IMPLICIT QUANTILE NETWORKS FOR EMULATION

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[1]DAVIDSON COLLEGE, [2]UNIVERSITY OF MARYLAND, [3]FLORIDA STATE UNIVERSITY

XVII QUARK CONFINEMENT AND THE HADRON SPECTRUM
4 AUGUST 2022

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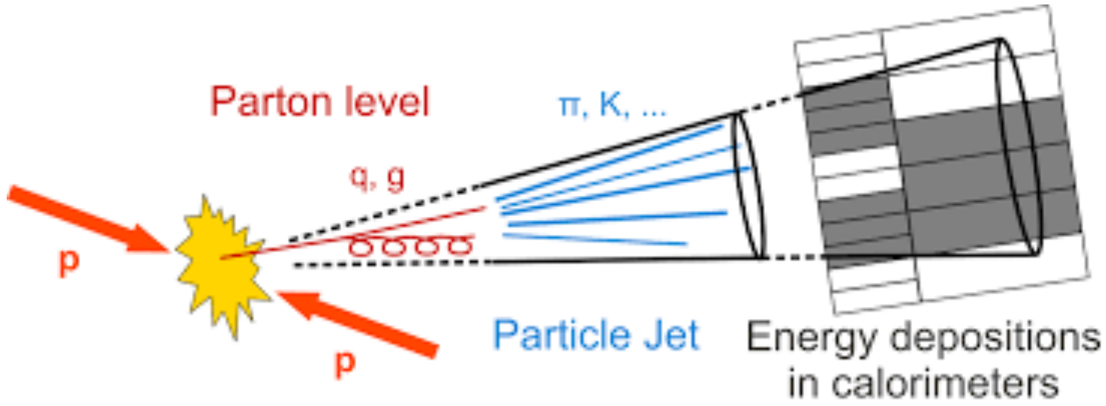
arXiv:1806.05575

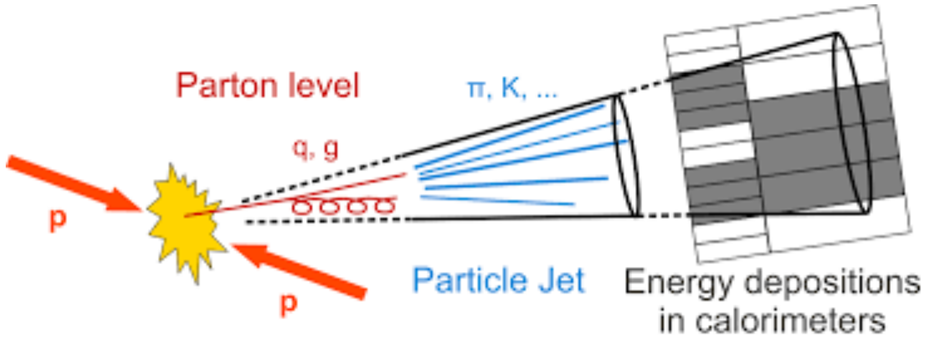
Proceedings of the 35th International Conference on Machine Learning, vol 80. pages 3936–3945. 10–15 Jul 2018

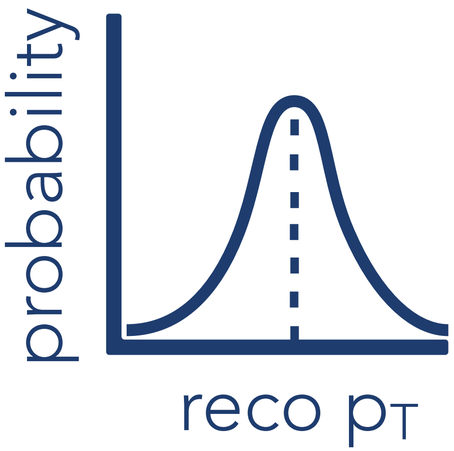
JET SIMULATION AND CORRECTION

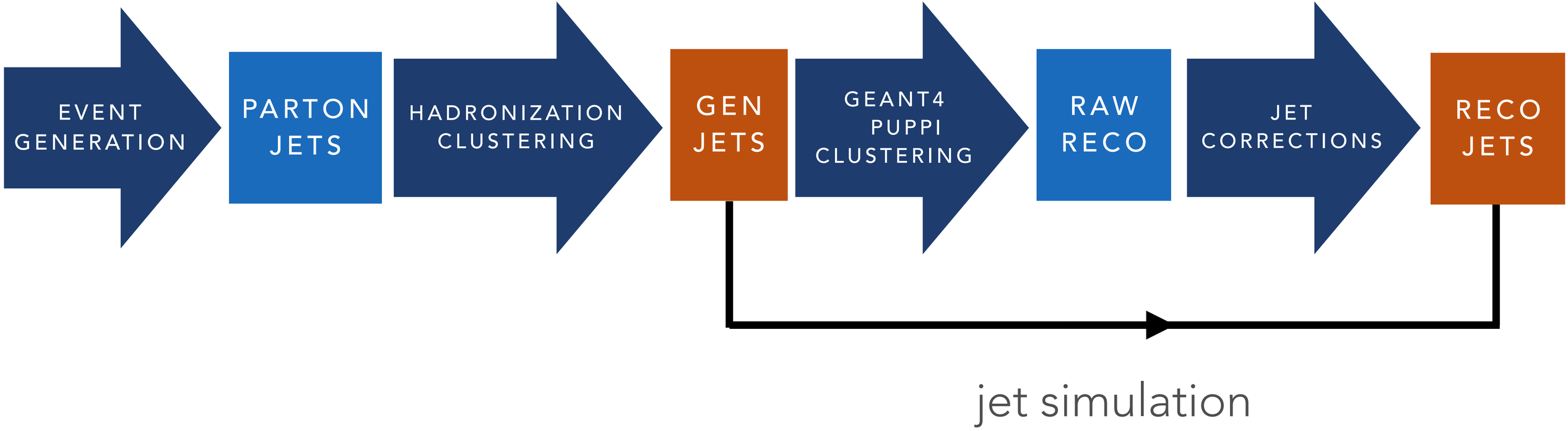


DATASET: Generated via Pythia8 + Delphes + anti-K_T + FastJet

NEED FOR DISTRIBUTION PREDICTIONS

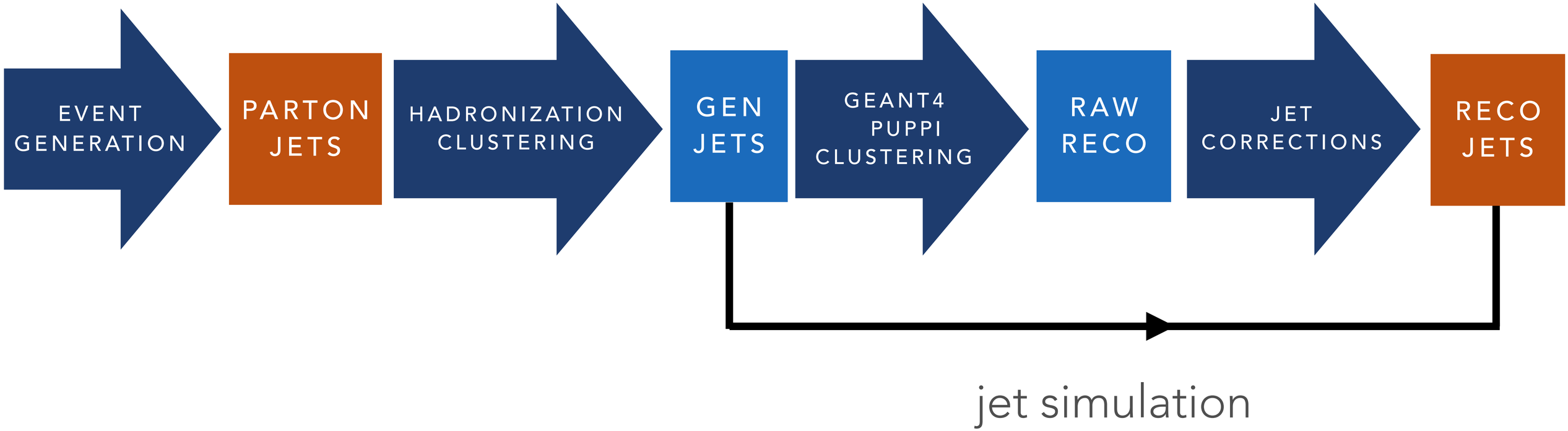




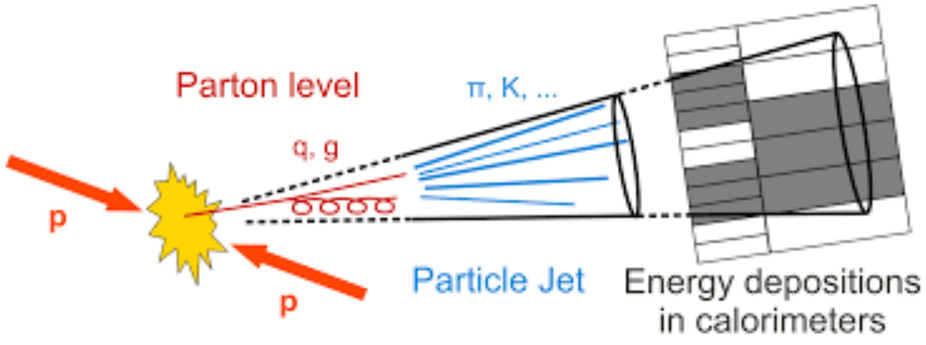


JET SIMULATION AND CORRECTION

J. BLUE, ET.AL., CHEP '21
EPJ WOC **251**, 03055 (2021) HTTPS://DOI.ORG/10.1051/EPJCONF/202125103055



EXISTING METHODS



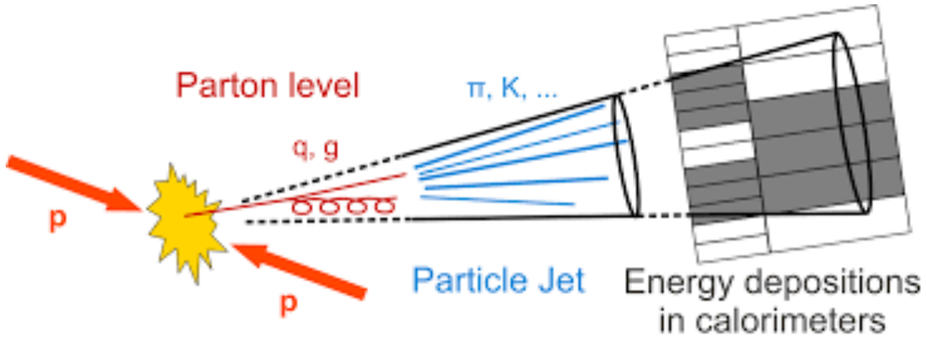
(conditional) generative adversarial networks

arXiv:1912.00477
arXiv:1807.01954
arXiv:1805.00850
arXiv:1712.10321

normalizing flows

arXiv:1904.12072
arXiv:2001.05486
arXiv:2001.10028
arXiv:2012.09873
arXiv:2106.05285

