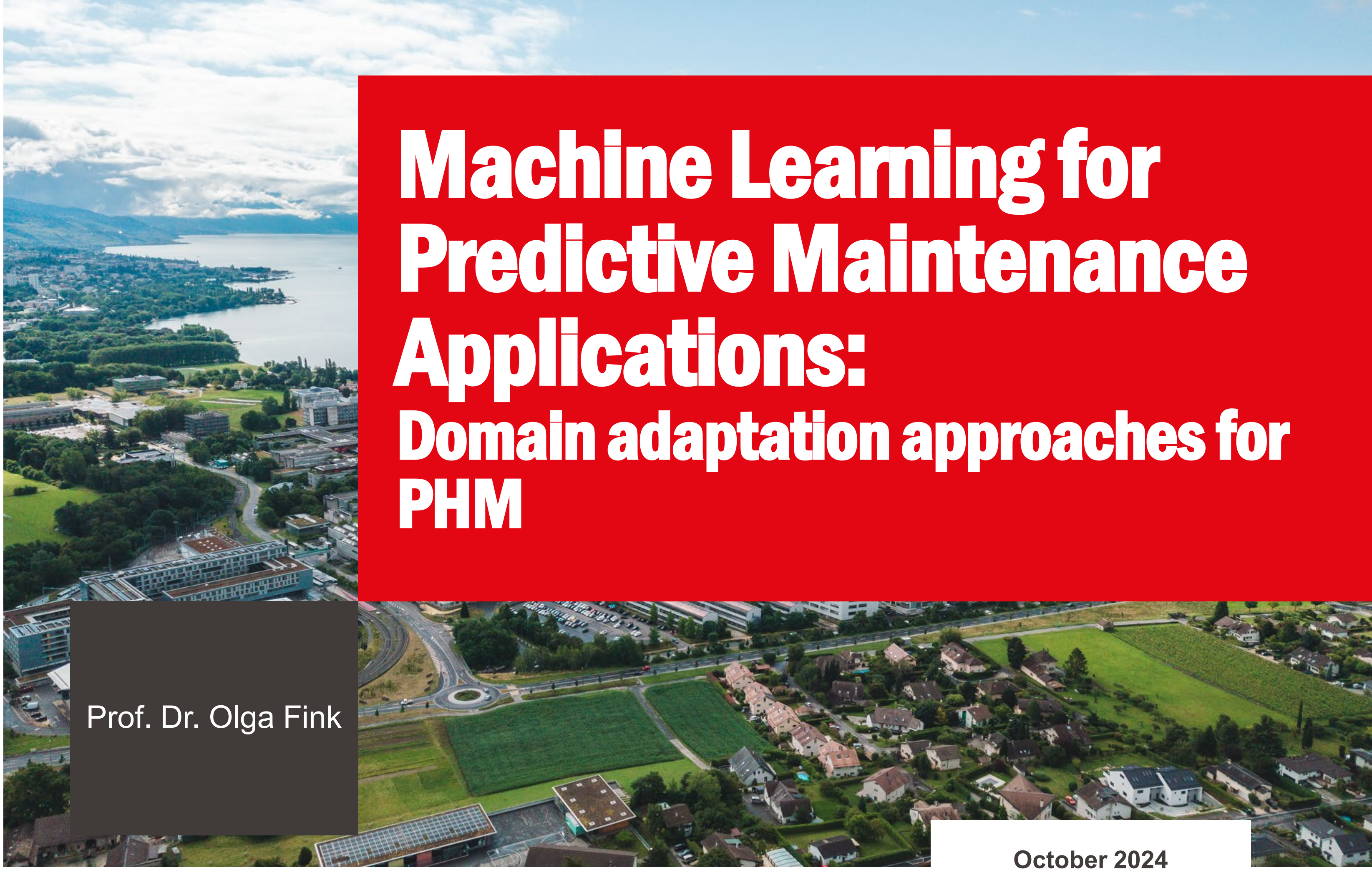


Machine Learning for Predictive Maintenance Applications:

Domain adaptation approaches for PHM

Prof. Dr. Olga Fink

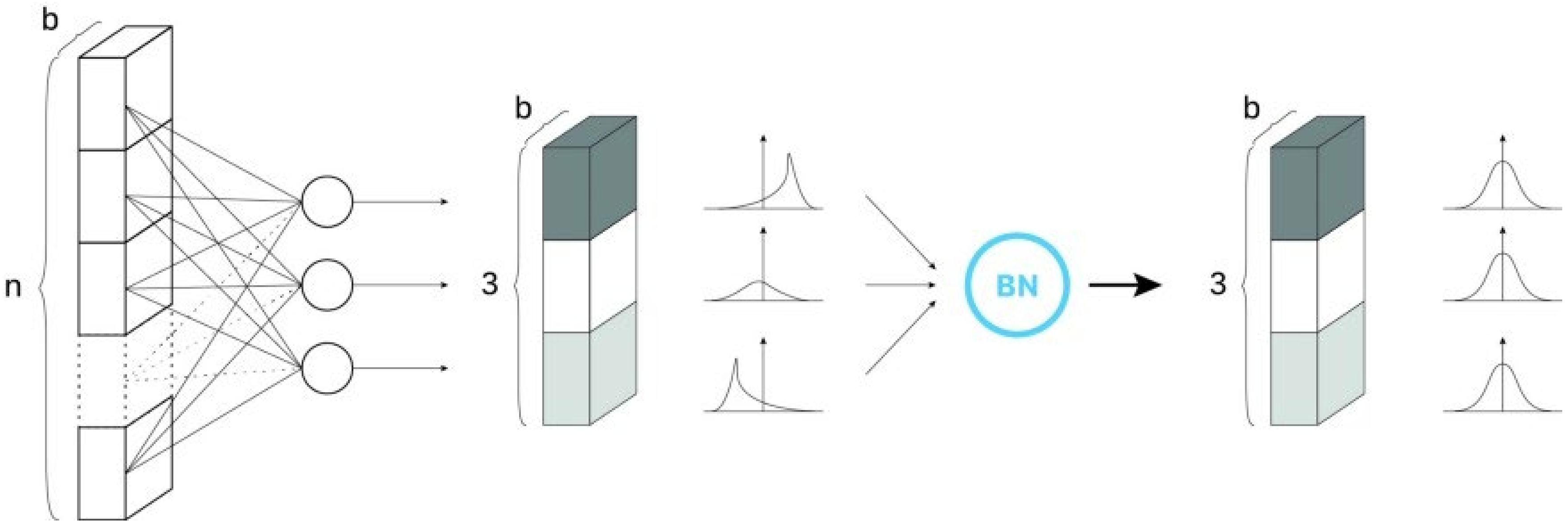
October 2024

École polytechnique fédérale de Lausanne

Recap: Batch Normalization

Basic principle Batch Normalization

- Makes the training faster and more stable



Source: Huber, 2020

Basic principle Batch Normalization

(1) $\mu = \frac{1}{n}\sum_i Z^{(i)}$

(2) $\sigma^2 = \frac{1}{n}\sum_i (Z^{(i)} - \mu)^2$

(3) $Z^{(i)}_{norm} = \frac{Z^{(i)} - \mu}{\sqrt{\sigma^2 - \epsilon}}$

(4) $\breve{Z} = \gamma * Z^{(i)}_{norm} + \beta$

- **Normalizing activation vectors from hidden layers** using the first and the second statistical moments (mean and variance) of the current batch.
- Applied right before (or right after)
- Linear transformation with γ and β
- γ and β trainable parameters
- Allows the model to choose the optimum distribution for each hidden layer, by adjusting those two parameters :
- γ allows to adjust the standard deviation
- β allows to adjust the bias, shifting the curve on the right or on the left side.

Source: Huber, 2020

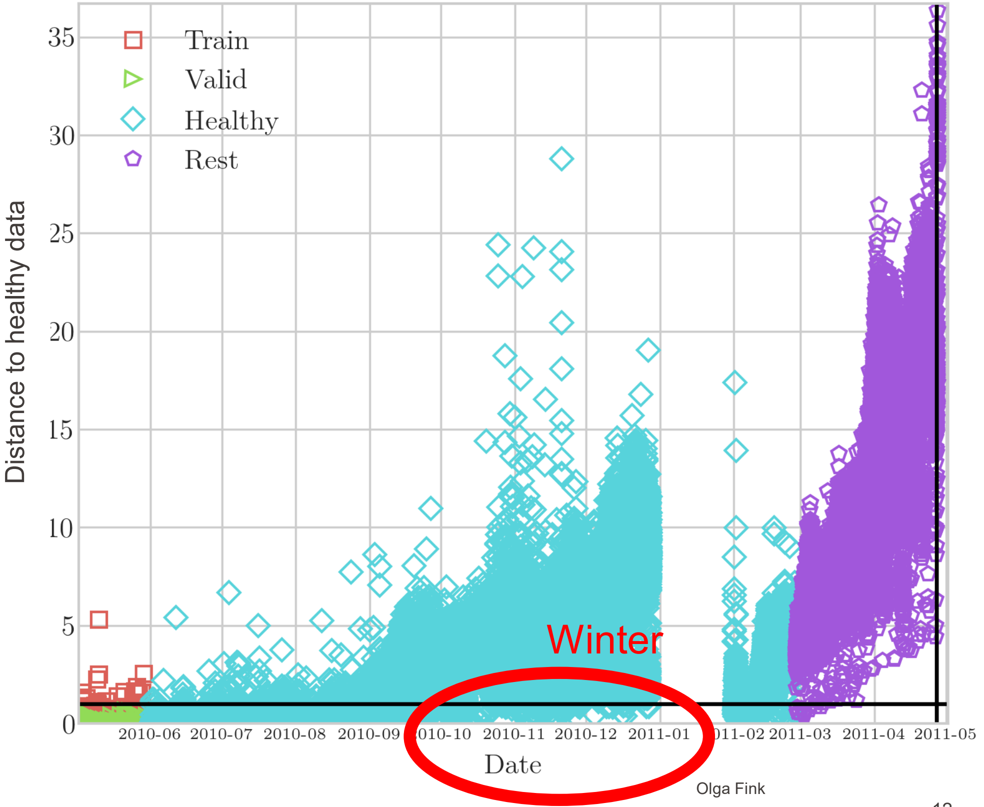
Why domain adaptation / transfer learning?

