What is the intrinsic dimensionality of the OMNI data? A dimensionality reduction study

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OMNI2 low-resolution data set

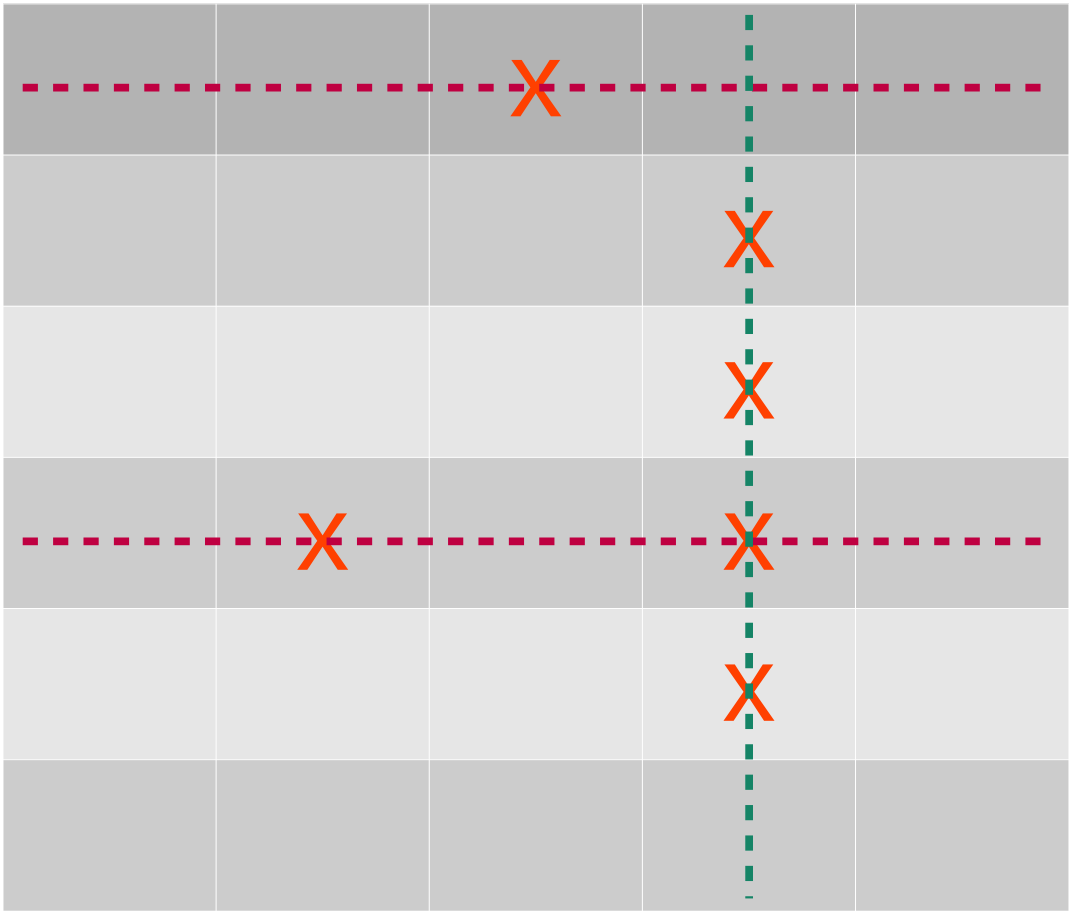
- 52 variables
  - IMF data
  - Solar wind parameters
  - Geomagnetic and solar activity indices
  - Energetic proton fluxes
- Hourly averages 1975 – 2019
- Non-physical variables removed (e.g. spacecraft ID)

[Credits: GSFC/SPDF and OMNIWeb]
https://spdf.gsfc.nasa.gov/pub/data/omni/low_res_omni/

