Domain Adversarial Neural Networks

A framework to train on labeled (simulated) and unlabeled (real) data

Marcus Engsig - bgr911
Gor Nahapetyan - xzn779
Frederik Hansen - bcp695
Johan Sieborg - hnw224

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Problem Statement

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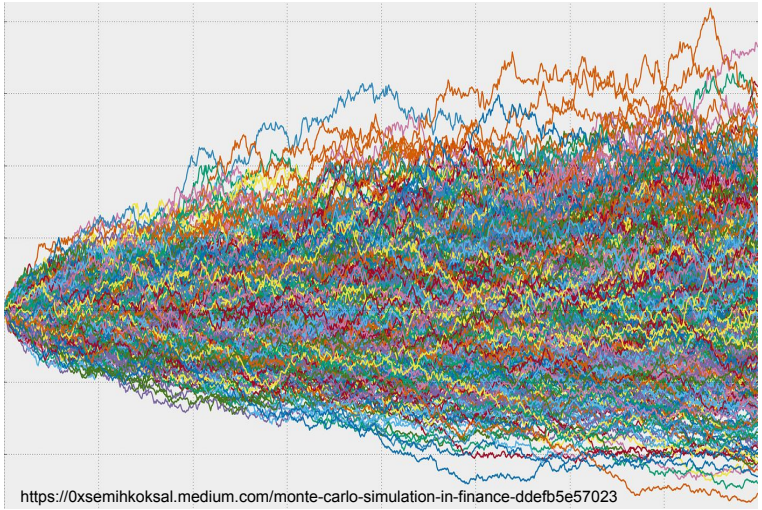

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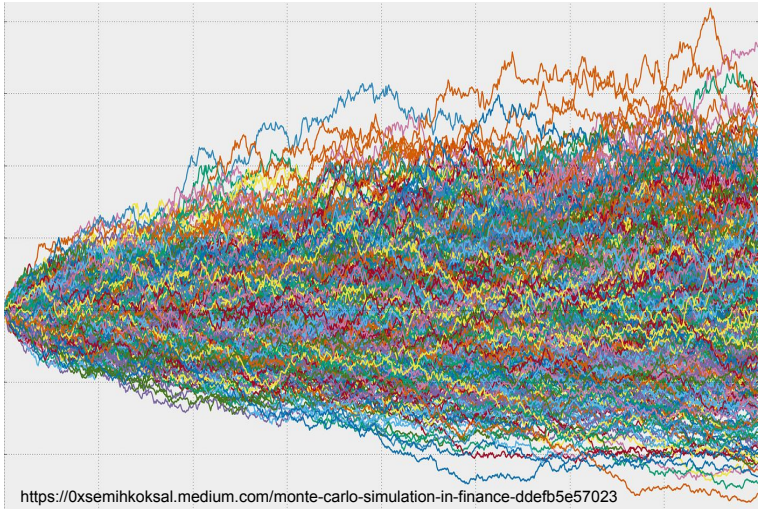

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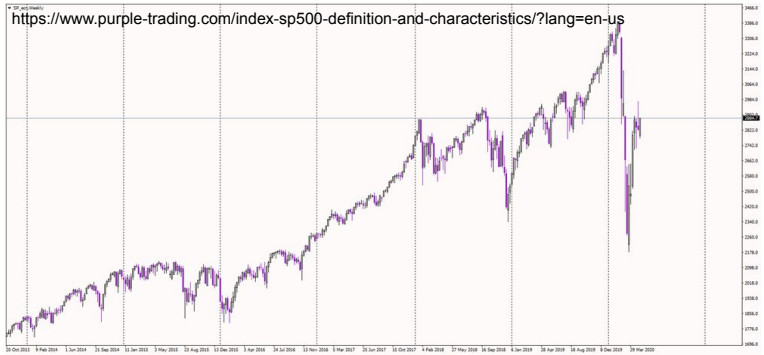

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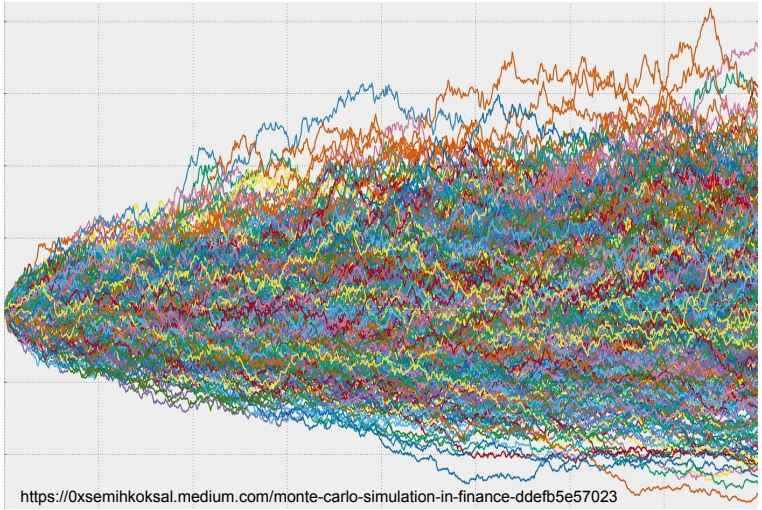

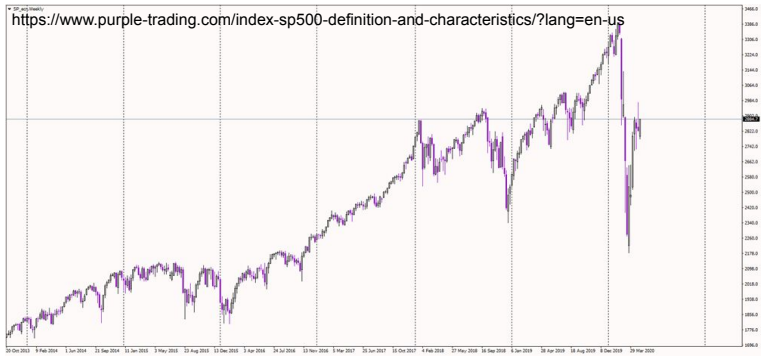

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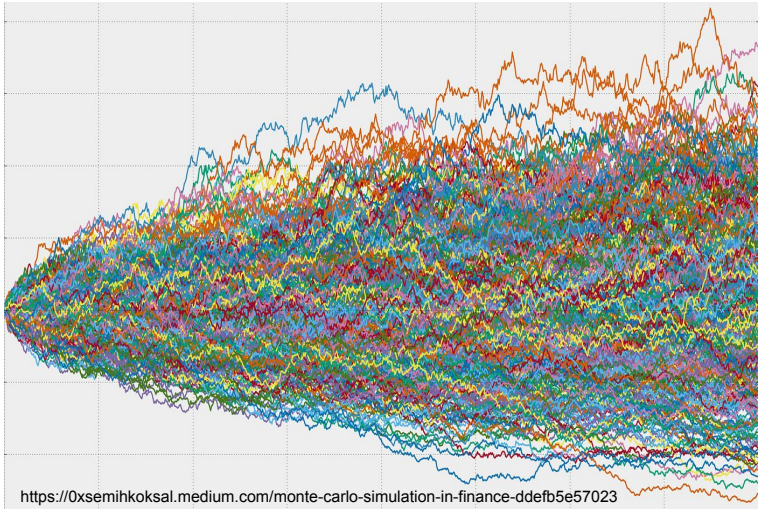

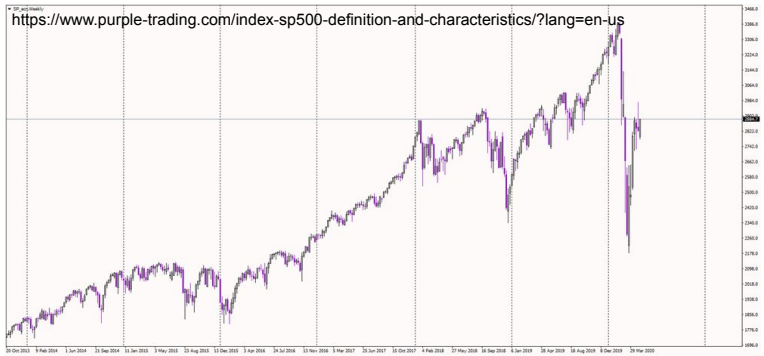

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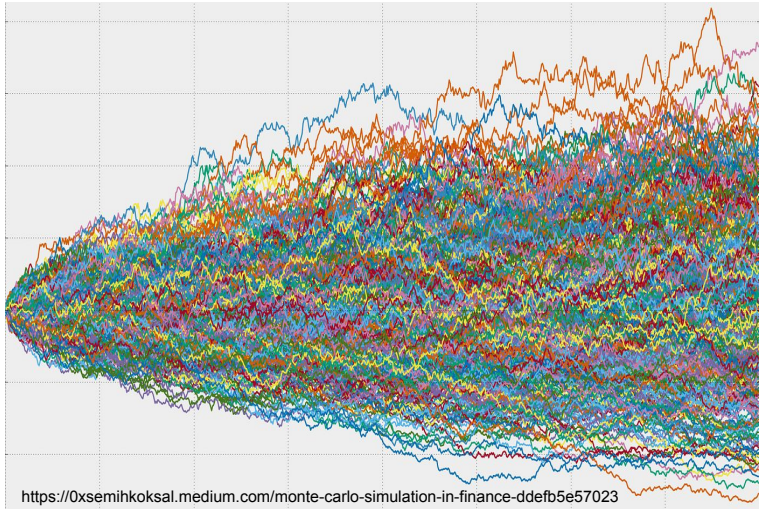

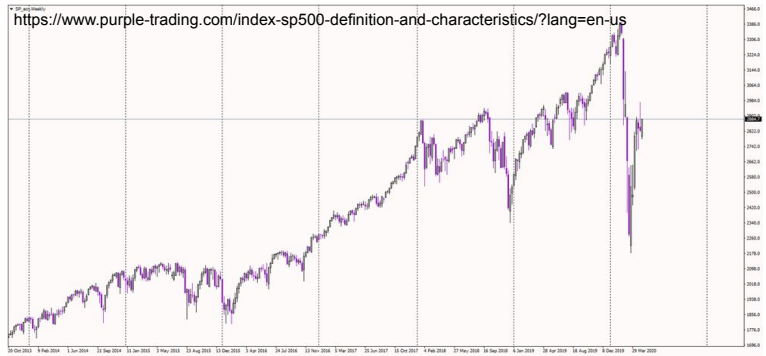

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Our dataset consists of:

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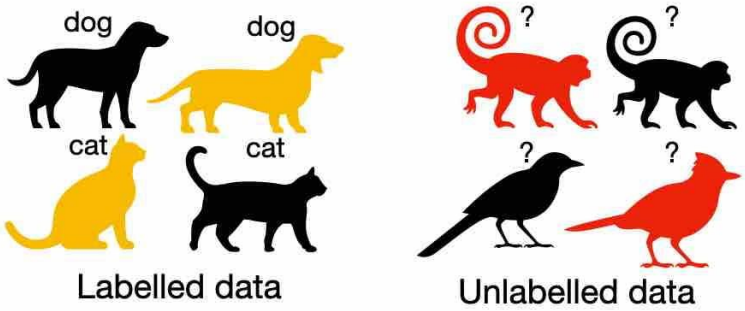

