

Deep Learning for Image Analysis - Learning from fewer annotations

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- 2 Strategies
- 3 Contrastive Learning
- 4 Weak supervision
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Deep Learning: there is just one catch ...

- Deep Learning is today the most powerful method for image classification, segmentation and object detection.
- Deep Learning can achieve or even go beyond human performance for these tasks.
- There is a snag: deep learning relies on massive annotation.
- Example: ImageNet contains 1.4 million annotated images [Russakovsky et al., 2015].

Deep Learning: there is just one catch ...

- Manual image annotation is annoying.
- Manual image annotation is expensive.
- Sometimes it is impossible to get a lot of annotated data.
- We need to address the need for massive image data sets by
 - using cheap annotations.
 - using different (abundant) annotated data.
 - using unlabeled data.

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Massive image annotation by crowd sourcing



Figure: Gamification for the annotation of protein localization patterns: the actual annotation task is "disguised" as a computer game. Image taken from [Sullivan et al., 2018]

- Crowd sourcing: generate massive annotated data sets by recruiting more people to do the annotations.
- This requires the implication of untrained experts (citizen science).
- Several strategies to reach many people, e.g. gamification.

Massive annotation by leveraging routinely acquired data

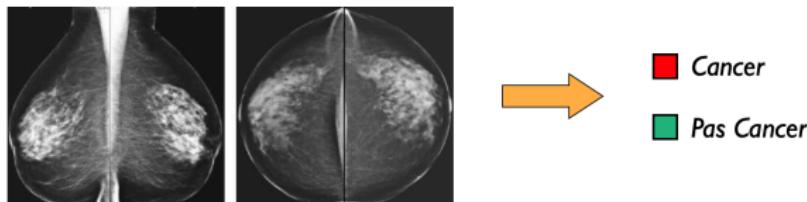


Figure: Radiology: mammographies are acquired routinely by physicians.

- In many fields, image data is routinely acquired (e.g. medical examinations).
- Origins of the image labels:
 - Routine annotation by a medical doctor.
 - Future evolution of the disease.
- Problem: we are limited in the tasks, i.e. in the variables that we can predict.

Massive image annotation by experimental design



Figure: A high resolution image can be predicted from a low resolution image. Image adapted from [Ouyang et al., 2018]

- In image restoration, we aim at predicting a high quality image from a lower quality image.
- Here, the ground-truth is entirely generated by the experimental setup (pairs of images are acquired).

Massive image annotation by experimental design

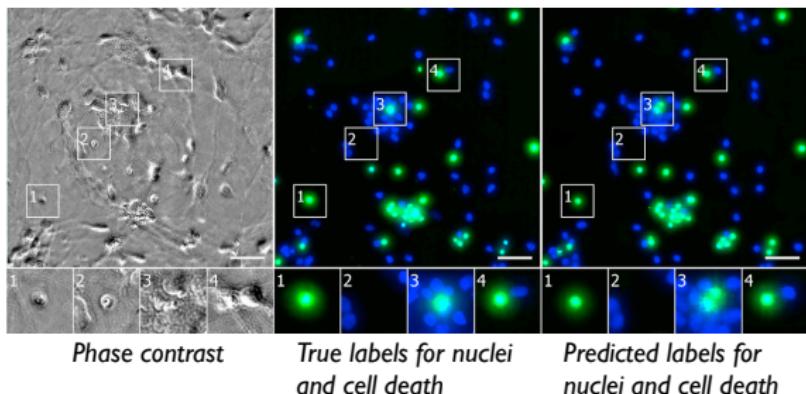


Figure: Image taken with a different modality can be predicted. Here, we show an example for a fluorescent microscopy image predicted from a phase contrast microscopy image. Image adapted from [Christiansen et al., 2018]

- We can also predict images taken with different modalities.
- This is interesting if one technique is more expensive or more invasive.
- Similarly, we can also use different experimental techniques to generate ground truth experimentally [J. Boyd et al., 2020].

Learning from simulated data

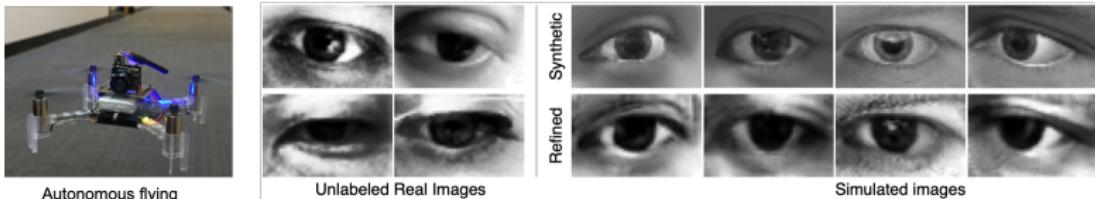


Figure: Two examples for learning from simulated data. Images from [Kang et al., 2019] and [Shrivastava et al., 2017].

