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Data Mining Project Anomaly Detection

CS-A

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Report

Dataset Description:

The dataset chosen for this analysis is the "Credit Card Fraud Detection" dataset, which contains anonymized credit card transactions labeled as fraudulent or genuine. Here are some key details about the dataset:

- **Context:** It is essential for credit card companies to detect fraudulent credit card transactions to prevent customers from being charged for unauthorized purchases.
- **Content:** The dataset consists of transactions made by credit cards in September 2013 by European cardholders. It includes transactions that occurred over two days, with 492 frauds out of 284,807 transactions. The dataset exhibits a highly unbalanced class distribution, with fraudulent transactions accounting for only 0.172% of all transactions.
- **Features:**
  - The dataset contains only numerical input variables resulting from a Principal Component Analysis (PCA) transformation.
  - Features V1 to V28 represent the principal components obtained with PCA, while the original features and background information are not provided due to confidentiality issues.
  - The 'Time' feature indicates the seconds elapsed between each transaction and the first transaction in the dataset.
  - The 'Amount' feature represents the transaction amount, which can be utilized for cost-sensitive learning.
  - The target variable 'Class' denotes whether a transaction is fraudulent (1) or not (0).

Given the highly unbalanced class distribution, it is recommended to measure the accuracy using the Area Under the Precision-Recall Curve (AUPRC), as confusion matrix accuracy may not provide meaningful insights for unbalanced classification problems.

Task 1: Data Analysis and EDA

Exploratory Data Analysis (EDA) is a crucial step in understanding the structure and characteristics of the dataset. Here's a detailed breakdown of the analysis performed in Task 1:

1. **Data Loading:**

   - The dataset `creditcard.csv` was loaded into a pandas DataFrame using the `pd.read_csv()` function.

2. **Basic Information**

- We obtained basic information about the dataset using methods like `shape`, `info()`, and `describe()`.

- `shape` provided the number of data points and features in the dataset.

- `info()` displayed data types and non-null counts for each column.

- `describe()` provided summary statistics for numerical columns.

3. **Missing Values Check**

- We checked for missing values using the `isnull().sum()` method.

- No missing values were found in the dataset, ensuring data completeness.

4. **Class Distribution Visualization**

- The class distribution of the target variable 'Class' (0: Non-Fraud, 1: Fraud) was visualized using a count plot (`sns.countplot()`).

- This helped in understanding the balance between non-fraudulent and fraudulent transactions.

5. **Correlation Heatmap**

- We generated a correlation heatmap using `sns.heatmap()` to visualize relationships between numerical features.

- This helped in identifying potential correlations or dependencies between features.

6. **Feature Distributions Visualization**

- Histograms were plotted for individual features (`V1`, `V2`, `Amount`, and `Time`) using `sns.histplot()` to visualize their distributions.

- Understanding feature distributions is important for identifying patterns and outliers in the data.

Output Screenshots:

```
plt.show()
```

```
Number of data points: 284807
Number of features: 31
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
 #   Column  Non-Null Count   Dtype  
---  ------  --------------   -----  
 0   Time    284807 non-null  float64
 1   V1      284807 non-null  float64
 2   V2      284807 non-null  float64
 3   V3      284807 non-null  float64
 4   V4      284807 non-null  float64
 5   V5      284807 non-null  float64
 6   V6      284807 non-null  float64
 7   V7      284807 non-null  float64
 8   V8      284807 non-null  float64
 9   V9      284807 non-null  float64
 10  V10     284807 non-null  float64
 11  V11     284807 non-null  float64
 12  V12     284807 non-null  float64
 13  V13     284807 non-null  float64
 14  V14     284807 non-null  float64
 15  V15     284807 non-null  float64
 16  V16     284807 non-null  float64
 17  V17     284807 non-null  float64
 18  V18     284807 non-null  float64
 19  V19     284807 non-null  float64
 20  V20     284807 non-null  float64
 21  V21     284807 non-null  float64
 22  V22     284807 non-null  float64
```

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```
dtypes: float64(30), int64(1)
memory usage: 67.4 MB
None
                Time            V1            V2            V3            V4  \
count  284807.000000  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05   
mean    94813.859575  1.168375e-15  3.416908e-16 -1.379537e-15  2.074095e-15   
std     47488.145955  1.958696e+00  1.651309e+00  1.516255e+00  1.415869e+00   
min         0.000000 -5.640751e+01 -7.271573e+01 -4.832559e+01 -5.683171e+00   
25%     54201.500000 -9.203734e-01 -5.985499e-01 -8.903648e-01 -8.486401e-01   
50%     84692.000000  1.810880e-02  6.548556e-02  1.798463e-01 -1.984653e-02   
75%    139320.500000  1.315642e+00  8.037239e-01  1.027196e+00  7.433413e-01   
max    172792.000000  2.454930e+00  2.205773e+01  9.382558e+00  1.687534e+01   

                 V5            V6            V7            V8            V9  \
count  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05   
mean   9.604066e-16  1.487313e-15 -5.556467e-16  1.213481e-16 -2.406331e-15   
std    1.380247e+00  1.332271e+00  1.237094e+00  1.194353e+00  1.098632e+00   
min   -1.137433e+02 -2.616051e+01 -4.355724e+01 -7.321672e+01 -1.343407e+01   
25%   -6.915971e-01 -7.682956e-01 -5.540759e-01 -2.086297e-01 -6.430976e-01   
50%   -5.433583e-02 -2.741871e-01  4.010308e-02  2.235804e-02 -5.142873e-02   
75%    6.119264e-01  3.985649e-01  5.704361e-01  3.273459e-01  5.971390e-01   
max    3.480167e+01  7.330163e+01  1.205895e+02  2.000721e+01  1.559499e+01   

