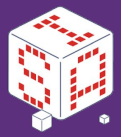

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Variational Autoencoders for Polyphonic Music Interpolation

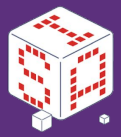
Pablo López Diéguez and Soo Von-Wun

TAAI 2020 – Technologies and Applications of Artificial Intelligence

Taipei, Taiwan

國立清華大學
NATIONAL TSING HUA UNIVERSITY

Outline



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01 Context

VAE

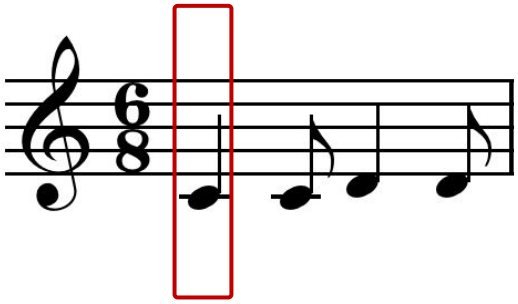
Variational Autoencoders for Polyphonic Music Interpolation

Variational Autoencoders for Polyphonic Music Interpolation

Polyphonic Music

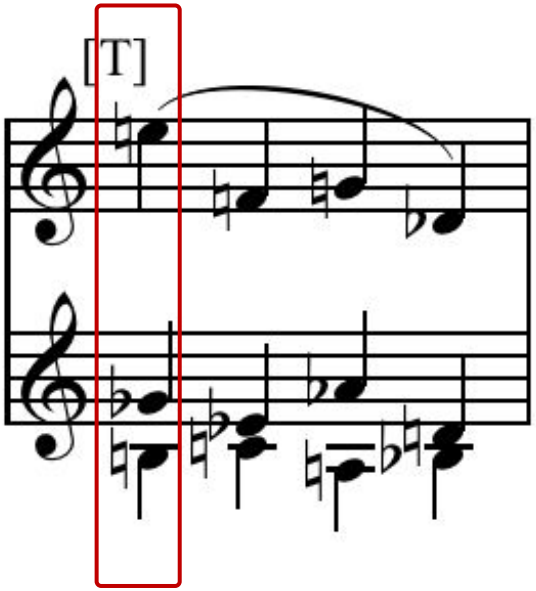
Texture (music)
- Monophonic music
- Polyphonic music

Monophonic



single note

Polyphonic



multiple notes

**timestep = time unit*

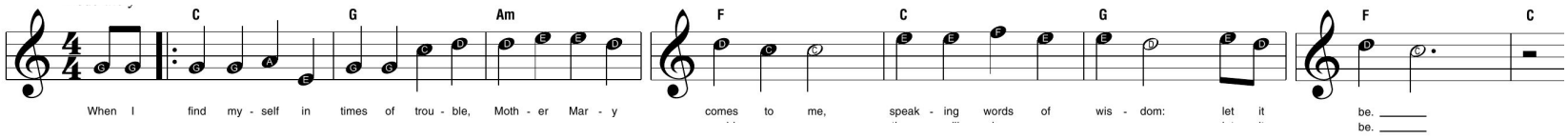
Variational Autoencoders for Polyphonic Music Interpolation

Interpolation

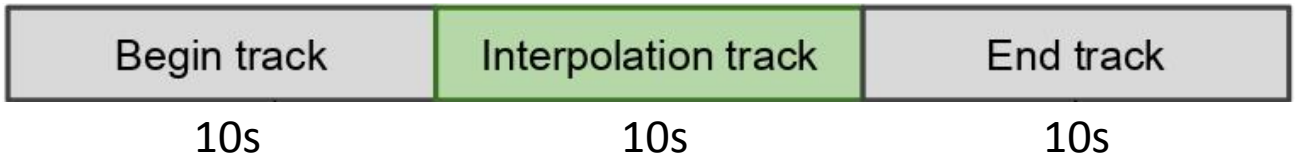
"Interpolation is a type of **estimation**, a method of constructing new **data points** within the range of a **discrete set** of known data points"
(Fleetwood, 1991)

Interpolation

In traditional Machine Learning, the generation of music is conditioned on the past events.

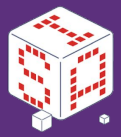


Past events *New prediction* *Future events*



Applications

- Music composition for scenes transitioning in cinema.
- Music composition between an advertisement and the TV show song.
- Real-time music interpolation for musicians.



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02 Related work

References

Google Brain magenta

"A Hierarchical Latent Vector Model for Learning Long-Term Structure in Music"
(Roberts *et. al*, 2018)

- VAE for modelling long-term sequences.
- Tested performance for interpolation.

- Not focusing on interpolation
- Low level heuristic
- Monophonic
- Data not available
- High training cost

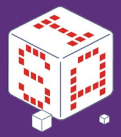
Linear sampling of latent-space: state-of-the-art method for interpolation

ETH zürich

"Modeling Dynamics and Instrumentation of Music with Applications to Style Transfer"
(Brunner *et. al*, 2018)

- VAE for style transfer.
- Tested performance for interpolation.
- Training: 48h on a single GPU.

- Not focusing on interpolation
- Low level heuristic
- Style classifier required
- High training cost



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03 Objectives

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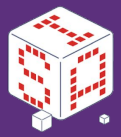
Objectives

01 Interpolation	Solving the interpolation problem.
02 Efficiency	Reducing the computational and time requirements of the state-of-the-art interpolation approaches.
03 Outperformance	Developing an interpolation technique that outperforms the state-of-the-art interpolation approaches.
04 Metrics	Proving the superiority of the models proposed with a set of objective metrics.



