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Exp - 3

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Aim: To design and implement a Gaussian Mixture Models for outcome prediction

Theory:

Gaussian Mixture Models (GMM) are powerful probabilistic models used for clustering and density estimation tasks.

Components of GMM:

1) Mixture Components
GMM assumes that the observed data is generated by mixture of several Gaussian distributors, each known as component or cluster

2) Probability Density Function (PDF)
The Pdf of a GMM is defined as a linear combination of K Gaussian distributions

$$P(x) = \sum_{k=1}^{K} \pi_k \mathcal{N}(x \mid \mu_k, \Sigma_k)$$

3) Parameters
The parameters of a GMM include the mean vectors (μ_k) covariance metrices (Σ_k) and mixing coefficients (π_k) for each component k.

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Expectation Maximization (EM) Algorithm:

1) Expectation Step

The algorithm computes the probability that each data point belongs to each component given the current parameter estimates. This step involves calculating the responsible of each component for each data point using Bayes' theorem

2) Maximization step

The algorithm updates the parameters (μ_K, Σ_K, π_K) to maximize the likelihood of the observed data.

3) Convergence

The EM algorithm iterates between the E step and M step until convergence.

Conclusion:

The experiment highlights the effectiveness, scalability, interpretability of Gaussian Mixture Models in outcome prediction tasks. By leveraging GMM unlocked valuable insights from data and make accurate predictions that drive business value and enhance decision making processes

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