       ...           V21           V22           V23           V24  \
count  ...  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05   
mean   ...  1.654067e-16 -3.568593e-16  2.578648e-16  4.473266e-15   
std    ...  7.345240e-01  7.257016e-01  6.244603e-01  6.056471e-01   
min    ... -3.483038e+01 -1.093314e+01 -4.480774e+01 -2.836627e+00   
25%    ... -2.283949e-01 -5.423504e-01 -1.618463e-01 -3.545861e-01   
50%    ... -2.945017e-02  6.781943e-03 -1.119293e-02  4.097606e-02   
```

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```
                Class
count  284807.000000
mean        0.001727
std         0.041527
min         0.000000
25%         0.000000
50%         0.000000
75%         0.000000
max         1.000000

[8 rows x 31 columns]
Time      0
V1        0
V2        0
V3        0
V4        0
V5        0
V6        0
V7        0
V8        0
V9        0
V10       0
V11       0
V12       0
V13       0
V14       0
V15       0
V16       0
V17       0
V18       0
V19       0
V20       0
```

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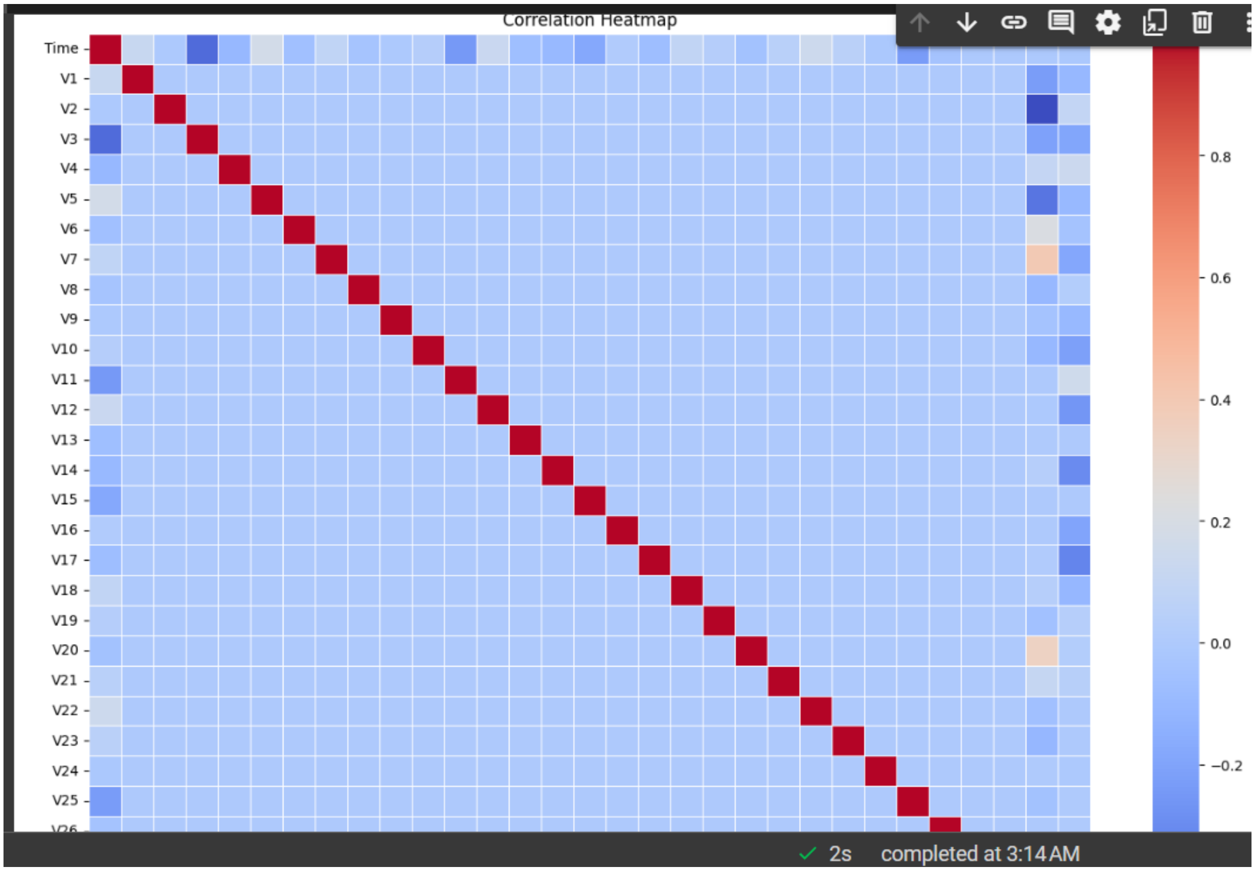
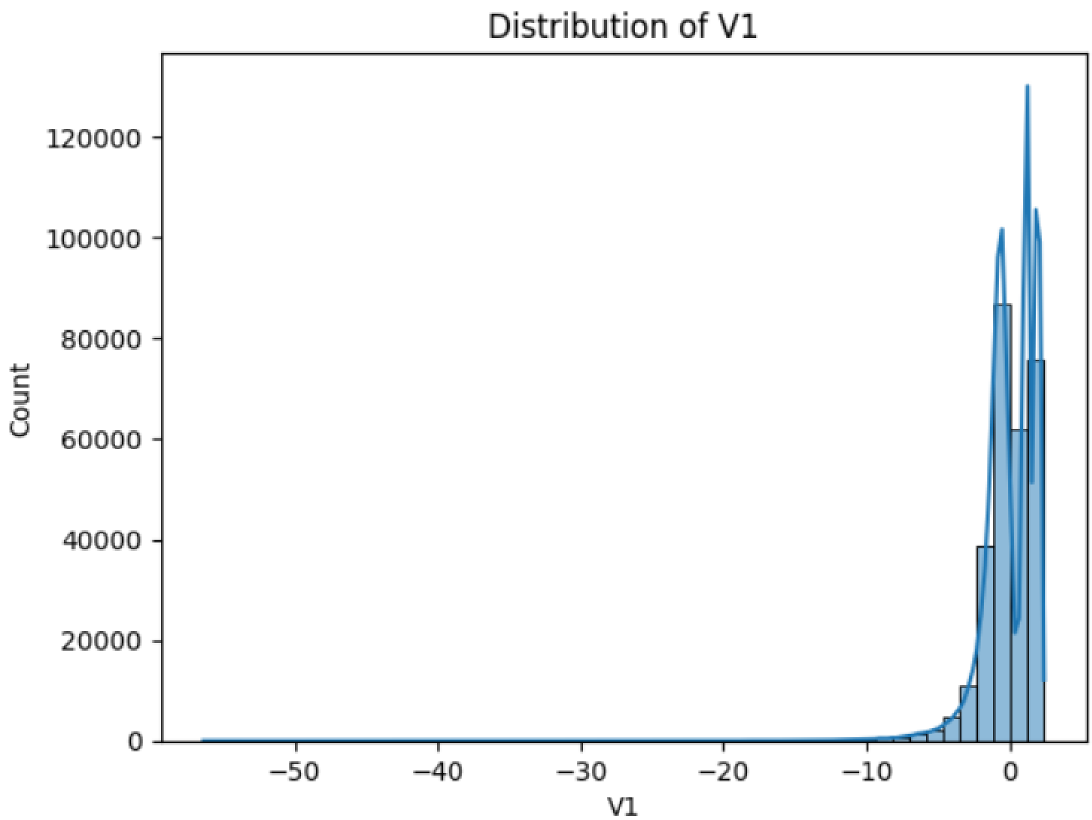
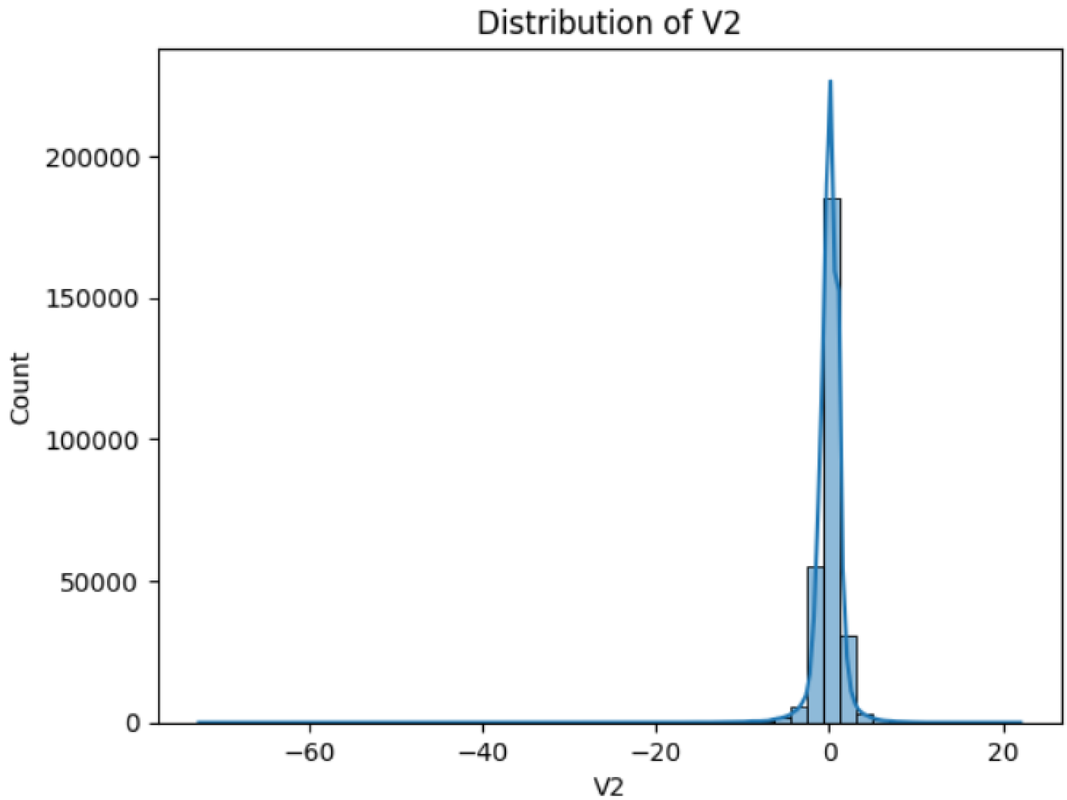