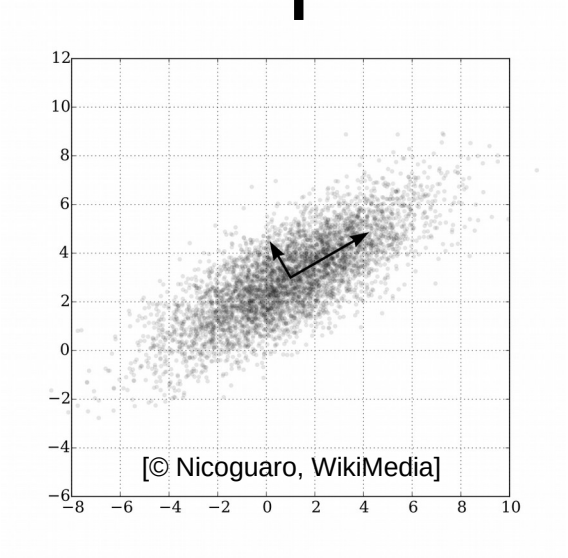
Data preprocessing

Step 1: Remove columns with too many missing values

Step 2: Remove rows with any missing value

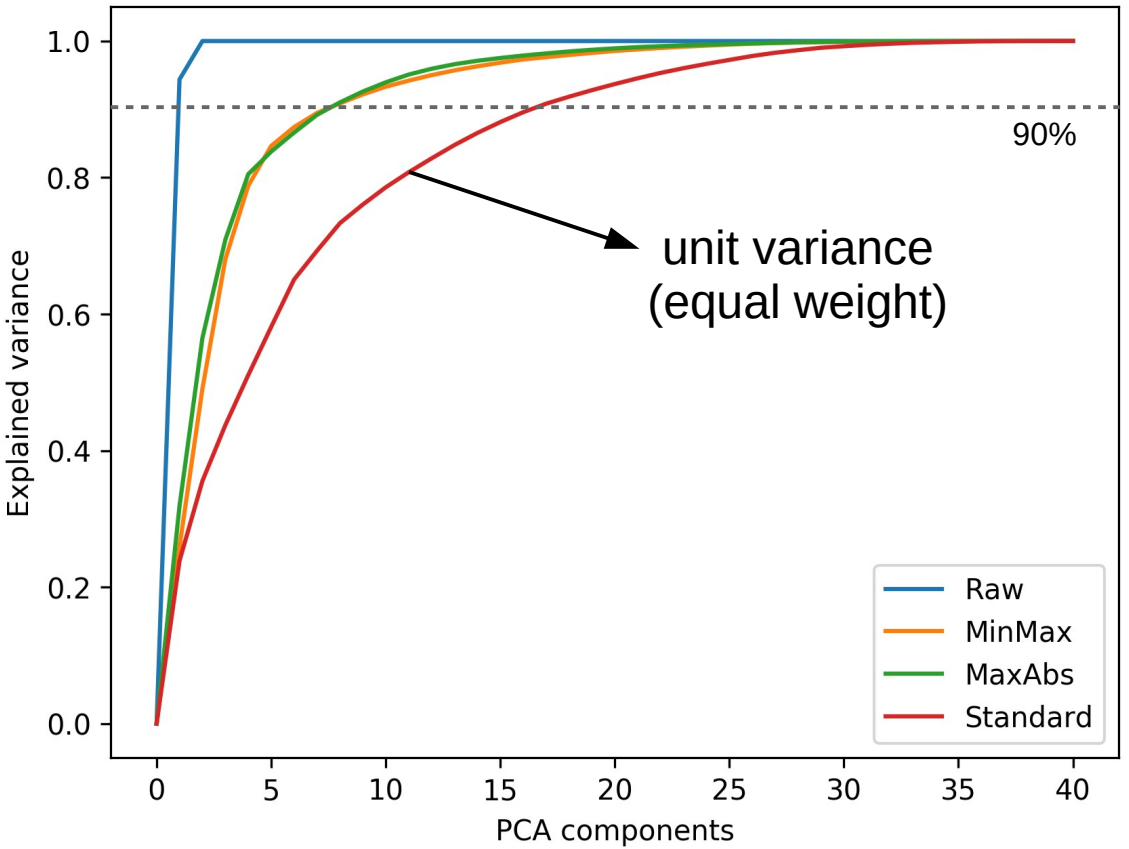


Principal Component Analysis (PCA)

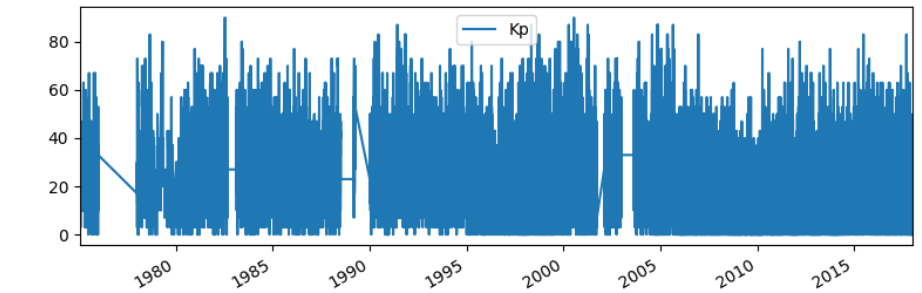


- Linear transformation
- Components in direction of most variance

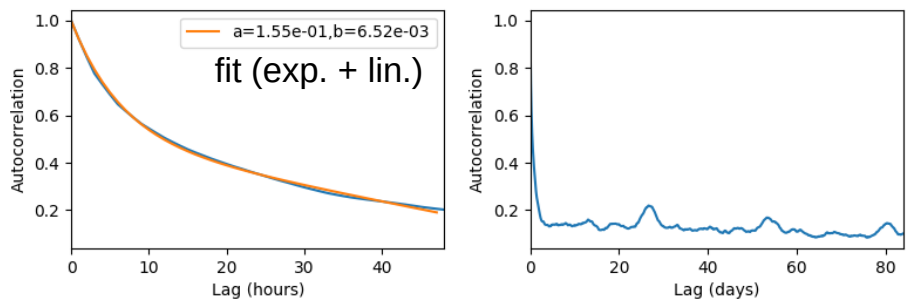
- Normalization is important!
- Difficult to interpret here



