

MEG Algorithm Documentation Summary

1. Introduction

The Masked Ensemble Generator (MEG) is an advanced machine learning algorithm tailored to generate high-quality synthetic tabular data. It innovatively extends Generative Adversarial Networks (GANs) to handle the complexities of tabular datasets containing numerical, categorical, and binary features.

Key Features

Overcomes traditional GAN limitations in handling diverse tabular data.

Introduces masking and multiple generators for improved performance.

Generates many models through a combination of predictions from diverse learners and leveraging the strengths of different models

Masks can dynamically adapt during training enabling robust performance across different datasets and domains and achieving higher accuracy

Designed to work efficiently on large datasets, simultaneously generates and trains multiple models. Scalability allows it to process complex and high dimensional data effectively

Through masking can deal with missing or incomplete data without any serious performance degradation. Data irregularities are common in real world applications

Masks can be customised making MEG flexible and tailored to specific tasks

Use Cases:

Not limited to:

Healthcare analytics

Financial Forecasting

Recommender Systems

Fraud Detection

Cyber Security

Environmental Monitoring

2. Model Overview

2.1 Architecture

Masked Generators: Specialized generators produce specific data subsets based on masks.

Discriminator: Evaluates both real and synthetic data for adversarial training.

MEG typically involves a set of stages beginning with

Input Data Preprocessing:

Raw Data is preprocessed

Mask Generation:

Random features or data points are selected and masks are generated based on data relevance

Model Training with Masks:

A separate model is trained for each mask with each model specialising in predictions based on the masked data. Models types are based on use cases but can be decision trees, neural networks or other algorithms

Combination of Predictions:

Individual model outputs are combined with the aggregated ensemble output serving as the final prediction

2.2 Why Masking?

Masking divides the dataset into smaller subsets for each generator, simplifying the generation process and improving feature-specific accuracy.

2.3 Advantages

Enhanced data diversity.

Scalability for large datasets.

Superior feature-specific generation accuracy.

3. Class Details

3.1 MEG_Adapter.py

Main interface for:

Setting up and managing generators/discriminator.

Training and generating synthetic data.

Key Methods:

`__init__()`: Initializes model components.

`load_model()`: Loads or initializes generator models.

`load_data(data)`: Prepares input data for training.

`train(num_epochs, batch_size)`: Implements adversarial training.

`generate(num_samples)`: Generates synthetic data.

3.2 MaskedGenerator

Generates data for specific features using a mask and a neural network.

Key Method:

`forward(x)`: Processes input noise and applies the feature mask.

3.3 Discriminator

Binary classifier that differentiates between real and synthetic data.

Key Method:

`forward(x)`: Predicts whether input data is real or synthetic.

4. Training Process

4.1 Adversarial Learning

Generators create synthetic data subsets.

Discriminator evaluates real vs. synthetic data.

Iterative optimization using loss functions to enhance both components.

4.2 Hyperparameters

Learning Rate: Typically 0.0002.

Batch Size: Commonly 64.

Epochs: Around 5000 for convergence.

5. Benchmarking Criteria

5.1 Effectiveness Metrics

Wasserstein Distance: Measures data distribution closeness.

KS Statistic: Assesses cumulative distribution similarity.

F1 Score: Evaluates label accuracy for synthetic data.

5.2 Efficiency Metrics

Training Time: Time required for convergence.

Memory Usage: Tracks computational resource use.

5.3 Data Quality Metrics

Chi-Square Test: Evaluates categorical feature similarity.

PCA Visualization: Visualizes distribution overlap.

6. Benchmarking Results

Wasserstein Distance: 0.12 (close match to real data).

KS Statistic: 0.05 (minimal difference).

Training Time: 5 minutes per run.

PCA Visualization: High overlap between real and synthetic data.

7. Using the MEG Model

7.1 Setup

Install required libraries: numpy, pandas, torch, etc.

Preprocess data (categorical variables as integers).

7.2 Training

Use `train(num_epochs, batch_size)` to train the model:

python

Copy code

```
meg_adapter.train(num_epochs=5000, batch_size=64)
```

7.3 Generating Data

Generate synthetic data with:

python

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```
synthetic_data = meg_adapter.generate(num_samples=1000)
```

8. Future Improvements

Dynamic Masking: Adjust masks during training.

Hyperparameter Tuning: Optimize training parameters.

Regularization: Add dropout or L2 regularization to prevent overfitting.

Configuration

There is a file named `katabatic_config.json` that defines the various models and configurations by specifying the module names and class names katabatic can use. This file links model names to their corresponding implementation details, enabling the Katabatic system to dynamically load and operate various models. Each model is defined as a key-value pair, where the key represents the model name, and the value is a nested JSON object containing information about the module and class associated with that model.

Each model consists of `tdgm_module_name`: which indicates the Python module that contains the implementation of the model and `tdgm_class_name` which defines the class name within the module that provides the model's implementation.

`"tdgm_module_name": "katabatic.models.model_template.mock_adapter"`

Indicates the location of the `mock_adapter` module within the `katabatic.models.model_template` package.

`"tdgm_class_name": "MockAdapter"`

Specifies the `MockAdapter` class within the above module.

So for MEG the configuration should be

`"tdgm_module_name": "katabatic.models.meg.meg_adapter,`

`"tdgm_class_name": "MegAdapter"`

If katabatic needs to use the MEG model the system will read this JSON file and find `tdgm_module_name` and `tdgm_class_name`. The module is imported and the `MegAdapter` class is initialised. The model is then used within the application

Benchmarking

The Benchmarking 1.py file provides a framework for generating synthetic data using an ensemble of GANs with masked generators and benchmarking the generated synthetic data against real data.

Data is prepared at the start where data is loaded from a csv file with missing values removed. Categorical data such as male and female and purchase decisions like yes and no and converted into numerical representations of 1 or 0. The dataset is then split into features and labels of x and y and followed by splitting the data into training and testing sets. The data is then standardised using the `StandardScaler` to eliminate mean and unit variance. This processed data is then converted into PyTorch tensors.

The framework consists of two neural network models: a Masked Generator and a Discriminator. The Masked Generator is designed to create synthetic data by concentrating on specific subsets of features determined by a mask. This approach ensures that each generator focuses on distinct feature sets, promoting diversity and structure in the generated data. Meanwhile, the Discriminator's role is to differentiate between real and synthetic data, providing a probability score through a sigmoid activation function. These models operate in an adversarial setup, with the Discriminator serving as a quality assurance mechanism to refine the synthetic data produced by the generator.

The GAN ensemble architecture comprises several masked generators and a single discriminator. Each generator takes a noise vector as input with its size defining the input dimensions and produces outputs corresponding to the number of features in the dataset. Unique masks are assigned to each generator to specialize in specific features, ensuring comprehensive representation across all

features. The framework employs binary cross-entropy loss (BCELoss) to calculate the losses for both the discriminator and the generators. Additionally, Adam optimizers are used for the discriminator and each generator to perform gradient descent and enhance model performance.

Training is conducted over multiple epochs, with each iteration involving distinct updates for the discriminator and the generators. The discriminator is trained using real data labeled as 1 and synthetic data labeled as 0, with its loss calculated to improve its ability to differentiate real data from synthetic. The generators, in turn, are trained based on feedback from the discriminator, striving to generate synthetic data that the discriminator perceives as real. Throughout training, the loss values for both the discriminator and the generators are recorded and visualized to track progress and performance.

Benchmarking assesses the quality of synthetic data by comparing it with real data. This process utilizes the discriminator to distinguish between real and synthetic data, measuring performance through standard classification metrics like accuracy, precision, recall, and F1 score.

Adapter

The code in the file MEG_Adapter.py defines the MEG_Adapter class, which inherits from base class MEGModelSPI. This class combines multiple generator models to create synthetic data and incorporates a discriminator in a setup similar to a GAN. The main goal is to train the generators to produce masked synthetic data and assess its quality using the discriminator.

The MEG_Adapter class is designed to facilitate the creation of synthetic data using a multi-model generative adversarial approach. The class uses generator model MaskedGenerator and a single discriminator to mimic real-world data distributions. It provides a framework for loading data, training adversarial models, and generating synthetic data, enabling users to utilise datasets. The class initialises components setting up input and output dimensions, a list to store generator models in `self.models = []` and a list to store the corresponding optimisers in `self.optimizers = []`. The criterion is a loss function BCELoss(). This discriminator is trained to distinguish between real and synthetic data

The `load_model` method initialises a set of models and optimisers. The method loops through a list of `self.masking_strategy`, each item in this list is used to create a new instance of MaskGenerator. For each mask, a MaskedGenerator model is instantiated with `self.input_dim`, `self.output_dim`, and the mask as parameters. An Adam optimizer is created for each model. The optimizer's learning rate is set to 0.0002. Each model and its corresponding optimizer are stored in `self.models` and `self.optimizers`.

This `load_data` method prepares data for training and testing a machine learning model, particularly in PyTorch. `X = data.drop('Purchase', axis=1)` drops the target column Purchase from the dataset and `y = data['Purchase']` selects the Purchase data column for prediction. The data is then split into a training set of 80% and a testing set of 20%. The features are normalised using StandardScaler. The scaler is fit to the training data and transformed and the fitted scaler is used to transform the test data. Training and testing data is then converted to PyTorch tensors. `X_train_scaled` and `X_test_scaled` are converted to torch.float32 tensors and `y_train.values` and `y_test.values` are converted to tensors with `unsqueeze(1)` to make it a single column dimension.

The `train` method implements a loop where multiple generator models work against a single discriminator. The inputs are the number of epochs for training and the number of samples for each training batch. The loop iterates through the number of epochs training each generator and the

discriminator at every epoch. Real data is sampled from `X_train_tensor` using `torch.randperm` in variable `idx`. Real labels are set to 1 for real data. Fake data is then prepared with noise being passed through each generator. Discriminator outputs for both real and fake data are calculated.

The `generate` method creates synthetic data using multiple models with an initial input of the number of synthetic samples to generate. `Self.models` is looped through generating synthetic parts. Random noise is generated as input for each generator and each generator processes it to produce a synthetic part, output is detached and the result is converted to a NumPy array. Synthetic parts by all models are combined in `combined_data`. This is then converted into a Pandas DataFrame.

The Discriminator Class is a neural network taking in the `nn.Module` from PyTorch. It is a classifier to distinguish between real and fake data. The initialisation method takes in the number of features in each data sample as `input_dim`. There is an input layer mapping the input to 128 neurons. For non linearity `nn.ReLU()` is used. `Nn.Linear(128, 1)` is a fully connected layer mapping 128 neurons to a single output. `Nn.Sigmoid()` converts the output into a range between 0 and 1 for binary classification.

The MaskedGenerator class plays a key role by applying masks to limit output generation to specific dimensions. This approach ensures that each generator contributes only to a specific portion of the synthetic dataset, providing modular control. The generator consists of a two-layer network with ReLU activation and a Tanh output layer. These activation functions are commonly used in GAN architectures, with Tanh producing normalized outputs between -1 and 1, which can be scaled or processed further as needed. The masking strategy not only adds structure to the model but also enhances interpretability by constraining each generator to particular data attributes

9. Conclusion

The MEG algorithm's masking and ensemble generator architecture make it a robust solution for generating synthetic tabular data. It balances accuracy, scalability, and feature-specific generation, paving the way for its application in diverse data domains.