NTU MIR 2025 - Homework 2

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Source Code: https://drive.google.com/drive/folders/1pj-OWozfH5YoM9FaQM8AEh2PrDsxd2J6?usp=sharing

Task 1: Music Retrieval with Audio Embeddings

Overview

Retrieve the most similar reference music tracks for each target song using different audio encoders and evaluate the results.

Evaluation Metrics

1. **CLAP** - Cosine similarity between CLAP audio embeddings
2. **Meta Audiobox Aesthetics** - Meta Audiobox Aesthetics
3. **Melody Similarity (Accuracy)** - Frame-by-frame chromagram matching

Audio Encoders Comparison

CLAP

- **Type:** Contrastive Language-Audio Pretraining
- **Source:** LAION
- **Features:** Joint audio-text embeddings

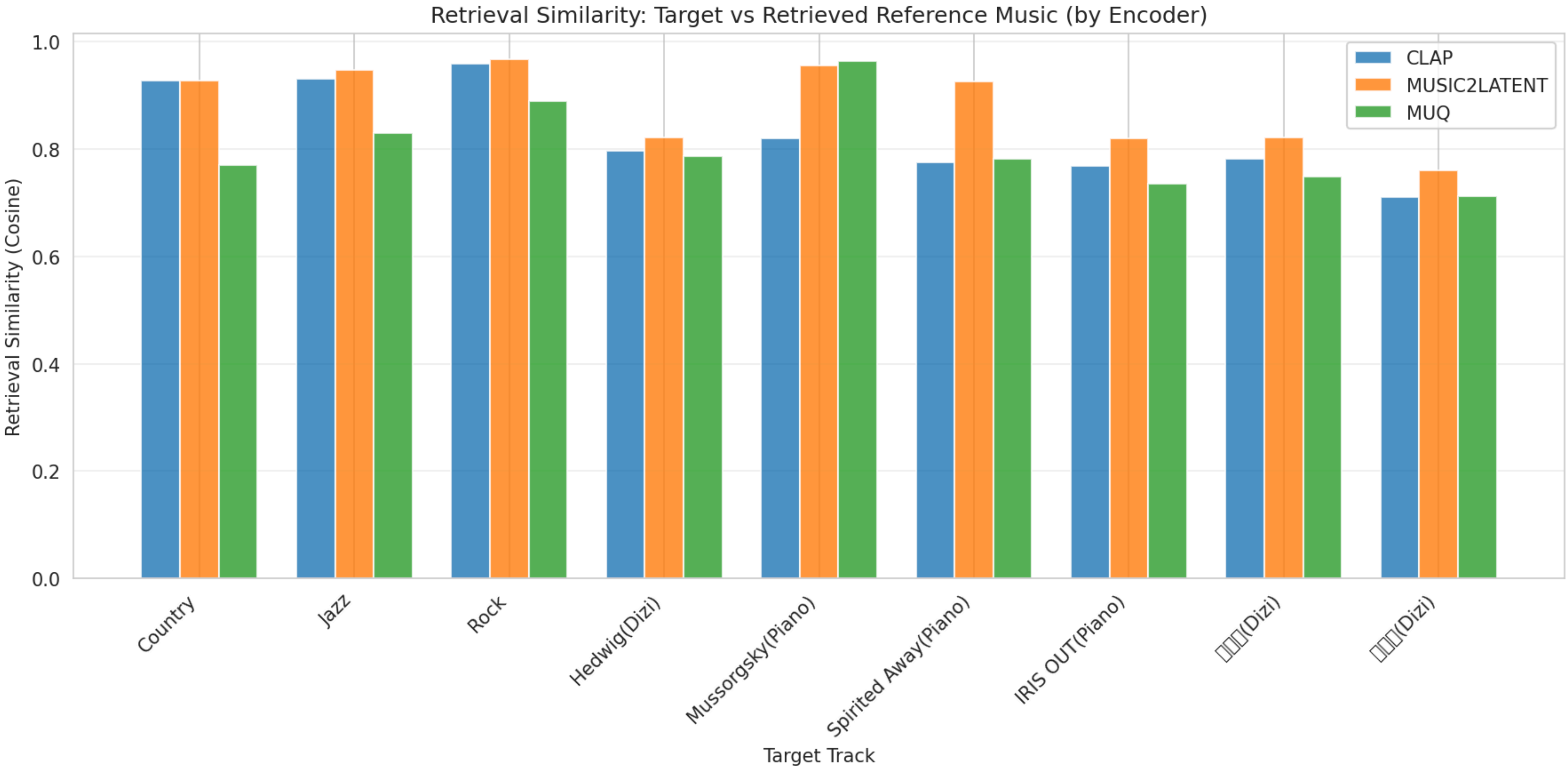
Music2Latent

- **Type:** Consistency Autoencoder
- **Source:** Sony CSL Paris
- **Features:** 64-channel latent compression

