



**UNIVERSITÉ  
DE GENÈVE**



# **ESR 3: Real time analysis strategies for reconstruction, exotic physics, and market analysis**

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**Anna Sfyrla, Steven Schramm**

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We acknowledge funding by the European Union's Horizon 2020 research and innovation programme, call H2020-MSCA-ITN-2020, under Grant Agreement n. 956086 (SMARTHEP).



**MARIE CURIE ACTIONS**



# Presentation Outline

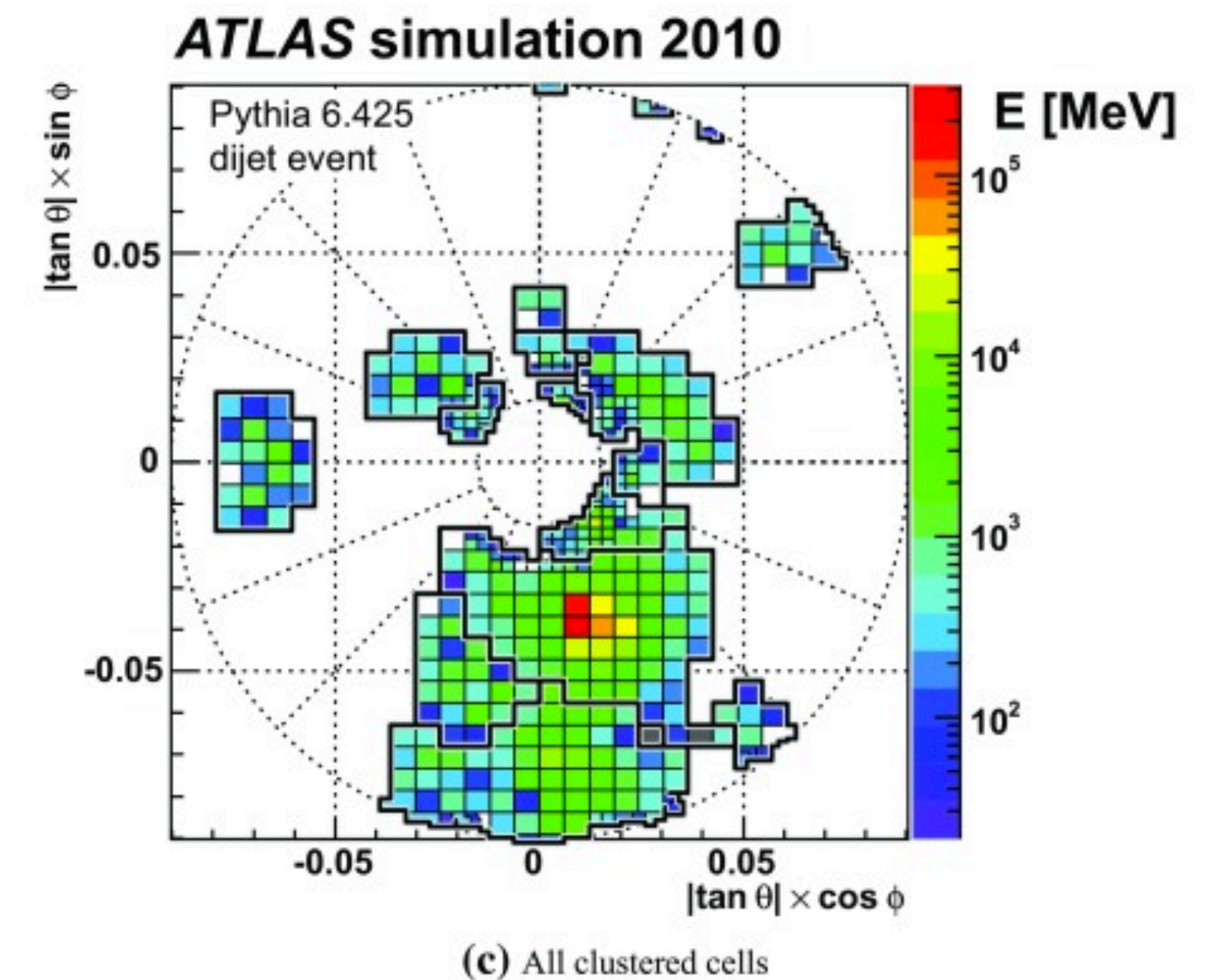
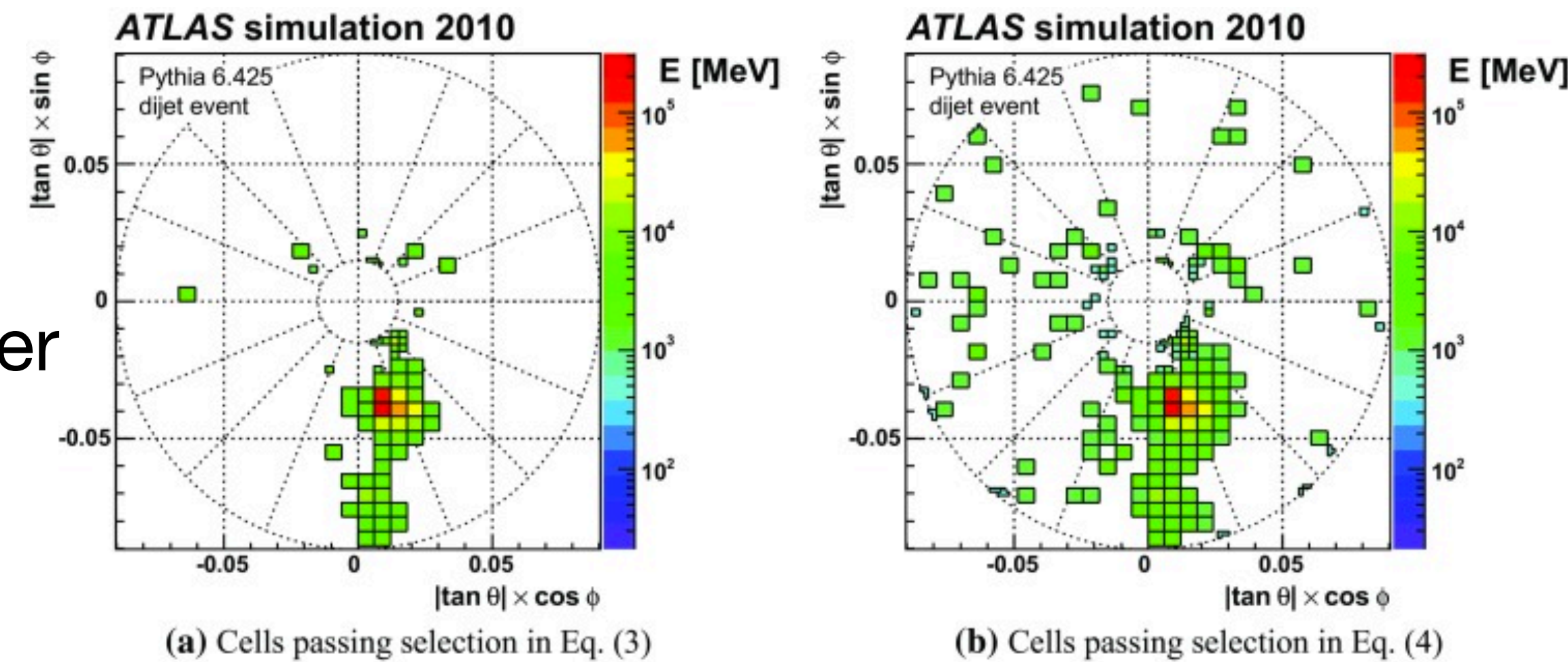
- **Qualification task**
  - **Object detection in ATLAS Trigger**
- **Secondment**
  - **Recurrent & Bayesian neural networks**
- **Other activities**

# Qualification Task

# Topoclustering

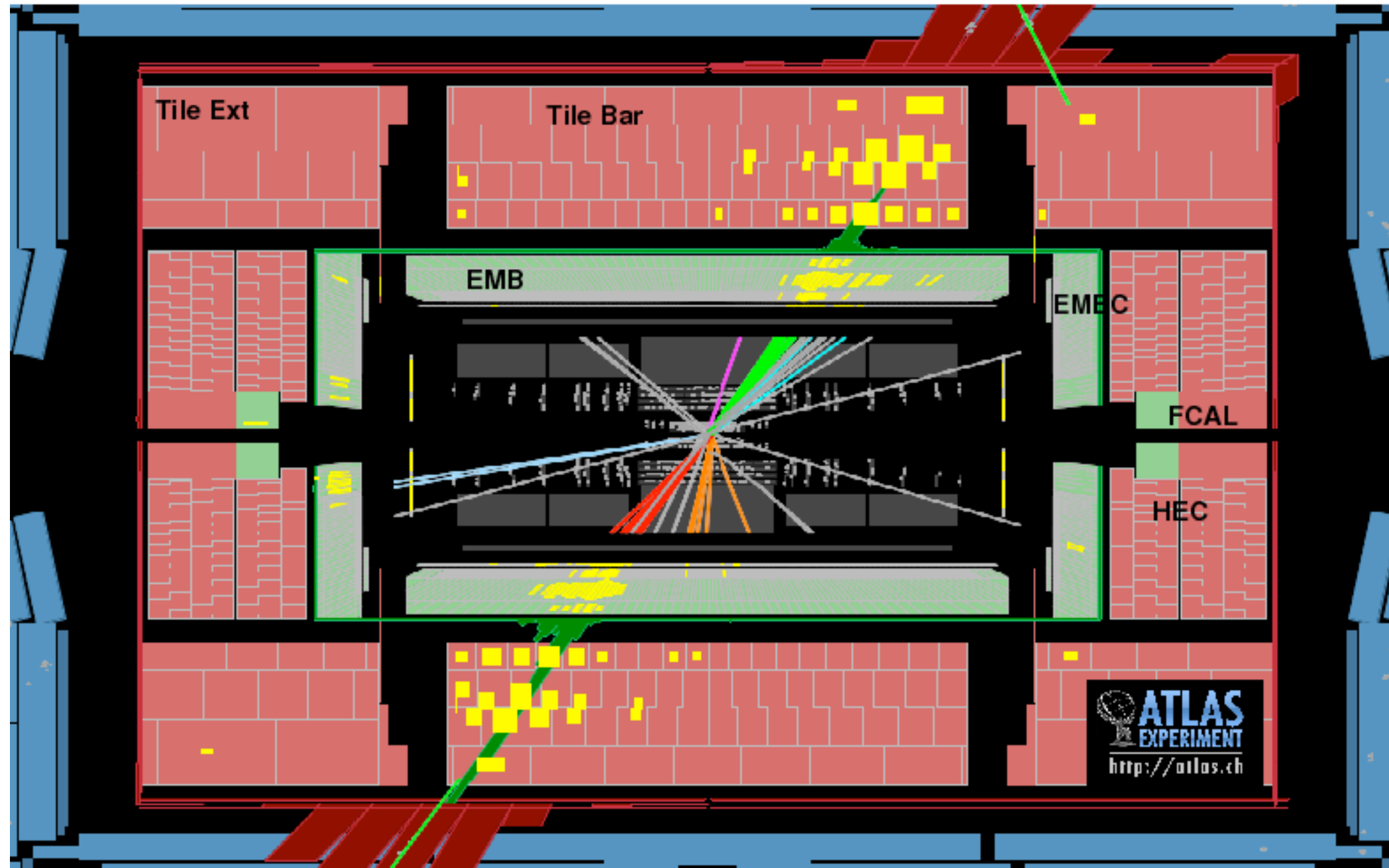
## Making of jet constituents

- ATLAS uses the **topoclustering** algorithm to cluster calorimeter cells together.
- The algorithm is **iterative**, it checks each cell in turn.
- It then checks all the neighbouring cells.
- This guarantees you “find” everything, but is very **slow!**
- The clusters go through several **post-processing** steps and are then used to make **jets**.



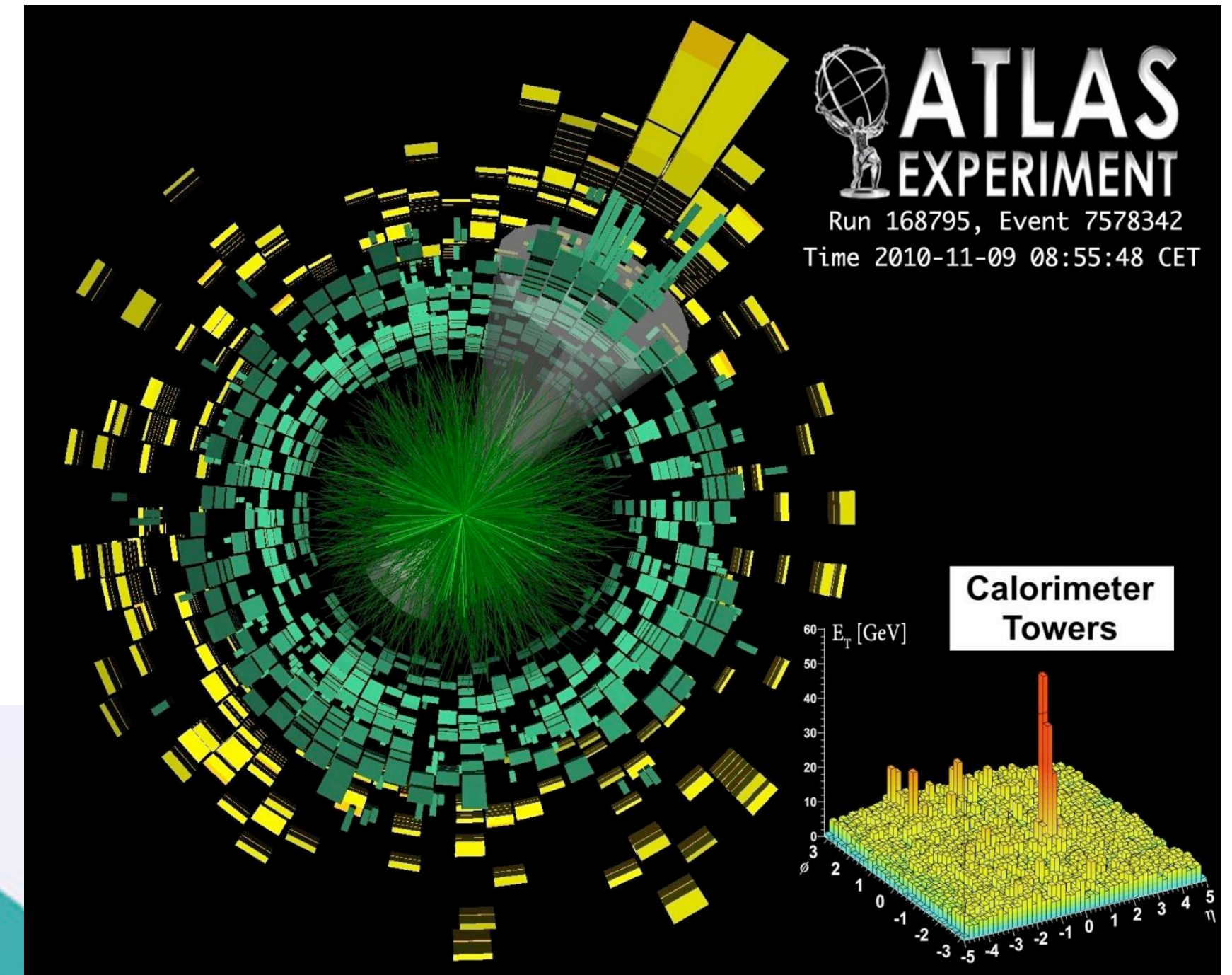
# Topoclustering

## You might have seen...



<https://cds.cern.ch/record/1409965>

<https://cerncourier.com/a/atlas-observes-striking-imbalance-of-jet-energies-in-heavy-ion-collisions/>



