Quantitative Text Analysis

University College Dublin

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Week 12 (22 April 2024)

Outline

1. From Bag-of-Words to the Transformer
2. Transformers
3. API
4. Lab Session

From Bag-of-Words to the Transformer

Bag-of-Words

Advantages

- Easy to implement
- Human-interpretable results
- Domain adaptation

Disadvantages

- Dimensionality curse.
- No solution for unseen words.
- Hardly capture semantic relations such as is-a, has-a, synonyms.
- Word order information is ignored.
- Slow for large vocabularies.

Word Embeddings

- Out of Vocabulary (OOV): word embeddings have a significant limitation in handling words that are not present in their training data.
- Static embeddings don't update with new information or vocabulary unless re-trained, making them less adaptable to evolving language use or new data.
- word embeddings struggle to effectively handle multiple-word expressions and compound words.
- word embeddings cannot adequately represent words with multiple meanings (polysemy) since each word is assigned a single, context-independent vector.

Transformers

Transformers

Bidirectional Context: from both left and right sides of a token within a sentence, unlike directional models which only read text left-to-right or right-to-left.

Transformer Architecture: Uses attention mechanisms to weigh the importance of each word in the sentence, no matter its position, which enhances understanding compared to BoW, which treats each word independently.

Subword Tokenization: BERT uses WordPiece tokenization, handling unknown words better than BoW by breaking them down into known subwords.

Fine-Tuning: Once pre-trained, BERT can be fine-tuned with additional output layers to perform well on a variety of specific tasks much better than non-contextual methods like BoW.

Position Embeddings: Includes position information which allows the model to understand ordering and structure in the text, offering significant advantages over BoW, which loses all order information.

Layer and **Attention Head** are two key components understanding and processing language.

- **Multi-Head Self-Attention:** allows the model to learn different features of each word in the input sequence from different subspaces. Self-Attention capture complex relationships between words.
- **Feed-Forward Neural Networks:** The output from each position is processed by the same feed-forward neural network, which is shared across all positions.

Attention Head

- **Diversity:** Each attention head has different parameters, so they can capture features in different representational subspaces. This diversity allows the model to understand the data more comprehensively.
- **Focus:** some heads may focus on capturing syntactic
- **Integrated Information Processing:** By combining the outputs of multiple attention heads, the model can synthesize information from different aspects, forming a richer text representation.

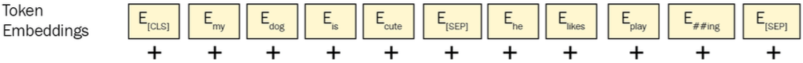
Tokens in Transformers:

- **[CLS]**: Used for sequence-level tasks like classification. The final hidden state of the [CLS] token is used to represent the entire sequence's sentiment, *e.g., "[CLS] I loved the new Batman movie! [SEP]"*.
- **[SEP]**: Separates sentences or sequences, useful for tasks involving two sentences, *e.g., "[CLS] What year was Batman released? [SEP] Batman was released in 2022. [SEP]"*.
- **[MASK]**: During pre-training, [MASK] is used for the Masked Language Model task, masking words randomly for the model to predict, *e.g., "The quick brown [MASK] jumps over the lazy dog" might mask "fox"*.

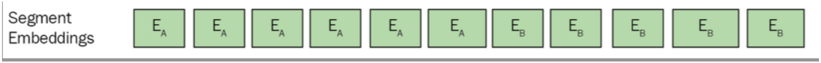
Input Text

```
text = "[CKS] my dog is cute [SEP] he likes ##ing [SEP]"
```

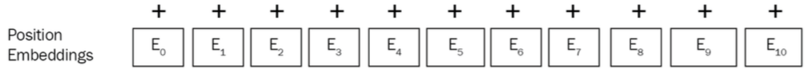
Token Embeddings These are vectors that represent each token in the input. Each token (like “[CLS]”, “my”, “dog”, “is”, “cute”, “[SEP]”, etc.) is converted into a vector called a token embedding. These embeddings capture the semantic meaning of each token.



Segment Embeddings: are used to distinguish between two different sentences or segments within the same input. In this case, the tokens belonging to the first sentence are marked with one segment embedding (E_A), and the tokens of the second sentence are marked with another (E_B).



Position Embeddings: Since BERT doesn't inherently capture the order of tokens, position embeddings are added to give the model information about the position of each token in the sequence. Each position in the sequence has a corresponding position embedding (E_0, E_1, E_2, etc.).



