

CSCA 5642: Introduction to Deep Learning

University of Colorado Boulder

Synthetic Brand Generation with Ensemble Methods

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Problem Statement and Data Overview

To showcase the application of **Generative Deep Learning** techniques for synthesizing realistic data.

This project is a continuation of my previous works on **Supervised Learning** and **Unsupervised Learning**, you can find more information in the appendix.

Detailed ESG (Environmental Social and Governance) dataset to the brand-level

Observations:	3605
Features:	77

ML Approach & Architecture

Model	Type	Purpose	Key Features
CTGAN ¹	Conditional GAN	Tabular synthesis	Mode-specific normalization, conditional vector
TVAE ²	Variational Autoencoder	Distribution learning	KL divergence, latent space regularization
Gaussian Copula	Statistical	Correlation preservation	Multivariate dependencies
GPT-2 Medium	Transformer LLM	Brand name generation	355M params, fine-tuned
Flan-T5 Small	Encoder-Decoder	Conditional text gen	Instruction-following

Ensemble Methods: Combine multiple generators with optimized weighting

Evaluation Metrics: Apply statistical tests (KS, correlation) to assess synthetic data quality

¹ Conditional Tabular Generative Adversarial Networks ² Tabular Variational Autoencoders

ML Approach Architecture

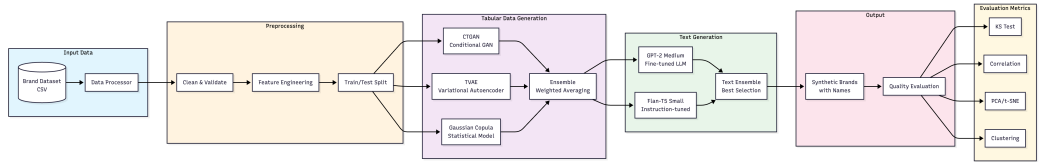


Figure: Pipeline

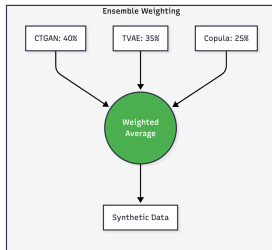


Figure: Ensemble Architecture

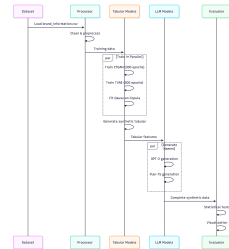


Figure: Sequence Diagram

Data Preprocessing and Exploration

Performed Data Cleaning, Handling Missing Values, Encoding Categorical Variables, and Feature Engineering.

```
1 # Load and process data
2 processor = BrandDataProcessor(DATA_PATH)
3 raw_data = processor.load_data()
```

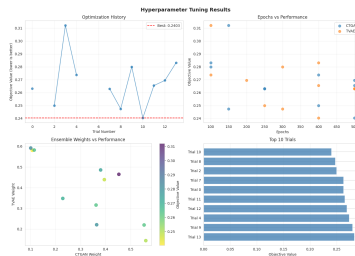
```
1 # Prepare for GAN training
2 train_df, val_df = processor.prepare_for_gan(test_size=0.2)
3
4 discrete_cols = processor.categorical_features
5 binary_cols = [col for col in train_df.columns if train_df[col].nunique() == 2
6                and set(train_df[col].unique()).issubset({0, 1})]
7 numerical_cols = [col for col in train_df.columns if col not in discrete_cols
8                  and col not in binary_cols]
```

```
1 # Clean data
2 cleaned_data = processor.clean_data()
```

Hyperparameter Tuning

Using Optuna to find optimal hyperparameters for the tabular synthesizers.

```
1 # Create tuner instance
2 tuner = HyperparameterTunerV2(
3     train_data=train_df,
4     discrete_cols=discrete_cols,
5     binary_cols=binary_cols,
6     eval_sample_size=min(1000, len(train_df)),
7     gen_sample_size=500,
8     verbose=True
9 )
10
11 # Run optimization
12 best_hyperparams = tuner.tune(
13     n_trials=N_TUNING_TRIALS,
14     timeout=TUNING_TIMEOUT,
15     seed=42,
16     show_progress_bar=True
17 )
18
19 # Save the best hyperparameters
20 tuner.save(HYPERPARAMS_PATH)
```



Best Parameters:

Parameter	Value
ctgan_epochs	500
tvae_epochs	400
batch_size	500
embedding_dim	256
generator_dim	[256, 256]
discriminator_dim	[128, 128]

