Comprehensive Spatiotemporal Trading Strategy
Complete Mathematical Framework

Version 3.0: A unified mathematical architecture integrating multi-timeframe analysis, probabilistic location modeling, Bayesian state tracking, momentum-adaptive scoring, and volatility-aware execution

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Raw OHLCV Data

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1.2 Component Relationships

Key Relationships:

- **Candlestick Features → Action Scores (A_i)**: Patterns are quantified from OHLC
- **Action Scores + Location Scores → Zone Strength ($S_{t,i}$)**: Context matters
- **Zone Strengths + Momentum → Adjusted Strength**: Market velocity modulates signals
- **Zone Strengths → Z-Space Matrix**: Spatiotemporal aggregation
- **Z-Space + Volatility → Adjusted Scores**: Risk normalization
- **Adjusted Scores + Bayesian State + Memory → Execution**: Final decision

Processing math: 100%

2. Core Candlestick Quantification

2.1 Real Body Size

Equation:

$$B_t = |C_t - O_t|$$

Purpose: Measures the directional conviction of a candle

Inputs:

- C_t = Close price at time t
- O_t = Open price at time t

Output: Absolute body size in price units

Relationships:

- Used in Doji-ness score: $D_t = f(B_t/(H_t - L_t))$
- Used in impulse penetration: $d_{t,i}^{imp} = f(W/B)$
- Pattern detection: Engulfing requires $B_2 > B_1$

Effect: Larger $B_t \to$ stronger directional signal $\to$ higher action score

2.2 Wick Components

Upper Wick:

$$W_t^u = H_t - \max(O_t, C_t)$$

Lower Wick:

$$W_t^{\ell} = \min(O_t, C_t) - L_t$$

Purpose: Quantifies rejection from price extremes

Inputs: High (H_t), Low (L_t), Open (O_t), Close (C_t)

Relationships:

- Normalized for cross-TF comparison: $\tilde{W}_t = W_t/(H_t - L_t)$
- Critical in Doji scoring via symmetry term
- Drives impulse penetration multiplier

Effect: Long wicks → price rejection → reversal potential

2.3 Normalized Wicks

Equations:

$$\tilde{W}_t^u = \frac{W_t^u}{H_t - L_t}$$

$$\tilde{W}_t^{\ell} = \frac{W_t^{\ell}}{H_t - L_t}$$

Purpose: Enable comparison across different volatility regimes and timeframes

Output: Values normalized to [0, 1]

Critical Usage: Doji symmetry calculation

2.4 Doji-ness Score

Processing math: 100% ation:

$$D_t = \exp\left(-\frac{\left(\frac{B_t}{H_t - L_t}\right)^2}{2\sigma_b^2}\right) \times \exp\left(-\frac{(\tilde{W}_t^u - \tilde{W}_t^\ell)^2}{2\sigma_w^2}\right)$$

Tunable Parameters:

- $\boldsymbol{\sigma_b} \in [0.01, 0.1]$: Body size sensitivity
  - Smaller values $\longrightarrow$ stricter Doji definition
  - Default: 0.05
- $\boldsymbol{\sigma_w} \in [0.05, 0.2]$: Wick symmetry requirement
  - Smaller values $\longrightarrow$ require more perfect symmetry
  - Default: 0.1

Mathematical Flow:

D_t multiplies directly with location kernel output in per-zone strength:

$$S_{t,i} = D_t \times K_i(d_{t,i}) \times C_i \times (1 + \kappa_m \cdot |M(t, y)|)$$

2.5 Two-Bar Reversal Patterns

Key Innovation:

Two-bar reversal patterns (engulfing, piercing, etc.) generate a different type of strength signal than single-candle patterns. They represent momentum reversal rather than indecision.

Two-Bar Pattern Strength:

$$A_{2bar} = \begin{cases} \beta_{eng} \cdot \frac{B_2}{B_1} & \text{if Engulfing} \\ \beta_{pierce} \cdot \frac{C_2 - L_1}{B_1} & \text{if Piercing Line} \\ \beta_{dcc} \cdot \frac{H_1 - C_2}{B_1} & \text{if Dark Cloud Cover} \end{cases}$$

WHERE TWO-BAR PATTERNS ARE USED:

Two-bar reversal patterns generate action scores (A_i) that feed into the Z-space matrix differently than Doji patterns:

1. **Input:** Two consecutive candles' OHLC data
2. **Process:** Pattern detection + relative size calculation
3. **Output:** An action strength A_{2bar} that replaces D_t in the per-zone strength formula
4. **Usage:** $S_{t,i} = A_{2bar} \times K_i(d_{t,i}) \times C_i \times (1 + \kappa_m \cdot |M(t,y)|)$

2.6 Penetration Depth Models

2.6.1 Basic Penetration Depth

$$d_{t,i} = \begin{cases} 0 & \text{if candle does not enter zone } i \\ \frac{\min(\max\{O_t, C_t, H_t, L_t\}, H_i) - L_i}{H_i - L_i} & \text{otherwise} \end{cases}$$

Processing math: 100%

Purpose: Measures how deeply price penetrates a location zone

Inputs:

- Candle OHLC values
- Zone boundaries: $[L_i, H_i]$

Output: Depth ratio $\in [0, 1]$

Usage: Input to skew-normal kernel $K_i(x)$

2.6.2 Impulse-Based Penetration (For Spike Detection)

$$d_{t,i}^{\text{imp}} = \left[\frac{H_t - L_t}{\bar{R}}\right]^{\gamma} \cdot \left[\frac{W_t^u + W_t^{\ell}}{B_t + \epsilon}\right]^{\delta} \cdot d_{t,i}$$

Components and Parameters:

