Bayesian Tutorial

- Bayes' Theorem — Simple Version:

  P(Hypothesis, Data | I) $\propto$ P(Data | Hypothesis, I) x P(Hypothesis | I)

where the symbol

  P(X | I) — Probability of finding (X | conditioned on all prior Information, | I).

- P(Hypothesis | I) Theorem — Prior Probability
  State of knowledge about the truth of the Hypothesis before analyzing current data. (knowledge of experimental results of various in vitro glucose measurements.)

- P(Data | Hypothesis, I) — Likelihood Function Probability the measured data is observed if the Hypothesis is true. Model functions are employed:

  * Empirical
  * Theoretical
  * Stochastic
  * Combination of Any/All

- P(Hypothesis | I) — Posterior Probability
  State of the knowledge about the truth of the Hypothesis in view of the measured data.

- Power of Bayes' Theorem — Relates the quantity of interest, the Probability that the Hypothesis is true given the data, to the Probability that we would have observed the measured data if the Hypothesis is true,

  P(Data | Hypothesis, I),

  the term that we have a better chance of being able to assign a probability to.

- Bayes' Theorem Encapsulates the Process of Learning — it builds upon all prior knowledge to the present experimental results.

  * New Information can easily be incorporated to enhance the confidence of the Posterior Probability.

- Bayesian Probabilities vs Classical Stochastic Probabilities

  * Bayesian Probabilities: Conditioned probabilities that present a *degree-of-belief* or plausibility—how much something is thought to be true, based on the evidence at hand.

  * Classical Stochastic Probabilities: *Long-run relative frequency* with which an event occurred, given many (strictly an infinite number) repeated (experimental) trails. Seen as a tool to deal with "randomness."