

# A Review of Variation Bayesian Gaussian Mixture Model

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# Introduction

## The disadvantage of K-Means

- Hard to decide the number of clusters
- **Poor** performance on **unbalanced dataset**

## Variational Bayesian Expectation Maximization(VBEM)

- Only need to choose the **maximum number of clusters, self-adapt to the best**
- **Better** performance on unbalanced dataset

# EM In General Form

In naive EM, the goal is to **maximize likelihood**  $\mathcal{L}(Y; \theta)$

$$\arg \max_{\theta} \mathcal{L}(Y; \theta) = \arg \max_{\theta} \log \int_Z p(Y, Z; \theta) dZ$$

where  $Y$  is observing data,  $Z$  is latent variable,  $\theta$  is the parameter

With ELBO, we can derive the **lower bound**  $\mathcal{L}(\theta, \gamma)$  of likelihood  $\mathcal{L}(Y; \theta)$

$$\begin{aligned} \mathcal{L}(\theta, \gamma) &= \mathbb{E}_q[\log(\frac{p(Y, Z; \theta)}{q(Z; \gamma)})] \\ &= \int_Z q(Z; \gamma) \log \frac{p(Y, Z; \theta)}{q(Z; \gamma)} dZ \\ &= \log p(Y; \theta) - KL[q(Z; \gamma) || p(Z|Y)] \\ &= \mathcal{L}(Y; \theta) - KL[q(Z; \gamma) || p(Z|Y)] \end{aligned}$$

## EM In General Form

Thus

$$\mathcal{L}(\theta, \gamma) = \mathcal{L}(Y; \theta) - KL[q(Z; \gamma) || p(Z|Y)]$$

Since the KL-divergence always  $\geq 0$

$$\arg \max_{\theta} \mathcal{L}(Y; \theta) \geq \arg \max_{\theta, \gamma} \mathcal{L}(\theta, \gamma)$$

With KKT and Lagrange multiplier, the optimization problem can be written as

$$\arg \max_{\theta, \gamma} \mathcal{L}(\theta, \gamma) = \arg \max_{\theta, \gamma} \mathcal{L}(Y; \theta) - \beta KL[q(Z; \gamma) || p(Z|Y)]$$

# EM In General Form

## Pseudo Code

Iterate until  $\theta$  converge

- E Step at k-th iteration

$$\gamma_{k+1} = \arg \max_{\gamma_k} \mathcal{L}(\theta_k, \gamma_k)$$

- M Step at k-th iteration

$$\theta_{k+1} = \arg \max_{\theta_k} \mathcal{L}(\theta_k, \gamma_{k+1})$$

# Variational Bayesian Expectation Maximization(VBEM)

In VBEM, we consider an **additional prior**  $p(\theta; \lambda)$

$$\begin{aligned}\log p(Y) &= \log \int_{Z, \theta} p(Y, Z, \theta; \lambda) dZ d\theta \\ &= \log \mathbb{E}_{q(Z; \phi^Z) q(\theta; \phi^\theta)} \left[ \frac{p(Y, Z | \theta) p(\theta; \lambda)}{q(Z; \phi^Z) q(\theta; \phi^\theta)} \right] \\ &\geq \mathbb{E}_{q(Z; \phi^Z) q(\theta; \phi^\theta)} \left[ \log \frac{p(Y, Z | \theta) p(\theta; \lambda)}{q(Z; \phi^Z) q(\theta; \phi^\theta)} \right]\end{aligned}$$

Thus, we get the ELBO  $\mathcal{L}(\phi^Z, \phi^\theta)$

$$\mathcal{L}(\phi^Z, \phi^\theta) = \mathbb{E}_{q(Z; \phi^Z) q(\theta; \phi^\theta)} \left[ \log \frac{p(Y, Z | \theta) p(\theta; \lambda)}{q(Z; \phi^Z) q(\theta; \phi^\theta)} \right]$$

# Variational Bayesian Expectation Maximization(VBEM)

According to the general form of EM

$$\arg \max_{\gamma_k} \mathcal{L}(\theta_k, \gamma_k)$$

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We can derive

$$\frac{d}{d\phi^Z} \mathcal{L}(\phi^Z, \phi^\theta) = 0, \quad \ln q(Z; \phi^Z) \propto \mathbb{E}_{q(\theta; \phi^\theta)} [\log p(Y, Z, \theta)]$$

$$\frac{d}{d\phi^\theta} \mathcal{L}(\phi^Z, \phi^\theta) = 0, \quad \ln q(\theta; \phi^\theta) \propto \mathbb{E}_{q(Z; \phi^Z)} [\log p(Y, Z, \theta)]$$