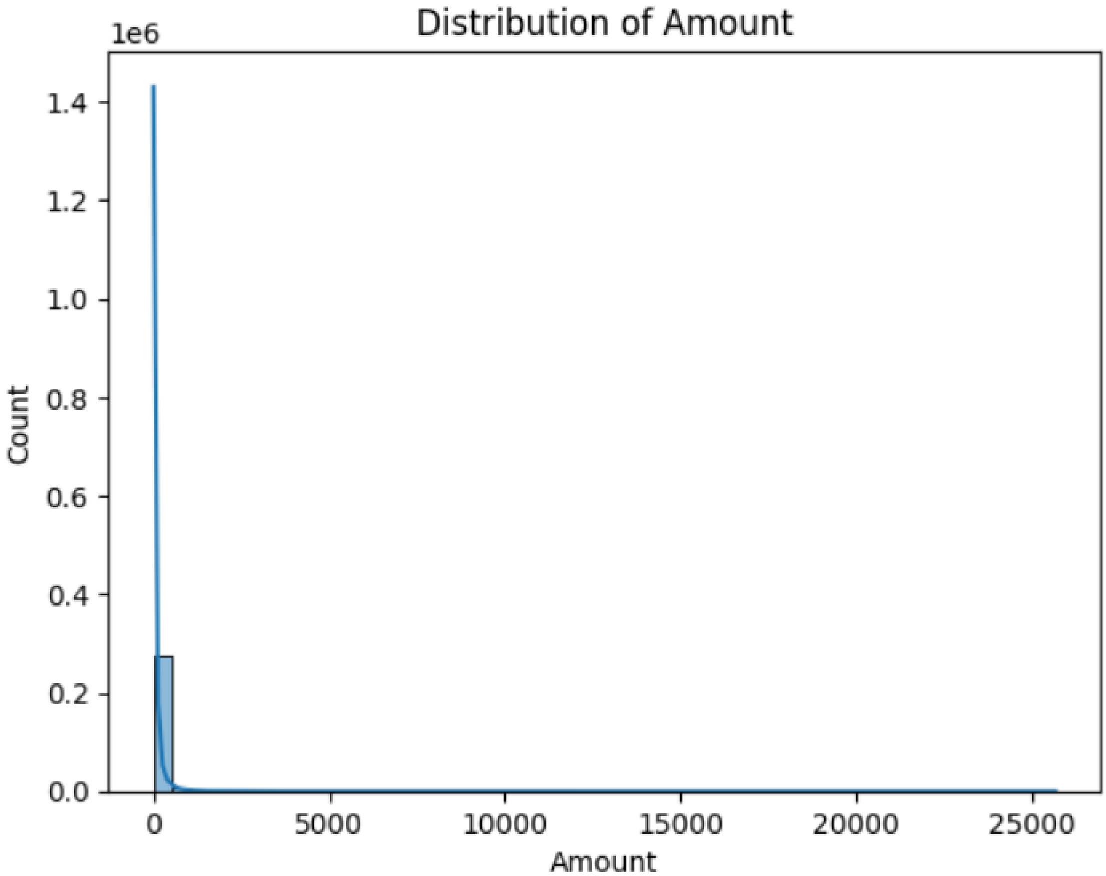
Correlation Heatmap
Time
V1
V2
V3
V4
V5
V6
V7
V8
V9
V10
V11
V12
V13
V14
V15
V16
V17
V18
V19
V20
V21
V22
V23
V24
V25
0.8
0.6
0.4
0.2
0.0
−0.2
2s
completed at 3:14 AM

