Department of Medical Physics and Biomedical Engineering
Centre for Medical Image Computing (CMIC)
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Deep Learning

MPHY0041 Machine Learning in Medical Imaging

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Research

Selected Research Topic

Multiple instance learning

Adversarial learning and generative models

Domain adaptation

Meta-learning

Unsupervised learning*

Reinforcement learning*

Graph networks*

Research| Multiple Instance Learning

Weakly-supervised learning and Weak labels

- Inaccurate supervision, e.g. noisy labels
- Incomplete supervision, e.g. partial labels
- Inexact supervision, e.g. multiple instance learning

Bags, instances and labels in MIL

Serge's key-chain

Serge **cannot** enter the *Secret Room*

Sanjoy's key-chain

Sanjoy **can** enter the *Secret Room*

Lawrence's key-chain

Lawrence **can** enter the *Secret Room*

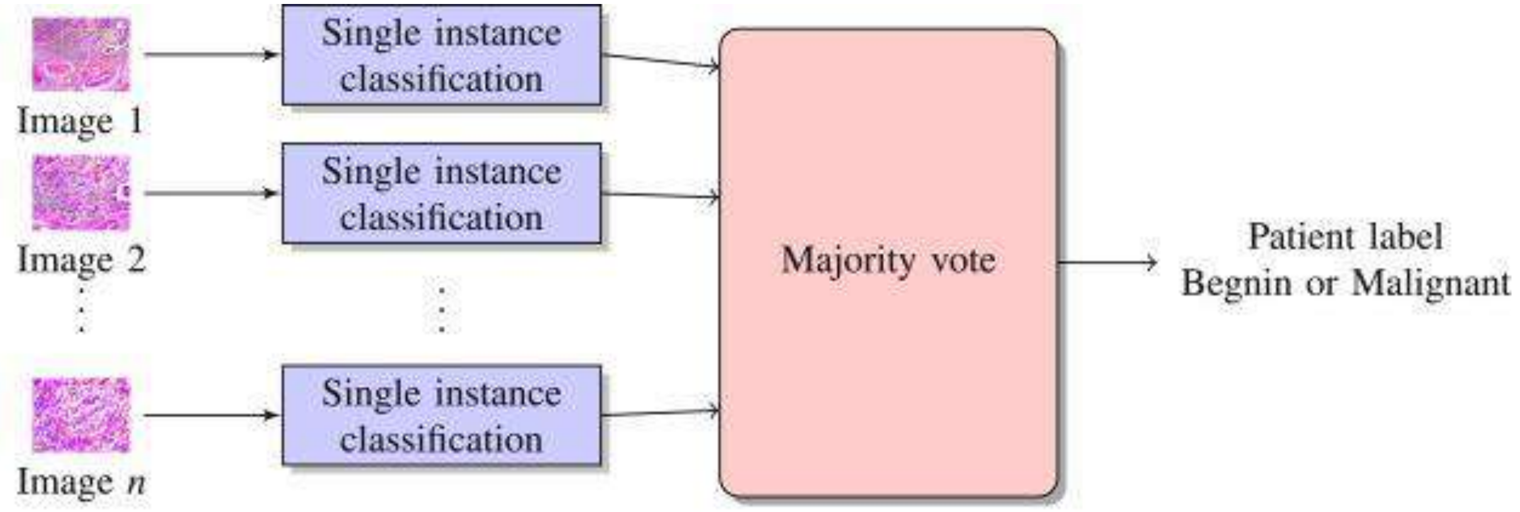
Linkage function between bag-level (known) and instance-level (to infer) relations

$$y_i = \begin{cases} 1 & \text{if } \exists j \text{ s.t. } y_{ij} = 1 \\ 0 & \text{otherwise} \end{cases}$$

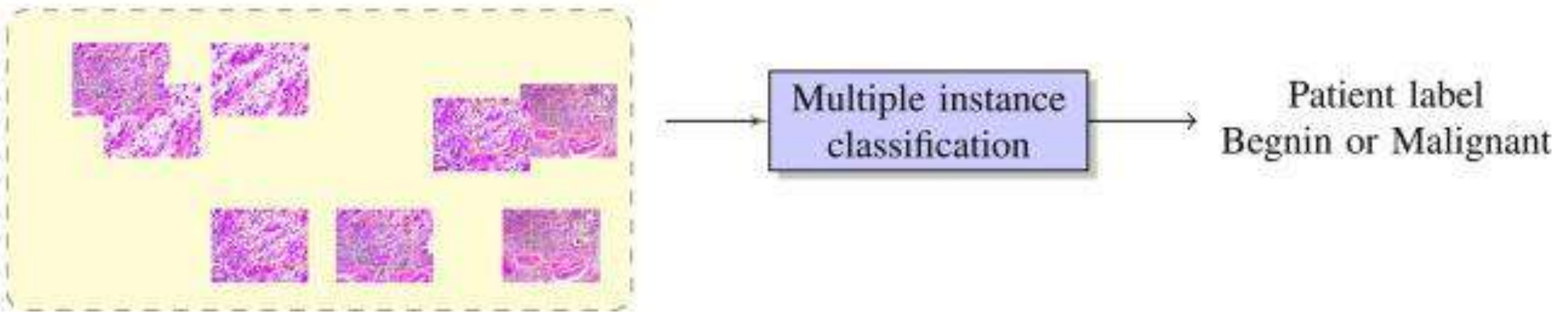
$$y_i = \max_j \{y_{ij}\}$$

$x_i \in \mathcal{X}$	i^{th} instance (supervised)
$X_i = \{x_{i1}, x_{i2} \ldots, x_{im}\}$	i^{th} bag with m instances x_{ij} (MIL)
$y_i \in \mathcal{Y}$	label of i^{th} instance (supervised) or i^{th} bag (MIL)
y_{ij}	true label of j^{th} instance in i^{th} bag
y'	$(2y - 1)$
n	instances (supervised) or number of bags (MIL)
m	number of instances per bag
d	dimensionality
$h(x)$	instance classifier
$H(X)$	bag classifier

