

AdapterSoup: Weight Averaging to Improve Generalization of Pretrained Language Models



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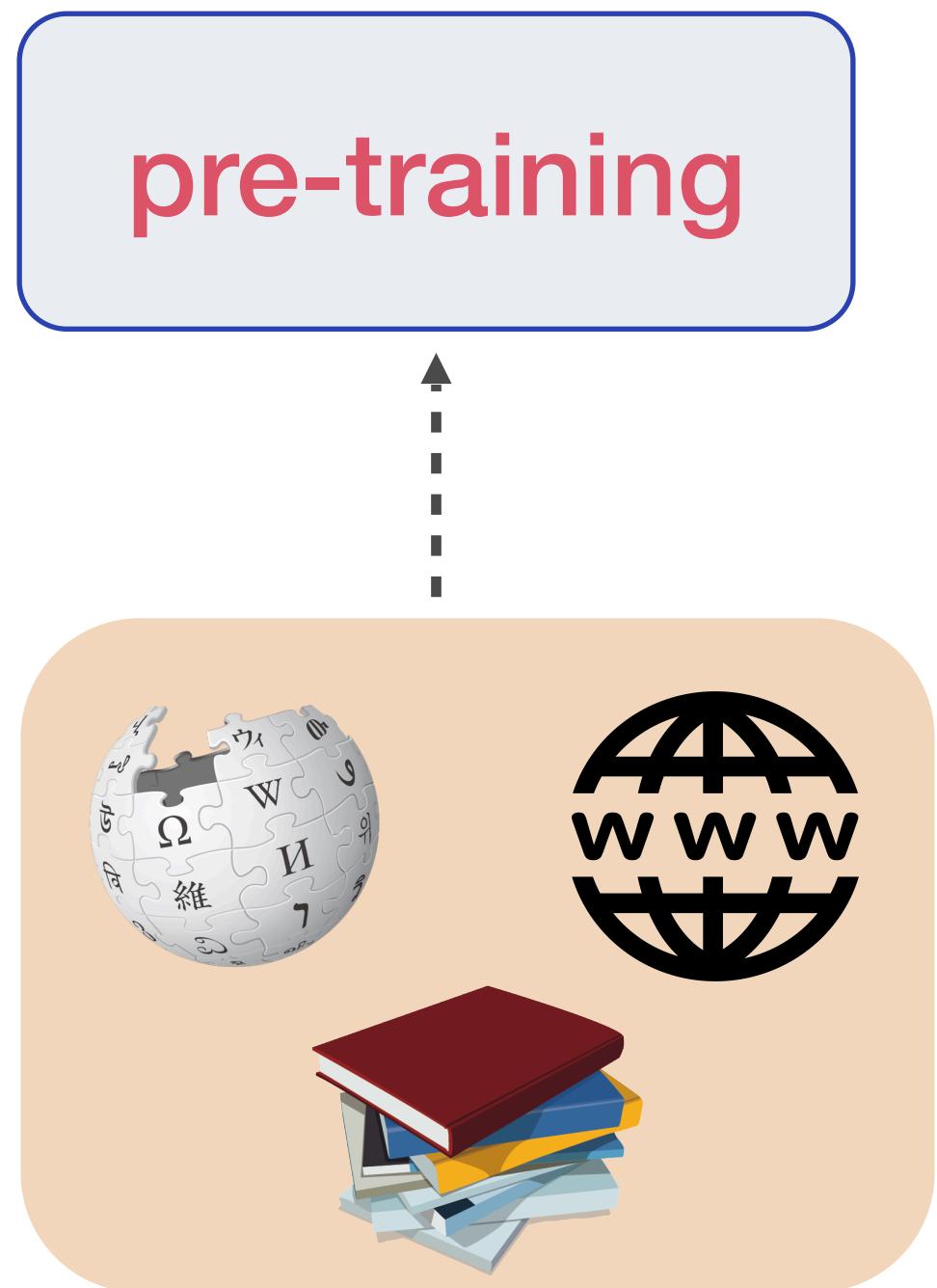
Presentation outline

- Motivation
- Proposed Approach
- Experiments
- Conclusion

- **Motivation**
- Proposed Approach
- Experiments
- Conclusion

Task: adapt a PLM to new domains

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*Pretrain a model using data from
heterogeneous domains*

Prior work

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 - Hierarchical domain adapters (*Chronopoulou et al., 2022*)
 - Prompt tuning (*Guo et al., 2022*)

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- Averaging the **weights** of fine-tuned models:
 - Model soups (*Wortsman et al., 2022*)
 - Fisher-weight averaging (*Matena and Raffel, 2022*)

