Injecting External Metadata into Foundational Time-Series Models for Epidemiological Forecasting

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Motivation and Problem Statement

- Disease outbreaks demand rapid decision-making from public health officials, with early interventions being crucial for minimizing impact
- Quality forecasting of outbreak progression can save lives, but early-stage data limitations often hamper traditional modeling approaches
- Current gap exists for models that can quickly adapt to new diseases without requiring extensive disease-specific modeling
- Text-guided epidemiological forecasting represents an untapped opportunity to improve prediction accuracy and generalizability
- Study aims to enhance foundational time-series models by integrating text metadata for more adaptive and responsive disease forecasting

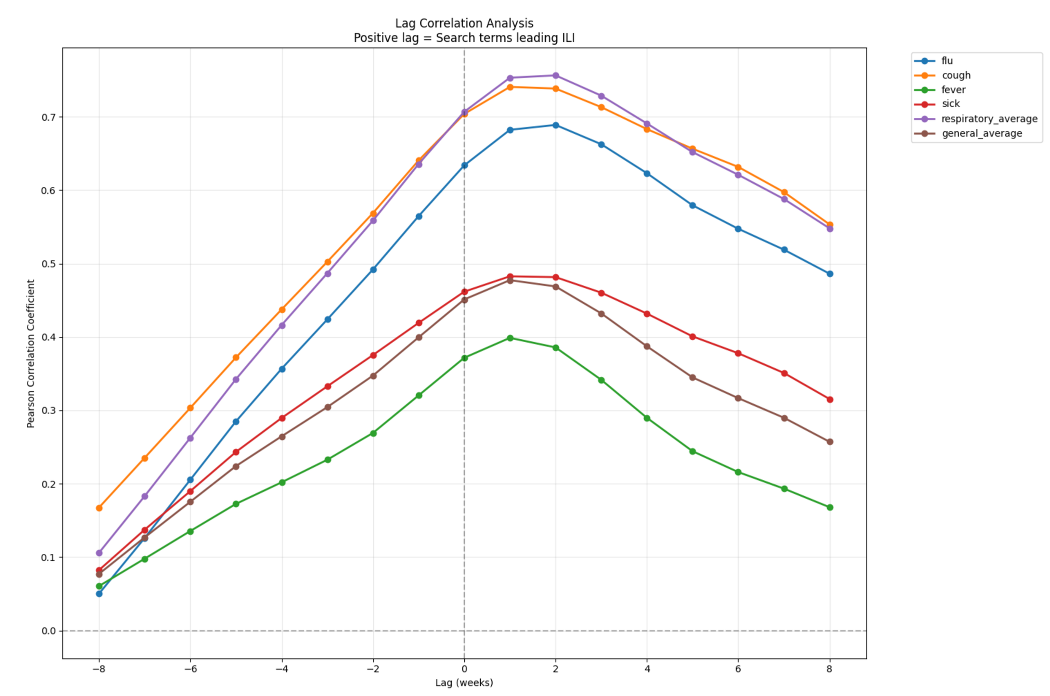
Data

- **Base Time-Series**: CDC Fluview Influenza-Like-Illness (ILI) surveillance data; downloaded through Fluview dashboard; weekly ILI data since 1997, 105 KB, 1412 records
- **Metadata:**
    - CDC Fluview PDF reports: Weekly CDC reports corresponding to ILI data since 2018 downloaded via webscraper; 247 entries; 6,047 KB
    - U.S Temperature Data: Temperatures averaged over NOAA stations across U.S., accessed through NOAA API, 438 KB, 4698 entries
    - Google Search Trends: Flu related search trends accessed through pytrends API since 2014, 574 entries, 23 KB
    - CDC Nationally Notifiable Infections Diseases and Conditions (NNDDSS): Weekly .txt reports for up to 117 diseases; downloaded via webscraper; 108,058 KB – 304 entries
    - New York Times: Article headlines containing flu related keywords; accessed via NYT API sine 2014

Proposed Approaches

- **Overall Approach**: Use Chronos, Amazon's foundational time series transformer, and SentenceTransformers to encode both time series and text input, combine them with cross attention and decode the fused encoding to get a forecasting output
- **Intuition:** Our approach leverages the best of both worlds: foundational models (FMs) trained on vast time-series data provide robust general forecasting capabilities, while the integration of disease-specific metadata allows for specialized adaptation to epidemiological patterns. This combination enables the model to both excel at standard forecasting tasks and respond dynamically to emerging health trends captured in metadata like news coverage.
- **Why it works:** Our overall approach to integrating metadata is supported by prior work [1]. The lag analysis below depicts the usefulness of our metadata as predictors.