- Simulation of large amounts of data with known ground truth.
- Train networks on simulated data.
- Problem: the data distributions between simulated and real data usually differ.

Learning from other datasets / other tasks

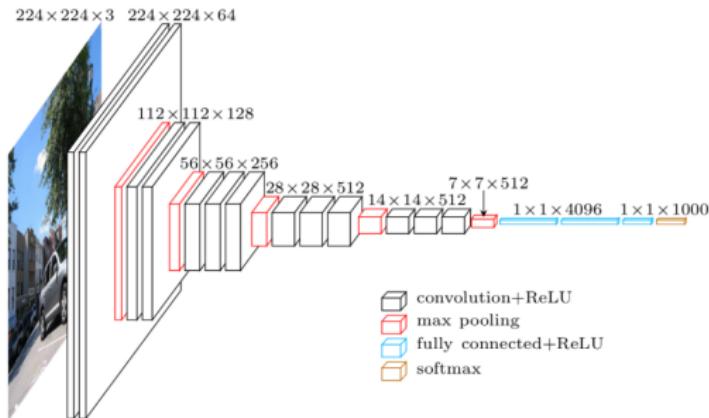


Figure: Image representations for transfer learning.

- Train a network on large annotated image bases.
- Use the learned representations to solve small scale problems (with or without fine-tuning) with few annotations.
- Problems:
 - Relevance of the used dataset.
 - Relevance of the tasks.

Subject of today

In this lecture, we will learn about three strategies to address the problem of massive datasets required for training of deep neural networks:

- 1 Contrastive Learning
- 2 Learning in a weakly supervised setting (typically coarse annotations)
- 3 Learning from simulations with domain adaptation

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Idea

- Transfer Learning: transferring learned representation from one data set (with potentially different tasks) to a new data set.
- If we can define pretext tasks with known labels, we can also leverage unlabeled data to learn representations, which might also be transferable.
- Pretext task: learn the identity of transformed images.
- Here, we present the paper "A simple framework for Contrastive Learning of Visual Representations" (SimCLR) [Chen et al., 2020].

SimCLR [Chen et al., 2020]

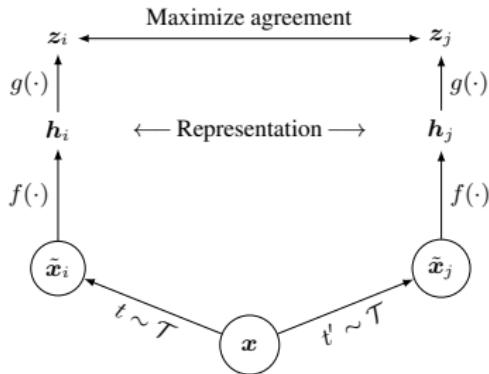


Figure: SimCLR workflow as defined in [Chen et al., 2020]

- For each image x , we calculate two transformed versions \tilde{x}_i and \tilde{x}_j by two transformations t and t' drawn from a set of parametrized transformations.
- For \tilde{x}_i and \tilde{x}_j , we calculate the representations h_i and h_j , respectively. $f(\cdot)$ is the neural network we want to learn.

SimCLR [Chen et al., 2020]

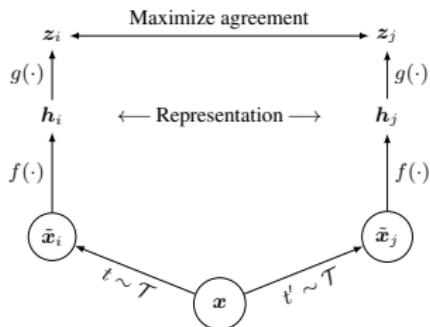


Figure: SimCLR workflow as defined in [Chen et al., 2020]

- The representations h_i and h_j are mapped to a space where contrastive loss is applied, by a small neural network $g(\cdot)$.
- The classification task is to identify among all transformed images for each transformed image x_i the transformed image x_j that originates from the same image.