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04 Theory

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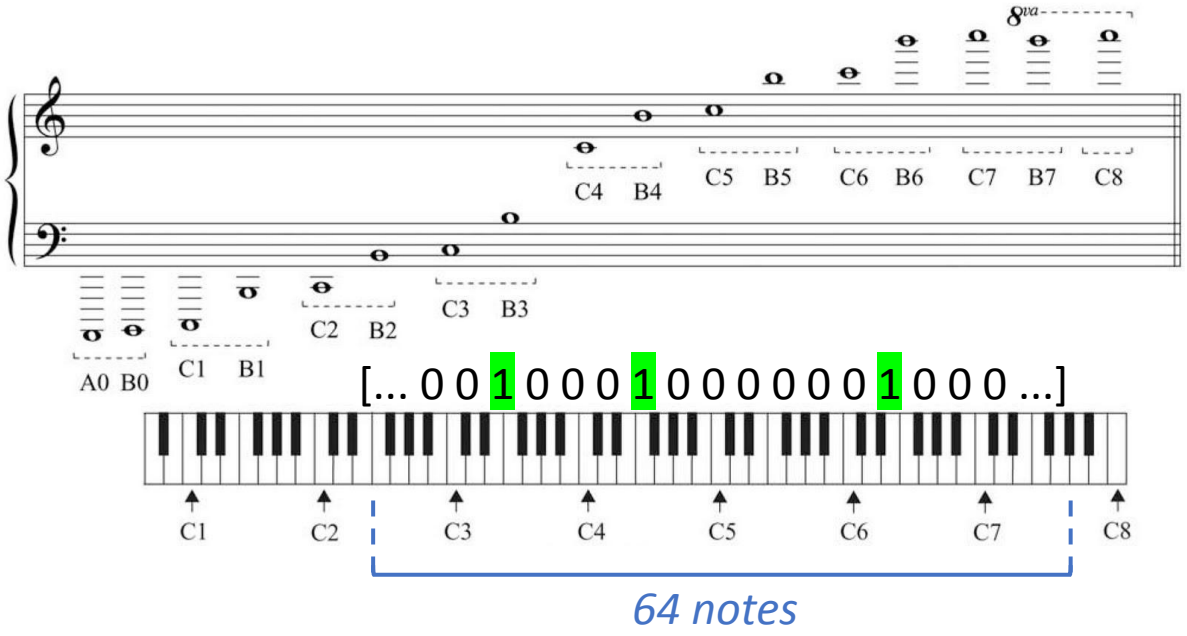
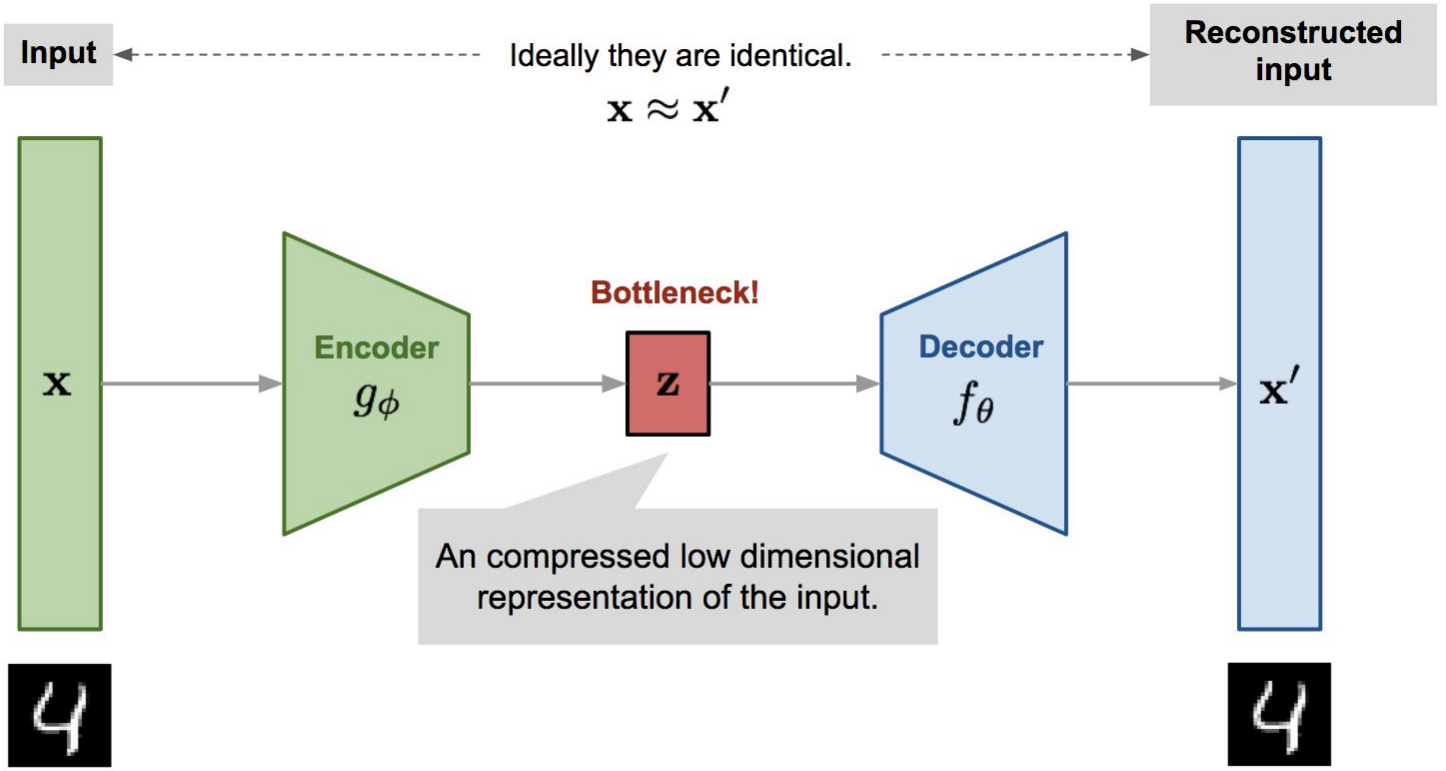
Music modelling

