THREE-DIMENSIONAL NUCLEON STRUCTURE WITH AI/ML

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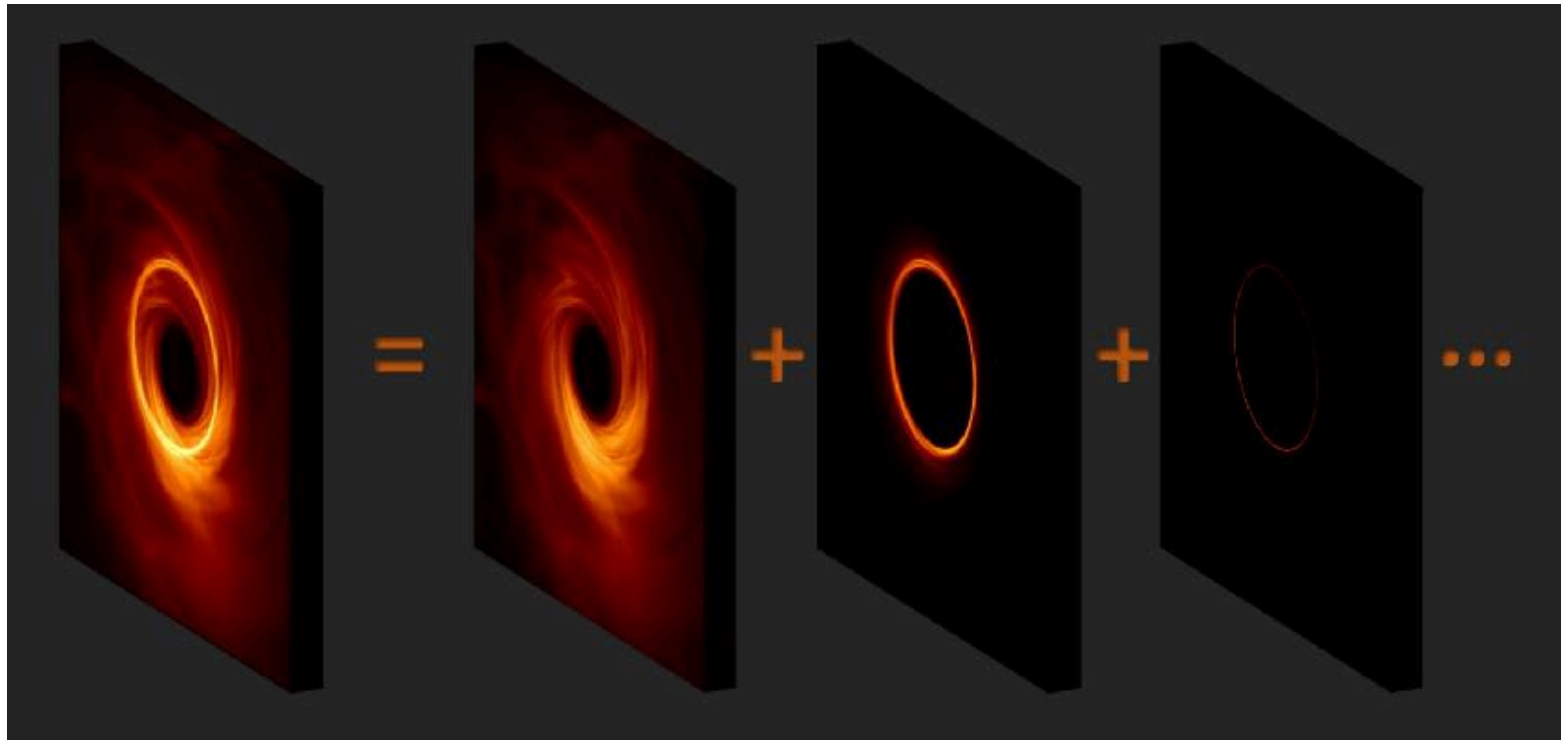
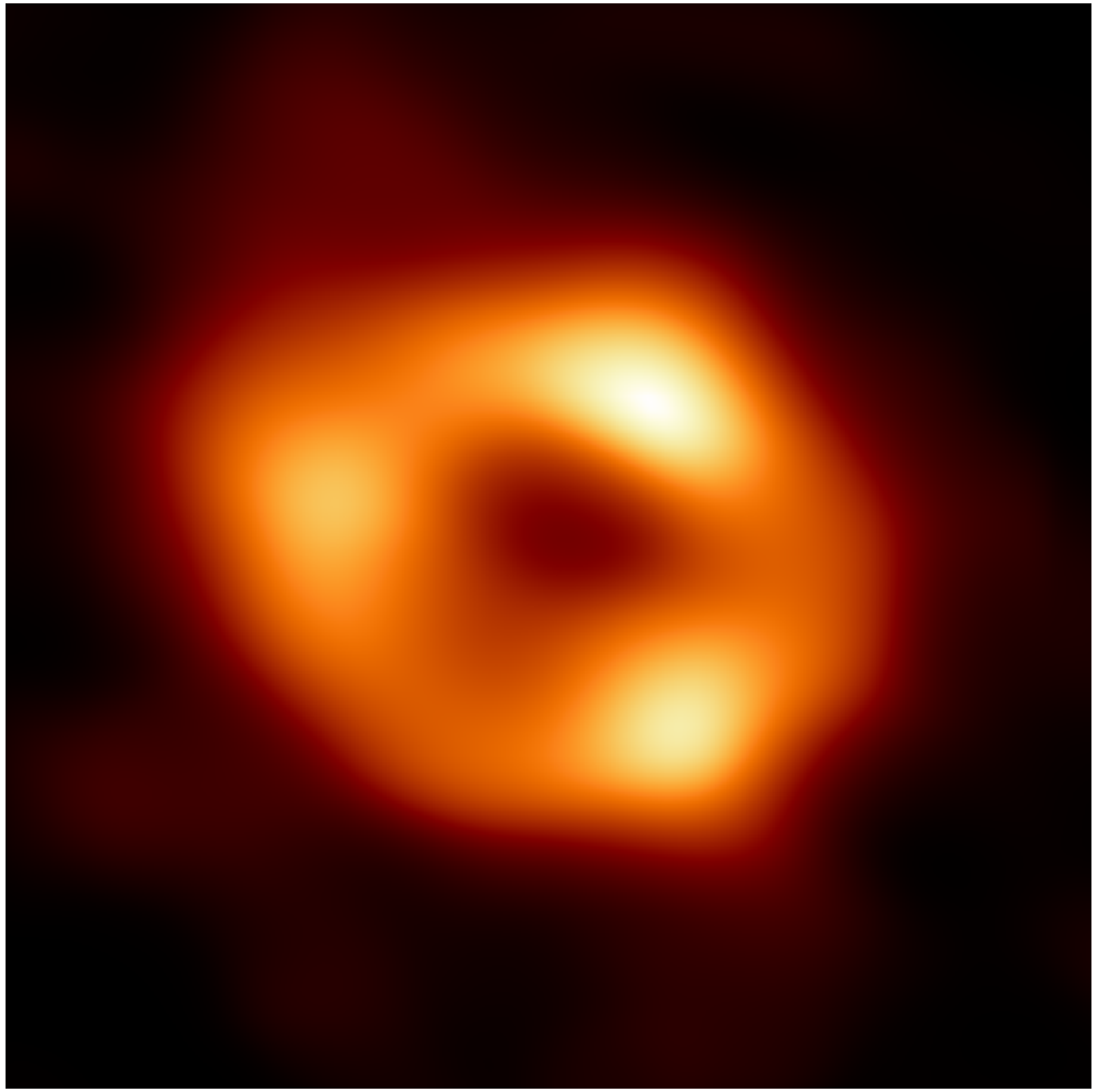
IMAGES ARE IMPORTANT

https://eventhorizontelescope.org/

Calculations and simulations

Observation and visualization



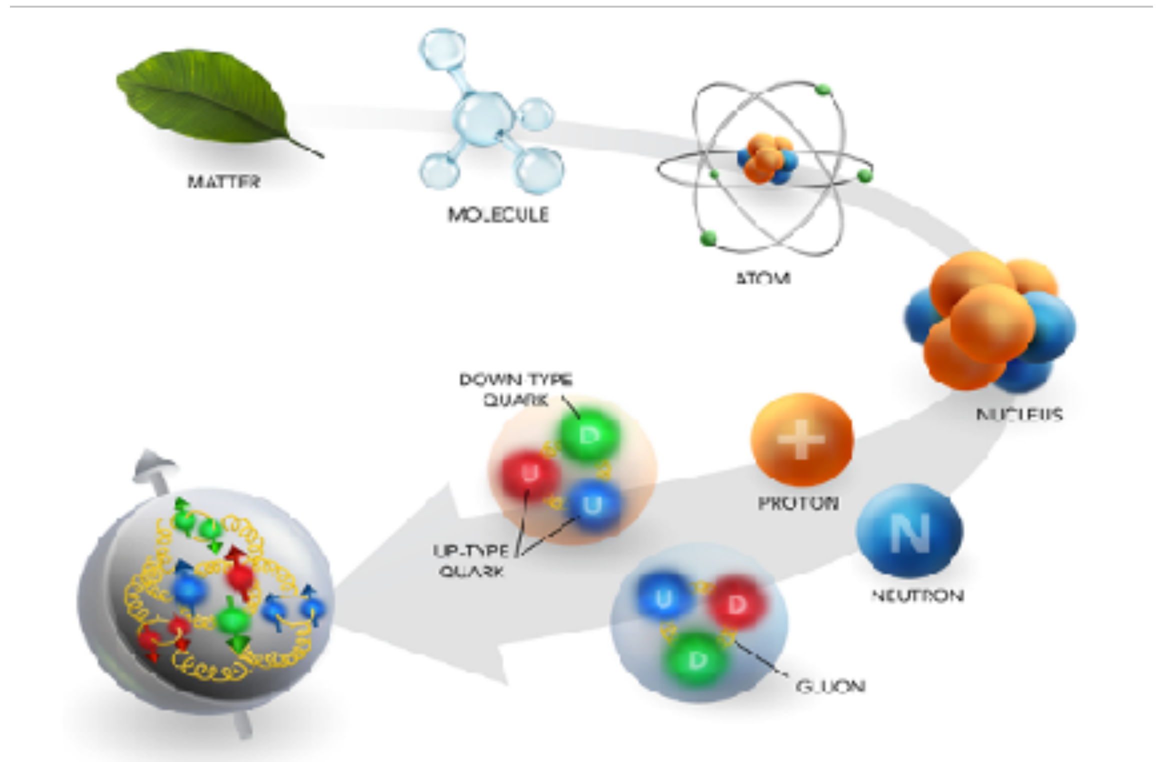


THE SUPERMASSIVE BLACK HOLE AT THE CENTRE OF OUR OWN MILKY WAY GALAXY

Images are great tools for science, they convey important concepts, and they are important for the outreach

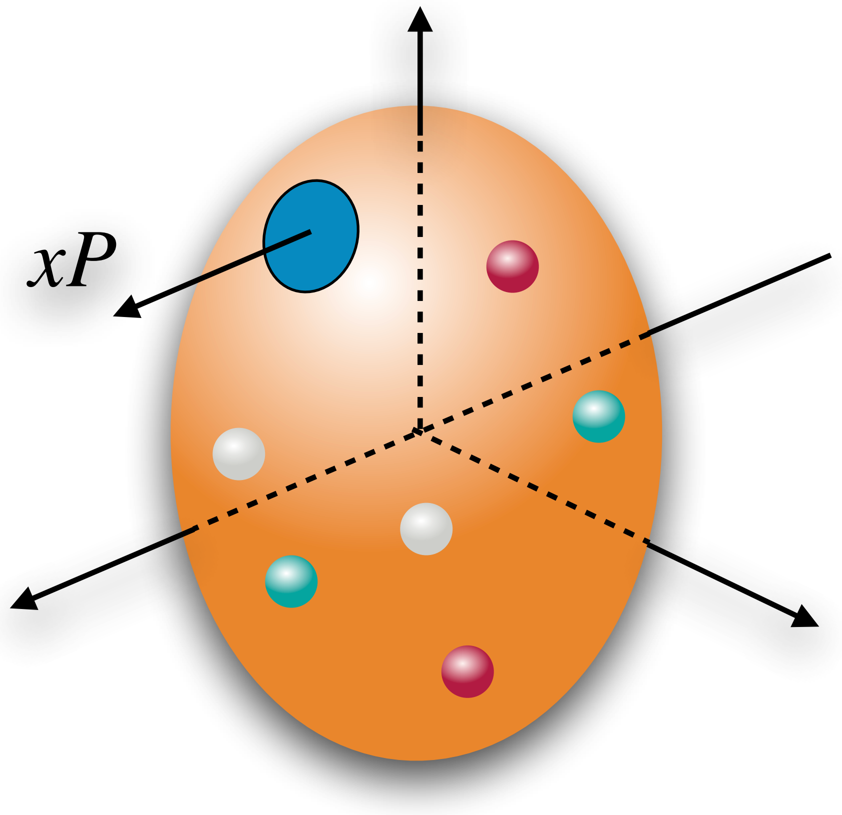
“If the photon ring is not perfectly circular but squashed, that could tell astronomers the black hole’s spin”

UNRAVELLING THE MYSTERIES OF RELATIVISTIC HADRONIC BOUND STATES



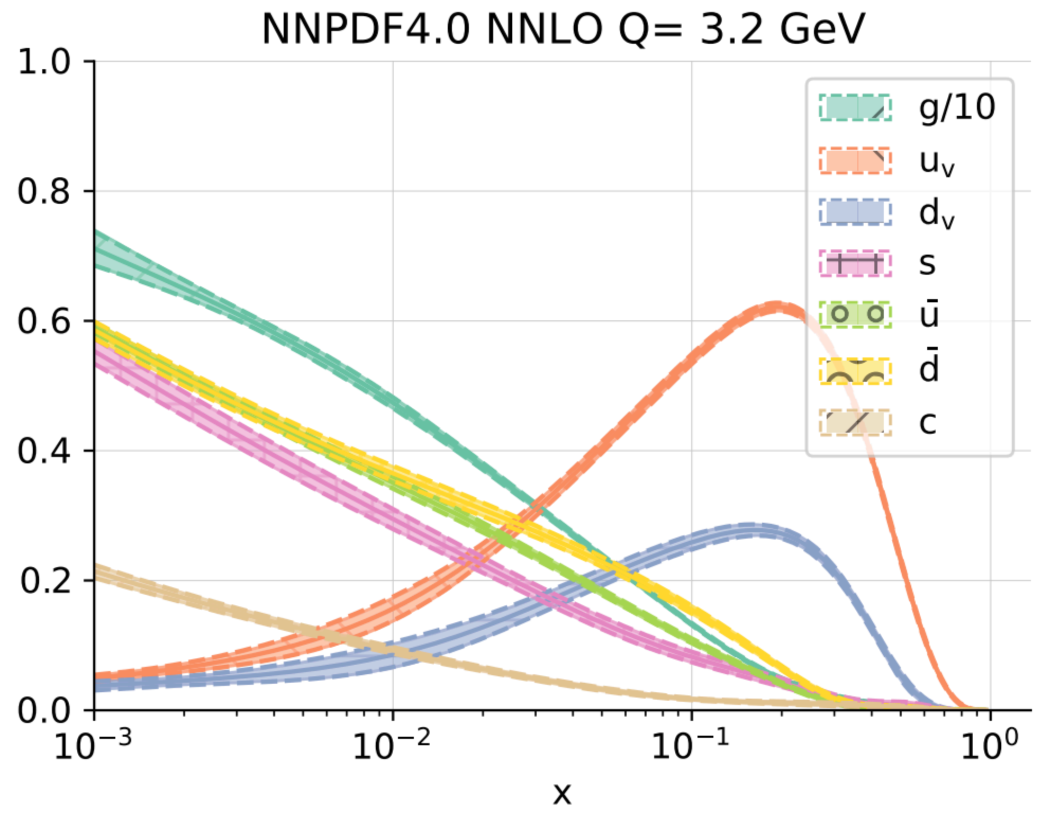
- Nucleons provide 98% of the mass of the visible universe
- One of the goals of the modern nuclear physics is to study details of the structure of the nucleon