SimCLR [Chen et al., 2020]

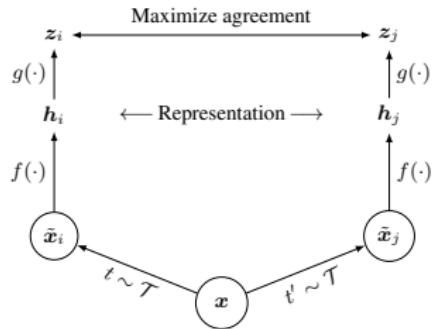


Figure: SimCLR workflow as defined in [Chen et al., 2020]

- We define the similarity of two representations as follows:

$$s(u, v) = \frac{u^T v}{\|u\| \|v\|} \quad (1)$$

- With this, we can define the contrastive loss as follows:

$$l_{i,j} = -\log \frac{\exp \frac{s(z_i, z_j)}{\tau}}{\sum_{k=1}^{2N} \mathbb{1}_{k \neq i} \exp \frac{s(z_i, z_k)}{\tau}} \quad (2)$$

SimCLR: transformations

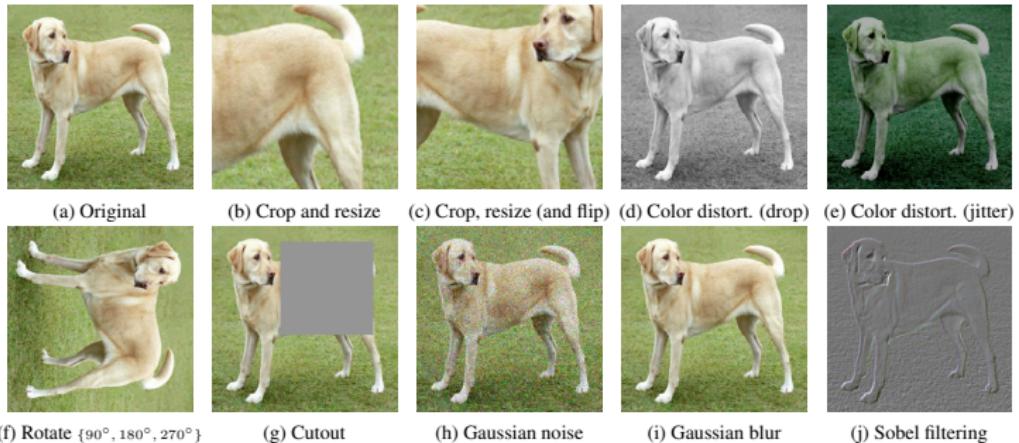


Figure: Transformations used in SimCLR [Chen et al., 2020]

SimCLR: results

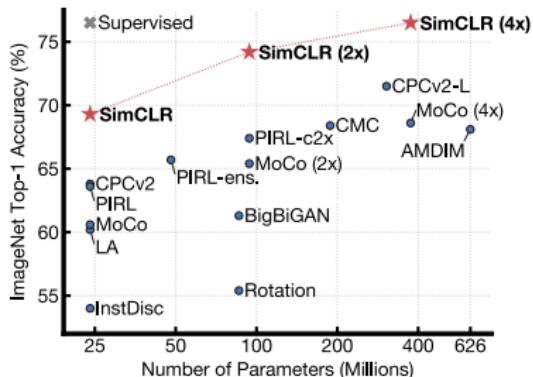


Figure: SimCLR: Results (linear evaluation) [Chen et al., 2020]

- Evaluation of representations by *linear evaluation* (result obtained by a linear classifier trained with the representation as features): the unsupervised approach comes reasonably close to a fully supervised approach.
- Transfer-learning results (not shown): Fine-tuning the obtained representations is on par with fine-tuning pretrained networks.

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What is weak supervision?

- Weak supervision refers to a situation, where the ground truth data we build our model on is in some sense imperfect [Zhou, 2018].
- Three types of weak supervision:
 - 1 **Incomplete supervision:** only a subset of training data are labeled (semisupervised setting).
 - 2 **Inexact supervision:** training data are labeled but not as exactly as required by the task we would like to perform.
 - 3 **Inaccurate supervision:** training data are labeled, but may contain mistakes.
- Here, we treat the case of inexact supervision.

Multiple Instance Learning (MIL): example



Figure: Principle of Multiple Instance Learning. Image taken from [Babenko,]

- Key-example: we are given a number of persons each of which has several keys. You are just given the information who is able to open the door.
- Examples:
 - Video tags without frame annotation
 - Medical imaging: image is positive in the presence of a lesion
 - Marketing: campaign sent out to a group of people

Multiple Instance Learning framework (MIL)

- MIL deals with problems with incomplete knowledge of labels in training sets.
- MIL assumes that instead of disposing of individual labels y_i for each sample x_i , we only have labels for subsets of samples, called "bags":

$$\begin{aligned} T &= \{(B_i, y_i)\} \\ B_i &= \{x_j\} \end{aligned} \tag{3}$$

- A bag is positively labeled if at least one instance in it is positive, and is negatively labeled if all instances in it are negative.

