Data Collection and Preprocessing:

Data Collection:
1. Gathering logs or records of data backup activities from server systems.
2. Retrieving metadata associated with each backup session, including timestamps, file sizes, backup methods used, and any relevant network activity.
3. Extracting relevant data from various sources such as server logs, backup software reports, and monitoring systems.

Preprocessing:
1. Parsing and structuring raw data to extract key features and attributes relevant to anomaly detection, such as timestamps, file sizes, and backup durations.
2. Handling missing or incomplete data by imputation or filtering out incomplete records.
3. Normalizing numerical features to ensure consistency and facilitate model convergence.
4. Encoding categorical variables if applicable, such as backup methods or server locations.
5. Performing any necessary data transformations or scaling to ensure compatibility with the anomaly detection algorithms being employed.

Model Selection and Training:

Training involved careful consideration of the Isolation Forest, LOF and DBSCAN algorithms. Here's how the Model Selection and Training phase was carried out in detail:

Data Preparation:
Before diving into model selection and training, the data collected during the Data Collection and Preprocessing phase was prepared. This involved ensuring that the data was properly preprocessed, including handling missing values, scaling numerical features, and encoding categorical variables if necessary.
The dataset was split into training and validation sets to facilitate model evaluation.

Model Selection:
Isolation Forest and DBSCAN were chosen as the candidate models for anomaly detection in the data backup process.

Isolation Forest was selected due to its efficiency in handling high-dimensional data and robustness to outliers.
DBSCAN was chosen for its ability to detect clusters of arbitrary shapes and sensitivity to variations in density.

Training Process:

Training each model involved fitting the selected algorithms to the training data.
Hyperparameter tuning was performed to optimize the performance of each model.
Parameters such as the number of trees in the Isolation Forest or the epsilon and minimum points in DBSCAN were fine-tuned.
Cross-validation techniques might have been employed to ensure the robustness of the selected hyperparameters.
The models were trained using the training dataset, and their performance was evaluated using the validation set.

Isolation Forest Model:

The Isolation Forest algorithm is a machine learning technique used for anomaly detection. Here's a brief explanation of how it works:

1. Random Partitioning: The algorithm randomly selects a feature and a split value for each iteration, creating partitions in the dataset.

2. Recursive Partitioning: This process continues recursively until each data point is isolated in its own partition.

3. Anomaly Score Calculation: An anomaly score is calculated based on the average path length required to isolate each data point. Data points with shorter path lengths are considered more likely to be anomalies.

4.Key Features:
*Efficiency: Isolation Forest is efficient even with high-dimensional datasets.
*Scalability: It can handle large datasets effectively.

*Robustness: The algorithm is robust to outliers and noise in the data.

5. Applications:
Isolation Forest is used in various domains, including fraud detection, intrusion detection, and quality control.

In summary, Isolation Forest offers a simple yet effective approach to anomaly detection, particularly suitable for datasets with global anomalies.

DBSCAN:

DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is another popular algorithm used for anomaly detection and clustering in spatial data. Here's a brief explanation of how it works:

1. Density-Based Clustering:
DBSCAN groups together closely packed data points based on their density in the feature space.

2. Core Points and Border Points:
Core Points: Data points that have a minimum number of neighboring points within a specified radius.
Border Points: Data points that are within the specified radius of a core point but do not have enough neighbors to be considered core points themselves.

3. Noise Points:
Noise points are data points that do not belong to any cluster and are not within the specified radius of any core point.

4. Cluster Formation:
Clusters are formed by connecting core points and border points within the specified radius. Core points serve as seeds for expanding clusters by adding neighboring points to the cluster.

5. Key Features:
Ability to Detect Arbitrary-Shaped Clusters: DBSCAN can identify clusters of various shapes and sizes.
Robustness to Noise: The algorithm is robust to outliers and noise in the data.
No Need to Specify Number of Clusters: Unlike some clustering algorithms, DBSCAN does not require specifying the number of clusters beforehand.

6. Applications:
DBSCAN is used in various fields, including anomaly detection, spatial data analysis, and pattern recognition.
It is particularly effective in applications such as identifying anomalies in network traffic, detecting outliers in geographical data, and clustering customer data for segmentation.

