
Fitting models to data

Bayesian Probabilistic
Programming

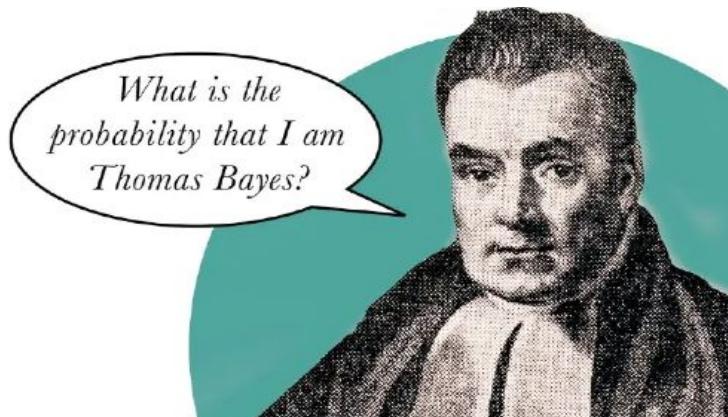


Hitesh Lala, ARI



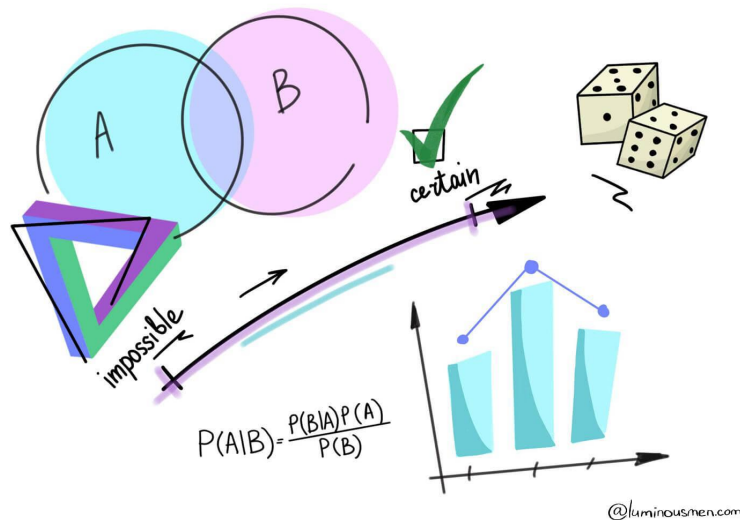
Background

- Basic Statistics: Probability, Conditional Probability, Probability Distributions
- Bayes' Theorem
- Python conversance



Bayesian Statistics

- Interpretation:
Quantifying Personal Belief
(Subjectivity)
- Methodology:
 - Set up Random Variables (incorporating uncertainty)
 - Determine Prior Probability
 - Compute Posterior Probability using Bayes' Theorem



Bayes' Theorem

The diagram illustrates Bayes' Theorem with the following components:

- LIKELIHOOD**: the probability of "B" being TRUE given that "A" is TRUE. This is represented by the term $P(B|A)$ in the numerator, highlighted in an orange box.
- PRIOR**: the probability of "A" being TRUE. This is represented by the term $P(A)$ in the numerator, highlighted in a teal box.
- POSTERIOR**: the probability of "A" being TRUE given that "B" is TRUE. This is represented by the term $P(A|B)$ on the left side of the equation, highlighted in a green box.
- The probability of "B" being TRUE**: This is represented by the term $P(B)$ in the denominator, highlighted in a pink box.

The equation is written as:

$$P(A|B) = \frac{P(B|A) P(A)}{P(B)}$$

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Published in 1763

Bayes' Theorem

$$\underbrace{p(\theta|D)}_{\text{posterior distribution}} = \frac{\underbrace{p(D|\theta)}_{\text{likelihood function}} \underbrace{p(\theta)}_{\text{prior distribution}}}{\int p(D|\theta) p(\theta) d\theta}$$

D : Data

θ : Model Parameters

Likelihood

- Generative Probabilistic Model
- A functional form

Evidence

- No one cares about the evidence
- Really hard to calculate
- Might not be possible to calculate in practical settings(?)



