Transductive Zero-Shot & Few-Shot Adaptation of Large Medical Vision Language Models


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ÉTS
Le génie pour l'industrie

CRCHUM
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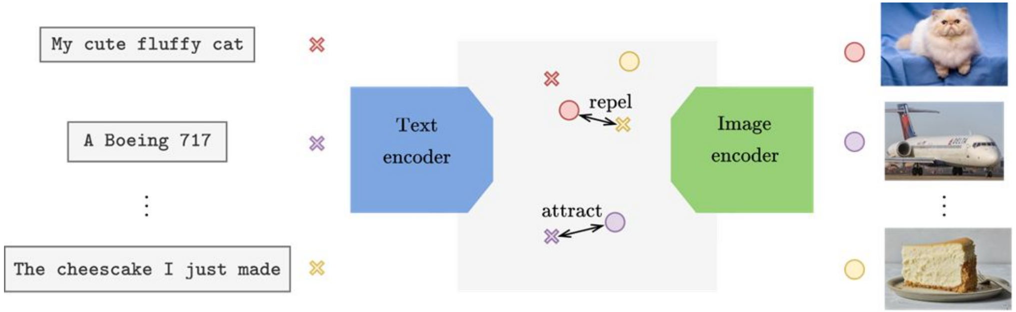
ILLS
International Laboratory
on Learning Systems

Lots of different Vision-Language Models out there

Among them…

- **CLIP: generic text-image pairs of internet**



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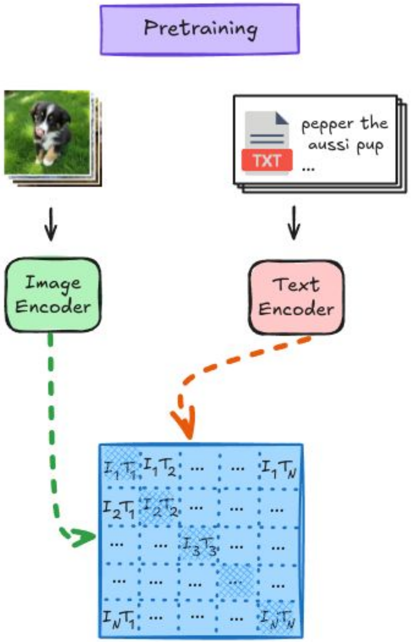
Generalist Vision-language Models (CLIP)



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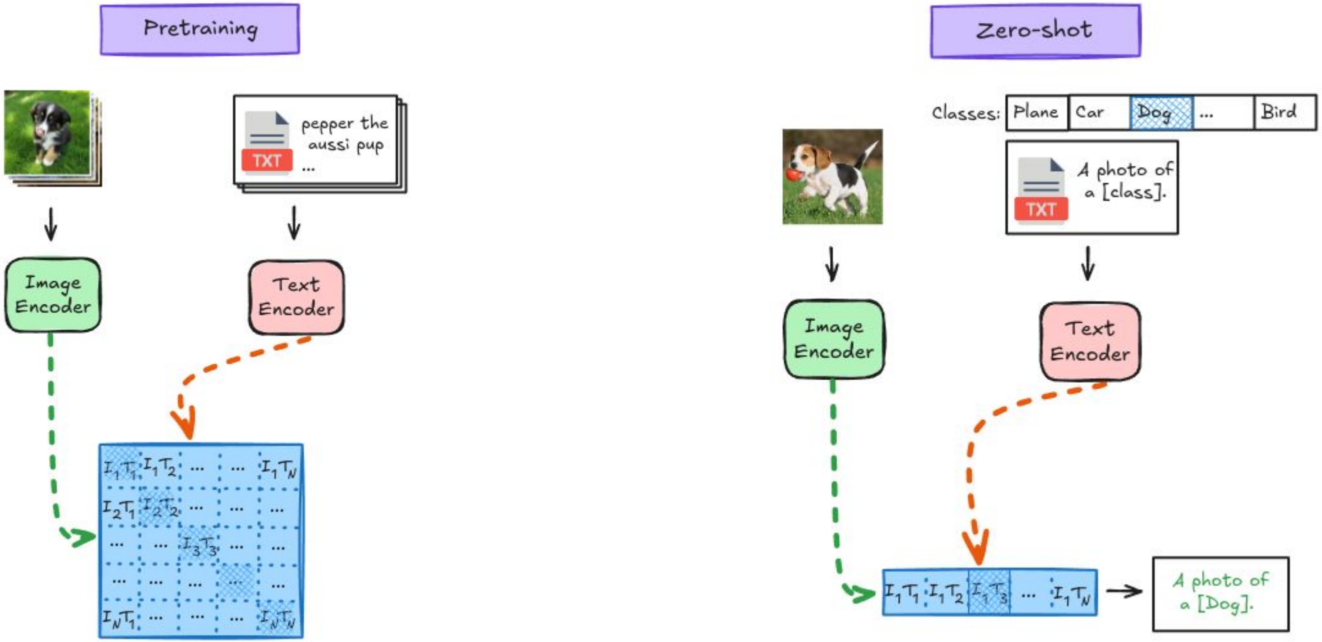

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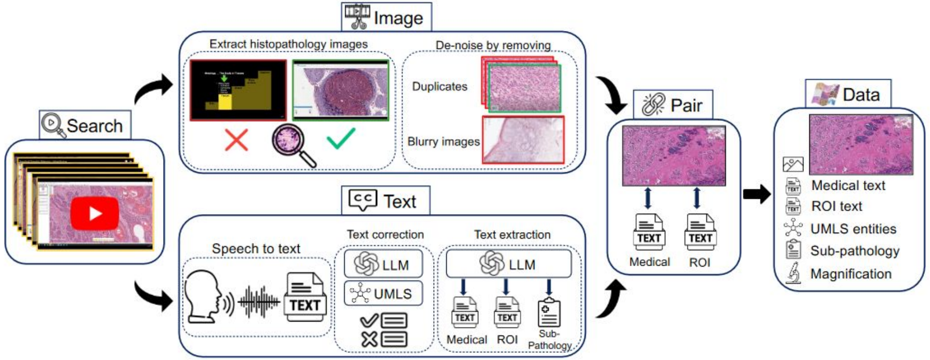

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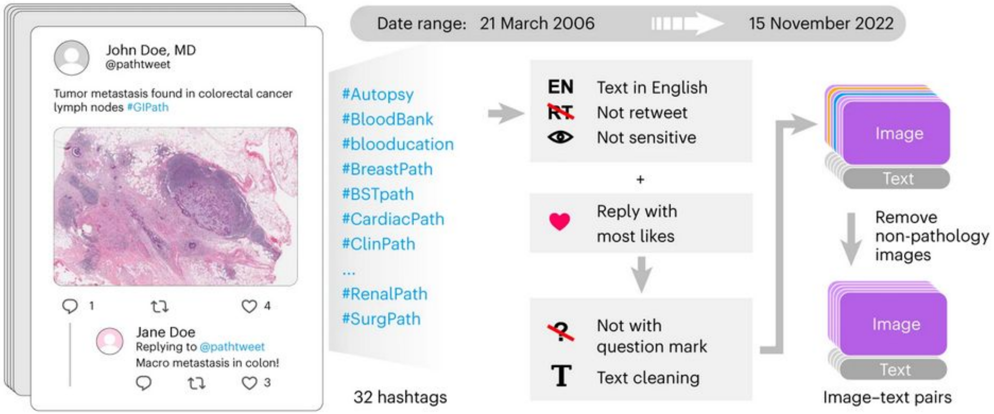

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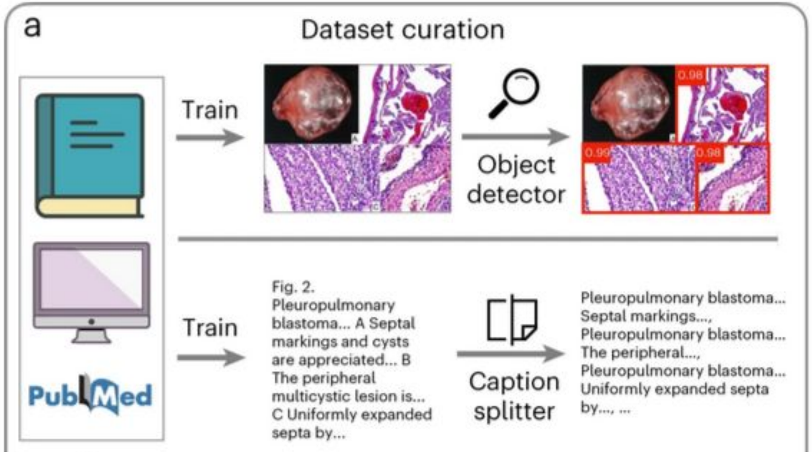

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How to leverage their representational power?

