1. Introduction
2. Literature Review
   1. Privacy and Forecasting
      1. Privacy preserving collaborative forecasting [1]
         1. Privacy concerns may manifest when a forecasting model requires personally private or commercially sensitive data from multiple sources
         2. Data transformation through noise addition (differential privacy) is simple to apply, but produces a trade-off between privacy and model accuracy
            1. Experiments showed that Laplacian noise significantly reduced the improvement of a VAR model over local AR models, with the AR model outperforming the VAR after data protection for a few data owners
   2. *Differential privacy can produce significant reductions in forecast accuracy. What about other data protection methods applied in univariate and multivariate settings? Data protection will adjust forecasts upwards or downwards from the original forecasted values. These adjustments parallel judgmental forecasting…*
   3. Judgmental Forecasting [2]
      1. Managers tend to exhibit ‘optimism’ bias, where upward adjustments tend to reduce accuracy, and downward adjustments tend to improve accuracy.
      2. Larger forecast adjustments are associated with accuracy improvements more than smaller adjustments (larger adjustments tend to be made when more certain about the forecast, smaller may be made for a variety of invalid reasons, e.g., exhibit control over forecasts, look like the manager is doing their job, etc.)
      3. Judgmental forecasts are inefficient, i.e., do not account for all available information optimally.
      4. Statistically significant association between forecast improvement and:
         1. Adjustment size (positive)
         2. Series volatility (negative)
   4. *While adjusted forecasts can be more accurate, there will be some level of information loss in the protected series. Some multivariate forecasting models may be able to overcome information loss in individual series using information from all series…*
   5. Global Forecasting Models [3]
      1. Simulations
         1. Complex, nonlinear global models are very competitive over local and linear global models when forecasting heterogeneous time series at both short and long series lengths.
      2. On real datasets
         1. LGBM performed the best (highest accuracy)
         2. Nonlinear global models are more competitive than local ARIMA and linear global in both homogenous and heterogeneous data scenarios
      3. Note that heterogeneous seasonal patterns can significantly degrade the performance of neural network models
      4. Including a clustering feature in global models can improve accuracy
3. Experimental Design
   1. Data
      1. M4 competition time series
         1. Allows us to test interaction between forecasting models and protection methods in different domains.
   2. Forecasting Models
      1. Local
         1. Exponential Smoothing
            1. SES
            2. DES
            3. TES
         2. ARIMA
         3. Facebook Prophet
         4. LinkedIn Greykite
      2. Global
         1. VAR
         2. LGBM
         3. RNN with LSTM cells
         4. NeuralProphet
   3. Protection Methods
      1. Top Coding (0.10, 0.20, 0.40)
      2. Bottom Coding (0.10, 0.20, 0.40)
      3. Additive Noise (1 and 2 standard deviations)
      4. Differential Privacy ( = 1, 2, 4.6, 10, 20)
      5. *k*-MTS
   4. Forecast Accuracy Metrics
      1. RMSE
      2. MAE
   5. Techniques to improve forecasting performance under privacy protection
      1. Global models – include additional covariates based on time series characteristics, e.g., spectral entropy, trend and seasonality strength, etc. (see *tsfeatures*), could be cluster indicators [3]
      2. This strategy may work particularly well with clustering-based protection schemes such as *k*-MTS
      3. Use this for the WHY, not improving accuracy
4. Results
5. Conclusion
6. References

[1] C. Gonçalves, R. J. Bessa, and P. Pinson, “A critical overview of privacy-preserving approaches for collaborative forecasting,” *Int. J. Forecast.*, vol. 37, no. 1, pp. 322–342, Jan. 2021, doi: 10.1016/j.ijforecast.2020.06.003.

[2] R. Fildes, P. Goodwin, M. Lawrence, and K. Nikolopoulos, “Effective forecasting and judgmental adjustments: an empirical evaluation and strategies for improvement in supply-chain planning,” *Int. J. Forecast.*, vol. 25, no. 1, pp. 3–23, Jan. 2009, doi: 10.1016/j.ijforecast.2008.11.010.

[3] H. Hewamalage, C. Bergmeir, and K. Bandara, “Global models for time series forecasting: A Simulation study,” *Pattern Recognit.*, vol. 124, p. 108441, Apr. 2022, doi: 10.1016/j.patcog.2021.108441.