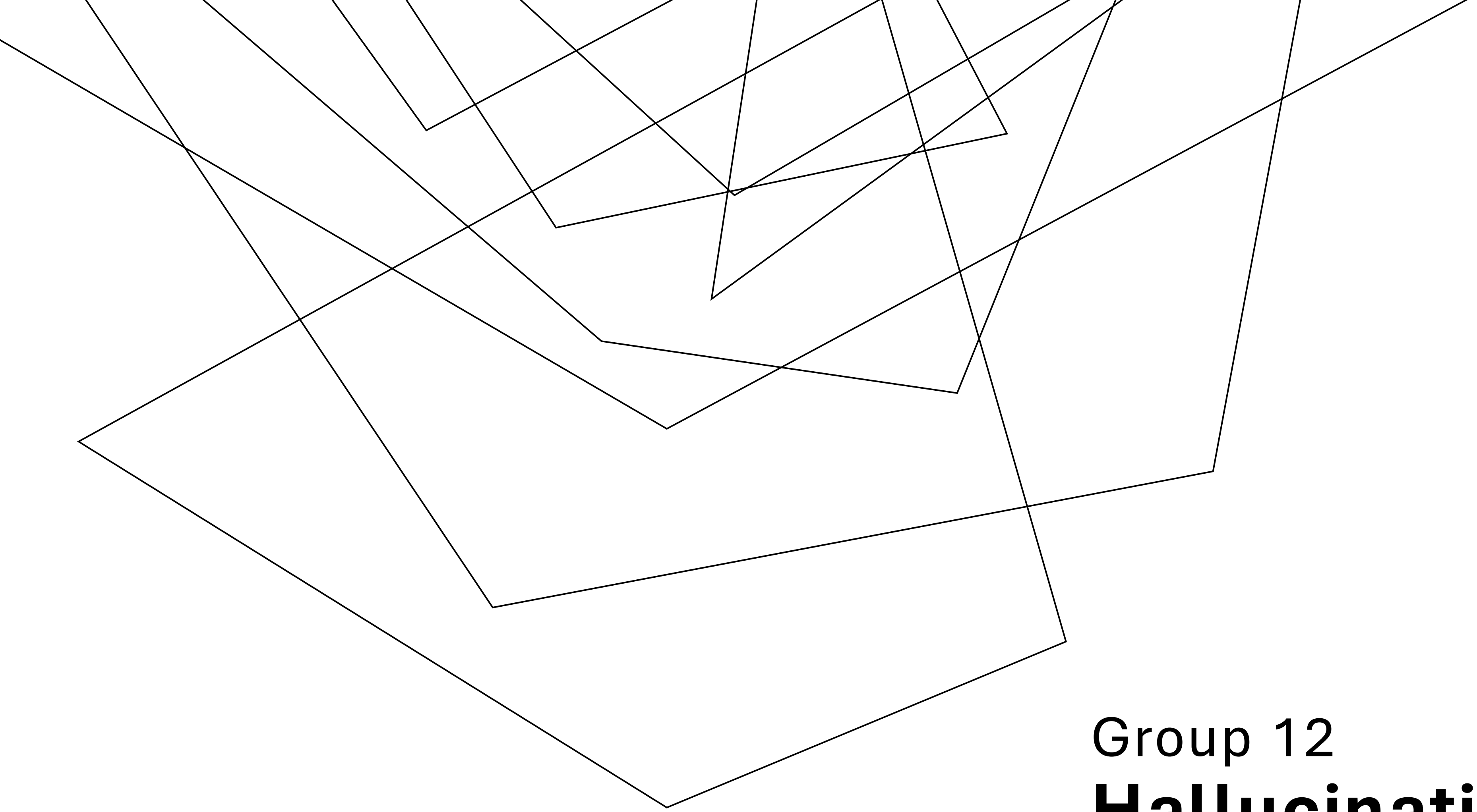


Group 12

# Hallucination Span detection

# Problem Overview

Find out what part of this LLM response is a hallucination.

When was "Animals" released?

"Animals" was released by Prince in 1977.

