



# Improved ML selection on sensor-on events

# Idea

## Classify tracks based on topology

- From cut based analysis: create a dataset of tracks
- Train the model on those tracks
- Ideally it will learn to generalise outside the cut region
- Sensor-on: easy to identify (cut on rho)
- Identify low-energy sensor-on events



$$\rho \equiv \frac{\text{sc\_rms}}{\text{sc\_nhits}} < 0.15$$

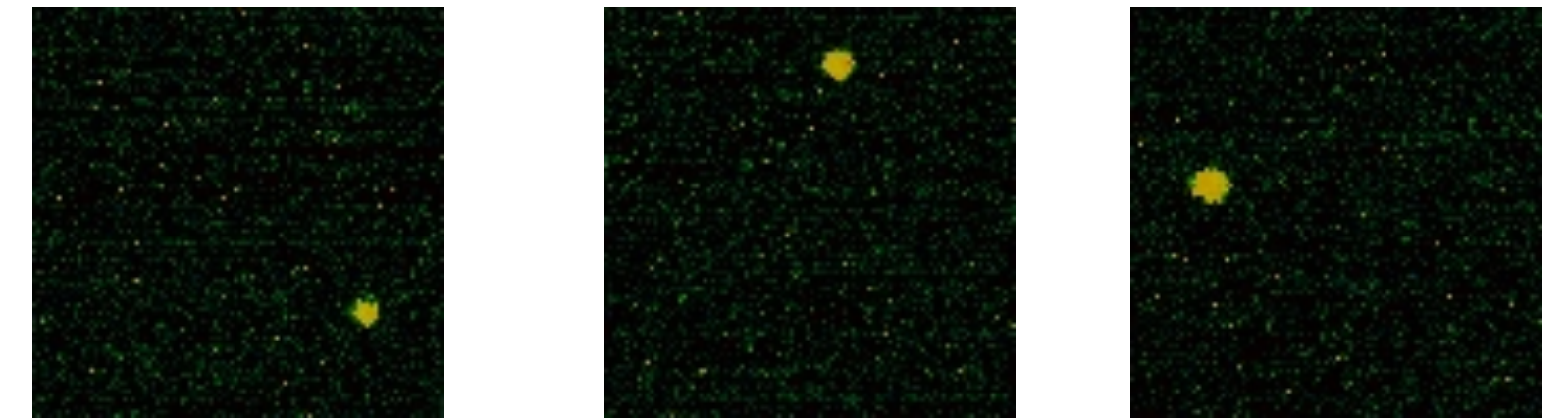
# The Dataset

- From cut on rho + visual inspection: select relevant events
- Cut a 100x100 patch around the coordinates of the sensor on event in the original image
- Data Augmentation: Position + Flips + 20° Rotations

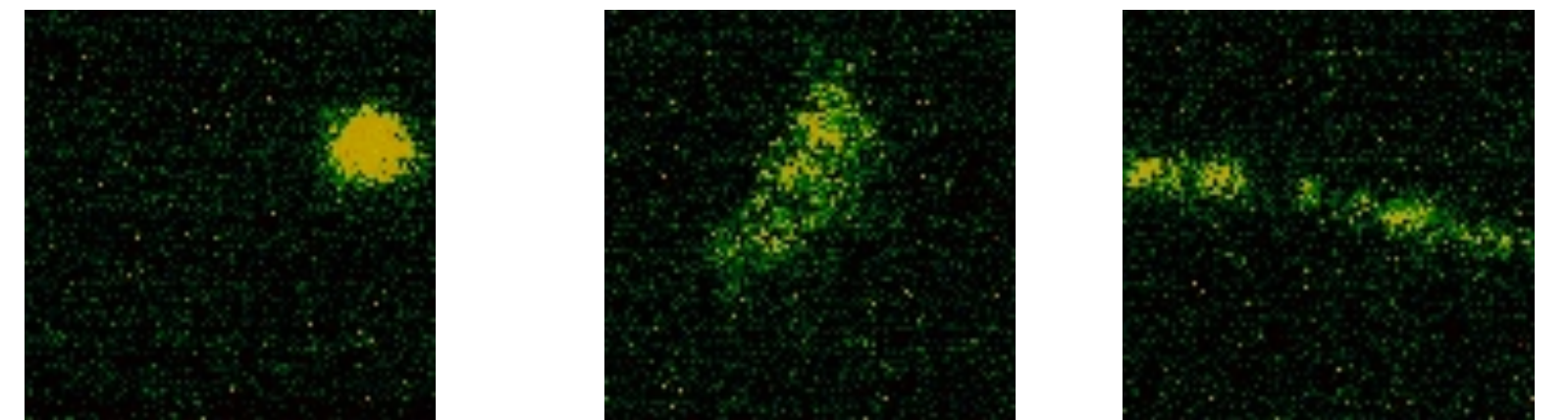
## Event Classes:

