



Modeling Melodic Feature Dependency with Modularized Variational Auto-Encoder

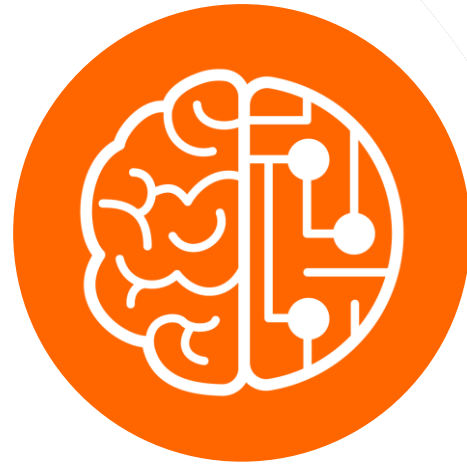
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Outline



Motivation



Approach



Experiments



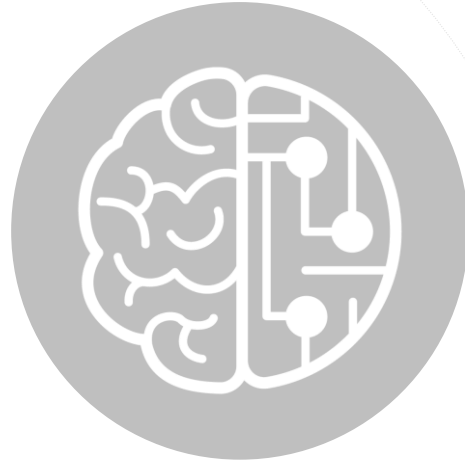
Conclusion



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Symbolic Music Generation



Sequence Modeling

- RNN (Recurrent Neural Networks)

Generative Modeling

- VAE (Variational Auto-Encoders)
- GAN (Generative Adversarial Networks)

- VRAE = RNN + VAE

- *modeling temporal dependency via recurrent units*
- *diverse generation via controllable codes*



Idea: modeling melodic dependency of notes in terms of time, duration, and pitch in a specific order

Contributions

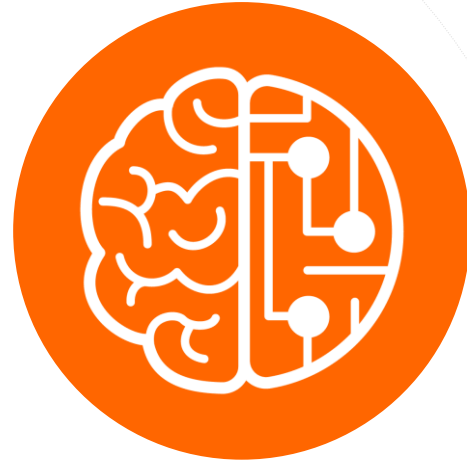
- ✓ incorporate domain knowledge by a *modularized* framework
- ✓ integrate *note-unrolling* to model the dependency between melodic features
- ✓ achieve better performance than other generative models



