1. **Revisit this doc and outline key points**

**Response to Reviewers**

* Thank reviewers/editors
* Summary of major changes\*
  + **Re-writing/position paper**
  + **Data**
* We uploaded code and data to Github and posted revised paper on a pre-print server

**Associate Editor Comments:**      
  
The manuscript concentrates on a timely and relevant topic. The approach is original and the point is well supported. The reviewers and I see that the manuscript potentially brings some interesting novel ideas that could be worth of publication. However, at this stage, there seems to be quite a lot of work to be done for the paper to get there.

Thank you. We appreciate your interest in our work. As suggested, we have made significant changes to make the paper worthy of publication.

Besides the point of the reviewers, I would like to insist on the fact the presentation of the work needs a serious upgrade. For instance, A figure like Figure 1 cannot end up in the final version of the paper. I would encourage the authors to be careful in the way to design and produce that figure. Similarly, in general, the paper looks like a draft, which makes it a bit tricky at stages (e.g., when I checked the validity of equations...). Using a more "profession" text editor (possibly Latex) could help a lot in improving the readability and make the work easier for the reviewers and I. Finally, for the maths, it would be good to be really thorough, e.g., one does not need to use "\*" for multiplication, the flow of information around eq. (2) is quite confusing (possibly introduce relevant notation first, for diag, 1, among others), etc.. Similarly, algorithms could be better presented.

Thank you for the feedback. We have re-written the entire draft in LaTeX and overhauled the presentation of our figures and algorithms. We have thoroughly reviewed the math and writing to improve readability.

**Reviewer 1 Comments:**

The authors propose a matrix-based privacy method called k-nearest time series + (k-nTS+) swapping that preserves time series features to maintain forecast accuracy. The proposed privacy method has been applied to a forecasting competition data set and proven its advantages through a series of empirical studies. Overall, the paper is well-structured and written, while its contribution is clearly explained and justified.

Below you may find some comments that could help further improve the current work.  
  
1. Page 5: When first introducing the k-nTS+ swapping method in Figure 2, the authors should provide more details on how it works. The framework now is primitive.

Thank you for this suggestion, we have increased the amount of detail in Figure X on page XX to better illustrate our proposed k-nTS+ method.

2. Section 2.3:  The literature review of time series features for forecast accuracy could profit from including the relevant works such as:  
  
   Kang Y, Cao W, Petropoulos F, et al. Forecast with forecasts: Diversity matters[J]. European Journal of Operational Research, 2022, 301(1): 180-190.  
  
   Li L, Kang Y, Petropoulos F, et al. Feature-based intermittent demand forecast combinations: accuracy and inventory implications[J]. International Journal of Production Research, 2022: 1-16.  
  
   Montero-Manso P, Athanasopoulos G, Hyndman R J, et al. FFORMA: Feature-based forecast model averaging[J]. International Journal of Forecasting, 2020, 36(1): 86-92.

We appreciate this suggestion and have added these sources to our literature review on page XX.

3. Section 4.1: Why only use the monthly micro dataset from M3 competition? I recommend using all M3 competition data and discussing the performance of the proposed k-nTS+ method for the data with different frequencies. More recent M4 Competition data is also a better option.

Thank you for this suggestion. We have revised our empirical application to focus on the M4 competition data instead. We now include discussion of the accuracy results and chosen features broken down by time series frequency. These results are included on pages XX – XX.

4. Section 4.2: The authors should clarify the details of the feature selection, e.g., why select such features for k-nTS and add new features for k-nTS+. The process seems subjective. The authors should give all the alternative features and explain the reason.

Thank you for pointing this out. On page XX, we now differentiate between manual feature selection for the M4 data based on the literature (sources here) and our machine-learning based feature selection method. On average, our proposed feature selection method for k-nTS+ improves forecast accuracy by X% on average across the different M4 frequencies compared to manual feature selection.

5. A brief discussion of the computational cost is useful for other researchers.

We agree and have included this discussion on page XX.

6. Is there any reason for the error measures used in sections 4.4 and 4.5 to differ? If MSE does not provide significantly different results than MAE, personally I would prefer a consistent measure to be used for both sections.

Thank you, we now use MAE to assess both the accuracy of forecasts in Section 4.4 and the accuracy of the random forest predictions of the forecast MAE in Section 4.5.

7. Figure 6: Each diagram should be numbered differently, such as A.1, A.2, A.3, B.1, B.2, B.3.

Thank you, we have adjusted Figure X accordingly.