A deep learning approach to MIL

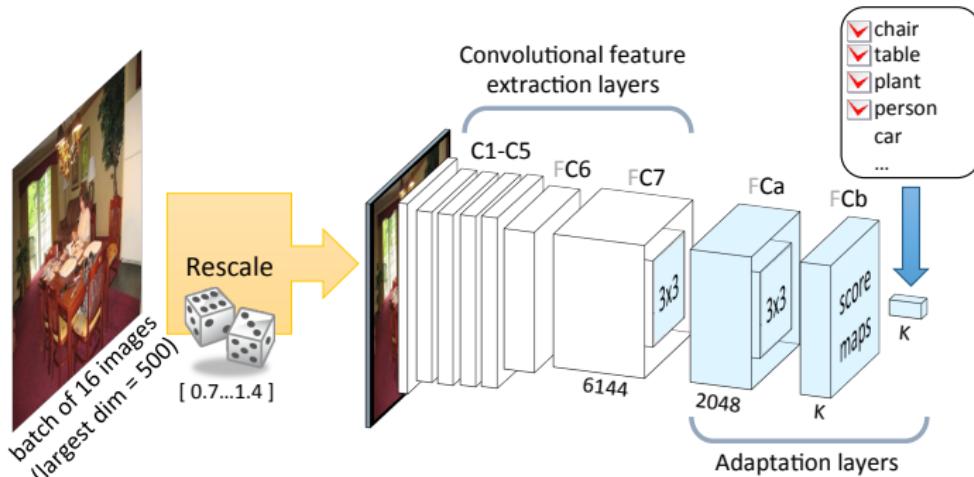


Figure: CNN architecture for Multiple Instance Learning. Image taken from [Oquab et al., 2015]

First, a standard CNN is applied as feature extractor (without fully connected layers). This maps an image X to a $n \times m \times l$ layer (l feature maps of spatial dimensions $n \times m$).

A deep learning approach to MIL

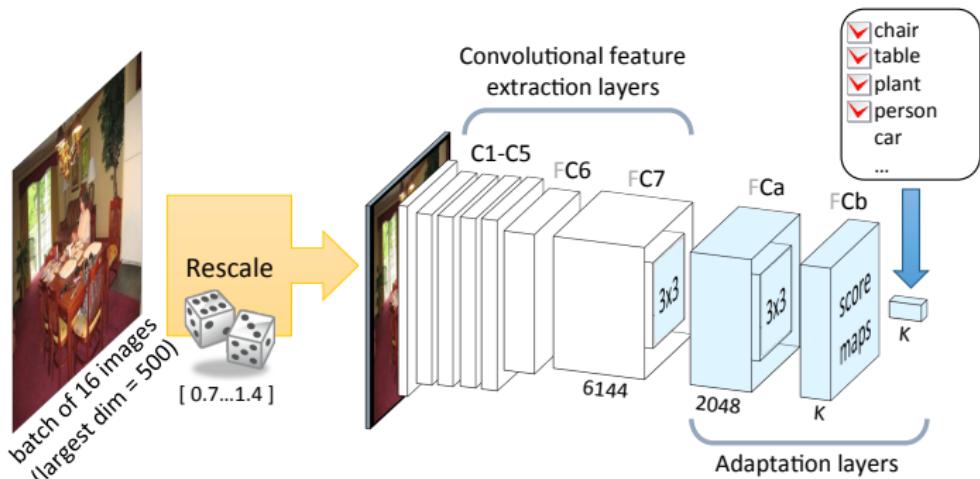


Figure: CNN architecture for Multiple Instance Learning. Image taken from [Oquab et al., 2015]

This layer is then mapped to a $n \times m \times K$ layer by 1×1 convolutions, where K is the number of output classes. Of note, a 1×1 convolutional layer is equivalent to a fully connected layer, if its input is a vector (spatial dimension 1). We can understand the 1×1 conv layer as parallel fully connected layers.