- Noise, Sensor\_on, Alfa, Other

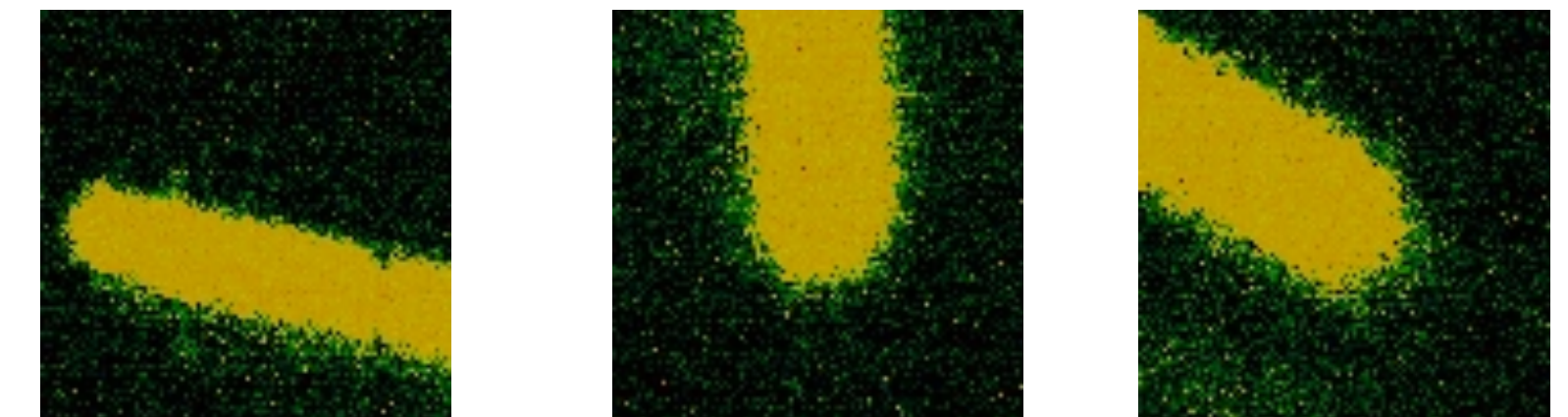
Sensor\_on



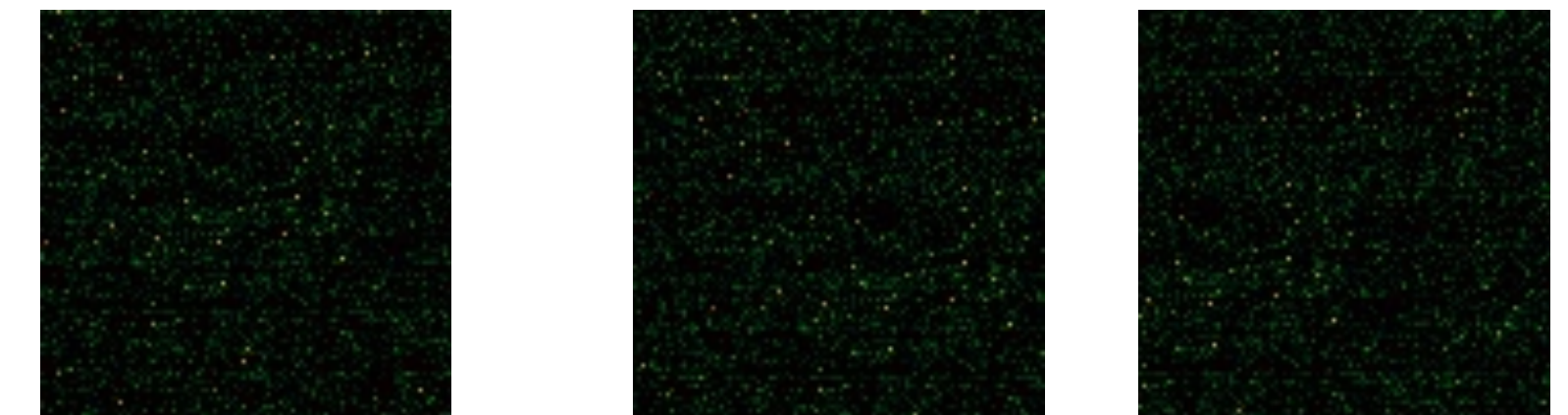
Other



Alfa



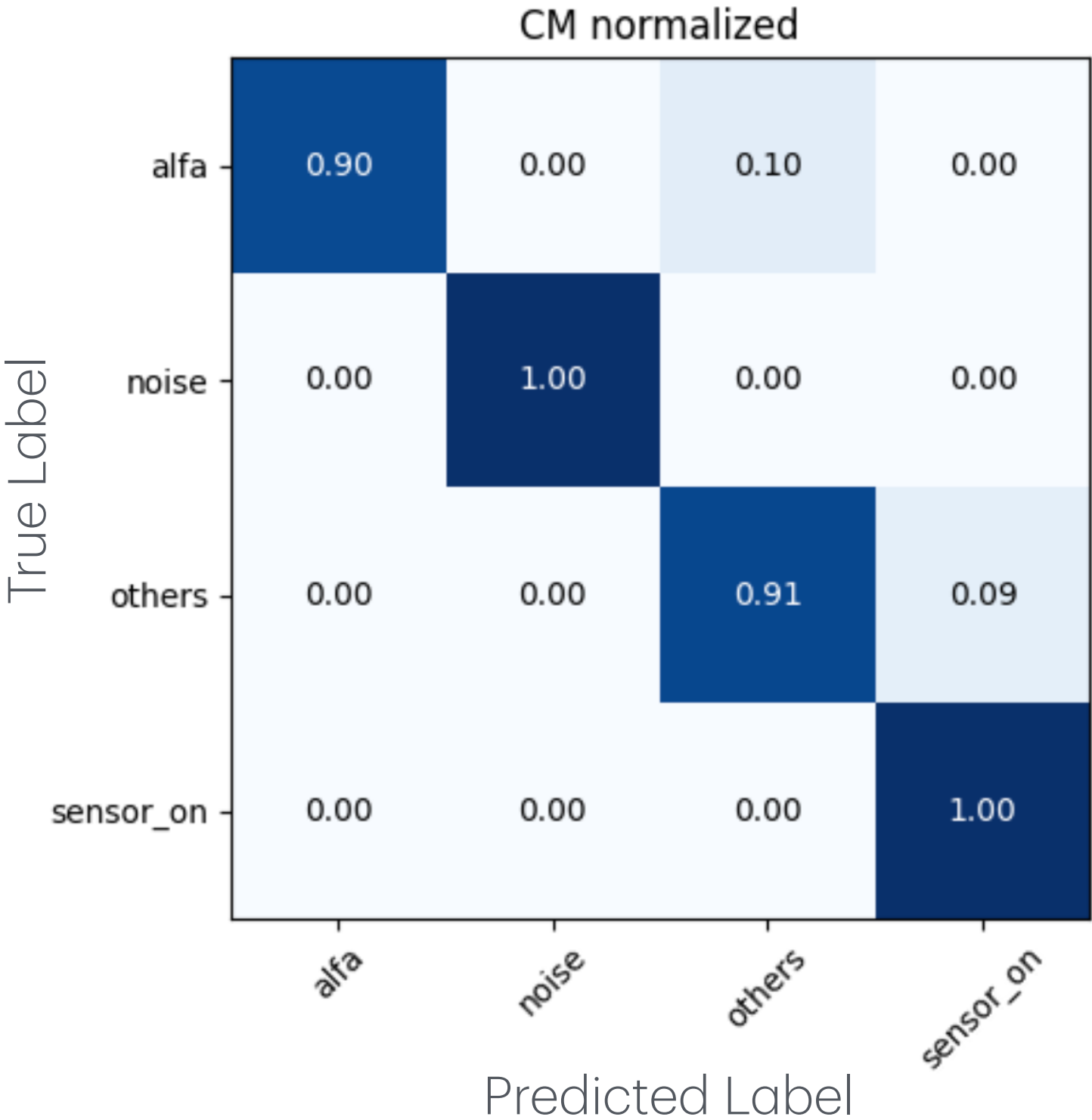