- **Range Ratio:** $\frac{H_t - L_t}{\bar{R}}$
  - $\bar{R}$ = Average range over last N bars
  - **Average Range Definition:** $\bar{R} = \frac{1}{N}\sum_{j=1}^{N}(H_{t-j} - L_{t-j})$
  - This is the full high-to-low range, not just body size
  - Captures relative size of current move
- **Wick-to-Body Ratio:** $\frac{W_t^u + W_t^{\ell}}{B_t + \epsilon}$
  - $\epsilon = 0.0001$ (prevents division by zero)
  - High ratio indicates rejection/spike
- $\gamma \in [1.0, 3.0]$: Range expansion sensitivity
  - Higher values reward larger relative moves
  - Default: 2.0
- $\delta \in [0.5, 2.0]$: Wick importance weight
  - Higher values prioritize wick-driven moves

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- Default: 1.5

3. Z-Space Matrix Architecture

3.1 Mathematical Definition

Domain:

$$S : \mathbb{R}^+ \times \mathbb{R} \times \mathcal{T} \rightarrow \mathbb{R}$$

Dimensions:

- $t \in \mathbb{R}^+$: Time coordinate (continuous)
- $x \in \mathbb{R}$: Price coordinate
- $y \in \mathcal{T}$: Timeframe from set $\mathcal{T} = \{1M, 5M, 15M, 1H, 4H, 1D\}$

3.2 Core Strength Equation

Master Z-Space Equation:

$$S(t, x, y) = \sum_{i=1}^{N} w_i \cdot A_i(x, y) \cdot L_i(x, y) + \beta_v \cdot V(x, y)$$

Component Breakdown:

- $\boldsymbol{A_i(x, y)}$: Action strength from pattern i
  - Derived from candlestick features

Processing math: 100%

- Pattern-specific (engulfing, doji, etc.)
- $\boldsymbol{L_i(x, y)}$: Location-based weight from zone i
  - Output of kernel functions
  - Incorporates penetration depth
  - **NOW includes momentum adjustment**
- $\boldsymbol{V(x, y)}$: Volatility component
  - $V(x, y) = w_1 \cdot \sigma_t(x, y) + w_2 \cdot \mathrm{ATR}_t(x, y)$
- $\boldsymbol{w_i}$: Pattern importance weights
- $\boldsymbol{\beta_v}$: Volatility influence weight

3.3 Dynamic Update Mechanism

Temporal Evolution:

$$S(t + \Delta t, x, y) = \gamma \cdot S(t, x, y) + (1 - \gamma)[A_{\text{new}}(x, y) \cdot L(x, y) + C(y) \cdot 1_{\text{series}}]$$

Update Parameters:

- $\gamma \in [0, 1]$: Memory decay factor
  - Higher → slower decay, more historical influence
  - Default: 0.95
- $\boldsymbol{C(y)}$: Cluster bonus for consecutive patterns
  - Amplifies strength when similar candles repeat
  - Timeframe-specific values
- $\boldsymbol{1_{\text{series}}}$: Indicator for series detection
  - 1 if consecutive similar candles detected
  - Similarity threshold: $||f_t - f_{t-1}|| < \delta$

Processing math: 100%

STER BONUS IS USED:

The cluster bonus function $C(y)$ is implemented as:

$$C(y) = \begin{cases} 0.5 & \text{if 3 consecutive similar candles on timeframe } y \\ 1.0 & \text{if 5 consecutive similar candles on timeframe } y \\ 1.5 & \text{if 7+ consecutive similar candles on timeframe } y \\ 0 & \text{otherwise} \end{cases}$$

This bonus is added to the strength score when the series indicator $1_{\text{series}} = 1$

Dynamic Strength Adjustment & Pattern Integration:

When pattern confidence scores (Section 8) detect forming patterns, they modify the Z-space update:

$$S(t + \Delta t, x, y) = \gamma \cdot S(t, x, y) \cdot (1 - \eta \cdot q^{\text{opposite}}) + \text{new terms}$$

Where q^{opposite} is the confidence of a pattern opposing the current bias

3.4 Cross-Timeframe Aggregation

Net Strength Score:

$$S_{\text{net}}(t) = \sum_{y \in \mathcal{T}} \alpha_y \cdot S(t, x_{\text{current}}, y)$$

Normalization Constraint:

$$\sum_{y \in \mathcal{T}} \alpha_y = 1$$

EXECUTION STRENGTH SIGNAL:

The $S_{\text{net}}(t)$ is the primary execution strength signal that feeds into:

Processing math: 100%

1. Bayesian hypothesis updates
2. Execution threshold checks: $S_{\text{net}}(t) > \theta$
3. Volatility-adjusted scoring: $S_{\text{adj}} = S_{\text{net}}/(1 + \kappa V)$

This aggregation updates dynamically every time any timeframe generates a new bar

Timeframe	Weight (α_y)	Role	Impact on System
1D	0.25	Strategic bias	Sets primary directional hypothesis
4H	0.35	Primary trend	Main trend confirmation
1H	0.20	Tactical positioning	Range definition
15M	0.15	Entry timing	Pattern confirmation
5M	0.05	Execution refinement	Precise entry/exit

4. Location Distribution Models

4.1 Dual-Layer FVG Architecture

Conceptual Model:

Fair Value Gaps are modeled as two overlapping components:

1. **Continuous Base Distribution:** General strength across acceptance region
2. **Discrete Micro-Comb Peaks:** Sharp reaction points for precision scoring

4.1.1 Base Distribution

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ion with Boundaries:

$$L_{\text{base}}(x) = \begin{cases} 0 & \text{if } x < x_0 \\ \frac{1}{x_1 - x_0} & \text{if } x_0 \leq x \leq x_1 \\ 0 & \text{if } x > x_1 \end{cases}$$