Parton Distribution Functions provide a fundamental description of the nucleon in terms of its partonic structure



$$f_{q/P}(x)$$

longitudinal

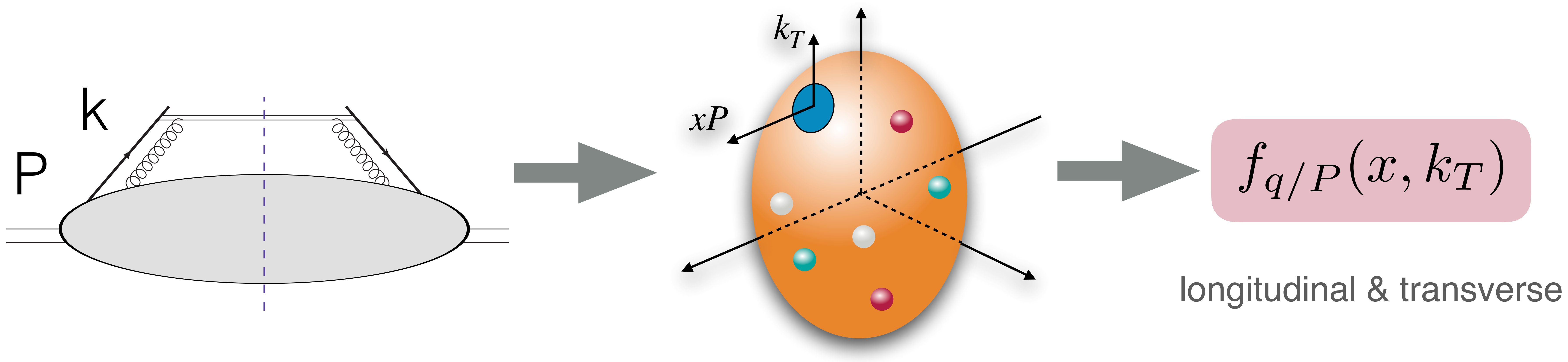


- Probability density to find a quark with a momentum fraction x
- 1D snapshot of fundamental constituents
- Study of confined quarks and gluons

HADRON'S PARTONIC STRUCTURE

To study the physics of the *confined motion of quarks and gluons* inside of the proton one needs a new type of the "hard probe" with two scales.

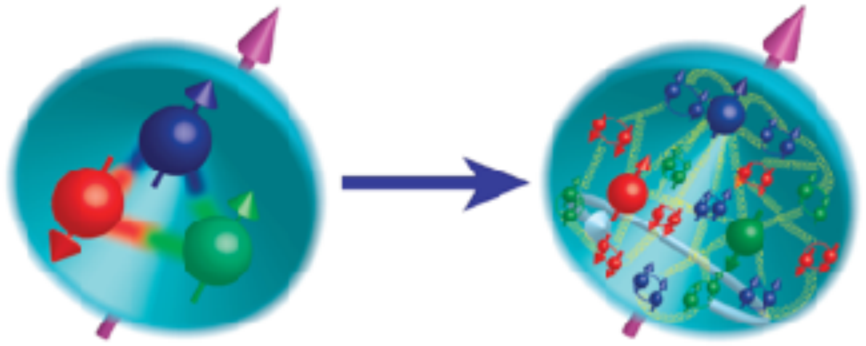
Transverse Momentum Dependent distributions (TMDs)



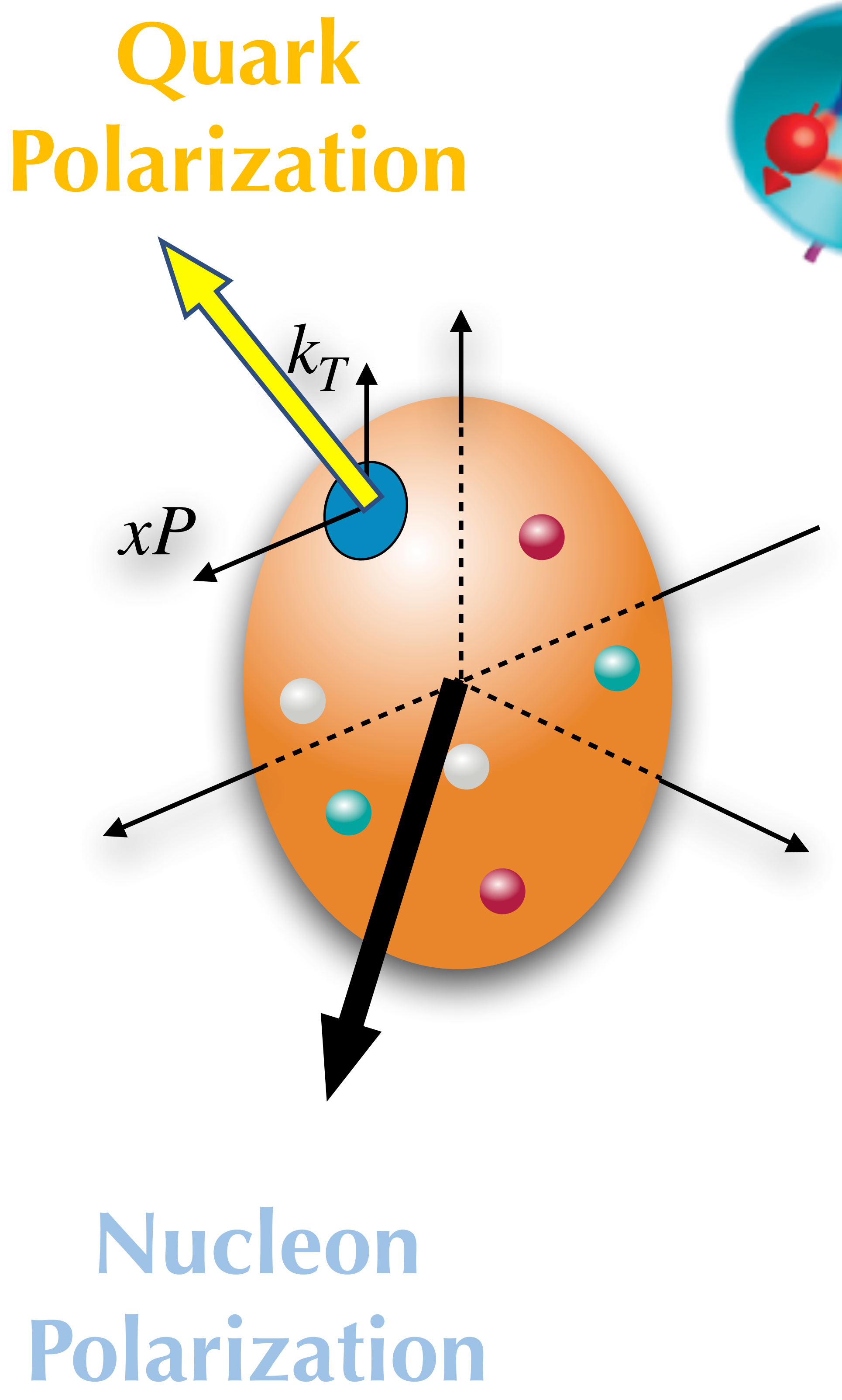
- One large scale (Q) sensitive to particle nature of quark and gluons
- One small scale (k_T) *sensitive to how QCD bounds partons* and to the detailed structure at ~fm distances. The imprint of the confinement mechanism
- TMDs provide detailed information on the spin structure
- TMDs contain new insights, e.g. qgq operators rather that just qq or gg and thus include correlations
- TMDs encode 3D structure in the momentum space (complementary to Generalized Parton Distributions)

TMDs WITH POLARIZATION

- *Our understanding of the hadron evolves:*



Nucleon emerges as a strongly interacting, relativistic bound state of quarks and gluons



Nucleon Polarization		Quark Polarization: Unpolarized (U)	Quark Polarization: Longitudinally Polarized (L)	Quark Polarization: Transversely Polarized (T)
	U	$f_1(x,k_T^2)$ Unpolarized		$h_1^\perp(x,k_T^2)$ Boer-Mulders
	L		$g_1(x,k_T^2)$ Helicity	$h_{1L}^\perp(x,k_T^2)$ Kozinian-Mulders,"worm" gear
	T	$f_{1T}^\perp(x,k_T^2)$ Sivers	$g_{1T}(x,k_T^2)$ Kozinian-Mulders, "worm" gear	$h_1(x,k_T^2)$ Transversity $h_{1T}^\perp(x,k_T^2)$ Pretzelosity

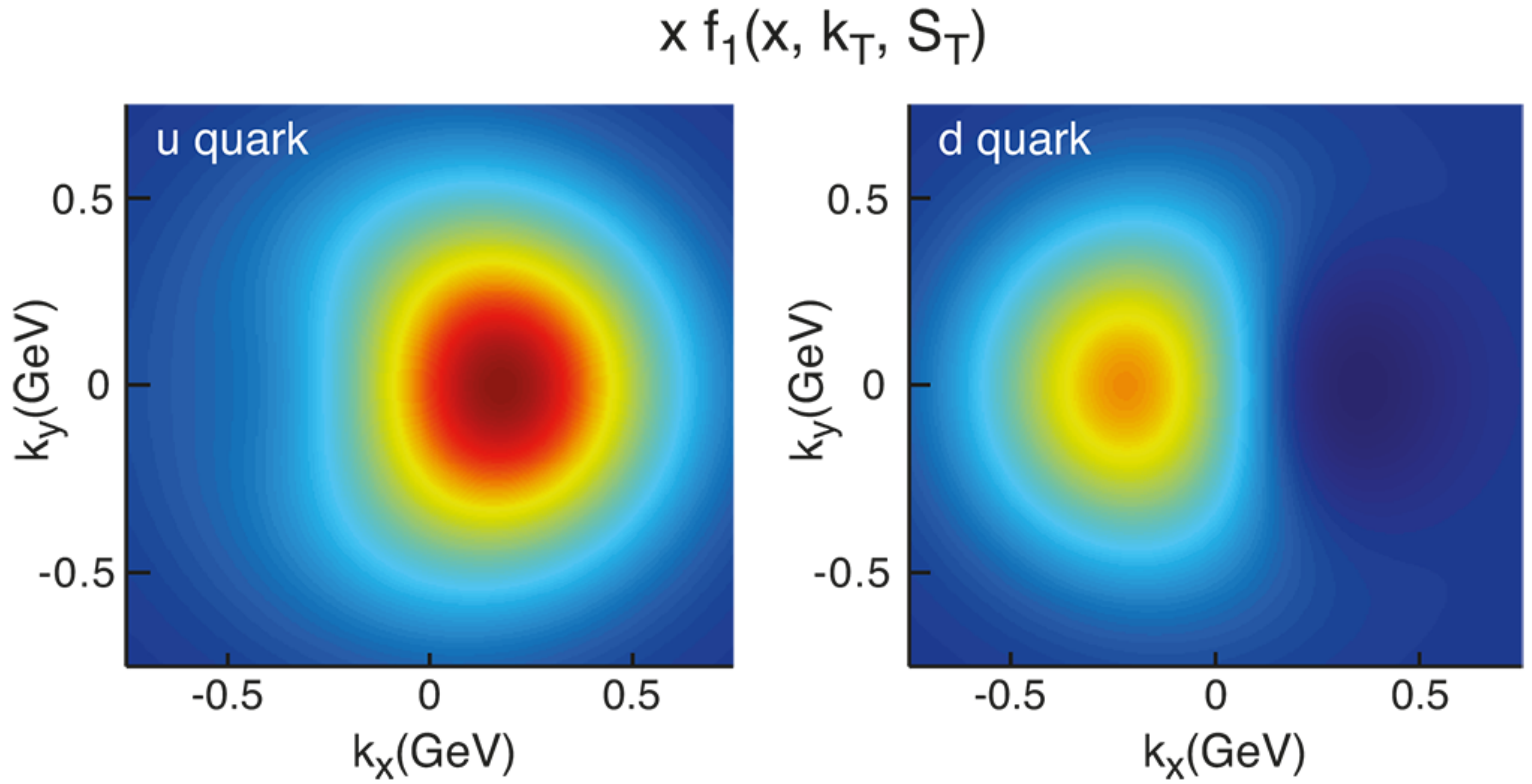
Analogous tables for:

- Gluons $f_1 \to f_1^g$ etc
- Fragmentation functions
- Nuclear targets $S \neq \frac{1}{2}$

SIVERS FUNCTION

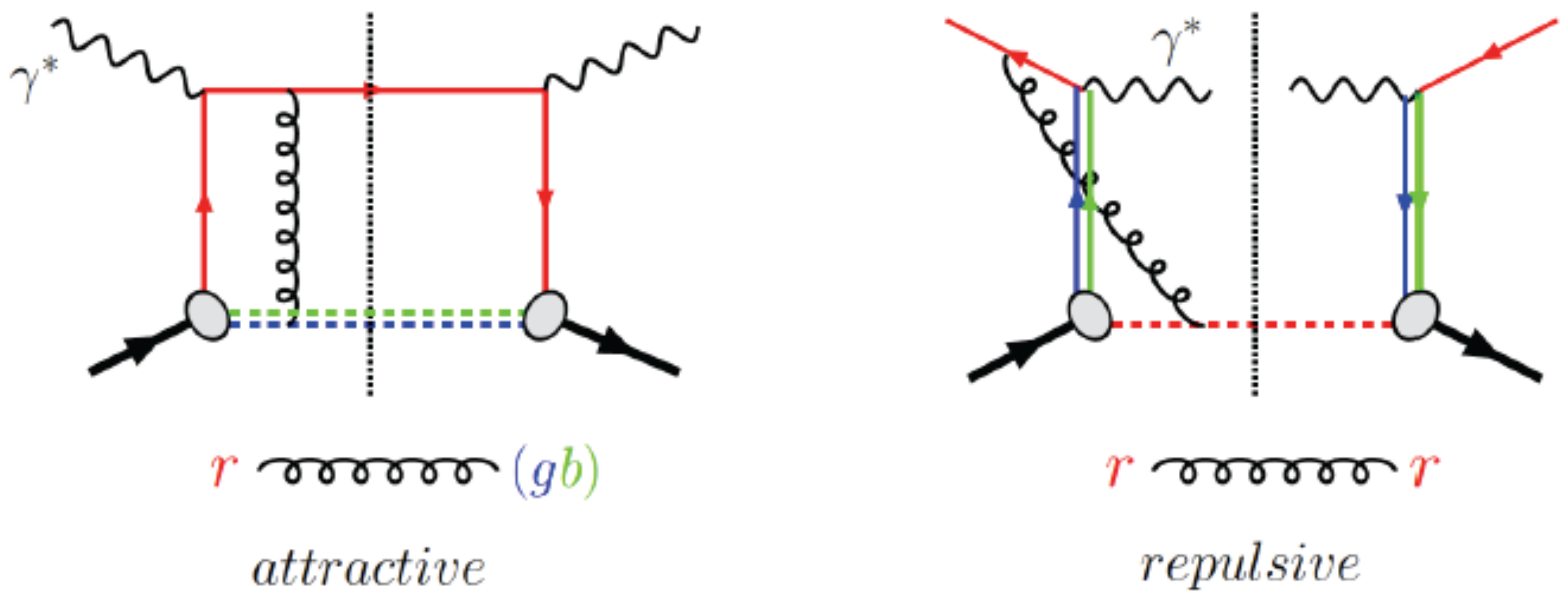
- Describes unpolarized quarks inside of the transversely polarized nucleon
- Encodes correlation of the orbital motion with the spin

