SDN based DDoS Detection using Deep Learning Techniques

Software-Defined Networking (SDN) is an emerging paradigm, which evolved in recent years to address the weaknesses in traditional networks. The SDN's main goal is to separate the control and data planes, making network management easier and enabling for more efficient programmability. The centralized structure of SDN brings new vulnerabilities. Distributed Denial-of-Service (DDoS) are the most prevalent and sophisticated threat. DDoS attack tries to disrupt the available services of a victim to block the victim from providing service to the legitimate users, by sending massive malicious requests from a large number of hijacked machines. DDoS attacks are easy to initiate, hard to defend and has strong destructive effect. So that accurate detection of DDoS attack is necessary.

Traditional machine learning approaches are impacted by lower detection rates and higher false-positive rates. Deep Learning (DL) is capable of automatically finding correlations in raw data, and so it can improve the DDOS detection rate. The DL approaches, such as the DNN, Auto Encoders, Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM) would increase the performance of DDoS detection.

- **Deep Neural Network (DNN)** is used for DDoS detection, goal is to tackle the problem of binary classification in the DDoS Detection System. Classify the network traffic into normal and DDOS attack traffic.

- **Auto Encoders (AE):** AE can be used as an anomaly detection algorithm. Here the DDoS attack traffic is anomaly. AE tries to minimize the reconstruction error part of its training. DDoS attacks are detected by checking the magnitude of the reconstruction loss. The DDoS attack will have higher reconstruction error than normal network traffic.

- **LSTM Auto Encoder:** The main issue in RNN is the vanishing gradient problem. To solve this and extracting long and short-term dependencies, as well as trends in DDoS attack sequences LSTM Auto Encoder can be used.

Dataset :

- **CICDDoS 2019:** CICDDoS2019 is a collection of benign and up-to-date popular DDoS attacks that closely resemble real-world data. This dataset includes a broad range of Distributed Denial of Service attacks. Newest publicly available dataset, which contain a comprehensive variety of DDoS attacks and addresses the gaps of the existing current dataset.

- DDoS attack SDN dataset– The SDN specific dataset created using the SDN architecture and includes UpToDate SDN DDoS traffic data.

Literature Survey :

NO	TITLE	TECHNIQUES USED	ADVANTAGES	DISADVANTAGES
1.	Machine Learning Approach Equipped with Neighborhood Component Analysis for DDoS Attack Detection in Software-Defined Networking [2021]	NCA KNN Decision Tree ANN SVM	NCA gives most relevant features by feature selection, UpToDate dataset	Does not give optimal number of features to be selected, The performance depends on the selected features
2.	Clustering based semi-supervised machine learning for DDoS attack classification [2019]	Agglomerative clustering K means clustering KNN, SVM, Random Forest	Optimizing and validating the model improves the performance	Clustering approach leads to high false positive values

3.	Detection of DDoS attacks with feed forward based deep neural network model [2021]	DNN	High accuracy	Failed to detect adversarial attack
4	A Deep CNN Ensemble Framework for Efficient DDoS Attack Detection in Software Defined Networks [2020]	RNN LSTM CNN RNN+LSTM	Improved accuracy Minimal computational complexity	Failed to detect adversarial DDoS attacks
5	DDoSNet: A Deep-Learning Model for Detecting Network Attacks [2020]	RNN AutoEncoder	DDoSNet gives the highest evaluation metrics in terms of recall, precision, F-score, and accuracy compared to the existing well known classical ML techniques	Vanishing gradient problem

Design Steps :

- ❑ Preprocessing of Dataset
- ❑ Implement Machine Learning models for DDoS detection
- ❑ Implement Deep Neural Network for DDoS detection
- ❑ Implement Auto Encoder for feature extraction and XGBOOST classifier for DDoS detection
- ❑ Implement Auto Encoder for the DDoS detection

- ❑ Implement Clustering Algorithms (K MEANS and DBSCAN) for DDoS detection
- ❑ Implement LSTM Auto Encoder for the DDoS detection
- ❑ Performance evaluation

Framework : Keras and tensorflow

Detailed Design Steps:-

- **Dataset Preprocessing:**

  - ❑ CICDDoS 2019 dataset in csv format is used for the experiment has been reduced to make it easier to train since it contains a large number of packages.
  - ❑ Eight features (Flow ID, SourceIP, SourcePort, DestinationIP, DestinationPort, Protocol, Timestamp, SimillarHTTP) that do not contribute to the training and 9 features (Bwd PSH Flags, Fwd URG Flags, Bwd URG Flags, Fwd Bytes/Bulk Avg, Fwd Packet/Bulk Avg, Fwd Bulk Rate Avg, Bwd Bytes/Bulk Avg, Bwd Packet/ Bulk Avg, Bwd Bulk Rate Avg) containing only ’0’ value were removed from the dataset and the model was trained with 66 features.
  - ❑ ’Normal’ is labeled ’0’ and DDoS attacks are labeled ’1’ in the dataset created to detect DDoS on network traffic.

Features Selected:

No	Feature Name	Decsription
1	Flow Duration	Duration of the flow in Microsecond
2	Tot Fwd packets	Number of forward packets per second
3	Tot Bwd packets	Number of backward packets per second
4	Tot len Fwd packets	Total size of packet in forward direction
5	Tot len Bwd packets	Total size of packet in backward direction
6	Fwd packet len max	Maximum size of packet in forward direction

7	Fwd packet len min	Minimum size of packet in forward direction
8	Fwd packet len mean	Mean size of packet in forward direction
9	Fwd packet len std	Standard deviation size of packet in forward direction
10	Bwd packet len max	Maximum size of packet in backward direction
11	Bwd packet len min	Minimum size of packet in backward direction
12	Bwd packet len mean	Mean size of packet in backward direction
13	Bwd packet len std	Standard deviation size of packet in backward direction
14	Flow byte/s	Number of flow bytes per second
15	Flow packet/s	Number of flow packet per second
16	Flow IAT mean	Mean time between two packets sent in the flow
17	Flow IAT std	Standard deviation time between two packets sent in the flow
18	Flow IAT max	Maximum time between two packets sent in the flow
19	Flow IAT min	Minimum time between two packets sent in the flow
20	Fwd IAT Total	Total time between two packets sent in the forward direction
21	Fwd IAT mean	Mean time between two packets sent in the forward direction
22	Fwd IAT std	Standard deviation time between two packets sent in the forward direction
23	Fwd IAT max	Maximum time between two packets sent in the forward direction
24	Fwd IAT min	Minimum time between two packets sent in the forward direction
25	Bwd IAT Total	Total time between two packets sent in the backward direction

26	Bwd IAT mean	Mean time between two packets sent in the backward direction
27	Bwd IAT std	Standard deviation time between two packets sent in the backward direction
28	Bwd IAT max	Maximum time between two packets sent in the backward direction
29	Bwd IAT min	Minimum time between two packets sent in the backward direction
30	Fwd URG Flags	Number of times the URG flag was set in packets travelling in the forward direction (0 for UDP)
31	Bwd URG Flags	Number of times the URG flag was set in packets travelling in the backward direction (0 for UDP)
32	Fwd Header len	Total bytes used for headers in the forward direction
33	Bwd Header len	Total bytes used for headers in the backward direction
34	Fwd packets/s	Number of forward packets per second
35	Bwd packets/s	Number of backward packets per second
36	Packet len min	Minimum length of a packet
37	packet len max	Maximum length of a packet
38	packet len mean	Mean length of a packet
39	packet len std	Standard deviation length of a packet
40	Packet len variance	Variance length of a packet
41	FIN flag count	Number of packets with FIN
42	SYN flag count	Number of packets with SYN
43	RST flag count	Number of packets with RST
44	PSH flag count	Number of packets with PSH

45	Ack flag count	Number of packets with Ack
46	URG flag count	Number of packets with URG
47	CWE flag count	Number of packets with CWE
48	ECE flag count	Number of packets with ECE
49	Down/up ratio	Download and upload ratio
50	Packet size avg	Average size of a packet
51	Fwd seg size avg	Average size observed in the forward direction
52	Bwd seg size avg	Average size observed in the backward direction
53	Subflow Fwd packets	The average number of packets in a sub flow in the forward direction
54	Subflow Fwd bytes	The average number of bytes in a sub flow in the forward direction
55	Subflow Bwd packets	The average number of packets in a sub flow in the backward direction
56	Subflow Bwd bytes	The average number of bytes in a sub flow in the backward direction
57	Fwd Act Data packets	Count of packets with at least 1 byte of TCP data payload in the forward direction
58	Fwd seg size min	Minimum segment size observed in the forward direction
59	Active mean	Mean time a flow was active before becoming idle
60	Active std	Standard deviation time a flow was active before becoming idle
61	Active max	Maximum time a flow was active before becoming idle
62	Active min	Minimum time a flow was active before becoming idle
63	Idle mean	Mean time a flow was idle before becoming active

