Intro to Bayes

Upcoming

Bayesian programming
Error Propagation
Forecasting competition 1!

Things to keep in mind:
Be thinking about a forecasting project.
Start looking for forecasting related papers that you want to lead for discussion.

I am going to look over your lab 3/4 and get you feedback this week

Intro to Bayes

Forecasting time:
~ 5% to build model make mean prediction.
~ 95% to fully quantify and propagate sources of uncertainty.

Why Bayes?

The era of raging debate between Bayesians and frequentists has mostly ended….

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1. Well developed theoretical basis (not so with Machine Learning (ML))
2. Explicit quantification of probability (impossible with frequentist or ML)
3. Easy to partition uncertainty into different sources (difficult with frequentist or ML).
4. Easily handles missing data or uncertainty in data
5. Prior-posterior updating given new data allows for updating forecasts based on new data.

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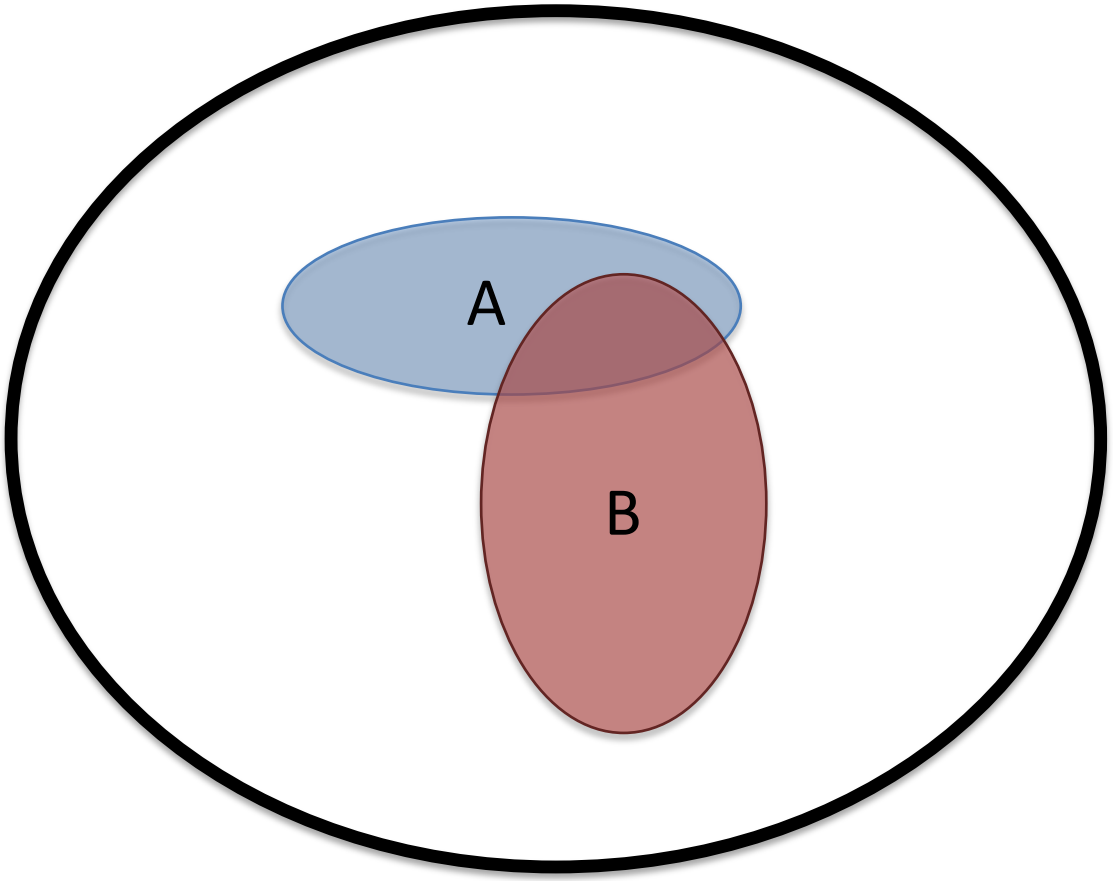
This doesn't mean that frequentist or ML approaches can't make valid and useful forecasts, Bayesian approaches just have a number of distinct advantages.

