Improving Operational Geomagnetic Index Forecasting

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British Geological Survey

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poster 13-4e

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What is more useful for predicting space weather:

A **Lasso** or a **RandomForest**?

BGS forecasts

BGS Global Geomagnetic Activity Forecast for

Forecast period (noon-to-noon GMT)	Forecast Global Activity level	
	Average	Max
17 NOV-18 NOV	QUIET	ACTIVE
18 NOV-19 NOV	QUIET	ACTIVE
19 NOV-20 NOV	ACTIVE	STORM G1

For more information about the forecast and activity categories see
www.geomag.bgs.ac.uk/education/activitylevels.html

Activity during last 72 hours

	Global			Local (UK)		
Date	Average	Max	At time (UT)	Average	Max	At time (UT)
14 NOV-15 NOV	QUIET	ACTIVE	21:00-00:00	QUIET	ACTIVE	18:00-21:00
15 NOV-16 NOV	ACTIVE	ACTIVE	21:00-00:00	ACTIVE	STORM G1	21:00-00:00
		ACTIVE	03:00-06:00			
16 NOV-17 NOV	QUIET	ACTIVE	12:00-18:00	QUIET	ACTIVE	15:00-18:00

Additional Comments

A high speed coronal hole wind stream arrived late on 15-NOV causing generally ACTIVE conditions in the 2nd interval. On arrival, MINOR-STORM (G1) levels were recorded in the UK at Hartland and Eskdalemuir geomagnetic observatories.

Since then, solar wind parameters begun to decline but are still slightly elevated. Further ACTIVE periods are possible in the 1st interval. A recurrent trans-equatorial coronal hole is currently in Earth-facing position. We expect the high speed wind stream from this coronal hole to arrive late in the 2nd or early in the 3rd interval.

Solar activity was moderate over the past 72 hours, with three M-class flares being observed from AR 2209 at the SE of the solar disk. However no Earth-directed coronal mass ejections ha ve been detected in available imagery. Further M or even X-class flares are possible from this region.

Departing region 2205 at the NW limb produced a C6 flare around 09:00 UT this morning. At this time there is no imagery available to confirm the presence of a CME.

Today's forecaster: Orsi Baillie

Time of forecast: 17 Nov 2014 11:08

- Daily geomagnetic forecast
  - next 3 days
- Online:

http://tinyurl.com/BGSSwForc

http://www.geomag.bgs.ac.uk/data_service/space_weather/3dforecast.html

- BGS **live forecast** in lobby today
- We show scoping study for new tool to help human forecasters
  - automatic prediction of 3 hourly a_p

