

Machine Learning for Long-lived Particle Searches



Benjamin Nachman

*with Sergei Gleyzer, Gregor Kasieczka,
and Gordon Watts*

Fifth workshop of the LHC LLP Community, May 2019

Motivation



Deep learning* has great potential to improve all areas of HEP.

Now is the time to ask what is the potential for LLPs!

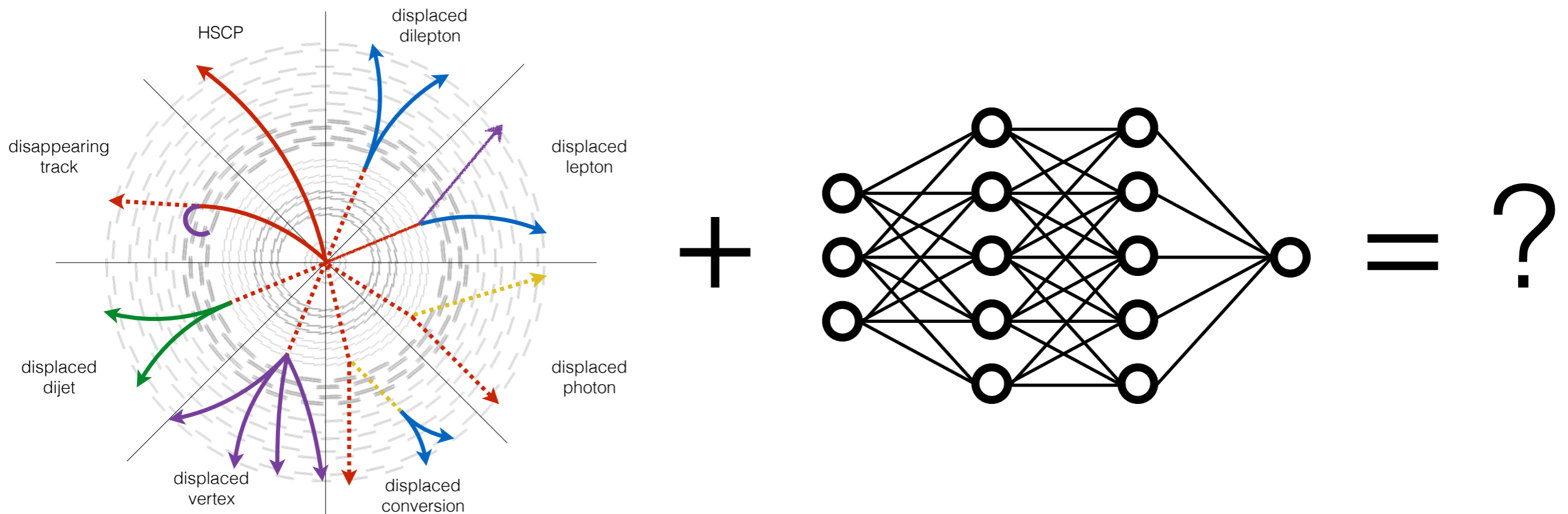


Image from [J. Antonelli](#) - please let me know if this is not the original source!

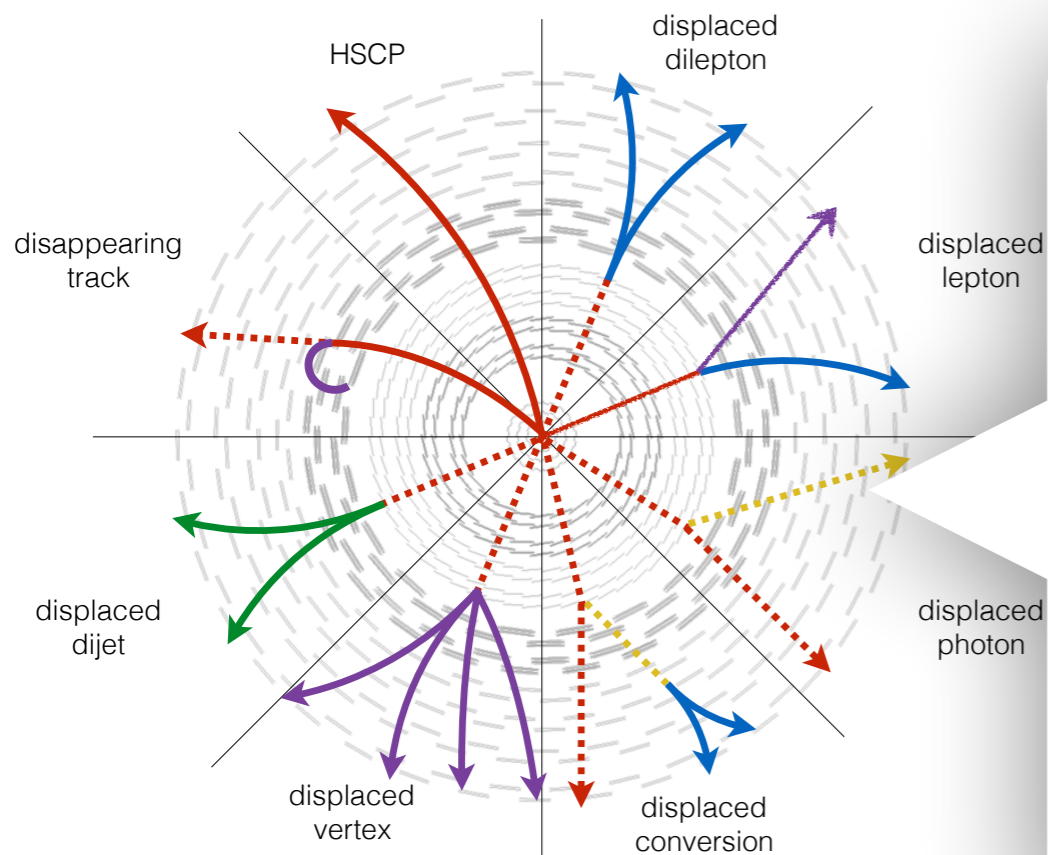
*This just means “machine learning”, but emphasizes that I’m talking about modern methods - today’s NN’s/BDTs/etc. are not those of LEP and the Tevatron...