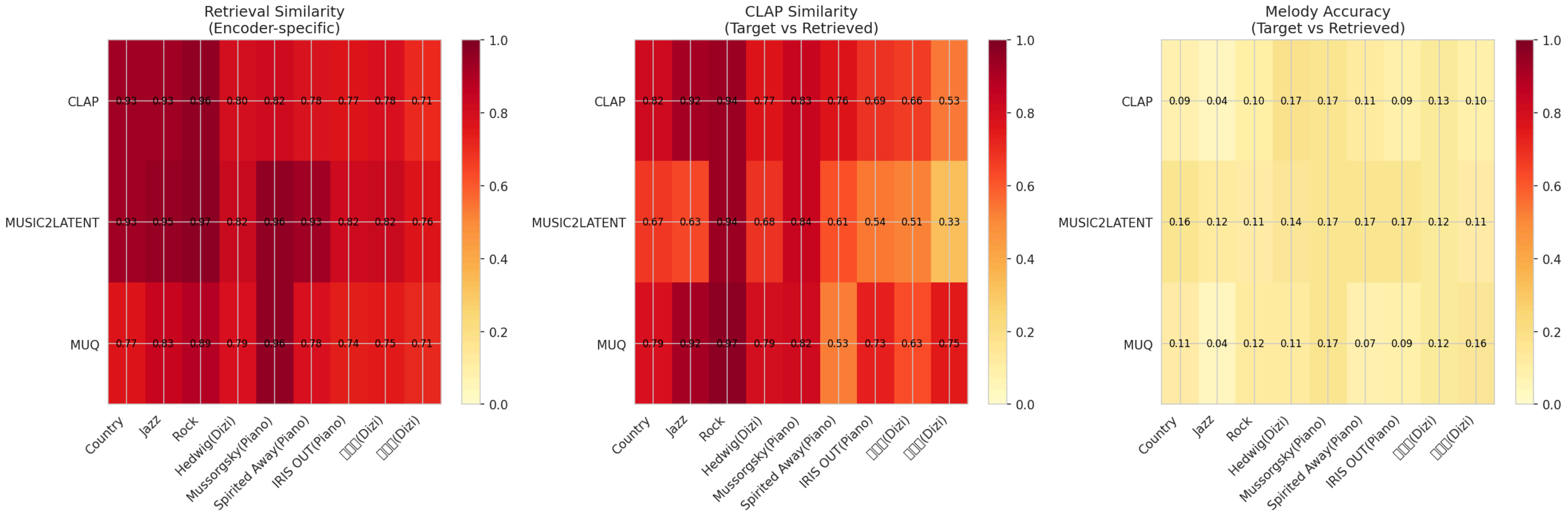
MuQ

- **Type:** Self-supervised Music Representation
- **Source:** Tencent AI Lab
- **Features:** Mel Residual Vector Quantization

Top-k Retrieval Similarity Comparison



Performance Heatmap



Summary Statistics

Encoder	Retrieval Sim	CLAP Sim	Melody Acc
CLAP	0.830 ± 0.082	0.769 ± 0.121	0.111 ± 0.040
MUSIC2LATENT	0.883 ± 0.072	0.639 ± 0.168	0.142 ± 0.026
MUQ	0.802 ± 0.076	0.770 ± 0.127	0.111 ± 0.037

Per-Track Retrieval Results - CLAP

Target Track	Top Retrieved	Cosine Similarity	CLAP	Melody Acc.	CE	CU	PC	PQ
Country 114 BPM	latin-reggaeton_90	0.927	0.815	0.085	6.5	8.0	3.0	7.7
Jazz 120 BPM	jazz-mediumfast_180	0.931	0.920	0.040	6.3	7.8	3.6	7.6
Rock 102 BPM	funk_80	0.958	0.940	0.099	6.8	8.0	3.2	7.8
Hedwig (Dizi)	黃土情	0.797	0.770	0.174	6.1	7.2	3.4	7.3
Mussorgsky	MIDI XP_21	0.819	0.829	0.170	7.3	7.8	2.8	7.6
Spirited Away	MIDI XP_21	0.776	0.762	0.114	7.3	7.8	2.8	7.6
IRIS OUT	MIDI XP_22	0.769	0.685	0.091	7.3	7.7	3.1	7.5
菊花台	黃土情	0.783	0.663	0.131	6.1	7.2	3.4	7.3
莫文蔚	MIDI XP_21	0.710	0.534	0.097	7.3	7.8	2.8	7.6