Fit a line to data

a.k.a. Linear Regression

$$Y = \alpha + (\beta \times X) + \sigma$$

MCMC

- Markov Chain Monte Carlo
- Metropolis Hastings
- Hamiltonian Monte Carlo (HMC)
- No U-turn Sampler (NUTS)

Visualize

pymc3 vs emcee

pymc3

- Provides a plethora of samplers - NUTS, etc.
- Much more than just MCMC - Neural Nets, etc.
- Inefficient sampler can be slow
- HMC-based efficient handling of large spaces
- Out-of-the-box handling

emcee

- Ensemble Sampler with Affine Invariance
- Expedited sampling of non-differentiable distributions
- Embarrassingly fast in low-dimensions
- Slower in higher dimensions
- No built-in distribution

OLS vs Robust Regression

- Using a Student's-T distribution as the likelihood
- Fatter tails as compared to a Normal distribution
- Immune to Outliers

*Regression is a powerful tool for forecasting.
Economists using it successfully predicted ten
out of the last two recessions.*

Model Selection

- LOO (Leave-one-out Cross-Validation)
- WAIC (Widely Applicable Information Criterion)
- Posterior Predictive Checks

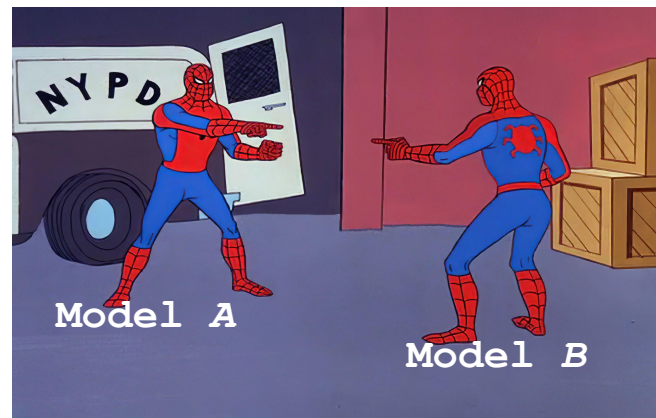
Inference is normal science.

Model-checking is revolutionary science.

Andrew Gelman

Model Comparison

- Kullback-Leibler Divergence - Mutual Information - Relative Entropy
- Null Hypothesis Significance Testing - T-test, F-test, χ^2 - test
- BEST (Bayesian Estimation Supersedes the T-Test)



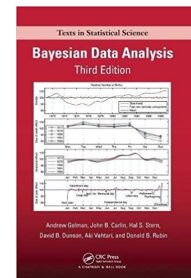
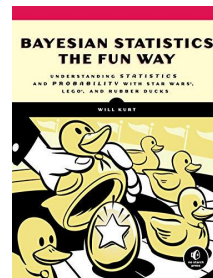
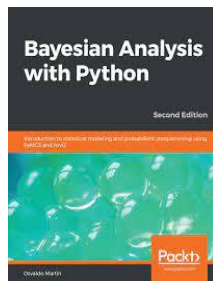
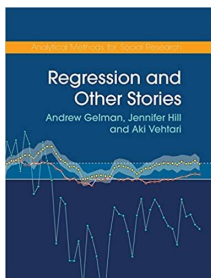
Beyond *just* fitting a line

- Outlier Detection
- Fitting a plane (or an n-dimensional hyperplane) to data
- Non-Linear Regression
- Gaussian Process Regression



Resources

- Andrew Gelman, Jennifer Hill, Aki Vehtari - Regression and Other Stories (2020)
- Oswaldo Martin - Bayesian Analysis with Python (2018)
- Will Kurt - Bayesian Statistics the Fun Way: Understanding Statistics and Probability with Star Wars, LEGO, and Rubber Ducks
- Andrew Gelman et. al. - Bayesian Data Analysis 3rd ed. (2020)
- Thomas Wiecki - [An Intuitive Guide to Bayesian Statistics](#)
- David W. Hogg et. al. - [Data analysis recipes: Fitting a model to data](#)
- Jake VanderPlas - [Frequentism and Bayesianism: A Practical Introduction](#)



Fin.

Thank you.