Mainshock-strongest aftershock relation in Northeastern Italy and Western Slovenia

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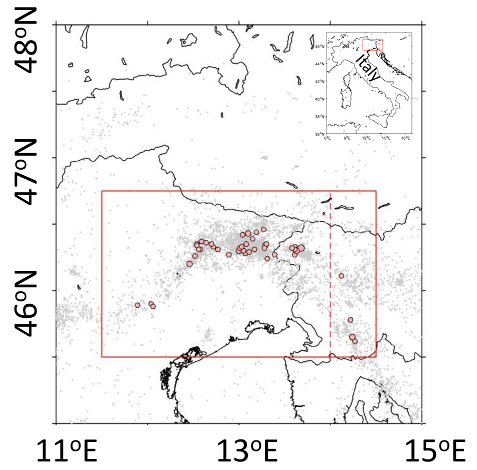
1. ABSTRACT

- We investigated the occurrence of large aftershocks following the most significant earthquakes that occurred in North-eastern Italy and Western Slovenia.
- Clusters are defined as "type A" if, given a main shock of magnitude Mm, the subsequent strongest earthquake in the cluster has magnitude Ma≥Mm-1; of type B otherwise.
- We used an improved version of a pattern recognition method developed by Gentili and Di Giovambattista 2017 for medium-high seismicity in Italy.
- In particular, we investigated the radiated energy and the the spatio-temporal evolution of the aftershocks occurring within a few days and the probability to have a strong earthquake depending on the time elapsed after the mainshock.
- In order to characterize the feature depending on the cluster type, we used decision trees as classifiers on single feature separately. The performances of the classification are tested by leave-one-out method.
- The analysis was performed on different time-spans after the mainshock to simulate the increase of information available as time passes during the seismic clusters.
- The method has been successfully applied to the 1976 Friuli cluster, in which a swarm of large earthquakes happened 4 mounths after the first mainshock and on two small cluster this year in the same are

2. DATABASE



The database we adopted was OGS Bulletins: an accurate local catalogue (1977-2018). Mc=2 till 1993 and 1.5 from 1994 (Peresan and Gentili, 2018)

http://www.crs.inogs.it/bollettino/RSFVG/RSFVG.en.html

Fig. 1: Selected area (before and after 2008) and clusters' epicenters (42 clusters)

- The area of sufficient completeness is detected based on the ratio R (R>0.8) between the number of ISC earthquakes that have an equivalent in OGS catalogue and the total number of earthquakes in ISC catalogue (Kossobokov et al. 1999, Peresan and Gentili, 2018).
- From 2008, the area could be extended 0.5 degrees eastward thanks to the collaboration with ARSO (Environmental Agency of the Republic of Slovenia)

3. CLUSTER IDENTIFICATION

- Clusters were selected by a windowing algorithm for the radius (ρ) and its duration (τ) identification. In this work the "mainshock" is the first event with M≥3.7 in a cluster and "aftershocks" are the following events. 42 clusters were detected.