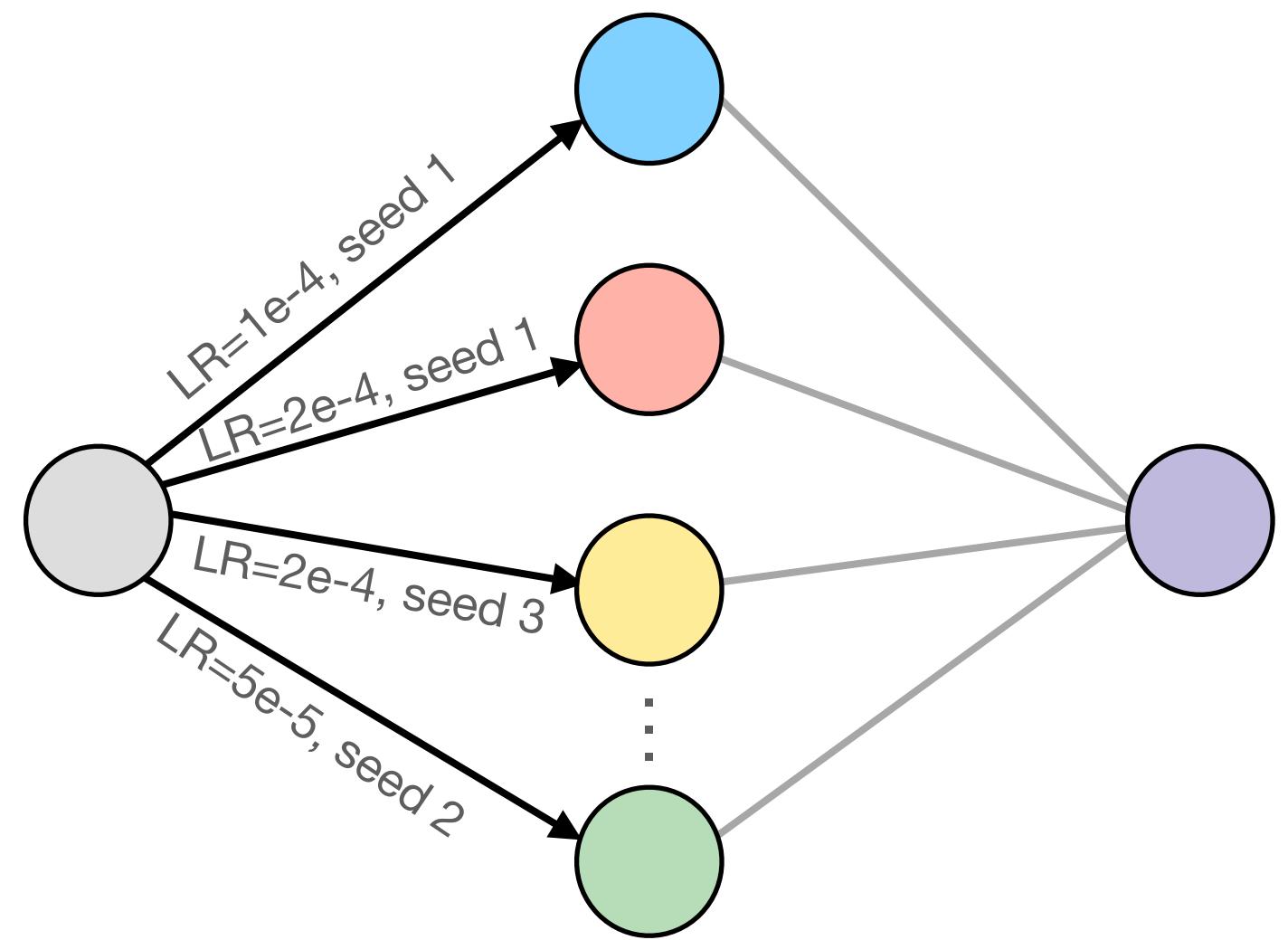
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Weight-space averaging

Model soups

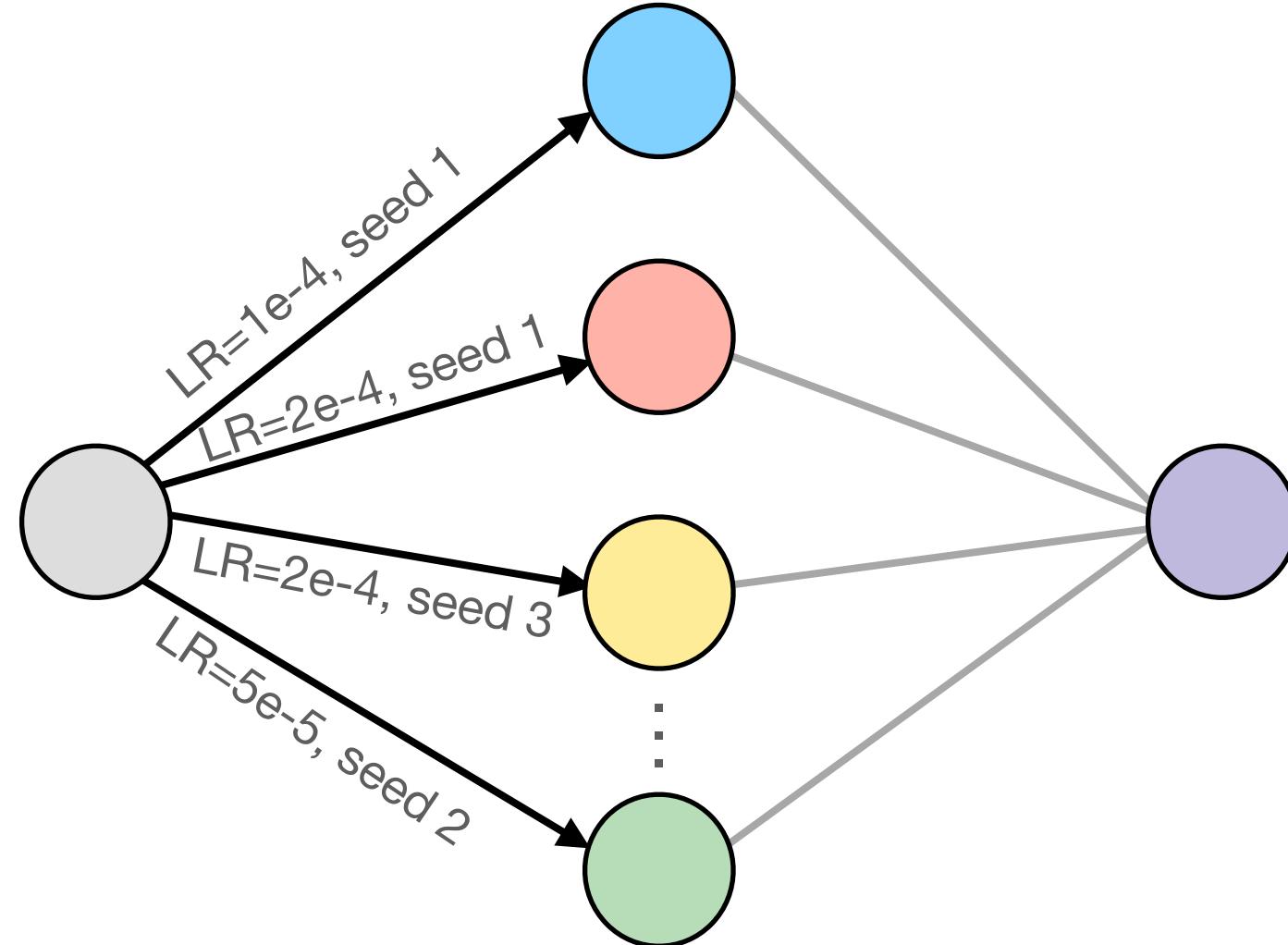
(Wortsman et al., 2022)



Weight-space averaging

Model soups

(Wortsman et al., 2022)



