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Deep Learning and

The NEXT Experiment

IML Machine Learning Working Group
CERN
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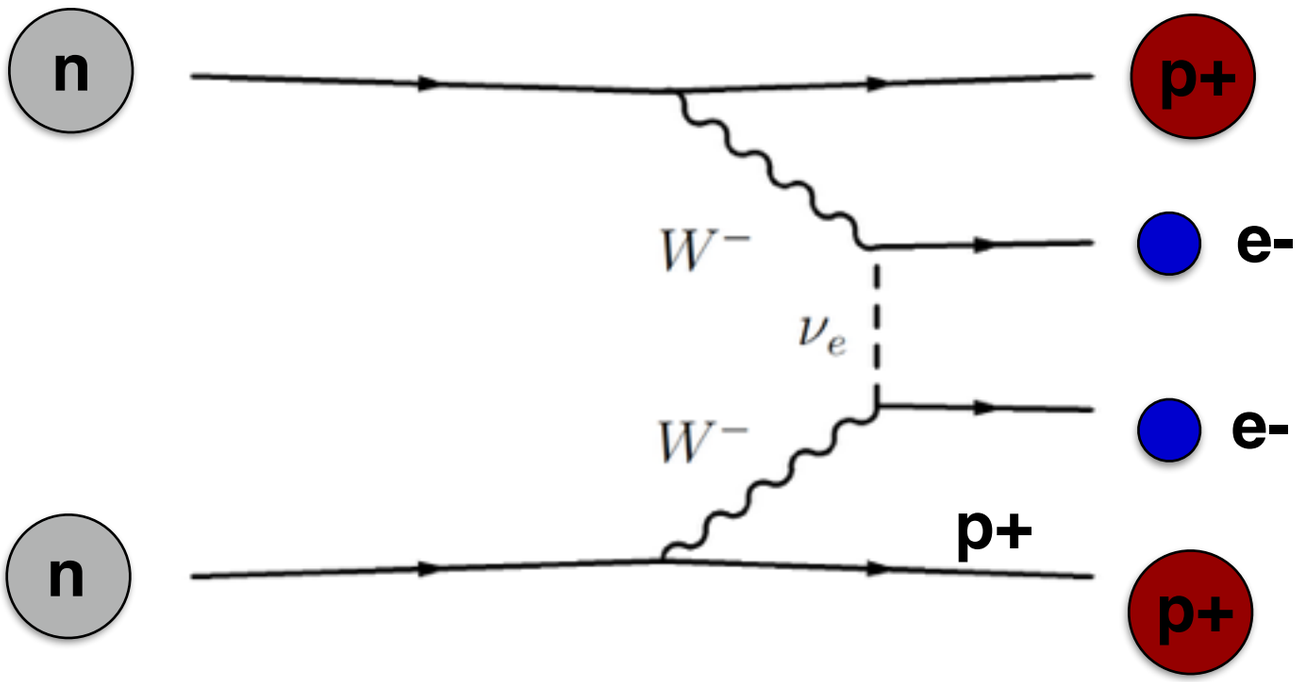
Neutrino **E**xperiment with a **X**enon **T**PC

LSC
Laboratorio Subterráneo de Canfranc

NEXT at Canfranc

- search for neutrinoless double-beta decay (0vßß)
- final proposed phase: 100 kg Xe, enriched to ^{136}Xe (90%)
- high pressure gas, electroluminescent TPC

Why 0vßß?



$^{136}Xe \longrightarrow {}^{136}Ba^{++} + 2e^-$

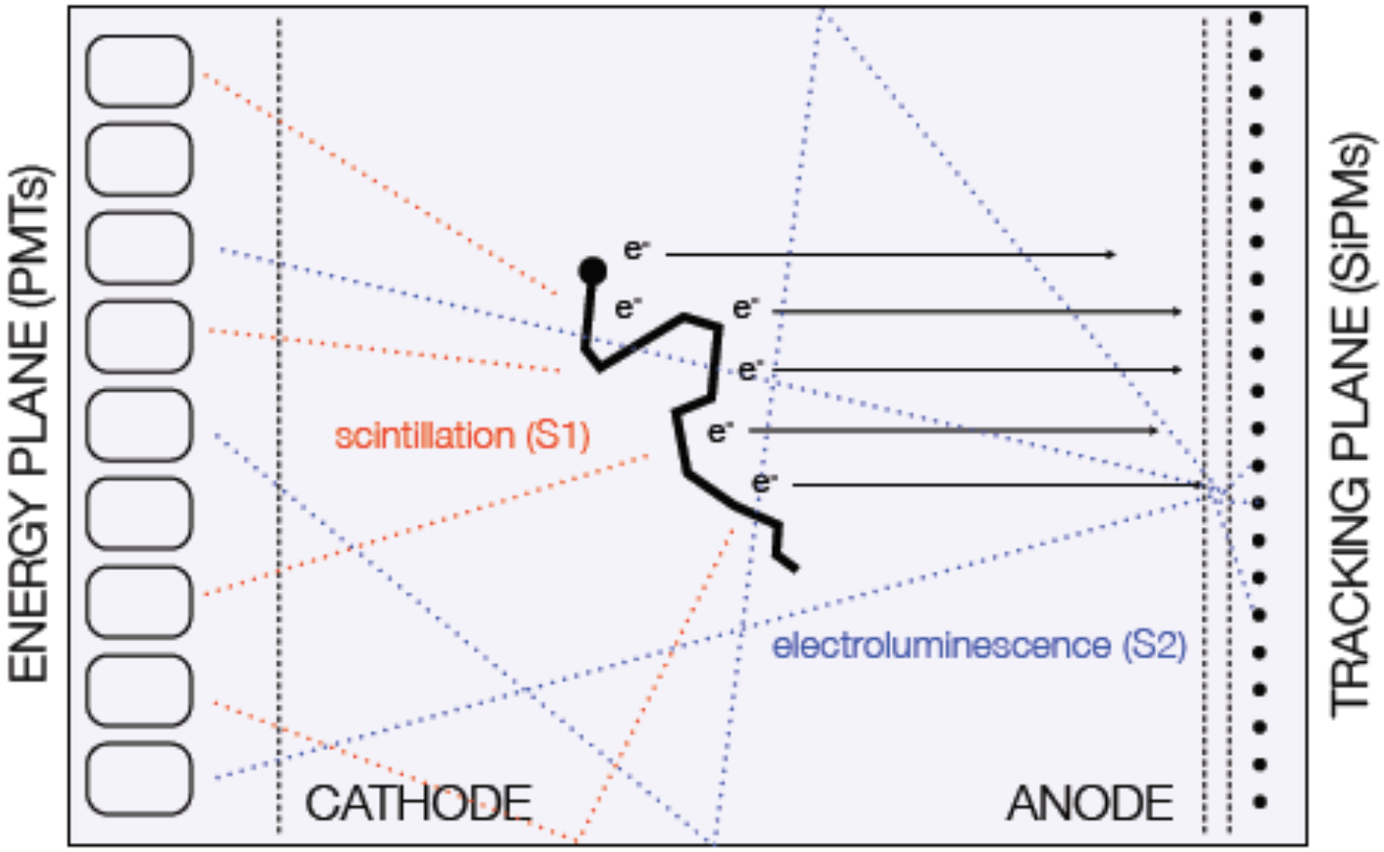
- 2 simultaneous ß decays
- 2 anti-neutrinos emitted become a virtual neutrino

An observation of 0vßß would:

- demonstrate that neutrinos are Majorana
  - new mass scale / mass generation mechanism?
- imply total lepton number violation
  - explanation of matter/anti-matter asymmetry (leptogenesis)?
- provide information on neutrino hierarchy and mass scale

An Electroluminescent HPXe TPC

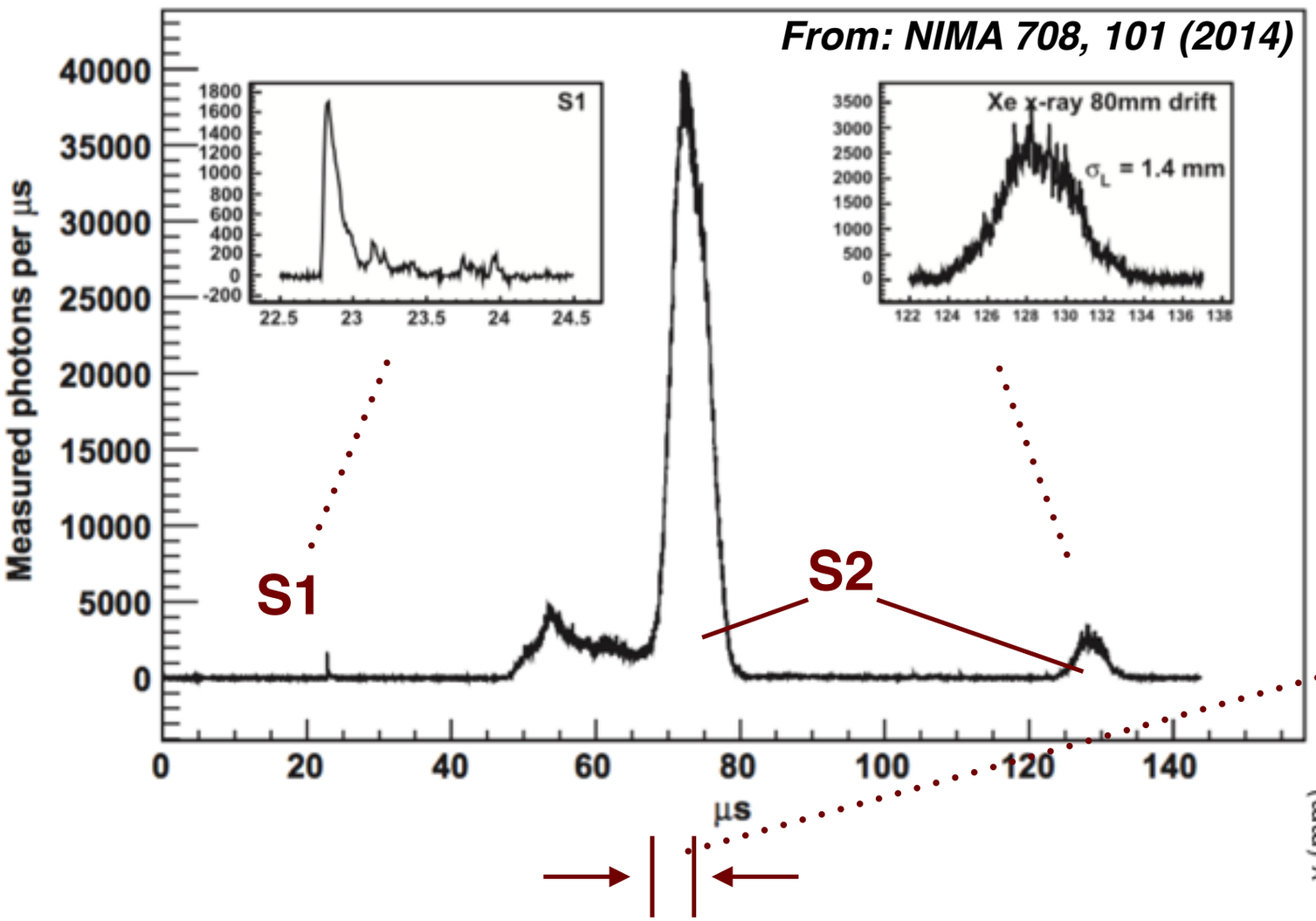
- ionization track drifted to electroluminescent readout plane
- S2 light detected by silicon photomultipliers (SiPMs) in the *tracking* plane, and PMTs in the *energy* plane
- initial S1 light measured by PMTs to provide t_0