MIDI (Musical Instrument Digital Interface)

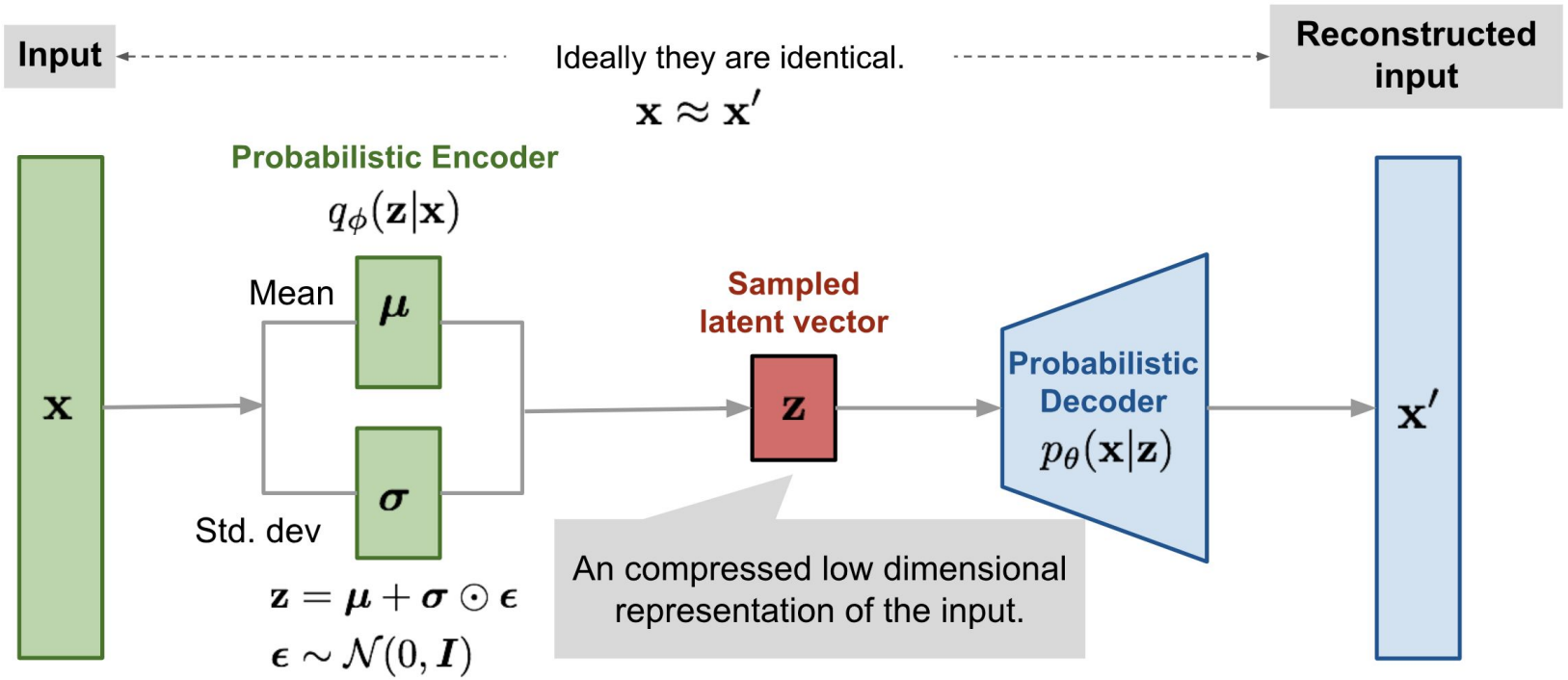
- Protocol to store musical information in a symbolic way.
- 128 values for pitches (notes).

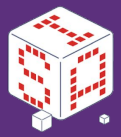


Autoencoder



Variational Autoencoder (VAE)





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05 Experiments

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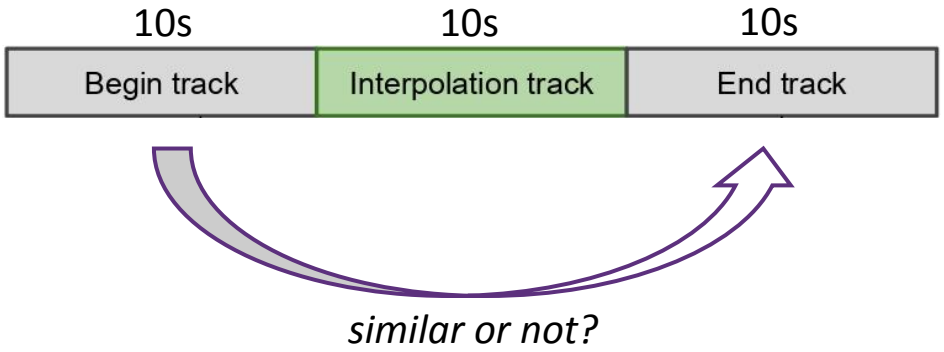
Dataset

- Lack of musical data for interpolation:



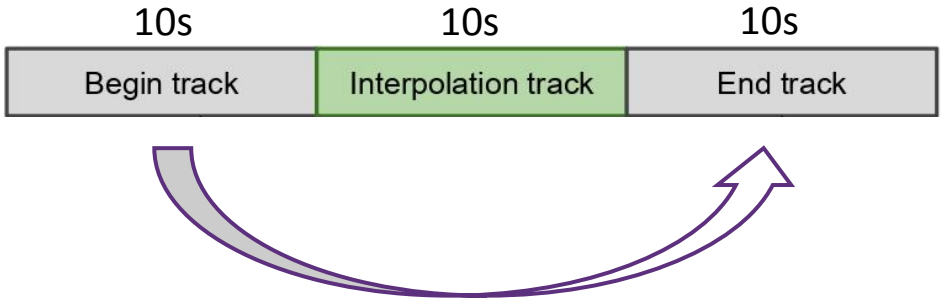
each training example

- Constructed **Hsinchu Interpolation Dataset** based on the Lahk MIDI Dataset:

  1) Extracted all the piano tracks.
  2) Divided them in segments of 30s.
  3) Evaluated similarity.