Where:

- $x_0 = x_{\text{FVG start}} + \epsilon$ (minimum penetration)
- $x_1 = x_{\text{FVG end}} - \epsilon$ (symmetric buffer)

$\boldsymbol{\epsilon} \in [1, 5]$ points: Minimum penetration threshold

- Prevents shallow touches from scoring
- Higher values require deeper commitment

4.1.2 Micro-Comb Peaks

Comb Distribution:

$$C(x) = \sum_{k=1}^{N} \exp\left(-\frac{(x - x_k)^2}{2\sigma^2}\right)$$

Peak Locations:

$$x_k = x_0 + k \cdot \frac{x_1 - x_0}{N + 1}$$

Comb Parameters:

Processing math: 100% : Number of micro-peaks

- Higher → more granular reaction point detection
- Default: 3 (start, middle, end)
- $\boldsymbol{\sigma} \in [0.01, 0.5]$: Peak sharpness
  - Smaller → narrower, more precise peaks
  - Default: 0.1

4.1.3 Combined Location Strength

Total Location Score:

$$L_{\text{total}}(x) = \beta_1 \cdot L_{\text{base}}(x) + \beta_2 \cdot C(x)$$

WHAT IS D_t AND WHERE DOES $L_{total}^{momentum}$ COME FROM?

- $\boldsymbol{D_t}$ is the Doji-ness score from Section 2.4 (or A_{2bar} for two-bar patterns)
- $\boldsymbol{L_{total}^{momentum}}$ comes from Section 5.3: $L_{total}^{momentum}(x) = L_{total}(x) \cdot (1 + \kappa_m \cdot |M(t, y)|)$
- Both feed into per-zone strength: $S_{t,i} = D_t \times K_i(d_{t,i}^{imp}) \times L_{total}^{momentum}$
- This $S_{t,i}$ is a **pattern-location interaction score**, not the final execution signal
- Multiple $S_{t,i}$ values (from different zones) sum to create $S_{T,k}$ for each timeframe

4.2 Directional Skew Model

Skewed Distribution:

$$L_{\text{skew}}(x) = L_{\text{base}}(x) \cdot [1 + \lambda(x - x_0)]$$

$\lambda \in [-2, 2]$: Directional bias parameter

Processing math: 100%

- $\lambda > 0$: Rewards deeper penetration (bullish into bearish FVG)
- $\lambda < 0$: Rewards shallow entry (bearish into bullish FVG)
- $\lambda = 0$: No directional bias

4.3 Skew-Normal Kernel Function

Kernel Definition:

$$K_i(x) = \frac{2}{\omega_i}\phi\left(\frac{x - \xi_i}{\omega_i}\right)\Phi\left(\alpha_i\frac{x - \xi_i}{\omega_i}\right)$$

WHERE THE SKEW-NORMAL KERNEL IS USED:

The skew-normal kernel $K_i(x)$ is applied to the penetration depth $d_{t,i}$ (or $d_{t,i}^{imp}$ for impulse) to convert raw depth into a strength score:

1. **Input: Penetration depth $d_{t,i} \in [0, 1]$ from a candle into zone i**
2. **Process: $K_i(d_{t,i})$ maps this depth to a strength value using the skewed distribution**
3. **Output: A strength multiplier that feeds into $S_{t,i}$**
4. **Purpose: Allows asymmetric scoring - deeper penetrations can be weighted more heavily (or less) depending on the skew parameter α_i**

Components:

- ϕ: Standard normal PDF
- Φ: Standard normal CDF
- ξ_i: Location parameter (preferred depth, typically 0.5 for midpoint)
- ω_i: Scale parameter (width of response)
- α_i: Shape parameter (skewness)
  - $\alpha_i > 0$: Right skew (rewards deeper penetration)
  - $\alpha_i < 0$: Left skew (rewards shallow penetration)

Processing math: 100%

- $\alpha_i = 0$: Symmetric (normal distribution)

4.4 Stacked Location Zones

Multi-Zone Confluence:

$$L_{\text{stacked}}(x) = \sum_{z \in \text{zones}} \gamma_z \cdot L_z(x)$$

Timeframe Adjustment:

$$L_{\text{adjusted}}(x, y) = L_{\text{stacked}}(x) \cdot (1 + \delta_y)$$

Zone Type	Weight (γ_z)	Characteristics
FVG	0.4	Liquidity void, sharp reactions
VWAP	0.3	Mean reversion anchor
Order Block	0.3	Institutional interest

Timeframe	Boost (δ_y)	Rationale
1H+	0.3	Higher TF zones more significant
15M	0.1	Moderate importance
5M	0.05	Minor boost

5. Momentum-Adaptive Location Scoring

Key Innovation:

Location acceptance regions and strength scores now adapt based on market momentum, allowing shallow entries in explosive moves while maintaining strict criteria in normal conditions.

5.1 Momentum Score Calculation

Per-timeframe momentum score:

$$M(t, y) = \frac{1}{n} \sum_{i=1}^{n} |r_i| \cdot \mathrm{sign}(r_i)$$

Where r_i are the recent returns on timeframe y.

