MarS: a Financial Market Simulation Engine Powered by Generative Foundation Model

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Outline

MarS (**Mar**ket **S**imulation Engine) powered by **LMM** (**L**arge **M**arket **M**odel)

- **Introduction**
- **MarS Overview**
- **MarS Detailed Design**
- **Experiments & Results**

Background

Foundation Model[1] Breakthroughs

- Generative Models in **NLP**: NLP Milestones (GPT-3 in 2020 to GPT-4 in 2023)
- Generative Models in **Vision and Simulation**: These simulation efforts primarily target the **physical world**, such as autonomous driving, robotics and games, by generating visual scenes or trajectories. Researchers treated video generation as a path to simulation.

[1] "Foundation Model" means models are trained on broad datasets and can be adapted to a wide range of downstream tasks.

Related Work

Agent-Based Market Simulators (Early Approaches)

- Multi-Agent Simulations: This tradition treats the market as an ecosystem of agents (e.g., liquidity providers, momentum traders), each following rules, to see emergent outcomes.
- ABIDES Platform (Amrouni et al., 2021))
- Pros and Cons:
  - can incorporate domain knowledge (e.g., specific trading behaviors or market rules) and produce interpretable scenarios (we can trace each agent's actions).
  - these models heavily rely on the **assumptions** made about agent behaviors.

Related Work

Generative Models for **Limit Order Books** (GANs)

- GANs could model financial time series, producing sequences that mimic real stock price movements.
- Series of GAN-based Simulators (Coletta et al.): generate LOB data, “world agent” concept, conditional LOB generators

- Pros and Cons:
  - reproduce stylized facts of markets, simulate millions of orders
  - **no interactivity** or controllability, instability or **mode collapse**

Related Work

Advanced Generative Market Models

- Incorporating microstructure data recurrent neural network model of the LOB that captures the time-evolution of the entire order book state
- State-Space Models: built on a Deep State Space Model architecture, their model processes the sequence of order messages (limit orders, cancellations, trades) and generates new sequences one event at a time
- Pros and Cons:
  - did not demonstrate the simulator's usefulness on downstream tasks
  - they generate data but typically cannot adjust to **external inputs** in the middle of a sequence.

Motivation

- **Realism vs. Complexity:** Traditional agent-based simulators often simplify behavior, and early generative models, even if statistically convincing, may miss critical market dynamics.
- **Lack of Interactivity:** No existing simulator allowed human or algorithmic interaction in the loop with full realism.
- **Controllability and Scenario Design:** Agent-based models allowed some scenario setup (via agent behaviors), but generative models so far offered no simple way to condition on scenarios
- **Validation and Utility:** stylized facts and distributional similarity were the benchmarks, stylized facts and distributional similarity were the benchmarks

Key Contribution

How MarS addresses these challenges?

- Large Market Model (LMM): A generative foundation model trained on **order-level market data** (like a "language model" but for financial orders)
- MarS Engine: A simulation platform built around LMM that produces **realistic market order streams**, integrating user inputs and scenario controls
- **Controllable** Scenario Generation: MarS introduces conditional generation features to let users shape the scenario
- Interactivity – **User-Injected Orders**: It allows the user (or a test algorithm) to inject orders into the simulation at any time, and the LMM will respond by generating the subsequent order flow conditional on those user actions

Overview

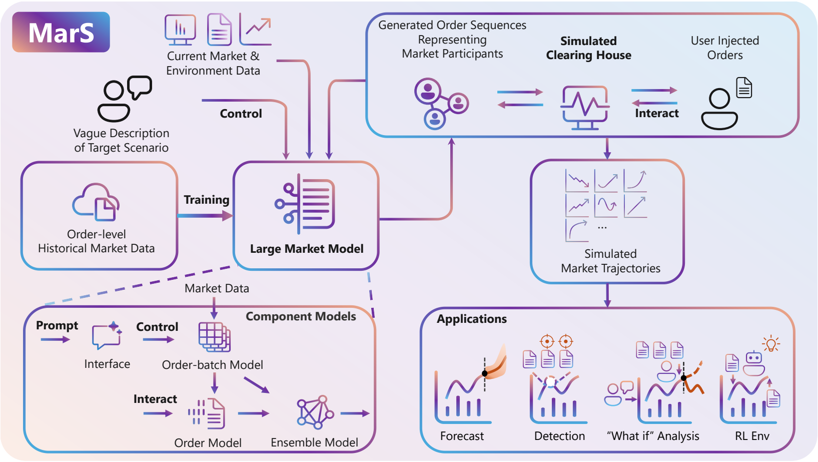
Components:

- LLM:
  - Order-Level Model
  - Order-Batch Model
  - Ensemble Model
- Simulated Clearing House

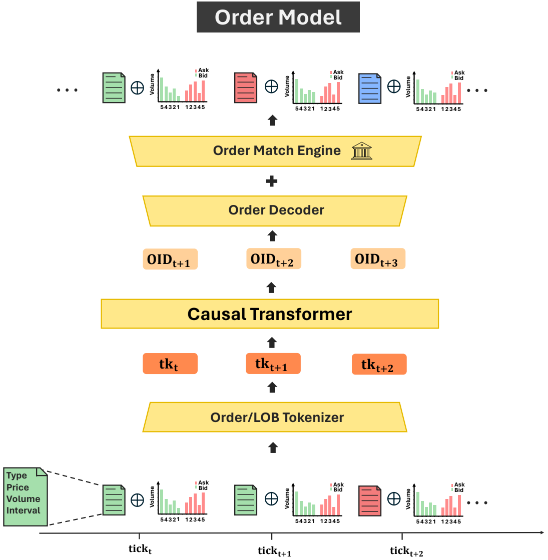
Workflow: Historical data → train LMM; At runtime → LMM generates orders → clearing house matches orders → feedback loop with updated market state for next generation

Applications Enabled: Forecasting, Risk/Anomaly detection, What-if analysis, RL trading environment

Overview


MarS
Current Market &
Environment Data
Vague Description
of Target Scenario
Control
Order-level
Historical Market Data
Training
Large Market Model
Generated Order Sequences
Representing
Market Participants
Simulated
Clearing House
User Injected
Orders
Interact
Simulated
Market Trajectories
Market Data
Prompt
Interface
Control
Order-batch Model
Component Models
Interact
Order Model
Ensemble Model
Applications
Forecast
Detection
"What if" Analysis
RL Env

Order-Level Model (Micro LMM)



Tokenization

$$Emb_i = \text{emb}(order_i) + \text{linear\_proj}\left(LOB_i^{\text{volumes}}\right) + \text{emb}\left(LOB_i^{\text{mid\_price}}\right).$$

Order Information

Input (encodes four sub-fields):

Field	Discrete Range
Type	{Ask, Bid, Cancel}
Price	$[-32, +32]$ (relative to mid-price)
Volume	$[0, 32]$
Interval	$[0, 16]$

Output: A d-dimensional vector (emb_dim)

Tokenization

$$Emb_i = \text{emb}(order_i) + \text{linear\_proj}\left(LOB_i^{\text{volumes}}\right) + \text{emb}\left(LOB_i^{\text{mid\_price}}\right).$$

LOB Depth

Input: A length-10 real-valued vector of order-book volumes

- representing the remaining order volumes of the first to fifth bid and ask levels respectively (bid1...bid5, ask1...ask5)

Output: A d-dimensional vector (emb_dim)

Tokenization

$$Emb_i = \text{emb}(order_i) + \text{linear\_proj}\left(LOB_i^{\text{volumes}}\right) + \text{emb}\left(LOB_i^{\text{mid\_price}}\right).$$

Mid-Price Background

Input: number of mid-price tick changes since market open (a discrete integer)

Output: A d-dimensional vector (emb_dim)

Tokenization - An Example

Assume the embedding dimension is $d = 4$ (for simplicity):

$\mathrm{emb}(order_i)$

- Input: order_type = Bid, price_level = 3, volume = 10, interval = 2
- Output: $[0.10,\ -0.20,\ 0.30,\ 0.40]$

$\mathrm{linear\_proj}(LOB_i^{\text{volumes}})$

- Input: LOB_volumes = [100,90,...,80](10 numbers)
- Output: $[-0.05,\ 0.02,\ 0.07,\ 0.01]$

$\mathrm{emb}(LOB_i^{\text{mid-price}})$

- Input: mid_price_index=15
- Output: $[0.03,\ 0.04,\ -0.01,\ 0.10]$

$Emb_i = [0.08,\ -0.14,\ 0.36,\ 0.51]$, is the **token embedding** at position i; it will be fed into the Causal Transformer to predict the next order.

