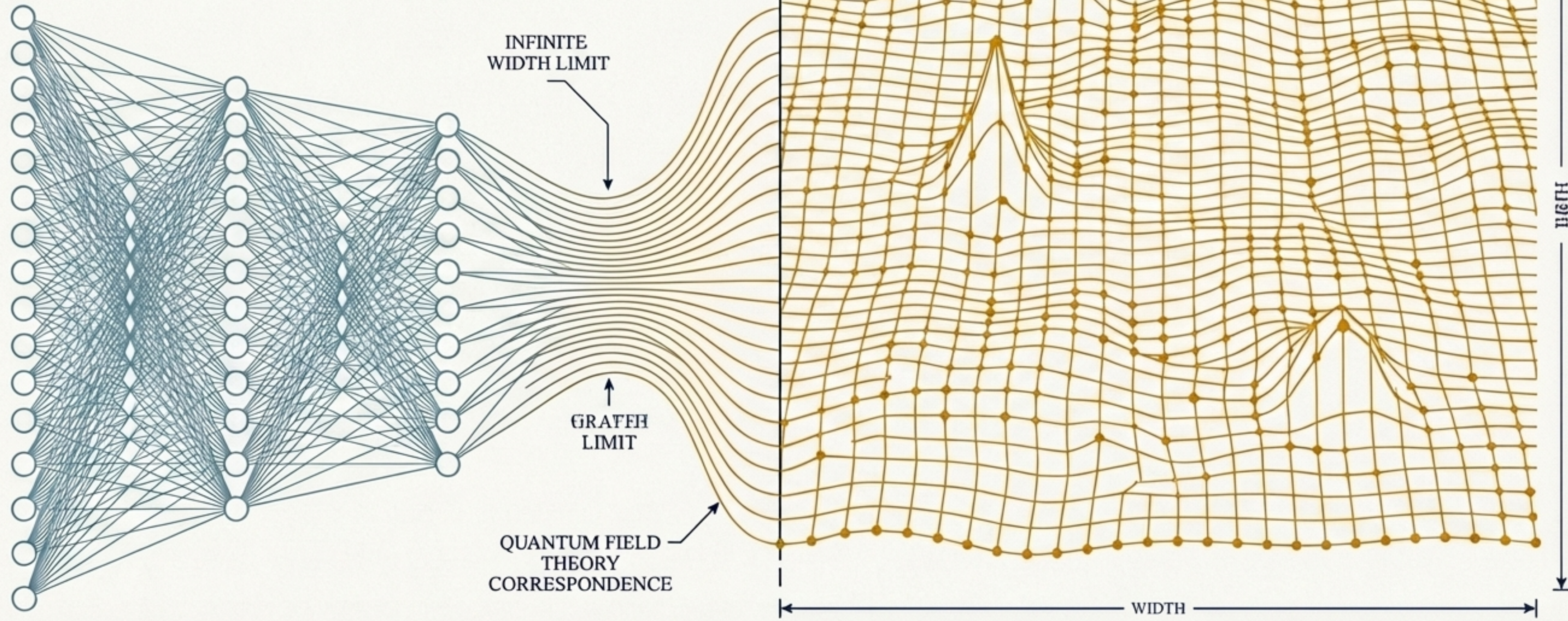


# String Theory from Infinite Width Neural Networks

*A Journal Club Synthesis: Principles & Capabilities of Neural Network Field Theory (NN-FT)*

Journal Club Reading Deck

arXiv:2601.06249



# Redefining the Field: From Path Integrals to Parameter Space

## Traditional QFT

Field Space

Action  $S[\phi]$

$$Z[J] = \int \mathcal{D}\phi e^{-\frac{1}{2}\phi K \phi + J\phi} =$$
$$= \exp\left(\frac{1}{2} \int J(x) G(x, y) J(y)\right)$$

