Improving Efficient Seismic Collapse Intensity Measures Using Machine Learning

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Background and Motivation

In Performance-Based Earthquake Engineering (PBEE) [1], one of the main objectives is to estimate the probability of collapse of a structure subjected to different acceleration ground motions. In this context, the capacity of accurately predicting if a ground motion produces collapse is extremely useful. For this purpose, researchers have proposed the use of intensity measures (IM's), as parameters that attempt to describe the damaging characteristics of ground motions that are important to estimate the seismic response of structures. Examples of IM's are the Peak Ground Acceleration (*PGA*, defined as the maximum absolute value of the acceleration ground motion), Spectral Acceleration Ordinates ($Sa(T_1)$, defined as the peak response of a single-degree-of-freedom (SDOF) system subjected to the ground motion [2]), and the Incremental Velocity (*IV*, defined as the maximum area under the acceleration time history between two consecutive zero crossings [3]). Then, in the PBEE framework, predictive equations of these IM's are used to estimate the probability of exceedance of different values (called Hazard Curves), and the probability of collapse of a given structure (using the Total Probability Theorem).

Although the PBEE framework uses a single IM value, the collapse prediction could be upgraded using Machine Learning. Here lays the objective of this project: to propose a set of features for predicting the collapse potential of acceleration ground motions using SVM and logistic regression models. A key issue here is that the probability of collapse of well-designed structures is relatively low (usually designed to be lower than 10% in 2,475 yrs return period earthquake), therefore we will be dealing with models that should be able to capture extremely rare events. For comparing the performances of different approaches, we will compare their Precision, Recall, and finally a combination of both: their F_1 score.

Methodology

Structural characteristics

We will focus on four different buildings typologies that can be used to represent the majority of the building stock in the city of San Francisco. The left panel of Figure 1 presents a schematic representation of the typologies: one and two-story houses, low-rise buildings (3-6 stories), medium-rise buildings (8-15 stories), and high-rise buildings (>16 stories). The right panel shows the way in which these real structures can be simplified into SDOF systems characterized by its corresponding period of vibration (T), lateral strength (F_y), and damping ratio (ζ). The lateral strength of each system was chosen such that the proportion of collapses of each SDOF is around 5%.

We will then focus on these simplified systems with T=0.2s, 0.5s, 1.0s, and 2.0s while ζ will be kept equal to 5% as usually done in practice. The force-displacement behavior of the simplified models was based on common structural engineering parameters [4], having a bilinear behavior with a post-yield stiffness ratio of -2%.

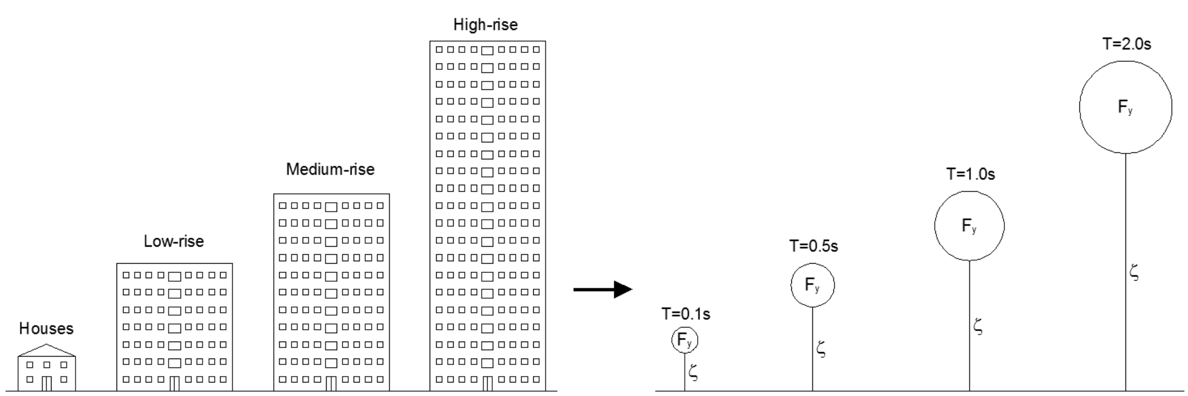

Figure 1. Building typologies and structural simplification. (Left) Real buildings, (Right) Simplification into a single-degree-of-freedom system with a period of vibration, strength (F_y), and damping ratio (ζ).