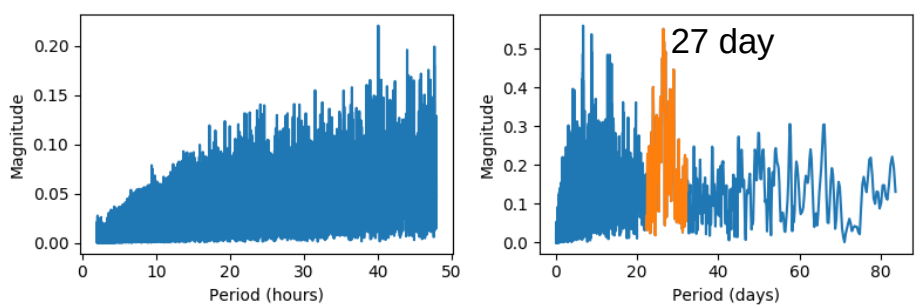
Exploring data – Kp example



Time series



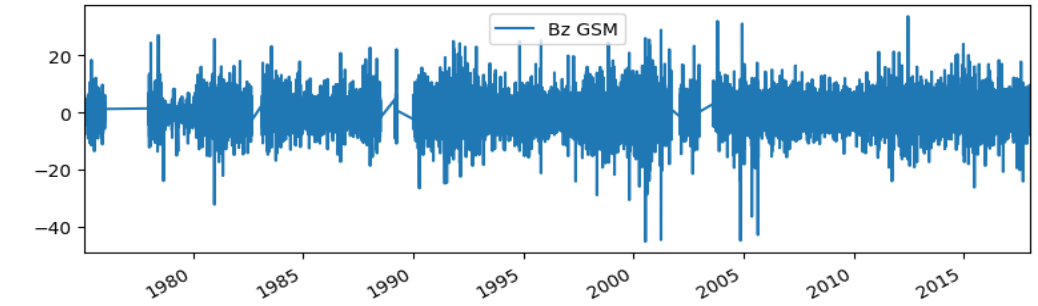
Autocorrelation

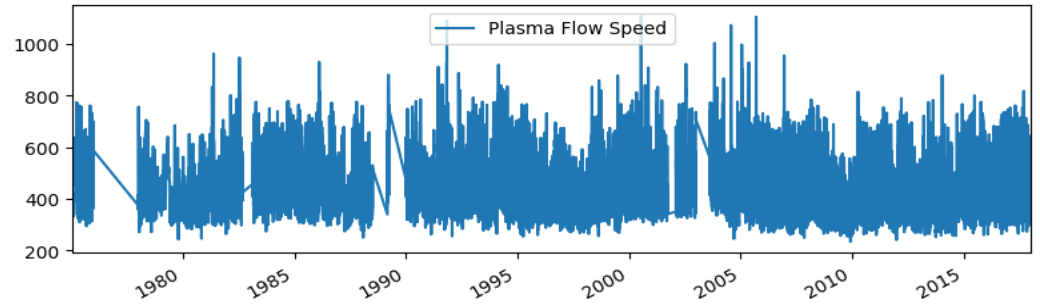


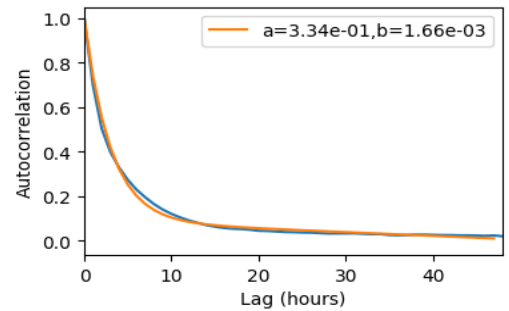
Fourier spectrum

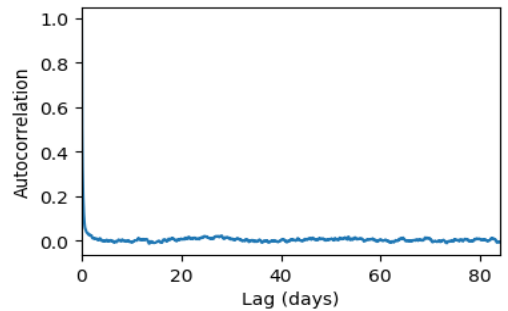
Bz GSM

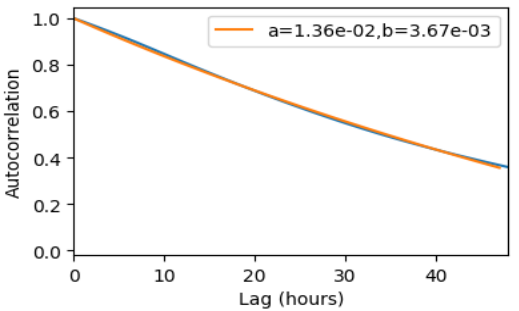
Plasma Flow Speed

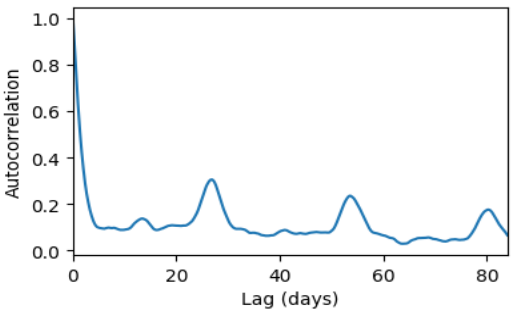


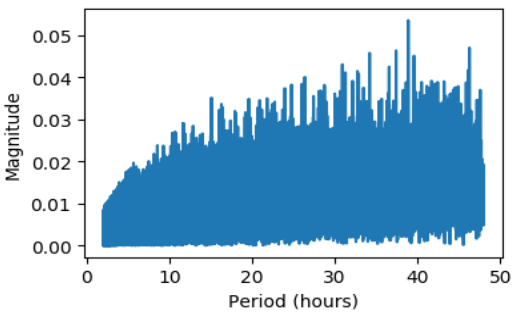


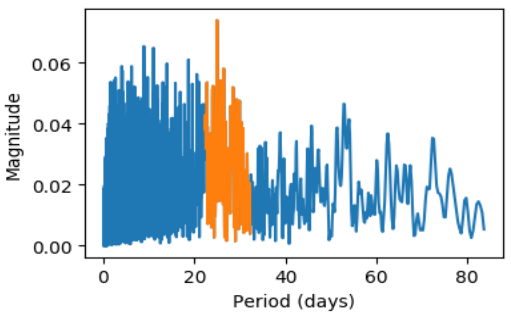


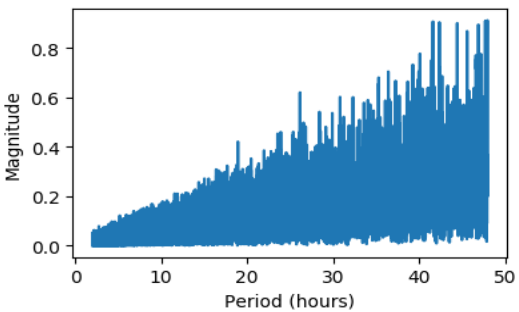


