# Few-shot Text Classification based on Pretrained Language Models: *An ~~Un~~finished* Research *Story*

Mohsen Tabasi


Final decision
Change direction
The first idea
Few-shot learning

# Few-Shot Learning

A brief Introduction

# Why Just a Few shots!?

- Supervised information are sometimes hard or impossible to acquire
- Large-scale data collection is laborious
- Humans are few-shot learners

This section (Introduction to few-shot learning) is derived from:

Wang, Yaqing, et al. "Generalizing from a few examples: A survey on few-shot learning." ACM Computing Surveys (CSUR) 53.3 (2020): 1-34.

# Relevant Problems

- Weakly supervised learning
- Imbalanced learning
- Transfer learning
- Meta-learning

# The Core Issue

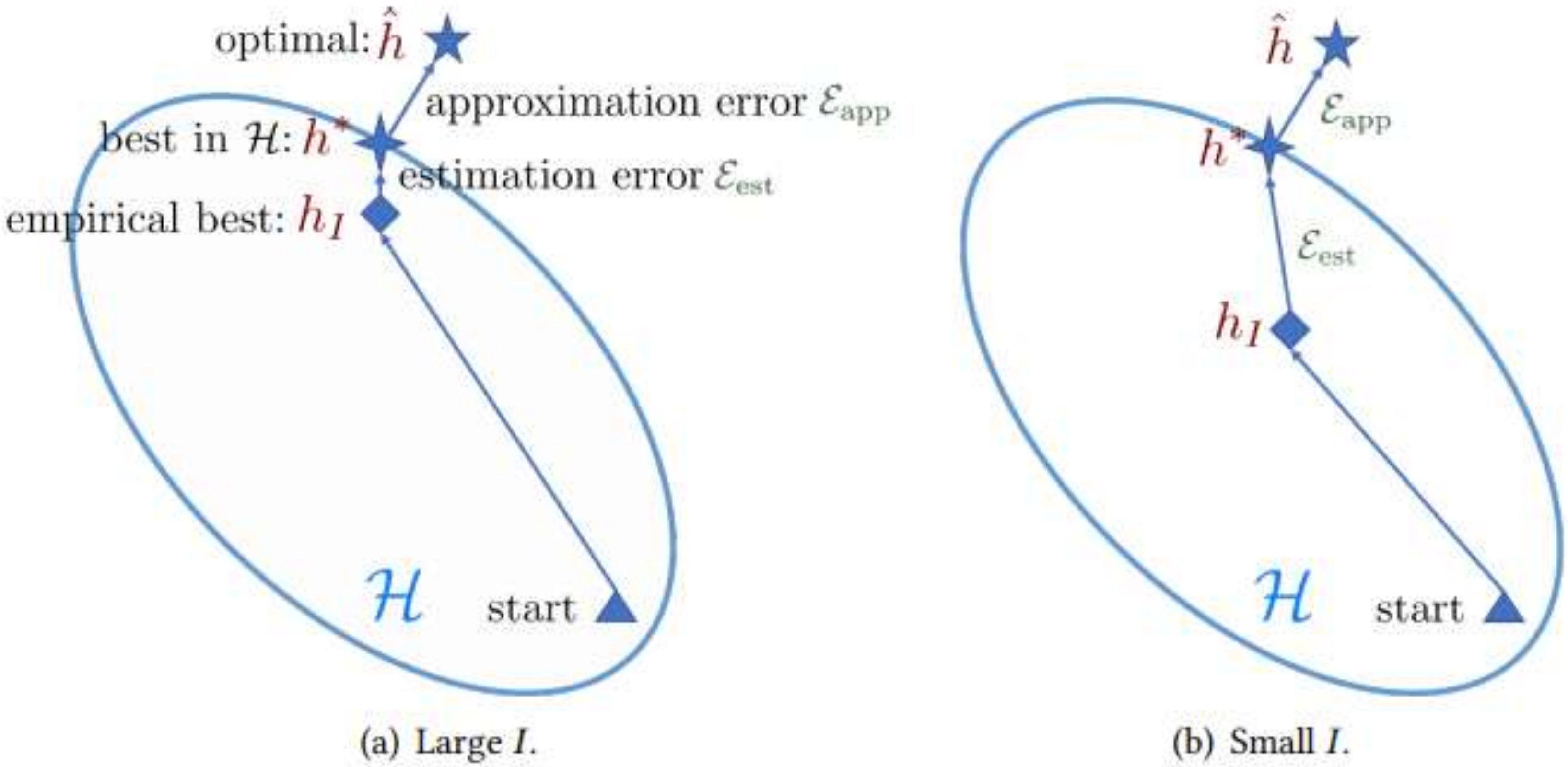
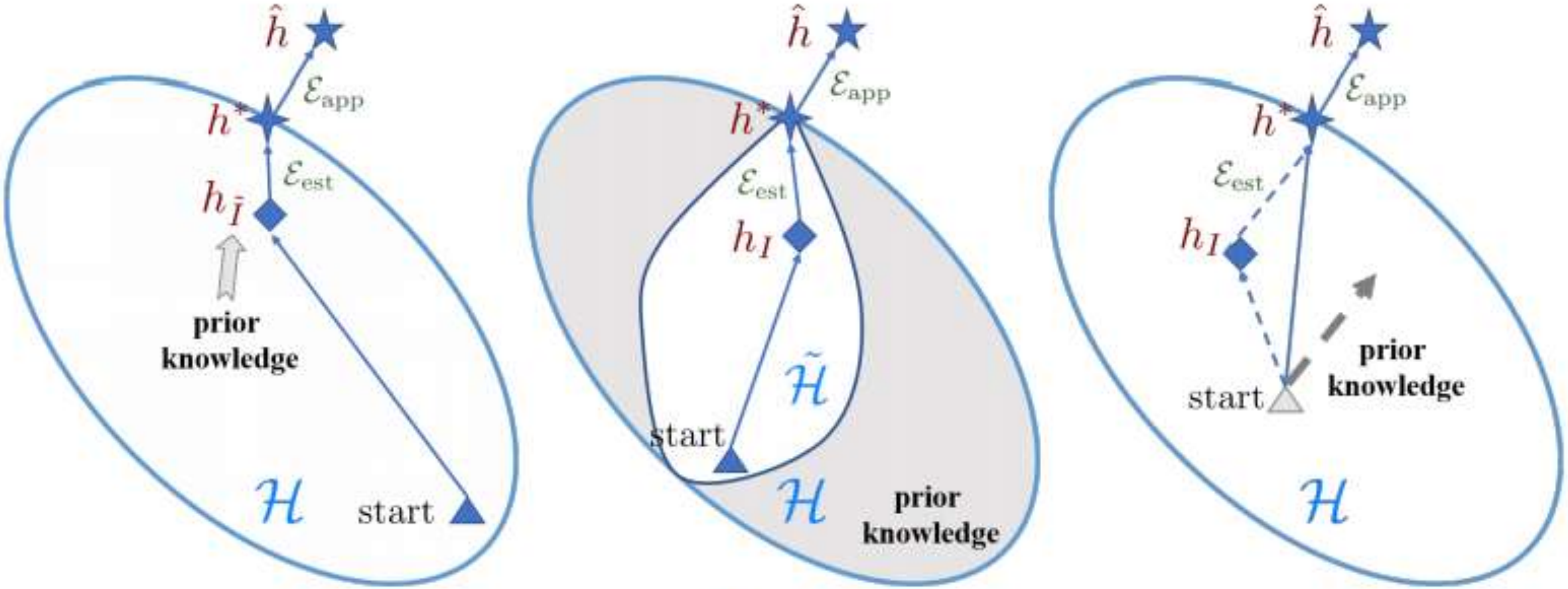



Fig. 1. Comparison of learning with sufficient and few training samples.

