Bayesian NVH metamodels to assess "pre-design" interior cabin noise using measurement databases

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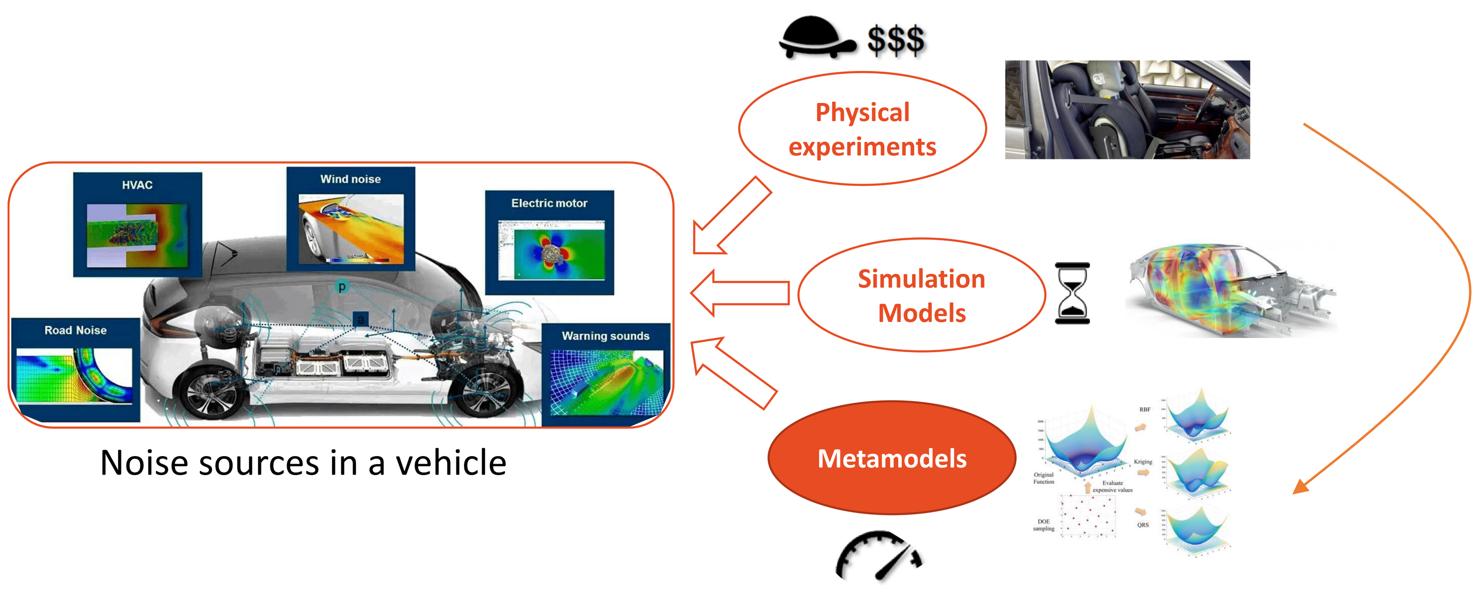
Context

