

Leveraging knowledge to design machine learning despite the lack of data

Transfer learning

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Inserm

Motivation

Leveraging knowledge to design machine learning despite the lack of data using Transfer Learning.

In recent years, considerable progress has been made in the implementation of decision support procedures based on machine learning methods through the exploitation of very large databases and the use of learning algorithms. In the industrial environment, the databases available in research and development or in production are rarely so voluminous and the question arises as to whether in this context it is reasonable to use machine learning methods. This talk presents research work around transfer learning and hybrid models that use knowledge from related application domains or physics to implement efficient models with an economy of data. Several achievements in industrial collaborations will be presented that successfully use these learning models to design machine learning for industrial small data regimes and to develop powerful decision support tools even in cases where the initial data volume is limited.

Leveraging knowledge to design machine learning despite the lack of industrial data.

Thanks to the Industrial Data Analytics and Machine Learning chair,
a joint work on Transfer Learning with

- ▶ **Mounir Atiq**, Transfer learning for fall detection, Tarket & IDAML, Centre Borelli (2018-2022)
- ▶ **Antoine de Mathelin**, Transfer learning in hybrid models for engineering design, Michelin & IDAML, Centre Borelli (2020-.)
- ▶ **Ludovic Minvielle**, Transfer learning for fall detection, Tarket & IDAML, Centre Borelli (2017-2020)
- ▶ **Sergio Peignier**, Transfer learning, IDAML & Centre Borelli (2018)
- ▶ **Guillaume Richard**, Transfer learning for Temporal data, EDF & Centre Borelli (2018-2021)
- ▶ **Nicolas Vayatis**, Director Centre Borelli, ENS-Paris-Saclay,
- ▶ **Industrial partners** Michelin, EDF, Takett....



Motivations / Transfer methods / Applications & Numerical results / packages

Data Sources & several Successes of "ML/AI" models

- **Imagenet** is a huge database containing more than $14 \cdot 10^6$ labeled images, 10^3 categories, available for object detection and image classification at a large scale, ... "quite expensive" labeling effort.

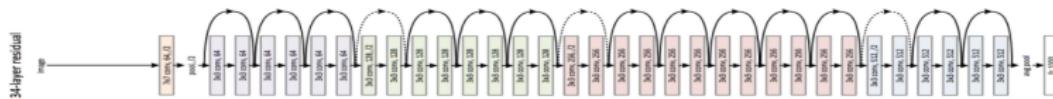


FIGURE – ResNet : a Convolutional Neural Network for image classification (credit :Resnet)

Top-performing deep architectures are trained on massive amounts of labeled data.

- **DeepL** relied on Linguee hudge data base.
Traduction of 1 M of words in one second

- **Plant Net** to recognize plants.

Classical framework for Supervised Machine learning

1. **Input/ output** (X, Y) (Features, labels set) defined by the operational need.
Ex : $X \in \mathbb{R}^d, \dots Y \in \mathbb{R}, \dots Y \in \{0, 1\} \dots$
2. **Data set.** $S = \{(x_i, y_i)\}_{i=1}^m \sim \mathcal{D}^m$ a learning/training sample of m iid pairs.
with \mathcal{D} an unknown joint probability distribution on the product space $X \otimes Y$
3. **Model** $\mathcal{H} = \{h_\theta | h_\theta : X \rightarrow Y\}$ a hypothesis class, θ parameter
classifiers or regressors depending on the nature of Y .
4. **Loss function** $\ell(y, h_\theta(x))$ providing a cost of $h_\theta(x)$ deviating from the true output $y \in Y$.

The best hypothesis is the one that minimizes the true risk, consequently, generalizes well :

$$R_{\mathcal{D}}^\ell(h_\theta) = \mathbb{E}_{(x,y) \sim \mathcal{D}} [\ell(h_\theta(x), y)]$$

The goal of learner consists of finding a good hypothesis function $h_\theta \in \mathcal{H}$ that captures in the best way possible the relationship between X and Y .

$$h_{\theta_{\text{opt}}} = \arg \min_{h_\theta} R_{\mathcal{D}}^\ell(h_\theta)$$

In practice : Empirical risk, large training sample, regularization, sparsity,...

Industrial needs towards Transfer Learning

Motivation 1. ML for Automatic Elderly fall detection.

Objective.

The Tarkett Floor in motion application tends to detect automatically falls based on sensor information and then trigger an alarm if necessary.



From a first Proof Of Concept (POC) to deployment :

1. **Data.** As it is not possible to gather large data base with falls of elderly people, a first supervised data base is created with young volunteers containing fall / no fall events.
2. **Predictive models.** POC to choose and evaluate the performance of a **ML model** to detect fall on previous data (performances ? true detection, false alarm...).
3. **Transfer learning.** How to **transfer** the previous model for elderly care...to a new population given few labeled data?
4. **Budgeted learning.** ... and what about in a real environment...

