



LABORATÓRIO DE INSTRUMENTAÇÃO
E FÍSICA EXPERIMENTAL DE PARTÍCULAS
partículas e tecnologia

Deep Learning for Searches at Colliders

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Outline



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Introduction

Personal Introduction

Miguel Crispim Romão

Post-Doc at LIP under the
BigDataHEP project since
mid 2019

Pheno Group

Competence Centre for
Simulation and Big Data



- BSc+MSc from Tecnico
- MAST from Cambridge
- PhD and first post-doc at Southampton (working with Steve F. King)
 - String Phenomenology and Model Building
 - Inflationary Cosmology
- Industry placement as principal data scientist and machine learning engineer at TalentTicker, a startup based in Cardiff
- Back to academia in LIP

Introduction

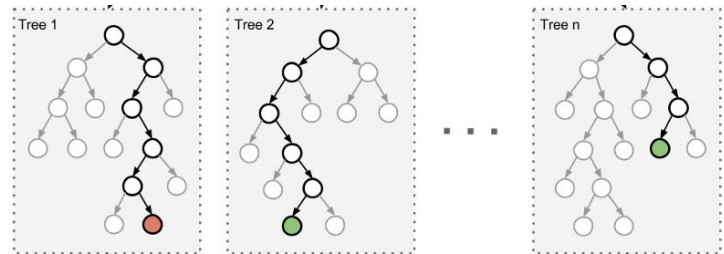
ML and DL in HEP

- Machine Learning has been part of the HEP toolkit for a long time
- Deep Learning is driving a renaissance in ML research and applications in every data driven industry
- HEP is a naturally data heavy endeavour => Only natural to study what DL can do for us
 - Better sensitivity at searches?
 - New possibilities for generic new physics analysis?
 - Replacement or Enhancement of Monte Carlo generation?
 - More efficient parameter space scanning?
 - etc

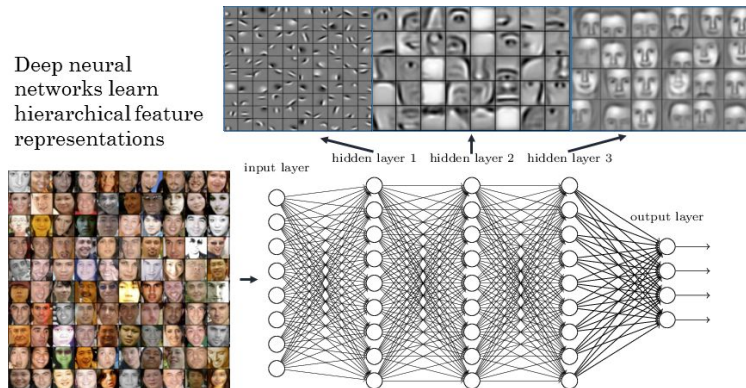
Introduction

ML/DL for new searches

- For new physics searches ML provides the possibility of isolating signal from background
- This increases sensitivity in dedicated searches, effectively making data more efficient
- Not unlike the usage of BDT for the Higgs discovery, but can DL improve on this?
- And what's the best approach when using DL?