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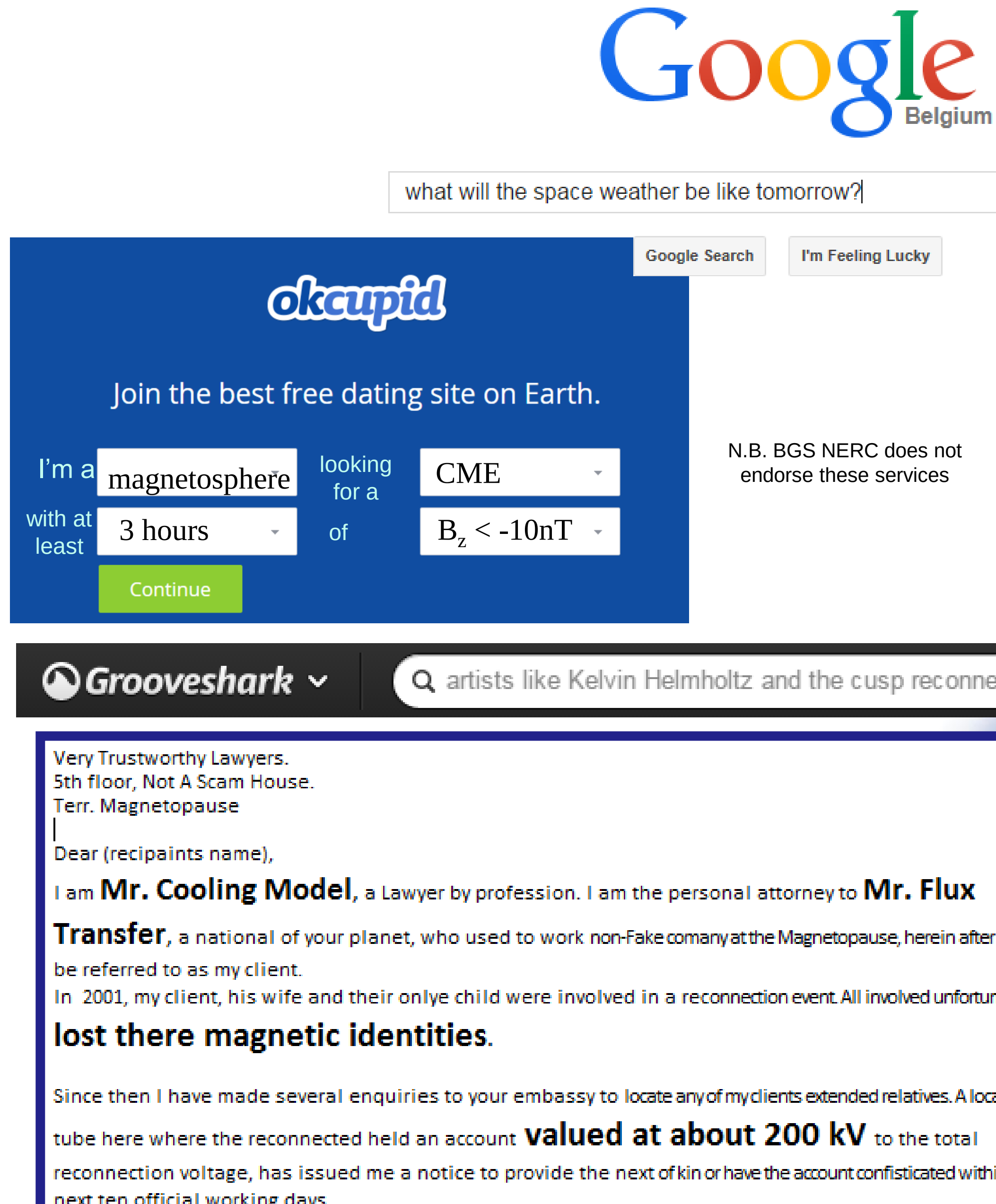
Space weather data assimilation

- Limited cf. NWP
- Heterogeneous
- Difficult to assimilate into physical models

- Can we use different approach: **Machine Learning**?

- ML underpins our online lives



N.B. BGS NERC does not endorse these services

BGS's next top model

- Select data from ~15 years holdings
- Train many ML algorithms
- **Competition**
  – what is best at predicting when shown unseen data
- **Winner?**
  – Any forecast skill?
  – Come see poster

