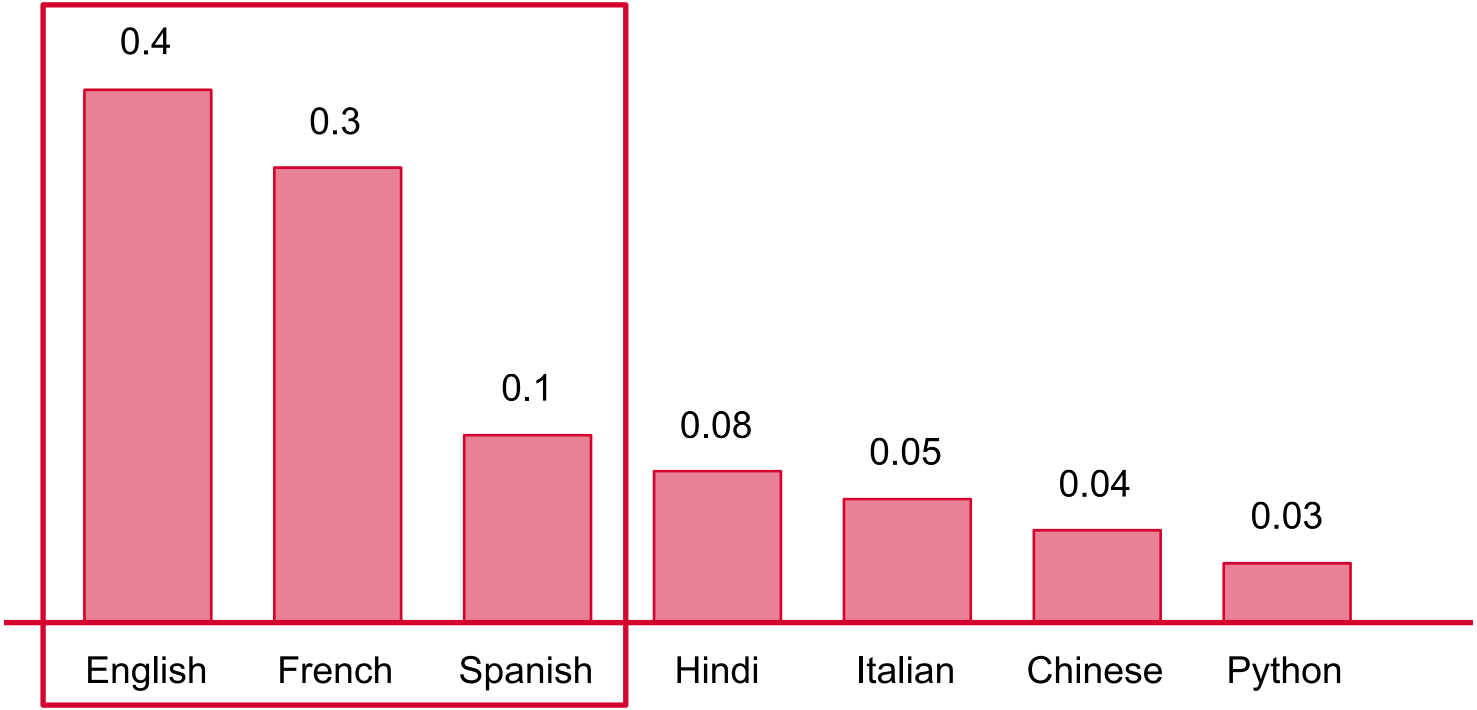


Top-p of 0.5



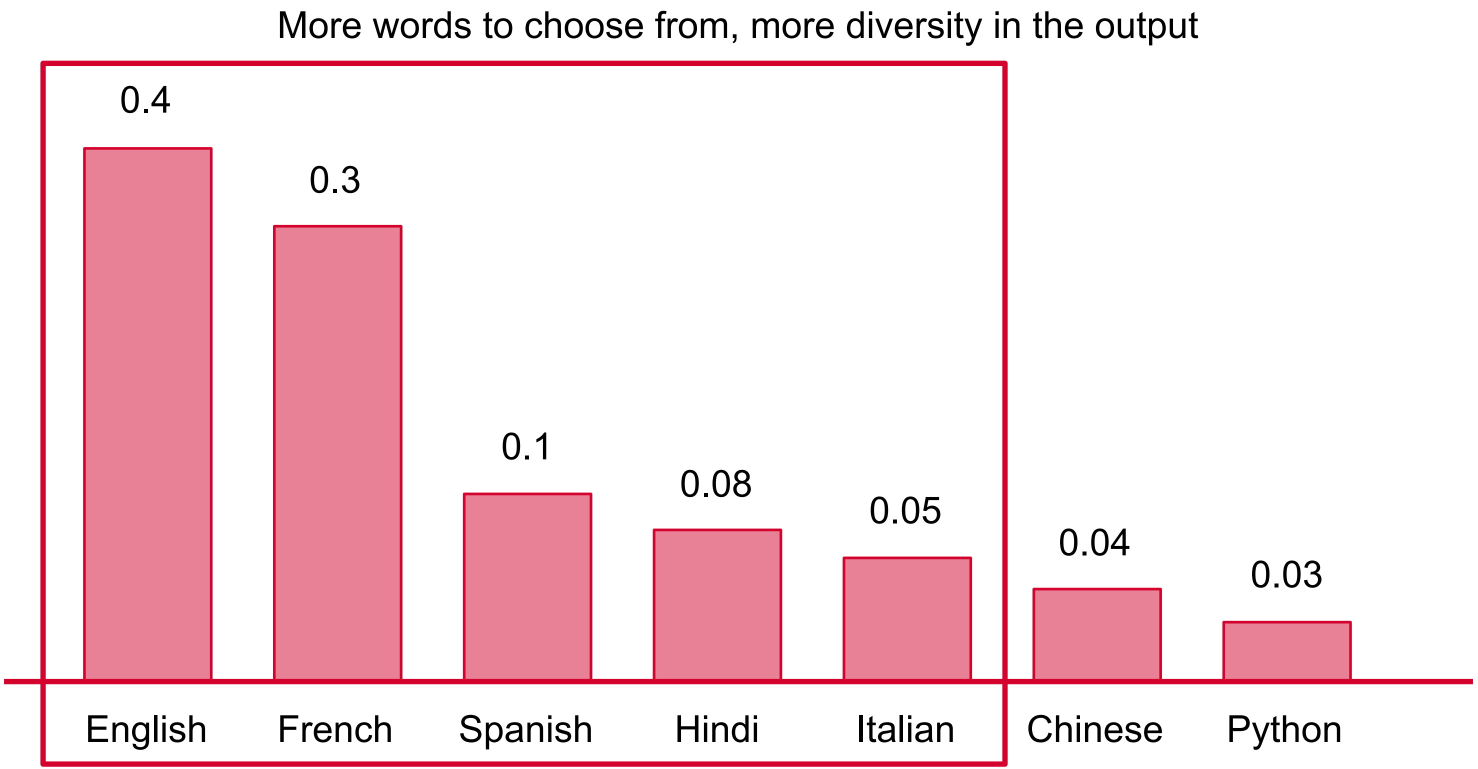
The next word selected will only choose between the smallest subset of words that exceeds the cumulative probability threshold