Sivers (1991)



AP (2010)

- The sign change of the Sivers function is a fundamental consequence of QCD



Brodsky, Hwang, Schmidt (2002), Collins (2002)

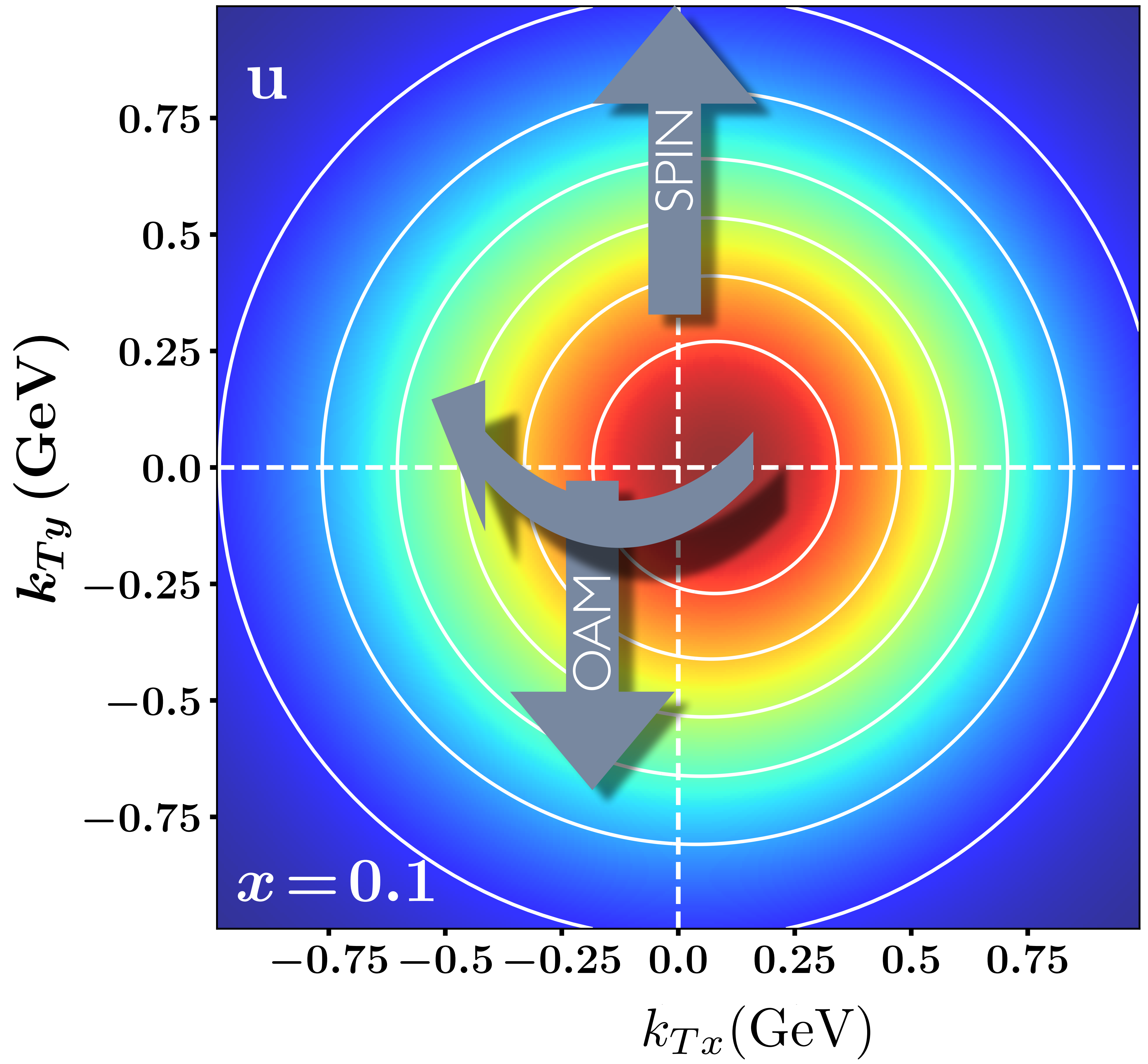
$$f_{1T}^{\perp SIDIS} = -f_{1T}^{\perp DY}$$

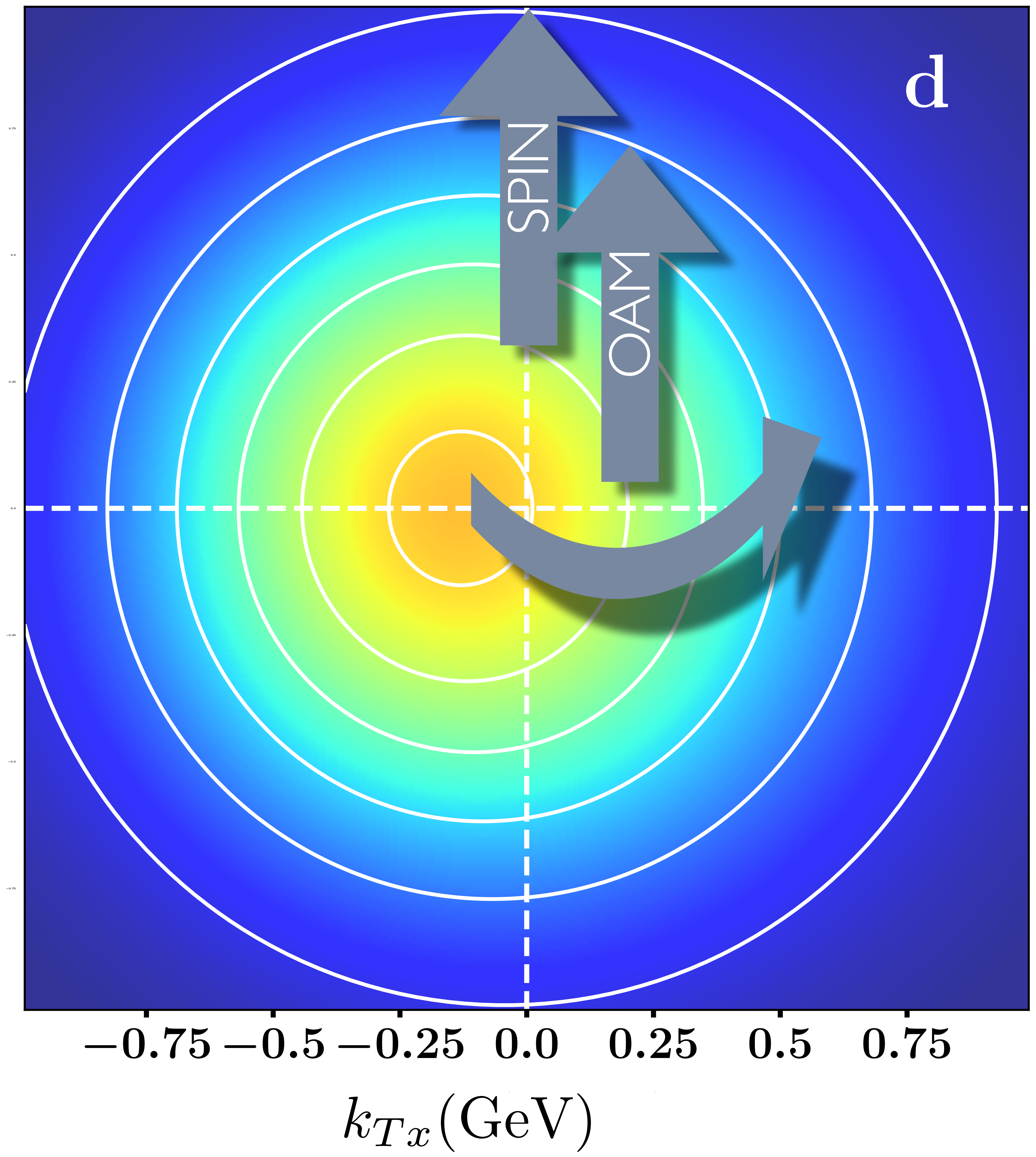
NUCLEON TOMOGRAPHY

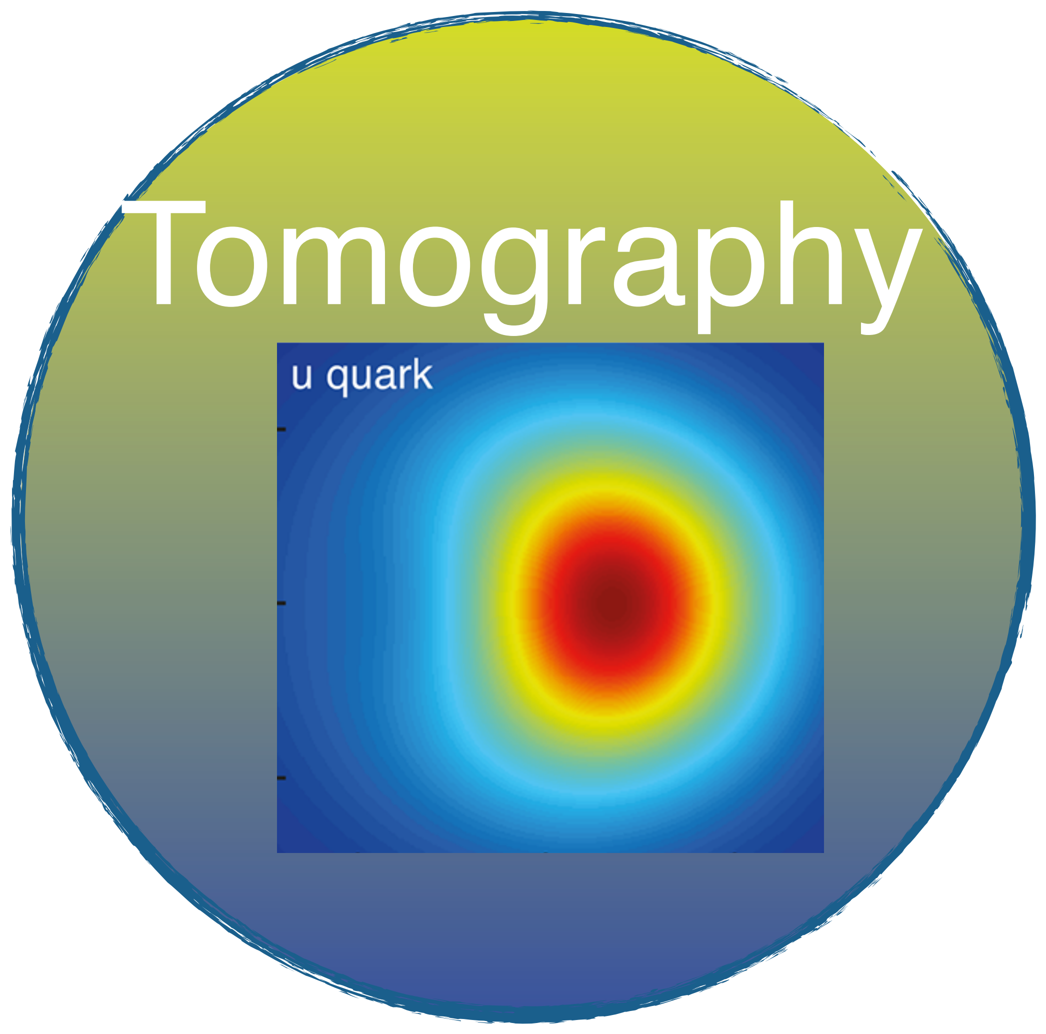
$$\rho_{1;q\leftarrow h^\uparrow}(x,\boldsymbol{k}_T,\boldsymbol{S}_T,\mu) = f_{1;q\leftarrow h}(x,k_T;\mu,\mu^2) - \frac{k_{Tx}}{M} f^{\perp}_{1T;q\leftarrow h}(x,k_T;\mu,\mu^2)$$

JAM20: Cammarota et al, Phys.Rev.D 102 (2020) 5, 05400 (2020)