…

Boosting Vision-Language Models for Histopathology Classification: Predict all at once

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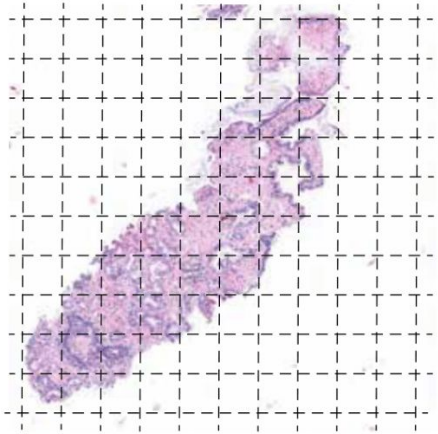
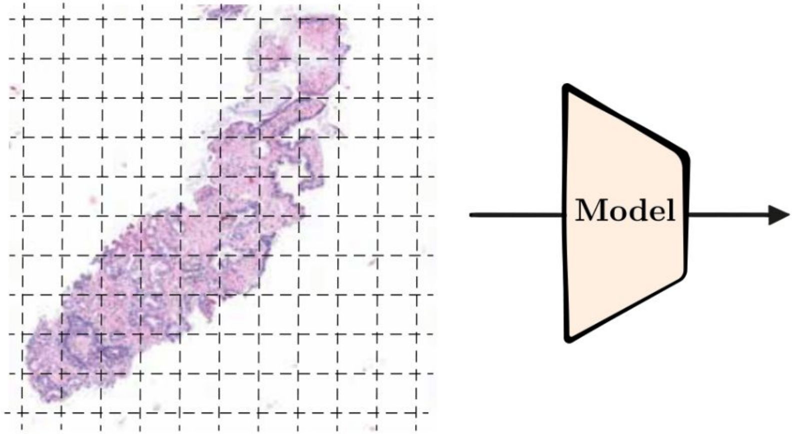
Inductive inference



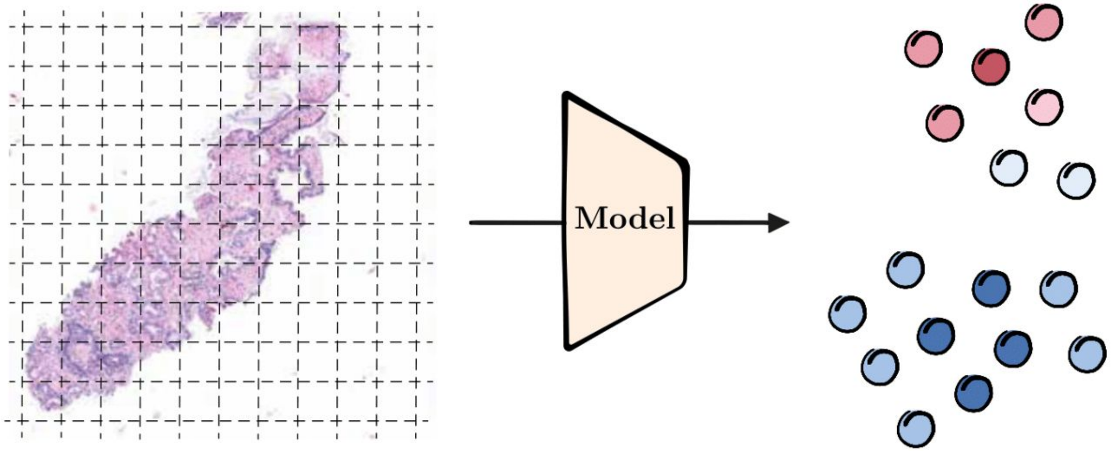
Large whole slides divided per patches, large-scale database, …

Inductive inference



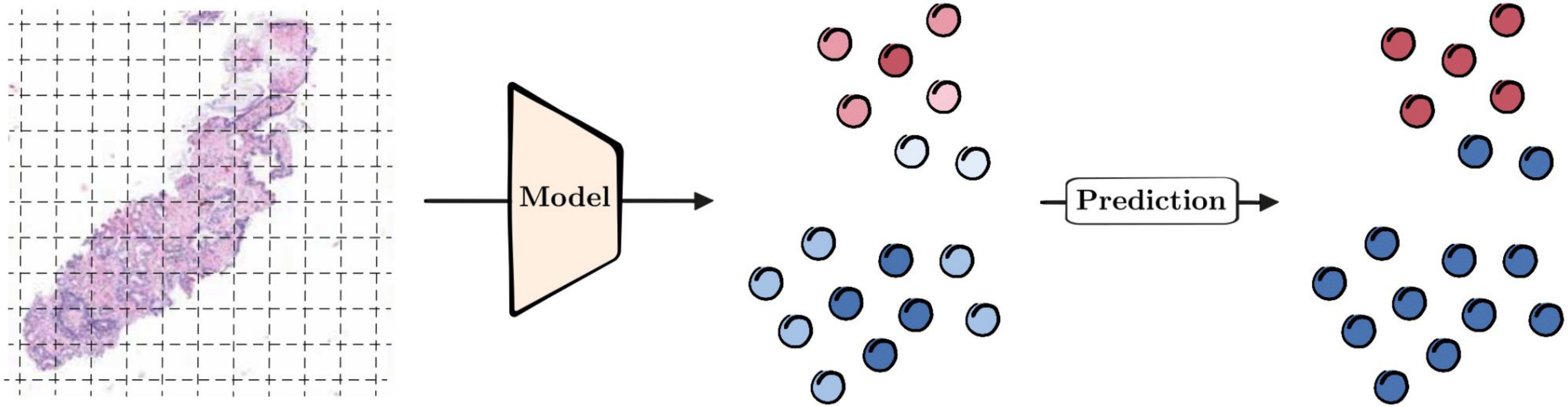
(1) If we have **enough annotated data**, we can train a Model and use it at inference time…

Inductive inference



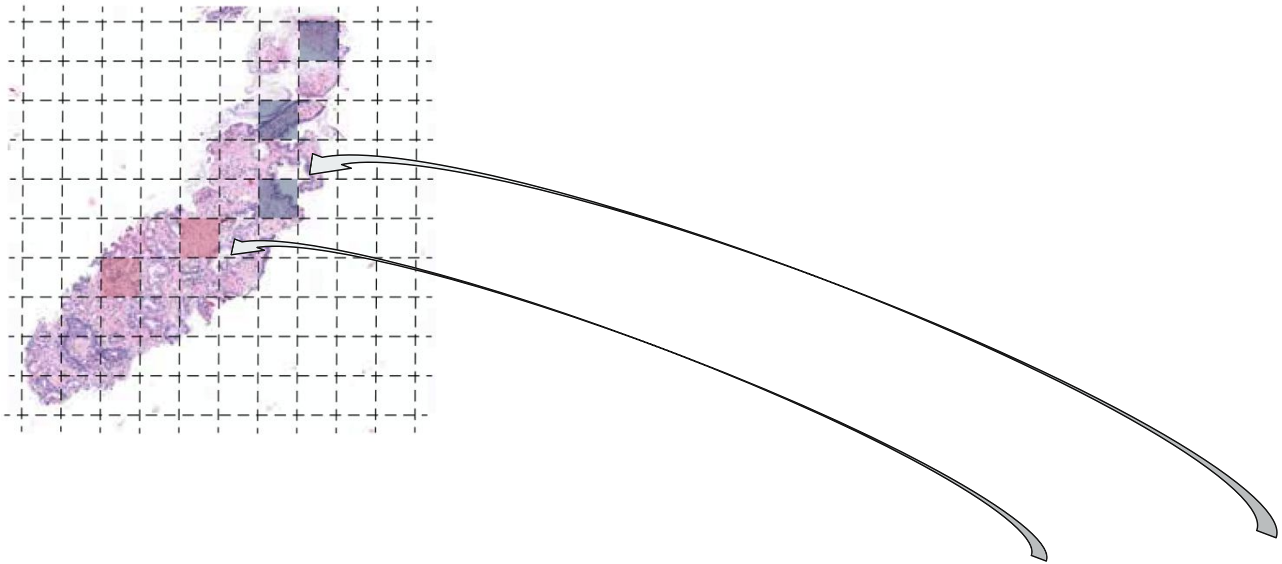
… which gives us more or less confident predictions …

Inductive inference



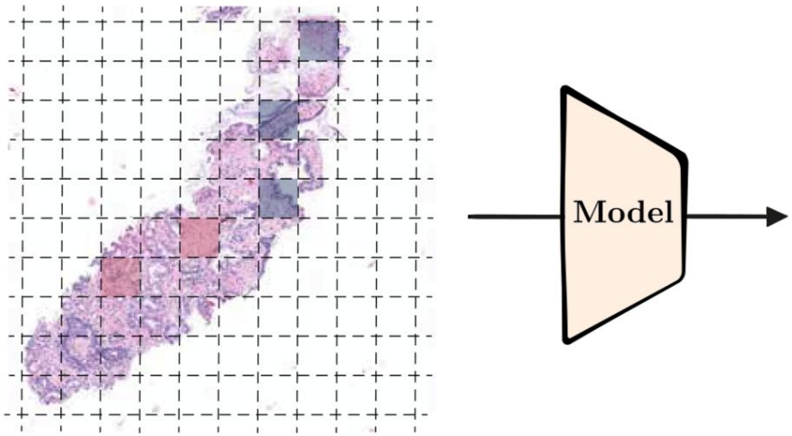
… and we take the most probable class for **each patch independently**.