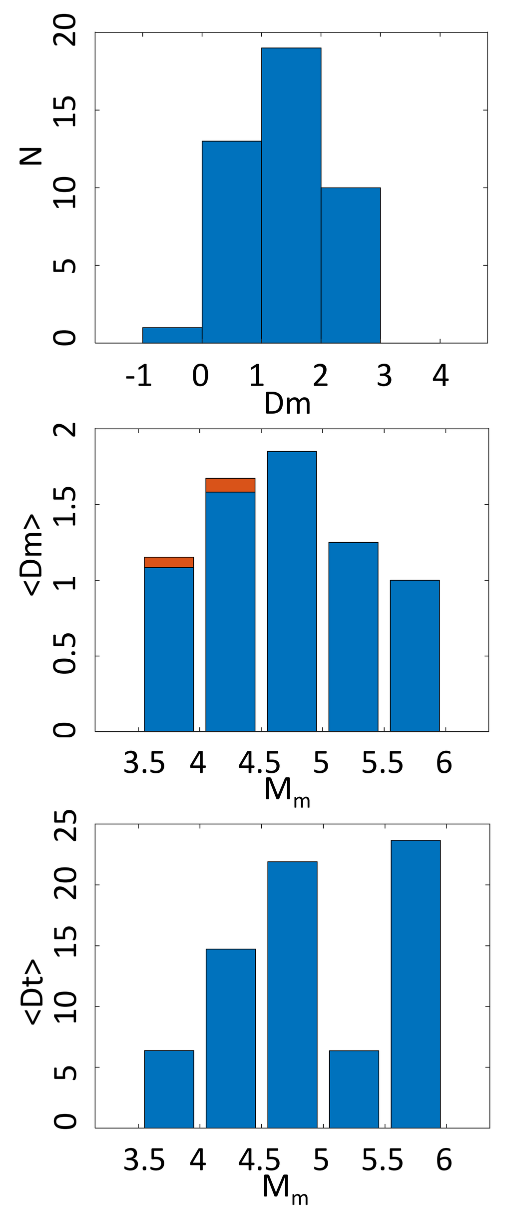
$$\rho = 10^{0.41 M_m - 1} + 2$$
$$\tau = 10^{0.33 M_m + 0.42}$$

Gentili and Bressan (2008) + 2 km

- If after the "mainshock" another event with magnitude ≥ Mm-1 occurs, the cluster is labeled as being of type "A"; otherwise it is considered of type "B" (Vorobieva 1999).

Fig. 3: Percentage (Perc) of clusters that have had the strongest aftershock. Red=A, Blue=B, black=all.

4. RESULTS: CLUSTERS' CHARACTERISTICS



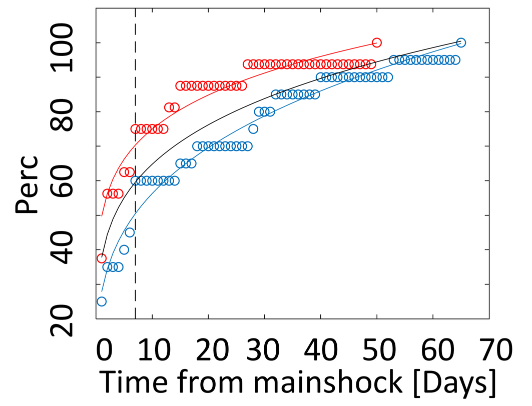
Mean Dm 1.3-1.4 in good agreement with Båth law (Båth, 1965).

For Mm>5 Dm decreases (orange: uncertainty when Ma<Mc).

Dt generally increases with Mm

Fig. 2: Clusters' characteristics: Dm =Mm–Ma; Dt =ta-tm ([Days]); <.> mean of .; a=strongest aftershock

Hp: larger earthquakes activate more complex tectonic structures => the probability to have a subsequent strong event and a longer interval between the mainshock and the strong event is higher.