# Variational Bayesian Expectation Maximization(VBEM)

## Pseudo Code

Iterate until  $\mathcal{L}(\phi^Z, \phi^\theta)$  converge

- E Step: Update the variational distribution on  $Z$

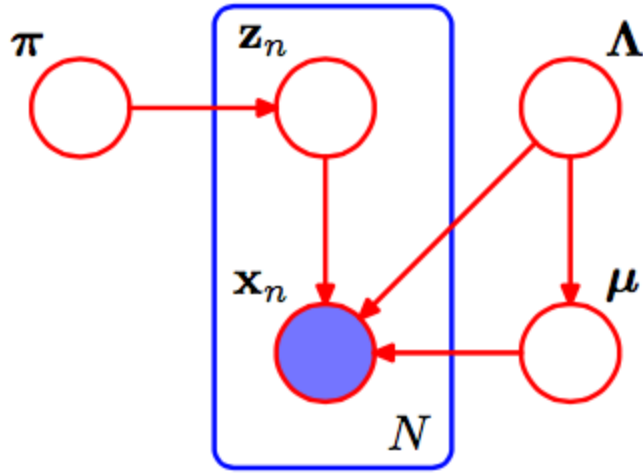
$$q(Z; \phi^Z) \propto e^{(\mathbb{E}_{q(\theta; \phi^\theta)} [\log p(Y, Z, \theta)])}$$

- M Step: Update the variational distribution on  $\theta$

$$q(\theta; \phi^\theta) \propto e^{(\mathbb{E}_{q(Z; \phi^Z)} [\log p(Y, Z, \theta)])}$$



# Variational Bayesian Gaussian Mixture Model(VB-GMM)



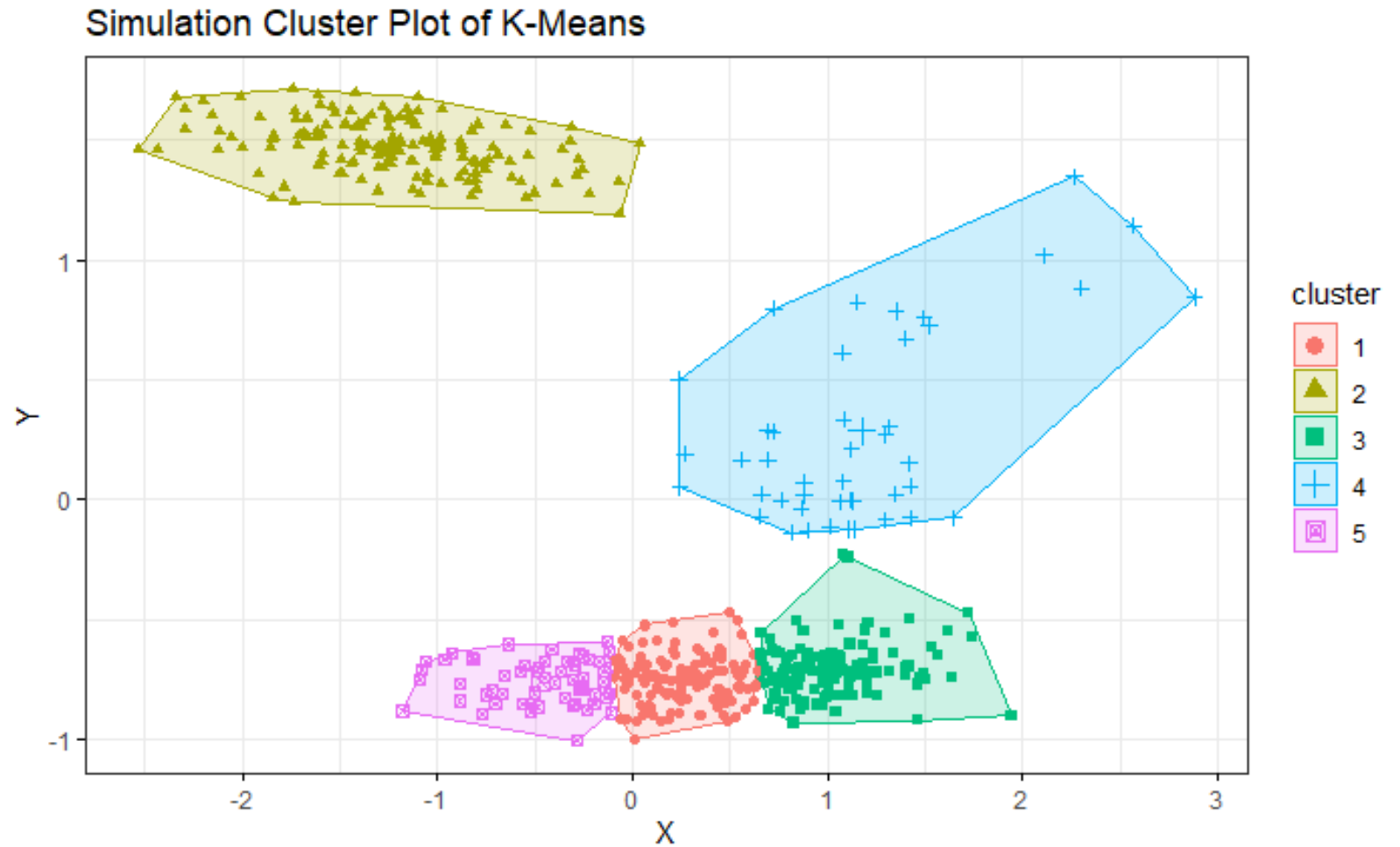
$$p(X, Z, \pi, \mu, \Lambda) = p(X|Z, \pi, \mu, \Lambda)p(Z|\pi)p(\pi)p(\mu|\Lambda)p(\Lambda)$$