64	Idle std	Standard deviation time a flow was idle before becoming active
65	Idle max	Maximum time a flow was idle before becoming active
66	Idle min	Minimum time a flow was idle before becoming active
67	Label	‘0’ denotes normal and ‘1’ denotes DDoS attack

- **DDoS Attack SDN Dataset:**

This is a SDN specific data set generated by using mininet emulator and used for traffic classification by machine learning and deep learning algorithms. The project start by creating ten topologies in mininet in which switches are connected to single Ryu controller. Network simulation runs for benign TCP, UDP and ICMP traffic and malicious traffic which is the collection of TCP Syn attack, UDP Flood attack, ICMP attack. Total 23 features are available in the data set in which some are extracted from the switches and others are calculated. Extracted features include Switch-id, Packet_count, byte_count, duration_sec, duration_nsec which is duration in nano-seconds, total duration is sum of duration_sec and durstaion_nsec, Source IP, Destination IP, Port number, tx_bytes is the number of bytes transferred from the switch port, rx_bytes is the number of bytes received on the switch port. dt field show the date and time which has been converted into number and a flow is monitored at a monitoring interval of 30 second. Calculated features include Packet per flow which is packet count during a single flow, Byte per flow is byte count during a single flow, Packet Rate is number of packets send per second and calculated by dividing the packet per flow by monitoring interval, number of Packet_ins messages, total flow entries in the switch, tx_kbps, rx_kbps are data transfer and receiving rate and Port Bandwidth is the sum of tx_kbps and rx_kbps. Last column indicates the class label which indicates whether the traffic type is benign or malicious. Benign traffic has label 0 and malicious traffic has label 1. Network simulation is run for 250 minutes and 1,04,345 rows of data is collected.

Feature Name	Description
dt	Transmission moment of packets over the network device
switch	Switch ID
src	IP address of the sender of the packets
dst	IP address to which the packets was sent
pktcount	Number of packets
bytecount	Number of bytes
dur	Duration
dur_nsec	Duration in nano seconds
tot_dur	Total duration of network flow
flows	Number of flow packets
packetins	Total flow entries in the switch
pktperflow	Packet count during a single flow
byteperflow	Byte count during a single flow
pktrate	Number of packets per sec
Pairflow	Number of flow packets per second
Protocol	Types of communications internet protocols
port_no	Port number of the sender of the packets

tx_bytes	Number of bytes transferred from the switch port
rx_bytes	Number of bytes received on the switch port
tx_kbps	Data transfer rate
rx_kbps	Data Receiving rate
tot_kbps	Sum of tx_kbps and rx_kbps

- **DDoS Detection Using Supervised Machine Learning Algorithms**
  - Load the dataset
  - Splitting the dataset into features and label
  - Splitting the dataset in to training and testing (40% for testing and 60% for training)
  - First create a Machine Learning model using **Logistic Regression** for DDoS detection
  - Evaluate the logistic Regression model
  - Create a Machine Learning model using **Gaussian Naïve bayes** algorithm
  - The Gaussian Naïve bayes model is trained and tested in the dataset
  - Evaluate the performance of Gaussian Naïve bayes model
  - Create a Machine Learning model using **Support Vector Machine (SVM)** algorithm
  - Train the SVM model on the dataset and test the model
  - Evaluate the performance of SVM model for DDoS detection
  - Create a Machine Learning model using **Decision Tree** algorithm
  - Train the Decision Tree model in the dataset and test the model
  - Evaluate the performance of Decision Tree model for DDoS detection
  - Create a Machine Learning model using **Random Forest** algorithm
  - Train the Random Forest model in the dataset and test the model
  - Evaluate the performance of Random Forest model for DDoS detection
  - Create a Machine Learning model using **Gradient Boosting** algorithm
  - Train the Random Forest model in the dataset and test the model

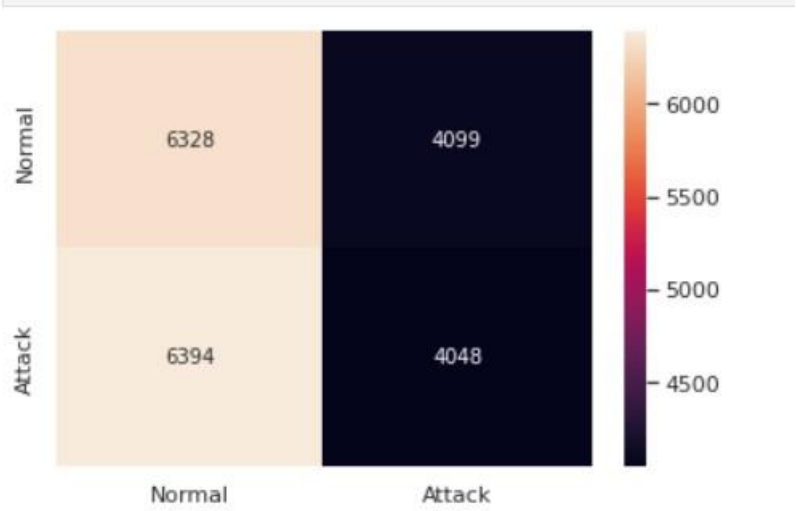
- Evaluate the performance of Random Forest model for DDoS detection
  - Results:

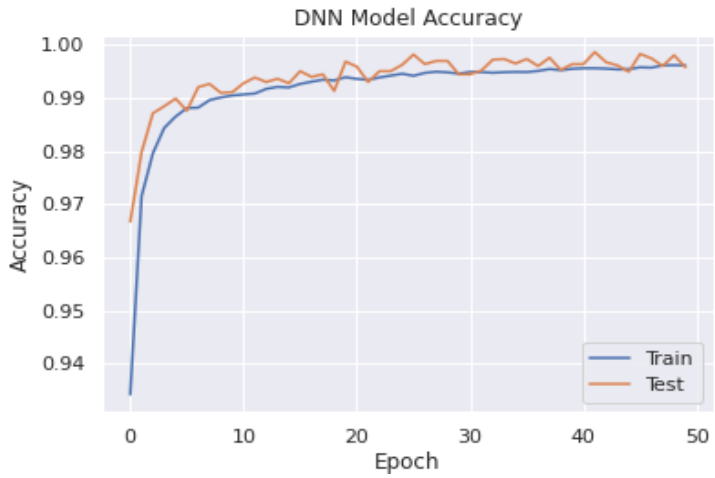
Evaluation Metrics	LR	GNB	SVM	DT	RF	GB
Accuracy (%)	77.11	67.35	78.44	99.95	100	98.52
Precision (%)	72.68	57.54	76.16	99.93	100	100
Recall (%)	66.29	62.41	65.17	99.95	100	100
F1 score (%)	75.54	66.17	76.67	99.95	99.95	98.46

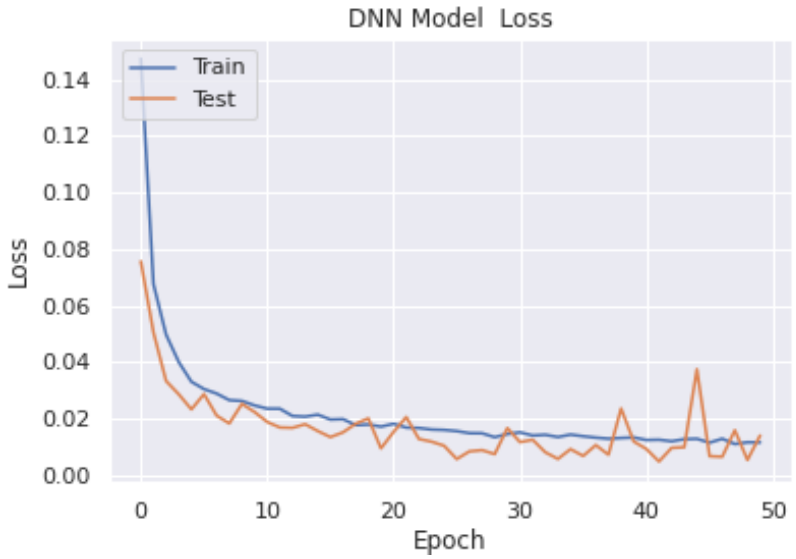
- **Deep Neural Network (DNN) for DDoS Detection**

- Load the dataset
- Splitting the dataset into features and label
- Splitting the dataset in to training and testing (20% for testing and 80% for training)
- Feature Scaling or Standardization using Standard Scaler
- Create DNN with sequential model having input layer, 3 hidden layer and output layer
- The input layer consist of 19 neurons corresponds to 19 features selected. The relu activation function used
- The hidden layers consist of equal number of 50 neurons and relu activation function is used
- There are also two dropout layers with dropout ratio 0.2
- The output layer consists of 2 neurons with sigmoid activation function because it is a binary classification problem
- The output label ‘0’ indicates the network traffic is normal and ‘1’ indicates the traffic is DDoS attack
- Compile the model using ‘Sparse categorical cross entropy’ loss function, ‘accuracy’` metrics and ‘adam’ optimizer
- Fit the model with 50 epochs and batch size selected is 16
- Plot the training and validation accuracy values
- Plot the training and validation loss values
- Make predictions on the test set

- Obtain confusion matrix
- Evaluate the model and obtain the accuracy
  - Result:- The accuracy obtained is **99.53 %**







- **Auto Encoder (AE) for DDoS Detection**

The Auto Encoder accepts high dimensional input data, compresses down to the latent space representation in the bottleneck hidden layer. The Decoder takes the latent representation of the data as an input to reconstruct the original input data. AE tries to minimize the reconstruction error part of its training. Anomalies are detected by checking the magnitude of the reconstruction loss.

