Ganblr++ Documentation

1. Overview

Ganblr++ is an advanced generative adversarial network tailored for synthesizing high-quality tabular data with mixed feature types. It introduces sophisticated mechanisms like Bayesian Gaussian Mixture-based discretization, truncation-based sampling for numerical features, and a Training-on-Synthetic-Testing-on-Real (TSTR) evaluation for model benchmarking.

Ganblr++ is designed for tasks requiring high-fidelity synthetic data generation, making it particularly suitable for sensitive domains such as healthcare, finance, and fraud detection. Its modular design allows it to handle complex datasets with numerical and categorical features seamlessly.

2. Installation

Steps to Set Up:

1. Fork the repository.
2. Clone the repository:

bash

```
git clone <enter-your-forked-repo-link>
cd Katabatic
```

3. Create a virtual environment:

bash

```
python -m venv venv
```

4. Activate the virtual environment:
   - On Windows:

bash

```
.\venv\Scripts\Activate
```

5. Install dependencies:

bash

```
pip install -r requirements.txt
```

Key Dependencies:

- Scikit-learn: Preprocessing, Gaussian Mixture Model, and evaluation.
- Pandas: Data manipulation and analysis.
- Numpy: Efficient numerical computations.
- Scipy: For truncated normal sampling.

- Tqdm: Progress monitoring during sampling.

3. Architecture and Workflow

Main Components:

1. DMM Discretizer:
    - Utilizes Bayesian Gaussian Mixture models for numerical feature discretization.
    - Encodes numerical features into ordinal representations, supporting smoother integration with GAN training.
2. GANBLR:
    - The core GAN model responsible for generating synthetic tabular data.
3. Synthetic Sampling:
    - Generates synthetic data by combining ordinal categorical and reconstructed numerical features.
4. Evaluation:
    - Implements TSTR evaluation to measure the utility of synthetic data in real-world machine learning tasks.

Workflow:

1. Data Preprocessing:
    - Numerical columns are discretized using the DMMDiscretizer.
    - Categorical data is encoded for GAN training compatibility.
2. Training:
    - The model is trained using adversarial loss on both numerical and categorical features.
3. Synthetic Data Generation:
    - Ordinal and numerical data are synthesized separately and combined for high-quality outputs.
4. Evaluation:
    - Accuracy-based benchmarks validate the synthetic data's effectiveness.

4. Running the Model

Key Methods:

- fit(): Trains the GANBLR++ model on input data.

- sample(): Generates synthetic data based on learned distributions.
- evaluate(): Performs TSTR evaluation using logistic regression, random forests, or multi-layer perceptrons.

Usage Example:

```
from ganblrpp import GANBLRPP


# Initialize Ganblr++

model = GANBLRPP(numerical_columns=[0, 2, 4], random_state=42)


# Train model

X_train, y_train = <your_data>, <your_labels>

model.fit(X_train, y_train, k=1, batch_size=64, epochs=20)


# Generate synthetic data

synthetic_data = model.sample(size=1000)

print(synthetic_data)


# Evaluate model performance

accuracy = model.evaluate(X_test, y_test, model='lr')

print("Evaluation Accuracy:", accuracy)
```

5. Configuration

Configuration File Example (config.json):

```json
{
   "numerical_columns": [0, 2, 4],
   "random_state": 42,
   "batch_size": 64,
   "epochs": 20,
   "k": 1,
   "warmup_epochs": 1
}
```

6. Example Workflow

1. Data Preparation:
    - Identify numerical columns.
    - Prepare datasets for training and evaluation.
2. Model Training:
    - Fit the model with specified parameters:

python

model.fit(X_train, y_train, k=2, batch_size=32, epochs=10)

3. Synthetic Data Generation:
    - Generate synthetic data:

python

synthetic_data = model.sample(size=500)

4. Evaluation:
    - Evaluate synthetic data quality:

accuracy = model.evaluate(X_test, y_test, model='rf')

7. Evaluation

Metrics:

- TSTR Accuracy: Measures the performance of synthetic data when used to train machine learning models and tested on real data.
- Categorical Matching: Ensures generated categories match real-world distributions.