- $p(X|Z, \pi, \mu, \Lambda)$  denotes the **Gaussian Mixture Model**
- $p(Z|\pi)$  denotes the **Latent Variables**
- $p(\pi)$  denotes the **Dirichlet Prior Distribution Over The Latent Variables  $Z$**
- $p(\mu|\Lambda)p(\Lambda)$  denotes the **Gaussian-Wishart Prior Distribution Over GMM  $X$**

**Ignore The Complex Derivation**

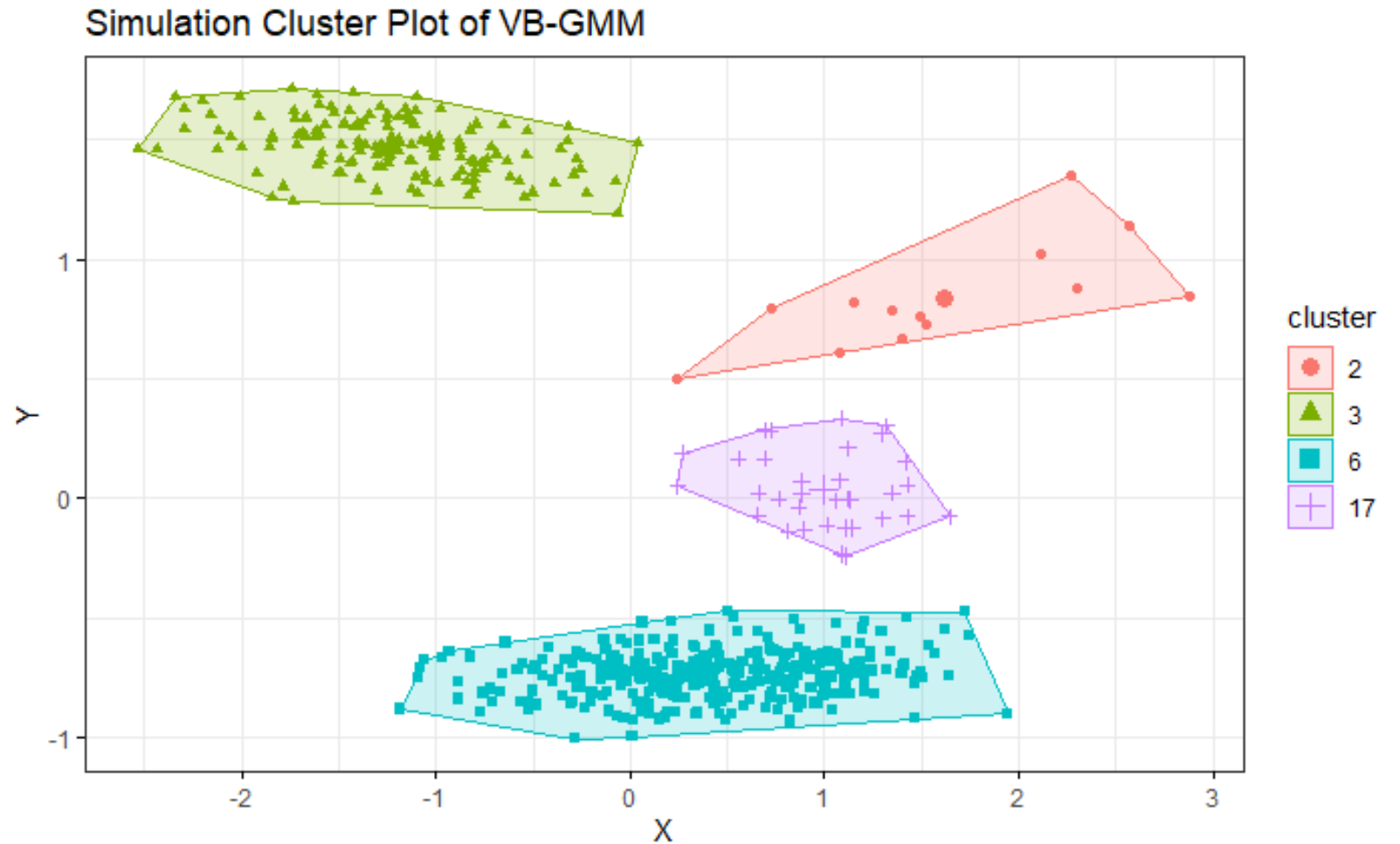
# K-means Cluster Plot

Fit On 5 Modal  
Simulation  
Dataset  
Generated by  
GMM



# VB-GMM Cluster Plot

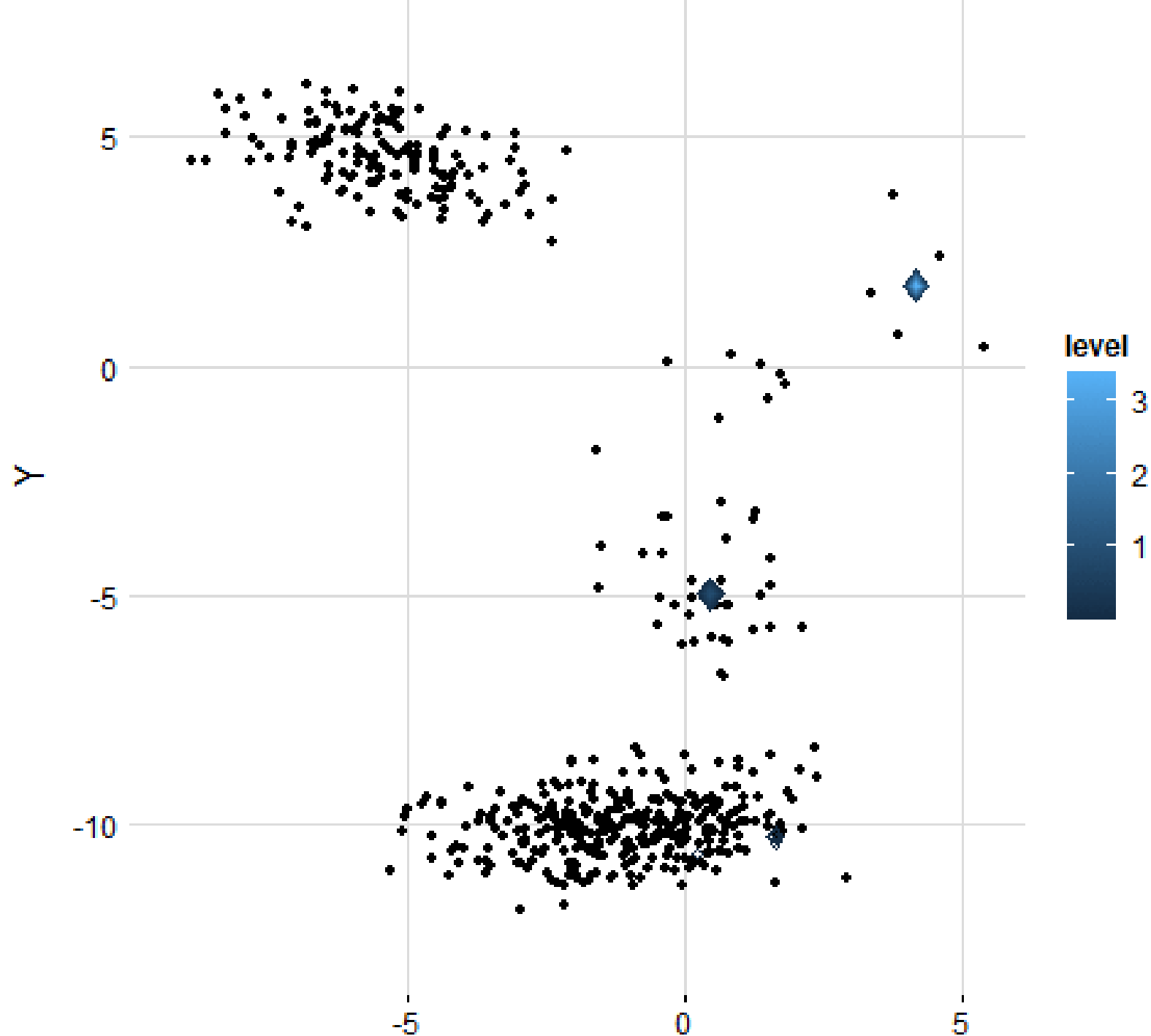
Fit On 5 Modal  
Simulation  
Dataset  
Generated by  
GMM