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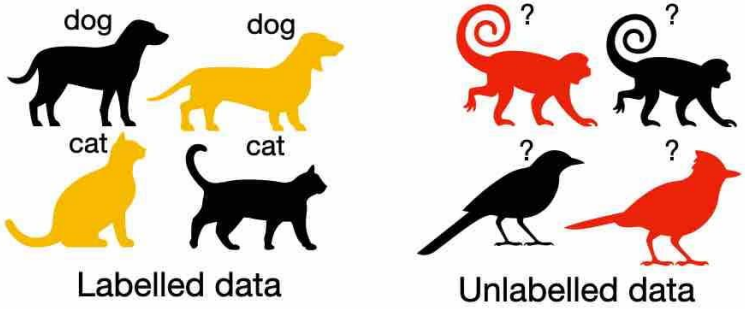

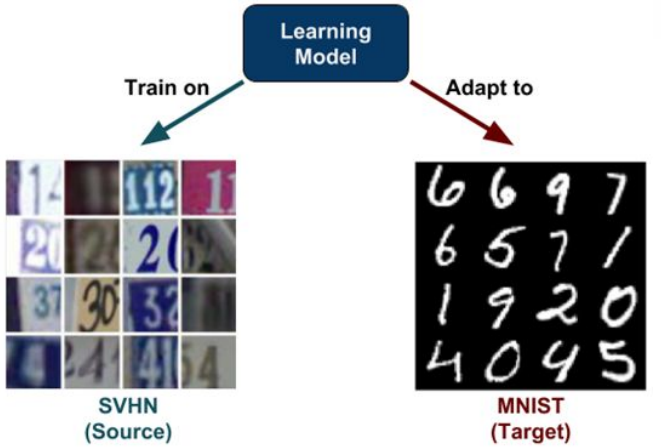

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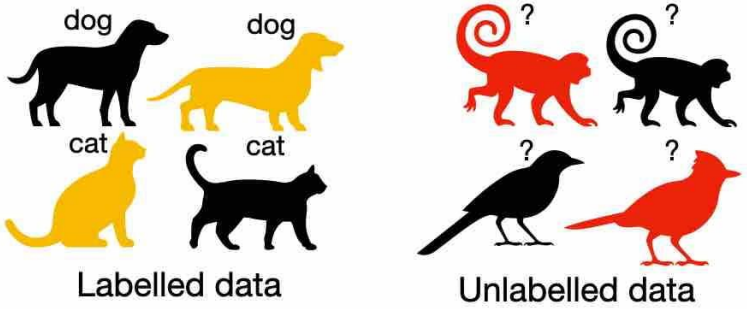

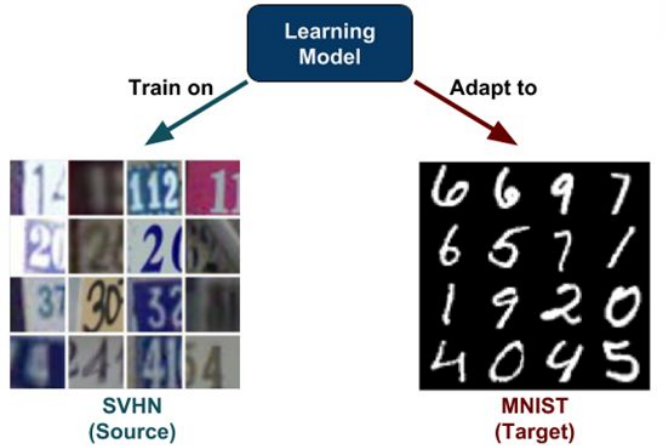

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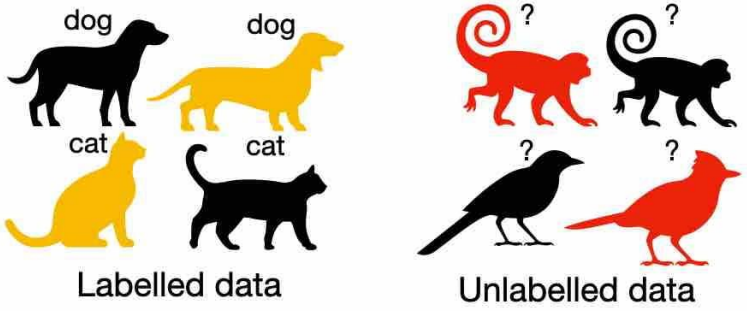
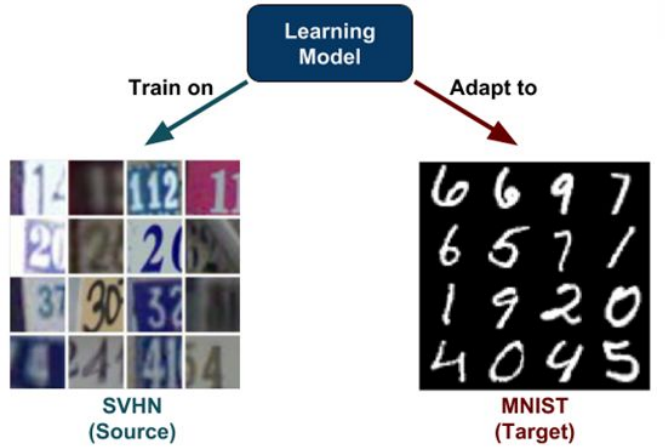
The label of being ‘simulated’ vs. ‘real’.





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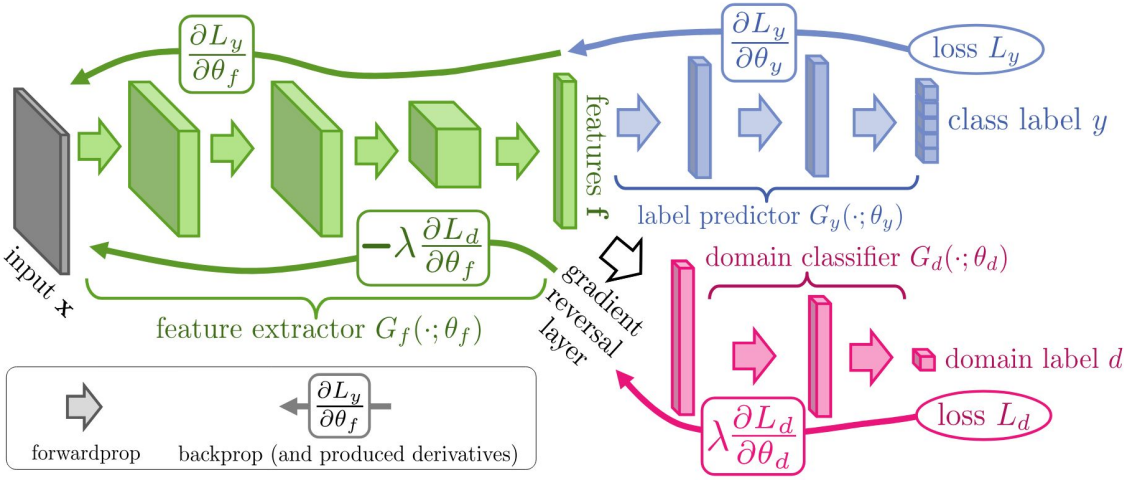

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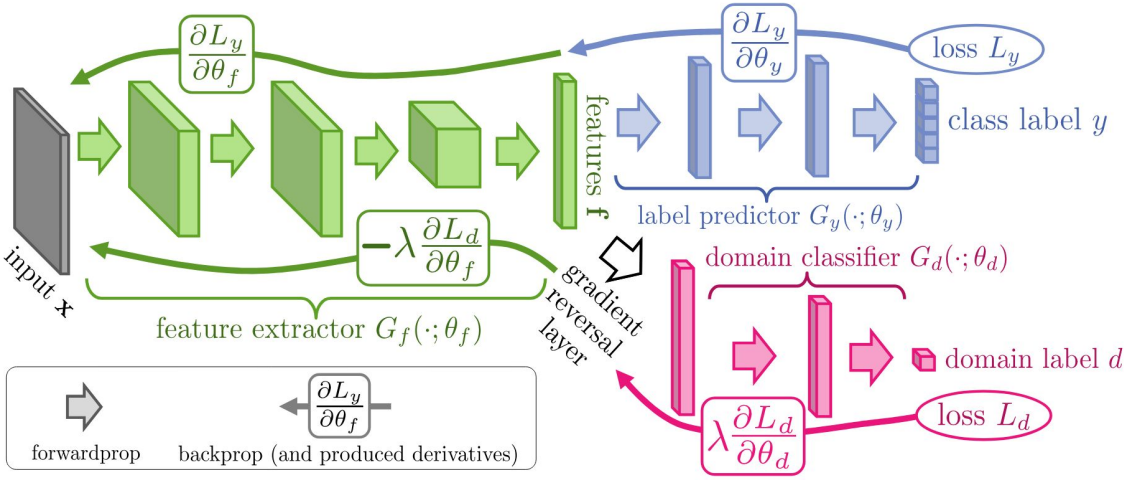

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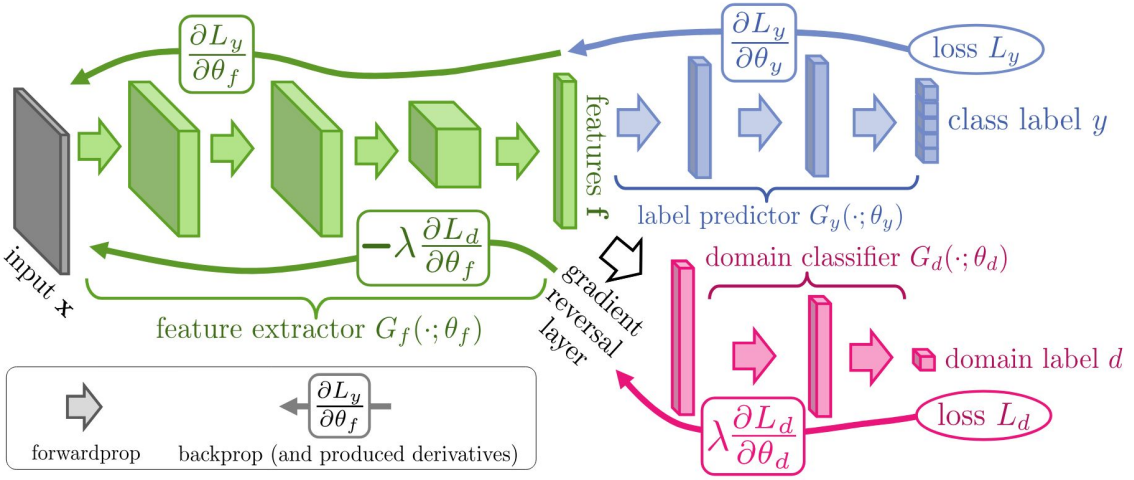

