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Magnetic Nonpotentiality in Photospheric Active Regions as a Predictor of Solar Flares

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Abstract. Based on several magnetic nonpotentiality parameters obtained from the vector photospheric active region magnetograms obtained with the Solar Magnetic Field Telescope at the Huairou Solar Observing Station over two solar cycles, a machine learning model has been constructed to predict the occurrence of flares in the corresponding active region within a certain time window. The Support Vector Classifier, a widely used general classifier, is applied to build and test the prediction models. Several classical verification measures are adopted to assess the quality of the predictions. We investigate different flare levels within various time windows, and thus it is possible to estimate the rough classes and erupting times of flares for particular active regions. Several combinations of predictors have been tested in the experiments. The True Skill Statistics are higher than 0.36 in 97% of cases and the Heidke Skill Scores range from 0.23 to 0.48. The predictors derived from longitudinal magnetic fields do perform well, however they are less sensitive in predicting large flares. Employing the nonpotentiality predictors from vector fields improves the performance of predicting large flares of magnitude ≥M5.0 and ≥X1.0.

Introduction

Based on the long-term reliable observations of the photospheric vector magnetic fields by SMFT, we adopt some nonpotentiality measures which are not available from observations of only line-of-sight magnetic fields to study the prediction of solar flares. The data for the input of the prediction model are obtained by local observations, and the key measures as predictors are available without manual operations.

From our experiments, the combinations of magnetic measures derived from longitudinal fields perform well in the flare prediction, however, they may be less sensitive than the measures from vector fields in predicting large flares. The information of transverse fields makes a limited contribution to the prediction of low magnitude flares, but it does improve the prediction for large flares such as ≥M5.0 and ≥X1.0 ones. Thus, it is reasonable to include transverse field components in flare predictions.

To avoid misleading the optimization work or misusing the results from a single verification measure, prediction results should be assessed carefully. It is helpful to consider *multiple* verification measures. A step like k-fold cross-validation is necessary for improving the generalization capability of the prediction models. The intrinsic properties of various data sets may make a specific tool perform rather differently, and hence, it is then significant to make comparisons in the same data environment.

Data

Table 1: Flaring (f) and Non-flaring (n-f) Sample Distributions

		Flaring Threshold				
Time Window	Category	C1.0	C5.0	M1.0	M5.0	X1.0
48 hr	f	918	427	252	71	42
	n-f	1255	1746	1921	2102	2131
24 hr	f	697	291	167	39	25
	n-f	1476	1882	2006	2134	2148
12 hr	f	475	181	95	22	17
	n-f	1698	1992	2078	2151	2156
6 hr	f	309	101	58	12	9
	n-f	1864	2072	2115	2161	2164

Predictor Groups

V06 ($\overline{\Delta\psi}$, $\overline{|J_z|}$, $\overline{|h_\mathrm{c}|}$, $|\alpha_\mathrm{av}|$, $\overline{\rho_\mathrm{free}}$, d_Em),
V08 ($\overline{\Delta\phi}$, $\overline{\Delta\psi}$, $\overline{|J_z|}$, $\overline{|h_\mathrm{c}|}$, $|\alpha_\mathrm{av}|$, $\overline{\rho_\mathrm{free}}$, d_E, d_Em),
L05 (d_Em, $\overline{\nabla_\mathrm{h}B_z}$, $(\nabla_\mathrm{h}B_z)_\mathrm{m}$, L_gnl, $\overline{\varepsilon(B_z)}$),
A10 ($\overline{\Delta\psi}$, $\overline{|J_z|}$, $\overline{|h_\mathrm{c}|}$, $|\alpha_\mathrm{av}|$, $\overline{\rho_\mathrm{free}}$, d_Em, $\overline{\nabla_\mathrm{h}B_z}$, $(\nabla_\mathrm{h}B_z)_\mathrm{m}$, L_gnl, $\overline{\varepsilon(B_z)}$),
A12 ($\overline{\Delta\phi}$, $\overline{\Delta\psi}$, $\overline{|J_z|}$, $\overline{|h_\mathrm{c}|}$, $|\alpha_\mathrm{av}|$, $\overline{\rho_\mathrm{free}}$, d_E, d_Em, $\overline{\nabla_\mathrm{h}B_z}$, $(\nabla_\mathrm{h}B_z)_\mathrm{m}$, L_gnl, $\overline{\varepsilon(B_z)}$).

