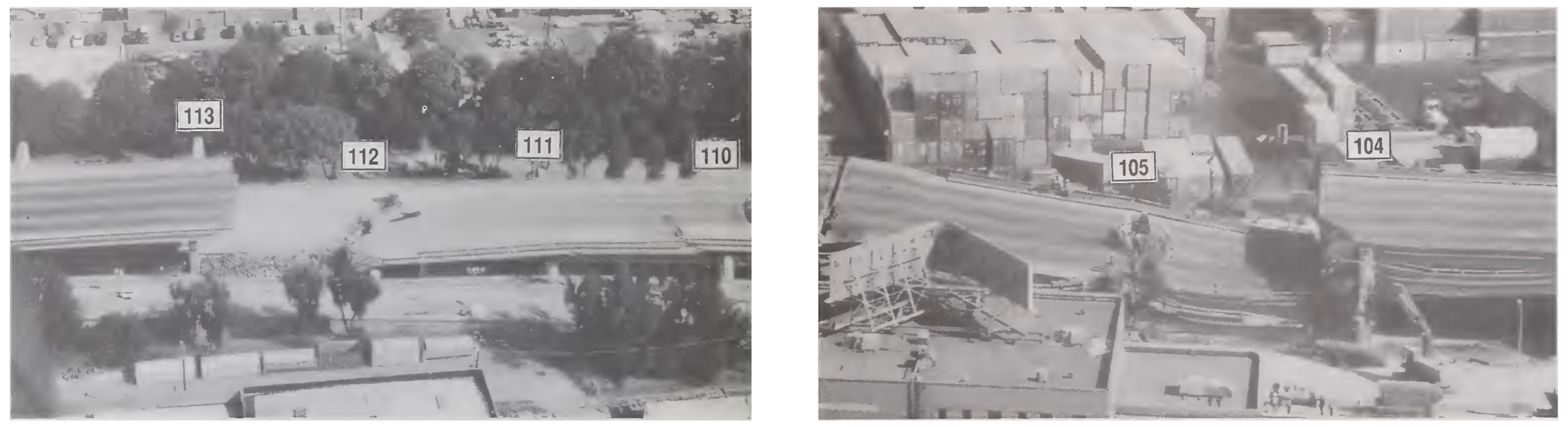
Predicting Bridge Performance under Earthquakes with Supervised Learning

Ziyang Jiang (zij004@Stanford.edu) , Xiao Zhang (zhx@Stanford.edu)
Department of Civil and Environmental Engineering, Stanford University

Motivation and Objective

Since 1970s, the seismic bridge design process has gone through a great change from “capacity-based” design to “performance-based” design. In this project, we try to train a model of bridge performance under earthquakes and predict how well/badly an existing bridge will perform in a future earthquake as well as guiding the design of a new bridge to survive possible future earthquakes.



Damages of I-880 Cypress Structure in Oakland after 1989 Loma Prieta Earthquake

Data

Our positive examples (failure) are obtained mainly from **government reports of historic earthquakes** happened around the world. Negative examples are obtained from **USGS earthquake search catalog**.

Data collection takes time and effort as there are not many available records of bridge failures due to earthquakes worldwide. For the same reason, our dataset is unbalanced. (i.e. the ratio of $\frac{\#negative\ examples}{\#positive\ examples}$ is around **10:1**). In this case, we use **bootstrap resampling with replacement** to up-sample the positive class and generate a training set with more reasonable number of positive and negative examples.

Positive Example

Negative Example

Features

The raw features we have in our dataset are bridge age, earthquake magnitude and its distance to epicenter.