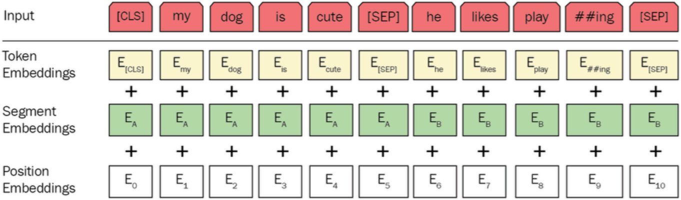


Figure 3.1 – The BERT model

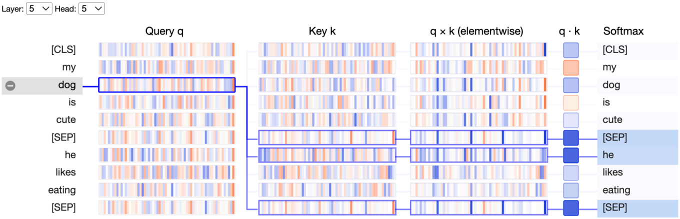
Source: Denis Rothman (2021, P. 78)

Attention Weights:

- Self-attention weights in Transformer models quantify the relevance of all tokens when assessing a particular one, aiding in the contextual understanding of words.
- This attention pattern can vary across different layers and heads, as each one might learn to focus on different aspects of the input.

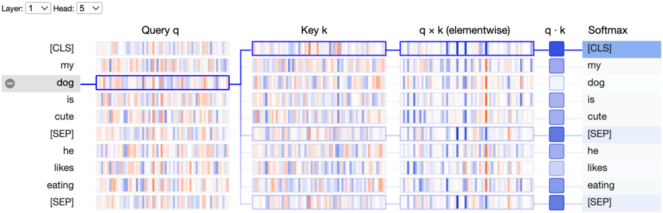
Dog in Layer 5

If there is a thick line from the word “dog” to “he”, it suggests that within the given head, the model pays more attention to “he” when processing the word “dog”.



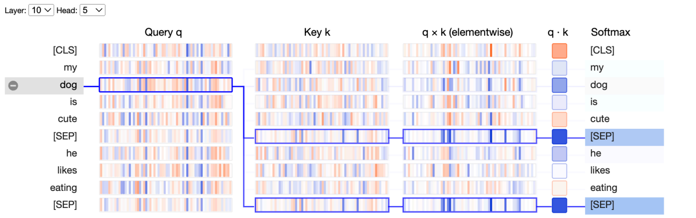
Code: *2024_qta_lab_week_12_transformers_supplements.ipynb*

Dog in Layer 1



Code: *2024_qta_lab_week_12_transformers_supplements.ipynb*

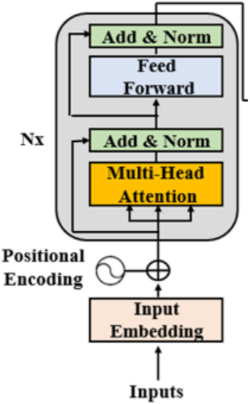
Dog in Layer 10



Code: *2024_qta_lab_week_12_transformers_supplements.ipynb*

Attention Is All You Need

Primary advantage is the ability to efficiently process sequential data while capturing long-distance dependencies between elements in the sequence (Vaswani, Ashish, et al. 2017).



In Transformer API

```
print(" input_ids: \n",encoded_input['input_ids'])
```

```
##  input_ids:
##  tensor([[  101,  1031, 23616,  2015,  1033,  2026,  3899,  2003, 10140,   102,
##           2002,  7777,  1001,  1001, 13749,   102,   102]])
```

```
print(" token_type_ids: \n",encoded_input['token_type_ids'])
```

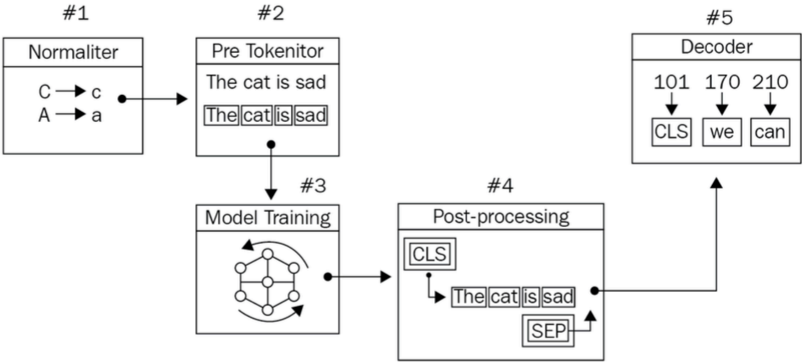
```
##  token_type_ids:
##  tensor([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]])
```

```
print(" attention_mask: \n",encoded_input['attention_mask'])
```

```
##  attention_mask:
##  tensor([[1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]])
```

Code: *2024_qta_lab_week_12_transformers_supplements.ipynb*

Tokenization in Transformers



Source: Denis Rothman (2021, P.106)

