Inferring Geo-spatial Neutral Similarity from Earthquake Data using Mixture and State Clustering Models

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Abstract: Traditionally, earthquake events are identified by prescribed and well formed geographical region boundaries. However, fixed regional schemes are subject to overlook seismic patterns typified by cross boundary relations that deem essential to seismological research. Rather, we investigate a statistically driven system that clusters earthquake bound places by similarity in seismic feature space, and is impartial to geo-spatial proximity constraints. To facilitate our study, we acquired hundreds of thousands recordings of earthquake episodes that span an extended time period of forty years, and split them into groups singled out by their corresponding geographical places. From each collection of place affiliated event data, we have extracted objective seismic features expressed in both a compact term frequency of scales format, and as a discrete signal representation that captures magnitude samples in regular time intervals. The distribution and temporal typed feature vectors are further applied towards our mixture model and Markov chain frameworks, respectively, to conduct clustering of shake affected locations. We performed extensive cluster analysis and classification experiments, and report robust results that support the intuition of geo-spatial neutral similarity.

1 INTRODUCTION

Modern seismological exploration of disseminating earthquake sites and magnitudes rests on both the advancement in instrumental seismometry and the analysis of macroseismic effects, including geological structures, population, and the landscape (Hough, 2014). To describe the severity of shaking, seismic effects are commonly assigned an intensity scale set by different yet fairly correlated standards, traditionally in the range of one to ten. In recent years, the development of methods to quantitatively and objectively analyze scale data, coupled with the emerging of online systems to generate unprecedented volumes of both real-time and archival earthquake data, had sparked renewed interest in research to assess global seismic intensity distribution. One indispensable resource for practitioners in the field is the United States Geological Survey (USGS, 2004) science organization, fully devoted to furnish impartial information on the health of our ecosystem. Amongst the many services, USGS provides a large web based repository of geo-spatially rich data for expressing earthquake events that are dynamically collected as they occur, and furthermore allows for this knowledge base to be programmatically accessible for software development. Figure 1 shows a high level, distributed earthquake scale around the globe, based on USGS data we acquired that reproduces an extent of four decades, from 1975 till 2014.

In our work, we investigate a discovery (Rajaraman and Ullman, 2011) method that extracts a statistical relation model of earthquake bound geographical locations from a large data set of hundreds of thousands of recorded seismic events, and incorporates both information retrieval (Manning et al., 2008) and unsupervised machine learning (Duda et al., 2001) techniques. Information retrieval (IR) is rapidly becoming the dominant form of data source access. Amongst multitude disciplines, IR encompasses the field of grouping a set of documents that enclose non structured content, to behave similarly with respect to relevance to information needs. Our work closely leverages IR practices by realizing a seismic bound place after a text document, composed of a collection of intensity scales and represented in a compact histogram of term frequencies format. For a broader context, we contrast this distribution feature form with a classic, discrete seismic signal constructed of a series of shake magnitudes over time that spans a course of several tens of years. Furthermore, we are interested in uncovering objectively the underlying cluster nature of hundreds of geographical sites, without re-

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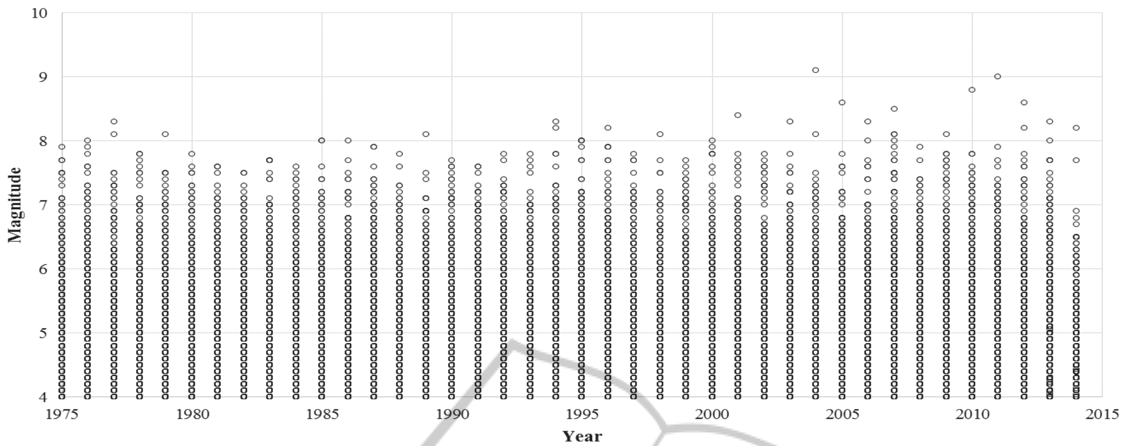


Figure 1: Earthquake events: showing magnitude scale as a function of time, tracking forty years from 1975 till 2014.

sorting to any prior knowledge of the erupting physical location, nor to constraining geo-spatial proximity as prescribed by the Flinn-Engdahl regionalization scheme (Young et al., 1995). To this extent, we use both finite mixture (Mclachlan and Peel, 2000) and Markov chain (Rabiner, 1989) models, recognized for providing effective and formal statistical framework to cluster high dimensional data of continuous nature.