# FSL Solutions

- Prior Knowledge is the key!

# FSL Solutions




(a) Data. (b) Model. (c) Algorithm.

Fig. 2. Different perspectives on how FSL methods solve the few-shot problem.

# The First Idea

Towards few-shot text classification

# Playing with MLM

- Lets go to colab!

# Few-shot w/ Cloze Questions

- Add a fixed pattern with a single [MASK] token to the input text
- Take BERT embeddings or LM probs for the [MASK] as features
- Train a linear classifier on few examples

# First Experiments, First Results

- Very promising in sentiment analysis (SST-2)
  - In comparison to Fine-tuning, Using [CLS] token embedding
- Not so impressive for language Inference (MNLI)
  - Not so intuitive patterns, Or maybe the model lacks knowledge!

- Special adaptation for Word-in-Context task
  - On par with fine-tuning approach

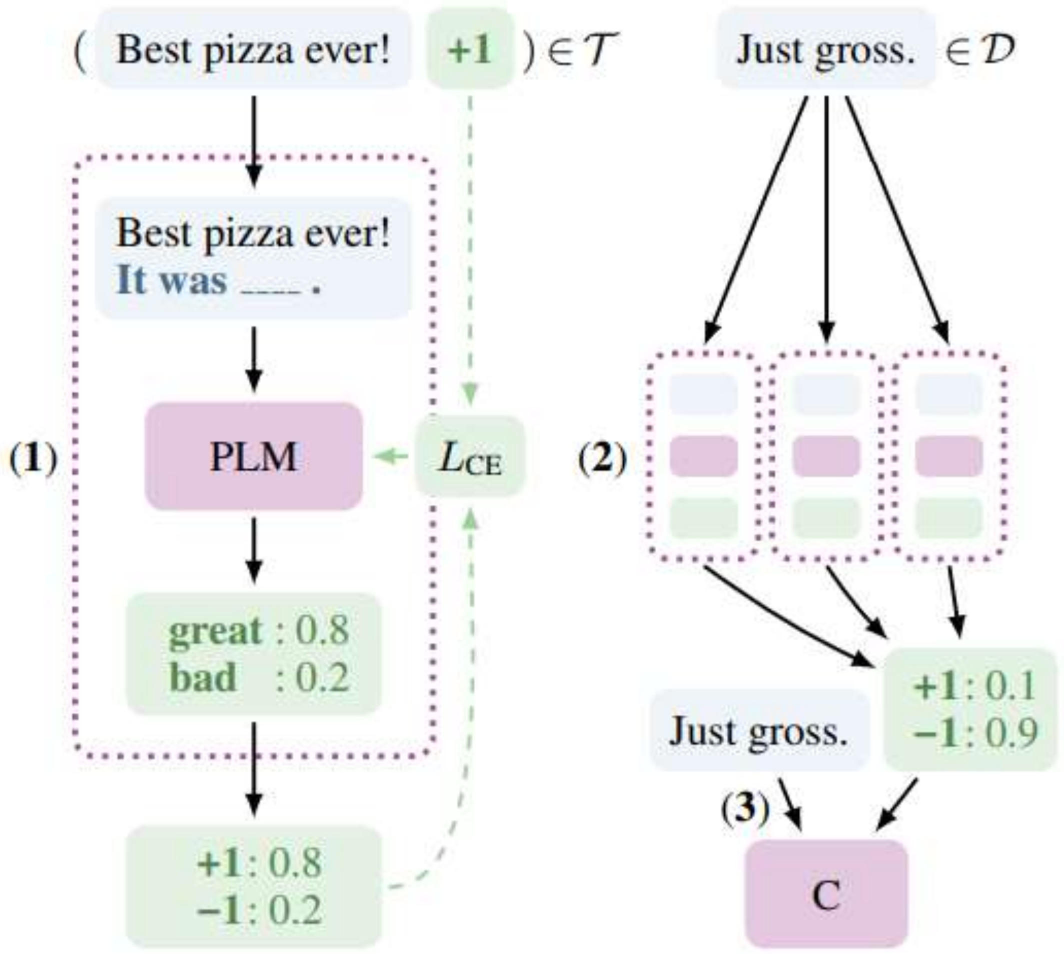
# Facing a Bitter Reality ☹

- A random paper search led to an AWESOME paper titled:

