BTP-1 Report

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Method

Our methodology followed a structured pipeline from domain understanding to model development:

- **Literature Review and Domain Understanding**:
  - Reviewed multiple research papers to gain an understanding of the working of earthquake phenomena.
  - Understood civil engineering aspects related to earthquake-resistant design of buildings.
  - Focused particularly on **Unreinforced Masonry (URM)** structures, which are highly vulnerable to seismic activity.
- **Identification of Load Effects**:
  - Analyzed two types of loading:
    - *In-plane loading*
    - *Out-of-plane loading*
  - Chose to focus exclusively on **out-of-plane loading** due to its dominance in failure modes of URM buildings.

- **Modeling Structural Behavior**:
  - Implemented the **Equivalent Frame Analysis Method** to simulate walls using *piers* and *spandrels*, capturing structural response under seismic loads.
- **Dataset Generation (Initial Phase)**:
  - Used **Limit Analysis** to compute the *critical acceleration* required to cause structural failure.
  - Considered simplified building topologies: one block with one door and up to two windows.
  - Inputs: Geometric features such as base coordinates, height, and width of each component.
  - Output: Corresponding critical acceleration.
- **Failure Mode Identification**:
  - Introduced a field for *applied acceleration*.
  - Compared applied and critical accelerations to determine the **governing failure mode**:
    - Pier failure
    - Spandrel failure
    - Coupled failure
  - Added the failure classification as an additional column in the dataset using analytical formulae.

- **Dataset Extension**:
  - Generalized the dataset to include more realistic cases with multiple doors and windows.
  - Maintained structural consistency while diversifying the input geometries.
- **Machine Learning Model Development**:
  - Trained a **neural network regression model** to predict critical acceleration based on geometric inputs.
  - Excluded failure mode classification from the learning task to isolate performance on regression accuracy.

Challenges

- Interdisciplinary Learning Curve:
  Gaining an understanding of the requirements and outcomes proved to be challenging initially due to the unfamiliar nature of the project field.

- Extension of Limit Analysis to Generalized Cases:
  While established analytical formulae were available for simple configurations, applying Limit Analysis to more generalized building topologies (with multiple openings) lacked direct references in literature. This required extensive research and the development of a custom methodology to extend the dataset generation process.

- Generalizing Dataset Design:
  Designing a dataset that accurately reflects real-world building configurations involved several challenges, especially in ensuring that extended topologies retained physical and structural realism.

Deliverables

- Comprehensive Dataset:
  - Created a reliable dataset of simplified and extended URM building topologies.
  - Each entry includes component geometry and computed critical acceleration.
  - Extended to include multiple doors and windows.
- Failure Mode Classification:
  - Labeled each sample with the type of failure using analytical criteria.
  - Introduced an applied acceleration field for comparison with critical acceleration.
- Machine Learning Model:
  - Built a regression model using neural networks to predict critical acceleration from building geometry.

- Achieved a training loss of ~1e-3, indicating strong learning performance.

- Plotted loss curves showing convergence and absence of overfitting.