A deep learning approach to MIL

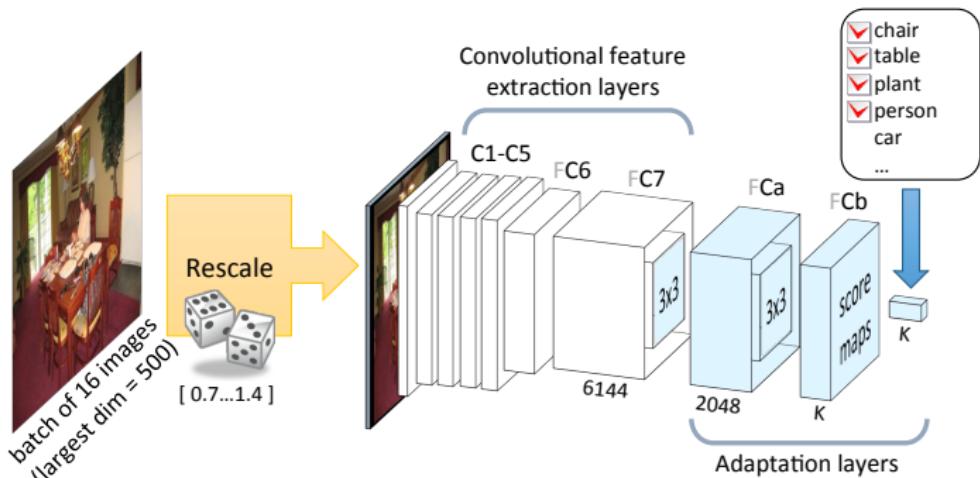


Figure: CNN architecture for Multiple Instance Learning. Image taken from [Oquab et al., 2015]

Each "pixel" in feature map FCb is thus the score vector for an input region. FCb therefore corresponds to a bag of image regions. We therefore maximize over the spatial dimensions:

$$s_k = \max_{i,j} f_{i,j}^k \quad (4)$$

A deep learning approach to MIL



Figure: Example for MIL by deep learning. Image adapted from [Oquab et al., 2015]

- Maximization over the spatial dimensions corresponds exactly to the MIL-paradigm: for the decision on the image label, it is sufficient to have one single positive region.
- This is a typical situation, when we want to detect objects in crowded images.

Discussion

- Improvement of image classification, as only the relevant region is taken into consideration.
- This is particularly useful, if the size of the relevant region is comparatively small.
- Objects can also be detected and this without expensive annotation (bounding boxes or pixel-wise annotation).
- In addition, the detection of different classes is eased by the setup.
- Limitations:
 - The max-operation might lead to instabilities.
 - Object extensions cannot be faithfully predicted.
 - The context is not taken into consideration.

Improvements on the WSL strategy

- Instead of taking the maximum score over all image regions [Durand et al., 2016]:
 - Select the s_{top} highest scoring regions
 - Select the s_{low} lowest scoring regions
- Intuition: taking $s_{top} > 1$ regions makes the algorithm more robust, taking s_{low} lowest scoring regions provides negative evidence for the class.

Application example: histopathology

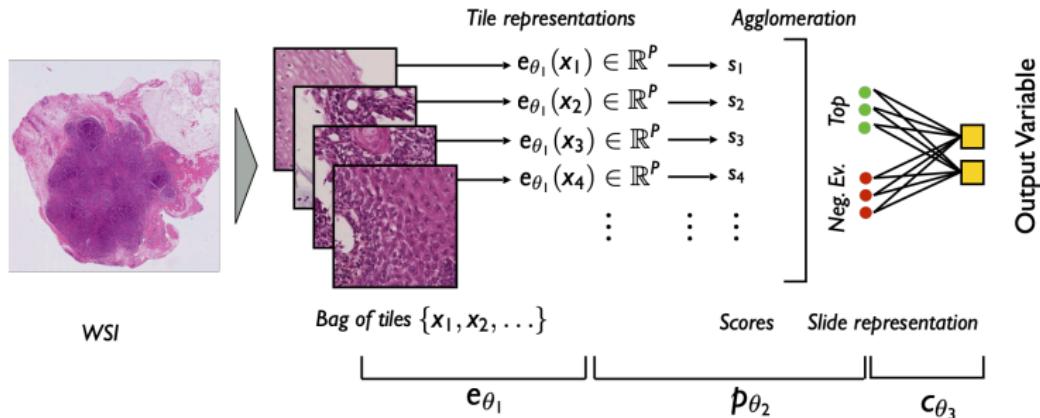


Figure: Example for MIL: classification of large images in histology.

- Histopathology images are extremely big.
- Sometimes, what we want to find can be small.
- There is slide-level annotation, but detailed annotation is scarce.

