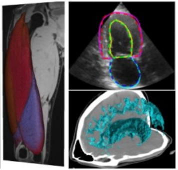
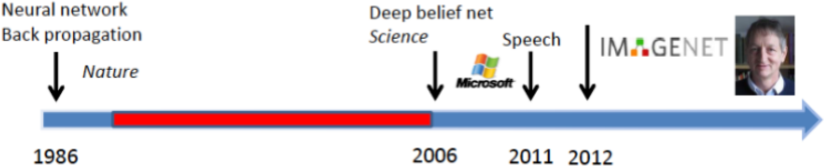
Beyond Full Supervision in Deep Learning

Nicolas Thome - Prof. at Cnam Paris
CEDRIC Lab, MSDMA Team

DeepImaging 2019 - PRISMES LABEX
April 18, 2019



Deep Learning Success since 2010



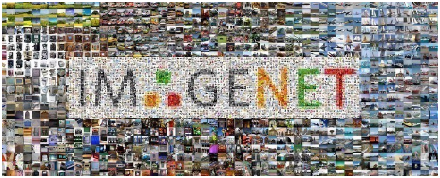
- **ILSVRC'12: the deep revolution**
  ⇒ outstanding success of ConvNets [Krizhevsky et al., 2012]

Rank	Name	Error rate	Description
1	**U. Toronto**	0.15315	Deep learning
2	U. Tokyo	0.26172	Hand-crafted features and learning models. Bottleneck.
3	U. Oxford	0.26979	
4	Xerox/INRIA	0.27058	

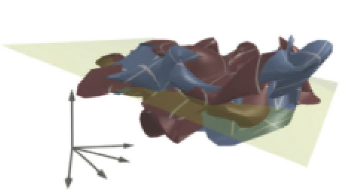
Deep ConvNet success at ILSVRC'12

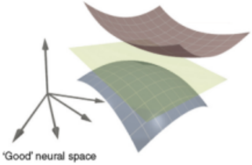
Two main practical reasons:

1. Huge number of labeled images (10^6 images)
   - Possible to train very large models without over-fitting
   - Larger models enables to learn rich (semantic) features hierarchies
2. GPU implementation for training
   - Relatively cheap and fast GPU
   - Training time reduced to 1-2 weeks (up to 50x speed up)



Representation Learning & Manifold Untangling





Raw data:
very tangled manifold

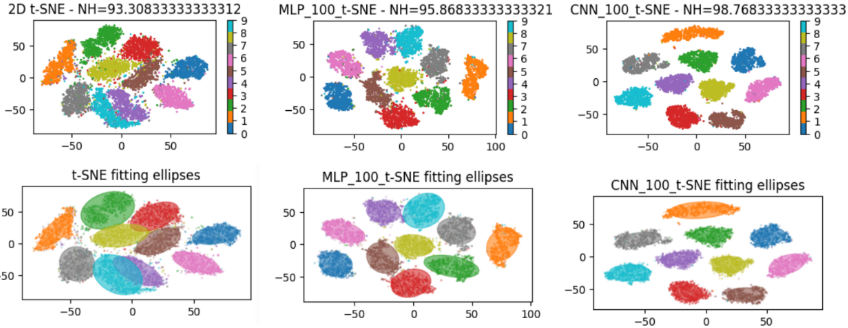
Deep Learning representations:
untangled manifold

- Deep Learning models gradually disentangle data manifold
- Deformations linearized: simple classifier in disentangled space!

Manifold Disentangling and ConvNets

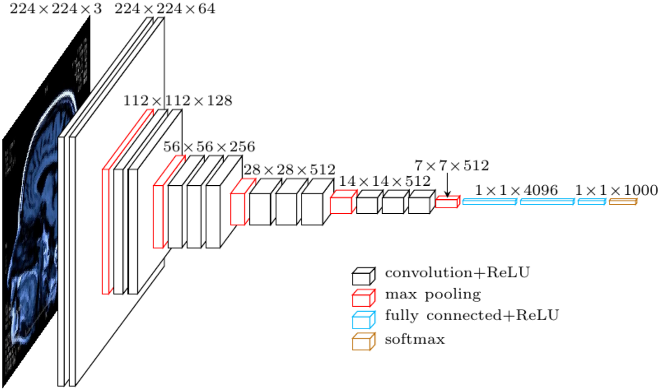
- Visualize data in input vs latent dimension with t-SNE [van der Maaten and Hinton, 2008]
- Ex: MNIST dataset

- **Deep models able to disentangle data manifold!**



Deep Learning (DL) for small-scale Datasets

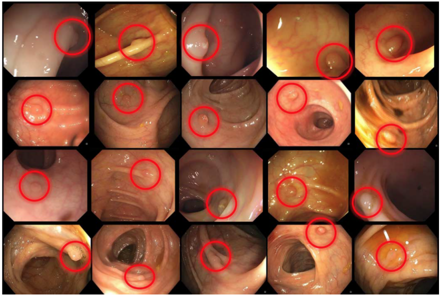
- Deep ConvNets require large-scale annotated datasets
- **Do we need to collect ImageNet scale dataset for medical image analysis?**
- **OPTION:** transferring representations learned from ImageNet: extract layer (fixed-size vector) ⇒ **"Deep Features" (DF)**

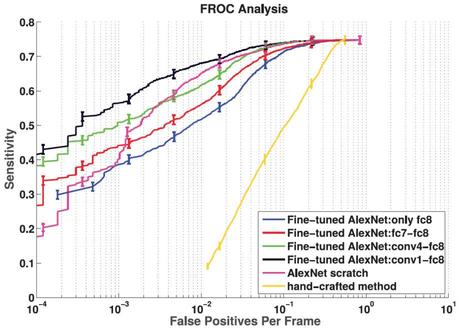


- **Now state-of-the-art for any visual recognition task** [Azizpour et al., 2016]

Deep Learning (DL) for Medical Image Analysis

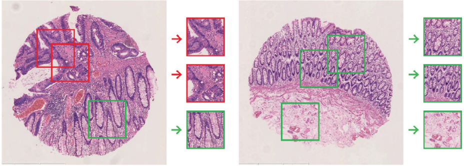
- **Deep Features very robust to domain shifts, *e.g.* medical images**
- Transfer & fine-tuning (ImageNet), *e.g.* Polyp Detection [Tajbakhsh et al., 2016]
- ConvNets: winners of recent challenges based on deep learning: Mammography, Melanoma Detection, *etc*
- Using ImageNet pre-training, *e.g.* Liver Tumor Segmentation (LiTS'17) challenge [Li et al., 2017]



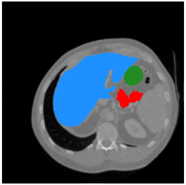


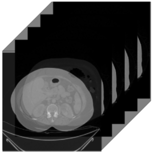
Deep Learning (DL) for Medical Image Analysis

- Large-scale datasets in medical imaging: more the exception than the rule
- Data labeling expensive, especially fine-grained annotations (*e.g.* segmentation)
  - Exacerbated in medical context: strong expertise required for labeling
- Solutions to tackle small-scale datasets with deep learning in this context:
  - Leveraging coarse annotations to perform precise predictions
  - Using (many) unlabelled data in addition to (few) labeled data


(a) cancer image (b) non-cancerimage

From [Xu et al., 2014]

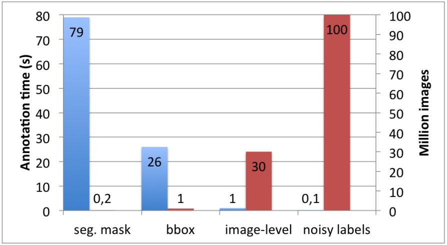

Few labeled data


Many unlabeled

Outline

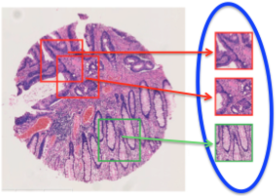
Weakly Supervised Learning

- Using full (precise) annotation, *e.g.* BB or segmentation masks
- **BUT:** full annotations expensive [Bearman et al., 2016]
  - Problem even more pronounced with medical images, *e.g.* segmentation often prohibitive
    - High resolution
    - 3D data
    - Videos
  - ⇒ **Training with weak supervision**, for performing accurate predictions
    - Ex: semantic segmentation from global labels