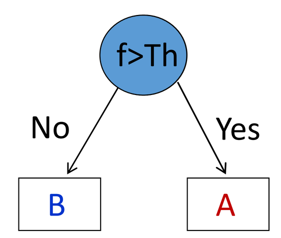


Perc=λT$^{\gamma}$ Fitting law

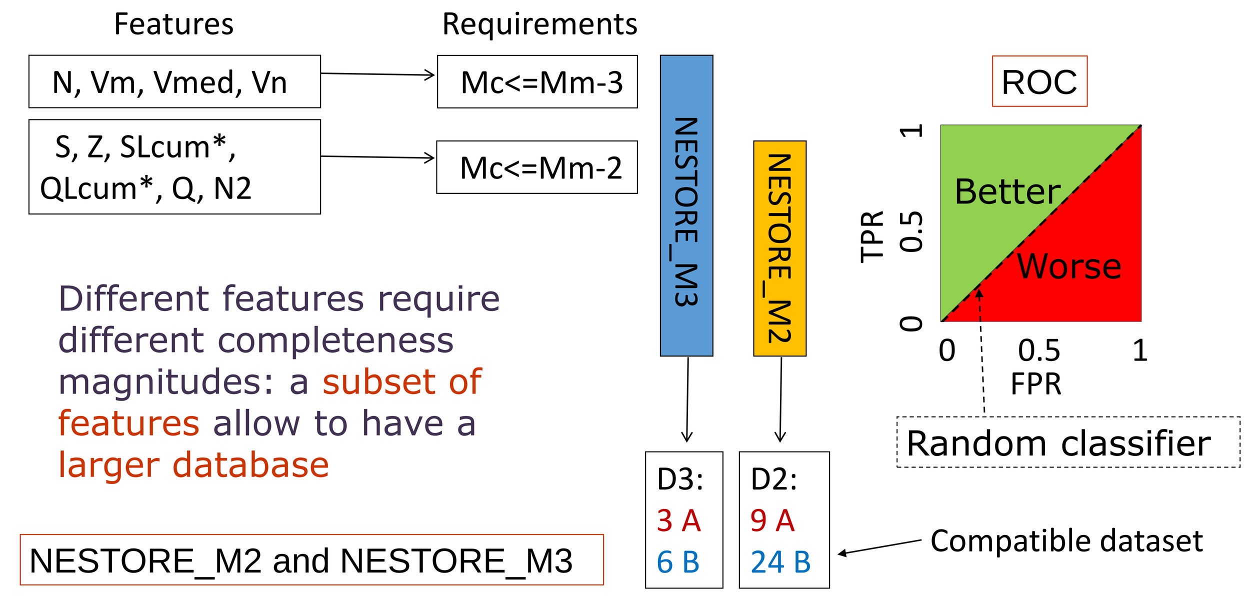
	γ	λ
All data	0.234±0.003	37.8±0.3
A data	0.178±0.005	49.7±0.7
B data	0.306±0.004	27.9±0.6

5. PATTERN RECOGNITION APPROACH

- NESTORE – (NExt STrOng Related Earthquake) is a software package for A clusters forecasting based on pattern recognition approach. It analyses the seismic data at increasing time intervals T after the mainshock.
- Tested features:
  - N, N2=number of aftershocks (with magnitude Mm-2 and Mm-1, respectively)
  - S=total equivalent source area
  - Q=cumulative radiated energy
  - Vm=variation of magnitude from event to event
  - Vmed=variation of average magnitude from day to day
  - Vn=variation of the number of aftershocks from day to day
  - Z=linear concentration of aftershock
  - SLcum, SLcum2 =deviation of S from the long term trend (SLcum2 with sliding window)
  - Qlcum, QLcum2=deviation of Q from the long term trend (QLcum2 with sliding window)
- Accordingly with Gentili and Di Giovambattista (2017), each feature has been evaluated by a pattern recognition approach using an independent decision tree (Jang et al., 1997).
- A one-node decision tree is trained: the algorithm identifies for each feature f a threshold Th so that if f≥Th the cluster is identified as A, otherwise B.



