

# Bayesian Model Calibration of Cavity Flow Noise



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# Data Source

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Gas Dynamics and Turbulence Laboratory

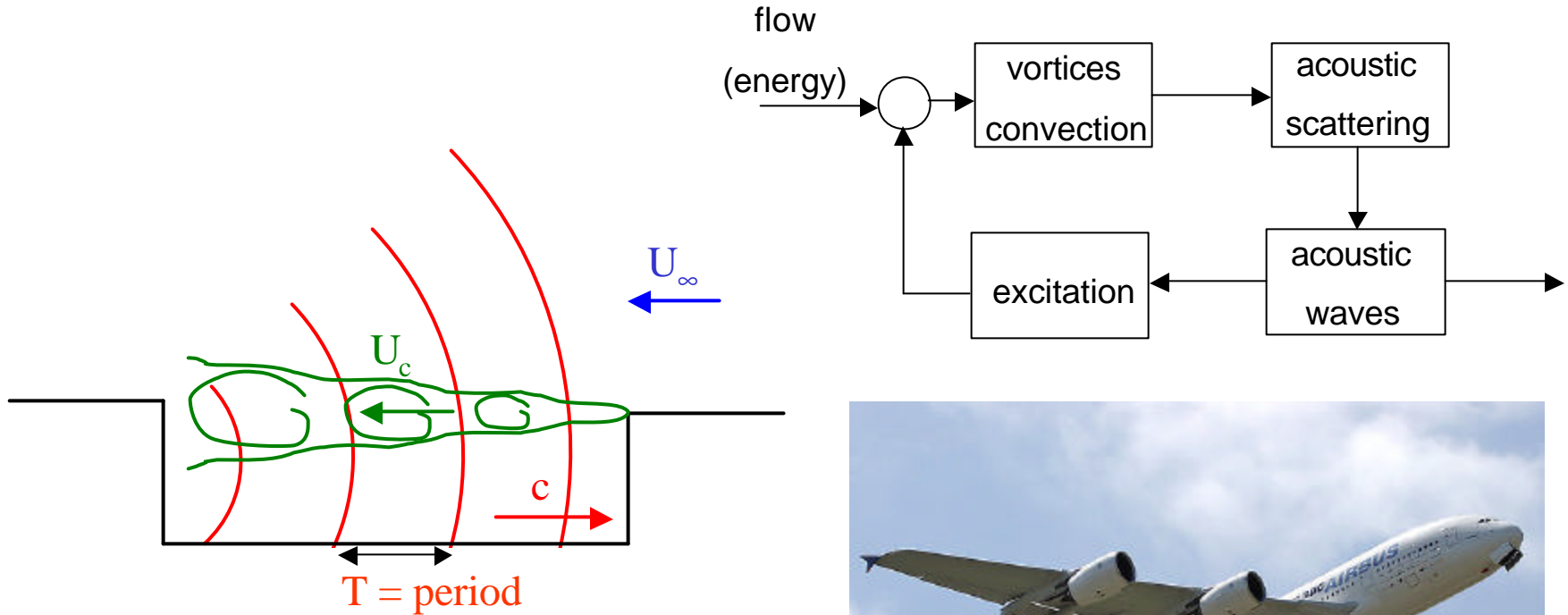
The Ohio State University

“Closed-loop, Active Flow Control (2004)”



