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WHITING SCHOOL
of ENGINEERING

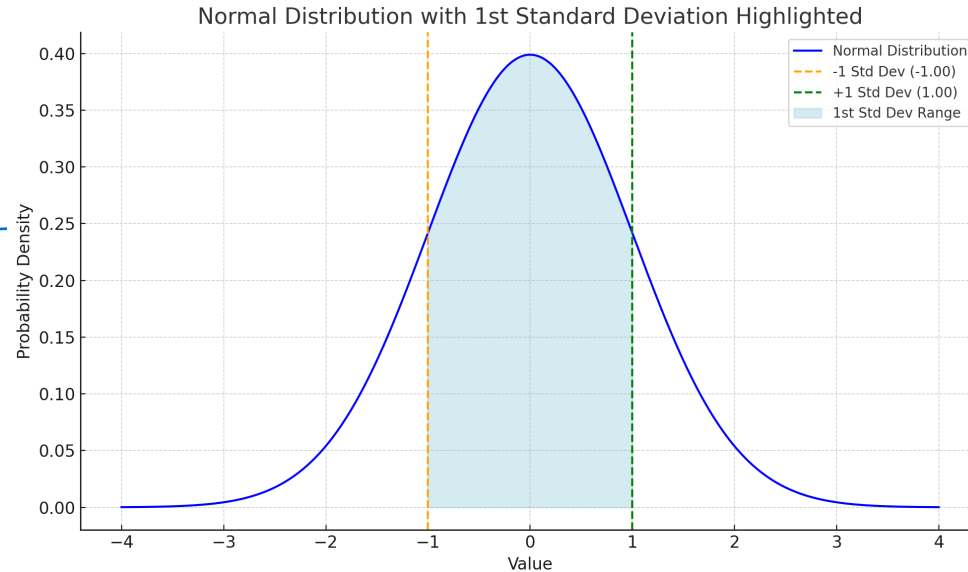
Algorithms for Data Science

Statistical Algorithms: Expectation Maximization (EM)

EM: Purpose

Even if data values of \mathcal{X}_n are unknown, the distribution $f(x_n | p)$ can be used to determine an estimate for p .

Probability of
the data point
in the
subpopulation.



EM: Algorithm

- Given an initial estimate of $p_k^{(0)}, m_k^{(0)}, \sigma_k^{(0)}$, EM iterates until convergence to a local maximum of the likelihood function:

- E-Step:**

$$p^i(k | n) = \frac{p_k^{(i)} g(x_n; m_k^{(i)}, \sigma_k^{(i)})}{\sum_{k=1}^K p_k^{(i)} g(x_n; m_k^{(i)}, \sigma_k^{(i)})}$$