Probability



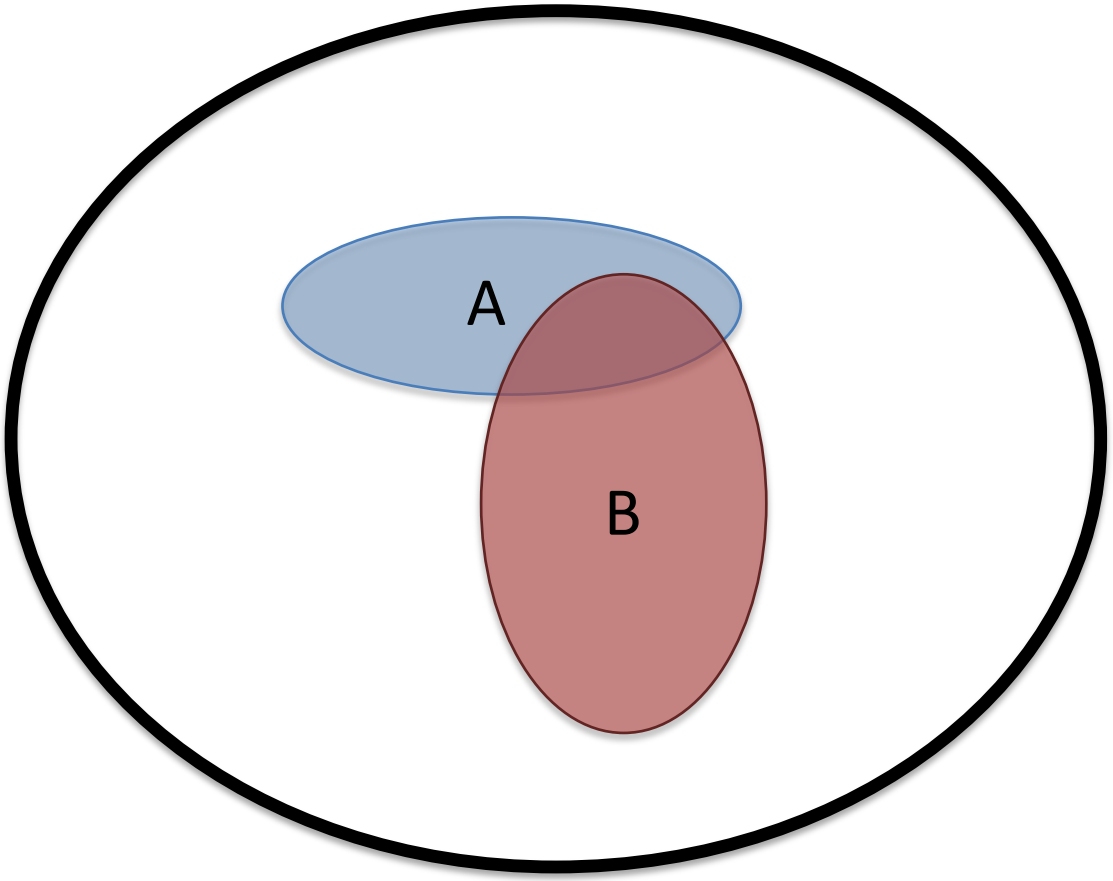
Marginal Probability

$$P(A) = Area\ of\ A$$

$$P(B) = Area\ of\ B$$

Adapted from Hobbs and Hooten 2015

Probability



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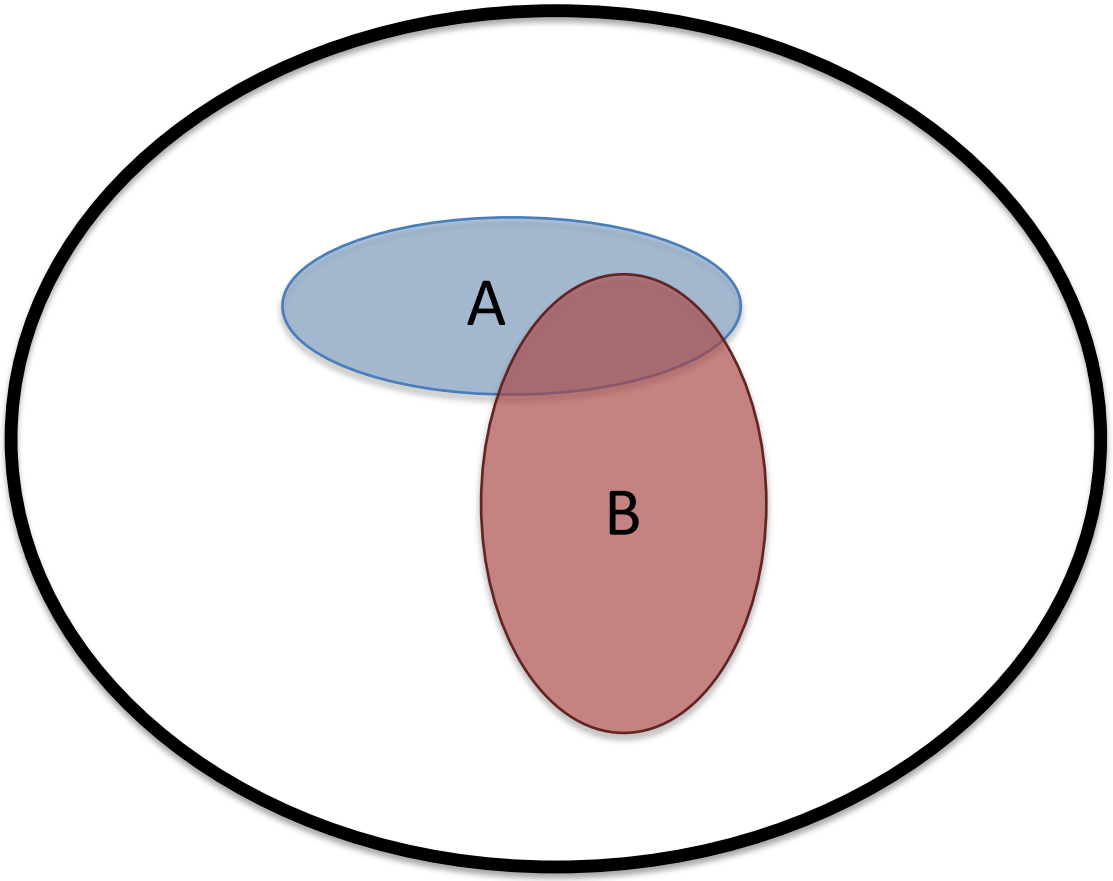

