Deep Learning Techniques for Music Generation (8)

Jean-Pierre Briot

Jean-Pierre.Briot@lip6.fr

Laboratoire d'Informatique de Paris 6 (LIP6)

Sorbonne Université – CNRS

Programa de Pós-Graduação em Informática (PPGI)

UNIRIO

Control

Deep Learning for Music Generation – Technical Challenges

1. ***Ex Nihilo* Generation**
   » vs Accompaniment (Need for Input)
2. **Length Variability**
   » vs Fixed Length
3. **Content Variability**
   » vs Determinism
4. **Control**
   » ex: Tonality conformance, Maximum number of repeated notes…
5. **Structure**
6. **Originality**
   » vs Conformance
7. **Incrementality**
   » vs Single-step or Iterative Generation
8. **Interactivity**
   » vs (Autistic) Automation
9. **Explainability**

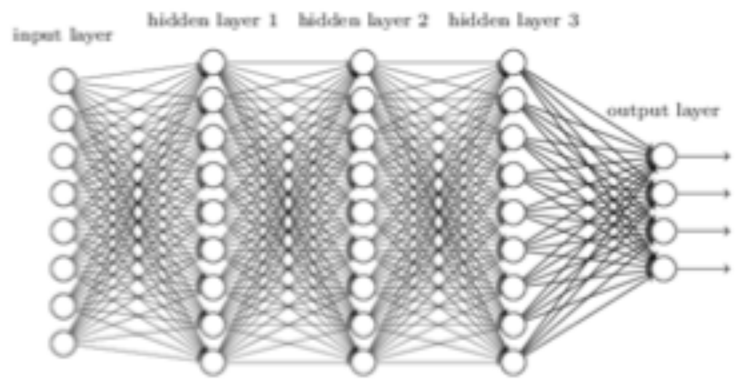
#4 Limitation – Control

- No Control on Generation
  - Tonality Conformance
  - Ending with the same note at the first one
  - Avoiding too many repetitions of the same note
  - Not too many notes
  - etc.

#4 Limitation – Control

- Strategies:
  - Sampling
  - Conditionning (Parametrization)
  - Input manipulation
  - Reinforcement
  - Unit Selection

  - Bottom up (Low-level adjustment)
    - Ex: Sampling
  - Top down (Structure imposition)
    - Ex: Unit and Selection



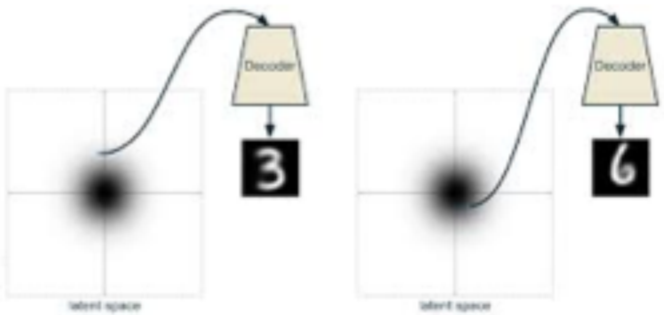
- Entry points (Hooks)
  - Input
  - Output
  - Encapsulation/Reformulation

#4 Limitation – Control – #1 Solution: Sampling

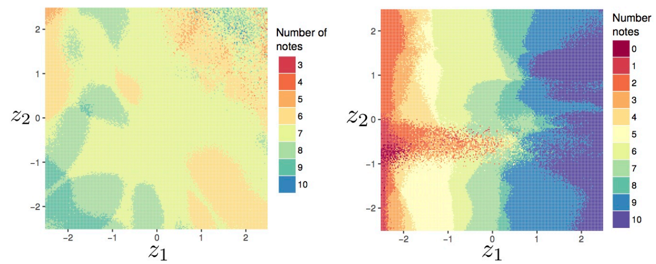
- Sampling Control
  - Content Variability
    - Threshold (to avoid notes too unlikely)

$$p_{threshold}(s_t|s_{<t}) := \begin{cases} 0 \text{ if } p(s_t|s_{<t})/max_{s_t}\,p(s_t|s_{<t}) < threshold, \\ p(s_t|s_{<t})/z \text{ otherwise.} \end{cases}$$

  - Variational Autoencoder

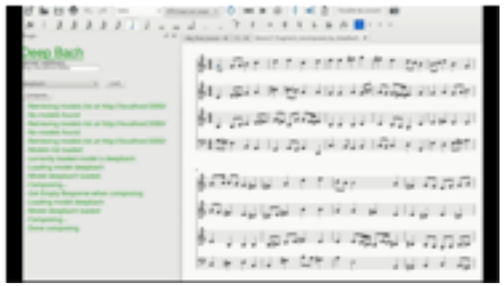


  - Geodesic Latent Space Regularization [Hadjeres & Nielsen, 2017]



(a) Without geodesic latent space regularization (b) With geodesic latent space regularization

  - Incremental Generation
    - DeepBach [Hadjeres et al., 2017]

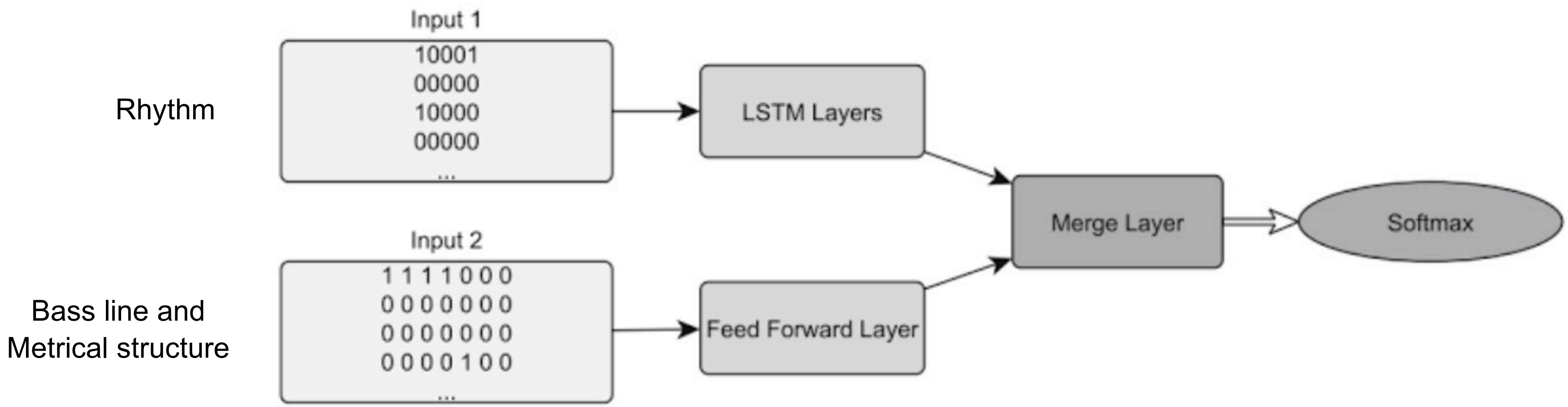


#4 Limitation – Control – #2 Solution: Conditioning

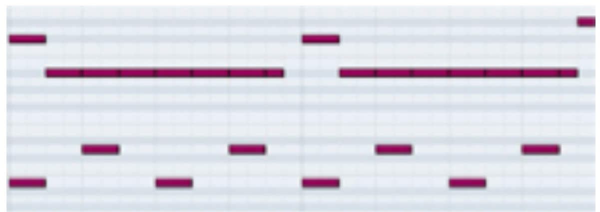
- Condition the architecture on some information
- To control/parameterize the architecture and the generation
- Ex:
  - Bass line
  - Beat structure
  - Chord progression
  - Previously generated note
  - Positional constraints on notes
  - Musical genre or style
  - Instrument

#4 Limitation – Control – #2 Solution: Conditioning
#1 Ex: Rhythm Generation [Makris et al., 2017]

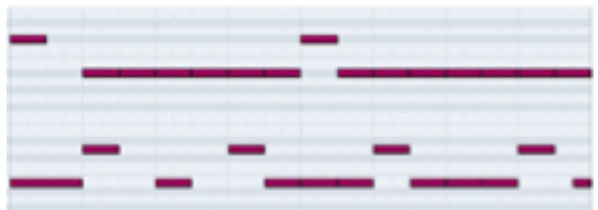
- Generates Drum lines
- Recurrent architecture – Iterative feedforward generation
- Trained on a datset of Drum and bass patterns



- Pop music dataset
- Example of generation

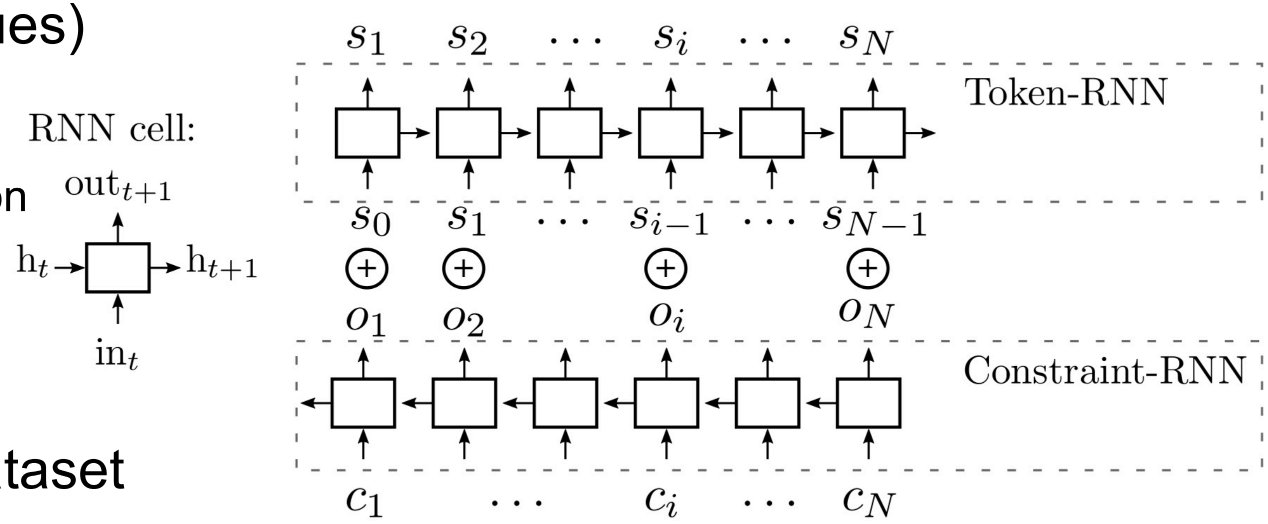


- Example of generation
- with a complex bass line conditioning



#4 Limitation – Control – #2 Solution: Conditioning
#2 Ex: Anticipation-RNN [Hadjeres et al., 2017]

- Generates Melodies
- Recurrent architecture – Iterative feedforward generation
- Positional Constraints (Note values)
- Backward Constraint-RNN
  - Summarizes constraints$_{[i,N]}$ information
  - Used as Conditioning input$_{i-1}$

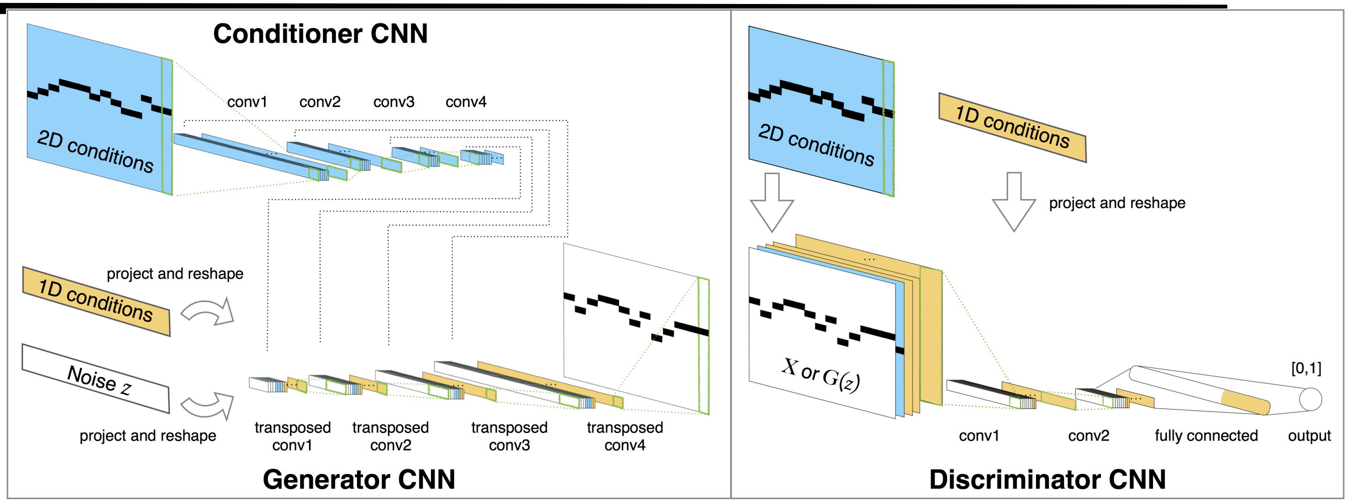


- Bach melodies (from chorale) dataset
- Examples of generation


(a)
(b)
(c)

#4 Limitation – Control – #2 Solution: Conditioning
#3 Ex: MidiNet [Yang et al., 2017]

- Conditioning information
  - Previous measure
  - Chord sequence



- Scope:
  - Previous measure (1D conditions)
  - Various previous measures (2D conditions)

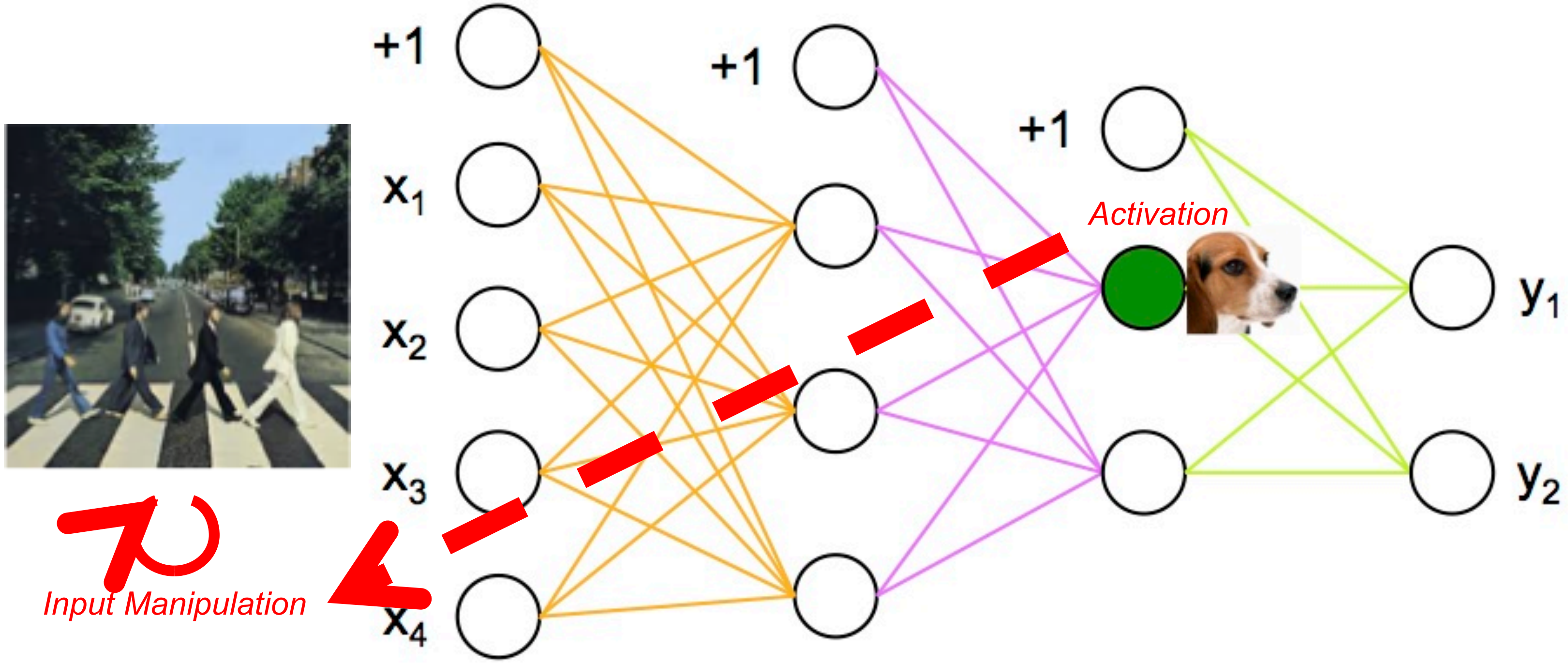
- Fine control:
  - Conditioning on previous measure 1D/2D and on chord sequence 1D/2D for one/all convolutional layers
  - Ex: previous measure 1D and on chord sequence 2D for all convolutional layers
    - » Follows more chord sequence

  - Pop music dataset https://soundcloud.com/vgtsv6jf5fwq/model3

#4 Limitation – Control – #3 Solution: Input Manipulation

- The input of the network is incrementally manipulated, guided by Gradient Descent Machinery, in order to match a target property
- Input:
  - Initial Input content
  - or brand New/Empty (randomly initialized)
- Target properties (Ex.):
  - Maximizing the activation of a specific unit, to exaggerate some visual element correlated (detection) to this unit
    - » Deep Dream [Mordvintsev et al., 2015]
  - Maximizing some similarity to a given target, to create a consonant melody
    - » DeepHear [Sun, 201X]
  - Maximizing both similarity to style and similarity to content
    - » Style transfer [Gatys et al., 2015]
  - Imposing higher level structure (form, tonality, meter)
    - » C-RBM [Lattner et al., 2016]

Deep Dream [Mordvintsev et al. 2015]