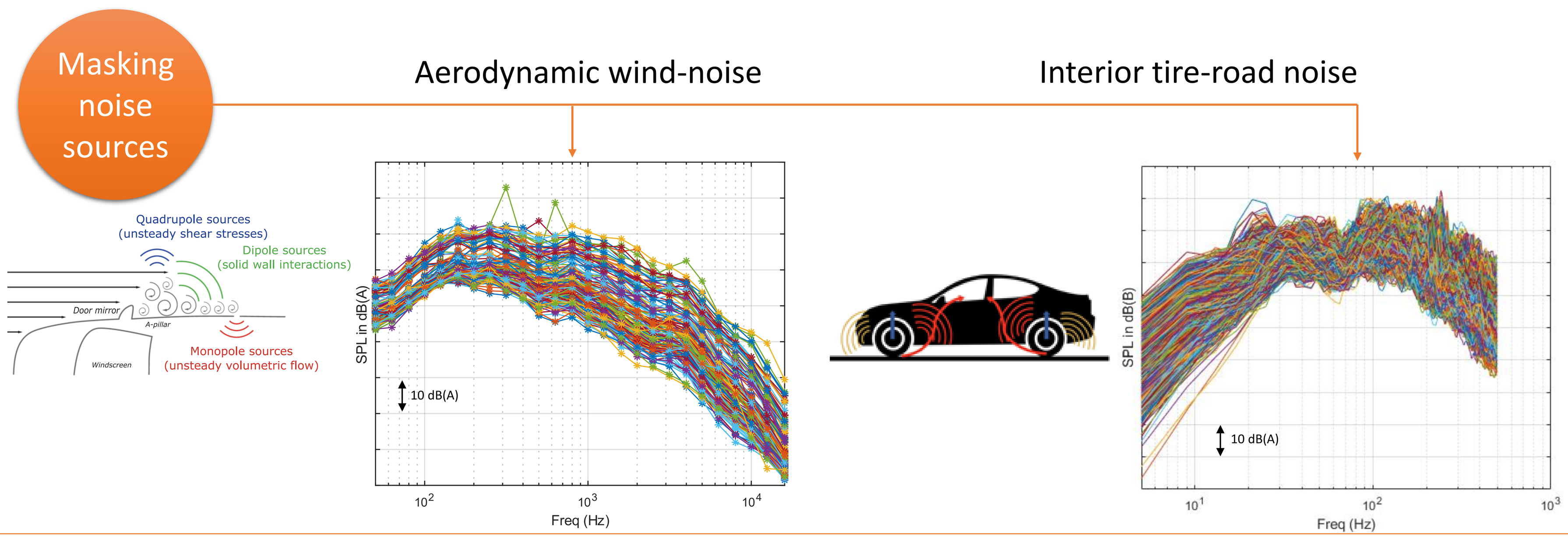
- Towards eco-efficient powertrains and acoustic comfort in automotive sector
- NVH (Noise, Vibration and Harshness) characteristics assessment of electric vehicles and downsized-IC engines (internal combustion)
- Electrification leads to masking noise (aerodynamic wind-noise, tire-road interaction, HVAC) becoming far more audible as they are no longer masked by IC-engines
- Early-stage design assessment of NVH risks is essential



