Alura: A Discipline-Driven Autonomous Trading Protocol

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Abstract

We propose *Alura*, an autonomous trading protocol for perpetual-futures markets that enforces predictable execution through a mathematically constrained *Discipline Engine*. A global parameter set—Equity, Profit Goal, Max Drawdown, and Maximum Position Count—defines a deterministic boundary for all trading activity. Market direction is computed using a composite scalar, the *Market Outlook Score* (MOS), aggregating price trend, momentum, volatility, volume asymmetry, and multi-timeframe slope alignment into a normalized range $[-1, 1]$.

Trades are executed only when MOS, Relative Volume (RVOL), and structural candle-position filters validate. The protocol operates as a rule-based economic agent with explicit risk caps, bounded leverage, and deterministic behavior.

1 Introduction

Financial automation systems often depend on heuristic or discretionary logic. Alura introduces a deterministic, constraint-propagated execution model governed by a mathematical *Discipline Index D*. All per-position behavior, equity allocation, and leverage selection derive from closed-form expressions.

The protocol integrates:

- A Discipline Engine for equity and drawdown constraints,
- Multi-timeframe market inference via MOS,
- A volume-participation validator (RVOL),
- A geometric candle-position filter for structural entry quality,
- A risk-bounded leverage derivation model.

2 Discipline Engine

Let the global constraint vector be:

$$I = \{E_0, P, M, N\}$$

where E_0 is initial trading equity, P is the total profit goal, M is the maximum allowed drawdown from E_0, and N is the maximum number of concurrent positions.

Per-position inherited constraints are:

$$E_{\text{pos}} = \frac{E_0}{N}, \qquad P_{\text{pos}} = \frac{P}{N}, \qquad M_{\text{pos}} = \frac{M}{N}.$$

Here E_{pos} is the nominal equity slice per position, P_{pos} is the target profit contribution, and M_{pos} is the maximum drawdown contribution per position.

2.1 Discipline Index

The Discipline Index expresses the tightness of constraint enforcement:

$$D = \frac{P \cdot N}{M \cdot E_0}.$$

A fundamental proportionality holds:

$$P = D\left(\frac{M}{N}\right)E_0.$$

Interpretation:

- $D > 1$ — strict discipline (conservative use of drawdown),
- $D \approx 1$ — balanced,
- $D < 1$ — relaxed (aggressive use of drawdown).

2.2 Guarantees

For all time t:

$$\sum E_i \leq E_0, \qquad \sum M_i \leq M, \qquad N_{\text{active}}(t) \leq N,$$

i.e., total allocated equity does not exceed the initial equity E_0, the realized or allocated drawdown contributions do not exceed M, and the number of active positions is capped by N.

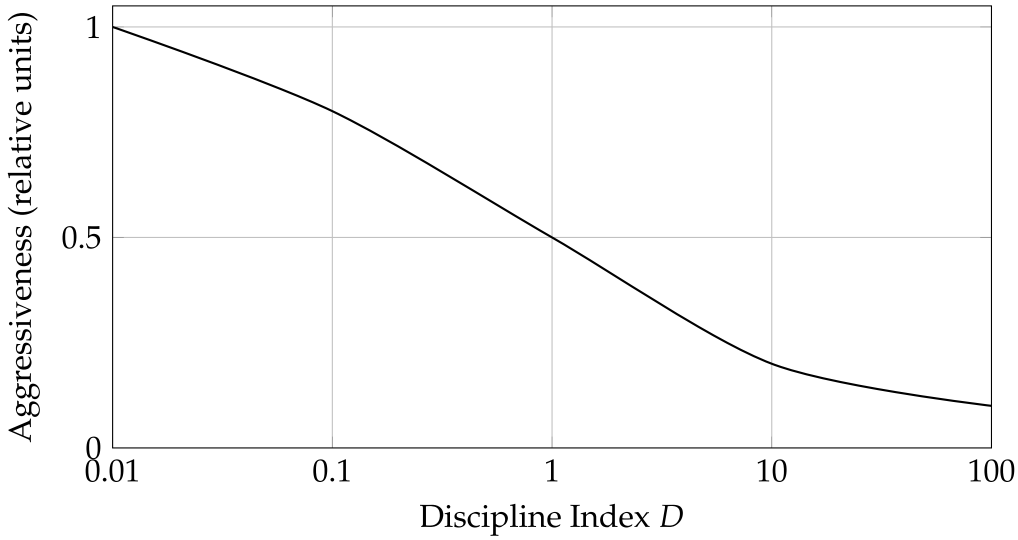

Figure 1: Discipline Index vs relative aggressiveness. Higher D corresponds to stricter, more conservative use of drawdown.