This span is hallucinated (false)

# Models in use

- Fact-checking models
    - Retrieval-based methods to verify against external data
    - FEVER dataset, Google Fact Check
- Consistency Models
    - Looks for internal inconsistencies
    - T5 - Google News summary
- Pre-trained Neural Nets
    - WordTune Spice – fact providing writing assistant
    - Transformer-based LLM

# Our architectures

- **Unsupervised GPT Prompting**
  Straight up asks GPT-4 for spans
- **SVMs**
- **Supervised mBERT Sequence Classifier**
  Trains NN on tokenized query-response pairs

# Data at hand

- 499 rows
- 18 languages: Arabic, Finnish, French, Gernman, Hindi, Italian, Swedish, and Chinese

| query | response | label |
|---|---|---|
| When was "Animals" released? | "Animals" was released by Prince in 1977. | [2,3] |
| | | |
| | | |

# Automatic Hallucination Detection in Model Outputs

## Leveraging GPT-4

# Implementation Overview

Automate hallucination detection for multilingual data.

- **Key Tools Used**:
    - GPT-4o Mini for detection.
    - JSON format for structured outputs.

# Zero-Shot GPT-4o

**Prompts:**

- You are an assistant tasked with finding errors in responses.
- The question was "{input}", and the response was "{output}". Identify the parts of the answer that are incorrect or unsupported by the question. Answer with only the incorrect spans in the answer as a list of token ranges (start and end indices), like in this example: "[(0,3),(8,20)]".

- Very weak results
- Tokens often outside string range
- Spaces between words or punctuation returned

# Summary and Future Work

## Key Findings

- **Challenges with GPT-4o Mini**:
  - Results were **unsatisfactory** for hallucination detection.
  - High variability and inconsistent outputs across languages.
- **Outcome**: Current approach is not reliable for automatic annotation in multilingual data.

# Why recall over precision?

Consider a lie detector …

Brushing off a lie is worse than being a little too suspicious of the truth.

## Feature Learning

# SVM

# Data preparation for SVM sequence classification

- tokenize & lemmatize

| | | |
|---|---|---|
| When was "Animals" released? | "Animals" was released by Prince in 1977. | [2,3] |
| where banana? | on table | [0, 0] |

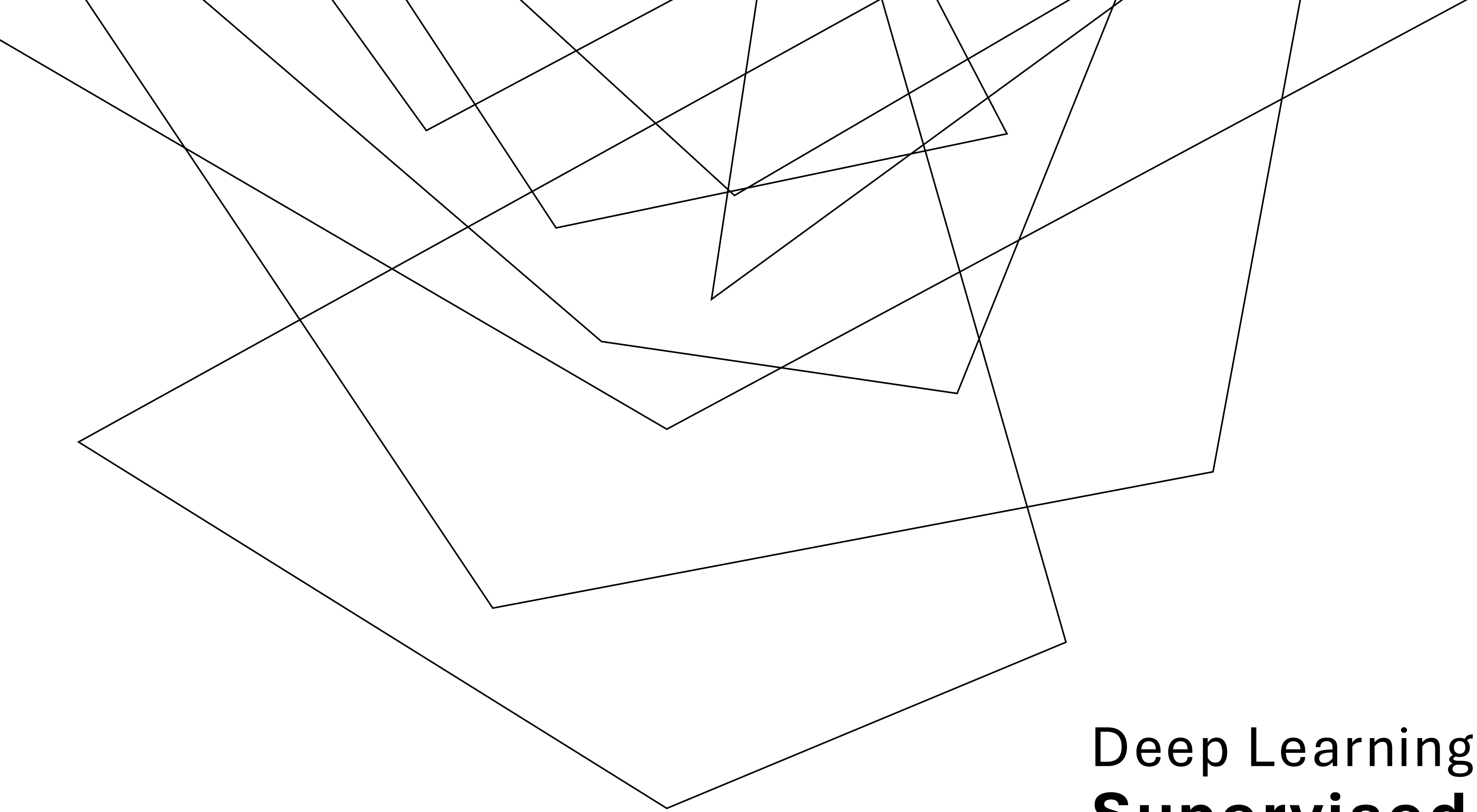
- Hallucination spans to binary token-labels

