Coronal and Solar Wind Models and Data Used to Drive and Validate Them

Science, Engineering, Computer Science

Daniel Iong *(daniong@umich.edu)*

University of Michigan, Ann Arbor

Mentor: Charles Nick Arge (GSFC 6710), *charles.n.arge@nasa.gov*

Co-mentors: *Michael Kirk (michael.s.kirk@nasa.gov), Daniel Da Silva (daniel.e.dasilva@nasa.gov)*

Abstract

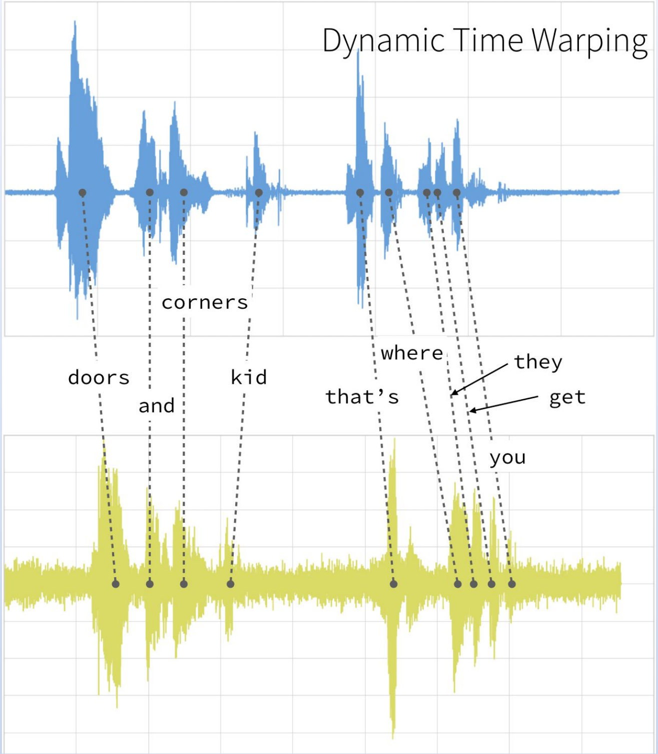
This project explores the use of dynamic time warping (DTW) for evaluating solar wind velocity and IMF polarity predictions from the Wang-Sheeley-Arge (WSA) model using an ensemble of ADAPT realizations as input. Dynamic time warping is an algorithm for measuring the similarity between two time series by first computing an optimal alignment between them. A canonical application of DTW is to cope with different talking speeds in speech recognition. Prediction models, such as the WSA model, have traditionally been evaluated using metrics such as root mean squared error or Pearson correlation coefficient. However, these metrics fail to account for local shifts and contractions between prediction and observation. We identify issues with applying the vanilla DTW algorithm to compare WSA model output with ACE observations and investigate potential extensions to mitigate some of these issues. Further work is needed to make the DTW algorithm more robust in this context.

Outline

1. Background
   - Dynamic Time Warping
   - WSA/ADAPT Model
2. Motivation
   - Example
3. Preliminary Results
4. Challenges/Open Questions
5. Summary

Background – Dynamic Time Warping (DTW)

- Algorithm for comparing two (*usually temporal*) sequences that may not be aligned/in sync (*local time-shifts, contractions, etc*)
- Used in a wide variety of domains (*speech recognition, financial markets, human motion analysis, etc*)



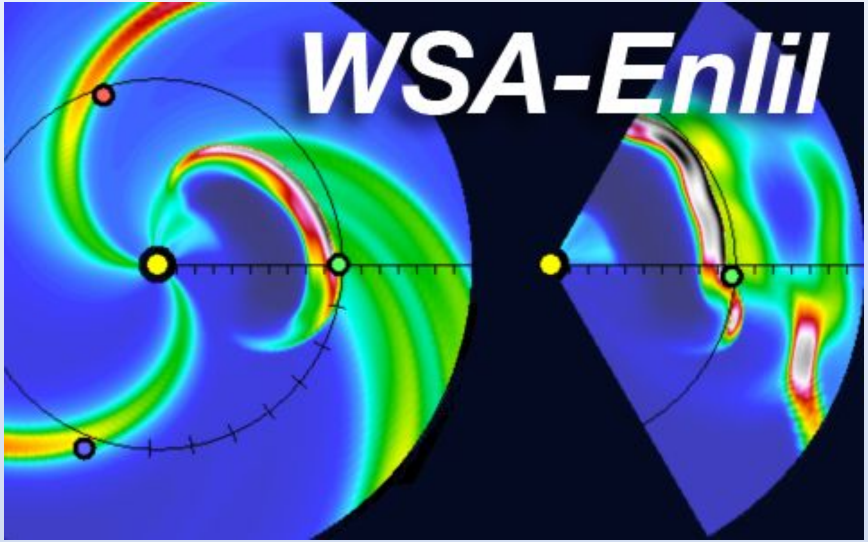
Source: https://databricks.com/blog/2019/04/30/understanding-dynamic-time-warping.html