Segmentation on whole-slide imaging in digital pathology

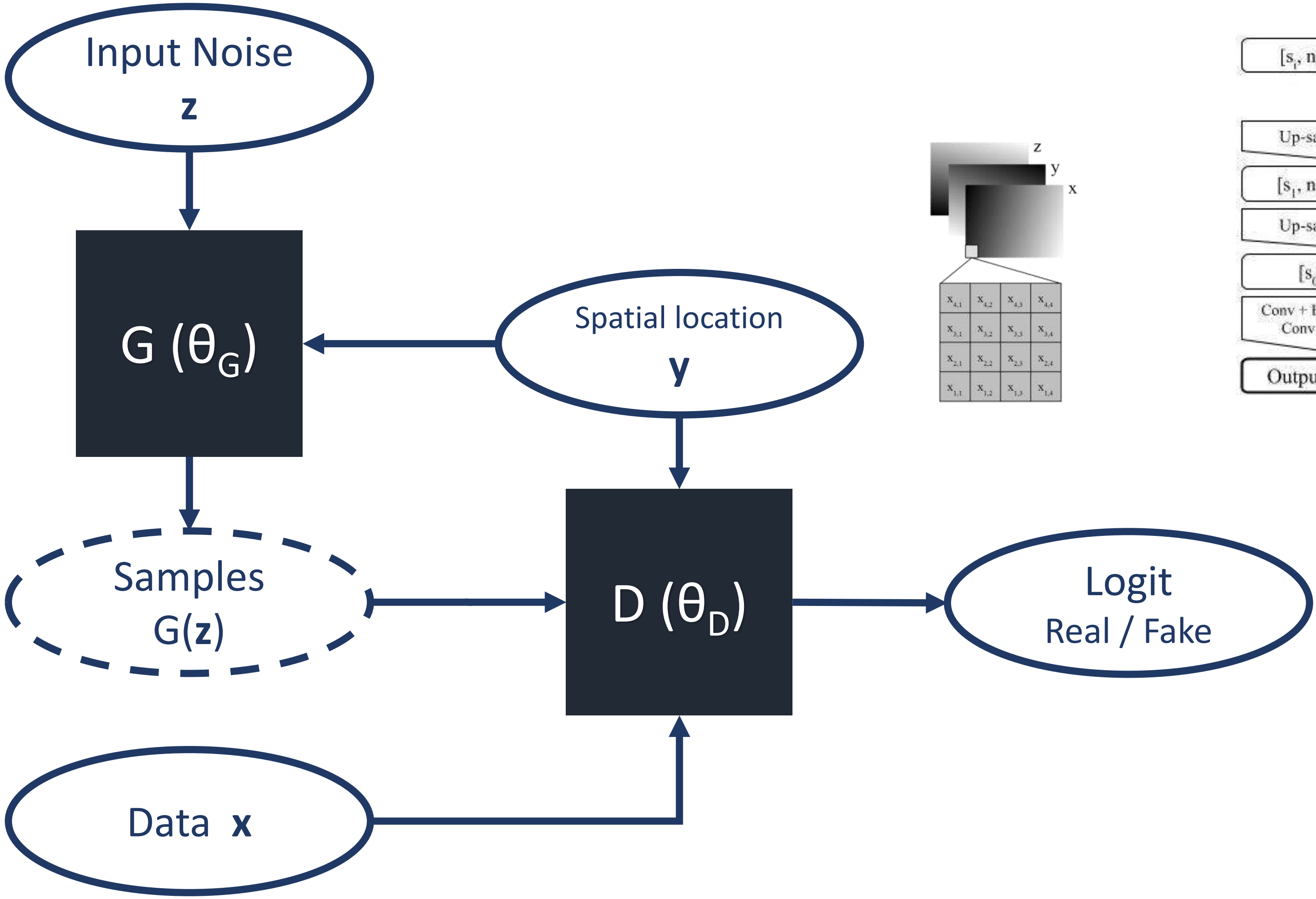


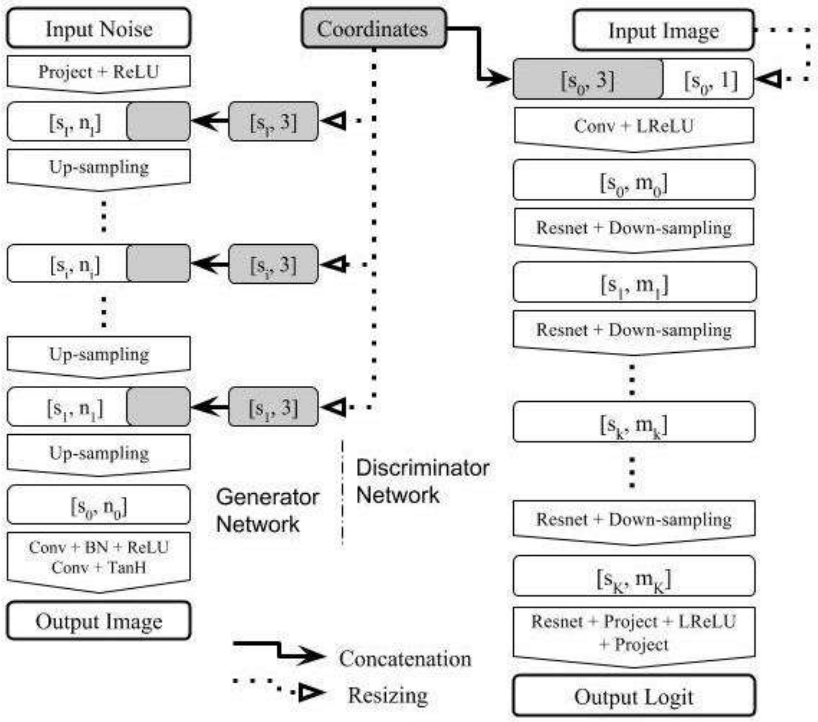
Multiple instance learning (MIL) setting



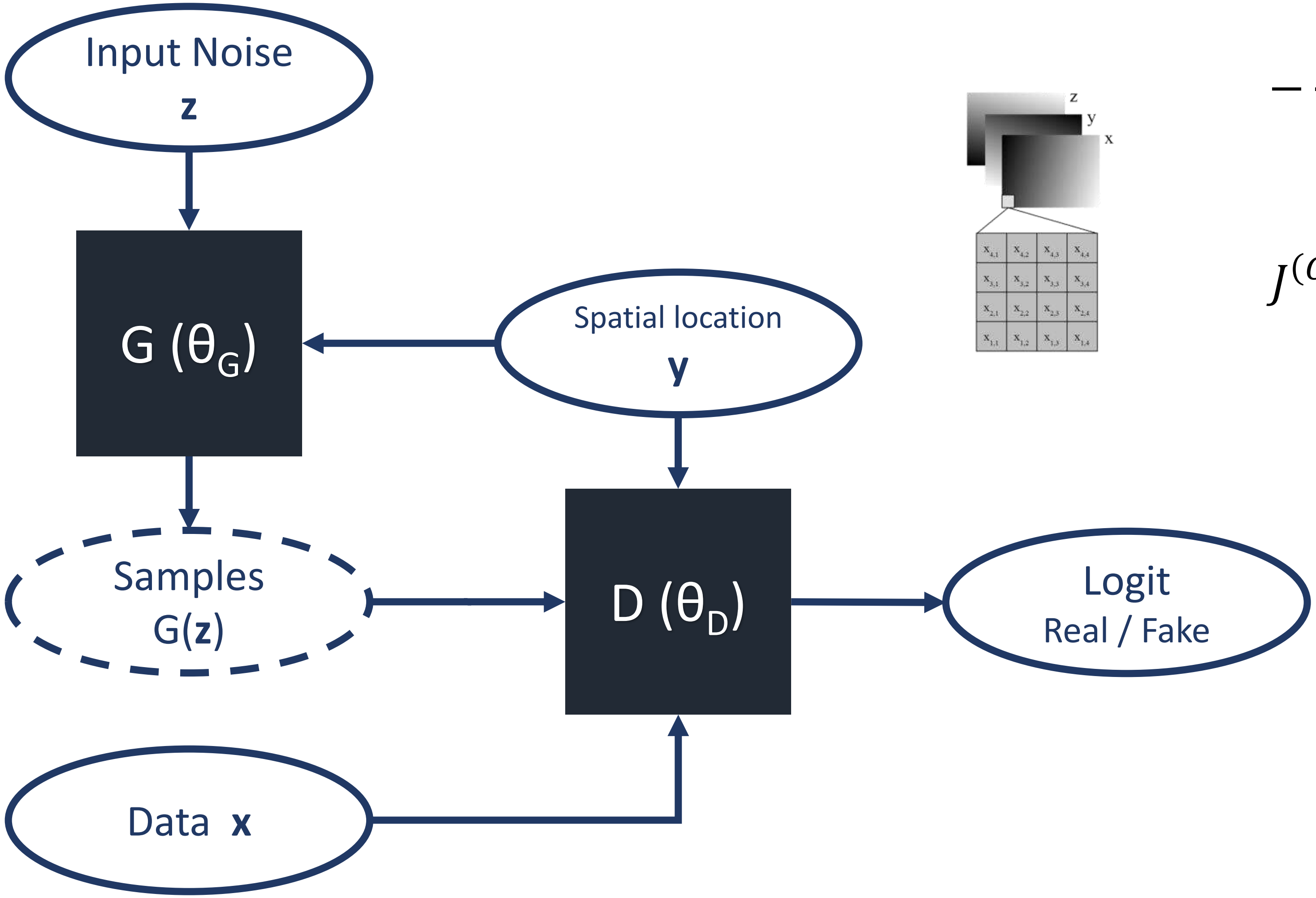
Research| Adversarial Learning and Generative Models

Generative adversarial networks (GANs)





Generative adversarial networks (GANs)



$$J^{(D)} = -\frac{1}{2}\mathbb{E}_{(\mathbf{x},\mathbf{y})\sim P_{data}} \log D(\mathbf{x},\mathbf{y}) - \frac{1}{2}\mathbb{E}_{\mathbf{z}\sim N,\mathbf{y}\sim P_{loc}} \log\big(1 - D(G(\mathbf{z},\mathbf{y}),\mathbf{y})\big)$$

$$J^{(G)} = -\frac{1}{2}\mathbb{E}_{\mathbf{z}\sim N,\mathbf{y}\sim P_{loc}} \log D(G(\mathbf{z},\mathbf{y}),\mathbf{y})$$

Generative adversarial networks (GANs)

