

$$H_0: \lambda_1 \leq \lambda_2 \quad H_a: \lambda_1 > \lambda_2$$

$$P(H_0 | X, Y, \lambda_1, \lambda_2) = \frac{P(X, Y | H_0, \lambda_1, \lambda_2) P_r(H_0)}{P(X, Y | H_0, \lambda_1, \lambda_2) P_r(H_0) + P(X, Y | H_a, \lambda_1, \lambda_2) P_r(H_a)}$$

Anthony Fontana
AMS 206
Final Exam
(Quiz)

likelihood:

$$\lambda_1^n \exp\left\{-\lambda_1 \sum_{i=1}^n x_i\right\} \cdot \lambda_2^n \exp\left\{-\lambda_2 \sum_{i=1}^n y_i\right\} = (\lambda_1 \lambda_2)^n \exp\left\{-\lambda_1 n\bar{x} - \lambda_2 n\bar{y}\right\}$$

Joint Prior:

$$\frac{b^a}{\Gamma(a)} \lambda_1^{-a-1} \exp\left\{-\frac{b}{\lambda_1}\right\} \cdot \frac{b^a}{\Gamma(a)} \lambda_2^{-a-1} \exp\left\{-\frac{b}{\lambda_2}\right\} = \left(\frac{b^a}{\Gamma(a)}\right)^2 (\lambda_1 \lambda_2)^{-a-1} \exp\left\{-\frac{b}{\lambda_1} - \frac{b}{\lambda_2}\right\}$$

$$P(X, Y | H_0, \lambda_1, \lambda_2) =$$

$$\int_0^\infty \int_0^{\lambda_2} \left(\frac{b^a}{\Gamma(a)}\right)^2 (\lambda_1 \lambda_2)^{-a-1} \exp\left\{-\frac{b}{\lambda_1} - \frac{b}{\lambda_2}\right\} \exp\left\{-\lambda_1 n\bar{x} - \lambda_2 n\bar{y}\right\} d\lambda_1 d\lambda_2$$

$$\Rightarrow \left(\frac{b^a}{\Gamma(a)}\right)^2 \int_0^\infty \int_0^{\lambda_2} (\lambda_1 \lambda_2)^{-a-1} \exp\left\{-\frac{b}{\lambda_1}\right\} \exp\left\{-\frac{b}{\lambda_2}\right\} \exp\left\{-\lambda_1 n\bar{x}\right\} \exp\left\{-\lambda_2 n\bar{y}\right\} d\lambda_1 d\lambda_2$$

$$\Rightarrow \left(\frac{b^a}{\Gamma(a)}\right)^2 \int_0^\infty \int_0^{\lambda_2} (\lambda_1 \lambda_2)^{-a-1} \exp\left\{-\frac{b}{\lambda_1} - \lambda_1 n\bar{x}\right\} \exp\left\{-\frac{b}{\lambda_2} - \lambda_2 n\bar{y}\right\} d\lambda_1 d\lambda_2$$

$$\Rightarrow \int_0^\infty \lambda_2^{n-a-1} \exp\left\{-\frac{b}{\lambda_2} - \lambda_2 n\bar{y}\right\} \underbrace{\int_0^{\lambda_2} \lambda_1^{n-a-1} \exp\left\{-\frac{b}{\lambda_1} - \lambda_1 n\bar{x}\right\} d\lambda_1}_{\substack{\text{Some ridiculously} \\ \text{complicated IVP that} \\ \text{I dont know how to do}}}$$

$$\begin{aligned} \exp\left\{-\frac{b}{\lambda_1} - \lambda_1 n\bar{x}\right\} &= \exp\left\{-\frac{b}{\lambda_1} - \lambda_1 \frac{(n\bar{x})}{\lambda_1}\right\} \\ &= \exp\left\{-b - \frac{\lambda_1 (n\bar{x})}{\lambda_1}\right\} \end{aligned}$$

$$\begin{aligned} \text{No idea} \xrightarrow{\text{how to integrate}} &= \exp\left\{-b - \frac{(\lambda_1^2 n \bar{x})}{\lambda_1}\right\} \\ \text{but} & \end{aligned}$$

