Partial and semi-supervision in Deep Learning

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GdR ISIS, Apprentissage faiblement supervisé ou non supervisé pour l'analyse d'images et de video

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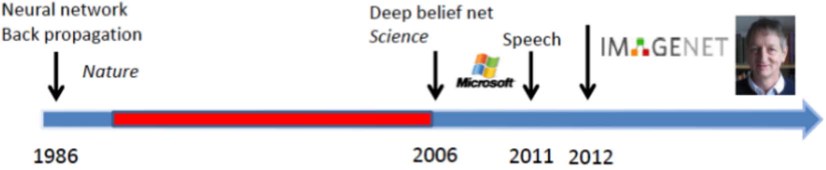
Deep Learning Success since 2010



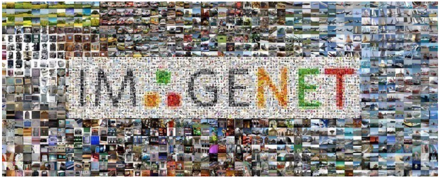
- **ILSVRC'12: the deep revolution**
  ⇒ outstanding success of ConvNets [Krizhevsky et al., 2012]

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	

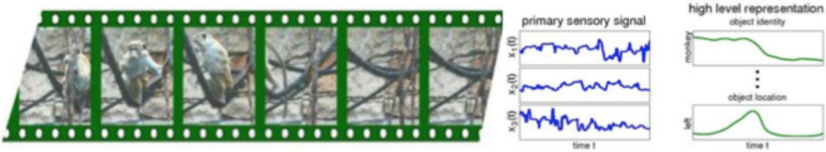
Deep ConvNet success at ILSVRC'12

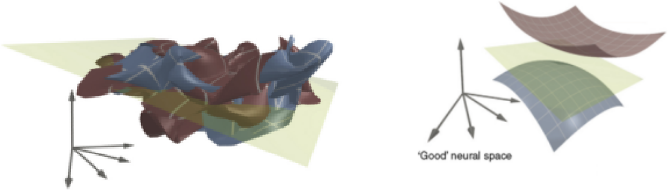
Two main practical reasons:

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





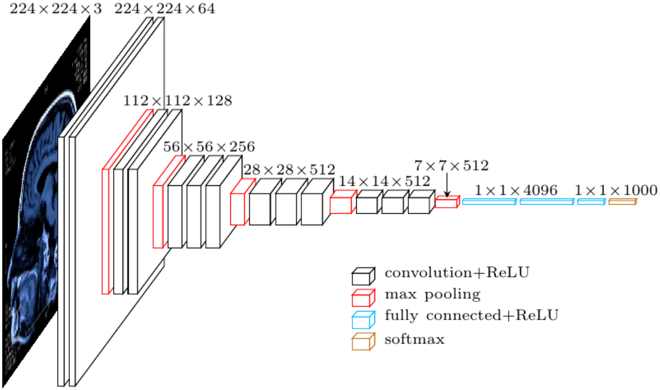
Raw data:
very tangled manifold

Deep Learning representations:
untangled manifold

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

Deep Learning (DL) for small-scale Datasets

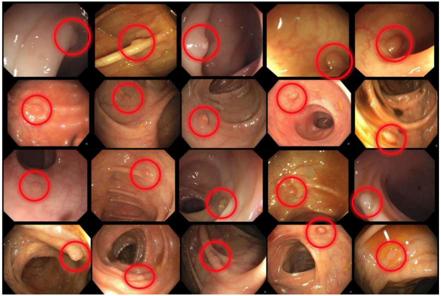
- Deep ConvNets require large-scale annotated datasets
- **Do we need to collect ImageNet scale dataset for medical image analysis?**
- **OPTION:** transferring representations learned from ImageNet: extract layer (fixed-size vector) ⇒ **"Deep Features" (DF)**

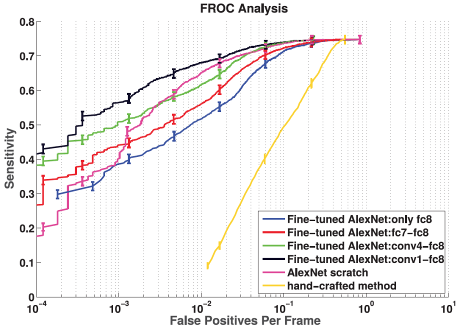


- **Now state-of-the-art for any visual recognition task** [Azizpour et al., 2016]