Fisher-weighted averaging

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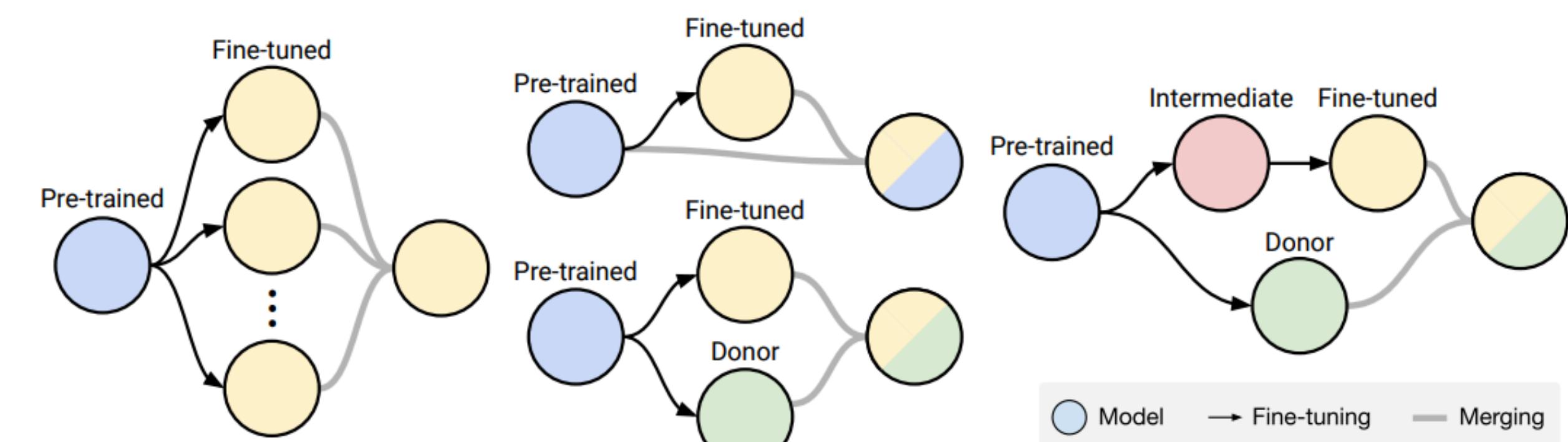
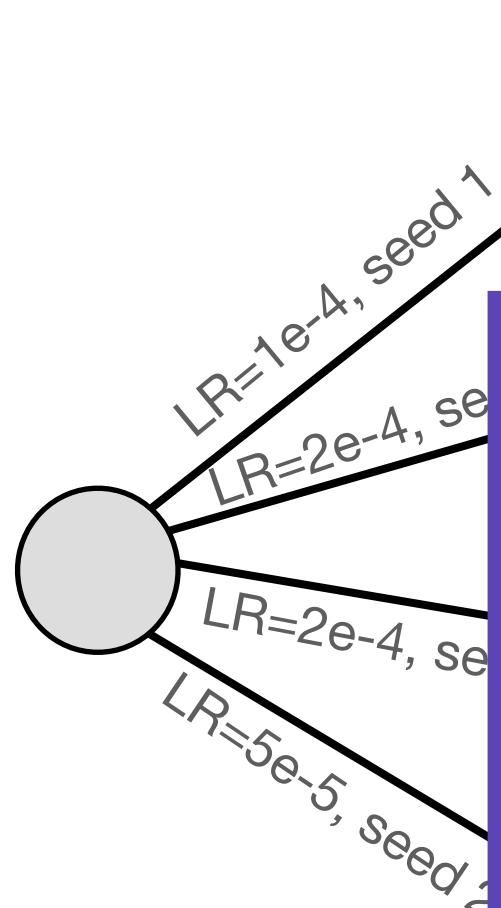


Fig. from Matena and Raffel (2022).

Weight-space averaging

Model soups

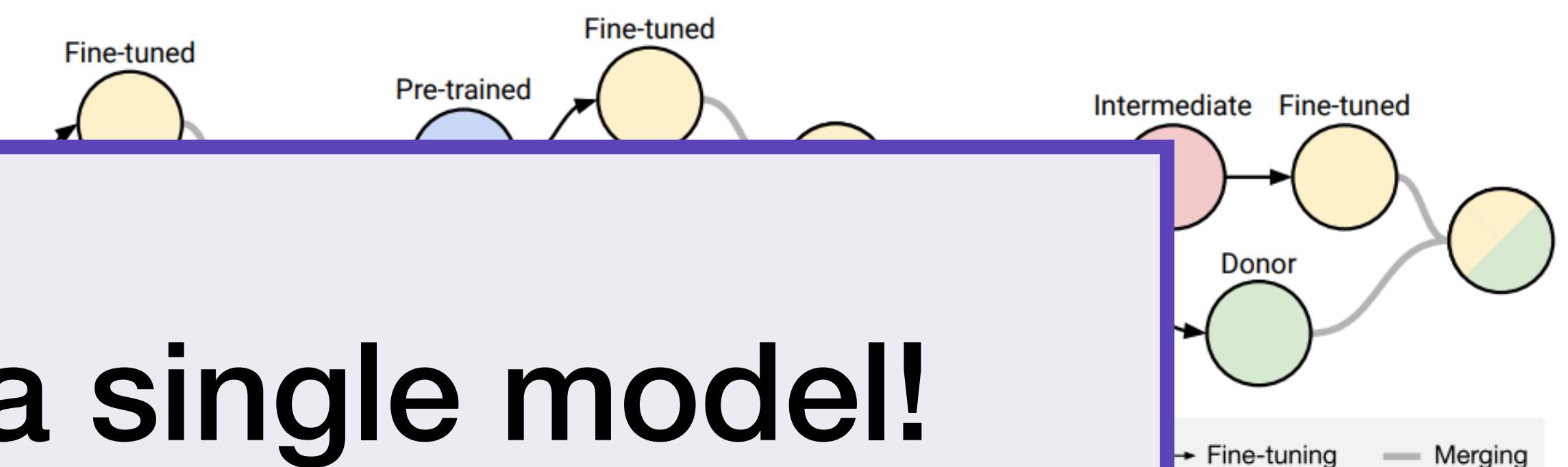
(Wortsman et al., 2022)



Inference cost of a single model!

Fisher-weighted averaging

(Matena and Raffel, 2022)



This work

- Can we average the weights of **independently trained adapters** to improve **domain generalization** of a PLM?