[Minvielle et al., 2017], [Minvielle et al., 2019], [Mounir et al., 2021]

Motivation 2. ML for Automatic tire wear detection

AI IdF 2019 Challenge organized by the IDAML chair
in collaboration with Michelin

Industrial objectives :

- Design an application for the
- 1/ detection and localization in an image
of a "new generation" wear indicator
 - 2/ Estimation of the wear level



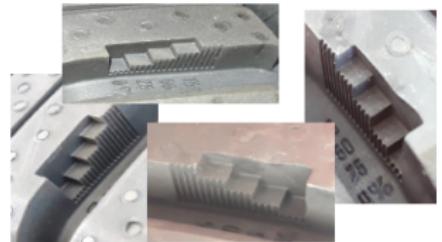
Data base : 1000 tire images with

- various tire views,
- different lighting conditions,
- with and without wear indicator (4 levels).

Learning : 500 labeled examples

(tire images, wear indicator, boundingbox position)

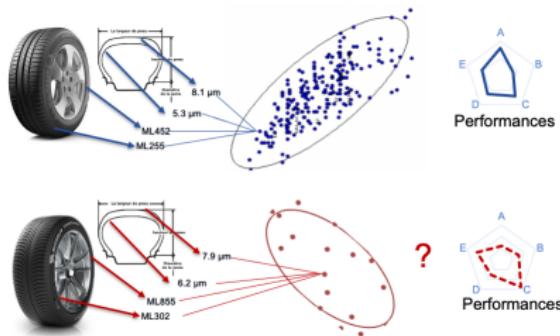
Blind Evaluation : 500 labeled images.



Motivation 3. ML for Product Design.

Industrial application in collaboration with Michelin, EDF

- ▶ New products are regularly manufactured with a long and costly development.
- ▶ Relative small data sets are gathered during the development of products as characteristics (color, shape, weight...) and performances.



Is-it possible to predict the performances of a new tire line given data previously gathered from **other** lines?

[Richard et al., 2021], [de Mathelin et al., 2021]

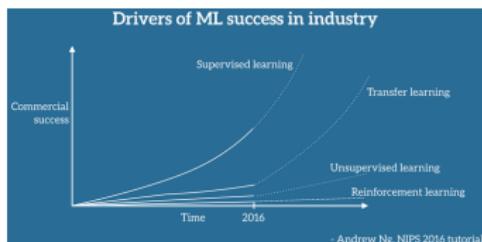
Machine Learning in the industry

Main observations :

- ▶ Often **small, moderate, evolving database**. Ex. manufacturing process.
- ▶ **Few or not labeled data**. Ex. Few production defaults.
- ▶ labeled-data is often difficult and time-consuming to acquire.
Ex. Experimental design to help selecting costly observation outputs.
- ▶ In many real-world applications, historical (training) data and newly collected (test) data may often exhibit **different statistical characteristics**.
- ▶ In many ML scenarios, training and test samples are supposed to be generated by the same (unknown) probability distribution.
- ▶ Needs for monitoring and diagnosis based on machine learning (ML) .
- ▶ Makes sense to **re-use knowledge** gained from related but distinct datasets.

Need of Transfer Learning, domain adaptation, few shot learning...

Transfer learning : the model can be pre-trained on data from a specific domain and then adapted to meet needs of a given task.



Transfer Learning in industry.

Outline

1. Introduction

- The success of ML models
- ML in industry

2. Transfer learning & Domain adaptation

- Framework
- Model-based TL
- Feature-based TL
 - Theoretical setup
- Instance-based TL.
 - The covariate shift assumption Covariate & Theoretical guarantees

3. Mixing strategies

4. The Open access Adapt library

Transfer learning & Domain Adaptation

Transfer learning in industry.

1. Introduction

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The Transfer learning framework

► Data collections : Source & Target

1. Source data \mathcal{S} .

$X_{\mathcal{S}} \otimes Y_{\mathcal{S}}$ the source input and output spaces associated with \mathcal{S}
 \mathcal{S}_X the marginal distribution of $X_{\mathcal{S}}$, $t_{\mathcal{S}}$ the source learning task

2. Target data \mathcal{T}

$X_{\mathcal{T}} \otimes Y_{\mathcal{T}}$ the Target input and output spaces associated with \mathcal{T}
 \mathcal{T}_X the marginal distribution of $X_{\mathcal{T}}$, $t_{\mathcal{T}}$ the Target learning task

△ Source and Target data are not drawn from the same distribution.

► Focus on the Target Risk. $R_{\mathcal{T}}^{\ell}(h) = \mathbb{E}_{(x,y) \sim \mathcal{T}}[\ell(h(x), y)]$ with ℓ the loss function.

► Supervised data or calibrated Model available for the source domain (enough data).

Transfer learning aims to improve the learning of the target predictive function :
 $f_{\mathcal{T}} : X_{\mathcal{T}} \rightarrow Y_{\mathcal{T}}$ for $t_{\mathcal{T}}$ using knowledge gained from \mathcal{S} where $\mathcal{S} \neq \mathcal{T}$

$\mathcal{S} \neq \mathcal{T}$ (joint distributions) implies several cases :

- $\mathcal{S}_X \neq \mathcal{T}_X$ i.e. $X_{\mathcal{S}} \neq X_{\mathcal{T}}$ (spaces) or $\mathcal{S}_X(X) \neq \mathcal{T}_X(X)$ (laws) or
- $t_{\mathcal{S}} \neq t_{\mathcal{T}}$ (i.e. $Y_{\mathcal{S}} \neq Y_{\mathcal{T}}$ (target task) or $\mathcal{S}(Y/X) \neq \mathcal{T}(Y/X)$ (conditional law))

... Seems to be a hard problem...