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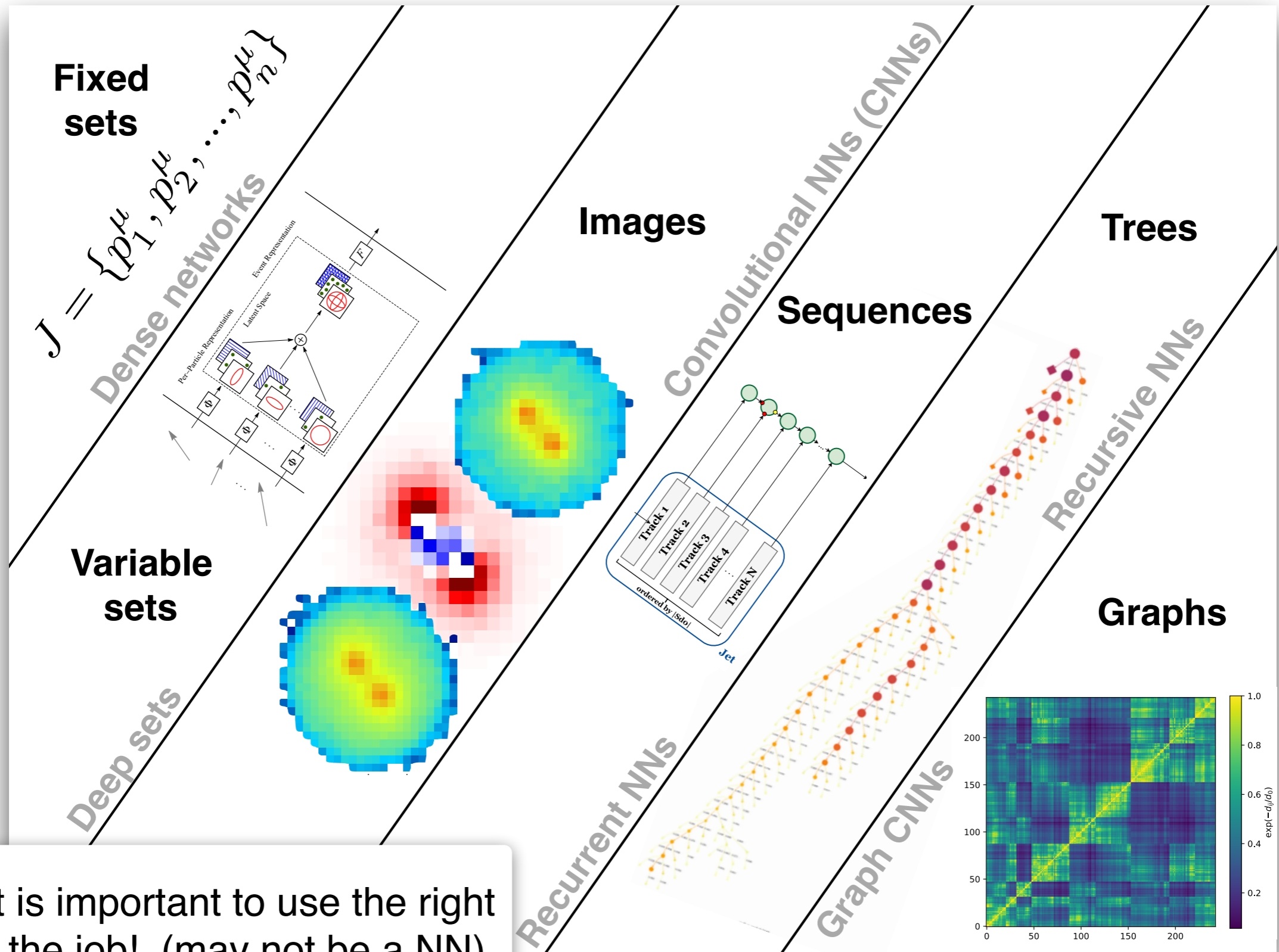
I don't have to tell you that LLPs have **unique challenges**. What I hope to tell you is about how **deep learning may be able to help**.

= ?

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The toolkit is large!

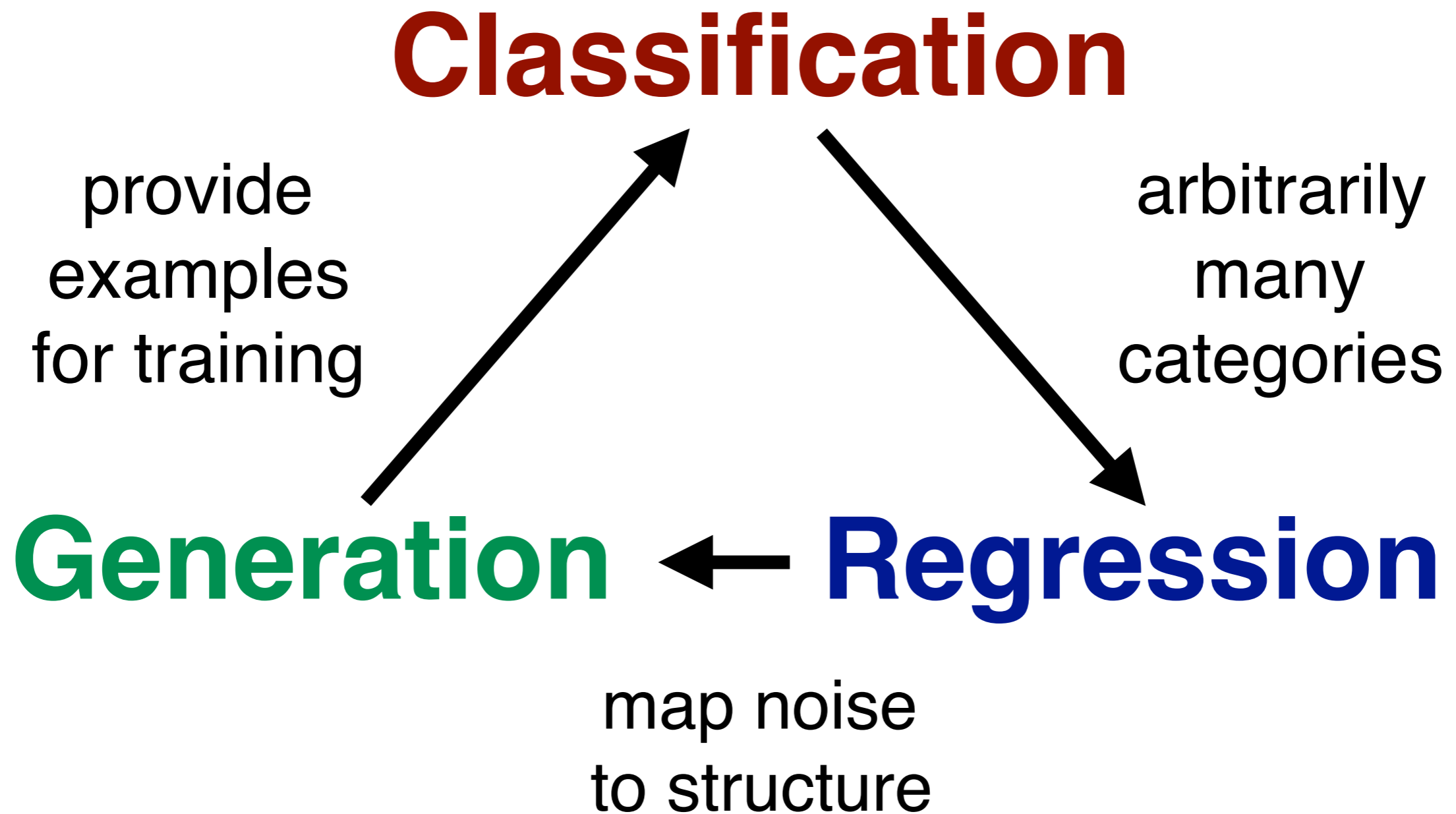


...and it is important to use the right tool for the job! (may not be a NN)

Not pictured: non-NN methods including modern BDTs, etc.

How can we use deep learning?

