INSIGHT INTO FAIR UNIVERSE: BINARY CLASSIFICATION OF TABULAR DATA AFFECTED BY SYSTEMATIC UNCERTAINTY

JDSE 2023

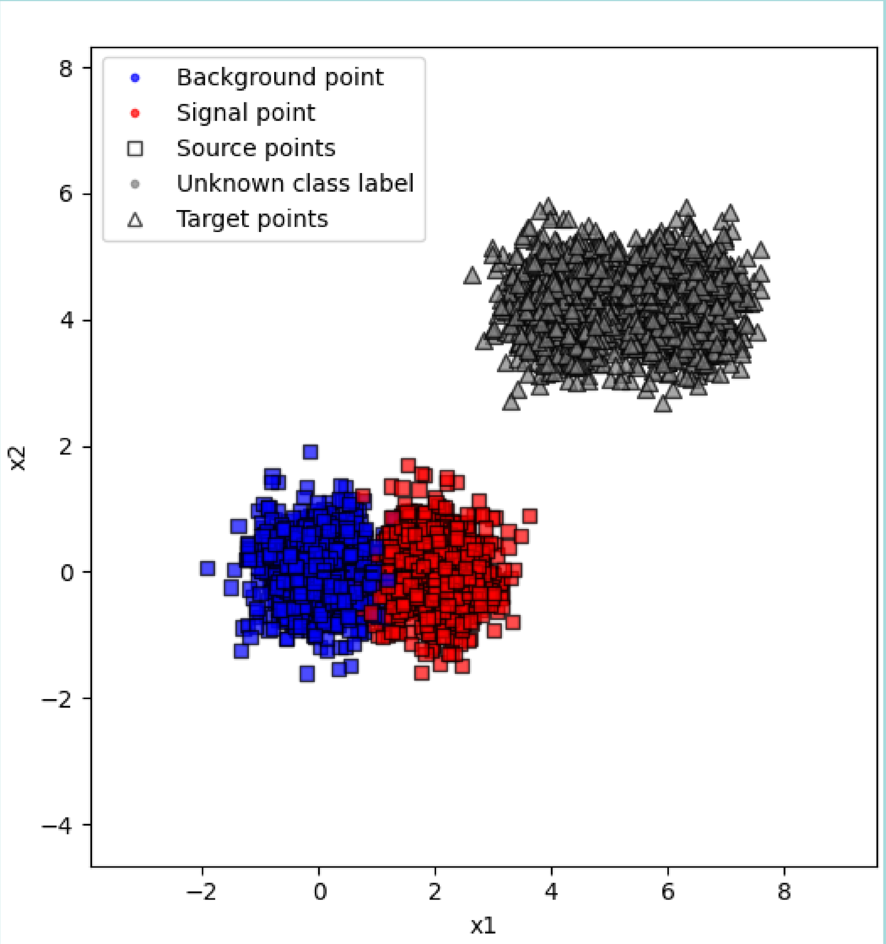
Mathis REYMOND [1], David ROUSSEAU [2]
1 : Master Artificial Intelligence - Université Paris-Saclay 2 : IJClab IN2P3 CNRS

INTRODUCTION

ABSTRACT

The Fair Universe project at LBNL is dedicated to creating an AI competition geared towards mitigating the impacts of systematic uncertainty in High Energy Physics. In the subsequent sections, we outline our perspective on the endeavor to establish a prototype competition. We compare two architectures for domain adversarial neural network : the two-branched architecture, that we have been working on, and an earlier architecture that was utilized within a comparable framework. Furthermore, we introduce an increased training framework for the two-branched architecture. Concluding our discussion, we offer a critique of the conventional approach taken in the comparison of such models.

