Takeaways:

Maze metaphor! Frequentist tried deadend again and again. Bayes learns the info, inputs it and tries another way, repeating till he gets out of the maze to the prized cake. :) Prior information does not necessarily make bayesian methods subjective, as recognized in previous readings we have plenty of biases already on our own. Don't be afraid to create new models like Stan if you see a gap in existing models!

Points:

- Greatest benefits of the Bayesian approach come not from default implementations, valuable as they can be in practice, but in the <u>active process of model building, checking, and improvement.</u>

- Bayesian methods are often characterized as "subjective" because the user must choose a prior distribution, that is, a mathematical expression of prior information.<u> The prior distribution requires information and user input, that's for sure, but I don't see this as being any more "subjective" than other aspects of a statistical procedure</u>, such as the choice of model for the data (for example, logistic regression) or the choice of which variables to include in a prediction, the choice of which coefficients should vary over time or across situations, the choice of statistical test, and so forth. Indeed, Bayesian methods can in many ways be more "objective" than conventional approaches in that Bayesian inference, with its smoothing and partial pooling, is well adapted to including diverse sources of information and thus can reduce the number of data coding or data exclusion choice points in an analysis.

- The essence of Bayesian statistics is the combination of information from multiple sources. We call this <u>*prior information,*</u> or hierarchical modeling, or dynamic updating, or partial pooling, but in any case it's all about putting together data to understand a larger structure. <u>**Big data**</u>, or data coming from the so-called internet of things, are inherently messy -> So statistical modeling is needed to put data from these different sources on a common footing.

Why Stan?

Can advance us towards these goals.

– Flexible (so I can fit the models I want and expand them in often unanticipated ways);

– Fast (so I can fit many models);

– Connected to other software (so I can prepare my datasets before entering them in the model, and I can graphically and otherwise explore the fitted model relative to the data);

– Open (so I can engage my collaborators and the larger scientific community in my work, and conversely so I can contribute by sharing my modeling expertise in a common language);

– Readable and transparent (both so I can communicate my models with others and so I can actually understand what my models are doing).