AliO: Output Alignment Matters in Long-Term Time Series Forecasting

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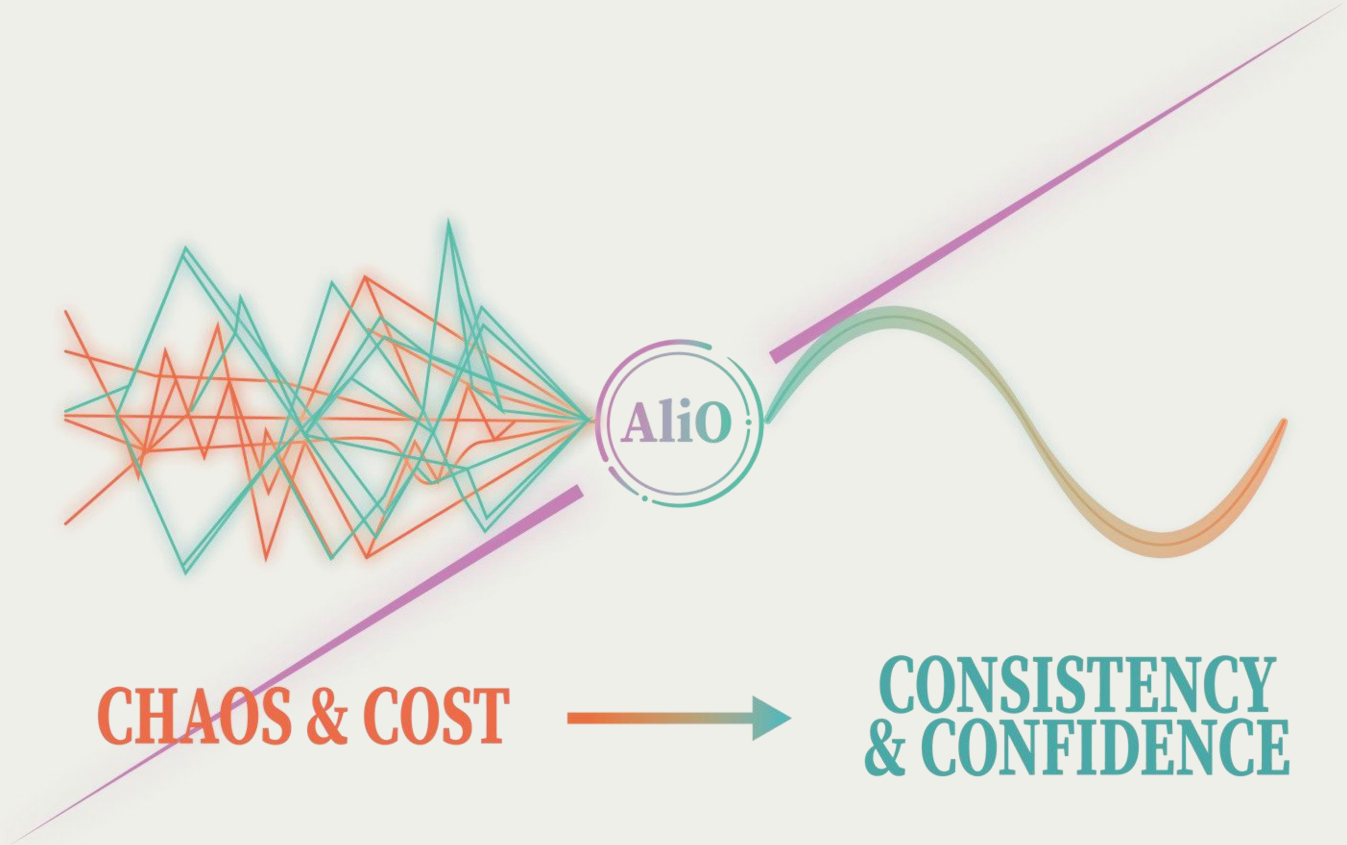

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NEURAL INFORMATION PROCESSING SYSTEMS

