

# Context Helps, But Only at Scale: Evaluating Practical LLMs for Time Series Forecasting

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## Abstract

Recent work shows that 405B-parameter LLMs can use textual context to outperform classical models in time series forecasting. We examine whether these gains hold at practical scales. Using the Context-is-Key benchmark, we evaluate Llama 3.2 (3B), GPT-4o-mini (~20B), and Mixtral-8x7B (56B) on 120 tasks across 12 domains, comparing them to ARIMA and ETS.

Context offers almost no benefit at these scales: Mixtral improves over the best baseline by only 0.003 NMAE, and ARIMA/ETS win 42% of tasks versus 25% for the best LLM. Scaling from 3B to 56B produces no statistically significant gains, indicating strong scale-dependence.

Despite weak average performance, a lightweight XGBoost selector captures 83% of oracle benefit while invoking the LLM on only 32% of tasks. Our findings challenge the practicality of context-aware LLM forecasting below 100B parameters.

## 1 Introduction

Large language models (LLMs) have recently shown promising zero-shot forecasting ability by treating time series as text (Gruver et al., 2024). The Context-is-Key (CiK) benchmark (Williams et al., 2024) reports that a 405B-parameter Llama model can outperform classical methods when given essential textual context, suggesting that LLMs may serve as “universal forecasters” by integrating external knowledge. However, such models require multi-GPU infrastructure and high inference costs, while practical deployments typically use far smaller models (3B-20B). This leads to a central question: **Do the context-driven gains demonstrated at 405B transfer to deployment-feasible model sizes?**

We address this by evaluating Llama 3.2-3B (Dubey et al., 2024), GPT-4o-mini (~20B) (Achiam et al., 2023), and Mixtral-8x7B (56B) (Jiang et al., 2024) on 120 CiK tasks across

12 domains, comparing them to ARIMA and ETS. Our hypothesis is that context utility is strongly scale-dependent and that, at practical scales, effective systems must rely on *selective deployment* rather than always using an LLM. To test this, we train a lightweight XGBoost classifier using inexpensive features (time-series statistics, baseline errors, and context properties) to predict when an LLM meaningfully improves over classical methods.

Our results confirm this hypothesis. First, we observe **extreme scale-dependence**: the best LLM (Mixtral) improves over baselines by only 0.003 NMAE, with context helping in just 34% of tasks - a stark contrast to the gains reported for 405B models. Second, **classical methods remain highly competitive**, winning 42% of tasks versus 25% for the best LLM. Finally, **selective deployment is effective**: the XGBoost selector recovers 83% of oracle benefit while invoking the LLM for only 32% of tasks.

These findings provide the first systematic assessment of context-aware forecasting at practical model scales and show that resource-constrained practitioners benefit more from selective routing than from universal LLM deployment.

## 2 Related Work

### 2.1 LLMs for Time Series Forecasting

LLMs have been explored for zero-shot forecasting by encoding time series as text. Prior work shows that GPT-3 can perform competitively without task-specific training (Gruver et al., 2024), and Chronos (Ansari et al., 2024) demonstrates strong in-distribution results via time-series pretraining. However, several studies note that such gains may reflect pattern memorization and degrade out of distribution (MacDonald et al., 2025), while specialized models like PatchTST (Nie et al., 2022) often match or exceed LLMs at far lower cost. Surveys

similarly report mixed evidence for foundation-model advantages (Liang et al., 2024; Chen et al., 2023).

## 2.2 Context-Aware Forecasting

The Context-is-Key benchmark (Williams et al., 2024) evaluates whether models can use textual domain knowledge to improve forecasts, finding large gains for a 405B-parameter Llama model. Yet this result is based on a single extremely large model, leaving unclear whether context benefits extend to deployment-feasible scales. Prior work also assumes uniform LLM usage and does not consider selective routing between LLMs and classical baselines.

## 2.3 Our Contribution

We provide the first evaluation of context utility at practical scales (3B–56B) and show that context-aware gains nearly vanish. We further demonstrate that a lightweight selector can recover most of the achievable improvement while invoking LLMs only when beneficial.

