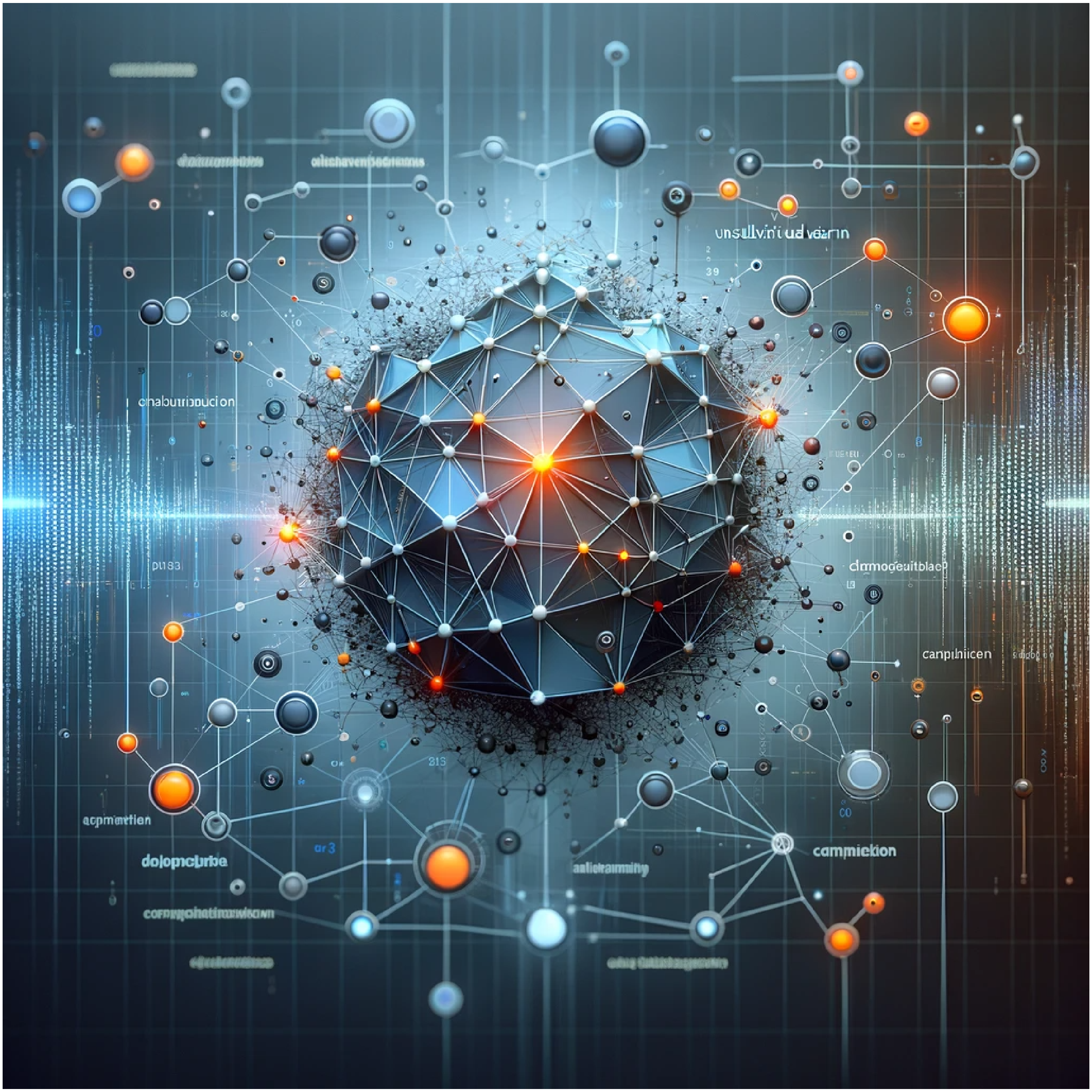


Enhanced Precision in Anomaly Detection

An Optimized k-Means Clustering Approach

- Huining Huang

Introduction

Anomaly Detection: Methods & Applications

Why It Matters:

- Identifies errors, fraud, and new patterns in data.

