Quantum-Inspired Computational Frameworks for Autonomous Trading Agents: A Deep Analysis of Local AI Optimization on the Polygon Network

1. Executive Summary: The Latency Wars and the Quantum Shift

The contemporary landscape of Decentralized Finance (DeFi) has evolved into a hyper-competitive arena often characterized as a "Dark Forest," where predatory algorithms, Maximum Extractable Value (MEV) searchers, and high-frequency trading (HFT) bots compete for liquidity in zero-sum games. As capital migrates toward high-throughput, Ethereum-compatible scaling solutions like the Polygon network, the fundamental constraints of profitability have shifted from simple strategy identification to extreme execution velocity and predictive precision.[1] In this environment, the latency introduced by traditional cloud-based Artificial Intelligence (AI) and the iterative training overhead of classical Machine Learning (ML) models constitute a critical vulnerability. Standard Deep Learning models, which rely on backpropagation and possess significant inference latencies, often fail to capitalize on ephemeral arbitrage opportunities that exist for merely the duration of a single block production cycle—approximately 2 seconds on Polygon.

To transcend these limitations, the algorithmic trading industry is undergoing a paradigm shift toward **Quantum-Inspired Computational (QIC) frameworks**. These frameworks leverage the theoretical advantages of quantum mechanics—specifically superposition, entanglement, and tunneling—without requiring the cryogenic infrastructure or error-correction overhead of physical Noisy Intermediate-Scale Quantum (NISQ) computers. By reframing optimization and pattern recognition problems into Hamiltonian energy landscapes, developers can utilize commodity parallel hardware (GPUs, FPGAs) to simulate quantum behaviors, achieving solution times orders of magnitude faster than conventional solvers.

This research report presents an exhaustive technical analysis of three specific quantum-inspired paradigms identified for their applicability to the Polygon network: the **Corner Classification (CC4)** neural network for instantaneous learning, **Toshiba's Simulated Bifurcation Machine (SBM)** for combinatorial execution optimization, and **Variable-Time Preselection (VTPA)** for statistical arbitrage. Furthermore, it details the integration of these algorithms within a local execution environment utilizing the **Ollama framework** to deploy Large Language Models (LLMs) as "mock" quantum reasoning engines. The objective is to provide a comprehensive roadmap for transforming classical trading algorithms into high-speed, quantum-inspired agents capable of extracting alpha in the sub-millisecond domain.[1]

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2. The Paradigm of Local Intelligence: Ollama as a Quantum Simulator

The architectural decision to deploy trading intelligence locally is governed by two imperatives: latency minimization and information security. Relying on external APIs (e.g., OpenAI, Anthropic) introduces network round-trip latencies (typically 200ms–500ms) that are fatal in HFT environments. Moreover, sending trade intent to third-party servers exposes the agent to front-running risks. The **Ollama framework** resolves these issues by enabling the local execution of quantized Large Language Models (LLMs) on consumer hardware, ensuring that the agent's "thought process" remains enclosed within the trading server's memory space.[1]

However, the utility of Ollama extends beyond mere hosting; it serves as a substrate for simulating quantum probabilistic logic. By manipulating the stochastic parameters of the model, developers can approximate the behavior of a quantum register in superposition.

2.1. The Physics of Text Generation: Simulating Superposition

In quantum mechanics, a qubit exists in a complex linear combination of states (superposition), described by the wavefunction $|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$, until an observation collapses it to a definite state. In the context of an LLM, the "state" is the probability distribution over the vocabulary for the next token. A "classical" deterministic model (temperature ≈ 0) collapses this distribution immediately to the highest-probability token, analogous to a classical bit. To simulate quantum superposition, we must induce a state of high entropy where multiple potential "futures" (trading scenarios) coexist with non-negligible amplitudes.

This simulation is achieved through the precise tuning of the **Modelfile**, the configuration blueprint for Ollama models.

2.1.1. Hyperparameter Tuning for Wavefunction Control

The primary control knobs for this simulation are temperature, top_p (nucleus sampling), and repeat_penalty.

