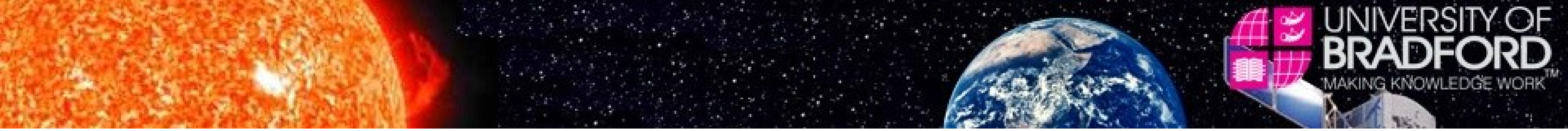

Automated Solar Flare Prediction: Is it a myth?

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Organisation of this talk:

- ❑ Introduction
- ❑ ASAP and SMART
- ❑ SMART properties and Association with Solar Flares
- ❑ Solar Flare prediction results
- ❑ Determining important SMART properties
- ❑ Conclusions

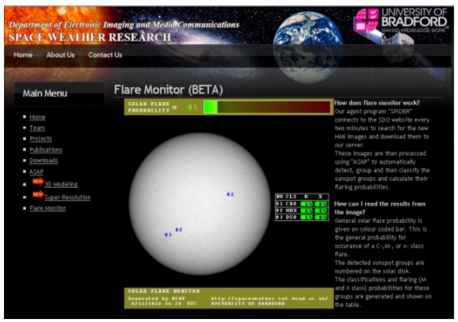
Introduction

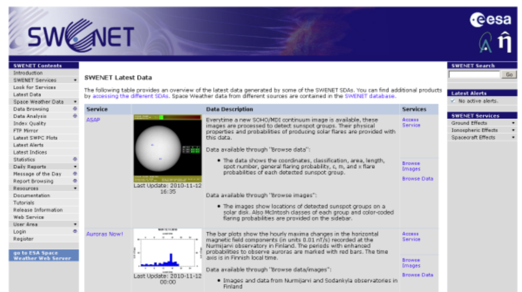
- Space Weather is st due to increased media coverage, new solar c and Mayan Calendar .
  - Last week, the Sci vidence on the Government's ability to deal with tific advice and evidence in emergencies. (Pro Prof. Paul Cannon (Royal Academy of Eng Director, National Grid)) http://tinyurl.com/2v
- It is important to be r activities because it is challenging.
- In this work I am going tion efforts in University of Bradford.

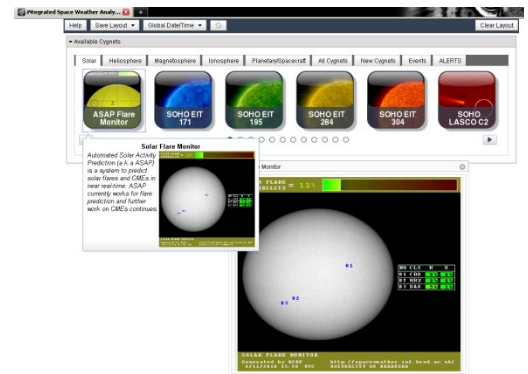
ASAP & SMART

ASAP

•ASAP is an automated solar flare prediction system that has been providing solar flare predictions and sunspot group classification since 2008.
•Recently have been updated to work with SDO/HMI images.
•Available in SWENET(ESA) and CCMC (NASA).







SMART

•SMART is an algorithm for tracking active regions from magnetogram images, developed in Trinity Collage Dublin by Paul Higgins, Dr. Gallagher, Dr. McAteer, Dr. Bloomfield [Higgins et al. 2010].
•SMART offers a direct diagnostic of the surface magnetic field and its variation over timescale of hours to years.
•SMART will form the basis of the active region extraction and tracking algorithm for the Heliophysics Integrated Observatory (HELIO).

Previous Work

Leka and Barnes carried out series of experiments to investigate the prediction capability of active regions properties derived from vector magnetograms.