Training Model vs. Fine-tuning

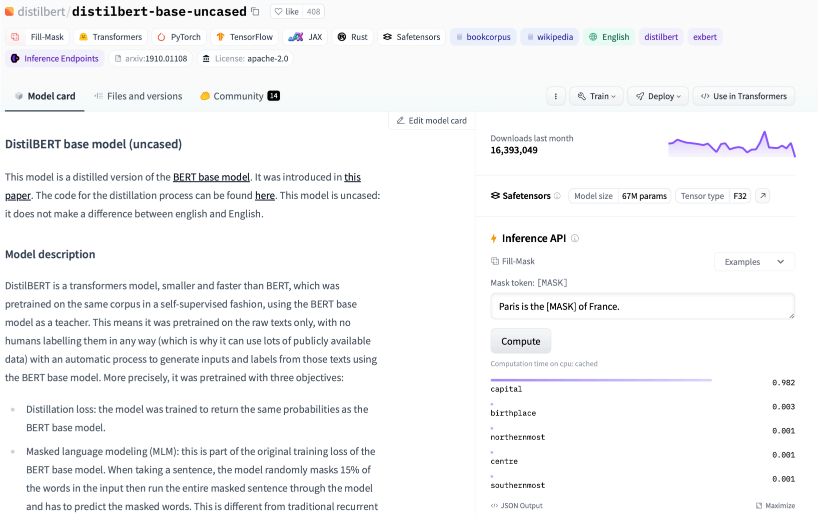
Aspect	Fine-tuning	Training from Scratch
Starting Point	Starts with a pre-trained model	Begins with randomly initialized model weights
Data Requirement	Requires less data due to prior learned features	Needs a large dataset to learn from
Time and Resources	Less time and resources needed	More time-consuming and resource-intensive
Use Cases	Suitable for adapting existing models to new tasks	Ideal for novel tasks with no existing models

API

HugginFace vs FLAIR NLP

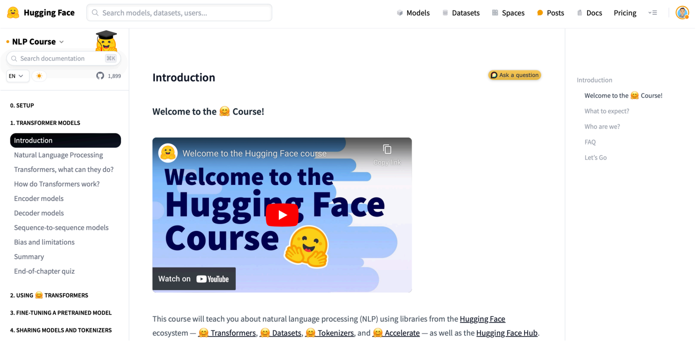
Feature	Hugging Face	FLAIR
Model Variety	Wide range of pre-trained transformer models	High-quality models for specific tasks like NER & PoS
Ease of Use	User-friendly, great for beginners and experts	User-friendly with a focus on PyTorch users
Integration	Integrates with PyTorch, TensorFlow, and JAX	Built on top of PyTorch
Community Support	Large, with extensive resources and a collaborative hub	Growing, research-oriented community
Use Cases	Broad range of NLP tasks	Specialized tasks where character-level modeling excels

Hugging Face Playground



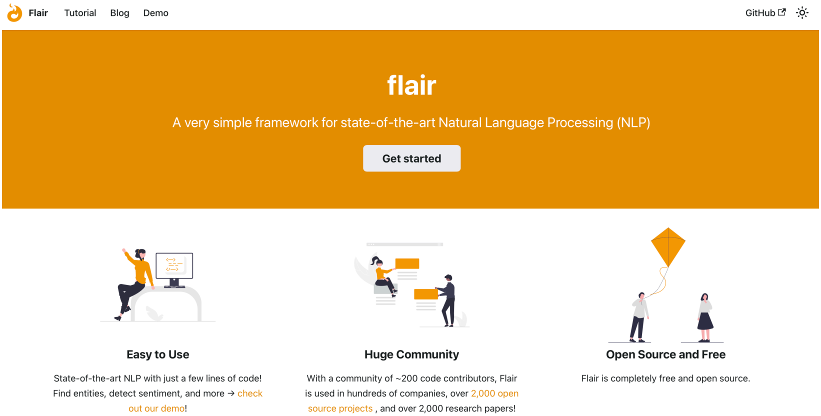
URL: https://huggingface.co/distilbert/distilbert-base-uncased

Huggin Face Tutorial



Source: https://huggingface.co/learn/nlp-course/chapter1/1

FLAIR NLP (More Focus on NLP Tasks)



Lab Session

Lab Session: Files

FLAIR NLP

- *2024_qta_lab_week_12_flair.ipynb*
- *2024_qta_lab_week_12.qmd* (flaiR)

Transformers API (Python)

- *2024_qta_lab_week_12_transformers.ipynb*
- *2024_qta_lab_week_12_transformers_supplements.ipynb*

Others

- *2024_qta_lab_week_11.ipynb (previous lab exercise in Python)*

Lab Session: Tasks

- We will experiment with and fine-tune a transformer model on annotated environmental policy data.
- We will use the DistilBERT model.

Clearing FLAIR and Its Cache

```r
clear_flair_cache()
```

```r
remove.packages("flaiR")
```