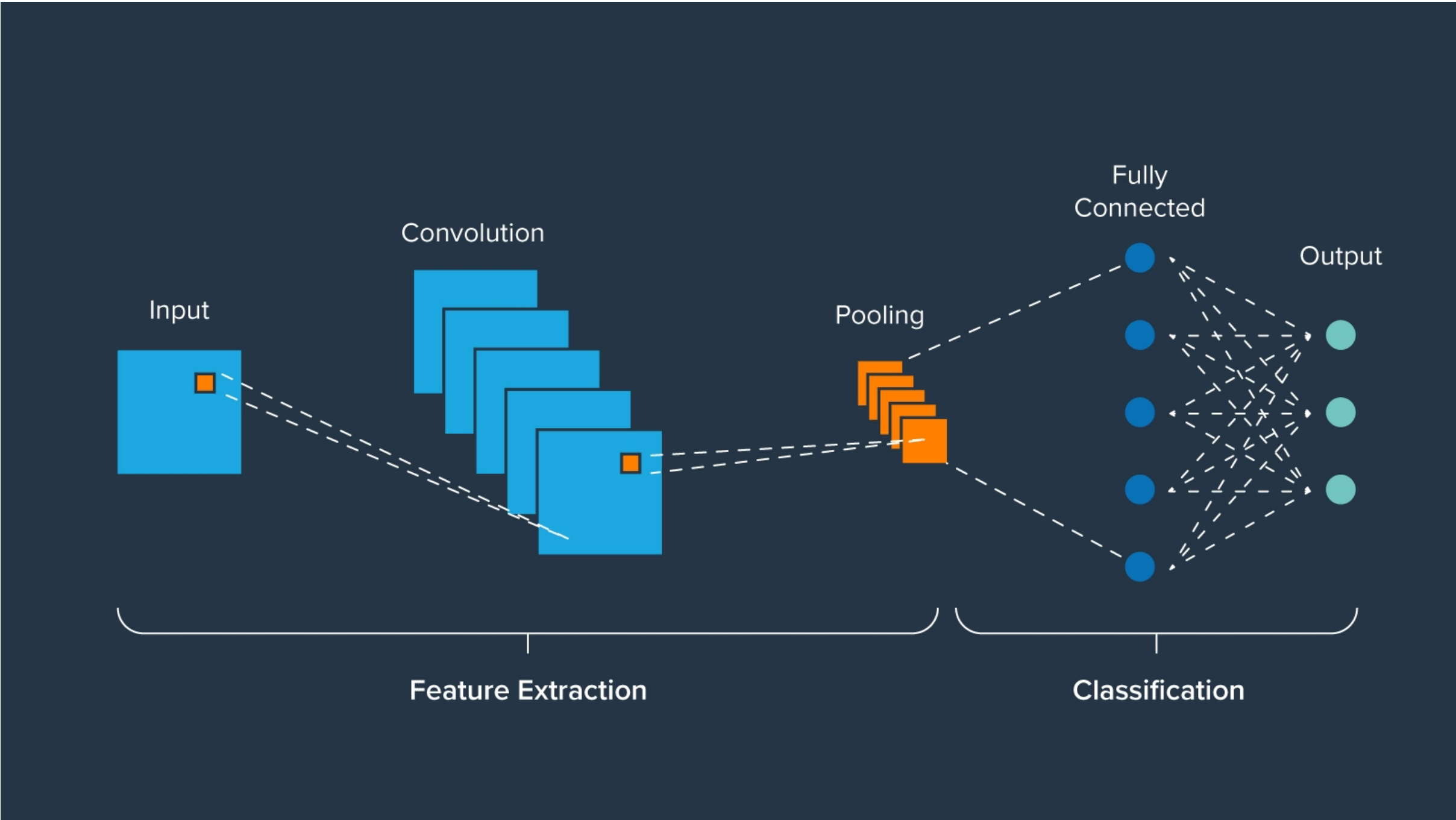
Noise



# The Model

- For now: simple convolutional classifier (test the approach)
- Train on 100x100 image patches selected via the help of cut based analysis

