Convolutional Generative Adversarial Networks with Binary Neurons for Polyphonic Music Generation

Hao-Wen Dong and Yi-Hsuan Yang

Research Center for IT Innovation, Academia Sinica, Taipei, Taiwan

[Demo Website] `https://salu133445.github.io/bmusegan/`

>> Introduction

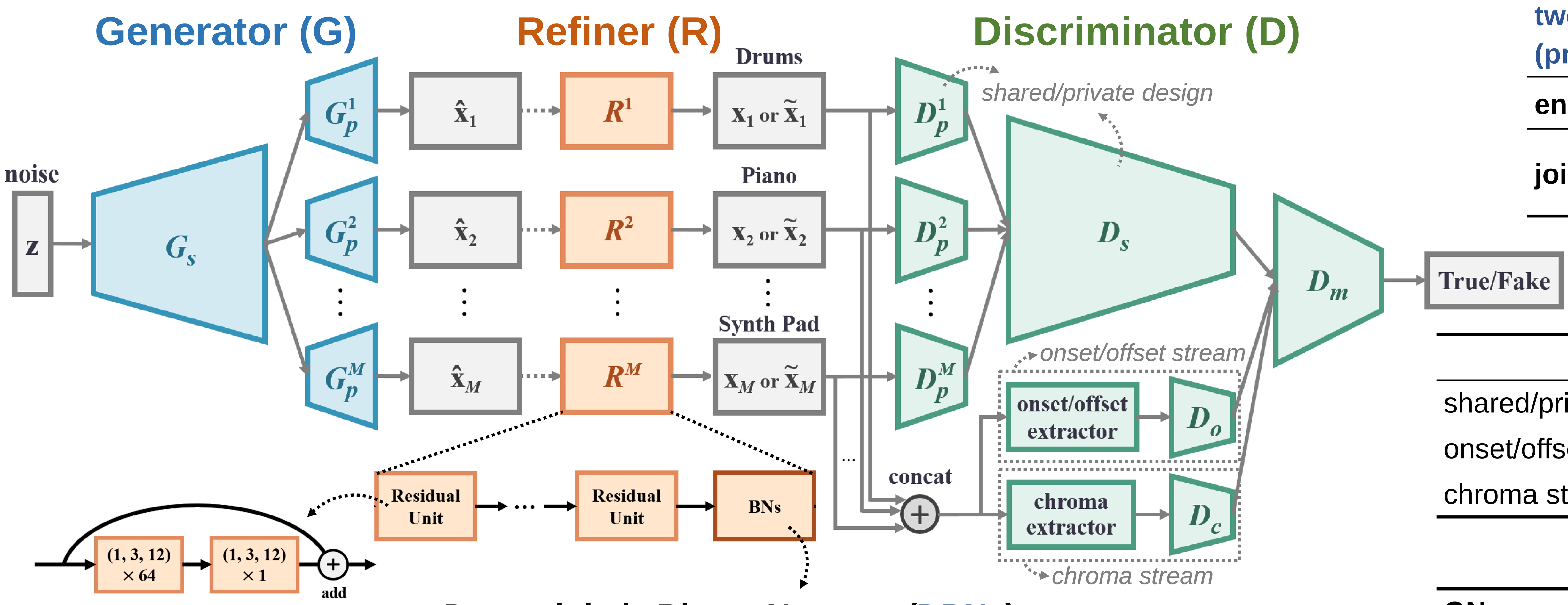
- ♯ MuseGAN [1] shows the promise of using GANs [2] with CNNs to generate ***multitrack pianorolls***. But it requires further postprocessing at test time to binarize the generator's (G) output
- ♯ **BinaryMuseGAN (proposed)** adopts ***binary neurons*** [3] to binarize G's output during training

	G's output	data
MuseGAN [1]	real	binary
BinaryMuseGAN (proposed)	**binary**	binary

>> Data

- ♯ Lakh Pianoroll Dataset (LPD) — *LPD-cleansed* subset
- ♯ Consider only songs with an ***alternative*** tag to make the training data cleaner
- ♯ 13,746 **4**-bar phrases from 2,291 songs
- ♯ **96** time steps in a bar, **84** possible pitches (C1 to B7)
- ♯ **8** tracks — Drums, Piano, Guitar, Bass, Ensemble, Reed, Synth Lead and Synth Pad
- ♯ Target output tensor shape — (**4**, **96**, **84**, **8**)