Training Tabular Ensemble Models

Training CTGAN, TVAE, and Gaussian Copula models

```
1  # Initialize Ensemble Synthesizer
2  tabular_ensemble =
3      EnsembleSynthesizer(
4          ctgan_epochs=CTGAN_EPOCHS,
5          ctgan_batch_size=BATCH_SIZE,
6          tvae_epochs=TVAE_EPOCHS,
7          tvae_batch_size=BATCH_SIZE,
8          gc_default_distribution='beta',
9          weights=ENSEMBLE_WEIGHTS,
10         verbose=True,
11         cuda=True
12     )
```

```
1  training_times = tabular_ensemble.
    train(
2      data=train_df,
3      discrete_columns=discrete_cols,
4      binary_columns=binary_cols
5  )
6  # Save models
7  tabular_ensemble.save_models(os.path
    .join(MODEL_DIR, '
    tabular_ensemble'))
8  # Optimize weights based on quality
9  optimized_weights = tabular_ensemble
    .optimize_weights(train_df,
        n_eval_samples=1000)
```

LLM Ensemble Training

Training GPT-2 Medium and Flan-T5 for brand name generation

```
1 # Initialize LLM Ensemble Generator
2 llm_generator = BrandNameGeneratorV2(
3     models=LLM_MODELS,
4     memory_efficient=True,
5     verbose=True
6 )
```

```
1 llm_generator.fine_tune(
2     brands_df=brands_df,
3     epochs=LLM_EPOCHS,
4     output_dir=os.path.join(MODEL_DIR, '
5                             llm_ensemble')
6 )
7 # Save ensemble config
8 llm_generator.save_model(os.path.join(MODEL_DIR, '
9                             llm_ensemble'))
```

Figure: Fine Tuning LLMs

Company Name	1st	2nd	3rd
PepsiCo	Coca Cola	Dr Pepper	Snapple's
Nestle	Tomatoes	Nutella	Nestle is a manufacturer...
Mars, Incorporated	Whole30	Kashi	Soylent

Table: Generated Brand Names by Model

Synthetic Data Generation

```
1 # Generate synthetic tabular features using ensemble
2 print("Generating synthetic features with ensemble...")
3 synthetic_features, failed_companies = tabular_ensemble.generate_stratified(
4     company_distribution=generation_targets,
5     verbose=True
6 )
```

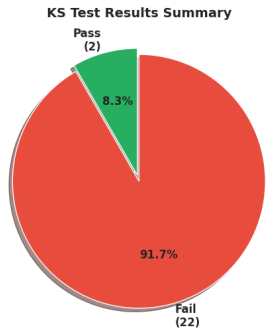
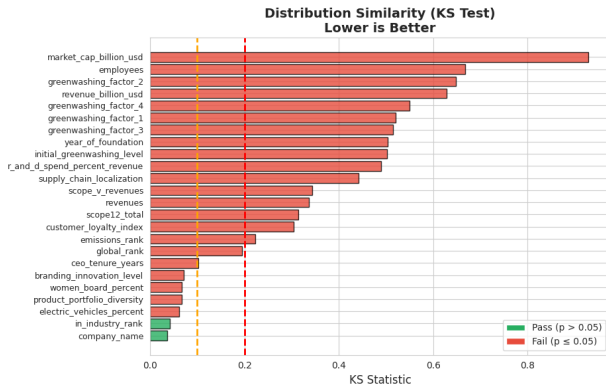
```
1 # Generate brand names using LLM ensemble
2 synthetic_with_names = llm_generator.generate_for_dataframe(
3     synthetic_df=synthetic_decoded,
4     temperature=DIVERSITY_TEMPERATURE,
5     verbose=True
6 )
```

Figure: Generating Synthetic Tabular Data and Brand Names

Synthetic Data Quality Evaluation

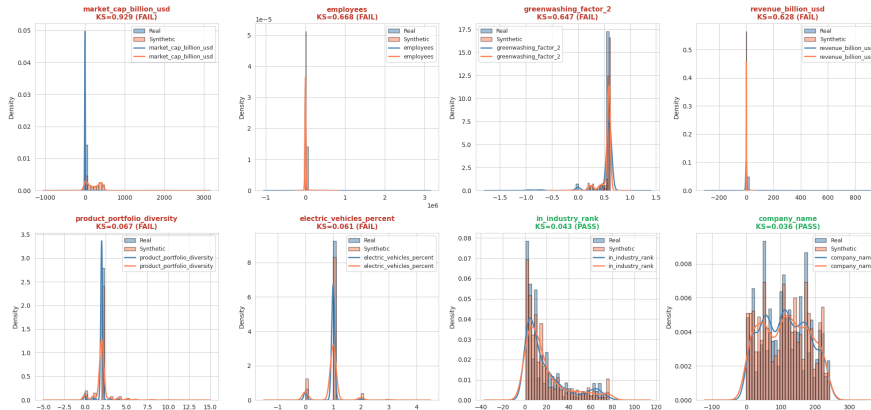
This phase comprehensively evaluates the quality of generated synthetic data through:

- **Tabular Data:** Prioritizing variance over fidelity for data augmentation.
- **Dimensionality Reduction:** PCA and t-SNE projections



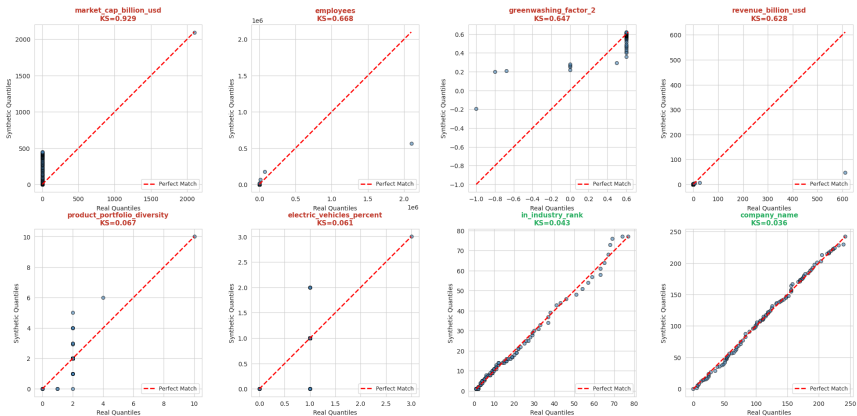
Distribution Comparison

Distribution Comparison: Real vs Synthetic Data
Top Row: Worst Performers | Bottom Row: Best Performers



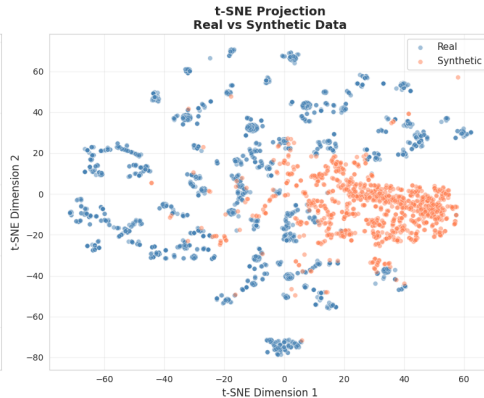
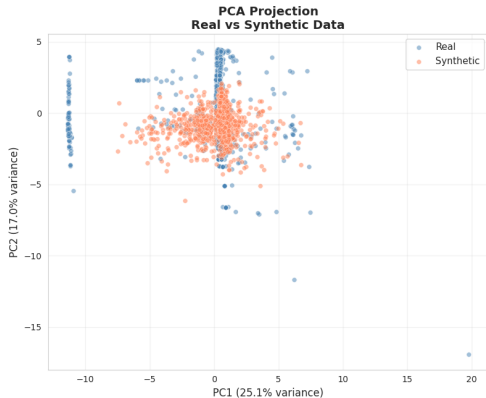
QQ Plot Comparison

Q-Q Plots: Real vs Synthetic Quantiles
Points on diagonal = Perfect distribution match

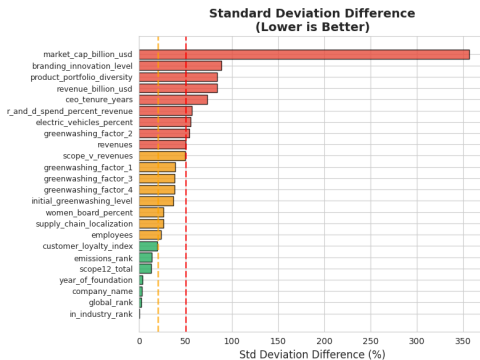
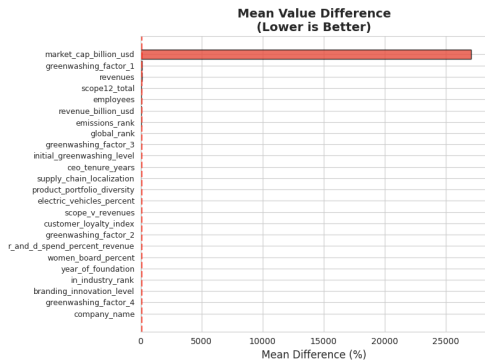


Dimensionality Reduction

Dimensionality Reduction: Synthetic Data Should Overlap with Real Data



Statistical Comparison



Conclusions, summary and future work

- Successful implementation of an ensemble-based synthetic data generation pipeline combining tabular synthesizers (CTGAN, TVAE, Gaussian Copula) and LLMs (GPT-2, Flan-T5) to create realistic brand-level ESG datasets.
- Trade-offs between fidelity and variance were effectively managed to produce diverse yet representative synthetic data.
- Optimal models in production-ready state with scalable architecture for future enhancements.