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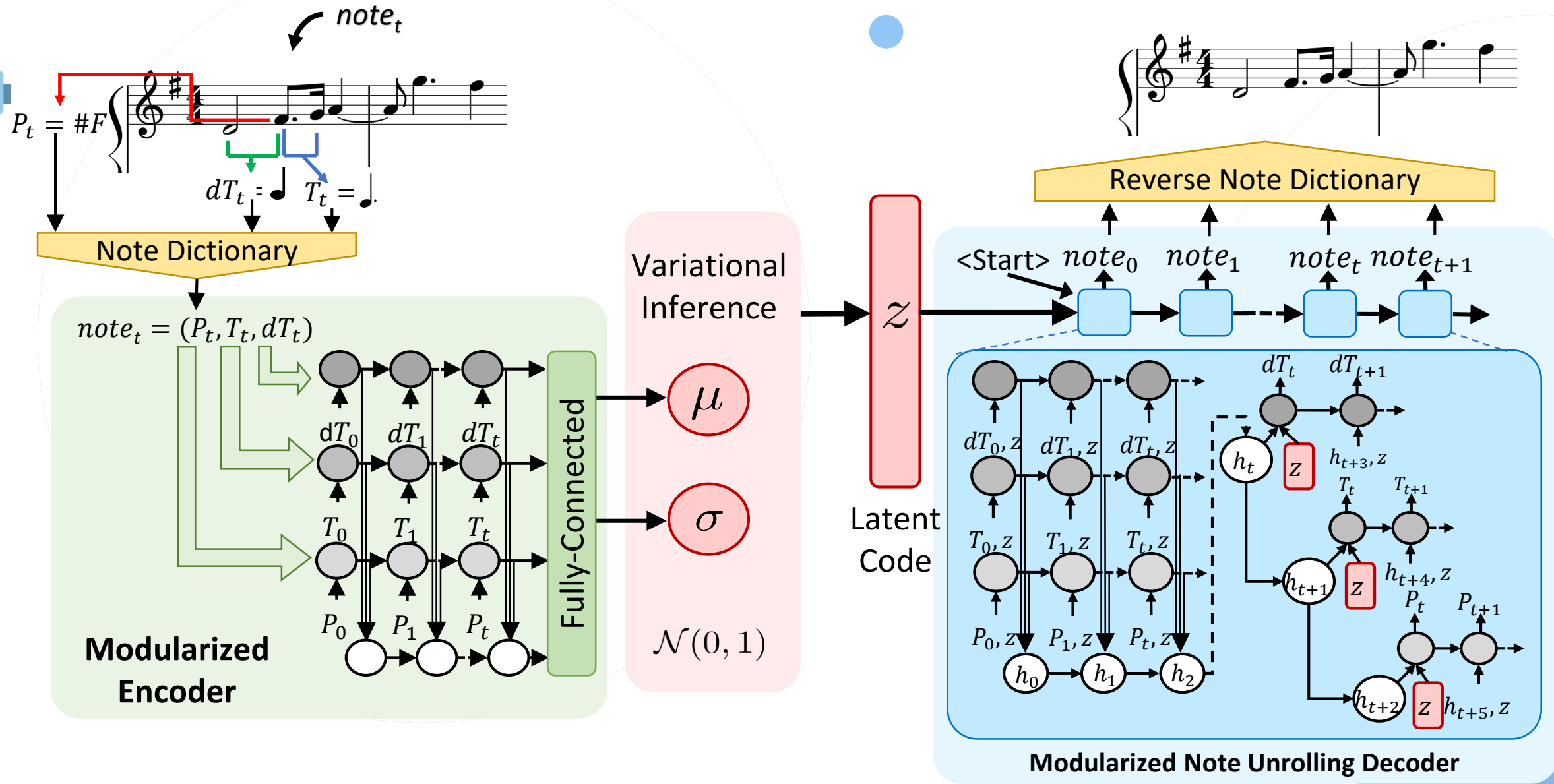
