

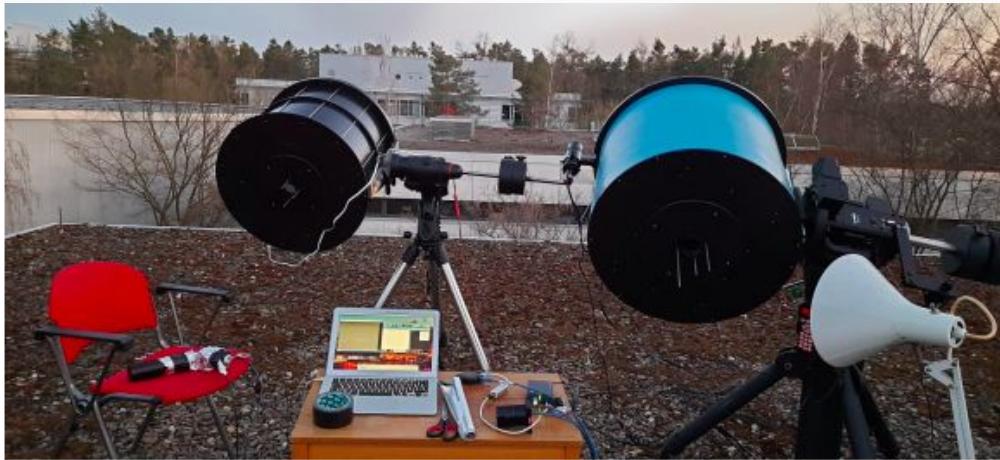
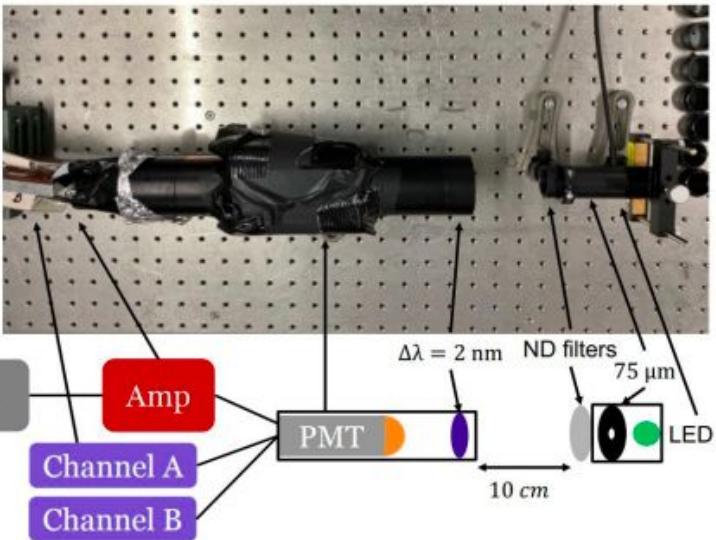
DL-based PMT photon counting and a normalizing-flow package for (astro-)particle physics



Thorsten Glüsenkamp, Feb 14th, IDT collaboration meeting

Two topics:

- 1) PMT rate reconstruction for high-intensity interferometry (Jigar Banderi, Dmitry Malyshev)
- 2) jammy_flows - a normalizing flow package tailored for (astro-) particle physics (Thorsten Glüsenkamp)



Calibration of Photomultiplier Tubes for Intensity Interferometry at H.E.S.S.