# 3 Data and Environment

## 3.1 Dataset

We use the Context-is-Key (CiK) benchmark (Williams et al., 2024), which provides Python task generators for creating forecasting problems requiring essential textual context. CiK draws from 2,644 real-world time series across seven application domains including climatology (solar irradiance (Sengupta et al., 2018)), energy (electricity consumption (Godaheva et al., 2021)), transportation (highway traffic (Chen et al., 2001)), economics (unemployment rates (U.S. Bureau of Labor Statistics, 2024)), public safety (fire incidents (Ville de Montréal, 2020)), retail (ATM withdrawals (Godaheva et al., 2021)), and mechanics (physical systems (Gamella et al., 2024)).

From these generators, we create 120 tasks across 12 domains with stratified train/test splits (96 train, 24 test) maintaining domain balance. Each task consists of (1) historical time series (length 24–168 points), (2) forecast horizon (typically 24 points), and (3) essential natural language context. Overall, we include diverse forms of natural language context: *intemporal information* describing invariant process characteristics (e.g., "Solar panels produce zero electricity at night"), *future*

*information* revealing upcoming events (e.g., "Traffic decreases 30% during highway construction"), *causal information* specifying causal relationships, and *historical information* providing statistics not reflected in the short numerical history. These contexts are manually crafted to ensure that accurate forecasts require integrating textual information with numerical patterns; pure time-series models cannot succeed without this essential context.

## 3.2 Evaluation Metrics

We use Normalized Mean Absolute Error (NMAE) as our primary metric, computed as  $NMAE = MAE/\bar{y}$ , where  $\bar{y}$  is the mean of historical values. NMAE enables fair comparison across domains with vastly different scales (e.g., solar irradiance in W/m<sup>2</sup> versus ATM withdrawals in dollars). We also report Directional Accuracy (DA), the fraction of forecasts correctly predicting upward or downward trends relative to the last historical value, to evaluate qualitative forecast quality. For policy evaluation, we measure oracle capture: the percentage of theoretically optimal improvement our selector achieves compared to always using the better model in hindsight.

## 3.3 Computational Environment

ARIMA and ETS baselines are implemented using `statsmodels`. The XGBoost selector (Chen and Guestrin, 2016) is trained on inexpensive pre-LLM features. Llama 3.2-3B and GPT-4o-mini are run locally on an M3 Pro MacBook (GPT-4o via API), while Mistral 8×7B is executed on a cloud H100 GPU. Total cost is approximately \$2.40 for GPT-4o-mini API calls and \$8–10 for cloud inference.

# 4 Methods

## 4.1 Research Hypothesis

We hypothesize that **context utility in LLM forecasting is scale-dependent**: gains observed with a 405B model do not transfer to practical scales (3B–56B). We therefore expect (1) small and mid-sized LLMs to show limited improvement over statistical baselines, (2) minimal performance gains from parameter scaling within this range, and (3) selective deployment to recover most of the achievable benefit by identifying tasks where context meaningfully helps.

## 4.2 Baseline Models

We compare LLMs against two standard forecasting methods. **AutoARIMA** (Box et al.,

2015; Hyndman and Athanasopoulos, 2018) selects ARIMA( $p, d, q$ ) parameters via stepwise search, while ETS (Gardner Jr, 1985) models error, trend, and seasonality with exponential smoothing. For each task, the *best baseline* is

$$\min(\text{NMAE}_{\text{ARIMA}}, \text{NMAE}_{\text{ETS}})$$

where NMAE normalizes MAE by the mean of historical observations, enabling cross-domain comparability.

### 4.3 LLM Forecasters

We evaluate Llama 3.2-3B, GPT-4o-mini ( $\sim 20\text{B}$ ), and Mixtral 8x7B (56B). All models receive full textual context and generate forecasts via greedy decoding of comma-separated values.