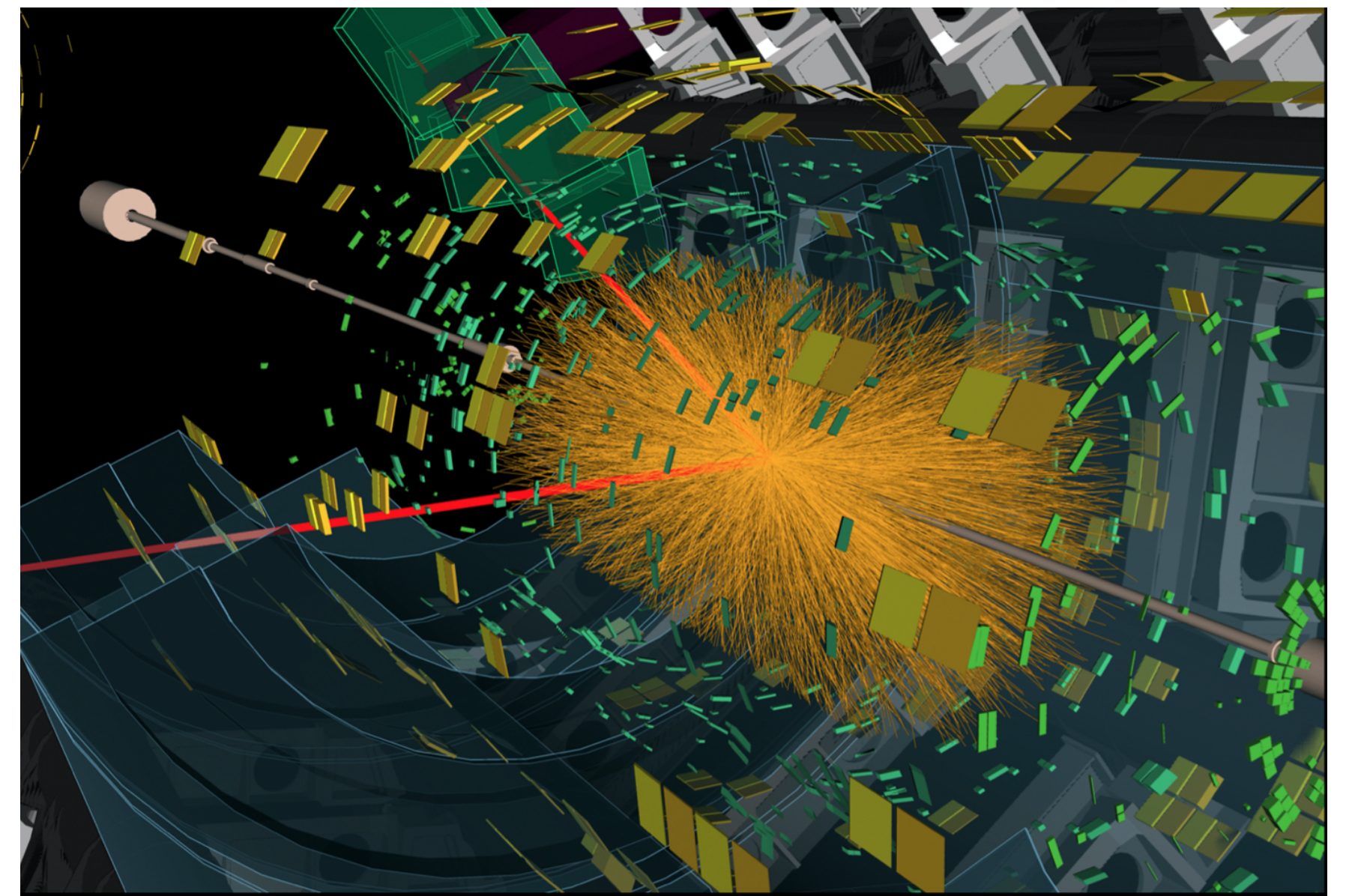
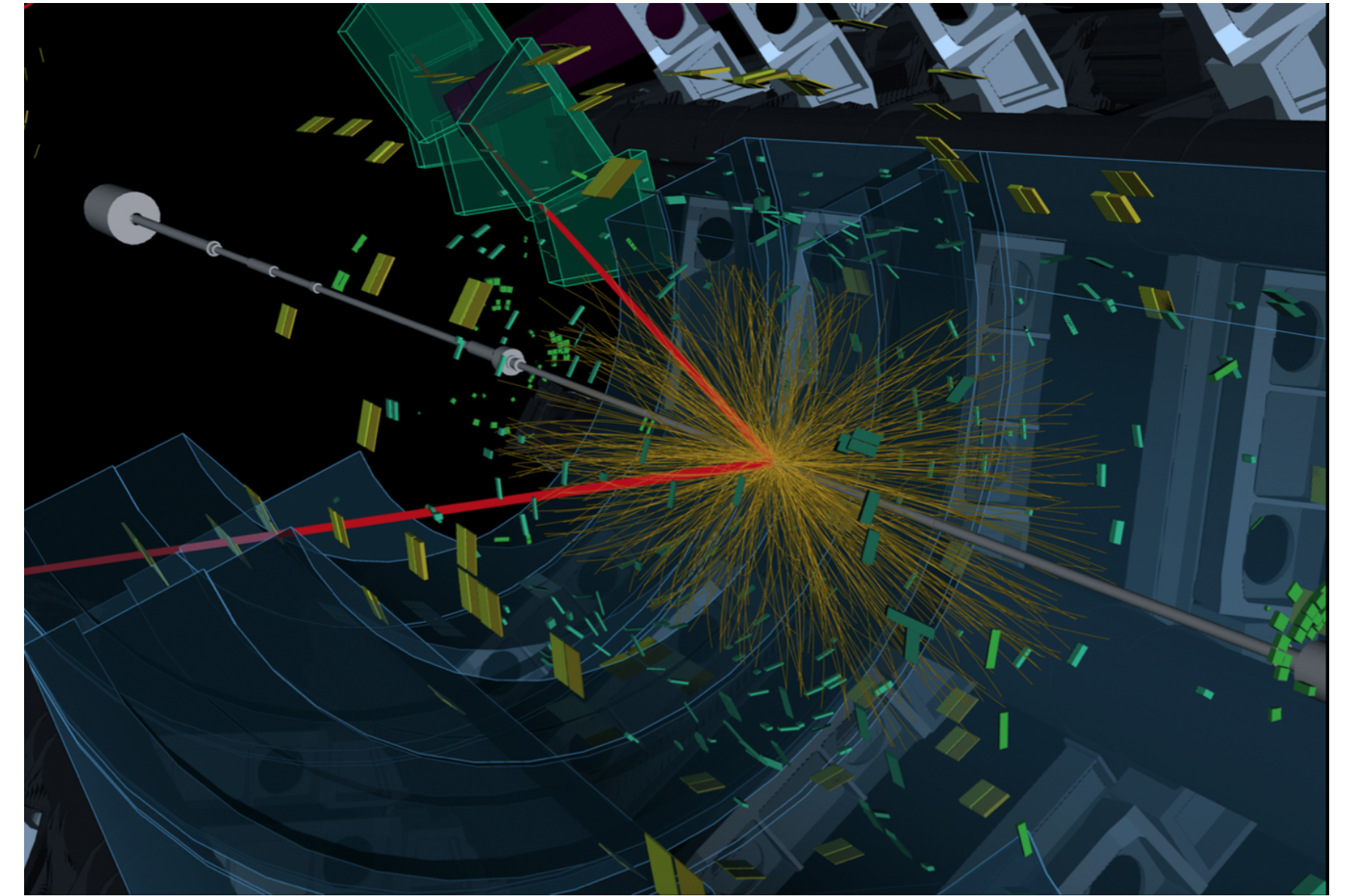
<https://www.eurekalert.org/multimedia/662188>



# What's the motivation?

## Why target this...

- **Topoclustering** is one of the most resource intensive algorithms in use in HLT.
- Crucial role in **jet** and **MET** reconstruction.
- Far worse **pile-up** conditions in HL-LHC.
- We pursue **faster** solutions with similar or improved performance.
- (And also less **energy consumption**).

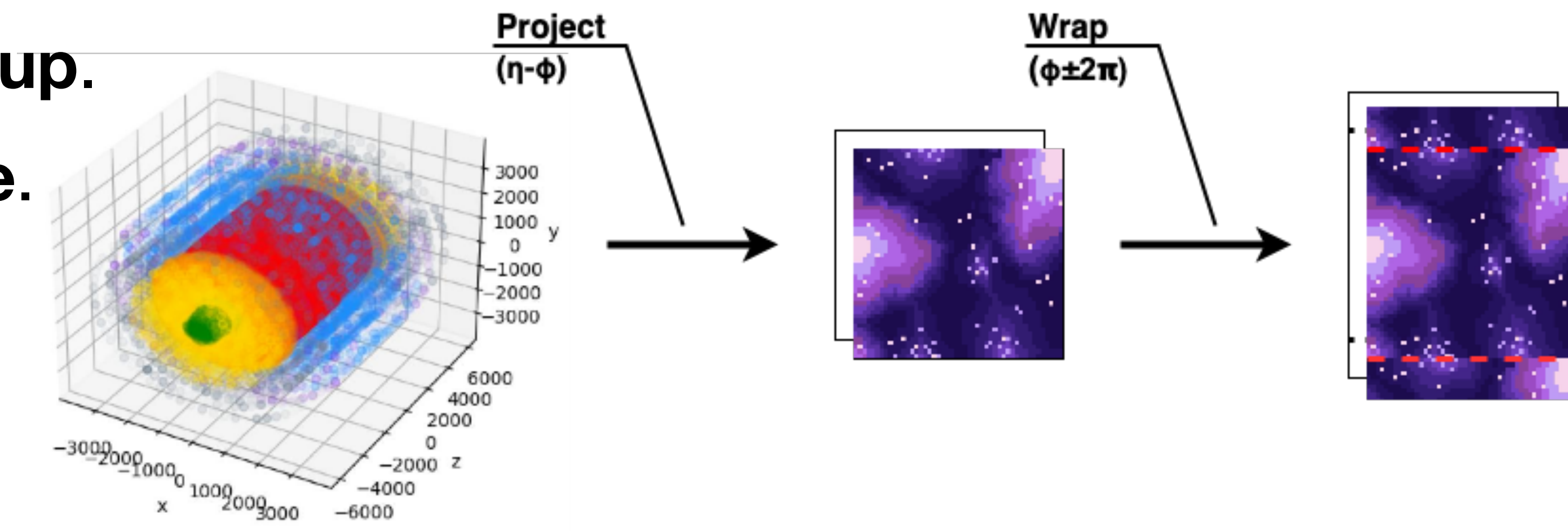
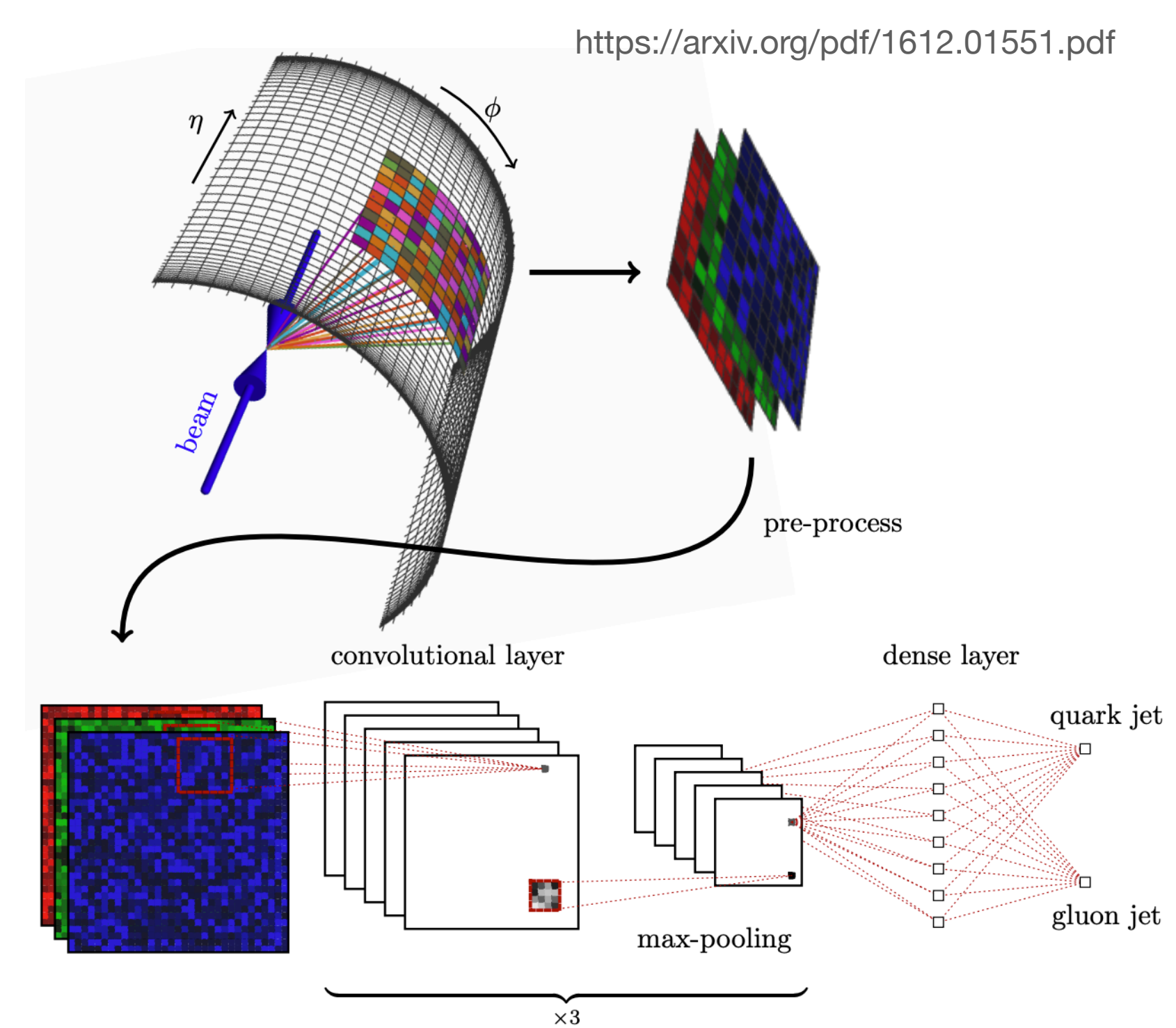


50 vs 200 p-p collisions per bunch crossing.