Some Challenges in Predictive Maintenance

- Varying and evolving operating conditions → Even healthy system conditions are not always representative due to limited observation time period
- Algorithms also for systems required that are newly taken into operation

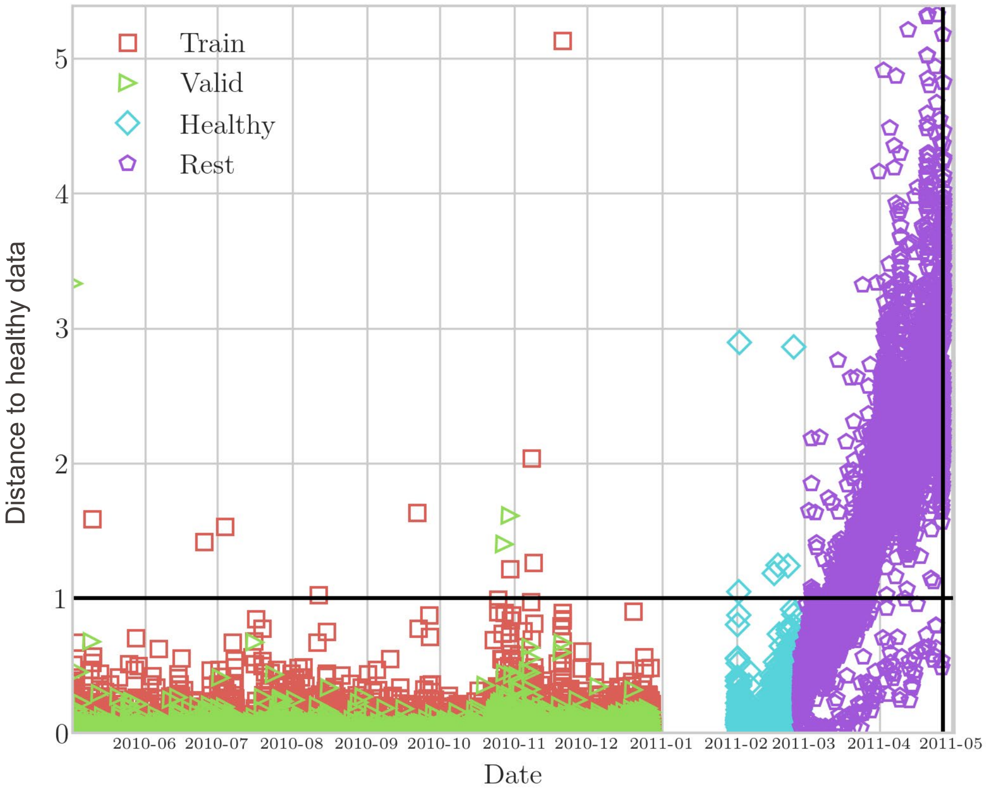
Example Gas Turbines

Only a short observation period

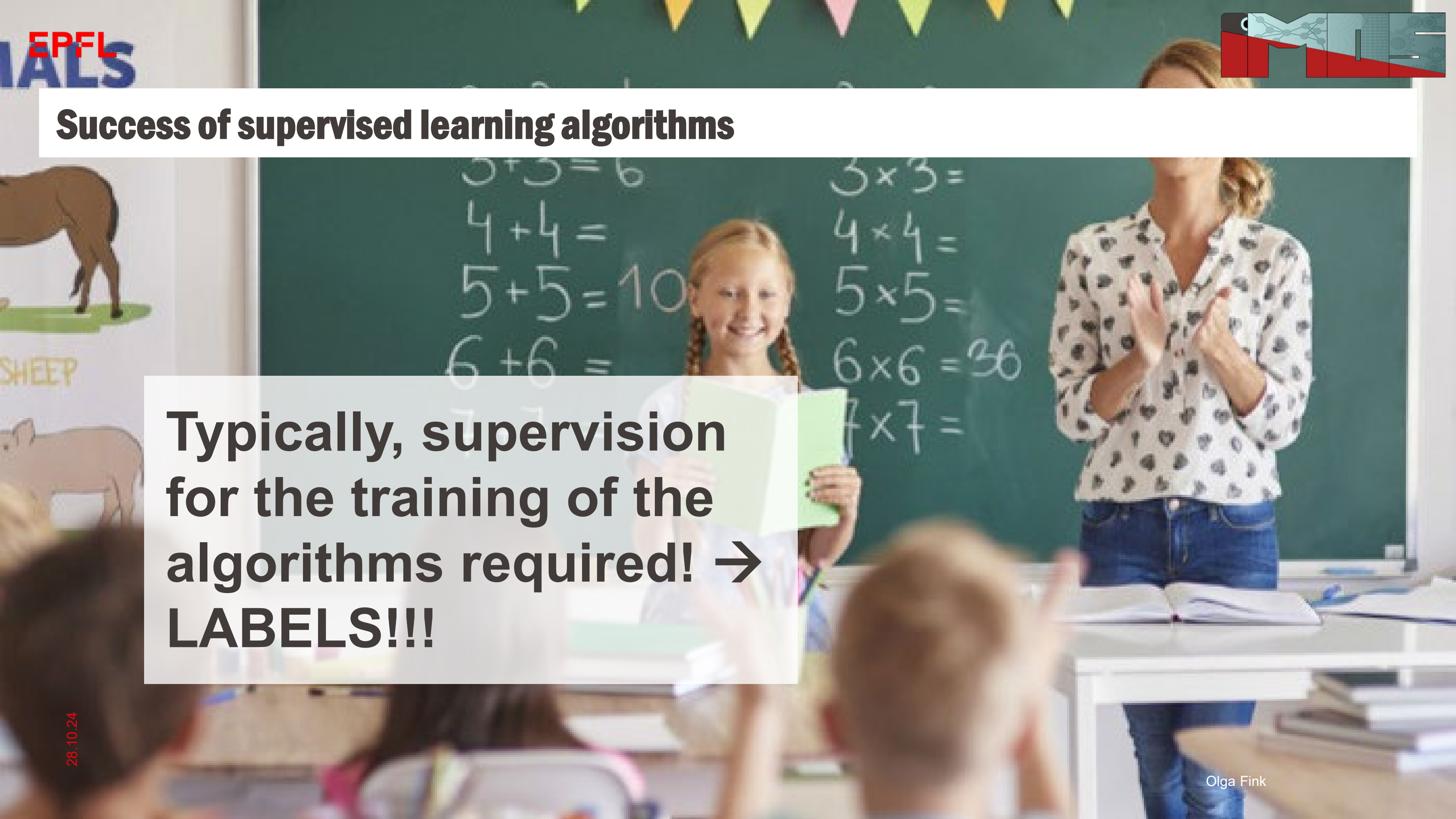


Example Gas Turbines

Extend the observation period



Success of supervised learning algorithms



Typically, supervision for the training of the algorithms required! → LABELS!!!

EPFL

Faults are equivalent to labels in intelligent maintenance

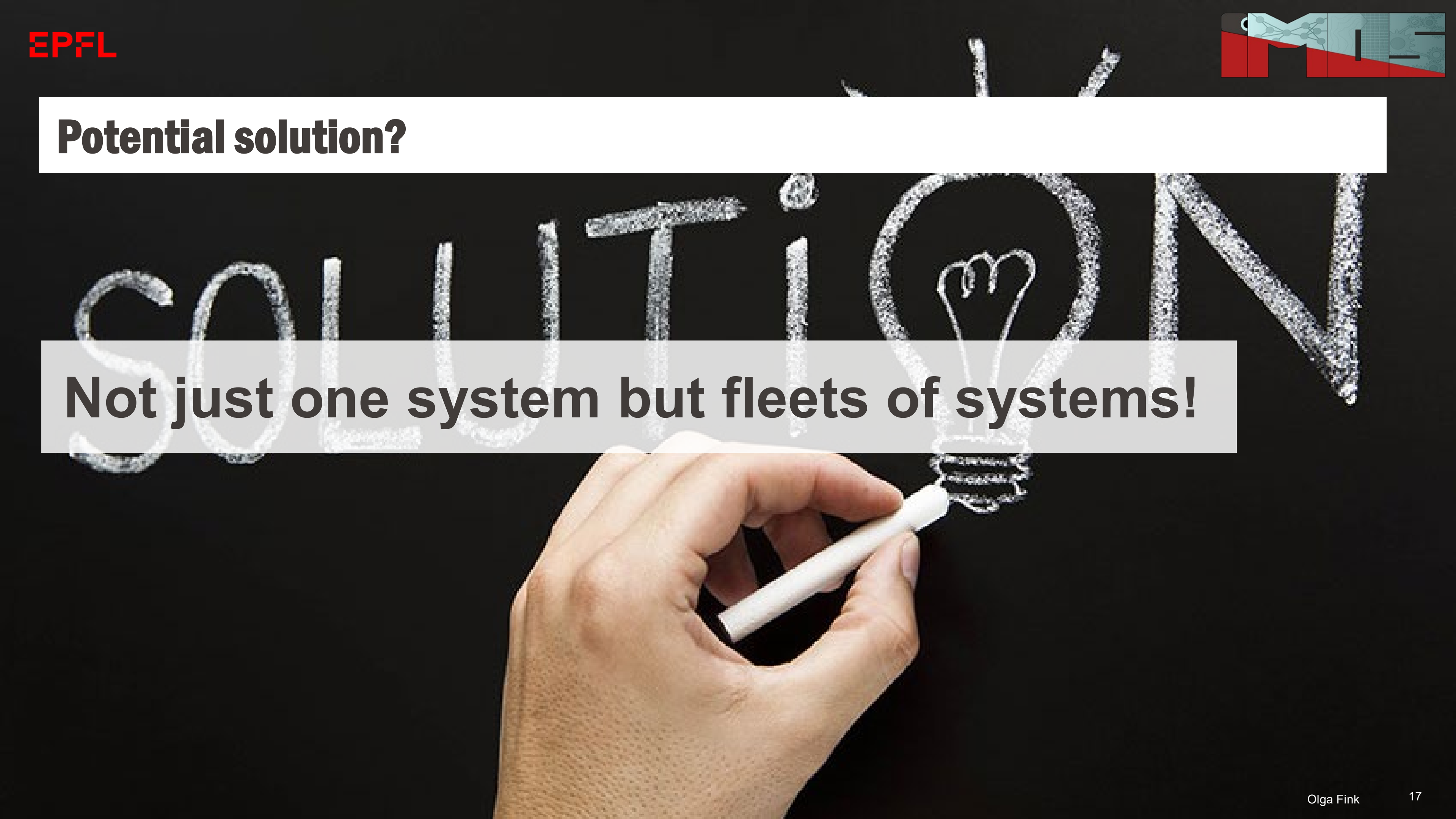
Faults in critical systems are rare → not possible to learn a good representation of faulty conditions

EPFL

How about a new system?

How long do we have to wait until we get reliable fault detection (diagnostics)?

Potential solution?



Not just one system but fleets of systems!

Fleets of complex systems?

Fleets of complex systems?

What do we start with?

- Limited number of faults (labels)
- Large variety of condition monitoring data under different operating conditions
- Several units of the same fleet (but units have variability in their configurations and operating conditions)
- Heterogenous operating conditions and configurations of the fleet units
- Limited observation time periods
- **Limited representativeness** of the collected data for the expected operating conditions

What are we trying to achieve?

- Compile representative training datasets that are valid for the specific units under the specific operating conditions (homogeneous datasets)
- Using labeled and unlabeled data as efficiently as possible at the level of an entire fleet
- Develop also algorithms for new units
- Transferring knowledge (on operating conditions and faults) between the single units of a fleet
- Learn robust features that are invariant to different operating conditions

Transfer learning / unsupervised Domain Adaptation

Different types of domain changes (images)

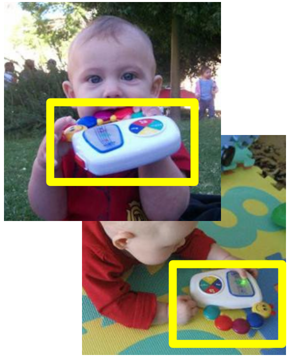
high quality

low quality

daylight

sunset

posed



“in the wild”

art

surveillance

Source: Saenko, 2012

Transfer learning in DL

- **Myth**: you can't do deep learning unless you have a million labelled examples for your problem.
- **Reality**
  - You can learn useful representations from **unlabelled data**
  - You can train on a nearby **surrogate objective** for which it is easy to generate labels → self-supervised learning
  - You can **transfer** learned representations from a related task