(Cui et al. 2006; Jing et al. 2006; Yang et al. 2012)

Method: Support Vector Classifier (Vapnik 1995)

Primal optimization problem:

$$\begin{aligned} \min_{\mathbf{w}\in\mathcal{H}, b\in\mathbf{R}, \boldsymbol{\xi}\in\mathbf{R}^l} \quad & \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{l}\xi_i\,, \\ \text{subject to} \quad & y_i(\mathbf{w}\cdot\phi(\mathbf{x}_i)+b) \geqslant 1-\xi_i\,,\ i=1,\cdots,l\,, \\ & \xi_i \geqslant 0\,,\ i=1,\cdots,l \end{aligned}$$

Dual optimization problem:

$$\begin{aligned} \min_{\boldsymbol{\alpha}} \quad & \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} y_i y_j \alpha_i \alpha_j K(\mathbf{x}_i,\mathbf{x}_j) - \sum_{j=1}^{l}\alpha_j\,, \\ \text{subject to} \quad & \sum_{i=1}^{l} y_i\alpha_i = 0\,, \\ & 0 \leqslant \alpha_i \leqslant C,\ i=1,\cdots,l \end{aligned}$$

Gaussian Radial Basis kernal: $K(\mathbf{x}_i,\mathbf{x}_j) = \exp(-\|\mathbf{x}_i-\mathbf{x}_j\|^2/\sigma^2)$
Discriminant function:

$$f(\mathbf{x}) = \mathrm{sgn}(\mathbf{w}^*\cdot\phi(\mathbf{x})+b^*) = \mathrm{sgn}\left(\sum_{i=1}^{l}\alpha_i^* y_i K(\mathbf{x},\mathbf{x}_i)+b^*\right)$$

Prediction Verification

Table 2: Definition of the 2×2 Contingency Table (Confusion Matrix)

	Predicted		
Observed	Yes	No	Total
Yes	x	y	$N_1 = x+y$
No	z	w	$N_0 = z+w$
			$N = x+y+z+w$

The so-called skill scores indicate the relative accuracy of a prediction to some standard reference predictions. The generic form of skill score is

$$\mathrm{SS} = \frac{S - S_\mathrm{ref}}{S_\mathrm{perfect} - S_\mathrm{ref}} \times 100\%,$$

where S is a particular measure of accuracy, S_ref a reference, and S_perfect the perfect prediction. A no-skill prediction scores 0, a positive score shows a better prediction than the reference, and the perfect prediction scores 1.

Table 3: Verification Measures (VM)

VM	Derivation	Formulation	w-Dominated	Range
Gilbert Skill Score	$\mathrm{GSS} = \frac{x-E_1}{(x-E_1)+y+z}$	$\mathrm{GSS} = \frac{x\cdot w-y\cdot z}{(y+z)(x+y+z+w)+x\cdot w-y\cdot z}$	→ CSI	$[-1/3, 1]$
Heidke Skill Score	$\mathrm{HSS} = \frac{(x-E_1)-(w-E_0)}{(x-E_1)+y+z+(w-E_0)}$	$\mathrm{HSS} = \frac{2(x\cdot w-y\cdot z)}{(x+y)(y+w)+(x+z)(z+w)}$	→ F_1	$[-1, 1]$
True Skill Statistic	$\mathrm{TSS} = \mathrm{POD} - \mathrm{POFD}$	$\mathrm{TSS} = \frac{x\cdot w-y\cdot z}{(x+y)(z+w)}$	→ POD	$[-1, 1]$
Clayton Skill Score	$\mathrm{CSS} = \mathrm{FOH} - \mathrm{DFR}$	$\mathrm{CSS} = \frac{x\cdot w-y\cdot z}{(x+z)(y+w)}$	→ FOH	$[-1, 1]$
Critical Success Index	$\mathrm{CSI} = \frac{x+w-w}{x+y+z+w-w}$	$\mathrm{CSI} = \frac{x}{x+y+z}$	CSI	$[0, 1]$
F_1 measure	$F_1 = 2(\mathrm{POD}^{-1}+\mathrm{FOH}^{-1})^{-1}$	$F_1 = \frac{2x}{2x+y+z}$	F_1	$[0, 1]$

cf., Woodcock 1976; Doswell et al. 1990; Schaefer 1990; Chinchor 1992; Murphy 1996.
$E_1 = (x+z)(x+y)/N$, the expected number of correct event predictions due to chance.
$E_0 = (y+w)(z+w)/N$, the expected number of correct non-event predictions due to chance.

