Distributed Imaging for Liquid Scintillator Detectors

Jacopo Dalmasson

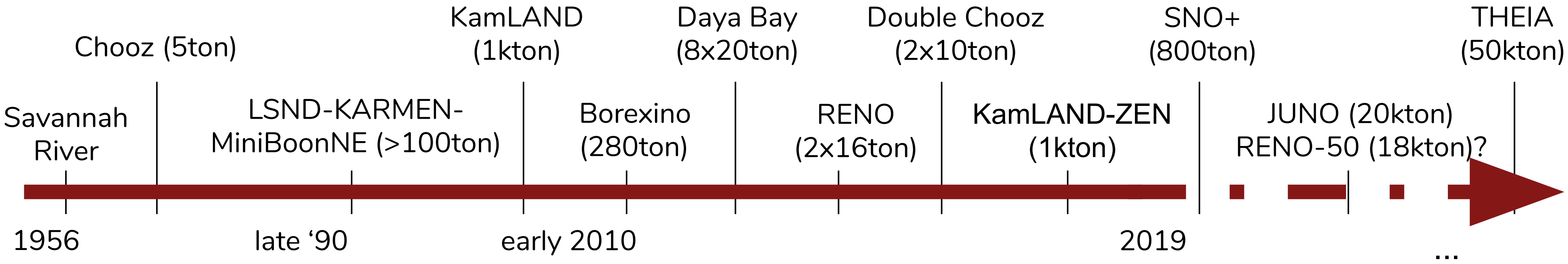
Stanford University – Physics Dept.

Outline

- Scintillator detector
- Distributed Imaging
- Detector Simulation
- Event Reconstruction
  - χ^2 method
  - CNN method
- Conclusion

J. Dalmasson et al. (2018), *PRD*, 97:052006

Liquid Scintillator Detectors



Organic Scintillators

- Good light yield (LY) ~10k/MeV
- Low energy threshold
- Quite fast (<5ns)
- Relative simple and inexpensive technology
- Self-absorption
- Delayed emission (10-100 ns)
- Isotropic → NO DIRECTIONAL INFORMATION

Distributed Imaging

Our Approach

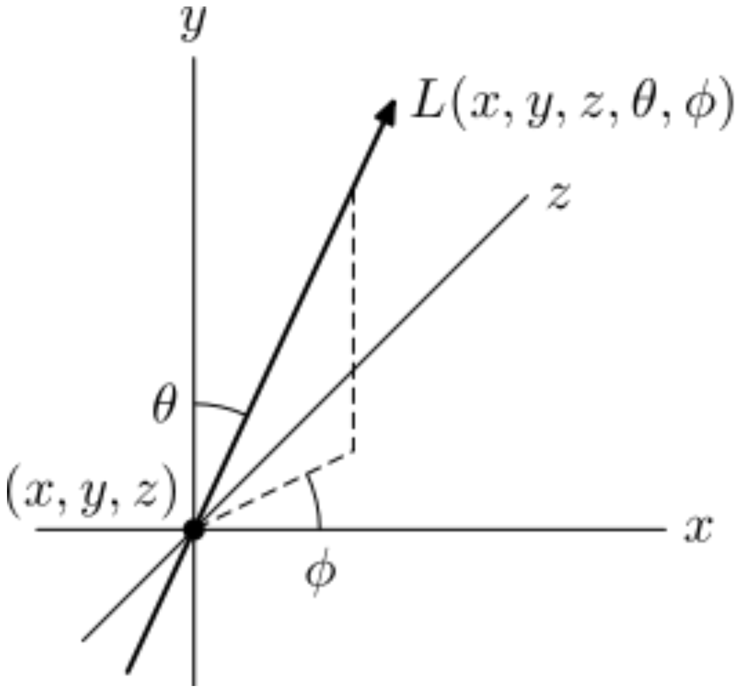
we want to improve the topology reconstruction by trying to retain the incoming direction information of the photons

ray described as (x,y,z,θ,φ)