Equivalence

## Neural Network Field Theory (NN-FT)

Architecture

$$\mathbb{E}_{\theta} [f_{\theta}(x)]$$

Parameter Space

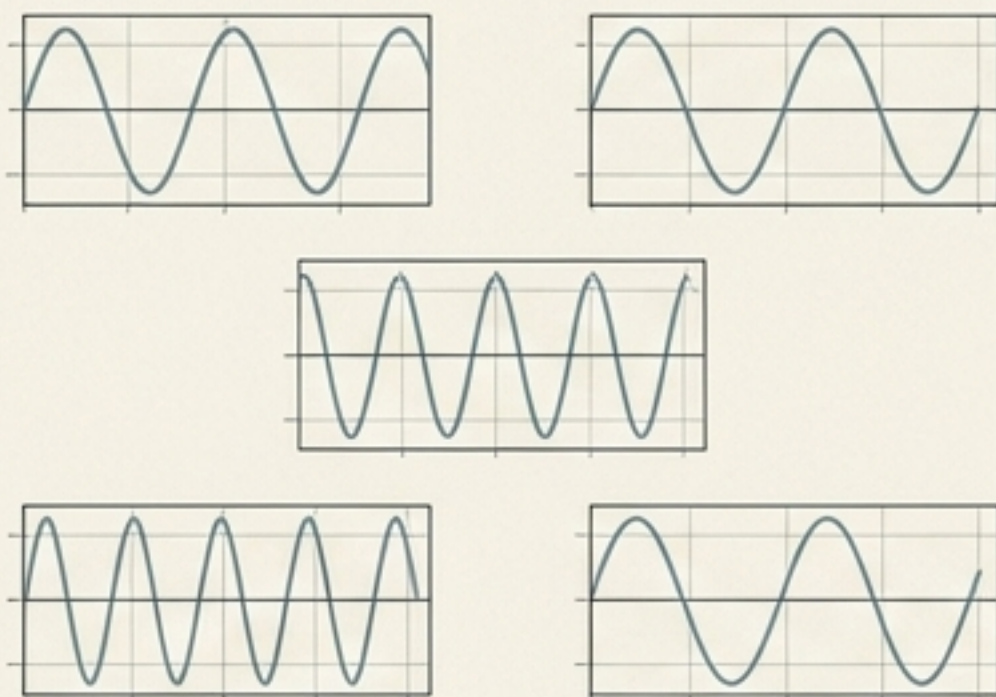
Architecture

A field theory is now defined entirely by two pieces of data:

1. An **Architecture** (Kinematics).
2. A **Parameter Density** (Dynamics).

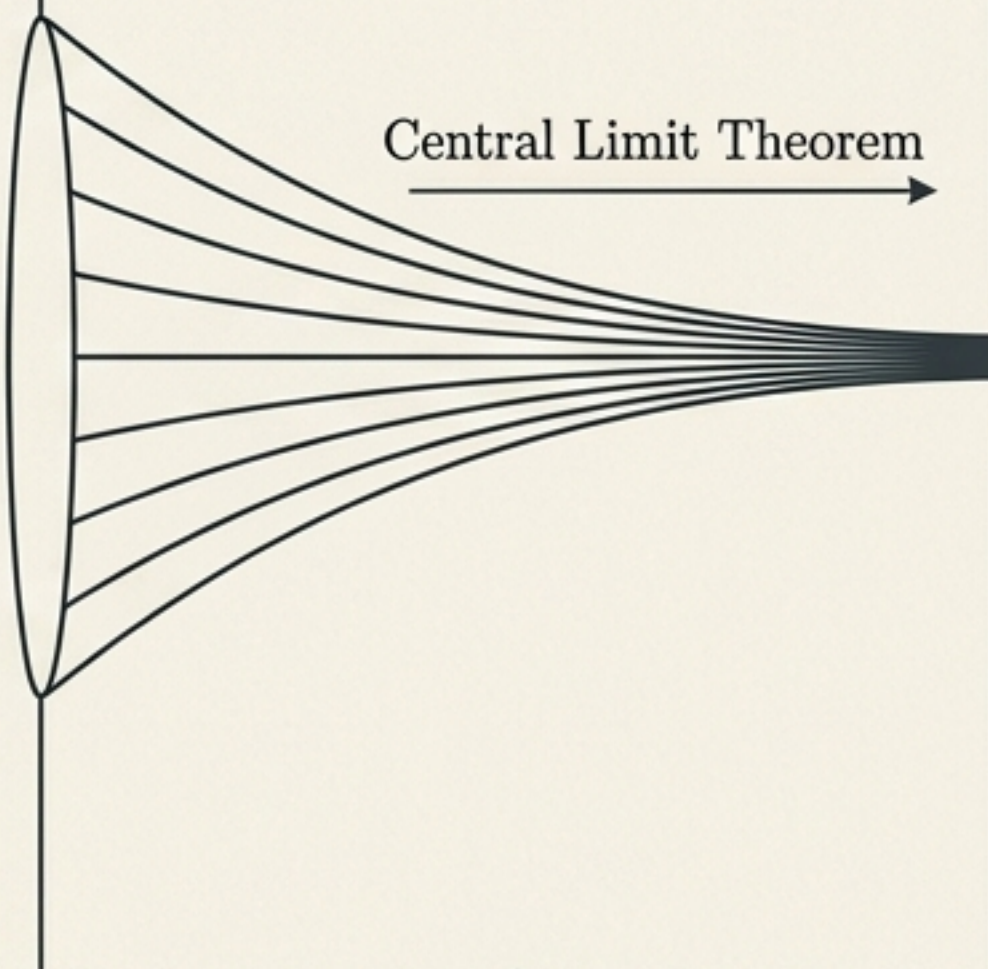
# The Bridge to Free Fields: Infinite Width Yields Gaussian Processes