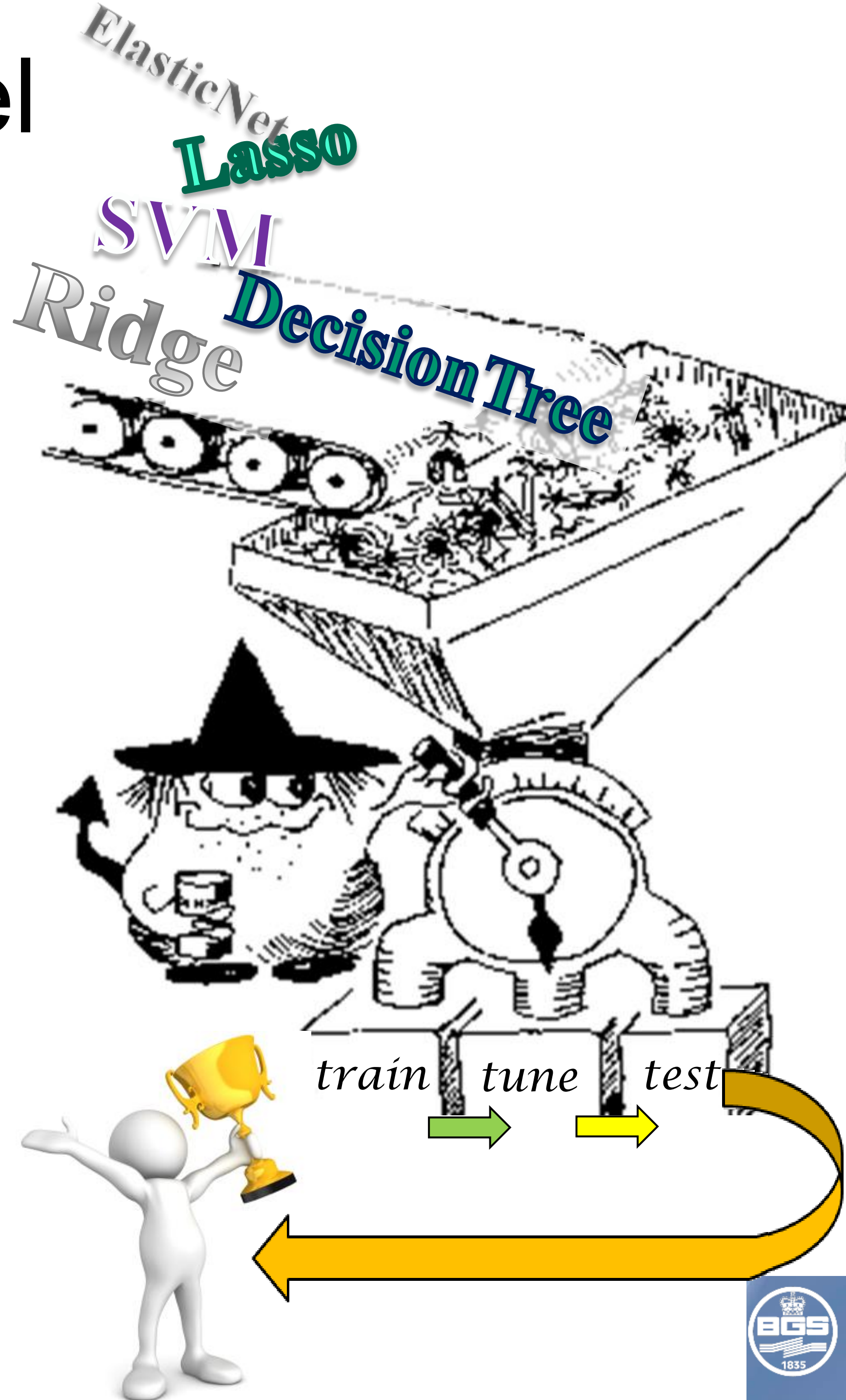


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Image credit Nils Olsen and comic-vine

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1. Introduction

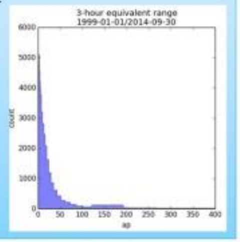
The interest in space weather has never been greater, with society becoming ever more reliant upon technology and infrastructure which are potentially at risk. Geomagnetic storms are potentially damaging to power-grids, communication systems and oil and gas operations.