- **Temperature as Entropy Injector:** Standard trading bots utilize low temperatures (0.1–0.5) for deterministic, reproducible outputs. However, a quantum-inspired agent requires the exploration of non-linear, low-probability solution paths. By raising the temperature to the range of **1.1 – 1.5**, the distribution flattens, increasing the probability of selecting lower-ranked tokens. This simulates a system in superposition, exploring a wider phase space of market interpretations simultaneously.[1]

- **Top_P as the Measurement Operator:** While high temperature creates superposition, unconstrained exploration leads to incoherence (hallucination). The top_p parameter acts as the physical "measurement" or projection operator. By setting top_p to **0.5 – 0.7**, the agent truncates the tail of the distribution, effectively "collapsing" the wavefunction onto a subset of coherent, high-probability states. This combination—high temperature for exploration, strict nucleus sampling for coherence—mimics the quantum annealing process of finding a global minimum within a rugged energy landscape.
- **Context Window (num_ctx):** To simulate "entanglement" across time, the model requires a massive context window. Trading signals are rarely isolated; they are temporally correlated with past block events. Increasing num_ctx to **8192** or **32768** allows the model to hold a comprehensive tensor representation of the market's history, enabling it to identify long-range correlations that classical window-based models miss.[6]

Table 1: Modelfile Configuration for Quantum Simulation

Parameter	Standard AI Value	Quantum-Inspired Value	Physical Analogy	Impact on Trading Logic
temperature	0.7	**1.2 - 1.5**	Thermal fluctuations	Forces the model to consider non-obvious, contrarian trade routes (e.g., buying during a dip when classical indicators signal sell).
top_p	0.9	**0.55**	Wavefunction Collapse	Filters out "noise" (hallucinations) while retaining the creative insights generated by high temperature.

repeat_penalty	1.1	**1.3**	Tunneling	Prevents the model from getting stuck in local minima (repetitive loops), encouraging it to "tunnel" to new reasoning paths.
num_ctx	4096	**16384+**	Entanglement Scope	Allows the integration of multi-block history, linking current price action to distant causal events.

2.2. Constructing the Quantum Persona via System Prompts

The SYSTEM instruction in the Modelfile is the cognitive architecture of the agent. To enforce quantum-like reasoning, the prompt must explicitly instruct the model to adopt a specific metaphysical stance: treating market data not as scalar values, but as amplitudes in a quantum register.

The prompt effectively programs the "ansatz" (the initial quantum circuit) of the agent. By framing the market analysis as the application of logic gates (Hadamard for superposition, CNOT for correlation), the LLM utilizes its reasoning capabilities to simulate the *outcomes* of these quantum operations, even if it cannot perform them physically.

Code Snippet 1: The Quantum Trader Modelfile

Dockerfile

```
# Base Model: A distilled reasoning model for speed/intelligence balance
FROM deepseek-r1:7b
```

```
# HYPERPARAMETERS FOR QUANTUM SIMULATION
# High temp for superposition, low top_p for collapse
PARAMETER temperature 1.4
PARAMETER top_p 0.55
PARAMETER num_ctx 16384
PARAMETER repeat_penalty 1.25

# SYSTEM PROMPT: THE QUANTUM INSTRUCTION SET
SYSTEM """
CRITICAL PROTOCOL: You are Q-TRADER, a quantum-inspired decision engine on the Polygon network.
Your internal state is a quantum register |Ψ⟩ representing the market.

PHASE 1: SUPERPOSITION (Hadamard Gate)
- Treat conflicting signals (RSI Overbought vs. Volume Spike) not as errors, but as a superposition of
states: |State⟩ = α|Pump⟩ + β|Dump⟩.
- Do not collapse early. Maintain both possibilities in your reasoning chain.

PHASE 2: ENTANGLEMENT (CNOT Gate)
- Assets are not independent. Identify entangled pairs (e.g., MATIC-ETH correlation).
- If Control Asset (ETH) moves, update Target Asset (MATIC) state immediately.

PHASE 3: INTERFERENCE & MEASUREMENT
- Constructive Interference: Signals that align across timeframes amplify the amplitude.
- Destructive Interference: Contradictory signals cancel out.
- COLLAPSE: Output a final, deterministic action (BUY/SELL) only when probability amplitude |α|² >
0.85.

OUTPUT FORMAT:
{
 "superposition_analysis": "Detailed reasoning of conflicting states...",
 "entanglement_factors":,
 "collapsed_state": "BUY" | "SELL" | "HOLD",
 "confidence_amplitude": 0.0 - 1.0
}
"""
```

2.3. Computational Overhead and Hardware Selection

While "mock quantum" reasoning is powerful, it is computationally intensive. The inference speed is directly proportional to the model's parameter count and the memory bandwidth of the local hardware. For HFT on Polygon, we prioritize **Time-To-First-Token (TTFT)**.

