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**EXCELENCIA
SEVERO
OCHOA**

A Machine Learning approach for parameter screening in Earthquake simulation.

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High Performance Machine Learning
Workshop 2018

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Introduction



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EARTHQUAKES

Natural hazard

Earthquakes are the result of rupture in the Earth's Crust.

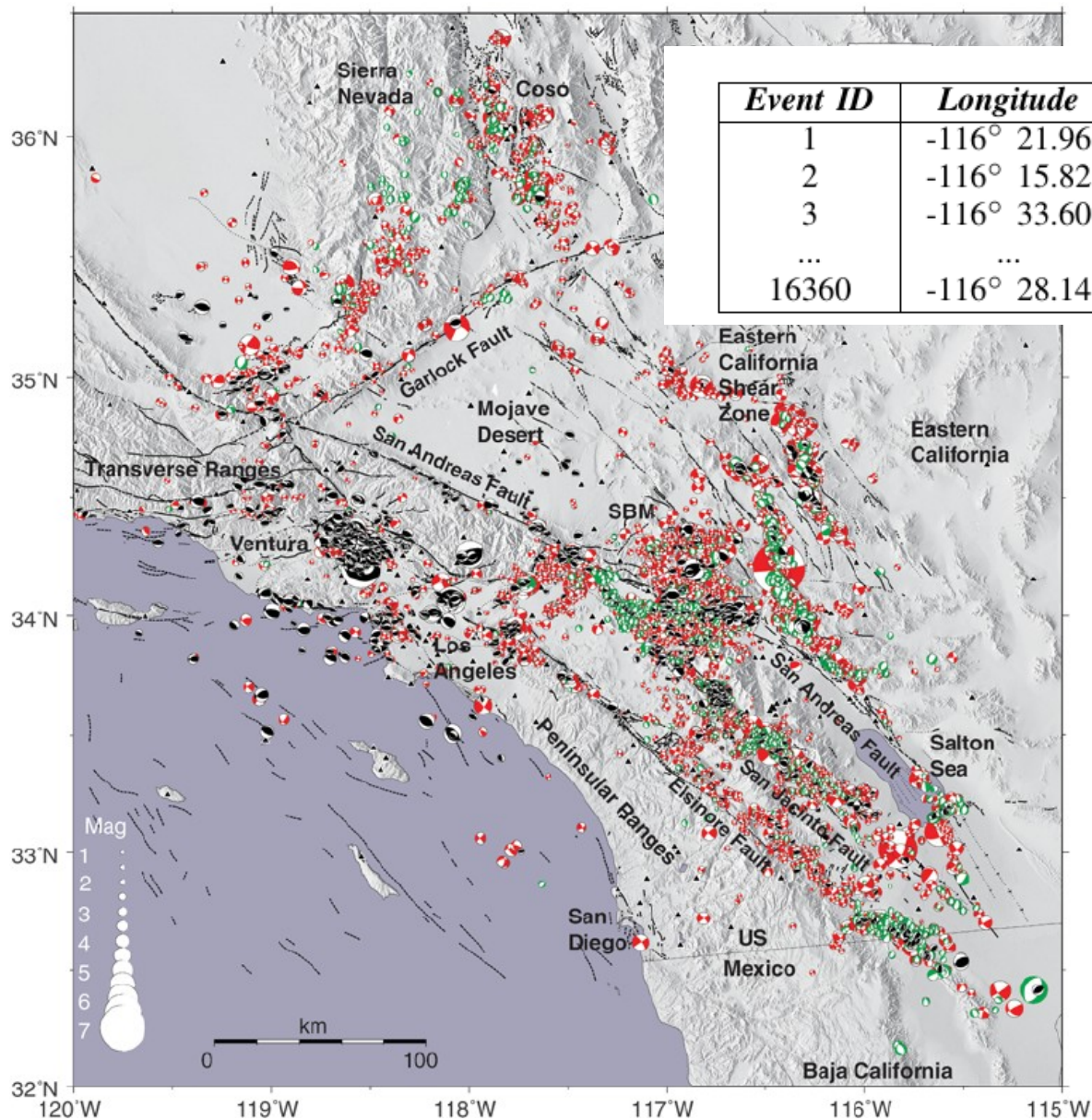
Aftershocks are defined as sequence of earthquakes with lower magnitude than the mainshock that triggered them.



