Unsupervised Learning Project: VAE for Hybrid Language Music Clustering

Neural Networks Course Project

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Abstract

This project implements a comprehensive Variational Autoencoder (VAE) based system for clustering hybrid language music tracks (English + Bangla). The implementation includes three progressive task levels (Easy, Medium, Hard) with increasing complexity, covering basic VAE clustering, multi-modal features, and advanced architectures including Conditional VAE and Beta-VAE. The system extracts meaningful latent representations from music lyrics data and performs unsupervised clustering to discover patterns. We compare VAE-based approaches with traditional baseline methods (PCA, Autoencoder) using multiple evaluation metrics including Silhouette Score, Calinski-Harabasz Index, Davies-Bouldin Index, Adjusted Rand Index, Normalized Mutual Information, and Cluster Purity. Results demonstrate the effectiveness of VAE-based representations for music clustering tasks.

1 Introduction

Music clustering is a fundamental task in music information retrieval, with applications in recommendation systems, playlist generation, and music discovery. Traditional approaches rely on hand-crafted features or linear dimensionality reduction techniques. However, deep learning methods, particularly Variational Autoencoders (VAEs), offer the potential to learn more expressive and meaningful representations.

This project focuses on clustering hybrid language music tracks, specifically English and Bangla songs, using VAE-based unsupervised learning. The goal is to extract latent representations from music data (lyrics and optionally audio) and perform clustering to discover patterns without explicit labels.

1.1 Motivation

Hybrid language music presents unique challenges:

- Different linguistic structures between languages
- Cultural and musical style variations
- Need for cross-lingual representation learning
- Limited labeled data for supervised approaches

VAEs provide a principled framework for learning latent representations that can capture semantic similarities across languages while maintaining the flexibility of unsupervised learning.

1.2 Contributions

The main contributions of this work include:

1. Implementation of multiple VAE architectures (Standard VAE, Beta-VAE, Conditional VAE)
2. Comprehensive evaluation using six different metrics
3. Comparison with baseline methods (PCA, Autoencoder)
4. Three-tiered implementation (Easy, Medium, Hard tasks)
5. Complete pipeline from data preprocessing to visualization

2 Related Work

2.1 Variational Autoencoders

Variational Autoencoders [1] combine probabilistic inference with neural networks to learn latent representations. The key innovation is the reparameterization trick, which enables gradient-based optimization of the variational lower bound.

2.2 Beta-VAE

Beta-VAE [2] introduces a hyperparameter β to control the trade-off between reconstruction quality and latent space disentanglement. Higher β values encourage more disentangled representations.

2.3 Conditional VAE

Conditional VAE (CVAE) [3] extends the standard VAE by conditioning on additional information such as class labels, enabling controlled generation and better clustering performance.

2.4 Music Clustering

Previous work on music clustering has explored various feature representations including MFCC, chroma features, and lyrics embeddings. VAE-based approaches have shown promise in learning compact and meaningful representations for clustering tasks.

3 Methodology

3.1 Dataset

We use the Song Lyrics Dataset from Kaggle (deepshah16/song-lyrics-dataset), which contains lyrics from multiple languages including English and Bangla. The dataset is preprocessed to extract TF-IDF features with the following parameters:

- Maximum features: 5000
- N-grams: (1, 2)
- Minimum document frequency: 2
- Maximum document frequency: 0.95

Features are normalized using StandardScaler before training.

3.2 VAE Architectures

3.2.1 Standard VAE

The standard VAE architecture consists of:

- **Encoder**: Multi-layer fully connected network with hidden dimensions [512, 256]
- **Latent Space**: 32-dimensional Gaussian distribution parameterized by mean μ and log-variance $\log \sigma^2$
- **Decoder**: Symmetric architecture to encoder
- **Activation**: ReLU with Dropout (0.2)
- **Output**: Sigmoid for reconstruction

The loss function is:

$$\mathcal{L} = \mathbb{E}_{q_\phi(z|x)}[\log p_\theta(x|z)] - \beta \cdot D_{KL}(q_\phi(z|x)||p(z)) \tag{1}$$

where $\beta = 1$ for standard VAE.

3.2.2 Beta-VAE

Beta-VAE uses the same architecture as Standard VAE but with $\beta > 1$ (default $\beta = 4.0$) to encourage disentanglement:

$$\mathcal{L}_{\beta\text{-VAE}} = \mathbb{E}_{q_\phi(z|x)}[\log p_\theta(x|z)] - \beta \cdot D_{KL}(q_\phi(z|x)||p(z)) \tag{2}$$

3.2.3 Conditional VAE

CVAE conditions both encoder and decoder on class labels y:

$$\mathcal{L}_{\text{CVAE}} = \mathbb{E}_{q_\phi(z|x,y)}[\log p_\theta(x|z,y)] - D_{KL}(q_\phi(z|x,y)||p(z|y)) \tag{3}$$

The encoder takes concatenated input $[x, y]$ and decoder takes $[z, y]$.

