References

- Rethinking the Role of Demonstrations: What Makes In-Context Learning Work? (https://arxiv.org/pdf/2202.12837.pdf)

What makes In-context Learning work ?

- [blog (http://ai.stanford.edu/blog/understanding-incontext/)](http://ai.stanford.edu/blog/understanding-incontext/)
- [paper (https://arxiv.org/pdf/2202.12837.pdf)](https://arxiv.org/pdf/2202.12837.pdf)
    - more empirical
    - various models
        - MetaICL: trained with InContextLearning objective
        - 2 methods: Direct vs Channel ???
    - gold-label vs random (uniform sampling) label: ground-truth not necessary
        - gold improves over zero shot
        - random: small decrease vs gold
            - **very** small for MetaICL
        - sampling for true label distribution: smaller decrease

How does In Context Learning work ?

In-context Learning describes a means of using a fixed LLM to solve a task

- by supplying some number k of *exemplars* (or *demonstrations*) of the new task
- as a *pre-prompt*
- and the presenting a prompt $\mathbf{x}$ to the model
- expecting the model to produce a $\mathbf{y}$
- that is the correct "response" to the task on input $\mathbf{x}$

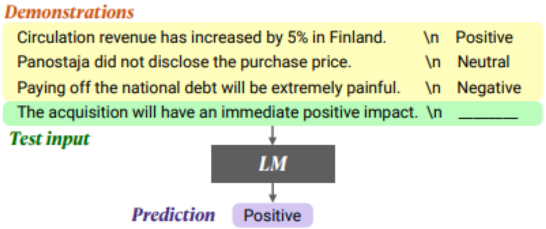


Figure 2: An overview of in-context learning. The demonstrations consist of k input-label pairs from the training data ($k = 3$ in the figure).

Atttribution: [https://arxiv.org/pdf/2202.12837.pdf#page=2 (https://arxiv.org/pdf/2202.12837.pdf#page=2)](https://arxiv.org/pdf/2202.12837.pdf#page=2)

In-Context Learning appears to be a way

- of extending a LM
- *without* further training
    - as opposed to Fine-Tuning
- since
    - the exemplars are given at *test* time
    - no parameter updates to the LLM occur

In-Context Learning uses a pre-trained LLM and the trick of using the Universal Text API

- to turn the new task
- into a text-continuation ("predict the next") task

That is:

- given some number k of exemplars: $\langle \mathbf{x}^{(1)}, \mathbf{y}^{(1)} \rangle, \ldots, \langle \mathbf{x}^{(k)}, \mathbf{y}^{(k)} \rangle$
- the prompt string $\mathbf{x}$

we create a sequence $\dot{\mathbf{x}}$ encoding the exemplars and prompt

- and ask the LLM model to predict
$$p(\mathbf{y}|\dot{\mathbf{x}})$$

A common way to create the sequence $\dot{\mathbf{x}}$ by concatenating the exemplars and prompt, using separator characters to as delimiters.

$$\begin{aligned}\dot{\mathbf{x}} = \text{concat}(\quad & \mathbf{x}^{(1)}, \langle \text{SEP}_1 \rangle, \mathbf{y}^{(1)}, \langle \text{SEP}_2 \rangle, \\ & \vdots \\ & \mathbf{x}^{(k)}, \langle \text{SEP}_1 \rangle, \mathbf{y}^{(k)}, \langle \text{SEP}_2 \rangle, \\ & \mathbf{x} \\ &)\end{aligned}$$

The LLM then computes

$$p(\mathbf{y}|\dot{\mathbf{x}})$$

For notational convenience, we will omit writing the concatenation

- and just write this as the conditional probability

$$p(\mathbf{y}|\mathbf{x}, \mathbf{x}^{(1)}, \mathbf{y}^{(1)}, \ldots, \mathbf{x}^{(k)}, \mathbf{y}^{(k)})$$

But why should this work ?

More interestingly

- what is a good theory
- and how can we test it

We will present a paper (https://arxiv.org/pdf/2202.12837.pdf) that attempts to present some insights into the process.