Finite mixture models are widely used in the field of cluster analysis (Fraley and Raftery, 2002) (Fraley and Raftery, 2007), and apply to a growing application space including web content search, gene expression linking, and image segmentation. They form an expressive set of classes for multivariate density estimation, and the entire observed data set of scale histograms is represented by a mixture of either continuous or discrete, parametric distribution functions. An individual distribution, often referred to as a component distribution, constitutes thereof a cluster. Traditionally, the likelihood paradigm provides a mechanism for estimating the unknown parameters of the mixture model, by deploying a method that iterates over the maximum likelihood. One of the more broadly used and well behaved technique to guarantee process convergence is the Expectation-Maximization (EM) algorithm (Dempster et al., 1977) that scales well with increased data set size. Upon completion, the likelihood function reflects the conformity of the model to the incomplete observed data. While not immediately applicable to our work, noteworthy is the research that further extends the empirical likelihood paradigm to a model, whose component dimension is unknown. Hence, both model fitting and selection must be determined from the data simultaneously, by using an approximation based on any of the Akaike Information Criterion (AIC) (Akaike, 1973), the Bayesian Information Criterion (BIC) (Schwarz, 1978), or the sum of AIC and BIC plus an entropy term (Ngatchou-Wandji and Bulla, 2013).

The discrete Hidden Markov Model (HMM) (Baum and Petrie, 1966) (Rabiner, 1989) is a probabilistic framework that formalizes a reasoning about a series of observations over time, to recover a set of states. The model is extensively used in many application domains including speech recognition, biological sequence analysis, and stochastic natured financial economics. HMM is described by a set of parameters that are estimated to maximize the probability of an observation. Much like the mixture model, it employs the maximum likelihood estimation principal and commonly uses the Baum-Welch algorithm (Baum, 1972), an analog to the EM method. In our work, we characterize a time progression of earthquake events, occurring in a prescribed geographical location, as a discrete seismic signal comprised of shake scale samples. A seismic signal thus forms an observation vector, and a collection of these temporal feature vectors are applied to HMM, deriving for each a log-likelihood measure. Unlike the mixture model, the grouping of observation vectors in HMM is not implicit, hence we follow HMM to perform hierarchical agglomerative clustering (Manning and Schutze, 2000) (Johnson, 1967) on log-likelihood values.

The main contribution of our work is a novel, statistically driven system that combines IR and unsupervised learning techniques to discover instinctive cluster patterns from presumed unlabeled seismic data, and best match earthquake bound geographical locations by objective similarity in feature space. In contrast to a more constraining approach that prescribes physical regionalization boundaries. The remainder of this paper is organized as follows. We overview the motivation for selecting seismic feature representations, leading to our compact formats of intensity scale distribution and a time series signal, in section 2. Section 3 reviews algorithms and provides theory to multivariate cluster analysis, discussing both the normal mixture model and Markov chain foundations, and the role of their respective EM method in estimating model parameters. Whereas in section 4, we present our evaluation methodology of seismic cluster analysis and classification, and report quantitative results of our experiments. We conclude with a discussion and future prospect remarks, in section 5.

2 SEISMIC FEATURES

We acquired seismic data from the USGS (USGS, 2004) science organization. USGS provides real-time earthquake data in a well-structured format, GeoJSON (GeoJSON, 2007), readily parsed by most programming languages. GeoJSON uses the popular JavaScript Object Notation (JSON) to encode a diverse set of geographic data structures. A GeoJSON object may represent any of a geometry, a feature or a collection of features. Typically, an earthquake event is characterized by a geometrical bounding box and a set of seismic features (Table 1). The three dimensional volume of eruption is defined by the minimum and maximum extent of each of the longitude, latitude, and depth attributes. An event specifies a rather extensive set of seismic properties, although many of them appear either unavailable or partially missing in the data frames we gathered. Most relevant features to our work include the magnitude, magnitude type, place, and time. The magnitude value is measured and recorded by a seismograph that responds to distinct seismic waves traveling through the ground, who are excited by relative motion of the earth. Whereas magnitude type identifies the method or algorithm to calculate the scale of the event. Most commonly used scales comprise of local (M_l), also referred to the Richter scale, surface-wave (M_s), body-wave (M_b), and moment (M_w) metrics. Moment scale is directly related to the faulting process and is considered a more consistent measure of earthquake size, unlike the rest that are accuracy limited by an upper bound. Nonetheless, all magnitude types yield approximately the same value for a given earthquake event. The place property is a named geographic location closest to the event, either a city or a region enumerated in the Flinn-Engdahl seismic and geographical, globe partitioning scheme (Flinn-Engdahl, 2000), along with the time of a shake occurrence, reported in milliseconds.

Our seismic dataset comprises several hundreds of thousands earthquake events that track an extended time period of several tens of years. The process of extracting features from this large seismic collection proceeds in several stages. First, we split the dataset into groups, each embedding all event occurrences in an identical place or region, chronologically. Our transformed dataset represents now a compilation of distinct places drawn out from our raw data, and totals several thousands data points. Let $P = \{p_1, p_2, \ldots, p_n\}$ be our observed, place subjected seismic data, with each place data point, p_i, retaining a different event count. Next, we derive from each data sample, p_i, two domain feature vectors to provide for unified dimensionality. An unnormalized, scale distribution vector $D \in \mathbb{N}^{|V|}$, with $|V|$ the number of possible magnitude values, and a time series vector $S \in \mathbb{R}^d$ of a sampling dimensionality d.

Table 1: Features extracted from a GeoJSON object that describes geometry and selected seismic properties of an earthquake event. Showing for each value range and units.

(a) Bounding Box.

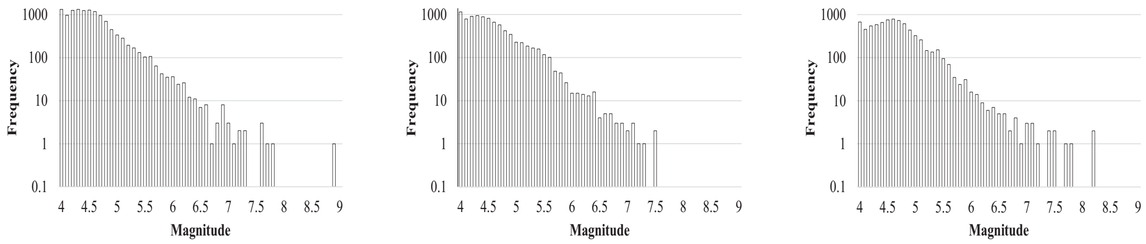
Dimension	Range	Units
longitude	$[-180.0°, +180.0°]$	degrees
latitude	$[-90.0°, +90.0°]$	degrees
depth	$[0, 1000]$	kilometer

(b) Seismic Properties.