# VB-GMM Contour Plot Animation

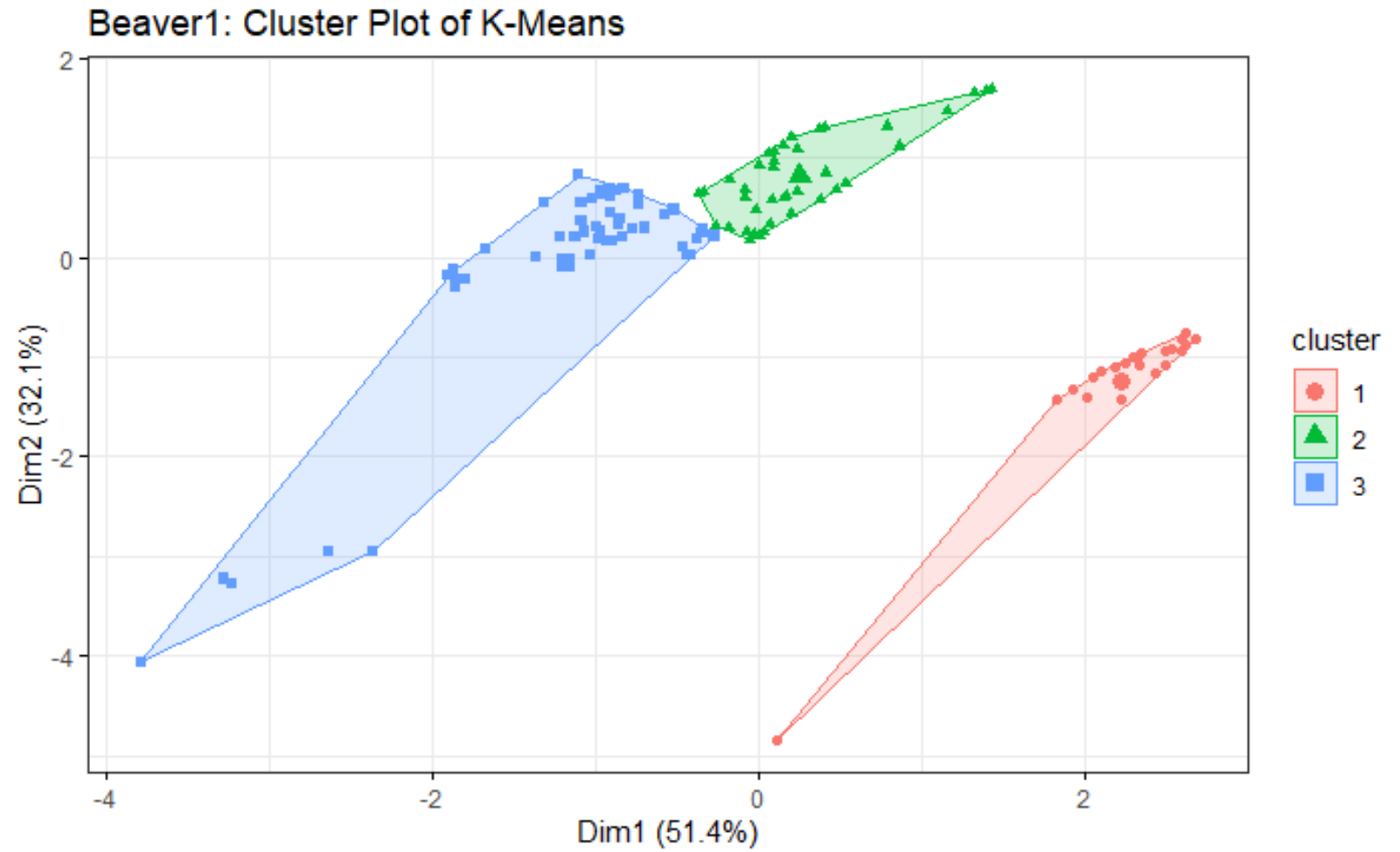
Fit On 5 Modal  
Simulation  
dataset

[Link](#)