Model Training Set

Data

- top 500 liquidity stocks in the Chinese stock market
- period from 2017 to 2023
- 16 billion order tokens

Architecture

- LLaMA2, sequence length is set at 1024 (Touvron et al., 2023)
- AdamW optimizer, fp16 precision (Loshchilov, 2017)
- DeepSpeed ZERO stage 2 (Rajbhandari et al., 2020)

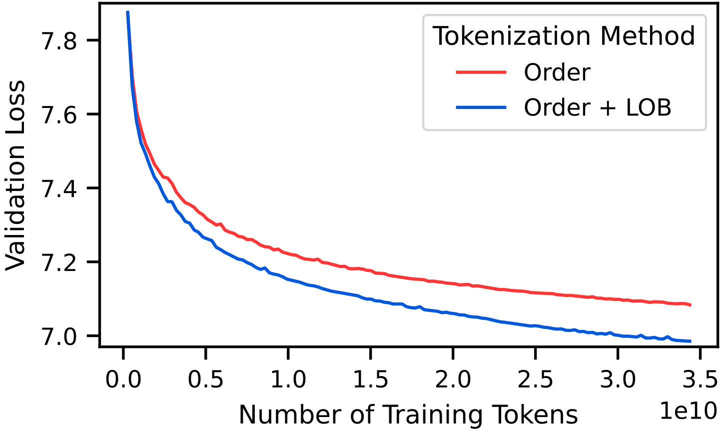
Batch size: 4096, sequence length: 1024 $\rightarrow$ 4 million tokens per optimization step

Model Training Set

Order vs. Order + LOB

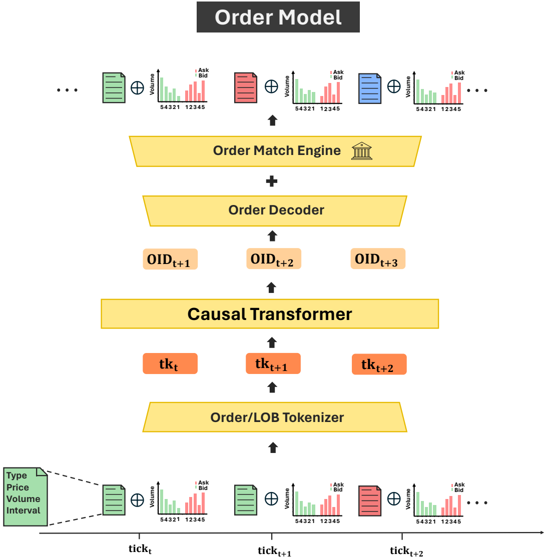
```
def forward(self, features: Tensor) -> Tensor:
    """Tokenize inputs."""
    ...
    embs = [
        self.emb_order_type(order_type),
        self.emb_price_level(price_level),
        self.emb_pred_order_volume(pred_order_volume),
        self.emb_order_interval(order_interval),
        # with LOB
        self.emb_chg_to_open(...),
        self.emb_time_to_open(...),
        self.lob_tokenizer(features[:, 5:15].to(dtype)),
    ]
    ...
    return tokens
```

Model Training Result



A comparative analysis of the tokenization process with and without LOB

Order-Level Model



Order Match Engine

Purpose: After matching, the system uses the "new order + updated book snapshot" as the next input and repeats the entire pipeline—until you've generated as many orders as you need.

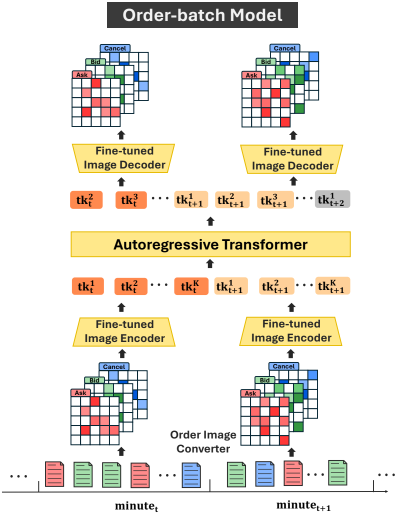
Match: Apply the exchange's matching rules to the decoded orders (decoded from logits): either execute trades against resting orders or add it as a new limit order, yielding an updated LOB state.