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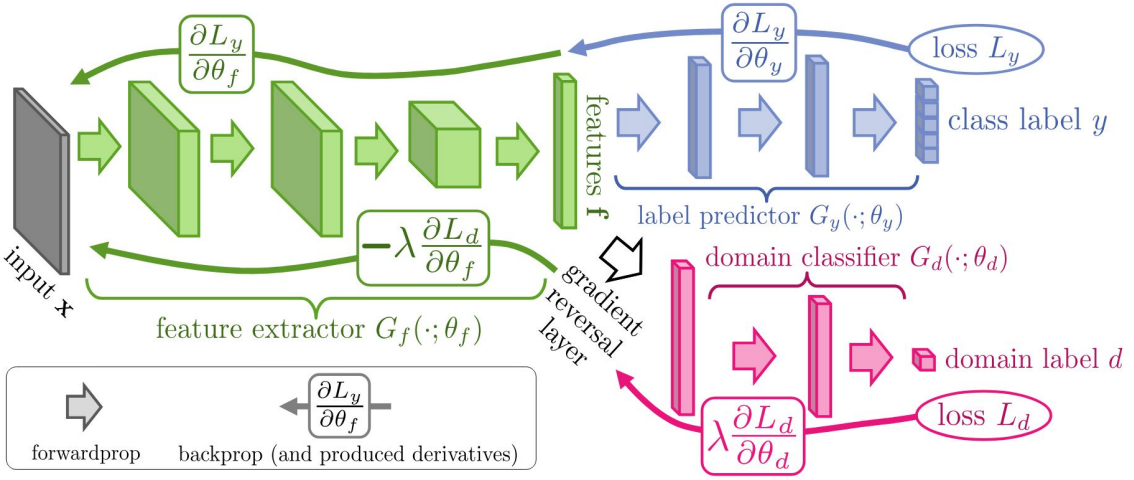

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3. The label predictor attempts to **classify** (main task) based on the **main-objective** labels from **only** the **simulated** data.

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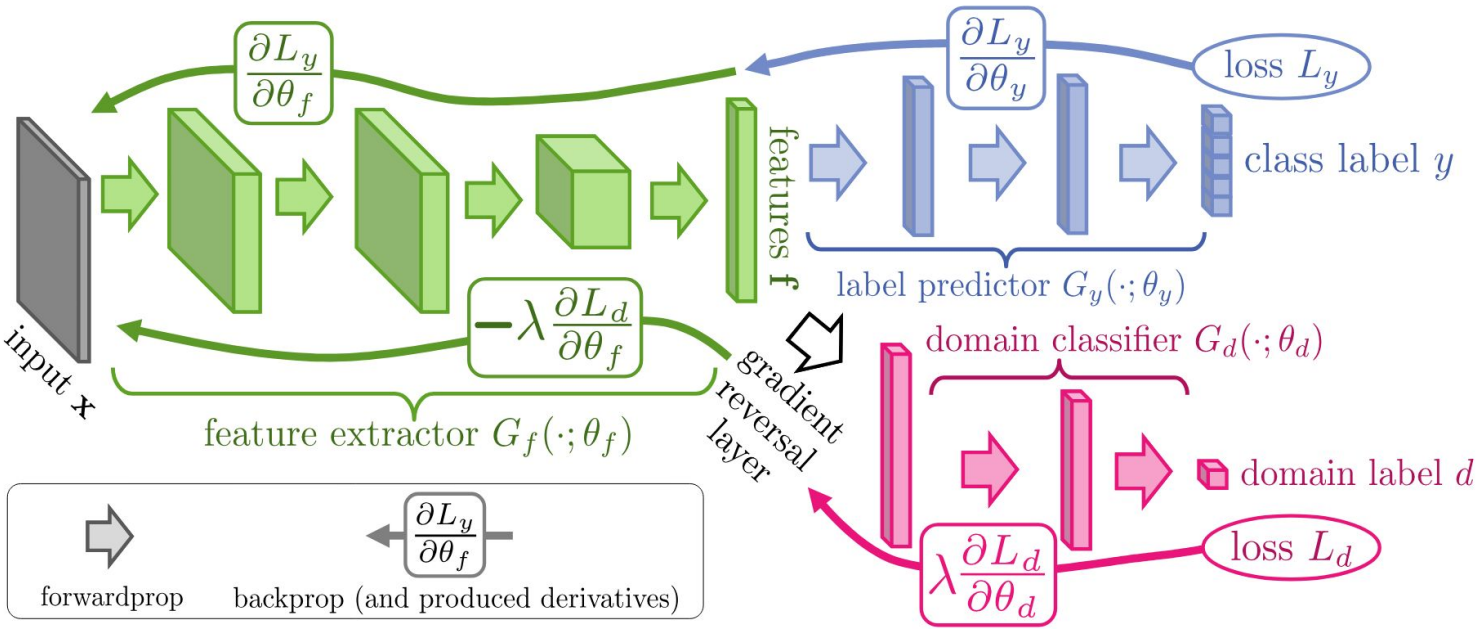
3. Train the Feature Extractor to '**fool**' the domain classifier → **reduce** simulated and real data into an **indistinguishable latent space**.



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Domain-Adversarial Training of Neural Networks

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Skolkovo Institute of Science and Technology (Skoltech)
Skolkovo, Moscow Region, Russia

Hana Ajakan HANA.AJAKAN.1@ULAVAL.CA
Pascal Germain PASCAL.GERMAIN@IFT.ULAVAL.CA
Département d'informatique et de génie logiciel, Université Laval
Québec, Canada, G1V 0A6

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Département d'informatique, Université de Sherbrooke
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Québec, Canada, G1V 0A6

Victor Lempitsky LEMPITSKY@SKOLTECH.RU
Skolkovo Institute of Science and Technology (Skoltech)
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Editor: Urun Dogan, Marius Kloft, Francesco Orabona, and Tatiana Tommasi

Abstract

We introduce a new representation learning approach for domain adaptation, in which data at training and test time come from similar but different distributions. Our approach is directly inspired by the theory on domain adaptation suggesting that, for effective domain transfer to be achieved, predictions must be made based on features that cannot discriminate between the training (source) and test (target) domains.

The approach implements this idea in the context of neural network architectures that are trained on labeled data from the source domain and unlabeled data from the target domain (no labeled target-domain data is necessary). As the training progresses, the approach promotes the emergence of features that are (i) discriminative for the main learning task on the source domain and (ii) indiscriminate with respect to the shift between the domains. We show that this adaptation behaviour can be achieved in almost any feed-forward model by augmenting it with few standard layers and a new *gradient reversal* layer. The resulting augmented architecture can be trained using standard backpropagation and stochastic gradient descent, and can thus be implemented with little effort using any of the deep learning packages.

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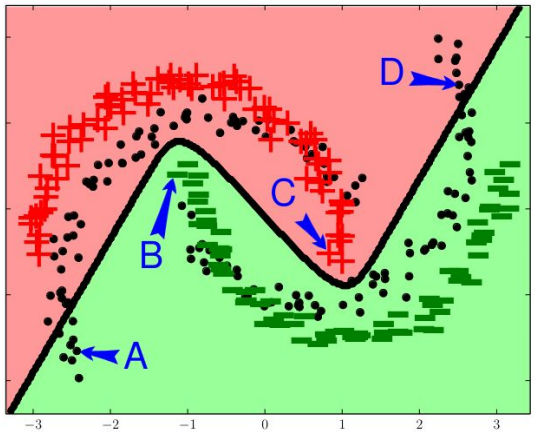

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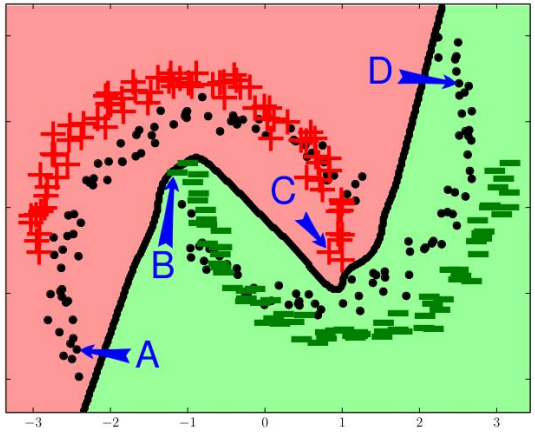

(Ganin et al. 2015)

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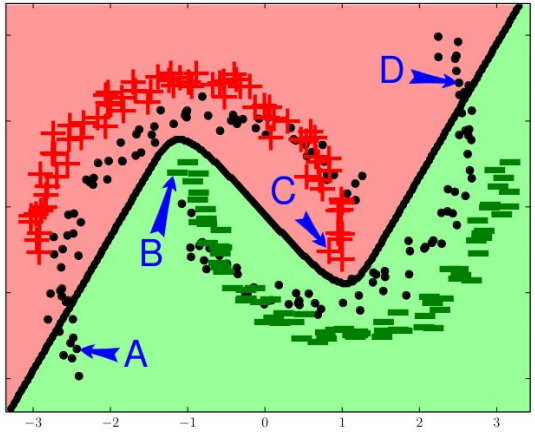

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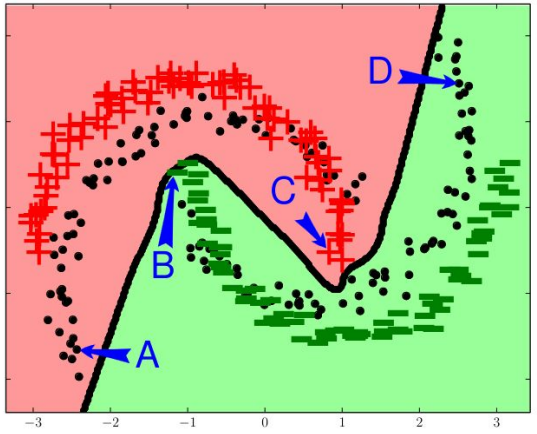
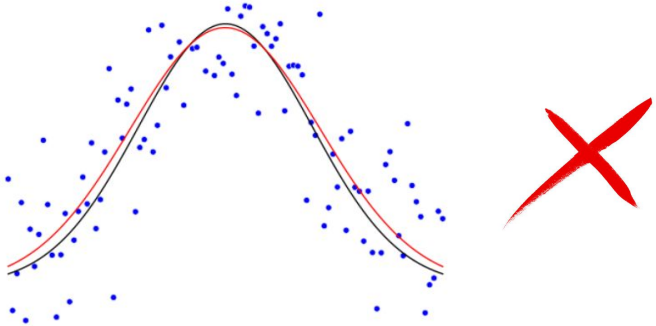


The data must be **fundamentally distinguishable**.