Top-p of 0.7

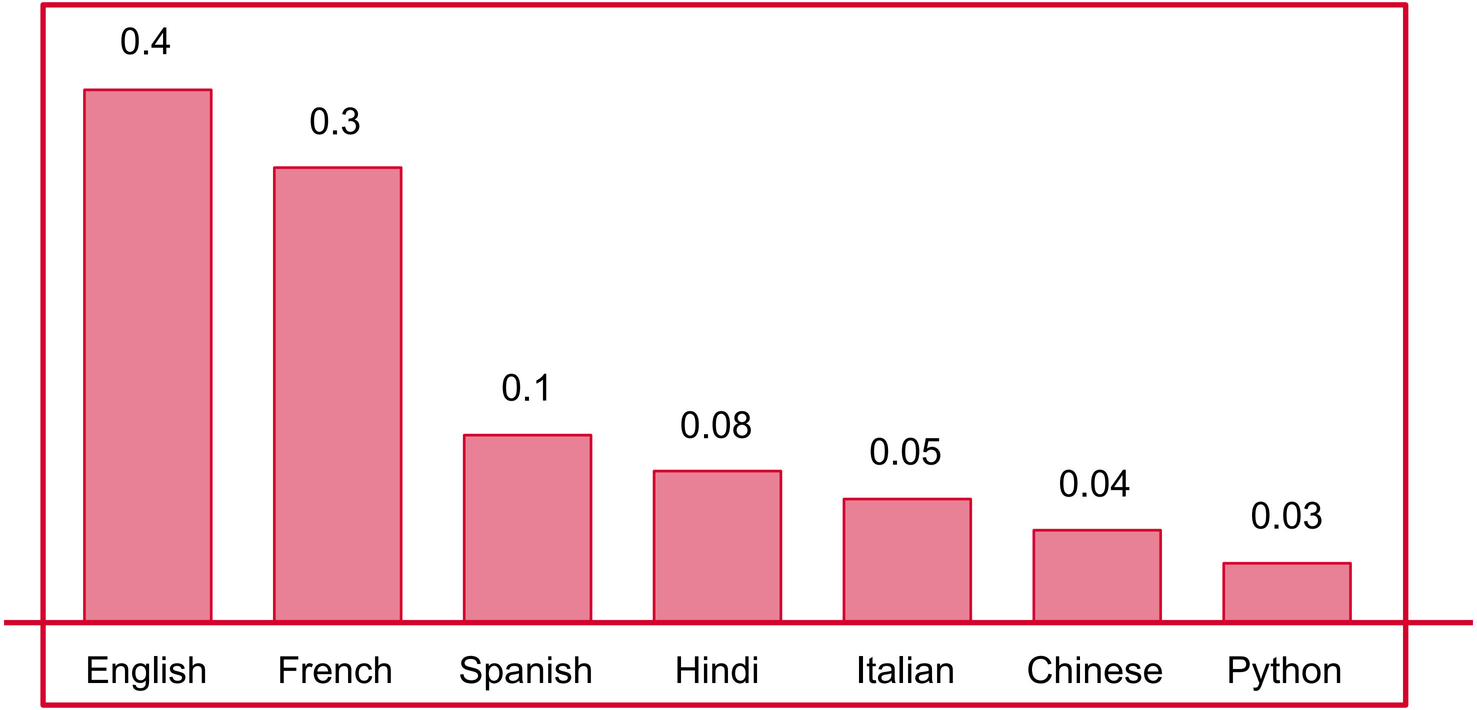


0.4
0.3
0.1
0.08
0.05
0.04
0.03
English
French
Spanish
Hindi
Italian
Chinese
Python

Top-p of 0.9


More words to choose from, more diversity in the output
0.4
0.3
0.1
0.08
0.05
0.04
0.03
English
French
Spanish
Hindi
Italian
Chinese
Python