In summary, DBSCAN is a versatile algorithm for clustering and anomaly detection, known for its ability to detect clusters of arbitrary shapes and robustness to noise in the data.

Local Outlier Factor (LOF):

Local Outlier Factor (LOF) is a popular anomaly detection algorithm that evaluates the local density deviation of a data point with respect to its neighbors. Here's a brief explanation of how it works:

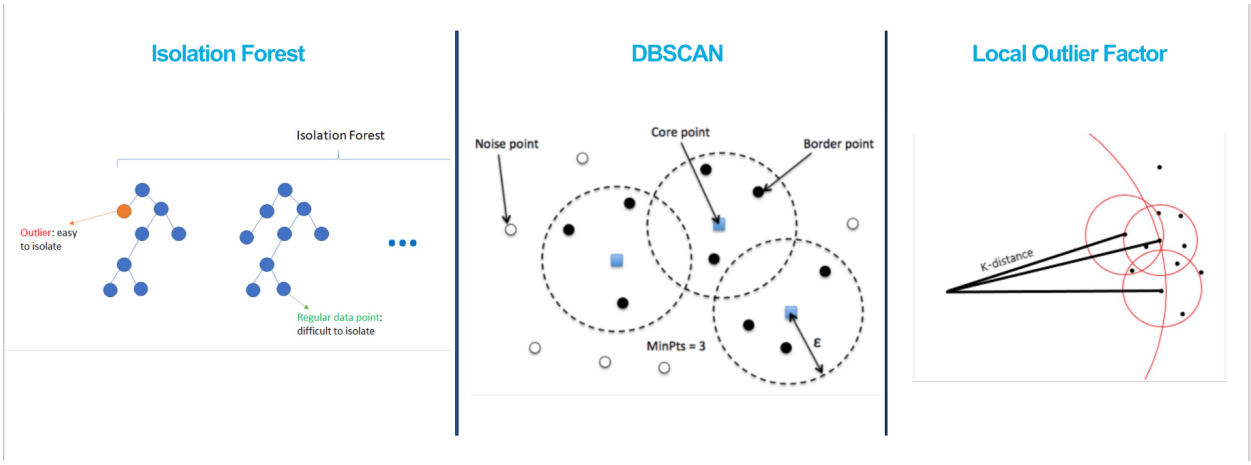
1. Local Density Estimation:
LOF assesses the density of each data point by comparing its density with the densities of its neighbors.
It calculates the local density of a data point by measuring the distance to its k-nearest neighbors.

2. Local Reachability Distance:
The local reachability distance of a data point quantifies how far it is from its neighbors in terms of density.
It is calculated as the inverse of the average density of the data point's k-nearest neighbors.
3. Local Outlier Factor Calculation:

The Local Outlier Factor (LOF) of a data point measures its degree of outlier-ness based on the local density compared to its neighbors.
It is computed as the average ratio of the local reachability distances of a data point to those of its neighbors.

4. Identification of Outliers:
Data points with high LOF values are considered outliers, as they have significantly lower local densities compared to their neighbors.
Higher LOF values indicate that a data point is more likely to be an outlier relative to its local neighborhood.

5. Key Features:
Sensitivity to Local Outliers: LOF is sensitive to anomalies that are isolated within dense regions of the dataset.
No Assumptions About Data Distribution: The algorithm does not rely on assumptions about the underlying data distribution.
Robustness to Noise: LOF can effectively identify outliers even in datasets with noisy or sparse regions.