Random noise augmentation:



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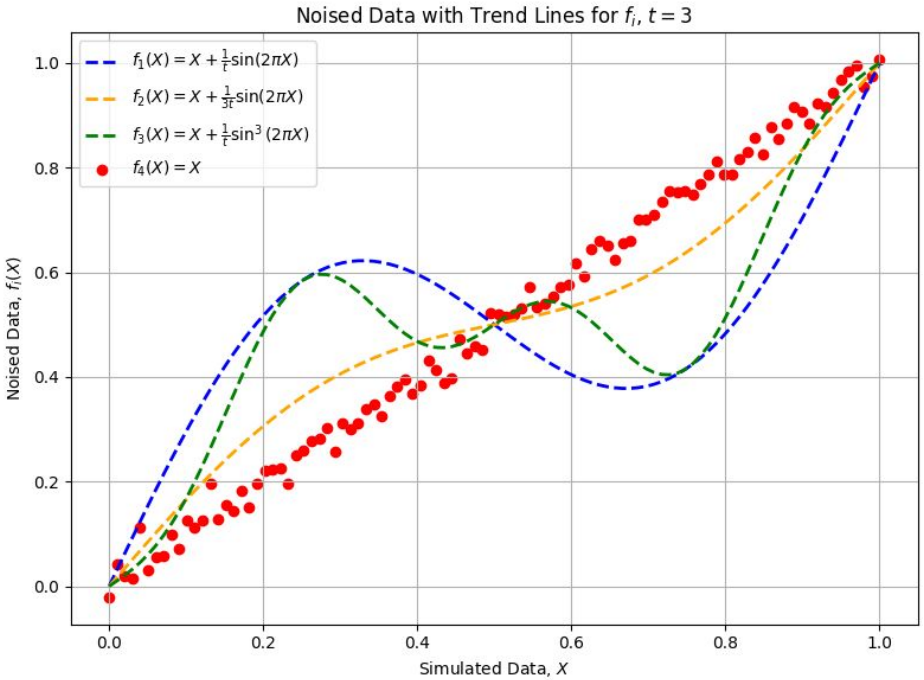

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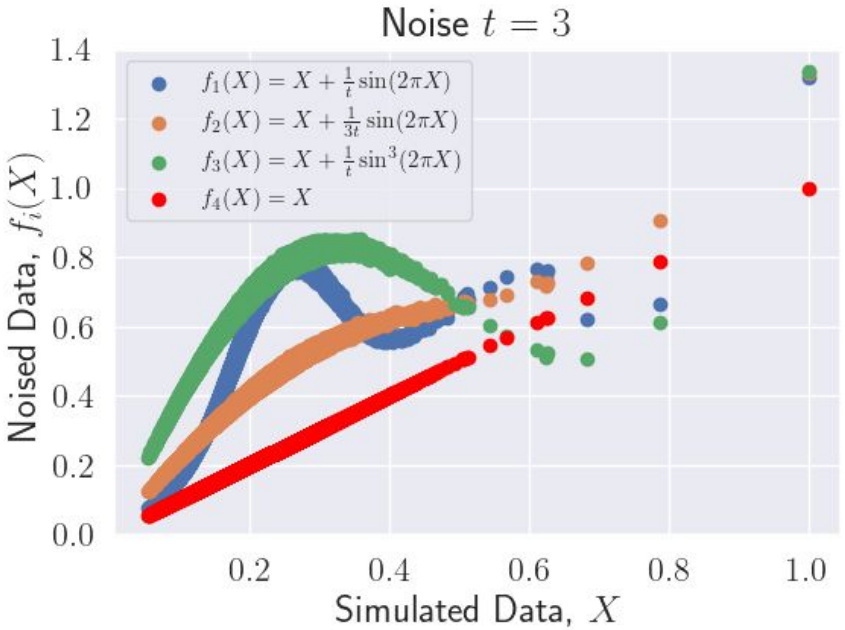

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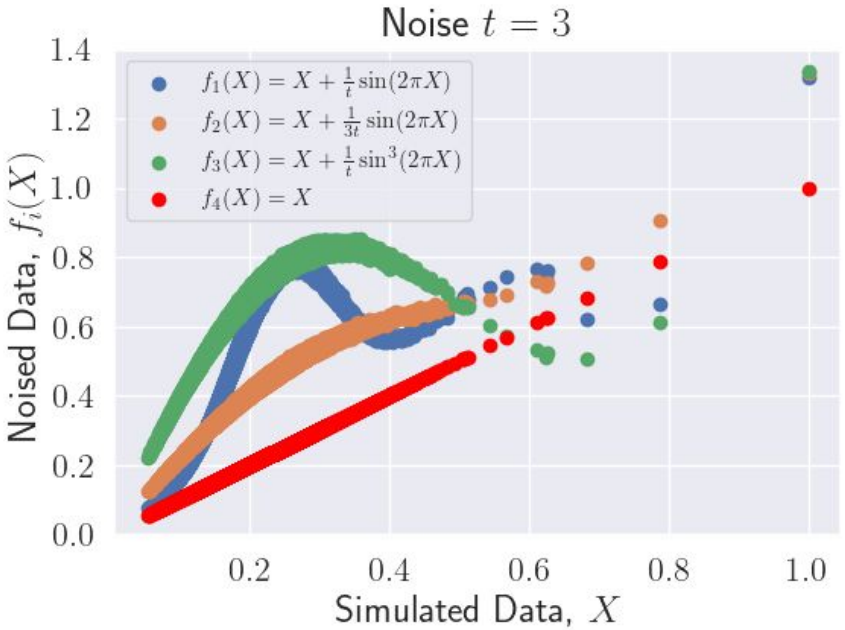
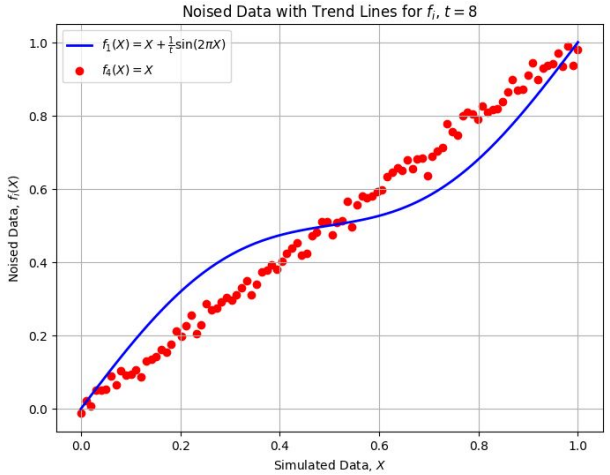


MLP - Our Null Hypothesis

We train an MLP: **t = 8**

1. Architecture: 6x10x10x10x5x1.
2. LR: 0.001 - with scheduler.
3. Validation loss early-stopper.



MLP - Our Null Hypothesis

We train an MLP: **t = 8**

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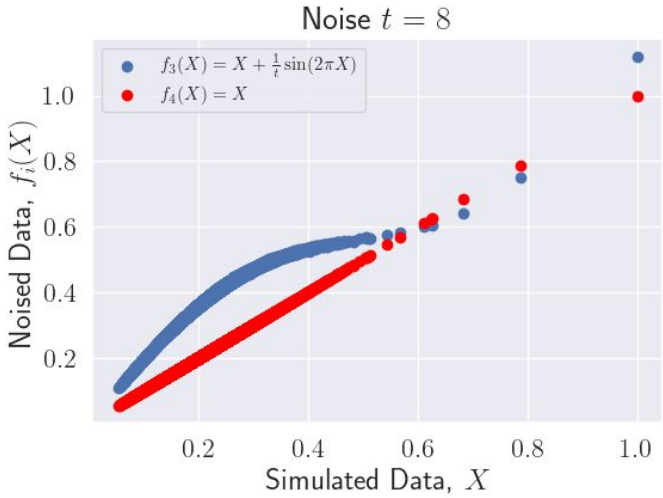
We **train** it on **‘simulated’ data**, and use it to **predict** the **‘real’ data**.



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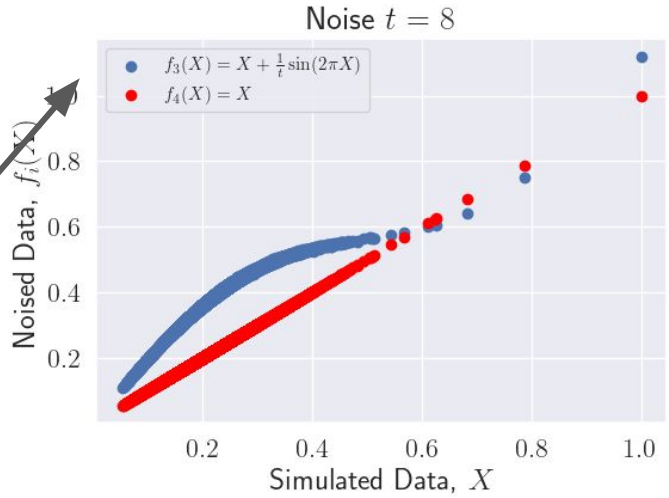

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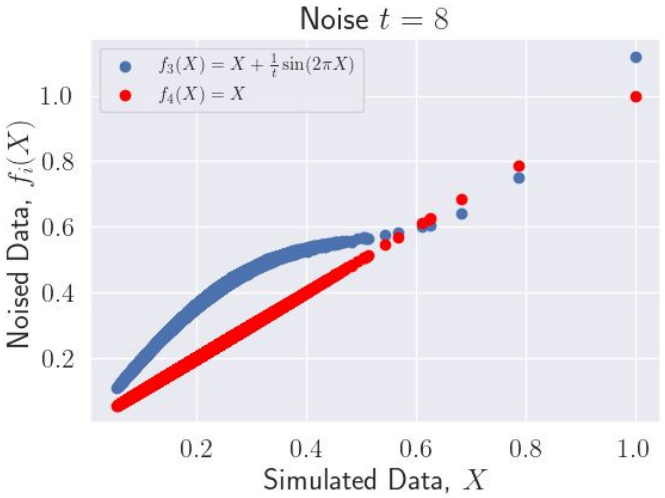
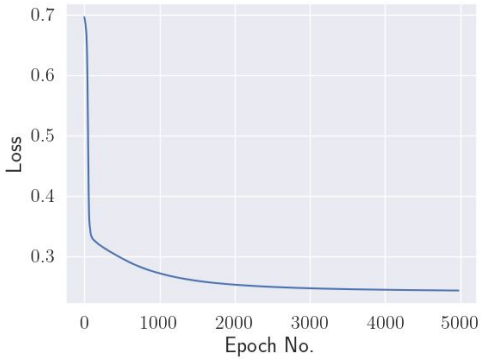
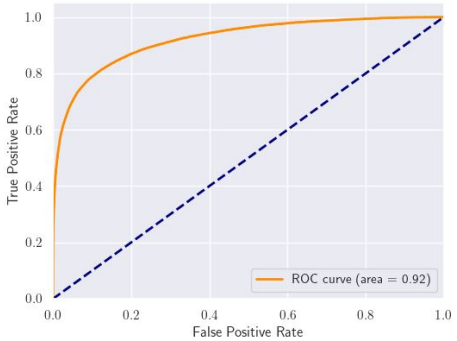




Real Accuracy = 0.889



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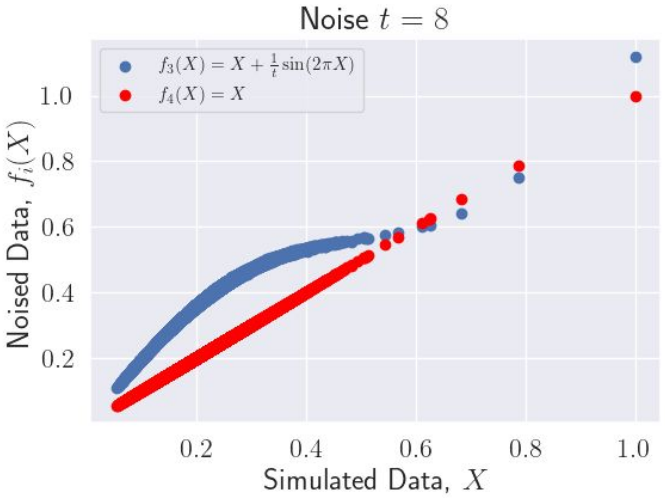
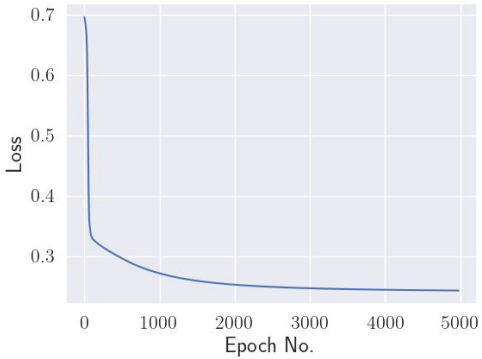
For small transformations MLPs do great!





