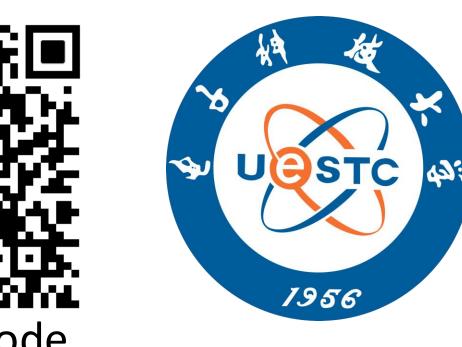


Interpretable Vision-Language Survival Analysis with Ordinal Inductive Bias for Computational Pathology





Luping Ji Pei Liu

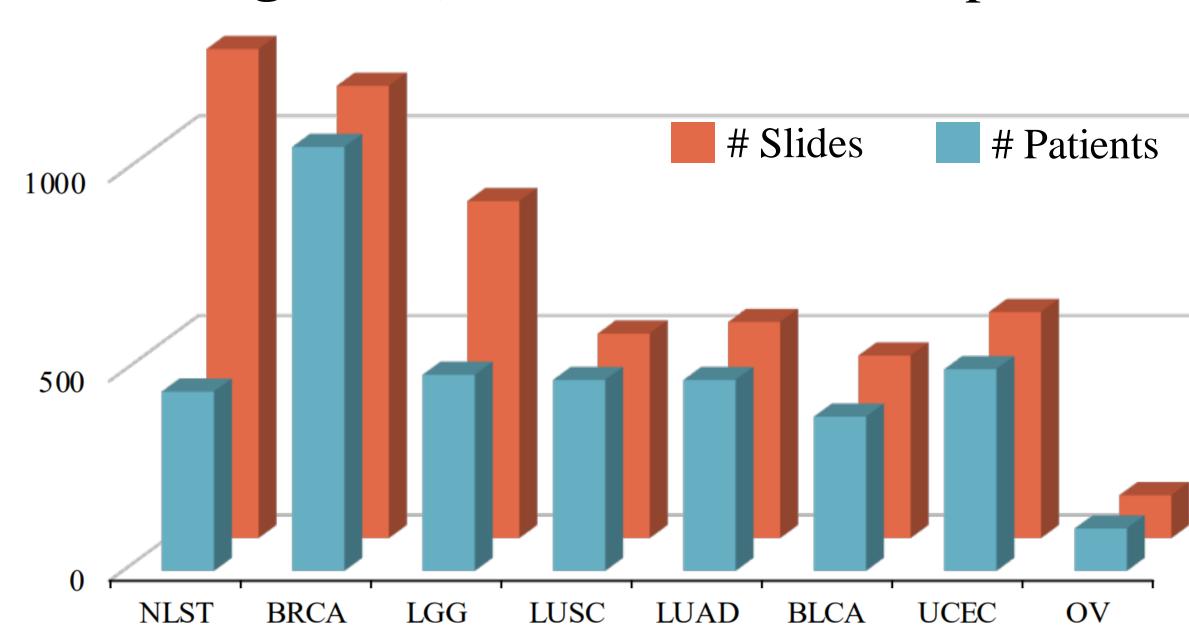
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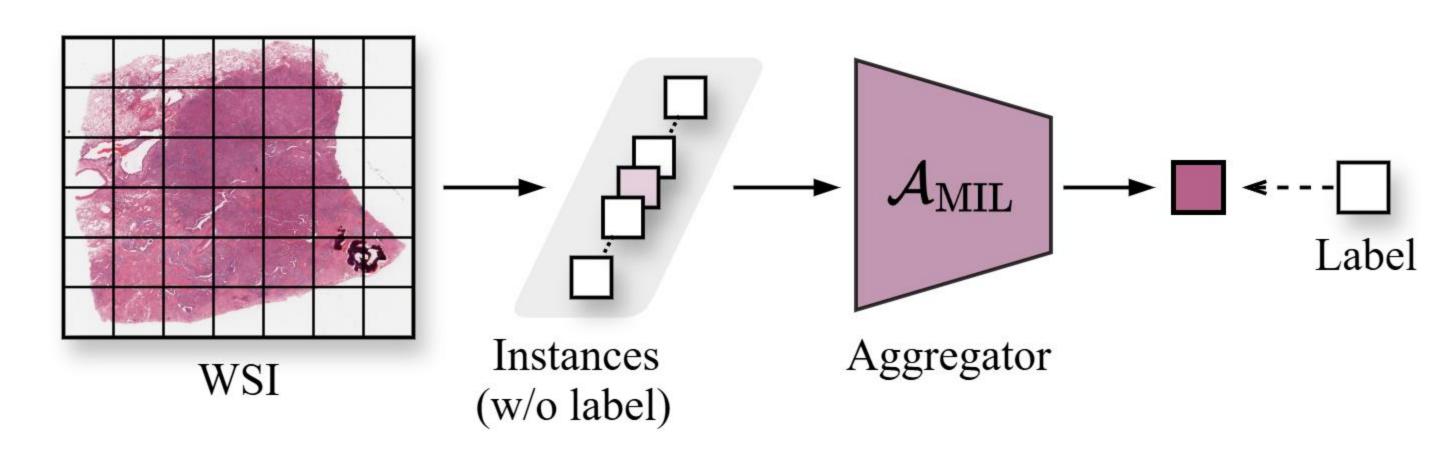
prompts