Geomagnetic indices

- Capture magnetic storm severity by summarising lots of data
- have become ubiquitous parameterisations of storm-time magnetic conditions
- required as inputs by a variety of models

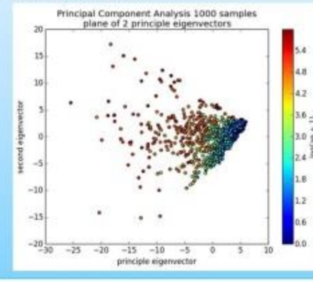
a_p index

- captures amplitude of the disturbance in horizontal part of the field (see e.g. [1] for more detail)
- tracks disturbances within a 3-hour interval
- indicates the global level of disturbance



2. Data

- Samples times over ~15 years of geomagnetic and solar wind data
- Storms rare but important
  - **Balance dataset** otherwise storms look like noise
- **Features** selected like
  - $\min(\vec{B}_{IMF\,z})_{last\ hour}$
  - $(a_p)_{2\ intervals\ ago}$
  - $\mathrm{mean}(v_{SW})_{3\ hours\ ago}$
- **Split**: training set, validation set, test set
- Training set **scaled**
  - $x_{sample} \rightarrow (x - \bar{x})/s$
  - Same scaling applied to other sets
- Some algorithms require $x_i \not\propto x_j$
  - use **Principal Component Analysis** to decompose



3. Techniques

Machine Learning

$$\vec{y} = \begin{bmatrix} a_{p\,1} \\ a_{p\,1} \\ \vdots \end{bmatrix} \qquad \mathbf{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots \\ x_{21} & x_{22} & \cdots \\ \vdots & \vdots & \ddots \end{bmatrix}$$

$n_{features}$, $n_{samples}$

- A branch of statistics
- We use **regression** algorithms here
- Data laid out as for matrix inversion (little like finding best fit line with 2D data)
- Many algorithms (see [2] for an excellent introduction), some are like linear regression e.g.

$$\boxed{\min_{\mathbf{w}}\left(\boxed{||\mathbf{X}\mathbf{w} - \vec{y}||_2^2} + \boxed{\alpha\rho||\mathbf{w}||_1} + \boxed{\frac{\alpha(1-\rho)}{2}||\mathbf{w}||_2^2}\right)}$$

Linear Regression   LR + = Lasso   LR + = Ridge

LR + Lasso + Ridge = ElasticNet

- Workflow:
  - **Training**: get coefficients $\mathbf{w}$ from $\mathbf{X}\mathbf{w} \stackrel{?}{=} \vec{y}_{new}$
  - **Tune** model parameters against validation set
  - **Test and score** model with test set $\mathbf{X}^{-1}\vec{y}_{known} = \mathbf{w}$
  - **Predict** new a_p from unseen data

ARIMA

- Auto-regressive moving average
- A linear regression over a windowed average of a_p
- Only input is a_p timeline
- Currently operational: used here as a baseline quality comparison

4.Results

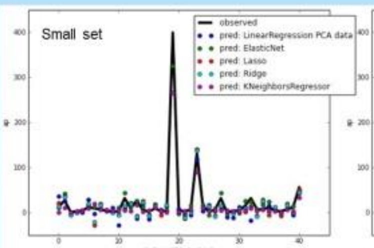
- Initial dataset with 205 samples (small set)
  - Some models much better at identifying storms than others
  - Large range in rms values and percentage of predictions which are close to the true value
- We then increased the total dataset size to 1000 samples (large set) and tested the best performing models
  - Again range of rms values
  - All the machine learning models out perform the ARIMA model in terms of rms, HitRate and skill (HSS)
- Positive results: worth pursuing for production system