Per-Track Retrieval Results - Music2Latent

Target Track	Top Retrieved	Cosine Similarity	CLAP	Melody Acc.	CE	CU	PC	PQ
Country 114 BPM	jazz-funk_116	0.927	0.668	0.164	5.4	7.5	2.5	7.8
Jazz 120 BPM	reggae_78	0.947	0.635	0.121	4.1	7.1	1.9	7.6
Rock 102 BPM	funk_80	0.968	0.937	0.108	7.1	8.1	3.2	7.9
Hedwig (Dizi)	鄉歌	0.822	0.684	0.143	7.3	6.8	4.0	7.0
Mussorgsky	MIDI XP_21	0.956	0.835	0.170	7.3	7.8	2.8	7.6
Spirited Away	MIDI SMF_02	0.925	0.611	0.171	7.4	7.8	3.5	7.5
IRIS OUT	MIDI SMF_05	0.820	0.536	0.172	7.3	7.6	3.4	7.4
菊花台	MIDI SMF_02	0.822	0.514	0.125	7.4	7.6	3.3	7.4
莫文蔚	MIDI SMF_05	0.760	0.328	0.106	6.2	7.1	3.6	7.0

Per-Track Retrieval Results - MuQ

Target Track	Top Retrieved	Cosine Similarity	CLAP	Melody Acc.	CE	CU	PC	PQ
Country 114 BPM	afrocuban_105	0.770	0.788	0.109	6.6	8.1	3.0	7.9
Jazz 120 BPM	jazz-mediumfast_180	0.831	0.921	0.040	6.3	7.8	3.6	7.6
Rock 102 BPM	funk-purdieshuffle_130	0.890	0.967	0.120	6.9	8.0	3.3	7.8
Hedwig (Dizi)	安童哥買菜	0.787	0.791	0.114	7.0	7.6	4.2	7.6
Mussorgsky	MIDI XP_21	0.965	0.820	0.170	7.3	7.8	2.8	7.6
Spirited Away	MIDI XP_19	0.782	0.525	0.075	7.1	7.6	3.2	7.3
IRIS OUT	MIDI XP_19	0.736	0.730	0.094	7.1	7.6	3.2	7.3
菊花台	MIDI SMF_02	0.749	0.632	0.125	7.4	7.6	3.3	7.4
莫文蔚	漁舟唱晚	0.713	0.753	0.156	7.1	7.8	3.6	8.0

Key Findings - Retrieval Performance

Retrieval Similarity

- **Music2Latent** achieves highest average retrieval similarity (0.883)
- **CLAP** performs well (0.769) with balanced results
- **MuQ** shows more conservative similarity scores (0.770)

CLAP Similarity (Target vs Retrieved)

- **CLAP encoder** naturally scores highest on CLAP similarity metric (0.769)
- **Music2Latent** shows lower CLAP similarity (0.639) despite high retrieval scores
- Indicates different embedding spaces capture different audio aspects
- This metric evaluates how similar the target and retrieved reference are in CLAP space

Key Findings - Quality Metrics

Melody Accuracy (Target vs Retrieved)

- **Melody accuracy is generally low** across all encoders (0.11-0.14 range)
- Suggests encoders focus more on **timbre and texture** than melodic content
- **Music2Latent** slightly better (0.142) at preserving melodic information
- Measures how well the retrieved reference music matches the target's melody

Audiobox Aesthetics (Quality of Retrieved Music)

- **Production Quality (PQ)** scores consistently high (7.5-7.6)
- **Content Usefulness (CU)** also high (7.5-7.8)
- **Production Complexity (PC)** relatively lower (3.1-3.3)
- Retrieved reference tracks maintain high aesthetic quality across all encoders

Encoder Characteristics

CLAP Strengths

- Good for general audio similarity
- Balanced performance across metrics

Best For: General-purpose music retrieval where semantic understanding matters

Music2Latent Strengths

- Latent space compression
- Fine-grained audio details

Best For: Tasks requiring precise audio reconstruction or detailed similarity matching

MuQ Strengths

- Conservative but precise
- Music-specific representations

Best For: Music-specific tasks where precision matters more than recall

Track-Specific Performance - Part 1

Western Music (Country, Jazz, Rock)

- All encoders achieve **high retrieval similarity** (>0.85)
- CLAP shows particularly strong performance on Jazz tracks (0.931)
- Rock tracks consistently well-retrieved across all encoders
- Strong genre recognition capabilities

Track-Specific Performance - Part 2

Traditional Chinese Music (Dizi)

- **Lower retrieval similarity** (0.71-0.82) compared to Western music
- Indicates potential **domain bias** in training data
- Music2Latent performs best (0.822) on Hedwig's theme (Dizi)