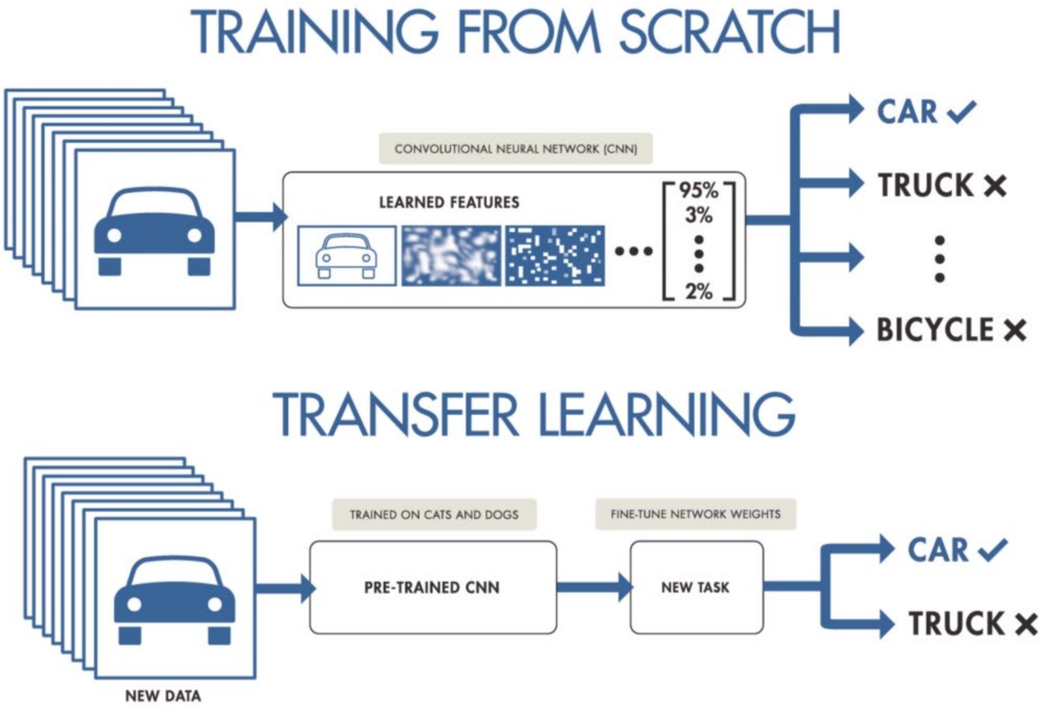
Source: Morros, 2017

Transfer Learning

- **The ability to apply knowledge learned in previous tasks to novel tasks**
  - Similar on human learning.
  - People can often transfer knowledge learnt previously to novel situations
    - Play classic piano →Play jazz piano
    - Maths →Machine Learning
    - Ride motorbike →Drive a car

Source: Morros, 2017

Making use of trained models



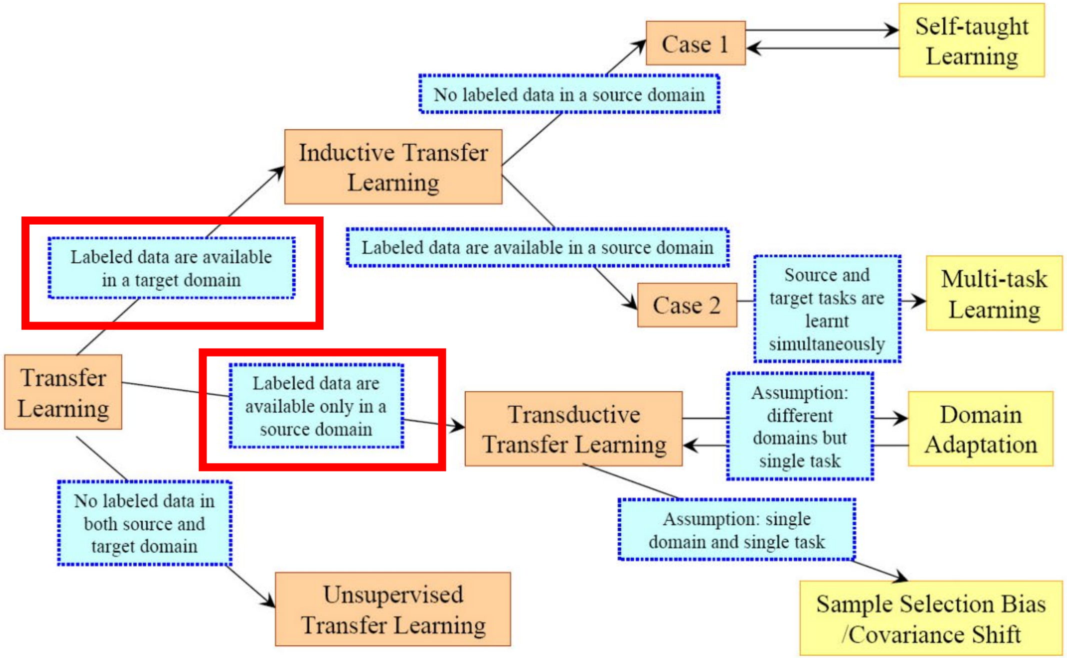
Source: H. Davidson Regua, 2020

Relationship between traditional ML and various transfer learning settings

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

Source: S. J. Pan & Q. Yang, 2009

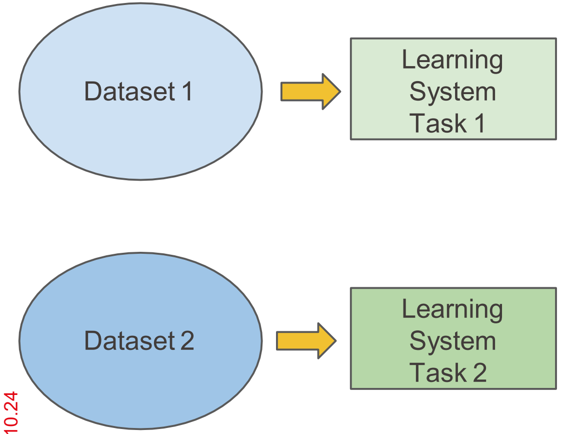
Different types of transfer learning



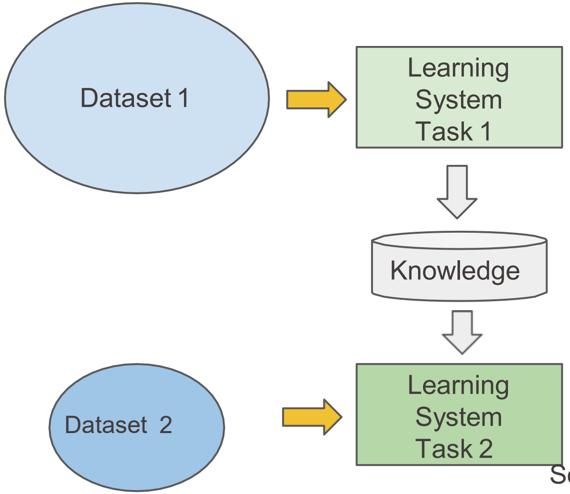
Source: S. J. Pan & Q. Yang, 2009

Traditional ML vs Transfer Learning

- Isolated, single task learning:
  - Knowledge is not retained or accumulated. Learning is performed
w.o. considering past learned knowledge in other tasks



- Learning of a new task relies on the previous learned tasks:
  - Learning process can be faster, more accurate and/or need less training data



Source: Morros, 2017

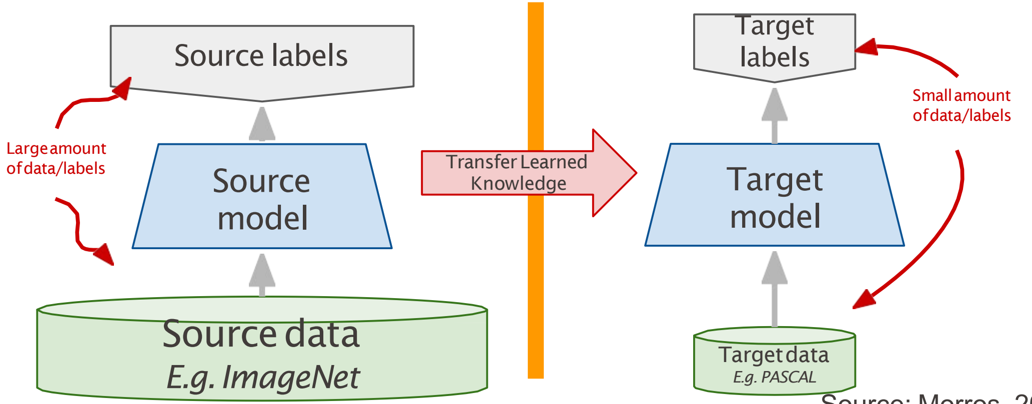
Transfer learning: idea

Instead of training a deep network from scratch for your task:

- Take a network trained on a different domain for a different **source task**
- Adapt it for your domain and your **target task**

Variations:

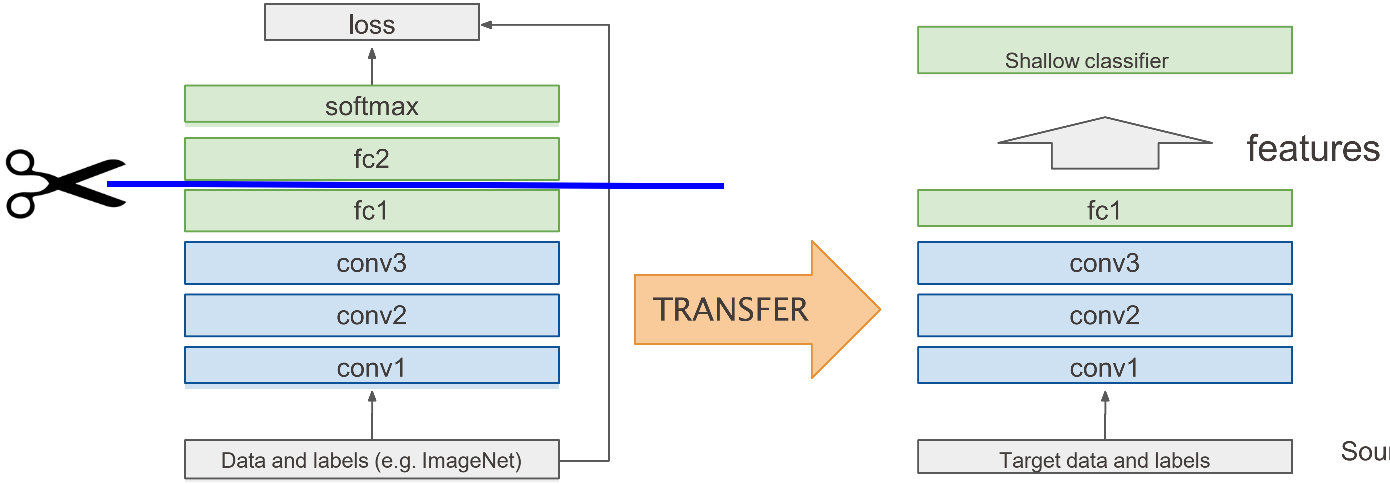
- Same domain, different task
- Different domain, same task



Source: Morros, 2017

“Off-the-shelf”

Idea: use outputs of one or more layers of a network trained on a different task as generic feature detectors. Train a new shallow model on these features.

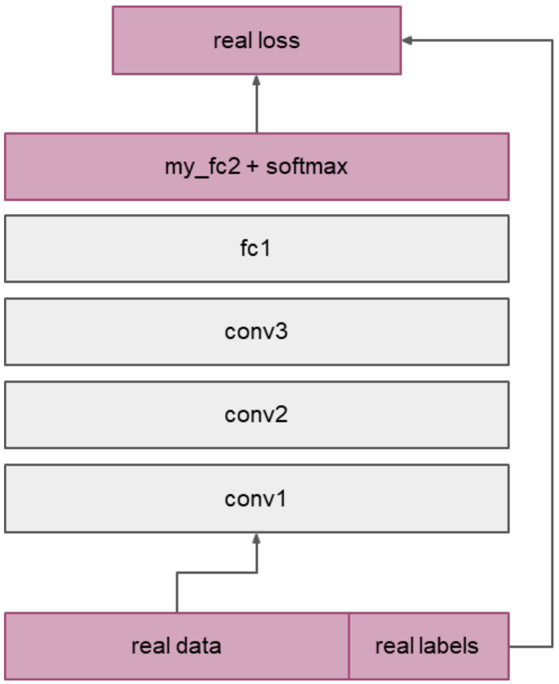


Source: Morros, 2017

EPFL

Fine-tuning: transfer learning

- Train deep net on “nearby” task for which it is easy to get labels using standard backprop
  - E.g. ImageNet classification
  - Pseudo classes from augmented data
- Cut off top layer(s) of network and replace with supervised objective for target domain
- **Fine-tune** network using backprop with labels for target domain until validation loss starts to increase



Source: Morros, 2017

Freeze or fine-tune?

