MOSAIC: MODULAR ORCHESTRATION FOR STRUCTURED AGENTIC INTELLIGENCE AND COMPOSITION

Anonymous authors
Paper under double-blind review

ABSTRACT

Automated data science is a structured model-selection problem. A solution must choose data transformations, feature representations, architecture, training procedure, evaluation protocol, and refinement strategy for a task. AutoML systems automate parts of this process, but typically search within predefined pipeline, model, and hyperparameter spaces. LLM-based agents offer greater flexibility through retrieval, code generation, and execution feedback, yet their modelling decisions are often unstructured, difficult to verify, and hard to reuse. We introduce MOSAIC (Modular Orchestration for Structured Agentic Intelligence and Composition), a structured agentic framework for memory-grounded model selection and workflow construction. Given a task and dataset, MOSAIC builds a semantic task profile, retrieves prior cases and source-code modules, and constructs a blueprint: an intermediate representation specifying selected modelling components, composition, interface constraints, and execution requirements. This blueprint turns model selection into a staged, context-grounded search and grounds LLM-based code generation in retrieved evidence rather than unconstrained synthesis. Candidate models are validated by execution and refined using diagnostic feedback, training traces, task metrics, and a failure-aware reinforcement learning policy. We instantiate MOSAIC on financial time-series forecasting and generation, where models must satisfy predictive accuracy, distributional fidelity, execution reliability, and downstream financial criteria such as risk and tail behaviour. Experiments against AutoML and agentic baselines show that MOSAIC improves task performance, execution success, and decision traceability, demonstrating the value of treating automated data science as structured, reusable, and execution-grounded model selection.

1 INTRODUCTION

Data science modelling (Domingos, 2012) requires data understanding, preprocessing, feature construction, model design, implementation, evaluation, and iterative refinement. These decisions are tightly coupled: modelling assumptions depend on the data, implementations depend on architectural choices, and effective refinements often require coordinated changes across the training procedure, model structure, and evaluation protocol.

AutoML systems automate important parts of this process, but typically do so by searching over predefined pipelines, model classes, and hyperparameter spaces (Feurer et al., 2022; Thornton et al., 2013). LLM-based agents offer a more flexible alternative. They can retrieve examples, generate code, run programs, and react to execution feedback (Yao et al., 2023; Wang et al., 2024a; Lv et al., 2024). However, this flexibility is often realised through free-form code generation. Existing data-science agents (Guo et al., 2024; Baek et al., 2025; Ang et al., 2025) typically lack both a structured memory of prior modelling work and a persistent intermediate representation of the workflow being constructed. As a result, they often behave as adaptive code generators rather than agents that systematically reuse, compose, verify, and improve modelling knowledge.

The central idea of MOSAIC is to make modelling memory explicit and operational. Prior tasks provide task-level memory (Ang et al., 2025; Shinn et al., 2023): which modelling strategies worked for related datasets, objectives, and constraints. Code repositories provide implementation-level memory: reusable modules for data processing, feature engineering, model construction, training, evaluation, and refinement (Novikov et al., 2025; Ellis et al., 2023). MOSAIC extracts, annotates,

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and retrieves such modules for a new task, and composes them through a structured intermediate representation.

This intermediate representation is a *blueprint*: a workflow-level object that sits between the task description and executable code. The blueprint specifies the required modelling capabilities, selected modules, composition order, dimensional compatibility constraints, and execution constraints. Code generation is therefore grounded in retrieved cases, extracted code modules, and an explicit workflow plan, rather than left to unconstrained LLM synthesis. Generated candidates are then executed, diagnosed, and refined using errors, logs, validation metrics, and training dynamics.

A second challenge is that model improvement is often a long-horizon process. Greedy edit-and-test loops can miss refinements whose benefits only appear after subsequent changes, such as introducing normalisation before changing the learning-rate schedule or modifying the model architecture before adjusting the loss. At the same time, learning a policy that edits code directly is difficult: the space of possible edits is extremely large, and useful feedback is only observed after the edited program is executed. MOSAIC therefore separates refinement decisions from code realisation. A learned policy selects structured high-level refinement actions, while a frozen LLM executor translates these actions into concrete code edits. The policy is trained offline from refinement trajectories and uses failure-aware trajectory branching, rollback, and invalid-action masking to convert execution failures and performance-degrading edits into reusable supervision.

We evaluate MOSAIC on financial time-series forecasting and generation. This is a demanding testbed because models must perform well under temporal validation, preserve statistical and dependence structure, and satisfy downstream financial metrics such as risk and tail behaviour. It therefore tests whether memory-grounded workflow construction improves not only task performance, but also execution reliability and decision traceability. Our contributions are:

- We formulate automated data science as *memory-grounded modular workflow construction*, where task solutions are built by retrieving, composing, executing, and refining reusable modelling capabilities.
- We introduce a *blueprint-based, repository-grounded synthesis framework* that retrieves prior cases and source-code modules, extracts reusable components, composes them into executable workflow blueprints, and generates task-adapted implementations.
- We formulate model refinement as a *failure-aware offline reinforcement learning* problem, where execution feedback, rollback, trajectory branching, and invalid-action masking are used to learn long-horizon refinement policies for LLM-mediated code editing.
- We evaluate MOSAIC on financial time-series forecasting and generation, showing improvements in predictive performance, distributional fidelity, execution reliability, and decision traceability relative to AutoML and agentic baselines.

2 Related Work

AutoML and Neural Architecture Search. AutoML systems such as AutoGluon (Shchur et al., 2023), Auto-sklearn (Feurer et al., 2022), and Optuna (Akiba et al., 2019) automate model selection and hyperparameter tuning, while neural architecture search methods explore predefined structural spaces (Zoph & Le, 2017; Elsken et al., 2019; Liu et al., 2018). However, these approaches operate over fixed search spaces and do not reason over task descriptions, retrieve prior cases, or synthesize new architectures from reusable modules. MOSAIC differs by treating model construction as a repository-grounded composition problem: it retrieves existing code, extracts modules, constructs a blueprint, and synthesizes executable models beyond fixed model-bank selection.

LLM-Based Agentic Systems. ReAct-style agents (Yao et al., 2023) interleave reasoning and action for interactive decision-making, while DS-Agent (Guo et al., 2024) and ResearchAgent (Baek et al., 2025) extend this paradigm to data science workflows through case-based reasoning and iterative self-critique. Broader auto-research systems, including AI Scientist (Lu et al., 2024) and Agent Laboratory (Schmidgall et al., 2025), automate larger parts of the research pipeline. Recent work also studies agentic component selection as optimisation over capability, cost, and compatibility (Yuan et al., 2025). However, existing agentic systems often lack task-specific formalisation of modelling modules, execution constraints, and reusable workflow structure. MOSAIC addresses this gap by imposing an explicit module-level workflow representation for financial time-series modelling.

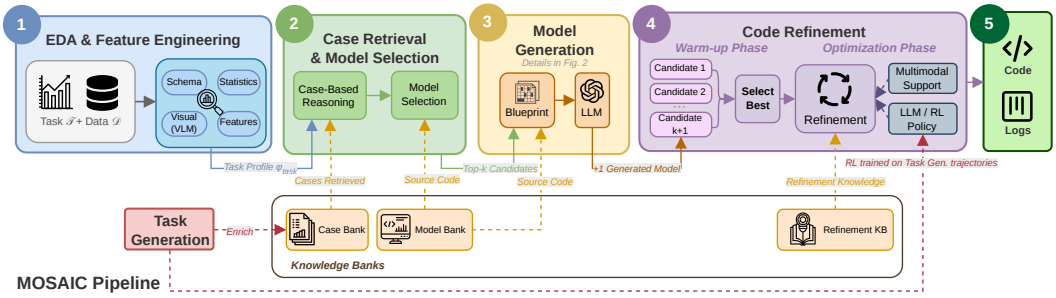


Figure 1: Overview of the MOSAIC pipeline.

LLM Code Generation and Program Refinement. Recent methods explore diverse strategies for optimising solutions in code space: AlphaEvolve (Novikov et al., 2025) applies evolutionary search with LLM-guided mutations, AIDE (Jiang et al., 2025) models generation as tree search with drafting, debugging, and improving operators, EffiLearner (Huang et al., 2024) drives iterative refinement through runtime execution feedback, and LLM4EFFI (Ye et al., 2025) separates high-level algorithmic reasoning from code synthesis. These methods optimise code but do not explicitly decompose the modelling problem into reusable time-series modules, with blueprint-level architectural constraints. MOSAIC instead grounds synthesis in extracted module representations, architecture-family-aware composition plans, and execution-based validation.

Reinforcement Learning for Sequential Decision-Making. Reinforcement Learning (RL) has been combined with LLMs by directly optimising LLM policies (Ouyang et al., 2022), using LLMs as high-level planners (Wang et al., 2024a), or using LLMs to design reward functions (Ma et al., 2024). Our setting is different: a learned refinement policy selects structured high-level actions, while a frozen LLM executor translates these actions into concrete code edits. We build on offline RL, particularly Implicit Q-Learning (Kostrikov et al., 2022), as well as invalid-action masking (Huang & Ontañón, 2022) and safe RL shielding (Alshiekh et al., 2018). MOSAIC adapts these ideas to LLM-mediated code refinement, where execution failures and performance-based rollbacks require construction of failure-aware trajectories and deployment-time action constraints.

3 Overview of MOSAIC

3.1 Problem Formulation

The goal is to build a statistical model that is suitable for the task at hand. This requires to choose an appropriate model class, specify its architecture, adapt it using domain-specific modelling and optimisation heuristics, select a training procedure, tune hyperparameters, and impose suitable regularisation. These choices are interdependent: the admissible model class depends on the data and task, the training method depends on the architecture, and the evaluation protocol depends on the intended downstream use.

We therefore formulate automated data modelling as a workflow construction problem. Rather than searching directly over parameters of a single model family, MOSAIC searches over a structured space of executable modelling workflows. Each workflow specifies how data are processed, which features are constructed, which model class and architecture are selected, how the model is trained and regularised, how domain-specific refinements are applied, and how the final output is evaluated.

Task specification. A modelling task is specified as $\mathcal{T} = (\mathcal{W}, \mathcal{D}, \mathcal{L})$, where $\mathcal{W}$ is the natural-language task description, $\mathcal{D}$ is the dataset together with its train/validation/test split, and $\mathcal{L}$ is the evaluation protocol. The evaluation protocol may include predictive losses, distributional metrics, and downstream financial criteria such as risk, tail behaviour, or portfolio performance. (See details in Appendix A and examples of tasks in Appendix H.9)

Knowledge banks. MOSAIC assumes access to external knowledge resources $\mathcal{K} = (\mathcal{E}_{\text{case}}, \mathcal{E}_{\text{code}}, \mathcal{E}_{\text{refine}})$, where $\mathcal{E}_{\text{case}}$ is a case bank of prior task–solution pairs, $\mathcal{E}_{\text{code}}$ is a repository of reusable model architectures, training routines, feature transformations, and evaluation components, and $\mathcal{E}_{\text{refine}}$ is a refinement knowledge bank containing domain-specific optimisation heuristics. These knowledge banks define the reusable modelling capabilities from which new workflows can be constructed (see Appendix B).

Modelling objective. Given a task $\mathcal{T}$ and knowledge banks $\mathcal{K}$, the objective is to select and execute a modelling solution m that performs well under the task-specific evaluation protocol. The solution m includes the modelling choices needed to obtain a trained model, such as the model class, architecture, training method, hyperparameters, regularisation, and domain-specific optimisation heuristics.

Let $P_{\mathcal{T}}$ denote the task distribution, and let $\mathcal{U}(\mathcal{T}, m)$ denote the loss obtained by executing modelling solution m on task $\mathcal{T}$. The objective is

$$m^{\star} \in \arg \min_{m \in \mathcal{A}(\mathcal{T},\mathcal{K})} \mathbb{E}_{\mathcal{T} \sim P_{\mathcal{T}}} \left[\mathcal{U}(\mathcal{T}, m) \right]. \tag{1}$$

This formulation makes explicit that the search is not only over the parameters of a fixed model, but over admissible modelling solutions selected for the task at hand. MOSAIC operationalises this search by representing such solutions as structured executable workflows, introduced next.

3.2 System Pipeline

Figure 1 illustrates MOSAIC as a staged search procedure for a modelling solution $m \in \mathcal{A}(\mathcal{T}, \mathcal{K})$. The system does not ask an LLM to generate the final model directly. Instead, it progressively constructs the context needed to make model search well posed: first from the task and data, then from retrieved cases, then from reusable code modules, and finally from execution feedback.

Given a task $\mathcal{T} = (\mathcal{W}, \mathcal{D}, \mathcal{L})$, MOSAIC first performs **semantic-aware exploratory data analysis (EDA)** and feature engineering augmented by VLM-based multimodal support (details in Appendix C). This produces a task profile

$$\phi_{\text{task}} = (\phi_{\text{schema}}, \phi_{\text{stat}}, \phi_{\text{visual}}, \phi_{\text{feat}}),$$

which summarises the dataset schema, statistical meta-features, visual time-series patterns, and engineered features. This profile acts as the first layer of context for model search. It is used to query the case bank $\mathcal{E}_{\text{case}}$ and retrieve prior tasks with similar data characteristics, objectives, and evaluation requirements. The retrieved cases, together with the model/-code bank $\mathcal{E}_{\text{code}}$, are then used to select the top-k candidate models, denoted by $m^{(k)} = (m_1, \ldots, m_k)$.

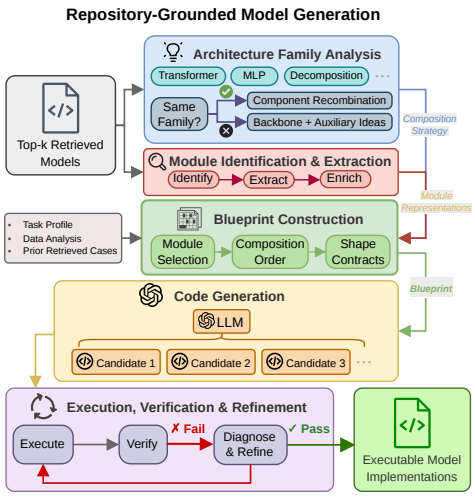


Figure 2: Overview of the repository-grounded model generation pipeline.

Repository-grounded model generation. This stage expands beyond direct model selection. As shown in Figure 2, the repository-grounded model generation module uses the top-k candidates as context for constructing a new candidate model. It first analyses the architectural families represented among the retrieved candidates, then extracts reusable modules from the corresponding source code, *e.g.* embeddings, encoders, and forecasting heads. These modules are enriched with semantic annotations and shape information, allowing them to be composed subject to dimensional and functional compatibility constraints. Further details are provided in Appendix D.

From this information, MOSAIC constructs a blueprint B: an intermediate representation that specifies the relevant modelling components, their composition order, their input–output interfaces, and the execution constraints required for a valid implementation. The LLM is then used as an executor of this structured context rather than as an unconstrained code generator. Conditioned on the retrieved cases, extracted modules, and blueprint, it synthesises a new candidate model m_{k+1}. This generated model is added to the original top-k candidates ($m^{(k)} = (m_1, \ldots, m_k)$), producing the candidate pool $m^{(k+1)} = (m^{(k)}, m_{k+1})$.

This staged construction can be viewed as a factorisation of the search for the final modelling solution. Informally,

$$\begin{aligned} p(m \mid \mathcal{T}, \mathcal{K}) \approx\ & p(m \mid m^{(k+1)}, h, \mathcal{E}_{\text{refine}})\, p(m_{k+1} \mid B, m^{(k)}, \mathcal{E}_{\text{code}}) \\ & \times p(B \mid \phi_{\text{task}}, m^{(k)}, \mathcal{E}_{\text{code}})\, p(m^{(k)} \mid \phi_{\text{task}}, \mathcal{E}_{\text{case}}, \mathcal{E}_{\text{code}})\, p(\phi_{\text{task}} \mid \mathcal{T}), \end{aligned}$$

where h denotes the execution history, including logs, errors, validation metrics, training traces, and loss-curve visualisations. This factorisation should be read as a procedural description rather than as a calibrated probabilistic model: each stage conditions the next one, narrows the search space, and grounds LLM generation in task-specific evidence.

