Formal Experiment Protocol: Prime-Indexed Discrete Scale Invariance (P-DSI) and Emergent Agency

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Goal: To test the core hypothesis of Prime Wave Theory (PWT) V15.2: that constraining Neural Network architecture or dynamics by prime-indexed discrete scale invariance (p-DSI) maximizes causal emergence (ΦDΦD) and robust agency compared to composite-indexed scaling.
Execution Mandate: Execute the full protocol, calculate all metrics, and return raw data tables and comparative analysis.

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1. Experimental Conditions and Independent Variables (ΛΛ)

The core manipulation is the scaling parameter ΛΛ, applied across two parallel experiments.

Scaling Conditions

Condition	Scaling Factors (ΛΛ)	Type	Rationale
Prime Condition (ΛPΛP)	{2,3,5,7,11} {2,3,5,7,11}	Prime	Hypothesized maximum agency/stability.
Composite Condition (ΛCΛC)	{4,6,8,9,10} {4,6,8,9,10}	Composite	Matched for magnitude against ΛPΛP.
Null Condition (ΛNΛN)	{1}{1}	Baseline	Control for non-scaled systems.

Experiment 1: Architectural Scaling (Static Constraint)

- **Network:** A simple 2-layer Feedforward Network (FFN) with one hidden layer.
- **Independent Variable:** Hidden layer width WW is set using the ΛΛ values.
- **Control/Normalization (CRITICAL):**
  Non-scaled inputs/outputs (e.g., 64/10 units) must remain consistent. When scaling WW using ΛΛ, total parameter count (FLOPs) must be matched as closely as possible for all ΛPΛP vs. ΛCΛC pairs. If precise matching is impossible, computational load must be documented and controlled for in the final analysis (e.g., run the smaller model for more epochs).

Experiment 2: Training Temporal Scaling (Dynamic Constraint)

- **Network:** A Recurrent Neural Network (RNN) or LSTM (fixed architecture, e.g., 256 units).
- **Independent Variable:** The period of the Cyclic Learning Rate (CLR) Scheduler PP is set using the ΛΛ values (i.e., P=λP=λ epochs).

- **Mechanism:** The learning rate cycles between β_{min} and β_{max} every λ epochs.
- **Control:** Total number of training steps and maximum learning rate (β_{max}) must be identical across all conditions.

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2. Agent, Task, and Environment Design

Task: Abstract Goal Pursuit (Blocksworld-like)

The task requires the agent to build structures, but the reward is complex and abstract, forcing causal emergence.

- **Environment:** A discrete grid environment (e.g., 10×10) where an agent manipulates 5 distinct block types.
- **Action Space:** Discrete (Move, PickUp, Place).
- **Reward Function (Abstract Goal):**
  The primary reward is **not** for meeting a specific block placement target. Instead, it is calculated based on:
  1. **Symmetry Score:** A high non-linear bonus for structures exhibiting horizontal or rotational symmetry.
  2. **Stability Score:** A non-linear penalty for block placements causing instability or requiring future corrective actions.
  3. **Goal:** The agent must *discover* low-level actions that maximize macro-level rewards (symmetry and stability).

Agent Architecture

- **Choice:** Recurrent Architecture (e.g., LSTM) or a policy-based RL agent (e.g., PPO or DQN) capable of memory and planning.
- **Input:** Current grid state representation (flattened or convolutional).
- **Output:** Action logits.

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3. Dependent Variables: Measuring Agency & Intelligence

All five scaling values in Λ_P and Λ_C, plus the null case Λ_N, must be run, and the results averaged over $N=5$ training runs per condition.

Metric	Definition & Protocol	PWT Prediction (Λ_P vs. Λ_C)
1. Causal Emergence (Φ_D)	Core information-theoretic measure of excess causal influence of macrostates over micro-states. Calculated on the latent representation (hidden state vector) of the network.	**Strongly Higher** in Λ_P

Metric	Definition & Protocol	PWT Prediction (ΛPΛP vs. ΛCΛC)
2. Generalization Gap	Performance difference between training set (10 structure goals) and held-out test set (5 unseen goals) after full training.	**Smaller Gap** in ΛPΛP (Better Generalization)
3. Forgetting Rate	Decay rate of performance on Task A after training on a new, unrelated Task B for 1/101/10 of original epochs.	**Lower Rate** in ΛPΛP (More Stable Memory)
4. Behavioral Complexity	Shannon entropy of the agent's action probability distribution over 100 evaluation episodes.	**Higher Complexity** in ΛPΛP (Avoids Repetitive Policies)
5. Spectral Signature	Fourier analysis of the internal network state dynamics. Record time-series of latent state for T≥10,000T≥10,000 timesteps, apply FFT, and plot on log-frequency scale.	**Peaks at** ωp=2πlnpωp =lnp2π in ΛPΛP (The "Prime Comb")
6. Negative Phase Dominance	Percentage of epochs where network dynamics are dominated by inhibitory or stabilizing feedback loops.	**Higher Percentage** in ΛPΛP

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4. Execution Protocol & Analysis

The executing AI must follow these steps:

1. **Environment Setup:** Implement the 10×1010×10 Blocksworld environment and the Abstract Reward Function.
2. **Network Implementation:** Implement the required network architectures (FFN for Exp 1, RNN/LSTM for Exp 2).
3. **Training Loop:** For each experiment and each scaling factor in ΛPΛP, ΛCΛC, and ΛNΛN:
    - Train N=5N=5 separate instances of the agent.
    - Record training metrics and time-series data for Metric 5.
4. **Metric Calculation:** For all 5×11=555×11=55 trained agents, run the standardized evaluation battery to calculate final values for Metrics 1–6.
5. **Data Analysis:**
    - Perform t-tests or ANOVA to compare mean scores for all metrics across ΛPΛP and ΛCΛC.
    - For Metric 5, perform Fourier transform and confirm presence/absence of Prime Comb spectral peaks.
6. **Deliverables:**
    - Summary of results (average and standard deviation) for all 6 metrics, comparing ΛPΛP and ΛCΛC.
    - Plot of the **log-frequency spectrum** (Metric 5) for a representative agent from ΛPΛP and ΛCΛC.

- Raw data table containing the 6 metric scores for all 55 agents.

Note: The core challenge for the executing AI will be the precise, computationally demanding calculation of ΦDΦD and the accurate Fourier analysis required by the Spectral Signature metric.