Record selection and analysis

It is well-known that San Francisco is in a very active seismic region and therefore we decided to use the Bay Area seismic hazard as our scenario and assembled a record database consistent with it. For the predictive model development phase, we gathered 1,680 ground motion records from events with magnitudes (M_w) between 5 and 8 and distances ranging from 0 to 100km. This record set has been obtained from the online Pacific Earthquake Engineering Center database [5].

Features and Target

A set of ten parameters computed from record characteristics was chosen as the attributes for the prediction problem:

1. Earthquake Magnitude (M_w)
2. Rupture-to-site distance (R_{jb})
3. Peak Ground Acceleration (*PGA*): Defined as the maximum absolute value of the acceleration ground motion.
4. Peak Ground Velocity (*PGV*): Defined as the maximum absolute value of the velocity ground motion.
5. Spectral acceleration (*Sa(T)*): Defined as the peak response acceleration of a SDOF system with period T [2].
6. Average spectral acceleration (*SaAvg*): Defined as the geometric mean of spectral accelerations between 0.2T and 3T [6].
7. Incremental velocity (*IV*): Defined as the maximum area under the acceleration time history between two consecutive zero crossings [3].
8. Filtered incremental velocity (*FIV*): Same as *IV*, but considering a filtered record, using a 3rd order Butterworth filter with high and low cut-off frequency of 2/T and 0.2/T, respectively.
9. Spectral shape factor (*SSP*): K-means clustering was used to separate all the records into five bins depending on their spectral shapes. As previous research has shown an important correlation between spectral shape and collapse capacity. Figure 2 shows an example for T = 1.0s.

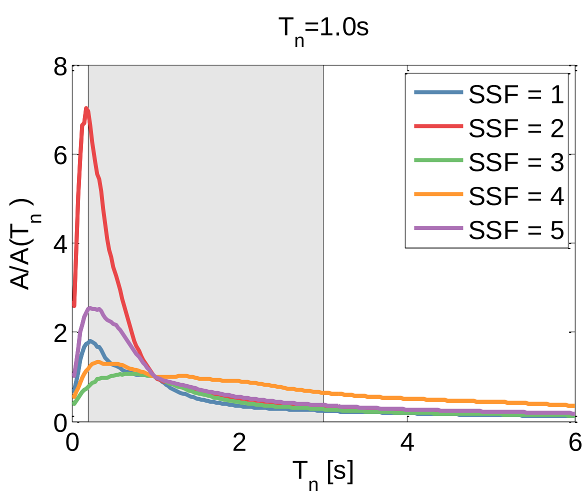

Figure 2. Centroids of the five clusters of spectral shape, using K-means clustering algorithm.

10. Significant Duration (*SD*): Defined as the time interval over which a specific percentage of the total cumulative squared acceleration is released. In this study, we used 5% and 75% as the thresholds [7].

Additionally, the logarithm of the 10 attributes was also taken into account, producing a vector with a total of 20 features ($x^{(i)} \in \mathbb{R}^{20}$) for each ground motion. Each of the simplified systems was subjected to the full set of records to find the ones that triggered collapse. Using results from these analyses we created the target vector ($y^{(i)}$). This is a binary-valued vector in which a value of +1 represents a ground motion causing collapse and -1 represents a non-collapse case.

Results

A total of eight models were trained and compared using a 70/30 Hold-Out Cross Validation algorithm, with 1,180 records for training and 500 records for testing. To compare test errors, the F_1-score is used, as the number of positive-labeled examples (collapses) is extremely small. The F_1-score is a measure that considers both the precision and the recall of the model.

