Generating new music with deep probabilistic models

Valentin Vignal

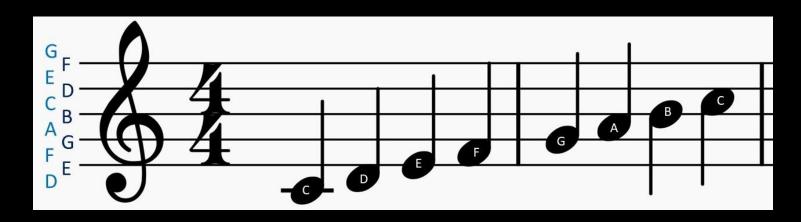
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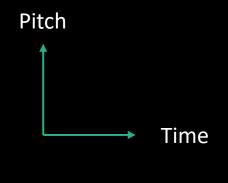
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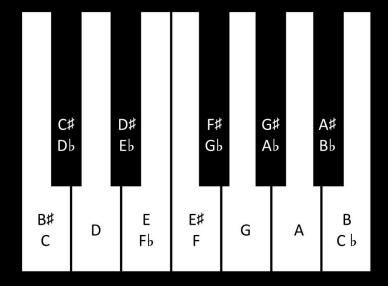
Background knowledge

- Musical Background
 - MIDI format
 - Music theory
 - Physical properties
- Deep learning background
 - AutoEncoder
 - Variational AutoEncoder
 - Multimodal Variational AutoEncoder

Musical Stave





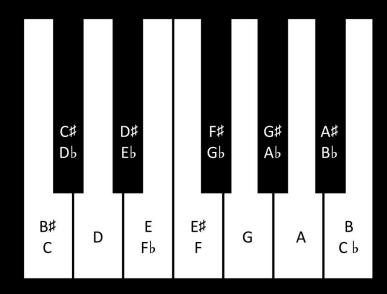


Note shape	Name	Note length
O	Whole note	4 beats
	Half note	2 beats
	Quarter note	1 beat
♪	Eighth note	½ beat
A	Sixteenth note	¼ beat

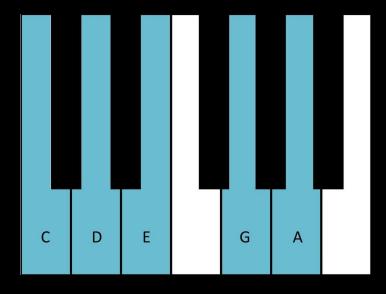
Musical Scale

A scale is a set of notes.

The white keys of a piano form the C major scale

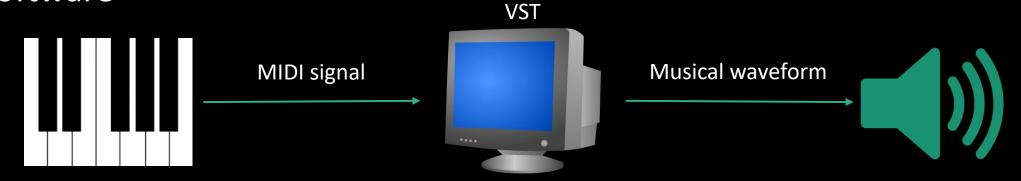


C major pentatonic



MIDI Format

It is a protocol to carry musical events between musical devices or software



- "Note on" event:
 - < NoteOn, channel, pitch, velocity >
- "Note off" event:
 - < NoteOff, channel, pitch, velocity >

- $channel \in [0, 15]$
- $pitch \in [0, 127]$
- $velocity \in [0, 127]$

MIDI format

Pianoroll



Harmonics

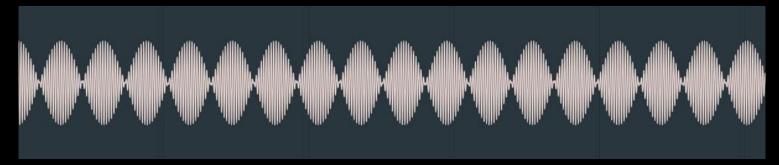
A musical sound is composed of harmonics

$$s(t) = \sum_{n=1}^{\infty} \alpha_n \sin(nft + \phi_n)$$

Harmonic number	Frequency (Hz)	Note Name	Musical Interval
1	440	A4	Unison
2	880	A 5	Octave
3	1320	E5	Fifth
4	1760	A6	Octave
5	2200	C#6	Major Third
6	2640	E6	Fifth

Resonance phenomena

Two sounds with a close frequency will generate a resonance phenomena



Resonance phenomena from a B4 and a C5

$$\cos(f) + \cos(f + \delta f) = 2\cos\left(\frac{2f + \delta f}{2}\right)\cos\left(\frac{\delta f}{2}\right)$$

Intervals

"Acceptable" intervals

Interval	Reason	Example with A4
Octave	Contained in tonic's Harmonics	A5
Minor Third	Share harmonics (A and C share E in their harmonics)	C6
Major Third	Contained in tonic's harmonics	C#6
Fifth	Contained in tonic's harmonics	E6