Success stories?... Theoretical guarantees? Assumptions?, Negative transfer?

Answers to the industrial partners.... open source algorithms...

Illustration of the Need of Transfer for Learning Machine

Transfer learning aims at providing ML models with a good generalization capability on a Target domain (**same domains**, **different domains**).

Target domain (ex I).

Same Domain $\{\mathcal{X}, P(X)\}$ &
task $\mathcal{T} = \{\mathcal{Y}, P(Y|X)\}$.

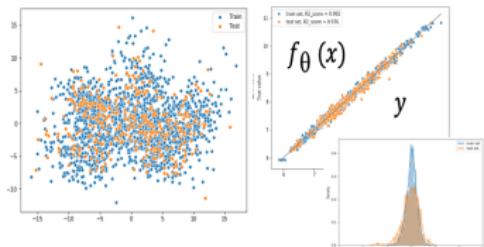


FIGURE – High Prediction capability.

Target domain (ex II).

Different Domain & same task.

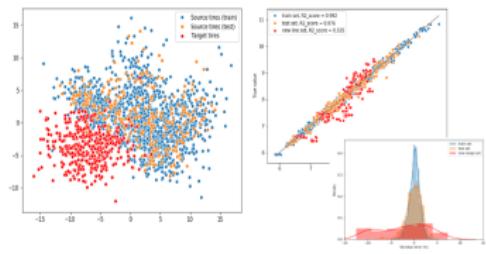


FIGURE – Low Prediction capability.

$$\begin{array}{c} P(x, y) \\ \text{Joint distribution} \\ \text{differences} \end{array} = \begin{array}{c} P(y/x) \\ \text{concept shift} \end{array} * \begin{array}{c} P(x) \\ \text{covariate-shift} \end{array}$$

Transfer Learning & Domain adaptation Methods

Several approaches to transfer knowledge from Source to Target domain.

- ▶ **Model-based.** Transfer the model parameters learnt on the source data to the target model.
- Train model available, not necessary the source data- .
- ▶ **Feature-based.** Find a new representation space to bring feature spaces closer.
-Source and Target Input data available-.
- ▶ **Instance-based.** Re-weight the source samples to bring the distributions closer.
-Source and Target Input data available-.

Theoretical guarantees ?

For example on the Target Risk given the source risk.

Examples of Industrial needs and success stories.

- ▶ **Model-based :** Image based tire wear estimation based on Deep architecture (Michelin) (Resnet...), Automatic fall detection based on decision trees/ RF (Tarkett).
- ▶ **Feature-based :** Domain adversarial neural networks (EDF, Michelin)
- ▶ **Instance-based :** Multi-source domain adaptations for Product design (Michelin) or Electricity prediction (EDF)

Transfer learning Model-based

Model-based Transfer learning. Ex1 : deep NN

Industrial Image classification

Automatic tire wear detection, IdF AI Challenge, 2019. Data base :

1000 tire images with various tire views, different lighting conditions, with and without wear indicator.

500 images for learning / 500 images for a blind evaluation.

Two following questions were addressed :

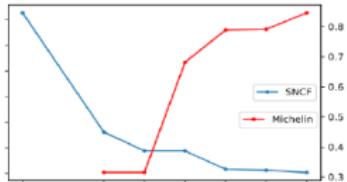
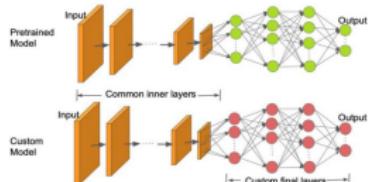
- 1/ detection and localization in an image of a "new generation" wear indicator
- 2/ Estimation of the wear level



Development based on Transfer learning

Poor performances obtained with trained model using only the tire data base (20%).

A source pre-trained model (RetinaNet, Yolo...) is used by the candidates (final perf 85%).



Predicted Class	True Class				
	N/I	25%	50%	75%	100%
N/I	215	0	0	0	2
25%	1	31	2	0	0
50%	0	9	32	1	3
75%	1	0	7	53	8
100%	0	0	0	5	59

FIGURE – Pre-trained model, first frozen weights (credit learnopencv.com)

Automatic fall detection. Features and data

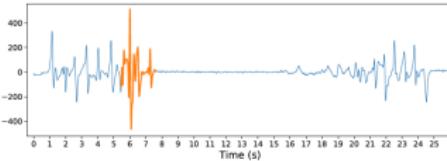
Objective.

The Floor in motion application tends to detect automatically falls based on sensor information and then trigger an alarm if necessary.