Top-p of 1



Choose from among all possible words, greatest possible diversity

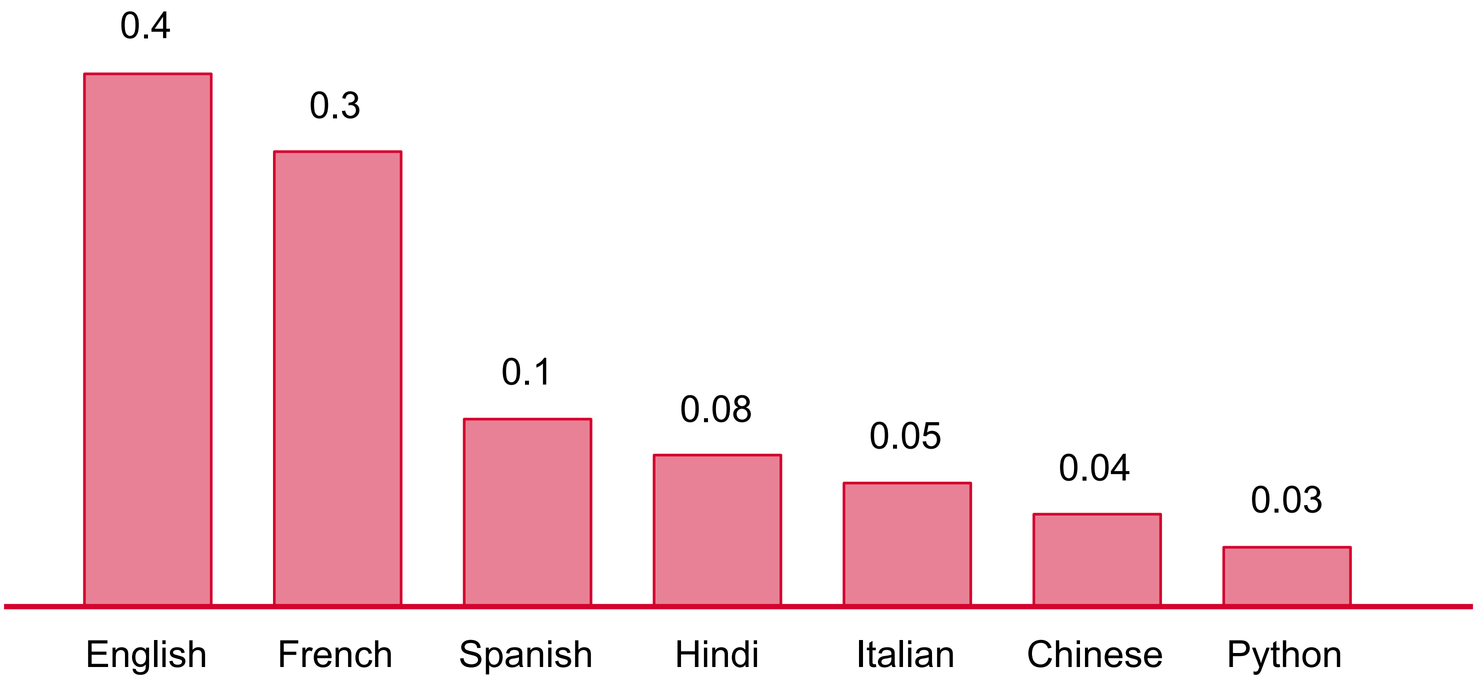
Top-k Sampling

- Words to choose from limited to the K most likely words at each step
- Value is any positive integer
- Smaller values will pick more likely words, so less diverse output
- Larger values will pick less likely words, more diverse output

