DOMAIN ADAPTATION FOR SYSTEMATICS

A case study

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Error sources

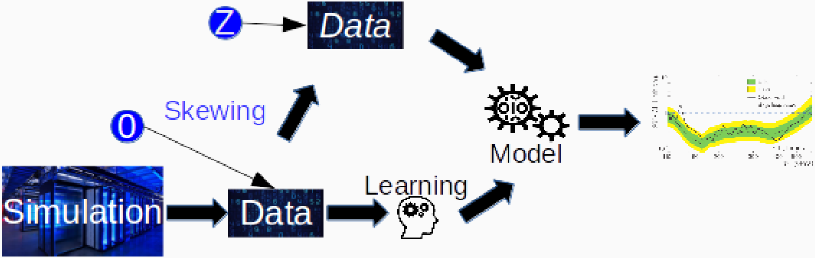
$$measure = value \pm err_{stat} \pm err_{syst}$$

Statistical error

- lack of training data
- wrong hyper-parameter settings
- wrong choice of algorithm
- etc

Systematic error

- measurement imperfections
- simulation limitations
- theoretical knowledge lacks



- $H \to \tau\tau$ simulation (HiggsML challenge data, Geant4)
- Skewing : rescaling τ energy $(+[1\%, 10\%])$
- [Adam-Bourdarios et al., 2014] & [Baldi et al., 2015]

Nail details

Physicist : We want to count higgs boson candidates and take into account systematics.

ML : Great ! I'd love to have an objective function ...

Physicist : minimize

$$\frac{\sigma_\mu}{\mu} = \sqrt{\left(\frac{\sqrt{s_0 + b_0}}{s_0}\right)^2 + \left(\frac{(s_z - s_0) + (b_z - b_0)}{s_0}\right)^2}$$

- s, selected signals (True posivites)
- b, selected backgrounds (False posivites)
- $*_z$, on the skewed test set
- $*_0$, on the nominal test set

Deep learning tools

- Data augmentation : train on both simulation and real data (or many simulations)
- Adversarial methods
  - *GAN* [Goodfellow et al., 2014] : Generate samples that are indistinguishable from real data
  - *DAN* [Ganin et al., 2015] : Find a common space for both simulation and real data
  - *PAN* [Louppe et al., 2016] : Correct the model to be pivotal
- *Tangent Propagation* [Simard et al., 1991] [Rifai et al., 2011] : Regularize training using known invariant

Available Hammers

What I tried

- Data augmentation : train on both simulation and real data (or many simulations)
- Adversarial methods
  - *GAN* [Goodfellow et al., 2014] : Generate samples that are indistinguishable from real data
  - *DAN* [Ganin et al., 2015] : Find a common space for both simulation and real data
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Fast Presentation : Tangent Propagation

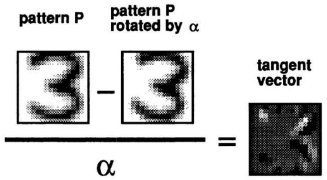
Key Ideas

- Regularize the derivative of the model according to the transformation.

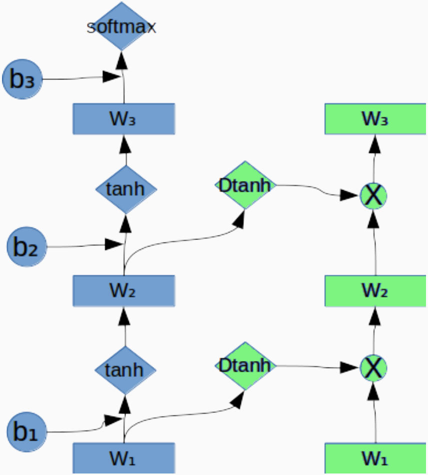
$$loss = E_{standard} + \lambda \sum_{x \in Data} \left| \frac{\partial G_w(s(x,\alpha))}{\partial \alpha} \right|^2_{\alpha=0}$$

- Compute this derivative with a forward propagation through a "linearized" network.