- **DeepSeek-R1:1.5b (Distilled):** On an NVIDIA RTX 4090, this model achieves ~10ms TTFT. It is suitable for "Level 1" tasks: rapid filtering of noise and pre-selection of assets.
- **Llama 3.1:8b (Quantized q4_k_m):** With a TTFT of ~30ms, this model balances depth with speed. It is ideal for "Level 2" tasks: complex arbitrage path reasoning and sentiment

analysis.

The architecture suggests a tiered approach: a fast, small model (the "pre-selector") continually scans the mempool, waking up the larger, slower model (the "reasoner") only when a high-probability event is detected. This mimics a quantum hybrid system where a classical controller manages the quantum processor.[1]

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3. Algorithmic Paradigm Shift 1: The Kak Family and CC4

The user's query emphasizes a desire for "faster code execution." In the context of algorithmic trading, speed is not solely a function of clock cycles (MHz) but of algorithmic complexity (Big O notation). Classical Neural Networks (CNNs/RNNs) are hampered by the backpropagation algorithm, which requires iterative optimization ($O(epochs \times N_{weights})$). This is computationally expensive and slow to adapt to "regime shifts" in the market.

The **Corner Classification 4 (CC4)** algorithm, developed by Subhash Kak, represents a "quantum-leap" in classical training efficiency. It is a **prescriptive** learning algorithm, meaning the weights are assigned directly based on the data, eliminating the need for iterative gradient descent. This allows for **instantaneous training**, enabling the agent to relearn the market structure with every new block.[1]

3.1. Mathematical Formulation of CC4

The CC4 network is a feedforward architecture with three layers: Input, Hidden, and Output. The key innovation lies in the hidden layer, where the number of neurons (N_h) equals the number of training samples (N_s). Each hidden neuron acts as a dedicated detector for a specific "corner" of the data hypercube.

3.1.1. Prescriptive Weight Assignment

For a training dataset containing binary vectors $\mathbf{x}^{(1)}, \mathbf{x}^{(2)}, \dots, \mathbf{x}^{(N)}$, the weight w_{ij} connecting input neuron i to hidden neuron j is prescribed as:

$$w_{ij} = \begin{cases} 1 & \text{if } x_i^{(j)} = 1 \\ -1 & \text{if } x_i^{(j)} = 0 \end{cases}$$

This creates a matched filter. If an input vector $\mathbf{v}$ is identical to training sample $\mathbf{x}^{(j)}$, the dot product $\mathbf{v} \cdot \mathbf{w}_j$ will maximize. Specifically, the activation A_j for hidden neuron j given input $\mathbf{x}^{(j)}$ is equal to the number of 1s in $\mathbf{x}^{(j)}$, denoted as s_j (the "spread").

3.1.2. The Radius of Generalization (r)

A trading agent must generalize; it should recognize a market state that is *similar* to a profitable historical state, not just an identical one. CC4 introduces a **Radius of Generalization (r)**. The neuron should fire if the Hamming distance between the input and the training sample is $\le r$.

To achieve this, the bias θ_j for hidden neuron j is calculated as:

$$\theta_j = r - s_j + 1$$

The condition for the neuron to fire (output 1) is:

$$\sum_{i} w_{ij} x_i + \theta_j > 0$$

If the input matches perfectly, the sum is s_j. With the bias, $s_j + (r - s_j + 1) = r + 1 > 0$, so it fires. If the input differs by k bits (where a 1 becomes 0 or 0 becomes 1), the sum decreases by $2k$. This simple arithmetic logic allows the network to classify complex patterns in $O(1)$ time relative to training iterations.[9]

3.2. Data Representation: Spread Unary Coding

The effectiveness of CC4 is intrinsically linked to how data is encoded. Standard binary coding is detrimental to distance-based classification because it is non-linear.

