Proposed strategy 1

The model used till now was the n -gram approach.

One approach which can be implemented is the Markov model.

If a document is given, each word can be bifurcated as a Markov chain of letters.

When the entire document is taken into account as one complete set of Markov chains, the set of starting and transitional probabilities can be calculated and referred to as a Markov Model for that particular language.

This proposed model in our research project which will not only identify the languages with a lower error rate, but will also result in faster identification speed as compared to N-gram model.

The occurrences of letters in a word can be regarded as a stochastic process and hence the word can be represented as a Markov chain where letters are states. The occurrence of the first letter in the word is characterized by the initial probability of the Markov chain and the occurrence of the other letter given the occurrence of its previous letter is characterized by the transition probability.

**Updated Strategy 1:**

In order to define an HMM completely, following elements are needed.

* The number of states of the model, *N*.
* The number of observation symbols in the alphabet, *M*. If the observations are continuous then *M* is infinite.
* A set of state transition probabilities tex2html_wrap_inline2612 .

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where tex2html_wrap_inline2616 denotes the current state.  
Transition probabilities should satisfy the normal stochastic constraints,

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and

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* A probability distribution in each of the states, tex2html_wrap_inline2622 .

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where tex2html_wrap_inline2626 denotes the tex2html_wrap_inline2628 observation symbol in the alphabet, and tex2html_wrap_inline2630 the current parameter vector.  
Following stochastic constraints must be satisfied.

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and

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If the observations are continuous then we will have to use a continuous probability density function, instead of a set of discrete probabilities. In this case we specify the parameters of the probability density function. Usually the probability density is approximated by a weighted sum of *M* Gaussian distributions tex2html_wrap_inline2638 ,

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where,

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tex2html_wrap_inline2646 should satisfy the stochastic constrains,

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and

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* The initial state distribution, tex2html_wrap_inline2652 .  
  where,

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Therefore we can use the compact notation

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to denote an HMM with discrete probability distributions, while

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to denote one with continuous densities. .

**Intro To Markov Models**

**1. Starter Sentence** | Definitely the best way to illustrate Markov models is through using an example. In this case we are going to use the same example that I was also presented when learning about Markov Models at [Make School](https://medium.com/@makeschool).

**2. Weighted Distributions** | Before we jump into Markov models we need to make sure we have a strong understanding of the **given starter sentence, weighted distributions,**and**histograms**.

**3. Special Additions** | Great! At this point you should be comfortable with the concept that our *sentence*consists of many **tokens** and **keys.** Additionally, you should understand the relationship between a **histogram**and **weighted distributions**.

References:

[1]<https://pdfs.semanticscholar.org/2bf0/8addb83f51befa8b4bc7ed16b54ed34018d0.pdf>

[2]<http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.149.630&rep=rep1&type=pdf>

[3] <http://www.cs.princeton.edu/courses/archive/spr05/cos126/assignments/markov.html>

[4]

http://jedlik.phy.bme.hu/~gerjanos/HMM/node4.html