Anomaly Searches with Tag N' Train

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Based on arXiv:2002.12376

JOHNS HOPKINS UNIVERSITY

Anomaly Detection Workshop
Summer 2020

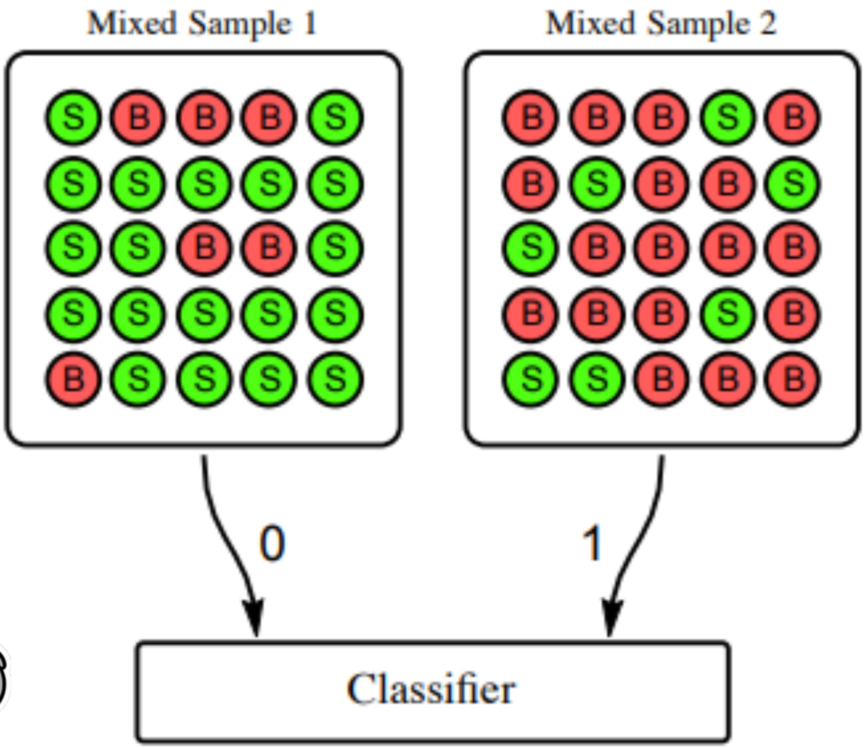
Outline

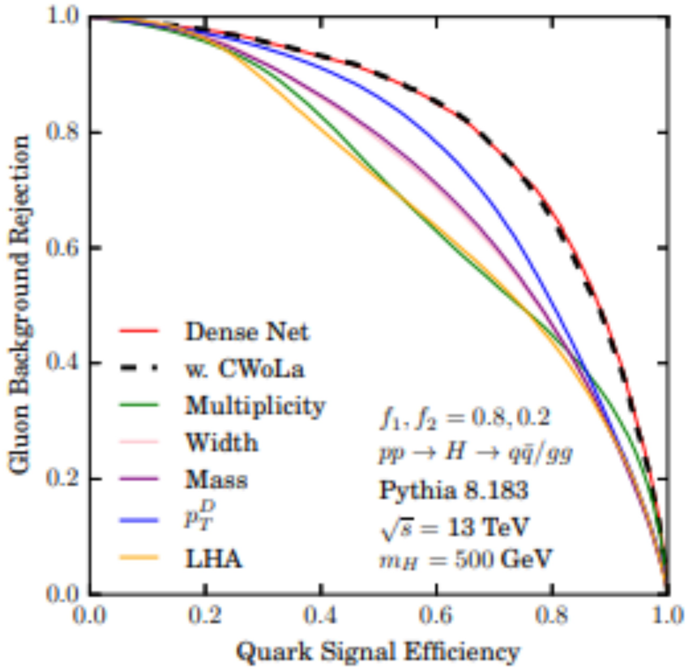
- How to train on data?
- The Tag N' Train algorithm
- Dijet anomaly search
- Future work

How To Train on Data?

Classification Without Labels

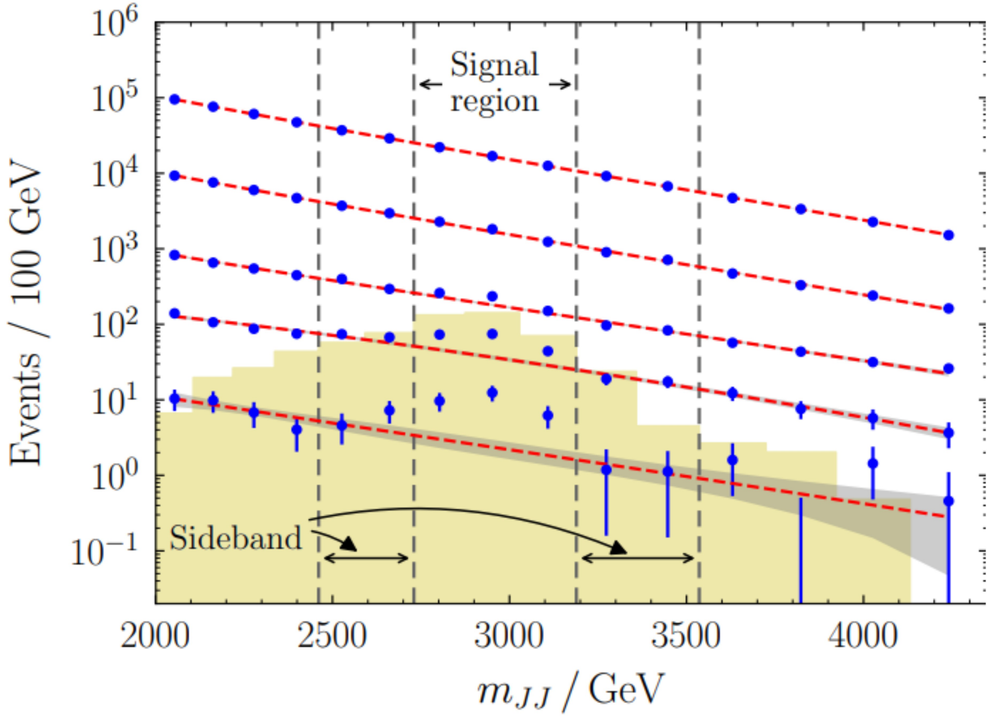
arXiv:1708.02949





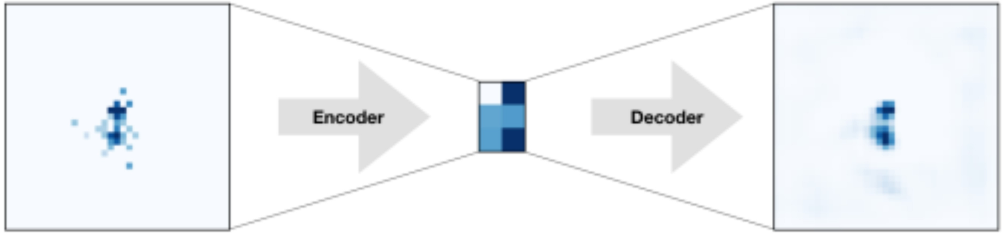
CWoLa Hunting

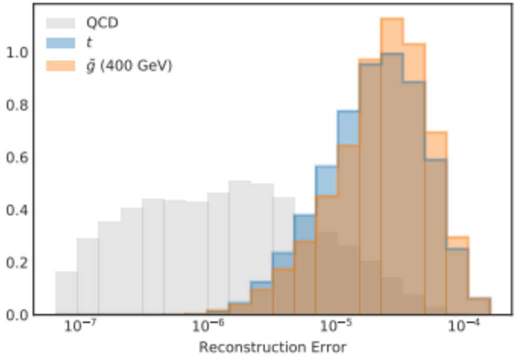
arxiv:1902.02634



- Signal region = dijet mass window
- Train a classifier on signal region vs. others
- Select events & bump hunt