Motivation

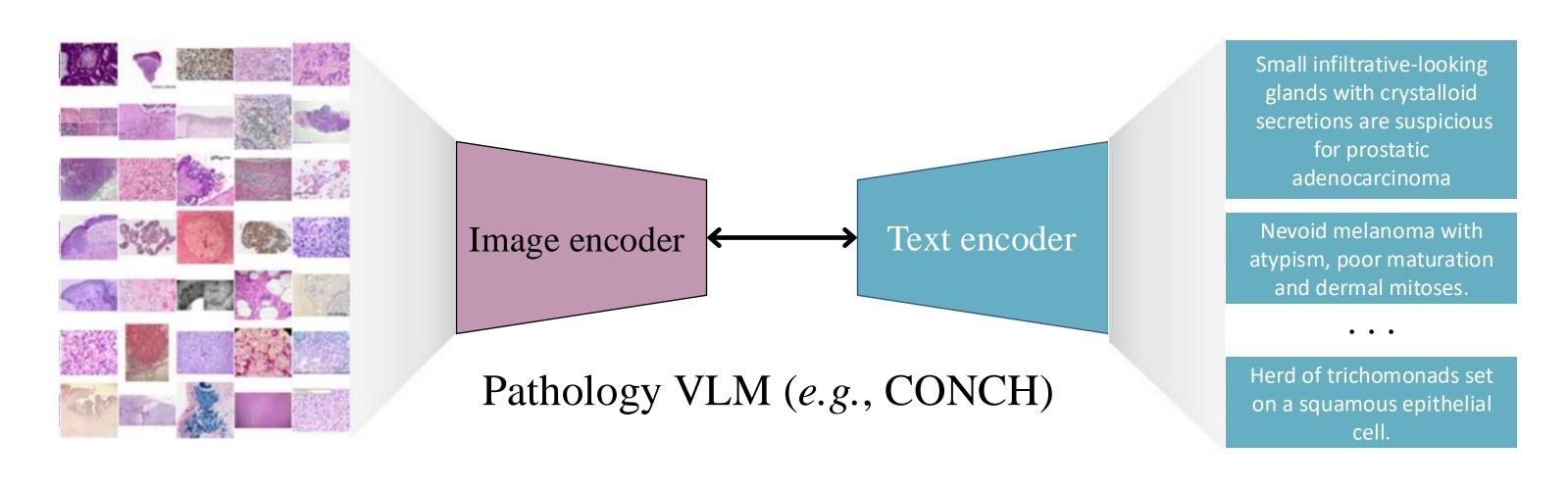
- The survival analysis of WSI (Whole-Slide Image) data has always faced two critical challenges:
- Scarce training data (often limited to 1,000 patients)