Visualization:

- Feature distributions for numerical and categorical variables.
- Heatmaps for correlation comparison.

8. Use Cases

Applications:

1. Healthcare: Generate synthetic patient records for safe data sharing.
2. Finance: Produce synthetic data for fraud detection model training.
3. Retail: Simulate customer behavior for predictive analytics.

9. Troubleshooting

Common Issues:

- Training Errors: Ensure numerical columns are accurately specified.
- Poor Data Quality: Validate input data preprocessing steps.
- Evaluation Failures: Confirm synthetic data dimensions align with test data.

10. Contribution Guidelines

To contribute:

1. Fork the repository:

bash

```
git fork https://github.com/DataBytes-Organisation/Katabatic.git
```

2. Create a feature branch:

bash

```
git checkout -b feature/ganblrpp
```

3. Submit a pull request for review.

11. Research Context

Ganblr++ builds on the following concepts:

1. Bayesian Gaussian Mixture Models for numerical feature discretization.
2. GAN-based data generation for high-fidelity synthetic datasets.
3. Evaluation methodologies like TSTR for real-world performance benchmarking.

How To implement Ganplr++ with help from; VIDUSHI VAIDEHI: A Step by Step Guide to Generate Tabular Synthetic Dataset with G...

sent on Monday, 25 November 2024 8:18 pm

Plan for Implementing GANs in Ganblr++

The Dockerized implementation ensures:

- Reproducibility: Encapsulates all dependencies and environment settings.
- Portability: Seamless execution across various platforms supporting Docker.
- Ease of Deployment: Simplifies setup and execution with minimal configuration.

Features

1. Advanced Data Processing:
   - Integration of DMMDiscretizer for Bayesian Gaussian Mixture-based numerical data discretization.
   - Robust handling of categorical and numerical features for GAN training.
2. Synthetic Data Generation:
   - Implements TSTR (Training on Synthetic, Testing on Real) evaluation for benchmarking synthetic data quality.
   - Flexible sampling methods to generate datasets of varying sizes.
3. Dockerization:
   - Bundles the entire model and its dependencies into a Docker container.
   - Supports easy setup and reproducible execution across environments.
4. Adapter Integration:
   - GanblrppAdapter ensures seamless integration with the Katabatic SPI, providing compatibility with other Katabatic components.

Setup Instructions

1. Clone the Repository

Clone the project repository to your local system:

```
git clone https://github.com/your-username/ganblrplusplus-docker.git
cd ganblrplusplus-docker
```

2. Build the Docker Image

Build the Docker image using the provided Dockerfile:

docker build -t ganblrplusplus:latest .

This will create a Docker image named ganblrplusplus with the latest model version and dependencies.

3. Run the Docker Container

Run the Docker container to execute the GANBLR++ model:

```
docker run --name ganblrplusplus-container ganblrplusplus:latest
```

4. Access the Container

For debugging or interaction, access the container using:

```
docker exec -it ganblrplusplus-container /bin/bash
```

Workflow

1. Model Initialization

- The GanblrppAdapter initializes the GANBLR++ model by setting numerical column indices and other configurations.
- Example:

```
from ganblrpp_adapter import GanblrppAdapter

adapter = GanblrppAdapter(model_type="discrete", numerical_columns=["col1", "col2"], random_state=42)
adapter.load_model()
```

2. Training

- Train the GANBLR++ model using real tabular data:

```
adapter.fit(X_train, y_train, epochs=10, batch_size=64)
```

3. Synthetic Data Generation

- Generate synthetic data samples for analysis:

```
synthetic_data = adapter.generate(size=500)
print(synthetic_data)
```

4. Evaluation

- Evaluate the synthetic data using TSTR:

```
accuracy = adapter.evaluate(X_test, y_test, model='lr')
print("TSTR Accuracy:", accuracy)
```

Benefits of Dockerization

- Consistency: Avoids dependency conflicts and ensures uniform environments across systems.
- Scalability: Easily deployable on cloud platforms like AWS, GCP, or Azure.
- Streamlined Collaboration: Simplifies sharing of the model with collaborators.