Multiple Instance Learning (MIL)

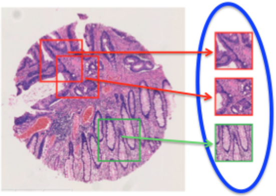
- Multiple Instance Learning (MIL) [Dietterich et al., 1997]: old model for Weakly Supervised Learning
- Model formulation: Example **b** composed of a bag of N_b instances: $\mathbf{b} = \{\mathbf{x}_h\}_{h \in \{1;N_b\}}$
  - **b**: image, $\{\mathbf{x}_h\}$ image regions
  - **b**: text document, $\{\mathbf{x}_h\}$ paragraphs
  - **b**: molecule, $\{\mathbf{x}_h\}$ molecule parts



From [Xu et al., 2014]

Multiple Instance Learning (MIL)

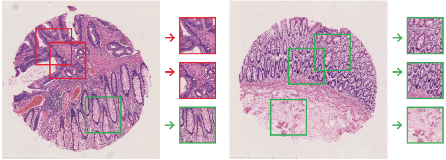
- Example $\mathbf{b}$ composed of a bag of N_b instances: $\mathbf{b} = \{\mathbf{x}_h\}_{h \in \{1;N_b\}}$
- Each instance $\mathbf{x}_h$ is described by a feature vector $\phi(\mathbf{b}, h) \in \mathbb{R}^d$
- Ex: $\mathbf{x}_h$ image region
  - $\phi(\mathbf{b}, h) \in \mathbb{R}^d$ pixels
  - $\phi(\mathbf{b}, h) \in \mathbb{R}^d$ handcrafted features (SIFT/HOG, etc)
  - $\phi(\mathbf{b}, h) \in \mathbb{R}^d$ Deep features



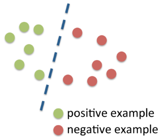
From [Xu et al., 2014]

Multiple Instance Learning (MIL)

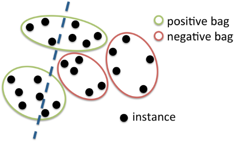
- Example **b** composed of a bag of N_b instances: $\mathbf{b} = \left\{\mathbf{x}_h\right\}_{j \in \{1;N_b\}}$
- MIL training formulation: A set a training N pairs $(\mathbf{b}_i, \mathbf{y}_i^*)$
  - $\mathbf{b}_i = \left\{\mathbf{x}_{i,h}\right\}_{j \in \left\{1;N_{b_i}\right\}}$ i^{st} example
  - $\mathbf{y}_i^*$ GT label, *e.g.* $\mathbf{y}_i^* = \pm 1$ for binary classification
  - **Weak supervision**: $\mathbf{y}_i^*$ provided at bag level
    - **MIL goal:** performing predictions at instance level



(a) cancer image (b) non-cancerimage



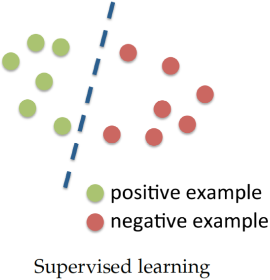
Supervised learning

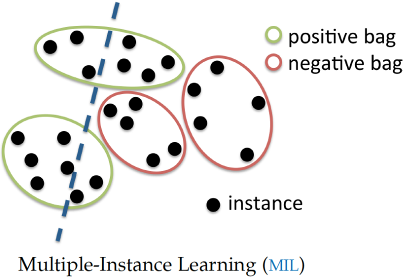


Multiple-Instance Learning (MIL)

Multiple Instance Learning (MIL)

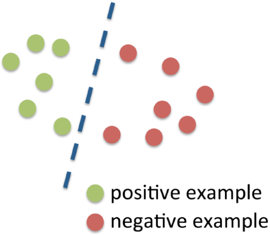
- **MIL: Weak supervision**: $\mathbf{y}_i^*$ provided at bag level $\mathbf{b}_i$, not at instance level $\mathbf{x}_{i,h}$
- **MIL hypothesis: all instance in negative bags are negative**
- **We need to pool (aggregate) over instances to train the model!**
  - Pooling over instance features: $g(\{\phi(\mathbf{b}_i, h)\}) := \phi_p(\mathbf{b}_i) \in \mathbb{R}^{d'}$, *e.g.* g avg or max
    - Perform bag prediction $\phi_p(\mathbf{b}_i)$ with prediction $f_{\mathbf{w}}$: $\hat{y}_i = f_{\mathbf{w}}(\phi_p(\mathbf{b}_i))$
    - Use any fully supervised learning algorithm to train $f_{\mathbf{w}}$ from $\mathbf{y}_i^*$
    - $\ominus$ not straightforward to perform instance prediction for general pooling function f and learning algorithm



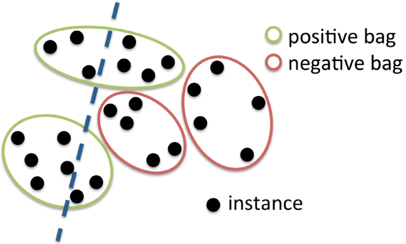


Multiple Instance Learning (MIL)

- **MIL: Weak supervision**: $\mathbf{y}_i^*$ provided at bag level $\mathbf{b}_i$, not at instance level $\mathbf{x}_{i,h}$
- **We need to pool (aggregate) over instances to train the model!**
  - Pooling over instance prediction scores:
  - Define predictor at the instance level $f_{\mathbf{w}}(\phi(\mathbf{b}_i, h))$, $\forall h \in \{1; N_{\mathbf{b}_i}\}$
    - Ex: binary classification: $f_{\mathbf{w}}(\phi(\mathbf{b}_i, h)) \in \mathbb{R}$, $sign[f_{\mathbf{w}}(\phi(\mathbf{b}_i, h))] \in \{-1; 1\}$
    - Pool over prediction scores to get bag prediction: $\hat{y}_i = g\{f_{\mathbf{w}}(\phi(\mathbf{b}_i, h))\}$, *e.g.* g avg or max



Supervised learning



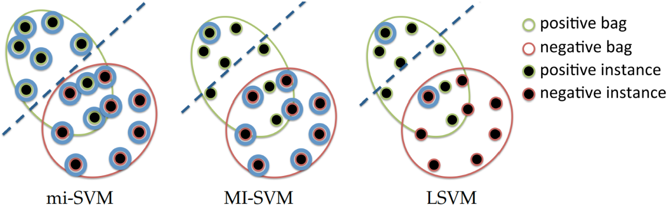
Multiple-Instance Learning (MIL)

Multiple Instance Learning

- SVM-MIL algorithms, *e.g.* [Andrews et al., 2003]: binary classification
  - Linear predictor on instances, *i.e.* $f_{\mathbf{w}}(\phi(\mathbf{b}_i, h)) = \langle \mathbf{w}; \phi(\mathbf{b}_i, h) \rangle$
  - Max pooling function g over instance scores $\Rightarrow$ bag prediction:

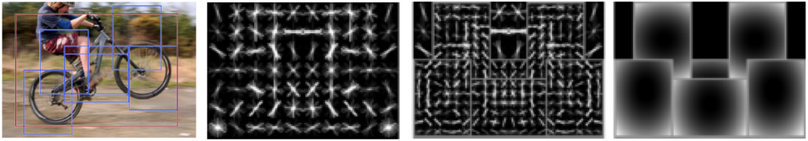
$$f_{\mathbf{w}}(\mathbf{b}_i)=\text{sign}\left[\max_{h \in N_{\mathbf{b}_i}} \langle \mathbf{w}, \phi(\mathbf{b}_i, h) \rangle\right] \quad (1)$$

