Lecture 1: Likelihood Review

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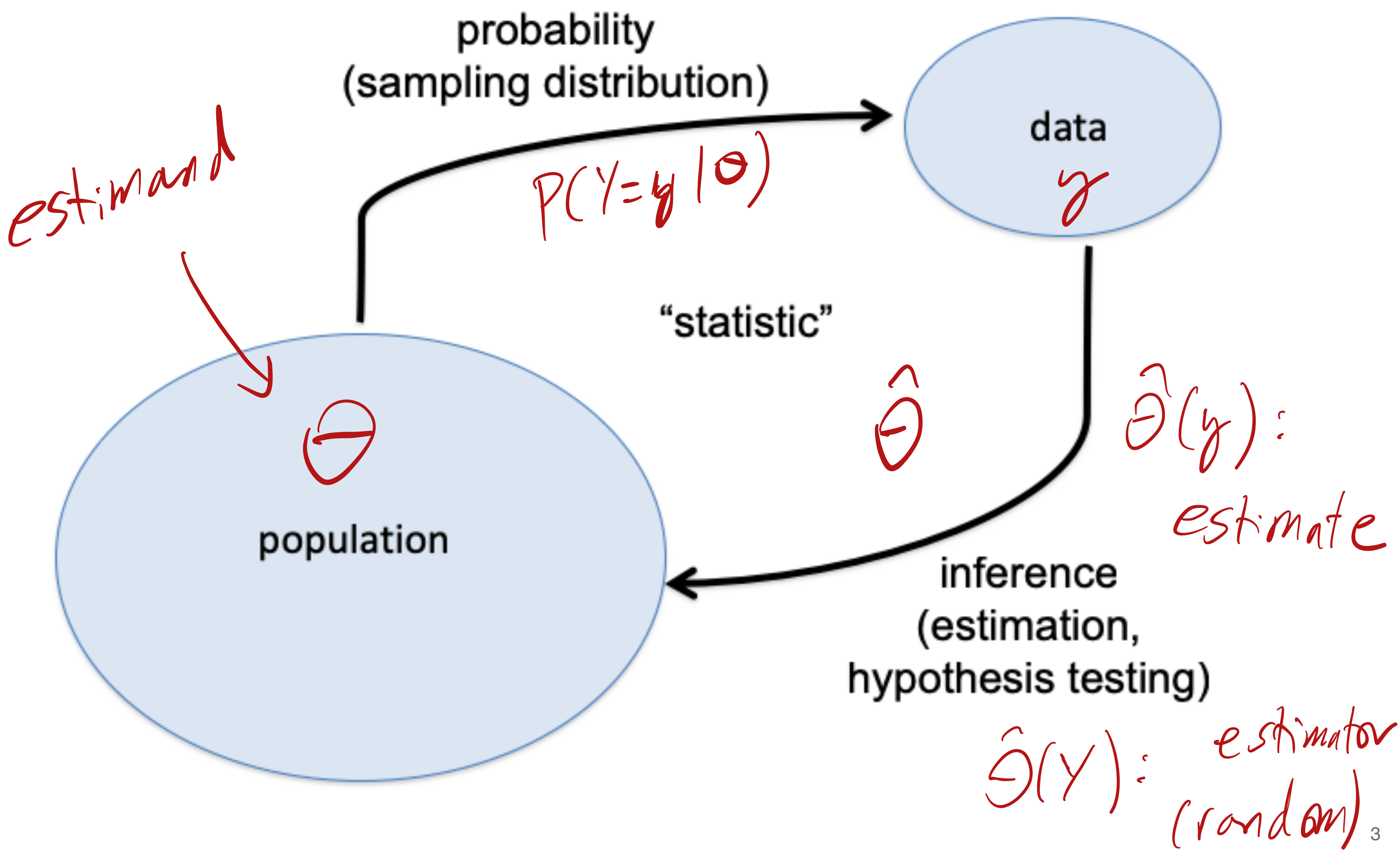
Logistics

tinyurl.com/stat215

- Read: BDA Chapters 1-2
- Sync content using link on course website
- Annotated lecture slides appear after class
- HW 1 this week.

