Deep-learning top taggers using Lorentz invariance

Based on
Kasieczka, Plehn, MR, Schell '17
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Top tagging

Modern top reconstruction

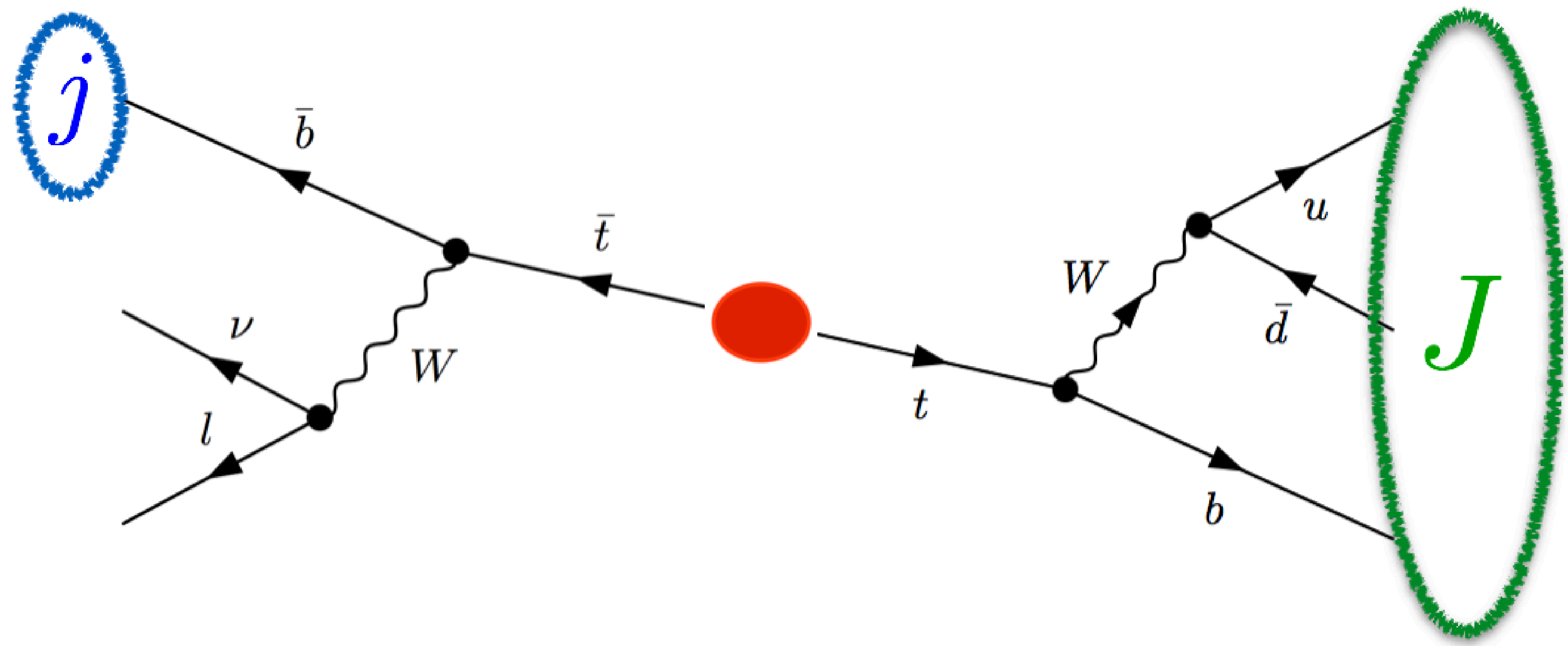
- Easy to reconstruct tops when decay products are well-separated

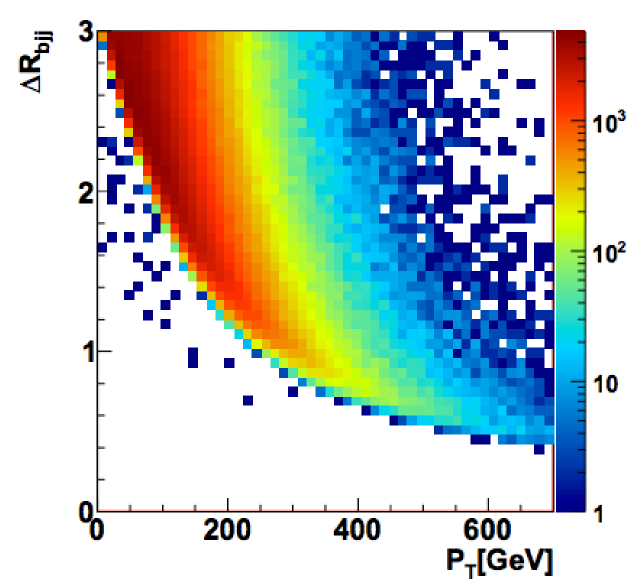
- But standard reconstruction methods fail when tops are highly-boosted