Anomaly Detection : Autoencoders





arXiv:1808.08992
arXiv:1808.08979
+ Others

- Train a network to compress and decompress the data
- Can train directly on data, no labels needed
- Anomalous events should have a higher reconstruction loss

Drawbacks

- CWoLa Hunting
  - Worry about sculpting QCD dijet mass distribution
  - Apply to non-resonant signals?

- Autoencoders
  - Only ‘learns’ what QCD looks like
  - Room for improvement as a Sig vs. Bkg classifier

The Tag N' Train Algorithm

How to Combine?

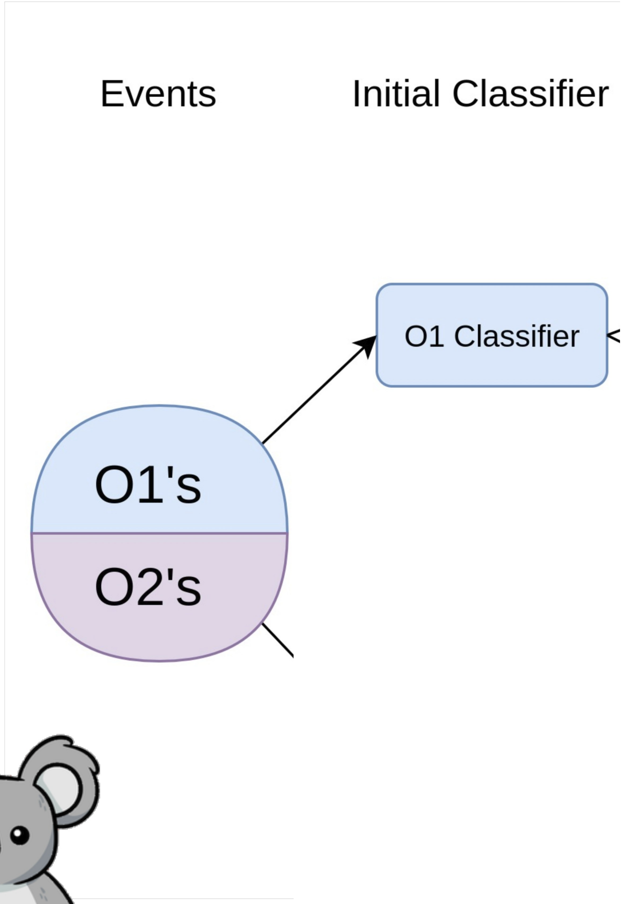
- CWoLa + autoencoders
- Find samples with enriched signal using autoencoders
- Train better classifiers using these samples

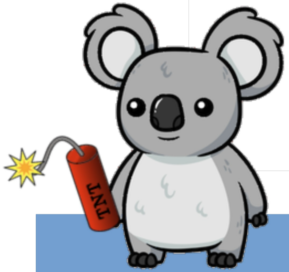
Tag N’ Train (TNT)

- A of training improved classifiers on data
- Assumptions:
  - Signal has **2 interesting objects** in it
  - One has a **starting classifier** for each object
  - Signal-like features in background events are uncorrelated between the 2 objects

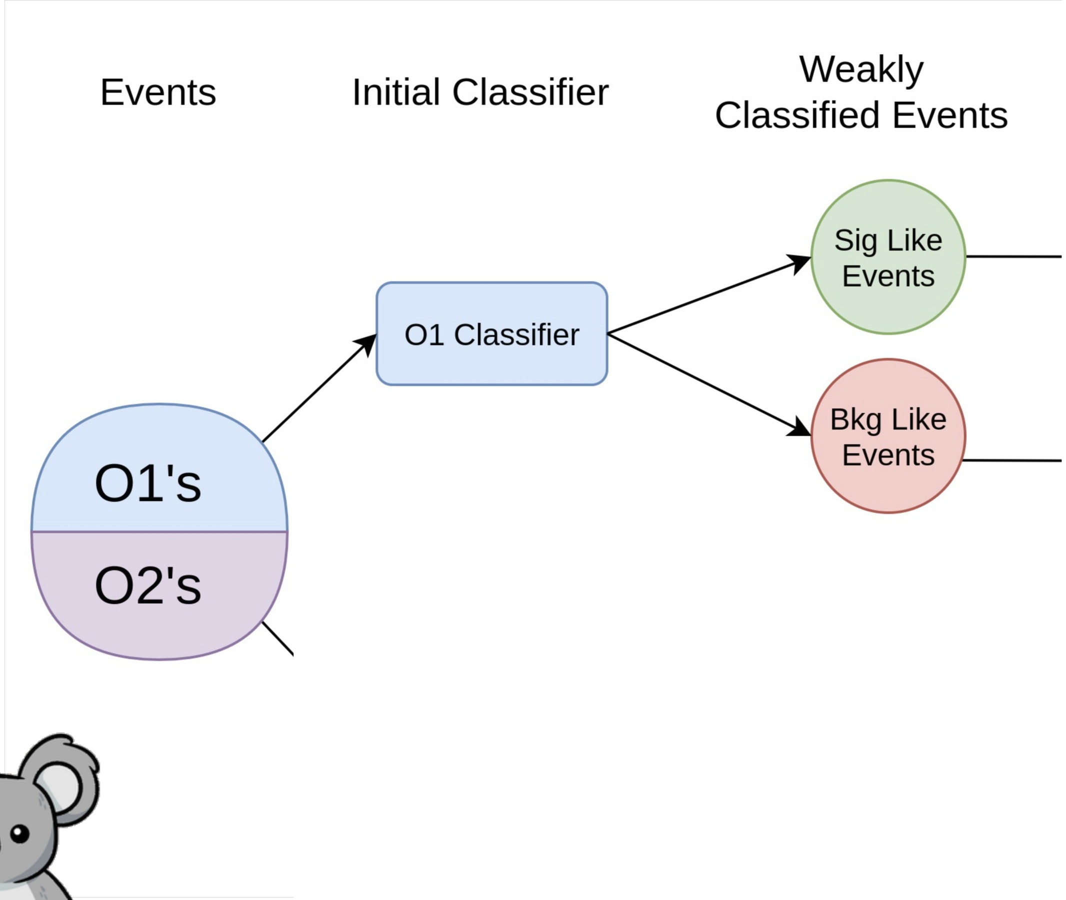
Tag with a weak classifier **N’ Train** a better one!