Population and Sample



Independent Random Variables

- $Y_1, \ldots, Y_n$ are random variables
- We say that $Y_1, \ldots, Y_n$ are *conditionally* independent given θ if $P(y_1, \ldots, y_n \mid \theta) = \prod_i P(y_i \mid \theta)$
- Conditional independence means that Y_i gives no additional information about Y_j beyond that in knowing θ

Exchangeability

The Likelihood Function

- The likelihood function is the probability density function of the observed data expressed as a function of the unknown parameter (conditional on observed data):
- A function of the unknown constant θ.
- Depends on the observed data $y = (y_1, y_2, \ldots, y_n)$
- Two likelihood functions are equivalent if one is a scalar multiple of the other

$$Y_i \overset{iid}{\sim} P(Y|\theta)$$

$$L(\theta) \propto \prod_{i=1}^{n} P(Y_i = y_i | \theta)$$

Sufficient Statistics

A statistic s(Y) is sufficient for underlying parameter θ if the conditional probability distribution of the Y, given the statistic s(Y), does not depend on θ.

$Y_1, \ldots Y_n \sim N(\theta, 1)$

$\bar{Y}$ is sufficient. $\Rightarrow Y_1, \ldots Y_n \mid \bar{Y} \sim N(0, 1-\frac{1}{n})$

(exercise)

Bayesian: $p(\theta \mid y_1, \ldots y_n) = p(\theta \mid s(y))$

Sufficient Statistics

- Let $L(\theta) = p(y_1, \ldots y_n \mid \theta)$ be the likelihood and $s(y_1, \ldots y_n)$ be a statistic
- *Factorization theorem*: $s(y)$ is a sufficient statistic if we can write:

$$L(\theta) = h(y_1 \cancel{, \ldots} y_n) g(s(y), \theta)$$

  - g is only a function of s(y) and θ only
  - h is *not* a function of θ
- $L(\theta) \propto g(s(y), \theta)$

The Likelihood Principle

- **The likelihood principle**: All information from the data that is relevant to inferences about the value of the model parameters is in the equivalence class to which the likelihood function belongs
- Two likelihood functions are equivalent if one is a scalar multiple of the other
- Frequentist testing and some design based estimators violate the likelihood principle

Binomial vs Negative Binomial

$Y \sim Bin(12, \theta)$, obs $y = 3$

$$L(\theta; y=3) = \cancel{\binom{12}{3}} \underline{\theta^3 (1-\theta)^9}$$

$X \sim NB(3, \theta)$, obs $x = 9$

$$L(\theta; x=9) = \cancel{\binom{11}{2}} \theta^3 (1-\theta)^9$$

$H_0: \theta = 1/2$

$H_a: \theta < 1/2$

Bin: pbinom(3, 12, $\theta = 1/2$) = .073

NB: 1 − PNBinom(8, 3, $\theta = 1/2$) = .033

Score and Fisher Information

L: likelihood

ℓ: log-likelihood.

- **The score function:** $\frac{d\ell(\theta;y)}{d\theta}$
  - $E[\frac{d\ell(\theta;Y)}{d\theta} \mid \theta] = 0$ (under certain regularity conditions)
- **Fisher information** is a measure of the amount of information a random variable carries about the parameter
  - $I(\theta) = E\left[\frac{(d\ell(\theta;Y)}{d\theta})^2 \mid \theta\right]$ (variance of the score)
  - Equivalently: $I(\theta) = -E\left[\frac{d^2\ell(\theta;Y)}{d^2\theta}\right]$