## Finite Nodes

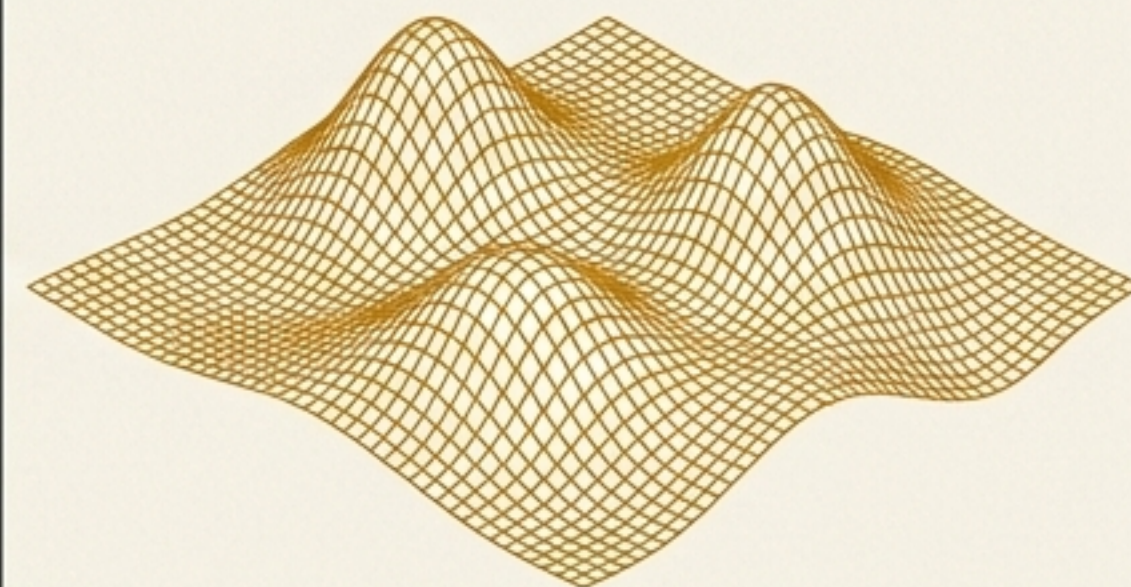


Single Neurons =  
Independent random variables.

## The $N \rightarrow \infty$ Limit






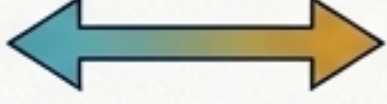


## The Result



$$\phi(x) \sim GP(m(x), k(x, y))$$

Infinite width exactly realizes a non-interacting (Free) Quantum Field Theory.  
The network output distribution is strictly Gaussian.

