Artificial Intelligence

And Cool Things We Can do With It

NLP
(Natural Language Processing

- Text Summarisation,
- Multilabel Classification,
- Semantic Search,
- Named Entity Recognition,
- Report/Text Q&A,
- Natural Language Inference,
- Text Translation,
- Information Extraction from physical documents
- Table Question Answering
- Conversational Bot,
- Text Generation

Text Summarisation

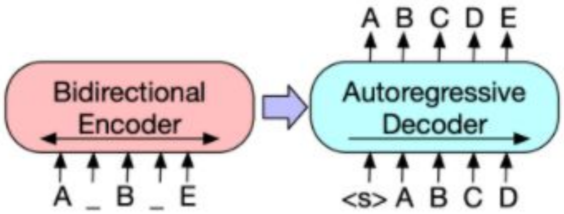
News, Posts, Threads, Topic Detection

Bidirectional Auto-Regressive Transformer (BART)

The Model

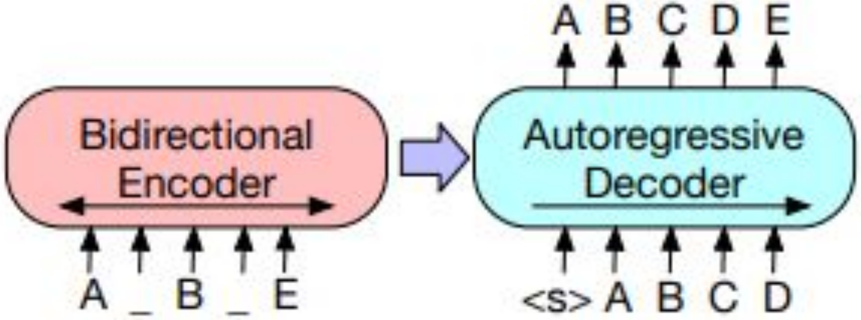
Introduced by Lewis et al. in BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension

BART is a denoising autoencoder for pretraining sequence-to-sequence models. It is trained by (1) corrupting text with an arbitrary noising function, and (2) learning a model to reconstruct the original text. It uses a standard Transformer-based neural machine translation architecture. It uses a standard seq2seq/NMT architecture with a bidirectional encoder (like BERT) and a left-to-right decoder (like GPT). This means the encoder's attention mask is fully visible, like BERT, and the decoder's attention mask is causal, like GPT2.



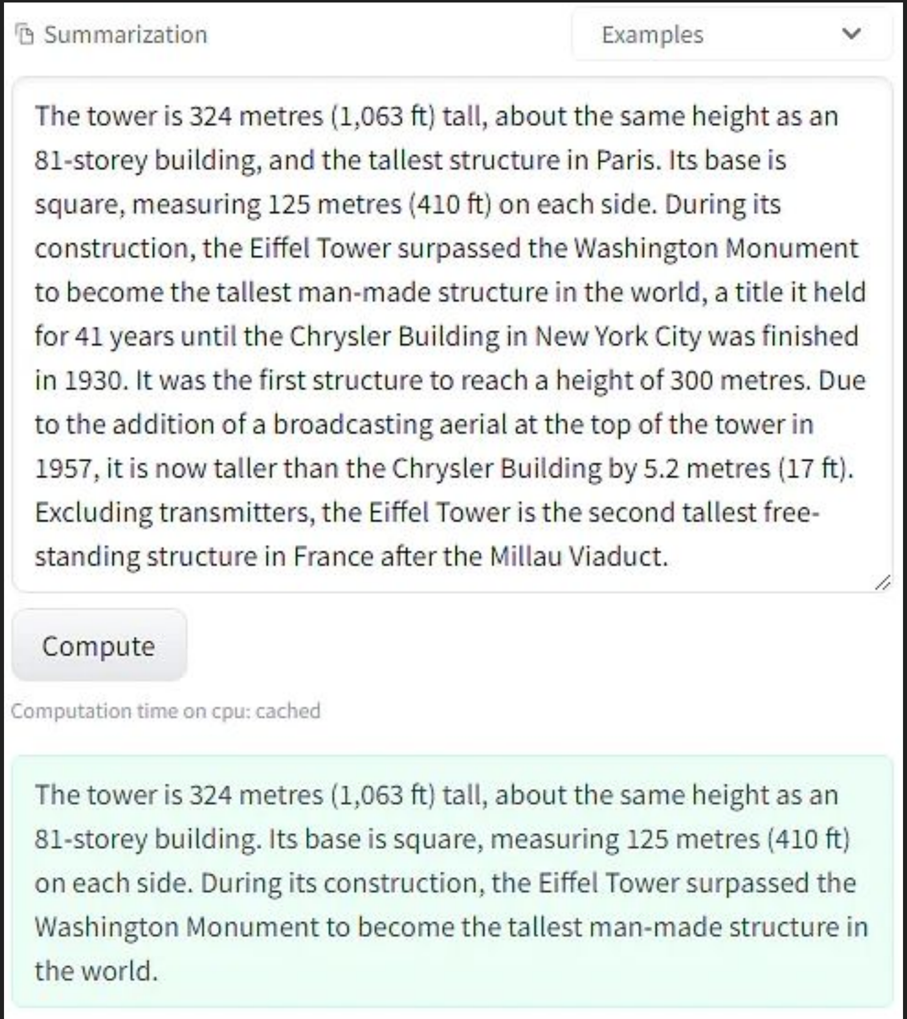
Source: BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension

How it Works



(c) BART: Inputs to the encoder need not be aligned with decoder outputs, allowing arbitary noise transformations. Here, a document has been corrupted by replacing spans of text with mask symbols. The corrupted document (left) is encoded with a bidirectional model, and then the likelihood of the original document (right) is calculated with an autoregressive decoder. For fine-tuning, an uncorrupted document is input to both the encoder and decoder, and we use representations from the final hidden state of the decoder.

Examples


Summarization
Examples
The tower is 324 metres (1,063 ft) tall, about the same height as an 81-storey building, and the tallest structure in Paris. Its base is square, measuring 125 metres (410 ft) on each side. During its construction, the Eiffel Tower surpassed the Washington Monument to become the tallest man-made structure in the world, a title it held for 41 years until the Chrysler Building in New York City was finished in 1930. It was the first structure to reach a height of 300 metres. Due to the addition of a broadcasting aerial at the top of the tower in 1957, it is now taller than the Chrysler Building by 5.2 metres (17 ft). Excluding transmitters, the Eiffel Tower is the second tallest free-standing structure in France after the Millau Viaduct.
Compute
Computation time on cpu: cached
The tower is 324 metres (1,063 ft) tall, about the same height as an 81-storey building. Its base is square, measuring 125 metres (410 ft) on each side. During its construction, the Eiffel Tower surpassed the Washington Monument to become the tallest man-made structure in the world.

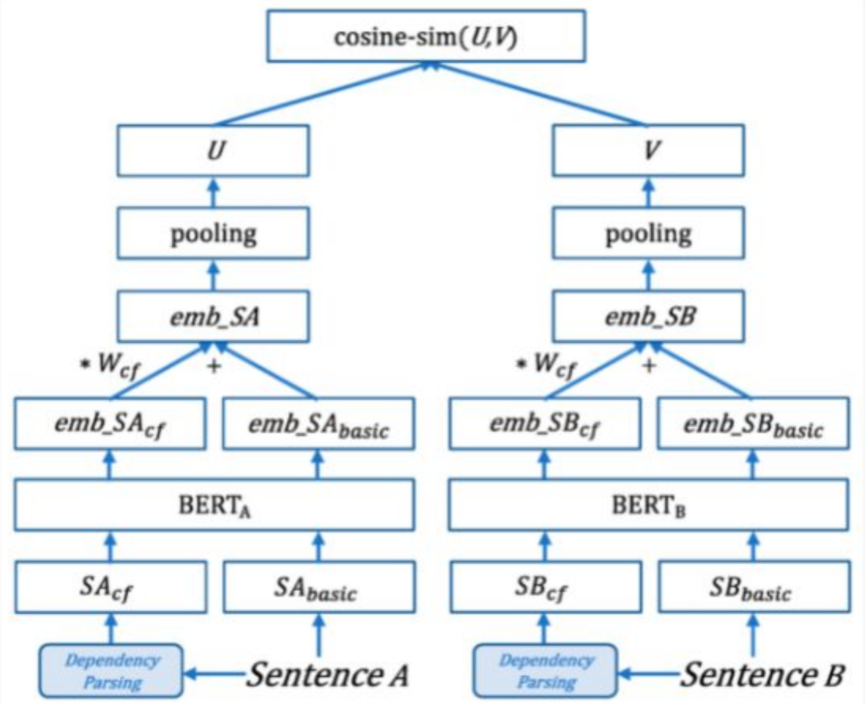
Semantic Search

Related Subjects, Users, Topics, Similar Texts

Sentence Transformer Models (SBERT-alike)

The Model

Figure 2. The overall architecture of the component focusing bidirectional encoder representations from transformers (CF-BERT) model (with semantic textual similarity tasks). The two BERT networks have tied weights (Siamese network structure).