# SELF EXCITED RESONANT FLOW NOISE

Driven by feedback mechanism

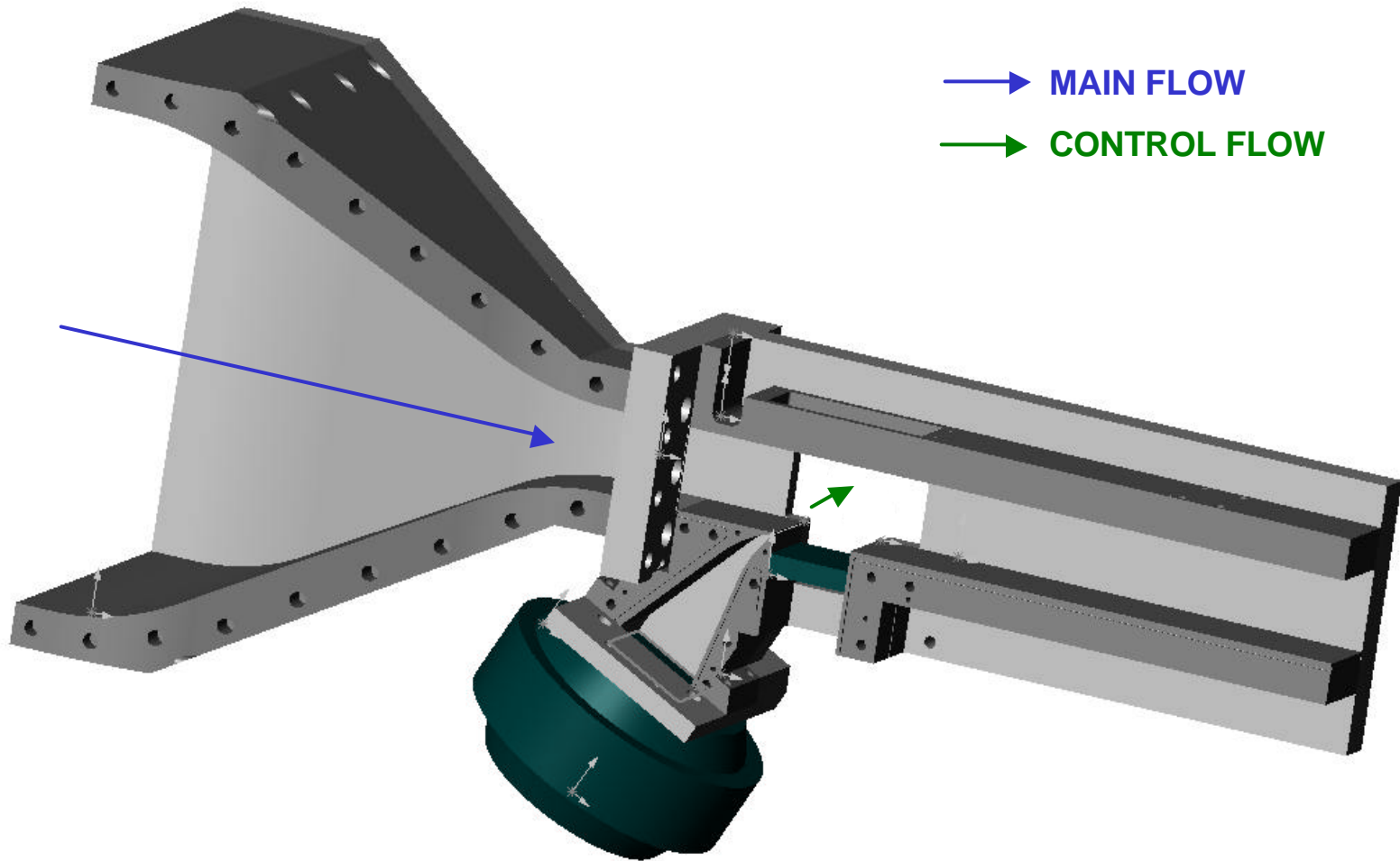


$$f = 1/T \quad [1/\text{second} \equiv \text{Hz}]$$

$$M_\infty = U_\infty / c$$

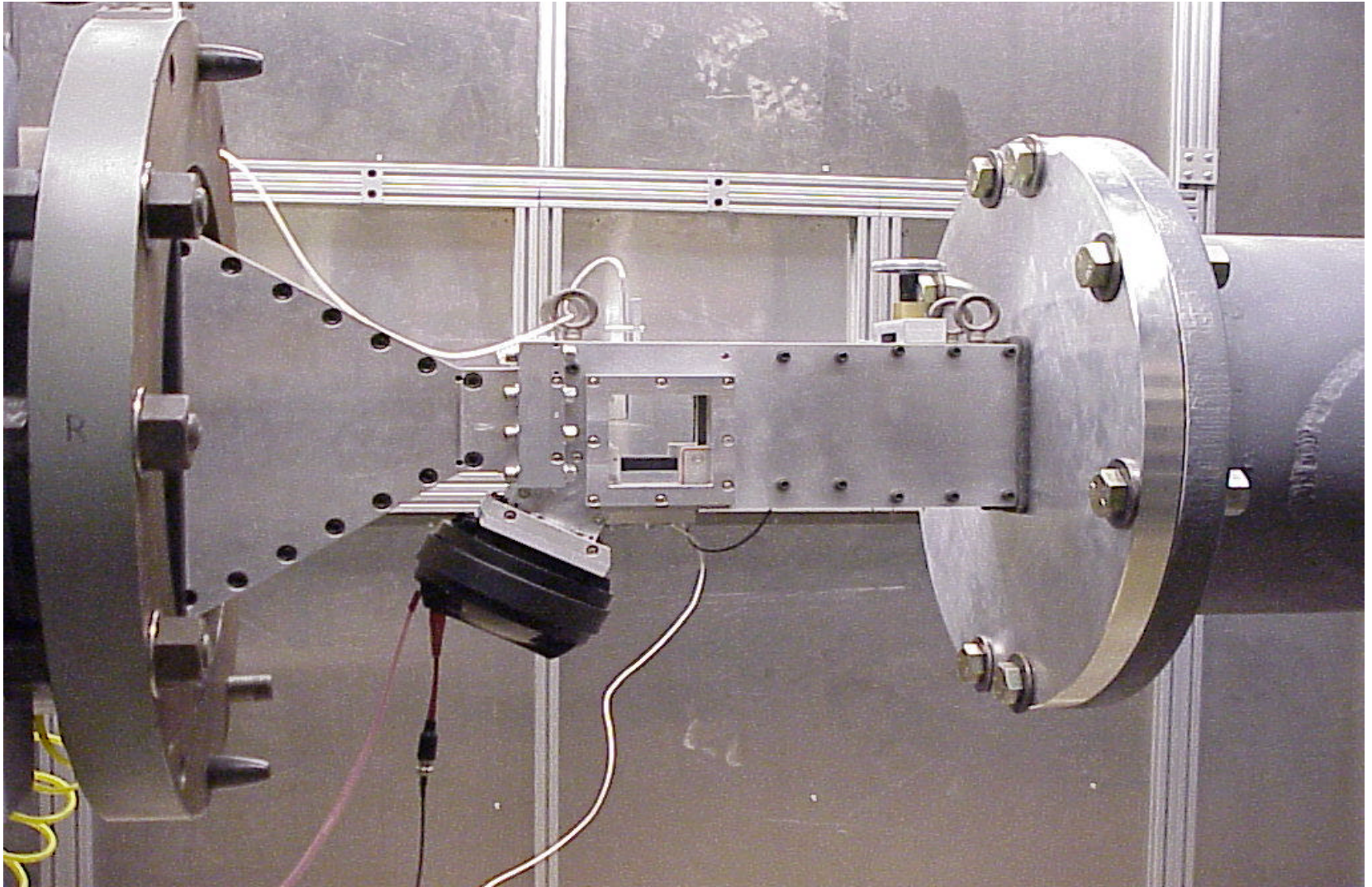


## 3-D VIEW OF THE TEST SECTION WITH NOZZLE AND ACTUATOR





## LATERAL VIEW OF THE ASSEMBLED FACILITY



## THE ROSSITER MODEL (1964)

a semi-empirical formula for resonant Strouhal number as a function of free stream Mach number