***"Exploiting Cloze Questions for Few Shot Text Classification and Natural Language Inference"***

- It is accepted at EACL 2021 as we talk…

# Pattern Exploiting Training (PET)



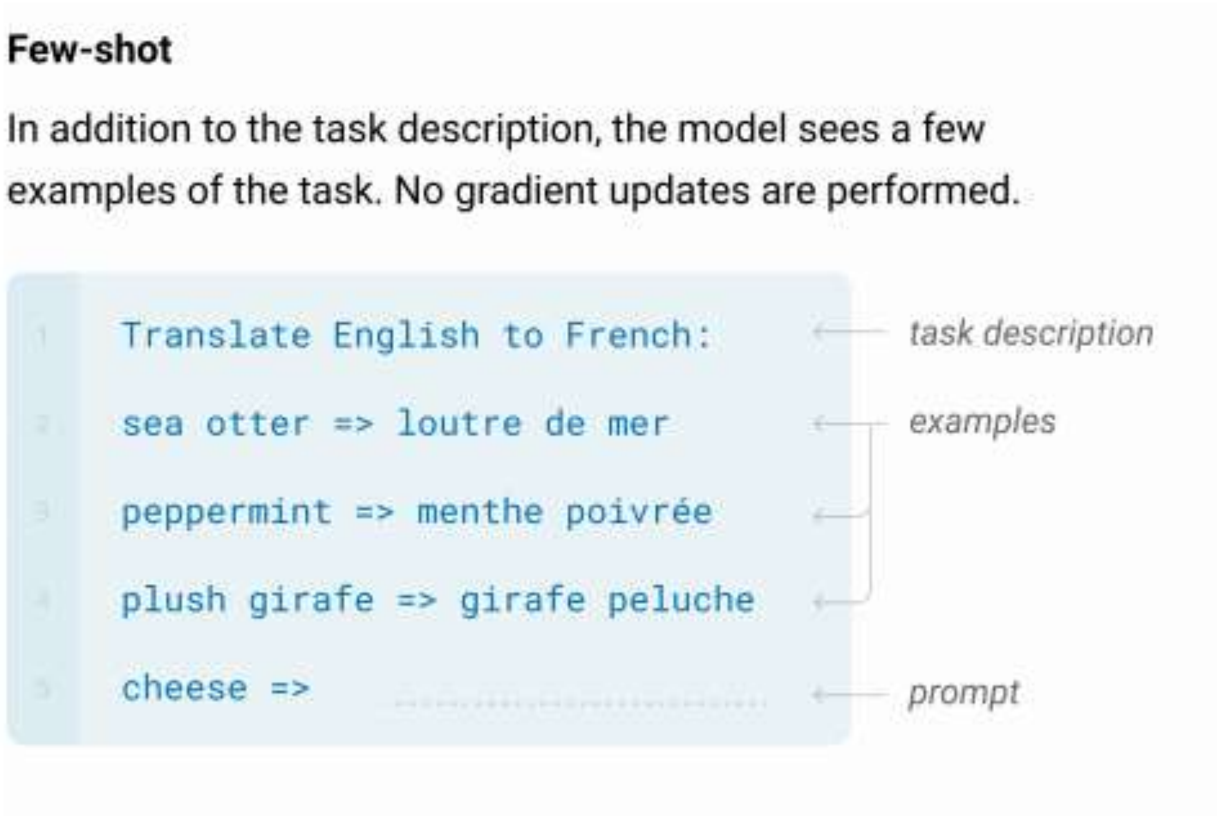

Schick, Timo, and Hinrich Schütze. "Exploiting Cloze-Questions for Few-Shot Text Classification and Natural Language Inference." *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*. 2021.

# Pattern Exploiting Training (PET)

| Line | Examples | Method | Yelp | AG's | Yahoo | MNLI (m/mm) |
|---|---|---|---|---|---|---|
| 1 | | unsupervised (avg) | 33.8 ±9.6 | 69.5 ±7.2 | 44.0 ±9.1 | 39.1 ±4.3 / 39.8 ±5.1 |
| 2 | $\|\mathcal{T}\| = 0$ | unsupervised (max) | 40.8 ±0.0 | 79.4 ±0.0 | 56.4 ±0.0 | 43.8 ±0.0 / 45.0 ±0.0 |
| 3 | | iPET | **56.7** ±0.2 | **87.5** ±0.1 | **70.7** ±0.1 | **53.6** ±0.1 / **54.2** ±0.1 |
| 4 | | supervised | 21.1 ±1.6 | 25.0 ±0.1 | 10.1 ±0.1 | 34.2 ±2.1 / 34.1 ±2.0 |
| 5 | $\|\mathcal{T}\| = 10$ | PET | 52.9 ±0.1 | 87.5 ±0.0 | 63.8 ±0.2 | 41.8 ±0.1 / 41.5 ±0.2 |
| 6 | | iPET | **57.6** ±0.0 | **89.3** ±0.1 | **70.7** ±0.1 | **43.2** ±0.0 / **45.7** ±0.1 |
| 7 | | supervised | 44.8 ±2.7 | 82.1 ±2.5 | 52.5 ±3.1 | 45.6 ±1.8 / 47.6 ±2.4 |
| 8 | $\|\mathcal{T}\| = 50$ | PET | 60.0 ±0.1 | 86.3 ±0.0 | 66.2 ±0.1 | 63.9 ±0.0 / 64.2 ±0.0 |
| 9 | | iPET | **60.7** ±0.1 | **88.4** ±0.1 | **69.7** ±0.0 | **67.4** ±0.3 / **68.3** ±0.3 |
| 10 | | supervised | 53.0 ±3.1 | 86.0 ±0.7 | 62.9 ±0.9 | 47.9 ±2.8 / 51.2 ±2.6 |
| 11 | $\|\mathcal{T}\| = 100$ | PET | 61.9 ±0.0 | 88.3 ±0.1 | 69.2 ±0.0 | 74.7 ±0.3 / 75.9 ±0.4 |
| 12 | | iPET | **62.9** ±0.0 | **89.6** ±0.1 | **71.2** ±0.1 | **78.4** ±0.7 / **78.6** ±0.5 |
| 13 | $\|\mathcal{T}\| = 1000$ | supervised | 63.0 ±0.5 | **86.9** ±0.4 | 70.5 ±0.3 | 73.1 ±0.2 / 74.8 ±0.3 |
| 14 | | PET | **64.8** ±0.1 | **86.9** ±0.2 | **72.7** ±0.0 | **85.3** ±0.2 / **85.5** ±0.4 |

Table 1: Average accuracy and standard deviation for RoBERTa (large) on Yelp, AG's News, Yahoo and MNLI (m:matched/mm:mismatched) for five training set sizes $|\mathcal{T}|$.

# GPT-3 as a few-shot learner


Brown, Tom B., et al. "Language models are few-shot learners." arXiv preprint arXiv:2005.14165 (2020).

# GPT-3 as a few-shot learner

| | |
|---|---|
| Context → | The bet, which won him dinner for four, was regarding the existence and mass of the top quark, an elementary particle discovered in 1995.<br>question: The Top Quark is the last of six flavors of quarks predicted by the standard model theory of particle physics. True or False?<br>answer: |
| Target Completion → | False |

**Figure G.31:** Formatted dataset example for RTE

| | |
|---|---|
| Context → | An outfitter provided everything needed for the safari.<br>Before his first walking holiday, he went to a specialist outfitter to buy some boots.<br>question: Is the word 'outfitter' used in the same way in the two sentences above?<br>answer: |
| Target Completion → | no |