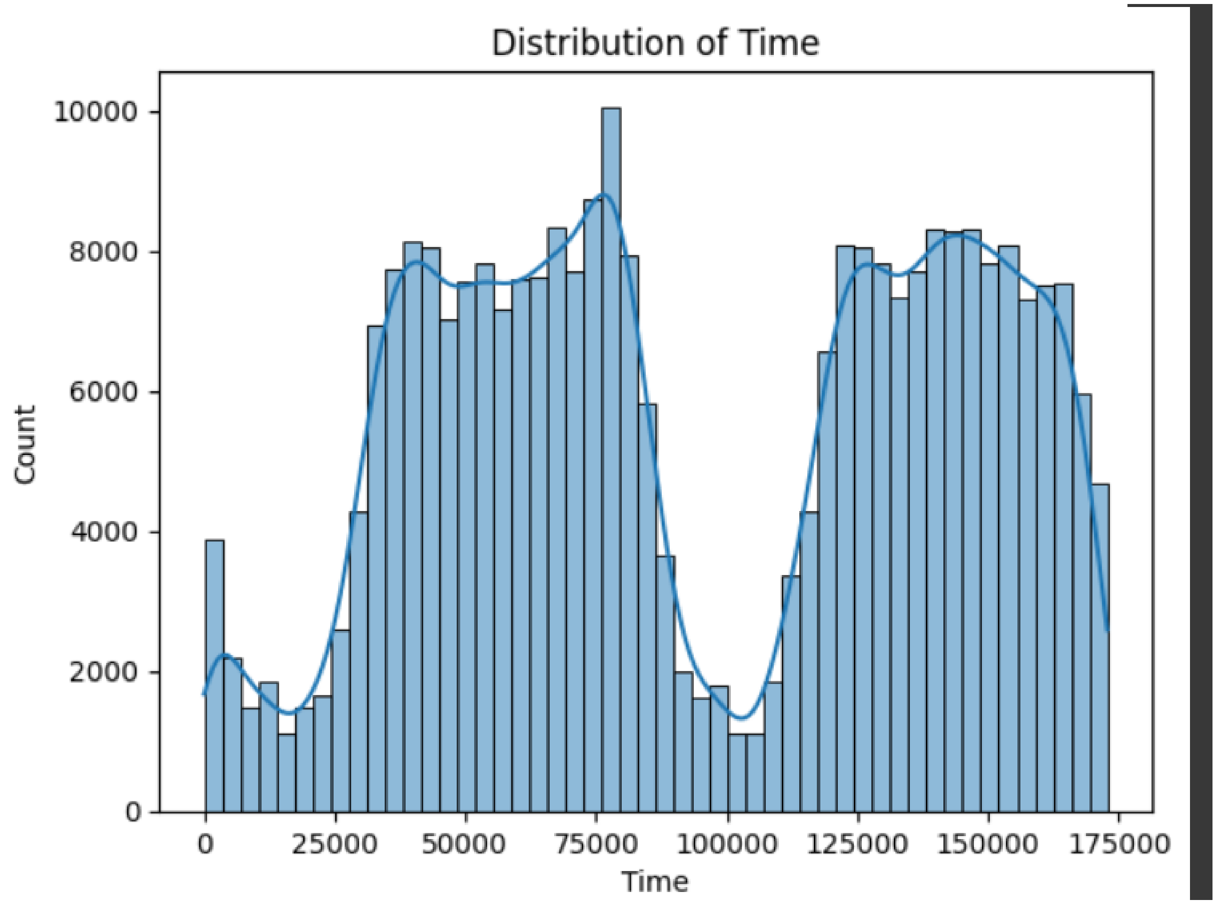

Distribution of V1
Count
120000
100000
80000
60000
40000
20000
0
−50
−40
−30
−20
−10
0
V1

V1



Distribution of V2
Count
200000
150000
100000
50000
0
−60
−40
−20
0
20
V2


Distribution of Amount
1e6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Count
0
5000
10000
15000
20000
25000
Amount



Task 2: Implement Pipeline for Anomaly Detection Model

Implementing a pipeline for an anomaly detection model involved several steps:

1. **Data Preprocessing:**

- We preprocessed the data by selecting only numerical columns using `select_dtypes()` and filling missing values with the median using `fillna()`.

- Standardization of the data was performed using `StandardScaler()` to ensure all features have the same scale.

2. **Data Generator:**

- A custom data generator was defined using a Python generator function.