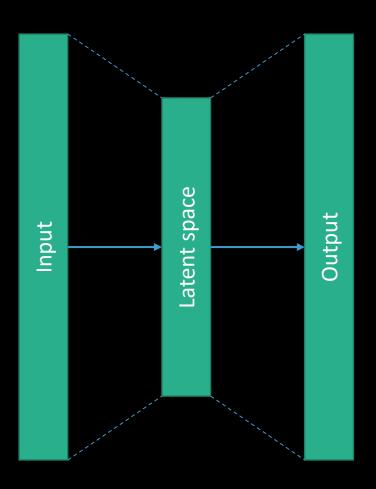
"Not acceptable" intervals

Interval	Reason	Example with A4
Semitone	Resonance phenomena between fundamental frequencies	A#5
Tone	Resonance phenomena between fundamental frequencies	B5
Tritone	Resonance phenomena between fundamental frequency and third harmonic (D and D#)	D#6

AutoEncoder

- Encode
 - Take the input
 - Encode it in the latent space
- Decoder
 - Take a point from the latent space
 - Reconstruct the output

The AutoEncoder tries to reconstruct the input $|space_{latent}| \ll |space_{input}|$



Variational AutoEncoder

• Tries to maximize the marginal likelihood $argmax_{\theta}[\log(p_{\theta}(x))]$, $x \in data$

$$\log(p_{\theta}(x)) = \log\left(\int_{z} p_{\theta}(x|z)p(z)dz\right)$$

Maximise the ELBO

$$ELBO(x) = \mathbb{E}_{q_{\phi}(Z|X)} \left(\log(p_{\theta}(x|Z)) \right) - \mathbb{D}_{KL} \left(q_{\phi}(z|x), p(z) \right)$$
$$p(z) \sim \mathcal{N}(0, 1)$$

 χ

Reparameterization trick

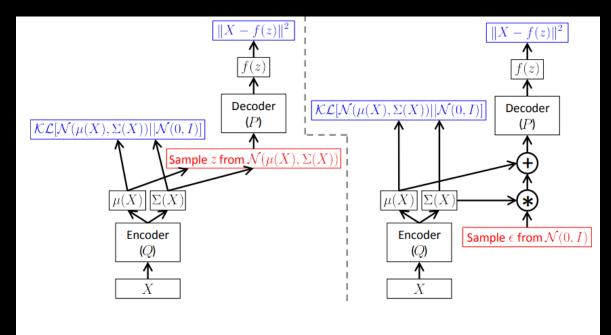


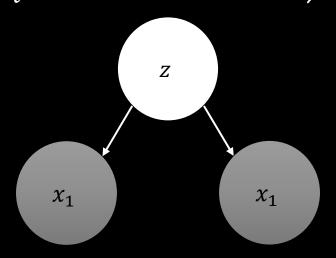
Figure 4: A training-time variational autoencoder implemented as a feed-forward neural network, where P(X|z) is Gaussian. Left is without the "reparameterization trick", and right is with it. Red shows sampling operations that are non-differentiable. Blue shows loss layers. The feedforward behavior of these networks is identical, but backpropagation can be applied only to the right network.

Reparameterization trick from C. Doersch "Tutorial on Variational Autoencoders"

Multimodal Variational AutoEncoder

- Introduced by Mike Wu to solve the multi-model inference
- Miximize the ELBO

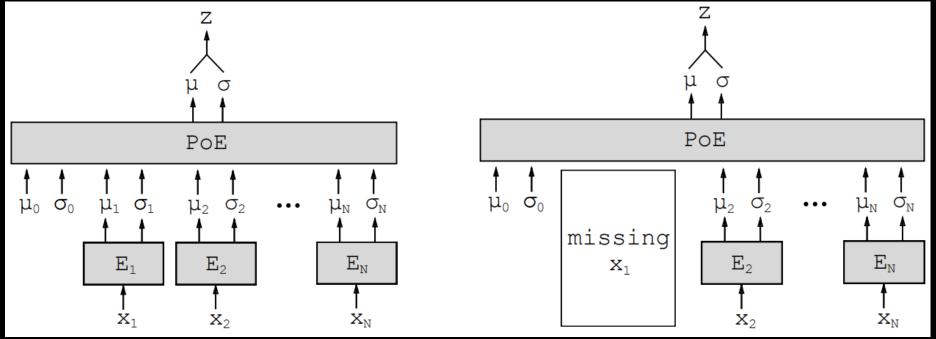
$$ELBO(x) = \mathbb{E}_{q_{\phi}(Z|X)} \left(\sum_{x_i \in X} \lambda_i \log(p_{\theta}(x|z)) \right) - \beta \, \mathbb{D}_{KL} \left(q_{\phi}(z|x), p(x) \right)$$



Product of Experts

Approximate the joint posterior

$$p(z|x_1,...,x_N) \propto p(z) \prod_{i=1}^N q(z|x_i)$$
 With $q(z|x_i)$ an estimator of $\frac{p(z|x_i)}{p(z)}$



Source: Mike Wu's paper

Related works

- Deep Bach
- Bach Bot
- Bach Doodle
- Music Transformer

Objectives

- Generate musical parts
 - Bach Bot
- Create an accompaniment
 - Bach Doodle

Music Representation

- Most of the works use MIDI dataset translated in text
- They consider only Sixteenth notes
- The dataset is usually transposed into C major or A minor
- Some metadata can be passed
 - Beat number
 - Tempo
 - Fermata symbol



Architectures used

- NADE
- AutoEncoder (most popular)
- VAE
- GAN
- Transformers

Contribution

- Objectives
- Data representation
- RMVAE
 - Global architecture
 - RPoE
 - Encoder/Decoder Architecture
 - Activation function
- Custom loss functions
 - Scale
 - Rhythm
 - Harmony