3 Market Outlook Score (MOS)

MOS evaluates directional bias:

$$MOS = \text{clamp}\left(\sum_{i=1}^{5} w_i S_i, -1, 1\right).$$

Each component $S_i \in [-1, 1]$ corresponds to trend, momentum, volatility, volume, or multi-timeframe alignment.

3.1 Trend Component

Trend score:

$$S_{\text{trend}} = \tanh(5T_{\text{raw}})$$

$$T_{\text{raw}} = 0.5\beta_{\text{norm}} + 0.3HHLL + 0.2\beta_{\text{EMA}}.$$

Regression slope:

$$\beta = \frac{L\sum iP_i - (\sum i)(\sum P_i)}{L\sum i^2 - (\sum i)^2}.$$

3.2 Momentum Component

$$S_{\text{momentum}} = \tanh\left(10M_{\text{combined}}\right)$$

$$M_{\text{combined}} = 0.6ROC + 0.4M_{\text{weighted}}$$

$$ROC = \frac{P_t - P_{t-N}}{|P_{t-N}|}.$$

3.3 Volume Component

$$S_{\text{volume}} = \tanh(2V_{\text{raw}}).$$

3.4 Volatility Component

$$S_{\text{volatility}} = \text{clamp}\left(25(0.02 - CV), -1, 1\right)$$
$$CV = \frac{\sigma_P}{|P|}.$$

3.5 Multi-Timeframe Component

$$S_{\text{MTF}} = \text{clamp}\left(\frac{\bar{\beta}_{MTF}}{\max(|\beta_i|, 1)} C_{\text{consistency}},\ -1, 1\right).$$

3.6 Decision Rule

$$MOS > 0.2 \Rightarrow LONG$$
$$MOS < -0.2 \Rightarrow SHORT$$
$$|MOS| \leq 0.2 \Rightarrow NO\ TRADE.$$

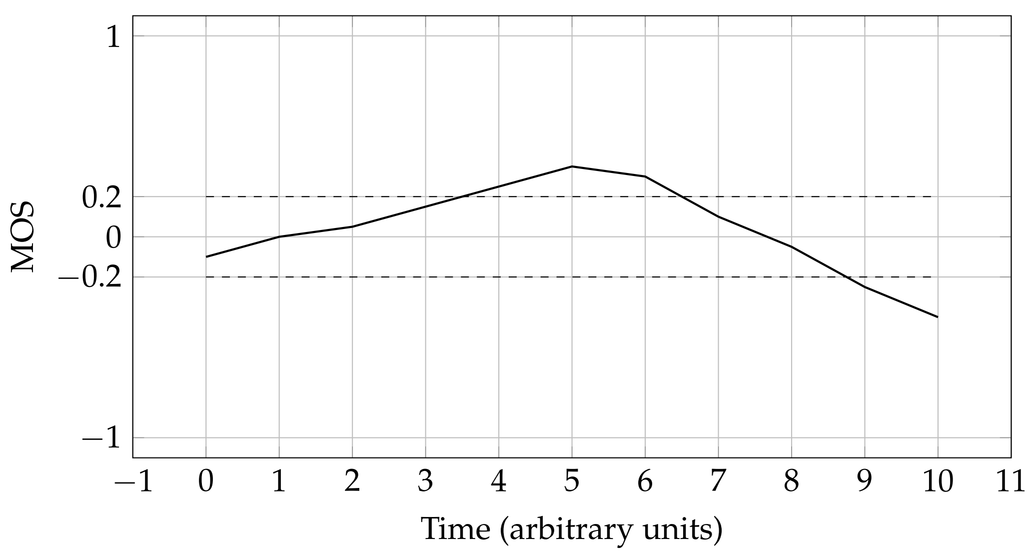

Figure 2: Example MOS evolution with decision thresholds at ±0.2. Crossings into upper and lower bands define LONG and SHORT regimes.