①

$$\begin{aligned}
 1b) \lim_{\alpha, \beta \rightarrow 0} (\lambda_1, \lambda_2) &\sim \frac{\beta^\alpha}{\Gamma(\alpha)} (\lambda_1, \lambda_2)^{\alpha-1} \exp\left\{-\frac{\beta}{\lambda_1} - \frac{\beta}{\lambda_2}\right\} \\
 &\propto \beta^\alpha (\lambda_1, \lambda_2)^{\alpha-1} \exp\left\{-\frac{\beta}{\lambda_1} - \frac{\beta}{\lambda_2}\right\} \\
 \Rightarrow \lim_{\alpha, \beta \rightarrow 0} \frac{1}{\lambda_1 \lambda_2} \exp\left\{-\frac{\beta}{\lambda_1} - \frac{\beta}{\lambda_2}\right\} &= \boxed{\frac{1}{\lambda_1 \lambda_2}}
 \end{aligned}$$

$$\begin{aligned}
 1c) \frac{P(x, y | H_0, \lambda_1, \lambda_2)}{P(x, y | H_c, \lambda_1, \lambda_2)}
 \end{aligned}$$

$$\begin{aligned}
 P(x, y | H_0, \lambda_1, \lambda_2) &= \int_0^\infty \int_0^{\lambda_2} \lambda_1^n \lambda_2^n \exp\{-\lambda_1 n \bar{x}\} \exp\{-\lambda_2 n \bar{y}\} d\lambda_1 d\lambda_2 \\
 &= \int_0^{\lambda_1} \lambda_1^{n-1} \exp\{-\lambda_1 n \bar{x}\} d\lambda_1 \int_0^\infty \lambda_2^{n-1} \exp\{-\lambda_2 n \bar{y}\} d\lambda_2
 \end{aligned}$$

Integrated to one,

inverse of normalizing parameter

$$\rightarrow \frac{\Gamma(n)}{(n\bar{y})^n} \int_0^{\lambda_1} \lambda_1^{n-1} \exp\{-\lambda_1 n \bar{x}\} d\lambda_1$$

$$\rightarrow P_c(H_c) + P_c(H_0) = 1 \rightarrow P_c(H_c) = 1 - P_c(H_0)$$

→ The probabilities make up the whole probability space
 so we know $1 - P_c()$ will have to equal the other;
 so $P_c(H_c) = 1 - P_c(H_0)$ which yields . . .

$$\begin{aligned}
 &\frac{\frac{\Gamma(n)}{(n\bar{y})^n} \int_0^{\lambda_1} \lambda_1^{n-1} \exp\{-\lambda_1 n \bar{x}\} d\lambda_1}{\frac{\Gamma(n)}{(n\bar{y})^n} \int_0^{\lambda_2} \lambda_2^{n-1} \exp\{-\lambda_2 n \bar{y}\} d\lambda_2} \\
 &= \frac{\int_0^\infty \lambda_1^{n-1} \exp\{-\lambda_1 n \bar{x}\} d\lambda_1}{\int_0^{\lambda_2} \lambda_2^{n-1} \exp\{-\lambda_2 n \bar{y}\} d\lambda_2}
 \end{aligned}$$

②

1d.) See Code

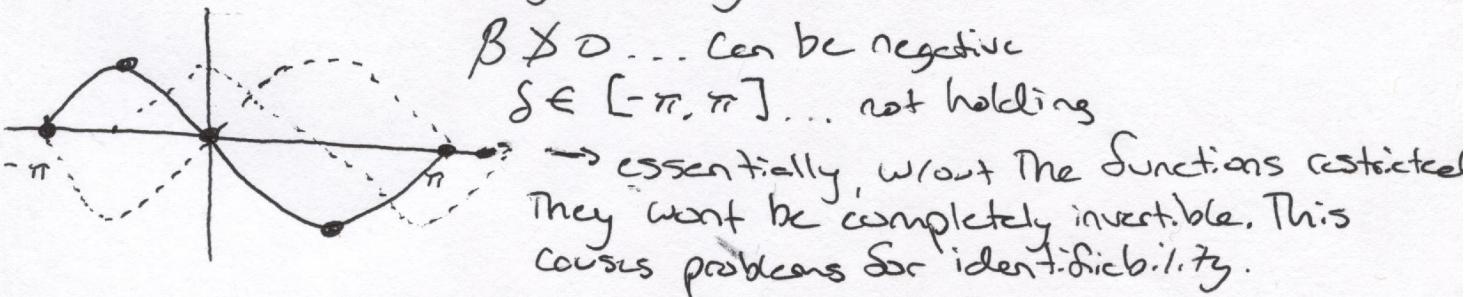
→ evidence in favor of null $\lambda_1 < \lambda_2$.