EXISTING METHODS



(conditional) generative adversarial networks

arXiv:1912.00477

arXiv:1807.01954

arXiv:1805.00850

arXiv:1712.10321

How to GAN away Detector Effects

Marco Bellagente[1], Anja Butter[1], Gregor Kasieczka[2], Tilman Plehn[1], and Ramon Winterhalder[1]

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2 Institut für Experimentalphysik, Universität Hamburg, Germany
bellagente@thphys.uni-heidelberg.de

Precise simulation of electromagnetic calorimeter showers using a Wasserstein Generative Adversarial Network

Martin Erdmann[a] Jonas Glombitza[a] Thorben Quast[a,b]

[a] *III. Physikalisches Institut A, Rheinisch Westfälische Technische Hochschule, Aachen, Germany*
[b] *EP-LCD, CERN, Geneva, Switzerland*

Fast and accurate simulation of particle detectors using generative adversarial networks

Pasquale Musella · Francesco Pandolfi

CaloGAN: Simulating 3D High Energy Particle Showers in Multi-Layer Electromagnetic Calorimeters with Generative Adversarial Networks

Michela Paganini,[1,2,*] Luke de Oliveira,[2,†] and Benjamin Nachman[2,‡]

[1] *Department of Physics, Yale University, New Haven, CT 06520, USA*
[2] *Lawrence Berkeley National Laboratory, Berkeley, CA, 94720, USA*

(Dated: January 1, 2018)

Flow-based generative models for Markov chain Monte Carlo in lattice field theory

M. S. Albergo,[1,2,3] G. Kanwar,[4] and P. E. Shanahan[4,1]

[1] *Perimeter Institute for Theoretical Physics, Waterloo, Ontario N2L 2Y5, Canada*
[2] *Cavendish Laboratories, University of Cambridge, Cambridge CB3 0HE, U.K.*
[3] *University of Waterloo, Waterloo, Ontario N2L 3G1, Canada*
[4] *Center for Theoretical Physics, Massachusetts Institute of Technology, Cambridge, MA 02139, U.S.A.*

`i-flow`: High-dimensional Integration and Sampling with Normalizing Flows

Christina Gao[1], Joshua Isaacson[1], and Claudius Krause[1]

[1] Theoretical Physics Department, Fermi National Accelerator Laboratory, Batavia, IL, 60510, USA

Event Generation with Normalizing Flows

Christina Gao,[1] Stefan Höche,[1] Joshua Isaacson,[1] Claudius Krause,[1] and Holger Schulz[2]

[1] *Fermi National Accelerator Laboratory, Batavia, IL, 60510, USA*
[2] *Department of Physics, University of Cincinnati, Cincinnati, OH 45219, USA*

Measuring QCD Splittings with Invertible Networks

Sebastian Bieringer[1], Anja Butter[1], Theo Heimel[1], Stefan Höche[2], Ullrich Köthe[3], Tilman Plehn[1], and Stefan T. Radev[4]

1 Institut für Theoretische Physik, Universität Heidelberg, Germany
2 Fermi National Accelerator Laboratory, Batavia, IL, USA
3 Heidelberg Collaboratory for Image Processing, Universität Heidelberg, Germany
4 Psychologisches Institut, Universität Heidelberg, Germany
heimel@thphys.uni-heidelberg.de

CaloFlow: Fast and Accurate Generation of Calorimeter Showers with Normalizing Flows

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Claudius Krause and David Shih

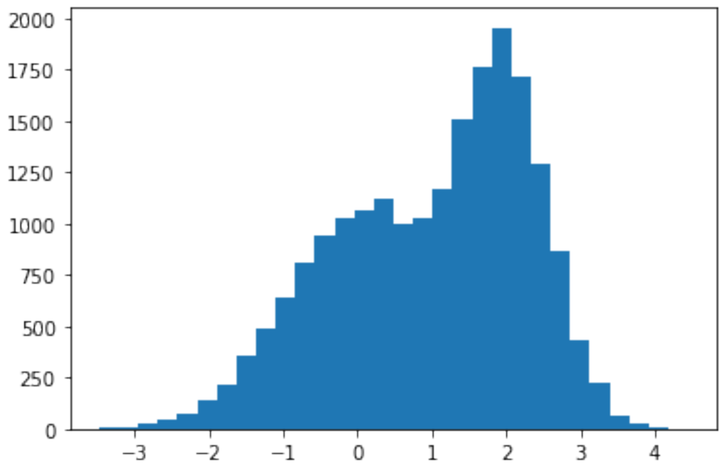
NHETC, Dept. of Physics and Astronomy, Rutgers University, Piscataway, NJ 08854, USA

E-mail: `Claudius.Krause@rutgers.edu`, `shih@physics.rutgers.edu`

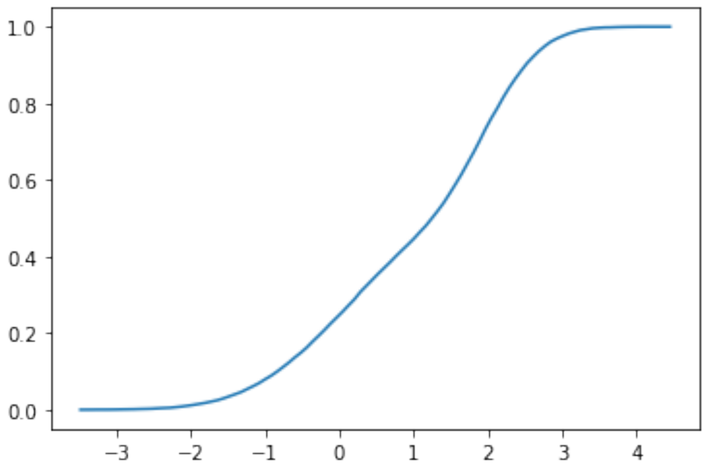
normalizing flows

arXiv:1904.12072
arXiv:2001.05486
arXiv:2001.10028
arXiv:2012.09873
arXiv:2106.05285

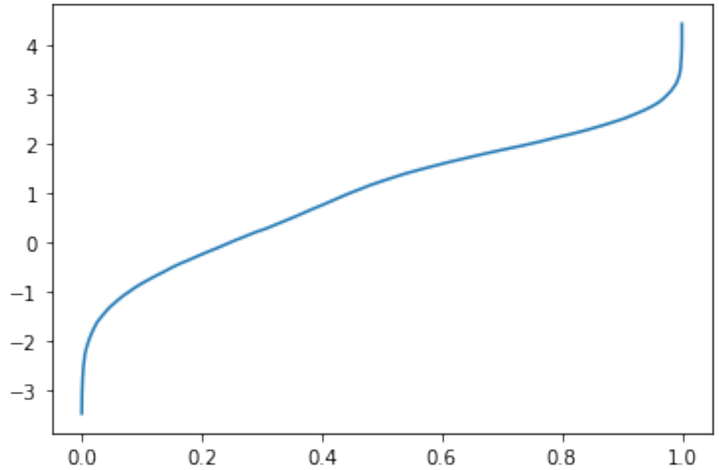
IMPLICIT QUANTILE NETWORKS STATS REVIEW



data

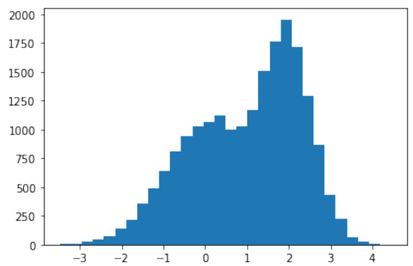


CDF

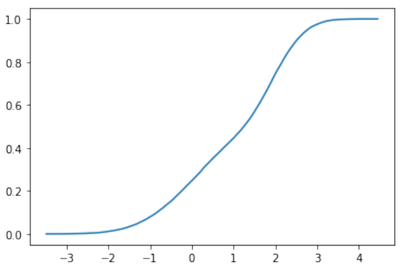


quantile function

IMPLICIT QUANTILE NETWORKS STATS REVIEW



data (x)



