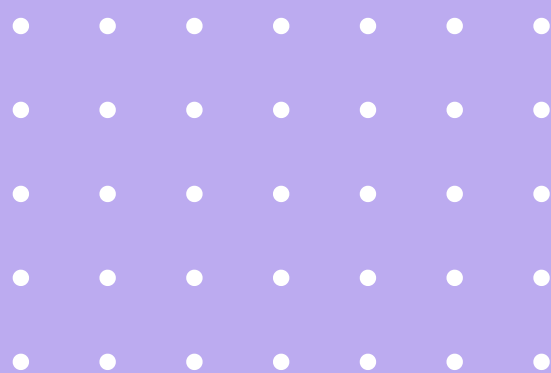


What Makes In-Context Learning Work?

(Min et al., 2022): Rethinking the Role of Demonstrations:
What Makes In-Context Learning Work

Presented by :

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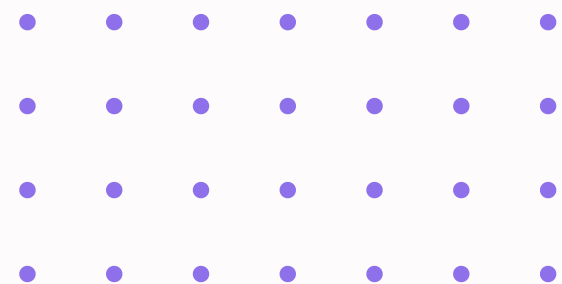
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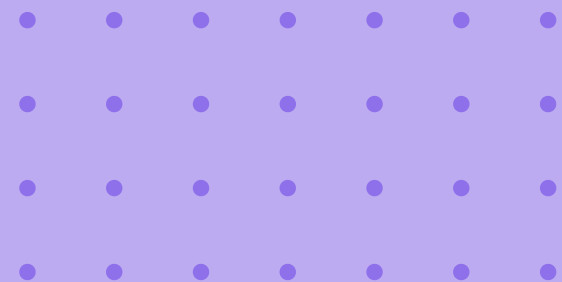
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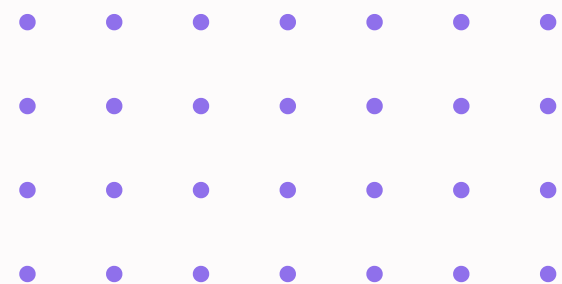


What is In-context learning?



What is In-context learning?

- "I love this movie!" => Positive
- "This is the worst day ever." => Negative
- "I am very happy today." => Positive
- "The food was terrible and cold." =>



The composition of ICL

simply conditioning(inference) on a few input-label pairs (demonstrations)

- demonstrations (示例)

- input text (X)

1. "I love this movie!"
2. "This is the worst day ever."
3. "It rains a lot today."

- label (Y)

Positive
Negative
Neutral

- input-label mapping

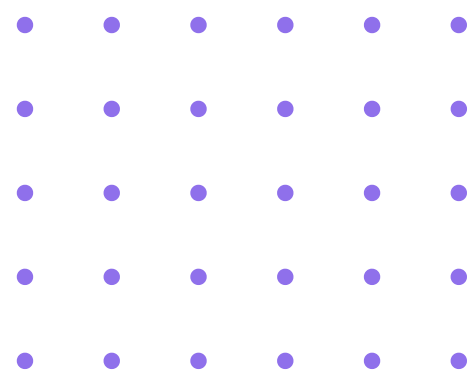
- test example

"The food was terrible and cold."

LM : negative !