Feature	Range	Units
mag	$[-1.0, 10.0]$	scale
mag type	M_l, M_s, M_b, M_w	string
place	Flinn-Engdahl region	string
time	date-time	milliseconds

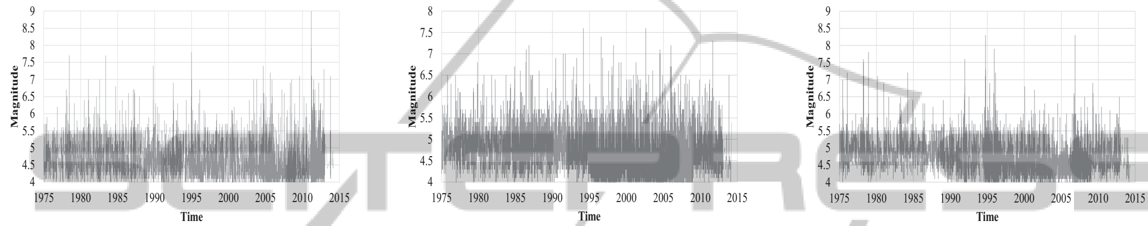
D formalizes a term frequency description that assigns each vector element a count of unique magnitude occurrences, accumulated in the events prescribed to a place data point, p_i. This is modeled after the *bag of words* (Baeza-Yates and Ribeiro-Neto, 1999) representation, a simple and one of the more effective text retrieval methods, founded on the premise that the respective order of events to emerge in a location, is ignored. In our work, we tend to events who record a scale in the $[4.0, 9.9]$ range and sampled in 0.1 increments, hence $|V|$, the dimensionality of D, amounts to 60 elements. Figure 2 outlines scale distribution feature vectors extracted from three distinct, place data points. The location compact format of bag of scale words is passed on to our mixture model to perform seismic place clustering, and follows efficient similarity calculations, directly from the well known Vector Space Model (Salton et al., 1975).

The raw, time series vector we extract is an irregular periodicity formulation of magnitudes, dispersed



(a) Honshu, Japan. (b) Fiji region. (c) Kuril Islands.

Figure 2: Scale distribution feature vector: showing in log scale the number of magnitude occurrences extracted from events associated with a place data point, for three geographical locations.



(a) Honshu, Japan. (b) Fiji region. (c) Kuril Islands.

Figure 3: Time series feature vector: resampled irregular raw signal using the year-week sampling mode, for three geographical locations. A sample of no event is assigned a zero magnitude.

sequentially along the course of our event capturing time frame of forty years. *S* is then further resampled with regular time intervals consisting of year-week, monthly and bi-monthly formats, thus leading to a time series feature vector of dimensionality depicted in Table 2. Our year-week sample index, $[0,53]$, follows the US rule, and for a place of multiple events, excited in the same week, we compute a weekly mean of all magnitudes to ensure a single scale is identified with a week. Whereas a week of no event defaults to the value of zero intensity. The monthly and bi-monthly sampling modes arise from a direct decimation of the year-week signal by a factor of four and eight, respectively. Time series vectors, resampled in the year-week mode for three geographical places are further illustrated in Figure 3. Subsequently, we use a hidden Markov chain (HMM) to model the durational and spectral variability of our generated seismic signal, *S*, that constitutes an observation vector.

Table 2: Time series vector: listing uniform resampling modes and corresponding dimensionality.

Year-Week	Monthly	Bi-Monthly
2120	530	265

3 PLACE CLUSTERING

Clustering procedures based on finite mixture models provide a flexible approach to multivariate statistics. They become increasingly preferred over heuristic methods, owing to their robust mathematical basis. Mixture models standout in admitting clusters to directly identify with the components of the model. To model our system probability distribution of scale count features, we deploy the well established, Normal (Gaussian) Mixture Model (GMM) (Mclachlan and Basford, 1988) (Mclachlan and Peel, 2000), known for its parametric, probability density function that is represented as a weighted sum of Gaussian component densities. GMM parameters are estimated from our incomplete training data, composed of bags of intensity scale words, using the iterative Expectation-Maximization (EM) (Dempster et al., 1977) algorithm. Correspondingly, for our place bound, seismic signal features we exploit the Hidden Markov Model (HMM) (Baum and Petrie, 1966) (Rabiner, 1989), using the Baum-Welch algorithm (Baum, 1972) to repeatedly recalibrate model parameters, and follow this process to construct an agglomerative hierarchy of seismic aware clusters, employing an efficient dynamic tree cutting technique.

