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Quantifying the precursors to brittle failure in rocks using synchrotron imaging and machine learning

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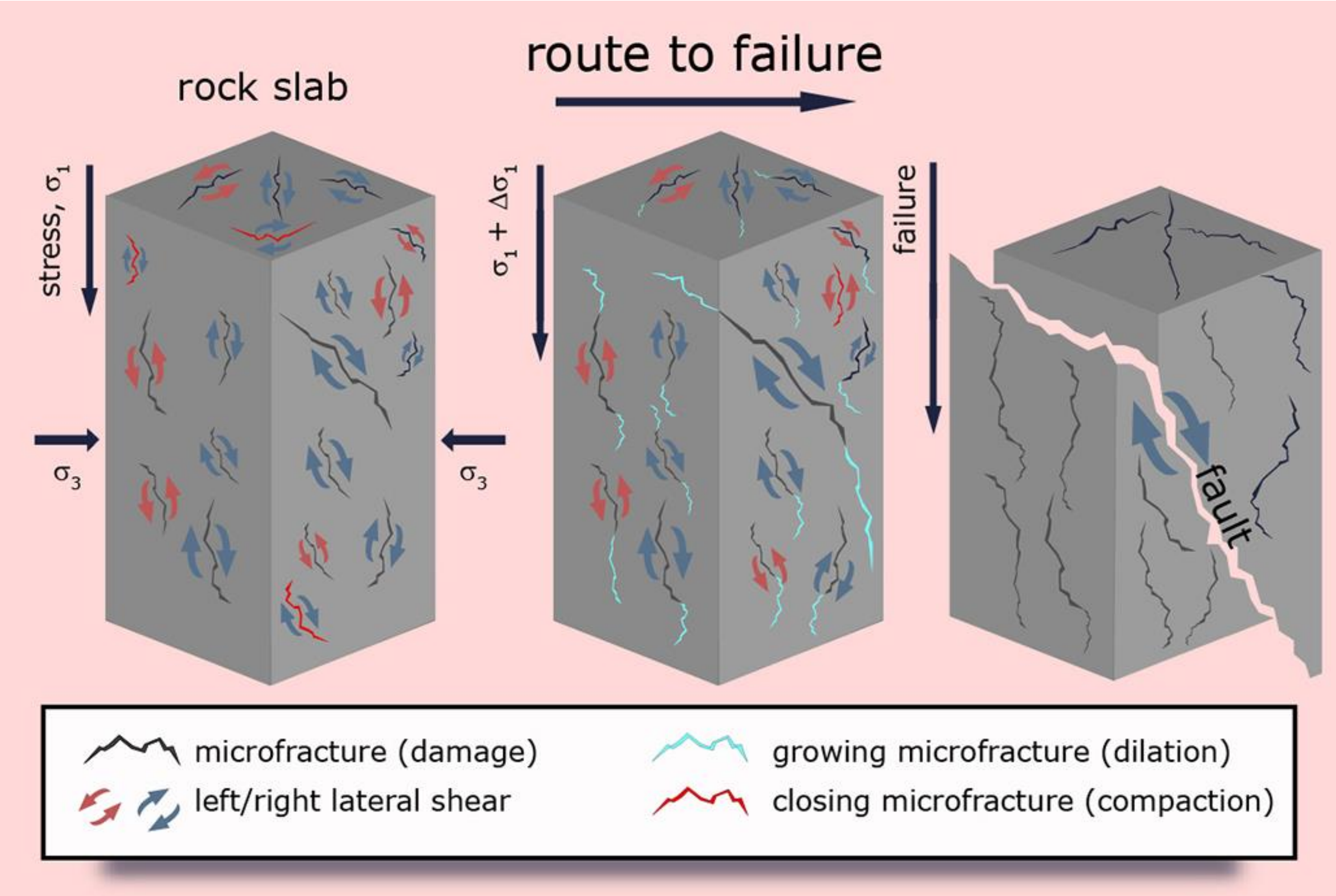
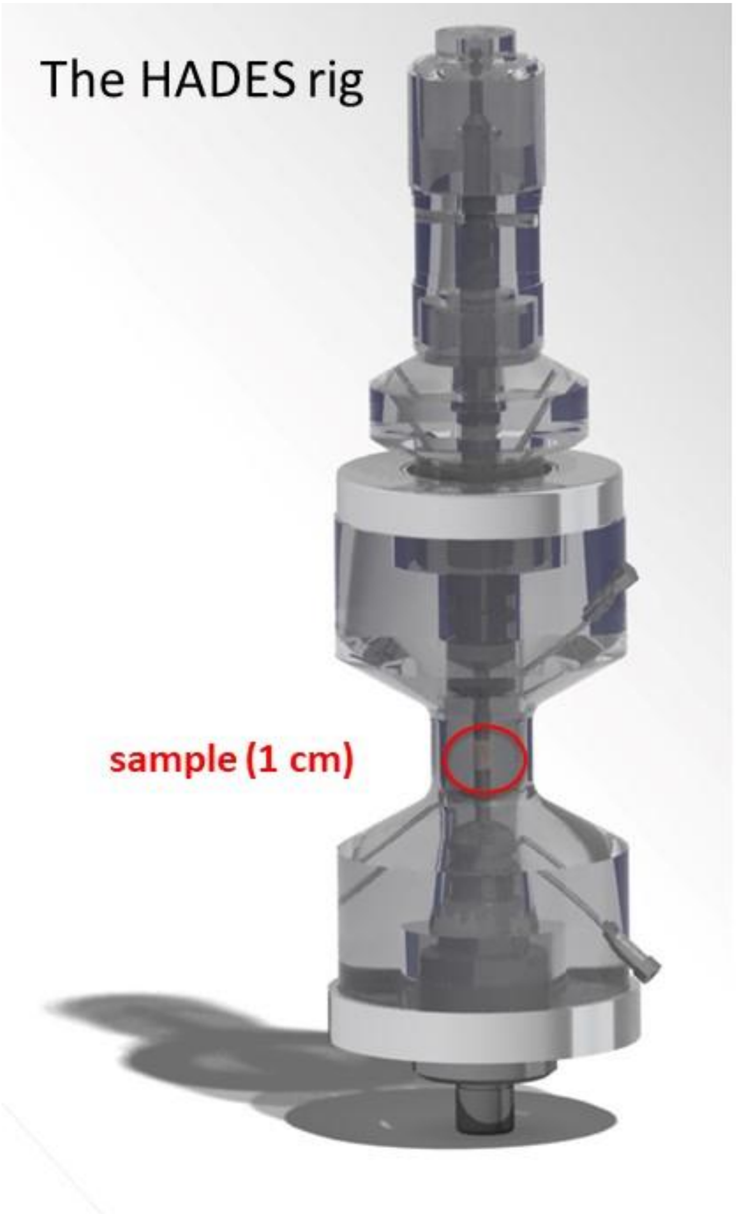
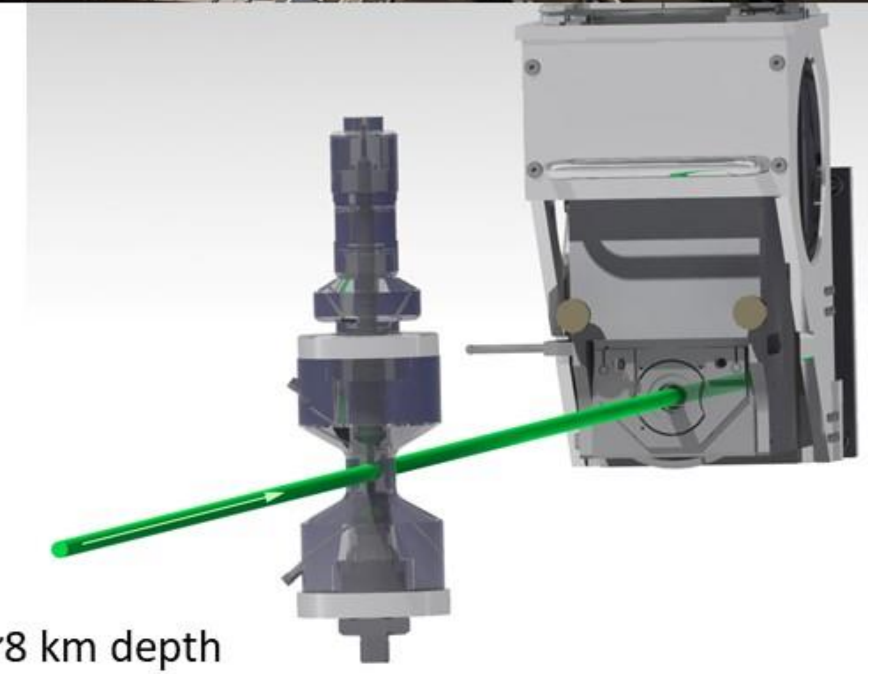
System-size failure under compression: a 3D preparation process