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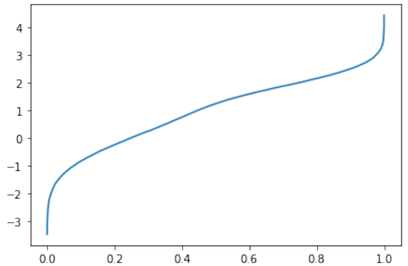
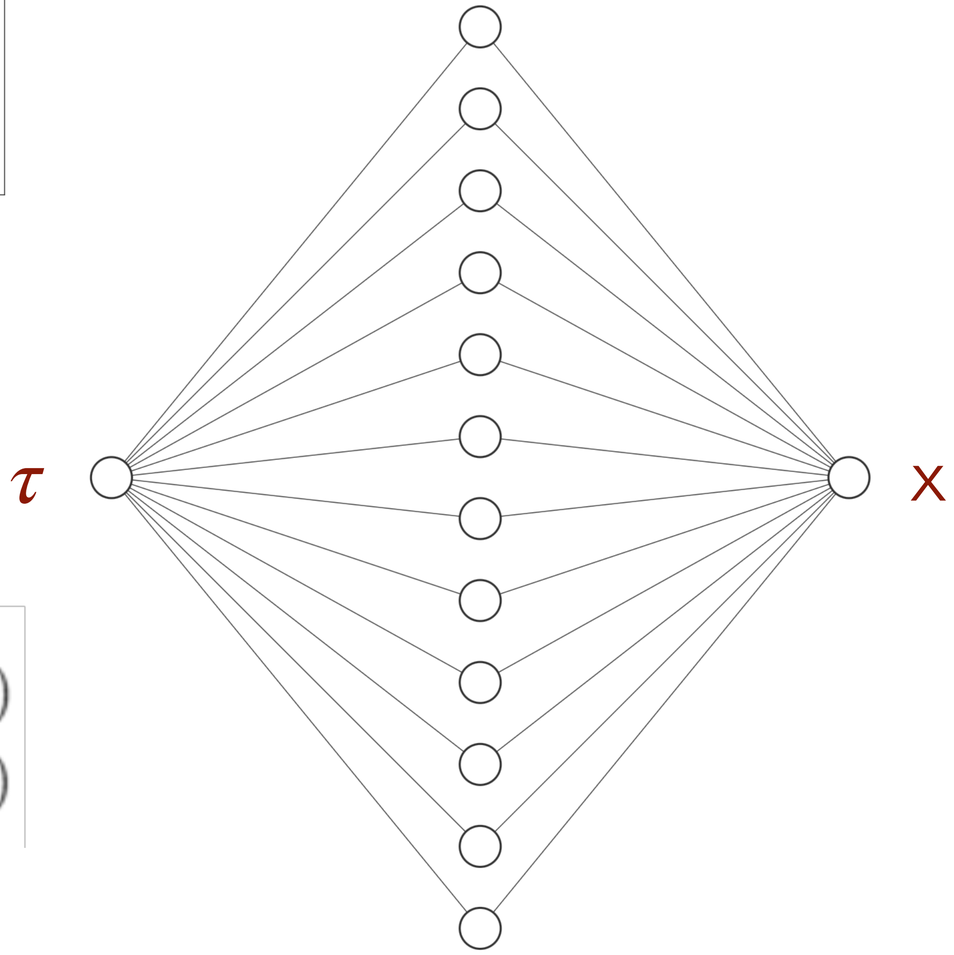
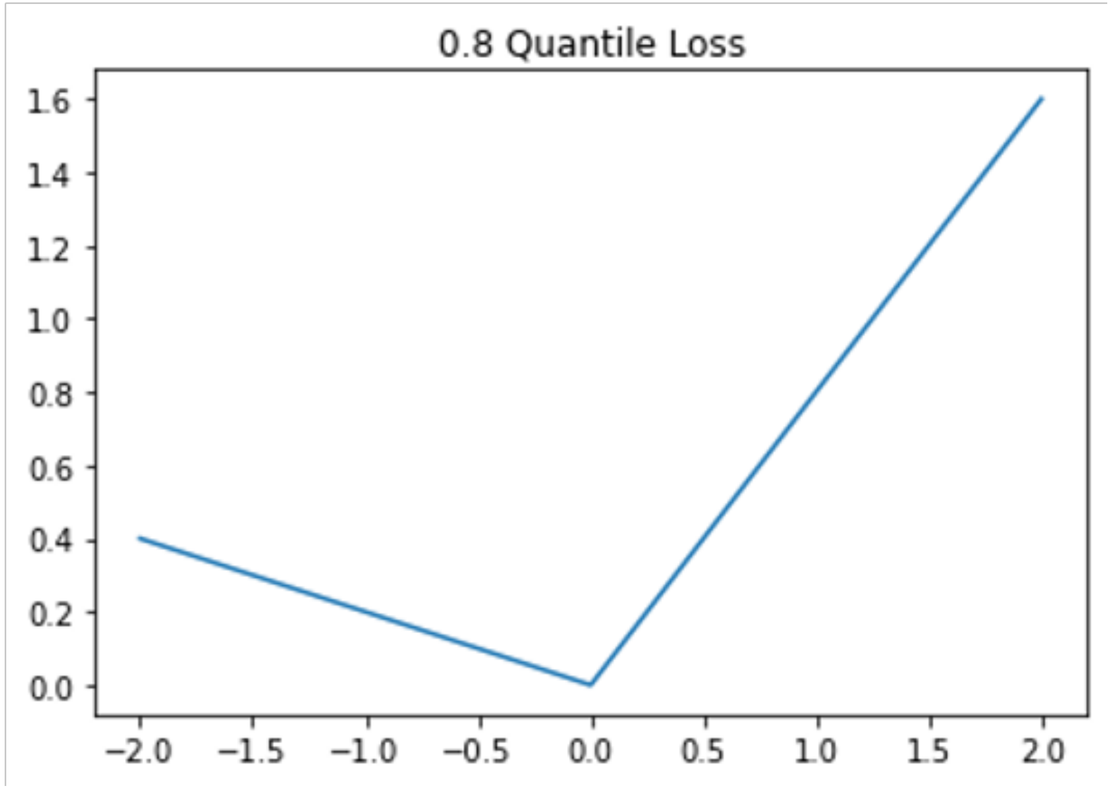


quantile function (τ)



$$\mathcal{L}(f, x, y, \tau) = \begin{cases} \tau(y - f(x, \tau)) & y \geq f(x, \tau) \\ (\tau - 1)(y - f(x, \tau)) & y < f(x, \tau) \end{cases}$$

IMPLICIT QUANTILE NETWORKS LOSS FUNCTION



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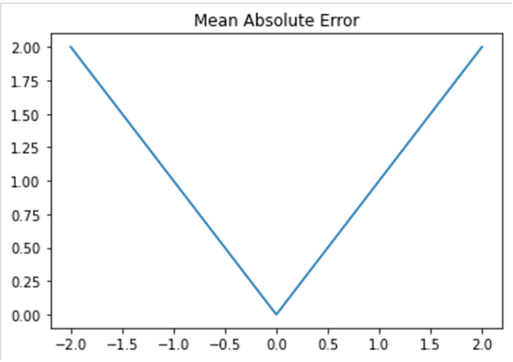

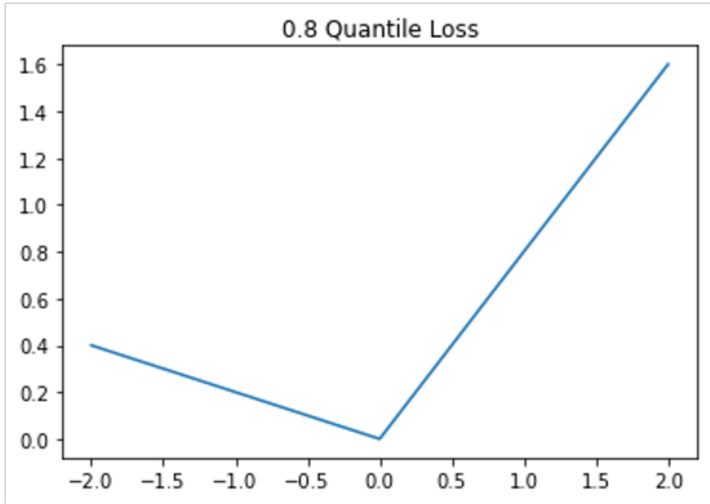

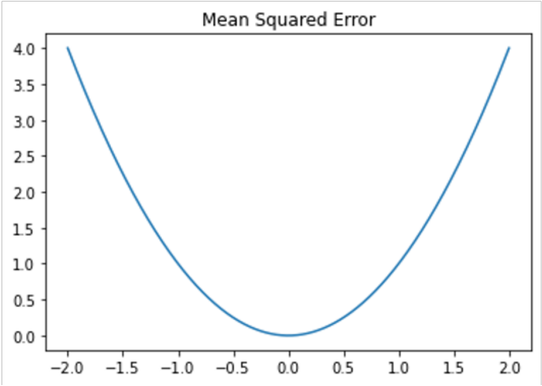

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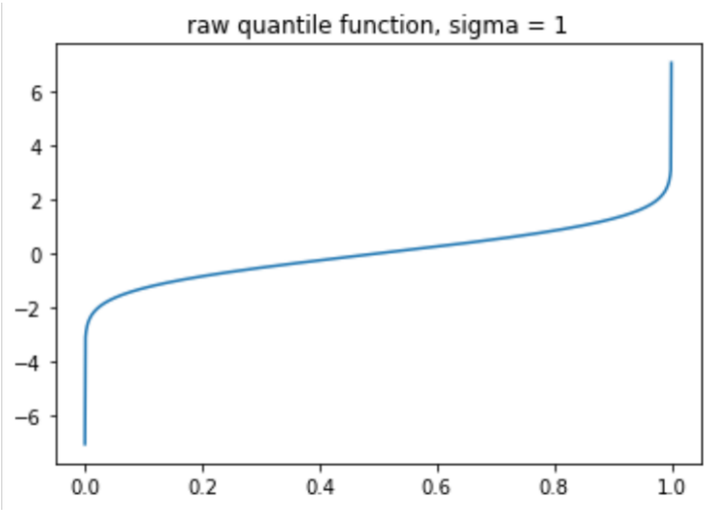
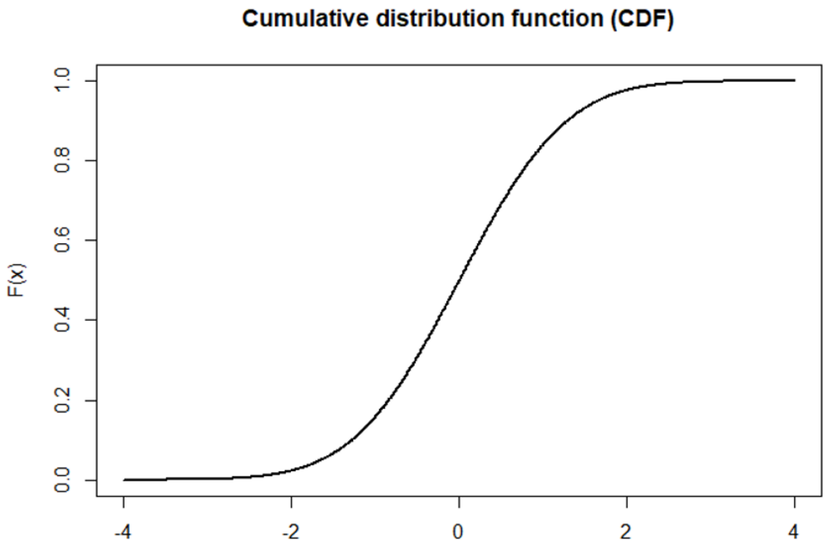
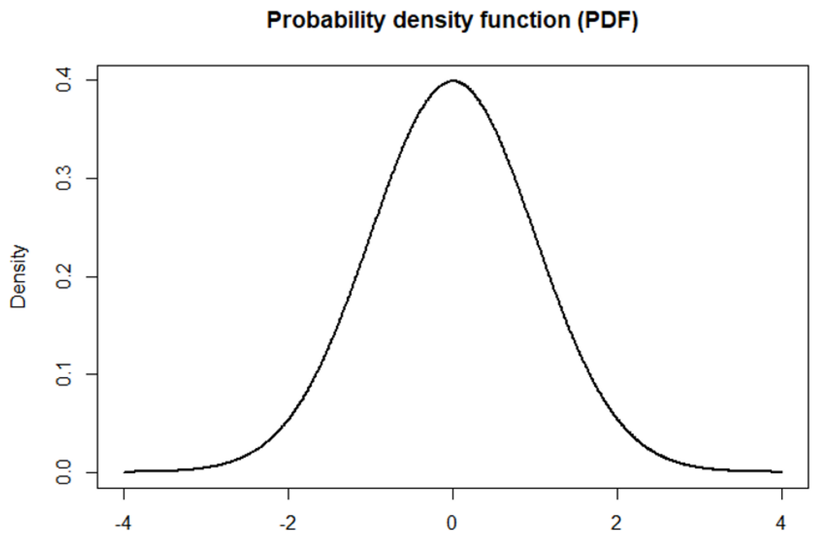