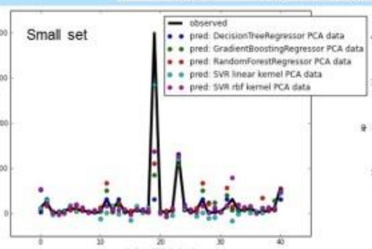
	rms	% within ± 5	% within ± 10	HitRate	HSS	FAR
Ridge	12.37	29.27	60.98	1.00	1.00	0.00
Lasso	17.63	26.83	53.66	1.00	1.00	0.00
ElasticNet	15.78	56.10	82.93	1.00	0.63	0.50
LinearRegression	14.88	31.71	51.22	1.00	1.00	0.00
DecisionTreeRegressor	17.96	73.17	87.80	0.33	0.48	0.00
GradientBoostingRegressor	36.29	68.29	73.17	1.00	0.55	0.57
RandomForestRegressor	25.42	60.98	73.17	1.00	0.63	0.50
KNeighborsRegressor	21.81	65.85	75.61	0.67	0.79	0.00
SVR_linear_kernel	23.93	41.46	63.41	1.00	1.00	0.00
SVR_rbf_kernel	43.65	48.78	78.05	1.00	0.72	0.40
1000 samples						
DecisionTreeRegressor	41.40	16.42	52.24	0.89	0.84	0.11
RandomForestRegressor	34.26	56.22	69.65	0.97	0.89	0.12
ElasticNet	36.48	34.33	56.72	0.95	0.91	0.08
SVR	38.18	35.82	63.68	0.90	0.88	0.07
LinearRegression	37.26	34.83	54.73	0.95	0.91	0.08
ARIMA	49.04	59.79	70.10	0.82	0.84	0.04

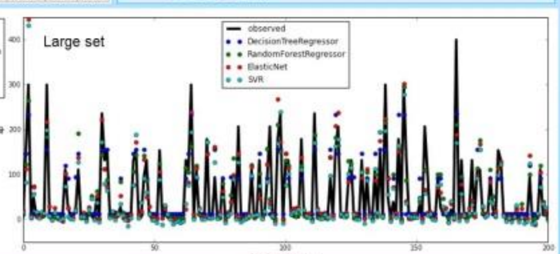
Metrics:

- **rms:** root-mean square error
- **% within ±N**: Percentage of predicted values within ±N of the observed value
- **HitRate:** how well do we predict the storms?
  - 1 = predicted every single storm
  - 0 = missed every storm
- **HSS:** Heidke skill score measures fractional improvement of the forecast over forecast by random chance
  - HSS = 2 (ad – bc) / [(a+ c)(c + d) + (a + b)(b + d)]
  - 1 = highly skilled
  - 0 = no skill
  - <0 = worse than random chance
- **FAR:** False alarm rate of storm prediction
  - 0 = no false alarms
  - 1 = all false alarms

Event Forecast	Storm Observed Yes	No	Forc Σ
Yes	a	b	a + b
No	c	d	c + d
Obs Σ	a + c	b + d	a+b+c+d = n

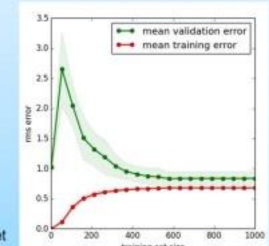






5.Summary and Future Work

- Scoping study results positive
  - value in predictions
  - proceed to operational system
- Here we only predict 1 a_p interval into future
  - Some models easily configures to predict multiple intervals
  - Others need new train, validate, test cycles
- Classification not regression
  - e.g. G1, ..., G5
  - More useful aid to human forecaster
  - Potentially easier computation
  - Up-weight storm categories: balance dataset
- More features per sample
  - Models converge with few training samples (see fig): models powerful enough
  - Data mine human forecasts, coronagraph data ...
  - Science potential in 'white-box' models: which features give useful info?



References
[1] McPherron, Magnetospheric Dynamics, in *Introduction to Space Physics*, edited by Kivelson, Russell, pp. 400-458, Cambridge University Press, 1995.
[2] Hastie *et al.*, *The Elements of Statistical Learning Data Mining, Inference, and Prediction*, Springer 2009(8)

This work is powered by Python-Scikit-learn
Pedregosa *et al.*, *Scikit-learn: Machine Learning in Python*, JMLR 12, pp. 2825-2830, 2011.

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