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Two-Layer Jaynesian Routing Model

We address four processing modes $k \in \{\text{Train}, \text{Clean}, \text{EDA}, \text{Release}\}$ for each scene s, based on its observed metadata-driven feature vector

$$\hat{\mathbf{x}}_s = \big[x_s^{\text{India}},\ \text{Imb}_s,\ \text{Div}_s,\ \text{Cloud}_s,\ \text{Month}_s,\ \text{Align}_s\big]^\top,$$

where

- $x_s^{\text{India}} \in \{0,1\}$ flags 1–10 m Indian tiles (**?**),
- $\text{Imb}_s, \text{Div}_s \in [0,1]$ quantify class imbalance and geographic diversity (**?**),
- $\text{Cloud}_s \in [0,100]\%$ is historical cloud cover (**?**),
- $\text{Month}_s \in \{1,\dots,12\}$ is month of acquisition,
- $\text{Align}_s \in [0,1]$ is a coarse alignment-quality score (**?**).

Layer 1: Hyperpriors

We place a symmetric Dirichlet prior on the base-rate vector $\boldsymbol{\pi} = (\pi_1,\dots,\pi_4)$,

$$\boldsymbol{\pi} \sim \text{Dirichlet}(\alpha_0,\dots,\alpha_0), \quad \alpha_0 > 0,$$

and weakly informative, max-entropy priors on the logistic weights $\boldsymbol{\beta}_k \in \mathbb{R}^d$:

$$\boldsymbol{\beta}_k \sim \mathcal{N}(\mathbf{0}, \sigma^2 I), \quad \sigma \sim \text{HalfCauchy}(1),$$

ensuring scale invariance and optimal shrinkage in hierarchical settings (**???**).

Layer 2: Scene-Level Routing

Each scene s draws a latent category T_s via a multinomial logistic (softmax) model:

$$P(T_s = k \mid \hat{\mathbf{x}}_s, \{\boldsymbol{\beta}_\ell\}, \boldsymbol{\pi}) = \pi_k \, \frac{\exp\big(\boldsymbol{\beta}_k^\top \hat{\mathbf{x}}_s\big)}{\sum_{\ell=1}^4 \exp\big(\boldsymbol{\beta}_\ell^\top \hat{\mathbf{x}}_s\big)}.$$

Posterior probabilities $\Pr(T_s = k \mid \hat{\mathbf{x}}_s)$ then trigger:

- $\Pr(T_s = \text{Train})$ high $\Rightarrow$ training-data extraction (**?**),
- $\Pr(T_s = \text{Clean})$ high $\Rightarrow$ dataset cleanup & alignment (**?**),
- $\Pr(T_s = \text{EDA})$ high $\Rightarrow$ imbalance/diversity/cloud/seasonality analysis (**?**),
- otherwise $\Rightarrow$ immediate release.

Stylized Facts Supporting Jaynesian Routing

1. **Metatadata-Only Triage:** Layer 1 operates purely on $\hat{\mathbf{x}}_s$, avoiding pixel loads and saving $\approx$80% of CNN compute (**?**).
2. **Max-Entropy Hyperpriors:** Half-Cauchy priors on σ provide weakly informative, invariant scale parameters that guard against over-confidence in low-data regimes (**??**).
3. **Dirichlet Base-Rates:** Symmetric Dirichlet(α_0) priors encode minimal commitment among modes, ensuring robust discovery of dominant processing needs without bias (**?**).
4. **Principled Uncertainty:** Full Bayesian posterior $\Pr(T_s = k)$ yields credible intervals for routing decisions, aligning SLAs with risk tolerance (**?**).
5. **Softmax Gating:** Multinomial logistic form admits smooth, differentiable routing probabilities, enabling gradient-based calibration of thresholds (**??**).
6. **Information-Geometric Anchoring:** Although not explicit here, the half-Cauchy and Dirichlet priors arise from maximum-entropy principles on the Fisher manifold (**??**), foreshadowing deeper geometry-aware extensions.
7. **Modular Extendability:** New categories or features (e.g. SAR-optical hybrid) integrate seamlessly by extending $\boldsymbol{\beta}$ or $\hat{\mathbf{x}}_s$ without altering core inference (**??**).
8. **Scalability:** The two-layer model admits NUTS or ADVI sampling in PyMC3/NumPyro at $\sim$1 s/scene on CPU, enabling cloud-scale deployment (**?**).