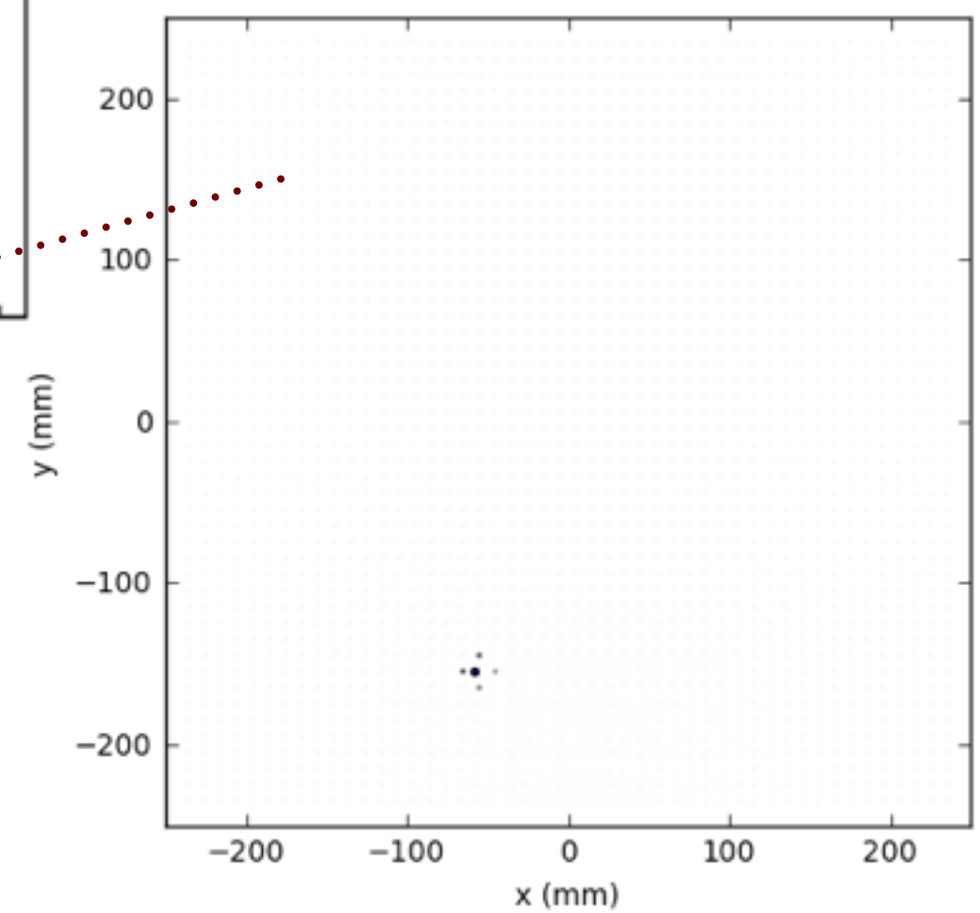
- **Simultaneous precise energy measurement and 3D event reconstruction**

Signals observed in an EL-TPC

Observed by the *energy plane* (PMTs)



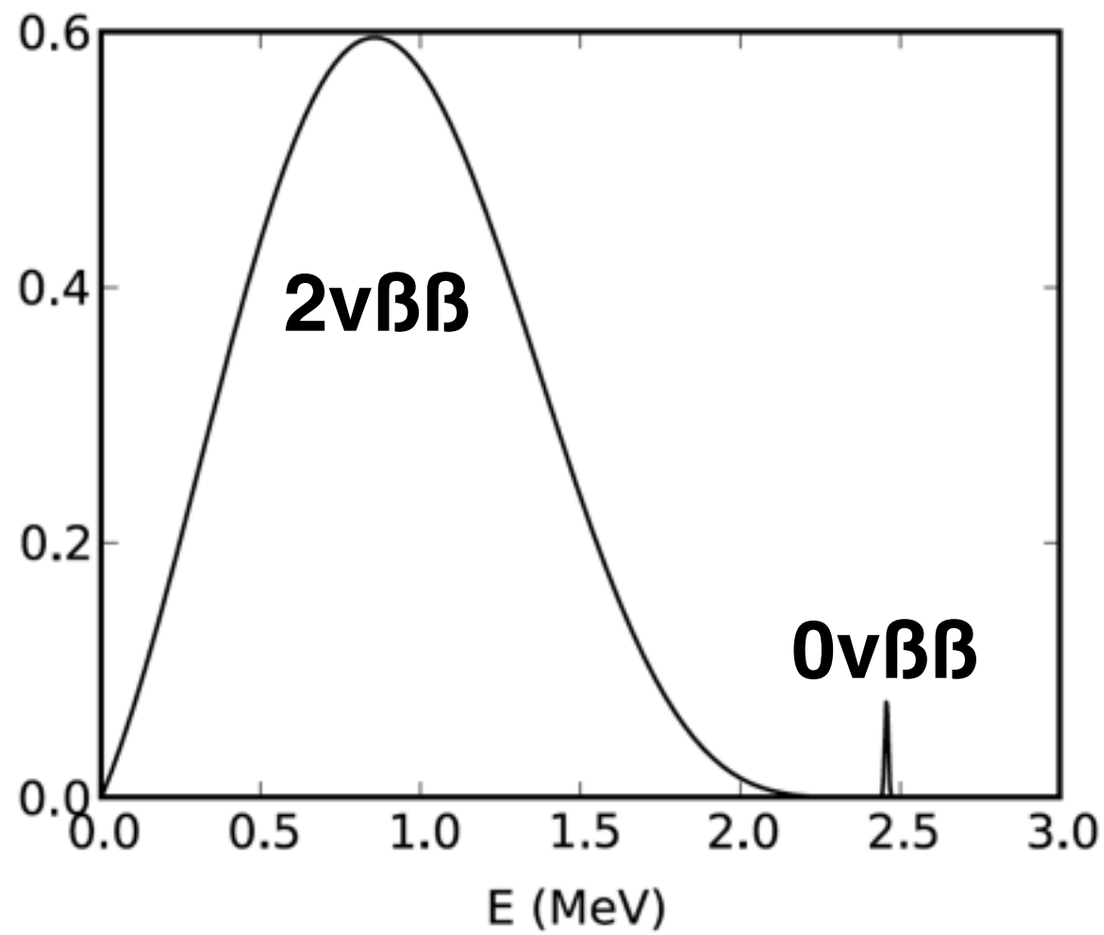
Observed by the *tracking plane* (SiPMs)



- S2 sliced into time (z) bins and SiPM measured signal can be used to determine (x,y)

What are we looking for?

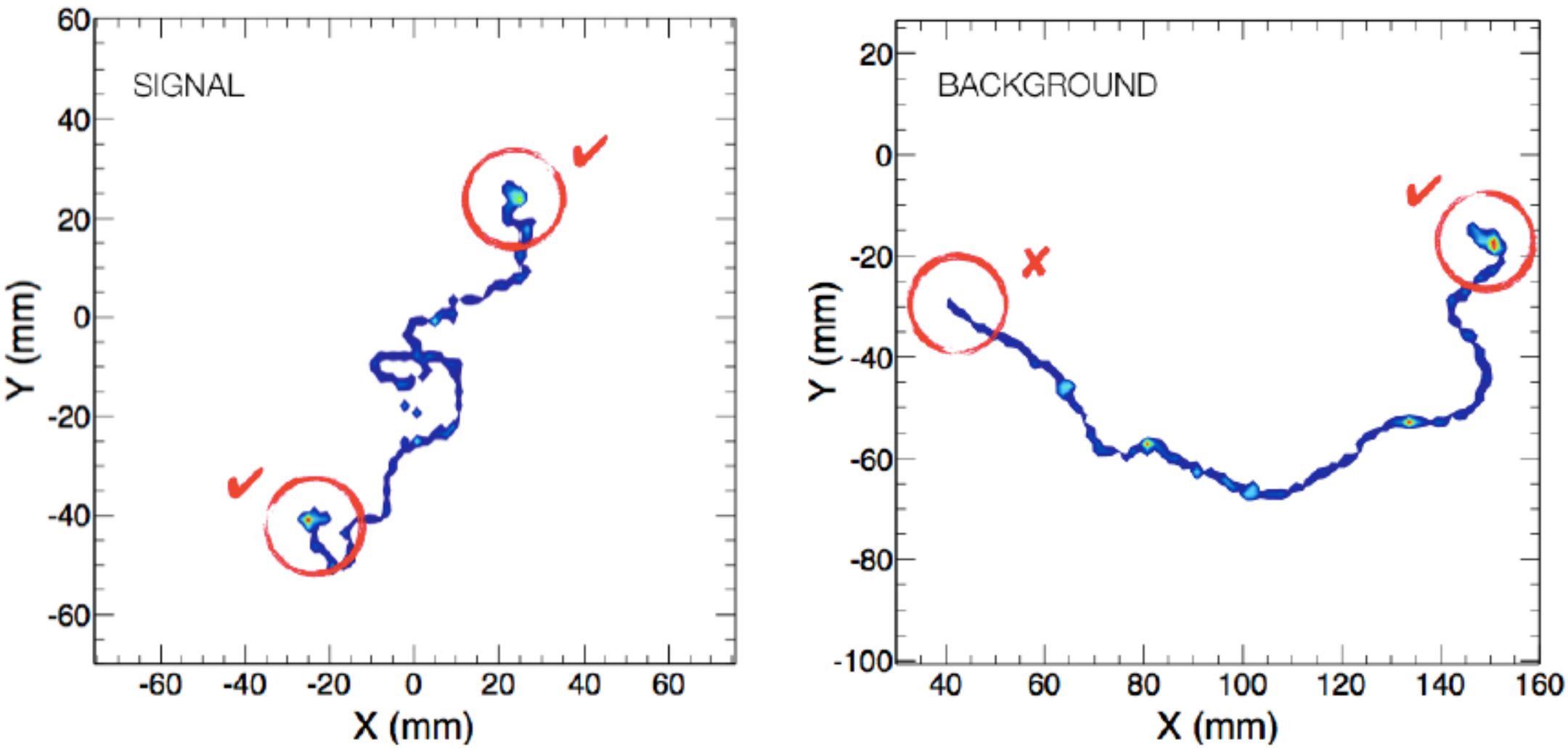
0vßß would yield 2 electrons of total energy = $Q_{ßß}$



- But we could still get background events that are not 0vßß but still fall into the energy peak

Topological signature in NEXT

JHEP 01, 104 (2016) [arXiv:1507.05902]



- Energetic electron leaves a high-density deposition at the end of its track (Bragg peak)
- Results in distinct topological signatures for **signal** and **background** events of the same energy