Record Trades or Book Updates:

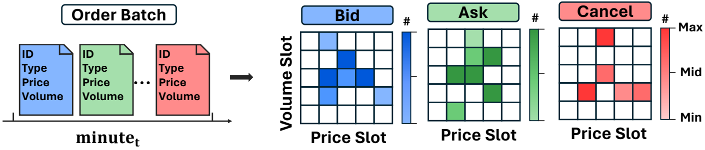
- If the order was executed, log the trade price and quantity.
- If it became a resting order, update the appropriate price-level queue in the book.

Build the next input features ...

Order-Batch Model (Macro LMM)



Order Image Converter



The order image converter transforms order data into a visual representation (**per minute for each stock**).

Input: All orders in 1 minute with

- **type:** bid, ask, cancel
- **price slot:** number of ticks above or below the mid-price
- **volume slot:** e.g. 1–10 shares=slot 1, 11–50 shares=slot 2

Output: A 32×32, 3 channels image with **pixel value** (representing the number of orders with the same attributes, with higher pixel values indicating more orders (clamped to [0–100]))

Order Image Converter - An Example

Consider the one-minute interval from 09:30:00 to 09:30:59 and observe the following eight events:

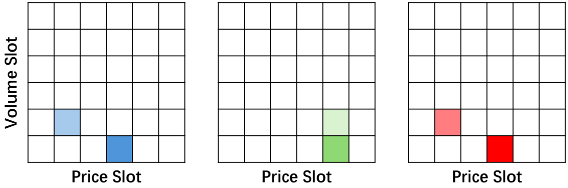
Index	Type	Price Slot (ticks from mid-price)	Volume (shares)
1	Bid	+1	5
2	Bid	+1	5
3	Bid	-2	20
4	Ask	+2	10
5	Ask	+2	10
6	Ask	+2	50
7	Cancel	+1	5
8	Cancel	-2	20

Volume slot 1 = 1–10 shares, slot 2 = 11–50 shares, and so on
X-axis (Price Slot): from 3 to +3 ticks, Y-axis (Volume Slot): slot 1, 2, . . .

Order Image Converter - An Example

Three "heatmaps" $\rightarrow$ a "snapshot":

- Blue channel (Bids):
  - (+1,slot 1): 2 orders (event 1 & 2) $\rightarrow$ value = 2
  - (-2,slot 2): 1 orders (event 3) $\rightarrow$ value = 1
- Green channel (Asks):
  - (+2,slot 1): 2 orders (event 4 & 5) $\rightarrow$ value = 2
  - (+2,slot 2): 1 orders (event 6) $\rightarrow$ value = 1
- Red channel (Cancels):
  - (+1,slot 1): 1 orders (event 7) $\rightarrow$ value = 1
  - (-2,slot 2): 1 orders (event 8) $\rightarrow$ value = 1



Tokenization

Purpose: convert each "order-batch image" into a discrete token sequence for autoregressive modeling

Model: a pre-trained VQGAN from LDM (Rombach et al., 2022), which was trained on the LAION-400M database (Schuhmann et al., 2021)

Input: A 32×32, 3 channels image

- Down-sampling factor $f = 4$: 32×32 → 8×8 latent grid
- Codebook size $Z = 8192$: number of discrete embeddings
- Code dimension $d = 3$: each token reconstructs an RGB patch

Output: Each 32×32×3 image → 8×8 = 64 tokens (indices in [0,8191])

Fine-tuning: from natural images to order images

Autoregressive Transformer

Purpose: Concatenate the tokens of N consecutive minutes into **one long sequence** and train an autoregressive transformer to **predict the next token** given all previous tokens

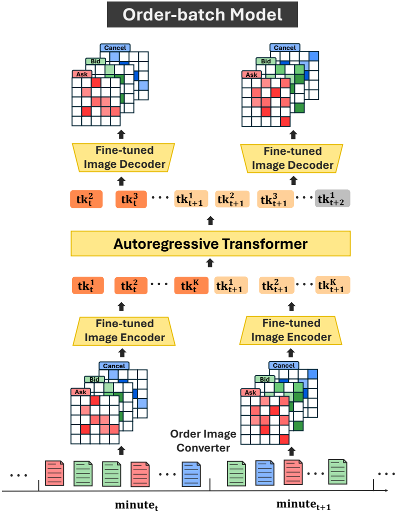
Model: LLaMA 2 (Touvron et al., 2023)

