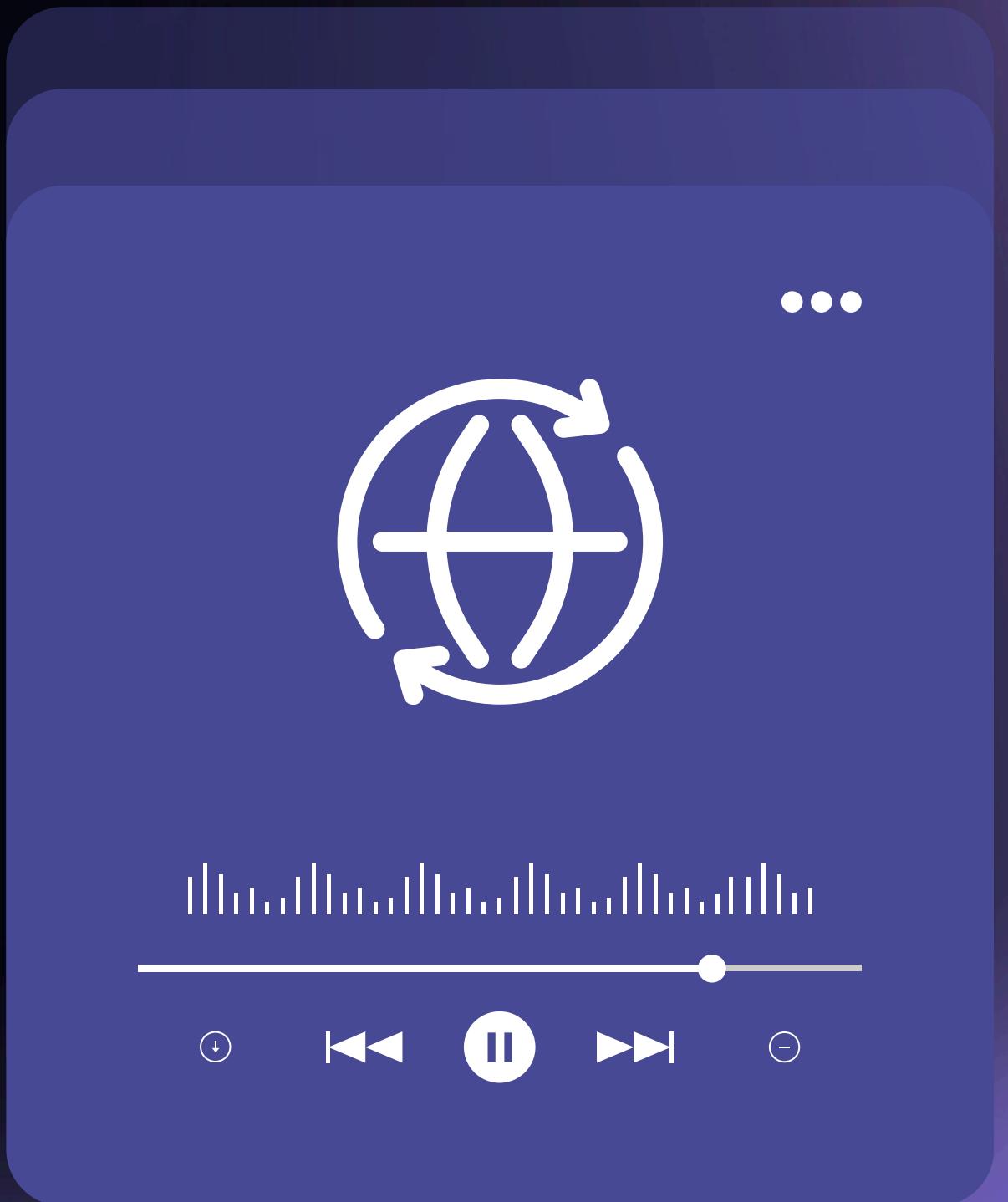


# Music Recommendation Application

Implementation of Large Language Models  
and MLOps



# Project Overview

The proliferation of digital music platforms has escalated the demand for sophisticated music recommendation systems that not only understand user preferences but also appreciate the complex musicality of songs.



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We address this need by deploying a state-of-the-art large-language model that processes a fusion of user interaction metrics and intrinsic song features to deliver personalized music recommendations through MLOp practices.