The eight models compared in this study are:

1. SVM model with Gaussian Kernel with dispersion parameter $\tau = 0.5$
2. SVM model with Gaussian Kernel with dispersion parameter $\tau = 2.0$
3. SVM model with 1st Order Polynomial Kernel
4. SVM model with 2st Order Polynomial Kernel
5. Logistic Regression model with threshold t = 0.10
6. Logistic Regression model with threshold t = 0.25
7. Logistic Regression model with threshold t = 0.50
8. Logistic Regression model with threshold t = 0.75

Model and Feature selection

As part of the 70/30 Hold-Out Cross Validation, the number of features was also changed. Therefore, for each of the eight models, the optimal sets of features (varying between one and six features per model) was also obtained. Figure 3 presents the variation of the F_1-score as we increased the number of features, for each of the SVM models and each structure. Figure 4, on the other hand, shows the same variation, but for the Logistic Regression models. As can be seen, both types of models (SVM and Logistic Regression) perform similarly well predicting collapse.

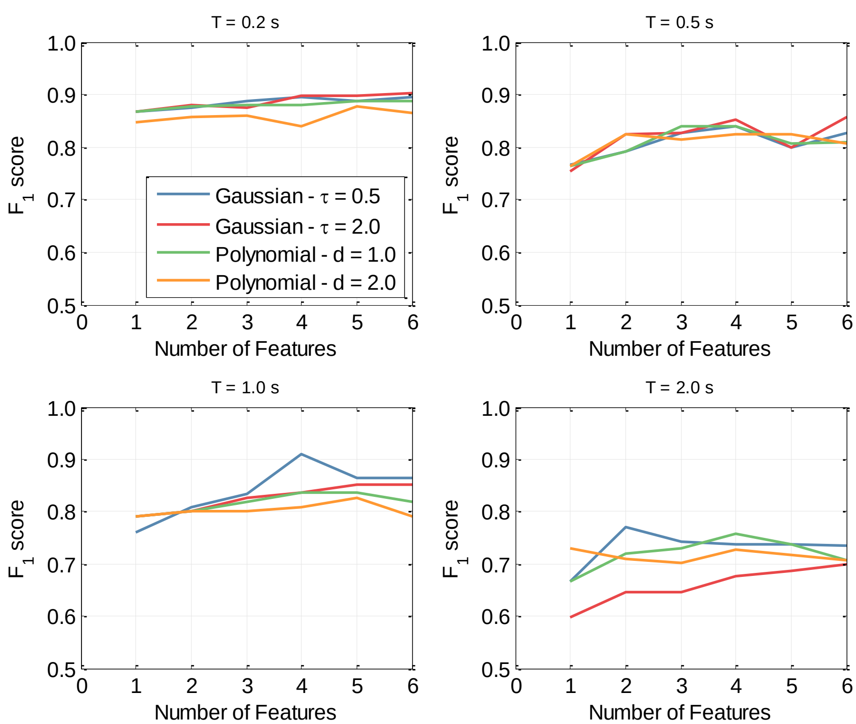

Figure 3. F_1-score as a function of the number of features for each SVM model.

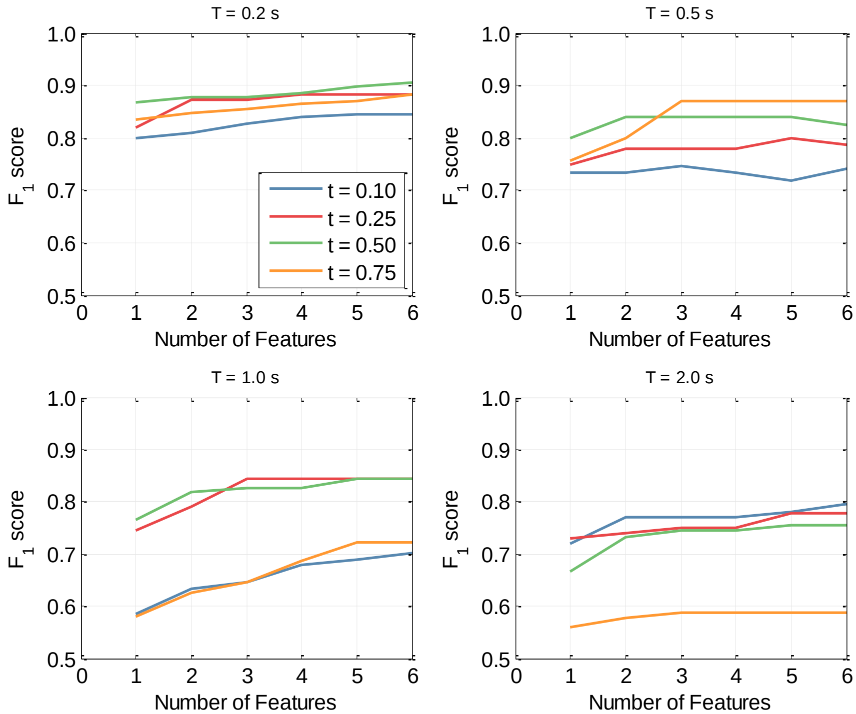

Figure 4. F_1-score as a function of the number of features for each Logistic Regression model.

