





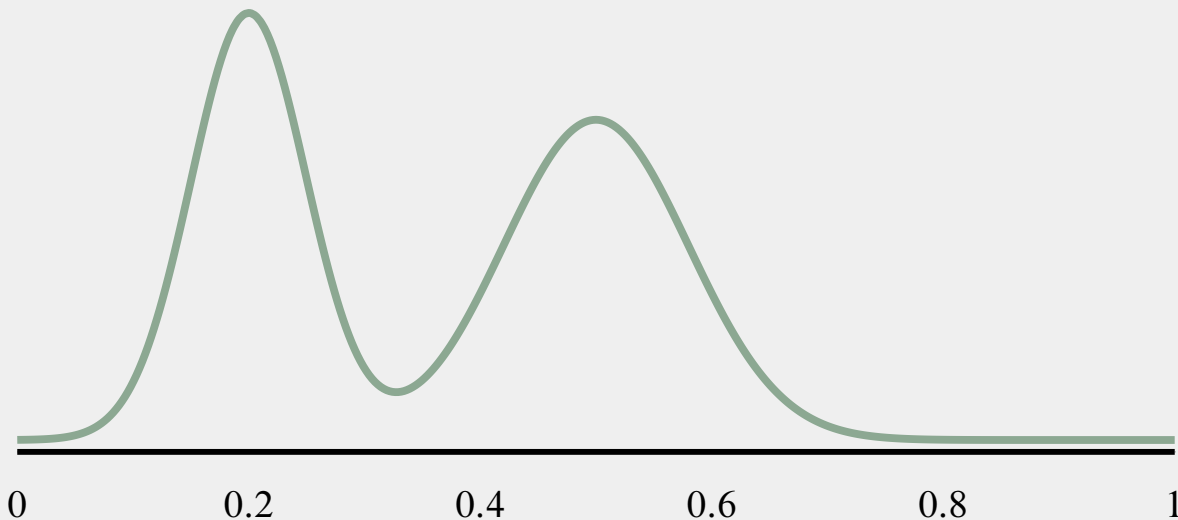
*Physical conjugate(?) prior*





# GAUSSIAN MIXTURE

$$p(\psi \mid \Theta) = \sum_{i=1}^k w_i \mathcal{N}(\psi \mid \mu_i, \sigma_i^2)$$





$\mathcal{N} \Gamma^{-1}$  is a conjugate prior for  $\mathcal{N}$  with unknown mean and variance.