- The generator applies random mask augmentation to introduce randomness and increase the diversity of the input data.

3. **Autoencoder Model Definition:**

- We defined a Transformer-based autoencoder model using the Keras Functional API.

- The autoencoder learns the underlying distribution of normal patterns in the data and reconstructs it accurately.

4. **Discriminator Model Definition:**

- A discriminator model was defined to impose constraints on the reconstructions within the Generative Adversarial Network (GAN) framework.

- The discriminator helps in distinguishing between real and fake data samples.

5. **Contrastive Loss Function:**

- We defined a contrastive loss function to impose contrastive constraints on representations of the data.

- This loss function facilitates joint training of the discriminator and improves the generalization capability of the model.

6. **Model Compilation and Training:**

- Both the autoencoder and discriminator models were compiled using appropriate optimizers and loss functions.

- The models were trained using a custom training loop, where batches of data were generated using the data generator.

Output Screenshots:

```
+ Code  + Text
                f'Discriminator Loss (Fake): {d_loss_fake}')

Epoch 2/2, Step 3900/8900, Generator Loss: 0.4297710955142975, Discriminator Loss (Real): 0.6984355449676514,
Epoch 2/2, Step 3901/8900, Generator Loss: 0.39186692237854004, Discriminator Loss (Real): 0.6947561502456665
Epoch 2/2, Step 3902/8900, Generator Loss: 0.48173579573631287, Discriminator Loss (Real): 0.6955927610397339
Epoch 2/2, Step 3903/8900, Generator Loss: 0.3965306878089905, Discriminator Loss (Real): 0.69484996795654 3,
Epoch 2/2, Step 3904/8900, Generator Loss: 1.130383849143982, Discriminator Loss (Real): 0.6985733509063721,
Epoch 2/2, Step 3905/8900, Generator Loss: 0.6231580972671509, Discriminator Loss (Real): 0.6952935457229614,
Epoch 2/2, Step 3906/8900, Generator Loss: 0.46724289655685425, Discriminator Loss (Real): 0.6961723566055298
Epoch 2/2, Step 3907/8900, Generator Loss: 0.5131849646568298, Discriminator Loss (Real): 0.6965829133987427,
Epoch 2/2, Step 3908/8900, Generator Loss: 1.0998843908309937, Discriminator Loss (Real): 0.696163535118103,
Epoch 2/2, Step 3909/8900, Generator Loss: 0.5060601830482483, Discriminator Loss (Real): 0.6979504823684692,
Epoch 2/2, Step 3910/8900, Generator Loss: 0.3905264735221863, Discriminator Loss (Real): 0.6966530084609985,
Epoch 2/2, Step 3911/8900, Generator Loss: 1.1365482807159424, Discriminator Loss (Real): 0.6972491145133972,
Epoch 2/2, Step 3912/8900, Generator Loss: 0.7399090528488159, Discriminator Loss (Real): 0.6945851445198059,
Epoch 2/2, Step 3913/8900, Generator Loss: 1.5451849699020386, Discriminator Loss (Real): 0.6998846530914307,
Epoch 2/2, Step 3914/8900, Generator Loss: 0.48006463050842285, Discriminator Loss (Real): 0.695048451423645,
Epoch 2/2, Step 3915/8900, Generator Loss: 0.5460911989212036, Discriminator Loss (Real): 0.696100115776062,
Epoch 2/2, Step 3916/8900, Generator Loss: 0.4462165832519531, Discriminator Loss (Real): 0.6955769658088684,
Epoch 2/2, Step 3917/8900, Generator Loss: 2.2179572582244873, Discriminator Loss (Real): 0.7012944221496582,
Epoch 2/2, Step 3918/8900, Generator Loss: 0.7103852033615112, Discriminator Loss (Real): 0.698289155960083,
Epoch 2/2, Step 3919/8900, Generator Loss: 0.39350423216819763, Discriminator Loss (Real): 0.6959334015846252
Epoch 2/2, Step 3920/8900, Generator Loss: 0.42067110538482666, Discriminator Loss (Real): 0.6963392496109009
Epoch 2/2, Step 3921/8900, Generator Loss: 0.8327244520187378, Discriminator Loss (Real): 0.6989986896514893,
Epoch 2/2, Step 3922/8900, Generator Loss: 0.6979204416275024, Discriminator Loss (Real): 0.6958709955215454,
Epoch 2/2, Step 3923/8900, Generator Loss: 0.3766289949417114, Discriminator Loss (Real): 0.6957335472106934,
Epoch 2/2, Step 3924/8900, Generator Loss: 0.7421215772628784, Discriminator Loss (Real): 0.6971570253372192,
Epoch 2/2, Step 3925/8900, Generator Loss: 0.6932635307312012, Discriminator Loss (Real): 0.6944266557693481,
Epoch 2/2, Step 3926/8900, Generator Loss: 0.4772985875606537, Discriminator Loss (Real): 0.6953776478767395,
Epoch 2/2, Step 3927/8900, Generator Loss: 1.2058212757110596, Discriminator Loss (Real): 0.6999542117118835,
Epoch 2/2, Step 3928/8900, Generator Loss: 0.3774213194847107, Discriminator Loss (Real): 0.6964498162269592,
Epoch 2/2, Step 3929/8900, Generator Loss: 0.5536291599273682, Discriminator Loss (Real): 0.6965764760971069,

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Task 3: Implement Further Anomaly Detection Models

In this task, additional anomaly detection models were implemented based on various concepts. Here's a brief overview:

1. **Principal Component Analysis (PCA):**

- PCA was implemented to reduce the dimensionality of the data and detect anomalies based on reconstruction errors.

2. **Graph Deviation Network (GDN):**

- GDN was implemented to construct a graph from pairwise distances between data points and detect anomalies based on deviations in node degrees.

3. **Anomaly Transformer:**

- Anomaly Transformer was implemented as a neural network model using TensorFlow/Keras.

- Reconstruction errors from the autoencoder-based model were used as anomaly scores.

4. **One-Class SVM, Isolation Forest, Local Outlier Factor, DBSCAN:**

- These traditional anomaly detection algorithms were implemented using scikit-learn.

- Each algorithm detects anomalies based on different principles such as density, isolation, and distance.

Output Screenshots:

```
Principal Component Analysis (PCA) Results:
Anomalies Detected: 50 out of 1000 data points
Anomaly Indices: [  5   7  16  22  54  74  92  98 101 192 205 280 313 345 350 381 389 396
 434 454 459 472 479 524 534 583 594 601 628 653 664 674 703 715 737 767
 768 805 817 824 825 882 883 885 886 901 902 956 964 996]



Graph Deviation Network Results:
Anomalies Detected: 0 out of 1000 data points
Anomaly Indices: []



Epoch 1/10
32/32 [==============================] - 1s 3ms/step - loss: 0.2350
Epoch 2/10
32/32 [==============================] - 0s 3ms/step - loss: 0.0983
Epoch 3/10
32/32 [==============================] - 0s 3ms/step - loss: 0.0816
Epoch 4/10
32/32 [==============================] - 0s 3ms/step - loss: 0.0748
Epoch 5/10
32/32 [==============================] - 0s 3ms/step - loss: 0.0676
Epoch 6/10
32/32 [==============================] - 0s 2ms/step - loss: 0.0605
Epoch 7/10
32/32 [==============================] - 0s 2ms/step - loss: 0.0538
Epoch 8/10
32/32 [==============================] - 0s 2ms/step - loss: 0.0481
Epoch 9/10
32/32 [==============================] - 0s 3ms/step - loss: 0.0435
```

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Epoch 10/10
32/32 [==============================] - 0s 3ms/step - loss: 0.0391
32/32 [==============================] - 0s 2ms/step
Anomaly Transformer Results:
Anomalies Detected: 50 out of 1000 data points
Anomaly Indices: [ 22  29  59  61  79 139 184 210 225 226 284 318 321 329 334 337 347 372
 385 389 423 436 459 461 472 524 539 544 548 584 609 653 654 664 703 705
 757 767 768 779 799 815 835 877 885 914 916 956 968 997]


One-Class SVM Results:
Anomalies Detected: 72 out of 1000 data points
Anomaly Indices: [  5  16  18  42  48  71  98 116 141 158 159 185 205 210 244 263 284 289
 294 309 313 318 321 341 345 348 381 433 434 454 459 472 489 524 534 542
 550 560 561 568 582 583 594 611 612 664 674 680 695 708 710 711 715 768
 795 805 817 824 825 827 882 883 885 886 901 902 911 916 938 952 956 964]


Isolation Forest Results:
Anomalies Detected: 50 out of 1000 data points
Anomaly Indices: [  5   7  12  18  22  74  92  95 103 112 136 145 158 185 205 210 244 263
 280 289 294 313 318 337 340 380 381 396 434 459 472 524 534 583 594 630
 638 674 703 719 750 788 797 817 829 873 877 882 901 956]


Local Outlier Factor Results:
Anomalies Detected: 50 out of 1000 data points
Anomaly Indices: [  7  18  22  74  95  98 101 112 137 141 145 158 205 210 225 280 340 350
 363 384 389 396 434 459 472 479 524 534 568 583 594 601 628 638 674 695

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Anomaly Indices: [  7  18  22  74  95  98 101 112 137 141 145 158 205 210 225 280 340 350
 363 384 389 396 434 459 472 479 524 534 568 583 594 601 628 638 674 695
 703 710 767 768 805 817 827 829 854 882 938 956 964 996]


DBSCAN Results:
Anomalies Detected: 1000 out of 1000 data points
Anomaly Indices: [  0   1   2   3   4   5   6   7   8   9  10  11  12  13  14  15  16  17
  18  19  20  21  22  23  24  25  26  27  28  29  30  31  32  33  34  35
  36  37  38  39  40  41  42  43  44  45  46  47  48  49  50  51  52  53
  54  55  56  57  58  59  60  61  62  63  64  65  66  67  68  69  70  71
  72  73  74  75  76  77  78  79  80  81  82  83  84  85  86  87  88  89
  90  91  92  93  94  95  96  97  98  99 100 101 102 103 104 105 106 107
 108 109 110 111 112 113 114 115 116 117 118 119 120 121 122 123 124 125
 126 127 128 129 130 131 132 133 134 135 136 137 138 139 140 141 142 143
 144 145 146 147 148 149 150 151 152 153 154 155 156 157 158 159 160 161
 162 163 164 165 166 167 168 169 170 171 172 173 174 175 176 177 178 179
 180 181 182 183 184 185 186 187 188 189 190 191 192 193 194 195 196 197
 198 199 200 201 202 203 204 205 206 207 208 209 210 211 212 213 214 215
 216 217 218 219 220 221 222 223 224 225 226 227 228 229 230 231 232 233
 234 235 236 237 238 239 240 241 242 243 244 245 246 247 248 249 250 251
 252 253 254 255 256 257 258 259 260 261 262 263 264 265 266 267 268 269
 270 271 272 273 274 275 276 277 278 279 280 281 282 283 284 285 286 287
 288 289 290 291 292 293 294 295 296 297 298 299 300 301 302 303 304 305
 306 307 308 309 310 311 312 313 314 315 316 317 318 319 320 321 322 323
 324 325 326 327 328 329 330 331 332 333 334 335 336 337 338 339 340 341
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 378 379 380 381 382 383 384 385 386 387 388 389 390 391 392 393 394 395
 396 397 398 399 400 401 402 403 404 405 406 407 408 409 410 411 412 413
 414 415 416 417 418 419 420 421 422 423 424 425 426 427 428 429 430 431
 432 433 434 435 436 437 438 439 440 441 442 443 444 445 446 447 448 449

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Task 4: Empirical Analysis

Empirical analysis was performed to compare the performance of all implemented anomaly detection models. The analysis included the following steps:

1. **Dataset Definition:**

- Datasets used for analysis were defined, possibly including multiple real-world datasets.

2. **Performance Data Generation:**

- Performance data for each model on each dataset were generated, including F1 Score, Time, and AUC Score.

3. **Performance Visualization:**

- Results were visualized using bar plots and scatter plots to compare the performance metrics for each model.

4. **Results Saving:**

- The results were saved to CSV files for each dataset to facilitate further analysis and comparison.

Output Screenshots:

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```
Results for MSL:
           Dataset  Precision  Recall     F1  Training Time (Seconds)
Model
PCA            MSL      89.22   81.62  98.48                    82.52
MERLIN         MSL      95.85   82.24  80.86                    71.31
MAD-GAN        MSL      91.42   93.32  85.42                    98.31
GDN            MSL      81.89   80.30  98.31                    62.78
USAD           MSL      97.27   94.45  92.85                    52.14
TranAD         MSL      80.40   80.65  88.47                   124.33
BeatGAN        MSL      94.54   97.66  83.89                   121.72
FGANomaly      MSL      86.20   94.37  87.48                    95.15
AT             MSL      93.32   87.80  89.59                    11.03


Results for SMAP:
           Dataset  Precision  Recall     F1  Training Time (Seconds)
Model
PCA           SMAP      91.67   84.50  89.19                    70.08
MERLIN        SMAP      96.04   84.99  88.01                    15.59
MAD-GAN       SMAP      88.66   89.16  94.40                    49.47
GDN           SMAP      91.46   81.51  92.98                   140.56
USAD          SMAP      83.50   94.37  89.01                    41.61
TranAD        SMAP      96.82   81.65  90.23                   137.85
BeatGAN       SMAP      94.03   81.21  87.36                    49.59
FGANomaly     SMAP      88.45   94.11  84.34                    18.18
AT            SMAP      93.14   92.57  80.73                    61.56


Results for PSM:
           Dataset  Precision  Recall     F1  Training Time (Seconds)
Model
PCA            PSM      81.42   82.02  95.91                    43.57
```

