

HistoEncoder

Towards a foundation model for
digital pathology

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+

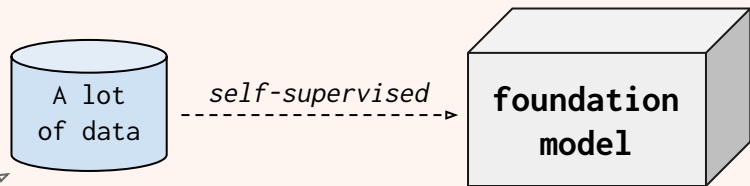


What is a foundation model?

LUMI

pre-training

Centralises information from vast amounts of data.



Prostate tissue samples from Helsinki University Hospital

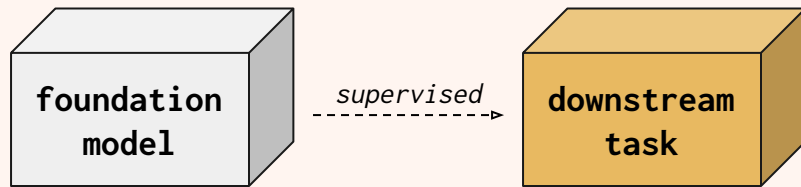


5.8 million tile images

898.4 million tile images

adaptation

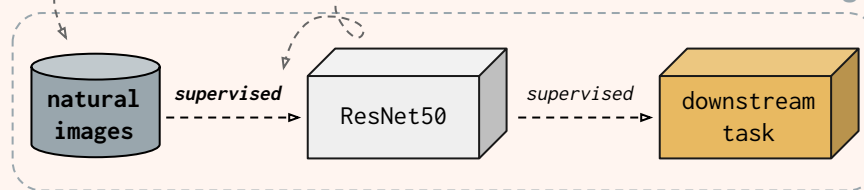
One model adapts easily to a wide range of downstream tasks.



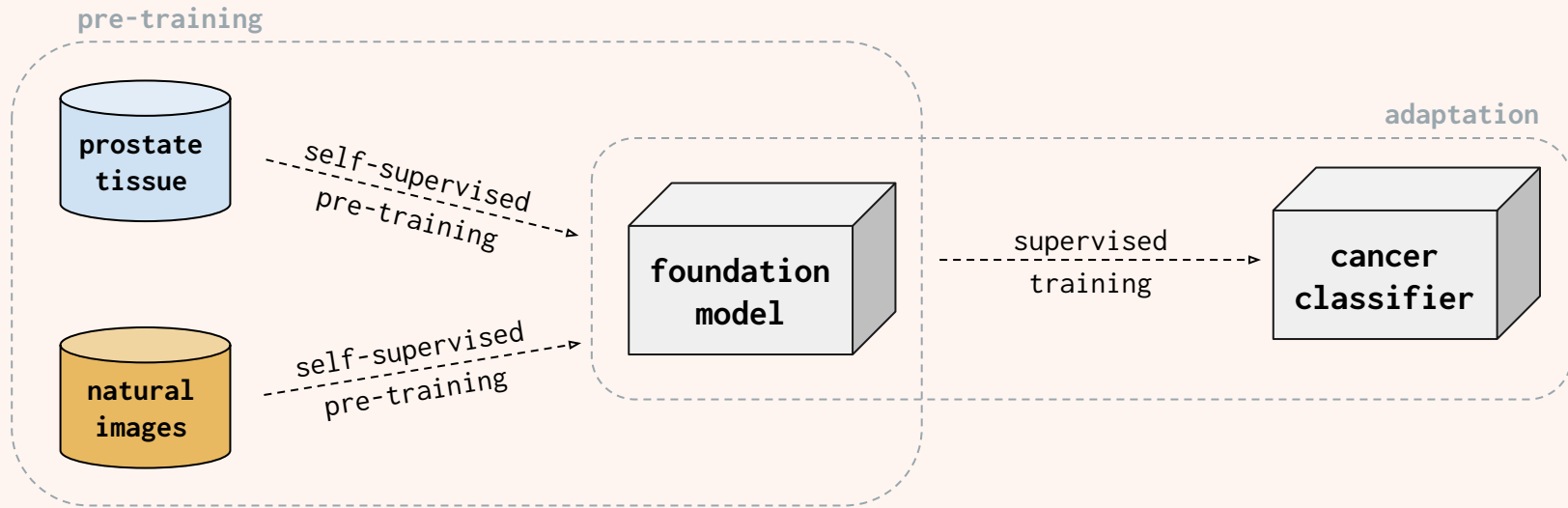
Dogs and cats differ widely from histological samples!!

supervised training is not good for pre-training!!