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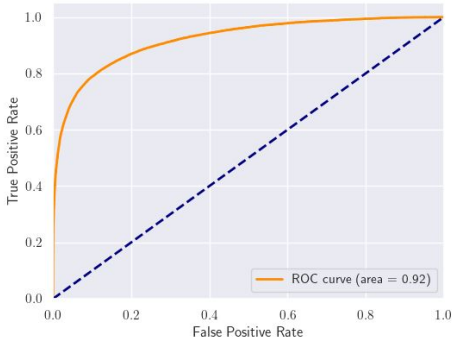

MLP - Our Null Hypothesis… Lets increase the noise!

We train an MLP: **t = 3**

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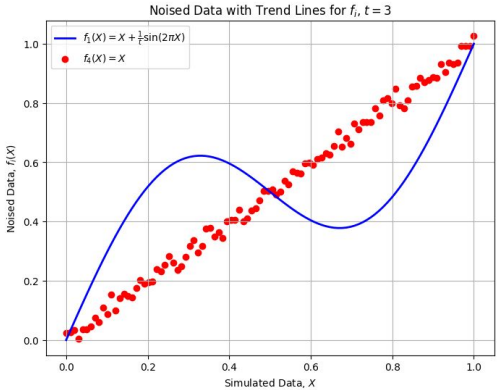

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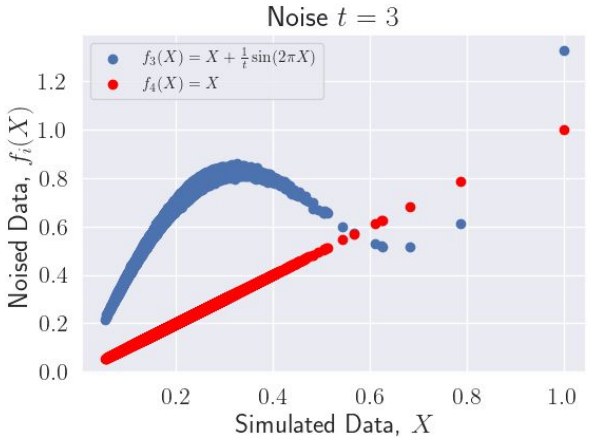

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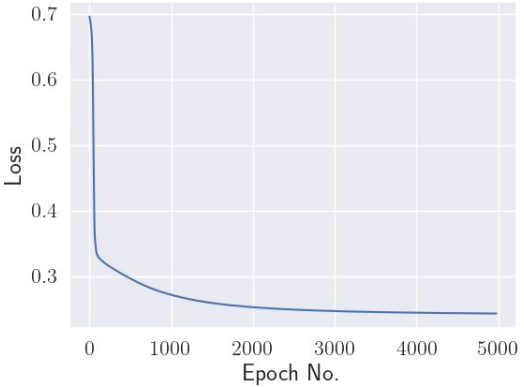

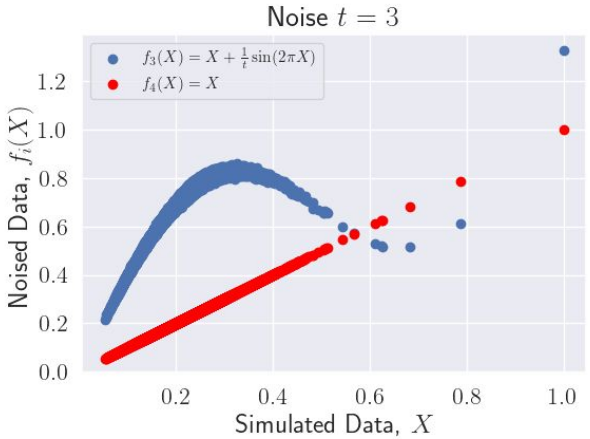

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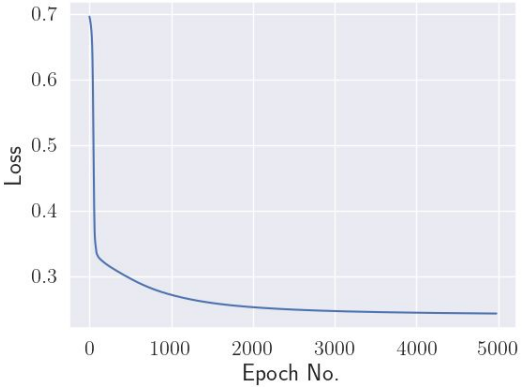
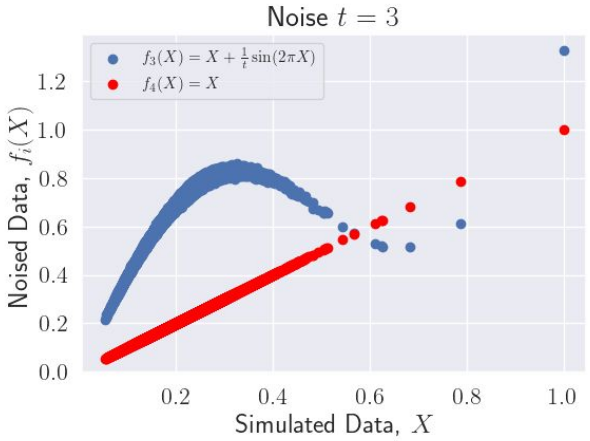
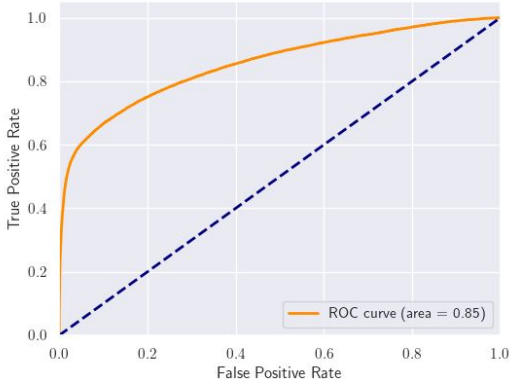




Real Accuracy = 0.693



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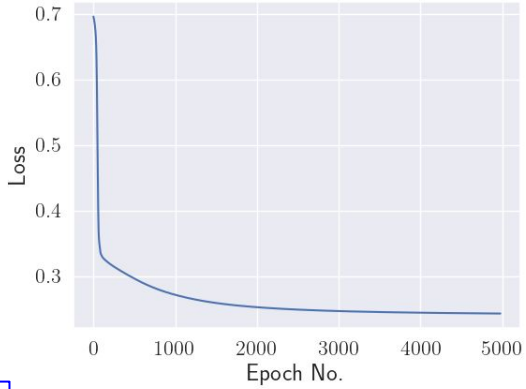

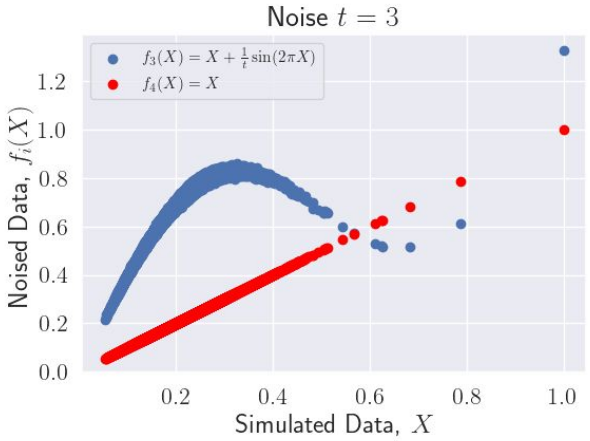

The MLP **breaks** when there is a clear **domain shift**.

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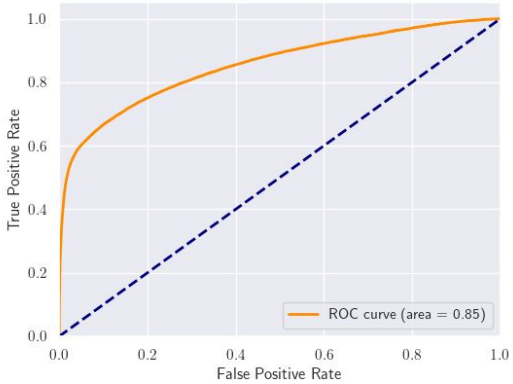
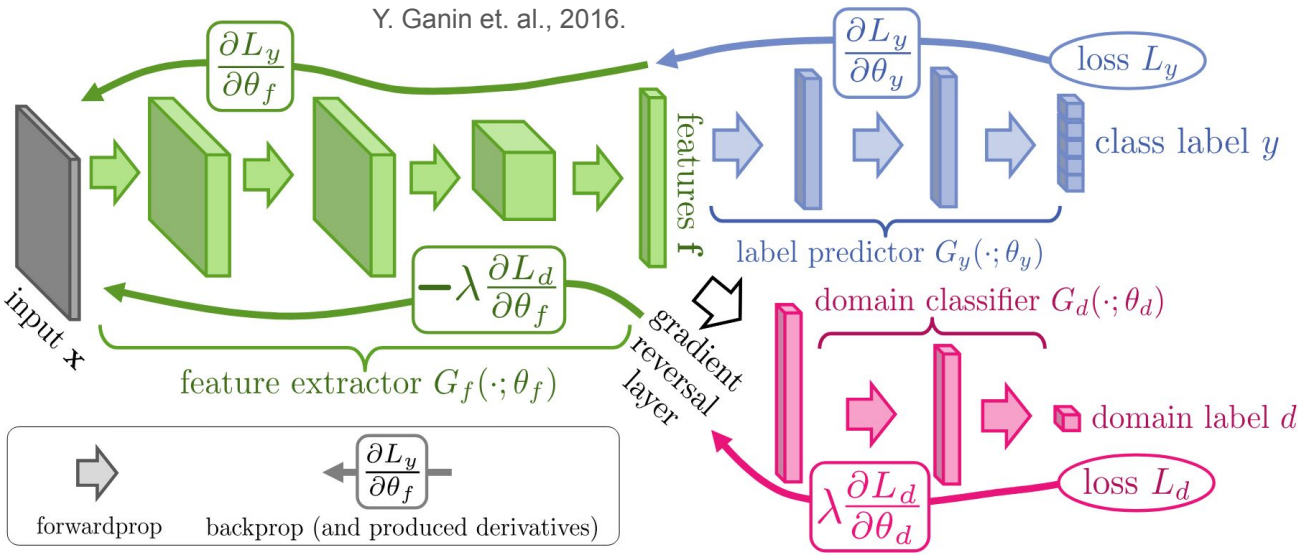