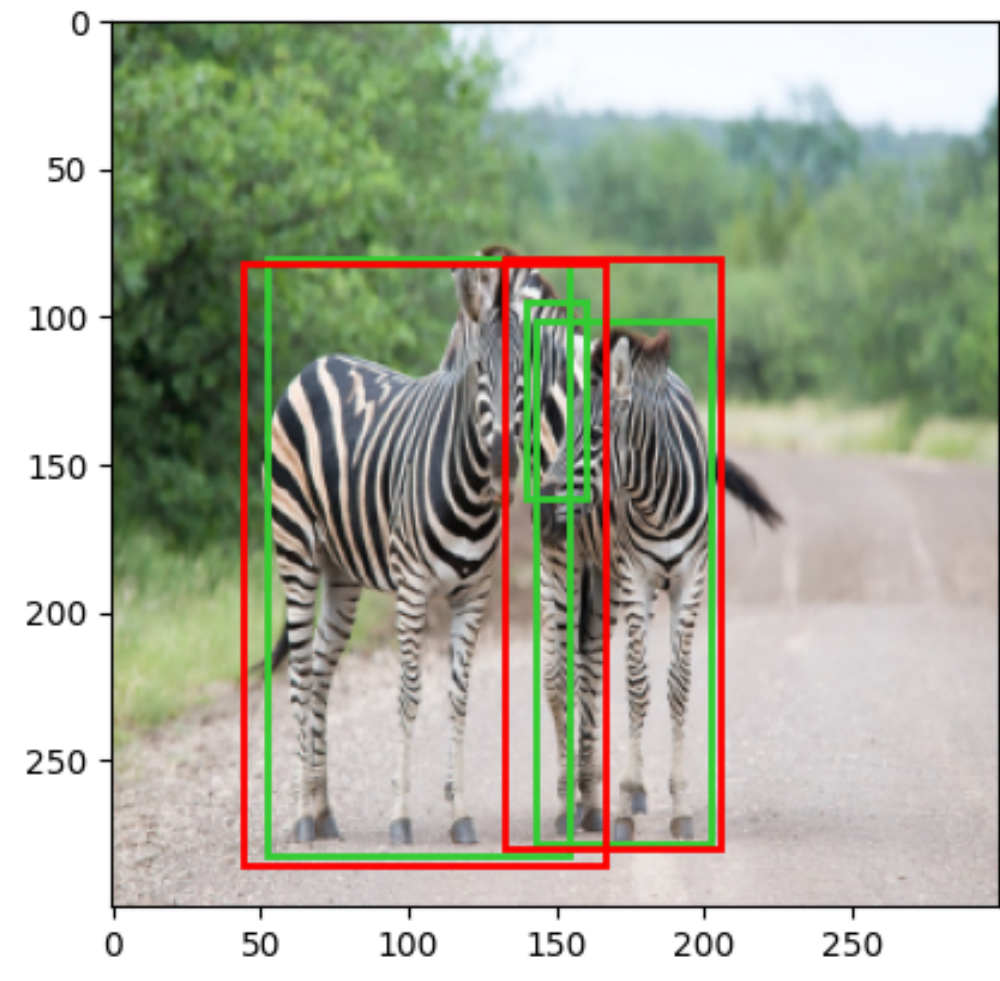
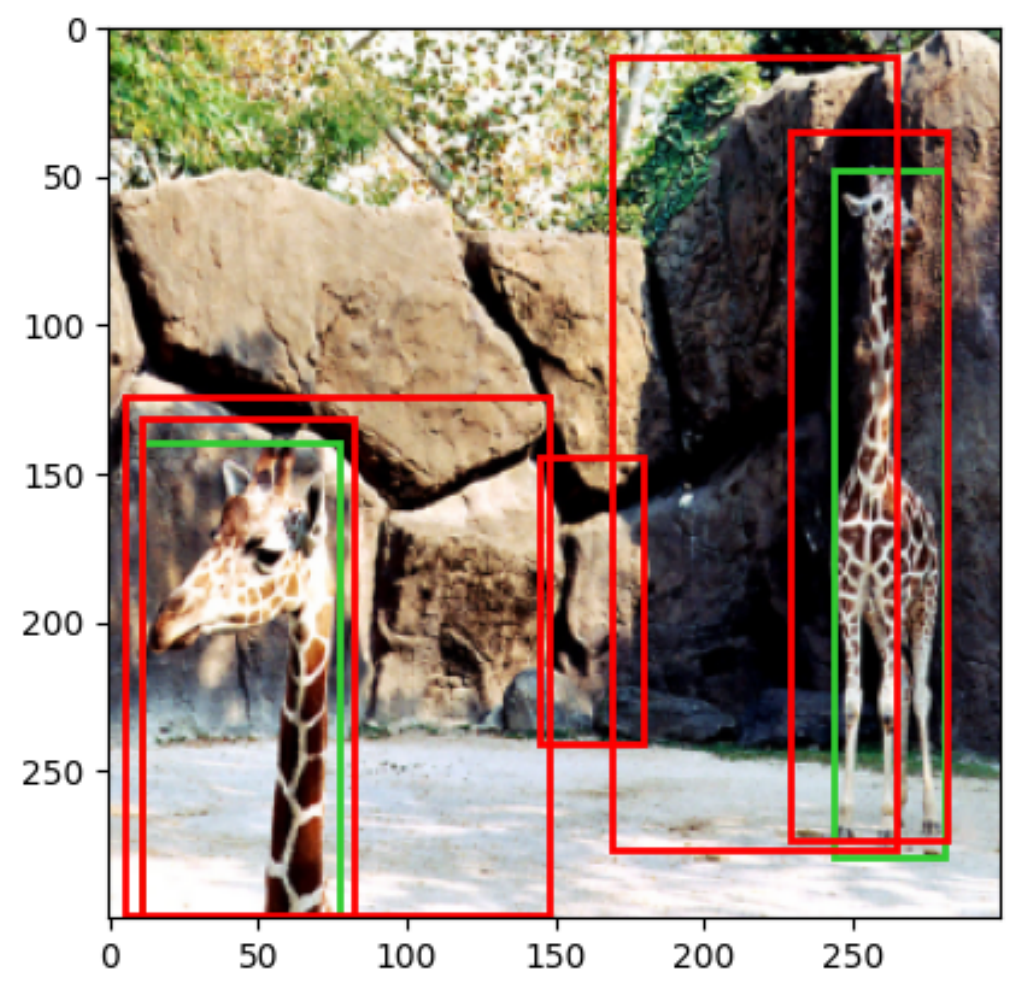
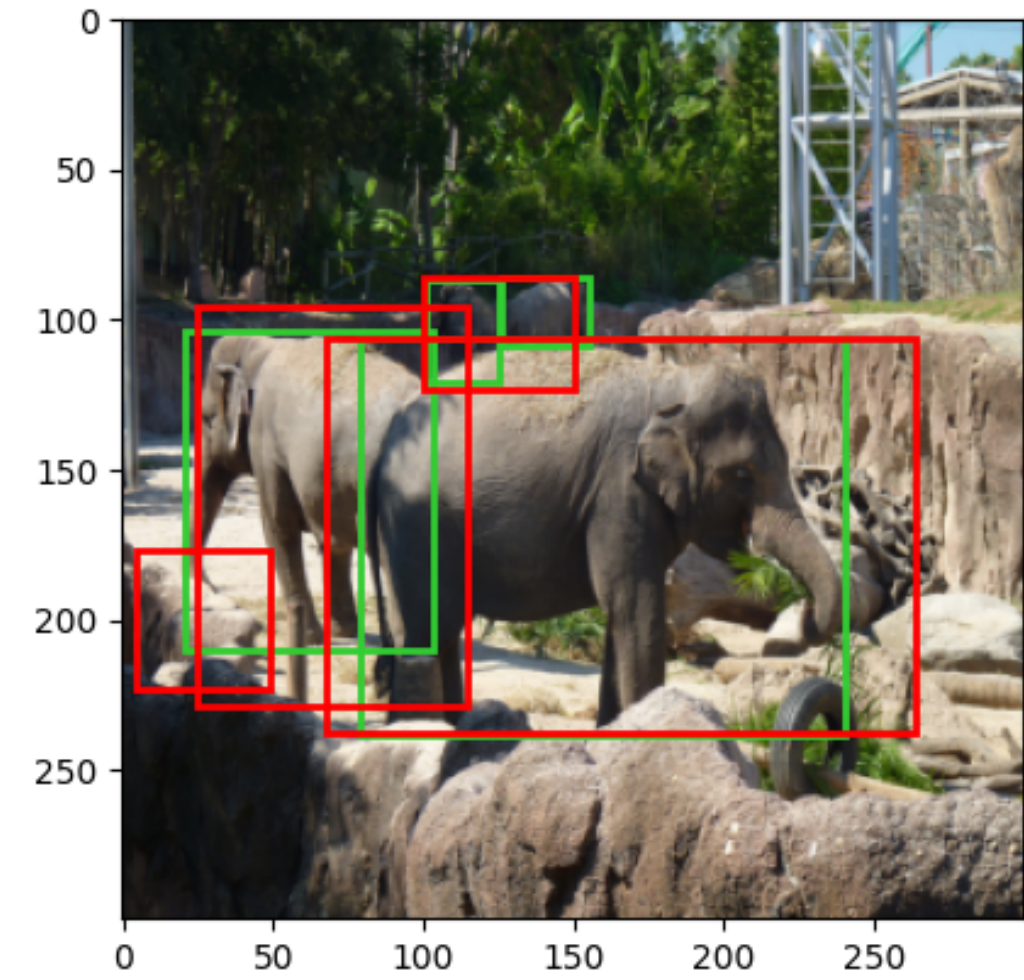
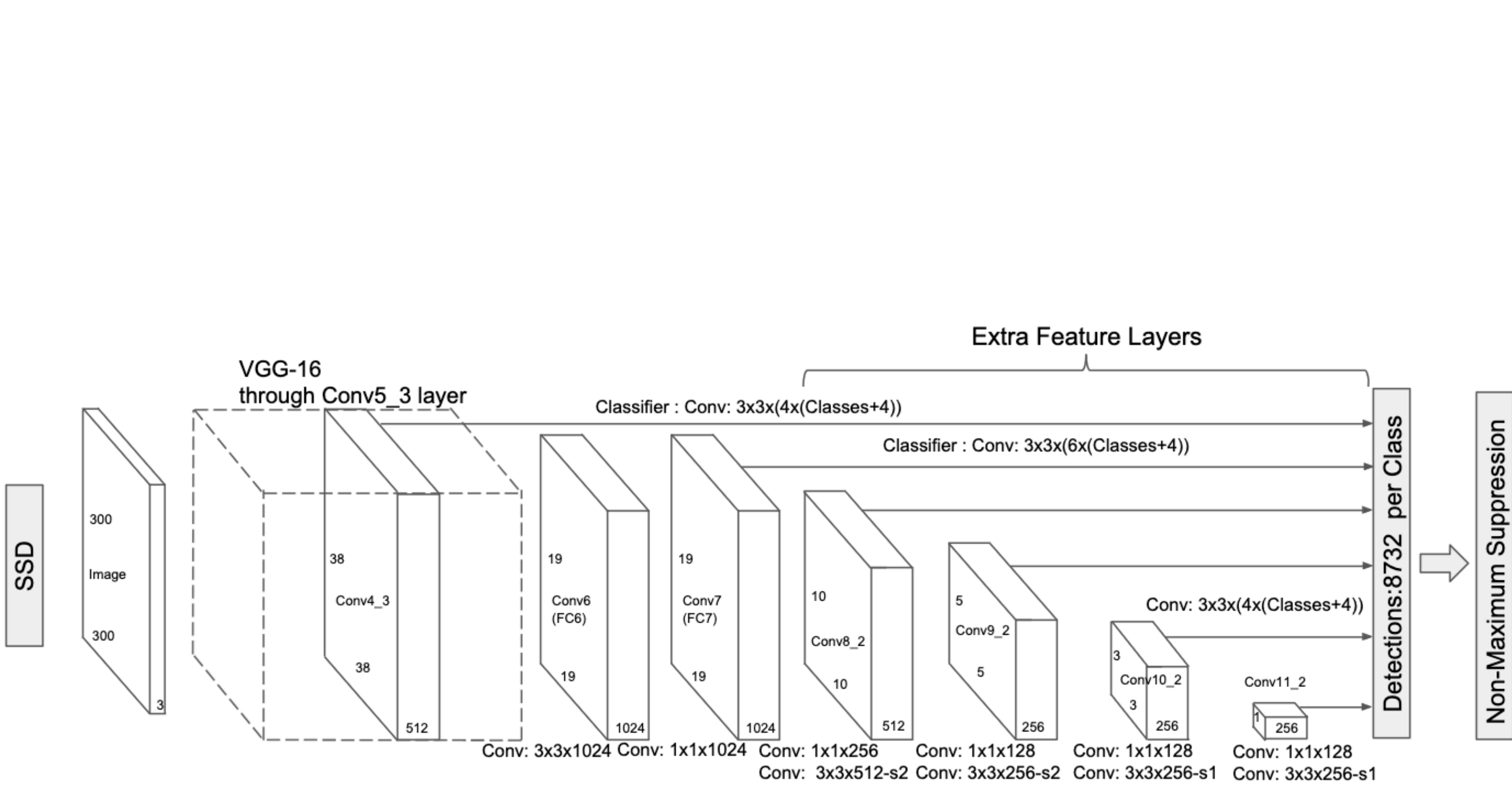
# ML to the rescue?

## Can we use object detection to help

- Qualification task explores use of deep **convolutional** neural networks (CNNs) to locate important **regions** of the **calorimeter** in  $(\eta, \phi)$ -space.
- Modern CNNs have **rapid inference** speed.
- Execution time **independent of pileup**.
- Could be ported to **faster hardware**.