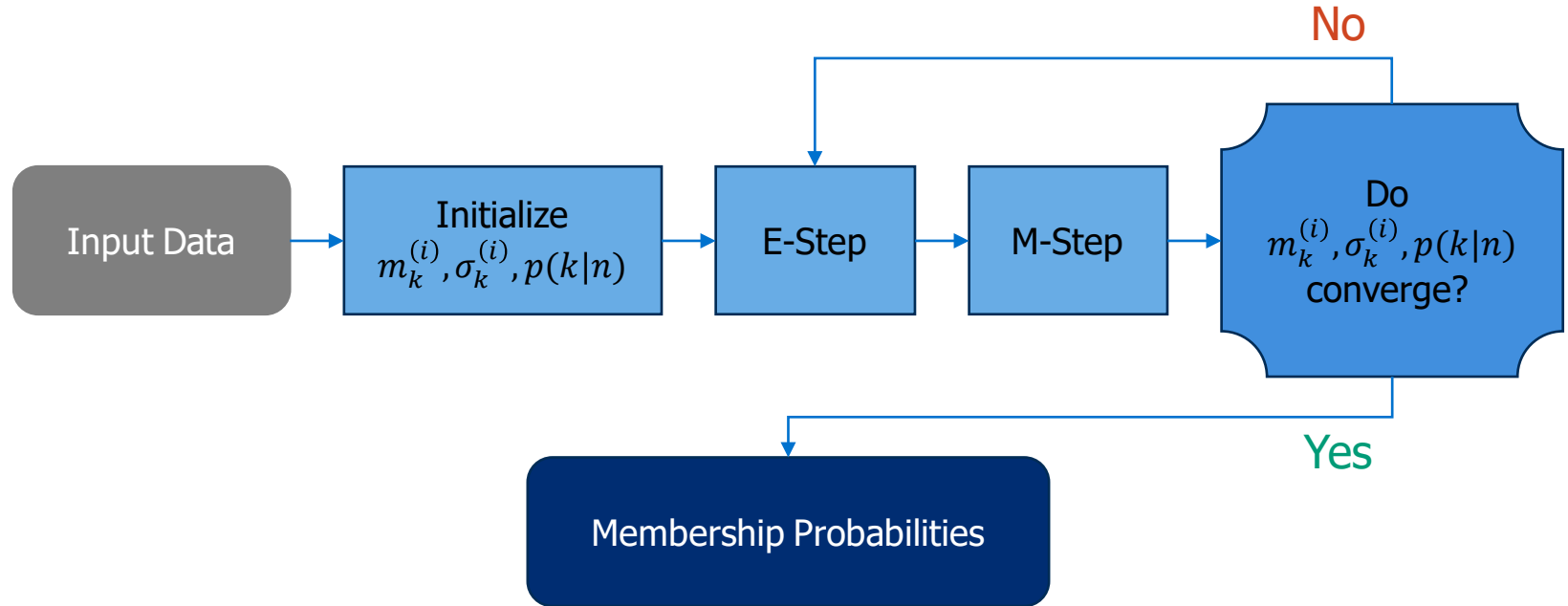
- M-Step:**

$$m_k^{(i+1)} = \frac{\sum_{n=1}^N p^i(k | n) x_n}{\sum_{i=1}^N p^i(k | n)}$$

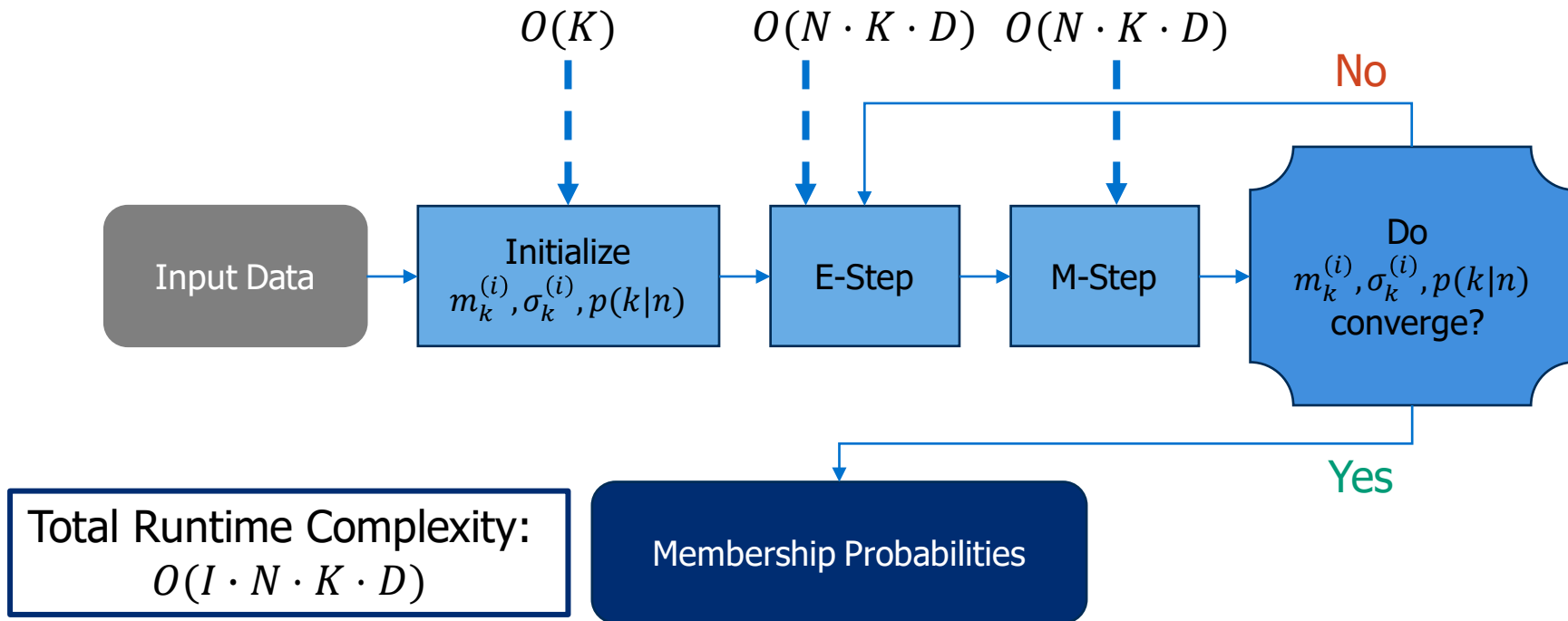
$$\sigma_k^{(i+1)} = \sqrt{\frac{1}{D} \frac{\sum_{n=1}^N p^i(k | n) \|x_n - m_k^{(i+1)}\|^2}{\sum_{n=1}^N p^i(k | n)}}$$