Objectives

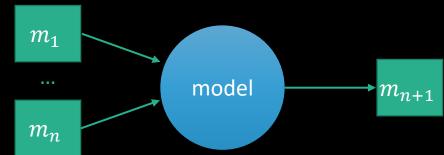
- Generate a music with several musical parts
- Create an accompaniment from a melody
- Create a melody from an accompaniment
- Create musical parts from other musical parts

Data representation

- I consider binary rhythm only (1 beat is divided in 2 equal beats)
- The smallest notes I consider are the Sixteenth notes



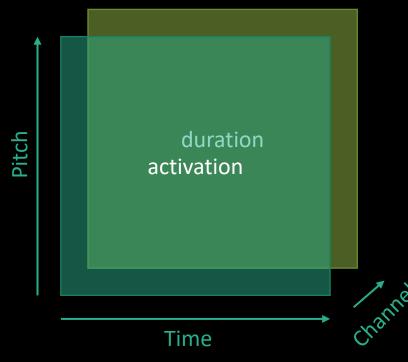
- A "step" is a measure
 - There are 16 Sixteenth notes division in a measure
 - From a fixed number of measures, the model will predict the next one



- 128 different pitches
- A tensor representing a measure: (16, 128, channels)

Data Representation – Polyphonic Music

(16, 128, channels=2)



- Activation channel:
 - Sigmoid activation function
 - Binary cross-entropy loss
- Duration channel:
 - ReLU activation function
 - Mean squared error loss

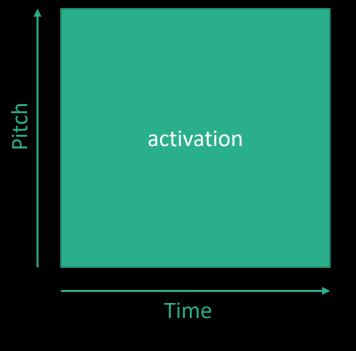
```
activation \ge 0.5 \Rightarrow a note is played activation < 0.5 \Rightarrow no note is played
```

 $duration = length_{note}$ in number of sixteenth notes

```
duration = 1 \Rightarrow
duration = 2 \Rightarrow
duration = 4 \Rightarrow
duration = 8 \Rightarrow
duration = 16 \Rightarrow
```

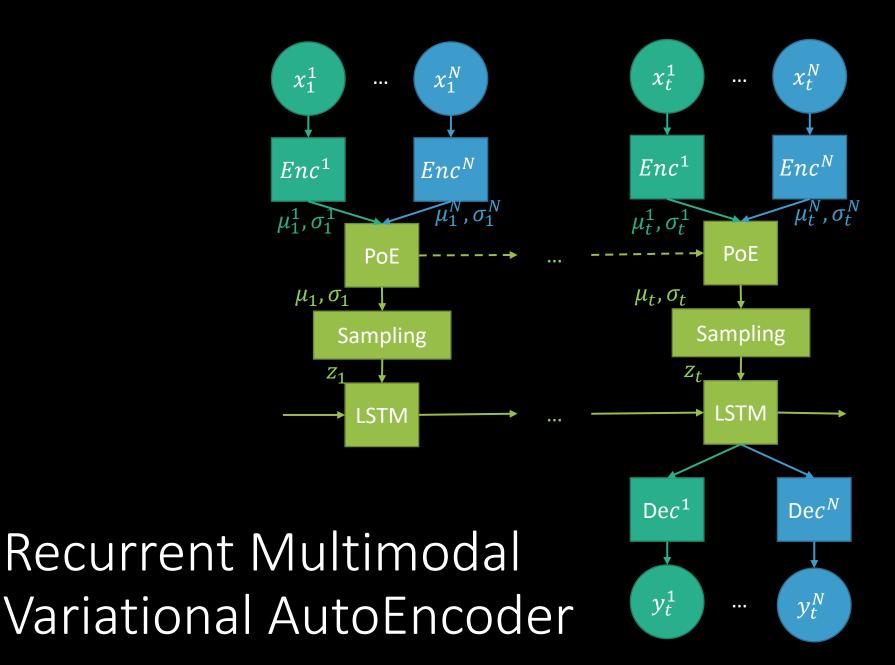
Data Representation – Monophonic Music

(16, 128 + 1, channels=1)

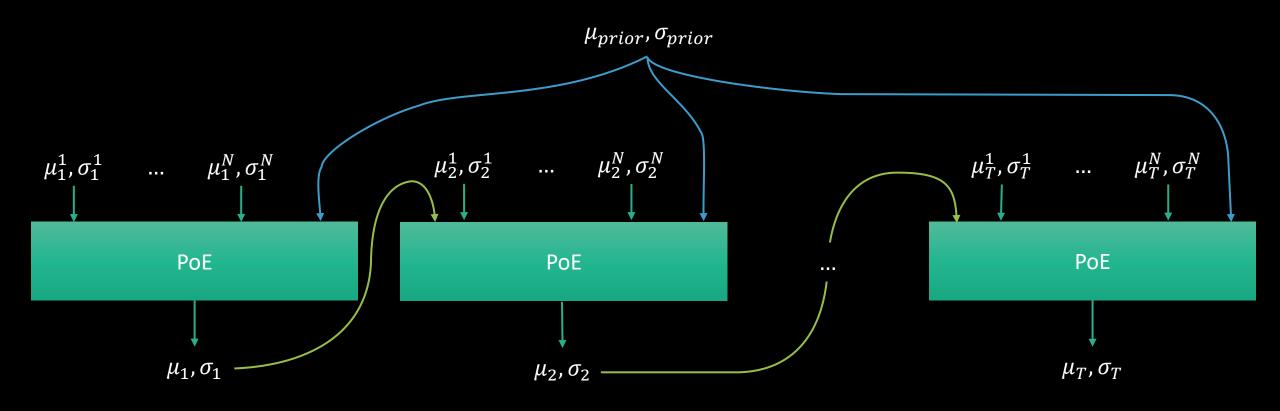


- Activation channel:
 - Softmax activation function
 - Categorical cross-entropy loss
 - Extra $note_{continue} \Rightarrow$ continue the previous note