Testing some theories

In order to test a theory

- various aspects of the exemplars are proposed as variables
- one variable at a time is perturbed
- the effect of the perturbations is measured across a range of benchmarks

- **and compare to measurements before the perturbation**

The results are summarized in the following diagram

- that we will subsequently refer to for each experiment

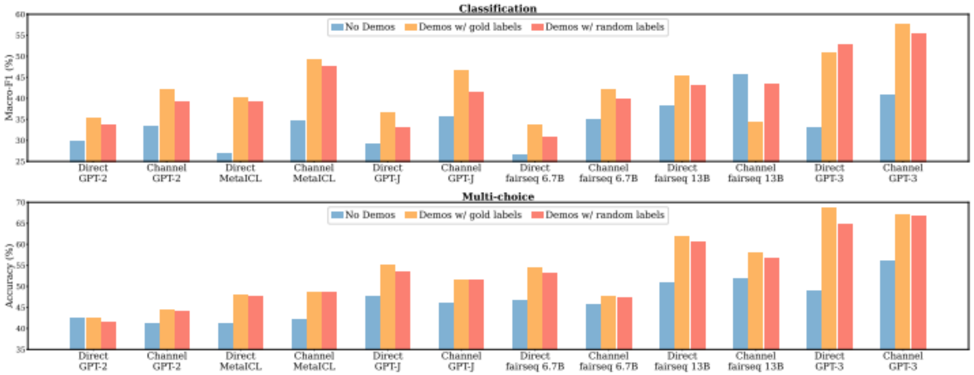


Figure 3: Results when using no-demonstrations, demonstrations with gold labels, and demonstrations with random labels in classification (top) and multi-choice tasks (bottom). The first eight models are evaluated on 16 classification and 10 multi-choice datasets, and the last four models are evaluated on 3 classification and 3 multi-choice datasets. See Figure 11 for numbers comparable across all models. **Model performance with random labels is very close to performance with gold labels** (more discussion in Section 4.1).

This chart shows the result of perturbations

- run across a variety of models
- of sizes ranging from 774M to 175B parameters
- each experiment is averaged across multiple benchmarks

The number of demonstrations, when present, is $k = 16$.

Zero shot verus $k \geq 1$ shot

The first experiment measures the effect of the presence/absence of exemplars.

In the diagram, compare

- "No demos": the blue bar
- "Gold labels": the gold bar

Conclusion

$k \geq 1$ exemplars *improves performance* relative to zero-shot.

Parts of the Context

The next set of experiments varies parts of the context (exemplars and prompt).

Given exemplars $\langle \mathbf{x}^{(1)}, \mathbf{y}^{(1)} \rangle, \ldots, \langle \mathbf{x}^{(k)}, \mathbf{y}^{(k)} \rangle$ the authors posit some salient characteristics

- the *input distribution* I from which the exemplar *features* are drawn $\mathbf{x}^{(1)}, \ldots, \mathbf{x}^{(k)}$
- the distribution L of the exemplar *labels* $\mathbf{y}^{(1)}, \ldots, \mathbf{y}^{(k)}$
- the feature/label mapping relationship M
  - i.e., the pair of $\mathbf{x}^{(\mathbf{i})}$ and $\mathbf{y}^{(\mathbf{i})}$, for $1 \leq i \leq k$
- formatting
  - the encoding of the exemplars and prompt into $\dot{\mathbf{x}}$

Feature/label mapping relationship

Let $\mathcal{C}$ denote the set from which exemplar labels are drawn.

In this experiment, replace

- correct label $\mathbf{y}^{(\mathbf{i})}$ for exemplar i
- with label $\tilde{\mathbf{y}}^{(\mathbf{i})}$ drawn at random (uniformly) from $\mathcal{C}$.

That is, we preserve I and L, but break M.

In the diagram, compare

- "Gold labels": the gold bar (true labels)
- "Random labels": the reddish bar

Conclusions

- Correct ("gold") labels improve performance over random labels
    - but not as much as expected, perhaps
- Random labels *improves performance* over *no exemplars*
    - "Ground truth" matters surprisingly little !