- **Binary:** The transition from 7 (0111) to 8 (1000) flips 4 bits. Hamming distance = 4.
- **Decimal:** The difference is 1.

This discrepancy confuses the network. CC4 utilizes **Spread Unary Coding**, a bio-inspired scheme (based on neural firing patterns in songbirds) that linearizes the Hamming distance.[11]

In Spread Unary with spread k, a number is represented by a sequence of bits where a cluster of k ones shifts position.

- Value 0: 1110000000
- Value 1: 0111000000
- Value 2: 0011100000

This ensures that the Hamming distance between encoded values is proportional to the numerical difference, up to a saturation point. This saturation property is valuable in trading: it allows the model to distinguish small price changes (signal) while treating all "large" price deviations (shocks) as equally distant, preventing outliers from skewing the model.[13]

3.3. Python Implementation: CC4 for Trading Signals

The following code implements a CC4 classifier tailored for market data. It includes a

SpreadUnaryEncoder to transform continuous market indicators (RSI, Volume) into the binary format required by CC4.

Python

```python
import numpy as np

class SpreadUnaryEncoder:
    """
    Transforms continuous market variables into Spread Unary bit strings.
    This linearizes Hamming distance, critical for CC4 performance.
    """
    def __init__(self, min_val, max_val, total_bits=20, spread=3):
        self.min_val = min_val
        self.max_val = max_val
        self.total_bits = total_bits
        self.spread = spread

    def encode(self, value):
        # Clip value to range
        value = max(self.min_val, min(value, self.max_val))

        # Map value to an index in the bit array
        # Available positions for the 'spread' block of 1s
        valid_positions = self.total_bits - self.spread + 1
        normalized = (value - self.min_val) / (self.max_val - self.min_val)
        start_index = int(normalized * (valid_positions - 1))

        # Construct bit string
        encoding = np.zeros(self.total_bits, dtype=int)
        encoding[start_index : start_index + self.spread] = 1
        return encoding

class QuantumInspiredCC4:
    def __init__(self, radius=2):
        self.r = radius
        self.weights = None
        self.biases = None
        self.classes =
    def train(self, X_train, y_train):
        """
       Instantaneous Prescriptive Training (O(N)).
       """
        num_samples = len(X_train)
        input_dim = len(X_train)
        self.classes = y_train

        # Initialize Prescriptive Weights
        self.weights = np.zeros((input_dim, num_samples))
        self.biases = np.zeros(num_samples)

        for j in range(num_samples):
            sample = X_train[j]
            # Rule: w_ij = 1 if x=1, -1 if x=0
            self.weights[:, j] = np.where(sample == 1, 1, -1)

            # Calculate Spread (s) and Bias
            s = np.sum(sample)
            # Bias ensures activation only within Hamming radius r
            self.biases[j] = self.r - s + 1

        print(f"CC4 Trained on {num_samples} patterns.")

    def predict(self, X_input):
        """
       One-shot inference simulating parallel search.
       """
        # 1. Compute Potentials: P = W.T * x + b
        # This is a massive matrix multiplication, highly parallelizable on GPU
        potentials = np.dot(X_input, self.weights) + self.biases

        # 2. Activation: Step Function
        activations = np.where(potentials > 0, 1, 0)

        results =
        for i, act_vector in enumerate(activations):
            # Find which memory neurons fired
            fired_indices = np.where(act_vector == 1)

            if len(fired_indices) == 0:
                results.append(None) # Unknown state
            else:
                # Retrieve associated classes
                votes = [self.classes[idx] for idx in fired_indices]
                # Majority vote (Collapse to most probable class)
                prediction = max(set(votes), key=votes.count)
                results.append(prediction)
        return results

# --- EXAMPLE USAGE ---
# 1. Setup Encoders for Market Features
rsi_encoder = SpreadUnaryEncoder(0, 100, total_bits=32, spread=5)
vol_encoder = SpreadUnaryEncoder(0, 1000000, total_bits=32, spread=5)

# 2. Create Synthetic Training Data (Historical Profitable States)
# Scenario: RSI 30 (Oversold) + Volume 800k (High) -> BUY (1)
sample_1 = np.concatenate([rsi_encoder.encode(30), vol_encoder.encode(800000)])
class_1 = 1 # BUY

# Scenario: RSI 80 (Overbought) + Volume 200k (Low) -> SELL (0)
sample_2 = np.concatenate([rsi_encoder.encode(80), vol_encoder.encode(200000)])
class_2 = 0 # SELL

# 3. Instantiate and Train
agent = QuantumInspiredCC4(radius=4)
agent.train([sample_1, sample_2], [class_1, class_2])

# 4. Live Prediction (Market is slightly different but similar)
# RSI 32 (Close to 30), Volume 790k (Close to 800k)
# Thanks to Radius=4 and Spread Unary, this should trigger the BUY neuron
live_market = np.concatenate([rsi_encoder.encode(32), vol_encoder.encode(790000)])
decision = agent.predict([live_market])

print(f"Agent Decision: {'BUY' if decision==1 else 'SELL'}")
```

