Noisy Channel Language Model Prompting for Few-shot Text Classification

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UWNLP Meta AI2

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22ND – 27TH MAY | 60TH MEETING | DUBLIN

LM Prompting

Using a frozen language model for a downstream task

(Brown et al. 2020)

LM Prompting

Using a frozen language model for a downstream task

“Why are boolean values capitalized in Python?”

(Brown et al. 2020)

LM Prompting

Using a frozen language model for a downstream task

“Why are boolean values capitalized in Python?”

<options>

Society & Culture

Computer & Internet

Business & Finance

Entertainment & Music

Politics & Government

⋮

(Brown et al. 2020)

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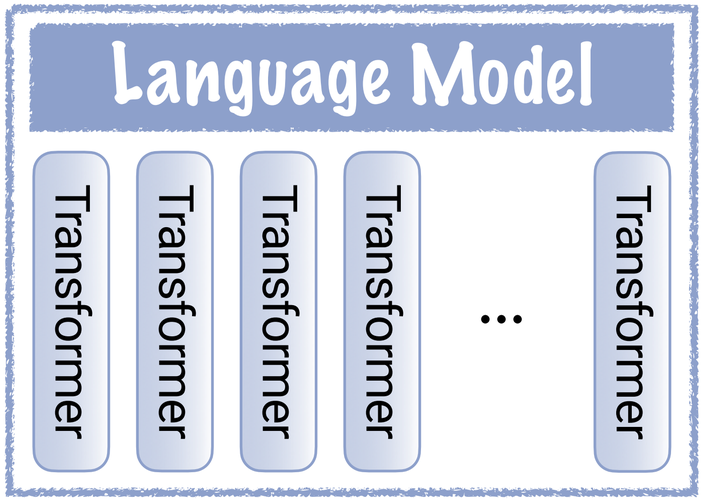

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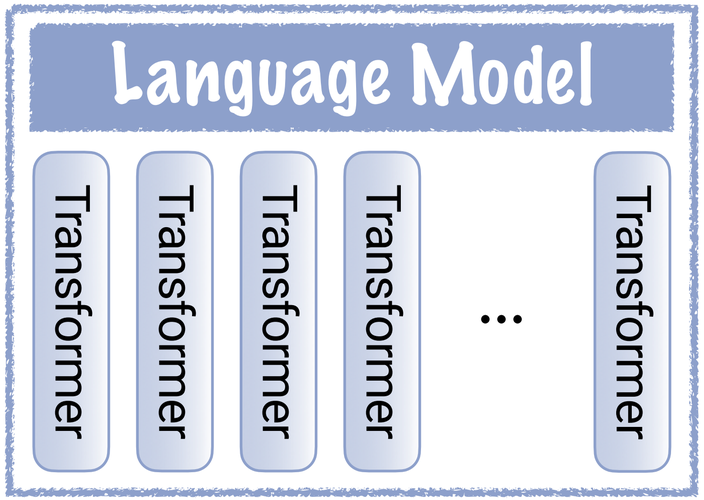

It is about Computer & Internet

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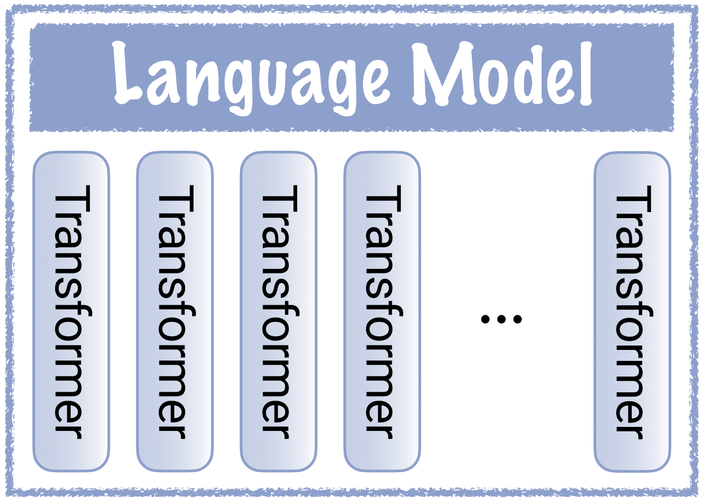

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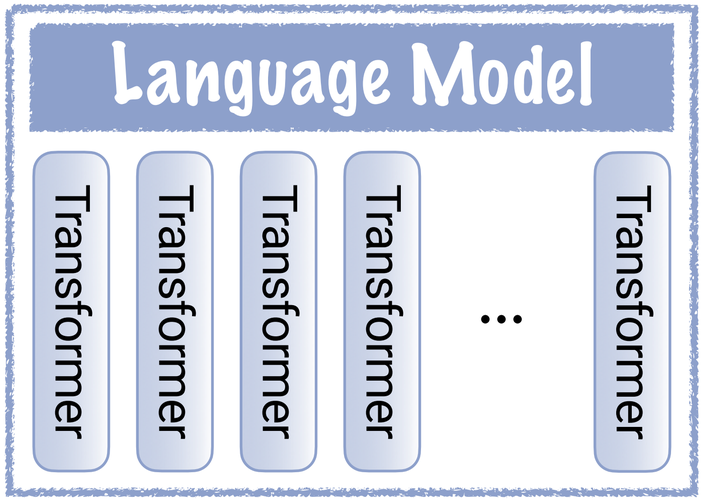

It is about Computer & Internet

V

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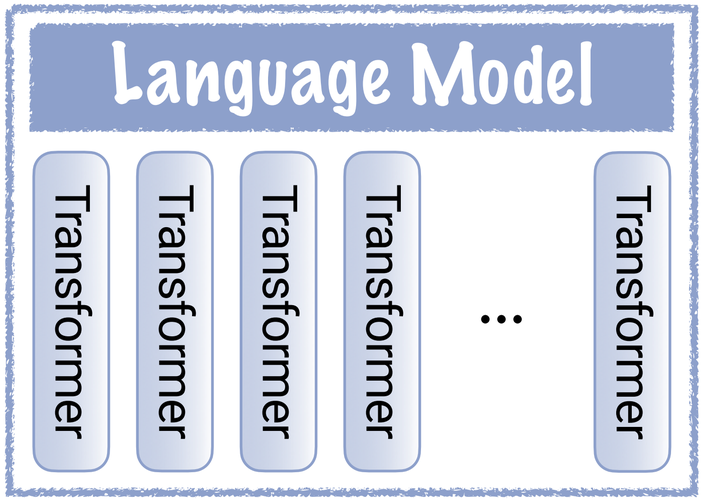

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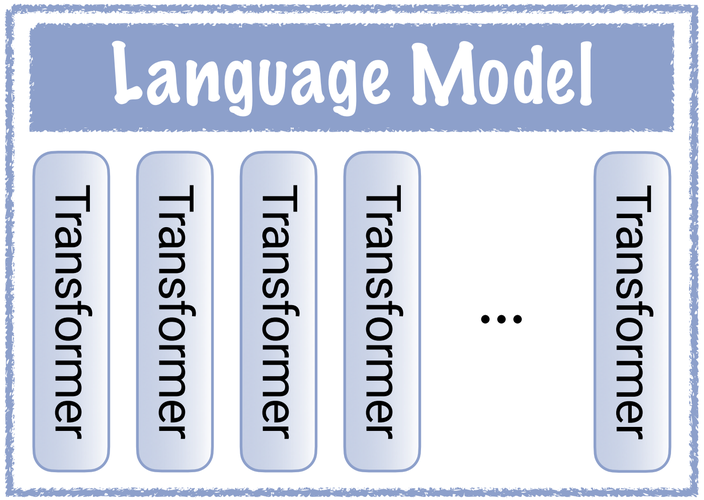

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More variations

(in-context learning, prompt tuning, etc..)

(Brown et al. 2020)

LM Prompting

(Brown et al. 2020)

LM Prompting

(Brown et al. 2020)

Promising results with a 175B model

And by Zhao et al. 2021, Holtzman et al. 2021, Shin et al. 2020, Jiang et al. 2020, Gao et al. 2021, Li & Liang 2021, Lester et al. 2021, etc…

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No or very limited number of trainable params

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LM Prompting

GPT-3

(Brown et al. 2020)

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Instability — high variance

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Low worst-case accuracy

Zhao et al. 2021, Perez et al. 2021, Lu et al. 2021

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How can we do better?

Noisy Channel Approach

Input

Output

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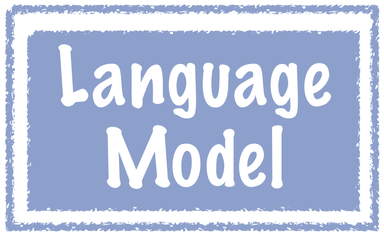

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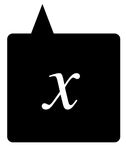

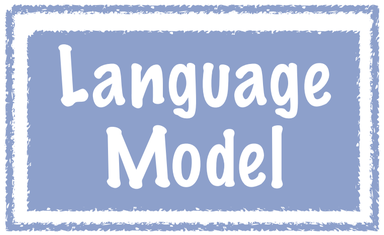

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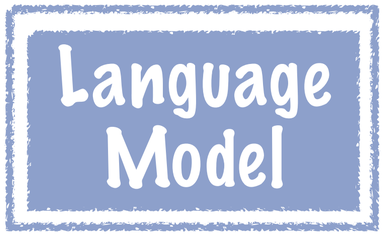

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y

Noisy Channel Approach

Direct	$P(y \mid x)$

Input

Output

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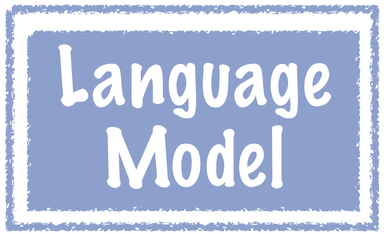

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Noisy Channel Approach

Direct	$P(y \mid x)$

Input

Why are boolean values capitalized in Python?

x

Language Model

Output

It is about Computer & Internet.

y

Noisy channel model:

$$P(y \mid x) = \frac{P(x \mid y)P(y)}{P(x)} \propto P(x \mid y)P(y)$$

Noisy Channel Approach

Input

Output

Direct $P(y|x)$

Why are boolean values capitalized in Python?

x

Language Model

It is about Computer & Internet.

y

Channel $P(x|y)P(y) \propto P(x|y)$

Noisy channel model:

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Method

x : Test input
y : Test output
$(x_1, y_1), \cdots, (x_k, y_k)$: Training data

Direct

Channel

Please see the paper for details!

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Direct

$\text{argmax}_{y \in \mathcal{Y}} P(y \mid x)$

Zero-shot

Channel

$\text{argmax}_{y \in \mathcal{Y}} P(x \mid y)$

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$\text{argmax}_{y \in \mathcal{Y}} P(y \mid x_1, y_1, \cdots, x_k, y_k, x)$	In-context learning	$\text{argmax}_{y \in \mathcal{Y}} P(x \mid y_1, x_1, \cdots, y_k, x_k, y)$

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$\text{argmax}_{y \in \mathcal{Y}} P(y \mid \mathbf{V}_{\text{prompt}}, x)$	Prompt tuning (Lester et al. 2021)	$\text{argmax}_{y \in \mathcal{Y}} P(x \mid \mathbf{V}_{\text{prompt}}, y)$

($\mathbf{V}_{\text{prompt}}$ is trainable)

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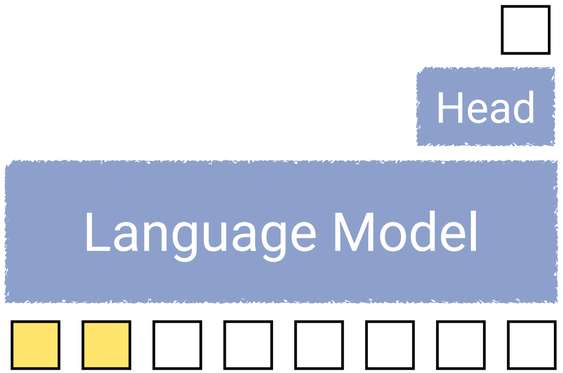

Prompt tuning (Lester et al. 2021)

(Yellow box = trainable)

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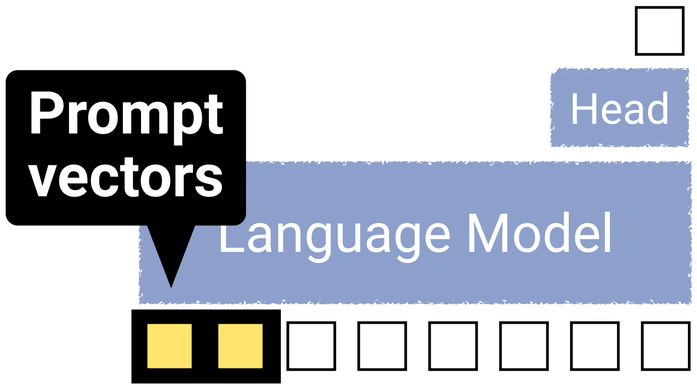

