Exploring Polyphonic Accompaniment Generation using Generative Adversarial Networks

D. Charitou[3], C. Garoufis[1,2,3], A. Zlatintsi[1,2,3] and P. Maragos[2,3]
danaecharitou@gmail.com, christos.garoufis@athenarc.gr, nancy.zlatintsi@athenarc.gr, maragos@cs.ntua.gr
[1]Institute of Language and Speech Proc., Athena Research Center, Athens, Greece
[2]Institute of Robotics, Athena Research Center, Athens, Greece
[3]School of ECE, National Technical University of Athens, Athens, Greece

Research & Innovation Information Technologies

For more information: https://i-mreplay.athenarc.gr/

1. Introduction

Motivation & Goal: designing a generative framework for **symbolic multi-track music generation** that is **structurally flexible** and **adaptable** to different musical configurations:

- **Unconditional Generation**: Generation of multi-track symbolic music from scratch.
- **Conditional Generation**: Generate the multi-track accompaniment, given a single track.

Contributions:

- Proposition of structural improvements upon the **unconditional** MuseGAN architecture [1].
- Extension of this framework to a **cooperative human-AI setup** for the generation of polyphonic accompaniments to user-defined tracks:
  - Exploration of multiple **structural variants** and **training schemes**
  - Two different candidate conditional instruments: **piano** and **guitar**.
- Evaluation of the produced samples for both cases
  - ***objectively***, using a set of widely used musical metrics, and
  - ***subjectively***, by conducting a listening test across **40 participants**.
- The proposed modifications and experiments:
  - in the **unconditional** case lead to auditory improvements over MuseGAN, and
  - in the **conditional** case provide useful insights about the properties of the generated music.

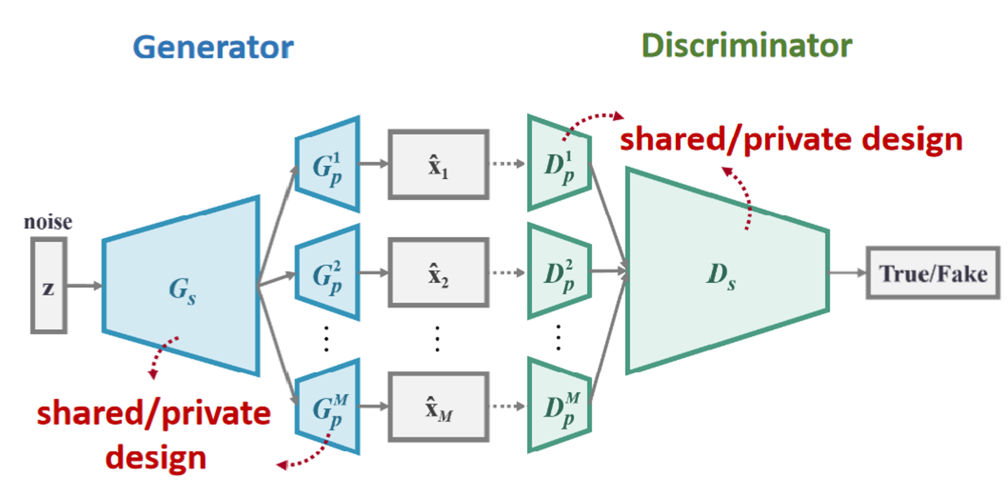
2. Methodology

Data format: Multi-track **pianorolls** (binary matrices, rows ⟷ notes, columns ⟷ timesteps)

- Five tracks: Bass (B), Drums (D), Guitar (G), Piano (P), Strings (S)

Unconditional model: a GAN model that generates musical phrases of variable length

