Predicting Time Lagged Effects of Solar Activity

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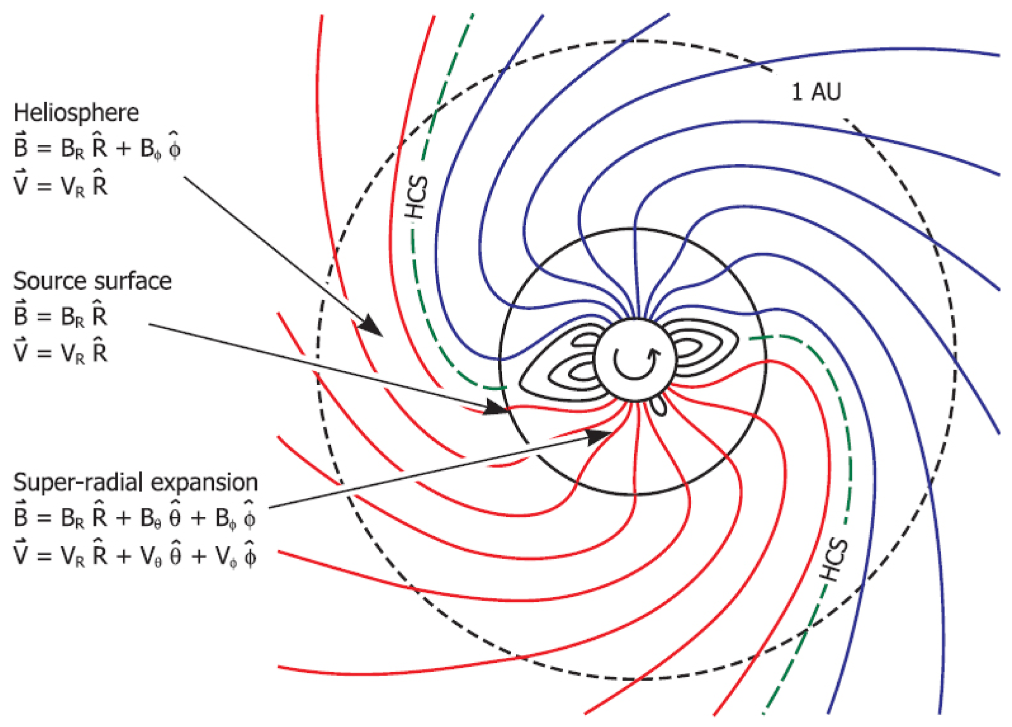
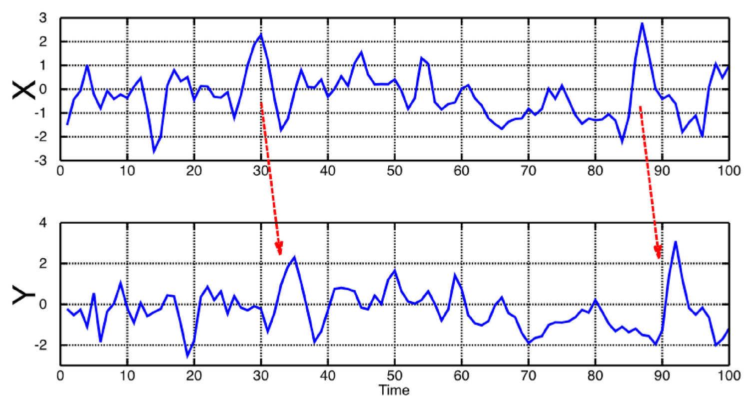
Origin of the Solar Wind



Supersonic expansion of the solar magnetic field leads to the formation of the *solar wind*. The charged particles follow the *Parker spiral* into the inter-planetary medium. Forecasting solar wind speed at 1 AU from solar observations is a challenging task because the propagation time of the solar wind is uncertain (2 to 5 days) and dynamic.

Dynamic Time-Lag Regression



Learning the the time delay between causes and effects, from data, is an important and challenging problem. We call this problem *Dynamic Time Lag Regression* (DTLR) and formulate it as follows.