$$\frac{1}{1 + \frac{\text{alt}}{\text{null}}} = .87$$

2a.) option 1: $\beta > 0$ and $\gamma \in [-\pi, \pi]$

option 2: β not restricted $\gamma \in [-\frac{\pi}{2}, \frac{\pi}{2}]$

→ Justification - The parameters will not be identifiable if not restricted. There will be infinitely many ways to fit a sinusoid function to a set of data, so no unique parameters can be found. This can be seen by graphing a $\sin(x)$...



- * → choosing the first restriction is easier for computation.
- * → I would choose uniform prior for δ . This is primarily because I have no background knowledge of the physics to make an informed judgement about the appropriate parameter values. Maybe if I were a physicist I would know.
- * → I would probably choose a normal prior for β . There doesn't seem to be a reason why amplitude will be non-normal.

③

$$2b) \quad y_i = \alpha + \beta \sin(\omega x_i + \delta) + \varepsilon_i \quad \varepsilon_i \sim N(0, \sigma^2)$$

$$\text{Show: } y_i = \alpha + \beta \sin(\omega x_i + \delta) = \alpha + \gamma_1 \sin(\omega x_i) + \gamma_2 \cos(\omega x_i) + \varepsilon_i$$

$$\text{use: } \sin(a+b) = \sin(a)\cos(b) + \cos(a)\sin(b)$$

$$= \alpha + \underbrace{\beta \cos(\delta) \sin(\omega x_i)}_{\gamma_1} + \underbrace{\beta \sin(\delta) \cos(\omega x_i)}_{\gamma_2} + \varepsilon_i$$

$$= \alpha + \gamma_1 \sin(\omega x_i) + \gamma_2 \cos(\omega x_i) + \varepsilon_i$$

$$\rightarrow \gamma_1 + \gamma_2 = \beta \cos(\delta) + \beta \sin(\delta)$$

want to use pythagorean identities to flesh out relationship between gammas

$$(\gamma_1 + \gamma_2)^2 = (\beta \cos(\delta) + \beta \sin(\delta))^2$$

$$\gamma_1^2 + \gamma_2^2 = \beta^2 \cos^2(\delta) + \beta^2 \sin^2(\delta)$$

$$\gamma_1^2 + \gamma_2^2 = \beta^2 \underbrace{(\cos^2(\delta) + \sin^2(\delta))}_{=1}$$

$$\text{so } \sqrt{\gamma_1^2 + \gamma_2^2} = \sqrt{\beta^2}$$

$$\underbrace{\beta = \sqrt{\gamma_1^2 + \gamma_2^2}}_{=} = \sqrt{\beta \cos^2(\delta) + \beta \sin^2(\delta)}$$

use Tangent identity to derive δ

$$\tan(\delta) = \frac{\gamma_2}{\gamma_1} = \frac{\beta \sin(\delta)}{\beta \cos(\delta)}$$

$$\boxed{\delta = \arctan\left(\frac{\gamma_2}{\gamma_1}\right)}$$

2c.) Note Multivariate so $D = (1, \cos(\omega x_i), \sin(\omega x_i))$

→ Full conditional for amplitude β

$$P(\beta | \omega, \sigma^2, y) \propto P(\beta, y | \omega, \sigma^2) = P(y | \beta, \omega, \sigma^2) \cdot P(\beta | \omega, \sigma^2)$$

$$\propto P(y | \beta, \omega, \sigma^2) \propto N(((D^T D)^{-1} D^T y), \sigma^2 (D^T D)^{-1})$$