Topological signature in NEXT

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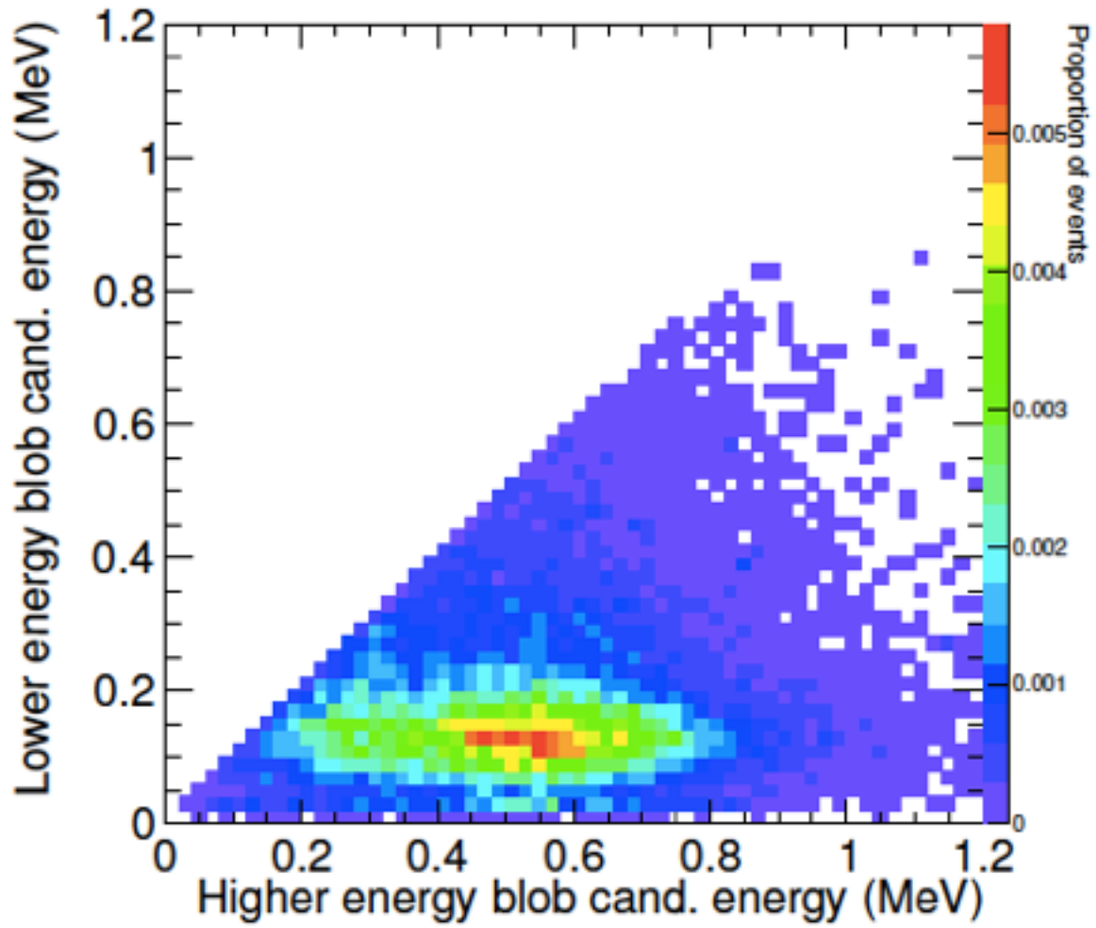
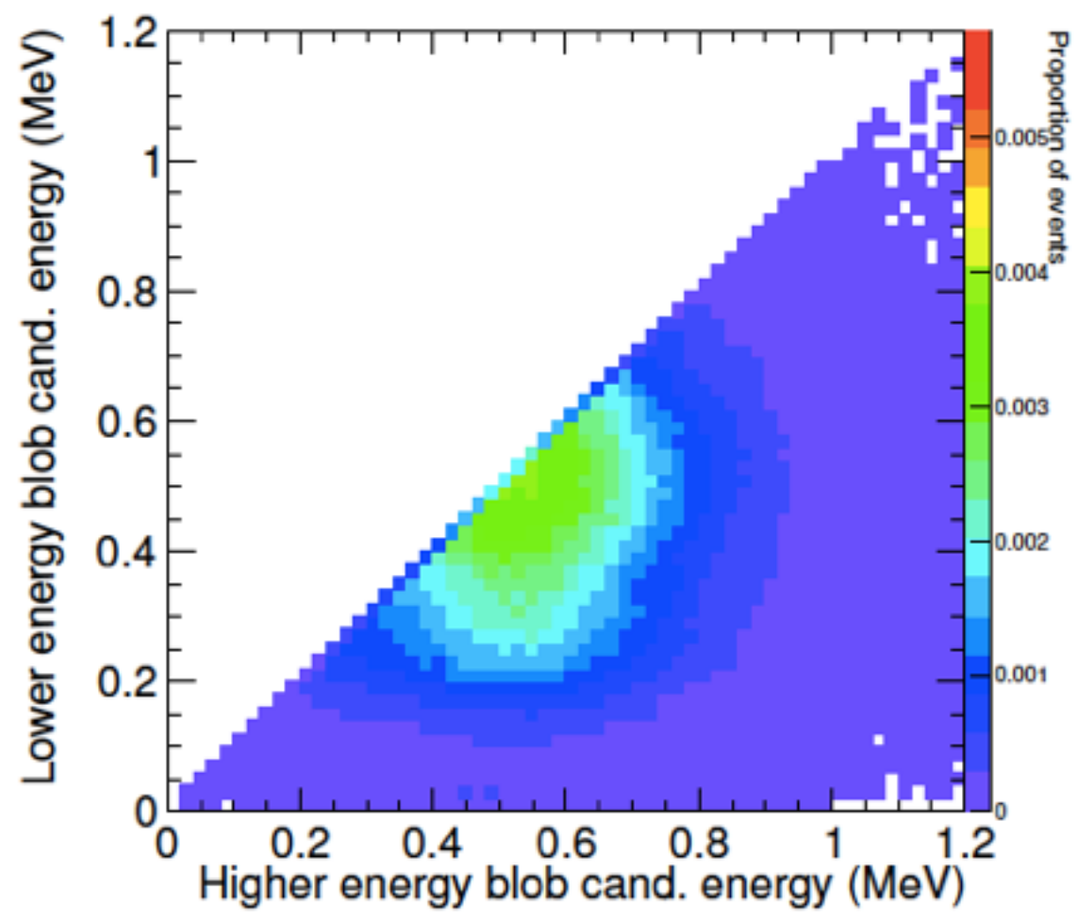




- Sum of energies in region enclosing ends of track provides main discriminant
- Geant4 Monte Carlo: (left) 2.44 MeV gammas from ^{214}Bi decay, (right) 0νββ events

NEXT-100: Background Rejection

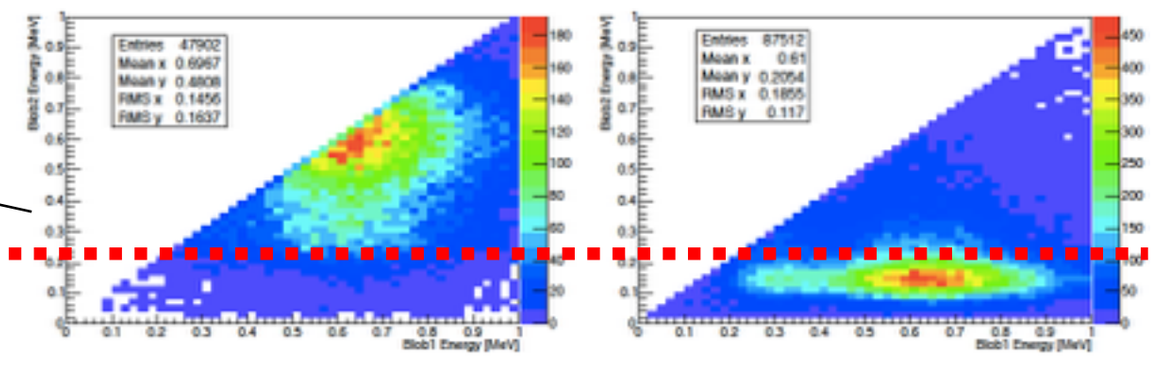
- **Monte Carlo-based study:** arXiv:1609.06202
  - Full NEXT-100 geometry, 10^5 initial signal events in active region, BG events (10^9 initial ^{208}Tl and 10^{10} initial ^{214}Bi) launched from field cage

	Signal Events		BG Events (^{208}Tl)		BG Events (^{214}Bi)	
Cut	$2\times2\times2$	$10\times10\times5$	$2\times2\times2$	$10\times10\times5$	$2\times2\times2$	$10\times10\times5$
(Initial events)	1.0	1.0	1.0	1.0	1.0	1.0
Energy	7.59×10^{-1}	7.59×10^{-1}	2.27×10^{-3}	2.27×10^{-3}	1.42×10^{-4}	1.42×10^{-4}
Fiducial	6.71×10^{-1}	6.68×10^{-1}	1.19×10^{-3}	1.17×10^{-3}	8.62×10^{-5}	8.54×10^{-5}
Single-Track	3.75×10^{-1}	4.79×10^{-1}	7.90×10^{-6}	1.81×10^{-5}	3.84×10^{-6}	8.75×10^{-6}
Classification*	3.23×10^{-1}	3.67×10^{-1}	7.70×10^{-7}	2.41×10^{-6}	2.90×10^{-7}	9.59×10^{-7}

Reconstruction granularity (mm^3)

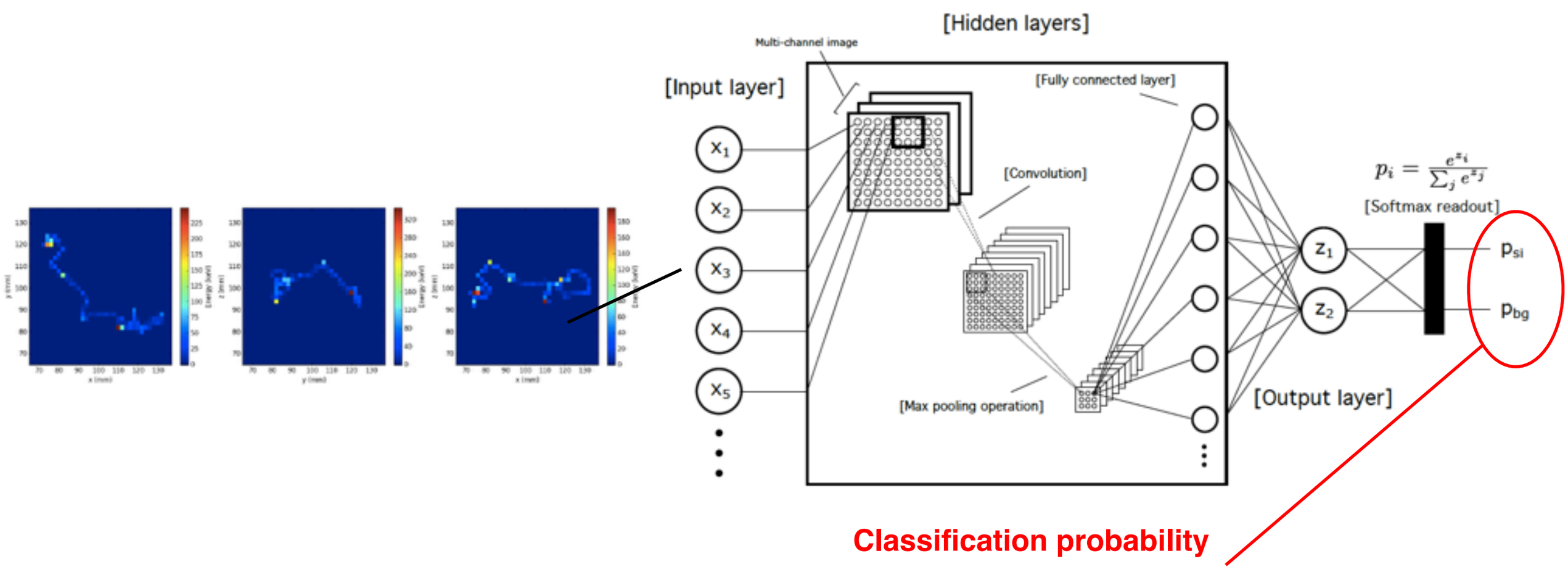
- 2 x 2 x 2 — optimistic, “low diffusion”
- 10 x 10 x 5 — current realistic case