M. Burkardt, Nucl.Phys.A 735 (2004)





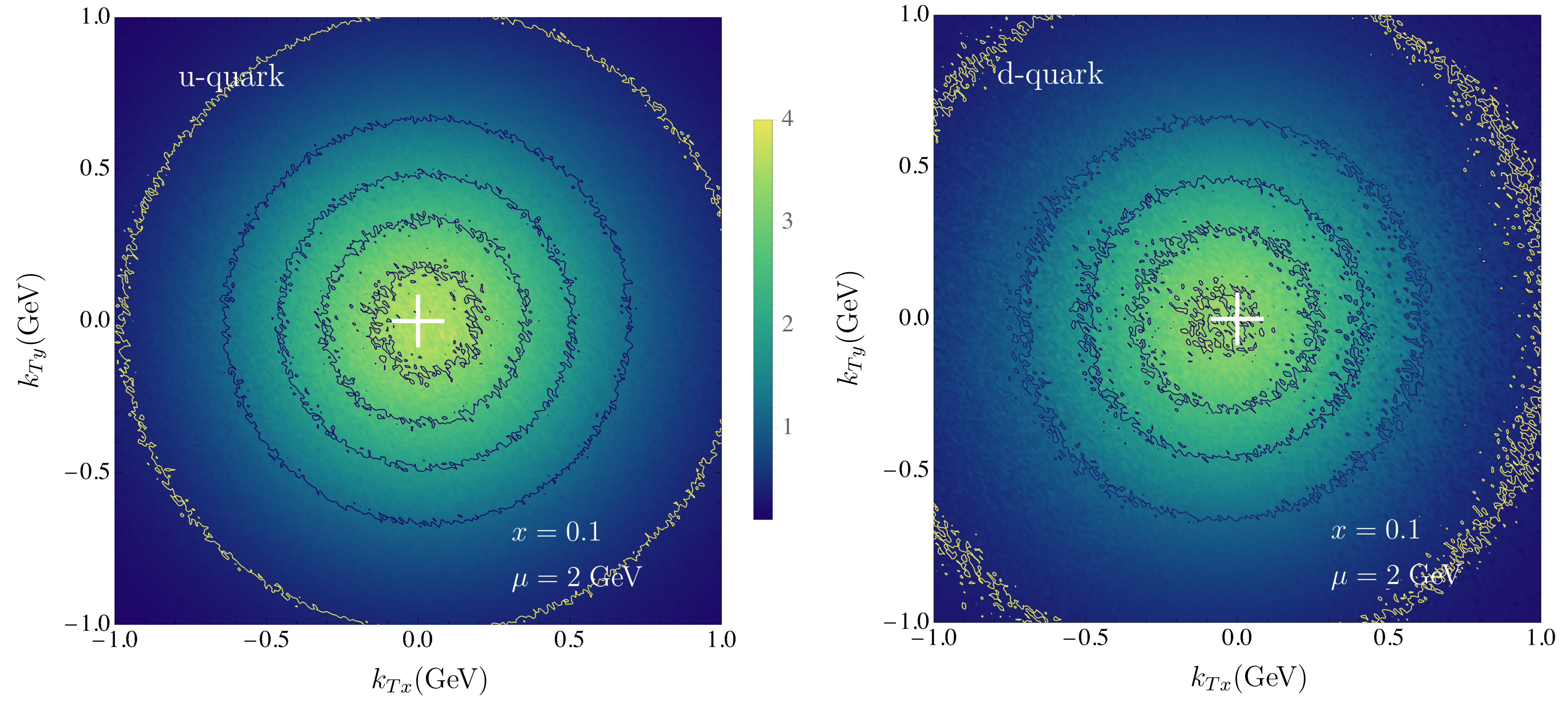


Caveat: no $\vec{r}$ is available to determine the OAM

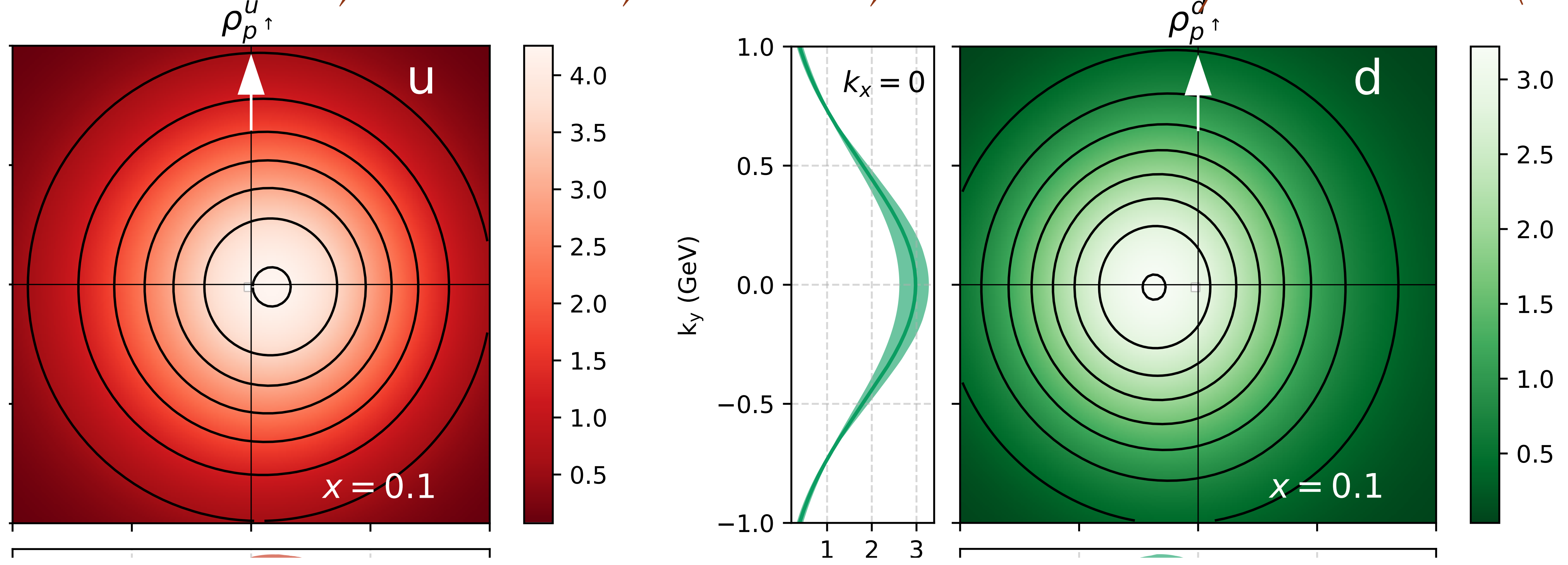
NUCLEON TOMOGRAPHY

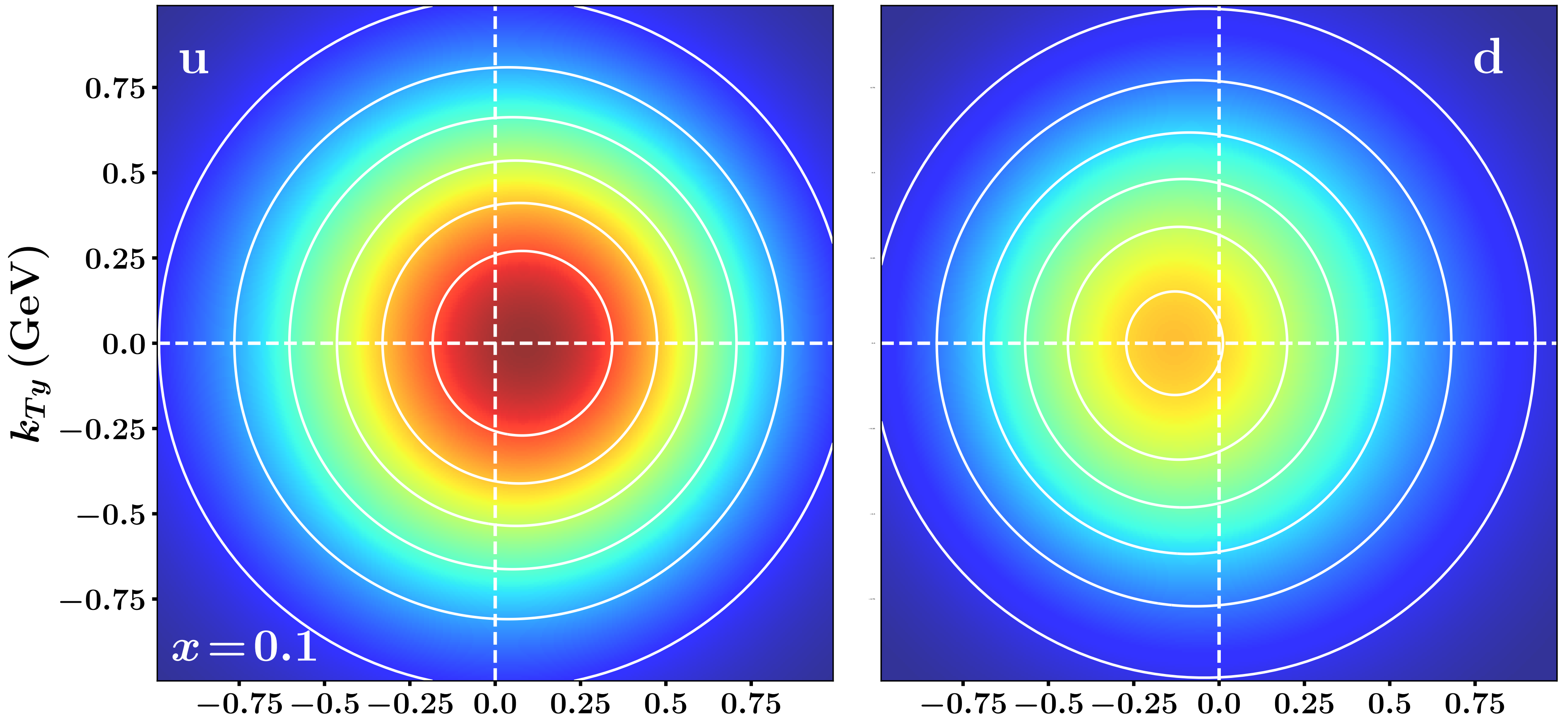
$$\rho_{1;q\leftarrow h^\uparrow}(x,\boldsymbol{k}_T,\boldsymbol{S}_T,\mu) = f_{1;q\leftarrow h}(x,k_T;\mu,\mu^2) - \frac{k_{Tx}}{M} f_{1T;q\leftarrow h}^{\perp}(x,k_T;\mu,\mu^2)$$

M. Bury, A. Prokudin, A. Vladimirov, Phys.Rev.Lett. 126 (2021)



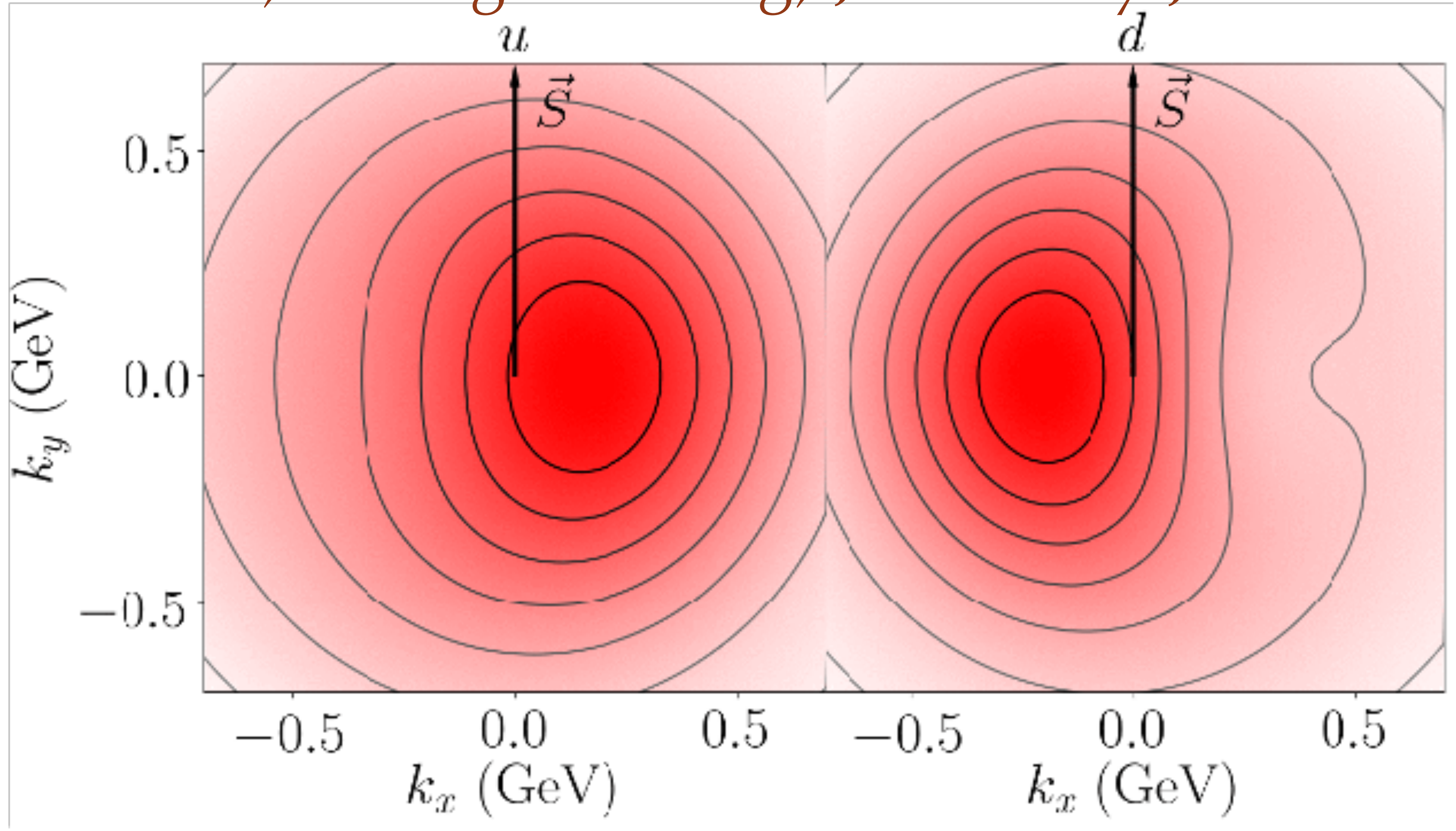
A. Bacchetta, F. Delcarro, C. Pisano, M. Radici Phys.Lett.B 827 (2020)





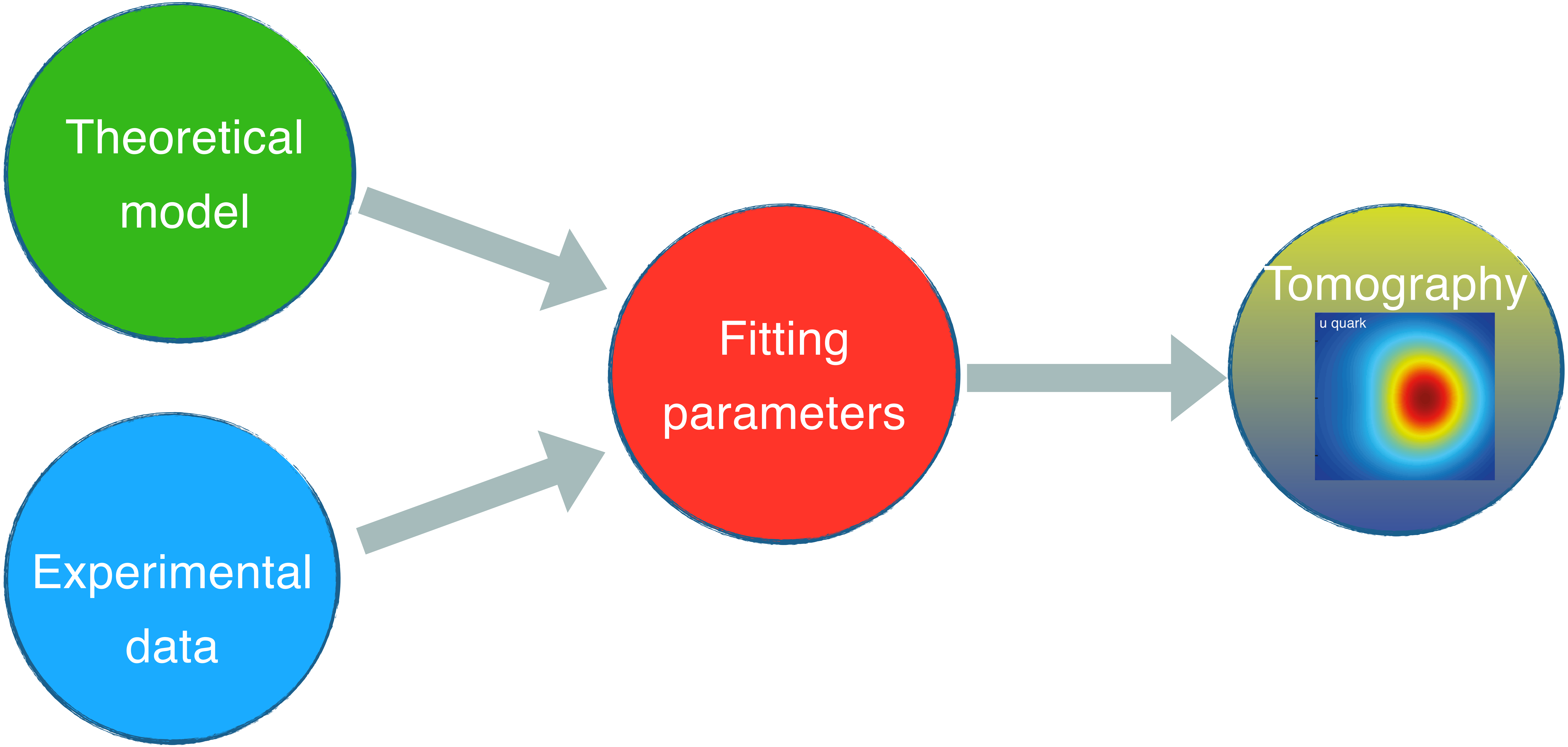
JAM20: Cammarota et al, Phys.Rev.D 102 (2020) 5, 05400 (2020)

