

# Using Julia to Accelerate Monte Carlo Event Generation with Neural Importance Sampling

Tom Jungnickel

Erlangen, 09.11.2023



**CASUS**

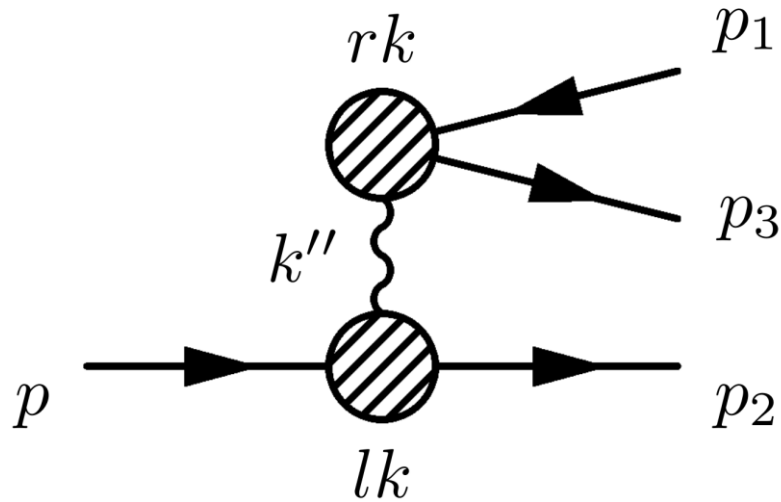
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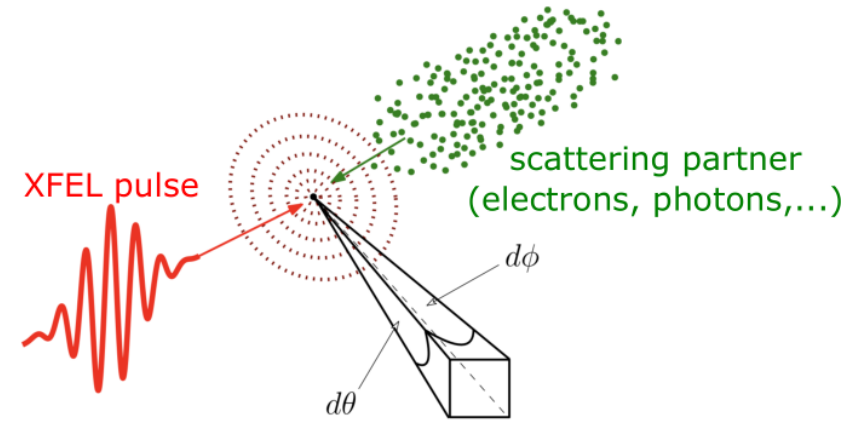