$$\left. \frac{\partial G_w(s(x,\alpha))}{\partial \alpha} \right|_{\alpha=0} = \nabla_x G_w(x). \left. \frac{\partial s(x,\alpha)}{\partial \alpha} \right|_{\alpha=0}$$

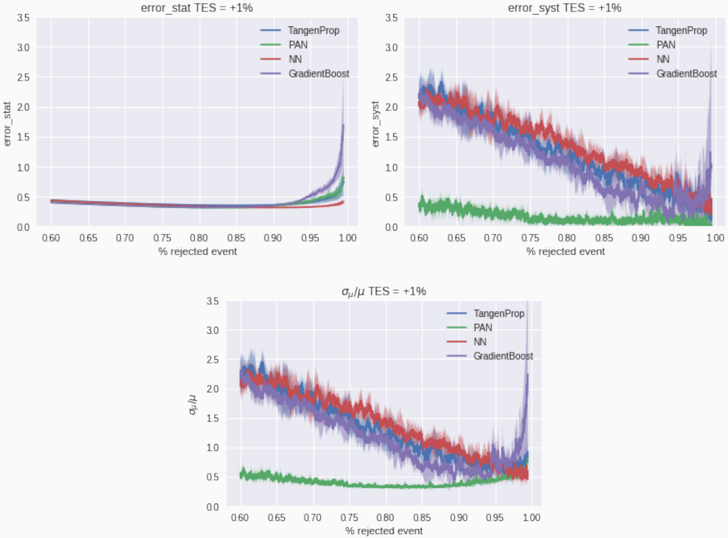


Jacobian Net

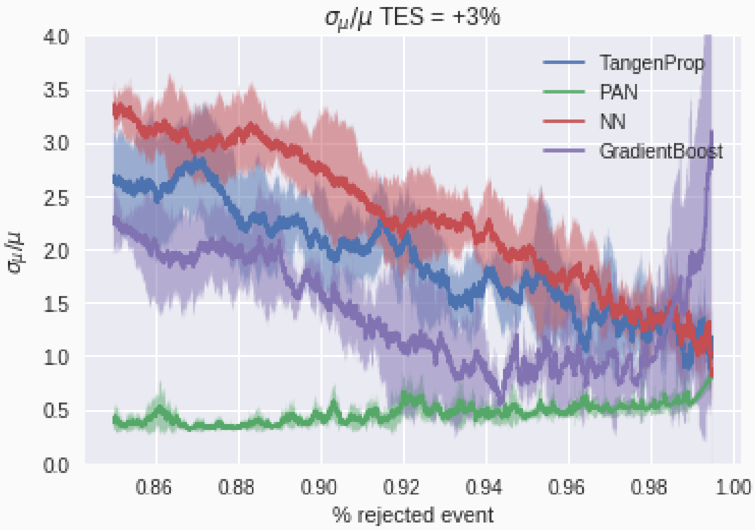


Tangent Propagation : standard network + ”linearized” model insertion

Systematics dominate



Adversarial training wins this nail



Discussion

Results

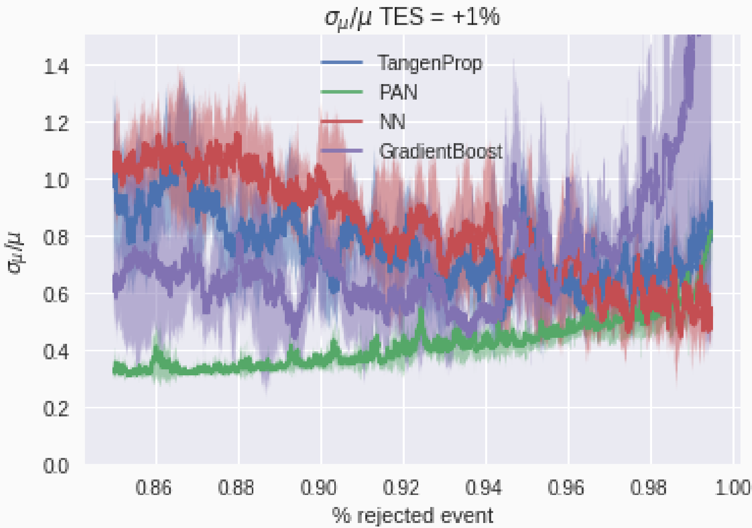
- Adversarial is hard to train but worth it.
- Boosting is still is the game (if high level features).
- Not giving up on Tangent Propagation.