- ❖ Import the required libraries and load the dataset
- ❖ The dataset consists of label '0' and '1', 0 denotes normal and 1 denotes the attack (Anomaly)
- ❖ Split the data for training and testing (20% for testing)
- ❖ Scale the data using Minmax scaler
- ❖ Use normal data only for training

  AE are trained to minimize the reconstruction error. The reconstruction errors are used as the anomaly score. When we train the AE on normal data, we can hypothesize that the anomalies will have higher reconstruction errors than normal data.
- ❖ Create an Auto Encoder class with output units equal to number of input data and the number of units in the bottleneck (code size) equal to 16

- ❖ The encoder of the model consists of 4 layers that encode the data into lower dimensions
- ❖ The decoder of the model consists of 4 layers that reconstruct the input data
- ❖ The model is compiled with metrics equal to mse and adam optimizer
- ❖ The model is trained with 200 epochs with a batch size of 16
- ❖ The reconstruction errors are considered as anomaly score. The Threshold is then calculated by summing the mean and standard deviation of the reconstruction errors
- ❖ The reconstruction error above this threshold is DDoS attack (anomalies)
    - ❑ Result : Accuracy obtained is **68.27 %**
- ❖ Optimize the model with keras tuner
    - ❑ Accuracy improved to **71.39 %**

- **Auto Encoder and XGBOOST for DDoS Detection**

  Auto Encoder is a type of neural network that can be used to learn a compressed representation of raw data. An autoencoder is composed of an encoder and a decoder sub-model. The encoder compresses the input, and the decoder attempts to recreate the input from the compressed version provided by the encoder. After training, the encoder model is saved, and the decoder is discarded. The encoder can then be used as a data preparation technique to perform feature extraction on raw data that can be used to train a different machine learning model.
  - ❖ Importing the required libraries
  - ❖ Load the dataset
  - ❖ Split the dataset in to train and test
  - ❖ Scale the dataset using Min Max scaler
  - ❖ Define the Auto Encoder model with encoder model, bottleneck, and decoder model
  - ❖ Fit the autoencoder model to reconstruct input
  - ❖ Define and save the encoder model without decoder
  - ❖ Compress the input data using encoder model
  - ❖ Import the XGBoost classifier
  - ❖ Encode the train data

- ❖ Encode the test data
- ❖ Fit the XGBoost classifier model on the training set
- ❖ Make predictions on the test data
- ❖ Calculate classification accuracy
    - ❑ Result :

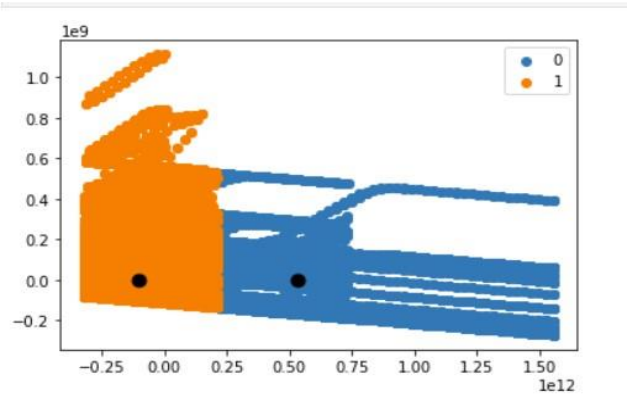
Evaluation Metric	Obtained Value
Accuracy	97.58 %
Precision	97.41 %
Recall	96.25 %
F1 score	97.43 %

- **K Means Clustering for DDoS Detection**

  K means clustering is an iterative clustering method that segments data into K clusters in which each observation belongs to the cluster with the nearest mean (Cluster Centroid)

  - ❖ Importing the required libraries
  - ❖ Load the data
  - ❖ Transform the data
  - ❖ PCA for dimensionality reduction
  - ❖ Here we have 2 clusters, Normal and Attack cluster
  - ❖ KMeans.fit_predict method returns the array of cluster labels each data point belongs to
  - ❖ Visualize cluster with label ‘0’ (Normal) using matplot library
  - ❖ Plot all clusters
  - ❖ Plot cluster centroids
  - ❖ Calculate the labelling accuracy of the model
    - ❑ Result :

Evaluation Metric	Obtained Value
Accuracy	51.01 %
Silhouette Coefficient	0.706
Homogeneity	0.046
Completeness	0.070
V-measure	0.056



- **K Means Clustering with PCA & TSNE**
  - ❖ K Means attempts to organize the data into a specified number of clusters. The goal of K Means is to identify similar data points and cluster them together while trying to distance each cluster as far as possible. Its "similarity" calculation is determined via Euclidean distance or an ordinary straight line between two points. K Means is very sensitive to scale and requires all features to be on the same scale. K Means will put more weight or emphasis on features with larger variances and those features will impose more influence on the final cluster shape. Clustering algorithms such as K Means have a difficult time accurately clustering data of high dimensionality (ie. too many features).
  - ❖ Compare PCA and t-SNE data reduction techniques prior to running K-Means clustering algorithm

❖ **Principal component analysis or (PCA)** is a classic method we can use to reduce high-dimensional data to a low-dimensional space. The beauty behind PCA is the fact that despite the reduction into a lower-dimensional space we still retain most (+90%) of the variance or information from our original high-dimensional dataset. The information or variance from our original features is "squeezed" into what PCA calls principal components (PC). The first PC will contain the majority of the information from the original features. The second PC will contain the next largest amount of information, the 3rd PC the third largest amount of info and so on and so on. The PC are not correlated (ie. orthogonal) which means they all contain unique pieces of information.

❖ **T-Distributed Stochastic Neighbor Embedding (t-SNE) :** t-SNE takes high-dimensional data and reduces it to a low-dimensional graph (2-D typically). It is also a great dimensionality reduction technique. Unlike PCA, t-SNE can reduce dimensions with non-linear relationships. In other words, if our data had this "Swiss Roll" non-linear distribution where the change in X or Y does not correspond with a constant change in the other variable. PCA would not be able to accurately distill this data into principal components. This is because PCA would attempt to draw the best fitting line through the distribution. T-SNE would be a better solution in this case because it calculates a similarity measure based on the distance between points instead of trying to maximize variance.

❖ T-SNE looks at the similarity between local or nearby points by observing the distance (Euclidean distance). Points that are nearby each other are considered similar. t-SNE then converts this similarity distance for each pair of points into a probability for each pair of points. If two points are close to each other in the high-dimensional space they will have a high probability value and vice versa. This way the probability of picking a set of points is proportional to their similarity. Then each point gets randomly projected into a low dimensional space. t-SNE is a visualization tool first and a dimensionality reduction tool second.

❖ We need to understand how well K-Means managed to cluster our data. **Silhouette Method:** This technique measures the separability between clusters. First, an average distance is found between each point and all other points in a cluster. Then it measures the distance between

each point and each point in other clusters. We subtract the two average measures and divide by whichever average is larger. We ultimately want a high (ie. closest to 1) score which would indicate that there is a small intra-cluster average distance (tight clusters) and a large inter-cluster average distance (clusters well separated).

❖ Standardize the data : The standardization of data will ultimately bring all features to the same scale and bringing the mean to zero and the standard deviation to 1.

❖ Applying K Means on the original dataset : apply K Means on the original dataset requesting 2 clusters. We achieved a silhouette score of 0.196 which is on the low end.