- **Energy cut:** select events in E in [2.4,2.5] MeV
- **Fiducial cut:** < 10 keV deposited within 2 cm of walls
- **Single-track cut:** events with 1 connected track
- **Classification:** “blob”-based analysis



NEXT-100: Background Rejection

- **Replace classification cut with a deep neural network (DNN)**
  - Trained on several hundred thousand independently generated events
  - Events converted to 2D color images (R, G, B) = (xy, yz, xz) projections and used to train GoogLeNet on DIGITS (Caffe interface)



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Classification*	3.23×10^{-1}	3.67×10^{-1}	7.70×10^{-7}	2.41×10^{-6}	2.90×10^{-7}	9.59×10^{-7}
Classification (DNN)	**3.23×10^{-1}**	**3.67×10^{-1}**			**1.80×10^{-7}**	**8.22×10^{-7}**

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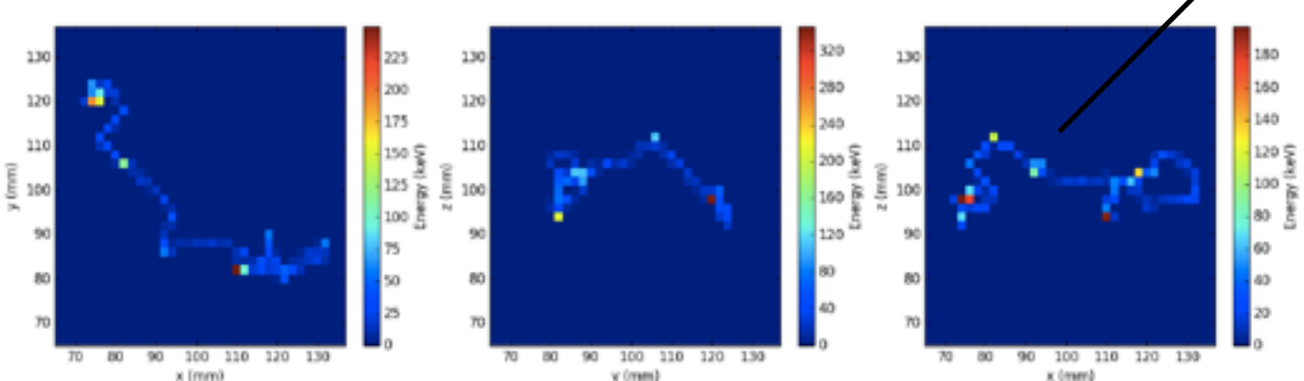
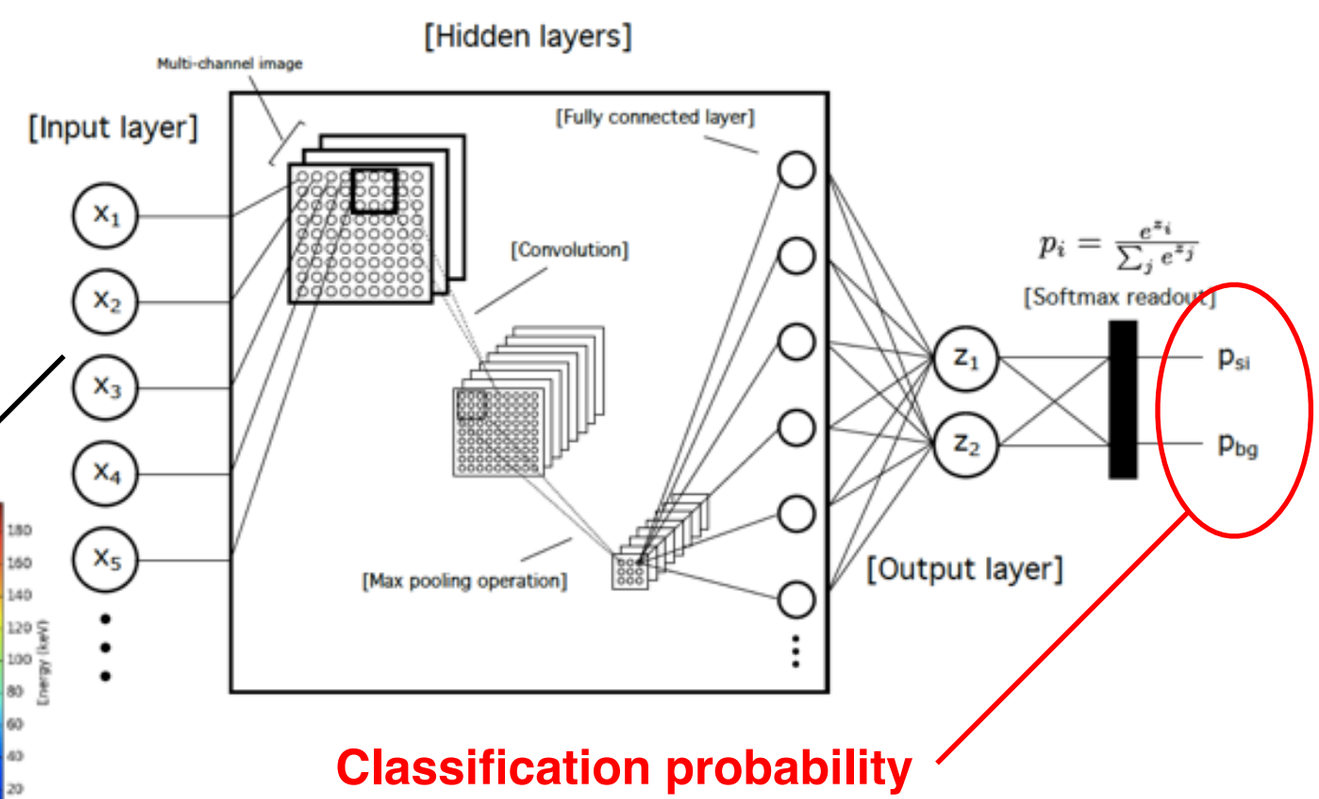
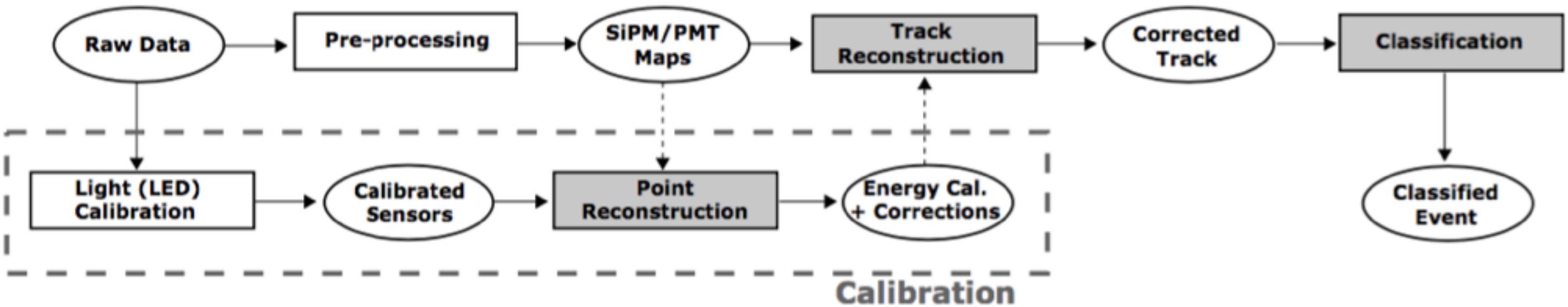




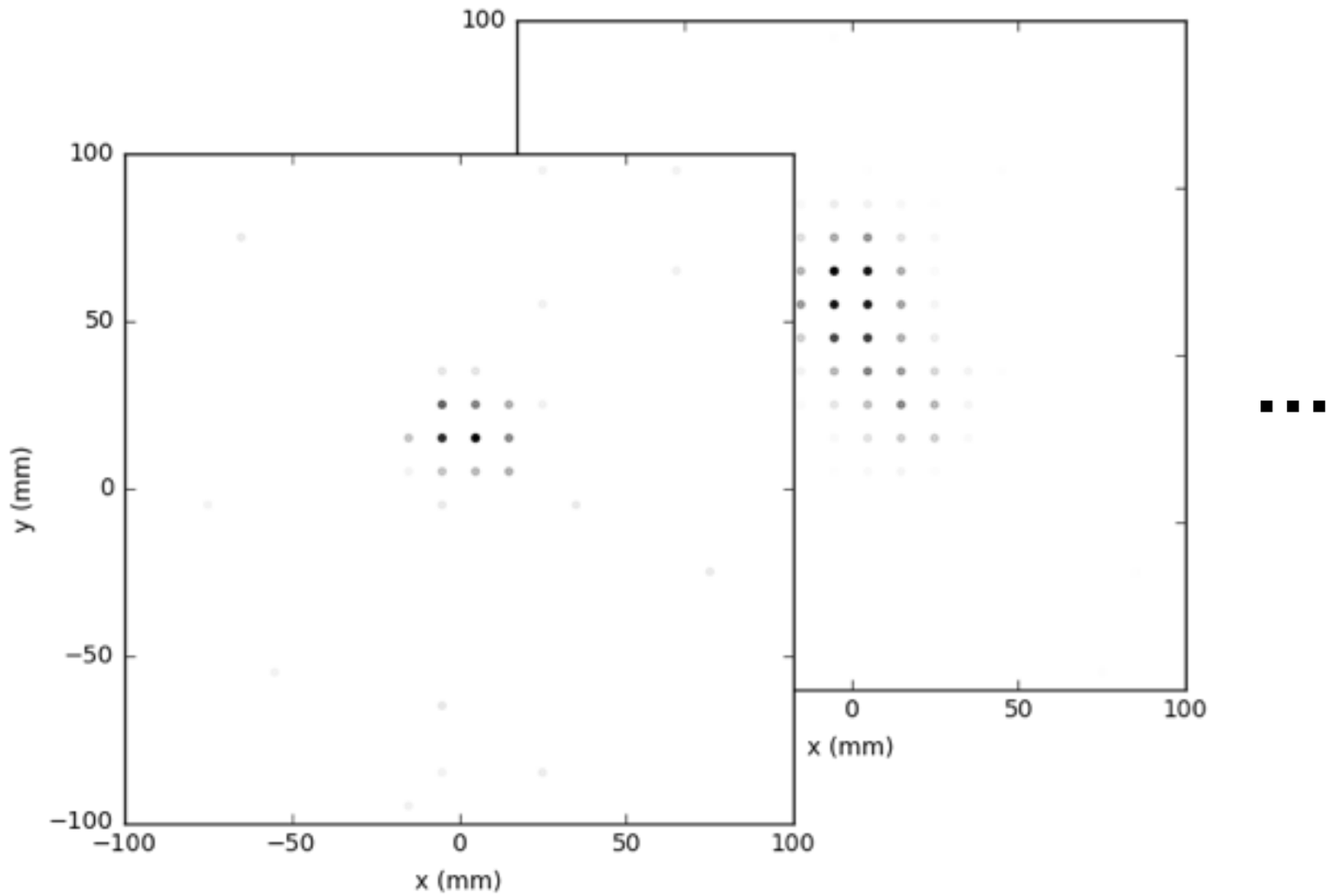
Examples (preliminary): Further applications of deep learning in NEXT