5

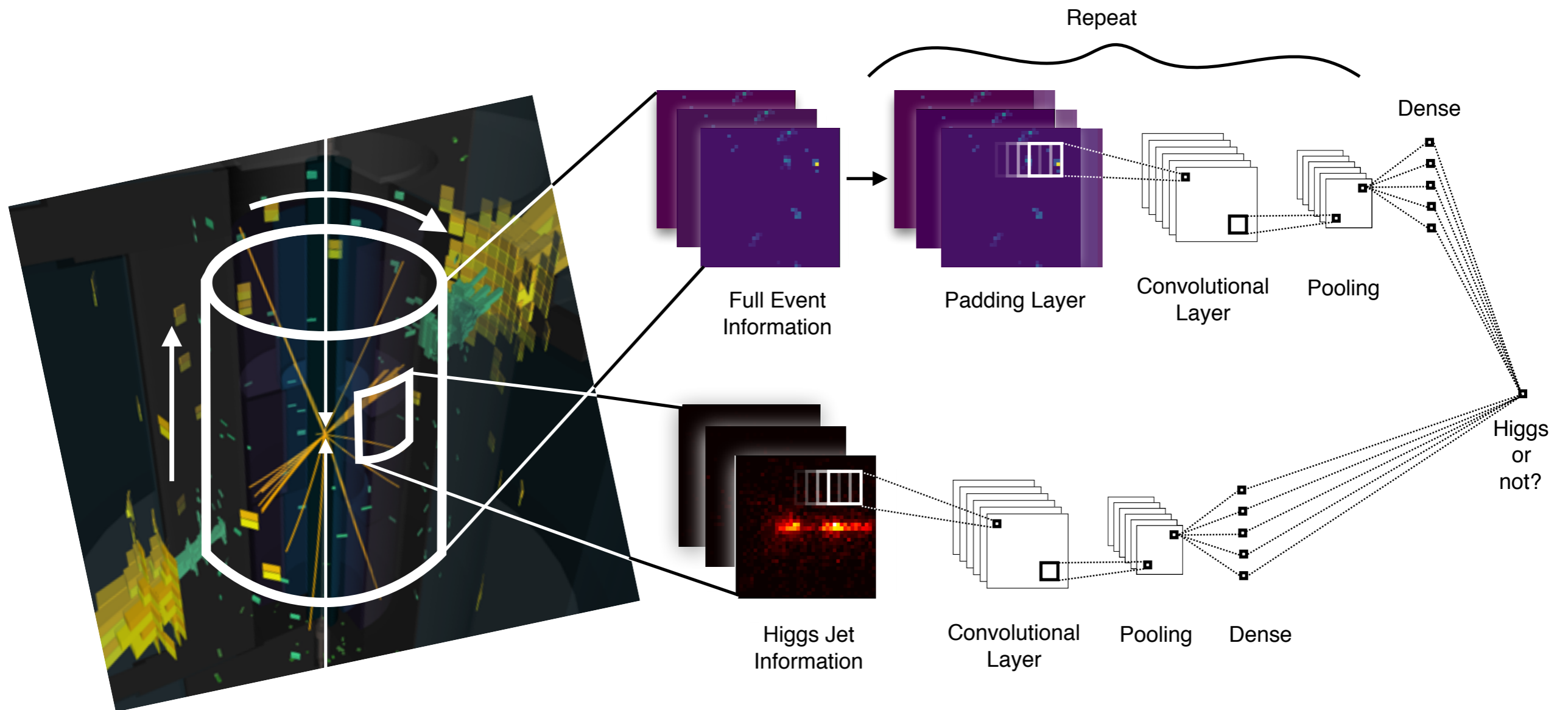


+Extra credit: weak/unsupervised learning and anomaly detection

Classification: signal vs. background



Low-level inputs + multiple detector systems.



Q: How to validate when simulations are not fully reliable, as is often true for LLP (more on this later)?

Regression: Ex. object energy

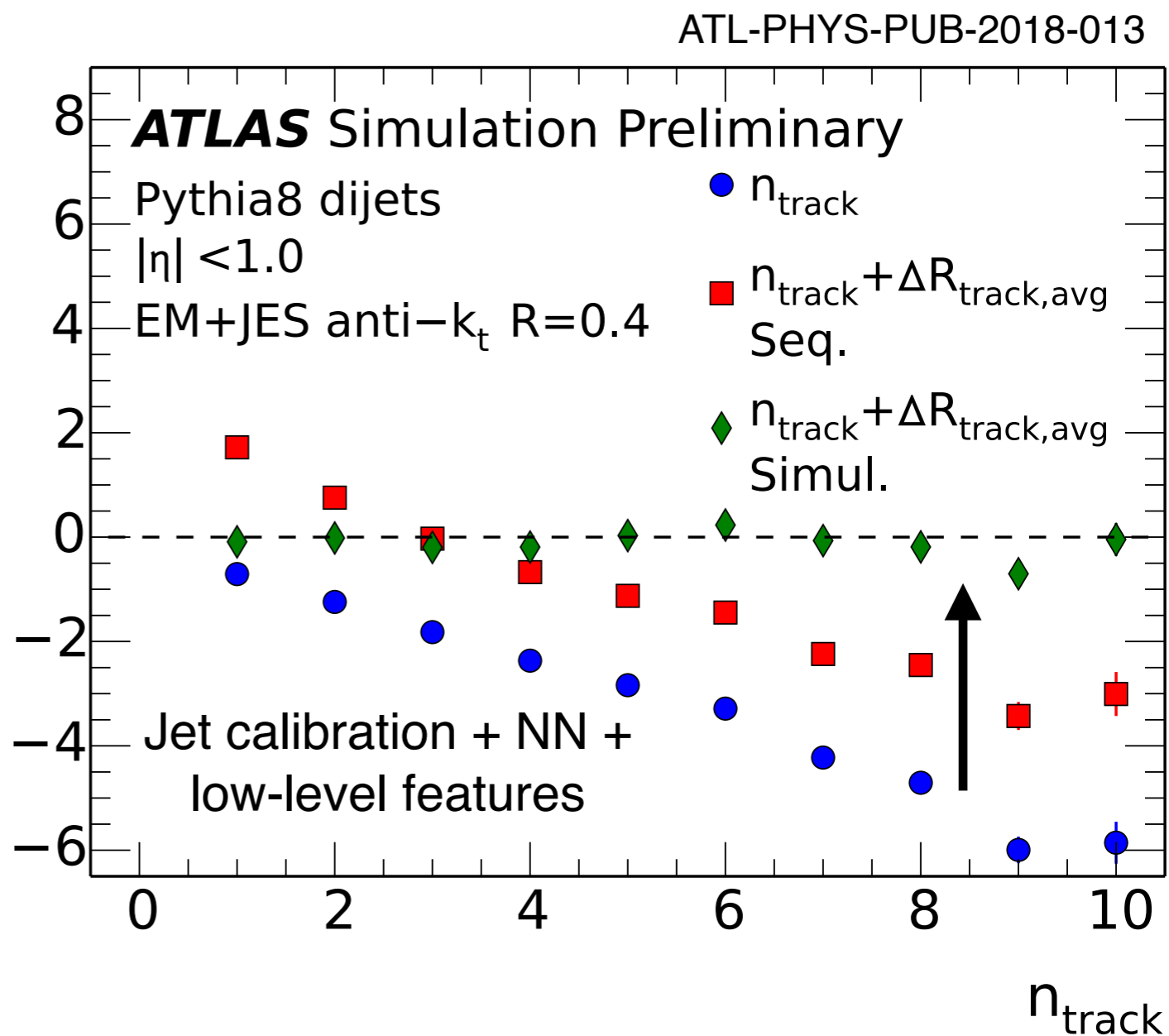


Can we automate the energy estimation of non-standard objects?