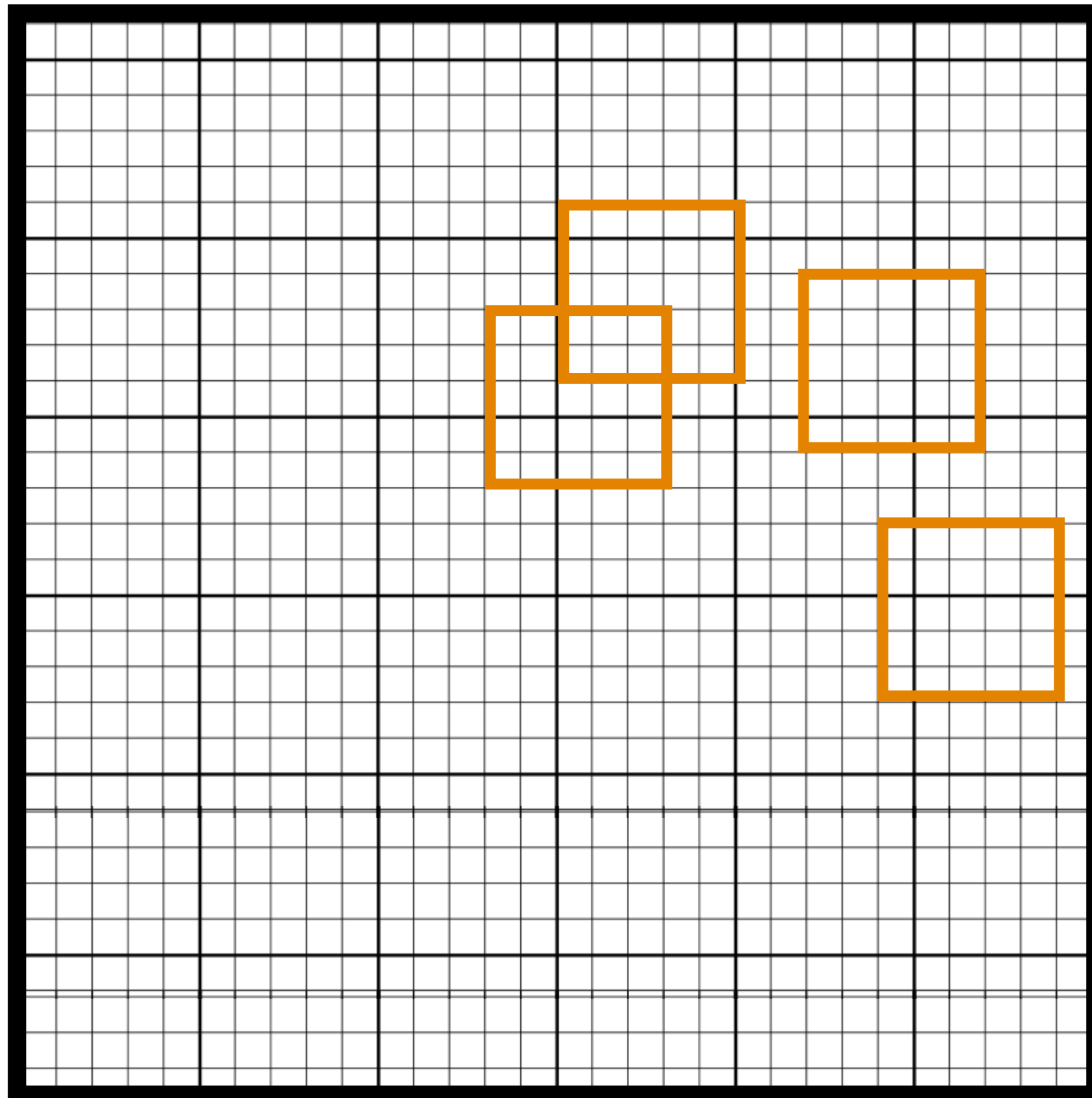
| Layer (type)                   | Output Shape         | Param # |
|--------------------------------|----------------------|---------|
| input_layer (InputLayer)       | (None, 100, 100, 3)  | 0       |
| conv2d (Conv2D)                | (None, 100, 100, 16) | 448     |
| max_pooling2d (MaxPooling2D)   | (None, 50, 50, 16)   | 0       |
| conv2d_1 (Conv2D)              | (None, 50, 50, 32)   | 4,640   |
| max_pooling2d_1 (MaxPooling2D) | (None, 25, 25, 32)   | 0       |
| conv2d_2 (Conv2D)              | (None, 25, 25, 64)   | 18,496  |
| max_pooling2d_2 (MaxPooling2D) | (None, 12, 12, 64)   | 0       |
| flatten (Flatten)              | (None, 9216)         | 0       |
| dense (Dense)                  | (None, 64)           | 589,888 |
| dropout (Dropout)              | (None, 64)           | 0       |
| dense_1 (Dense)                | (None, 4)            | 260     |



# Using the model on real data

“Faking” Higher resolution

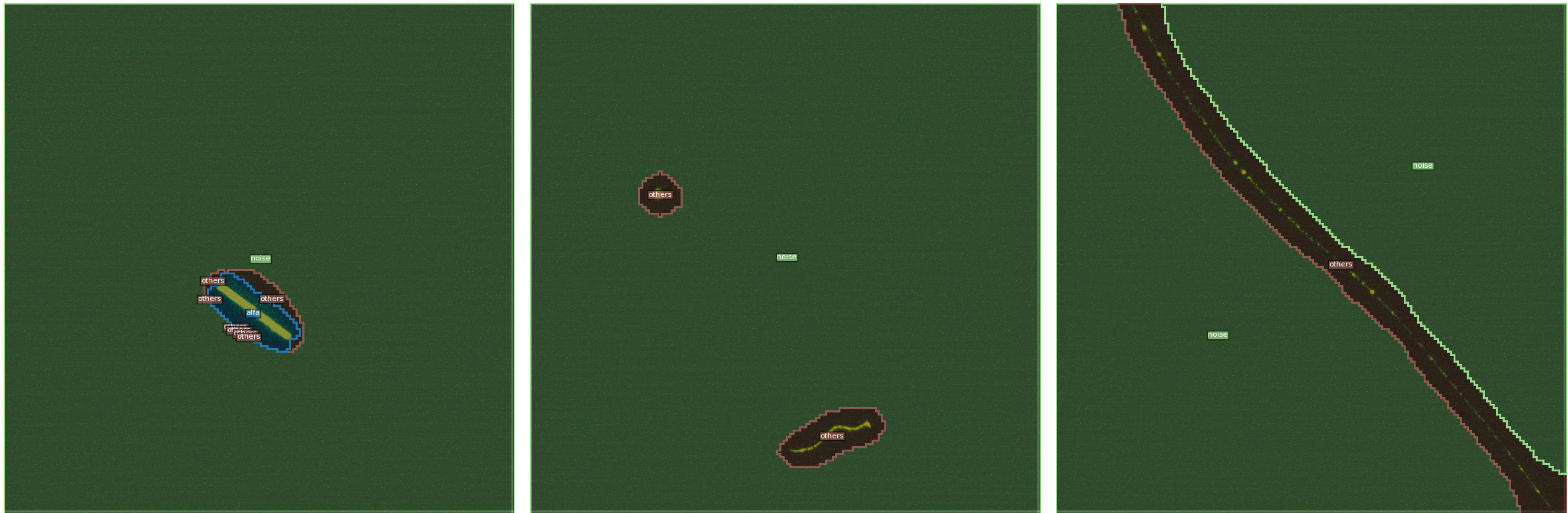
- Idea:



- Move the model across the image with stride 10
- Each 10x10 area will be classified multiple times
- Take the mean probability -> classify
- More resilient to errors
- Independent of the model, possibility to swap it out and use on other aspects

