Deep Learning Techniques for Music Generation
Control (8)

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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

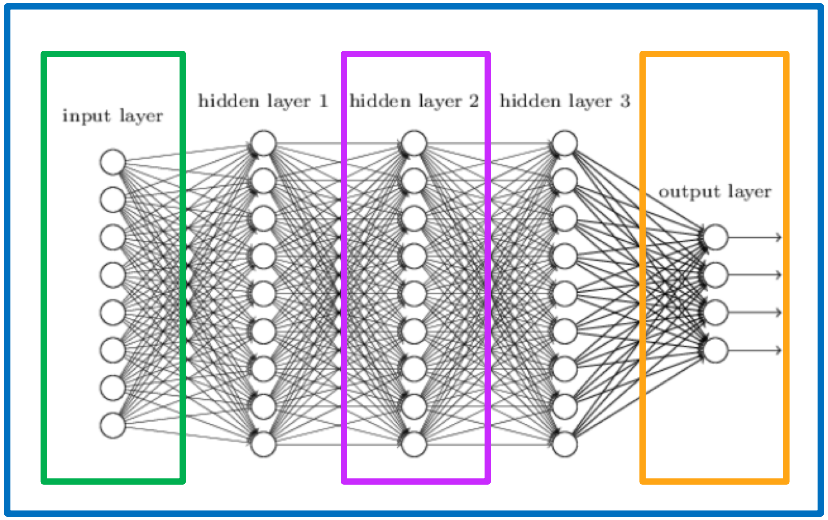
- No Control on Generation
  - Tonality Conformance
  - Ending with the same note at the first one
  - Avoiding too many repetitions of the same note
  - Not too many notes
  - etc.

4 Limitation – Control

- Indirect 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
  - Hidden
  - Output
  - Encapsulation/Reformulation

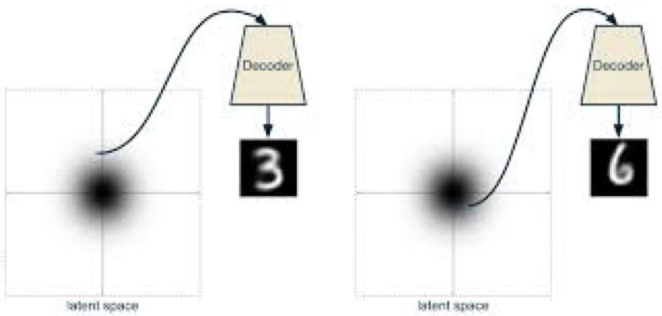


#4 Limitation – Control – #1 Solution: Sampling

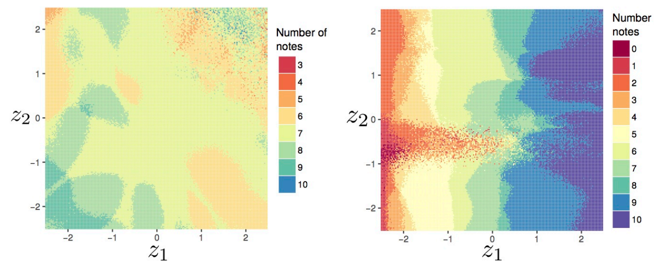
- Sampling Control
  - Content Variability
    - » Threshold (to avoid notes too unlikely)

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

  - Variational Autoencoder

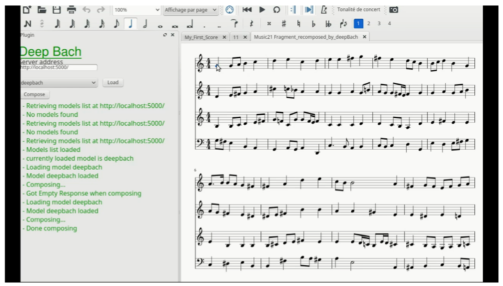


  - Geodesic Latent Space Regularization [Hadjeres & Nielsen, 2017]



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

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

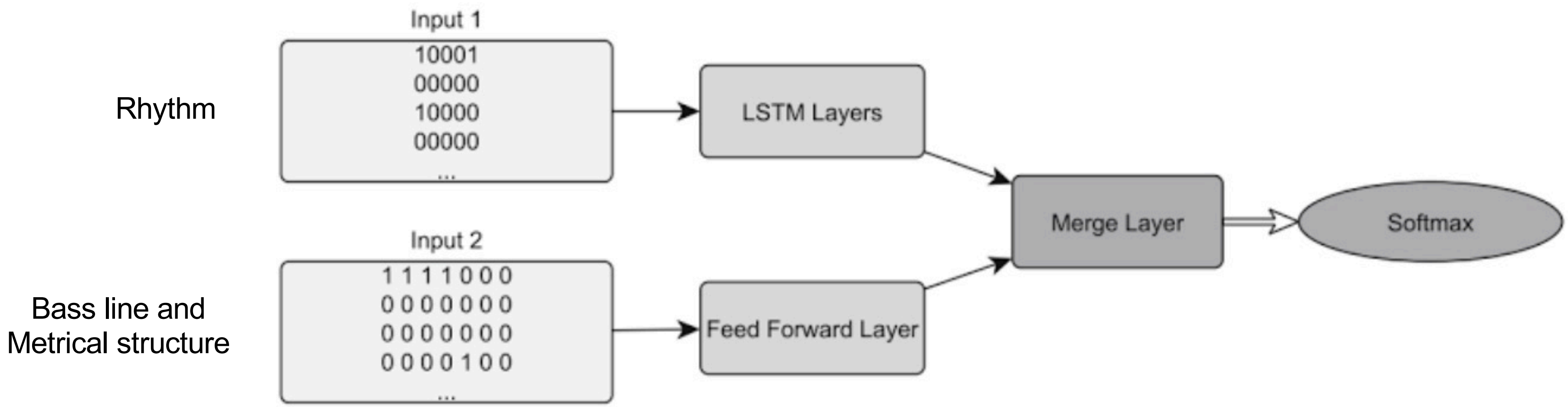


#4 Limitation – Control – #2 Solution: Conditioning

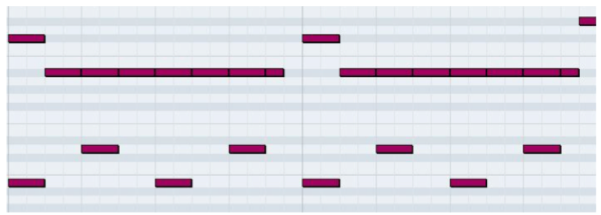
- Condition the architecture on some information
- To control/parameterize the architecture and the generation
- Ex:
  - Bass line
  - Beat structure
  - Chord progression
  - Previously generated note
  - Positional constraints on notes
  - Musical genre or style
  - Instrument

#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



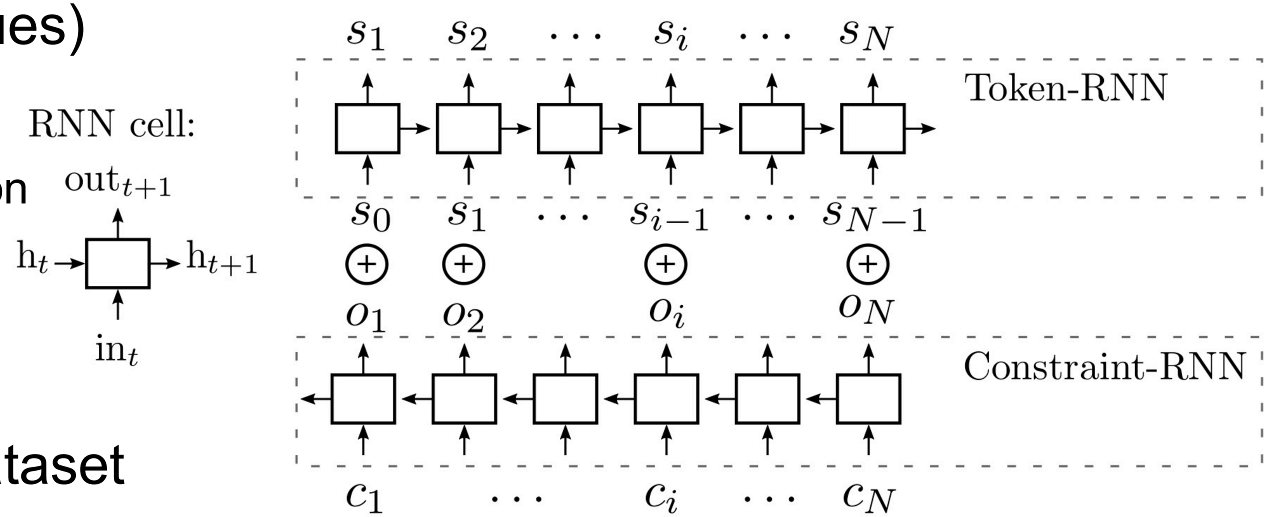
- Pop music dataset
- Example of generation