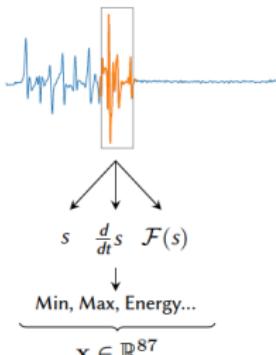
Experimental dataset

- ▶ 28 volunteers aged 25 to 45
- ▶ 742 signals collected in **controlled environment**
- ▶ 55% fall, 45% non-fall
- ▶ varied fall events (forward, backward...) and activities of daily living (walking, sitting...)



Time series as *feature vector*. At every timestamp:

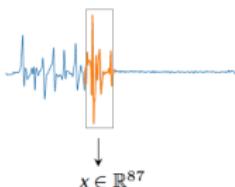
1. Window over the signal: 2.5 s
2. Compute feature vector: 29 statistical measures (Min, Max, Shannon energy, Percentile,...) over three representations of the signal



Automatic fall detection. The ML model.

Time series as *feature vector*. At every timestamp:

1. Window over the signal: 2.5 s
2. Compute feature vector: 29 statistical measures (Min, Max, Shannon energy, Percentile,...) over three representations of the signal



3. Classification model: Random Forest (Breiman [1]), based on **decision trees**

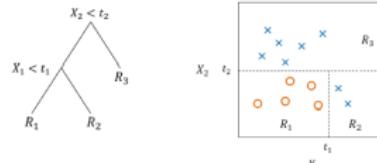
Decision tree

Feature space $\mathcal{X} = \mathbb{R}^Q$. Division of \mathcal{X} into non-overlapping regions R_1, \dots, R_j . Algorithm CART: recursive binary splits [2] that solve:

$$\arg \max_{X_q, \tau} \text{IG} , \quad (\text{information gain})$$

with $\text{IG}(X_q, \tau) = I(n) - \frac{N_l}{N_n} I(l) - \frac{N_r}{N_n} I(r)$,

and $I(n) = \text{Gini}(n) = \sum_k p_{nk}(1 - p_{nk})$.



$$\text{Prediction function: } f(x) = \sum_{j=1}^J c_j \mathbf{1}(x \in R_j)$$

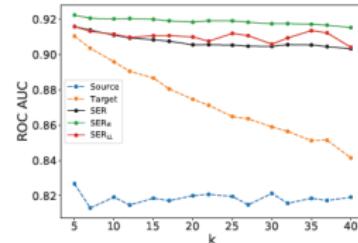
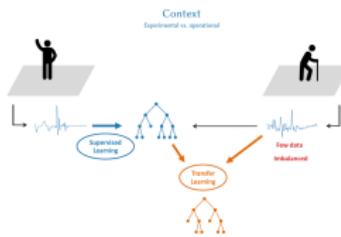
Model	Accuracy	TPR	FPR
LR	86.8 ± 1.5	90.5 ± 2.4	17.7 ± 4.9
LDA	85.5 ± 1.2	91.0 ± 2.1	21.7 ± 3.7
k-NN	87.0 ± 1.9	89.2 ± 1.4	16.0 ± 4.7
SVM	87.6 ± 3.2	90.0 ± 4.5	15.5 ± 6.8
MLP	88.2 ± 1.5	92.4 ± 1.2	17.3 ± 4.1
RF	88.2 ± 1.5	91.7 ± 3.5	16.2 ± 6.2

Comments:

- ▶ Parametric methods perform worse than non-parametric
- ▶ RF is slightly better than others

Model-based Transfer learning for decision trees

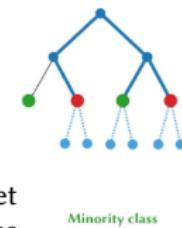
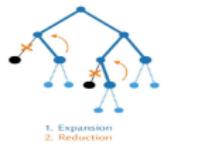
Fall detection. Strong benefits for transferring knowledge from Source to Target :



Segev et al. 2017.

SER : Structure Expansion and Reduction

SER has to be adapted to take into account class imbalance (few falls) with conditional reduction [Minvielle et al., 2019]



- Idea : train on source domain, extend on target domain the actives nodes, then cut the inactives edges.

- Idea : preserve nodes from minority class

SER_R If node is of minority class, then no pruning	SER_{LL} If node is of minority class and still significant considering Target and $R_L > 0.5$, then no pruning
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Transfer learning Feature-based

Feature-based TL.

Deep network to confuse source and target input feature data...

Domain Adversarial Neural Networks. [Ganin and Lempitsky, 2015].

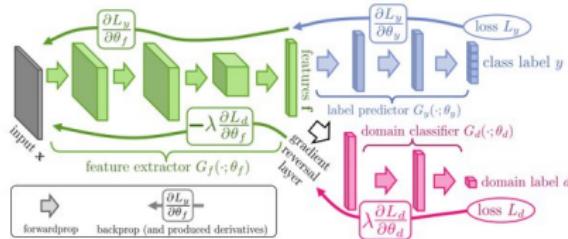


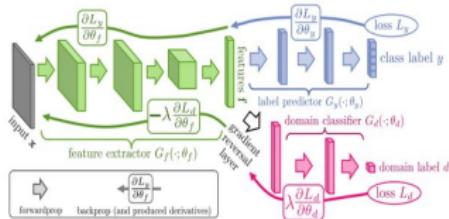
FIGURE – credit [Ganin and Lempitsky, 2015].