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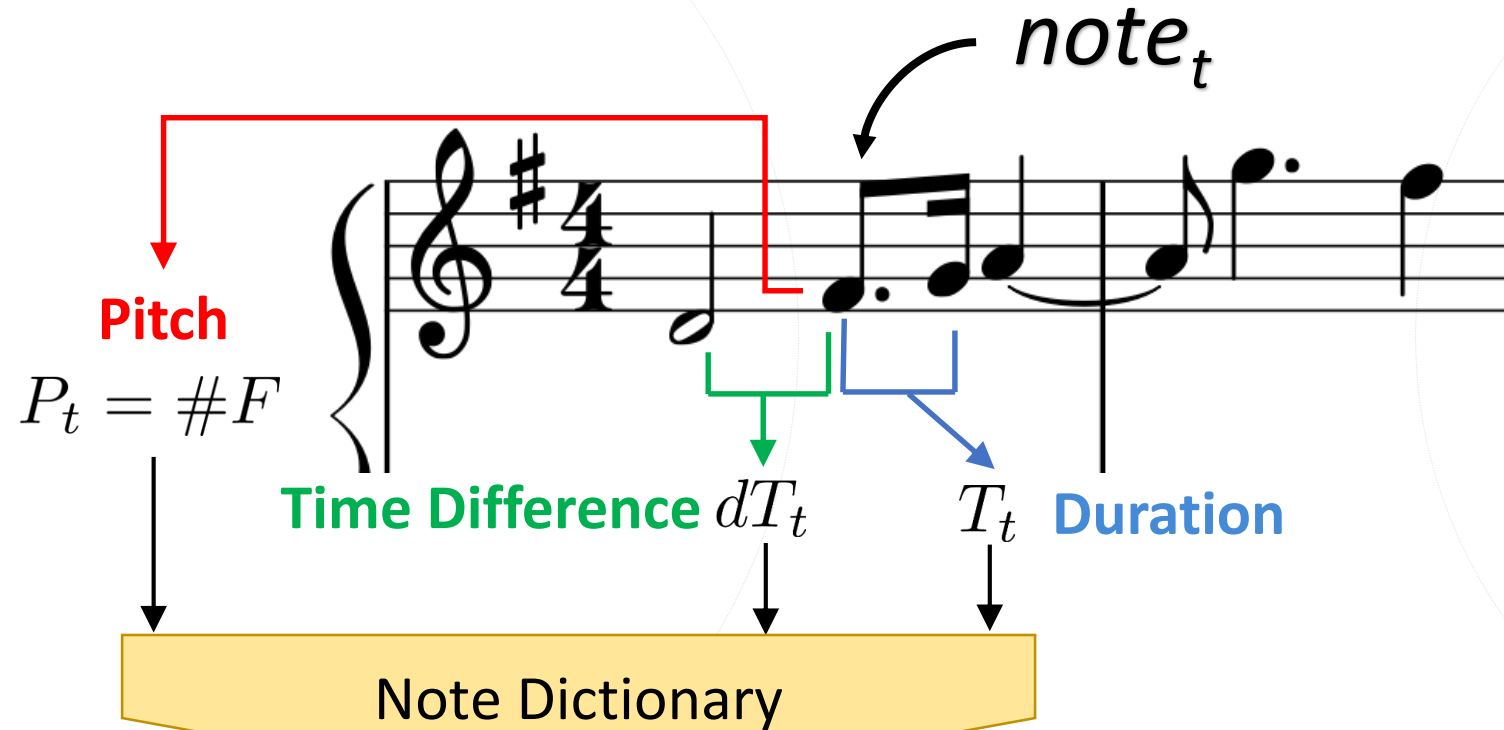
MVAE: Modularized Variational Auto-Encoder