Deep neural networks learn hierarchical feature representations





Recent Work

Transferability of Deep Learning Models in Searches for New Physics at Colliders

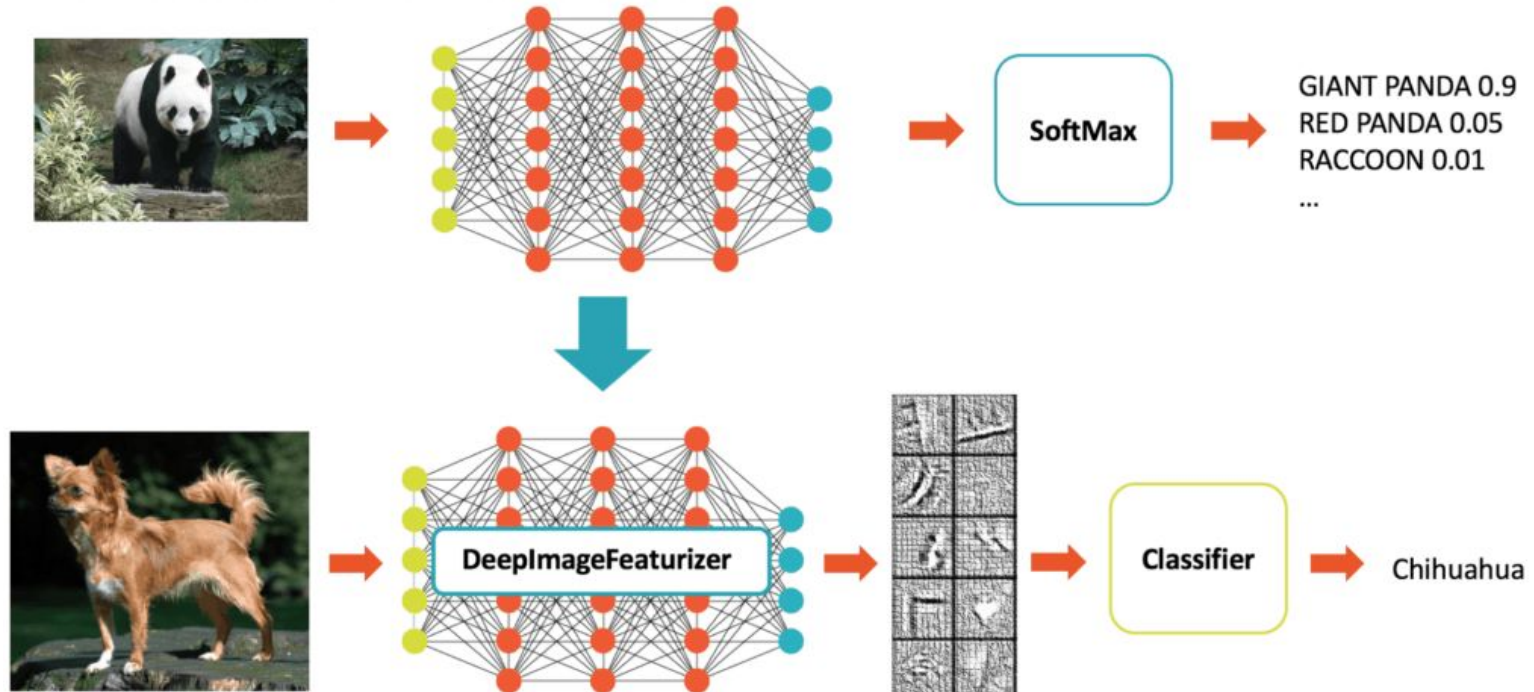
MCR, N. F. Castro, R. Pedro,
T. Vale

1912.04220

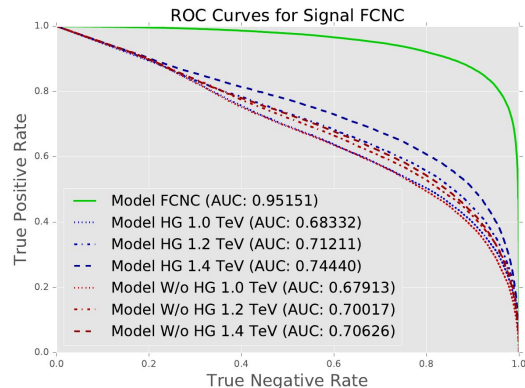
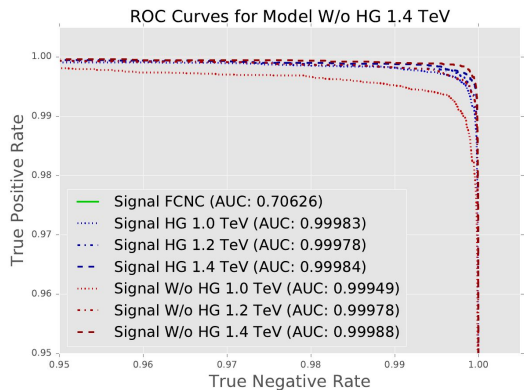
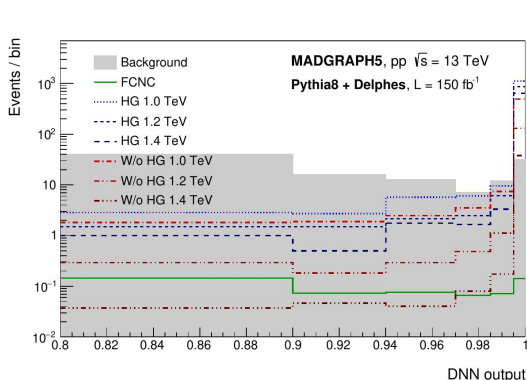
Late stages of peer review in
PRD