# The NN-FT Rosetta Stone

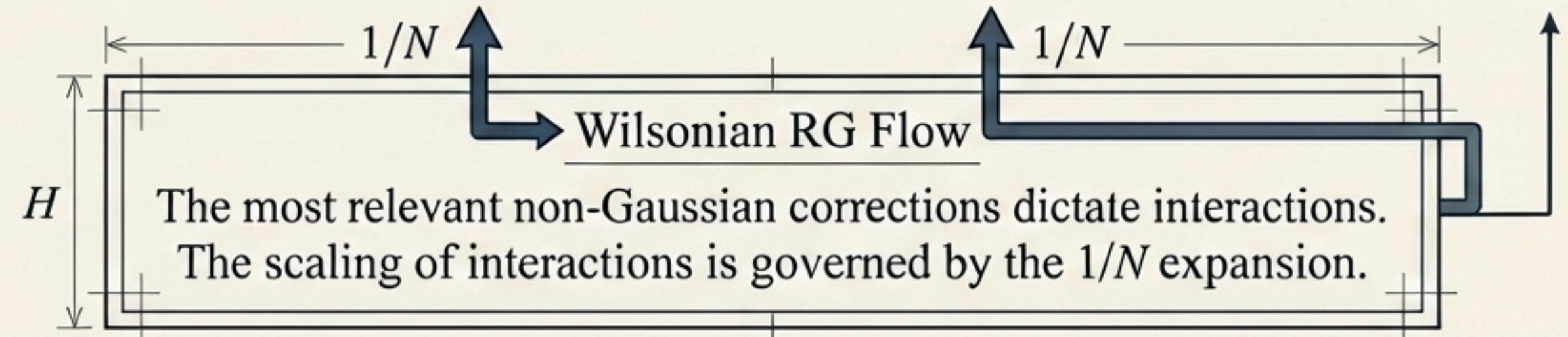
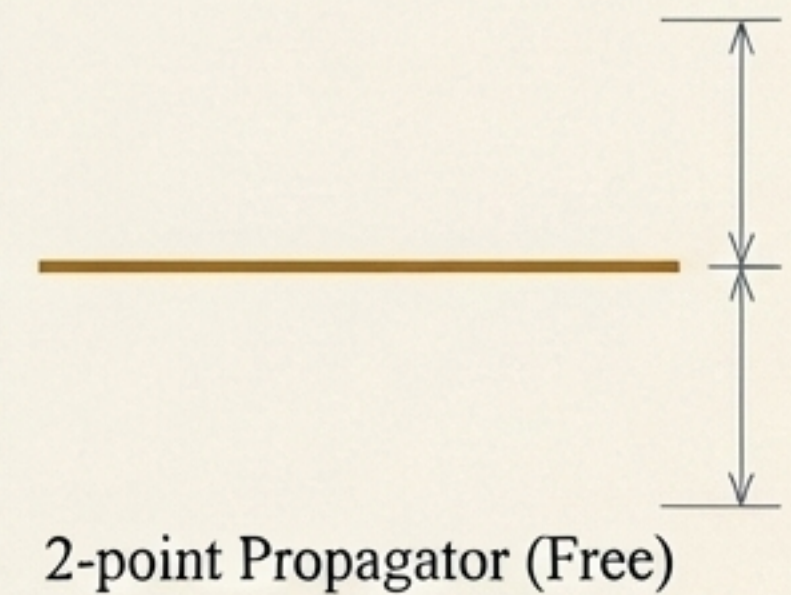
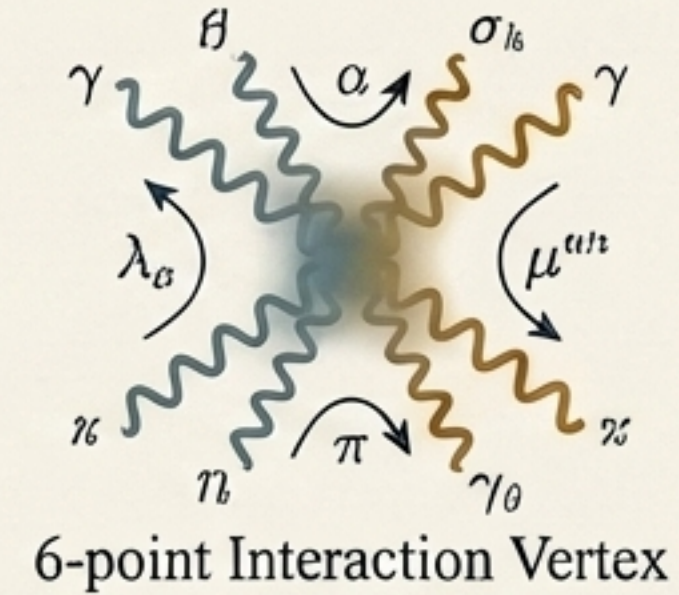
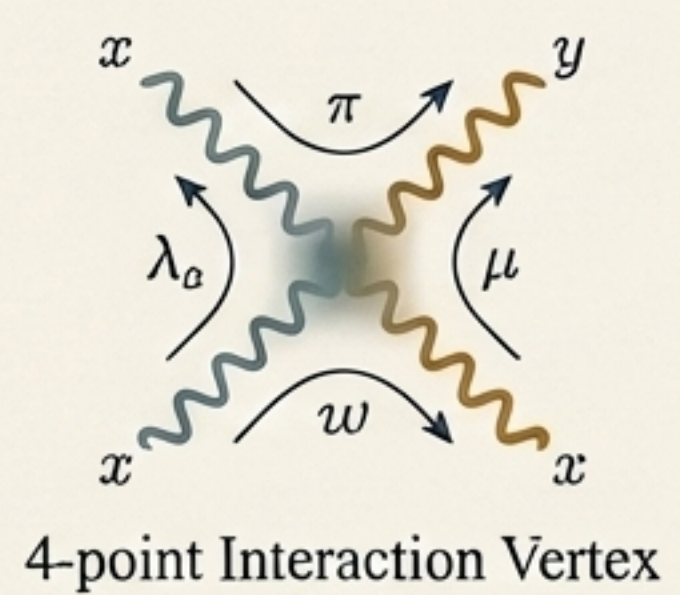
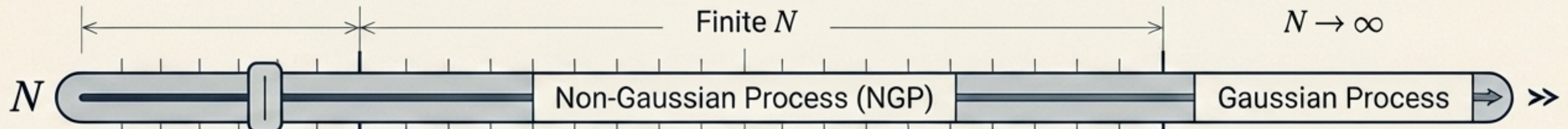
Machine Learning (Cyan)		Quantum Field Theory (Amber)
Input $x$		Spacetime / Momentum point
Network Output $f(x) / \phi(x)$		Interacting Field
Infinite Width ( $N \rightarrow \infty$ )		Free Theory (Gaussian Process)
Finite Width ( $1/N$ )		Interaction Strength (Non-Gaussianities)
Variance of Weights ( $\sigma_a^2$ )		Coupling Constant / String Tension ( $\alpha'$ )
Kernel $K(x, y)$		Feynman Propagator $\langle \phi(x)\phi(y) \rangle = k(x, y)$

This dictionary allows us to 'read' particle physics directly from neural network architectures.

# Finite Width Generates Particle Interactions

arxiv : 2008.08601

$N \rightarrow \infty$



# Architecture as Geometry: Defining the Bosonic String

$$X^\mu(z) = \frac{C}{\sqrt{N}} \sum_{i=1}^N \frac{a_i^\mu}{|W_i|} \cos \left( \frac{1}{2} (W_i z + \bar{W}_i \bar{z}) + c_i \right)$$

## Network Output = Spacetime Embedding

The output of the neural network represents the position of the string  $X^\mu(z)$  in target spacetime. The complex coordinate  $z$  on the worldsheet is the input.