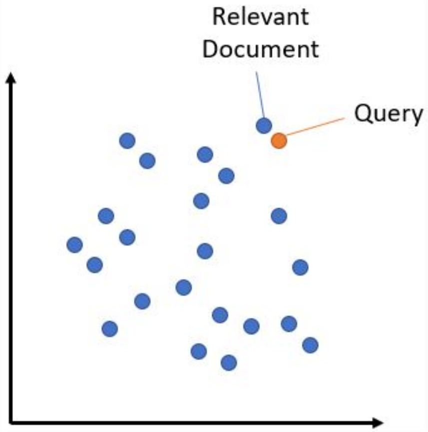
How it Works

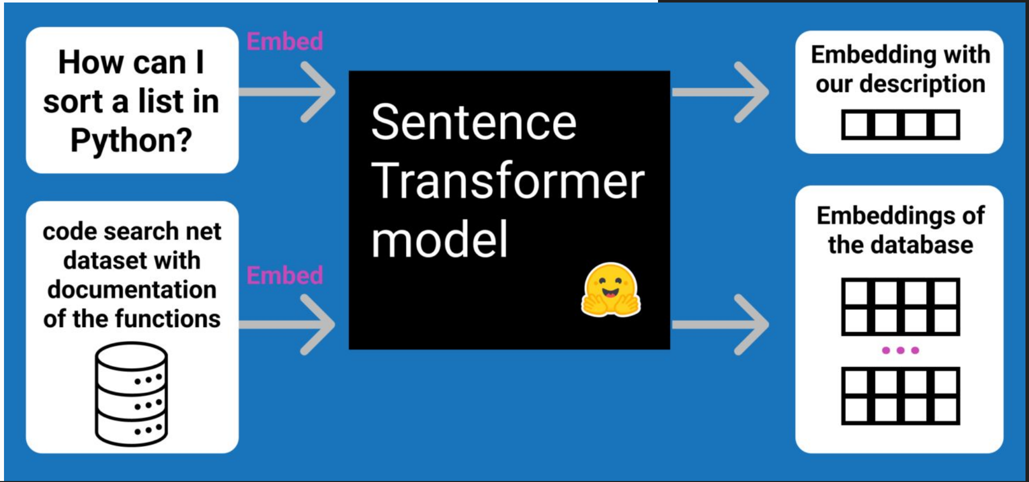
The Model

Semantic search seeks to improve search accuracy by understanding the content of the search query. In contrast to traditional search engines which only find documents based on lexical matches, semantic search can also find synonyms.

The idea behind semantic search is to embed all entries in your corpus, whether they be sentences, paragraphs, or documents, into a vector space.

At search time, the query is embedded into the same vector space and the closest embeddings from your corpus are found. These entries should have a high semantic overlap with the query.





Examples

Please enter here the description of a Python function you want to create, we will look for similar ones in Github.

Create a dictionary

How many similar functions you want?

2 − +

Find them.

Amazing! These are the functions in the code search net dataset that better match the language of our specific description. The 'func_documentation_string' column shows the documentation description of the function in Github, the 'repository_name' column shows the name of the repository where the function is, and 'func_code_url' takes you the function.

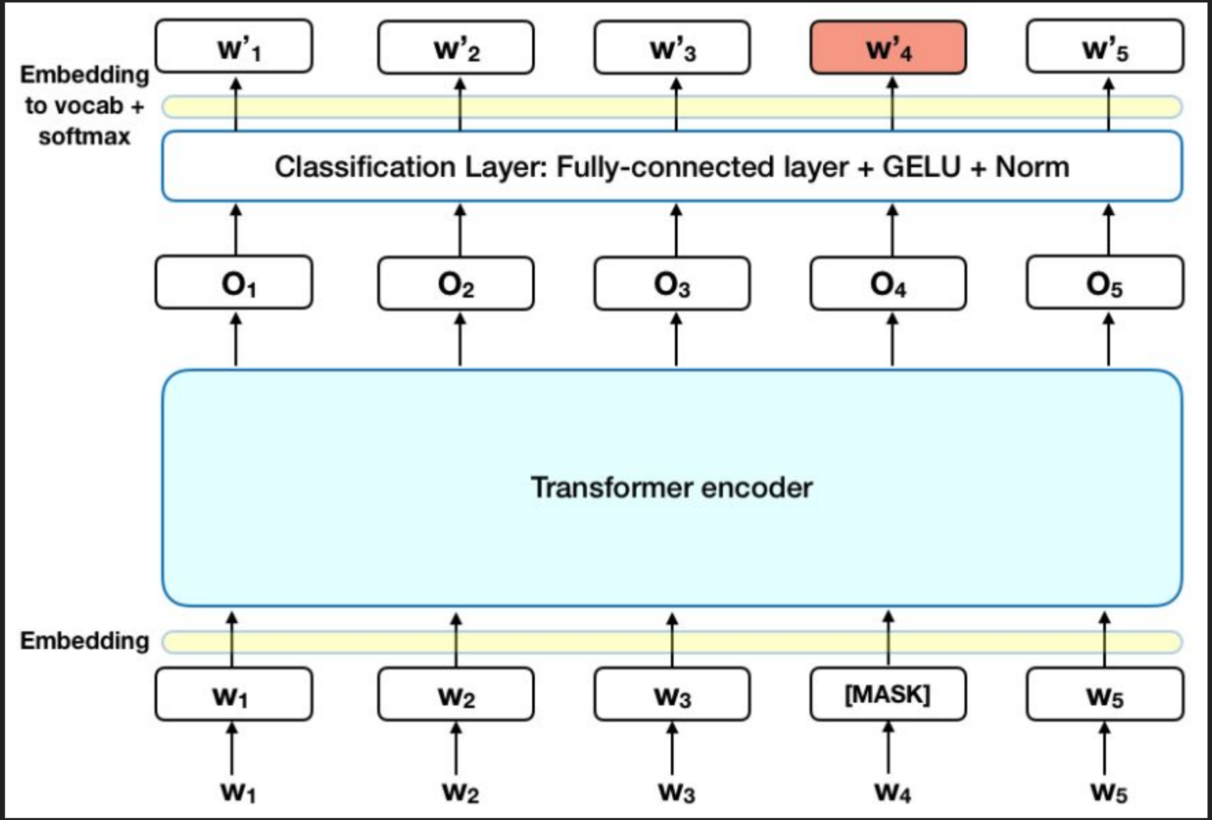
	func_documentation_string	repository_name	func_code_url
5850	Compile a dictionary.	Sean1708/HipPy	https://github.com/Sean1708/HipPy/blob/d0ea8fb1e417f1fedaa8e215e3d420b90c4de691/hippy/compiler
194327	create a blank dictionary	santoshphilip/eppy	https://github.com/santoshphilip/eppy/blob/55410ff7c11722f35bc4331ff5e00a0b86f787e1/eppy/EPlusInte L174

