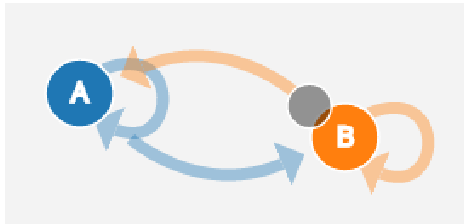
Southern New Hampshire University

DAT 520 Module Six Overview

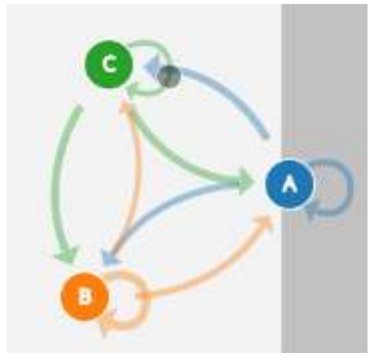


What is a Markov process? In precise language, a **Markov process** consists of two parts: a known number of states and the transition probabilities for moving between those states.

Sometimes there is a conditional probability event that happens repeatedly. Each time the cycle repeats, the ending state from the previous run gets fed in as the input to the next run, until the cycle completes. If there are many cycles, the Markov process tends to stabilize in value.

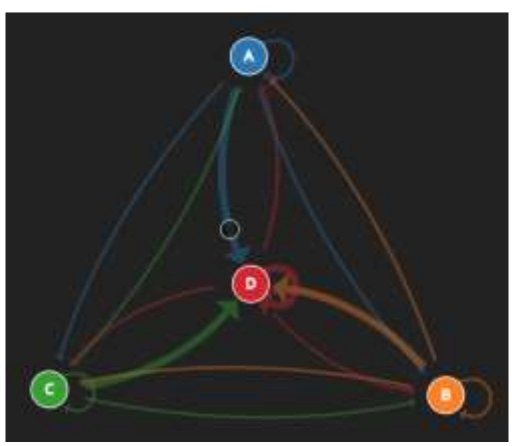
Operationalizing a Markov process into a tree takes finesse. The exercises in this module will show how a static probability and a cyclic probability can have a profound effect on the results of a decision tree.

In previous modules you saw how conditional probability combines probabilities of two or more events in a chain. A Markov process brings reality into the probabilistic system, since life may only sometimes happen in chains. Rather, life often occurs as a stochastic process, which means a random walk through possibilities rather than a straight line. A Markov process is different than straight-up conditional probability because it does not presuppose one single path through the probabilistic maze.



A Markov process considers the possibilities as a black box in which you enter on one side, but what happens on the inside is unknown; and then you exit on the other side again in a known state. So you do not know the precise events of what is going on inside the box, but you know the beginning, have an idea how the interior states relate to one another, and you can calculate the end state. That is a lot more like life.

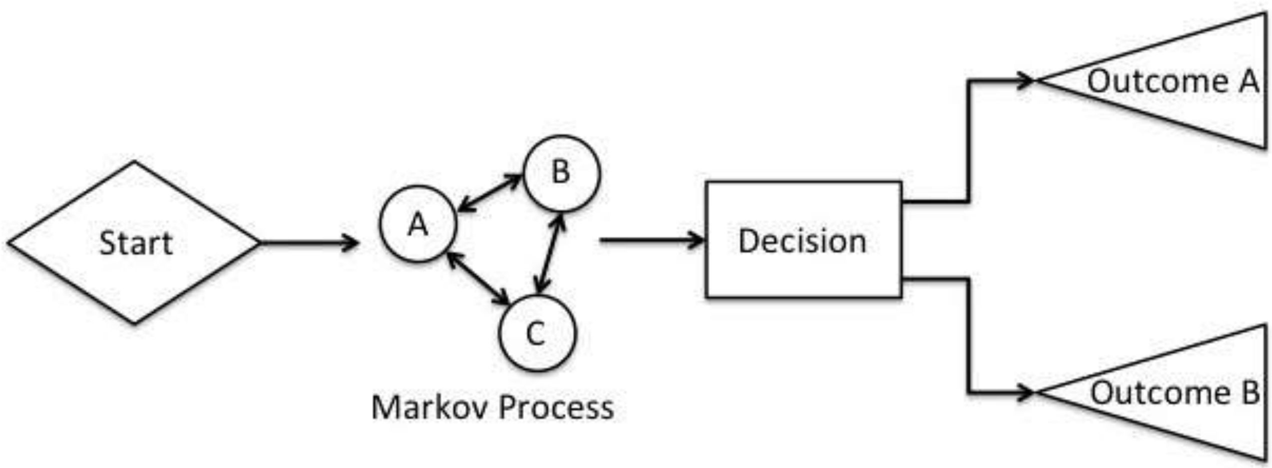
Here is an example. You go into a supermarket with a list of things that you need to get, but you do not remember perfectly where they are. So, you start shopping on one side of the store, collecting the items you need and checking them off the list. They may not appear on the list in the exact order that you collected them, and you may have to go up and down the aisles a few times to find what you need, but you are keeping track on your list. If you plotted your travels on a map, you would make this sort of random, squiggly line around the store until you got all the things on your list and went to the checkout. (And you will probably have a few more things in your cart that were not on your list!) Finally, you pay and leave. So you know what you started with and you know how you ended, but you do not necessarily know exactly how it all happened on the inside of the store. That is similar to how a Markov process works.



To bring this back to a decision model, what you are doing is collecting all the different types of inputs that go into your decision and assigning them initial states. In a Markov process, their arrangement in relation to one another is less defined and the states of a single trip through them is not defined; but the beginning state is known, and the probabilities of getting from A to B to C to D and back again are known. Therefore, the final state can be calculated, depending on how many trips through the system occurred.

In this module, we are going to look at how you can calculate these Markov processes on your own by hand. And then we are going to use last module's spreadsheet to calculate a Markov process that we then will use in the decision tree model as one of our percentages.

Here is where it gets really interesting. For accurate decision modeling, you want to have access to both straightforward conditional probability and black-box Markov processes. You may have some events that occur in a specific order, but embedded among those events are parts that are a Markov system. Imagine repeated trips to the doctor for treatments for a long-term illness.



A simple decision tree with conditional probabilities and an embedded Markov Process.

For the Markov portion of a model like this, you will need to have the starting inputs and transitions to calculate the Markov process and therefore to know the output for the next step in the decision tree. Then, in terms of modeling, just use it as one node in the chain of conditional probability. You can have Markov processes within other Markov processes. You can have many-branched mixtures of conditional probabilities and Markov processes, etc. The combinations are infinite. Once you understand how conditional probability and Markov processes function on their own and in these combinations, you can model any probabilistic system.