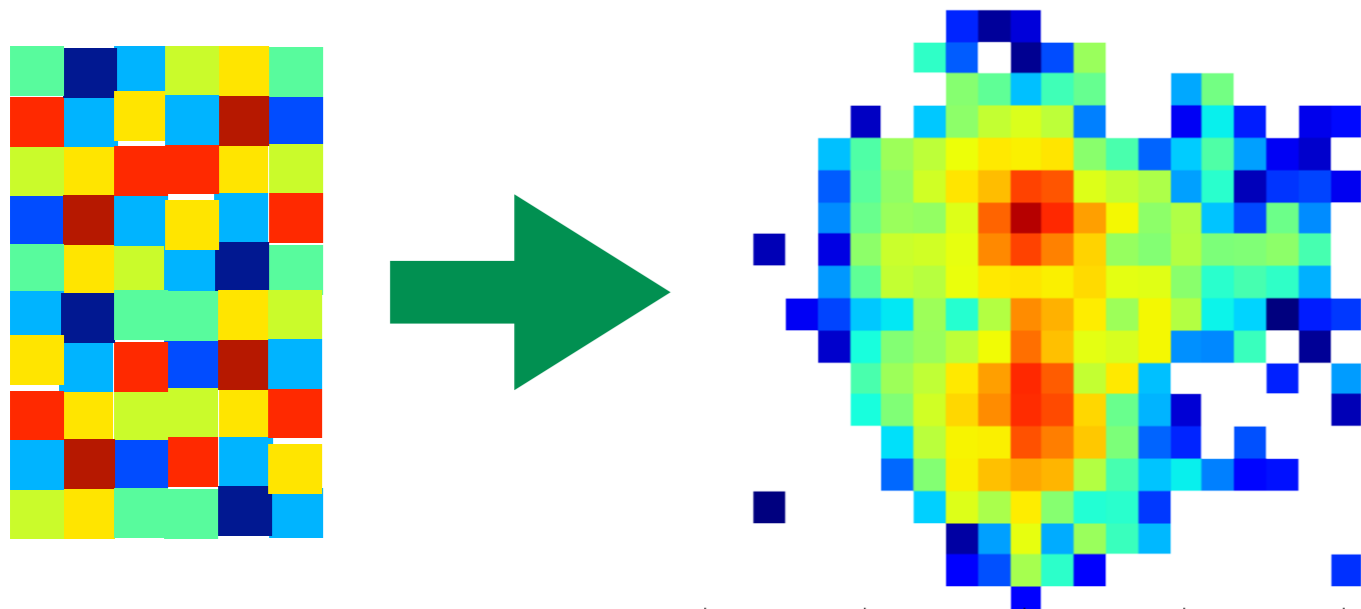
Augment standard algorithms with non-standard information?

Warning: need to worry about prior dependence. This is a ~solved problem with “**generalized numerical inversion**”

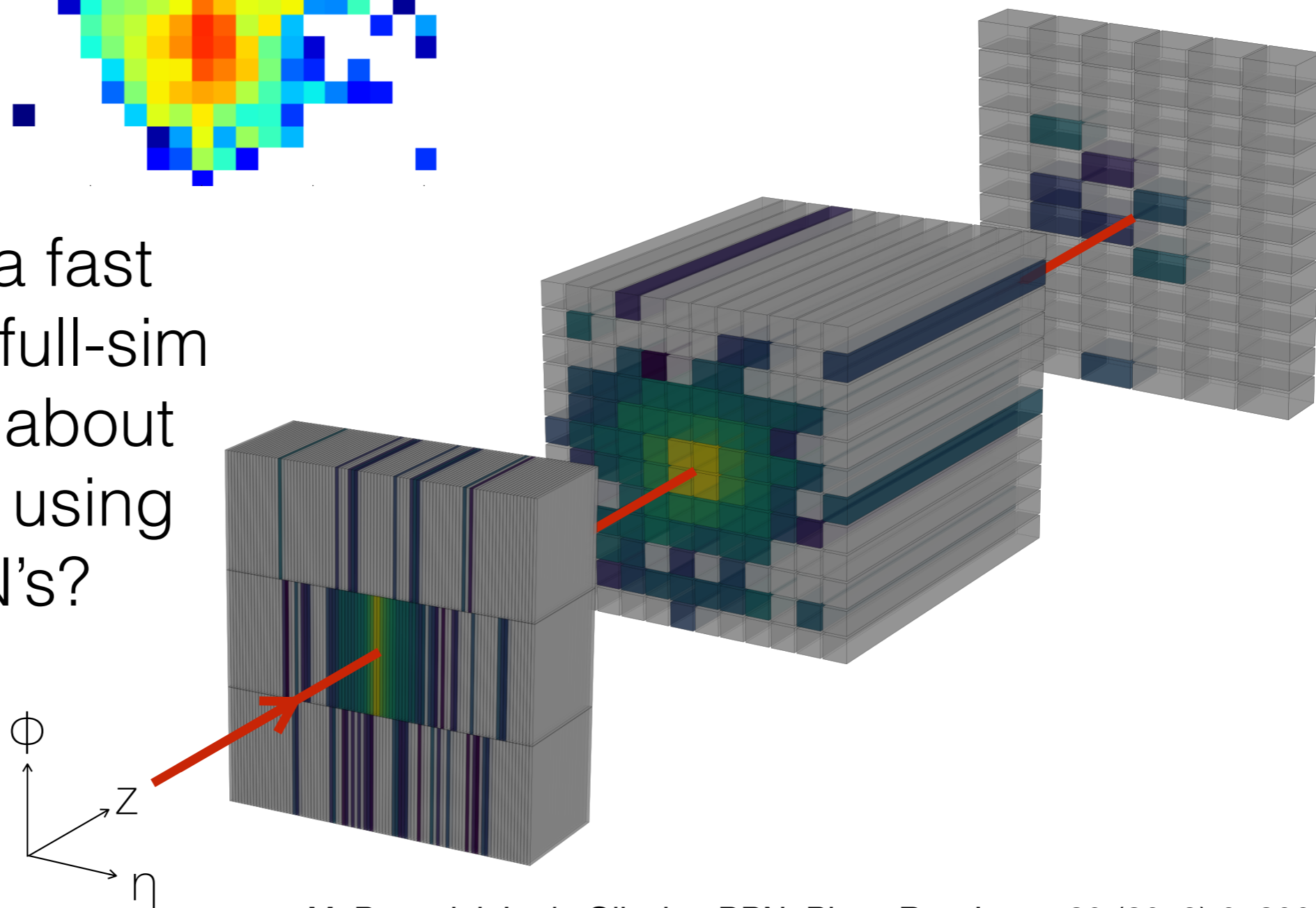
$\frac{d(\text{energy response})}{d(\text{angular spread of jet})}$



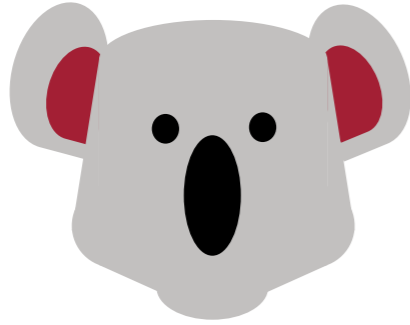
Generation: Ex. CaloGAN



Can we design a fast sim that captures full-sim level information about strange showers using generative NN's?



Extra Credit 1: No labels (“weak supervision”)