PROBLEM STATEMENT



Given a labelled source set, perform binary classification of a target set plagued with systematic uncertainty

fig. 1.1

DOMAIN ADVERSARIAL NEURAL NETWORKS (DANN)

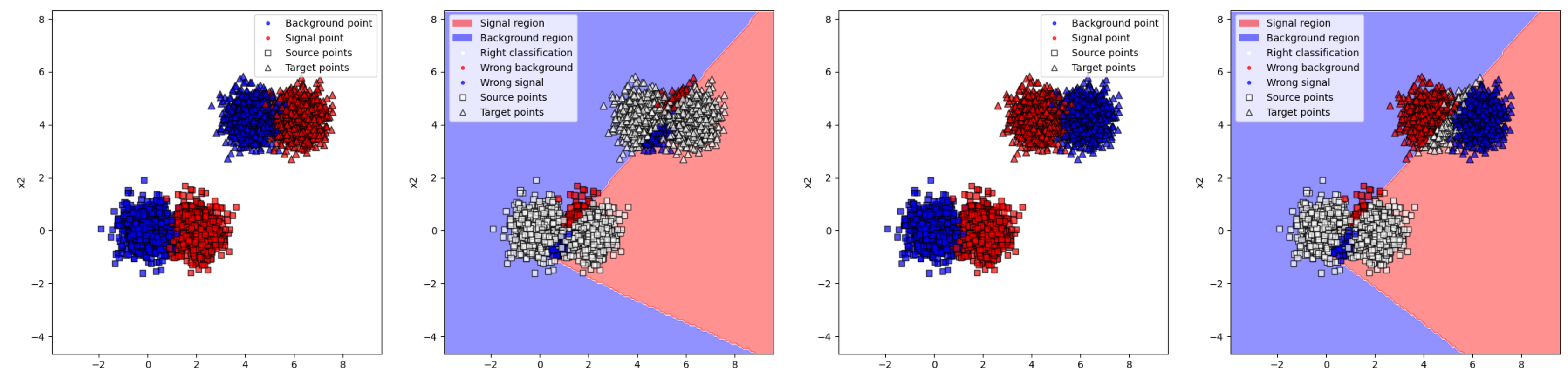


fig. 2.1 fig. 2.2 fig. 2.3 fig. 2.4

DANNs perform domain adaptation. They are made of two components :

- a classifier, which learns classification with labelled source data
- an adversary, which is responsible for transfer learning from source to target domain

The adversary enables the classifier to predict source and target data labels indiscriminately.

DANN does not have access to target labels. Consequently, the learning process is identical in [fig. 2.1] and [fig. 2.3], leading to the elaboration of similar decision boundaries in [fig. 2.2] and [fig. 2.4]. However, it's important to note that the two cases are not equivalent, and the performance on the target set is notably poor in [fig. 2.4].

MAIN EXPERIMENTS AND RESULTS

PIVOT VS TWO-BRANCHED

Pivot Model

- Learns to adapt to multiple target domains simultaneously, which can lead to conflicts in the learning process
- [Fig. 3.1] Performs exceptionally well on the source set
- [Fig. 3.2] Decision boundary is not suited for the target set and the pivot model performs poorly on it