Background – Dynamic Time Warping (DTW)

- DTW computes an optimal match between sequences subject to certain restrictions:
  1. Matching is monotonically non-decreasing
     - i.e. can't map points backwards
  2. Each point from one sequence must be matched to 1+ points in the other.
  3. Endpoints map to each other.
     - This can be relaxed.
- Only need to specify a distance measure between two individual points (e.g. Euclidean, absolute difference, etc).
  - Sequences can be multivariate if an appropriate distance is specified.
- Solved by dynamic programming in polynomial time.
- Outputs 2 values:
  - Average distance between sequences after they've been matched.
  - How much sequences have been warped (warp area).

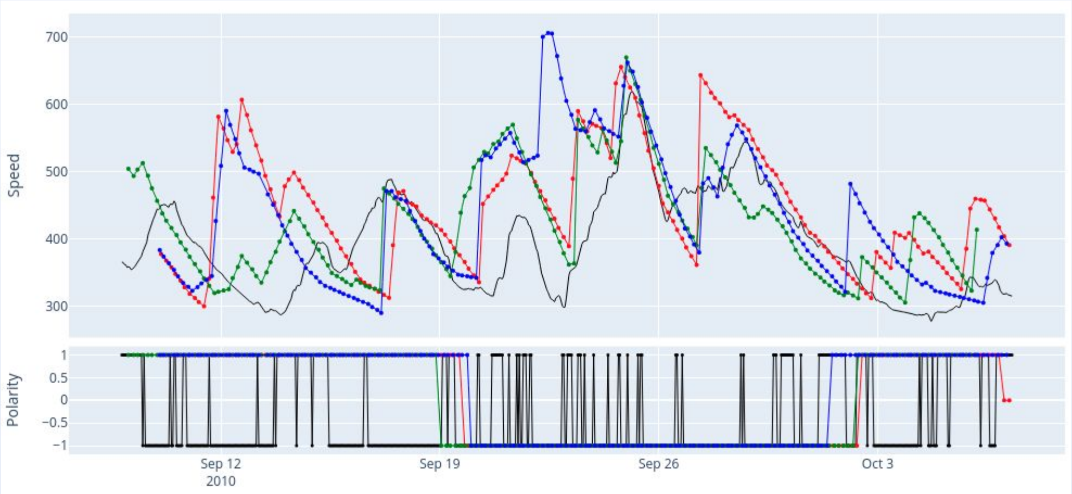
Background – WSA/ADAPT Model

- The **Wang-Sheeley-Arge (WSA) model** predicts solar wind speed and interplanetary magnetic field (IMF) polarity at any point in the inner heliosphere using global photospheric magnetic field maps as input.
- The **Air Force Data Assimilative Photospheric Flux Transport (ADAPT) model** provides ensemble sets of photospheric field maps (consisting of 12 realizations) that are used as input into models like the WSA model.