Multilabel Classification

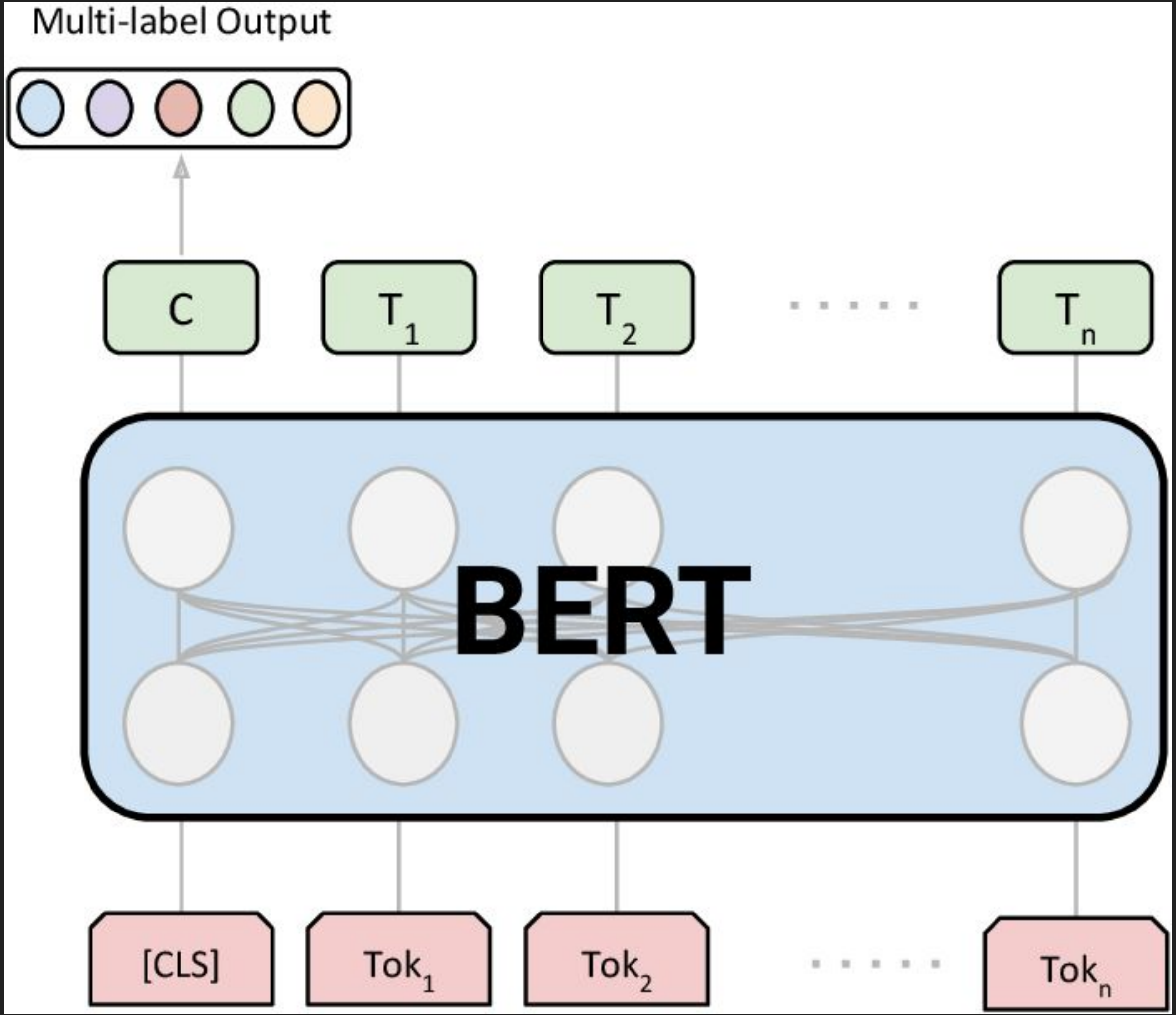
Toxic speech, Sentiment, Emotions, Hate speech

Bidirectional Encoder Representations from Transformers (BERT)

The Model



How it Works



Examples

```
from transformers import pipeline
classifier = pipeline("sentiment-analysis",model='bhadresh-savani/distilbert
prediction = classifier("I love using transformers. The best part is wide ra
print(prediction)
```

`return_all_scores=True` should be in the `pipeline()` argument.

Output:

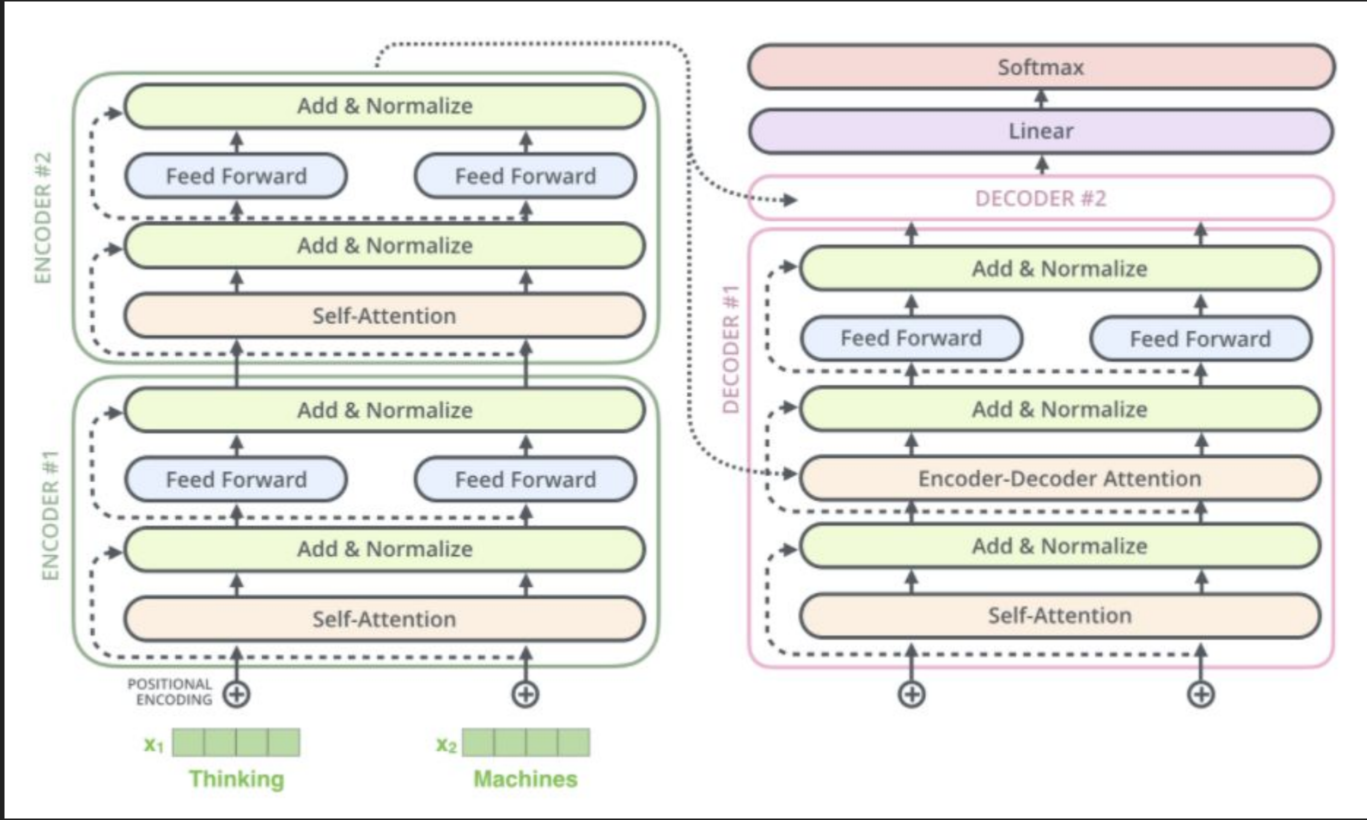
```
[[
{'label': 'sadness', 'score': 0.0006792712374590337},
{'label': 'joy', 'score': 0.9959300756454468},
{'label': 'love', 'score': 0.0009452480007894337},
{'label': 'anger', 'score': 0.0018055217806249857},
{'label': 'fear', 'score': 0.00041110432357527316},
{'label': 'surprise', 'score': 0.0002288572577526793}
]]
```

NER (Named Entity Recognition)