4 Relative Volume (RVOL)

Relative Volume:

$$RVOL = V_t / SMA_n(V)$$

Dynamic threshold:

$$T_{\text{RVOL}} = \max\left(0.8,\ T_{\text{base}} m_r + 0.002L + 0.5ATR_{\%}\right),$$

where L here denotes leverage, and $ATR_{\%}$ is ATR expressed as a percentage.

Trade validity condition:

$$RVOL \geq T_{\text{RVOL}}.$$

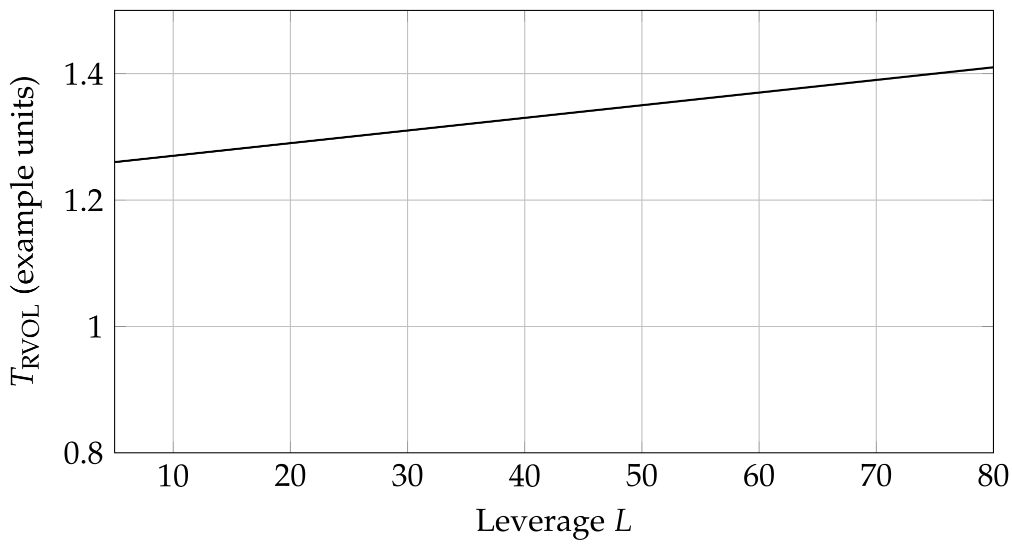

Figure 3: Illustrative dynamic RVOL threshold as a function of leverage. Higher leverage demands higher relative volume.

5 Candle Position Filter

Candle-relative closing position:

$$pos = \frac{C_t - L_t}{H_t - L_t}.$$

Rules:

$$pos \leq 0.25 \Rightarrow LONG\ valid,$$
$$pos \geq 0.75 \Rightarrow SHORT\ valid.$$

6 Leverage and TP/SL Derivation

We now derive leverage and TP/SL in terms of equity and max drawdown.

Per-position values:

$$E = \frac{E_0}{N}, \qquad G = \frac{P_{\text{total}}}{N}, \qquad M_{\text{pos}} = \frac{M_{\text{total}}}{N},$$

where E is equity allocated per position, G is the per-position profit goal, and M_{pos} is the per-position contribution to the max drawdown budget.

Profit-Constrained Leverage

To achieve profit goal G with TP percentage between TP_{min} and TP_{max}:

$$L_{TP,\text{min}} = \frac{100G}{E \cdot TP_{\text{max}}}, \qquad L_{TP,\text{max}} = \frac{100G}{E \cdot TP_{\text{min}}}.$$

Drawdown-Constrained Leverage

To keep the per-position loss within M_{pos} with SL percentage between SL_{min} and SL_{max}:

$$L_{SL,\text{min}} = \frac{100M_{\text{pos}}}{E \cdot SL_{\text{max}}}, \qquad L_{SL,\text{max}} = \frac{100M_{\text{pos}}}{E \cdot SL_{\text{min}}}.$$