at $t=t_D$: traditional LS detector

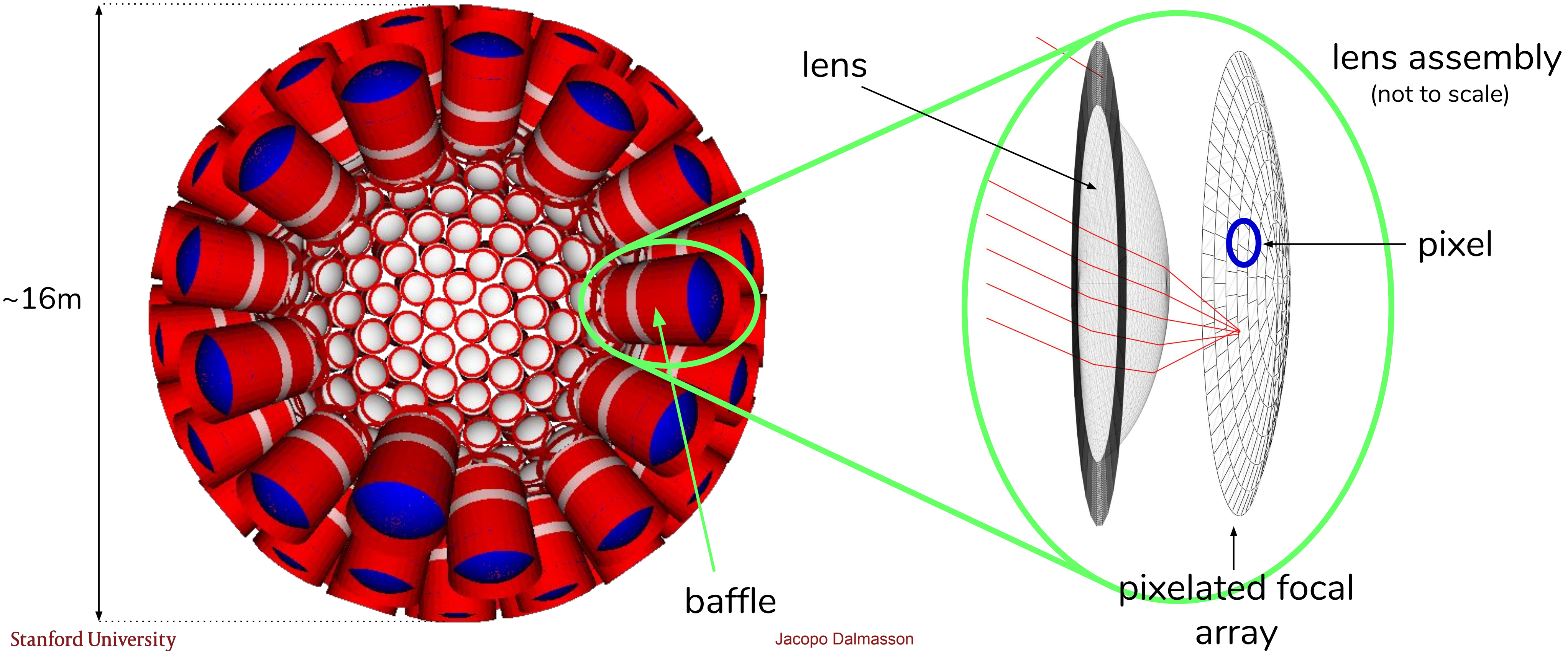
our goal

typical source has high emittance in this phase space

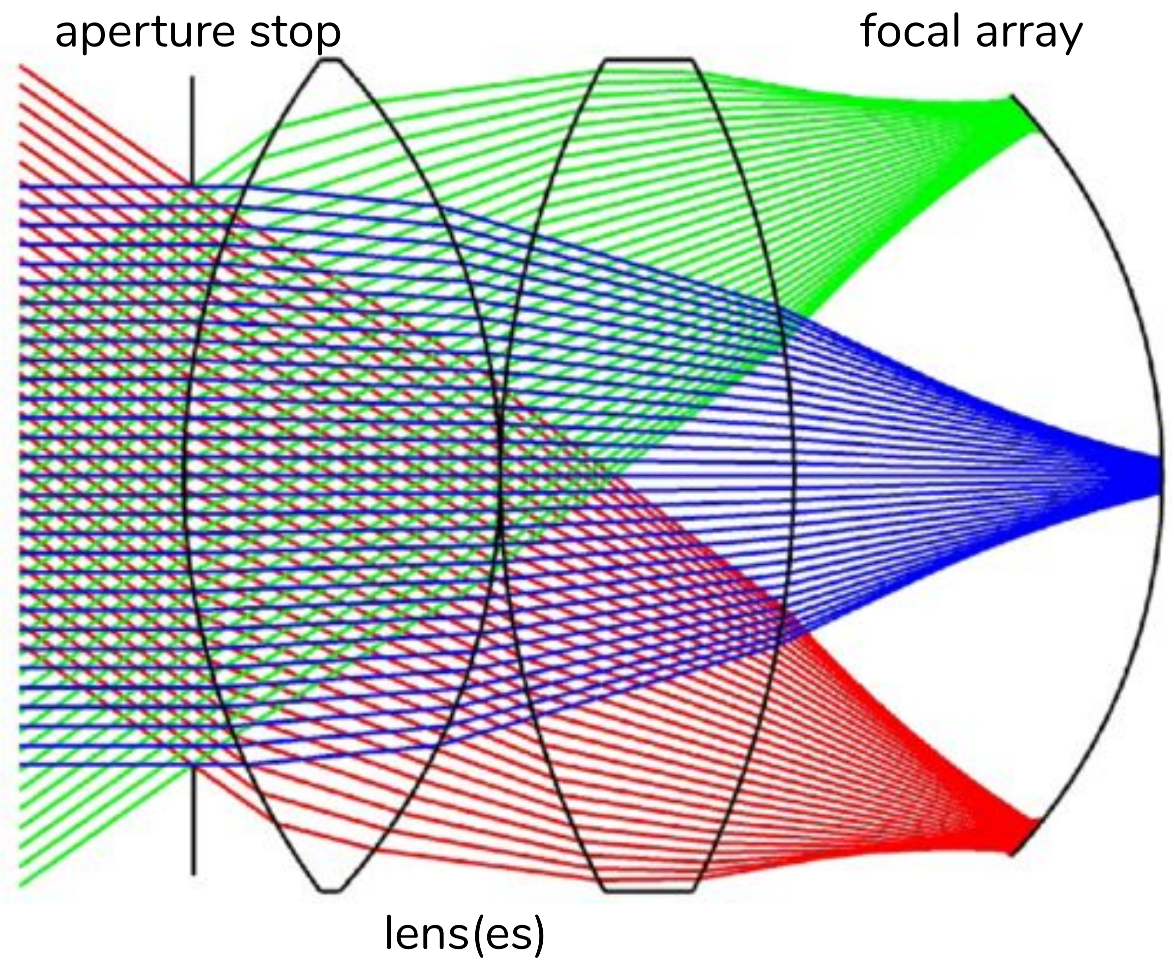


Detector Conceptual Design

θ, φ can be measured by placing converging lens(es) in front of finely segmented photodetectors



Angle/Position Map



how do we do it?

- measure the direction of the photon hitting each lens assembly
- collage from each lens assembly these reconstructed directions and triangulate back

→ **DISTRIBUTED IMAGING**

caveat:

- photon occupancy per lens assembly very low (~20 ph/lens)
- lens system focuses parallel rays
- → no real image is produced for a single lens assembly

Distributed Imaging