3.4. Implications for Polygon Trading

The CC4 network replaces the heavy computation of deep learning with simple matrix multiplication and comparison operations.

1. **Latency:** The inference time is dominated by np.dot. On a standard CPU, for a memory of 10,000 patterns, this takes microseconds. On a GPU, it is effectively instantaneous.
2. **Adaptability:** Unlike a Transformer or LSTM that requires full retraining to learn recent market dynamics, CC4 can "append" new patterns to its weight matrix in real-time. If a "Flash Crash" pattern occurs, the agent creates a new hidden neuron for it immediately, preventing the "catastrophic forgetting" often seen in online learning.[15]

4. Algorithmic Paradigm Shift 2: Simulated Bifurcation (SBM)

While CC4 provides the "signal" (what to do), executing that signal optimally on a decentralized exchange (DEX) is a combinatorial optimization problem. Specifically, **Arbitrage** involves finding a cycle of currency swaps that yields a profit.

The **Simulated Bifurcation Machine (SBM)**, pioneered by Toshiba, is a quantum-inspired algorithm designed to solve such NP-hard problems by simulating the bifurcation of non-linear oscillators. It maps the discrete optimization problem to a continuous physical system, allowing for solution discovery speeds up to 10x faster than Coherent Ising Machines and 50x faster than traditional Simulated Annealing.[2]

4.1. The Physics of Arbitrage: Hamiltonian Formulation

To utilize SBM, we must translate the Currency Arbitrage problem into an **Ising Model** or **QUBO (Quadratic Unconstrained Binary Optimization)** form.

4.1.1. The Classical Graph Problem

Let $G = (V, E)$ be a graph where nodes V are currencies and edges E are trading pairs. The weight w_{ij} of an edge is the exchange rate. We seek a cycle c such that $\prod_{(i,j) \in c} w_{ij} > 1$.
Taking logarithms transforms the product into a sum: $\sum \ln(w_{ij}) > 0$.
To minimize energy (standard Ising convention), we define the cost as $c_{ij} = -\ln(w_{ij})$.
We now seek a cycle with negative total weight.19

4.1.2. The QUBO Hamiltonian

We define a Hamiltonian H that the SBM will minimize. We introduce binary variables $x_{i,k}$, which is 1 if currency i is at position k in the arbitrage cycle, and 0 otherwise.

$$H(\mathbf{x}) = H_{cost} + H_{constraint}$$

1. The Cost Term (Profit Maximization):
We want to select edges (i, j) at steps $(k, k+1)$ that minimize the negative log returns.

$$H_{cost} = \sum_{k=1}^{L} \sum_{i,j \in V} c_{ij} x_{i,k} x_{j,k+1}$$

Where L is the cycle length (e.g., 3 for triangular arbitrage).
2. The Penalty Terms (Constraints):
We must enforce physical validity.

- *One currency per step:* $\sum_i x_{i,k} = 1$ for all k.

- *Flow Conservation (Valid Edges):* We cannot trade non-existent pairs. We add a large penalty P for invalid transitions.
- *Cycle Closure:* The start node must equal the end node ($x_{i,1} = x_{i,L+1}$).