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Joint Probability

$$P(A, B) = Shared\ Area\ of\ A\ \&\ B$$

Conditional Probability

$$P(B|A) = \frac{Shared\ Area\ of\ A\ \&\ B}{Area\ of\ \ A}$$

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

Adapted from Hobbs and Hooten 2015

Probability

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

Algebraic rearrangement

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Intro to Bayesian Inference

The goal is to ”learn” about parameters given observed data

Parameters Data

$$[\theta|y] = \frac{[\theta, y]}{[y]} \qquad [\theta, y] = [y|\theta]\,[\theta]$$

$$[\theta|y] = \frac{[y|\theta]\,[\theta]}{[y]}$$

Notation: $P(A)$ is the same as $[A]$

Intro to Bayesian Inference

The goal is to ”learn” about parameters given observed data

Likelihood Prior

Posterior

$$[\theta|y] = \frac{[y|\theta]\,[\theta]}{[y]}$$

Normalizing Constant

Intro to Bayesian Inference

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Posterior Likelihood Prior

$$[\theta|y] \propto [y|\theta]\,[\theta]$$

Intro to Bayesian Inference

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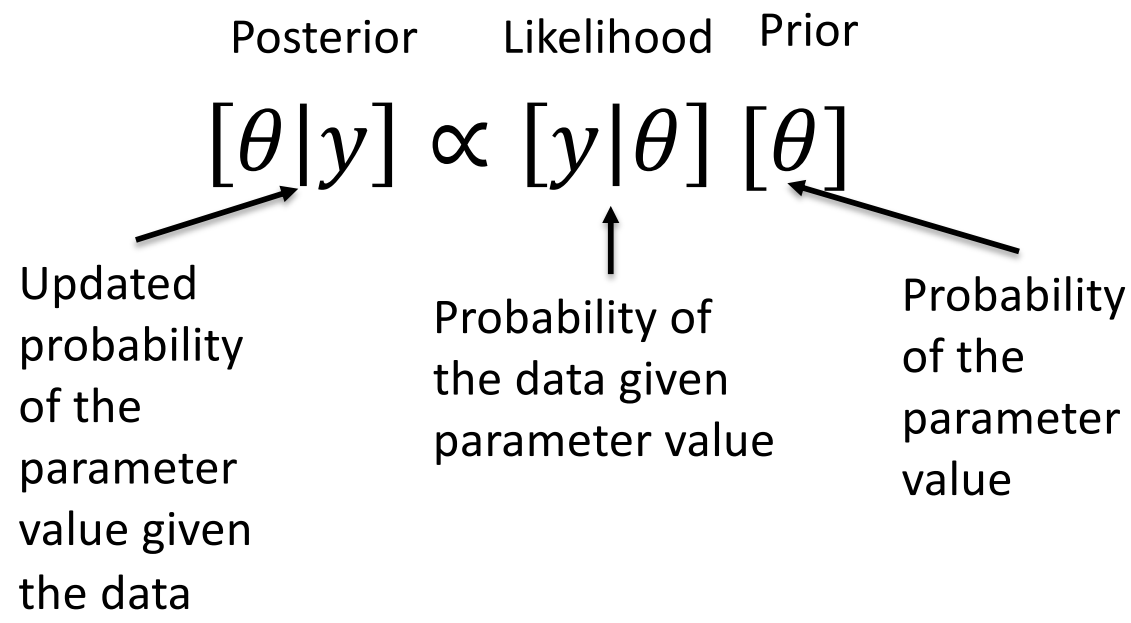
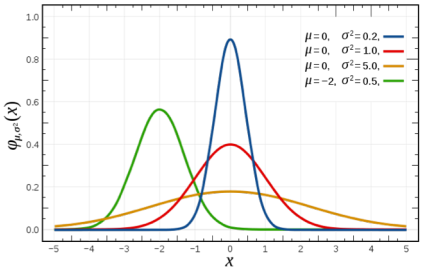


