Local Degree of Freedom Ductility Demand

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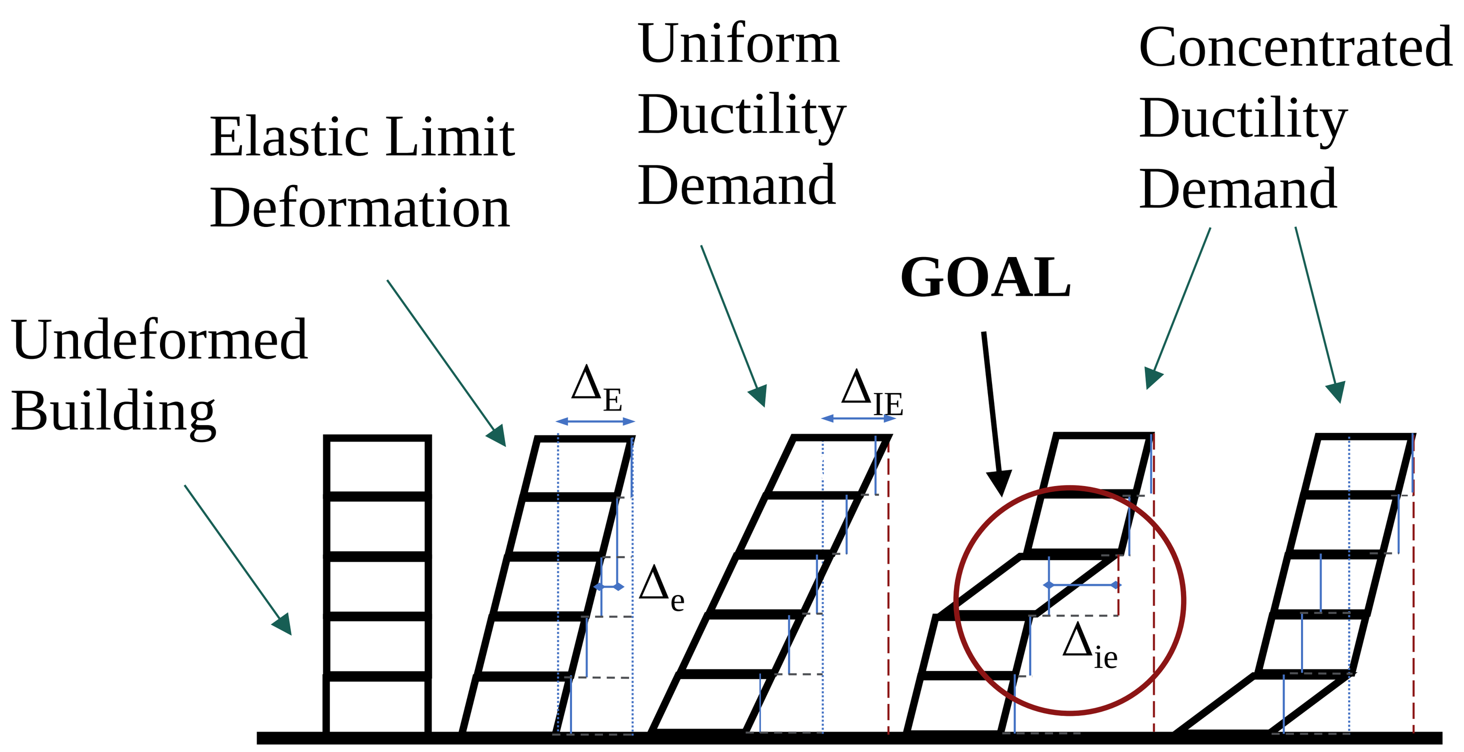
Predicting:

To predict the maximum ductility in any story (i.e. max μ_s) along a 2D building during an earthquake. In Earthquake Engineering is of great importance to estimate the probability of collapse and how to prevent it during an earthquake. Collapse is highly related to story deformations and is most likely to begin in the story whose inter-story drift is the highest.



Building Ductility

$$\mu_B = \frac{\Delta_{IE} + \Delta_E}{\Delta_E}$$

Story Ductility

$$\mu_s = \frac{\Delta_{ie} + \Delta_e}{\Delta_e}$$

Models:

