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.

$$\text{"Animals" was released } \underbrace{\text{by Prince}}_{\text{This span is hallucinated (false)}} \text{ in 1977.}$$

Data at hand

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

query	response	label
When was "Animals" released?	"Animals" was released by Prince in 1977.	[[22, 29]]

Why recall over precision?

Consider a lie detector ...

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

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
- **SVM**
  Feature-based statistical model
- **Supervised mBERT Sequence Classifier**
  Trains NN on tokenized query-response pairs

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.

Input features

- 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

Labelling single tokens

... as opposed to labelling the full sequence

query	response	label
When was "Animals" released?	"Animals" was released in 1965 by Pink Floyd, founded in 1965.	[4]

query	response	label
When was "Animals" released?	released	0
When was "Animals" released?	in	0
When was "Animals" released?	1965	1
When was "Animals" released?	1965	0

Feature Learning

Support Vector Machine

Data preparation for SVM sequence classification

- tokenize & lemmatize

When was "Animals" released?	"Animals" was released by Prince in 1977.	[3,4]
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, 0, 1, 1, 0, 0]
where banana?	table	[1]

SVM Model training

Tokenization

- Used the same mBERT tokenizer as the main deep learning model

Training

- Use sklearn SVC
- Balanced class weights

Axes of experimentation in training

What we've tried

- In/exclude query
- In/exclude POS tokens
- Training params:
  - Kernel
  - C
  - class_weight

More ideas to try out

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

  e.g. taking votes of multiple classifiers

Evaluation of SVM model

Results

- Best parameters
  - Kernel: rbf
  - C=0.5
  - Balanced class weights
- Low recall (0.36) and precision (0.46)

Conclusions

- SVM may not be good at finding contextual relationships between tokens
- Maybe a different tokenizer would return better results
- Query and POS tokens should be included
- Low recall, meaning model is not good at finding hallucinations

Maybe a deep learning solution will generalize better

Deep Learning

Supervised mBERT Sequence Classifier

Data preparation for sequence classification

- tokenize & lemmatize
- Hallucination spans to binary token-labels
- Concatenate input data (incl. Support tokens)
- Create "ignore labels"

CrossEntropy ignores labels of -100

- Pad the data to fixed length

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

↓

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

↓

[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]

↓

[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]

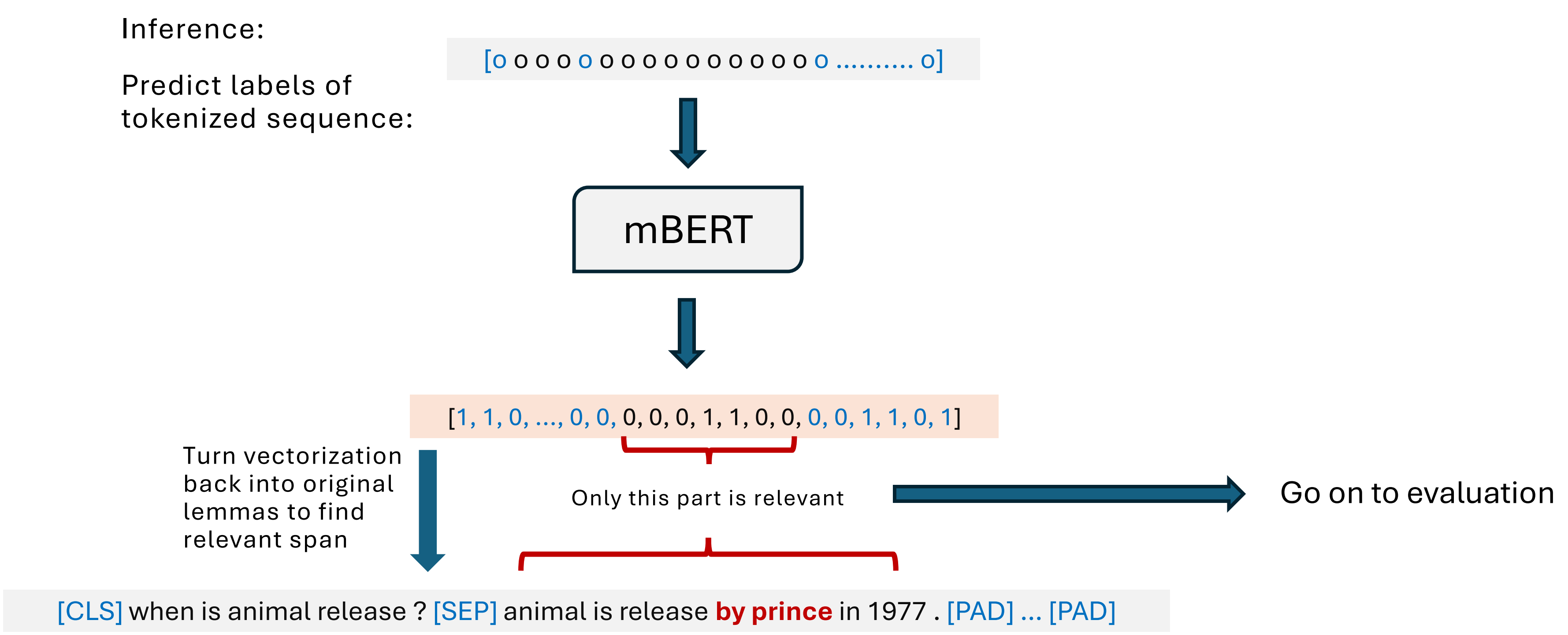
[-100, ... , -100, 1, -100, - 100, -100, ..., -100]