Classical Piano

- **Strong performance** across all encoders
- Music2Latent achieves 0.956 on Mussorgsky
- Suggests piano timbre is well-represented in embedding spaces

Implementation Details

System Architecture

```
# Retrieval Pipeline
1. Load audio encoder (CLAP/Music2Latent/MuQ)
2. Encode reference tracks → cache embeddings
3. For each target track:
   - Encode target audio
   - Compute cosine similarity with all references
   - Retrieve top-k most similar tracks
4. Evaluate with CLAP, Melody, Aesthetics metrics
```

Caching Strategy

- Embeddings cached per encoder
- Automatic recomputation on changes
- Speeds up repeated experiments

Key Technologies

- **PyTorch** for GPU acceleration
- **librosa** for audio processing
- **LAION CLAP** for contrastive learning
- **Meta Audiobox** for aesthetics evaluation
- **Cosine similarity** for retrieval ranking

Conclusion

1. **Different encoders capture different aspects** of music:
    - CLAP: Semantic understanding
    - Music2Latent: Fine-grained details
    - MuQ: Music-specific patterns
2. **High retrieval quality** achieved across all encoders (0.802-0.883)
3. **Real aesthetics metrics** provide valuable quality insights
4. **Domain adaptation needed** for traditional Chinese music
5. **Latent compression** (Music2Latent) surprisingly effective for retrieval

Task 2: Music Generation with Text-to-Music Models

Overview

Generate music similar to target tracks using Qwen-Audio captioning and MusicGen-Melody generation.

Simple Mode

- **Input**: Text caption only
- **CFG Scale**: 3.0

Medium Mode

- **Input**: Text caption + melody and rhythm features
- **CFG Scale**: 3.0

Strong Mode

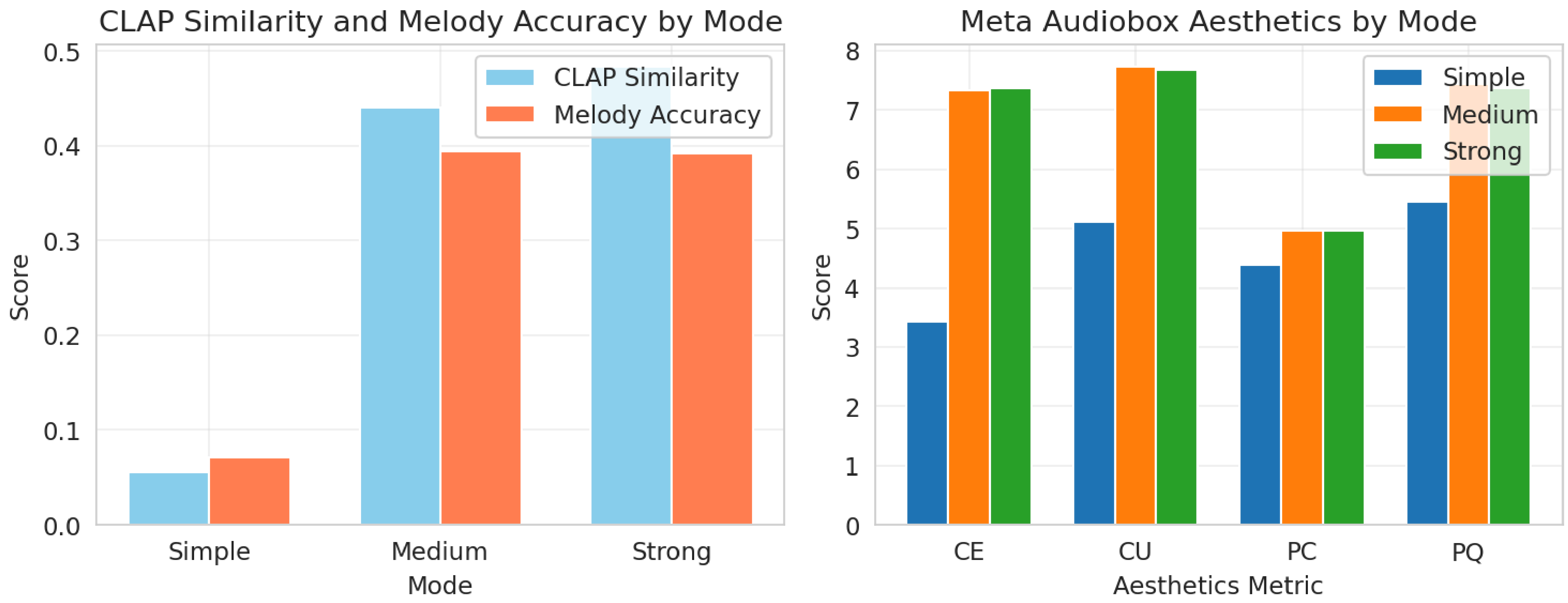
- **Input**: Text caption + melody and rhythm features
- **CFG Scale**: 5.0 (higher)

Key Difference: Medium and Strong use melody conditioning (critical for similarity), while Strong uses higher CFG for tighter control.