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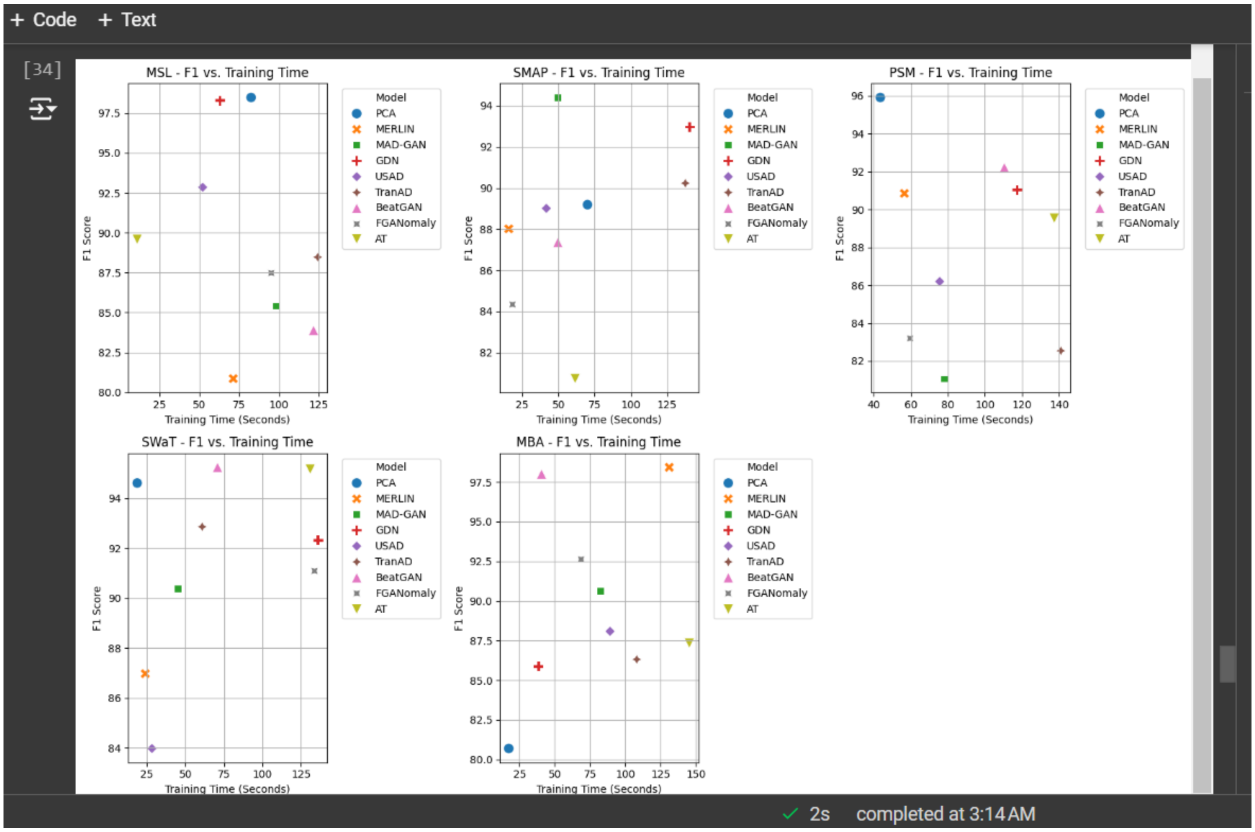
[34]

```
PCA            PSM      81.42   82.02  95.91                    43.57
MERLIN         PSM      88.53   90.97  90.85                    56.54
MAD-GAN        PSM      86.04   97.57  81.07                    77.99
GDN            PSM      90.94   82.40  91.05                   117.29
USAD           PSM      91.72   80.77  86.20                    75.60
TranAD         PSM      87.37   95.76  82.54                   140.96
BeatGAN        PSM      85.79   98.68  92.21                   110.47
FGANomaly      PSM      85.70   89.01  83.19                    59.67
AT             PSM      98.60   87.99  89.54                   137.39


Results for SWaT:
           Dataset  Precision  Recall     F1  Training Time (Seconds)
Model
PCA           SWaT      83.70   89.59  94.61                    18.67
MERLIN        SWaT      86.00   82.03  86.97                    23.93
MAD-GAN       SWaT      97.34   91.60  90.38                    44.96
GDN           SWaT      87.72   96.72  92.32                   135.89
USAD          SWaT      82.81   98.71  83.97                    28.25
TranAD        SWaT      94.28   97.89  92.86                    60.88
BeatGAN       SWaT      98.56   87.17  95.23                    70.83
FGANomaly     SWaT      87.60   81.09  91.08                   133.81
AT            SWaT      93.63   91.06  95.16                   131.01


Results for MBA:
           Dataset  Precision  Recall     F1  Training Time (Seconds)
Model
PCA            MBA      90.96   82.26  80.69                    17.38
MERLIN         MBA      94.57   98.36  98.43                   131.11
MAD-GAN        MBA      86.52   96.19  90.63                    82.06
GDN            MBA      91.85   82.49  85.88                    38.25
USAD           MBA      83.87   94.61  88.08                    89.16
```