Dataset

- **Neural Network** to evaluate similarity:



- After evaluating all piano tracks:

Hsinchu Interpolation Dataset
containing 30,830 tracks of 30s each.

Experiments

01 Random Data

02 Bi-LSTM

03 VAE

04 VAE+NN

Experiments

01 Random Data

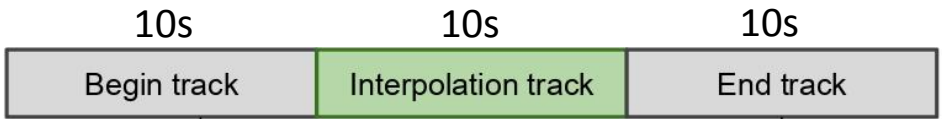
02 Bi-LSTM

03 VAE

04 VAE+NN

01 Random Data

- Naive and **non-Machine-Learning** approach to the interpolation problem.
- Use a Bernoulli random variable to choose the new element of the interpolation track.

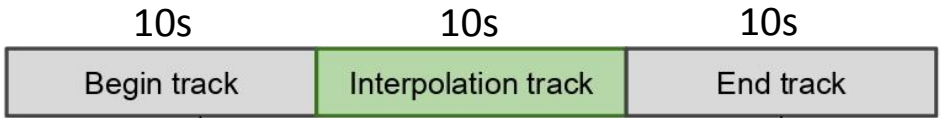


- Every timestep (time unit) we randomly choose an element from the begin track or from the end track.

Baseline model 01

02 Bi-LSTM

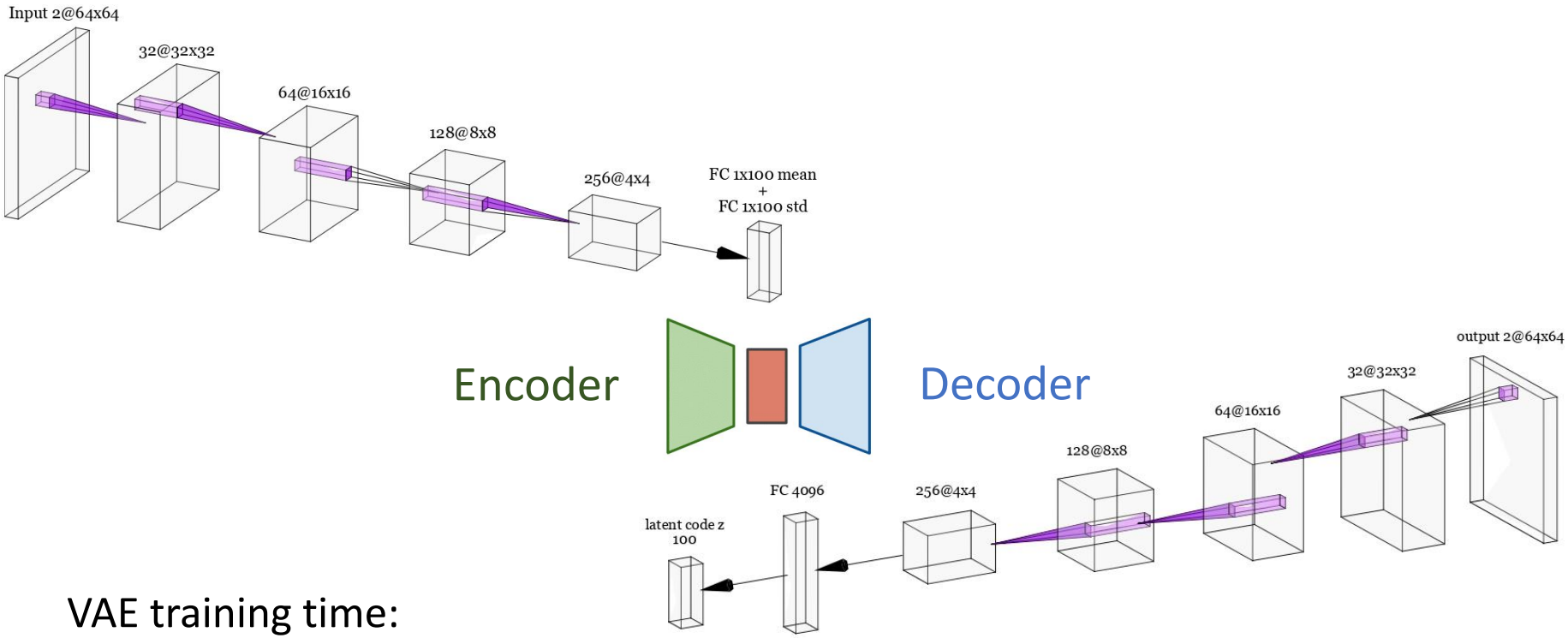
- Bidirectional Long Short-Term Memory.
- LSTM can capture local structure of **melody** and long-term structure of **musical style**.
- Bidirectional models can learn from begin and end tracks.