- Leka and Barnes (2007) investigate which property combinations and the property/properties that can offer the best prediction. They investigated 74 properties of ARs for the period 2001-2004. They arrived to the following conclusions:
  - No single property was significant to distinguish between flaring and flare-quite ARs.
  - The following combination are the most significant, however, they are strongly correlated: Active regions with large total flux, vertical currents, significant excess energy, significant current helicity.
  - The best property that is related to large flares is total excess photospheric magnetic energy.

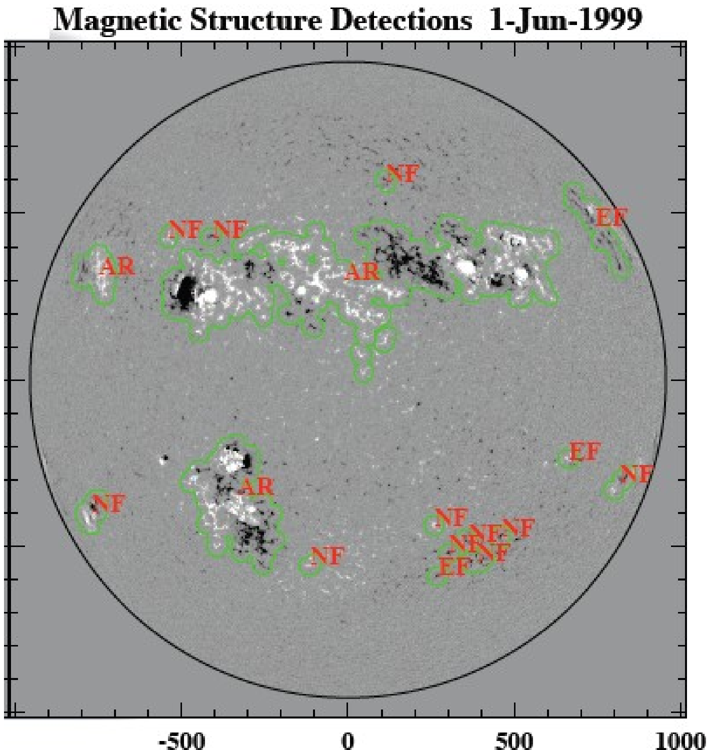
- Barnes et. al. (2007) used all 74 properties to find the best prediction capability. ARs were classified at different levels as “flaring” if produces at least C, M, or X flares within 24 hours. Otherwise, AR classifies as “flare-quite”. The climatological skill score was as follows:
  - Skill Score for C> : 0.346
  - Skill Score for M> :0.252
  - Skill Score for X> : 0.123

- Colak and Qahwaji 2008, used machine learning algorithm to create a flare prediction system called (ASAP). The system predict if a flare of class C, M, or X would occur within 24 hrs. The system evaluation are shown below.

<table>
<tr><th colspan="10">Prediction Performance of ASAP</th></tr>
<tr><th rowspan="2">Training Data</th><th rowspan="2">Testing Data</th><th colspan="3">No. of
Flaring ARs</th><th rowspan="2">TPR</th><th rowspan="2">ACC</th><th rowspan="2">FAR</th><th rowspan="2">MSE</th><th rowspan="2">HSS</th></tr>
<tr></tr>
<tr><td rowspan="3">1 Jan 1982 – 31 Dec 2006
-(1Feb 1999 – 31Dec 2002)</td><td rowspan="3">1Feb 1999 –31Dec 2002</td><td colspan="3">5,175</td><td rowspan="3">0.814</td><td rowspan="3">0.805</td><td rowspan="3">0.301</td><td rowspan="3">0.146</td><td rowspan="3">0.512</td></tr>
<tr><td>C</td><td>M</td><td>X</td></tr>
<tr><td>4,469</td><td>663</td><td>43</td></tr>
</table>

SMART Properties

- AR records were generated by the *Solar Monitor Active Region Tracking* (SMART) system [Higgins et al. 2010].
- SMART detects, tracks and catalogues ARs using SOHO/MDI magnetogram images separated by 96 minutes and extracted from *Flexible Image Transport System* (FITS) files.
- SMART detect ARs differently than NOAA.
- **Period**: from April 1996 – December 2008, Solar Cycle 23.