Input: 1024 tokens

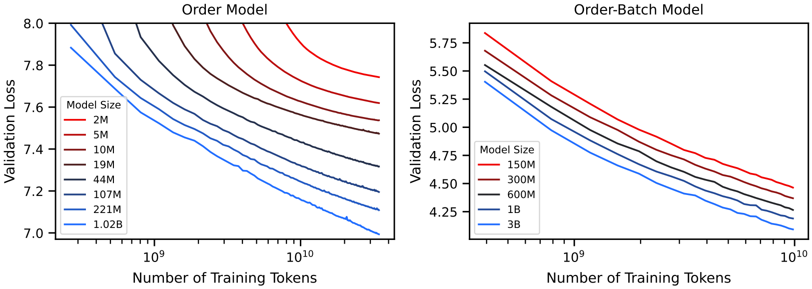
- 16 minutes$\times$64 tokens/minute $\rightarrow$ total sequence length $=$ 16$\times$64 $=$ 1024 (well below LLaMA2's 4096 context limit)

Output: autoregressively generate 64 new tokens

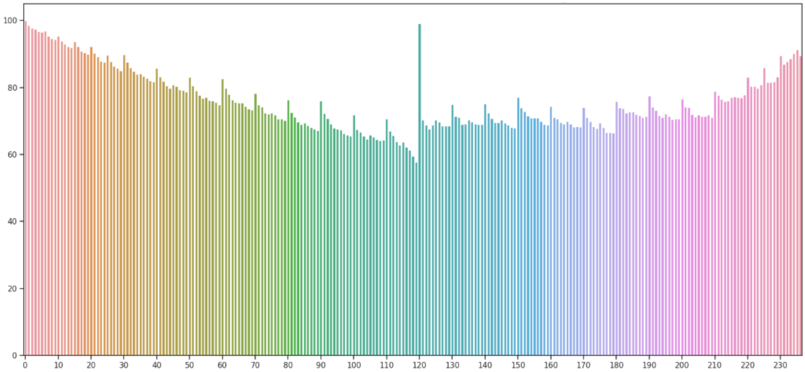
Order-Batch Model



Training Loss: Order-level and Order-Batch Model



Intraday Distribution of the Average Number of Orders



X-axis: Ranges from 0 to 239, representing the 240 consecutive minutes of a trading day (0–119: Morning session, 09:30–11:29 (120 minutes), 120–239: Afternoon session, 13:00–14:59 (120 minutes))

Y-axis: Average number of orders per minute (averaged across all sample stocks)

Pros and Cons of Order-level and Order-Batch Model

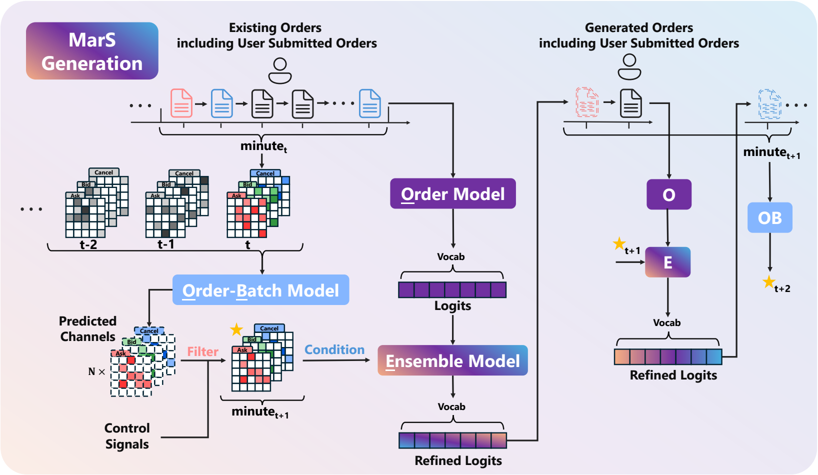
Order-level model:

- This model generates orders individually and is designed to reflect **short-term market impacts** rapidly.
- However, it lacks the ability to generate **target scenarios** over the long run.

Order-batch model:

- This model generates **order channels**, representing the macro behavior of the market, and can be used to follow control signals.
- However, it lacks the ability for **interactive** market simulation.