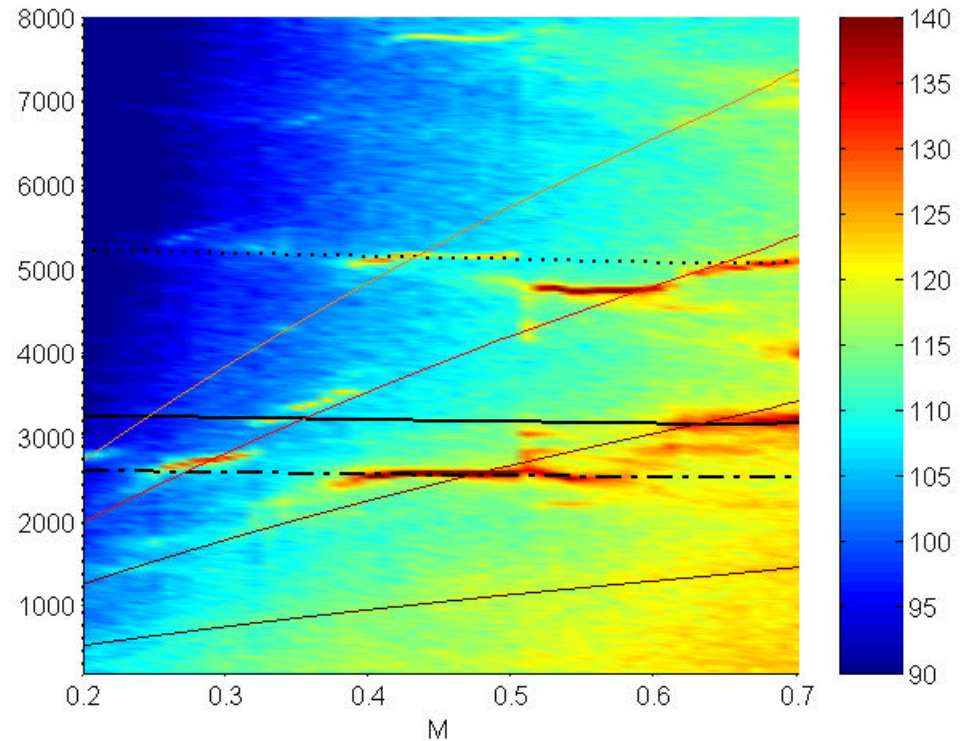
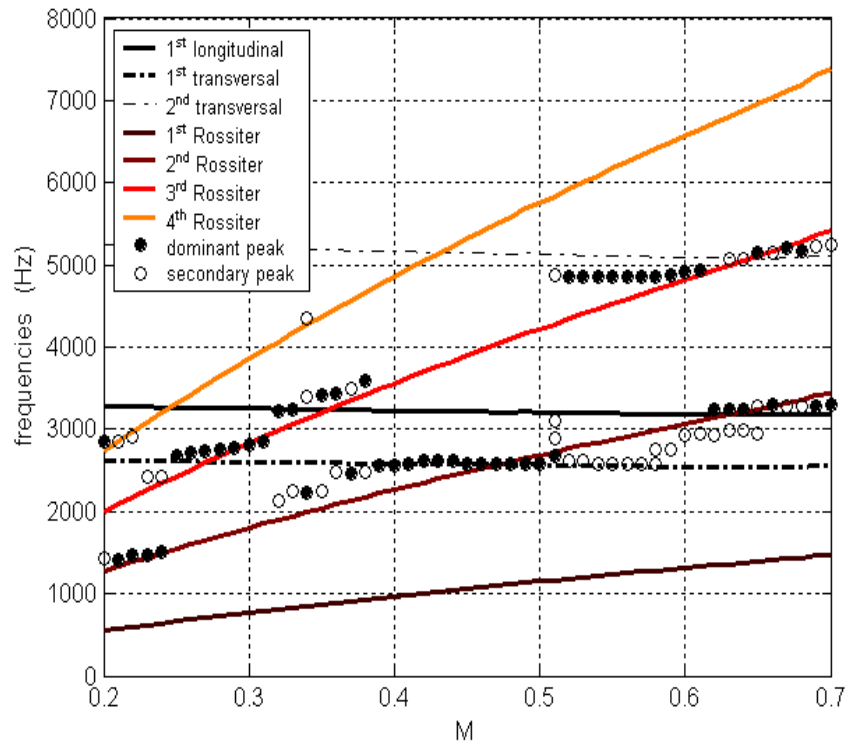
$$St_n = \frac{f_n L}{U_\infty} = \frac{n - a}{M_\infty \left( 1 + \frac{g - 1}{2} M_\infty^2 \right)^{-1/2} + \frac{1}{\beta}}$$

***u*** is the mode number

***a*** is the **phase shift** (in fractions of a wavelength) of the acoustic scattering process

***b*** is the **ratio** of the convective speed of the disturbance to the free stream velocity:  $\beta = U_c / U_\infty$

# ROSSITER'S PREDICTION AND EXPERIMENTAL RESULTS



# Notation

- $X \rightarrow$  control variable (Mach number)  
where  $X \in [0.20, 0.70]$   
 $N \rightarrow$  mode number  $N \in \{2, 3, 4\}$
- $Y(x, n) \rightarrow$  observed freq at  $X = x$ , and  $N = n$
- $\eta(x, n, (a, b)) \rightarrow$  freq accd'g to Rossiter model  
where  $Y(x), \eta(x, n, (a, b)) > 0$
- $V(x, n) \rightarrow$  true unknown freq at  $X = x$  and  $N = n$



