

The Next Level in Automated Solar Flare Forecasting

The EU FLARECAST Project

Manolis K. Georgoulis^{*} & the FLARECAST Team

*RCAAM of the Academy of Athens



FLARE CAST



H2020-PROTEC-2014 RIA; Project No.: 640216

What is FLARECAST?

FLARECAST is an EC H2020 project aiming to develop an advanced solar flare prediction system based on automatically extracted physical properties of solar active regions, coupled with state-of-the-art solar flare prediction methods and validated using the most appropriate forecast verification measures.





Top-level objectives:

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- **Science:** Understand the drivers of solar flare activity and improve flare prediction
- **R2O:** Provide a globally accessible flare prediction service that facilitates expansion
- **Communication:** Engage with SWx end users and inform policy makers and the public

How do we do it - FLARECAST Architecture



FLARECAST steps and data types in a nutshell

□ Four steps; three data types:

• Step 1: Data acquisition

External data:

- SDO / HMI NRT SHARPs
- NOAA / SWPC SRS data
 - Active region numbers
 - AR locations
 - Flare occurrences

- Step 2: Feature property extraction
- Step 3: Prediction training / execution
- Step 4: Forecast verification

Science data:

- Extracted properties
- Prediction algorithm config.
- Predictions
- Validation

Infrastructure data:

- Algorithm management
- Workflow management

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Step 1: Data acquisition



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SDO / HMI data

- SHARP vector magnetograms NRT (hmi.sharp_720s_nrt)
- LOS magnetograms (hmi.M_720s)
- SHARP vector magnetograms definitive (hmi.sharp_720s)
- □ SRS active region (SWPC)

(YYYY_events.tar.gz)

□ Flare association (GOES)



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Step 2: Feature property extraction



Pretty much everything proposed as promising for flare prediction over the past 25 years

		(To do / In progress / Under testing / Delivered)
Solar Region Summary properties	TCD	Delivered
GOES X-ray events	TCD	Delivered
		0
SHARP properties (Bobra et al. 2014)	TOD	Delivered
Magnetic helicity injection rate (Berger & Field 1984)	TCD	Delivered
Magnetic energy injection rate (Kusano et al. 2002)	TCD	Delivered
Non-neutralized currents (Georgoulis et al., 2012)	AA	Delivered
Flow field characteristics (Deng et al. 2006; Wang et al. 2014)	TOD	Delivered
Magnetic bipolar feature characteristics	TCD	Under testing (further investigated in WP6)
Flow field characteristics	TCD	Under testing (further investigated in WP6)
	Solar Region Summary properties GOES X-ray events SHARP properties (Bobra et al. 2014) Magnetic helicity injection rate (Berger & Field 1984) Magnetic energy injection rate (Berger & Field 1984) Non-neutralized currents (Georgouils et al. 2012) Flow field characteristics (Deng et al. 2005; Wang et al. 2014) Magnetic bipoter fieature characteristics Flow field characteristics	Solar Region Summary properties TCD GOES X-ray events TCD SHARP properties (Bobra et al. 2014) TCD SHARP properties (Bobra et al. 2014) TCD Magnetic helicity injection rate (Berger & Field 1984) TCD Magnetic energy injection rate (Rusano et al. 2012) AA Non-neutralized currents (Georgouis et al. 2012) AA Flow field characteristics (Deng et al. 2006; Wang et al. 2014) TCD Magnetic bipoter fieldure characteristics TCD Flow field characteristics TCD

More than 100 fe	atures (pre	edictors) f	or each
magnetogram!			

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LOS magnetograma			
Details	Effective connected magnetic field strength ($\rm B_{eff}$) (Georgoulia & Rust, 2007)	**	Delivered
Details	Fractal dimension (Georgoulis, 2012)	AA	Delivered
Details	Multi-fractal structure function s(q) inertial range index k (Georgoulia, 2012)	**	Delivered
Details	Fourier power spectral index (Guerra et. al., 2015)	TCD	Delvered
Detells	GWT power spectral index (Hewett et. al., 2008)	TCD	Delivered
Details	Generalised correlation dimension (Georgoutis, 2012)	AA	Delivered
Details	Holder exponent h (Conion et al., 2010)	AA	Delivered
Details	Hausdorff dimension D(h) (Conion et al., 2010)	AA	Delivered
	WTMM (Conion et al., 2010)	TCD	Under testing (further investigated in WP6)
Details	Decay index (Zuccarelio et al. 2014)	TCD	Delivered
Details	Magnetic polarity inversion line characteristics (Mason & Hoeksema 2010)	TCD	Delivered
Details	3D magnetic null point (Greene 1992)	TCD	Delivered
Details	R (Schrijver 2007)	TCD	Delivered
Details	LWL _{SG} (Falconer et al. 2008) *	TCD	Delivered
Details	Ising energy (Ahmed et al. 2010)	AA	Delivered
Details	WG_M and $S_{l\text{-}f}$ (Korsos et al. 2015)	AA	Delivered
Details	Magnetic helicity injection rate proxy (Park et al. 2013)	TCD	Delivered