- k=3 the amount of pairs

- An input-label pairs



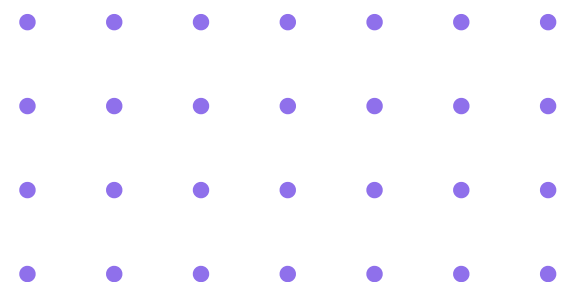
Comparing with Fine-tuning

- **Pros**

- No parameter tuned / gradient updated
- Much fewer examples
- Higher versatile (泛用性強)

- **Cons**

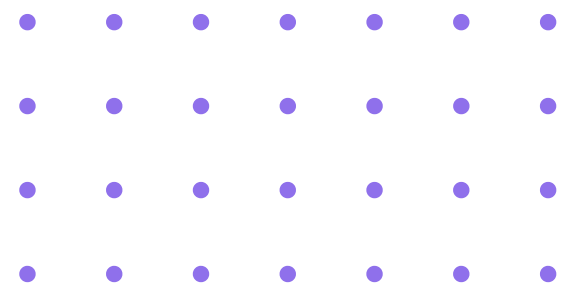
- Less accuracy in specific tasks



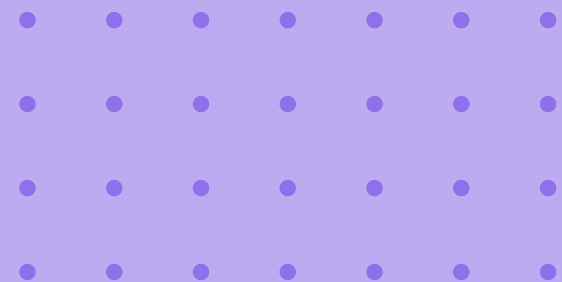
We don't know how models in-context learn

Objective of the paper :

Analyze empirically which aspects of the prompt affect downstream task performance

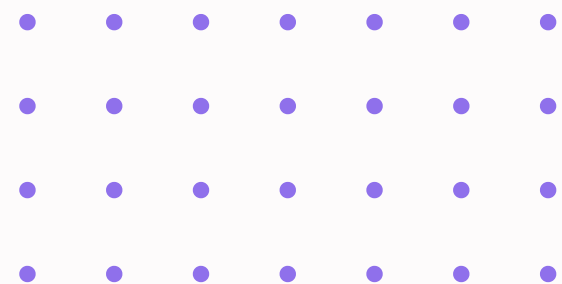


Experimental Process & Result



Aspect 1

**Is the ground truth
input-label pairs
matter?**



Gold Labels vs Random Labels

• Gold Labels

• input (X)

1. "I love this movie!"
2. "This is the worst day ever."
3. "It rains a lot today."

• label (Y)

Positive
Negative
Neutral

"The food was terrible and cold."

LM : negative !

• Random Labels

• input (X)

1. "I love this movie!"
2. "This is the worst day ever."
3. "It rains a lot today."

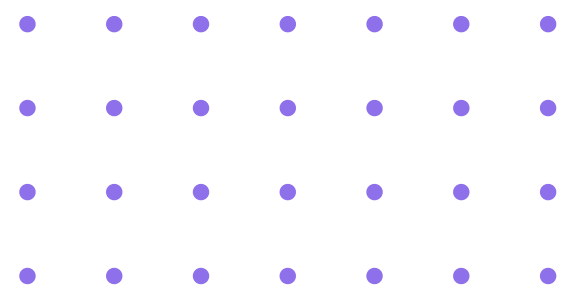
• label (Y)

Neutral
Positive
Negative

"The food was terrible and cold."

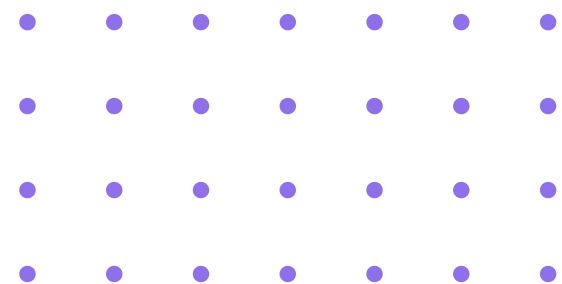
LM : negative !

labels are randomly paired with input !



