Comparison of deep transfer learning strategies for digital pathology

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22 June 2018

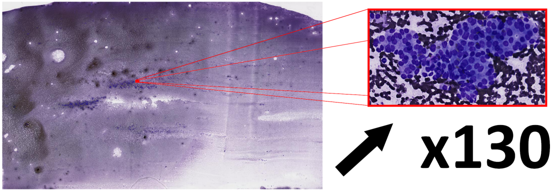
CVMI 2018, poster **FP249**

Digital pathology

"Digital pathology incorporates the acquisition, management, sharing and interpretation of pathology information — including slides and data — in a digital environment"

Digital slides:

- big data: up to millions of biological objects per multi-gigapixel image
- high variability: content, staining, acquisition,...
- data scarcity: annotating data is expensive and tedious



Need for efficient and versatile computer vision methods that can cope with data scarcity !

Deep transfer learning

Because of data scarcity, deep transfer learning is a promising approach for digital pathology.

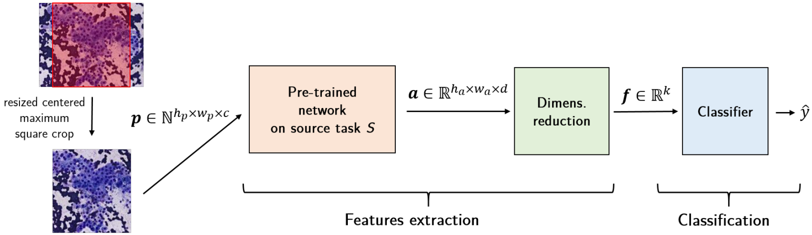
Deep transfer learning alleviates deep learning requirements:

- requires less data
- requires less computing resources and time

Using pre-trained networks

There are mainly two ways of using pre-trained networks:

1. using pre-trained features off-the-shelf (OTS)



2. fine-tuning the networks

Deep transfer learning: how to ?

Goal: devising guidelines and best practices for deep transfer learning in digital pathology:

- Fine-tuning *vs.* OTS features: which one works better ?
- Which network works better ?
- Where to extract OTS features ?
- ...

Deep transfer learning: how to ?

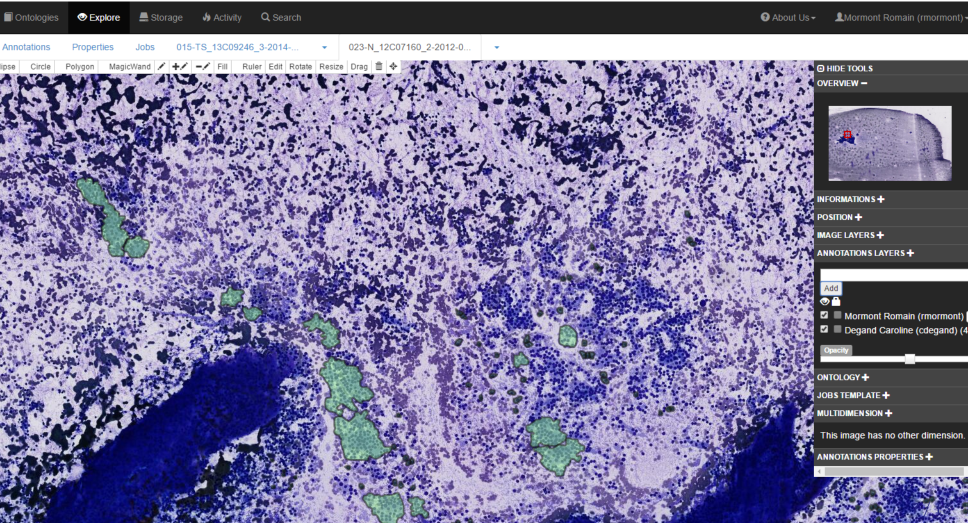
We have carried out several experiments with ImageNet as source task:

- OTS vs. fine-tuning
- Networks: ResNet50, DenseNet201, VGG16/19, InceptionResNetV2,...
- Features classifiers: SVM , extra-trees (ET),...
- OTS features extraction at increasing depth
- ...

Cytomine

cytomine is an open-source web-based environment enabling collaborative multi-gigapixel image analysis (uliege.cytomine.org)

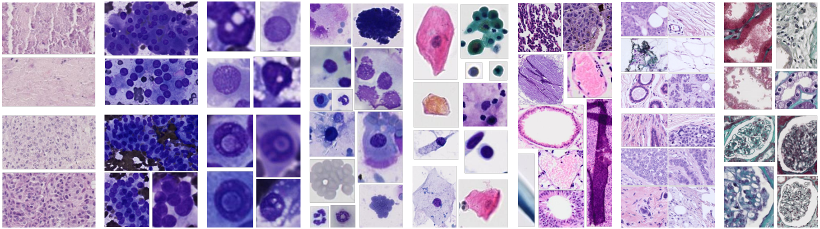
Marée & al., Bioinformatics; 2016



Datasets

8 image classification datasets.