Fisher Information

$$Y_1, \ldots, Y_n \overset{iid}{\sim} N(\mu, \overbrace{\sigma^2}^{\text{known}})$$

$$L(\mu) \propto \prod_{i=1}^{n} \cancel{\frac{1}{\sqrt{2\pi\sigma^2}}}\, e^{-\frac{(y_i-\mu)^2}{2\sigma^2}}$$

$$\propto \underbrace{e^{-\frac{(\bar{y}-\mu)^2}{2\sigma^2/n}}}_{g(s(y),\theta)}$$

$$\ell(\mu) = -\frac{(\bar{y}-\mu)^2}{2\sigma^2/n}, \quad \ell'(\mu) = \frac{(\bar{y}-\mu)}{\sigma^2/n}, \quad \ell'' = \frac{-n}{\sigma^2}$$

$$I(\mu) = -E_\mu\left[-\frac{n}{\sigma^2}\right] = \frac{n}{\sigma^2}$$

Data Generating Process

Data Generating Process (DGP)

- I select 100 random students at UCSB to 10 free throw shots at the basketball court
- Assume there are two groups: experienced and inexperienced players
- Skill is identical conditional on experience level

Data Generating Process (DGP)

- Tell a plausible story: some students play basketball and some don't.
- Before you take your shots we record whether or not you have played before.

θ_1 : pr. make for skilled

```
assume theta_1 > theta_0
for (i in 1:100)
  - Generate z_i from Bin(1, phi)
    - p_i = theta_0 if z_i=0
    - p_i = theta_1 if z_i=1
  - Generate y_i from a Binom(10, p_i)
return y = (y_1, ... y_100) and z = (z_1, ..., z_100)
```