3.1 Normal Mixture Model

Let $X = \{x_1, x_2, ..., x_n\}$ be our observed collection of seismic bound places, each represented as an intensity scale, term frequency vector $I \in \mathbb{N}^d$. An additive mixture model, defines a weighted sum of k components, whose density function is formulated by equation 1:

$$p(x|\Theta) = \sum_{j=1}^{k} w_j p_j(x|\theta_j), \tag{1}$$

where w_j is a mixing proportion, signifying the prior probability that an observed place x, belongs to the j^{th} mixture component, or cluster. Mixing weights, satisfy the constraints $\sum_{j=1}^{k} w_j = 1$, and $w_j \geq 0$. The component probability density function, $p_j(x|\theta_j)$, is a d-variate distribution, parameterized by θ_j. Most commonly, and throughout this work, $p_j(x|\theta_j)$ is the multivariate normal (Gaussian) density (equation 2), characterized by its mean vector $\mu_j \in \mathbb{R}^d$ and a covariance matrix $\Sigma_j \in \mathbb{R}^{dxd}$. Hence, $\theta_j = (\mu_j, \Sigma_j)$, and the mixture parameter vector $\Theta = \{\theta_1, \theta_2, ..., \theta_k\}$.

$$\frac{1}{(2\pi)^{\frac{d}{2}} \sqrt{|\Sigma_j|}} \exp\left(-\frac{1}{2}(x-\mu_j)^T \Sigma_j^{-1} (x-\mu_j)\right) \tag{2}$$

Seismic places, distributed by mixtures of multivariate normal densities, are members of clusters that are centered at their means, μ_j, whereas the cluster geometric feature is determined by the covariance matrix, Σ_j. For efficient processing, our covariance matrix is diagonal, $\Sigma_j = diag(\sigma_{j1}^2, \sigma_{j2}^2, ..., \sigma_{jd}^2)$, and thus clusters are of an ellipsoid shape, each nonetheless of a distinct dimension. To fit the normal mixture parameters onto a set of training feature vectors, we use the maximum likelihood estimation (MLE) principal. Furthermore, in regarding the set of seismic places as forming a sequence of n independent and identically distributed data samples, the likelihood corresponding to a k-component mixture, becomes the product of their individual probabilities:

$$L(\Psi|X) = \Pi_{i=1}^{n} \sum_{j=1}^{k} w_j p_j(x_i|\theta_j), \tag{3}$$

where $\Psi = \{\Theta, w_1, w_2, ..., w_k\}$. However, the multiplication of possibly thousands of fractional probability terms, incurs an undesired numerical instability. Therefore, by a practical convention, MLE operates on the log-likelihood basis. As a closed form solution to the problem of maximizing the log-likelihood, the task of deriving Ψ analytically, based on the observed data X, is in many cases computationally intractable. Rather, it is common to resort to the standard, expectation-maximization (EM) algorithm, considered the primary tool for model based clustering.

To add more flexibility in describing the distribution $P(X)$, the EM algorithm introduces new independences via k-variate hidden variables $Z = \{z_1, z_2, ..., z_n\}$. They mainly capture uncertainty in cluster assignments, and are estimated in conjunction with the rest of the parameters. The combined observed and hidden portions form the complete data set $Y = (X, Z)$, where $z_i = \{z_{i1}, z_{i2}, ...z_{ik}\}$ is an unobserved vector, with indicator elements

$$z_{ic} = \begin{cases} 1, & \text{if } x_i \text{ belongs to cluster } c \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

EM is an iterative procedure, alternating between the expectation (E) and maximization (M) steps. For the hidden variables z_i, the E step estimates the posterior probabilities w_{ic} that a place object x_i belongs to a mixture cluster c, given the observed data and the current state of the model parameters

$$w_{ic} = \frac{w_c p_c(x_i|\mu_c, \Sigma_c)}{\sum_{j=1}^{k} w_j p_j(x_i|\mu_j, \Sigma_j)}. \tag{5}$$

Then the M step maximizes the joint distribution of both the observed and hidden data, and parameters are fitted to maximize the expected log-likelihood, based on the conditional probabilities, w_{ic}, computed in the E step. The E step and M step are iterated until convergence or up to a set limit of iterations, after which a scale distribution feature vector, x_i, is assigned to a cluster, corresponding to the highest conditional or posterior probability of its membership. EM typically performs well once the observed data reasonably conforms to the mixture model, and by ensuring robust selection of random values assigned to starting parameters, the algorithm warrants convergence to either a local maximum or a stationary value.

3.2 Hidden Markov Model

The Hidden Markov Model (HMM) (Baum and Petrie, 1966) (Rabiner, 1989) formulates an effective statistical framework to describe time varying processes of physical systems. HMM is a stochastic model of a signal that at regularly spaced time samples undergoes state transitions conforming to a set of probabilities identified for each state. HMM models the joint probability of a collection of the random variables $O = \{o_1, o_2, ..., o_T\}$ and $Q = \{q_1, q_2, ..., q_T\}$, over time T. O comprises a set of discrete event observations in a time series feature vector. An observation takes one of M possible symbols $\in \{v_1, v_2, ..., v_M\}$, expressed by the magnitudes $\in \{4.0, 4.1, ..., 9.9\}$ along with the value zero to mark a no-event element, thus making the vocabulary size $M = 61$. Q is hidden, with each its elements set to one of N admissible states $\in \{1,2,...,N\}$. Under the discrete Markov chain, there are two conditional independence assumptions about these random variables that make related algorithms tractable. Namely, the t^{th} hidden variable only depends on the $(t-1)^{st}$ hidden variable, and the t^{th} observation solely rests on the t^{th} state. These hypotheses resonate well with our seismic signal, constructed of loosely coupled and independent place events. We further assume that the underlying hidden Markov chain, defined by $P(Q_t|Q_{t-1})$, is time homogeneous and represented as a stochastic transition matrix $A = \{a_{ij}\} \in \mathbb{R}^{NxN}$, where $a_{ij} = P(Q_t = j|Q_{t-1} = i)$. Time $t = 1$ is deemed a special case specified by the initial state distribution $\pi_i = P(Q_1 = i)$. Respectively, the probability of an observation symbol at time t for state j is expressed by the emission matrix $B = \{b_j(v_t)\} \in \mathbb{R}^{MxN}$, where $b_j(v_t) = \{P(O_t = v_t|Q_t = j)\}$. Parametrically, an HMM is compactly represented as $\lambda = (A,B,\pi)$, and our goal is to solve the HMM learning problem for each of our observed, place constructed seismic signals, by maximizing the probability of an observation vector O, $P(O|\lambda)$, and iteratively estimating the model parameters.