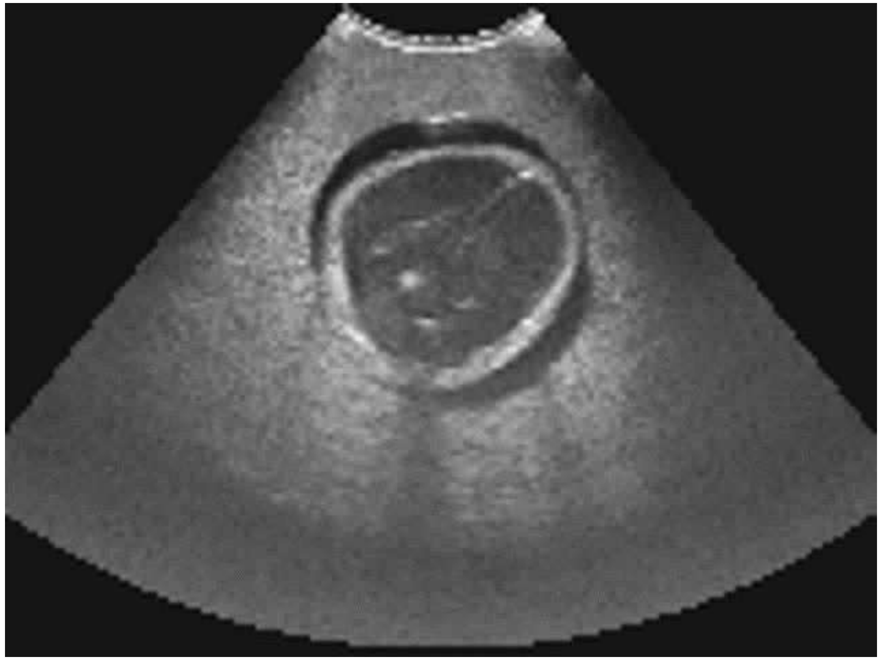


Image synthesis

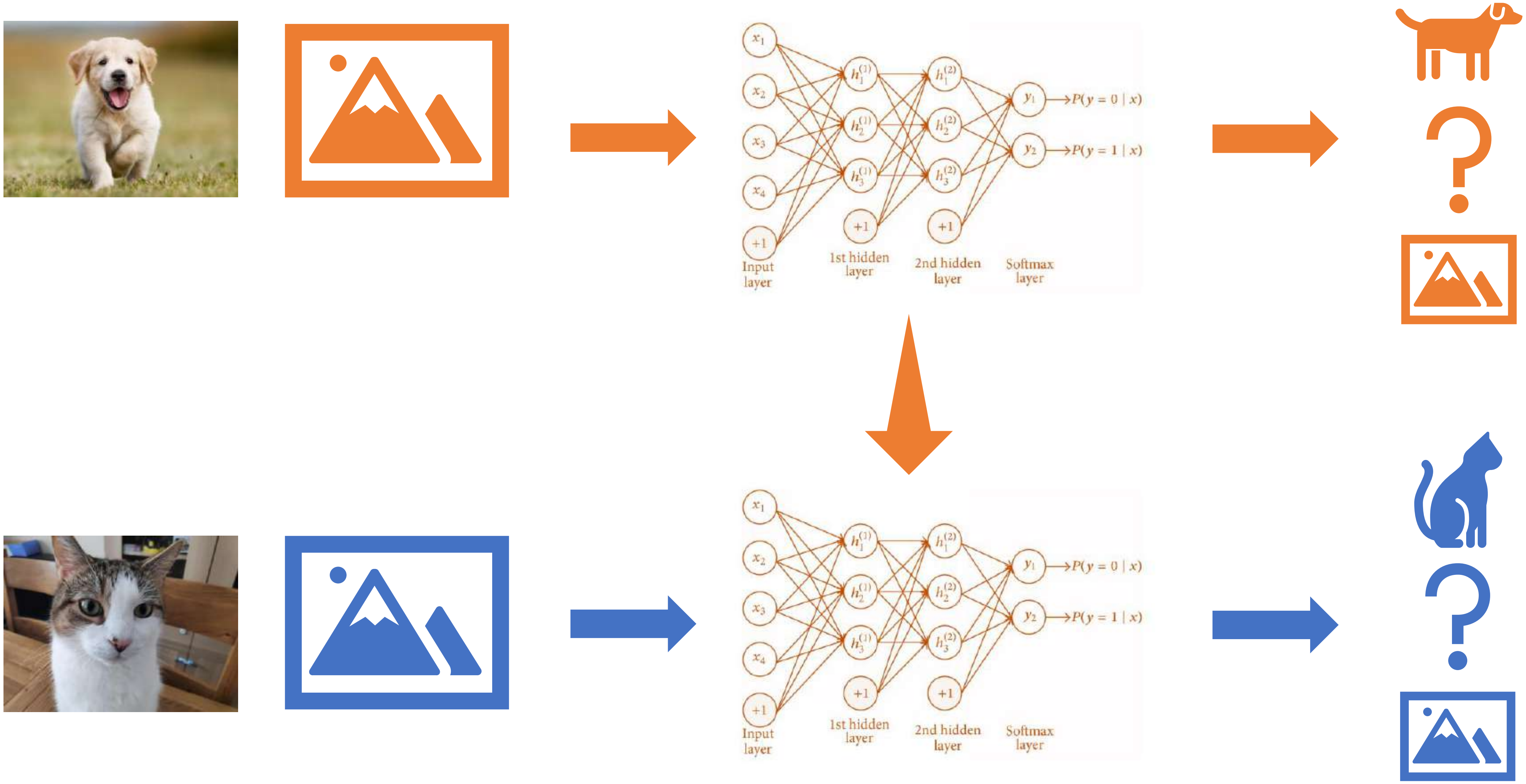
Regularisation by minimising divergence

Image-to-image translation

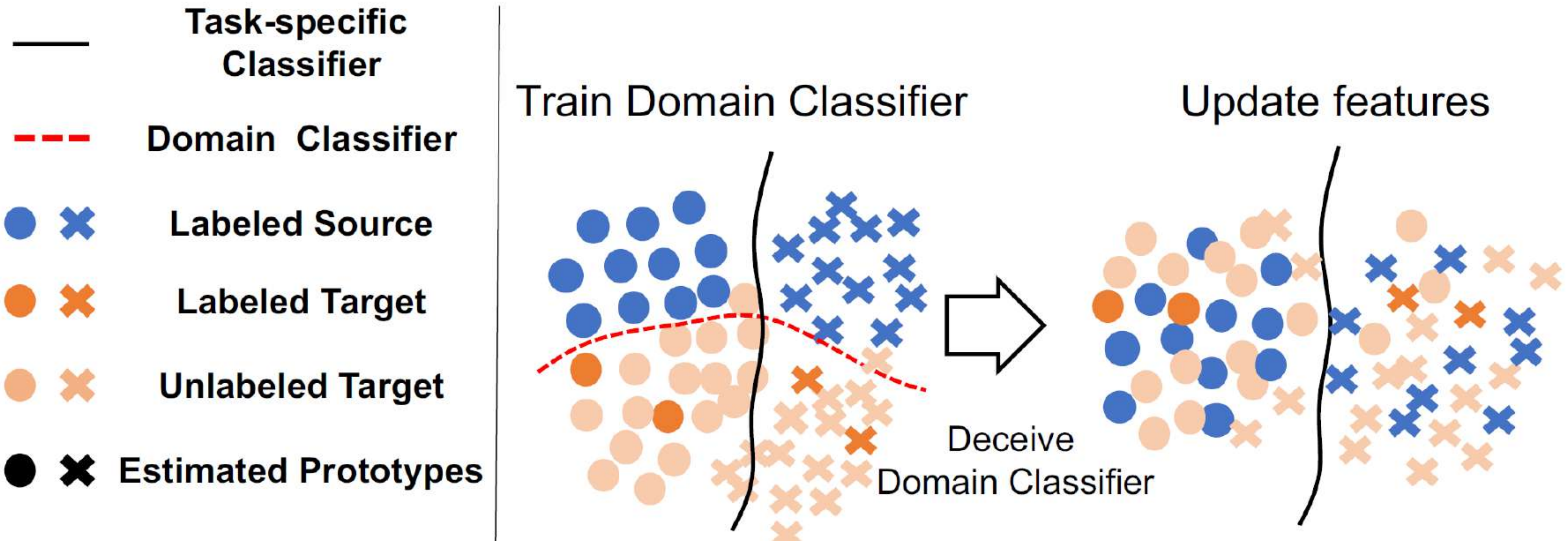
Domain adaptation

Research| Domain Adaptation

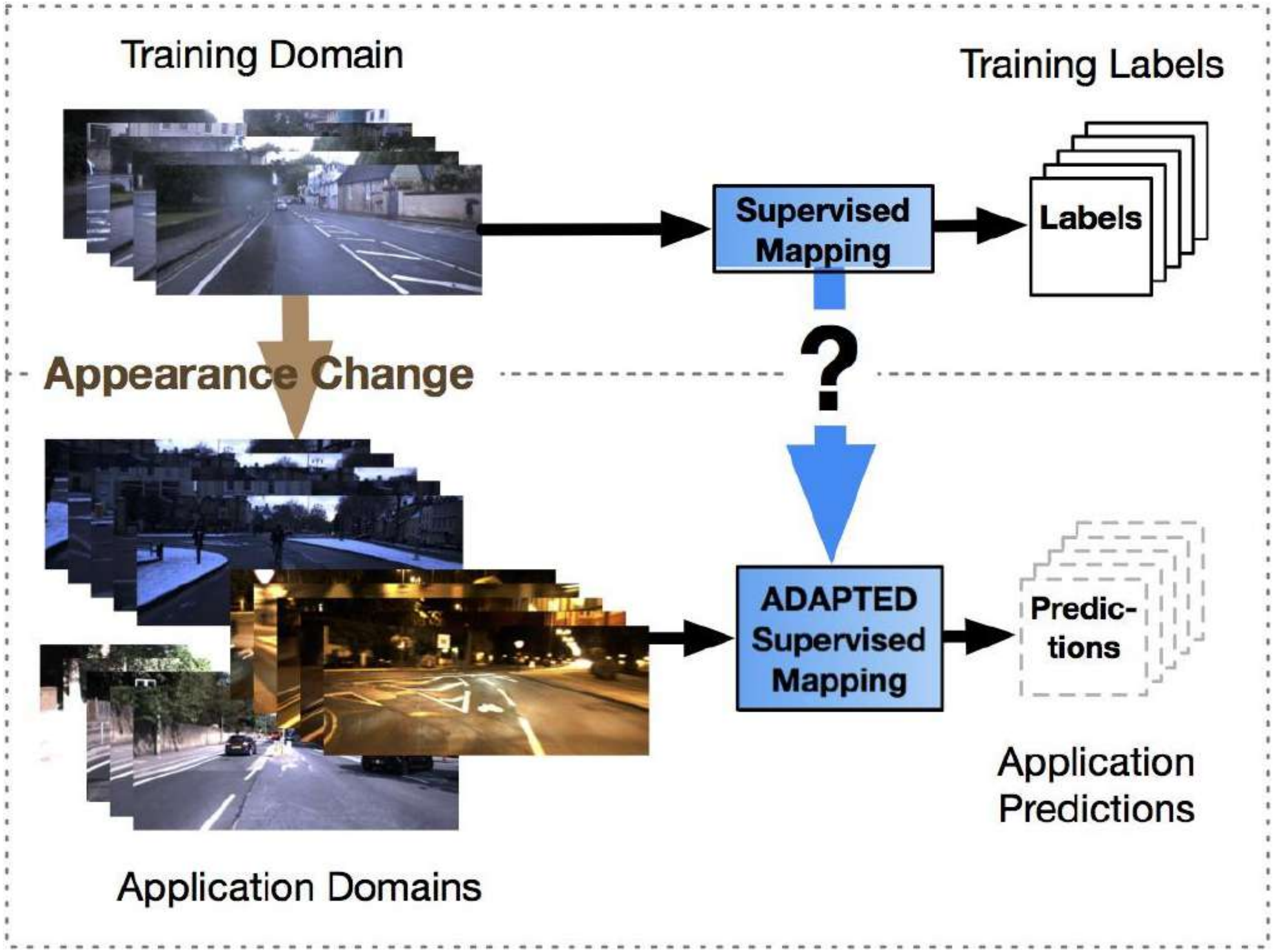
Research| Domain Adaptation

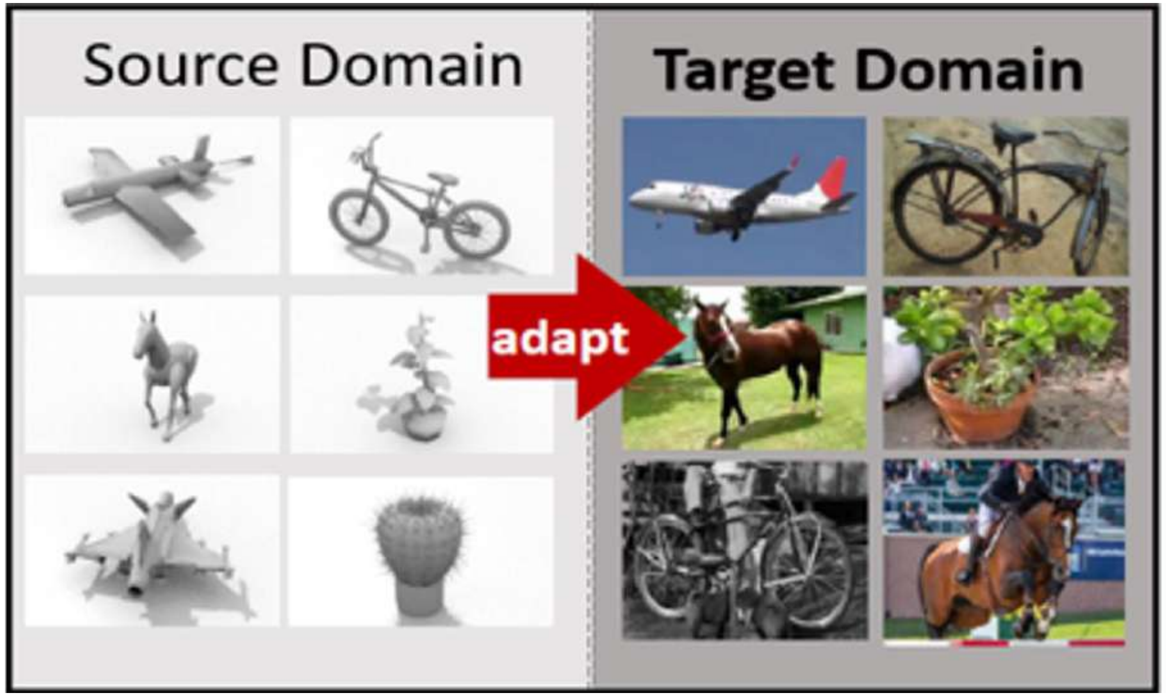


- Unsupervised domain adaptation
- Semi-supervised domain adaptation



- Availability between domains





- Labelled data are expensive or infeasible
- Distribution "shift" between training and test data sets

e.g. synthetic or semi-synthetic (image) data – different data distribution

- Different types of training data

e.g. movie vs. books, MR vs. CT

- Y. Gannin et al. 2016: Unsupervised domain adaptation
  - Find a classifier:
    a) Discriminativeness (the ability to classify)
    b) Domain-invariance (the ability to use ONLY domain-independent features to classify)
  - By:
    1) Label classifier (to predict the correct labels)
    2) Domain classifier (to find the features that can discriminate between source and target domain and NOT use them)