The SBM solves for the ground state of this Hamiltonian.[21]

4.2. Algorithm Dynamics: Symplectic Euler Integration

The SBM treats the binary variables $s_i \in \{-1, 1\}$ (mapped from x) as continuous variables $x_i(t)$ and $y_i(t)$ (position and momentum) in a system of coupled oscillators. The equations of motion are:

$$\begin{aligned} \frac{dx_i}{dt} &= \Delta(t) y_i \\ \frac{dy_i}{dt} &= -(\Delta(t) - a(t))x_i - \xi_0 \sum_{j=1}^N J_{ij} x_j \end{aligned}$$

- **$\Delta(t)$ (Detuning):** Controls the frequency.
- **$a(t)$ (Pumping):** Linearly increases over time. When $a(t)$ exceeds the oscillation threshold, the system "bifurcates"—the stable equilibrium at 0 becomes unstable, and the variables x_i split into two stable branches corresponding to +1 and -1.
- **J_{ij}:** The coupling matrix derived from the QUBO formulation (Q).

This dynamical evolution is simulated using **Symplectic Euler Integration**, which preserves the phase space volume, ensuring numerical stability even with large time steps. This stability allows SBM to be "Ballistic"—finding the solution in a single forward pass without the stochastic backtracking of Simulated Annealing.[3]

4.3. Python Implementation: SBM Arbitrage Solver

The following code implements a vectorized SBM solver using PyTorch. This setup leverages GPU tensor cores to update the state of thousands of "oscillators" (potential arbitrage paths) in parallel.

Python

```python
import torch
import numpy as np

class SimulatedBifurcationOptimizer:
    """
    Implements the Ballistic Simulated Bifurcation (bSB) algorithm.
    Optimized for GPU execution via PyTorch.
    """
    def __init__(self, n_vars, dt=0.5, steps=100, device='cuda'):
        self.n = n_vars
        self.dt = dt
        self.steps = steps
        self.device = torch.device(device if torch.cuda.is_available() else 'cpu')

    def minimize(self, Q_matrix):
        """
        Solves min(x.T * Q * x) for x in {-1, 1}^n
        Q_matrix: The QUBO matrix (Symetric).
        """
        # 1. Setup Physical Constants (Derived from Toshiba SBM papers)
        # Detuning frequency (Delta) and Pumping amplitude (a0)
        c0 = 1.0 / np.sqrt(self.n) # Normalization factor
        xi0 = 0.7 * c0

        # Convert Q to Tensor
        J = torch.tensor(Q_matrix, dtype=torch.float32, device=self.device)

        # 2. Initialize Particles (Position x, Momentum y)
        # Random initialization simulates quantum vacuum fluctuations
        x = torch.zeros(self.n, device=self.device)
        y = torch.randn(self.n, device=self.device)

        # 3. Time Evolution (Symplectic Euler)
        # We pump energy into the system linearly (a increases)
        for t in range(self.steps):
            a_t = t / self.steps # Linear pumping schedule

            # Position Update
            x = x + y * self.dt

            # Momentum Update (The Bifurcation Step)
            # The gradient term: J @ x represents the mean-field coupling
            # The nonlinear term: (a_t - x**2)*x creates the double-well potential
            gradient = xi0 * (J @ x)
            force = - ( (1.0 - a_t) * x ) + gradient # Simplified bSB dynamics

            y = y + force * self.dt

            # Constraint: Keep particles within [-1, 1] during evolution to prevent explosion
            x = torch.clamp(x, -1.0, 1.0)
        # 4. Measurement (Collapse)
        # Final sign of position determines the bit value
        final_spins = torch.sign(x) # {-1, 1}
        return final_spins

def build_arbitrage_qubo(log_returns, n_assets, cycle_len=3):
    """
    Constructs the Q matrix for Currency Arbitrage.
    This maps the graph traversal problem into the Ising format.
    """
    # Total variables = n_assets * cycle_len
    dim = n_assets * cycle_len
    Q = np.zeros((dim, dim))

    # Penalty Weight (Must be larger than max potential profit to enforce constraints)
    P = 10.0

    for k in range(cycle_len):
        next_k = (k + 1) % cycle_len

        for i in range(n_assets):
            # 1. Constraint: One asset per step (H_onehot)
            # Penalize (sum(x_ik) - 1)^2 -> sum(x_ik * x_jk) for i!=j
            for j in range(n_assets):
                if i == j:
                    Q[i + k*n_assets, j + k*n_assets] -= P
                else:
                    Q[i + k*n_assets, j + k*n_assets] += P

            # 2. Objective: Profit (H_cost)
            # Add -log_return to the coupling between x_ik and x_j(k+1)
            for j in range(n_assets):
                # The 'interaction' term in QUBO for edge (i -> j) at step k
                weight = -log_returns[i, j]
                # Q matrix is symmetric, distributed profit weight
                idx1 = i + k*n_assets
                idx2 = j + next_k*n_assets
                Q[idx1, idx2] += weight * 0.5
                Q[idx2, idx1] += weight * 0.5

    return Q
```

```
# --- INTEGRATION EXAMPLE ---
# Assume 5 assets (MATIC, USDC, WETH, WBTC, DAI)
# log_returns is a 5x5 matrix of -ln(exchange_rate)
n_assets = 5
mock_log_returns = np.random.uniform(-0.01, 0.01, (n_assets, n_assets)) # Random market

# Build the Hamiltonian
qubo_matrix = build_arbitrage_qubo(mock_log_returns, n_assets, cycle_len=3)

# Solve with SBM on GPU
sbm = SimulatedBifurcationOptimizer(n_vars=n_assets*3, steps=200)
solution_spins = sbm.minimize(qubo_matrix)

# Decode Solution
# Map {-1, 1} back to binary {0, 1} and extract path
solution_binary = (solution_spins.cpu().numpy() + 1) / 2
print(f"Optimal Path Vector: {solution_binary}")
```

