



# Tech Talk: Bayesian Analysis

Overview on the next coolest thing in town

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# Why Bayesian Analysis?

## Reason

1. Provides a framework for continuous learning.
2. Enable us to quantify uncertainty.
3. Provides a different paradigm for solving problems, more creative.

$$P(H|E) = \frac{P(H) * P(E|H)}{P(E)}$$

Diagram illustrating the components of Bayes' Theorem:

- $P(H)$ : Prior Probability
- $P(E|H)$ : Likelihood of the evidence 'E' if the Hypothesis 'H' is true
- $P(E)$ : Prior probability that the evidence itself is true
- $P(H|E)$ : Posterior Probability of 'H' given the evidence



# Simple AB Testing

## Background

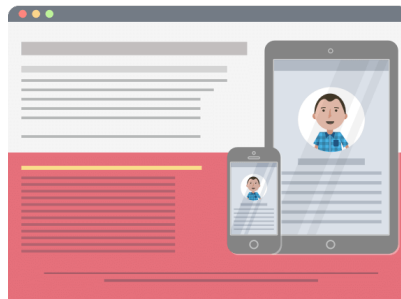
Given 2 versions of web pages, A and B.

Page A has 500 visits and 110 click-through.

Page B has 1000 visits and 520 click-through.

We would like to know:

- Which version works better for conversion
- How much uplift
- How certain are we about the analysis



example.com/a.html

22%  
CONVERSION



example.com/b.html

52%  
CONVERSION

# Simple AB Testing

## Frequentist Way

### Establish the null hypothesis

Version A and version B have the same conversion rate.

$$H_0: P_A = P_B$$

### Establish the alternative hypothesis

Version B's conversion rate is not equal to Version A.

$$H_1: P_A \neq P_B$$

### Perform t-test and look at p-value

Reject null hypothesis if p-value is  $< 0.05$

$$\text{0.0001} < \text{0.05}$$

p-value                      Significance Level

Probability that we would observe a value more extreme by chance is 0.0001.

Hence, reject the null hypothesis, we prefer Version B to Version A.

# Simple AB Testing

## Bayesian Way

### Establish the prior belief

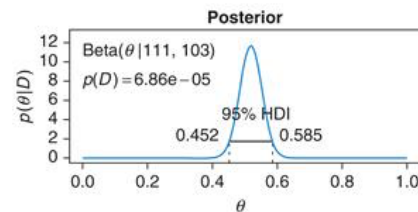
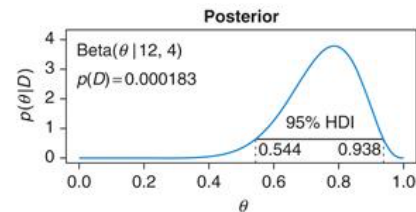
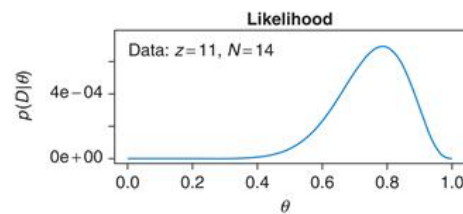
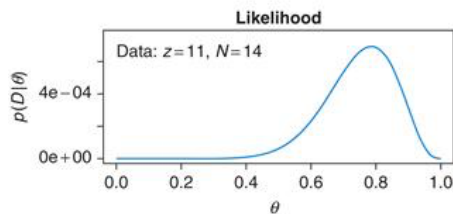
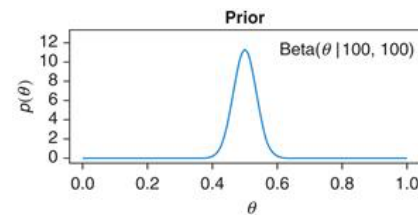
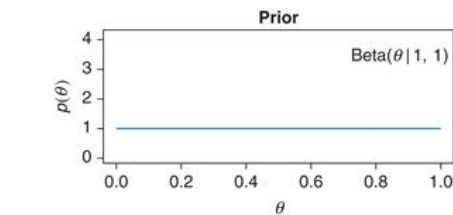
We have some weak belief that both Version A and Version B have uniform Beta(1,1).

### Update our belief with data

Use Bayes rule to update our prior beliefs to get the posterior belief.