Finally, the $k+1$ candidates enter a two-phase refinement stage. In the warm-up phase, all candidates are executed and evaluated in parallel. The best-performing candidate is then refined in an optimisation phase using the refinement knowledge bank $\mathcal{E}_{\text{refine}}$ and execution feedback. Refinement can be driven by the learned RL policy with LLM executor described in Section 3.3. The resulting output is an executable modelling solution selected through retrieval, blueprint construction, LLM-based realisation, execution, and refinement.

3.3 RL-Guided Long-Horizon Refinement

After repository-grounded generation and execution verification, MOSAIC obtains a pool of executable candidate models. The refinement stage aims to improve the selected candidate through a sequence of structured edits. This is naturally a sequential decision problem: a locally neutral or even slightly degrading edit, such as adding normalisation, changing the learning-rate schedule, or modifying regularisation, may enable subsequent improvements. Conversely, an apparently plausible edit may lead to an unstable or poorly performing model and should not be repeatedly explored from the same state.

We formulate refinement as a finite-horizon decision process over executable models. At refinement step t, the state is $s_t = (m_t, \mathcal{M}_t)$, where m_t is the current executable model, including its architecture, training configuration, and hyperparameters, and $\mathcal{M}_t$ denotes the accompanying model diagnostics. These diagnostics include validation loss induced by the evaluation $\mathcal{L}$, execution logs, and any failure information observed so far. Thus, the state records not only the current model, but also the evidence needed to decide how it should be refined.

The action space consists of structured refinement strategies rather than raw code edits. An action $a_t \in \mathcal{A}_{\text{ref}}$ may specify, for example, to add normalisation, modify dropout, change the learning-rate schedule, tune batch size, adjust regularisation, alter model capacity, or replace a modelling component. The action is therefore a high-level modelling decision. A frozen LLM executor then translates this structured action into concrete code changes, which are executed to obtain the next model and diagnostics.

This policy–executor interface can be written as the following factorisation:

$$p(s_{t+1} \mid s_t) = \sum_{a_t, e_t} p(s_{t+1} \mid e_t, s_t) p(e_t \mid a_t, s_t) \pi(a_t \mid s_t),$$

where $\pi(a_t \mid s_t)$ is the refinement policy, $p(e_t \mid a_t, s_t)$ is the LLM executor that realises the selected strategy as a code edit e_t, and $p(s_{t+1} \mid e_t, s_t)$ is the execution environment obtained by running the edited program. In this way, the RL policy learns to choose refinement strategies, while the LLM remains responsible for implementing them.

The goal is to minimise the task-specific loss over a refinement horizon. Let $\mathcal{L}(s_t) := \mathcal{L}(\mathcal{T}, m_t)$ denote the loss obtained by executing the model m_t on task $\mathcal{T}$. For a refinement policy π, we seek

$$\pi^\star \in \arg\min_{\pi} \mathbb{E}_\pi \left[\sum_{t=0}^{H-1} \gamma^t \left(\mathcal{L}(s_{t+1}) - \mathcal{L}(s_t) \right) \right],$$

subject to the constraint that each visited model remains executable and satisfies the required interface and numerical-validity checks. Here the reward $r_t = -\left(\mathcal{L}(s_{t+1}) - \mathcal{L}(s_t)\right)$ and γ is the discount factor.

Offline trajectory construction. The refinement policy is trained offline. For each generated training task, MOSAIC instantiates an executable modelling program and explores alternative refinement paths using an LLM-based refinement agent. At each step, the agent proposes a structured refinement action, the LLM realises it as a concrete code edit, the edited program is executed, and the resulting loss and diagnostics are recorded. This produces trajectories of the form $(s_0, a_0, r_0, s_1, a_1, \ldots, s_H, r_H)$, where each state contains both the current model and its diagnostics.

A key difficulty is that LLM-mediated refinement produces many failed or degrading branches. MOSAIC therefore uses execution guardrails. A *hard failure* occurs when the edit cannot be

executed, for example because of a syntax error, shape mismatch, missing dependency, NaN loss, or timeout. In this case, the transition is stored as a terminal failed transition and the system rolls back to the last valid executable checkpoint. A *soft failure* occurs when the edit is executable but causes sustained degradation in the validation loss. In this case, the system rolls back to the previous best checkpoint rather than continuing from the degraded model.

These rollbacks create a tree-structured refinement process rather than a single linear trajectory. To preserve valid learning trajectories, MOSAIC uses trajectory branching, as illustrated in Figure 7 and detailed in Appendix E. Suppose the refinement path reaches a good checkpoint $s^\star$, then explores a sequence of edits that leads to degraded states and triggers a rollback. Instead of storing the raw path with a discontinuous transition back to $s^\star$, the rollout is split into two branches: (1) failure branch: $s^\star \to \cdots \to s_{\text{bad}}$, and (2) continuation branch: $s^\star \to \cdots$.

The failure branch is retained as negative supervision, while the continuation branch records the subsequent valid search from the restored checkpoint. The action that initiated the failed branch is stored in a state-specific invalid-action mask $\mathcal{I}_{\text{invalid}}(s^\star)$. Thus, the system does not merely discard bad refinements: it learns which actions should not be repeated from the same diagnostic state.

Offline learning and deployment. The branched trajectories define an offline dataset of states, structured refinement actions, losses, next states, terminal indicators, and invalid-action masks. We train a refinement policy on this dataset using offline RL, instantiated in our experiments with Implicit Q-Learning (Kostrikov et al., 2022). The policy is trained to select actions that reduce long-horizon loss while avoiding actions that previously caused hard failures or soft reverts. During training, actions in $\mathcal{I}_{\text{invalid}}(s)$ are masked for the corresponding state.

At deployment, the learned policy is frozen. For a new task, MOSAIC observes the current state $s_t = (m_t, \mathcal{M}_t)$ and selects the best available refinement action under a dynamic valid-action mask:

$$a_t \in \arg \min_{a \in \mathcal{A}_{\text{valid}}(s_t)} Q(s_t, a),$$

where $\mathcal{A}_{\text{valid}}(s_t)$ excludes actions already known to fail from the current state. The selected action is realised by the LLM executor, the resulting code is executed, and the diagnostics are updated. If the edit triggers a hard failure or soft revert, MOSAIC restores the last valid checkpoint, adds the failed action to the dynamic mask, and queries the policy again. The RL module therefore provides long-horizon strategy selection, while the selected strategy is executed by the LLM for flexibility.

4 Experiments

4.1 Experimental Setup

Datasets and Tasks. We evaluate MOSAIC on financial time-series forecasting and generation. Forecasting targets accurate prediction of future prices, while generation aims to synthesise realistic time-series that preserve key statistical and structural properties of the original data. Both tasks are further assessed through downstream financial metrics. We adopt three widely-used financial datasets (Ang et al., 2026; 2025): (1) Hourly closing prices for a set of 20 cryptocurrency trading pairs against USDT (Tether) in 2024 (**Crypto**); (2) High-frequency limit order book data sourced from the LOBSTER platform, covering NASDAQ-listed equities with millisecond-resolution event streams including order submissions, cancellations, and executions (**LOB**); and (3) Daily closing prices for 10 major U.S. stocks from January 2020 to December 2024, covering business days only (**Stock**); details in Appendix F.

Baselines. At the system level, we benchmark against DS-Agent (Guo et al., 2024), ResearchAgent (Baek et al., 2025), TS-Agent (Ang et al., 2025) AutoGluon (Shchur et al., 2023) (forecasting), and Optuna (Akiba et al., 2019) (generation). At the module level, we compare Repository-Grounded Model Generation against AlphaEvolve (Novikov et al., 2025), AIDE (Jiang et al., 2025), EffiLearner (Huang et al., 2024), and LLM4EFFI (Ye et al., 2025), and RL for Refinement against BC (Pomerleau, 1988), DQN (Mnih et al., 2015), and an LLM-only policy, each integrated as a drop-in replacement. All agents use GPT-5.4 (OpenAI, 2026), GPT-4o (OpenAI, 2023), Claude Opus 4 (Anthropic, 2025), and Nova Pro (Intelligence, 2025).

Evaluation Protocol. We follow prior work (Ang et al., 2025) and report standard forecasting metrics, including RMSE, MAE, MAPE, and sMAPE, as well as generation metrics, including Marginal,

Correlation, Autocorrelation, and Covariance distances. We also report ΔVaR and ΔES on Crypto, ΔSharpe for forecasting, and system-level Success Rate. For model generation, we report Win Rate, the proportion of generated models selected as the final system output after joint refinement with retrieved candidates. For RL, we report Steps to Best Incumbent (abbreviated as Steps), measuring how many refinement steps are needed to reach the best performing candidate. We further ablate EDA, Feature Engineering, and Multimodal Support using the same metrics. All reported metrics are averaged over five independent runs to ensure statistical reliability.

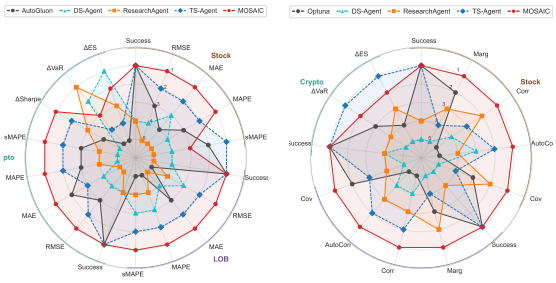


Figure 3: Forecasting performance across datasets, metrics, and LLM backbones. Each metric is averaged over five runs.

Module and Ablation Definitions. For clarity, we denote system variants as follows: **ModelGen (MOSAIC)** performs repository-grounded model generation without RL, using the LLM for refinement if candidates are valid; **IQL (MOSAIC)** applies RL-guided refinement independently of ModelGen; **EDA (MOSAIC)** removes EDA, Feature Engineering, and Multimodal Support; and **Full MOSAIC** runs the complete system, with refinement guided by RL when ModelGen does not yield a winning candidate, and otherwise by the LLM. More implementation details are in Appendix G, including a time and cost breakdown.

4.2 Overall Evaluation

Time Series Forecasting. MOSAIC consistently achieves the best results on forecasting tasks across three datasets and four LLM backbones, as supported by Figure 3 and results in Appendix H.1. Averaged across backbones, RMSE is reduced by 8% on LOB, 5% on Crypto, and 3% on Stock relative to TS-Agent, with individual backbones showing gains up to 19% (LOB-Claude) and 8% (Crypto-GPT-5.4). Compared to AutoGluon, average RMSE reductions reach 33% on LOB. For risk-aware metrics on Crypto, average ΔSharpe is reduced by over 21% relative to TS-Agent, with the GPT-4o backbone alone showing a 46% reduction. Ranking profiles (Figure 4(a)) confirm this consistency, with the system forming the outermost contour on nearly all axes. The gains may result from the model generation module and the RL-based refinement policy, which learns non-myopic editing strategies from offline trajectories.



(a) Forecasting Ranking (b) Generation Ranking

Figure 4: Radar charts for ranking.

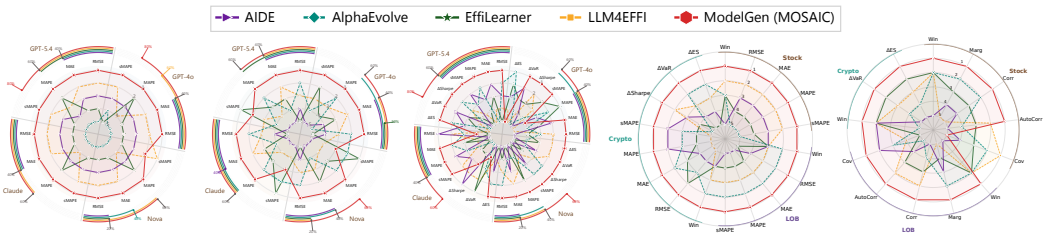
Time Series Generation. Figure 4(b) summarizes generation ranking profiles. MOSAIC dominates on LOB and Stock, reducing average Marginal distance by over 32% and Correlation by 27% compared to TS-Agent on LOB, and Marginal by over 23% on Stock. These gains are driven by the model generation module's ability to synthesise novel generative architectures tailored to each dataset's distributional characteristics. On Crypto, it outperforms DS-Agent, ResearchAgent, and Optuna on both ΔVaR and ΔES, though TS-Agent achieves lower tail-risk distances on this dataset. MOSAIC also maintains full coverage across all dataset–backbone pairs, unlike DS-Agent and ResearchAgent, whose success rates range from 20% to 100%. The enhanced reliability confirms the benefit of our RL approach on the generation tasks. Detailed tables are provided in Appendix H.2.

Generalization Beyond Finance Data. We further test MOSAIC on four forecasting tasks beyond our financial benchmarks, spanning macroeconomic, commodity, climate, and energy domains (GPT-

5.4, same configuration), where it achieves the best or tied-best RMSE on all four tasks. Details are provided in Appendix H.8.

4.3 Modular Analysis

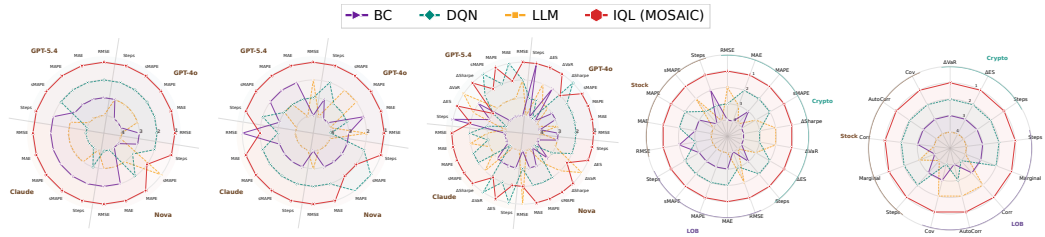
Repository-Grounded Model Generation. Figure 5 shows the model generation module achieves the highest average Win Rate on both forecasting (65% vs. 48%) and generation (63% vs. 42%), with the best financial metrics on Crypto. These advantages stem from the architecture-family-aware blueprint and the validation loop that filters faulty implementations. More details are in Appendix H.3.



(a) Stock (b) LOB (c) Crypto (d) Forecasting Avg. (e) Generation Avg.

Figure 5: Model generation module comparison. (a)–(c): per-dataset Win Rate (outermost ring) and metric performance broken down by LLM backbone. (d)–(e): ranking profiles averaged across backbones for forecasting and generation respectively.

Reinforcement Learning for Refinement. Figure 6 shows that IQL-based refinement wins 83% of metric comparisons across datasets and LLM backbones, while converging in fewer steps than LLM-only refinement (8.7 vs. 10.0 on average). BC and DQN are competitive on isolated metrics but less consistent, suggesting that offline RL captures more reliable refinement strategies than purely prompt-driven or simpler RL alternatives. More details are in Appendix H.4.



(a) Stock (b) LOB (c) Crypto (d) Forecasting Avg. (e) Generation Avg.

Figure 6: RL module comparison. (a)–(c): per-dataset metric performance broken down by LLM backbone. (d)–(e): ranking profiles averaged across backbones for forecasting and generation. Steps denotes Steps to Best Incumbent.

4.4 Ablation Studies

EDA, Feature Engineering, and Multimodal Support. Table 1 ablates the EDA and multimodal module, with TS-Agent as a lower bound. Removing these components leads to consistent degradation of up to 55% across generation and financial metrics, confirming that statistical and visual priors are essential for downstream performance. Per-LLM breakdowns are provided in Appendix H.5.