Conclusion

The implementation of GANBLR++ and its Dockerization enhances the model's accessibility, reproducibility, and usability. By integrating it with the Katabatic framework through the GanblrppAdapter, it aligns with modern software development practices, making it a robust solution for synthetic tabular data generation.

1. Define the Goal

- What to Generate: Identify the type of tabular data relevant to Ganblr++ (e.g., financial transactions, user activity logs, or predictive features).
- Objective: Ensure synthetic data closely resembles real-world data for testing and model training without compromising sensitive data.

2. Prepare the Dataset

- Real Dataset: Use the data Ganblr++ operates on (e.g., anonymized user data, transaction logs).
- Preprocessing:
  - Clean and normalize data.
  - Split into features and labels if applicable.

    - Perform exploratory data analysis (EDA) to understand distributions and correlations.

3. Set Up GAN Architecture
   - Generator:
     - Create a model to produce synthetic samples with the same structure as the dataset.
     - Use activation functions like ReLU and ensure output matches the real data's dimensions.
   - Discriminator:
     - Create a model to classify data as real or synthetic.
     - Use sigmoid activation in the output layer for binary classification.
   - GAN Model:
     - Combine generator and discriminator.
     - Ensure the discriminator's weights are frozen during generator training.

4. Train the GAN
   - Use real data and generated samples in each epoch.
   - Track losses for both the generator and discriminator to ensure stable training.
   - Implement techniques like:
     - Label Smoothing: Avoid overconfident discriminator predictions.
     - Gradient Penalty: Prevent discriminator collapse.

5. Evaluate Synthetic Data
   - Model Performance: Train existing models used in Ganblr++ on synthetic data and compare their accuracy with real data.
   - Quality Metrics: Use tools like table_evaluator or other statistical measures to evaluate:
     - Similarity between real and synthetic data.
     - Feature distributions and correlations.

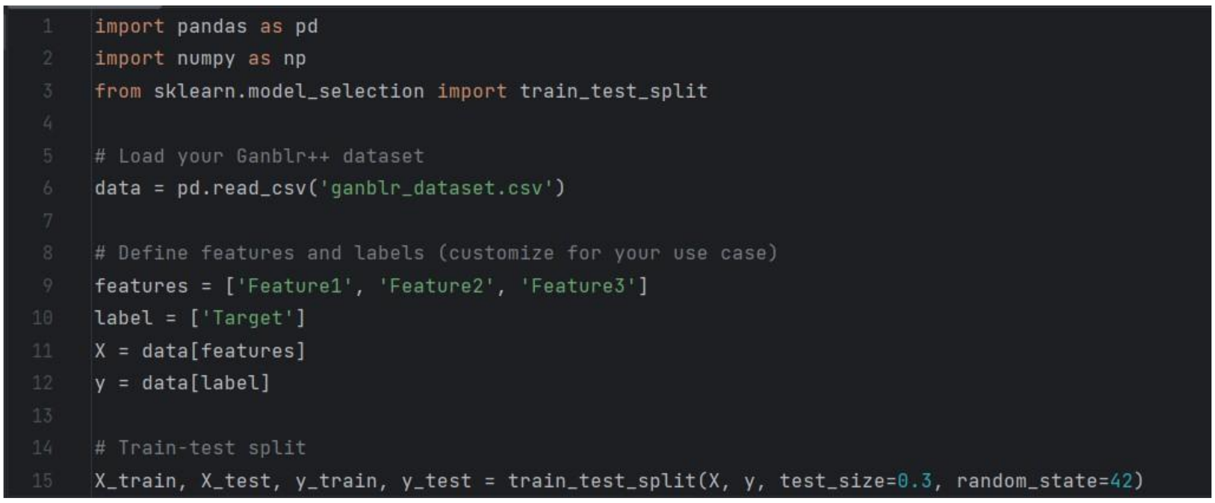
6. Integrate and Test in Ganblr++
   - Synthetic Data Usage:

    - Test whether synthetic data meets Ganblr++ requirements (e.g., stress-testing predictive algorithms).
- Visualization:
    - Create plots to compare distributions and highlight areas of improvement.