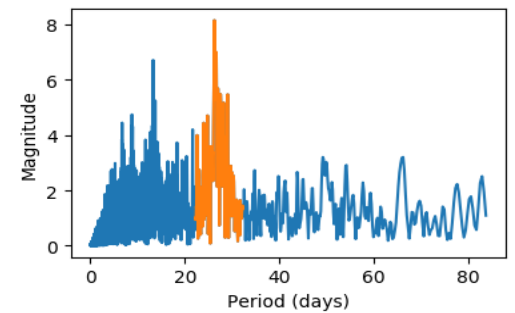




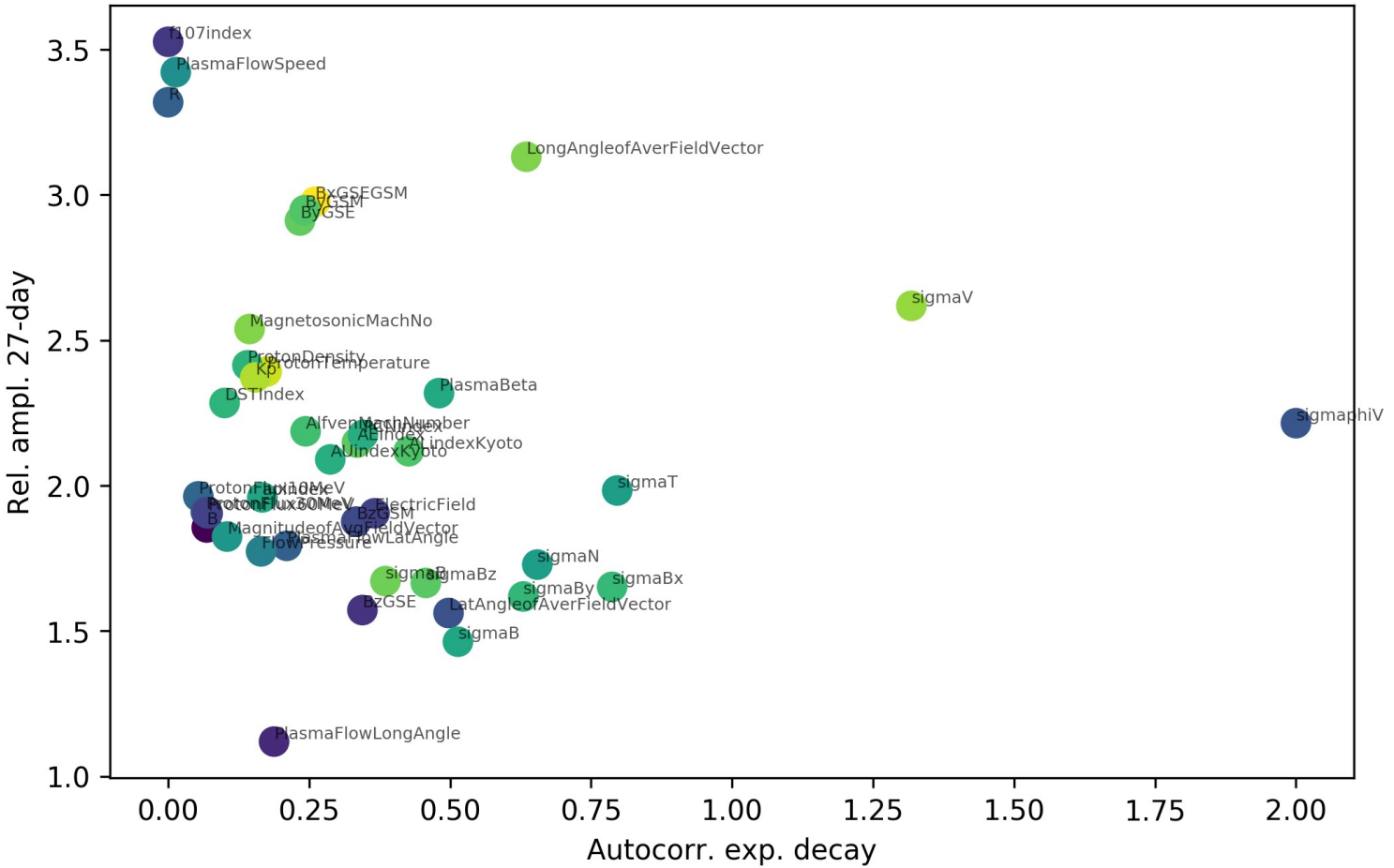








Distribution of variables



Ranking variables by predictive power

- Linear model (**y** = A**x** + **b**)
  - Feature: x_i
  - Target: **X** = (x_1, x_2, …, x_N)
- Measure R^2 score (components or average)

$$R^2 = 1 - \frac{\langle (f(x) - y)^2 \rangle}{\mathrm{Var}(y)}$$

$\bar{R}^2$	**Top 5**
0.188	Kp
0.180	AE Index
0.167	ap index
0.162	AL index (Kyoto)
0.161	sigma B
0.160	PC(N) index