Few-shot transductive inference



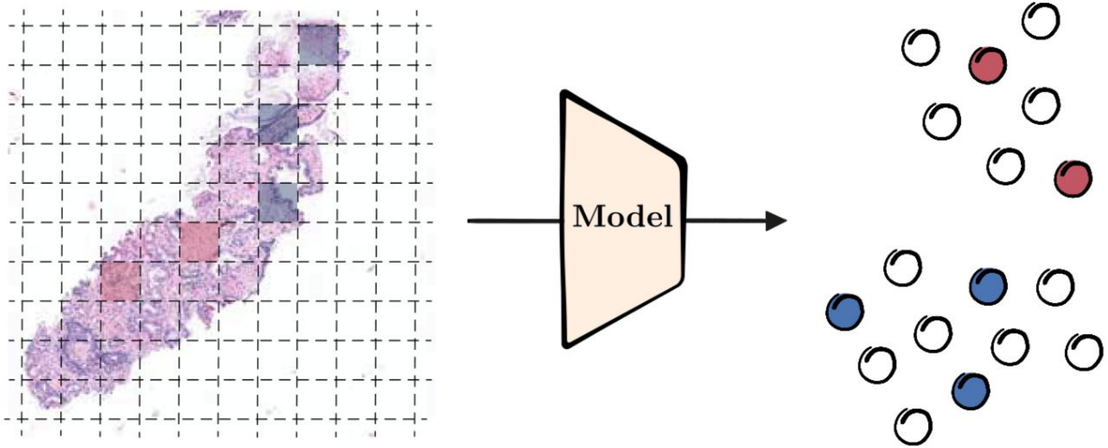
Large whole slides divided per patches, large-scale database, … **+ a few annotated patches**

Few-shot transductive inference



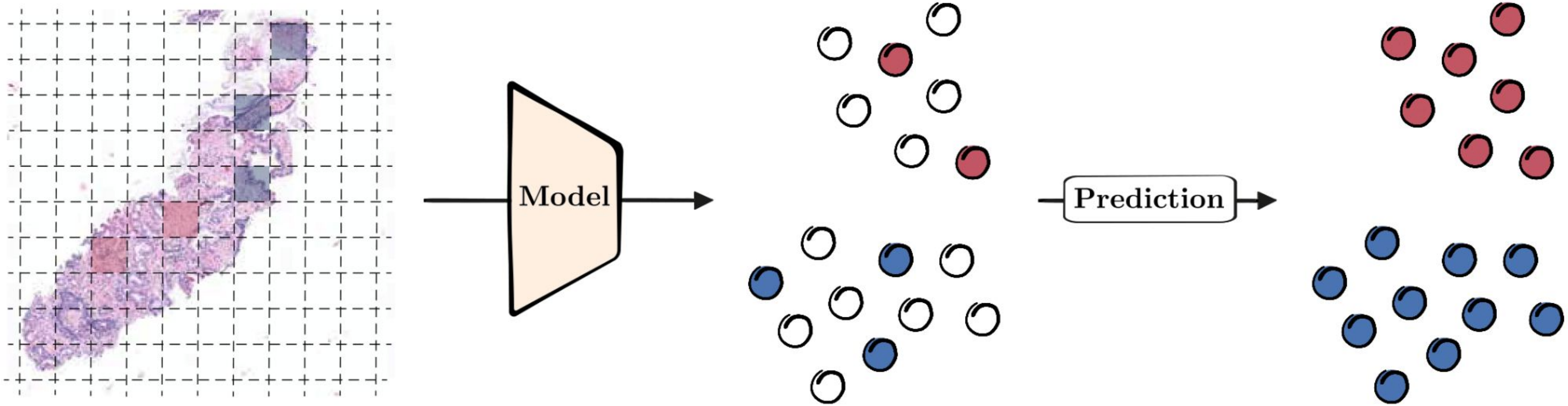
(2) We can use a good embedder (even self-supervised!) …

Few-shot transductive inference



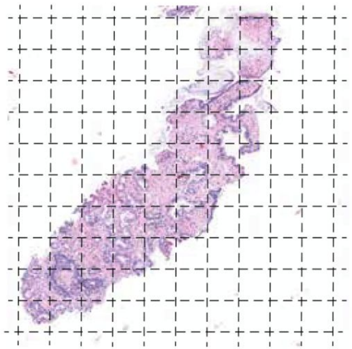
… which gives a good representation …

Few-shot transduction inference



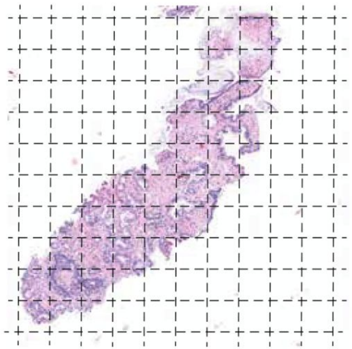
… we can leverage **data structure** and the few-labeled patches !

Unsupervised transductive inference



Large whole slides divided per patches, large-scale database, … ~~+ a few annotated patches~~

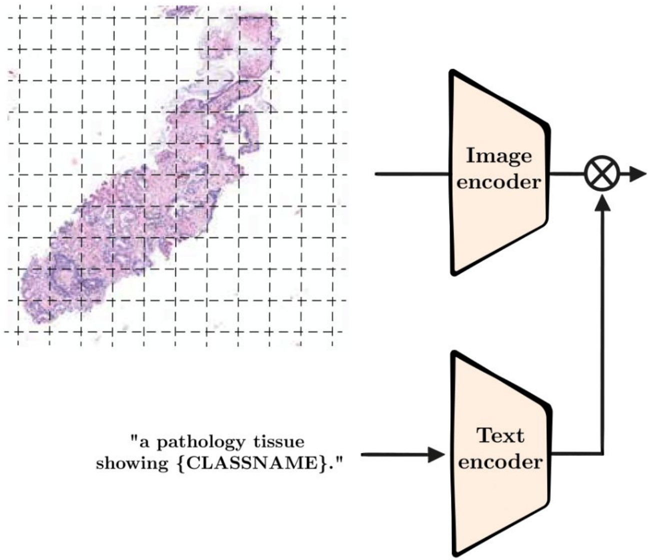
Unsupervised transductive inference



"a pathology tissue
showing {CLASSNAME}."

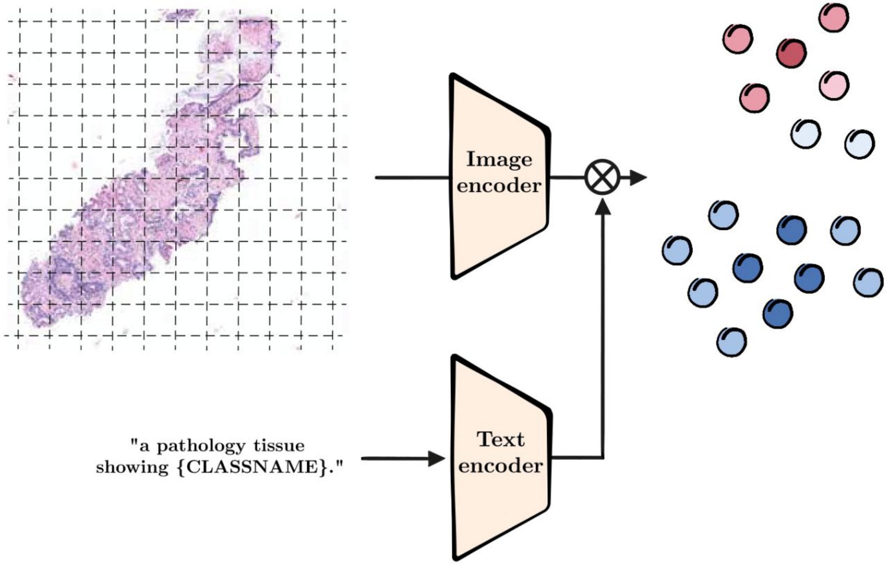
Large whole slides divided per patches, large-scale database, … **+ text description for each class**

