Application of Machine learning techniques to a stick-slip dynamics of a particulate media

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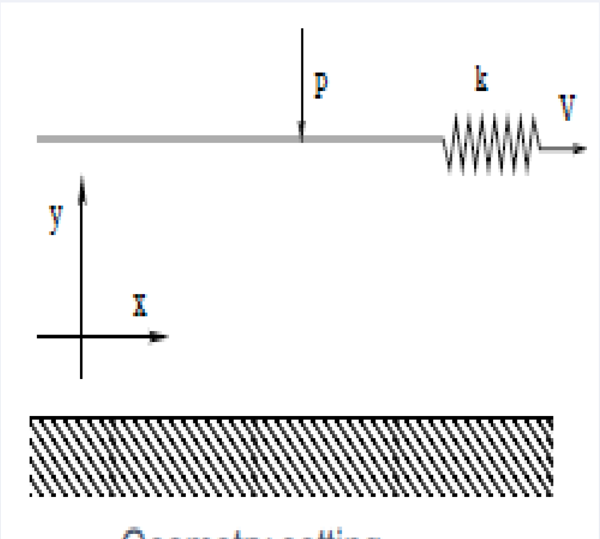
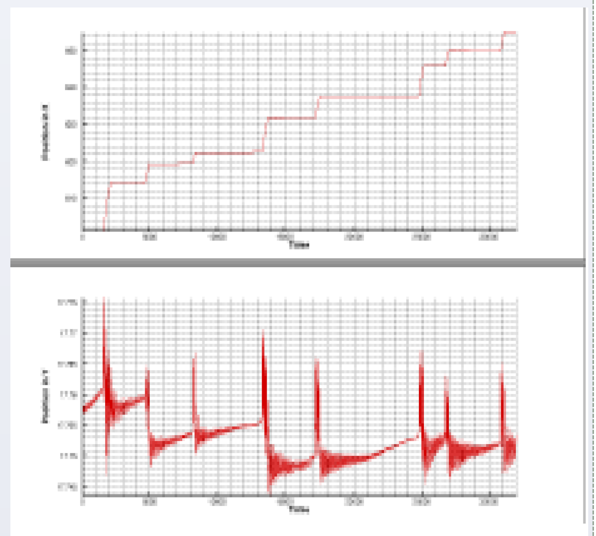
INTRODUCTION

A spring attached to the top wall of a system consists of granular material is pulled by a constant velocity V with confined pressure P.

