

Hidden Markov Models

Theoretical Aspects. Octave Implementation. Applications

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Romanian Asociation for Artificial Intelligence

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PART 1.

Intro

PART 2.

Theory of HMMs

PART 3.

Demo & Discussions

Outline

Intro

1 ARIA Education Workshops

- ARIA's Mission
- ARIA Education
- Workshop Program

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Today's Program

9:00	Registration
10:00	Rahaturi despre ARIA
11:00	HMM Theory

Theory of HMMs

2 Machine Learning Applications for HMM

- Machine Learning
- Where do HMMs fit into Machine Learning?

3 Theory of HMMs

- The 3 things you want from an HMM
- Mathematical Foundations for HMMs
- Notation Conventions & Framework Description

4 Implementing HMMs

- Using the Model for Estimations: the Forward-Backward algorithm
- Learning from Observations: Baum-Welch algorithm
- Uncovering Hidden states: Viterbi algorithm

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What is Machine Learning?

Machine Learning

..**Trascau** is a beautiful horse.

Machine Learning Applications

- Computer Vision: Google Car
- Machine Translation
- Speech Recognition
- Recommender Systems
- Intelligent Advertising

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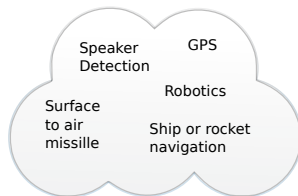
Machine Learning Classification

Types of Machine Learning Problems

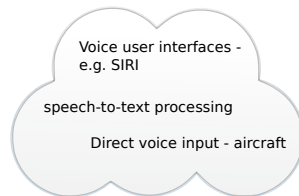
- Regression
- Classification
- Reinforcement Learning
- supervised learning (eg. ..)
- unsupervised

Sequence / Temporal problems (I)

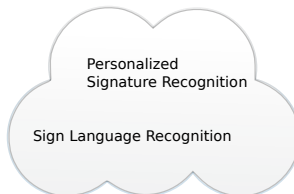
OBJECT TRACKING



SPEECH RECOGNITION



GESTURE RECOGNITION



Sequence / Temporal problems (II)

BIOINFORMATICS

Protein Sequencing

Modeling of a gene
regulatory network

ECONOMICS

stock price prediction

econometrics

- estimate a country's economic indicators across time -

Sequence / Temporal problems (III)

Some tools of the trade:

- DBN
- Kalman Filters
- HMMs

Probabilistic Reasoning over Time

Applications for HMMs

- Robot localization

Applications for HMMs

- Robot localization
- DNA sequence analysis

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Applications for HMMs

- Robot localization
- DNA sequence analysis
- Hand-Writing Recognition
- Speech Recognition (newxt on baywatch)

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The 3 fundamental problems [Rabiner, 1989]

- Particularization of temporal inference problems to HMMs

Evaluation Problem

Given a model and a sequence of observations, how do we compute the probability that the **observed sequence** was produced by the model?

The 3 fundamental problems [Rabiner, 1989]

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Best Explanation of Observations Problem

Given a model and a sequence of observations how do we choose a corresponding sequence of **states** which *gives meaning* to the observations? How do we *uncover* the hidden part of the model?

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Model Estimation (Training) Problem

Given some observed sequences, how do we adjust the **parameters** of an HMM model that best tries to explain the observations?

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- **Mathematical Foundations for HMMs**
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Elements of an HMM

- N Hidden States : $S_1, S_2, \dots S_N$
- M Observable Variables : $O_1, O_2, \dots O_M$

Parameters:

- Transition Function / Matrix between states
- Emission probabilities
- Initial state probabilities

Formalisation of the estimation problem



Formalisation of problem # 2

- $P(Q_1) = \sum_{x=\{1,2\}}^N P(Q_2)\theta\Pi$
- $P(Q_i|q_i = s_x) = i \times x \cdot i \dots$

Formalisation of parameters estimation problem



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Notation Conventions

Variables in Octave

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Viterbi s-a nascut in ...

Demo & Discussions

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- 5 A Case for HMMs in Symbol Recognition
- 6 Types of HMMs
- 7 Discussions and Recap

Summary

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[Forward-Backward Algorithm](#)
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 - given an HMM, estimating the probability of an observed sequence
[Forward-Backward Algorithm](#)
 - given observed data, estimating the parameters of an HMM
[Baum-Welch Algorithm](#)
 - uncovering the hidden states [Viterbi Algorithm](#)

References I



Rabiner, L. (1989).

A tutorial on hidden markov models and selected applications in speech recognition.

Proceedings of the IEEE, 77(2):257–286.

Thank you!