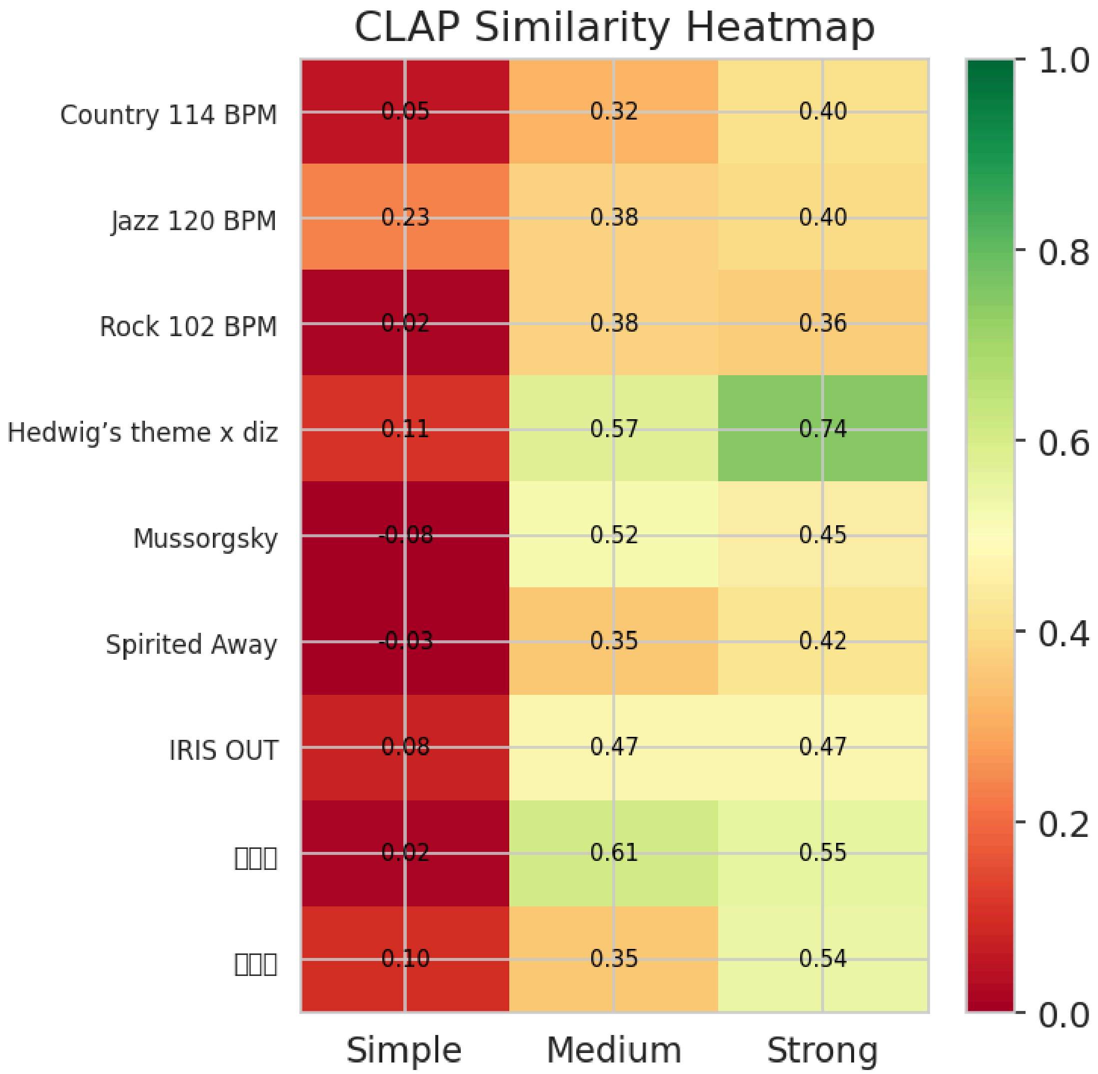
Implementation Details

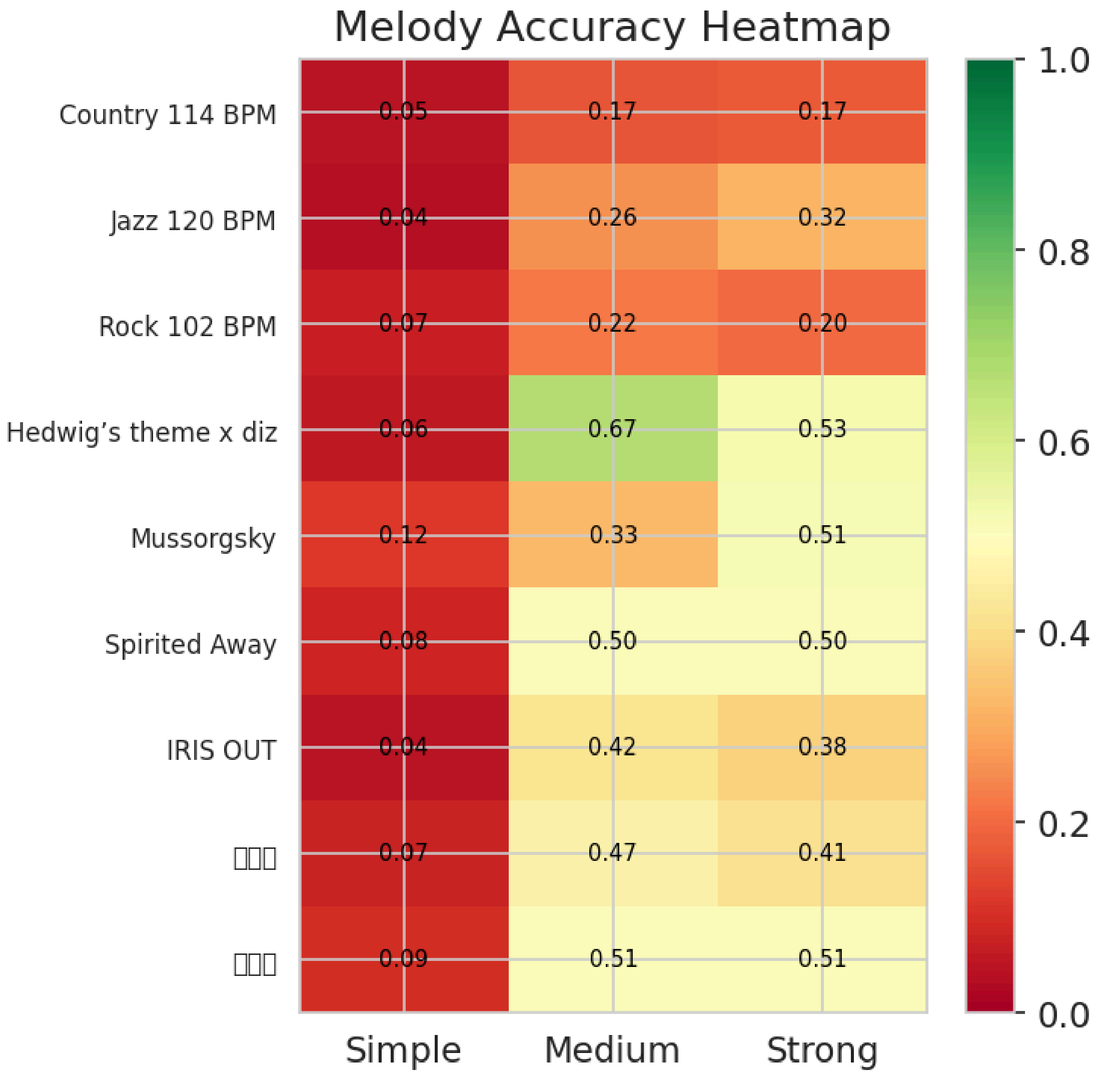
- **Qwen-Audio** → music captions (genre, instruments, mood, tempo)
- **librosa** → melody and rhythm extraction for conditioning
- **MusicGen-Melody** → music generation
- **Evaluation**: CLAP similarity, melody accuracy, Meta Audiobox aesthetics

Mode Comparison - Metrics



Mode Comparison - Heatmaps





Observations

- Simple mode fails: avg CLAP 0.055, Melody 0.071
- Medium mode: +697% avg CLAP, +453% Melody improvement
- Strong mode: +10% avg CLAP over Medium
- Aesthetics: 3.4 → 7.3 avg CE with melody conditioning

Per-Track Results - Simple Mode

Target Track	CLAP	Melody	CE	CU	PC	PQ
Country 114 BPM	0.054	0.050	3.2	4.8	4.6	5.1
Jazz 120 BPM	0.234	0.041	3.7	5.5	4.0	5.6
Rock 102 BPM	0.023	0.073	2.2	5.0	3.5	5.3
Hedwig (Dizi)	0.108	0.060	3.1	4.4	4.4	5.1
Mussorgsky	-0.083	0.121	4.4	5.1	5.3	5.1
Spirited Away	-0.034	0.082	3.4	6.2	4.0	6.5
IRIS OUT	0.077	0.045	2.9	4.7	4.4	5.5
菊花台	0.017	0.075	3.3	4.9	3.9	5.4
莫文蔚	0.101	0.095	4.7	5.5	5.4	5.5