Unsupervised transductive inference



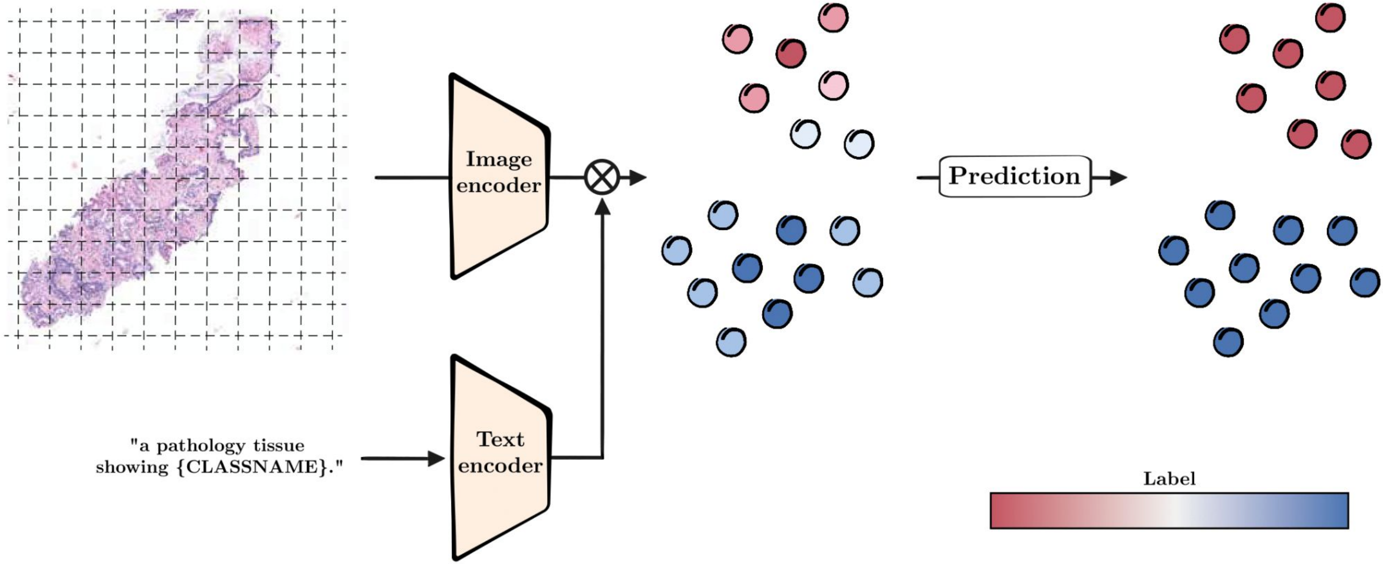
(3) we leverage **Vision-Language Models** (VLMs) trained on large-scale unsupervised text-image data…

Unsupervised transductive inference



… text-image similarities give us (noisy) **zero-shot predictions** for each patch …

Unsupervised transductive inference



… these **zero-shot predictions** can be used in combination with the **data structure!**

Our algorithm (in short)

$$\mathcal{L}_{\text{Zero-Shot}}(\mathbf{z}, \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \underbrace{-\frac{1}{|\mathcal{Q}|}\sum_{i \in \mathcal{Q}} \mathbf{z}_i^\top \log(\mathbf{p}_i)}_{\text{GMM clustering}} \underbrace{- \sum_{i \in \mathcal{D}} \sum_{j \in \mathcal{D}} w_{ij} \mathbf{z}_i \mathbf{z}_j}_{\text{Laplacian reg.}} + \underbrace{\sum_{i \in \mathcal{Q}} \mathrm{KL}_\lambda(\mathbf{z}_i || }_{\text{Text knowledge}}$$

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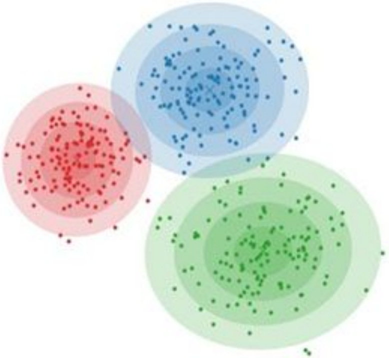

We model features as a balanced Gaussian Mixture Model (**GMM**).

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Similar patches should have **similar predictions**!

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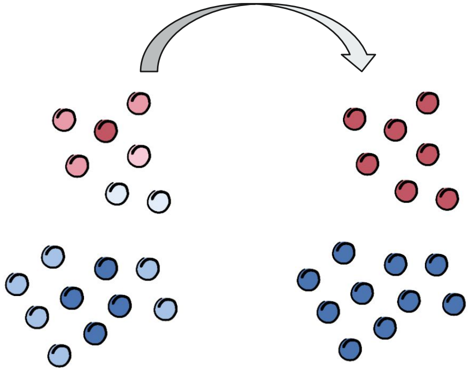

New predictions should remain **as close as possible to the initial (zero-shot)** ones (while minimizing the 2 other terms!)

Our algorithm (in short)

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Solving procedure of 3 update equations

$\longrightarrow$ just a **few lines of code**!

function Histo-TransCLIP(f, t, τ)

// Text-based pseudo-labels $\hat{\mathbf{y}}$

$\hat{\mathbf{y}}_i = \text{softmax}(\tau \mathbf{f}_i^T \mathbf{t}) \quad \forall i$

// Initialize z, μ, Σ

$\mathbf{z}_i = \hat{\mathbf{y}}_i \quad \forall i$

$\boldsymbol{\mu}_k = \text{top\_confident\_average}(\mathbf{f}, \hat{\mathbf{y}}) \quad \forall k$

$\text{diag}(\boldsymbol{\Sigma}) = \frac{1}{n\_features}$

// Iterative procedure

while not_converged **do**

for l = 1:... **do**

$$\mathbf{z}_i^{(l+1)} = \frac{\hat{\mathbf{y}}_i \odot \exp(\log(\mathbf{p}_i) + \sum_{j \in \mathcal{Q}} w_{ij} \mathbf{z}_j^{(l)})}{(\hat{\mathbf{y}}_i \odot \exp(\log(\mathbf{p}_i) + \sum_{j \in \mathcal{Q}} w_{ij} \mathbf{z}_j^{(l)}))^\top \mathbb{1}_K} \quad \forall i$$

$$\boldsymbol{\mu}_k = \frac{\sum_{i \in \mathcal{Q}} z_{i,k} \mathbf{f}_i}{\sum_{i \in \mathcal{Q}} z_{i,k}} \quad \forall k$$

$$\text{diag}(\boldsymbol{\Sigma}) = \frac{1}{|\mathcal{Q}|} \sum_{i \in \mathcal{Q}} \sum_k z_{i,k} (\mathbf{f}_i - \boldsymbol{\mu}_k)^2$$

return $\mathbf{z}$

Our algorithm (in short)

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Really fast to solve
$\longrightarrow$ just a **few seconds for 100,000 patches**

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#Patches	Features	Histo-TransCLIP
10^2	$\sim$ 1 sec.	$\sim$ 0.1 sec.
10^3	$\sim$ 4 sec.	$\sim$ 0.2 sec.
10^4	$\sim$ 28 sec.	$\sim$ 0.4 sec.
10^5	$\sim$ 5 min.	$\sim$ 6 sec.

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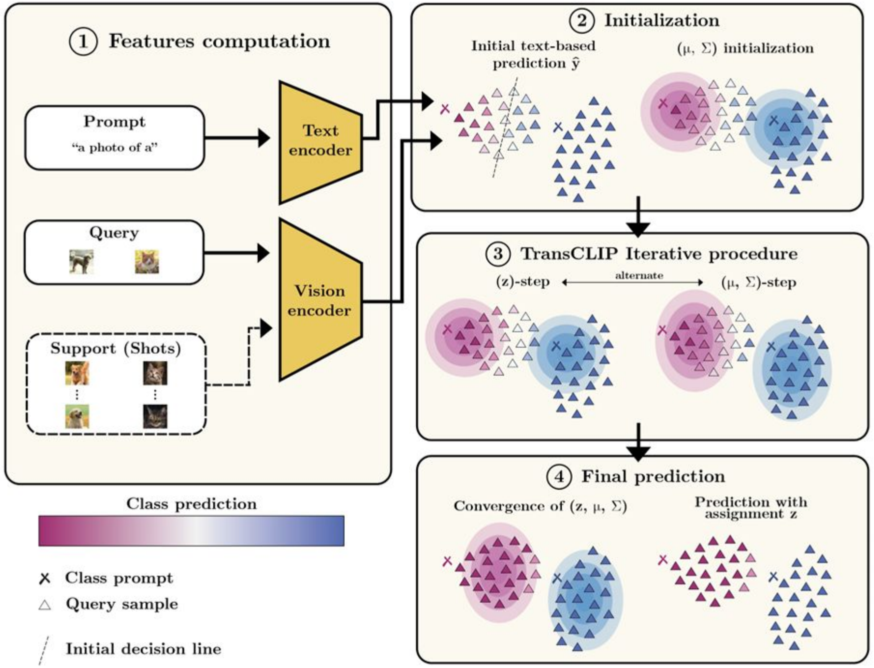