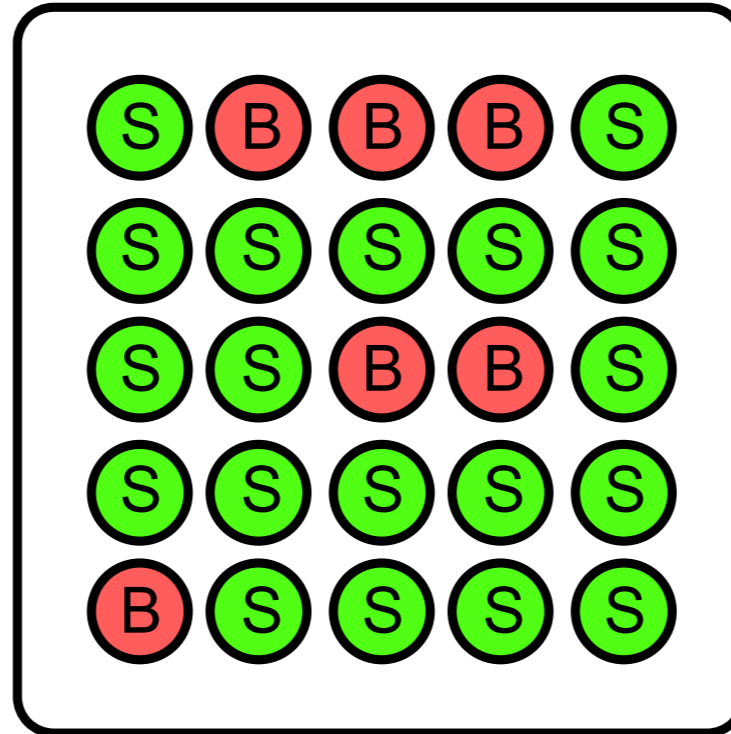
CWoLa

*Classification
Without Labels*

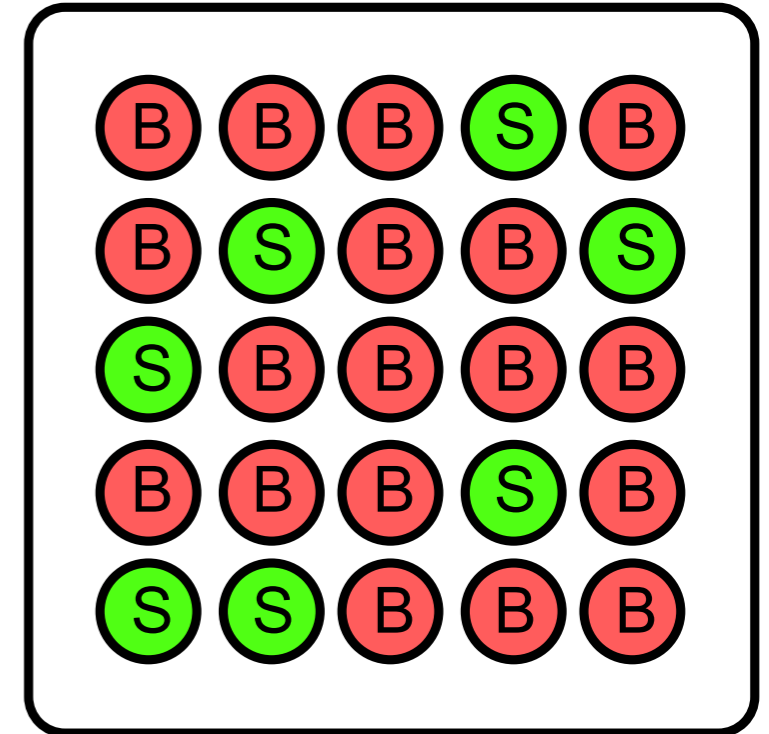
One solution: Train
directly on data using
mixed samples