Loss Function:

$$L = \frac{1}{m}\sum\left(\frac{(\hat{y} - y)}{y}\right)^2$$

Linear Regression

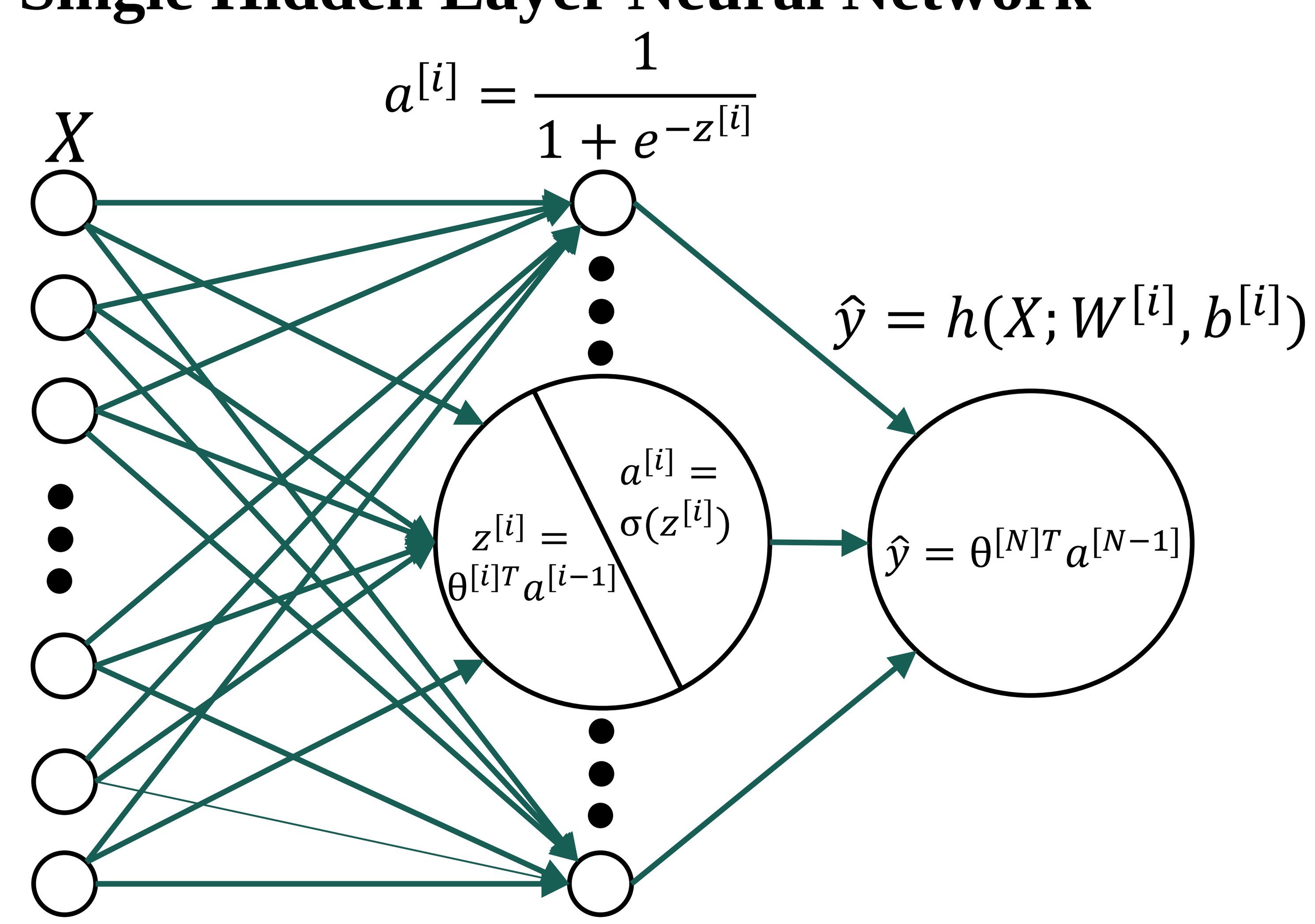
$$\theta := (X^T X)^{-1} X^T \vec{y}$$

Weighted Linear Regression

$$\theta := (X^T W X)^{-1} X^T W \vec{y}$$

$$w_{jj}^{(i)} = \exp(-(x^{(i)} - x)^T \Sigma_x^{-1} (x^{(i)} - x)/2)$$

Single Hidden Layer Neural Network



Results:

Model	L(θ)	(L(θ))^0.5
LR	0.29	0.54
WLR	0.13	0.36
NN	0.05	0.22
Reg NN	0.035	0.18

Model Remarks:

1. The loss function was modified with respect to conventional ones for the output to sustain a physical meaning.
2. For output comparison and simplicity, training was executed with same 80-10-10 hold-out cross validation.

Discussion:

Keeping in mind the nature of the problem, in which inelastic behavior is accepted, linear regression was found more accurate than expected. The gain in accuracy with weighted linear regression may not be sufficient to justify how expensive this process becomes. Neural Networks were found to be highly accurate and efficient for computation. Forward and backward propagation resulted of great advantage.