Probability Distributions

Continuous

Normal: Any value from -Inf to Inf,
Mean is independent of variance



Daily carbon flux

Discrete

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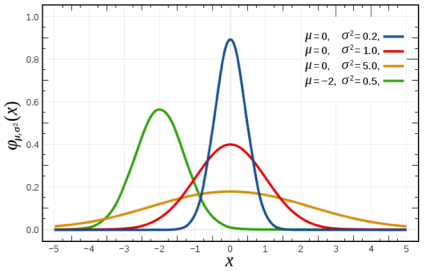
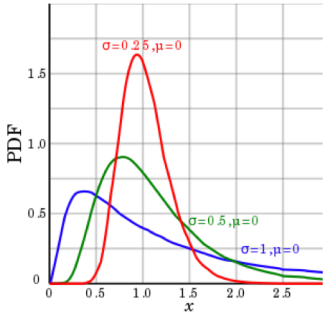


Daily carbon flux

Log Normal: Any value from >0 to Inf, Variance scales with mean



Population Density

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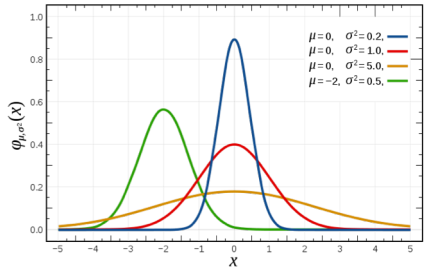

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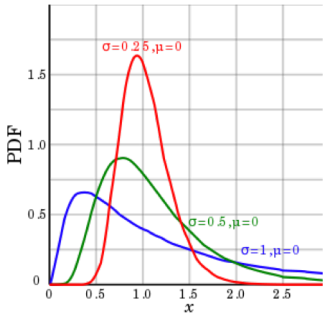

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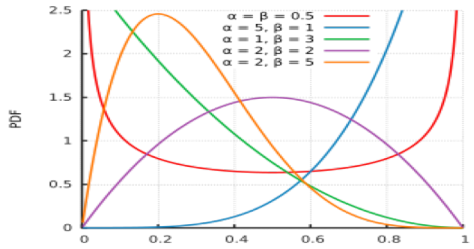
Beta: Any value from >0 to <1, Variance scales with mean



Survival Prob.

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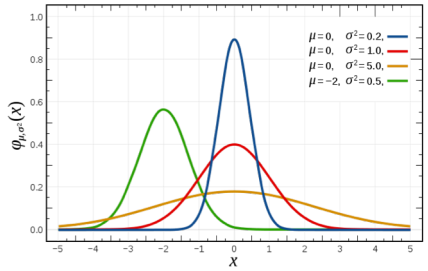

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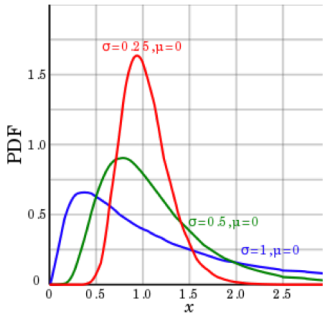

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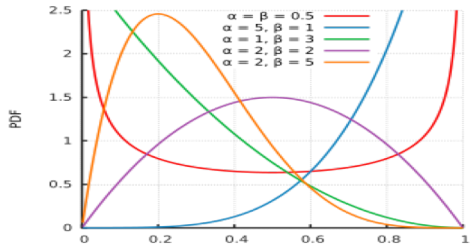

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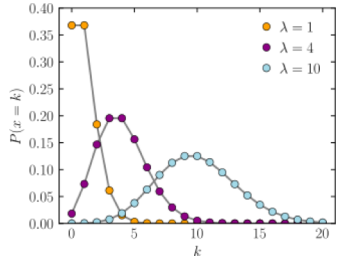

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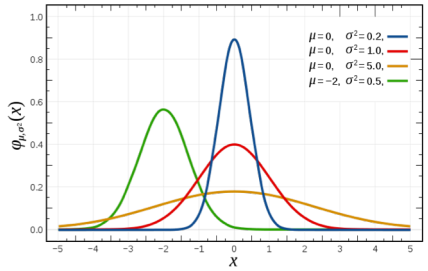

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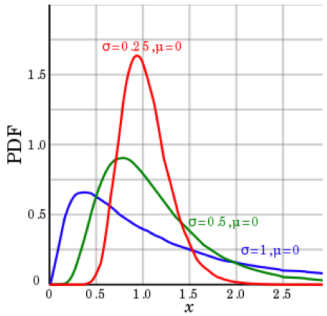

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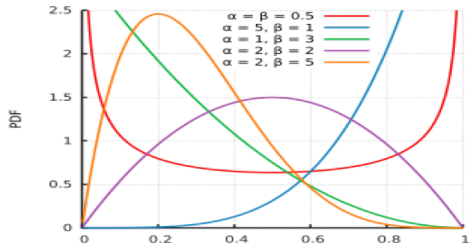

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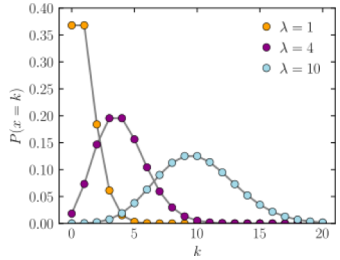