N.B. one of these could be
sim and one could be data

Mixed Sample 1



Mixed Sample 2



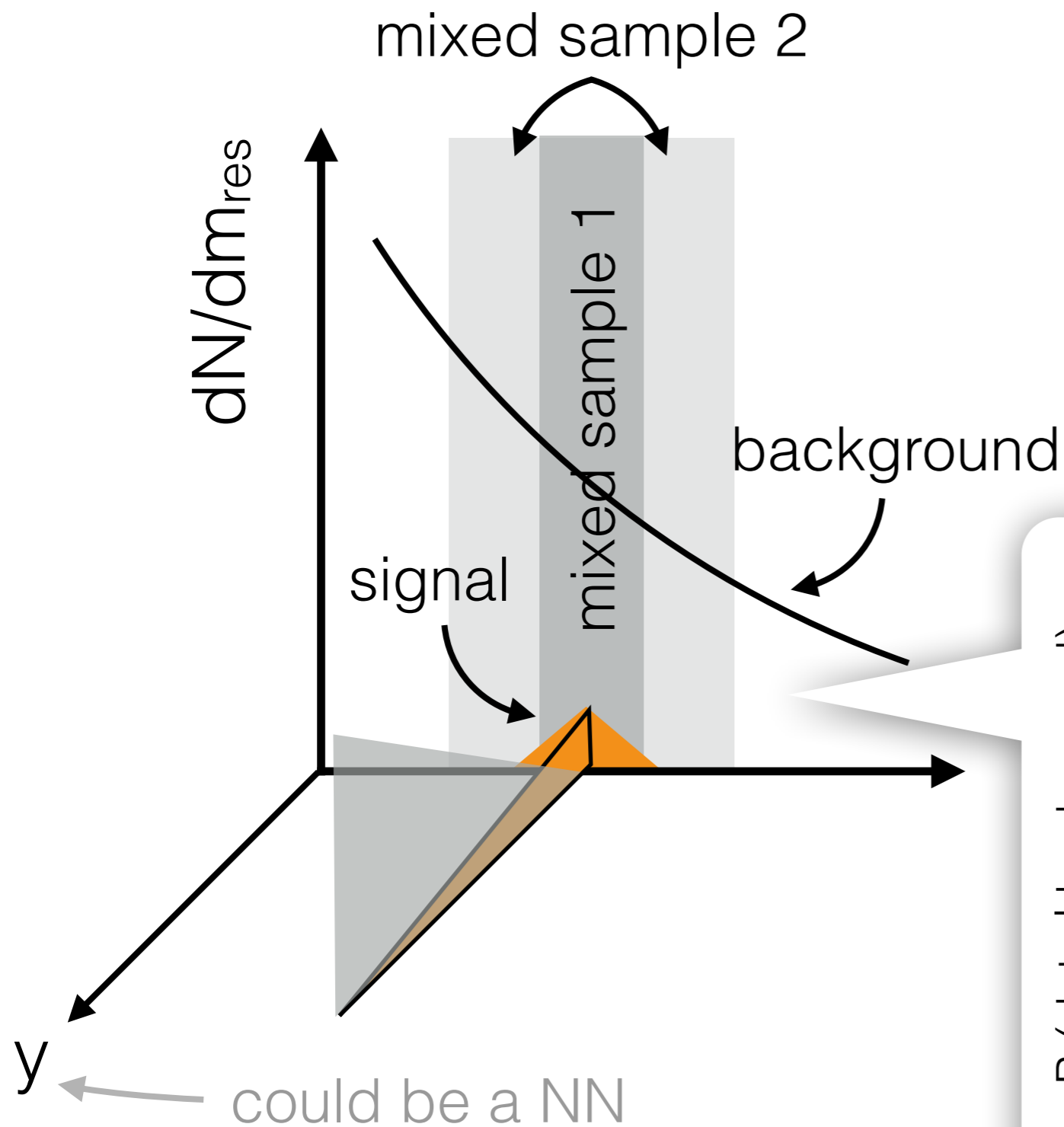
0

1

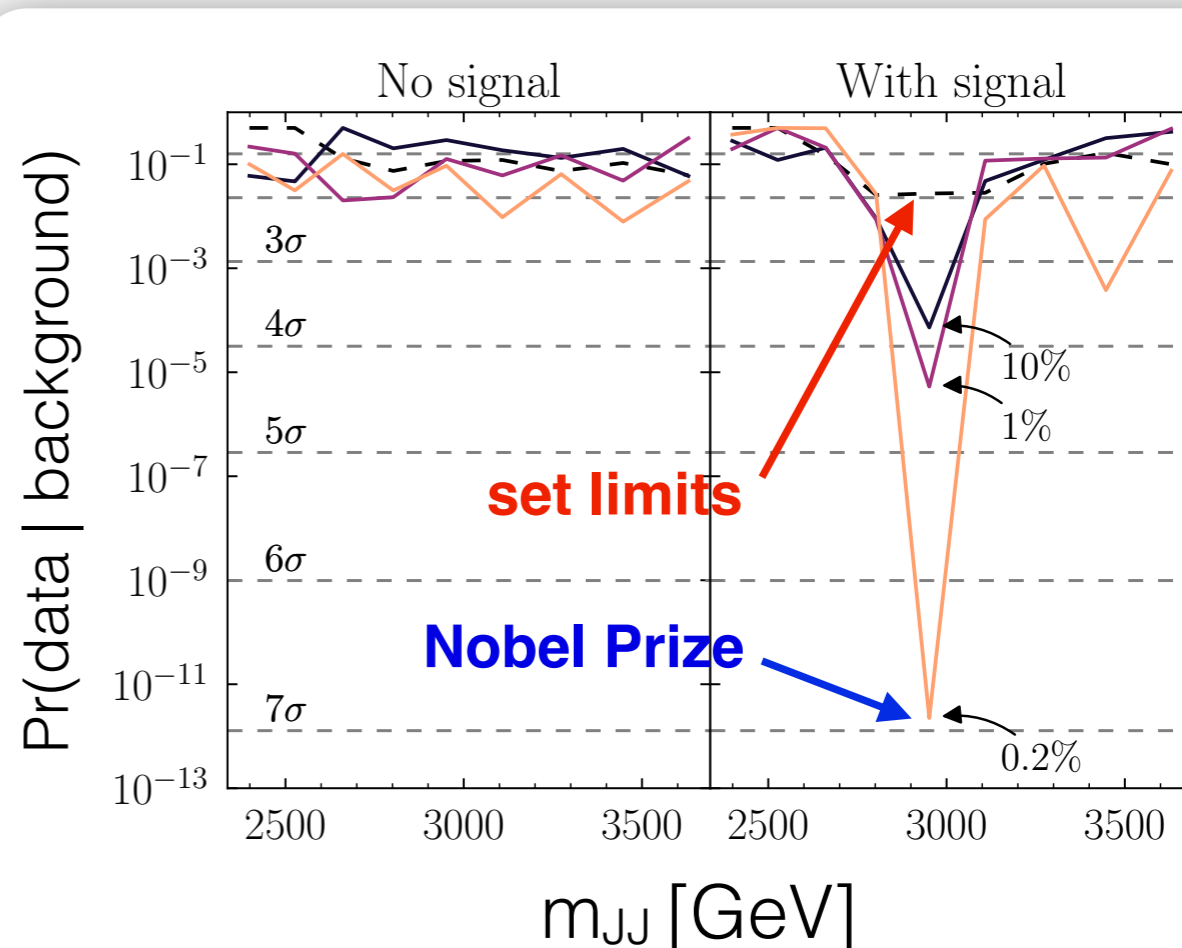
Classifier

Extra Credit 2: No simulation (s or b)

10



Dark jets and more?



For more, see also B. Dillon, D. Faroughy, J. Kamenik, 1904.04200,
T. Roy, A. Vijay, 1903.02032, O. Cerri et al. 1811.10276,
T. Heimel et al. SciPost Phys. 6 (2019) 030, M. Farina, Y. Nakai, D. Shih, 1080.08992.