Tag N' Train

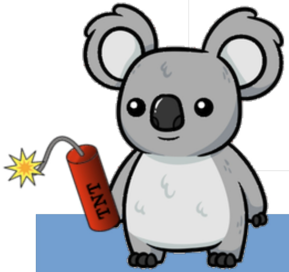




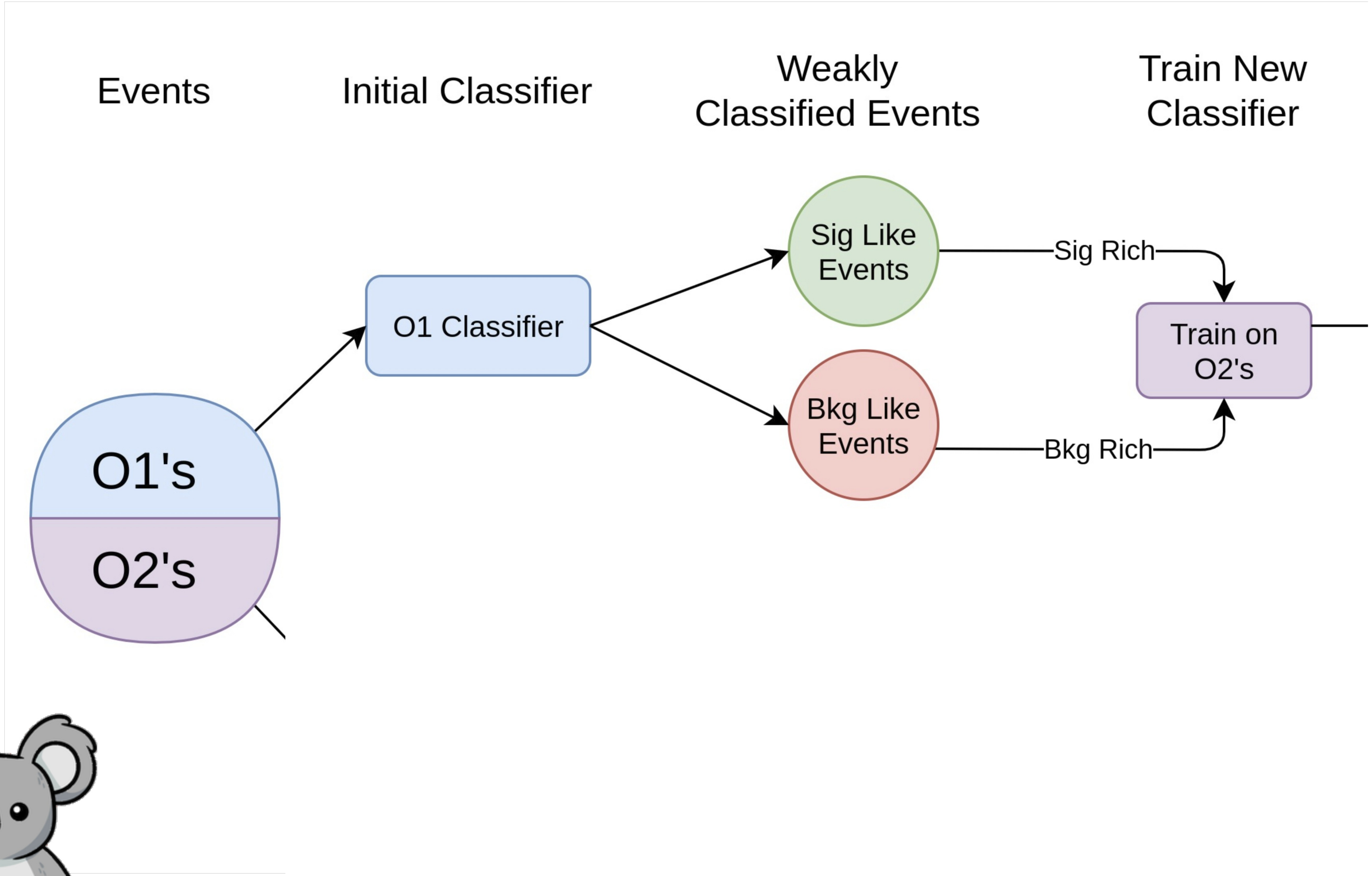
Tag N' Train

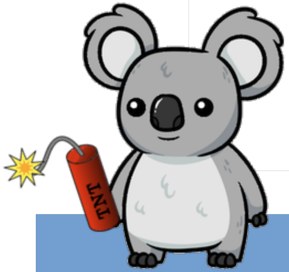


Events
Initial Classifier
Weakly
Classified Events
O1 Classifier
Sig Like
Events
Bkg Like
Events
O1's
O2's