| | | |
|---|---|---|
| [when] [is] [animal] [release] [?] | [animal] [is] [release] [by] [Prince] [in] [1977] [.] | [0, 0, 1, 1, 0, 0, 0] |
| where banana? | table | [1] |

- Concatenate input data (incl. Support tokens)
- Create "ignore labels"

CrossEntropy ignores labels of -100

| | |
|---|---|
| [CLS] when is animal release ? [SEP] animal is release by prince in 1977 . | [-100, ..., -100, 0, 0, 1, 1, 0, 0, 0] |
| [CLS] where banana ? [SEP] table | [-100, ... , -100, 1] |



### Deep Learning

# Supervised mBERT Sequence Classifier

# Input features for mBERT

- Full response sequence (as opposed to single tokens)
- Query for context (is this a must?)
- Part-of-Speech tag
  - Used by us:
    - UPOS – Universal POS categories
    - XPOS – Language-specific details

More ideas:

- Named entity recognition
  - Very similar task – finding factual data that's potentially wrong
- Contextual features – abrupt topic changes

# Data preparation for sequence classification

| | | |
|---|---|---|
| When was "Animals" released? | "Animals" was released by Prince in 1977. | [2,3] |
| where banana? | on table | [0, 0] |

- tokenize & lemmatize
- Hallucination spans to binary token-labels

| | | |
|---|---|---|
| [when] [is] [animal] [release] [?] | [animal] [is] [release] [by] [Prince] [in] [1977] [.] | [0, 0, 1, 1, 0, 0, 0] |
| where banana? | table | [1] |

- Concatenate input data (incl. Support tokens)
- Create "ignore labels"

CrossEntropy ignores labels of -100

| | |
|---|---|
| [CLS] when is animal release ? [SEP] animal is release by prince in 1977 . | [-100, ..., -100, 0, 0, 1, 1, 0, 0, 0] |
| [CLS] where banana ? [SEP] table | [-100, ... , -100, 1] |

- Pad the data to fixed length

| | |
|---|---|
| [CLS] when is animal release ? [SEP] animal is release by prince in 1977 . [PAD] ... [PAD] | [-100, ..., -100, 0, 0, 1, 1, 0, 0, 0, -100, ..., -100] |
| [CLS] where banana ? [SEP] table [PAD] [PAD] [PAD] [PAD] [PAD] [PAD] [PAD] ... [PAD] | [-100, ... , -100, 1, -100, - 100, -100, ..., -100] |

# Training a model with the prepared data

[CLS] when is animal release ? [SEP] animal is release by prince in 1977 . [PAD] ... [PAD]

[-100, ..., -100, 0, 0, 1, 1, 0, 0, 0, -100, ..., -100]