Future : What kind of hammer for what kind of nail

- Build a zoo with data stained with systematics
- Try GANs, DANs

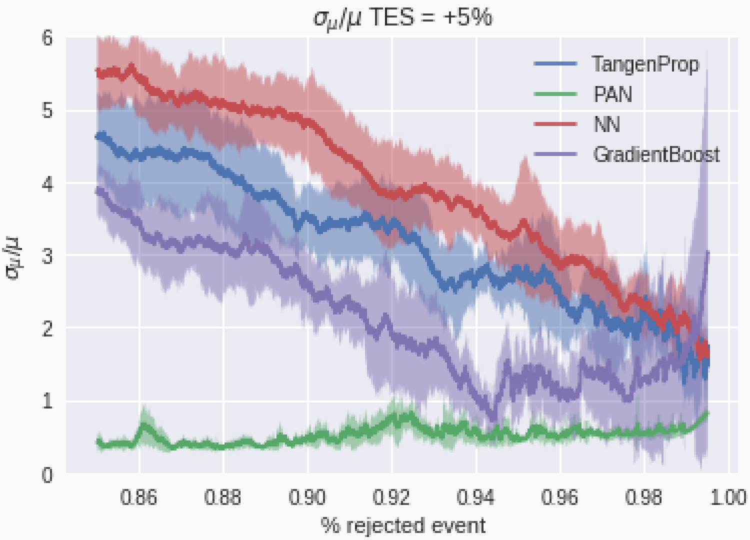
Questions ?

Backup 1%



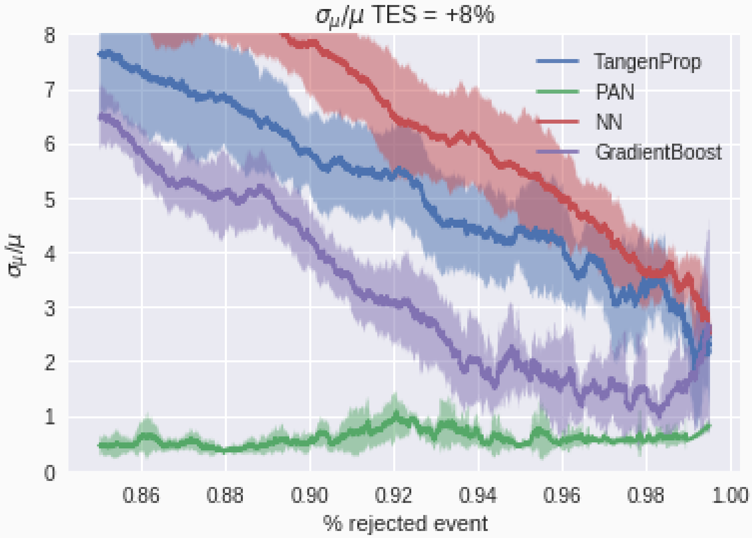
σ_μ/μ TES = +1%
TangenProp
PAN
NN
GradientBoost
σ_μ/μ
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
0.86
0.88
0.90
0.92
0.94
0.96
0.98
1.00
% rejected event

Backup 5%



σ_μ/μ TES = +5%
6
5
4
3
2
1
0
σ_μ/μ
0.86
0.88
0.90
0.92
0.94
0.96
0.98
1.00
% rejected event
TangenProp
PAN
NN
GradientBoost

Backup 8%



σ_μ/μ TES = +8%
σ_μ/μ
% rejected event
TangenProp
PAN
NN
GradientBoost
0
1
2
3
4
5
6
7
8
0.86
0.88
0.90
0.92
0.94
0.96
0.98
1.00

ML resistance

For the ML community not focusing on optimizing classification/regression error is counter intuitive.

Magic words :

”Non additive (function) error”

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