Anomaly Detection in Adversarial Neural Networks

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March 31, 2021

Outline

Particle Jets

- Our aim is to study jets; collimated flow of particles (hadrons) [**1, 2**].
- By studying these jets, our hope is to find new physics Beyond the Standard Model.

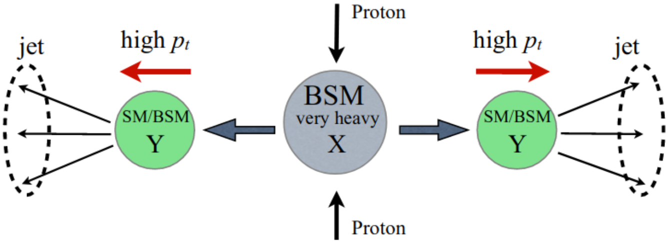

Figure: Typical BSM jet substructure experiment: two protons collide to create a resonance X. This resonance then decays into the lighter Y states, which could be W/Z/Higgs bosons, or other lighter BSM particles [**1**].

Collision Kinematics

- It is helpful to adopt the coordinate system employed at the LHC. Thus, a particle's (relativistic) 3-momentum is given by $\vec{p} = (p_x, p_y, p_z)$.

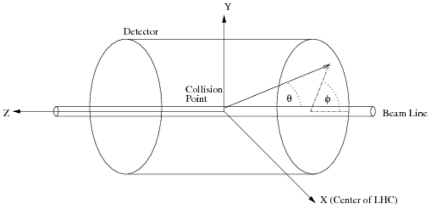

Figure: ATLAS and CMS coordinate system. The azimuthal angle ϕ circles the z-axis, while θ is measured from z [**3**].

- Many experiments are symmetric about ϕ, and so we can focus on the transverse momentum magnitude $p_T = \sqrt{p_x^2 + p_y^2}$ for our purposes.
- From this geometry it follows that $\tan\phi = \dfrac{p_y}{p_x}$ and $\tan\theta = \dfrac{p_T}{p_z}$.

Collision Kinematics

- The rapidity w (i.e. $\tanh w = v$) is usually given in terms of the pseudo-rapidity η. This is easily obtained for highly relativistic particles, since we can substitute $m = 0$ (i.e. $E = |\vec{p}|$) for this case:

$$w = \frac{1}{2}\ln\frac{E + p_z}{E - p_z} = -\ln\sqrt{\frac{E - p_z}{E + p_z}} = -\ln\sqrt{\frac{1 - \cos\theta}{1 + \cos\theta}}$$

- In the last part we've substituted $E = |\vec{p}|$ and used the definition of θ. Note that these are Lorentz invariant quantities. With a simple trig identity, we can therefore define the pseudo-rapidity:

$$\eta = -\ln(\tan(\theta/2)) \tag{1}$$

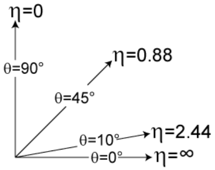

Figure: Correspondence between η and θ parameters [4].

ATLAS Di-Jet Event

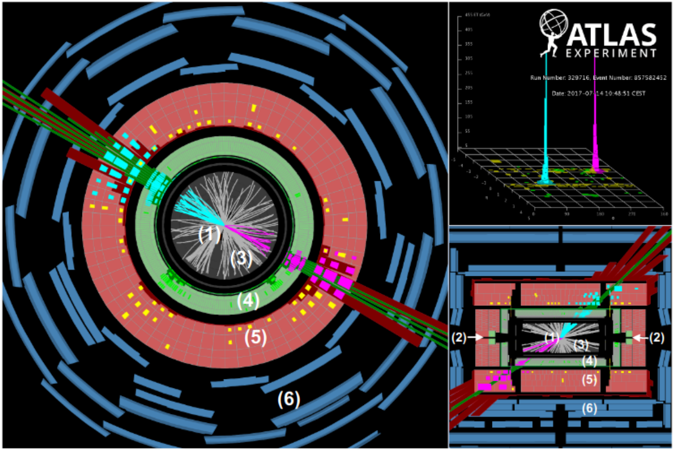

Figure: A proton-proton collision recorded by ATLAS depicting a two jet creation. The upper right-hand side contains calorimeter clusters of transverse energies in the (ϕ, η) plane; the z-direction is into the page [1].