Deep Learning (DL) for Medical Image Analysis

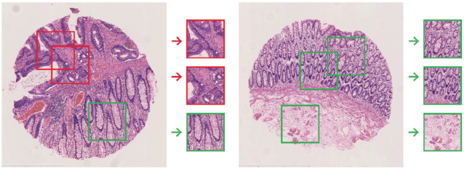
- **Deep Features very robust to domain shifts, *e.g.* medical images**
- Transfer & fine-tuning (ImageNet), *e.g.* Polyp Detection [Tajbakhsh et al., 2016]
- ConvNets: winners of recent challenges based on deep learning: Mammography, Melanoma Detection, *etc*
- Using ImageNet pre-training, *e.g.* Liver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





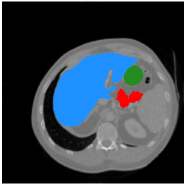
Deep Learning (DL) for Medical Image Analysis

- 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

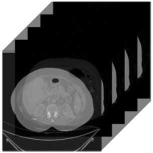


(a) cancer image (b) non-cancerimage

From [Xu et al., 2014]



Few labeled data



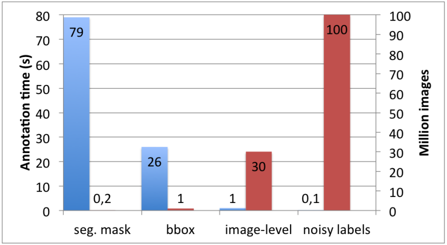
Many unlabeled

Outline

1. Learning with Weak Supervision
2. Semi-Supervised Learning

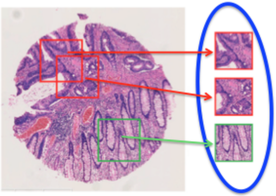
Weakly Supervised Learning

- 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)

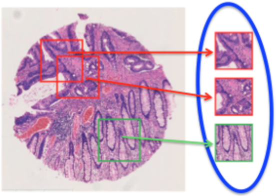
- Multiple Instance Learning (MIL) [Dietterich et al., 1997]: old model for Weakly Supervised Learning
- Model formulation: Example **b** composed of a bag of N_b instances: $\mathbf{b} = \{\mathbf{x}_h\}_{h \in \{1;N_b\}}$
  - **b**: image, $\{\mathbf{x}_h\}$ image regions
  - **b**: text document,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



From [Xu et al., 2014]

Multiple Instance Learning (MIL)

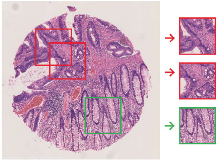
- Example $\mathbf{b}$ composed of a bag of N_b instances: $\mathbf{b} = \{\mathbf{x}_h\}_{h \in \{1;N_b\}}$
- Each instance $\mathbf{x}_h$ is described by a feature vector $\phi(\mathbf{b}, h) \in \mathbb{R}^d$
- Ex: $\mathbf{x}_h$ image region
  - $\phi(\mathbf{b}, h) \in \mathbb{R}^d$ pixels
  - $\phi(\mathbf{b},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



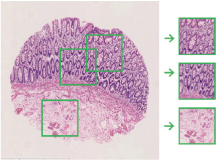
From [Xu et al., 2014]

Multiple Instance Learning (MIL)

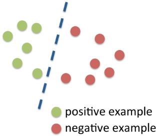
- Example $\mathbf{b}$ composed of a bag of N_b instances: $\mathbf{b} = \{\mathbf{x}_h\}_{h \in \{1;N_b\}}$
- MIL training formulation: A set a training N pairs $(\mathbf{b}_i, \mathbf{y}_i^*)$
  - $\mathbf{b}_i = \{\mathbf{x}_{i,h}\}_{h \in \left\{1;N_{b_i}\right\}}$ i^{st} example
  - $\mathbf{y}_i^*$ 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



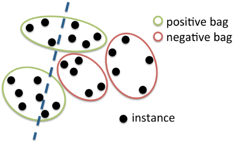
(a) cancer image



(b) non-cancerimage



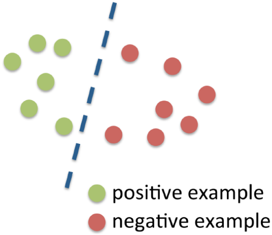
Supervised learning



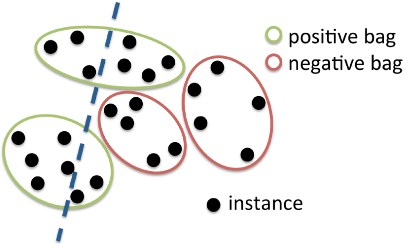
Multiple-Instance Learning (MIL)

Multiple Instance Learning (MIL)