Argmax of activation is played



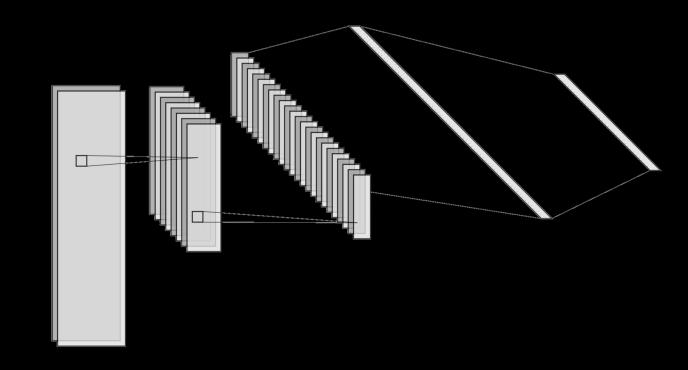
Recurrent Product of Experts



Convolutional Encoder/Decoder

Input tensor: (16, 128, channels)

- Encoder
 - Convolutional layers
 - Fully Connected layers
- Decoder
 - Fully Connected layers
 - Transposed Convolutional layers
 - 1 Fully Connected layer



Convolutional filter: (5, 5)

Recurrent Encoder/Decoder

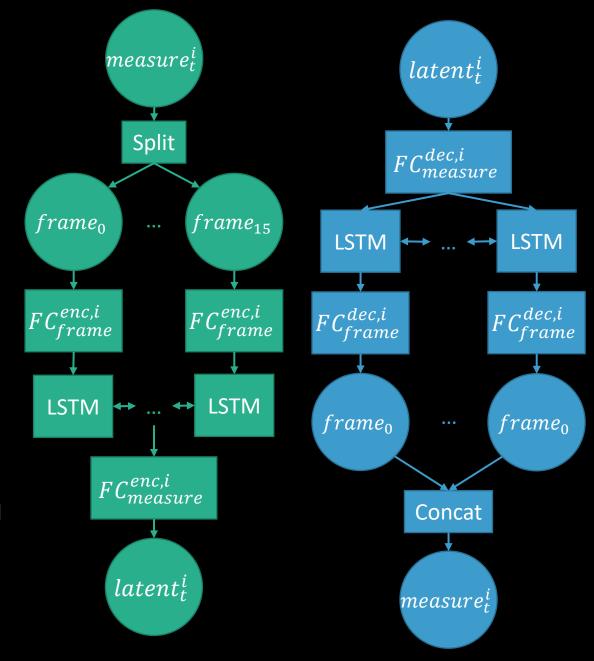
Input tensor: (16, 128)

Encoder

- 1. Split the measure into several frames
- 2. Encode the frames with fully connected layers
- 3. Extract the latent space with bidirectional LSTM
- 4. Encode the latent space with fully connected layers

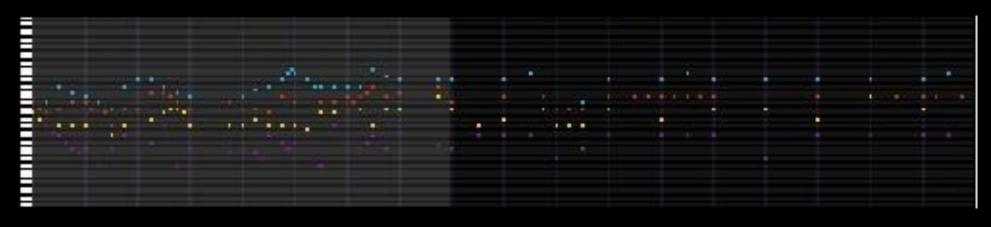
Decoder

- 1. Decode the latent space with fully connected layers
- 2. Generate the encoded frames with bidirectional LSTM
- 3. Decode the frames with fully connected layers
- 4. Concatenate the frames to create the measure



Activation and Loss function

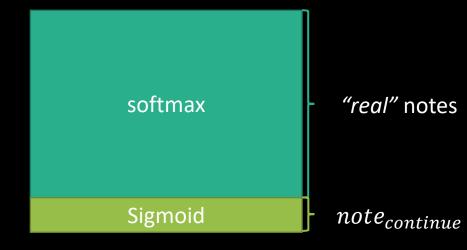
- Softmax activation
- Categorical crossentropy loss