Table 1: Ablation study of the EDA and multimodal module. All metrics are averaged across four LLM backbones. Subscripts F and G denote forecasting and generation respectively. Best results per dataset are **bolded**. – indicates metric not applicable.

Dataset	Variant	Forecasting				Generation				Financial (Crypto only)				
		RMSE↓	MAE↓	MAPE↓	sMAPE↓	Marg↓	Corr↓	ACorr↓	Cov↓	ΔSharpe_F↓	ΔVaR_F↓	ΔES_F↓	ΔVaR_G↓	ΔES_G↓
Stock	MOSAIC	**7.907**	**4.853**	**2.011**	2.004	**0.387**	**0.356**	**0.085**	**0.892**	–	–	–	–	–
	EDA (MOSAIC)	7.958	4.912	2.031	2.038	0.477	0.409	0.321	0.903	–	–	–	–	–
	TS-Agent	8.167	4.957	2.076	**1.862**	0.507	0.399	0.314	0.922	–	–	–	–	–
LOB	MOSAIC	**0.144**	**0.107**	**0.048**	**0.048**	**0.587**	**0.216**	**0.217**	**0.184**	–	–	–	–	–
	EDA (MOSAIC)	0.158	0.112	0.050	0.050	0.911	0.457	0.627	0.289	–	–	–	–	–
	TS-Agent	0.157	0.115	0.052	0.052	0.870	0.296	0.295	0.255	–	–	–	–	–
Crypto	MOSAIC	**0.210**	**0.052**	**1.548**	**1.553**	–	–	–	–	**7.970**	**0.013**	**0.015**	0.075	0.095
	EDA (MOSAIC)	0.216	0.054	1.607	1.608	–	–	–	–	11.188	0.067	0.094	0.088	0.122
	TS-Agent	0.220	0.055	1.628	1.629	–	–	–	–	10.169	0.015	0.022	**0.072**	**0.093**

Table 2: Ablation study of the model generation module. All metrics are averaged across four LLM backbones. Subscripts F and G denote forecasting and generation respectively. Best results per dataset are **bolded**. – indicates metric not applicable.

Dataset	Variant	Forecasting				Generation				Financial (Crypto only)					Win	
		RMSE↓	MAE↓	MAPE↓	sMAPE↓	Marg.↓	Corr.↓	ACorr.↓	Cov.↓	ΔSharpe_F↓	ΔVaR_F↓	ΔES_F↓	ΔVaR_G↓	ΔES_G↓	F↓	G↓
Stock	ModelGen (MOSAIC)	**7.841**	**4.829**	**2.002**	**1.990**	**0.355**	**0.359**	**0.083**	**0.905**	–	–	–	–	–	**70**	**65**
	w/o Mod. Und.	8.315	5.099	2.119	2.082	0.488	0.397	0.208	0.934	–	–	–	–	–	20	10
	w/o Blueprint	8.434	5.133	2.140	2.100	0.502	0.401	0.310	0.934	–	–	–	–	–	15	5
	w/o Verify	8.231	5.074	2.123	2.111	0.490	0.408	0.196	0.949	–	–	–	–	–	15	15
	Naive LLM	8.279	5.032	2.111	2.155	0.509	0.403	0.301	0.935	–	–	–	–	–	5	5
LOB	ModelGen (MOSAIC)	**0.141**	**0.104**	**0.047**	**0.047**	**0.547**	**0.196**	**0.208**	**0.176**	–	–	–	–	–	**60**	**65**
	w/o Mod. Und.	0.154	0.113	0.051	0.051	0.753	0.252	0.261	0.227	–	–	–	–	–	20	15
	w/o Blueprint	0.160	0.117	0.053	0.052	0.798	0.259	0.264	0.235	–	–	–	–	–	5	5
	w/o Verify	0.159	0.116	0.053	0.052	0.843	0.297	0.292	0.249	–	–	–	–	–	10	5
	Naive LLM	0.164	0.117	0.053	0.053	0.801	0.259	0.264	0.236	–	–	–	–	–	5	5
Crypto	ModelGen (MOSAIC)	**0.208**	**0.052**	**1.545**	**1.549**	–	–	–	–	**6.226**	**0.012**	**0.013**	0.082	0.098	**65**	**60**
	w/o Mod. Und.	0.220	0.055	1.646	1.639	–	–	–	–	8.345	0.014	0.018	0.076	0.096	20	20
	w/o Blueprint	0.227	0.055	1.646	1.645	–	–	–	–	8.567	0.015	0.020	0.073	**0.092**	10	5
	w/o Verify	0.223	0.055	1.664	1.661	–	–	–	–	8.423	0.014	0.018	0.073	0.093	20	10
	Naive LLM	0.234	0.056	1.648	1.647	–	–	–	–	9.945	0.015	0.021	**0.072**	0.093	5	0

Repository-Grounded Model Generation. Table 2 ablates the model generation module. Removing any single component leads to consistent degradation of up to 30% across metrics, with Naive LLM performing worst. Win rates further confirm this, with the full ModelGen achieving up to 70% across comparisons versus near-zero for ablated variants. Per-LLM breakdowns are in Appendix H.6.

Reinforcement Learning for Refinement. Table 3 ablates the RL module, where Soft Revert contributes most; its removal degrades performance by up to 27% and increases refinement steps by roughly 20%. Removing Trajectory Branching or Invalid Action Masking also hurts, though to a lesser extent. These results confirm that each RL component plays a distinct role in stable refinement. Per-LLM breakdowns are in Appendix H.7.

Table 3: Ablation study of the RL module. All metrics are averaged across four LLM backbones. Subscripts F and G denote forecasting and generation respectively. Best results per dataset are **bolded**. – indicates metric not applicable.

Dataset	Variant	Forecasting				Generation				Financial (Crypto only)					Steps	
		RMSE↓	MAE↓	MAPE↓	sMAPE↓	Marg.↓	Corr.↓	ACorr.↓	Cov.↓	ΔSharpe_F↓	ΔVaR_F↓	ΔES_F↓	ΔVaR_G↓	ΔES_G↓	F↓	G↓
Stock	IQL (MOSAIC)	**8.062**	**4.918**	**2.036**	**2.036**	**0.464**	**0.355**	**0.087**	**0.877**	–	–	–	–	–	**8.65**	**8.70**
	w/o Invalid Action Masking	8.111	4.955	2.059	2.057	0.481	0.371	0.095	0.892	–	–	–	–	–	9.05	9.10
	w/o Soft Revert	8.296	5.094	2.143	2.135	0.560	0.428	0.119	0.984	–	–	–	–	–	10.40	10.55
	w/o Trajectory Branching	8.211	5.028	2.104	2.102	0.519	0.397	0.105	0.943	–	–	–	–	–	9.75	9.70
LOB	IQL (MOSAIC)	**0.149**	**0.113**	**0.051**	**0.051**	**0.674**	**0.257**	**0.250**	**0.209**	–	–	–	–	–	**8.70**	**8.85**
	w/o Invalid Action Masking	0.151	0.114	0.052	0.052	0.709	0.265	0.256	0.216	–	–	–	–	–	9.10	9.25
	w/o Soft Revert	0.160	0.124	0.056	0.056	0.858	0.306	0.314	0.271	–	–	–	–	–	10.45	10.65
	w/o Trajectory Branching	0.155	0.119	0.054	0.054	0.777	0.283	0.286	0.243	–	–	–	–	–	9.75	9.85
Crypto	IQL (MOSAIC)	**0.213**	**0.053**	**1.562**	**1.569**	–	–	–	–	**11.773**	**0.016**	**0.019**	**0.064**	**0.091**	**8.60**	**8.55**
	w/o Invalid Action Masking	0.216	0.054	1.584	1.588	–	–	–	–	12.179	0.017	0.020	0.068	0.097	9.00	9.00
	w/o Soft Revert	0.226	0.057	1.661	1.656	–	–	–	–	13.686	0.018	0.025	0.081	0.119	10.40	10.35
	w/o Trajectory Branching	0.221	0.055	1.623	1.622	–	–	–	–	12.928	0.018	0.023	0.076	0.108	9.75	9.65

4.5 Case Study

We present case studies of **model generation example** and **task generation** in Appendix H.9. In particular, the model generation example illustrates how MOSAIC composes novel architectures: GPT-4o builds a hybrid model for cryptocurrency forecasting (RMSE 0.207 vs. 0.218 for TS-Agent), while Claude Opus 4 assembles a diffusion-based model for LOB generation (Marginal 0.554 vs. 0.767 for Diffusion-TS alone).

5 Conclusion

We introduced MOSAIC, a structured agentic framework for automated data-science modelling that bridges rigid AutoML pipelines and unconstrained LLM-based code generation. Rather than treating model building as direct program synthesis, MOSAIC formulates it as a structured search over admissible modelling workflows by introducing an explicit blueprint layer between task understanding and executable implementation. Experiments on financial time-series tasks show that this approach yields robust, high-performing, and interpretable data-science solutions.

Limitations and Future Work. The MOSAIC framework is currently subject to several limitations. Its performance ceiling depends on the quality of knowledge banks, and it assumes reliable module extraction from heterogeneous repositories, which may not always hold in practice. Stronger guarantees are also needed to characterize the dimensional and functional compatibility of synthesized modules. Future work could address these challenges through adaptive methods that enhance the knowledge base, together with more robust verification procedures.

AI USE STATEMENT

In this work, we used generative AI tools to assist with manuscript writing and presentation, including language refinement, improving clarity and conciseness, and polishing the organization and expression of the text. We did not use generative AI tools to generate research ideas, theoretical results, experimental results, or scientific claims. All AI-assisted content was carefully reviewed, revised, and verified by the authors. We take full responsibility for the final content of this work, including all text, claims, and artifacts produced with the assistance of generative AI.

ETHICS STATEMENT

This work studies automated model selection, code generation, and refinement for financial time-series forecasting and generation using historical market data. The reported experiments do not involve human subjects or the collection of individual-level personal information. MOSAIC relies on retrieved modelling components and LLM-generated code, which may inherit implementation errors, modelling assumptions, or other limitations from the underlying models and knowledge sources. Moreover, although the evaluated tasks include financial forecasting, generation, and risk-related metrics, the resulting models and outputs should be regarded as research artifacts rather than financial advice.

REPRODUCIBILITY STATEMENT

Section 4 and Appendices F–H describe the datasets, preprocessing, experimental setup, model and pipeline configurations, evaluation protocols, and complete experimental results. Appendix G additionally provides implementation details, including hardware, LLM configurations, training hyperparameters, and offline RL settings. All reported metrics are averaged over five independent runs.

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A Task Generation Details

We employ an automated task-generation module to construct diverse, executable time-series forecasting and generation tasks, forming a scalable corpus of tasks that can be converted to trajectory data for offline RL of refinement policies.

Given a high-level instruction specifying task-generation requirements, the pipeline generates tasks with controlled variation in task type, data source, asset universe, temporal range, window construction, data transformation, and evaluation protocol, inducing a heterogeneous task distribution over which the refinement policy can observe diverse modelling choices, failure modes, and refinement strategies. Concrete examples of such instructions are provided in the case study in Appendix H.9.

Let $\mathcal{B}_{\text{data}}$ denote the dataset bank and $\mathcal{B}_{\text{eval}}$ the evaluation-template bank. Given the instruction $\mathcal{I}$, the task generator $\mathcal{G}$ produces

$$\{\mathcal{T}_i\}_{i=1}^{N} = \mathcal{G}(\mathcal{I}; \mathcal{B}_{\text{data}}, \mathcal{B}_{\text{eval}}),$$

where each $\mathcal{T}_i = (\mathcal{W}_i, \mathcal{D}_i, \mathcal{L}_i)$ is a financial time-series task consisting of a dataset $\mathcal{D}_i$, an evaluation protocol $\mathcal{L}_i$, and a structured task description $\mathcal{W}_i$.

A.1 Dataset Bank

The dataset bank $\mathcal{B}_{\text{data}}$ serves as a controlled source of diversity for RL training, and is intentionally constructed to be distinct from the datasets in the main experiments (LOB, Crypto, Stock). In particular, we enforce disjointness at the asset-universe level to eliminate overlap between training tasks and evaluation tasks to prevent information leakage. The bank consists of representative financial time-series panels across equities, foreign exchange, commodities, cryptocurrencies, and interest-rate term structures. Each dataset is associated with metadata describing its asset universe, sampling frequency, date coverage, market context, and admissible transformations. All datasets are preprocessed into aligned multivariate panels with missing observations removed. Table 4 summarises the datasets currently included in $\mathcal{B}_{\text{data}}$.

Table 4: Dataset bank $\mathcal{B}_{\text{data}}$.

Dataset	Frequency	Source	Coverage
60 U.S. large-cap equities	daily	Yahoo Finance	U.S. large-cap equities across energy, healthcare, financials, consumer, technology, communications, and industrial sectors; 2002-05-23 to 2026-04-08
16 Foreign exchange pairs	daily	Yahoo Finance	G10 and emerging-market currency pairs in a largely USD-centered daily panel; 2005-01-03 to 2026-03-30
17 commodity futures series	daily	Yahoo Finance	Precious metals, energy, grains, and soft commodities represented by daily futures series; 2000-11-02 to 2026-03-31
22 Cryptocurrencies	hourly	Yahoo Finance	USD-denominated crypto assets including majors, smart-contract platforms, DeFi and infrastructure tokens, privacy coins, and meme assets, non overlapping with tasks used for evaluation; 2024-04-09 to 2026-04-08
10 U.S. Treasury maturities	daily	FRED	U.S. par-yield maturities covering the short, intermediate, and long ends of the yield curve; 1993-10-01 to 2023-12-29

A.2 Generation Process

The generation process consists of two main steps. First, the module plans multiple structured task specifications from the same instruction. Second, each specification is instantiated into an executable task through dataset construction, evaluation construction, validation, constrained refinement, and final description synthesis. See concrete examples of generated forecasting and generation tasks in Appendix H.9 on Case Study.

B KNOWLEDGE BANK DETAILS

The system maintains three read-only external resources that collectively provide domain knowledge, executable code, and refinement guidance.

Case Bank ($\mathcal{E}_{case}$). The case bank contains curated task-solution pairs spanning both forecasting and generation. Each entry records a task description, dataset characteristics, the recommended model, and a summary of the solution methodology. Cases are drawn from financial benchmarks, competition entries, and peer-reviewed studies on financial time-series analysis (Ang et al., 2026; Ni et al., 2021; Lou et al., 2023; Ni et al., 2023; 2024). The case bank covers diverse asset classes including equities, cryptocurrencies, foreign exchange, and commodities, with tasks ranging from multi-step price forecasting to regime-switching generation and conditional market simulation. In addition, successful trajectories collected during offline RL training are summarized by the LLM and appended to the case bank, enriching it with empirically validated solutions.

Code Base ($\mathcal{E}_{code}$). The code base consists of a model bank and an evaluation measure bank, both implemented as standalone Python modules.

The *model bank* includes five forecasting models spanning major architectural paradigms: Autoformer (Wu et al., 2021) and PatchTST (Nie et al., 2023) (Transformer-based), TimesNet (Wu et al., 2023) (temporal CNN), DLinear (Zeng et al., 2023) (linear), and TimeMixer (Wang et al., 2024b) (token-mixing). For generation, it includes ten models: TimeGAN (Yoon et al., 2019), RCGAN (Esteban et al., 2017), PCFGAN (Lou et al., 2023), QuantGAN (Wiese et al., 2020), COSCIGAN (Seyfi et al., 2022) (GAN-based), TimeVAE (Desai et al., 2021) (VAE-based), DiffusionTS (Yuan & Qiao, 2024) (diffusion-based), FourierFlow (Wang et al., 2025) (flow-based), and LS4 (Zhou et al., 2023), FIDE (Galib et al., 2024) .