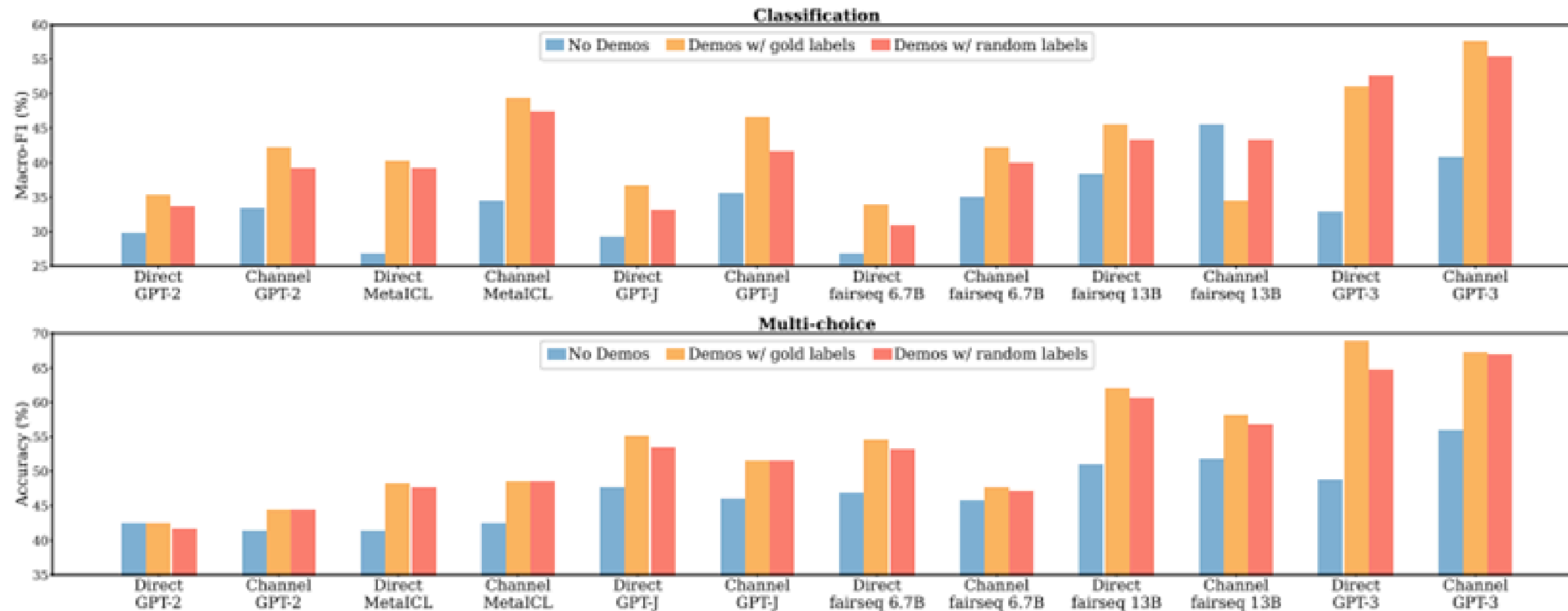
Experimental method:

- using following 3 types of prompt
 1. Demonstrations w/ gold labels (correct label)
 2. Demonstrations w/ random labels (incorrect label)
 3. No demonstrations (zero-shot)



Result

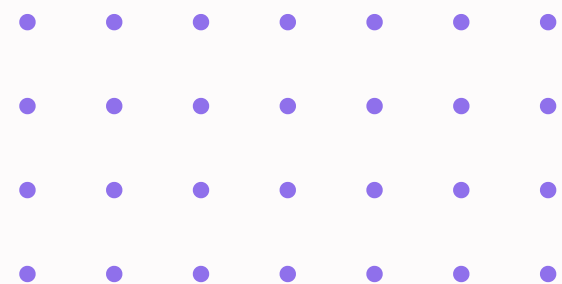
1. demonstrations significantly improves the performance
2. random labels only **marginally hurts** performance (0–5%)



Takeaways

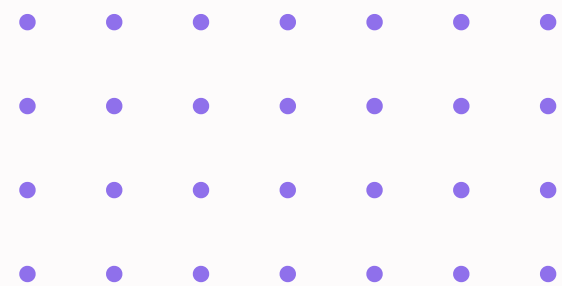
Is the ground truth input-label pairs matter?