DANN : A neural net architecture and an optimization process to solve both

1. **Supervised Task** based on Source data to learn the model using an iid sample $\{(x_1, y_1), \dots, (x_n, y_n)\} \sim (P(X, Y))^n$, $\hat{h} = \arg \min_{h \in \mathcal{H}} \sum_{i=1}^n \ell(h(x_i), y_i)$
2. **Unsupervised Domain Adaptation** using Source and Target inputs to minimize a distance characterizing the domain divergence.

Feature-based TL.

Domain Adversarial Neural Networks.
[Ganin and Lempitsky, 2015]



Source obs $i : (x_i, y_i, d_i = 0)$

Label obs $i : (x_i, d_i = 1)$

L_y / L_d : label/ domain loss.

Optimization criteria :

$$\begin{aligned} E(\theta_f; \theta_y, \theta_d) \\ = \sum_{\substack{i=1 \dots N \\ d_i=0}} L_y(G_y(G_f(x_i; \theta_f); \theta_y), y_i) \\ - \lambda \sum_{i=1 \dots N} L_d(G_d(G_f(x_i; \theta_f); \theta_d), d_i) \end{aligned}$$

The backpropagation optimisation procedure aims to compute the parameters $(\theta_f; \theta_y, \theta_d)$ such that

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

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

Stochastic updates with learning rate μ

$$\theta_f \leftarrow \theta_f - \mu \left[\frac{\partial L_y^i}{\partial \theta_f} - \lambda \frac{\partial L_d^i}{\partial \theta_f} \right]$$

$$\theta_y \leftarrow \theta_y - \mu \frac{\partial L_y^i}{\partial \theta_y}$$

$$\theta_d \leftarrow \theta_d - \mu \frac{\partial L_d^i}{\partial \theta_d}$$



Theoretical setup for domain adaptation

BenDavid et al. introduced in 2006 the \mathcal{H} -divergence for 01 loss function, in the setting of binary classification ($\ell_{01}(h(x), y) = 1$ if $h(x) = y$; otherwise 0)

- Given two domain distributions \mathcal{D}_S^X and \mathcal{D}_T^X over X, and a hypothesis class \mathcal{H} , the \mathcal{H} -divergence between \mathcal{D}_S^X and \mathcal{D}_T^X for classification is defined by :

$$d_{\mathcal{H}}(\mathcal{D}_S^X, \mathcal{D}_T^X) = 2 \sup_{h \in \mathcal{H}} \left| \Pr_{x \sim \mathcal{D}_S^X} [h(x) = 1] - \Pr_{x \sim \mathcal{D}_T^X} [h(x) = 1] \right|$$

- The \mathcal{H} -divergence relies on the capacity of the hypothesis class \mathcal{H} to distinguish between examples generated by \mathcal{D}_S^X from examples generated by \mathcal{D}_T^X .

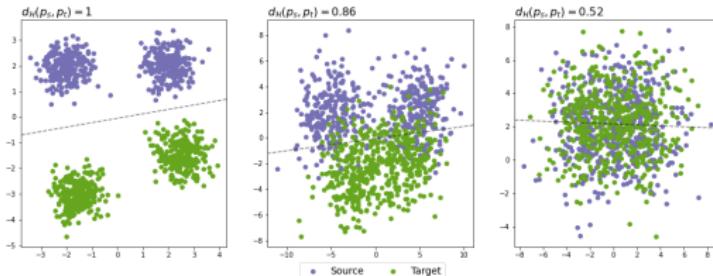


FIGURE – Divergence/discrepancy illustration with linear classifiers. [Richard et al., 2021]

Theoretical setup for domain adaptation

The **discrepancy** introduced by Ben David et al. 2007, Mansour et al. 2009 measures the availability to discriminate between Source and Target input features distribution.

- ▶ Considering two labeling functions f, g and the symmetric loss ℓ over pairs of labels which obeys the triangle inequality.

The expected loss over any marginal distribution Q is defined by :

$$L_Q(f, g) = \mathbb{E}_Q(\ell(f(X), g(X)))$$

- ▶ Consider a hypothesis class \mathcal{H} and the marginal distributions S on source domain and T on target domain, the discrepancy distance between these two is defined as :

$$\text{disc}_{\mathcal{H}, L}(S, T) = \sup_{h, h' \in \mathcal{H}} |L_S(h, h') - L_T(h, h')|$$

Domain adaptation bound

Mansour et al. 2009 established a bound for the Target risk using the discrepancy :

$$\mathbf{R}_T(h) \leq \mathbf{R}_S(h, h_S^*) + \text{disc}_{\mathcal{H}, \ell}(S, T) + \lambda$$

where

$$R_Q(h) = \mathbb{E}_Q(\ell(h(X), Y)),$$

$$R_Q(h, h') = L_Q(h, h') = \mathbb{E}_Q(\ell(h(x), h'(x))), h, h' \in \mathcal{H}$$

$$h_S^* = \arg \min_{h \in \mathcal{H}} \mathbf{R}_S(h), h_T^* = \arg \min_{h \in \mathcal{H}} \mathbf{R}_T(h),$$

ideal hypothesis for Source and Target domain.

$$\lambda = \mathbf{R}_S(h_T^*) + \mathbf{L}_T(h_S^*, h_T^*)$$

Comments

- ▶ **First term** : source risk, can be minimized with source labels
- ▶ **Second term** : discrepancy between domains → to minimize!
- ▶ **Third term** : risk of the ideal hypothesis on the source and target samples. **Assumed to be small** and not controlled in unsupervised DA.