$$N = \frac{1}{\sqrt{R_1 R_2}} \sqrt{\frac{\tau_e}{T}}$$

Photon rates

$$\frac{S}{N} = C \cdot \epsilon \cdot n(\nu) \cdot \sqrt{\frac{T}{\tau_e}}$$

Source flux → $n(\nu)$

Observation time → T

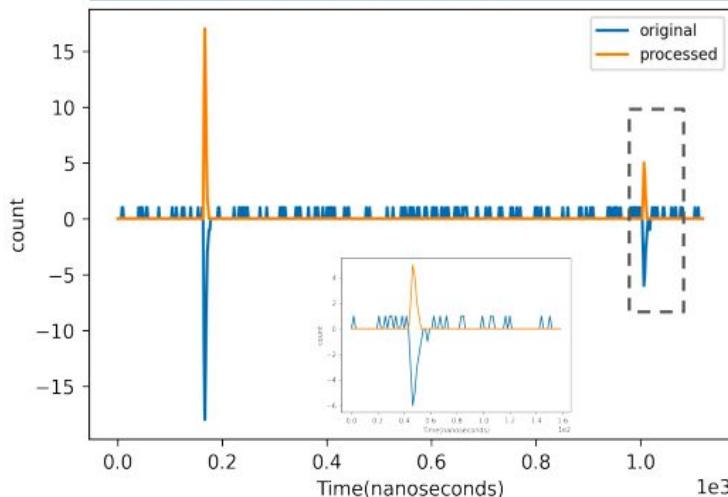
Telescope collection area → C

Photon detection efficiency of the system → ϵ

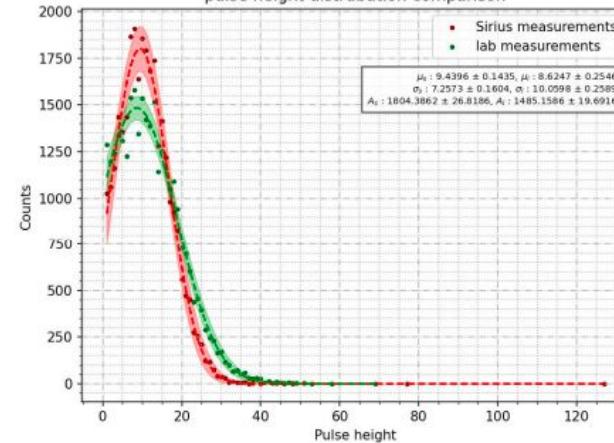
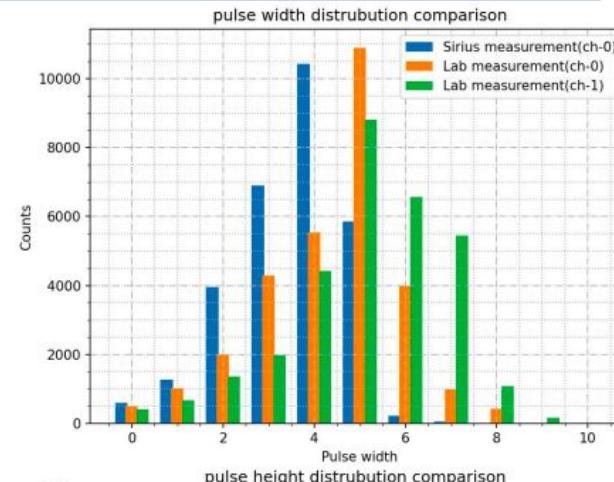
Optical bandwidth → $\sqrt{\frac{T}{\tau_e}}$