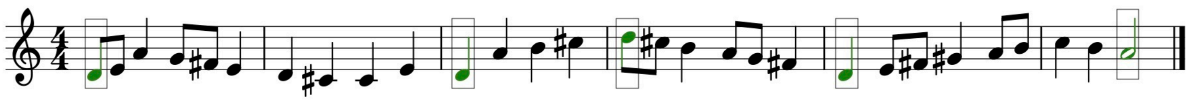
- Example of generation
- with a complex bass line conditioning

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

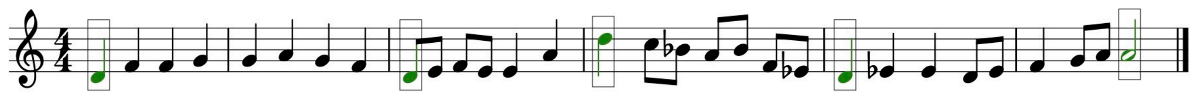
- Generates Melodies
- Recurrent architecture – Iterative feedforward generation
- Positional Constraints (Note values)
- Backward Constraint-RNN
  - Summarizes $\text{constraints}_{[i,N]}$ information
  - Used as Conditioning input_{i-1}



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

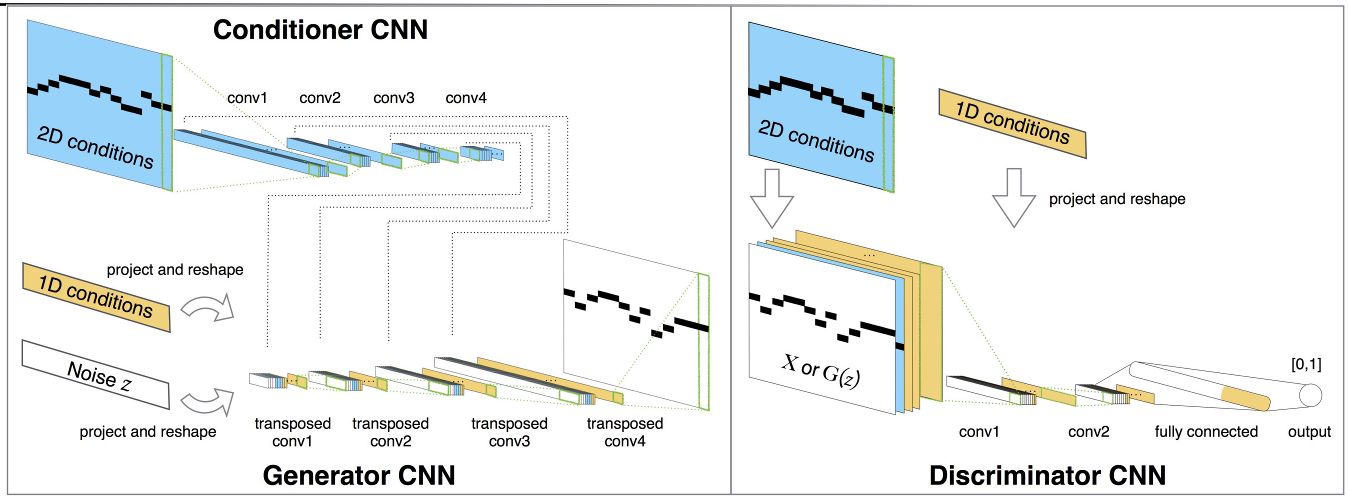

(a)


(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)

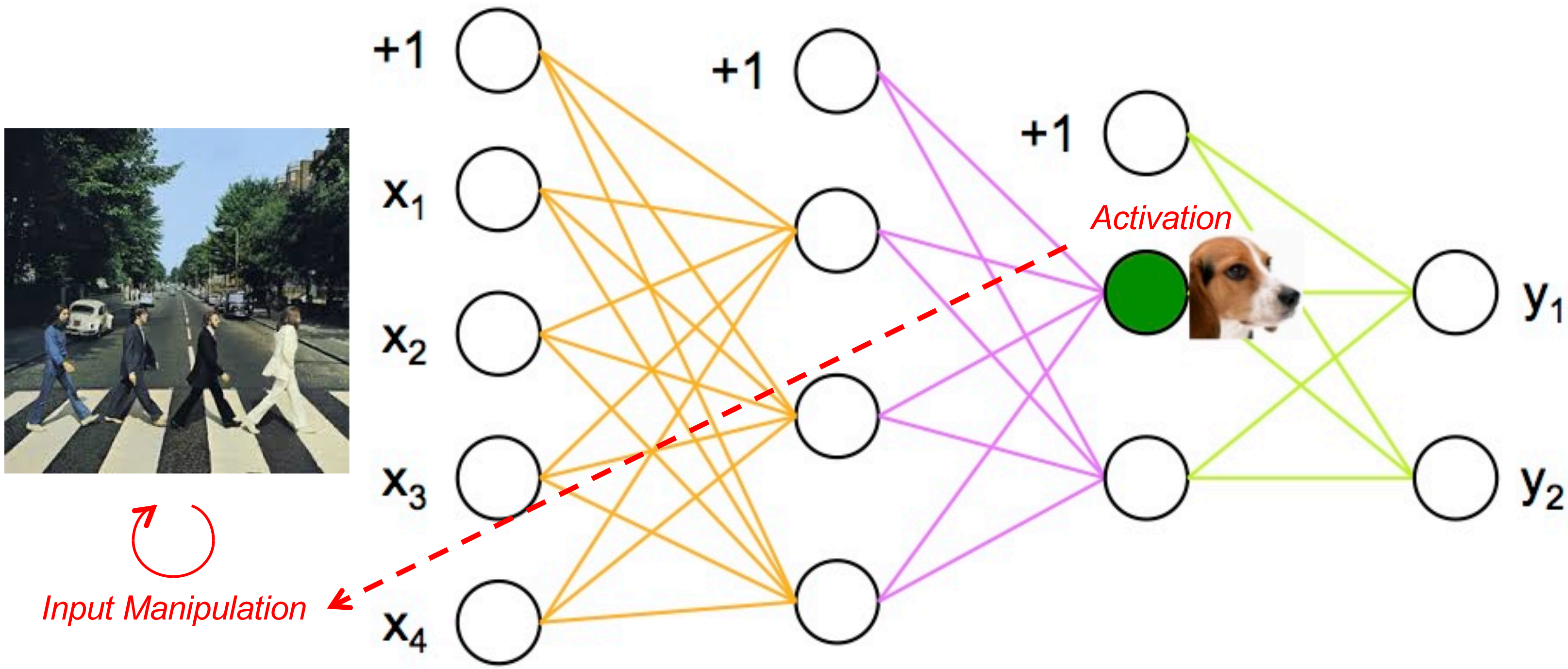
- Fine control:
  - Conditioning on previous measure 1D/2D and on chord sequence 1D/2D for one/all convolutional layers
  - Ex: previous measure 1D and on chord sequence 2D for all convolutional layers
    - » Follows more chord sequence

  - 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]



