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

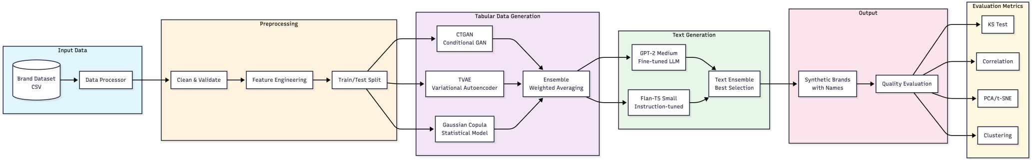


Figure: Pipeline

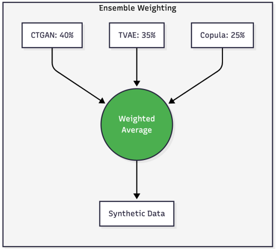


Figure: Ensemble Architecture

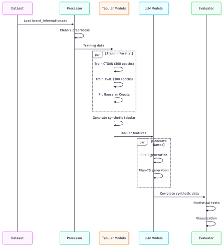


Figure: Sequence Diagram

Data Preprocessing and Exploration

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

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

```
# Prepare for GAN training
train_df, val_df = processor.prepare_for_gan(test_size=0.2)

discrete_cols = processor.categorical_features
binary_cols = [col for col in train_df.columns if train_df[col].nunique() == 2
    and set(train_df[col].unique()).issubset({0, 1})]
numerical_cols = [col for col in train_df.columns if col not in discrete_cols
    and col not in binary_cols]
```

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

Hyperparameter Tuning

Using Optuna to find optimal hyperparameters for the tabular synthesizers.

```python
# Create tuner instance
tuner = HyperparameterTunerV2(
    train_data=train_df,
    discrete_cols=discrete_cols,
    binary_cols=binary_cols,
    eval_sample_size=min(1000, len(train_df)),
    gen_sample_size=500,
    verbose=True
)

# Run optimization
best_hyperparams = tuner.tune(
    n_trials=N_TUNING_TRIALS,
    timeout=TUNING_TIMEOUT,
    seed=42,
    show_progress_bar=True
)

# Save the best hyperparameters
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 CTGAN, TVAE, and Gaussian Copula models

```python
# Initialize Ensemble Synthesizer
tabular_ensemble = EnsembleSynthesizer(
    ctgan_epochs=CTGAN_EPOCHS,
    ctgan_batch_size=BATCH_SIZE,
    tvae_epochs=TVAE_EPOCHS,
    tvae_batch_size=BATCH_SIZE,
    gc_default_distribution='beta',
    weights=ENSEMBLE_WEIGHTS,
    verbose=True,
    cuda=True
)
```

```python
training_times = tabular_ensemble.train(
    data=train_df,
    discrete_columns=discrete_cols,
    binary_columns=binary_cols
)
# Save models
tabular_ensemble.save_models(os.path.join(MODEL_DIR, 'tabular_ensemble'))
# Optimize weights based on quality
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

```python
# Initialize LLM Ensemble Generator
llm_generator = BrandNameGeneratorV2(
    models=LLM_MODELS,
    memory_efficient=True,
    verbose=True
)
```

```python
llm_generator.fine_tune(
    brands_df=brands_df,
    epochs=LLM_EPOCHS,
    output_dir=os.path.join(MODEL_DIR, '
        llm_ensemble')
)
# Save ensemble config
llm_generator.save_model(os.path.join(MODEL_DIR, '
    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