Our algori

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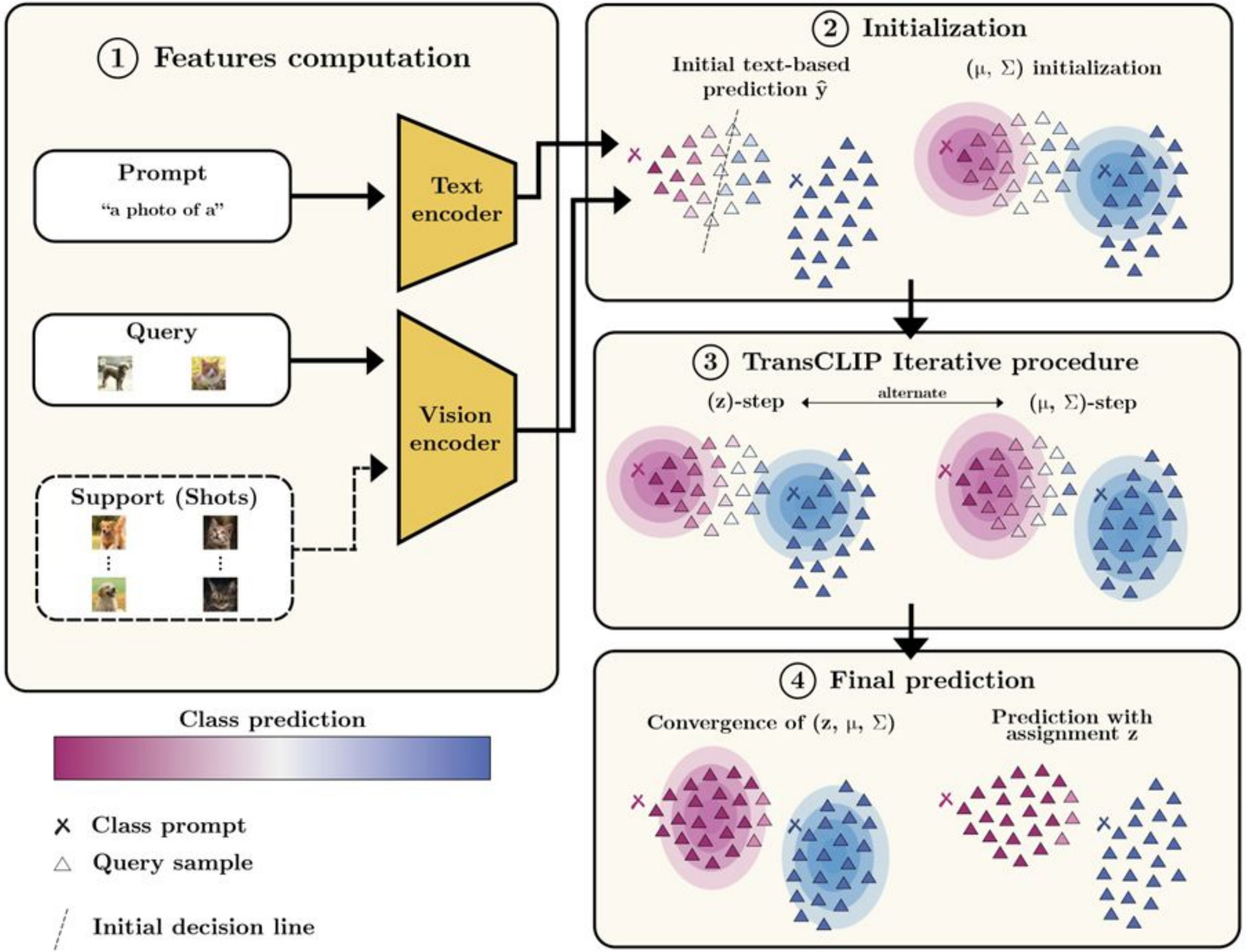

Results

Dataset	Method	CLIP	Quilt-B16	Quilt-B32	PLIP	CONCH
SICAP-MIL	Zero-shot	**29.85**	40.44	**35.04**	46.84	27.71
	Histo-TransCLIP	24.72	**58.49**	28.18	**53.23**	**32.58**
LC(Lung)	Zero-shot	**31.46**	43.00	76.24	84.96	84.81
	Histo-TransCLIP	25.62	**50.53**	**93.93**	**93.80**	**96.29**
SKINCANCER	Zero-shot	4.20	15.38	39.71	22.90	58.53
	Histo-TransCLIP	**11.46**	**33.33**	**48.80**	**36.72**	**66.22**
NCT-CRC	Zero-shot	25.39	29.61	53.73	63.17	66.27
	Histo-TransCLIP	**39.61**	**48.40**	**58.13**	**77.53**	**70.36**
Average	Zero-shot	22.73	32.1	51.18	54.47	59.33
	Histo-TransCLIP	**25.35**	**47.69**	**57.26**	**65.32**	**66.36**
	$\Delta_{\text{transductive}}$	**+2.62**	**+15.59**	**+6.08**	**+10.85**	**+7.03**

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Results: generic pre-training

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Results: histopathology pre-training

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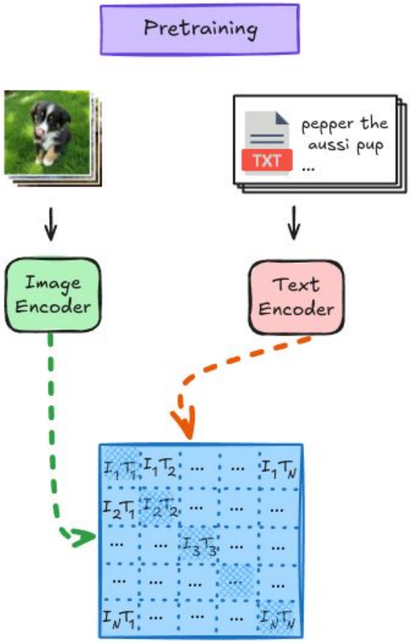
	$\Delta_{\text{transductive}}$	**+2.62**	**+15.59**	**+6.08**	**+10.85**	**+7.03**

Generalist Vision-language Models (CLIP)



Radford, Alec, et al. "Learning transferable visual models from natural language supervision." PMLR, 2021.

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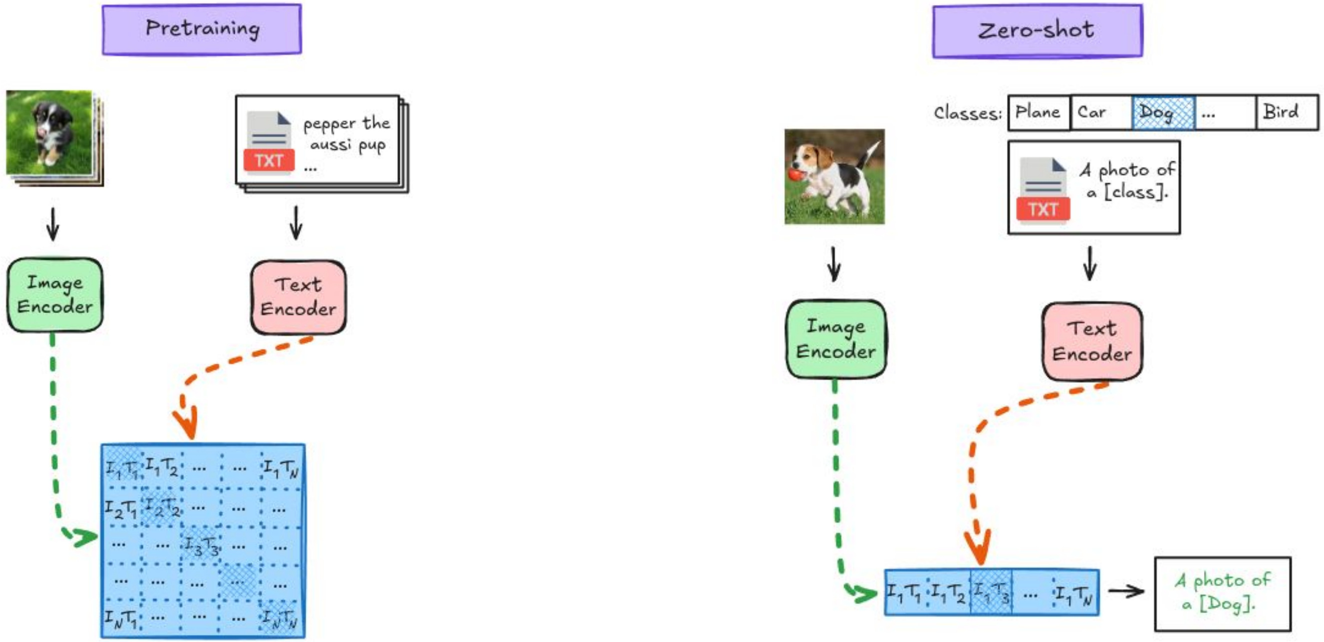