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



Supervised learning



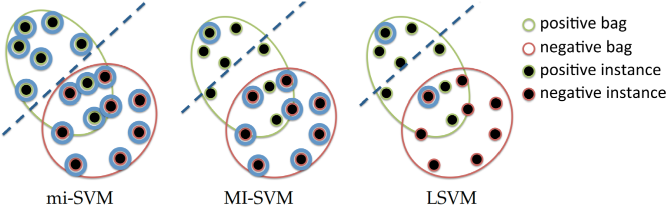
Multiple-Instance Learning (MIL)

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:

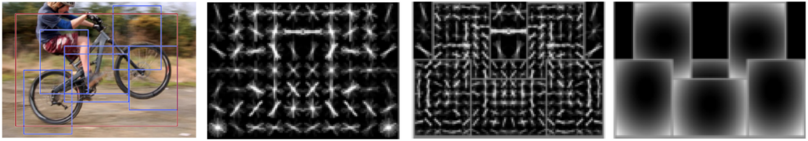
$$f_{\mathbf{w}}(\mathbf{b}_i) = \text{sign}\left[\max_{h \in N_{\mathbf{b}_i}} \langle \mathbf{w}, \phi(\mathbf{b}_i, h) \rangle\right] \quad (1)$$

- 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

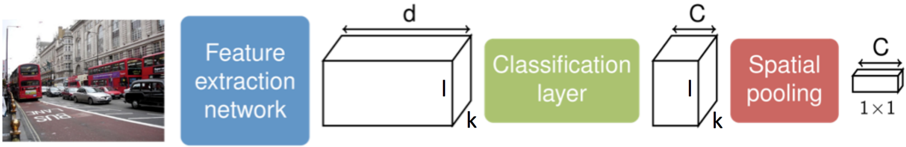
(b) Part filters in higher resolution

(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)

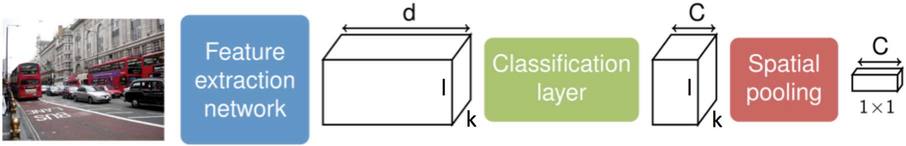
Multiple Instance Learning and Deep Learning

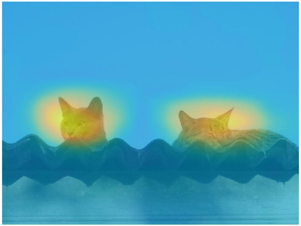
- Using MIL model in the Deep Learning era: deep architecture for WSL



- **Feature extractor** ⇒ 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



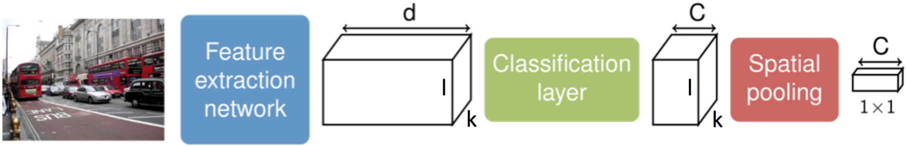


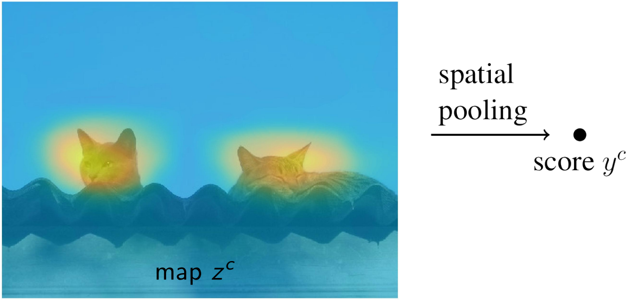
- **Classification:** projection to get a class prediction for each instance
  - $z_h^c = f_{\mathbf{w}_c}\left(\phi(\mathbf{b}_i, h)\right),\ \forall h \in \{1; N_b\},\ \forall c \in \{1; C\}$
  - $k \times l \times C$ tensor: Class Activation Maps (CAM)

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

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

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

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

- Classifying only with the max scoring region

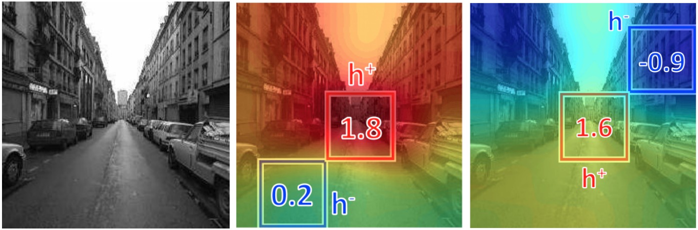
- Loss of contextual information

max+min pooling

- **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 **x** | $s(\textbf{street}) = 2$ | $s(\textbf{highway}) = 0.7$