- Instead of trying to resolve decay products individually, merge all into “fat jet”

Kaplan, Rehermann, Schwartz, Tweedie ‘08
Plehn, Spannowsky, Takeuchi, Zerwas ‘10

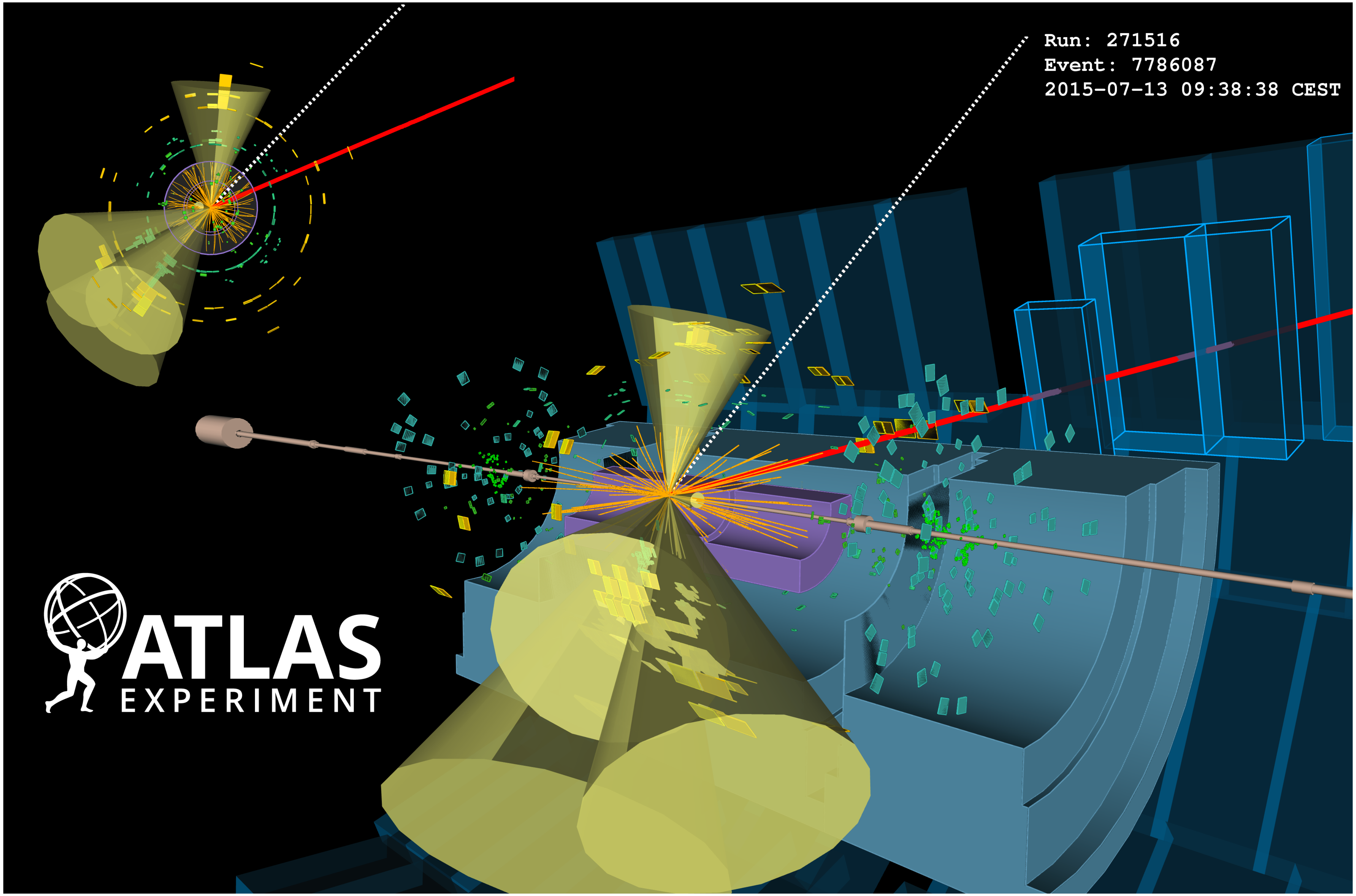
- By now this is well-understood experimentally and theoretically