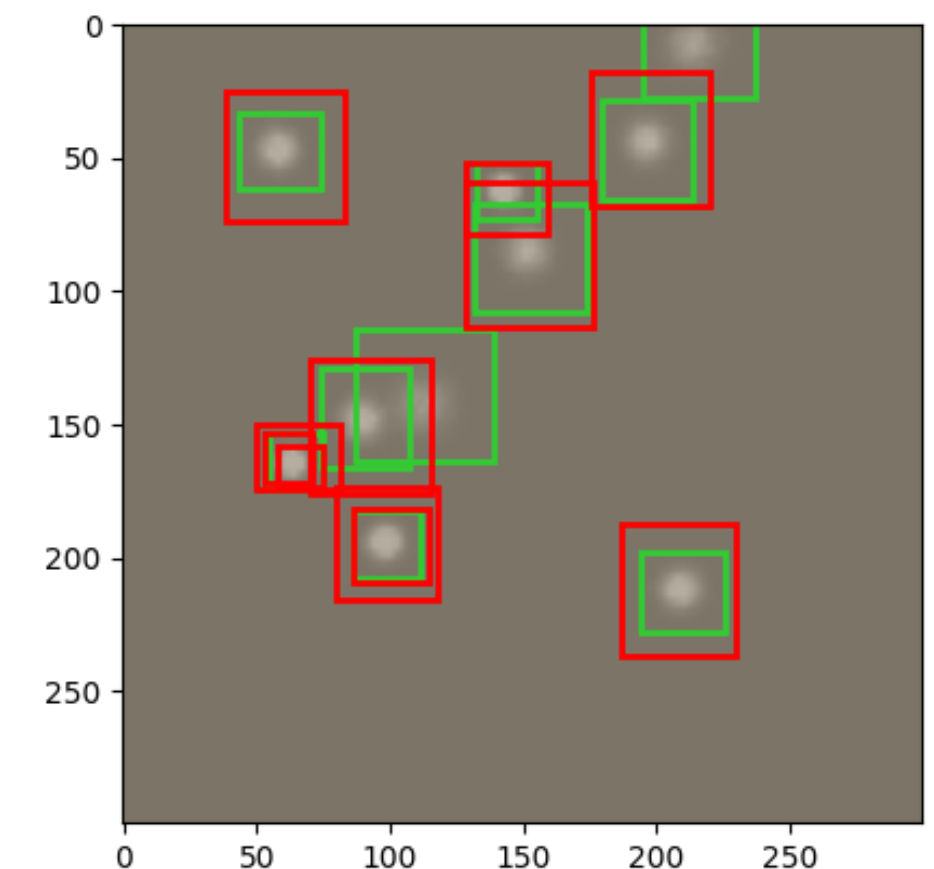
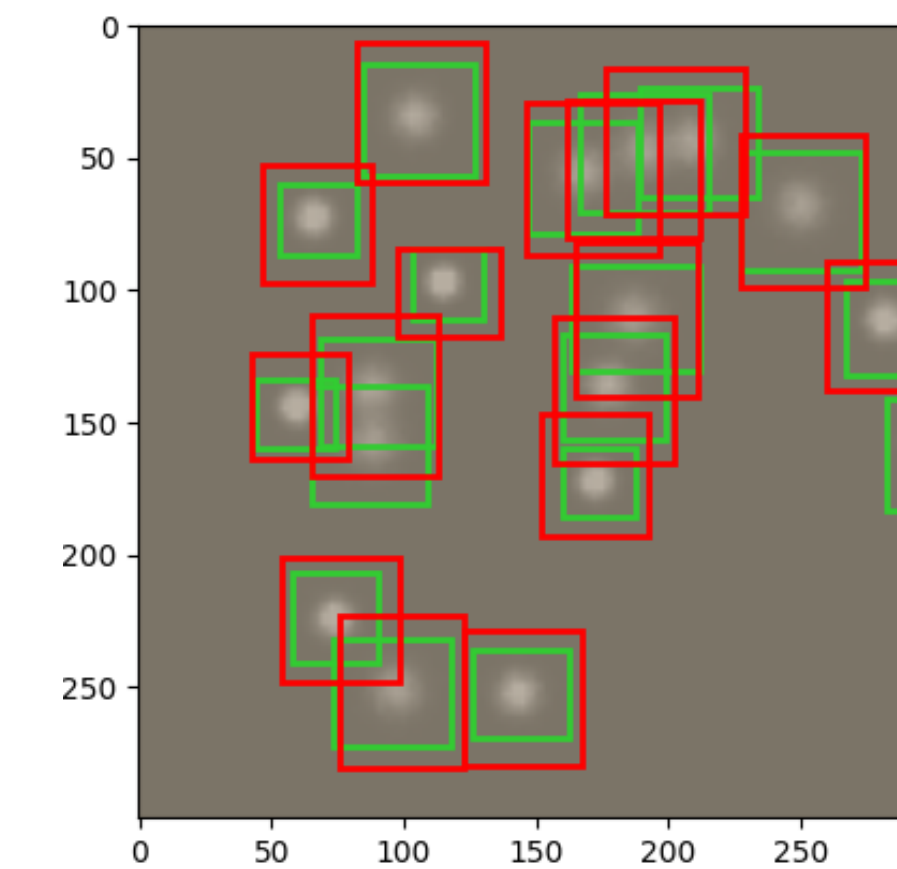
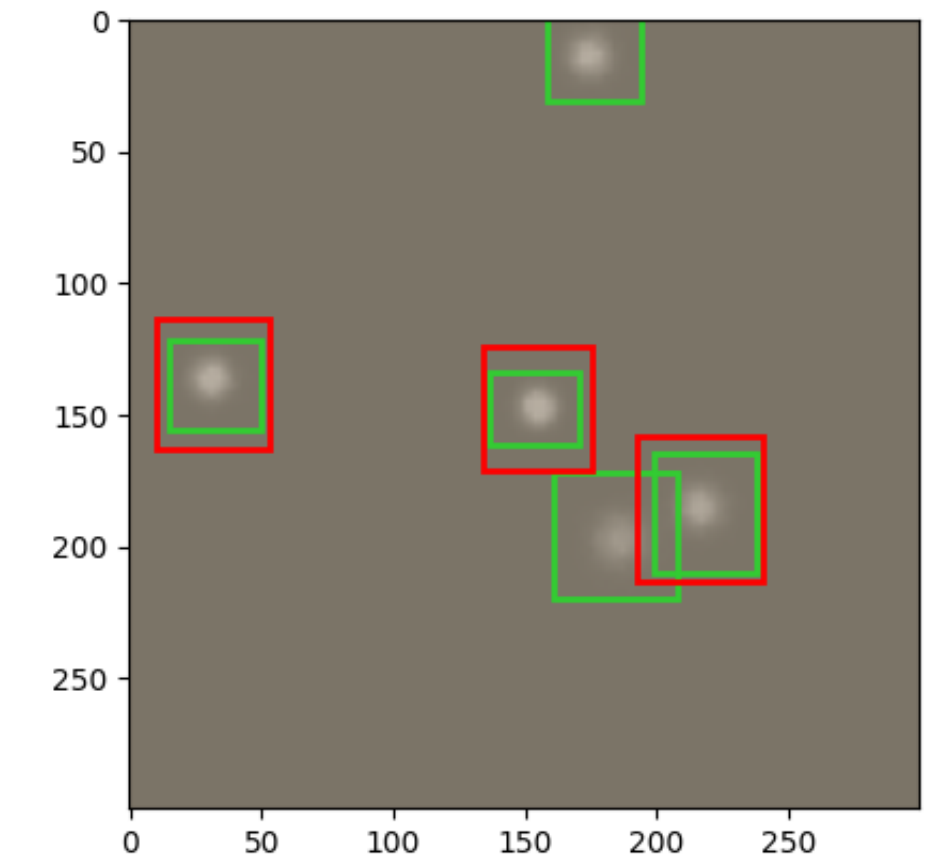
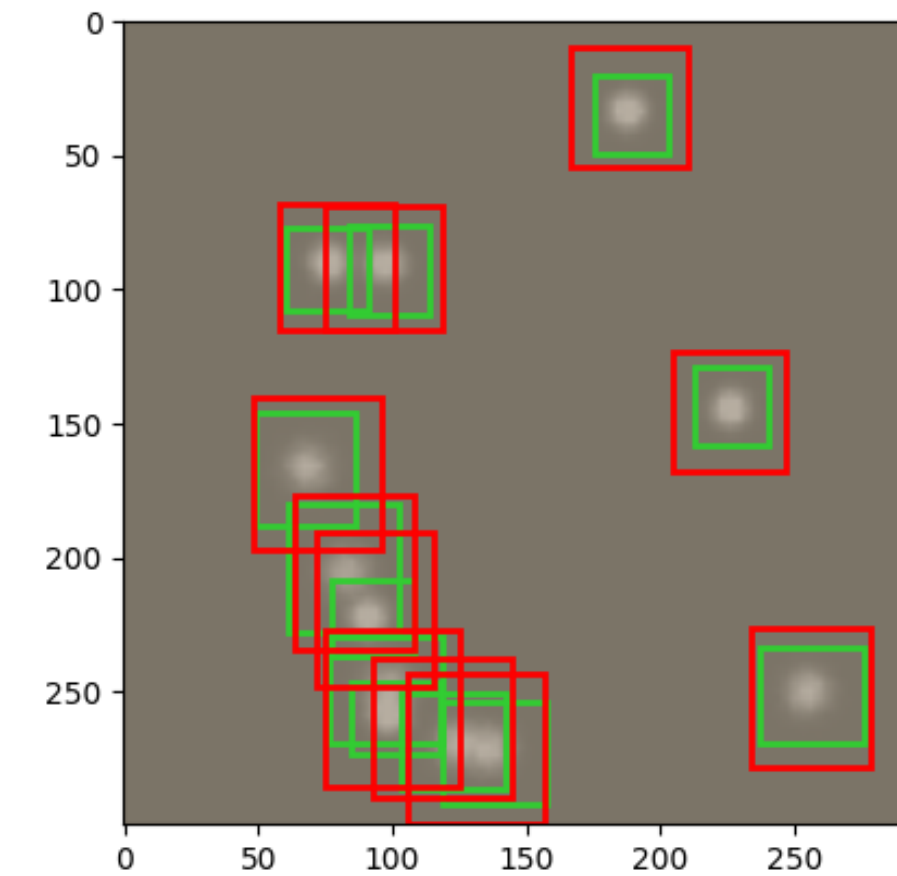
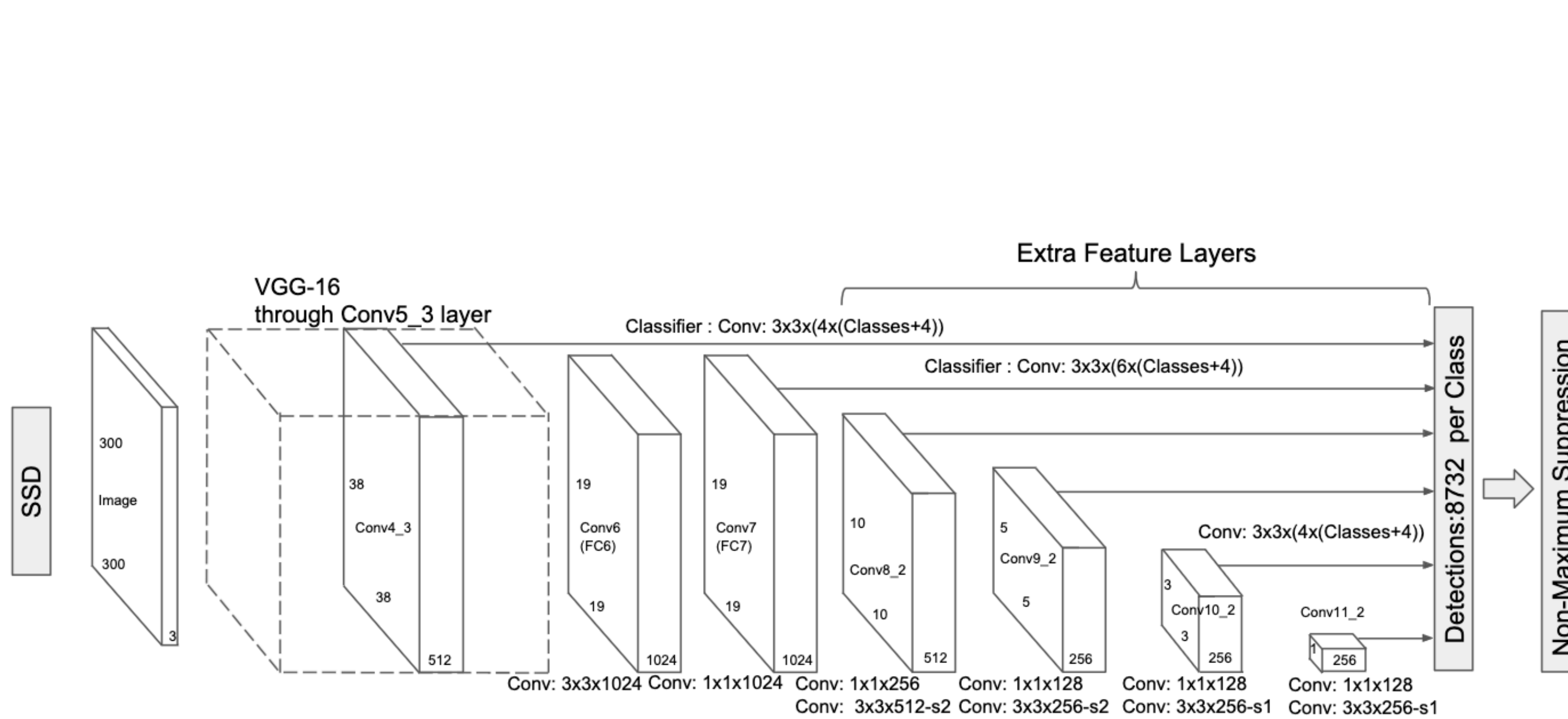
# Aside: SSD Model on animals