Generalize pooling function [Durand et al., 2019]

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

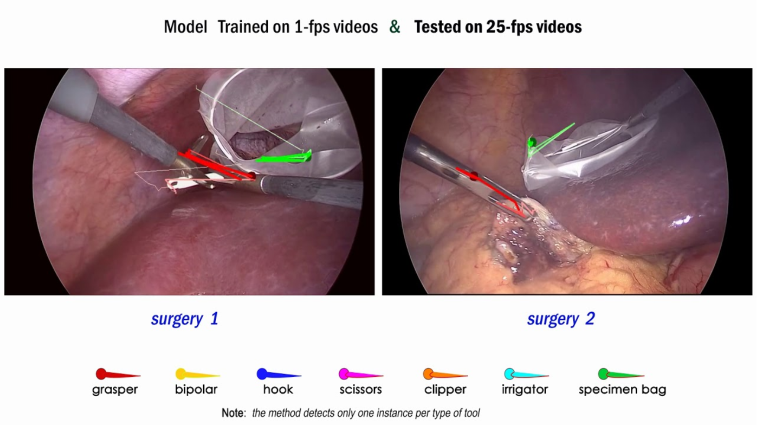
- Varying β_h^+, β_h^- $\Rightarrow$ recovering pooling functions used in well-known probabilistic and max-margin models
- Smoothly interpolate between these extreme cases