$$\Delta R \sim \frac{2m}{p_T}$$

We see something like this



Jets as images

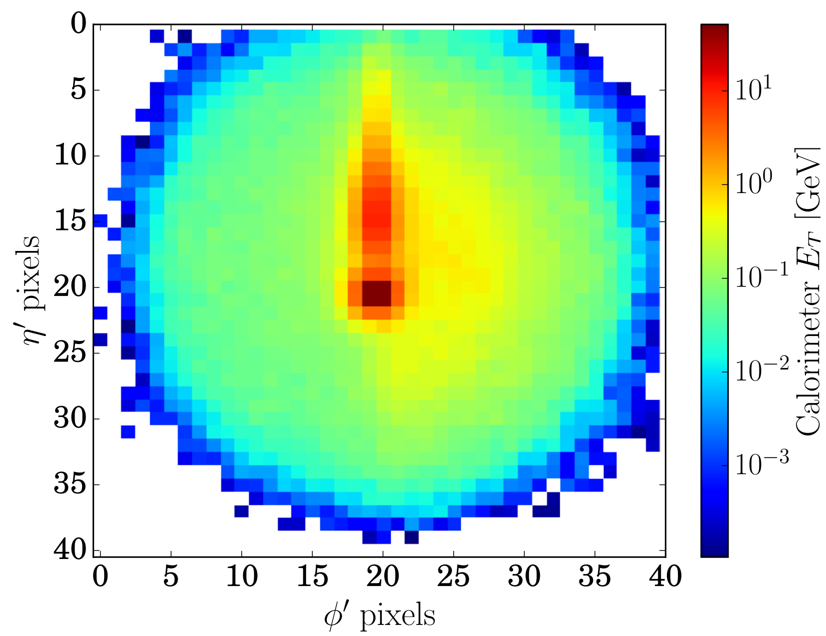
de Olivera, Kagan, Mackey, Nachman, Schwarzmann ‘15

Can recent advances in machine learning benefit particle physics?

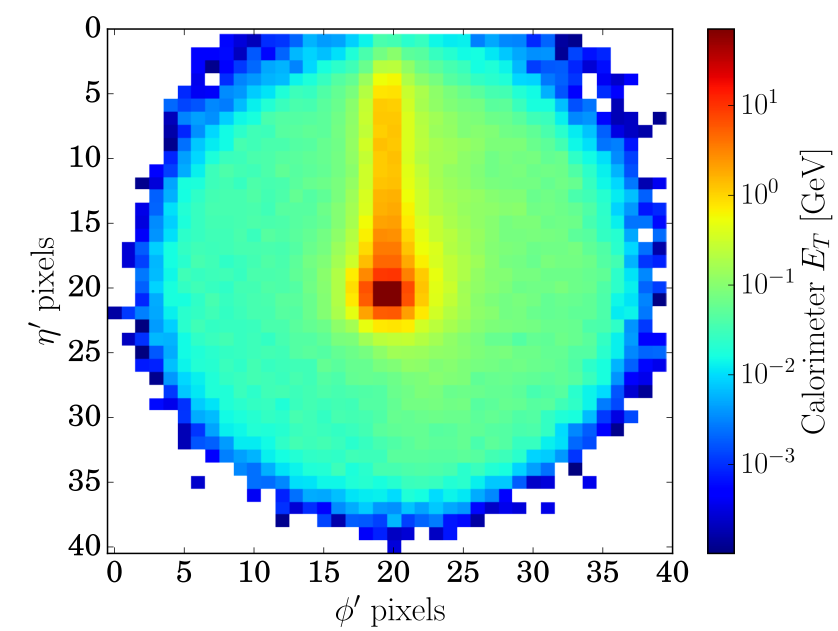
- View calorimeter plane as 2-d “image” with energy deposits as pixels
- After some pre-processing, train a *convolutional neural network* (no details here) on sample of top jets and QCD background