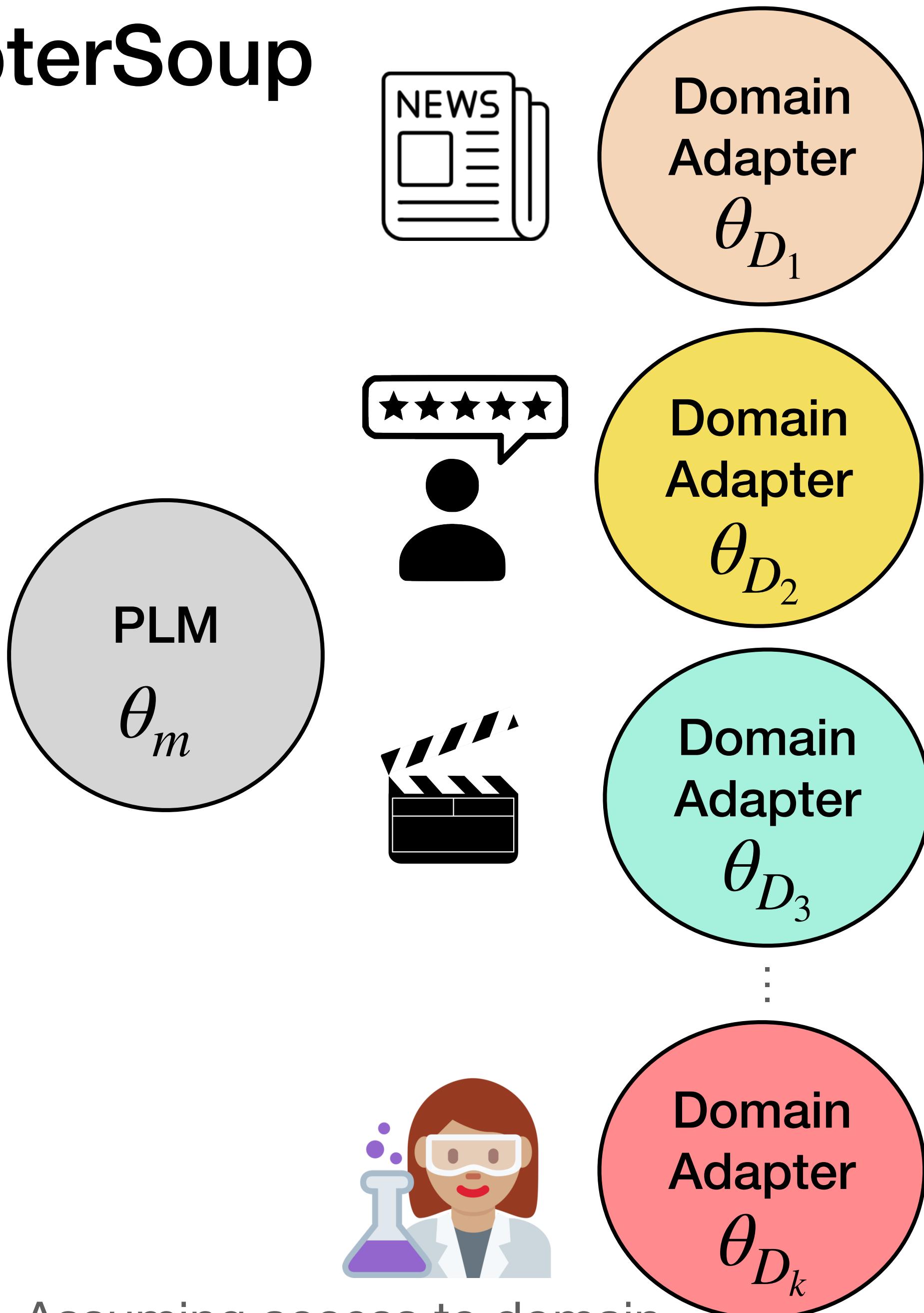
This work

- Can we average the weights of **independently trained adapters** to improve **domain generalization** of a PLM?
- How to select which adapters to combine?