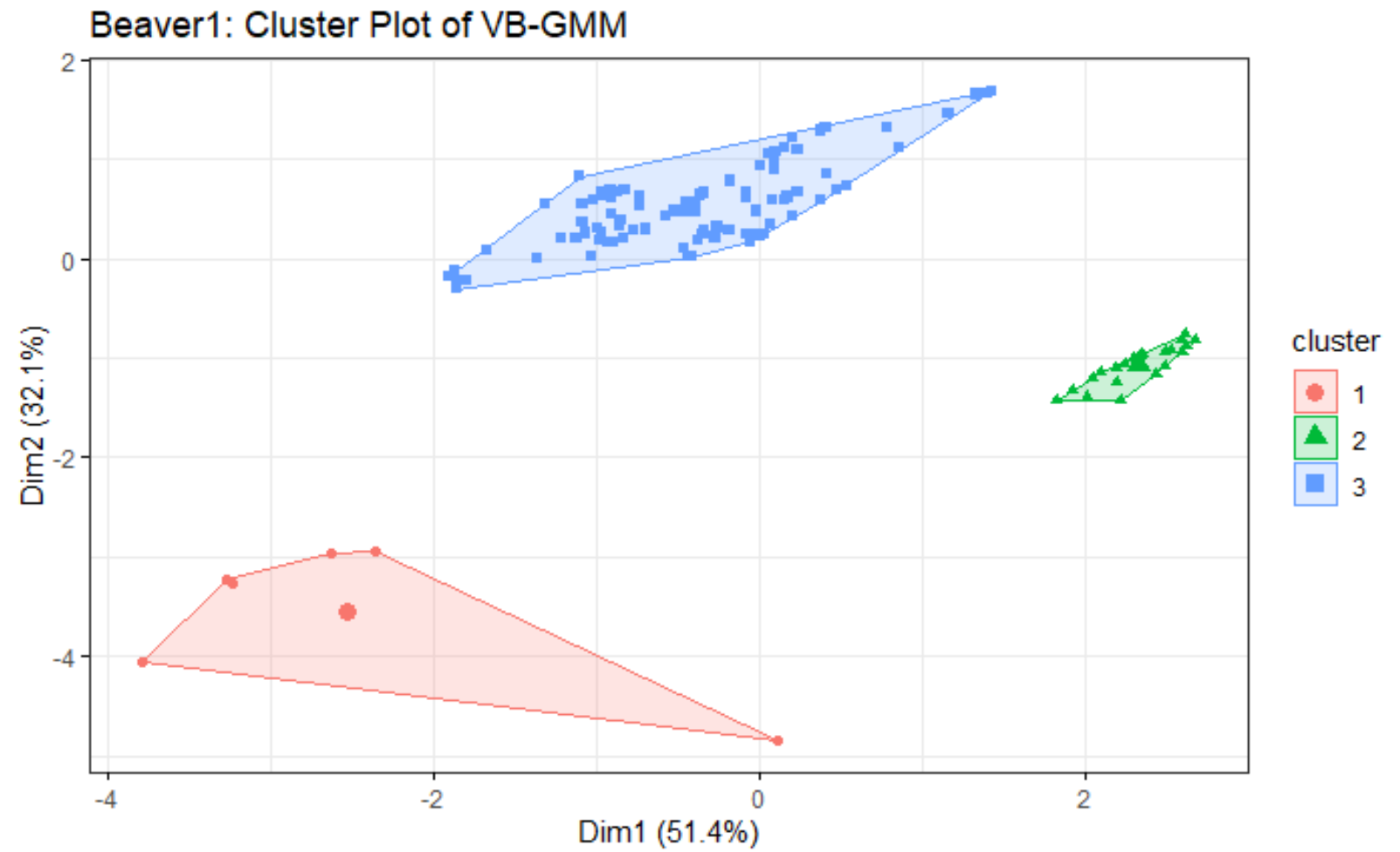
# K-means Cluster Plot

Fit On Beaver1  
dataset



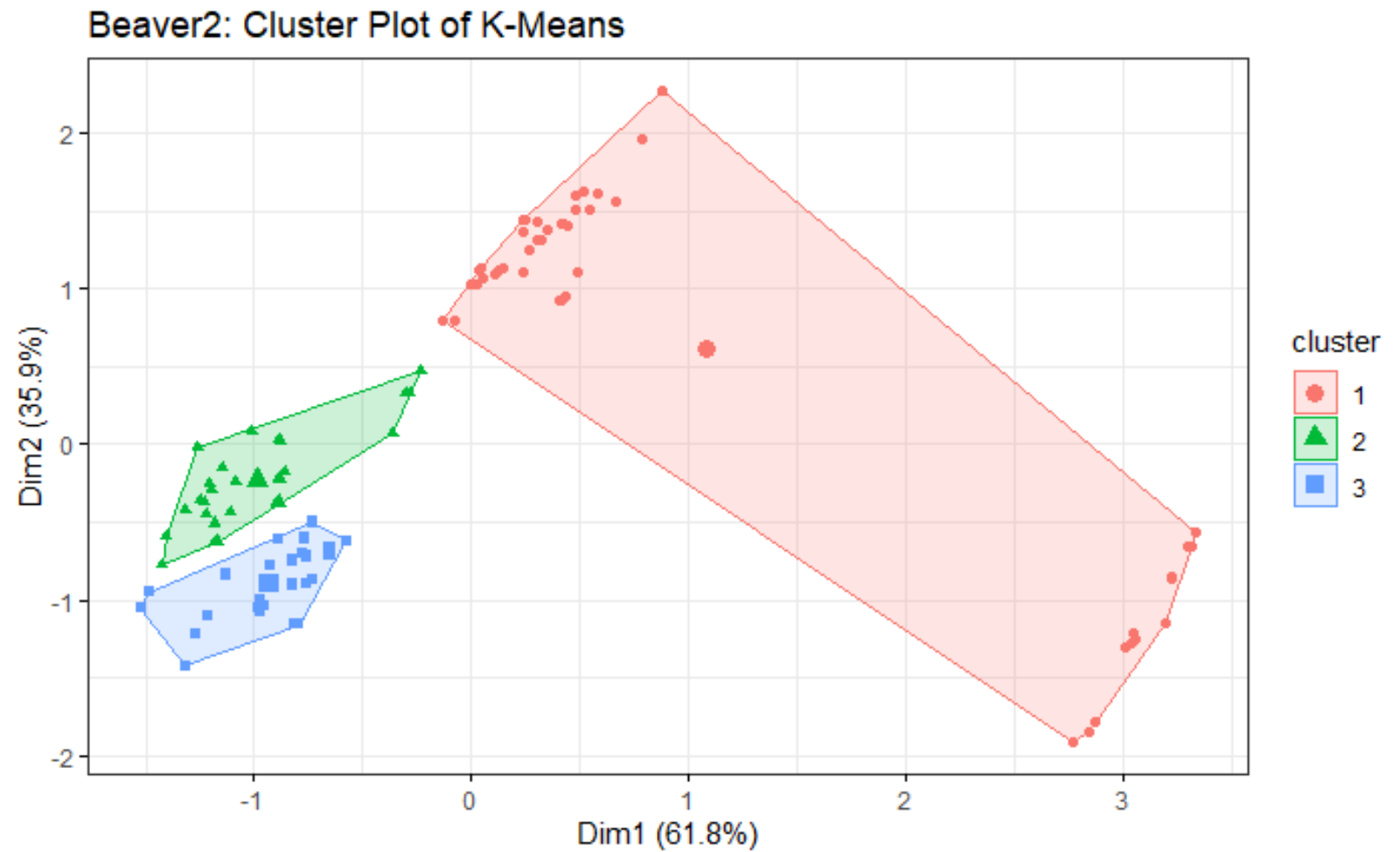