Paul Higgins 2009

AR properties generated by SMART		
No	**AR Properties**	**Description**
1	**Type-Polarity**	Unipolar/Multipolar
2	**Type-Size**	Big/Small
3	**Type-Evolution**	Emerging/Decaying
4	**Area_Mmsq**	Area of the region [Megameters squared].
5	**Bflux_Mx**	Total Unsigned Magnetic Flux of the region [Maxwells]. $\phi_{uns,t,i} = \sum_{pix}\lvert\phi_{t,i}\rvert$
6	**Bfluxp_Mx**	Total Positive Flux in the region [Maxwells]. $\phi_{+,t,i} = \sum_{pix}(\phi_{t,i} > 0)$
7	**Bfluxn_Mx**	Total Negative Flux in the region [Maxwells]. $\phi_{-,t,i} = \sum_{pix}(\phi_{t,i} < 0)$
8	**Bfluximb**	Flux Imbalance Fraction in the region [Fraction]. $\phi_{imb,t,i} = \frac{\lvert(\phi_{+,t,i} - \lvert\phi_{-,t,i}\rvert)\rvert}{\phi_{uns,t,i}}$
9	**DBfluxDt_Mx**	Flux Emergence Rate [Mx/second]. $\frac{d\phi}{dt}\Big\rvert_{t,i} = \frac{(\lvert B_t\rvert - \lvert B_{t-\Delta t}\rvert) \times A_{cos,t,i}}{\Delta t}$
10	**Bmin_G**	Minimum B value in the region[Gauss].
11	**Bmax_G**	Maximum B value in the region [Gauss].
12	**Bmean_G**	Mean B value in the region [Gauss].
13	**Lnl_Mm**	Neutral Line Length in the region [Mega meters].
14	**Lsg_Mm**	High Gradient Neutral Line Length in the region [Mega meters].
15	**MxGrad_GpMm**	Maximum Gradient along the Neutral Line [Gauss / Megameter].
16	**MeanGrad**	Mean Gradient along the Neutral Line [Gauss / Megameter].
17	**MednGrad**	Median Gradient along the Neutral Line[Gauss / Megameter].
18	**Rval_Mx**	Schrijver R-Value[Maxwells],(Schrijver, 2007).
19	**WLsg_GpMm**	Falconer WLsg value[Gauss / Megameter], (Falconer et al., 2008).
20	**R_Str**	Schrijver R-Value with a lower threshold for summing flux[Maxwells].
21	**WLsg_Str**	A modified version of WLsg.

AR-Flares Associations

- AR properties generated by SMART, and NGDC flare record, for the period of 1996-2008, have been associated in order to indicate flaring and non-flaring ARs.
  - **Flaring ARs:** Flares of class C, M, or X are associated to an active region information 24 hrs. before the flare starting time.
  - **Non-Flaring ARs:** AR that have not erupted B, C, M, or X flare pre and post 72 hours.

- Only ARs, which are located within 45° from the solar disk centre are considered.

Association Outputs			
	C	M	X
Active Region to Flare Samples	3,938	594	52
	Total: 4,584		
Active Region to No-Flare Samples	256,016		

Flare Prediction Capability of SMART Data

- Cascade Correlation Neural Networks(CCNN) Machine Learning (ML) have been applied to investigate the prediction capability of the data.
- CCNN applied to the associated data with 10 fold cross validation to determine the general prediction capability of the associated data.

Association Dataset			
	C	M	X
Active Region to Flare Samples	3,938	594	52
	Total: 4,584		
Active Region to No-Flare Samples	256,016		

Machine Learning Prediction Evaluation Results with 10 Fold Cross Validation									
	Training MSE	Testing MSE	TPR,	FPR	TNR	FNR	FAR	ACC	HSS
Apr1996 –Dec2008	0.0038	0.0048	0.6695 (3,069)	0.0017 (435)	0.9983 (255,581)	0.3305 (1,515)	0.1215	0.9926	0.7561