The *evaluation measure bank* (Ang et al., 2025) provides standardised metric implementations for both tasks. For forecasting: RMSE, MAE, MAPE, sMAPE, and downstream financial metrics including Sharpe Ratio, Value at Risk (VaR), and Expected Shortfall (ES). For generation: Marginal Distribution, Correlation, Autocorrelation, and Covariance scores, along with VaR and ES for tail-risk evaluation.

Refinement Knowledge Bank ($\mathcal{E}_{refine}$). The refinement knowledge bank encodes domain-specific best practices organized into three categories:

Data preparation: standardization, outlier handling (winsorising, clipping), and temporal data augmentation where domain-appropriate.

Training optimisation: early stopping based on validation metrics, learning rate scheduling (e.g., ReduceLROnPlateau), mini-batch strategies that preserve temporal ordering, and regularization via weight decay and dropout.

Tuning and evaluation: systematic hyperparameter search over learning rate, batch size, and regularization coefficients; walk-forward validation for temporal generalisation; and overfitting diagnostics comparing training and validation trajectories.

Each entry provides actionable guidance that the refinement stage can directly apply as code modifications without altering the model architecture.

C SEMANTIC-AWARE EDA WITH MULTIMODAL SUPPORT

EDA & Feature Engineering. To bridge the gap between raw numerical data and LLM reasoning, the MOSAIC pipeline begins with a semantic-aware EDA module that maps continuous statistical properties into discrete, text-based semantic anchors. Rather than merely computing basic statistics, the module extracts high-level meta-features, such as data scale, task type, volatility, feature interdependence via correlation, and Augmented Dickey-Fuller test results (Said & Dickey, 1984). Alongside the data schema and target variable statistics, these structured tags embed essential statistical priors directly into the prompt context.

Multimodal Support by VLM. Beyond textual summaries, complex temporal dynamics, such as regime shifts, heavy-tailed distributions, and cross-variable dependencies, are more naturally captured visually. To accommodate this, the EDA module generates standardised analytical plots (e.g., temporal

line charts, correlation heatmaps) for subsequent analysis by a VLM. The resulting visual report and textual EDA summary are concatenated with the task description to form an enriched, multimodal query. This unified query guides the case-based reasoning retrieval stage, helping to mitigate the semantic mismatch that arises when raw numerical data are matched against textual knowledge sources. Furthermore, injecting this context into the LLM prompt grounds model selection in explicit semantic and visual evidence. By leveraging these structured data priors, the system reduces the impact of pre-training bias to infer suitable architectural traits, prioritising models that intrinsically fit the target data distribution over generic baselines.

D Repository-Grounded Model Generation

Beyond selecting from a fixed model bank, the model generation module balances retrieval and innovation: it identifies relevant existing models while using LLMs to recombine their components into new executable architectures, thereby expanding the search space and potential performance ceiling.

Architecture Family Analysis. Based on the top-k retrieved models, the system classifies candidates into architectural families (e.g., decomposition-based methods, MLP, and Transformers). If models share the same architectural family, extracted modules (e.g., encoder blocks, embeddings) can be directly reused. Otherwise, the top-ranked model provides the backbone, and modules from other models inform high-level design principles for blueprint construction.

Module Identification and Extraction. For these candidates, the system performs static analysis of source code via abstract syntax tree parsing to identify reusable neural network modules. For each identified module, it extracts the source definition, forward pass signature, import dependencies, key operators (e.g., attention, convolution, decomposition).

Each extracted module is then enriched with deterministic shape analysis, deriving expected input and output tensor dimensions from the source code, and with semantic annotations from an LLM capturing its functional role, design assumptions, and operational characteristics. Together, these form unified module representations that support downstream composition.

Blueprint Construction. Given the module representations and the composition strategy determined above, the system constructs a structured blueprint by jointly considering the task profile, upstream data analysis results, and retrieved prior cases. The blueprint specifies which modules to use, their composition order, and the dimensional constraints for inter-module compatibility, elevating model descriptions into executable composition plans and separating architectural reasoning from code synthesis.

Code Generation. Given the blueprint, an LLM generates executable model code. To promote diversity, each generation call is conditioned on a distinct structural variant within the blueprint's architectural framework, such as alternative gating mechanisms or different residual connection patterns, producing multiple candidate implementations from the same composition plan.

Execution, Verification, and Refinement. Each generated candidate undergoes execution based validation. The system dynamically loads the generated code, instantiates the model with appropriate task dimensions, and performs a forward pass to verify output shape consistency and numerical stability. When verification fails, the system classifies the error type, constructs a targeted revision prompt incorporating the failing code and full diagnostic trace, and resubmits to the LLM for correction. This cycle repeats for a bounded number of iterations, yielding verified, executable model implementations ready for downstream training and evaluation.

E Trajectory Branching Mechanism Details

MOSAIC uses a trajectory branching mechanism to preserve both successful refinements and failed edits as useful supervision for offline RL. As shown in Figure 7, all branches share the prefix trajectory up to the last valid checkpoint $s_\star$. At $s_\star$, the state-specific invalid-action mask $\mathcal{I}_{\text{invalid}}(s_\star)$ already contains structurally infeasible or redundant actions before failure-induced updates, such as incompatible hyperparameter edits or no-op edits that set a hyperparameter to its current value. If an action causes a hard failure, such as an execution error, timeout, or NaN, MOSAIC records an immediate terminal failure branch with a penalty. If an action causes a soft failure, where the code

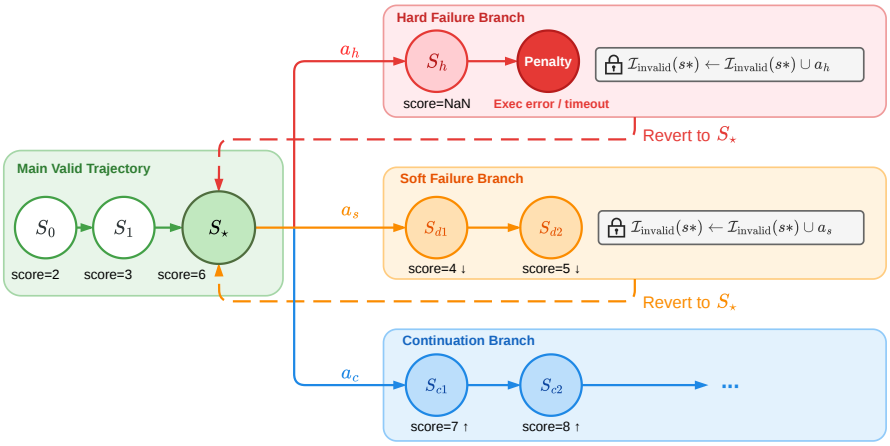

Figure 7: Diagram of failure-aware trajectory branching and invalid-action masking

remains executable but the validation score degrades across multiple consecutive steps, MOSAIC records the degraded trajectory as a soft-failure branch. In both cases, the failed action is added to the invalid-action mask $\mathcal{I}_{\text{invalid}}(s_\star)$, and the main rollout reverts to $s_\star$ before continuing along a valid branch. This converts failed refinements into negative training signals while preventing the policy from repeatedly selecting invalid actions.

F Dataset Details

Table 5: Dataset configurations for forecasting (left) and generation (right).

Dataset	Freq.	Dim.	Forecasting				Generation	
			Seq. / Label / Pred.	Stride (Tr./Te.)	Eval. Targets	Split	Window	Split
Crypto	1 h	20	72 / 24 / 3	12 / 3	All 20	70/15/15	60	70/15/15
LOB	10 s	14	72 / 24 / 3	12 / 3	5 (OHLCV)	70/15/15	60	70/15/15
Stock	1 B	10	60 / 20 / 3	1 / 3	All 10	70/15/15	60	70/15/15

We evaluate on three financial datasets spanning different asset classes, frequencies, and data regimes. All datasets are split chronologically (70%/15%/15%) to prevent look-ahead bias. Channel-wise z-score normalization is fitted on the training split and applied to all splits. Tables 5 summarizes task-specific configurations.

- **Crypto.** Hourly closing prices for 20 cryptocurrency trading pairs against USDT, covering a one-year period in 2024 (8,784 time steps, 20 channels).
- **LOB.** Limit order book data for a NASDAQ-listed equity, sourced from the LOBSTER platform. Raw event-level data is aggregated into 10-second bars with 14 microstructure features (OHLCV, buy/sell volume, trade counts, order flow statistics, and derived indicators). This dataset represents a challenging low-data regime common in proprietary financial settings. For forecasting, 5 price-related targets (open, high, low, close, VWAP) are evaluated; for generation, all 14 features are modeled.
- **Stock.** Daily closing prices for 10 major U.S. equities from 2020 to 2024 (1,257 business days, 10 channels). All channels serve as targets for both tasks.

Rolling windows are constructed with task-specific parameters. Training uses a denser stride to maximize sample utilization, while validation and test use non-overlapping strides to ensure independent evaluation.

G Implementation Details

Hardware. All experiments were conducted on a server equipped with one NVIDIA H200 GPU, an AMD EPYC 9355 32-Core Processor CPU, and 128 GB of RAM.

Table 6: Computational cost of a single MOSAIC run on the Stock forecasting task with GPT-5.4. API cost is estimated at $2.50 and $15 per million input and output tokens. – indicates not applicable.

Stage	Wall-clock (s)	GPU time (s)	LLM calls	Input tokens	Output tokens	API cost (USD)	Execution success
Profiling & Retrieval	9	–	1	710	355	0.01	–
Model Generation	1,109	–	21	184,410	50,714	1.22	–
Warm-up Phase	221	515	36	112,640	23,296	0.63	18/18
Optimization Phase	1,237	58	12	37,014	7,472	0.20	6/6
MOSAIC (total)	**2,576**	**573**	**70**	**334,774**	**81,837**	**2.06**	**24/24 (100%)**

LLM Configuration. The system uses four LLM clients with separate roles: a reasoning LLM for case retrieval, model selection, and EDA interpretation; a code-editing LLM for refinement and fine-tuning modifications; a code-generation LLM for blueprint-based model synthesis; and a VLM for multimodal analysis of EDA plots and training curves. By default, all four use GPT-4o with temperature 0.7 and a maximum output budget of 8,192 tokens. When evaluating with alternative backbones (GPT-5.4, Claude Opus 4, Nova Pro), all four clients are switched to the corresponding model simultaneously. Case retrieval embeddings are computed using all-MiniLM-L6-v2.

Pipeline Configuration. The system retrieves k=3 candidate models via case-based reasoning, with 3 retrieved cases informing model selection. Model generation module produces up to 3 candidate implementations per blueprint, with a maximum of 2 revision rounds for execution-based verification. The RL refinement stage uses 6 warm-up steps and 6 optimisation steps, with a debug retry limit of 3 and an execution timeout of 18,000 seconds per run.

Training and Model Hyperparameters. Training hyperparameters are initialized with shared defaults: learning rate 10^{-4}, batch size 128, maximum 300 epochs with early stopping (patience 20). Model-specific architectural parameters (e.g., d_{model}, number of layers, attention heads) are initialized from default configurations provided with each model in the model bank. Both training and architectural hyperparameters are iteratively adjusted by the LLM during the refinement stage based on execution feedback and validation metrics.

Reinforcement Learning Training Details. We train two separate offline IQL agents, one for each task type. For time series forecasting, the agent is trained on 4,456 real refinement transitions collected from 653 episodes across 83 tasks, with a discrete action space of 39 actions (17 structural refinement operations and 22 hyperparameter-tuning bins across 4 slots: learning rate, dropout, layers, batch size). For time series generation, the agent is trained on 2,288 transitions from 509 episodes across 75 tasks, with a discrete action space of 49 actions (17 structural operations and 32 hyperparameter-tuning bins across 6 slots: learning rate, dropout, layers, batch size, hidden dim, and latent dim). Both agents share the same architecture and training configuration: states are encoded as 65-dimensional feature vectors summarizing training dynamics, refinement history, hyperparameter bins, and task context, processed by a shared MLP encoder followed by separate Q-, V-, and policy heads. All networks are optimised with Adam (lr $= 3 \times 10^{-4}$), with weight decay 10^{-4} applied to the Q- and V-networks. The IQL hyperparameters are set as follows: expectile level 0.7, AWR temperature 3.0, discount factor 0.95, EMA target update rate 0.005, maximum advantage weight 20, and gradient clipping threshold 1.0. Rewards are normalised before training, and each agent is trained for 30,000 gradient steps with batch size 256.

Computational Cost. Table 6 breaks down the cost of a single end-to-end MOSAIC run on the Stock forecasting task with GPT-5.4 as the backbone. A full run takes 2,576 s of wall-clock time (about 43 minutes) and 573 s of GPU time, and makes 70 LLM calls for an estimated API cost of $2.06. Model generation and the optimization phase account for most of the wall-clock time (43% and 48%), while 90% of the GPU time is spent in the warm-up phase, where all candidates are trained and evaluated. Model generation also accounts for the largest share of the API cost (59%), as it processes the most tokens. All 24 executions (18 in warm-up and 6 in optimization) completed successfully.

H Full Experimental Results

H.1 System-Level Forecasting Results

Tables 7 and 8 report the full per-LLM forecasting results. MOSAIC achieves the best or near-best performance across all four LLM backbones on every dataset. The improvement is most pronounced on LOB with Claude, where RMSE drops to 0.116, a 19% reduction over TS-Agent (0.143) and 46% over AutoGluon (0.215). Averaged across backbones, LOB RMSE is reduced by 8%, Crypto

Table 7: System-level forecasting performance on three datasets. Each metric is averaged over five runs. Best result per LLM per dataset is **bolded**.

Dataset	Model	RMSE ↓				MAE ↓				MAPE (%) ↓				sMAPE (%) ↓				Success (%) ↑			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
Crypto	MOSAIC	**0.207**	**0.202**	**0.217**	**0.214**	**0.051**	**0.051**	**0.054**	**0.052**	**1.543**	**1.531**	**1.583**	**1.535**	**1.547**	**1.534**	**1.591**	**1.540**	**100**	**100**	**100**	**100**
	TS-Agent	0.224	0.220	0.218	0.219	0.056	0.055	**0.054**	0.055	1.647	1.626	1.620	1.621	1.647	1.629	1.616	1.623	**100**	**100**	**100**	**100**
	DS-Agent	0.230	0.223	0.258	0.232	0.061	0.059	0.075	0.072	1.965	1.945	2.519	2.215	1.957	2.050	2.485	2.215	60	60	60	60
	ResearchAgent	0.239	0.232	0.301	0.222	0.063	0.064	0.081	0.061	1.895	1.911	2.480	2.083	1.903	1.856	2.518	2.082	60	60	60	60
	AutoGluon	0.223				0.055				1.661				1.668				**100**			
LOB	MOSAIC	**0.149**	**0.150**	**0.116**	**0.161**	**0.112**	**0.112**	**0.083**	**0.122**	**0.051**	**0.050**	**0.037**	**0.055**	**0.051**	**0.050**	**0.037**	**0.055**	**100**	**100**	**100**	**100**
	TS-Agent	0.154	0.158	0.143	0.174	0.116	0.115	0.101	0.130	0.053	0.052	0.045	0.058	0.053	0.052	0.045	0.058	**100**	**100**	**100**	**100**
	DS-Agent	0.171	0.184	0.196	0.183	0.121	0.127	0.140	0.126	0.055	0.064	0.063	0.059	0.054	0.055	0.063	0.059	**100**	**100**	60	60
	ResearchAgent	0.205	0.204	0.203	0.192	0.147	0.145	0.145	0.142	0.066	0.068	0.065	0.061	0.066	0.068	0.065	0.061	40	80	80	60
	AutoGluon	0.215				0.123				0.066				0.066				**100**			
Stock	MOSAIC	**7.847**	**7.815**	**7.904**	**8.064**	**4.804**	**4.804**	**4.843**	**4.963**	**1.982**	**1.981**	**2.005**	**2.075**	1.991	1.982	1.956	2.086	**100**	**100**	**100**	**100**
	TS-Agent	8.017	8.079	7.982	8.590	4.912	4.964	4.905	5.047	2.046	2.060	2.076	2.123	**1.770**	2.062	**1.765**	**1.850**	**100**	**100**	**100**	**100**
	DS-Agent	8.557	8.445	8.559	8.732	5.193	5.169	5.150	5.207	2.137	2.288	2.177	2.244	1.969	1.986	2.055	2.099	80	80	**100**	60
	ResearchAgent	9.410	9.321	9.570	9.791	5.677	5.588	5.738	5.910	2.498	2.624	2.420	2.590	2.053	2.623	2.238	2.331	80	80	80	80
	AutoGluon	8.430				5.258				2.174				**1.890**				**100**			

Table 8: Forecasting financial metrics on the Crypto dataset. Each metric is averaged over five runs. Best per LLM per dataset is **bolded**.