Detector Simulation

Event Simulation

event simulated with Chroma package* (GPU based)

- $LY_{e/\gamma}$ = 8000 ph/MeV
- 300nm<λ_{em}<320nm
- $L_{attenuation} \gg r_{detector}$
- $n_{scintillator}$ = 1.5

scintillator

we simulated two geometries: icosahedron and sphere

- ~100k pixels (multi-anode PMT)
- 30% QE
- dome-shaped focal array

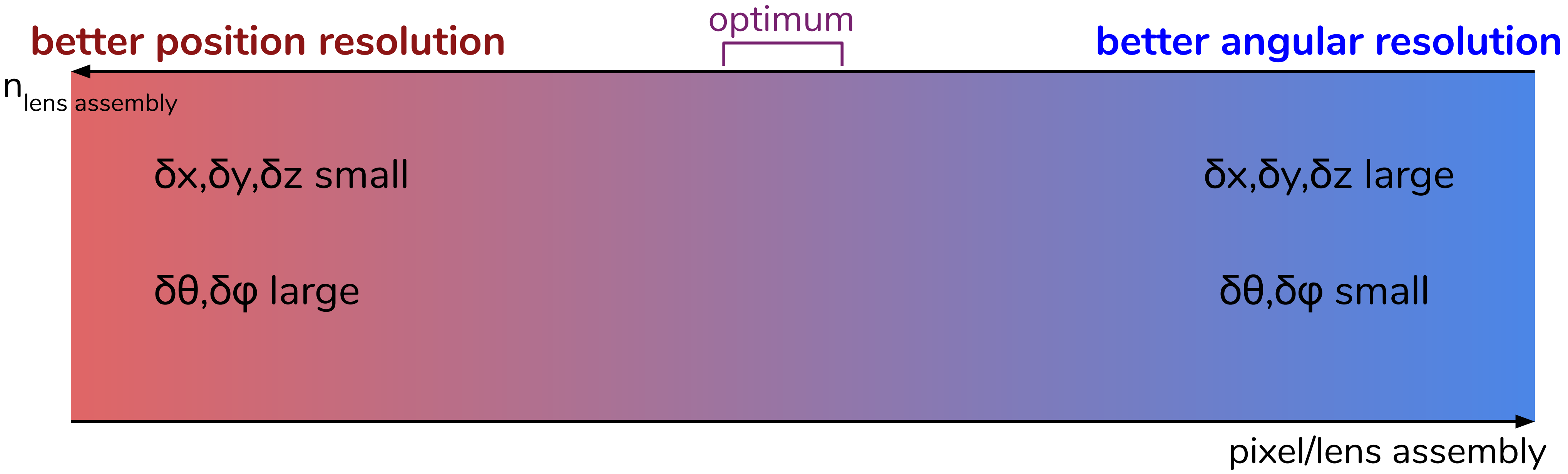
photodetector

*https://chroma.bitbucket.io/

Detector Optimization

for a given geometry and lens design an optimization on the size of the lens have been performed keeping the total number of pixel fixed to ~100k

how the uncertainties on ($\delta x, \delta y, \delta z, \delta\theta, \delta\varphi$) are affected?