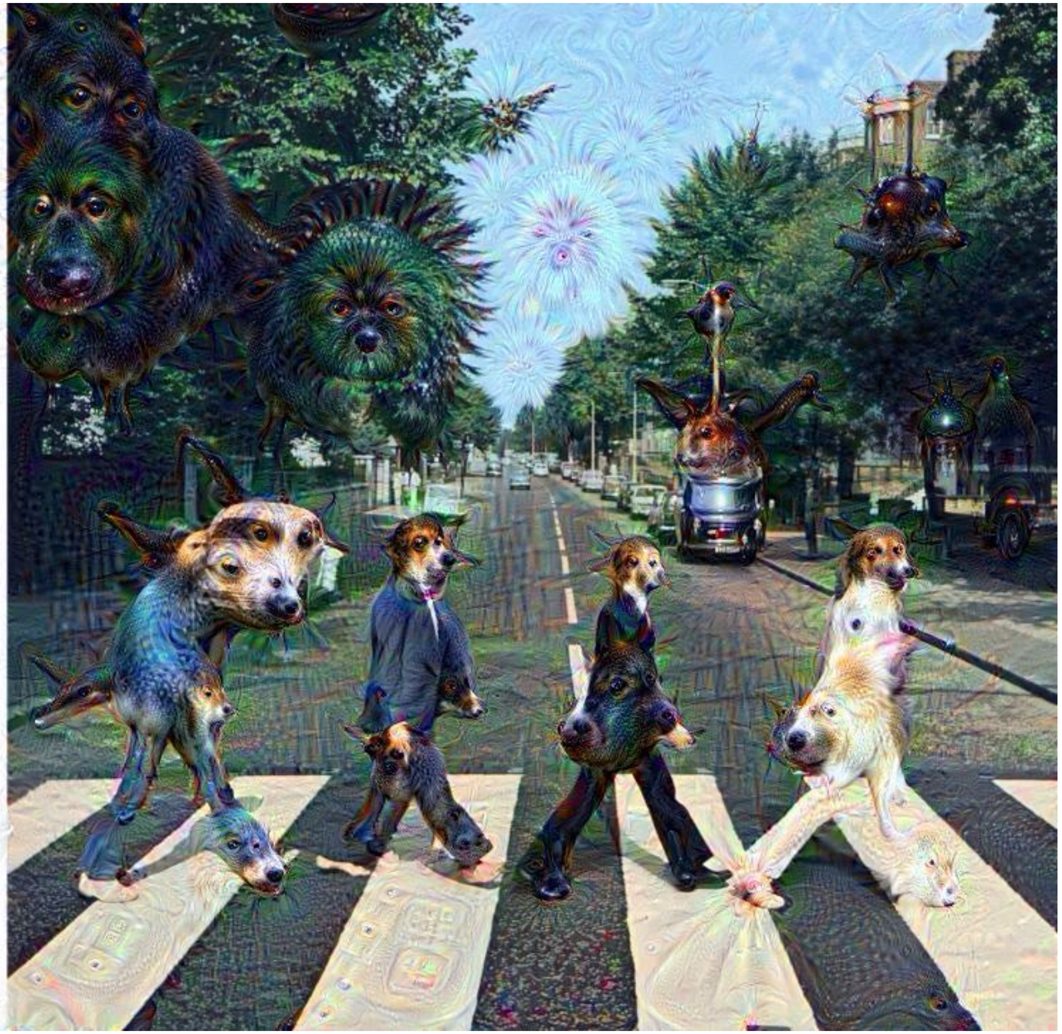
- Network is (or has been) trained on a large images dataset
- The objective is ~~to minimize the cost~~ to maximize the activation of a specific unit (neuron) which activates for a specific pattern(s), ex. a dog face