Dataset	Domain	Cls	Total	
			Images	Slides
Necrosis (N)	Histo	2	882	13
ProliferativePattern (P)	Cyto	2	1857	36
CellInclusion (C)	Cyto	2	3638	45
MouseLba (M)	Cyto	8	4284	20
HumanLba (H)	Cyto	9	5420	64
Lung (L)	Histo	10	6331	882
Breast (B)	Histo	2	23032	34
Glomeruli (G)	Histo	2	29213	205



Results

Fine-tuning is the best performing strategy

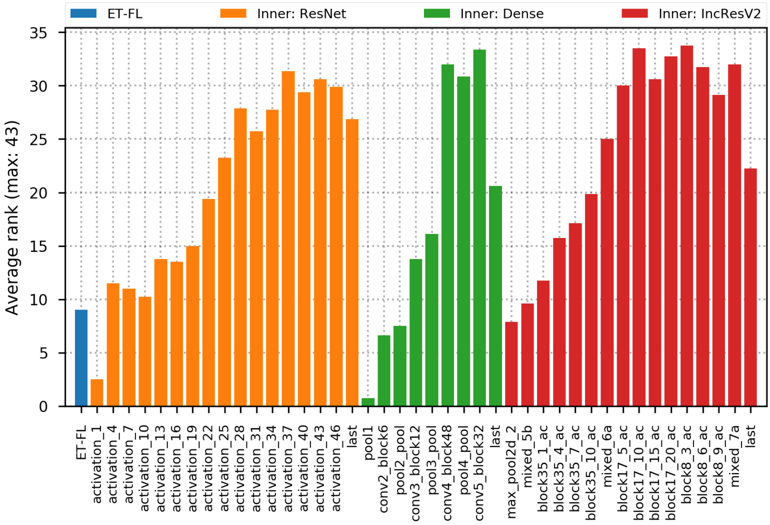
Fine-tuning is often the best performing method
... but OTS features are close on most problems and less computationally expensive !

	Datasets							
Strategy	**Cell**	**Prolif**	**Glom**	**Necro**	**Breast**	**Mouse**	**Lung**	**Human**
Baseline (ET-FL)	0.9250	0.8268	0.9551	0.9805	0.9345	0.7568	0.8547	0.6960
Last layer	0.9822	0.8893	0.9938	*0.9982*	0.9603	0.7996	0.9133	0.7820
Feat. select.	0.9676	0.8861	0.9843	**0.9994**	0.9597	0.7438	0.8941	0.7703
Merg. networks	*0.9897*	**0.8984**	0.9948	0.9864	0.9549	*0.8169*	0.9155	0.7928
Merg. layers	0.9808	0.8906	0.9944	0.9964	0.9639	0.7941	0.9268	0.7977
Inner ResNet	0.9748	*0.8959*	0.9949	0.9964	0.9664	0.8131	*0.9291*	*0.8113*
Inner DenseNet	0.9862	**0.8984**	*0.9962*	0.9917	0.9699	0.8012	0.9268	0.7967
Inner IncResV2	0.9873	0.8948	*0.9962*	*0.9982*	*0.9720*	0.8137	0.9234	0.7713
Fine-tuning	**0.9926**	0.8797	**0.9977**	0.9970	**0.9873**	**0.8727**	**0.9405**	**0.8641**
Metric	Roc AUC					Accuracy (multi-class)		

Best in **bold**, second best in *italic*

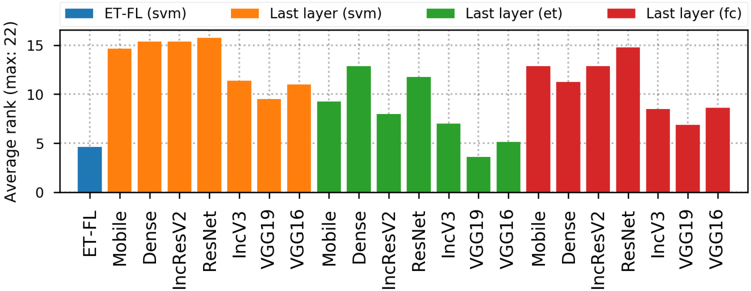
Results

When working with OTS features, use some inner layer features



Results

More recent networks like DenseNet or ResNet work better



See also: Kornblith, S., Shlens, J., & Le, Q. V. (2018). *Do Better ImageNet Models Transfer Better?*. arXiv preprint arXiv:1805.08974.

Conclusion

Main takeaways:

- Fine tuning is the best performing method
- OTS features often close to fine-tuning and less computationally expensive
- Prefer inner layers OTS features to last layers OTS features
- Use more recent networks such as DenseNet and ResNet

Thank you !

Meet me at poster **FP249** for more information !