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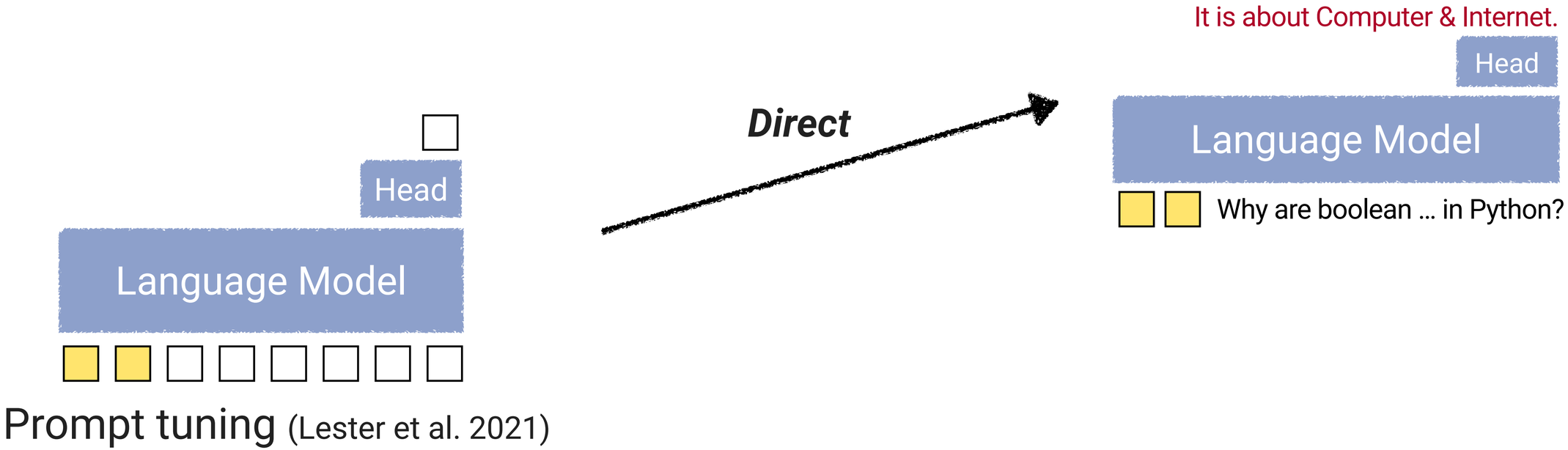

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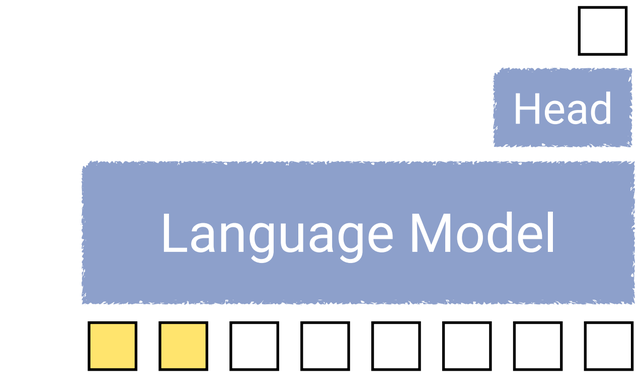

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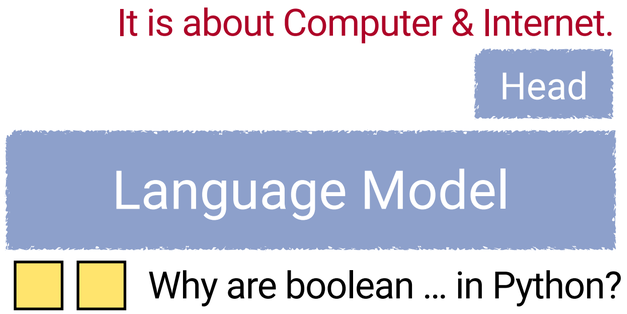

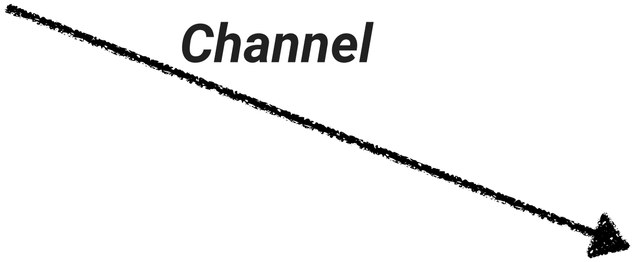

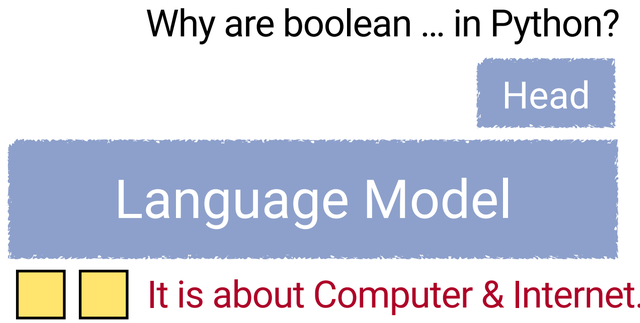

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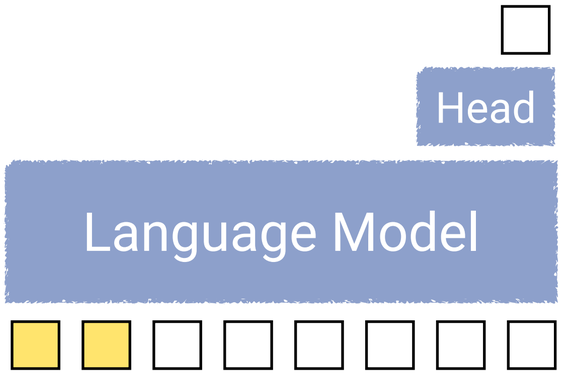

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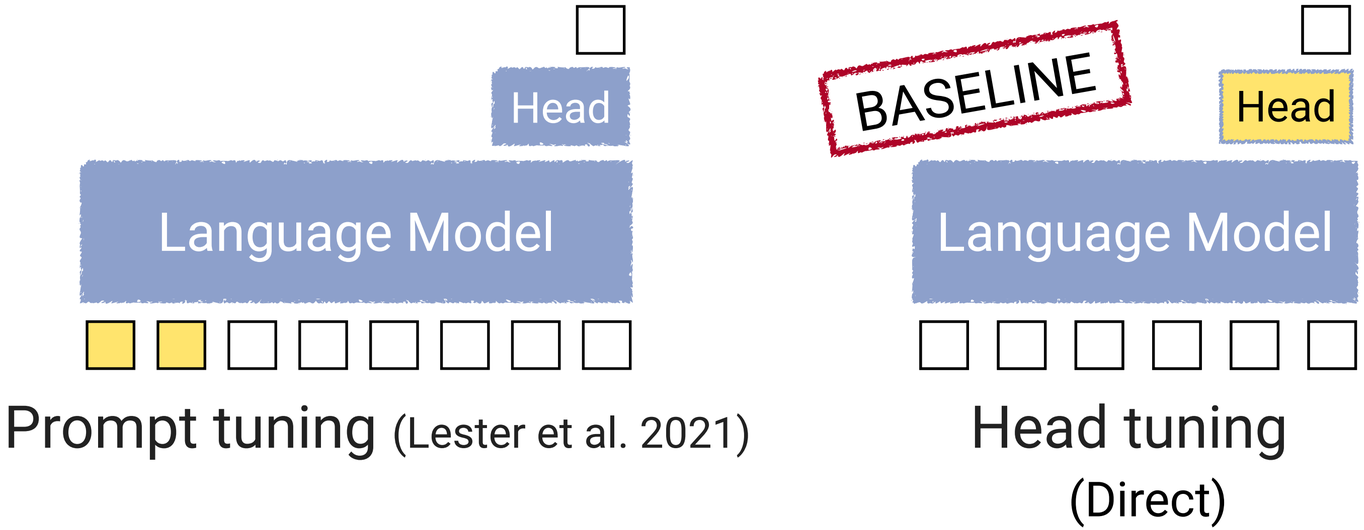

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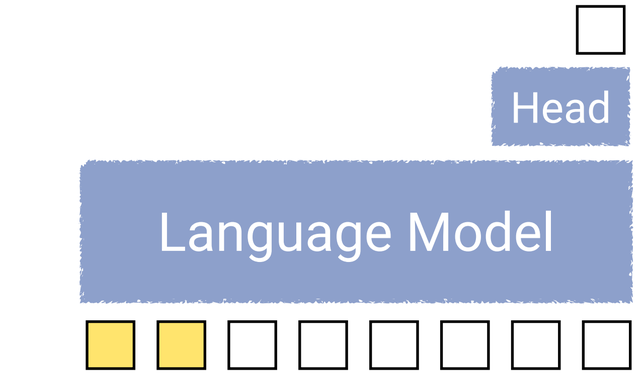

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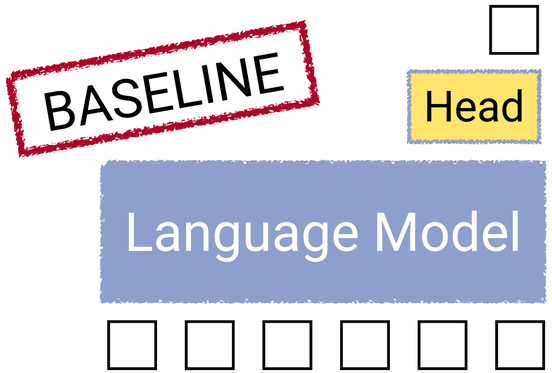
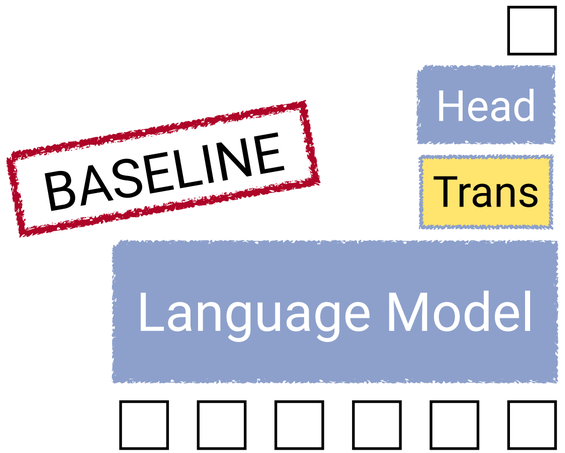


Head tuning
(Direct)



Transformation tuning
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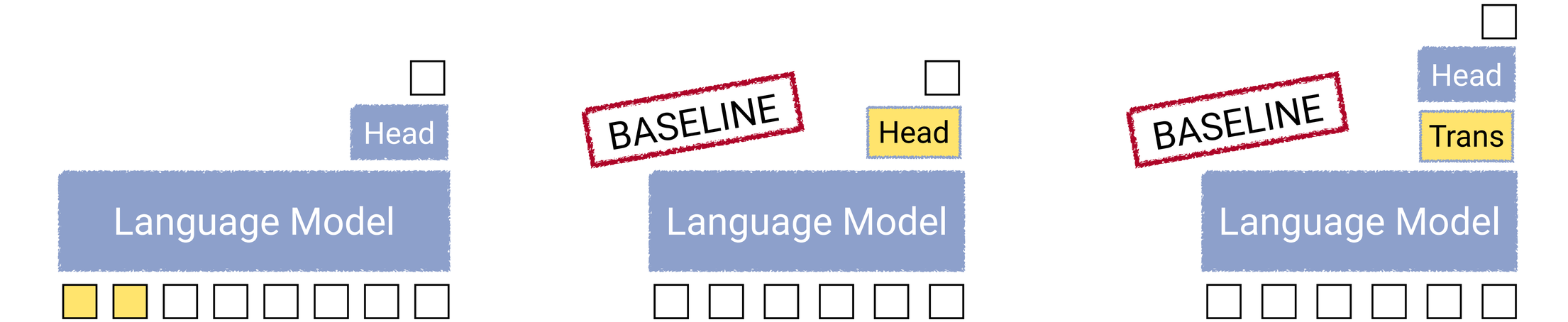

Prompt tuning (Lester et al. 2021)

Head tuning
(Direct)

Transformation tuning
(Direct)

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tune ~0.002% of the total parameters

Why would it work better?

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1. Few-shot learning

Noisy channel models are shown to work better in a **few-shot** setup — theoretically (Ng and Jordan, 2002) and empirically (Ding and Gimpel, 2019)

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Direct The company anticipated its operating profit to improve. → Positive

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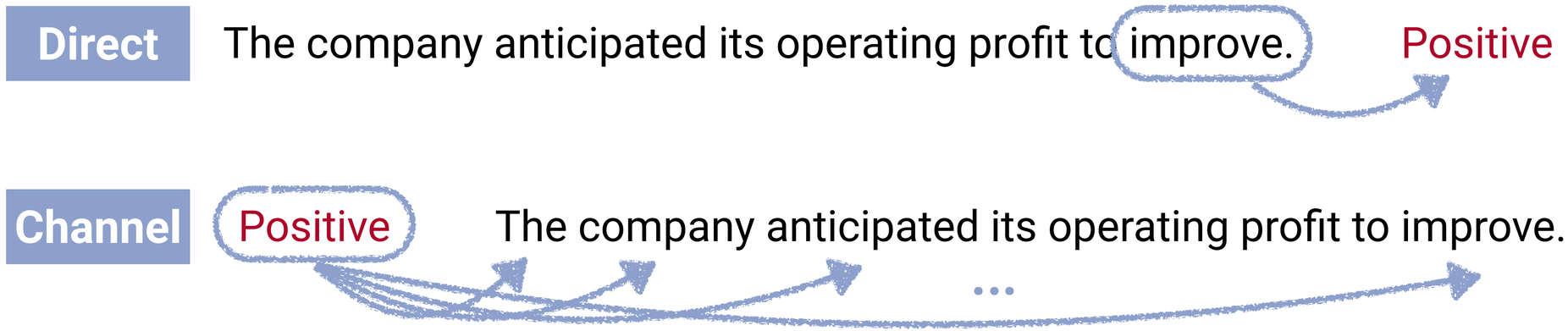

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2. Distribution shifts

Noisy channel models are shown to work better under **distribution shifts** (Yogtama et al. 2017, Lewis and Fan, 2018)

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Pre-training

(Typical) language model

Testing

(input, output) pair
on a downstream task

1) LM prompting always needs to deal with **distribution shifts**

Why would it work better?