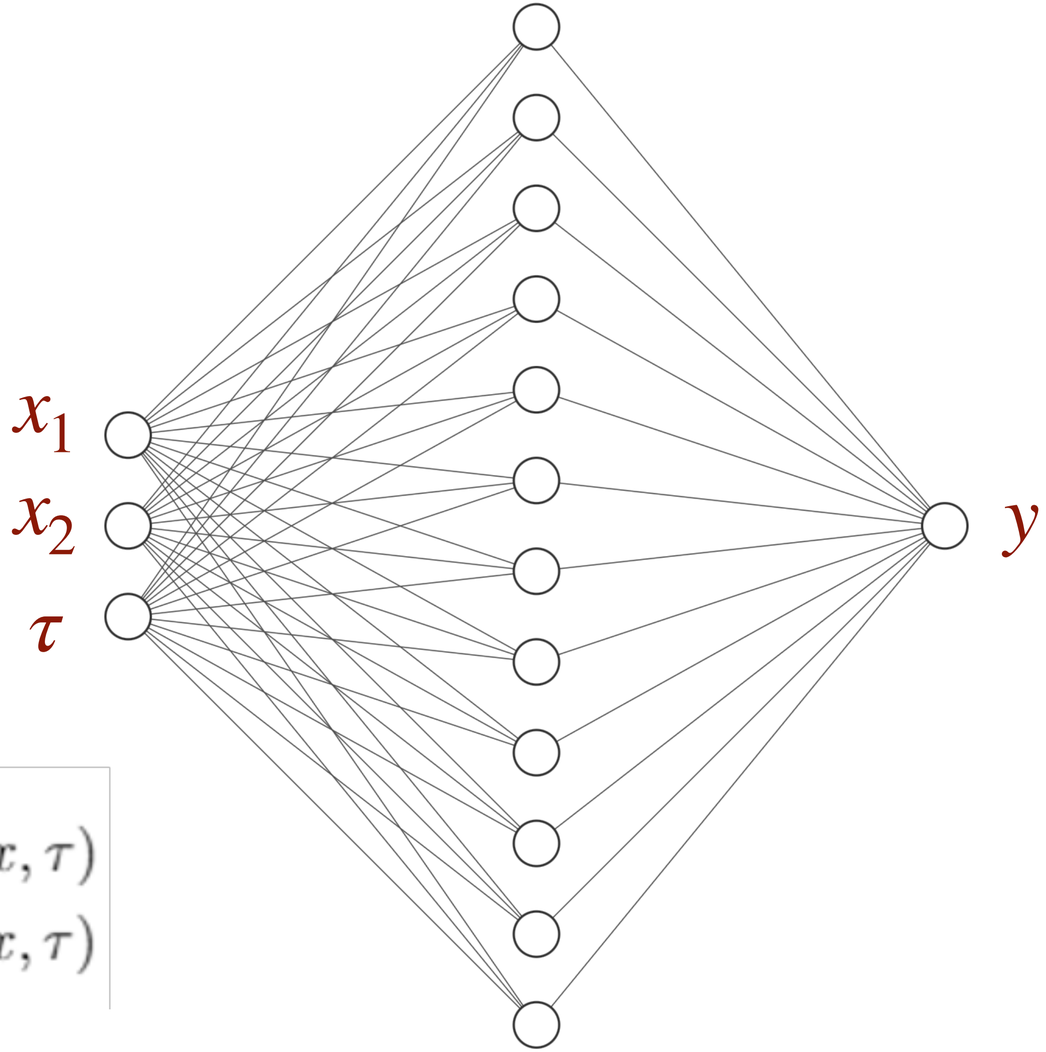
$$\mathcal{L}(f,x,y,\tau) = \begin{cases} \tau(y - f(x,\tau)) & y \geq f(x,\tau) \\ (\tau - 1)(y - f(x,\tau)) & y < f(x,\tau) \end{cases}$$

regularization $\begin{cases} \left(\frac{dy}{d\tau}\right)^2 & \frac{dy}{d\tau} < 0 \\ 0 & \frac{dy}{d\tau} \geq 0 \end{cases}$

IMPLICIT QUANTILE NETWORKS ARCHITECTURE

$$p(y \mid x_1, x_2)$$

$$(x_1, x_2) \rightarrow y$$



$$\mathcal{L}(f, x, y, \tau) = \begin{cases} \tau(y - f(x, \tau)) & y \geq f(x, \tau) \\ (\tau - 1)(y - f(x, \tau)) & y < f(x, \tau) \end{cases}$$

IMPLICIT QUANTILE NETWORKS ARCHITECTURE

$$p(p'_T, \eta', \phi', m' \mid p_T, \eta, \phi, m)$$

$$(p_T, \eta, \phi, m) \rightarrow (p'_T, \eta', \phi', m')$$

$$p(y^{(1)}, y^{(2)}, \ldots, y^{(n)} \mid \mathbf{x}) = p(y^{(1)} \mid \mathbf{x}) p(y^{(2)} \mid \mathbf{x}, y^{(1)}) \prod_{i=3}^{n} p(y^{(i)} \mid \mathbf{x}, y^{(1)}, \ldots, y^{(i-1)})$$

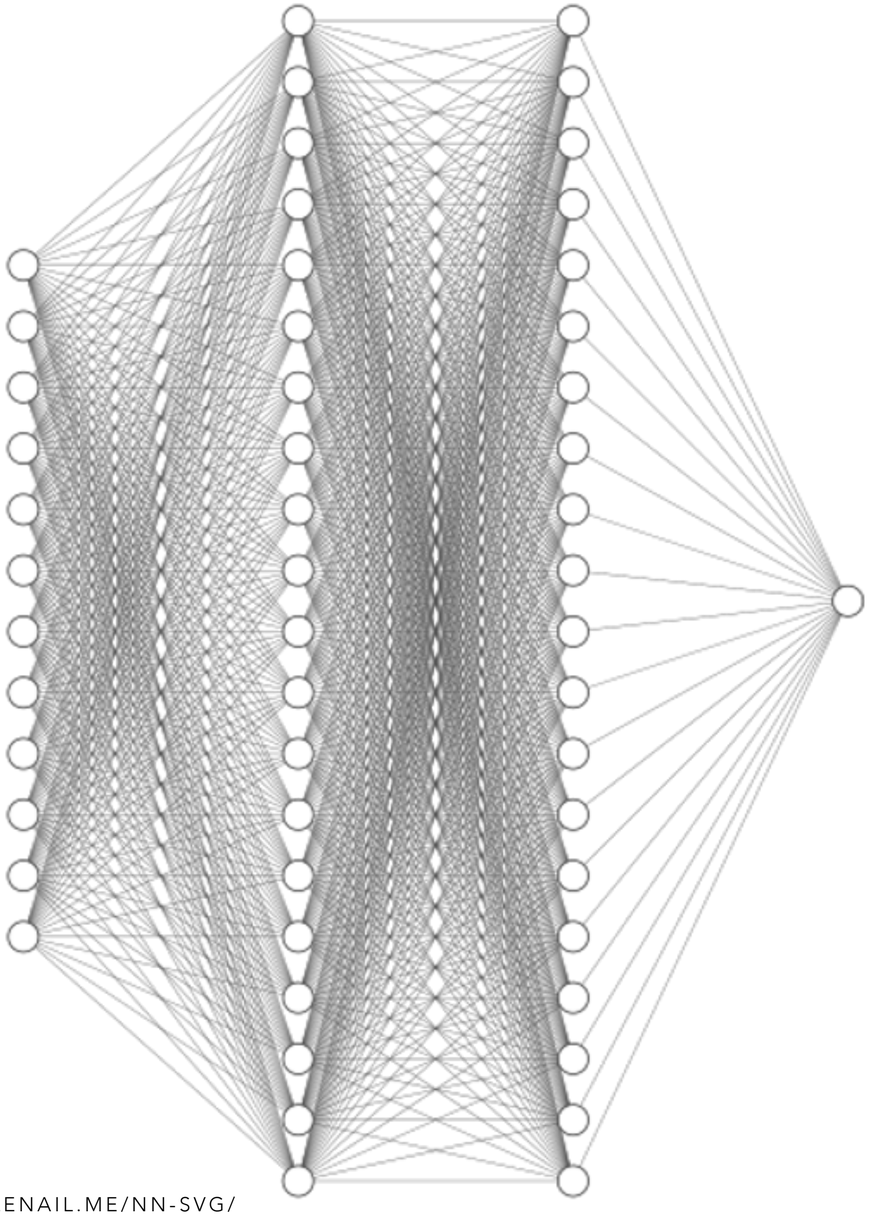
IMPLICIT QUANTILE NETWORKS ARCHITECTURE

$$p(p'_T, \eta', \phi', m' \mid p_T, \eta, \phi, m)$$

$$(p_T, \eta, \phi, m) \rightarrow (p'_T, \eta', \phi', m')$$

$$p(y^{(1)}, y^{(2)}, \ldots, y^{(n)} \mid \mathbf{x}) = \boxed{p(y^{(1)} \mid \mathbf{x})}\boxed{p(y^{(2)} \mid \mathbf{x}, y^{(1)})}\prod_{i=3}^{n}\boxed{p(y^{(i)} \mid \mathbf{x}, y^{(1)}, \ldots, y^{(i-1)})}$$