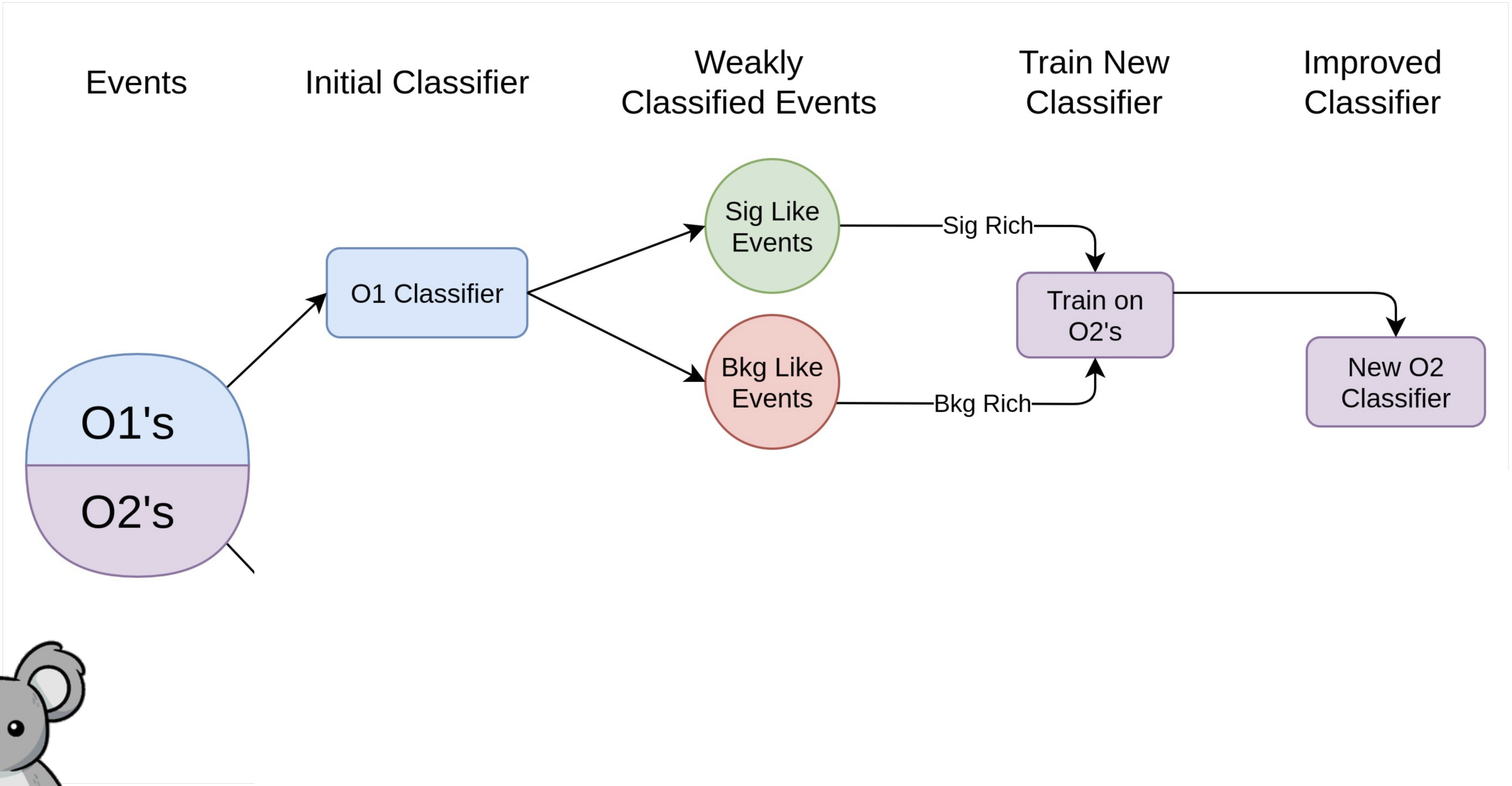


Tag N’ Train

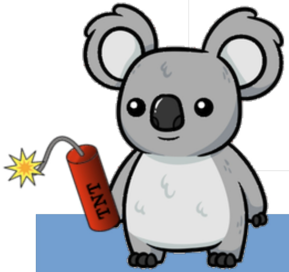

Events
Initial Classifier
Weakly Classified Events
Train New Classifier
O1's
O2's
O1 Classifier
Sig Like Events
Bkg Like Events
Sig Rich
Bkg Rich
Train on O2's


TNT

Tag N' Train

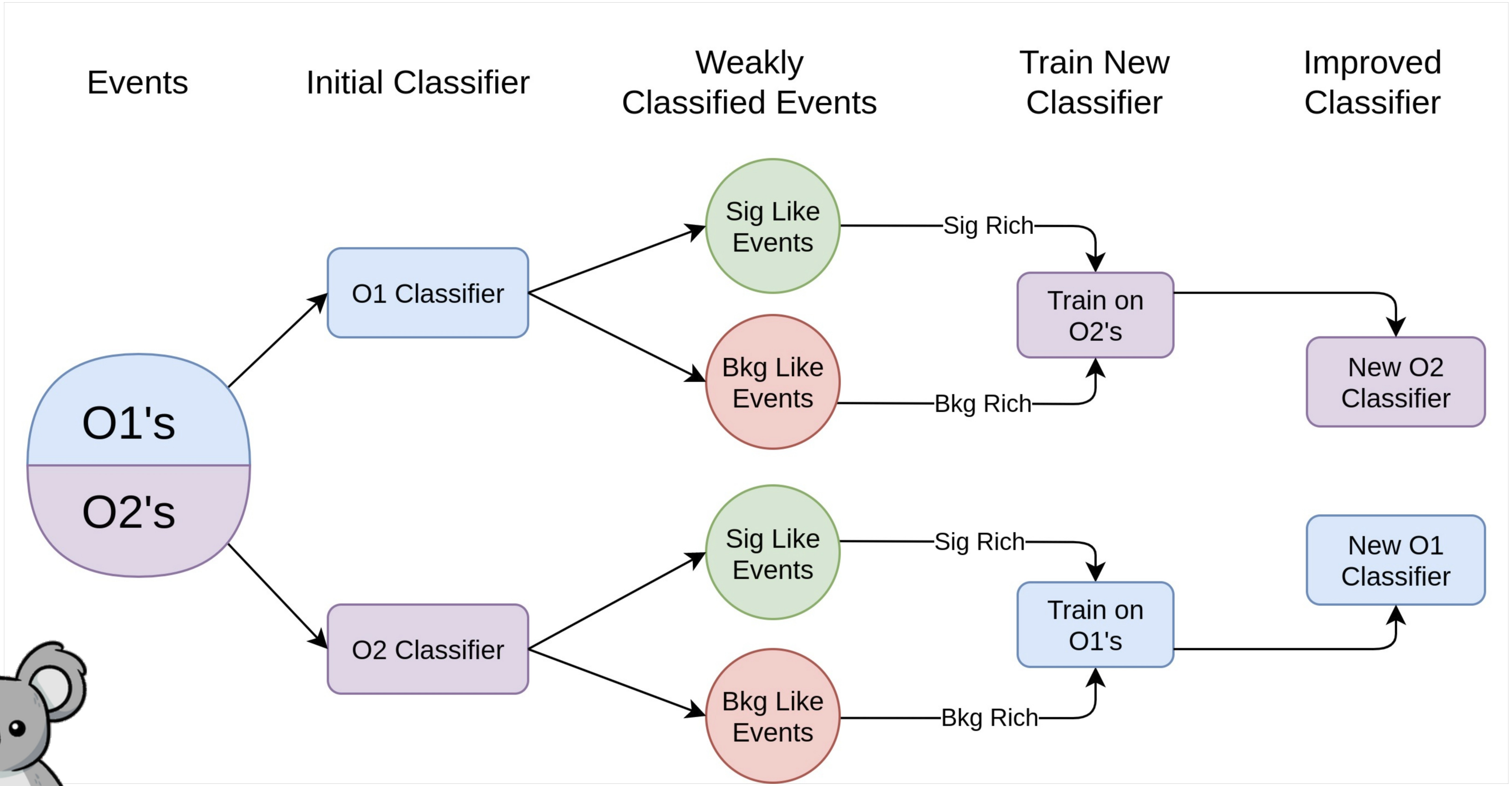


Events
Initial Classifier
Weakly Classified Events
Train New Classifier
Improved Classifier
O1's
O2's
O1 Classifier
Sig Like Events
Bkg Like Events
Sig Rich
Bkg Rich
Train on O2's
New O2 Classifier