[CLS] where banana ? [SEP] table [PAD] [PAD] [PAD] [PAD] [PAD] [PAD] [PAD] ... [PAD]

[-100, ... , -100, 1, -100, - 100, -100, ..., -100]

- Vectorize the data with ***bert-base-multilingual-cased***

[o o o o o o o o o o o o o o o o ......... o]

[-100, ..., -100, 0, 0, 1, 1, 0, 0, 0, -100, ..., -100]

[o o o o o o o o o o o o o o o o ......... o]

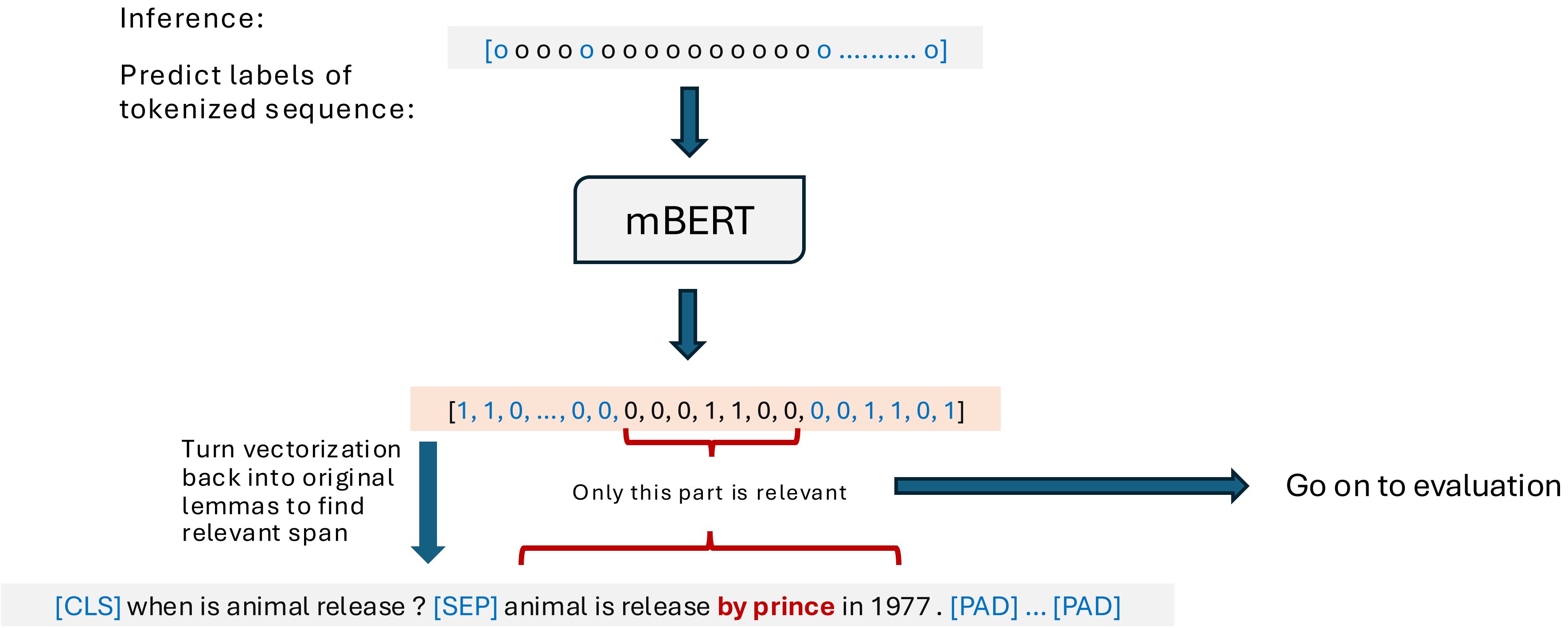
[-100, ... , -100, 1, -100, - 100, -100, ..., -100]

train

mBERT

***BertForTokenClassification***

# Model application



Inference:

Predict labels of tokenized sequence:

[o o o o o o o o o o o o o o o o ………. o]

mBERT

[1, 1, 0, …, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1]

Turn vectorization back into original lemmas to find relevant span

Only this part is relevant

Go on to evaluation

[CLS] when is animal release ? [SEP] animal is release **by prince** in 1977 . [PAD] … [PAD]

# Participating in the MUSHROOM Challenge?

Challenge

| Original Text | Character labels | Tokens | Token labels |
|---|---|---|---|
| "Animals" was released by Prince in 1977. | [[22,31]] | ", animal, ", ist, release, by, Prince, in, 1977, . | [[5, 7]] |
| Green Floyd consisted of 5 members. | [[0, 5], [25,26]] | green, floyd, consist, of, 5, member, . | [[0, 1], [4, 5]] |

preprocessing

Number of characters changed.
Pattern matching with original strings?