System resolution → $\sqrt{\frac{T}{\tau_e}}$

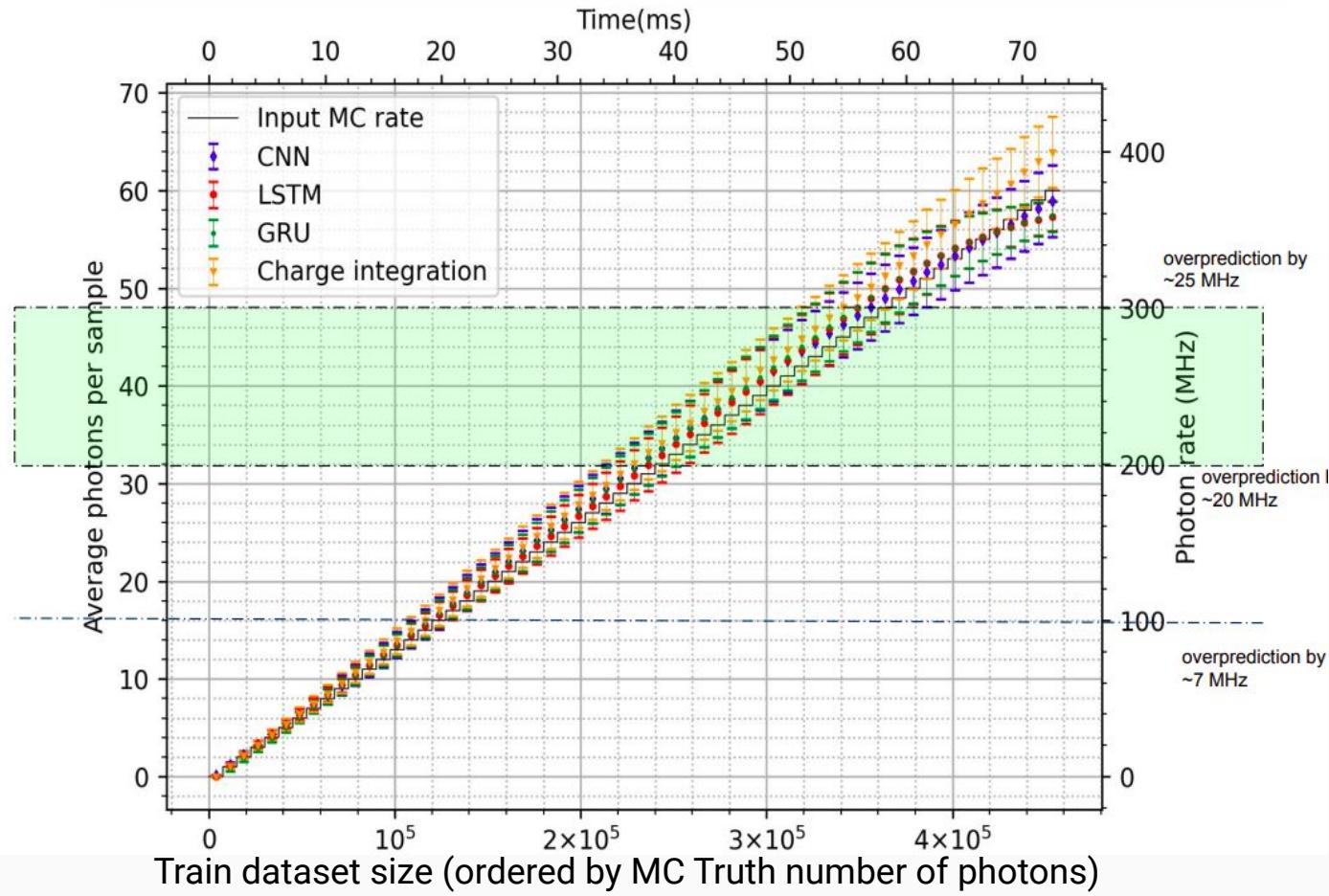
Data preprocessing



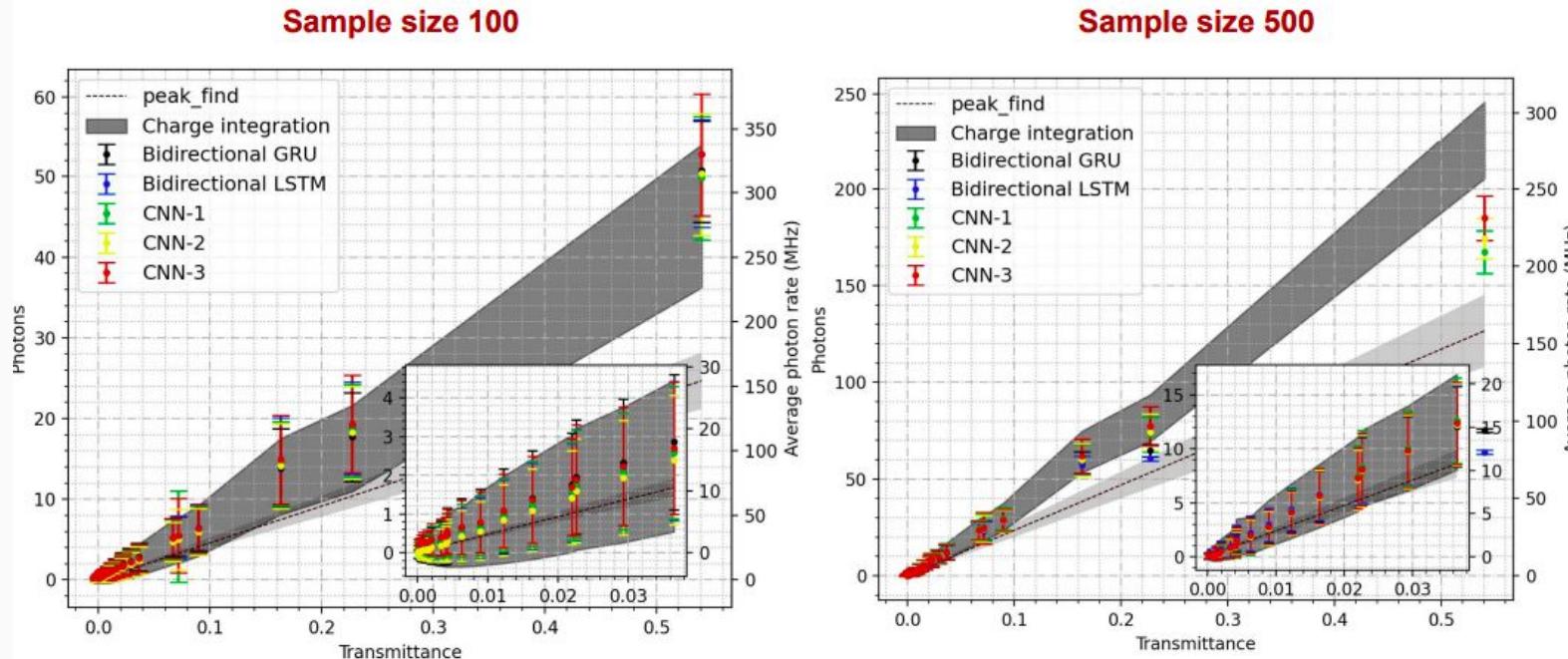
- Extraction of photon shapes after preprocessing with sample size 100
- Shape set splitting for training testing and validation by 20%
- MC-data creation for selected sample size
- Input: 1D-waveform, output: number of photon peaks in sample
- Train selected neural network
- Evaluate network(test dataset)
- Testing of network
 - Lab : waveform with different transmission
 - Sirius : measurement at different instances