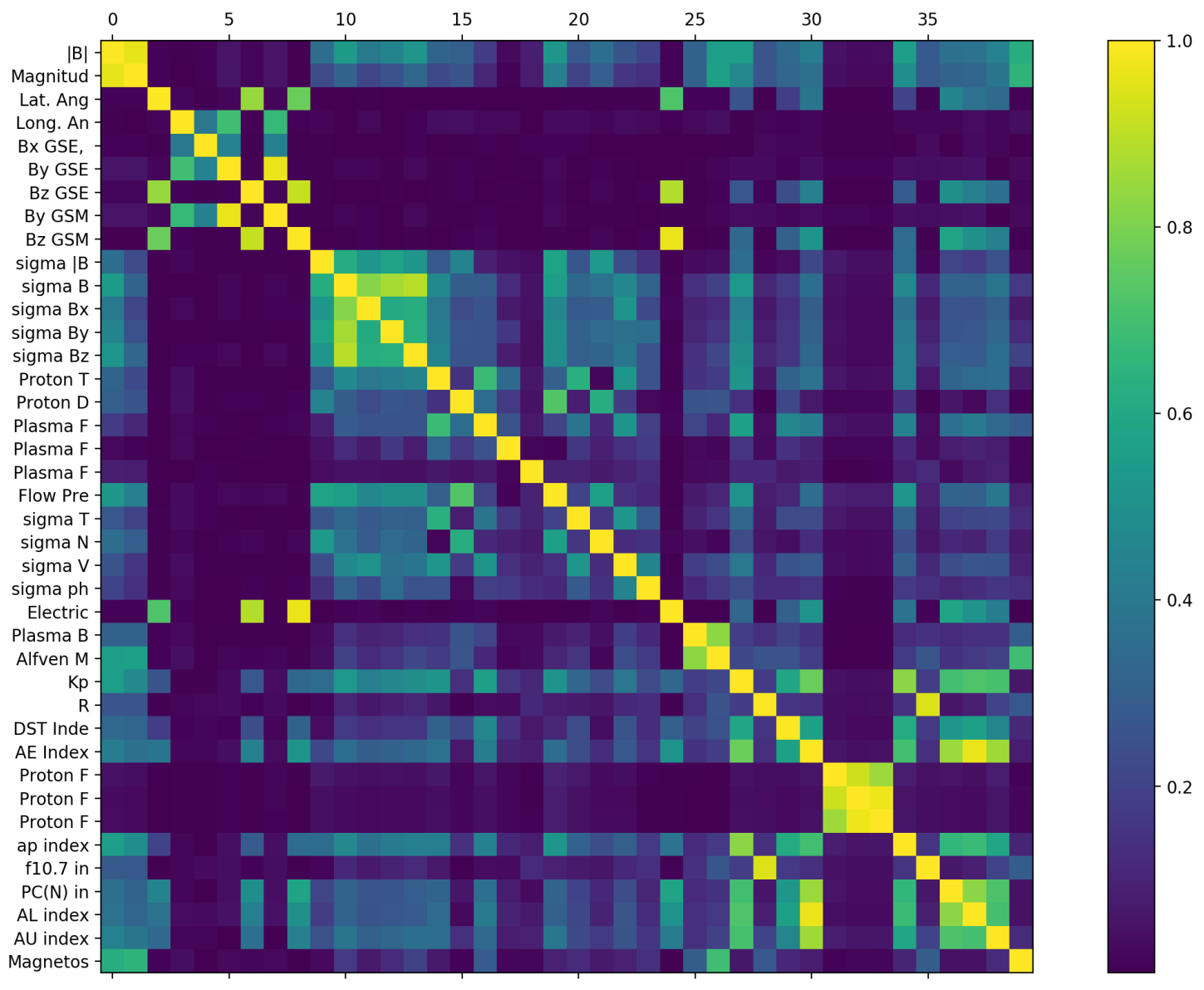
Which variables do they predict?

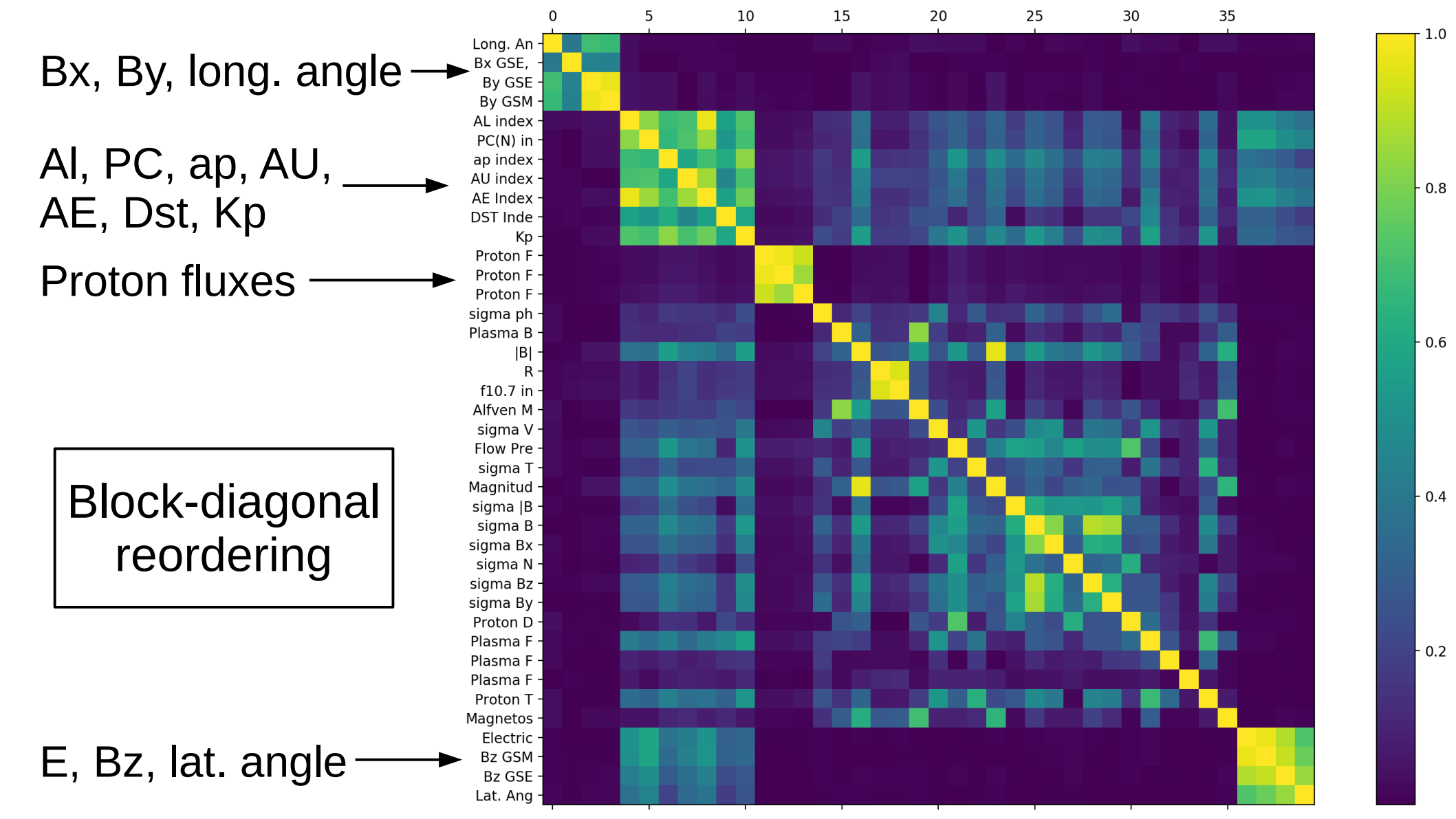
$\bar{R}^2$	**Bottom 5**
0.0608	Plasma Beta
0.0539	sigma phi V
0.0525	Long. Angle of Aver. Field
0.0387	Bx GSE, GSM
0.0361	Plasma Flow Long. Angle
0.0290	Plasma Flow Lat. Angle