Dataset	Model	ΔSharpe ↓				ΔVaR ↓				ΔES ↓			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
Crypto	MOSAIC	**6.654**	**4.329**	**10.687**	**10.211**	0.012	**0.012**	0.015	0.014	**0.014**	0.015	0.016	**0.016**
	TS-Agent	12.431	4.530	11.297	12.416	0.015	0.015	0.017	0.015	0.019	0.022	0.024	0.023
	DS-Agent	30.572	29.352	39.897	30.868	**0.010**	0.014	**0.013**	0.015	**0.014**	**0.014**	**0.013**	0.017
	ResearchAgent	12.850	13.236	11.942	21.249	**0.010**	0.014	0.014	**0.013**	0.015	0.015	0.019	0.017
	AutoGluon	22.639				0.022				0.031			

by 5%, and Stock by 3%. For risk-aware metrics on Crypto, MOSAIC with GPT-4o achieves a ΔSharpe of 6.65, a 46% reduction over TS-Agent (12.43); with GPT-5.4, ΔSharpe reaches 4.33, the lowest overall. DS-Agent and ResearchAgent exhibit ΔSharpe exceeding 10 across most backbones. MOSAIC maintains a 100% success rate across all configurations, whereas DS-Agent drops to 60% on multiple datasets. These improvements are attributable to the model generation module's ability to synthesize task-adapted architectures, the EDA module's grounding of model selection in data characteristics, and the RL policy's non-myopic refinement decisions.

Table 9: System-level generation performance on LOB and Stock. Each metric is averaged over five runs. Best result per LLM per dataset is **bolded**.

Dataset	Model	Marginal ↓				Correlation ↓				AutoCorrelation ↓				Covariance ↓				Success (%) ↑			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
LOB	MOSAIC	**0.590**	**0.579**	**0.554**	0.626	**0.216**	**0.182**	0.225	0.239	**0.199**	**0.247**	**0.193**	**0.228**	**0.181**	**0.177**	0.188	**0.192**	**100**	**100**	**100**	**100**
	TS-Agent	0.713	1.180	0.767	0.822	0.243	0.472	0.235	**0.233**	0.234	0.477	0.215	0.254	0.234	0.332	0.234	0.221	**100**	**100**	**100**	**100**
	DS-Agent	1.167	1.187	1.242	1.200	0.308	0.646	0.352	0.305	0.317	0.492	0.273	0.271	0.328	0.333	0.321	0.326	40	60	**100**	20
	ResearchAgent	0.619	0.802	0.814	**0.617**	0.241	0.632	**0.138**	0.243	0.240	0.611	0.244	0.243	0.239	0.340	**0.136**	0.341	80	80	**100**	20
	Optuna	0.824				0.711				0.527				0.210				**100**			
Stock	MOSAIC	**0.408**	**0.371**	**0.383**	**0.385**	**0.357**	**0.343**	0.345	**0.378**	**0.091**	0.087	**0.081**	**0.081**	**0.881**	**0.902**	**0.880**	**0.903**	**100**	**100**	**100**	**100**
	TS-Agent	0.455	0.681	0.421	0.473	0.397	0.437	0.361	0.401	0.129	**0.075**	0.193	0.859	0.910	0.939	0.909	0.930	**100**	**100**	**100**	**100**
	DS-Agent	1.371	0.774	0.427	0.482	0.397	0.594	0.472	0.422	0.208	0.442	0.106	0.568	0.944	0.942	0.913	0.912	**100**	**100**	**100**	20
	ResearchAgent	0.481	0.464	0.463	0.461	0.394	0.402	**0.305**	0.404	0.093	0.805	0.263	0.664	0.916	0.917	0.915	0.926	**100**	**100**	**100**	60
	Optuna	0.422				0.528				0.865				0.920				**100**			

Table 10: Generation financial metrics and success rate on the Crypto dataset. Each metric is averaged over five runs. Best per LLM per dataset is **bolded**.

Dataset	Model	ΔVaR ↓				ΔES ↓				Success (%) ↑			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
Crypto	MOSAIC	0.072	0.073	**0.075**	**0.078**	**0.087**	0.096	**0.104**	**0.095**	**100**	**100**	**100**	**100**
	TS-Agent	**0.068**	**0.044**	0.084	0.091	0.103	**0.054**	0.111	0.104	**100**	**100**	**100**	**100**
	DS-Agent	0.103	0.096	0.119	0.096	0.148	0.147	0.152	0.130	80	80	**100**	40
	ResearchAgent	0.093	0.094	0.099	0.103	0.105	0.105	0.134	0.105	80	80	**100**	40
	Optuna	0.091				0.126				**100**			

H.2 System-Level Generation Results

Tables 9 and 10 present the full generation results. MOSAIC achieves the lowest Marginal and Correlation distances on both LOB and Stock across most backbones. On LOB with GPT-5.4, Marginal distance drops to 0.579 compared to 1.180 for TS-Agent and 1.187 for DS-Agent, a reduction exceeding 50%. Averaged across backbones, LOB Marginal is reduced by 32% and Correlation by 27% relative to TS-Agent. On Stock, MOSAIC with GPT-5.4 achieves the lowest Marginal (0.371) and Correlation (0.343) distances, with average Marginal reduced by 24%. For Crypto tail-risk metrics, MOSAIC achieves competitive ΔVaR and the lowest ΔES on three of four backbones, though TS-Agent obtains lower ΔVaR with GPT-4o (0.068 vs. 0.072) and GPT-5.4 (0.044 vs. 0.073). Throughout, MOSAIC maintains a 100% success rate, while DS-Agent and

Table 11: Model generation module comparison: forecasting metrics. Each metric is averaged over five runs. Best per LLM per dataset is **bolded**.

Dataset	Model	RMSE ↓				MAE ↓				MAPE (%) ↓				sMAPE (%) ↓				Win (%) ↑			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
Crypto	ModelGen (MOSAIC)	**0.205**	**0.202**	0.219	**0.205**	**0.051**	**0.051**	0.055	**0.051**	**1.530**	**1.514**	**1.615**	**1.523**	**1.531**	**1.519**	1.621	**1.525**	**60**	**80**	**60**	**60**
	AlphaEvolve	0.218	0.218	0.215	0.218	0.055	0.055	**0.054**	0.054	1.627	1.610	1.619	1.609	1.629	1.611	1.621	1.610	**60**	60	40	40
	AIDE	0.218	0.217	0.218	0.218	0.055	0.054	**0.054**	0.055	1.611	1.614	**1.615**	1.621	1.611	1.612	**1.615**	1.623	40	60	40	20
	EffiLearner	0.218	0.218	**0.213**	0.217	0.054	0.054	**0.054**	0.055	1.617	1.616	1.625	1.614	1.617	1.616	1.625	1.614	40	60	40	20
	LLM4EFFI	0.217	0.218	0.219	0.217	0.054	0.055	0.055	0.055	1.619	1.620	1.621	1.613	1.620	1.620	1.620	1.615	40	60	40	40
LOB	ModelGen (MOSAIC)	**0.153**	**0.155**	**0.095**	**0.160**	**0.115**	**0.115**	**0.067**	0.119	**0.052**	**0.051**	**0.030**	0.054	**0.052**	**0.052**	**0.030**	0.054	**60**	**60**	**60**	**60**
	AlphaEvolve	0.158	0.162	0.167	0.164	0.116	0.120	0.119	0.121	**0.052**	0.054	0.054	0.053	**0.052**	0.054	0.054	0.053	**60**	40	**60**	40
	AIDE	0.171	0.162	0.211	0.166	0.122	0.120	0.153	0.121	0.055	0.054	0.069	0.060	0.055	0.054	0.069	0.060	40	40	40	40
	EffiLearner	0.190	0.158	0.200	0.162	0.136	0.117	0.145	**0.115**	0.061	0.053	0.065	**0.052**	0.061	0.053	0.065	**0.052**	20	**60**	**60**	20
	LLM4EFFI	0.168	0.157	0.197	0.162	0.121	0.116	0.146	0.120	0.054	0.052	0.066	0.054	0.054	0.053	0.065	0.054	40	40	**60**	20
Stock	ModelGen (MOSAIC)	**7.805**	**7.769**	**7.867**	**7.924**	**4.774**	**4.790**	**4.840**	**4.910**	**1.967**	**1.977**	**2.017**	**2.045**	**1.977**	**1.979**	**1.939**	2.064	**80**	**80**	**60**	**60**
	AlphaEvolve	8.554	8.254	8.225	8.194	5.273	5.072	5.074	5.047	2.156	2.098	2.091	2.091	2.168	2.108	2.101	2.096	40	40	40	40
	AIDE	7.920	7.929	8.035	8.190	4.865	4.885	4.982	5.020	2.018	2.009	2.038	2.073	2.022	2.020	2.053	2.083	40	40	40	20
	EffiLearner	8.092	8.076	7.936	8.208	4.986	4.989	4.858	5.043	2.064	2.043	2.018	2.079	2.069	2.057	2.015	2.088	40	60	40	20
	LLM4EFFI	7.864	7.876	8.058	8.012	4.818	4.825	4.973	4.936	2.000	1.990	2.053	2.050	2.004	1.999	2.060	**2.057**	60	60	**60**	**60**

Table 12: Model generation comparison: Crypto financial metrics (forecasting). Each metric is averaged over five runs. Best per LLM per dataset is **bolded**.

Dataset	Model	ΔSharpe ↓				ΔVaR ↓				ΔES ↓			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
Crypto	ModelGen (MOSAIC)	**2.074**	**2.431**	10.924	9.477	**0.010**	**0.011**	**0.014**	**0.012**	**0.011**	**0.013**	**0.014**	**0.014**
	AlphaEvolve	6.949	7.370	27.326	7.219	0.014	0.014	0.020	0.016	0.020	0.020	0.028	0.024
	AIDE	5.898	5.890	**4.009**	18.636	0.015	0.017	0.017	0.016	0.022	0.025	0.025	0.024
	EffiLearner	9.715	6.947	24.718	**2.571**	0.016	0.016	0.020	0.016	0.024	0.024	0.028	0.023
	LLM4EFFI	8.211	3.552	8.842	5.962	0.015	0.016	0.017	0.016	0.023	0.024	0.024	0.023

ResearchAgent drop as low as 20% on LOB and Stock with weaker backbones. The consistent advantage across distributional metrics reflects the model generation module's capacity to compose generative architectures tailored to each dataset's statistical properties.

Table 13: Model generation comparison: generation metrics. Each metric is averaged over five runs. Best per LLM per dataset is **bolded**.

Dataset	Model	Marginal ↓				Correlation ↓				AutoCorrelation ↓				Covariance ↓				Win(%) ↑			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
LOB	ModelGen (MOSAIC)	**0.556**	**0.536**	**0.513**	**0.582**	**0.195**	**0.168**	**0.214**	**0.206**	**0.194**	0.212	**0.191**	**0.233**	**0.169**	**0.162**	**0.187**	**0.186**	**60**	**80**	**60**	**60**
	AlphaEvolve	1.142	0.668	0.785	0.734	0.375	0.256	0.265	0.252	0.579	0.175	0.201	0.497	0.298	0.229	0.228	0.229	40	40	**60**	40
	AIDE	1.534	0.709	0.725	0.588	1.059	0.188	0.237	0.209	0.614	0.099	0.250	0.253	0.336	0.179	0.197	0.195	20	40	40	40
	EffiLearner	0.570	0.680	1.504	1.380	0.220	0.185	0.286	0.371	0.215	0.102	0.198	0.442	0.198	0.171	0.335	0.329	20	60	**60**	40
	LLM4EFFI	0.728	0.646	1.558	1.403	0.216	0.185	0.286	0.369	0.197	**0.083**	0.195	0.362	0.195	0.174	0.333	0.328	40	60	**60**	20
Stock	ModelGen (MOSAIC)	0.362	**0.326**	**0.382**	**0.350**	**0.364**	**0.339**	**0.360**	**0.374**	**0.090**	**0.091**	**0.078**	**0.073**	0.894	0.893	**0.911**	0.923	**60**	**80**	**60**	**60**
	AlphaEvolve	**0.354**	0.356	0.406	0.411	0.413	0.382	0.361	0.446	0.093	0.094	0.079	0.822	**0.870**	**0.873**	0.918	0.875	40	40	40	40
	AIDE	0.380	0.363	0.646	0.421	0.482	0.401	0.514	0.444	0.093	0.094	0.097	0.876	0.901	0.894	0.939	0.883	20	40	40	20
	EffiLearner	0.364	0.356	0.411	0.652	0.402	0.382	0.381	0.573	0.094	0.094	0.273	0.081	0.894	**0.873**	**0.911**	0.886	40	60	40	20
	LLM4EFFI	0.362	0.452	0.444	0.826	0.393	0.370	0.526	0.655	0.094	0.237	0.092	0.080	0.894	0.929	0.916	**0.328**	40	40	40	40

Table 14: Model generation comparison: Crypto financial metrics (generation). Each metric is averaged over five runs. Best per LLM per dataset is **bolded**.

Dataset	Model	ΔVaR ↓				ΔES ↓				Win (%) ↑			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
Crypto	ModelGen (MOSAIC)	**0.081**	**0.082**	**0.081**	**0.082**	**0.082**	**0.103**	**0.105**	**0.102**	**60**	**60**	**60**	**60**
	AlphaEvolve	0.111	0.110	0.089	0.213	0.125	0.125	0.110	0.213	40	40	40	20
	AIDE	0.233	0.108	0.112	0.105	0.235	0.117	0.125	0.131	40	**60**	40	20
	EffiLearner	0.112	0.109	0.120	0.114	0.115	0.117	0.122	0.152	40	**60**	40	20
	LLM4EFFI	0.106	0.110	0.086	0.159	0.109	0.123	0.109	0.178	40	**60**	40	20

H.3 Model Generation Module Comparison

Tables 11–14 present the full per-LLM code generation module comparison. On forecasting, MOSAIC's model generation module (ModelGen) achieves the lowest RMSE on LOB with Claude (0.095), outperforming the next best alternative by over 39%. On Crypto, it achieves the lowest Sharpe Ratio Difference (2.07 with GPT-4o) while all competitors exceed 3.5. On generation, ModelGen leads on LOB across all four metrics and all backbones, with Marginal distances 20–55% lower than alternatives. Win Rate further confirms these advantages: ModelGen achieves 60–80% Win Rate across datasets and backbones, while alternatives rarely exceed 40%. The structured blueprint with shape contracts enables principled module recombination that outperforms unconstrained evolutionary, tree-based, and feedback-driven search strategies.

Table 15: RL module comparison: forecasting metrics. Each metric is averaged over five runs. Best per LLM per dataset is **bolded**.