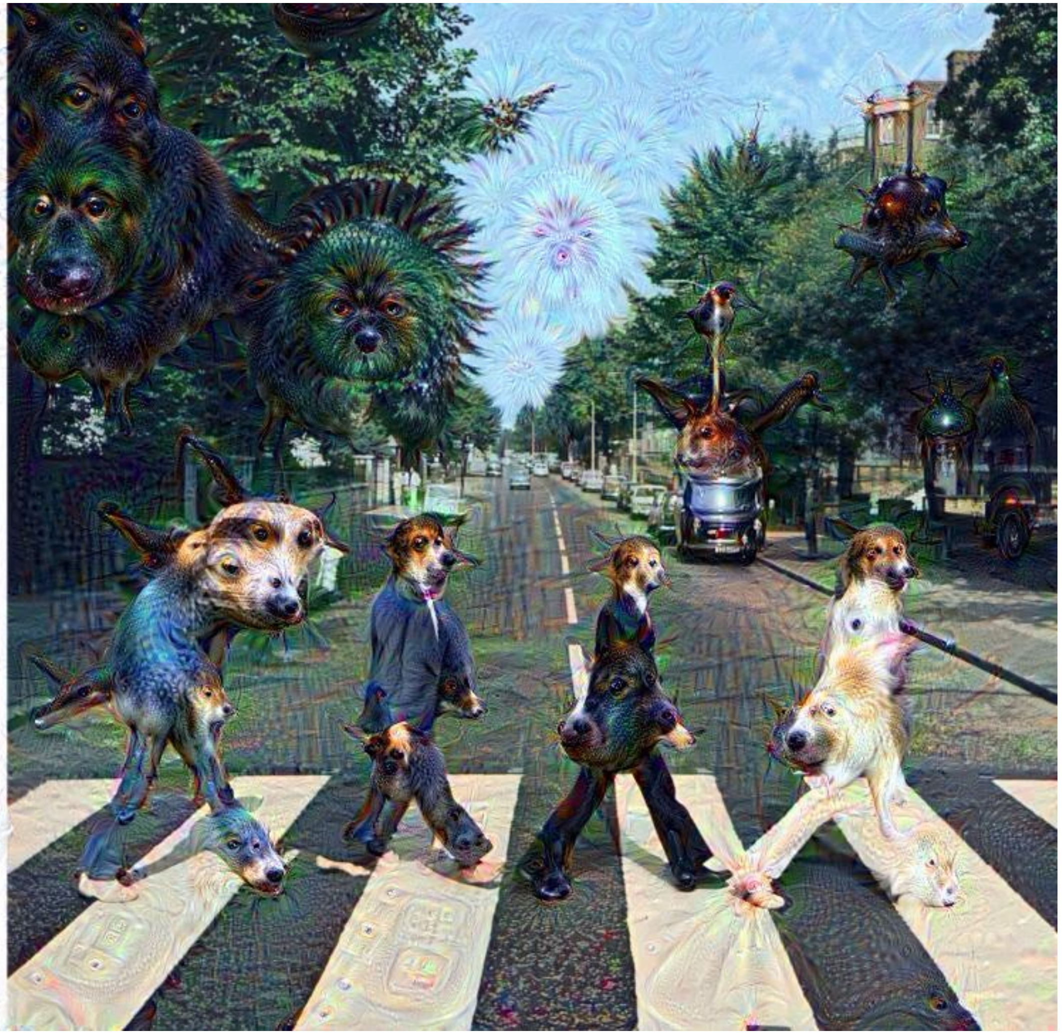


- Network is (or has been) trained on a large images dataset
- The objective is ~~to minimize the cost~~ to maximize the activation of a specific unit (neuron) which activates for a specific pattern(s), ex. a dog face 
- An initial image is iteratively slightly altered (ex: jitter, under gradient ascent control) to maximize that specific activation
- This will favor emergence of occurrences of that specific pattern in the image

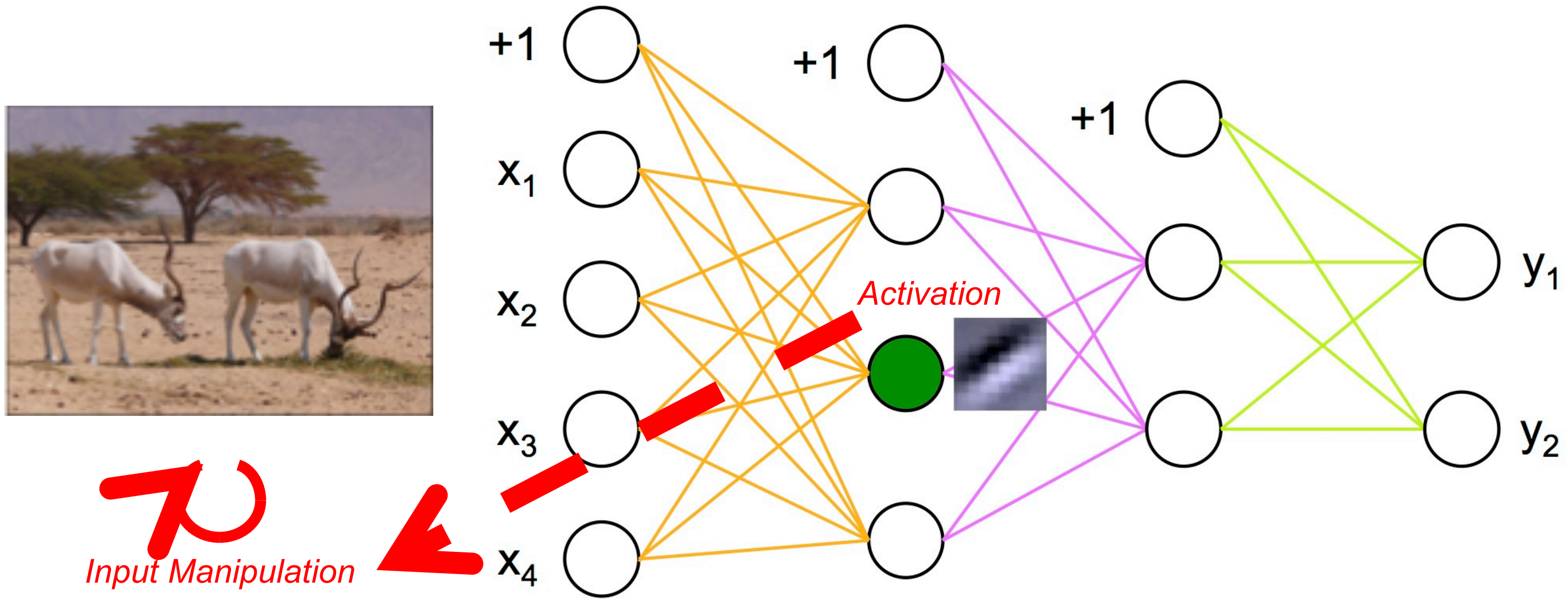
Deep Dream

Initial Image

Deep Dream Image

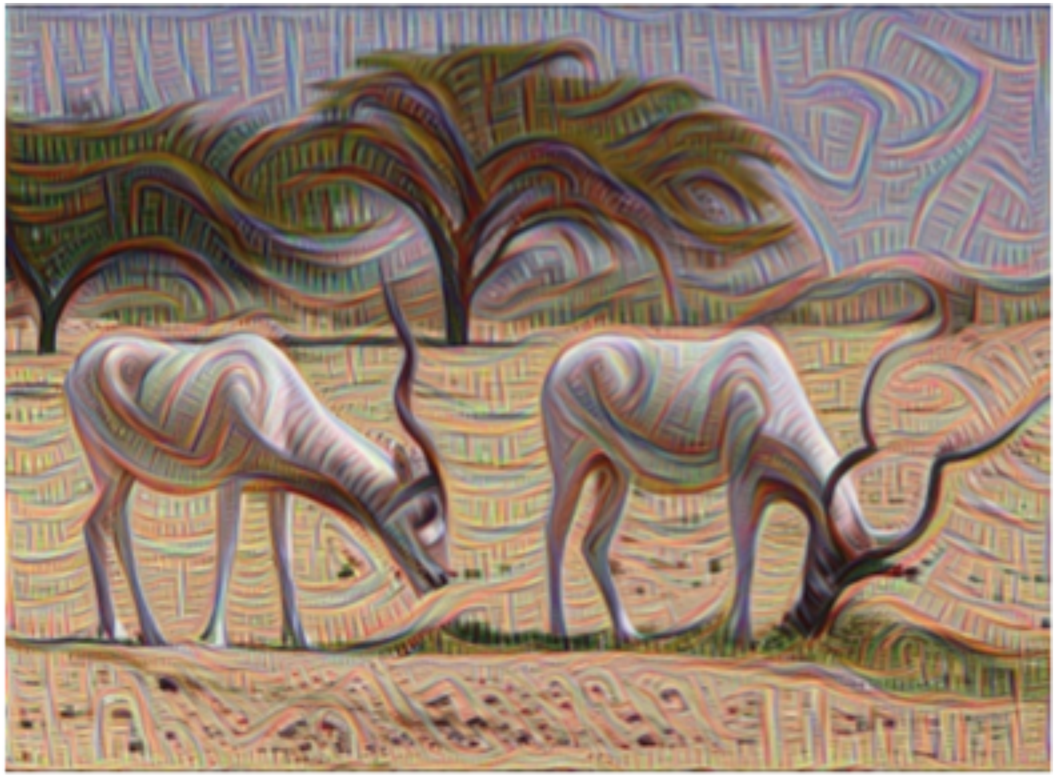


Deep Dream



- Case of a lower-level unit (neuron) pattern 
- Results in texture insertion

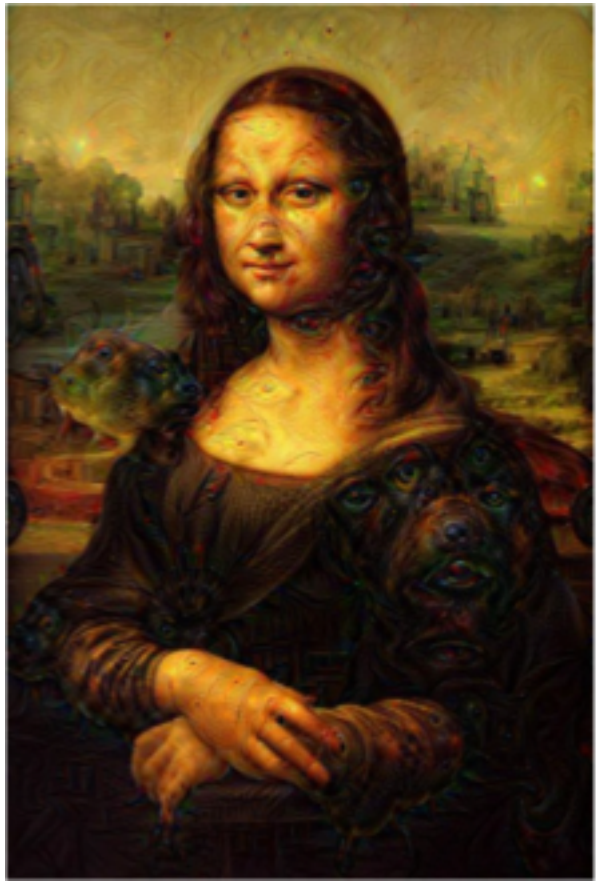
Deep Dream

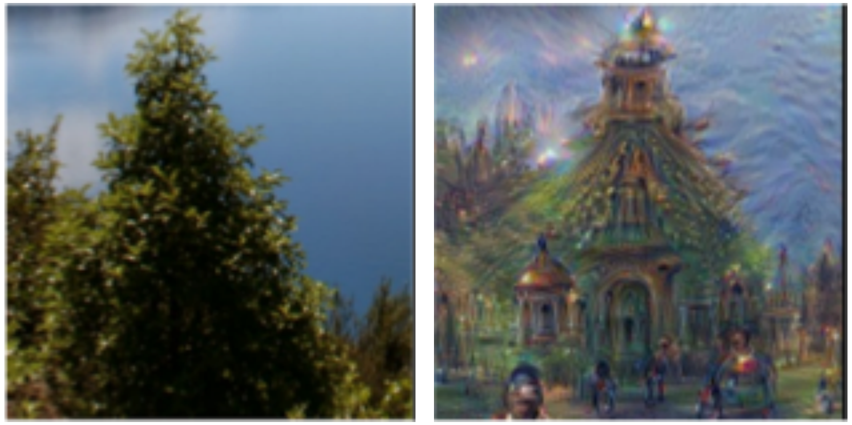


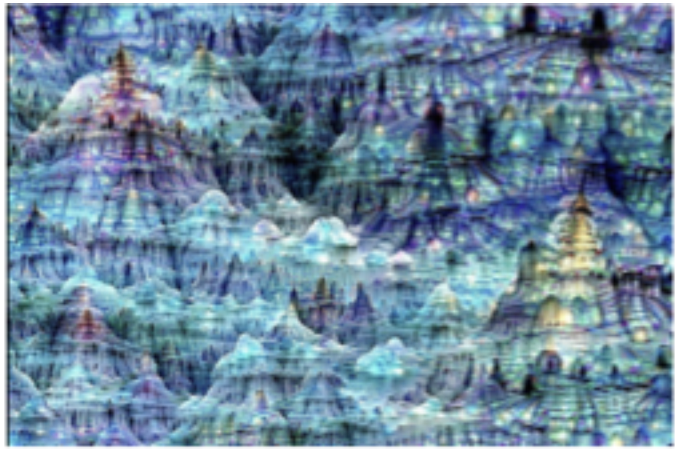
Lower Layer Unit Maximization Resulting image

Deep Dream

- One may use other maximization strategies (joint, similarity measures, etc.), alterations, etc., resulting in various transformation effects





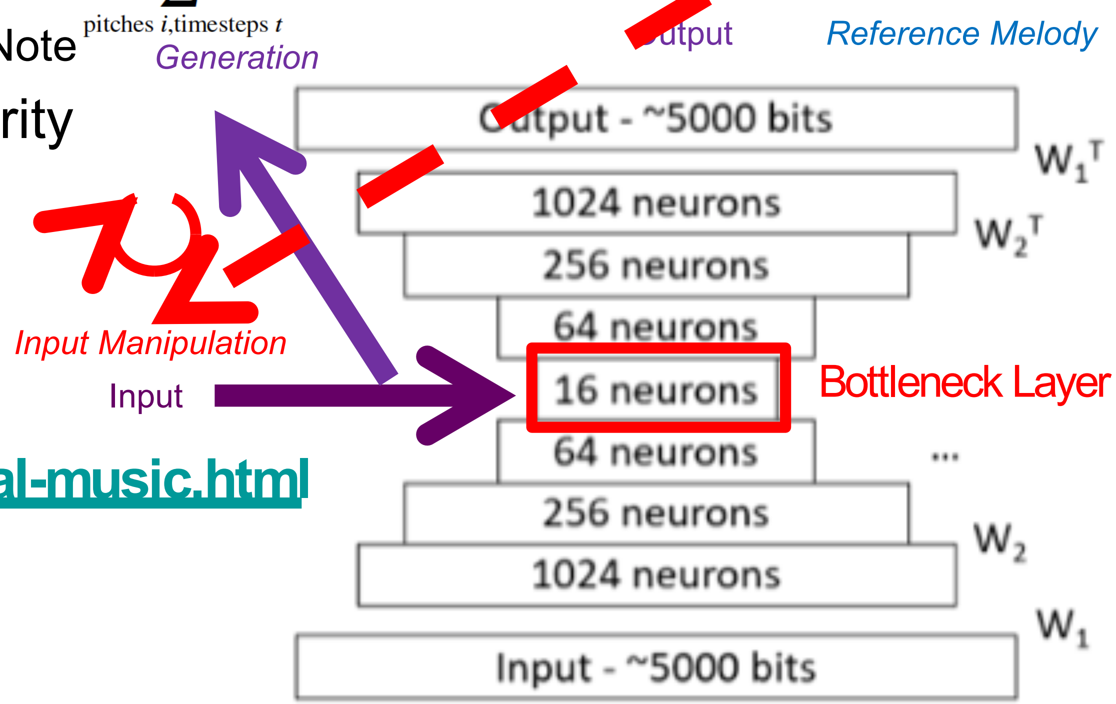


DeepHear [Sun, 2016]

Generation of Consonant Melody as a naive Accompaniment/Counterpoint to an Existing Reference Melody

- Input Random Data into 16 Neurons Bottleneck Layer
- Generated Melody: Output of the Higher Layer Decoder
- Alter the Input Data in order to Maximize Similarity between Generated Melody and Reference Melody $err(S) = \sum_{\text{pitches } i, \text{timesteps } t} ((i,t) \text{ in melody}) \cdot (1 - S[i,t])^2$ Similarity

  Penalize Missing Note when Melody has Note
- Controlled by Gradients of Similarity



https://fephsun.github.io/2015/09/01/neural-music.html

Style Transfer

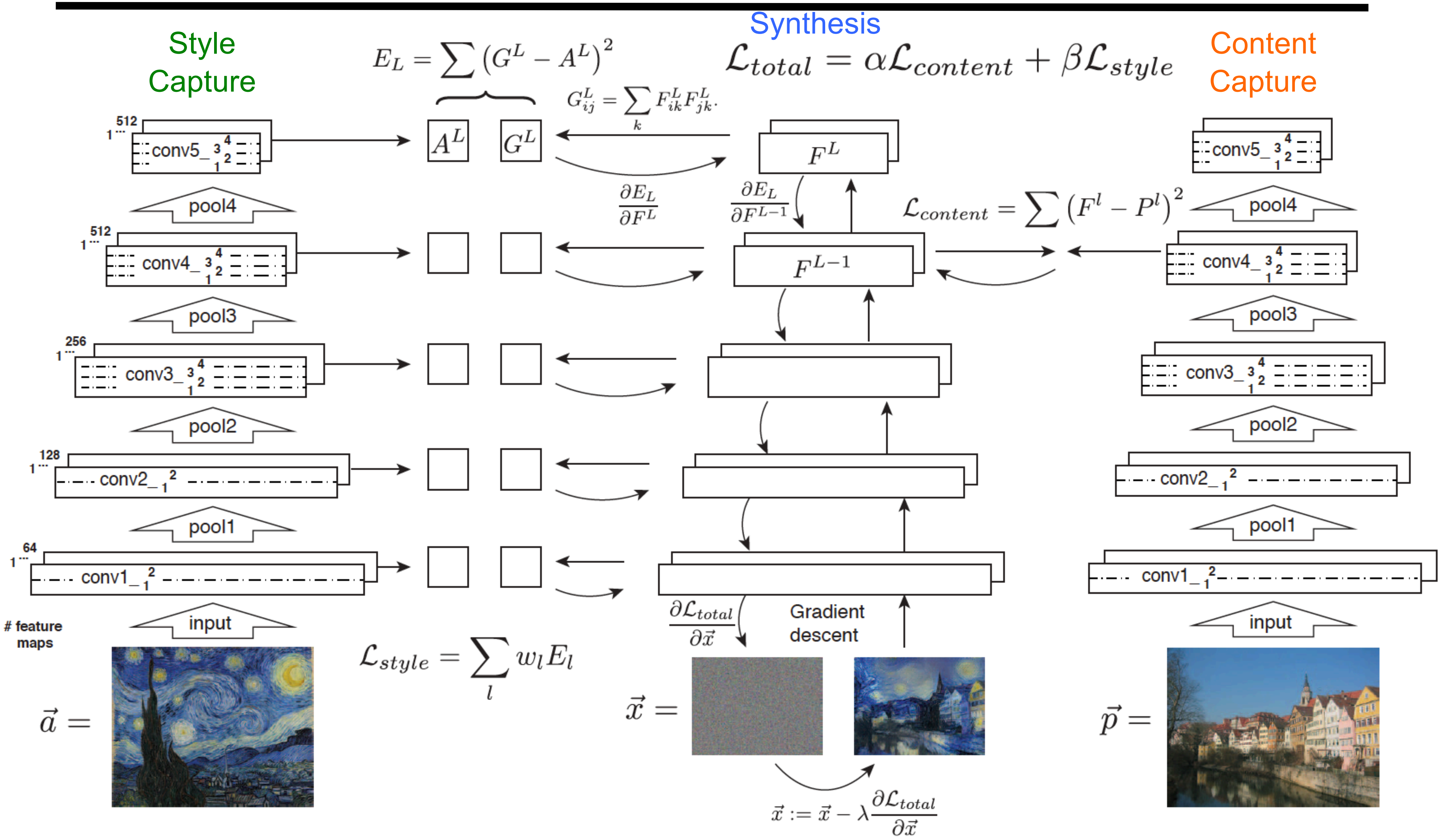
Style Transfer [Gatys et al., 2015]

1. Train Network with Images
2. Content Capture of 1st (Content) Image
   - Feed Forward 1st Image into Deep Network
   - Capture Content information
     - » Activations of filters/neurons for each layer

3. Style Capture of 2nd (Style) Image
   - Feed Forward 2nd Image into Deep Network
   - Capture Style information
     - » Feature space(s) : Correlations between feature filters/neurons for each layer