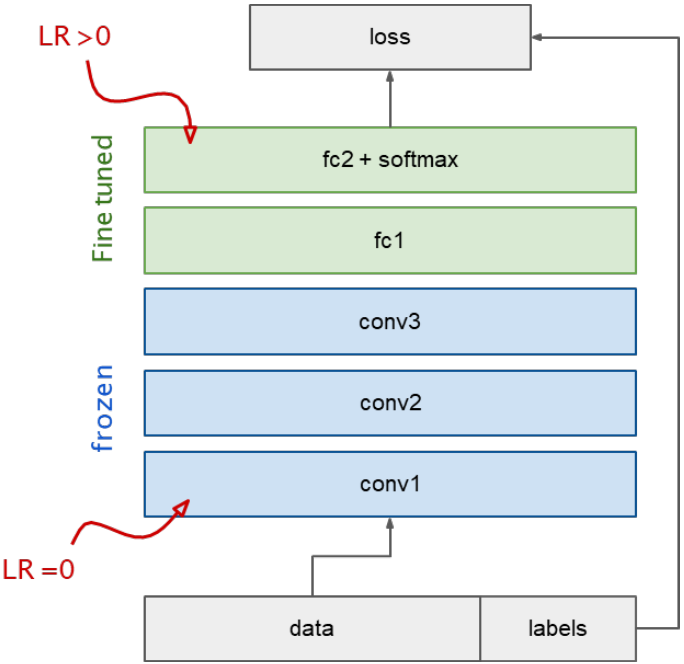
Bottom *n* layers can be frozen or fine tuned.

- **Frozen**: not updated during backprop
- **Fine-tuned**: updated during backprop

Which to do depends on target task:

- **Freeze**: target task labels are scarce, and we want to avoid overfitting
- **Fine-tune**: target task labels are more plentiful

In general, we can set learning rates to be different for each layer to find a tradeoff between freezing and fine tuning



Source: Morros, 2017

Unsupervised domain adaptation

- Labeled training data from a source domain

$$\mathcal{D}_s = \{(\mathbf{x}_s^1, \mathbf{y}_s^1), ..., (\mathbf{x}_s^m, \mathbf{y}_s^m)\}, \mathbf{y}_s^i \in Y.$$

- Unlabeled data from a target domain

$$\mathcal{D}_t = \{\mathbf{x}_t^1, ..., \mathbf{x}_t^n\}.$$

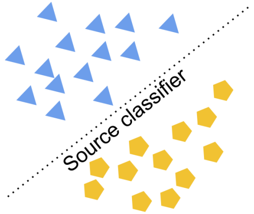
- Test data from the same target domain

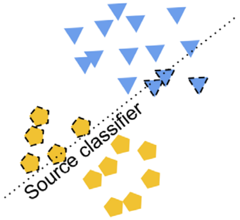
$$\mathcal{D}_{test} = \{\mathbf{x}_{test}^1, ..., \mathbf{x}_{test}^o\},$$

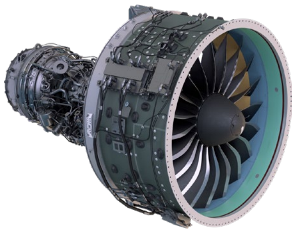
Domain Shift - Target domain different from Source domain

Source

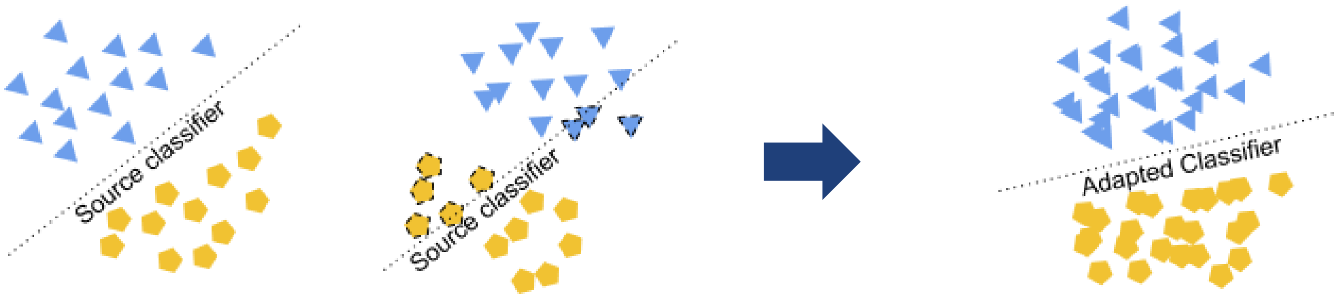
Target



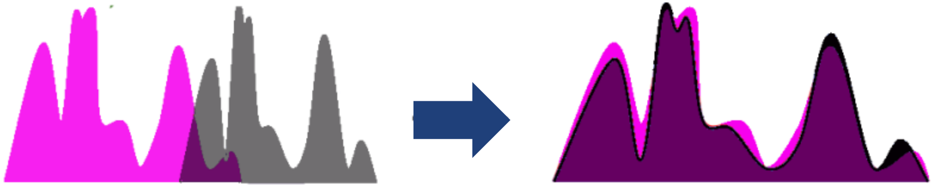




Unsupervised Domain Adaptation

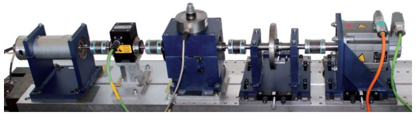


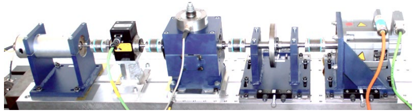
Labeled Source Domain **Unlabeled Target Domain** **Adapted Domain**



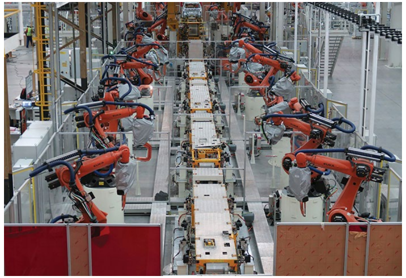
Transferability / Generalizability

- Between different operating conditions

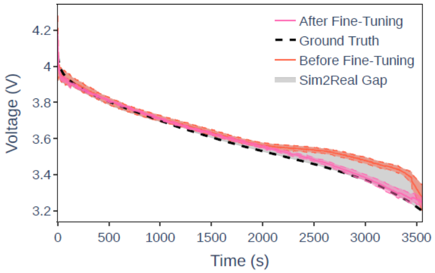




- Between different units of a fleet



- From simulated data to real conditions



Wang, Qin, Gabriel Michau, and **Olga Fink** (2021): "Missing-Class-Robust Domain Adaptation by Unilateral Alignment", *IEEE Transactions on Industrial Electronics, 68 (1), 663-671*.

Case Study on CWRU (Case Western Reserve University) Bearing Dataset

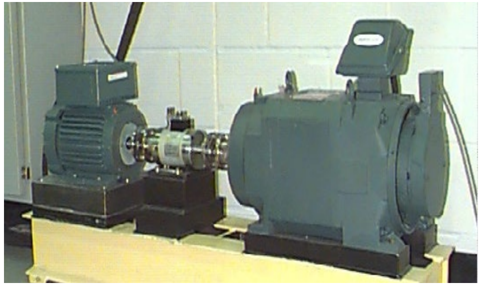
- Dataset information
  - Ten Classes classification

Fault	Class Label									
	0	1	2	3	4	5	6	7	8	9
Loc	NA[1]	IF	IF	IF	BF	BF	BF	OF	OF	OF
Size	0	7	14	21	7	14	21	7	14	21

  - Four loads for domain adaptation

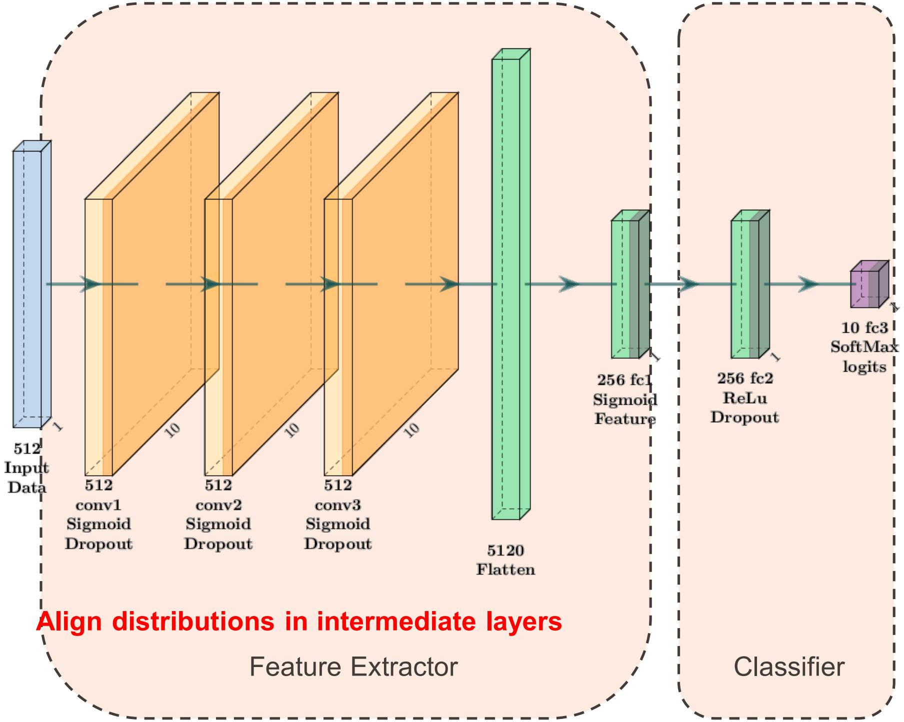
    Labeled source load, Unlabeled target load

Motor Load (HP)	Approx. Motor Speed (rpm)
0	1797
1	1772
2	1750
3	1730



- Data Preprocessing
  - 200 sequences of 1024 points for each recording
  - each converted to 512D Fourier coefficients by FFT

Basic Network

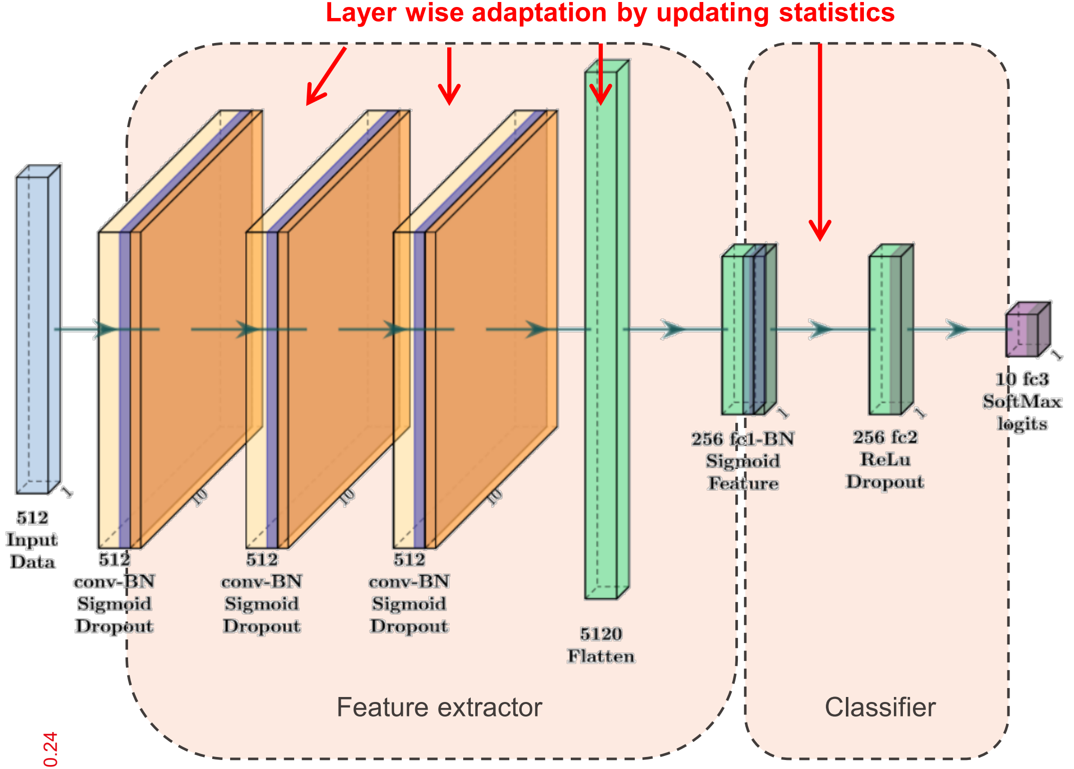


- Feature Extractor
  - Three convolutional layers
  - Flatten and dense layer
- Classifier
  - Fully-connected Layer
- How should we add domain adaptation ability to this network?