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

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

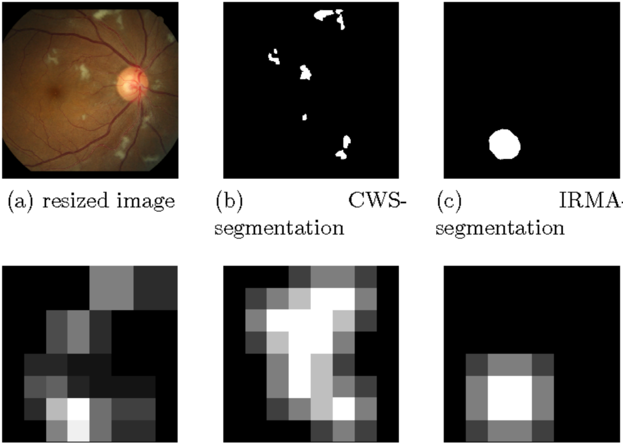
MIL for medical image analysis

- 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

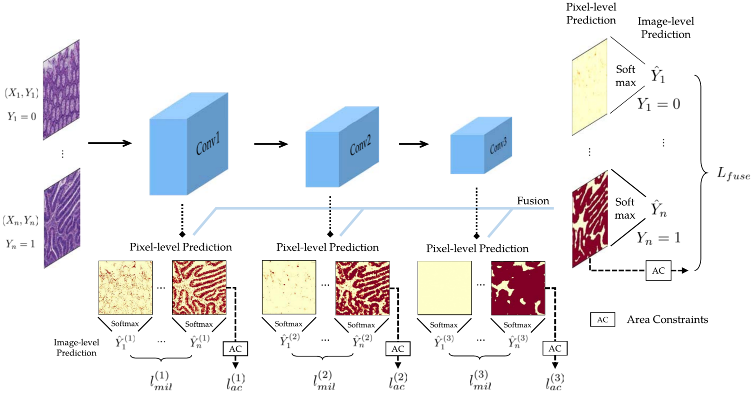


(a) resized image (b) CWS-segmentation (c) IRMA-segmentation

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

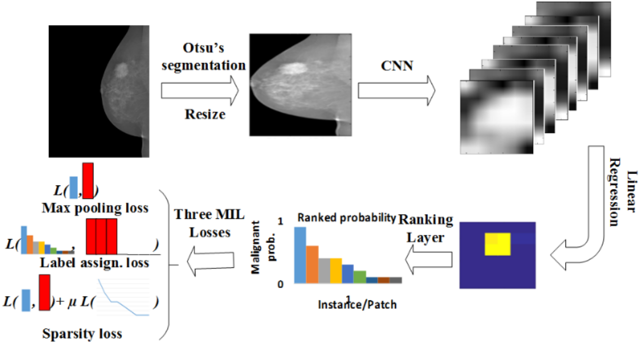
MIL for medical image analysis

- 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

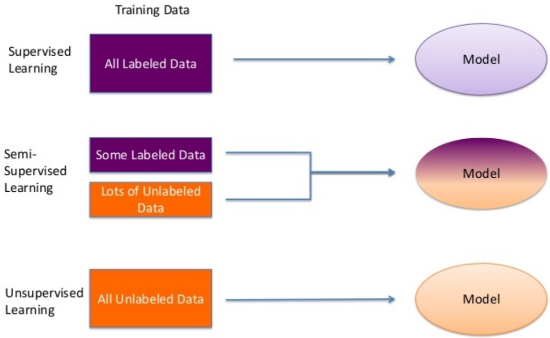
- Integrating constraints from medical knowledge in deep MIL objective [Zhu et al., 2017]
  - Deep MIL (max pool) for lesion detection in mammography
  - MIL loss including sparse prior constraint on lesion classification
    - Lesion ~ 2% of image size



Outline

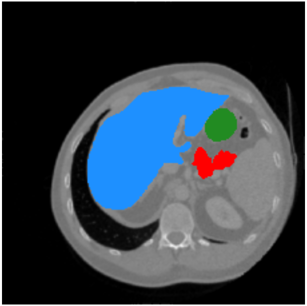
Semi Supervised Learning (SSL)

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

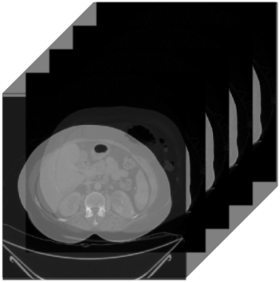


Credit: S. Jain

Semi Supervised Learning (SSL)



Few labeled data

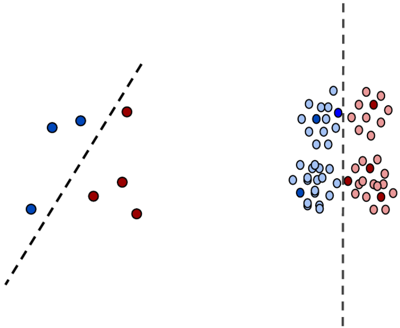


Many unlabeled

- 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]

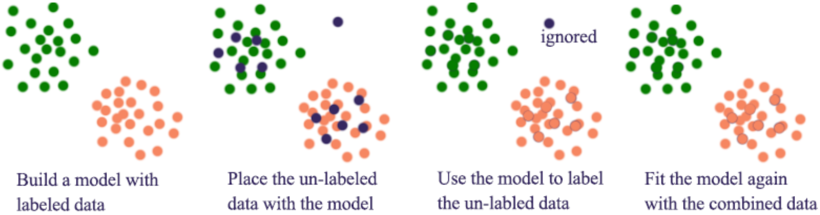


Fully supervised SSL

- 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

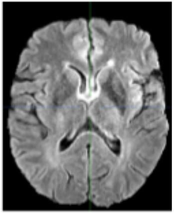
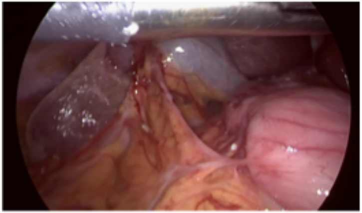
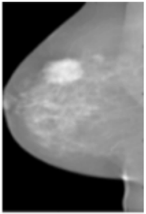
1. Train a model with labelled data $\mathcal{A}$
2. Until convergence:
   - Seek a sub-set of "easy" unlabelled data $\mathcal{U}_e$
   - Label each element in $\mathcal{U}_e$
   - Retrain model on $\mathcal{A} \cup \mathcal{U}_e$
   - Ex for medical image analysis: SMILE [Petit et al., 2018]



Credit: J. Hui

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

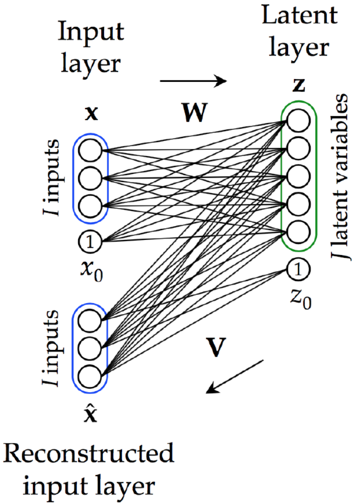
Auto-Encoders

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

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

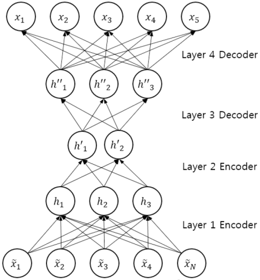
- If $f = g = Id$ (linear auto-encoder): $\sim$ PCA:

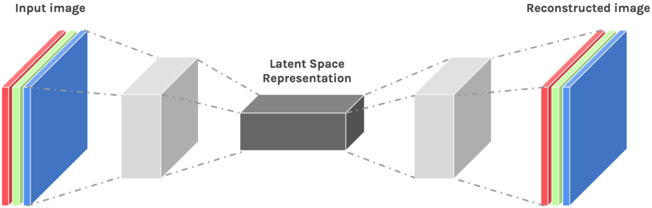
$$C = \sum_{i=1}^{N} ||\mathbf{x}_i - \mathbf{W}^t\mathbf{W}\mathbf{x}||^2$$



Deep Auto-Encoders

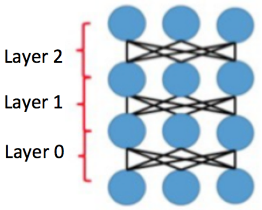
- AE: limited to linear feature extraction
- Add fully connected layers ⇒ more complex representations
- Add convolutional / deconvolutional layers: adapted to local feature extraction (images)



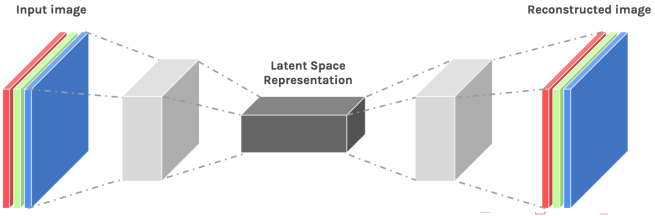


Training deep Auto-Encoders

- 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

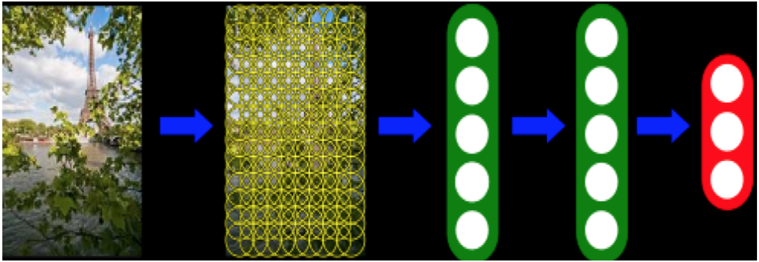


Training deep Auto-Encoders

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

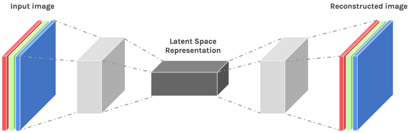
$$\mathcal{L} = \lambda_c \mathcal{L}_c + \lambda_r \mathcal{L}_r$$

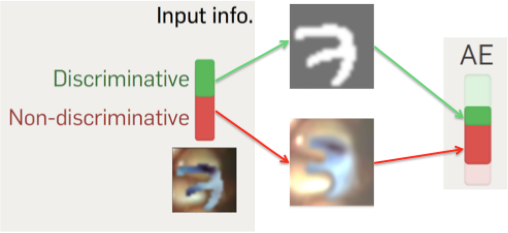
- $\mathcal{L}_c$ supervised cost, *e.g.* classification
- $\mathcal{L}_r$ unsupervised cost, *e.g.* reconstruction
- Joint training of both tasks



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

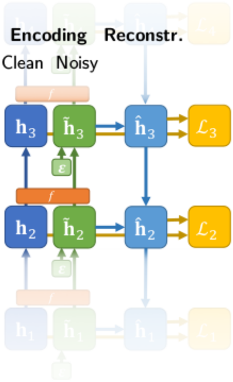


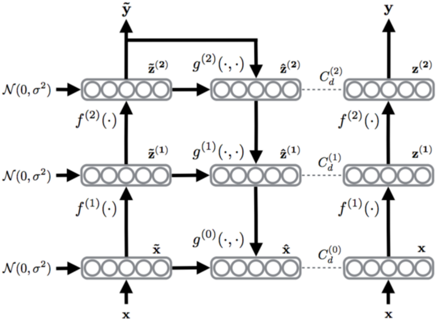


- **Two current alternatives to unsupervised learning:**
  1. Objective without reconstruction
  2. Casting unsupervised training as classification

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

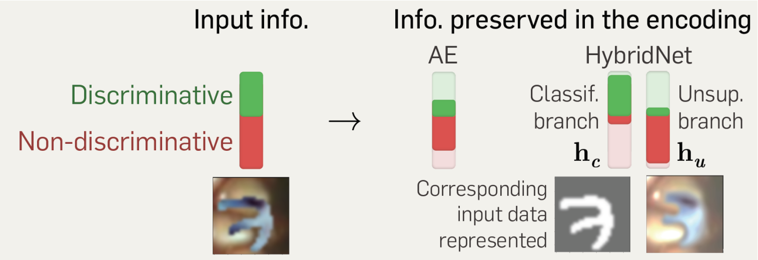
- "An autoencoder which can discard information"
- Layer above does not reconstruct layer below only with its activation
- Solution: Provide the details to learn only the abstract features
  - Decoder has a noisy version of the input to reconstruct