• Learning from gigapixel images under weak supervision

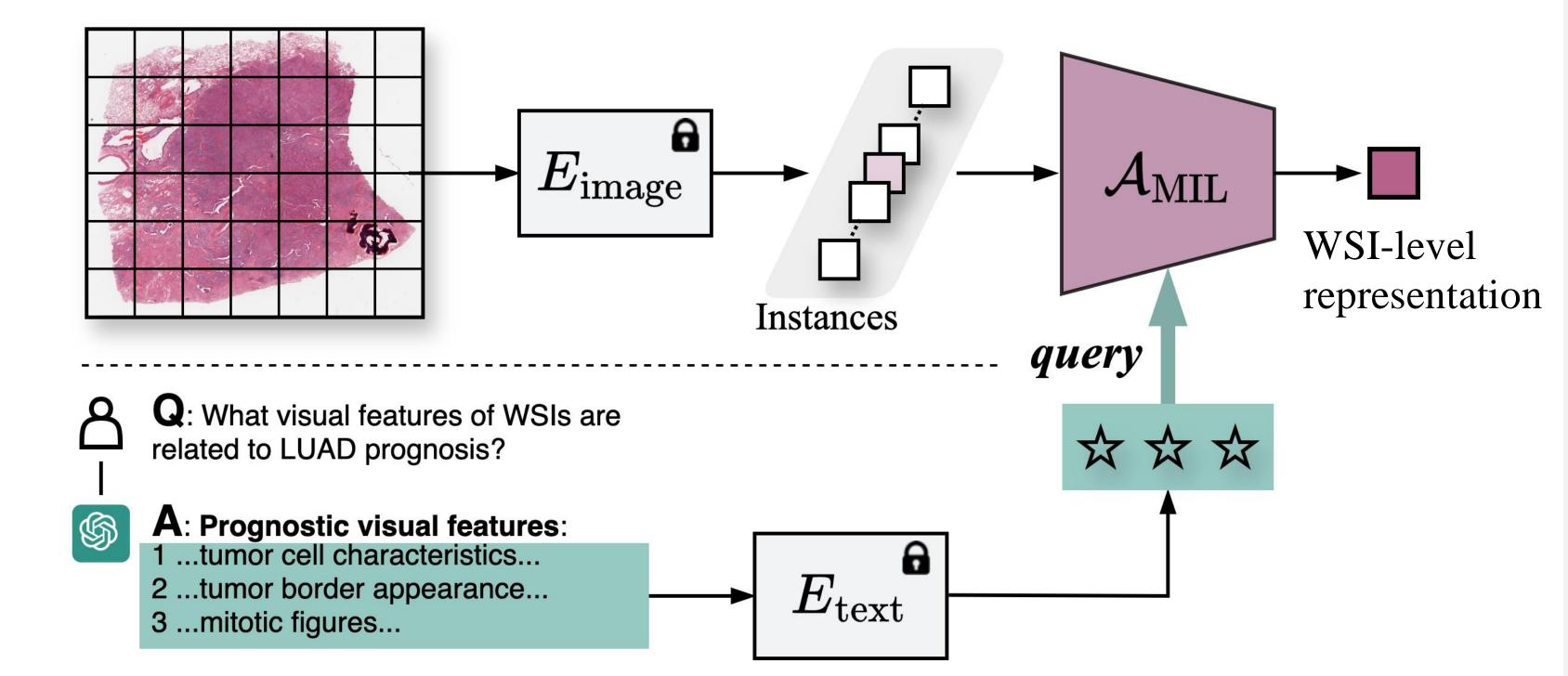


- VLMs (Vision-Language Models) offer promising means:
- VLMs show clear advantages in data-efficiency
- Prior knowledge as text prompt to provide auxiliary signals