Figure: PCC Lag Analysis with Search Terms



Conclusions & Next Steps

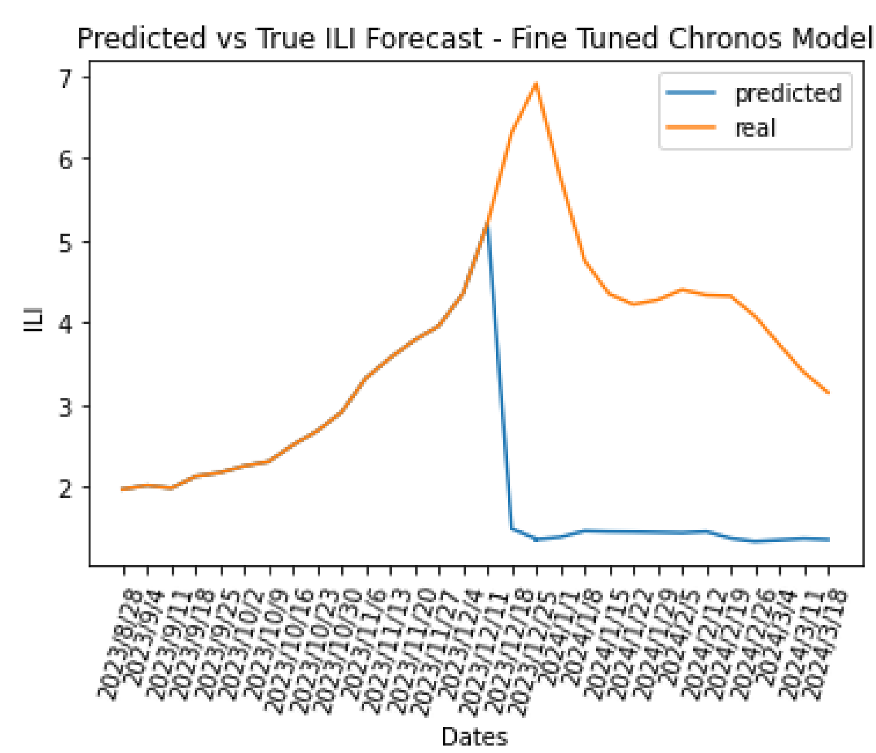
- **Overall**: Text-based metadata can be used with a time series FM to improve epidemiological disease forecasting
- Our approach offered improvements offer both the base FM and ARIMA methods
- Metadata allows for much better prediction accuracy and capturing of complex patterns
- **Next steps:**
    - Ablation studies to isolate effects of metadata sources
    - Clean metadata to reduce noisiness
    - Test method for other diseases and base time-series forecasting models

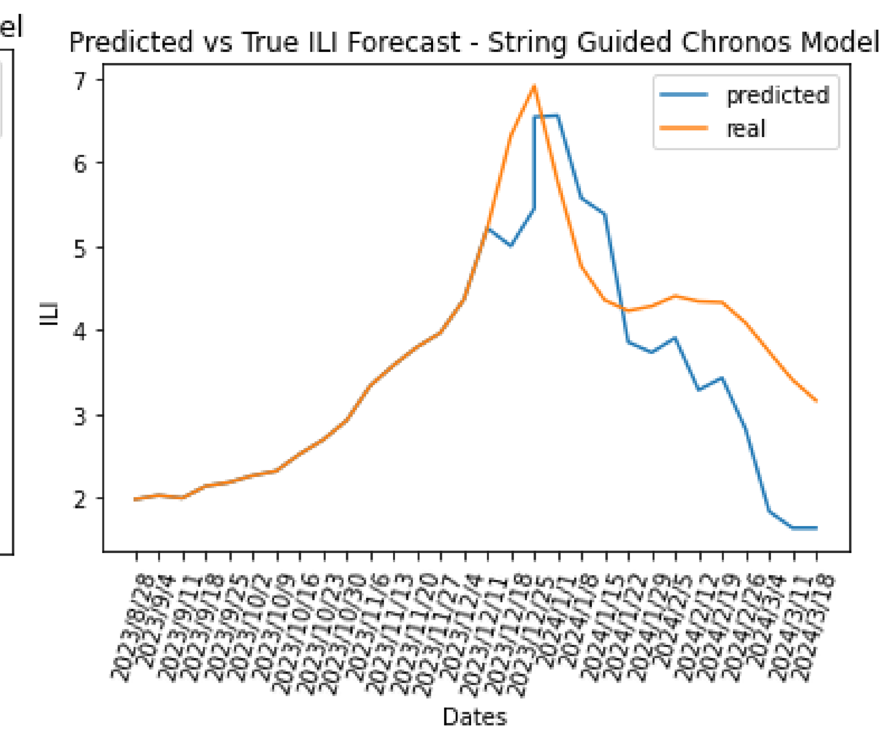
Experiment and Results

- Tested combinations of metadata inputs and fusion techniques
- All failed except using only the search term and temperature metadata with CrossAttention fusion
- Believe other metadata was too noisy
- Postulate that the sum and concatenation fusion modules failed to generate good results because they did not foster a synthesis that allowed for complex interactions between the string metadata and time series encodings
- With working model, compared Chronos fine-tuned on only ILI, Chronos infused with text metadata and ARIMA model
- *Chronos with text-metadata outperformed all compared methods:*

Model	MSE
Text Metadata Integrated Chronos	3.46
ARIMA	4.12
Fine tuned Chronos (no text metadata)	5.41

- The plots below show the true data and the predictions for the two Chronos models on a snippet of the test set
- Base fine-tuned model tends to get "confused", predicting a large spike when the ILI is trending downward and shooting down when the ILI is supposed to spike. The text guided model is seemingly able predict complex trends in the data, for instance being able to peak when necessary and drop afterward in example





[1] Bian Y. Zhong J. Wen X. Xu-Q. Xu, Z. 2024. Beyond Trend and Periodicity:Guiding Time Series Forecasting with Textual Cues. (May 2024). https://doi.org/10.48550/arxiv.2405.13522