<https://arxiv.org/abs/1512.02325>



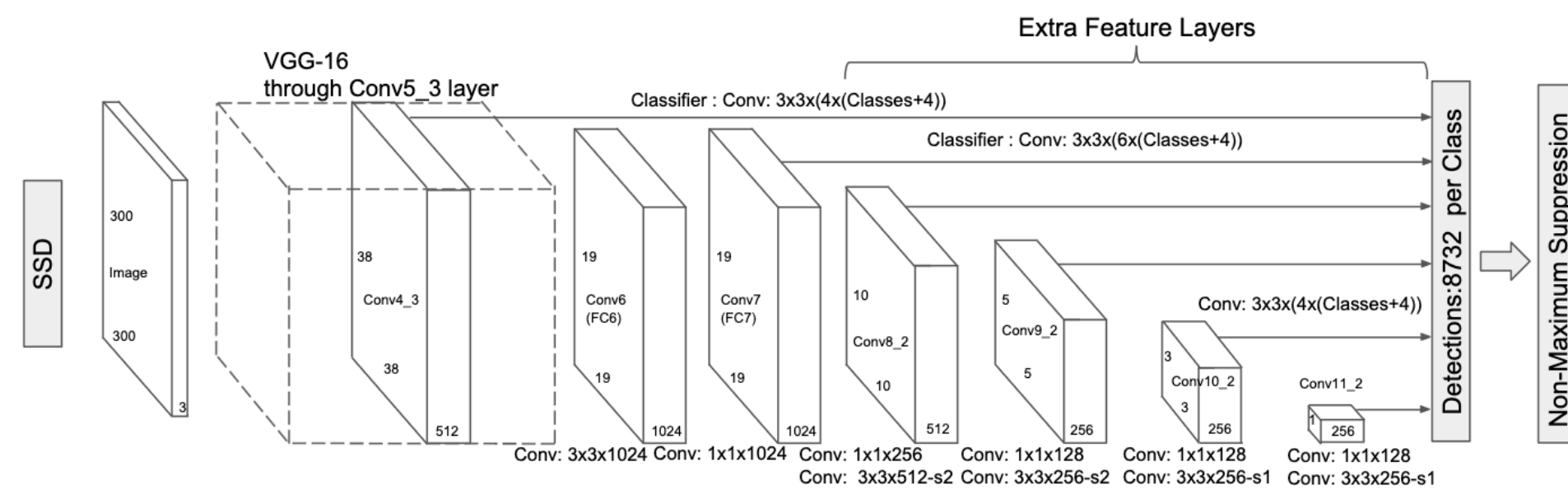
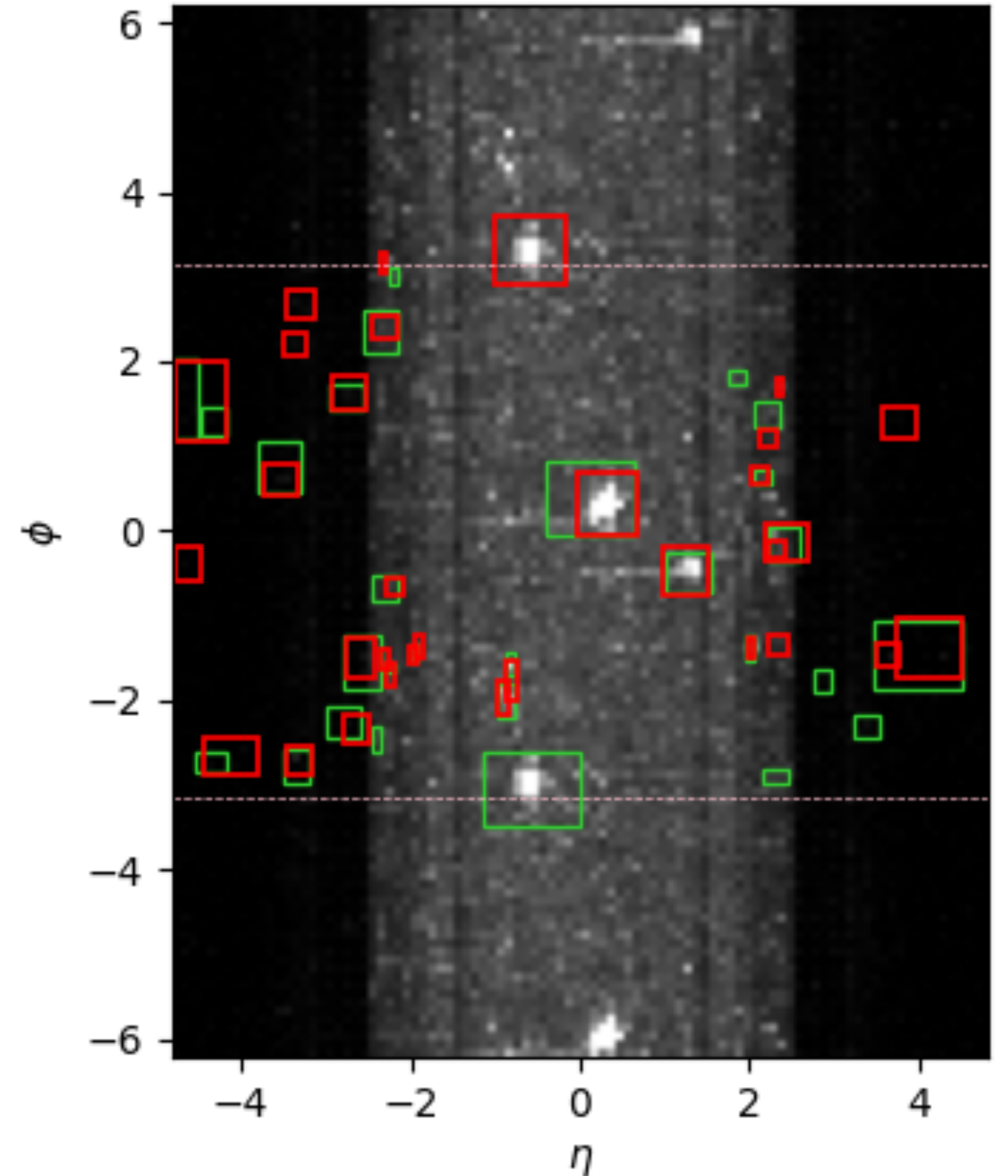
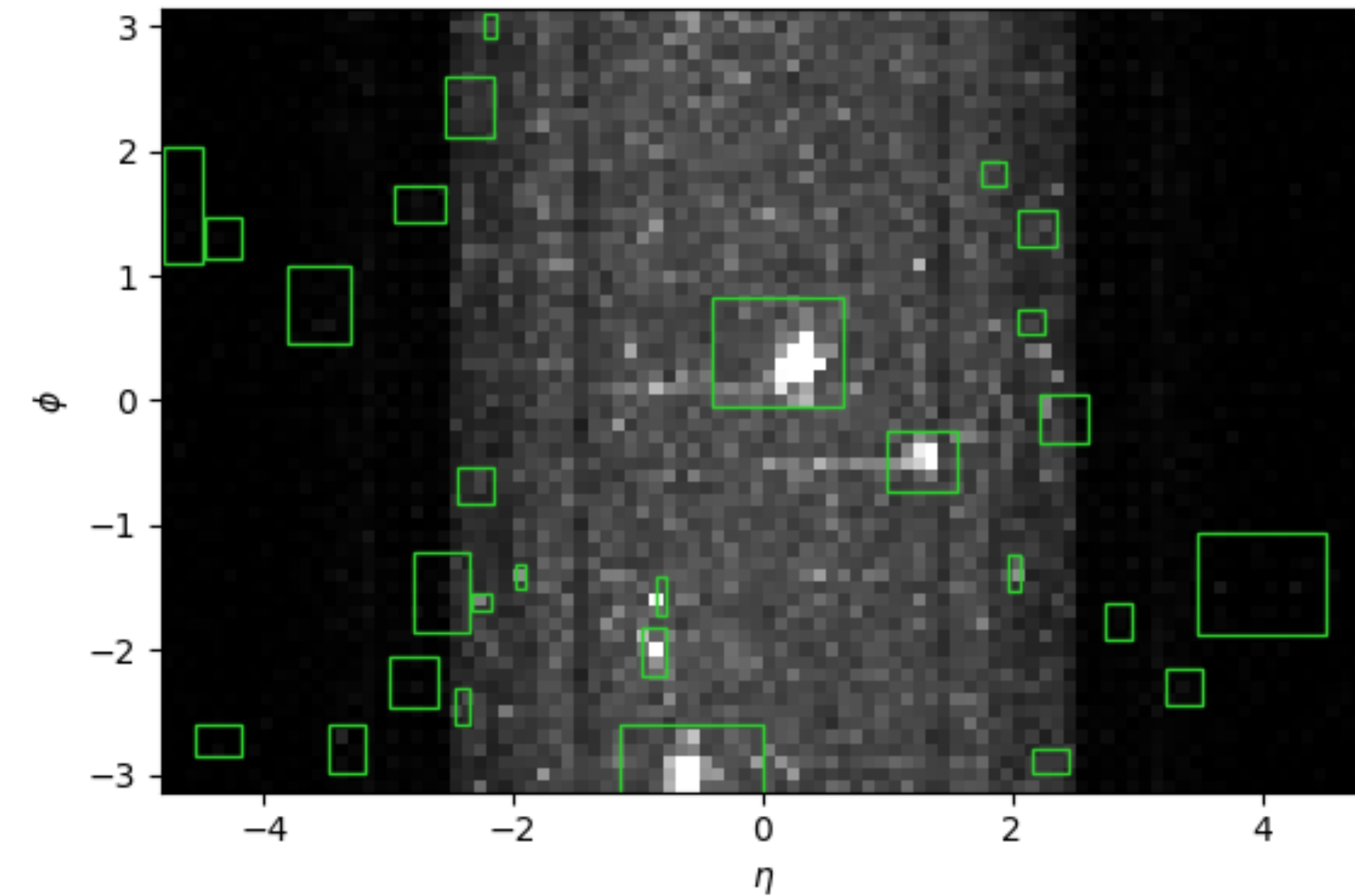
# Aside: SSD Model on Gaussian blobs



<https://arxiv.org/abs/1512.02325>

# SSD on physics

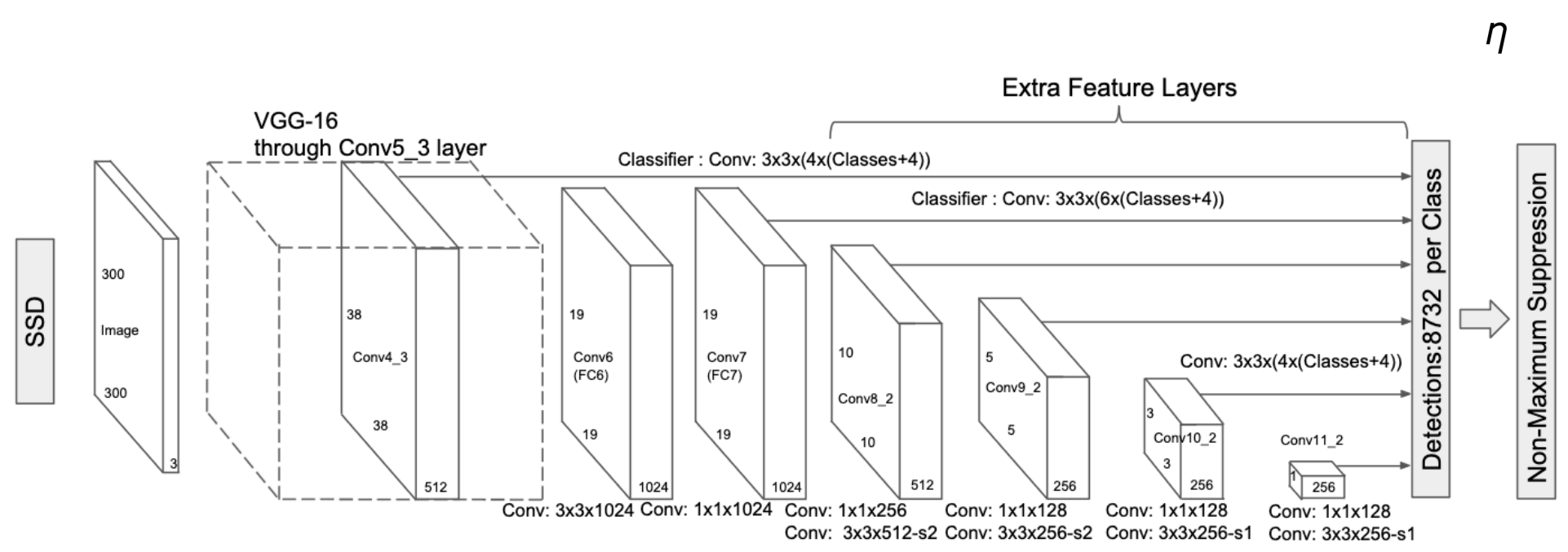
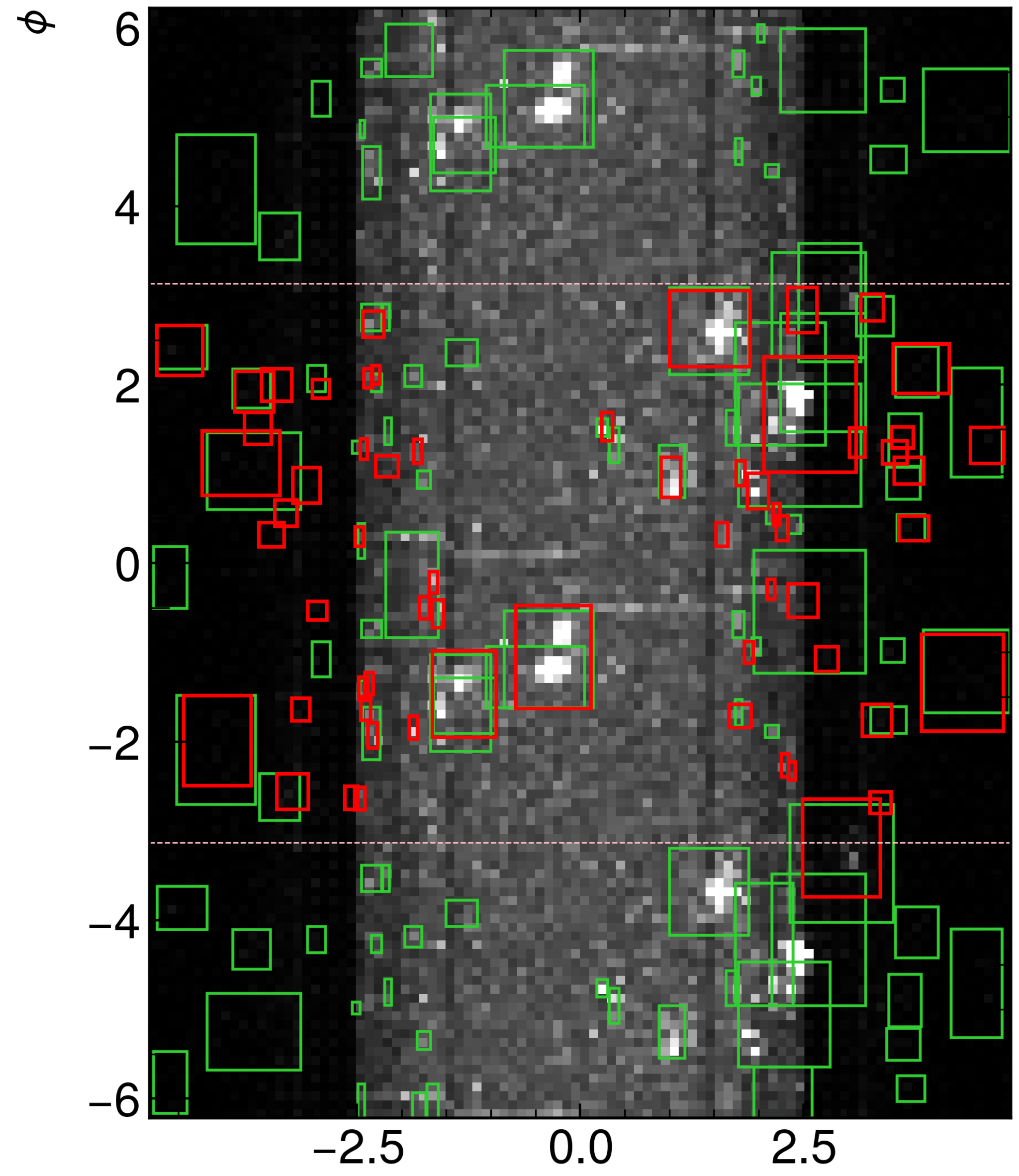
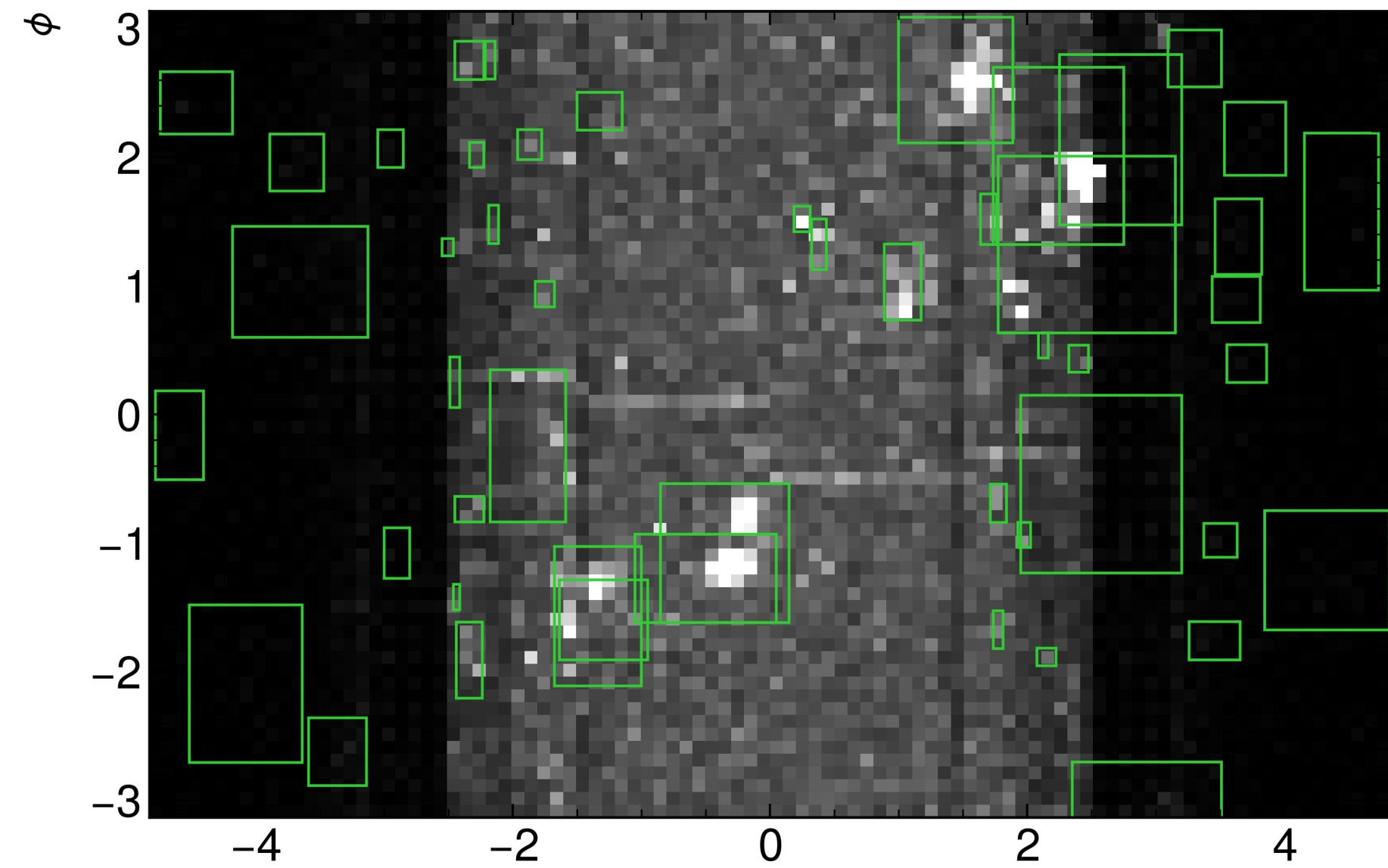
Does it work in the calorimeter?