Feasible Range

The feasible leverage range is:

$$L_{\text{feasible}} \in \big[\max(L_{TP,\text{min}}, L_{SL,\text{min}}, L_{\text{min}}),\ \min(L_{TP,\text{max}}, L_{SL,\text{max}}, L_{\text{max}})\big].$$

TP and SL Percentages

Once leverage L_{sel} is selected, the TP and SL percentages implied by the equity and drawdown budgets are:

$$TP\% = \frac{G}{EL_{\text{sel}}} \cdot 100, \qquad SL\% = \frac{M_{\text{pos}}}{EL_{\text{sel}}} \cdot 100.$$

Risk-reward ratio:

$$RRR = \frac{TP\%}{SL\%} = \frac{G}{M_{\text{pos}}}.$$

7 Decision Function

$$\Phi_{LONG} = (MOS > 0.2) \land (RVOL \geq T_{\text{RVOL}}) \land (pos \leq 0.25)$$
$$\Phi_{SHORT} = (MOS < -0.2) \land (RVOL \geq T_{\text{RVOL}}) \land (pos \geq 0.75)$$

Otherwise:

NO TRADE.

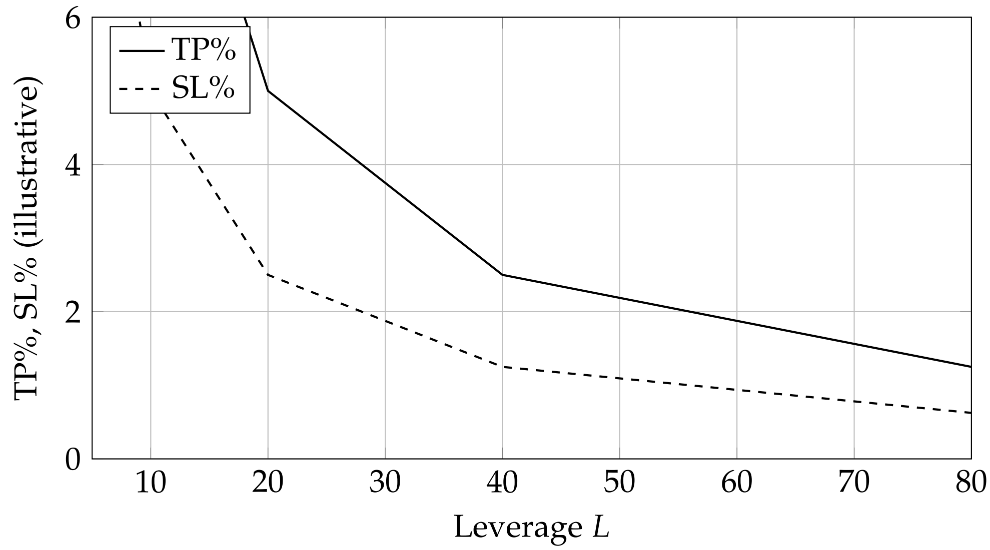

Figure 4: Illustrative TP% and SL% as functions of leverage. Dollar risk and reward are fixed by equity and drawdown budgets; percentages shrink as leverage increases.

8 Risk Architecture

Constraints:

$$N_{\text{active}}(t) \leq N$$

$$\text{Per-position loss (contribution to drawdown)} \leq \frac{M}{N}.$$

A simple cooldown mechanism can be defined as:

$$\Delta t_{\text{cooldown}} = \begin{cases} 3h & \text{if TP or SL triggered,} \\ 0 & \text{otherwise.} \end{cases}$$

9 Conclusion

Alura implements a deterministic, mathematically constrained trading protocol enforcing strict equity discipline, drawdown-aware risk allocation, adaptive leverage selection, and multi-filter signal validation. The framework is transparent and rule-bound: every decision arises from explicit formulas and user-defined parameters, enabling predictable behavior and controlled use of max drawdown.