- 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

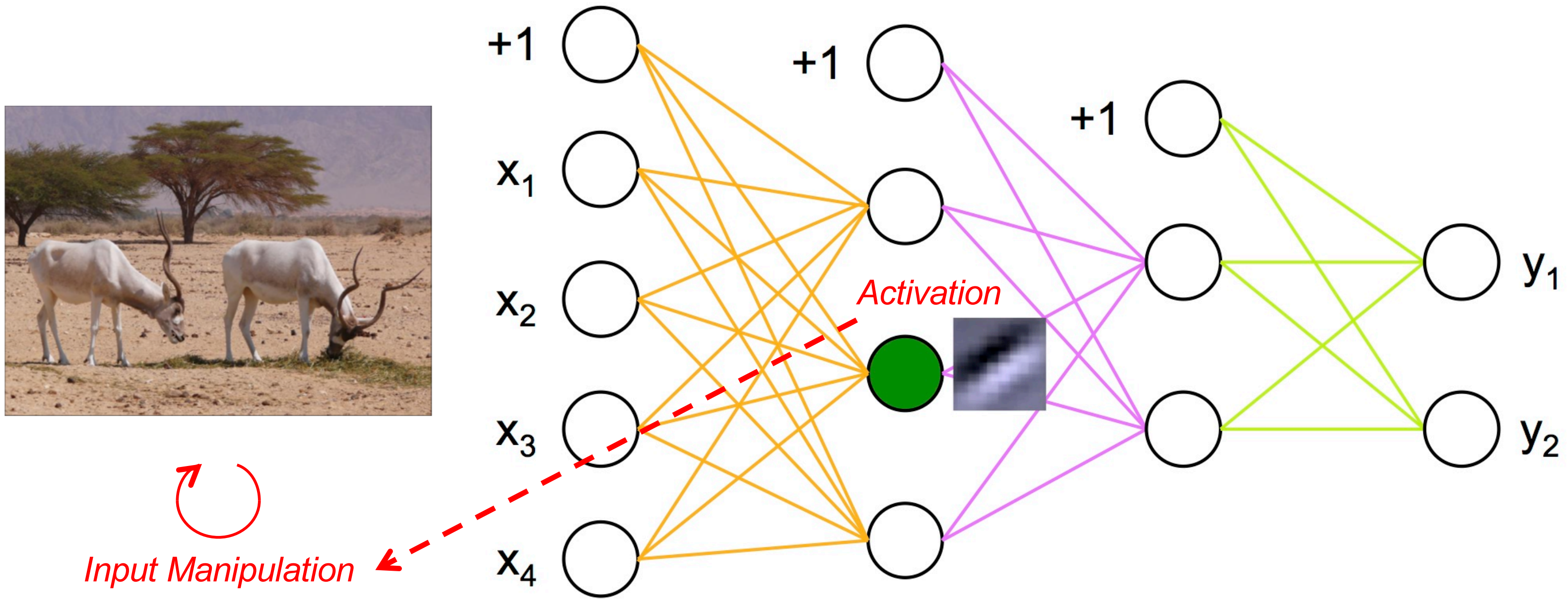
Deep Dream

Initial Image

Deep Dream Image

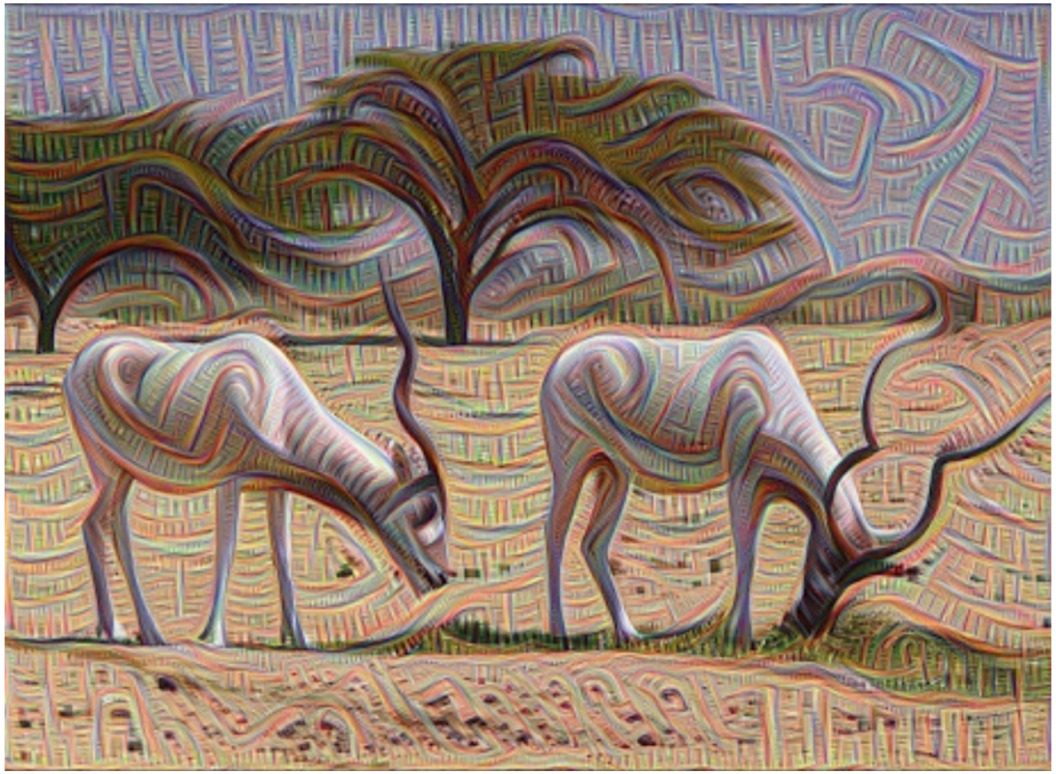


Deep Dream



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

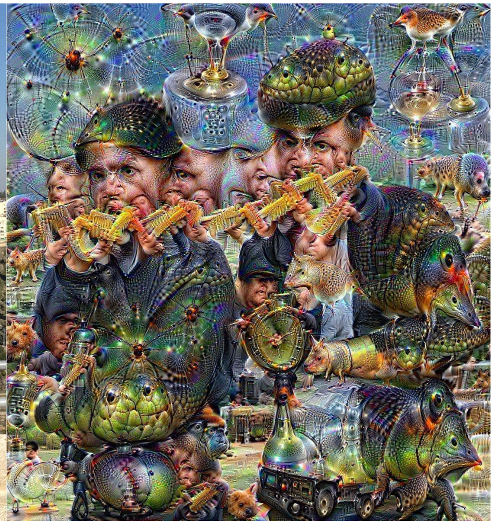
Deep Dream

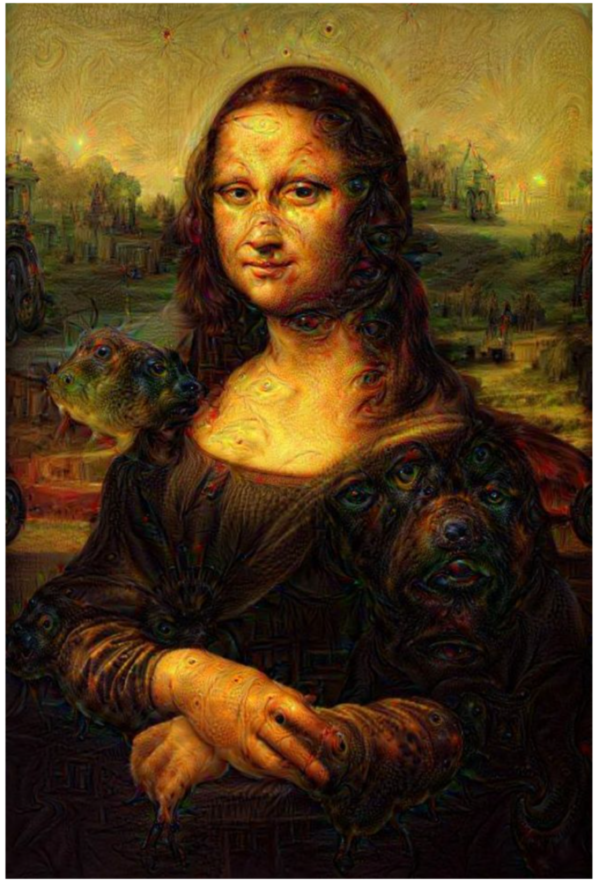


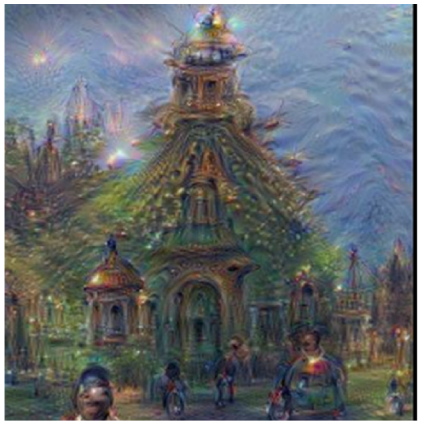
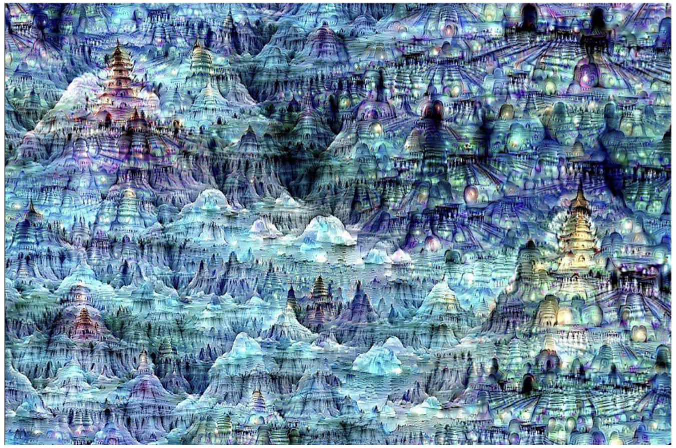
Lower Layer Unit Maximization Resulting image

Deep Dream

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



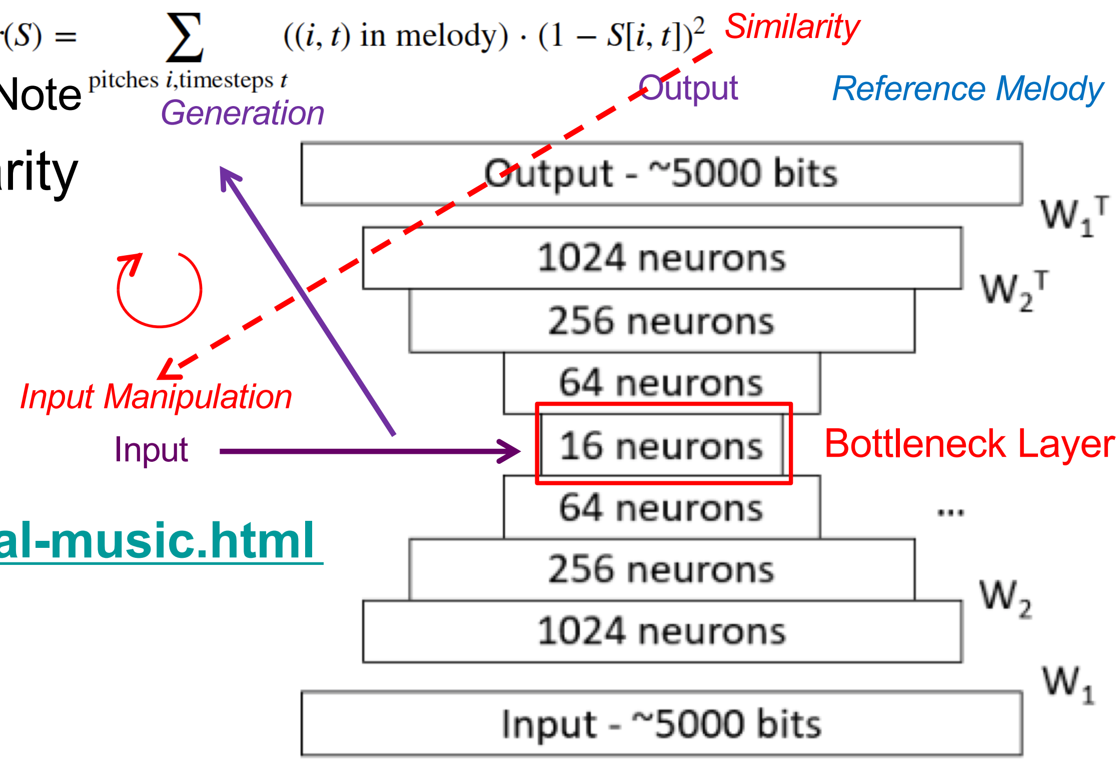



DeepHear [Sun, 2016]

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 $err(S) = \sum_{\text{pitches } i, \text{timesteps } t} ((i,t) \text{ in melody}) \cdot (1 - S[i,t])^2$