transfer learning



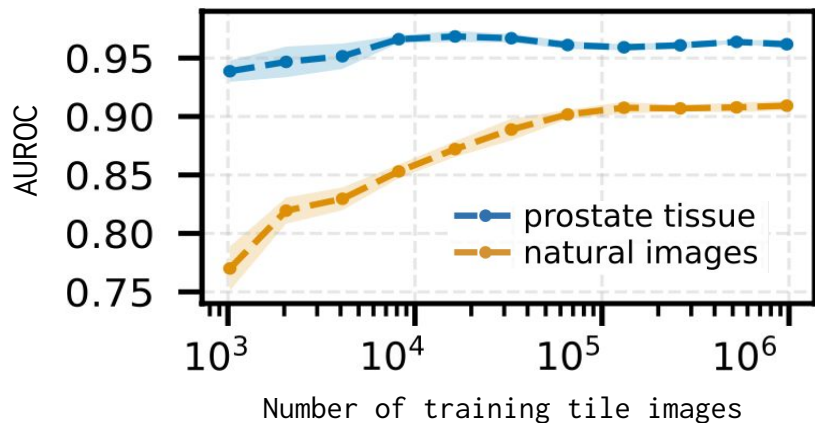
Does domain specific pre-training help?



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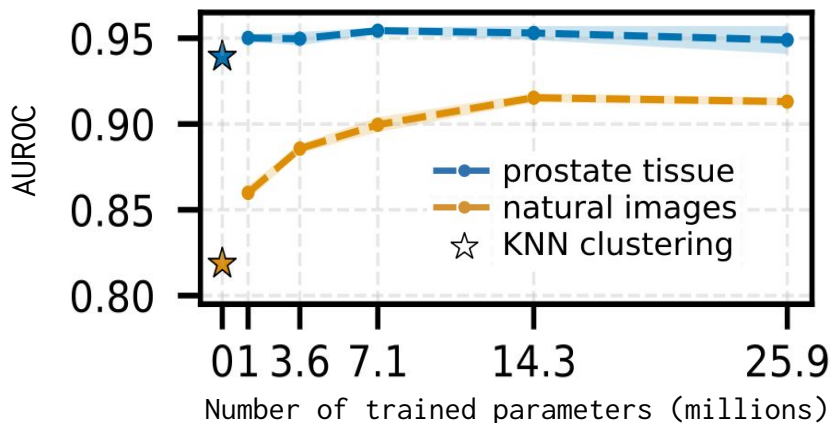
common model sizes

small MLP	~1 million
ResNet-18	11 million
ResNet-50	24 million
ResNet-101	42 million
ViT-Base	86 million



**Fine-tuning requires
~1000 times less training data!!**

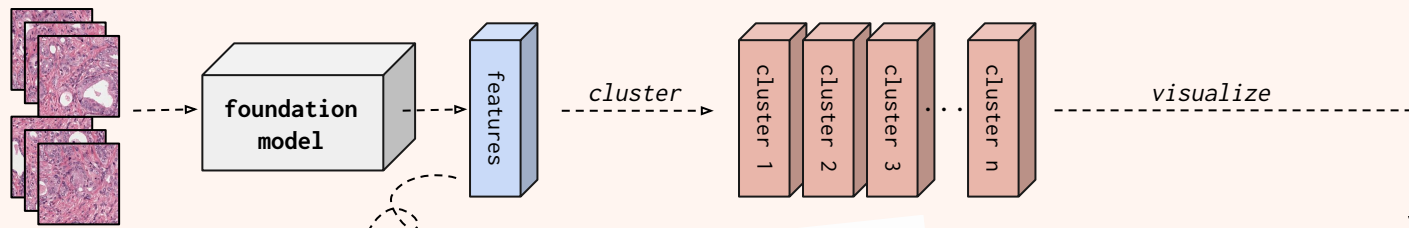
**Task 1: Limit the amount of
training data**



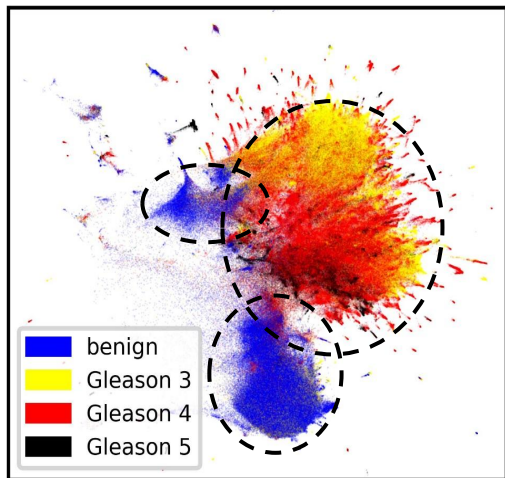
**Build competitive classifiers without
any training!**

**Task 2: Limit the number of
trained parameters**

Automatically annotate datasets by clustering...?