Adversarial Hypothesis Discrepancy Minimization

Algorithm

1. $\mathcal{L}_h = \mathbf{R}_S$ updates h to minimize the source loss
2. $\mathcal{L}_{h'} = -HDisc$ updates h' to maximize discrepancy
3. $\mathcal{L}_\theta = HDisc + \mathbf{R}_S$ updates ϕ_θ to minimize discrepancy and source loss

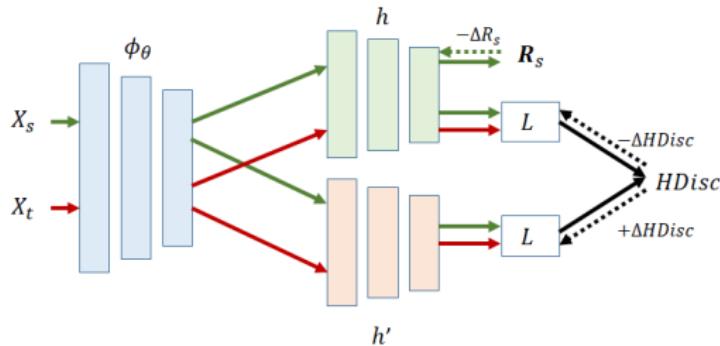


FIGURE – Adversarial Hypothesis Discrepancy Minimization (**AHDM**) using Neural Networks

Adversarial Objective : $\min_{h \in \mathcal{H}} \max_{h' \in \mathcal{H}} \mathbf{R}_S(h) + |\mathbf{L}_S(h, h') - \mathbf{L}_T(h, h')|$

$\min_{\phi_\theta, h \in \mathcal{H}_Z} \max_{h' \in \mathcal{H}_Z} \mathbf{R}_S(h \circ \phi_\theta, y_S) + |\mathbf{R}_T(h \circ \phi_\theta, h' \circ \phi_\theta) - \mathbf{R}_S(h \circ \phi_\theta, h' \circ \phi_\theta)|$

Transfer learning Instance-based

Instance-based TL.

The risk computed on the Target may be related to the risk on the Source domain.

$$\begin{aligned}
 R_{\mathcal{T}}^{\ell}(h) &= \mathbb{E}_{(x,y) \sim \mathcal{T}} \ell(h(x), y) = \int_{(x,y) \in \mathcal{X} \times \mathcal{Y}} \mathcal{T}(x, y) \ell(h(x), y) dx dy \\
 &= \int_{(x,y) \in \mathcal{X} \times \mathcal{Y}} \frac{\mathcal{T}(x, y)}{\mathcal{S}(x, y)} \mathcal{S}(x, y) \ell(h(x), y) dx dy \\
 &= \mathbb{E}_{(x,y) \sim \mathcal{S}} [w(x, y) \ell(h(x), y)] \\
 &= \mathbb{E}_{(x,y) \sim \mathcal{S}} \left[\frac{\mathcal{T}_X(x) \mathcal{T}(y/x)}{\mathcal{S}_X(x) \mathcal{S}(y/x)} \ell(h(x), y) \right]
 \end{aligned}$$

Rem : The support of \mathcal{T}_X is contained in the support of \mathcal{S}_X , $\mathcal{S}(x, y) > 0$.



Instance-based TL.

The **covariate shift assumption**. The predictive dependency remains unchanged between Source and Target while the marginal distributions change.

Covariate shift assumption $\left\{ \begin{array}{l} \mathcal{S}(Y/X) = \mathcal{T}(Y/X) \\ \mathcal{T}_X(X) \neq \mathcal{S}_X(X) \end{array} \right.$

$$\begin{aligned} R_T^\ell(h) &= \underset{(x,y) \sim \mathcal{T}}{E} \ell(h(x), y) \\ &= \underset{(x,y) \sim \mathcal{S}}{E} \left[\frac{\mathcal{T}_X(x) \mathcal{T}(y/x)}{\mathcal{S}_X(x) \mathcal{S}(y/x)} \right] \ell(h(x), y) \\ &= \underset{(x,y) \sim \mathcal{S}}{E} \left[\frac{\mathcal{T}_X(x)}{\mathcal{S}_X(x)} \right] \ell(h(x), y) \end{aligned}$$

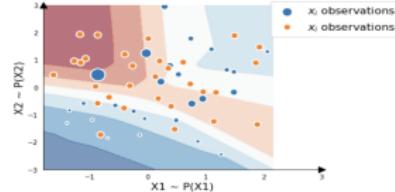


Figure – Importance Weighting Source (blue) and target (orange) input samples are drawn according to two different distributions $p_s(x), p_t(x)$. The source samples are reweighted according to the density ratio $w(x) = p_t(x)/p_s(x)$

Mixing strategies

Mixing strategies

Unsupervised Multi-source domain adaptation for regression

Application : Non intrusive load monitoring. From the house consumption, estimation of the consumption of an appliance over a period of time.