Application example: metastasis detection

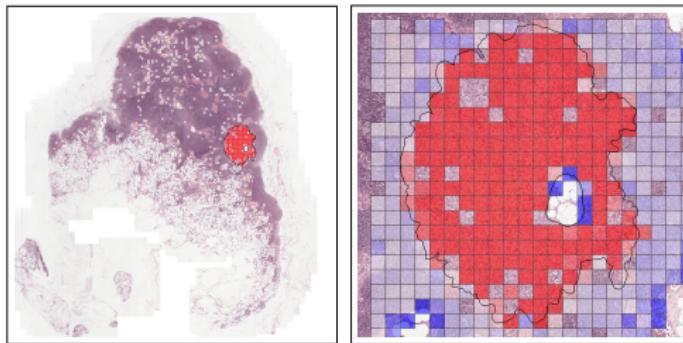


Figure: Example for MIL for tumor detection. Image adapted from [Courtiol et al., 2017]

Here, [Courtiol et al., 2017] use the WELDON algorithm to detect metastases. Only global annotation is used. The results are on par with classification / detection algorithms trained on detailed annotation.

An alternative to standard MIL based on attentions

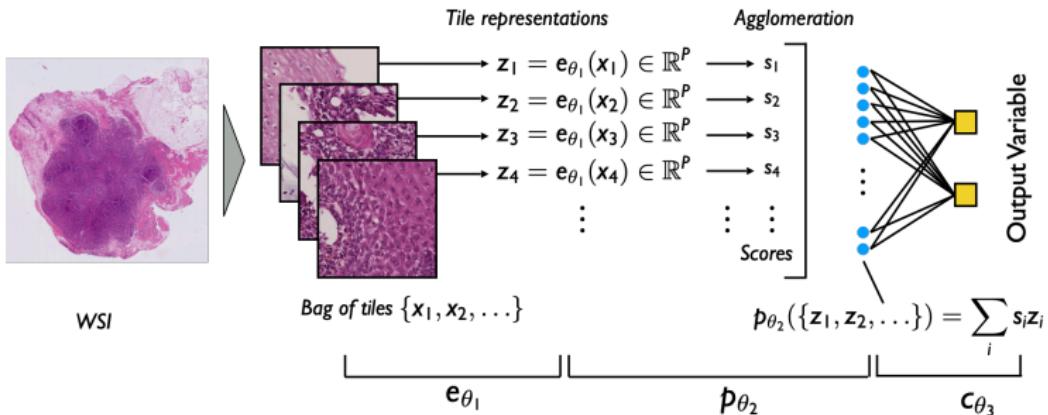


Figure: Attention-based approach for histology image classification.

- Attention scores are predicted from the tile images.
- The slide representation is the weighted sum of the tiles.

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Simulation for the generation of training data

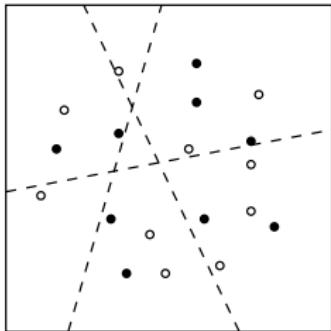
- With simulation, we can generate arbitrary quantities of data with known ground truth.
- Simulation is regularly used for benchmarking of methods.
- Usually, simulation provides us with data similar to real world data, but not identical.
- For this reason, the use of simulated data for training neural networks is limited.
- Idea: can we overcome the differences between simulated and real data by explicit algorithmic strategies?

Domains

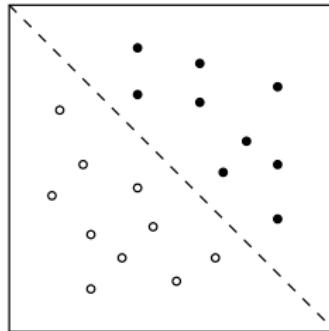
- Domain adaptation: learning a discriminative classifier when training data does not follow the same distribution as the test data.
- Let \mathcal{X} be an input space and $\mathcal{Y} = \{1, \dots, L\}$ the set of L possible labels. We call a domain the distribution over $\mathcal{X} \times \mathcal{Y}$.
- Here we consider two domains: the source domain \mathcal{D}_S and the target domain \mathcal{D}_T .
- The n source samples are then drawn from \mathcal{D}_S , the $N - n$ test samples from \mathcal{D}_T :

$$\begin{aligned} S &= \{(x_i, y_i)\}_{i=1}^n \sim \mathcal{D}_S^n \\ T &= \{(x_i, y_i)\}_{i=n+1}^N \sim \mathcal{D}_T^{N-n} \end{aligned}$$

The divergence of domains



(a) Low divergence



(b) High divergence

Figure: Illustration of h-divergence between domains.

- The divergence of domains can be quantified by trying to classify samples according to their source label.
- Hence, we train a classifier from a training set $T = \{(x_i, d_i)\}$:

$$d_i = \begin{cases} 0, & \text{if } x_i \sim \mathcal{D}_S^X \\ 1, & \text{if } x_i \sim \mathcal{D}_T^X \end{cases} \quad (5)$$

- In this case, the h-divergence can be written as $2(1 - 2\epsilon)$, where ϵ is the error of the classifier.

