JOHNS HOPKINS
WHITING SCHOOL
of ENGINEERING

Algorithms for Data Science

Unsupervised Learning: Evaluation Metrics

Evaluation Metrics in Unsupervised Learning

Provide insights into algorithm quality based on properties like compactness, separation, and anomaly detection effectiveness.

Internal Metrics

Evaluate clustering quality based on intrinsic data properties.

Detection Metrics

Quantify model performance in identifying anomalies.

Internal Metrics

Measuring clustering quality based on intrinsic properties of the data.

- **Silhouette Score:**

$$\text{Silhouette} = \frac{b - a}{\max(a, b)}$$

  - Where:
    - a: Mean intra-cluster distance.
    - b: Mean nearest-cluster distance.
    - Higher absolute values indicate better clustering.

Internal Metrics

Measuring clustering quality based on intrinsic properties of the data.

- **Davies-Bouldin Index:**

$$DB = \frac{1}{k}\sum_{i=1}^{k}\max_{j \neq i}\frac{s_i + s_j}{d_{i,j}}$$

  - Where:
    - s_i: Average dispersion of cluster i.
    - $d_{i,j}$,: Distance between cluster centroids i and j.
    - Lower values indicate better clustering.

Internal Metrics

Measuring clustering quality based on intrinsic properties of the data.

- **Inertia:**

$$WCSS = \sum_{i=1}^{N} \min_{j} \left\| x_i - c_j \right\|^2$$

  - Where:
    - x_i: The i-th observation.
    - c_j: The centroid of the j-th cluster.
    - Lower values indicate better clustering but biased by choice of k.

Anomaly Detection Metrics

Quantify performance in identifying anomalies within data.

- **Precision:**

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

Minimizing FPs

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

Minimizing FNs

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

Balances
Precision & Recall

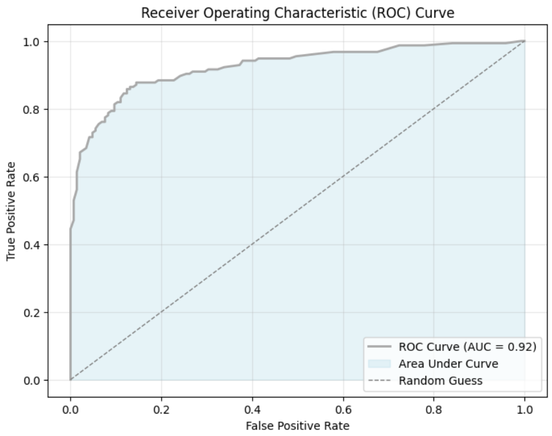
Area Under the ROC Curve (AUC-ROC)

ROC Curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various decision thresholds.

AUC quantifies the overall performance of the model by measuring the area under the ROC curve.

Interpretation:

- $AUC = 1.0$ -> Perfect Model
- $AUC = 0.5$ -> Random Guessing



Key Takeaways

1. **Unsupervised Learning:**
   - ✓ Focused on uncovering hidden patterns in unlabeled data with applications in clustering, anomaly detection, and dimensionality reduction.
2. **Clustering Methods:**
   - ✓ Algorithms like K-Means and DBSCAN group data based on similarity and provide a foundation for anomaly detection and exploratory analysis.
3. **Anomaly Detection:**
   - ✓ Techniques like One-Class SVM identify outliers by learning boundaries that separate normal data from anomalies.
4. **Evaluation Metrics:**
   - ✓ Internal metrics assess clustering quality, while metrics like AUC-ROC and F1-Score evaluate anomaly detection models.

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