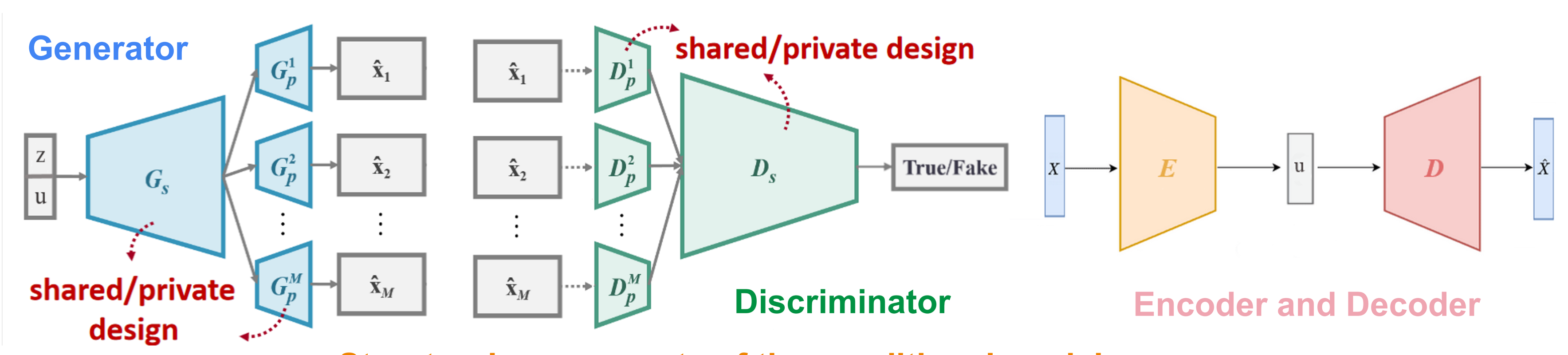
- **shared-private** design for both Generator and Discriminator [3].
- convolutional layers developed with respect to **tonal/rhythmic parameters** (i.e. bar lengths)



Architecture of the unconditional model

- **Generator:** consists of a *shared* network G_s, followed by M *private* subnetworks G_p each one corresponding to one track.
- **Discriminator:** mirrors the structure of the Generator: M *private* subnetworks D_p, one *shared* network D_s.

Conditional model: extension of the unconditional model to a co-operative setup.



Structural components of the conditional model

Structural modifications:

- **Conditional Generator**: Generates 4 pianoroll tracks, which accompany the conditional one
  - comprises only 4 *private* subnetworks instead of 5.
- **Conditional Discriminator**
  - **Global:** incorporates 5 *private* subnetworks and evaluates all 5 tracks collectively.
  - **Local:** incorporates only 4 *private* subnetworks and evaluates only the *accompaniment* tracks as an independent musical composition.
- **Encoder/Decoder module**, produces embeddings of the conditional tracks
  - Decoder used only during training, to facilitate a reconstruction objective.

3. Experimental Setup

Dataset:

Lakh Pianoroll Dataset (174,154 multi-track **pianorolls** derived from the Lakh MIDI Dataset).

➔ We employ the *LPD-5-cleansed* version, containing only the 5-track pianorolls with the higher matching confidence score to MSD entries [2], a "Rock" tag and 4/4 time signature.

Preprocessing:

- Temporal **downsampling**.
- Removal of notes outside the desired pitch range.
- Randomized selection of samples that contain an **adequate amount of notes**.
- Final dataset size: 15,600 phrases from 7,323 songs.

Training Protocol:

- Wasserstein-GAN loss function with gradient penalty: $\min_G \max_D \mathbb{E}_{\mathbf{x}\sim p_d}[D(\mathbf{x})] - \mathbb{E}_{\mathbf{z}\sim p_{\mathbf{z}}}[D(G(\mathbf{z}))] + \mathbb{E}_{\hat{\mathbf{x}}\sim p_{\hat{\mathbf{x}}}}[(\|\nabla_{\hat{\mathbf{x}}} D(\hat{\mathbf{x}})\|_2 - 1)^2]$

Unconditional setup:

- The training strategy is established on consecutive interchanges between k optimization steps of the Discriminator and one optimization of the Generator.

Conditional setup:

- Updating both Global and Local Discriminators during the same training steps.
- Aggregating their feedback for the optimization of the Generator.
- **Encoder/Decoder** (2 training modes):
  - 1-phase training: the Encoder is **trained jointly** with the GAN.
  - 2-phase training: the Encoder is **pre-trained** along with the Decoder (with a pianoroll reconstruction MSE loss and an embedding KL divergence loss).

Musical metrics: Empty Bars (**EB**), Used Pitch Classes (**UPC**), Qualified Notes (**QN**), Drum Pattern (**DP**), Tonal Distance (**TD**), Used Pitches (**UP**), Scale Ratio (**SR**), Polyphonic Rate (**PR**).

Configurations:

- **C1**: Pitch range: 84 notes, 24 timesteps/beat, 4 beats/bar (MuseGAN's generative setup)
- **C2**: Pitch range: 72 notes, 4 timesteps/beat, 4 beats/bar (lower resolution).