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Noisy channel models are shown to work better under **distribution shifts** (Yogtama et al. 2017, Lewis and Fan, 2018)

1) LM prompting always needs to deal with **distribution shifts**

2) Channel model may be better at predicting **unseen** labels

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$$\mathscr{D}_{\text{train}} = \{(x_i, y_i)\}_{i=1}^{N} \qquad \{(y_i)\}_{i=1}^{N} = \{\text{positive, negative}\}$$

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Panostaja did not disclose the purchase price. 

neutral

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neutral ←*likely very low*

1) LM prompting always needs to deal with **distribution shifts**

2) Channel model may be better at predicting **unseen** labels

Why would it work better?

2. Distribution shifts

Noisy channel models are shown to work better under **distribution shifts** (Yogtama et al. 2017, Lewis and Fan, 2018)

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(experiments showing this later!)

Experimental Setup

Dataset	Task	# labels
SST-2	Sentiment analysis (movie)	2
SST-5	Sentiment analysis (movie)	5
MR	Sentiment analysis (movie)	2
CR	Sentiment analysis (electronics)	2
Amazon	Sentiment analysis (Amazon)	5
Yelp	Sentiment analysis (Yelp)	5
TREC	Question classification (answer type)	6
AGNews	News classification (topic)	4
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DBPedia	Ontology classification	14
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GPT-2
LARGE

(# params = 770M)

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Training data: K=16

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GPT-2 LARGE (# params = 770M)

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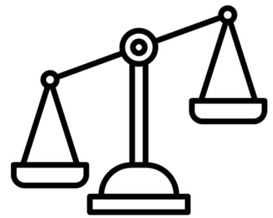

No Guarantee

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GPT-2 LARGE (# params = 770M)

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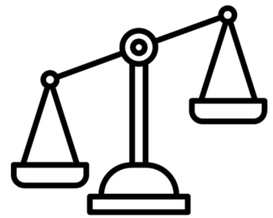

No Guarantee

80 different runs

(4 x 

, 5 x 
, 4 x 
)

label words *data* *train*

Results – Prompt tuning setup

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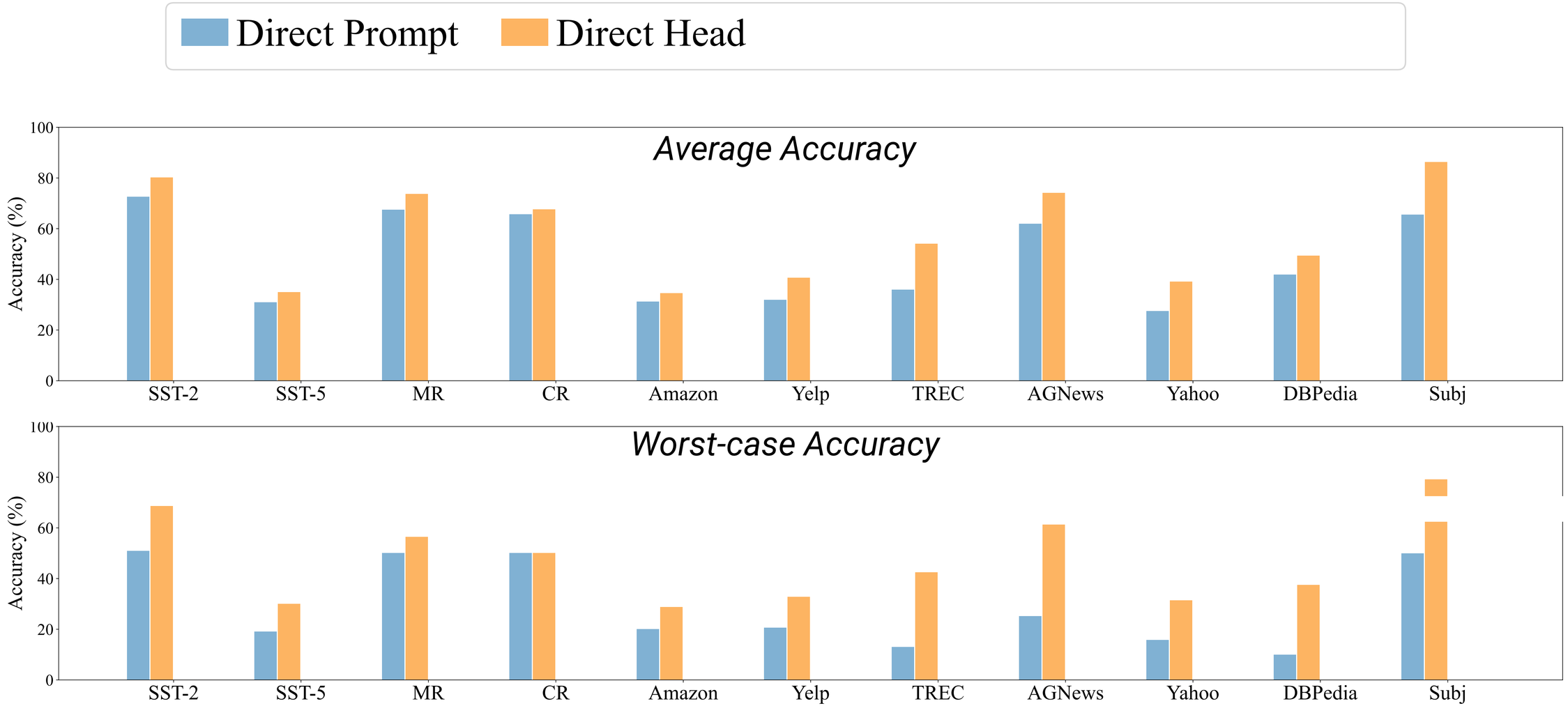

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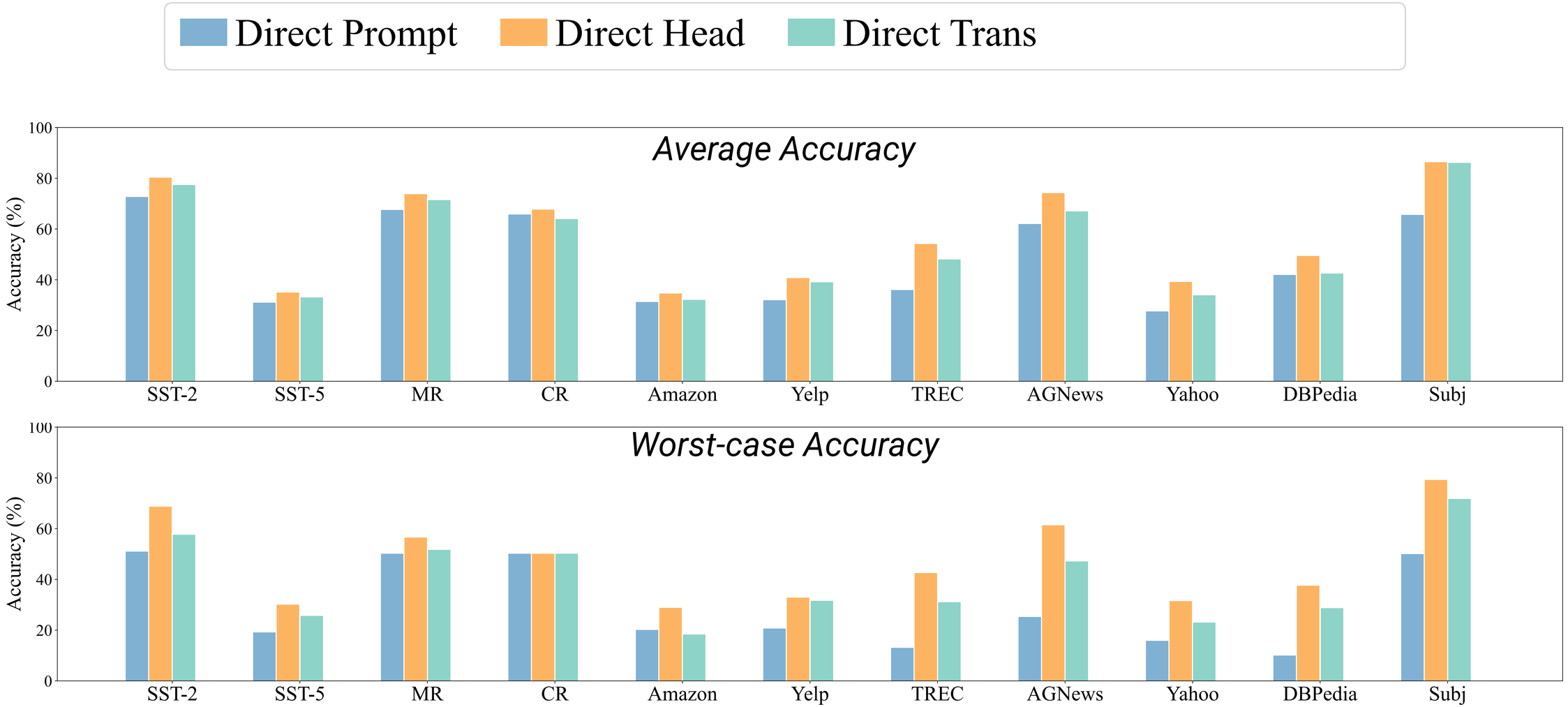

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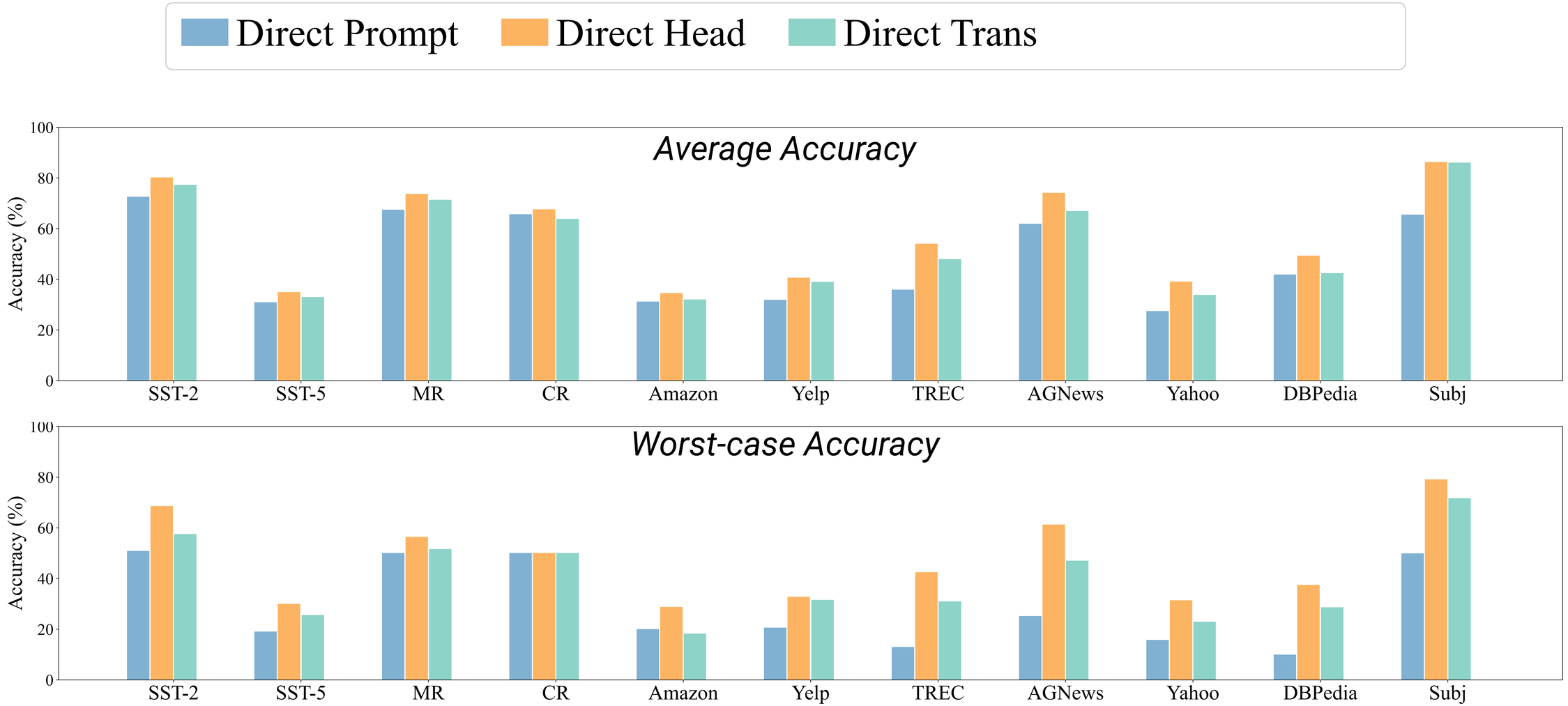
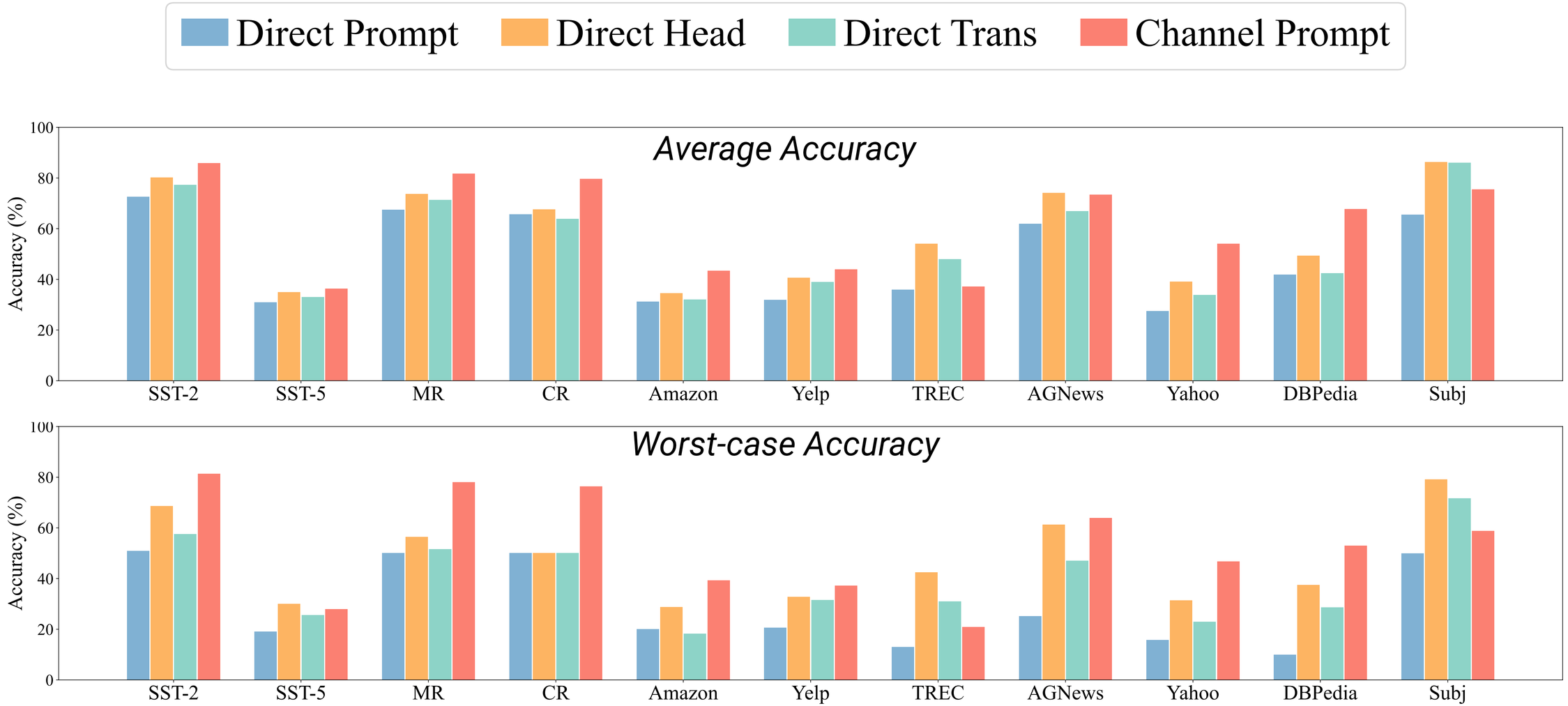