Baseline model 02

03 VAE

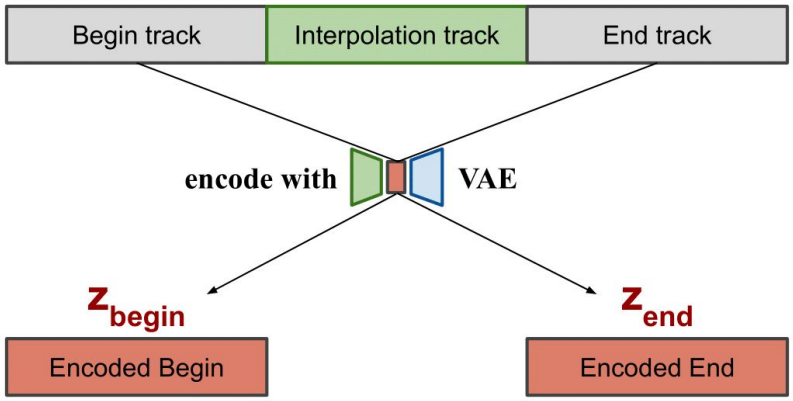
Encoder and decoder are based on convolutional neural networks.



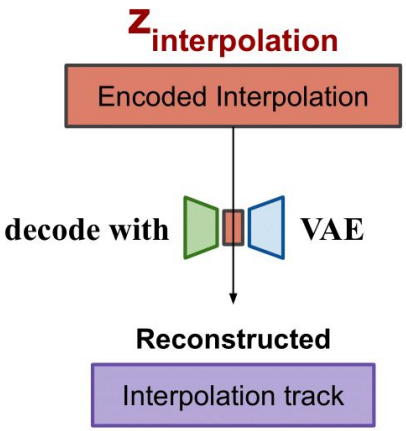
VAE training time:
4h on a single GPU

03 VAE

Interpolation method: linear sampling of latent space



$$\frac{z_{begin} + z_{end}}{2} = z_{interpolation}$$



Ideally they are identical.

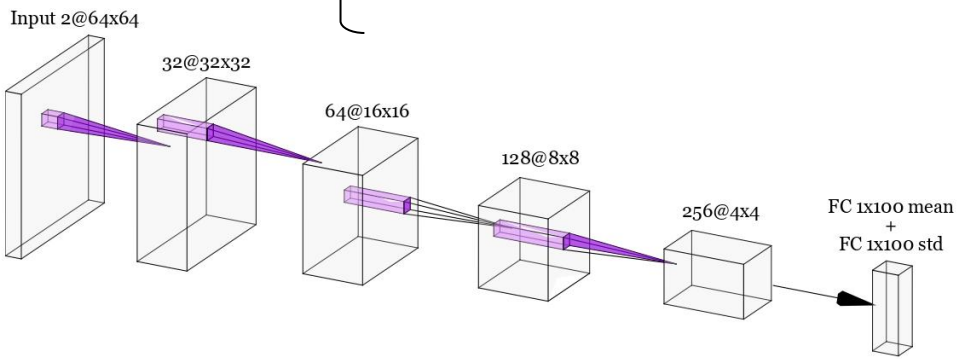
Interpolation track ≈ Interpolation track

