Physics-inspired top tagging

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Based on
Kasieczka, Plehn, MR, Schell ‘17
Butter, Kasieczka, Plehn, MR ‘17
Kasieczka, Kiefer, Plehn, MR (in progress)

CHEP conference, Sofia, July 2018
Top tagging

Reconstructing highly-boosted top decays

- Easy to reconstruct tops when decay products are well-separated
- But standard reconstruction methods fail when tops are highly-boosted
- Instead of trying to resolve decay products individually, merge all into “fat jet”
- By now this is well-understood experimentally and theoretically

\[ \Delta R \sim \frac{2m}{p_T} \]
We see something like this
Jets as images

Can recent advances in DNNs benefit jet physics?

- View calorimeter plane as 2-d “image” with energy deposits as pixels
- After some pre-processing, train a **convolutional neural network** (no details here) on sample of top jets and QCD background
- Last layer of network converts weights for each image into probability of it being either top or QCD
Jets as images

Test performance against traditional taggers and BDT

- Can see mild improvement in background rejection
- Deep neural networks outperform BDT classifiers - logical next step for machine learning on real data
- Preprocessing actually causes loss of information in final classification

But images have many limitations

- Cannot include tracking information
- Not adaptable for non-uniform detectors
- Can we use more physics-motivated inputs, not “pixels”?
Beyond images: LoLa

Why not use the jet constituent 4-vectors directly?

Two ingredients:

1. CoLa* - learns the jet clustering history

\[ k_{\mu,i} \xrightarrow{\text{CoLa}} \tilde{k}_{\mu,j} = k_{\mu,i} \ C_{ij} \]

- Test on-shell conditions
\[ \tilde{k}_{\mu,1}^2 = (k_{\mu,1} + k_{\mu,2} + k_{\mu,3})^2 = m_t^2 \]
\[ \tilde{k}_{\mu,2}^2 = (k_{\mu,1} + k_{\mu,2})^2 = m_W^2 \]

2. LoLa** - learns the kinematics

\[ \tilde{k}_j \xrightarrow{\text{LoLa}} \hat{k}_j = \begin{pmatrix} m^2(\tilde{k}_j) \\ p_T(\tilde{k}_j) \\ w_{jm}^{(E)} E(\tilde{k}_m) \\ w_{jm}^{(d)} d_{jm}^2 \end{pmatrix} \]

transform 4-vectors into: invariant mass, pT, energy and Minkowski distance

effectively a rotation in observable space

* CoLa = Combination Layer
** LoLa = Lorentz Layer
Performance of LoLa

First test: do we do better than images?

- Using calorimeter information only, no improvement over images (unsurprising)
- Evidence that LoLa learns the same features as image-based approach
- Far less training time, fewer weights, fewer inputs required
- Same performance for much less CPU time = suggests we should move away from images

But how does LoLa improve physics performance?
Ultra-boosted tops

Calorimeter resolution degrades for high pT tops

More likely that jet constituents will land on same cell, so loss of information

Use much higher-resolution tracking

Same number of constituents at high pT so no loss of info

Massive increase in performance

Impact on resonance searches?
Quark-gluon tagging

Also well-suited to NN-based taggers (but more challenging)

- Discrimination based on splitting functions and ratio of Casimir operators CA/CF
- Broad phenomenological applications
- e.g. improving searches for invisible Higgs decays with monojets

![Graphs and diagrams]

- Even with optimistic systematics, not yet competitive
- More optimisation to be done

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95% excl. BR

L [fb⁻¹]

E. Kasieczka, P. Kiefer, T. Plehn, M. Rabey (in progress)
Reference dataset

Have your own NN-based tagger you’d like to test?

• Community sample available in compressed h5 or ROOT format

• Details and instructions available as Google Doc at:
https://docs.google.com/document/d/1Hcuc6LBxZNX16zjEGeq16DAzspkDC4nDTyjMplbWHRo/edit

• This is a living document, please update it with your own NN performance results!

• Some results should be presented at BOOST next week, keep your eyes peeled!
Conclusions

• Recent developments in machine learning have found novel and exciting applications in top tagging

• Two approaches presented here: image-based and 4-vector based

• Both show excellent ability to identify hadronic top decays

• LoLa approach has more physics-motivated inputs + simpler network architecture + less CPU time

• Ability to include tracking and extend to very high pT

• Broad pheno applications, including BSM

• Time to start on real data?
Backup: DeepTop analysis

Signal: all-hadronic ttbar, Background: QCD dijets

(PYTHIA8 + Delphes)

Cluster calorimeter towers or particle-flow objects into fat jets

Sort jet constituents by pT, feed four-vectors into NN

300k signal and background events

Train/test/validation split: 60/20/20
Backup: preprocessing

Don’t want to waste network parameters on learning special relativity, pre-process to remove this dependence.

**shift**

**rotate**

**flip**

**crop**

**tops**

**QCD**