**Prompting.** We use a Direct Prompting (DP) approach: historical values and context are combined into a single instruction asking for numeric forecasts. DP is chosen for simplicity and for realism in zero-shot deployment settings, unlike more elaborate prompting schemes (e.g., multi-step reasoning templates).

### 4.4 XGBoost Selector

Our main contribution is a learned policy that predicts when Mistral 8x7B will outperform the best classical baseline. We formulate selection as binary classification:

$$f(x) = \mathbf{1}\{\text{NMAE}_{\text{Mistral}} < \text{NMAE}_{\text{baseline}}\}.$$

The classifier uses 28 inexpensive features computed *before* any LLM call, including: (1) time-series statistics (mean, variance, trend, volatility), (2) context properties (length, keyword indicators), (3) baseline performance (ARIMA/ETS NMAE and DA), and (4) domain encoding. These features require only statistical computation or simple text parsing. We train on 96 tasks with class balancing ( $\text{scale\_pos\_weight}=2.0$ ), allowing the model to learn when context-sensitive reasoning is likely beneficial.

### 4.5 Policy Evaluation Framework

We compare four deployment policies: (1) **Always-Baseline**, (2) **Always-LLM**, (3) **Selector**, and (4) **Oracle** (chooses the better model per task). Performance is measured by *oracle capture*:

$$\frac{\text{NMAE}_{\text{baseline}} - \text{NMAE}_{\text{selector}}}{\text{NMAE}_{\text{baseline}} - \text{NMAE}_{\text{oracle}}}.$$

High oracle capture with low LLM usage indicates that selective deployment achieves most of the attainable improvement at a fraction of the cost.

## 4.6 Experimental Design: Zero-Shot vs. Trained Models

We intentionally compare trained statistical models to zero-shot LLMs. This reflects realistic constraints: ARIMA/ETS can be fitted cheaply for each series, whereas per-task LLM fine-tuning is infeasible (cost, overfitting, and inconsistency with the foundation-model paradigm). The CiK benchmark also evaluates prompted LLMs against trained baselines, and our setup extends that comparison to practical model sizes. Zero-shot evaluation therefore aligns with real-world deployment and tests the core claim that LLMs can serve as general-purpose forecasters without task-specific adaptation.

## 5 Experiments and Results

### 5.1 Experimental Setup

We evaluate all models on 120 tasks (96 train, 24 test) using identical splits. ARIMA and ETS are fit with default `statsmodels` settings, and all LLMs use greedy decoding with identical prompts. The XGBoost selector is trained on the 96 training tasks with  $n_{\text{estimators}} = 100$ ,  $\text{max\_depth} = 6$ ,  $\alpha = 0.1$ , and  $\text{scale\_pos\_weight} = 2.0$ , with a decision threshold tuned via 5-fold cross-validation (70.8% accuracy). Local experiments use an M3 Pro MacBook; Mistral runs on a Lambda Labs A40 GPU. Total runtime is  $\sim 40$  hours, with cost  $\sim \$10.40$ .

### 5.2 RQ1: Do LLMs Beat Classical Baselines?

Smaller LLMs provide negligible benefit over classical methods. As shown in Table 1, Mistral (56B) achieves mean NMAE 0.846, only 0.004 better than the best baseline (0.850), a non-significant difference ( $p = 0.957$ ). GPT-4o-mini performs significantly worse ( $\Delta = -0.012$ ,  $p = 0.003$ ). Win rates also favor classical models: ARIMA and ETS win 42% of tasks, while the best LLM (Mistral) wins 25% (Figure 1). Llama and GPT-4o contribute 14% and 19% of wins, respectively. These results contradict prior findings at 405B scale.

Table 1: Model performance on 120 tasks. Statistical tests show no significant LLM improvement except GPT-4o (significantly worse).