No way back?!

# Axes of experimentation

What we've tried

- In/exclude query
- In/exclude POS tokens
- Skip or truncate overflowing sequences
- Max length of encodings
- Training params:
    - Learning rate
    - Batch size
    - Patience
    - Max epochs
    - Different optimizer

More ideas to try out

- Different loss calculation (weighted?)
- Different tokenizers
- Data augmentation through translation
- Data balancing (?)
- More sources of knowledge

  e.g. taking votes of multiple classifiers
- Different pretrained models
    - Multilingual
    - Separate models per language

# Excluding the query?

| | | |
|---|---|---|
| When was "Animals" released? | "Animals" was released by Prince in 1977. | [2,3] |
| where banana? | on table | [0, 0] |

| | |
|---|---|
| [animal] [is] [release] [by] [Prince] [in] [1977] [.] | [0, 0, 1, 1, 0, 0, 0] |
| table | [1] |

| | |
|---|---|
| [CLS] [SEP] animal is release by prince in 1977 . | [-100, -100, 0, 0, 1, 1, 0, 0, 0] |
| [CLS] [SEP] table | [-100, -100, 1] |

| | |
|---|---|
| [CLS] [SEP] animal is release by prince in 1977 . [PAD] ... [PAD] | [-100, -100, 0, 0, 1, 1, 0, 0, 0, -100, ..., -100] |
| [CLS] [SEP] table [PAD] [PAD] [PAD] [PAD] [PAD] [PAD] [PAD] ... [PAD] | [-100, -100, 1, -100, - 100, -100, ..., -100] |

# Including POS tokens

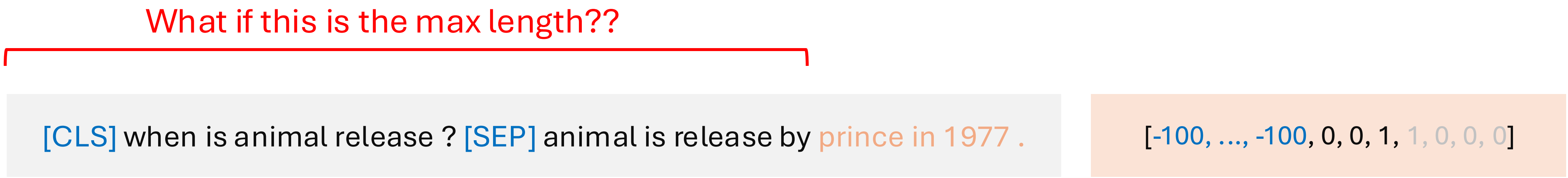
UPOS: universal (NOUN, VERB, ADJ, ADV, PRON, ADP, CONJ )

XPOS: language-specific (e.g. in english NN is a noun and NNs is a plural noun)

| | |
|---|---|
| [CLS] where banana ? [SEP] on table | [-100, …, -100, 1] |
| [CLS] where ADV WRB banana NOUN NN ? PUNCT . [SEP] on ADP IN table NOUN NN | [-100, …, -100, 1, -100, -100, 1, -100, -100] |

Optimizer ignores POS tokens

# Supervised mBERT: what to do with overflows?



What if this is the max length??

[CLS] when is animal release ? [SEP] animal is release by prince in 1977 .