>> System



Deterministic Binary Neurons (DBNs) $DBN(x) = u(\sigma(x) - 0.5)$

Stochastic Binary Neurons (SBNs) $SBN(x) = u(\sigma(x) - v), v \sim U[0, 1]$

Training Strategies

two-stage (proposed)	[stage 1] pretrain G and D [stage 2] train R and D (G is fixed)
end-to-end	train G, R and D jointly
joint	[stage 1] pretrain G and D [stage 2] train G, R and D

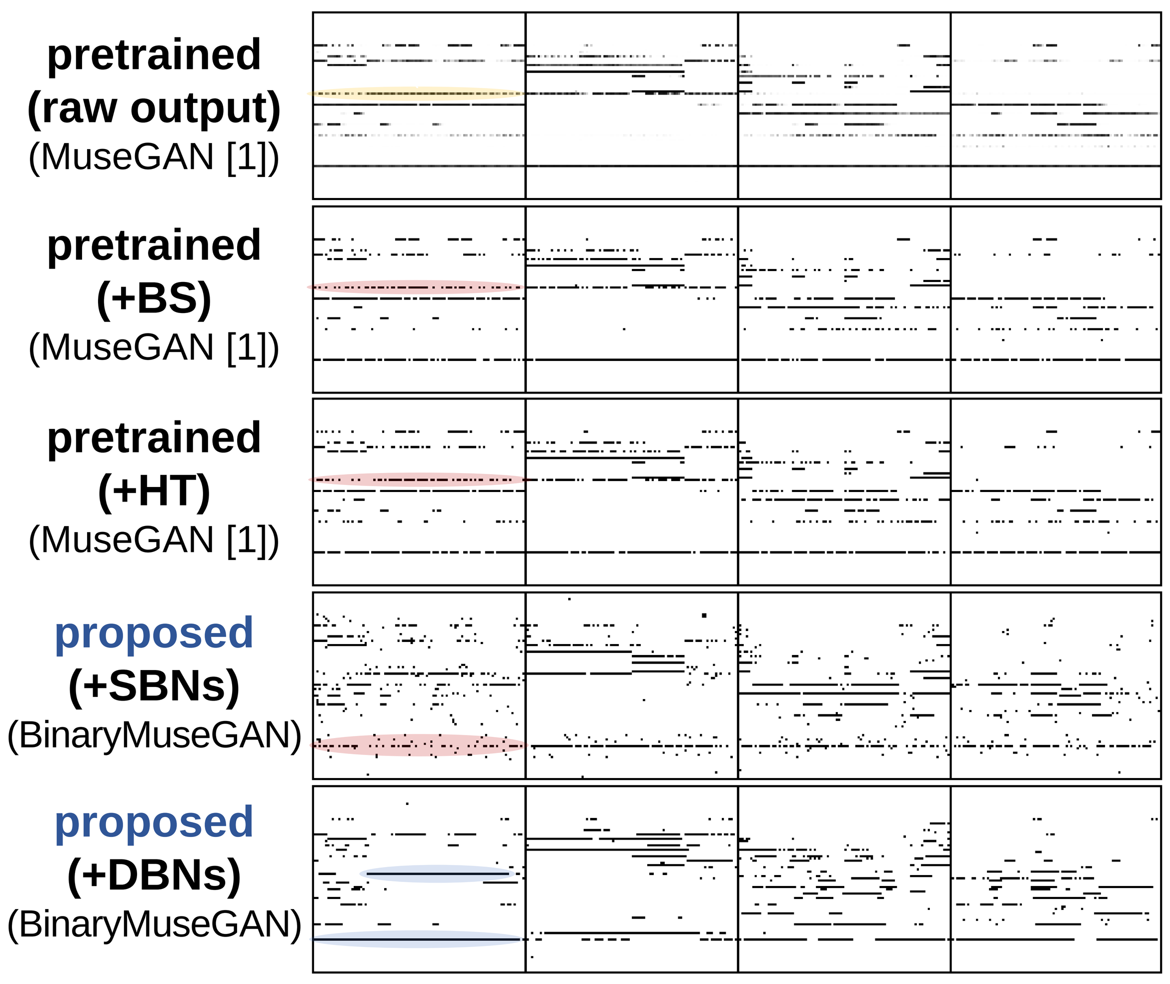
Models

	proposed	ablated-I	ablated-II
shared/private design	✓	✓	
onset/offset stream	✓		
chroma stream	✓		