Direct Head Tuning is a powerful baseline

Results – Prompt tuning setup



Channel Prompt Tuning outperforms Direct models

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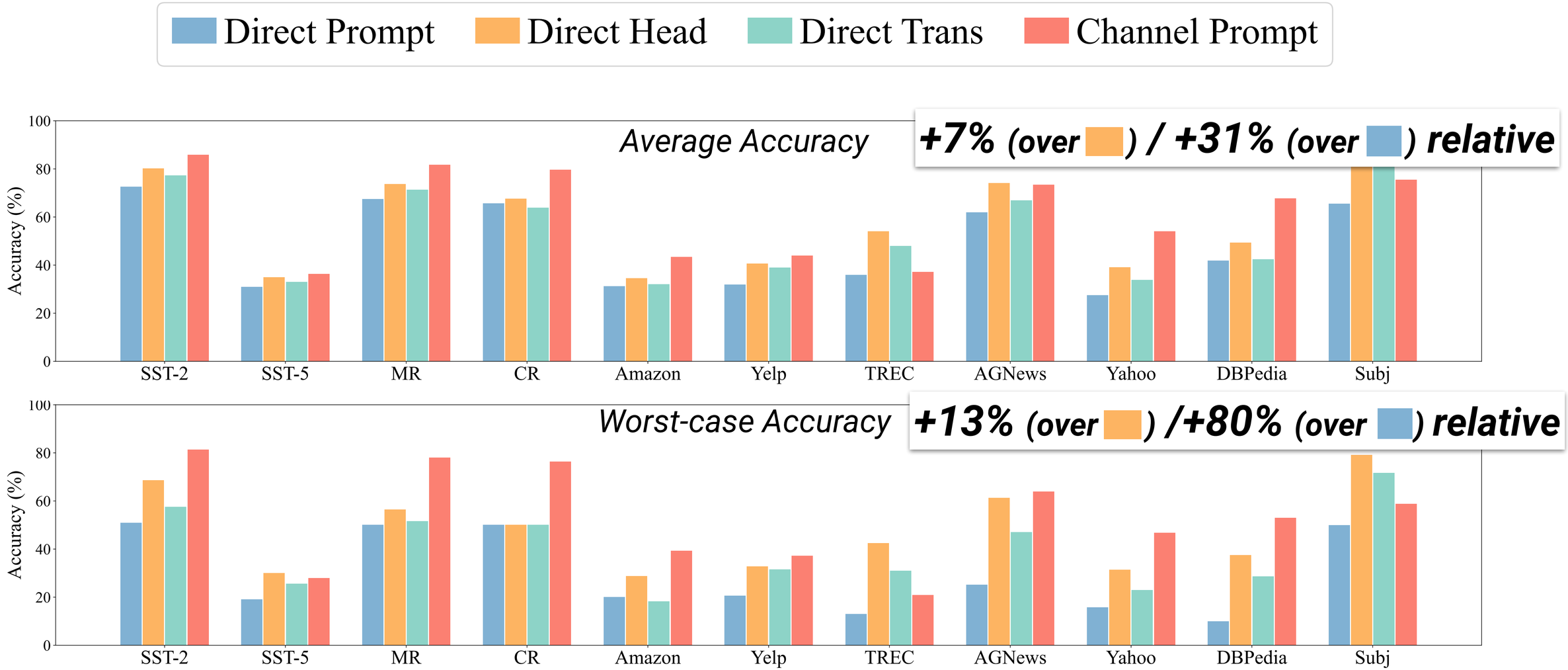

Channel Prompt Tuning outperforms Direct models
(more significantly in worst-case accuracy)

Ablations

Impact of imbalance in training data

Ablations

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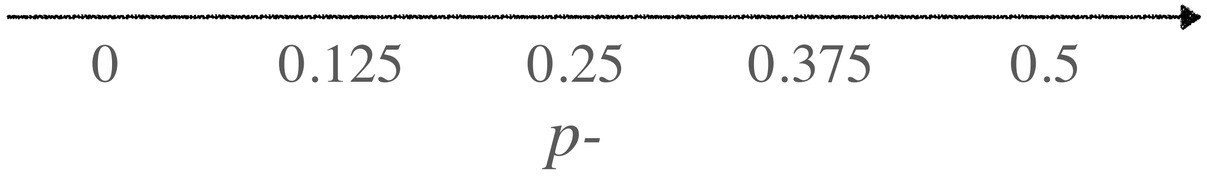
Binary classification datasets

Ablations

Impact of imbalance in training data

Binary classification datasets



Ablations

Impact of imbalance in training data

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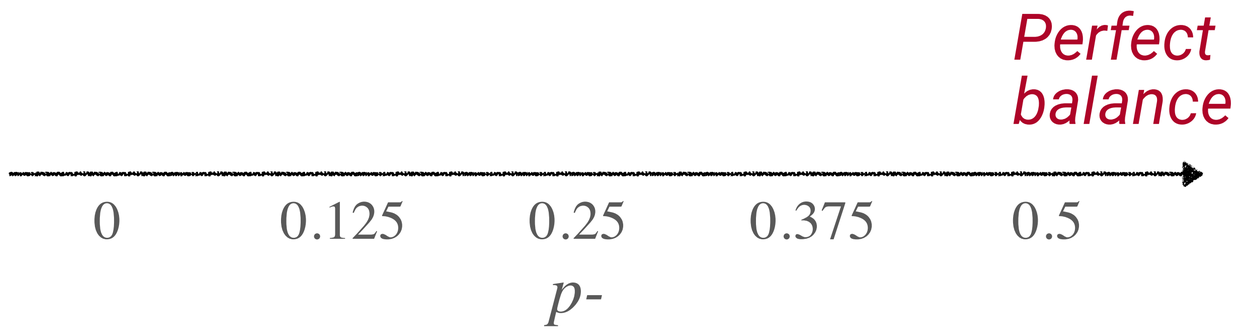

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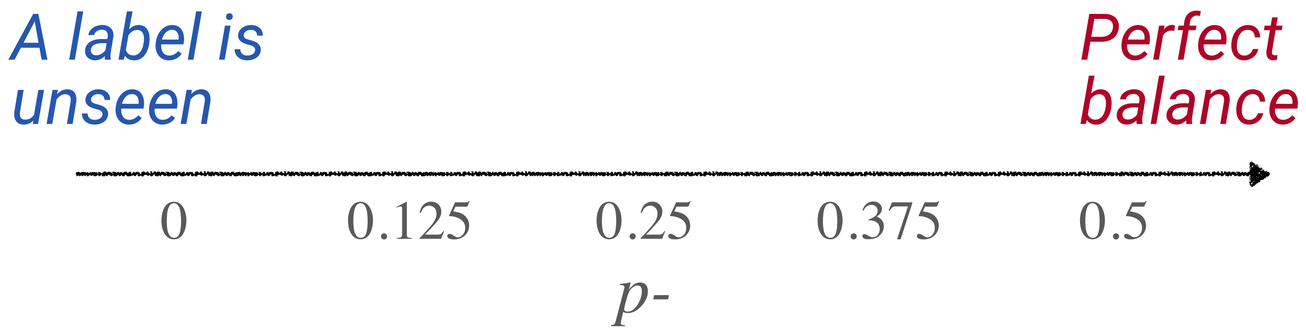

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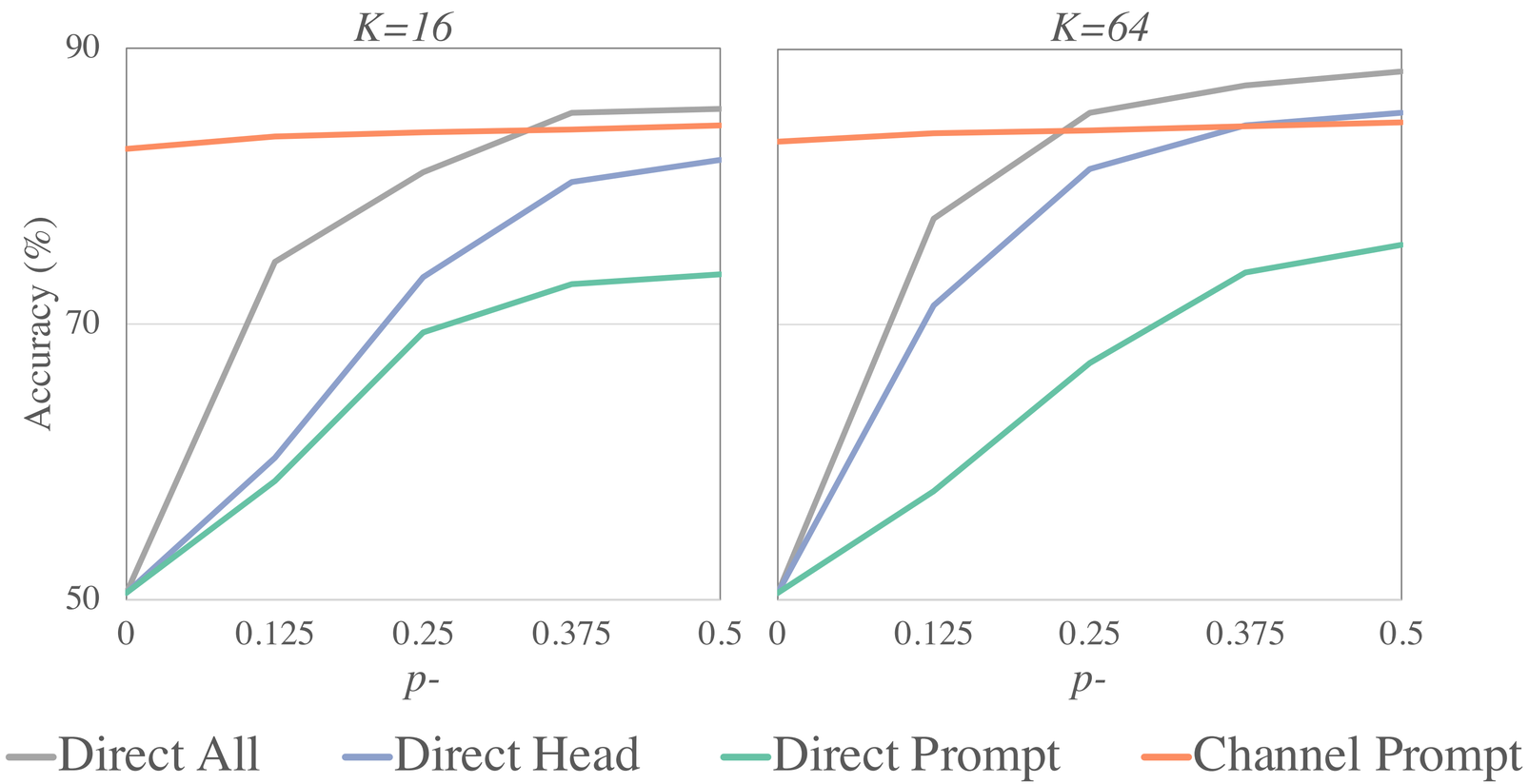