### Calculate the High Density Interval (HDI)

Calculate the HDI which gives 95% range of conversion rate.



# Simple AB Testing

## Frequentist Way

Which version works better for conversion?



Reject the null hypothesis that conversion rate of A and B are equal.

How certain are we?



Probability of observing the data as extreme as the p-value is very unlikely.

How much uplift?



We don't really know

## Bayesian Way

We are 96% confident that B is better than A.

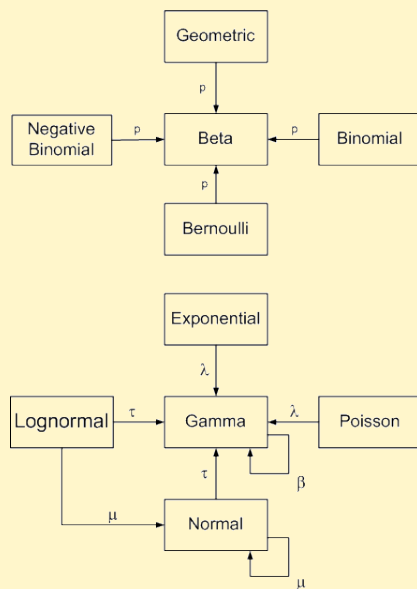
95% probability that the conversion rate for A and B lies between 19%-26%, 49%-55% respectively.

95% probability that the conversion rate is 25%-35% higher for B.

# Methods to Perform Bayesian Updates

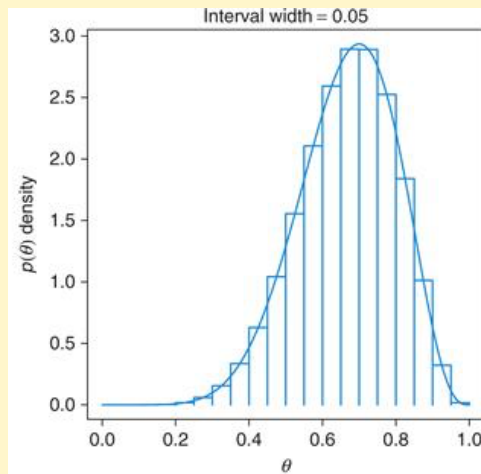
## Analytical

Using conjugate priors.  
Mathematically tractable.



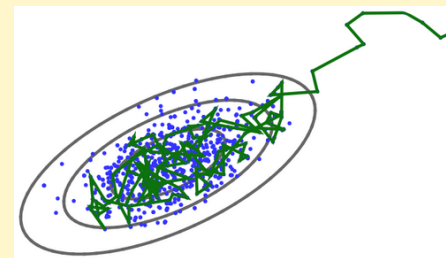
## Approximation

Approximate posterior using grid method. More freedom in specifying prior distribution.



## MCMC

Markov Chain Monte Carlo.  
Metropolis-Hastings algorithm draws samples from the posterior distribution. Samples are only from those high probability regions.



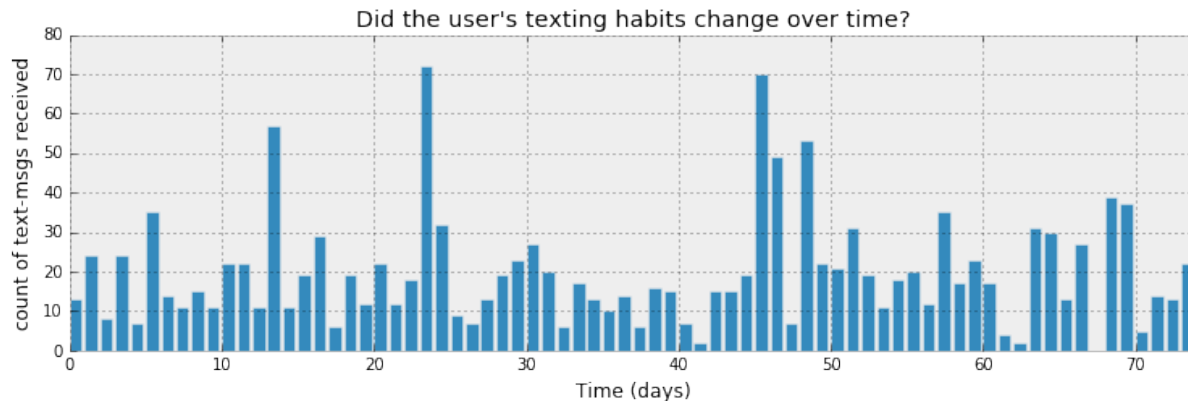


# Hierarchical Models

## Background

We have some daily text-message counts from a user of our system. We suspect that there's some change in user's usage rate at some time. We would like to know:

- Did user text message habit change?
- When did it change?