Renard et al. PNAS, 2019

A technology rupture in rock physics experiments: 4D *in-situ*





The European Synchrotron Radiation Facility, Grenoble, France

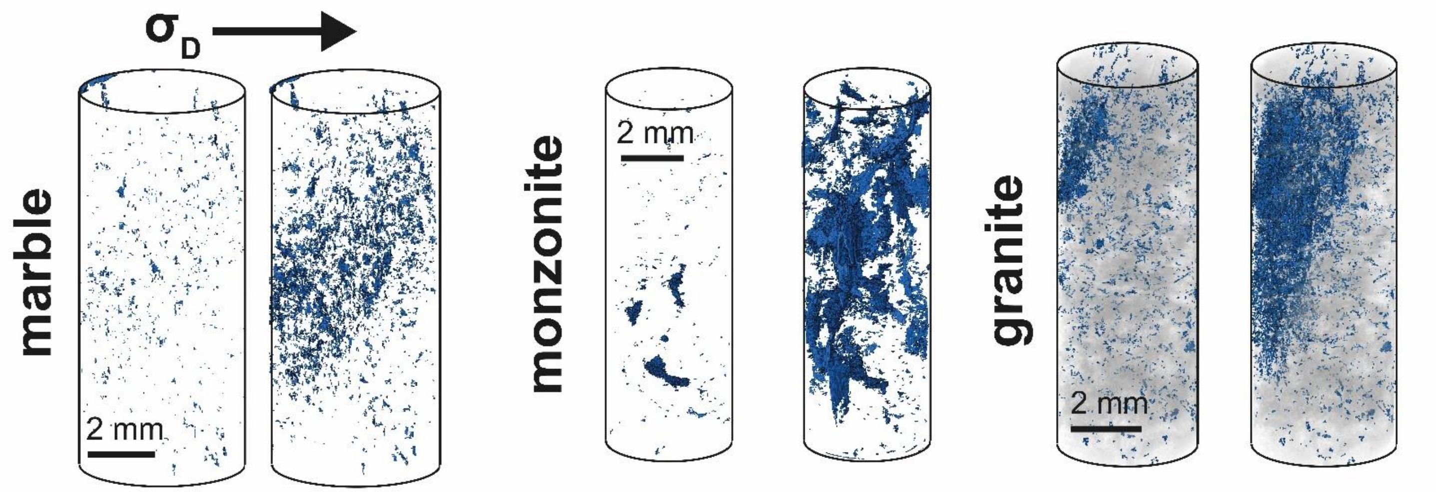
Time-lapse imaging of rock samples at micrometer spatial resolution, under conditions of pressure and temperature relevant to study earthquakes and faulting.