4. Objective Evaluation

Unconditional Generation (comparison to baseline/MuseGAN)

	Instruments	EB B	EB D	EB G	EB P	EB S	UPC B	UPC G	UPC P	UPC S	QN B	QN G	QN P	QN S	DP D	TD (↓) B-G	TD (↓) B-S	TD (↓) B-P	TD (↓) G-S	TD (↓) G-P	TD (↓) S-P
training data	*baseline*	8.06	8.06	19.4	24.8	10.1	1.71	3.08	3.28	3.38	90.0	81.9	88.4	89.6	88.6	-	-	-	-	-	-
	ours	1.6	1.1	4.1	5.1	3.2	2.48	4.16	4.2	4.57	91.7	85.3	89.7	89.7	83.1	-	-	-	-	-	-
Baseline	jamming	6.59	2.33	18.3	22.6	6.10	1.53	3.69	4.13	4.09	71.5	56.6	62.2	63.1	93.2	1.56	1.60	1.54	1.05	0.99	1.05
	composer	0.01	28.9	1.34	0.02	0.01	2.51	4.20	4.89	5.19	49.5	47.4	49.9	52.5	75.3	1.37	1.36	1.30	0.95	0.98	0.91
	hybrid	2.14	29.7	11.7	17.8	6.04	2.35	4.76	5.45	5.24	44.6	43.2	45.5	52.0	71.3	1.34	1.35	1.32	0.85	0.85	0.83
	ablated	92.4	100	12.5	0.68	0.00	1.00	2.88	2.32	4.72	0.00	22.8	31.1	26.2	0.0	-	-	-	-	-	-
Ours	C_1	0.0	**0.7**	0.4	1.3	1.2	3.63	4.67	**4.64**	5.29	55.6	**75.8**	**74.1**	**75.9**	59.5	0.2	0.22	0.2	0.21	0.2	0.21
	C_2	**0.3**	0.0	**0.9**	**1.9**	**2.1**	**2.89**	**4.4**	4.88	**5.14**	**59.0**	58.2	57.2	60.8	**79.6**	0.86	0.91	0.9	0.98	0.99	0.97

- Both models approximate adequately the statistics of the real distribution.
- **QN** and **DP**: our framework outperforms almost all baseline variations (colored cells).
- **TD**: C_1 surpasses all baseline architectures (generating harmonic samples)
  - **Shared-private design** helps in creating harmonically coherent tracks.
- C_2 is weaker than C_1 → **fine-grained resolution** assists in the generative process.

Conditional Generation

		AutoEncoder	Local Discriminator
Piano	P_{00}	-	-
	P_{01}	-	✓
	P_{10}	✓	-
	P_{11}	✓	✓
Guitar	G_{00}	-	-
	G_{01}	-	✓
	G_{10}	✓	-
	G_{11}	✓	✓

Piano models:

- 2-phase training (P_{10} and P_{11}) mostly benefits the **note density** (**EB**) of the generated samples.
- Bass more sparse than the original (**EB** equal to 17.4%) for P_{10}
- Local Discriminator (P_{01} and P_{11}) benefits **tonality** (**SR**, **UP**), **fragmentation** (**QN**) and **polyphonicity** (**PR**) of each track.

Instruments	EB B	EB D	EB G	EB P	EB S	UPC B	UPC G	UPC P	UPC S	QN B	QN G	QN P	QN S	UP B	UP G	UP P	UP S
Piano train	1.6	1.0	5.0	5.6	3.7	2.47	4.09	4.19	4.5	91.6	85.6	90.0	89.7	2.71	5.68	5.85	6.71
Guitar train	1.8	0.9	4.3	5.2	3.6	2.47	4.21	4.14	4.49	91.8	87.5	91.6	90.5	2.7	5.85	5.84	6.75
P_{00}	0.6	0.0	2.2	-	2.4	2.71	3.93	-	**4.33**	51.4	56.5	-	58.9	2.94	5.79	-	**6.28**
P_{01}	0.2	0.0	1.8	-	1.5	2.57	**4.09**	-	4.76	**58.2**	56.1	-	**61.7**	2.94	**5.77**	-	7.17
P_{10}	17.4	**0.2**	**3.0**	-	**4.4**	1.68	3.9	-	4.3	50.7	49.2	-	55.1	1.74	5.05	-	6.07
P_{11}	**1.6**	0.0	0.7	-	0.9	**2.56**	4.19	-	5.16	54.8	**56.6**	-	51.0	**2.84**	5.43	-	7.3
G_{00}	0.8	0.0	-	2.1	1.8	**2.51**	-	5.04	**4.59**	**62.5**	-	49.3	**60.3**	**2.77**	-	7.31	6.91
G_{01}	0.0	0.0	-	3.1	0.0	3.05	-	4.31	5.28	57.6	-	52.4	59.6	3.36	-	6.18	7.69
G_{10}	**1.6**	0.0	-	1.8	**3.5**	2.35	-	**4.28**	4.01	50.2	-	**59.5**	58.6	2.59	-	**6.13**	5.88
G_{11}	0.4	**0.2**	-	**3.3**	0.6	2.32	-	4.62	4.66	55.6	-	47.8	57.9	2.46	-	6.4	**6.68**