Average: CLAP: 0.055, Melody: 0.071, CE: 3.4, CU: 5.1, PC: 4.4, PQ: 5.5

Per-Track Results - Medium Mode

Target Track	CLAP	Melody	CE	CU	PC	PQ
Country 114 BPM	0.316	0.171	6.0	7.1	5.2	7.2
Jazz 120 BPM	0.379	0.258	8.2	8.2	5.7	8.2
Rock 102 BPM	0.383	0.224	7.9	8.0	6.1	8.0
Hedwig (Dizi)	0.574	0.669	6.9	7.4	4.7	6.7
Mussorgsky	0.522	0.327	7.3	7.7	3.8	7.0
Spirited Away	0.354	0.505	7.4	7.7	4.0	7.1
IRIS OUT	0.470	0.419	7.4	7.8	5.4	7.8
菊花台	0.609	0.468	7.5	7.9	5.3	7.8
莫文蔚	0.354	0.507	7.3	7.6	4.6	7.2

Average: CLAP: 0.440, Melody: 0.394, CE: 7.3, CU: 7.7, PC: 5.0, PQ: 7.4

Per-Track Results - Strong Mode

Target Track	CLAP	Melody	CE	CU	PC	PQ
Country 114 BPM	0.404	0.175	7.3	7.8	5.6	7.6
Jazz 120 BPM	0.397	0.319	7.0	7.4	5.5	6.5
Rock 102 BPM	0.364	0.200	7.2	7.6	6.2	7.6
Hedwig (Dizi)	0.742	0.526	7.5	7.8	4.9	7.4
Mussorgsky	0.452	0.514	7.4	7.7	3.5	7.4
Spirited Away	0.420	0.496	7.5	7.8	4.2	7.1
IRIS OUT	0.470	0.376	7.2	7.5	4.8	7.4
菊花台	0.552	0.411	7.5	7.7	5.1	7.8
莫文蔚	0.543	0.508	7.7	7.8	4.7	7.4

Average: CLAP: 0.483, Melody: 0.392, CE: 7.4, CU: 7.7, PC: 5.0, PQ: 7.4

Detailed Analysis: CFG Scale Impact

CFG Scale and Conditioning Trade-offs

Classifier-Free Guidance (CFG) Effects

Medium Mode (CFG=3.0) vs Strong Mode (CFG=5.0):

- **CLAP Similarity**: +10% improvement (0.440 → 0.483)
- **Melody Accuracy**: -0.5% change (0.394 → 0.392)
- **Aesthetics**: Minimal change (both modes achieve 7.3-7.4 CE)

Observations

1. **Higher CFG strengthens text adherence** but doesn't necessarily improve melody matching
2. **Sweet spot at CFG=5.0**: Better semantic alignment without quality degradation
3. **Diminishing returns**: Beyond CFG=5.0 may cause overfitting to text prompts