Person, Location, Time, Organisation

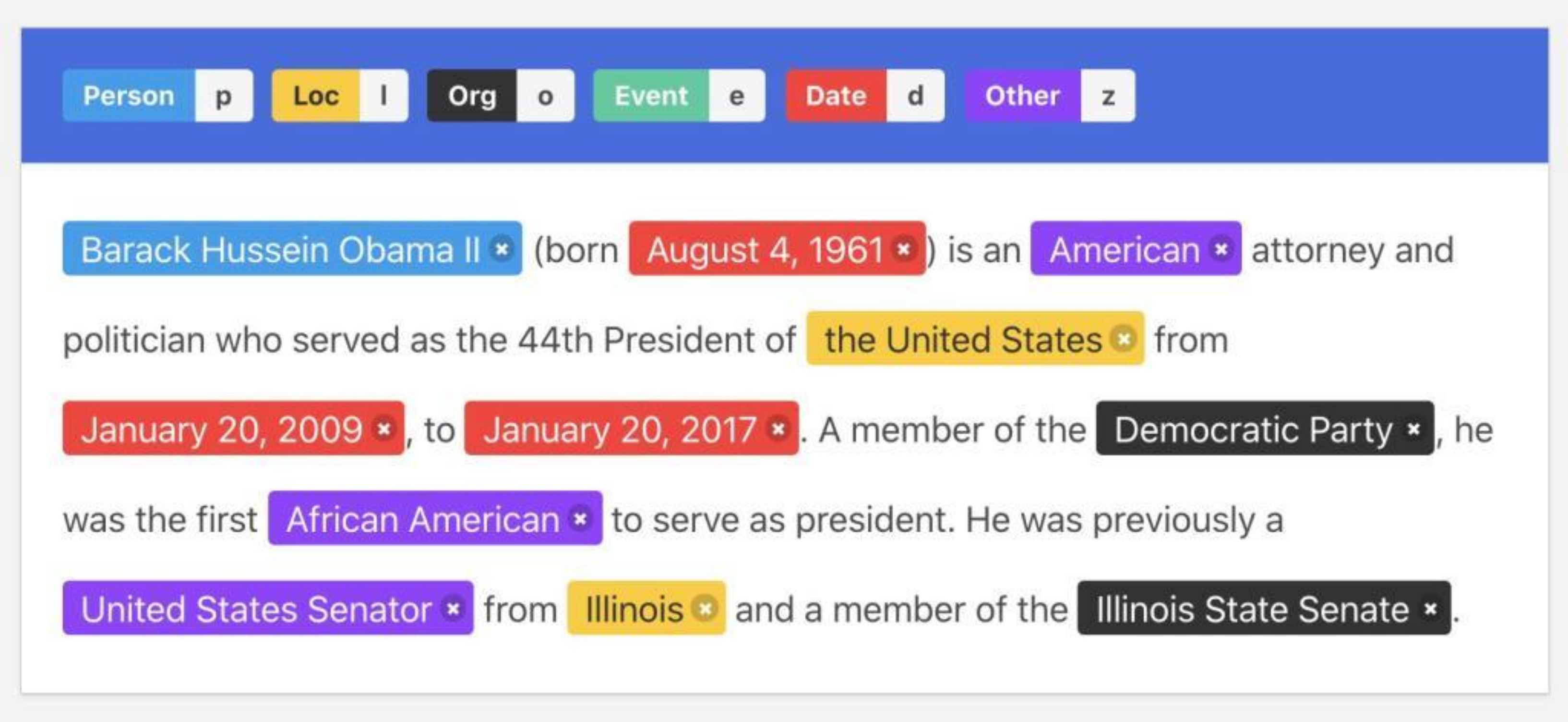
T5

The Model



Softmax
Linear
DECODER #2
DECODER #1
Add & Normalize
Feed Forward
Feed Forward
Add & Normalize
Encoder-Decoder Attention
Add & Normalize
Self-Attention
ENCODER #2
Add & Normalize
Feed Forward
Feed Forward
Add & Normalize
Self-Attention
ENCODER #1
Add & Normalize
Feed Forward
Feed Forward
Add & Normalize
Self-Attention
POSITIONAL ENCODING
x_1
Thinking
x_2
Machines

How it Works


Person p
Loc l
Org o
Event e
Date d
Other z
Barack Hussein Obama II (born August 4, 1961) is an American attorney and politician who served as the 44th President of the United States from January 20, 2009, to January 20, 2017. A member of the Democratic Party, he was the first African American to serve as president. He was previously a United States Senator from Illinois and a member of the Illinois State Senate.

Drawbacks & Challenges

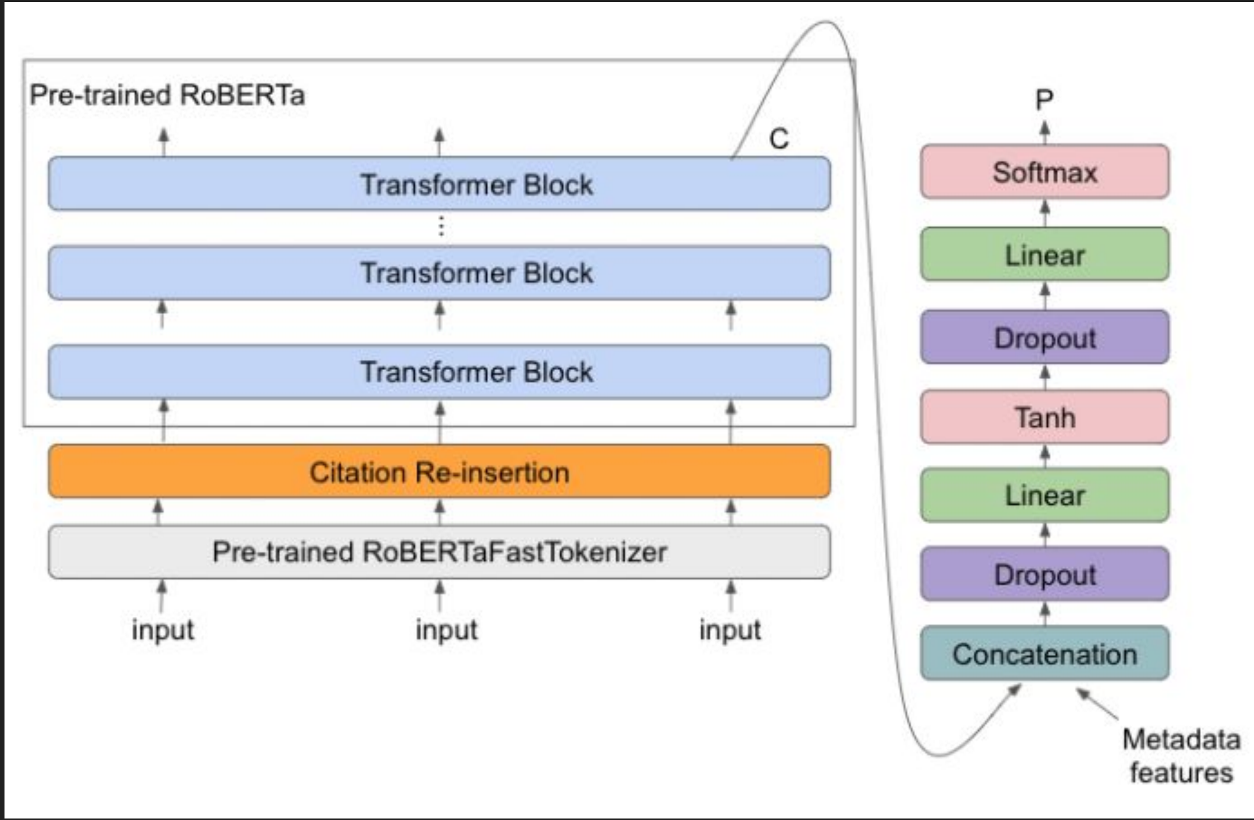
The Model

Report (Text) Analysis

Parse the text (report), answer question based on the information in this report.

Robustly Optimised BERT (RoBERTa)

The Model



How it Works

Bidirectional Encoder Representations from Transformers (BERT) is a transformer-based machine learning technique for natural language processing (NLP) pre-training developed by Google. BERT was created and published in 2018 by Jacob Devlin and his colleagues from Google. In 2019, Google announced that it had begun leveraging BERT in its search engine, and by late 2020 it was using BERT in almost every English-language query. A 2020 literature survey concluded that "in a little over a year, BERT has become a ubiquitous baseline in NLP experiments", counting over 150 research publications analyzing and improving the model.The original English-language BERT has two models: (1) the BERTBASE: 12 encoders with 12 bidirectional self-attention heads, and (2) the BERTLARGE: 24 encoders with 16 bidirectional self-attention heads. Both models are pre-trained

Question used for QA (you can also edit, and experiment with the answers)

How many languages does bert understand?

Run QA inference (get answer prediction)

Answer: **over 70**

Answer context (and score): ... _ On December 9, 2019, it was reported that BERT had been adopted by Google Search for **over 70** languages. In October 2020, almost every single English-based query was processed by BERT_ ... (score: 0.293)

Answer JSON:


```
{
  "score" : 0.29271575808525085
  "start" : 3486
  "end" : 3493
  "answer" : "over 70"
}
```