# Recap: Physical background

## Event generation for strong-field QED scattering processes



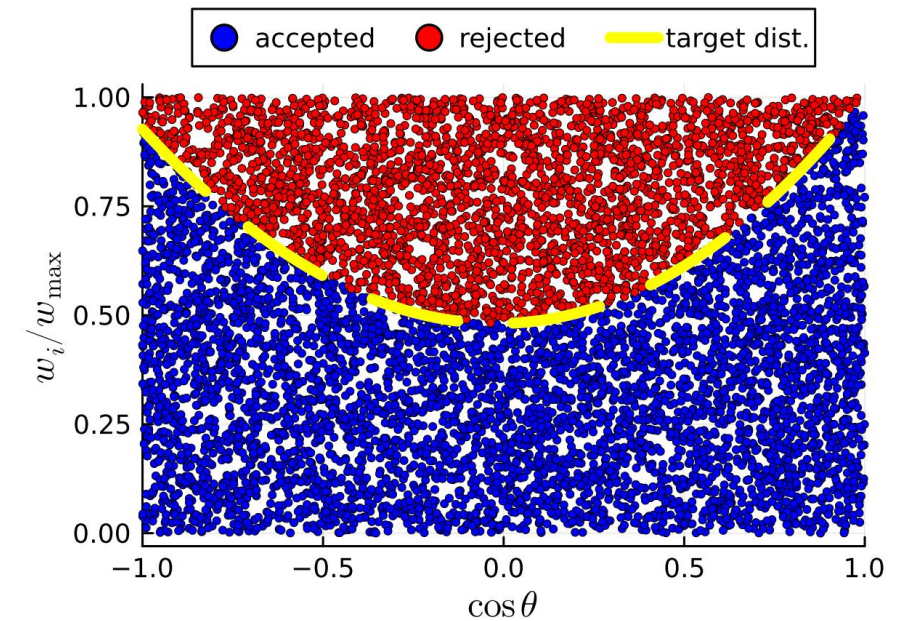
Feynman-diagrams



Differential cross sections

# Monte Carlo Event Generation

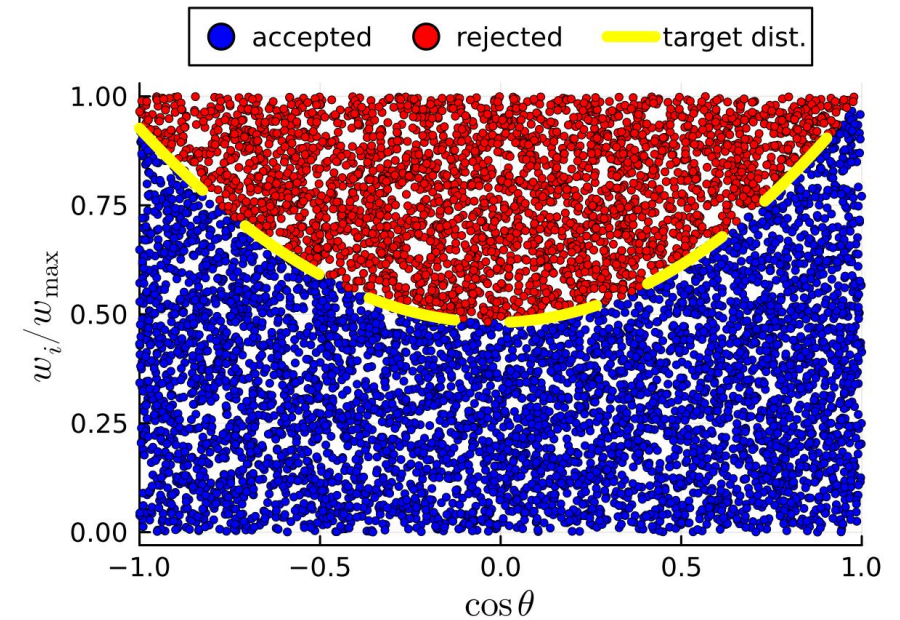
- Weight  $w(x) := \frac{d\sigma}{dx}$





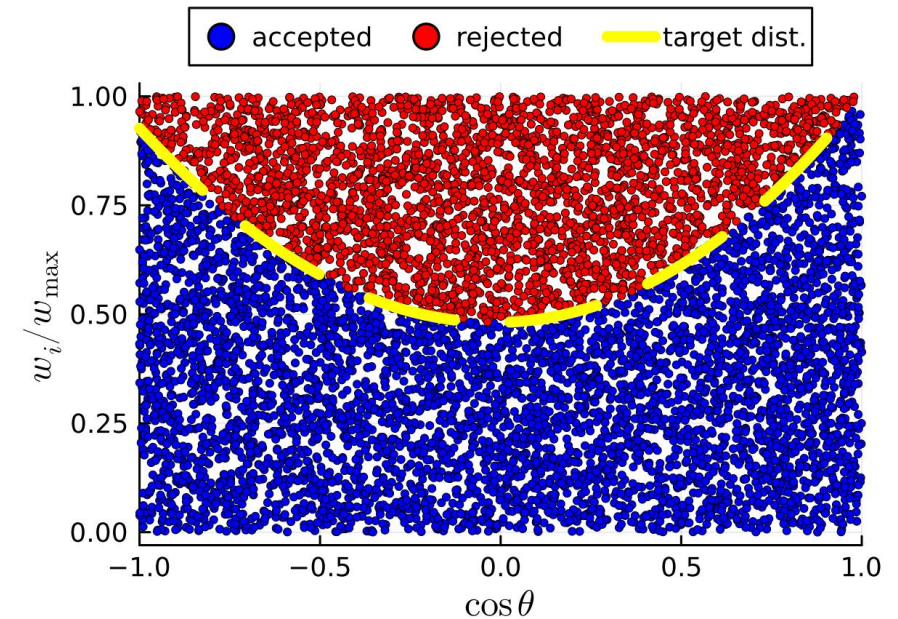
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- Unweighting
  1.  $w_{i,\text{rel}} = \frac{w_i}{w_{\text{max}}}$
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  3. accept  $x$  if  $u < w_{i,\text{rel}}$



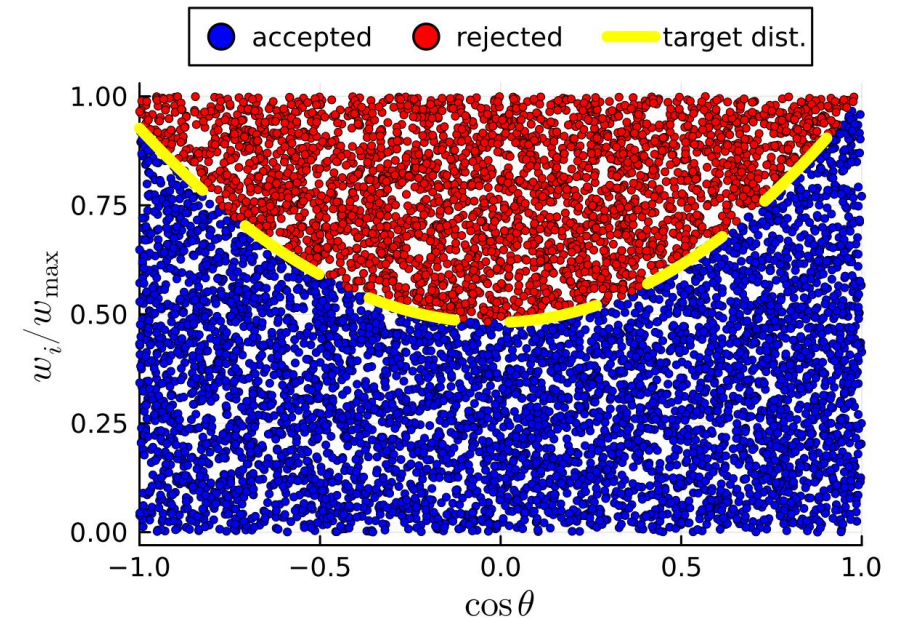
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 $w(x) \approx cg(x)$