  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]

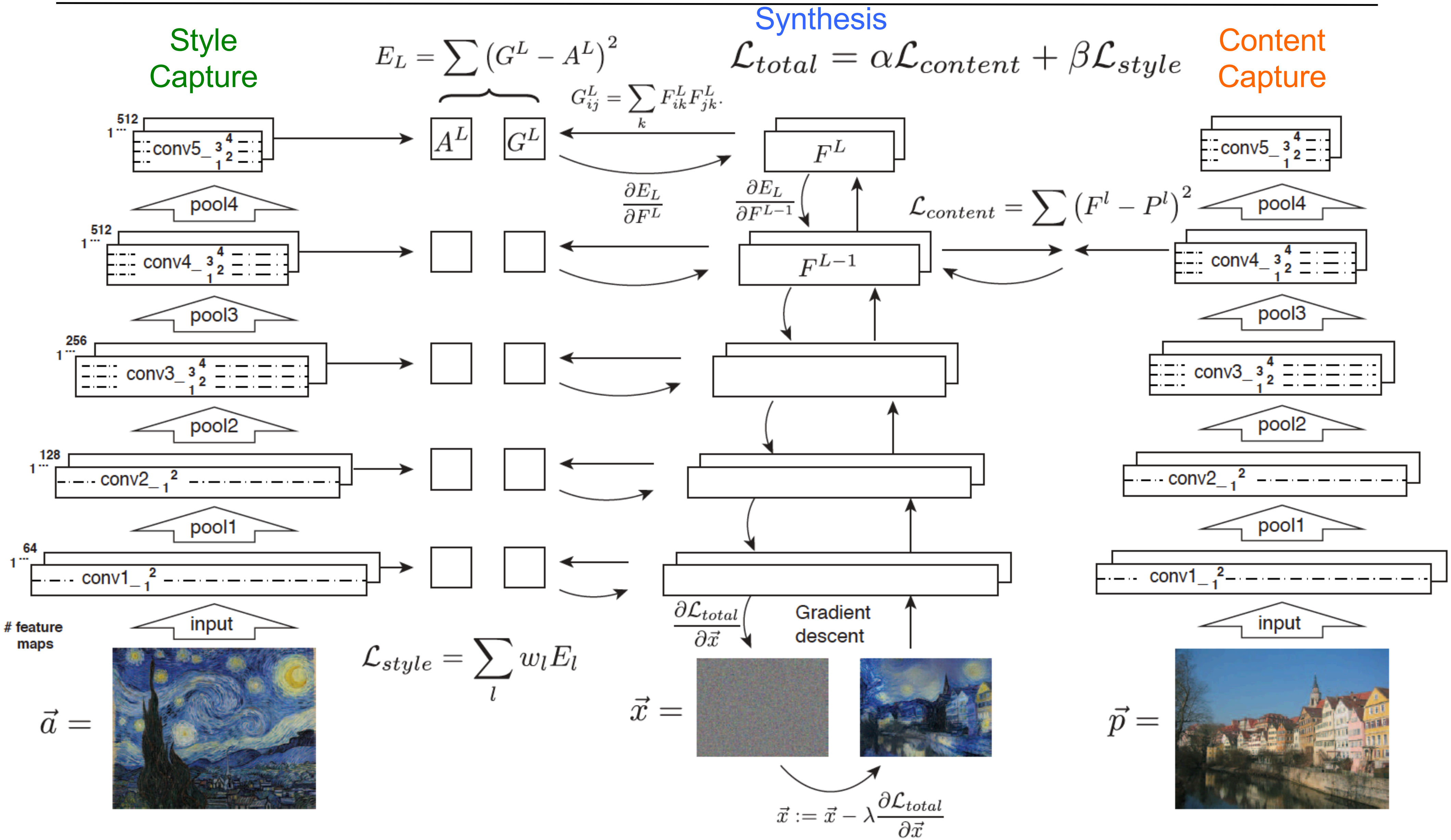
1. Train Network with Images
2. Content Capture of 1st (Content) Image

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

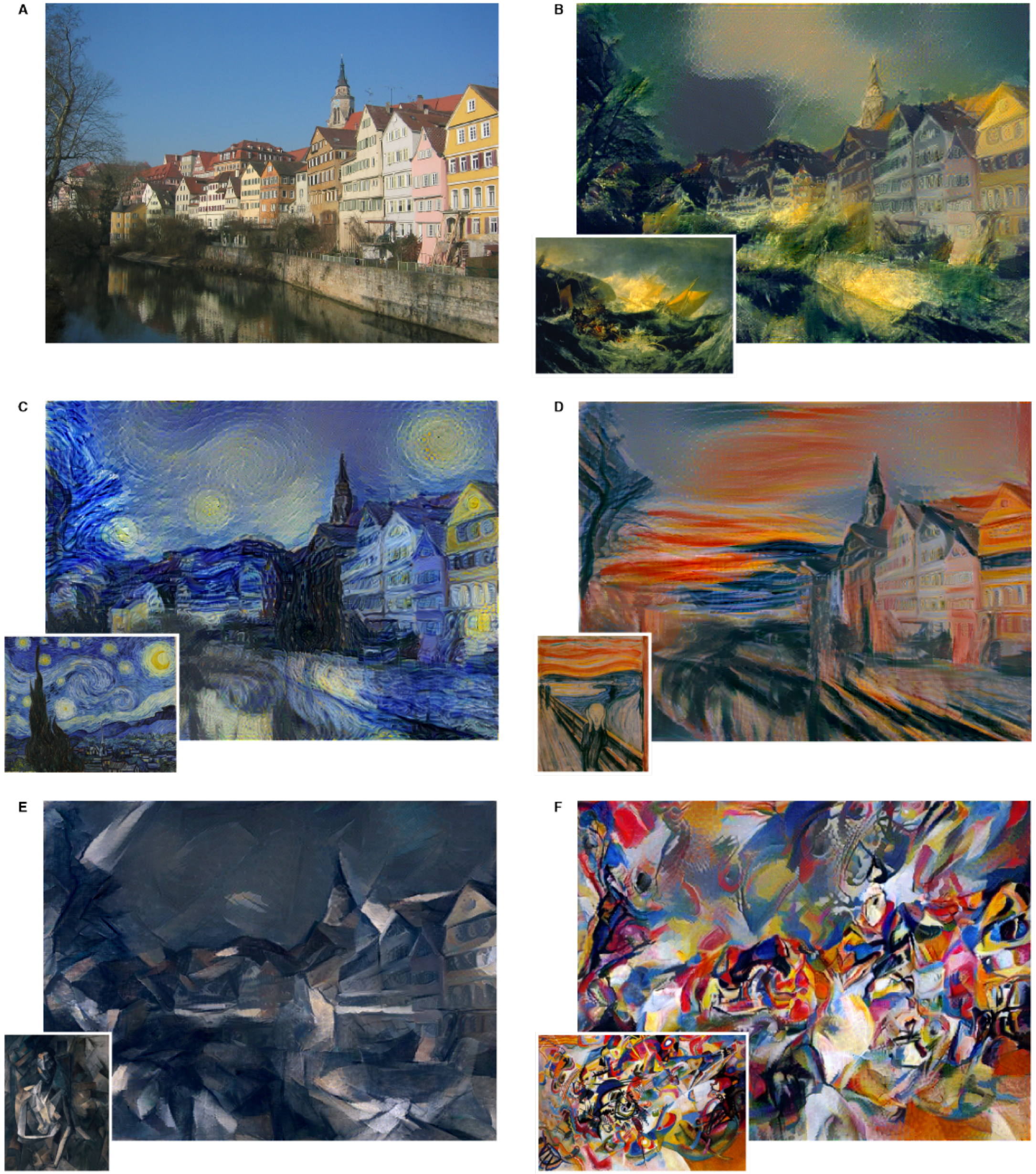
   - Feed Forward 2nd Image into Deep Network
   - Capture Style information
     - » Feature space(s) : Correlations between feature filters/neurons for each layer
4. Search/Synthetize Hybrid Image