- **Point reconstruction:** take point-like events of a known energy and compute their x-y position. This along with their measured energy gives a calibration to correct for geometrical (x,y) effects in light collection.
- **Track reconstruction:** produce an image of the entire track (this was previously only considered using "classical" algorithms)
- **Classification:** signal vs. background as already discussed.

*** Note:** the following experiments were done using **Keras (Tensorflow)**

Classification: why reconstruct first?



- Use a **3D convolutional net** (several 3D convolutional layers + one 128-neuron fully connected layer + one 1-neuron readout layer) where the input is 20x20x60 matrix of SiPM signals
- See: https://jerenner.github.io/next-dnn-topology

Classification: why reconstruct first?

- **Potential improvement in a "full" (sensors simulated) Monte Carlo, but requires further study**

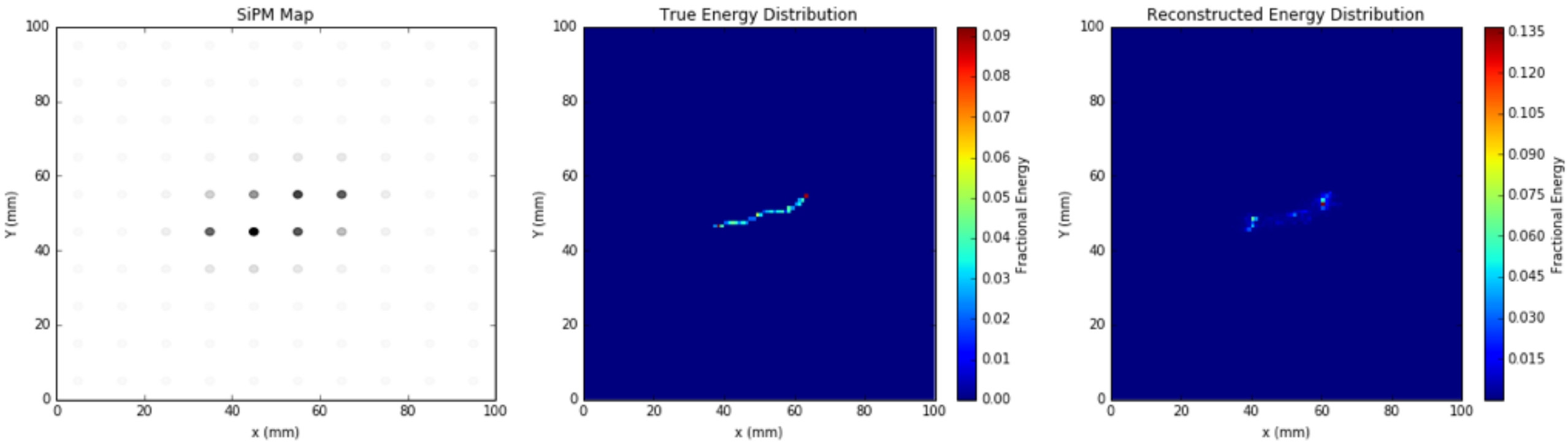
- **Classical analysis**

	Single-electron		0vbb	
Input Events	49997	100,00 %	49997	100,00 %
Fiducial	35780	71,56 %	36088	72,18 %
Single-track	14437	28,88 %	16406	32,81 %
Blobs	1869	3,74 %	11251	22,50 %

- **DNN analysis**

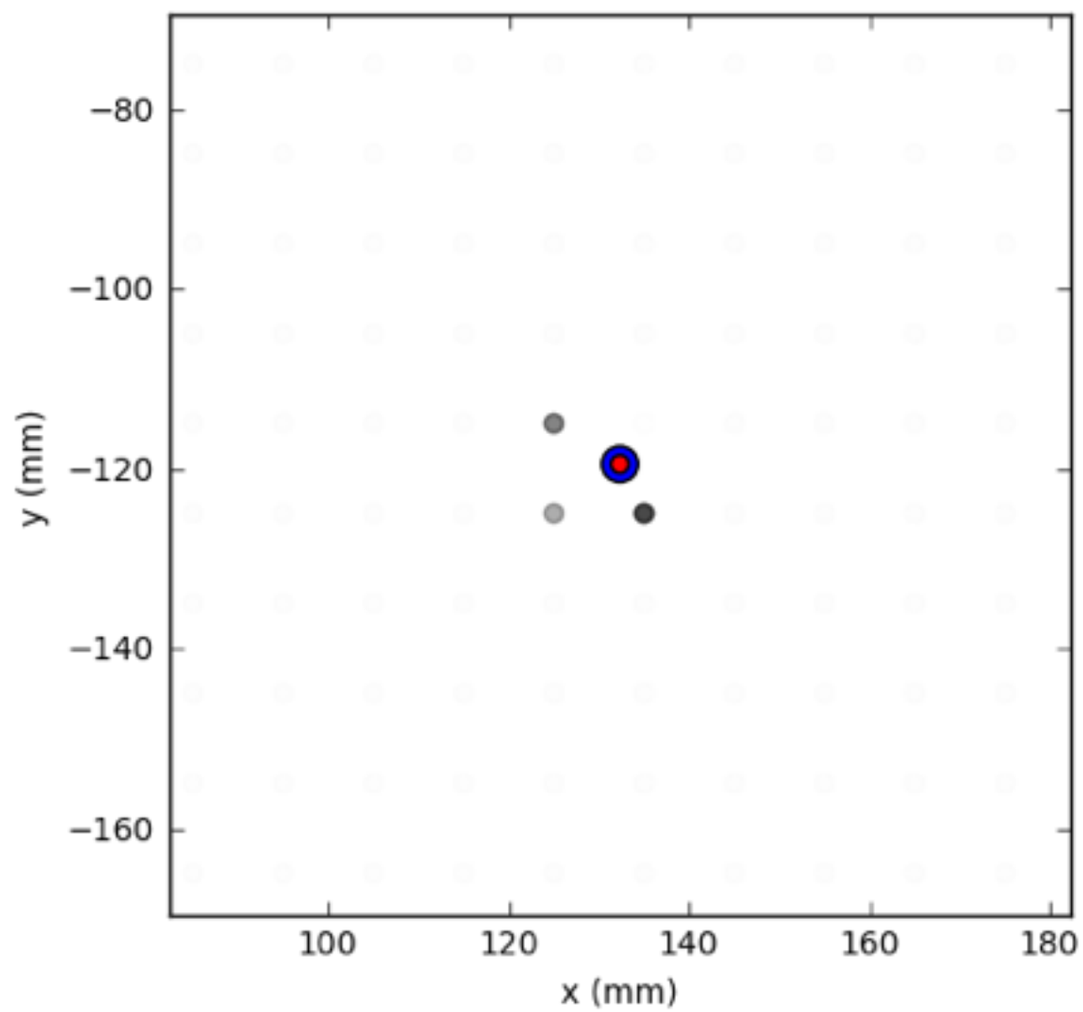
	Single-electron		0vbb	
Input Events	49997	100,00 %	49997	100,00 %
Fiducial (window)	44657	89,32 %	47412	94,83 %
DNN	1100	2,20 %	11251	22,50 %

Track Reconstruction



- Simulate SiPM response for many events and construct the true energy distribution (1 mm resolution) for z-slices of some size
- Train a 2D CNN to reconstruct the distribution from the simulated pattern of SiPM signals
- Probably only useful to produce an image of the track (classification, which is the ultimate goal, would ideally skip this step)

Point Reconstruction



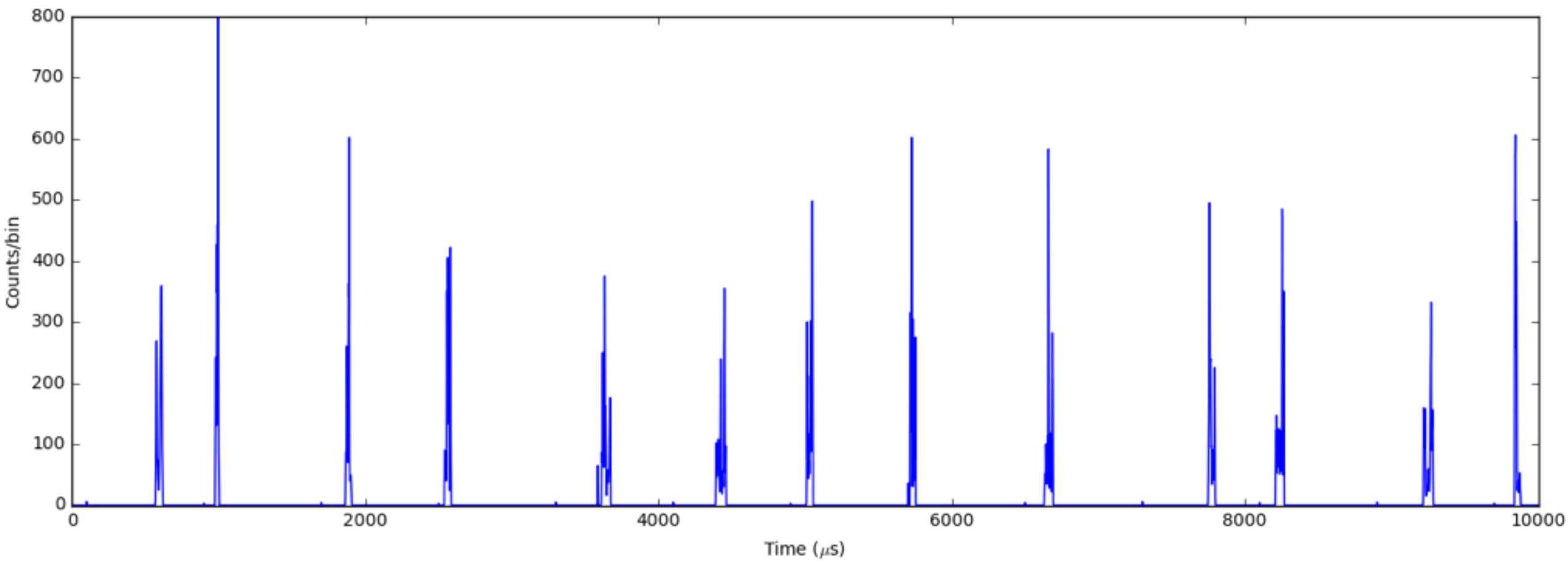
- Simulate point-like (40 keV) events and resulting single 2D projection of SiPM signals
- Reconstruct the (x,y) coordinates using a multi-layer fully-connected NN (above example: blue is true point, red is reconstructed)
- Later use the NN to reconstruct (x,y) for 40 keV electron tracks produced by ^{83m}Kr decay in actual detector