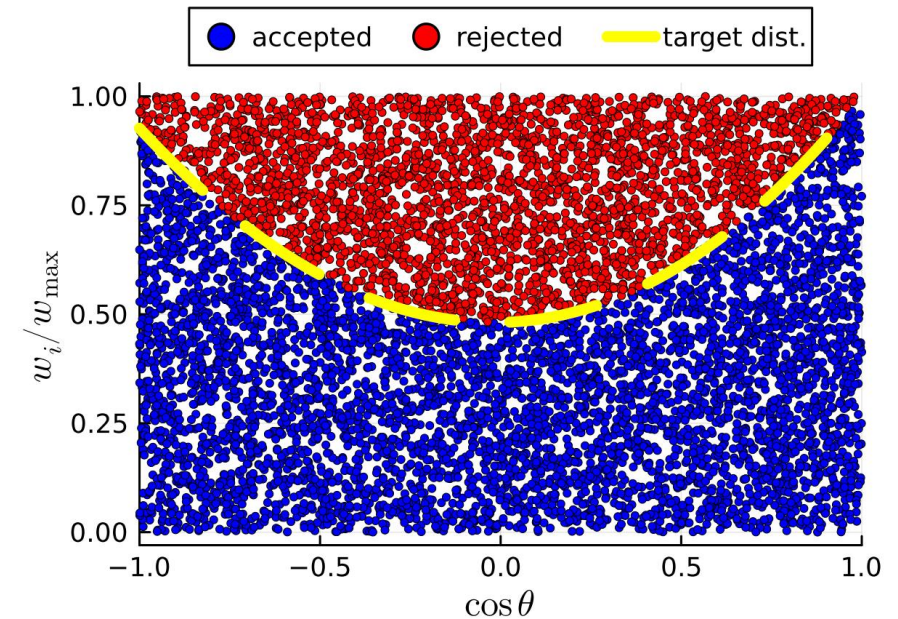




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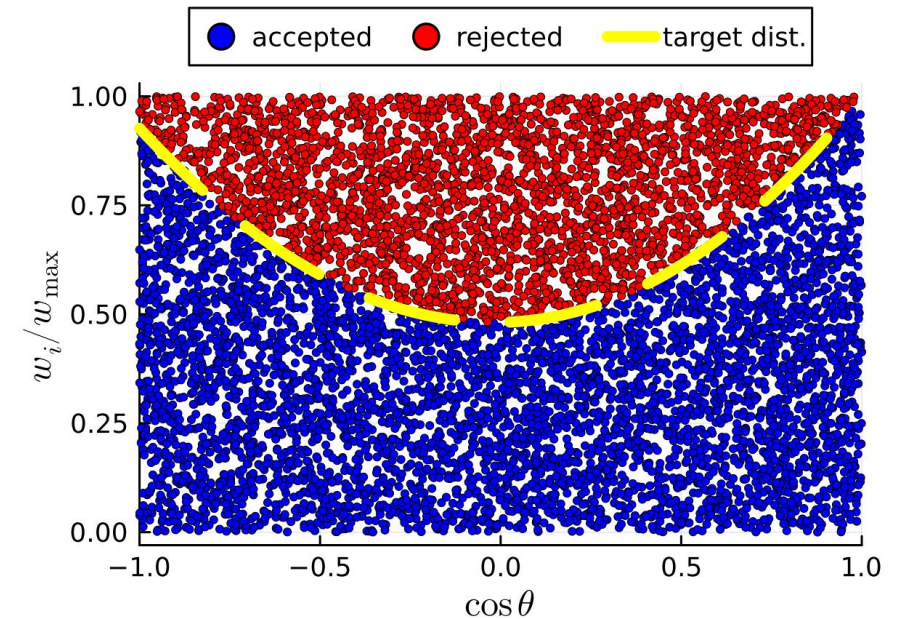
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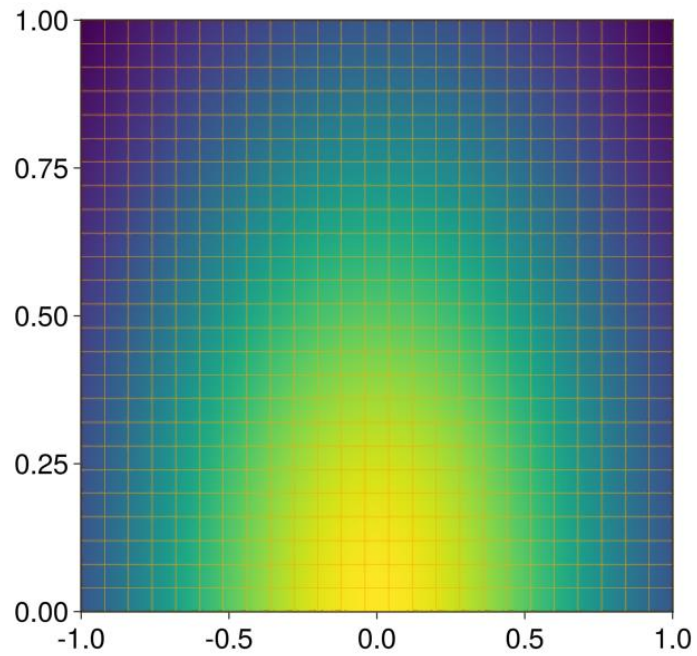
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# Importance Sampling

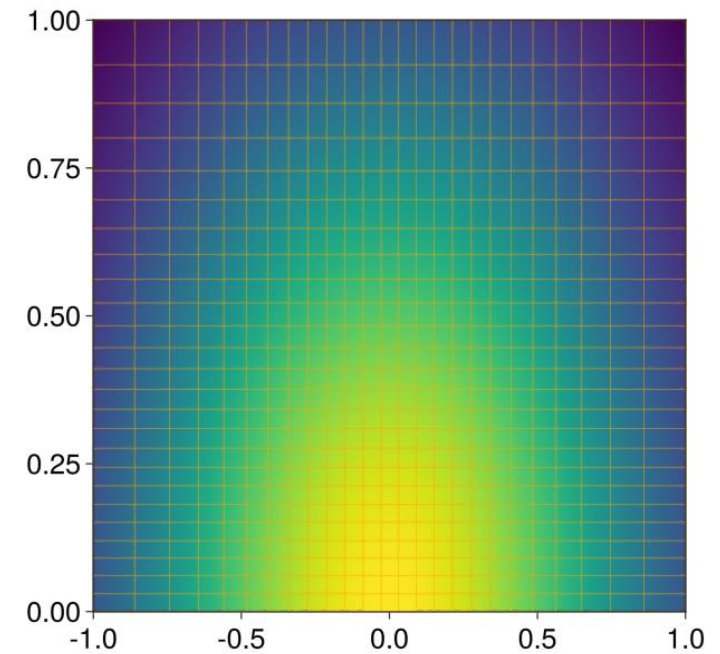
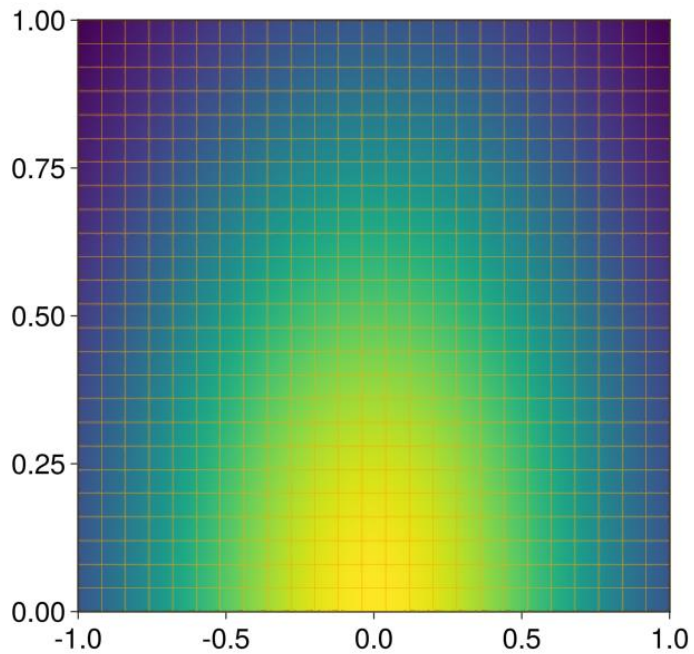
## The classical approach - VEGAS