4. Search/Synthetize Hybrid Image
   - Feed Forward Random Image into Deep Network
   - Compute its Style and Contents features
   - Compute the Style and Contents Loss/Differences (with Content Image and Style Image)
   - Compute the Gradients (Standard Back-Propagation)
   - Update the Image with λ*Gradients
     - » λ : update rate
   - Iterate until reaching Target Losses

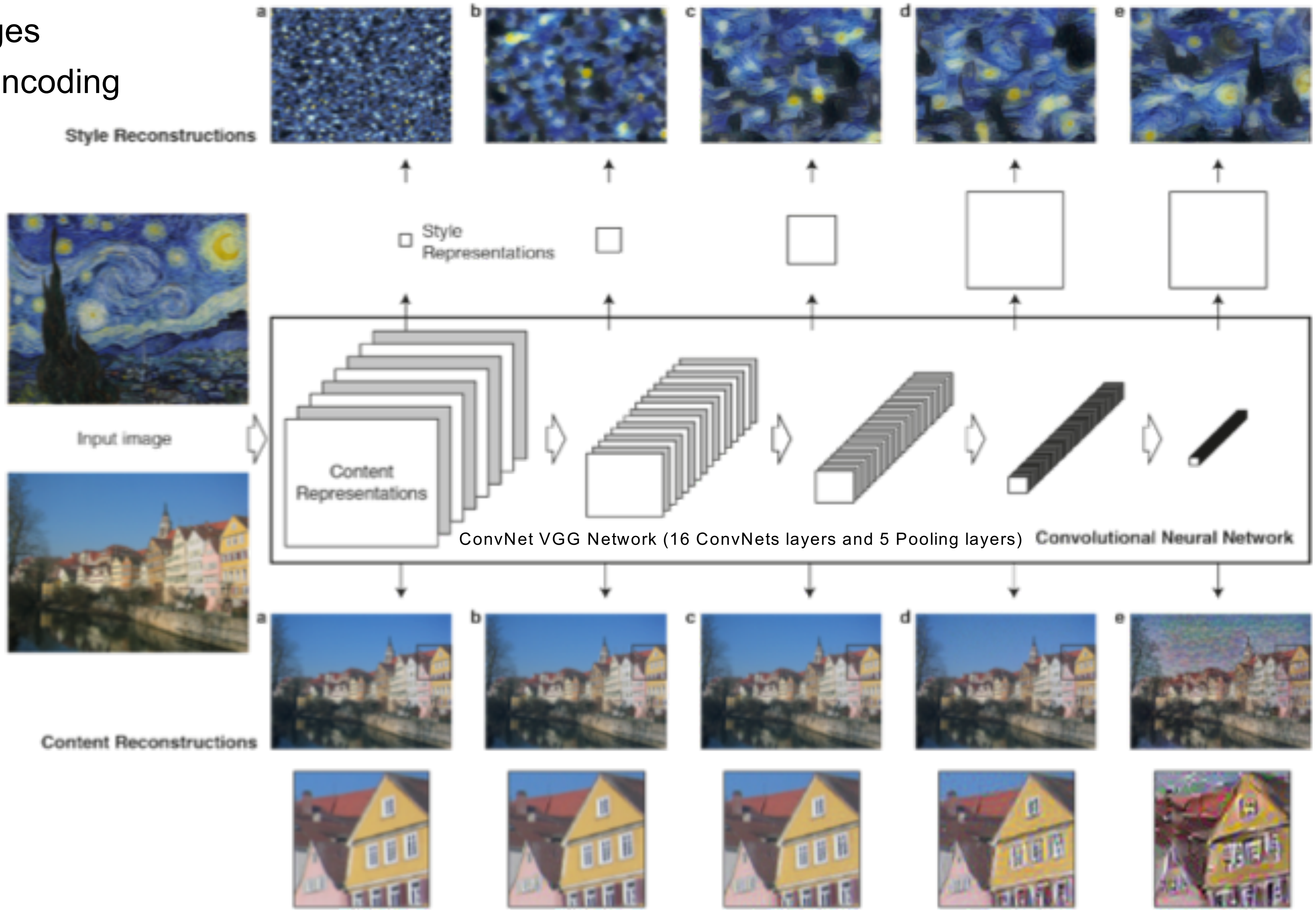
Style Transfer



Style Transfer
(Guess the Artist/Painting :)

Style Transfer

Recontructing Images
from the Network Encoding



Style Transfer

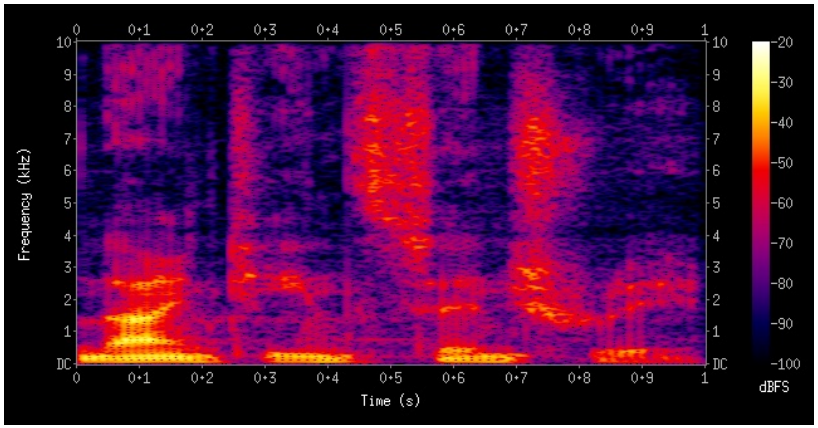
Style Transfer

- Has been applied to music
  - Ex: [Ulyanov & Lebedev, 2016]
  - Audio (Spectrogram)

    https://dmitryulyanov.github.io/audio-texture-synthesis-and-style-transfer/

- Generally more difficult
  - Music = Temporal Data (Images)
  - Temporal (horizontal) correlations =/= Harmonic (vertical) correlations (anisotropy)
  - as opposed to horizontal =~ vertical correlations for images (isotropy)

harmonic (vertical) correlations



temporal (horizontal) correlations

anisotropic

correlations

correlations

isotropic

Audio texture synthesis and style transfer [Ulyanov & Lebedev, 2016]

Content

Walkyries

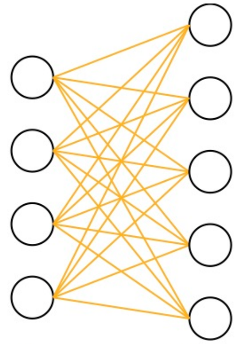
Rap (Eminem)

Style

Empire

Text (Gettysburg)

#4 Limitation – Control – #3 Solution: Input Manipulation & #1 Solution: Sampling

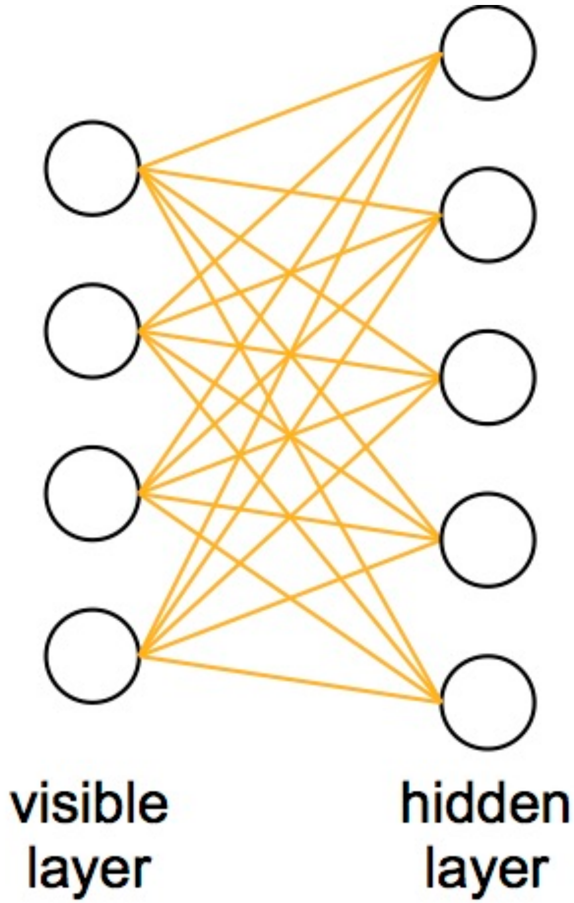


- Constrained sampling, C-RBM [Lattner et al., 2016]
- Convolutional Restricted Boltzmann Machine (RBM)
- Combination of:
  - Input Manipulation guided by Gradient Descent of current sample
    - » to impose Higher-Level Structure/Constraints:
      - Structure
      - Tonality
      - Meter
  - Sampling Control, by Selective Gibbs sampling (SGS)
    - » at a Selected Low-Level (subset of variables)
    - » to realign selectively the sample to the learnt distribution

Restricted Boltzmann Machine (RBM) [Hinton & Sejnowski, 1986]

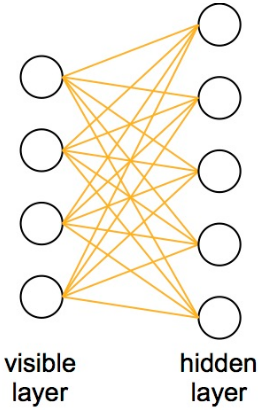
- Generative Stochastic Neural network
- Can learn a Probability Distribution over its set of inputs
- Was used for Pre-Training [Hinton & Salakhutdinov, 2006]
- Analog to Autoencoder
  - No Output
    - Input Layer also acts as an Output
  - Stochastic
  - Boolean, or Multinomial/Discrete or Continuous (Values)
- Can learn efficiently with few examples

- Generation of a sample from the model learnt:
  - Random initialization of the visible layer vector v
    - Following a standard uniform distribution
  - Run Gibbs sampling until convergence

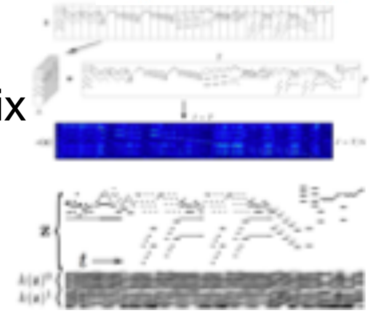


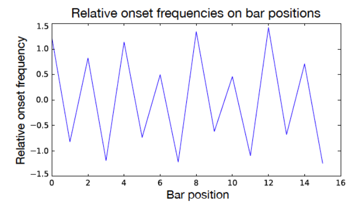
Input Manipulation & Constrained sampling

- Constrained sampling, C-RBM [Lattner et al., 2016]
- Convolutional Restricted Boltzmann Machine (RBM)



- Combination of:
  – Input Manipulation guided by Gradient Descent of current sample
    » to impose Higher-Level Structure/Constraints:
      - Structure (Structure Repetition, Ex: AABA), via Self-Similarity Matrix
      - Tonality, via Similarity of Distribution of Pitch-Classes
      - Meter (Rhythm Pattern/Signature and Beat Accent)

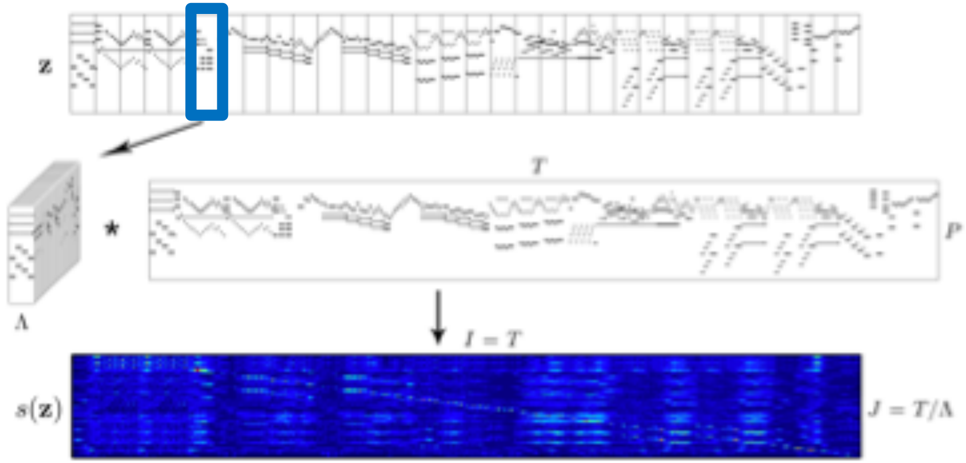




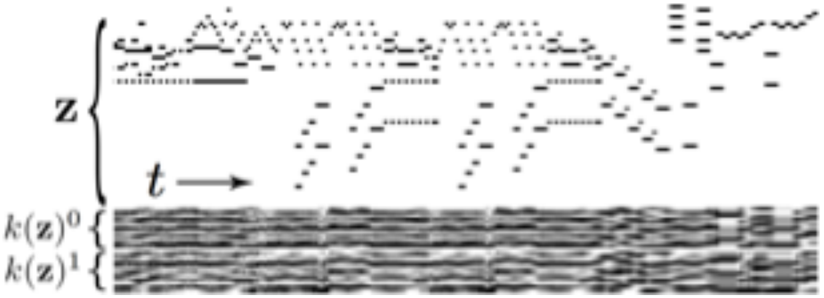
  – Sampling Control, by Selective Gibbs sampling (SGS)
    » at a Selected Low-Level (subset of variables)
    » to realign selectively the sample to the learnt distribution
  – Alternate IP/GD and SGS, controlled by Simulated Annealing
  – But not exact as, e.g., Markov Constraints [Pachet & Roy, 2011]

Input Manipulation & Constrained sampling

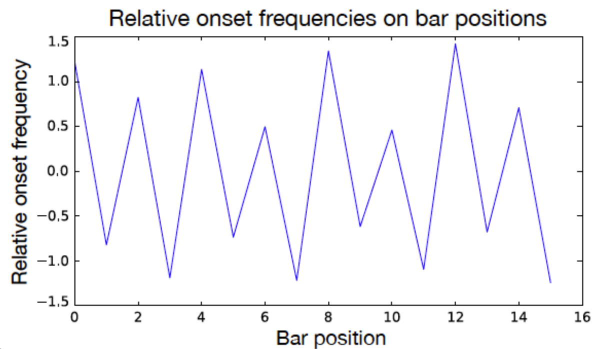
- Structure (Repetition Structure, Ex: AABA)
  - » Self-Similarity Matrix
  - » For each Music Slice



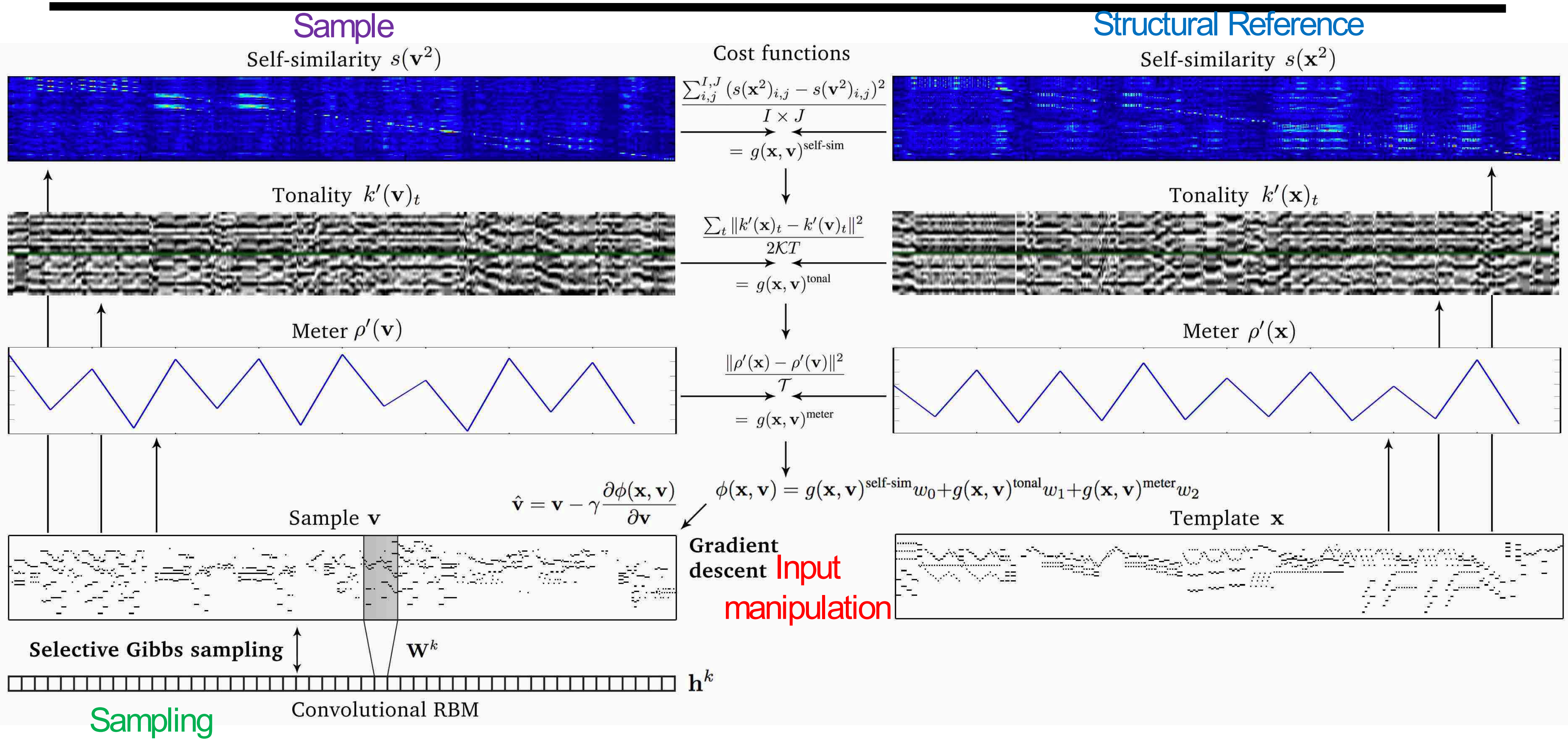
- Tonality, via Similarity of Distribution of Pitch-Classes
  - » Key Estimation Vectors over Time



- Meter
  - » Duration and Accent Patterns (ex: on 1st and 3rd Beats)
  - » Via Relative Occurrence of Note Onsets



C-RBM [Lattner et al., 2016]