- Motivation
- **Proposed Approach**
- Experiments
- Conclusion

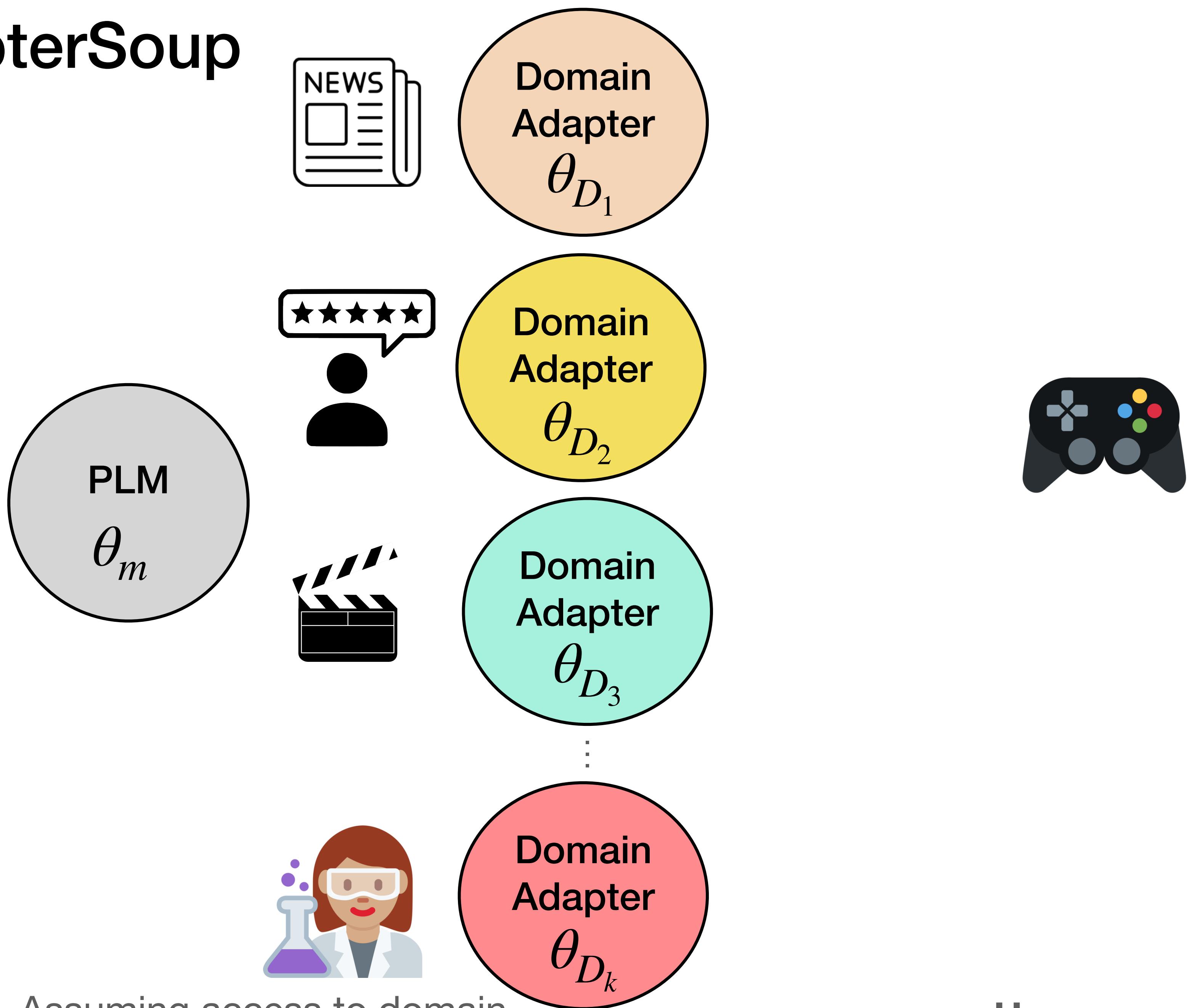
AdapterSoup

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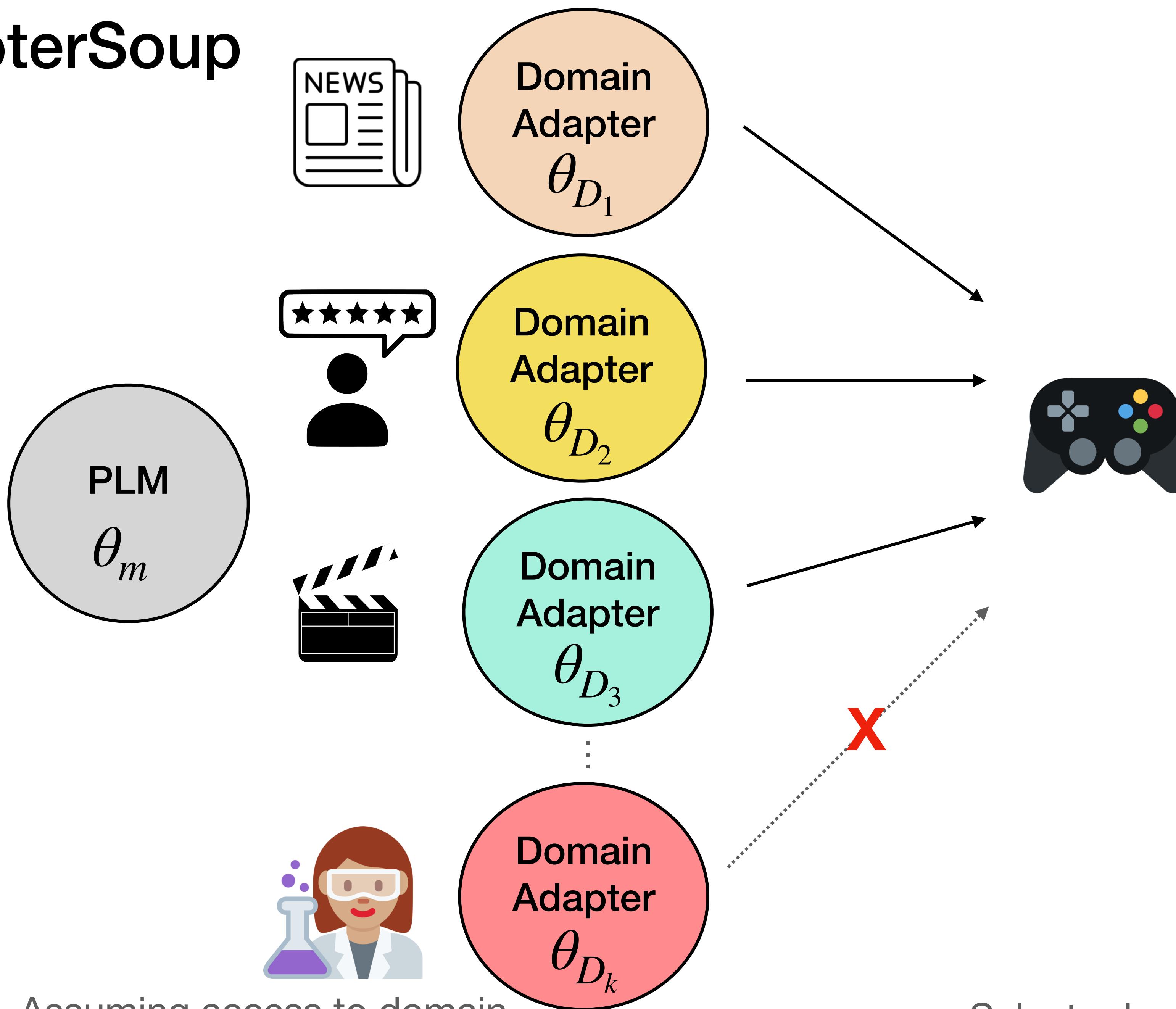