[14] X. Li, W. Zhang, and Q. Ding, "Cross-domain fault diagnosis of rolling element bearings using deep generative neural networks," IEEE Transactions on Industrial Electronics, 2018.

EPFL

Background: Adaptive Batch Normalization (AdaBN)



$$\hat{x_j} = \frac{x_j - \mathbb{E}[x_{\cdot j}]}{\sqrt{Var[x_{\cdot j}]}}$$

$$y_j = \gamma_j \hat{x_j} + \beta_j,$$

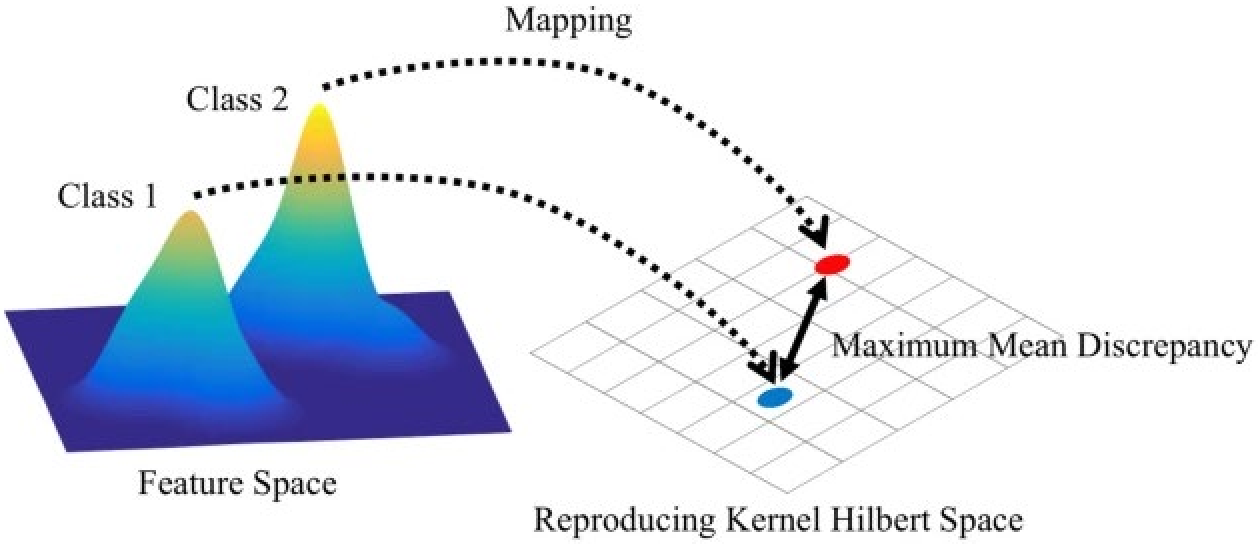
- Idea

  Keep different batch norm statistics for source and target.
- Pros

  Simplicity. Very little computational resource required.
- Cons

  Performance not optimized

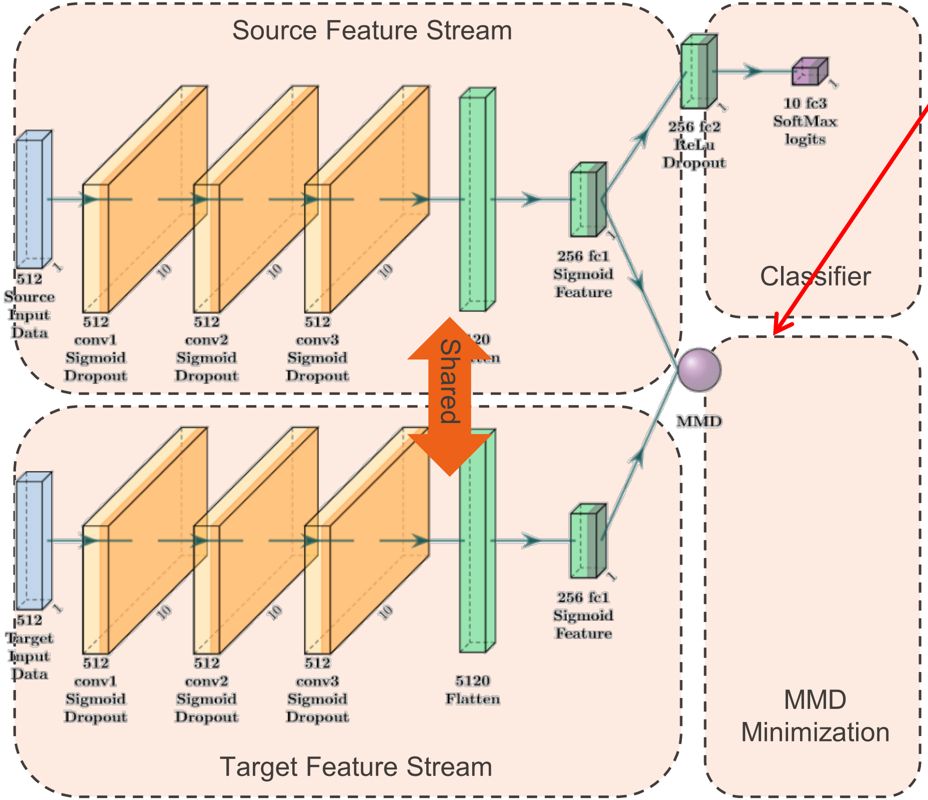
Maximum Mean Discrepancy



$$\mathcal{L}_D(\mathbf{X}^s, \mathbf{X}^t) = \mathrm{MMD}(\mathbf{X}^s, \mathbf{X}^t) = \left\| \frac{1}{n^s} \sum_{i=1}^{n^s} \phi(\mathbf{x}_i^s) - \frac{1}{n^t} \sum_{j=1}^{n^t} \phi(\mathbf{x}_j^t) \right\|_{\mathcal{H}}^2$$

ϕ: mapping function
X^s: feature matrix in source domain
X^t: feature matrix in target domain

Background: Maximum Mean Discrepancy Minization



Estimate distribution difference between source and target features by MMD.

- Idea

  MMD as an additional loss to minimize.

- Pros

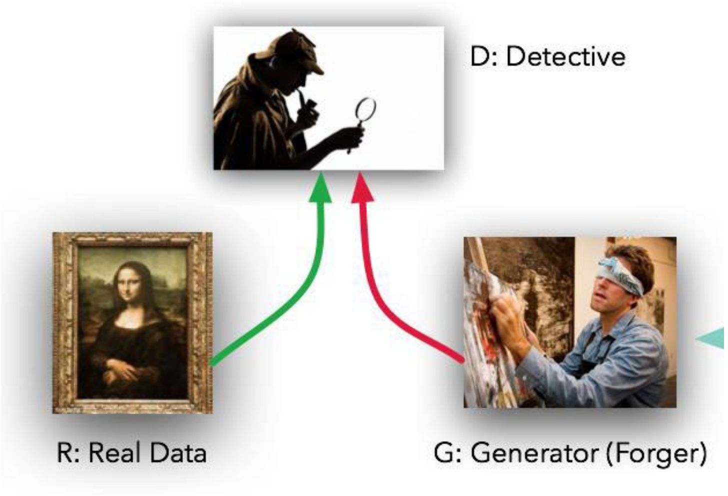
  MMD **directly estimates the distance** between source and target distributions.

- Cons

  Multiple kernels are needed in reality, leads to dramatically **increased model complexity**

X. Li, W. Zhang, Q. Ding, and J.-Q. Sun, "Multi-layer domain adaptation method for rolling bearing fault diagnosis," Signal Processing, vol. 157, pp. 180–197, 2019.

Adversarial Training



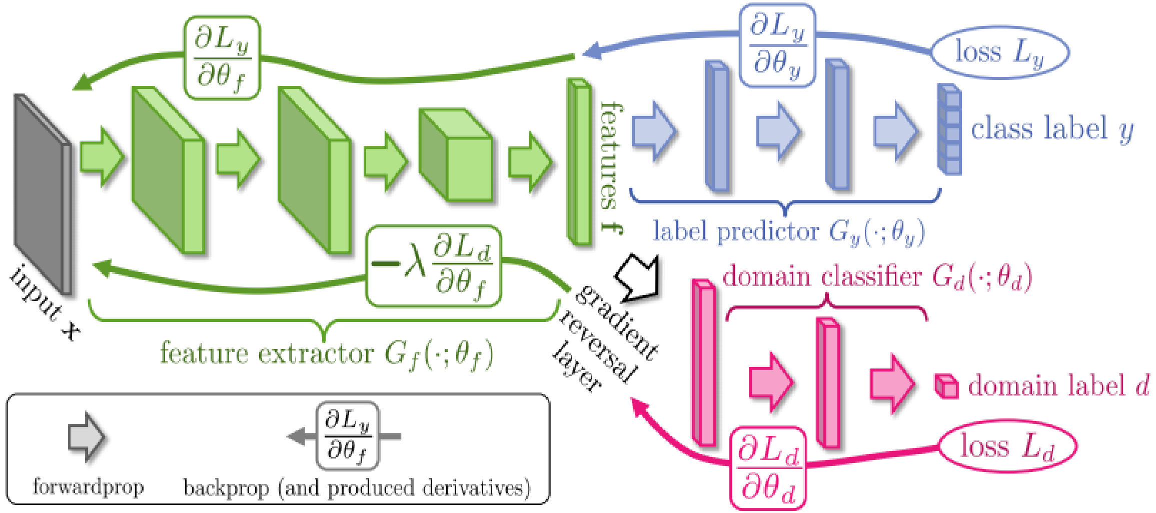
Generative Adversarial Networks (GAN)

Figure 1 https://github.com/devnag/pytorch-generative-adversarial-networks

Adversarial Networks in DA

Domain adaptation for deep learning , Kate Saenko

Domain-Adversarial Training (DANN) in detail



$$E(\theta_f, \theta_y, \theta_d) = \sum_{\substack{i=1..N \\ d_i=0}} L_y\left(G_y(G_f(\mathbf{x}_i;\theta_f);\theta_y), y_i\right) -$$

$$\lambda \sum_{i=1..N} L_d\left(G_d(G_f(\mathbf{x}_i;\theta_f);\theta_d), y_i\right) =$$

$$= \sum_{\substack{i=1..N \\ d_i=0}} L_y^i(\theta_f, \theta_y) - \lambda \sum_{i=1..N} L_d^i(\theta_f, \theta_d)$$

$$(\hat{\theta}_f, \hat{\theta}_y) = \arg\min_{\theta_f, \theta_y} E(\theta_f, \theta_y, \hat{\theta}_d)$$

$$\hat{\theta}_d = \arg\max_{\theta_d} E(\hat{\theta}_f, \hat{\theta}_y, \theta_d) .$$