- the ground truth input-label pairs are not necessary to achieve performance gains
- Using incorrect labels is better than no examples



Aspect 2

**Is the distribution
of the input text
matter?**



What Is the distribution of input ?

- in-distribution

- **input (X)** social media!

- **label (Y)**

1. "I love this movie!"
2. "This is the worst day ever."

Positive
Negative

- **test example** social media!

"The food was terrible and cold."

- OOD (Out-of-Distribution)

- **input (X)** financial statements

- **label (Y)**

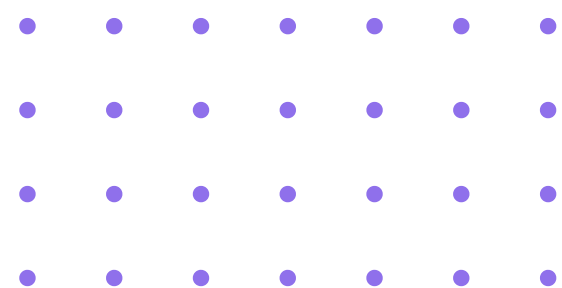
1. "The stock prices soared after the company's earnings report!"
2. "Investors are concerned about the ongoing market volatility."

Positive
Negative

- **test example** social media!

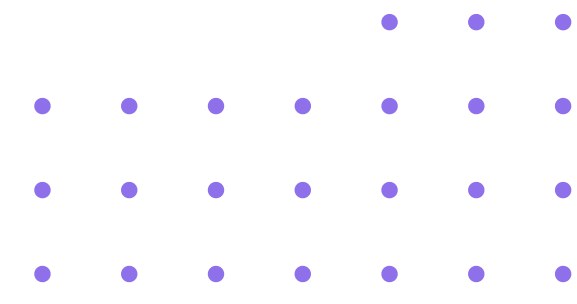
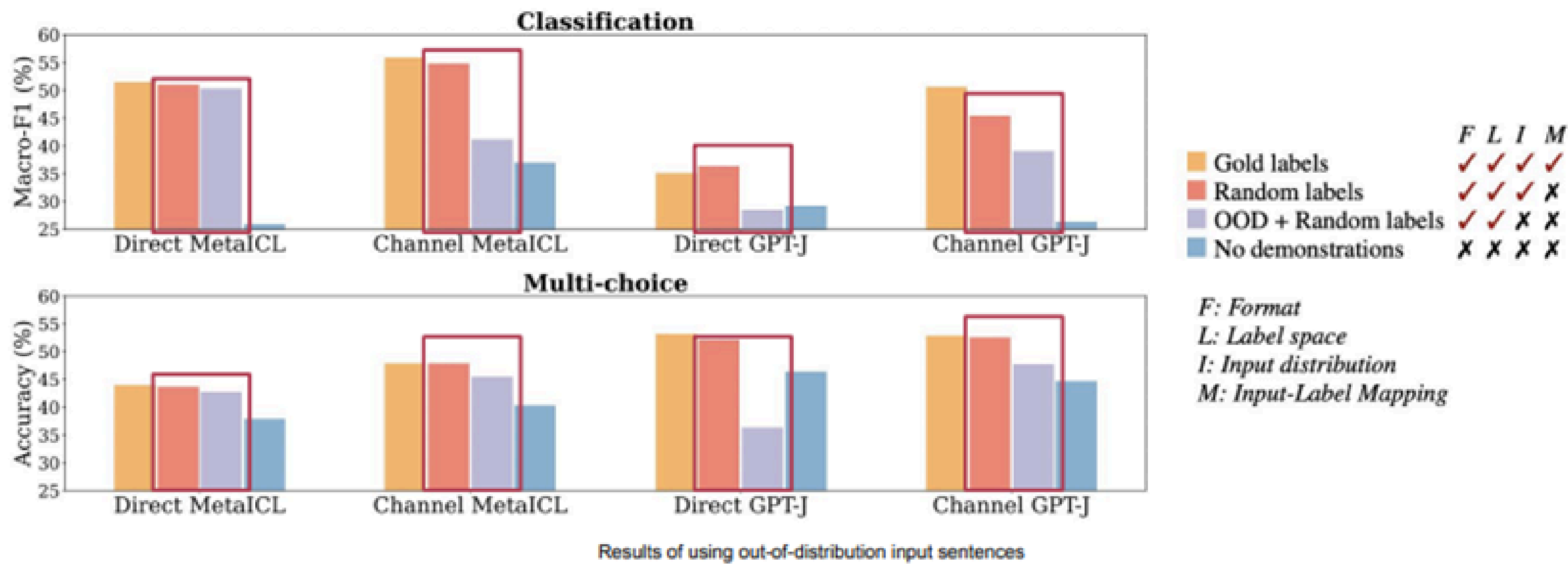
"The food was terrible and cold."