		Details
Worked Well	Ensemble Architecture	CTGAN, TVAE, GC complemented; TVAE 54% weight (KS: 0.11), GC preserved correlations (MSE: 0.0197)
	Scalable Pipeline	Stratified generation, conditional synthesis, Google Drive persistence
	LLM Brand Names	GPT-2 + Flan-T5 achieved 95.4% success rate, memory-efficient
Challenges	LLM Quality Issues	Full sentences, competitor leakage, repetitive patterns, 4.6% fallback
Future Work	Tabular Synthesis	Feature preprocessing, constrained generation, TabDDPM, validation
	LLM Enhancement	Negative examples, stricter validation, RAG, style conditioning
	Architecture	Attention-based models, hierarchical pipeline, discriminator filtering

References Bibliography

1. **CTGAN (Conditional Tabular GAN)**
 - Xu, L., Skoularidou, M., Cuesta-Infante, A., & Veeramachaneni, K. (2019). *Modeling Tabular Data using Conditional GAN*. NeurIPS 2019.
 - Paper: <https://arxiv.org/abs/1907.00503>
 - Implementation: SDV Library
2. **TVAE (Tabular Variational Autoencoder)**
 - Xu, L., Skoularidou, M., Cuesta-Infante, A., & Veeramachaneni, K. (2019). *Modeling Tabular Data using Conditional GAN*. NeurIPS 2019.
 - Part of the same paper as CTGAN, presenting VAE-based alternative
3. **Gaussian Copula**
 - Patki, N., Wedge, R., & Veeramachaneni, K. (2016). *The Synthetic Data Vault*. IEEE DSAA 2016.
 - Paper: <https://dai.lids.mit.edu/wp-content/uploads/2018/03/SDV.pdf>
4. **SDV (Synthetic Data Vault) Library**
 - Documentation: <https://docs.sdv.dev/sdv/>
 - GitHub: <https://github.com/sdv-dev/SDV>
5. **GPT-2**
 - Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., & Sutskever, I. (2019). *Language Models are Unsupervised Multitask Learners*. OpenAI.
 - Paper: https://cdn.openai.com/better-language-models/language_models_are_unsupervised_multitask_learners.pdf
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 - Wolf, T., et al. (2020). *Transformers: State-of-the-Art Natural Language Processing*. EMNLP 2020.
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10. **Davies-Bouldin Index**
 - Davies, D. L., & Bouldin, D. W. (1979). *A cluster separation measure*. IEEE Transactions on Pattern Analysis and Machine Intelligence, (2), 224-227.
11. **Optuna**
 - Akiba, T., Sano, S., Yanase, T., Ohta, T., & Koyama, M. (2019). *Optuna: A Next-generation Hyperparameter Optimization Framework*. KDD 2019.
 - Paper: <https://arxiv.org/abs/1907.10902>
 - Documentation: <https://optuna.org/>
12. **TabDDPM (Diffusion Models for Tabular Data)**
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 - Paper: <https://arxiv.org/abs/2209.15421>
13. **CTAB-GAN+**
 - Zhao, Z., Kunar, A., Birke, R., & Chen, L. Y. (2022). *CTAB-GAN+: Enhancing Tabular Data Synthesis*. arXiv preprint.
 - Paper: <https://arxiv.org/abs/2204.00401>
14. **Synthetic Data Generation Survey**
 - Jordon, J., Yoon, J., & van der Schaar, M. (2022). *Synthetic Data - what, why and how?* arXiv preprint.
 - Paper: <https://arxiv.org/abs/2205.03257>

Appendix Other Repositories

- **Supervised Learning:** <https://github.com/dyegofern/csc5622-supervised-learning>
- **Unsupervised Learning:** <https://github.com/dyegofern/csc5632-unsupervised-learning>