For earthquake engineering purposes, it is practically unfeasible to use more than three features as IMs because as part of the probabilistic seismic demand analysis, one needs to estimate the probability of observing different levels of the parameter used to characterize collapse. Therefore, we recommend a three-parameter vector that gives the best results for each typology as we have to develop procedures to estimate the annual rate of exceeding different levels of these new IM vectors. Although the SVM models perform slightly better, the Logistic Regression models are a lot faster to train and require less parameters (two to seven θ's, depending on the number of features, while SVM models require 1,160 α's, one for each training example). This is why we decide to recommend, for each structure, the best three-feature value Logistic Regressions model as the optimal method. Note that the threshold value should change to maximize the F_1-score.

<u>*Confusion matrices*</u>

Figures 5 and 6 show the Confusion Matrix of each structure, using the corresponding best three-feature Logistic Regression. On each table, the optimal threshold of the Logistic Regression for determining collapse and the best three features are presented, as well as the Precision, Recall and F_1-score of each one. Similar confusion matrices and precision, recall and F_1-scores were also computed for the five SVM cases but are not reported here due to space limitations.

threshold = 0.5
log(SaAvg), PGA, Sa(T)

T = 0.2 s		**Predicted -1**	**Predicted +1**	
True	**-1**	1489	18	Precision = 0.89
True	**+1**	37	136	Recall = 0.79 F_1-score = 0.83

threshold = 0.75
SaAvg, SSF, SD

T = 0.5 s		**Predicted -1**	**Predicted +1**	
True	**-1**	1579	2	Precision = 0.96
True	**+1**	45	54	Recall = 0.55 F_1-score = 0.69

Figure 5. Confusion Matrices for the two short period structures.

threshold = 0.25
SaAvg, M_w, SD

T = 1.0 s		Predicted -1	Predicted +1
True	-1	1536	30
True	+1	20	94

Precision = 0.76
Recall = 0.82
F_1-score = 0.79

threshold = 0.1
SaAvg, R_{jb}, M_w

T = 2.0 s		Predicted -1	Predicted +1
True	-1	1377	122
True	+1	7	174

Precision = 0.59
Recall = 0.96
F_1-score = 0.73

Figure 6. Confusion Matrices for the two long period structures.

Discussion of results

In general we see that *SaAvg* is a very good predictor of collapse but the 2nd and 3rd features vary depending on the type of structures. This could be expected as different types of systems are affected by different frequencies that are implicitly taken into account with some features (e.g. the high frequency content affecting the short period structure is indirectly measured by PGA).

The information of the joint occurrence of the three parameters used in the vector IMs that we are suggesting would be represented using a joint hazard curve [8]. Then, by integrating the probability of collapse at a certain IM level with the probability of experiencing that IM level we can compute the mean annual frequency of collapse which is an extremely useful output in the PBEE methodology as it informs a stakeholder about the risk of the structure.

Future work

- Develop a ground motion prediction equation of the joint distribution of these new IM vectors.
- Make our predictions structure-type specific: Masonry, Concrete, Steel. This implies modeling the structural response using different force-deformation behaviors instead of the simplified one used in this study.
- ***Different and promising idea***: Apply Markov decision processes in active control of structures during earthquakes. The idea here is that during a seismic event, the structure response is recorded and used to modify in "real time" some mechanical properties of the structure (such as its stiffness or damping) in order to reduce the lateral displacement demands. If we are able to reduce them, the structure will suffer less damage, therefore reducing the probability of collapse, and the future repair costs. In other words, we could teach a structure how to adapt to an earthquake excitation in its base [9].

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