Nepal 2015, Mw = 8.1

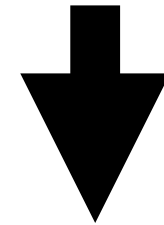
Our observational span is still too short to be able to draw strong (predictive) conclusions about when, where, and how big the next earthquake will be.





Seismic catalogs

<i>Event ID</i>	<i>Longitude</i>	<i>Latitude</i>	<i>M_w</i>	<i>Time [days]</i>
1	-116° 21.96	34° 13.26	4.3	.285E-02
2	-116° 15.82	34° 26.71	4.8	.352E-02
3	-116° 33.60	34° 24.60	4.2	.3567E-02
...
16360	-116° 28.14	34° 24.30	0.9	.365E+03



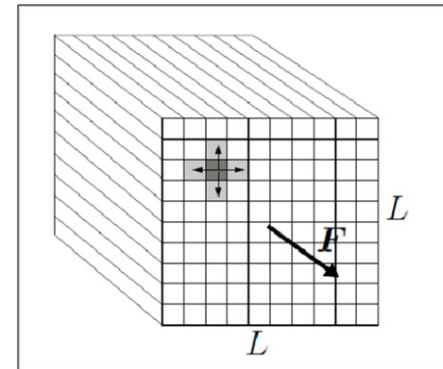
Statistical measures

Statistical Measures	Aftershock Sequences		
	<i>LND</i>	<i>HM</i>	<i>NOR</i>
$\langle M \rangle$	2.52	2.50	2.6
D_0 (Eq. 1)	1.61	1.51	1.46
M_{max}	6.3	5.8	5.6
M_c	2.1	2.1	2.1
b (Eq. 3)	1.0	1.03	0.94
q (Eq. 5)	1.49	1.47	1.49
$H(\Delta)$ (Eq. 2)	0.64	0.67	0.62
$PMOL$ (Eq. 4)	1.43	1.32	1.32

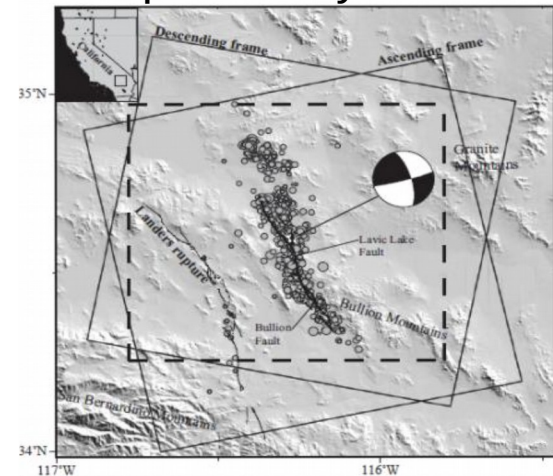
FIBER BUNDLE MODEL



- numerical simulations
- discrete element model developed to study the rupture process in heterogeneous materials (e.g. textiles, composites, Earth's crust, etc.)