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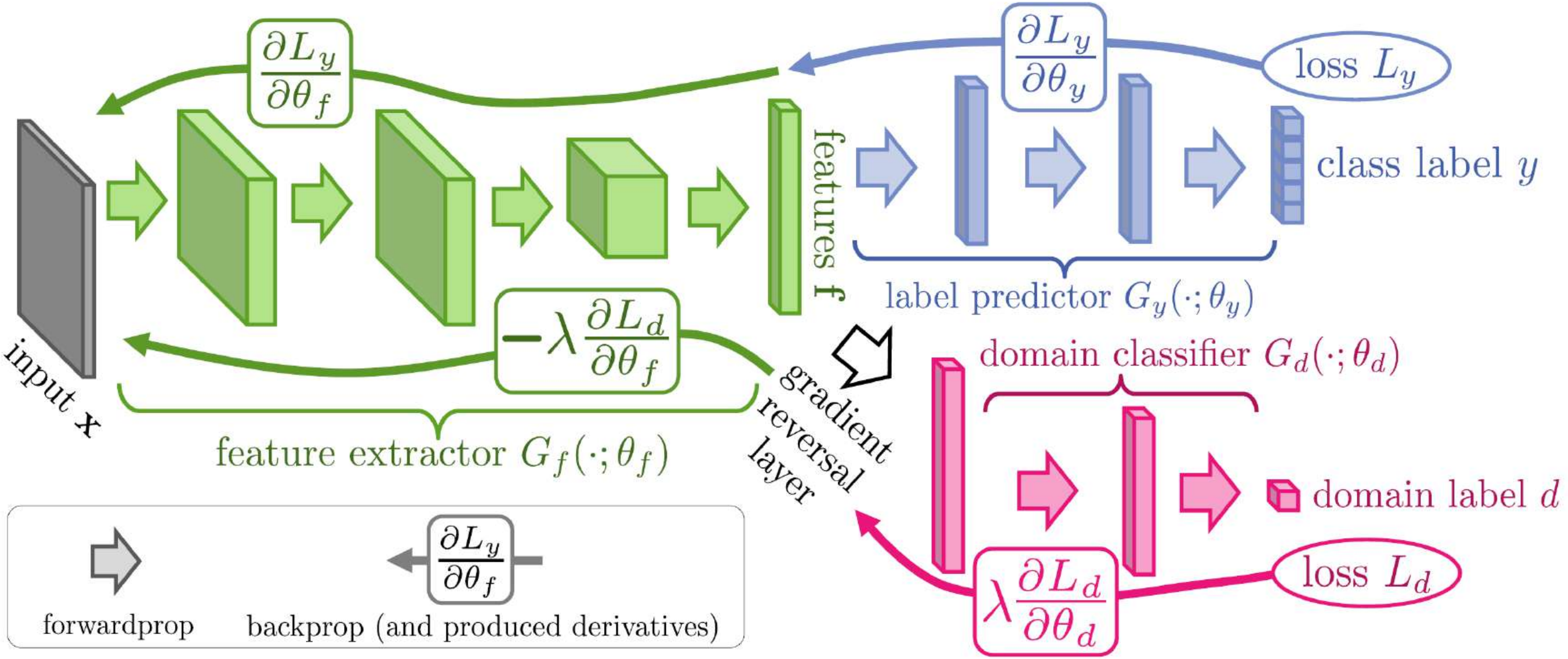
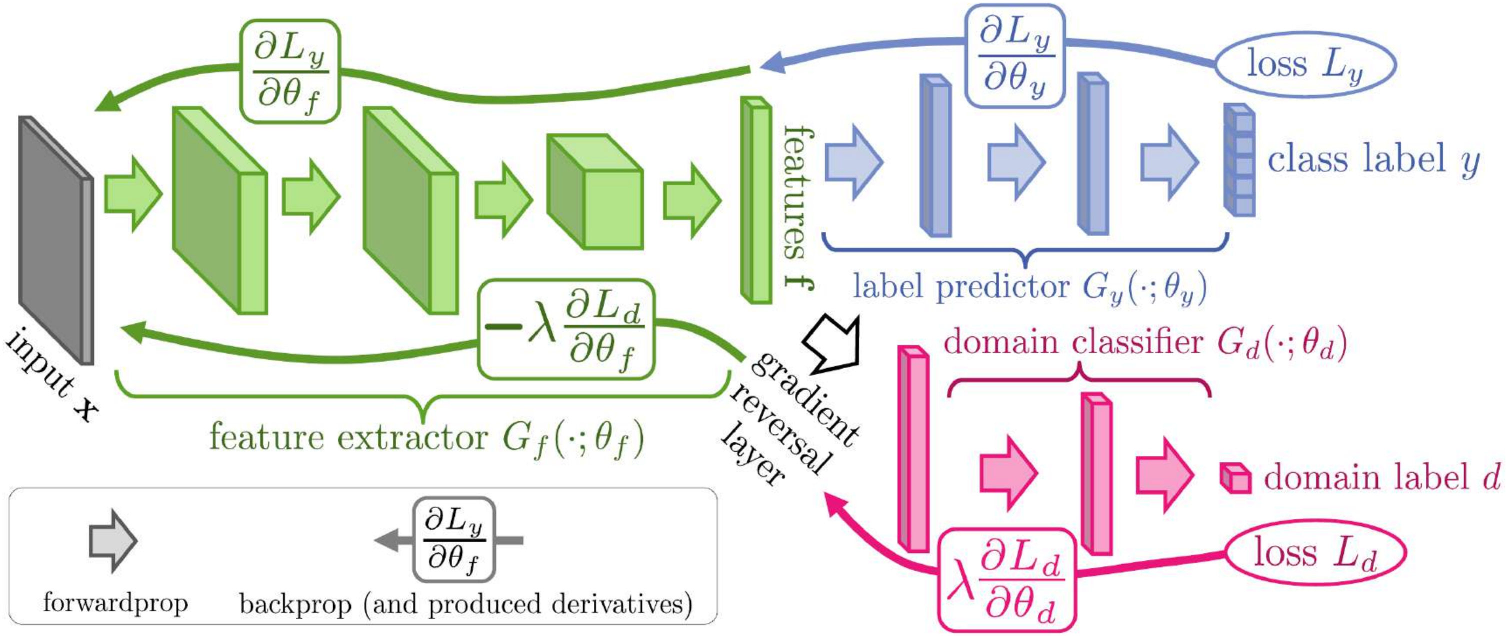
- That is:
  1) Minimise the loss of the label classifier
  2) Maximise the loss of the domain classifier
  3) Minimise the loss of domain classifier to train the domain classifier

➡ Adversarial learning



$\frac{\partial L_y}{\partial \theta_f}$
$\frac{\partial L_y}{\partial \theta_y}$
loss L_y
features $\mathbf{f}$
class label y
label predictor $G_y(\cdot; \theta_y)$
$-\lambda \frac{\partial L_d}{\partial \theta_f}$
input $\mathbf{x}$
gradient reversal layer
domain classifier $G_d(\cdot; \theta_d)$
feature extractor $G_f(\cdot; \theta_f)$
domain label d
loss L_d
$\lambda \frac{\partial L_d}{\partial \theta_d}$
forwardprop
backprop (and produced derivatives)



$$(\hat{\theta}_f, \hat{\theta}_y) = \underset{\theta_f,\theta_y}{\operatorname{argmin}}\ E(\theta_f, \theta_y, \hat{\theta}_d),$$

$$\hat{\theta}_d = \underset{\theta_d}{\operatorname{argmax}}\ E(\hat{\theta}_f, \hat{\theta}_y, \theta_d).$$

$$\theta_f \longleftarrow \theta_f - \mu\left(\frac{\partial \mathcal{L}_y^i}{\partial \theta_f} - \lambda\frac{\partial \mathcal{L}_d^i}{\partial \theta_f}\right),$$

$$\theta_y \longleftarrow \theta_y - \mu\frac{\partial \mathcal{L}_y^i}{\partial \theta_y},$$

$$\theta_d \longleftarrow \theta_d - \mu\lambda\frac{\partial \mathcal{L}_d^i}{\partial \theta_d},$$

$$\mathcal{L}_y^i(\theta_f, \theta_y) = \mathcal{L}_y\big(G_y(G_f(\mathbf{x}_i;\theta_f);\theta_y), y_i\big),$$

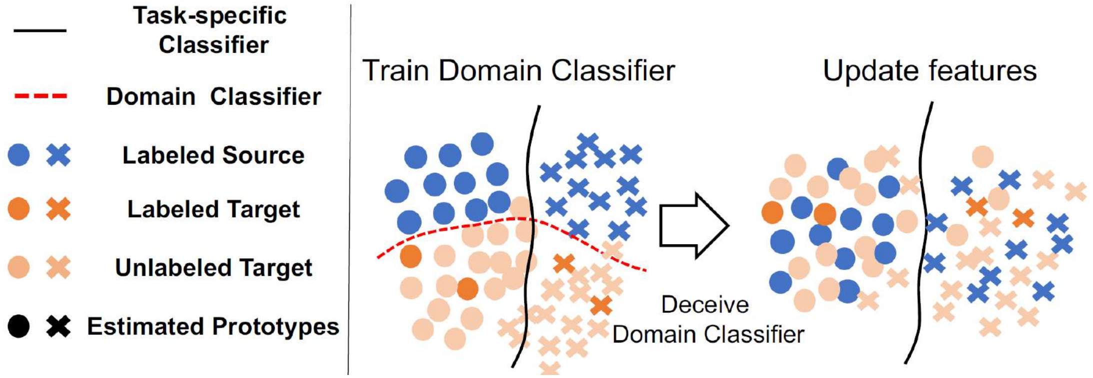
$$\mathcal{L}_d^i(\theta_f, \theta_d) = \mathcal{L}_d\big(G_d(G_f(\mathbf{x}_i;\theta_f);\theta_d), d_i\big).$$