Summary

- Deep learning can be applied to several aspects of the analysis in NEXT and has shown potential to yield improvement
- Several MC-based studies have been carried out, but tests involving actual data are required
- The intermediate-scale (10kg) TPC called NEXT-NEW is currently running in the LSC (Canfranc); we expect to have initial data to which these ideas can be applied in the near future

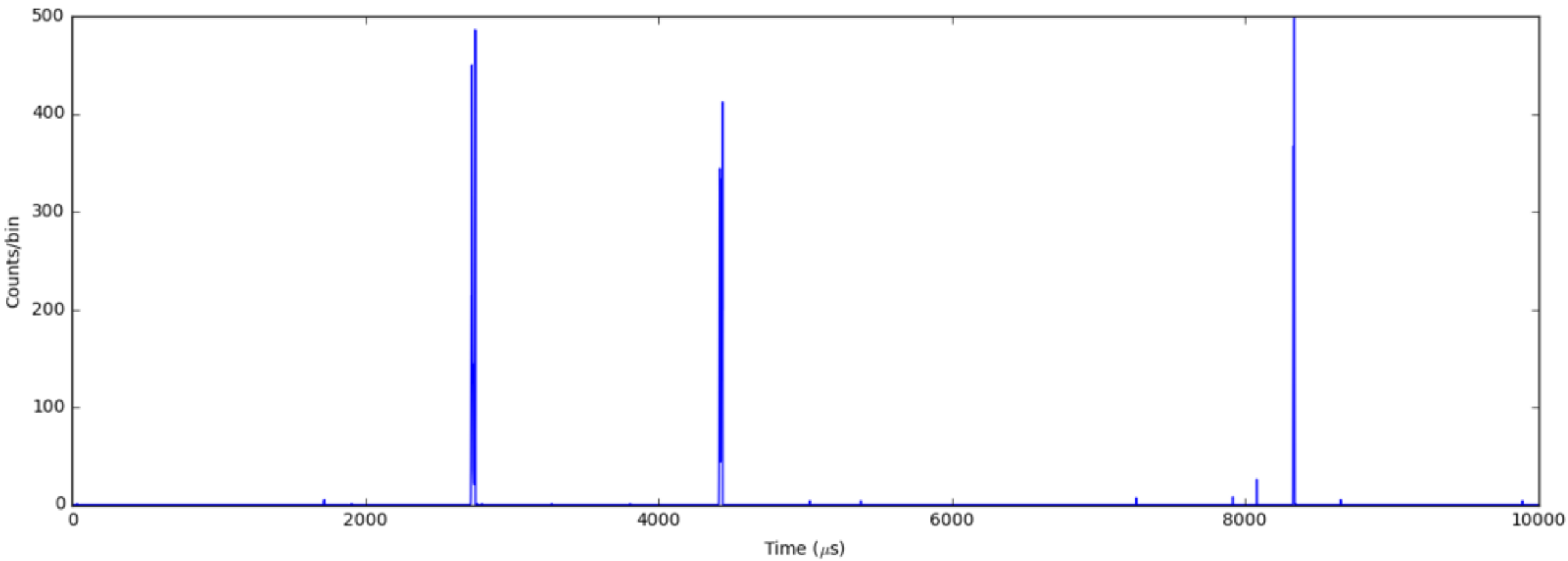
“Deep Analysis”

- Extract features from raw signals with deep learning
- For example, consider a concatenation of 1000 Monte Carlo events (sample of this shown below):



“Deep Analysis”

- Use a LSTM (long short-term memory) recurrent neural network (RNN) to predict the next value given sequence of 10 values
- Can generate a waveform with similar features (though still some discrepancies)



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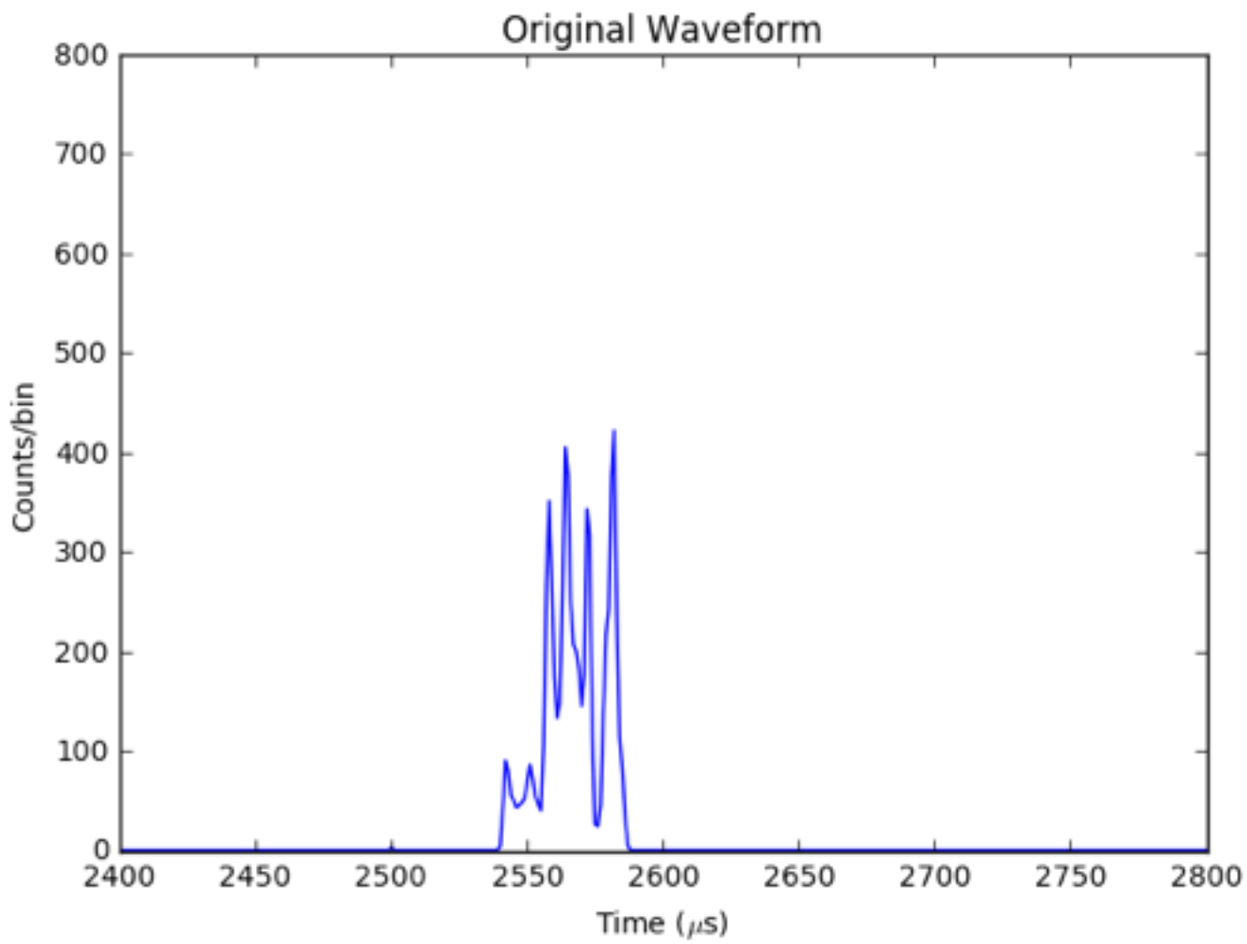
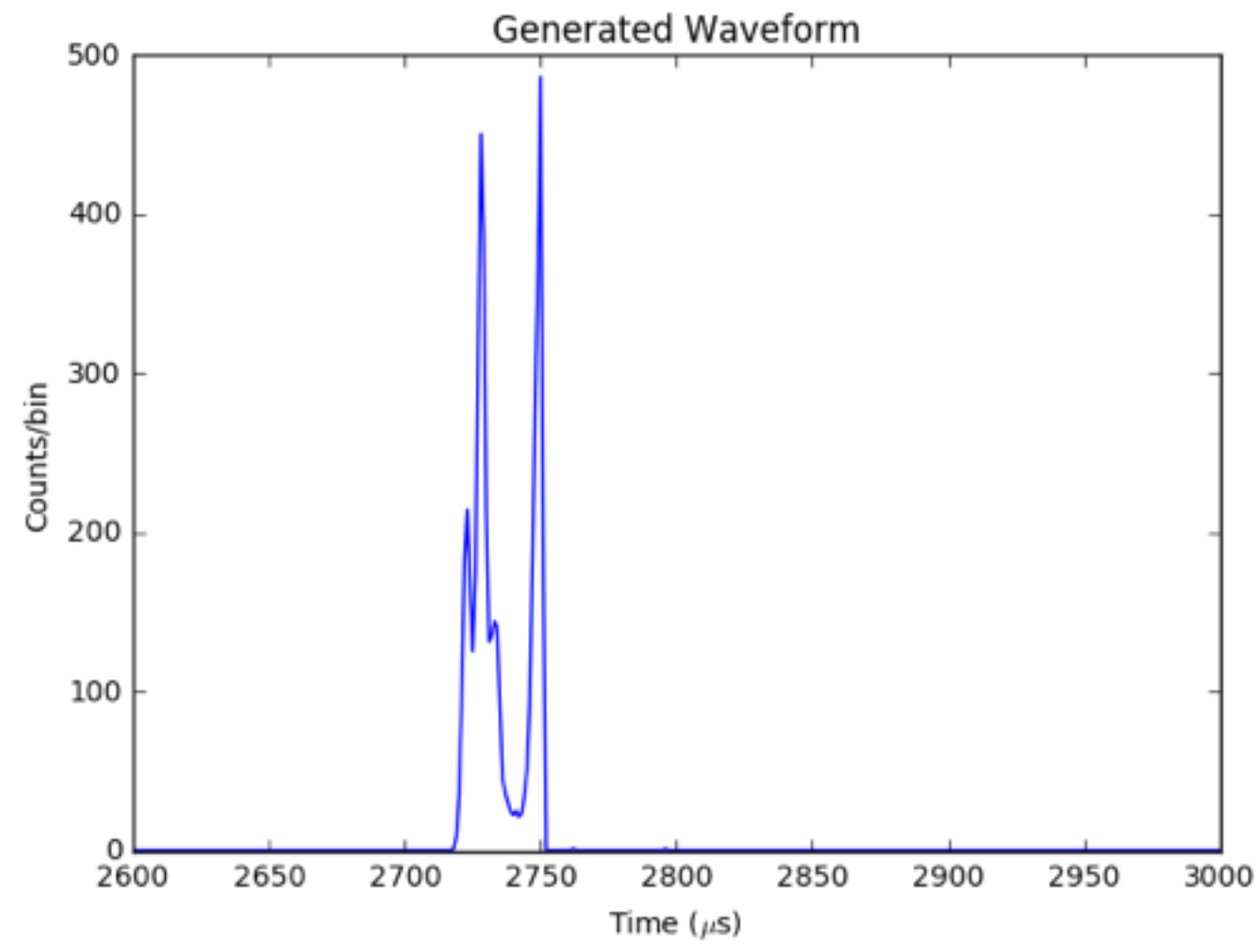
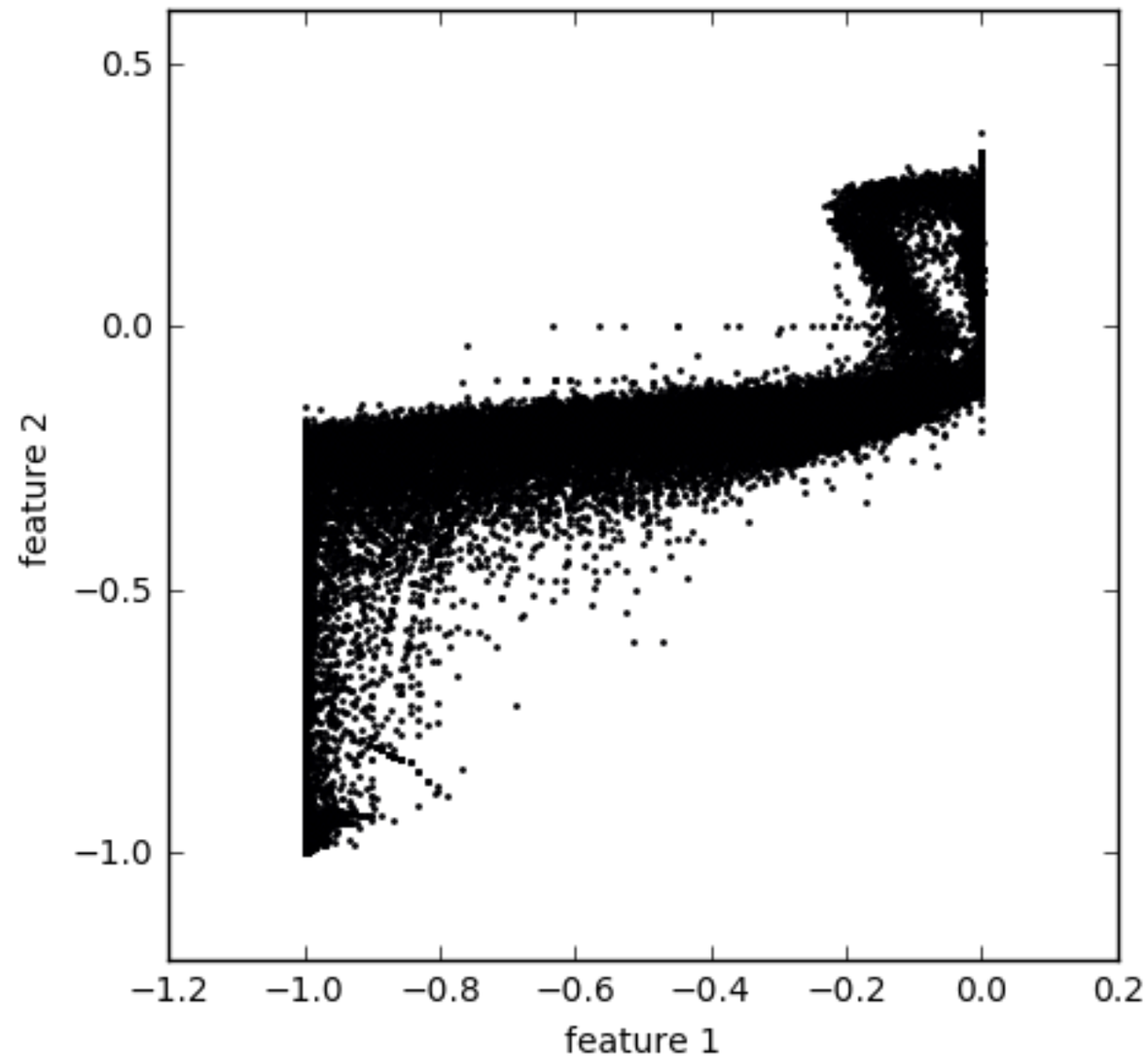