Distributed Imaging

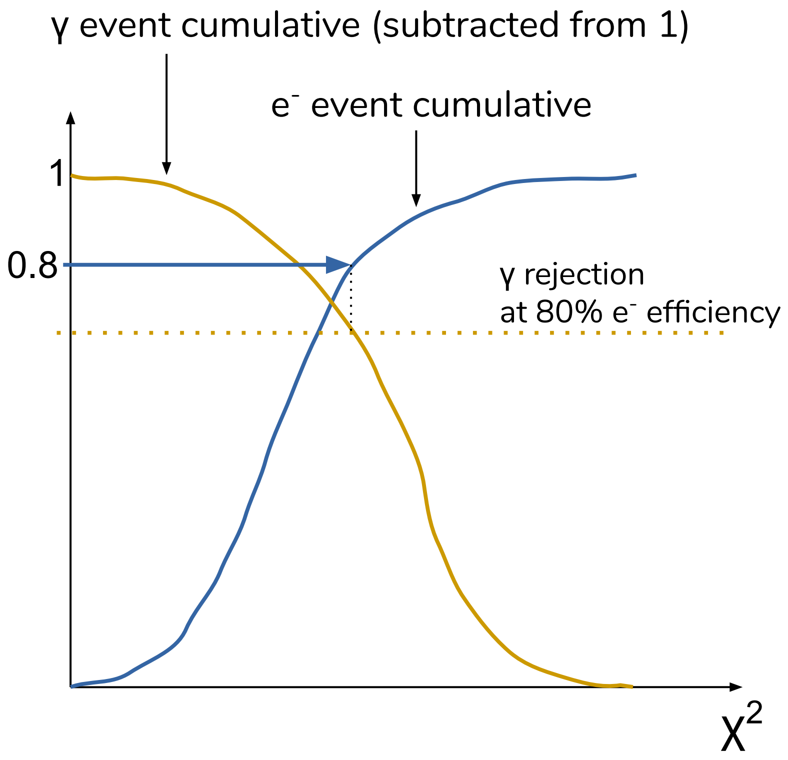
Event Reconstruction

Event Reconstruction - χ^2 method

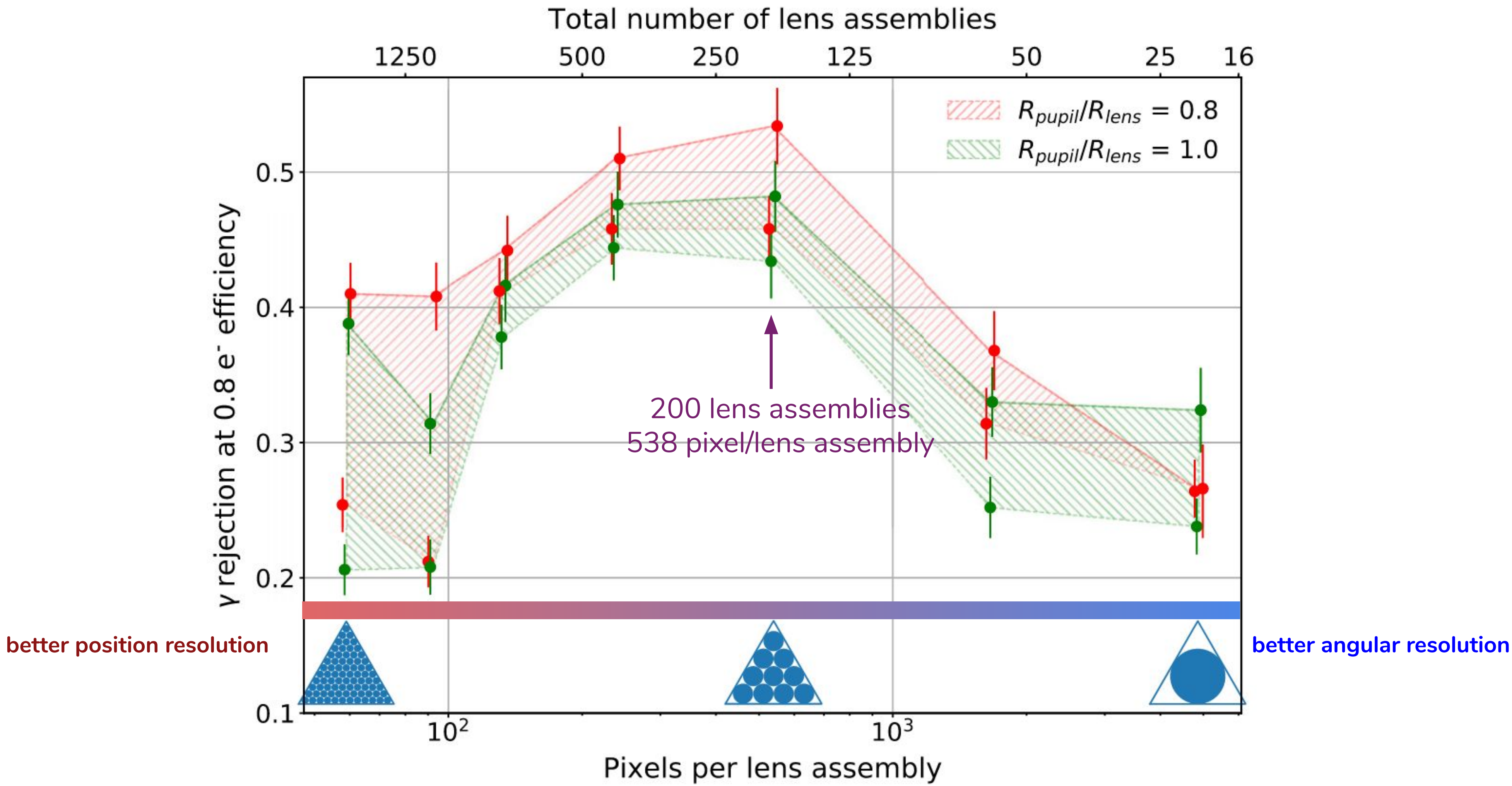
we tried to estimate how well we can statistically discriminate e^- from γ events at 2MeV (icosahedron geometry), varying the detector configuration. In order to achieve this we had to:

- calibrate the detector
- produce e^- template as reference event

for each different detector configuration:



Main Result – Discrimination Efficiency



Event Reconstruction - CNN method

discrimination between γ/e^- ⟷ binary classification problem

patterns on each focal array ⟷ image grayscale

simulation of well known physics ⟷ labeling training data

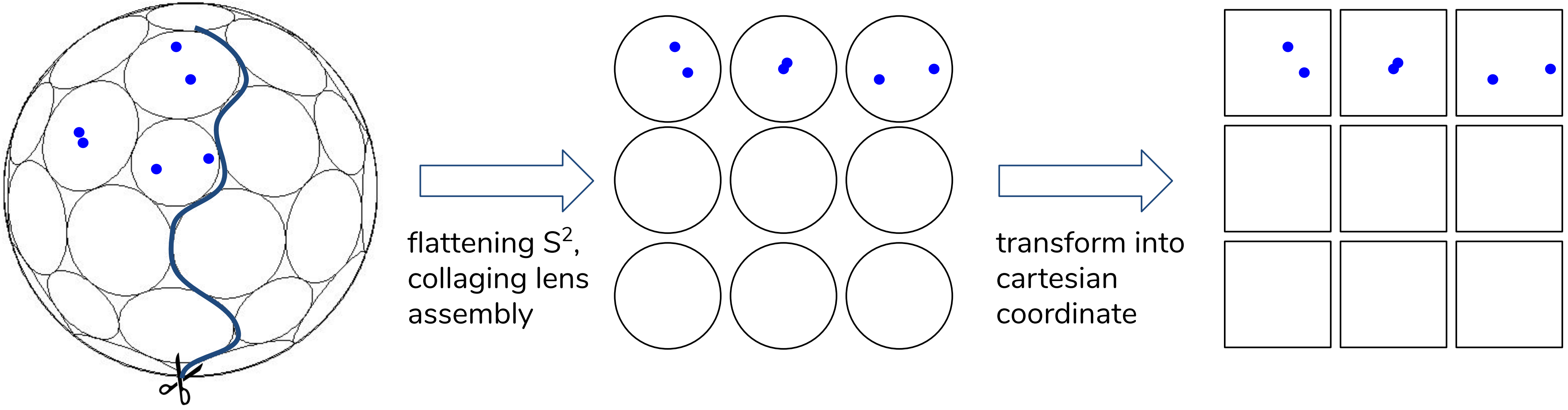
↓

CNN model

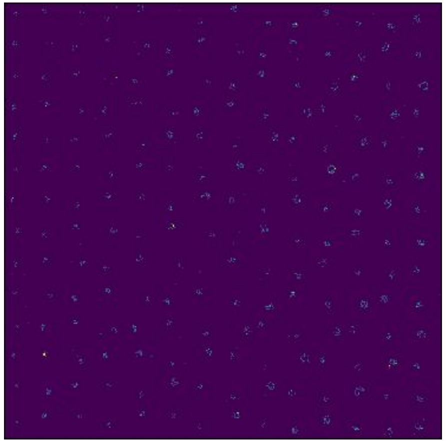
Trade offs:

- no need for a dedicated detector calibration
- no need for a e^- template
- data preparation for the network
- hyperparameters optimization

