Seismic waveform classification

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Volcanic processes and their whistle-blowing seismic signatures – can we decipher the message?
Global earthquake monitoring

Waveform data of approx. 2000 seismic broadband stations available in near-real-time (latency < 1 minute)

Task: Detect signals of interest, associate and locate.
→ Basis for local/regional early-warning - postEQ damage estimates / rescue operations
Explosion monitoring (UN CTBTO)
Seismic sequence prior to Merapi-type eruption

courtesy of Drs. E.N. Budi, Dr. J. Wassermann
Similarity of speech signals and seismic signals

waveforms

production models

from Deller et al., 1993 for speech generation

from Dahm, 1991 for volcanic tremor

FIGURE 3.7. A schematic representation of the vocal system.

Hidden Markov Models (HMMs)

Speech recognition → typical machine learning domain
Among many attempts a rather successful approach:
Description of speech segments by Hidden Markov Models
Continuous Automatic Classification of Seismic Signals of Volcanic Origin at Mt. Merapi, Java, Indonesia.

Applying HMMs to volcanic speech
Classification example
Challenges for automatic waveform classification

* **compressed signal representation** →
  Question of best feature space?
  Suitability of feature selection for classification task

* **data abundance, but training sample scarcity!** →
  Selecting training sets for supervised learning of classifiers is tedious and difficult –
  Our objects of interest are typically non-repeatable natural phenomena ↔ distinct situation when compared to other domains, where lab data can be acquired.

* **signal class definition diffuse!** →
  experts may disagree on exact membership (no golden standard available!)
Training the classifier – preparation of training data set
Training the classifier – learning while recording
Training the classifier – retraining
Formally speaking this is a factorisation of a joint system:

\[ \Pr(X_1, \ldots, X_5) = \Pr(X_1) \Pr(X_2) \Pr(X_5|X_3) \Pr(X_4|X_2) \]

Breaking down a system into its constituents
Define a generating system as a Graphical Model that “captures” seismic waves in terms of their spectral decomposition (features):

- Each freq. band influences neighboring freq. Band (across scale):
  \[
  \forall i : c_{i,t} \leftrightarrow c_{i,t+1} \leftrightarrow c_{i,t+2} \leftrightarrow \ldots
  \]

- Each freq. band “evolves” in time (temporal relationship):
  \[
  \forall i : c_{i,t} \leftrightarrow c_{i,t+1} \leftrightarrow c_{i,t+2} \leftrightarrow \ldots
  \]
From HMMs to Graphical Models

- Models a multivariate (joint) distribution.
- Edges model statistical (in)dependencies. Along the edges the “strength” of influence (model parameters)
- Here: 5 features per time-slice (colour coded).
From HMMs to Graphical Models

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- Edges model statistical (in)dependencies. Along the edges the “strength” of influence (model parameters)

- Transform this Markov Network into a Dynamic Bayesian Network.
From HMMs to Graphical Models
Graphical Models

- GMs are a marriage between probability theory and graph theory

- A natural tool for dealing with 2 problems: uncertainty and complexity

- GMs provide an intuitively appealing interface by which humans can model highly-interacting sets of variables

- GMs come with general-purpose inference and reasoning mechanisms

- Many existing statistical techniques can be formulated as GMs

- The GM formalism provides a framework for the design of new systems.