<https://arxiv.org/abs/1512.02325>

# SSD on physics

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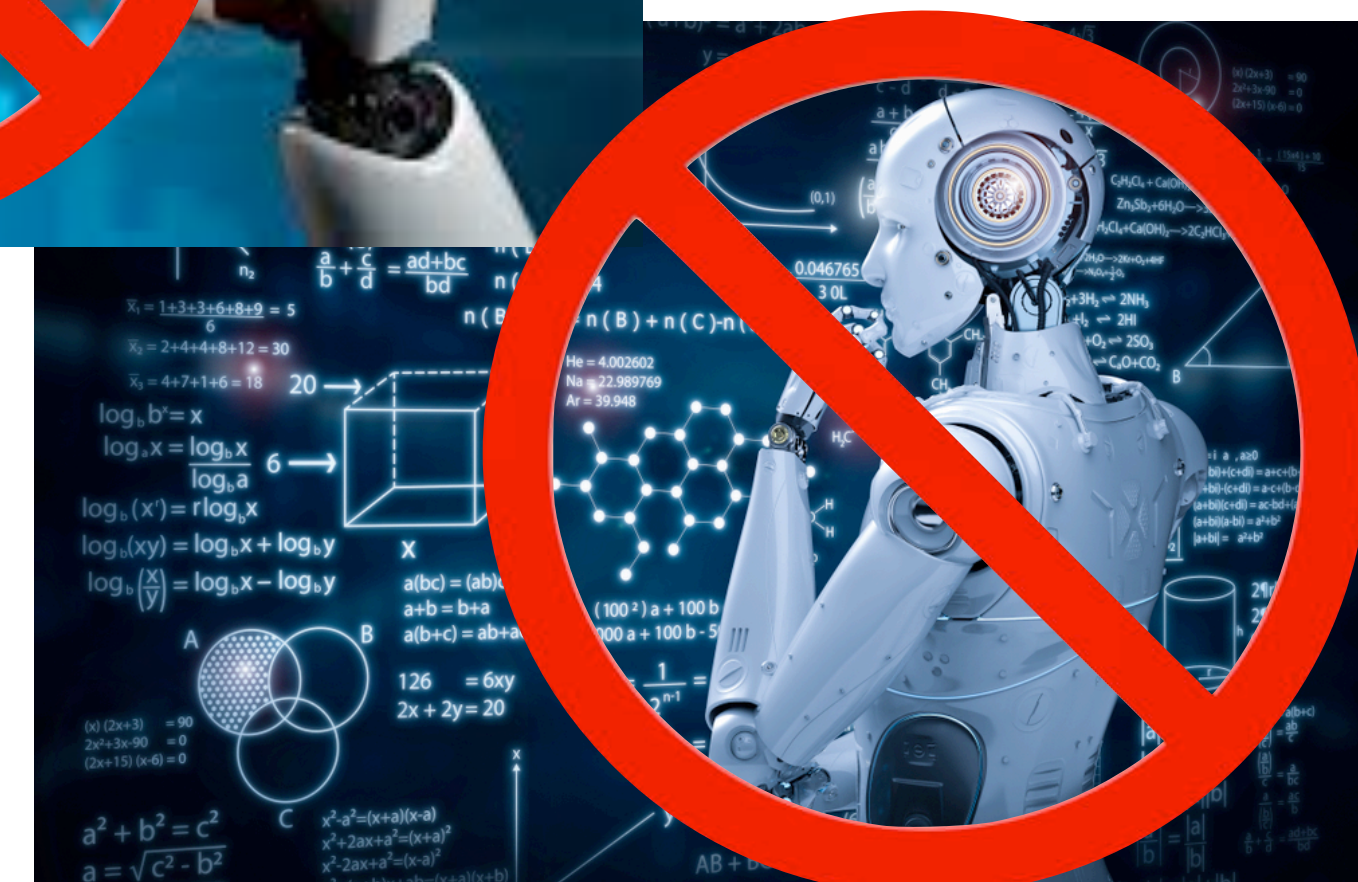
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# Secondment

# Lightbox, Geneva

## Market Analysis for Financial Firm

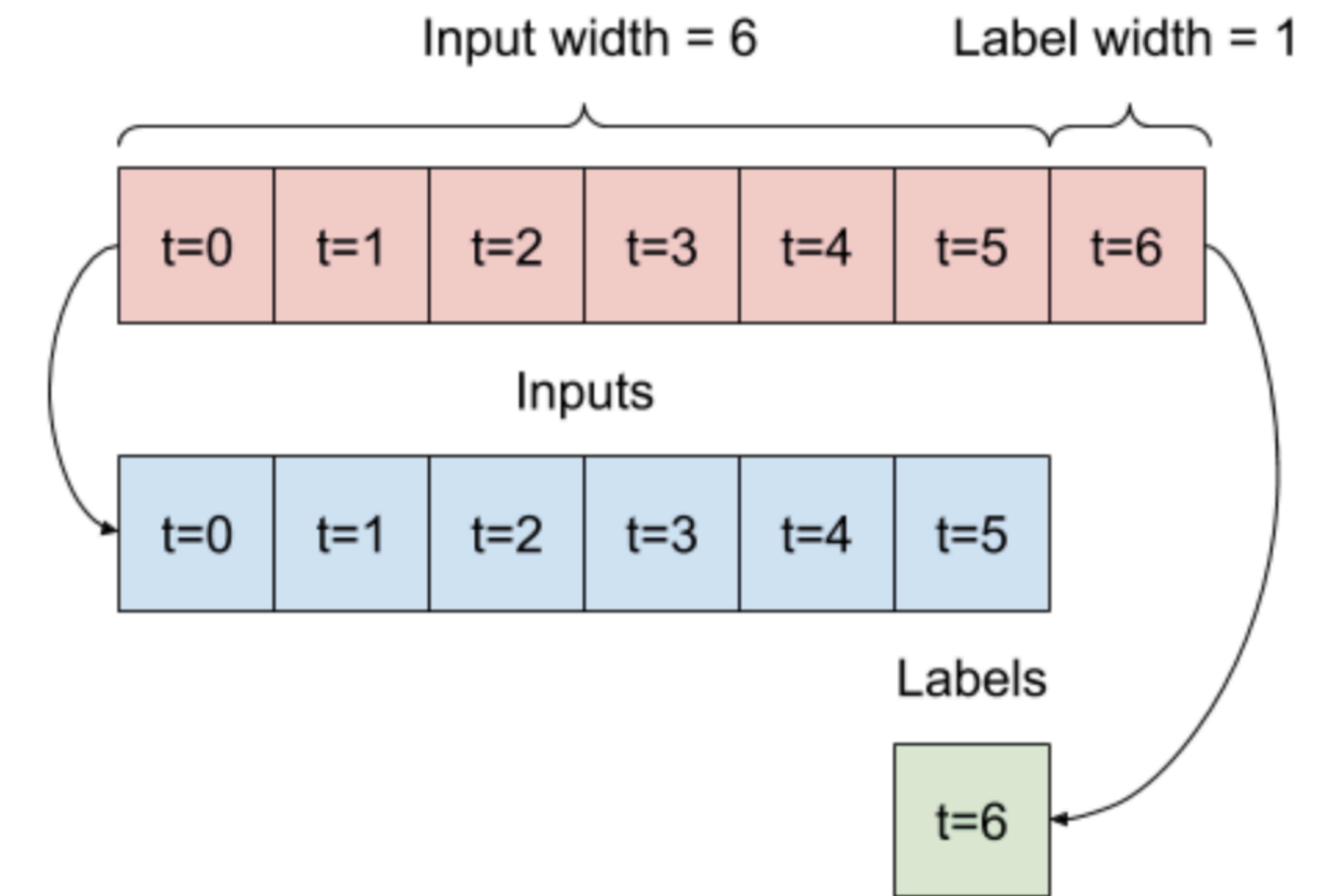
- **NOT prediction of the future!**
- Using ML and other data science tools to give signals/inform a financial strategy.
- Already widely adopted.
- A lot of different advice/practices compared to physics and academia.
- Time series data - handle with care!



<https://www.tapinto.net/towns/elizabeth/articles/3-applications-of-machine-learning-and-ai-in-finance-2d5c4825-e0ad-4dda-bec6-22e91842eaa7>

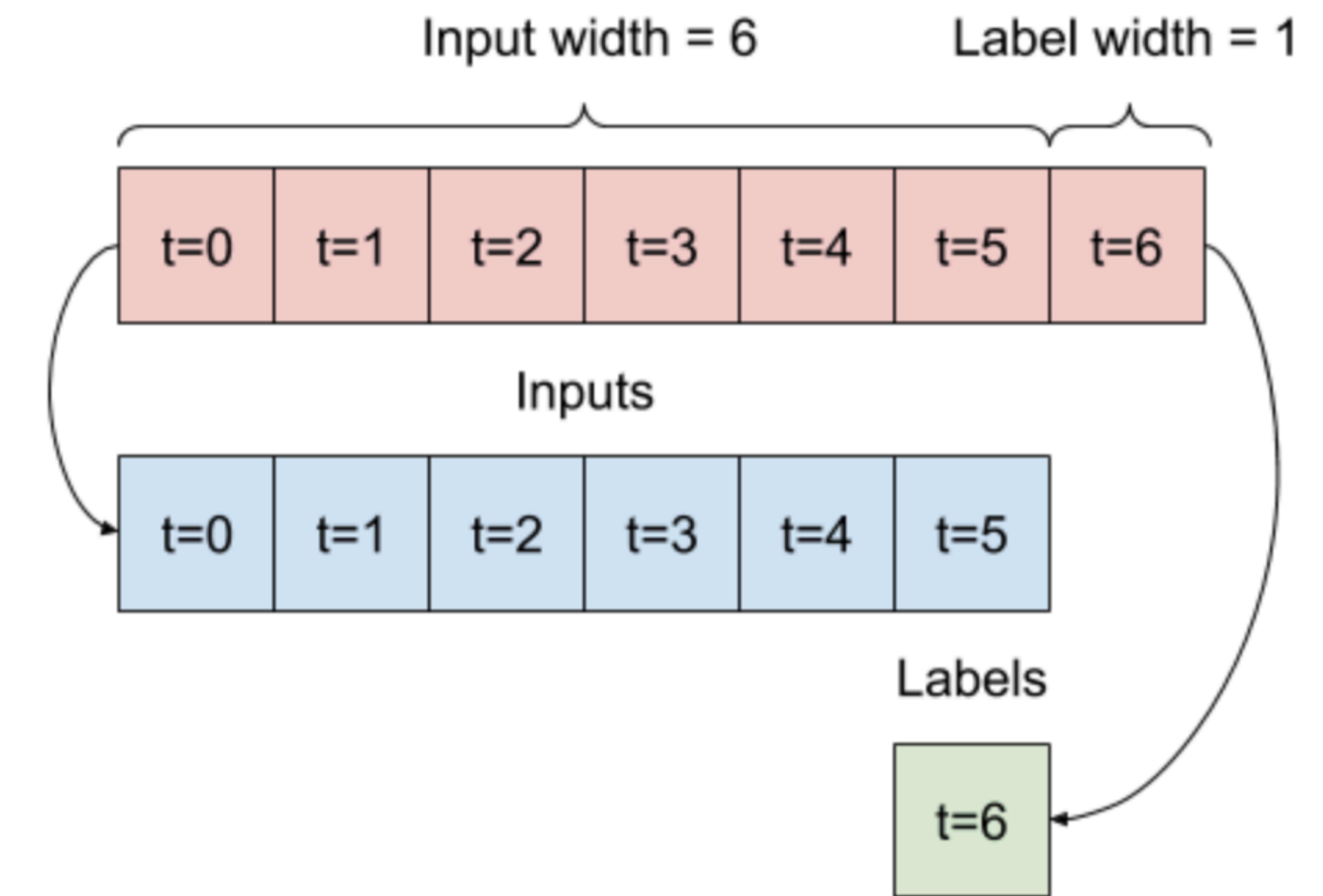
# Time Series Data

- Focus on **time series data**, different underlying (stocks, commodities, FX).
- Split into **training** (past) and **validation/test** (future) data.
- In a **recurrent neural network (RNN)** we use a 14 step **window** as input.
- Forecast **horizon** can change, most common choice is one step.