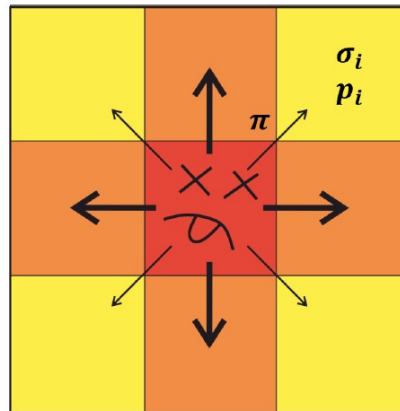
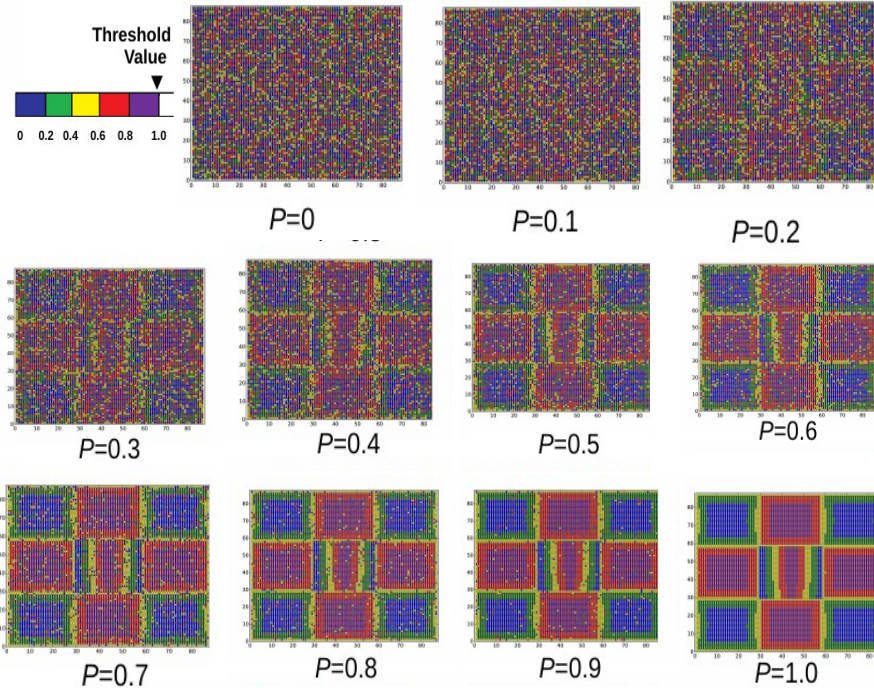
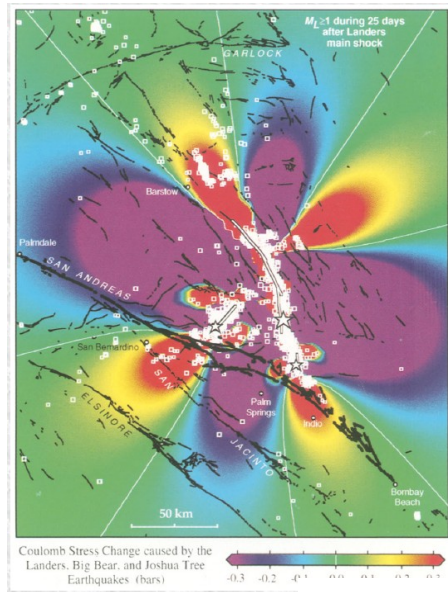


- describes the interactions of individual cells
- transfer load rules
- initial load probability distribution function



- ability to model aftershocks
- aftershocks located around the active faults

captures spatio-temporal
distribution of seismic events

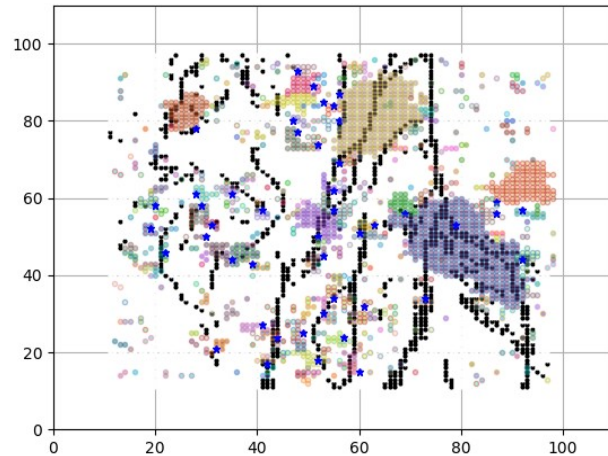


Load transfer to the neighbors

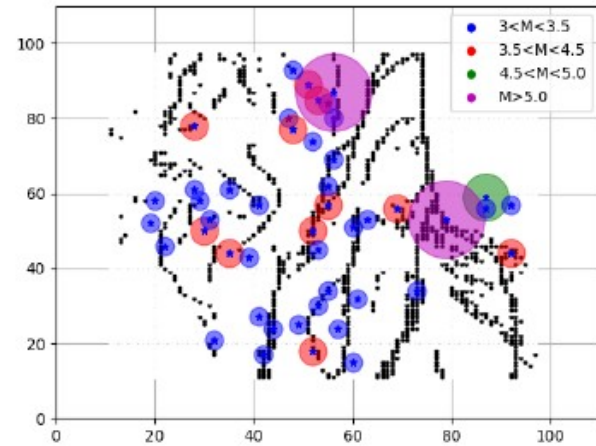
Input parameters:
P: initial organization
probability
 π : transfer value
N: lateral grid size