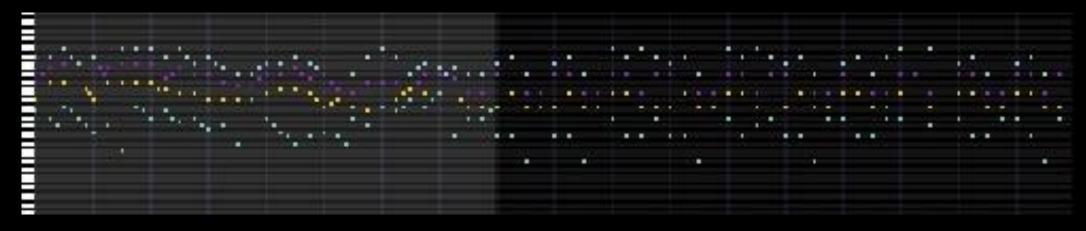




Activation and Loss function

- note_{continue}
 - Sigmoid activation
 - Binary crossentropy
- "real" notes
 - Softmax activation
 - Catergorical crossentropy







Prior knowledge with loss function

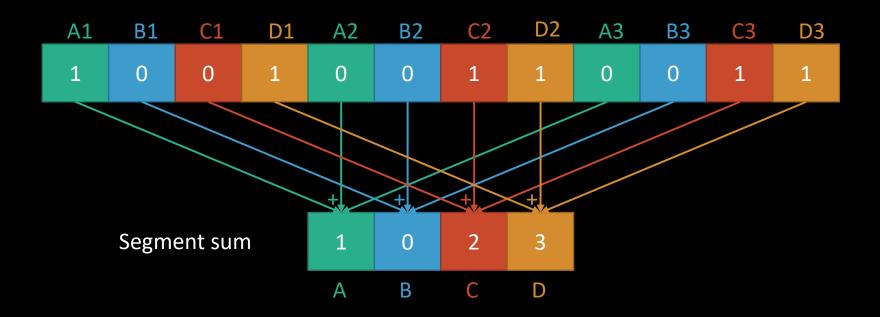
- Help the model to do "acceptable mistakes"
 - Give a reward (decrease the loss)
- Prevent the model to do "unacceptable mistakes"
 - Give a penalty (increase the loss)

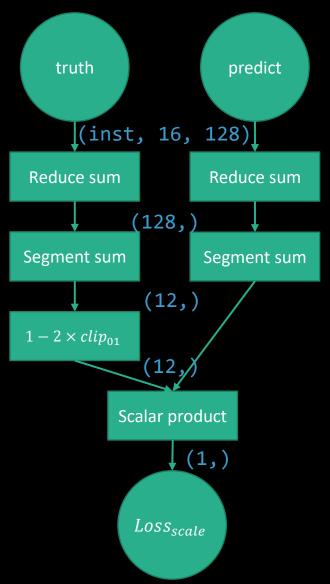
```
var loss;
var reward > 0;
var penalty > 0;
if (soundsGood(note<sub>predicted</sub>)) {
    loss -= reward;
} else {
    loss += penalty;
}
```

Scale loss

Reconstruct the local scale with the notes present in the *truth* tensor

Incite the model to generate note present in the truth tensor

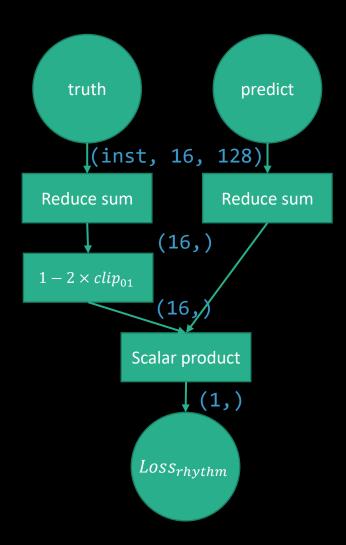




Rhythm loss

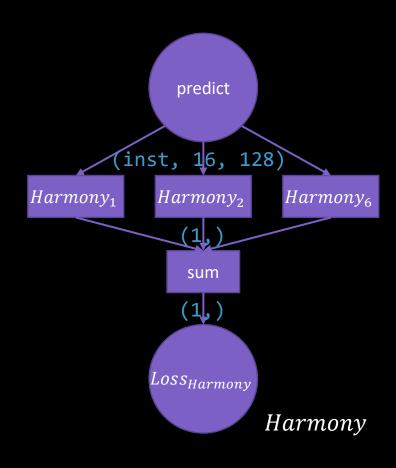
Reconstruct the local rhythm with the notes present in the *truth* tensor

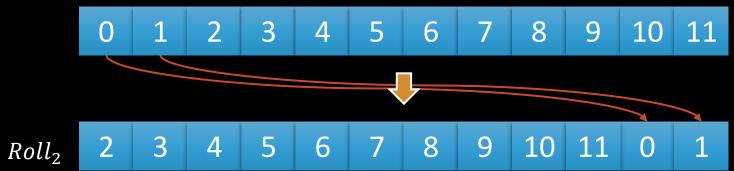
Incite the model to generate notes when a note is played in the *truth* tensor

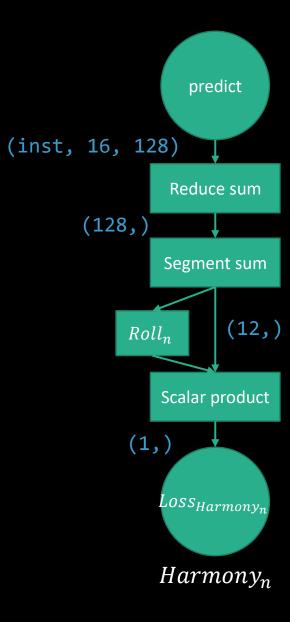


Harmony loss

- 3 intervals are dissonant on their own:
 - Semitone
 - Tone
 - Tritone
- Harmony prevent the model to play these intervals