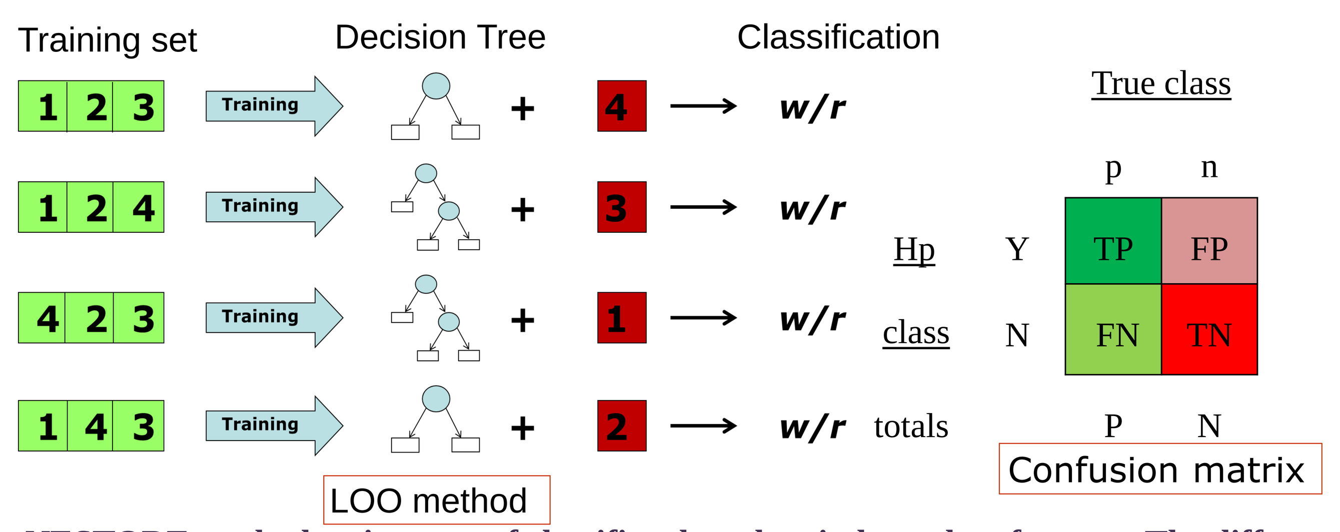
Binary 1-node decision tree : circle is a decision node; rectangles are leaves



Different features require different completeness magnitudes: a subset of features allow to have a larger database

NESTORE_M2 and NESTORE_M3

- Using Mc<=Mm-3 the number of clusters that can be analyzed is low => we developed NESTORE_M2
- In order to compare precursors performances we selected 6 different time periods (in days: [0, 0.25] [0,0.5] [0,0.75] [0,1], [0, 2], [0, 3]) and for each time period we calculated the values of all the tested precursors.
- We checked the performances by the LeaveOneOut (or LOO) method: each learning set is created by taking all the samples except one, the test set being the sample left out. The procedure is repeated for all the samples
- The test allowed to obtain the confusion matrix and derived information like ROC diagrams (A = p; B = n).



LOO method

Confusion matrix

$$Recall = TPR = \frac{TP}{P}$$
$$Precision = \frac{TP}{Y}$$
$$Accuracy = \frac{TP + TN}{P + N}$$
$$FPR = \frac{FP}{N}$$
$$Informedness = TPR - FPR$$

- NESTORE method trains a set of classifiers based on independent features. The different classification results need to be combined in a unique classification "Probability of Class A". We used a Bayesian approach (Bailer-Jones et al. 2011):

$$P(A|D_1 \dots D_N) = \frac{[N(B)]^{N-1} \prod_{n=1}^{N} p_n}{[N(B)]^{N-1} \prod_{n=1}^{N} p_n + [N(A)]^{N-1} \prod_{n=1}^{N} (1 - p_n)}$$

p_n=P(A|Dn) is the probability to have A cluster given a value Dn of the n feature, N(A), N(B): number of A, B, N: number of classes.