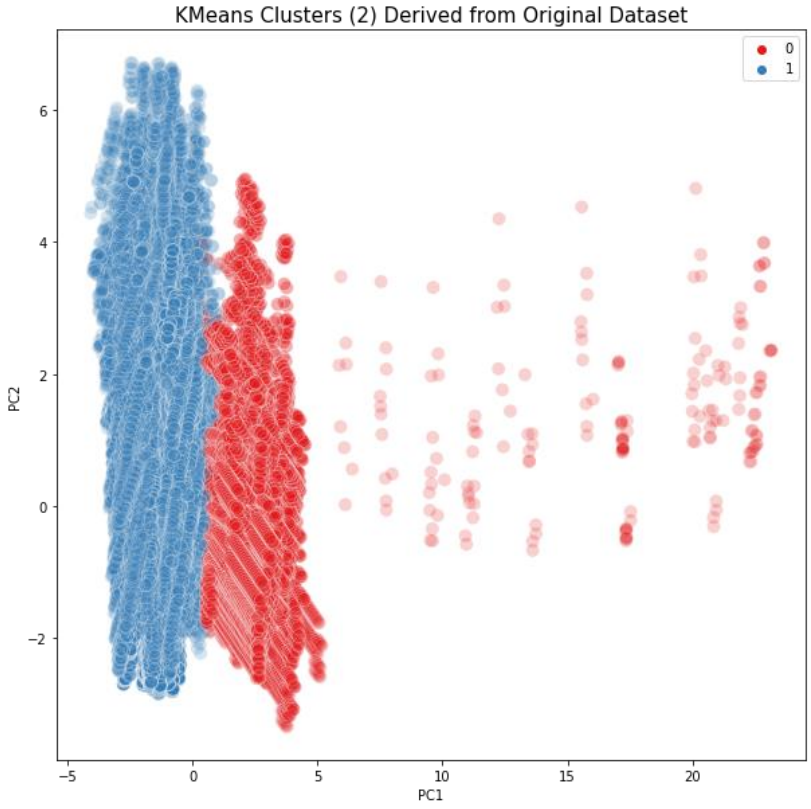
❖ Feature Reduction via PCA : Using PCA to reduce the dataset into 2 principal components we can plot the K Means derived clusters

❖ Applying K Means to PCA principal components : Now that we have reduced the original dataset of 19 features to just 2 principal components let's apply the K Means algorithm. We can see a definite improvement in K Means ability to cluster our data when we reduce the number of dimensions to 2 principal components. K Means PCA Scaled Silhouette Score: 0.4613677492070967

❖ Feature Reduction via t-SNE : In this section we will reduce our data once again using t-SNE and compare K Means results to that of PCA K Means. We will reduce down to 2 t-SNE components. t-SNE is a computationally heavy algorithm. Computational time can be reduced using the 'n_iter' parameter.

❖ Applying K Means to t-SNE clusters : Applying KMeans to our 2 t-SNE derived components we were able to obtain a Silhouette score of 0.3413. If we recall the Silhouette score obtained from K Means on PCA's 2 principal components was 0.4613

❖ Comparing PCA and t-SNE K Means derived clusters : First merge the K Means clusters with the original unscaled features. We'll create two separate data frames. One for the PCA derives K Means clusters and one for the t-SNE K Means clusters. Obtain univariate review of the clusters by comparing the clusters based on each individual feature.




```
[ ]  df_scale2 = df_scale.copy()
     kmeans_scale = KMeans(n_clusters=2, n_init=100, max_iter=400, init='k-means++', random_state=42).fit(df_scale2)
     print('KMeans Scaled Silhouette Score: {}'.format(silhouette_score(df_scale2, kmeans_scale.labels_, metric='euclidean')))
     labels_scale = kmeans_scale.labels_
     clusters_scale = pd.concat([df_scale2, pd.DataFrame({'cluster_scaled':labels_scale})], axis=1)

     KMeans Scaled Silhouette Score: 0.1961007339513506
```

```
[ ]  pca = PCA(n_components=2)
     pca_scale = pca.fit_transform(df_scale)
     pca_df_scale = pd.DataFrame(pca_scale, columns=['pc1','pc2'])
     print(pca.explained_variance_ratio_)
```

```
[0.23682893 0.13383368]
```

```
[ ]  kmeans_pca_scale = KMeans(n_clusters=2, n_init=100, max_iter=400, init='k-means++', random_state=42).fit(pca_df_scale)
     print('KMeans PCA Scaled Silhouette Score: {}'.format(silhouette_score(pca_df_scale, kmeans_pca_scale.labels_, metric='euclidean')))
     labels_pca_scale = kmeans_pca_scale.labels_
     clusters_pca_scale = pd.concat([pca_df_scale, pd.DataFrame({'pca_clusters':labels_pca_scale})], axis=1)
```

```
KMeans PCA Scaled Silhouette Score: 0.4613677492070967
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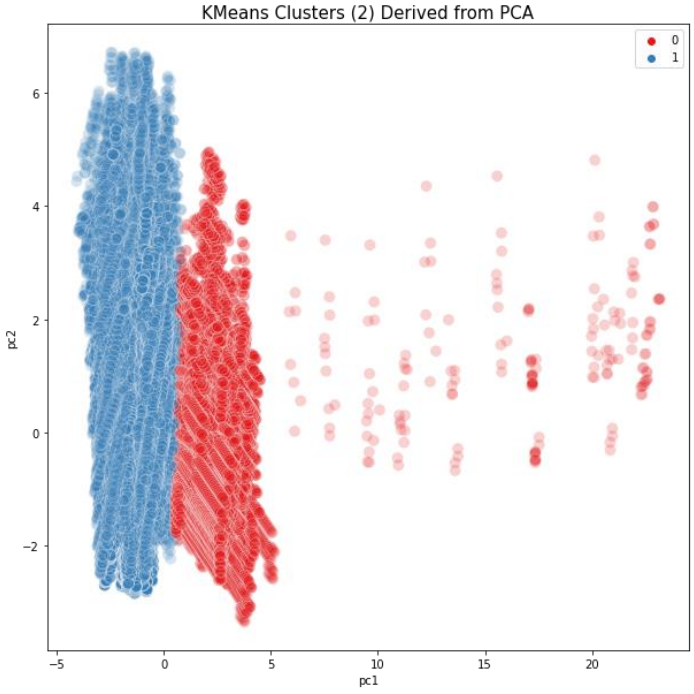

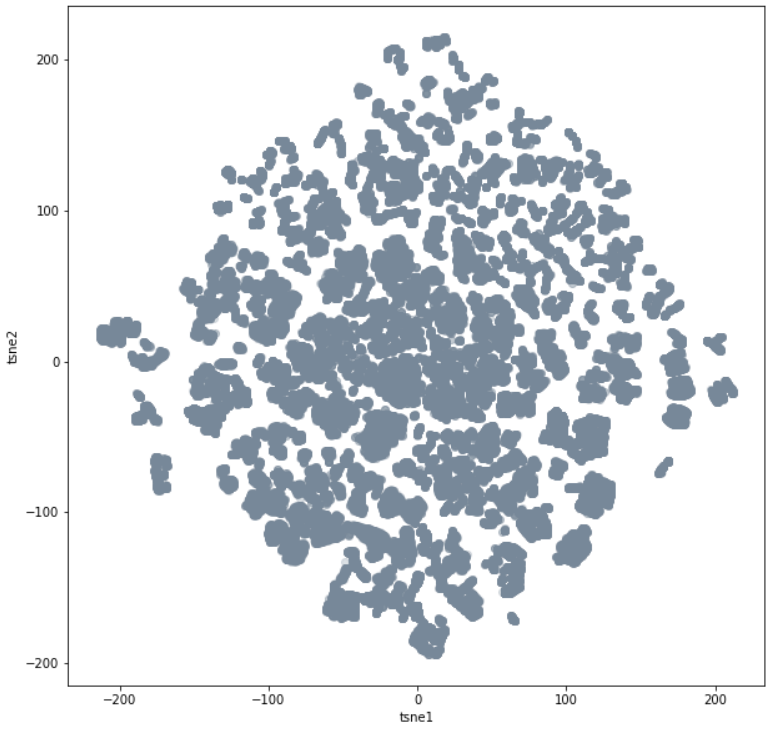


```
[ ]  kmeans_tsne_scale = KMeans(n_clusters=2, n_init=100, max_iter=400, init='k-means++', random_state=42).fit(tsne_df_scale)
     print('KMeans tSNE Scaled Silhouette Score: {}'.format(silhouette_score(tsne_df_scale, kmeans_tsne_scale.labels_, metric='euclidean')))
     labels_tsne_scale = kmeans_tsne_scale.labels_
     clusters_tsne_scale = pd.concat([tsne_df_scale, pd.DataFrame({'tsne_clusters':labels_tsne_scale})], axis=1)
```