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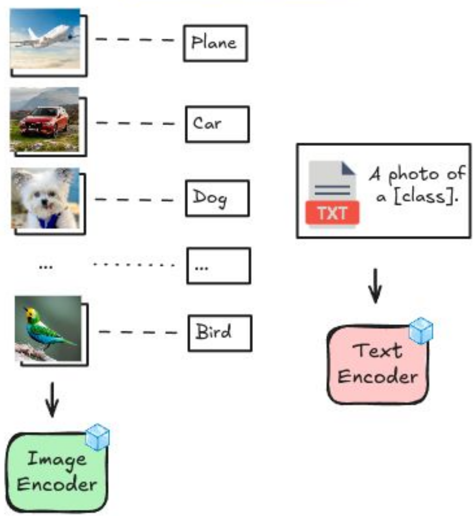
Few-Shot Adaptation (linear probe)



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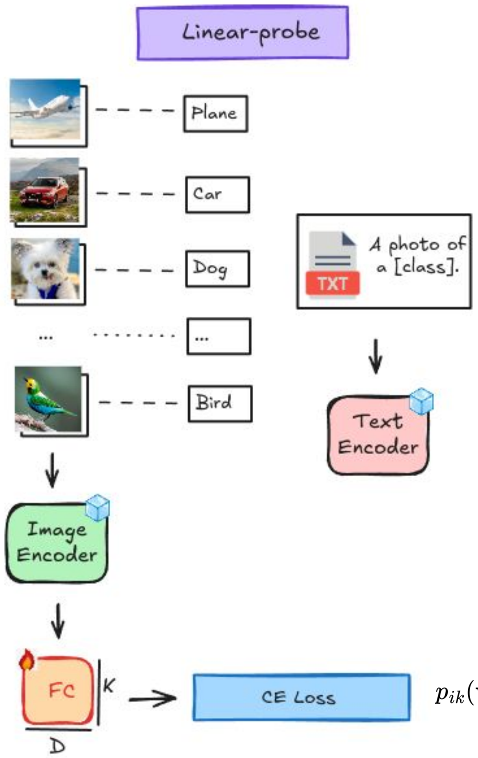

Features Learned FC weights

$$p_{ik}(\mathbf{w}) = \frac{\exp\left(\mathbf{f}_i^t \mathbf{w}_k\right)}{\sum_{j=1}^{K} \exp\left(\mathbf{f}_i^t \mathbf{w}_j\right)}$$

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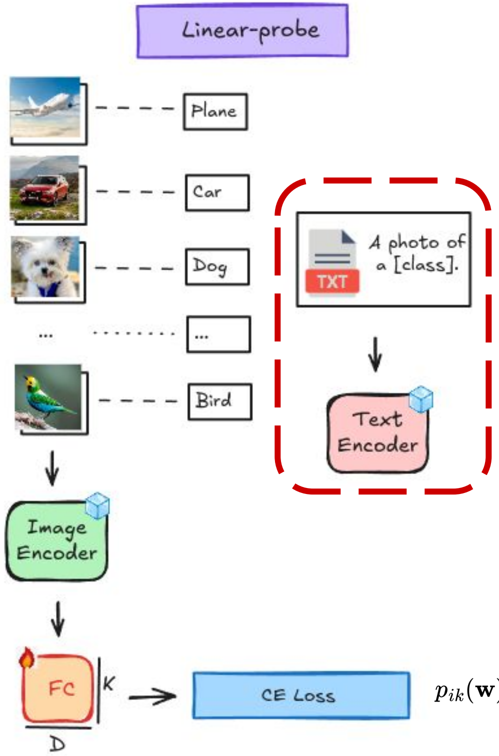
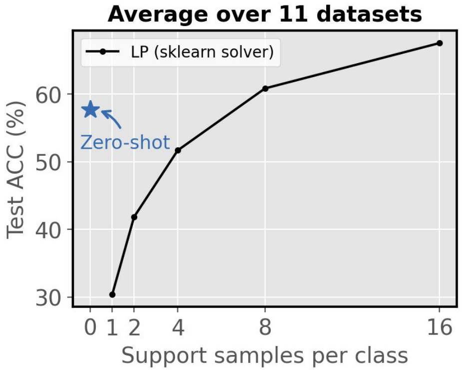


Doesn't use text information during adaptation.

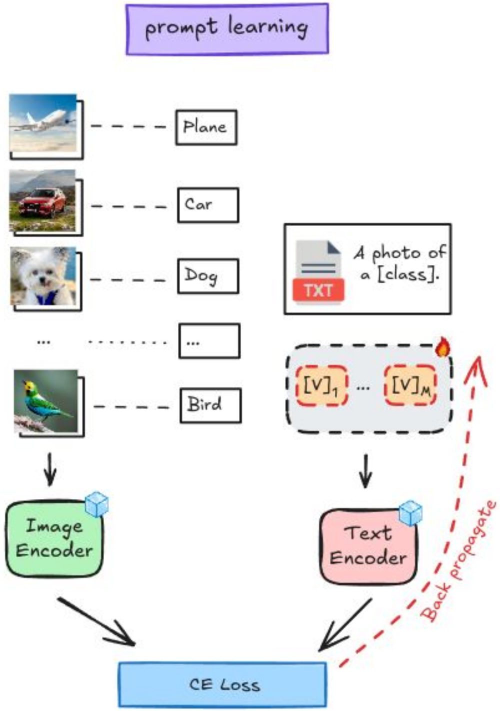
$$p_{ik}(\mathbf{w}) = \frac{\exp\left(\mathbf{f}_i^t \mathbf{w}_k\right)}{\sum_{j=1}^{K} \exp\left(\mathbf{f}_i^t \mathbf{w}_j\right)}$$



Linear Probe below Zero shot!!

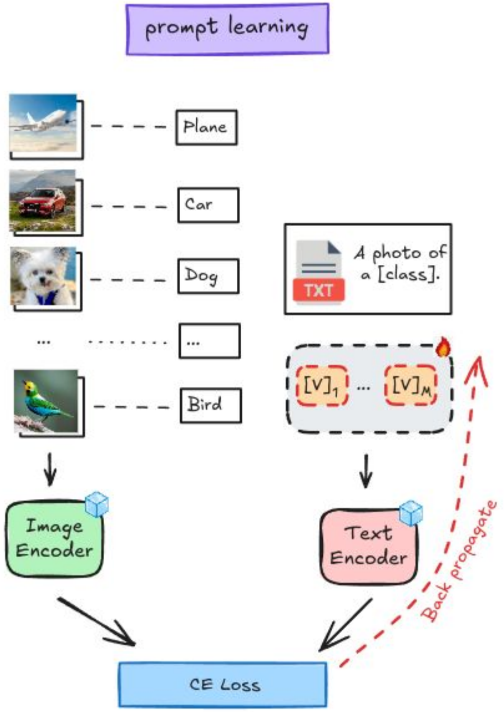
Radford, Alec, et al. "Learning transferable visual models from natural language supervision." PMLR, 2021.

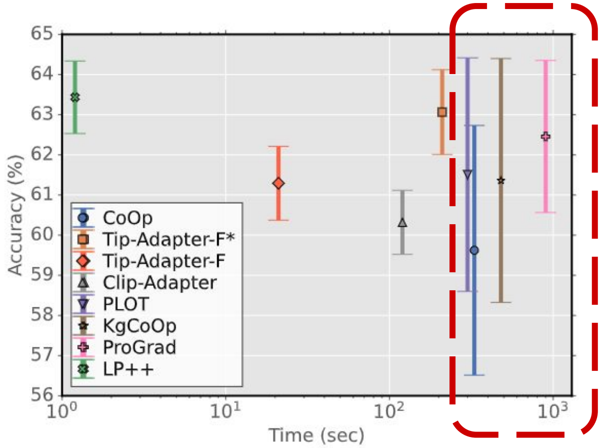
Few-Shot Adaptation (prompt learning)



Prompt learning: Zhou, Kaiyang, et al. "Learning to prompt for vision-language models." *IJCV* (2022).