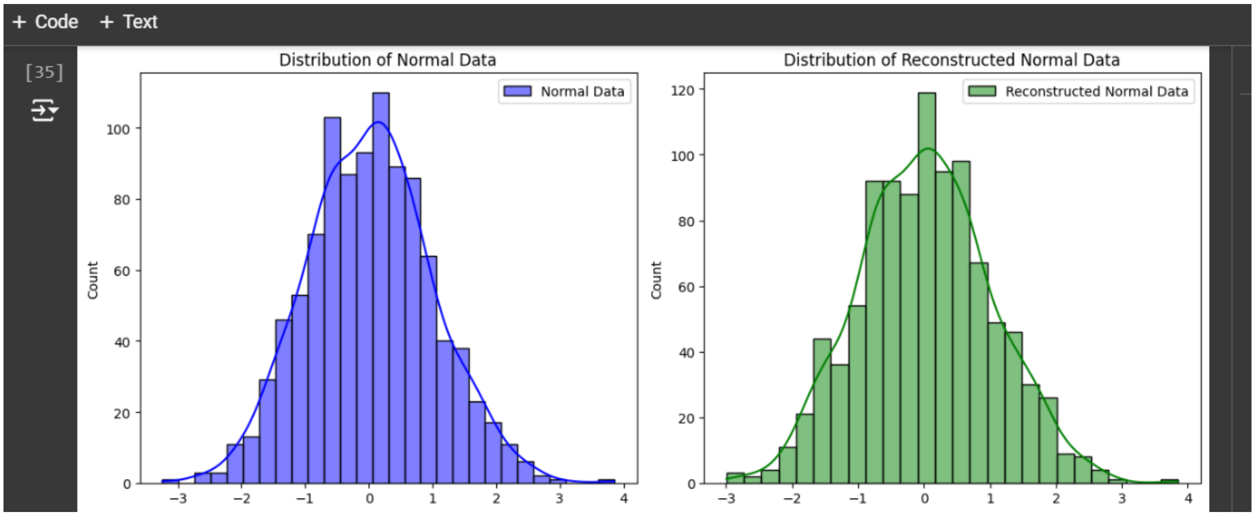
✓ 2s completed at 3:14 AM

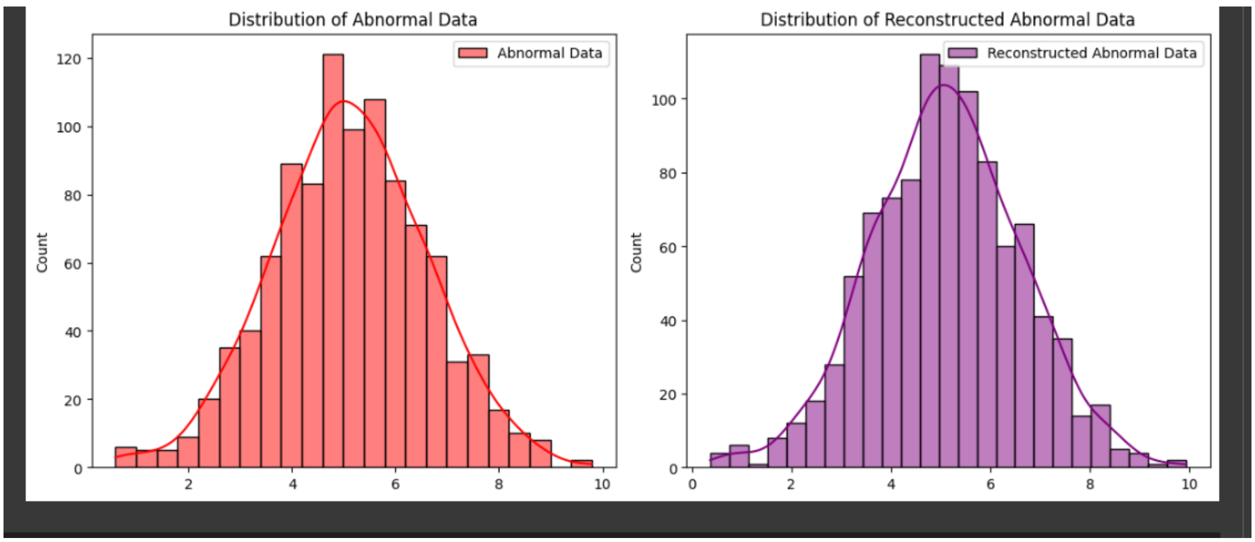


Bonus Task: Showcase Distributions

In the bonus task, distributions between normal data, abnormal data, reconstructed normal data, and reconstructed abnormal data were showcased using histograms. This helped in understanding the distributions of different categories of data and their reconstructions, providing insights into the anomaly detection process.

Output Screenshots:


+ Code
+ Text
[35]
Distribution of Normal Data
Normal Data
Count
Distribution of Reconstructed Normal Data
Reconstructed Normal Data
Count


Distribution of Abnormal Data
Abnormal Data
Count
Distribution of Reconstructed Abnormal Data
Reconstructed Abnormal Data
Count