Results

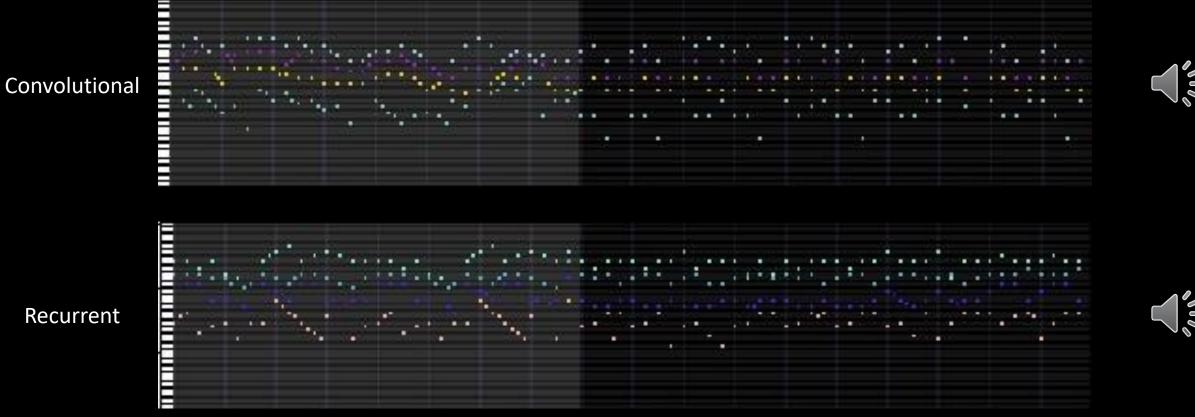
- Implemented tasks
- Experiments
 - Transposed data
 - Model size
 - Scale and Rhythm losses
 - Harmony loss
 - RPoE layer

Generate

The generate takes several measures and generate the next one

```
var seed; // list of measures
var n; // number of measures to generate
function generate(seed, n) {
   var seedLength = seed.length;
   var generated = seed;
   for (k=1; k<=n; k++) {
      var input = genetared[-seedLength:];
      var output = model.predict(input);
      generated.push(output);
   }
   return generated;
}</pre>
```

Generate – Convolutional and Recurrent encoder/decoder







Fill

Re-generate a voice of a song

```
var song; // list of measures
var instrument; // Instrument to replace
function fill(song, instrument) {
    song.deleteInstrument(isntrument);
    var filled = song;
    for (k=0; k < song.length - seedLength; k++) {
        var input = genetared[k:k + seedLength];
        var output = model.predict(input);
        filled[k + seedLength, instrument] = output[instrument];
    }
    return filled;
}</pre>
```

Fill

Original





Replace first voice



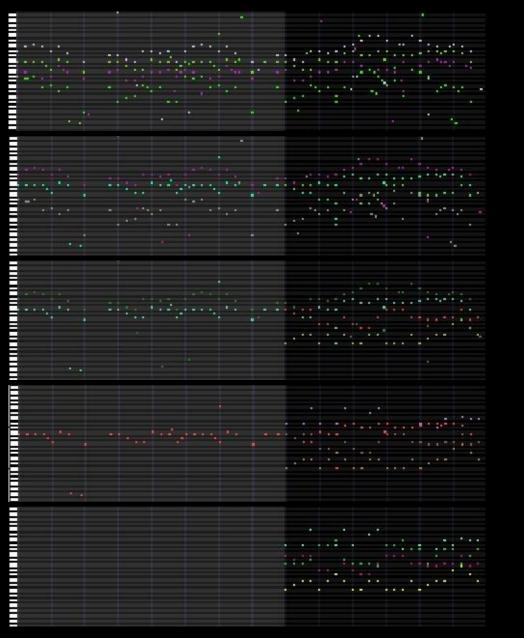


Redo

Recreate a song by replacing one by one every voices

```
var song; // list of measures
function redo(song) {
   var redone = song;
   for (k=0; k < nbInstruments; k++) {
      redone = fill(redone, k);
   }
   return redone;
}</pre>
```