Model Evaluation

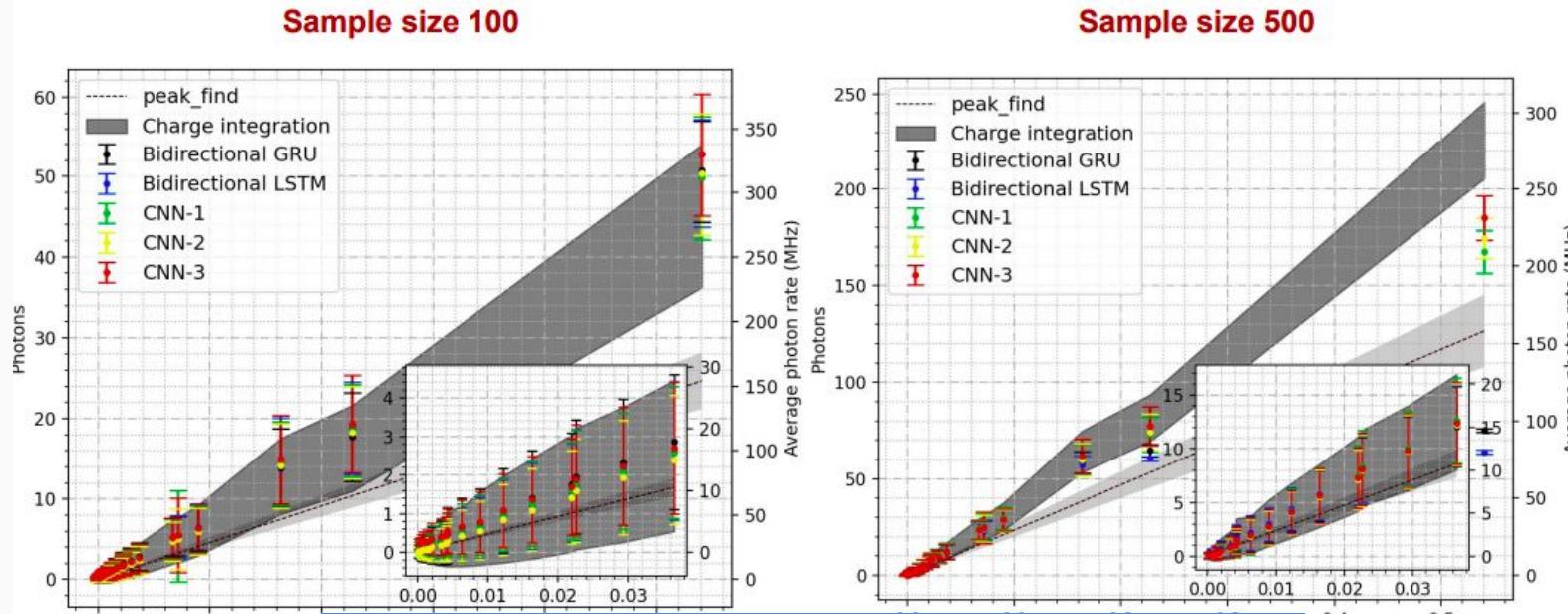


Prediction comparison (Lab)



Different points correspond to measurements with different grey filters, and corresponding transmittances are plotted on the x-axis

Prediction comparison (Lab)



Conclusion: Calibration of PMT rate possible with neural networks

Different points correspond to measurements with different grey filters, and corresponding transmittances are plotted on the x-axis

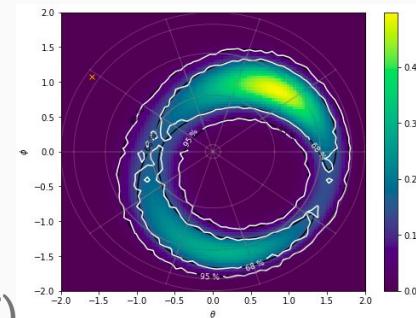
jammy_flows - a normalizing flow package tailored for (astro-) particle physics

Motivation:

Particle physics needs precise normalizing flows together with coverage guarantees

We need PDFs of directions (defined on the sphere \rightarrow manifold PDF)

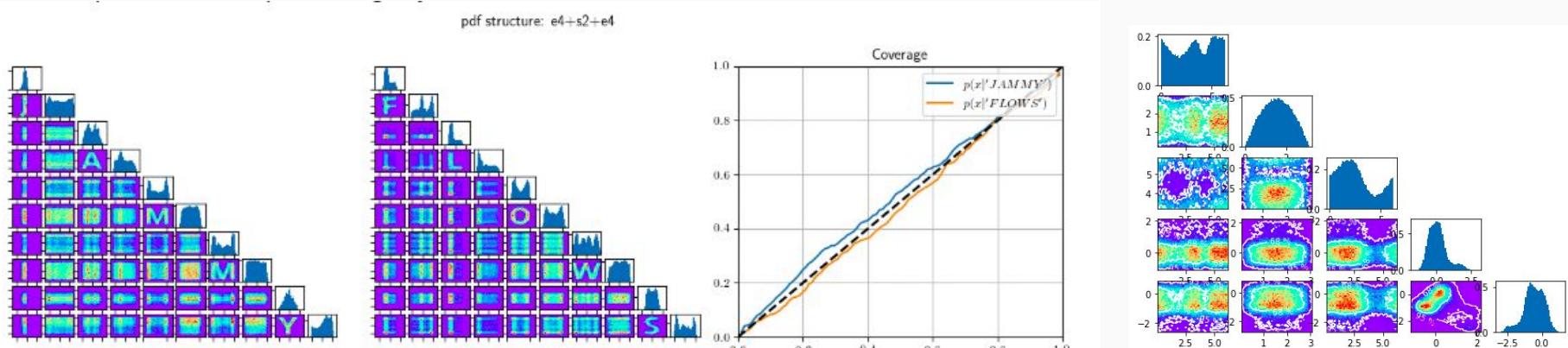
We would like to have joint PDFs (e.g. PDF defined jointly on Euclidean space and the sphere, i.e. a PDF on \mathbb{S}^2 with arbitrary correlation structure)



jammy_flows - a normalizing flow package tailored for (astro-) particle physics

A partial feature list:

1. Coverage for arbitrary manifold tensor product distributions automatically supported as defined in (<https://arxiv.org/abs/2008.05825>)



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2. Supports best-in-class flows for Euclidean, spherical, simplex, line manifolds + automatic forward/backward pass cross-checks

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A partial feature list:

1. Coverage for arbitrary manifold tensor product distributions automatically supported as defined in (<https://arxiv.org/abs/2008.05825>)
2. Supports best-in-class flows for Euclidean, spherical, simplex, line manifolds + automatic forward/backward pass cross-checks
3. Easy to get going with 1 line of code

jammy_flows - a normalizing flow package tailored for (astro-) particle physics

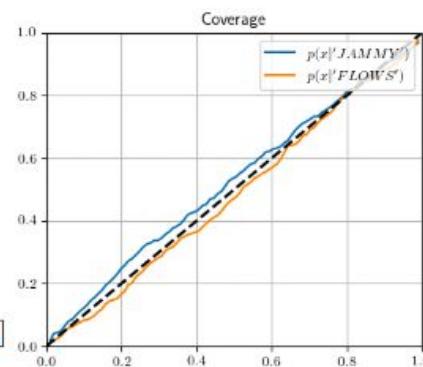
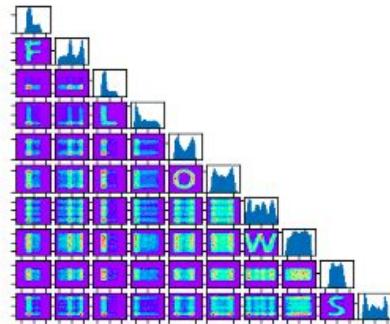
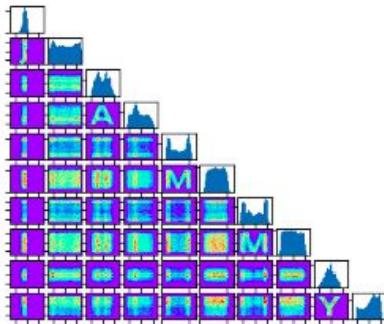
```
import jammy_flows
```

```
pdf=jammy_flows.pdf("e4+s2+e4", "gggg+n+gggg")
```

Any flow is injective \rightarrow can composite flows: $f_{\text{tot}} = f_1(f_2(\dots f_n(x))$
for more complexity

“gggg” $\rightarrow f_1(f_2(f_3(f_4(x))))$

Simple to use:



1 line defines a
(conditional) PDF that can
be trained

\rightarrow gets you fast to 80%/90%

Still possible:
customization for flexibility

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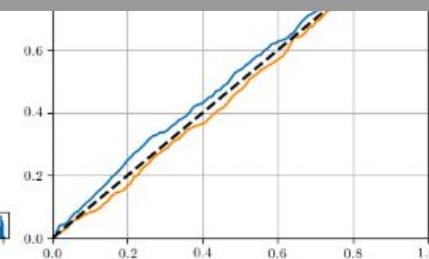
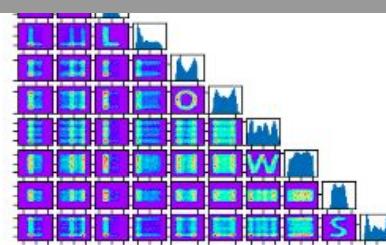
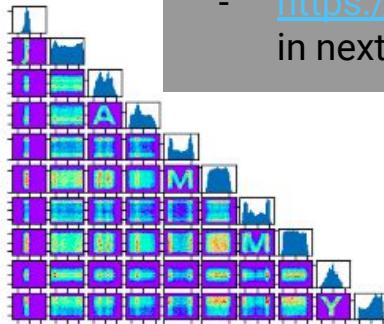
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```

"gggg" $\rightarrow f_1(f_2(f_3(f_4(x))))$

- Precise normalizing flows with coverage a common goal
- Lets make it a community effort
- https://github.com/thoglu/jammy_flows (currently still beta, first release in next 1-2 months)



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al) PDF that can

\rightarrow gets you fast to 80%/90%

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