Momentum regime classification:

$$\mathrm{Regime}(t, y) = \begin{cases} \text{"explosive"} & \text{if } |M(t, y)| > 2\sigma_m \\ \text{"trending"} & \text{if } \sigma_m < |M(t, y)| \leq 2\sigma_m \\ \text{"normal"} & \text{if } |M(t, y)| \leq \sigma_m \end{cases}$$

WHERE MOMENTUM IS INTEGRATED:

The momentum score $M(t, y)$ is calculated from:

$$r_i = \frac{C_i - C_{i-1}}{C_{i-1}}$$

Where C_i is the close price of bar i on timeframe y. The momentum then:

1. Adjusts FVG acceptance regions (Section 5.2)
2. Modifies location scores via $L_{total}^{momentum}$ (Section 5.3)
3. Feeds into Bayesian state updates as evidence
4. Gates execution based on momentum regime

5.2 Dynamic FVG Acceptance Region

When momentum is strong, the FVG acceptance region expands dynamically:

Original acceptance region: $[x_0, x_1]$

Momentum-adjusted acceptance:

$$x_0^{adj} = x_0 - \varphi \cdot |M(t, y)| \cdot (x_1 - x_0)$$

$$x_1^{adj} = x_1 + \varphi \cdot |M(t, y)| \cdot (x_1 - x_0)$$

Where $\varphi \in [0, 0.5]$ is the expansion factor.

5.3 Momentum-Weighted Location Score

The total location score now incorporates momentum:

$$L_{total}^{momentum}(x) = L_{total}(x) \cdot (1 + \kappa_m \cdot |M(t, y)|)$$

Where $L_{total}(x) = \beta_1 \cdot L_{skew}(x) + \beta_2 \cdot C(x)$

And $L_{skew}(x) = L_{base}(x) \cdot [1 + \lambda(x - x_0)]$

Integration Note:

This momentum-weighted score replaces the standard L_{total} in the Per-Zone Strength calculation (Component 8), giving:

$$S_{t,i} = D_t \times K_i(d_{t,i}^{imp}) \times C_i \times (1 + \kappa_m \cdot |M(t,y)|)$$

6. Bayesian State Tracking System

6.1 Extended State Space with Velocity

New Feature: Velocity Dimension

The Bayesian state space now includes a velocity dimension to capture momentum regimes:

Extended state space:

$$\text{States} = \{(d, v) : d \in \{\text{Bull, Bear, Neutral}\}, v \in \{\text{Explosive, Normal, Exhausted}\}\}$$

New transition probabilities reflect momentum persistence:

- $P(\text{Bull}_{\text{Explosive}} \to \text{Bull}_{\text{Normal}})$ = high after time
- $P(\text{Bull}_{\text{Explosive}} \to \text{Bear}_{\text{Explosive}})$ = low (momentum rarely reverses instantly)
- $P(\text{Bull}_{\text{Normal}} \to \text{Bull}_{\text{Explosive}})$ = moderate (breakouts possible)

6.2 Bayesian Update Mechanism

Processing math: 100%

Posterior Update Rule (with velocity):

$$P(H_t^{(d,v)} | D_{1:t}) = \frac{P(D_t | H_t^{(d,v)}, V_t) \cdot P(H_{t-1}^{(d,v)})}{\sum_{H'} P(D_t | H'^{(d,v)}, V_t) \cdot P(H'^{(d,v)}_{t-1})}$$

Components:

- $\boldsymbol{H_t^{(d,v)}}$: Hypothesis with direction and velocity at time t
- $\boldsymbol{D_t}$: Observable data
  - $S_{\text{net}}(t)$: Aggregate strength score
  - Pattern detections
  - Volume metrics
  - **Momentum state $\boldsymbol{M(t, y)}$**
- $\boldsymbol{V_t}$: Current volatility state
- $\boldsymbol{P(H_{t-1}^{(d,v)})}$: Prior belief from previous update

6.3 Multi-Timeframe Hypothesis Structure

Information Flow:

- **A Priori (Prior Beliefs):**
  - Source: Higher timeframes (4H, 1D)
  - Role: Establish baseline directional bias
  - Update frequency: Slow
- **A Posteriori (Evidence):**
  - Source: Lower timeframes (15M, 5M, 1M)
  - Role: Provide continuous evidence stream
  - Update frequency: Fast

Processing math: 100%

- **Now includes momentum regime evidence**

6.4 Likelihood Function

Composite Likelihood:

$$P(D_t | H_t^{(d,v)}, V_t) = \prod_{e \in \text{Evidence}} P(e | H_t^{(d,v)}, V_t)^{w_e}$$

THE BIG PI SYMBOL ($\prod$) EXPLAINED:

The product symbol $\prod$ means we multiply all the individual evidence probabilities together:

$$\prod_{e \in \text{Evidence}} P(e | H_t^{(d,v)}, V_t)^{w_e} = P(e_1 | H_t)^{w_1} \times P(e_2 | H_t)^{w_2} \times \ldots \times P(e_n | H_t)^{w_n}$$

How we use the output:

1. This composite likelihood is a single probability value
2. It represents how likely we are to see all current evidence given a specific hypothesis
3. Higher values mean the evidence supports the hypothesis
4. This feeds directly into the Bayesian update equation above

Evidence Types and Weights:

- Aggregate strength score: $w_e = 0.4$
- Pattern formations: $w_e = 0.3$
- Location interactions: $w_e = 0.2$
- Volume anomalies: $w_e = 0.1$
- **Momentum regime: $w_e = 0.15$ (redistributed)**

Processing math: 100%

6.5 Hidden Markov Model Extension

State Transition:

$$\alpha_T(z) = \sum_{z'} \alpha_{T-1}(z')\Pi_{z',z}\ell(S_T|z)$$

HMM Parameters:

- **Π**: State transition matrix
  - $\Pi_{i,j}$ = Probability of transitioning from state i to j
  - **Now 9x9 matrix for (direction, velocity) pairs**
- $\boldsymbol{\mu_z}, \boldsymbol{\sigma_z}$: Emission parameters for each state

7. Volatility Integration Framework

7.1 Core Volatility Metrics

7.1.1 Realized Volatility

$$\sigma_t = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(r_i - \bar{r})^2}$$