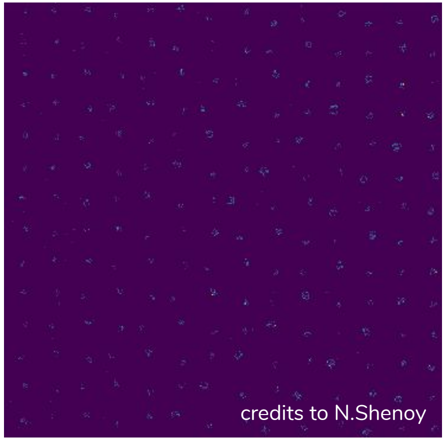
Data Preparation



e⁻ sample image

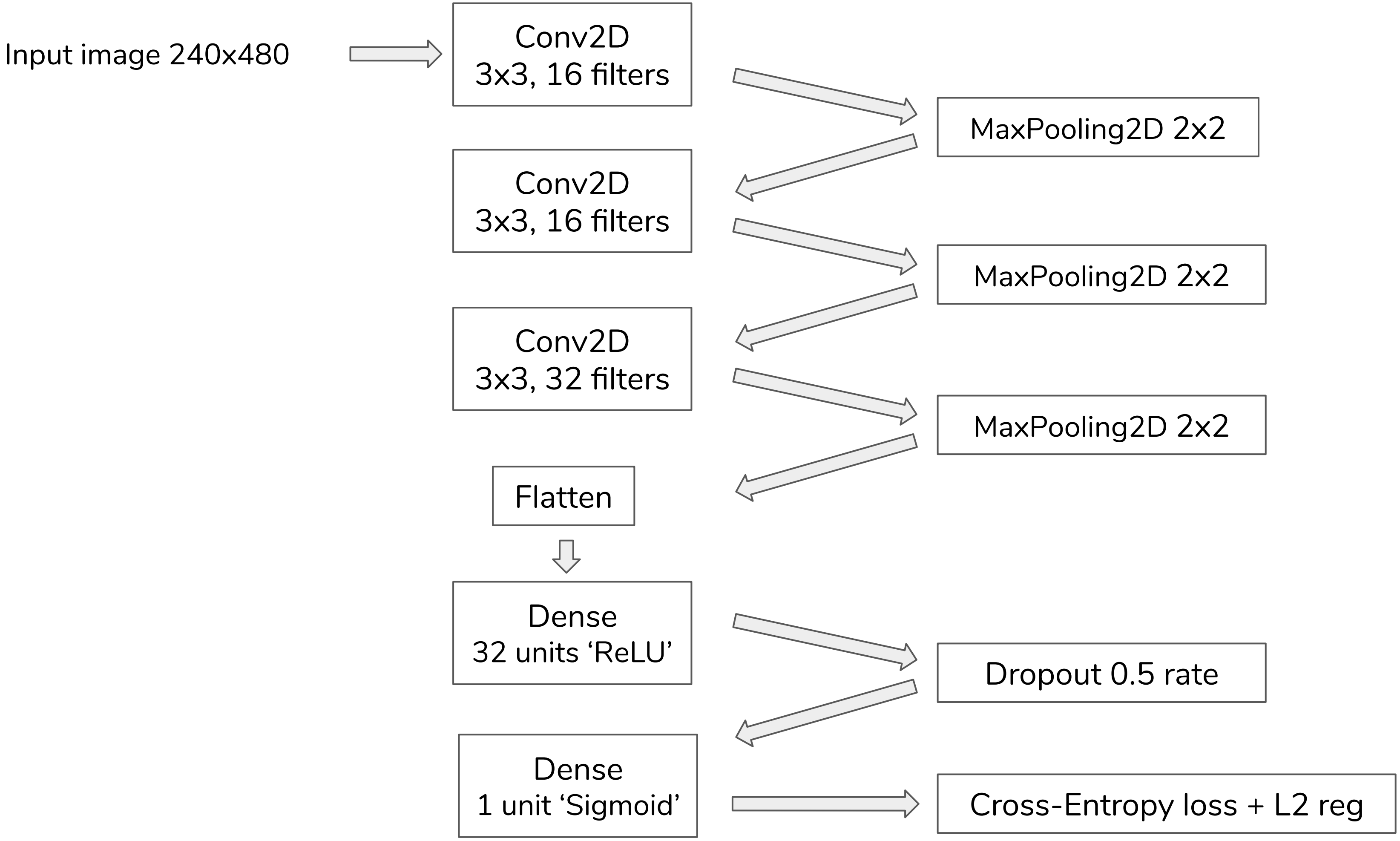


γ sample image



no data normalization carried out

Architecture



Hyperparameter Optimization - Benchmark

We did a raster scan of the following hyperparameters:

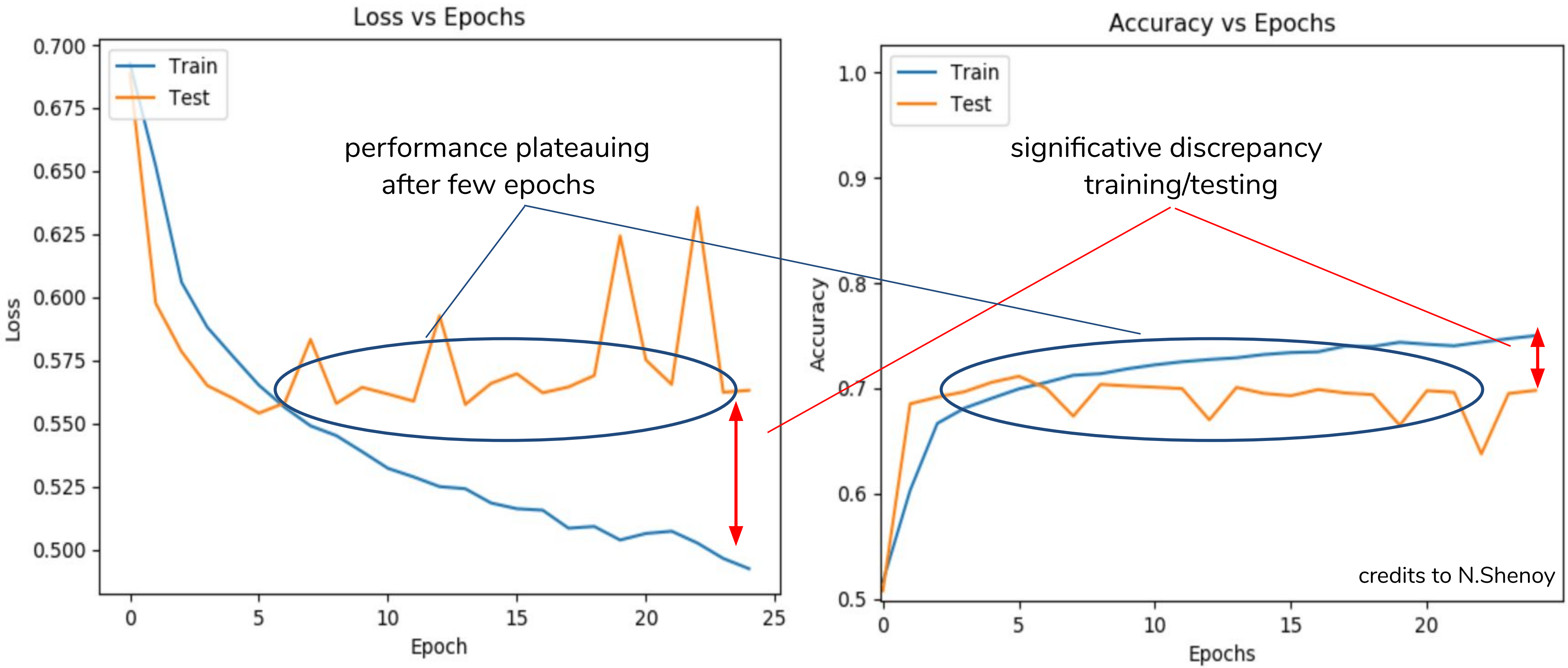
- Epochs/batch size
- Learning rate/decay
- Weight constraints/decay

-> no random search

how did this affected the accuracy?

60% → Hyperparameter optimization → 68% → Weight Decay → 71%

Debugging the Learning Process



Consistent with a learning rate too high? Varying it didn't seem to help a lot (min 10^{-3})

Comparison with the χ^2 method

We decided to use the 200 lenses detector as a benchmark comparison of the two methods