## Parameter Definitions: Weights & Symmetries

$a_i^\mu$ : Output Weights  $\sim$  Isotropic Gaussian  
Ensures Spacetime Rotational Invariance (Lorentz symmetry).

$W_i$ : Frequencies  $\sim$  Uniform( $B_\lambda^2 \setminus B_c^2$ )  
Momentum modes on the annulus, defined over a fundamental domain in the complex plane.

$c_i$ : Bias  $\sim$  Uniform $[-\pi, \pi]$   
Enforces Worksheet Translation Invariance.

## Activation = Mode Expansion & Translation Invariance

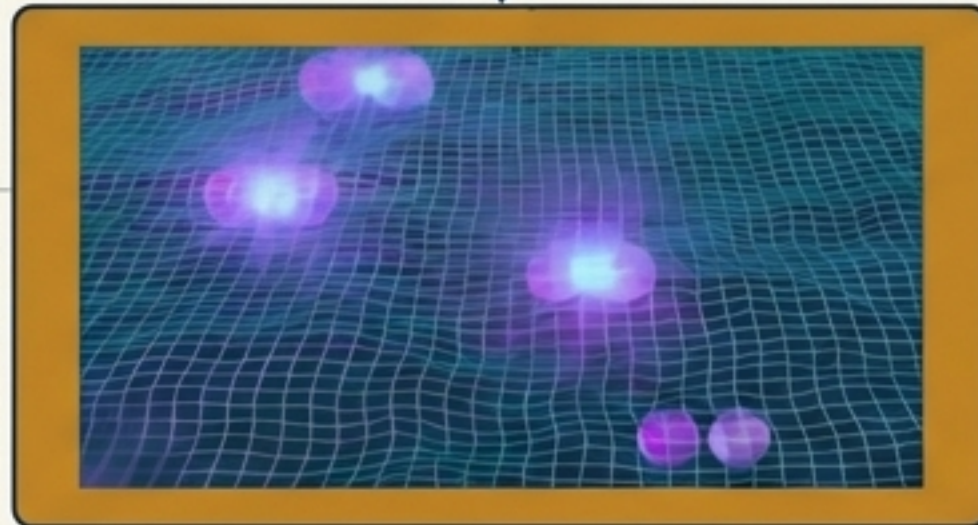
The cosine activation function represents the mode expansion of the string. The **uniform bias**  $c_i \sim [-\pi, \pi]$  enforces **Translation Invariance** on the worldsheet, a key geometric symmetry.

*The string is an ensemble of neural networks. The architecture itself enforces the geometric symmetries of the worldsheet.*

# Tuning the String: Variance Sets the Tension

$$\langle X^\mu(z) X^\nu(w) \rangle = \frac{\sigma_a^2 C^2}{2} \mathbb{E}_W \left[ \frac{\cos[(W \Delta z + \bar{W} \Delta \bar{z})/2]}{|W|^2} \right] \delta^{\mu\nu},$$

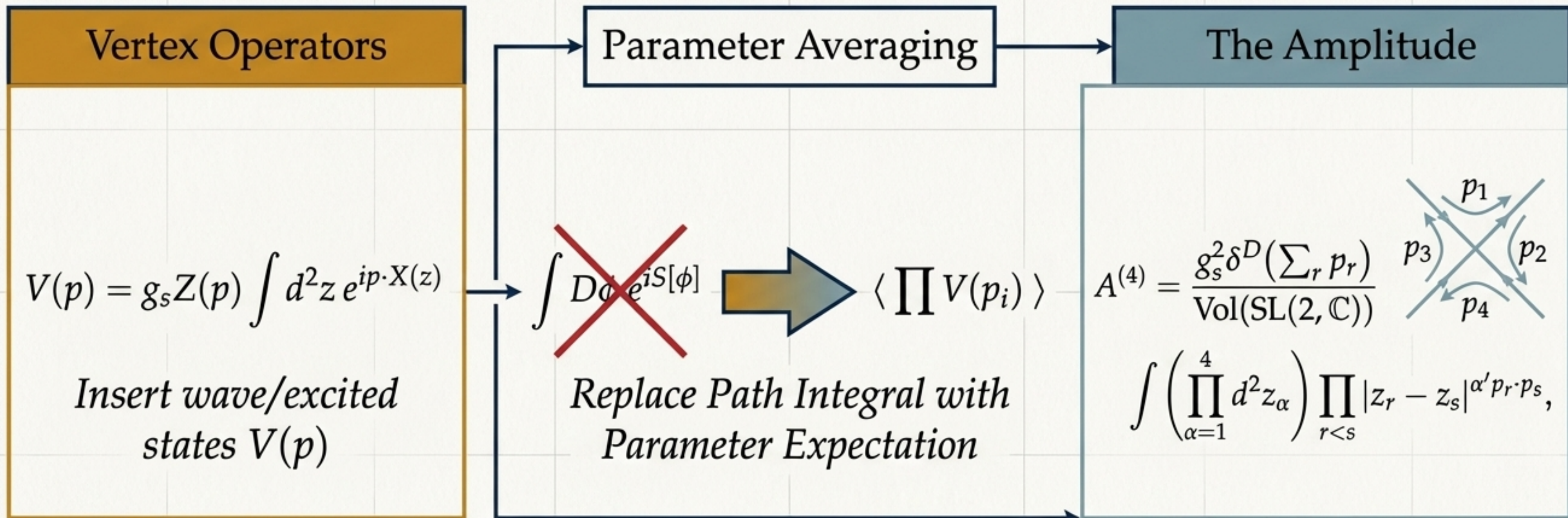
$$\langle X^\mu X^\nu \rangle(r) = \alpha' \int_\epsilon^\Lambda d|W| \frac{J_0(r|W|)}{|W|} \delta^{\mu\nu} = \alpha' \delta^{\mu\nu} \left[ -\log r + \log \frac{2\Lambda}{\epsilon e^\gamma} + \dots \right],$$