- Training variants:
  - LSVM: use max prediction for $\oplus$ and $\ominus$ bags
  - MI-SVM: use max prediction for $\oplus$ but all $\ominus$ instances
  - mi-SVM: use all $\ominus$ instances and relabel $y^*_{i,h} \in \pm 1$ all $\oplus$ instances



Multiple Instance Learning

- SVM-MIL algorithms: historically applied to part-based object detection [Felzenszwalb et al., 2010] $\Rightarrow$ **Deformable Part Model (DPM)**
- Adapted in the object detection context
  - Supervision: bounding box
  - Latent variable: position of objet "parts"
  - Features for each part $\phi(\mathbf{b}_i, h)$: Handcrafted HoG



(a) Root filter

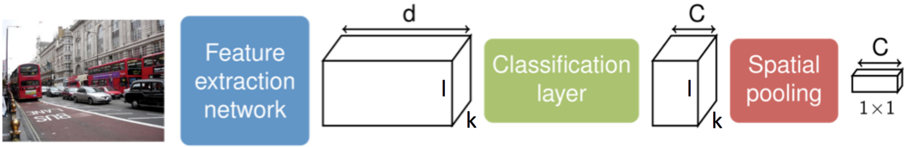
(b) Part filters in higher resolution

(c) A spatial model for part locations

- PASCAL VOC "Lifetime Achievement" Prize in 2010
- PAMI Longuet-Higgins Prize at CVPR'18 (Retrospective Best Paper from CVPR'08)

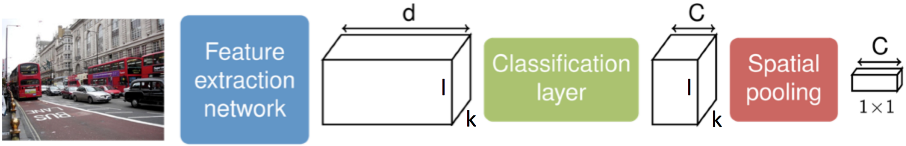
Multiple Instance Learning and Deep Learning

- Using MIL model in the Deep Learning era: deep architecture for WSL

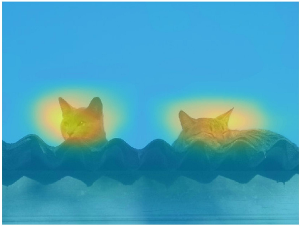


- **Feature extractor** $\Rightarrow$ tensor of size $k \times l \times d$
- **MIL notations:** $N_b = k \times l$ instances (regions)
  - Each instance h represented by deep features $\phi(b, h) \in \mathbb{R}^d$

Multiple Instance Learning and Deep Learning



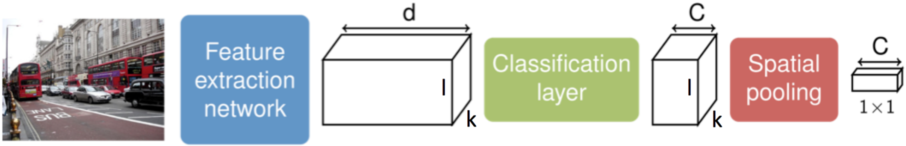
- **Classification:** projection to get a class prediction for each instance
  - $z_h^c = f_{\mathbf{w}_c}\left(\phi(\mathbf{b}_i, h)\right), \; \forall h \in \{1; N_b\}, \; \forall c \in \{1; C\}$
  - $k \times l \times C$ tensor: Class Activation Maps (CAM)

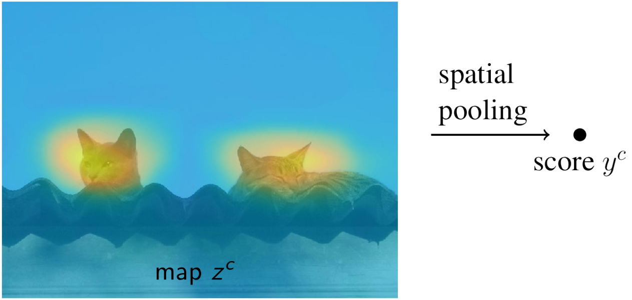


- **Pooling:** class prediction aggregation to train model from global labels

$$\hat{z}_c = g\left[\{z_h^c\}_{h \in \{1;N_b\}}\right], \; \forall c \in \{1; C\}$$

How to pool?





Max [Oquab et al., 2015]

$$y^c = \max_h z_h^c$$

Average (GAP) [Zhou et al., 2016]

$$y^c = \frac{1}{N} \sum_h z_h^c$$

Average pooling limitation

- Classifying with all regions
- Not efficient for small objects: lots of "noisy" regions

Max pooling limitation

Max pooling

$$y^c = \max_h z_h^c \tag{2}$$

- Classifying only with the max scoring region

- Loss of contextual information

Max pooling limitation

Max pooling

$$y^c = \max_h z_h^c \quad (2)$$

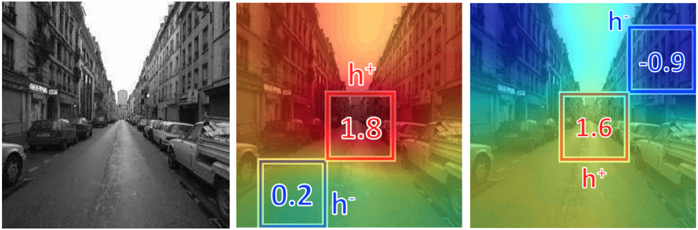
- Classifying only with the max scoring region


- Loss of contextual information

- **MANTRA [Durand et al., 2015]:** `max+min` **pooling function**

$$y^c = \max_h z_h^c + \min_h z_h^c \tag{3}$$

- $\mathbf{h}^+$: presence of the class → high $\mathbf{h}^+$
- $\mathbf{h}^-$: localized evidence of the absence of class: **negative evidence**



street image $\mathbf{x}$ $s(\textbf{street}) = 2$ $s(\textbf{highway}) = 0.7$

Generalize pooling function [Durand et al., 2019]

$$y^c = \frac{1}{2\beta_h^+} \log\left[\frac{1}{|\mathcal{H}|}\sum_{\mathbf{h}\in\mathcal{H}} e^{\beta_h^+ z_h^c}\right] + \frac{1}{2\beta_h^-} \log\left[\frac{1}{|\mathcal{H}|}\sum_{\mathbf{h}\in\mathcal{H}} e^{\beta_h^- z_h^c}\right] \tag{4}$$

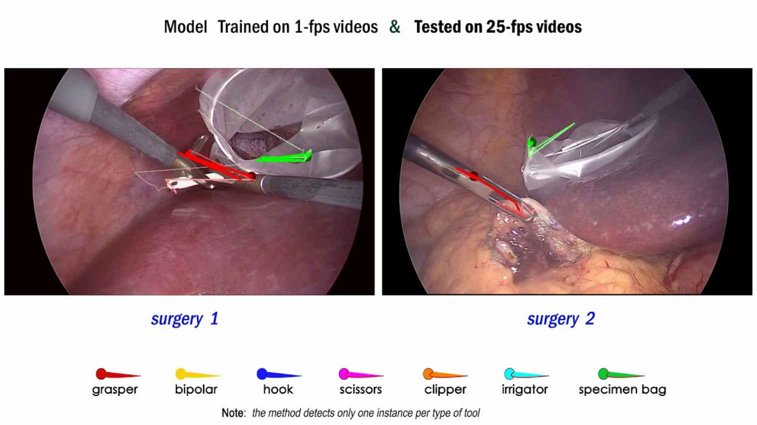
- Varying β_h^+, β_h^- $\Rightarrow$ recovering pooling functions used in well-known probabilistic and max-margin models
- Smoothly interpolate between these extreme cases

Model	Pooling Function	β_h^+	β_h^-
HCRF [Quattoni et al., 2007]	log-sum-exp	1	1
GAP [Zhou et al., 2016]	average	$\rightarrow 0$	$\rightarrow 0$
LSSVM [Yu and Joachims, 2009]	`max`	$\rightarrow +\infty$	$\rightarrow +\infty$
MANTRA [Durand et al., 2015]	`max+min`	$\rightarrow +\infty$	$\rightarrow -\infty$

Table: State-of-the-art WSL models with corresponding parameters.