Background – WSA/ADAPT Model

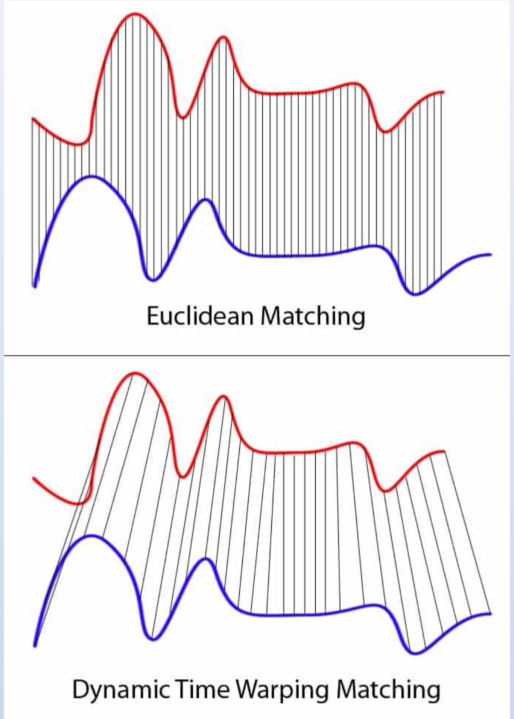
Example of WSA model predictions using 3 different ADAPT realizations as input:



- Not all 12 ADAPT realizations should be used as input into the WSA model
- Evaluation metrics are needed to choose the ones that produce the best agreement between WSA predictions and in situ observations.
- **Getting structure correct may be more important than timing.**

Root Mean Squared Error (RMSE)

- RMSE measures the **average squared difference** between points *with the same index*.
  - Adequate when ordering doesn't matter
  - Only measures differences in magnitude (y-axis) for time sequences
- RMSE is **restrictive** when used to compare time sequences
  - Doesn't account for differences in timing (x-axis)
  - Can only compare sequences of same length



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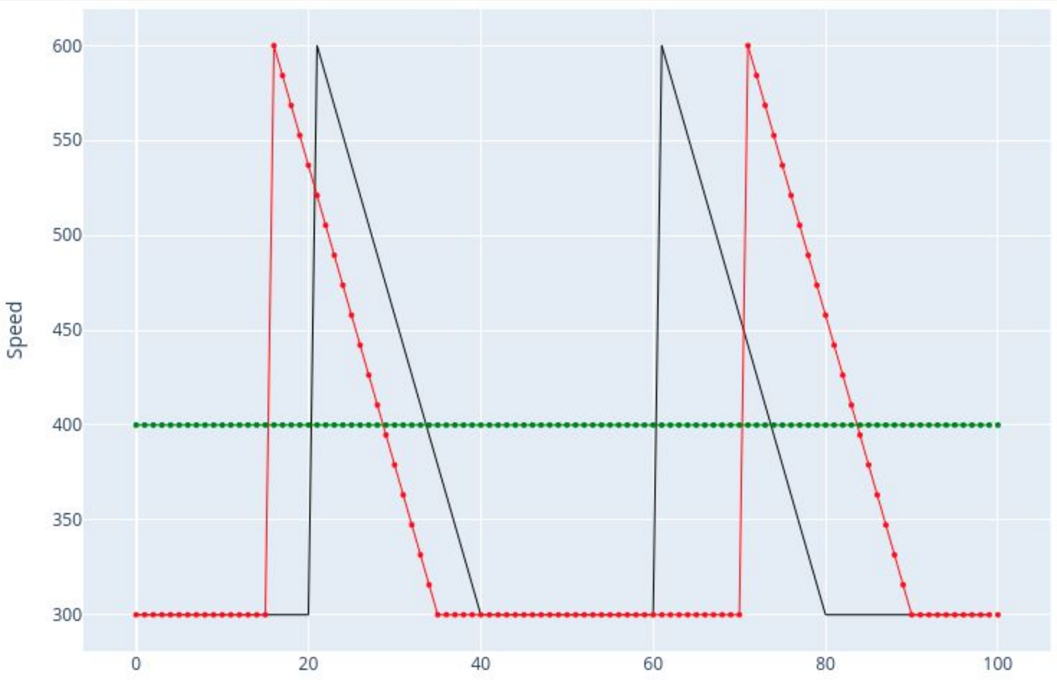
Motivation - Example