```
KMeans tSNE Scaled Silhouette Score: 0.34130406379699707
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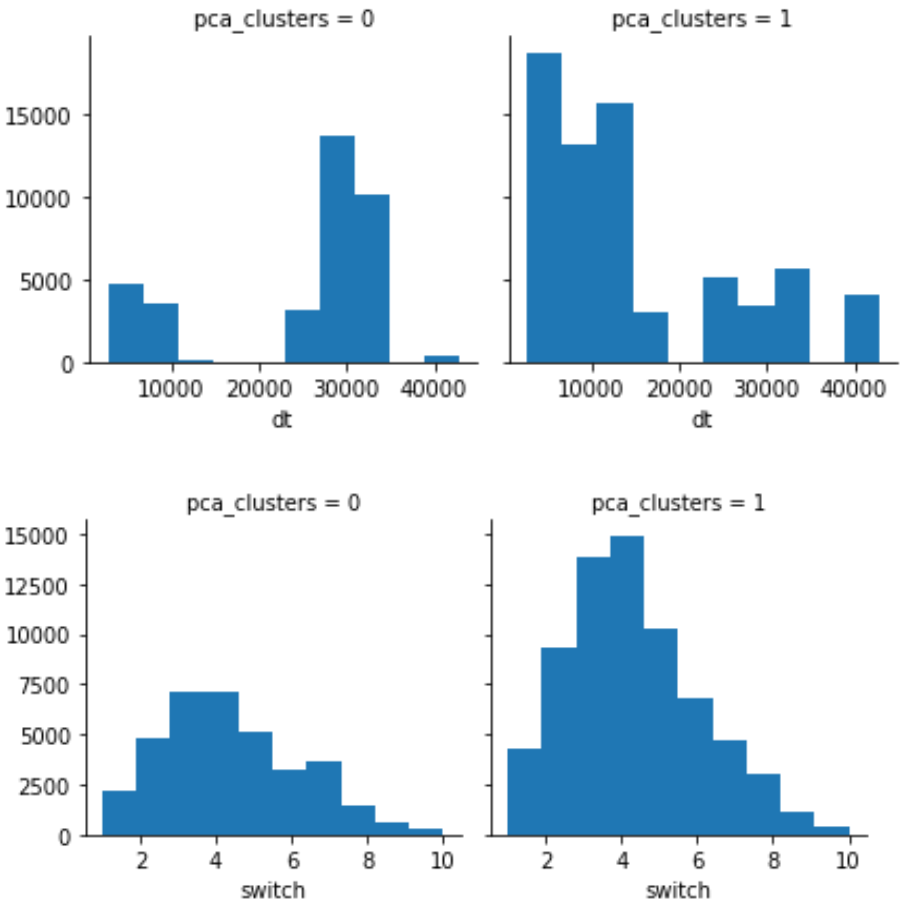
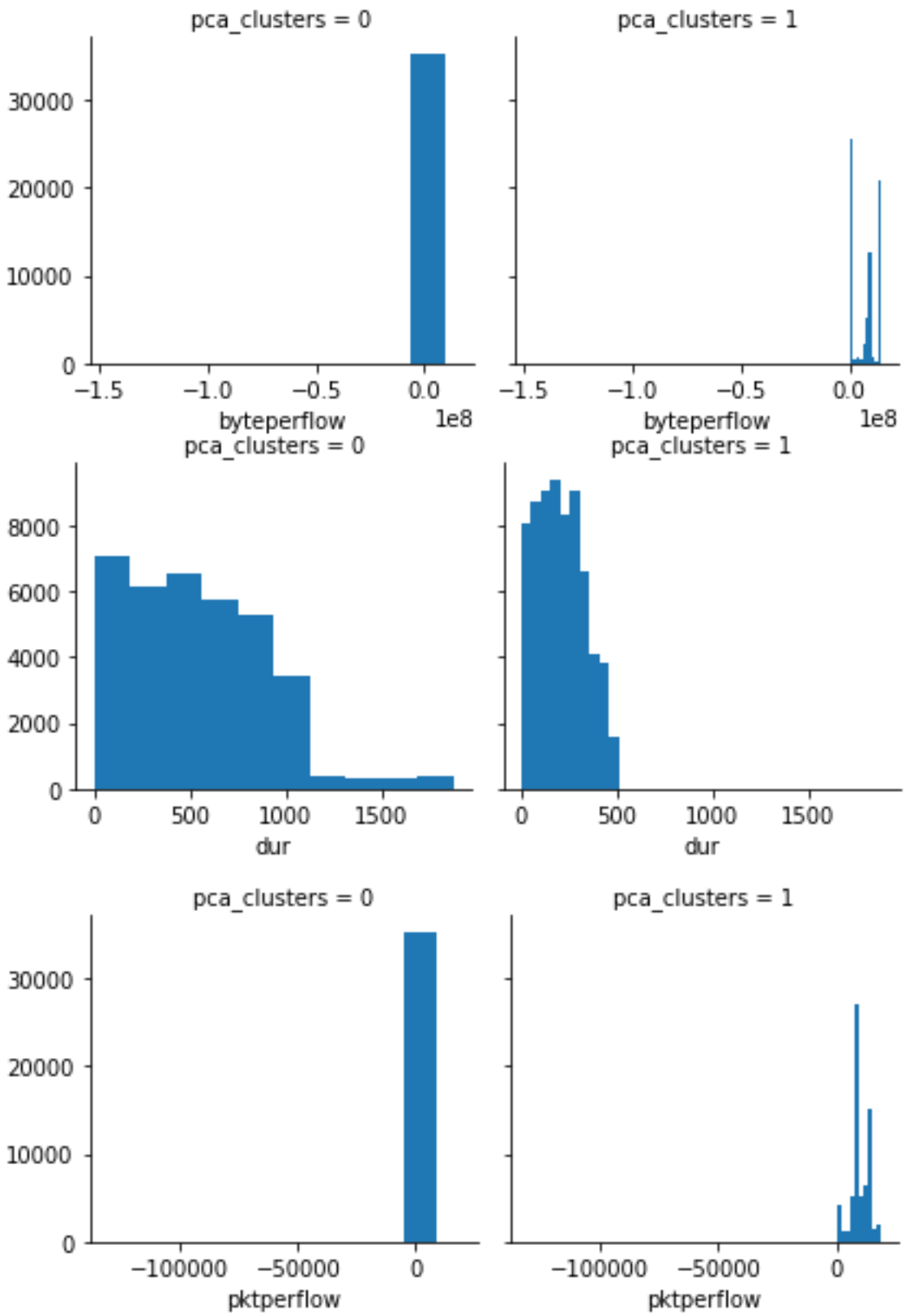