```python
# Generate synthetic tabular features using ensemble
print("Generating synthetic features with ensemble...")
synthetic_features, failed_companies = tabular_ensemble.generate_stratified(
    company_distribution=generation_targets,
    verbose=True
)
```

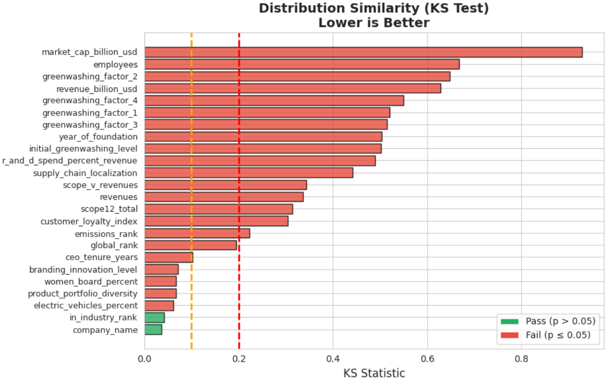
```python
# Generate brand names using LLM ensemble
synthetic_with_names = llm_generator.generate_for_dataframe(
    synthetic_df=synthetic_decoded,
    temperature=DIVERSITY_TEMPERATURE,
    verbose=True
)
```

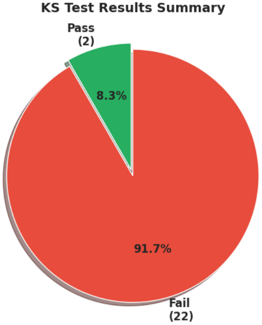
Figure: Generating Synthetic Tabular Data and Brand Names

Synthetic Data Quality Evaluation

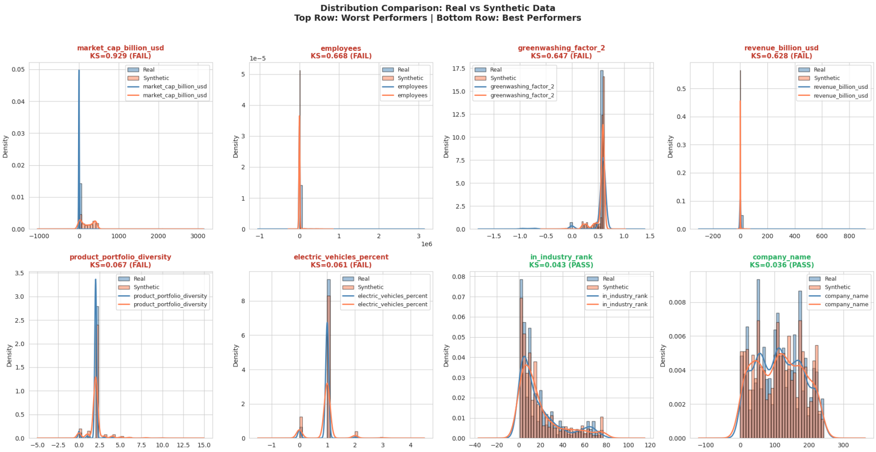
This phase comprehensively evaluates the quality of generated synthetic data through:

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

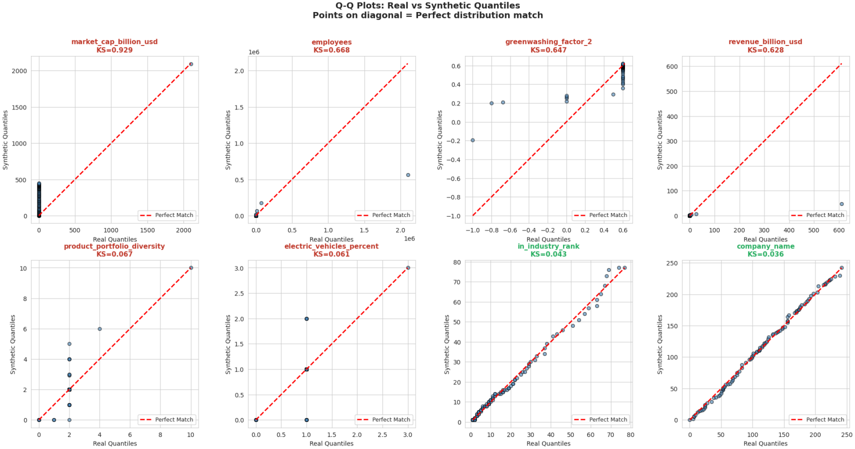




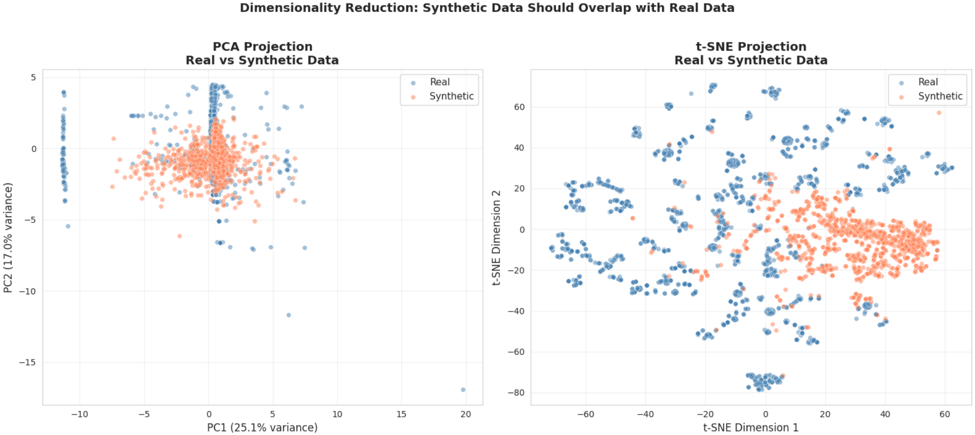
Distribution Comparison



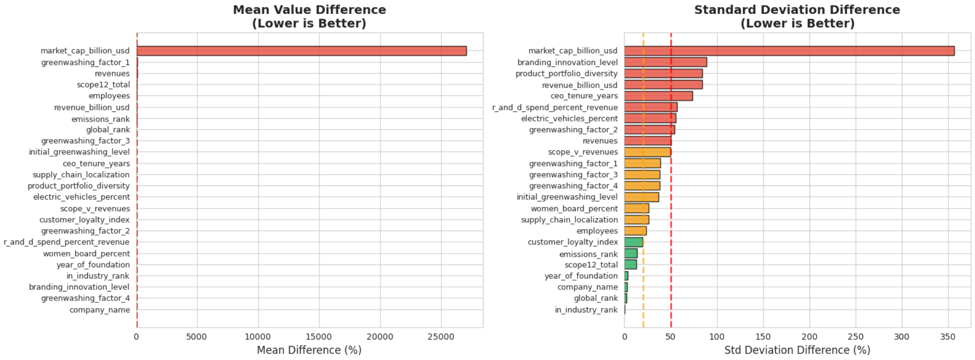
QQ Plot Comparison



Dimensionality Reduction



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
6. **Flan-T5**
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   - Paper: https://arxiv.org/abs/2210.11416
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   - Wolf, T., et al. (2020). *Transformers: State-of-the-Art Natural Language Processing*. EMNLP 2020.
   - Documentation: https://huggingface.co/docs/transformers/
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   - Massey Jr, F. J. (1951). *The Kolmogorov-Smirnov test for goodness of fit*. Journal of the American Statistical Association, 46(253), 68-78.
9. **Silhouette Score**
   - Rousseeuw, P. J. (1987). *Silhouettes: a graphical aid to the interpretation and validation of cluster analysis*. Journal of Computational and Applied Mathematics, 20, 53-65.
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)**
    - Kotelnikov, A., Baranchuk, D., Rubachev, I., & Babenko, A. (2023). *TabDDPM: Modelling Tabular Data with Diffusion Models*. ICML 2023.
    - 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/csca5622-supervised-learning
- **Unsupervised Learning**: https://github.com/dyegofern/csca5632-unsupervised-learning

Appendix Mermeid Code