# Hierarchical Models

## The Model

Priors

$$\tau \sim \text{DiscreteUniform}(1, 70)$$

$$\Rightarrow P(\tau = k) = \frac{1}{70}$$

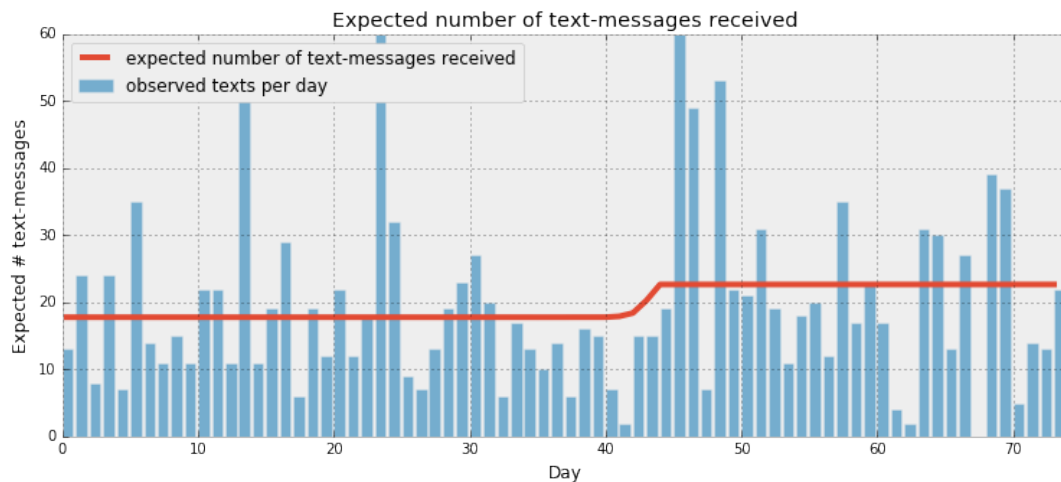
$$\lambda_1 \sim \text{Exp}(\alpha)$$

$$\lambda_2 \sim \text{Exp}(\alpha)$$

$$\lambda = \begin{cases} \lambda_1 & \text{if } t < \tau \\ \lambda_2 & \text{if } t \geq \tau \end{cases}$$