The fact that an *incorrect* M improves performance relative to no exemplars is surprising.

This suggests

- that the exemplars are used to infer the *task to be performed*
- once the task has been identified
  - the exemplar mis-labeling is ignored
- the model is able to perform the task as it was *trained* during training

See the [Signifier theory in the module (hPrompt_Engineering_Suggestions.ipynb#Signifier:-direct-specification)](hPrompt_Engineering_Suggestions.ipynb#Signifier:-direct-specification)

Input distribution

In this experiment

- each exemplar input $\mathbf{x^{(i)}}$ is replaced by
- a random $\mathbf{x}^{(\mathbf{i})}_{\text{rand}}$ drawn from a text corpus *other than the one used for Training*

We note that this experiment *also* breaks the feature/label relationship M

- we preserve the original labels $\mathbf{y}^{(\mathbf{i})}$ for exemplar i
- which is not necessarily related to $\mathbf{x}^{(\mathbf{i})}_{\text{rand}}$

We can contrast the results of this experiment the effect of breaking M alone.

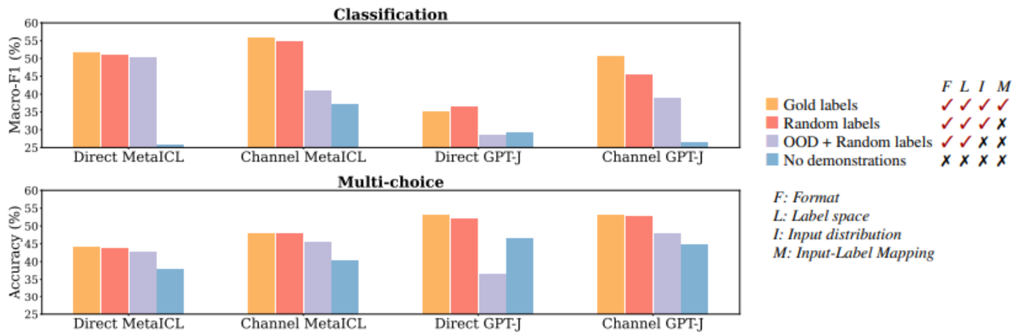


Figure 8: Impact of the distribution of the inputs. Evaluated in classification (top) and multi-choice (bottom). The impact of the distribution of the input text can be measured by comparing ■ and ■. The gap is substantial, with an exception in Direct MetaICL (discussion in Section 5.1).

In the above diagram, compare

- the lavender (third bar from left): perturbed I and M
- the red bar (second bar from left): perturbed M alone

Conclusions

The M relationship is broken in both cases. But

- preserving the original distribution I of exemplar features
- improves performance relative to changing the distribution

Why might this be ?

The suggestion is that the model was trained with the LLM objective ("predict the next")

- from a training distribution
- and $\mathbf{x}_{\text{rand}}$ is from a *different* distribution
- so the model struggles on non-training input

