Blueprints for Training Information Bottlenecks for Collider Analyses

Prasanth Shyamsundar, Fermilab Quantum Institute
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Collaborators/Related projects

Has strong connections to

  Doojin Kim, Kyoungchul Kong, Konstantin T. Matchev, Myeonghun Park, PS

• “An upcoming pheno paper”, Kevin Pedro, PS

Has loose connections to

  Kyoungchul Kong, Konstantin T. Matchev, Stephen Mrenna, PS

• “Optimal event selection and categorization in high energy physics, Part 1: Signal discovery”,
  arXiv:1911.12299 [physics.data-an], Konstantin T. Matchev, PS

And most of the representation learning work in the literature
The goal

Learn analysis variables (selection cuts, etc.) with ML

WHY:

1. Most collider analyses use analysis variables.
2. See (1)

How they are typically used:

Histograms, function fits, etc. to compare data to production level simulations. We know how to do this part very well.

How they are typically picked:

Human intelligence, simulation studies (“theorist’s” simulators are okay)
Event variables are information bottlenecks

- Information bottlenecks
- Representation learning
- Feature engineering

Many ways to model such networks (Interpretable and/or physics informed architectures).

How can we train them?
Route 1: General purpose representation learning

- Examples: Self-supervision, contrastive learning, VAEs, other smart latent space constructions.
- Some techniques only perform well when learning high-dim representations.
- Great for industry applications (sometimes a priori unexpected applications).
- Great for anomaly detection strategies.
- Great as intermediate representations to be processed further.
- Not always great as analysis variables.
  a) Analysis variables often need to be ultra-low dimensional.
  b) Their typical use-case is very specific: signal discovery, parameter estimation.
Route 2: Fully differentiable analysis pipeline

• The idea here is to make the entire (or most of the) analysis pipeline including selection cuts, histogram bin edges, neural networks, etc. differentiable (read: tunable via backprop).

• Now one can do a full analysis with simulated data, compute the sensitivity, use it as the gain function and train the analysis pipeline via gradient ascent.

Pros:

The possibilities opened by a fully tunable analysis pipeline.

Cons (once available):

Training steps will be computationally expensive (one full analysis per step)
Small batch sizes may not be reliable for sensitivity estimation
Risk of over-tuning the analysis if not careful
The common feature in ALL these approaches

Every (I think?) representation learning technique

1) Designs a task to perform with the representation
2) Trains the representation on performance on that task

What tasks do we perform in particle physics?
Signal discovery and parameter estimation are both classification tasks

- Background vs Background+Signal
- \( mW = 80.434 \text{ GeV} \) vs \( mW = 80.357 \text{ GeV} \)

Idea: Use classification as the task to perform with the NN variable
Point background and signal hypotheses (i.e., no unknown parameters)

- Aux classifies bkg vs sig using main’s output.
- Main does its best to help aux (not adversarial)
- Main is being evaluated on David’s metric defined as: (more distinguishable is better)

\[
D(\text{main network}) = -\text{Trained classifier cost} + \text{constant shift}
\]
Q: Why not use one network to do the whole thing?

A: Unknown signal parameters…

(Prasanth’s conceptual test for comparing approaches: Can it learn the invariant mass?)
How to handle unknown signal parameters with regular classifiers?

1. Parameterized NNs: NN(event | parameter)
   This maps each event to a function of the parameter, not a number.
   Space age stuff. I want stone age.

2. Mix signals events from different parameter values together in one global dataset.
   Cannot learn the invariant mass (mass peaks get washed out).
   Will only work if there’s a feature that doesn’t move around much as the parameter changes.
What will this learn for sharp resonant signals?

Some linear combination of likelihoods at different param values?
No. It’ll learn the invariant mass!

Assorted thoughts:
- Events in real data come from one signal param value. So, aux should get to condition on $\theta$.
- What’s maximized is $\text{Avg-over-theta}[D(P_b||P_s,\theta)]$.
- $\pi$ is NOT a prior. It specifies our priority.
- Aux isn’t interesting to me, post-training. But $v(x)$ from main is.

**Blueprint 1: Variable for signal discovery with unknown params**

\[
P_0(x, \theta) = \pi(\theta)P_b(x) \quad P_1(x, \theta) = \pi(\theta)P_s(x|\theta)
\]
This maximizes the information content in a single event about theta.

\[ P_0(x, \theta) = \pi(\theta) \int d\theta' \pi(\theta') P(x|\theta') \quad P_1(x, \theta) = \pi(\theta) P(x|\theta) \]
The architecture was able to learn invariant mass, $m_{T}$, and a variable correlated with $m_{T^2}$ for the appropriate topologies. This was a successful first demonstration of the principle.

This approach can be refined (classifier loss doesn’t correlate perfectly with sensitivity in this approach).

More results for harder analyses in Kevin Pedro’s talk.
Blueprint 3: Refined blueprint for param estimation

Some notes:
\( \theta_0 \) and \( \theta_1 \) need not be iid.
\( \pi \) can be a correlated distribution.

Aux can be modeled as
\[ \text{Aux}(v, \theta_0, \theta_1) = \varphi(v, \theta_1) - \varphi(v, \theta_0) \]

where \( \varphi \) is a backend nn sitting inside Aux.

See: arXiv:2210.01680 [stat.ML], Kyoungchul Kong, Konstantin T. Matchev, Stephen Mrenna, Prasanth Shyamsundar

This maximizes Average-over-thetas\([D(P_{\theta_0} \| P_{\theta_1})]\)

Some results in Kevin Pedro’s talk.
More blueprints exist…

• Can be extended from continuous NN-variables to NN-event-selectors and categorizers

• Make analysis variables/event selectors sensitive
  Over a range of unknown theory parameters
  Over a range of analysis choices like pre-selection cuts (avoid fine tuning)
  Haven’t figured out the best way to handle nuisance params yet.

• **Train variables complementary to a known variable**

• **Decorrelate event selectors from a known variable**

• Train variables for parameter estimation in the presence of background

• By choosing the right loss functions, we can maximize statistical distances between (Bkg) and (Bkg + \(\alpha\) Sig).
Summary

• One can train information bottlenecks with blueprints like these to improve the sensitivity of modeled searches and parameter measurements without compromising on robustness.

• A variety of useful properties can be incorporated into the bottlenecks.

• Trivially deployment-ready technique, with a lot of use cases in analyses.

• Happy to discuss more if anyone wants to try these out.

• Undecided about the publication pipeline (there might be a minimal preprint some day).

This talk focused on the roses. Thorns, buds (and interesting physics) in Kevin Pedro’s talk later today.
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