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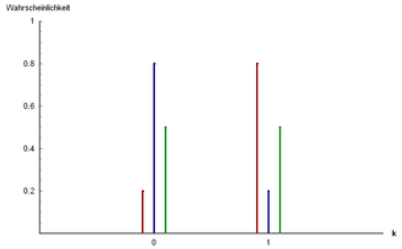

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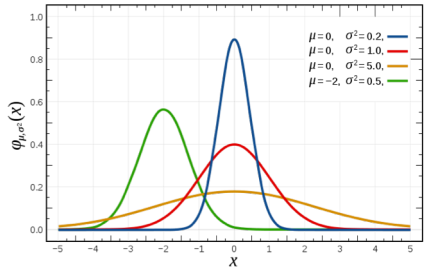

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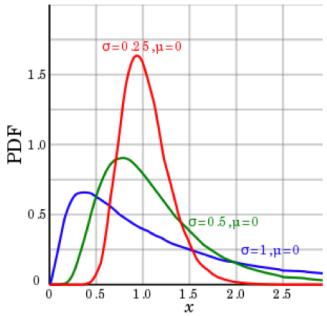

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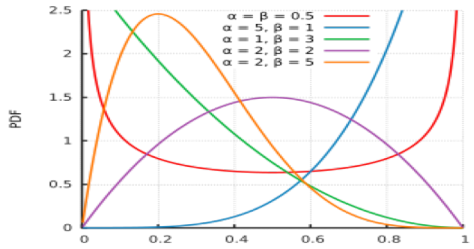

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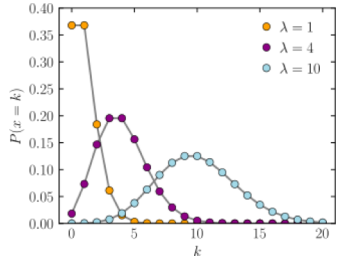

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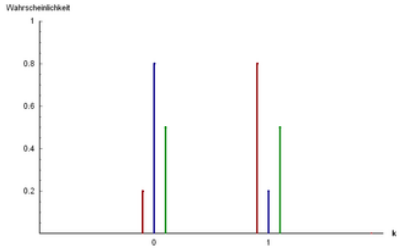
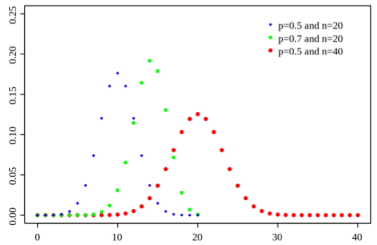


Individual Survival

Binomial: 0 to Inf., Outcome of multiple Bernoulli events



Deaths in a population

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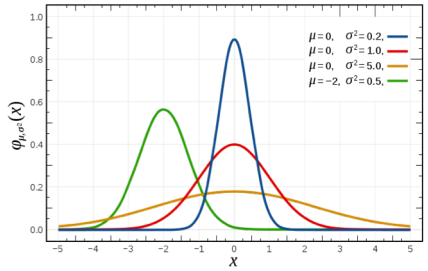

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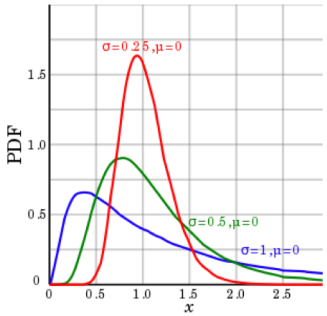

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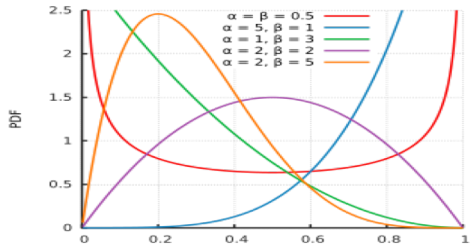

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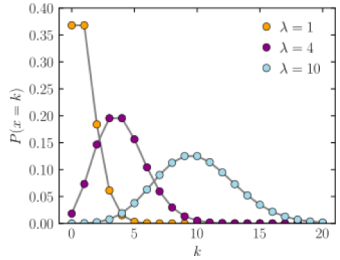

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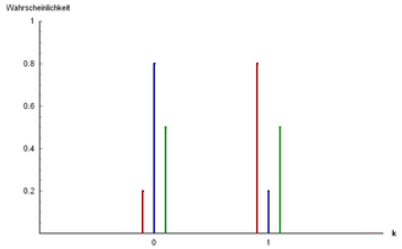

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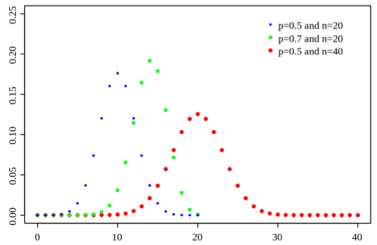

Deaths in a population

Picking a likelihood

Likelihood should match the data and data generating process.