8. Figure 7: The ordinate title should not have "average"? It is unclear what "time series features for each privacy method" means exactly.

Thank you for pointing this out. We have adjusted the titles for Figure X to be more informative.

**Reviewer 2 Comments:**

The authors propose a method for preserving data privacy in time series data through a swapping technique. This approach focuses on maintaining forecast accuracy by swapping the data values only if the essential features of the time series, such as mean and autocorrelation function (ACF), are likely to remain unchanged. The proposed method assumes a centralized approach, where a single data owner possesses the time series data. In this scenario, a forecaster selects a forecasting model F, and the data owner performs data swapping to prevent a decline in F accuracy.  
  
While the idea sounds interesting, the paper requires further clarification and enhancements to address the following points:  
  
- Applications: The authors should provide further clarification on the potential applications of their proposed method.

Thank you.

* Imputing missing values
* Nowcasting
* Anonymization of commercially sensitive time series

We discuss these potential applications in Section XX on page XX.

- The authors should explain why the data owner cannot provide the forecaster with the original or degraded model weights. This comparison would help illustrate the advantages and limitations of the proposed approach. Additionally, discussing whether this method could be extended or applied to cases where data are owned by multiple data owners (decentralized scenario) would be beneficial.

Sharing the distribution (time series) is better than just the model parameters. We are sharing data that works well for multiple forecasting models.

\*\*Advantage: we are not assuming a model\*\*

Thank you for the suggestion.

Note that (Citations) focus on scenarios where a data owner provides the forecaster with model weights.

* The data owner *could* provide model weights, but…
  + this can expose sensitive time series values (citation)
  + the data owner faces increased burden from running and adjusting models on behalf of the forecaster
* Our method is advantageous because…
  + It produces protected time series with plausible features
  + An entire time series data set can be shared with forecasters who
    - Can assess various forecasting models
    - Can assess multiple use cases
* The forecasting competition use case requires time series data.
* Multiple data owners scenario
  + Data owners could each apply the method to their own time series before sharing/pooling data together
  + A central (trusted) party could apply the method after the data from multiple owners has been pooled – might increase willingness to share data by reducing privacy concerns (potentially an alternative solution to incentivizing sharing through a data market).
  + If data is limited, it might make sense to augment each data owners’ series with synthetic time series with similar features to give them something to swap with (future research?)

We include this discussion on page XX in Section XX.

- A crucial aspect missing is the impact of the swapping process on forecasting accuracy in a real-world setting. For instance, if a forecaster aims to perform a one-timestep ahead forecast using a VAR (Vector Autoregression) model with a lag of 1, he would require the value of X[T] to predict X[T+1]. Therefore, it is essential to evaluate whether the swapping process can change the last point of the time series without significantly affecting the forecasting accuracy.

Subsection for Var illustration + equations, maybe simpler model as well.

We’ve included a new data set to simulate a real world setting.

Figure 6 in the paper shows that the last point in the window is very close to the original one. Does this mean that a curious forecaster could reconstruct the data by running the model for some time?

Time series reconstruction is a valid concern particularly when time series models are shared that utilize lags of sensitive time series values (Citation here).

In our case, while the last value in the window appears to be very close to the original one, this will not always be the case. For example, the protected point in time period 59 is significantly lower than the original. A curious forecaster may attempt to reconstruct the time series data, but the success would likely be limited since swapping is performed on the basis of feature similarity, not the similarity of time series values.

Could discuss this from DP perspective

Could look at other privacy metrics – are time series features themselves privacy risks?

Under our scenario you only release one protected dataset

Detailed comments:  
- Acronyms meaning is missing. Some examples: SES, DES, LGBM, OOB, MSE, MAE, etc.

We have now provided the meanings for all acronyms.

- Equations should not be figures, e.g., (1) and (5).

We have re-written the paper in LaTeX and all equations are now properly formatted.

- Figures 2 and 8 should be of better quality.

We have revised Figures X and X to improve their quality.

- Figure 4: I suggest a unique plot with different color/shape lines representing the methods.

Thank you for this suggestion. We have revised Figure X accordingly.

- Notation needs to be introduced appropriately in many equations - see, e.g., (9).

We have added introductions to all notation where appropriate in the text.

- I would include the detailed proposal version in the main text.

**I believe this reviewer is referring to the detailed algorithm in the appendix?**

- Text needs revision. Typo example: "matices", sometimes ':' is used instead of '='.

Thank you. We have carefully edited the text for typos and to improve readability.