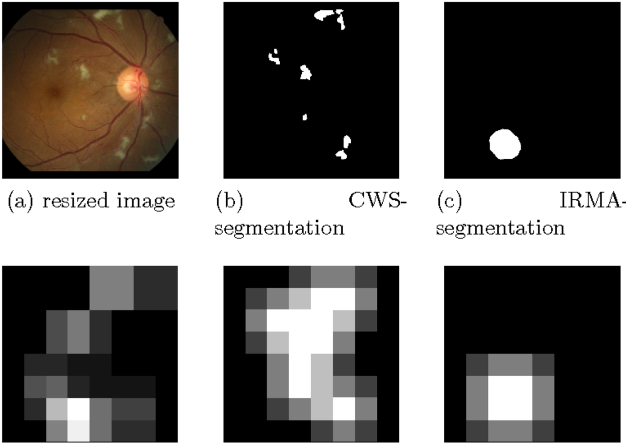
MIL for medical image analysis

- MIL directly adapted for detection of pattern from global label in medical image/videos
  - Specific lesion type in images
  - Specific surgical gesture in videos, *e.g.* [Nwoye et al., 2019]



MIL for medical image analysis

- Medical images: high resolution with small details
  - Multi-resolution adaptation MIL [Quellec et al., 2012]
  - Weighted average over scales

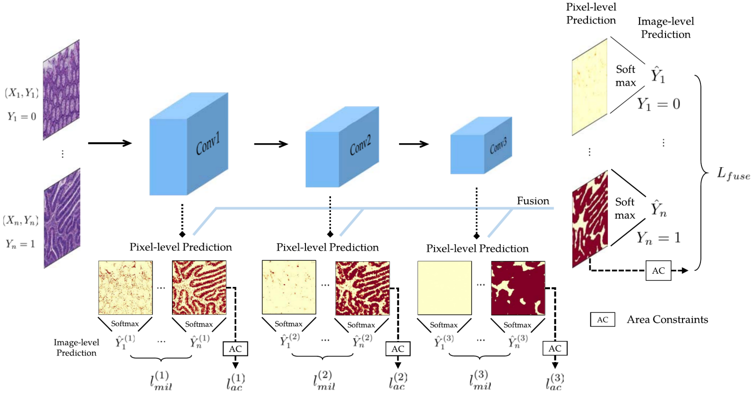


(a) resized image (b) CWS-segmentation (c) IRMA-segmentation

(d) local relevance (e) CWS-label (f) IRMA-label

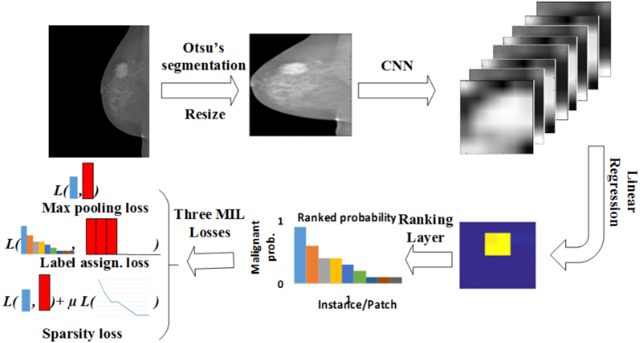
MIL for medical image analysis

- MIL with constraints [Jia et al., 2017]
  - Deep MIL (max pool) with FCN for Histopathology
  - Multi-resolution: MIL loss applied at various conv layers
  - Leveraging additional annotation, *i.e.* relative area size of the cancerous region within image



MIL for medical image analysis

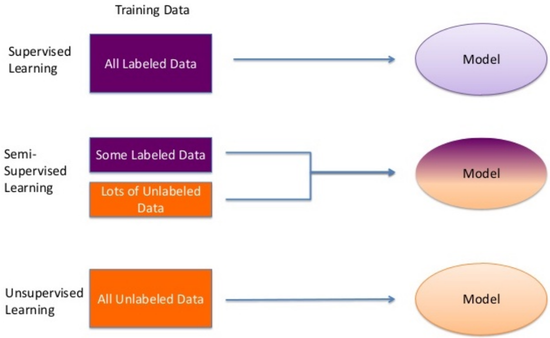
- Integrating constraints from medical knowledge in deep MIL objective [Zhu et al., 2017]
  - Deep MIL (max pool) for lesion detection in mammography
  - MIL loss including sparse prior constraint on lesion classification
    - Lesion ~ 2% of image size



Outline

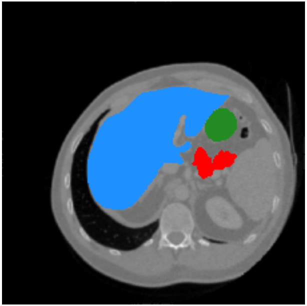
Semi Supervised Learning (SSL)

- Semi-supervised *vs* fully supervised *vs* unsupervised
- Some (few) labeled data, many unlabeled data
  - Medical context: annotations costly $\Rightarrow$ SSL useful

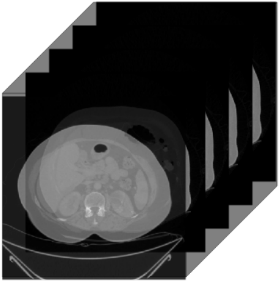


Credit: S. Jain

Semi Supervised Learning (SSL)



Few labeled data

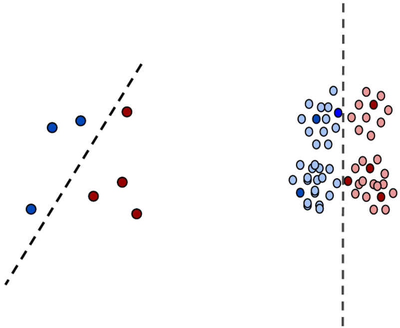


Many unlabeled

- Two main strategies :
    1. Adapting supervised objective with unlabelled data
    2. Use alternative objective for unlabelled data, *e.g.* reconstruction

SSL: Adapting supervised objective to unlabeled data

- Using unlabeled data structure, *e.g.* transductive SVMs [Joachims, 1999]

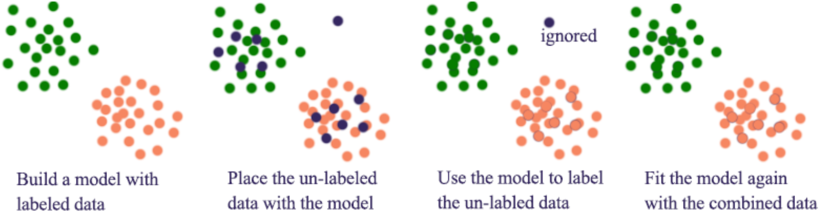


Fully supervised SSL

- OR re-labelling each unlabelled data in training set
  - Same motivation as in mi-SVM
  - Iterative unlabelled data predictions, *e.g.* Curriculum learning [Bengio et al., 2009]