[-100, ..., -100, 0, 0, 1, 1, 0, 0, 0]

**Options for handling overflow:**

- Ignore and train anyway
  - → Encoder will truncate the data!
- Skip observation entirely

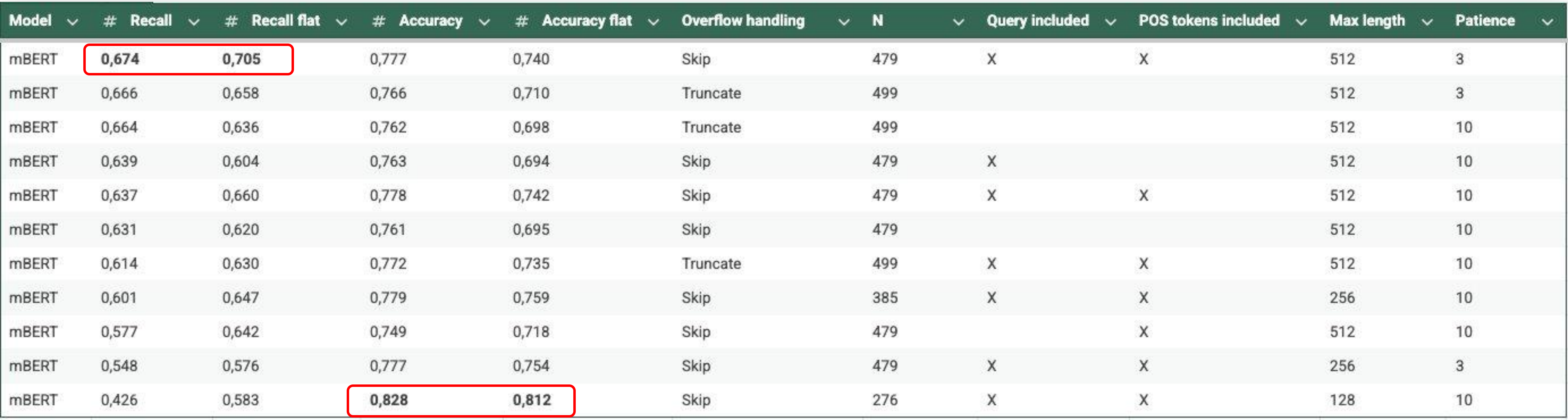
# mBERT Results

Average of all rows' sequences

All sequences concatenated

Number of observations after skipping

Number of tokens in sequence

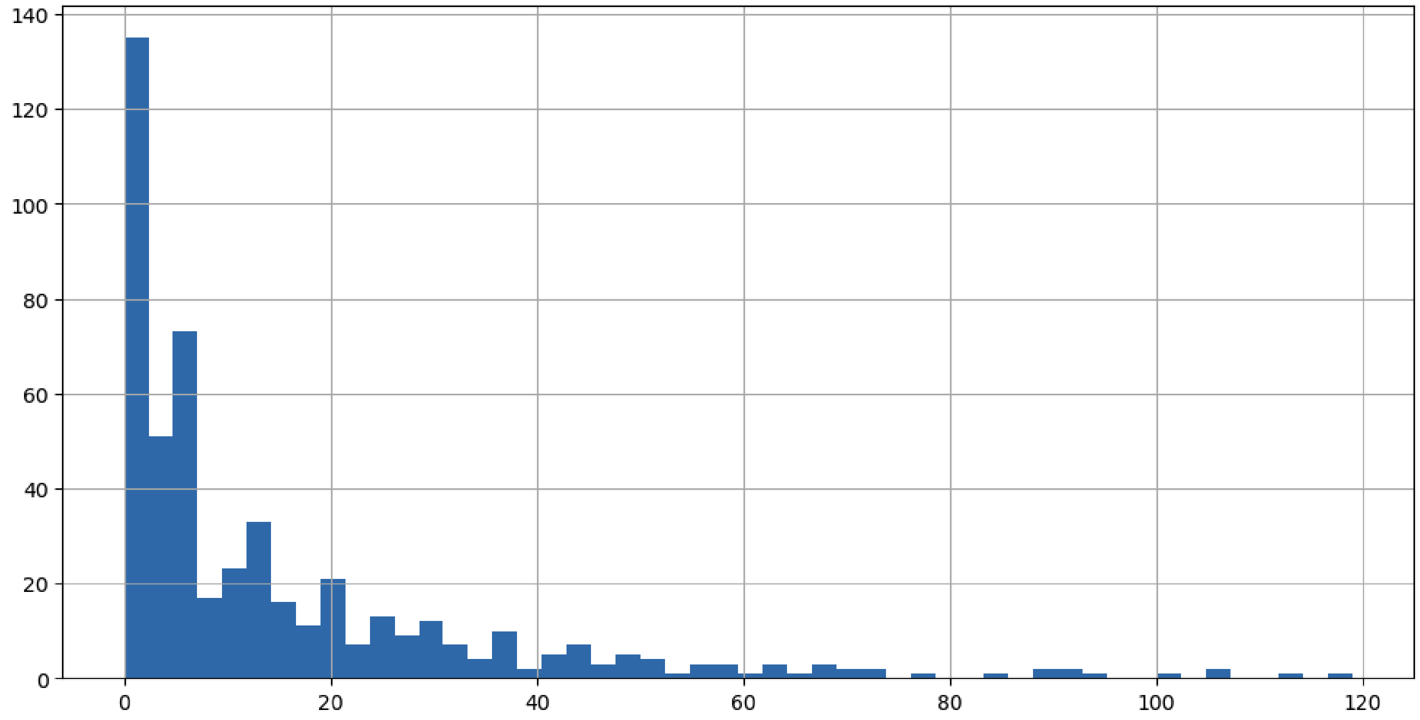


| Model | # Recall | # Recall flat | # Accuracy | # Accuracy flat | Overflow handling | N | Query included | POS tokens included | Max length | Patience |
|---|---|---|---|---|---|---|---|---|---|---|
| mBERT | **0,674** | **0,705** | 0,777 | 0,740 | Skip | 479 | X | X | 512 | 3 |
| mBERT | 0,666 | 0,658 | 0,766 | 0,710 | Truncate | 499 | | | 512 | 3 |
| mBERT | 0,664 | 0,636 | 0,762 | 0,698 | Truncate | 499 | | | 512 | 10 |
| mBERT | 0,639 | 0,604 | 0,763 | 0,694 | Skip | 479 | X | | 512 | 10 |
| mBERT | 0,637 | 0,660 | 0,778 | 0,742 | Skip | 479 | X | X | 512 | 10 |
| mBERT | 0,631 | 0,620 | 0,761 | 0,695 | Skip | 479 | | | 512 | 10 |
| mBERT | 0,614 | 0,630 | 0,772 | 0,735 | Truncate | 499 | X | X | 512 | 10 |
| mBERT | 0,601 | 0,647 | 0,779 | 0,759 | Skip | 385 | X | X | 256 | 10 |
| mBERT | 0,577 | 0,642 | 0,749 | 0,718 | Skip | 479 | | X | 512 | 10 |
| mBERT | 0,548 | 0,576 | 0,777 | 0,754 | Skip | 479 | X | X | 256 | 3 |
| mBERT | 0,426 | 0,583 | **0,828** | **0,812** | Skip | 276 | X | X | 128 | 10 |