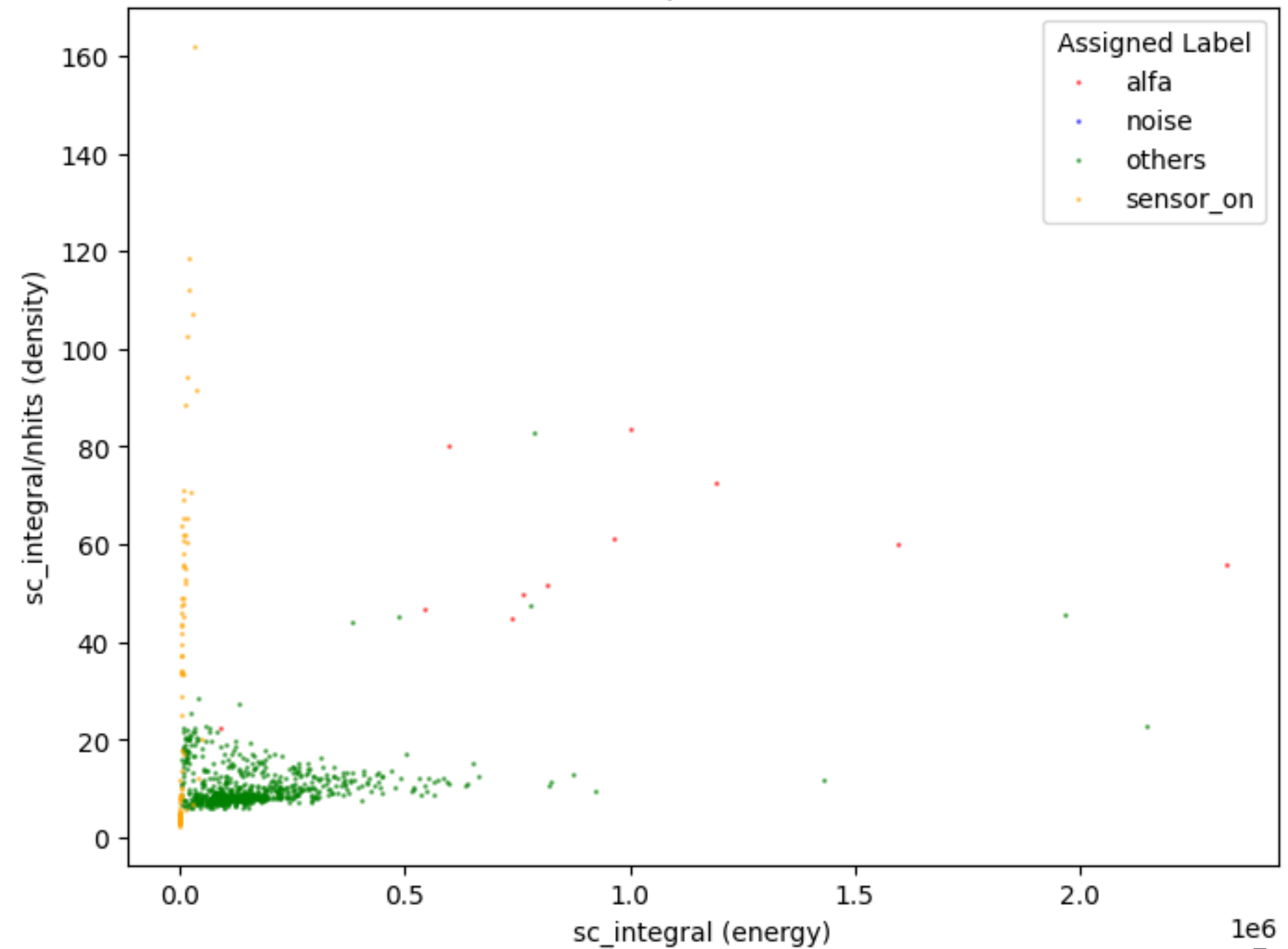
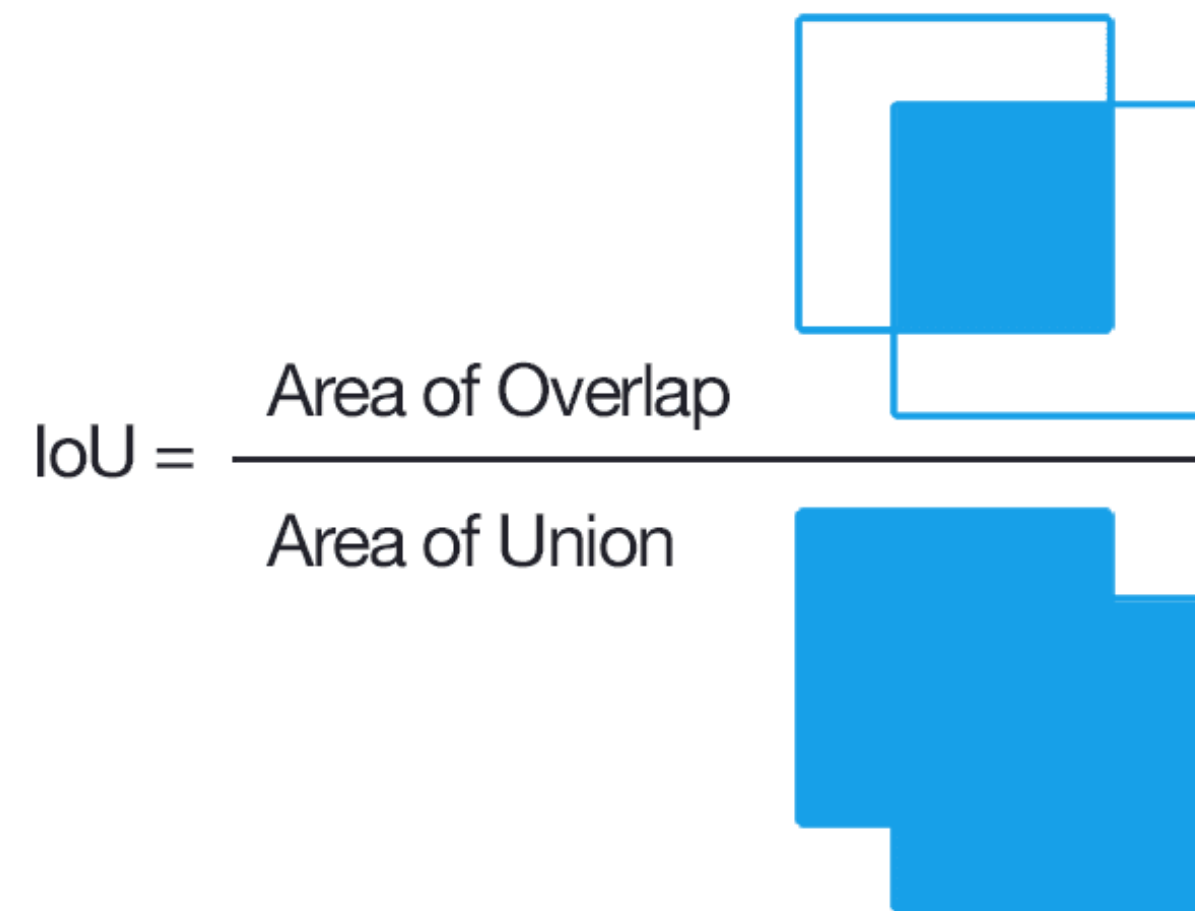
# Some Examples