AFTERSHOCKS: Statistical patterns

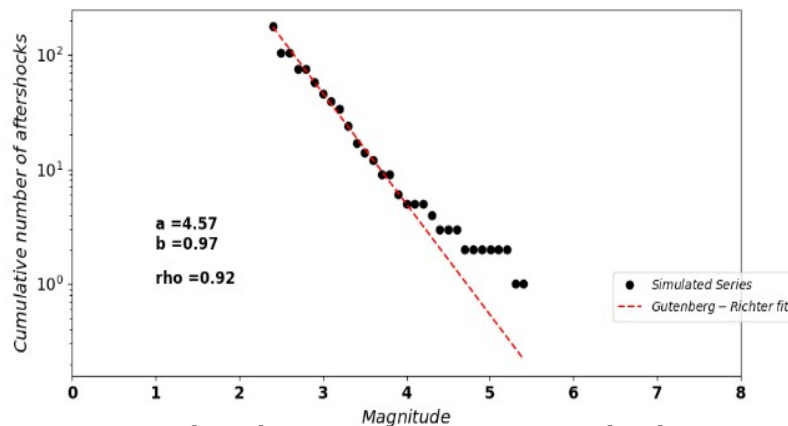
Modeling spatial distribution around faults and its magnitude



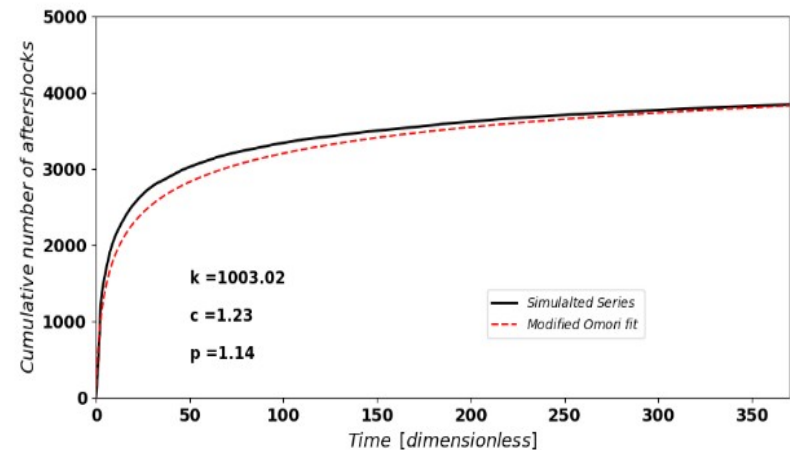
Raw spatial distribution



Magnitude spatial representation



Magnitude- Frequency relation
Gutenberg-Richter law



Omori-Utsu law: Describes in a power law the aftershock time behavior

Objective

To estimate the FBM parameters that better reproduce real seismic characteristics.

Methodology



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REAL DATA

Three aftershocks that occurred in Southern California:

- 1) Landers (LND) – 1992, $M = 7.3$, # of seismic events = 30547
- 2) Northridge (NOR) – 1994, $M = 6.7$, # of seismic events = 11252
- 3) Hector Mine (HM) – 1999, $M = 7.1$, # of seismic events = 16360

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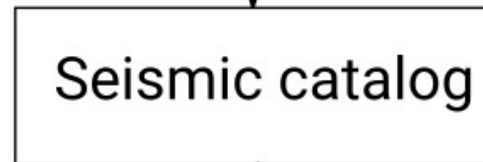
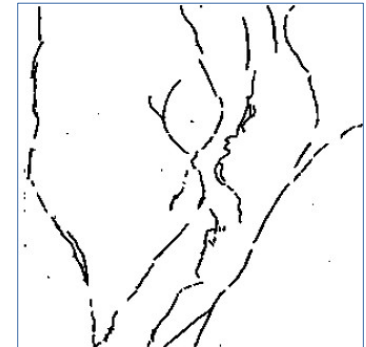
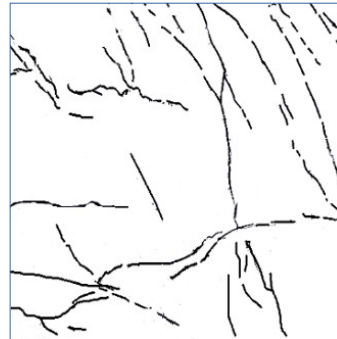
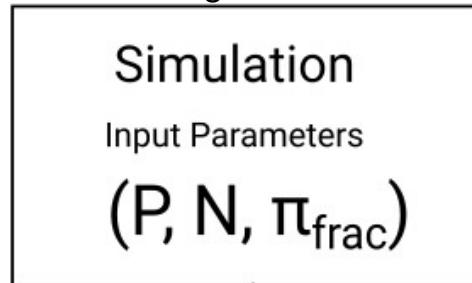
TABLE III
STATISTICAL MEASURES FOR THE REAL AFTERSHOCK SEQUENCES.