Key Methodologies:

1. **Statistical Methods:** Spot deviations using statistical models.
2. **Machine Learning-Based Methods:** Supervised and unsupervised learning for complex data.
3. **Proximity-Based Methods:** Use distance metrics like DBSCAN for outlier detection.

Applications Across Domains:

- Finance, Industry, Cybersecurity.

Considerations:

- Balance between method complexity and data attributes.

Sources: [11-16]

Literature Review

Clustering-Based Anomaly Detection: Overview & Methods

Significance in Sectors:

- Cybersecurity, Healthcare, Finance

Primary Clustering Methods:

- **Density-Based:** DBSCAN
- **Distribution-Based:** GMMs
- **Centroid-Based:** K-means
- **Connectivity-Based:** Hierarchical Clustering

Method Highlights:

- DBSCAN: Detects sparse points in dense regions [1].
- GMMs: Labels anomalies based on probabilistic distributions [2].
- K-means: Outliers far from centroids [3].
- Hierarchical: Small, detached cluster points [4].

Sources: [1-4]

Clustering-Based Anomaly Detection: Analysis & Future

Comparative Analysis:

- Density vs. Distribution: Flexibility vs. Probabilistic Models [1][2].
- Centroid vs. Connectivity: Scalability vs. Detailed Structuring [3][4].

Challenges & Practical Applications:

- Scalability and Parameter Sensitivity.
- Interpretability in Complex Models [2][4].
- Utilized in Fraud Detection, Network Security [5][7].

Research Gaps & Future Directions:

- Real-time data stream integration and interpretability [10].
- Deep learning precision, e.g., Reverse Distillation [9].

Sources: [1-10]

K-means Based Anomaly Detection Algorithm: Overview

Anomaly Score:

- Anomaly score $A(x)$ defined by distance to cluster center, standard deviation, and density factor.

$$A(x) = \frac{D(x, C_i)}{\sigma(C_i) + \epsilon} \times \rho(C_i)$$

Algorithm Steps:

1. **Data Preprocessing:** Standardization and imputation.
2. **Determine Optimal Clusters k:** Elbow method/silhouette score.
3. **Centroid Initialization:** Advanced methods (e.g., k-means++).
4. **Clustering Execution:** Using distance metric M.
5. **Compute Cluster Properties:** Standard deviation $\sigma(C_i)$ and density factor $\rho(C_i)$.

Algorithm continues on next slide...

K-means Based Anomaly Detection: Execution & Post-Processing

Algorithm Steps Continued:

6. **Anomaly Set Initiation:** Initialize an empty set for anomalies.
7. **Anomaly Scoring & Detection:**

- Assign points to nearest cluster.
- Calculate anomaly score.
- Establish dynamic threshold T.
- Append outliers to anomaly set A.

8. **Post-Processing:** Domain-specific filters or secondary model application.

Threshold Strategy:

- Dynamic threshold $T = \alpha \times \text{median}\{A(D)\}$ or percentile-based.

Post-Processing:

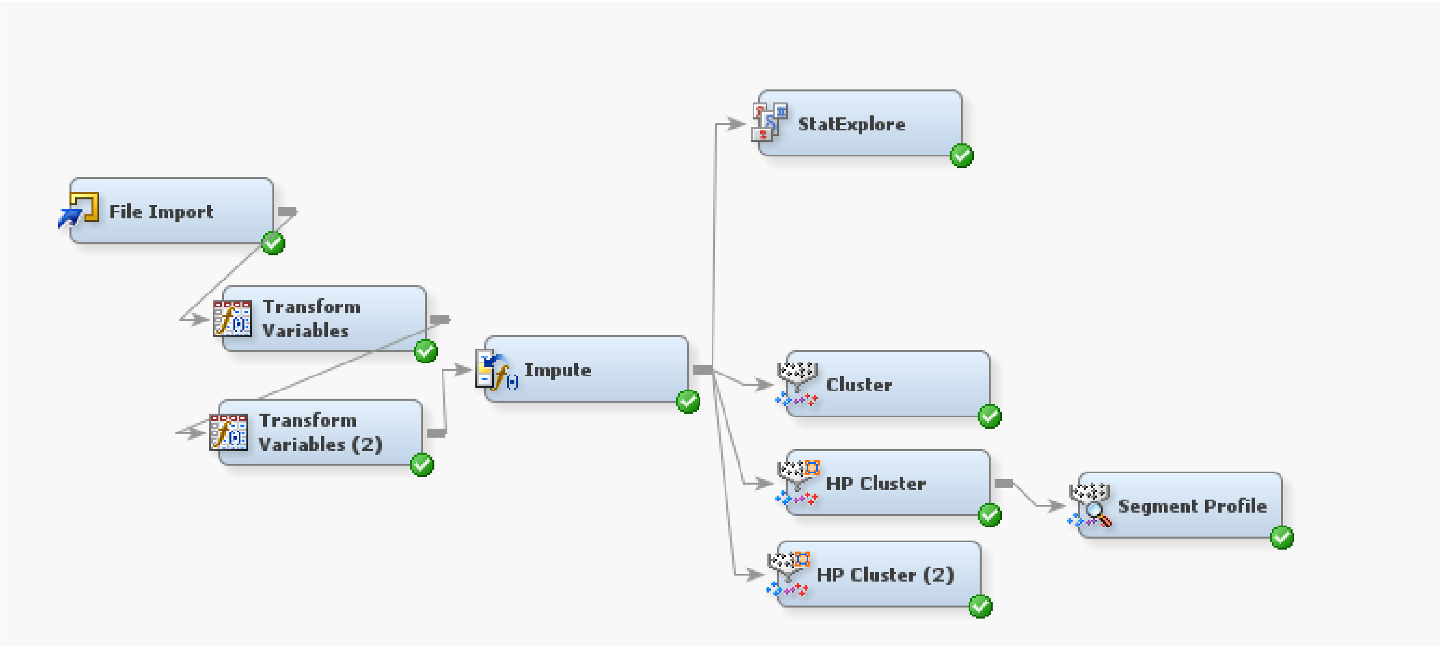
- Enhances detection precision by mitigating false positives.

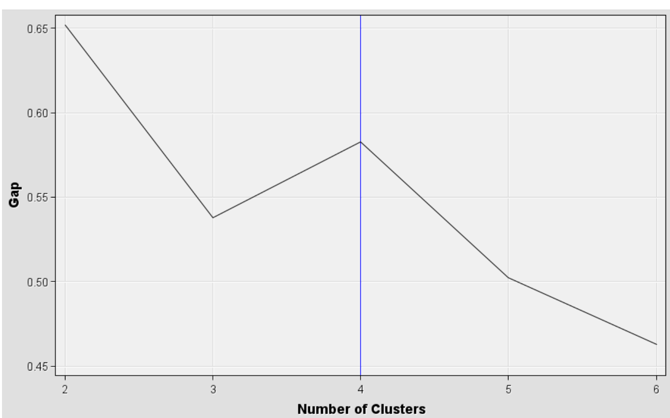
Final Output:

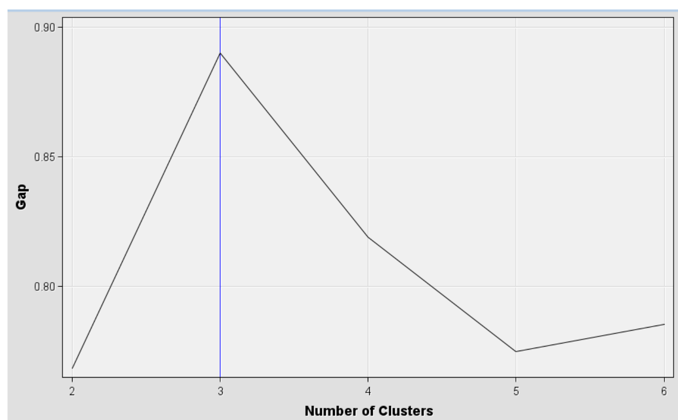
- Refined set of anomalies A based on defined criteria.