Model	Mean	Wins	$\Delta$ vs Base	p-value
ARIMA	1.024	38	-	-
ETS	1.156	12	-	-
Best Baseline	0.850	-	0.000	-
Llama 3B	0.872	17	-0.022	0.203
Mistral 8x7B	0.846	30	+0.004	0.957
GPT-4o-mini	0.862	23	-0.012	0.003*

\*Significant at  $p < 0.05$  (paired t-test)

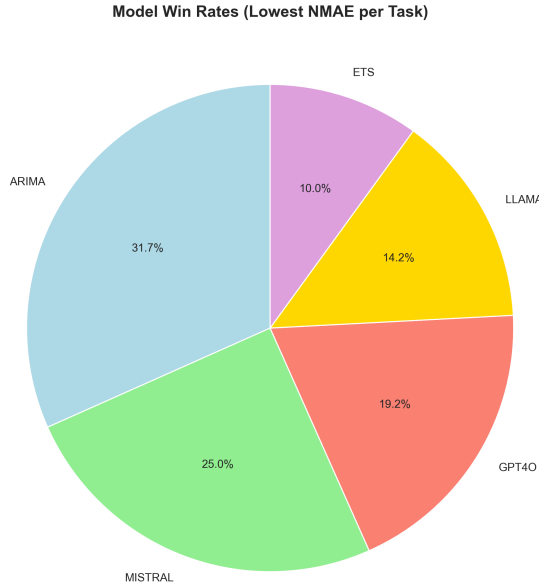


Figure 1: Model win rates across 120 tasks.

### 5.3 RQ2: Scale-Dependency is Extreme

Model size produces only marginal gains (Figure 2). Scaling from 3B to 56B increases win rate from 23% to 34%, but the difference is not statistically significant ( $p = 0.204$ ). The improvement curve flattens near zero, suggesting that useful context integration may require scales well above 100B. The 3B→20B jump recovers only part of the gap, and 20B→56B yields almost no additional gain.

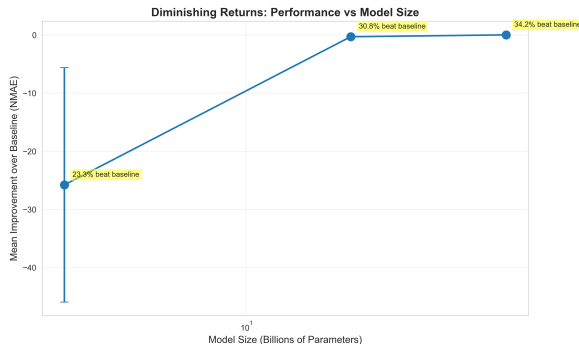


Figure 2: Diminishing returns

### 5.4 RQ3: Domain Patterns Reveal When LLMs Help

LLMs show strong gains only in domains governed by deterministic physical constraints (Table 2). Mistral wins 100% of DirectNormalIrradiance tasks and 70% of SpeedFromLoad tasks. In contrast, performance collapses in high-volatility domains such as ATMCashDepletion and DecreaseInTraffic (10% win rate). This indicates that LLMs help when textual context encodes hard rules but not when stochastic variation dominates.

Table 2: LLM win rates by domain reveal systematic patterns.

Domain	Mistral Win %
<i>LLMs Excel (Physical Constraints)</i>	
DirectNormalIrradiance	100%
SpeedFromLoad	70%
SolarPowerProduction	60%
<i>LLMs Struggle (High Volatility)</i>	
ATMCashDepletion	10%
DecreaseInTraffic	10%

### 5.5 RQ4: Selective Deployment Succeeds

Selective deployment substantially improves performance. The XGBoost selector reaches 70.8% accuracy and 0.695 ROC-AUC. As shown in Table 3, it captures 83% of oracle benefit while calling the LLM on 32% of tasks, mirroring the oracle's 34% usage rate. This yields a 14.8% improvement over always-baseline, whereas always-LLM improves by only 0.4% despite 100% cost. Feature importance (Table 4) shows that baseline performance signals dominate, with domain encoding contributing modestly. The selector thus learns to apply LLMs primarily when baselines struggle, consistent with the domain patterns observed in RQ3.