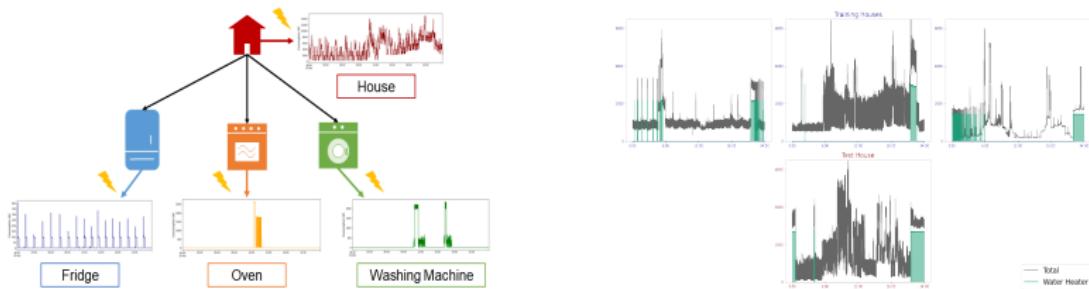


FIGURE – Water heater consumption estimation : input is the whole consumption (gray curve 2s sampling), variable to predict is the whole Water Heater consumption, $y \in \mathbb{R}$ (green area)

Adaptation with Multiple Sources

Unsupervised Multi-source Domain Adaptation.

[Richard et al., 2021]

- ▶ K independent source domains \mathcal{D}_k such that $\mathcal{D}_k = \{X_k, f_k\}$ where X_k is the input data with associated marginal distribution $X_k \sim p_k$ and f_k the true labeling function of the domain ($f_k : \mathcal{X} \rightarrow \mathcal{Y}$)
- ▶ A target domain $\mathcal{D}_t = \{X_t, f_t\}$ with $X_t \sim p_t$.
- ▶ A labeled source sample $\mathcal{S}_k = \{x_k^i, y_k^i\}$ of size m with an associated empirical probability \hat{p}_k and $y_k^i \in \mathcal{Y}$. Similarly, we consider an unlabeled target sample $\mathcal{S}_t = \{x_t\}$ of size n with an associated empirical probability of \hat{p}_t .

How to mix sources ?

We introduce the α -weighted source domain $\mathcal{D}_\alpha = \{p_\alpha, f_\alpha\}$ such that :

- ▶ $\alpha \in \Delta = \{\alpha \in \mathbb{R}^K; \alpha_k \geq 0, \sum_{k=1}^K \alpha_k = 1\}$
- ▶ $p_\alpha = \sum_{k=1}^K \alpha_k p_k$
- ▶ $f_\alpha : x \rightarrow (\sum_{k=1}^K \alpha_k p_k(x) f_k(x)) / (\sum_{j=1}^K \alpha_j p_j(x))$

[Richard et al., 2021], theoretical guarantees.

Adversarial Learning with HDisc. Benefits to mix the sources. Application to NILM.

At a given iteration,
four losses are minimized sequentially :

1. $\mathcal{L}_h = \alpha_k \epsilon_k$ updates h to minimize the source loss
2. $\mathcal{L}_{h'} = -HDisc$ updates h' to maximize discrepancy
3. $\mathcal{L}_\theta = HDisc + \sum_{k=1}^K \alpha_k \epsilon_k$ updates ϕ_θ to minimize discrepancy and source loss
4. $\mathcal{L}_\alpha = HDisc + \lambda \|\alpha\|_2$ updates α to minimize the discrepancy between α -weighted domain and target domain

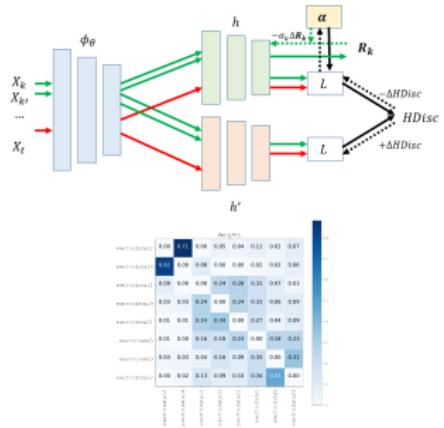


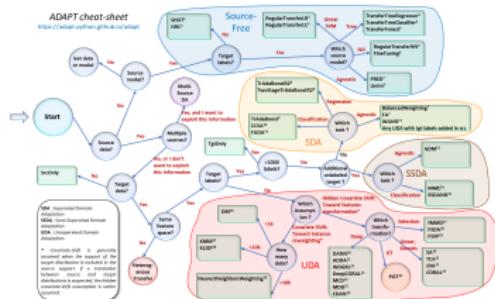
TABLE – Average Mean Absolute Error (kWh) over 5 runs for each method and house