Miguel G. Echevarria, Zhong-Bo Kang, John Terry JHEP 01 (2021) 126



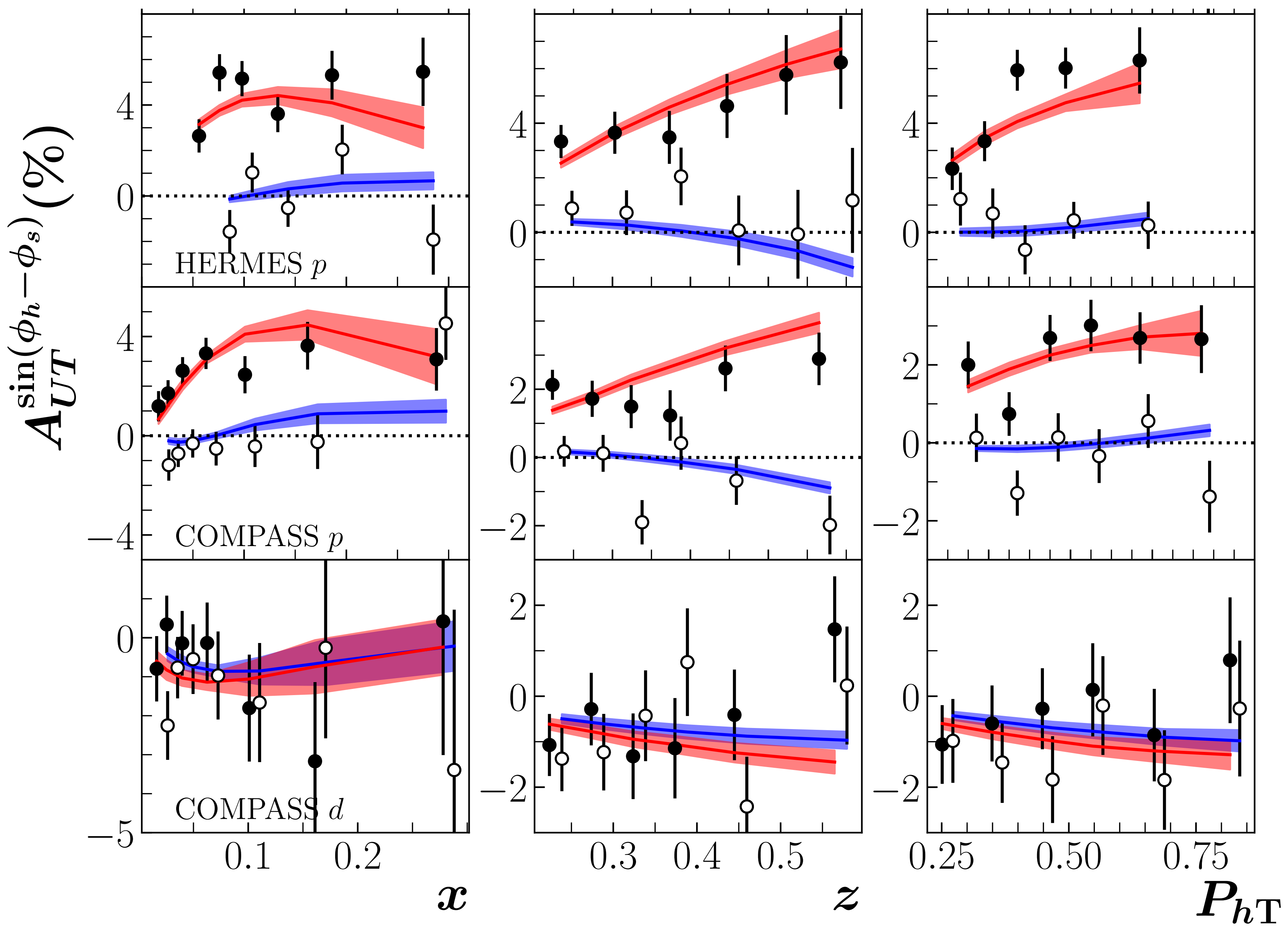
- The shift in the transverse plane is generated by the Sivers function
- The opposite signs of the shift are consistent with the lattice QCD findings on the opposite signs of the OAM for u and d quarks

DATA ANALYSIS – HOW TRADITIONALLY WE DO IT



DATA ANALYSIS – RESULTS

Sivers asymmetry



JAM20: Cammarota et al, Phys.Rev.D 102 (2020) 5, 05400 (2020)

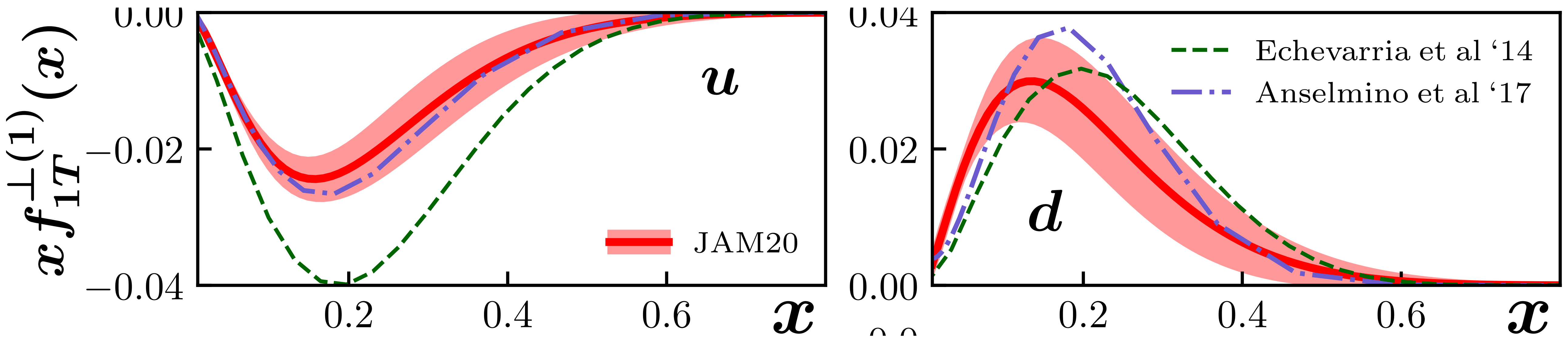
Experimental data

$$F^q(x) = \frac{N_q\, x^{a_q} (1-x)^{b_q} \left(1 + \gamma_q\, x^{\alpha_q} (1-x)^{\beta_q}\right)}{\mathrm{B}[a_q+2, b_q+1] + \gamma_q \mathrm{B}[a_q+\alpha_q+2, b_q+\beta_q+1]}$$

Theoretical model

$$\frac{\chi^2}{npoints} = \frac{85.4}{88} = 0.97$$

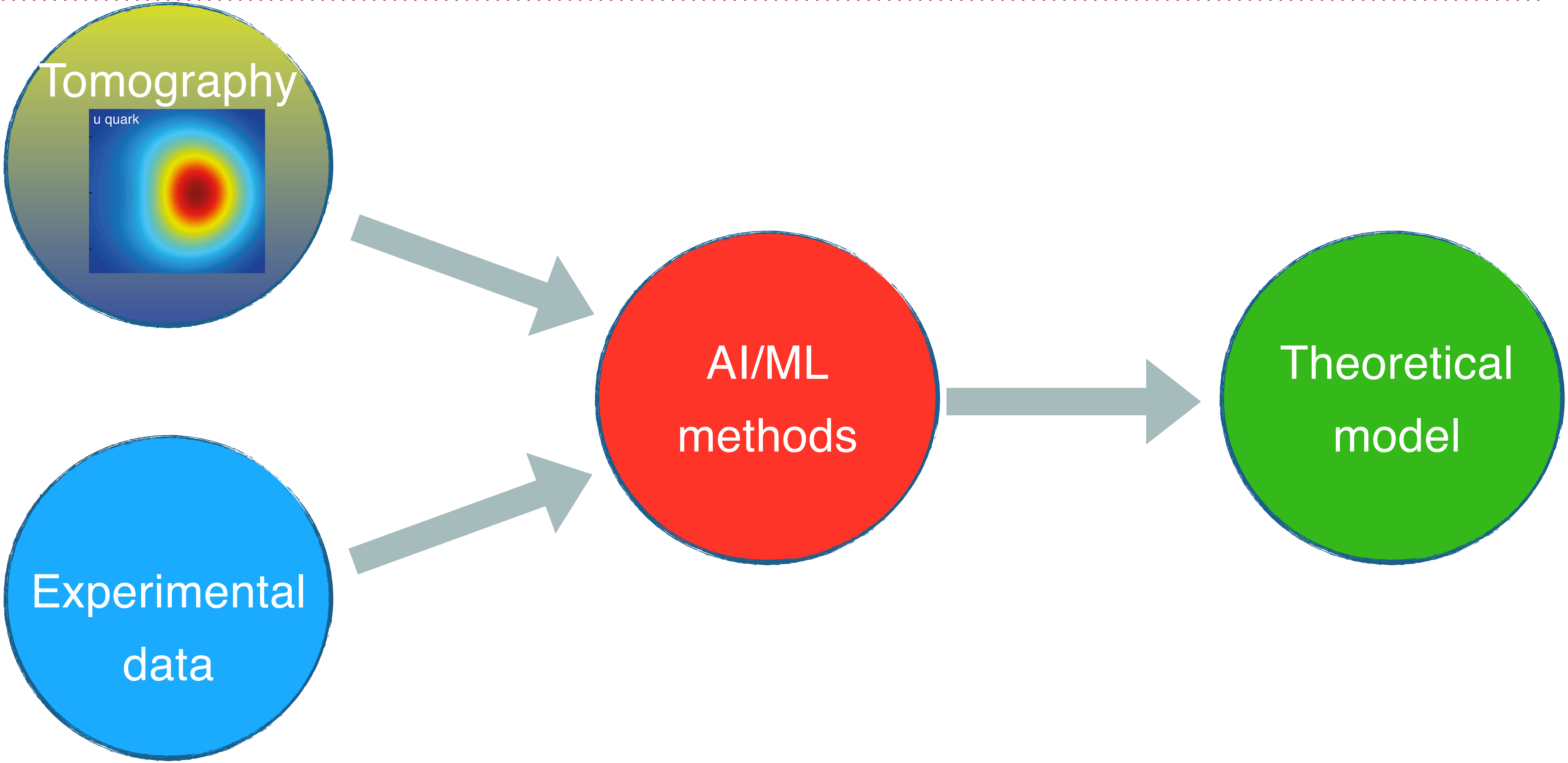
Fitting parameters



Sivers function

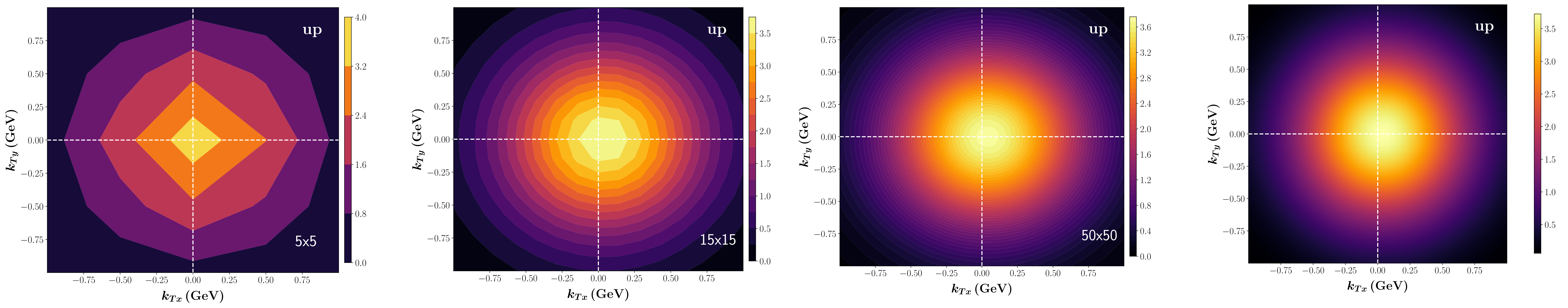
$$f_{1T}^{\perp(1)}(x)$$

DATA ANALYSIS – THE NEW WAY



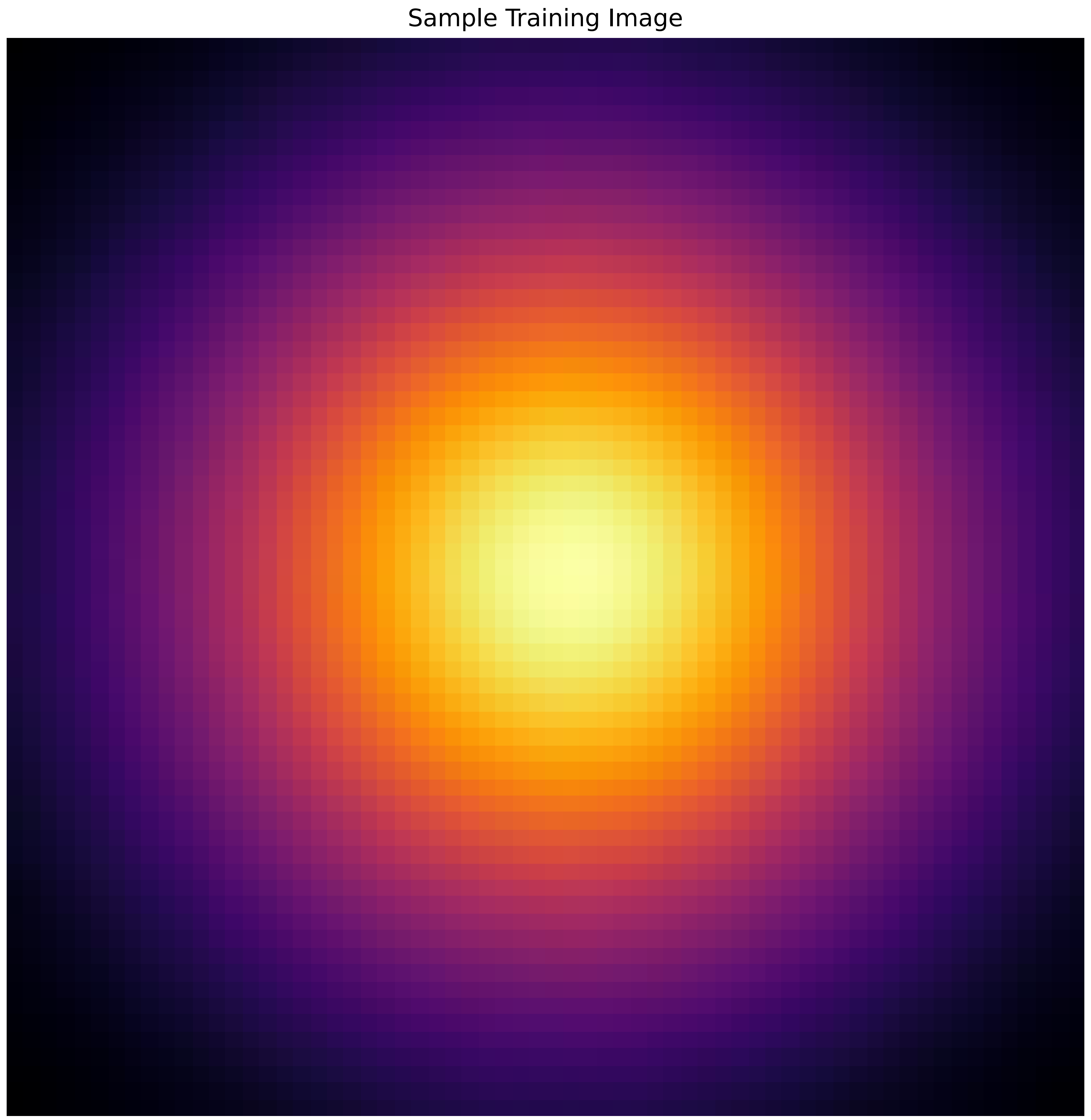
WHY DO WE WANT IT?