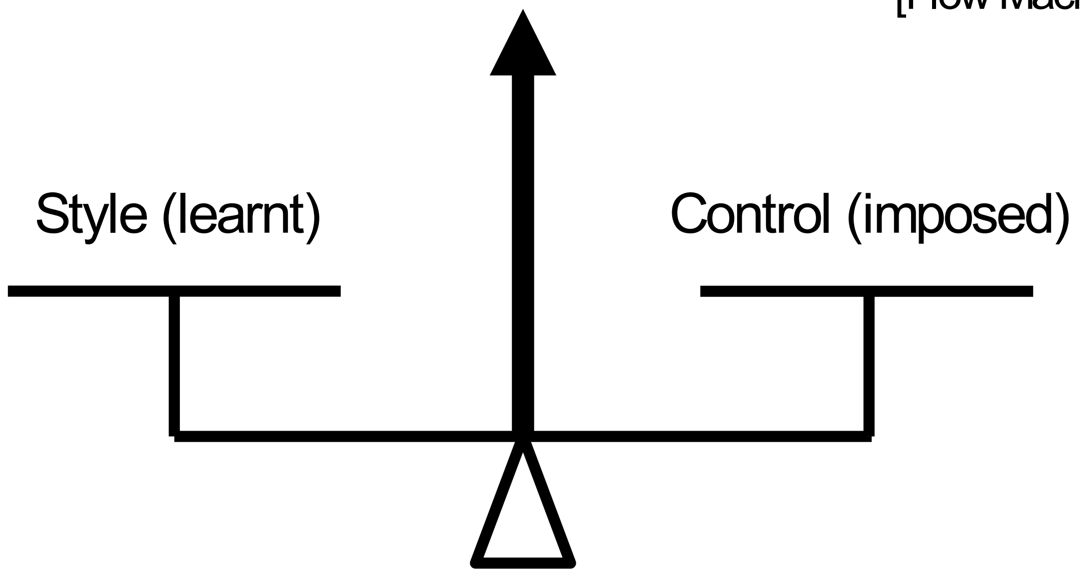


Both Manipulation and Sampling of Input because RBM's "Output" is its Input

https://soundcloud.com/pmgrbm

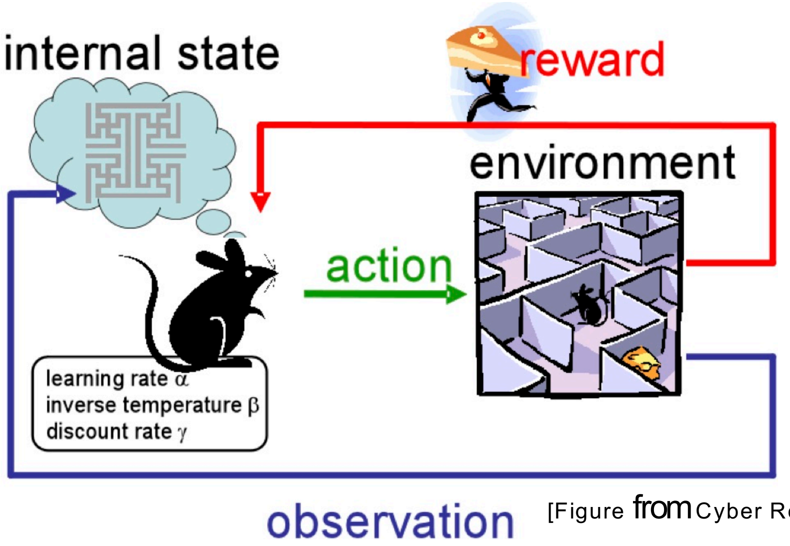
Style vs/and Control

[Flow Machines]



#4 Limitation – Control –
#4 Solution: Reinforcement Learning

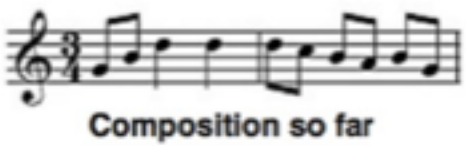
- Reformulation of Melody Generation as a Reinforcement Learning Problem



[Figure from Cyber Rodent Project]

  - Sequential decision/action problem
  - Objective: Learn via past decisions/actions a near optimal policy (state -> action) for maximizing the gain (sum of rewards)

- State: Melody generated so far (Succession of notes)

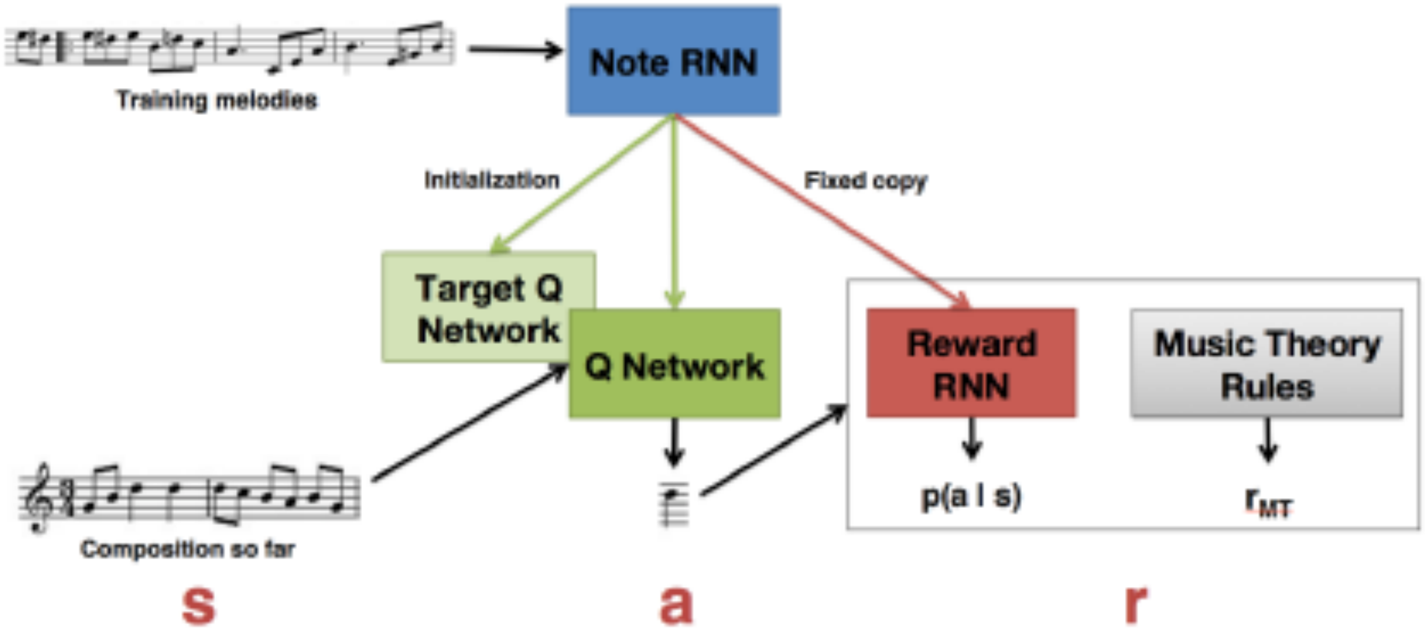


- Action: Generation of next note 

Deep Reinforcement Learning (RL) – RL-Tuner [Jaques et al., 2016]

- *RNN (Recurrent Neural Network) Trained on the Corpus*

- Reward = Combination of:
  - Adherence to What has been Learnt by the RNN
    - » Similarity to the Prediction by the RNN
  - Adherence to Music Theory Rules
    - » Tonality, Avoid excessive repetitions…
    - » Open: Arbitrary User-defined Targets



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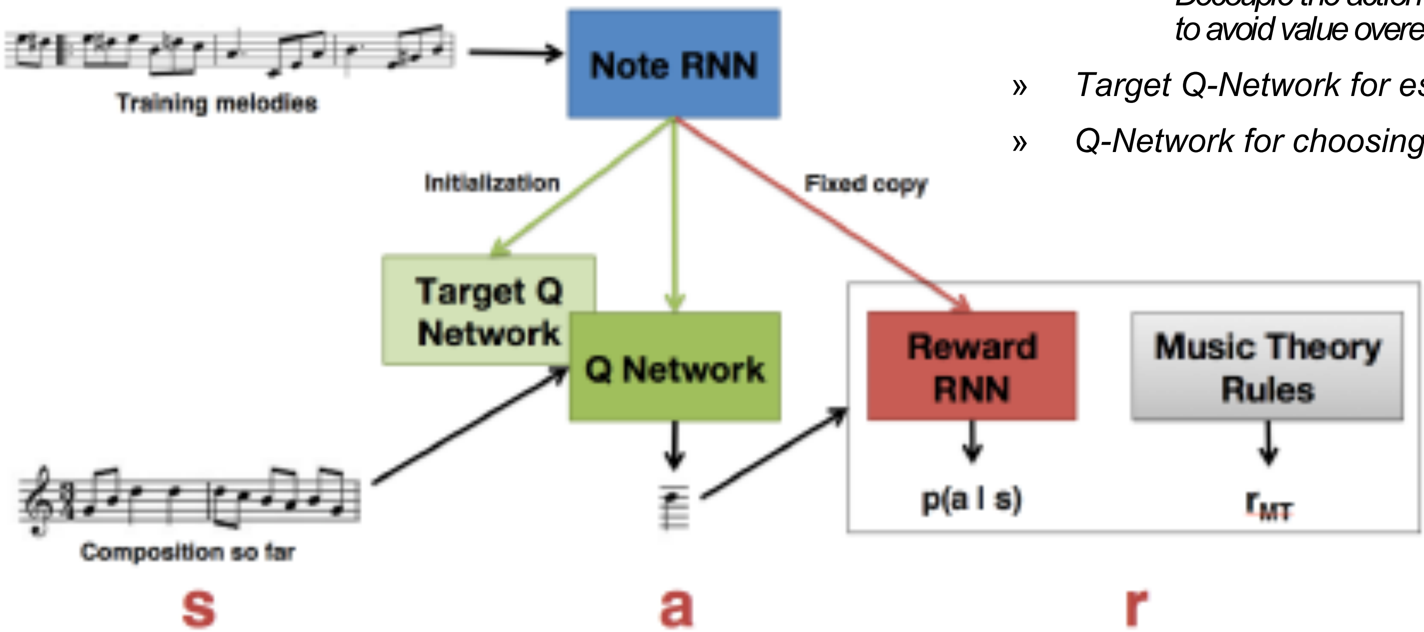
- *Reinforcement Learning implemented via Deep Learning ! (Deep Reinforcement learning)*
- *Double Deep Reinforcement Learning*
  - » *Double Q-Learning [Hasselt et al., 2015]*
    - *Decouple the action selection from the evaluation, to avoid value overestimation*
  - » *Target Q-Network for estimating Gain (Q)*
  - » *Q-Network for choosing next Action (next Note)*

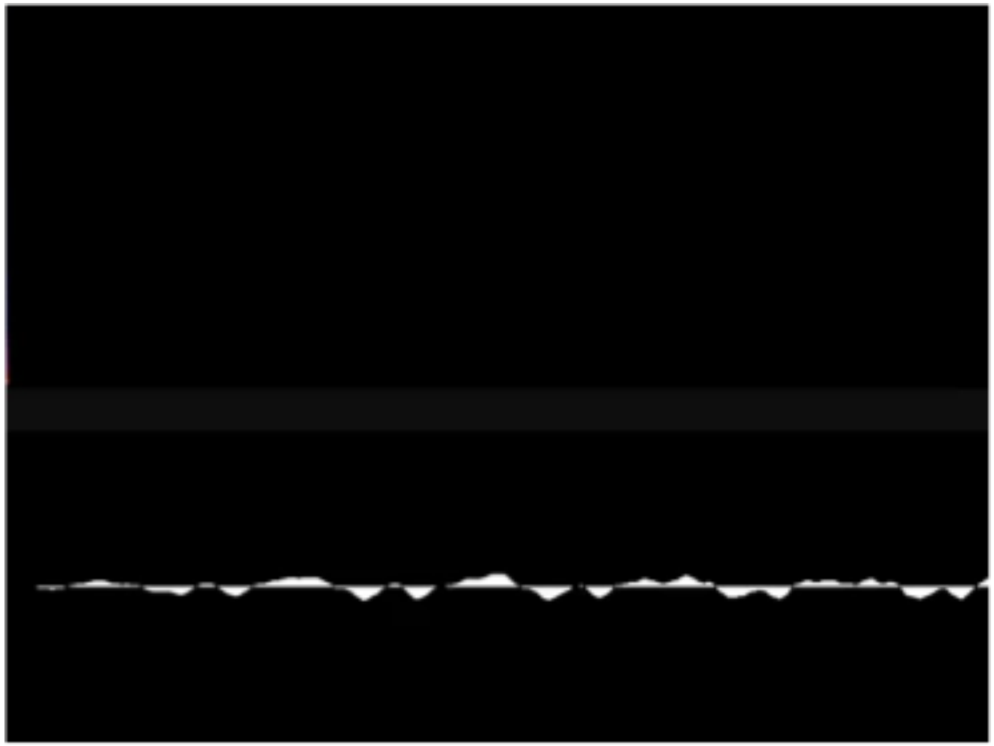


RL-Tuner – Results

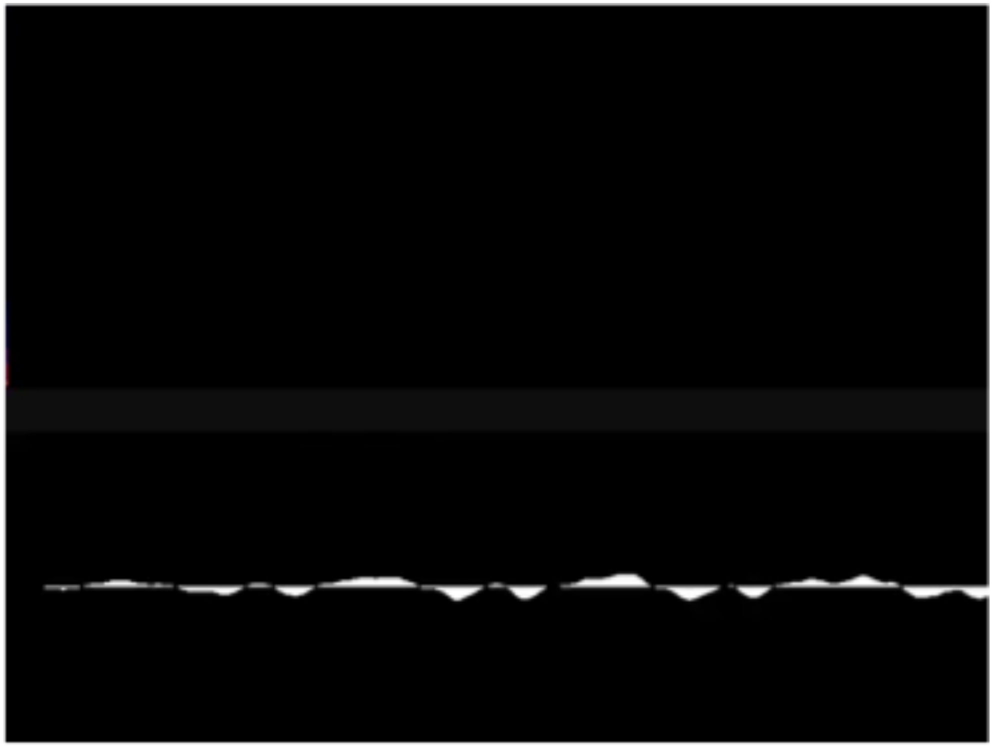
without with

Behavior	Note RNN	Q-*Learning*	Psi	G
Notes excessively repeated	63.3%	**0.0%**	**0.02%**	**0.03%**
Notes not in key	0.1%	1.0%	0.6%	28.7%
Mean autocorrelation (lag 1,2,3)	-.16, .14, -.13	**-.11, .03, .03**	**-.10, -.01, .01**	.55, .31, .17
Leaps resolved	77.2%	**91.1%**	**90.0%**	52.2%
Compositions starting with tonic	0.9%	**28.8%**	**28.7%**	0.0%
Compositions with unique max note	64.7%	56.4%	59.4%	37.1%
Compositions with unique min note	49.4%	51.9%	**58.3%**	**56.5%**
Notes in motif	5.9%	**75.7%**	**73.8%**	**69.3%**
Notes in repeated motif	0.007%	**0.11%**	**0.09%**	**0.01%**

RL-Tuner – Demo



LSTM

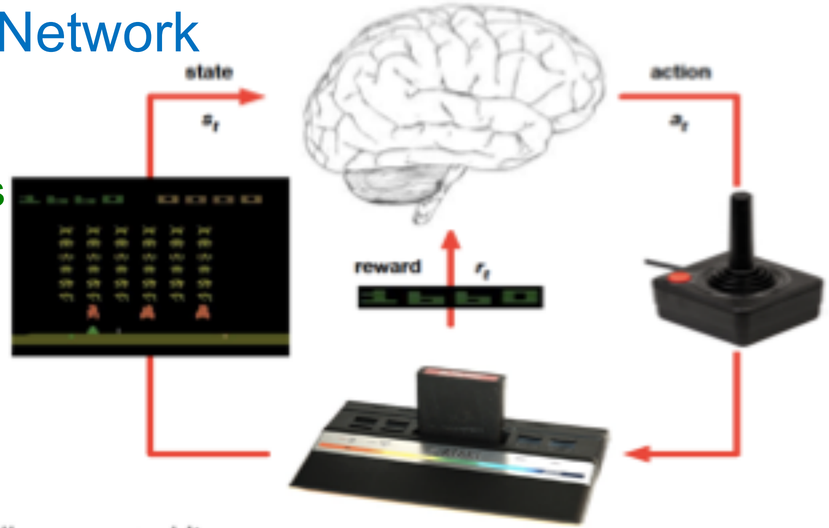


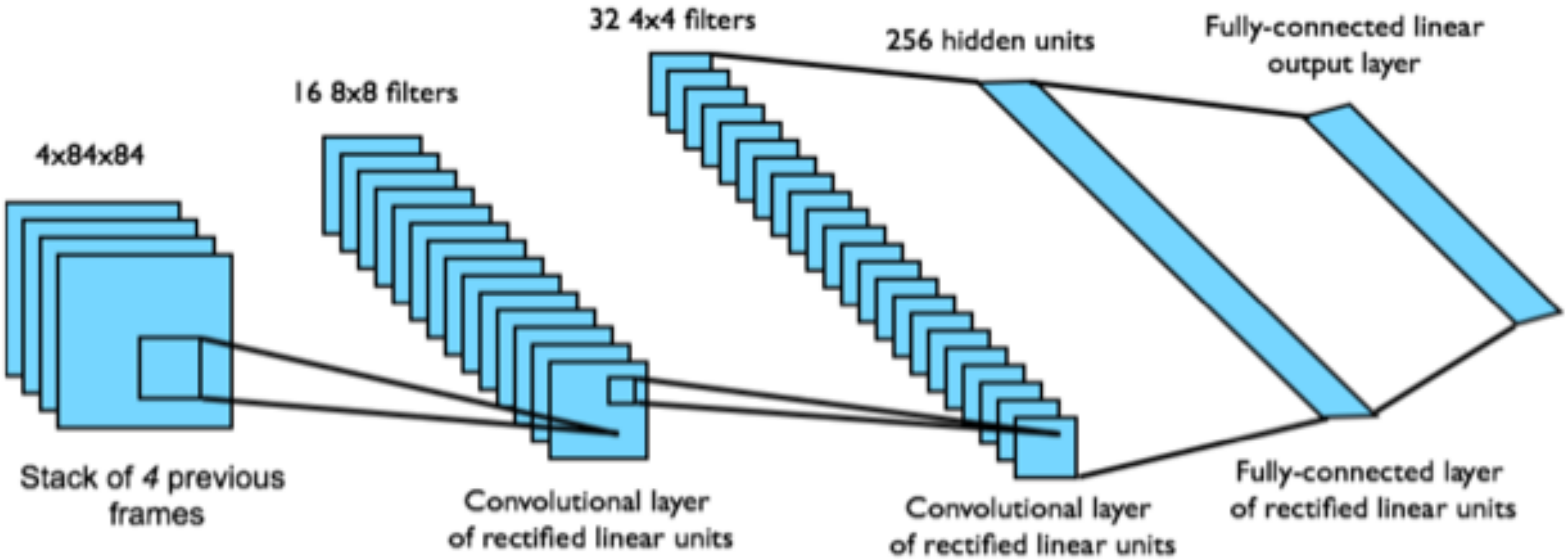
RL-Tuner

https://magenta.tensorflow.org/2016/11/09/tuning-recurrent-networks-with-reinforcement-learning

Deep Q-Learning [Minh et al. 2013]

- Atari Games Playing (DeepMind Technologies)
- Represent/Estimate Q Value function
  (Gain for a <state, action> pair) as a Deep Q-Network
- Training of Q Value function Network
  - Inputs: Game screen raw pixels & joystick/button positions
  - Outputs: Q-values (captured from game play)
    - » Reward € {-1, 0, 1}
- On-Line Training through Game Play
- Works with ANY (ATARI) Game !