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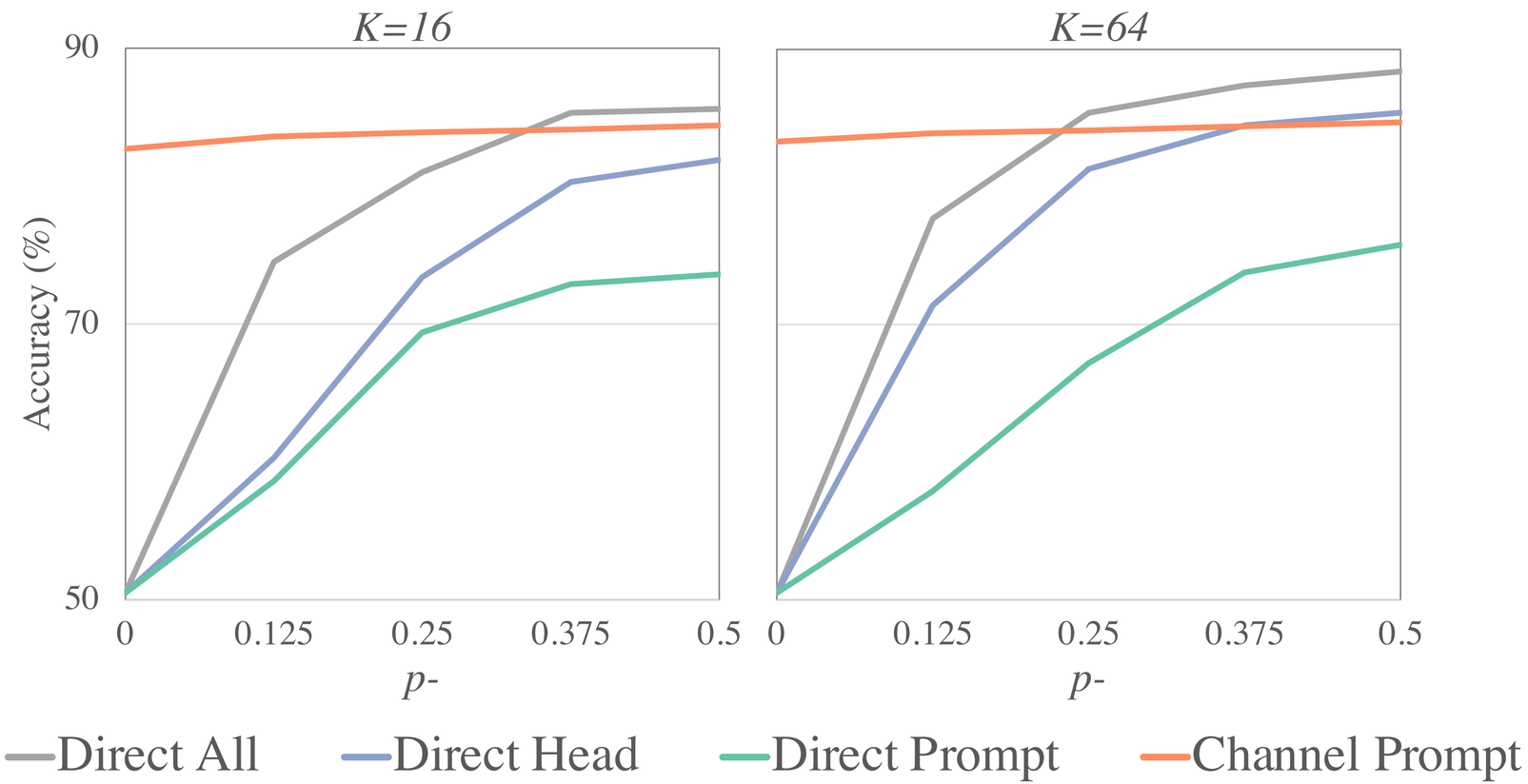
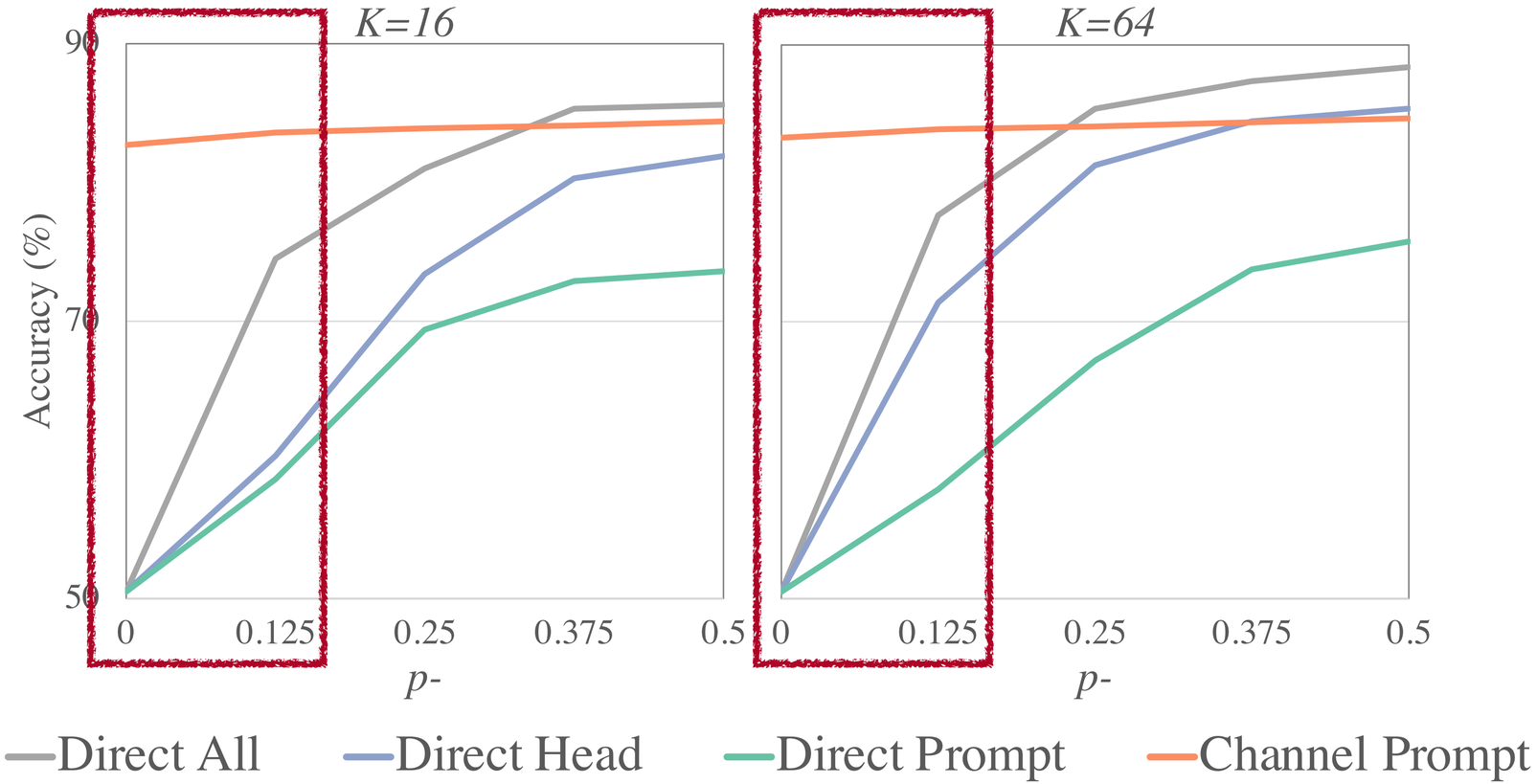


Channel models are much less sensitive to imbalance in training data

Ablations

Impact of imbalance in training data



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Channel models do well even with unseen labels

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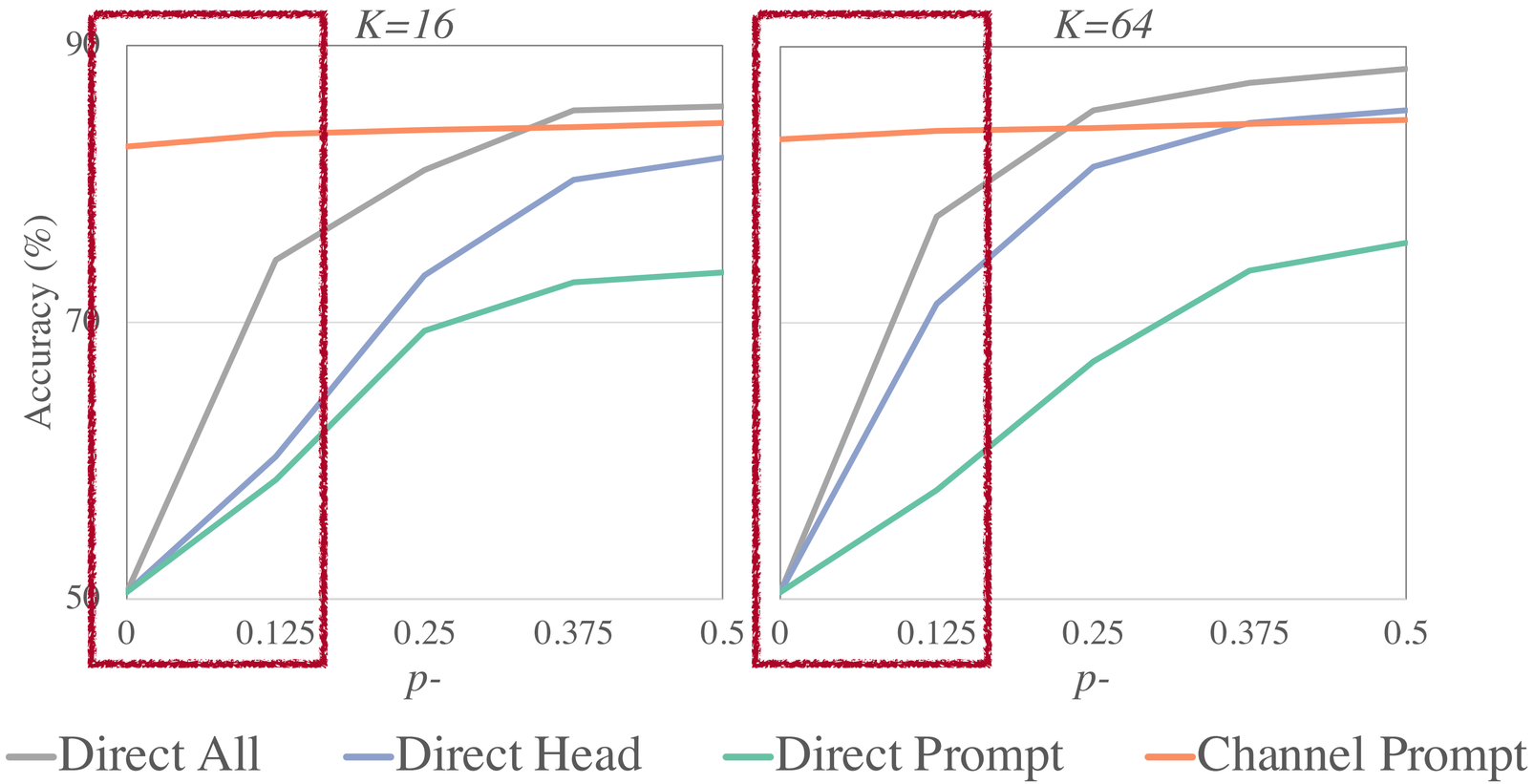

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Channel models do well even with unseen labels

(Likely because labels are conditioning variables)