SYNTHETIC DATA

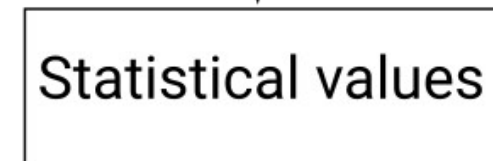
P: initial organization probability

π : transfer value

N: lateral grid size

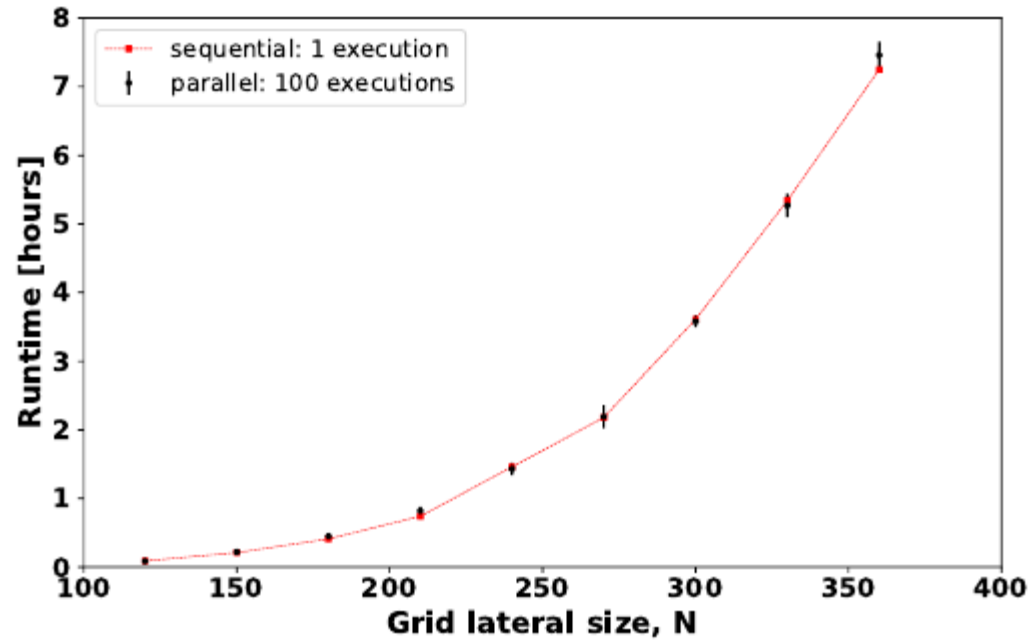


Event ID	X	Y	Ruptured Area [cells]	time [dimensionless]
1	7	30	30	0.946E-04
2	45	66	15	0.284E-02
3	14	22	65	0.556E-01
...
2540	87	72	9	0.125E+04



Stat. Vals.	Aftershock Sequences		
	LND	HM	NOR
	Params.	Params.	Params.
	$P = 0$ $N = 240$ $\pi_{frac} = 0.95$	$P = 0$ $N = 240$ $\pi_{frac} = 0.85$	$P = 0$ $N = 210$ $\pi_{frac} = 0.85$
$\langle M \rangle$	2.37 ± 0.01	2.32 ± 0.01	2.30 ± 0.01
D_0 (Eq. 1)	1.61 ± 0.01	1.61 ± 0.01	1.52 ± 0.01
M_{max}	5.87 ± 0.21	4.9 ± 0.48	5.49 ± 0.36
M_{min}	$2.06 \pm 1.21e-7$	$2.07 \pm 1.14e-7$	$2.06 \pm 1.21e-7$
b (Eq. 3)	0.73 ± 0.06	1.07 ± 0.17	0.78 ± 0.10
q (Eq. 5)	1.61 ± 0.03	1.50 ± 0.05	1.57 ± 0.03
$H(\Delta)$ (Eq. 2)	0.52 ± 0.03	0.53 ± 0.03	0.52 ± 0.02
$PMOL$ (Eq. 4)	1.21 ± 0.58	1.12 ± 0.27	1.29 ± 0.46