# Statistical Formulation 1

- $Y(x_i) = \text{True Freq } V(x_i, n_i) +$   
 $\text{Measurement error } e(x_i, n_i) , i=1,2,\dots,n$
- $\text{True Freq } V(x_i, n_i) =$   
 $\text{Rossiter model } h(x_i, n_i, (a,b)) +$   
 $\text{Deviation of Rossiter model from the true}$   
 $\text{process } d(x_i, n_i)$

# Statistical formulation 2

- $Y(x_i, n_i) = V(x_i, n_i) + e(x_i, n_i)$  ,  $i=1,2,\dots,n$   
 $e(x_i, n_i) \sim \text{MVN}(\mathbf{0}, \mathbf{s}^2 \mathbf{I})$   
 $\mathbf{s}^2 \sim \text{IG}(\mathbf{SA}, \mathbf{SB})$
- $V(x_i, n_i) = \mathbf{B} \eta(x_i, n_i, (\mathbf{a}, \mathbf{b})) + \delta(x_i, n_i)$   
 $\mathbf{a} \sim \text{Beta}[\mathbf{AA}, \mathbf{AB}]$   
 $\mathbf{b} \sim \text{Beta}[\mathbf{BA}, \mathbf{BB}]$

# Statistical formulation 2

$$\delta(x_i, n_i) \sim \text{MVN}(\mathbf{m}, \mathbf{S})$$

$$\mathbf{m} = \mathbf{0}$$

$$\mathbf{S} = \{s_{ij}\} = \mathbf{l}^{-1} \exp(-\mathbf{f} |x_i - x_j|^2) + \mathbf{k} \cdot \mathbf{d}_{ij}$$

where

$$\mathbf{d}_{ij} = \mathbf{I}(i=j)$$

$$\mathbf{l} \sim \text{Gamma}(\mathbf{LA}, \mathbf{LB})$$

$$\mathbf{f} \sim \text{Gamma}(\mathbf{PA}, \mathbf{PB})$$

$$\mathbf{k} \sim \text{Gamma}(\mathbf{KA}, \mathbf{KB})$$

## Parameter Vector

$$q = [ (a, b), s^2, l, f, k ]$$

## Posterior Distribution

$$\mathbf{L}(q | y) \propto \mathbf{L}(q | y) \cdot [q]$$

$$\propto \mathbf{L}(q | y) \cdot$$

$$[a] [b] [s^2] [l] [f][k]$$

# Metropolis Hastings within Gibbs

*We need to sample from*

- i.  $[ \mathbf{h}(\mathbf{x}) \mid \text{rest}, \mathbf{Y} ] \sim \text{MVN} ( \mathbf{m}^*, \mathbf{S}^* )$
- ii.  $[ \mathbf{s}^2 \mid \text{rest}, \mathbf{Y} ] \sim \text{Inverse Gamma}$
- iii.  $[ (\mathbf{a}, \mathbf{b}) \mid \text{rest}, \mathbf{Y} ] \propto \exp\{ - \mathbf{g}_1 ( \mathbf{h}(\mathbf{x}_i), (\mathbf{a}, \mathbf{b}), (\mathbf{l}, \mathbf{j}, \mathbf{k}) ) \}$ 
  - Metropolis-Hastings Step
- iv.  $[ (\mathbf{l}, \mathbf{j}, \mathbf{k}) \mid \text{rest}, \mathbf{Y} ] \propto \exp\{ - \mathbf{g}_2 ( \mathbf{h}(\mathbf{x}_i), (\mathbf{a}, \mathbf{b}), (\mathbf{l}, \mathbf{j}, \mathbf{k}) ) \}$ 
  - Metropolis-Hastings Step