“Deep Analysis”

- Is this even useful?
- Note that if we have a machine that can do this, it must have learned something about the system. How can we extract this information?
  - Try to extract it from the outputs of specific neurons in the network



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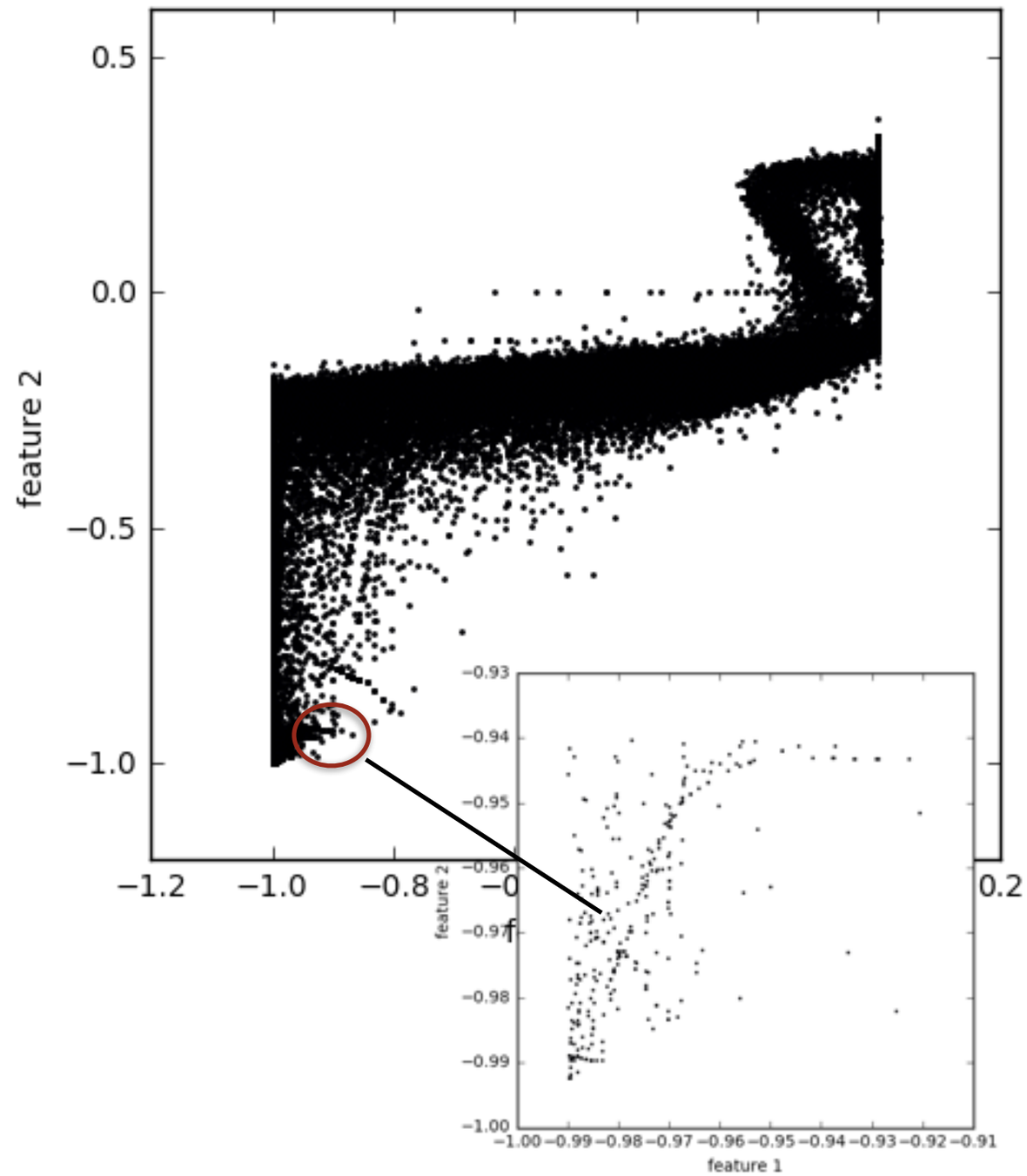