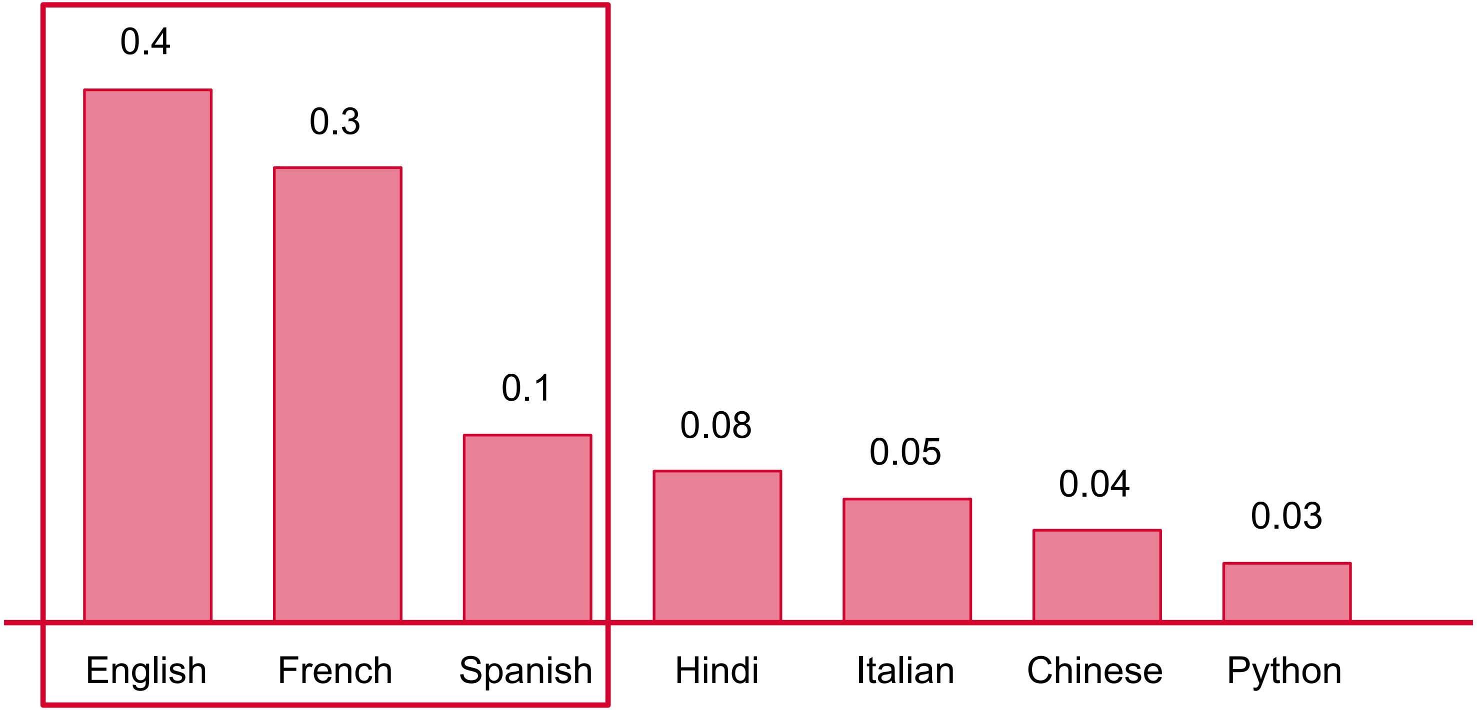
Top-k Sampling

Top-K sampling limits the next-word selection to the **K most likely words** predicted by the model at each generation step.

Sort All Words in Order of Probability

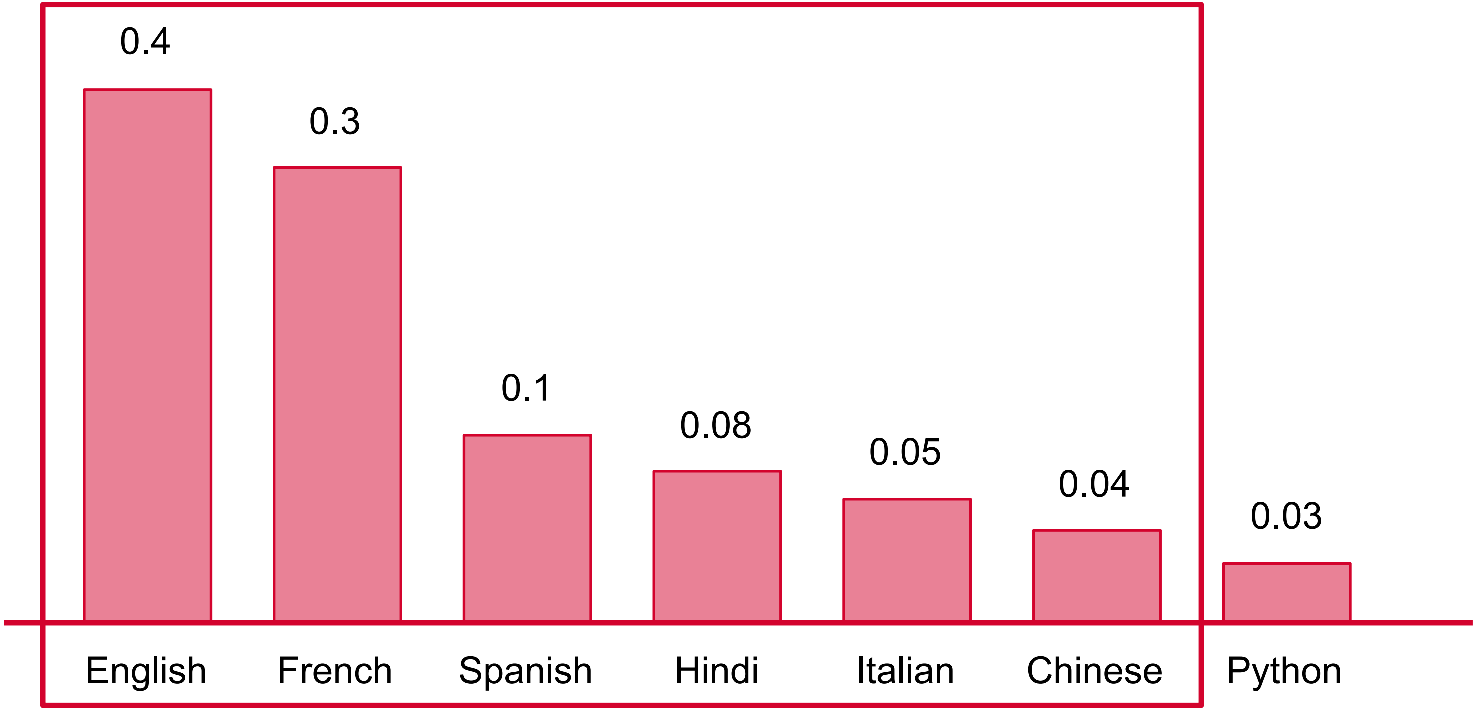


Top-k of 3



The next word selected will only choose between the top 3 words in terms of probability

Top-k of 6



The next word selected will only choose between the top 6 words in terms of probability