Correlation matrix

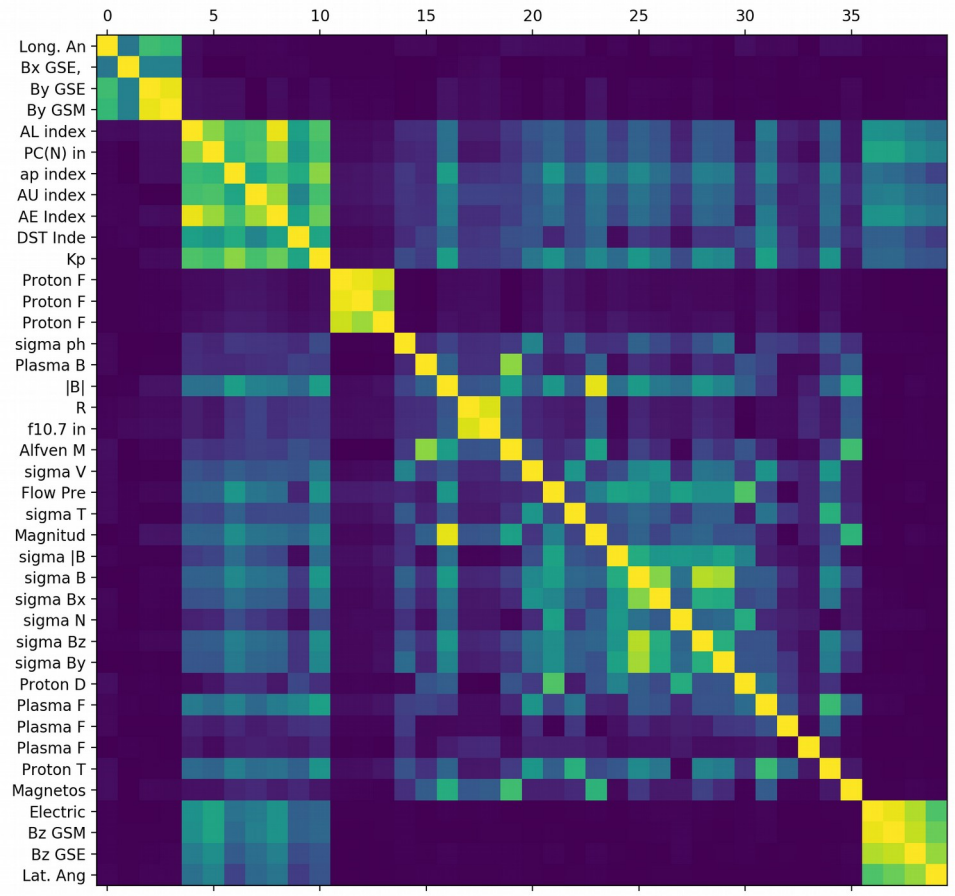
For a linear model

$$\mathrm{corr}(x, y) = \sqrt{R^2}$$

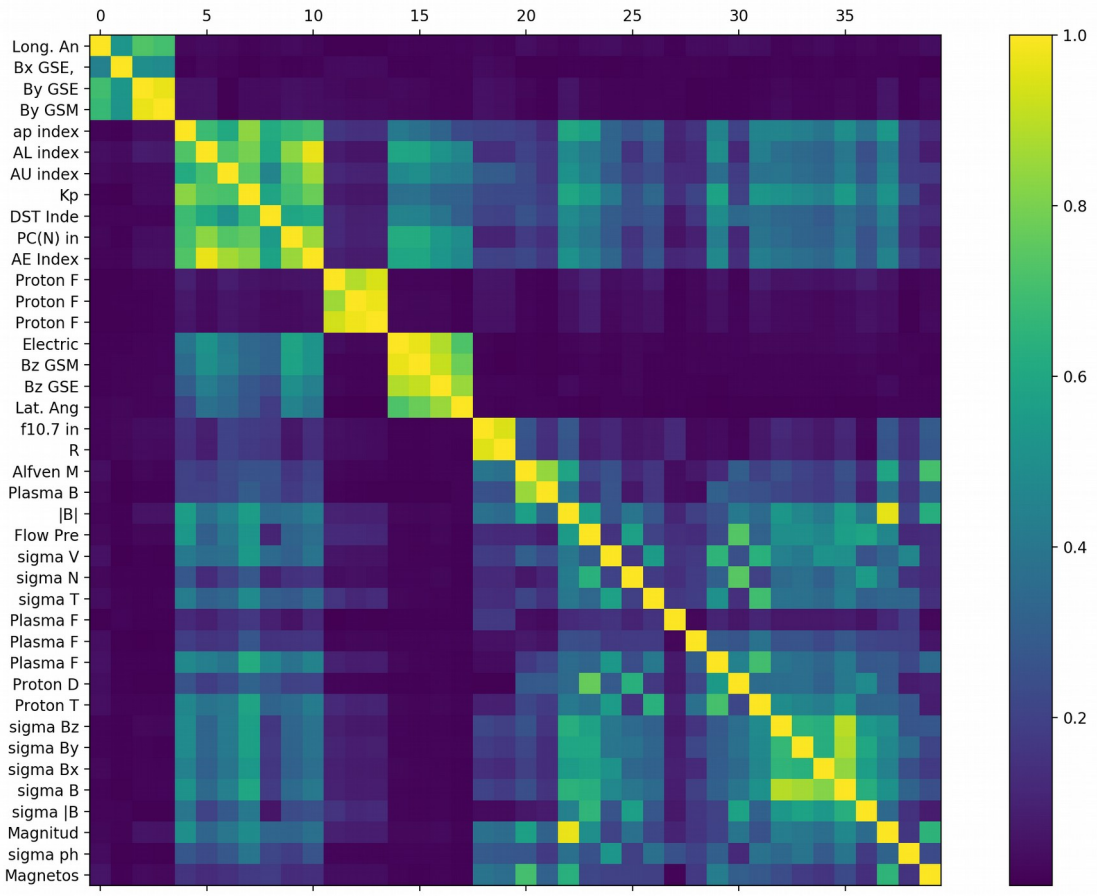



Bx, By, long. angle
Al, PC, ap, AU, AE, Dst, Kp
Proton fluxes
Block-diagonal reordering
E, Bz, lat. angle
0
5
10
15
20
25
30
35
Long. An
Bx GSE,
By GSE
By GSM
AL index
PC(N) in
ap index
AU index
AE Index
DST Inde
Kp
Proton F
Proton F
Proton F
sigma ph
Plasma B
|B|
R
f10.7 in
Alfven M
sigma V
Flow Pre
sigma T
Magnitud
sigma |B
sigma B
sigma Bx
sigma N
sigma Bz
sigma By
Proton D
Plasma F
Plasma F
Plasma F
Proton T
Magnetos
Electric
Bz GSM
Bz GSE
Lat. Ang
1.0
0.8
0.6
0.4
0.2