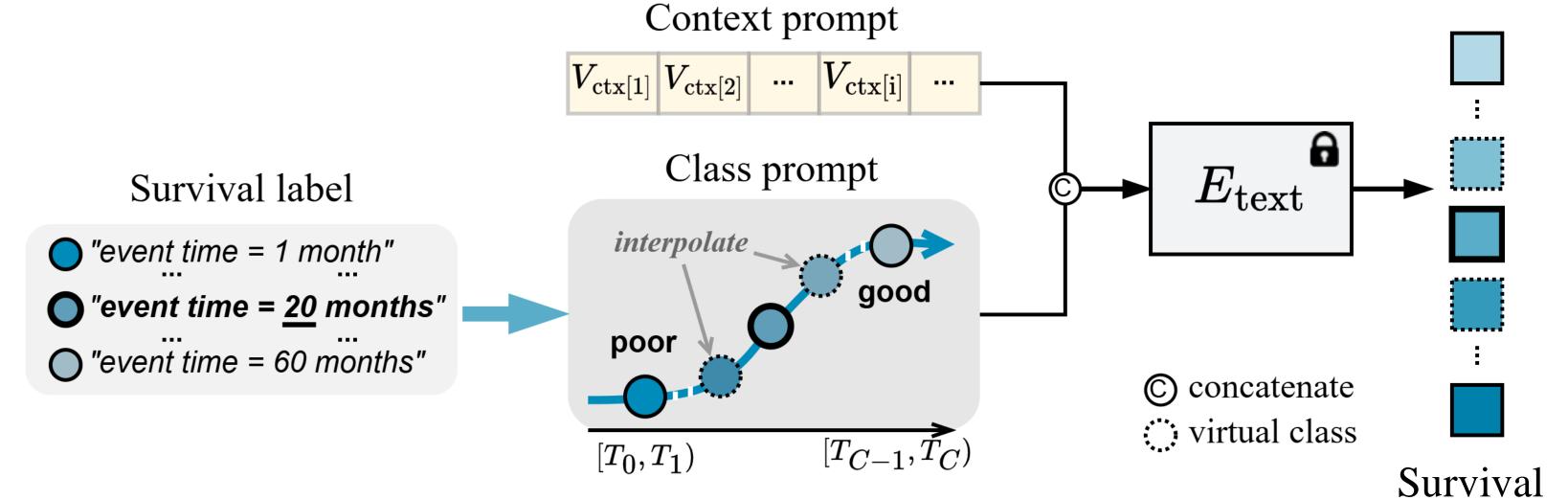


Method

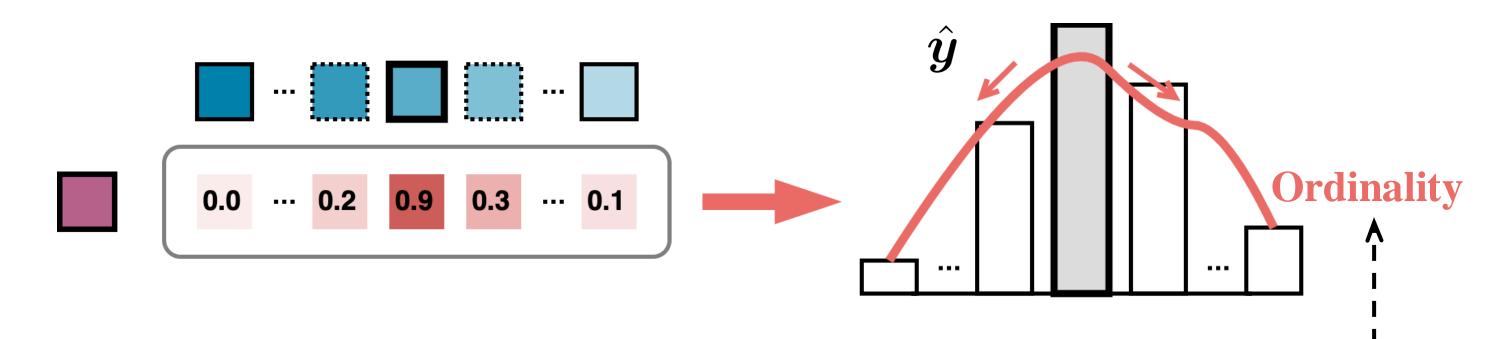
- Vision-Language Survival Analysis (VLSA):
- WSI representation learning with prognostic priors (from LLMs)