Likelihood

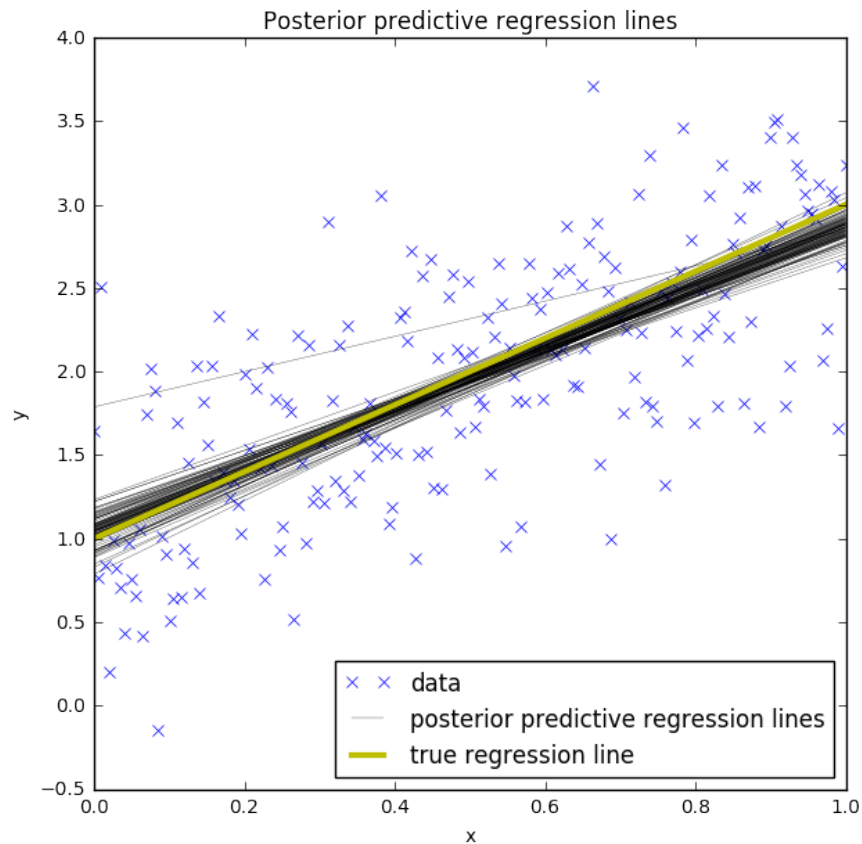
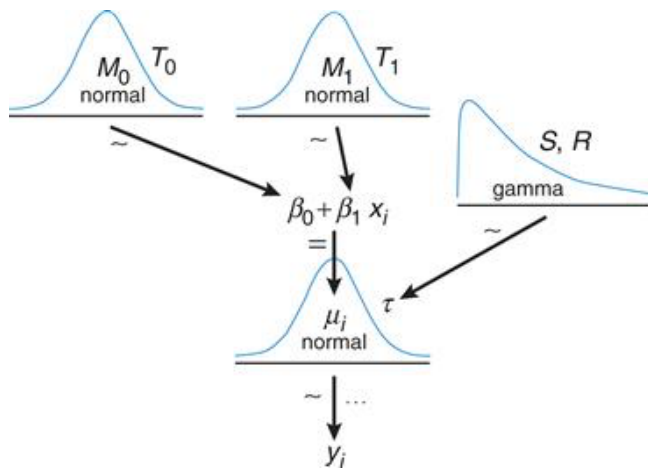
$$C_i \sim \text{Poi}(\lambda)$$



# Bayesian Machine Learning

## Linear Regression

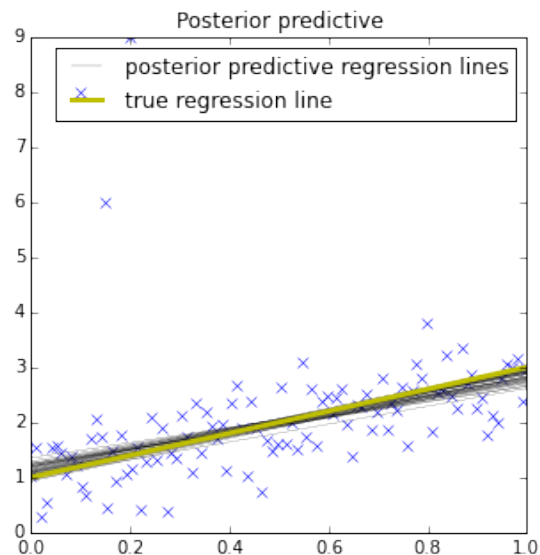
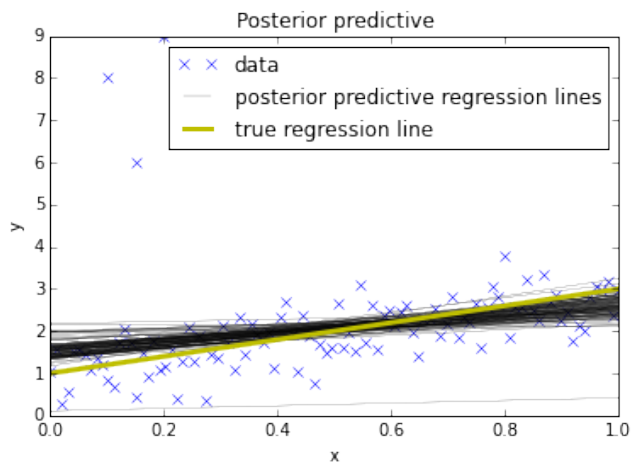
Estimate coefficients with MCMC. MCMC allows to sample for multiple regression lines to estimate uncertainty of regression line.