10 Extensibility and Customization

Although the Alura framework provides a mathematically structured foundation, it is intentionally designed to be open-ended. Traders may freely modify thresholds, weights,

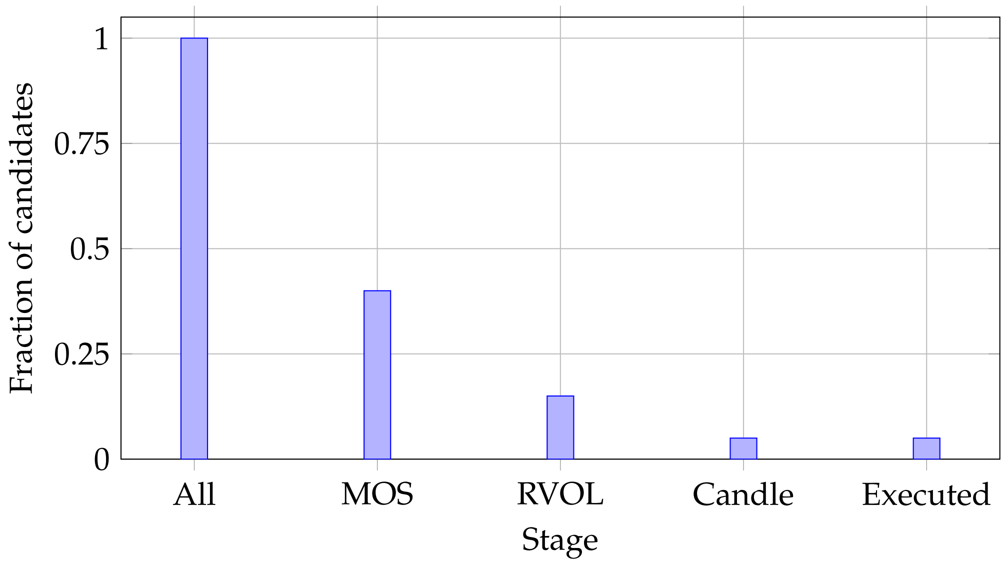

Figure 5: Illustrative filter cascade. Each stage rejects a fraction of candidates; only the highest quality signals reach execution.

and behavioral constraints to align the system with their preferred risk profile, trading horizon, or market conditions.

The following components are explicitly modifiable:

- MOS thresholds for LONG/SHORT signals,
- RVOL thresholding logic, including multipliers and dynamic adjustments,
- Candle-position entry limits,
- Weighting of trend, momentum, volume, volatility, and multi-timeframe components,
- ATR sensitivity parameters and leverage bound rules,
- TP/SL ranges and rounding conventions,
- Equity and max drawdown allocations per position.

Users may extend the framework by adding new filters or strategies, such as:

- market-regime classifiers,
- correlation or concentration screens,
- microstructure or order-flow indicators,
- statistical arbitrage factors,
- machine-learning based scoring components,

- custom risk, drawdown, or cooldown rules.

Alura should be viewed not as a fixed system but as a modular, extensible protocol. Its components can be replaced, generalized, or expanded without violating the core discipline guarantees.

11 Open-Ended Research Directions

The system is deliberately left extensible so researchers and practitioners can improve or adapt its behavior. Potential avenues include:

- adaptive learning of MOS weights via reinforcement learning or meta-optimization,
- dynamic RVOL thresholding guided by regime clustering or structural volatility,
- portfolio-level optimization and cross-asset capital allocation constraints under a shared max drawdown budget,
- integration of slippage, liquidity curves, and depth-of-market data,
- non-linear trend estimation (wavelets, Bayesian filters),
- generalized Discipline Index definitions for portfolio-level or multi-strategy systems.

These suggestions are not prescriptive; they illustrate the flexibility of the underlying design.

12 Disclaimer

This paper does not guarantee profits, accuracy, or any specific win rate. All mathematical expressions, thresholds, and procedures described herein are provided for educational and experimental purposes only. Trading perpetual futures involves significant financial risk, including the possibility of complete capital loss and full utilization of the defined max drawdown.

No algorithm, indicator, or model described in this document should be interpreted as a promise of successful performance in live market conditions. Past performance does not imply future results. Users must conduct independent research, testing, and validation before applying any method described herein.

The Alura framework is a tool, not a guarantee. All trading decisions and associated risks are the sole responsibility of the user.

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