Flare Prediction Capability of SMART Data

- The associated data was tested further twice:
  - *First*, by training the ML on the data Apr1996-Dec2008 excluding the period (1Feb1999-31Dec2002), which is used for testing. This have been chosen to compare the performance with ASAP.
  - *Second*, by training the ML on all of the data Apr1996-Dec2008 and testing the ML on data from the period 1Jan2010 – 31Jul2010

The input and the results are shown below:

Training Datasets

Period	Total Samples	No-Flare	C	M	X
Apr 1996 – Dec 2008 – (1 Feb 1999 – 31 Dec 2002)	110,078	108,539	1,301	211	27
			Total: 1,539		
Apr 1996 – Dec 2008	260,600	256,016	3,938	594	52
			Total: 4,584		

Testing Datasets

Period	Total Samples	No-Flare	C	M	X
1 Feb 1999 – 31 Dec 2002	150,522	147,477	2,637	383	25
			Total: 3,045		
1 Jan 2010 – 31 Jul 2010	7,088	7,051	34	3	0
			Total: 37		

Machine Learning Testing Results

Input Data	Training Network	MSE	TPR	FPR	TNR	FNR	FAR	ACC	HSS
Feb1999 – Dec2002	Apr1996 – Dec2008 -(1Feb1999 –31Dec2002)	0.0053	0.6624 (2,017)	0.0015 (221)	0.9985 (147,256)	0.3376 (1,028)	0.1012	0.9917	0.7586
Jan2010 – Aug2010	Apr1996 – Dec2008	0.0016	0.5135 (19)	0.0000 (0)	1.0000 (7,051)	0.4865 (18)	0.0000	0.9975	0.6774

- The 21 AR properties generated by SMART can be used to provide highly accurate flare prediction system, according to the conditions specified in the association algorithm, that is:
    - An AR can produce a flare of class C, M, or X within 24 hrs.

    OR
    - The AR will not produce any flare of class B, C, M, or X within 72 hrs
- Some of 21 AR properties are highly correlated though, as shown in the table below. This might be the reason behind the high prediction capability of the data.

There is a need to indicate those properties that are most important for flare prediction and feature Selection statistical methods have been applied for this purpose.