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Property extraction: example



A number of papers published; more f



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Number of properties per month

Flare association

-5.5

-5.0

-4.5

Log GOES FLux Peak Intenisty

-6.0



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-3.0

-3.5

-4.0

B-class C-class M-class

X-class

Step 3: Prediction training / execution



A total of 22 prediction algorithms tested, most of them in points in time and some in timeseries

Statistical			Discriminant analysis	
	Buitana (Bhirdrath aniat in time)		Multi-layer perceptron with back-propagation (point-in- time)	
	Poisson (McIntosh 24-hour evolution)		Multi-layer perceptron with back-propagation (time series)	
	Probit regression		Radial basis function networks (point-in-time)	
	Logit regression		Radial basis function networks (time series)	
	Linear regression		(point-in-time)	
	Bayesian binary quantile regression with lasso		Recurrent neural network with evolutionary algorithm (time series)	
Unsupervised			Support vector machine (point-in-time)	
	and the second		Support vector machine (time series)	
k-mea	k-means clustering	Time series		
	Probabilistic k-means (Fuzzy C-means) clustering	preprocessing		
	Possibilistic k-means dustering		Discrete Wavelet Transform	
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Categories of FLARECAST prediction algorithms

Statistical

- Supervised learning
- Unsupervised learning
- Timeseries analysis
 - Non machine-learning
 - Machine-learning
 - Timeseries (not implemented in this release of FLARECAST

Machine-learning methods

- Standard
- Advanced
- Innovative



Typical example of multi-layer perceptron



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Typical flowchart of a genetic algorithm

Step 4: Forecast verification — binary



Binary validation: Flare (YES) or No Flare (NO)

	Forecast Flare	Forecast No-flare
Observed Flare	TP	FN
Observed No-flare	FP	TN

SS =

2 x 2 contingency table

- TP : true positives
- FN : false negatives
- FP : false positives
- TN : true negatives

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Generalized skill score:

 $\frac{\text{score} - \text{score}_{ref}}{\text{score}_{perfect} - \text{score}_{ref}}$

Different skill scores for different purposes:

• Heidke (HSS - ref. random prediction) $HSS = \frac{2(\mathrm{TP} + \mathrm{TN}) - N}{2}$ Appleman (HSS - ref. climatology) $ApSS = \frac{TP - FP}{TP}$

True skill statistic (TSS) 0

TSS = POD - POFD

Step 4: Forecast verification – probabilistic

A probability 0 < p < 1 is assigned to each prediction



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Correlates forecast probability with observed frequency 0 Reliability, skill, resolution 0 $MSE_{forecast}$ SS = 1Generalized skill score: 0 MSE_{ref} MSE = $(o_i - p_i)^2$ Brier skill score: 0 $\bar{o} \equiv \{0, 1\}$ $\frac{\text{MSE}(\bar{o}, p)}{\text{MSE}(\bar{o}, \tilde{o})}$ BSS = \tilde{o} : climatology



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Validation: preliminary results



Properties relying on line-of-sight field used (<u>full earthward solar disk</u>)

• Event definition:

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- \geq M1.0 flares within 24 hours
- Trained on 14-Sep-2012 to 31-Dec-2014
- Tested on 1-Jan-2015 to 31-Mar-2016
- Only showing verification for flare yes/no classifying algorithms

Prediction Algorithm	Probability of Detection POD	Probability of False Detection POFD	True Skill Statistic TSS
Hybrid Lasso	0.94	0.20	0.74
Hybrid Logit	0.90	0.20	0.70
Random Forest	0.71	0.07	0.65
Probabilistic K-means	0.65	0.40	0.25
Support Vector Classifier	0.14	0.02	0.12
K-means	0.02	0.01	0.01
Sim. Ann. K-means	0.00	0.32	-0.32
Fuzzy K-means	0.08	0.66	-0.57

Courtesy: Shaun Bloomfield

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Validation: preliminary results