Conditions of pressure and temperature: ~8 km depth

Renard, Cordonnier et al., J. Syn. Rad., 2016

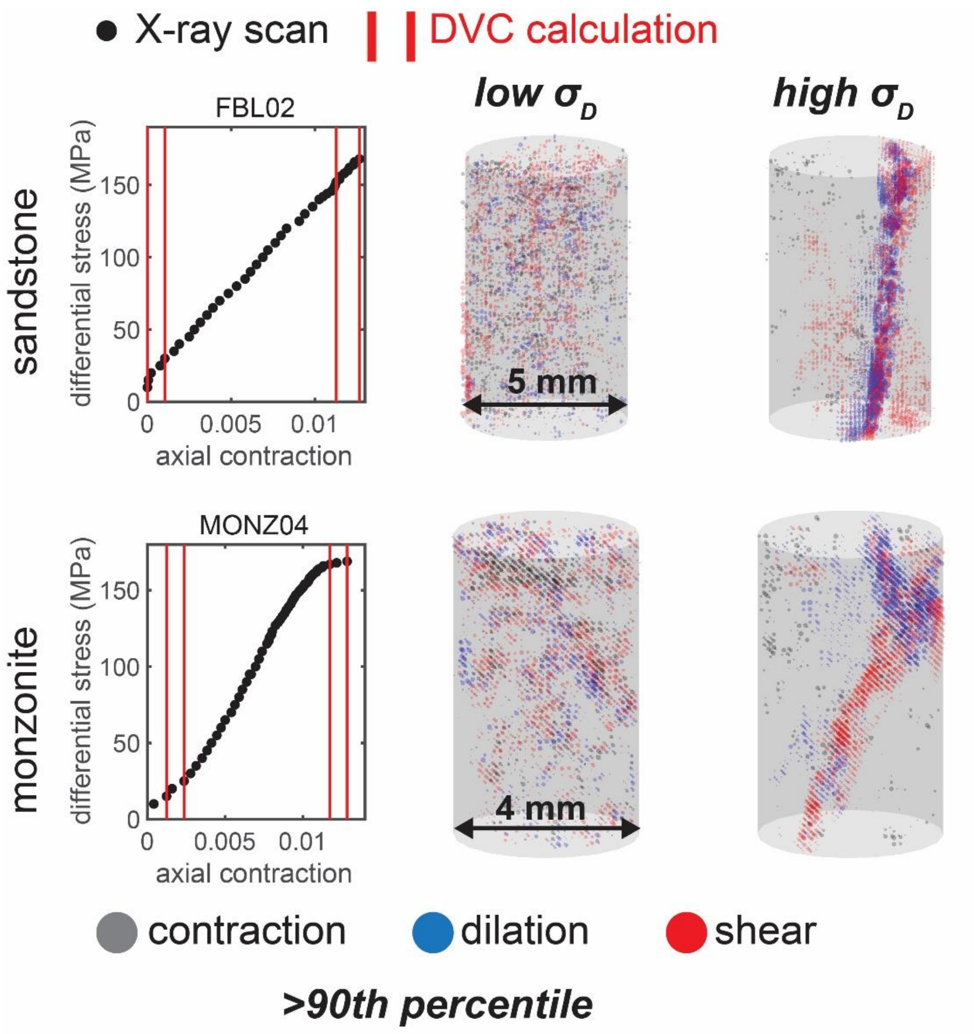
A technology rupture in rock physics experiments: 4D *in-situ*

Direct imaging of microstructure



Renard et al., EPSL, 2017; Renard et al., JGR; 2018; Kandula et al., JGR 2019; Renard et al., PNAS, 2019; McBeck et al., GRL, 2019; McBeck et al, GJI, 2020; McBeck et al., EPSL (in review).

Strain populations (digital volume correlation)