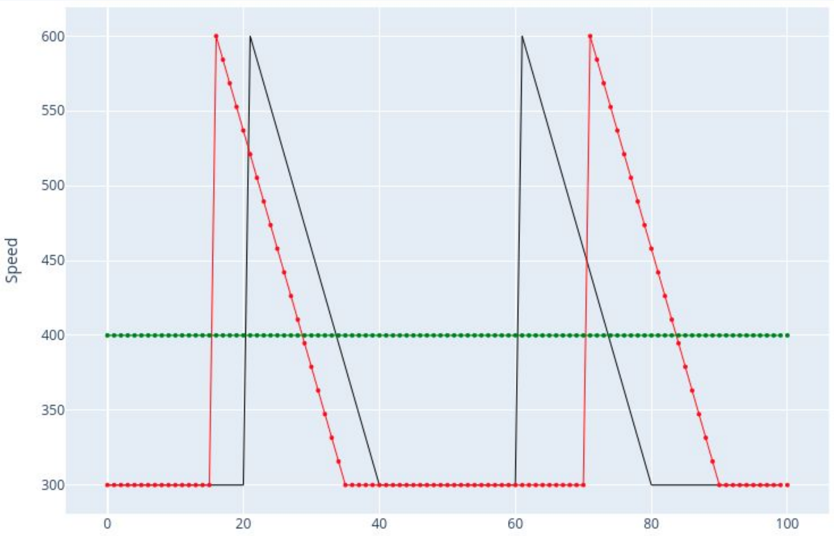
Which prediction is better?



Example taken from Owens et al. (2005)

Motivation – Example

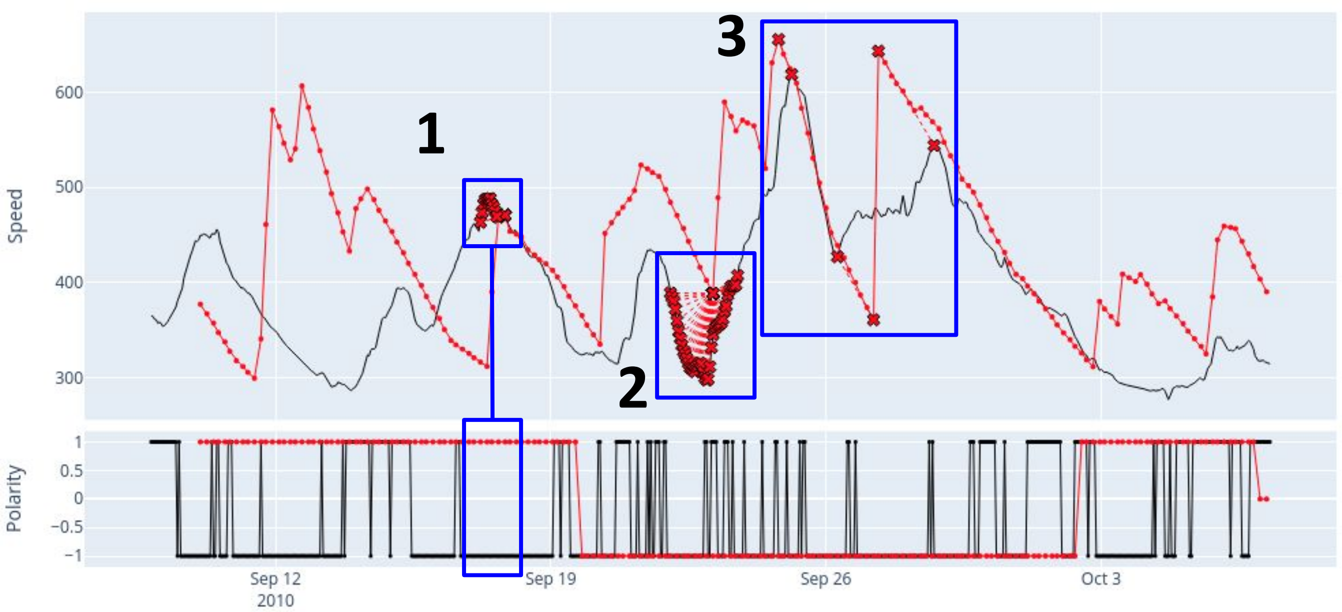
RMSE of straight line: 101.55
RMSE of predictions: 114.7
DTW distance: 0 ← diff. in magnitude (y-axis)
Warp area: 6.16 ← diff. in timing (x-axis)



- RMSE tells you straight line is better than predictions!
  - RMSE leads to an unintuitive evaluation.
- DTW matches the peaks correctly in this toy example.
- **Caveat:** Actual predictions rarely look like this.