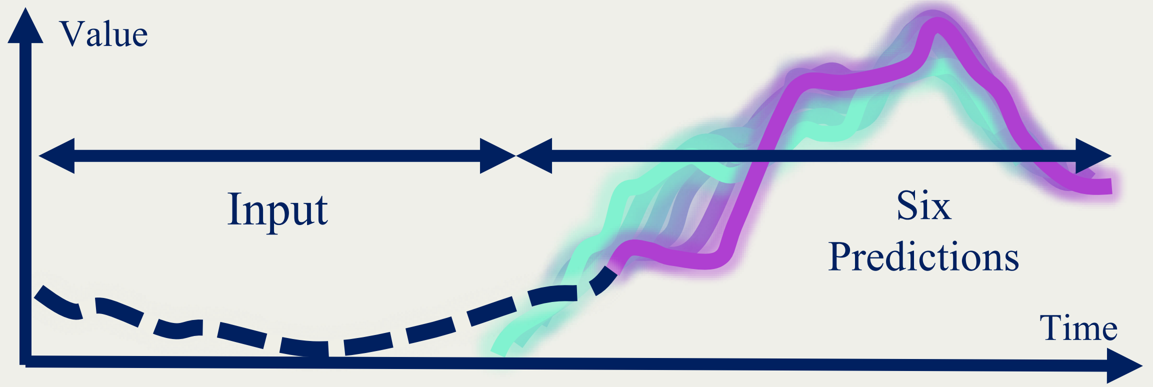
The Problem: Models are Accurate, but Not Reliable

Motivation

- Long-term Time Series Forecasting is crucial for real-world planning, like budgeting for electricity demand or weather forecasting.

The *Output Alignment Problem*

- The phenomenon where, during rolling forecasting, state-of-the-art models produce inconsistent predictions for the overlapping future timestamp.

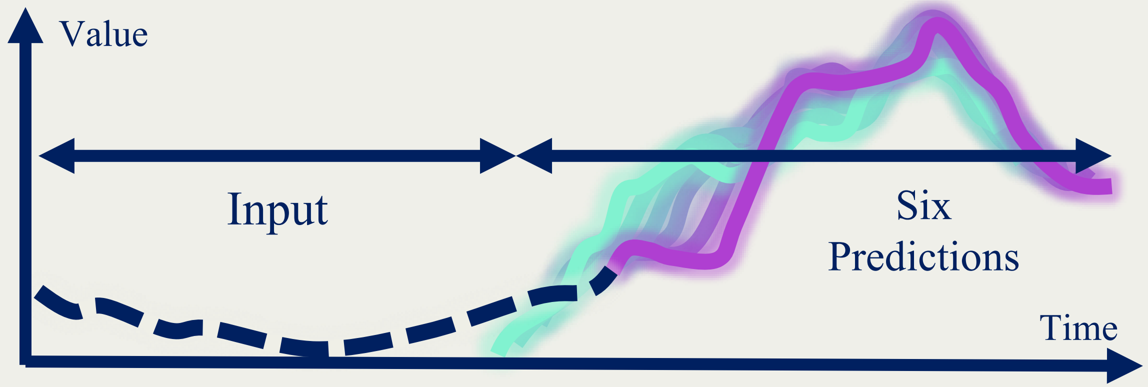


Chaos & Misaligned Prediction

The Problem: Models are Accurate, but Not Reliable

Why This Matters (Societal Impact)

- *User Distrust*
  - Fluctuating forecasts make users lose trust in the system.
- *Economic Waste*
  - Inconsistent predictions (e.g., for energy demand) force costly rescheduling and budget reallocation, wasting time and resources.

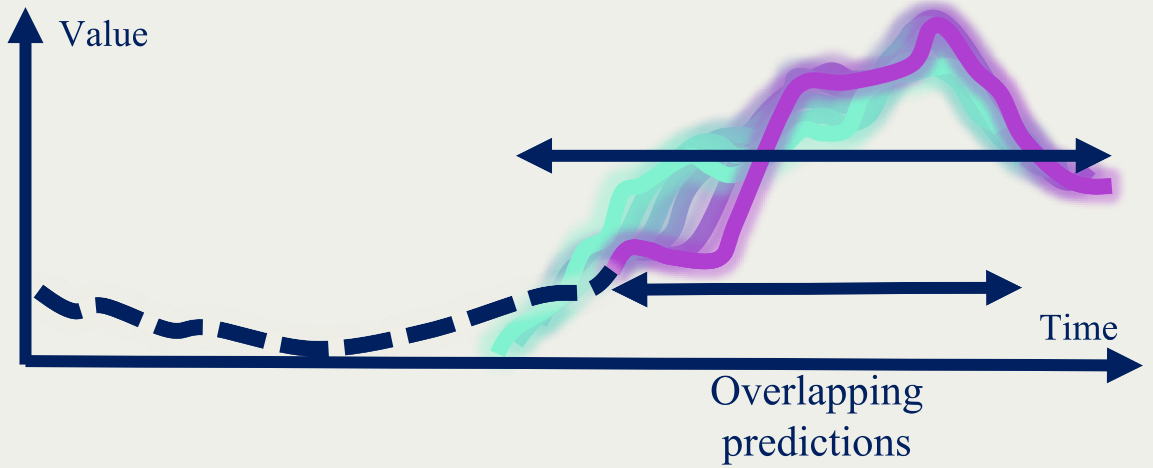


Cost & Mistrust

Our Solution: The TAM Metric & AliO Loss

A New Metric: TAM (Time Alignment Metric)

