**Revision due October 19th**

8/21 – 8/25

*Running Code for Full M3 Dataset*

* Compare random swapping with swapping weighted by the correlation between the target series and the k-nearest neighbors
* Track computation time of:
  + ~~Generating baseline protected data sets~~
  + Training forecasting models on baseline data sets
  + Performing feature selection process using RReliefF and RFE
  + Performing k-nTS+ swapping
  + **Sum the above for total computation time of methodology**
    - Computation time will vary with the number of series automatically since there are different numbers of series across frequencies and domains
    - Decide whether we want to vary the number of features for a fixed number of time series to see how that affects computation time
      * The number of features would affect the feature selection and swapping processes only
* Save VAR model weights from original and *k*-nTS+ protected data sets
* Change error measures to MAE for consistency
* Rule for window selection
  + 2x seasonal period when sufficient data
    - Under this scenario, all features can be computed
  + Less than 2x seasonal period, have to choose window and adjust features (some require more than 2x seasonal period such as STL decomposition)

\*\*\* Made changes to code to improve computational speed.

* Reduced Bayesian optimization iterations to 15
* Reduced number of RNN ensemble models to 5
* Reduced RFE iterations to 25

8/28 – 9/01

* Finish results for M3 and M5 datasets
  + M5: take all disaggregates with the same frequency, do the swapping, check how one level up aggregates are forecasted (also see if the neighbor chosen was within the same sub-hierarchy)
    - LGBM on protected and unprotected disaggregates, compare that accuracy, and compare accuracy of aggregated forecasts
  + Perform reidentification attack on fake time series generated from protected and original VAR model weights (citation on time series reconstruction)
    - Simulate time series from VAR weights
    - Use the same sampled original time series points to re-identify the simulated series and the protected time series, compare identification probabilities
  + Need to compare original weights vs. degraded weights vs. original data vs. protected data
  + Compare information contained in *k*-nTS+ protected time series compared to simulated time series from VAR model weights
    - Visualize features of simulated time series from VAR compared to features of *k*-nTS+ protected series in principal components feature space (something like below). Allows us to compare joint distribution of all features, rather than comparing individual feature distributions
    - Presumably, the series from VAR would only have variation in a few directions corresponding to the features it maintains. This would result in much less diversity than what is shown in the plot below. The distributions from the original and k-nTS+ protected data will be similar.

A screenshot of a computer

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* + - Side-by side comparisons of the *k*-nTS+ protected version of time series compared to simulated VAR series (something like below)

A screenshot of a computer screen

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9/04 – 9/08

*Forecast for M5 data, VAR only protecting period T, and assemble results*

* Forecast for granular M5 data and aggregated M5 data
* Results for VAR model with only protecting the last time period of the time series
* Compute new results
  + Table of accuracy across frequencies

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* + Single table showing average feature ranks
* Overhaul existing figures (especially figure 1)
  + Replace ARIMA simulation with series A and B with useful features.
* Compare forecasts for aggregated M5 data to aggregated protected forecasts

9/11 – 9/15

* Re-write empirical section and add new results
  + Table displaying the average rankings of time series features selected for k-nTS+
  + Differentiate between manual features selection (based on the literature) and machine learning feature selection
  + Tables and results described above
  + Discussion of computational cost
    - Provide bounds?
  + Comparison of sharing protected data vs. protected model weights using results above
    - Discuss whether the method can be extended or applied to cases with multiple data owners
  + Discussion of swapping process in a real-world setting – M5 data, and VAR[1]
  + Discussion of how performance changes across data frequencies
  + Discussion of affects of data availability on available features and how this affects performance

9/18 – 9/22

*Re-write introduction and literature review*

* Add suggested sources from reviewer
  + 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.
* Add advantages and limitations of k-nTS+ compared to providing the forecaster with the original or degraded model weights
* Reposition the paper as proposing a machine learning based feature selection method paired with a swapping mechanism for privacy
* Reframe the contributions as outlined in the reviewer response document
* Improve diagram of k-nts+ (reference below as example)

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9/25 – 9/29

*Re-write method section and conclusions*

* Discuss potential applications of method (imputation, nowcasting, anonymization)
* Citation to support reidentification risk measurement (EMA?)
* Discuss limitation of only measuring one privacy risk
* Discussion of whether k-nTS+ can be extended/applied to cases where data are owned by multiple data owners

10/02 – 10/06

* Address minor reviewer comments (acronyms, introducing notation, etc.)

10/09 – 10/13

* Convert draft from Word to LaTeX

10/16 – 10/19

* Finalize and submit response document, revised paper, and submit

Send updated response document.

Email Matt and Jin with requests.

Need to be pushy.