Noise sources in a vehicle

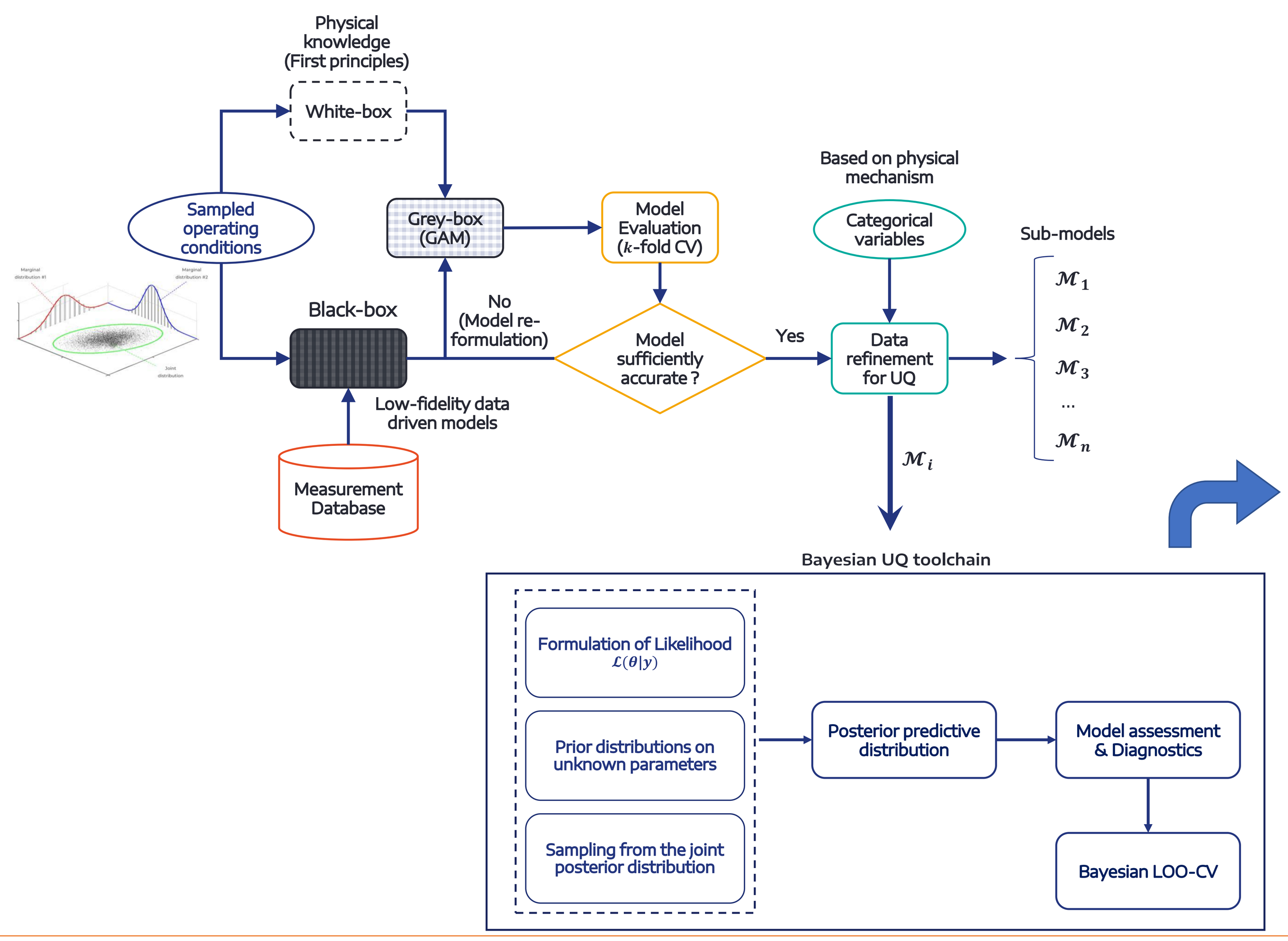
Challenges

- No precise design/ information available about the vehicle during early-stage design ⟹ (time-consuming) physical models no longer useful
- Too many design alternatives ⟹ increased level of uncertainty
- Quantify the highly uncertain behavior due to manufacturing tolerances, operating conditions, and natural variability in measurements [1]
- Need to have fast computing models to evaluate design alternatives



Methodology

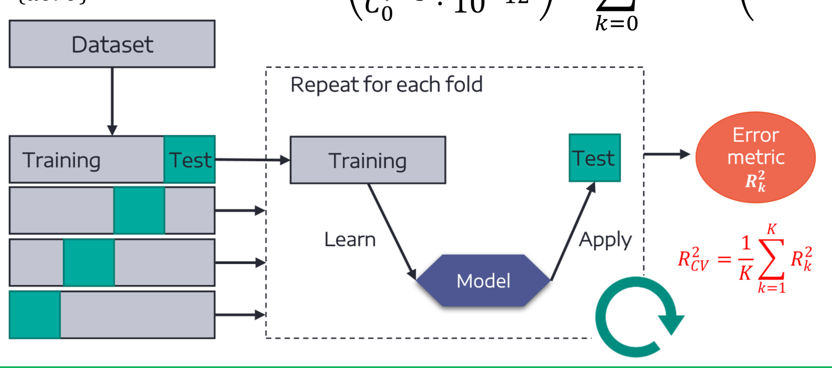
- Develop stochastic metamodels considering:
  - Physical laws ⟹ model parameters with physical sense (interpretable)
  - Available measurement databases
  - The prior knowledge (domain expert) ⟹ Bayesian modelling approach
  - Generalized Additive Models (GAMs)