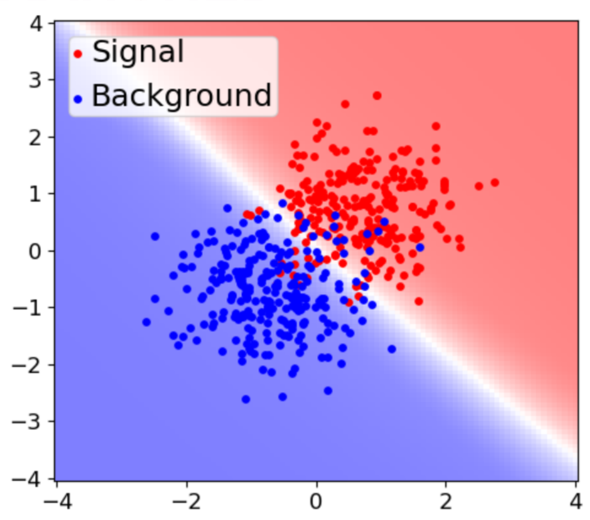


fig. 3.1

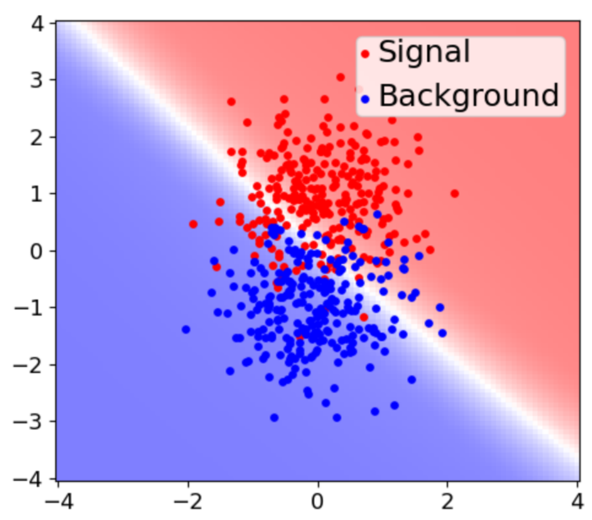


fig. 3.2

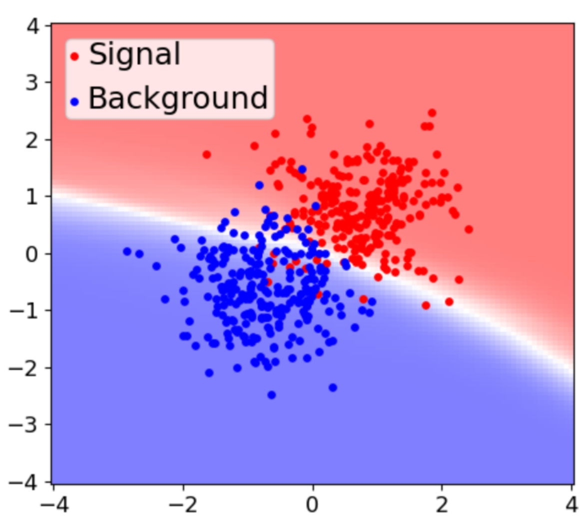


fig. 3.3

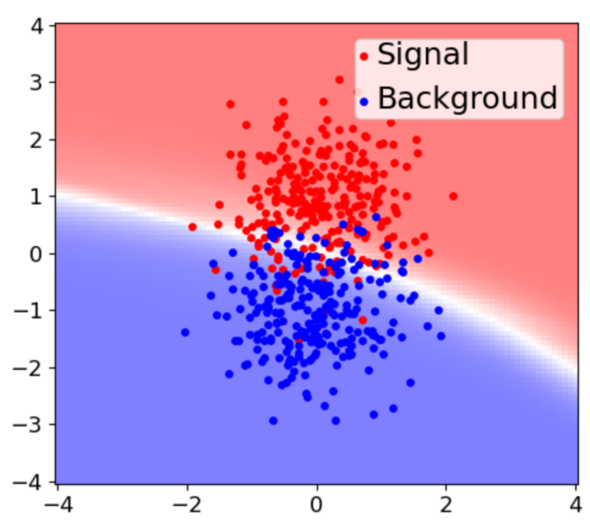


fig. 3.4

Two-Branched Model

- Learns to adapt to a single target domain
- Training involves a trade-off between source and target domains.
- Slightly worse performance on the source set
- Significantly better performance on the target set