- OOD: input sentences are randomly sampled from an external corpus



Result

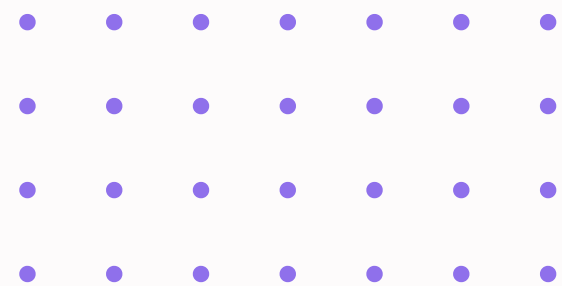
performance **decreases significantly** (up to 16%)



Is better templates matter?

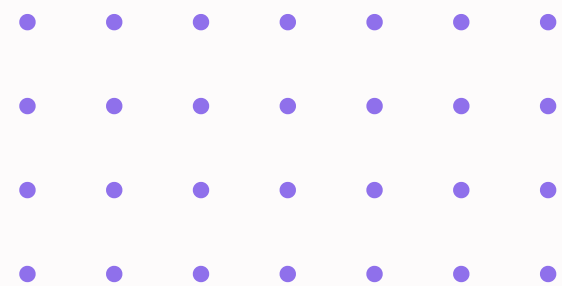
- in-distribution inputs **substantially increase** performance

Takeaways



Aspect 3

**Is label space
matter?**



What Is label space?

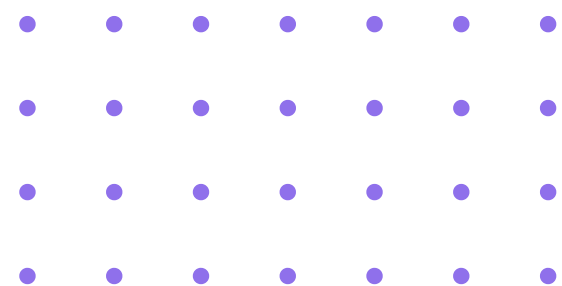
- input (X)

1. "I love this movie!"
2. "This is the worst day ever."
3. "It rains a lot today."

- label (Y)