1. **Inputs**: Two time series, the causes $x(t)$ and the observed effects $y(t)$
2. **Outputs**: A function $f : \mathcal{X} \to \mathbb{R}$ which maps each input pattern $x(t_1)$ to an output $y(t_2)$, and $g : \mathcal{X} \to \mathbb{R}^+$ which maps the time delay between the input and output patterns $t_2 = t_1 + g(x(t_1))$.

$$y(t+\Delta(t)) = f[x(t)]$$
$$\Delta(t) = g[x(t)]$$

Proposed Solution

Define for every time step t, a time window $[t+\ell, t+\ell+h)$.

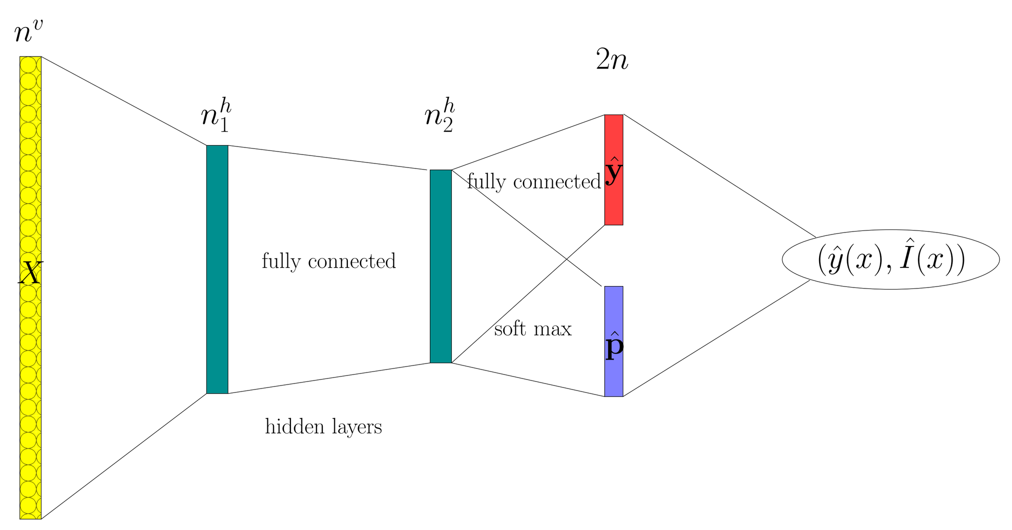
Inputs: Time series $x(t) \in \mathbb{R}^n$

Model Outputs:

1. Targets $\hat{\mathbf{y}} = [\hat{y}(t+\ell), \ldots, \hat{y}(t+\ell+h-1)]$
2. Time Lag Probabilities $\hat{\mathbf{p}} = [\hat{p}(t+\ell), \ldots, \hat{p}(t+\ell+h-1)]$, $\sum_{i=0}^{h-1} \hat{p}_i = 1$

Predictions: For an input $x(t)$, predict the target $\hat{y}(t+\ell+i^*)$ corresponding to the most probable propagation time $i^* = \arg\min_i \hat{p}_i(x(t))$

Architecture: The proposed model architecture takes the form of a neural network model as seen below.



Model Training: We need an objective/loss function which: 1. rewards accurate predictions for time window: $\hat{\mathbf{y}}$ and 2. penalises $\hat{\mathbf{p}}$ in a principled manner. After trying several candidates, we settled on:

$$\mathcal{L}[\mathbf{x},\mathbf{y};\hat{\mathbf{y}},\hat{\mathbf{p}},\sigma,\alpha] = -|T|\log(\sigma) - \frac{1}{n_m}\sum_m \Big[\sum_{i\in T} \frac{1}{2\sigma^2}\big(y_{m+i} - \hat{y}_i(x_m)\big)^2 - \log\big(Z_m(\hat{\mathbf{y}},\hat{\mathbf{p}},\sigma,\alpha)\big)\Big],$$

with n_m being the mini-batch size and Z_m is given as:

$$Z_m(\hat{\mathbf{y}},\hat{\mathbf{p}},\sigma,\alpha) = \sqrt{(1+\alpha)}\sum_{i\in T}\hat{p}_i(x_m)\exp\Big(-\frac{1}{2\sigma^2}\alpha\big(y_{m+i} - \hat{y}_i(x_m)\big)^2\Big).$$

After initialisation, the model parameters are updated in an alternating fashion. 1. Update the neural network parameters; keep α and σ fixed. 2. Update α and σ; keep the network parameters fixed.