# False Negatives

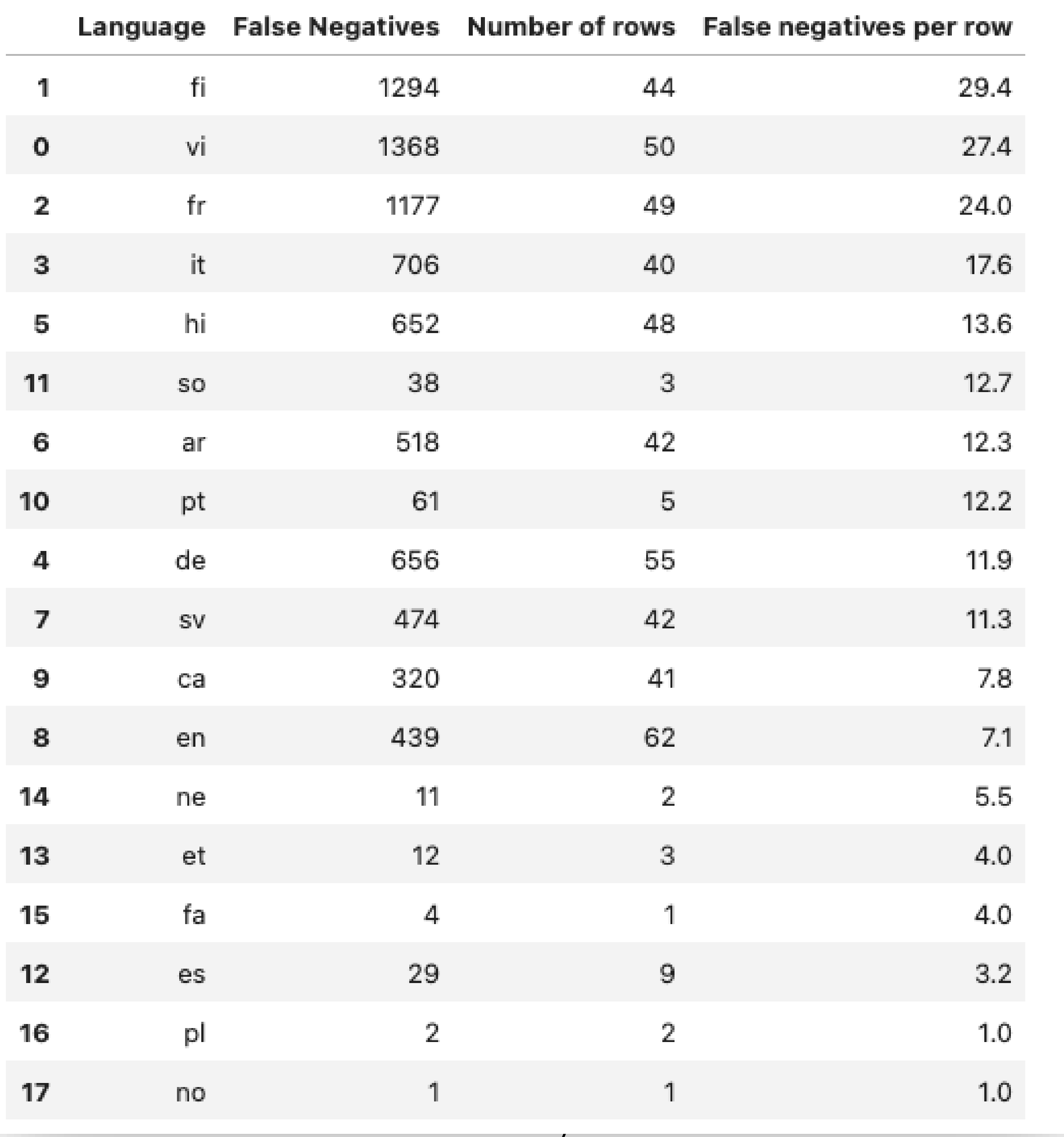
- Out of 499 rows
  479 have min 1 False Negative

- 40 of them include year numbers



# False Negatives per language

*fi = Finnish*
*vi = Vietnamese*
*hi = Hindi*
*so = Somali*
*ar = Arabic*



| | Language | False Negatives | Number of rows | False negatives per row |
|---|---|---|---|---|
| **1** | fi | 1294 | 44 | 29.4 |
| **0** | vi | 1368 | 50 | 27.4 |
| **2** | fr | 1177 | 49 | 24.0 |
| **3** | it | 706 | 40 | 17.6 |
| **5** | hi | 652 | 48 | 13.6 |
| **11** | so | 38 | 3 | 12.7 |
| **6** | ar | 518 | 42 | 12.3 |
| **10** | pt | 61 | 5 | 12.2 |
| **4** | de | 656 | 55 | 11.9 |
| **7** | sv | 474 | 42 | 11.3 |
| **9** | ca | 320 | 41 | 7.8 |
| **8** | en | 439 | 62 | 7.1 |
| **14** | ne | 11 | 2 | 5.5 |
| **13** | et | 12 | 3 | 4.0 |
| **15** | fa | 4 | 1 | 4.0 |
| **12** | es | 29 | 9 | 3.2 |
| **16** | pl | 2 | 2 | 1.0 |
| **17** | no | 1 | 1 | 1.0 |

# More findings

**Ok ... sorry**

**Number are not preprocessed properly**

```
     False negatives:   " 1 . 005
Actual hallucinations:   " 1 . 005
Recall: 0.0
        From response: der italienisch Gemeinde " Ponzano " liegen auf ein Höhenlage von etwa 1 . 005 Meter . Quelle : < | im _ end | "
        Query: auf welcher Höhe liegen der italienisch Gemeinde Ponzone ? .
```

**Speaking of punctuation ...**

Out of **7762** false negative tokens

**2158** are punctuation!

Finnish and Hindi texts on average had twice as many false negative punctuations.

**What is this?**

An image?

Not always prepended by "Quelle:"

appears in ~20 rows

only after German or French texts