θ_0 : " not skilled

ϕ : Pr. being skilled

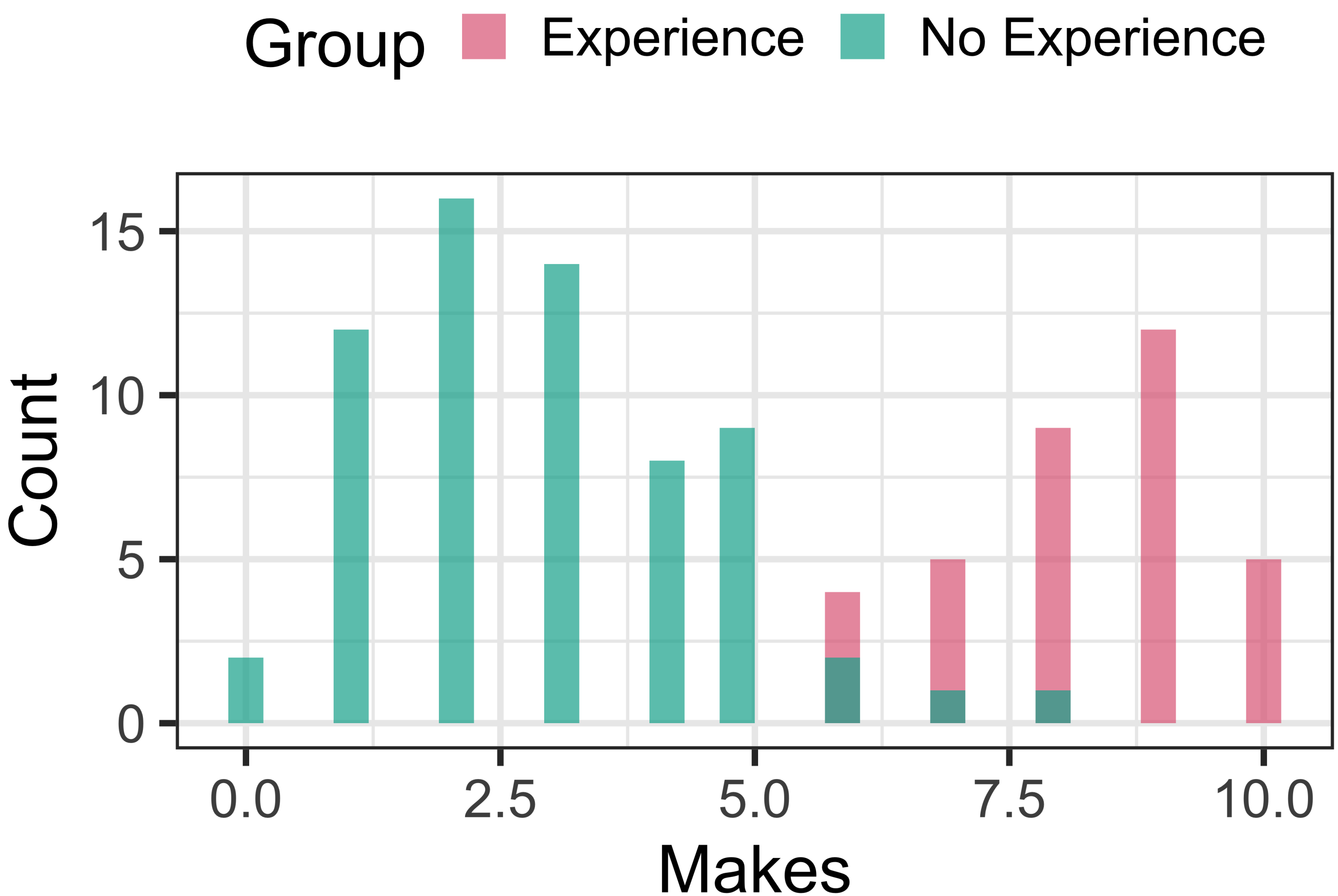
Mixture models

$$Z_i = \begin{cases} 0 & \text{if the } i^{th} \text{ if student doesn't play basketball} \\ 1 & \text{if the } i^{th} \text{ if student does play basketball} \end{cases}$$

$$Z_i \sim Bin(1, \phi)$$

$$Y_i \sim \begin{cases} \text{Bin}(10, \theta_0) & \text{if } Z_i = 0 \\ \text{Bin}(10, \theta_1) & \text{if } Z_i = 1 \end{cases}$$

A Mixture Model



Note: z is observed

$$L(\theta_0, \theta_1, \phi) \propto \prod_{i=1}^{n} P(y_i, z_i \mid \theta_1, \theta_0, \phi)$$

$$= \prod_{i=1}^{n} \Pr(y_i \mid z_i, \theta_0, \theta_1)\, P(z_i \mid \phi)$$

$$= \prod \left[\phi \left[\cancel{\binom{10}{y_i}} \theta_1^{y_i} (1-\theta_1)^{10-y_i} \right] \right]^{z_i} \times$$

$$\left[(1-\phi) \left[\cancel{\binom{10}{y_i}} \theta_0^{y_i} (1-\theta_0)^{10-y_i} \right] \right]^{1-z_i}$$

simplify

Sufficient statistics When Z_i is observed

Together, the following quantities are sufficient for $(\theta_0, \theta_1, \phi)$

- $\sum y_i z_i$ (total number of shots made by experienced players)
- $\sum y_i(1 - z_i)$ (total number of shots made by inexperienced players)
- $\sum z_i$ (total number experienced players)

$100 - \Sigma z_i$ # inexp.