A quick reminder on DANNs



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

Domain Adversarial Neural Networks on noisy data

We train an DANN: **t = 3, λ = 50**

1. Architecture: Main task 6x10x10x10x5x1,
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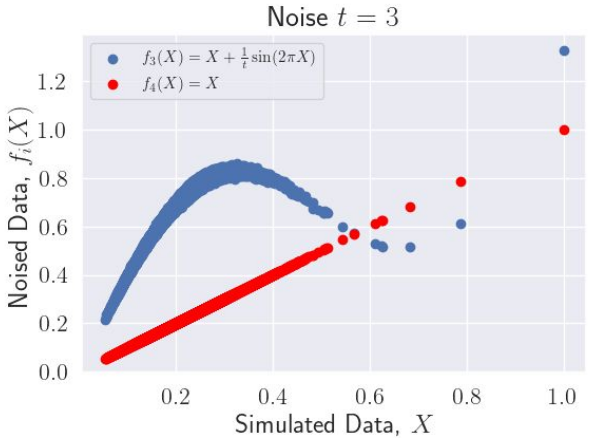

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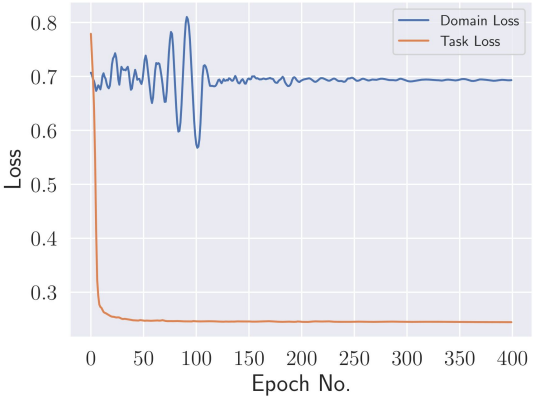

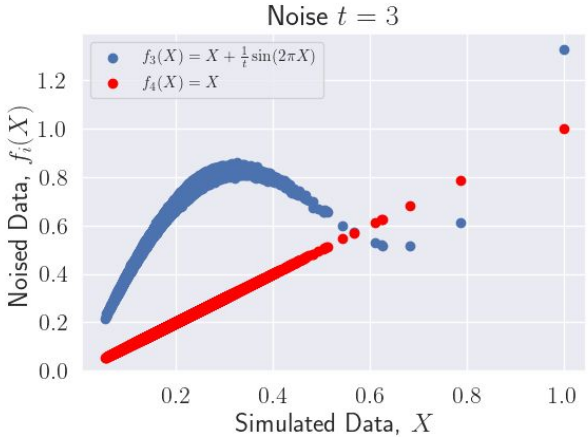

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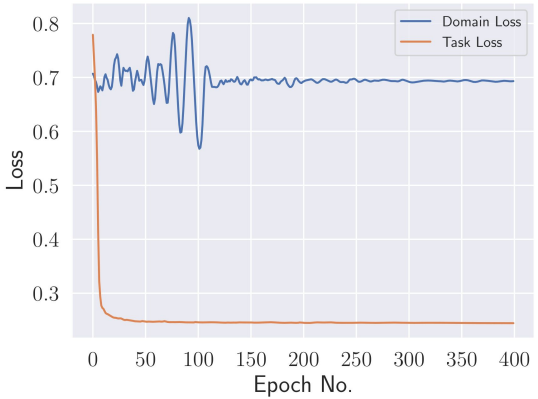

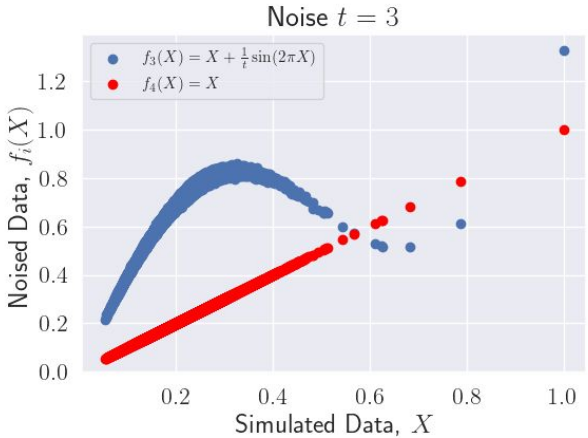

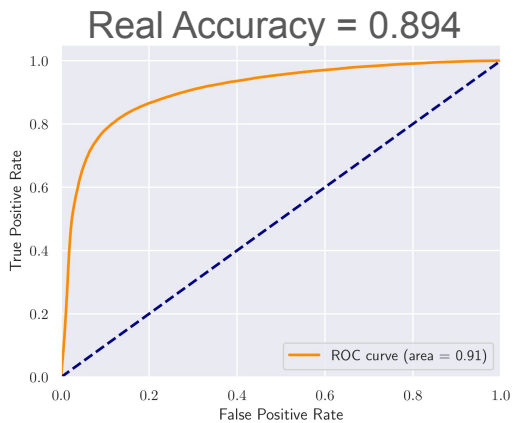

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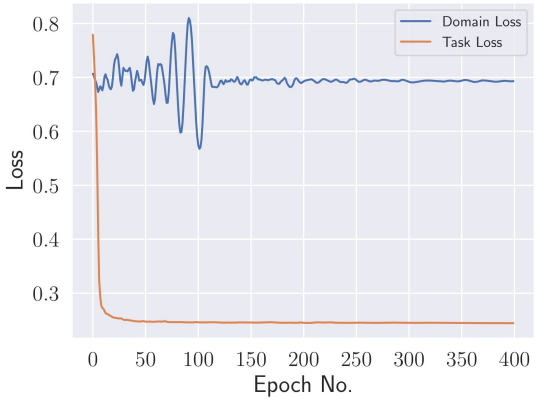
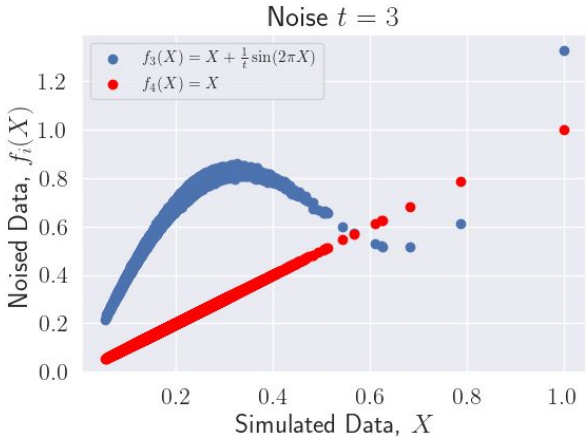


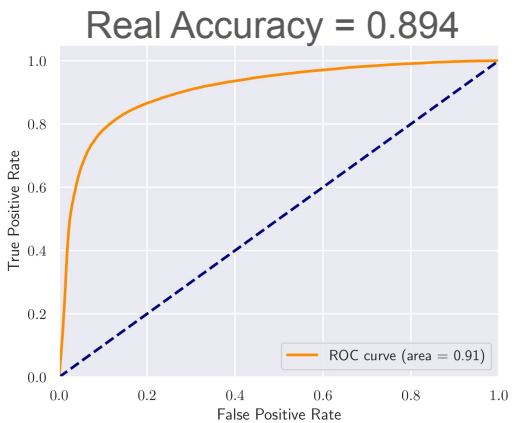


MLP:

Real Accuracy = 0.693

DANN:

Real Accuracy = 0.894



Exploring DANNs further - Multiple Transformations

We train an DANN: **$t = 3, \lambda = 150$**

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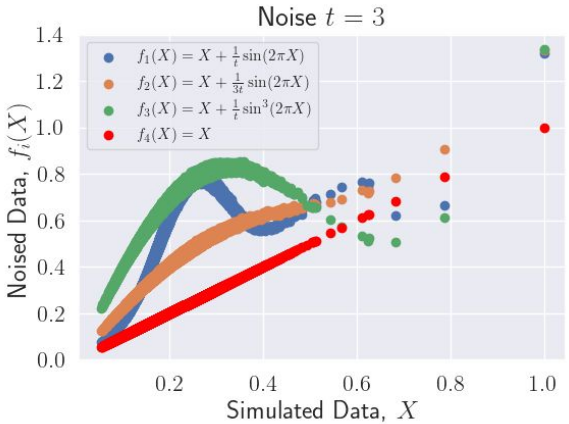

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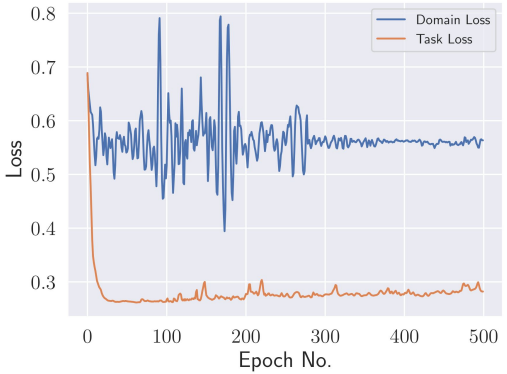

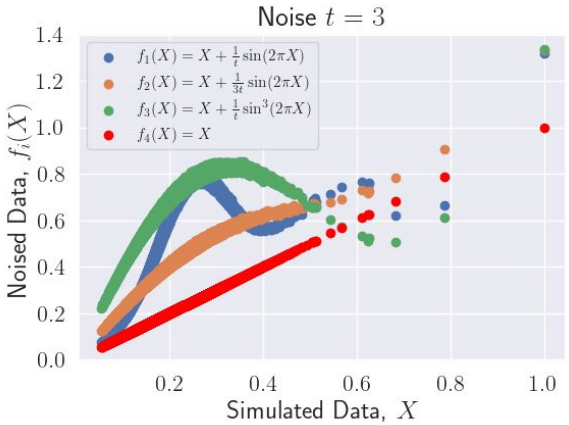

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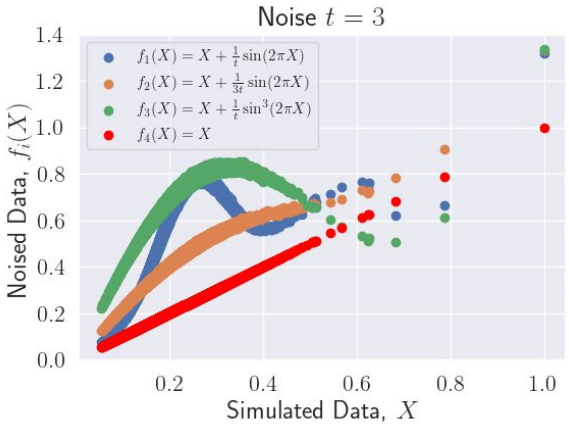
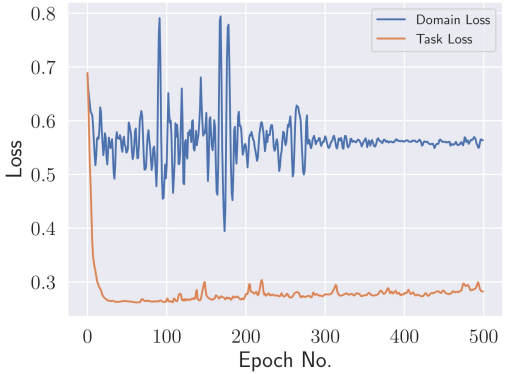
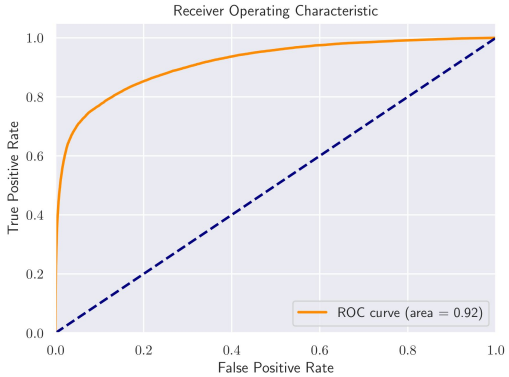