Results

Table 4: Verification Results from Testing SVM Classifier

Prediction		Verification Measure										
Flare Level	Time Window	POD	FOH	POCN	CSI	F_1	TSS	CSS	HSS	GSS	ACC	N_0/N
⩾C1.0	48 hr	0.707±0.011	0.690±0.013	0.782±0.008	0.538±0.013	0.698±0.011	0.474±0.020	0.472±0.020	0.473±0.020	0.312±0.018	0.742±0.010	0.578
	24 hr	0.677±0.019	0.617±0.013	0.840±0.008	0.478±0.016	0.645±0.014	0.478±0.022	0.458±0.020	0.466±0.021	0.306±0.018	0.761±0.010	0.679
	12 hr	0.653±0.028	0.508±0.010	0.895±0.007	0.399±0.013	0.569±0.014	0.475±0.024	0.404±0.014	0.430±0.016	0.275±0.013	0.786±0.006	0.781
	6 hr	0.560±0.026	0.423±0.022	0.923±0.004	0.317±0.017	0.479±0.020	0.430±0.026	0.346±0.025	0.378±0.024	0.235±0.018	0.826±0.009	0.858
⩾C5.0	48 hr	0.627±0.026	0.549±0.019	0.906±0.005	0.415±0.020	0.584±0.020	0.500±0.027	0.455±0.024	0.474±0.025	0.313±0.021	0.825±0.008	0.803
	24 hr	0.626±0.028	0.457±0.022	0.939±0.004	0.357±0.018	0.524±0.018	0.507±0.026	0.396±0.024	0.437±0.022	0.282±0.019	0.847±0.008	0.866
	12 hr	0.485±0.044	0.400±0.028	0.952±0.004	0.283±0.028	0.435±0.033	0.419±0.044	0.352±0.031	0.379±0.035	0.239±0.029	0.896±0.006	0.917
	6 hr	0.595±0.064	0.250±0.029	0.979±0.003	0.219±0.029	0.351±0.038	0.508±0.065	0.229±0.032	0.306±0.041	0.187±0.029	0.898±0.006	0.954
⩾M1.0	48 hr	0.642±0.028	0.433±0.021	0.950±0.004	0.350±0.021	0.516±0.023	0.531±0.030	0.383±0.024	0.438±0.026	0.284±0.021	0.860±0.007	0.884
	24 hr	0.550±0.039	0.419±0.023	0.962±0.003	0.314±0.023	0.474±0.028	0.486±0.039	0.381±0.026	0.424±0.030	0.273±0.023	0.907±0.004	0.923
	12 hr	0.554±0.056	0.344±0.021	0.979±0.002	0.266±0.025	0.415±0.030	0.505±0.052	0.323±0.022	0.382±0.031	0.240±0.024	0.934±0.004	0.956
	6 hr	0.523±0.067	0.225±0.028	0.986±0.002	0.191±0.028	0.312±0.039	0.474±0.067	0.211±0.030	0.286±0.040	0.173±0.028	0.939±0.004	0.973
⩾M5.0	48 hr	0.634±0.048	0.319±0.020	0.987±0.002	0.268±0.020	0.419±0.025	0.587±0.047	0.306±0.021	0.393±0.026	0.247±0.020	0.942±0.004	0.967
	24 hr	0.329±0.114	0.434±0.094	0.988±0.002	0.231±0.075	0.353±0.093	0.321±0.114	0.422±0.095	0.343±0.094	0.224±0.075	0.980±0.003	0.982
	12 hr	0.460±0.104	0.275±0.067	0.994±0.001	0.213±0.056	0.338±0.075	0.447±0.105	0.269±0.067	0.329±0.076	0.207±0.056	0.982±0.002	0.990
	6 hr	0.667±0.139	0.220±0.038	0.998±0.001	0.202±0.042	0.327±0.058	0.654±0.139	0.218±0.039	0.322±0.059	0.198±0.042	0.985±0.002	0.994
⩾X1.0	48 hr	0.522±0.070	0.487±0.141	0.991±0.001	0.326±0.072	0.474±0.082	0.507±0.070	0.477±0.141	0.462±0.084	0.316±0.073	0.976±0.005	0.981
	24 hr	0.480±0.102	0.375±0.094	0.994±0.001	0.262±0.061	0.401±0.078	0.469±0.102	0.369±0.095	0.392±0.079	0.256±0.061	0.983±0.003	0.982
	12 hr	0.533±0.062	0.278±0.023	0.996±0.001	0.214±0.010	0.353±0.013	0.522±0.061	0.274±0.023	0.346±0.013	0.210±0.010	0.985±0.002	0.990
	6 hr	0.700±0.200	0.169±0.055	0.999±0.001	0.167±0.056	0.270±0.084	0.688±0.199	0.167±0.056	0.265±0.084	0.164±0.056	0.987±0.003	0.996

The full version of the table available in the electronic version contains the V06, V08, L05, and A10 predictor results. A12's results are shown in Table 4, in which each value with its error is the arithmetical mean of the specific verification measure in k times testing.

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