Adapting a grid by minimizing the variance in each bin

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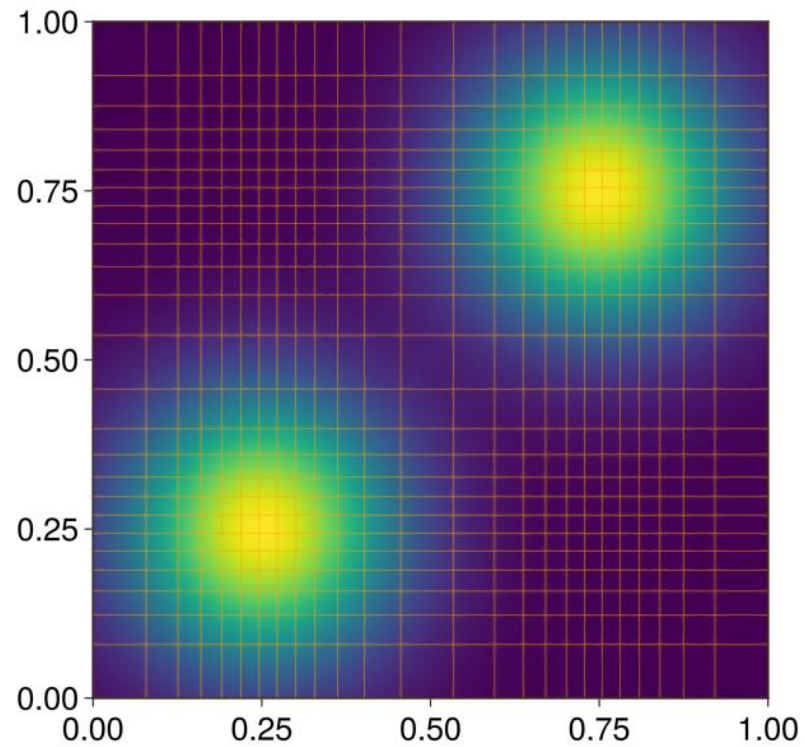


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# Importance Sampling

## The problem with VEGAS

### Adaption of ghost peaks for non coordinate aligned targets

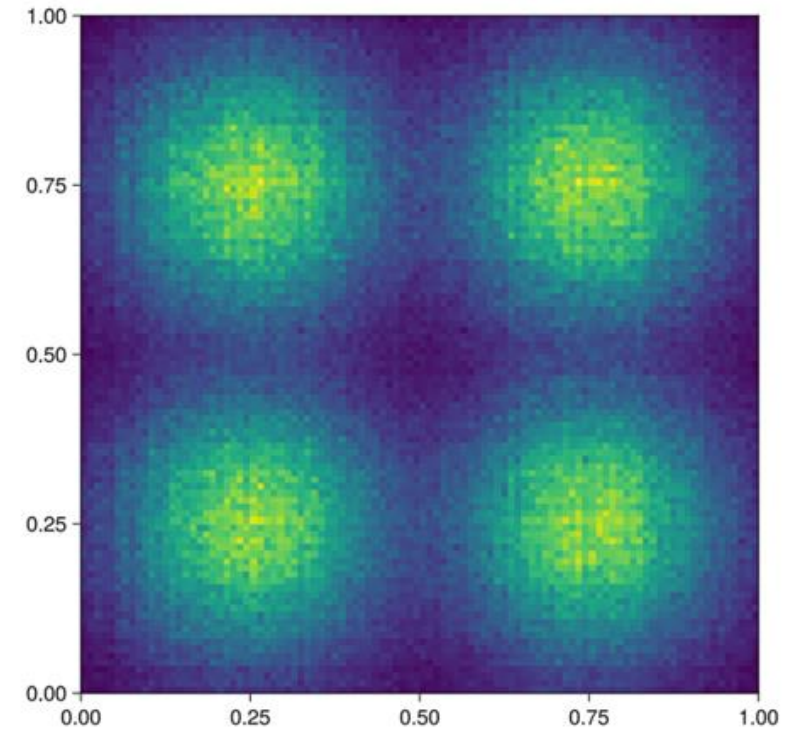
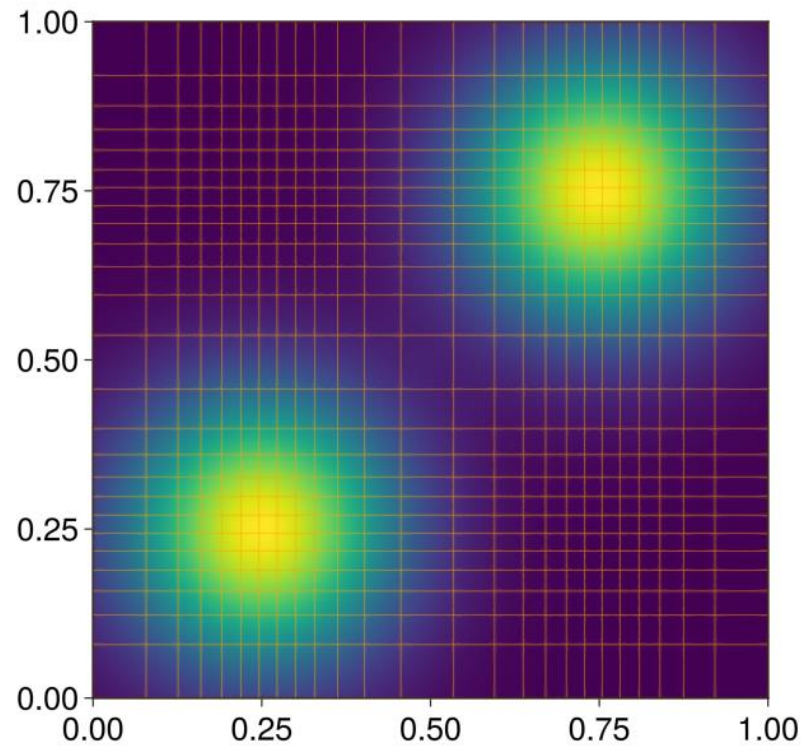