Assuming access to domain
adapters D_1, D_2, \dots, D_k

AdapterSoup



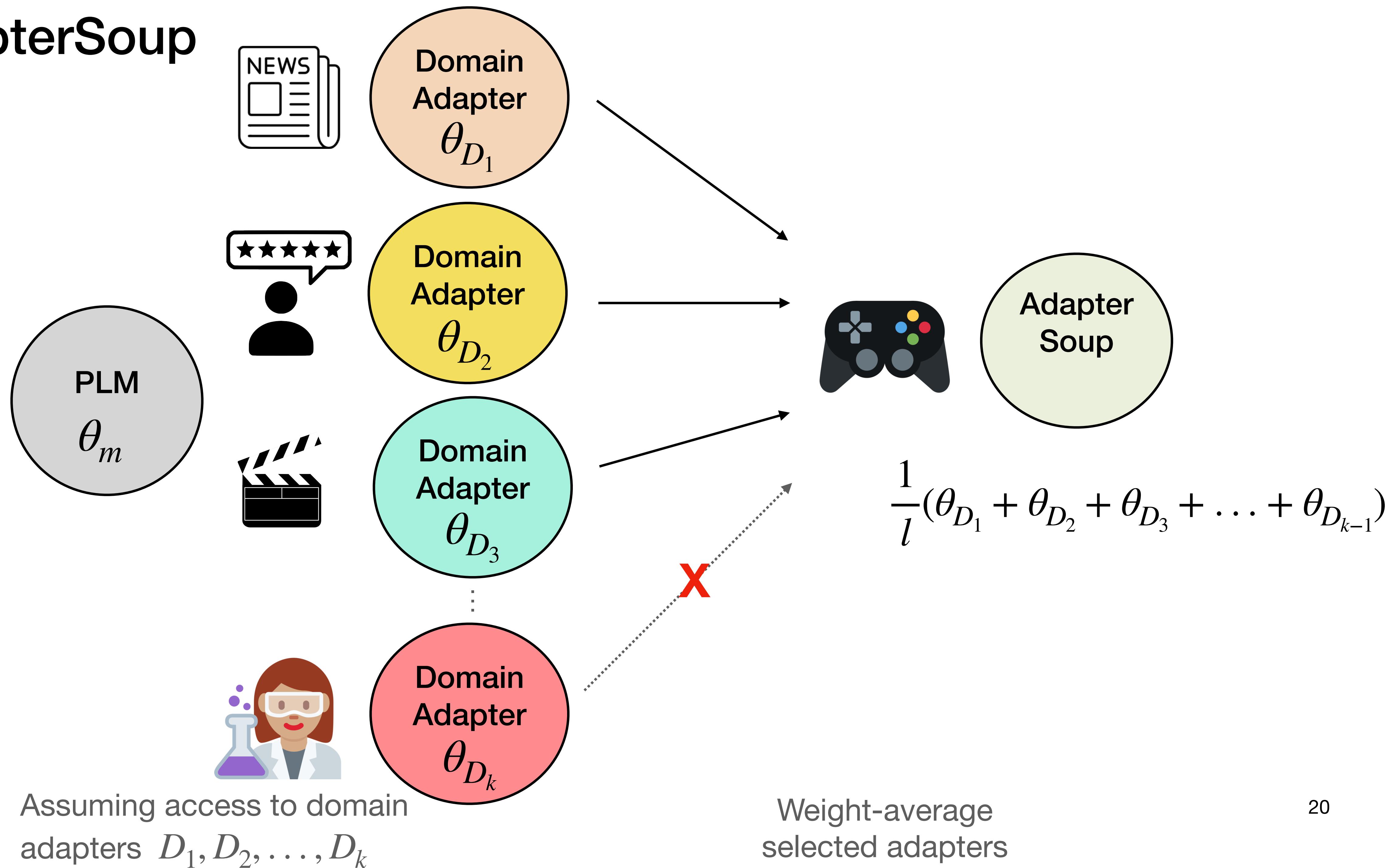
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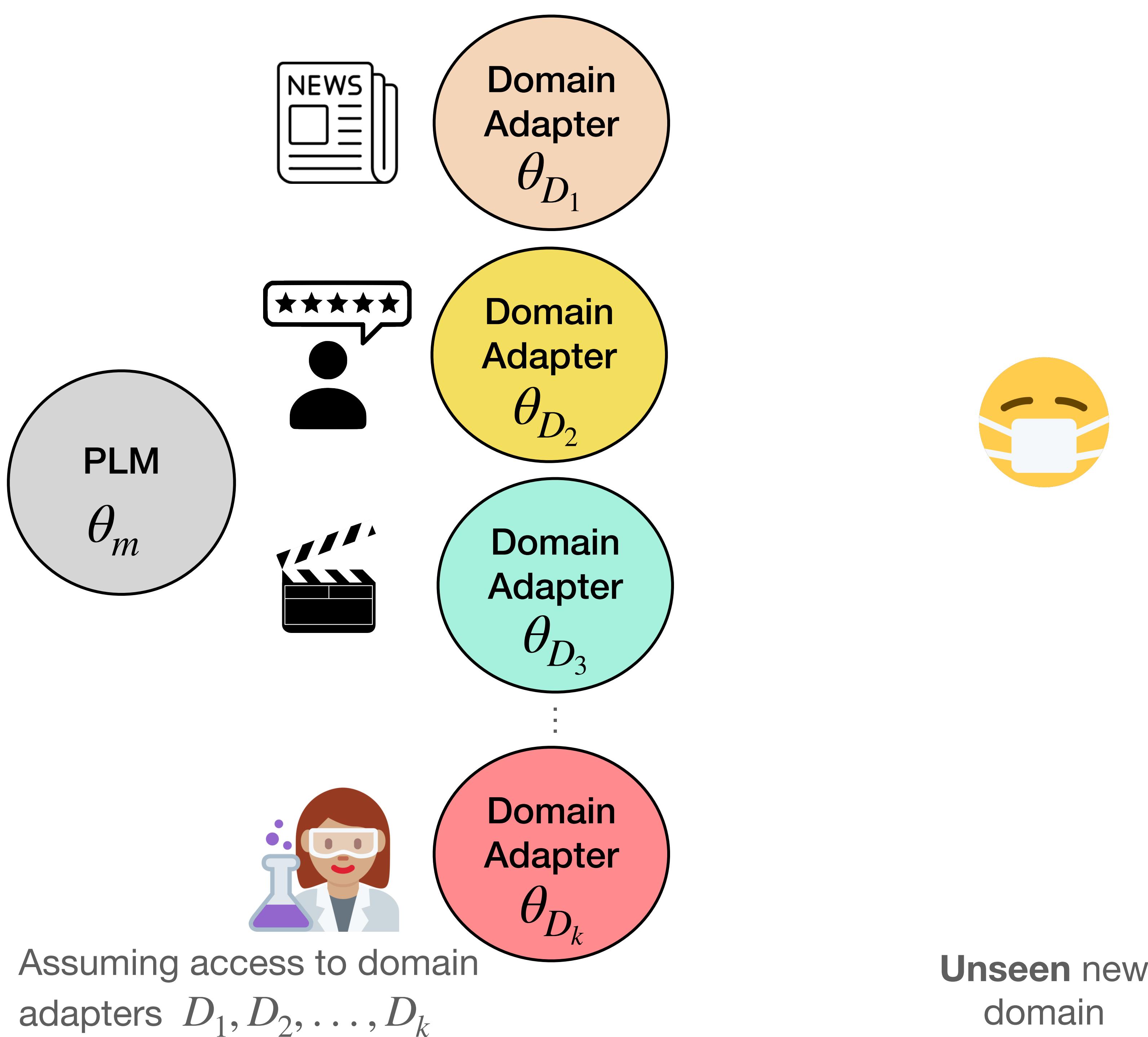