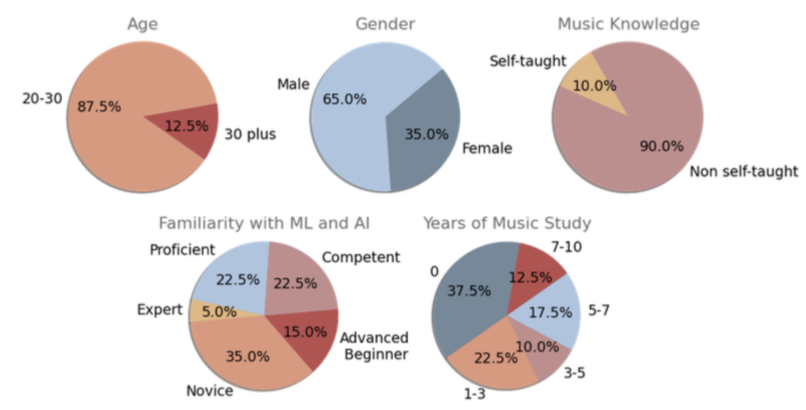
Instruments	TD (↓) B-G	TD (↓) B-S	TD (↓) B-P	TD (↓) G-S	TD (↓) G-P	TD (↓) S-P	SR B	SR G	SR P	SR S	PR B	PR D	PR G	PR P	PR S	DP D
Piano train	-	-	-	-	-	-	75.9	74.4	74.1	72.8	1.1	15.2	55.7	61.8	62.3	82.9
Guitar train	-	-	-	-	-	-	75.4	73.5	73.4	73.1	0.8	15.5	59.7	61.0	62.6	85.0
P_{00}	0.82	0.83	0.88	0.87	0.95	**0.94**	81.7	**75.8**	-	77.1	**1.2**	13.3	40.6	-	44.2	**86.1**
P_{01}	0.79	0.81	0.85	**0.85**	**0.94**	**0.94**	**77.1**	76.3	-	75.6	1.5	**15.2**	**48.7**	-	**59.9**	86.3
P_{10}	**0.74**	**0.73**	**0.81**	0.94	1.02	1.01	82.2	80.6	-	79.0	0.2	10.1	22.2	-	30.2	87.0
P_{11}	0.83	0.92	0.97	0.99	1.12	1.17	80.7	77.6	-	**72.3**	1.9	9.7	38.2	-	56.3	86.2
G_{00}	**0.83**	0.85	0.9	0.96	1.01	0.98	84.7	-	80.9	**77.0**	1.1	10.9	-	53.9	53.4	87.1
G_{01}	0.87	0.87	**0.83**	**0.93**	**0.92**	**0.86**	86.7	-	83.6	83.9	2.8	**14.9**	-	**55.3**	**60.8**	**86.0**
G_{10}	0.84	**0.84**	0.84	**0.93**	0.95	0.89	82.0	-	79.8	85.4	**0.7**	6.0	-	37.5	44.0	91.7
G_{11}	0.89	0.87	0.88	1.06	1.09	0.97	**78.0**	-	**76.9**	80.5	**0.9**	9.7	-	42.1	54.4	83.7

Guitar models:

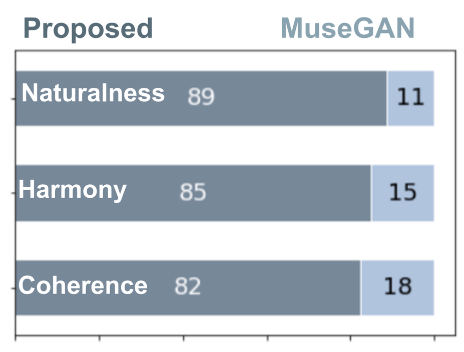
- 2-phase training (G_{10} and G_{11}) benefits **note density** (**EB**) and **tonality** (**UP**, **SR**),
- Local Discriminator: stronger **harmonic relations** between the tracks (**TD**), improving also **rhythm** (**DP**) and **texture** elements such as **PR**.