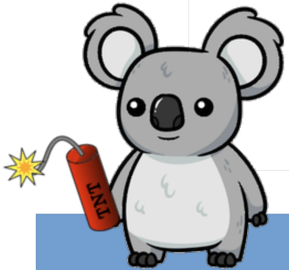


TNT

Tag N' Train

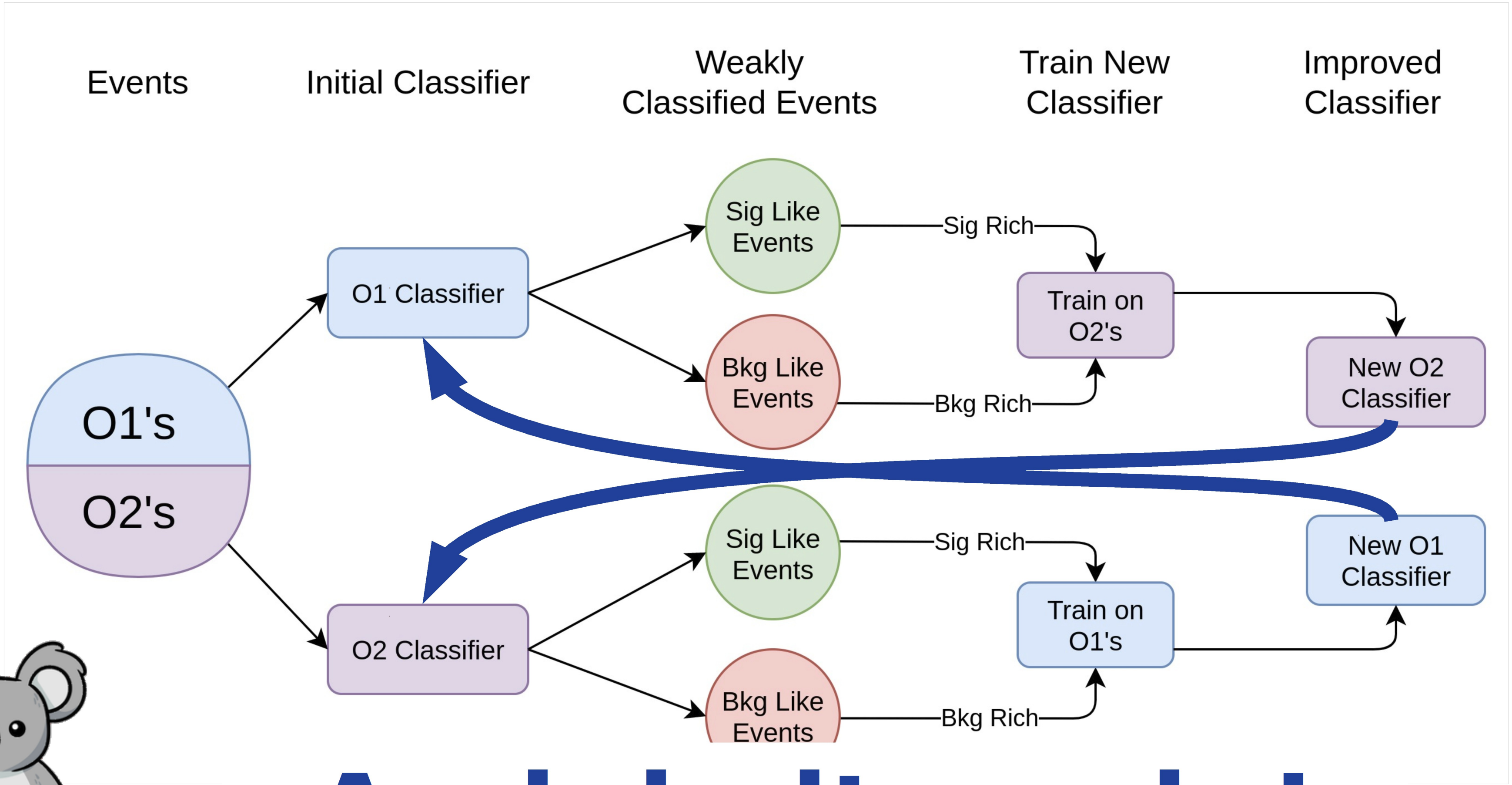


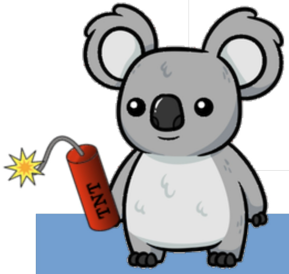
Events
Initial Classifier
Weakly Classified Events
Train New Classifier
Improved Classifier
O1's
O2's
O1 Classifier
O2 Classifier
Sig Like Events
Bkg Like Events
Sig Like Events
Bkg Like Events
Sig Rich
Bkg Rich
Sig Rich
Bkg Rich
Train on O2's
Train on O1's
New O2 Classifier
New O1 Classifier



TNT

Tag N' Train



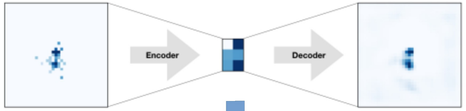


And do it again!

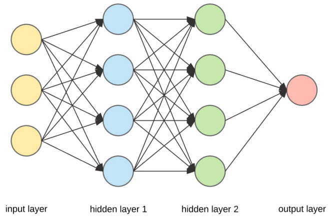
Dijet Anomaly Search

Applying TNT to a Resonance Search

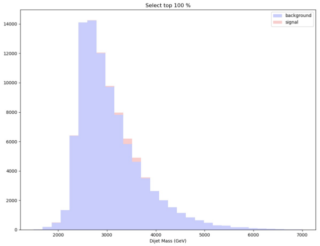
Events A

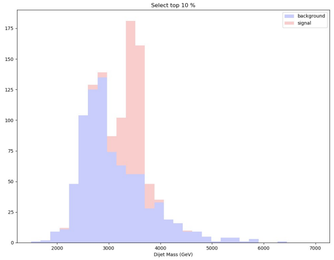


Events B



Events C



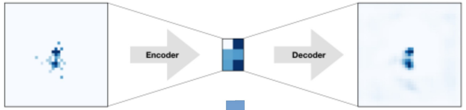


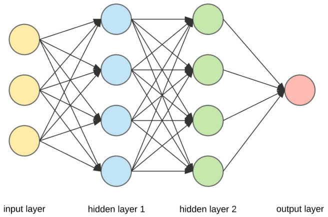
Applying TNT to a Resonance Search

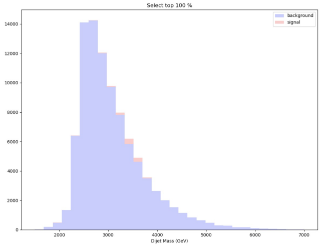
Events C

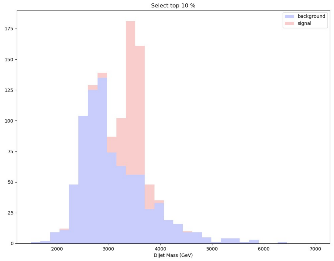
Events A

Events B









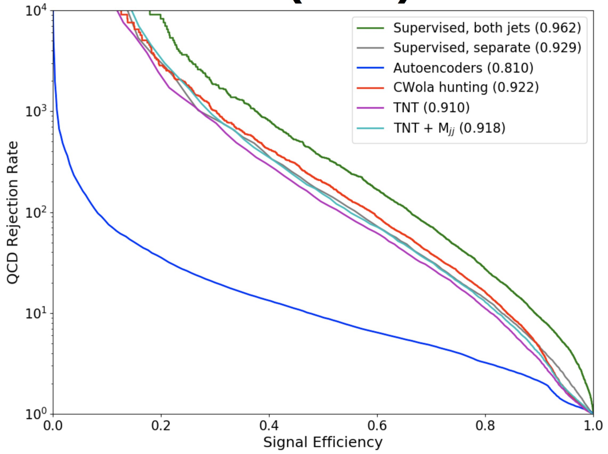
Cross-Validate!