Jet Classification

- Different sources of jets are present, and we need to be able to distinguish them from one another.
- If the Y state is a W boson, for example, it will decay into quarks, which hadronize together for high energies (i.e. large boost). These are known as the *signal* jets.
- Alternatively, *background* jets are QCD jets originating from quarks and gluons; the process of differentiating between these two is jet quark-gluon tagging.
- Similarly we may use flavor tagging to distinguish between heavy light and heavy jet sources.
- Flavor tagging relies on reconstructing collision paths near the interaction point using high-resolution calorimeter sensors; quark-gluon tagging relies on reconstructions from data takes during particle collision at one location [**5**].

Generative Adversarial Networks

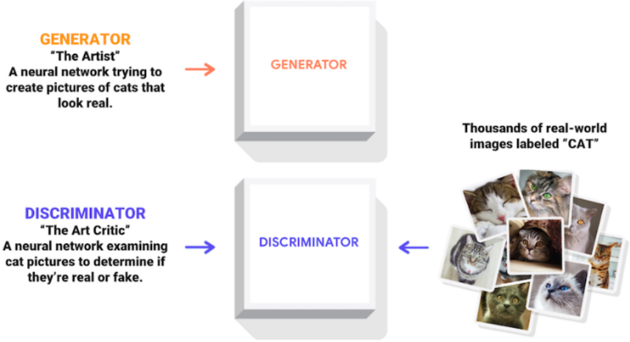

Figure: Training of two Neural Networks to distinguish between signal and background jet sources [**6**].

Generative Adversarial Networks

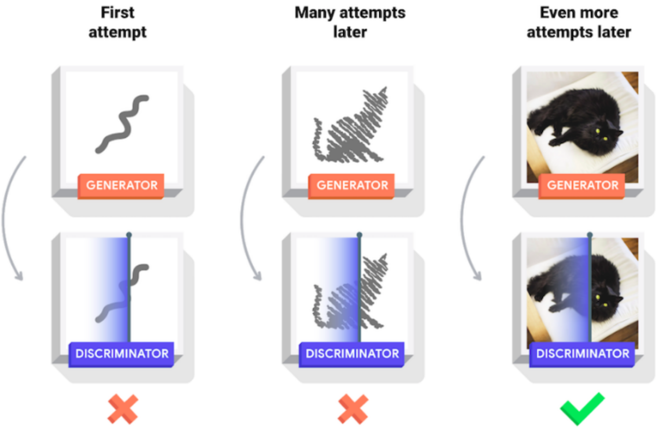

Figure: The process ends when the discriminator is unable to distinguish between source and background jet production [**6**].

Results

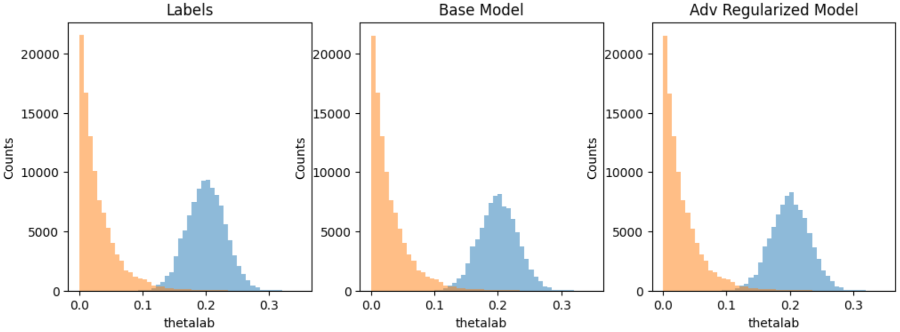

Figure: Some results from the GAN notebook provided [**7**].

- The 20,000 labels were split evenly between signal and background jets. There were a total of 18,508 and 18,520 correctly predicted base and regularized models, respectively.
- Similarly, there were a total of 8,532 and 9,976 correctly predicted base models for signal and background jets, respectively.

Next Steps/Conclusion

- The network training can be either supervised, weakly-supervised, or unsupervised. The unsupervised training optimizes a function given some inputs; they learn directly from background sources, and look for events with low momentum [**5, 6, 8**].
- Anomaly detection can be implemented once the GAN are trained in a similar fashion as was used to separated signal from background events.
- Care must be taken, as single events are insignificant. Only when we consider a statistical ensemble can an anomaly be verified.
- Compare to "Flying Elephant" $\rightarrow$ Anomaly in our regular world. However, to know if it is normal for X amount of elephants to be at a watering hole, we must know the overall population density.
- Lastly, we note that the project is far from complete. The main goal at this point remains to mold the GAN program into something that we can use for anomaly experiments.

References

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