- We would like to not know how fuzzy the image is and what impact new measurements will have on it.
- We would like to harness rapidly evolving methods of the Artificial Intelligence and Machine Learning
- We would like to contribute to fostering new generations of nuclear scientists and of the digital literate workforce
- Last but not least, we would like to open new avenues of studies of the nucleon structure



PRELIMINARY STUDIES

- A slice of the Sivers function at $x = 0.1,\ Q^2 = 10\ (\mathrm{GeV}^2)$ as a function of k_{Tx}, k_{Ty}
- Use google colab or jupyter hub at Jefferson Lab, PyTorch [Paszke et al., 2019]
- Tomographic scans of the nucleon with a particular pixelization, 64x64
- Reproduce the tomographic scans using two ML models: GAN, Normalizing flow



GENERATIVE ADVERSARIAL NETWORKS (GANS)

I. Goodfellow et al (2014)

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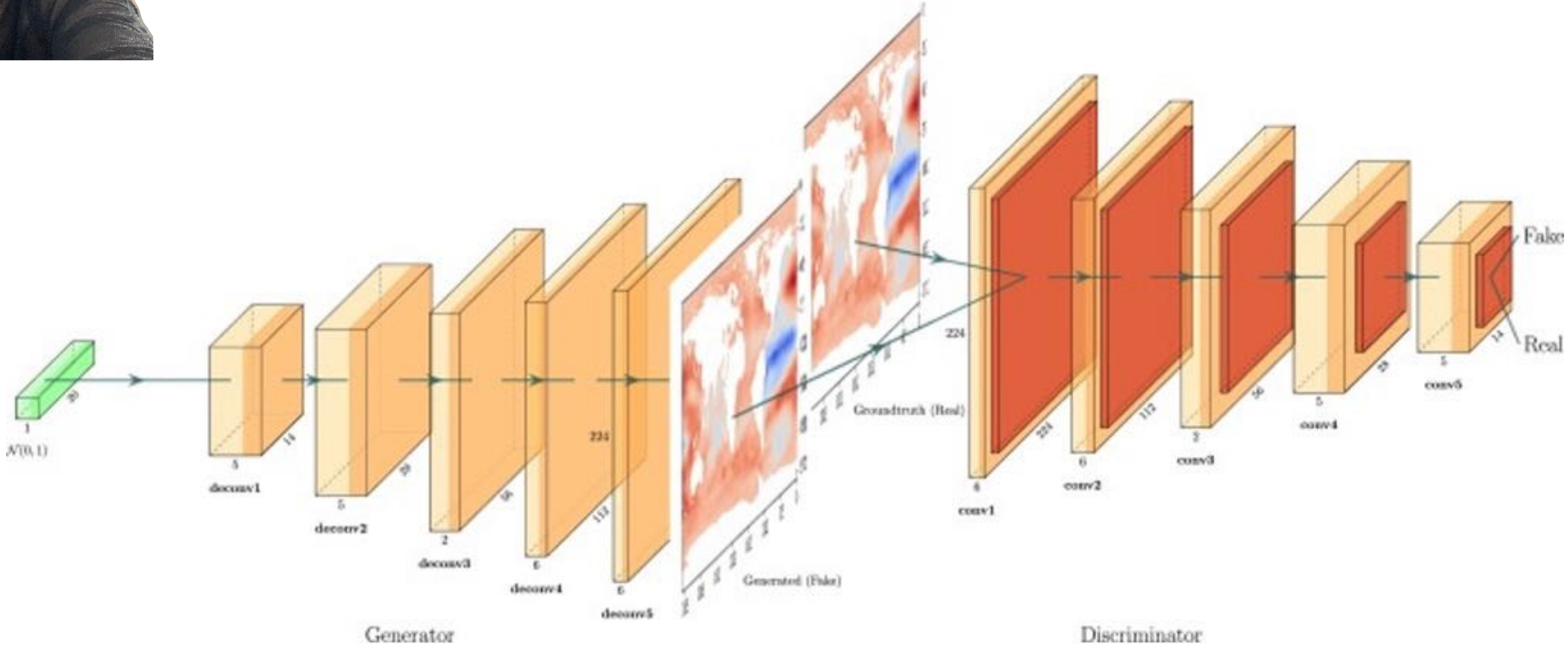
https://pytorch.org/tutorials/beginner/dcgan_faces_tutorial.html

https://github.com/pytorch/examples/blob/main/dcgan/main.py



GENERATIVE ADVERSARIAL NETWORKS (GANS)

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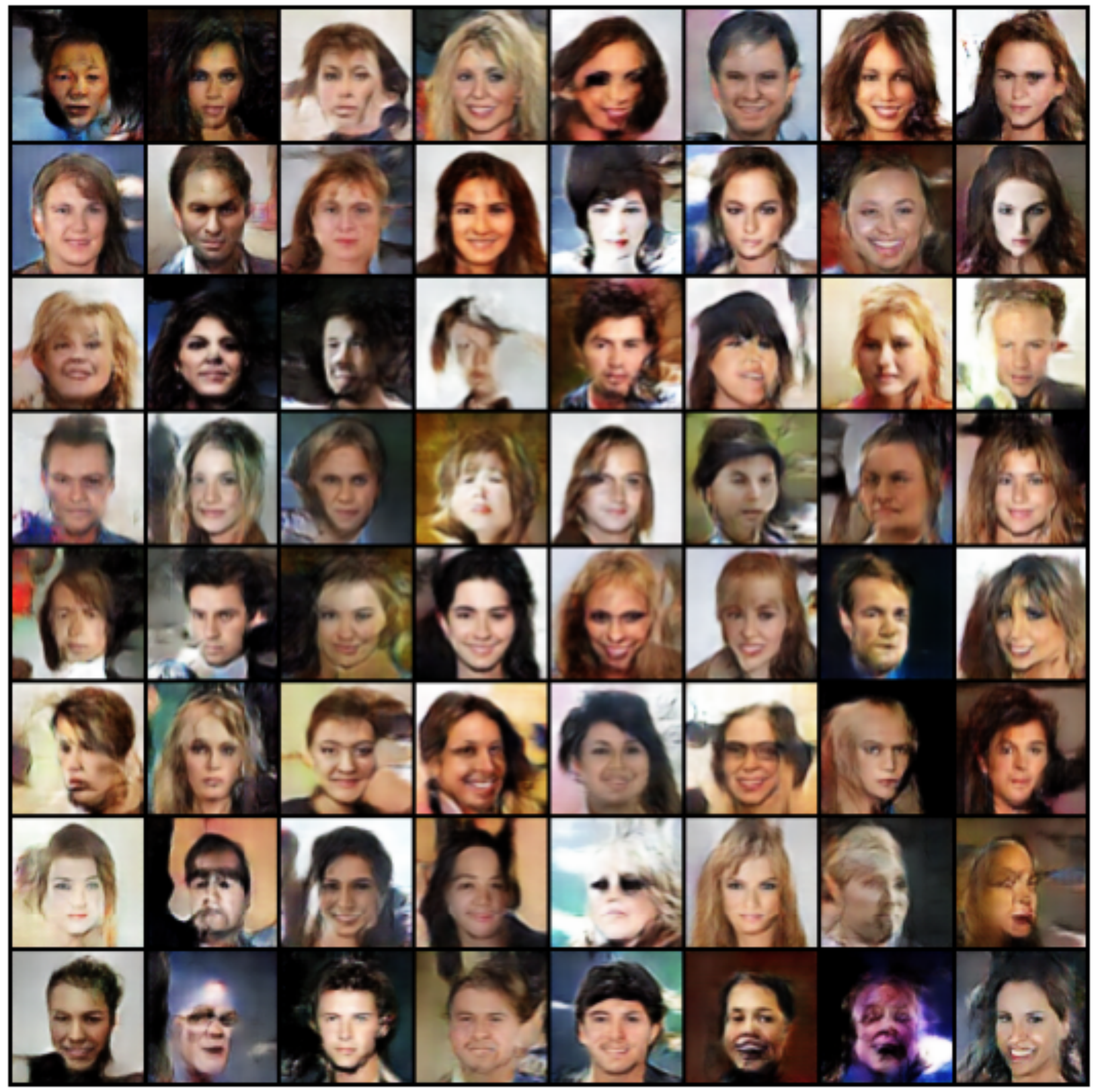
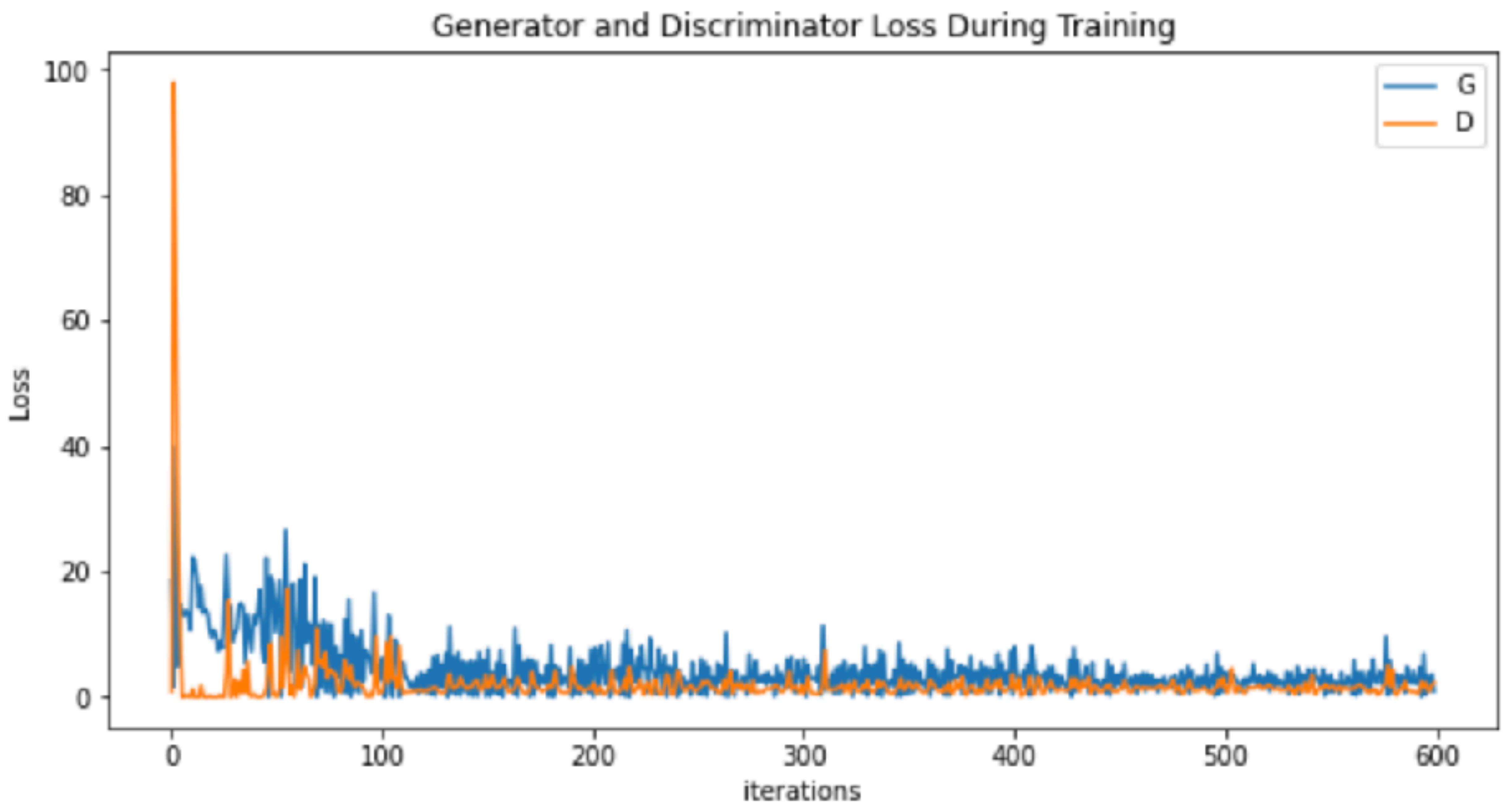
Real Images

Fake Images



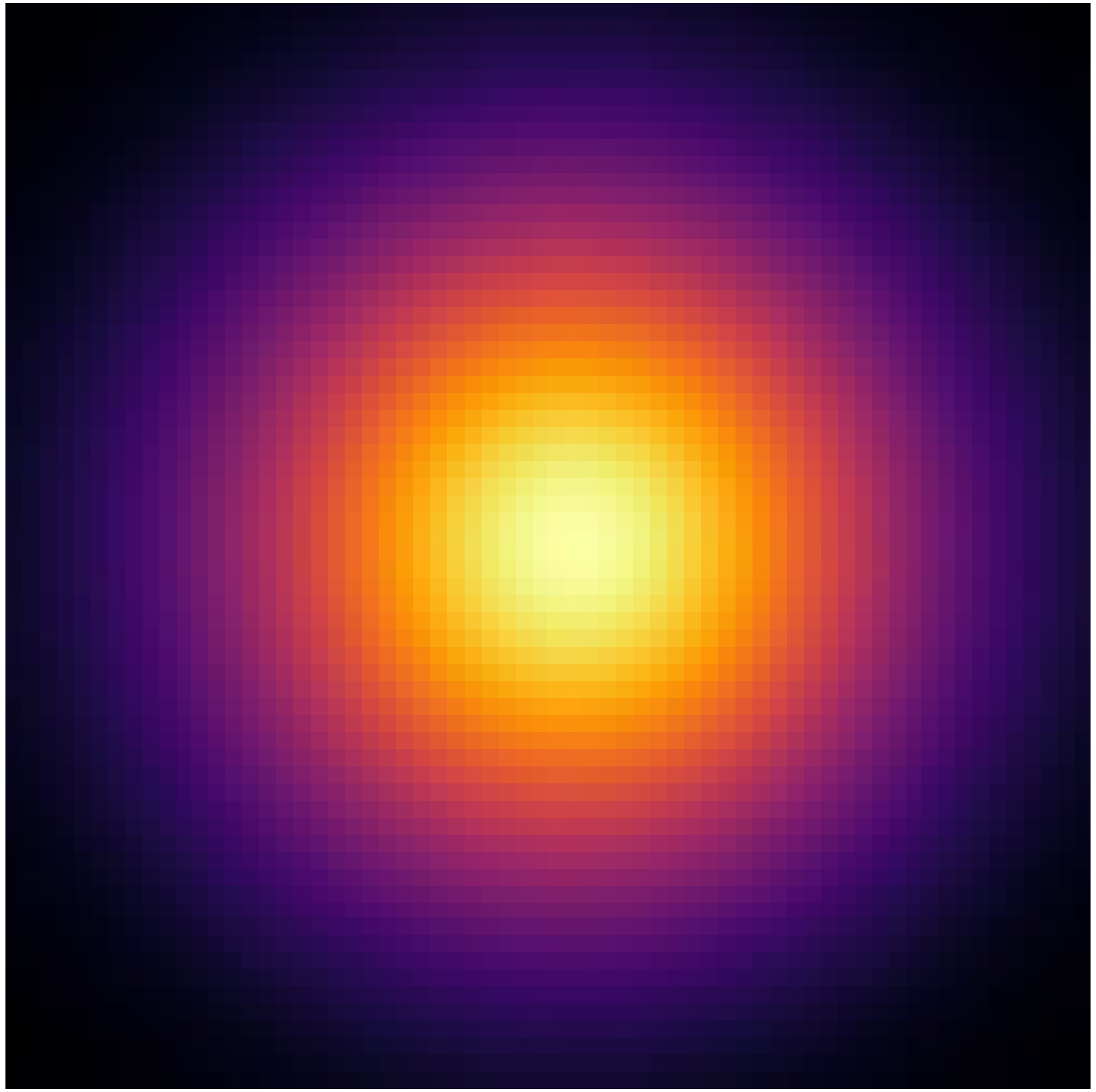
SET UP

- 465 replicas of the images
- Generator and discriminator, both 4 hidden layers
- Binary Cross Entropy as the loss function (very naive as we have only one class of images)
- Training for 600 epochs with no early stopping