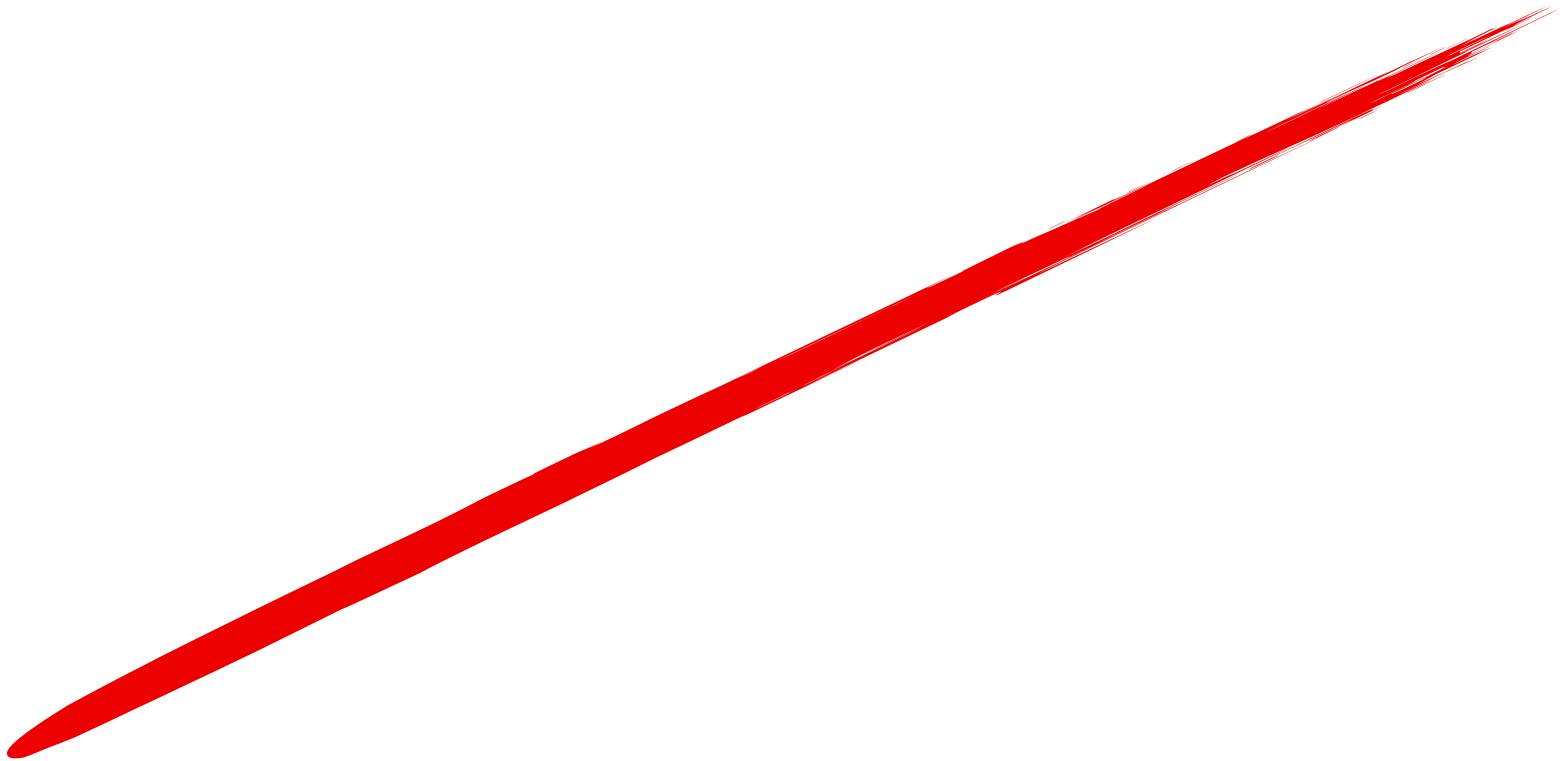


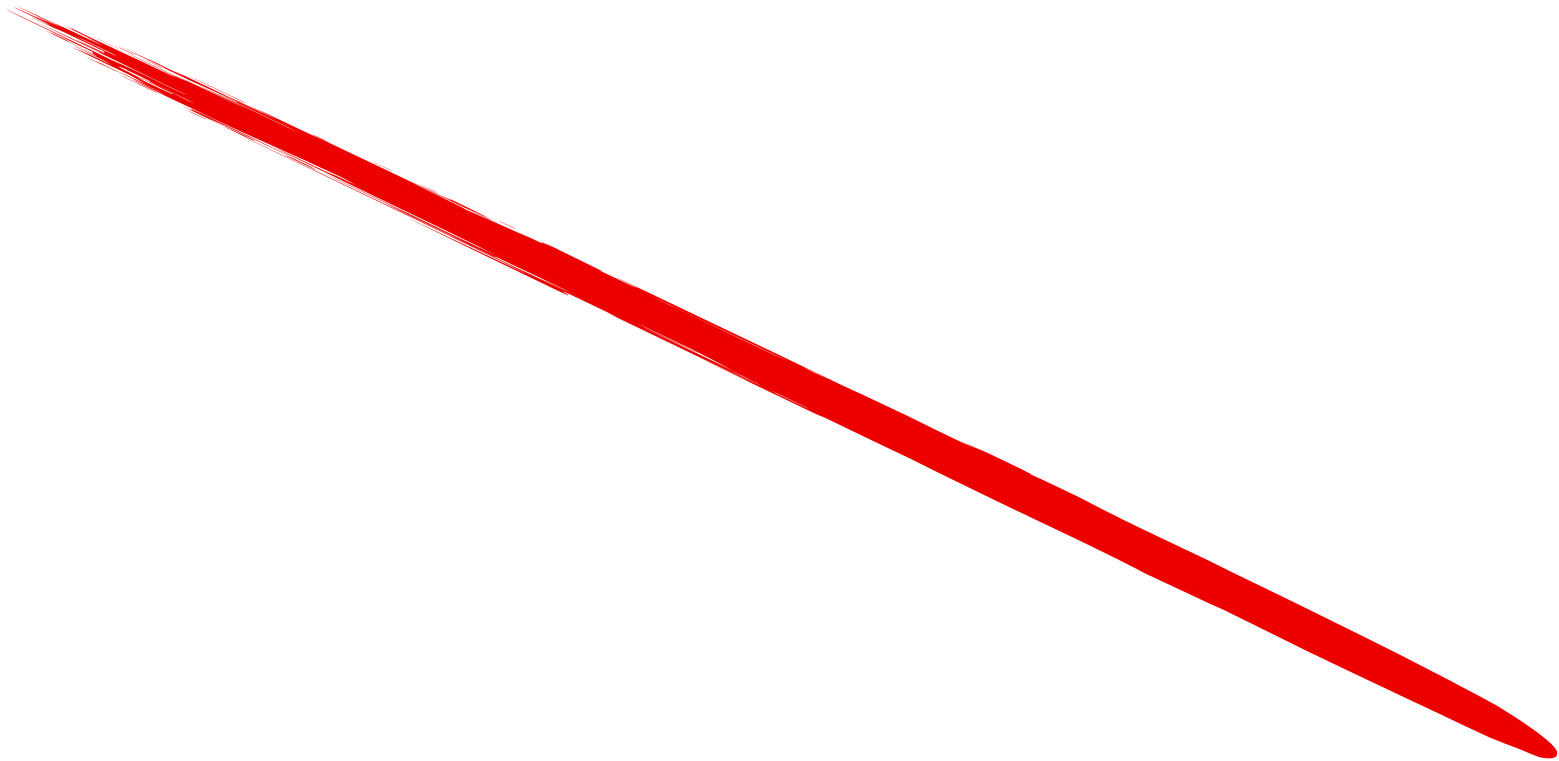
$$p(\Theta \mid \Psi) = \text{Dir}(\boldsymbol{w} \mid \boldsymbol{a}).$$

$$\prod_{i=1}^k \mathcal{N}\Gamma^{-1}\left(\mu_i, \sigma_i^2 \mid \tau_i, \kappa_i, \beta_i, \gamma_i\right)$$

## POSTERIOR (???)

$$p(\Theta \mid \psi, \Psi) = \frac{1}{M} \left[ \sum_{j=1}^k c_j \operatorname{Dir}(\boldsymbol{w} \mid \tilde{\boldsymbol{a}}_j) \cdot \mathcal{N}\Gamma^{-1}(\mu_j, \sigma_j^2 \mid \tilde{\tau}_j, \tilde{\kappa}_j, \tilde{\beta}_j, \tilde{\gamma}_j) \cdot \prod_{i \neq j}^k \mathcal{N}\Gamma^{-1}(\mu_i, \sigma_i^2 \mid \tau_i, \kappa_i, \beta_i, \gamma_i) \right]$$













**nn**

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123























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**MI**







































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Insight: Updating the beliefs imply updating the semantics weights  $w_i$ , which in hand are updated using the previous slide!

**Thm 3.**



functions (measurements) {

Arrayments\_hist=[]\Parameters for the predictive post

for  $\psi$  in  $\text{measurements}$  do {

$$\text{prior} \equiv p(\theta | \psi, \Psi)$$

~~\Calatrusticient nonentsthe postrior~~



$$\text{Array moments} = E[g_j(\theta)] = M_{g_j}(\theta) (\text{posterior})$$

moments\_hist.push(moments)

$$approx\_post = p(nonevents | \theta) \backslash \backslash Approximate posterior as DNI$$



$$p_{\text{prior}}(\psi | E[\text{merits\_hist}]) \backslash \backslash \text{Gaussian mixture}$$