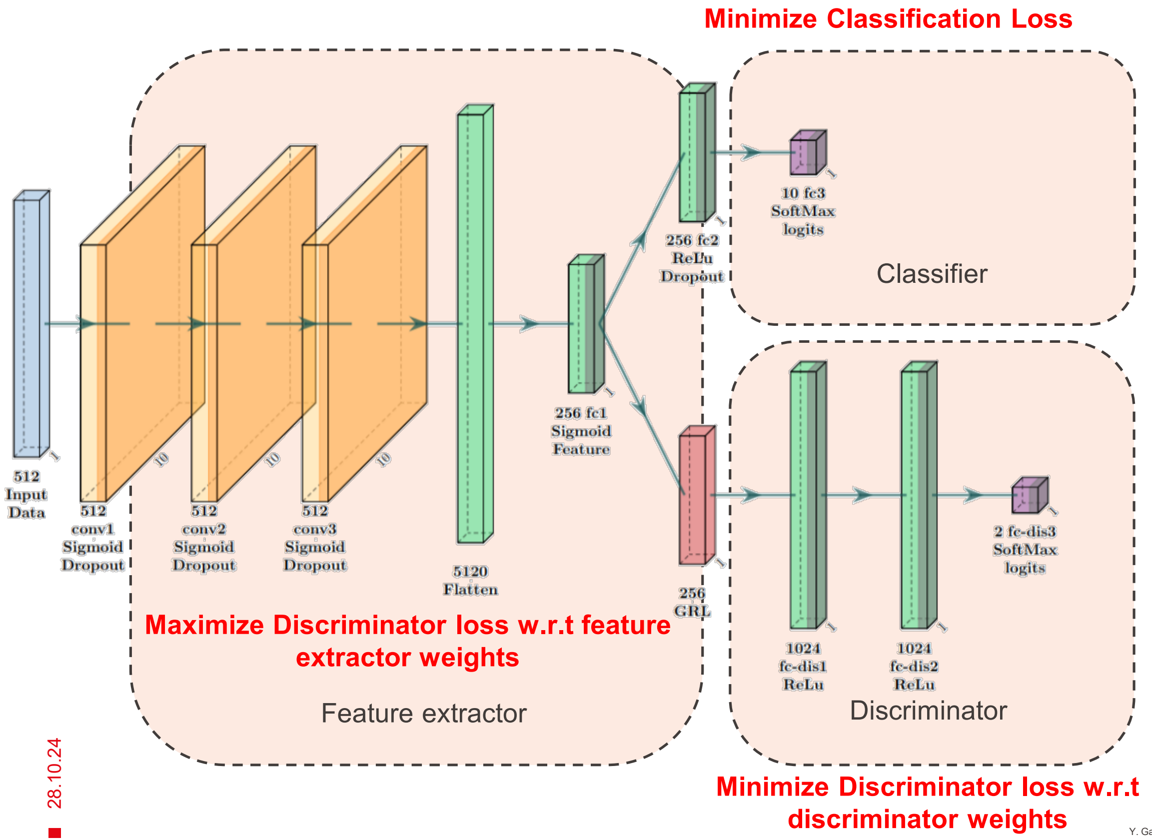
f: feature extractor

y: classifier

d: discriminator

Y. Ganin and V. Lempitsky, "Unsupervised domain adaptation by backpropagation," International Conference on Machine Learning. 2015.

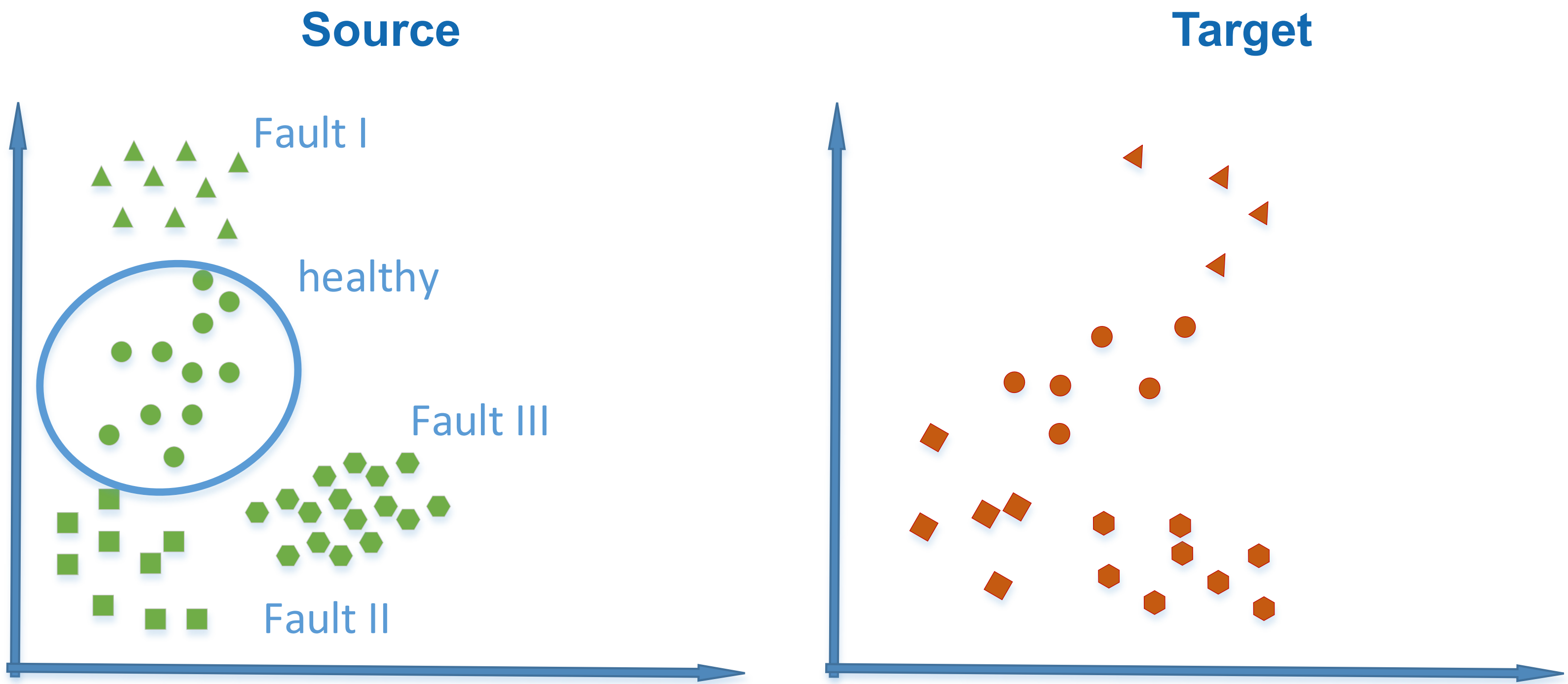
Domain-Adversarial Training (DANN)



- Strategy: Discriminator
  - Train a discriminator to distinguish between target and source
  - Force the feature extractor to generate unbiased features

Y. Ganin and V. Lempitsky, "Unsupervised domain adaptation by backpropagation," arXiv preprint arXiv:1409.7495, 2014

Feature alignment: all faults known



Model Performance on CWRU Dataset

- Same basic architecture
- Same budget for hyper-parameter tuning
- Same optimizer and learning rate

	Baseline	AdaBN	MMD	DANN
3-1	89.42%	94.42%	98.53%	98.41%
0-2	93.65%	99.30%	99.98%	99.96%
…	…	…	…	…
Mean Accuracy	94.99%	97.82%	99.42%	99.07%

Average over **5** runs, trained on a NVIDIA GTX 1080

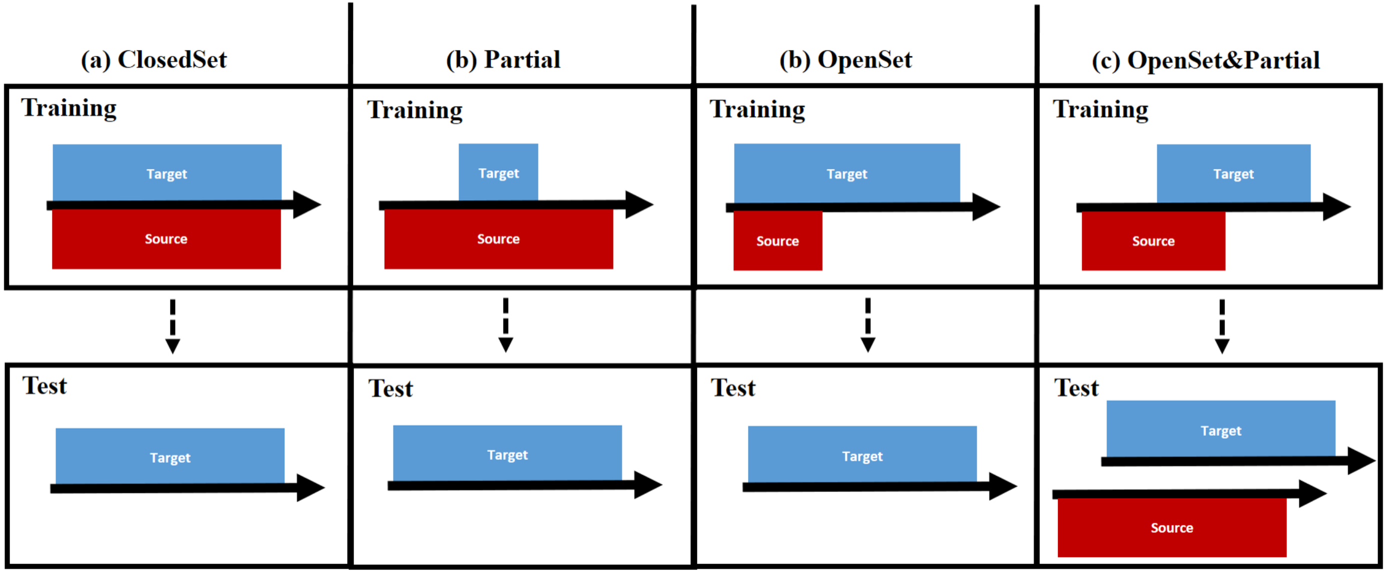
Model Efficiency

	Baseline	AdaBN	MMD	DANN
Mean Accuracy	94.99%	97.82%	99.42%	99.07%
Training Time	84 s	133 s	266 s	177 s
	Linear	Linear	Quadratic	Linear

w.r.t. # training samples

Partial / Openset Domain adaptation

Four DA configurations according to label space discrepancies



Rombach, K., G. Michau & O. Fink: Controlled Generation of Unseen Faults for Partial and Open-Partial Domain Adaptation, Reliability Engineering and System Safety

Standard DA

Source - Train	Target - Train	Target - Test
Healthy	Healthy	Healthy
Fault 1	Fault 1	Fault 1
Fault 2	Fault 2	Fault 2
Fault 3	Fault 3	Fault 3
Fault x	Fault x	Fault x

Partial DA (Cao et al. 2018)

Source - Train	Target - Train	Target - Test
Healthy	Healthy	Healthy
Fault 1	Fault 1	Fault 1
Fault 2		
Fault 3		
Fault x		

Partial DA under «extreme» setup

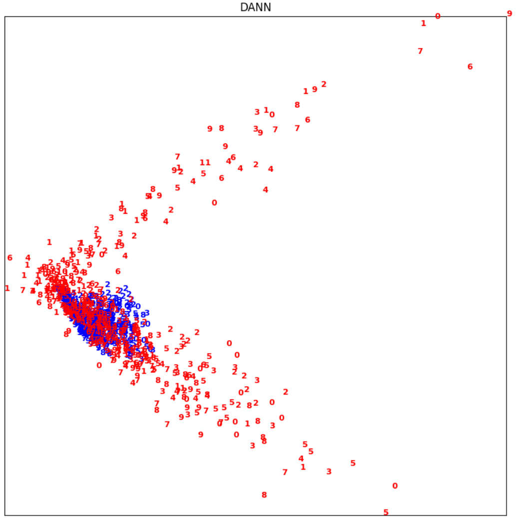
Source - Train	Target - Train	Target - Test
Healthy	Healthy	Healthy
Fault 1		Fault 1
Fault 2		Fault 2
Fault 3		Fault 3
Fault x		Fault x