Technical Details

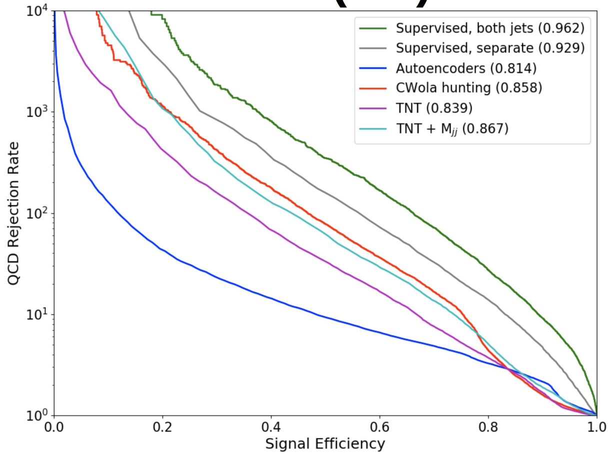
- 2 objects: heavy jet and light jet in event
- TNT Classifiers and autoencoders are CNN’s based on jet images (details in backup)
- Top 20% ‘sig-like’, bottom 40% ‘background-like’
  - Optional: require signal events in dijet mass window
- Combine 2 classifiers into 1
  - Require both jet’s scores be in top X% of scores

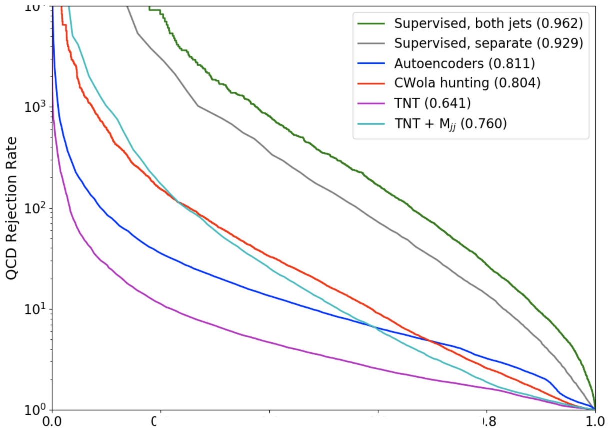
Classification Performance

9% (35%)

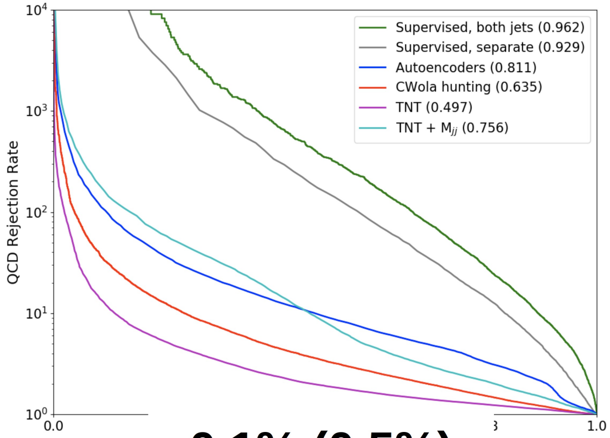


1% (6%)





0.3% (1.7%)

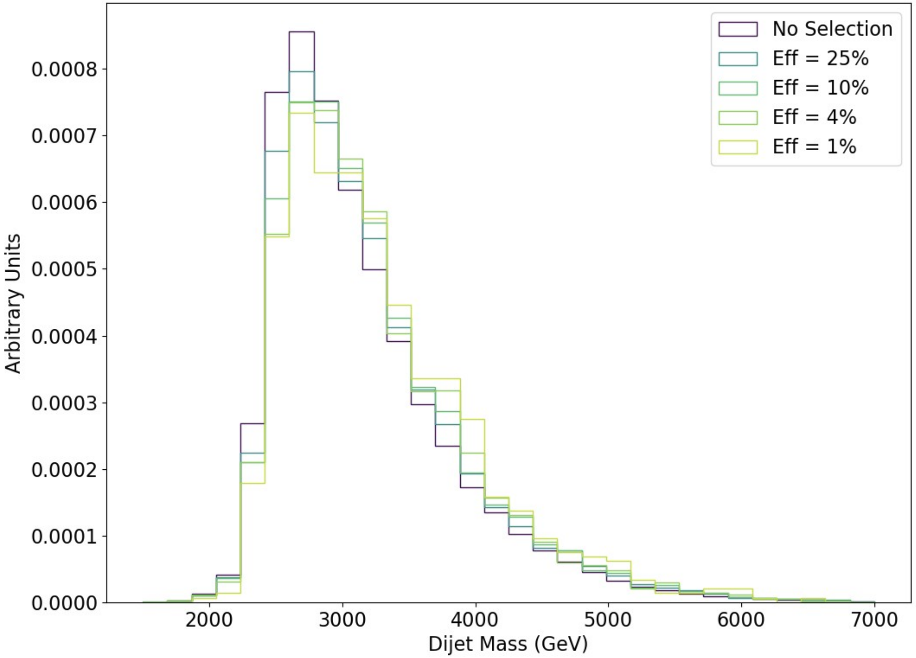


0.1% (0.5%)

- Compare performance of techniques for different amounts of signal
- S/B in full sample (in M_{jj} SR)
- Autoencoders performance indep. of signal
- TNT + M_{jj} matches CWoLa hunting at high signals
- TNT + M_{jj} can maintain performance at low signals

R&D Dataset

Dijet Mass Sculpting

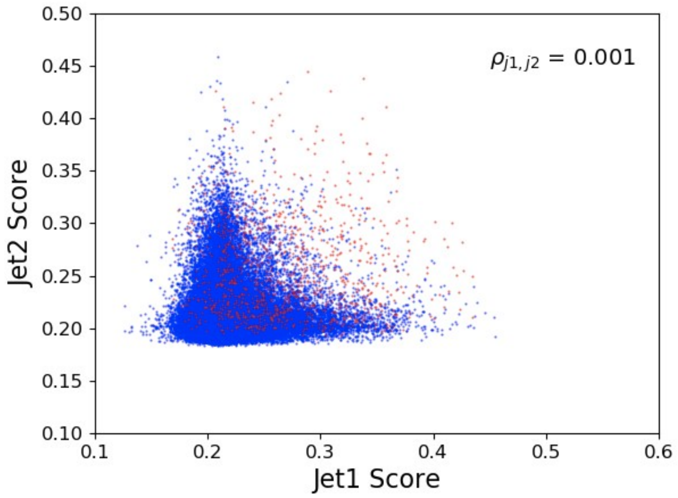


- No sculpting of dijet mass!
  - Images p_T normalized
- Decorrelation methods also possible
  - Pt reweighting tried, found no difference