Drawbacks & Challenges

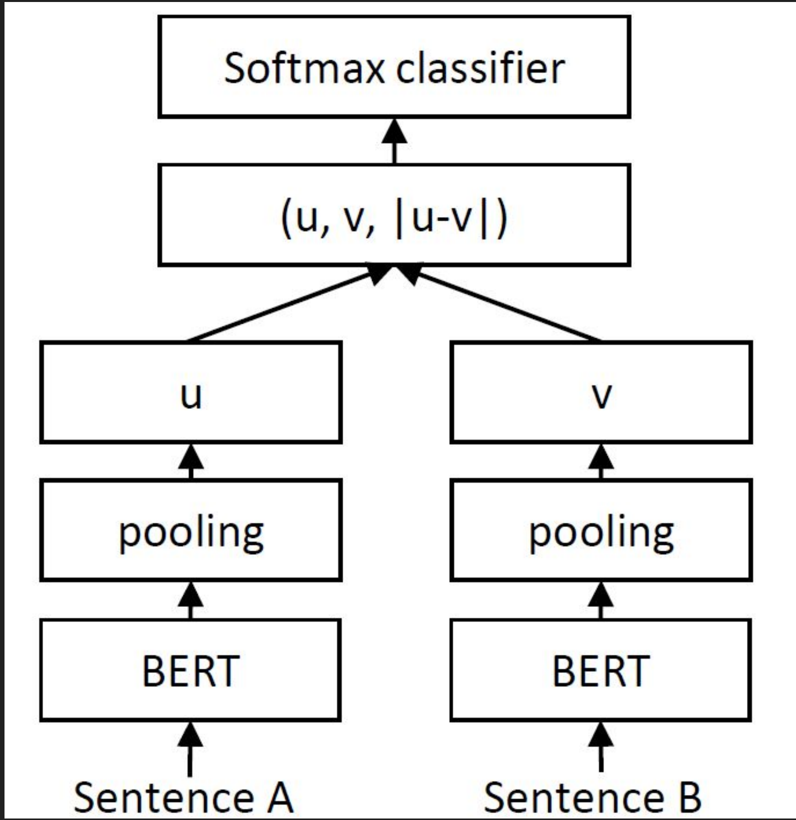
The Model

NLI (Natural Language Inference)

The NLI Model Determines the Relationship Between two given texts (contradiction, entailment, neutral)

The Model

SBERT



How it Works

Given two sentence (premise and hypothesis), Natural Language Inference (NLI) is the task of deciding if the premise entails the hypothesis, if they are contradiction or if they are neutral. Commonly used NLI dataset are SNLI and MultiNLI.

Sentence A (Premise)	Sentence B (Hypothesis)	Label
A soccer game with multiple males playing.	Some men are playing a sport.	entailment
An older and younger man smiling.	Two men are smiling and laughing at the cats playing on the floor.	neutral
A man inspects the uniform of a figure in some East Asian country.	The man is sleeping.	contradiction

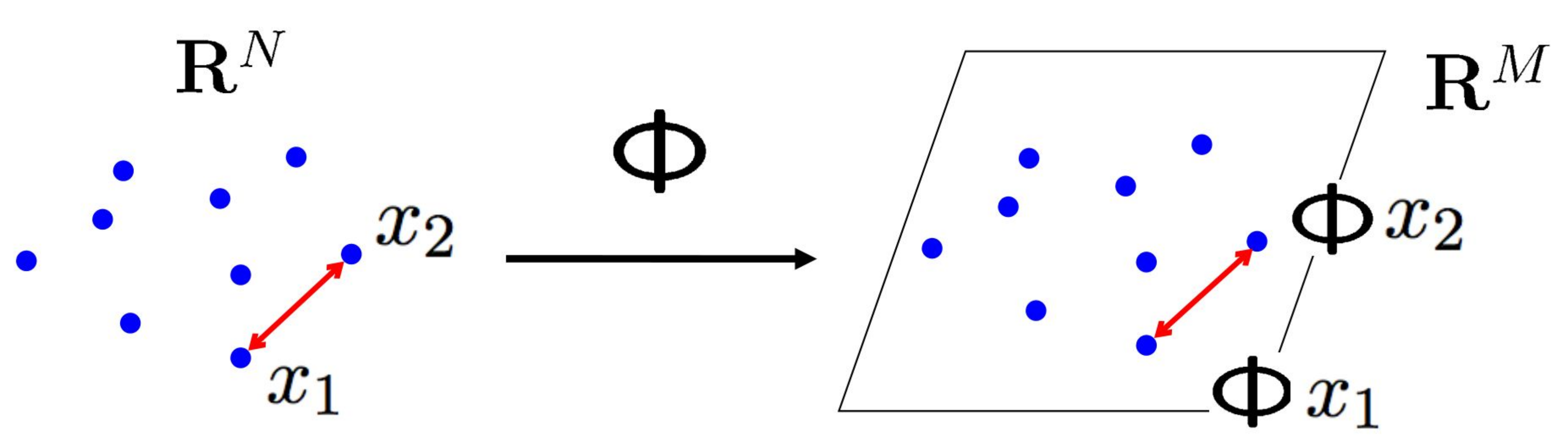
Drawbacks & Challenges

The Model

Translation

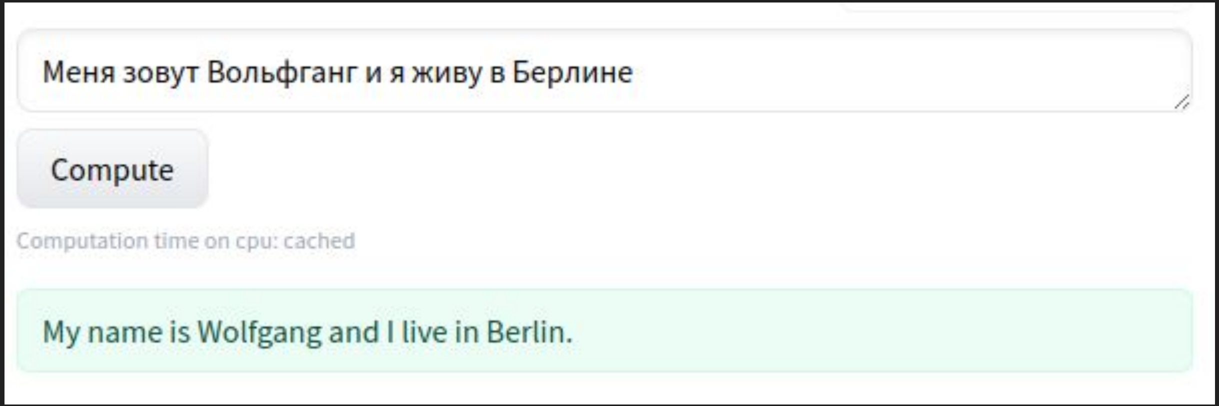
In-house translation engine (i.e. fine-tuned on Russian slang used by the criminals “fenya”, “torch-slang”)
Example: “chefir”