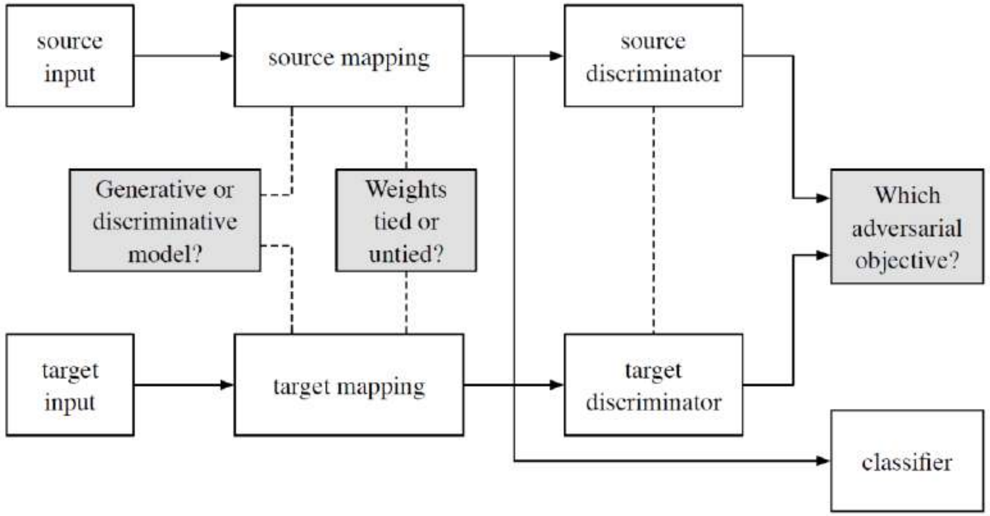
$$E(\theta_f, \theta_y, \theta_d) = \frac{1}{n}\sum_{i=1}^{n}\mathcal{L}_y^i(\theta_f, \theta_y) - \lambda\left(\frac{1}{n}\sum_{i=1}^{n}\mathcal{L}_d^i(\theta_f, \theta_d) + \frac{1}{n'}\sum_{i=n+1}^{N}\mathcal{L}_d^i(\theta_f, \theta_d)\right),$$

Distance between source and target distribution, e.g. H-divergence ©

$$\hat{d}_{\mathcal{H}}(S(G_f), T(G_f)) = 2\left(1 - \min_{\eta\in\mathcal{H}}\left[\frac{1}{n}\sum_{i=1}^{n} I[\eta(G_f(\mathbf{x}_i))=0] + \frac{1}{n'}\sum_{i=n+1}^{N} I[\eta(G_f(\mathbf{x}_i))=1]\right]\right).$$

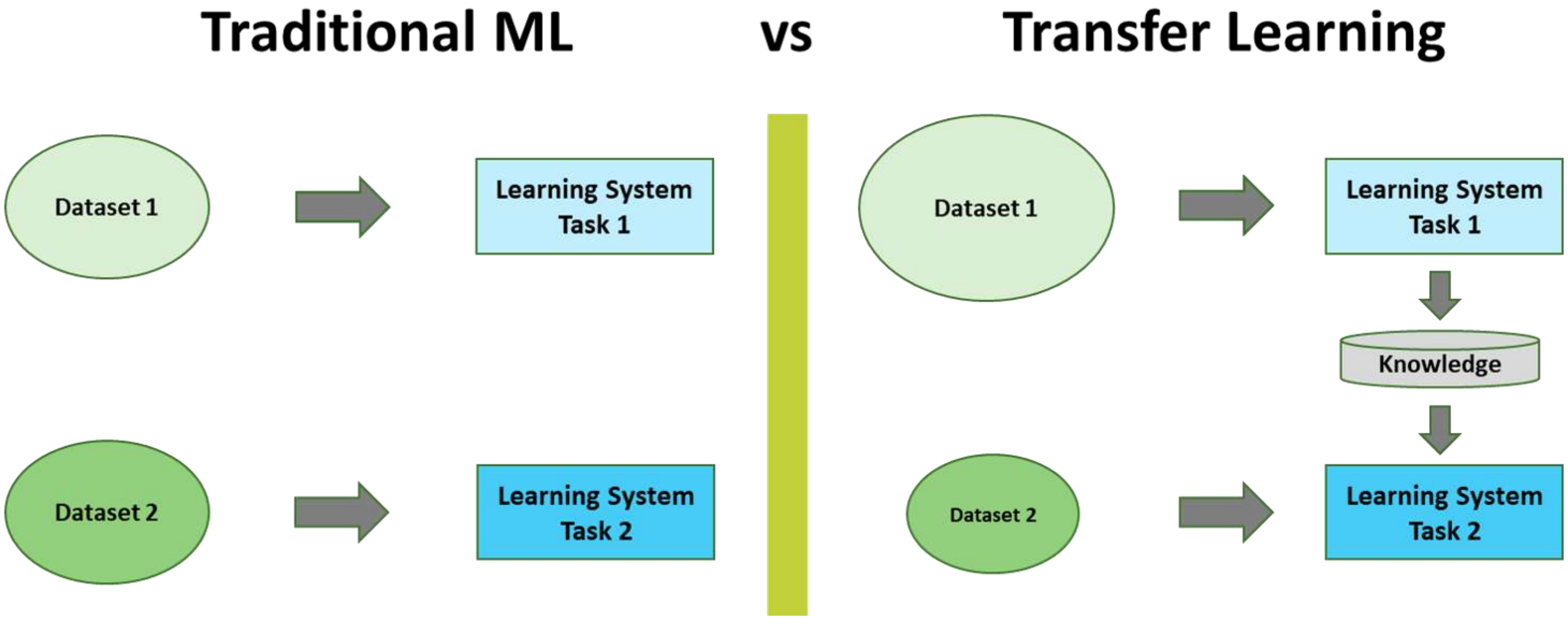
$$\mathcal{L}_d^i(\mathbf{W}, \mathbf{b}, \mathbf{u}, z) = \mathcal{L}_d(G_d(G_f(\mathbf{x}_i; \mathbf{W}, \mathbf{b}); \mathbf{u}, z), d_i)$$