Dataset	Model	RMSE ↓				MAE ↓				MAPE ↓				sMAPE ↓				Steps to Best Incumbent ↓			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
Crypto	IQL (MOSAIC)	**0.209**	**0.203**	**0.214**	0.227	**0.053**	**0.053**	**0.052**	**0.053**	**1.563**	**1.596**	**1.536**	**1.552**	**1.571**	1.596	**1.545**	**1.563**	**8.8**	8.4	8.6	**8.6**
	BC	0.220	0.215	0.235	0.236	0.060	0.054	0.056	0.056	1.629	1.611	1.685	1.612	1.638	1.612	1.677	1.627	**8.8**	**7.8**	9.6	9.4
	DQN	0.216	0.215	0.218	0.233	0.056	**0.053**	0.055	0.055	1.610	1.599	1.582	1.591	1.622	**1.586**	1.597	1.606	9.0	9.0	**8.4**	9.0
	LLM	0.221	0.215	0.219	**0.220**	0.058	0.054	0.054	0.057	1.687	1.609	1.630	1.630	1.671	1.609	1.628	1.624	10.0	9.6	9.8	9.4
LOB	IQL (MOSAIC)	**0.144**	**0.143**	0.147	**0.162**	**0.108**	**0.108**	**0.107**	**0.127**	**0.050**	**0.049**	**0.048**	0.058	**0.050**	**0.049**	**0.048**	0.058	**8.8**	**8.6**	**8.4**	**9.0**
	BC	0.159	0.155	**0.146**	0.176	0.111	0.109	0.109	0.140	0.057	**0.049**	0.051	0.058	0.057	**0.049**	0.051	0.058	9.6	9.8	9.2	10.2
	DQN	0.160	0.151	0.148	0.172	0.113	0.110	0.108	0.135	0.056	**0.049**	0.050	**0.057**	0.056	**0.049**	0.050	**0.057**	9.4	9.4	9.0	9.8
	LLM	0.154	0.145	0.150	0.173	0.117	0.110	0.109	0.145	0.054	**0.049**	0.053	0.060	0.054	**0.049**	0.053	0.060	10.0	10.6	9.6	10.4
Stock	IQL (MOSAIC)	**8.013**	**8.001**	**7.958**	**8.275**	**4.922**	**4.859**	**4.847**	**5.042**	**2.042**	**1.997**	**1.986**	**2.120**	**2.049**	**1.995**	**1.982**	2.118	**8.8**	**8.4**	**8.2**	**9.2**
	BC	8.139	8.136	8.072	8.389	5.085	5.052	4.944	5.107	2.094	2.079	2.040	2.260	2.116	2.093	2.053	2.273	9.6	9.6	9.4	10.0
	DQN	8.104	8.067	8.114	8.467	5.019	5.001	4.981	5.165	2.069	2.078	2.062	2.205	2.080	2.086	2.097	2.187	9.4	10.2	9.6	9.8
	LLM	8.142	8.173	8.095	8.446	5.079	5.082	4.957	5.132	2.083	2.091	2.058	2.241	2.104	2.111	2.071	**2.113**	9.6	9.8	10.0	10.6

Table 16: RL module comparison: Crypto financial metrics (forecasting). Each metric is averaged over five runs. Best per LLM per dataset is **bolded**.

Dataset	Model	ΔSharpe ↓				ΔVaR ↓				ΔES ↓			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
Crypto	IQL (MOSAIC)	13.524	**11.924**	**10.331**	**11.313**	**0.015**	0.018	0.017	0.016	**0.019**	**0.020**	**0.019**	**0.019**
	BC	15.935	16.437	12.683	15.678	0.016	0.017	0.017	0.017	0.024	0.025	0.026	0.025
	DQN	**12.488**	12.797	13.992	17.989	0.017	0.018	**0.016**	0.016	0.023	0.025	0.024	0.024
	LLM	14.948	13.934	11.846	12.482	0.017	**0.016**	0.017	**0.015**	0.022	0.024	0.027	0.025

Table 17: RL module comparison: generation metrics. Each metric is averaged over five runs. Best per LLM per dataset is **bolded**.

Dataset	Model	Marginal ↓				Correlation ↓				AutoCorrelation ↓				Covariance ↓				Steps to Best Incumbent ↓			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
LOB	IQL (MOSAIC)	**0.645**	**0.754**	**0.621**	**0.692**	**0.248**	**0.238**	**0.241**	0.285	**0.206**	0.384	**0.195**	**0.216**	**0.201**	**0.231**	**0.192**	**0.204**	**8.8**	**9.0**	8.6	**9.0**
	BC	0.757	0.902	0.736	0.814	0.298	0.280	0.291	0.286	0.248	0.470	0.240	0.260	0.236	0.336	0.230	0.242	9.8	10.2	**8.4**	10.0
	DQN	0.719	0.957	0.708	0.774	0.282	0.295	0.322	**0.272**	0.282	0.450	0.226	0.247	0.267	0.325	0.217	0.228	9.4	9.8	9.2	9.6
	LLM	0.798	0.868	0.781	0.847	0.256	0.294	0.303	0.280	0.261	**0.274**	0.251	0.264	0.249	0.267	0.247	0.248	10.2	10.4	10.0	10.6
Stock	IQL (MOSAIC)	0.480	**0.553**	**0.388**	**0.440**	**0.349**	**0.365**	**0.326**	0.386	**0.088**	**0.070**	**0.082**	**0.092**	**0.864**	0.944	**0.838**	**0.868**	**8.8**	**8.6**	**8.4**	**9.0**
	BC	0.492	0.646	0.455	0.560	0.437	0.420	0.381	0.398	0.114	0.104	0.104	0.138	0.918	0.915	0.902	0.957	9.8	9.6	9.4	10.0
	DQN	**0.473**	0.626	0.487	0.499	0.390	0.400	0.373	**0.374**	0.111	0.088	0.098	0.127	0.905	**0.899**	0.884	0.930	9.4	9.2	9.0	9.6
	LLM	0.512	0.596	0.472	0.548	0.429	0.441	0.373	0.411	0.123	0.100	0.112	0.984	0.960	0.950	0.934	0.984	10.4	10.0	9.8	10.4

Table 18: RL module comparison: Crypto financial metrics (generation). Each metric is averaged over five runs. Best per LLM per dataset is **bolded**.

Dataset	Model	ΔVaR ↓				ΔES ↓				Steps to Best Incumbent ↓			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
Crypto	IQL (MOSAIC)	0.058	0.061	**0.066**	**0.071**	**0.094**	**0.086**	**0.101**	**0.083**	**8.8**	**8.6**	**8.2**	**8.6**
	BC	0.060	0.063	0.079	0.080	0.116	0.101	0.121	0.101	9.4	9.6	9.0	8.8
	DQN	**0.057**	**0.059**	0.075	0.083	0.126	0.097	0.116	0.096	9.2	9.2	8.8	9.2
	LLM	0.064	0.068	0.085	0.092	0.122	0.109	0.120	0.105	10.0	10.2	9.2	9.8

H.4 Reinforcement Learning Comparison

Tables 15–18 present the full RL module comparison results. IQL-based MOSAIC shows the most consistent overall advantage across forecasting, generation, financial metrics, and refinement efficiency. For forecasting, IQL achieves the best or near-best error metrics on most dataset–backbone combinations, while also reaching the best incumbent in fewer refinement steps than BC, DQN, and LLM-only refinement. On Crypto financial metrics, IQL is strongest on most ΔSharpe and ΔES results, although DQN or LLM occasionally achieves slightly lower ΔVaR for individual backbones. For generation, IQL again dominates most Marginal, Correlation, Autocorrelation, and Covariance distances on LOB and Stock, and obtains the best ΔES and fastest refinement on Crypto, while DQN is competitive on some ΔVaR entries. Overall, these results suggest that the IQL policy provides more stable long-horizon refinement decisions than other RL algorithms, or prompt-only LLM refinement, improving both final model quality and the speed of reaching the best candidate.

H.5 EDA and Multimodal Ablation

Tables 19–22 present the full per-LLM ablation results for the EDA and multimodal module. Removing these components severely degrades generation fidelity; for instance, LOB Marginal distance spikes by up to 75% on Claude (0.554 → 0.969). In downstream financial tasks, their absence causes the Crypto ΔSharpe to deteriorate drastically (e.g., 6.654 → 20.039 on GPT-4o). For forecasting, semantic EDA consistently outperforms the baseline TS-Agent, improving Stock RMSE across all backbones (e.g., 8.079 → 7.815 on GPT-5.4). These breakdowns confirm that while advanced

Table 19: EDA and multimodal ablation: forecasting metrics. Each metric is averaged over five runs. Best per LLM is **bolded**.

Dataset	Variant	RMSE ↓				MAE ↓				MAPE (%) ↓				sMAPE (%) ↓			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
Crypto	MOSAIC	**0.207**	**0.202**	**0.217**	**0.214**	**0.051**	**0.051**	**0.054**	**0.052**	**1.543**	**1.531**	**1.583**	**1.535**	**1.547**	**1.534**	**1.591**	**1.540**
	EDA (MOSAIC)	0.211	0.216	0.218	0.219	0.052	0.054	0.055	0.055	1.568	1.616	1.614	1.630	1.567	1.617	1.616	1.631
	TS-Agent	0.224	0.220	0.218	0.219	0.056	0.055	**0.054**	0.055	1.647	1.626	1.620	1.621	1.647	1.629	1.616	1.623
LOB	MOSAIC	**0.149**	**0.150**	**0.116**	**0.161**	**0.112**	**0.112**	**0.083**	0.122	**0.051**	**0.050**	**0.037**	0.055	**0.051**	**0.050**	**0.037**	0.055
	EDA (MOSAIC)	0.167	0.156	0.143	0.164	0.121	0.113	0.096	**0.120**	0.055	0.051	0.042	**0.054**	0.055	0.051	0.042	**0.054**
	TS-Agent	0.154	0.158	0.143	0.174	0.116	0.115	0.101	0.130	0.053	0.052	0.045	0.058	0.053	0.052	0.045	0.058
Stock	MOSAIC	**7.847**	**7.815**	**7.904**	8.064	**4.804**	**4.804**	**4.843**	4.963	**1.982**	**1.981**	**2.005**	2.075	1.991	**1.982**	1.956	2.086
	EDA (MOSAIC)	7.892	7.958	8.047	**7.932**	4.845	4.857	5.005	**4.942**	1.997	2.010	2.064	**2.053**	2.007	2.016	2.073	2.057
	TS-Agent	8.017	8.079	7.982	8.590	4.912	4.964	4.905	5.047	2.046	2.060	2.076	2.123	**1.770**	2.062	**1.765**	**1.850**

Table 20: EDA and multimodal ablation: Crypto financial metrics (forecasting). Each metric is averaged over five runs. Best per LLM is **bolded**.

Dataset	Variant	ΔSharpe ↓				ΔVaR ↓				ΔES ↓			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
Crypto	MOSAIC	**6.654**	**4.329**	10.687	10.211	**0.012**	**0.012**	**0.015**	**0.014**	**0.014**	**0.015**	**0.016**	**0.016**
	EDA (MOSAIC)	20.039	9.401	**7.887**	**7.427**	0.078	0.016	0.093	0.082	0.102	0.024	0.142	0.108
	TS-Agent	12.431	4.530	11.297	12.416	0.015	0.015	0.017	0.015	0.019	0.022	0.024	0.023

backbones can occasionally compensate for missing modalities, explicitly injecting statistical and visual priors is strictly necessary to guarantee robust generation quality and financial safety across varying model scale.

H.6 Model Generation Ablation

Tables 23–26 report the full per-LLM ablation results, complementing the averaged analysis in the main text. The patterns hold consistently across all four backbones. Blueprint planning is the most critical component: removing it causes Win Rate to drop to 0% on LOB and Stock with most backbones, and degrades RMSE by up to 52% on LOB (Claude: 0.095 → 0.145). Module understanding contributes the second largest effect, with its removal increasing LOB Marginal distance by 28–63% depending on backbone. The verify/revise loop primarily affects reliability rather than peak performance: without it, Win Rate drops to 0–20% on most configurations even when metric values remain competitive, confirming that unverified implementations frequently contain runtime errors. Naive LLM achieves near-zero Win Rate across all backbones and datasets, with the sole exception of GPT-5.4 on LOB (20%), demonstrating that unstructured generation cannot reliably produce models competitive with repository-grounded synthesise regardless of backbone capability.

H.7 Reinforcement Learning Ablation

Tables 27–30 present the full RL ablation results. The full IQL-based MOSAIC variant consistently achieves the best results across nearly all datasets, LLM backbones, and evaluation metrics, confirming the importance of the proposed failure-aware refinement design. Removing invalid action masking leads to mild but consistent degradation, suggesting that preventing repeated or incompatible actions improves refinement stability. In contrast, removing soft revert causes the largest performance drop and requires more steps to reach the best incumbent, indicating that retaining executable but degrading edits can push the refinement trajectory into poorer program states. Removing trajectory branching also harms performance, especially on generation metrics, showing that preserving failed or reverted segments as negative supervision is useful for offline policy learning. Overall, the ablations demonstrate that invalid-action masking, soft rollback, and trajectory branching are complementary components for stable long-horizon refinement.

H.8 Generalization to Additional Domains

We evaluate MOSAIC on four additional forecasting datasets. Climate (1,272 weekly observations, 6 variables) and Energy (1,622 weekly observations, 9 variables) are taken from the Time-MMD benchmark (Liu et al., 2024a). FRED-MD (630 monthly observations, 4 macroeconomic targets) is a monthly U.S. macroeconomic panel (McCracken & Ng, 2016). Metal (2,617 daily observations, 2015–2025) is a panel of eight metal futures (gold, silver, copper, aluminium, zinc, lead, nickel, and tin), computed as daily log returns of main-contract closing prices, retrieved from Sina Finance via the AKShare API (Sina Finance, 2025; King & Zhang, 2022). The prediction length is 12 for Energy

Table 21: EDA and multimodal ablation: generation metrics. Each metric is averaged over five runs. Best per LLM is **bolded**.

Dataset	Variant	Marginal ↓				Correlation ↓				Autocorrelation ↓				Covariance ↓			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
LOB	MOSAIC	**0.590**	**0.579**	**0.554**	**0.626**	**0.216**	**0.182**	**0.225**	0.239	**0.199**	**0.247**	**0.193**	**0.228**	**0.181**	**0.177**	**0.188**	**0.192**
	EDA (MOSAIC)	0.946	0.844	0.969	0.884	0.440	0.381	0.340	0.668	0.734	0.582	0.400	0.791	0.290	0.274	0.311	0.280
	TS-Agent	0.713	1.180	0.767	0.822	0.243	0.472	0.235	**0.233**	0.234	0.477	0.215	0.254	0.234	0.332	0.234	0.221
Stock	MOSAIC	**0.408**	**0.371**	**0.383**	**0.385**	**0.357**	**0.343**	**0.345**	**0.378**	**0.091**	0.087	**0.081**	0.081	**0.881**	**0.902**	0.880	**0.903**
	EDA (MOSAIC)	0.450	0.396	0.433	0.631	0.374	0.393	0.461	0.407	0.750	0.101	0.361	**0.074**	0.912	0.913	**0.850**	0.938
	TS-Agent	0.455	0.681	0.421	0.473	0.397	0.437	0.361	0.401	0.129	**0.075**	0.193	0.859	0.910	0.939	0.909	0.930

Table 22: EDA and multimodal ablation: Crypto financial metrics (generation). Each metric is averaged over five runs. Best per LLM is **bolded**.