Metrics

QN	qualified (no shorter than a 32th note) note rate
PP	polyphonicity (more than 3 pitches are played) rate
TD	tonal distance [4] between the piano and guitar

>> Results



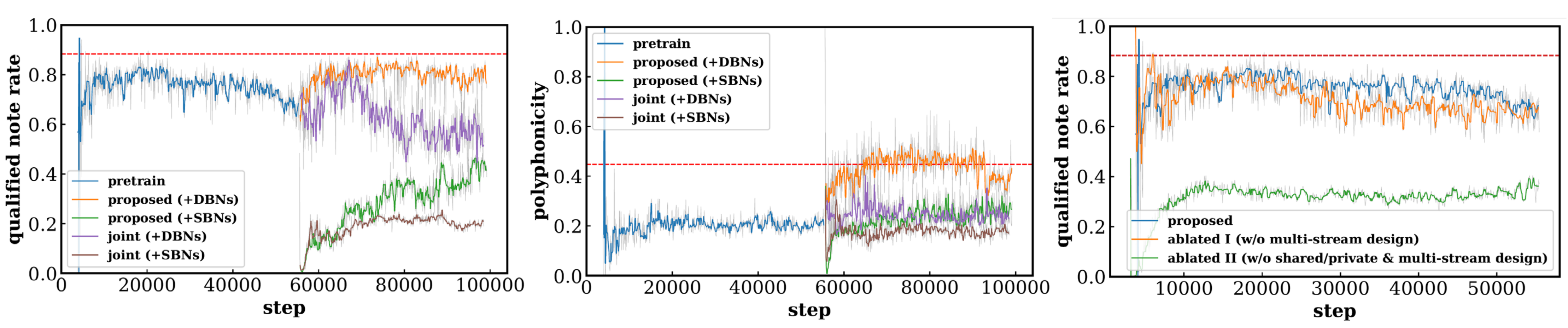
(**HT**—hard thresholding; **BS**—Bernoulli sampling)

Evaluation Results

(value closer to the training data is better)

	training data	pretrained		proposed		joint		end-to-end		ablated-I		ablated-II	
		BS	HT	SBNs	DBNs	SBNs	DBNs	SBNs	DBNs	BS	HT	BS	HT
QN	0.88	**0.67**	**0.72**	0.42	**0.78**	0.18	0.55	**0.67**	0.28	0.61	0.64	0.35	0.37
PP	0.48	0.20	0.22	**0.26**	**0.45**	0.19	0.19	0.16	**0.29**	0.19	0.20	0.14	0.14
TD	0.96	**0.98**	1.00	**0.99**	0.87	**0.95**	1.00	1.40	1.10	1.00	1.00	1.30	1.40

(Underlined and bold font indicate respectively the top and top-three entries with values closest to those shown in the 'training data' column.)



>> Conclusions

- ♯ While the generated results appear preliminary and lack musicality, we showed the potential of adopting binary neurons in a music generation system
- ♯ Using DBNs leads to better objective scores than hard thresholding, Bernoulli sampling and SBNs
- ♯ It might also be interesting to use binary neurons in music transcription (binary-valued outputs as well)

>> References

[1] Hao-Wen Dong, Wen-Yi Hsiao, Li-Chia Yang, and Yi-Hsuan Yang. MuseGAN: Symbolic-domain music generation and accompaniment with multi-track sequential generative adversarial networks. In *Proc. AAAI*, 2018.

[2] Ian J. Goodfellow et al. Generative adversarial nets. In *Proc. NIPS*, 2014.

[3] Yoshua Bengio, Nicholas Léonard, and Aaron C. Courville. Estimating or propagating gradients through stochastic neurons for conditional computation. *arXiv preprint arXiv:1308.3432*, 2013.

[4] Christopher Harte, Mark Sandler, and Martin Gasser. Detecting harmonic change in musical audio. In *Proc. ACM Workshop on Audio and Music Computing Multimedia*, 2006.