- How does a Neural Net trained to separate a specific signal from background behaves when shown a new signal?
- How does this impact upper limits on new physics?
- Focused on three classes of signals:
 - FCNC
 - VLQ from SM production
 - VLQ from Heavy Gluon production

Transferability of Deep Learning Models in Searches for New Physics at Colliders



Transferability of Deep Learning Models in Searches for New Physics at Colliders



Transferability of Deep Learning Models in Searches for New Physics at Colliders

Some take-home messages:

- Clear evidence that DL models provide sensitivity when presented a novel signal
- Transferability is stronger within signals with similar novel final states
- Even when trained on VLQ, the derived limits for FCNC signal were better than fitting to reconstructed variables
- DL might provide the representational power required for generic search solutions



Future (and Current) Work

Future (and Current) Work

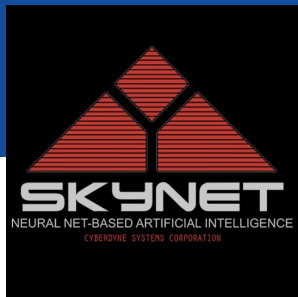
We have been focusing on extending the usage of DL to many HEP applications

- DL and data-driven methods for QCD studies of jet quenching
- On more efficient parameter space sampling in model building (A. Morais and P. Ferreira)
- New observables for searches of new physics

Future (and Current) Work

We have many other avenues of research on ML/DL in HEP that we want to adress

- What are the best methodologies of DL for new searches?
- Can we make DL more interpretable and use it to produce new observables?
- What solutions will generative models provide?
- How much of the Monte Carlo simulation can be offset to ML?
- What other aspects of HEP can benefit from ML automation?
- And are always open for more synergies and collaborations!



Thanks!



Extra bonus material

DNN details

TABLE I. Hyperparameters used by all DNNs.

Hyperparameter	Value
Hidden Layers	3
Units	352
Unit Activation Function	Selu
Unit Weights Initialiser	LeCun Normal
Dropout Rate	10%
Initial Learning Rate	10^{-3}
Optimizer	Nadam
Maximum Epochs	1000

Upper Limits (mus)

TABLE II. Upper limits on signal strength, μ , from the fit to the DNN output distribution for all combinations of train and test signals, and from the fit to the H_T distribution.