return approx, predinv\_pos

# Physical conjugate(?) prior

## DIRICHLET NORMAL-INVERSE-GAMMA

$$p(\Theta | \Psi) = \text{Dir}(\mathbf{w} | \mathbf{a}).$$

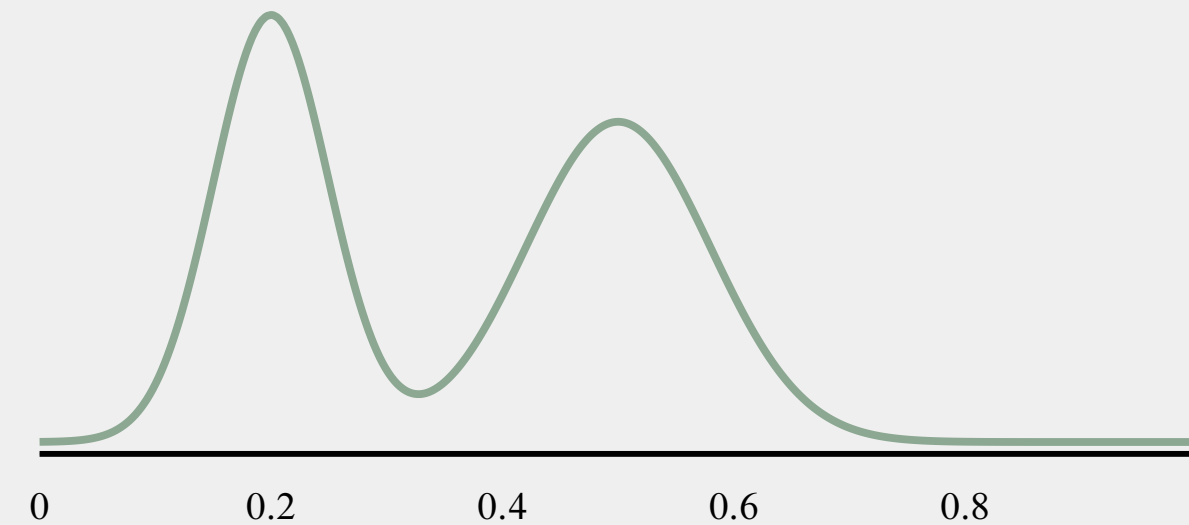
$$\prod_{i=1}^k \mathcal{N}\Gamma^{-1}(\mu_i, \sigma_i^2 | \tau_i, \kappa_i, \beta_i, \gamma_i)$$

$\mathcal{N}\Gamma^{-1}$  is a conjugate prior for  $\mathcal{N}$  with unknown mean and variance.

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## GAUSSIAN MIXTURE

$$p(\psi | \Theta) = \sum_{i=1}^k w_i \mathcal{N}(\psi | \mu_i, \sigma_i^2)$$



=

## POSTERIOR (???)

$$p(\Theta | \psi, \Psi) = \frac{1}{M} \left[ \sum_{j=1}^k c_j \text{Dir}(\mathbf{w} | \tilde{\mathbf{a}}_j) \cdot \mathcal{N}\Gamma^{-1}(\mu_j, \sigma_j^2 | \tilde{\tau}_j, \tilde{\kappa}_j, \tilde{\beta}_j, \tilde{\gamma}_j) \cdot \prod_{i \neq j}^k \mathcal{N}\Gamma^{-1}(\mu_i, \sigma_i^2 | \tau_i, \kappa_i, \beta_i, \gamma_i) \right]$$

## Thm 3.

```

func moments(measurements) {
  Array moments_hist = [] \ \ Parameters for the predictive post.
  for  $\psi$  in measurements do {
    posterior = p( $\theta$  |  $\psi, \Psi$ )
    \ \ Calculate sufficient moments of the posterior
    Array moments = E[gj( $\theta$ )] = Mgj( $\theta$ )(posterior)
    moments_hist.push(moments)
    approx_post = p(moments |  $\theta$ ) \ \ Approximate posterior as DNIG
  }
  predictive_posterior = p( $\psi$  | E[moments_hist]) \ \ Gaussian mixture
  return approx_post, predictive_posterior
}

```

**Insight:** Updating the beliefs imply updating the semantics weights  $w_i$ , which in hand are updated using the previous slide!

# *The Big Picture*