pca_clusters = 0
pca_clusters = 1
15000
10000
5000
0
10000
20000
30000
40000
dt
pca_clusters = 0
pca_clusters = 1
15000
12500
10000
7500
5000
2500
0
2
4
6
8
10
switch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pca_clusters = 1
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20000
10000
0
−1.5
−1.0
−0.5
0.0
byteperflow
1e8
pca_clusters = 0
pca_clusters = 1
8000
6000
4000
2000
0
0
500
1000
1500
dur
pca_clusters = 0
pca_clusters = 1
30000
20000
10000
0
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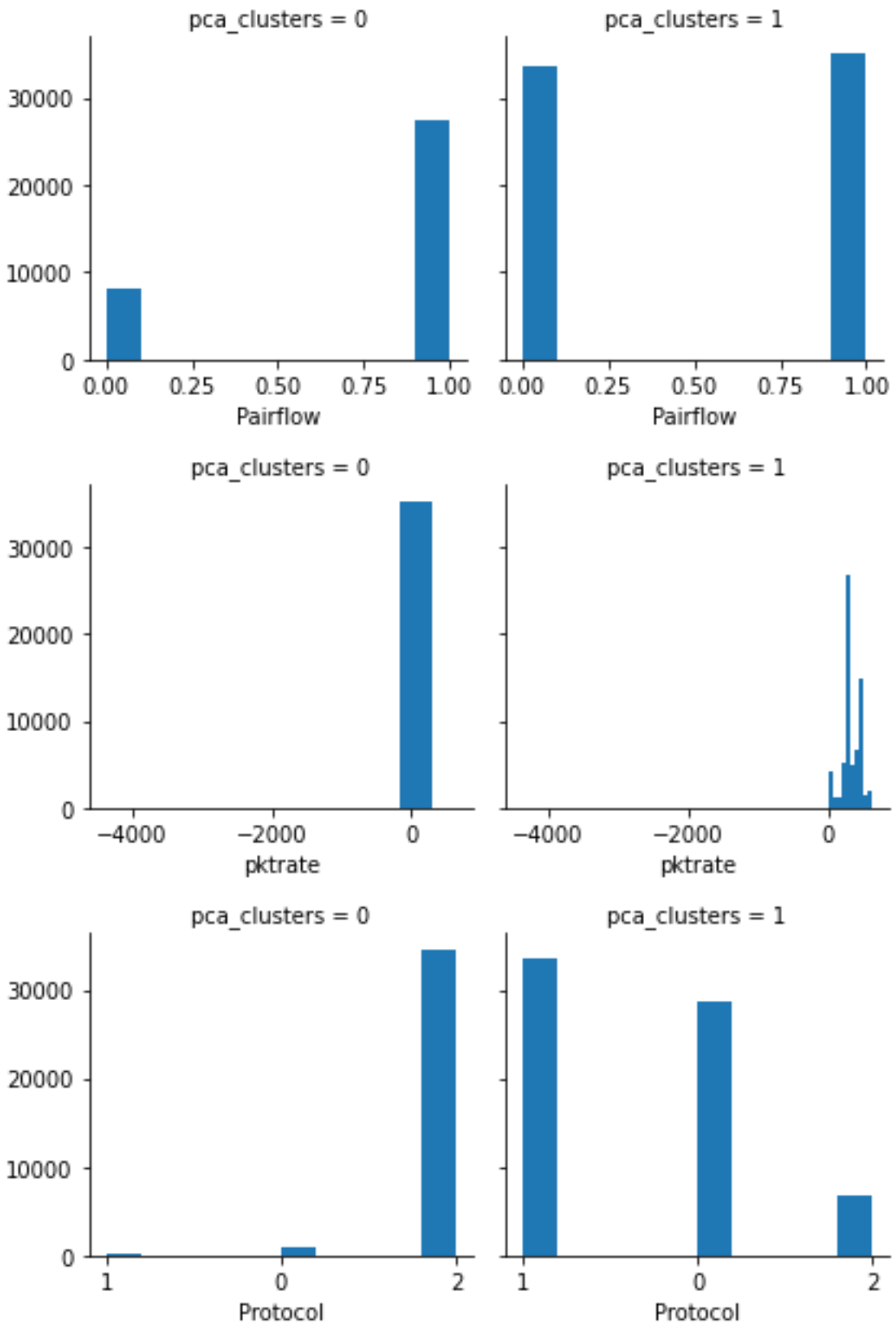
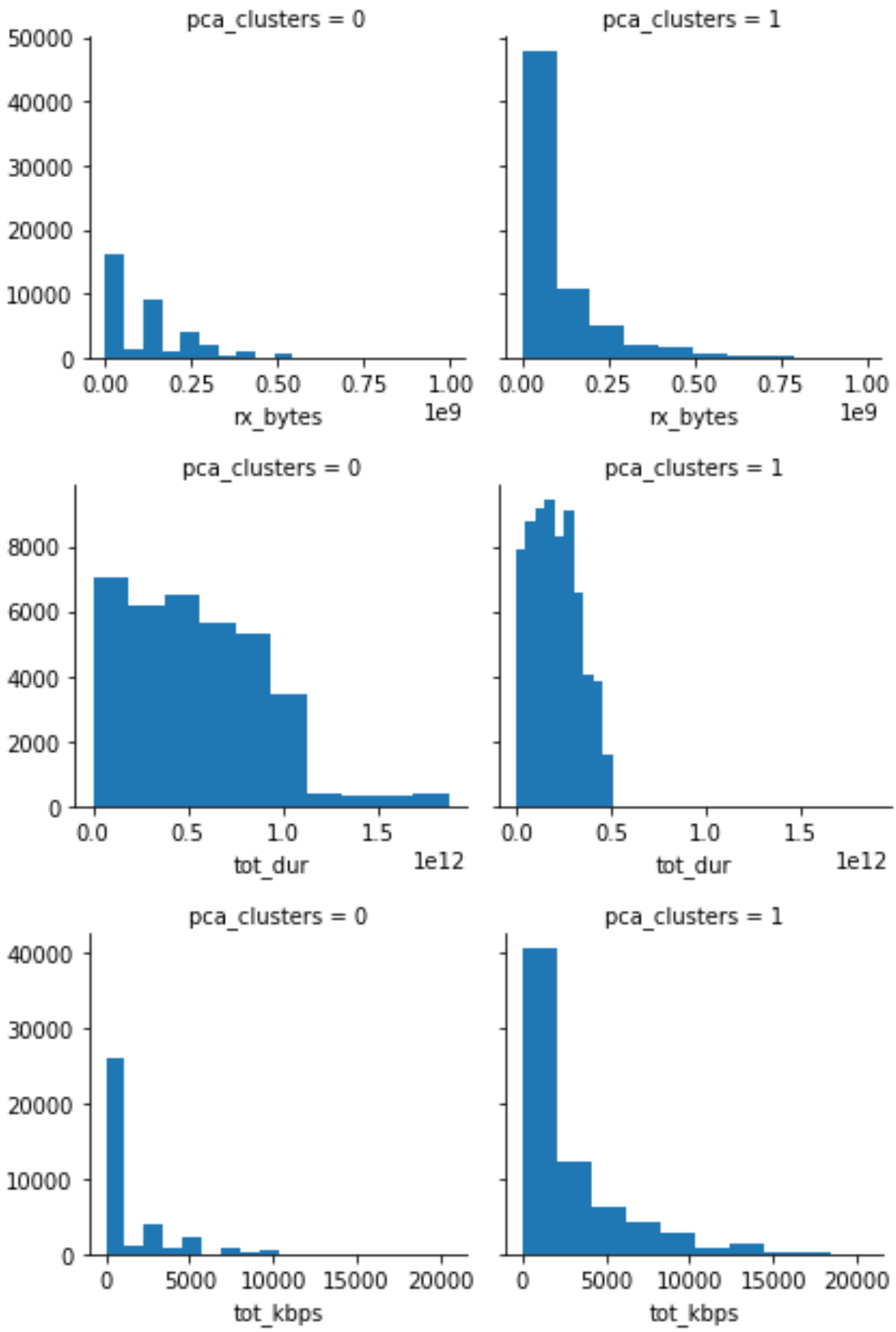
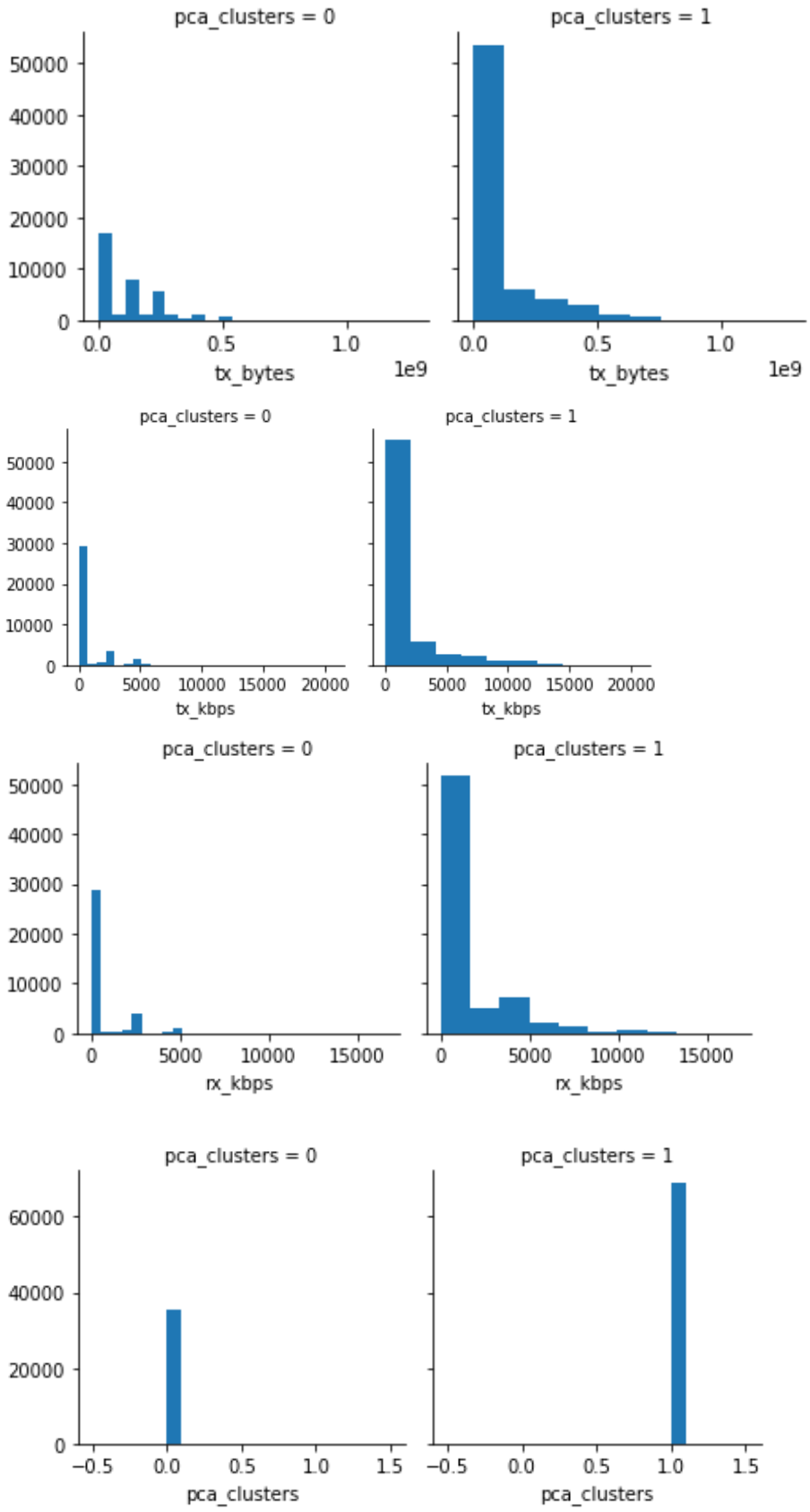
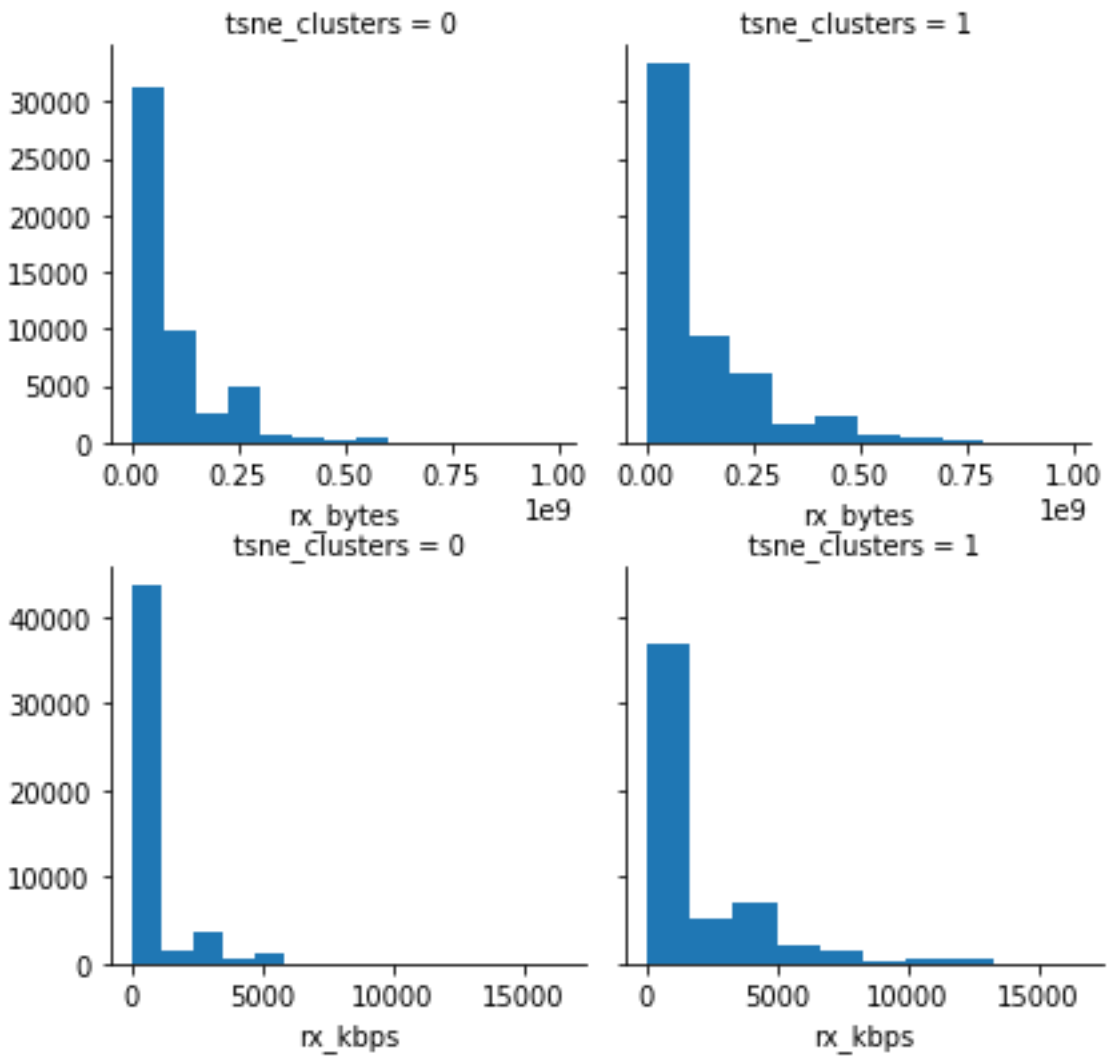
−50000
0
pktperflow