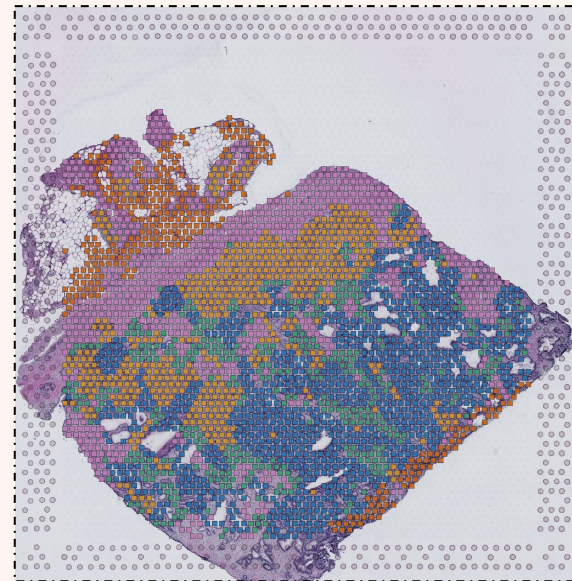
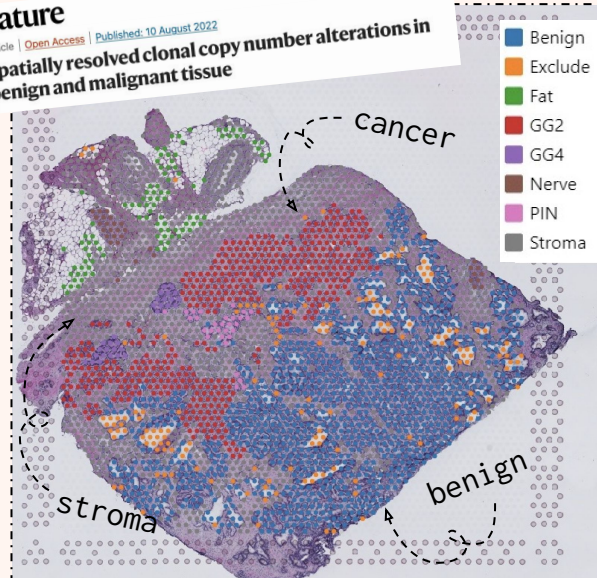
UMAP of epithelium tissue



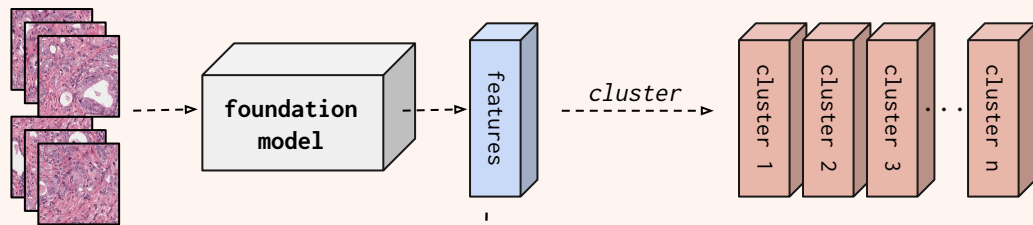
nature

Article | [Open Access](#) | Published: 10 August 2022

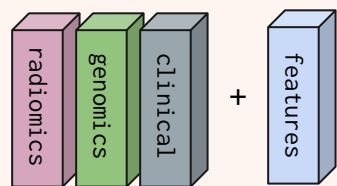
Spatially resolved clonal copy number alterations in benign and malignant tissue



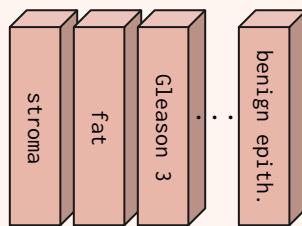
Building multi-modal models...?



Case 1: Tile-level data



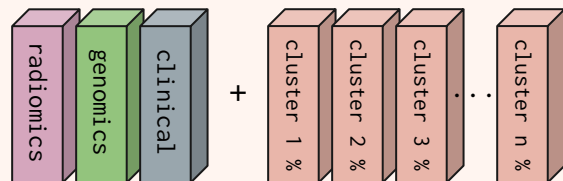
Calculate cluster percentages at a **patient-level**.



patient-level
cluster percentages

idkey	stroma	fat	Gleason3	...
0001	0.031	0.024	0.101	...
0002	0.183	0.210	0.017	...
0003	0.049	0.001	0.078	...
...
0999	0.227	0.012	0.279	...