Few-Shot Adaptation (prompt learning)



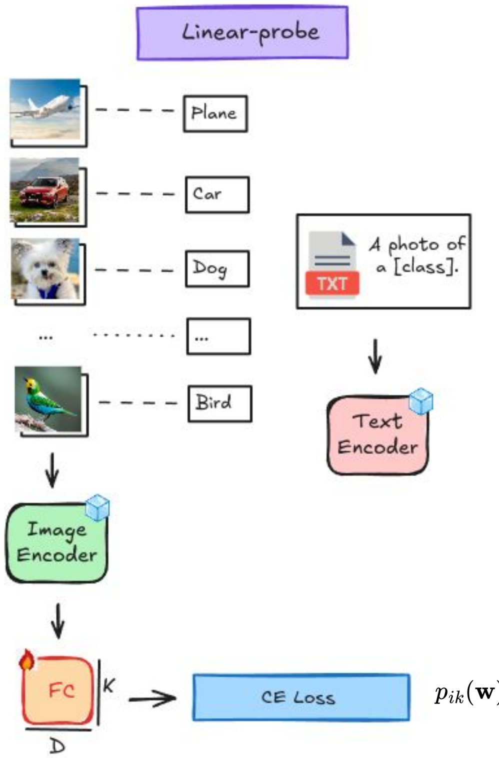


Heavy computational & memory load

Not valid in black-box scénario

Prompt learning: Zhou, Kaiyang, et al. "Learning to prompt for vision-language models." *IJCV* (2022).
Figure from: Huang, Y, et al. . “LP++: A Surprisingly Strong Linear Probe for Few-Shot CLIP” . CVPR (2024).

Few-Shot Adaptation (linear probe)



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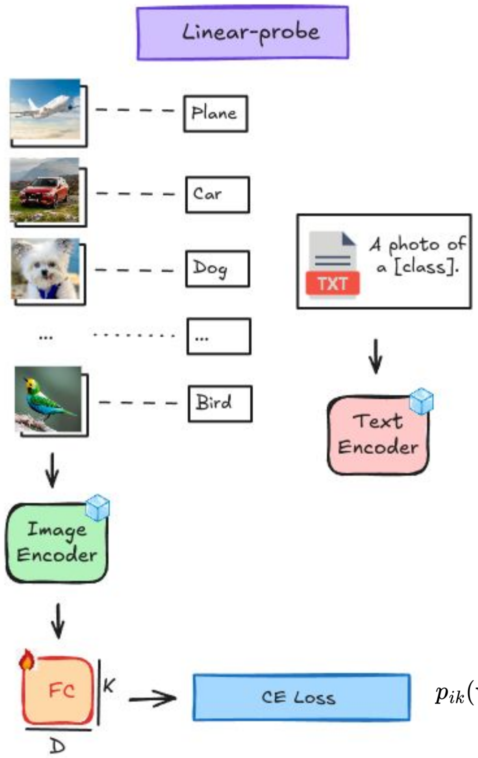
Few-Shot Adaptation (linear probe)



Features

Learned FC weights

$$p_{ik}(\mathbf{w}) = \frac{\exp\left(\mathbf{f}_i^t \mathbf{w}_k\right)}{\sum_{j=1}^{K} \exp\left(\mathbf{f}_i^t \mathbf{w}_j\right)}$$

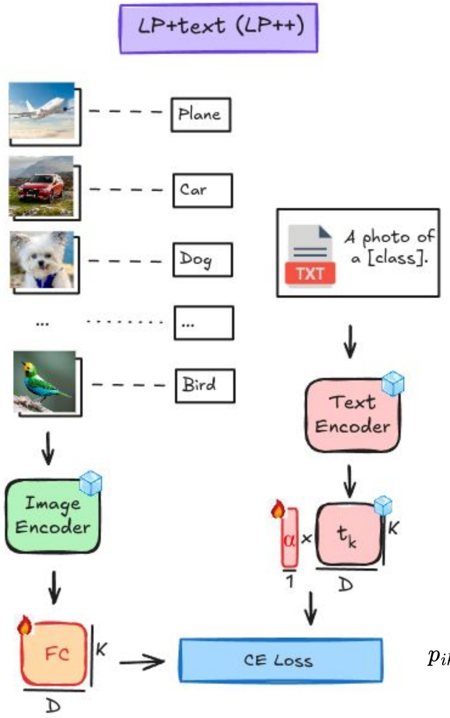
LP+text (LP++)

learnable image-text blending parameters

Text Prototype

$$p_{ik}(\mathbf{w}, \alpha) = \frac{\exp\left(\mathbf{f}_i^t(\mathbf{w}_k + \alpha_k \mathbf{t}_k)\right)}{\sum_{j=1}^{K} \exp\left(\mathbf{f}_i^t(\mathbf{w}_j + \alpha_j \mathbf{t}_j)\right)}$$

Few-Shot Adaptation (LP++)



W: visual class prototypes

t_k: text class prototypes

α: blending parameter

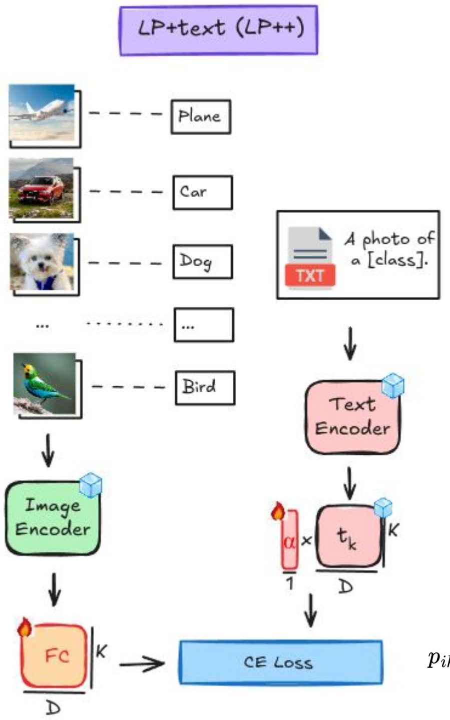
K: number of classes

D: featuremap dimension

$$p_{ik}(\mathbf{w}, \alpha) = \frac{\exp\left(\mathbf{f}_i^t(\mathbf{w}_k + \alpha_k \mathbf{t}_k)\right)}{\sum_{j=1}^{K} \exp\left(\mathbf{f}_i^t(\mathbf{w}_j + \alpha_j \mathbf{t}_j)\right)}$$

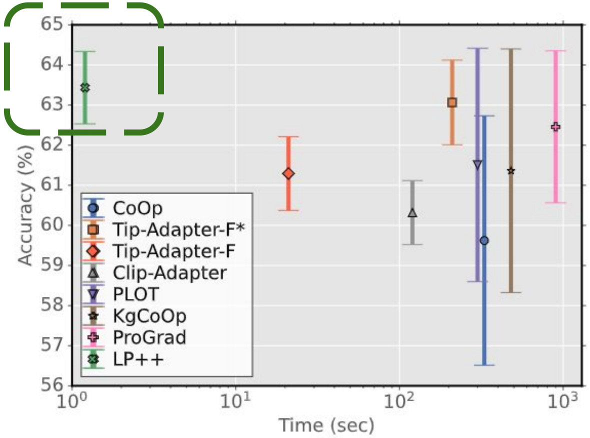
Huang, Y, et al. . "LP++: A Surprisingly Strong Linear Probe for Few-Shot CLIP" .CVPR 2024.

Few-Shot Adaptation (LP++)



Orders-of-magnitude faster

Préserve black-box



$$p_{ik}(\mathbf{w}, \alpha) = \frac{\exp\left(\mathbf{f}_i^t(\mathbf{w}_k + \alpha_k \mathbf{t}_k)\right)}{\sum_{j=1}^{K} \exp\left(\mathbf{f}_i^t(\mathbf{w}_j + \alpha_j \mathbf{t}_j)\right)}$$

