Hidden Markov Models

Theoretical Aspects. Octave Implementation. Applications

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PART 1.
Intro

PART 2.
Theory of HMMs

PART 3.
Demo & Discussions

Outline

Intro

Outline

Outline

1. ARIA Education Workshops
   - ARIA's Mission
   - ARIA Education
   - Workshop Program

Outline

ARIA EDU

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Outline

Today's Program

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

Theory of HMMs

Outline

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

Outline

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

Outline

Machine Learning Classification

Types of Machine Learning Problems

- Regression
- Classification
- Reinforcement Learning

- supervised learning (eg. ..)
- unsupervised

Sequence / Temporal problems (I)

OBJECT TRACKING

- Speaker Detection
- GPS
- Robotics
- Surface to air missille
- Ship or rocket navigation

SPEECH RECOGNITION

- Voice user interfaces - e.g. SIRI
- speech-to-text processing
- Direct voice input - aircraft

GESTURE RECOGNITION

- Personalized Signature Recognition
- Sign Language Recognition

Sequence / Temporal problems (II)

BIOINFORMATICS

Protein Sequencing

Modeling of a gene regulatory network

ECONOMICS

stock price prediction

econometrics
- estimate a country's econmic 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

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- Hand-Writing Recognition
- Speech Recognition (newxt on baywatch)

Outline

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?

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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?

Outline

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

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Formalisation of problem # 2

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

Formalisation of parameters estimation problem

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Outline

Notation Conventions

Variables in Octave

Outline

Outline

Outline

Viterbi s-a nascut in ...

Demo & Discussions

Outline

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  - given observed data, estimating the parameters of an HMM
    Baum-Welch Algorithm
  - uncovering the hidden states Viterbi Algorithm

References I

Rabiner, L. (1989).
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Proceedings of the IEEE, 77(2):257–286.

Thank you!