Where:

Processing math: 100%

$$r_i = \log\left(\frac{P_i}{P_{i-1}}\right)$$

HOW TO CALCULATE REALIZED VOLATILITY FROM BAR DATA:

Given OHLCV data, we calculate realized volatility using close-to-close returns:

1. **Calculate log returns:** $r_i = \log(C_i / C_{i-1})$ where C_i is close of bar i
2. **Calculate mean return:** $\bar{r} = \frac{1}{N}\sum_{i=1}^{N} r_i$
3. **Calculate variance:** $\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(r_i - \bar{r})^2$
4. **Take square root:** $\sigma_t = \sqrt{\sigma^2}$
5. **Annualize if needed:** $\sigma_{annual} = \sigma_t \times \sqrt{252}$ for daily data

Variables:

- N = lookback window (e.g., 20 bars)
- P_i = Price at time i (typically close price)
- r_i = Log return for period i

7.1.2 Average True Range

$$\mathrm{ATR}_t = \frac{1}{n}\sum_{i=1}^{n} \mathrm{TR}_i$$

True Range:

$$\mathrm{TR}_i = \max\left(H_i - L_i, |H_i - C_{i-1}|, |L_i - C_{i-1}|\right)$$

WHERE VOLATILITY METRICS ARE INTEGRATED:

Processing math: 100%

Volatility metrics are integrated at multiple points:

1. **Z-Space Matrix:** $S(t, x, y) = \sum w_i A_i L_i + \beta_v V(x, y)$
2. **Adjusted Scoring:** $S_{adj} = S_{net}/(1 + \kappa V)$
3. **Bayesian Updates:** $P(D_t | H_t, V_t)$ - conditions on volatility
4. **Execution Filters:** Block trades if $Z_{vol} > \epsilon_{vol}$
5. **Position Sizing:** Size = Budget/Volatility

7.2 GARCH(1,1) Model

Volatility Evolution:

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

GARCH Constraints:

- $\omega > 0$: Ensures positive variance
- $\alpha, \beta \geq 0$: Non-negativity
- $\alpha + \beta < 1$: Stationarity condition

Typical Values:

- $\omega = 0.00001$
- $\alpha = 0.05$
- $\beta = 0.94$

7.3 Volatility-Adjusted Scoring

Processing math: 100% pace:

$$S_{\mathrm{adj}}(t, x, y) = \frac{S(t, x, y)}{1 + \kappa \cdot V(x, y)}$$

Volatility Score:

$$V(x, y) = w_1 \cdot \sigma_t(x, y) + w_2 \cdot \mathrm{ATR}_t(x, y)$$

Impact on System:

- High volatility → Lower adjusted scores
- Prevents overreaction during volatile periods
- Modulates both strength scores and Bayesian updates

7.4 Fat Tail Risk Management

Generalized Pareto Distribution:

$$F(x \mid \xi, \beta) = 1 - \left(1 + \xi \frac{x}{\beta}\right)^{-1/\xi}$$

Expected Shortfall:

$$\mathrm{ES}(u) = \frac{\beta + u\xi}{1 - \xi}$$

FAT TAIL RISK VARIABLES EXPLAINED:

Purpose: Model extreme events beyond normal distributions

Variables:

 ss value above threshold (e.g., penetration depth beyond normal)

- ξ (xi): Shape parameter
  - $\xi > 0$: Heavy tail (power law decay)
  - $\xi = 0$: Exponential tail
  - $\xi < 0$: Finite tail
- $\boldsymbol{\beta}$: Scale parameter (spread of the distribution)
- $\boldsymbol{u}$: Threshold above which we model the tail

Usage: When penetration depth exceeds threshold u, we use GPD to model the extreme event probability and adjust position sizes accordingly

7.5 Volatility Execution Filters

Z-Score Filter:

$$Z_{\text{vol}}(t) = \frac{\sigma_t - \mu_\sigma}{\sigma_\sigma}$$

Rejection Condition:

$$\text{Reject if } Z_{\text{vol}}(t) > \epsilon_{\text{vol}}$$

$\boldsymbol{\epsilon_{\text{vol}}}$: Typically 2.5

- Prevents entries during extreme volatility spikes
- Lower values $\longrightarrow$ more conservative

8. Pattern Recognition and Formation

8.1 Pattern Confidence Scoring

Processing math: 100%

Confidence Score:

$$q_T^{(p)} = \sigma(\kappa(\text{Corr}_T - \tau))$$

Pattern Correlation:

$$\text{Corr}_T = \frac{\mathbf{y}_T^T\mathbf{m}}{||\mathbf{y}_T|| \cdot ||\mathbf{m}||} \in [-1, 1]$$

WHERE PATTERN CONFIDENCE IS USED:

Pattern confidence scores modify the system in three ways:

1. **Strength Adjustment:** Via $S^{adj} = S^{agg} \times (1 - \eta q^{bear})$ (Section 8.2)
2. **Bayesian Evidence:** Feeds into D_t as pattern formation evidence
3. **Execution Gating:** Can block trades if opposing pattern confidence > threshold

Components:

- $\mathbf{y}_T$: Feature vector of last N bars
  - Contains: $[B_{T-N+1}, W^u_{T-N+1}, W^\ell_{T-N+1}, \ldots, B_T, W^u_T, W^\ell_T]$
- $\mathbf{m}$: Normalized pattern template (e.g., M-pattern)
- $\boldsymbol{\sigma}(\cdot)$: Sigmoid function $= \frac{1}{1+e^{-x}}$

Pattern Parameters:

- $\boldsymbol{\tau} \in [0.6, 0.9]$: Minimum correlation threshold
  - Higher → stricter pattern matching
- $\boldsymbol{\kappa} \in [5, 20]$: Steepness of confidence transition
  - Higher → sharper on/off behavior