End of Algorithm Presentation

Algorithmic Implementation and Cluster Analysis







Anomaly Detection Methodology

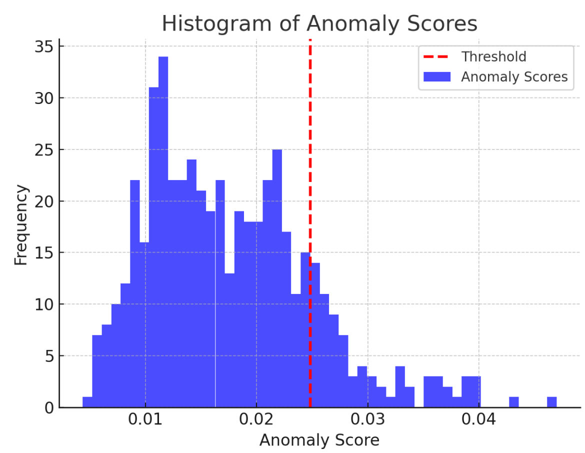
K-Means Anomaly Detection Framework

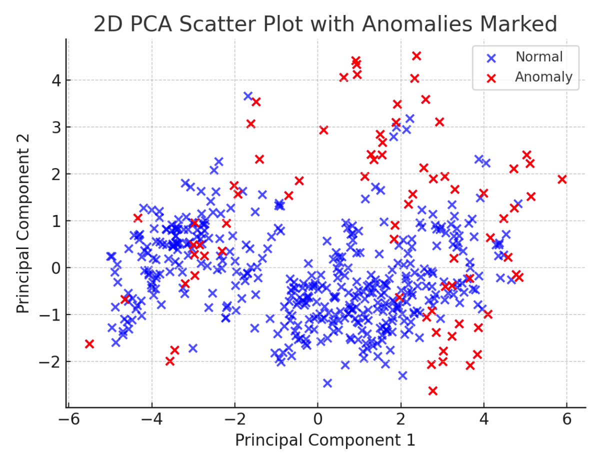
- Initial clustering with SAS Enterprise Miner
- Transition to Python for enhanced anomaly detection
- Anomaly score based on distance to centroid, cluster density, and deviation
- Dynamic thresholding to identify outliers
- 76 anomalies detected from the dataset

$A(x) = \frac{D(x,C_i)}{\sigma(C_i)+\epsilon} \times \rho(C_i)$, where $D(x, C_i)$

Insights from Anomaly Visualization

- Dimensionality reduction using PCA for visualization
- Histogram of anomaly scores with threshold line
- Scatter plot: normal data vs. anomalies
- Anomaly distribution table by cluster
- Higher anomaly rates suggest potential subgroups





Cluster ID	Anomaly Count	Total Count	Anomaly Rate
1	49	141	34.75%
2	22	174	12.64%
3	5	191	2.62%

Analysis of Anomalies in the Boston Housing Dataset

- **Attribute Contributions:**
  - High NOX levels in anomalies.
  - Unusual PTRATIO and RM indicating rarity.
  - Anomalies with lower TAX rates.
- **Practical Implications:**
  - Anomalies with higher MEDV values.
  - Varied CRIM rates among anomalies.
- **Algorithm Limitations:**
  - Sensitivity to attribute extremes.
  - Potential for false identifications.
- **Future Research:**
  - Importance of contextual analysis.
  - Need for integrated valuation approaches.

References/Questions

- Citing relevant literature and studies referenced in the paper.
- Open floor for questions and further discussion.