Physical String Tension

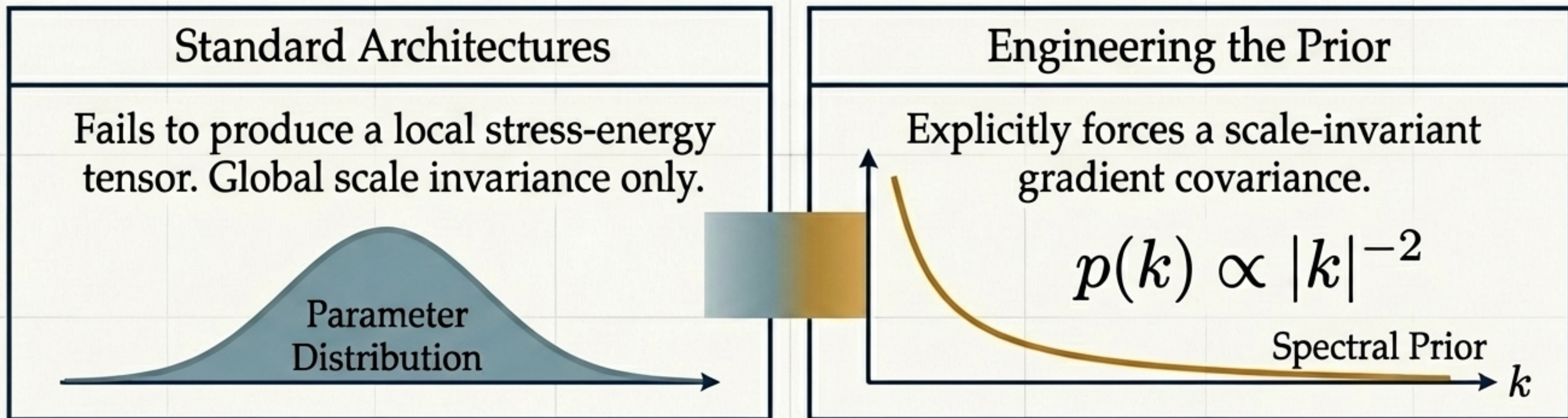
The string length  $l_s \propto \sqrt{\alpha'}$  is exclusively determined by  $\sigma_a$ , the standard deviation of the neural network's output weights.

# Virasoro-Shapiro Amplitudes Without Path Integrals



Crossing symmetry, Regge behavior, and UV softness emerge natively from the neural network's parameter statistics.