Data Representation

- Represent note events via different features

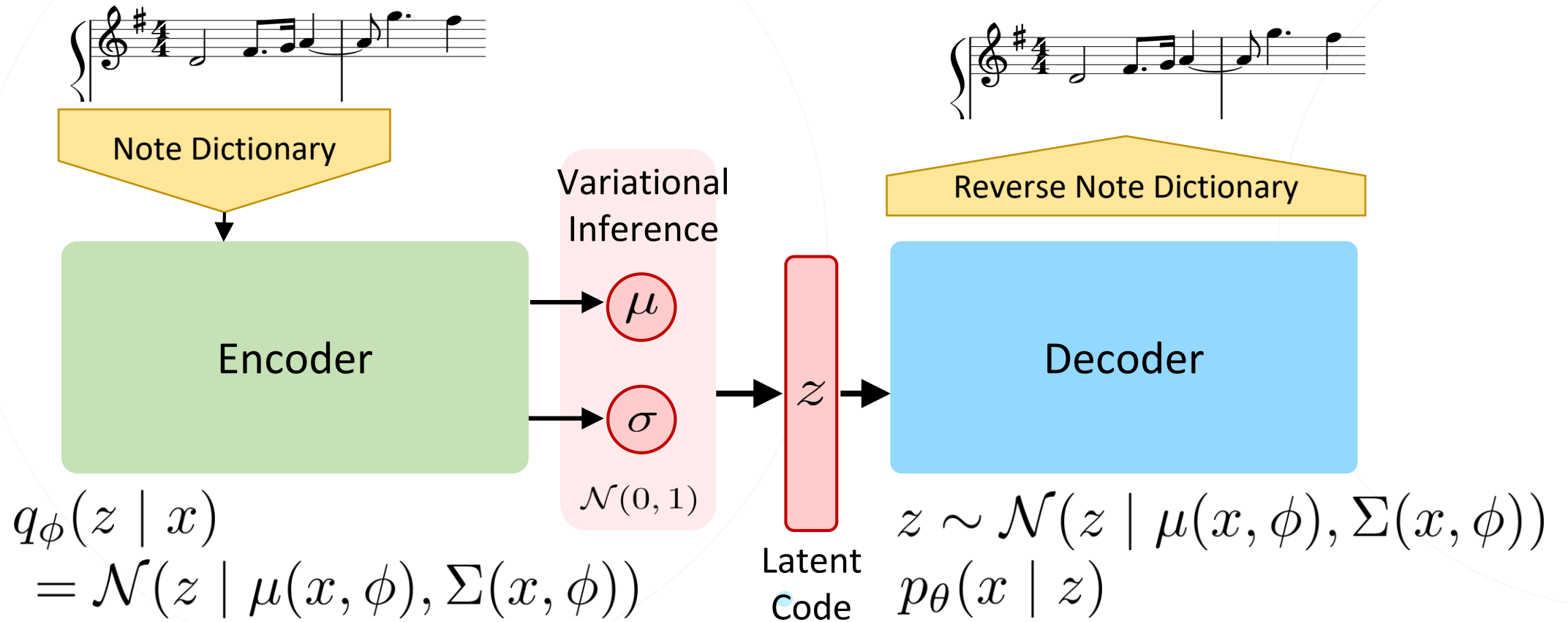


$$note_t = (P_t, T_t, dT_t)$$