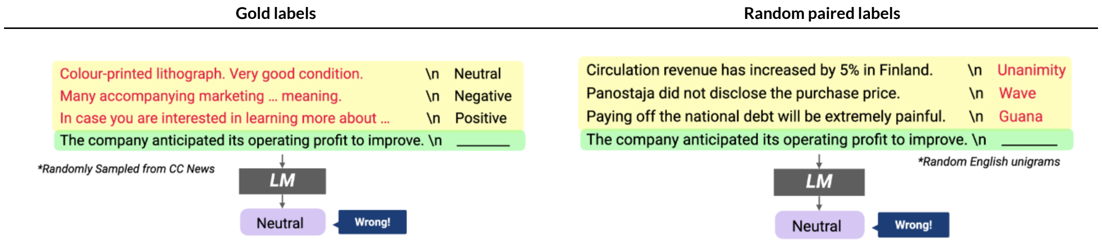
Output distribution

In this experiment

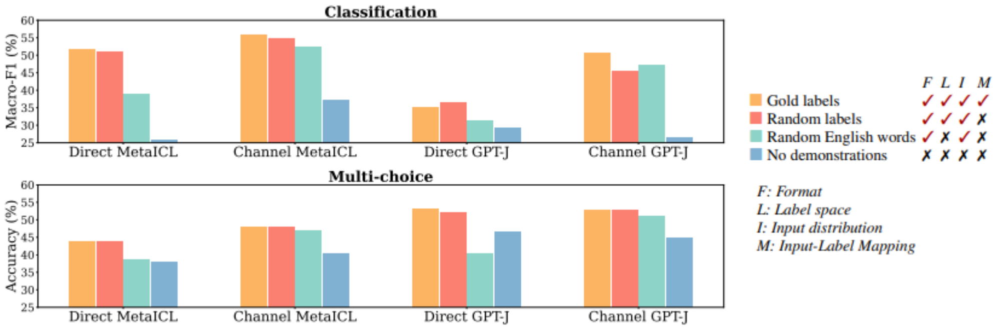
- each exemplar label $\mathbf{y}^{\mathbf{(i)}}$ (from $\mathcal{C}$) is replaced by
- $\tilde{\mathbf{y}}^{\mathbf{(i)}}$ a *random* English word from $\mathcal{C}_{\text{rand}}$

Note that we *also break* M

- e.g., $\mathbf{y}^{\mathbf{(i)}} = \mathbf{y}^{(i')}$ does not imply $\tilde{\mathbf{y}}^{\mathbf{(i)}} = \tilde{\mathbf{y}}^{(i)}$



Attribution: [http://ai.stanford.edu/blog/understanding-incontext/ (http://ai.stanford.edu/blog/understanding-incontext/)](http://ai.stanford.edu/blog/understanding-incontext/)



Classification
Macro-F1 (%)
Multi-choice
Accuracy (%)
Direct MetaICL
Channel MetaICL
Direct GPT-J
Channel GPT-J
F L I M
Gold labels ✓ ✓ ✓ ✓
Random labels ✓ ✓ ✓ ✗
Random English words ✓ ✗ ✓ ✗
No demonstrations ✗ ✗ ✗ ✗
F: Format
L: Label space
I: Input distribution
M: Input-Label Mapping

In the above diagram, compare

- the red bar: random labels
- the turquoise bar (third from left): random words

The difference: Although we break M in both cases

- in the "random labels" case: the labels are chosen from the correct output distribution $\mathcal{C}$
- in the "random words" case: the labels come from a distribution other than $\mathcal{C}$

Conclusions

The M relationship is broken in both cases. But

- preserving the original distribution L of exemplar labels
- improves performance relative to changing the distribution of labels

Formatting

In this experiment

- *format* is defined as the *pairing* of a feature and label within an exemplar
- not necessarily a *correct pairing*: mapping M not necessarily correct

One experiment is run

- with *only* exemplar features (and no exemplar labels): $\mathbf{x}^{(1)}, \ldots, \mathbf{x}^{(k)}$
- natural comparison is with experiment of correct format
    - $\mathbf{x}^{(\mathbf{i})}$
    - paired with random English words (from $\mathcal{C}_{\text{rand}}$) as labels

A second experiment is run

- with *only* exemplar labels (and no exemplar features): $\mathbf{y}^{(1)}, \ldots, \mathbf{y}^{(k)}$
- natural comparison is with experiment of correct format
    - a random $\mathbf{x}^{\mathbf{(i)}}_{\text{rand}}$ drawn from a text corpus
    - paired with $\mathbf{y}^{\mathbf{(i)}}$

Both comparison experiments

- preserve the format: feature/exemplar pairs
- without preserving M
- or the distribution I in the first case, and L in the second case