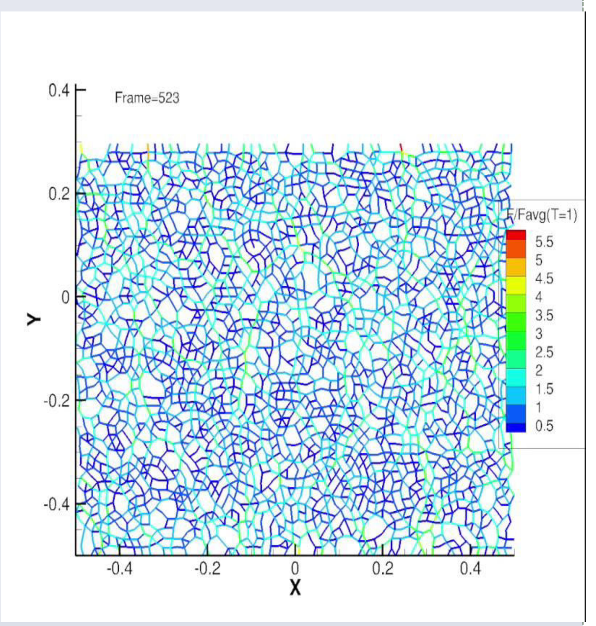


Geometry setting

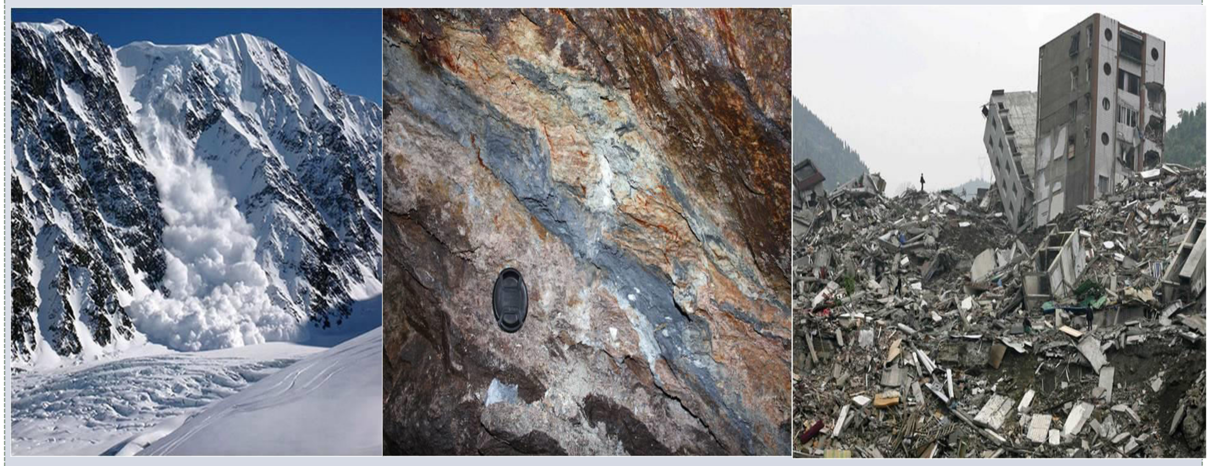


Top wall position

- We use MD simulation to carry out 2D stick-slip simulations.
- Analyze mesoscale information such as force networks to understand the macroscopic system response (slip).
- Main focus is to use Machine learning on the data carried out from large time dependent data sets to simpler well-defined mathematical structures.



MOTIVATION



Earthquake and Avalanches

OBJECTIVES

- Understand the stick-slip behaviour from the persistence diagram information.
- Differentiate stick phase from the slip phase.
- Using Machine learning predict the next slip or how often slip is happening.

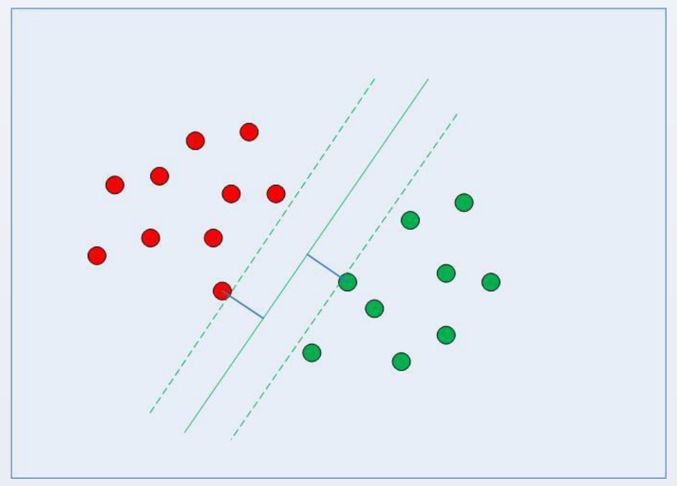
METHODS

Persistence Diagrams: Information about Betti numbers, connectivity and development of the force network structure.

- Zeroth betti number β_0 – number of connected components.
- First betti number β_1 – number of loops/voids.

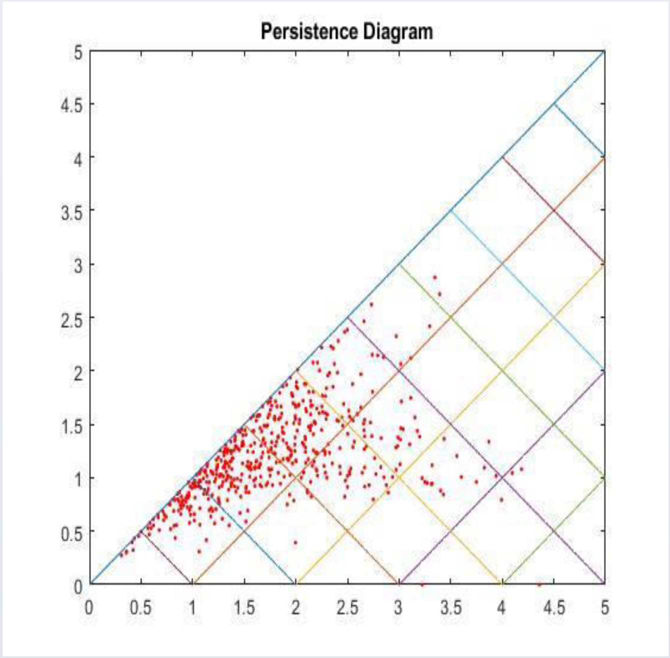
ML-algorithm:

- Logistic Regression - For a point x in feature space, project it onto α to convert it into a real number z in the range $-\infty$ to ∞ such that $z = \beta + \boldsymbol{\alpha}.\mathbf{X} = \beta + \alpha_1 X_1 + \alpha_2 X_2 + \ldots + \alpha_d X_d$ with a logistic function $p = 1/(1+e^{-z})$.
- Support Vector Machine (SVM) - Finds the most optimal decision boundary.