Mixture models

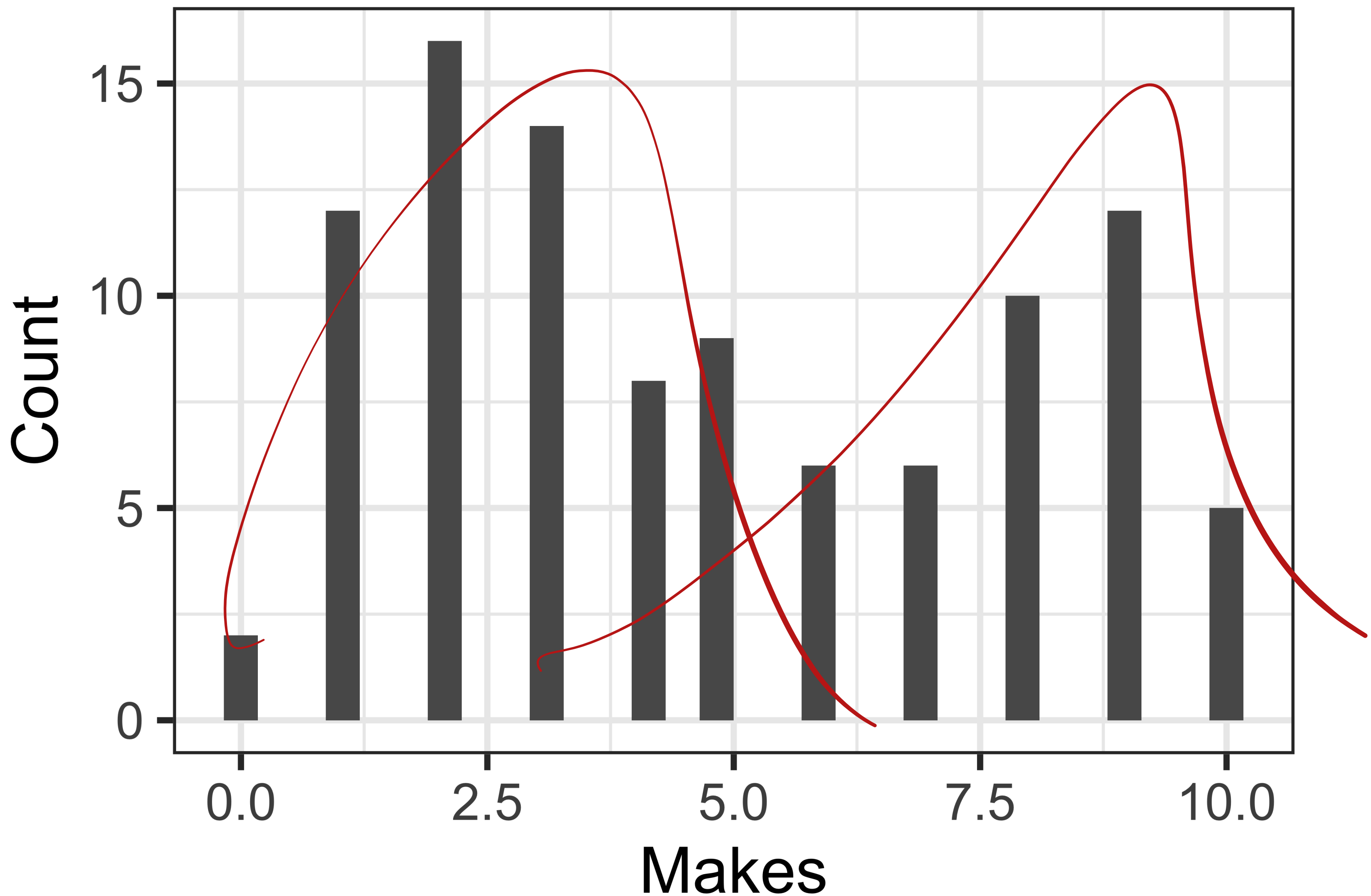
- A mixture model is a probabilistic model for representing the presence of subpopulations
- The subpopoluation to which each individual belongs is not necessarily known
  - e.g. do we ask: “have you played basketball before?”
- When z_i is not observed, we sometimes refer to it as a clustering model
  - *unsupervised* learning

Data Generating Process (DGP)

```
for (i in 1:100)
  - Generate z_i from Bin(1, phi)
    - p_i = theta_1 if z_i=1
    - p_i = theta_0 if z_i=0
  - Generate y_i from a Binom(10, p_i)
return y = (y_1, ... y_100)
```

This time we don’t record who has experience with basketball.