Kasieczka, Plehn, MR, Schell ‘17

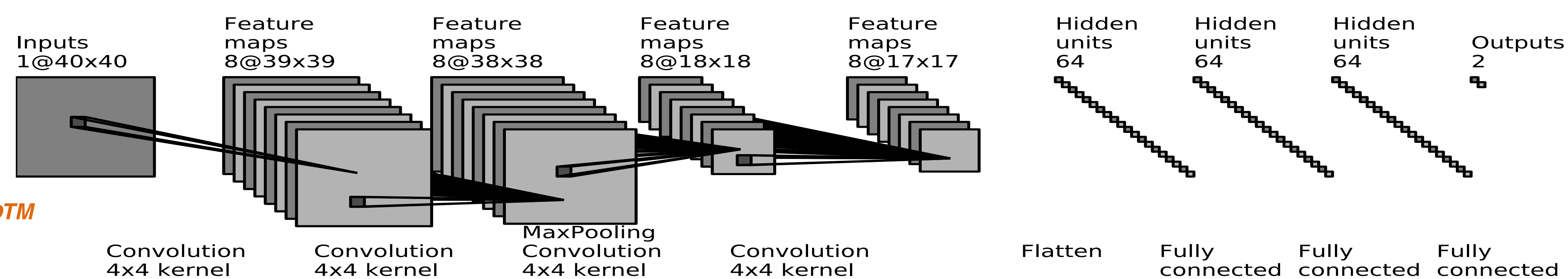
tops



QCD



- Last layer of network converts weights for each image into probability of it being either top or QCD



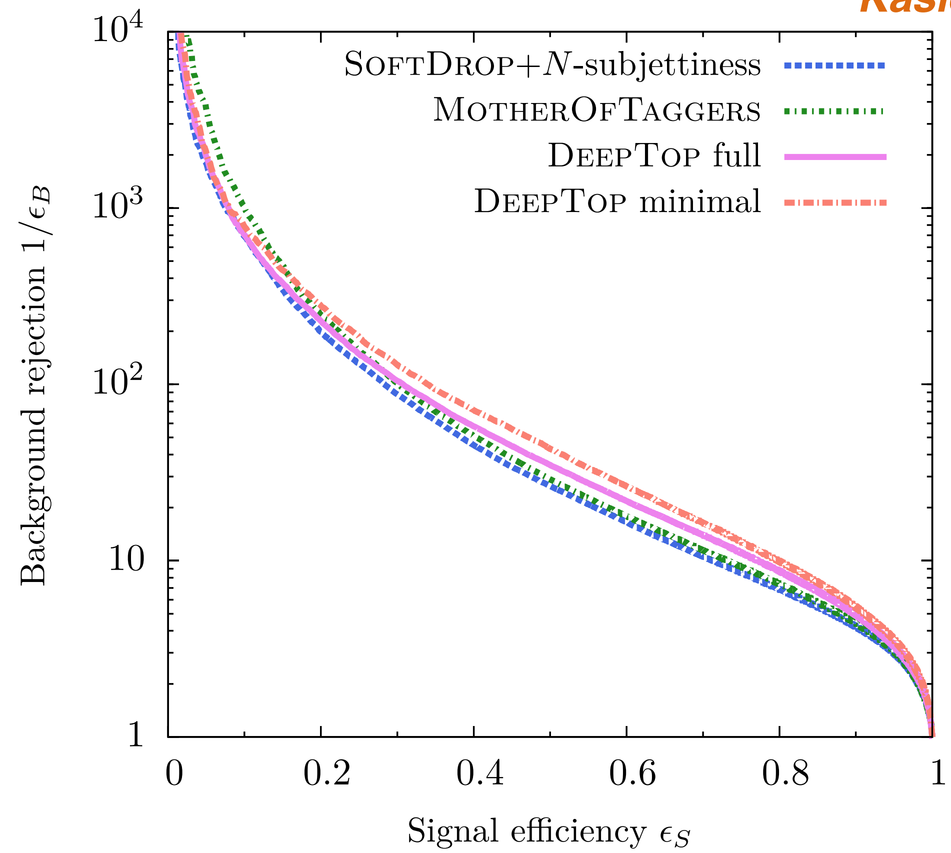
DEEPTOP™

Jets as images

Test performance against traditional taggers and BDT

Kasieczka, Plehn, MR, Schell '17

- Can see up to 50% 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 weird "pixels"?

