*e*-Machine Estimation and Forecasting Comparative Study of Inference Methods

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Natural Computation, 2014

### Outline



#### Motivation

- ε-Machines and Time Series
- Baum-Welch Algorithm
- The Future, The Comparison Project

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### $\epsilon$ -Machines and Time Series.

•  $\varepsilon$ -machines eat sequences of alphabet symbols: {...,  $X_{-2}, X_{-1}, X_0, X_1, X_2, ...$ }

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Let's compare with time series methods?

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  - Stock price data
  - Life

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- Spectral analysis
- Principal component analysis
- Neural networks

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#### Neural networks

Tools for investigating time-series data include:

- · Consideration of the autocorrelation function and the spectral density function (also cross-correlation functions and cross-spectral density functions)
- Scaled cross- and auto-correlation functions to remove contributions of slow components<sup>[8]</sup>
- · Performing a Fourier transform to investigate the series in the frequency domain
- · Use of a filter to remove unwanted noise
- · Principal component analysis (or empirical orthogonal function analysis)
- · Singular spectrum analysis
- "Structural" models:
  - · General State Space Models
  - Unobserved Components Models
- Machine Learning
  - Artificial neural networks
  - Support Vector Machine
  - Fuzzy Logic
- Hidden Markov model
- Control chart
  - · Shewhart individuals control chart

[Dmitry +  $\varepsilon$ -machines] vs. [Time series]

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• Too many! Pick battles you can win!

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# Baum-Welch - What is it?

The Baum-Welch algorithm - a method for inferring the most likely parameters of a Hidden Markov Model responsible for some given string of data.

Example	
Input	

- Number of states n
- Network topology and initial guess for the parameters of the HMM heta
  - Parameters are the start distribution, state transition probabilities, and symbol emission probabilities at each state.
- A sequence of outputted symbols  $Y = \{Y_1, Y_2, ..., Y_n\}$

#### Example

#### Output

• New parameters  $\theta'$  with the property that  $P(Y|\theta') \ge P(Y|\theta)$ .

### Baum-Welch - How does it work?

• Belongs to a broad class of EM algorithms - expectation maximization.

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### Baum-Welch - How does it work?

- Belongs to a broad class of EM algorithms expectation maximization.
- Too many details:
  - Makes a forward pass to compute  $\alpha_i(t) = P("y_1,...,y_t",X_t = i|\theta)$ 
    - \* Probability of seeing "word" and ending up in state *i* at time *t*.
  - Makes a backwards pass to compute  $\beta_i(t) = P("y_{t+1},...,y_T"|X_t = i, \theta)$ 
    - \* Probability of having the last T t symbols be the specified "word", assuming that you ended up in state *i* at time *t*.
  - Combined these in the update step to calculate

 $\xi_{ij}(t) = P(X_t = i, X_{t+1} = j | Y, \theta)$ 

- ★ Probability of transitioning  $i \rightarrow j$  at time t.
- \*  $\xi_{ij}(t)$  can be computed as a function of  $\alpha_i$ 's and  $\beta_i$ 's
- Where this eventually gets us:
  - ★ Summing ξ<sub>ij</sub>(t) over time, we can compute the expected number of transitions from state i → j, as well as i → \*.
  - \* This will allow us to compute the expected transition probabilities between states.
  - \* And! Similarly, we can compute the expected symbol emission matrix for each state.

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- ★ Starting probabilities.

• We can run this procedure again.

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- Thus, Baum-Welch algorithm is an iterative, gradient-based optimizer in the space of HMM parameters.

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- "Hill-climber" algorithm.



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 Gets stuck in local optima, so you have to seed it and rerun it with many starting conditions.

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Pause

• Given impoverished data [small sample], do they differ in their rate of convergence to the true HMM as sample size is increased?

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- Maybe run-time speed, but that's tough have to prove to C-language speed demons that you have a fast implementation.
- As fun side-project / implementation, would like to translate HMMs into some audio signal [for ex. each symbol corresponds to a pitch being emitted].
  - ► See if the HMMs the algorithms produce "sound" different.

Sidenote: IPython.

• IPython is great for Windows machines that have run VM's.

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• It is Sage-like, here is my workflow:

# Sidenote: IPython.

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File Edit View Insert Cell Kernel Help O	<pre>[] f = urllib.urlopen("https://dl.dropbox.com/s/dn9qnr/19djtexe/X.txt". dataDmitry = []</pre>	
	<pre>for line in f: temp = int(line) dataImitry.append(str(temp))</pre>	
In (1): import numpy as np from sklearn import hum import line as t	print dataDmitry [11, 00, 11, 11, 11, 10, 11, 10, 11, 10, 10	
<pre>In (9): states = 1 alphabet = 2 statypob = np.candom.random(states) statypob = statypob / sum(statypob) statypob = statypob / sum(statypob) for i (n trapp(fam)(statypamant)) for i (n trapp(fam)(statypamant))</pre>	1, 00, 01, 11, 11, 11, 11, 11, 11, 11, 1	
<pre>transmat[i] = transmat[i]/sum(transmat[i]) emissionprob = np.random.random((alphabet, alphabet)) for i in range(lon(emissionprob)):     emissionprob[i] emissionprob[i]</pre>	<pre># Use from_string to define a very blased Blased Coin in CMPy booin str = "Q Q 0 0.1; Q Q 1 0.9" booin = cmm.from_string(booin_str. </pre>	
print startprob print transmat print enissiongrob	<pre># draw machine booin.draw()</pre>	
[ 1.] [ [ 1.]] [ [ 0.34097063 0.65902837] [ 0.42242454 0.37828344]]	Couldn't import dot_parser, loading of dot files will not be pos	
In [14]: print startprob print transmat print emissionprob		
[ 1.] [[ 1.]] [[ 0.407063 0.65902837] [ 0.62161656 0.37838344]]	booin_prior = bem.InferEM(booin) print booin_prior.summary_string() Epsilon Machine Inference	
<pre>In [10]: model = hmm.MultinomialNBM(states, startprob, transmat) model emissionprob = emissionprob</pre>	🐐 Local_maximum.png 🔹 🌞 Random-data-pluspng 🎽 🖉 Show all down	

## Thank you!

Thank you! Everybody!