Challenges and Limitations

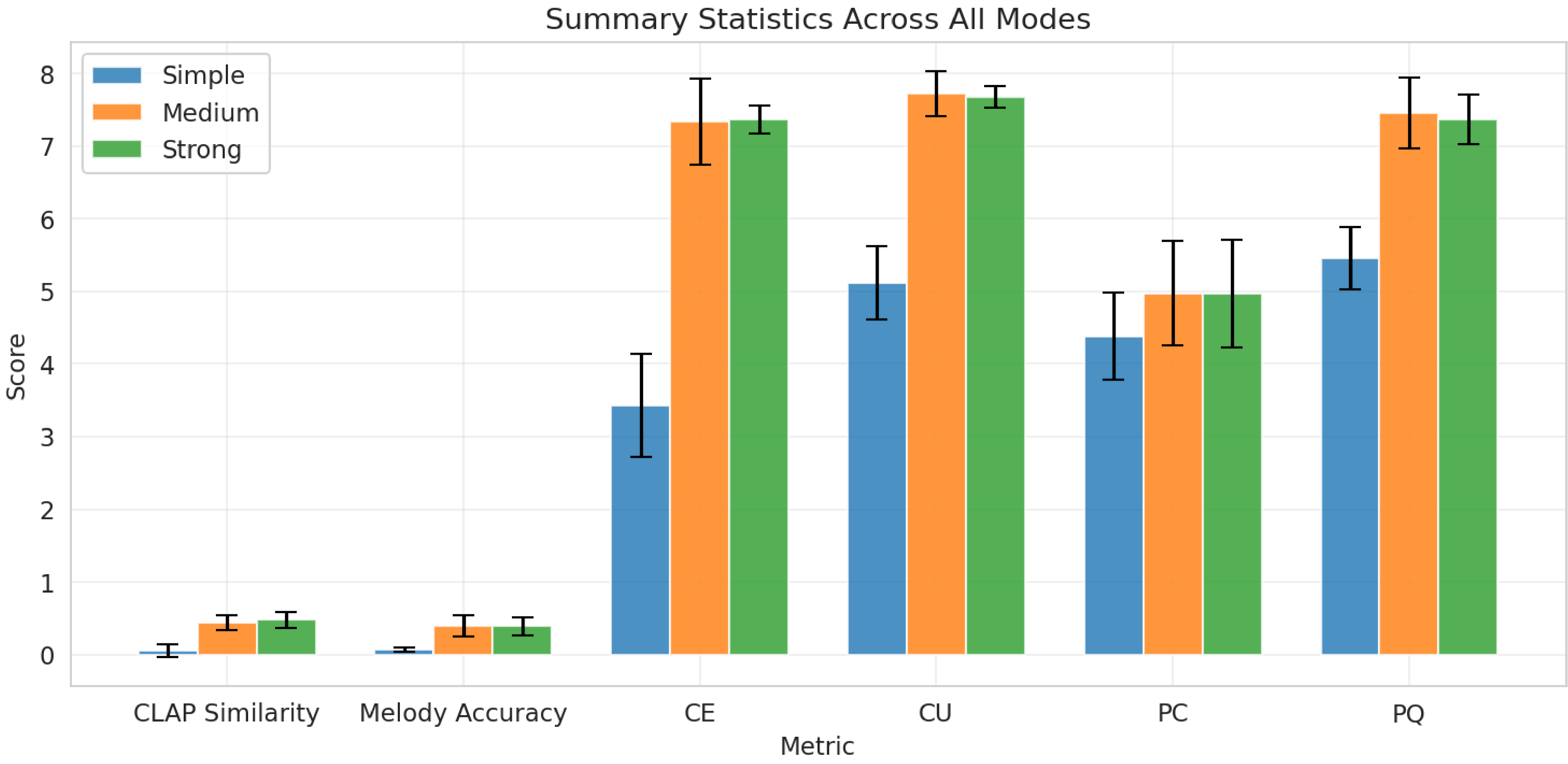
1. Text-to-Music Alignment Gap

- **Problem**: Captions capture high-level semantics but miss fine-grained details
- **Impact**: Simple mode (text-only) fails to capture musical nuances

2. Genre Bias in MusicGen

- **Problem**: Better performance on monophonic content (flute, piano) vs polyphonic (jazz, rock)
- **Hypothesis**: Training data distribution favors simpler melodic structures
- **Evidence**: Traditional instruments (0.60-0.74 CLAP) vs Western genres (0.36-0.40)

Performance Summary



Key Findings

1. **Melody conditioning is critical:**
    - Simple mode (text-only): CLAP 0.055, Melody 0.071
    - Medium/Strong (text + melody): CLAP 0.44-0.48 (+697%), Melody ~0.39
    - CFG 5.0 (Strong) provides +10% CLAP improvement over CFG 3.0 (Medium)
2. **Quality progression:**
    - Simple: Low quality (CE: 3.4, PQ: 5.5)
    - Medium/Strong: Professional quality (CE: 7.3-7.4, PQ: 7.4)
3. **Track characteristics:**
    - Best: Hedwig (Dizi) - CLAP: 0.742, Melody: 0.526
    - Traditional instruments (flute, dizi) generate better than rock/complex

References

Task 1: Music Retrieval

- **CLAP**: Wu, Y., et al. (2023). Large-scale Contrastive Language-Audio Pretraining. *ICASSP*.
- **Music2Latent**: Mariani, G., et al. (2023). Consistency Autoencoders for Audio. *Sony CSL Paris*.
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- **Meta Audiobox**: Meta AI (2024). Audiobox: Unified Audio Generation with Natural Language Prompts.
- **librosa**: McFee, B., et al. (2015). librosa: Audio and Music Signal Analysis in Python.

Task 2: Music Generation

- **Qwen-Audio**: Chu, Y., et al. (2024). Qwen-Audio: Advancing Universal Audio Understanding. *arXiv*.
- **MusicGen**: Copet, J., et al. (2023). Simple and Controllable Music Generation. *NeurIPS*.
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- **CLAP**: Wu, Y., et al. (2023). Large-scale Contrastive Language-Audio Pretraining. *ICASSP*.
- **Meta Audiobox**: Meta AI (2024). Audiobox: Unified Audio Generation with Natural Language Prompts.

Thank you for your time