   - 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



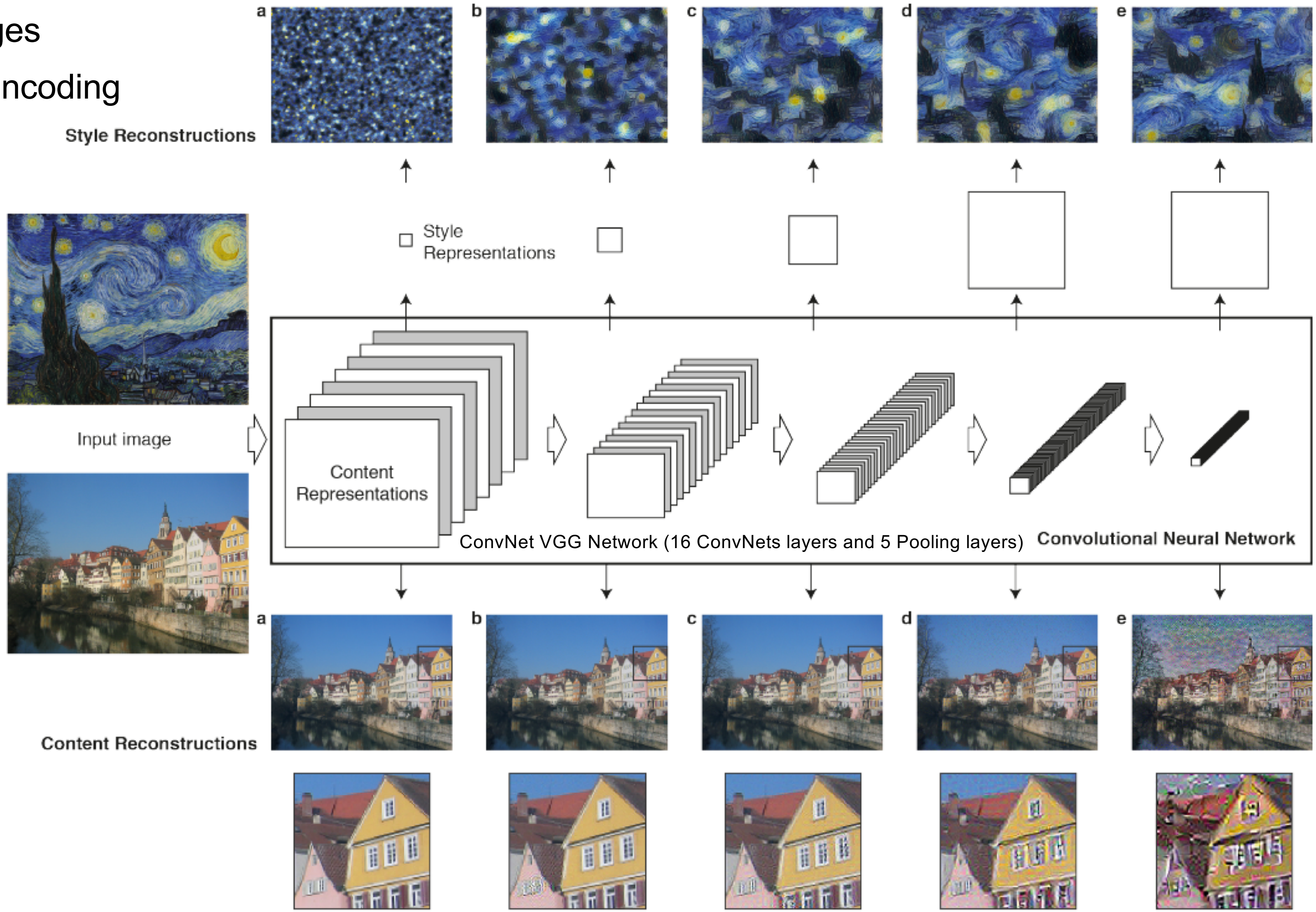
Style Transfer
(Guess the Artist/Painting :)



Style Transfer

Recontructing Images

from the Network Encoding



Style Transfer

layers features used

5 (all)

4

3

2

1

style > content

content > style

content/style ratio

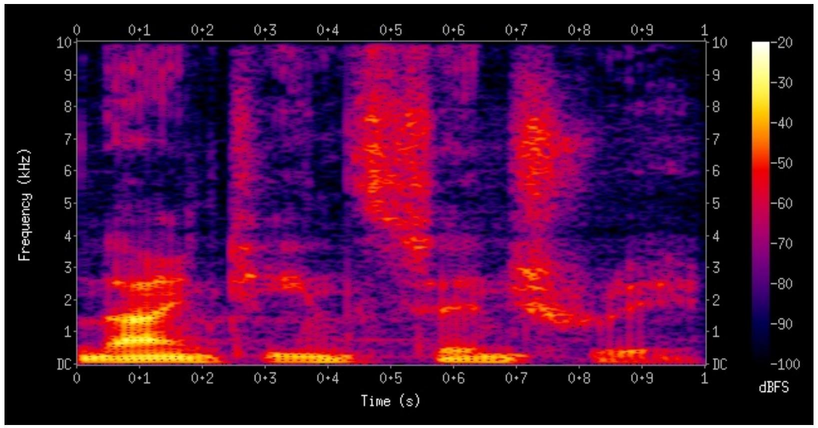
Style Transfer

- 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)

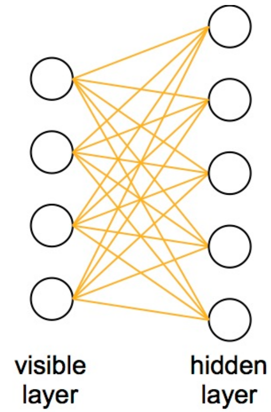
Style

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)

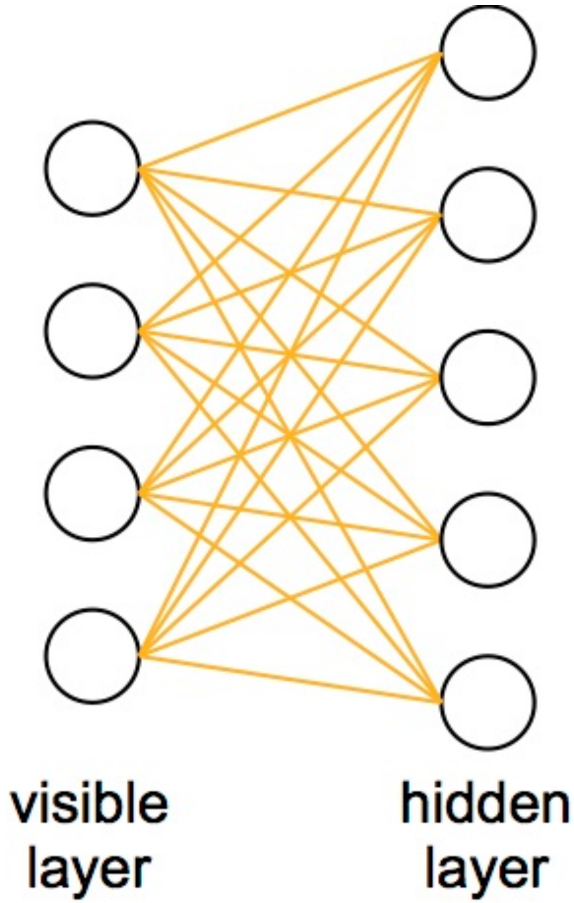


- Combination of:
  - Input Manipulation guided by Gradient Descent of current sample
    - » to impose Higher-Level Structure/Constraints:
      - Structure
      - Tonality
      - Meter
  - Sampling Control, by Selective Gibbs sampling (SGS)
    - » at a Selected Low-Level (subset of variables)
    - » to realign selectively the sample to the learnt distribution

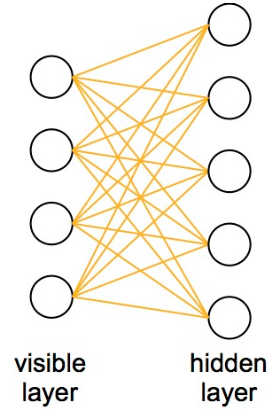
Restricted Boltzmann Machine (RBM) [Hinton & Sejnowski, 1986]