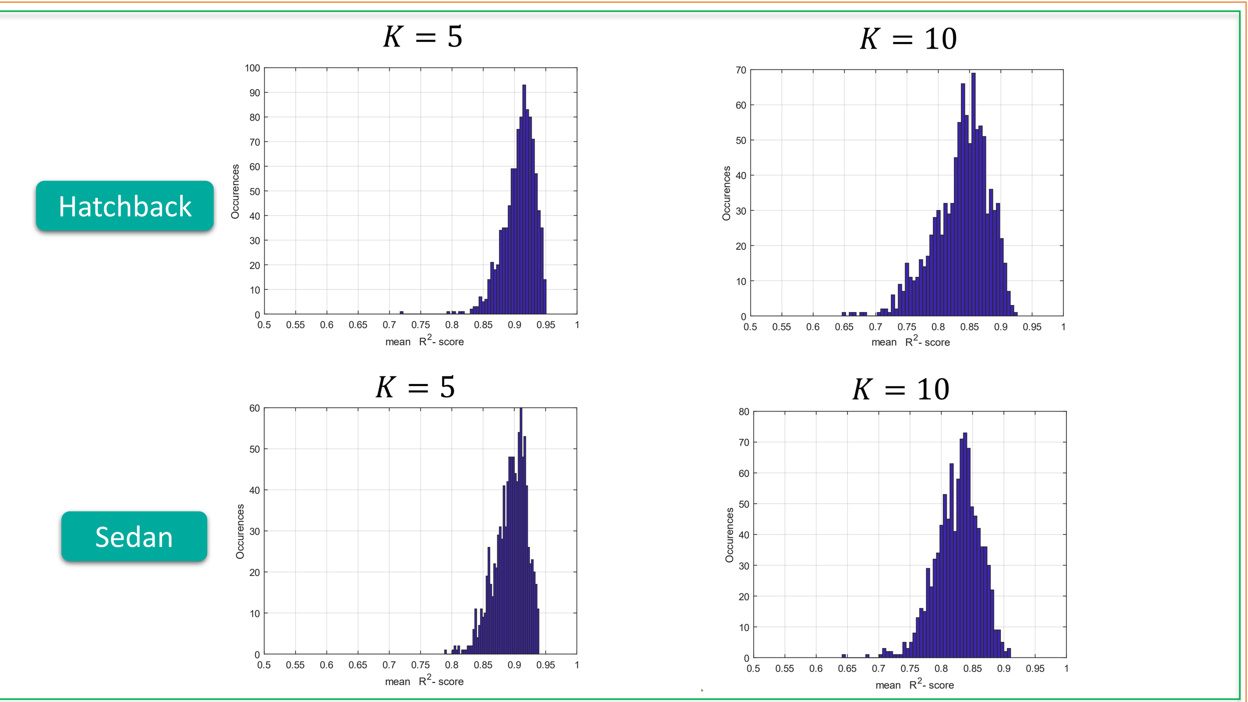


Deterministic models with K-fold Cross Validation

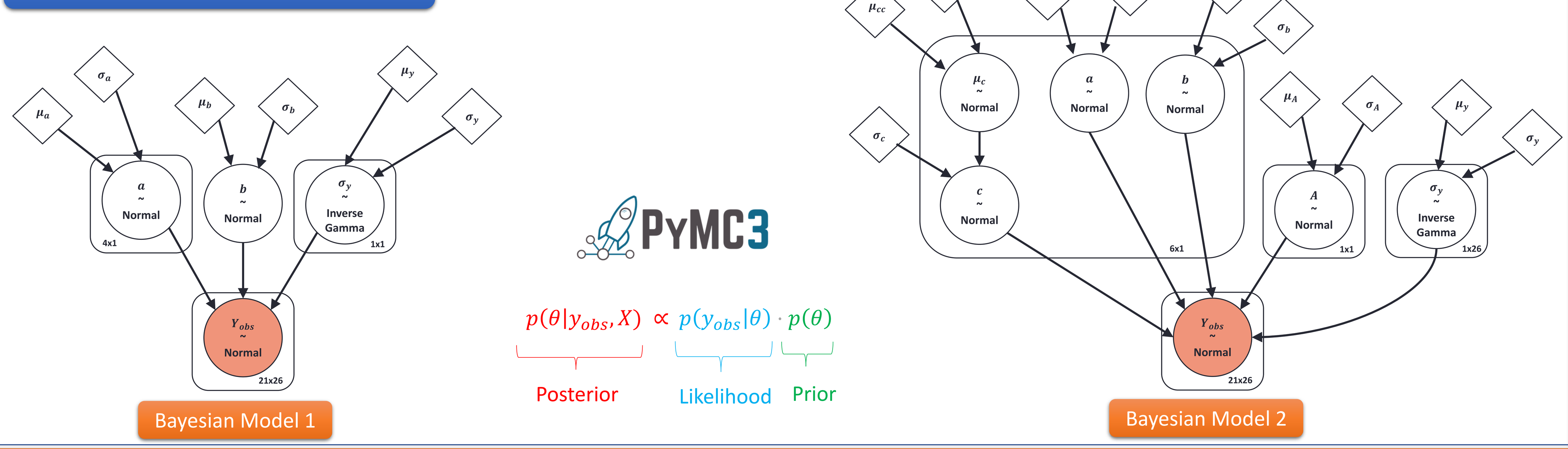
$$L^{[1]}_{\{aero\}}(\boldsymbol{v},\boldsymbol{\omega}) = 10 \cdot \log_{10}\left(\frac{b \cdot \boldsymbol{v}^r}{C_0^{r-3} \cdot 10^{-12}}\right) + \sum_{i=0}^{m} a_i \boldsymbol{\omega}^i$$