Variational Auto-Encoder

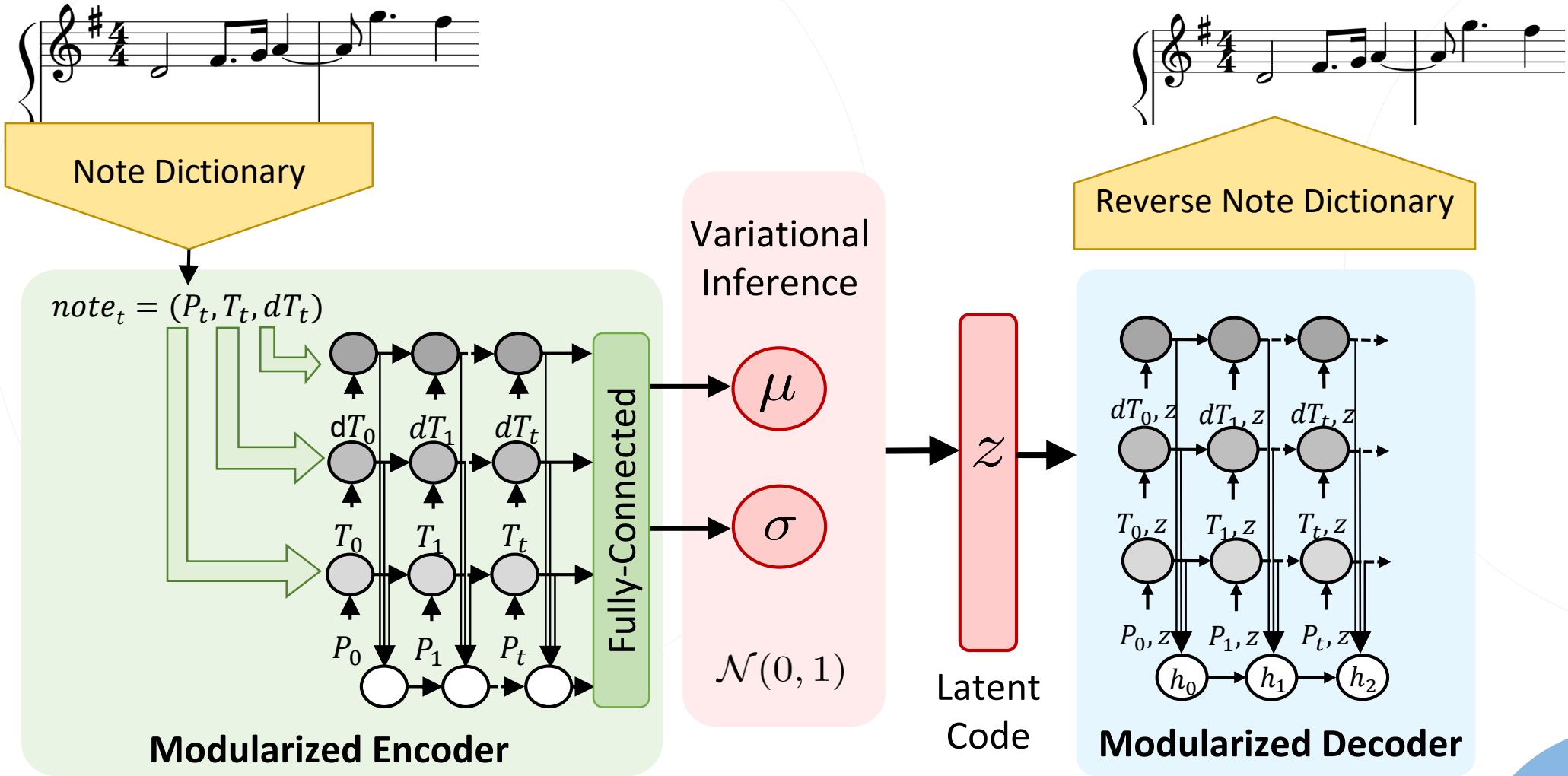
- Given an input $x = (x_1, \dots, x_t)$, the goal is to reconstruct the input