Also:

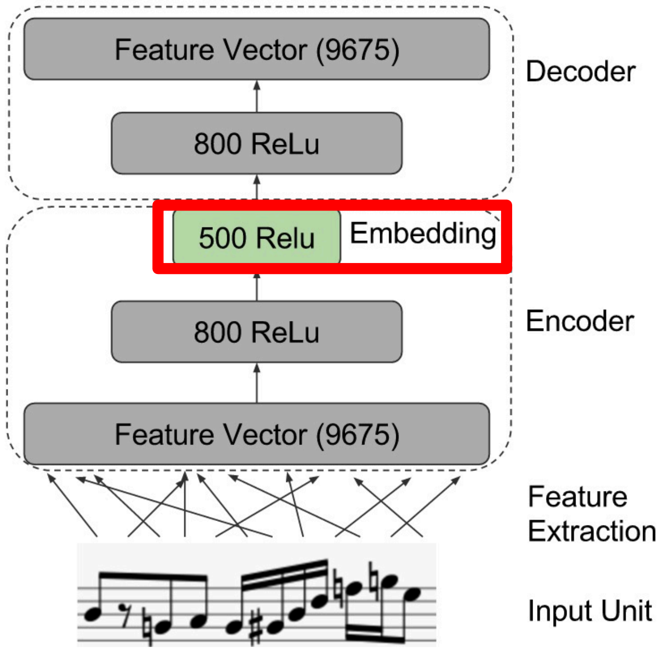
AlphaGo
[Silver et al., 2016]

AlphaGo Zero
[Silver et al., 2017]

#4 Limitation – Control –
#5 Solution: Unit Selection [Bretan et al., 2016]

- Concatenation of Music Units Queried from a Database
- Key Process: Unit Selection, based on:
  - Successor Semantic Relevance
  - Concatenation Cost
  - *Inspired by Text-to-Speech Generation Systems*

- Feature Extraction
  - By Stacked Autoencoders
  - To Create Features Vector (Embedding) Representation of Units
  - Used to Compute Distances between Units
  - To Control Unit Selection

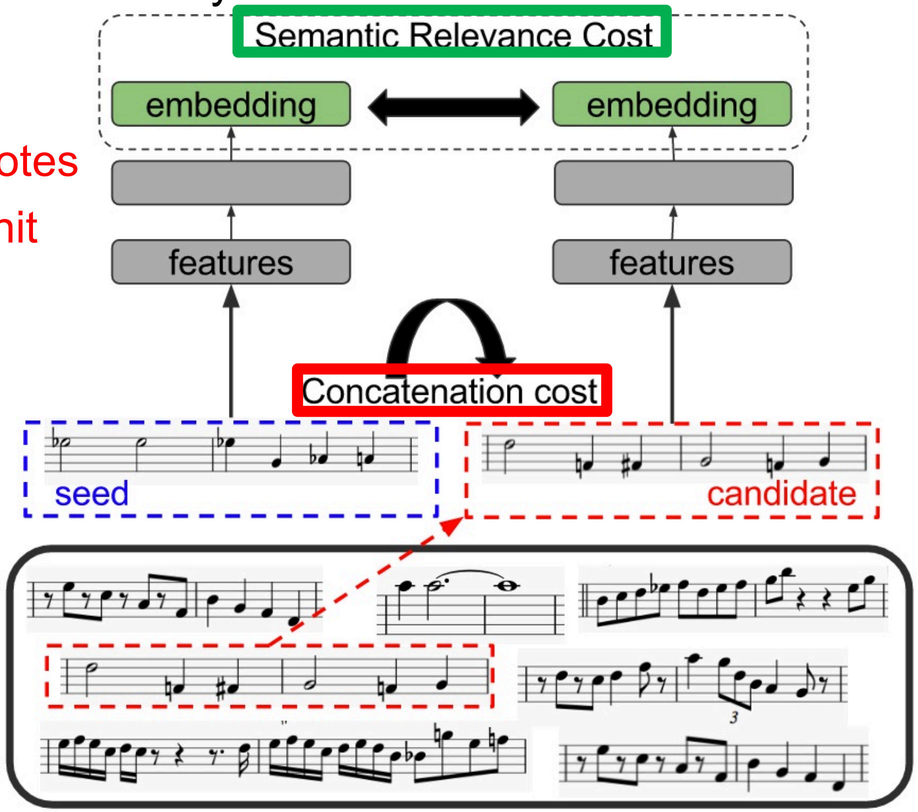


- *Top Down Approach*
  - Structure (Next Unit Features)
  - Fill (Select Best Fit Unit)

Unit Selection

Unit Selection, based on:

- Successor Semantic Relevance
  - » Based on a model of transition between units
  - » As learnt by a 1st LSTM Recurrent Network
  - » Relevance = distance to the (ideal) next unit as predicted by the model
- Concatenation Cost
  - » Based on another model of transition between notes
  - » Between last note of unit and first note of next unit
  - » As learnt by a 2nd LSTM Recurrent Network
- Combination of the two criteria by a heuristic process



- As for Mozart Dice Music
- BUT with constraints on combination

Unit Selection – Demo

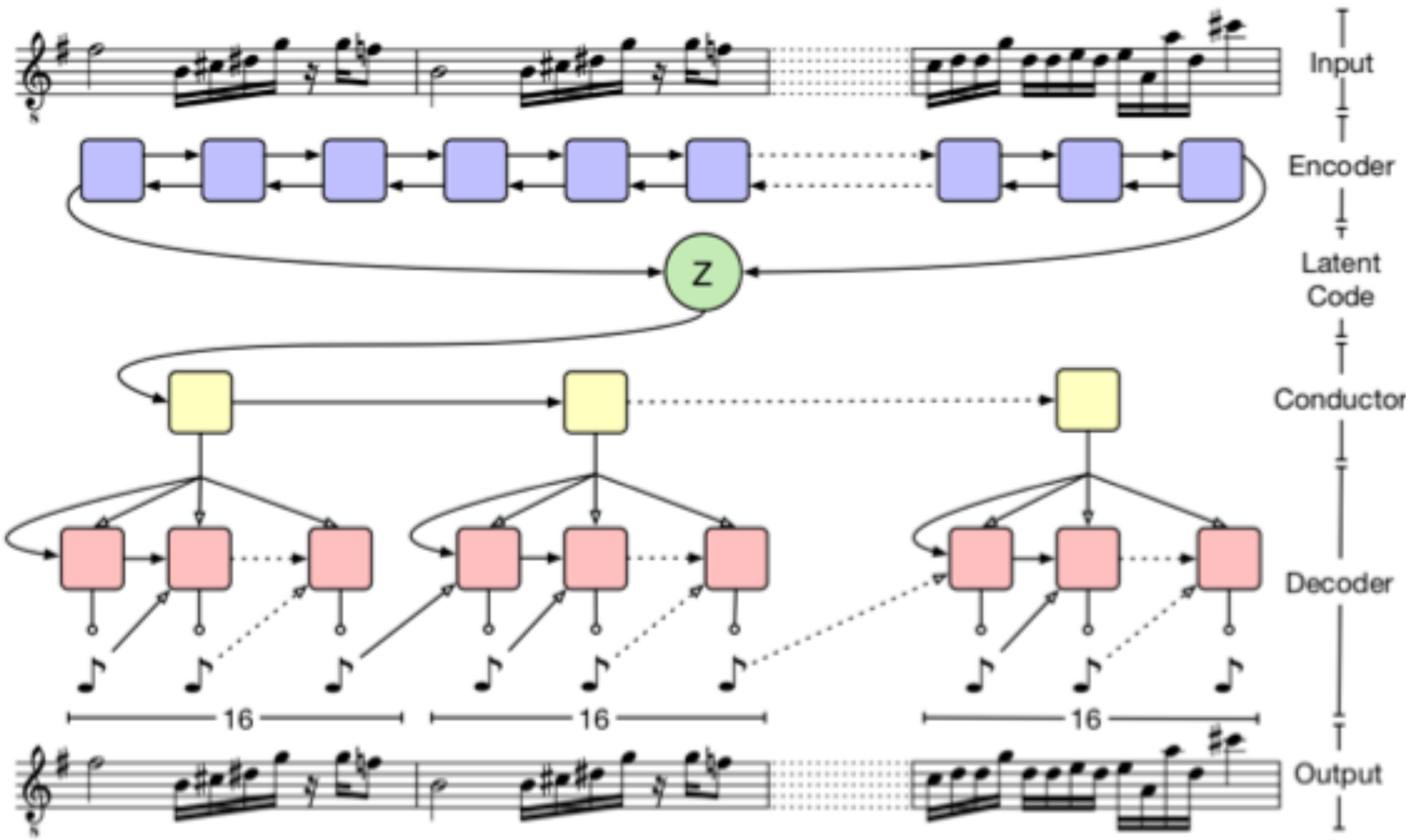
https://www.youtube.com/watch?v=BbyvbO2F7ug&feature=youtu.be

#5 Limitation – Structure

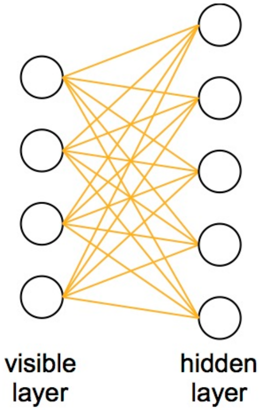
- No Sense of Direction
- No Structure

#5 Limitation – Structure – #1 Solution – Hierarchical RNN

- MusicVAE [Roberts et al., 2018]
- Hierarchical
  - Conductor RNN
  - Bottom RNN
- Long term generation
- Structure



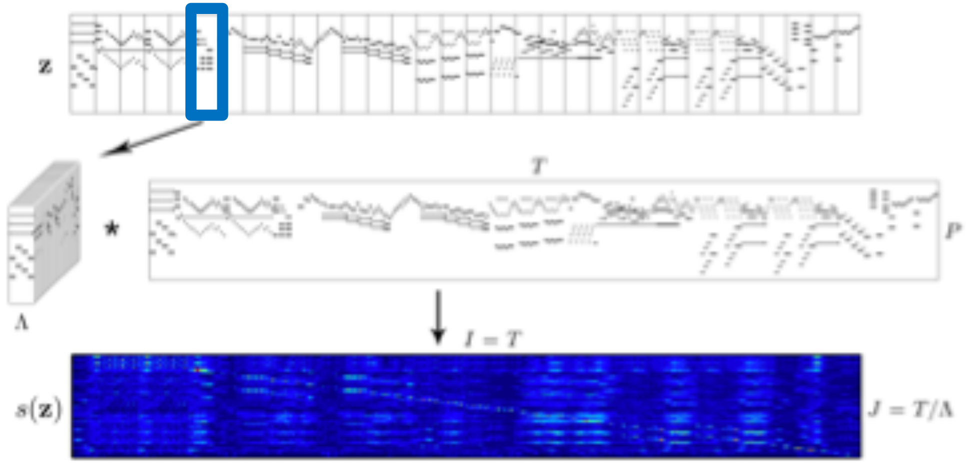
#5 Limitation – Structure – #2 Solution – Structure Imposition



- Constrained sampling, C-RBM [Lattner et al., 2016]
- Convolutional Restricted Boltzmann Machine (RBM)
- Combination of:
  - Input Manipulation guided by Gradient Descent of current sample
    - » to impose Higher-Level Structure/Constraints:
      - Structure
      - Tonality
      - Meter
  - Sampling Control, by Selective Gibbs sampling (SGS)
    - » at a Selected Low-Level (subset of variables)
    - » to realign selectively the sample to the learnt distribution

Input Manipulation & Constrained sampling

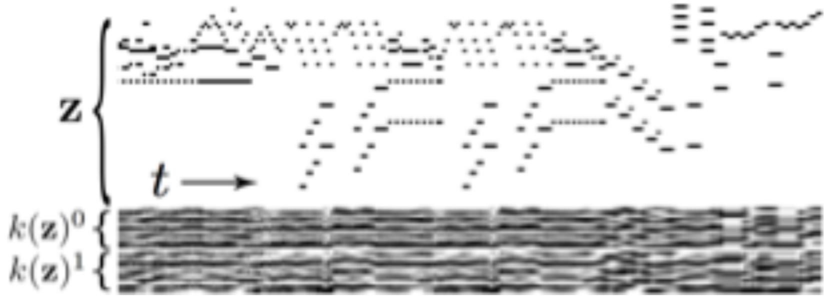
- Structure (Repetition Structure, Ex: AABA)
  - » Self-Similarity Matrix
  - » For each Music Slice



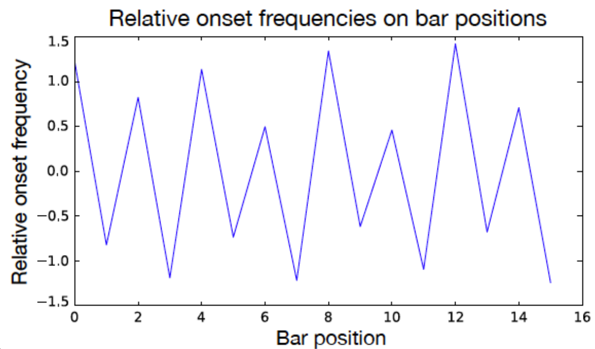
- Tonality, via Similarity of Distribution of Pitch-Classes
  - » Key Estimation Vectors over Time

12 Major Keys

12 Minor Keys



- Meter
  - » Duration and Accent Patterns (ex: on 1st and 3rd Beats)
  - » Via Relative Occurrence of Note Onsets



#6 Limitation – Originality

- Deep Learning will favor Conformance to a Corpus
- How to favor Originality/Creativity?

- Ex: CAN (Creative Adversarial Networks) architecture
  [Elgammal et al., 2017] to favor the generation of new Styles

Generative Adversarial Networks (GAN) [Goodfellow et al., 2014]

- Training Simultaneously 2 Neural Networks
  - Generator
    - » Transforms Random noise Vectors into *Faked* Samples
  - Discriminator
    - » Estimates probability that the Sample came from training data rather than from G
  - Minimax 2-player game $\min_G \max_D V(G,D) = log(D(x)) + log(1 - D(G(z)))$

	Prediction by D
D(x): P_D(x from real data)	*(Correct)*
D(G(z)): P_D(G(z) from real data)	*(Incorrect)*
1 - D(G(z)): P_D(G(z) from Generator)	*(Correct)*

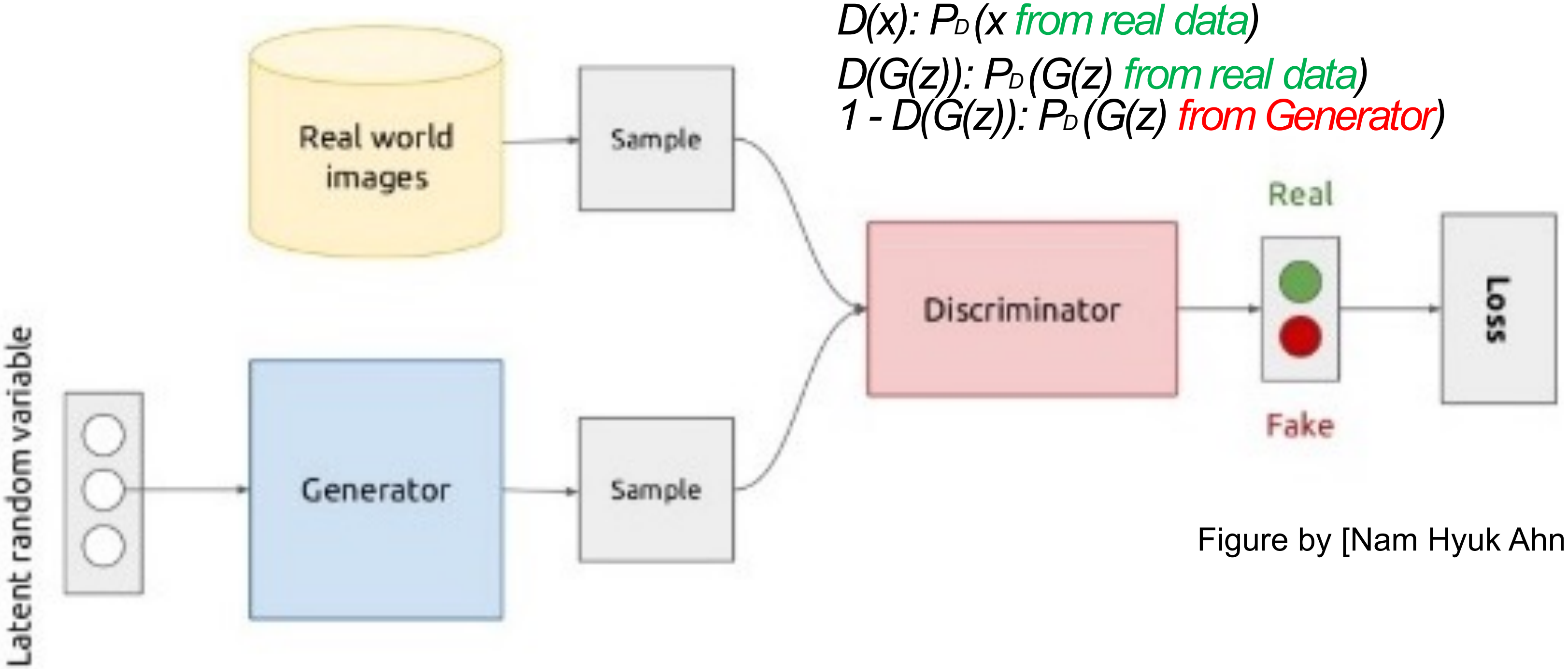
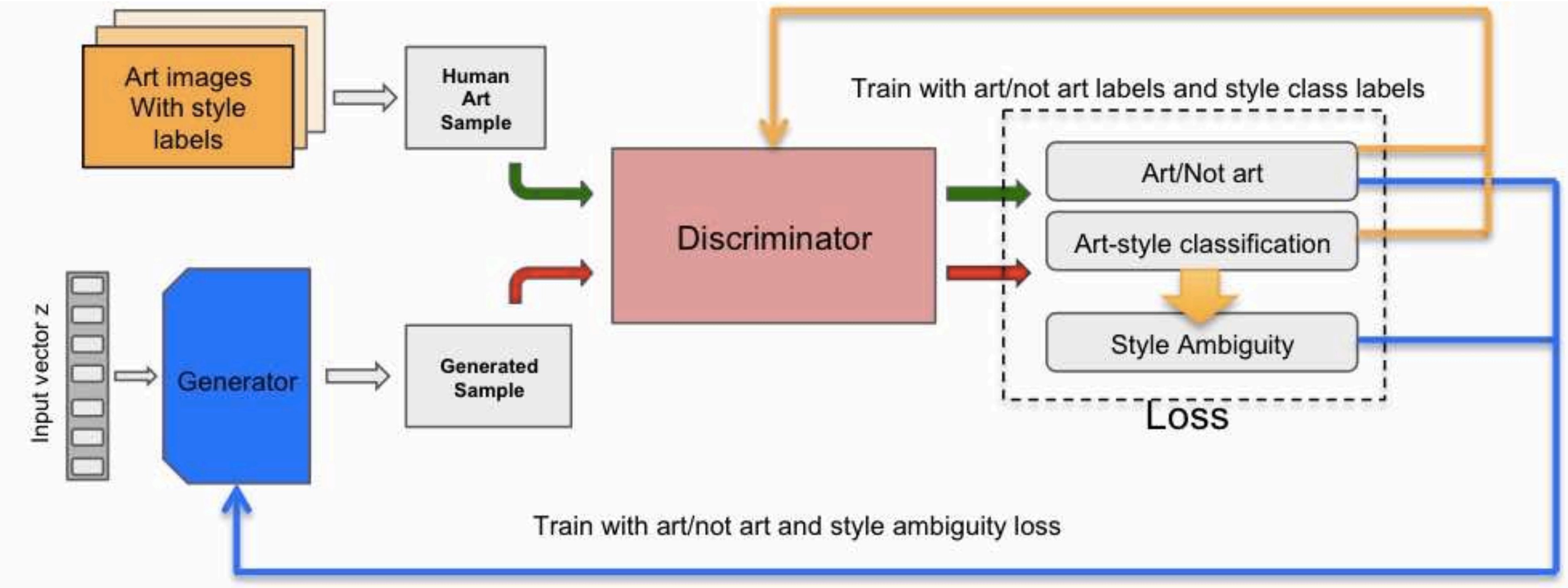