IMPLICIT QUANTILE NETWORKS ARCHITECTURE

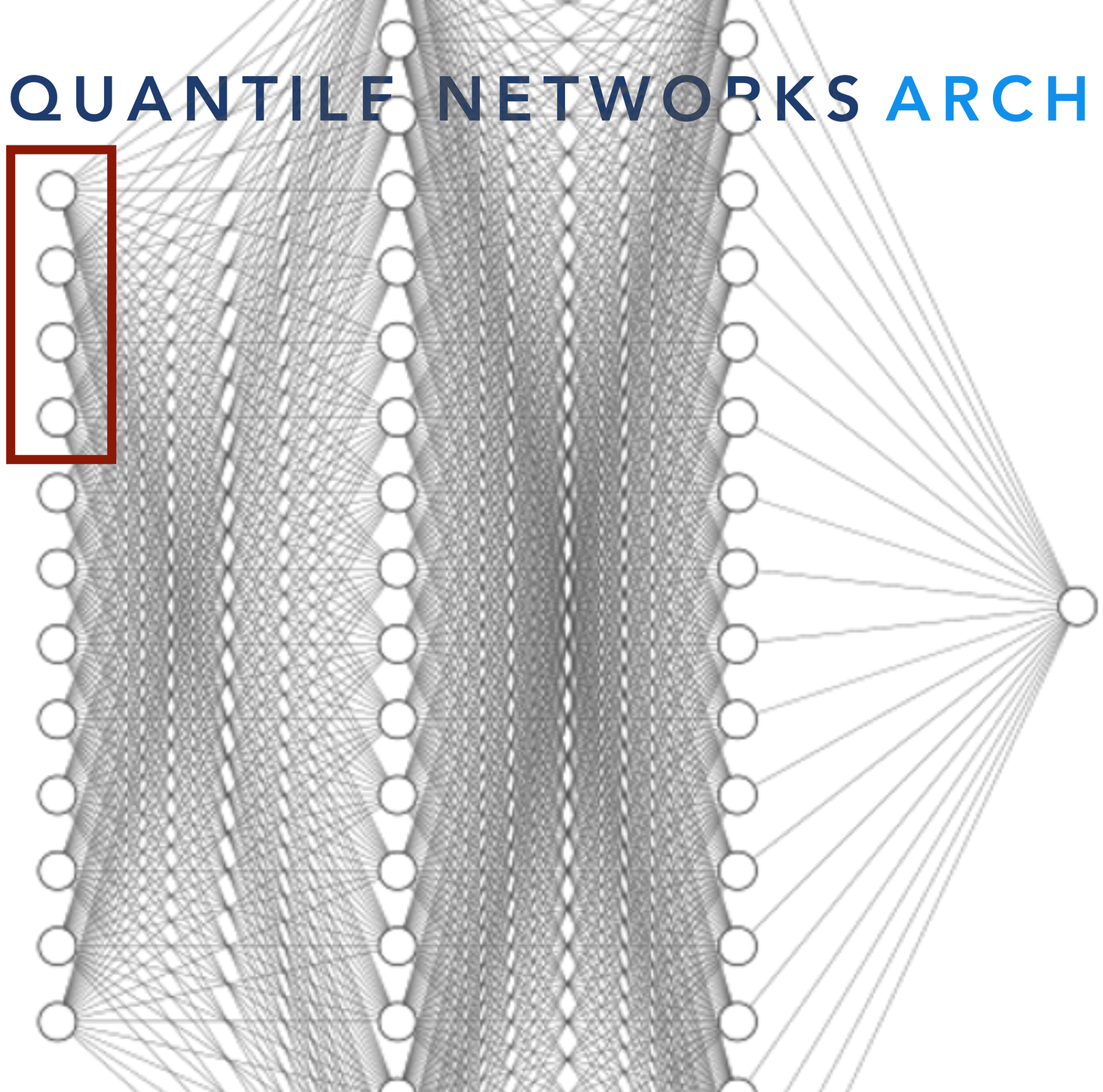


$$(p_T, \eta, \phi, m) \rightarrow (p'_T, \eta', \phi', m')$$

IMAGE CREDIT: HTTPS://ALEXLENAIL.ME/NN-SVG/

IMPLICIT QUANTILE NETWORKS ARCHITECTURE

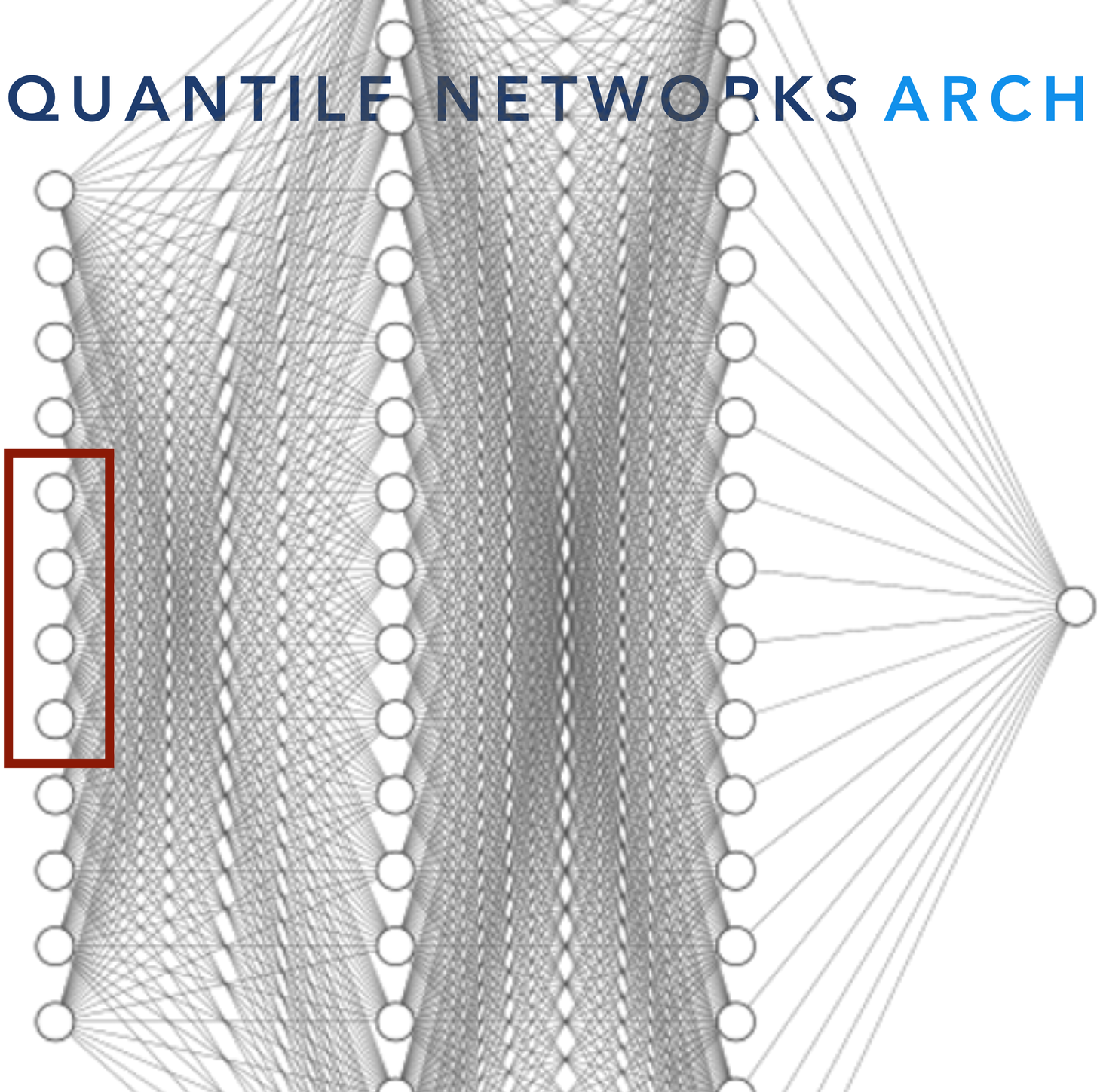
(p_T, η, ϕ, m)



IMPLICIT QUANTILE NETWORKS ARCHITECTURE

(p'_T, η', ϕ', m')

[0,0,1,0]