Dataset	Variant	ΔVaR ↓				ΔES ↓			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
Crypto	MOSAIC	0.072	0.073	**0.075**	**0.078**	**0.087**	0.096	**0.104**	**0.095**
	EDA (MOSAIC)	0.078	0.098	0.093	0.082	0.102	0.135	0.142	0.108
	TS-Agent	**0.068**	**0.044**	0.084	0.091	0.103	**0.054**	0.111	0.104

and 6 for the others. We use GPT-5.4 as the backbone; all other settings follow the main experiments. We compare against TS-Agent, one of the strongest agentic baselines, AutoGluon, iTransformer (Liu et al., 2024b), and PatchTST (Nie et al., 2023). MAPE is omitted because some targets are close to zero.

As shown in Table 31, MOSAIC achieves the best or tied-best RMSE on all four datasets and is best on every metric for Energy. On Metal, it ties iTransformer on RMSE and MAE. On Climate, it performs on par with TS-Agent. Overall, MOSAIC is best or tied for best on most datasets.

H.9 Case Study

Model Generation Examples. We present two representative examples from the model generation module, illustrating the two composition modes: component-level recombination within a shared architectural family, and idea-level transfer across families.

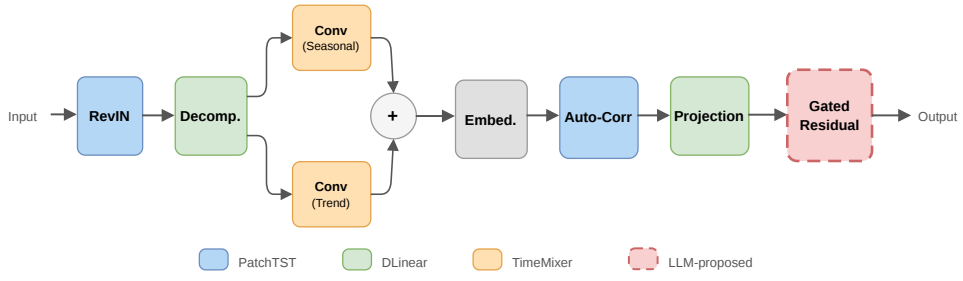

Figure 8: Generated model architecture for hourly cryptocurrency forecasting by GPT-4o.

❶ ***Case 1: Forecasting on Crypto.***

Using the LLM GPT-4o, we generate task-specific architectures for hourly cryptocurrency price forecasting (Figure 8). The top-k shortlist contains PatchTST, DLinear, and TimeMixer, all sharing a decomposition-and-projection paradigm. The family classifier selects direct component recombination. The generated architecture combines DLinear's series decomposition with TimeMixer's multi-scale convolution branches and PatchTST's auto-correlation attention, connected through a temporal embedding layer. The blueprint stage adds a gated residual head, automatically designed by the LLM to suit the task, blending the network output with the most recent observation via a learned gate. During the execute-verify-refine loop, a shape mismatch at the projection head is detected and automatically corrected by inserting separate temporal and channel linear layers. The resulting hybrid achieves RMSE 0.205 versus 0.217 for the best single-model baseline (PatchTST), with Sharpe Ratio Difference reduced from 12.4 to 2.07.

Table 23: Model generation ablation: forecasting metrics. Each metric is averaged over five runs. Best per LLM per dataset is **bolded**.

Dataset	Variant	RMSE ↓				MAE ↓				MAPE (%) ↓				sMAPE (%) ↓				Win (%) ↑			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
Crypto	ModelGen (MOSAIC)	**0.205**	**0.202**	**0.219**	**0.205**	**0.051**	**0.051**	0.055	**0.051**	**1.530**	**1.514**	**1.615**	**1.523**	**1.531**	**1.519**	1.621	**1.525**	**60**	**80**	**60**	**60**
	w/o Mod. Und.	0.222	0.216	0.223	0.220	0.056	0.055	0.055	0.054	1.655	1.624	1.681	1.623	1.622	1.644	1.656	1.636	20	20	20	20
	w/o Blueprint	0.228	0.222	0.221	0.238	0.056	0.056	**0.053**	0.056	1.679	1.636	**1.615**	1.656	1.676	1.644	1.633	1.628	20	20	0	0
	w/o Verify	0.223	0.220	0.226	0.224	0.056	0.055	0.056	0.055	1.662	1.645	1.718	1.631	1.676	1.670	1.646	1.651	20	20	20	20
	Naive LLM	0.225	0.225	0.237	0.247	0.055	0.057	0.058	0.055	1.659	1.675	1.627	1.630	1.657	1.687	**1.620**	1.626	0	20	0	0
LOB	ModelGen (MOSAIC)	**0.153**	**0.155**	**0.095**	**0.160**	**0.115**	**0.115**	**0.067**	**0.119**	**0.052**	**0.051**	**0.030**	**0.054**	**0.052**	**0.052**	**0.030**	**0.054**	**60**	**60**	**60**	**60**
	w/o Mod. Und.	0.159	0.162	0.123	0.172	0.120	0.117	0.086	0.129	0.055	0.054	0.039	0.058	0.054	0.053	0.038	0.058	20	20	20	20
	w/o Blueprint	0.156	0.166	0.145	0.172	0.117	0.119	0.100	0.132	0.053	0.055	0.046	0.058	**0.052**	0.053	0.045	0.058	0	20	0	0
	w/o Verify	0.162	0.160	0.142	0.173	0.121	**0.115**	0.101	0.129	0.055	0.052	0.045	0.060	0.054	**0.052**	0.045	0.058	20	0	0	20
	Naive LLM	0.169	0.170	0.143	0.173	**0.115**	0.120	0.102	0.130	0.053	0.056	0.045	0.058	0.053	0.054	0.045	0.059	0	20	0	0
Stock	ModelGen (MOSAIC)	**7.805**	**7.769**	**7.867**	**7.924**	**4.774**	**4.790**	**4.840**	**4.910**	**1.967**	**1.977**	**2.017**	**2.045**	**1.977**	**1.979**	**1.939**	2.064	**80**	**80**	**60**	**60**
	w/o Mod. Und.	8.219	8.220	8.266	8.555	4.995	5.113	5.070	5.217	2.105	2.077	2.137	2.158	1.981	2.111	2.113	2.121	20	20	20	20
	w/o Blueprint	8.374	8.372	8.369	8.622	5.126	5.186	5.193	5.025	2.116	2.143	2.173	2.128	1.992	2.165	2.121	2.123	20	20	20	0
	w/o Verify	8.291	8.249	7.888	8.496	5.071	5.098	4.916	5.212	2.117	2.135	2.065	2.176	2.101	2.104	2.201	**2.040**	20	20	0	20
	Naive LLM	8.511	8.089	8.010	8.508	5.309	4.882	4.905	5.034	2.197	2.062	2.053	2.133	2.120	2.084	2.213	2.203	20	0	0	0

Table 24: Model generation ablation: Crypto financial metrics (forecasting). Each metric is averaged over five runs. Best per LLM is **bolded**.

Dataset	Variant	ΔSharpe ↓				ΔVaR ↓				ΔES ↓			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
Crypto	ModelGen (MOSAIC)	**2.074**	**2.431**	**10.924**	**9.477**	**0.010**	**0.011**	**0.014**	**0.012**	**0.011**	**0.013**	**0.014**	**0.014**
	w/o Mod. Und.	7.191	3.518	11.458	11.211	0.013	0.014	0.016	0.014	0.016	0.018	0.020	0.019
	w/o Blueprint	7.150	3.581	11.325	12.212	0.013	0.013	0.017	0.016	0.016	0.018	0.024	0.023
	w/o Verify	7.072	3.544	11.528	11.547	0.013	0.013	0.016	0.014	0.016	0.018	0.020	0.019
	Naive LLM	12.500	3.627	11.382	12.272	0.015	0.014	0.017	0.015	0.020	0.019	0.024	0.023

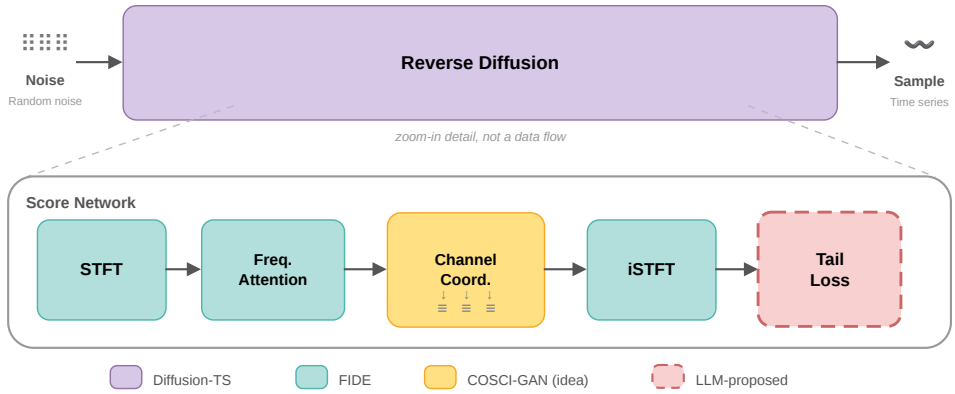

Figure 9: Generated model architecture for high-frequency LOB generation by Claude Opus 4.

❷ *Case 2: Generation on LOB.*

For unconditional generation of high-frequency order-flow sequences, the LLM Claude Opus 4 produces a blueprint shown in Figure 9. The shortlist contains Diffusion-TS, FIDE, and COSCI-GAN, spanning diffusion-based and GAN-based families. The family classifier designates Diffusion-TS as the primary backbone. FIDE, being in the same family, contributes its frequency-inflated score block as a direct replacement for the original time-domain encoder. COSCI-GAN contributes at the idea level only: its per-channel coordination principle is reinterpreted as a channel-factorised conditioning module inside the diffusion score network, avoiding the instability that would arise from directly grafting adversarial components into a score-matching objective. The blueprint also introduces a tail-aware loss weighting targeting the heavy-tailed distributions flagged by EDA. Guided by insights from the retrieved prior cases, the model blueprint incorporates per-channel residual connections to mitigate mode collapse observed in the initial sample visualisation. The final model achieves Marginal distance 0.513 versus 0.767 for Diffusion-TS alone, and Autocorrelation distance 0.191 versus 0.215.

These two cases demonstrate that the module's blueprint-constrained composition, whether through direct component substitution or cross-family idea transfer, produces novel architectures that outperform their constituent candidates while remaining executable and stable.

Table 25: Model generation ablation: generation metrics. Each metric is averaged over five runs. Best per LLM per dataset is **bolded**.

Dataset	Variant	Marginal ↓				Correlation ↓				AutoCorrelation ↓				Covariance ↓				Win(%) ↑			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
LOB	ModelGen (MOSAIC)	**0.556**	**0.536**	**0.513**	**0.582**	**0.195**	**0.168**	**0.214**	**0.206**	**0.194**	**0.212**	**0.191**	**0.233**	**0.169**	**0.162**	**0.187**	**0.186**	**60**	**80**	**60**	**60**
	w/o Mod. Und.	0.655	0.874	0.770	0.715	0.224	0.321	0.237	0.224	0.220	0.351	0.215	0.256	0.208	0.252	0.232	0.214	20	20	0	20
	w/o Blueprint	0.718	0.880	0.772	0.824	0.246	0.323	0.234	0.232	0.234	0.353	0.212	0.256	0.232	0.252	0.233	0.223	0	20	0	0
	w/o Verify	0.701	1.167	0.674	0.831	0.247	0.471	0.237	0.232	0.233	0.470	0.212	0.253	0.230	0.329	0.218	0.219	0	0	20	0
	Naive LLM	0.718	0.886	0.769	0.830	0.244	0.323	0.236	0.231	0.231	0.356	0.216	0.255	0.231	0.256	0.235	0.220	0	20	0	0
Stock	ModelGen (MOSAIC)	**0.362**	**0.326**	**0.382**	**0.350**	**0.364**	**0.339**	0.360	**0.374**	**0.090**	0.091	**0.078**	**0.073**	**0.894**	**0.893**	0.911	**0.923**	**60**	**80**	**60**	**60**
	w/o Mod. Und.	0.421	0.682	0.421	0.427	0.395	0.432	**0.358**	0.403	0.110	0.075	0.193	0.455	0.935	0.940	**0.904**	0.958	20	0	0	20
	w/o Blueprint	0.432	0.678	0.422	0.477	0.407	0.442	0.359	0.396	0.114	**0.074**	0.193	0.857	0.955	0.926	0.911	0.944	20	0	0	0
	w/o Verify	0.431	0.685	0.422	0.424	0.397	0.445	0.380	0.410	0.113	0.075	0.138	0.457	0.939	0.938	0.949	0.973	20	0	20	20
	Naive LLM	0.459	0.681	0.427	0.470	0.392	0.430	0.388	0.399	0.127	**0.074**	0.139	0.862	0.914	0.940	0.953	0.930	0	0	20	0

Table 26: Model generation ablation: Crypto financial metrics (generation). Each metric is averaged over five runs. Best per LLM is **bolded**.

Dataset	Variant	ΔVaR ↓				ΔES ↓				Win (%) ↑			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
Crypto	ModelGen (MOSAIC)	0.081	0.082	**0.081**	**0.082**	**0.082**	0.103	**0.105**	**0.102**	**60**	**60**	**60**	**60**
	w/o Mod. Und.	0.073	0.054	0.085	0.090	0.096	0.069	0.113	0.108	20	20	20	20
	w/o Blueprint	0.073	**0.044**	0.085	0.091	0.098	**0.053**	0.111	0.105	20	0	0	0
	w/o Verify	0.074	**0.044**	0.083	0.090	0.098	0.054	0.110	0.107	20	0	0	20
	Naive LLM	**0.068**	**0.044**	0.084	0.091	0.104	0.054	0.111	0.104	0	0	0	0

Generated Task Examples. The following cases show how a human-written instruction is transformed into a structured task specification and then into a final task description generated by the pipeline.

❶ ***Case 1: Foreign-exchange generation.***

This case illustrates an unsupervised generation task for developed-market foreign-exchange returns, where generated windows are evaluated by distributional, temporal, and cross-asset dependence metrics.

Case 1(a): Instruction

Create five executable financial time-series generation tasks using the foreign-exchange dataset only.

Task type: Each task must be generative and unsupervised. A usable sample is a full fixed-length window. There is no forecasting horizon, label, supervised input/output pair, or internal train-target split within a window.

Data constraints: The data source must be foreign exchange. Each task must select an explicit, meaningful, non-empty subset of assets. The task should not use all available assets. The preferred number of target assets is between 1 and 12.

Statistical requirements: Each task should generate realistic multi-asset foreign-exchange trajectories and should emphasize heavy tails, volatility clustering, temporal dependence, and cross-asset dependence.

Diversity requirements: Since the source dataset is fixed, tasks should vary in window length, stride, asset subset, liquidity profile, and time range. The generated set should include narrow, moderate, and broad asset configurations.

Feasibility requirements: The date range and window parameters should ensure at least 100 validation windows and 100 test windows.

Evaluation requirements: If a shared generative evaluation package is provided, use it as the default evaluation path. Otherwise, select appropriate metrics from the evaluation-template library. The evaluation should include correlation, marginal distribution, autocorrelation, and covariance scores.

Case 1(b): Generated Task Specification

Task brief: Generate 60-day windows of developed-market foreign-exchange pairs to capture stable developed-market dynamics.

Task type: Generation

Dataset plan:

```
dataset_id = foreign_exchange,
selection_locked = True.
```

Parameter plan:

Table 27: RL ablation: forecasting metrics. Each metric is averaged over five runs. Best per LLM per dataset is **bolded**.