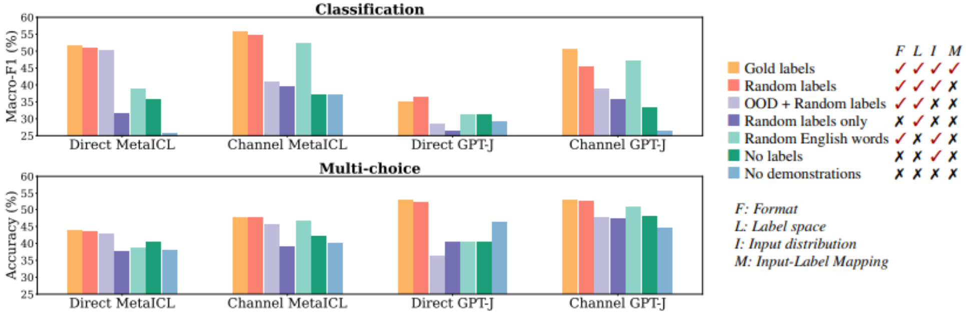


Figure 10: Impact of the format, i.e., the use of the input-label pairs. Evaluated in classification (top) and multi-choice (bottom). Variants of demonstrations without keeping the format (■ and ■) are overall not better than no demonstrations (■). Keeping the format is especially significant when it is possible to achieve substantial gains with the label space but without the inputs (■ vs. ■ in Direct MetaICL), or with the input distribution but without the labels (■ vs. ■ in Channel MetaICL and Channel GPT-J). More discussion in Section 5.3.

Conclusions

- Not keeping the format has performance *on par* with **no demonstrations** at all
- Keeping the format retains most of the benefit achievable with either
  - correct I (but incorrect M)
  - or correct L (but incorrect M)

The suggestion is that correct format an important feature

- to enable the LLM to recognize the task from exemplars

Exemplars that differ from the LLM

The on-line articles makes another interesting observation.

Observe the encoding of

- the exemplars $\langle \mathbf{x}^{(1)}, \mathbf{y}^{(1)} \rangle, \ldots, \langle \mathbf{x}^{(k)}, \mathbf{y}^{(k)} \rangle$
- the prompt string $\mathbf{x}$

into the string $\dot{\mathbf{x}}$ that is the input to the LLM

$$\begin{aligned}
\dot{\mathbf{x}} = \text{concat}(\quad & \mathbf{x}^{(1)}, \langle \text{SEP}_1 \rangle, \mathbf{y}^{(1)}, \langle \text{SEP}_2 \rangle, \\
& \vdots \\
& \mathbf{x}^{(k)}, \langle \text{SEP}_1 \rangle, \mathbf{y}^{(k)}, \langle \text{SEP}_2 \rangle, \\
& \mathbf{x}
\end{aligned}$$

The distribution from which encoded $\dot{\mathbf{x}}$ is drawn

- is probably *much different* than
- the distribution (Internet text documents) on which the LLM was trained

in several ways

- syntax
    - sentences (e.g., exemplars)
    - are not naturally separated by an inter-example separator $\langle \mathrm{SEP} \rangle$ (whatever is chosen) in the training distribution
- coherence
    - exemplars i and $i+1$
    - many not naturally follow one another in the training distribution
        - may be different topics
        - but demonstrate the same concept (that is why they were chosen as exemplars)

The article posits that

- these encoding anomalies
- are low-frequency noise
- that the LLM is able to ignore
- providing there is more "signal" in the exemplars

A theory of In-Context Learning

A more theoretical paper (https://arxiv.org/pdf/2111.02080.pdf) and accompanying online article (http://ai.stanford.edu/blog/understanding-incontext/)

- combine these experimental insights
- into a theory
- and mathematical model of the theory
- that is consistent with the experimental results

The authors posit

- during training, the LLM learns "concepts", for example
    - abstract ideas
        - question answering
        - sentiment
    - plans
        - how to solve a multi-step task: travel directions