Domain adaptation by adversarial training

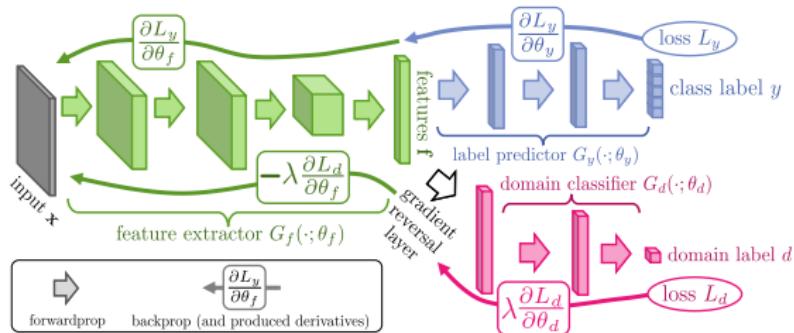


Figure: Domain adaptation by adversarial training. Image taken from [Ganin et al., 2016]

- We seek a representation that provides good prediction results, but low h -divergence.
- This means that this representation (f in the figure) should not allow us to distinguish between source domain and target domain.

Domain adaptation by adversarial training

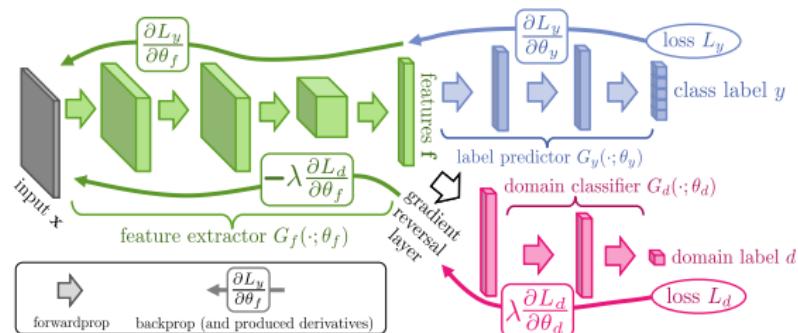


Figure: Domain adaptation by adversarial training. Image taken from [Ganin et al., 2016]

For this we consider the following architecture [Ganin et al., 2016]:

- $G_f(\cdot, \theta_f)$: feature extractor
- $G_y(\cdot, \theta_y)$: label predictor
- $G_d(\cdot, \theta_d)$: domain classifier

Domain adaptation by adversarial training

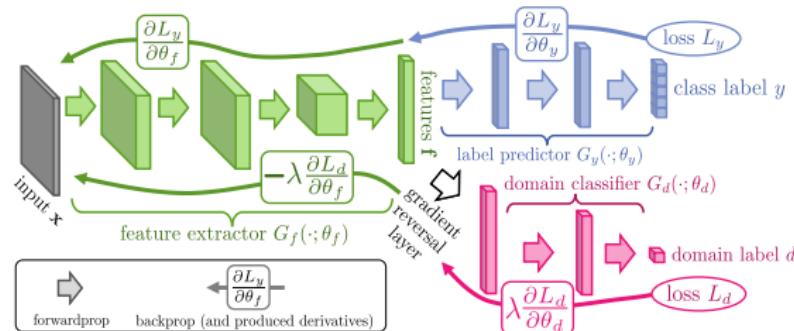


Figure: Domain adaptation by adversarial training. Image taken from [Ganin et al., 2016]

The forward propagation produces then the following loss:

$$L(\theta_f, \theta_y, \theta_d) = L_y(\theta_f, \theta_y) - \lambda L_d(\theta_f, \theta_d) \quad (6)$$

where $L_y(\theta_f, \theta_y)$ is the standard prediction loss for samples from the training set (and thus the source domain), while $L_d(\theta_f, \theta_d)$ is the domain loss, calculated on all samples (labeled samples from the source domain and the unlabeled samples from the target domain).