Processing math: 100%

8.2 Dynamic Strength Adjustment

Pattern-Adjusted Strength:

$$S^{\text{adj}} = S^{\text{agg}} \times (1 - \eta \cdot q^{\text{bear}})$$

HOW PATTERN-ADJUSTED STRENGTH IS USED:

This is NOT another strength index, but a modifier of the aggregate strength:

1. Start with S^{agg} from cross-timeframe aggregation
2. If bearish pattern forming: multiply by $(1 - \eta q^{bear})$ to reduce bullish strength
3. If bullish pattern forming: multiply by $(1 + \eta q^{bull})$ to enhance bullish strength
4. The adjusted S^{adj} then feeds into execution decisions

$\boldsymbol{\eta} \in [0, 1]$: Controls pattern influence

- 0 = Ignore forming patterns
- 1 = Full pattern influence
- Default: 0.5

8.3 Two-Bar Reversal Patterns

Pattern	Bar 1 Condition	Bar 2 Condition	Interpretation
Bullish Engulfing	$C_1 < O_1$ (bearish)	$C_2 > O_2$ AND $O_2 < C_1$ AND $C_2 > O_1$	Strong reversal up
Bearish Engulfing	$C_1 > O_1$ (bullish)	$C_2 < O_2$ AND $O_2 > C_1$ AND $C_2 < O_1$	Strong reversal down
Piercing Line	$C_1 < O_1$	$C_2 > O_2$ AND $C_2 \geq L_1 + 0.5(B_1)$	Bullish reversal
Dark Cloud Cover	$C_1 > O_1$	$C_2 < O_2$ AND $C_2 \leq H_1 - 0.5(B_1)$	Bearish reversal

Pattern	Bar 1 Condition	Bar 2 Condition	Interpretation
Tweezers	$H_1 \approx H_2$ or $L_1 \approx L_2$ within δ		Double test rejection

8.4 Multi-Candle Series Detection

Similarity Measure:

$$\text{Similar} = ||f_t - f_{t-1}|| < \delta$$

Feature Vector:

$$f_t = [B_t, \tilde{W}^u_t, \tilde{W}^\ell_t, \text{Direction}_t]$$

Series Bonus Application:

If 3+ similar candles detected:

$$S^{\text{series}} = S^{\text{base}} \times (1 + C(y))$$

Where $C(y)$ is timeframe-specific cluster bonus

9. Market Maker Reversion Models

9.1 Support/Resistance Band Detection

Rolling Pivot Detection:

$$R^{\text{sup}}_t = \max_{i=t-W}^{t} H_i$$

Processing math: 100%

$$R_t^{\inf} = \min_{i=t-W}^{t} L_i$$

W: Rolling window size

- Varies by timeframe
- Example: 20 bars for 15M, 50 bars for 5M

9.2 Market Maker Reversion Score

Composite MMRS:

$$M_t = \exp\left(-\frac{(L_t - R_t^{\inf})^2}{2\sigma_r^2}\right) \times \exp\left(-\frac{\epsilon^2}{2\sigma_t^2}\right)$$

Components:

- **Spatial Component:** $(L_t - R_t^{\inf})$
  - Distance from current low to support
  - Closer $\rightarrow$ higher score
- **Temporal Component:** $\epsilon = |t_e^* - t_e|$
  - Timing error vs expected reversion
  - $t_e = t_0 + \tau_{\text{peak}}$

9.3 Temporal Symmetry Analysis

Processing math: 100%

Rise/Fall Symmetry:

$$R_{\text{MM}} = 1 - \left| \frac{\Delta t_{\text{rise}} - \Delta t_{\text{fall}}}{\Delta t_{\text{rise}} + \Delta t_{\text{fall}}} \right|$$

Time Measurements:

- $\Delta t_{\text{rise}} = t_{\text{peak}} - t_{\text{entry}}$
- $\Delta t_{\text{fall}} = t_{\text{reversion}} - t_{\text{peak}}$
- Perfect symmetry $\rightarrow R_{\text{MM}} = 1$

9.4 Umbrella Pattern Detection

9.4.1 High Timeframe Structure

Three-Point Symmetry:

$$\text{Sym}_{\text{umbrella}} = \exp\left(- \frac{(P_{\text{left}} + P_{\text{right}} - 2P_{\text{head}})^2}{2\sigma^2} \right)$$

9.4.2 Low Timeframe Decomposition

Multi-Peak Analysis:

Processing math: 100%

$$\text{SubwaveSym}(t) = \frac{1}{N_p}\sum_{i=1}^{N_p}\exp\left(-\frac{(P_i - P_{\text{mid}})^2}{2\sigma_p^2}\right)$$

Cross-Timeframe Integration:

- High TF defines macro structure
- Low TF confirms with micro peaks
- Both must align for high confidence

10. Imbalance Memory System

New System Component:

This system tracks significant directional moves that create future reversion targets, storing them in memory for days or weeks.