```
flowchart TB
    subgraph INPUT["Input Data"]
        A[(Brand Dataset<br/>CSV)] --> B[Data Processor]
    end
    subgraph PREPROCESS["Preprocessing"]
        B --> C[Clean \& Validate]
        C --> D[Feature Engineering]
        D --> E[Train/Test Split]
    end
    subgraph TABULAR["Tabular Data Generation"]
        E --> F1[CTGAN<br/>Conditional GAN]
        E --> F2[TVAE<br/>Variational Autoencoder]
        E --> F3[Gaussian Copula<br/>Statistical Model]
        F1 --> G[Ensemble<br/>Weighted Averaging]
        F2 --> G
        F3 --> G
    end
    subgraph TEXT["Text Generation"]
        G --> H1[GPT-2 Medium<br/>Fine-tuned LLM]
        G --> H2[Flan-T5 Small<br/>Instruction-tuned]
        H1 --> I[Text Ensemble<br/>Best Selection]
        H2 --> I
    end
    subgraph OUTPUT["Output"]
        I --> J[Synthetic Brands<br/>with Names]
        J --> K[Quality Evaluation]
    end
    subgraph EVAL["Evaluation Metrics"]
        K --> L1[KS Test]
        K --> L2[Correlation]
        K --> L3[PCA/t-SNE]
        K --> L4[Clustering]
    end
    style INPUT fill:\#e1f5fe
    style PREPROCESS fill:\#fff3e0
    style TABULAR fill:\#f3e5f5
    style TEXT fill:\#e8f5e9
    style OUTPUT fill:\#fce4ec
    style EVAL fill:\#fff8e1
```

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

```
sequenceDiagram
    participant D as Dataset
    participant P as Processor
    participant T as Tabular Models
    participant L as LLM Models
    participant E as Evaluator
    D->>P: Load brand\_information.csv
    P->>P: Clean \& preprocess
    P->>T: Training data
    par Train in Parallel
        T->>T: Train CTGAN (300 epochs)
        T->>T: Train TVAE (300 epochs)
        T->>T: Fit Gaussian Copula
    end
    T->>T: Generate synthetic tabular
    T->>L: Tabular features
    par Generate Names
        L->>L: GPT-2 generation
        L->>L: Flan-T5 generation
    end
    L->>E: Complete synthetic data
    E->>E: Statistical tests
    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