Curriculum learning for SSL

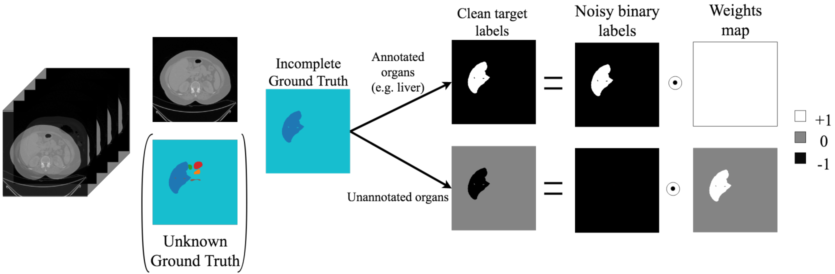
1. Train a model with labelled data $\mathcal{A}$
2. Until convergence:
   - Seek a sub-set of "easy" unlabelled data $\mathcal{U}_e$
   - Label each element in $\mathcal{U}_e$
   - Retrain model on $\mathcal{A} \cup \mathcal{U}_e$



Credit: J. Hui

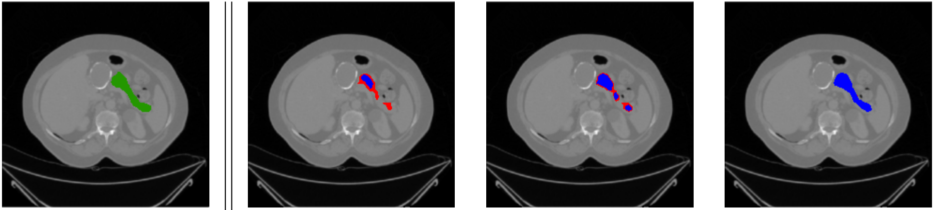
Case Study: SMILE [Petit et al., 2018]

- **Semantic segmentation of 3D abdominal CT-scans**
  - Clinical experts: focus on a subset of organs
  - Pixels with un-annotated organs $\Rightarrow$ missing annotations
- **Semantic Segmentation with Incomplete Annotations (SMILE)**
  - **Training: only use pixels for which annotation is certain (no missing organ)**
    - K ($+1 \Leftrightarrow$ background) classes $\Rightarrow$ K binary classifiers for each pixel
    - Organ(s) missing the whole volumes, organ present: complete annotation
    - **Missing organs in volume: only use pixels for other organs with -1 target label, ignore others**



Case Study: SMILE [Petit et al., 2018]

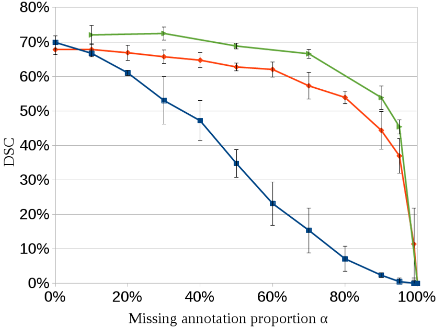
- SMILE training: labelled (certain annotations) & un-annotated pixels
- **SMILEr** $\Rightarrow$ SSL with Curriculum: take advantage of un-labelled pixels
  - Init with SMILE (easy) examples $\mathcal{A}$, $\mathcal{U}_e^0 \leftarrow \varnothing$
  - For t $\leftarrow$ 1 to T, for each binary classifier:
    - Select $\mathcal{H}^t$ new un-labelled positive examples
      // $\mathcal{H}^t$: $\gamma_t = \frac{t}{T}\gamma_{max}$ top scoring pixels (blue) among predictions $\hat{y}_i^+$ (red)
    - $\mathcal{U}_e^t \leftarrow \mathcal{U}_e^{t-1} \cup \mathcal{H}^t$
    - Re-train model with augmented training set $\mathcal{A} \cup \mathcal{U}_e^t$



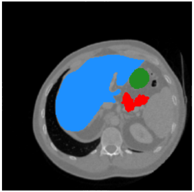
Unknown GT || $t = 1,\ \gamma_1 = 0.33$ | $t = 2,\ \gamma_2 = 0.66$ | $t = 3,\ \gamma_3 = 1$

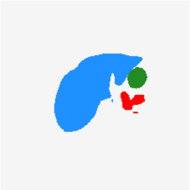
SMILE Results

- Experiments on 72 3D CT-scans for 3 organs: liver, pancreas and stomach
- Partial annotations generated: randomly removing α% of organs



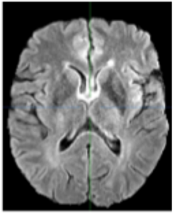
- Baseline: blue
- SMILE: orange ; SMILEr: green
- **SMILEr** α = **70%** ~ **baseline** α = **0%**

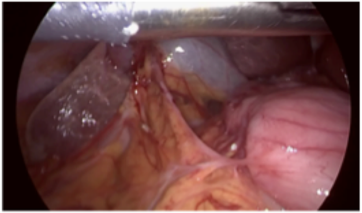
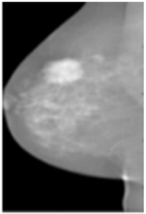




Semi Supervised Learning (SSL) with Unsupervised Objective

- SSL: labelled and unlabelled data
- Simple option: combine supervised cost, *e.g.* classification, with unsupervised objective
- Unsupervised objective: extract (deep) representations without labels



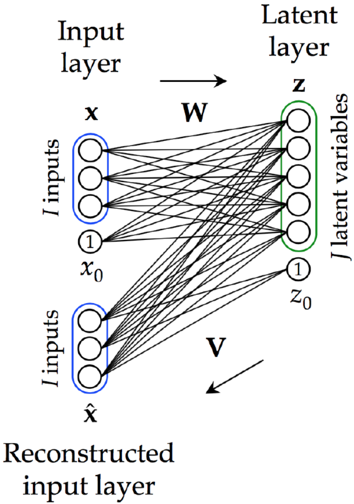
Auto-Encoders

- $\mathbf{z} = f(\mathbf{W}\mathbf{x})$
- $\hat{\mathbf{x}} = g(\mathbf{V}\mathbf{x})$
  - Often, $\mathbf{V} = \mathbf{W}^t$
- **Auto-encoder objective function: reconstruction**

$$C = \sum_{i=1}^{N} ||\mathbf{x}_i - \hat{\mathbf{x}}||^2$$

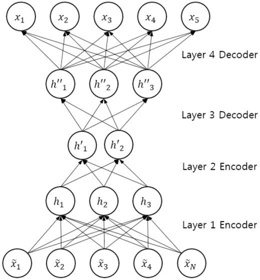
- If $f = g = Id$ (linear auto-encoder): $\sim$ PCA:

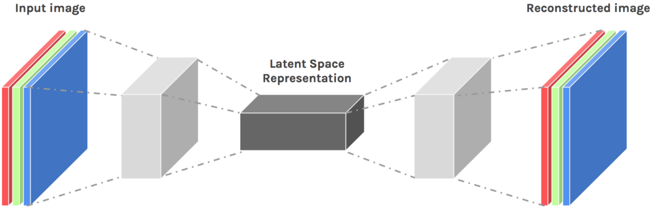
$$C = \sum_{i=1}^{N} ||\mathbf{x}_i - \mathbf{W}^t\mathbf{W}\mathbf{x}||^2$$



Deep Auto-Encoders

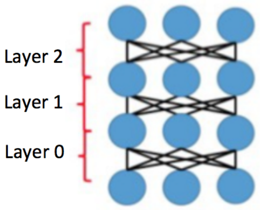
- AE: limited to linear feature extraction
- Add fully connected layers $\Rightarrow$ more complex representations
- Add convolutional / deconvolutional layers: adapted to local feature extraction (images)



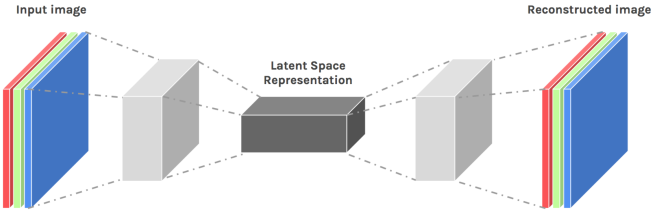


Training deep Auto-Encoders

- How to train deep unsupervised objective?
  - Fully connected deep AEs: layer-by layer tuning [Hinton et al., 2006]