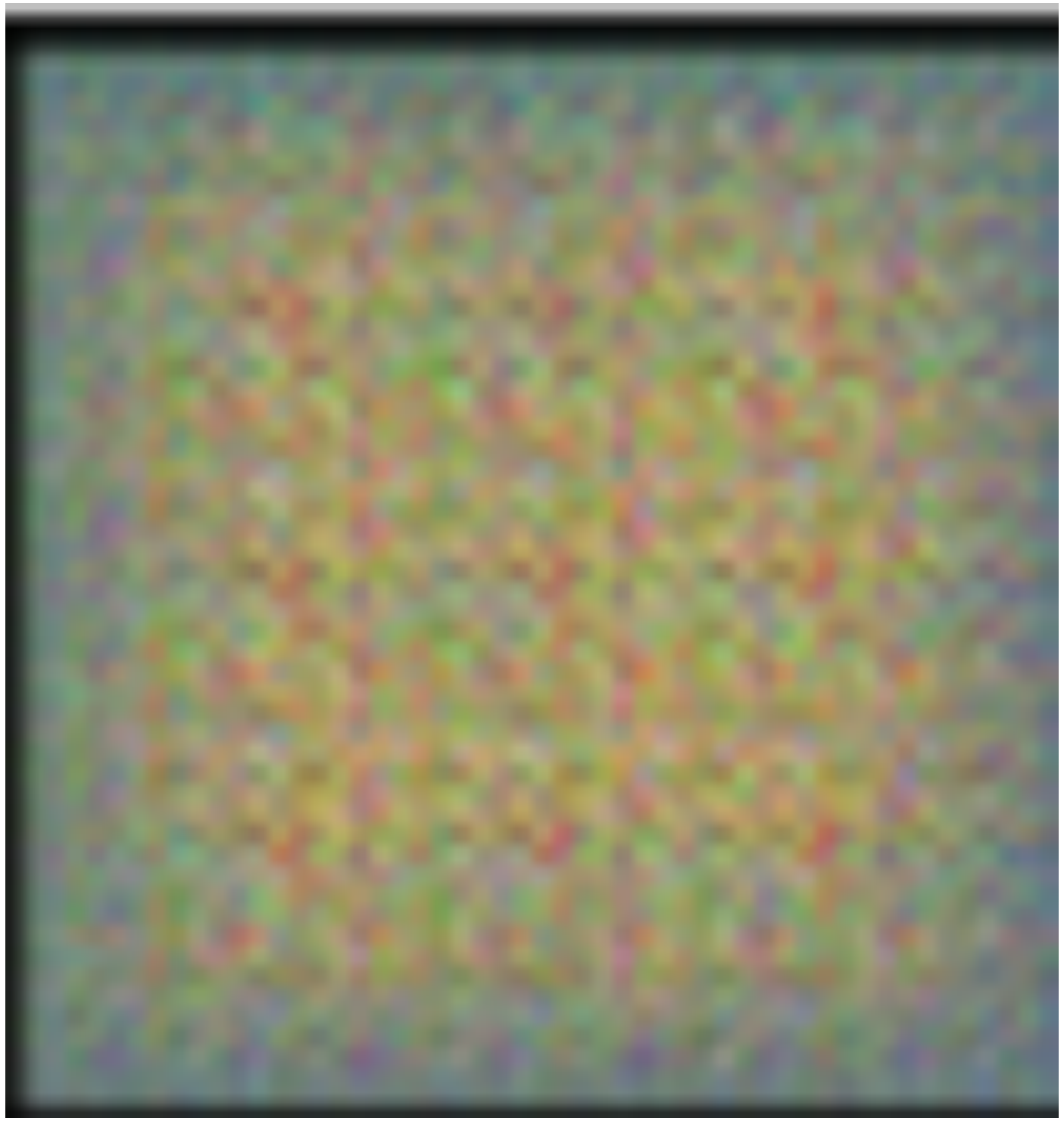
RESULTS

Real Images



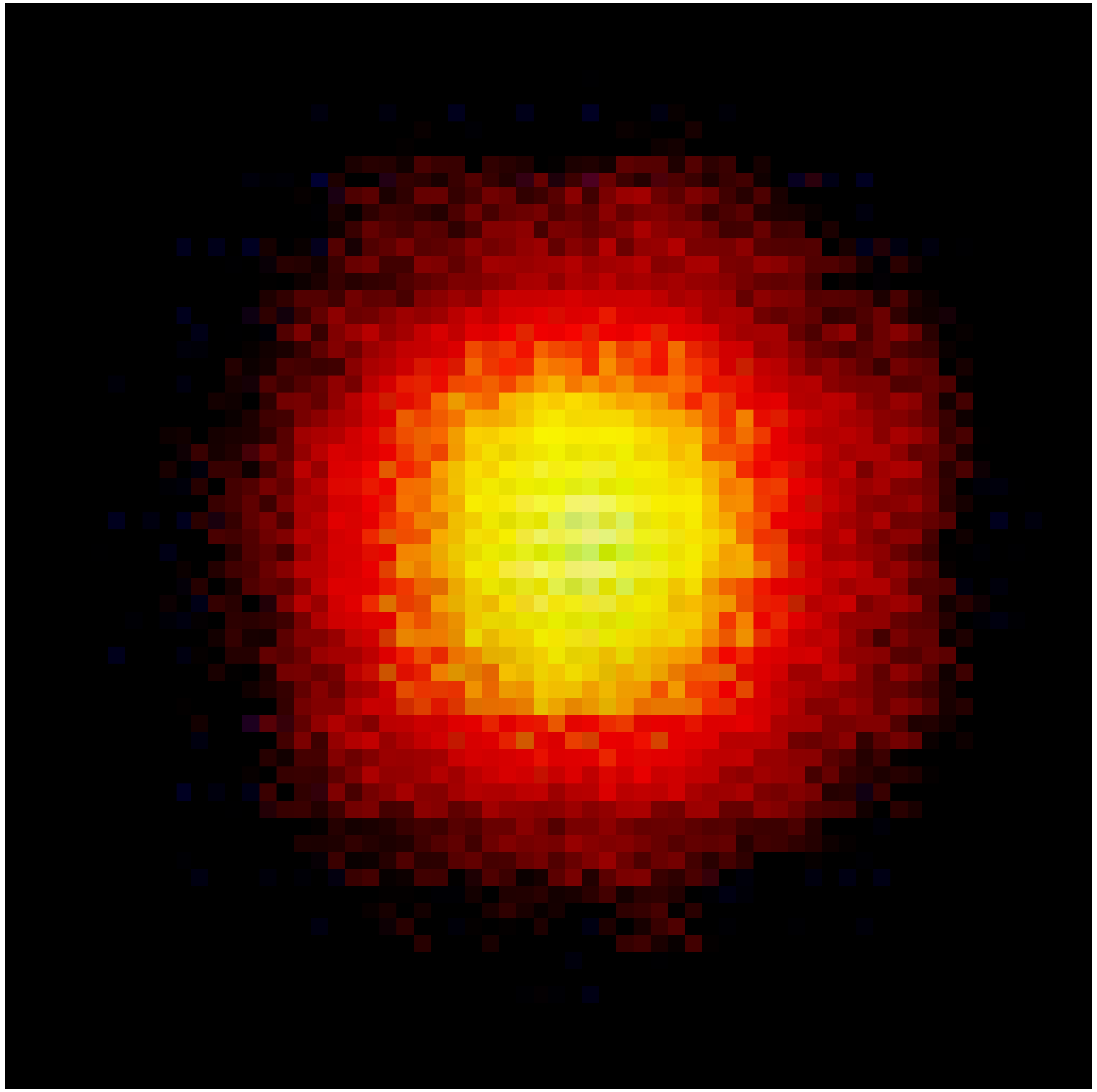
RESULTS

Noise

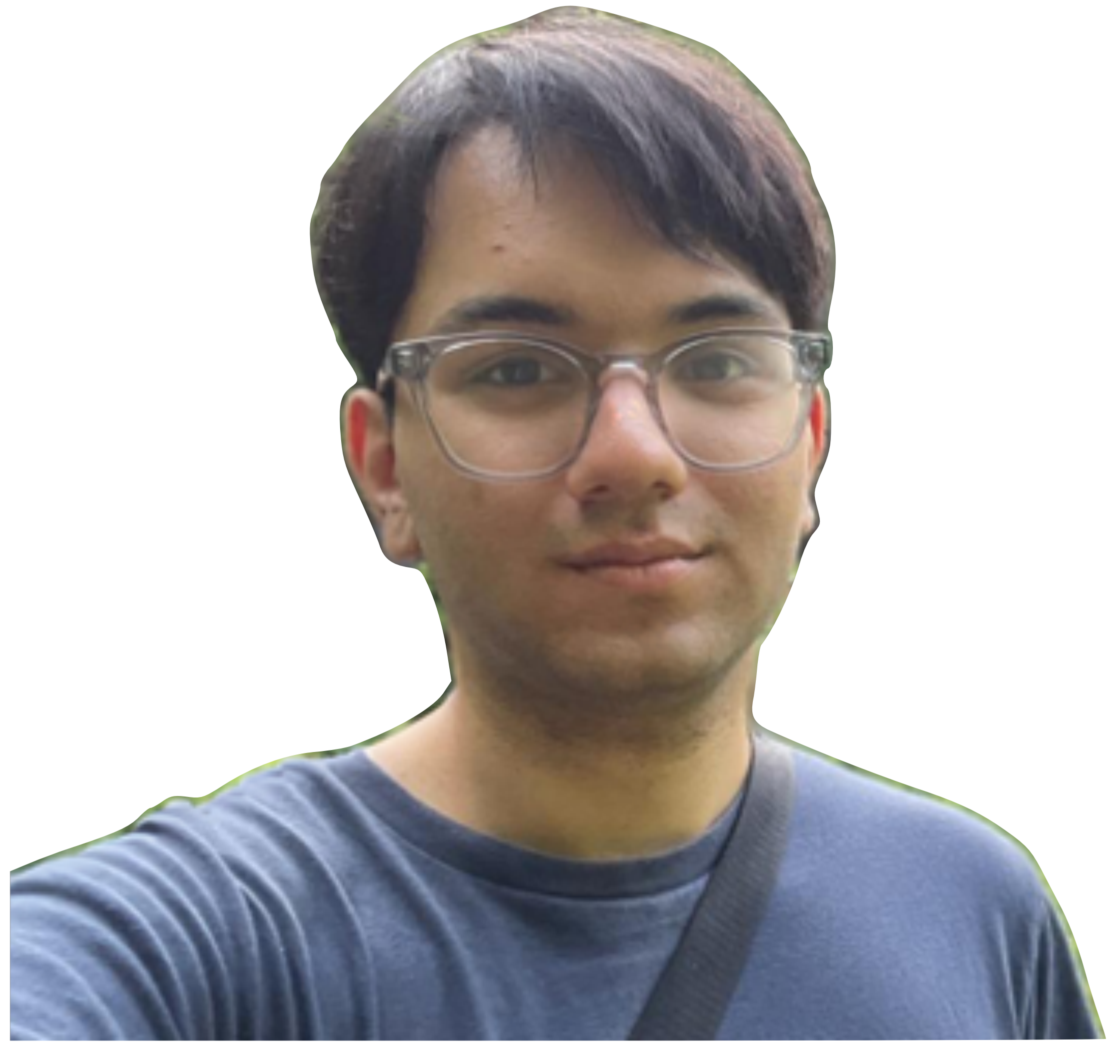


Training

Generated image



NORMALIZING FLOW



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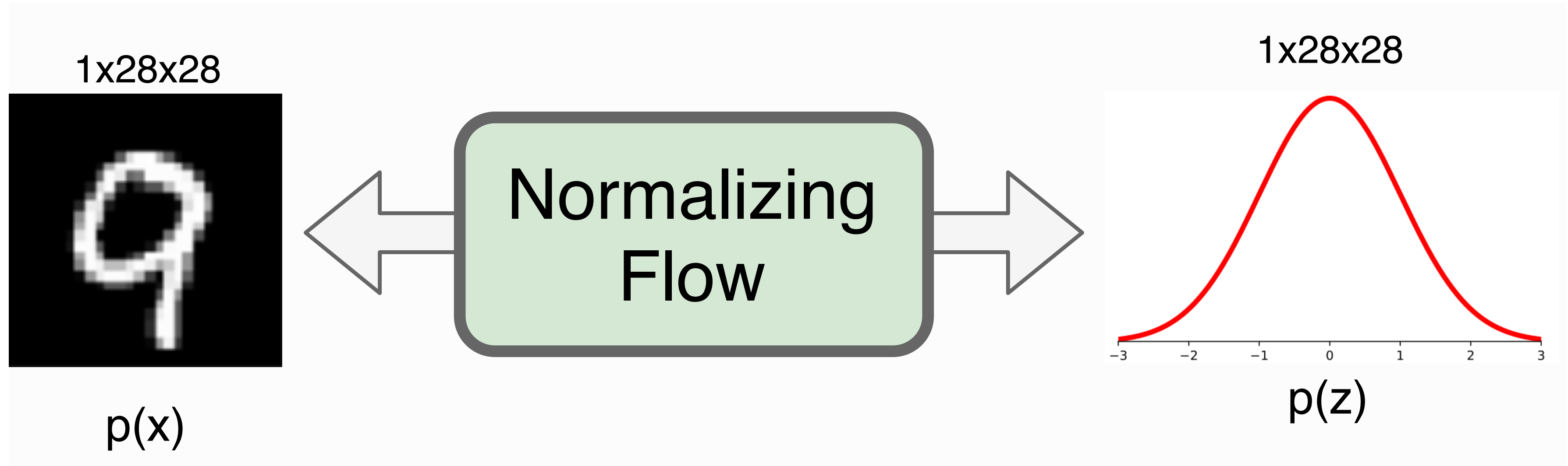
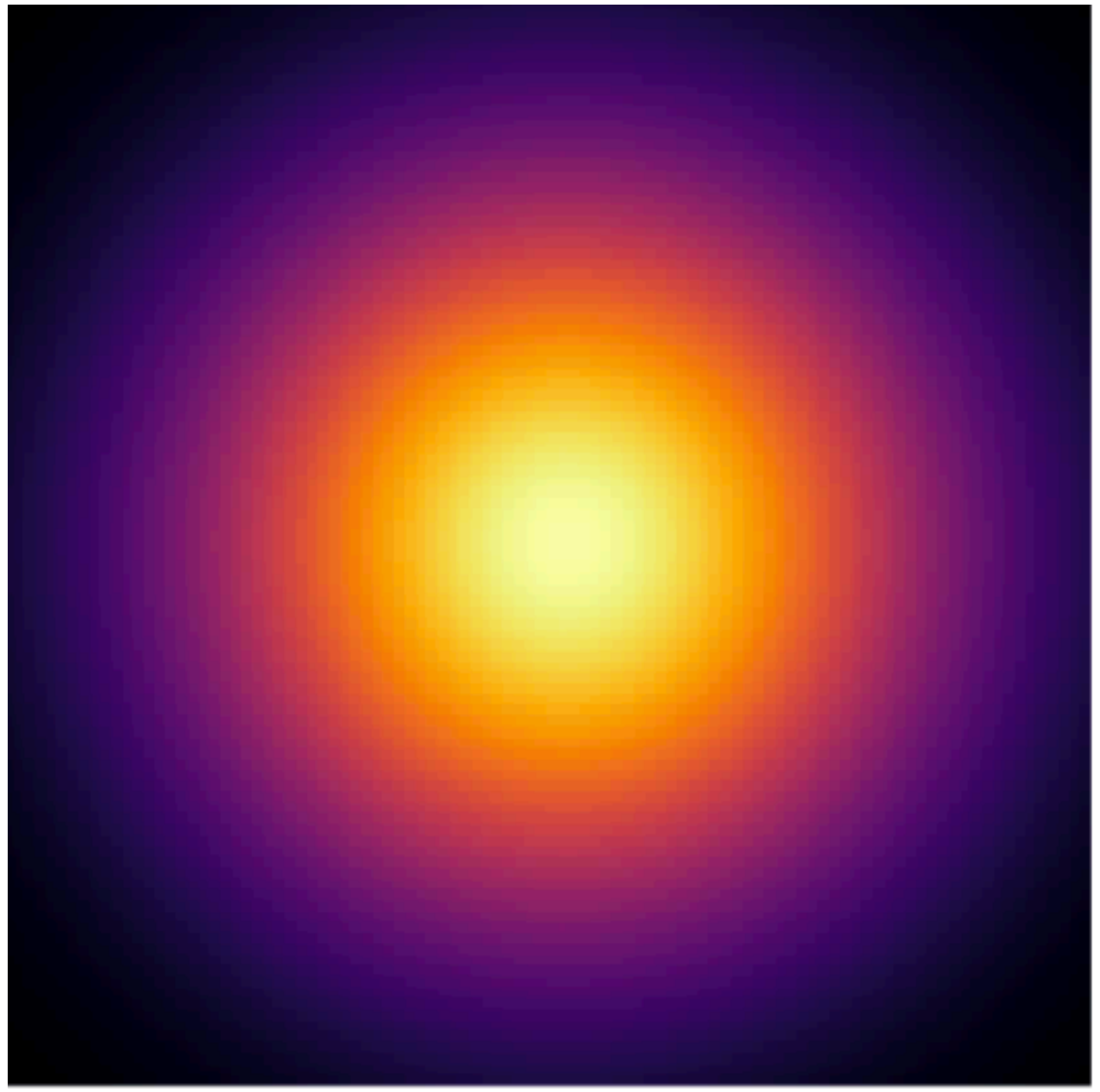
normflows: V. Stimper et al https://arxiv.org/pdf/2302.12014