A Mixture Model



A finite mixture model

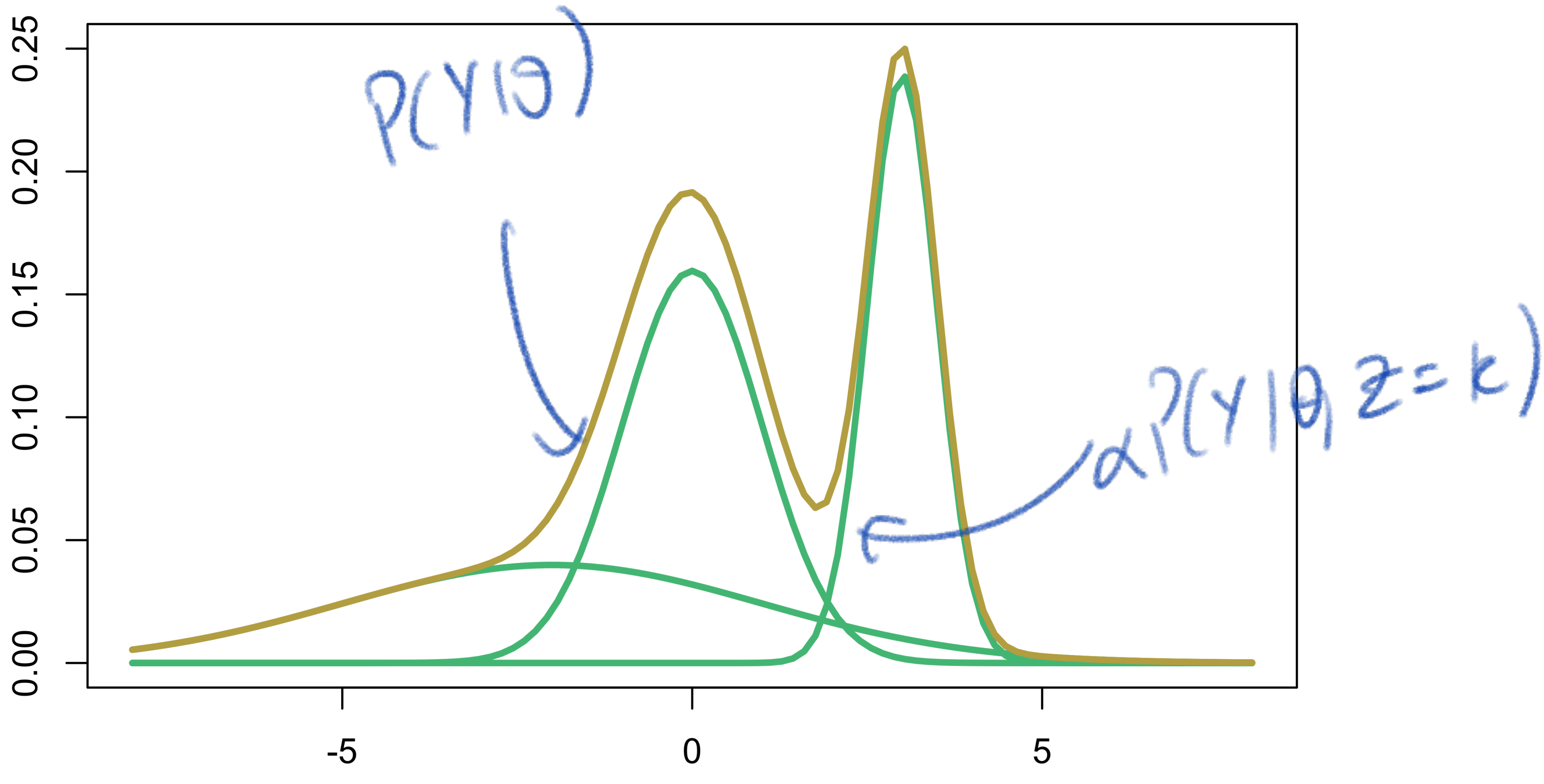
- Often crucial to understand the complete data generating process by introducing *latent variables*
- Write the *observed data likelihood* by integrating out the latent variables from the *complete data likelihood*