Real Accuracy = 0.899



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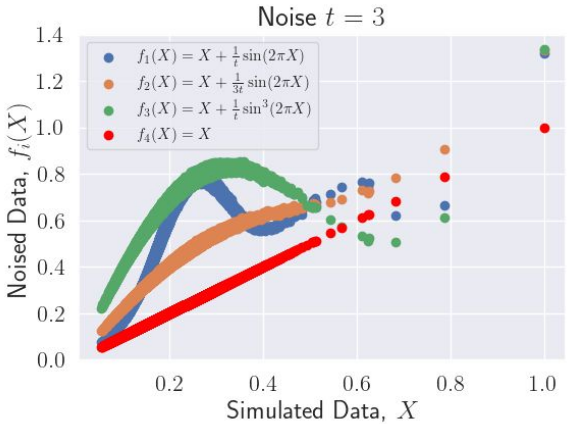

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Real Accuracy = 0.693

DANN:
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Hybrid-DANN:
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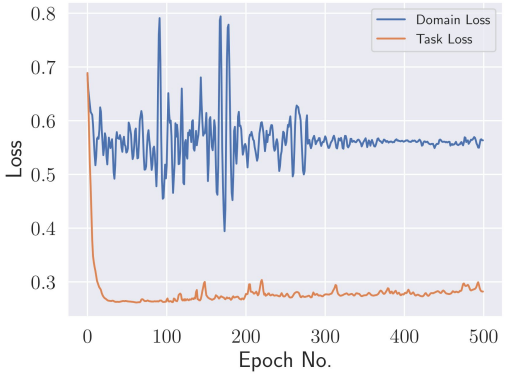

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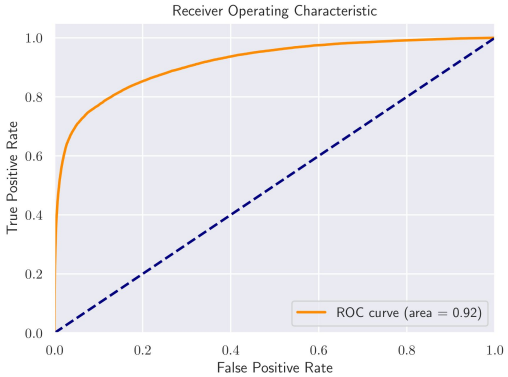
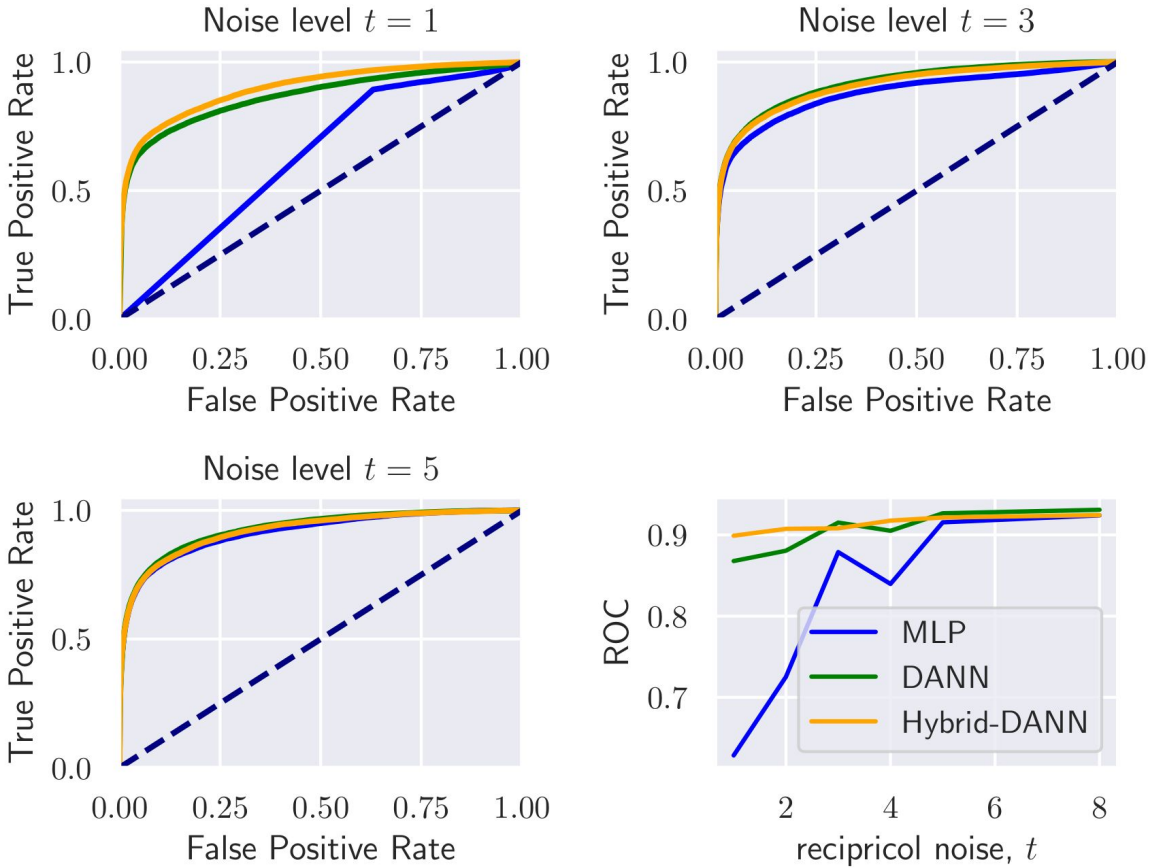


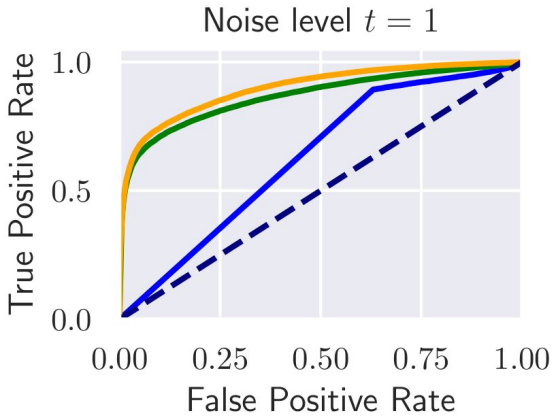
Main Results

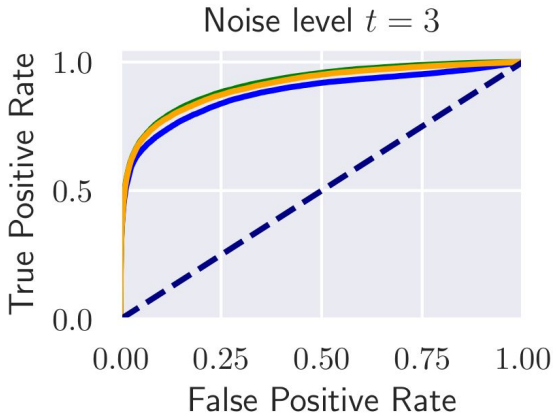
- DANNs provide a methodology to generalize simulated data to real data.

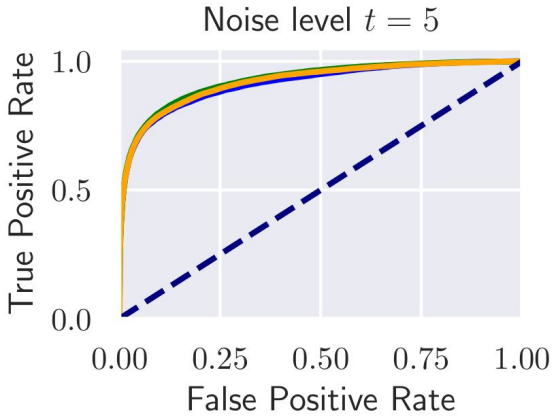


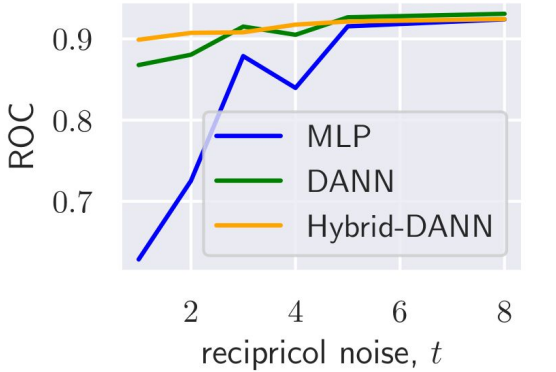
Main Results

- DANNs provide a methodology to generalize simulated data to real data.
- Relative increase in performance increases as quality of simulation decreases.