Without history

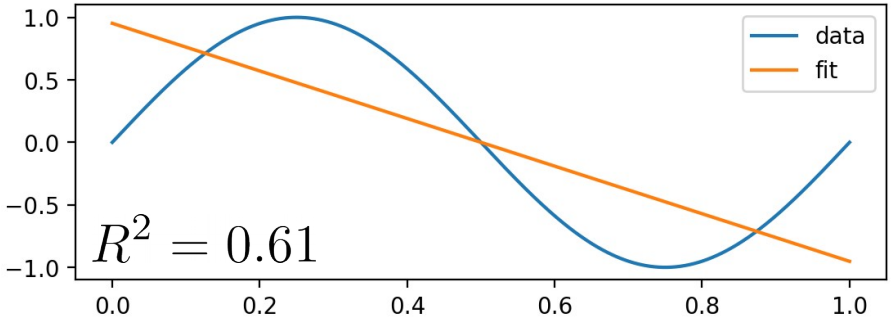


24h history

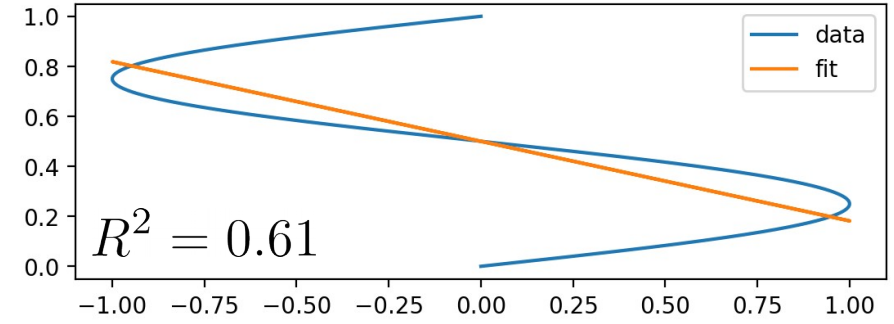


Linear vs non-linear models

Linear model

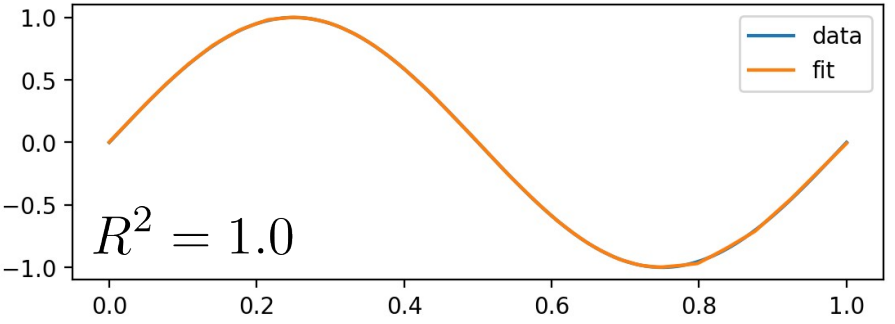


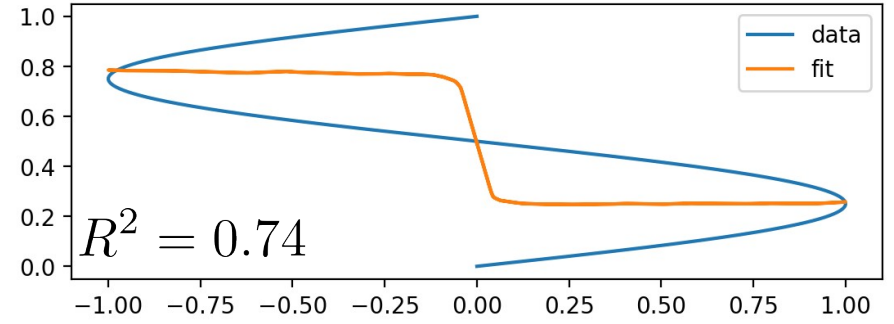
$x \rightarrow \sin(x)$



$\sin(x) \rightarrow x$

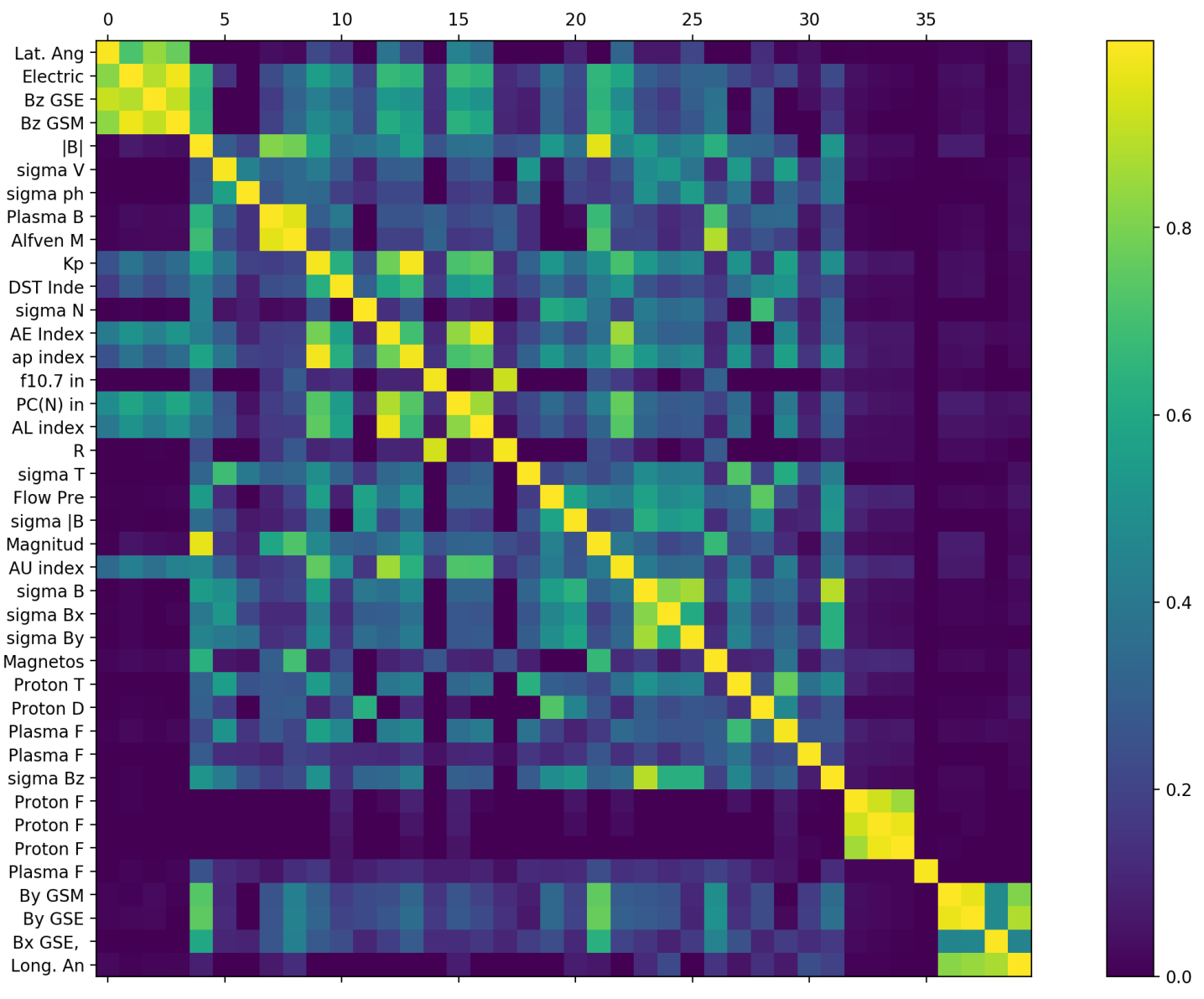
Neural network





Neural network
24h history
Shown is $\sqrt{R^2}$

asymmetry linked to causality?



Summary

- PCA: ~17 variables for 90% of variance (with proper normalization)
- Autocorrelation times and strength of 27-day periodicities are spread out; no obvious clusters
- Correlation matrices and their non-linear generalization help to discover relations between variables

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