**Figure G.32:** Formatted dataset example for WiC

# PET strikes again!

| | Model | Params (M) | BoolQ Acc. | CB Acc. / F1 | COPA Acc. | RTE Acc. | WiC Acc. | WSC Acc. | MultiRC EM / F1a | ReCoRD Acc. / F1 | Avg – |
|---|---|---|---|---|---|---|---|---|---|---|---|
| dev | GPT-3 Small | 125 | 43.1 | 42.9 / 26.1 | 67.0 | 52.3 | 49.8 | 58.7 | 6.1 / 45.0 | 69.8 / 70.7 | 50.1 |
| | GPT-3 Med | 350 | 60.6 | 58.9 / 40.4 | 64.0 | 48.4 | 55.0 | 60.6 | 11.8 / 55.9 | 77.2 / 77.9 | 56.2 |
| | GPT-3 Large | 760 | 62.0 | 53.6 / 32.6 | 72.0 | 46.9 | 53.0 | 54.8 | 16.8 / 64.2 | 81.3 / 82.1 | 56.8 |
| | GPT-3 XL | 1,300 | 64.1 | 69.6 / 48.3 | 77.0 | 50.9 | 53.0 | 49.0 | 20.8 / 65.4 | 83.1 / 84.0 | 60.0 |
| | GPT-3 2.7B | 2,700 | 70.3 | 67.9 / 45.7 | 83.0 | 56.3 | 51.6 | 62.5 | 24.7 / 69.5 | 86.6 / 87.5 | 64.3 |
| | GPT-3 6.7B | 6,700 | 70.0 | 60.7 / 44.6 | 83.0 | 49.5 | 53.1 | 67.3 | 23.8 / 66.4 | 87.9 / 88.8 | 63.6 |
| | GPT-3 13B | 13,000 | 70.2 | 66.1 / 46.0 | 86.0 | 60.6 | 51.1 | 75.0 | 25.0 / 69.3 | 88.9 / 89.8 | 66.9 |
| | GPT-3 | 175,000 | 77.5 | 82.1 / 57.2 | 92.0 | 72.9 | **55.3** | 75.0 | 32.5 / 74.8 | **89.0 / 90.1** | 73.2 |
| | PET | 223 | 79.4 | 85.1 / 59.4 | **95.0** | 69.8 | 52.4 | **80.1** | **37.9 / 77.3** | 86.0 / 86.5 | 74.1 |
| | iPET | 223 | **80.6** | **92.9 / 92.4** | **95.0** | **74.0** | 52.2 | **80.1** | 33.0 / 74.0 | 86.0 / 86.5 | **76.8** |
| test | GPT-3 | 175,000 | 76.4 | 75.6 / 52.0 | **92.0** | 69.0 | 49.4 | 80.1 | 30.5 / 75.4 | **90.2 / 91.1** | 71.8 |
| | PET | 223 | 79.1 | 87.2 / 60.2 | 90.8 | 67.2 | **50.7** | **88.4** | **36.4 / 76.6** | 85.4 / 85.9 | 74.0 |
| | iPET | 223 | **81.2** | **88.8 / 79.9** | 90.8 | **70.8** | 49.3 | **88.4** | 31.7 / 74.1 | 85.4 / 85.9 | **75.4** |
| | SotA | 11,000 | *91.2* | *93.9 / 96.8* | *94.8* | *92.5* | *76.9* | *93.8* | *88.1 / 63.3* | *94.1 / 93.4* | *89.3* |

Table 1: Results on SuperGLUE for GPT-3 primed with 32 randomly selected examples and for PET / iPET with ALBERT-xxlarge-v2 after training on FewGLUE. State-of-the-art results when using the regular, full size training sets for all tasks (Raffel et al., 2020) are shown in italics.

# Recap

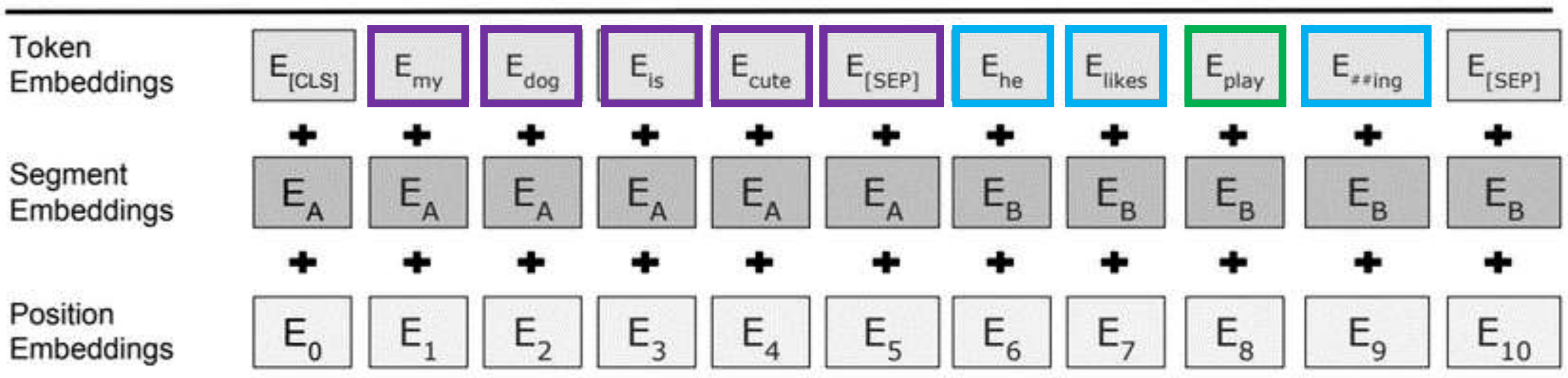
- PET (iPET) leaves no room for few-shot performance improvement!
- Although PET was published several month before in arxiv, It was neither accepted in any conference, nor being referenced by other works.
- This direction seems to be still intact in some aspects…
- Which aspects?!?!

# Heroic Exercise! ☺

Not leaving this so easily…

# Learn the Pattern

- As PET seems to get the most out of cloze questions, we can search for best possible pattern
  - Choose a pattern template, e.g. [sentence] [PAD] [PAD] [MASK] [PAD]
  - Learn an embedding vector for each [PAD] token
  - Set nearest in-vocab word for each position as the final pattern



# Learn the Pattern

- As PET seems to get the most out of cloze questions, we can search for best possible pattern
  - Choose a pattern template, e.g. [sentence] [PAD] [PAD] [MASK] [PAD]
  - Learn an embedding vector for each [PAD] token
  - Set nearest in-vocab word for each position as the final pattern
- Failed! Why?
- Improvement when starting from a valid pattern!*