10.1 Imbalance Event Storage

An imbalance event is stored when price moves exceed threshold $\tau_{imbalance}$:

Event Structure:

- Timestamp: t
- Timeframe: y
- Direction: sign(move)
- Magnitude: $|\text{move}_{\text{points}}|$
- Duration: Δt

Processing math: 100%

- Price range: $[p_{start}, p_{end}]$
- Decay factor: $e^{-\gamma_{mem} \cdot \text{age}}$

10.2 Reversion Expectation Score

When price approaches old imbalance zones:

$$R_{imbalance}(p, t) = \sum_i w_i \cdot \exp\left(-\frac{(p - p_{imbalance,i})^2}{2\sigma_{rev}^2} \right) \cdot e^{-\gamma_{mem}(t - t_i)}$$

Integration Note:

The imbalance memory enhances the existing MMRS calculation:

$$M_t^{enhanced} = M_t + \omega_{mem} \cdot R_{imbalance}(L_t, t)$$

11. Execution Logic and Signal Synthesis

11.1 Master Execution Condition

Boolean Product:

$$\text{Execute} = 1_{S_{\text{net}} > \theta} \times 1_{\text{Location}} \times 1_{\text{Hypothesis}} \times 1_{\text{Volatility}} \times 1_{\text{Range}} \times 1_{\text{Momentum}}$$

ALL conditions must be TRUE (logical AND) for execution

Processing math: 100%

11.2 Detailed Execution Criteria

Criterion	Mathematical Condition	Purpose	Typical Values
Strength Threshold	$S_{\text{net}}(t) > \theta$	Ensures sufficient signal quality	$\theta \in [50, 100]$
Location Confirmation	$\sum_{k=1}^{N} 1_{\text{comb crossed}} \geq \kappa$	Validates zone interaction	$\kappa \geq 2$
Hypothesis Alignment	$P(H_t^{(d,v)} = \text{Direction}) > p_{\text{entry}}$	Confirms directional bias with velocity	$p_{\text{entry}} > 0.6$
Volatility Gate	$Z_{\text{vol}}(t) < \epsilon_{\text{vol}}$	Prevents chaos entries	$\epsilon_{\text{vol}} = 2.5$
Range Alignment	$\lvert P_t - R_{\text{boundary}} \rvert < \delta_{\text{range}}$	Entry at key levels	$\delta_{\text{range}} = 5$ pts
Momentum Compatible	$\text{Regime}(t, y) \neq$ "exhausted"	Avoids fading strong moves	N/A

11.3 Execution Strength with Alignment

Composite Execution Score:

$$S_{\text{exec}}(t) = S_{\text{net}}(t) \cdot C_{\text{align}}(t) \cdot 1_{\text{MMRS}^{enhanced}(t) > \tau}$$

Alignment Coefficient:

$$C_{\text{align}}(t) = \exp\left(-\frac{1}{|\mathcal{T}|} \sum_{y \in \mathcal{T}} \left(\frac{\mu_y - \bar{\mu}}{\sigma_y} \right)^2 \right)$$

WHAT IS THE ALIGNMENT COEFFICIENT?

Processing math: 100%

The alignment coefficient measures how well zone centers across different timeframes cluster around the same price:

- $\boldsymbol{\mu_y}$: Center price of the primary zone on timeframe y
  - For FVG: midpoint of the gap
  - For VWAP: the VWAP value itself
  - For Order Block: midpoint of the block
- $\bar{\boldsymbol{\mu}}$: Mean of all zone centers = $\frac{1}{|\mathcal{T}|} \sum_y \mu_y$
- $\boldsymbol{\sigma_y}$: Standard deviation of zone prices on timeframe y
  - Measures how spread out the zones are
  - Calculated from recent zone formations
- $\boldsymbol{\mathcal{T}}$: Set of timeframes being considered

How S_{exec} is used:

1. This is the FINAL execution score
2. It combines strength, alignment, and reversion potential
3. Only if $S_{exec} > \theta_{exec}$ do we proceed to trade
4. Higher alignment → zones agree → stronger conviction

11.4 Position Sizing

Kelly-Inspired Formula:

$$f^* = \frac{p \cdot b - q}{b} \times \frac{1}{\sigma_t}$$

Components:

- $\boldsymbol{p} = P(H_t^{(d,v)} = \text{Correct Direction})$: Win probability
- $\boldsymbol{b}$: Win/loss ratio from backtest

Processing math: 100% Loss probability

- $\mathbf{1/\sigma_t}$: Volatility adjustment

11.5 Risk Management

11.5.1 Stop Loss Placement

$$\text{Stop Distance} = k_{\text{stop}} \times \text{ATR}_t \times \sqrt{h}$$

- $k_{\text{stop}} \in [1.5, 2.5]$: ATR multiplier
- h: Expected holding period in bars
- Square root scaling accounts for time decay

11.5.2 Target Placement

$$\text{Target} = \min_{y \in \mathcal{T}} R_{\text{opposite}}(y)$$

Logic: Take profit at nearest opposing range boundary across all timeframes

12. Complete Parameter Reference

12.1 Master Parameter Table

Category	Parameter	Symbol	Range	Default	Effect of Increase
Candlestick	Body sensitivity	σ_b	[0.01, 0.1]	0.05	Fewer Dojis detected
	Wick symmetry	σ_w	[0.05, 0.2]	0.1	Stricter symmetry required
	Impulse sensitivity	γ	[1.0, 3.0]	2.0	Larger moves weighted more
	Wick-to-body bias	δ	[0.5, 2.0]	1.5	Wick size matters more
Location Model	Min penetration	ϵ	[1, 5] pts	2	Deeper entry required
	Comb peak count	N	[1, 10]	3	More granular detection
	Peak sharpness	σ	[0.01, 0.5]	0.1	Narrower reaction zones
	FVG skew	λ	[-2, 2]	0	Stronger directional bias
	Base weight	β_1	[0, 1]	0.7	Continuous score dominates
	Comb weight	β_2	[0, 1]	0.3	Peak crossings matter more
Momentum	FVG expansion factor	φ	[0, 0.5]	0.2	Shallower entries OK in trends
	Momentum influence	κ_m	[0, 2]	0.5	Momentum matters more
	Momentum threshold	σ_m	[0.5, 2] ATR	1.0	Higher = less explosive detection
System	TF weights	α_y	[0, 1]	Varies	Higher TF dominates bias
	Execution threshold	θ	[0, 100]	70	Fewer, stronger signals
	Memory decay	γ	[0.9, 0.99]	0.95	Longer historical influence
	Cluster bonus	$C(y)$	[0, 2]	0.5	Series patterns amplified
	Location decay	τ	[5, 200] bars	50	Zones stay active longer
Volatility	Vol influence	κ	[0.1, 2.0]	0.5	More vol dampening