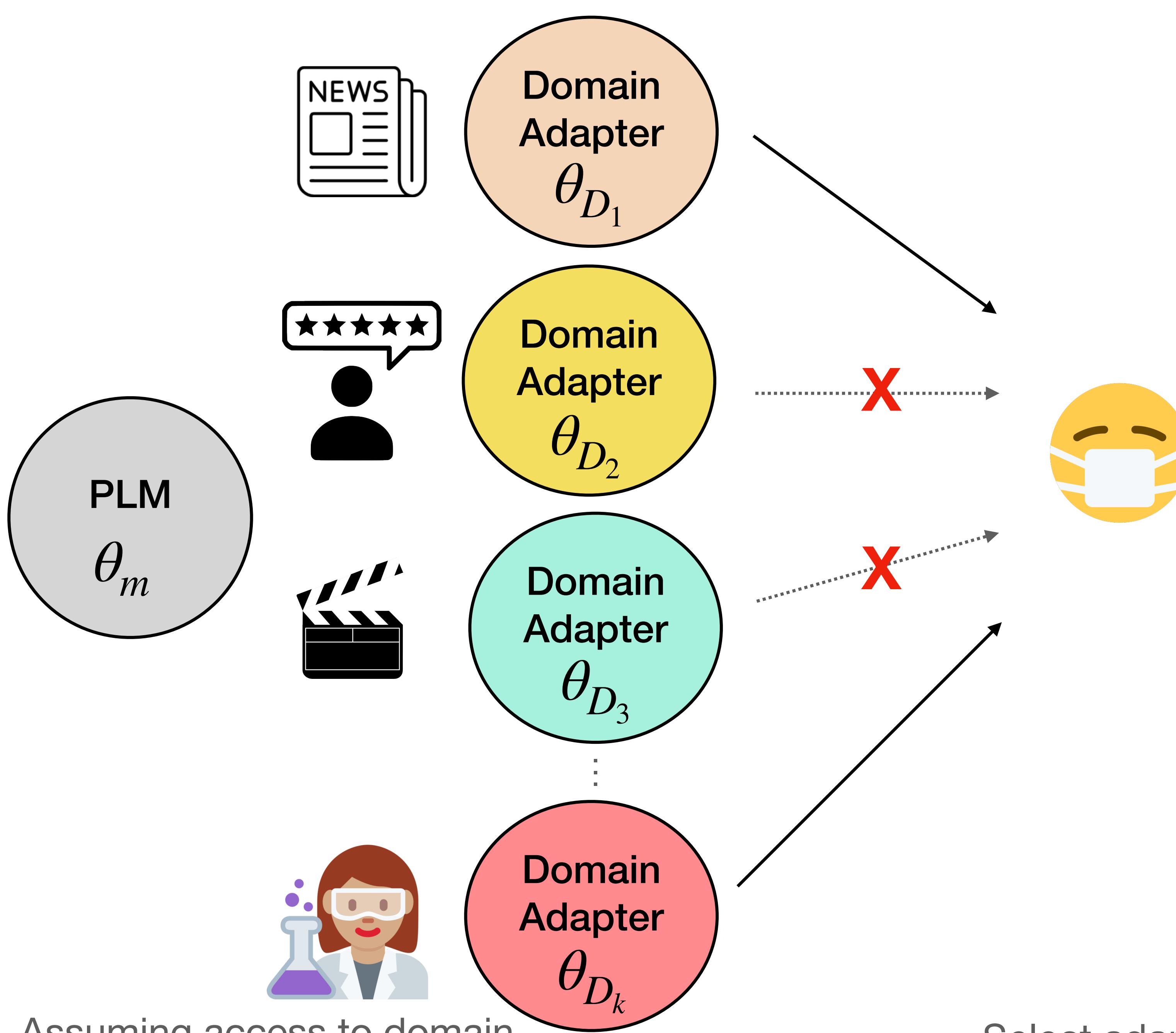
Assuming access to domain
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Select adapters
for new domain

AdapterSoup

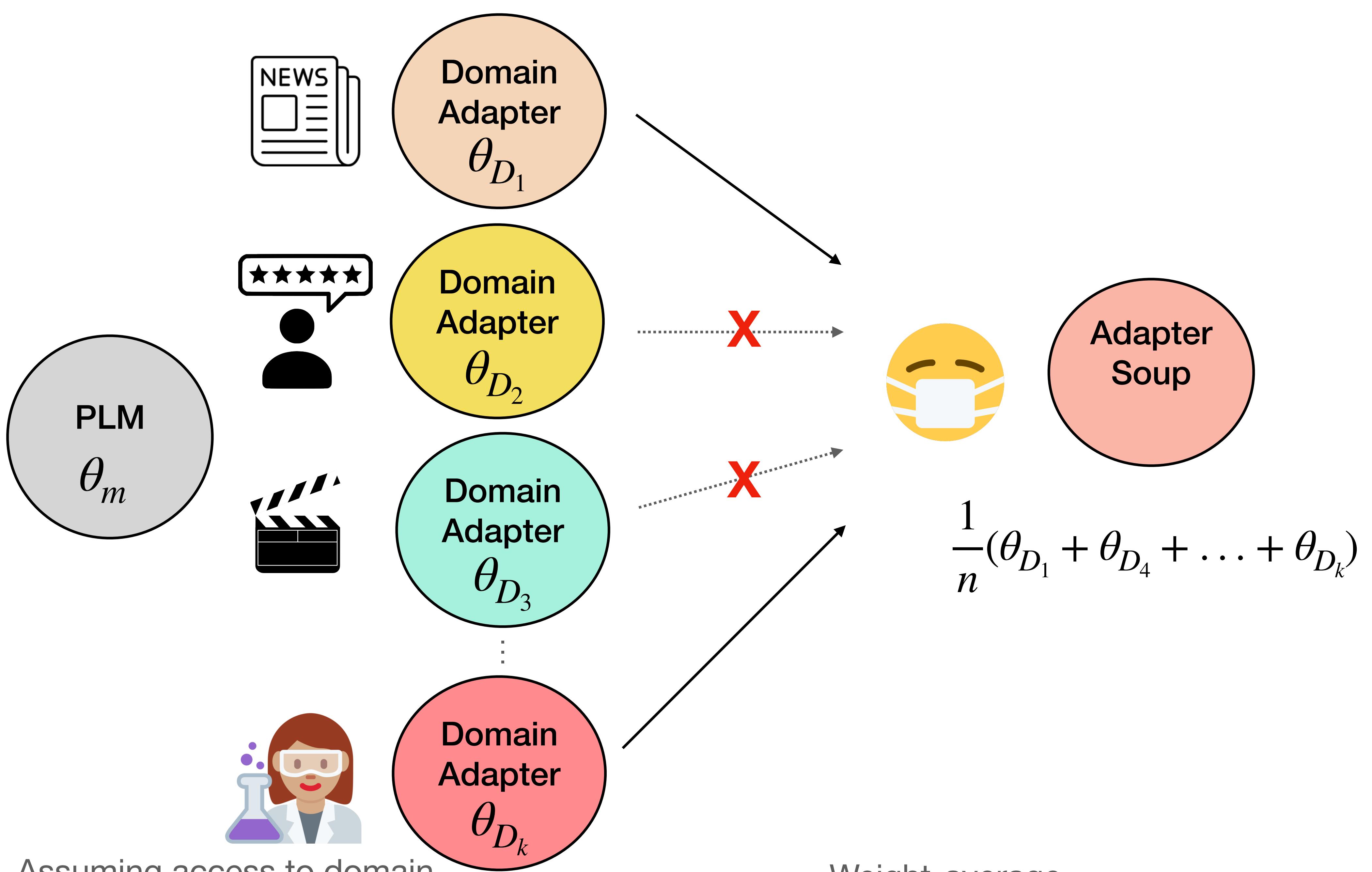






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Select adapters
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Assuming access to domain
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Weight-average
selected adapters

How are the domain adapters selected?