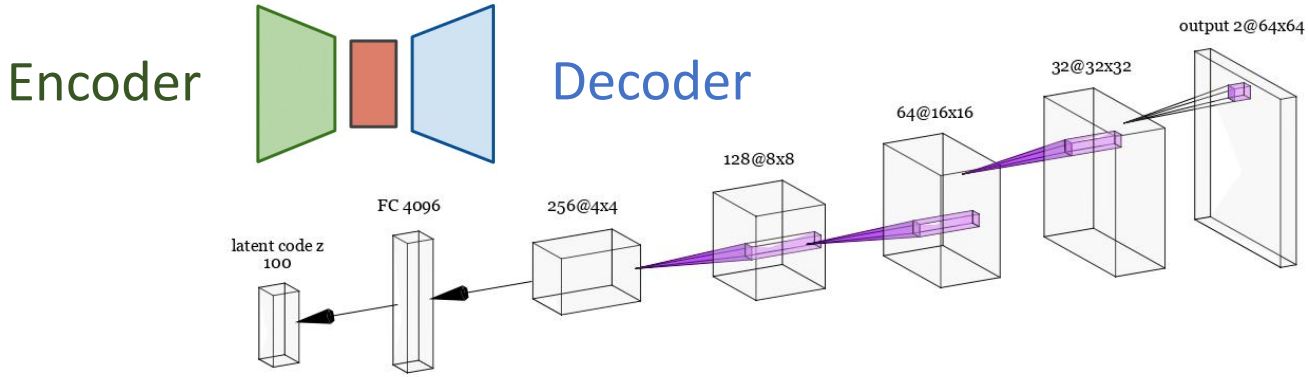
04 VAE + NN

VAE + NN
- VAE
- NN

04 VAE + NN

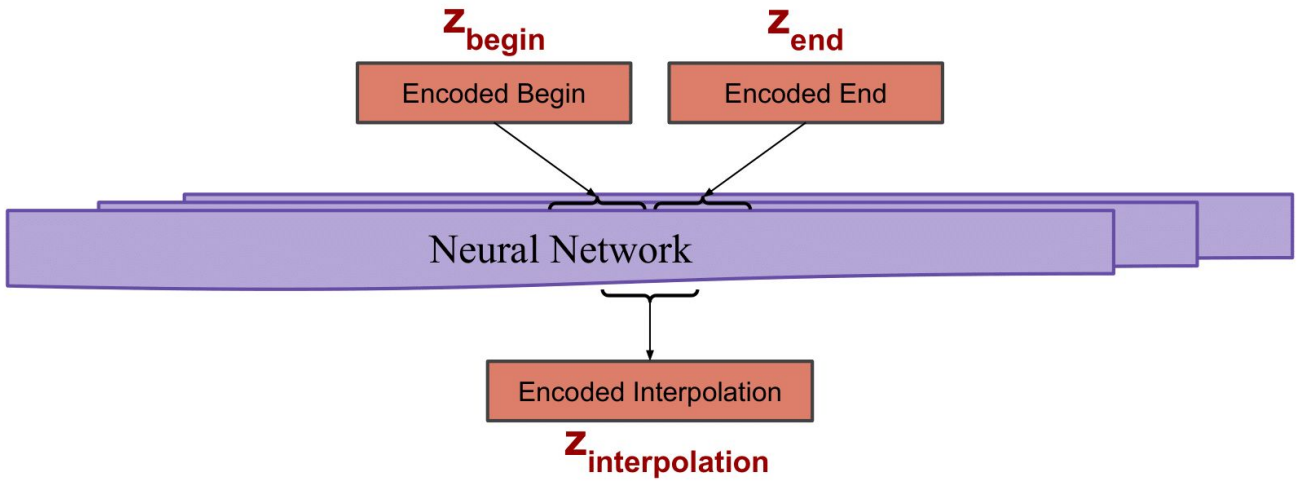
VAE + NN — VAE





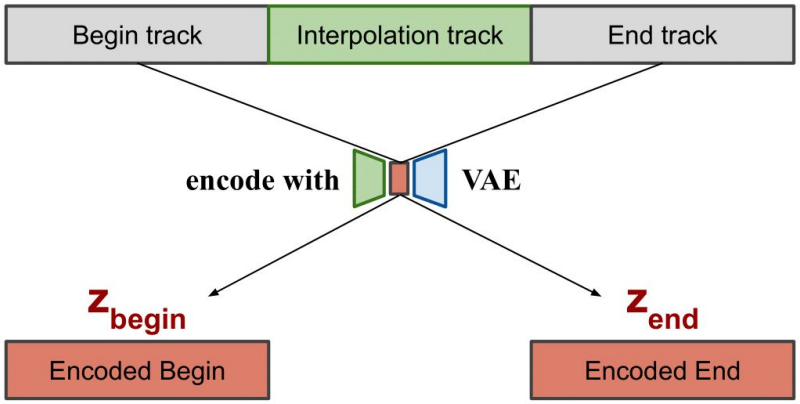
04 VAE + NN

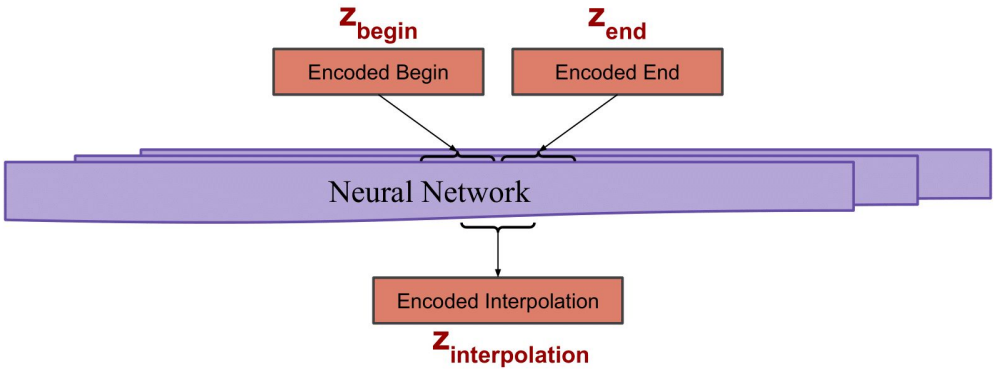
VAE + NN — NN

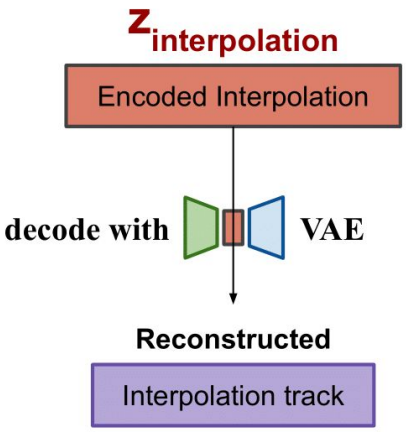


04 VAE + NN

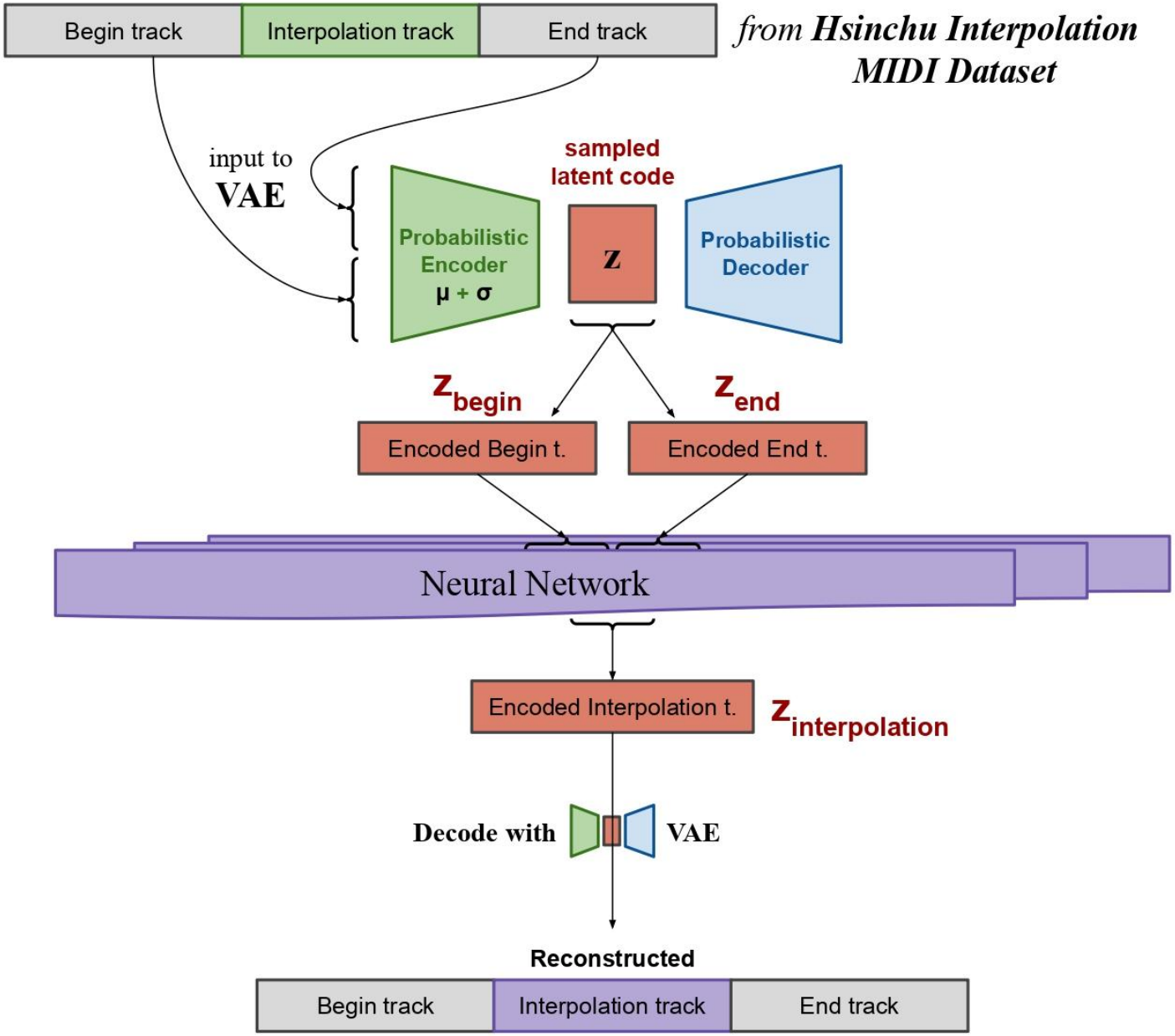
Interpolation method: direct estimation of the interpolation encoded vector