The Model



How it Works

Sample Translation



Drawbacks & Challenges

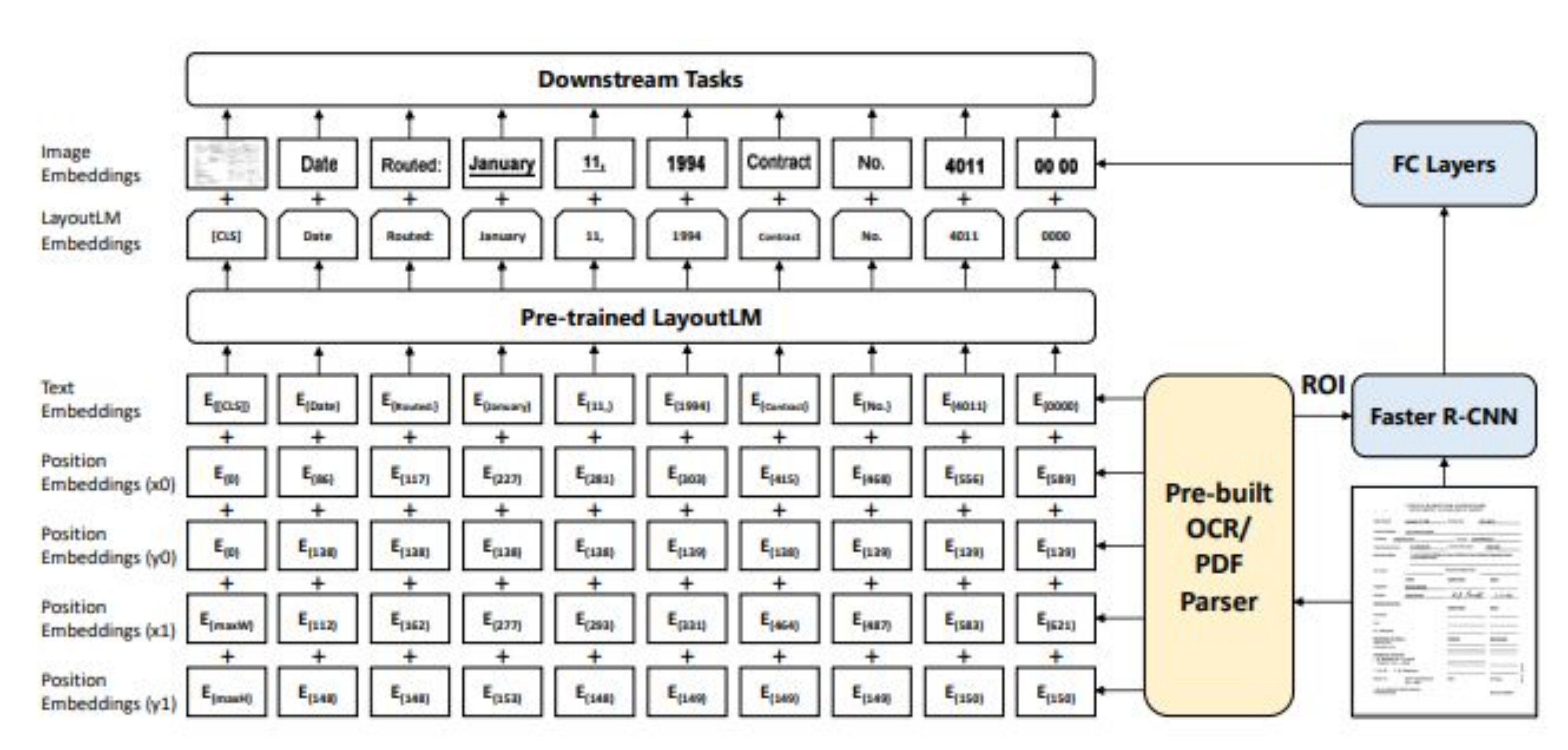
The Model

Information Extraction

From physical documents (Fake IDs, Invoices, etc)

LayoutLM

The Model



How it Works

The Model

Drawbacks & Challenges

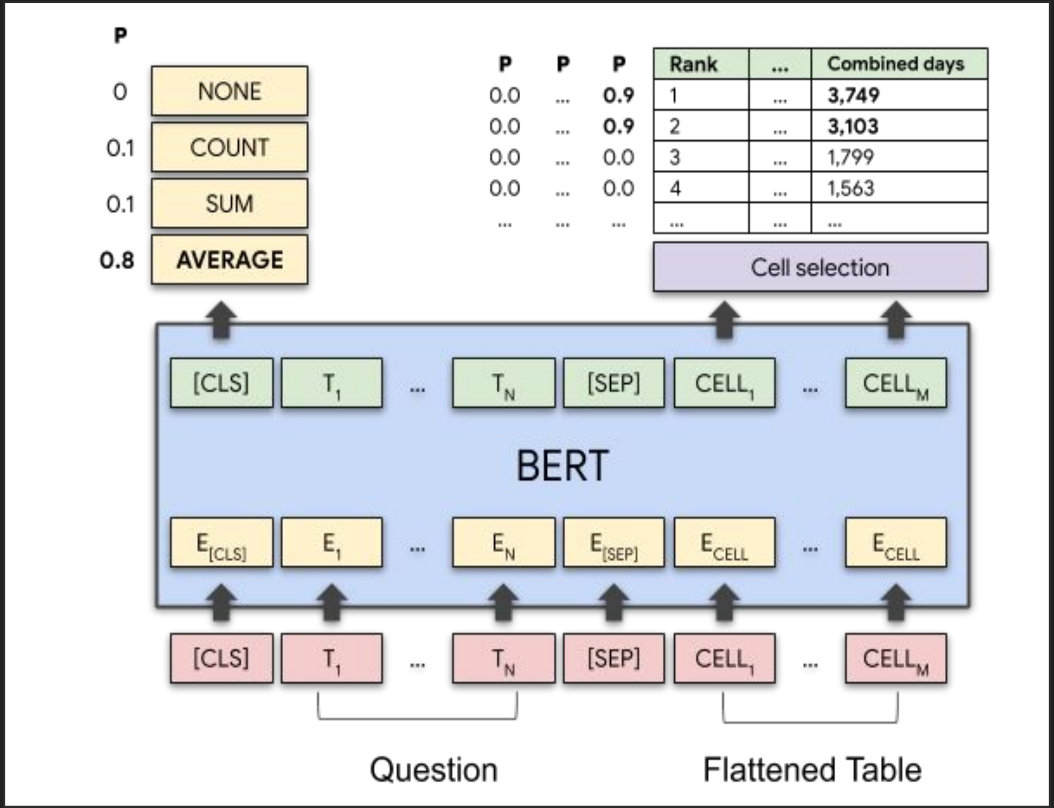
The Model

Table Question Answering

Model to answer questions related to the table data

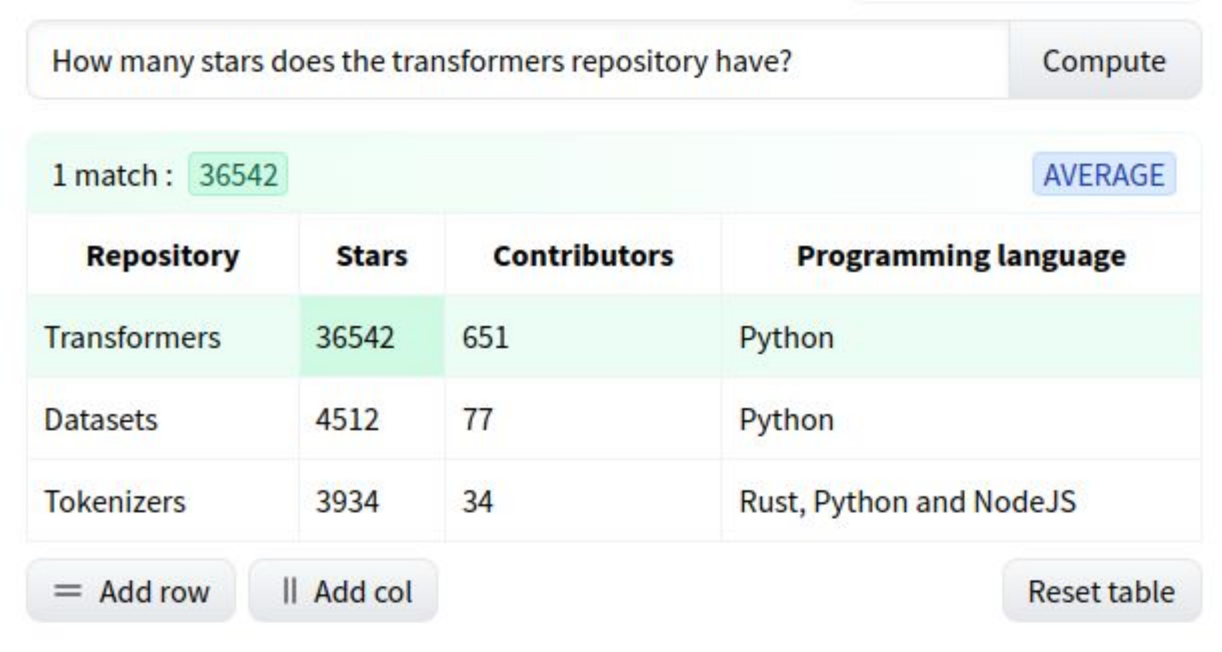
TAble PArSing (TAPAS)

The Model



How it Works

TAPAS is a BERT-like transformers model pretrained on a large corpus of English data from Wikipedia in a self-supervised fashion. This means it was pretrained on the raw tables and associated texts only, with no humans labelling them in any way (which is why it can use lots of publicly available data) with an automatic process to generate inputs and labels from those texts. More precisely, it was pretrained with two objectives:



Repository	Stars	Contributors	Programming language
Transformers	36542	651	Python
Datasets	4512	77	Python
Tokenizers	3934	34	Rust, Python and NodeJS