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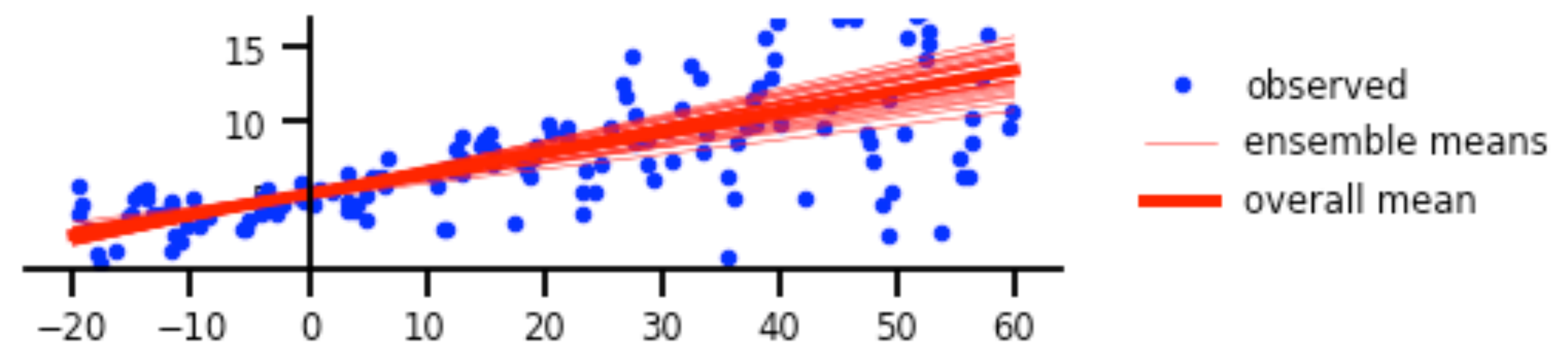
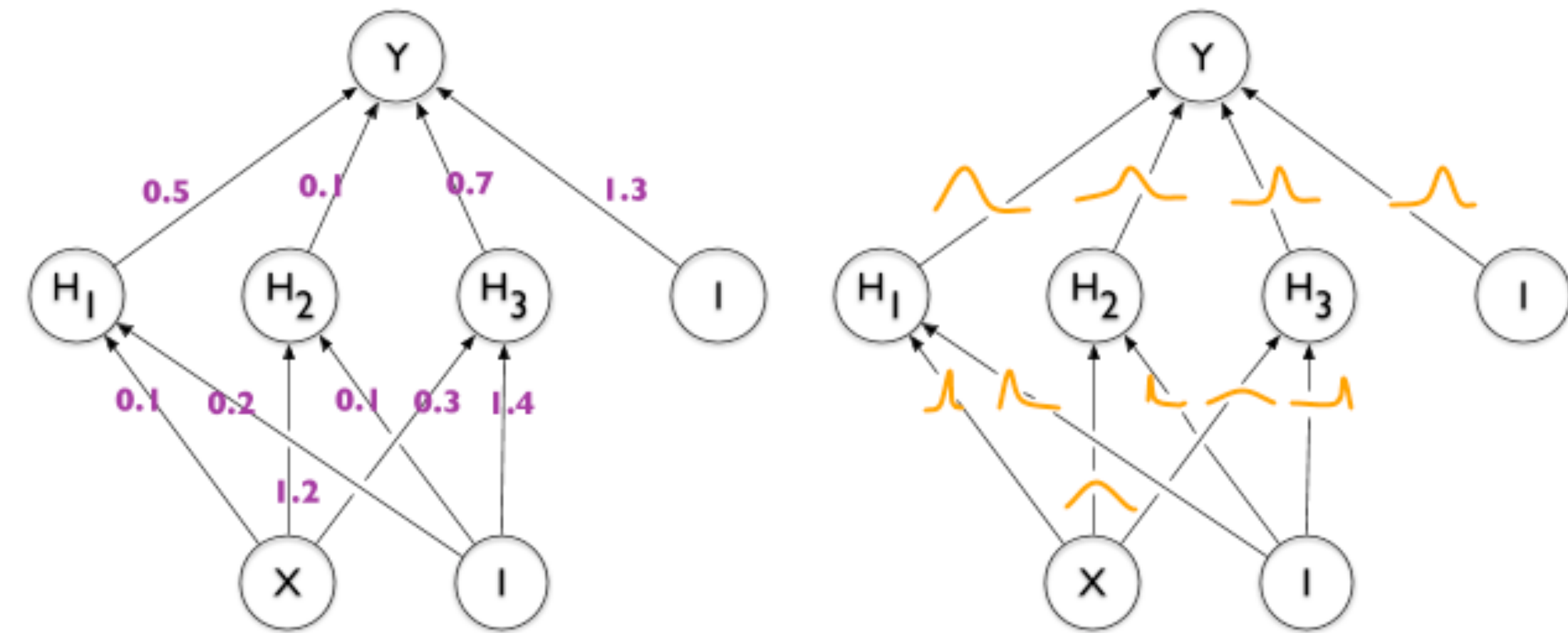
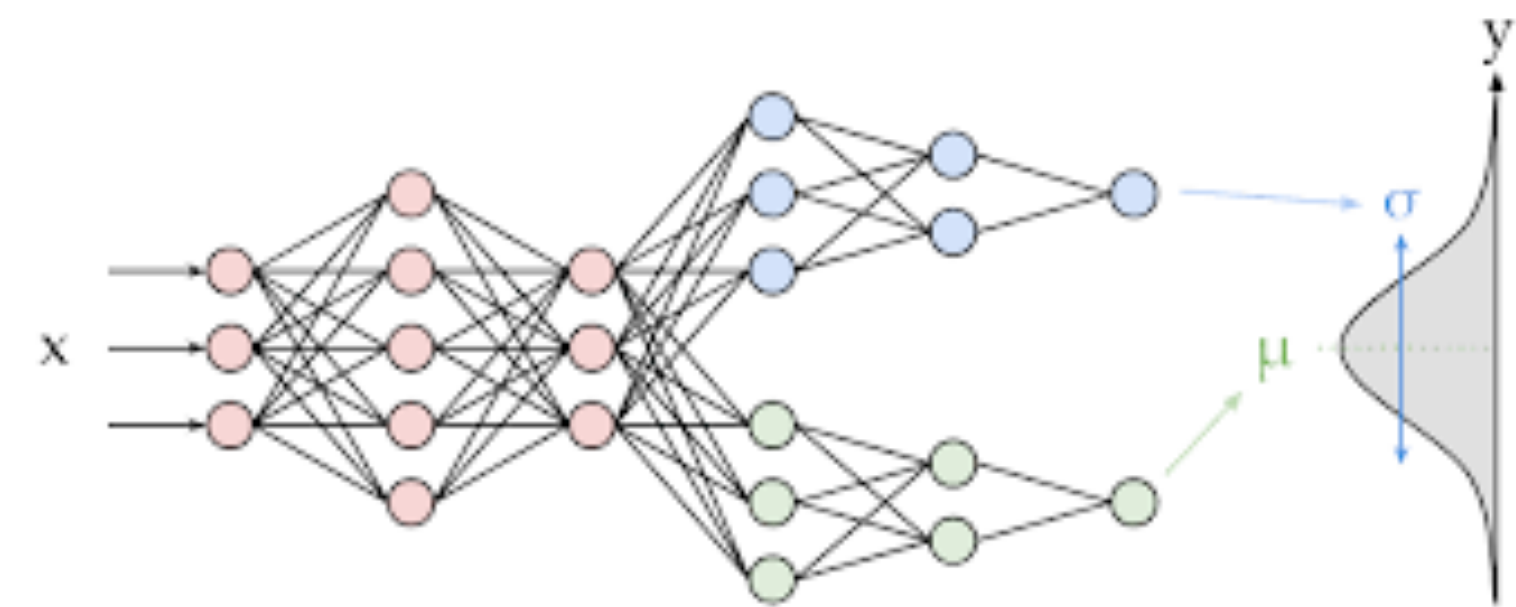
<https://www.axi.com/int/blog/education/trading-indicators>



# Bayesian Neural Networks

## A quick detour

- **Bayesian** neural networks (BNNs) model the **uncertainty** associated to a prediction.
- Rather than a weights leading to a single **deterministic** output their weights define PDFs.
- The model output can also be a **'distribution'**.
- Very robust to **noisy** data, hard to **overtrain**.



[https://www.tensorflow.org/probability/examples/Probabilistic\\_Layers\\_Regression](https://www.tensorflow.org/probability/examples/Probabilistic_Layers_Regression)

<https://brendanhasz.github.io/2019/07/23/bayesian-density-net.html>

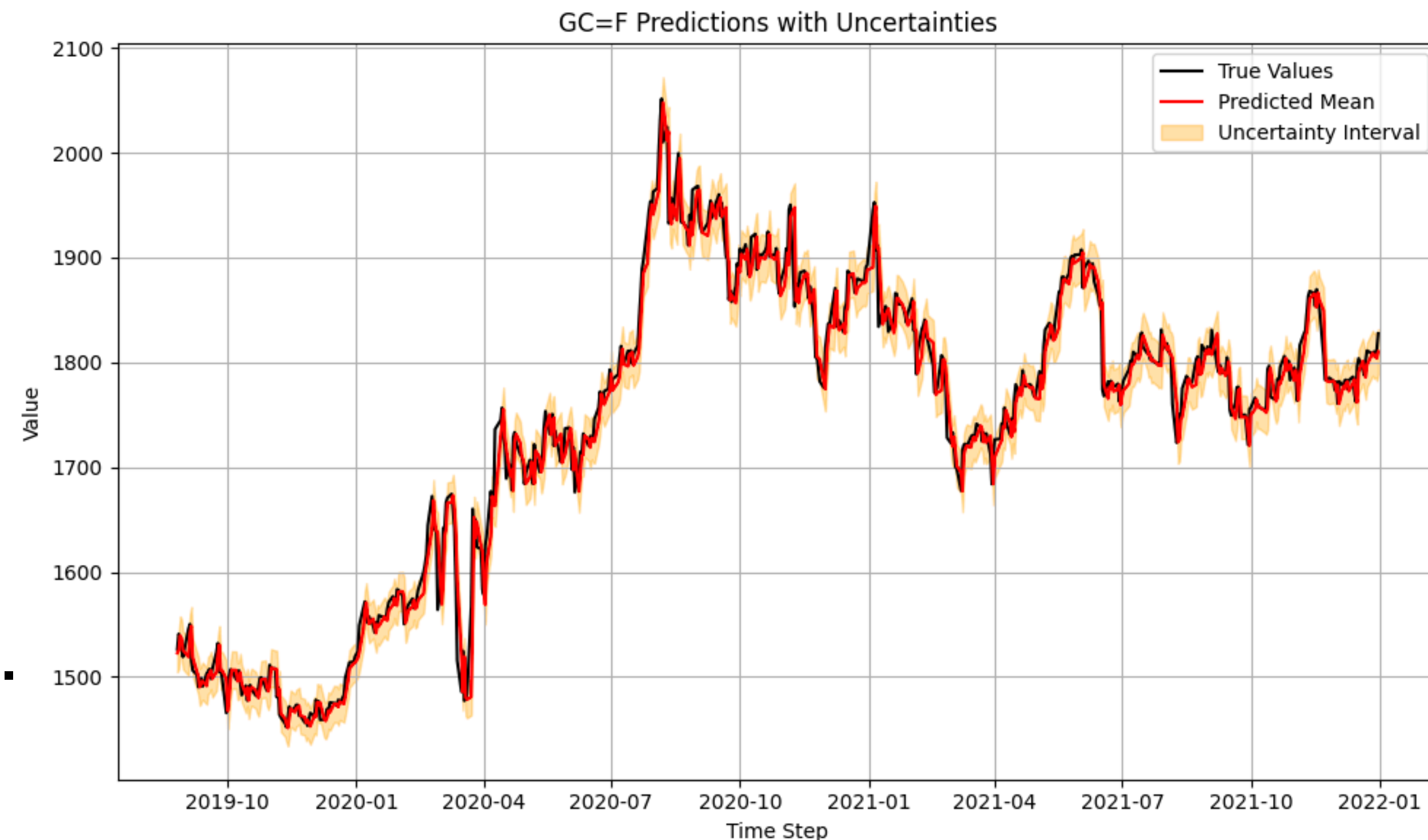
<https://neptune.ai/blog/bayesian-neural-networks-with-jax>



# Our work

## Combine LSTM + Bayesian Output

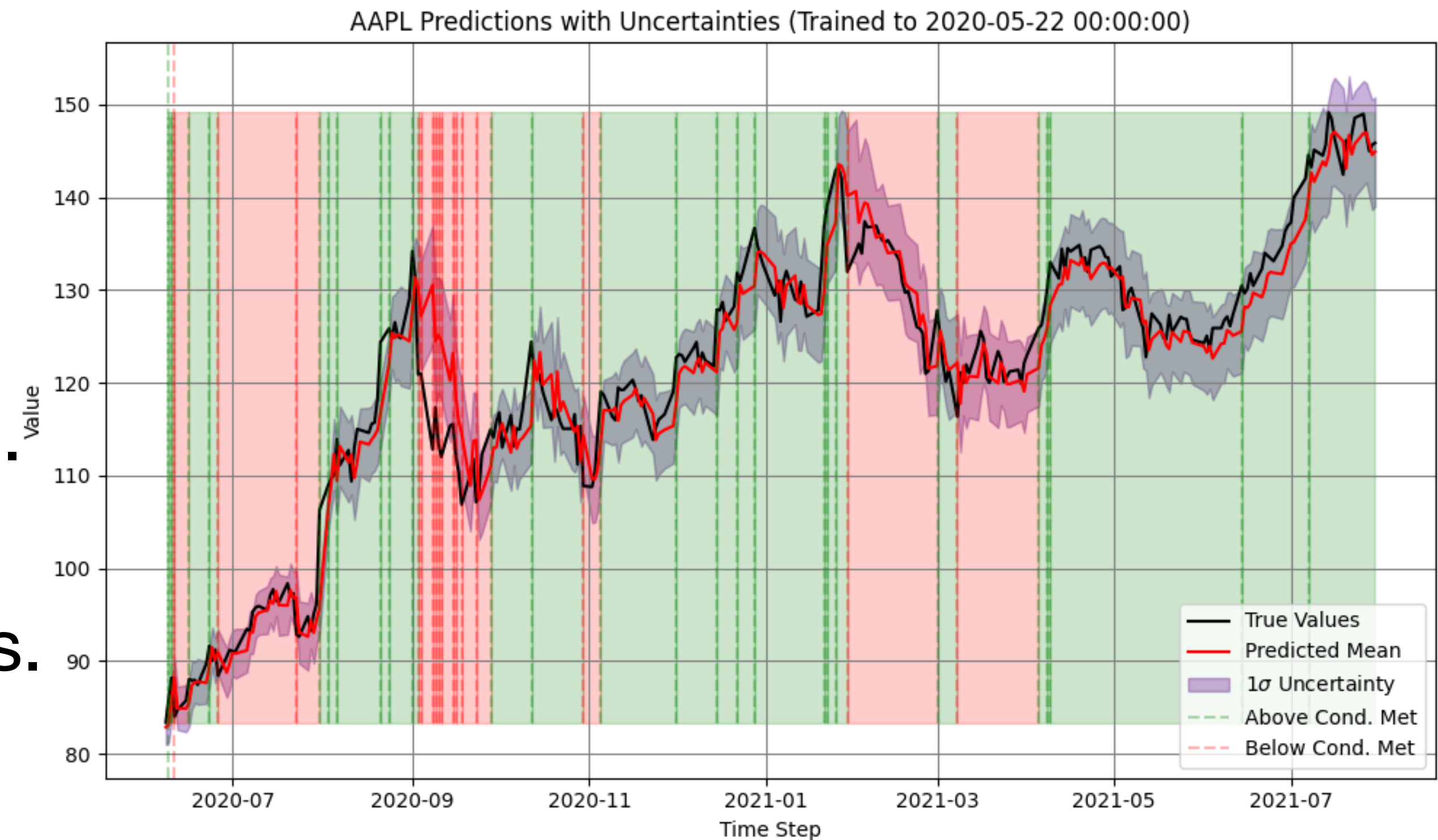
- We use the uncertainty estimation of BNNs to guide a small LSTM backed model (~20k parameters).
- At each time step **model outputs a Gaussian (or student's-T) distribution.**
- Use  $\sigma$  as a **quality/confidence score.** Use this to filter buy and sell decisions.
- Predictions highly **dependent on training size** (training sample regime) and **forecast window**.
- (And a small excursion into transfer learning...)



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# Conclusion

- Object detection in ATLAS trigger, promising though requires **more validation** and rigorous **training + optimising**.
- Secondment **project prototype** finished. Now work on improvements in **robustness** before any **potential deployment**.
- More tests with **different** time series **data** (frequency, duration, horizon, etc.)
- To join ATLAS physics analysis with ML/TLA focus.