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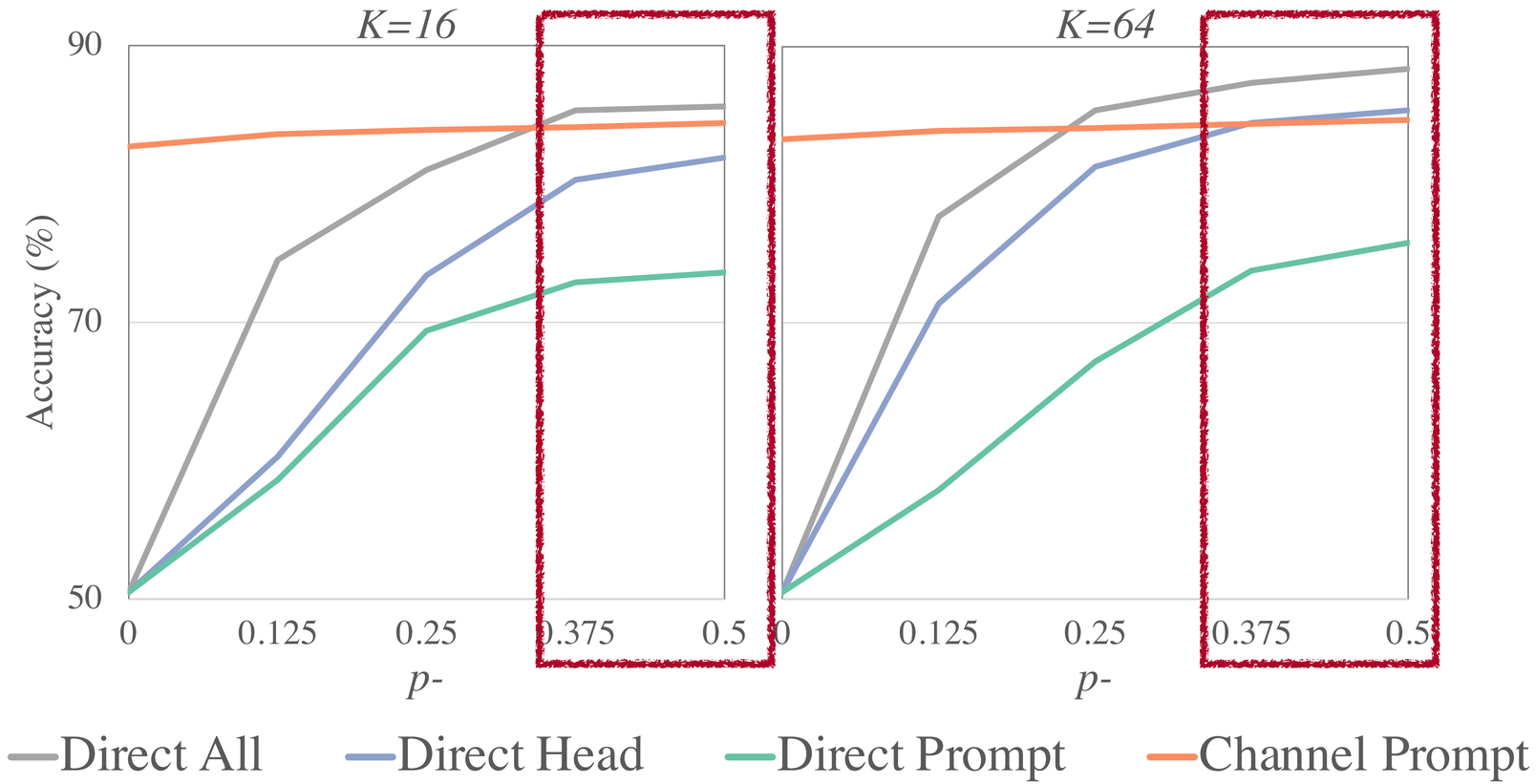

Direct models can be better with perfect balanced data

Ablations

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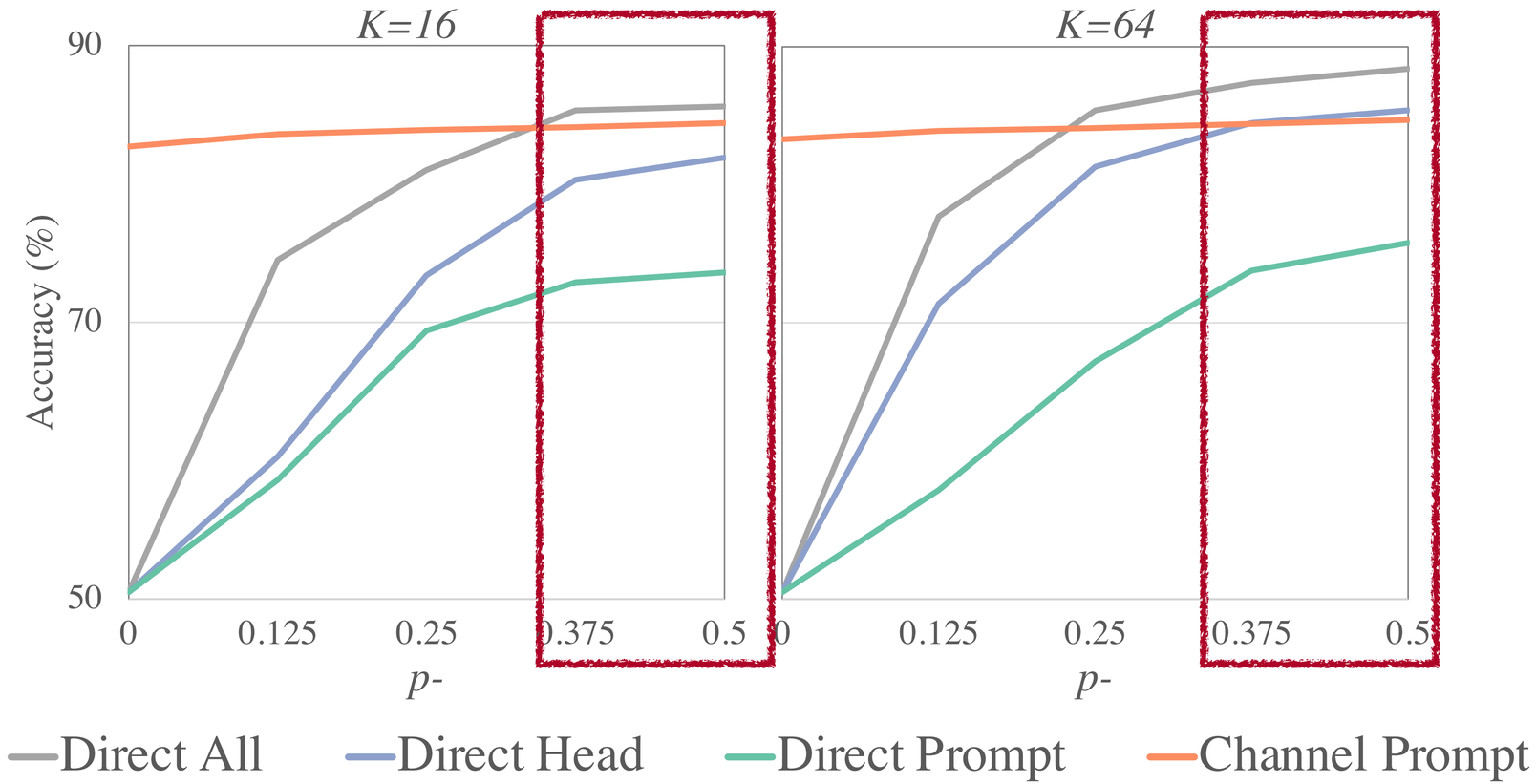

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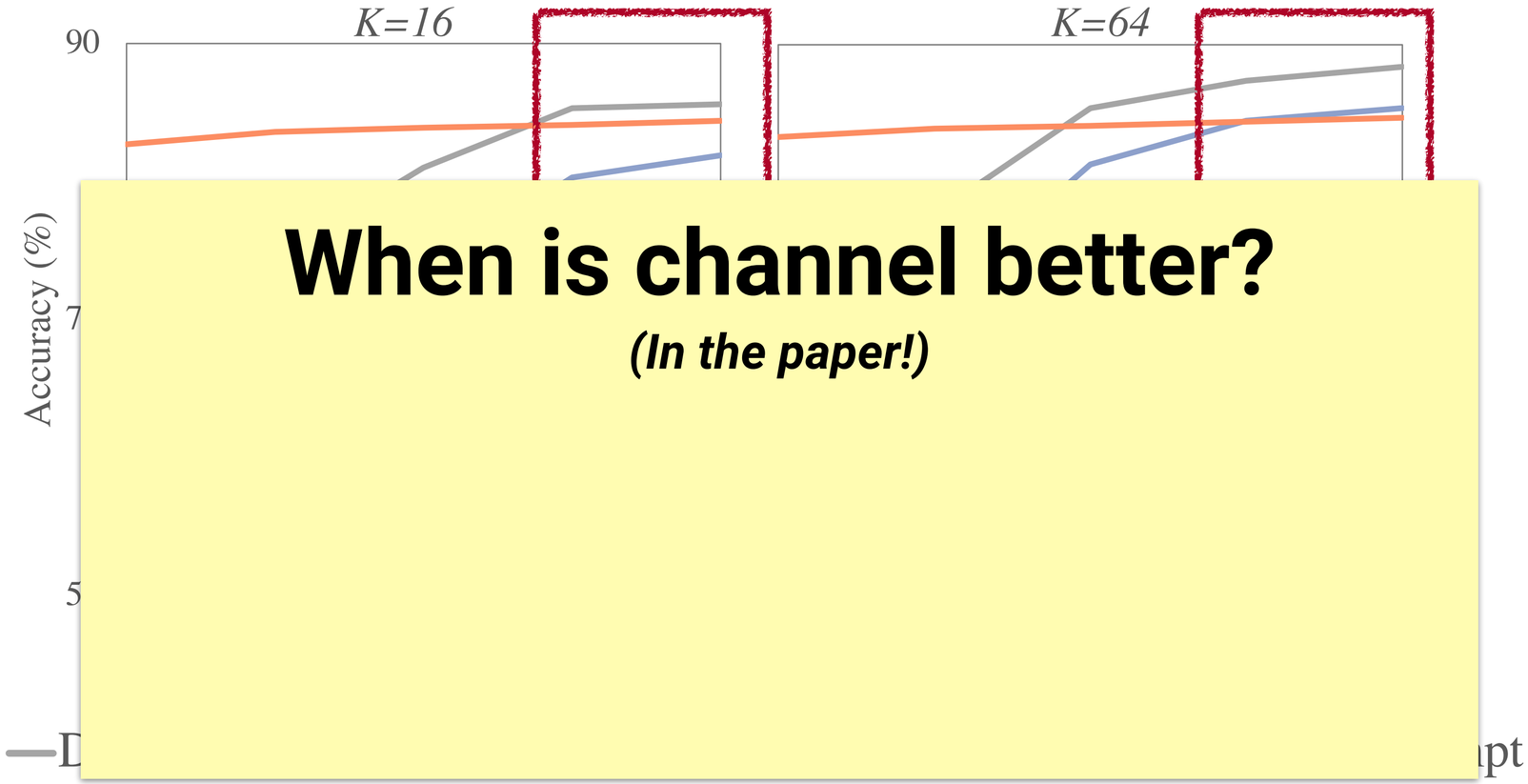

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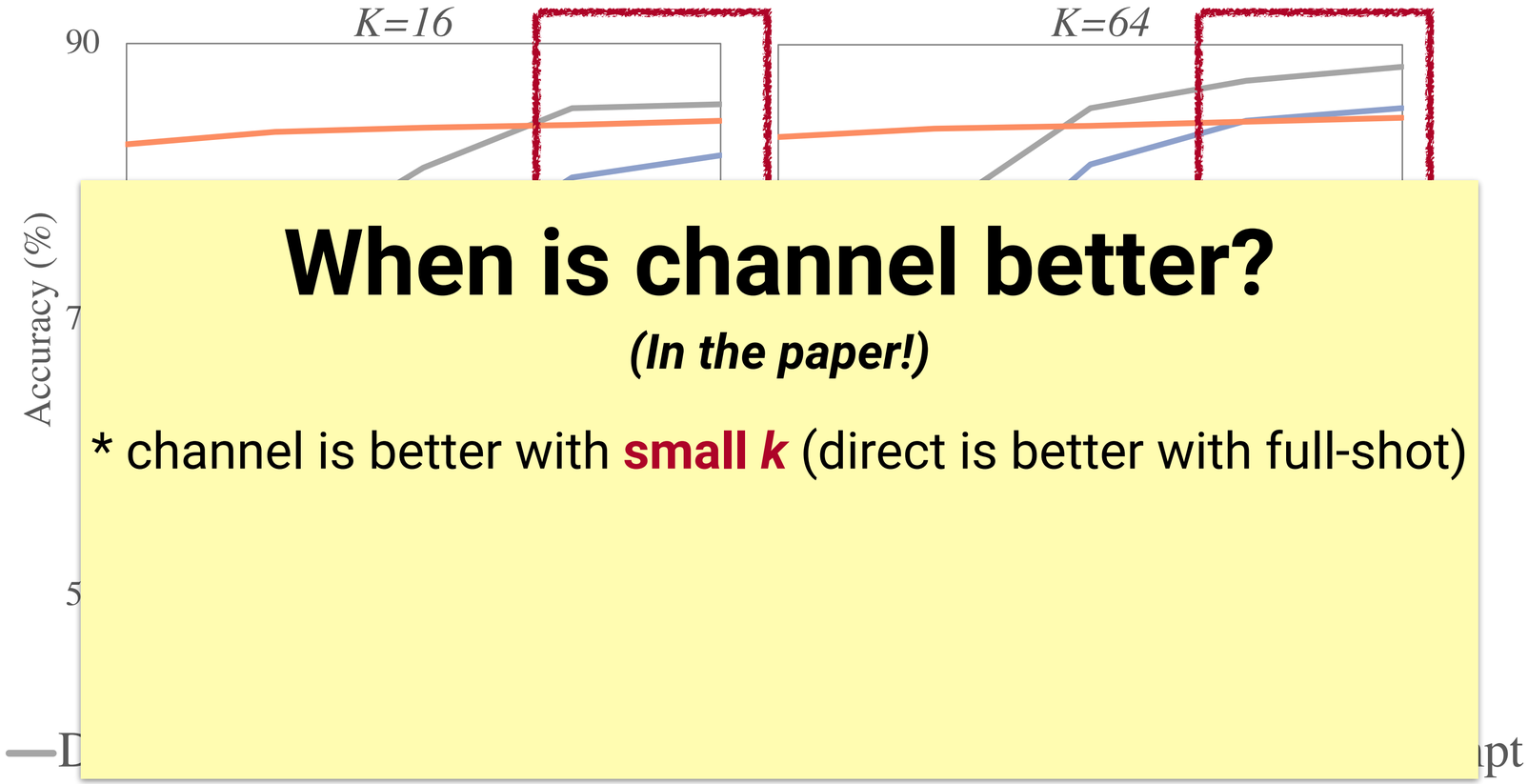

When is channel better?