- 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

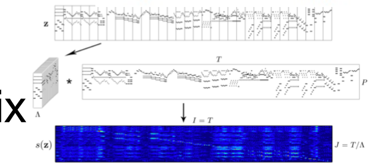
- Generation of a sample from the model learnt:
  - Random initialization of the visible layer vector v
    - » Following a standard uniform distribution
  - Run Gibbs sampling until convergence



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)
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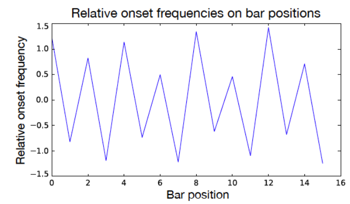
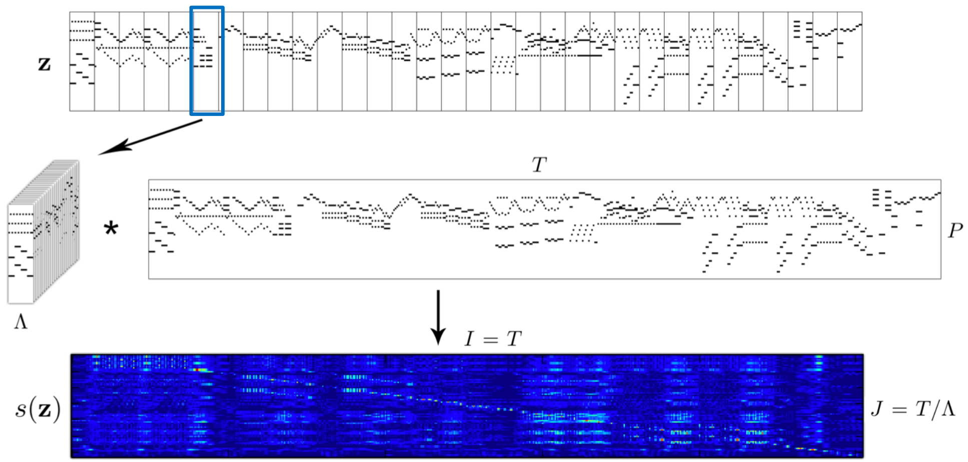


  - Alternate IP/GD and SGS, controlled by Simulated Annealing
  - But not exact as, e.g., Markov Constraints [Pachet & Roy, 2011]

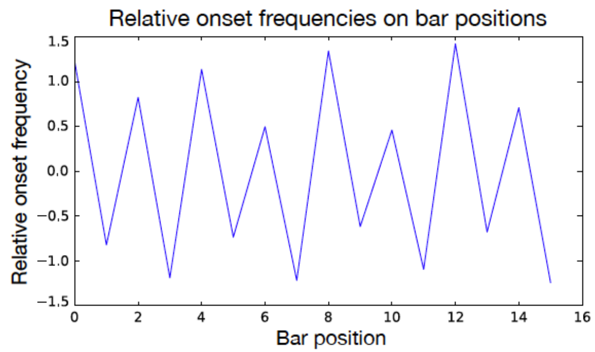
Input Manipulation & Constrained sampling

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

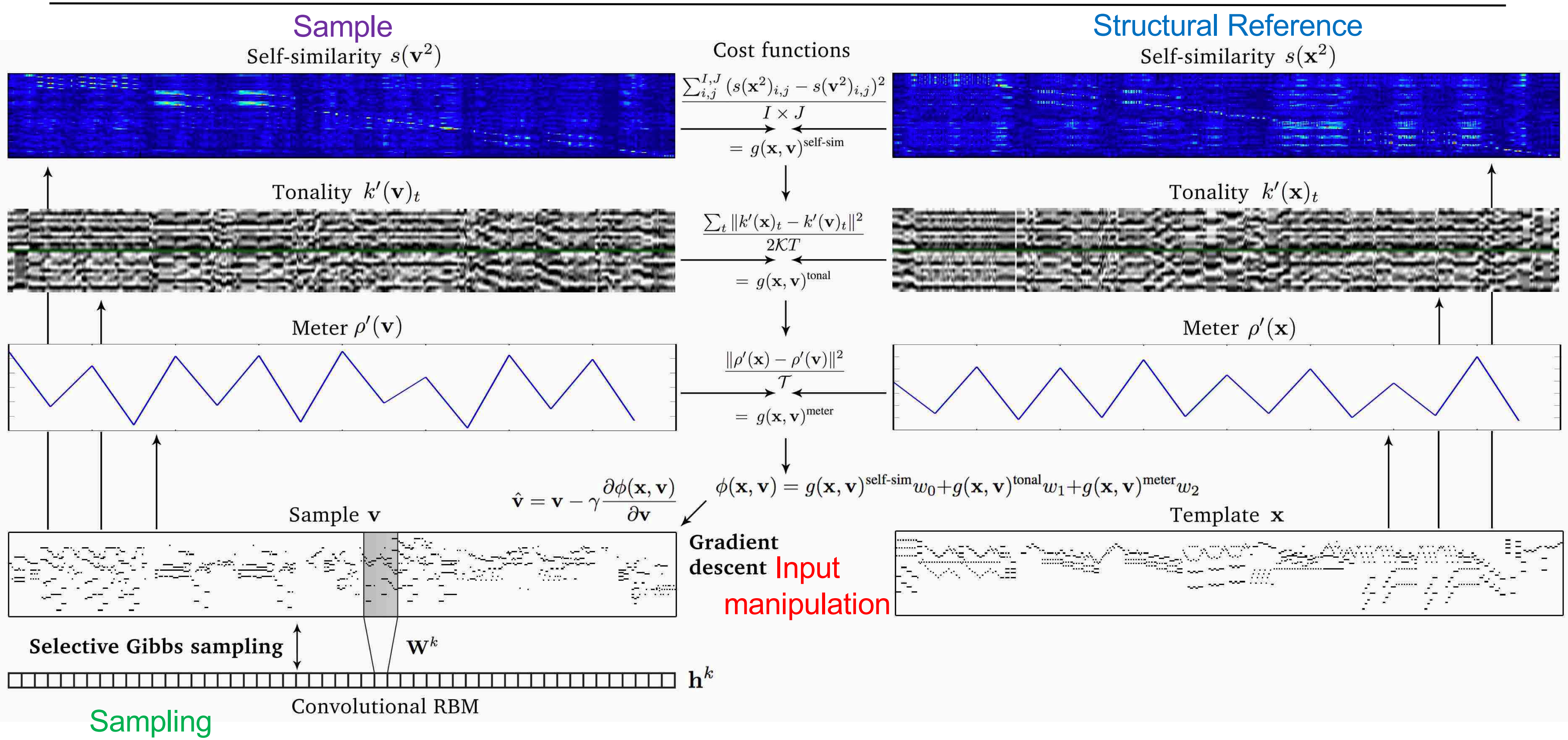


- Tonality, via Similarity of Distribution of Pitch-Classes
  - » Key Estimation Vectors over Time