Ideas → Reality

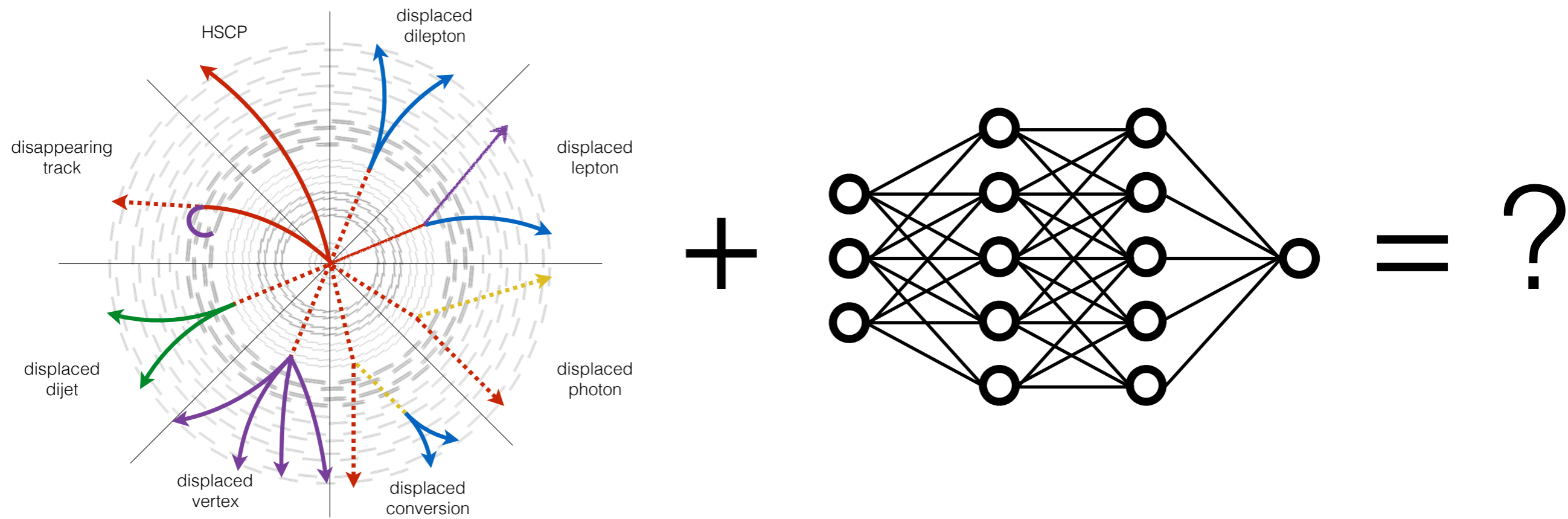
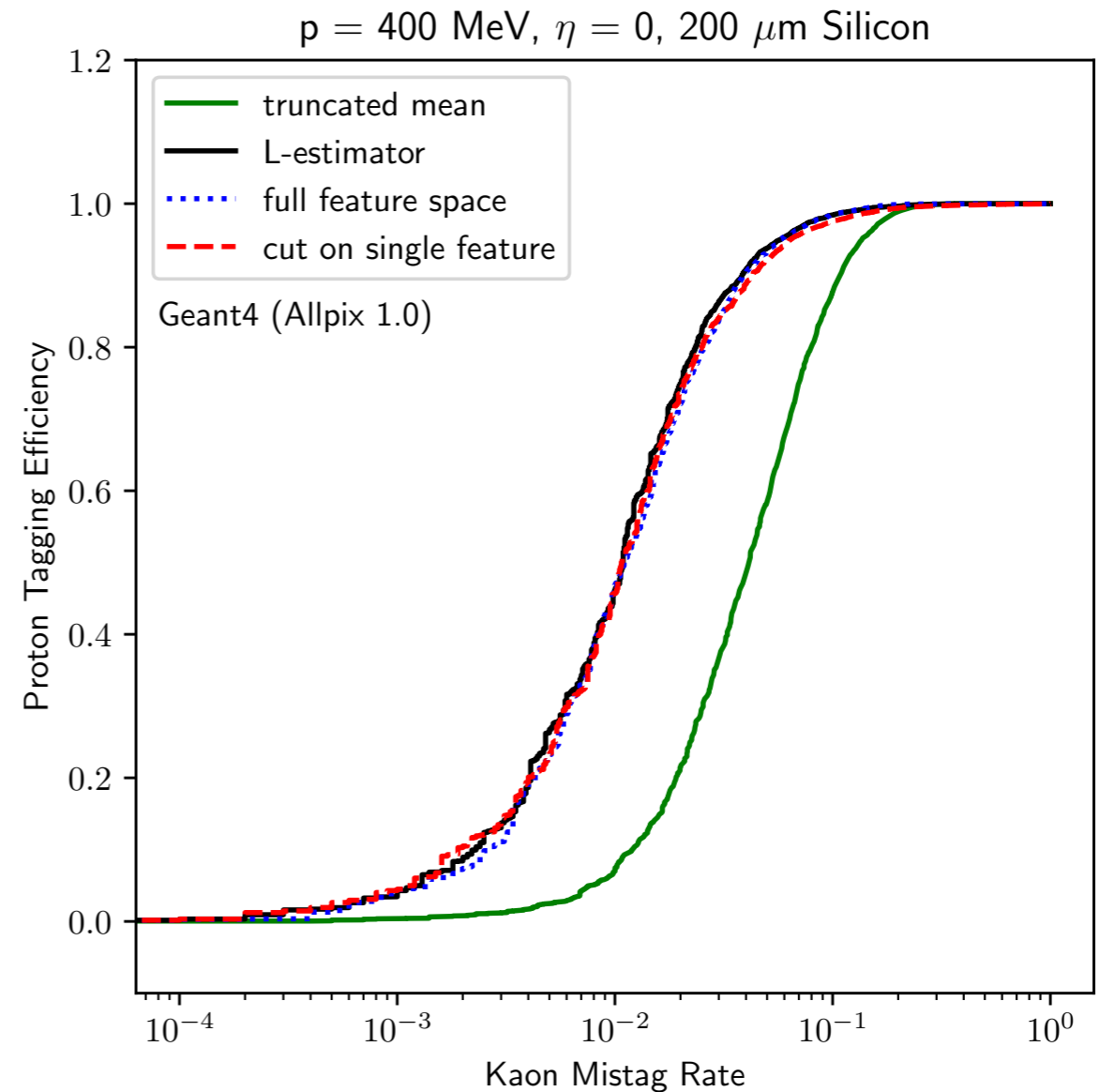
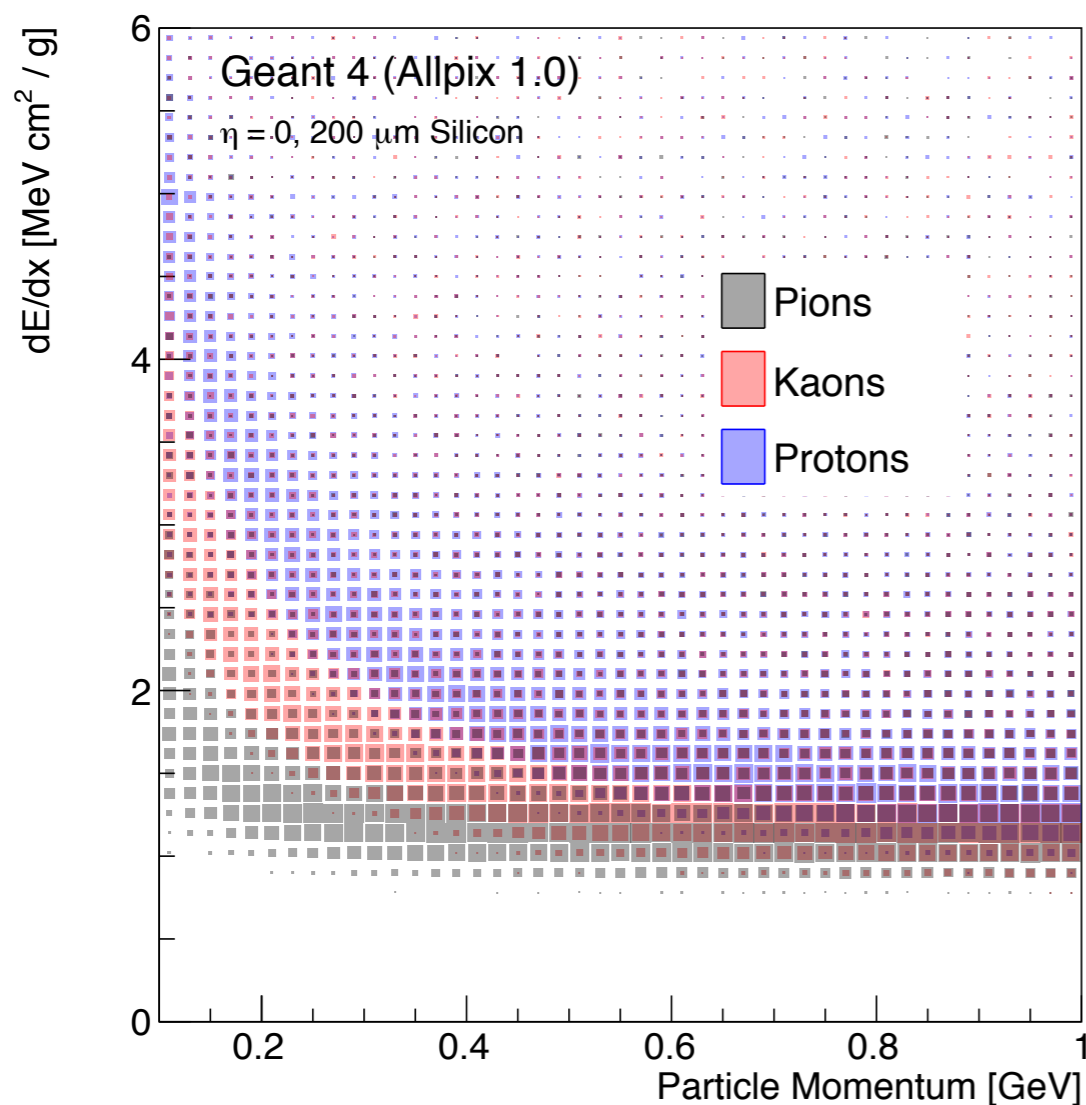


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An actual example (for classification)



HCP can be identified with high dE/dx in pixel detectors. Often, people use truncated mean. What is the best way to combine charge info?



ML is good for asking questions like this, even if the ultimate answer is simpler than “use a NN”

Trigger strategies

displaced jet calibration

odd jet tagging

Reconstruction Techniques

calorimeter/tracker information

non-standard tracking

Simulation

delayed signals

Analysis Strategy/ Interpretation

supervised / semi-supervised

Plan for the workshop

14

13:30 → 14:15 Working Groups Kick-off Talks

40-S2-D01 - Salle Dirac

13:30

Machine Learning for LLPs

15m

Speaker: Ben Nachman (Lawrence Berkeley National Lab. (US))

16:00 → 17:00 Parallel session: Machine Learning WG Preparation

40-S2-D01 - Salle Dirac

Conveners: Ben Nachman (Lawrence Berkeley National Lab. (US)), Gordon Watts (University of Washington (US)), Gregor Kasieczka (Hamburg University (DE)), Sergei Gleyzer (University of Florida (US))

...informal discussion of what is already being done

09:00 → 10:30 Parallel session: Machine Learning WG Session 1

40-S2-D01 - Salle Dirac

Conveners: Ben Nachman (Lawrence Berkeley National Lab. (US)), Gordon Watts (University of Washington (US)), Gregor Kasieczka (Hamburg University (DE)), Sergei Gleyzer (University of Florida (US))

*...discussion of **census** and start discussion of techniques
(next page)*

11:00 → 12:30 Parallel session: Machine Learning WG Session 2

40-S2-D01 - Salle Dirac

Conveners: Ben Nachman (Lawrence Berkeley National Lab. (US)), Gordon Watts (University of Washington (US)), Gregor Kasieczka (Hamburg University (DE)), Sergei Gleyzer (University of Florida (US))

...continue brainstorming techniques → LLP ideas; brief tutorial possible time/interest permitting