INCREASED DANN

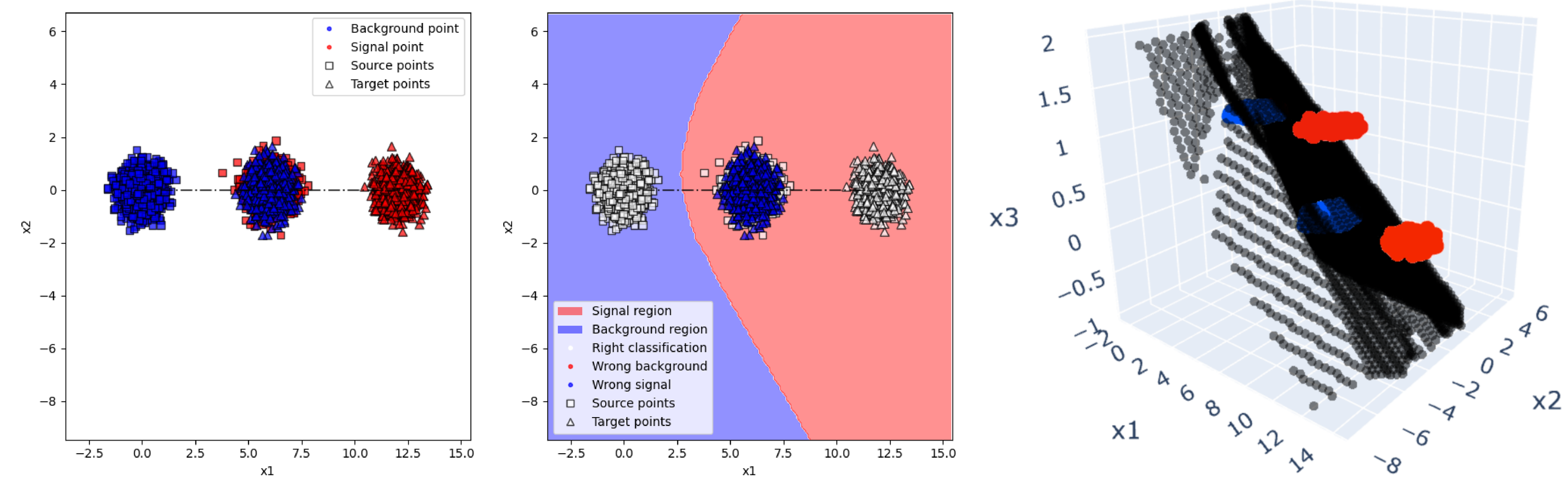


fig. 4.1 fig. 4.2 fig. 4.3

- [Fig.4.1]Source signal and target background distributions are overlapping
- [Fig.4.2] DANN fails to adapt the decision boundary to the target set
- To fix this, we propose adding a new feature dimension taking the value:
  - "xs" for source samples
  - "xt" for target samples
- This addition ensures no overlap between source and target distributions
- It allows the model to leverage set membership information directly from the features
- [Fig.4.3] Source points (x3=1) and target points (x3=0) do not overlap, and the decision surface effectively separates the signal from the background in both sets

QUANTITATIVE RESSULTS

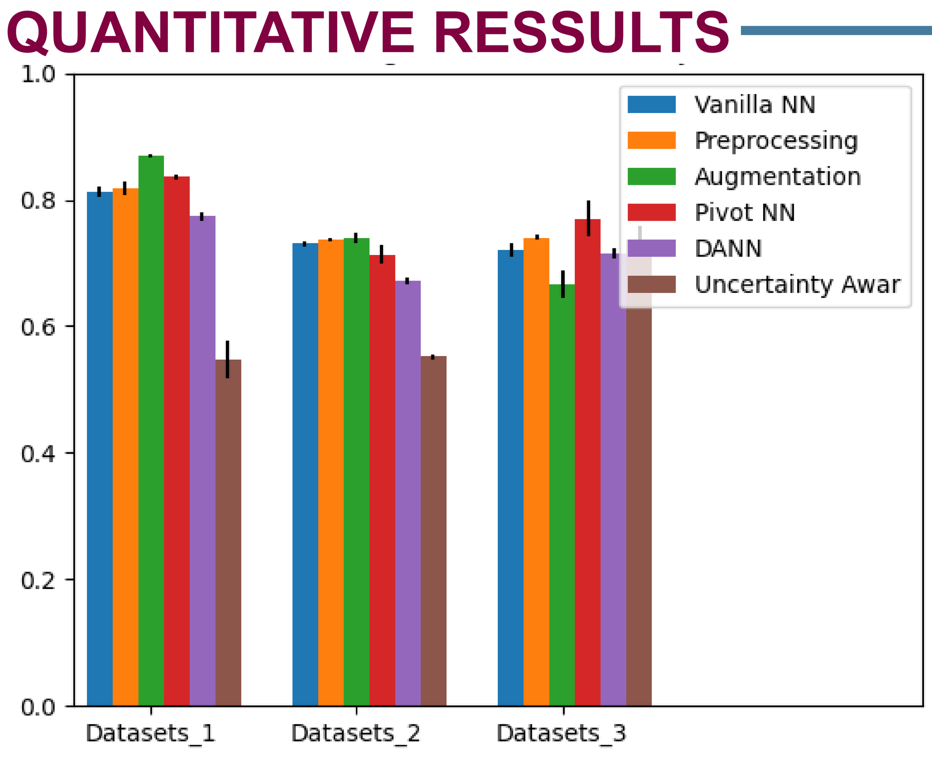


fig. 5.1

Challenges in Fair Model Comparison:

- Final terms of use are not yet established
- Traditional fairness concepts are less applicable when comparing models radically different
- [Fig. 5.2] The relative performance of models varies depending on the choice of hyper-parameters, such as the number of parameters
- When optimizing models, how can we ensure that the optimization process is equally effective for all models ?