Procedure:

- For each persistence diagram, find out the number of points in each cell.
- Vectorize the persistence images according to their number of points in each cell.
- Reshape them into (n, dim) which used as the input X where n is the number of PDs and dim is the dimension of the vectors.
- If the velocity of the top wall > threshold velocity then it refers to slip (1), otherwise stick (0). This set of 0's and 1's used for the output Y.
- Choose 80% of the data as training set and the rest 20% as testing set randomly.

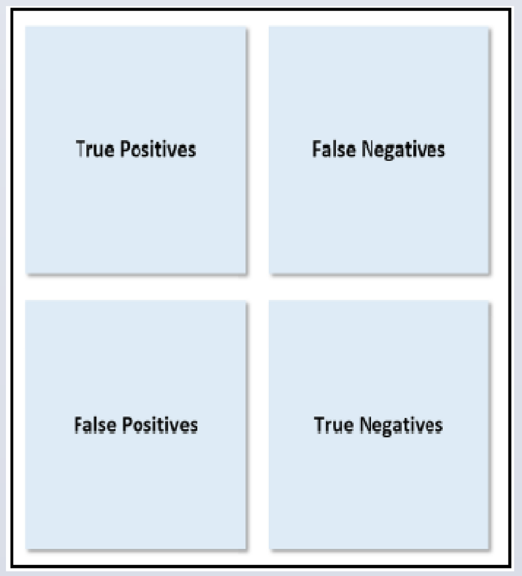


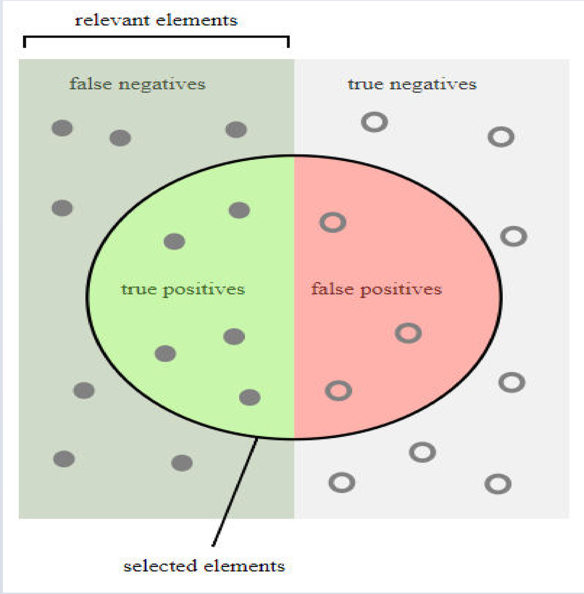
Measures:

Precision Score: $\frac{TruePositive}{TruePositive + FalsePositive}$

Recall Score: $\frac{TruePositive}{TruePositive + FalseNegative}$

f1 Score: Harmonic mean of Precision score and Recall score.





RESULTS

- **199 PDS (LR):**

Precision:	0.92
Recall:	0.80
f1:	0.86

- **10000 PDs (SVM):** Contains 2 slip events.

Stick-slip:

Class	Precision	Recall	f1
0	0.58	0.74	0.65
1	0.70	0.53	0.60

Stick-Just before the slip:

Class	Precision	Recall	f1
0	0.75	0.83	0.79
1	0.84	0.77	0.80

RESULTS

- **300000 PDs (SVM):**

Stick-slip:

Class	Precision	Recall	f1
0	0.70	0.76	0.73
1	0.74	0.67	0.70

Stick-Just before the slip:

Class	Precision	Recall	f1
0	0.75	0.83	0.79
1	0.84	0.77	0.80

CONCLUSIONS

- SVM works better than Logistic Regression for large amount of data.
- Identify different topological measures which trigger slip event.
- Use different machine learning techniques to get more clear prediction.

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