# Bayesian Machine Learning

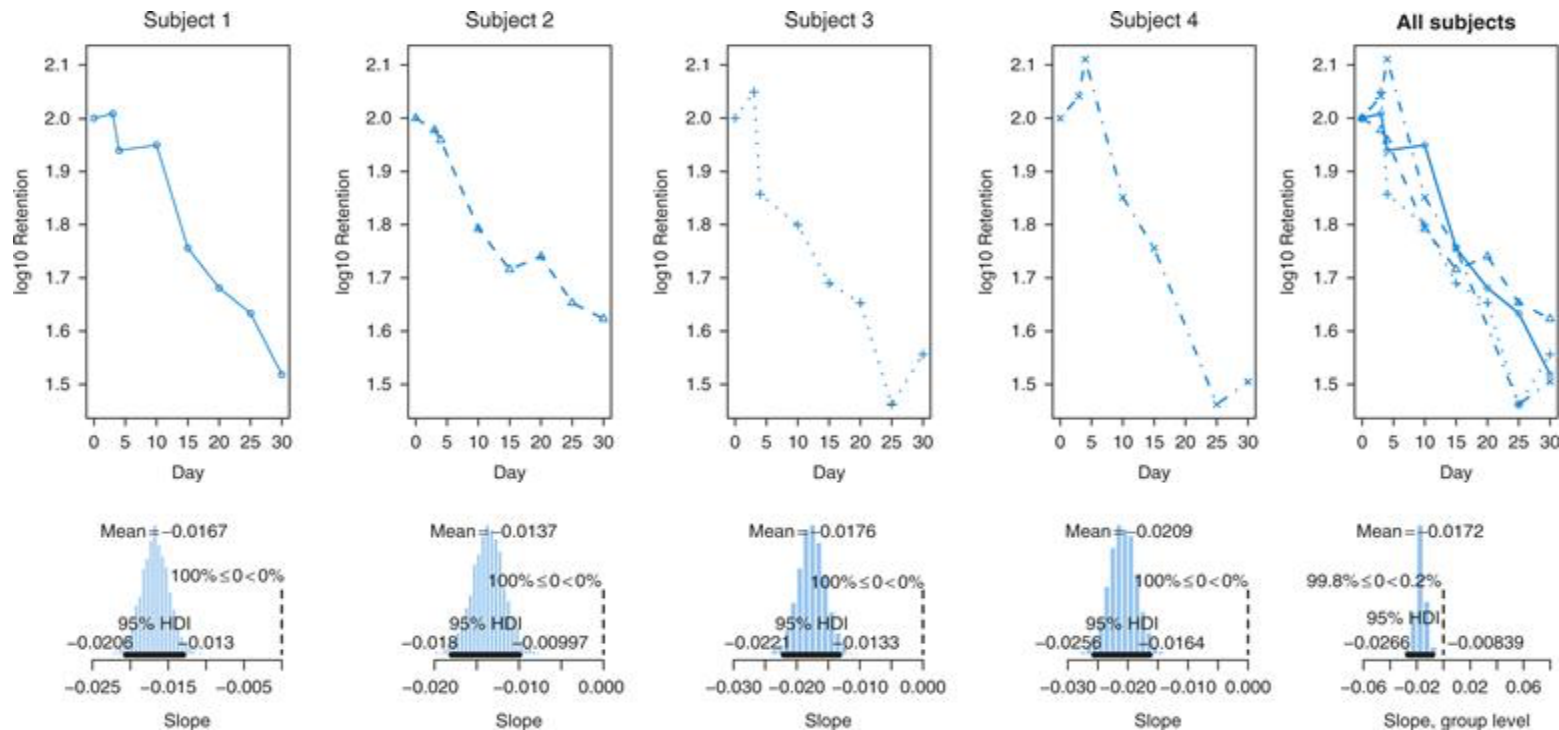
## Robust Linear Regression

Use Student-t distribution instead of normal Gaussian distribution. Having more mass at tails allows regression line not be heavily influenced by outliers.



# Bayesian Machine Learning

## Hierarchical Linear Regression



# Why Bayesian Analysis?

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## Reason

1. Provides a framework for continuous learning.
  - Beta shape parameters can be continuously updated
2. Enable us to quantify uncertainty.
  - Credible intervals, 95% High Density Intervals
3. Provides a different paradigm for solving problems, more creative
  - Hierarchical Modeling

**Thank You.**