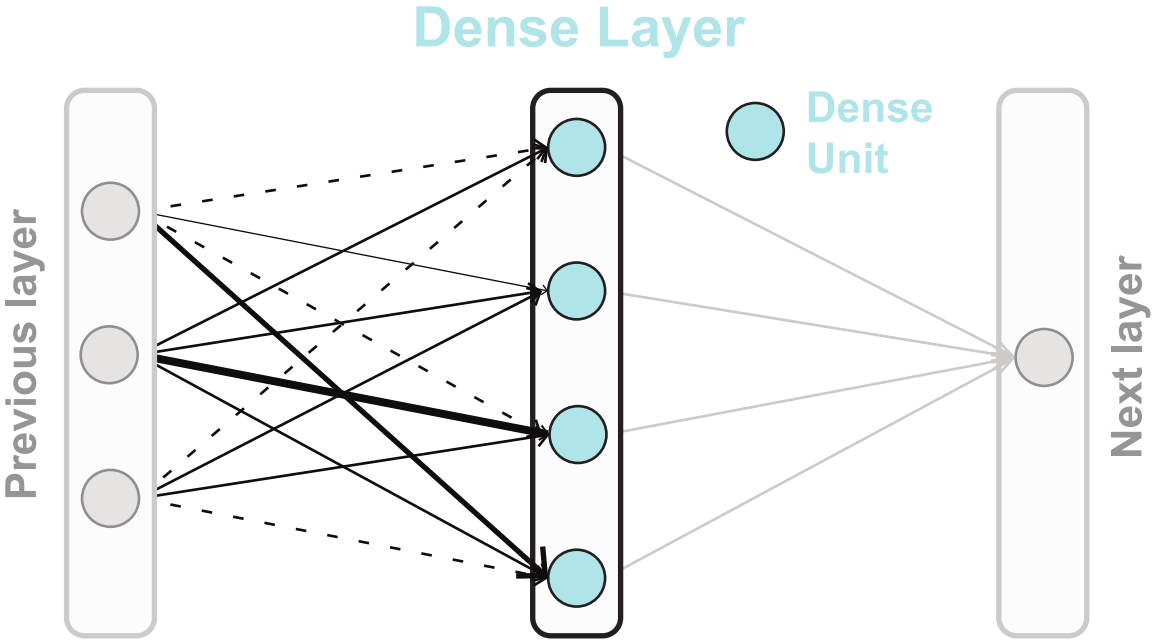
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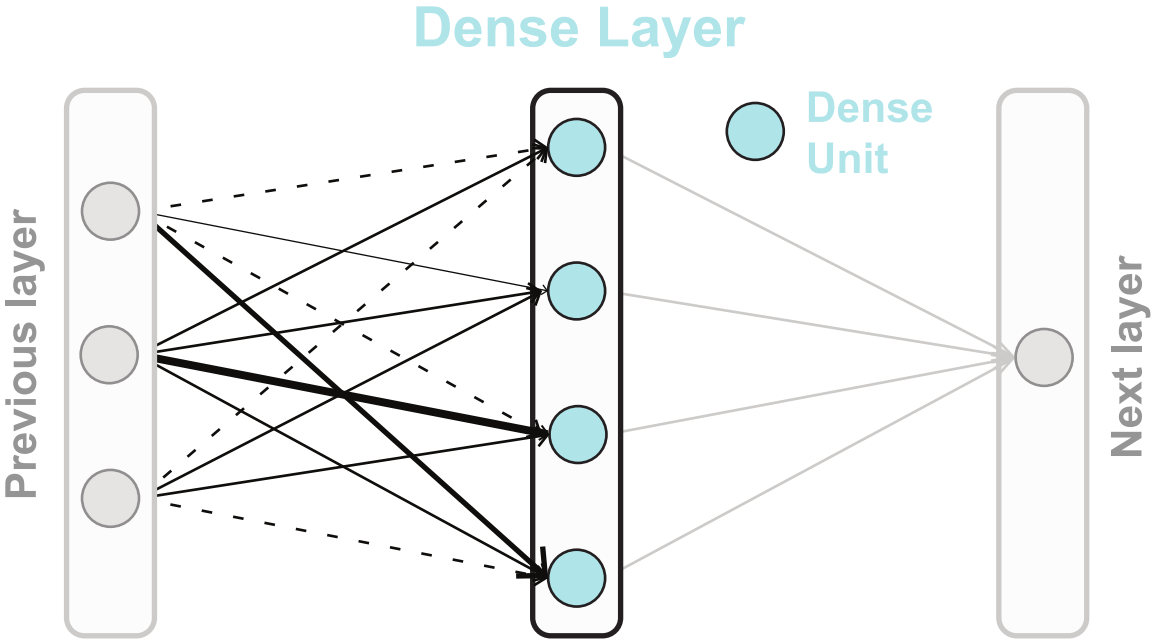