3.2.4 Autoencoder Baseline

A non-variational autoencoder serves as a baseline, using deterministic encoding without KL divergence:

$$\mathcal{L}_{\text{AE}} = ||x - \hat{x}||^2 \tag{4}$$

3.3 Clustering Algorithms

We employ multiple clustering algorithms:

3.3.1 K-Means

Standard K-Means clustering with $k = 5$ clusters and k-means++ initialization.

3.3.2 Agglomerative Clustering

Hierarchical clustering with Ward linkage criterion.

3.3.3 DBSCAN

Density-based clustering with $\epsilon = 0.5$ and minimum samples = 5.

3.3.4 PCA Baseline

Principal Component Analysis with 32 components (matching latent dimension) followed by K-Means.

3.4 Evaluation Metrics

3.4.1 Unsupervised Metrics

Silhouette Score:

$$s(i) = \frac{b(i) - a(i)}{\max(a(i), b(i))} \tag{5}$$

where $a(i)$ is the average distance to points in the same cluster and $b(i)$ is the minimum average distance to points in other clusters.

Calinski-Harabasz Index:

$$CH = \frac{\text{tr}(B_k)/(k-1)}{\text{tr}(W_k)/(n-k)} \tag{6}$$

where B_k is between-cluster dispersion and W_k is within-cluster dispersion.

Davies-Bouldin Index:

$$DB = \frac{1}{k} \sum_{i=1}^{k} \max_{j \neq i} \left(\frac{\sigma_i + \sigma_j}{d_{ij}} \right) \tag{7}$$

where σ_i is average distance in cluster i and d_{ij} is distance between centroids.

3.4.2 Supervised Metrics (when labels available)

Adjusted Rand Index (ARI): Measures agreement between predicted clusters and ground truth labels, adjusted for chance.

Normalized Mutual Information (NMI):

$$\mathrm{NMI}(U,V) = \frac{2I(U;V)}{H(U)+H(V)} \tag{8}$$

Cluster Purity:

$$\mathrm{Purity} = \frac{1}{n}\sum_k \max_j |c_k \cap t_j| \tag{9}$$

where c_k is cluster k and t_j is true class j.

4 Implementation

4.1 Easy Task

The Easy Task implements a basic VAE + K-Means pipeline:

1. Load and preprocess lyrics dataset
2. Initialize VAE with architecture [512, 256] hidden layers
3. Train VAE for 50 epochs with learning rate 10^{-3}
4. Extract 32-dimensional latent representations
5. Apply K-Means clustering with $k = 5$
6. Compare with PCA baseline
7. Evaluate using Silhouette Score and Calinski-Harabasz Index
8. Generate t-SNE and UMAP visualizations

4.2 Medium Task

The Medium Task extends the Easy Task with:

- Enhanced VAE architecture: [512, 256, 128] hidden layers
- Multiple clustering algorithms: K-Means, Agglomerative, DBSCAN
- Comprehensive evaluation: All unsupervised metrics + ARI (if labels available)
- Comparative analysis of clustering methods

4.3 Hard Task

The Hard Task implements the most comprehensive approach:

- Multiple VAE architectures: Beta-VAE ($\beta = 4.0$), CVAE, Autoencoder
- Comprehensive comparison: All architectures + PCA baseline
- Full evaluation suite: All 6 metrics
- Advanced visualizations: Training histories, latent space plots
- Best method identification

5 Experiments

5.1 Experimental Setup

- **Dataset**: Song Lyrics Dataset (Kaggle)
- **Features**: TF-IDF (max 5000 features)
- **Training**: 50 epochs, batch size 32, learning rate 10^{-3}
- **Latent Dimension**: 32
- **Clusters**: 5
- **Device**: CUDA GPU when available, else CPU

5.2 Results

5.2.1 Easy Task Results

The Easy Task demonstrates that VAE-based representations outperform PCA baseline:

- VAE learns more expressive latent representations
- Better cluster separation in latent space
- Higher Silhouette Score and Calinski-Harabasz Index

5.2.2 Medium Task Results

Multiple clustering algorithms show different characteristics:

- K-Means: Fast and effective for well-separated clusters
- Agglomerative: Captures hierarchical structure
- DBSCAN: Identifies density-based clusters, may find varying number of clusters

5.2.3 Hard Task Results

Comprehensive comparison reveals:

- Beta-VAE achieves better disentanglement with $\beta = 4.0$
- CVAE improves performance when labels are available
- Autoencoder provides competitive baseline
- VAE-based methods generally outperform PCA

6 Discussion

6.1 Key Findings

1. **VAE vs PCA**: VAE-based representations consistently outperform PCA, demonstrating the value of non-linear dimensionality reduction.
2. **Architecture Impact**: Deeper networks (Medium/Hard tasks) learn more expressive representations, improving clustering quality.
3. **Beta Parameter**: Higher β values in Beta-VAE encourage disentanglement but may reduce reconstruction quality. $\beta = 4.0$ provides a good balance.
4. **Clustering Algorithms**: Different algorithms suit different data characteristics. K-Means works well for spherical clusters, while DBSCAN handles irregular shapes.
5. **Multi-modal Potential**: While current implementation focuses on lyrics, the framework supports audio features (MFCC, spectrograms) for multi-modal learning.

6.2 Limitations

- Audio features not fully integrated (requires audio files)
- Limited to TF-IDF features for lyrics
- Fixed architecture (not auto-tuned)
- Single dataset format support
- Computational cost increases with deeper networks

6.3 Future Work

1. **Audio Integration**: Full implementation of audio feature extraction (MFCC, spectrograms) and multi-modal fusion
2. **Hyperparameter Optimization**: Automated hyperparameter tuning for optimal performance
3. **Advanced Architectures**: Convolutional VAE for spectrogram features, Transformer-based encoders
4. **Evaluation**: User studies to validate cluster quality from human perspective
5. **Scalability**: Efficient implementations for large-scale datasets

7 Conclusion

This project successfully implements a comprehensive VAE-based system for hybrid language music clustering. The three-tiered approach (Easy, Medium, Hard) demonstrates progressive complexity and increasing sophistication. Results show that VAE-based representations outperform traditional linear methods like PCA, and advanced architectures (Beta-VAE, CVAE) provide additional benefits for specific use cases.

The implementation is complete, well-documented, and ready for use in Google Colab or local environments. All evaluation metrics are implemented, and the system provides detailed analysis and visualization of results. Future work should focus on multi-modal integration, hyperparameter optimization, and scalability improvements.

Acknowledgments

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References

[1] Kingma, D. P., & Welling, M. (2013). Auto-encoding variational bayes. *arXiv preprint arXiv:1312.6114.*

[2] Higgins, I., et al. (2016). beta-vae: Learning basic visual concepts with a constrained variational framework. *ICLR.*

[3] Sohn, K., Lee, H., & Yan, X. (2015). Learning structured output representation using deep conditional generative models. *NeurIPS.*

[4] Pedregosa, F., et al. (2011). Scikit-learn: Machine learning in Python. *Journal of machine learning research*, 12(Oct), 2825-2830.

[5] Paszke, A., et al. (2019). PyTorch: An imperative style, high-performance deep learning library. *NeurIPS.*

A Code Structure

The implementation consists of the following main components:

- **Dataset Loading**: LyricsDataset class for PyTorch DataLoader
- **VAE Models**: VAE, BetaVAE, ConditionalVAE, Autoencoder classes
- **Training**: Functions for training different architectures
- **Clustering**: K-Means, Agglomerative, DBSCAN, PCA implementations
- **Evaluation**: Comprehensive metric computation
- **Visualization**: t-SNE, UMAP, training history plots
- **Task Functions**: run_easy_task(), run_medium_task(), run_hard_task()

B Configuration Parameters

Default configuration parameters:

- Epochs: 50
- Batch Size: 32
- Latent Dimension: 32
- Number of Clusters: 5
- Max Features: 5000
- Learning Rate: 10^{-3}
- Beta (Beta-VAE): 4.0

All parameters are configurable through function arguments.

C Usage Instructions

C.1 Google Colab

1. Install dependencies:

```
    !pip install torch torchvision numpy pandas scikit-learn matplotlib
       seaborn tqdm umap-learn kagglehub
```

2. Load code:

```
    exec(open('colab_complete.py').read())
```

3. Download dataset:

```
    dataset_path = download_dataset()
```

4. Run tasks:

```
    run_easy_task(dataset_path, epochs=50, batch_size=32)
    run_medium_task(dataset_path, epochs=50, batch_size=32)
    run_hard_task(dataset_path, epochs=50, batch_size=32, beta=4.0)
```