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# Psychological Classification of Predicting Students Academic Performance using Hidden Markov Model

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## Abstracts

Hidden Markov Model are commonly used to analyse real world problems. Modeling and predicting human behavior is an active research domain. Machine learning techniques to build a statistical model using observations. This paper emphasizes how hidden markov model is used potentially as a tool for predicting the academic performance of students in a psychological approach. This tool helps trainer to improve the performance of each students for the next assessment. Using hidden markov model(HMM) the hidden state of each student can be examined , according to the Observations of the students (marks), we can able to predict the hidden state in a Psychological way. That is ,Whether the students are in Stress, Hardwork, Unhealthy ,Lazy at the time of Assessment. Based on the statistical method and probability theory we can classify the students behavior.

**Keywords**: Hidden Markov Model (HMM), Forward-Backward Algorithm, Viterbi algorithm , Bernoulli process , HMM learning , HMM training..

## Introduction to Hidden Markov Model (HMM)

A Hidden Markov model (HMM) is a statistical Markov model in which the unobserved states are identified through Markov Process. HMM can be considered the simplest dynamic Bayesian network. it is closely related to an early work of optimal nonlinear filtering problem called stochastic processes.

In simpler markov models like markov chain, the state is directly visible to the observer, and therefore the state transition probablities are the parameters. In a Hidden Markov model, the state is not directly visible, but output, dependent on the state, is visible. Each state has a probability distribution over the possible output tokens. Therefore the sequence of tokens generated by an HMM gives some information about the sequence of states. Note that the adjective 'hidden' refers to the state sequence through which the model passes, not to the parameters of the model; the model is still referred to as a 'hidden' Markov model even if these parameters are known exactly.

Hidden markov model are especially known for their applications in temporal pattern recognition such as speech , handwriting, musical score following, partial discharges and bio informatics.

A hidden Markov model can be considered a generalization of a mixture model where the hidden variables which control the mixture component to be selected for each observation, are related through a Markov process rather than independent of each other.

To learn a HMM you have to specify its size (i.e. How many states and how many different observations are there). To train the HMM you have to put the training data (in this case multiple sequences of observations) into the appropriate vector structure. Discrete observations here are represented as integers and the observations structure is a vector of vectors, each of which represents a sequence of Observation. Learning itself is achieved using one of two algorithm K-mean approximation and Baum-Welch. The latter is a local optimization algorithm and therefore needs an initial HMM.

The simplest way is to let K-mean generate the initial hmm and then use baum-welch to optimal the initial HMM.

To make prediction using the learned HMM, you have to first find the state with the highest probability of being the one the system in right now. This is done using the Viterbi algorithm which identifies the most likely state sequence to have generated the given sequence of observations.Given this state you can calculate the most likely next observations.

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## Example : Coin Flipping

Assume that there are coins, one being biased towards heads (60% of the time it lands heads), one biased towards tails (60% of the time it lands tails). Assume further that a person picks up one of the coins and starts flipping it repeatedly (without you knowing which coin it is). From the sequence of results (heads or tails), learn a model that predicts if the next observation will be heads or tails. To do this (actually without knowing that the coins are biased or how biased they are) we can set up a HMM learner that learns a HMM that models the process of flipping the coin. In this case we decide to let it learn a HMM with 2 states and 2 observations (heads =0, tails = 1). Two states should be sufficient there are only two possible coins.

## States of hidden markov model

The prediction process is achieved by following states, Observation state, adjustment state and prediction state. The experiment results are encouraging and serve to show the promise of HMM in PSAP and they show accuracy in the next action prediction reaching up to 92%.

Hidden Markov models are broadly used in science, engineering and other areas such as speech recognition , optical character recognition, machine translation, bioinformatics , computer vision, finance and economics and in general sciences.

The Hidden Markov Model (HMM) is a variant of a finite state machine having a set of hidden states, **Q**, an output alphabet (observations), **O**, transition probabilities, **A**, output (emission) probabilities, **B**, and initial state probabilities, **Π**. The current state is not observable. Instead, each state produces an output with a certain probability (**B**). Usually the states, **Q**, and outputs, **O**, are understood, so an HMM is said to be a triple, (A , B,Π)

Hidden states $\boldsymbol{Q} = \{ q_i \}, i = 1, \dots, N$ .

Transition probabilities $\boldsymbol{A} = \{a_{ij} = P(q_j \text{ at } t+1 \mid q_i \text{ at } t)\}$, where $P(a \mid b)$ is the conditional probability of $a$ given $b$, $t = 1, \dots, T$ is time, and $q_i$ in $\boldsymbol{Q}$. Informally, $\boldsymbol{A}$ is the probability that the next state is $q_j$ given that the current state is $q_i$.

Observations (symbols) $\boldsymbol{O} = \{ o_k \}, k = 1, \dots, M$

Emission probabilities $\boldsymbol{B} = \{ b_{ik} = b_i(o_k) = P(o_k \mid q_i) \}$, where $o_k$ in $\boldsymbol{O}$. Informally, $\boldsymbol{B}$ is the probability that the output is $o_k$ given that the current state is $q_i$.

Initial state probabilities $\boldsymbol{\Pi} = \{p_i = P(q_i \text{ at } t = 1)\}$.

A Hidden markov model(HMM) is a stochastic model which describes a process where the state depends on previous state in a non deterministic way. HMM observes a sequence of emissions, but doesn't know the sequence of states the model went through to generate the emissions. The HMM analyses seek to recover the sequence of states from the observed data.