Models

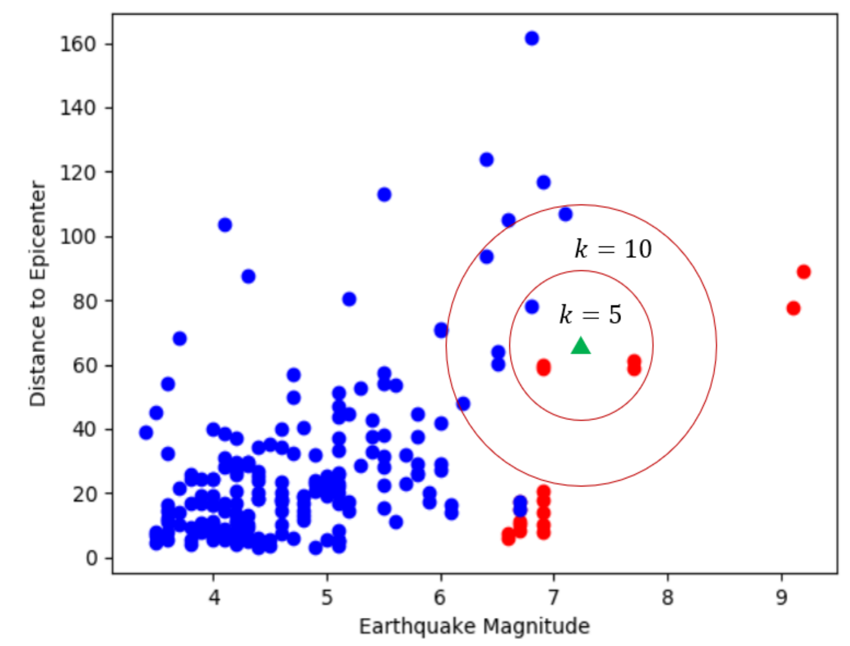
1. Logistic Regression

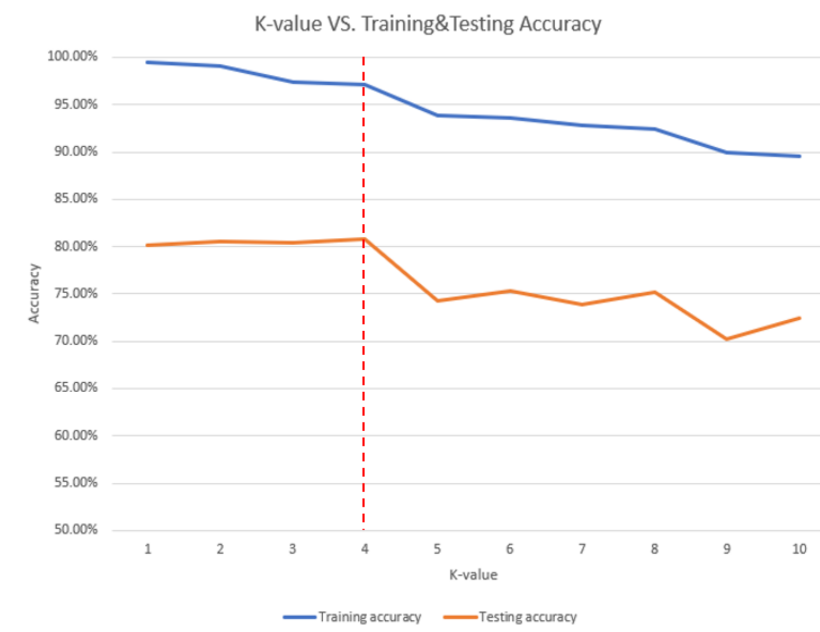
$$l(\theta) = \sum_{i=1}^{m} y^{(i)} \log h\left(x^{(i)}\right) + \left(1 - y^{(i)}\right) \log\left(1 - h\left(x^{(i)}\right)\right)$$

2. Quadratic Discriminant Analysis

$$p(x) = \frac{1}{(2\pi)^{n/2}|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu)\right)$$

3. K-Nearest Neighbor Classifier





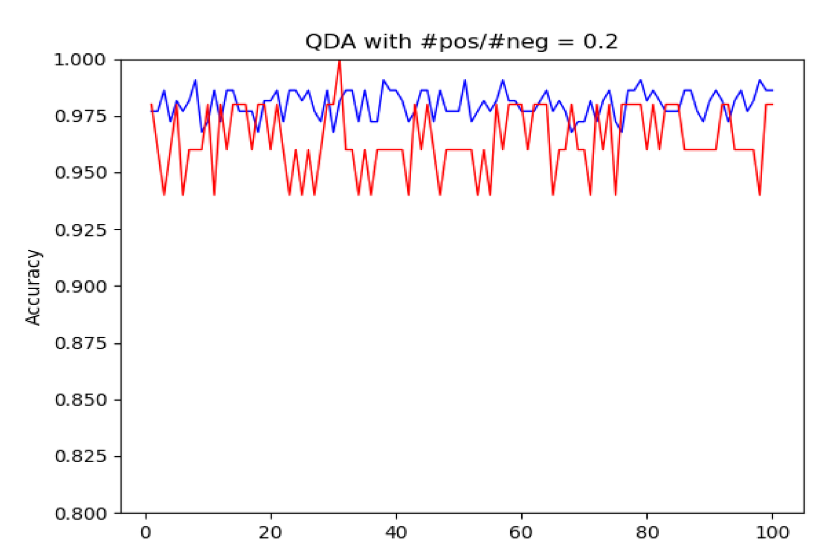
Optimal (threshold) K-value is: $k = 4$.