$$
\begin{aligned}
p(Y \mid \theta) &= \sum_z p(Y, Z = z \mid \theta) \\
&= \sum_z p(Y \mid Z = z, \theta) p(Z = z \mid \theta)
\end{aligned}
$$

In general we can write a K component mixture model as:

$$
p(Y) = \sum_k^K \pi_k p_k(Y) \text{ with} \sum \pi_k = 1
$$

Finite mixture models



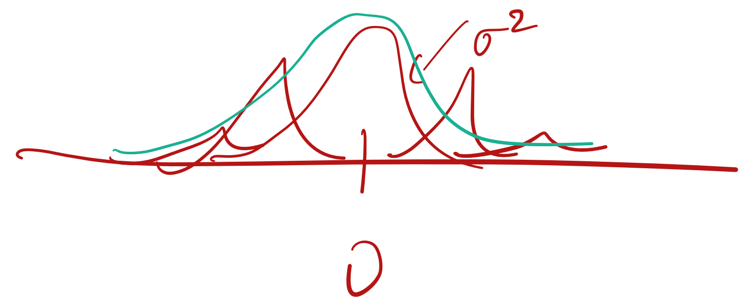
$$L(\theta_0, \theta_1, \phi) \propto \prod_{i=1}^{n} P(y_i \mid \theta_0, \theta_1, \phi)$$

$$\propto \prod^{n} \left[\sum_{z=0}^{1} \underline{P(y_i, z_i = z_i \mid \theta_0, \theta_1, \phi)} \right]$$

$$\propto \prod^{100} \left[\phi \cancel{\binom{10}{y_i}} \theta_1^{y_i} (1-\theta_1)^{10-y_i} + (1-\phi) \cancel{\binom{10}{y_i}} \theta_0^{y_i} (1-\theta_0)^{10-y_i} \right]$$

Infinite Mixture Models

- Often helpful to think about infinite mixture models
- Example 1: normal observations with normally distributed mean



$$\mu_i \sim N(0, \tau^2)$$
$$Y_i \sim N(\mu_i, \sigma^2)$$

What is the distribution of Y_i given τ^2 and σ^2 (integrating over μ)?

Calculus: $P(Y \mid \tau^2, \sigma^2) =$

$$\int_{-\infty}^{\infty} P(Y \mid \mu, \sigma^2) P(\mu \mid \tau^2) \, d\mu$$

MGFs

$$\begin{cases} Y_i = \mu_i + \varepsilon \\ \varepsilon \sim N(0, \sigma^2) \\ Y_i \sim N(0, \sigma^2 + \tau^2) \end{cases}$$

$$Y_i = \mu_i + \varepsilon, \quad \varepsilon \sim N(0,1)$$

$$\stackrel{\sim}{=} N(\mu_i, 1)$$

Infinite Mixture Models

Example 2: Poisson observations with random rates

$$\lambda \sim Gamma(\alpha, \beta)$$
$$Y \sim Pois(\lambda)$$

$E[\lambda] = \frac{\alpha}{\beta}$

$Var(\lambda) = \frac{\alpha}{\beta^2}$

$$P(y \mid \alpha, \beta) = \int_\lambda P(y \mid \lambda) P(\lambda \mid \alpha, \beta)\, d\lambda$$

$$= \int \frac{\lambda^y e^{-\lambda}}{y!} \frac{\beta^\alpha \lambda^{\alpha-1} e^{-\beta\lambda}}{\Gamma(\alpha)}\, d\lambda$$