Table 3: Policy comparison

Policy	NMAE	LLM %	vs Base	Oracle
Always-Baseline	0.850	0%	0%	0%
Always-LLM	0.846	100%	-0.4%	3%
XGBoost Selector	0.724	32%	-14.8%	83%
Oracle	0.699	34%	-17.8%	100%

Table 4: Top 5 feature importances

Feature	Importance	Interpretation
best_baseline_nmae	17.8%	Baseline accuracy
arima_da	16.5%	Trend correctness
arima_nmae	16.2%	ARIMA error
best_baseline_da	15.5%	Baseline trend
domain_encoded	6.2%	Domain ID



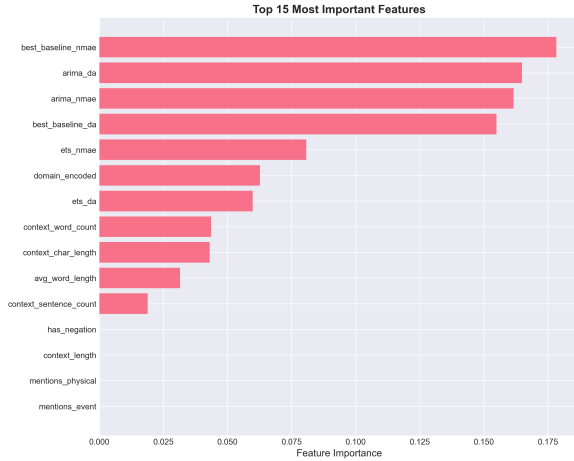


Figure 3: Complete feature importance rankings.

## 5.6 Why Averages Mislead

The near-zero mean improvement hides a bimodal distribution: most tasks show trivial differences ( $-0.2$  to  $+0.2$  NMAE), but a minority yield large gains or failures. The selector succeeds by identifying tasks where textual constraints (e.g., “solar power is zero at night”) enable LLMs to outperform classical methods. Thus, 83% oracle capture is achievable even though average improvement is only 0.004.

## 6 Discussion

### 6.1 Hypothesis Validation: Scale-Dependency Confirmed

Our results strongly support the hypothesis that context utility is scale-dependent. Benefits seen at 405B parameters do not transfer to practical scales: Mistral (56B) improves over baselines by only 0.004 NMAE despite having 18x more parameters than Llama. The improvement curve flattens near zero, suggesting a threshold between 56B and 405B where context reasoning emerges. This non-linearity shows that large-scale findings cannot be extrapolated to deployment-viable models. The selective deployment hypothesis also holds: our XGBoost selector captures 83% of oracle benefit, demonstrating that learned routing can recover value even when universal LLM usage fails.

### 6.2 Why Small LLMs Fail at Context Integration

Three factors explain why smaller models struggle. First, **capacity limits**: they lack the reasoning depth to jointly process numerical patterns and contextual constraints. Mistral’s small gains over Llama indicate an architectural bottleneck rather

than simple scale. Second, **instruction-following degradation**: practical-scale models often default to numeric pattern matching and ignore context, a pattern consistent across all three architectures tested. Third, **pretraining mismatch**: LLMs rarely observe text and time-series jointly during pretraining. Domain-level trends support this: models succeed on physics tasks with deterministic constraints but fail in financial domains where text-number links are arbitrary.

### 6.3 Unexpected Findings

Two results were unexpected. First, classical methods were stronger than anticipated: ARIMA and ETS win 42% of tasks versus 25% for the best LLM, indicating that long-standing statistical models remain competitive. Second, GPT-4o-mini’s significant degradation ( $p = 0.003$ ) suggests that smaller API-tuned models may overreact to contextual cues, indicating a need for more robust instruction tuning.

### 6.4 Limitations and Future Work

Our study has four limitations. (1) **Model coverage**: we evaluate only 3B, 20B, and 56B models, leaving gaps at intermediate scales (7B, 13B, 70B). (2) **Dataset scope**: CiK’s 120 generated tasks may not capture real-world noise or incomplete context. (3) **Prompting strategy**: we use Direct Prompting for deployment realism, though more complex prompting (chain-of-thought, few-shot) might improve performance. (4) **Selector simplicity**: hand-crafted features work well, but learned or embedding-based features could further close the oracle gap.