## Bernoulli process

In probability and statistics, a bernoulli process is a finite or infinite sequences of binary random variables, so it is a discrete time stochastic process that takes only two values , canonically 0 or 1. The Component Bernoulli variables $X_i$ that ate identical and independent, a Bernoulli process is a repeated coin flipping, possibly with an baised coin (but with consistent unfairness).
Every variable $X_i$ in the sequence is associated with a Bernoulli trial or experiment. They all have the same Bernoulli distribution. Much of what can be said about the Bernoulli process can also be generalized to more than two outcomes (such as the process for a six-sided die); this generalization is known as the Bernoulli scheme.

The problem of determining the process, given only a limited sample of the Bernoulli trials, called the problem of checking whether a coin is fair.

## Forward & backward algorithm

Using Forward & Backward algorithm for hidden markov model which computes the posterior marginals of all hidden state variables given a sequence of observations/emissions O1 :t = O1,---Ot for all hidden state variables Xk € {X1,....Xt}, the distribution P(Xk|O1:t).
This inference task is usually called smoothing. The algorithm makes use of the principle of dynamic programming to compute efficiently the values that are required to obtain the posterior marginal distributions in two passes.

The first pass goes forward in time while the second goes backward in time; hence the forward-backward algorithm will performed.

## The forward-backward method

The forward method computes:

$$p(K_1, \dots, K_{t-1}) = \sum^{N} \alpha_i(t)$$

the backward method computes (t>1):

.

$$p(K_t, \dots, K_T) = \sum_{i=1}^{N} \beta_i(t)$$

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We can do the forward-backward method which computes $p(K_1,\ldots,K_T)$ using formula (using any choice of $t=1,\ldots,T+1$!):

$$L = p(K_1,\ldots,K_T) = \sum_{I=1}^{N} \alpha_i(t)\beta_i(t)$$

## Viterbi algorithm

Using viterbi algorithm we can find the path in a sequence of observed state.The Viterbi algorithm is a dynamic programming algorithm for finding the most likely sequence of hidden states – called the Viterbi path – that results in a sequence of observed events, especially in the context of Markov information sources and hidden Markov models.

Suppose we are given a Hidden Markov Model (HMM) with state space S, initial probabilities $\pi_i$ of being in state $i$ and transition probabilities $a_{i,j}$ of transitioning from state $i$ to state $j$. Say we observe outputs $y_1,\ldots,y_T$. The most likely state sequence $x_1,\ldots,x_T$ that produces the observations is given by the recurrence relations:

$V_{1,k} =$ P(y1 | k).$\pi_k$
$V_{t,k} =$ P(yt | k). $max_{x\in S}(a_{x,k} \cdot V_{t-1,x})$

Here $V_{t,k}$ is the probability of the most probable state sequence responsible for the first $t$ observations that has $k$ as its final state.

The Viterbi path can be retrieved by saving back pointers that remember which state $x$ was used in the second equation. Let Ptr(k,t) be the function that returns the value of x used to compute $V_{t,k}$ if $t > 1$, or $k$ if $t = 1$. Then:

$x_T = argmax_{x\in S}(V_{T,x})$
$x_{t-1} =$ Ptr($x_t$,t)

Here we're using the standard definition of arg max. The complexity of this algorithm is $O(T \; X \; |S|^2)$

## Psychological Classification of Predicting Students Academic Performance using Hidden Markov Model

This paper emphasis the use of Hidden markov model and Probablity concepts to find the hidden states of each student behavior.

In the above discussed concepts HMM , Bernoulli process , Forwrad & Backward algorithm , Maximum likelihood algorithm to predict the students performance in the assessments of Academic marks will be useful to improve the performance of each students.

Using 100 training set data to predict each students psychological behavior at the time of assessment, for example the students is in which state either lazy , unhealthy, hardwork , mental stress etc.
Using HMM to find the behavior of students at each assessment at state of level.the following example shows you that the Observed state & Hidden stats should be found using the tool.

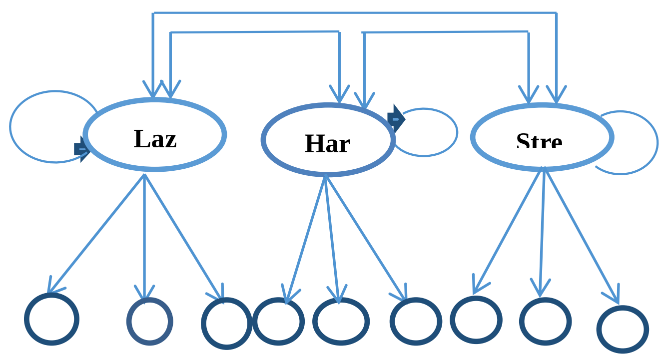


***Figure 1.Classification of students performance***

In the figure the below mentioned circles are S1,S2,S3 are Subject marks Observations.

Student Name : Saishravan .K

| Subjects | Marks(OS) | Hidden States |
|---|---|---|
| Computer Science | 78 | Hardwork |
| Language | 56 | Lazy |
| Maths | 85 | Hardwork |

Student Name : Ashwathi .N

| Subjects | Marks (OS) | Hidden States |
|---|---|---|
| Computer Science | 45 | Stress |
| Language | 56 | Lazy |
| Maths | 78 | Hardwork |

OS – Observed State

To create this tool using forward & backward methods and viterbi algorithm in matlab.This research will gives a good result and a clear classification of students psychological behavior and to improve the academic performance. The Hidden states are identified through applying the above methods.

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During the continuous assessment made by the faculty , this tool will predict the students behavior at the time of assessment without knowing the students. This type of sequential learning can be made in artificial intelligence.

## Conclusion

The paper described that hidden states are observed through the assessment conducted by the faculties. This tool is useful to improve the quality of students performance in the next assessment. It is artificial intelligence based tools using Hidden Markov model , Viterbi algorithm amd maximum likelihood. Further we can extend the thesis to find the psychological behavior of employees at the time of Work,Projects(Failure , Success).

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