# Learn the Input (Not Few-shot Only)

- DeepDream

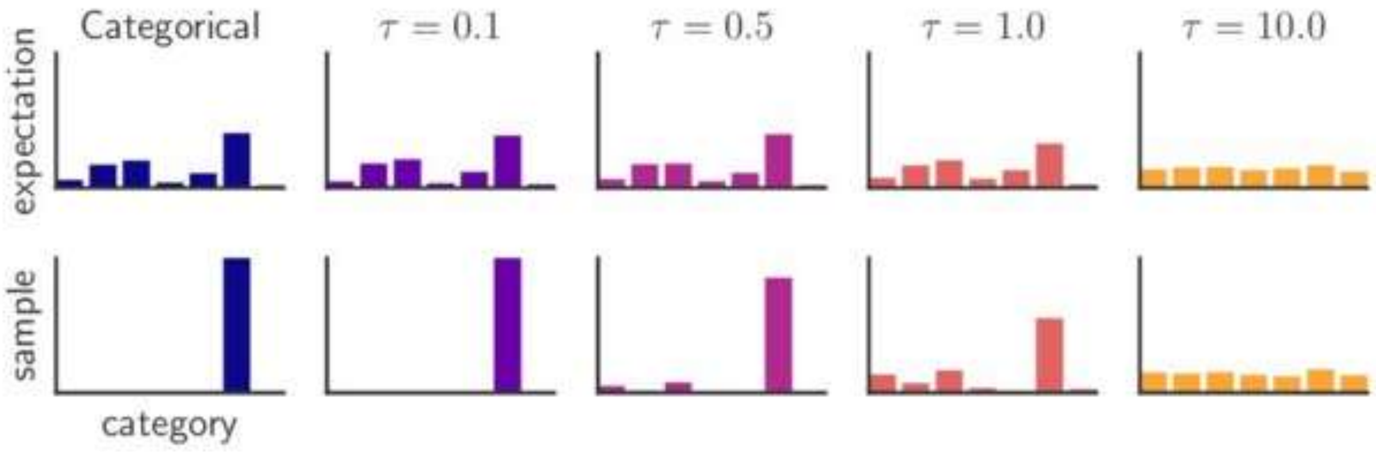
# Learn the Input (Not Few-shot Only)

- If we can find an input text which satisfies a given objective, we can move towards…

- Text Dream
- Model Interpretation
- Adversarial Attack

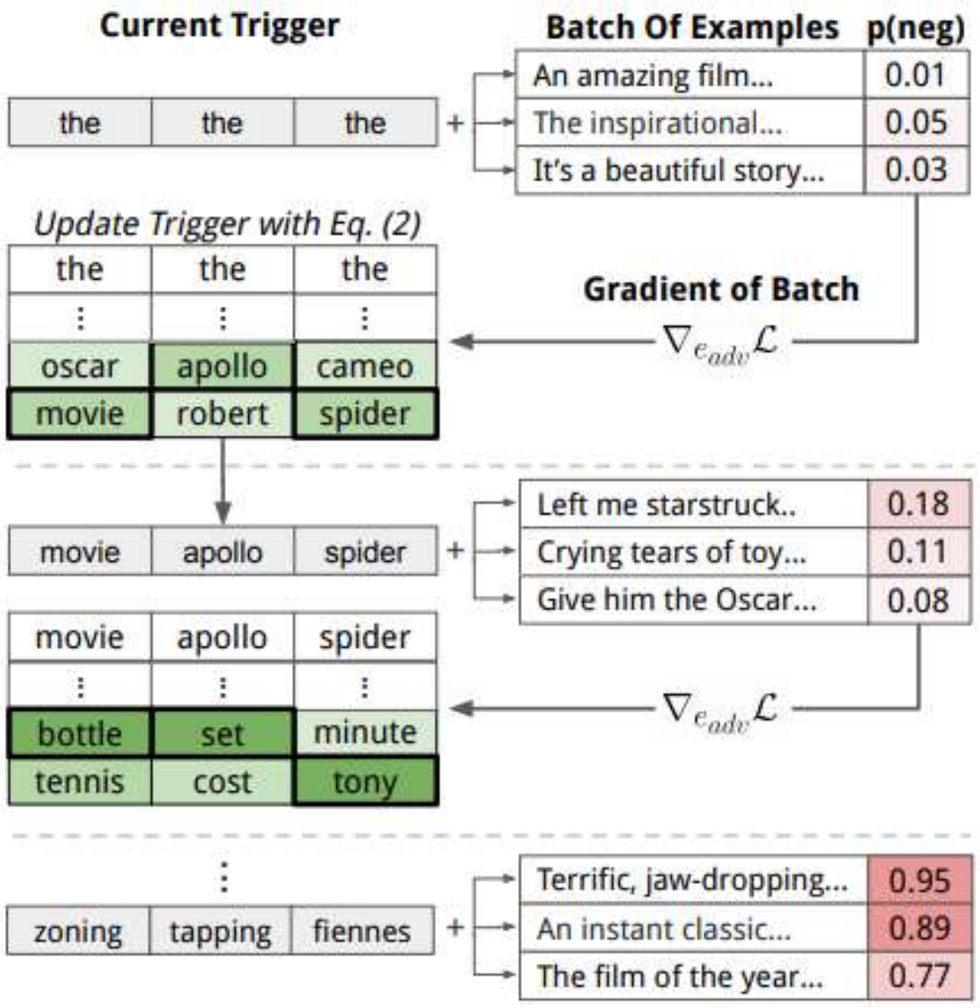
# Improve Input Search method

- Learn weights of a Gumbel Softmax instead of embedding vectors




- Beam Search
  - The most promising search method, which let us return to learning patterns for few-shot text classification