Visualization on Feature Space

DA in Real Life

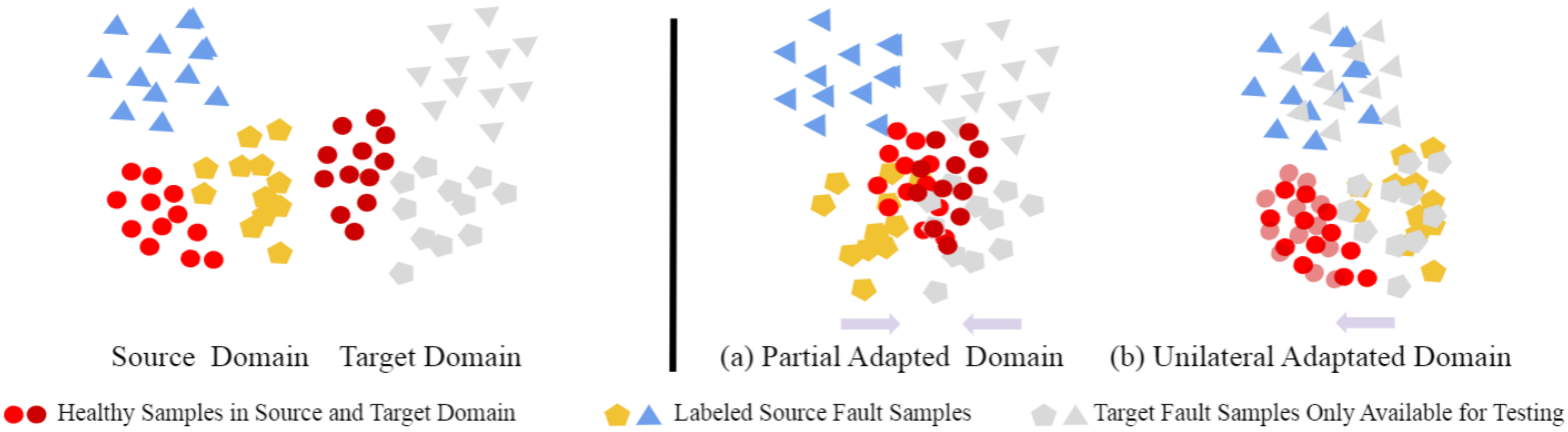
Source - Train	Target - Train	Target - Test
Healthy	Unknown	Healthy
Fault 1	Unknown	Fault 1
Fault 2	Unknown	Fault 2
Fault 3		Fault 3
Fault x		Fault x

Aligning Complete Source with Partial Target is Wrong



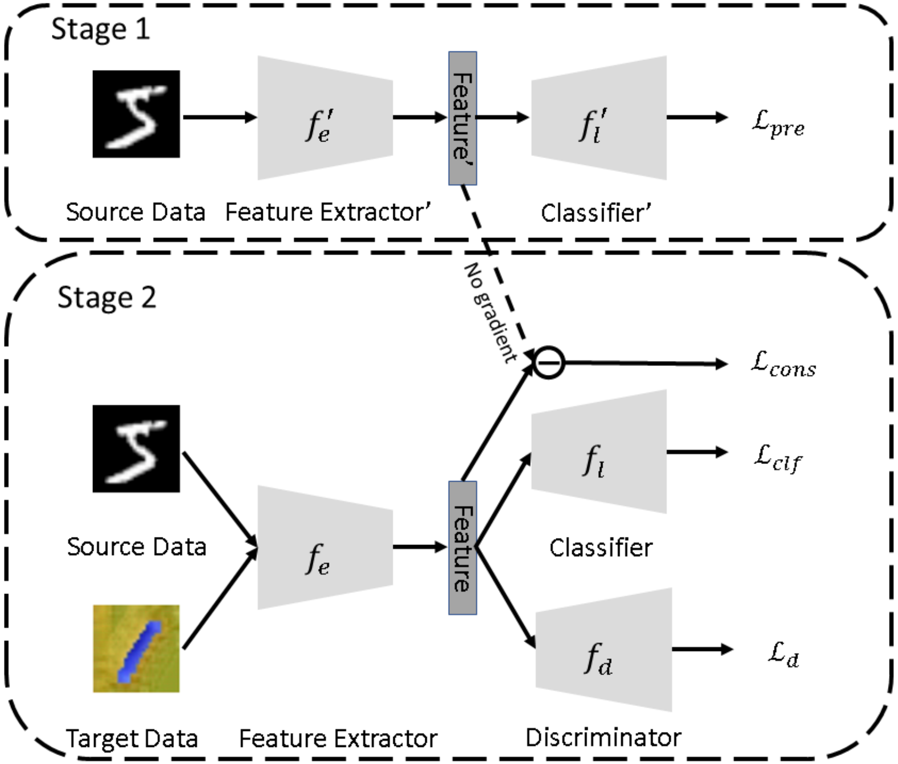
Feature Visualization on DANN Method
Part of target features (Red) are aligned with complete source data (Blue)

Our Proposed Method: Bilateral vs Unilateral



Wang, Qin, Gabriel Michau, and **Olga Fink** (2021): "Missing-Class-Robust Domain Adaptation by Unilateral Alignment", *IEEE Transactions on Industrial Electronics, 68 (1), 663-671*.

Our proposed approach



- Intuition
  - Preserve discriminability learned from source.
- Stage 1
  - Train a source feature extractor
- Stage 2
  - Train the main net
  - Make use of this additional info to construct a

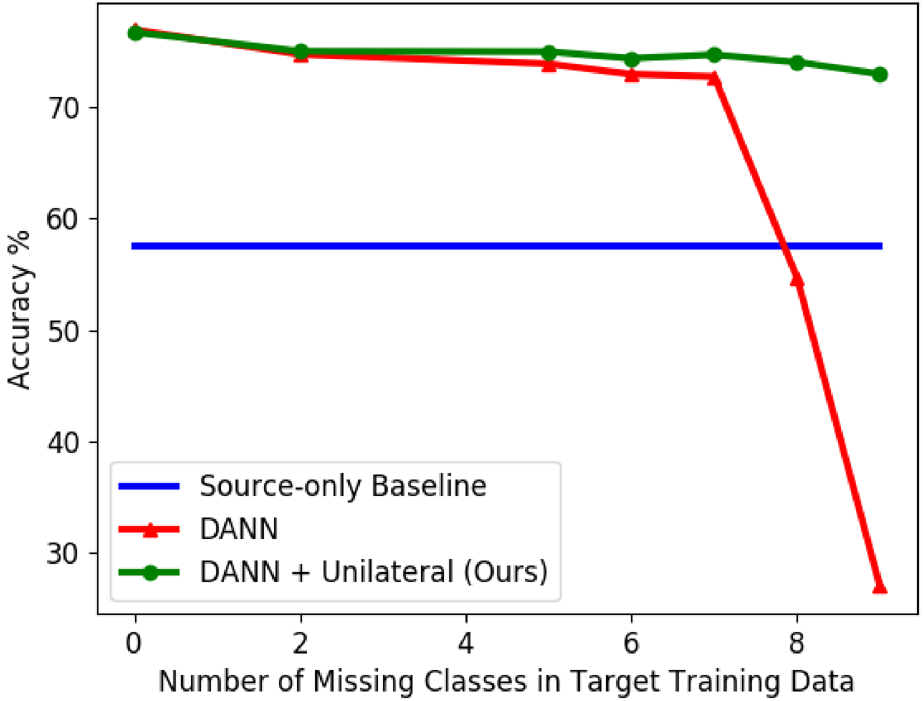
$$\mathcal{L}_{cons} = \frac{1}{K}\sum_{j=1}^{K} ||f(x_s)_j - f'(x_s)_j||_1,$$

  - $\mathcal{L} = \mathcal{L}_{clf} + \mathcal{L}_d + \lambda_{cons}\mathcal{L}_{cons}.$

parts.

Wang, Qin, Gabriel Michau, and Olga Fink (2021): "Missing-Class-Robust Domain Adaptation by Unilateral Alignment", *IEEE Transactions on Industrial Electronics, 68 (1), 663-671*.

Results



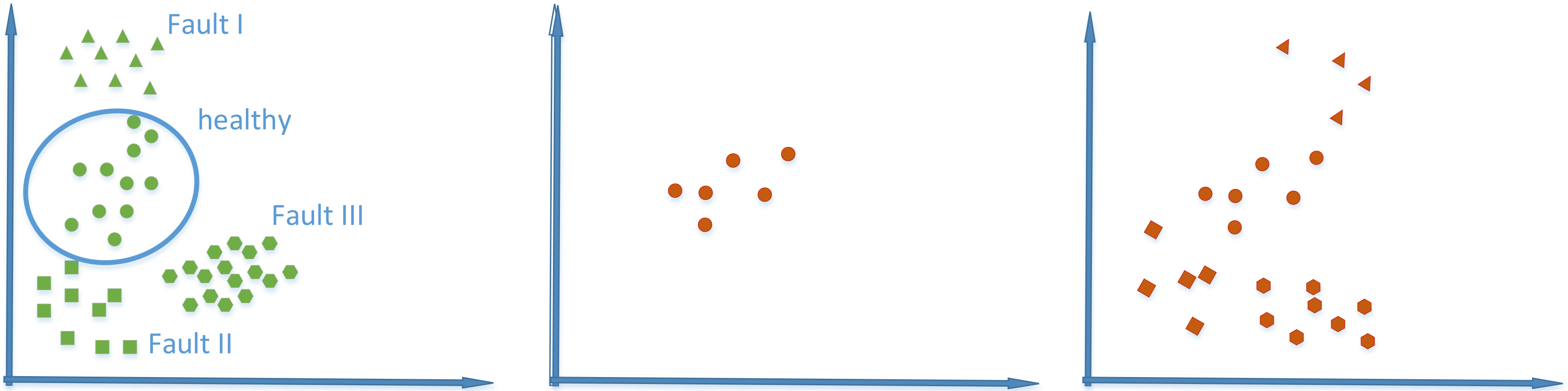
Wang, Qin, Gabriel Michau, and Olga Fink (2021): "Missing-Class-Robust Domain Adaptation by Unilateral Alignment", *IEEE Transactions on Industrial Electronics, 68 (1), 663-671*.

Feature alignment: only healthy condition in target known

Source

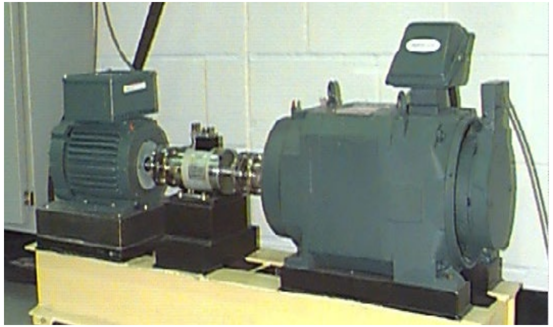
Target at training time

Target at testing time



EPFL

Transfer between operating conditions just knowing the health!



Bearing Case Study (CWRU)

- Ten Classes
  One healthy class, Nine fault classes
- Four Loads (Domains)
- Transfer between different load conditions
- Vibration Signals

- Same basic architecture
- Same budget for hyper-parameter tuning
- Same optimizer and learning rate

	Baseline	Unilateral alignment
Mean Accuracy	94.99%	**98.07%**

Wang, Qin, Gabriel Michau, and Olga Fink (2021): "Missing-Class-Robust Domain Adaptation by Unilateral Alignment", *IEEE Transactions on Industrial Electronics, 68 (1), 663-671*.