Approaches for Fair Model Comparison:

1. **Metric-Based Approach:**
   - Define an inter-model fairness metric based on hyper-parameters
   - Clearly state this metric for external criticism
2. **AI Challenge Approach:**
   - Aim for optimal training of all models
   - As each contestant wants its model to be the best, each model is likely to be fine-tuned to its best potential

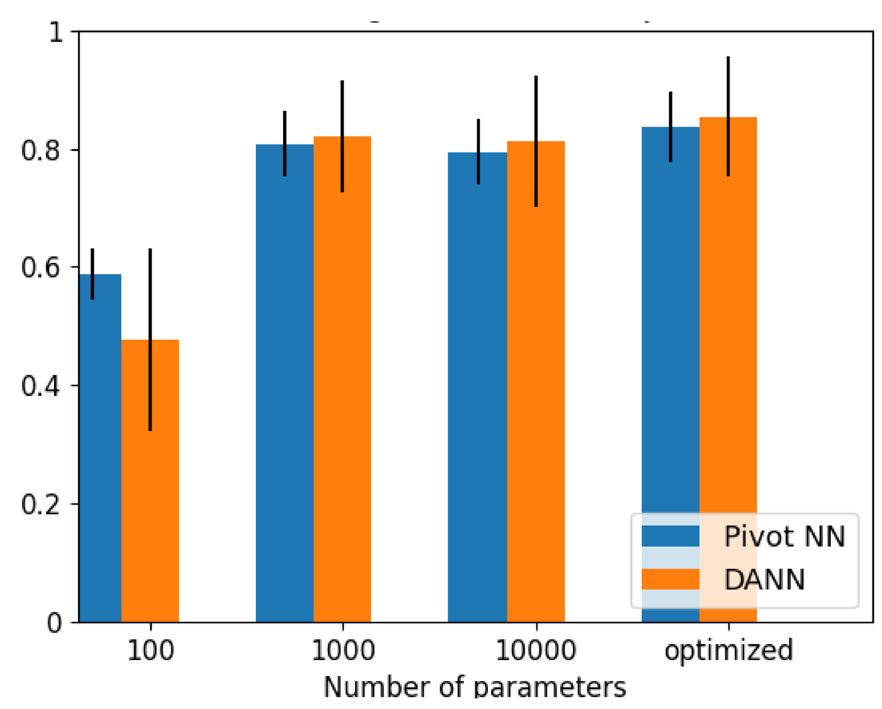


fig. 5.2

OUTRODUCTION

ACKNOWLEDGEMENTS

I would like to thank Isabelle Guyon and David Rousseau for their exceptional guidance, Ihsan Ullah for technical support, and Ragansu Chakkappai for enlightening remarks and constructive feedback on my work.

WHAT'S NEXT

☐ Tests with real physics data
☐ Incorporate the estimation task into the pipeline.
☐ Evaluate increased DANN on traditional domain adversarial tasks

REFERENCES

[1] Patrick Riley. New 'Fair Universe' Project Aims to Build Supercomputer-Scale AI Benchmarks for HEP and Beyond. Nov. 2022.
[2] Gilles Louppe, Michael Kagan, and Kyle Cranmer. Learning to Pivot with Adversarial Networks. 2017. arXiv:1611.01046[stat.ML].
[3] Aishik Ghosh, Benjamin Nachman, and Daniel Whiteson. "Uncertainty-aware machine learning for high energy physics". In: Physical Review D 104.5 (Sept. 2021). doi: 10.1103/physrevd.104.056026.
[4] Yaroslav Ganin et al. Domain-Adversarial Training of Neural Networks. 2016. arXiv:1505.07818 [stat.ML].

GITHUB : https://github.com/Mathisnplus1/fair-universe AUTHOR'S EMAIL : MATHIS.REYMOND74@GMAIL.COM