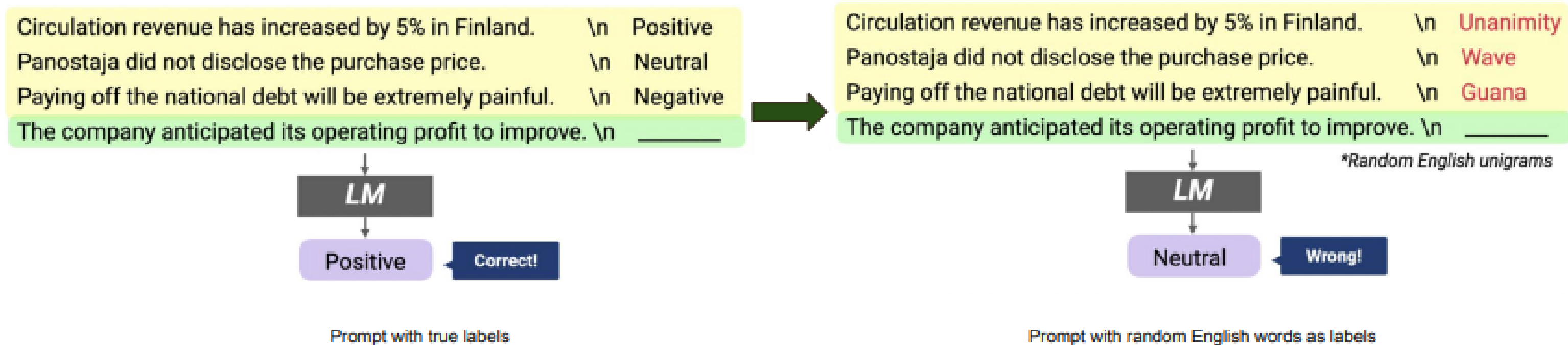
Positive
Negative
Neutral

- All possible label(Y) options in a specific task
- Sentiment analysis : {positive, negative}
- Classification problem: {finance, science, politic}



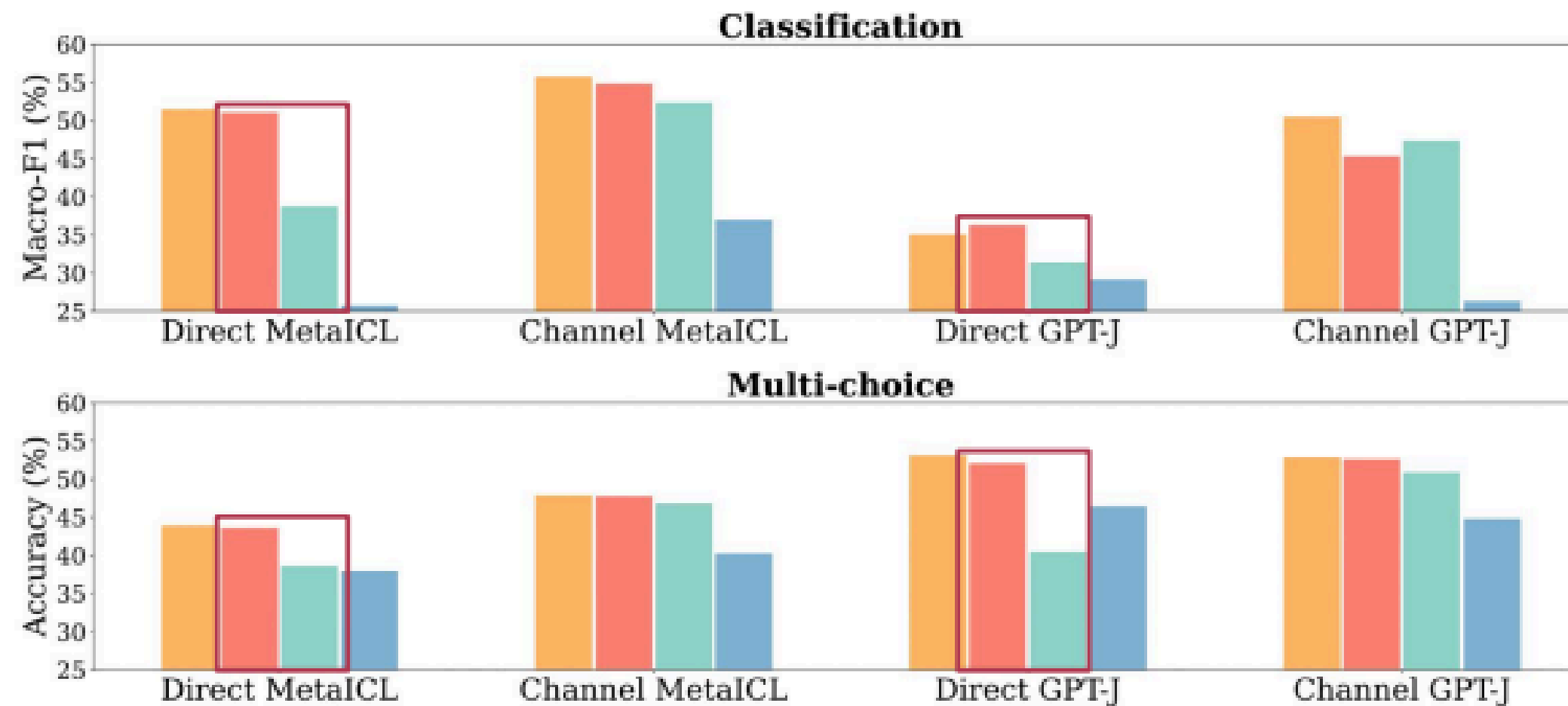
Experimental method:

- Using random labels from an incorrect label space
 1. Demonstrations w/ gold labels (correct label)
 2. Demonstrations w/ random labels (incorrect label)
 3. Demonstrations w/ **incorrect label space**
 4. No demonstrations (zero-shot)

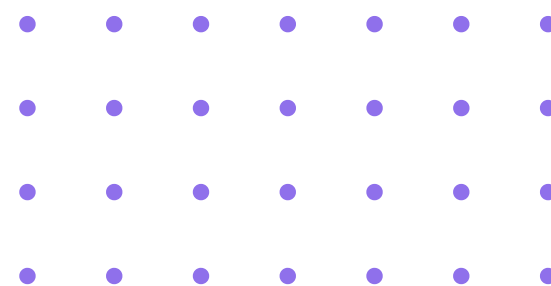


Result

- Labels not in the correct label space result in performance **decreases of up to 16% absolute** in direct models



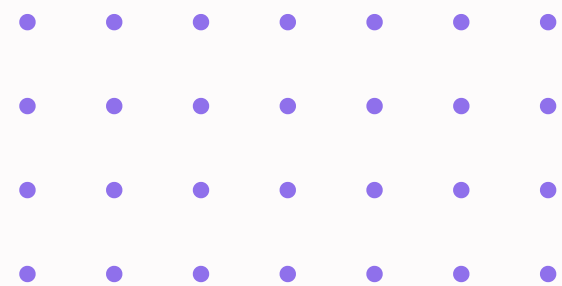
Results of using random English words as labels



Is label space matter?

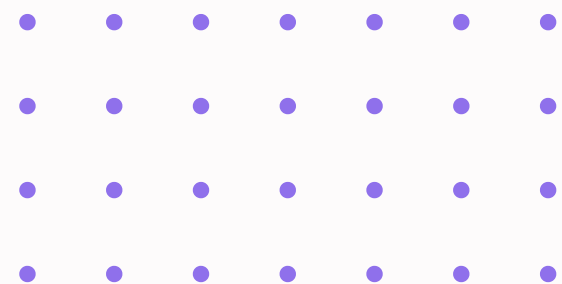
- correct label space **substantially increase** performance in direct models

Takeaways



Aspect 4

**Is format of
prompt matter?**



Input-label pairing

- Remove labels(Y)

- **input (X)**

1. "I love this movie!"
2. "This is the worst day ever."
3. "It rains a lot today."

"The food was terrible and cold."

LM : negative !

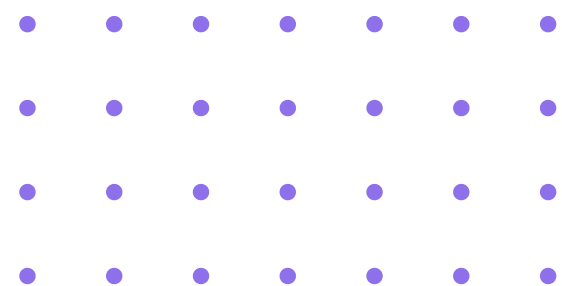
- Remove input text(X)