Dataset	Variant	RMSE ↓				MAE ↓				MAPE (%) ↓				sMAPE (%) ↓				Steps_{R} ↓			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
Crypto	IQL (MOSAIC)	**0.209**	**0.203**	**0.214**	**0.227**	**0.053**	**0.053**	**0.052**	**0.053**	**1.563**	**1.596**	**1.536**	**1.552**	**1.571**	**1.596**	**1.545**	**1.563**	**8.80**	**8.40**	**8.60**	**8.60**
	w/o Invalid Action Masking	0.212	0.207	0.216	0.229	**0.053**	0.054	0.053	0.054	1.590	1.609	1.559	1.579	1.593	1.609	1.564	1.586	9.20	8.80	9.00	9.00
	w/o Soft Revert	0.225	0.218	0.224	0.238	0.059	0.055	0.056	0.057	1.696	1.656	1.642	1.648	1.683	1.657	1.637	1.649	10.60	10.40	10.40	10.20
	w/o Trajectory Branching	0.219	0.213	0.221	0.233	0.056	0.055	0.054	0.055	1.644	1.632	1.603	1.615	1.636	1.634	1.599	1.621	10.00	9.60	9.80	9.60
LOB	IQL (MOSAIC)	**0.144**	**0.143**	**0.147**	**0.162**	**0.108**	**0.108**	**0.107**	**0.127**	**0.050**	**0.049**	**0.048**	**0.058**	**0.050**	**0.049**	**0.048**	**0.058**	**8.80**	**8.60**	**8.40**	**9.00**
	w/o Invalid Action Masking	0.146	0.144	0.148	0.165	0.110	**0.108**	0.108	0.130	0.051	**0.049**	0.049	0.059	0.051	**0.049**	0.049	0.059	9.20	9.00	8.80	9.40
	w/o Soft Revert	0.159	0.151	0.154	0.178	0.120	0.114	0.113	0.148	0.056	0.052	0.054	0.061	0.055	0.052	0.054	0.061	10.60	10.40	10.00	10.80
	w/o Trajectory Branching	0.152	0.147	0.151	0.172	0.115	0.111	0.111	0.140	0.053	0.051	0.052	0.060	0.053	0.051	0.051	0.060	9.80	9.80	9.40	10.00
Stock	IQL (MOSAIC)	**8.013**	**8.001**	**7.958**	**8.275**	**4.922**	**4.859**	**4.847**	**5.042**	**2.042**	**1.997**	**1.986**	**2.120**	**2.049**	**1.995**	**1.982**	**2.118**	**8.80**	**8.40**	**8.20**	**9.20**
	w/o Invalid Action Masking	8.058	8.047	8.013	8.325	4.959	4.904	4.885	5.074	2.057	2.019	2.009	2.154	2.065	2.024	2.012	2.129	9.20	8.80	8.60	9.60
	w/o Soft Revert	8.252	8.239	8.176	8.518	5.103	5.093	5.013	5.168	2.119	2.105	2.087	2.261	2.137	2.125	2.103	2.177	10.20	10.40	10.20	10.80
	w/o Trajectory Branching	8.165	8.152	8.087	8.438	5.036	5.013	4.944	5.121	2.087	2.067	2.052	2.211	2.106	2.083	2.067	2.152	9.60	9.80	9.40	10.20

Table 28: RL ablation: Crypto financial metrics (forecasting). Each metric is averaged over five runs. Best per LLM is **bolded**.

Dataset	Variant	ΔSharpe ↓				ΔVaR ↓				ΔES ↓			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
Crypto	IQL (MOSAIC)	**13.524**	**11.924**	**10.331**	**11.313**	**0.015**	**0.018**	**0.017**	**0.016**	**0.019**	**0.020**	**0.019**	**0.019**
	w/o Invalid Action Masking	13.947	12.319	10.695	11.756	0.016	**0.018**	**0.017**	**0.016**	0.020	0.021	0.020	0.021
	w/o Soft Revert	15.385	14.274	12.246	12.836	0.018	0.019	0.019	0.017	0.023	0.025	0.026	0.025
	w/o Trajectory Branching	14.722	13.187	11.483	12.319	0.017	0.019	0.018	0.017	0.021	0.022	0.024	0.023

```
window_size = 60,
log_return = True,
stride = 5,
start_time = 2005-01-03,
end_time = 2026-03-30,
target_assets = eur_usd, gbp_usd, usd_jpy, usd_chf, usd_cad, nzd_usd,
train/val/test = (0.70, 0.15, 0.15).
```

Evaluation plan:

```
mode = library_metrics,
focus = realism and dependence structure.
```

The evaluation protocol includes four library metrics:

```
correlation_score: L2 difference between cross-feature correlation matrices.
marginal_distribution_score: L2 distance between per-feature flattened marginal
↪  distributions.
autocorrelation_score: L2 difference of per-feature autocorrelation up to the maximum
↪  lag.
covariance_score: L2 difference between cross-feature covariance matrices.
```

Constraints: The task must remain generative, with no forecasting horizon or supervised input/output split. The source dataset must remain foreign exchange. The target assets must be an explicit non-empty subset and must not include all available assets. The task must contain sufficient train, validation, and test windows after chronological splitting.

Executability rationale: The period from 2005-01-03 to 2026-03-30 provides over 4,000 daily observations. With a 60-day window and stride 5, this yields over 700 rolling windows, sufficient for the required train, validation, and test splits. Restricting the task to six developed-market foreign-exchange pairs gives a moderate-dimensional system with meaningful cross-asset dependence and manageable generative-modelling complexity.

Case 1(c): Final Task Description

Task overview: This task involves generative modelling of 60-day multivariate sequences of developed-market currency pairs. The objective is to synthesize realistic financial time-series windows that preserve cross-asset dependence and marginal distributional properties of the underlying foreign-exchange data.

Problem statement: The model must generate synthetic 60-day log-return windows for six currency pairs:

```
eur_usd, gbp_usd, usd_jpy, usd_chf, usd_cad, nzd_usd
```

The task is strictly generative and does not involve forecasting, prediction horizons, labels, or supervised input–target decomposition. The solver must learn the joint distribution of these six return series and generate sequences matching historical statistical properties. The realised dataset contains 760 training samples, 163 validation samples, and 164 test samples, each with a fixed window length of 60 days.

Table 29: RL ablation: generation metrics. Each metric is averaged over five runs. Best per LLM per dataset is **bolded**.

Dataset	Variant	Marginal ↓				Correlation ↓				AutoCorrelation ↓				Covariance ↓				Steps_G↓			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
LOB	IQL (MOSAIC)	**0.642**	**0.748**	**0.616**	**0.691**	**0.250**	**0.242**	**0.242**	0.294	**0.202**	0.386	**0.193**	**0.219**	**0.201**	**0.238**	**0.193**	**0.206**	**8.80**	**9.00**	**8.60**	**9.00**
	w/o Invalid Action Masking	0.675	0.779	0.651	0.732	0.260	0.253	0.255	**0.293**	0.220	**0.367**	0.210	0.226	0.212	0.246	0.196	0.210	9.20	9.40	9.00	9.40
	w/o Soft Revert	0.825	0.907	0.815	0.886	0.286	0.306	0.320	0.314	0.277	0.425	0.269	0.286	0.263	0.285	0.262	0.272	10.60	10.80	10.40	10.80
	w/o Trajectory Branching	0.747	0.837	0.727	0.797	0.273	0.273	0.283	0.303	0.245	0.410	0.228	0.261	0.234	0.265	0.232	0.240	9.80	10.00	9.60	10.00
Stock	IQL (MOSAIC)	**0.481**	**0.551**	**0.385**	**0.440**	**0.350**	**0.357**	**0.326**	**0.387**	**0.094**	**0.072**	**0.088**	**0.096**	**0.861**	**0.941**	**0.832**	**0.873**	**8.80**	**8.60**	**8.40**	**9.00**
	w/o Invalid Action Masking	0.495	0.568	0.400	0.461	0.367	0.375	0.341	0.400	0.099	0.080	0.098	0.101	0.876	0.952	0.846	0.894	9.20	9.00	8.80	9.40
	w/o Soft Revert	0.546	0.626	0.495	0.571	0.442	0.454	0.386	0.430	0.140	0.112	0.126	0.099	0.971	0.987	0.956	1.023	10.80	10.40	10.20	10.80
	w/o Trajectory Branching	0.526	0.594	0.449	0.507	0.400	0.415	0.363	0.410	0.121	0.092	0.110	0.098	0.925	0.962	0.909	0.976	9.80	9.60	9.40	10.00

Table 30: RL ablation: Crypto financial metrics (generation). Each metric is averaged over five runs. Best per LLM is **bolded**.

Dataset	Variant	ΔVaR ↓				ΔES ↓				Steps_G↓			
		GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova	GPT-4o	GPT-5.4	Claude	Nova
Crypto	IQL (MOSAIC)	**0.058**	**0.061**	**0.066**	**0.071**	**0.094**	**0.086**	**0.101**	**0.083**	**8.80**	**8.60**	**8.20**	**8.60**
	w/o Invalid Action Masking	0.061	0.064	0.070	0.076	0.101	0.091	0.106	0.089	9.20	9.00	8.80	9.00
	w/o Soft Revert	0.069	0.073	0.088	0.095	0.127	0.113	0.128	0.110	10.40	10.60	10.00	10.40
	w/o Trajectory Branching	0.066	0.069	0.080	0.087	0.116	0.102	0.116	0.099	9.80	9.80	9.40	9.60

Dataset: The dataset is derived from the foreign-exchange source and processed into a clean, synchronised 16-dimensional panel. The data span 2005-01-03 to 2026-03-30. Close prices are transformed into log-returns, after which rolling windows are constructed with window size 60 and stride 5. The realised tensor shapes are:

```
train = [760, 60, 6],
val = [163, 60, 6],
test = [164, 60, 6].
```

The resulting artifact is stored as a processed dataset package.

Evaluation: The generated samples are evaluated using:

```
correlation_score, marginal_distribution_score, autocorrelation_score,
↪  covariance_score, avg_sharpe_diff, avg_var_diff, avg_es_diff
```

Quick reference:

```
task_type = generation,
dataset = foreign_exchange,
window_size = 60,
stride = 5,
assets = eur_usd, gbp_usd, usd_jpy, usd_chf, usd_cad, nzd_usd.
```

❷ ***Case 2: Equity log-return forecasting.***

This case illustrates a supervised multi-asset forecasting task for retail and leisure equities, where a historical input window is used to predict a future return horizon for the same target assets.

Case 2(a): Instruction

Create multiple, distinct executable, sensible, implementable equity forecasting tasks using the equity source only.

Task requirements: Each task type must be forecasting. Forecasting here means a supervised time-series forecasting task. Each usable sample has a clear input/output structure: a historical input window over target assets is used to predict a future target horizon for those same target assets. Keep forecasting semantics explicit throughout; do not describe the task as full-window generation or as an unsupervised modelling problem.

Each data source must be equity time-series and should remain a standard source throughout planning. If a dataset is pre-selected externally for the run, every child task must use the same dataset and diversify through parameter choices rather than dataset choice. Multiple assets should be used as input context to capture cross-asset dependence in a volatile market setting.

Target assets must be an explicit, meaningful, manually chosen, non-empty list. Use the same target asset list for both forecasting input context and forecast outputs. Use at least 6 target assets, preferably 7–25 when supported by the dataset. The forecasting target should be operationally meaningful and reflect changing correlation structure. Asset selection should account for asset-to-asset correlation and redundancy.

Table 31: Forecasting results on four additional datasets with GPT-5.4. Each metric is averaged over five runs. Best per dataset is **bolded**. sMAPE exceeds 100 on FRED-MD and Metal because some targets are close to zero.

Model	FRED-MD			Metal			Climate			Energy		
	RMSE ↓	MAE ↓	sMAPE (%) ↓	RMSE ↓	MAE ↓	sMAPE (%) ↓	RMSE ↓	MAE ↓	sMAPE (%) ↓	RMSE ↓	MAE ↓	sMAPE (%) ↓
MOSAIC	**0.0082**	0.0035	144	**0.012**	**0.0084**	176	**3.2**	2.2	**23**	**0.26**	**0.18**	**5.9**
TS-Agent	0.010	0.0040	**136**	0.013	0.0087	178	**3.2**	**2.1**	**23**	0.29	0.20	6.3
AutoGluon	0.011	0.0036	148	0.017	0.012	**147**	3.3	2.2	24	0.29	0.20	6.5
iTransformer	0.011	0.0045	143	**0.012**	**0.0084**	159	3.3	2.2	25	0.30	0.20	6.5
PatchTST	0.010	**0.0034**	147	0.013	0.0090	173	3.7	2.2	42	0.29	0.20	6.0

Diversity requirements: Since the data source is fixed as equity time-series, tasks should diversify in forecasting horizon, stride, asset selection, time range, input window, and regime framing while preserving empirical and operational meaning. The date range should not be too narrow, and validation and test splits should contain sufficient samples.

Evaluation requirements: A fixed forecasting evaluation package will be provided. The task description must state exactly that metrics include `mae`, `mse`, `rmse`, `mape`, `smape`, `sharpe ratio`, `VaR`, and `ES`. Do not invent other information.

Implementation expectations: The task should read like a sensible, implementable equity forecasting task. Avoid synthetic replacements or generic dataset choices. Keep all instructions precise, implementable, and suitable for automatic task generation.

Case 2(b): Generated Task Specification

Task brief: Forecast 10-day returns for a diversified basket of retail and leisure stocks.

Task type: Forecasting

Dataset plan:

```
dataset_id = equity,
selection_locked = True.
```

Parameter plan:

```
train/val/test = (0.70, 0.15, 0.15),
log_return = True,
horizon = 10,
stride = 2,
input_window = 50,
target_assets = low, sbux, tjx, hd, nike, dis,
forecast_shuffle_train_after_split = True.
```

Evaluation plan:

```
mode = library_metrics,
focus = consumer sentiment tracking.
```

The evaluation protocol uses standard forecasting error and risk metrics:

```
metrics = mae, mse, rmse, mape, smape, sharpe ratio, VaR, ES.
```

Constraints: The task must use `standard_equity` only. The target asset list must contain at least 6 assets. The same target assets must be used for both the historical input window and the forecasting output horizon. The task must remain supervised forecasting, with explicit input/output structure.

Executability rationale: Retail and leisure stocks are sensitive to consumer spending and seasonal demand. A 50-day input window captures short-term market and sector trends, while a 10-day horizon defines a meaningful forecasting target. The selected 6-asset basket supports cross-asset dependence modelling while remaining computationally manageable.

Case 2(c): Final Task Description

Task overview: This task involves multi-asset forecasting of 10-day log returns for a basket of retail and leisure equities. The objective is to capture consumer sentiment trends and sector-specific volatility in retail-sensitive markets.

Problem statement: The model must predict the 10-day log-return horizon for 6 retail and leisure assets:

`low, sbux, tjx, hd, nike, dis`

Each sample contains a 50-day historical input window and a subsequent 10-day forecasting target for the same assets. The solver operates on 2,073 training samples, 446 validation samples, and 447 test samples. The model must account for the 2-day stride used in window construction. This task is meaningful for tracking consumer spending sensitivity and seasonal retail trends.

Dataset: The dataset is derived from the `equity` source, covering daily close prices from 2002-05-23 to 2026-04-08. Prices are transformed into log-returns and split chronologically using a 70/15/15 ratio before windowing. The realised tensor shapes are:

`train_X = [2073, 50, 6], train_Y = [2073, 10, 6],`
`val_X = [446, 50, 6], val_Y = [446, 10, 6],`
`test_X = [447, 50, 6], test_Y = [447, 10, 6].`

The dataset is provided as a processed archive containing complete multivariate observations for the selected assets.

Evaluation: The forecasts are evaluated using:

`mae, mse, rmse, mape, smape, sharpe ratio, VaR, ES`

Quick reference:

```
task_type = forecasting,
dataset = equity,
input_window = 50,
horizon = 10,
stride = 2,
assets = low, sbux, tjx, hd, nike, dis,
metrics = mae, mse, rmse, mape, smape, sharpe ratio, VaR, ES.
```