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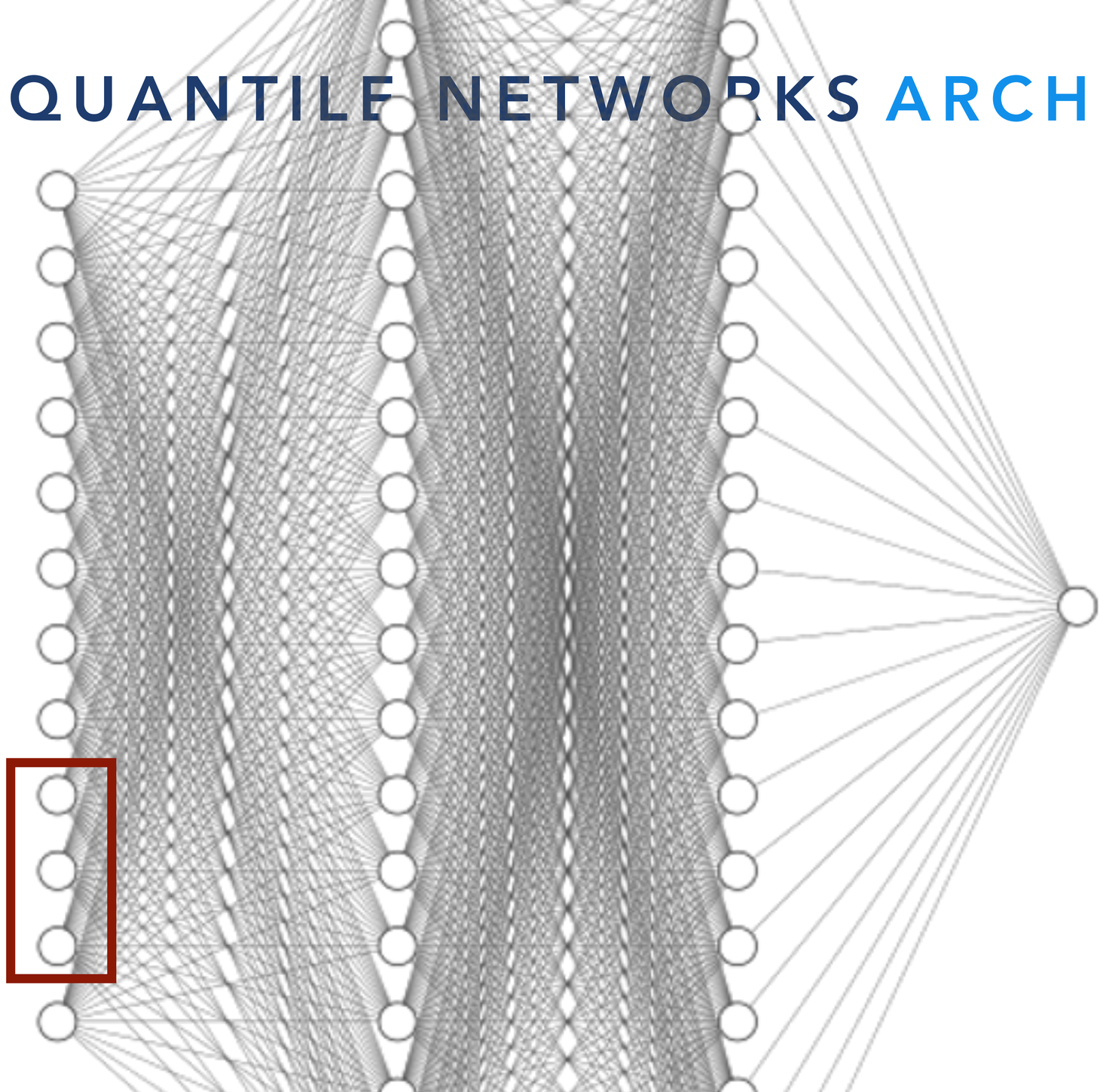
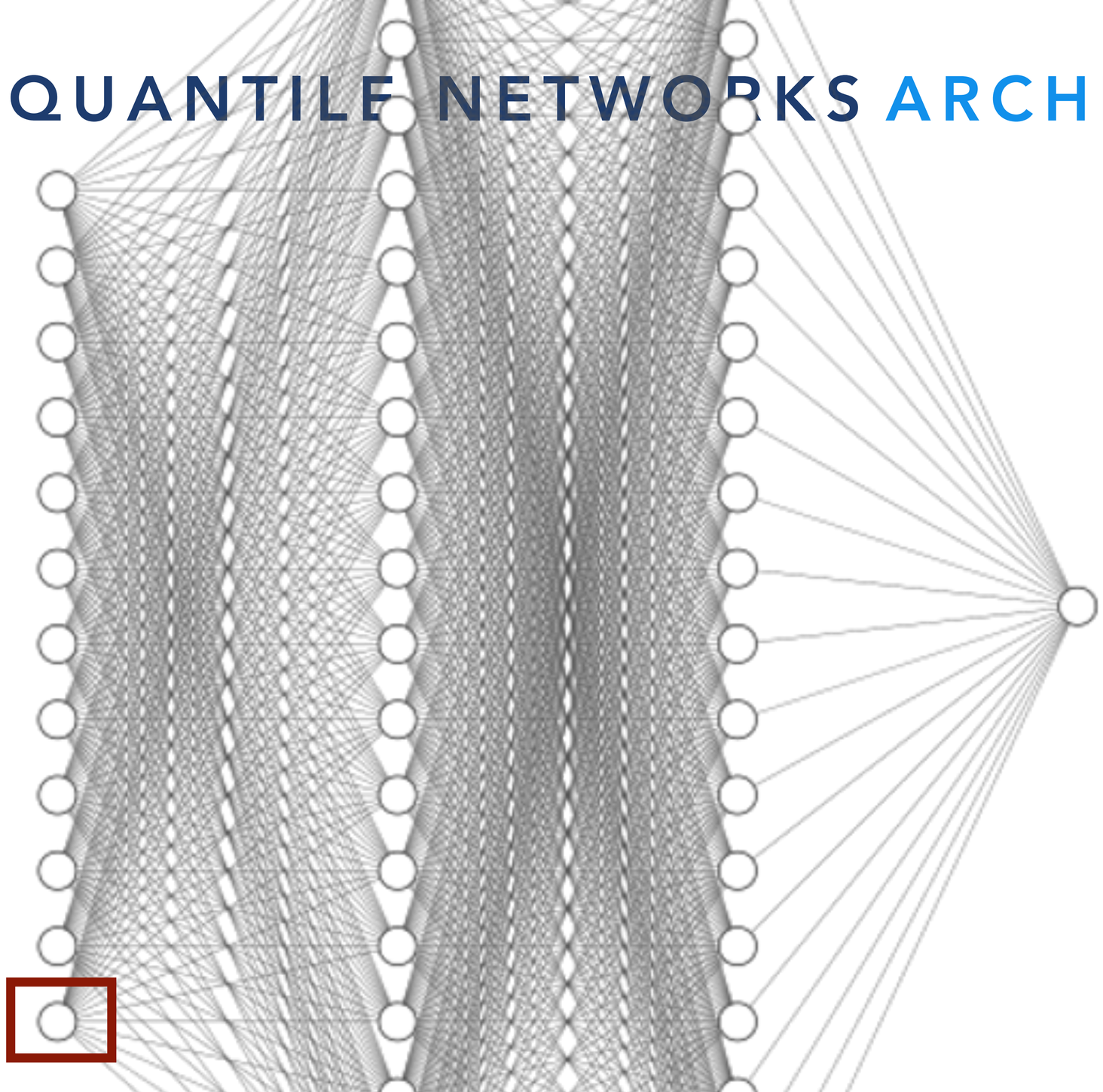


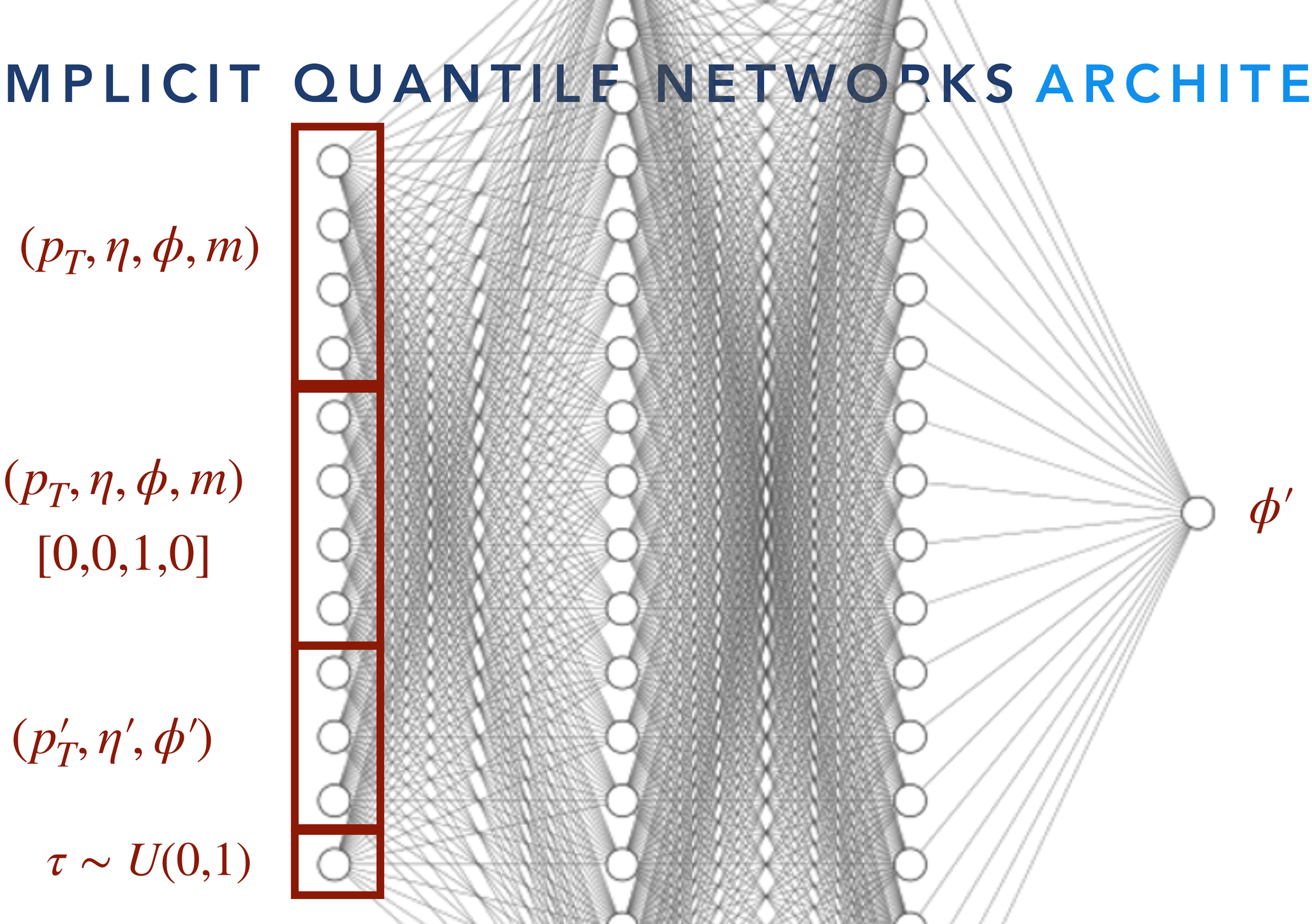
(p'_T, η', ϕ')