Picking a likelihood

Likelihood should match the data and data generating process. What matters is the conditional distribution not the raw data distribution.

Questions to ask:
Are the data continuous or discrete?
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How does the variance of the data change as a function of the mean?

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$Normal(\mu, \sigma^2)$ $Poisson\ (\lambda)$

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$Normal(\mu, \sigma^2)$

- Continuous
- Values from –Inf to Inf
- Variance constant and independent of mean
- No Skew

$Poisson\ (\lambda)$

- Discrete
- Values from 0 to Inf
- Variance=mean
- Skewed at low values

Picking priors

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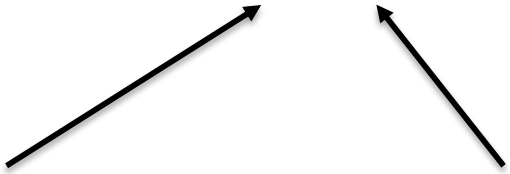

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Continuous, must be positive

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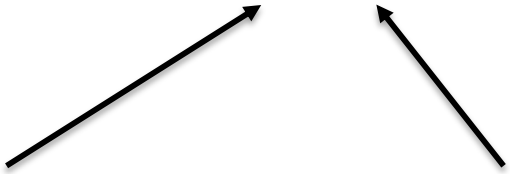

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$Normal(\mu_p, \sigma_p^2)$

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Gamma(a_p, b_p)

$Poisson\ (\lambda)$

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Picking priors

Priors represent existing belief or knowledge about a parameter.

When do priors need to be informative?
When can they be uninformative?

Some parameters can almost reliably estimated by data. E.g.: Regression parameters

Some parameters will rarely ever be indefinable without prior information. E.g.: Observation Error

Picking priors

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When do priors need to be informative?
When can they be uninformative?

In practice, selecting priors can be part of the model development process.

If a parameter is not identifiable, additional data may be needed.

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First, they allow for the incorporation of expert knowledge.

Second, they often provide essential information to put risk or forecast in context.

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The disease has a 1% prevalence (prior probability)

P(Disease | Positive)= (P(Positive | Disease)*P(Disease))/P(Positive)

Why are priors important?

First, they allow for the incorporation of expert knowledge.

Second, they often provide essential information to put risk or forecast in context.

Disease test with 95% sensitivity is given to 100,000 people, 7,000 come back positive. (Data)

The disease has a 1% prevalence (prior probability)

P(Disease | Positive)= (P(Positive | Disease)*P(Disease))/P(Positive)

(.95*.01)/0.07=.135

Only 13.5% of people that test positive have the disease!

Posterior Calculations

If prior is conjugate, we can calculate the posterior analytically.

Conjugate: Posterior distribution is the same as prior with parameters updated based on data

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Conjugate: Posterior distribution is the same as prior with parameters updated based on data

Likelihood $\mathbf{y} \sim Poisson\ (\lambda)$

Prior $\lambda \sim Gamma\ (a_{prior}, b_{prior})$

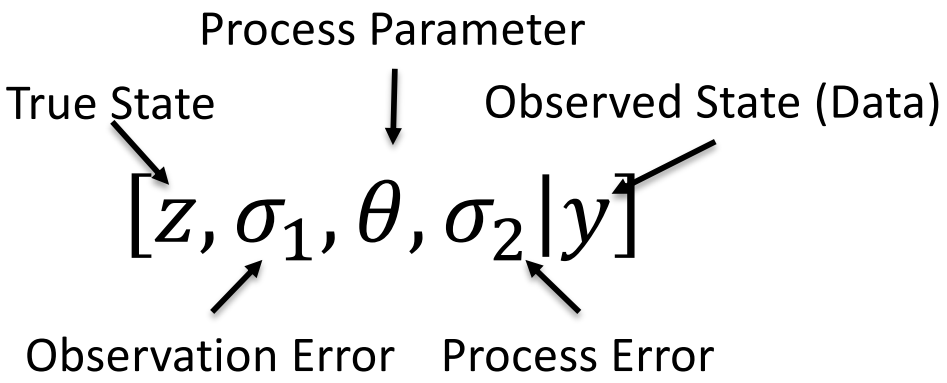
Posterior $\lambda|\mathbf{y} \sim Gamma\ (a_{prior} + \sum_{i=1}^{n} y_i\ , b_{prior} + n)$

The mathematical calculations underlying this can be found online in a number of sources.

Complex problems

The power of Bayesian inference comes in modeling complex problems

Examples of complex problems: Multiple datasets, unobserved (latent) states, autocorrelation, etc.