$$L^{[2]}_{\{aero\}}(\boldsymbol{v},\boldsymbol{\omega}) = 10 \cdot \log_{10}\left(\frac{b \cdot \boldsymbol{v}^r}{C_0^{r-3} \cdot 10^{-12}}\right) + \sum_{k=0}^{n} a_k \exp\left(-\frac{(\boldsymbol{\omega} - b_k)^2}{c_k^2}\right)$$

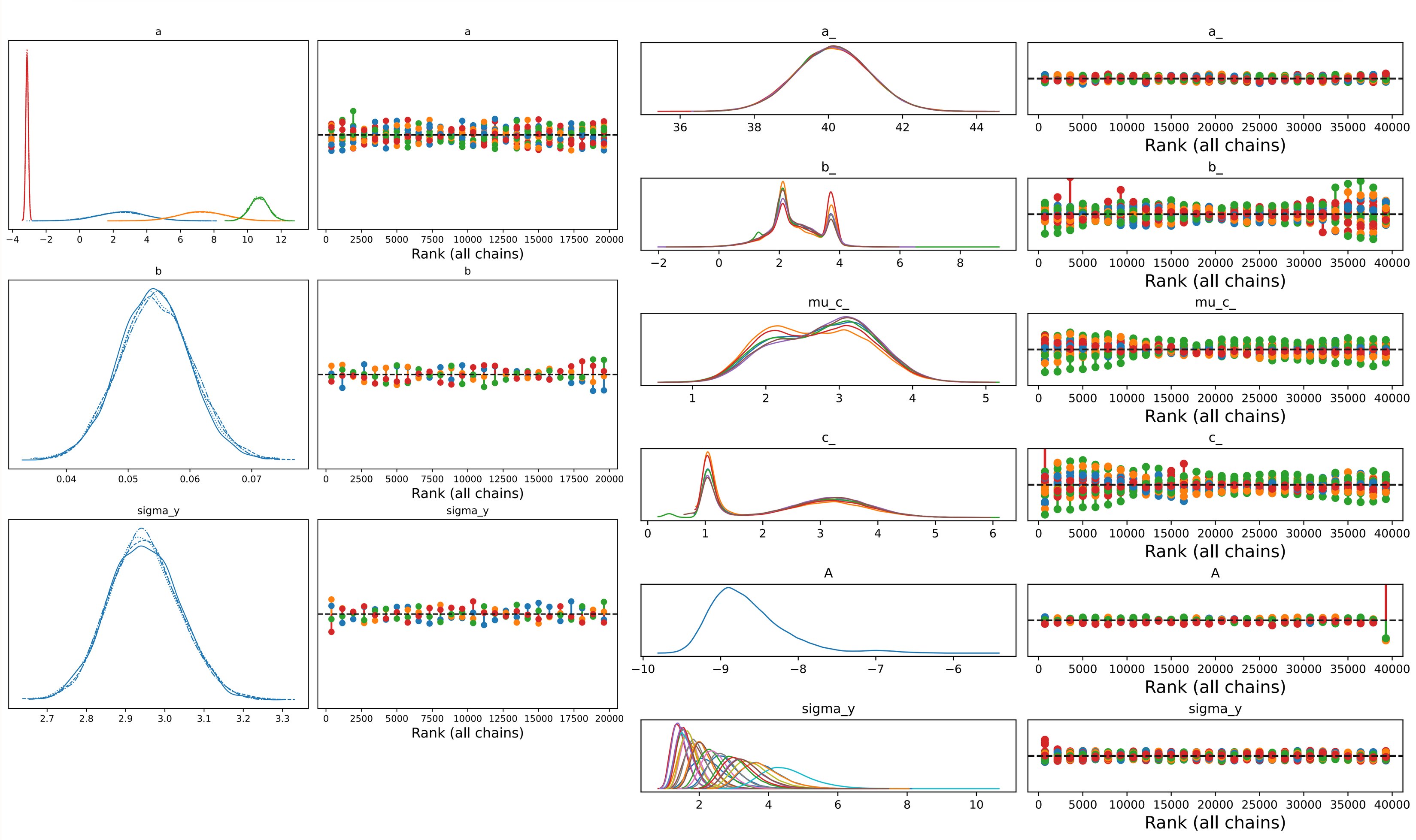




Bayesian Hierarchical Models



Model assessment and MCMC convergence diagnostics