Ensemble Model Overview



Workflow

Ensemble Model - Refinement:

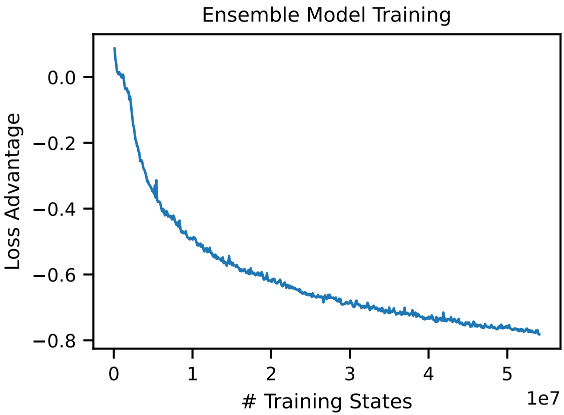
Input:

- raw logits from the Order Model
- the target channel distribution (condition)

Process: Apply **cross-attention** so that macro-level channel information refines the micro-order logits.

Output: **Refined logits**

Ensemble Model Training Result



X-axis represents the number of training samples

Y-axis represents the loss advantage over the order model

Simulated Clearing House (Order Match Engine)

Core Function:

- **Real-time matching:** when a new order is input, the simulated clearing house immediately matches buys against sells according to the chosen matching rules (MTCH_R)
- **Order book updates:** Matched quantities are removed from the LOB; any remainder stays in the book as an unfilled order

Output: current LOB snapshot

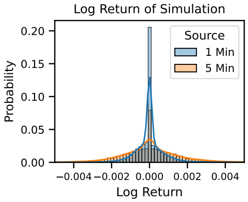
Continuous Loop: a dynamic sandbox

Training vs. Simulation

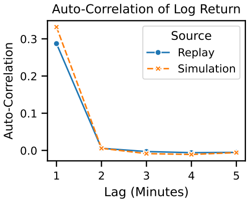
- **During training**, real historical LOB snapshots (replay data) are used as conditioning inputs so the model learns **accurate responses** without compounding batch-model noise.
- **During live simulation**, the model uses the clearing-house's own live LOB outputs as its macro input, closing the loop end-to-end.

Realistic Simulations

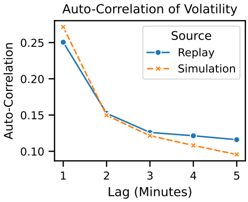
Three stylized facts:



(a) Aggregational Gaussianity

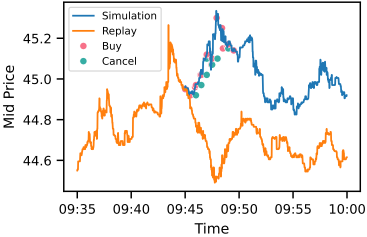


(b) Absence of Autocorrelations

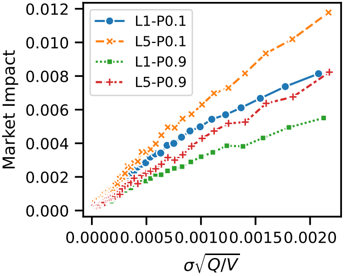


(c) Volatility Clustering

Interactive Simulations



(a) Synthetic market interaction

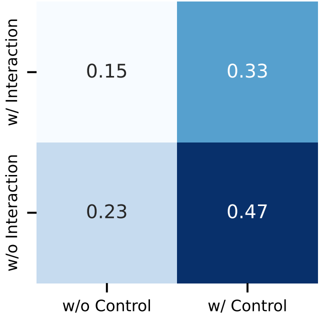


(b) Square-Root-Law Validation

Time-Weighted Average Price (TWAP) Strategy

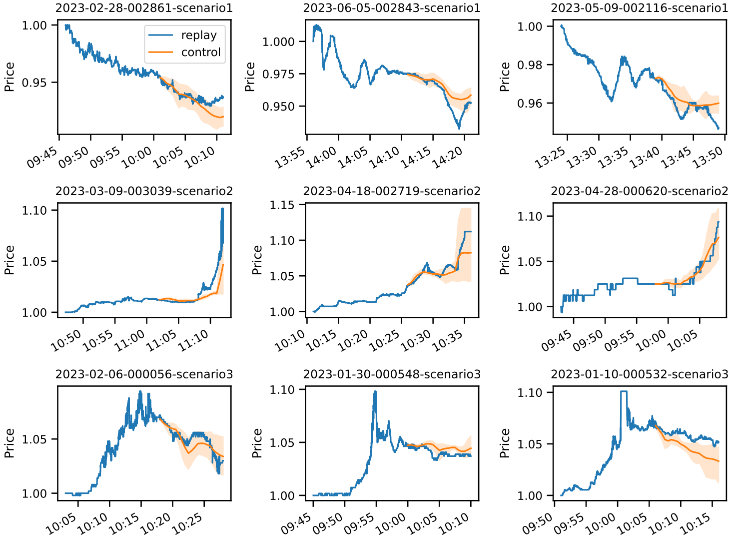
- Maximum Passive Volume Ratio (PVR) $\rightarrow$ P
- Aggressive Price (AP) $\rightarrow$ L