Redo







Step 1
Replace instrument 3



Step 2 Replace instrument 4



Step 3
Replace instrument 1



Step 4
Replace instrument 2



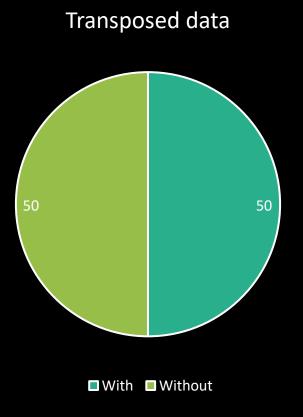
Experiments

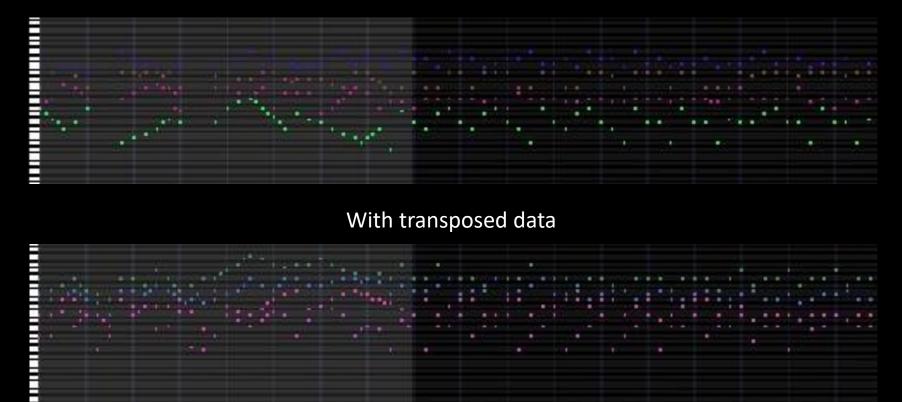


Transposed data

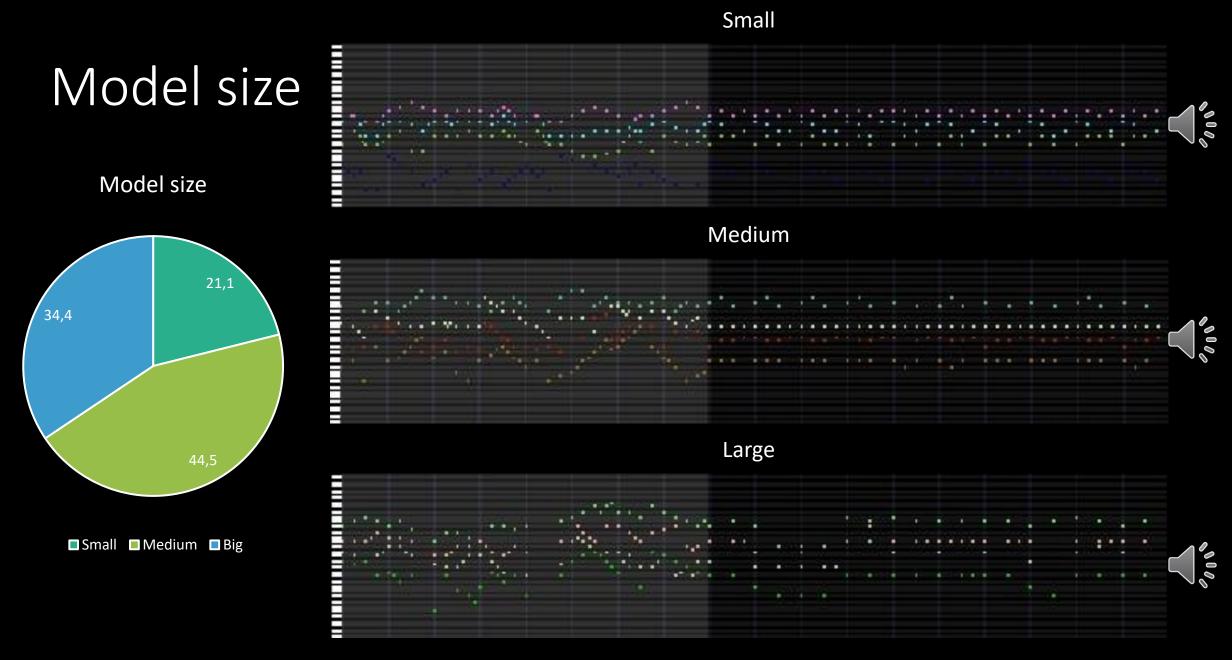


Without transposed data







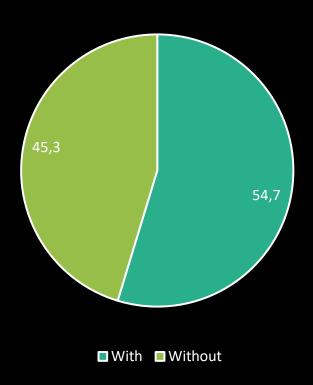


Scale and Rhythm losses

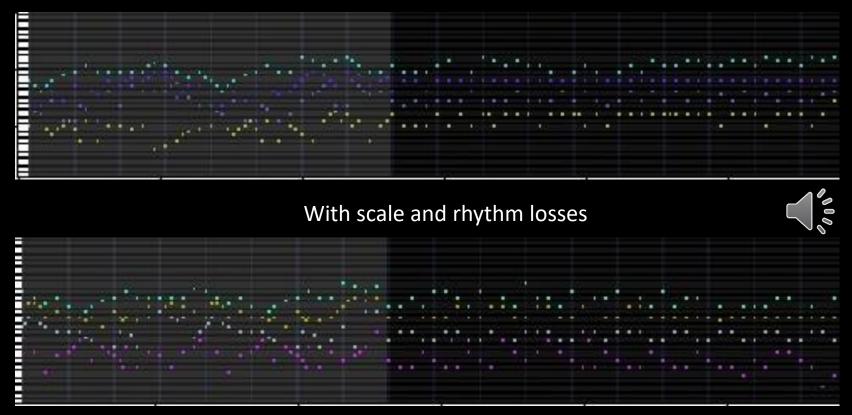








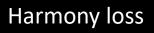
Without scale and rhythm losses

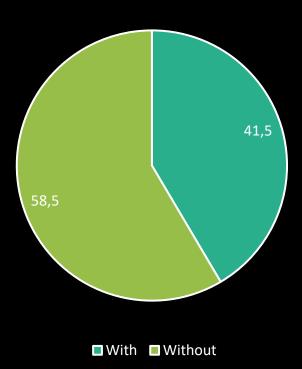


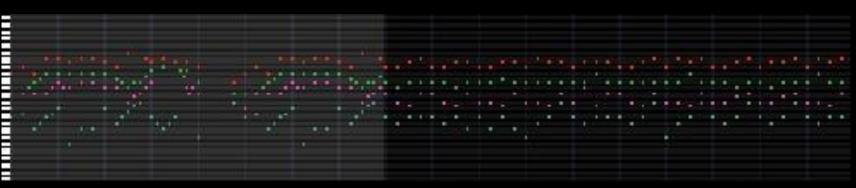
Harmony

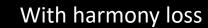
Without harmony loss



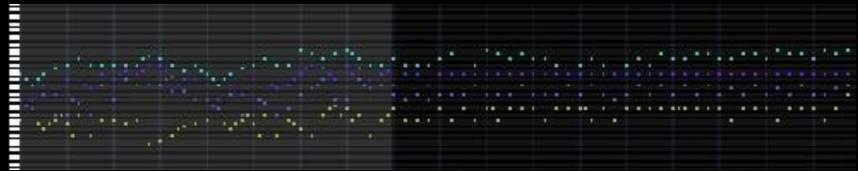


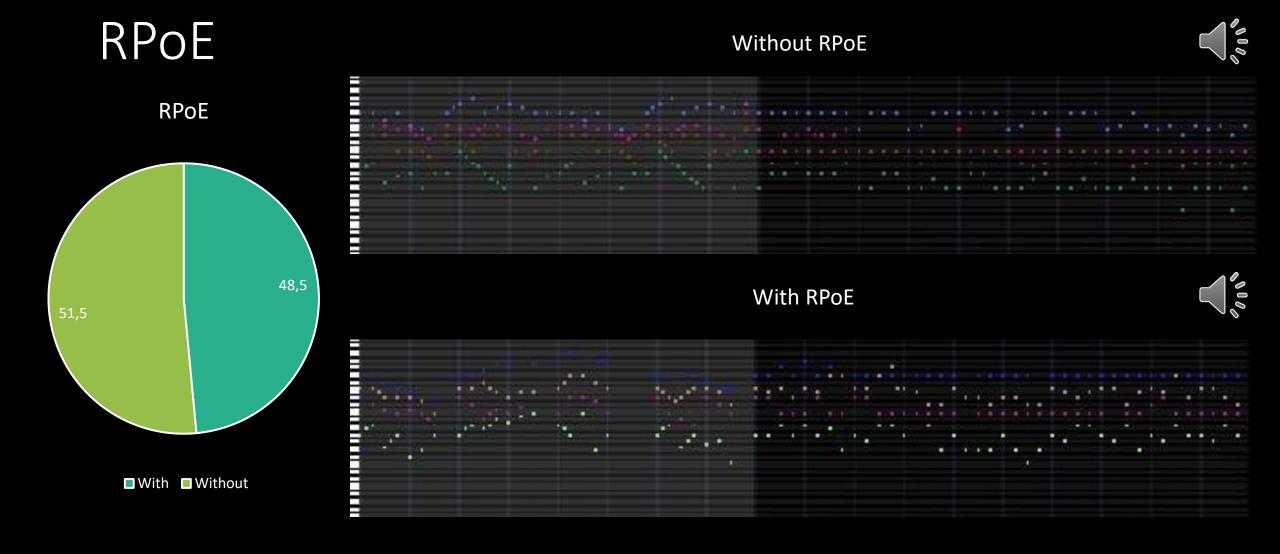












Band Player

- Take a trained model and play with the user
 - The model had to be trained to predict the second next measure (for real time purpose)
- Demonstration

Conclusion

- The RMVAE is an architecture able to handle several tasks
- The results are poor in complexity and variations
- The different loss functions and the RPoE layer don't help the training.

Future works:

- An exploration on most of the hyper parameter could help the model to perform better