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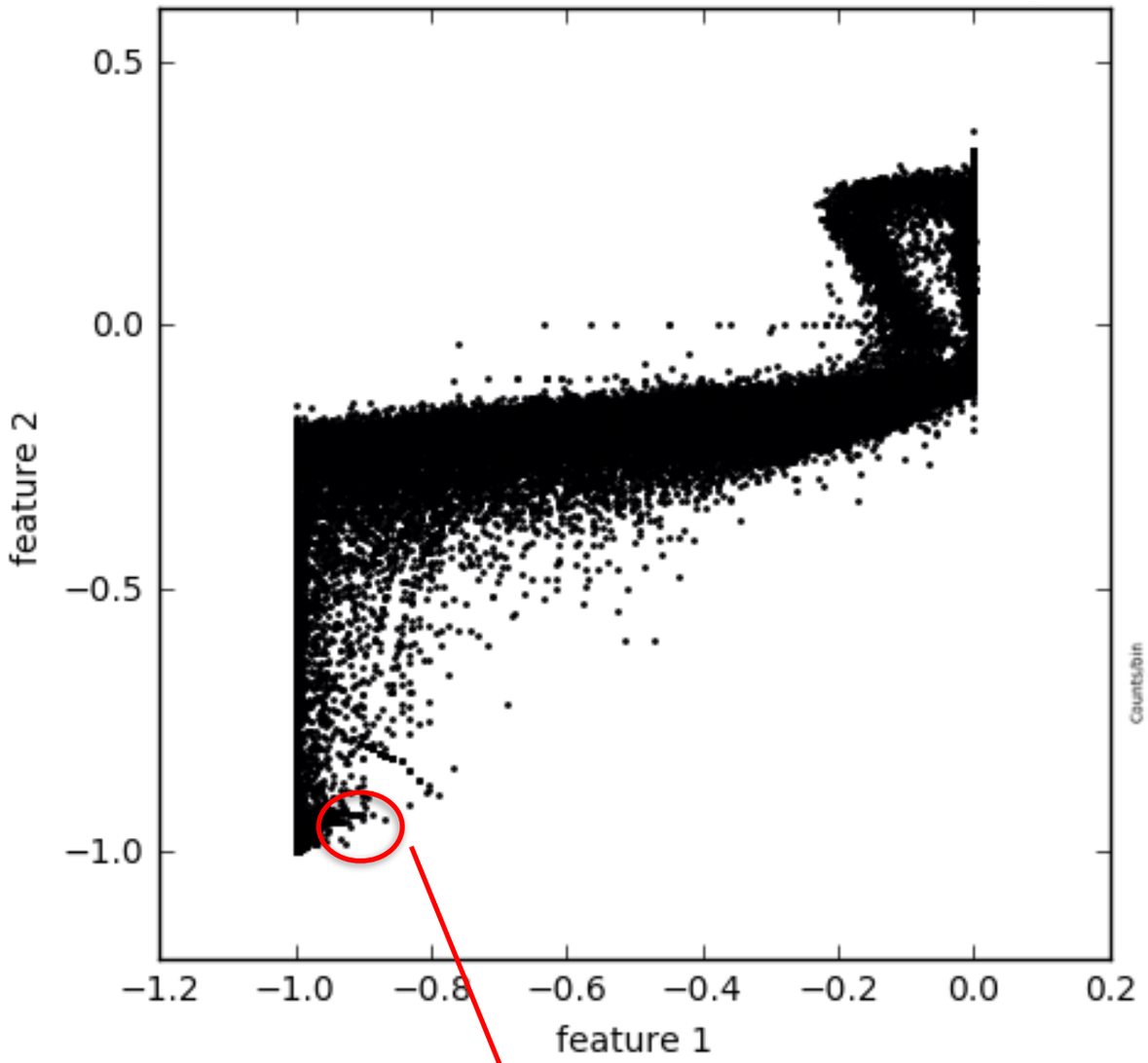
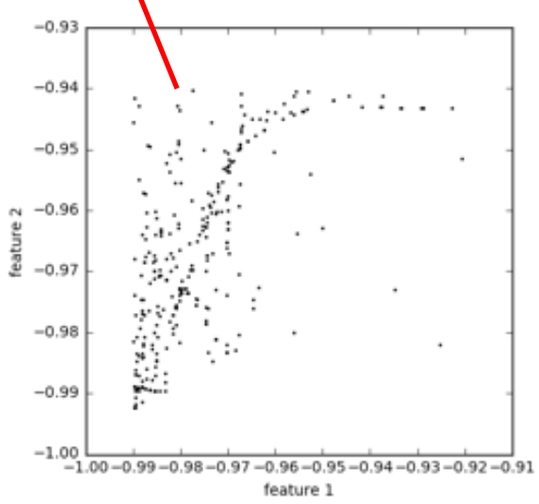
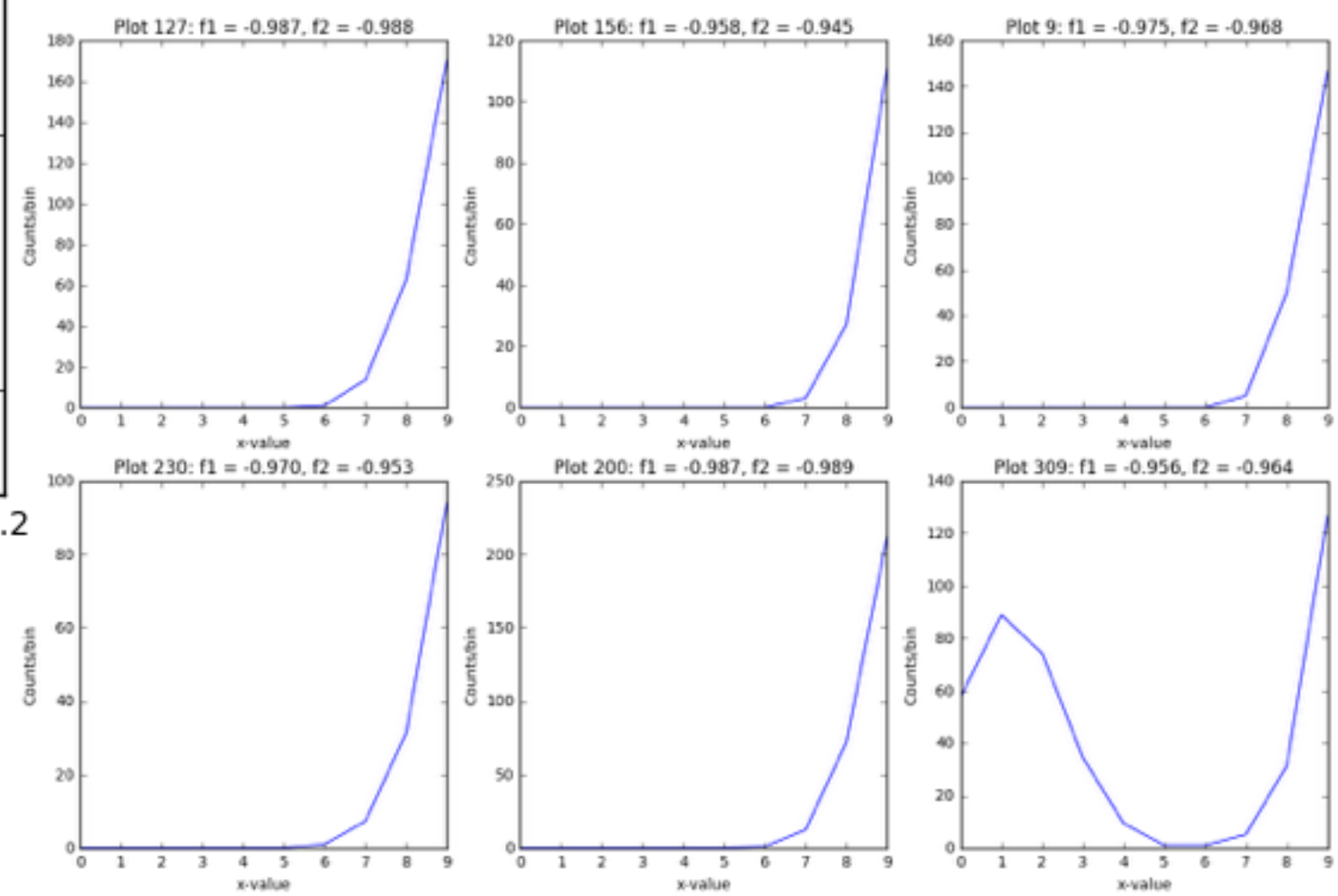




- Certain waveform segments fall in different locations in feature space



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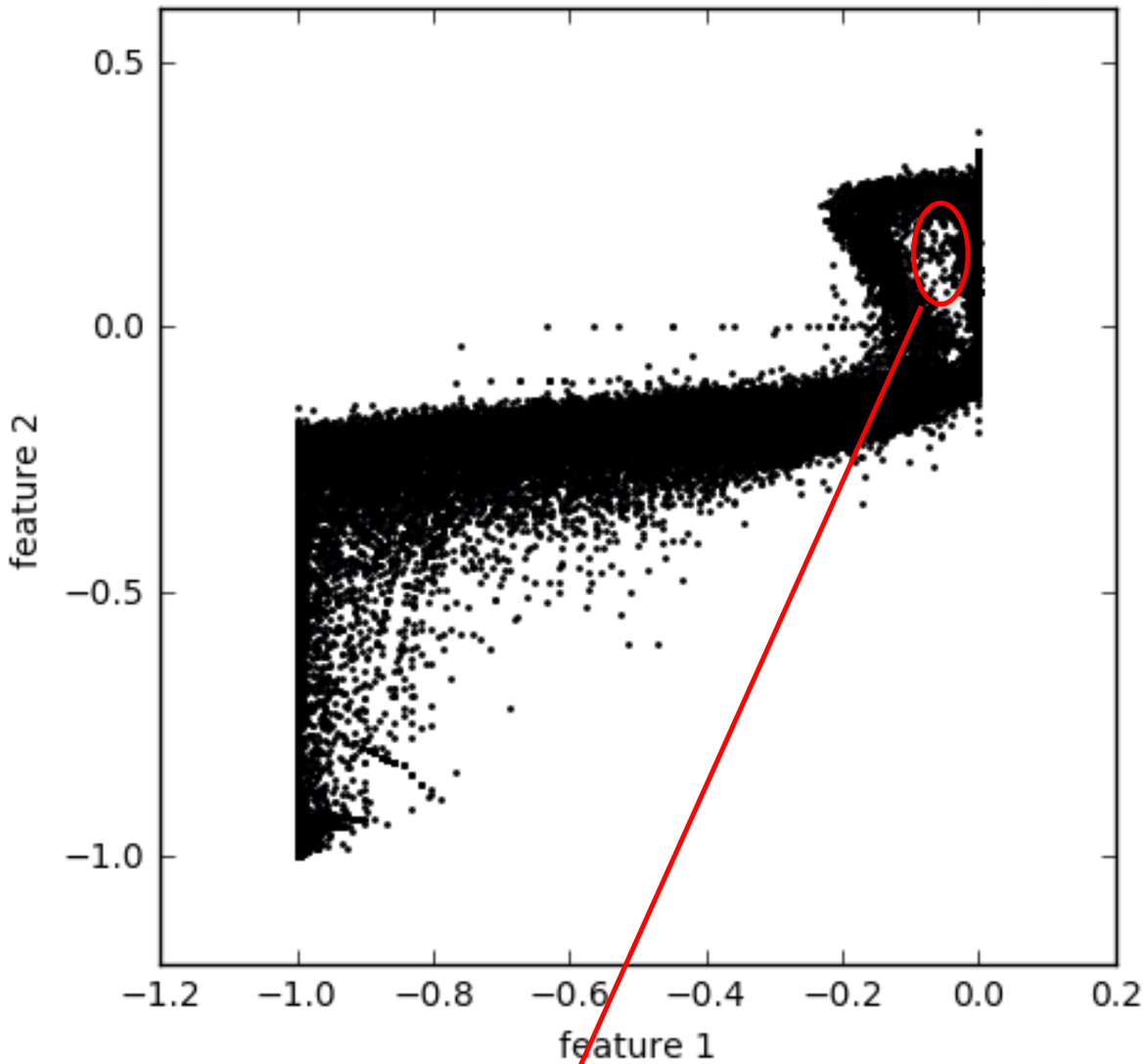

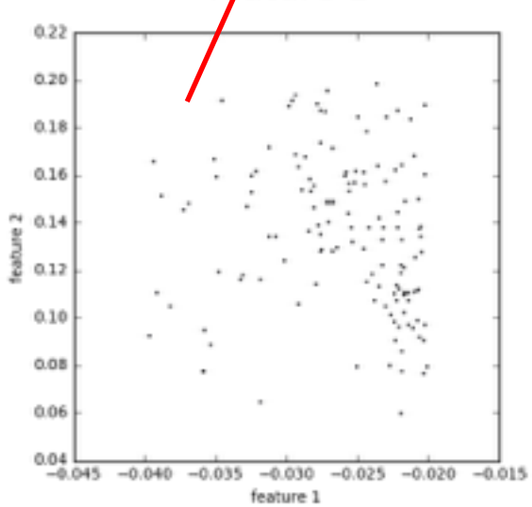

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