Correlation Coefficient between the Properties as well as the Class

	v1	v2	v3	v4	v5	v6	v7	v8	v9	v10	v11	v12	v13	v14	v15	v16	v17	v18	v19	v20	v21	Class	
v1	1.000	0.391	-0.007	0.429	0.316	0.248	0.311	-0.898	-0.004	-0.614	0.593	-0.010	0.291	0.216	0.552	0.631	0.618	0.144	0.187	0.178	0.240	0.209	v1
v2	0.391	1.000	-0.005	0.401	0.243	0.196	0.232	-0.415	0.000	-0.380	0.380	0.007	0.155	0.117	0.282	0.308	0.296	0.078	0.101	0.096	0.129	0.114	v2
v3	-0.007	-0.005	1.000	-0.005	-0.003	0.000	-0.006	0.006	0.012	0.002	-0.010	-0.009	-0.007	-0.008	-0.009	-0.008	-0.007	-0.006	-0.008	-0.005	-0.008	-0.003	v3
v4	0.429	0.401	-0.005	1.000	0.798	0.637	0.771	-0.491	0.002	-0.558	0.555	-0.003	0.672	0.574	0.605	0.461	0.392	0.509	0.518	0.591	0.604	**0.543**	v4
v5	0.316	0.243	-0.003	0.798	1.000	0.896	0.849	-0.375	0.226	-0.479	0.494	0.106	0.752	0.686	0.589	0.412	0.339	0.633	0.631	0.700	0.705	**0.577**	v5
v6	0.248	0.196	0.000	0.637	0.896	1.000	0.527	-0.295	0.585	-0.320	0.457	0.317	0.591	0.540	0.462	0.322	0.265	0.499	0.496	0.551	0.554	0.457	v6
v7	0.311	0.232	-0.006	0.771	0.849	0.527	1.000	-0.367	-0.263	-0.537	0.402	-0.174	0.737	0.672	0.579	0.406	0.335	0.618	0.619	0.684	0.691	**0.561**	v7
v8	-0.898	-0.415	0.006	-0.491	-0.375	-0.295	-0.367	1.000	0.004	0.658	-0.629	0.012	-0.345	-0.262	-0.582	-0.626	-0.600	-0.182	-0.226	-0.223	-0.287	-0.253	v8
v9	-0.004	0.000	0.012	0.002	0.226	0.585	-0.263	0.004	1.000	0.013	0.023	0.301	-0.004	-0.005	-0.004	-0.004	-0.004	-0.004	-0.006	-0.003	-0.005	-0.003	v9
v10	-0.614	-0.380	0.002	-0.558	-0.479	-0.320	-0.537	0.658	0.013	1.000	-0.343	0.411	-0.491	-0.400	-0.664	-0.618	-0.561	-0.306	-0.359	-0.360	-0.433	-0.377	v10
v11	0.593	0.380	-0.010	0.555	0.494	0.457	0.402	-0.629	0.023	-0.343	1.000	0.427	0.487	0.401	0.630	0.579	0.522	0.310	0.356	0.363	0.427	0.381	v11
v12	-0.010	0.007	-0.009	-0.003	0.106	0.317	-0.174	0.012	0.301	0.411	0.427	1.000	-0.013	-0.011	-0.017	-0.015	-0.013	-0.008	-0.011	-0.009	-0.013	-0.006	v12
v13	0.291	0.155	-0.007	0.672	0.752	0.591	0.737	-0.345	-0.004	-0.491	0.487	-0.013	1.000	0.942	0.714	0.462	0.368	0.872	0.883	0.938	0.962	**0.715**	v13
v14	0.216	0.117	-0.008	0.574	0.686	0.540	0.672	-0.262	-0.005	-0.400	0.401	-0.011	0.942	1.000	0.647	0.412	0.327	0.944	0.975	0.932	0.984	**0.661**	v14
v15	0.552	0.282	-0.009	0.605	0.589	0.462	0.579	-0.582	-0.004	-0.664	0.630	-0.017	0.714	0.647	1.000	0.882	0.782	0.508	0.617	0.556	0.689	**0.563**	v15
v16	0.631	0.308	-0.008	0.461	0.412	0.322	0.406	-0.626	-0.004	-0.618	0.579	-0.015	0.462	0.412	0.882	1.000	0.966	0.289	0.387	0.319	0.446	0.355	v16
v17	0.618	0.296	-0.007	0.392	0.339	0.265	0.335	-0.600	-0.004	-0.561	0.522	-0.013	0.368	0.327	0.782	0.966	1.000	0.221	0.304	0.245	0.355	0.276	v17
v18	0.144	0.078	-0.006	0.509	0.633	0.499	0.618	-0.182	-0.004	-0.306	0.310	-0.008	0.872	0.944	0.508	0.289	0.221	1.000	0.935	0.965	0.929	**0.561**	v18
v19	0.187	0.101	-0.008	0.518	0.631	0.496	0.619	-0.226	-0.006	-0.359	0.356	-0.011	0.883	0.975	0.617	0.387	0.304	0.935	1.000	0.889	0.973	**0.606**	v19
v20	0.178	0.096	-0.005	0.591	0.700	0.551	0.684	-0.223	-0.003	-0.360	0.363	-0.009	0.938	0.932	0.556	0.319	0.245	0.965	0.889	1.000	0.937	**0.630**	v20
v21	0.240	0.129	-0.008	0.604	0.705	0.554	0.691	-0.287	-0.005	-0.433	0.427	-0.013	0.962	0.984	0.689	0.446	0.355	0.929	0.973	0.937	1.000	**0.678**	v21
Class	0.209	0.114	-0.003	0.543	0.577	0.457	0.561	-0.253	-0.003	-0.377	0.381	-0.006	0.715	0.661	0.563	0.355	0.276	0.561	0.606	0.630	0.678	1.000	Class
	v1	v2	v3	v4	v5	v6	v7	v8	v9	v10	v11	v12	v13	v14	v15	v16	v17	v18	v19	v20	v21	Class	