- *Motivation*
  - We can’t fix what we can’t measure.
  - Existing metrics like MSE only measure accuracy (prediction vs. ground truth), not consistency (prediction vs. prediction).
- *What it is*
  - We propose the TAM (Time Alignment Metric), the first metric to quantify output alignment by measuring the average discrepancy between overlapping predictions.



Our Solution: The TAM Metric & AliO Loss

A New Method: AliO (Align Outputs)

- *Objective*
  - To simultaneously improve output alignment (low TAM) and maintain or enhance forecasting accuracy (low MSE).
- *How it Works*
  - AliO is a novel loss function that minimizes the discrepancy between lagged predictions in both the time and frequency domains.
- *Model-Agnostic*
  - AliO is not a new model. It's a loss function that can be seamlessly added to any existing LTSF model (like PatchTST, DLinear, etc.) without modifying its architecture.

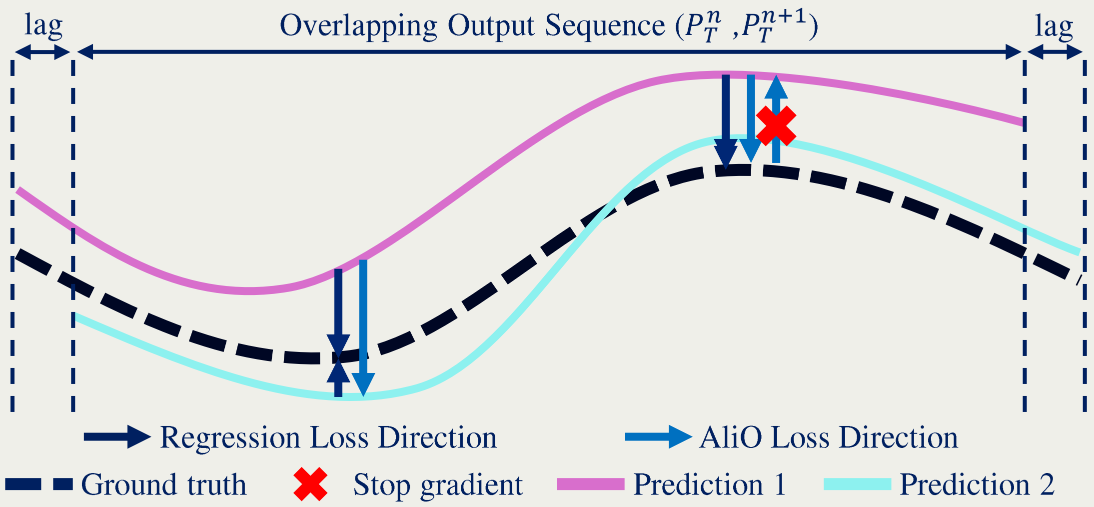
How AliO Works: Regression Pulling (RegPull)

- *The problem*
  - Simply minimizing `L2(Prediction 1, Prediction 2)` could hurt accuracy by pulling both predictions away from the Ground Truth.
- *Regression Pulling (RegPull)*
  - At each overlapping timestamp, identify which prediction point is closer to the Ground Truth.
  - Apply a `stop-gradient` operation to that closer point.
  - The loss now pulls the further point towards the closer point.
- *The Effect*
  - This ensures the alignment loss (AliO Loss) **only** moves predictions in a direction that **also** reduces the regression loss (MSE).
- *Result*
  - We improve consistency (up to 58.2%) and reinforce accuracy (up to 27.5%)