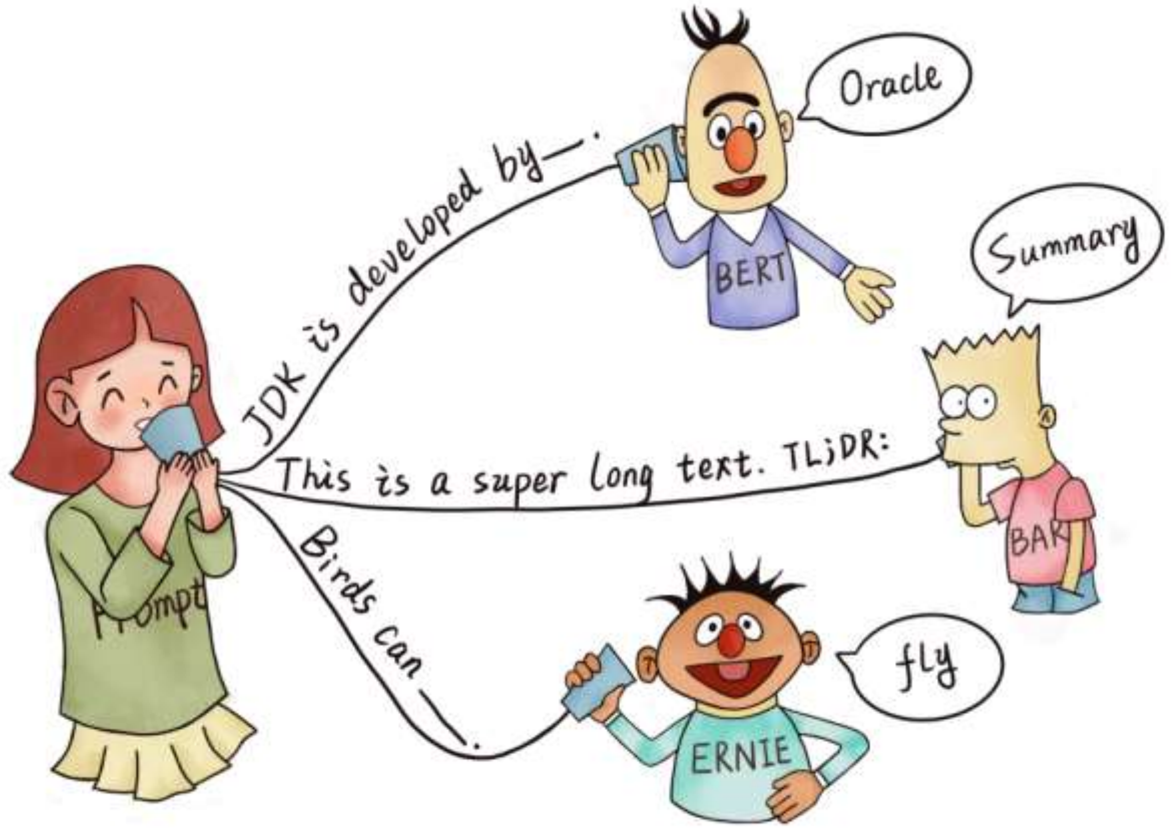
# Improve Input Search method



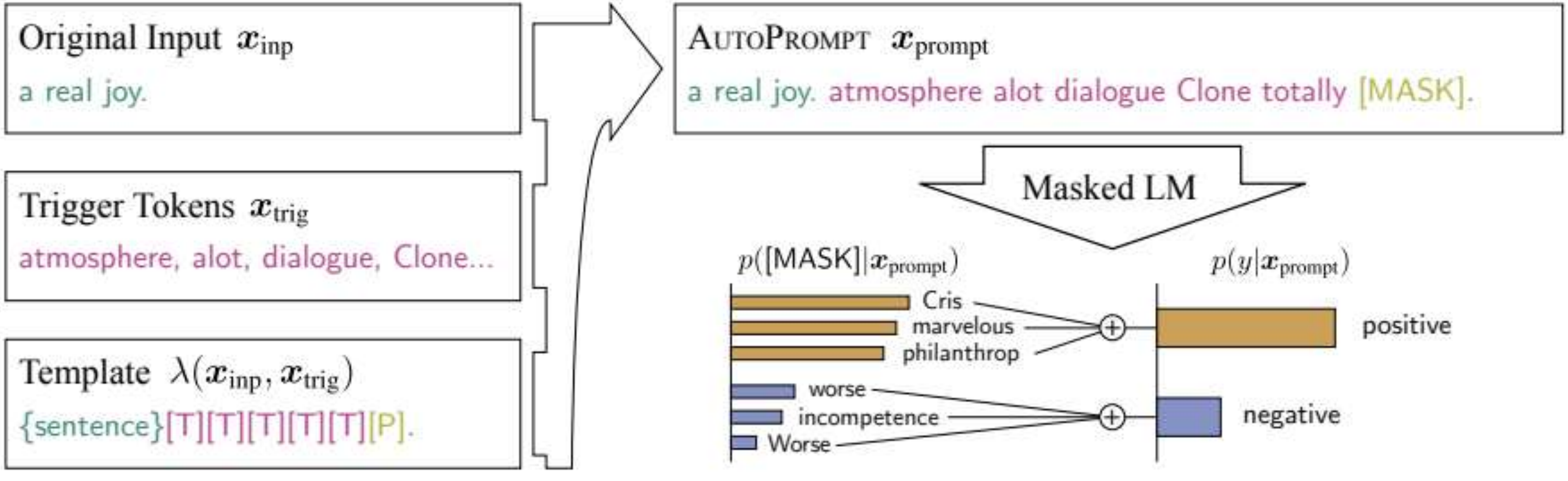
# Facing another Bitter Reality!

- While we were patiently looking for a promising pattern search method…
- Few-shot text classification using cloze questions (or prompts) has become a (rather small) trend…

# Facing another Bitter Reality!

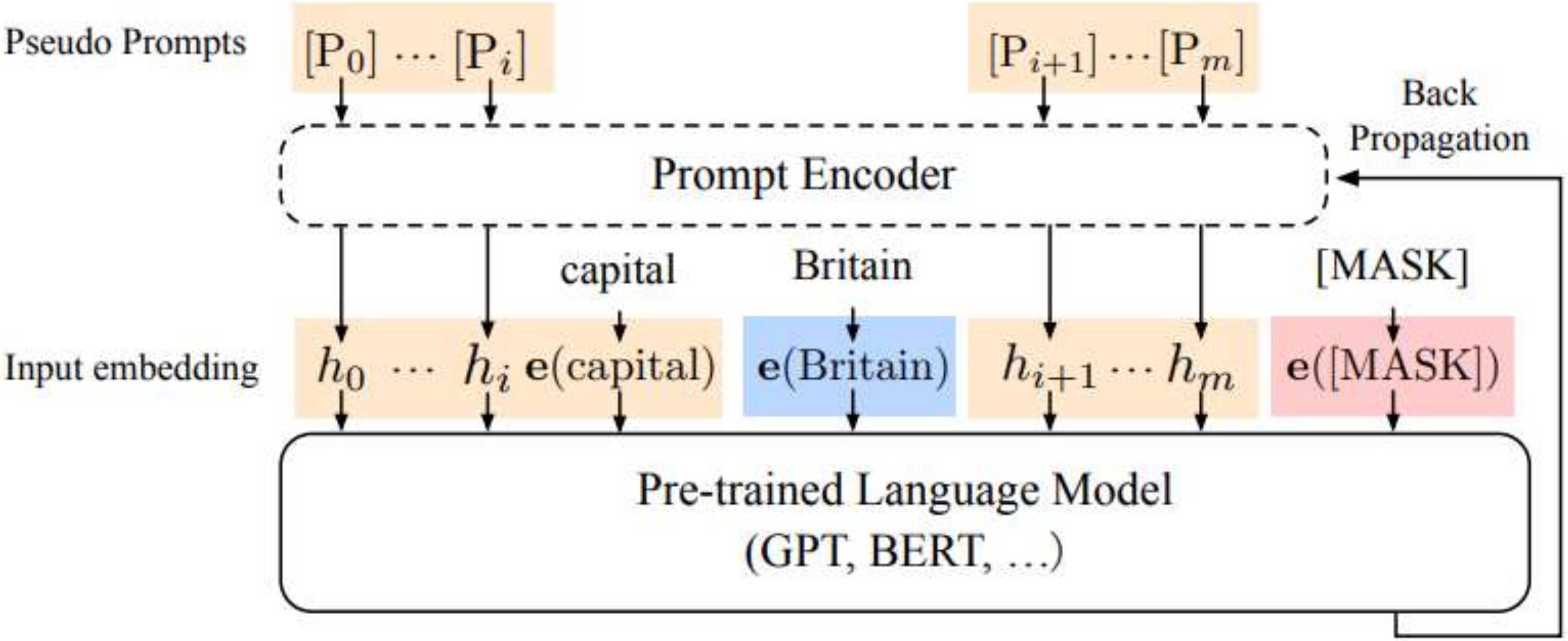


# AutoPrompt




Shin, Taylor, et al. "Eliciting Knowledge from Language Models Using Automatically Generated Prompts." *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. 2020.