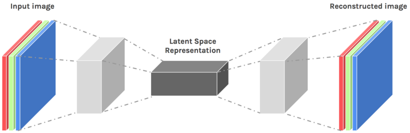


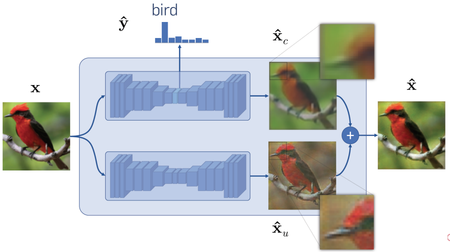
Beyond Reconstruction: HybridNet [Robert et al., 2018]

- **Disentangling** discriminative & complementary information for reconstruction



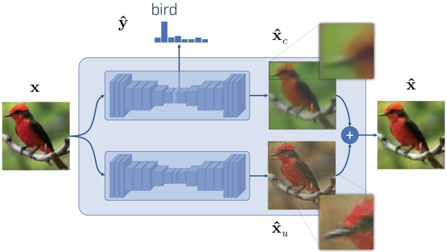
- **Two-branch architecture** *vs* single-branch for AE

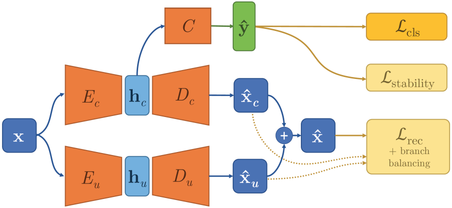




Beyond Reconstruction: HybridNet [Robert et al., 2018]

- **HybridNet: training** two-branch architecture





- **Classification loss:** standard cross-entropy $\Rightarrow \mathcal{L}_{cls} = CE\left(\mathbf{y}^*, \hat{\mathbf{y}}\right) = -log\left(\hat{y}_{c^*}\right)$
- **Stability loss:** [Sajjadi et al., 2016, Laine and Aila, 2017, Tarvainen and Valpola, 2017]
  - $\mathcal{L}_{stability} = ||\hat{\mathbf{y}} - \tilde{z}||^2$, $\tilde{z}$ distorsion, *e.g.* exp mov avg [Laine and Aila, 2017]
- **Reconstruction loss:** $\mathcal{L}_{rec} = ||\mathbf{x} - \hat{\mathbf{x}}||^2 = ||\mathbf{x} - (\hat{\mathbf{x}}_c + \hat{\mathbf{x}}_u)||^2$
  - **Branch balancing:** back-prop only in one branch: $max\left(||\mathbf{x} - \hat{\mathbf{x}}_c||^2; ||\mathbf{x} - \hat{\mathbf{x}}_u||^2\right)$

HybridNet [Robert et al., 2018]: Experiments

Classif.	Stability	Reconstr.	Branch balanc.	CIFAR-10 2000 labels
✓				71.5
✓	✓			74.6
✓		✓		72.4
✓		✓	✓	75.2
✓	✓	✓	✓	81.6

- All terms important
  - **Branch balancing ⇒ important for branch cooperation**
- Exploiting input data and reconstruction
  - Important gain compared to stability

- Semi-supervised experiments in several datasets with ResNet-based model
- Improve over stability & AE-based baselines

Dataset	CIFAR-10		STL-10	SVHN
Nb. of labeled images	1000	4000	1000	1000
Nb. of unlabeled images	~50k		~100k	~600k
AE-based (Ladder[1])		20.40		
AE-based (SWWAE[2])			25.7	23.6
Stability only (MT[5])	10.10	6.23	16.8	4.2
Classif. baseline	45.22	15.45	18.0	10.0
HybridNet	**8.81**	**6.09**	**15.9**	**2.5**