11:35 → 12:50 Working Groups Summary Talks

503-1-001 - Council Chamber

11:35

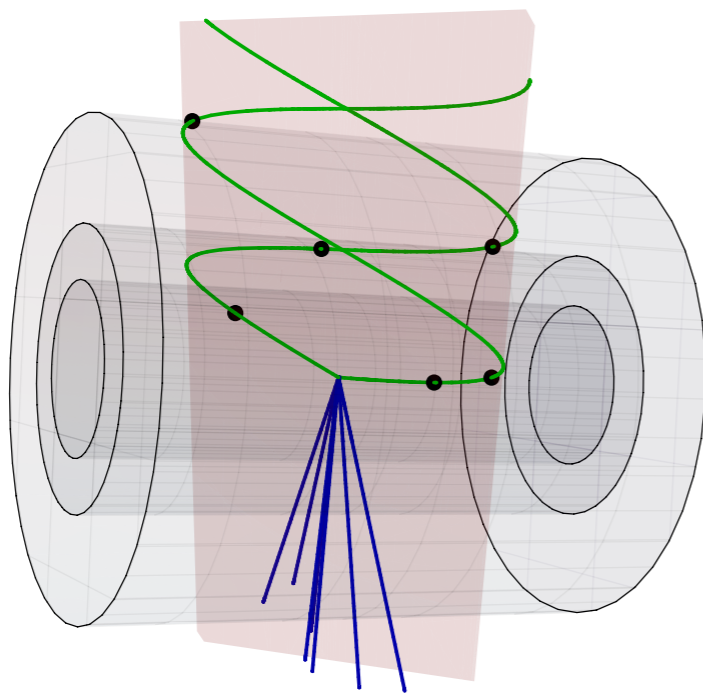
Machine Learning with LLPs Summary

10m

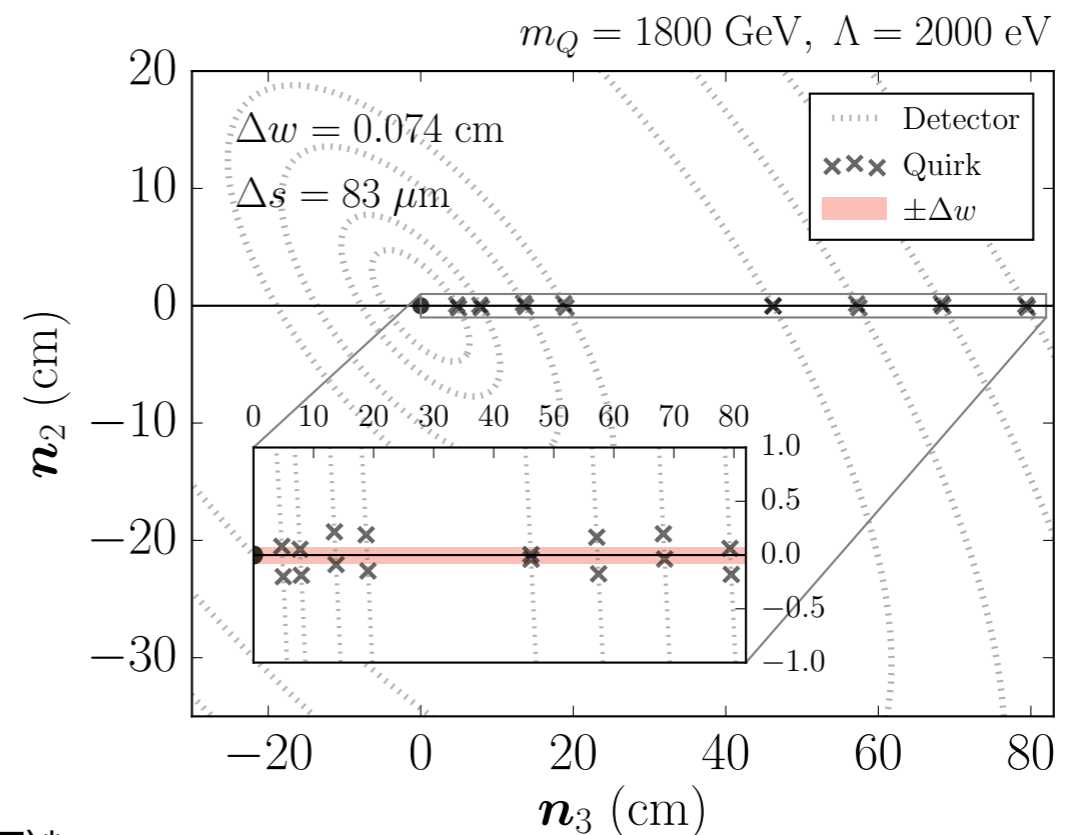
Speaker: Gregor Kasieczka (Hamburg University (DE))

There are many non-ML studies out there that maybe can be reused for ML studies.

Example: quirks



S. Knapen et al., Phys. Rev. D 96, 115015 (2017)*



...we may also be able to put together public collaboration datasets - please keep an open mind!

*I did not ask Simon, Tim, Michele, or Jack if we could use their simulation - this is only an example of something that may be useful and if there is interest, we should ask them!

Conclusions and Outlook

There has already been great work, but a lot of ML potential untapped - an exciting future is ahead!

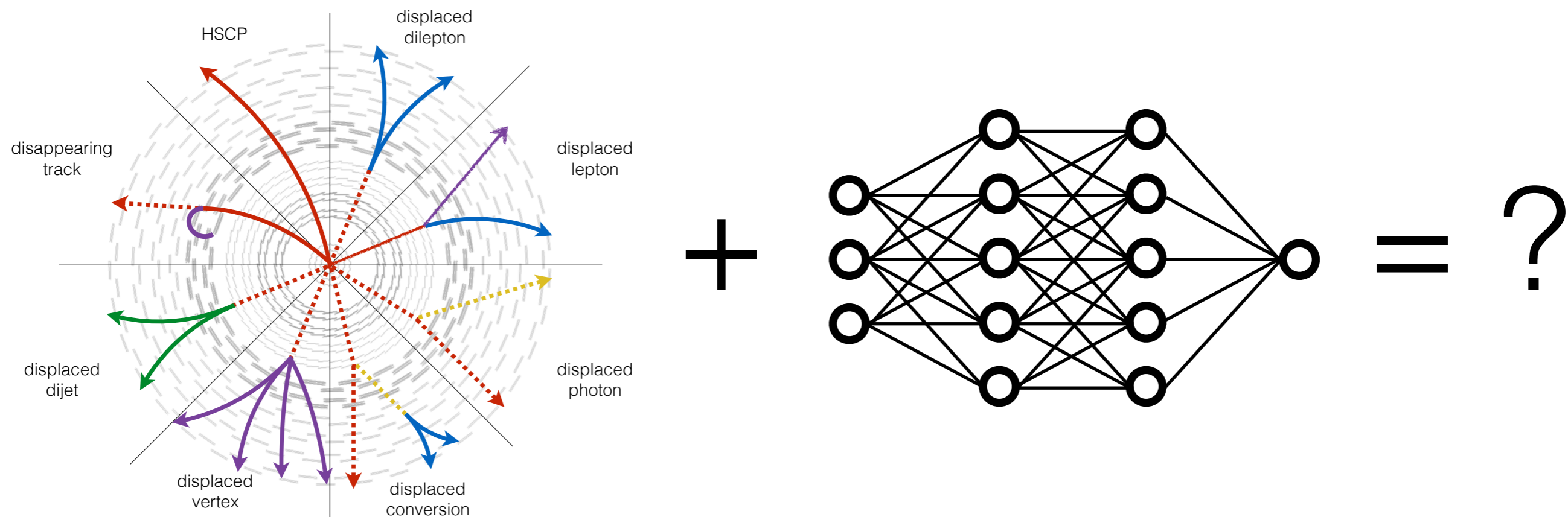


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Questions?