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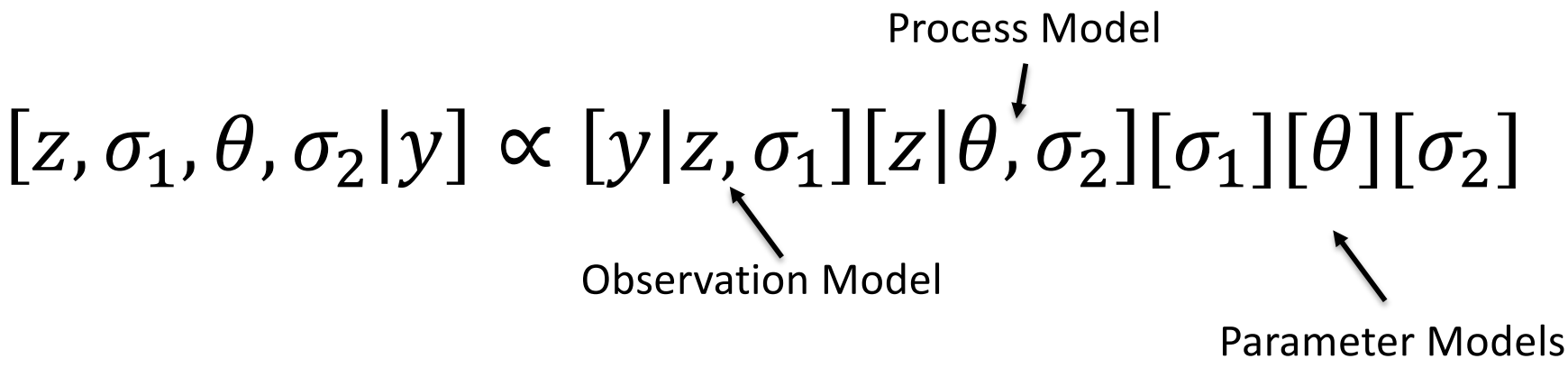

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Process Model

$$[z, \sigma_1, \theta, \sigma_2 | y] \propto [y | z, \sigma_1][z | \theta, \sigma_2][\sigma_1][\theta][\sigma_2]$$

Observation Model

Parameter Models

This is an example of a hierarchical model

DAG (Directed Acyclic Graphs)

Thinking about and breaking down complex, hierarchical models

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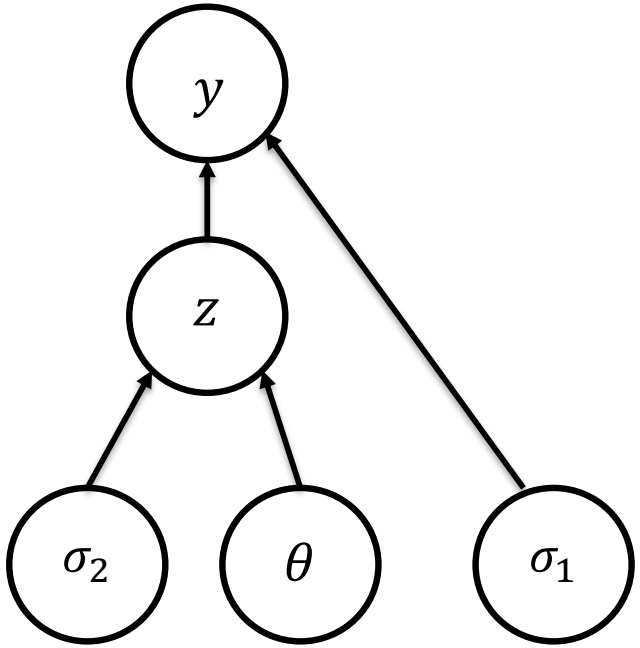

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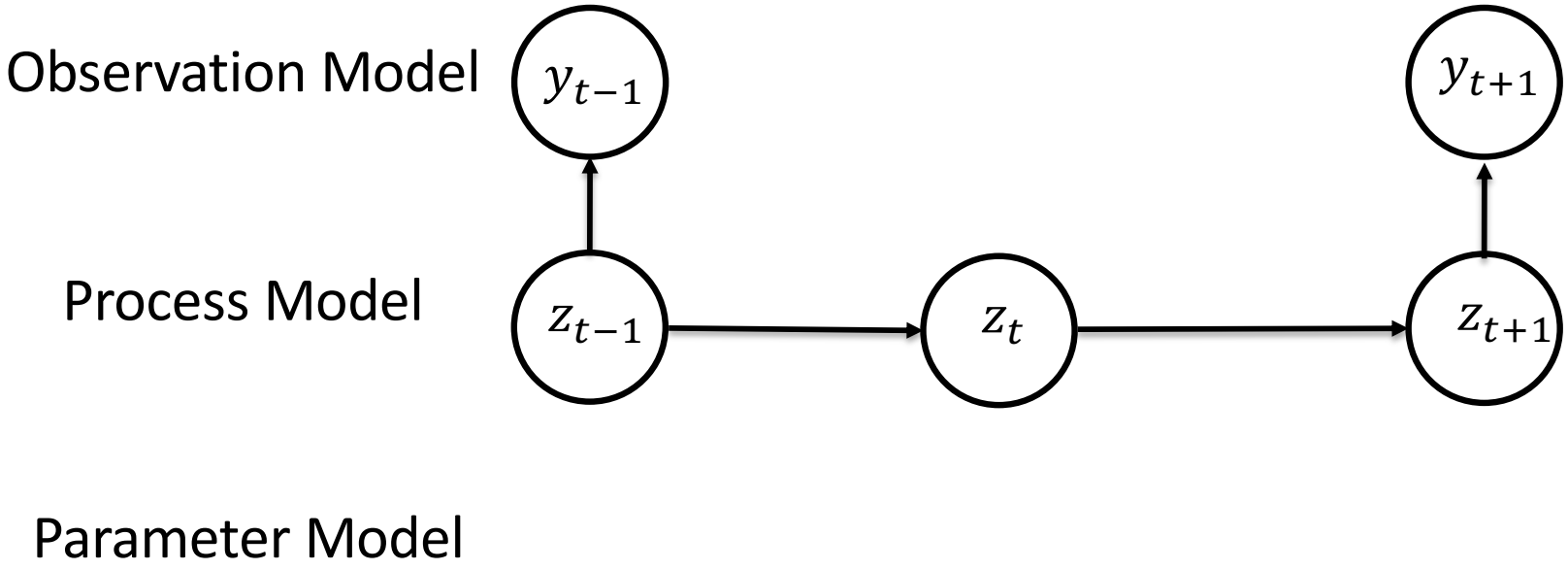
Observation Model