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# Thanks for listening

# Backup

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 64)	17408
dense (Dense)	(None, 64)	4160
dense_1 (Dense)	(None, 32)	2080
dense_2 (Dense)	(None, 16)	528
dense_3 (Dense)	(None, 8)	136
dense_variational (DenseVariational)	(None, 2)	54
distribution_lambda (DistributionLambda)	((None, 1), 0 (None, 1))	0
Total params: 24366 (95.18 KB) Trainable params: 24366 (95.18 KB) Non-trainable params: 0 (0.00 Byte)		

# Parabolic SAR

The PSAR indicator is used to determine trend direction and potential reversals in price. Establish trend first then, If the trend is up, buy when the indicator moves below the price. If the trend is down, sell when the indicator moves above the price. A buy signal occurs when the PSAR moves from above to below the price, while a sell signal occurs when the dots move from below to above the price.



$$\begin{aligned} \text{RPSAR} &= \text{Prior PSAR} + \\ &[\text{Prior AF} (\text{Prior EP} - \text{Prior PSAR})] \\ \text{FPSAR} &= \text{Prior PSAR} - \\ &[\text{Prior AF} (\text{Prior PSAR} - \text{Prior EP})] \end{aligned}$$

**where:**

RPSAR = Rising PSAR

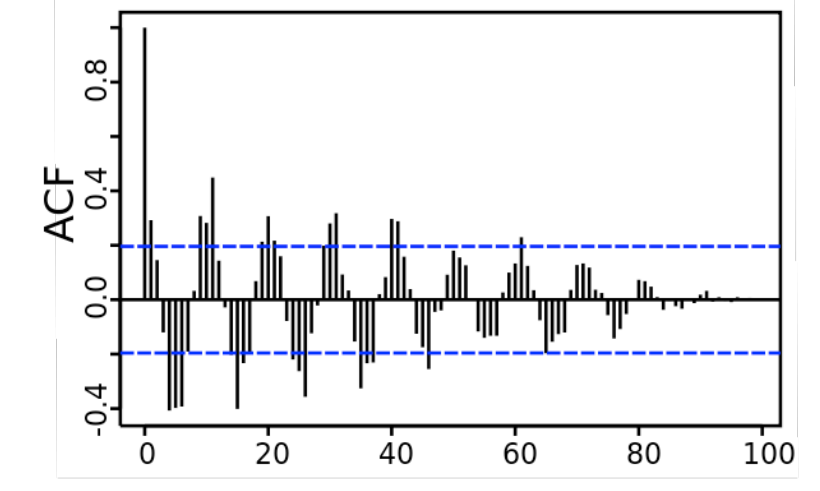
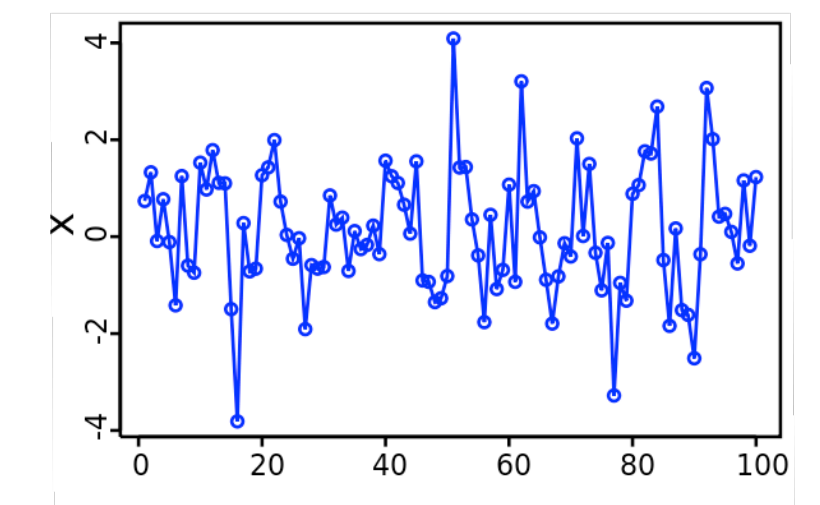
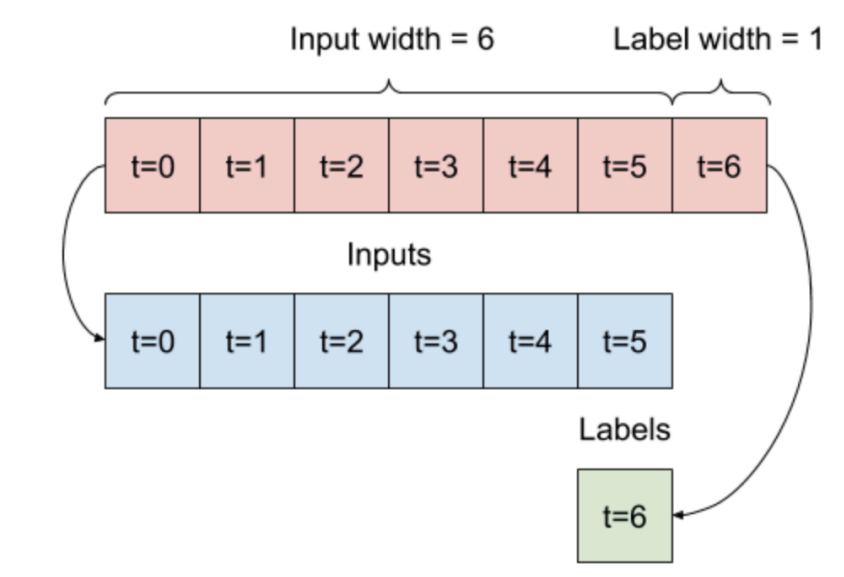
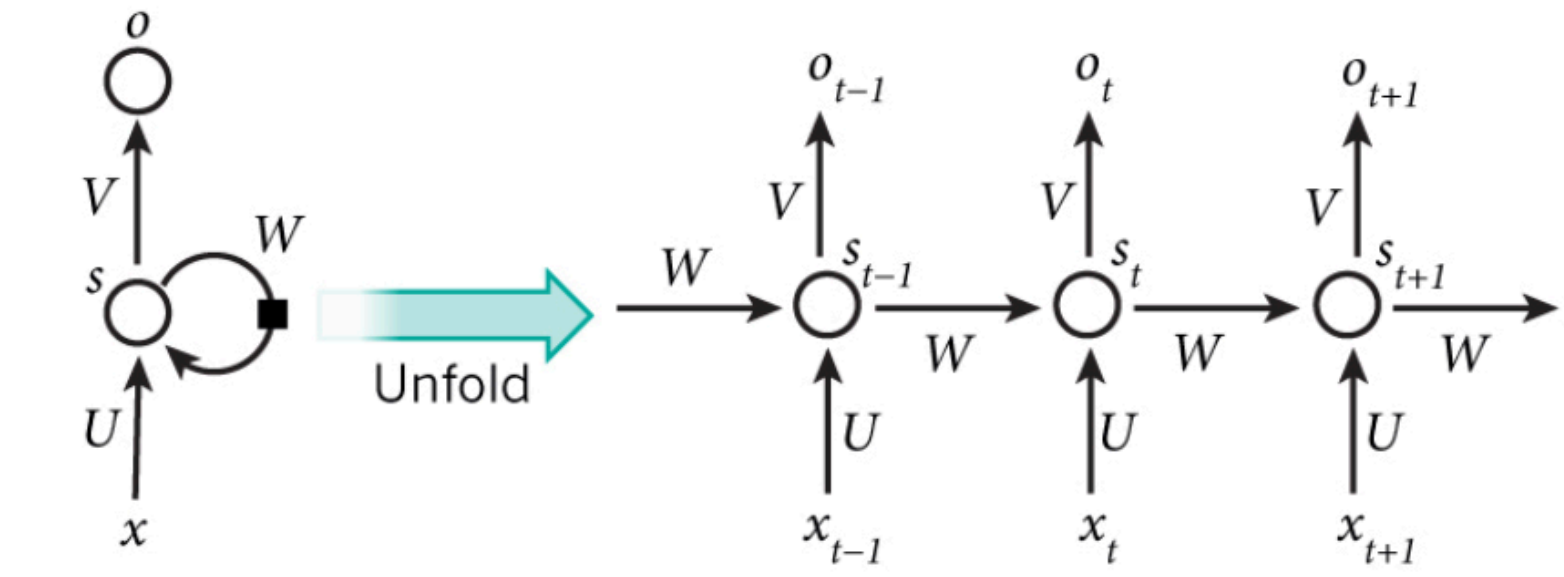
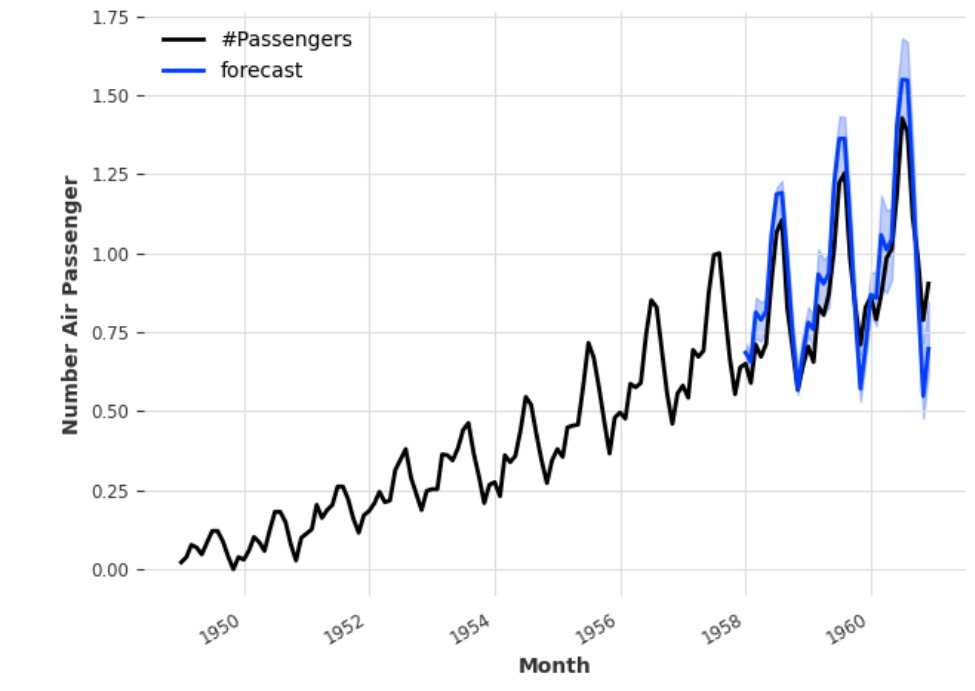
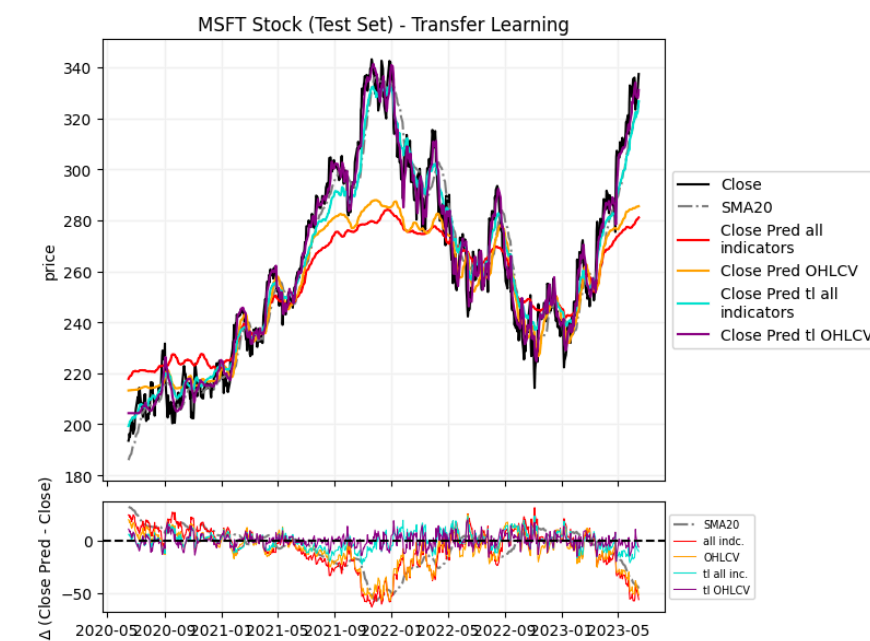
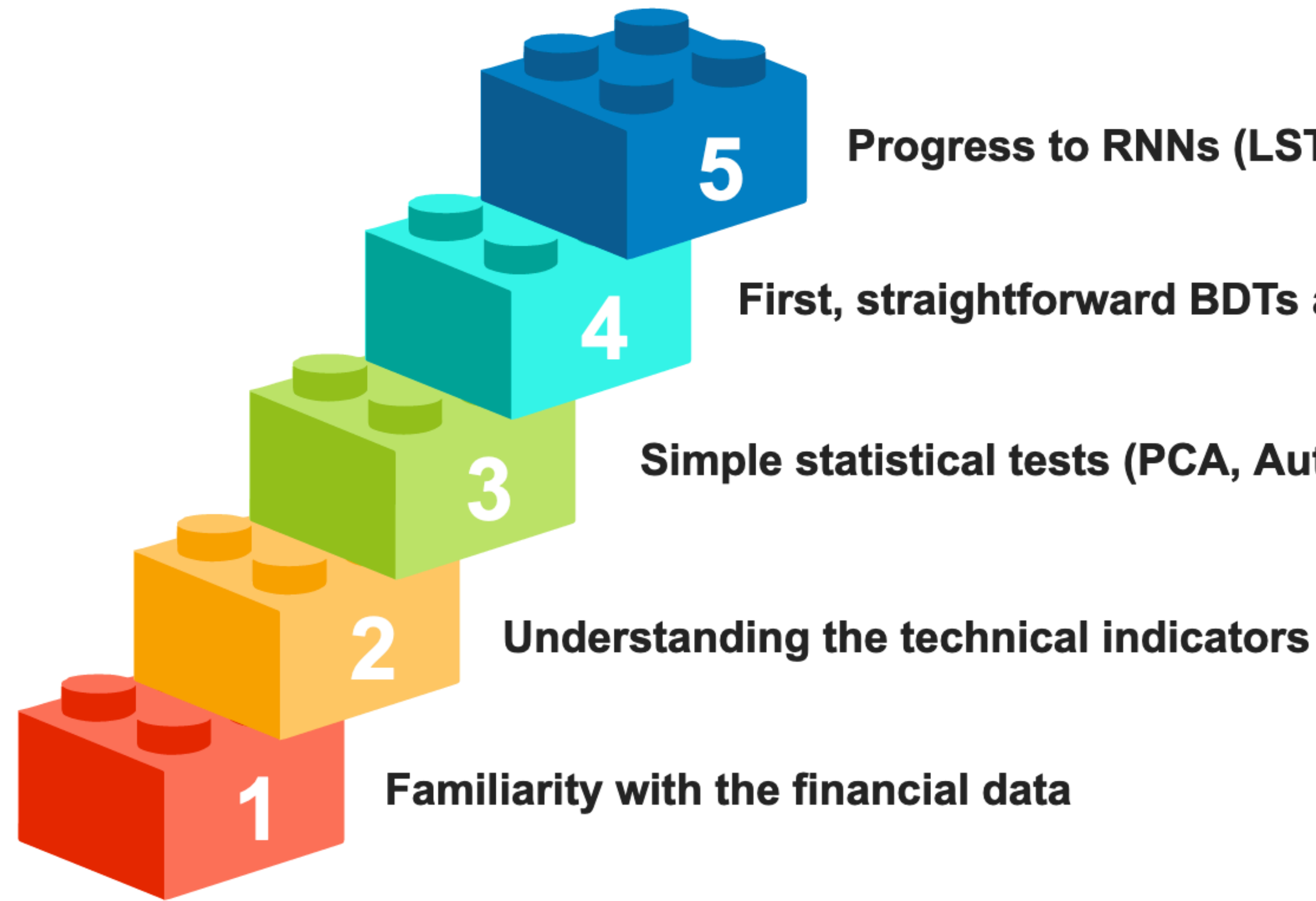
AF = Acceleration Factor, it starts at 0.02 and increases by 0.02, up to a maximum of 0.2, each time the extreme point makes a new low (falling SAR) or high (rising SAR)

FPSAR = Falling PSAR

EP = Extreme Point, the lowest low in the current downtrend (falling SAR) or the highest high in the current uptrend (rising SAR)

# Our work

## A bit of trial and error



<https://otexts.com/fpp3/acf.html>  
<https://arxiv.org/pdf/1412.3555.pdf>

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# Miscellaneous activities

# Additional engagements

## In Geneva:

- University course in statistical methods
- University course in scientific computing in physics
- 3rd Symposium on AI for Industry, Science and Society
- High performance computing cluster training

## At CERN:

- ATLAS Control Room Shifter Training for trigger + DQ
- PyRoot + Scikit-HEP masterclasses/tutorials
- ECSB Lecture Series
- Radioactivity safety course

## Elsewhere:

- CHIPP PhD Winter School, Leukerbad Jan. 2023
- 3rd COMCHA School, Oviedo Oct. 2023