Figure by [Nam Hyuk Ahn, 2017]

#6 Limitation – Originality – #1 Partial Solution: Creative Adversarial Networks (CAN) [Elgammal et al., 2017]

- Extension of GAN
- Combining 2 (Contradictory) Objectives:
  - How Discriminator believes that the sample comes from the training dataset (GAN)
  - How Easily the Discriminator can classify the sample into established styles (classes)
    - » If there is strong ambiguity (i.e., various classes are equiprobable), this means that the sample is difficult to fit within the existing art styles
    - » Maybe a new style has been created…



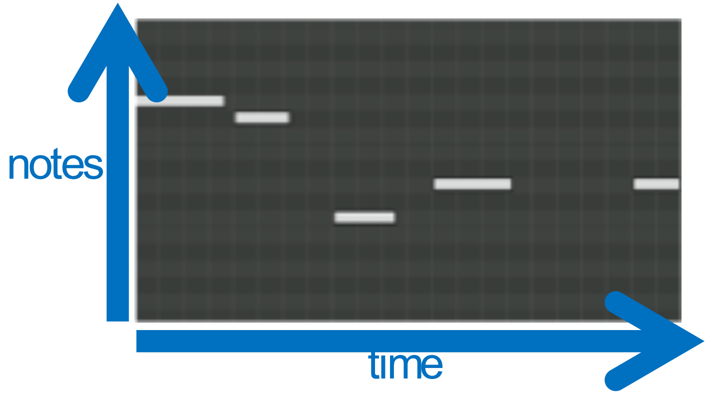
Creative Adversarial Networks (CAN) – Ex. of Paintings Generated

Table 1: Artistic Styles Used in Training

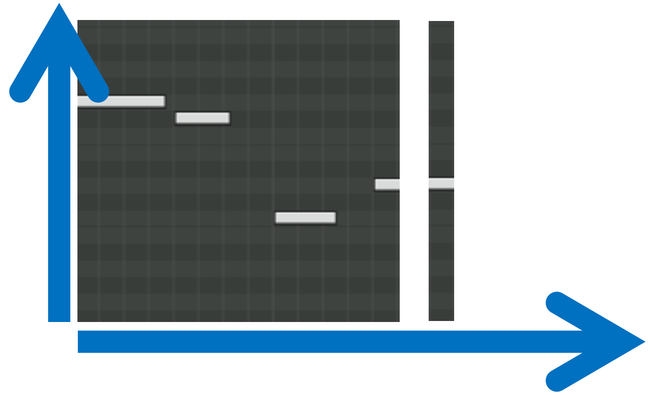
Style name	Image number	Style name	Image number
Abstract-Expressionism	2782	Mannerism-Late-Renaissance	1279
Action-Painting	98	Minimalism	
Analytical-Cubism	110	Naive Art-Primi	
Art-Nouveau-Modern	4334	New-Realism	
Baroque	4241	Northern-Renai	
Color-Field-Painting	1615	Pointillism	
Contemporary-Realism	481	Pop-Art	
Cubism	2236	Post-Impression	
Early-Renaissance	1391	Realism	
Expressionism	6736	Rococo	
Fauvism	934	Romanticism	
High-Renaissance	1343	Synthetic-Cubis	
Impressionism	13060	Total	

#7 Limitation – Incrementality

- Instantiation of Notes
  - Feedforward Models
    - » Global/One shot

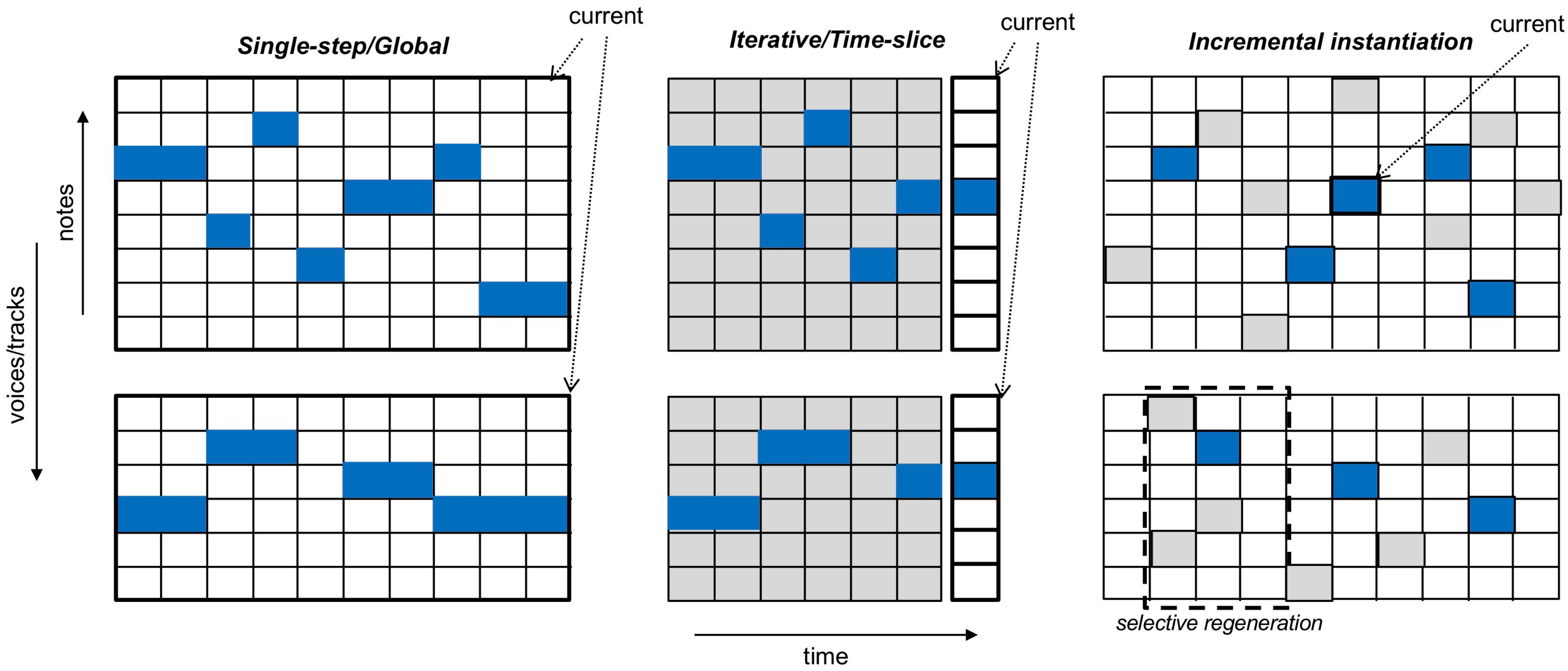


  - Recurrent Models
    - » Note by Note
    - » Following Time Steps



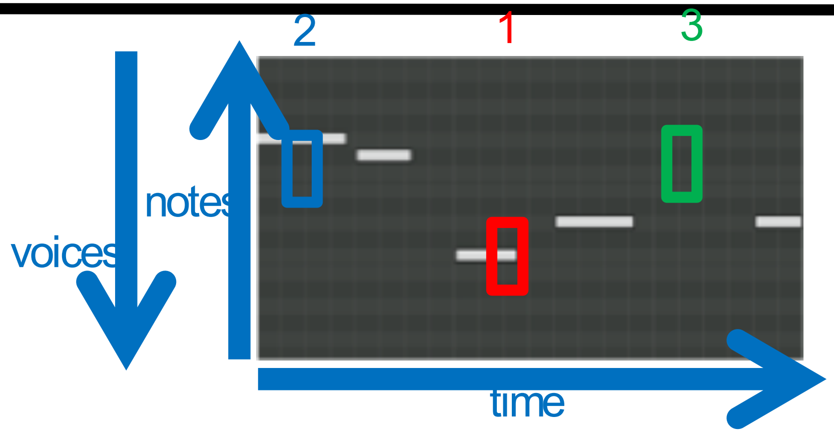
  - ?
    - » Arbitrary Part/Direction

#7 Limitation – Incrementality



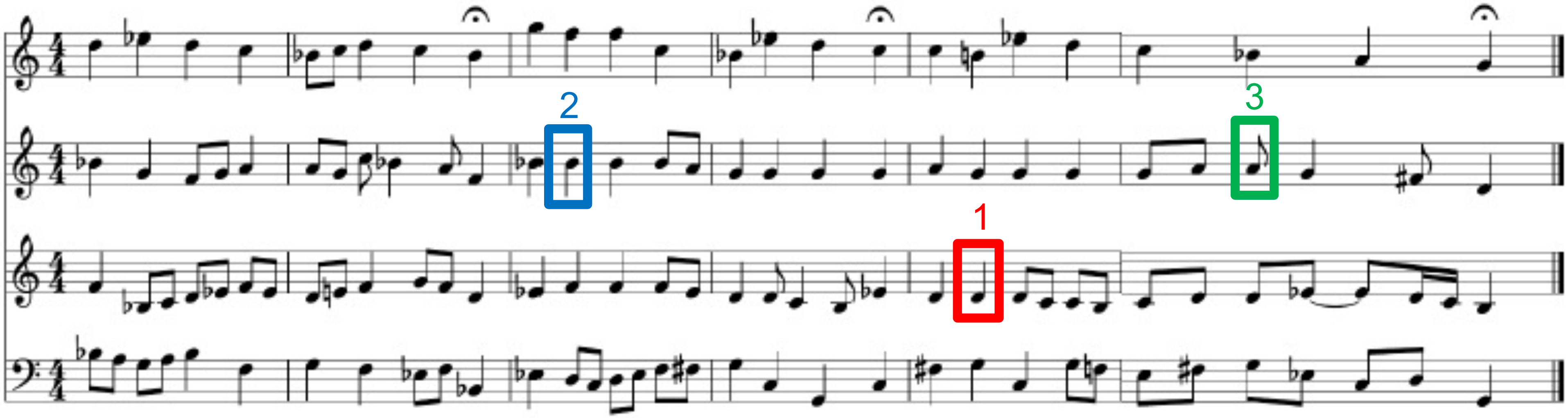
#7 Limitation – Incrementality – #1 Solution: DeepBach [Hadjeres et al., 2017]

- Incremental Sampling
  - Iterative
  - Pseudo-Gibbs Sampling
  - Iterative
  - « Random »

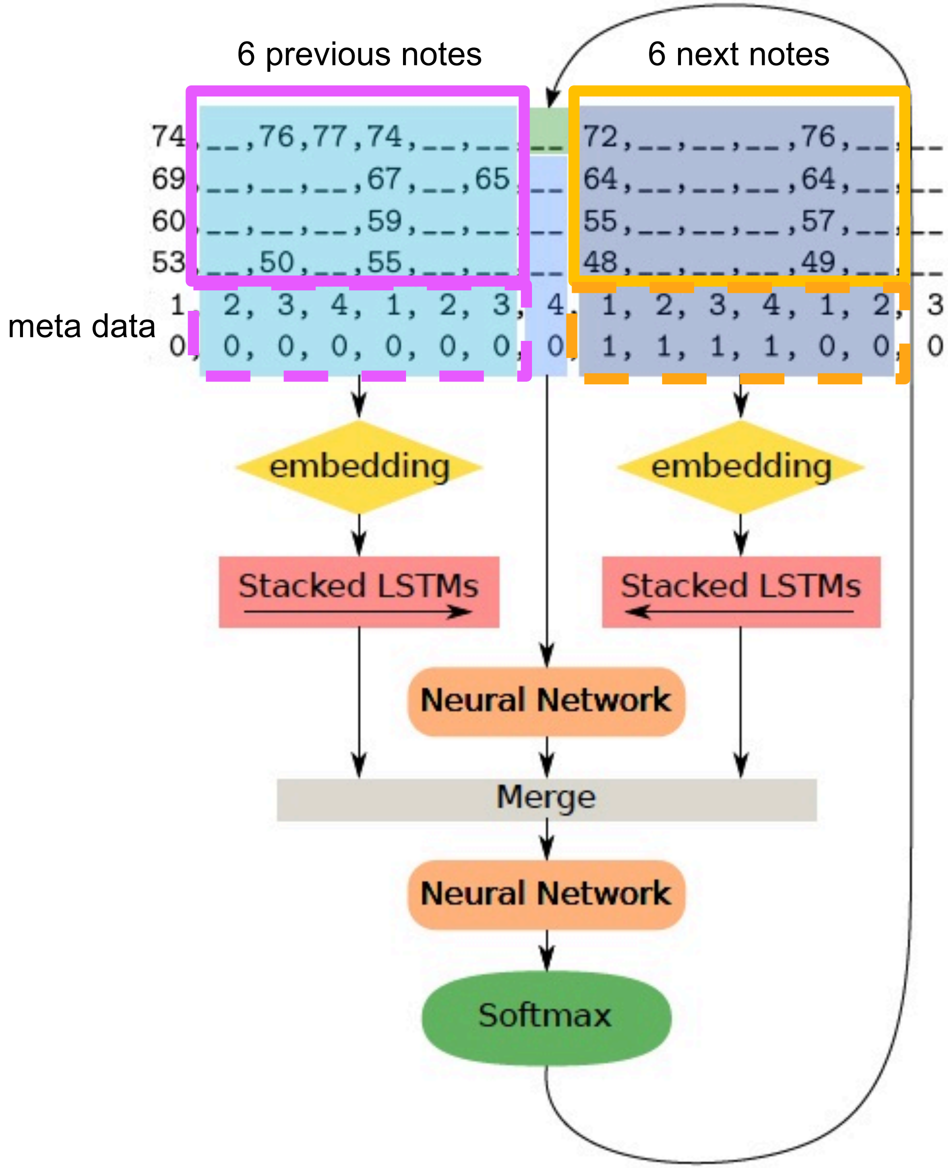


- Bach Chorales
  - 4 voices

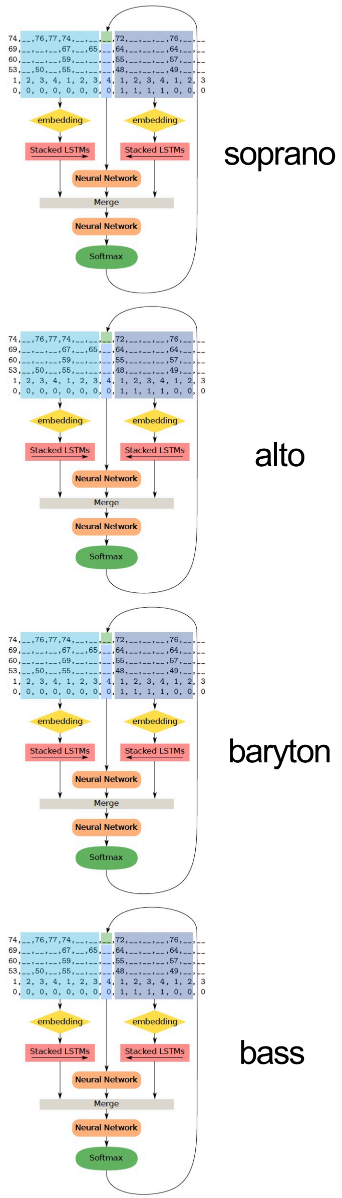
for m from 1 to M **do**
  Choose voice i uniformly between 1 and 4
  Choose time t uniformly between 1 and L
  Re-sample $\mathcal{V}_i^t$ from $p_i(\mathcal{V}_i^t | \mathcal{V}_{\setminus i,t}, \mathcal{M}, \theta_i)$



DeepBach

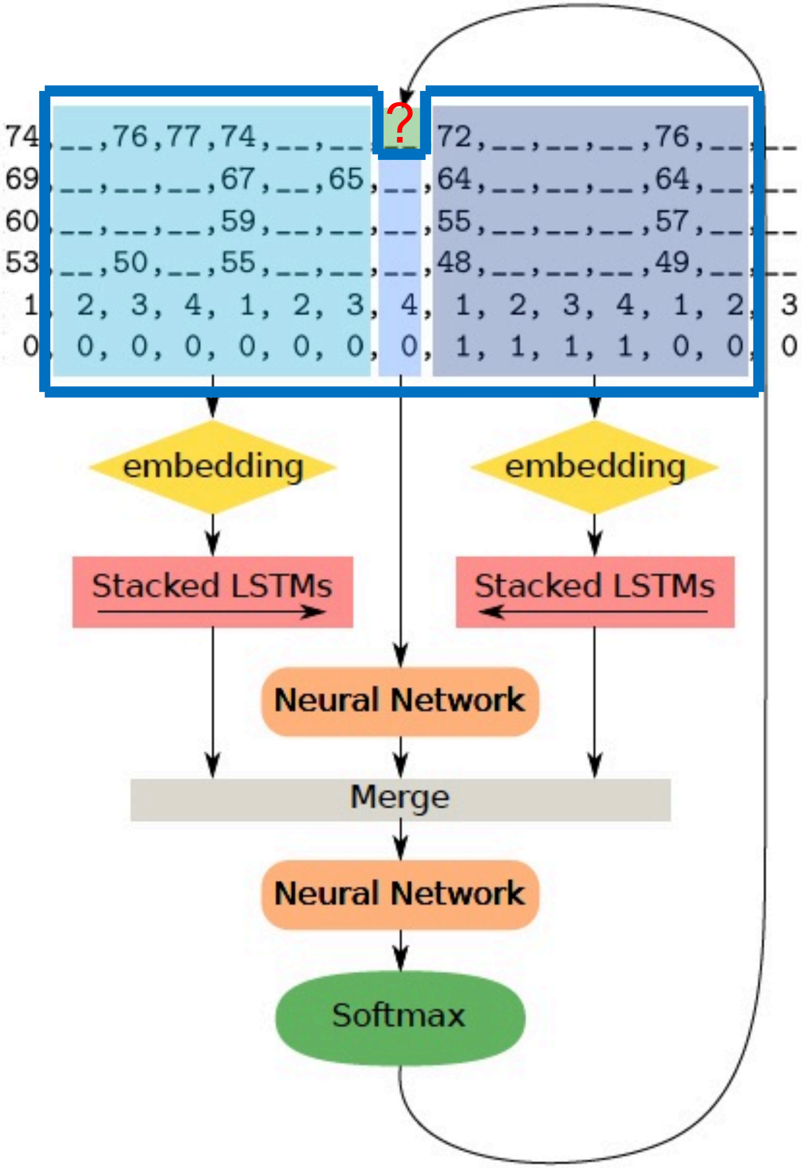


6 previous notes
6 next notes
meta data
embedding
embedding
Stacked LSTMs
Stacked LSTMs
Neural Network
Merge
Neural Network
Softmax