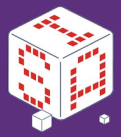






Ideally they are identical.


Begin track
Interpolation track
End track
from Hsinchu Interpolation MIDI Dataset
input to VAE
sampled latent code
Probabilistic Encoder
μ + σ
z
Probabilistic Decoder
z begin
z end
Encoded Begin t.
Encoded End t.
Neural Network
Encoded Interpolation t.
z interpolation
Decode with
VAE
Reconstructed
Begin track
Interpolation track
End track



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06 Results

Evaluation

- Objective
  - Compute error on the actual tracks
  - Compute error on the latent vectors
- Subjective

Evaluation

- Objective
  - Compute error on the actual tracks
  - Compute error on the latent vectors

  Error: Mean squared error (**MSE**) from previous papers.
  The **lower** the closer to the human compositions.

- Subjective

Objective evaluation

- Objective — Compute error on the actual tracks

Random (1)	Bi-LSM (2)	VAE (3)	VAE+NN (4)	Improv. (4) vs (1)	Improv. (4) vs (2)	Improv. (4) vs (3)
0.0581	0.0470	0.0494	**0.0431**	25.82%	8.30%	12.75%

- **VAE+NN** is better than Random Data baseline
- **VAE+NN** is better than Bi-LSTM baseline
- **VAE+NN** is better than **VAE**

Objective evaluation

- Objective — Compute error on the actual tracks

τ	Bi-LSTM (1)	VAE (2)	VAE+NN (3)	Improvement (3) vs (1)	Improvement (3) vs (2)
0.10	**0.0600**	0.0934	0.0840	- 40%	10.06%
0.20	0.0554	0.0673	**0.0464**	16.25%	31.05%
0.30	0.0528	0.0523	**0.0384**	27.27%	26.58%
0.40	0.0479	0.0443	**0.0371**	22.55%	16.03%
0.50	0.0447	0.0375	**0.0364**	18.57%	2.93%
0.60	0.0434	0.0375	**0.0365**	15.90%	2.67%
0.70	0.0401	0.0374	**0.0364**	9.23%	2.67%
0.80	0.0398	0.0374	**0.0364**	8.54%	2.67%
0.90	0.0392	0.0373	**0.0364**	7.14%	2.41%

- **VAE** is better than Bi-LSTM baseline in 7 out of 9 thresholds
- **VAE+NN** is better than Bi-LSTM baseline in 8 out of 9 thresholds.
- **VAE+NN** is better than **VAE** in all thresholds