IMPLICIT QUANTILE NETWORKS ARCHITECTURE



$\tau \sim U(0,1)$

IMPLICIT QUANTILE NETWORKS ARCHITECTURE



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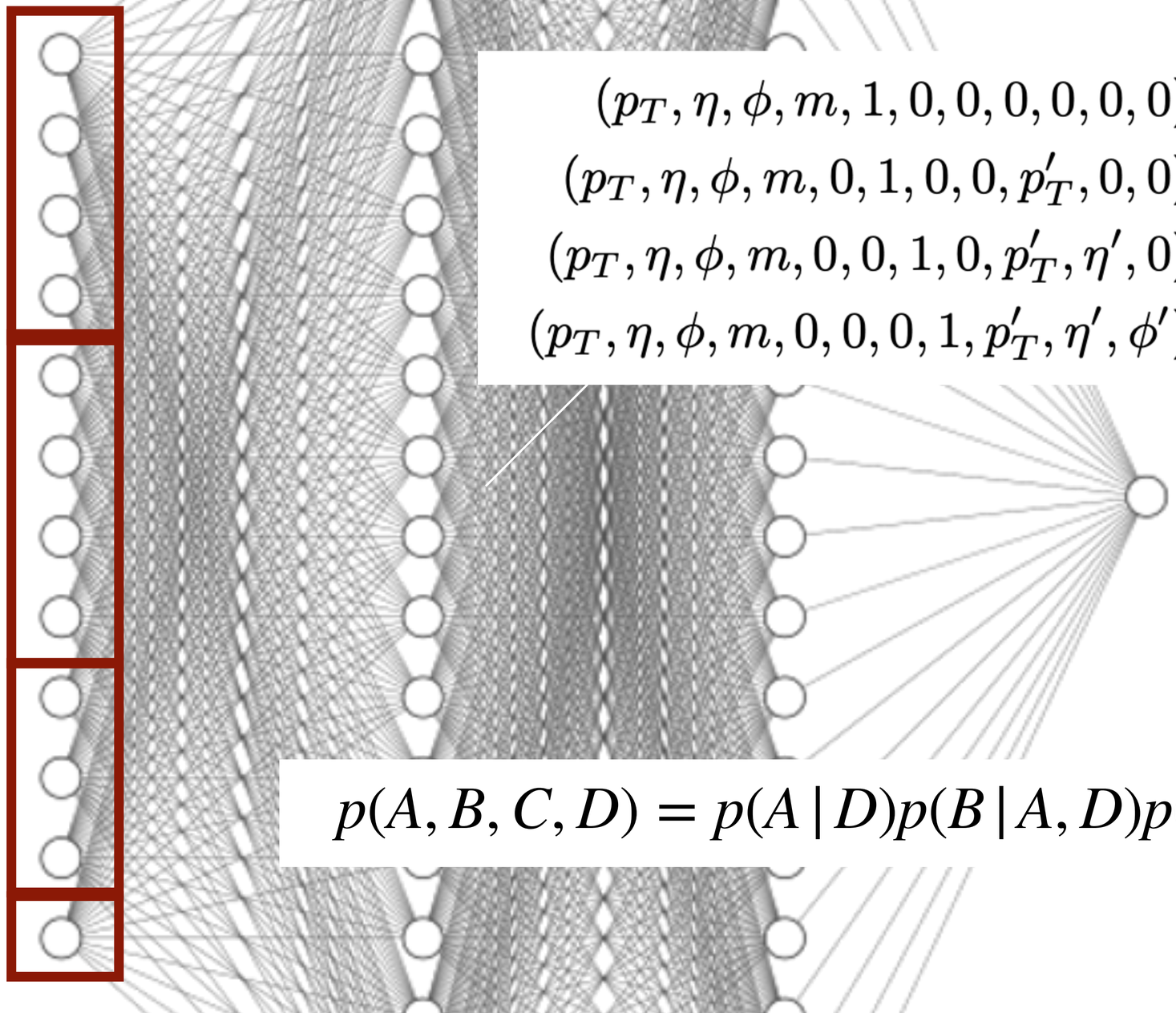


(p_T, η, ϕ, m)

(p_T, η, ϕ, m)
[0,0,1,0]

(p'_T, η', ϕ')

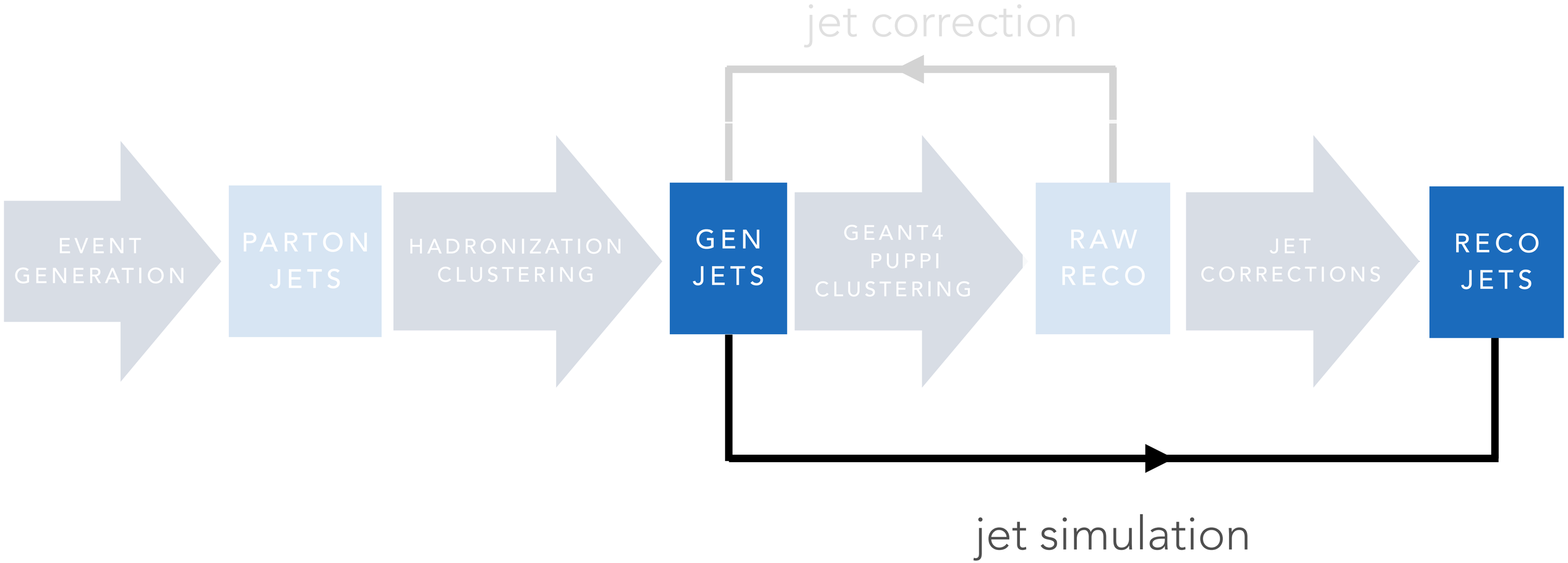
$\tau \sim U(0,1)$

$$(p_T, \eta, \phi, m, 1, 0, 0, 0, 0, 0, 0) \rightarrow (p'_T),$$
$$(p_T, \eta, \phi, m, 0, 1, 0, 0, p'_T, 0, 0) \rightarrow (\eta'),$$
$$(p_T, \eta, \phi, m, 0, 0, 1, 0, p'_T, \eta', 0) \rightarrow (\phi'),$$
$$(p_T, \eta, \phi, m, 0, 0, 0, 1, p'_T, \eta', \phi') \rightarrow (m'),$$