6. RESULTS: PATTERN RECOGNITION; SINGLE FEATURES

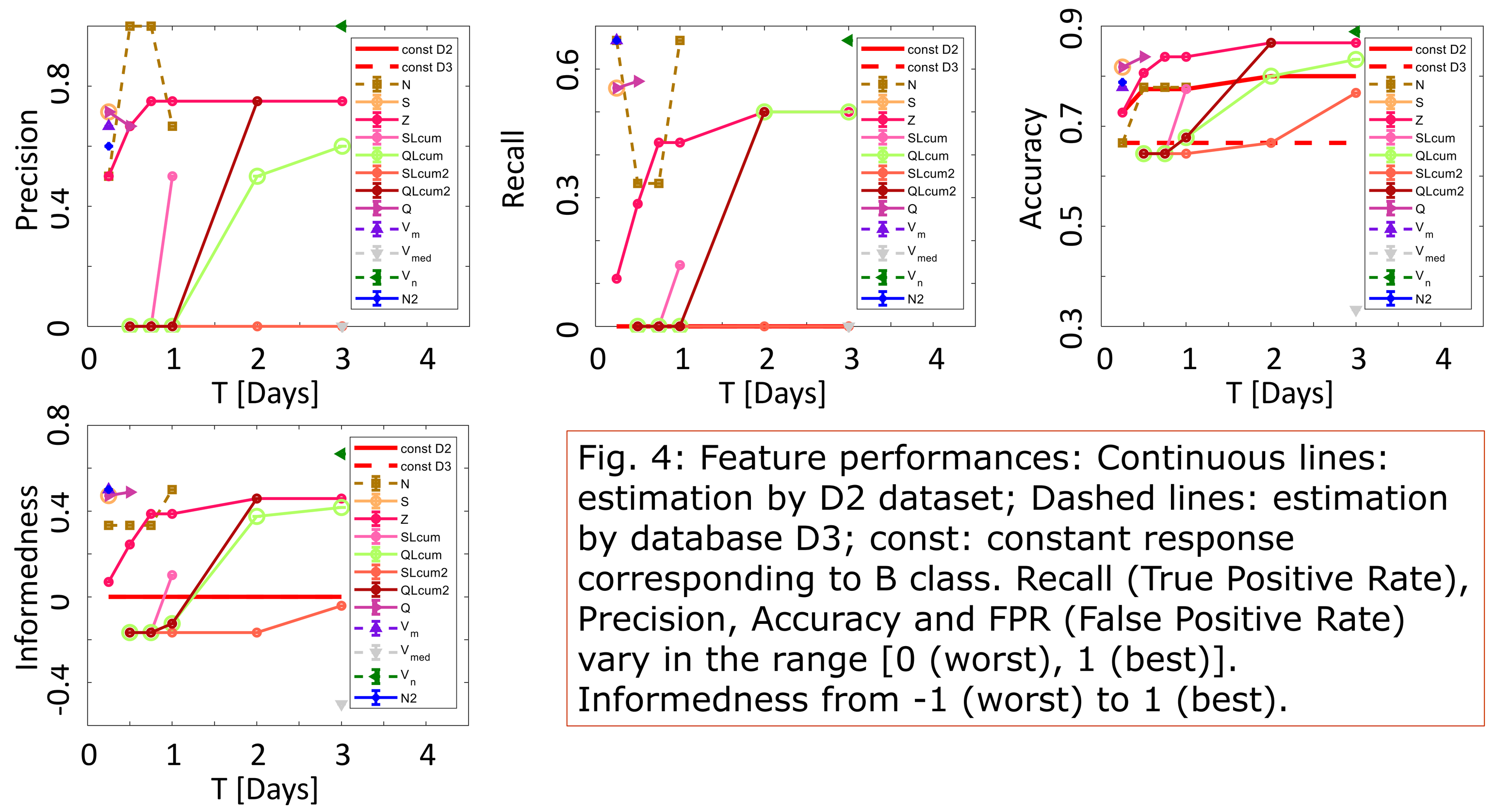


Fig. 4: Feature performances: Continuous lines: estimation by D2 dataset; Dashed lines: estimation by database D3; const: constant response corresponding to B class. Recall (True Positive Rate), Precision, Accuracy and FPR (False Positive Rate) vary in the range [0 (worst), 1 (best)]. Informedness from -1 (worst) to 1 (best).