$$p_k^{(i+1)} = \frac{1}{N} \sum_{n=1}^N p^i(k | n)$$

EM: Algorithm



EM: Runtime Analysis



EM: Correctness

Theorem: The EM algorithm converges to a local maximum of the likelihood function for the observed data.

1. E-Step:

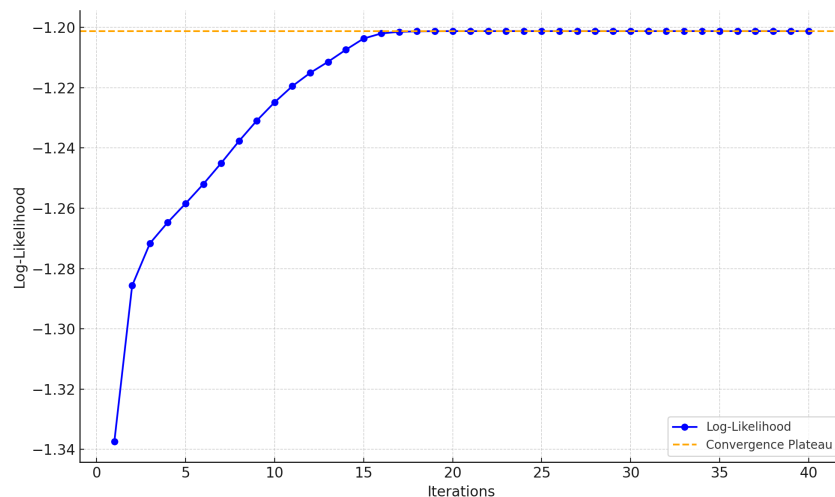
- Computes the expected value of the complete data log-likelihood.
- Ensures the expected likelihood does not decrease.

2. M-Step:

- Updates parameters by maximizing the expected log-likelihood.
- Guarantees monotonic increase in likelihood.

3. Monotonic Convergence:

- Likelihood increases or remains constant at each iteration.
- Stops at a local maximum when convergence criteria are met.



EM: Applications

Gaussian Mixture Models

Clustering data into a predefined number of clusters, where each cluster is modeled as a Gaussian distribution.

Hidden Markov Models

Sequence analysis where states are hidden but observations are available.

Missing Data Imputation

Filling in incomplete datasets by estimating missing values iteratively.



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