# Enforcing Local Symmetry: The Log-Kernel Architecture

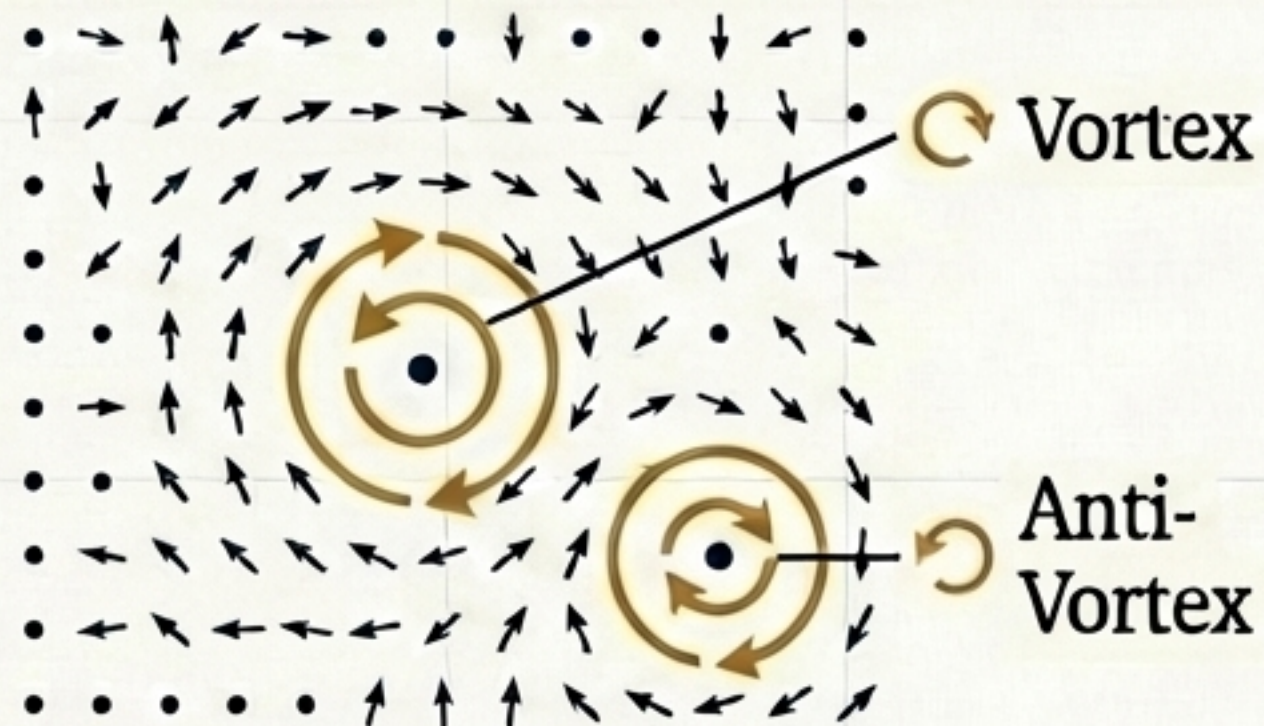


Theoretical Central Charge:  $c = 1$

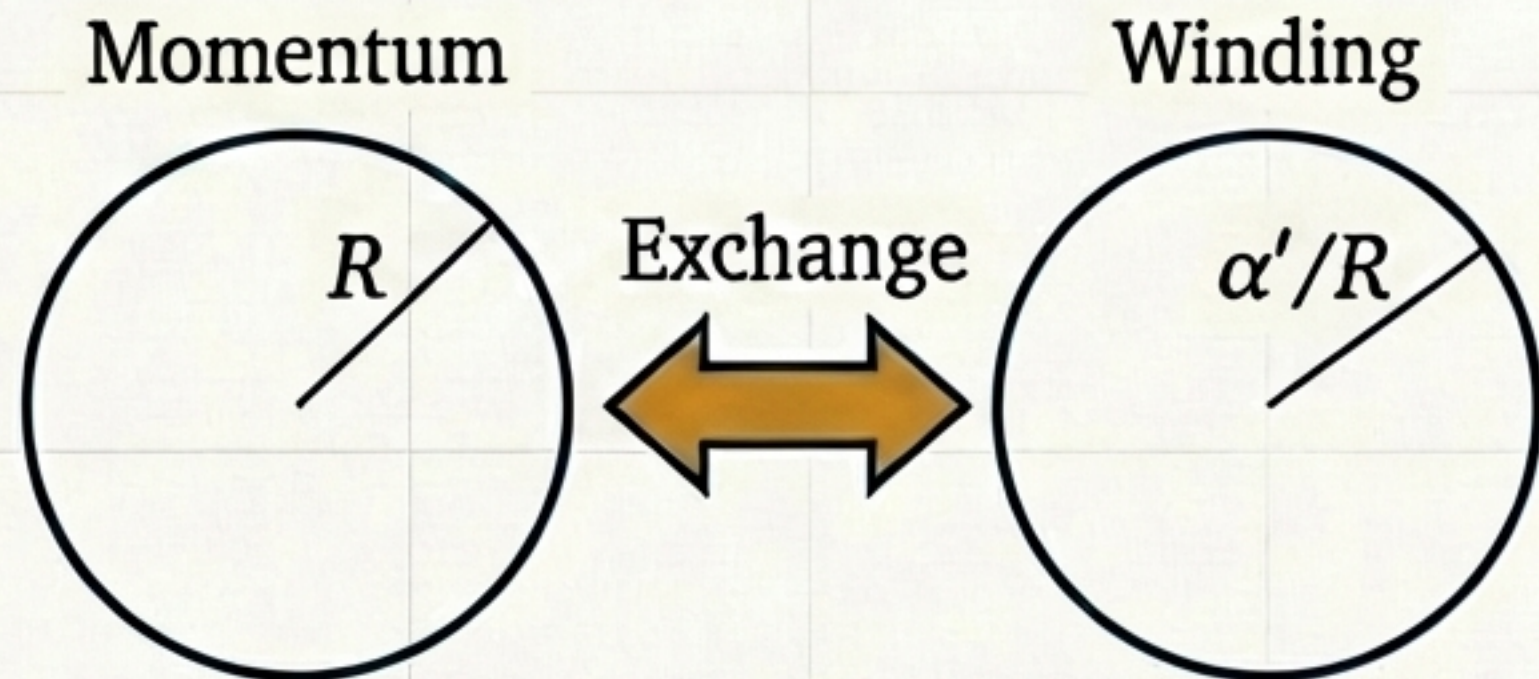
Experimental Central Charge:  $c_{\text{exp}} = 0.9958 \pm 0.0196$

By carefully engineering the probability measure of the network ensemble itself, we can force the hidden layer to act as a conformal reservoir.