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

Modularized Encoder and Decoder

- Each feature is modeled by its own RNN

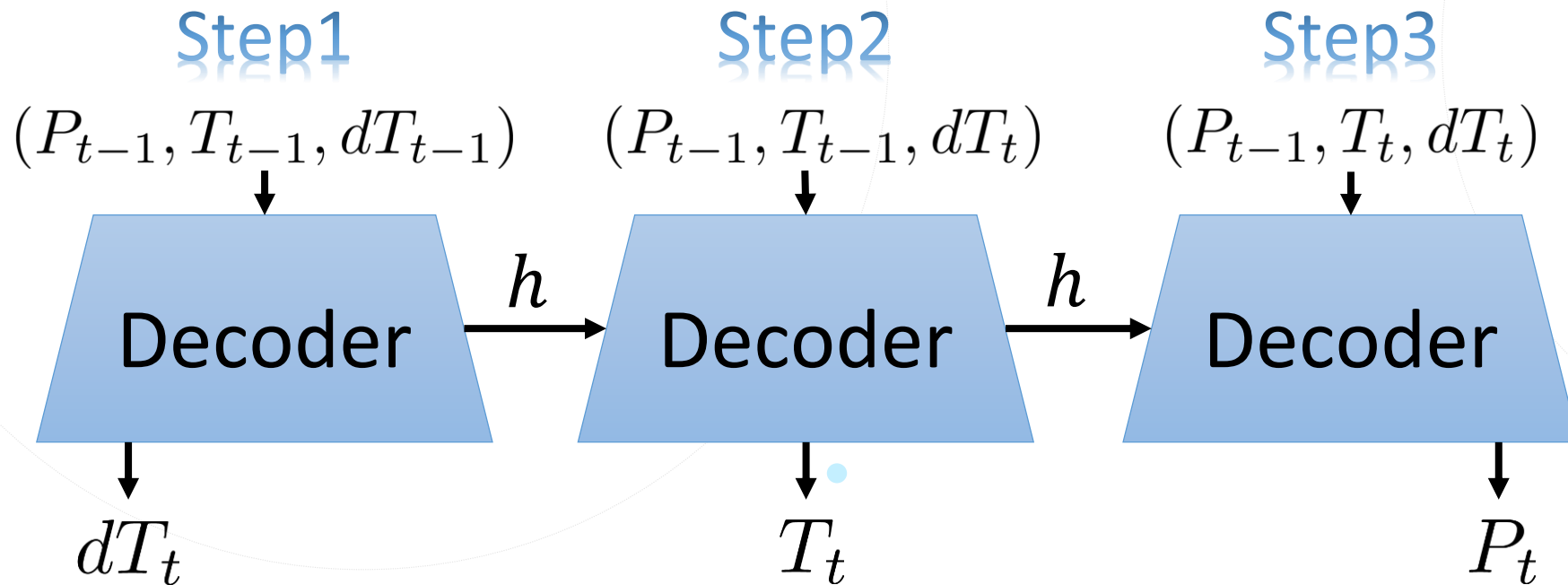




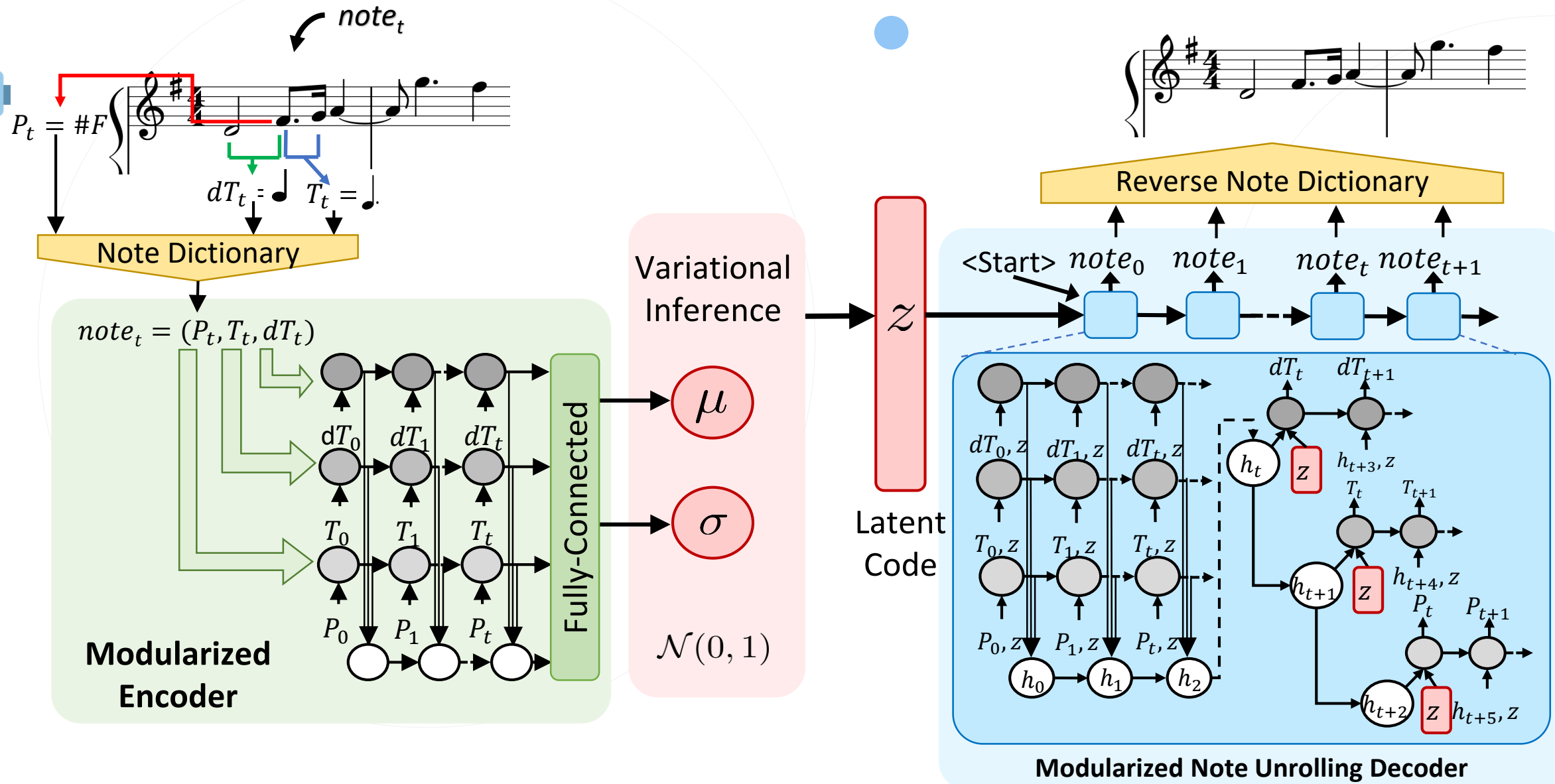
Modularized Note-Unrolling Decoder

- Modeling inter-feature dependency in a specific order

$$p(P_t, T_t, dT_t \mid \text{note}_{1:t-1}) \\ = p(dT_t \mid \text{note}_{1:t-1}) \times p(T_t \mid \text{note}_{1:t-1}) \times p(P_t \mid \text{note}_{1:t-1})$$