High Performance Computing



FBM is sequential

Mare Nostrum 4 supercomputer
Total peak performance:
13,7 Pflops/s



Machine Learning

- Support Vector Machines (SVM) with radial basis kernel and sigmoid kernel
- Flexible Discriminant Analysis (FDA)
- Random Forest (RF)

Data: feature set

Result: average performance
initialization;

while $i = 1$ to 50 **do**

 # Apply cross validation;

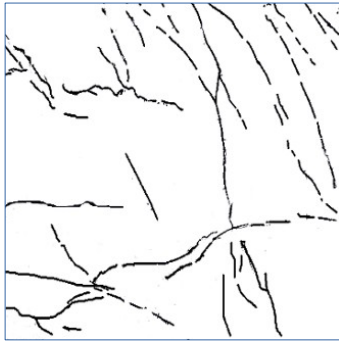
 performance = CrossValidation(sampled, classifier,
 $k=5$);

end

 # return the average performance;
avg-performance;

Experimental Setting

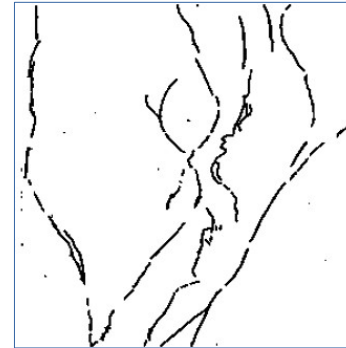
1) Three geometrical Fault Configurations



LND



HM



NOR

2) Parameters

$P = [0.0, 0.08, 0.16, 0.24]$

$\pi = [0.65, 0.75, 0.85, 0.9, 0.95]$

$N = [120, 150, 180, 210, 240, 270, 300, 330, 360, 390]$

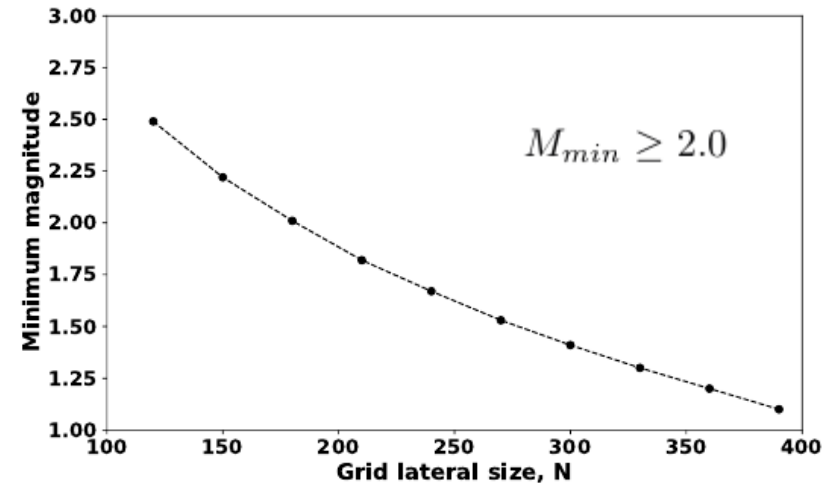
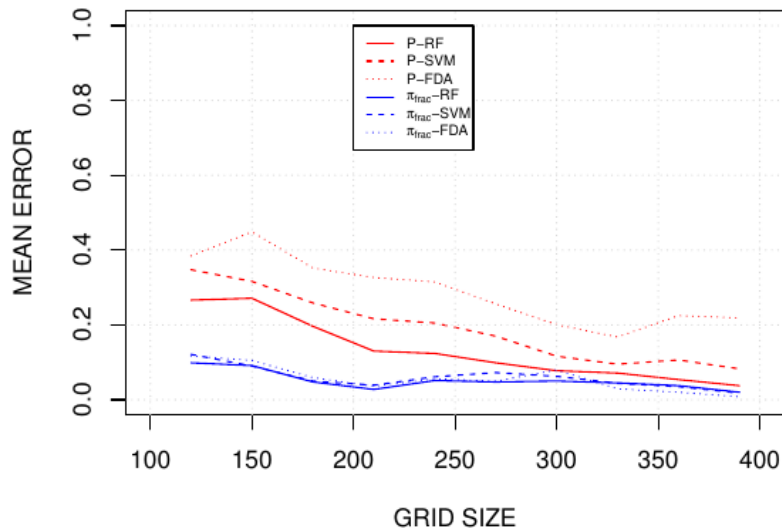
Results