Butter, Kasieczka, Plehn, MR '17

Beyond images: LoLa

Why not use the jet constituent 4-vectors directly?

Two ingredients:

1. CoLa* - learns the jet clustering history

$$k_{\mu,i} \xrightarrow{\text{CoLa}} \widetilde{k}_{\mu,j} = k_{\mu,i}\, C_{ij}$$

$$C = \begin{pmatrix} 1 & 0 & \cdots & 0 & C_{1,N+2} & \cdots & C_{1,M} \\ 0 & 1 & & \vdots & C_{2,N+2} & \cdots & C_{2,M} \\ \vdots & \vdots & \ddots & 0 & \vdots & & \vdots \\ 0 & 0 & \cdots & 1 & C_{N,N+2} & \cdots & C_{N,M} \end{pmatrix}$$

- Test on-shell conditions

$$\tilde{k}^2_{\mu,1} = (k_{\mu,1} + k_{\mu,2} + k_{\mu,3})^2 = m_t^2$$

$$\tilde{k}^2_{\mu,2} = (k_{\mu,1} + k_{\mu,2})^2 = m_W^2 \,.$$

2. LoLa** - learns the kinematics

$$\tilde{k}_j \xrightarrow{\text{LoLa}} \hat{k}_j = \begin{pmatrix} m^2(\tilde{k}_j) \\ p_T(\tilde{k}_j) \\ w^{(E)}_{jm}\, E(\tilde{k}_m) \\ w^{(d)}_{jm}\, d^2_{jm} \end{pmatrix}$$