Category	Parameter	Symbol	Range	Default	Effect of Increase
	Vol spike limit	ϵ_{vol}	[2.0, 3.0]	2.5	More conservative
	GARCH alpha	α	[0.01, 0.1]	0.05	More reactive to shocks
	GARCH beta	β	[0.9, 0.99]	0.94	More persistent vol
Pattern	Min correlation	τ	[0.6, 0.9]	0.75	Stricter pattern match
	Confidence steep	κ	[5, 20]	10	Sharper on/off
	Pattern influence	η	[0, 1]	0.5	Stronger pattern impact
Market Maker	Spatial std dev	σ_r	[1, 10] pts	5	Wider acceptance range
	Temporal std dev	σ_t	[1, 10] bars	3	More timing tolerance
Memory	Imbalance threshold	$\tau_{imbalance}$	[50, 200] pts	100	Larger moves remembered
	Memory decay	γ_{mem}	[0.001, 0.1]	0.01	Faster forgetting
	Memory weight	ω_{mem}	[0, 1]	0.3	Historical levels matter more
	Reversion width	σ_{rev}	[5, 50] pts	20	Wider zone of influence
Execution	Min comb hits	κ	[1, N]	2	Stricter zone validation
	Entry probability	p_{entry}	[0.5, 0.8]	0.6	Higher confidence required

12.2 Parameter Relationships

Critical Dependencies:

- **σ_b and σ_w**: Together define Doji strictness
- **γ and δ**: Together control spike detection sensitivity
- **β_1 and β_2**: Must sum close to 1 for balanced scoring
- : Must sum to exactly 1

- **κ and ϵ_{vol}**: Together control volatility filtering
- **φ and κ_m**: Together control momentum adaptation
- **γ_{mem} and ω_{mem}**: Balance memory influence vs decay

12.3 Optimization Guidelines

Parameter Tuning Priority:

1. **High Impact:** θ, α_y, p_{entry}, κ_m
2. **Medium Impact:** ϵ, κ, σ_b, σ_w, φ
3. **Fine Tuning:** All others

Optimization Methods:

- **Grid Search:** For discrete parameters (N, κ)
- **Bayesian Optimization:** For continuous parameters
- **Walk-Forward Analysis:** For robustness testing

13. Master Equations Summary

13.1 The Complete Strength Score Equation

Per-Zone Strength:

$$S_{t,i} = A_{pattern} \times K_i(d_{t,i}^{imp}) \times L_{total}^{momentum}(x) \times C_i$$

Where:

- $A_{pattern} = D_t$ for doji or A_{2bar} for two-bar patterns

Processing math: 100%

- $d_{t,i}^{imp} = \left[\frac{H_t - L_t}{\bar{R}}\right]^{\gamma} \cdot \left[\frac{W_t^u + W_t^{\ell}}{B_t + \epsilon}\right]^{\delta} \cdot d_{t,i}$
- $L_{total}^{momentum}(x) = [\beta_1 L_{skew}(x) + \beta_2 C(x)] \times (1 + \kappa_m |M(t,y)|)$
- $C_i = \prod_j c_{i,j}$ (confluence multiplier)

13.2 The Complete Z-Space Matrix

Spatiotemporal Strength:

$$S(t, x, y) = \sum_{i=1}^{N} w_i \cdot S_{t,i} + \beta_v \cdot V(x, y)$$

With Dynamic Update:

$$S(t+\Delta t, x, y) = \gamma \cdot S(t, x, y) \cdot (1 - \eta q^{opposite}) + (1-\gamma)[A_{new} \cdot L + C(y) \cdot \mathbb{1}_{series}]$$

13.3 The Complete Execution Signal

Net Strength:

$$S_{net}(t) = \sum_{y \in \mathcal{T}} \alpha_y \cdot S(t, x_{current}, y)$$

Volatility Adjusted:

$$S_{adj}(t) = \frac{S_{net}(t)}{1 + \kappa V(t)}$$

Final Execution Score:

$$S_{exec}(t) = S_{adj}(t) \cdot C_{align}(t) \cdot \mathbb{1}_{MMRS^{enhanced}(t) > \tau}$$

13.4 The Complete Location Score

Total Location Distribution:

$$L_{final}(x,y) = \left[\sum_{z \in zones} \gamma_z L_z(x)\right] \cdot (1 + \delta_y) \cdot (1 + \kappa_m |M(t,y)|)$$

Where Each Zone:

$$L_z(x) = \beta_1 L_{base}(x) \cdot [1 + \lambda(x-x_0)] + \beta_2 \sum_{k=1}^N \exp\left(-\frac{(x-x_k)^2}{2\sigma^2}\right)$$

13.5 The Complete Volatility Integration

Volatility Score:

$$V(x,y) = w_1 \cdot \sigma_t(x,y) + w_2 \cdot ATR_t(x,y)$$

With GARCH Evolution:

$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

And Execution Filter:

$$\text{Trade Allowed} = \mathbb{1}_{Z_{vol}(t) < \epsilon_{vol}}$$

This document represents a complete mathematical specification of the Spatiotemporal Trading Strategy.

Version 3.0 includes momentum-adaptive scoring, imbalance memory, and extended state spaces.

All equations, parameters, and relationships are defined for direct implementation.