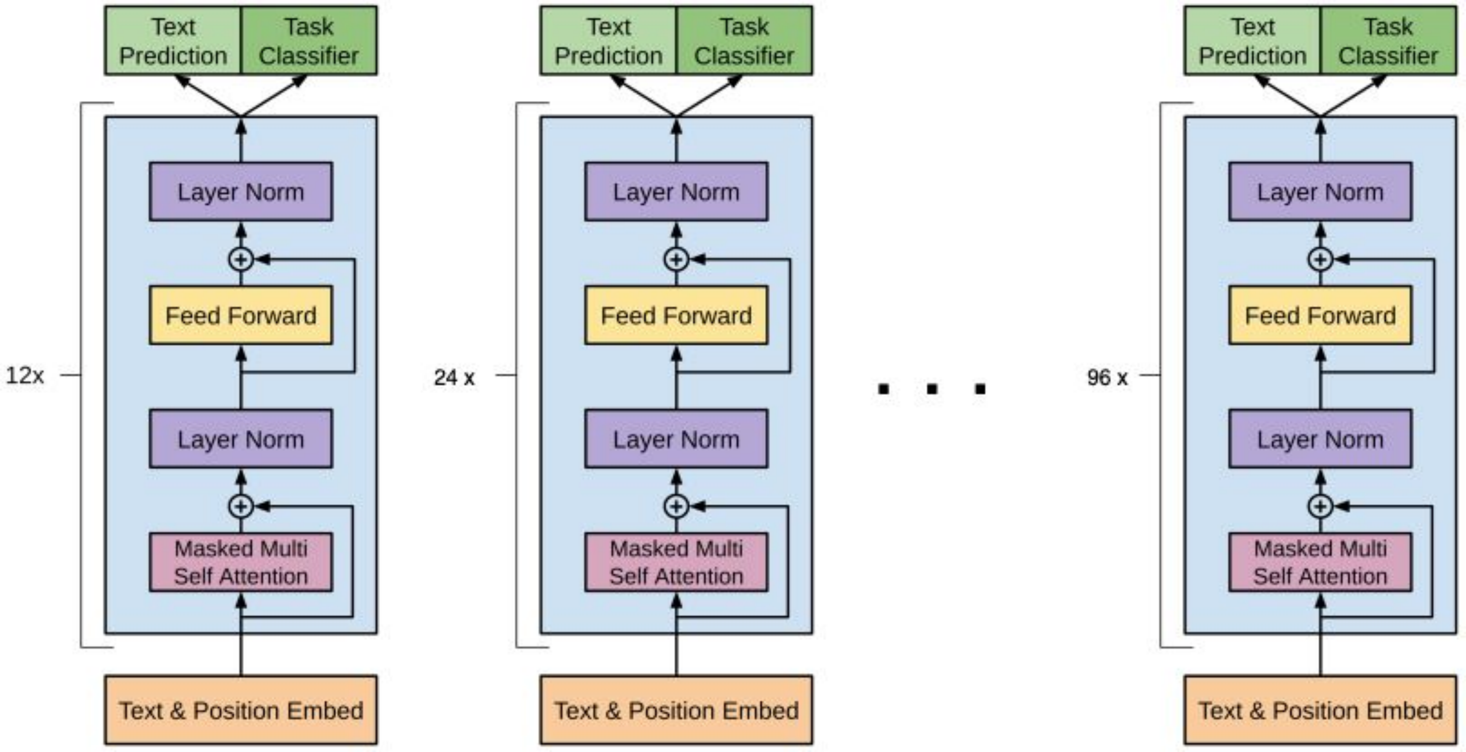
Drawbacks & Challenges

The Model

Text Generation

Impersonation, Content generation assistance

The Model



Text Prediction
Task Classifier
Layer Norm
Feed Forward
Layer Norm
Masked Multi Self Attention
Text & Position Embed
12x
Text Prediction
Task Classifier
Layer Norm
Feed Forward
Layer Norm
Masked Multi Self Attention
Text & Position Embed
24 x
. . .
Text Prediction
Task Classifier
Layer Norm
Feed Forward
Layer Norm
Masked Multi Self Attention
Text & Position Embed
96 x

How it Works

My name is Julien and I like to

Compute

Computation time on cpu: 0.835 s

My name is Julien and I like to play video games, though I can't really talk about that part of my personality here... And I was wondering how it's going to feel to have my family say goodbye, to be the player who had

```
A patient and a sworn enemy,
To one manly gentleman helps to make off
One fairer feather: so, happily, I thank thee.

HENRY BOLINGBROKE:
Welcome, Harry; welcome, Somerset: but that
Me too shall be revenged on you.

WARWICK:
O happy friend I had, as it were a curse,
To leave his country of so fair a life!

SOMERSET:
What foul beast is that in your chamber,
Whose big ears and proud eyes shall slander thee
For so blasphemous a charge?
```

Elon Musk

@elonmusk

I want → I want to build a city that is home to all the people! We know what the future of the world looks like 🙌🚀

My dream is → My dream is a super powerful Tesla Autopilot that doesn't have a problem with high-yield tires, but at 500 miles the roof starts to look like a giant tree corral.

Drawbacks
&
Challenges

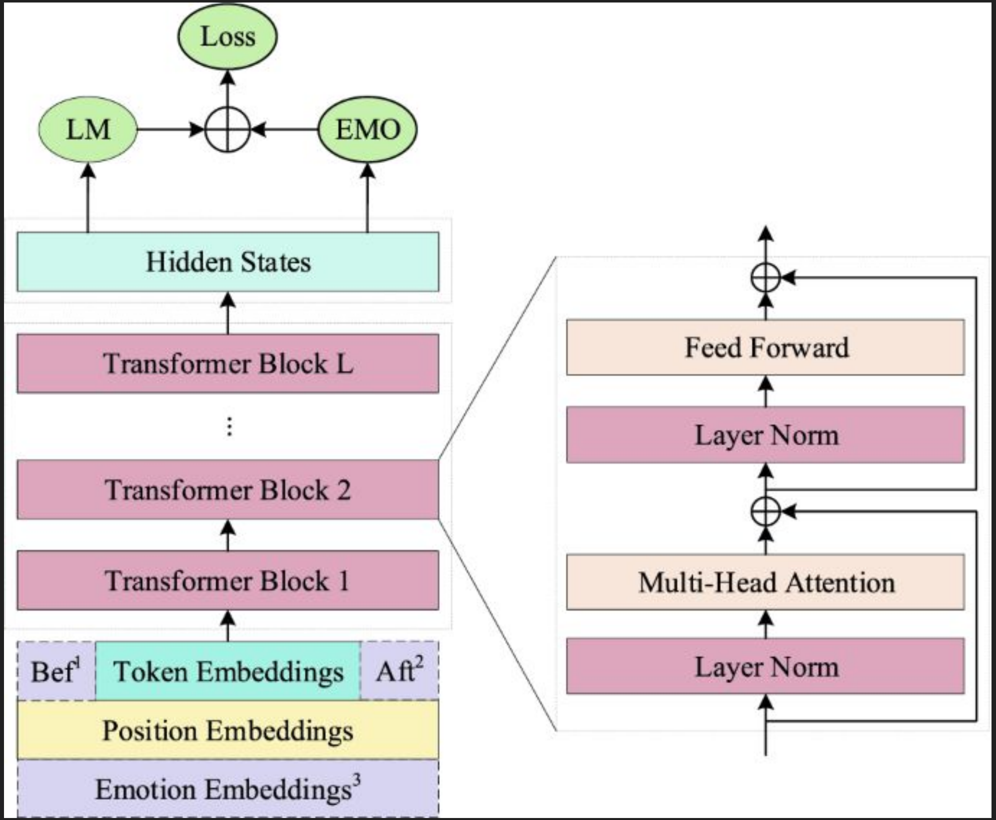
The Model

Conversational Bot

Improving User Experience by answering questions related to the data, platform/service-related questions, training.

DialoGPT

The Model



How it Works

Sample Conversation

- Multi-turn generation examples from an interactive environment:

Role	Response
User	Does money buy happiness?
Bot	Depends how much money you spend on it .
User	What is the best way to buy happiness ?
Bot	You just have to be a millionaire by your early 20s, then you can be happy .
User	This is so difficult !
Bot	You have no idea how hard it is to be a millionaire and happy . There is a reason the rich have a lot of money