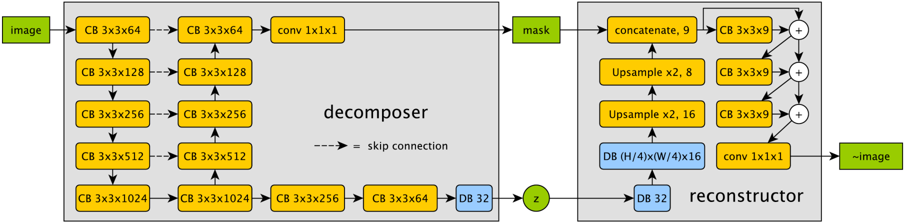
Hybrid Architectures for Medical Images

- 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

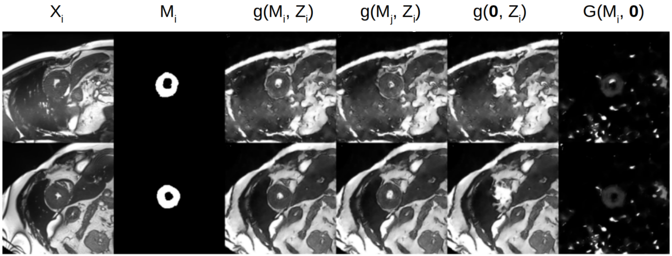
Large reconstruction loss: poor segmentation

- 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]

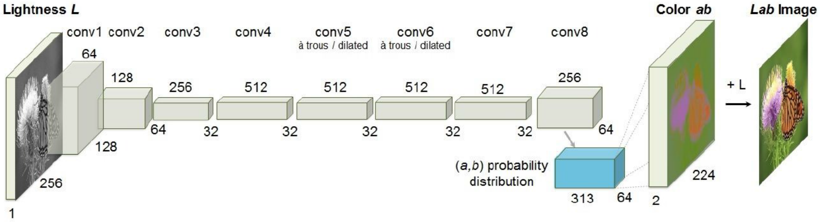
	ACDC					QMRI			
Labelled images	284	142	68	34	11	157	78	39	19
U-Net	0.782	0.657	0.581	0.356	0.026	0.686	0.681	0.441	0.368
GAN	**0.787**	0.727	0.648	0.365	0.080	**0.795**	0.756	0.580	0.061
SDNet	0.771	**0.767**	**0.731**	**0.678**	**0.415**	0.794	**0.772**	**0.686**	**0.424**

Beyond Reconstruction: Self-Supervised Training

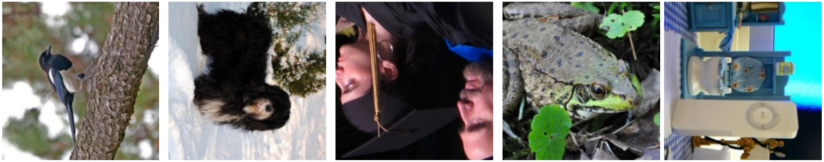
- **Self-supervised training: unsupervised problem ⇒ supervised one**
- Performing prediction on data, *e.g.*
  - Relative position of regions
  - Temporal prediction (next frames)
- ***"Auxiliary", "pretext"* task**
  - Good auxiliary task requires solving high-level recognition ⇒ useful features for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

Self-Supervised Training: some auxiliary tasks

- Image colorization [Zhang et al., 2016]



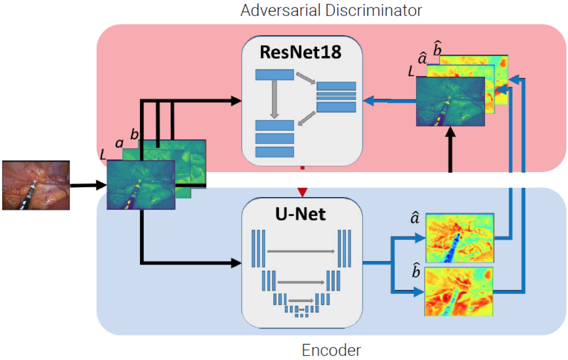
- Predicting image orientation [Gidaris et al., 2018]



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

Self-Supervised Training in Medical Imaging

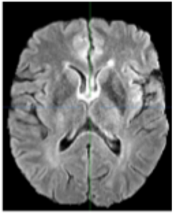
- **Auxiliary task:** endoscopic video colorization [Ross et al., 2018] in (L,a,b) space
  - cGAN approach: predict color (a,b) from luminance L
    - Generator (U-Net): $L \rightarrow (\hat{a}, \hat{b})$
    - Discriminator (ResNet): $L, a, b \rightarrow$ real, $L(\hat{a}, \hat{b}) \rightarrow$ *fake*

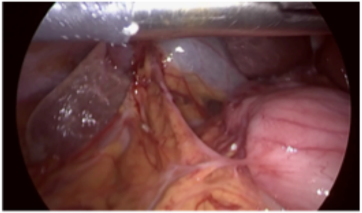
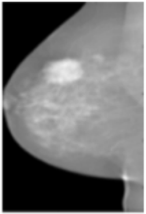


- **Target task:** instrument segmentation

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



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