# Capturing Global Structure: Topology & Dualities

**A**
**BKT Transition**


Incorporating discrete network parameters unlocks the Berezinskii-Kosterlitz-Thouless transition at high temperatures.

**B**
**T-Duality**


The network recovers the Buscher rules and exhibits exact invariance under the exchange of momentum and winding.

Continuous neural sectors encode local degrees of freedom;  
discrete latent variables encode topological and flux sectors.

# Expanding the Particle Zoo: Fermions & Ghosts

Symmetry Emergence

Emergence of the  $\mathcal{N}=1$  super-Virasoro algebra.

Correlators

$$\langle bc \rangle(p) \propto \frac{1}{\bar{p}}$$

Architecture & Parameters

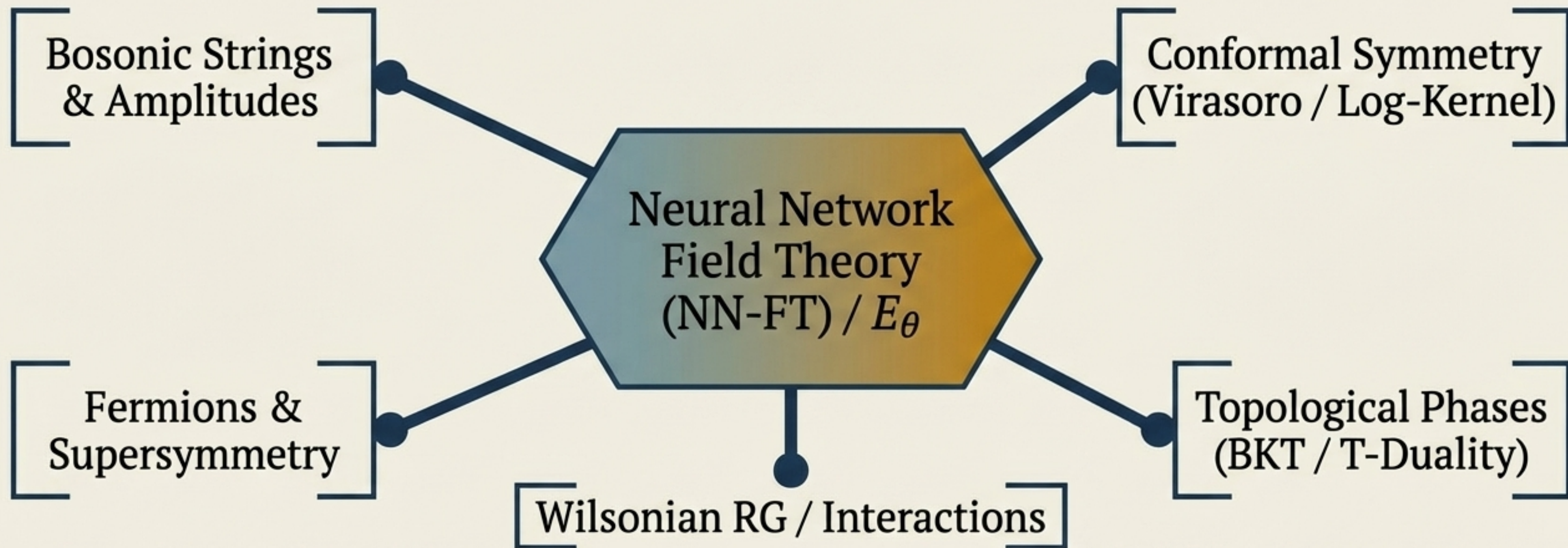
$$\mathbb{E}[\beta_k \chi_l] = \sigma^2 \delta_{kl}$$

Complex frequencies  $w_k \in \mathbb{C}$  and Grassmann weights.

NN-FT is not limited to commuting scalars. Grassmann-valued neural networks perfectly replicate fermionic statistics and supercurrent correlators.

fermionic statistics and supercurrent correlators through one neural network, experimentally.

# Synthesis: The NN-FT Ecosystem

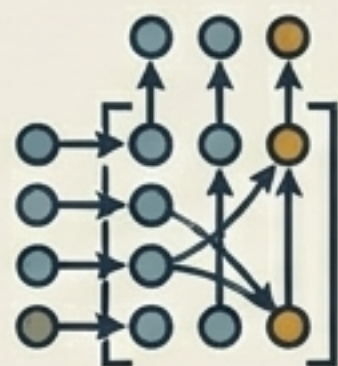


Any architecture with a GP limit—MLPs, CNNs, or Transformers—can theoretically be mapped to a corresponding field theory. The architecture dictates the kinematics; the prior dictates the dynamics.

# Future Horizons: Where Do We Go From Here?

## Architecture Exploration

What novel scattering amplitudes emerge if we replace MLPs with Transformers or CNNs? What is the physics of self-attention?



## Exotic Dualities

If T-duality is natively encoded, can Mirror Symmetry or S-duality be programmed into network priors?



## Scientific ML

Can we use scale-invariant architectures (like the Log-Kernel) as inductive biases to drastically improve training on critical phenomena or turbulence data?



*“The worldsheet path integral is now an integral over neural network parameter space.”*