Applying this technique on random independent pictures

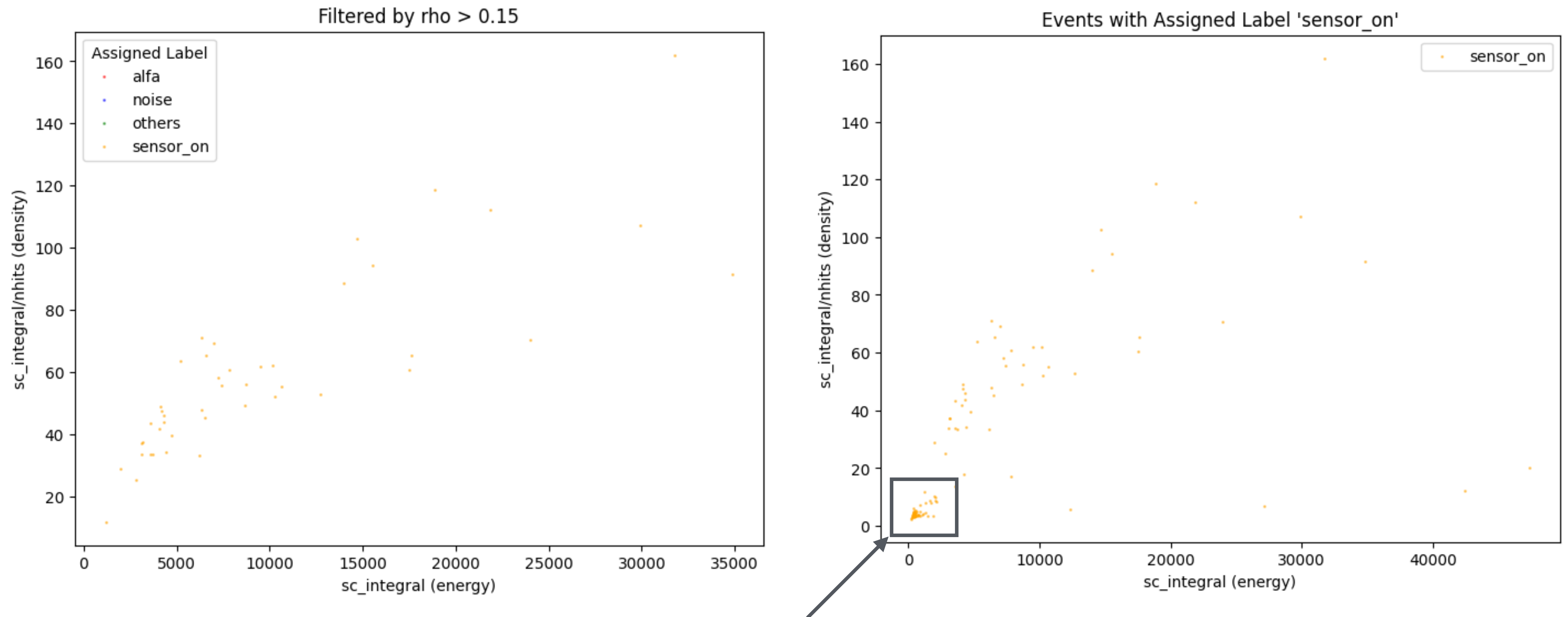


# Label Matching to Data

- Evaluate IoU between model prediction and Reco “boxes” (via `sc_xmin`, `sc_ymin`, ...)
- Assign label to dataframe based on IoU