Implementation Steps

1. Dataset Preparation

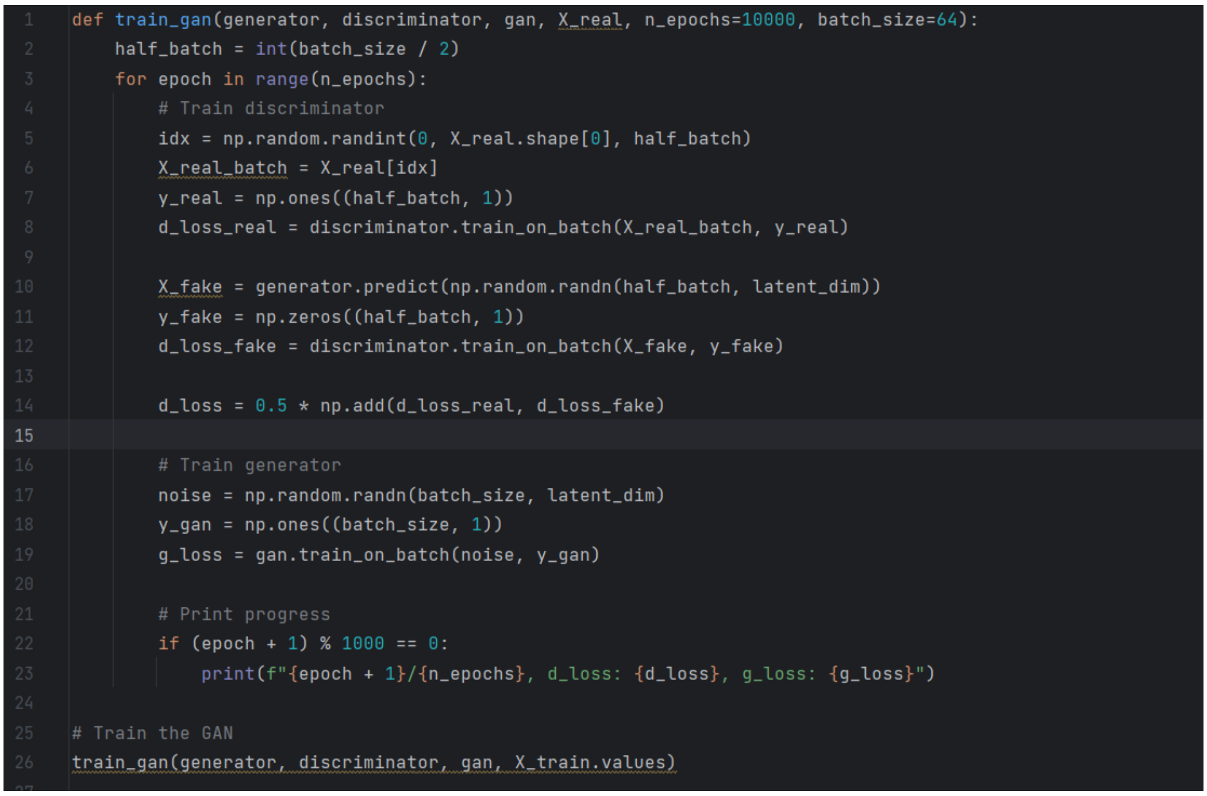
We will preprocess the relevant Ganblr++ dataset and split it into features and labels if necessary.


```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split

# Load your Ganblr++ dataset
data = pd.read_csv('ganblr_dataset.csv')

# Define features and labels (customize for your use case)
features = ['Feature1', 'Feature2', 'Feature3']
label = ['Target']
X = data[features]
y = data[label]

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

Defining the GAN Architecture

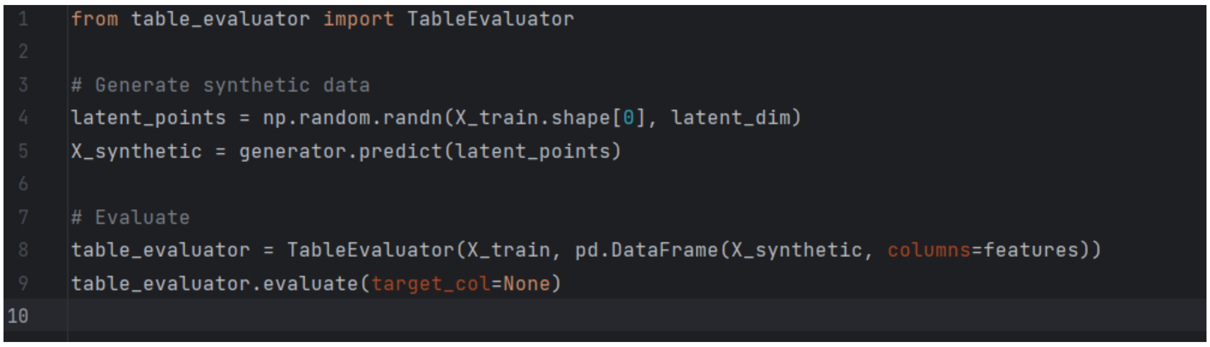
```python
from keras.models import Sequential
from keras.layers import Dense