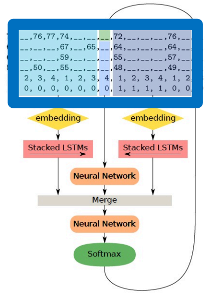


soprano
alto
baryton
bass

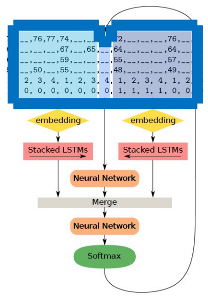
DeepBach



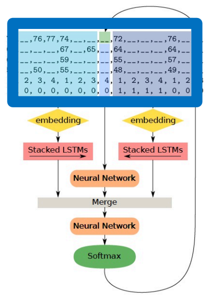
alto



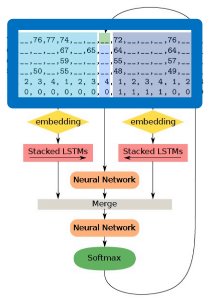
soprano



alto

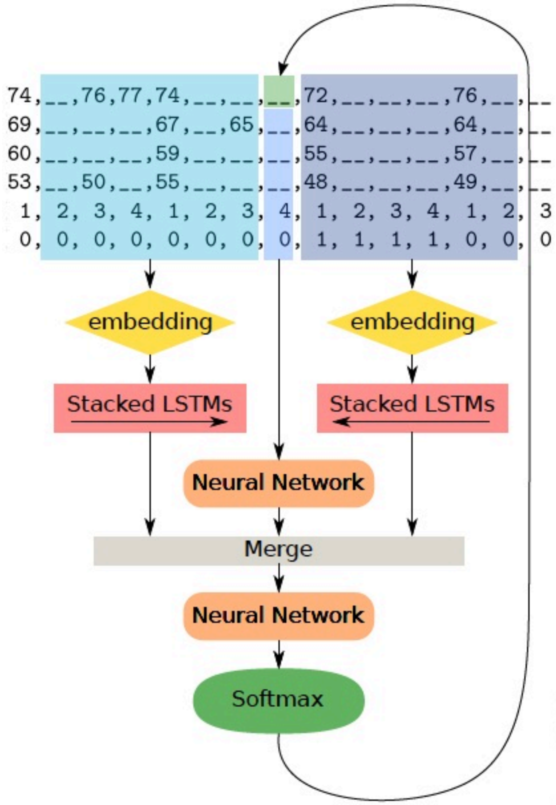


baryton

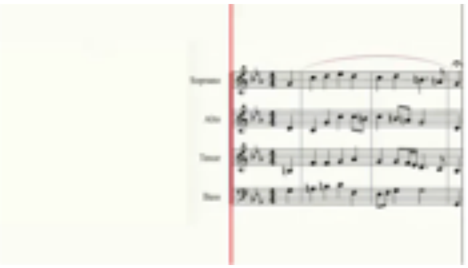


bass

DeepBach



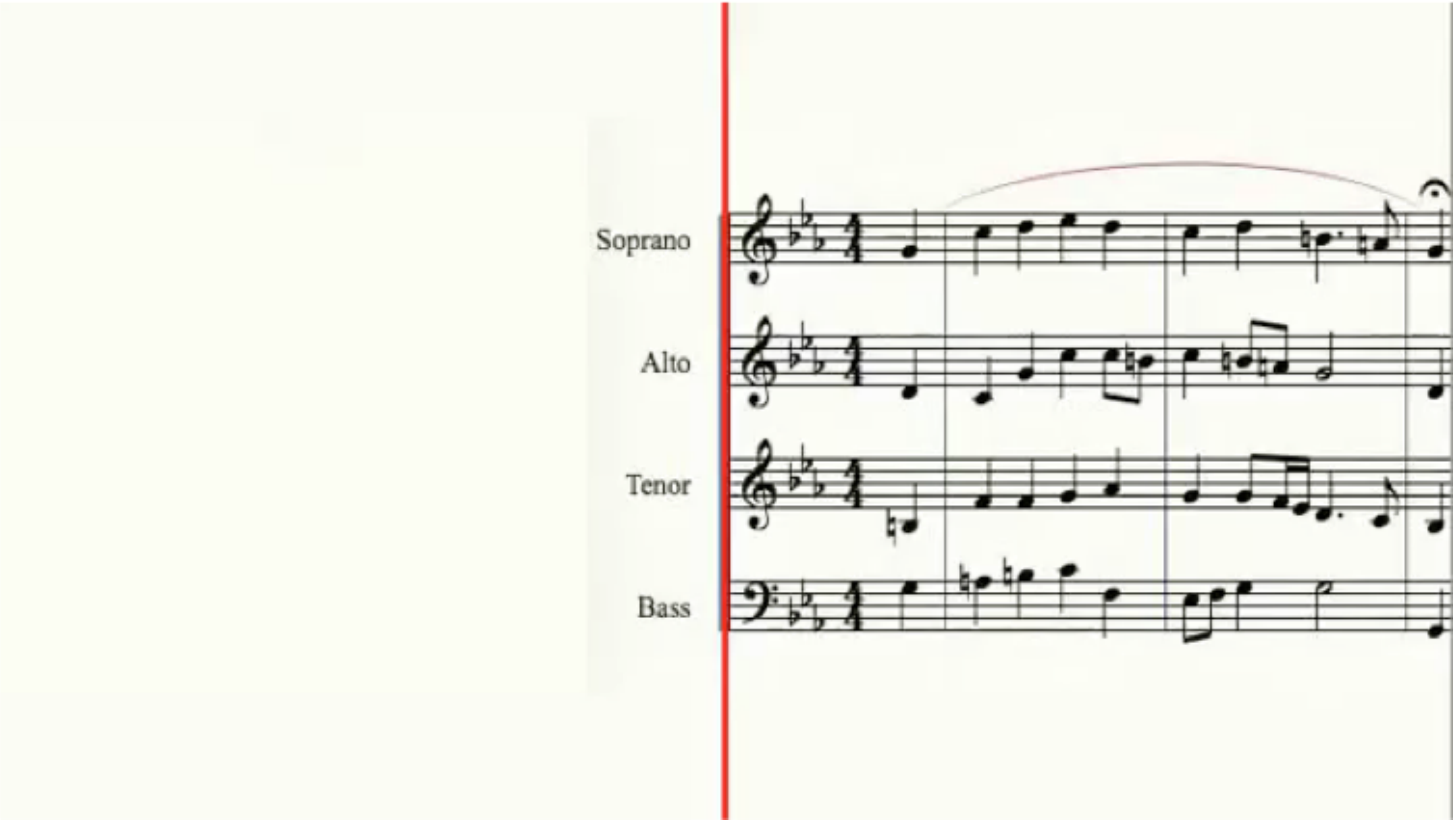
74,__,76,77,74,__,__,__,72,__,__,__,76,__,__
69,__,__,__,67,__,65,__,64,__,__,__,64,__,__
60,__,__,__,59,__,__,__,55,__,__,__,57,__,__
53,__,50,__,55,__,__,__,48,__,__,__,49,__,__
1, 2, 3, 4, 1, 2, 3, 4, 1, 2, 3
0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0
embedding
embedding
Stacked LSTMs
Stacked LSTMs
Neural Network
Merge
Neural Network
Softmax



Wer nur den lie=ben Gott läßt walten / und hof=
Der wird Ihn wunder=lich er=halten / in al=

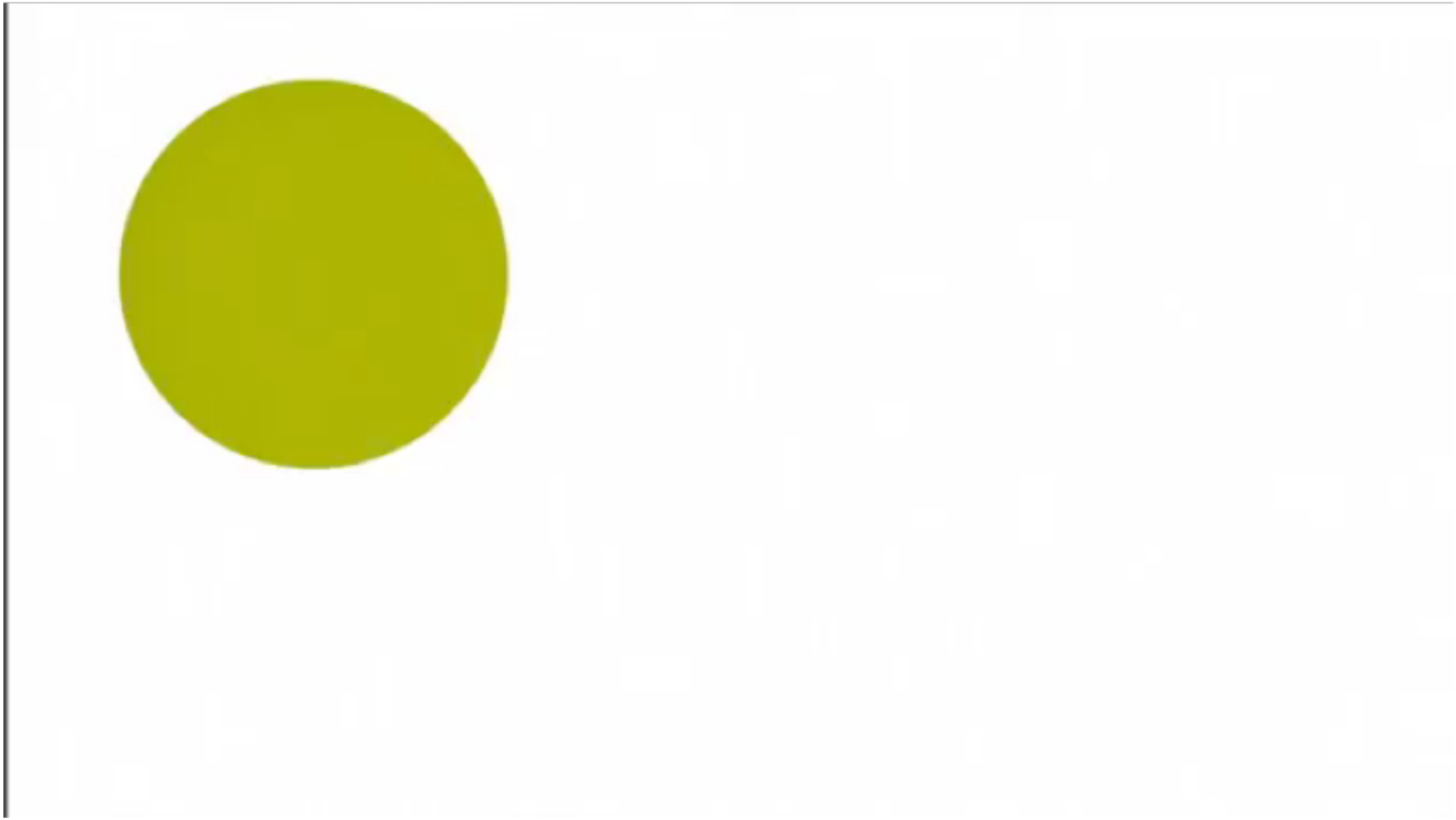
Wer nur den lie - ben Gott lässt wal - ten und hof-fet auf ihn al - le - zeit,
den wird er wun-der-bar er - hal - ten in al-lem Kreuz und Trau-rig - keit.

DeepBach – Demo



https://www.youtube.com/watch?v=QiBM7-5hA6o

Turing Bach Test



https://www.youtube.com/watch?v=DPNHbtiXGEM

#8 Limitation – Interactivity – #1 Solution: DeepBach [Hadjeres et al., 2017]

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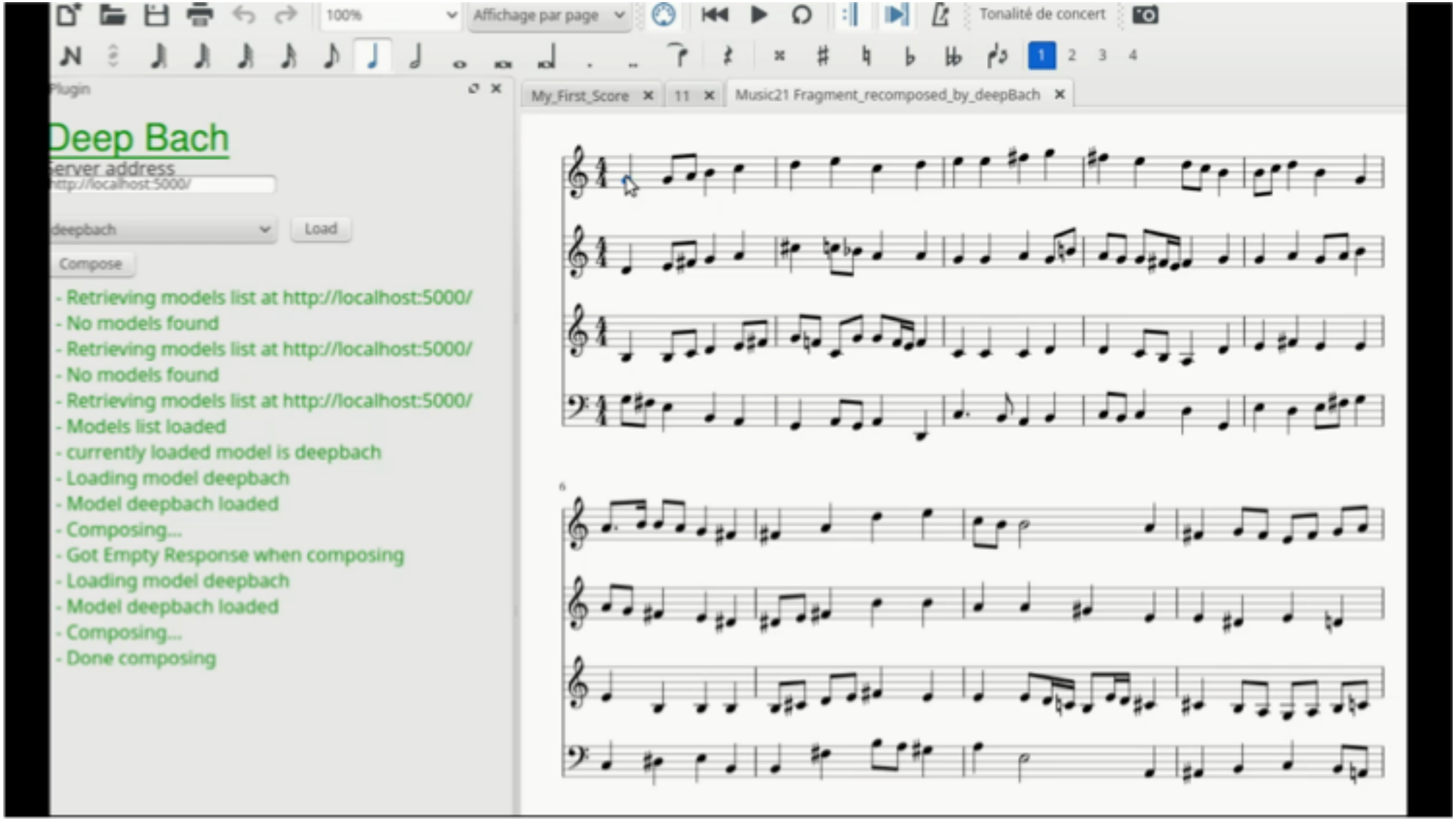


https://www.youtube.com/watch?time_continue=28&v=OkkKjy3WRNo

#8 Limitation – Interactivity – #2 Solution: Flow Composer [Papadopoulos et al., 2016]

Fully Autonomous Automated Generator

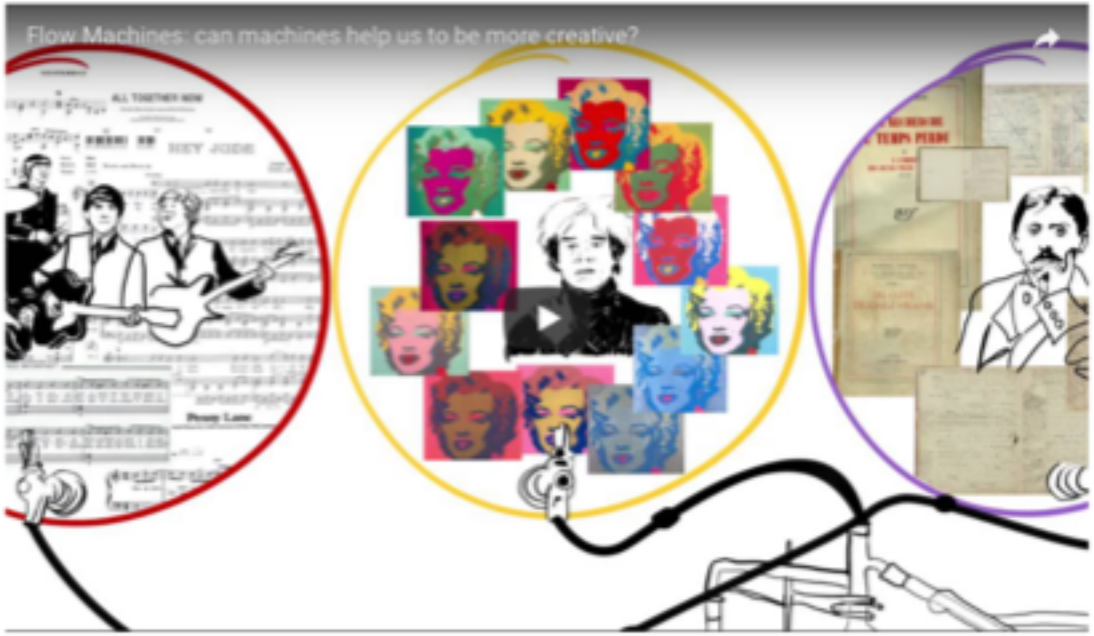
vs Assistant for Human Artists (Composers, Arrangers, Instrumentists…)

Flow Machines Project [Pachet et al., 2012]