pca_clusters = 0
pca_clusters = 1
30000
20000
10000
0
0.00
0.25
0.50
0.75
1.00
Pairflow
pca_clusters = 0
pca_clusters = 1
30000
20000
10000
0
−4000
−2000
0
pktrate
pca_clusters = 0
pca_clusters = 1
30000
20000
10000
0
1
0
2
Protocol


pca_clusters = 0
pca_clusters = 1
50000
40000
30000
20000
10000
0
0.00
0.25
0.50
0.75
1.00
rx_bytes
1e9
8000
6000
4000
2000
0.0
0.5
1.0
1.5
tot_dur
1e12
40000
30000
20000
10000
0
5000
10000
15000
20000
tot_kbps


pca_clusters = 0
pca_clusters = 1
50000
40000
30000
20000
10000
0
0.0
0.5
1.0
tx_bytes
1e9
pca_clusters = 0
pca_clusters = 1
50000
40000
30000
20000
10000
0
0
5000
10000
15000
20000
tx_kbps
pca_clusters = 0
pca_clusters = 1
50000
40000
30000
20000
10000
0
0
5000
10000
15000
rx_kbps
pca_clusters = 0
pca_clusters = 1
60000
40000
20000
0
−0.5
0.0
0.5
1.0
1.5
pca_clusters