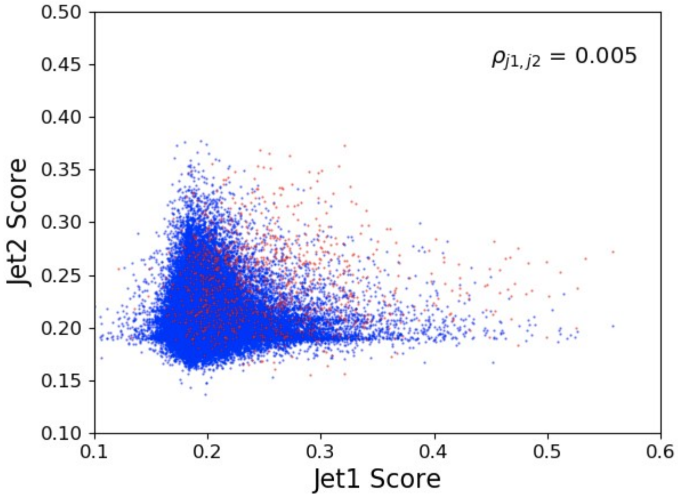
R&D Dataset

Assumption: Correlations

“Pure” CWoLa



Tag N’ Train

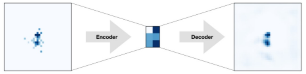


- Key assumption: Anomalous features of background events are uncorrelated
- Empirically (?) seems to hold

R&D Dataset

Trade Offs*

(V)AE’s



+ Performance indep. of amount of signal

+ Minimal assumptions

— Inherently ‘anti-QCD’ rather than a ‘pro-signal’

CWoLa Hunting

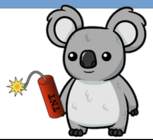
+ Great performance for large to medium signals

+ Can do full-event classification

— Assumption: resonant signal

— Must fully decorrelate features with M_{jj}

TNT



+ Great performance for medium/large signals and maintains performance for smaller signals

+ Mass sculpting mitigation possible

— Requires a starting classifier

— Assumption: Signal has 2 interesting objects

*Of course there are other interesting techniques with different trade offs too

Future Work

Future Work

- Explore architectures and inputs for TNT classifiers
  - High-level vs. low-level features
  - Beyond just jet substructure: SV's, tracking information, leptons, etc.
- Explore in a non-resonant search
  - Sub-dominant backgrounds with 'interesting' jets (e.g. ttbar)?
- Can supervised searches be incorporated within this framework?
  - e.g. Start with a W and top classifiers trained in MC

Conclusions

- New **Tag N' Train** algorithm for training classifiers on data
- Works well in dijet anomaly search
- Trade offs between various techniques
- Lot's of room to explore!

Conclusions

- New **Tag N' Train** rith r training classifiers on data
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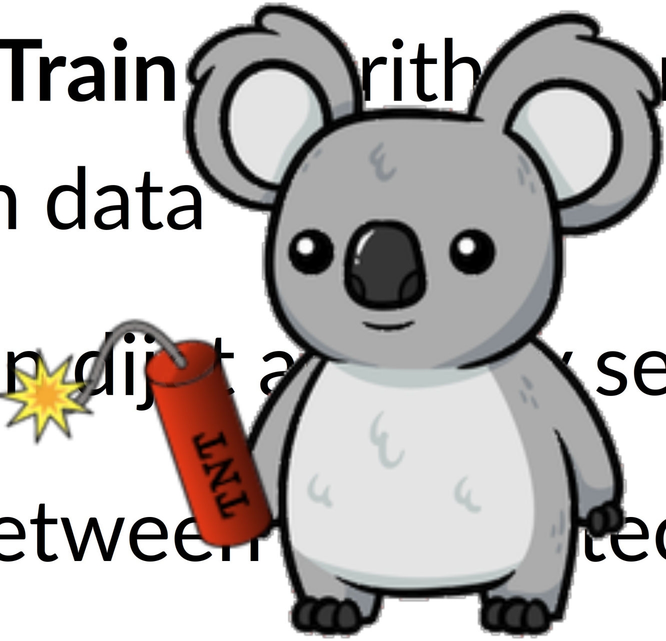


Backup

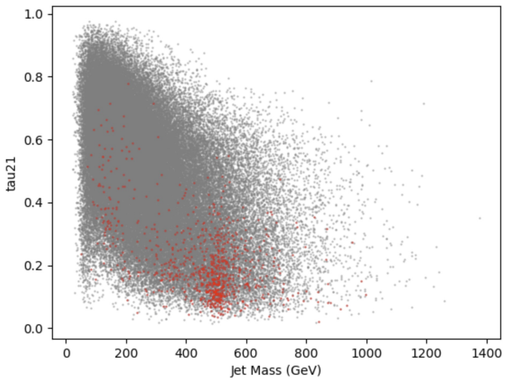
Technical Details

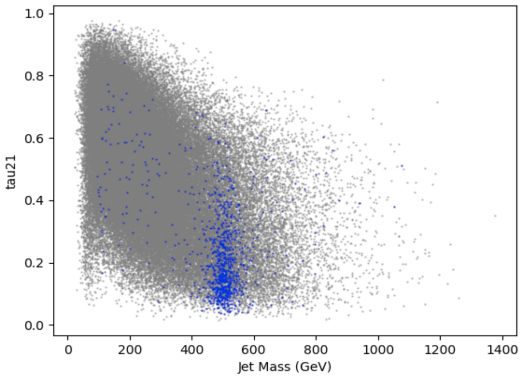
- Anti-kT R = 1 jets
- Jet images, mostly based on “Pulling out All the Tops” (1803.00107)
  - 40x40 pixels covering +/- 0.7 in $\Delta\eta$ and $\Delta\varphi$
  - Centered, rotated and flipped before pixelizing
  - Normalized so sum of all pixel intensities is 1
- Autoencoders are CNN’s with a ~20k params and a latent size of 6
- Classifiers are CNN’s with ~7k parameters
- Further details in the paper, github