Skill comparison (at least C1 flares) ACC Probit Neural Networks Sensitivity SVC-CV SimAnn Fuzzy C-Means SimAnn C-Means FAR Random Forest I1-logit Hybrid HSS TSS 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9

Massone et al., (2018)



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FLARECAST Science: explorative research



Understand solar magnetic eruptions

- Improve future flare prediction, involving use of timeseries
- Investigate suitability of forecast window and latency
- □ Advance CME prediction

Study of eruptive flares in synthetic MHD configurations

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Pariat et al. 2017

FLARECAST Science: explorative research





Understand solar magnetic eruptions

Improve future flare prediction, involving use of timeseries

Investigate suitability of forecast window and latency

□ Advance CME prediction

Kontogiannis et al. 2017

Feasibility of non-neutralized currents in active regions as flare predictors

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FLARECAST top-level objectives: Technology

- API accessible databases (<u>api.flarecast.eu</u>)
- Open-source Architecture based on Docker engine and containers
- Pick-and-mix installation



FLARECAST top-level objectives: communication

Communicating with the scientific community

Edit

http://flarecast.eu/research/publications

Watching

Pages / Management

/ Publications and Conferences 0

FLARECAST Publication Plan

Created by D. Shaun Bloomfield, last modified by Etienne Pariat on Mar 31, 2017

At least nineteen (19) envisioned refereed papers, of which:

- Six (6) are already published; two
 (2) are in press
- □ Three (3) are under review

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Al, either in open-access journals or in ArXiv

□ At least eight (8) are in preparation

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FLARECAST top-level objectives: communication
 Communicating with industry and government



http://flarecast.eu/industry/first-stakeholder-workshop

First Stakeholders
 Workshop, Met Office
 12-13 January 2017

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Second Users
 Workshop, ESWW14,
 29 November 2017

http://flarecast.eu/secondstakeholder-workshop

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http://flarecast.eu/outreach-activities

FLARECAST top-level objectives: communication Communicating with the public Il Secolo XIX, Genova, 13 September 2016



Athens, 30.09.2017

EU Researchers Night, TCD, Dublin, 30.09.2016

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Science Café,

AA, Athens, 13.11.2017



Zurich, 11.11.2016

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Ricercatori a caccia di tempeste solari

ità e Cnr stanno creando una squadra di tecnici e scienziati internaziona

SANTTENEN SERVICE



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FLARECAST user interface: how it will work



Three different levels of service exploitation:

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- Administrator: control, workflow manager
- Scientist: edit metadata; visualize data
- End user: view / query data; visualize prediction





□ FLARECAST is arguably the most systematic, cost- and effort-intensive solar flare prediction project worldwide at this time.

The project has diverse objectives, comprising Science, R2O and Communication. Impressively diverse expertise has been used

□ FLARECAST data, codes and infrastructure are <u>fully and openly accessible worldwide</u> and can be used to avoid effort duplication in future SWx forecasting efforts.

FLARECAST architecture is modular and expandable. Integrated SWx forecasting platforms might conceivably use and expand it



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FLARECAST / FLARECAST-citing papers (so far)



G. Barnes, et al.: A Comparison of Flare-Forecasting Methods. I. Results from the "All-Clear" Workshop, Astrophysical Journal, 829, article.id 89, 2016, DOI: 10.3847/0004-637X/829/2/89

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- S. Murray, et al.: Flare Forecasting at the Met Office Space Weather Prediction Center, Space Weather, 15, 577, 2017, DOI: 10.1002/2016SW001579
- E. Pariat, et al.: Relative Magnetic Helicity as a Diagnostic of Solar Eruptity, *Astronomy & Astrophysics*, **601**, A125, 2017, DOI: 10.1051/0004-6361/201630043
- □ C. Guennou, et al.: Testing Predictors of Eruptivity Using Parametric Flux Emergence Simulations, J. Space Weather & Space Climate, 7, A17, 2017, DOI: 10.1051/swsc/2017015
- I. Kontogiannis, et al.: Non-Neutralized Electric Currents in Solar Active Regions and Flare Productivity, Solar Physics, 292, 159, 2017, DOI: 10.1007/s11207-017-1185-1
- K. Florios, et al.: Forecasting Solar Flares Using Magnetogram-Based Predictors and Machine Learning, Solar Physics, 2017, in press
- A. M. Massone, et al.: Machine Learning for Solar Flare Forecasting, In Machine-Learning Techniques for Space Weather (E. Camporeale, S. Wing, J. Johnson, Editors), Elsevier, 2018, in press

Three more have been submitted; around ten are in preparation

BACKUP SLIDES