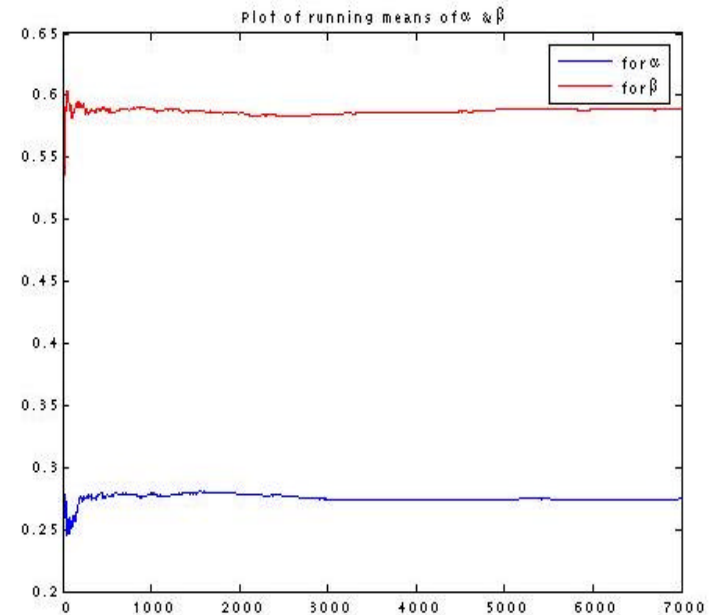
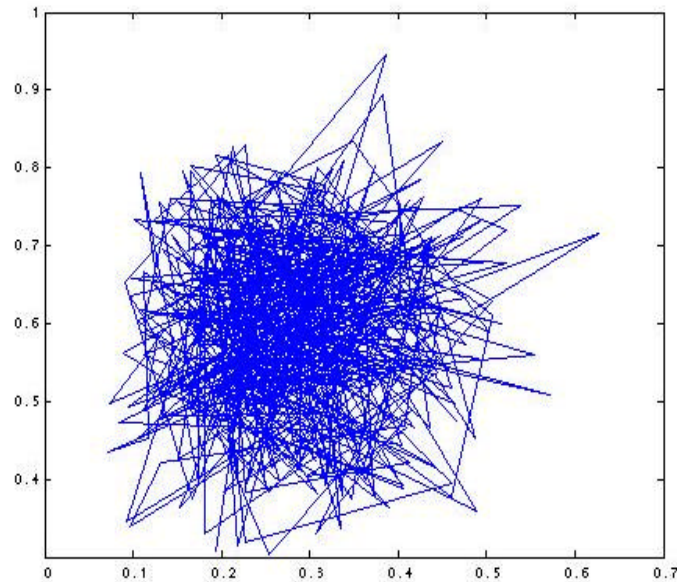


# Priors and Initial Values

Parameter	Distribution	Hyperparameters
$a$	Beta (AA, AB)	Prior Mode = 0.250, 0.800 AA+AB = 10
$b$	Beta (BA, BB)	Prior Mode = 0.625, 0.100 BA+BB = 10
$s^2$	IGamma (SA, SB)	SA = 4.0    SB = 0.5
$l$	Gamma (LA, LB)	LA = 0.2    LB = 0.2
$f$	Gamma (PA, PB)	PA = 20.0    PB = 2.0
$k$	Gamma (KA, KB)	KA = 2.0    KB = 1.0