(In the paper!)

* channel is better with **small *k*** (direct is better with full-shot)

Direct models can be better with perfect balanced data

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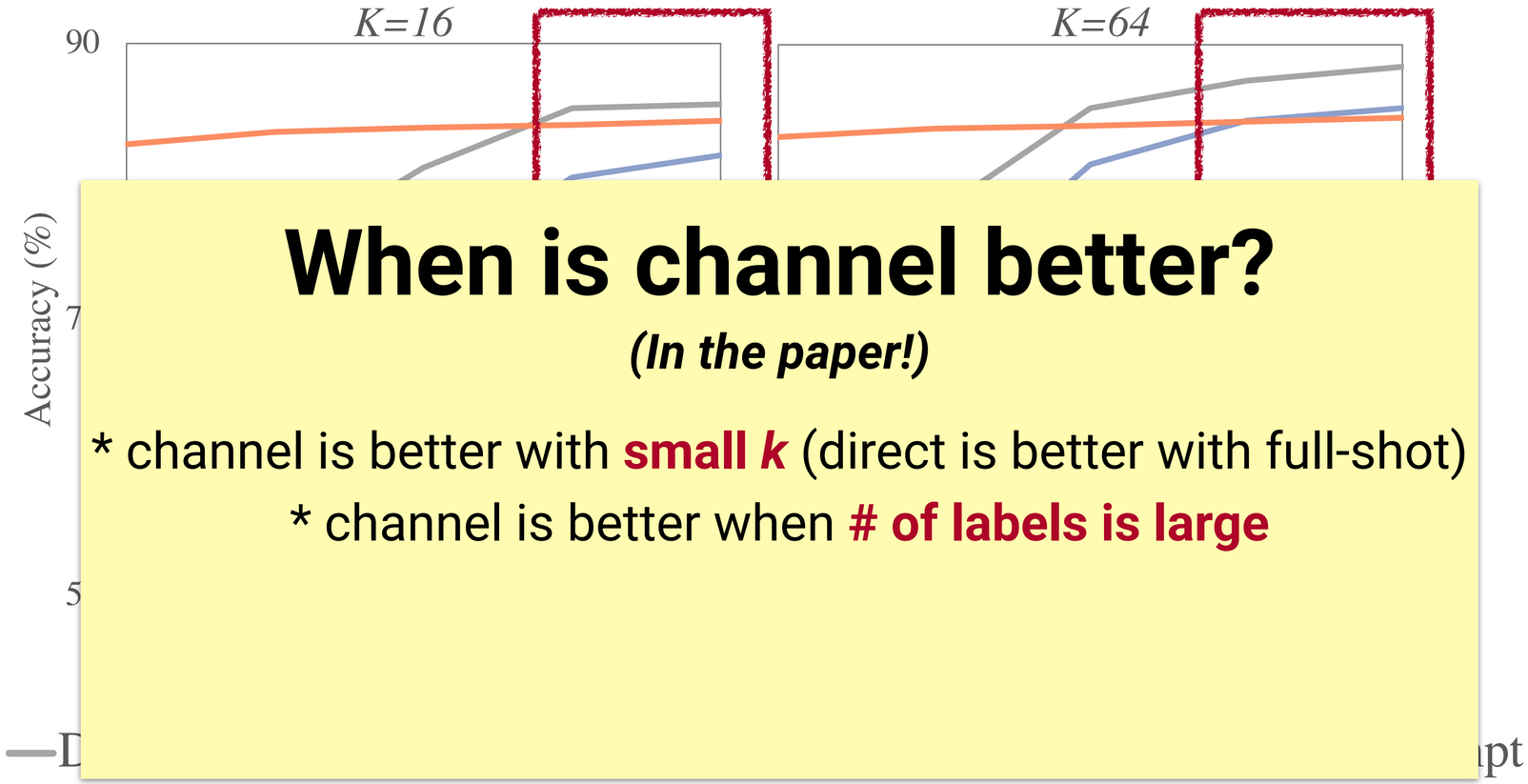

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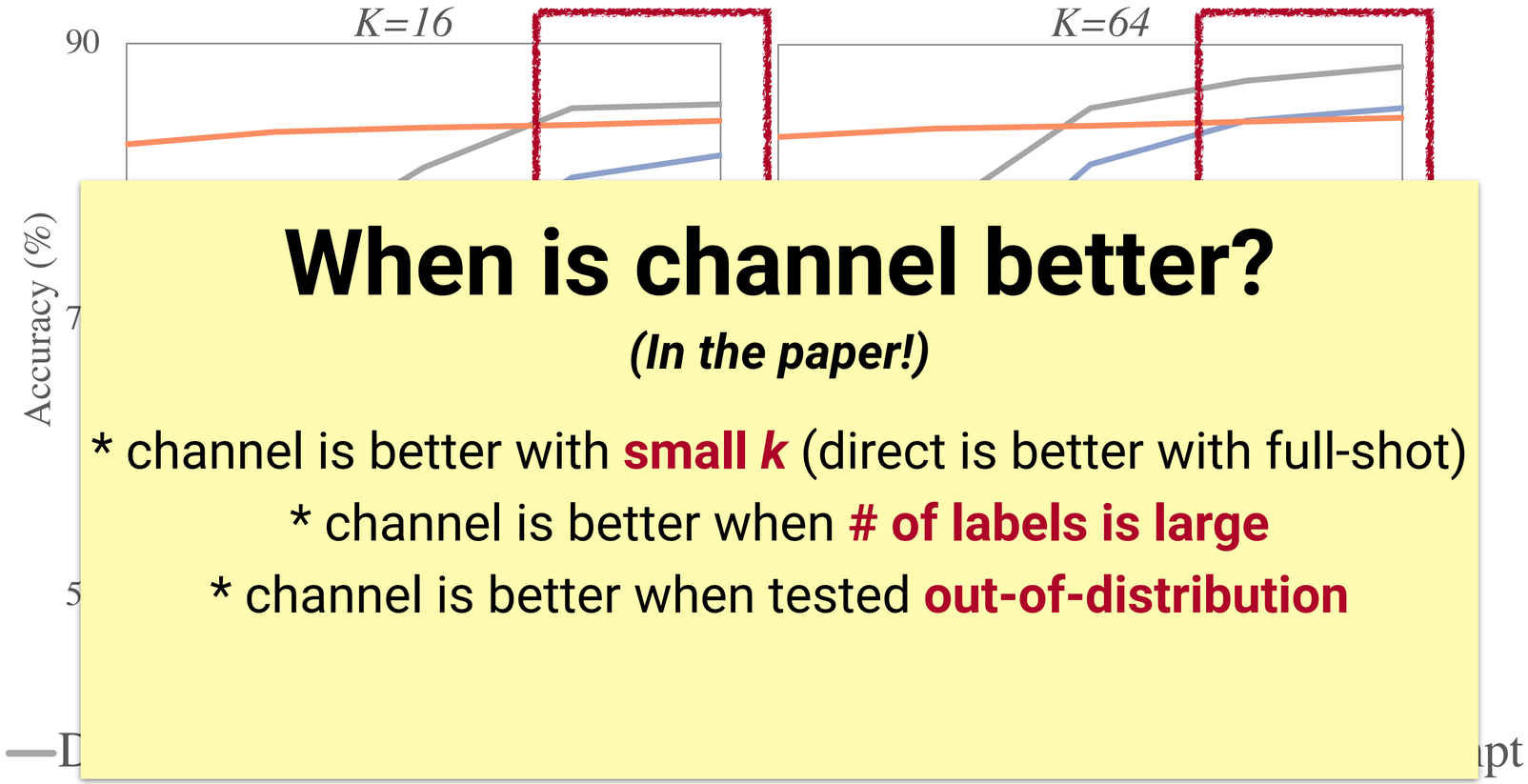

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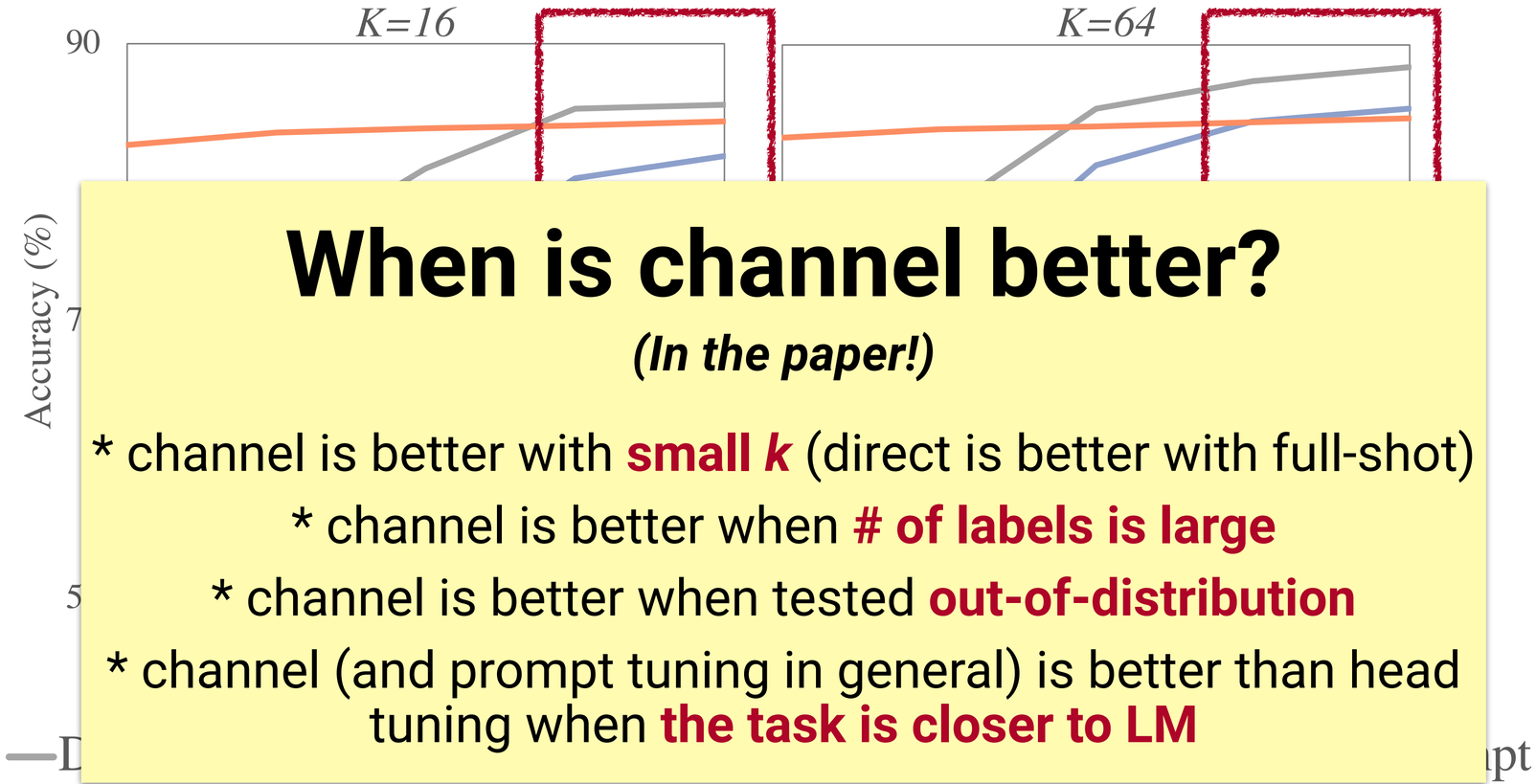

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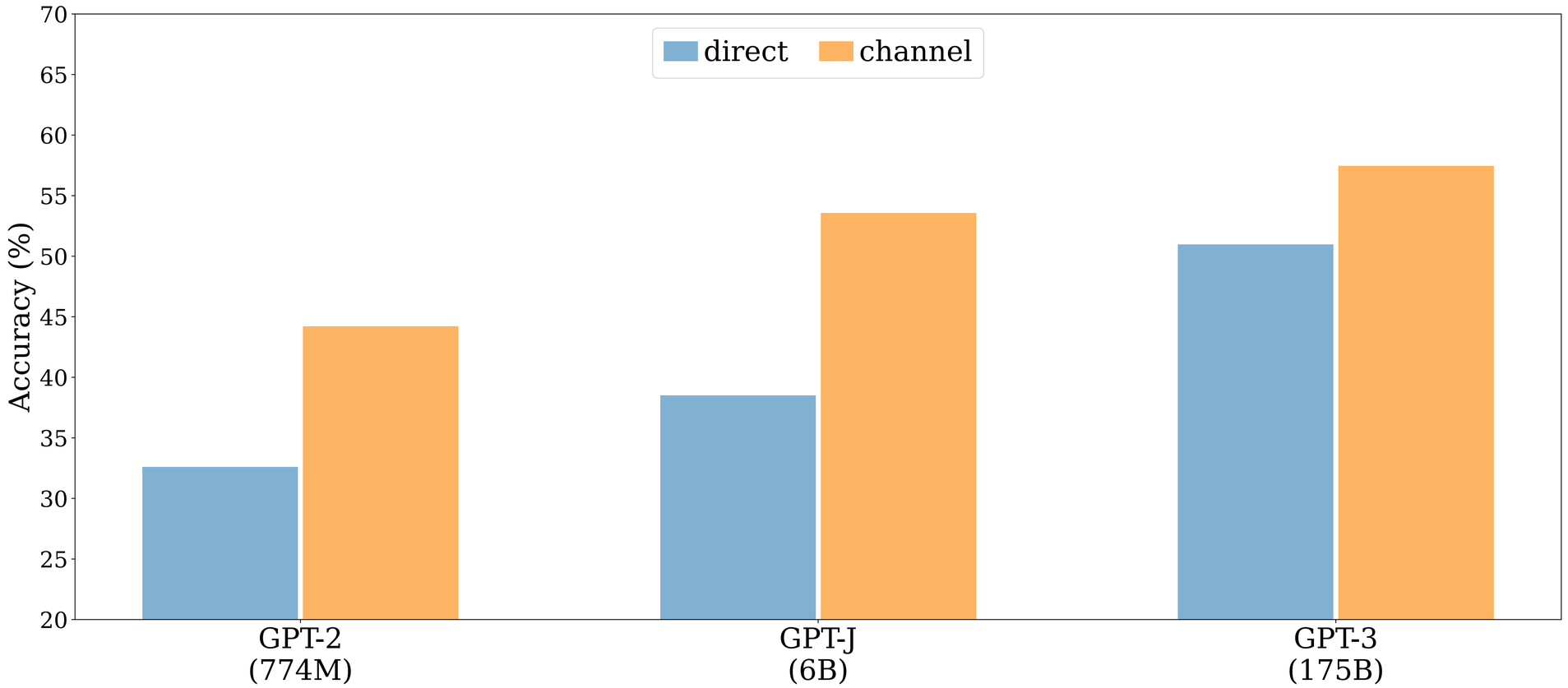
* channel (and prompt tuning in general) is better than head tuning when **the task is closer to LM**