Dual-domain AliO

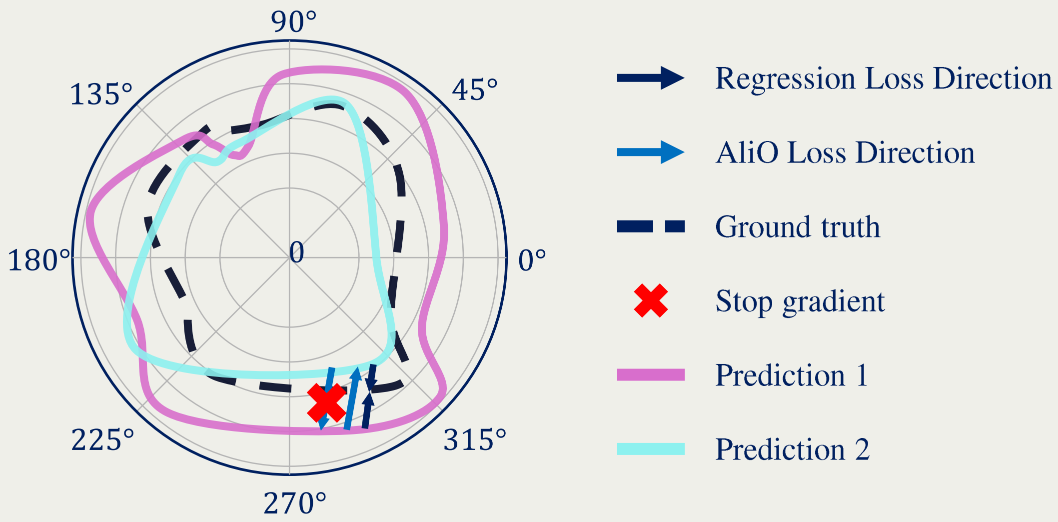
Time-domain AliO

- Red **X** is **stop-gradient** preventing the wrong direction.



Frequency-domain AliO

- Red **X** is **stop-gradient** preventing the wrong direction.

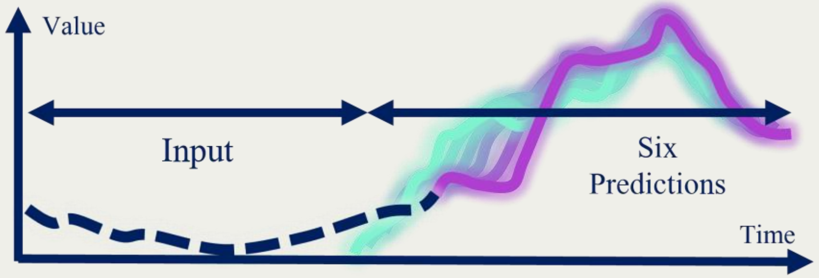


Radius: amplitude

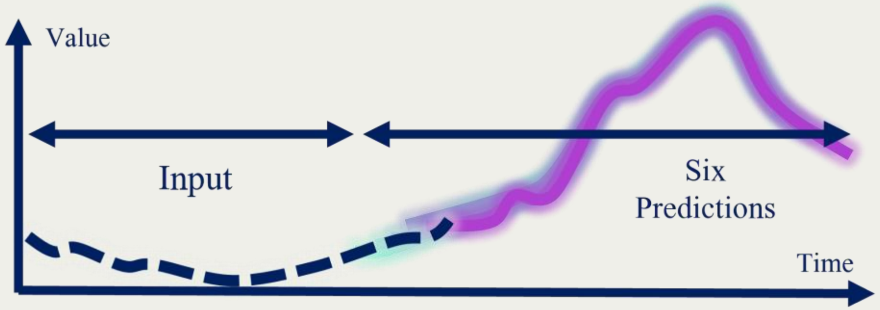
Angle: phase

AliO Improves Both Alignment & Accuracy

- **Quantitative Result**
  - Consistency (TAM): Achieved up to **58.2% improvement**.
  - Accuracy (MSE): Simultaneously **maintained or enhanced** forecasting performance by up to **27.5%**.
- **Qualitative Result**
  - Models trained with AliO produce stable and consistent forecasts.



Chaos & Misaligned Prediction



Consistent & Confident Prediction

Conclusion: Alignment is a New Pillar of LTSF

We...

- Identified the `Output Alignment Problem,` a key source of unreliability.
- Proposed TAM, the first metric to quantify this consistency.
- Developed AliO, a model-agnostic loss that fixes the problem, improving both reliability and accuracy.

Future Impact

- This work pioneers `Data-Model Robustness through time` - making models robust to overlapping timestamps.
- We argue that the field must treat consistency (TAM) as critical as accuracy (MSE) for building trustworthy, real-world forecasting systems (i.e., rolling forecasting).

Thank you