Akin to the EM algorithm used for mixture models, we adopted the Baum-Welch (BW) method (Baum, 1972) to find the maximum likelihood estimation of the HMM parameters, for each of our generated, shake signal vectors. The method starts by choosing arbitrary values for the model parameters. It then proceeds to compute the forward probability, $\alpha_i(t)$, for the partial observation $\{o_1,...,o_t\}$ ending in state i at time t, and the backward probability, $\beta_i(t)$, for the complementary sequence $\{o_{t+1},...,o_T\}$ that started on state i, at time $(t+1)$. Time T is bound to the resampling mode set for the time series vectors, matching the sizes depicted in Table 2. Both $\alpha_i(t)$ and $\beta_i(t)$ are calculated efficiently using recursion. The algorithm then creates two auxiliary variables: $\gamma_i(t)$ (equation 6) as the probability of being in state i at time t, normalized over the entire observed symbols

$$\gamma_i(t) = \frac{\alpha_i(t)\beta_i(t)}{\sum\limits_{j=1}^{N}\alpha_j(t)\beta_j(t)}, \tag{6}$$

and $\xi_{ij}(t)$ (equation 7) representing the joint probability of being successively in state i at time t and in state j at time $(t+1)$, normalized for the integrated feature vector

$$\xi_{ij}(t) = \frac{\alpha_i(t)a_{ij}\beta_j(t+1)b_j(o_{t+1})}{\sum\limits_{i=1}^{N}\sum\limits_{j=1}^{N}\alpha_i(t)a_{ij}\beta_j(t+1)b_j(o_{t+1})}. \tag{7}$$

From γ and ξ, the definition of intuitive update rules to the model parameters ensues, as shown in equations 8, 9, and 10, respectively

$$\pi_i = \gamma_i(1), \tag{8}$$

$$a_{ij} = \frac{\sum\limits_{t=1}^{T-1}\xi_{ij}(t)}{\sum\limits_{t=1}^{T-1}\gamma_i(t)}, \tag{9}$$

$$b_j(k) = \frac{\sum\limits_{t=1}^{T}\delta_{O_t,v_k}\gamma_j(t)}{\sum\limits_{t=1}^{T}\gamma_j(t)}. \tag{10}$$

In the BW algorithm, the steps of computing forward and backward probabilities, calculating γ and ξ, and updating model parameters, repeat finite times or until convergence is reached. For each of the seismic signal vectors, the procedure returns the log-likelihood value that we further use for hierarchical clustering.

3.3 Agglomerative Merge

Unlike a mixture model, there is no implicit clustering directly derived from HMM. Therefore, the log-likelihood values we computed for each of our observed seismic vectors, serve as input for further feature matching grouping. We opted for hierarchical clustering (Manning and Schutze, 2000) (Johnson, 1967) over flat data structures, with the former intended for more detailed data analysis, and found agglomerative grouping more intuitive in our design compared to the divisive approach. The clustering algorithm starts with each individual geographical place as its own cluster, and successively combines clusters that are most similar. This process builds a tree topology from bottom-up and is repeated until it reaches the root node that merges all of our seismic places. For n geographical places we compute an nxn matrix of similarity coefficients, and update the matrix as the hierarchy is constructed. We chose the Euclidean distance as the similarity metric, and applied a subset of the most commonly used linkage methods (Kaufman and Rousseeuw, 1990) that determine how clusters are merged. Similarity functions must obey monotonicity to warrant the operation of merging does not increase similarity, and furthermore are agnostic to the merge order. Linking procedures along with their corresponding formulas are further listed in Table 3. The single linkage measures the distance between nearest neighbors of the combined clusters, whereas the complete procedure evaluates the two farthest member points. In average mode, the mean distance of all inter-group pairs is computed, and for the Ward minimum variance method (Ward, 1963), notably is its tendency to join clusters with a small number of observations, and be strongly biased towards producing clusters of roughly the same size.

Table 3: Dissimilarity formulas in merging clusters A and B, for selected linkage methods (d - distance, c - centroid).

Linkage Method	Cluster Dissimilarity
Single	$\min_{a \in A, b \in B} d[a,b]$
Complete	$\max_{a \in A, b \in B} d[a,b]$
Average	$\frac{1}{\lvert A \rvert \lvert B \rvert} \sum_{a \in A} \sum_{b \in B} d[a,b]$
Ward	$\sqrt{\frac{2\lvert A \rvert \lvert B \rvert}{\lvert A \rvert + \lvert B \rvert}} \lvert\lvert c_A - c_B \rvert\rvert_2$

Our hierarchical clustering implementation exploits a dynamic tree cut method that expands on the work by Langfelder et al. (Langfelder et al., 2007), and detects a set of coherent groups, each with its correlated seismic features of shake affected places. We use an adaptive branch height approach to generate a user defined, number of clusters. The algorithm respects the order of merges encountered in building our tree, and for each similarity measure it traverses the tree in a top-down manner, until the number of clusters desired becomes stable. Starting at the root node that represents a single cluster, the search descends the tree nodes comparing for each its similarity measure to a provided adaptive threshold. The subtrees of a successful horizontal cut are then explored down to their leaf nodes to extract their corresponding geographical seismic places. Agglomerative clustering is typically visualized as a dendrogram, shown in Figure 4 for our top one hundred seismic places of the highest event count. The dendrogram depicted resulted from employing the Ward linkage method, known to form more evenly distributed clusters. Graphically, each merge is represented by a horizontal line, and the y coordinate of the horizontal line is the similarity measure of the two clusters that were merged.

