

Smart Applications: My Update

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Enhancing Forecasting System with
Explainability and Performance



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Introduction

I worked on Team A: topic 7, handling all the aspects regarding explainability.

- **ForecastExplainer** → Generates bounds and local explainability
- **RagExplainer** → Connects context to LLM's answers

Possible improvements:

- Forecasting system lacked global explainability.
- Response times for predictions and explanations were improvable.

All the updates and the code developed can be found on my [GitHub repository](#).

Pre-Update State

Local Explainability:

- Implemented with **LIME** (perturbation-based).
- Model-agnostic but computationally expensive.

Uncertainty Bounds:

- Generated with **bootstrapping** (perturbation-driven).
- Time-consuming approach.

Environment	Sequence Length	Predictions	Time (seconds)
Local Machine	15	30	2.93
Website (with GUI)	15	30	4.60

Update 1: Global Explainability

Approach:

- Introduced SHAP-based global explainability.
- Computed SHAP values for the dataset using **shap.TreeExplainer**.

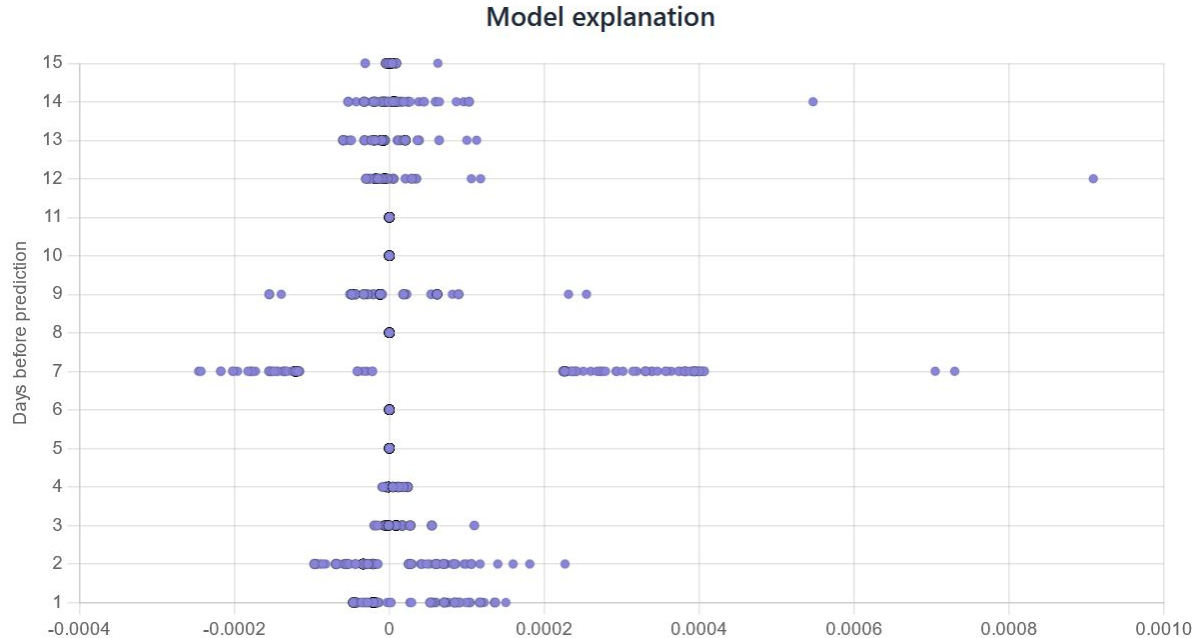
Advantage:

- Provides users with insights into overall feature importance.

Feature Explanation:

- Visual representation of SHAP values for feature importance (Spread-out points: High feature impact, Points near zero: Minimal impact)

Bee Swarm Plot for Global Explainability



Bee swarm plot of SHAP values for feature importance across all the dataset.

This chart illustrates the overall behavior of the model, showing how different days generally affect predictions. Spread-out dots indicate significant impact, while dots near zero show minimal effect.

Codebase Changes for Global Explainability

Implementing this feature required understanding and modifying the codebases across multiple topics:

Topic 7	Updated ForecastExplainer to calculate and return global SHAP values alongside predictions.
Topic 4	Interface classes managing communication between the backend and GUI were updated to include global SHAP values in their structures.
Topic 6	A new GUI section was added to display the global SHAP values as a bee swarm plot, with clear instructions for interpreting the plot.

Update 2: Performance Optimization

Approach:

- Replaced LIME with SHAP for local explainability of predictions.
- Used **shap.TreeExplainer** for XGBoost, reducing perturbation steps.

Result:

- Execution times were significantly reduced in both test and real-world scenarios:
 - a. Local: 94.54% reduction.
 - b. Website: 82.17% reduction.

Performance Measurements

Summary of Results (obtained with 10 measures averaged):

- Local Machine: Before: 2.93s → After: 0.16s.
- Website: Before: 4.60s → After: 0.82s.

Environment	Sequence Length	Predictions	Method	Time (seconds)	Reduction (%)
Local Machine	15	30	LIME + Bootstrapping	2.93	-
Local Machine	15	30	SHAP + Bootstrapping	0.16	94.54
Website (with GUI)	15	30	LIME + Bootstrapping	4.60	-
Website (with GUI)	15	30	SHAP + Bootstrapping	0.82	82.17

Alternative Approaches

Residuals-Based Bounds:

- Residuals-based bounds were explored and developed as an alternative.
- Allows for further executions time reduction.
- Challenges:
 - a. Lack of a validation set for proper residual estimation.
 - b. Reliance on normally distributed residuals (not guaranteed in this scenario).

Future Potential:

- This approach is suitable for scenarios with better-controlled data, where some samples can be reserved exclusively for residual computation.

Summary of Updates

Key Achievements:

- Introduced **global explainability** with SHAP values.
- Enabled deeper study of model behavior.
- Transitioned from LIME to SHAP for **faster local explanations**.
- Execution times were reduced by over 80%, now consistently under 1 second.

Final Output:

- Faster, more transparent, and user-friendly forecasting system.
- Provided a foundation for future updates and improvements.