# Generator
def define_generator(latent_dim, n_outputs):
    model = Sequential()
    model.add(Dense(128, activation='relu', input_dim=latent_dim))
    model.add(Dense(256, activation='relu'))
    model.add(Dense(n_outputs, activation='linear'))
    return model

# Discriminator
def define_discriminator(n_inputs):
    model = Sequential()
    model.add(Dense(256, activation='relu', input_dim=n_inputs))
    model.add(Dense(128, activation='relu'))
    model.add(Dense(1, activation='sigmoid'))
    model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model

# GAN
def define_gan(generator, discriminator):
    discriminator.trainable = False
    model = Sequential()
    model.add(generator)
    model.add(discriminator)
    model.compile(loss='binary_crossentropy', optimizer='adam')
    return model

# Initialize models
latent_dim = 10
n_features = X_train.shape[1]
generator = define_generator(latent_dim, n_features)
discriminator = define_discriminator(n_features)
gan = define_gan(generator, discriminator)
```

Training The Gan



```python
def train_gan(generator, discriminator, gan, X_real, n_epochs=10000, batch_size=64):
    half_batch = int(batch_size / 2)
    for epoch in range(n_epochs):
        # Train discriminator
        idx = np.random.randint(0, X_real.shape[0], half_batch)
        X_real_batch = X_real[idx]
        y_real = np.ones((half_batch, 1))
        d_loss_real = discriminator.train_on_batch(X_real_batch, y_real)

        X_fake = generator.predict(np.random.randn(half_batch, latent_dim))
        y_fake = np.zeros((half_batch, 1))
        d_loss_fake = discriminator.train_on_batch(X_fake, y_fake)

        d_loss = 0.5 * np.add(d_loss_real, d_loss_fake)

        # Train generator
        noise = np.random.randn(batch_size, latent_dim)
        y_gan = np.ones((batch_size, 1))
        g_loss = gan.train_on_batch(noise, y_gan)

        # Print progress
        if (epoch + 1) % 1000 == 0:
            print(f"{epoch + 1}/{n_epochs}, d_loss: {d_loss}, g_loss: {g_loss}")