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Experiment 1: Grid size and minimum magnitude

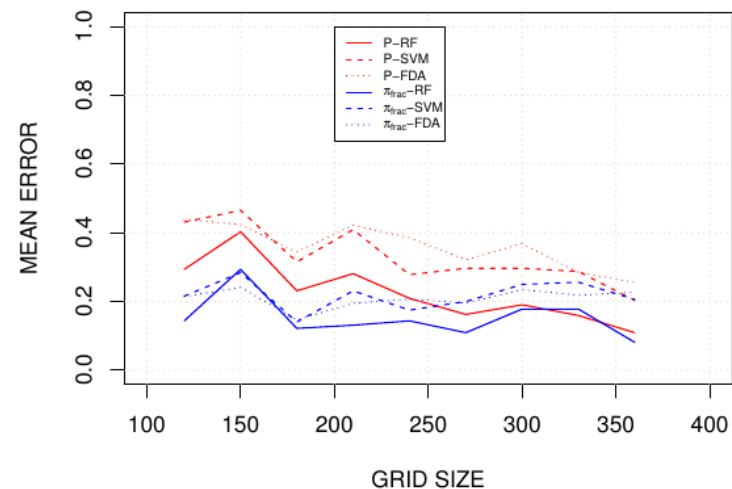


Larger N satisfies smaller minimum magnitudes, but larger grid size requires more computational hours to execute the simulation

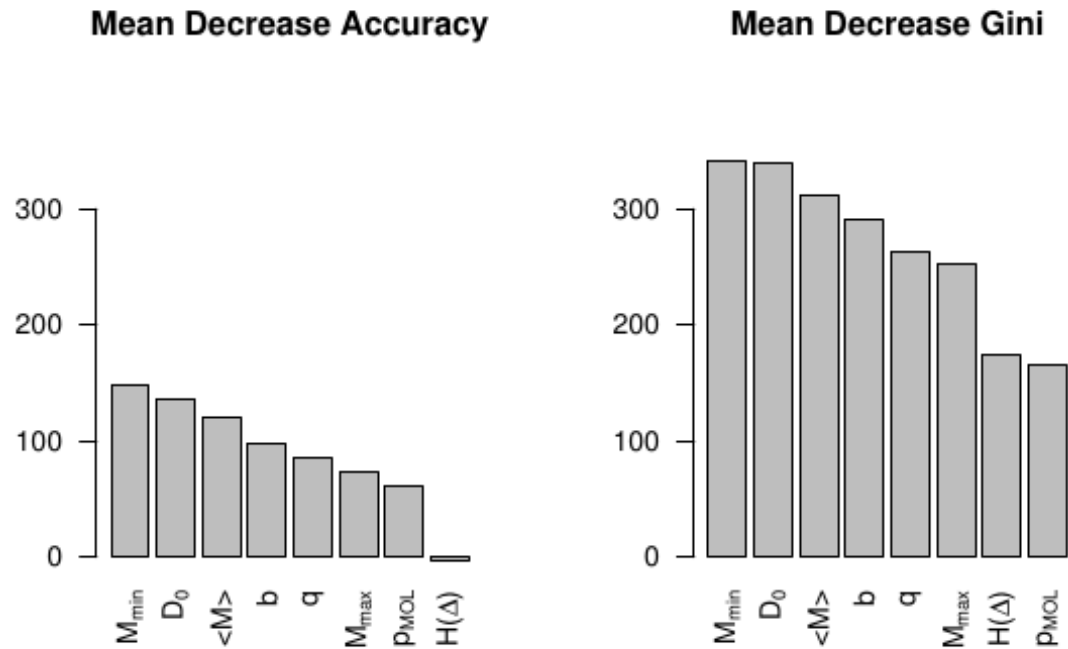
CLASSIFICATION CRITERIA

P: initial organization probability

π : transfer value



Experiment 2: Selecting most important aftershock statistical values.