Direct models can be better with perfect balanced data

Extension to larger models

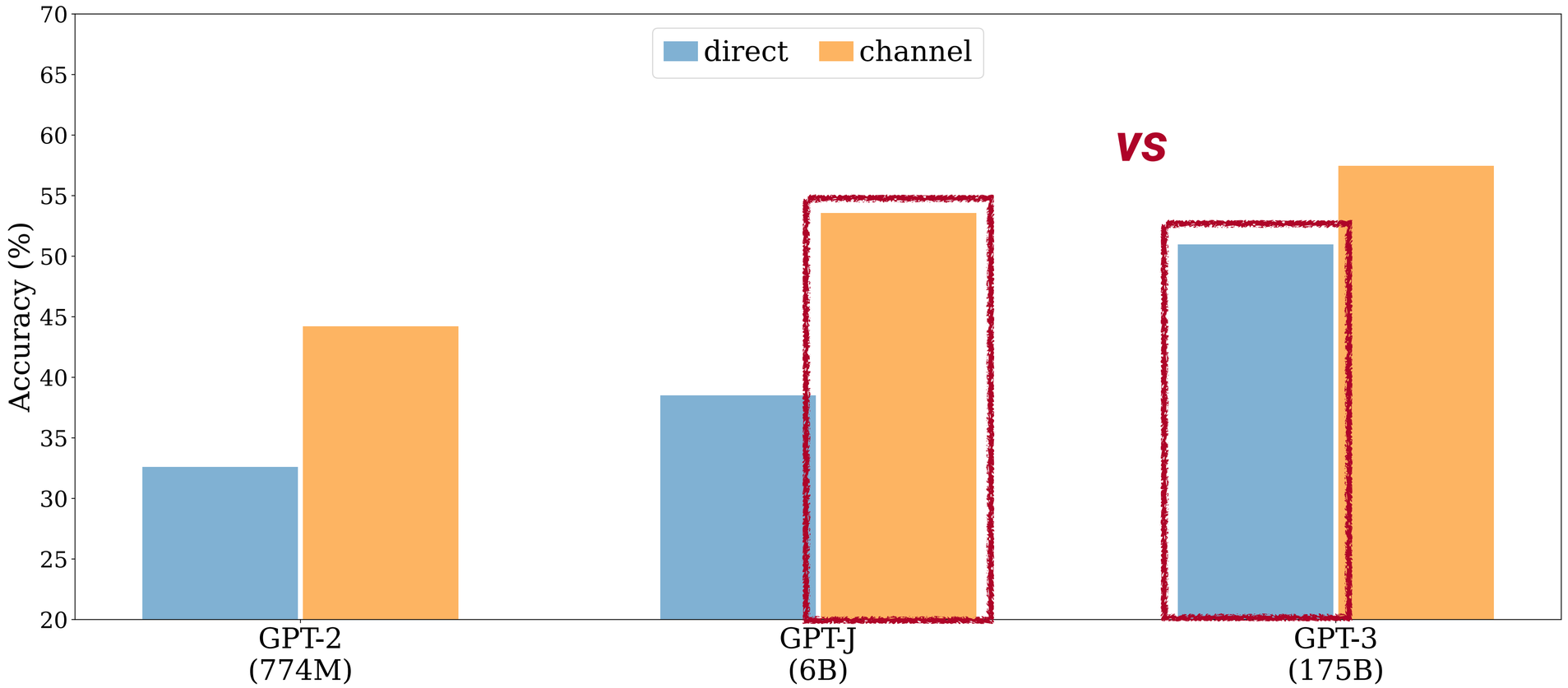
*Channel outperforms direct across **774M to 175B** models*



(on three classification datasets)

Extension to larger models

*Channel outperforms direct across **774M to 175B** models*
*Channel method allows outperforming **x30** bigger models*



(on three classification datasets)

Takeaways

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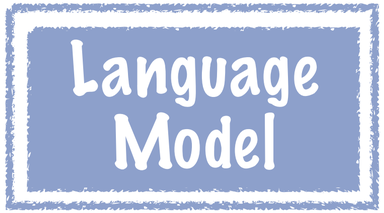
LM Prompting



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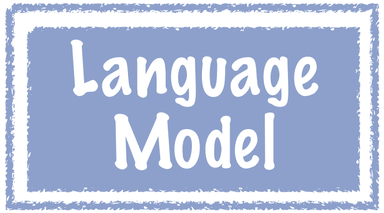

Variance ↑ Worst-case accuracy ↓

Takeaways

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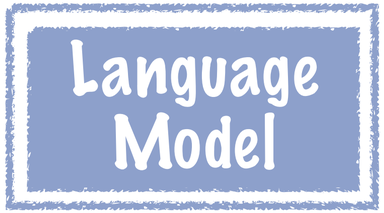

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Noisy Channel Approach

$$P(y \mid x) = \frac{P(x \mid y)P(y)}{P(x)} \propto P(x \mid y)P(y)$$

Takeaways

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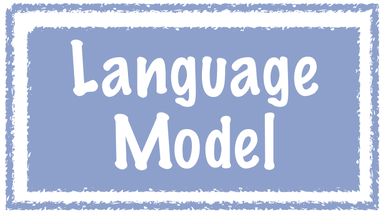

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on 10 classification datasets

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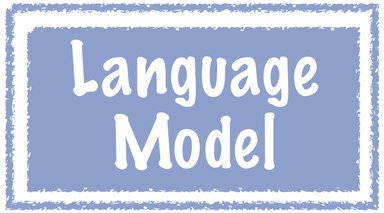

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When is it better?

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Variance ↓ Worst-case accuracy ↑

on 10 classification datasets

Takeaways

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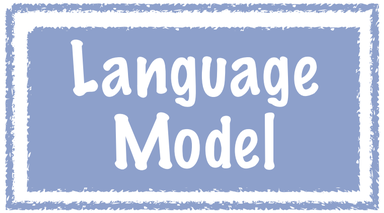

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Small k

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Variance ↓ Worst-case accuracy ↑

on 10 classification datasets

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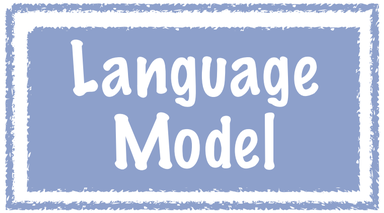

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When is it better?

Small k

Large # of labels

Noisy Channel Approach

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Variance ↓ Worst-case accuracy ↑

on 10 classification datasets

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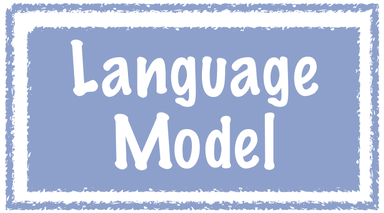

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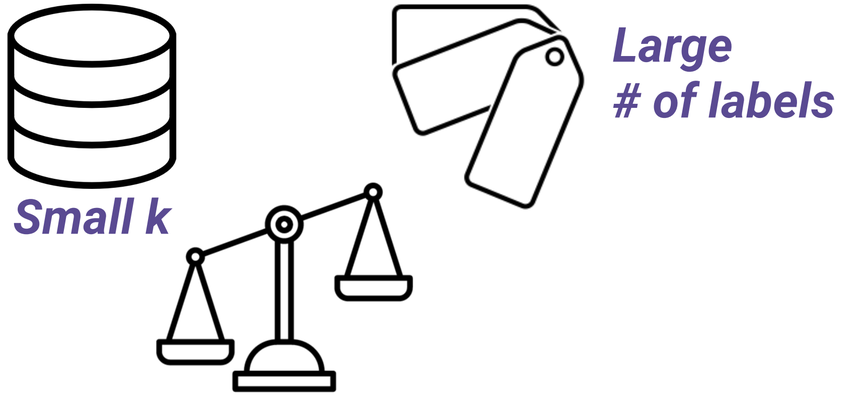

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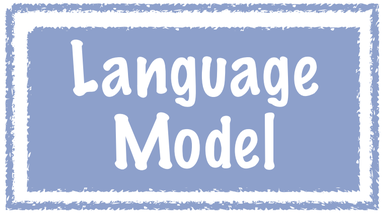

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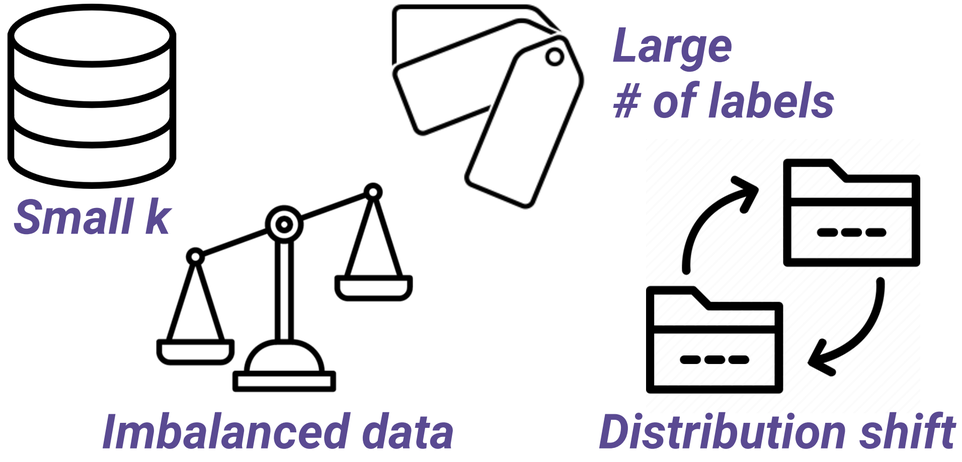

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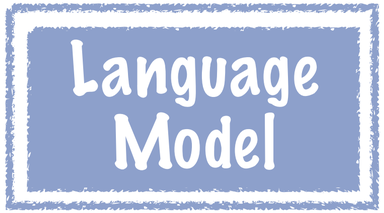

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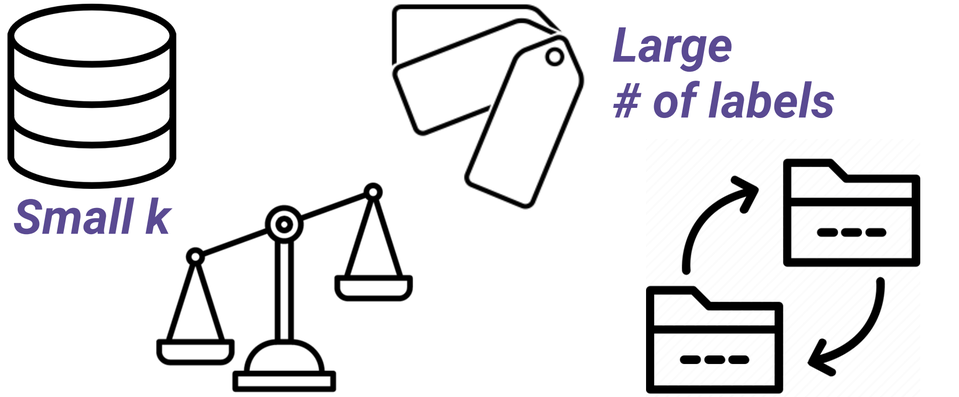
on 10 classification datasets

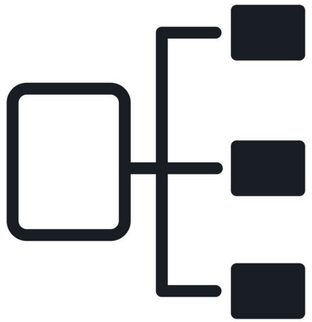
When is it better?



Limitations

Limited to classification

Extension needed!



Thank you for listening

Paper: https://arxiv.org/abs/2108.04106
Code: https://github.com/shmsw25/Channel-LM-Prompting/
Demo: http://qa.cs.washington.edu:2021/

Contact: sewon@cs.washington.edu / @sewon__min

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