  - Deep conv AE: training whole architecture, *i.e.* all layers, jointly

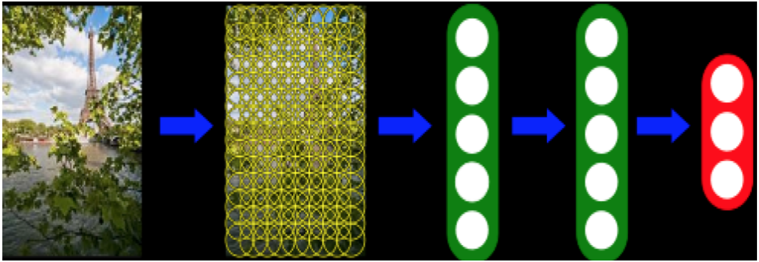


Training deep Auto-Encoders

- How to combine supervised and unsupervised objectives in SSL?
  - Used unsupervised as pre-training, supervised as fine-tuning
  - Used an hybrid objective function:

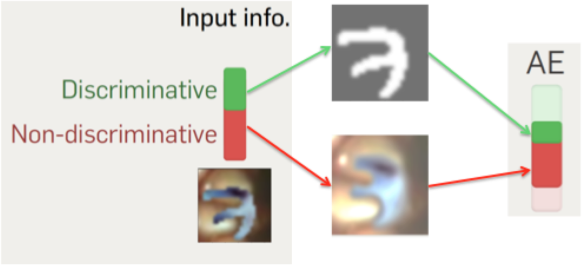
$$\mathcal{L} = \lambda_c \mathcal{L}_c + \lambda_r \mathcal{L}_r$$

- $\mathcal{L}_c$ supervised cost, *e.g.* classification
- $\mathcal{L}_r$ unsupervised cost, *e.g.* reconstruction
- Joint training of both tasks



Unsupervised Learning: Beyond Reconstruction

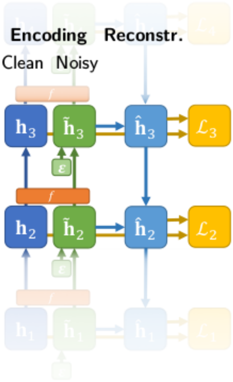
- **Unsupervised objective: why reconstruction?**
- **Reconstruction: what if ultimate goal requires generalization to a set of examples, *e.g.* classification?**
  - Deeper representation ⇔ more abstract ⇔ generalization ⇔ loss of information
  - **Classification & reconstruction: contradictory roles**
  - $\mathcal{L} = \lambda_c \mathcal{L}_c + \lambda_r \mathcal{L}_r$ with standard deep AE sub-optimal to disentangle discriminative from non-discriminative information

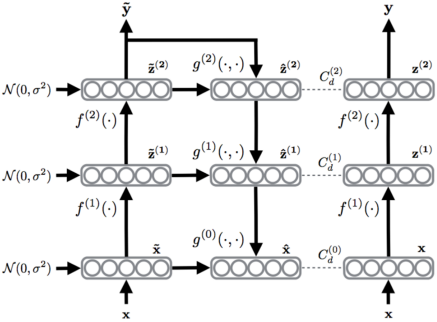


- Two current alternatives to unsupervised learning:
  1. Objective without reconstruction
  2. Casting unsupervised training as classification

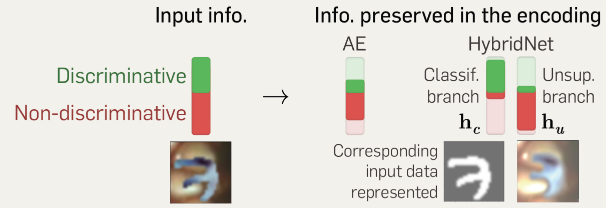
Beyond Reconstruction: Ladder Networks [Rasmus et al., 2015]

- "An autoencoder which can discard information"
- Layer above does not reconstruct layer below only with its activation
- Solution: Provide the details to learn only the abstract features
  - Decoder has a noisy version of the input to reconstruct

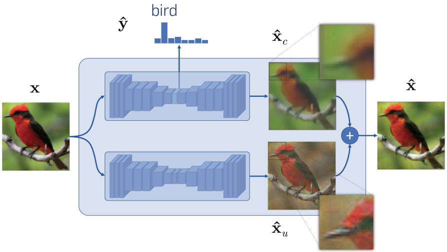


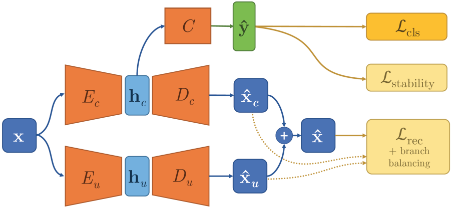


Beyond Reconstruction: HybridNet [Robert et al., 2018]



- **HybridNet: disentangling discriminative and complementary information for reconstruction**
- **Two-branch architecture**





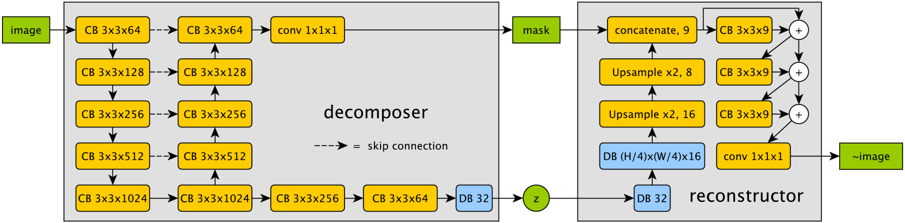
Hybrid Architectures for Medical Images

- SDNet (Spatial Decomposition) [Chartsias et al., 2018]
- SSL: Combining segmentation (cardiac MR) and reconstruction loss
    - **Motivation:** Combining losses with a single model challenging

Large segmentation loss: poor reconstruction

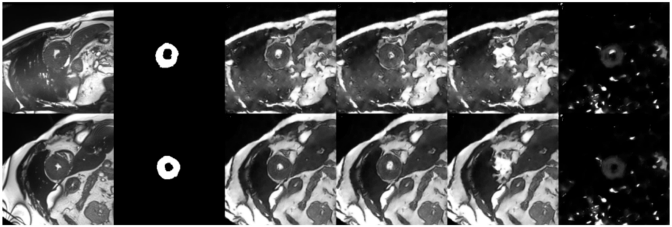
Large reconstruction loss: poor segmentation

- SDNet: 2-branch, segmentation (spatial) & global appearance layout



SDNet [Chartsias et al., 2018]

- 2-brach architecture ⇒ help disentangling
  - Nice latent space arithmetic properties



- Improvement for SSL compared *e.g.* U-Net [Ronneberger et al., 2015]

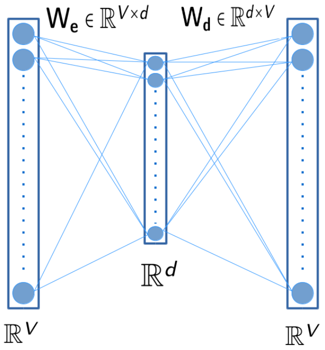
	ACDC					QMRI			
Labelled images	284	142	68	34	11	157	78	39	19
U-Net	0.782	0.657	0.581	0.356	0.026	0.686	0.681	0.441	0.368
GAN	**0.787**	0.727	0.648	0.365	0.080	**0.795**	0.756	0.580	0.061
SDNet	0.771	**0.767**	**0.731**	**0.678**	**0.415**	0.794	**0.772**	**0.686**	**0.424**