Feature Selection

- The Feature Selection (FS) process aims to study the significance of the input features (AR properties in our case) with respect to the prediction classes (flaring probability in our case). FS is widely used in combination with machine learning to enhance data analysis and prediction capability.
- **FS advantages:**
  1. Reduce the number of input features.
  2. Enable machine learning or predictors to be cost effective and faster.
  3. Improve the prediction accuracy of machine learning systems.
  4. Data understanding; provide a physical insight onto the importance of input features.
- The feature selection process has been carried out as follow:
  - **I.** selecting the features; This have been carried out using two feature selection methods which are **Correlation-Based Feature Selection (CFS)** and **Minimum Redundancy Maximum Relevance (MRMR).** This step was re-run for 20 times on 50% of the data, which are selected randomly, in order to find the most common selected features.
  - **II.** evaluate features performance. This have been carried out using CCNN machine learning in order to calculate the perdition performance of the selected features.

- **CFS:** supervised feature evaluation method, with a filter strategy, multivariate searching approach, and output the selected features as a subset of features. CFS select features according to their correlation coefficients. selecting a subset of features that are highly correlated with the class and uncorrelated with each other.

- **MRMR**: supervised feature selection method, with a filter strategy, multivariate feature selection approach, and output the selected features as a list features according to their weights. MRMR select features that are mutually dissimilar to each other, but highly related to the class.

- In this research, the feature selection toolbox in *Waikato Environment for Knowledge Analysis* (WEKA) [Witten and Frank, 2005], was used.

Feature Selection

- CFS output subset of features, while MRMR output all feature according to their importance.
- CFS and MRMR can be run with different options, i.e. the input data is normalized or discretised, the search through the features is forward or backward, and the features inter-correlation value and the feature-class correlation value are divided or subtracted.
- Few experiments have been run with all of the options above.
- The results at each time was different, however, some of the features appeared in all of the results.
- Features were grouped according to their frequencies and the prediction capability of each group was evaluated using ML.

Selected Features Frequencies from Different Feature Selection Methods and Options

Property No	v1	v2	v3	v4	v5	v6	v7	v8	v9	v10	v11	v12	v13	v14	v15	v16	v17	v18	v19	v20	v21
Property Selection Repetitions	0	0	0	2	2	2	3	0	1	0	2	0	4	4	4	1	1	3	4	4	4
4 times													v13	v14	v15				v19	v20	v21
>=3 times							v7						v13	v14	v15			v18	v19	v20	v21
>=2 times				v4	v5	v6	v7				v11		v13	v14	v15			v18	v19	v20	v21
>=1 times				v4	v5	v6	v7		v9		v11		v13	v14	v15	v16	v17	v18	v19	v20	v21

Machine Learning Prediction Evaluation Results with 10 Fold Cross Validation on the Selected Features

Property Selection Repetitions	TPR	FPR	TNR	FNR	FAR	ACC	HSS
4	0.603	0.002	0.998	0.397	0.149	0.991	0.701
>=3	0.604	0.002	0.998	0.396	0.146	0.991	0.703
>=2	0.627	0.002	0.998	0.373	0.130	0.992	0.725
>=1	0.641	0.002	0.998	0.359	0.132	0.992	0.734

Machine Learning Prediction Evaluation Results with 10 Fold Cross Validation 21 Features

	Training MSE	Testing MSE	TPR	FPR	TNR	FNR	FAR	ACC	HSS
Apr1996 –Dec2008	0.0038	0.0048	0.6695 (3,069)	0.0017 (435)	0.9983 (255,581)	0.3305 (1,515)	0.1215	0.9926	0.7561

Conclusions

- Automated Solar Flare Prediction is a myth?? NO
- Properties extracted by SMART can be used to predict solar flares better than currently online ASAP.
- Certain SMART properties related to neutral lines such as : Neutral line length , high gradient neutral line length, maximum gradient along the neutral line length are important indicators of flaring or non-flaring.
- SMART properties related to area and total flux are important discriminators for solar flares.
- Also Schrijver R-value and Falconer WLsg values are important properties.
- In the future these properties might be combined with ASAP to provide better solar flare prediction results. (Possible name: SMART ASAP)