Posterior kernel density estimate plots of parameters and rank plots [2]

Potential Scale Reduction Factor ($\hat{R}$) [2]

Ratio of standard deviation of all samples from all chains to the root mean square of the individual within-chain standard deviations

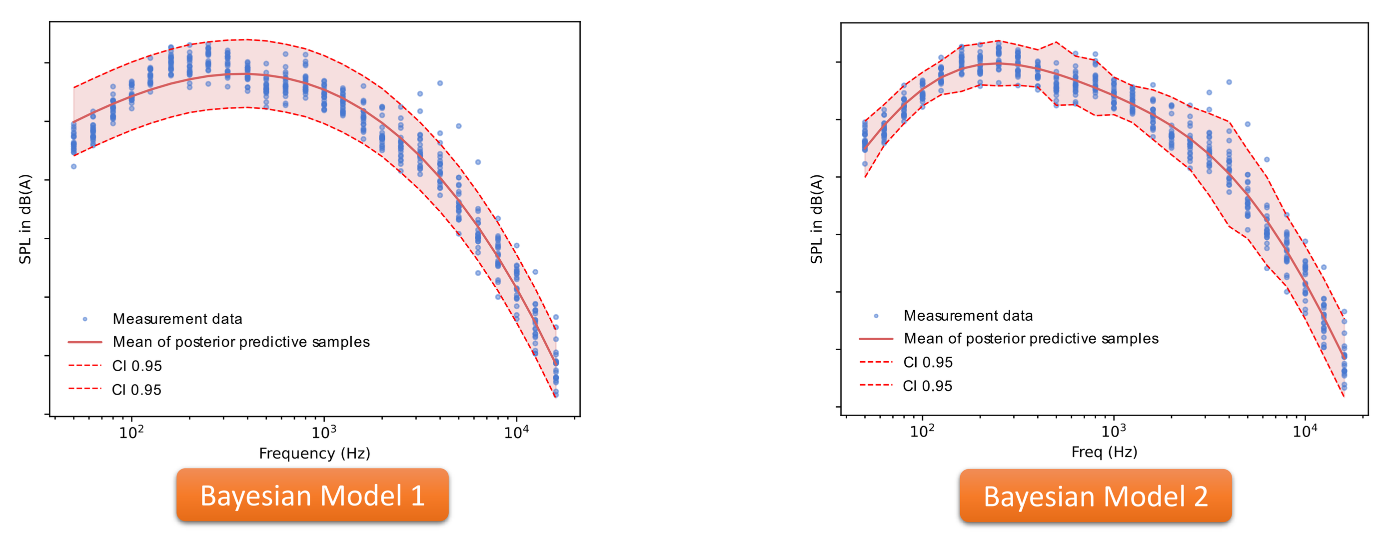
$$\hat{R} = \sqrt{\frac{\widehat{\mathrm{var}}^+(\theta|y)}{W}}$$