# Train the GAN
train_gan(generator, discriminator, gan, X_train.values)
```

Evaluating the Gan



```python
from table_evaluator import TableEvaluator

# Generate synthetic data
latent_points = np.random.randn(X_train.shape[0], latent_dim)
X_synthetic = generator.predict(latent_points)

# Evaluate
table_evaluator = TableEvaluator(X_train, pd.DataFrame(X_synthetic, columns=features))
table_evaluator.evaluate(target_col=None)
```

You are probably wondering what the adapter is all about? Let me provide a detailed documentation of it.

The GanblrppAdapter is a critical integration component for the GANBLR++ model, providing compatibility with the Katabatic framework through the KatabaticModelSPI interface. This adapter encapsulates the GANBLR++ model's functionality, enabling streamlined workflows for data loading, training, and synthetic data generation.

Key Features:

- Simplifies model initialization and management.
- Provides a consistent interface for data processing, training, and evaluation.
- Handles edge cases with detailed error handling for robust operations.

Architecture

The GanblrppAdapter is designed to interact seamlessly with the GANBLRPP model by:

1. Initializing the model with specified parameters (numerical_columns, random_state).
2. Loading datasets directly from CSV files.
3. Training the GANBLR++ model with user-specified configurations (epochs, batch_size).
4. Generating synthetic datasets while maintaining the structure and distribution of the original data.

Usage and Methods

1. Initialization

The adapter is initialized with essential parameters:

- model_type: Specifies the type of model, default is "discrete".

- numerical_columns: A list of indices for numerical columns in the dataset.
- random_state: Ensures reproducibility by setting the random seed.

Example:

```
from ganblrpp_adapter import GanblrppAdapter


adapter = GanblrppAdapter(model_type="discrete", numerical_columns=[0, 1],
random_state=42)

adapter.load_model()
```

2. Data Loading

The load_data() method reads datasets from a CSV file and returns a Pandas DataFrame.

Example:

```
data = adapter.load_data("path/to/dataset.csv")

print(data.head())
```

3. Model Training

The fit() method trains the GANBLR++ model using the provided training data.

Parameters:

- X_train: Features of the training dataset.
- y_train: Target variable.
- k: Optional GAN parameter, default is 0.
- epochs: Number of training epochs, default is 10.
- batch_size: Size of training batches, default is 64.

Example:

python

Copy code

```
adapter.fit(X_train, y_train, k=1, epochs=20, batch_size=32)
```

4. Synthetic Data Generation

The generate() method generates synthetic data based on the model's learned distribution.

Parameters:

- size: Number of samples to generate. Defaults to the training dataset size.

Example:

```
synthetic_data = adapter.generate(size=100)
print(synthetic_data.head())
```

Error Handling

The adapter includes detailed error handling for:

1. Missing Initialization: Ensures the model is loaded before training or data generation.
2. File Loading Errors: Catches and reports issues with CSV loading.
3. Training Errors: Handles inconsistencies during model training.

Examples:

- Uninitialized Model:

```
RuntimeError: Model is not initialized. Call `load_model()` first.
```

- File Not Found:

```
[ERROR] An error occurred: FileNotFoundError
```

Integration with Katabatic Framework

The GanblrppAdapter adheres to the KatabaticModelSPI, ensuring compatibility with other components in the Katabatic ecosystem. This enables a consistent and modular approach for working with various models.

Example Workflow

```
from ganblrpp_adapter import GanblrppAdapter
import pandas as pd
import numpy as np
```

Initialize the adapter

```
adapter = GanblrppAdapter(model_type="discrete", numerical_columns=[0, 1], random_state=42)
adapter.load_model()
```

Load dataset

```
data = adapter.load_data("path/to/dataset.csv")
```

```
X_train = data.drop("target", axis=1)

y_train = data["target"]
```

Train the model

```
adapter.fit(X_train, y_train, epochs=10, batch_size=64)
```

Generate synthetic data