How are the domain adapters selected?

Uniform average

- Weight-average all trained adapters

$$\textit{AdapterSoup}(x) = f(x, \frac{1}{k} \sum_{i=1}^k \theta_i)$$

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uniform soup (*Wortsman et al., 2022*)

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Sentence similarity

- sentence-BERT to compute sentence embeddings (*Reimers and Gurevych, 2019*)

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Sentence similarity

- sentence-BERT to compute sentence embeddings (*Reimers and Gurevych, 2019*)
- AdapterSoup in order of **highest cosine sim.**

How are the domain adapters selected?

Clustering

- Using PLM representations of our k training domains, we fit a GMM with k components (*Aharoni and Goldberg, 2020*)

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Clustering

- Using PLM representations of our k training domains, we fit a GMM with k components (*Aharoni and Goldberg, 2020*)
- Weight-average adapters of training domains that are **closest to new domain**

- Motivation
- Proposed Approach
- **Experiments**
- Conclusion

Experimental setup

- PLM: GPT-2
- Adapters: bottleneck size 64
- Baselines:
 - GPT-2 (no further training)
 - single adapter selected using sentence similarity, clustering

Datasets

We use data from C4 (Raffel et al., 2020)

Training Domain	Train (Eval.) Tokens
dailymail.co.uk	25M (3M)
wired.com	18M (2M)
express.co.uk	16M (2M)
npr.org	25M (3M)
librarything.com	3M (500K)
instructables.com	25M (3M)
entrepreneur.com	16M (2M)
link.springer.com	28M (4M)
insiderpages.com	8M (1M)
ign.com	10M (1M)
eventbrite.com	11M (1M)
forums.macrumors.com	22M (3M)
androidheadlines.com	14M (2M)
glassdoor.com	4M (500K)
pcworld.com	14M (2M)
csmonitor.com	23M (3M)
lonelyplanet.com	6M (1M)
booking.com	30M (4M)
journals.plos.org	53M (6M)
frontiersin.org	38M (6M)
medium	22M (3M)

Novel Domain	Train (Eval.) Tokens
reuters.com	17M (2M)
techcrunch.com	13M (2M)
fastcompany.com	14M (2M)
nme.com	5M (1M)
fool.com	34M (4M)
inquisitr.com	13M (2M)
mashable.com	14M (2M)
tripadvisor.com	7M (1M)
ncbi.nlm.nih.gov	23M (3M)
yelp.com	68M (6M)

Results

↓ Perplexity shown

Method	10 Evaluation Domains										Avg.
	reuters	techcrunch	fastco	nme	fool	inquisitr	mashable	tripadv	ncbi	yelp	
GPT-2 (zero-shot)	21.5	27.7	27.9	28.2	23.8	22.4	27.1	40.4	20.7	36.2	27.6
Single Adapter Chosen Using:											
- Sentence similarity	18.9	22.0	22.0	23.1	22.9	18.4	25.3	37.0	18.2	49.4	24.4
- Clustering	17.6	22.4	24.0	21.1	23.3	18.7	23.6	37.7	18.2	44.3	24.0
AdapterSoup (Weight-space average):											
- Uniform	18.2	23.1	22.9	22.2	22.4	18.4	23.1	37.0	19.1	36.2	24.3
- Sentence similarity	17.6	22.0	21.3	20.7	22.2	18.4	22.4	36.2	17.6	35.2	23.4
- Clustering	17.3	21.8	21.3	21.1	22.2	17.8	22.2	34.8	17.6	34.8	23.1
Oracle											
- Best adapter per domain	17.6	22.0	21.5	21.1	22.9	17.8	22.2	37.0	18.2	35.9	23.6
- Clustering + 2 best	17.3	21.8	21.3	20.7	22.0	17.6	22.0	33.4	17.6	33.4	22.7
Hierarchy adapter	16.4	20.1	20.1	20.1	22.2	16.4	22.2	33.1	18.2	34.5	22.3

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Using (almost any) AdapterSoup is preferable to GPT-2 without further training or to a single adapter

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Hierarchy adapter: lower ppl but at a (much) higher training and inference cost

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AdapterSoup using clustering: best performance
at the inference cost of a single adapter

Analysis

Novel Domain i	Sentence Sim.	Clustering
tripadvisor	booking	booking
	insiderpages	insiderpages
	lonelyplanet	
ncbi	journals	journals
	frontiersin	frontiersin
	springer	springer
reuters	csmonitor	dailymail
	wired	express
	entrepreneur	

Models selected using AdapterSoup with sentence similarity and clustering

Analysis

Novel Domain i	Sentence Sim.	Clustering
tripadvisor	booking insiderpages	booking insiderpages lonelyplanet
ncbi	journals frontiersin springer	journals frontiersin springer
reuters	csmonitor wired entrepreneur	dailymail express

- Tripadvisor & Ncbi: Both methods select almost same domains
- Reuters: good match with clustering, sentence sim. selects non-related domains

Models selected using AdapterSoup with sentence similarity and clustering

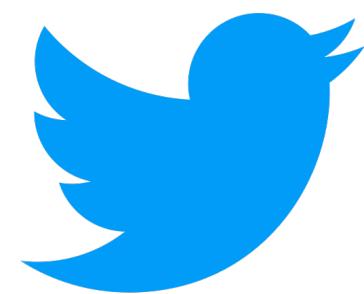
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Key Takeaways

- AdapterSoup: weight-space averaging of selected adapters trained on top of a PLM to adapt to new domains
- Cost of a model at inference time
- Improves domain generalization of a PLM

Thanks!

paper: arxiv.org/abs/2302.07027



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