Controllable Simulations

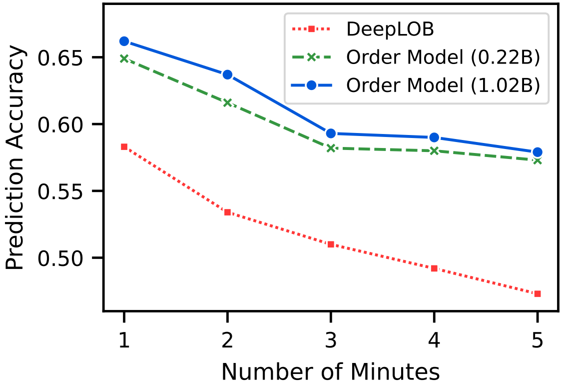


Configurations **with control but no interaction** achieve the highest correlation scores, while introducing interaction reduces control precision ($0.47 \rightarrow 0.33$).

Different Scenario Generation

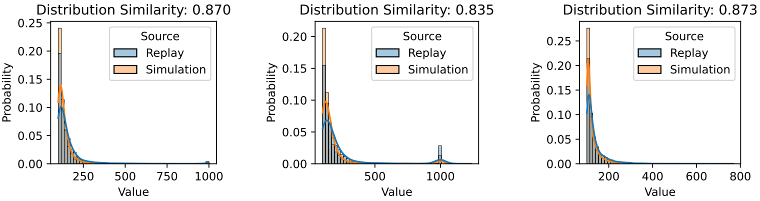


Forecasting



$$l = \frac{\frac{1}{n}\sum_{i=1}^{n} m_i - m_0}{m_0}.$$

Detection

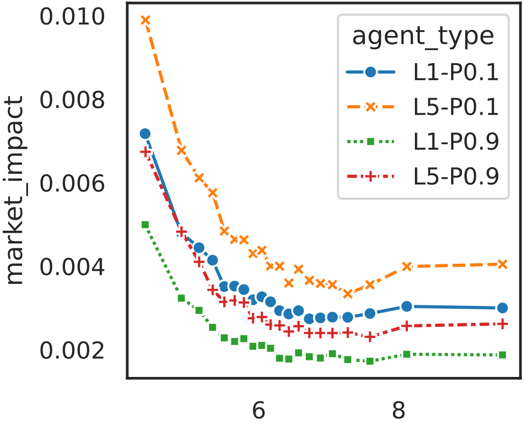


(a) Pre-manipulation (b) Manipulation period (c) Post-manipulation

Three periods, each 522 trading days

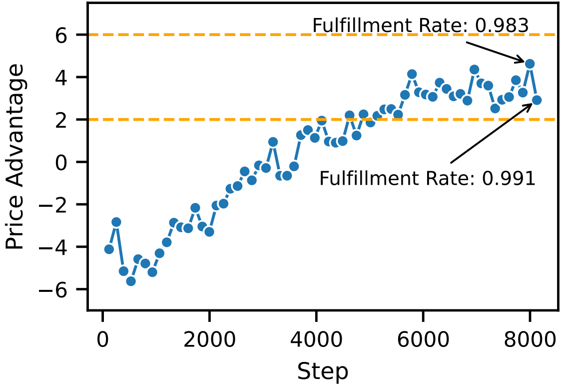
x: Spread value is defined as **best ask price - best bid price**

'What if' Analysis on Market Impact



New factor: Resiliency (From symbolic regression and genetic algorithms)

RL Environment



Performance of the trading agent (Baseline: best-configured TWAP agent)

Conclusion

MarS is

a comprehensive financial system for orders with these capabilities
- Realism, High-Resolution, Controllability, Interactivity

a powerful tool for a wide range of downstream applications:

- Forecast Tool: based on recent orders and LOB, simulating future market trajectories
- Detection System: identifies potential risks not apparent from current observations
- Analysis Platform: answers a wide range of "what if" questions by providing a realistic simulation environment
- Agent Training Environment: the realistic and responsive nature of MarS makes it ideal for training reinforcement learning agents