Parameter Models

Example 2: Missing data time series



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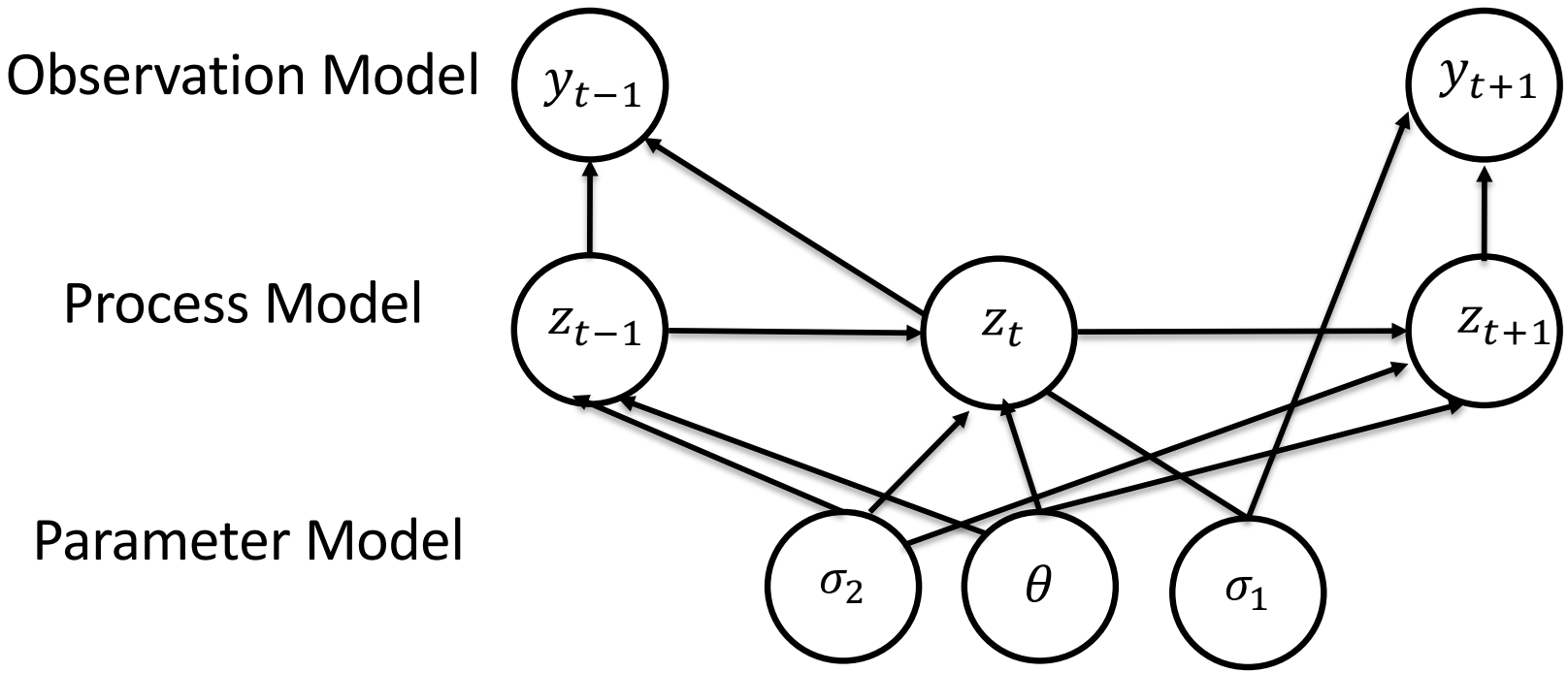

Example 3: Making a forecast!