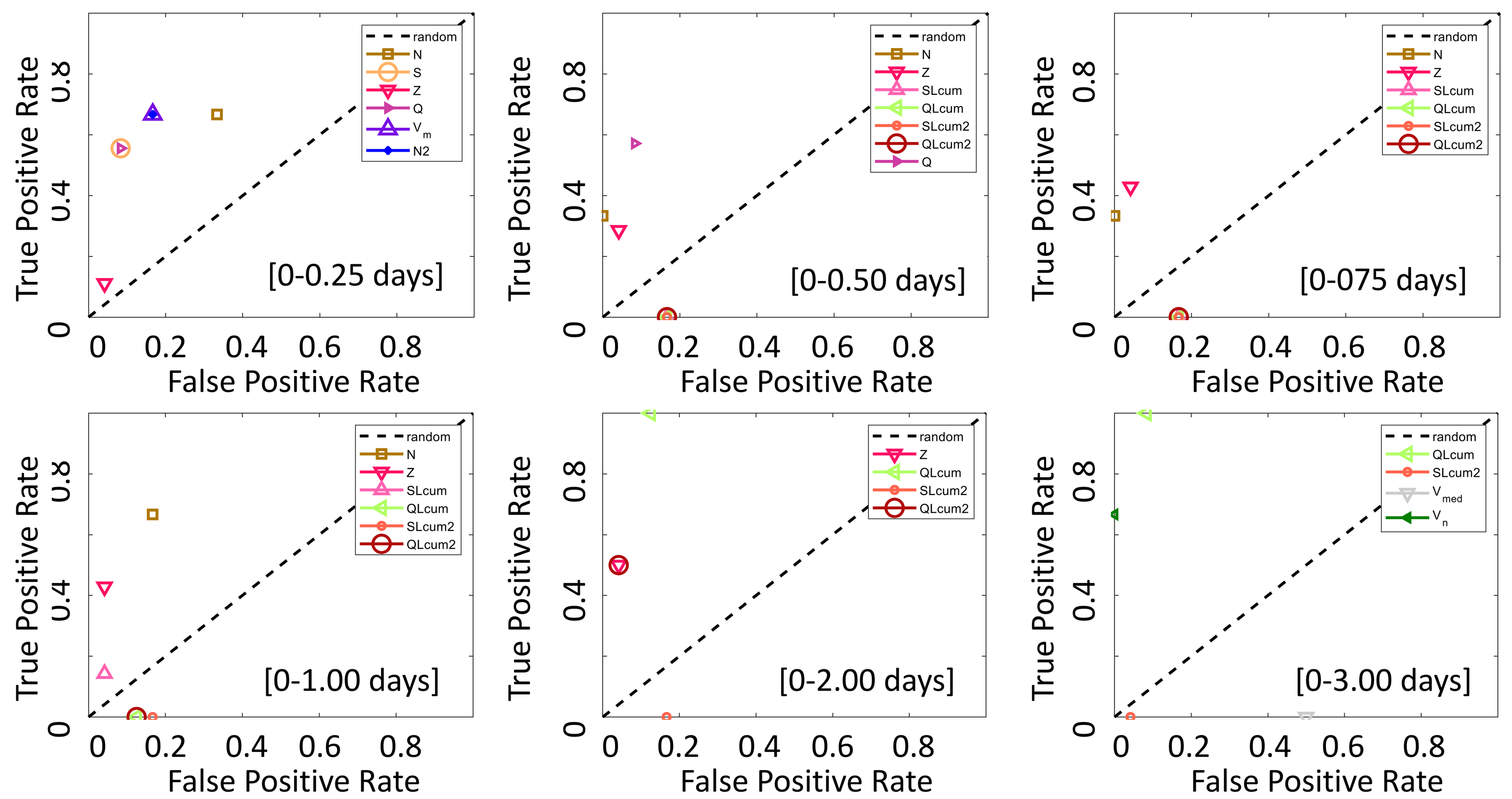


Fig. 5: Receiver Operating Characteristics (ROC) graph (Swets et al., 2000). It depicts the trade-off between benefits (true positives) and costs (false positives)