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## Approach

# Data

The cloud database chosen has data related to:

1. User-to-Song rating/playback information
2. Song-to-Song similarity information based on musicality.

• DATASET 1

**millionsong\_dataset.csv**

• DATASET 2

**music\_data.csv**

• DATASET 3

**user\_preferences.csv**

# Methods

## Approach

### Model Preprocessing & Training

### Exploratory Analysis & Prototyping

### ML Production Cloud Pipeline

Get million song subset  
data song list Get metadata  
and join the data use genre  
similarity and genre to train  
the model on similarity

Exploring track and user  
preference related data

AWS RDBS, My SQL

...

# Methods

Approach

Re-training &  
CI/CD

06

Production of  
reccomendations

Evaluation with  
Colab

02

Evaluating Model and  
Accuracy

UI/UX Using  
Gradio

03

Implementing model with  
user experience using  
gradio and huggingface as a  
tool

...

# Experiments

## 1 Spotify API

Testing data related to  
Spotify API

## 2 LastFM API

Connecting User Preferences  
to the Million Song Dataset  
and LastFM API

## 3 EDA

Exploratory Data Analysis of  
the Synthetic User Preferences

...

# Training

The screenshot shows a Jupyter Notebook cell with the title "Training". The code in the cell is as follows:

```
In [ ]: import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader
import numpy as np

# Define the neural network model with Dropout and Batch Normalization
class ImprovedSongRecommender(nn.Module):
    def __init__(self, input_size, num_titles):
        super(ImprovedSongRecommender, self).__init__()
        self.fc1 = nn.Linear(input_size, 128)
        self.bn1 = nn.BatchNorm1d(128)
        self.fc2 = nn.Linear(128, 256)
        self.bn2 = nn.BatchNorm1d(256)
        self.fc3 = nn.Linear(256, 128)
        self.bn3 = nn.BatchNorm1d(128)
        self.output = nn.Linear(128, num_titles)
        self.dropout = nn.Dropout(0.5)

    def forward(self, x):
        x = torch.relu(self.bn1(self.fc1(x)))
        x = self.dropout(x)
        x = torch.relu(self.bn2(self.fc2(x)))
        x = self.dropout(x)
        x = torch.relu(self.bn3(self.fc3(x)))
        x = self.dropout(x)
        x = self.output(x)
        return x

# Adjusting input size for the model
input_size = X_train.shape[1] # Number of features in the input
num_unique_titles = len(label_encoders['title'].classes_) # Number of unique titles

# Initialize the model with the correct input size and output size
model = ImprovedSongRecommender(input_size, num_unique_titles)

# Initialize the optimizer and loss function
optimizer = optim.AdamW(model.parameters(), lr=0.001, weight_decay=0.01)
criterion = nn.CrossEntropyLoss()

# Use a learning rate scheduler
scheduler = optim.lr_scheduler.StepLR(optimizer, step_size=3, gamma=0.1)

# Early stopping parameters
patience = 3
min_delta = 0.01
best_val_loss = np.inf
patience_counter = 0

# Function to train the model
def train_model(model, X_train, y_train, X_test, y_test):
    global best_val_loss, patience_counter
    train_loader = DataLoader(list(zip(X_train.values.astype(float), y_train)), batch_size=32, shuffle=True)
    test_loader = DataLoader(list(zip(X_test.values.astype(float), y_test)), batch_size=32, shuffle=False)

    model.train()
    for epoch in range(20): # Increase the number of epochs
        for i, (x, y) in enumerate(train_loader):
            y_hat = model(x)
            loss = criterion(y_hat, y)
```

