Hidden Markov Model

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Hidden Markov modelling is a probabilistic class of graphical models allowing a sequence of unknown (hidden) variables to be predicted from a group of observed variables. For a system which is been model is assumed to be in Markov process, let it be X, which is in unobservable state and another process, let it be Y is observable and whose behaviour depends on X. Then we can interpretate X by observing Y. An HMM can be seen as a time-driven network with observations made in sequence of time steps to predict the best sequence of hidden conditions. The reason why the model is known as the Hidden Markov Model is because we build an inference model based on Markov's assumptions. The premise of the Markov process is essentially that, given the present, "the future is independent from the past." In other words, provided we know our existing condition, no previous knowledge is necessary to forecast the future state. HMM is specified by a set of states Q, a set of transition probabilities A, a set of observation likelihoods B, a defined start state and end state(s), and a set of observation symbols O, is not constructed from the state set Q which means observations may be disjoint from states. A simple example of an HMM is predicting the weather (hidden variable) based on the type of clothes that someone wears (observed). i.e. we can estimate the weather to an extend on the basis of their clothing. On a sunny day someone wear a plan cloth, but on rainy day they were rain coat and on winter sweater. In this example we can see that each state only depends on the present state and not on any other prior states. We must gather three types of information in order to determine the joint probability of a sequence of hidden states. In general, the hidden states are referred to as "states," whereas the observed states are referred to as "observations."

1. Transition data — the probability of transitioning to a new state conditioned on a present state.

2. Emission data — the probability of transitioning to an observed state conditioned on a hidden state.

3. Initial state information — the initial probability of transitioning to a hidden state. This can also be looked at as the prior probability.

HMM too is built upon several assumptions and important assumption of which is:

- Output independence assumption: Output observation is conditionally independent of all other hidden states and all other observations when given the current hidden state.

In Hidden Markov Model we study two type of probability:

1. Emission probabilities: Emission probabilities are the probability of the observation we make in the model of all observable state. As the clothing pattern in weather example.

2. Transition probabilities: The probabilities that explain the transition to/from hidden states are Transition probabilities. For example the probability of change of weather from one state to other.

The Hidden Markov model is used in different field like thermodynamics, statistical mechanics, physics, chemistry, economics, finance, signal processing, information theory, pattern recognition, bioinformatics. HMMs provide a formal foundation for creating probabilistic models of linear sequence 'labelling' problems. They offer a conceptual toolset for creating complicated models just by sketching an image. Genefinding, profile searches, multiple sequence alignment, and regulatory site identification are just a few of the tools that use them. The Legos of computational sequence analysis are HMMs.