tsne_clusters = 0
tsne_clusters = 1
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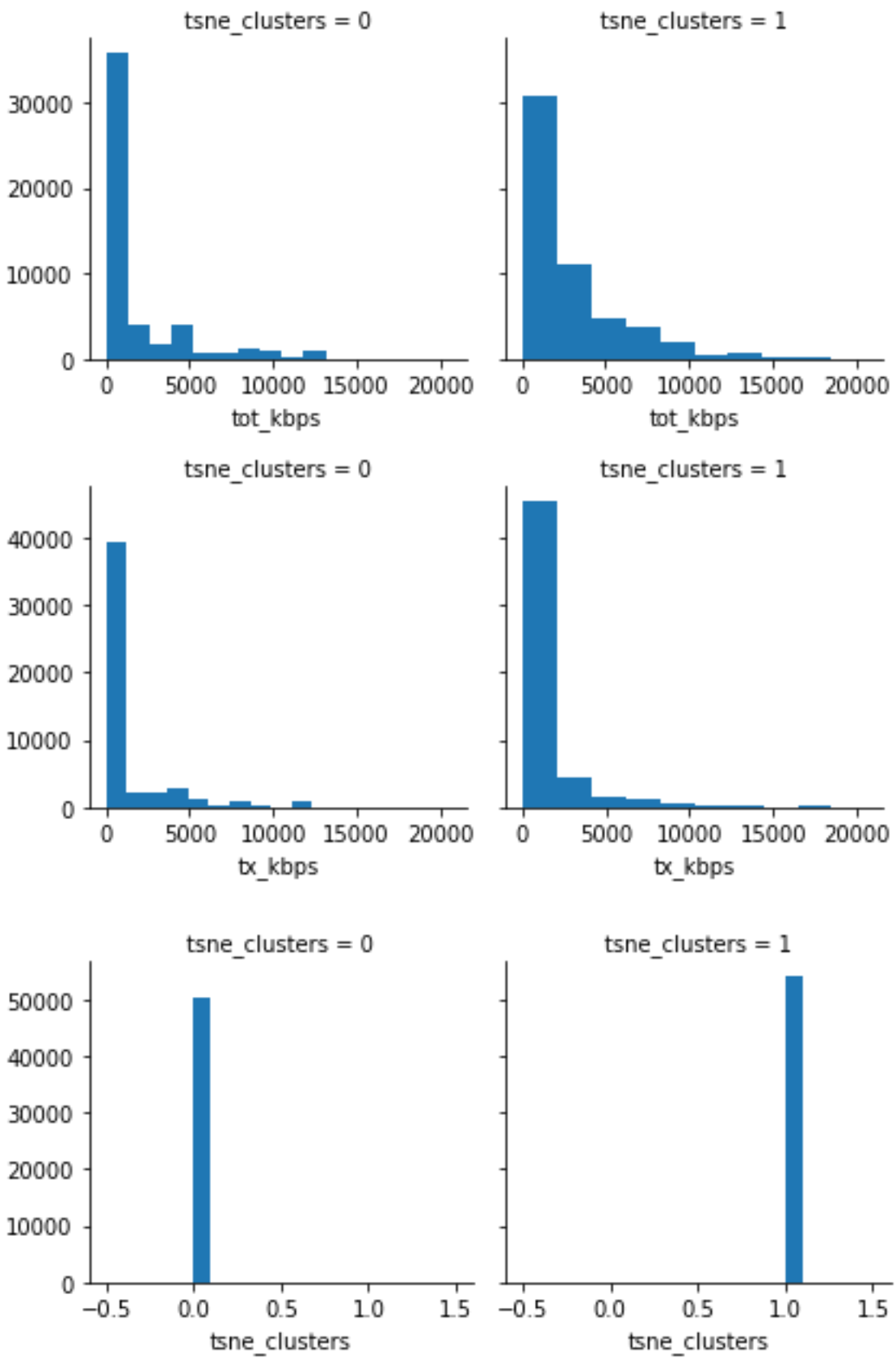
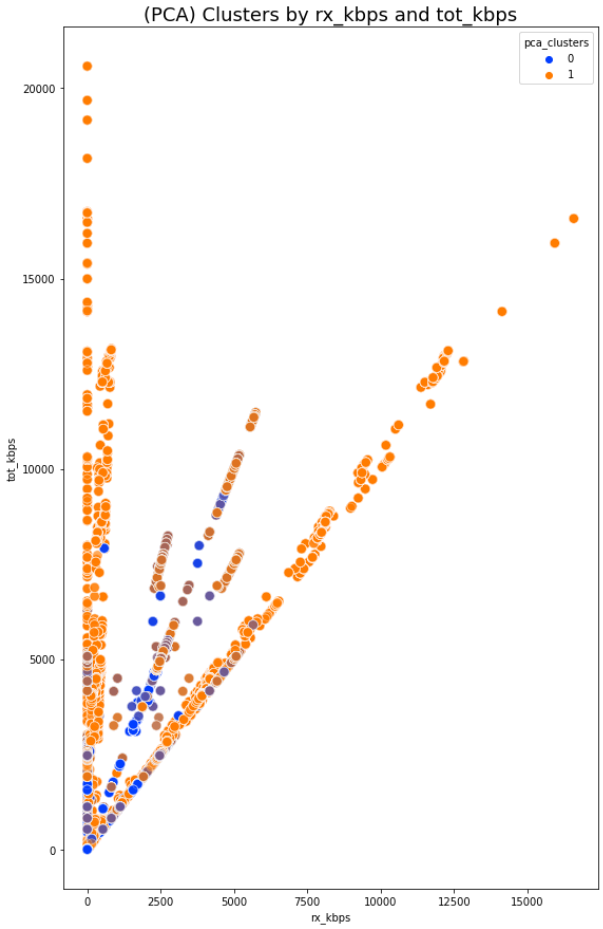
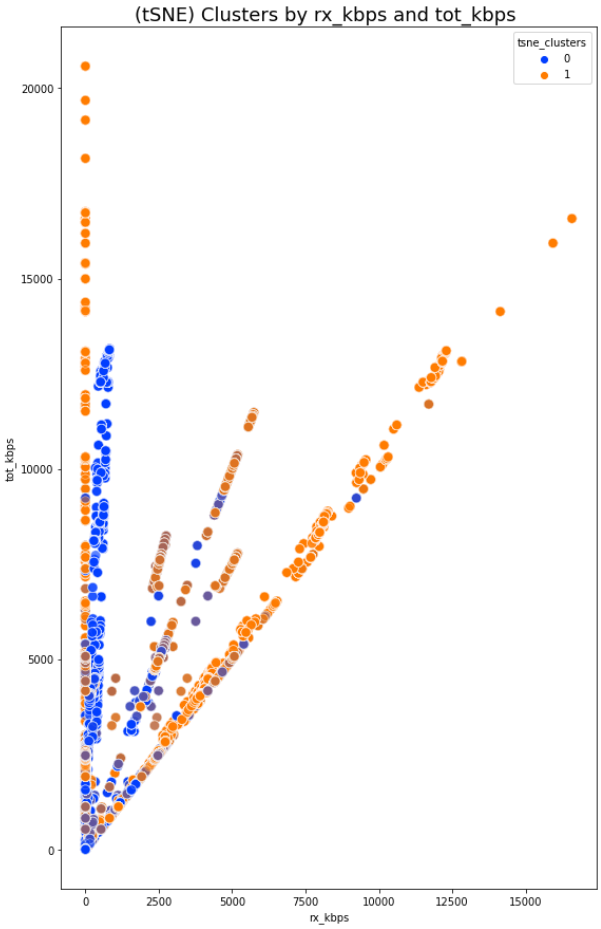
25000
20000
15000
10000
5000
0
0.00
0.25
0.50
0.75
1.00
1e9
rx_bytes
tsne_clusters = 0
tsne_clusters = 1
40000
30000
20000
10000
0
0
5000
10000
15000
rx_kbps


tsne_clusters = 0
tsne_clusters = 1
30000
20000
10000
0
0
5000
10000
15000
20000
tot_kbps
tsne_clusters = 0
tsne_clusters = 1
40000
30000
20000
10000
0
0
5000
10000
15000
20000
tx_kbps
tsne_clusters = 0
tsne_clusters = 1
50000
40000
30000
20000
10000
0
−0.5
0.0
0.5
1.0
1.5
tsne_clusters

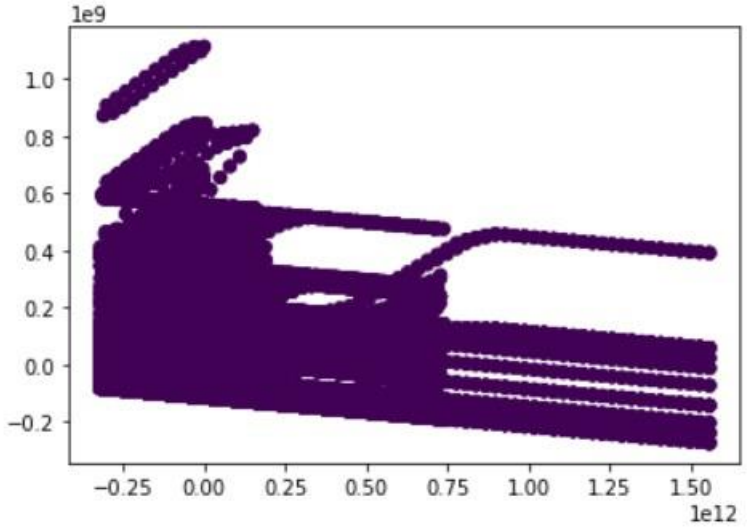

(PCA) Clusters by rx_kbps and tot_kbps
pca_clusters
0
1
tot_kbps
rx_kbps
0
5000
10000
15000
20000
0
2500
5000
7500
10000
12500
15000


(tSNE) Clusters by rx_kbps and tot_kbps
tsne_clusters
0
1
tot_kbps
rx_kbps
0
5000
10000
15000
20000
0
2500
5000
7500
10000
12500
15000

- **DBSCAN for DDoS Detection**

  - ❖ Import the required libraries
  - ❖ Load the dataset
  - ❖ Apply PCA and reduced the features in to two principal components PC1 and PC2
  - ❖ Compute DBSCAN
  - ❖ Set epsilon = 0.5 and min samples = 10
  - ❖ Fit the model
  - ❖ Evaluate the metrics
    - ❑ Results:-

Evaluation Metric	Obtained Value
Silhouette Coefficient	-0.399



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