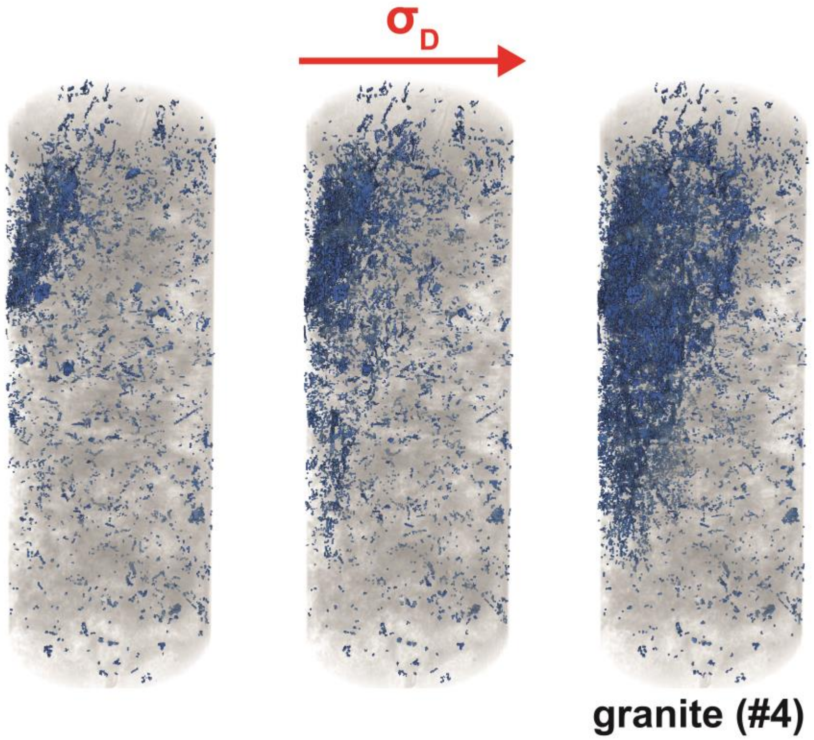


4D data of damage (microfractures) and incremental strain fields (digital volume correlation) are analysed with machine learning techniques to :

- Characterize the parameters that control **microfracture growth** in rocks (damage evolution);
- Estimate the **distance to failure** from the global properties of strain and microfractures populations.

Machine learning analysis of fracture growth

Objective: from an early state of damage, it is possible to predict which fracture will grow ?



around 10,000 microfractures

1) Perform in situ X-ray microtomography experiments of the triaxial compression of rocks.

2) Track individual fractures throughout 50-100 scans for each experiment.

3) Calculate characteristics of each identified fracture and fracture network.

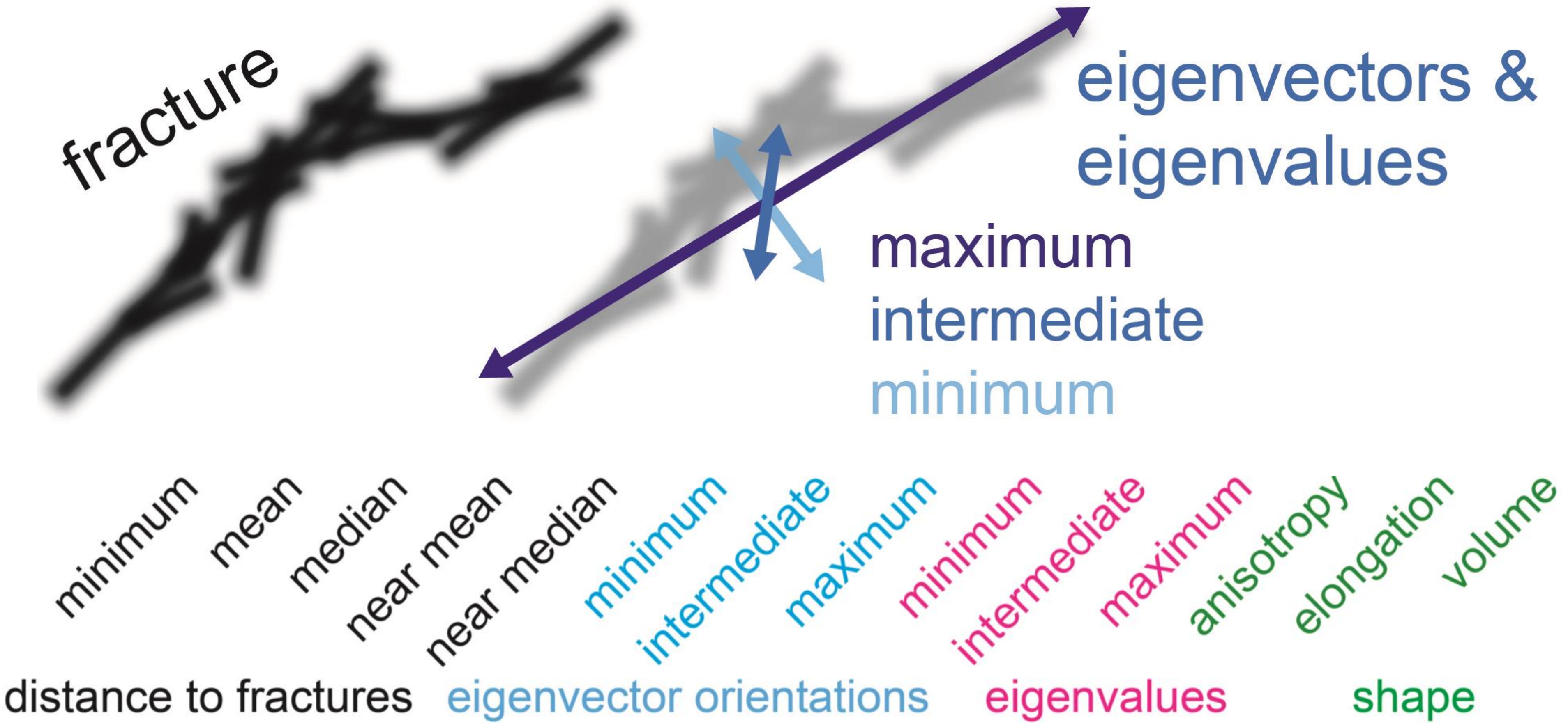
4) Develop logistic regression models to predict whether or not a fracture grows using characteristics as feature inputs.