Beyond Reconstruction: Self-Supervised Training

- **Self-supervised training: unsupervised problem ⇒ supervised one**
- Performing prediction on data, *e.g.*
  - Relative position of regions
  - Temporal prediction (next frames)
- ***"Auxiliary", "pretext"* task**
  - Good auxiliary task requires solving high-level recognition ⇒ useful features for the ultimate task
  - Automatic labeling for auxiliary task ⇒ no manual supervision

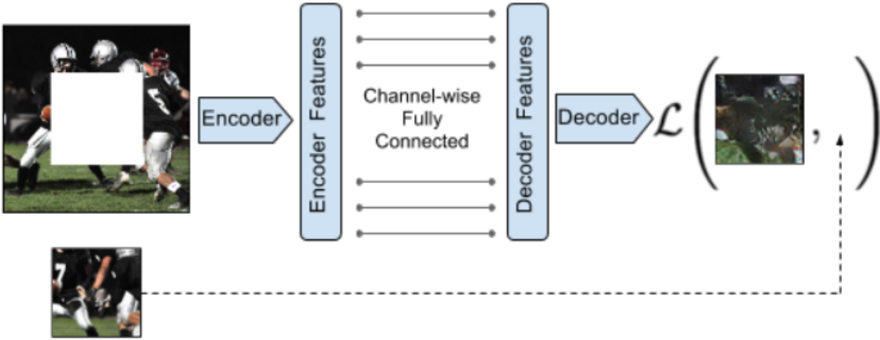
Word2Vec [Mikolov et al., 2013]

- Embedding of words: project a word in $\mathbb{R}^d$ space
- **Word2Vec auxiliary:** predict a word given its context
  - Assumption: similar words appears in similar contexts, *i.e.* distributional hypothesis in NLP
  - Input: Bag of Words of context $\mathbf{x} \in \mathbb{R}^V$, V vocabulary size
  - $\mathbf{h} = \mathbf{W}_e\mathbf{x}$, $\hat{\mathbf{x}} = \mathbf{W}_d\mathbf{h}$ + soft max: classify central word



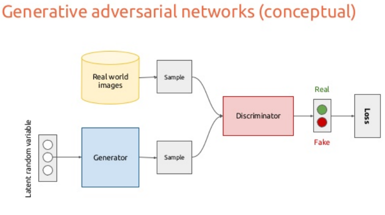
Context-Encoders [Pathak et al., 2016]: Word2Vec for Images

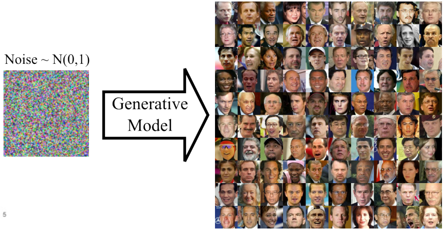
- **Auxiliary task: Inpainting**



Generative Adversarial Networks (GAN) [Goodfellow et al., 2014]

- Unsupervised problem ⇒ 2-player game theory problem
- Interesting results: optimal generator learns data distribution

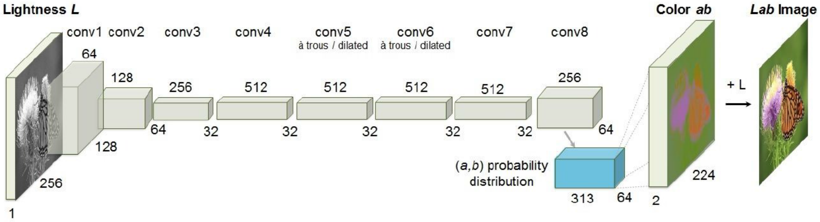




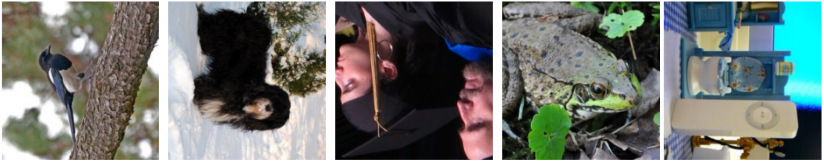
- Adversarial cost used beyond generation for distribution matching
- Next course!

Self-Supervised Training: other auxiliary tasks

- Image colorization [Zhang et al., 2016]



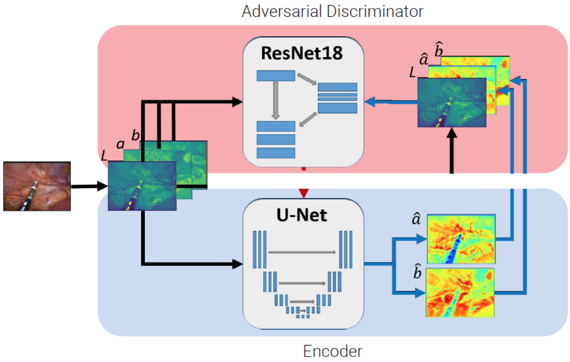
- Predicting image orientation [Gidaris et al., 2018]



90° rotation | 270° rotation | 180° rotation | 0° rotation | 270° rotation

Self-Supervised Training in Medical Imaging

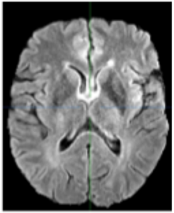
- **Auxiliary task:** endoscopic video colorization [Ross et al., 2018] in (L,a,b) space
  - cGAN approach: predict color (a,b) from luminance L
    - Generator (U-Net): $L \rightarrow (\hat{a}, \hat{b})$
    - Discriminator (ResNet): $L, a, b \rightarrow$ real, $L(\hat{a}, \hat{b}) \rightarrow$ *fake*

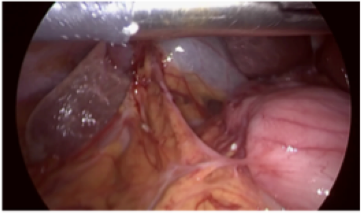
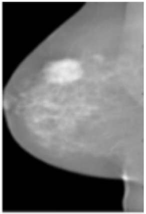


- **Target task:** instrument segmentation

Conclusion

- Deep models: huge volume of annotated data
  - Annotation cost exacerbated in healthcare
- Learning from weak supervision (WSL)
  - Very relevant for localized tasks (*e.g.* segmentation) in medical images: high-resolution, 3D, videos, *etc*
  - Pooling function (local prediction → global label) crucial
  - Constraining models which medical *prior* knowledge useful
- Learning from (few) labeled data and (many) unlabeled supervision (SSL)
  - Re-labeling unlabeled data, *e.g.* Curriculum-based approaches
  - Beyond reconstruction with:
    - Architectures for disentangling supervised from unsupervised signals
    - Self-supervision



References I

[Andrews et al., 2003] Andrews, S., Tsochantaridis, I., and Hofmann, T. (2003).
Support vector machines for multiple-instance learning.
In *Advances in Neural Information Processing Systems (NIPS)*.

[Azizpour et al., 2016] Azizpour, H., Razavian, A. S., Sullivan, J., Maki, A., and Carlsson, S. (2016).
Factors of transferability for a generic convnet representation.
IEEE Trans. Pattern Anal. Mach. Intell., 38(9):1790–1802.

[Bearman et al., 2016] Bearman, Russakovsky, Ferrari, and Fei-Fei (2016).
What's the Point: Semantic Segmentation with Point Supervision.
ECCV.

[Bengio et al., 2009] Bengio, Y., Louradour, J., Collobert, R., and Weston, J. (2009).
Curriculum learning.
In *Proceedings of the 26th Annual International Conference on Machine Learning*, ICML '09, pages 41–48.

[Chartsias et al., 2018] Chartsias, A., Joyce, T., Papanastasiou, G., Semple, S., Williams, M., Newby, D. E., Dharmakumar, R., and Tsaftaris, S. A. (2018).
Factorised spatial representation learning: Application in semi-supervised myocardial segmentation.
In *MICCAI (2)*, volume 11071 of *Lecture Notes in Computer Science*, pages 490–498. Springer.