# Recap: Neural Networks

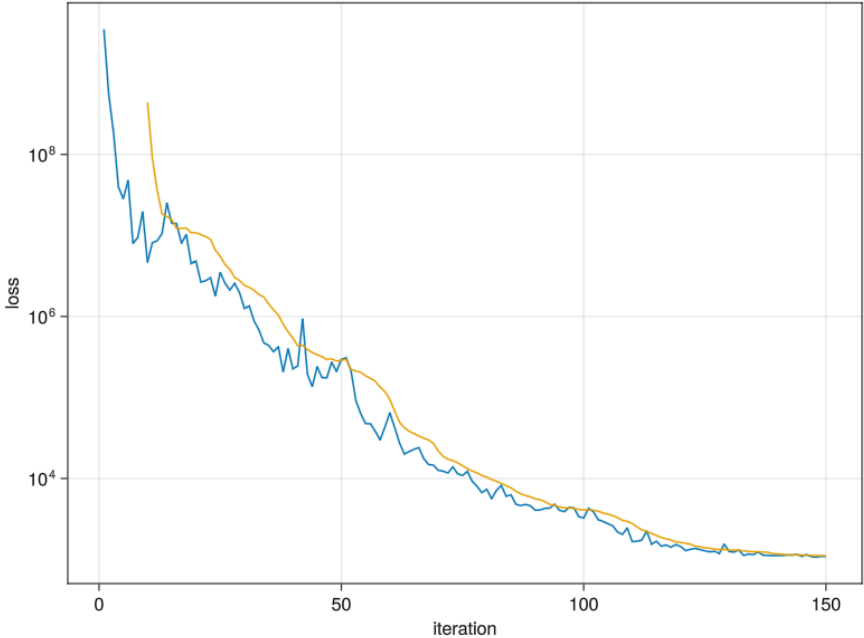


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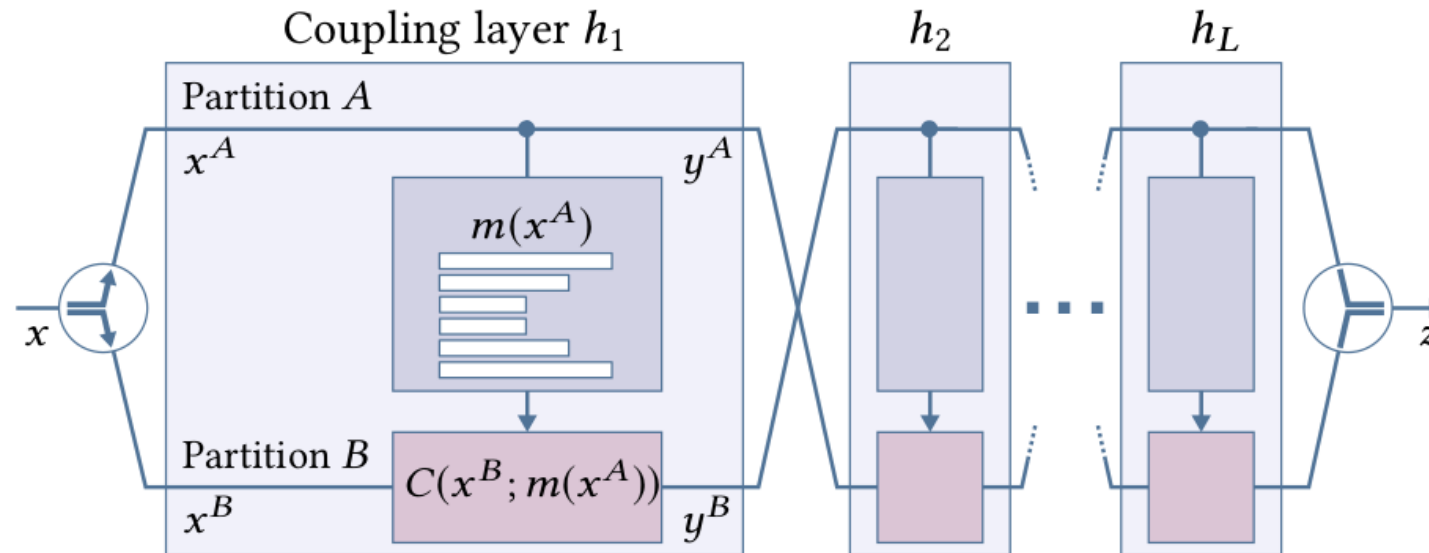
Change network parameters to reduce the loss



# Importance sampling

Enhancing efficiency through neural networks

## Neural Importance sampling



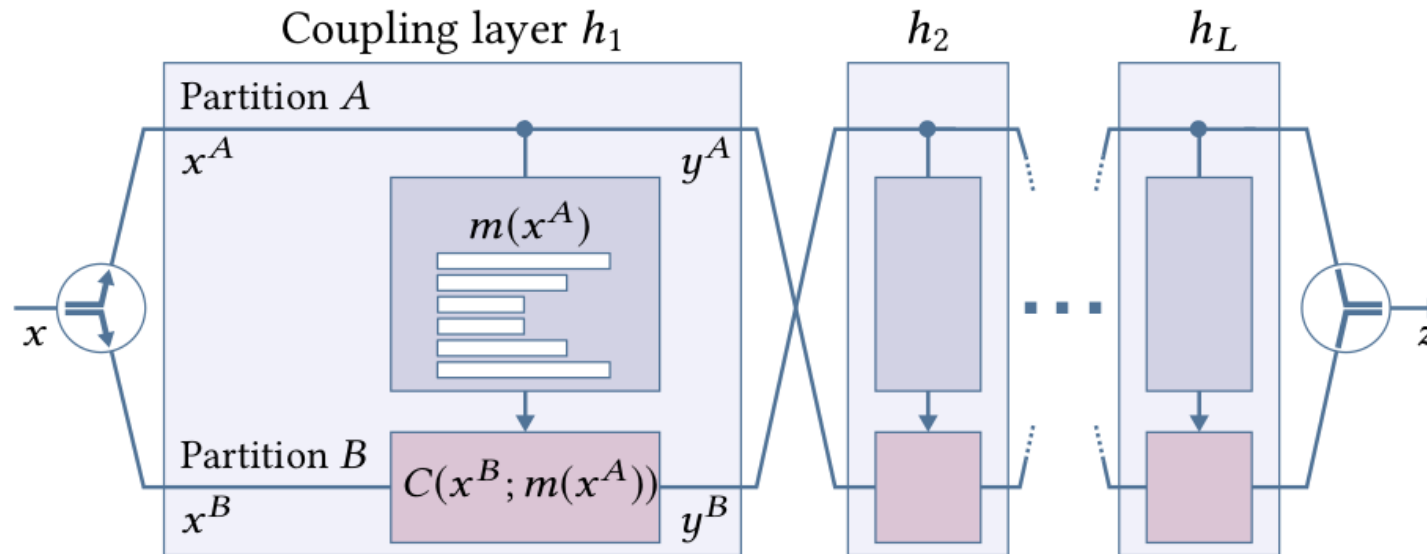
Transform a part of the input data in each layer

[T. Müller et al., ACM Transactions on Graphics (ToG) 38.5 (2019)]