Concepts

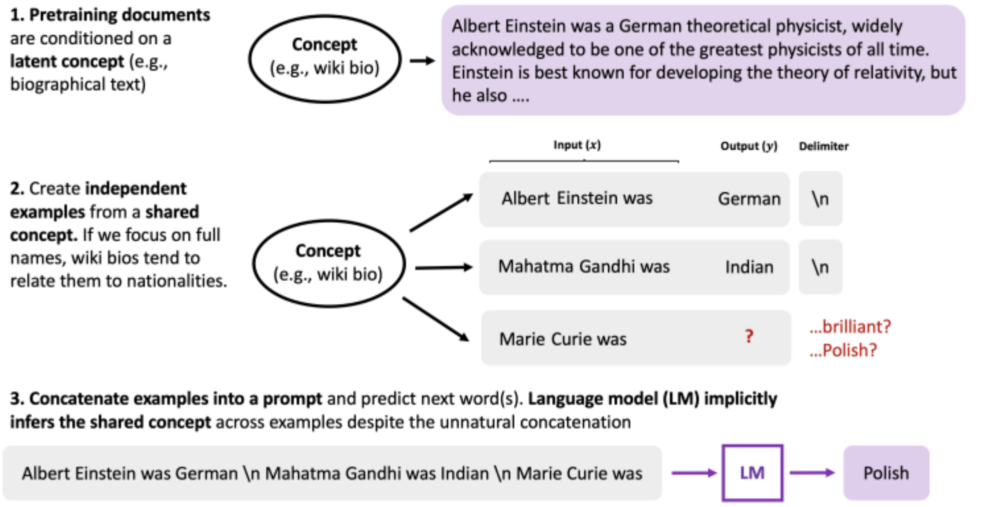


Figure 1: In-context learning can emerge from modeling long-range coherence in the pretraining data. During pretraining, the language model (LM) implicitly learns to infer a latent concept (e.g., wiki bios, which typically transition between name (Albert Einstein) → nationality (German) → occupation (physicist) → ...) shared across sentences in a document. Although prompts are unnatural sequences that concatenate independent examples, in-context learning occurs if the LM can still infer the shared concept across examples to do the task (name → nationality, which is part of wiki bios).

Attribution: https://arxiv.org/pdf/2111.02080.pdf#page=2 (https://arxiv.org/pdf/2111.02080.pdf#page=2)

The model's LLM "predict the next" training objective did not specify to goal of learning concepts.

But

- summarizing a large number of similar training documents (e.g., collection of biographies)
- in a parameters-constrained model
- logically suggests that concepts emerge as a way of reducing parameter usage

The authors suggest that the LLM's probability of outputting $\mathbf{y}$ given prompt $\mathbf{x}$ is formed by

$$p(\mathbf{y}|\mathbf{x}) = \int_{c \in \text{Concepts}} p(\mathbf{y}|\mathbf{x}, c) p(c) \; d(c)$$

That is, the output

- is the sum over all concepts
- of the probability of outputting $\mathbf{y}$ given prompt $\mathbf{x}$ and concept c

Furthermore: the context (i.e., exemplars) of in-context learning

- helps the LLM identify the concept c
- to which the prompt $\mathbf{x}$ implicitly refers

The experimental results seem to suggest that the exemplars

- don't need to be fully accurate
  - the model tolerates inaccurate mappings M between feature input space I and label space L
- that correctly identifying I and L through the exemplars is
  - advantageous
  - but not completely necessary
- that the *format* of the exemplar
  - paired features and labels
  - is important

Under this theory

- the exemplars **are not teaching** new concepts
    - hence M can be inaccurate
- but serving to help the LLM **identify** a concept learned in training

That is, the encoded exemplars in $\dot{\mathbf{x}}$

- are related to $p(c)$

Once the concept c is identified, the output $\mathbf{y}$ depends

- on the distributions I and L
- on the mapping M

that were learned during training.

The actual output $\mathbf{y}$

$$p(\mathbf{y}|\mathbf{x}, \mathbf{c})$$

depends on training examples

- the exemplars
  $\langle \mathbf{x}^{(1)}, \mathbf{y}^{(1)} \rangle, \ldots, \langle \mathbf{x}^{(k)}, \mathbf{y}^{(k)} \rangle$
  do not appear in the equation

In [2]:

```
print("Done")
```

Done