5) Use recursive feature elimination to identify the fracture characteristics that are the best explanatory features.

6) Track the statistical properties of the best explanatory features for growing and not growing fractures.

Fracture characteristics (14 in total) that may control growth

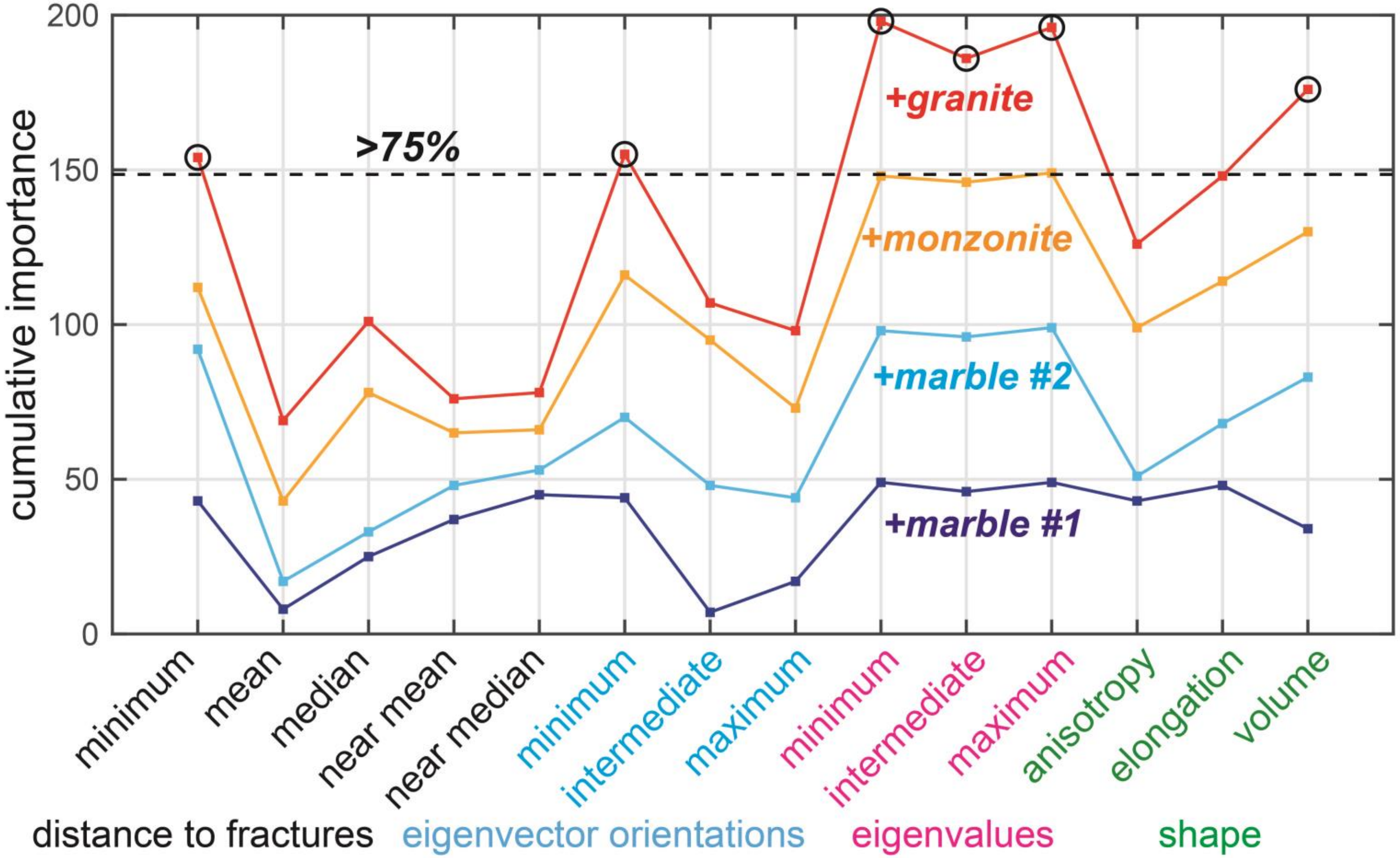
Shape, volume and orientation (9 characteristics)
Distance to other fractures (5 characteristics)