Magnitude Features: M_{\min} , $\langle M \rangle$, b , q

Fractal Dimension: D_0

Experiment 3: Estimating optimal FBM parameters

- Used important features
- Trained with synthetic sequences
- Classification label (P , π_{frac} , and N)

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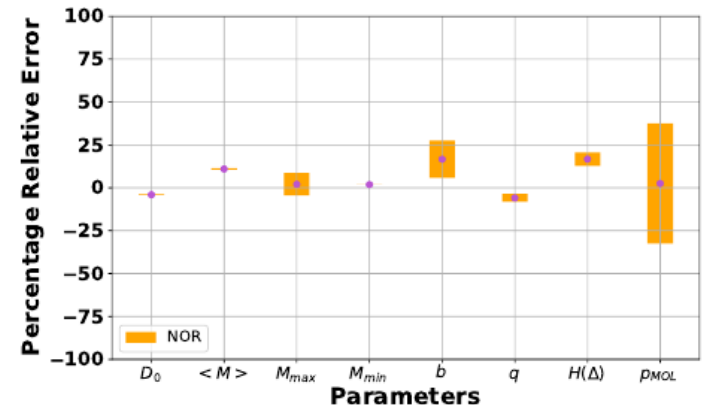
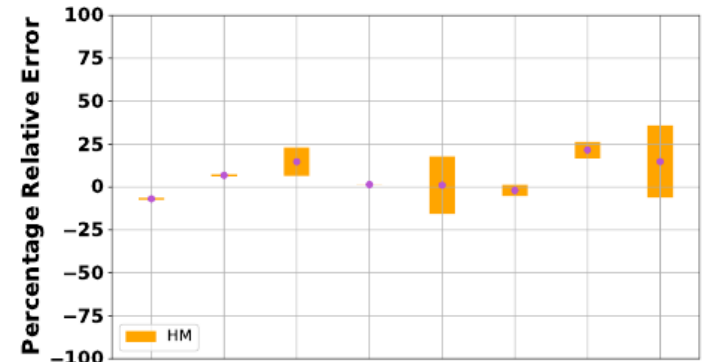
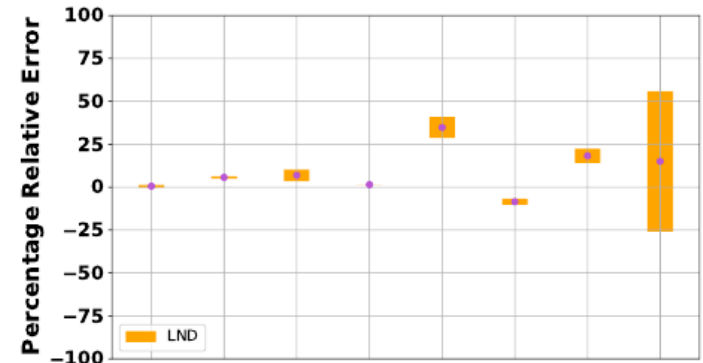
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$N > 210$

Sufficiently large

TABLE III

STATISTICAL MEASURES FOR THE REAL AFTERSHOCK SEQUENCES.



Conclusions and future work



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CONCLUSIONS

- ML is an efficient tool for parameter screening
- ML is a useful tool to study the properties of the FBM model.
- HPC and ML enables us to model highly realistic series of aftershocks, indistinguishable from real ones by the standard seismological measures
- opens the possibility of producing longer and most complex studies involving decades of observations and larger study areas

FUTURE WORK

- increase number of real aftershock sequences with the aim of generalizing our methodology.
- Artificial Neural Networks will be tested and compared to the algorithms used in the present work.
- use partially learned ML models to drive parameter exploration of simulation runs in order to reduce the number of simulations needed to approximate a mapping between FBM parameters and earthquake statistics.
- development of a software package that contains not only the simulator but also the optimal parameter screening



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Thank you



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