			Test						
			FCNC	HG			No HG		
				HG, 1.0 TeV	HG, 1.2 TeV	HG, 1.4 TeV	1.0 TeV	1.2 TeV	1.4 TeV
Train	FCNC		6^{+2}_{-2}	$0.14^{+0.07}_{-0.04}$	$0.18^{+0.08}_{-0.06}$	$0.22^{+0.10}_{-0.06}$	$0.4^{+0.2}_{-0.1}$	$1.2^{+0.5}_{-0.4}$	4^{+1}_{-2}
	HG	1.0 TeV	50^{+20}_{-20}	$0.03^{+0.01}_{-0.01}$	$0.04^{+0.02}_{-0.01}$	$0.06^{+0.04}_{-0.02}$	$0.06^{+0.03}_{-0.02}$	$0.27^{+0.15}_{-0.09}$	$1.1^{+0.6}_{-0.3}$
		1.2 TeV	50^{+20}_{-20}	$0.022^{+0.011}_{-0.007}$	$0.03^{+0.02}_{-0.01}$	$0.05^{+0.03}_{-0.02}$	$0.05^{+0.02}_{-0.02}$	$0.22^{+0.11}_{-0.07}$	$0.9^{+0.5}_{-0.3}$
		1.4 TeV	40^{+20}_{-10}	$0.022^{+0.012}_{-0.007}$	$0.03^{+0.02}_{-0.01}$	$0.05^{+0.03}_{-0.01}$	$0.05^{+0.02}_{-0.02}$	$0.22^{+0.11}_{-0.07}$	$0.9^{+0.5}_{-0.3}$
	No HG	1.0 TeV	90^{+50}_{-30}	$0.020^{+0.010}_{-0.007}$	$0.027^{+0.014}_{-0.009}$	$0.04^{+0.02}_{-0.01}$	$0.04^{+0.03}_{-0.01}$	$0.19^{+0.09}_{-0.07}$	$0.7^{+0.4}_{-0.2}$
		1.2 TeV	40^{+20}_{-10}	$0.022^{+0.011}_{-0.007}$	$0.03^{+0.02}_{-0.01}$	$0.05^{+0.02}_{-0.02}$	$0.05^{+0.02}_{-0.02}$	$0.22^{+0.11}_{-0.07}$	$0.9^{+0.4}_{-0.3}$
		1.4 TeV	50^{+20}_{-20}	$0.023^{+0.012}_{-0.008}$	$0.03^{+0.02}_{-0.01}$	$0.05^{+0.03}_{-0.02}$	$0.05^{+0.02}_{-0.02}$	$0.22^{+0.11}_{-0.08}$	$0.9^{+0.5}_{-0.3}$
Fit to H_T distribution			90^{+40}_{-20}	$0.11^{+0.04}_{-0.04}$	$0.11^{+0.05}_{-0.03}$	$0.12^{+0.05}_{-0.04}$	$0.3^{+0.1}_{-0.1}$	$0.8^{+0.3}_{-0.2}$	$1.7^{+0.7}_{-0.5}$

Normalised μ s

TABLE III. Normalised limits obtained for all combinations of training and testing signals.

			Test						
			FCNC	HG			No HG		
				HG, 1.0 TeV	HG, 1.2 TeV	HG, 1.4 TeV	1.0 TeV	1.2 TeV	1.4 TeV
Train	FCNC		$1.0^{+0.4}_{-0.3}$	5^{+2}_{-2}	6^{+2}_{-2}	4^{+2}_{-1}	9^{+4}_{-3}	6^{+2}_{-2}	4^{+2}_{-1}
	HG	1.0 TeV	9^{+4}_{-3}	$1.0^{+0.5}_{-0.3}$	$1.3^{+0.7}_{-0.4}$	$1.2^{+0.6}_{-0.4}$	$1.3^{+0.7}_{-0.4}$	$1.2^{+0.6}_{-0.4}$	$1.3^{+0.7}_{-0.4}$
		1.2 TeV	8^{+4}_{-2}	$0.8^{+0.4}_{-0.2}$	$1.0^{+0.5}_{-0.3}$	$1.0^{+0.5}_{-0.3}$	$1.1^{+0.5}_{-0.4}$	$1.0^{+0.5}_{-0.3}$	$1.0^{+0.5}_{-0.3}$
		1.4 TeV	7^{+3}_{-2}	$0.8^{+0.4}_{-0.3}$	$1.0^{+0.5}_{-0.3}$	$1.0^{+0.5}_{-0.3}$	$1.1^{+0.6}_{-0.4}$	$1.0^{+0.5}_{-0.3}$	$1.0^{+0.5}_{-0.4}$
	No HG	1.0 TeV	20^{+9}_{-5}	$0.7^{+0.4}_{-0.2}$	$0.8^{+0.4}_{-0.3}$	$0.8^{+0.4}_{-0.3}$	$1.0^{+0.5}_{-0.3}$	$0.9^{+0.4}_{-0.3}$	$0.8^{+0.4}_{-0.3}$
		1.2 TeV	7^{+3}_{-2}	$0.8^{+0.4}_{-0.2}$	$1.0^{+0.5}_{-0.3}$	$0.9^{+0.5}_{-0.3}$	$1.1^{+0.5}_{-0.4}$	$1.0^{+0.5}_{-0.3}$	$1.0^{+0.5}_{-0.3}$
		1.4 TeV	9^{+4}_{-3}	$0.8^{+0.4}_{-0.3}$	$1.0^{+0.5}_{-0.3}$	$1.0^{+0.5}_{-0.3}$	$1.1^{+0.6}_{-0.3}$	$1.0^{+0.5}_{-0.3}$	$1.0^{+0.5}_{+0.3}$