# Project 1: Landslide Inventory with PINN

Mark Asch - ML-PREP

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# CONTEXT

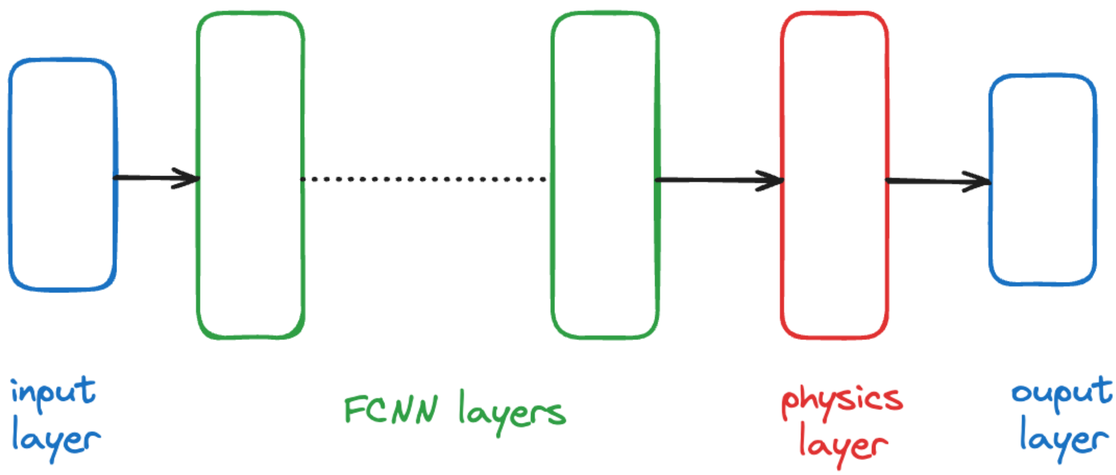
# Landslide Inventories

Until very recently, regional-scale landslide predictions have primarily relied on data-driven models [PINN, ISPRS, ESDA], which, by definition, are not coupled with the physics of the landslide failure mechanism. In this project we will combine/couple a data-driven approach with a variant of PINN that includes the physics of Newmark's Formula in the machine learning process.

In this preparatory project, we will:

- read and understand the paper [PINN];
- download their code and data from here;
- run various simulations and comparisons to evaluate the code;
- acquire a PHIVOLCS dataset and apply the method, or at least show the feasibility... (to be finalized later).

# PINN




- The usual PINN approach is described in detail in my course notes and in the references therein. Recall that we just add terms to the loss function to enforce the physics. This is particularly adapted to (partial) differential equations.

- In [PINN], the authors use a variant of PINN, well-adapted to physics equations that do not contain derivatives.

- The idea is to create a "feature layer" that constrains the output of the FCNN (fully-connected neural network) to satisfy the feature equations. In this case, Newmark's Formula.

- This approach is often used to enforce periodicity in a NN solution that is supposed to present cyclic behaviour.

# Setup Instructions

1. Set up an ML-PREP team.

2. Download the code and data file—see above.

3. Make sure that you know how to code and execute pytorch-based ML using GPUs—see the very basic pytorch tutorials on the github.

4. Refactor the existing code to use scikit-learn with Pytorch—see this very good tutorial example.

# Project Steps

1. Read the paper [PINN] and make a summary of the main approaches and findings. Eventually consult the references of the paper for further information.

2. Load data (see above). Write a very precise and complete description of the data contents, with detailed explanation of each one of the features. This will be important for later application to PHIVOLCS data.

3. Execute the code with the existing, published configuration.

4. Draw detailed conclusions. What do you think will need to be done to apply all the above to existing, available Philippines data?

# Additional Steps

1. Compare the above results with those obtaind by removing the "physics layer". What effects does the PINN approach contribute to? Are there improvements? Is it worth the cost/effort?

2. In the code of [PINN], no hyperparameter tuning has been performed. In particular, a somewhat arbitrary NN architecture is proposed. Write a nested-CV code to perform tuning on selected parameters, and in particular examine the possibility to reduce the dilmensions of the NN. Before doing this, one needs to have a good understanding of the structure of a FCNN. Please consult relevant references for this.

3. The final threshold used in the sigmoid layer, is set at $5$cm. Modify this value and observe the effects. For PHIVOLCS data, we will surely have to explore different values.

4. Implement, and compare a classical PINN approach, where the Newmark formula is added to the loss function. How does this compare in precision and CPU time with the "physics layer" approach?

5. (Advanced) Use SPECFEM to simulate a so-called full waveform seismic signal, and use this to compute and provide the necessary PGA data.

6. (Very advanced) Use a recurrent neural network (LSTM, for example) to learn a time-dependent response, based on the full waveform seismic signal.

# References

## References

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