Solar Wind Forecasting

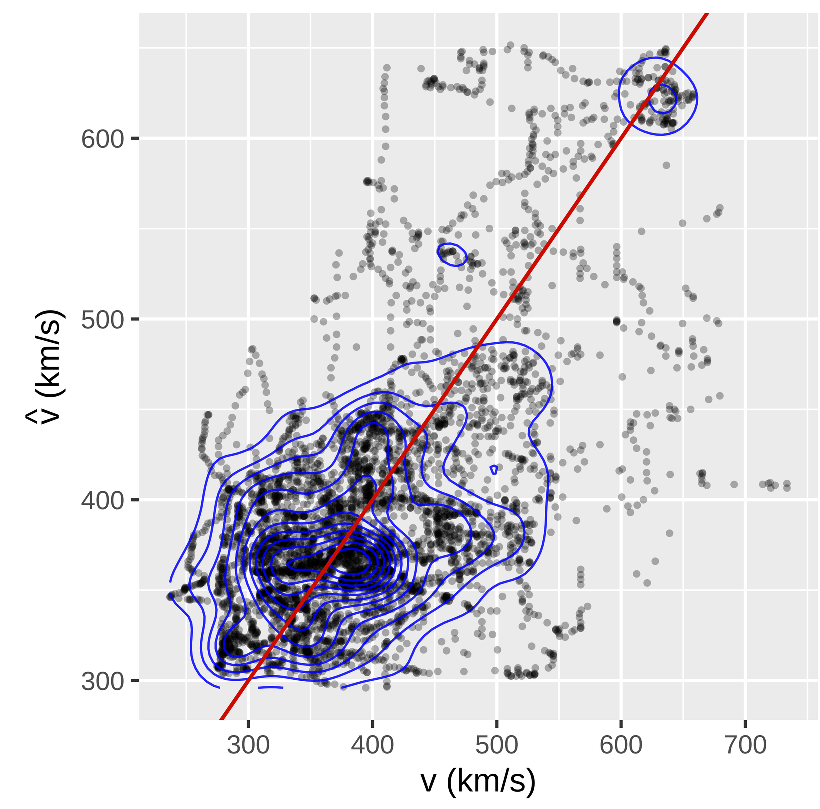
Input Data

- Magnetic flux-tube expansion $\log \mathbf{f}_S$ and source surface field $\mathbf{B}_{ss}$. Both computed from GONG synoptic maps using the *Current-Sheet Source Surface* (CSSS) [2] model.
- Φ, the Carrington longitude of the computed of each time-stamped $\mathbf{f}_S$.
- Sun spot number SSN and $F_{10.7}$ indices from OMNI.
- The solar wind speed 27 days before the data time-stamp, v_{27}

Validation: 9-fold cross-validation on Carrington rotations: 2077, 2090, 2104, 2117, 2130, 2143, 2157, 2171, and 2184.

Benchmarks: On Carrington rotation 2077, model benchmarks from Reiss et al. [1] were used. We also trained a fixed time-lag baseline model, which forecasts solar wind speed with a time horizon of $t + h/2$.

Results



Results of 9-fold cross validation.

Model	M.A.E	R.M.S.E
DTLR (this work)	54.41	66.22
Fixed Lag Baseline	67.33	80.39
WS [a]	74.09	85.27
DCHB [b]	83.83	103.43
WSA [c]	68.54	82.62
Ensemble Median (WS)	71.52	83.36
Ensemble Median (DCHB)	78.27	100.04
Ensemble Median (WSA)	62.24	74.86
Persistence (4 days)	130.48	161.99
Persistence (27 days)	66.54	78.86

Performance Comparison on CR 2077: DTLR , Fixed Lag Base Line vs Reiss et al. [1]

References

[1] *Reiss Martin A., MacNeice Peter J., Mays Leila M., Arge Charles N., Möstl Christian, Nikolic Ljubomir, Amerstorfer Tanja.* Forecasting the Ambient Solar Wind with Numerical Models. I. On the Implementation of an Operational Framework // The Astrophysical Journal Supplement Series. feb 2019. 240, 2. 35.

[2] *Zhao Xuepu, Hoeksema J. Todd.* Prediction of the interplanetary magnetic field strength // Journal of Geophysical Research: Space Physics. 1995. 100, A1. 19–33.

[a] Wang Sheeley
[b] Distance from the Coronal Hole Boundary
[c] Wang Sheeley Arge