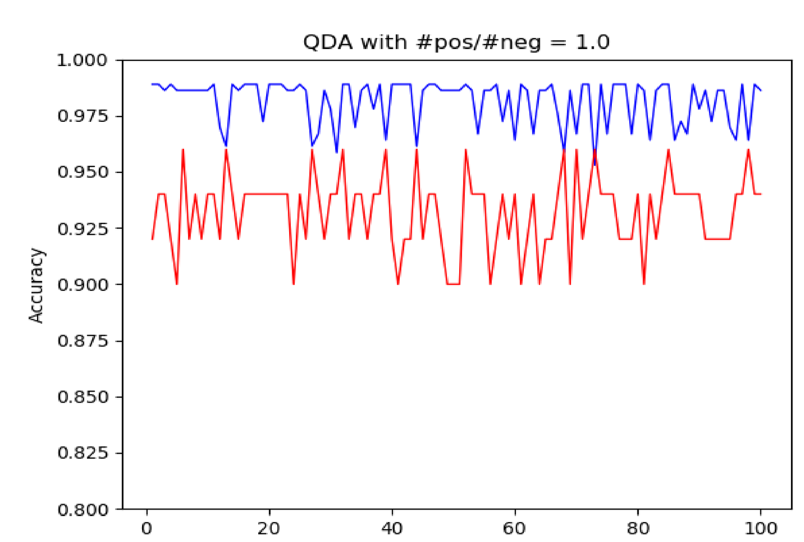
Results

The following training and testing accuracy are the average results from 5 cases with different #pos/#neg ratio after resampling:

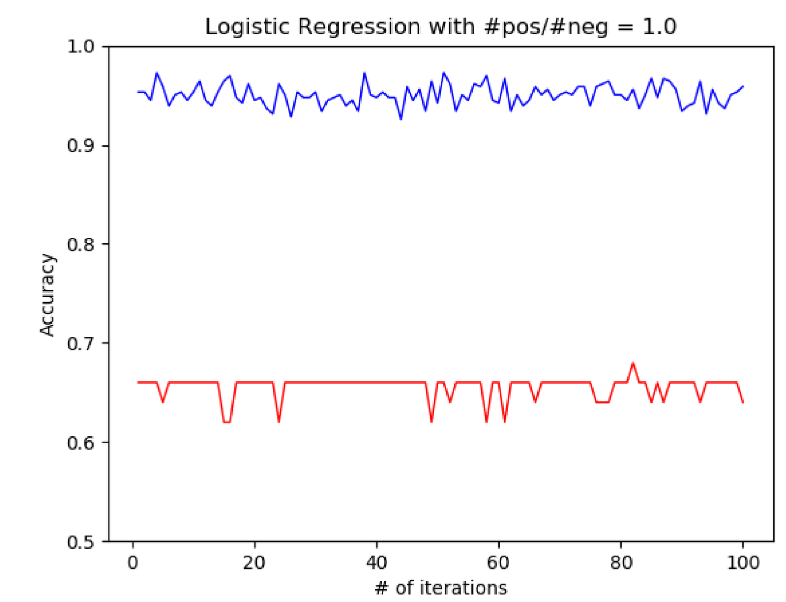
Model	Training Accuracy	Testing Accuracy
Logistic Regression	95.4%	73.8%
QDA	97.8%	**94.8%**
KNN	97.1%	80.8%