# Comparison with Rho cut

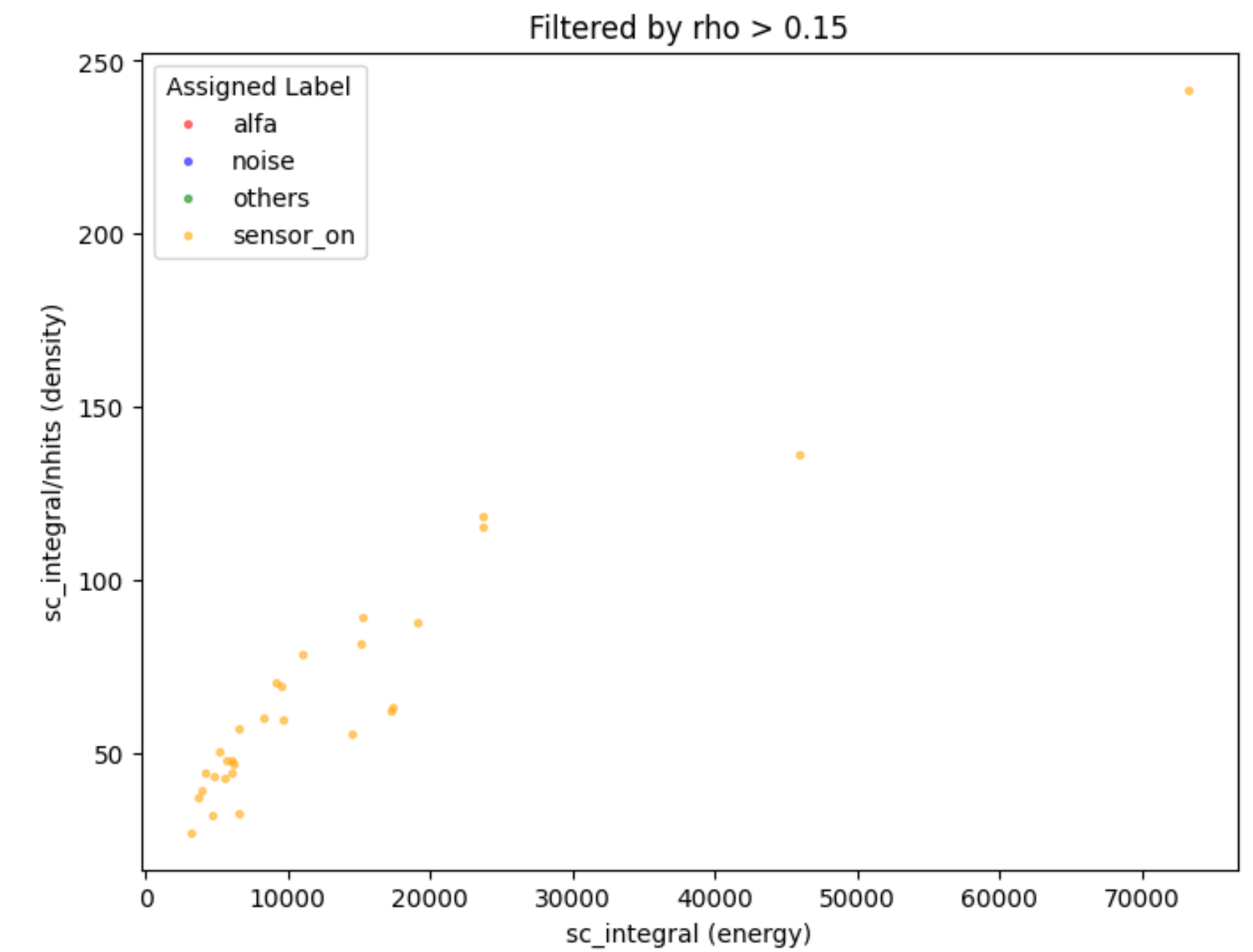
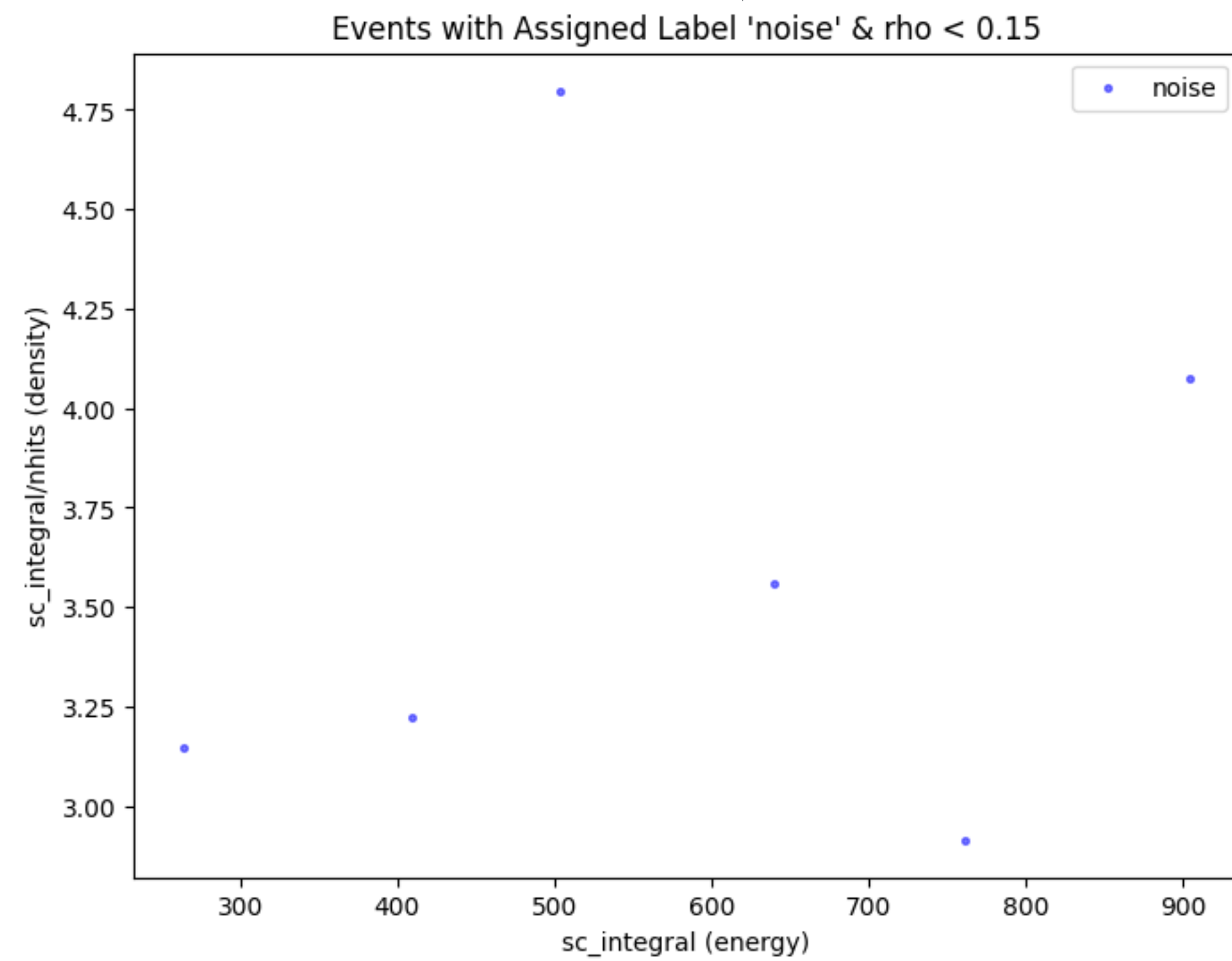


Model finds more Sensor on events at low energy than rho cut

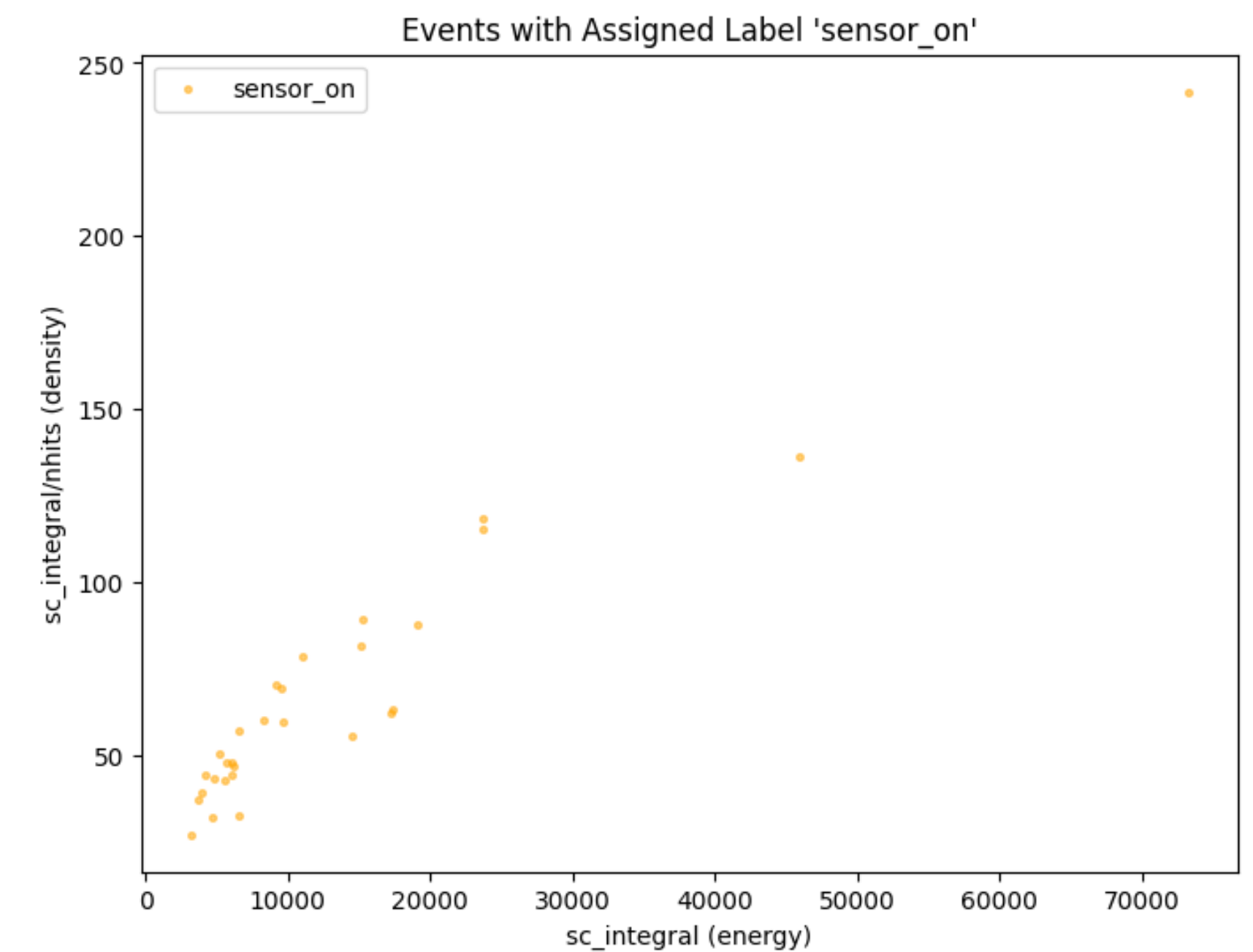
How can we be sure they are real sensor-on?