MVAE: Modularized Variational Auto-Encoder





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Experimental Setup

- Data: a merged set of Nottingham, Piano-midi.de, JSB Chorales
- Q1: Is the *modularized encoder* better?
 - Baseline – BachProp (Colombo & Gerstner, 2018)
- Q2: Is the *variational* inference important?
 - Baseline – modularized auto-encoder
- Q3: Is the *note-enrolling* important?
 - Ablation test



Human Evaluation

- 1-6 scales (1: machine-generated; 6: human-generated)
- Collect 85 scores for each model

Model	Reconstruction Error	KL Divergence	Human Score	
			μ	σ
BachProp	240.16	-	3.51	1.61
Modularized AutoEncoder	20.79	-	2.77	1.65
Proposed w/o note unrolling	85.88	264.00	3.22	1.73
Proposed w/ note unrolling	73.19	30.37	4.24	1.54
Real data	-	-	4.34	1.55



- ✓ A1: The *modularized encoder* is better.
- ✓ A2: The *variational* inference is necessary.
- ✓ A3: The *note-enrolling* is important.

Latent Space Analysis

- Interpolation distribution

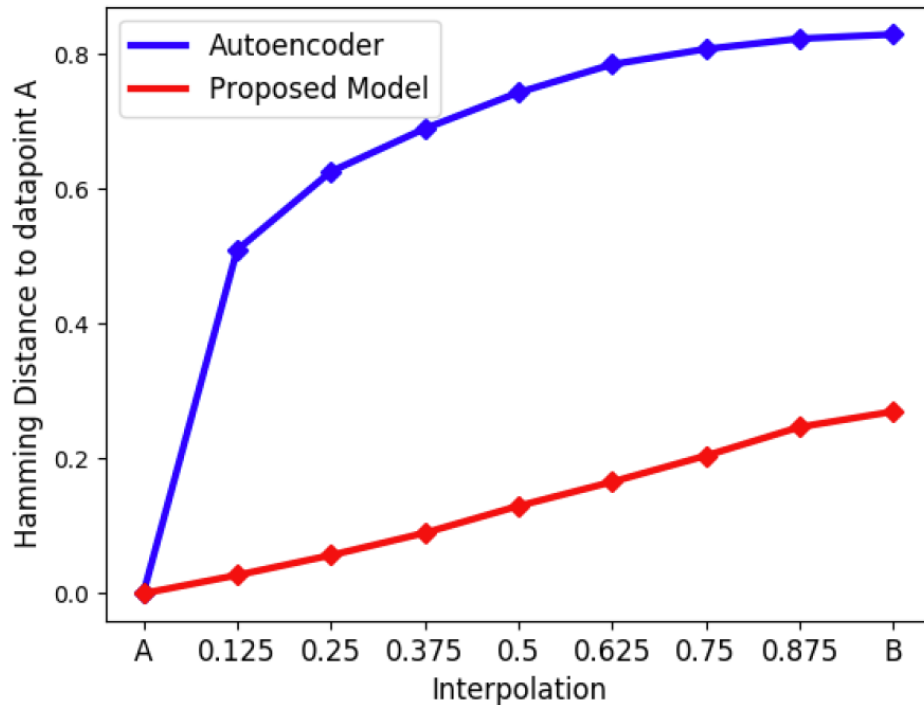


Fig. 2. Average distance between two random datapoints on Z .