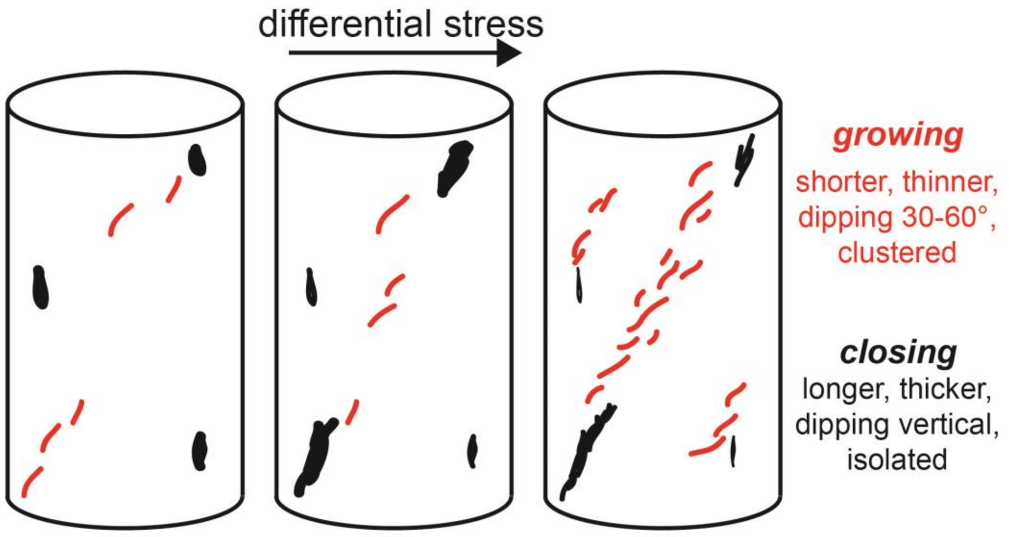
McBeck et al., GRL, 2019

What controls fracture growth ?

A machine learning approach identifies the most important microfracture parameters.



Conclusion:
The parameters that control fracture growth and closing can be identified, opening to future studies that will develop data-driven models of brittle deformation in rocks.



McBeck et al., GRL, 2019