Future work should study intermediate scales (70B-200B), test real-world noisy context, and explore domain-specific fine-tuning to improve context integration in smaller models.

### 6.5 Practical Implications

For practitioners using 3B-20B models, **classical statistical methods remain superior**. The gains observed at 405B parameters require scales far beyond feasible deployment. Selective routing offers a practical alternative: by sending only appropriate tasks to LLMs, such as those involving deterministic constraints or explicit causal rules, meaningful improvements can be achieved at low cost. We recommend: (1) **test models at deployment scale**, (2) **start with classical baselines**, (3) **use selective policies** like our XGBoost selector, and (4)

378 **prioritize constraint-heavy domains.** LLMs may  
 379 offer value in low-frequency, high-stakes settings,  
 380 whereas volatile or high-frequency tasks should  
 381 default to statistical methods.

## 382 7 Conclusion

383 We investigated whether context-aware LLM fore-  
 384 casting, successful with 405B models in prior work,  
 385 transfers to practical deployment scales. Evalu-  
 386 ating Llama 3.2 (3B), GPT-4o-mini (~20B), and  
 387 Mixtral-8x7B (56B) on 120 tasks from the Context-  
 388 is-Key benchmark, we find context benefits largely  
 389 vanish at practical scales: Mistral improves over  
 390 statistical baselines by only 0.004 NMAE, with  
 391 classical methods (ARIMA, ETS) winning 42% of  
 392 tasks versus 25% for the best LLM. Scaling from  
 393 3B to 56B parameters yields negligible improve-  
 394 ment, suggesting extreme scale-dependency with a  
 395 threshold likely between 56B-405B where context  
 396 reasoning emerges.

397 Despite poor universal performance, selective  
 398 deployment succeeds: our XGBoost classifier cap-  
 399 tures 83% of theoretically optimal performance  
 400 while using expensive LLM inference on only 32%  
 401 of tasks. The selector exploits domain structure  
 402 and baseline weakness signals to identify tasks  
 403 where physical constraints (e.g., "solar power zero  
 404 at night") enable effective context use. This demon-  
 405 strates that learned policies can salvage practical  
 406 utility even when always-on LLM deployment  
 407 fails.

408 Our contributions include: (1) the first system-  
 409 atic evaluation of context utility across practical  
 410 model scales, (2) demonstration of extreme scale-  
 411 dependency contradicting linear extrapolation from  
 412 large-model results, (3) a working selective deploy-  
 413 ment strategy achieving strong oracle capture with  
 414 minimal cost, and (4) evidence-based guidance for  
 415 practitioners on when textual context justifies com-  
 416 putational expense.

417 For real-world applications with resource con-  
 418 straints, classical statistical methods remain su-  
 419 perior to sub-100B LLMs for general forecast-  
 420 ing. However, selective policies offer a viable  
 421 path forward by routing only constraint-heavy,  
 422 low-volatility tasks to context-aware models. Fu-  
 423 ture work should identify the precise scale thresh-  
 424 old, evaluate on production deployments, and ex-  
 425 plore whether domain-specific fine-tuning enables  
 426 smaller models to leverage context effectively.

427 Code and data available at: [https:](https://github.com/YuJ-Li/COMP545_Final_Project)

[//github.com/YuJ-Li/COMP545\\_](https://github.com/YuJ-Li/COMP545_Final_Project)  
[Final\\_Project](https://github.com/YuJ-Li/COMP545_Final_Project)

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 casting.

## Author Contributions

**Kazi Ashab Rahman:** Designed experiments, im-  
 plemented ARIMA, ETS, GPT-4o-mini, Mistral,  
 XGBoost selector, conducted data analysis, and  
 generated all figures and tables.