$$E[Y] = E[E[Y|\lambda]] = E[\lambda] = \alpha/\beta$$

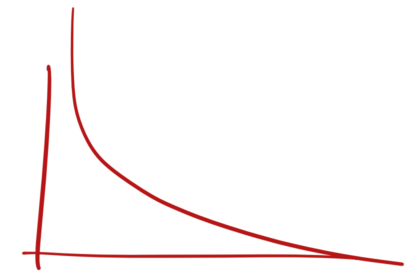
$$\mathrm{Var}(Y) = \underline{E}[\underline{V}\mathrm{ar}(Y|\lambda)] + \underline{V}\mathrm{ar}(\underline{E}[Y|\lambda])$$

$$= E[\lambda] + \mathrm{Var}(\lambda)$$

$$= \frac{\alpha}{\beta} + \frac{\alpha}{\beta^2} = \frac{\alpha}{\beta}\left(1 + \frac{1}{\beta}\right)$$

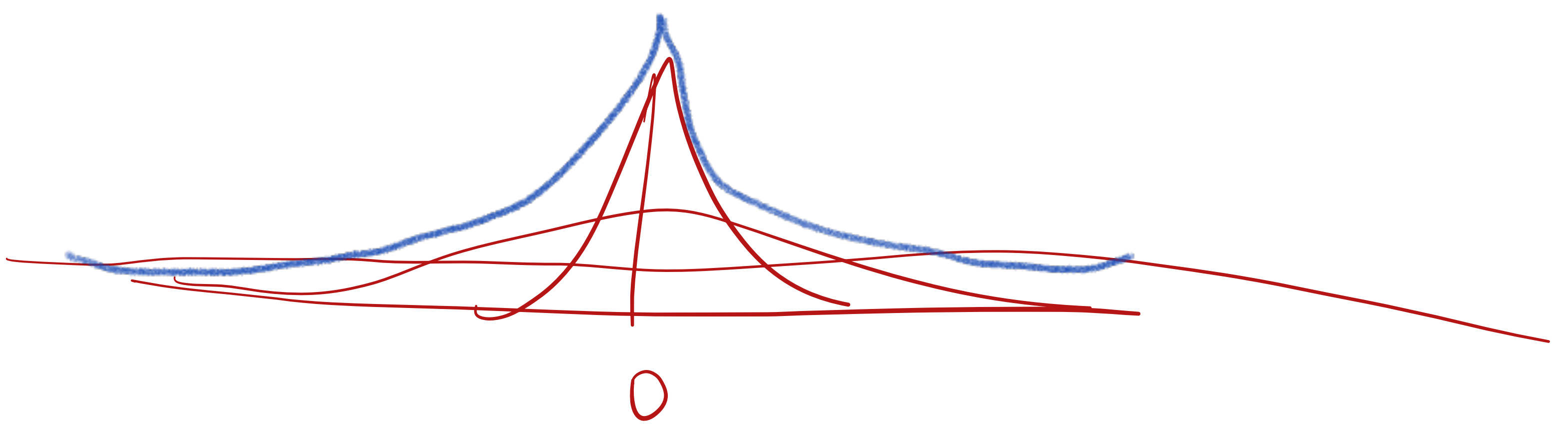
Infinite Mixture Models

- Example 3: normal observations with exponentially distributed scale



$$\sigma_i^2 \sim Exponential(1/2)$$
$$Y_i \sim N(0, \sigma_i^2)$$

What is the distribution of Y_i?



$$Z_1 \sim N(0,1)$$

$$Z_2 \sim N(0,1)$$

$$C \sim \frac{Z_1}{Z_2}$$

$$cZ_1 \sim N(0, c^2)$$

$$\left(\frac{1}{Z_2}\right)\left(Z_1\right)$$

Summary

- Likelihood, log likehood
- Sufficient statistics
- Fisher information
- Mixture models

Assignments

- Read chapter 1-2 BDA3