# VB-GMM Cluster Plot

Fit On Beaver1  
dataset



# K-means Cluster Plot

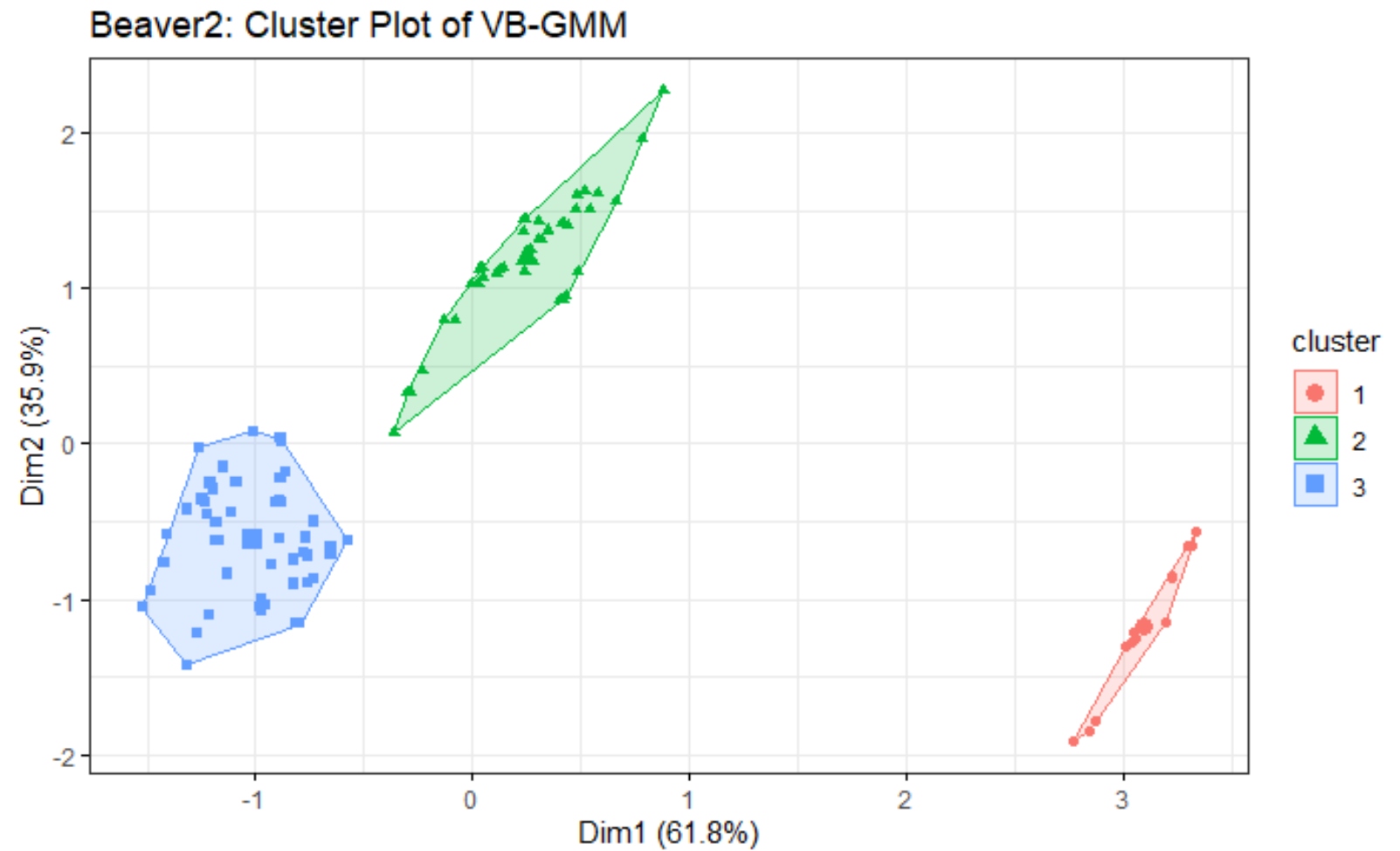
Fit On Beaver2  
dataset





# VB-GMM Cluster Plot

Fit On Beaver2  
dataset



**Thanks For Listening**