Example taken from Owens et al. (2005)

Preliminary Results



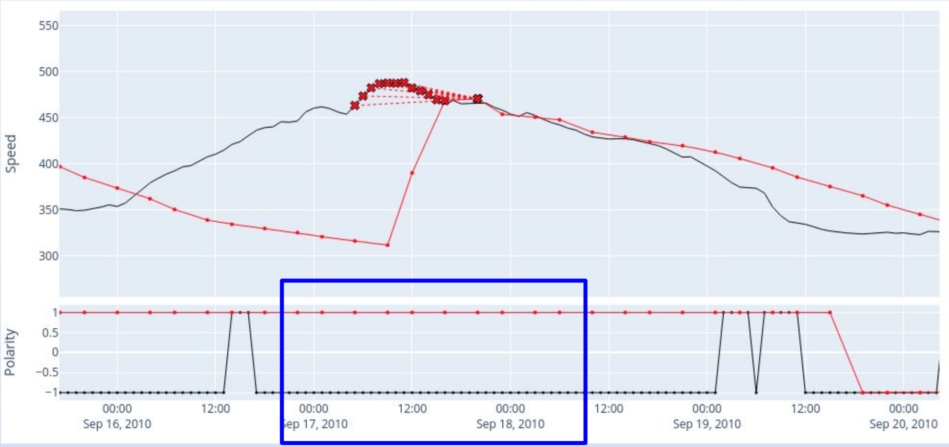
☹ 1. Speed looks good, DTW matches peak correctly, but IMF polarity is wrong.

☹ 2. Speed is overestimated, DTW matches dip to many points so structure is matched incorrectly.

☺ 3. Speed looks ok, DTW matches peaks correctly

Challenges/Open Questions

1. How to properly incorporate auxiliary variables (*e.g. IMF polarity*) into DTW?
    - Speed predictions are coming from wrong source region when IMF polarity is incorrectly predicted.
    - Directly incorporating IMF polarity into local distance is difficult.



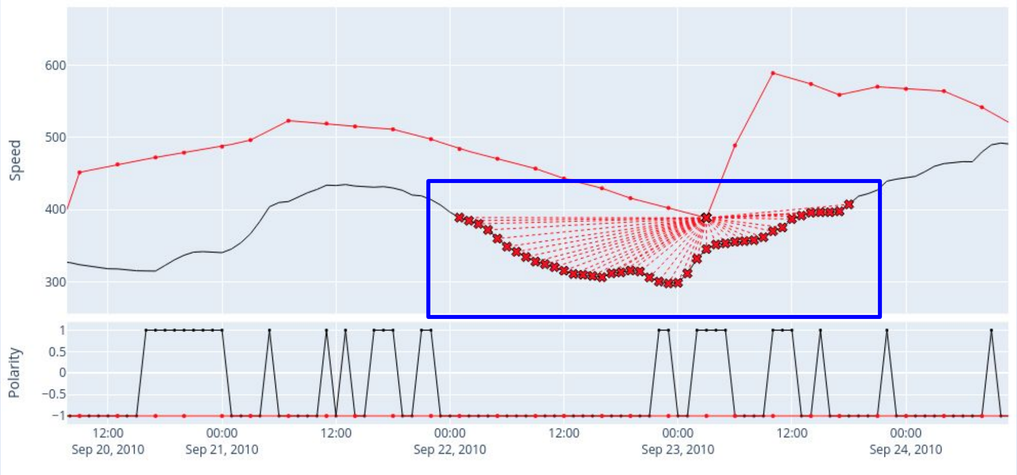
IMF polarity is incorrectly predicted in this region.

Proposed solution: Weighting scheme based on IMF polarity for calculating DTW distance

- Work in progress

Challenges/Open Questions

2. DTW sometimes matches one point to many points, especially when discrepancy between prediction and observation is large.



Proposed solution: weighted/penalized DTW (Clifford et al. 2009, Jeong et al. 2011)

Concluding Remarks

- There are still unanswered questions regarding the efficacy of DTW for WSA model evaluation.
  - What are desirable/undesirable properties of DTW?
- We are getting closer towards adapting DTW algorithm for WSA model evaluation
  - There are still open issues that we are investigating.
- Cross disciplinary collaboration is difficult but rewarding.
- **Next steps:**
  1. Extend DTW algorithm to tackle challenges mentioned.
  2. Construct more realistic toy examples to experiment with.
  3. Apply DTW to more data to evaluate robustness.

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