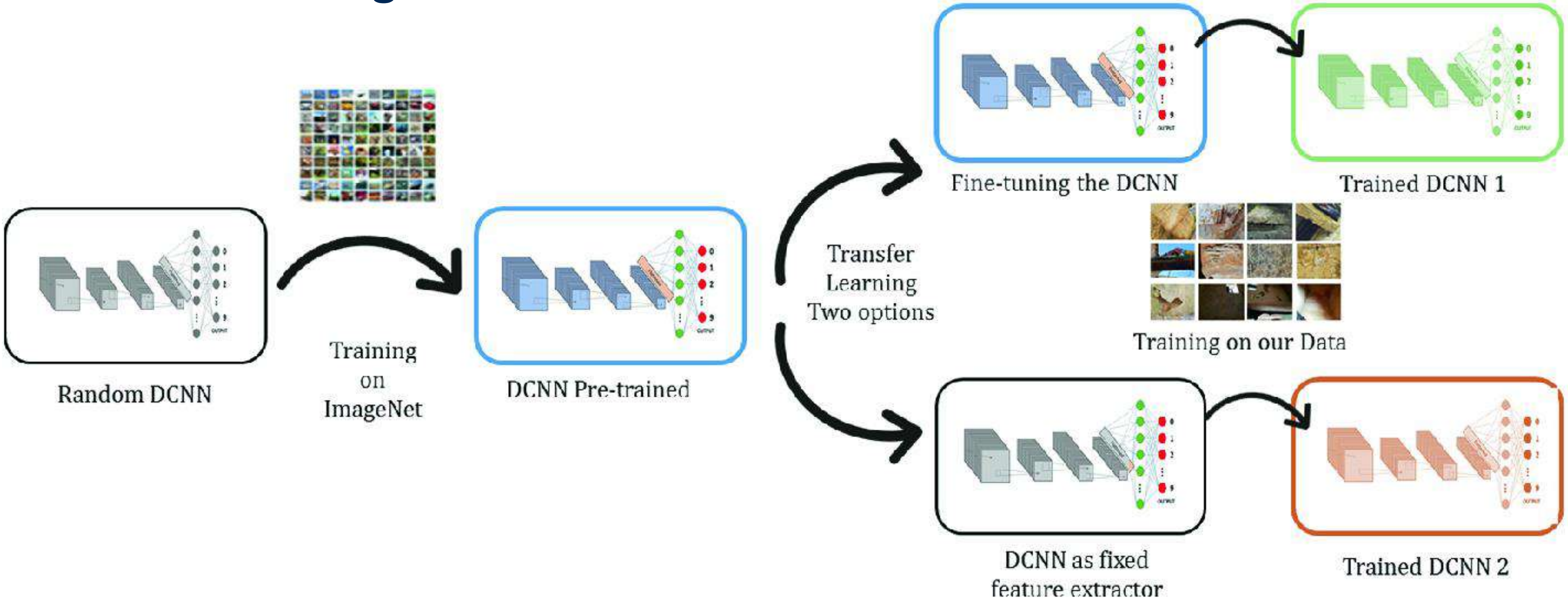


Research| Meta-Learning

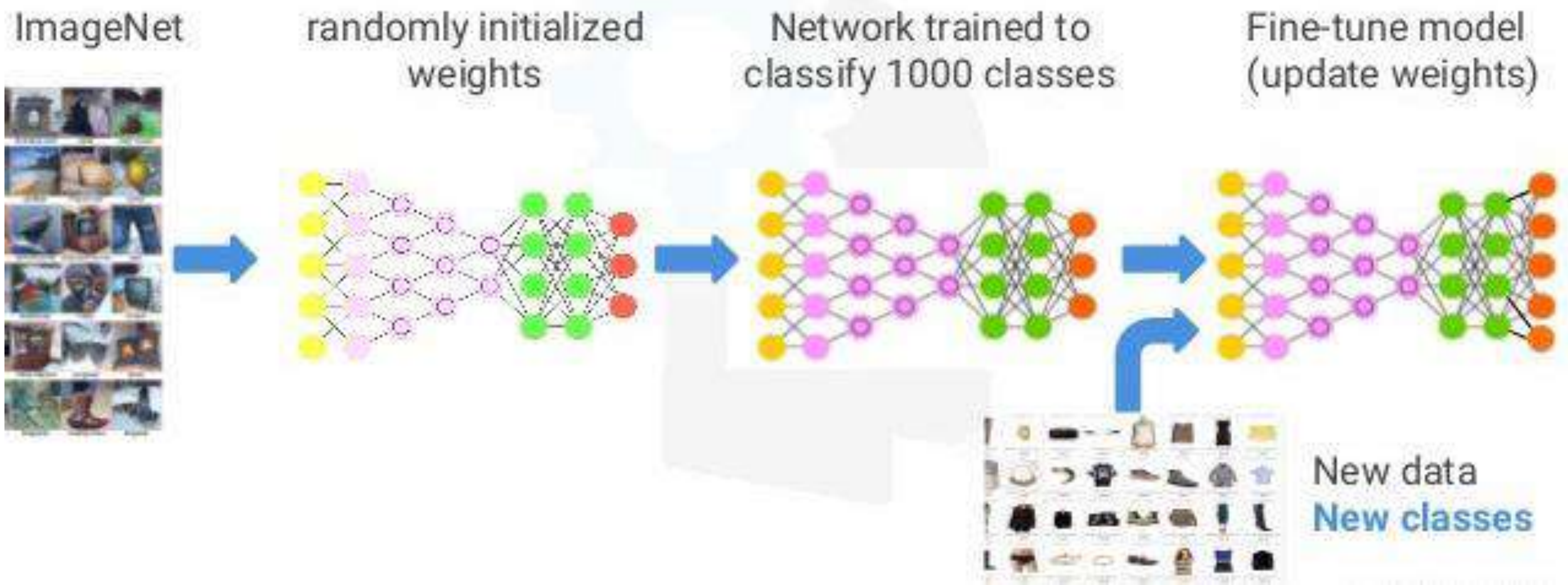
Transfer learning



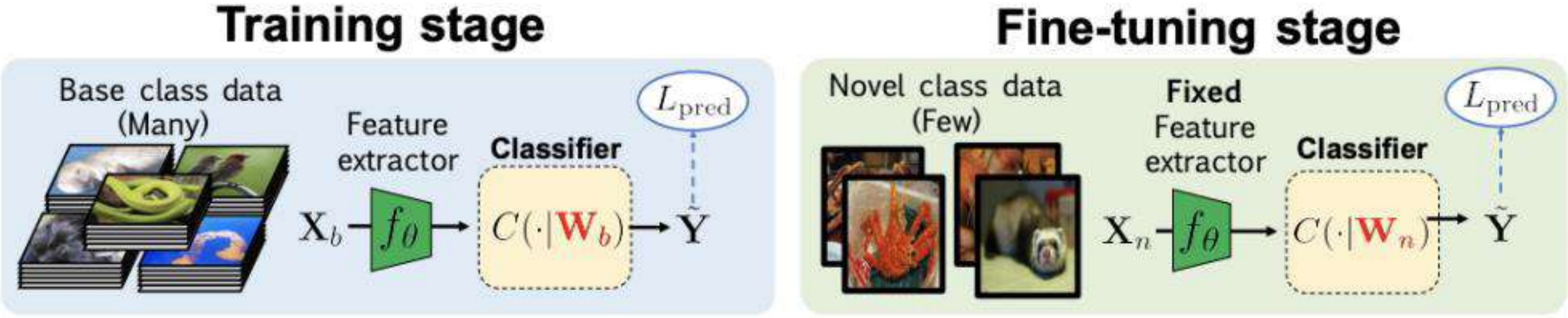
Transfer learning

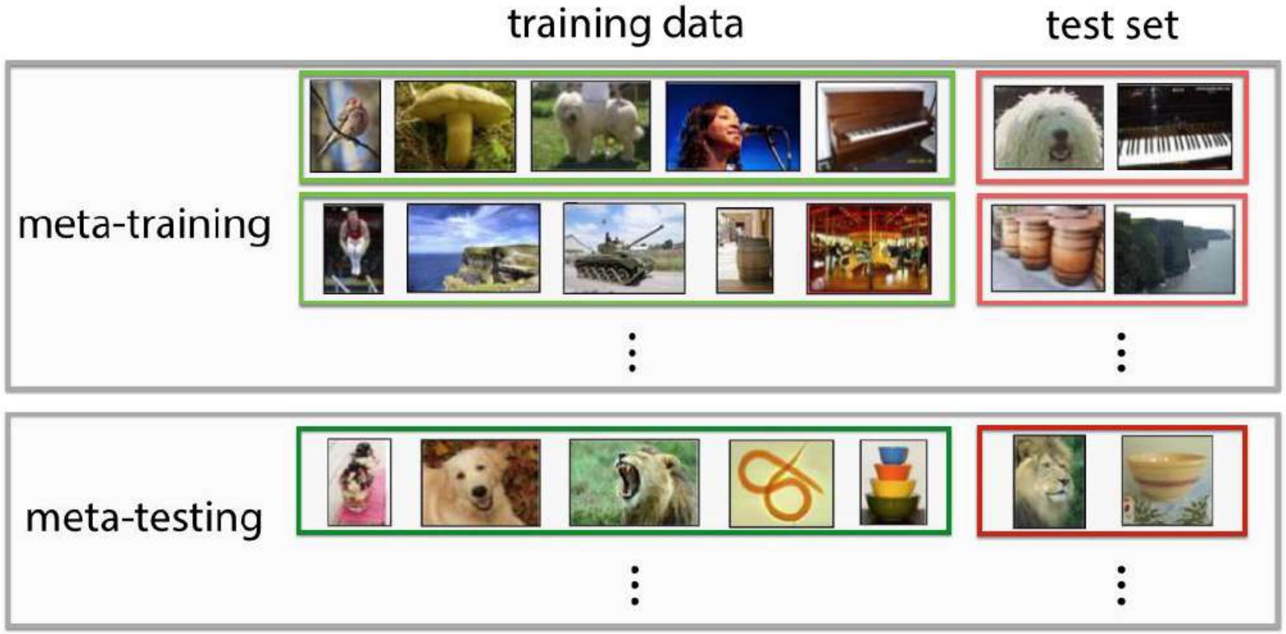


Transfer learning for few-shot learning



Few-shot learning and meta-learning

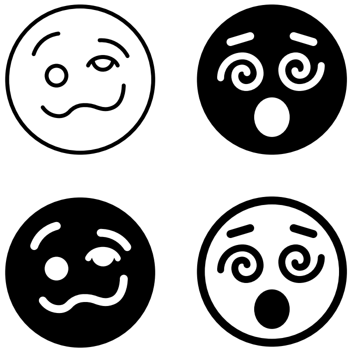




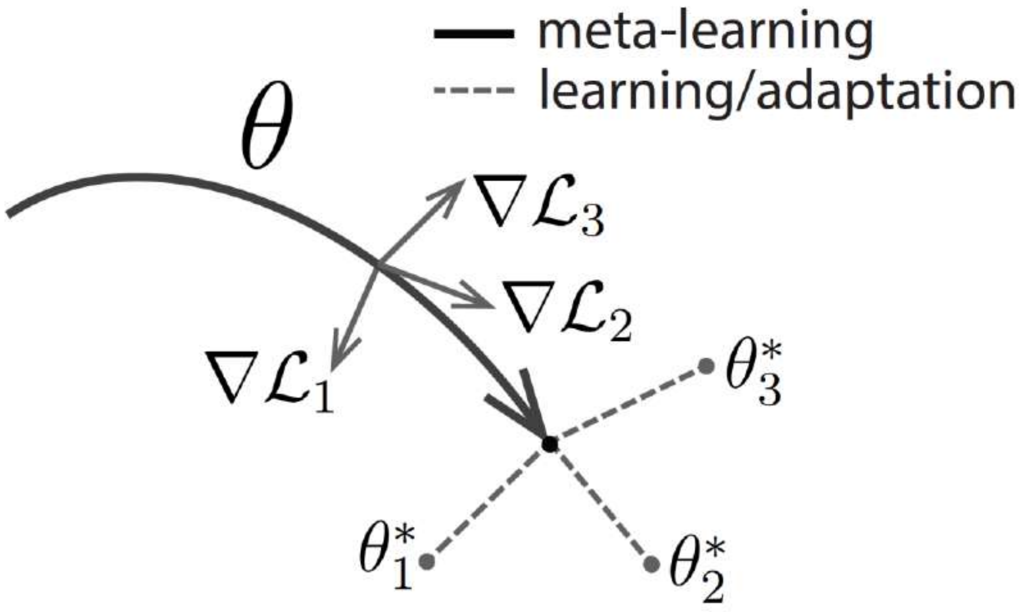
Terminology and taxonomy

Learning Settings		Source and Target Domains	Source and Target Tasks
Traditional Machine Learning		the same	the same
Transfer Learning	*Inductive Transfer Learning* / *Unsupervised Transfer Learning*	the same	different but related
		different but related	different but related
	Transductive Transfer Learning	different but related	the same

Transfer Learning Settings	Related Areas	Source Domain Labels	Target Domain Labels	Tasks
Inductive Transfer Learning	Multi-task Learning	Available	Available	Regression, Classification
	Self-taught Learning	Unavailable	Available	Regression, Classification
Transductive Transfer Learning	Domain Adaptation, Sample Selection Bias, Co-variate Shift	Available	Unavailable	Regression, Classification
Unsupervised Transfer Learning		Unavailable	Unavailable	Clustering, Dimensionality Reduction