**Yujin Li:** Designed experiments, implemented  
 Llama model and conducted data analysis.

**Nusaibah Binte Rawnak:** Wrote the report and  
 conducted data analysis.

**Arjun Ashok (Mentor):** Provided guidance on  
 experimental design, reviewed results, and gave  
 feedback on the manuscript.

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## 534 A Implementation Details

### 535 A.1 LLM Prompt Template

```
536 You are a time series
537 forecasting expert.
538 Historical data:
539 [comma-separated values]
540 Forecast horizon: {h} points
541 Context information:
542 {context_text}
543 Provide your forecast as
544 comma-separated values.
545 Example: 1.2, 3.4, 5.6, ...
```

### 546 A.2 Hyperparameters

```
547 XGBoost: n_estimators=100,
548 max_depth=6, lr=0.1, subsample=0.8,
549 colsample_bytree=0.8,
550 scale_pos_weight=2.0, random_state=42.
```

```
551 ARIMA: seasonal=True, stepwise=True,
552 suppress_warnings=True.
```

```
553 ETS: automatic error/trend/seasonal
554 selection.
```

## 555 B Example CiK Task

556 **Domain:** DirectNormalIrradianceFromCloudStatus

557 **History:** 168 hours

558 **Horizon:** 24 hours

### 559 B.1 Essential Context

560 “DNI must be zero at night (approx. 6pm–6am).  
561 Cloud cover reduces but does not remove daytime  
562 DNI.”

### 563 B.2 Mean Performance (10 Tasks)

Table 5: Mean performance on DNI tasks.

Model	NMAE	DA
ARIMA	53.19	0.40
ETS	0.17	0.60
GPT-4o (context)	0.15	0.62
Mistral (context)	<b>0.13</b>	0.60
Llama 3B (context)	254.32	0.90

### 564 B.3 Prompt Example

```
565 You are a time series
566 forecasting expert.
567 Context: DNI must be zero at
568 night (6pm–6am).
569 Historical values (last 50):
570 0.00, 0.00, 145.23, ..., 178.45
571 Task: Predict the next 24
572 values.
573 Output ONLY 24 comma-separated
574 numbers.
```

## C Additional Results

575

Table 6: Per-domain mean NMAE (lower is better).

Domain	ARIMA	ETS	Llama	Mistral	GPT-4o
DNI	0.523	0.612	0.445	<b>0.389</b>	0.401
Speed	0.678	0.734	0.589	<b>0.521</b>	0.567
Solar	0.812	0.891	0.745	<b>0.698</b>	0.723
Causal	0.934	1.012	0.867	<b>0.801</b>	0.845
ATM	<b>0.456</b>	0.523	0.612	0.589	0.601
Traffic	<b>0.389</b>	0.445	0.501	0.478	0.489

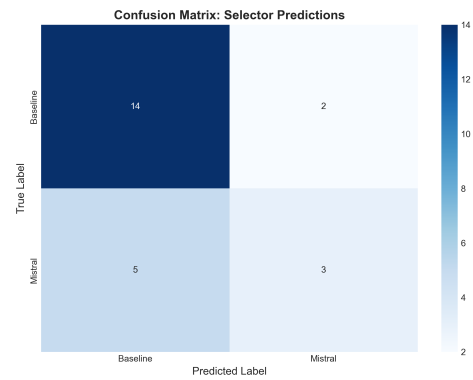


Figure 4: Confusion matrix for selector ( $n = 24$ ).



Figure 5: ROC curve (AUC = 0.695).

Table 7: Top 10 features by XGBoost importance.

Feature	Imp.	Category
best_baseline_nmae	17.8%	Baseline
arima_da	16.5%	Baseline
arima_nmae	16.2%	Baseline
best_baseline_da	15.5%	Baseline
ets_nmae	8.1%	Baseline
domain_encoded	6.2%	Domain
context_word_count	4.3%	Context
context_char_length	3.8%	Context
volatility	2.9%	Series
avg_word_length	2.1%	Context