Objective evaluation

- Objective — Compute error on the latent vectors

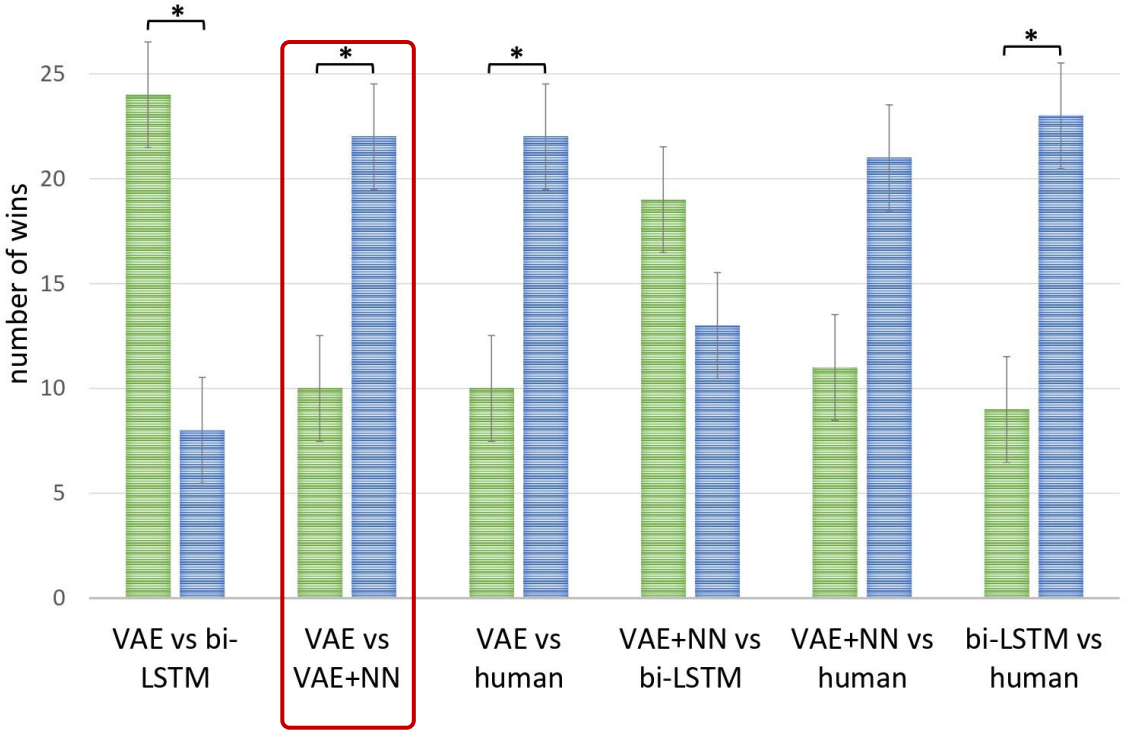
VAE (1)	VAE+NN (2)	Improvement (2) vs (1)
1.3726	**1.0611**	22.69%

- **VAE+NN** is better than **VAE** by 22.69%

Subjective evaluation

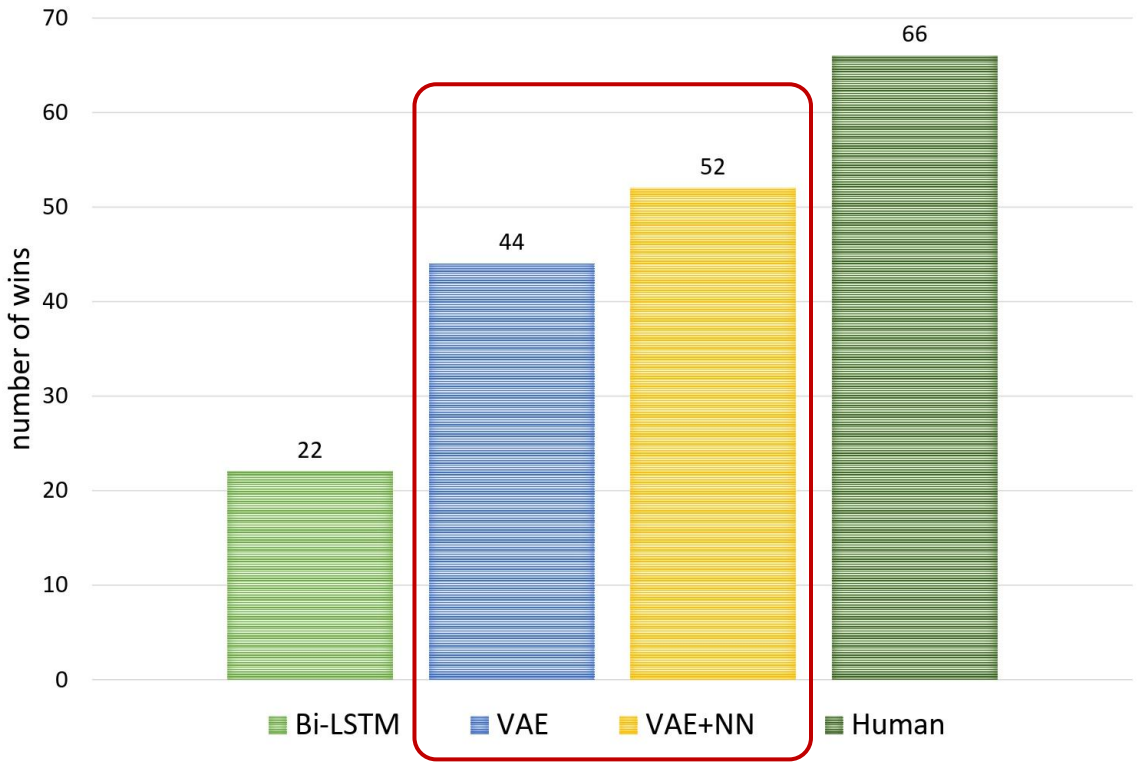
- **32** participants from **8** different countries in Africa, America, Asia and Europe.
- **65.6%** had a musical background.
- Pair-wise comparisons of tracks from all the models.
- All possible combinations were compared.

Subjective evaluation



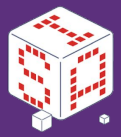
- VAE and VAE+NN models were preferred over the bi-LSTM baseline.
- Human interpolations were preferred in general.
- VAE+NN was preferred over VAE.
- Our interpolation approach was preferred over the state-of-the-art approach.

Subjective evaluation



Subjective evaluation

10s	10s	10s
Begin track	Interpolation track	End track
human 01	**VAE**	**human 02**



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07 Conclusion

Conclusion

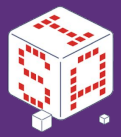
1. Used **VAE** to solve the problem of polyphonic music interpolation.
2. Reduced VAE training due to the **Hsinchu Interpolation Dataset** created.
3. Our proposed models (VAE and VAE+NN) outperform the baselines.
4. Our interpolation approach (VAE+NN) outperforms the state-of-the-art interpolation approaches (VAE):
    - Objective evaluation
    - Subjective evaluation

Future work

1. Explore other **architectures** for VAE.

2. **Expand** the Hsinchu Interpolation Dataset.

3. Explore other Machine Learning **models** to directly estimate the encoded **interpolation** vector.



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