$$|ev_i\rangle = \alpha_i|e^-\rangle + \beta_i|\gamma\rangle$$

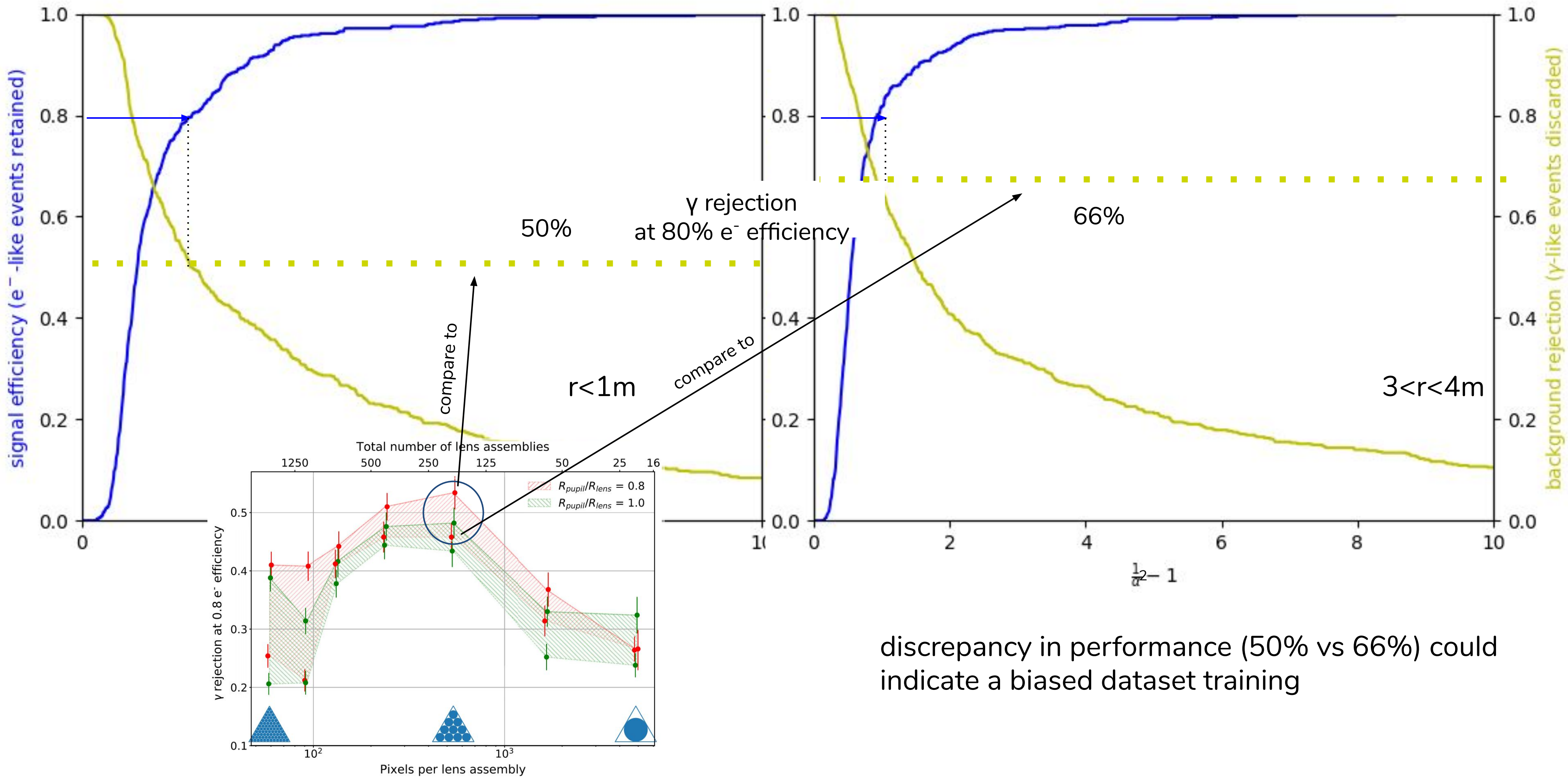
α_i^2 = output of the softmax for the i-th event

indicating the electroness of each event

$$\updownarrow$$

χ^2 m with the e^- template

Comparison with the χ^2 method



discrepancy in performance (50% vs 66%) could indicate a biased dataset training

What Can We Learn from This?

- some learning process by the network -> not trivial
- results comparable if not better than the ones obtained with the χ^2 method -> possible room for improval
- the network seems to be somehow sensitive to the location of the event
- what can we say about the architecture?

Current and Next Steps

Open Topics - Points of Improvement

- different lens design
  - non-imaging photon recovery
  - timing
- machine learning analysis
  - more expertise on CNN
  - study position/angular resolution trade-off with CNN
  - BDT, autoencoders, sparse data,...

hardware

software

Conclusion

Conclusion

- **distributed imaging** is a new technique to reconstruct images from high emittance sources, as the case for scintillation. This technique could enable **better background rejection** through topology reconstruction in a rare event detector
- to achieve this, we substituted photodetectors with lens assemblies composed by **lens(es)** in front of a **pixelated focal array**
- to test the performance on e^-/γ rejection, we simulated a detector tiled with such lens assemblies and a preliminary lens design. A **trade off** between **position** and **angular resolution** can be observed in the overall performance.
- a **ML based** approach proves to be suitable in discriminating e^-/γ. So far, CNN have been studied and proved to be competitive with a more traditional discrimination method based on χ^2. A tailored architecture and optimization of the network could potentially outperform the latter one

Acknowledgment

thanks to:

- *N. Shenoy (working on the network), G. Gratta*

with previous work of:

- *S. Steven, J. Bentley, K. Wells, S. Kravitz, A. Jamil, M. Malek, J. Su*

for more information:

- J. Dalmasson et al. (2018), *PRD*, 97:052006
- jdalmass@stanford.edu
- http://grattalab3.stanford.edu/neutrino/index.html