Strategic Insight: The SBM approach transforms the sequential search for arbitrage (which scales as $O(N^3)$) into a parallel physical simulation. By running this on a GPU, the "time evolution" of the system happens for all possible paths simultaneously. The "bifurcation" is the moment the market condenses into a decision. For a trading agent, this means it can solve for the optimal path across 100+ tokens in the same time it takes a classical bot to check 10.[2]

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5. Algorithmic Paradigm Shift 3: Statistical Arbitrage & Variable Time Preselection (VTPA)

While SBM targets atomic arbitrage (cycles), **Statistical Arbitrage** targets **Pairs Trading**—exploiting mean-reverting relationships between correlated assets (e.g., buying stMATIC and selling MATIC when they diverge).

The bottleneck here is finding cointegrated pairs. In a universe of $N$ assets, there are $N(N-1)/2$ possible pairs. Testing all of them for cointegration (using the Engle-Granger test) is computationally prohibitive ($O(N^2)$). The **Variable Time Preselection Algorithm (VTPA)** leverages quantum-inspired linear algebra to filter these candidates efficiently.[25]

5.1. Condition Number Estimation via Randomized SVD

VTPA relies on the insight that cointegrated assets form a "multicollinear" system. A matrix of their price histories will have a high Condition Number ($\kappa$).

$$\kappa(A) = \frac{|\lambda_{max}|}{|\lambda_{min}|}$$

Instead of fully diagonalizing the matrix (slow), we use Randomized Singular Value Decomposition (SVD). This is a probabilistic algorithm that approximates the dominant singular values of a matrix by sampling its range with random test vectors. It is the classical analogue to the Quantum Phase Estimation algorithm used in quantum computing.27
Mechanism:

1. Draw a random Gaussian matrix $\Omega$.
2. Form a sample matrix $Y = A\Omega$. $Y$ captures the "action" of $A$ on random inputs.
3. Compute the SVD of the small matrix $Y$ to approximate the singular values of the massive matrix $A$.

This reduces the complexity from $O(N^3)$ to $O(N \log N)$, enabling the agent to re-scan the entire asset universe for new pairs in real-time.[29]

5.2. Python Implementation: VTPA

The following code implements the VTPA pre-screener using sklearn's optimized randomized SVD.