4 EMPIRICAL EVALUATION

To validate our system in practice, we have implemented a software library that realizes the cluster analysis of seismic places in several stages. After collecting and cleaning the archived earthquake data, our library commences with extracting both static and dynamic, location based feature vectors. They take the formulation of scale distribution and temporal signals, successively fed into our mixture and Markov chain models, respectively. Our features are regarded as unlabeled, and follow either an implicit or explicit clustering. Constructed groups of places are then contextually contrasted against a standardized, seismic regionalization scheme (Flinn-Engdahl, 2000).

4.1 Experimental Setup

Our work exploits the R programming language (R, 1997) to acquire the raw earthquake data and further clean it to serve useful in our software environment. We have managed to retrieve from USGS a total of 326,267 recorded events occurred in a forty years interval that started on the first year-week of 1975 till the fourteenth year-week in 2014. Shake events are spread across 3,247 geographical places, however 1,300 of those are affected by a single incident, and additional 1,579 sites enumerate under 100 episodes. To reason statistically for conducting cluster analysis, this leaves out then 368 places of sustainable feature vectors. Tables 4 and 5 lists top five places of highest event count and of largest magnitudes, respectively.

Table 4: Top five places of highest seismic event count.

Place	Event Count
Honshu, Japan	12293
Fiji Islands Region	8887
Kuril Islands	7584
Vanuatu Islands	6750
Tonga Islands	6064

Table 5: Top five places of highest magnitude, showing for each statistical summarization of scale distribution.

Place	Min	Max	Mean	SD
Northen Sumatra	4	9.1	4.60	0.45
Honshu, Japan	4	9	4.61	0.44
Bio-Bio, Chile	4	8.8	4.62	0.45
Southern Sumatra	4	8.5	4.77	0.47
Southern Peru	4	8.4	4.66	0.49

The Flinn-Engdahl scheme defines 50 geo-spatial regions and lists succinctly a total of 757 unique locations across. On the other hand, our captured event recordings exposed dozens of affiliated place names that are not registered in the standard seismic sites. Secondly, and particularly in recent years, name descriptions appear extremely verbose and embed excessive orientation information and absolute distance in kilometers from the set location. This disparity against the Flinn-Engdahl listings required both an additional pass of earthquake data cleanup to tidy up name strings, and to properly correlate the recorded

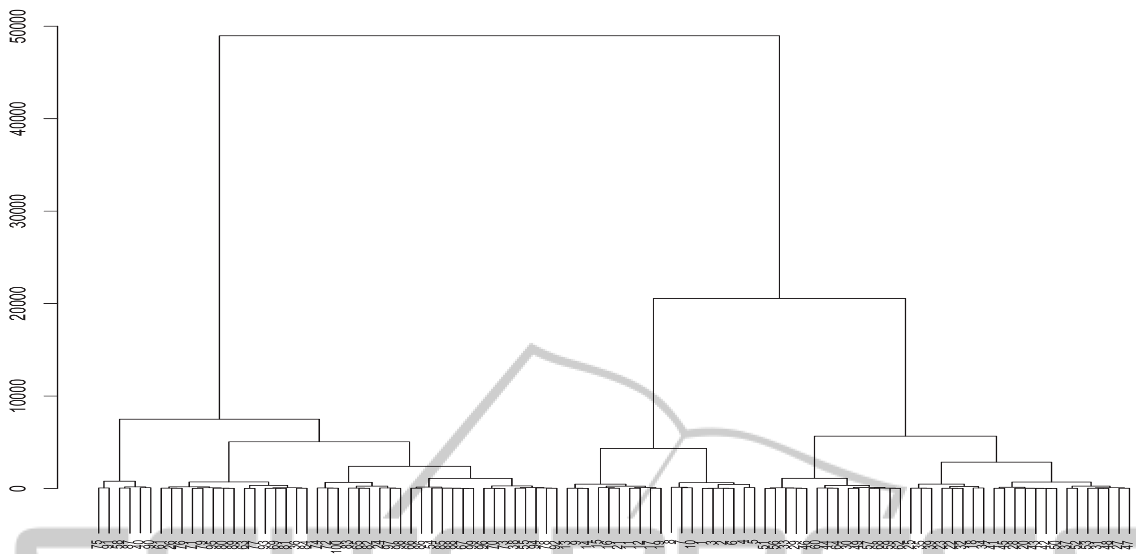


Figure 4: Agglomerative clustering dendrogram shown for the top one hundred seismic locations of the highest event count. This process uses the Ward linkage method, known for producing a more evenly cluster distribution.

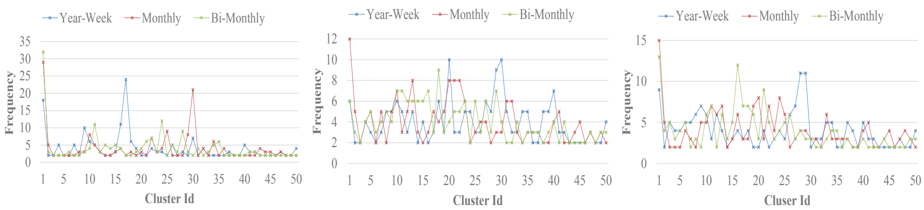
data with the standard representation, our implementation extends the source directory of Flinn-Engdahl model by 42 sites. Thus bringing the total number of seismic places to 789, all distributed and abide by the originally specified, fifty geographical regions.