Domain adaptation by adversarial training - Optimization

- More formally, we write:

$$\begin{aligned} L_y(\theta_f, \theta_y) &= \frac{1}{n} \sum_{i=1}^n L_y(G_y(G_f(x_i, \theta_f), \theta_y), y_i) \\ L_d(\theta_f, \theta_d) &= \frac{1}{n} \sum_{i=1}^n L_d(G_d(G_f(x_i, \theta_f), \theta_d), d_i) \\ &+ \frac{1}{N-n} \sum_{i=n}^N L_d(G_d(G_f(x_i, \theta_f), \theta_d), d_i) \\ L(\theta_f, \theta_y, \theta_d) &= L_y(\theta_f, \theta_y) - \lambda L_d(\theta_f, \theta_d) \end{aligned}$$

- This loss has to be minimized with respect to some parameters and maximized with respect to other parameters:

$$\begin{aligned} (\hat{\theta}_f, \hat{\theta}_y) &= \arg \min_{\theta_f, \theta_y} L(\theta_f, \theta_y, \hat{\theta}_d) \\ \hat{\theta}_d &= \arg \max_{\theta_d} L(\hat{\theta}_f, \hat{\theta}_y, \theta_d) \end{aligned}$$

Domain adaptation by adversarial training - gradient reversal

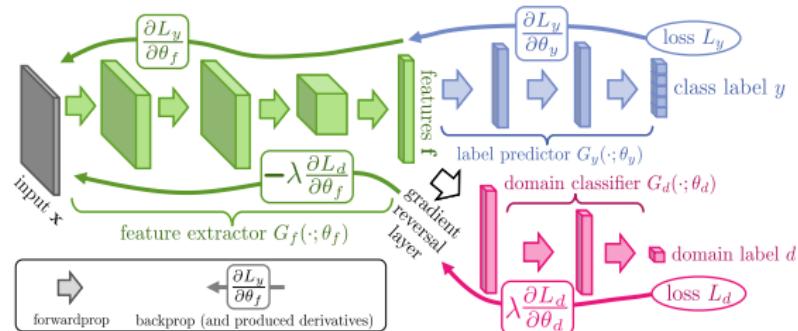


Figure: Domain adaptation by adversarial training. Image taken from [Ganin et al., 2016]

The solution of simultaneous minimization and maximization can be elegantly solved by reversing a gradient layer during back-propagation, as indicated in the figure.

Application example: character classification

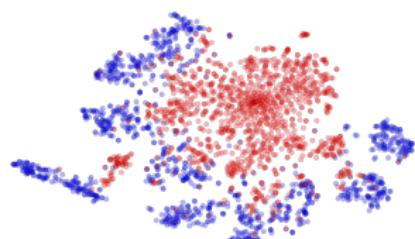
	MNIST	SYN NUMBERS	SVHN	SYN SIGNS
SOURCE				
TARGET				

Figure: Domain adaptation between simulated and real data. MNIST: hand-written digits, MNIST-M: MNIST on top of random image patches, SYN Numbers: simulation created by varying Windows fonts, SVHN: street view house numbers, Image taken from [Ganin et al., 2016]

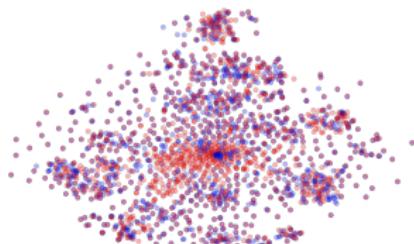
Results indicate that the achievable improvements can reach up to 20% in cases where the simulations are relatively far from the real-world examples.

Application example: character classification

MNIST \rightarrow MNIST-M: top feature extractor layer

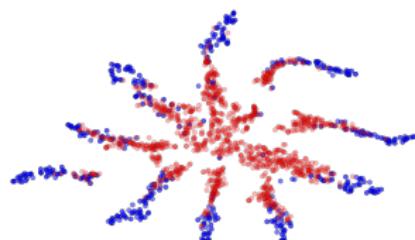


(a) Non-adapted

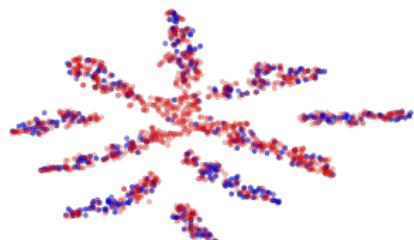


(b) Adapted

SYN NUMBERS \rightarrow SVHN: last hidden layer of the label predictor



(a) Non-adapted



(b) Adapted

Figure: Learned representations with and without domain adaptation. Domains are colored in red and blue. Image taken from [Ganin et al., 2016].

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Conclusion

- The need for large annotated data sets is currently a bottleneck in many real-world applications of deep learning.
- There is a number of strategies to overcome massive manual image annotation.
- Here, we have seen three strategies:
 - 1 Contrastive Learning.
 - 2 Learning from weakly supervised data
 - 3 Learning from simulations
- Usually, the way in which we setup the annotation strategy usually also influences the methodological developments.

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