[Dietterich et al., 1997] Dietterich, T. G., Lathrop, R. H., and Lozano-Pérez, T. (1997).
Solving the multiple instance problem with axis-parallel rectangles.
Artif. Intell.

[Durand et al., 2015] Durand, T., Thome, N., and Cord, M. (2015).
MANTRA: Minimum Maximum Latent Structural SVM for Image Classification and Ranking.
In *IEEE International Conference on Computer Vision (ICCV)*.

[Durand et al., 2019] Durand, T., Thome, N., and Cord, M. (2019).
Exploiting negative evidence for deep latent structured models.
IEEE Transactions on Pattern Analysis and Machine Intelligence, 41(2):337–351.

References II

[Felzenszwalb et al., 2010] Felzenszwalb, P. F., Girshick, R. B., McAllester, D., and Ramanan, D. (2010).
Object detection with discriminatively trained part-based models.
IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI).

[Gidaris et al., 2018] Gidaris, S., Singh, P., and Komodakis, N. (2018).
Unsupervised representation learning by predicting image rotations.
In *ICLR*, volume abs/1803.07728.

[Goodfellow et al., 2014] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., and Bengio, Y. (2014).
Generative adversarial nets.
In Ghahramani, Z., Welling, M., Cortes, C., Lawrence, N. D., and Weinberger, K. Q., editors, *Advances in Neural Information Processing Systems 27*, pages 2672–2680. Curran Associates, Inc.

[Hinton et al., 2006] Hinton, G. E., Osindero, S., and Teh, Y.-W. (2006).
A fast learning algorithm for deep belief nets.
Neural Comput., 18(7):1527–1554.

[Jia et al., 2017] Jia, Z., Huang, X., Chang, E. I., and Xu, Y. (2017).
Constrained deep weak supervision for histopathology image segmentation.
IEEE TRANSACTIONS ON MEDICAL IMAGING,, 36(11).

[Joachims, 1999] Joachims, T. (1999).
Transductive inference for text classification using support vector machines.
In *Proceedings of the Sixteenth International Conference on Machine Learning*, ICML '99, pages 200–209, San Francisco, CA, USA. Morgan Kaufmann Publishers Inc.

[Krizhevsky et al., 2012] Krizhevsky, A., Sutskever, I., and Hinton, G. E. (2012).
Imagenet classification with deep convolutional neural networks.
In *Advances in neural information processing systems*, pages 1097–1105.

[Li et al., 2017] Li, X., Chen, H., Qi, X., Dou, Q., Fu, C., and Heng, P. (2017).
H-denseunet: Hybrid densely connected unet for liver and liver tumor segmentation from CT volumes.
CoRR, abs/1709.07330.

References III

[Mikolov et al., 2013] Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., and Dean, J. (2013).
Distributed representations of words and phrases and their compositionality.
In Burges, C. J. C., Bottou, L., Welling, M., Ghahramani, Z., and Weinberger, K. Q., editors, *Advances in Neural Information Processing Systems 26*, pages 3111–3119. Curran Associates, Inc.

[Nwoye et al., 2019] Nwoye, C., Mutter, D., Marescaux, J., and Padoy, N. (2019).
Weakly supervised convolutional lstm approach for tool tracking in laparoscopic videos.
In *International Conference on Information Processing in Computer-Assisted Interventions (IPCAI)*.

[Oquab et al., 2015] Oquab, M., Bottou, L., Laptev, I., and Sivic, J. (2015).
Is object localization for free? – Weakly-supervised learning with convolutional neural networks.
In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

[Pathak et al., 2016] Pathak, D., Krähenbühl, P., Donahue, J., Darrell, T., and Efros, A. (2016).
Context encoders: Feature learning by inpainting.

[Petit et al., 2018] Petit, O., Thome, N., Charnoz, A., Hostettler, A., and Soler, L. (2018).
Handling missing annotations for semantic segmentation with deep convnets.
In *Deep Learning in Medical Image Analysis - and - Multimodal Learning for Clinical Decision Support - 4th International Workshop, DLMIA 2018, and 8th International Workshop, ML-CDS 2018, Held in Conjunction with MICCAI 2018, Granada, Spain, September 20, 2018, Proceedings*, pages 20–28.

[Quattoni et al., 2007] Quattoni, A., Wang, S. B., Morency, L.-P., Collins, M., and Darrell, T. (2007).
Hidden conditional random fields.
IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI).

[Quellec et al., 2012] Quellec, G., Lamard, M., Abràmoff, M. D., Decencière, E., Lay, B., Erginay, A., Cochener, B., and Cazuguel, G. (2012).
A multiple-instance learning framework for diabetic retinopathy screening.
Medical image analysis, 16 6:1228–40.

[Rasmus et al., 2015] Rasmus, A., Valpola, H., Honkala, M., Berglund, M., and Raiko, T. (2015).
Semi-supervised learning with ladder networks.
In *Proceedings of the 28th International Conference on Neural Information Processing Systems - Volume 2*, NIPS'15, pages 3546–3554, Cambridge, MA, USA. MIT Press.

References IV

[Robert et al., 2018] Robert, T., Thome, N., and Cord, M. (2018).
Hybridnet: Classification and reconstruction cooperation for semi-supervised learning.
In *The European Conference on Computer Vision (ECCV)*.

[Ronneberger et al., 2015] Ronneberger, O., P.Fischer, and Brox, T. (2015).
U-net: Convolutional networks for biomedical image segmentation.
In *Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, volume 9351 of *LNCS*, pages 234–241. Springer.
(available on arXiv:1505.04597 [cs.CV]).

[Ross et al., 2018] Ross, T., Zimmerer, D., Vemuri, A. S., Isensee, F., Wiesenfarth, M., Bodenstedt, S., Both, F., Kessler, P., Wagner, M., Müller, B., Kenngott, H., Speidel, S., Kopp-Schneider, A., Maier-Hein, K. H., and Maier-Hein, L. (2018).
Exploiting the potential of unlabeled endoscopic video data with self-supervised learning.
Int. J. Computer Assisted Radiology and Surgery, 13(6):925–933.

[Tajbakhsh et al., 2016] Tajbakhsh, N., Shin, J. Y., Gurudu, S. R., Hurst, R. T., Kendall, C. B., Gotway, M. B., and Liang, J. (2016).
Convolutional neural networks for medical image analysis: Fine tuning or full training?
IEEE Transactions on Medical Imaging, PP(99):1–1.

[van der Maaten and Hinton, 2008] van der Maaten, L. and Hinton, G. E. (2008).
Visualizing high-dimensional data using t-sne.
Journal of Machine Learning Research, 9:2579–2605.

[Xu et al., 2014] Xu, Y., Zhu, J.-Y., Chang, E. I., Lai, M., and Tu, Z. (2014).
Weakly supervised histopathology cancer image segmentation and classification.
Medical Image Analysis, 18(3):591–604.

[Yu and Joachims, 2009] Yu, C.-N. and Joachims, T. (2009).
Learning structural svms with latent variables.
In *ICML*.

References V

[Zhang et al., 2016] Zhang, R., Isola, P., and Efros, A. A. (2016).
Colorful image colorization.
In *ECCV (3)*, volume 9907 of *Lecture Notes in Computer Science*, pages 649–666. Springer.

[Zhou et al., 2016] Zhou, B., Khosla, A., Lapedriza, A., Oliva, A., and Torralba, A. (2016).
Learning Deep Features for Discriminative Localization.
In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

[Zhu et al., 2017] Zhu, W., Lou, Q., Vang, Y. S., and Xie, X. (2017).
Deep multi-instance networks with sparse label assignment for whole mammogram classification.
In Descoteaux, M., Maier-Hein, L., Franz, A., Jannin, P., Collins, D. L., and Duchesne, S., editors, *Medical Image Computing and Computer Assisted Intervention âĹŠ MICCAI 2017*, pages 603–611, Cham. Springer International Publishing.