4.2 Experimental Results

Our cluster analysis process is completely anonymous and assumes no prior knowledge of earthquake event locations. It solely relies on automatic feature extraction from recorded data, and incorporates statistical methods that facilitate the search of unsolicited seismic patterns, to discover global relations of earthquake occurrences that are not necessarily bound to geo-spatial proximity. In our software, both the number of seismic places to select from our earthquake data and the number of generated clusters are system level, user settable parameters. For our reported experiments we use consistently the recorded data of the top 200 geographical sites that underwent each at least 300 seismic events, and further split the locations into 50 logical clusters. First, we derive the implicit groups of geo-spatial proximity nature, by simply looking up an experimental place name from the extended and manually constructed Flinn-Engdahl directory structure, incorporated into our software. This distribution of places into already defined regional clusters, serves a useful comparative reference in analyzing our generic statistical approach, composed of a mixture model, whose components directly entail the partitions of places, and a Markov chain that follows hierarchical clustering and a dynamic tree cutting procedure. To match the Flinn-Engdahl scheme for analysis, both the number of components and the number of subtrees are set in our software to fifty, respectively.

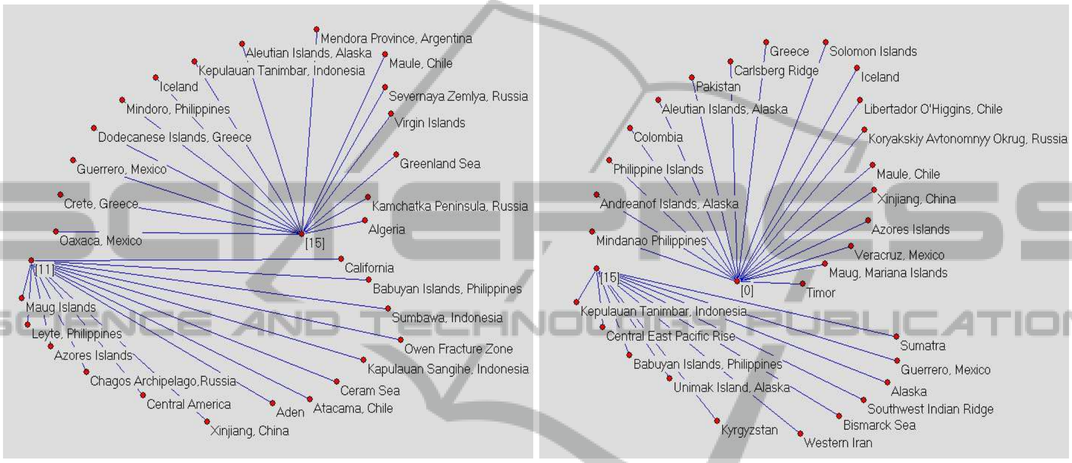
Figure 5: Seismic place distribution across 50 clusters: bottom row is the geographically based Flinn-Engdahl model, middle row depicts the mixture model results, and the top row shows the Markov chain outcome. Lighter grey color implies a higher membership place count.

Unless otherwise noted, for the Markov chain model we apply the year-week resampling mode to the time series, feature vector, and report agglomerative clustering results using the single linkage method. Figure 5 shows cluster distribution of seismic places in Flinn-Engdahl, mixture model, and Markov chain formulations. A grey stripe represents a group, and the lighter its intensity the higher the membership place count. In excluding empty clusters, identified by black stripes, populated location collections total 40, 38, and 50 for our three clustering paradigms, respectively. Our analysis experiments exploit 200 places spread across 50 relational arrays, or four seismic sites per cluster, on average, and Table 6 provides complementary statistical summarization of cluster place membership, emphasizing single member groups of no association in the 1-Place column.



(a) Single linkage method. (b) Complete linkage method. (c) Average linkage method.

Figure 6: Place membership distribution in clusters for the Markov chain model, shown for the agglomerative single, complete, and average linkage methods, and parameterized for each by year-week, monthly and bi-monthly resampling modes.



(a) Mixture model. (b) Markov chain.

Figure 7: Graphically visualized two cluster networks for each the mixture model and Markov chain clustering frameworks.

The Markov chain approach stands out in both finding seismic relations for at least a pair of places, and moreover, it employs the full set of fifty groups.

Figure 6 further depicts an interpretation of place membership distribution for the Markov chain model, reviewing the single, complete and average linking methods, each parametrized by the seismic signal resampling modes, including year-week, monthly and bi-monthly intervals. Results pertaining to the Ward linkage method are intentionally precluded to avoid reporting any bias towards even place divisions. Partition allocations for the complete and average link functions appear on a fairly equal scale and show a convincing behavior resemblance. Whereas at first inspection, the simple similarity method differs strikingly from the rest and has three peaks that stand apart for groups of about 20 to 30 place members. However, in barring the outliers and rescaling the remaining member counts, a clear indication of equivalence ensues. While the place term frequency in a cluster varies orthogonally to any of modifying the linkage method or the resampling mode, notably is the strong inclusive correlation often observed across classes generated out-of-order by different linkage methods. Figure 7(b) shows for network node 0 a super group created by the single linkage, and Figure 8 presents for that node, both the complete and average similarity methods, producing subgroups that are fully contained in the aforementioned super class.

Table 6: Statistical measures of distributed, cluster place membership for the three clustering paradigms. The 1-Place column identifies single member groups of no relations.

Model	Min	Max	Med	SD	1-Place
Flinn-Engdahl	0	24	2	4.48	8
Mixture Model	0	16	3	4.06	4
Markov Chain	2	24	3	4.07	0

Apart from the intuition of seismic similarity resulting from geo-spatial proximity, as prescribed in the Flinn-Engdahl model, we are interested in patterns that relates places by their closeness in feature space, for both the scale frequency and time series representations that feed into our mixture model and Markov chain, respectively. Figure 7 shows graphically the networks of two cluster nodes and their contextual place descendants, for each of our clustering frame-