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# Flux.jl

## Julia meets AI

**Just a few lines of code to train your first model**





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```
dim = 2
bins = 10
c11 = CouplingLayer(dim, 1, bins)
c12 = CouplingLayer(dim, 1, bins)
m1 = MaskLayer([false, true])
model = Flux.f32(Chain(c11, m1, c12) |> gpu)
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```
opt_state = Flux.setup(Adam(0.001), model)
for epoch in 1:1000
    data = CUDA.rand(Float32, dim, 1024)
    val, grads = Flux.withgradient(m -> loss(m, f, data), model)
    Flux.update!(opt_state, model, grads[1])
end
```

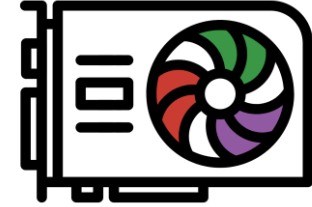
# Parallelization

Getting started without writing kernels thanks to broadcasting

- Single calculation on CPU:

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dσpT(k, p, p1, p2, p3)
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QEDbase.SFourMomentum



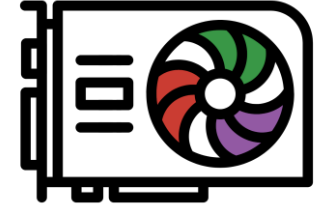
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gk, gp, gp1, gp2, gp3 = generat_momenta(10^5) .|> gpu