7. RESULTS: PROB(A) FORECASTING ON INDEPENDENT DATA

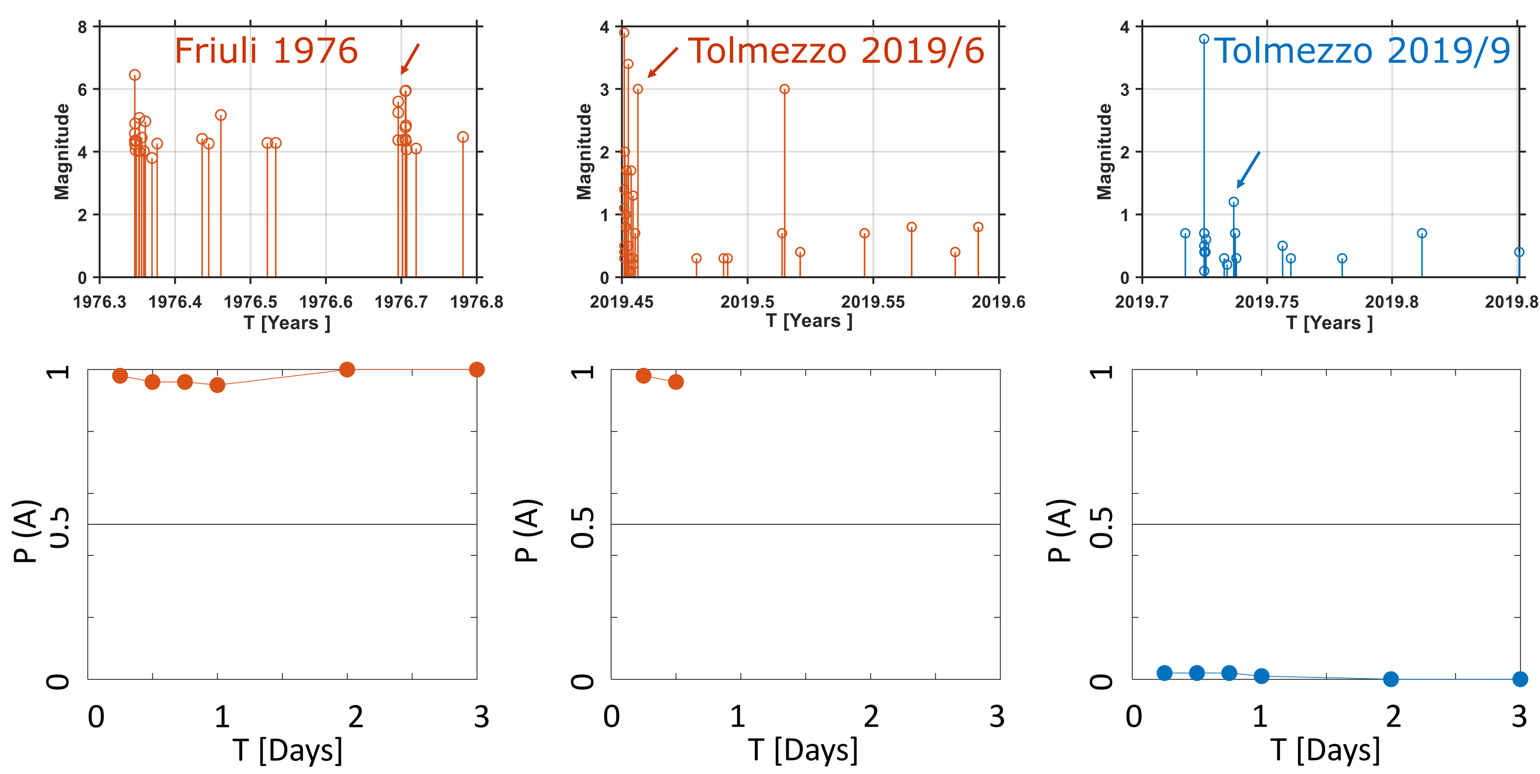


Fig. 6: NESTORE_M2 successfully estimates A probability P(A)