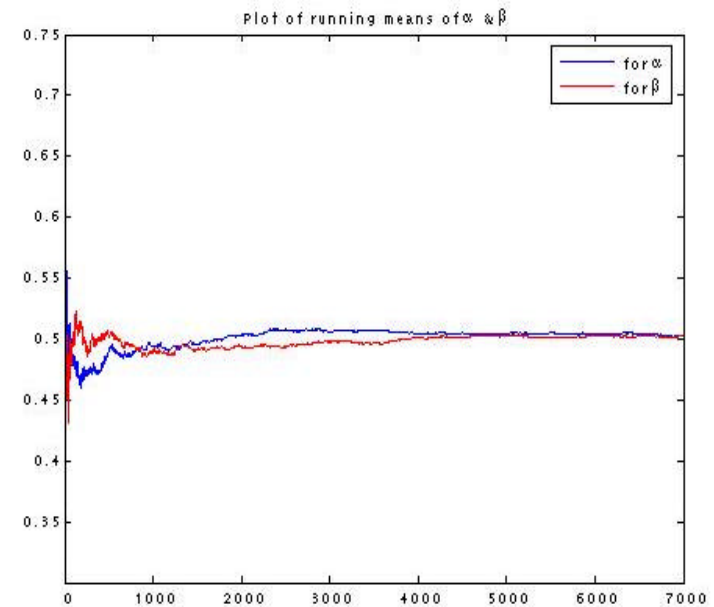
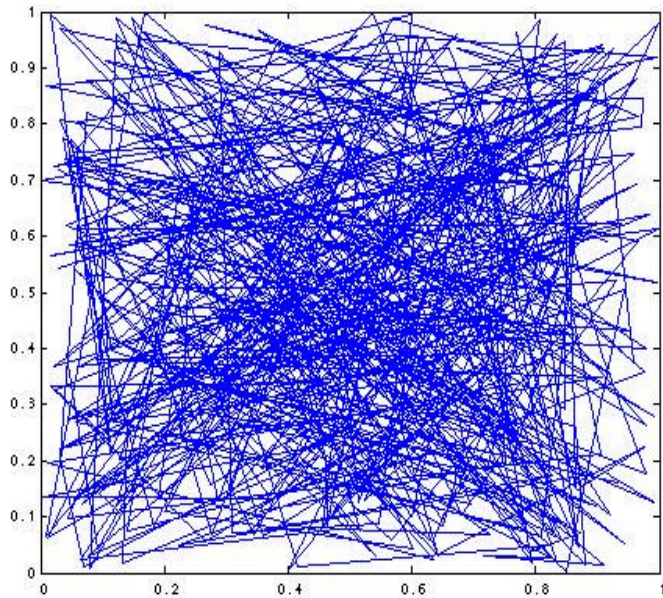
# Mixing & Convergence Checks 1

## Independent Beta Priors



# Mixing & Convergence Checks 2

## Independent Uniform Priors



# Posterior Inference (Iterations =7000)

*Burn-in* = 2000 , *Thin* = 10, *Samples* = 500

<i>Parameter</i>	<i>Mean</i>	<i>SD</i>	<i>Q1</i>	<i>Median</i>	<i>Q3</i>	<i>95% Credible Intervals</i>	
<i>a</i>	0.27	0.10	0.20	0.27	0.34	0.10	0.49
<i>b</i>	0.59	0.11	0.52	0.59	0.66	0.37	0.80
<i>Note: {(AA+AB) = 10 ; (BA+BB) = 10} {(AA+AB) = 10 ; (BA+BB) = 10}</i>							
<i>a</i>	0.48	0.30	0.22	0.47	0.75	0.02	0.97
<i>b</i>	0.51	0.30	0.26	0.52	0.76	0.03	0.98
<i>Note: {(AA+AB) = 2 ; (BA+BB) = 2} {(AA+AB) = 2 ; (BA+BB) = 2}</i>							