5. Subjective Evaluation: Listening Test

- **40 participants**, recruited via social circles
- **Unconditional Generation**: Comparison to the original MuseGAN configuration, in **pairs**.
- **Conditional Generation**: Comparison between our developed configurations, as well as real samples, in **triplets** (conditional track + two accompaniments)
- **Criteria**: Music Naturalness, Harmonic Consistency, Musical Coherence



Unconditional Generation



- The proposed framework outperforms MuseGAN with respect to all the examined musical aspects.
  - ➢ Improvement in **Naturalness** & **Coherence** is attributed to our parameterized architecture that emphasizes on rhythmical attributes.
  - ➢ **Stronger harmonic relations** among the tracks and **enhanced tonality** as a result of the shared/private design.

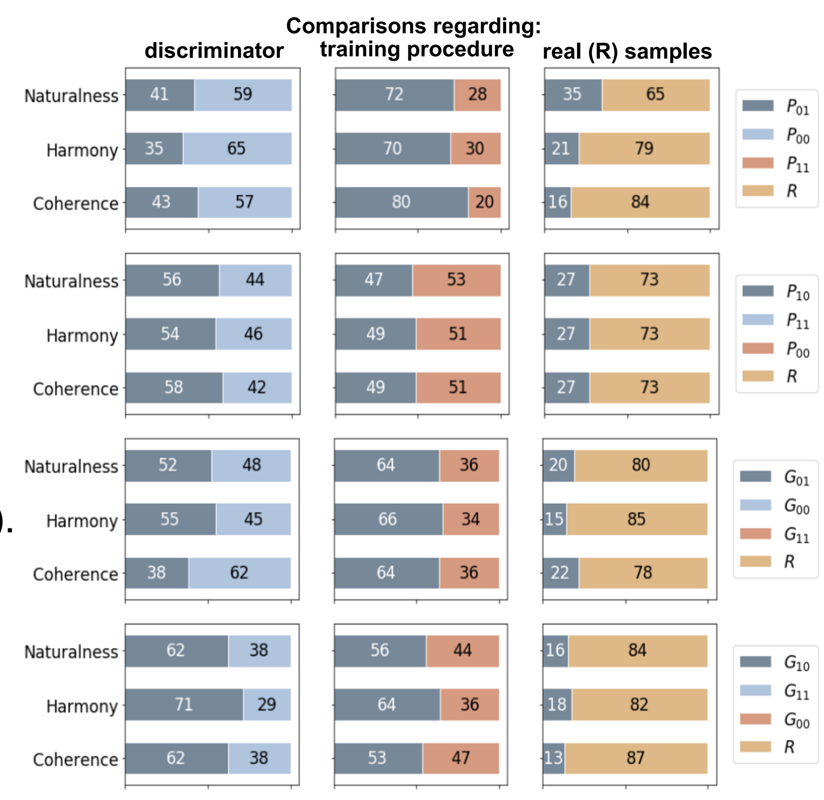
Conditional Generation

Piano models:

- Fake accompaniments are easily distinguishable
- P_{01} best compared to real on **Naturalness** (35%).
- P_{01} outperforms P_{11} with respect to all the examined musical aspects, especially **Coherence**.

Guitar models:

- Fake versions are **easily distinguishable** under all musical criteria (preference ranging from 13 to 20%).
- G_{10} outperforms G_{00} and G_{11} regarding all musical aspects (2-phase mode with Global Discriminator).
- G_{01} surpasses G_{11}, indicating that the most suitable training practice for the architecture of both Discriminators is the 1-phase mode.



6.Conclusions

- Proposed a **configurable generative framework** capable of:
  - creating multi-track polyphonic musical phrases **from scratch**,
  - generating multi-instrumental **accompaniments** for human-composed tracks.
- Hierarchical **shared/private design** for both Generator and Discriminator modules.
- **Objective and subjective evaluation**:
  - **Outperform** MuseGAN in the unconditional setup under 3 musical criteria.
  - Provide **useful insights** on training and structural schemes for conditional setups.
- **Future work**: validate our findings on transformer-based architectures and use other feature representations.

References

[1] H.-W.Dong et al., "MuseGAN: Multi-track Sequential Generative Adversarial Networks for Symbolic Music Generation and Accompaniment", in *Proc. AAAI 2018*.
[2] T. Bertin-Mahieux et al., "The Million Song Dataset", in Proc. ICWWW 2012.
[3] H.-W. Dong and Y.-H. Yang, "Convolutional Generative Adversarial Networks with Binary Neurons for Polyphonic Music Generation", *arXiv preprint arXiv:1804.09399*, 2018.

Acknowledgements

This research was supported by the Hellenic Foundation for Research and Innovation (H.F.R.I.) under the "3rd Call for H.F.R.I. Research Projects to support Post-Doctoral Researchers" (Project Number: 7773).