Appendix Mermaid Code

```
1 flowchart TB
2   subgraph INPUT["Input Data"]
3     A["(Brand Dataset<br/>CSV)"] --> B[Data Processor]
4   end
5   subgraph PREPROCESS["Preprocessing"]
6     B --> C[Clean \& Validate]
7     C --> D[Feature Engineering]
8     D --> E[Train/Test Split]
9   end
10  subgraph TABULAR["Tabular Data Generation"]
11    E --> F1["CTGAN<br/>Conditional GAN"]
12    E --> F2["TVAE<br/>Variational Autoencoder"]
13    E --> F3["Gaussian Copula<br/>Statistical Model"]
14    F1 --> G[Ensemble<br/>Weighted Averaging]
15    F2 --> G
16    F3 --> G
17  end
18  subgraph TEXT["Text Generation"]
19    G --> H1["GPT-2 Medium<br/>Fine-tuned LLM"]
20    G --> H2["Flan-T5 Small<br/>Instruction-tuned"]
21    H1 --> I[Text Ensemble<br/>Best Selection]
22    H2 --> I
23  end
24  subgraph OUTPUT["Output"]
25    I --> J["Synthetic Brands<br/>with Names"]
26    J --> K[Quality Evaluation]
27  end
28  subgraph EVAL["Evaluation Metrics"]
29    K --> L1[KS Test]
30    K --> L2[Correlation]
31    K --> L3["PCA/t-SNE"]
32    K --> L4[Clustering]
33  end
34  style INPUT fill:#e1f5fe
35  style PREPROCESS fill:#fff3e0
36  style TABULAR fill:#f3e5f5
37  style TEXT fill:#e8f5e9
38  style OUTPUT fill:#fce4ec
39  style EVAL fill:#fff8e1
```

```
1 flowchart LR
2   subgraph ENSEMBLE["Ensemble Weighting"]
3     direction TB
4     W1["CTGAN: 40\%"] --> MIX["(Weighted<br/>Average)"]
5     W2["TVAE: 35\%"] --> MIX
6     W3["Copula: 25\%"] --> MIX
7     MIX --> OUT[Synthetic Data]
8   end
9   style ENSEMBLE fill:#f5f5f5
10  style MIX fill:#4caf50,color:#fff
```

```
1 sequenceDiagram
2   participant D as Dataset
3   participant P as Processor
4   participant T as Tabular Models
5   participant L as LLM Models
6   participant E as Evaluator
7   D->>P: Load brand\_information.csv
8   P->>P: Clean \& preprocess
9   P->>T: Training data
10  par Train in Parallel
11    T->>T: Train CTGAN (300 epochs)
12    T->>T: Train TVAE (300 epochs)
13    T->>T: Fit Gaussian Copula
14  end
15  T->>T: Generate synthetic tabular
16  T->>L: Tabular features
17  par Generate Names
18    L->>L: GPT-2 generation
19    L->>L: Flan-T5 generation
20  end
21  L->>E: Complete synthetic data
22  E->>E: Statistical tests
23  E->>E: Visualization
```

Appendix Tools & Libraries

- **PyTorch** - Deep learning framework powering the neural network components of CTGAN and TVAE synthesizers
- **Scikit-learn** - Machine learning utilities for PCA, t-SNE, clustering (AgglomerativeClustering), and evaluation metrics (silhouette score, Davies-Bouldin index)
- **SDV (Synthetic Data Vault)** - Primary library for tabular synthetic data generation, providing:
 - **CTGAN** - Conditional Tabular GAN for generating realistic tabular data
 - **TVAE** - Tabular Variational Autoencoder for distribution-preserving synthesis
 - **Gaussian Copula** - Statistical model capturing feature dependencies
- **Hugging Face Transformers** - State-of-the-art NLP library for text generation using pre-trained language models
- **PEFT (Parameter-Efficient Fine-Tuning)** - Efficient fine-tuning techniques for large language models
- **BitsAndBytes** - 8-bit quantization for memory-efficient model loading
- **Accelerate** - Distributed training and mixed precision utilities
- **SentencePiece** - Tokenization library for handling text preprocessing
- **Optuna** - Automated hyperparameter tuning framework using Bayesian optimization for finding optimal model configurations
- **Pandas** - Data manipulation and analysis
- **NumPy** - Numerical computing and array operations
- **SciPy** - Statistical tests (Kolmogorov-Smirnov test) for distribution comparison
- **Matplotlib** - Core plotting library for creating figures
- **Seaborn** - Statistical data visualization with enhanced aesthetics
- **Plotly** - Interactive visualizations (if used)
- **Google Colab** - Cloud-based Jupyter notebook environment with GPU support
- **Google Drive** - Persistent storage for models and outputs