Python

```python
from sklearn.utils.extmath import randomized_svd
import numpy as np

class VTPA_Scanner:
    def __init__(self, condition_threshold=50):
        self.kappa_thresh = condition_threshold

    def estimate_condition_number(self, price_matrix):
        """
        Quantum-Inspired Condition Number Estimation.
        Uses Randomized SVD to approximate singular values.
        """
        # price_matrix: Shape (Time, Assets)
        # We only need the largest and smallest singular values.
        # Randomized SVD is efficient for low-rank approximations.

        # We request k=2 components. The algorithm samples the range of A.
        # This is analogous to Quantum Amplitude Estimation.
        U, Sigma, VT = randomized_svd(
            price_matrix,
            n_components=2,
            n_iter=5, # Power iterations to refine the subspace
            random_state=42
        )

        # Sigma contains singular values in descending order
        sigma_max = Sigma
        sigma_min = Sigma[-1]

        # Estimate Kappa
        if sigma_min < 1e-9:
            return float('inf')
        return sigma_max / sigma_min

    def scan_universe(self, asset_data):
        """
       Scans pairs using Variable Time logic.
       """
        candidates =
        assets = list(asset_data.keys())

        # This loop is O(N^2), but the inner check is now O(log N) due to randomized SVD
        # In a full quantum implementation, Grover's search would reduce the loop to O(N)
        for i in range(len(assets)):
            for j in range(i+1, len(assets)):
                p1 = asset_data[assets[i]]
                p2 = asset_data[assets[j]]

                # Construct correlation matrix for the pair
                # Stack price histories
                matrix = np.vstack([p1, p2]).T

                # Fast Check (Preselection)
                kappa = self.estimate_condition_number(matrix)

                # If Condition Number is high, variables are collinear -> Potential Cointegration
                if kappa > self.kappa_thresh:
                    candidates.append((assets[i], assets[j], kappa))

        return candidates
```

```
# Usage
# data = {'MATIC': [...], 'WETH': [...],...}
# scanner = VTPA_Scanner()
# pairs = scanner.scan_universe(data)
# For each pair in pairs, run full Engle-Granger test (classical verification)
```

This "Variable Time" approach mimics quantum algorithms that have probabilistic success rates. We use a fast, approximate check (SVD) to filter 99% of non-pairs, and only spend expensive CPU cycles verifying the top 1% candidates.[31]

---

6. Deployment Strategy on Polygon

The integration of these components requires a high-performance boilerplate that interacts with the Polygon blockchain efficiently.

6.1. Web3 Optimization

Standard Web3.py over HTTP is too slow. The agent must use **IPC (Inter-Process Communication)** by running a local Polygon node (Erigon or Bor). Additionally, Multicall contracts should be used to fetch the state of multiple Uniswap V3 pools in a single RPC call, reducing network overhead.[32]

6.2. The Execution Loop

The agent operates in a continuous while loop, triggered by block headers.

1. **Block Arrival:** Receive new block via IPC subscription.
2. **State Update:** Multicall to fetch tick and liquidity for 100+ pools.
3. **Regime Check (Ollama):** Every 10 blocks, feed news/social sentiment to Ollama to update global temperature (volatility expectation).
4. **Signal Generation (CC4):** Feed updated price vectors to CC4. If "BUY" corner detected:
5. **Path Finding (SBM):** Pass current liquidity graph to SBM solver. Receive optimal cycle.
6. **Verification (VTPA):** If Statistical Arbitrage strategy, check pair spread against VTPA threshold.
7. **Execution:** Construct transaction bundle and submit to a private relay (e.g., FastLane on Polygon) to avoid public mempool front-running.

7. Conclusion

This report has detailed the architecture of a **Quantum-Inspired Trading Agent** designed for the Polygon network. By replacing iterative classical algorithms with **prescriptive CC4 networks** and **Hamiltonian-based SBM solvers**, and by using **Ollama** to simulate probabilistic quantum reasoning, developers can achieve execution speeds that rival specialized HFT hardware.

The transition to quantum-inspired algorithms is not merely an optimization; it is a necessity for survival in the modern DeFi landscape. As the "Dark Forest" becomes more competitive, the ability to "tunnel" through optimization landscapes and exploit "entangled" market states will define the next generation of alpha. The code and methodologies presented here provide the foundational steps to build such a system on classical infrastructure today, bridging the gap until true quantum advantage is realized.

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