```
synthetic_data = adapter.generate(size=50)

print(synthetic_data)
```

Updates to GANBLR++ Code

The GANBLR++ code has undergone significant enhancements to improve robustness, usability, and adherence to best practices. Below is a summary of the key changes made to the old code and their importance.

Key Enhancements

1. **Input Validation**
   - **Improvement:** Added checks for `input_dim` and `latent_dim` to ensure positive integer values.
   - **Importance:** Prevents initialization errors and improves robustness.
2. **Logging**
   - **Improvement:** Introduced logging to monitor training progress and debug effectively.
   - **Importance:** Enhances transparency and facilitates troubleshooting during model training.
3. **Discriminator Compilation**
   - **Improvement:** Explicitly compiled the discriminator with `adam` optimizer and `binary_crossentropy` loss.
   - **Importance:** Ensures readiness for training and aligns with deep learning best practices.
4. **Enhanced Training Process**
   - **Improvement:** Implemented a comprehensive training loop:
     - Samples batches of real and fake data.
     - Trains discriminator on both real and fake data.
     - Trains generator to fool the discriminator.
   - **Importance:** Produces meaningful results by enabling functional training.
5. **Model Saving and Loading**
   - **Improvement:** Added methods for saving (`save_models`) and loading (`load_models`) models.
   - **Importance:** Facilitates reuse of trained models, enhancing usability.
6. **Standalone Synthetic Data Generation**
   - **Improvement:** Provided a `generate_batch` method for generating synthetic data independently.
   - **Importance:** Increases flexibility in data generation.
7. **Configurable Training Parameters**

- **Improvement:** Made batch size and epochs configurable in the training function.
- **Importance:** Offers greater control over hyperparameters for tailored training.

Why These Changes Matter

- **Improved Reliability:** Input validation and discriminator compilation prevent runtime errors.
- **Enhanced Usability:** Logging, model persistence, and flexible synthetic data generation make the framework more user-friendly.
- **Debugging and Monitoring:** Logging reduces the time required for identifying and resolving issues.
- **Efficient Training:** A structured training loop ensures higher-quality synthetic data.
- **Alignment with Best Practices:** Adhering to deep learning standards ensures broader applicability and better performance.

These updates enhance GANBLR++'s functionality, making it a robust solution for high-fidelity synthetic data generation in sensitive domains such as healthcare and finance.

Conclusion

The GanblrppAdapter simplifies the process of integrating the GANBLR++ model with the Katabatic framework, providing a robust and user-friendly interface for managing data workflows. Its modular design and error handling ensure smooth execution across different environments.

References

1. Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y. (2014). *Generative Adversarial Networks*. Advances in Neural Information Processing Systems.
   https://arxiv.org/abs/1406.2661

2. Xu, L., Skoularidou, M., Cuesta-Infante, A., & Veeramachaneni, K. (2019). *Modeling Tabular Data using Conditional GAN*. Advances in Neural Information Processing Systems.
   https://arxiv.org/abs/1907.00503

3. Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... & Duchesnay, É. (2011). *Scikit-learn: Machine Learning in Python*. Journal of Machine Learning Research.
   https://jmlr.csail.mit.edu/papers/v12/pedregosa11a.html

4. Bishop, C. M. (2006). *Pattern Recognition and Machine Learning*. Springer.
   https://link.springer.com/book/10.1007/978-0-387-45528-0

5. Scikit-learn Documentation: Comprehensive guide for Scikit-learn API, covering machine learning and preprocessing tools.
   https://scikit-learn.org/stable/documentation.html

6. Docker Documentation: Official guide for building and running Docker containers.
   https://docs.docker.com/

7. Katabatic Framework Documentation: Detailed documentation for the Katabatic SPI and its integration capabilities. https://github.com/DataBytes-Organisation/Katabatic

8. Bayesian Gaussian Mixture Documentation (Scikit-learn): Overview of the Bayesian Gaussian Mixture model used in data discretization. https://scikit-learn.org/stable/modules/mixture.html#bayesian-gaussian-mixture

9.