Case 2: Patient-level data

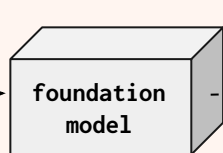
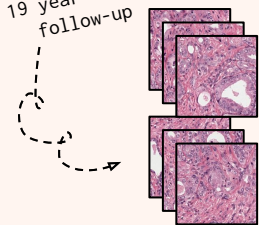


Each cluster contains
similar histological
patterns!

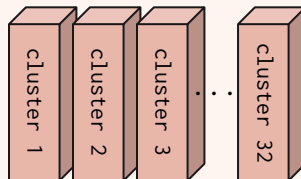
**Distribution of histological
patterns for a given patient!!**

Prostate cancer specific death

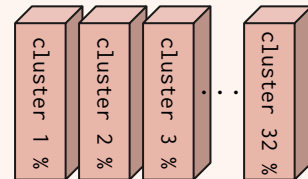
432 patients with
19 year median
follow-up



cluster



count cluster
percentages



32 clusters!

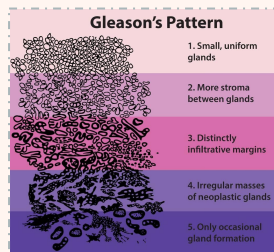
The CAPRA-S score: a straightforward tool for improved prediction of outcomes after radical prostatectomy

Matthew R. Cooperberg, MD, MPH,⁽¹⁾⁽²⁾ Joan F. Hilton, MPH, ScD,⁽¹⁾⁽²⁾ and Peter R. Carroll, MD, MPH⁽¹⁾

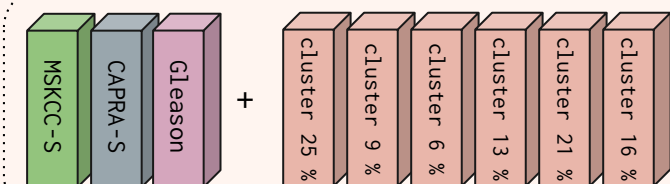
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Risk of Dying of Prostate Cancer in Men With a Rising PSA After Radical Prostatectomy

This nomogram can be used by patients to estimate the risk of dying of prostate cancer if their cancer recurs, signaled by a rising PSA, after radical prostatectomy. The nomogram predicts the likelihood, in a man initially treated with surgery, that he will die of prostate cancer five, ten, and 15 years from the time his PSA begins to rise.

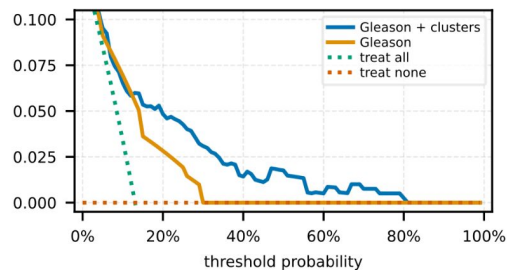


Cox proportional hazards model (+ lasso)

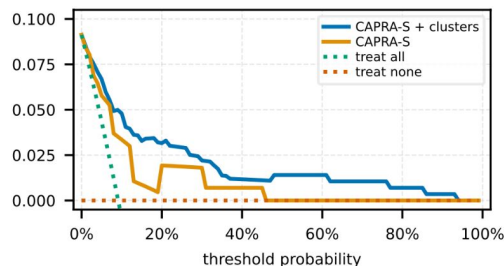


drop clusters
based on
parameter
importance

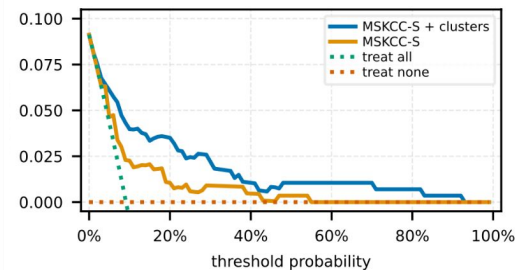
Gleason grade group



CAPRA-S score



MSKCC-S survival probability



Significantly
higher net
benefit!



Summary

Foundation model fine-tuning requires no training
or 1000x less training data.

Images with similar histological patterns
produce similar embedded features.

Pre-annotate
whole datasets!!

```
● ● ●  
# Cut slide images into small tiles.  
HistoPrep -i 'slides/*.tiff' -o tiles/ --width 512  
# Extract & cluster features for all tiles.  
HistoEncoder extract -i tiles/ -m prostate_medium  
HistoEncoder cluster -i tiles/ -n 8 16 32 64 128
```

Combine histomics
with other data
modalities!!!

<https://github.com/jopo666/HistoEncoder>