Method	TCN (1 source)	DANN (1 source)	CORAL (1 source)	AHDM (1 source)	MDAN (7 sources)	AMSHDM (7 sources)	Whole cons.
electricdata12	4.78	4.87	4.51	4.38	5.28	4.11	16.45
electricdata14	5.62	5.98	4.89	4.82	6.39	4.76	14.02
electricdata11	3.12	3.28	2.68	2.71	2.88	2.31	8.55
electricdata19	1.89	1.97	1.79	1.73	1.92	1.67	7.12
electricdata21	3.46	3.32	2.95	2.93	3.62	2.77	6.10
electricdata5	1.90	2.05	1.79	1.81	1.86	1.80	4.16
electricdata9	2.29	1.96	1.60	1.87	2.30	1.42	3.90
electricdata22	2.12	1.99	1.79	1.87	2.04	1.74	3.72

From Theory to Practice : The Adapt library

ML Feedbacks in Industry :

- ▶ labeled-data is often difficult and time-consuming to acquire
- ▶ Makes sense to re-use knowledge gained from related but distinct datasets.
- ▶ Transfer learning : the model can be pre-trained on data from a specific domain and then adapted to meet needs of a given task.
- ▶ Development of the Adapt library :



The screenshot shows the 'Welcome to the ADAPT package!' page of the ADAPT Python Toolbox. It features a navigation bar with 'Search', 'Contact', and 'About'. Below is a 'Modules' section with several cards:

- Feature-Based**: Describes domain adaptation based on the covariates of source features that have similar behavior with respect to the test or target domain.
- Algorithms**: Includes 'PCA', 'CCA', 'SVD', 'LDA', 'TSNE', 'PCA', 'CCA', 'SVD', 'LDA', 'TSNE', 'PCA', 'CCA', 'SVD', 'LDA', 'TSNE'.
- Network-Based**: Describes domain adaptation based on the structure of training data used to extract the differences between source and target domains.
- Algorithms**: Includes 'PCA', 'CCA', 'SVD', 'LDA', 'TSNE', 'PCA', 'CCA', 'SVD', 'LDA', 'TSNE'.
- Parameter-Based**: Describes domain adaptation by re-parameterizing one or two parameters such that the source data are adapted to build a model that fits the target data.
- Algorithms**: Includes 'PCA', 'CCA', 'SVD', 'LDA', 'TSNE', 'PCA', 'CCA', 'SVD', 'LDA', 'TSNE'.
- Small Examples**
- Classification**: Shows a scatter plot of 'The classification CD task' with 'Data' and 'Model' sections.
- Regression**: Shows a scatter plot of 'The regression CD task' with 'Data' and 'Model' sections.
- Two-Miner**: Shows a scatter plot of 'The two-miner CD task' with 'Data' and 'Model' sections.
- Real-World Examples**
- Sample Bias**: Shows a scatter plot of 'The sample bias CD task' with 'Data' and 'Model' sections.
- Flow-Testing**: Shows a scatter plot of 'The flow-testing CD task' with 'Data' and 'Model' sections.
- Deep-Domain Adaptation**: Shows a scatter plot of 'The deep-domain adaptation CD task' with 'Data' and 'Model' sections.

At the bottom, it says: "This work has been funded by Michelin and the Institut Data Analysis and Machine Learning that have CNRS Paris Saclay, Gif-sur-Yvette center."

[A. de Mathelin et. al, 2020].

a joint work on Transfer Learning

thanks to the Industrial Data Analytics and Machine Learning chair



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Motivations / Transfer methods / Applications & Numerical results / packages



Thank you!

References

-  de Mathelin, A., Richard, G., Deheeger, F., Mougeot, M., and Vayatis, N. (2021).
Adversarial weighting for domain adaptation in regression.
In *2021 IEEE 33rd International Conference on Tools with Artificial Intelligence (ICTAI)*, pages 49–56. IEEE.
-  Ganin, Y. and Lempitsky, V. (2015).
Unsupervised domain adaptation by backpropagation.
In *International conference on machine learning*, pages 1180–1189. PMLR.
-  Minvielle, L., Atiq, M., Peignier, S., and Mougeot, M. (2019).
Transfer learning on decision tree with class imbalance.
In *2019 IEEE 31st international conference on tools with artificial intelligence (ICTAI)*, pages 1003–1010. IEEE.
-  Minvielle, L., Atiq, M., Serra, R., Mougeot, M., and Vayatis, N. (2017).
Fall detection using smart floor sensor and supervised learning.
In *2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 3445–3448.
-  Mounir, A., Sergio, P., and Mathilde, M. (2021).
Constrained prediction time random forests using equivalent trees and genetic programming : application to fall detection model embedding.
In *2021 IEEE 33rd International Conference on Tools with Artificial Intelligence (ICTAI)*, pages 690–697. IEEE.
-  Richard, G., Mathelin, A. d., Hébrail, G., Mougeot, M., and Vayatis, N. (2021).
Unsupervised multi-source domain adaptation for regression.
In *Machine Learning and Knowledge Discovery in Databases : European Conference, ECML PKDD 2020, Ghent, Belgium, September 14–18, 2020, Proceedings, Part I*, pages 395–411. Springer.