# P-Tuning




Liu, Xiao, et al. "GPT Understands, Too." arXiv preprint arXiv:2103.10385 (2021).

# Recap 2

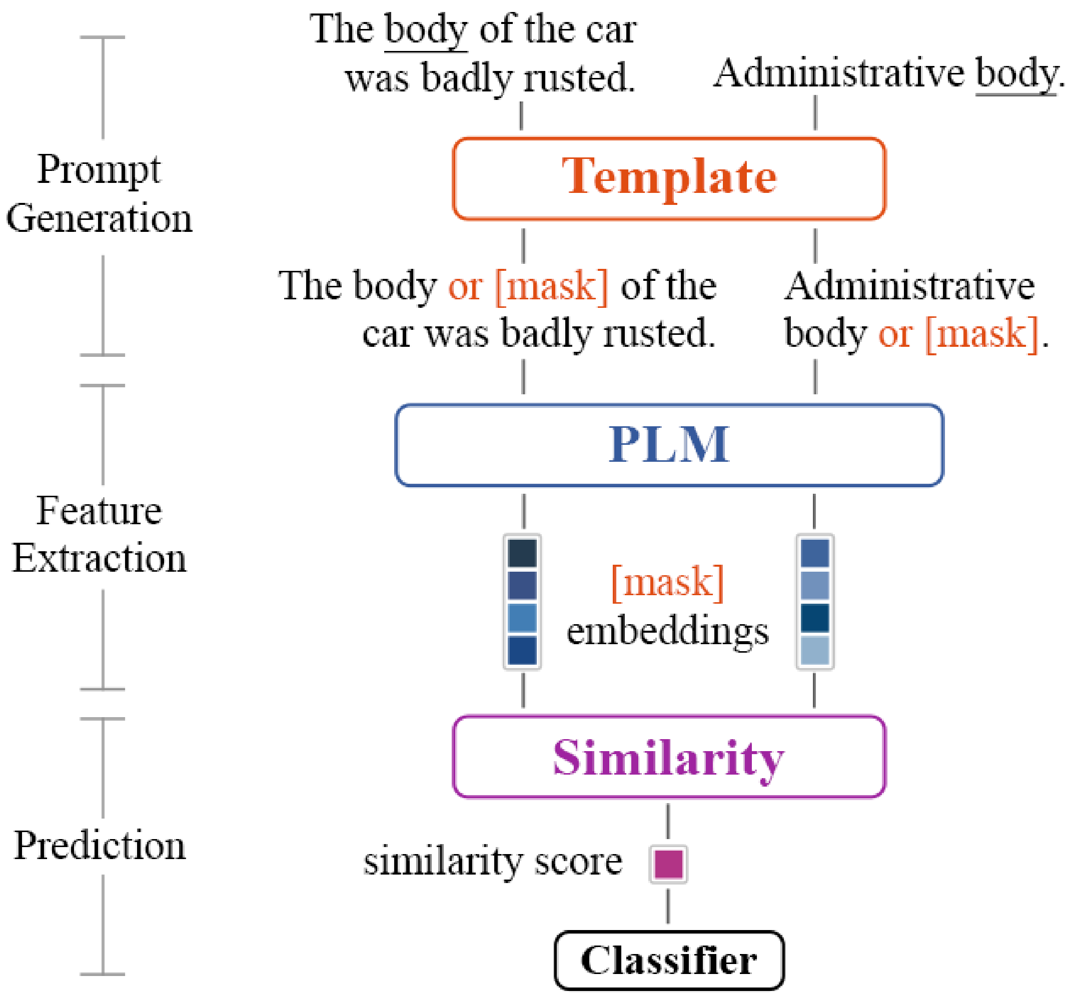
- We were one (or more) steps behind a new trend, in which we could be pioneers!
- Some of the results we simply skip, may become the main idea of some papers…

# The Final Decision

How to avoid falling behind?

# Publishing Our Findings

***"Exploiting Language Model Prompts using Similarity Measures: A Case Study on the Word-in-Context Task"***



# Publishing Our Findings

**PET** (one of multiple patterns)
*<s1>* *<s2>* Does *<w>* have the same meaning in both sentences? __

Unnatural way

**GPT3**
*<s1>* *<s2>*
question: Is the word '*<w>*' used in the same way in the two sentences above?
answer: __

# Publishing Our Findings

| Method | WiC | |
|---|---|---|
| | dev | test |
| Random Baseline | 50.0 | 50.0 |
| Fine-tuned RoBERTa-Large | - | 69.9 |
| GPT3 few-shot | 55.3 | 49.4 |
| PET (ALBERT-xxlarge-v2) | 52.4 | 50.7 |
| P-Tuning (GPT2-medium) | 56.3 | - |
| SP-cosine | 60.9 | 63.6 |
| SP-Spearman | 70.2 | 70.2 |
| SP-RBO | 66.6 | 63.4 |
| SP-RBO w/ stem | **71.1** | **70.9** |

Table 1: Accuracy scores for Word-in-Context task. SP models are based on RoBERTa-Large.

# Publishing Our Findings

There was a **blockage** or — in the sewer, so we called out the plumber.

**Top-5:** something, leak, obstruction, defect, overflow

We had to call a plumber to clear out the **blockage** or — in the drainpipe.

**Top-5:** debris, obstruction, water, leak, crack

The **body** or — of the car was badly rusted.

**Top-5:** trunk, roof, chassis, frame, grill

Administrative **body** or —.

**Top-5:** agency, institution, government, commission, equivalent

The **drawing** or — of water from the well.

**Top-5:** use, extraction, taking, pumping, consumption

He did complicated pen-and-ink **drawings** or — like medieval miniatures.

**Top-5:** paintings, sculptures, something, more, looked

# My Thesis

Towards a happy ending?!