# Testing

The screenshot shows a Jupyter Notebook cell with the title "Testing". The code in the cell is as follows:

```
In [ ]: import torch
from joblib import load

# Define the same neural network model
class ImprovedSongRecommender(nn.Module):
    def __init__(self, input_size, num_titles):
        super(ImprovedSongRecommender, self).__init__()
        self.fc1 = nn.Linear(input_size, 128)
        self.bn1 = nn.BatchNorm1d(128)
        self.fc2 = nn.Linear(128, 256)
        self.bn2 = nn.BatchNorm1d(256)
        self.fc3 = nn.Linear(256, 128)
        self.bn3 = nn.BatchNorm1d(128)
        self.output = nn.Linear(128, num_titles)
        self.dropout = nn.Dropout(0.5)

    def forward(self, x):
        x = torch.relu(self.bn1(self.fc1(x)))
        x = self.dropout(x)
        x = torch.relu(self.bn2(self.fc2(x)))
        x = self.dropout(x)
        x = torch.relu(self.bn3(self.fc3(x)))
        x = self.dropout(x)
        x = self.output(x)
        return x

# Load the trained model
model_path = '/content/improved_model.pth'
num_unique_titles = 4855 # Update this to match your dataset

model = ImprovedSongRecommender(input_size=2, num_titles=num_unique_titles)
model.load_state_dict(torch.load(model_path, map_location=torch.device('cpu')))
model.eval()

# Load the label encoders and scaler
label_encoders_path = '/content/new_label_encoders.joblib'
scaler_path = '/content/new_scaler.joblib'

label_encoders = load(label_encoders_path)
scaler = load(scaler_path)

# Create a mapping from encoded indices to actual song titles
index_to_song_title = {index: title for index, title in enumerate(label_encoders['titles'])}

def encode_input(tags, artist_name):
    tags = tags.strip().replace('\n', '')
    artist_name = artist_name.strip().replace('\n', '')

    try:
        encoded_tags = label_encoders['tags'].transform([tags])[0]
    except ValueError:
        encoded_tags = label_encoders['tags'].transform(['unknown'])[0]

    try:
        encoded_artist = label_encoders['artist_name'].transform([artist_name])
    except ValueError:
        encoded_artist = label_encoders['artist_name'].transform(['unknown'])

    return encoded_tags, encoded_artist
```

# Evaluation

The screenshot shows a Jupyter Notebook interface with several code cells. The code is written in Python and uses PyTorch for training and evaluating a neural network model.

```
# Split data into features and target
X = df_scaled[['tags', 'artist']]
y = df_scaled['song']

# Split the dataset into training and testing sets
X_valid, X_test, y_valid, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
print("Data split into validation and testing sets.")

Data split into validation and testing sets.

In [313... import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader
import numpy as np
from sklearn.metrics import accuracy_score

In [314... valid_loader = DataLoader(list(zip(X_valid.values.astype(float), y_valid))), batch_size=32, shuffle=False)
test_loader = DataLoader(list(zip(X_test.values.astype(float), y_test))), batch_size=32, shuffle=False)

In [315... valid_accuracy = 0
test_accuracy = 0
for features, labels in valid_loader:
    preds = model(features.float()).detach()

    # Get the predicted class (the one with the highest score)
    _, predicted_class = torch.max(preds, 1)

    # Convert to numpy arrays
    predicted_class_np = predicted_class.numpy()
    labels_np = labels.numpy()

    # Calculate accuracy
    accuracy = accuracy_score(labels_np, predicted_class_np)
    valid_accuracy += accuracy

for features, labels in test_loader:
    preds = model(features.float())
    # Get the predicted class (the one with the highest score)
    _, predicted_class = torch.max(preds, 1)

    # Convert to numpy arrays
    predicted_class_np = predicted_class.numpy()
    labels_np = labels.numpy()

    # Calculate accuracy
    accuracy = accuracy_score(labels_np, predicted_class_np)
    test_accuracy += accuracy

In [316... print('The loss of the model on the unseen validation dataset is: ', valid_accuracy)
print('The loss of the model on the unseen test dataset is: ', test_accuracy)

The loss of the model on the unseen validation dataset is: 2.0
The loss of the model on the unseen test dataset is: 0.0
```

# Gradio Demo

[link](#)

Implementation

Music Recommendation System

Enter Tags (e.g., rock, jazz, pop)

rock

Get Recommendations

Heartburn

Crazy

Hurry Up And Come

Hotel

If I Ain't Got You

Heartburn

Thumbs Up  Thumbs Down

Crazy

Thumbs Up  Thumbs Down

Hurry Up And Come

Thumbs Up  Thumbs Down

**Conclusion**

# Future work

We successfully produced a music recommendation system using traditional MLOp practices. For future work, we could potentially scale this larger and implement the system with existing music listening platforms.



# Thank you for listening

For any questions feel free to contact our team.