* also note these parameters are now vectors of observations

→ Full conditional for noise

$$P(\sigma^2 | \omega, \beta, y) \propto P(\sigma^2 y | \omega, \beta) = P(y | \omega, \beta, \sigma^2) P(\sigma^2)$$

$$\propto N(x_i, D\beta, \sigma_n^2) \sigma^2$$

$$\propto \text{IG}\left(\frac{n}{2}, \underbrace{\frac{1}{2}(y - D\beta)^T(y - D\beta)}_{\sigma^2}\right)$$

→ Frequency → needs Monte Carlo Random Walk Metropolis Hastings

$$P(\omega | \beta, \sigma^2, y) \propto \exp\left\{-\frac{1}{2\sigma^2}(y - D\beta)^T(y - D\beta)\right\}$$

extra credit: $\gamma_1, \gamma_2 \sim N(0, \sigma^2)$ iid ...

$$\sum_{i=1}^n \gamma_i \sim \chi^2 \quad [\text{chi-square}; \text{DF} = 2]$$

The sum of a bunch of iid normals yields χ^2

$\beta = \sqrt{\gamma_1^2 + \gamma_2^2} = \sqrt{x^2}$ Square root of some chi-square,
call this variable "x"

$$\beta = \sqrt{x} \Rightarrow \beta^2 = x$$

→ Problem boils down to finding the pdf of a function
of a random variable.

(5)

→

2c (Continued.)

2d

This problem needs a Jacobian transformation.

Suppose X is continuous and Random and $g: \mathbb{R} \rightarrow \mathbb{R}$ is strictly monotonic and differentiable ... $Y = g(X)$ (in our case $X \sim \chi^2$)

$$f_y(y) = \begin{cases} \frac{f_x(x_1)}{|g'(x_1)|} & \text{where } g(x_1) = y \\ 0 & \text{if } g(x) = y \text{ no sol} \end{cases}$$

$$|J| = \frac{\partial x}{\partial \beta} = |2\beta| \quad \chi^2 = \frac{1}{2^{\frac{k}{2}} \Gamma(\frac{k}{2})} x^{\frac{k}{2}-1} e^{-\frac{x}{2}} \quad k=2$$
$$= \frac{1}{2 \Gamma(1)} \beta^{\frac{2}{2}-1} e^{-\frac{\beta^2}{2}} \quad \text{But it can be shown for } k=2, \text{ this special case leads to Rayleigh}$$
$$\therefore \frac{1}{2 \Gamma(1)} \left(\beta^2\right)^{1-\frac{1}{2}} \exp\left\{-\frac{\beta^2}{2}\right\} |2\beta| = \beta \exp\left\{-\frac{\beta^2}{2}\right\}, \beta > 0$$

If $X \sim \text{Rayleigh}(1)$ Then $\chi^2 \sim \chi^2(2)$

→ Now for S $\gamma_1 = \beta \cos(\delta) \quad \gamma_2 = \beta \sin(\delta)$

$$\delta(S) = \frac{1}{2\pi} \quad S \in [-\pi, \pi]$$

⑥



$$Y = \cos(\delta) \quad Y \sim \text{Unif}[-1, 1]$$

$$\begin{aligned}f_y(y) &= \sum_{\cos(\delta)=y} f_\delta(\cos^{-1}(y)) \left| \frac{\partial \delta}{\partial y} \right| \\&= \sum_{\cos(\delta)=y} f_\delta(\cos^{-1}(y)) \left| \frac{1}{-\sin(\cos^{-1}(y))} \right| \\&= \frac{1}{2\pi} \cdot \frac{1}{|\sin(\cos^{-1}(y))|} \quad \forall \cos^{-1}(y) \in [0, \pi] \\f_y(y) &= \frac{1}{\pi |\sin(\cos^{-1}(y))|} \quad y \in [-1, 1]\end{aligned}$$

- c.) See Code for simulations
- d.) See Code for MCMC
- e.) See output on other document
- f.) . . .
- g.) No clue
- h.) Yes, I found it by visual inspection

⑦