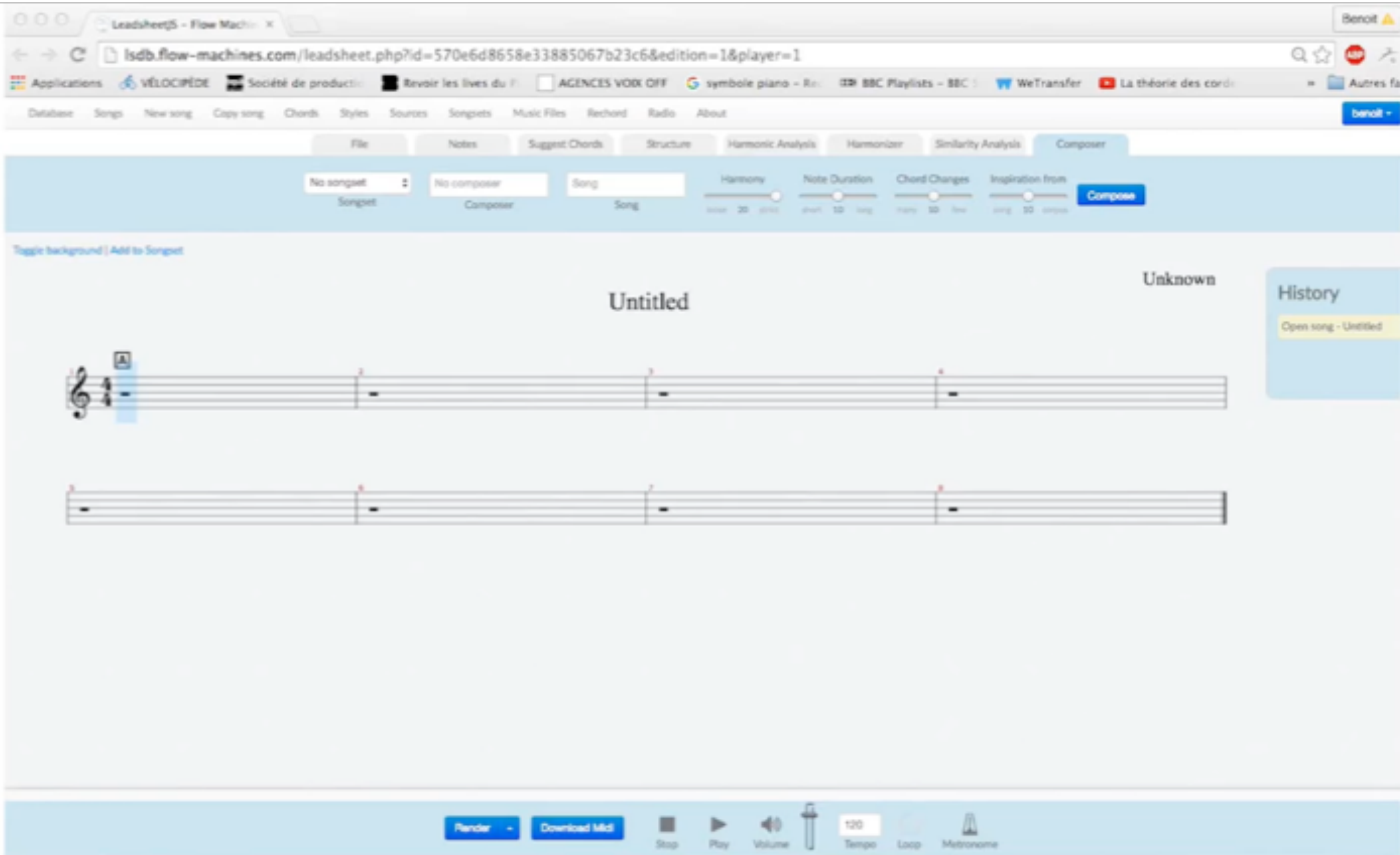
Flow Machines are cutting-edge algorithms, made to explore new ways to create.

Flow Machines collaborate with musicians to compose the future.

Flow Machines are AI music-making.



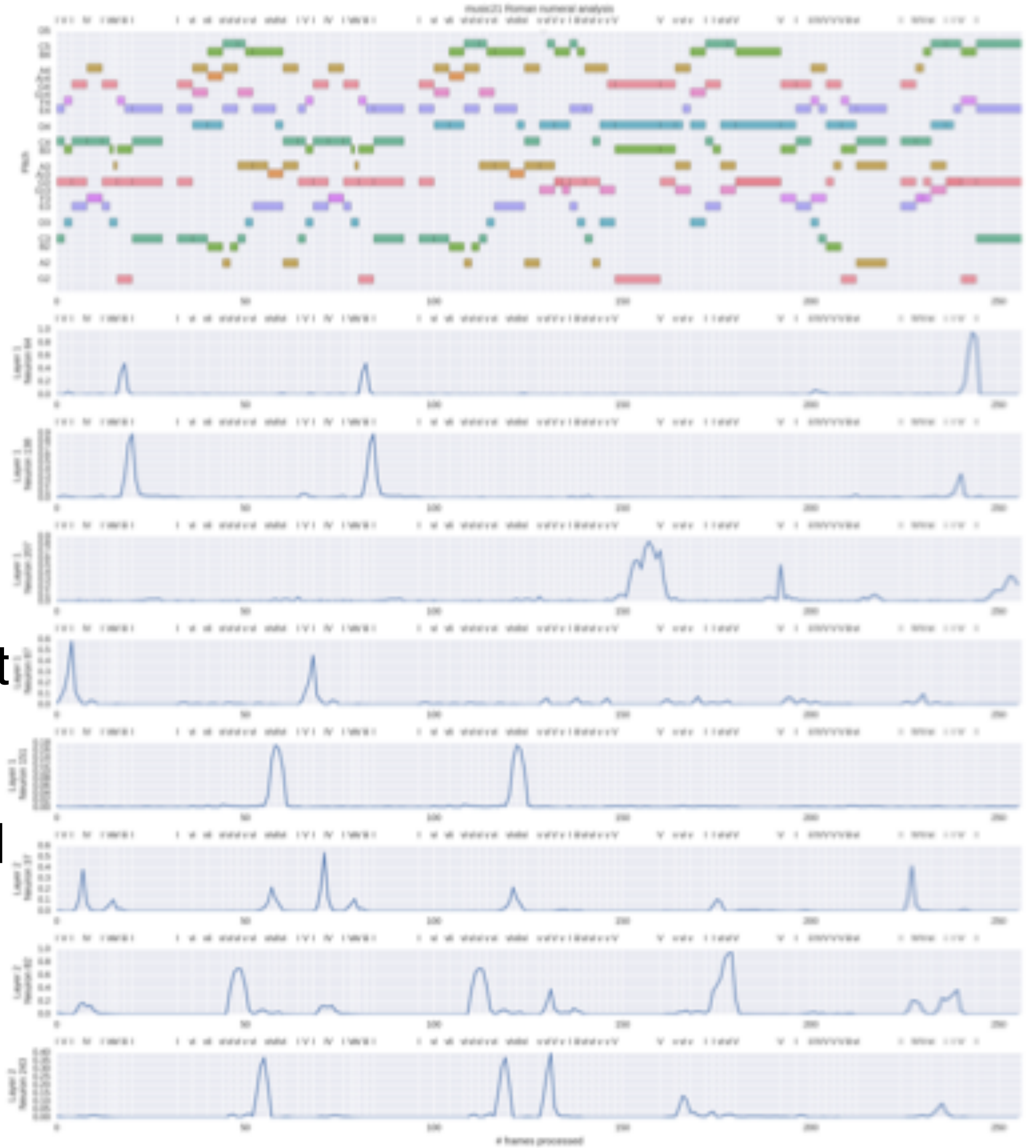
FlowComposer – Demo



https://www.youtube.com/watch?time_continue=5&v=SDnkX8v8caY

#9 Limitation – Explainability
– #1 Partial Solution: BachBot [Liang, 2016]

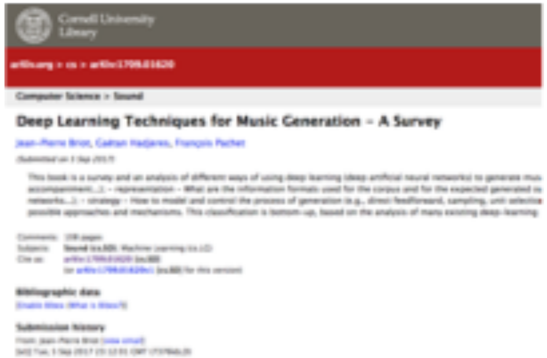
- Ex: BachBot correlation analysis [Liang, 2016]



- The first two (Layer 1/Neuron 64 and Layer 1/Neuron 138) seem to pick out (specifically) perfect cadence with root position chords in the the tonic key
- There are no imperfect cadences here; just one interruption into bar 14
- Layer 1/Neuron 87: the I6 chords on the first downbeat and its reprise 4 bars later
- Layer 1/Neuron 151: the two equivalent a minor (originally b minor) cadences that end phrases 2 and 4
- Layer 2/Neuron 37: Seems to be looking for I6 chords: strong peak for a full I6; weaker for other similar chords (same bass)

References

J.-P. Briot, G. Hadjeres, F. Pachet, Deep Learning Techniques for Music Generation – A Survey, ArXiv:1709.01620, September 2017.

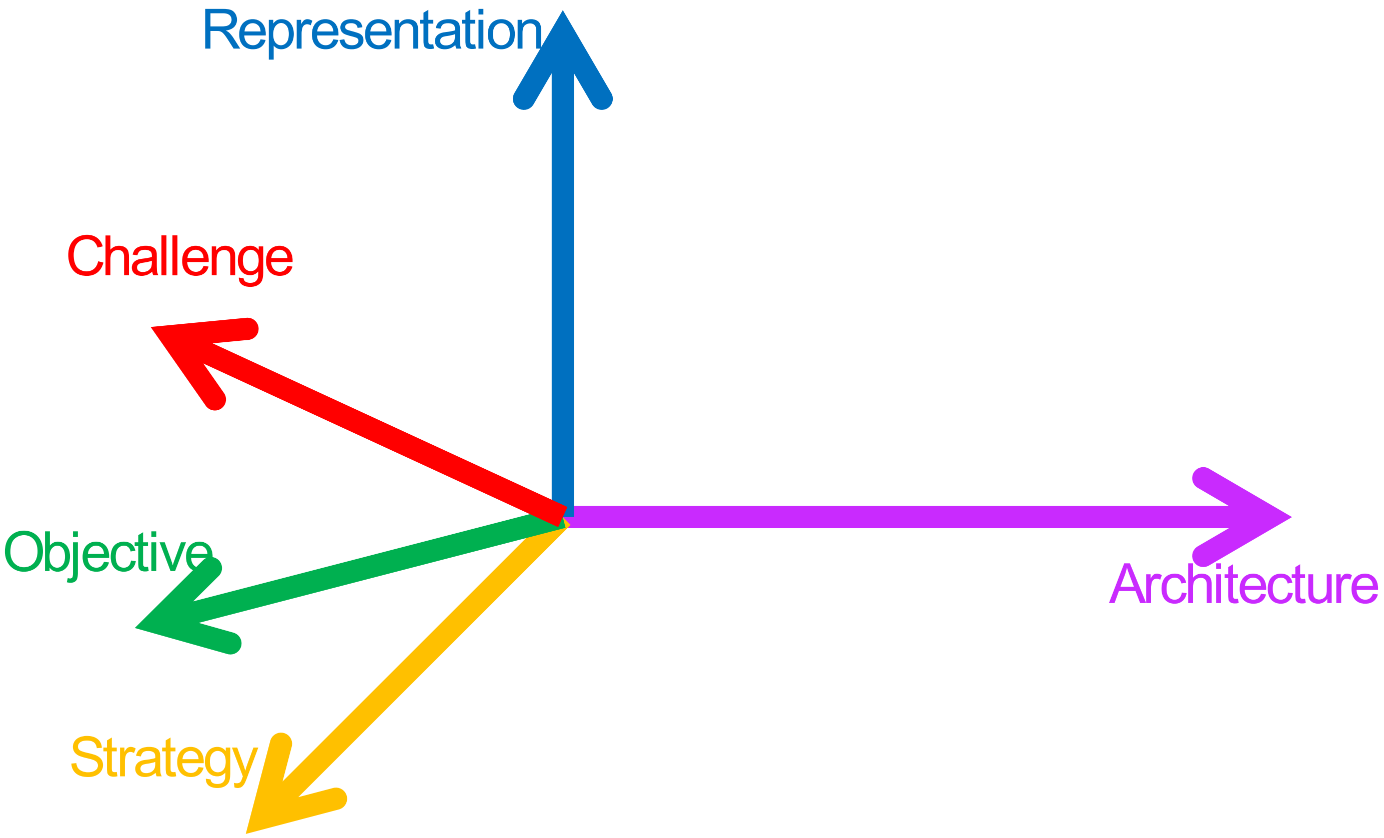


J.-P. Briot, G. Hadjeres, F. Pachet, Deep Learning Techniques for Music Generation, Computational Synthesis and Creative Systems Series, Springer Nature, 2019.

J.-P. Briot, F. Pachet, Music Generation by Deep Learning – Challenges and Directions, Neural Computing and Applications (NCAA), Special Issue on Deep Learning for Music and Audio, October 2018.

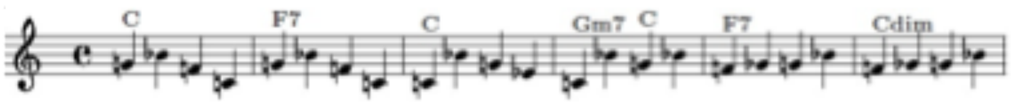
Survey/Analysis

4+1 dimensions



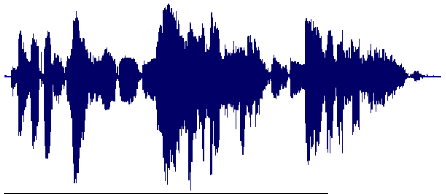
Objective

- Melody
  - Monodic
  - Polyphonic
- Polyphony (Multiple Voices/Tracks)
- Accompaniment
  - Counterpoint
    - » Melody
    - » Melodies (Chorale)
  - Chords
- Melody + Harmony/Chords
- Leadsheet

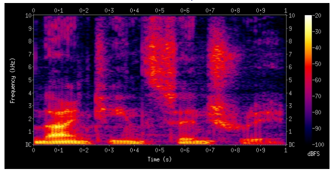


Representation

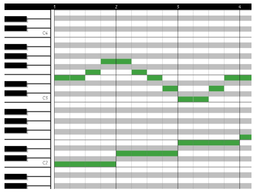
- Signal
  - Waveform



  - Spectrum



- Symbolic
  - MIDI
  - Piano roll



  - Text

```
|:eA (3AAA g2 fg|eA (3AAA BGGf|eA (3AAA g2 fg|1afge d2 gf:|2afge d2 cd||
|:eaag efgf|eaag edBd|eaag efge|afge dgfg:|
```

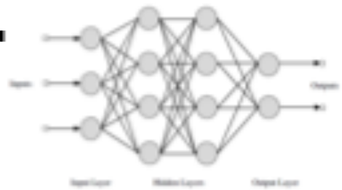
  - Chord

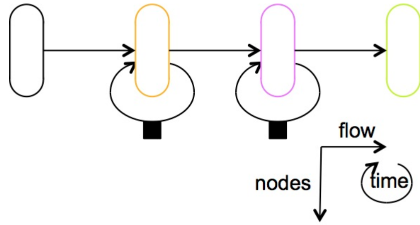
EbMaj7/G

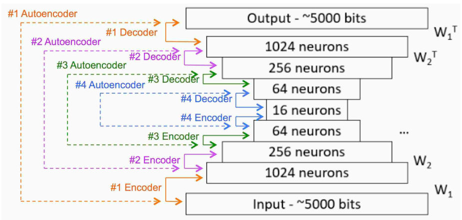
  - Lead sheet
  - Rhythm

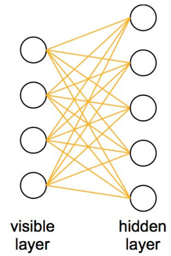
Architecture

- Feedforward
- Recurrent (RNN)
  - Long Short-Term Memory (LSTM)
- Autoencoder
  - Stacked Autoencoders
- Restricted Boltzmann Machine (RBM)
- Variational Autoencoder (VAE)

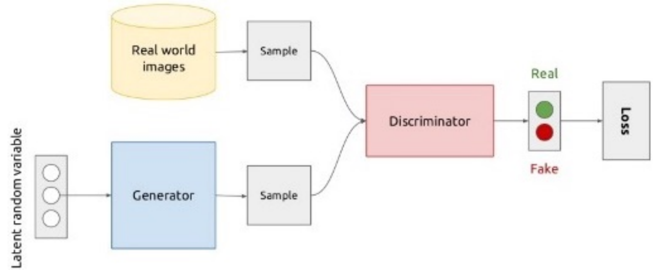




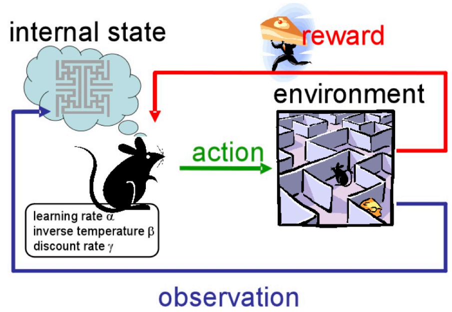




- Patterns
  - Convolutional
  - Conditioning
  - Generative Adversarial Networks (GAN)



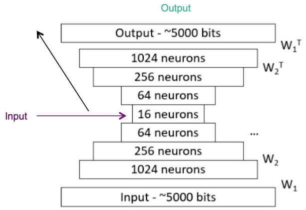
- Reinforcement Learning



- Compound
  - RNN Encoder-Decoder
  - …

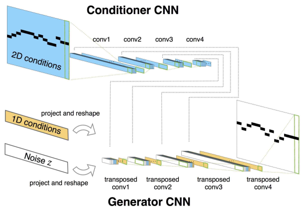
Strategy

- Feedforward
  - Single-Step Feedforward
  - Iterative Feedforward
  - Decoder Feedforward



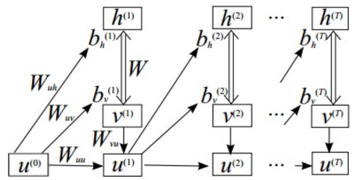
[Sun, 2016]

- Conditioning



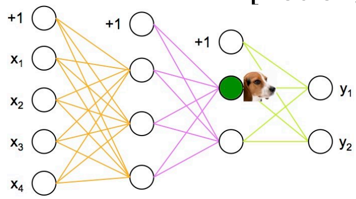
[Yang et al., 2017]

- Sampling

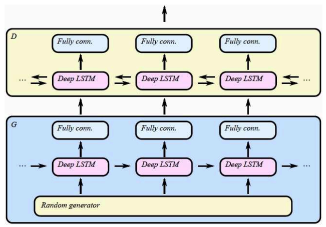


[Boulanger-Lewandowski et al., 2012]

- Input Manipulation

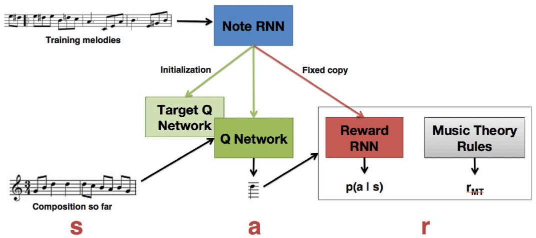


- Adversarial



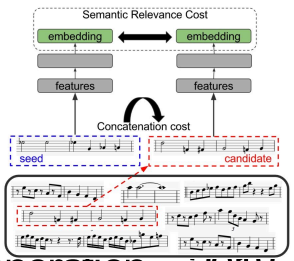
[Mogren, 2016]

- Reinforcement



[Jaques et al., 2016]

- Unit Selection



[Bretan et al., 2016]

Acknowledgements

- Gaëtan Hadjeres
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- CNRS
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- ERC Flow Machines
- Sony CSL-Paris
- Spotify CTRL
- PUC-Rio
- CAPES
- UNIRIO

Thank You – Questions