- The scale loss can be improved by including some scale templates

References

- C. Doersch, "Tutorial on Variational Autoencoders," arXiv:1606.05908
 [cs, stat], Jun. 2016. [Online]. Available:
 http://arxiv.org/abs/1606.05908
- M. Wu and N. Goodman, "Multimodal Generative Models for Scalable Weakly-Supervised Learning," in Advances in Neural Information Processing Systems 31, S. Bengio, H. Wallach, H. Larochelle, K. Grauman, N. Cesa-Bianchi, and R. Garnett, Eds. Curran Associates, Inc., 2018, pp. 5575–5585. [Online]. Available: http://papers.nips.cc/paper/ 7801-multimodal-generative-modelsfor-scalable-weakly-supervised-learning. pdf

Questions

Thank you for your attention.

Product of Experts details

$$p(z|x_{1},...,x_{N}) = \frac{p(x_{1},...,x_{N}|z)p(z)}{p(x_{1},...,x_{N})} = \frac{p(z)}{p(x_{1},...,x_{N})} \prod_{i=1}^{N} p(x_{i}|z)$$

$$= \frac{p(z)}{p(x_{1},...,x_{N})} \prod_{i=1}^{N} \frac{p(z|x_{i})p(x_{i})}{p(z)} = \frac{\left(\prod_{i=1}^{N} p(z|x_{i})\right)}{\prod_{i=1}^{N-1} p(z)} \frac{\left(\prod_{i=1}^{N} p(x_{i})\right)}{p(x_{1},...,x_{N})}$$

$$\propto \frac{\prod_{i=1}^{N} p(z|x_{i})}{\prod_{i=1}^{N-1} p(z)} = p(z) \prod_{i=1}^{N} q(z|x_{i})$$

With $q(z|x_i)$ an estimator of $\frac{p(z|x_i)}{p(z)}$