# Continue Exploring

- Use generative LMs (GPT-2)
- Get rid of a fixed pattern and single mask token
- Generate class descriptors with custom beam search decoding

# Continue Exploring

```
pattern: " remake",   prob: 0.0027, diff: 0.0642, val_prob: 0.0047, val_diff: 0.2756
pattern: " sequel",   prob: 0.0044, diff: 0.0951, val_prob: 0.0071, val_diff: 0.2633
pattern: " parody",   prob: 0.0046, diff: 0.0972, val_prob: 0.0050, val_diff: 0.1256
pattern: " disaster", prob: 0.0029, diff: 0.1826, val_prob: 0.0026, val_diff: 0.1197
pattern: " horror",   prob: 0.0022, diff: 0.1016, val_prob: 0.0025, val_diff: 0.1169
pattern: " complete", prob: 0.0065, diff: 0.2084, val_prob: 0.0064, val_diff: 0.0964
pattern: " sad",      prob: 0.0029, diff: 0.1036, val_prob: 0.0025, val_diff: 0.0891
pattern: " failure",  prob: 0.0016, diff: 0.1340, val_prob: 0.0012, val_diff: 0.0886
```

LENGTH=2: 100% 64/64 [01:02<00:00, 1.03it/s]

```
pattern: " complete failure", prob: 0.0347, diff: 0.5473, val_prob: 0.0313, val_diff: 0.5793
pattern: " complete waste",  prob: 0.0260, diff: 0.7117, val_prob: 0.0257, val_diff: 0.4531
pattern: " total failure",   prob: 0.0393, diff: 0.3501, val_prob: 0.0357, val_diff: 0.5599
pattern: " total waste",     prob: 0.0181, diff: 0.5776, val_prob: 0.0191, val_diff: 0.5343
pattern: " shoddy",          prob: 0.1251, diff: 0.5867, val_prob: 0.1267, val_diff: 0.6957
pattern: " sad example",     prob: 0.0188, diff: 0.0536, val_prob: 0.0180, val_diff: 0.3511
pattern: " total disaster",  prob: 0.0340, diff: 0.3309, val_prob: 0.0352, val_diff: 0.4283
pattern: " terrible example", prob: 0.0223, diff: 0.0064, val_prob: 0.0222, val_diff: 0.3898
```

LENGTH=3: 100% 64/64 [00:40<00:00, 1.57it/s]

```
pattern: " complete failure to",    prob: 0.0262, diff: 0.0580, val_prob: 0.0220, val_diff: 0.2777
pattern: " total failure to",       prob: 0.0209, diff: 0.0687, val_prob: 0.0177, val_diff: 0.3208
pattern: " failure to address",     prob: 0.0048, diff: 0.0549, val_prob: 0.0051, val_diff: 0.2569
pattern: " shoddy remake",          prob: 0.0132, diff: 0.0204, val_prob: 0.0165, val_diff: 0.1716
pattern: " failure to understand",  prob: 0.0191, diff: 0.0469, val_prob: 0.0164, val_diff: 0.2287
pattern: " complete failure by",    prob: 0.0048, diff: 0.0067, val_prob: 0.0047, val_diff: 0.0908
```

# A Few-shot Classification Method

تولید خودکار
یا
توسط انسان

Prompt

**۱. تولید محرک برای هر توصیف**

بازم از این خودکار ایرانی میخرم. کیفیتش درجه یک و عالی است.

بازم از این خودکار ایرانی میخرم. فکر میکنم سرم کلاه رفت.

**متن ورودی**

بازم از این خودکار ایرانی میخرم.

Sentiment Analysis

**تحلیل احساسات**

(نظرات خریداران)

# A Few-shot Classification Method

## ۲. امتیازدهی به توصیف ها

بازم از این خودکار ایرانی میخرم. کیفیتش درجه یک و عالی است.

بازم از این خودکار ایرانی میخرم. فکر میکنم سرم کلاه رفت.

مدل زبانی

۲/۱ بازم از این خودکار ایرانی میخرم. کیفیتش درجه یک و عالی است.

۰/۶ بازم از این خودکار ایرانی میخرم. فکر میکنم سرم کلاه رفت.

**متن ورودی**

بازم از این خودکار ایرانی میخرم.

# A Few-shot Classification Method

## ۳. تصمیم گیری درباره خروجی

**متن ورودی**

بازم از این خودکار ایرانی میخرم.

۲/۱ بازم از این خودکار ایرانی میخرم. کیفیتش درجه یک و عالی است.

۰/۶ بازم از این خودکار ایرانی میخرم. فکر میکنم سرم کلاه رفت.

**Classifier**

**کلاس مثبت**

# Scoring Function

$\underbrace{\text{فکر میکنم سرم کلاه رفت.}}_{d \text{ توصیف}}$ $\underbrace{\text{بازم از این خودکار ایرانی میخرم.}}_{x \text{ ورودی}}$

بازم از این خودکار ایرانی میخرم. فکر میکنم سرم کلاه رفت.

$$\Delta PP_M(x, d) \stackrel{\text{def}}{=} \frac{PP_M(d|x)}{PP_M(d)}$$

مدل زبانی

**تغییر سرگشتگی**

# Scoring Function

توصیف $d$

ورودی $x$

$$\underbrace{\text{بازم از این خودکار ایرانی میخرم.}}_{}$$

بازم از این خودکار ایرانی میخرم. فکر میکنم سرم کلاه رفت.

بخش پیشوندی

بخش پاسخ

$$\Delta PP_M(x,d) \stackrel{\text{def}}{=} \frac{PP_M(d|x)}{PP_M(d)}$$

مدل زبانی

**تغییر سرگشتگی**

# Manual Descriptions

## کلاس مثبت

- در کل بنظرم فوق العاده است
- یک محصول باکیفیت و کاربردی
- من خریدش رو حتما پیشنهاد میکنم
- کیفیت ساخت درجه یک و عالی

## کلاس منفی

- در کل بنظرم واقعا افتضاحه.
- یک محصول بی کیفیت و بلا استفاده
- من خریدش رو اصلا پیشنهاد نمیکنم
- کیفیت ساخت پایین در حد فاجعه

# Generated Descriptions

## کلاس مثبت

- در کل خرید این محصول **رضایت شما عزیزان هست**
- در کل خرید این محصول **هم خوبه؛ هم**
- در کل خرید این محصول **پیشنهاد خوبیه.**
- در کل خرید این محصول **نسبتا راحته..**

## کلاس منفی

- در کل خرید این محصول **را قبول کردم در**
- در کل خرید این محصول **هیچ فایده خاصی نداشت**
- در کل خرید این محصول **بی کیفیت بود من**
- در کل خرید این محصول **یک اشتباه بسیار بزرگی**

# Generated Descriptions

## Sci/Tech

- This is all about **giving people more control**
- This is all about **improving customer experience through**
- This is all about **building better tools.**
- This is all about **using technology that works**

## World

- This is all about **winning an election that**
- This is all about **control of foreign policy**
- This is all about **money and power…**
- This is all about **who should rule in**

AG News Classification

# An Example

"Future Doctors, Crossing Borders Students at the Mount Sinai School of Medicine learn that diet and culture shape health in East Harlem"

| Index | Descriptions | PPL Change | Class |
|---|---|---|---|
| 1 | This is all about **diplomatic solutions** | 1.02 | World (Gold Label) |
| 2 | This is all about **world politics** | 0.87 | |
| 3 | This is all about **war and peace** | 0.80 | |
| 4 | This is all about **extremism and terrorism** | 1.41 | |
| 5 | This is all about **science and technology** | 0.44 | Sci/Tech (Predicted) |
| 6 | This is all about **new inventions and discoveries** | 0.82 | |
| 7 | This is all about **making life easier for users** | 2.89 | |
| 8 | This is all about **high - end devices** | 2.47 | |

# Questions?

# References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