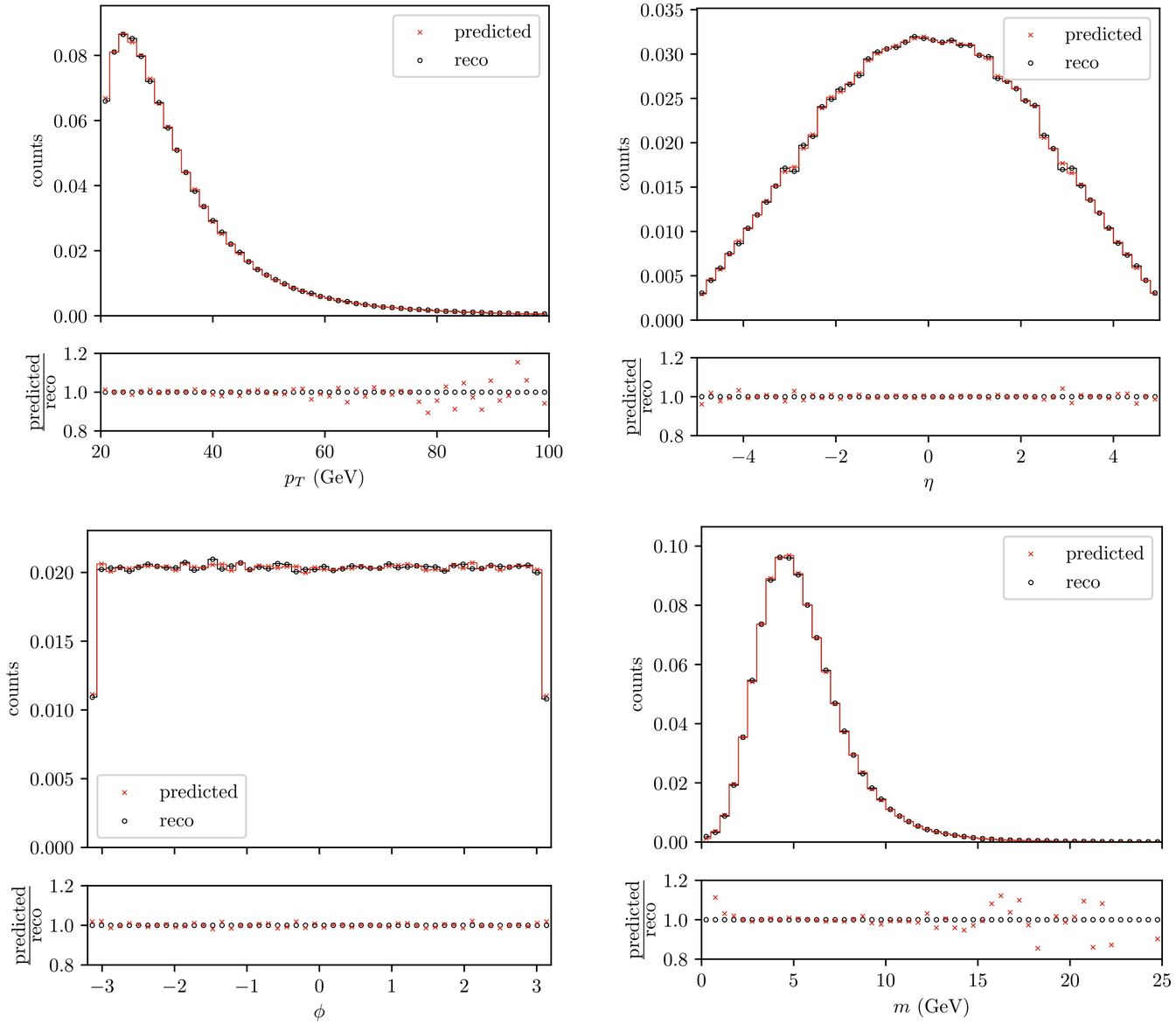
ϕ'

$$p(A, B, C, D) = p(A \mid D) p(B \mid A, D) p(C \mid A, B, D)$$

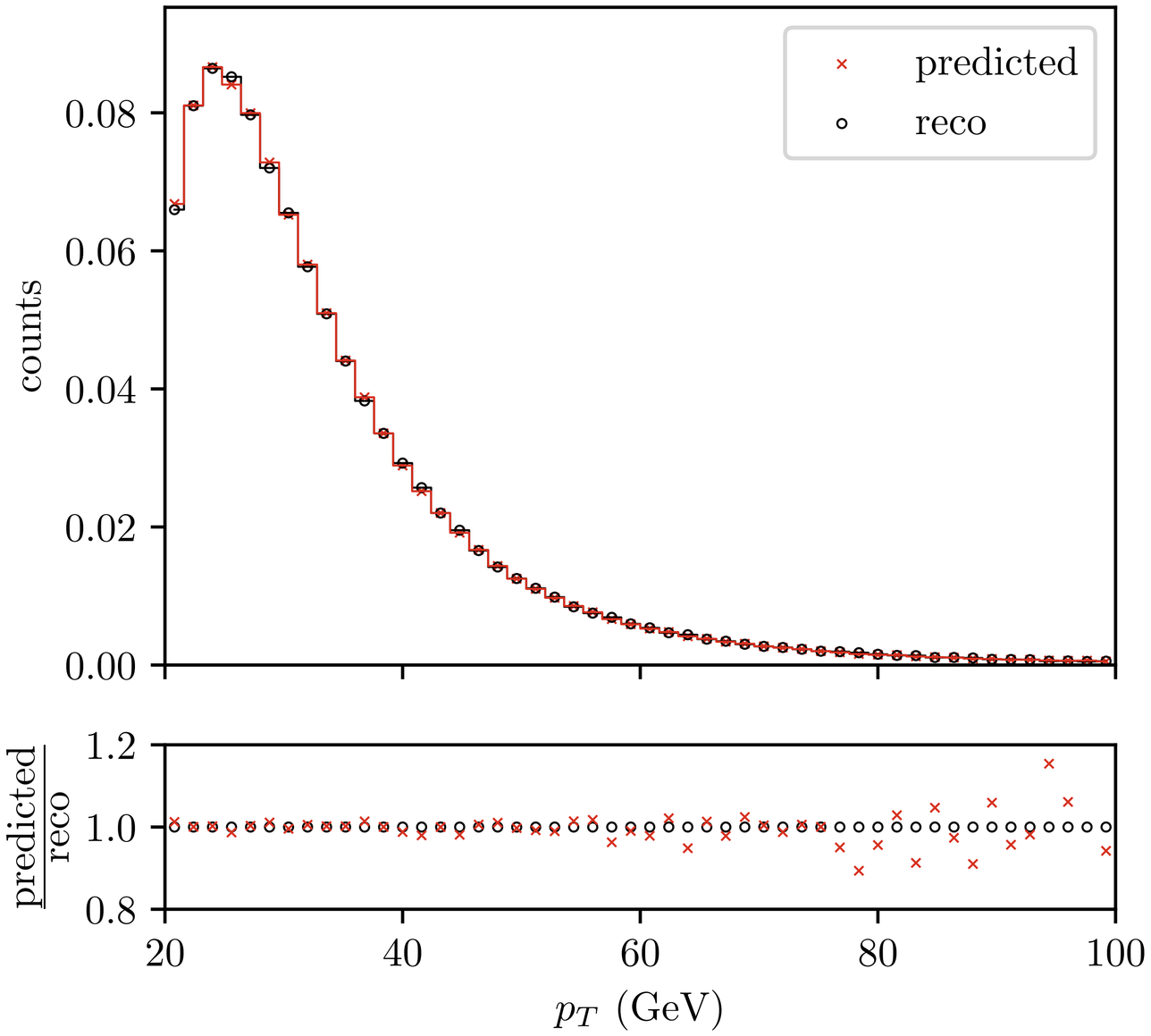
RESULTS JET SIMULATION



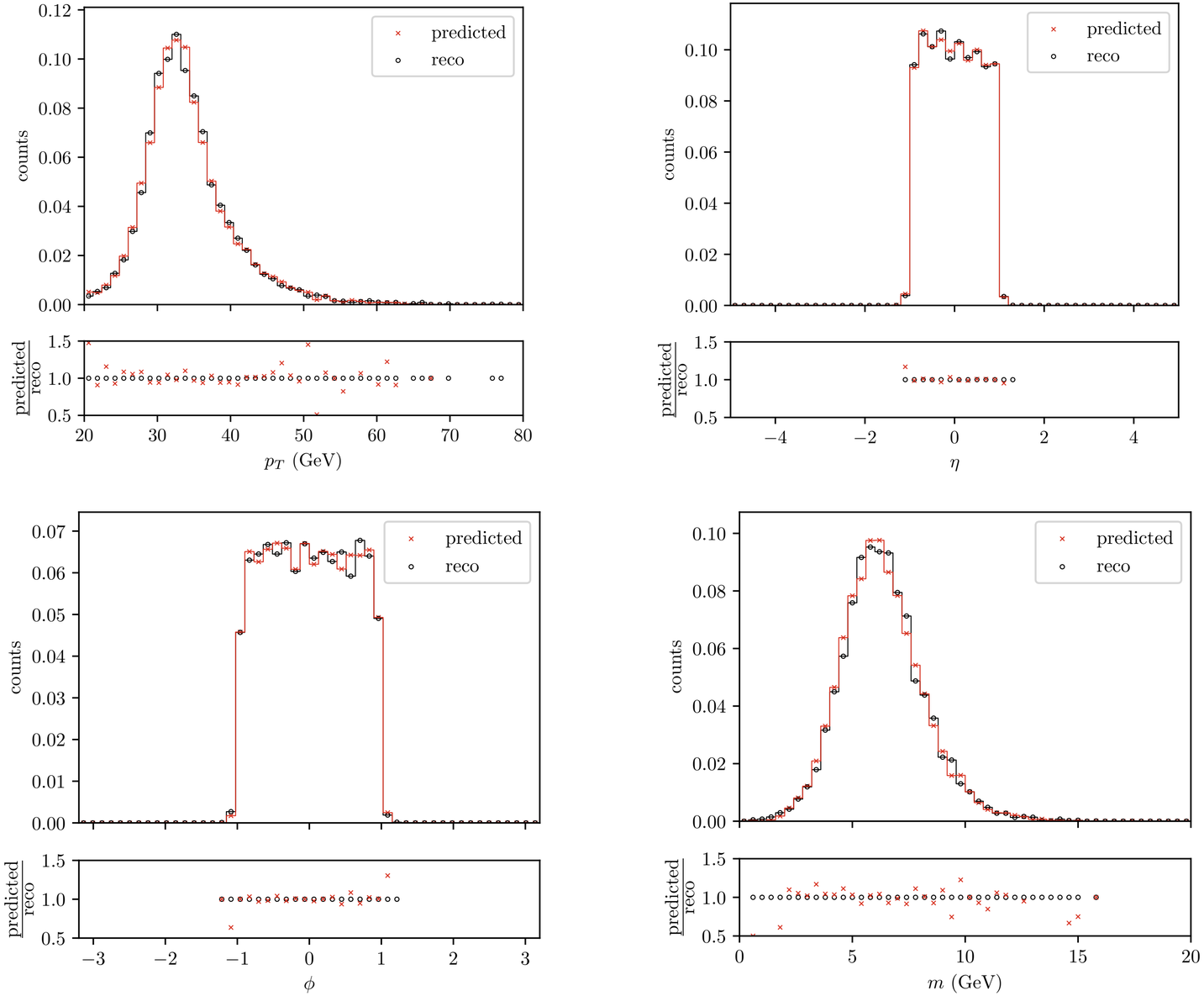
RESULTS JET SIMULATION



RESULTS JET SIMULATION



RESULTS JET SIMULATION: SUBSPACE



THANK YOU!

BRADEN KRONHEIM[1,2], **MICHELLE KUCHERA[1]**, HARRISON PROSPER[3], RAGHU RAMANUJAN[1], ALI AL KADHIM[3]

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