- **label (Y)**

Positive
Negative
Neutral

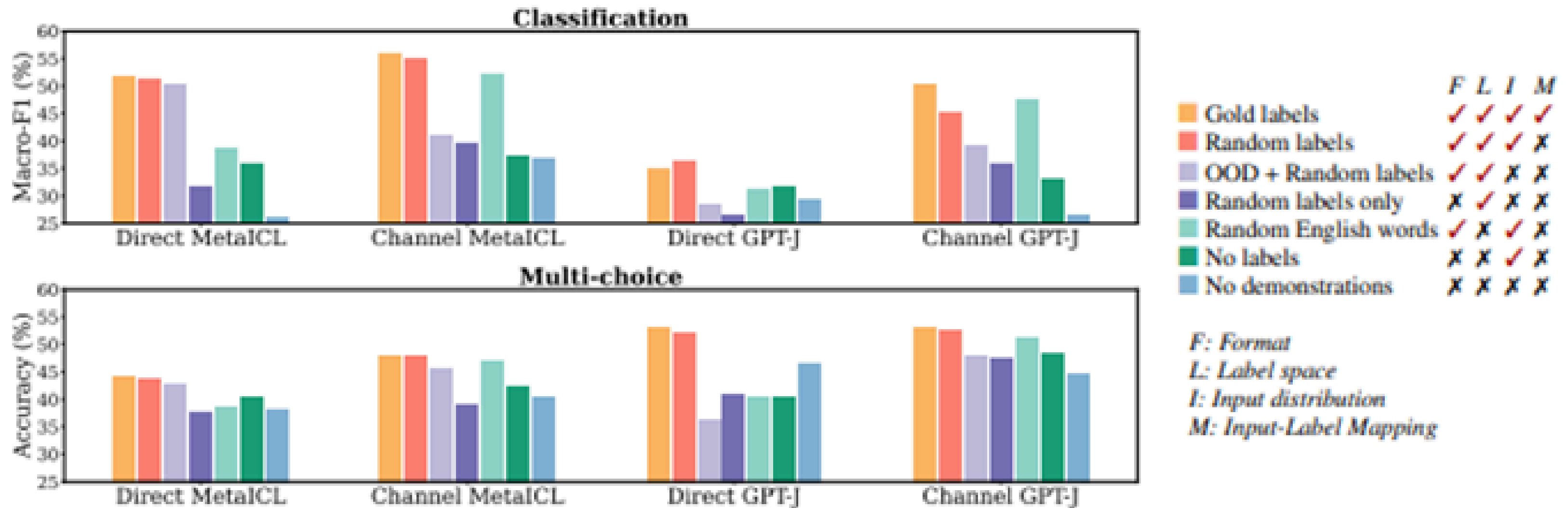
"The food was terrible and cold."

LM : negative !



Result

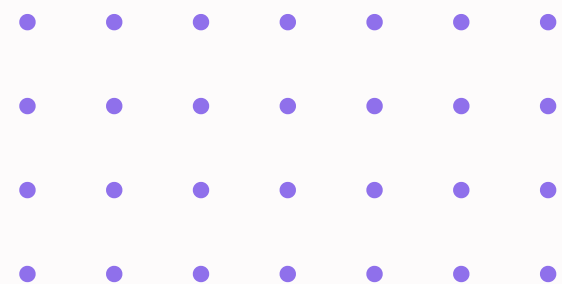
- Not using the input-label format **decreases performance**
- Using OOD inputs and random English words as labels is better than only keeping one part of the format or having no demonstrations



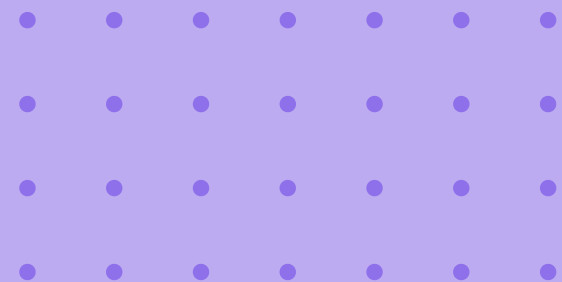
Takeaways

Is the format matter?

- The format of the prompt **significantly increase** performance

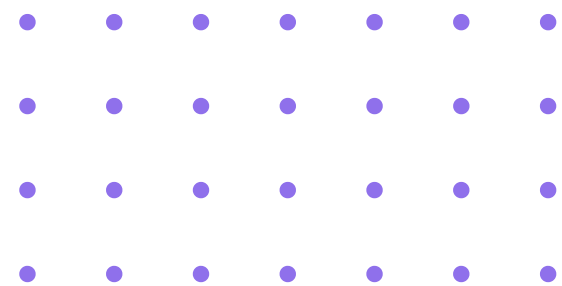


Conclusion



What Makes ICL Work?

- the vital factors:
 - 1.in-distribution input txet
 - 2.label space
 - 3.Input-label pairing format
- not really matter factor:
 - 1.the number of correct labels



Q / A



Questions

- Provide one advantage of In-context Learning over Fine-tuning
- When we do not know the answer (label) of the input text, randomly assigning it a label within the correct label space will result in better or worse performance compared to not using demonstrations?