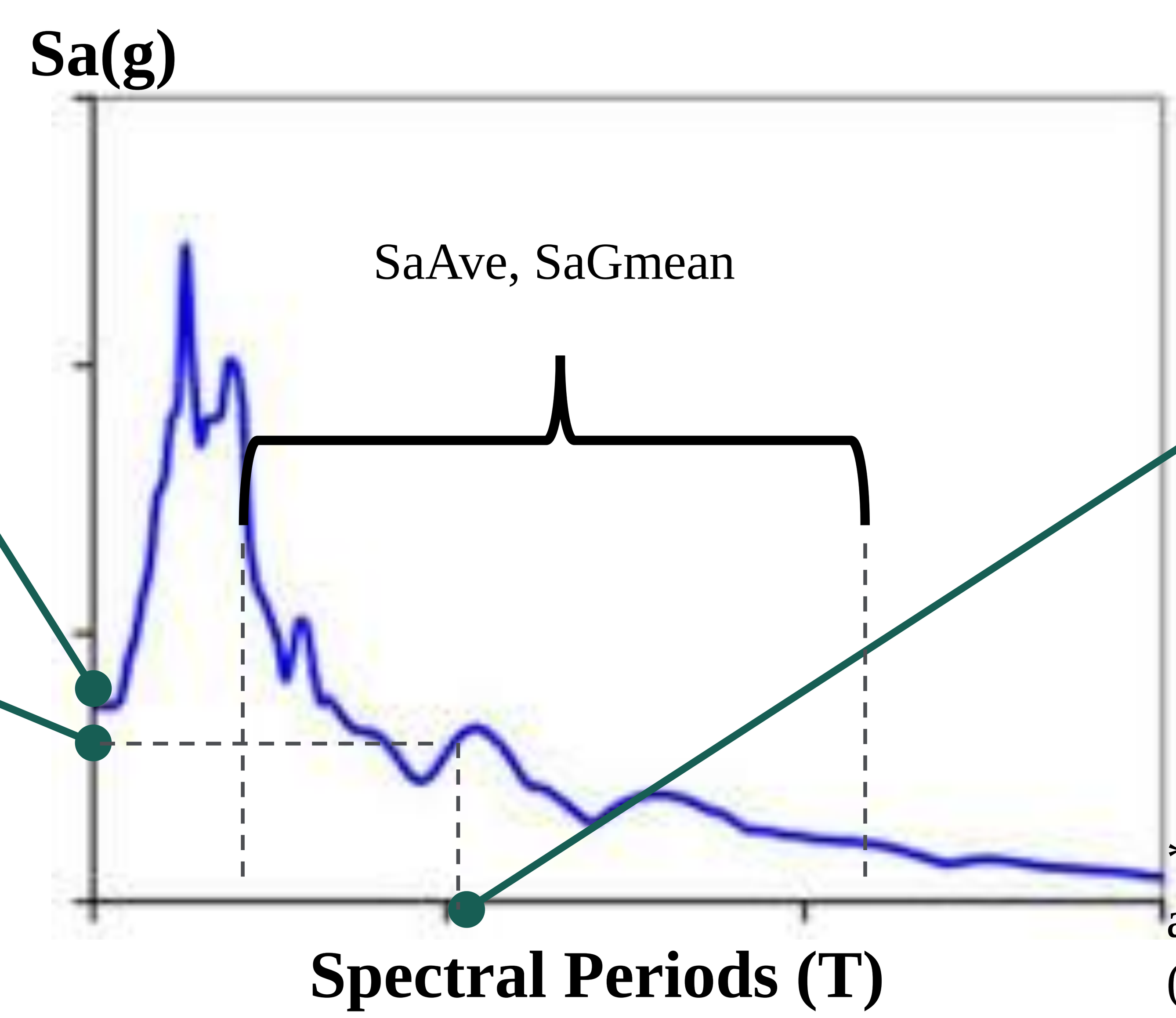
Data and Features

Ground Motion Properties

1. Peak Ground Acceleration (PGA)
2. Peak Ground Velocity (PGV)
3. Peak Ground Displacement (PGD)
4. Strong GM Duration (90% Arias intensity)

Composite Properties

5. Spectral Acceleration at T1 (SaT1)
6. Geometric Mean of Spectral accelerations at T1 (SaGmean)
7. Average Spectral acceleration at T1 (SaAve)



Building Properties

8. # Stories
9. T1, Fundamental Period of Vibration (5 variations)
10. µ, Design Ductility (4 variations)

*34,020 samples data set after preprocessing results (27 GM discarded)

Future Work:

The application of Machine Learning techniques appears to be useful and accurate for predicting random phenomena in Earthquake Engineering. Trying to reduce the number of features and "playing" in neural networks with multiple layers and with the number of units in such layers would be the next steps of this work. Also, extrapolating this work to predicting the combination of effects in three-dimensional buildings considering the three components of an earthquake ground motion is of special interest.

References:

1. Eads, L. (2013). *Seismic collapse risk assessment of buildings: effects of intensity measure selection and computational approach* (Doctoral dissertation, Stanford University).
2. ASCE. (2010). "Minimum design loads for buildings and other structures." ASCE/SEI 7-10 including Supplement No.1, Reston, VA