# Test on other Pedestal Runs

- Tested on independent pedestals (small sample)
- For now model performed the same as rho cut
- Need more pedestal runs
- Isolated some noise events which made it past  $\rho < 0.15$  (2% of total)



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# Conclusion

## Going Forward

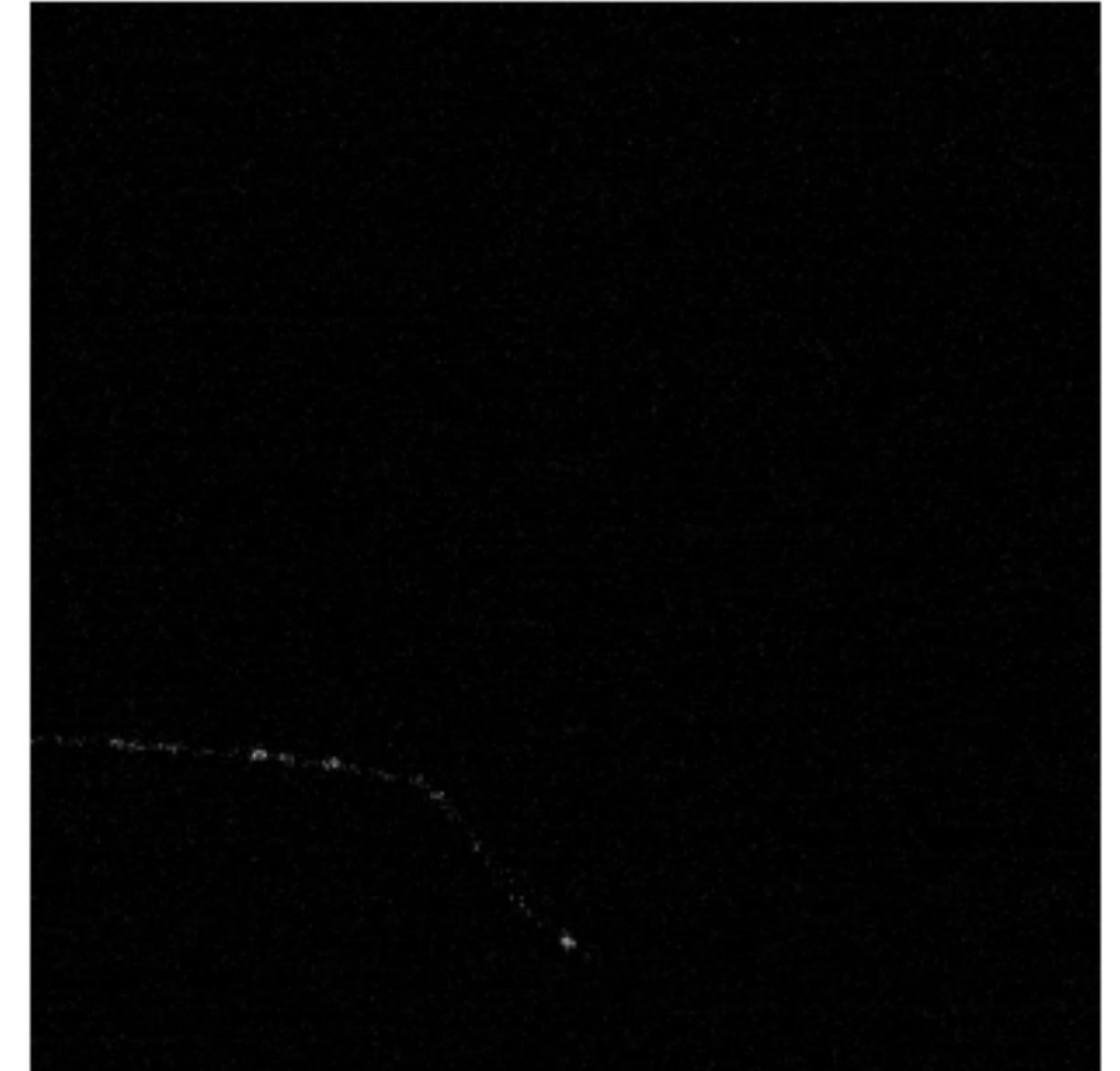
- The model works and has a lot of room for improvement:
- A bigger dataset is likely to vastly improve performance
- Model Architecture can be modified to increase resolution and performance

# What's next ?

Image segmentation: in development

- From Redpixes: Truth Mask
- Train on real images, goal: reconstruct relevant pixels from reco
- Quality cuts on reco to create classes of events (automate the dataset creation process)
- Identify relevant pixels from images and classify them

Raw



Merged Mask