train

mBERT

BertForTokenClassification

Model application



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

No way back?!

Number of characters changed.
Pattern matching with original strings?

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

Results

Average of all rows' sequences

All sequences concatenated

Number of observations after skipping

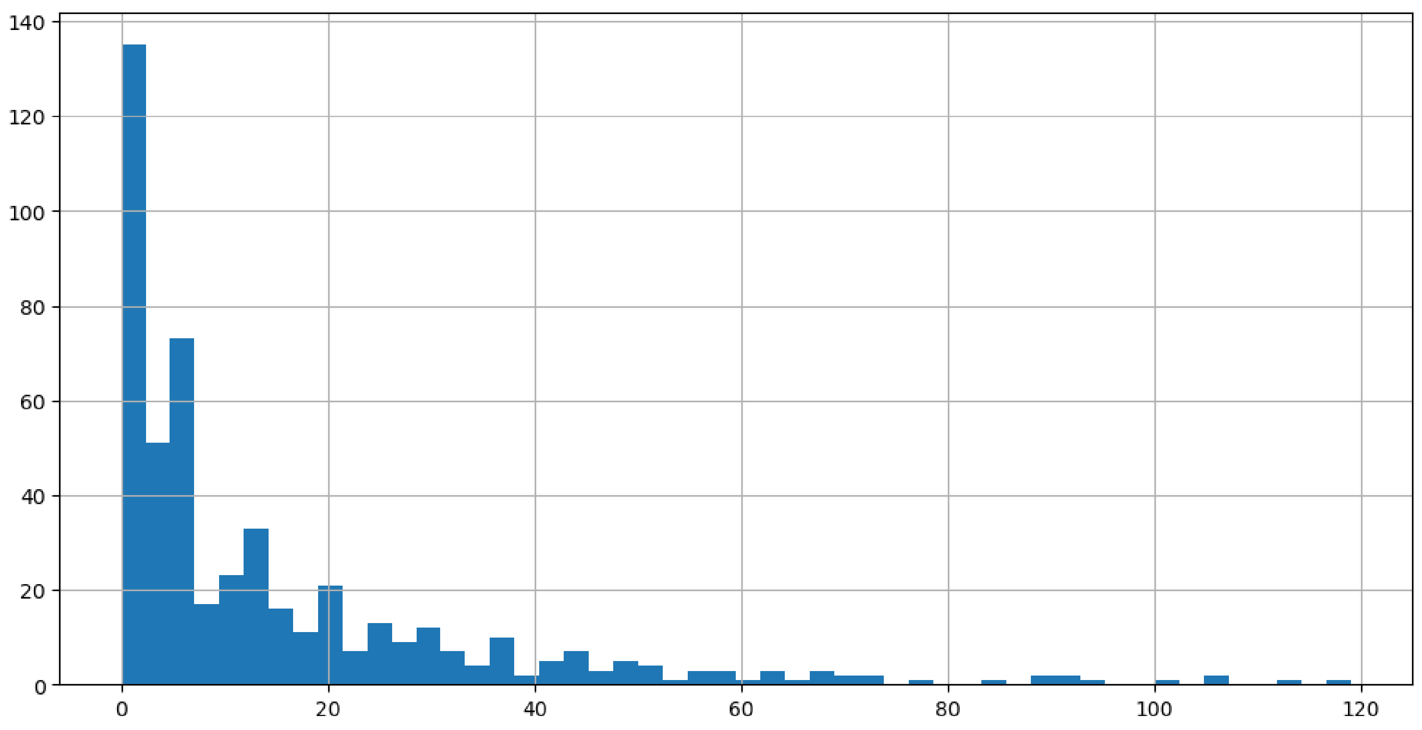
Number of tokens in sequence

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
SVM		0,364		0,534			X	X	512	
SVM		0,203		0,582			X		512	
SVM		0,259		0,540				X	512	
SVM		0,315		0,588					512	

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

Questions?