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

effectively a rotation in observable space

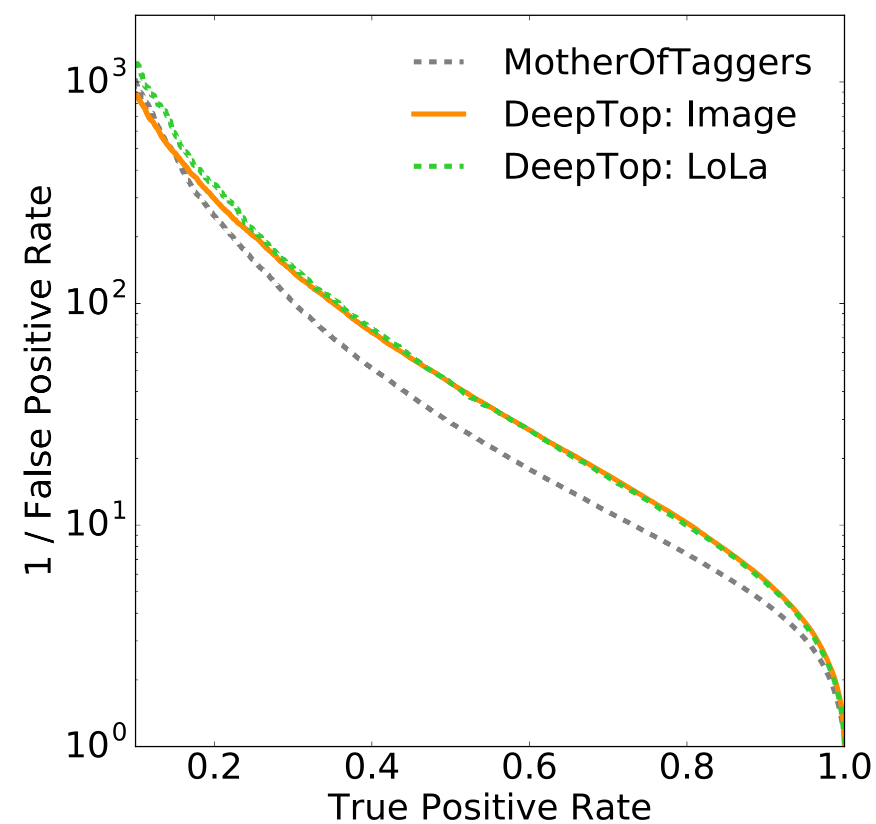
** CoLa = Combination Layer*

*** 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?

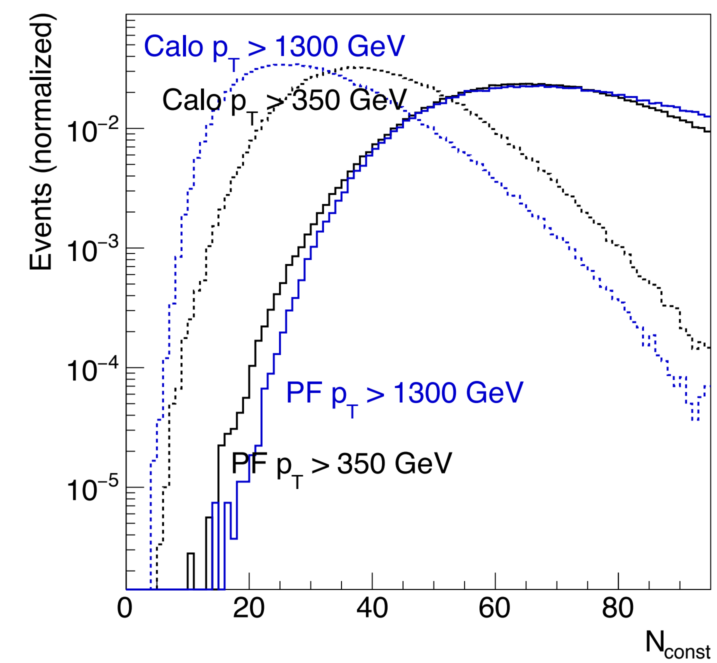
Ultra-boosted tops

Calorimeter resolution degrades for high pT tops

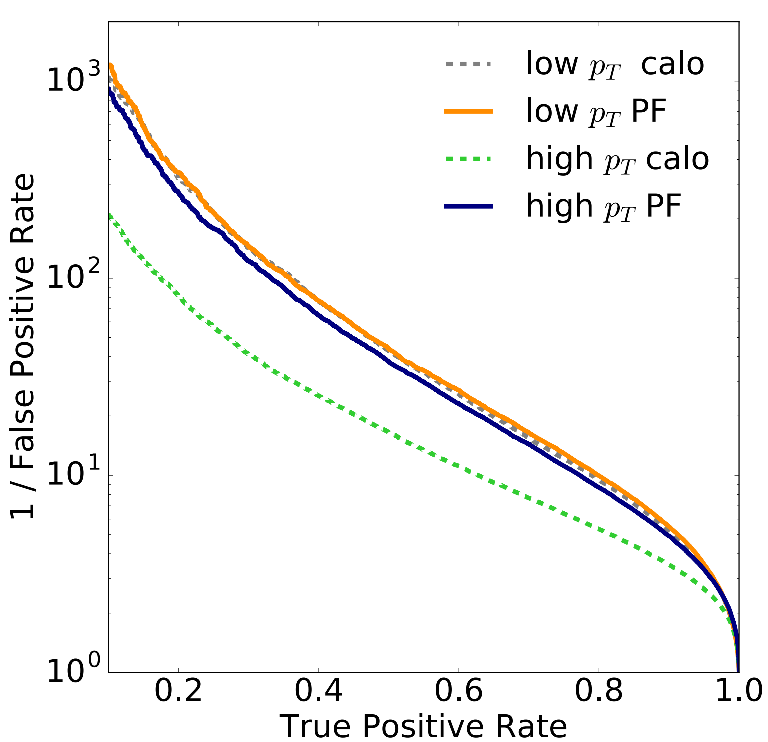
More likely that jet constituents will land on same cell, so loss of information

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?

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-based approach has more physics-motivated inputs, simpler network architecture, less CPU time
- Ability to include tracking and extend to very high pT
- Time to start on real data?

Backup: Analysis details

Signal: all-hadronic ttbar, Background: QCD dijets

(PYTHIA8 + Delphes)

Cluster calorimeter towers or particle-flow objects into fat jets

$$\text{C-A } \Delta R = 1.5$$
$$350 \text{ GeV} < p_{T,J} < 450 \text{ GeV}$$
$$|\eta_J| < 1.0$$

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