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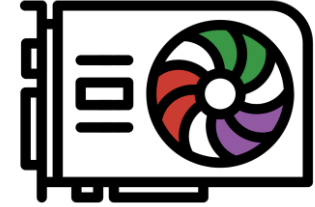
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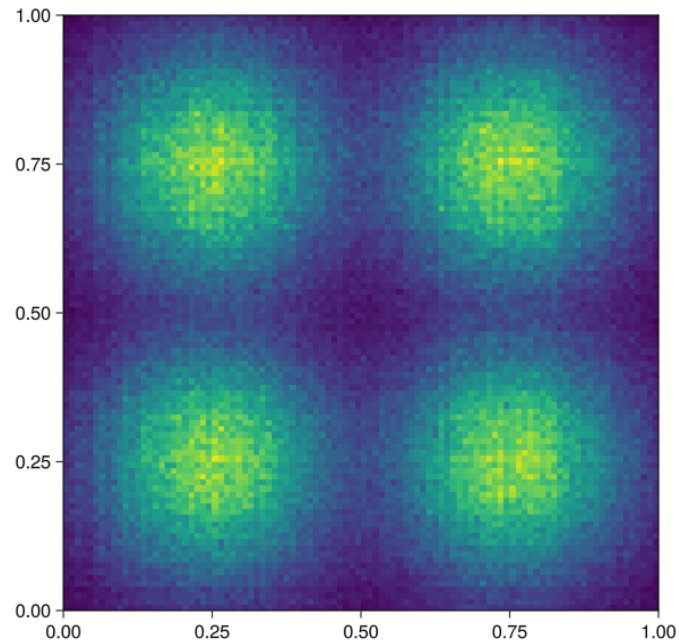
```
dσpT.(gk, gp, gp1, gp2, gp3)
```



# Results

## Sampling two gaussians in 5d

Work in progress!

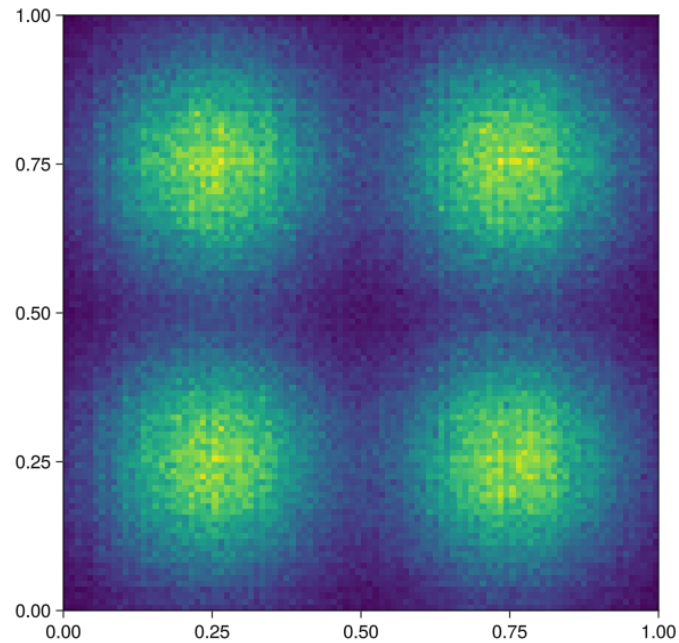


Proposal from VEGAS

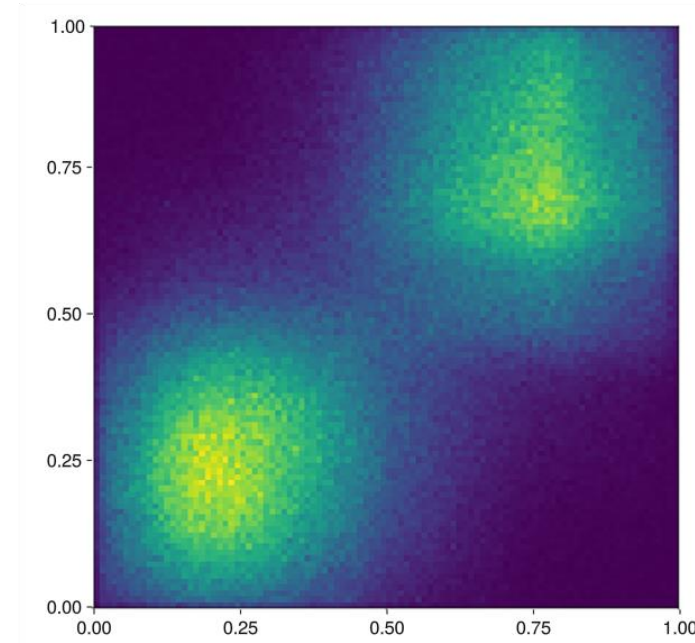
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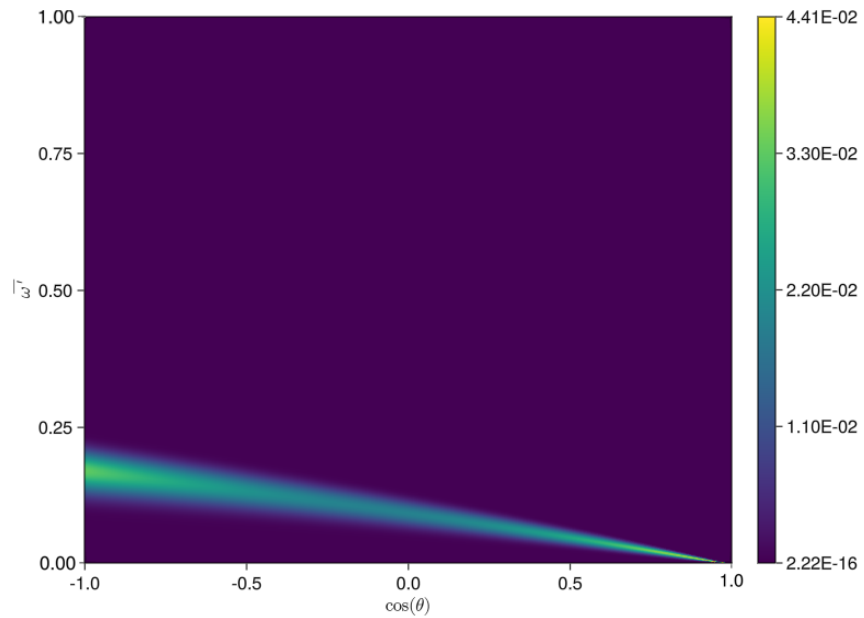


Proposal from NIS

# Results

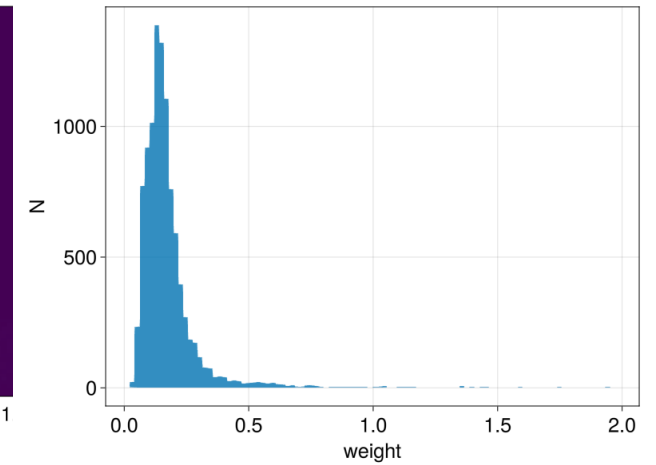
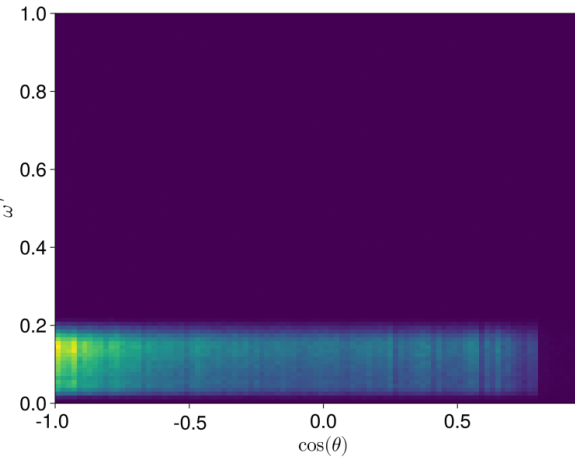
## Sampling the strong-field Compton process

Work in progress!

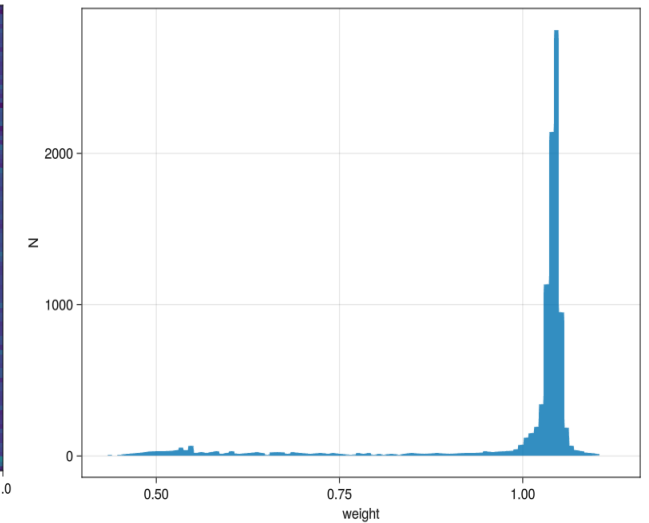
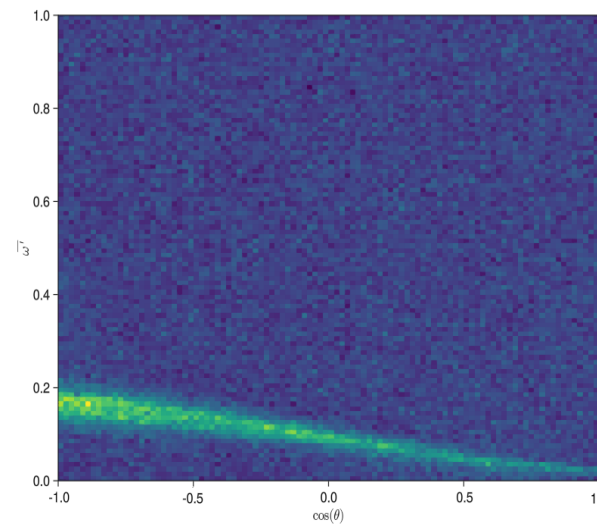


Ground truth

VEGAS:  $I_3$

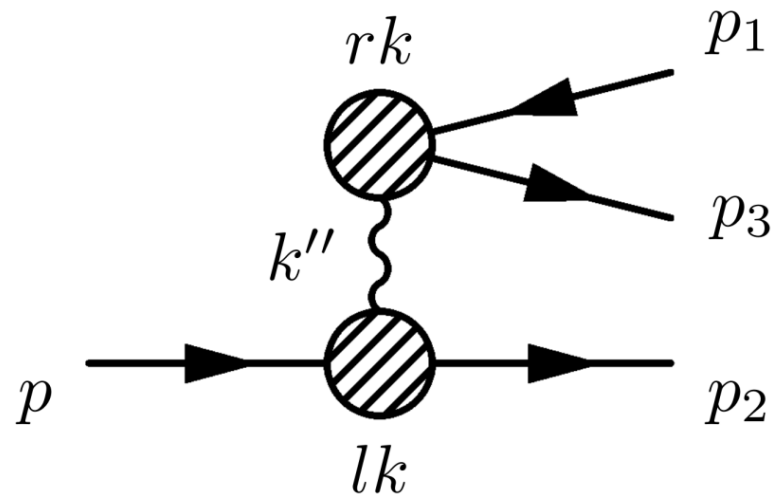


NIS:



# Outlook

- network tuning
- application to the strong-field trident process (5d)



# Acknowledgements

## Collaborators

- Uwe Hernandez Acosta
- Klaus Steiniger
- Michael Bussmann
- Simeon Ehrig
- Anton Reinhard





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