Survival prompt learning: context & ordinal class prompts



Survival prediction: patient's incidence function



• Objective function: $\mathcal{L} = \mathcal{L}_{\text{MLE}} + \beta \cdot \mathcal{L}_{\text{EMD}}$ --

$$\mathcal{L}_{\text{MLE}} = -\left[\delta \cdot \log(\hat{y}_c) + (1 - \delta) \cdot \log(1 - \sum_{i=1}^{c-1} \hat{y}_i)\right]$$

Experiments & Results

■ Comparison with baselines & Ablation study on MIL methods

Method		TCGA BLCA BRCA GBMLGG LUAD			IIIAD	UCEC	Average CI MAE		D-cal Count
								WIAL	Count
	ABMIL	0.5581	0.5825	0.7935	0.6121	0.6667	0.6426	29.83	4
		(± 0.031)	(± 0.035)	(± 0.032)	(± 0.050)	(± 0.033)			
	TransMIL	0.5885	0.6140	0.7956	0.5708	0.6380	0.6414	30.43	5
		(± 0.055)	(± 0.060)	(± 0.015)	(± 0.050)	(± 0.067)			
	ILRA	0.5549	0.5705	0.7742	0.5179	0.6503	0.6136	32.59	4
>		(± 0.053)	(± 0.067)	(± 0.014)	(± 0.081)	(± 0.064)			
	R ² T-MIL	0.5775	0.5473	0.7757	0.5711	0.6510	0.6245	32.54	4
		(± 0.024)	(± 0.095)	(± 0.024)	(± 0.076)	(± 0.087)			
	DeepAttnMISL	0.5646	0.5346	0.6750	0.4678	0.6259	0.5736	52.10	5
		(± 0.035)	(± 0.036)	(± 0.048)	(± 0.039)	(± 0.085)			
	Patch-GCN	<u>0.6124</u>	0.6375	0.7999	0.5922	<u>0.7212</u>	0.6726	<u>26.70</u>	2
		(± 0.031)	(± 0.033)	(± 0.021)	(± 0.053)	(± 0.025)			
	MI-Zero _{Surv} †	0.5541	0.5788	0.3842	0.5209	0.6623	0.5400	25.63	
		(± 0.034)	(± 0.028)	(± 0.063)	(± 0.049)	(± 0.059)			0
	ABMIL _{Prompt}	0.5717	0.6215	0.7825	0.5984	0.6762	0.6500	25.68	4
		(± 0.035)	(± 0.084)	(± 0.020)	(± 0.052)	(± 0.063)			
1	CoOp	0.5971	0.5994	0.7853	0.5750	0.6840	0.6482	28.70	_
>		(± 0.033)	(± 0.086)	(± 0.015)	(± 0.064)	(± 0.070)			5
	OrdinalCLIP	0.6037	0.6202	0.7893	0.6053	0.6836	0.6604	28.01	_
		(± 0.043)	(± 0.046)	(± 0.018)	(± 0.065)	(± 0.036)			5
	VLSA (ours)	0.6176	0.6652	0.8002	0.6370	0.7571	0.6954	25.15	_
		(± 0.025)	(± 0.057)	$(\pm \ 0.010)$	(± 0.027)	(± 0.045)			5
Attention		0.6083	0.6180	0.7908	0.6048	0.6908	0.6625	26.78	5
		(± 0.047)	` /	(± 0.017)	(± 0.063)	(± 0.035)			
Learnable prototypes		0.5872	0.6201	0.7853	0.6061	0.6845	0.6566	26.76	4
	armable prototypes	(± 0.048)	` /	(± 0.013)	(± 0.053)	(± 0.052)	0.0500	20.70	•
Prognostic texts		0.6159	0.6614	0.7985	0.6314	0.7491	0.6912	25.05	4
		(± 0.025)	(± 0.047)	(± 0.009)	(± 0.028)	(± 0.049)	0.0712		
Prognostic texts + FT		0.6176	0.6652	0.8002	0.6370	0.7571	0.6954	25.15	5
	OSHOBILO IOAIS TIT	(± 0.025)	(± 0.057)	(± 0.010)	(± 0.027)	(± 0.045)	0.0734	23.13	9

■ Visualization results: ordinality & prediction interpretation