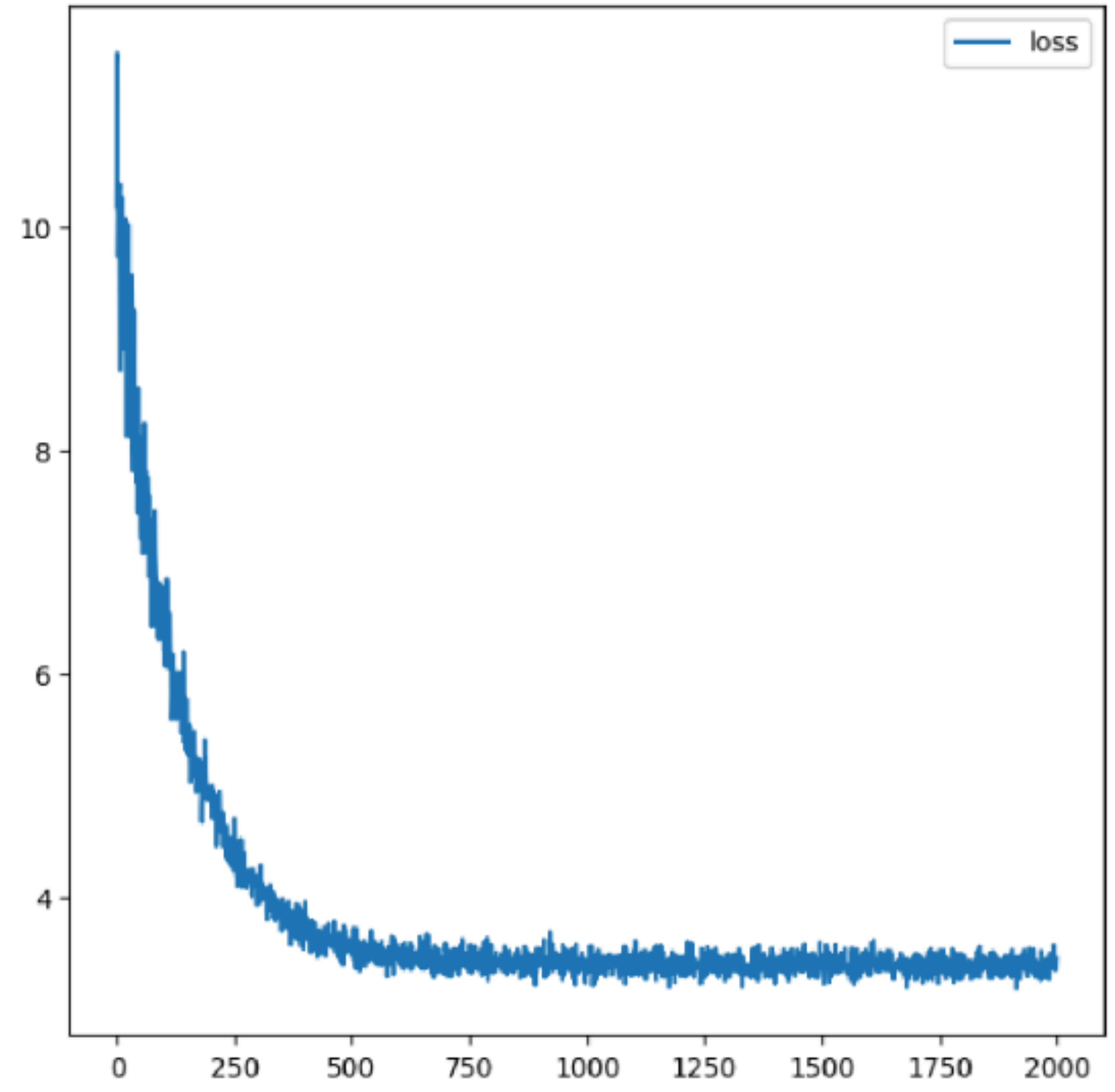
https://github.com/VincentStimper/normalizing- flows



SET UP

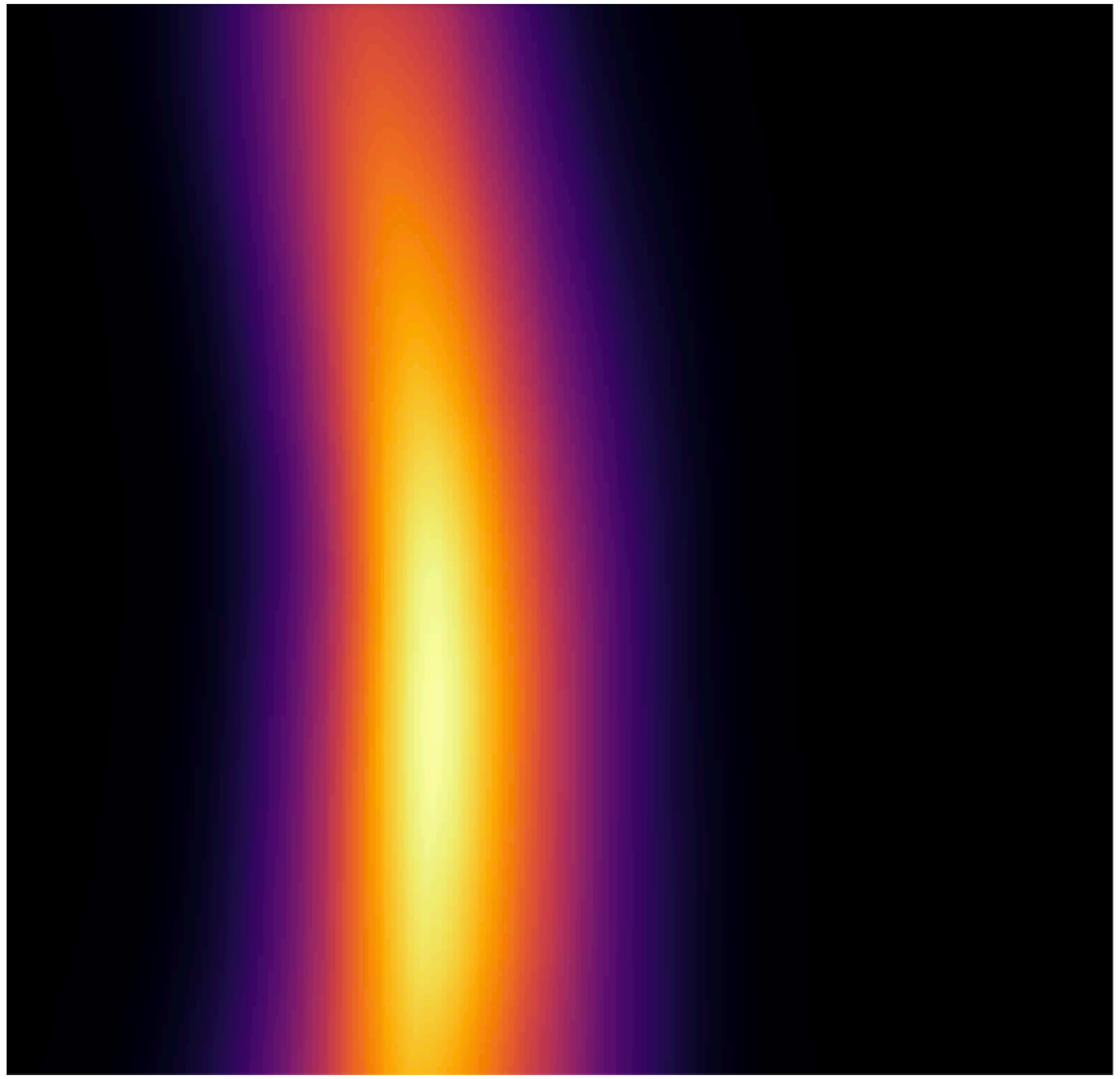
- 100x100 image
- Real-valued non-volume preserving (real NVP) transformations, https://arxiv.org/abs/1605.08803
- Training for 2000 epochs with no early stopping



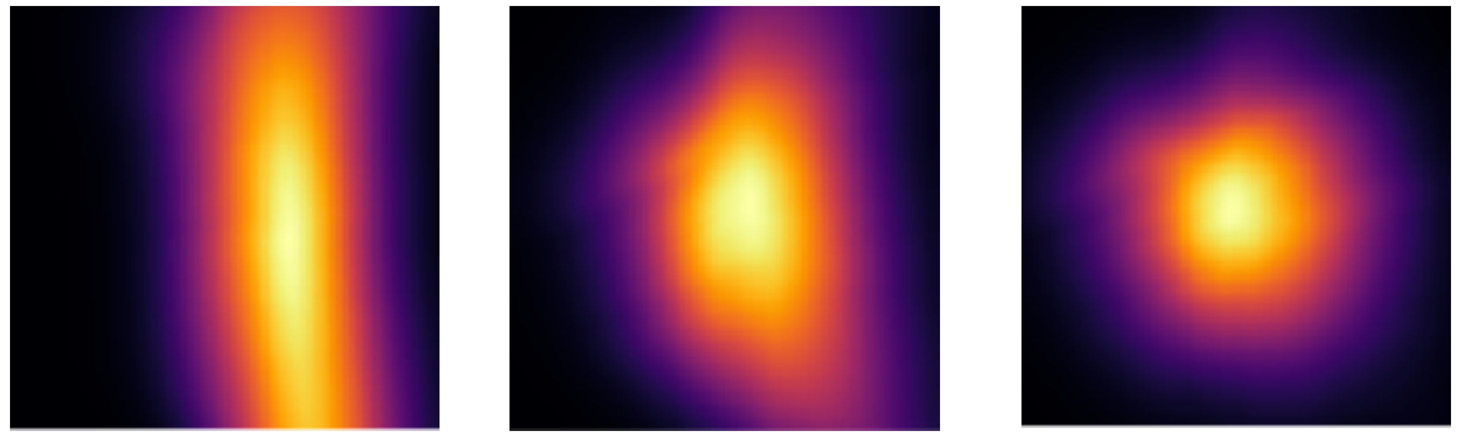


RESULTS

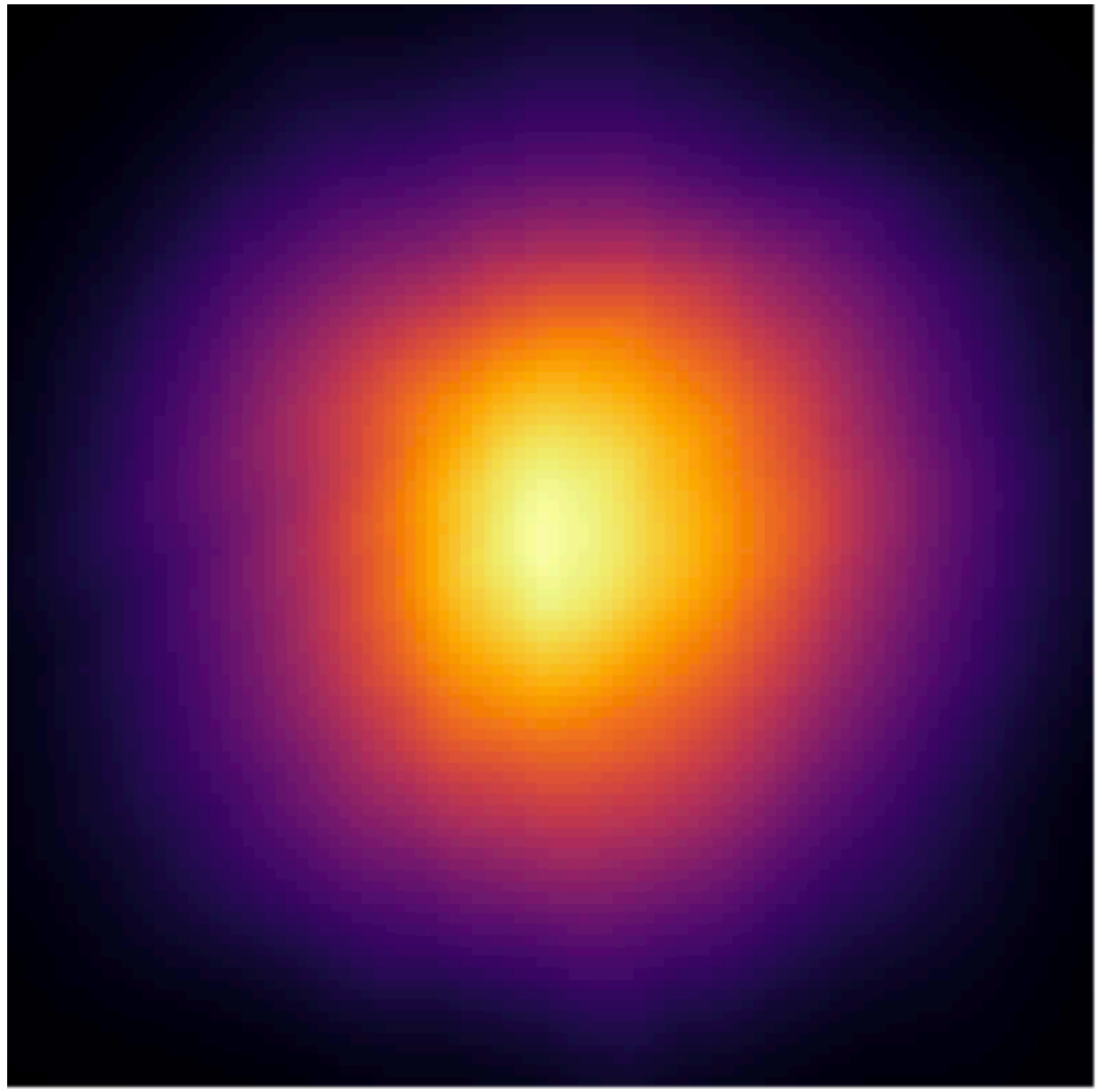
Initial guess



Training



Final result



QUESTIONS (IN LIEU OF CONCLUSIONS)

- Which ML method to use?
- How to tune hyper-parameters?
- How to model 3D structure accounting for other dependences, x-dependence etc?
- How to create multidisciplinary working groups?
- Where to request computer resources?
- If you want to examine our notebooks, just ask!