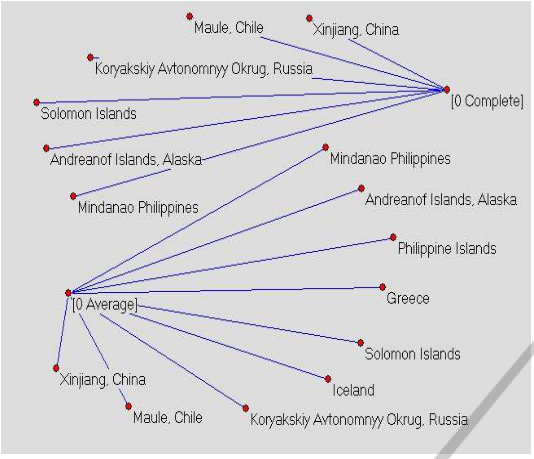


Figure 8: Graphically visualized cluster networks produced by using complete and average linkage methods.

works. Emanating from a statistical process of grouping unlabeled earthquake bound locations, an immediate observation of the cluster content identifies seismic behavior similarities in geographical places that are both close and far apart physically. For example, cluster id 15 (Figure 7(a)), originated in the composition of scale distribution features, incorporates European, African, North and South American, and Asian countries including Iceland, Greece, Algeria, Alaska, Mexico, and the Philippines. Similarly, cluster id 11 (Figure 7(a)) has California from North America, Aden in Africa, Eastern Europe Russia, and Asian Indonesia. Corollary, assemblies of time series features (Figure 7(b)) configure sites of different continents and show little resemblance to the Flinn-Engdahl geo-spatial regional scheme. The discovery of unsolicited seismic patterns promotes less dependence on a constraint physical partition profile and encourages more flexible and autonomous ecological relations, based on objective macroseismic effects (Hough, 2014).

Our software is flexible to let the user set both the number of quake affected places and the number of clusters to generate, in each of the mixture model and Markov chain formulations. Constructing groups composed of a larger site count, enable us to perform classification and measure system level accuracy. For classification, we use a k-nearest neighbor (KNN) (Cormen et al., 1990) baseline model that computes a Euclidean-squared distance between a randomly selected, test seismic vector against the remaining training feature vectors, in either a distribution scale or a signal based representation. We then apply a normalized majority rule to ten nearest samples to a test feature vector, and derive a seismic score. This score is further accumulated and averaged for each cluster, and the matching cluster corresponds to the highest

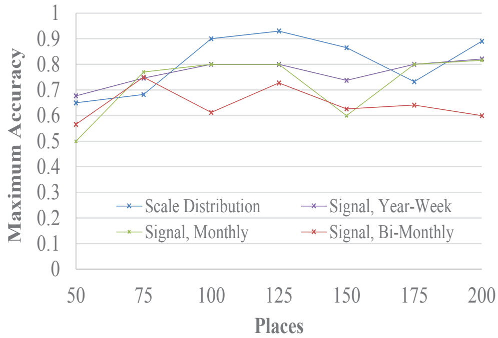


Figure 9: Classification maximum accuracy as a function of ascending number of places, split into five clusters and parametrized by seismic feature type.

average scoring, cluster id. Figure 9 shows classification maximum accuracy for a five-cluster partition as a function of a non descending place count, and parametrized by a seismic feature type. Scale distribution features depict a slightly higher accuracy compared to the seismic signal form, mostly ascribed to sparseness of the latter due to samples of no seismic action, and evidently, a coarser mode of time series resampling results in a mild decline of accuracy rate.

To the best of our knowledge and based on literature published to date, we are unaware of seismic analysis systems with similar goals to evenhandedly contrast our results against. The seismo-surfer (Theodoridis, 2001), developed for seismic data management and mining employs the k-means algorithm for clustering. By specifying n geo-places and k clusters, k-means time complexity is $O(kn)$ for each iteration, however the number of iterations to converge can be very large. Conversely, in our experiments both the EM and BW algorithms ran efficiently well under 100 iterations to convergence, along with setting the likelihood delta threshold to $1e^{-10}$. Whereas computational complexity of a bottom-up hierarchical clustering is $O(n^2 logn)$, yet the process terminates early once the desired number of clusters is reached. Another key architectural difference is the localized spatio-temporal nature of queries into the seismo-surfer database, as our design seeks more broader shake relations that span the universe mostly unconditionally.

5 CONCLUSIONS

We have demonstrated the apparent potential in deploying information retrieval and unsupervised machine learning methods, to accomplish the discovery of geo-spatial free similarity of earthquake bound places. By disregarding any prior location knowledge from presumed unlabeled seismic data, our proposed system is generic and scalable and relies entirely on objective closeness metrics in feature space that removes dependency on a more constraining regional scheme. For each of our distribution and signal type feature vectors, both cluster analysis and classification results affirm seismic pattern relations that cross continent boundaries, suggesting similarity of impartial macroseismic effects.

The data we acquired comprised of a large number of hundreds of thousands earthquake events, recorded in an extended period of time of four decades, and affected a few thousands sites around the world. However, only a few hundreds of places, each bearing at least several hundreds of shake occurrences, are statistically reasoned and pertinent to our probabilistic system approach. Advancing the growth of the seismic training set is imperative to our work and directly affects classification robustness. Yet using geographical locations that endured under one hundred seismic events is a suboptimal choice for our system, giving rise to highly sparse feature vectors. Alternatively, we contend that by coalescing locations of a small event count into a macro seismic site, based on geo-spatial proximity considerations, our training collection size is likely to increase further and proportionally let us gain a more stable classification process.

A direct progression of our work is to assume no foregoing knowledge of the number of seismic clusters to generate, and discover both the model fitting and the selection dimension directly from the incomplete seismic training set, using a combination of Akaike and Bayesian information criteria. We look forward to further incorporate the three dimensional geometrical data provided in a GeoJSON object, and possibly detect seismic similarity along either a longitude or a latitude extent perspective. Lastly, the flexibility of our software allows us to pursue a higher level, inter-cluster network study to better understand second order set of seismic relations.

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