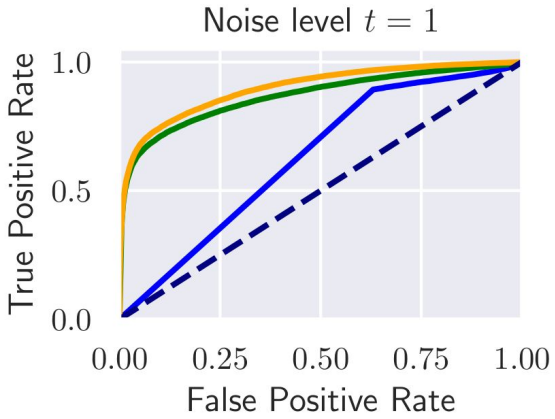


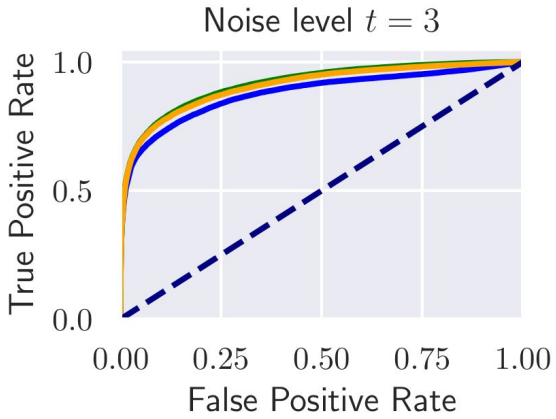


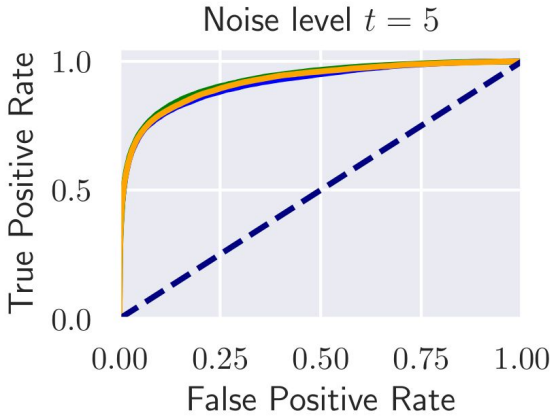


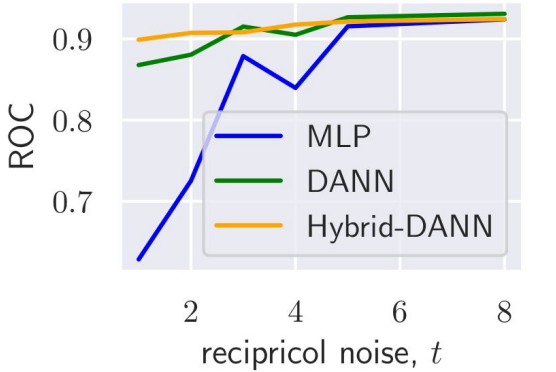
Main Results

- DANNs provide a methodology to generalize simulated data to real data.
- Relative increase in performance increases as quality of simulation decreases.
- Multiple noise profiles can be generalized via a Hybrid-DANN approach, taking advantage of pairwise learning.









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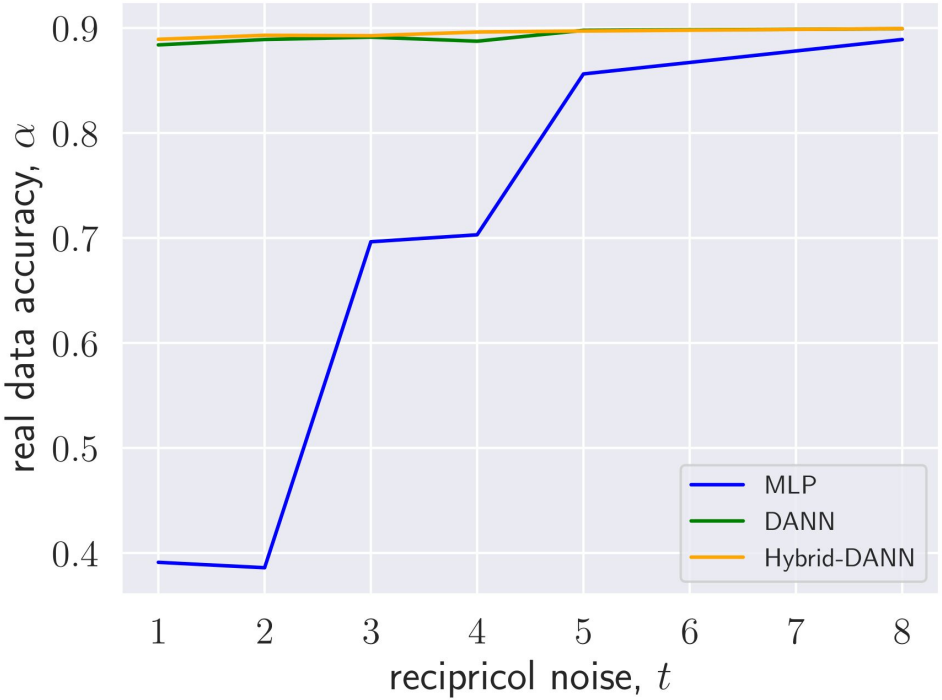
- DANNs provide a methodology to generalize simulated data to real data.
- Relative increase in performance increases as quality of simulation decreases.
- Multiple noise profiles can be generalized via a Hybrid-DANN approach, taking advantage of pairwise learning.

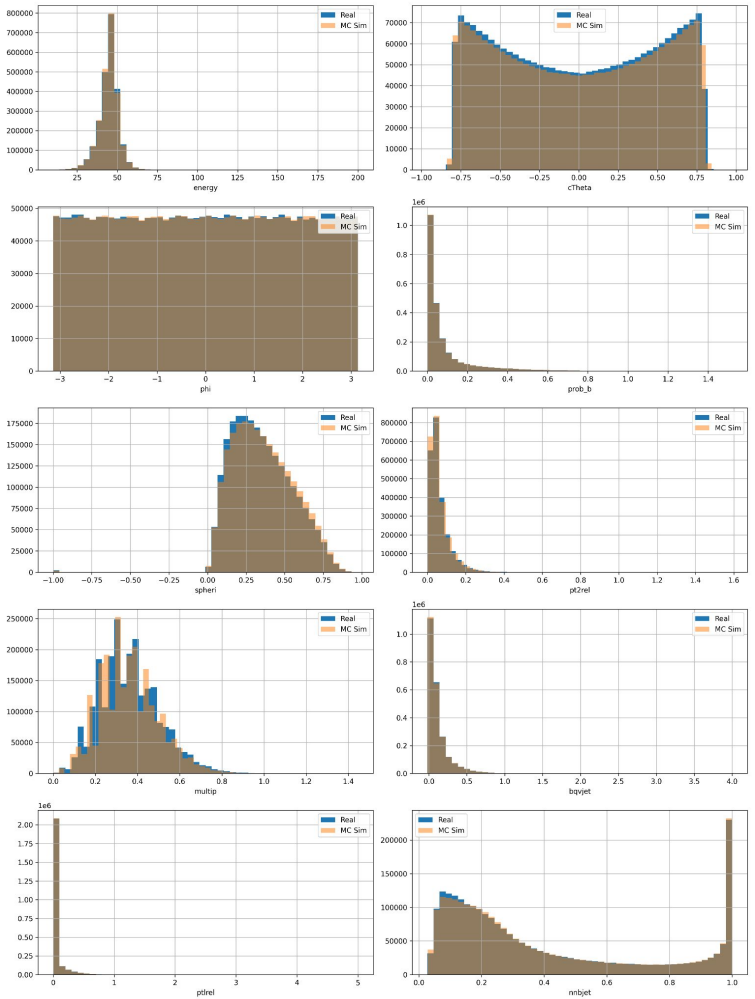


Main Results

We provided theoretical results with theoretical domain shifts.

- The target Aleph Bjet dataset had no domain shift.
- Indistinguishable from MC data.

Consequently, DANNs and Hybrid-DANNs are ineffective, as the fundamental adversarial cannot discriminate.



Thank you for your time (:

Appendix:

Ganin, Yaroslav, Evgeniya Ustinova, Hana Ajakan, Pascal Germain, Hugo Larochelle, François Laviolette, Mario Marchand, and Victor Lempitsky. 2015. “Domain-Adversarial Training of Neural Networks.” http://arxiv.org/abs/1505.07818

GitHub:

https://github.com/mengsig/APML_DANN

Real Data - Aleph data results

- Unfortunately, due to the lack of a domain shift between the Monte Carlo and real data, DANNs were not applicable. In summary we found for t = 3:

ML-Architecture	Naive MLP	DANN	Hybrid-DANN
Real Data Accuracy	0.853	0.732	0.841

- Showcasing that the Domain Adversarial Neural Networks could not discriminate the real and simulated data. Moreover, the Hybrid-DANN only does better than the DANN due to the pairwise learning that exists in this architecture.
- That however, does not mean that DANNs are not applicable to real data! It just means that they are applicable when there is a real domain shift in the data!

Different DANN backpropagation

- In our initial implementation (see Github **_novel_learning.py files), we treated the entire model as a single entity, and did backpropagation in the following manner.
  - Forward pass of simulated data with full gradient checkpointing.
  - Forward pass of real data without gradient checkpointing in the Label Classifier.
  - Gradient reversal layer between Feature Extractor and Domain Classifier.
  - Full back-propagation based on the sum off

    total_loss = label_loss + lambda * domain_loss

  - This resulted in similar results to the real DANN, but for different reasons, as the Domain Classifier had substantially higher accuracy. Occasionally, this model outperformed the normal DANN.

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- We use a metric called **consistency:**

$$\text{Consistency} = 1 - \frac{1}{N}\sum_{i=1}^{N}\left|\hat{y}_i - \frac{1}{k}\sum_{j\in k\text{-NN}(x_i)}\hat{y}_j\right|$$

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Prediction of i-th observation

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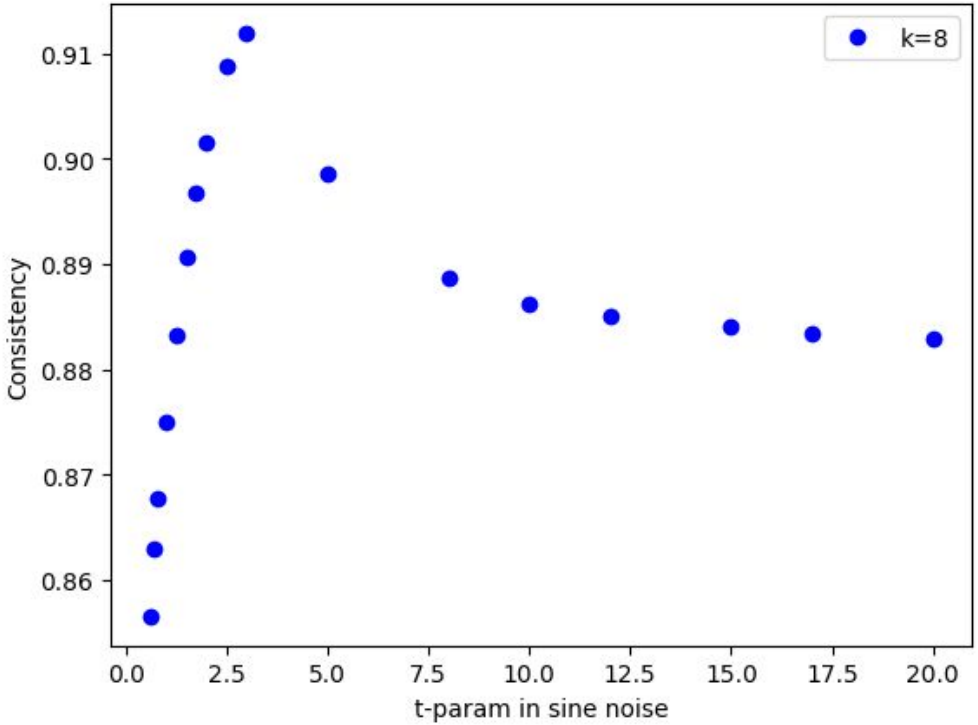
Predictions of its
k-nearest neighbors

Consistency metric - sinusoidal transformation



Consistency metric - Gaussian transformation