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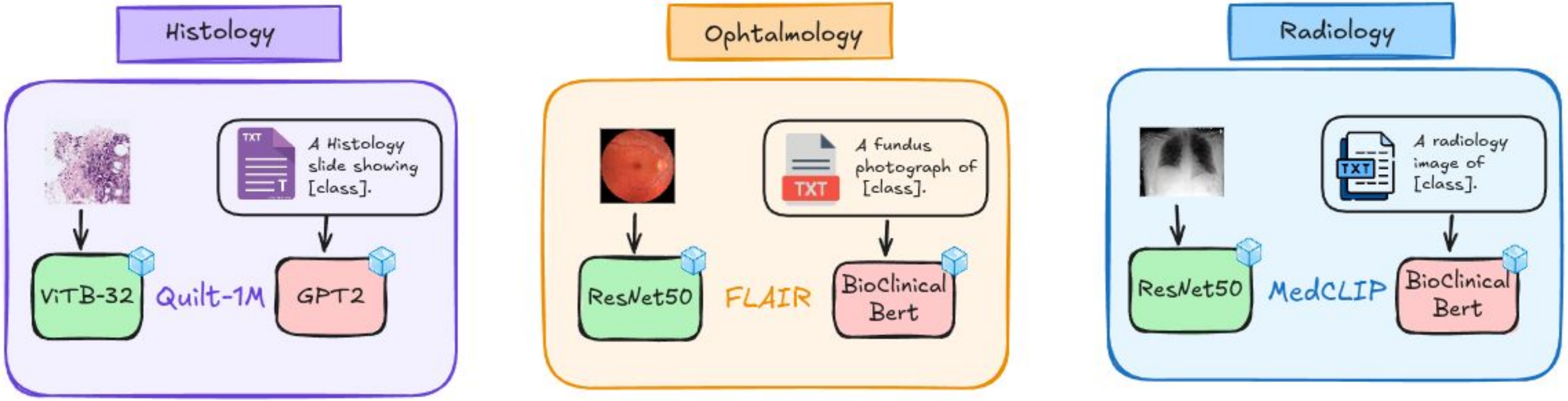
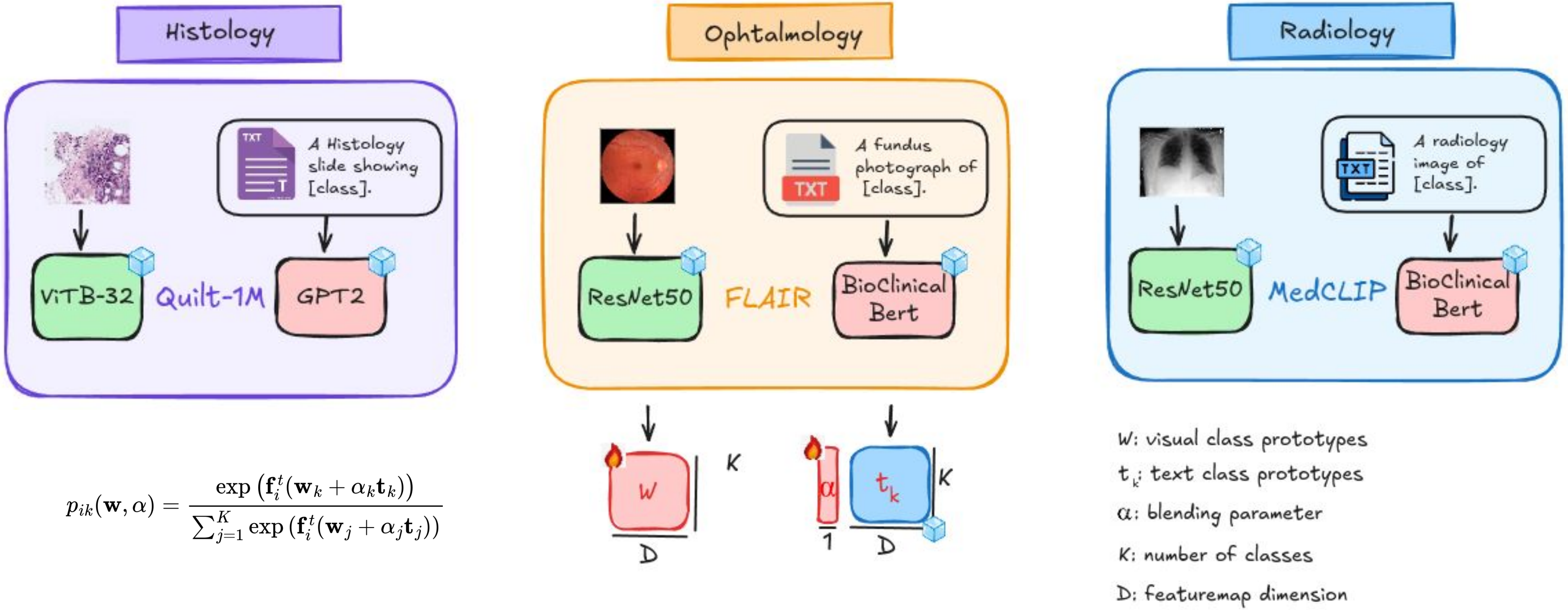
Medical VLMs



FLAIR: Silva-Rodríguez et al., A Foundation Language-Image Model of the Retina, MedIA 2024
Quilt-1M: Ikezogwo et al., One Million Image-Text Pairs for Histopathology, NeurIPS 2023
MedCLIP: Wang et al., Contrastive Learning from Unpaired medical images and text, EMNLP 2022

Few-Shot Adaptation in Medical VLMs

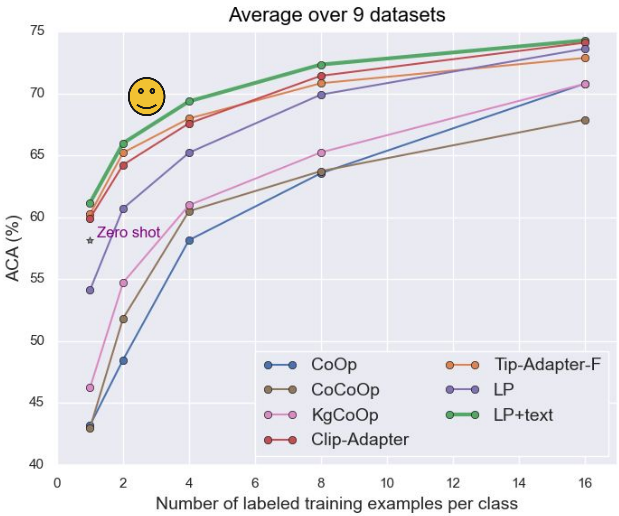


$$p_{ik}(\mathbf{w},\alpha) = \frac{\exp\left(\mathbf{f}_i^t(\mathbf{w}_k + \alpha_k \mathbf{t}_k)\right)}{\sum_{j=1}^{K} \exp\left(\mathbf{f}_i^t(\mathbf{w}_j + \alpha_j \mathbf{t}_j)\right)}$$

Shakeri, F, et al. "Few-shot adaptation of medical vision-language models." *MICCAI*, 2024.

Few-Shot Adaptation in Medical VLMs

3 modalities / 9 datasets



LP+text is competitive!

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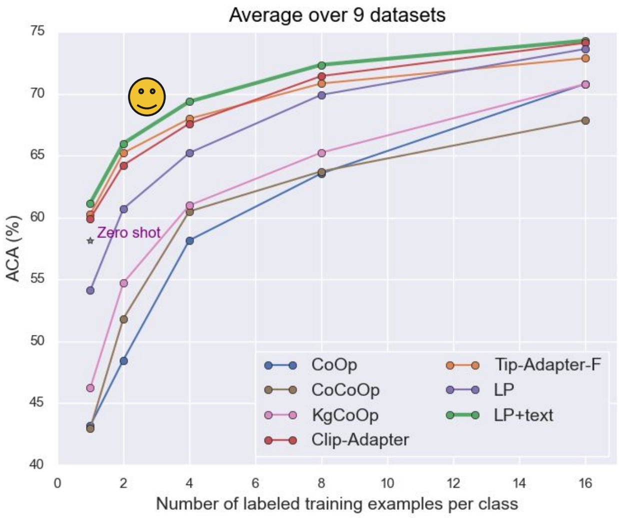
Few-Shot Adaptation in Medical VLMs

3 modalities / 9 datasets



LP+text is <u>competitive</u>!

LP+text is <u>extremely efficient</u>!

- Adaptation in a **matter of seconds**
- Trainable on **commodity GPUs**
- **Black-box adaptation**

Methods	Category	Training Time	Black-box	#Parameters
Zero-shot [21]		n/a	✓	n/a
CoOp [35]	*Prompt-Learning*	3min	✗	$K \times n_{ctx1} \times D$
CoCoOp [34]		12min	✗	$n_{ctx2} \times D + C$
KgCoOp [31]		3min	✗	$K \times n_{ctx1} \times D$
Clip-Adapter [5]	*CLIP-based Adapters*	2min	✓	$2(D_1 \times D_2)$
Tip-adapter-F [32]		2min	✓	$K \times S \times D$
LP	*Linear probe*	43s	✓	$K \times D$
LP+text [7]		4s	✓	$K(D+1)$

Shakeri, F, et al. "Few-shot adaptation of medical vision-language models." *MICCAI*, 2024.

References

- Few-shot Adaptation of Medical Vision Language Models [Spotlight]
  F Shakeri, Y Huang, JR Silva, H Bahig, A Tang, J Dolz, IB Ayed
  IMedical Image Computing and Computer Assisted Intervention (MICCAI), 2024

- LP++: A Surprisingly Strong Linear Probe for Few-Shot CLIP
  Y Huang, F Shakeri, J Dolz, M Boudiaf, H Bahig, IB Ayed
  IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2024

- Boosting Vision-Language Models for Histopathology Classification: Predict all at once [Best Paper Award]
  M Zanella, F Shakeri, Y Huang, H Bahig, IB Ayed
  MICCAI Workshop on Foundation Models for General Medical AI (MedAGI), 2024

Questions? :)

Thank you for your attention!