Model-agnostic meta-learning (MAML)

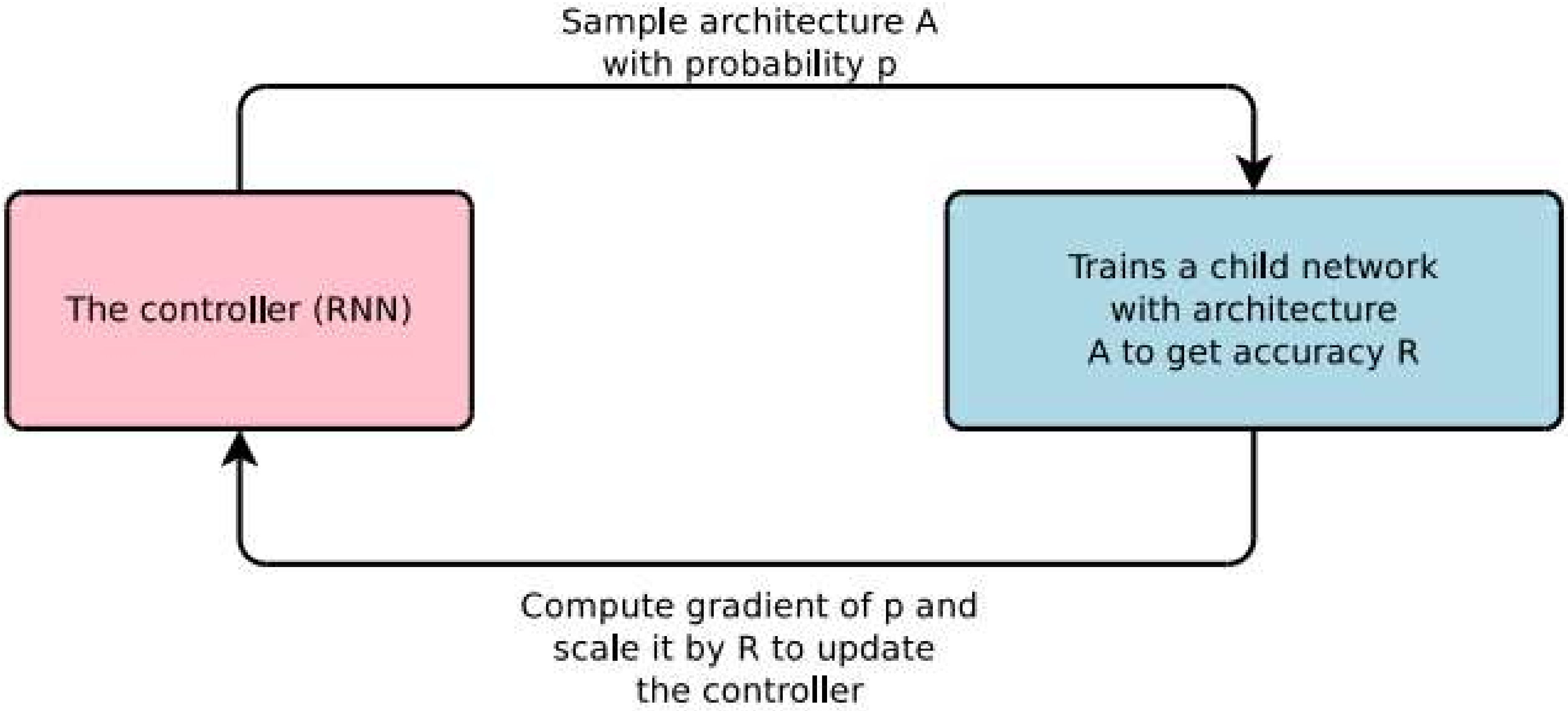


Algorithm 1 Model-Agnostic Meta-Learning

Require: $p(\mathcal{T})$: distribution over tasks
Require: α, β: step size hyperparameters

randomly initialize θ
while not done **do**
  Sample batch of tasks $\mathcal{T}_i \sim p(\mathcal{T})$
  for all $\mathcal{T}_i$ **do**
    Evaluate $\nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$ with respect to K examples
    Compute adapted parameters with gradient descent: $\theta_i' = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$
  end for
  Update $\theta \leftarrow \theta - \beta \nabla_\theta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}(f_{\theta_i'})$
end while

Searching for hyper-parameters (architecture, loss, data augmentation…)



"Transferability" from computer vision to medical imaging

- Applications:
  - Encoder-decoder U-Net - segmentation
  - Optical flow – registration
  - GANs – synthesis
  - …
- Data size
- Data availability
- Data variability, equipment, protocols, demography etc.
- Ground-truth, inc. label uncertainty, fidelity etc.
- Test significance, e.g. 1% effect size, 20 subjects, ~10% variance
- Clinical relevance