Results:

Backup_log_Final_result.ipynb

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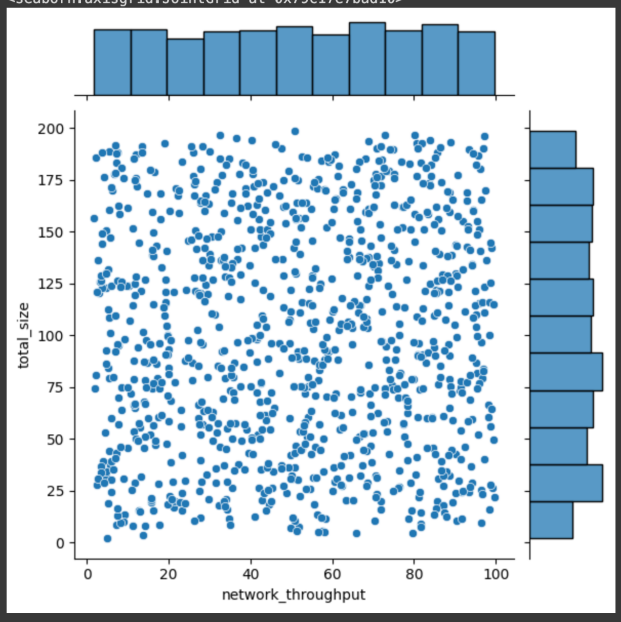
```
# Plot showing the distribution of the data
sns.jointplot(x=df.network_throughput, y=df.total_size)
```

```
<seaborn.axisgrid.JointGrid at 0x79c17e7bad10>
```



Feature Engineering

```
[ ] # Add a feature which indicates the ratio of the total size to the network throughput
    df['size_to_nt'] = df.total_size / df.network_throughput
    df.head()
```

	total_size	no_of_files	network_throughput	time_taken	size_to_nt
0	19.6	27	15.76	5.9	1.243655
1	86.7	56	35.97	7.6	2.410342
2	50.2	117	57.90	4.6	0.867012
3	114.4	69	66.86	5.3	1.711038
4	88.7	114	51.86	3.8	1.710374

Split the dataset into training and testing data.

```
[ ] # Split the data for training and testing purpose.
    train_data, test_data = train_test_split(df, test_size=0.2, random_state=42)
    len(train_data.index), len(test_data.index)
```

Backup_log_Final_result.ipynb

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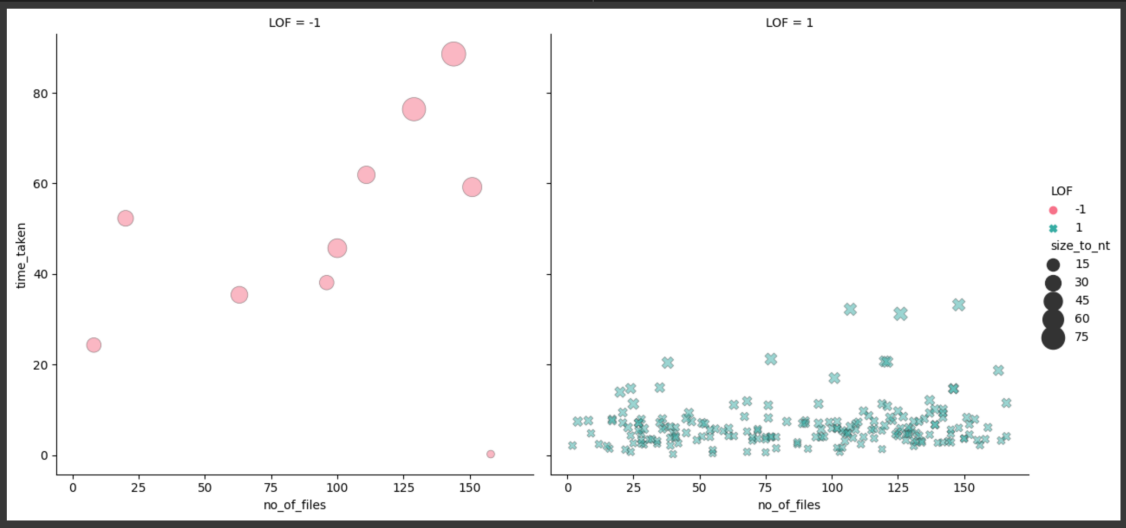
Connect Colab AI

```
                height=6, data=test_data, palette=sns.color_palette("husl", 2))
plt.show()
```



colab.research.google.com/drive/1CWeEVXgPtPfgeY4ehh6zgBFY7IE2IE-J?usp=sharing%E2%80%8B

Backup_log_Final_result.ipynb

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```
                height=6, data=test_data)
plt.show()
```