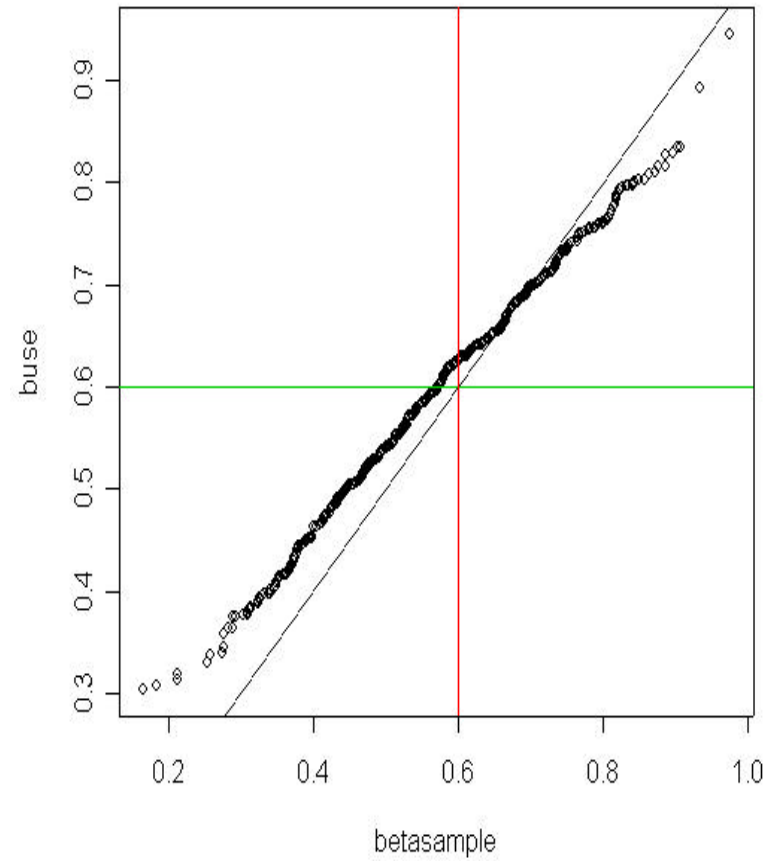
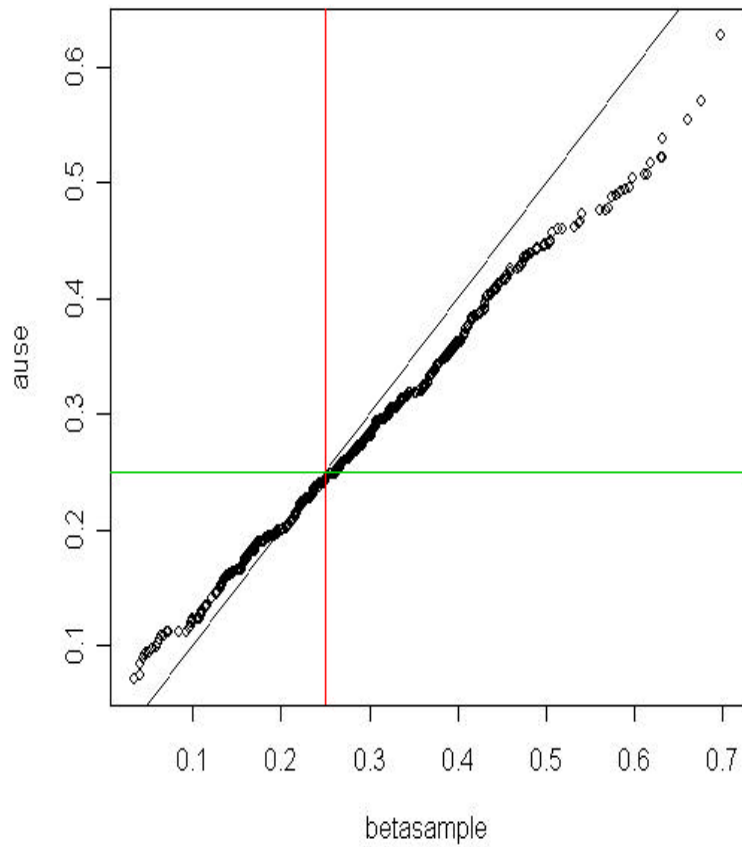
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<i>a</i>	0.26	.06	0.22	0.26	0.30	0.15	0.38
<i>b</i>	0.60	0.06	0.55	0.60	0.64	0.48	0.72
<p><i>Note: {(AA+AB) = 30 ; (BA+BB) = 30} {(AA+AB) = 30 ; (BA+BB) = 30}</i></p> <p><i>Mode set at a = 0.25 , b =0.60</i></p>							
<i>a</i>	0.79	0.05	0.76	0.79	0.82	0.69	0.88
<i>b</i>	0.11	0.04	0.08	0.11	0.14	0.05	0.20
<p><i>Note: {(AA+AB) = 30 ; (BA+BB) = 30} {(AA+AB) = 30 ; (BA+BB) = 30}</i></p> <p><i>Mode set at a = 0.80 , b =0.10</i></p>							



# QQ Plot of Posterior and Prior CDF of $[a, b, /y]$



# Summary of Findings

- *Posterior means:*  **$a = 0.27$**  ,  **$b = 0.59$**

*MC Std Error:*  **$a = 0.10$**  ,  **$b = 0.11$**

*95% Credible intervals:*

**$a \hat{I} (0.10, 0.49)$**  ;  **$b \hat{I} (0.37, 0.80)$**

- Overall convergence was achieved at 2000<sup>th</sup> iteration; Quality of mixing was acceptable; Choice of thinning interval was OK
- Posterior distribution is not invariant to the choice of prior mode.

# Next Steps

- Use statistical approach to choose the “peak” frequencies
- Use discriminant analysis to identify mode number in conjunction with Bayesian set-up
- Re-parameterization of space to speed up computation time, and convergence
- Try multiplicative error model for  $V(\mathbf{x}, n)$