Reminder: Key concepts of self supervision

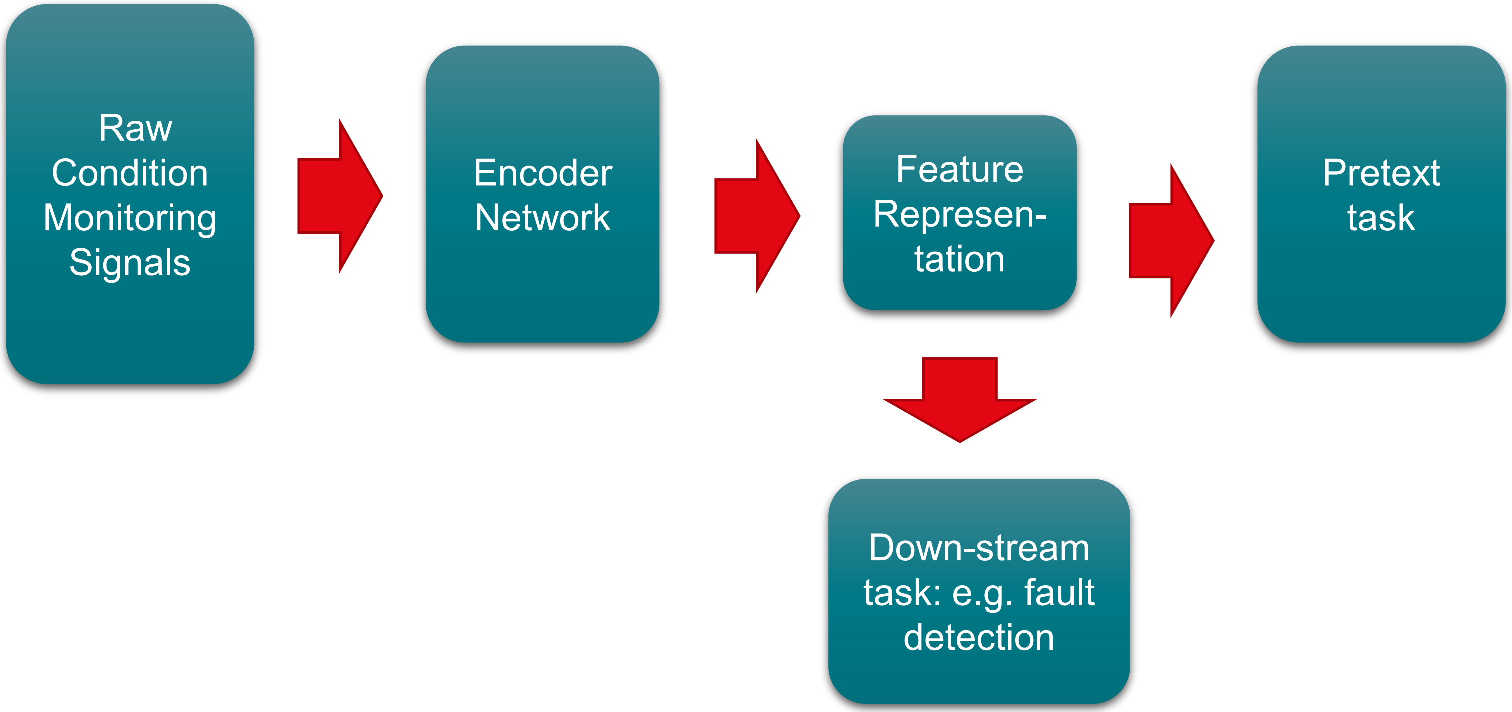
Self-supervised learning

- Pretext task → important strategy for learning data representations under self-supervised mode
- Self-defined pseudo-labels
- Pseudo-labels automatically generated based on the attributes found in the unlabeled data

Reminder: important pretext tasks

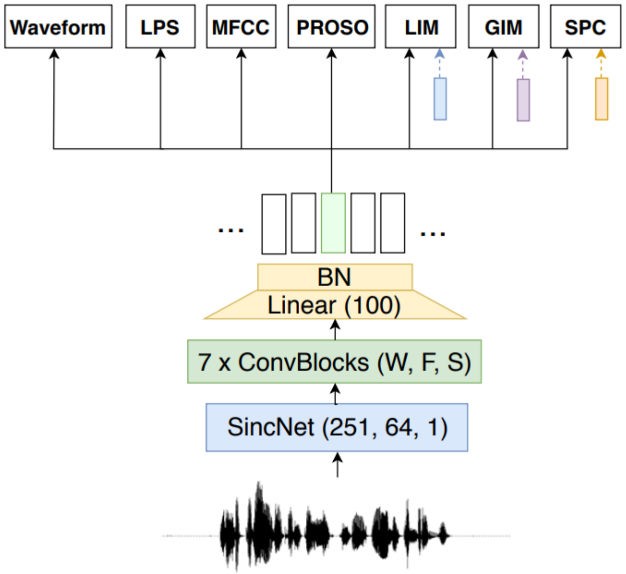
- color transformations
- geometric transformations
- context-based tasks
- cross-modal-based tasks

Basic idea of self-supervised learning



Self supervision for time series data

Learning Problem-agnostic Speech Representations from Multiple Self-supervised Tasks



- Waveform: predict the input waveform in an auto-encoder fashion.
- Log power spectrum (LPS)
- Mel-frequency cepstral coefficients (MFCC)
- Prosody (four basic features per frame, namely the interpolated logarithm of the fundamental frequency, voiced/unvoiced probability, zero-crossing rate, and energy)
- Local info max (LIM)
- Global info max (GIM)
- Sequence predicting coding (SPC)

Pascual, Santiago, Mirco Ravanelli, Joan Serrà, Antonio Bonafonte, and Yoshua Bengio. "Learning Problem-Agnostic Speech Representations from Multiple Self-Supervised Tasks}}." *Proc. Interspeech 2019* (2019): 161-165.

Learning Problem-agnostic Speech Representations from Multiple Self-supervised Tasks

Table 1: *Accuracies using PASE and an MLP as classifier. Rows below the "all workers" model report absolute accuracy loss when discarding each worker for self-supervised training.*

Model	Classification accuracy [%]		
	Speaker-ID (*VCTK*)	Emotion (*INTERFACE*)	ASR (*TIMIT*)
PASE (All workers)	97.5	88.3	81.1
– Waveform	−1.3	−3.9	−0.3
– LPS	−1.5	−5.3	−0.5
– MFCC	−2.4	−3.2	−0.7
– Prosody	−0.5	−5.3	−0.1
– LIM	−0.8	−1.3	−0.0
– GIM	−0.6	−0.5	−0.3
– SPC	−0.4	−1.6	−0.0

Table 2: *Accuracy comparison on the considered classification tasks using MLPs and RNNs as classifiers.*

Model	Classification accuracy [%]					
	Speaker-ID (*VCTK*)		Emotion (*INTERFACE*)		ASR (*TIMIT*)	
	MLP	RNN	MLP	RNN	MLP	RNN
MFCC	96.9	72.3	90.8	91.1	81.1	84.8
FBANK	98.4	75.1	94.1	92.8	80.9	85.1
PASE-Supervised	97.0	80.5	93.8	92.8	82.1	84.7
PASE-Frozen	97.3	82.5	91.5	92.8	81.4	84.7
PASE-FineTuned	**99.3**	**97.2**	**97.7**	**97.0**	**82.9**	**85.3**

Pascual, Santiago, Mirco Ravanelli, Joan Serrà, Antonio Bonafonte, and Yoshua Bengio. "Learning Problem-Agnostic Speech Representations from Multiple Self-Supervised Tasks}}." *Proc. Interspeech 2019* (2019): 161-165.

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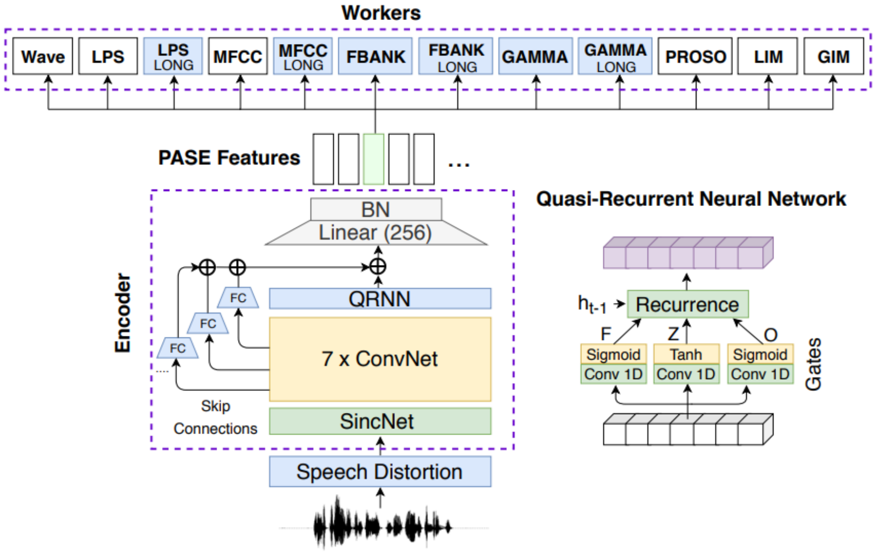
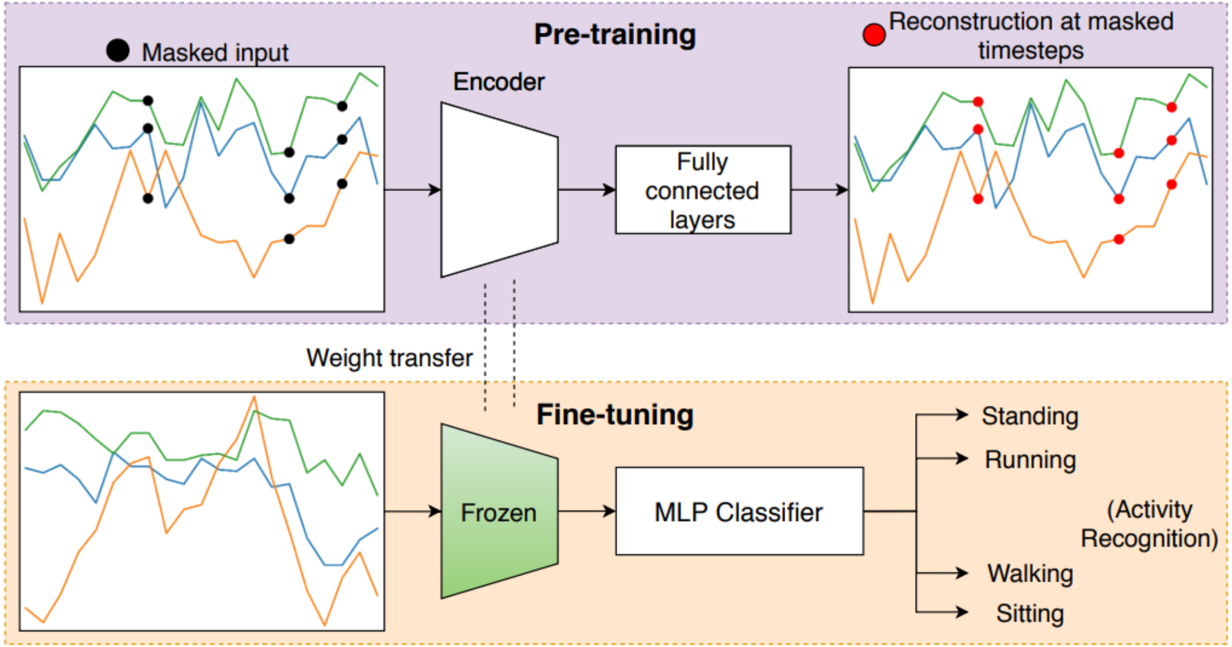
Multi-task self-supervised learning for Robust Speech Recognition



Disturbance	*p*	*Description*
Reverberation	0.5	Convolution with a large set of impulse responses derived with the image method.
Additive Noise	0.4	Non-stationary noises from the FreeSound and the DIRHA datasets.
Frequency Mask	0.4	Convolution with band-stop filters that randomly drops one band of the spectrum.
Temporal Mask	0.2	Replacing a random number of consecutive samples with zeros.
Clipping	0.2	Adding a random degree of saturation to simulate clipping conditions.
Overlap Speech	0.1	Adding another speech signal in background that overlaps with the main one.

Ravanelli, M., Zhong, J., Pascual, S., Swietojanski, P., Monteiro, J., Trmal, J., & Bengio, Y. (2020). Multi-task self-supervised learning for Robust Speech Recognition. arXiv preprint arXiv:2001.09239.

Masked Reconstruction Based Self-Supervision



Haresamudram, Harish, et al. "Masked reconstruction based self-supervision for human activity recognition." *Proceedings of the 2020 international symposium on wearable computers*. 2020.