Understanding Signal

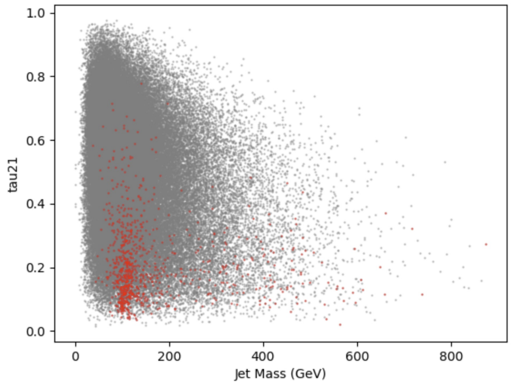
TNT Selection | **Truth**

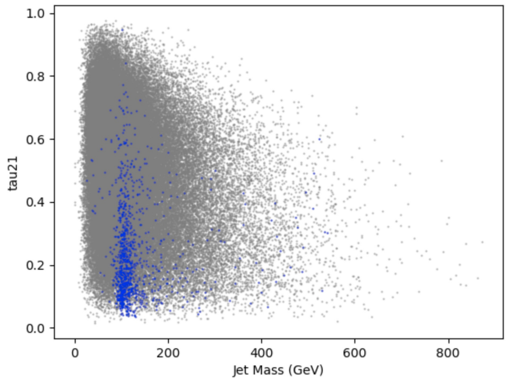
Heavy Jet





Light Jet

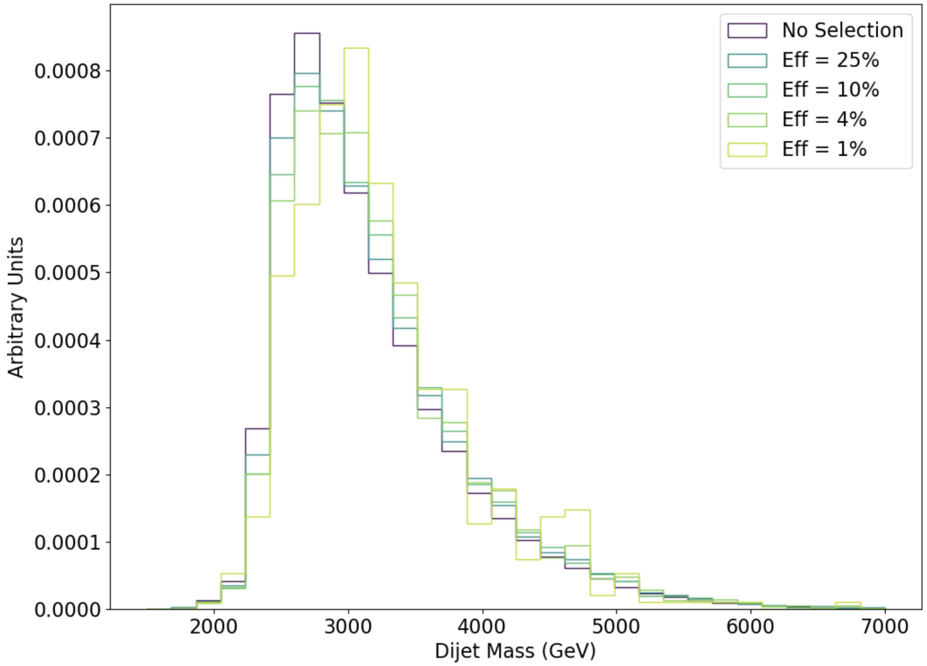




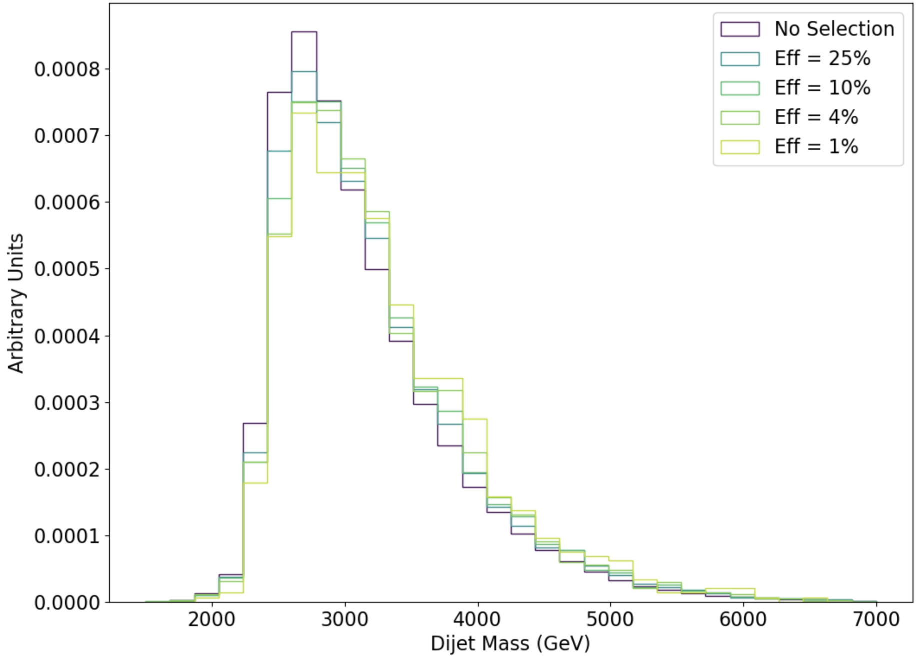
R&D Dataset

Mass Sculpting Comparison

CWoLa Hunting



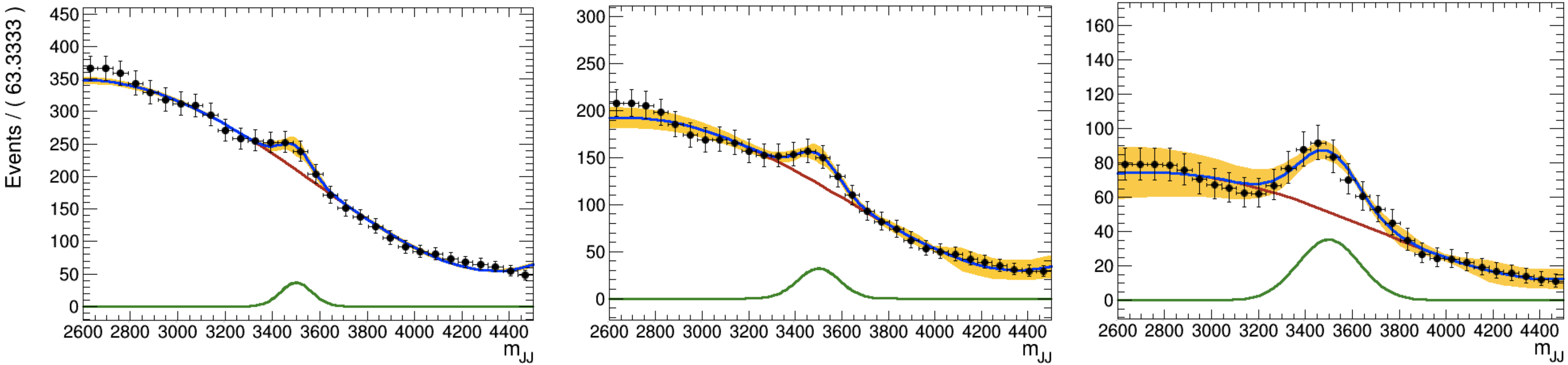
TNT + M_{jj} Window



R&D Dataset

Bump Hunting

R&D
Dataset

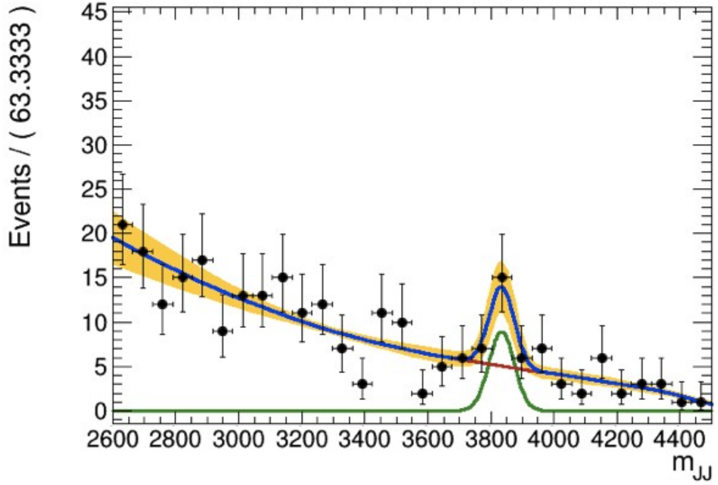


3.1σ **4.2σ** **7.7σ**

Tighter Selection

R&D
Dataset

Black Box1 Results (Shown in January)



- Resonance at ~ 3800 GeV
- 4 sigma evidence after combining samples
- Nothing seen in quick scan of black boxes 2 and 3