Smooth curve: meaningful interpolation points

- Visualization

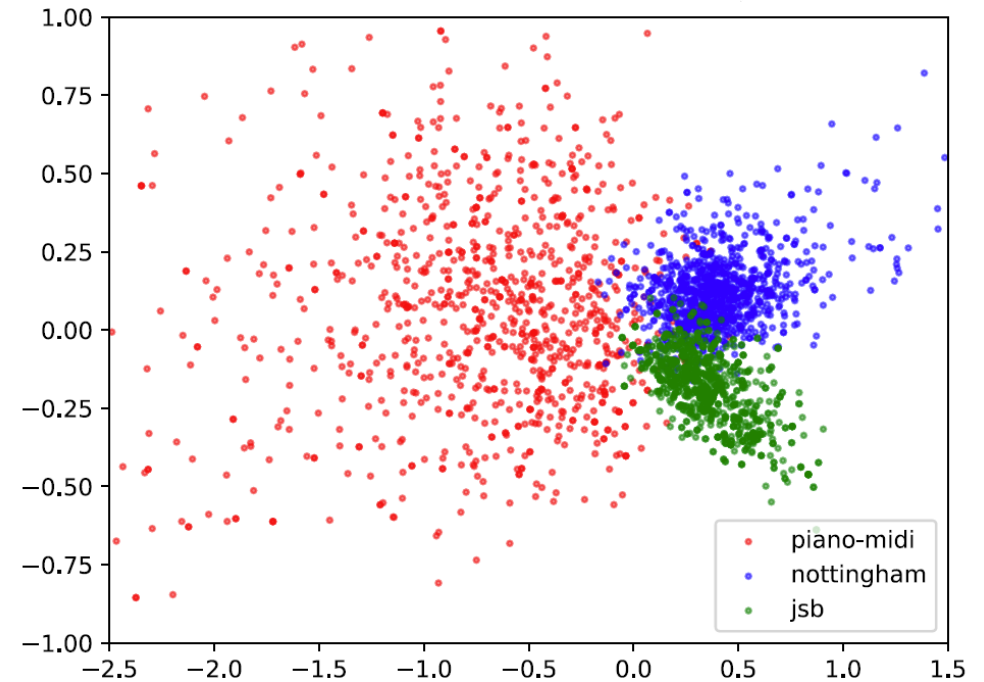


Fig. 3. Visualization on the latent space via PCA, where three different types of music are separated in Z .

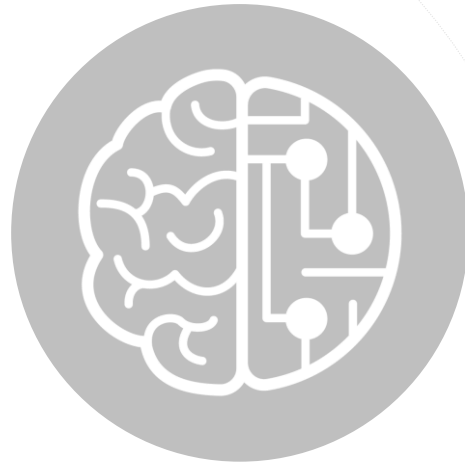
Distinct features for different music characteristics
→ informative latent codes



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Conclusion

- We propose a VAE with a *modularized* framework to model the melodic dependency between note attributes
- The proposed note event representations bring better flexibility
- The experiments in a merged dataset with diverse music types show the superior performance of our MVAE
 - ✓ The *modularized encoder* is better.
 - ✓ The *variational* inference is necessary.
 - ✓ The *note-enrolling* is important.
 - ✓ The learned latent codes are informative





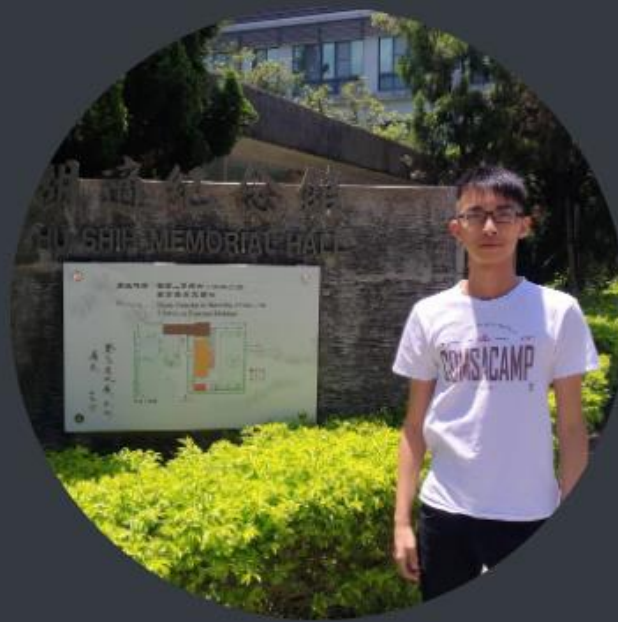
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Demo & Code Available @

- <http://mvae.miulab.tw>