$$\widehat{\mathrm{var}}^+(\theta|y) = \frac{N-1}{N}W + \frac{1}{N}B$$

W ⟹ within-chain variances
N ⟹ total number of draws per chain
B ⟹ between-chain variances
$\hat{R}$ should be 1.0 (ideally)

$\hat{R} = 1.0$	Bayesian Model 1
$\hat{R} = 1.06$	Bayesian Model 2

Posterior predictive distribution and Bayesian LOO-CV

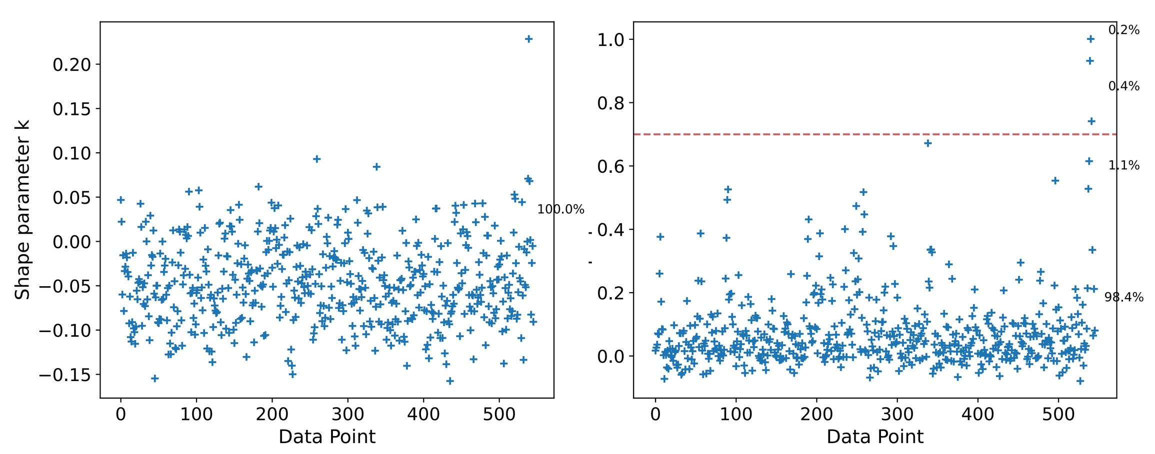


Expected log pointwise predictive density [3]

$$\mathrm{ELPD}_{\mathrm{LOO-CV}} = \sum_{i=1}^{n} \log \int f(y_i|\theta) p(\theta|y_{-i}) d\theta \rightarrow \mathrm{ELPD}_{\mathrm{PSIS-LOO}} = \sum_{i}^{n} \log \sum_{j}^{s} w_i^j f(y_i|\theta) \rightarrow w_i^j = \frac{p(\theta^j|y_{-i})}{p(\theta^j|y)} \propto \frac{1}{p(y_i|\theta^j)}$$

→ Replaced by estimated Pareto distribution

	Bayesian Model 2	Bayesian Model 1
Rank	0	1
LOO	-1259.2	-1367.6
Penalization-LOO	40.7	5.2
Standard error	22.6	24.1



[1] Durand, Jean-François, Christian Soize, and Laurent Gagliardini. "Structural-acoustic modeling of automotive vehicles in presence of uncertainties and experimental identification and validation." The Journal of the Acoustical Society of America 124.3 (2008): 1513-1525

[2] Vehtari, Aki, et al. "Rank-normalization, folding, and localization: An improved $\hat{R}$ for assessing convergence of MCMC (with Discussion)." Bayesian analysis 16.2 (2021): 667-718.

[3] Vehtari, Aki, Andrew Gelman, and Jonah Gabry. "Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC." Statistics and computing 27.5 (2017): 1413-1432.

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