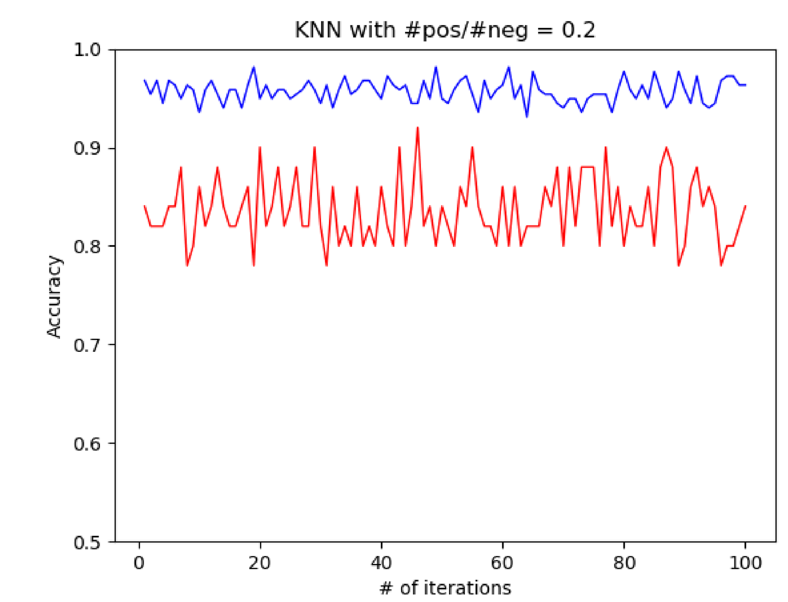
From table above, quadratic discriminant analysis appears to have the highest testing accuracy (94.8%, around 28% higher than logistic regression and 17% higher than KNN).

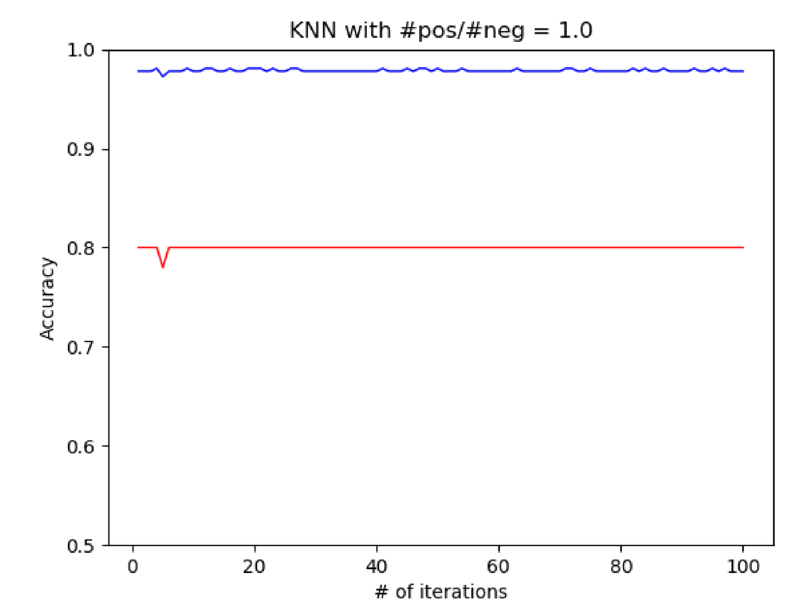




Results (Cont’d)







Observations

In this project, we pre-process the raw dataset with bootstrap resampling and implement 3 supervised learning models on the training set. During training process, we observe that the accuracy **decreases** as we increase the **size of resampling**. However, since the test set is also unbalanced, a very high testing accuracy may **not** be meaningful as it always tends to predict the result to be negative.

To view this study in a broader scope, it may be observed that there are usually lots of different constraints (on features, data size, physical meanings of results, etc.) in civil engineering scenarios, which may impact the practicality of machine learning in such kind of studies.

Future Work

- **Expand size of dataset** (increase # of positive examples)
- **Run tests on other generative models**
- **Implement multi-class classification** (No damage = 0, Mild/Severe damage = 1, Collapsed = 2, etc.)

References

1. G. Dupret and M. Koda, “Bootstrap re-sampling for unbalanced data in supervised learning,” Jul. 2000.
2. C. Kellerman, “Earthquakes,” *NIST*, 28-Feb-2017. https://www.nist.gov/topics/disaster-failure-studies/studies-hazard-types/earthquakes.