Drawbacks & Challenges

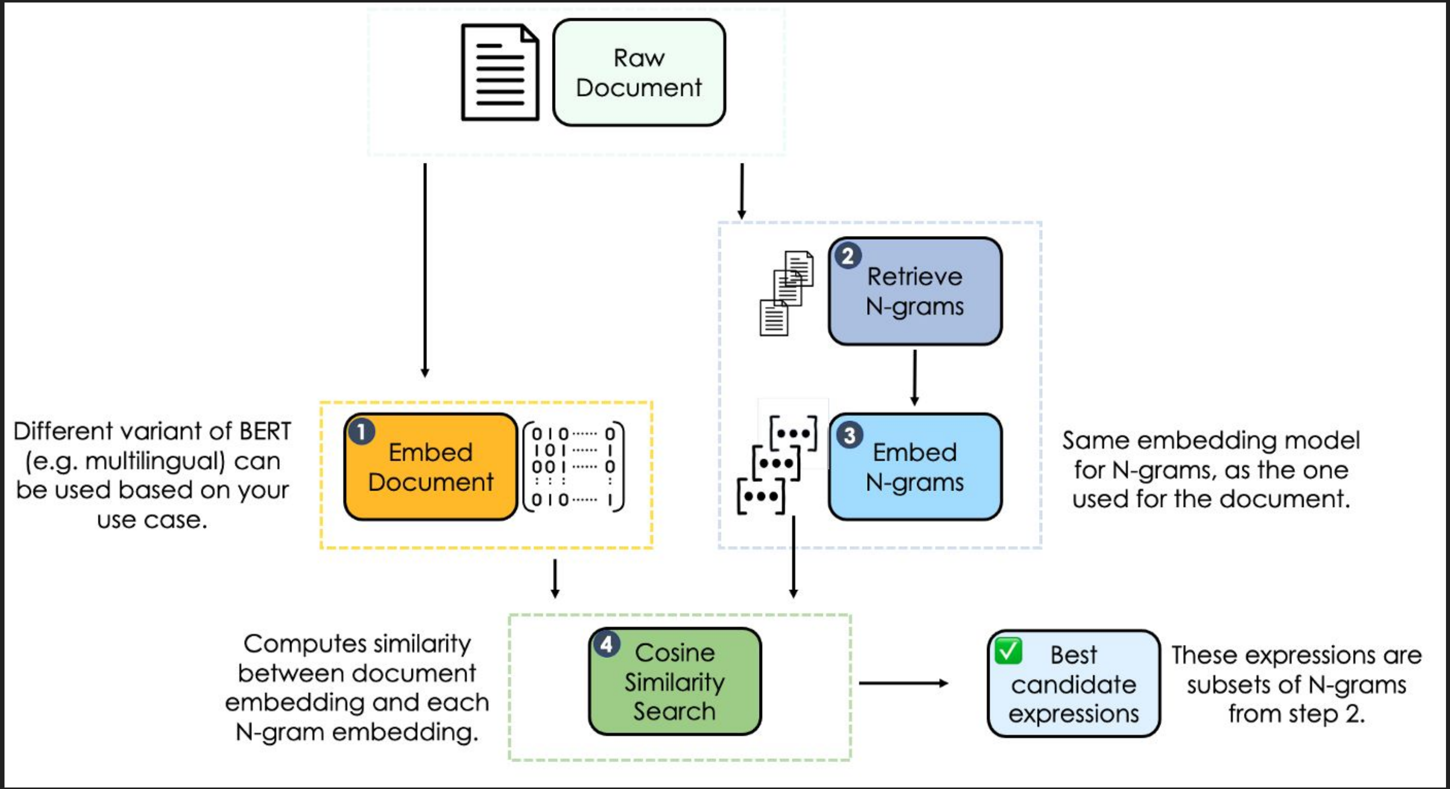
The Model

Keyword/KeyPhrases Extraction

Extracting words/keyphrases that is supposedly form the main topic of the text

KeyBert

The Model



How it Works

First, the document texts are annotated with spaCy part-of-speech tags. Second, keyphrases are extracted from the document texts whose part-of-speech tags match a predefined regex pattern. By default, the vectorizers extract keyphrases that have zero or more adjectives, followed by one or more nouns using the English spaCy part-of-speech tags. Finally, the vectorizers calculate document-keyphrase matrices. Apart from the matrices, the package can also provide us with the keyphrases extracted via part-of-speech.

By default, the vectorizer is initialized for the English language. That means, an English `spacy_pipeline` is specified, no `stop_words` are removed, and the `pos_pattern` extracts keywords that have zero or more adjectives, followed by one or more nouns using the English spaCy part-of-speech tags.

How it Works

The Model

Supervised learning is the machine learning task of learning a function that maps an input to an output based on example input-output pairs. It infers a function from labeled training data consisting of a set of training examples. In supervised learning, each example is a pair consisting of an input object (typically a vector) and a desired output value (also called the supervisory signal). A supervised learning algorithm analyzes the training data and produces an inferred function, which can be used for mapping new examples. An optimal scenario will allow for the algorithm to correctly determine the class labels for unseen instances. This requires the learning algorithm to generalize from the training data to unseen situations in a 'reasonable' way (see inductive bias).

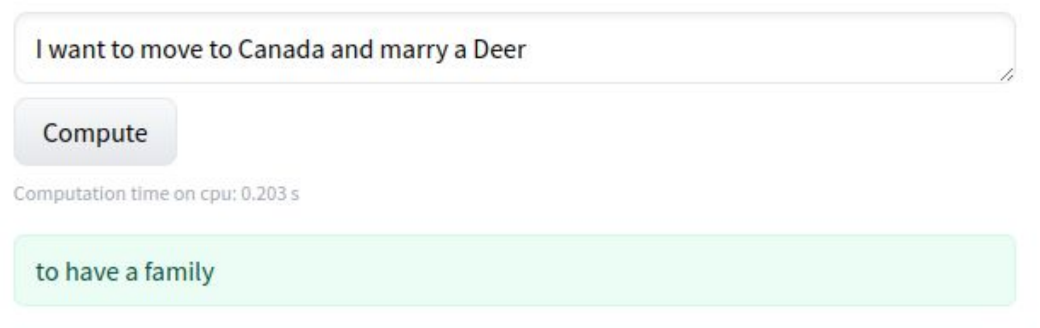
```
>>> kw_model.extract_keywords(doc, keyphrase_ngram_range=(3, 3), stop_words='english',
                              use_maxsum=True, nr_candidates=20, top_n=5)
[('set training examples', 0.7504),
 ('generalize training data', 0.7727),
 ('requires learning algorithm', 0.5050),
 ('supervised learning algorithm', 0.3779),
 ('learning machine learning', 0.2891)]
```

Intent Prediction

To understand the intent behind the text

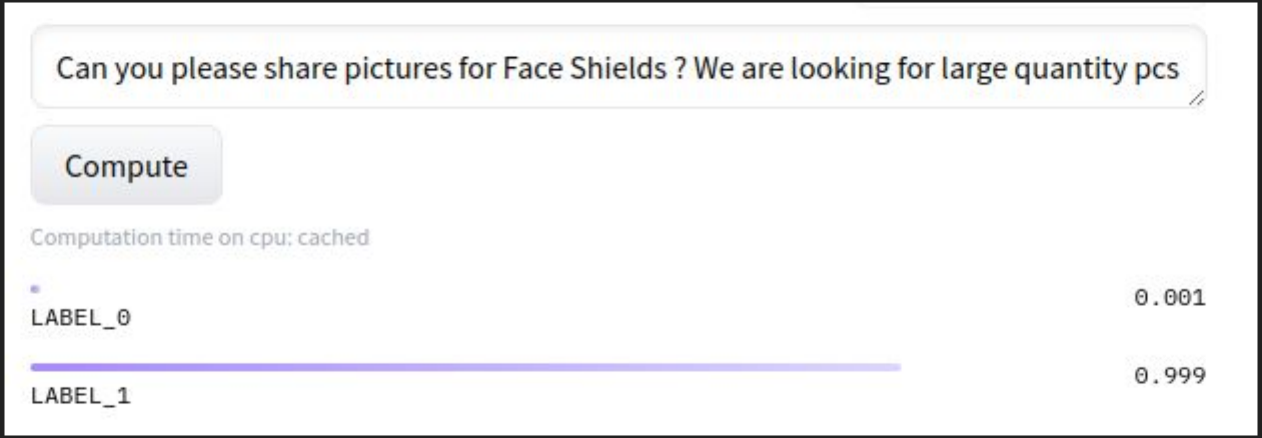
t5-base-finetuned-e2m-intent

The Model



How it Works

Buy/Sale Intent



Images

- Object Detection
- Image Classification
- Image Enhancement

Object Detection

Capturing Product Images, Reflections

The Model

The Model

How it Works

The Model

Drawbacks & Challenges

The Model

Image Classification

Possible product classification by its type, visual quality, color, kind, etc.

The Model

How it Works

The Model

Drawbacks & Challenges

The Model

Image Enhancement

Improving the quality of the image for further analysis

The Model

How it Works

The Model

Drawbacks & Challenges

The Model

Data Analysis

- Trend Analysis and Prediction
- Sales Analysis and Prediction
- Customer Segmentation
- Price Analysis
- Product Analysis

Trend Analysis and Prediction

Market dynamics, Expansion, Saturation, Product domination

The Model

How it Works

The Model

Drawbacks & Challenges

The Model

Sales Analysis and Prediction

Vendor/Market sales analysis, Demands/Seasonal demands, Bestsellers

The Model

How it Works

The Model

Drawbacks & Challenges

The Model

Customer Segmentation

By market, by area, by product, by quantity, by price, by quality

The Model

How it Works

The Model

Drawbacks
&
Challenges

The Model

Price Analysis

Catalog, Price dynamics, Sold-outs

The Model

How it Works

The Model

Drawbacks & Challenges

The Model

Product Analysis

- Type, Origin, Quality, Delivery methods, Refunds, Alerts, N/As

The Model

How it Works

The Model

Drawbacks
&
Challenges

The Model