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



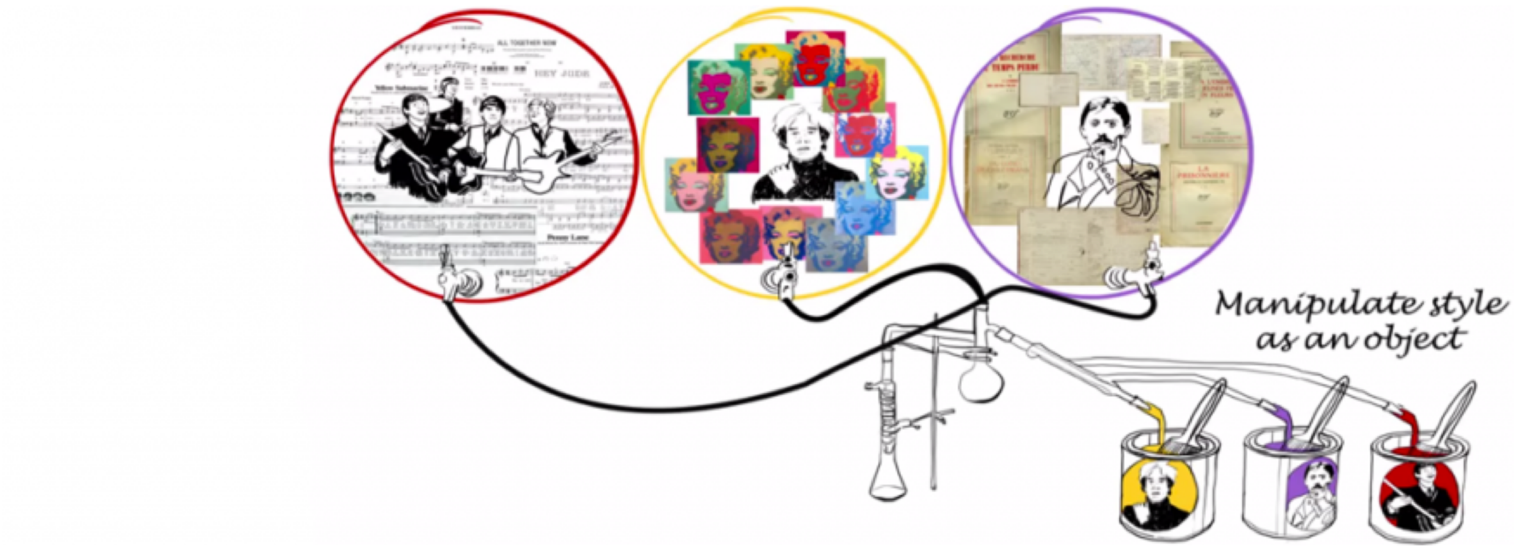
C-RBM [Lattner et al., 2016]



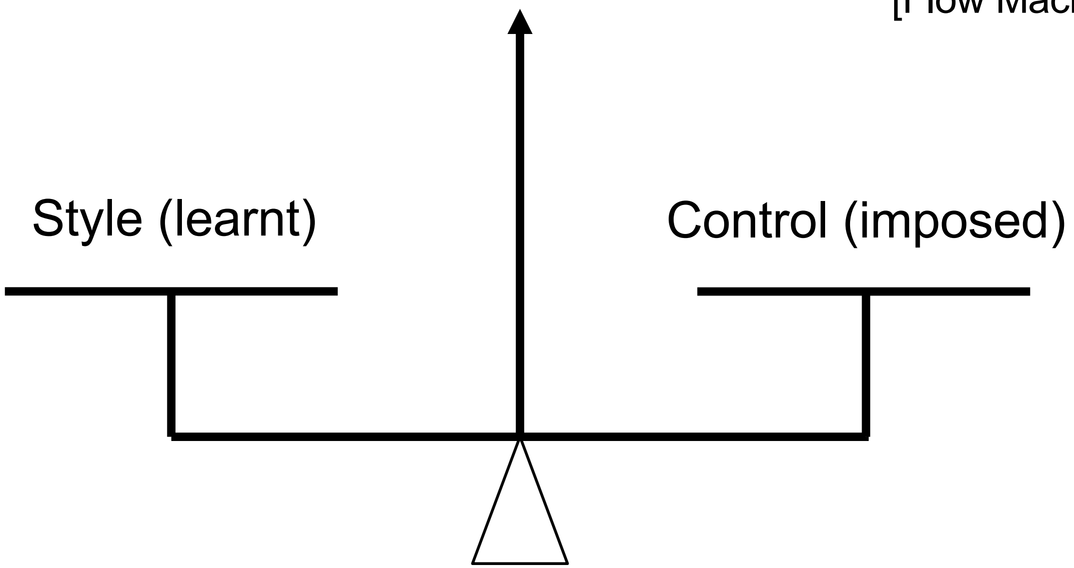
Both Manipulation and Sampling of Input because RBM's "Output" is its Input

https://soundcloud.com/pmgrbm

Style vs/and Control

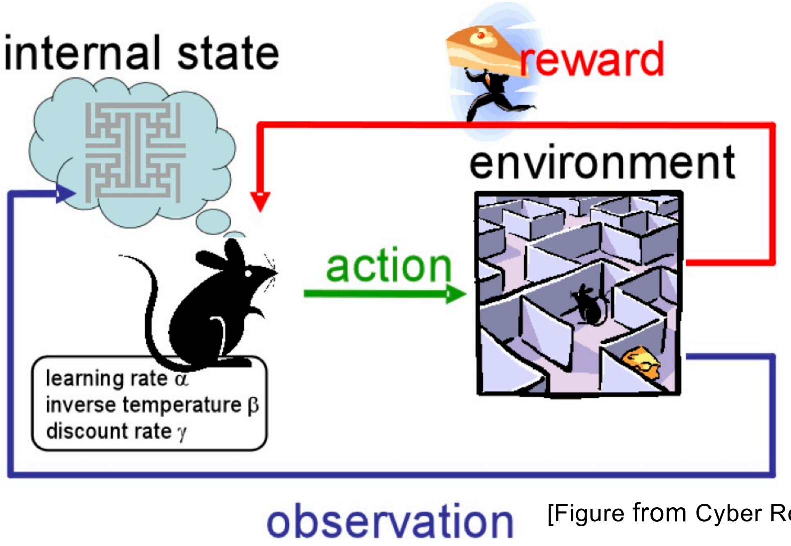


[Flow Machines]



#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)

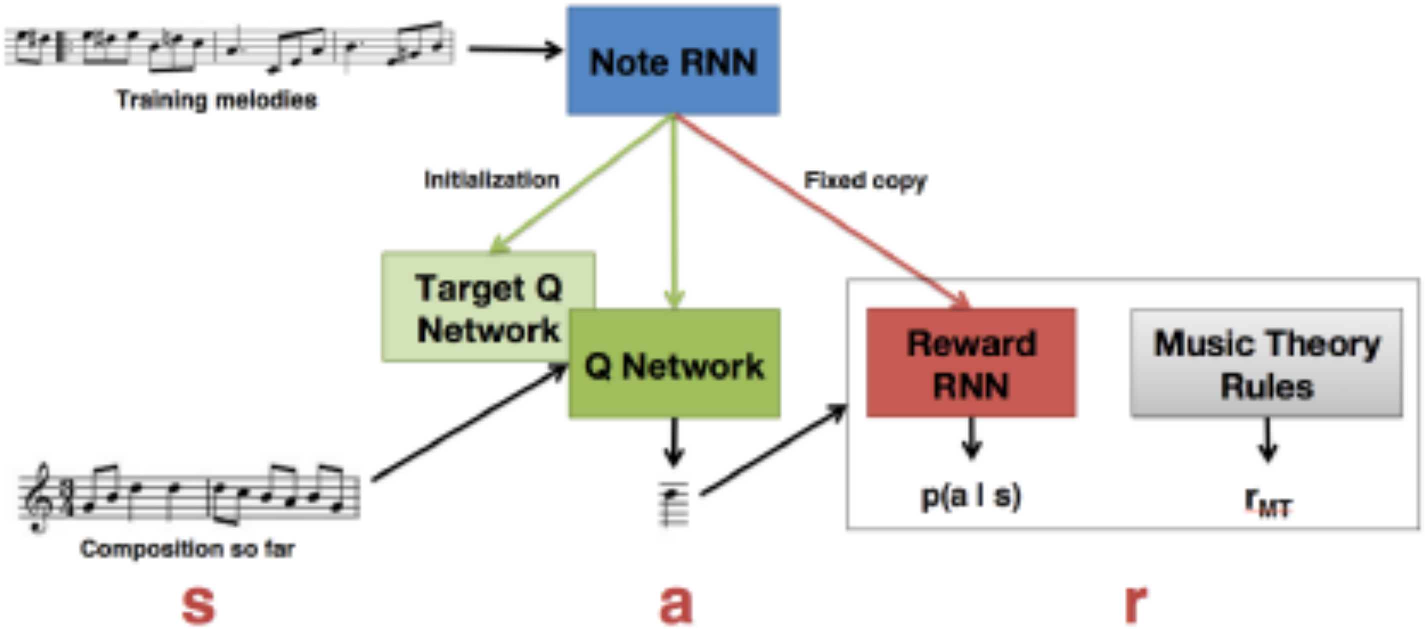
- State: Melody generated so far (Succession of notes)

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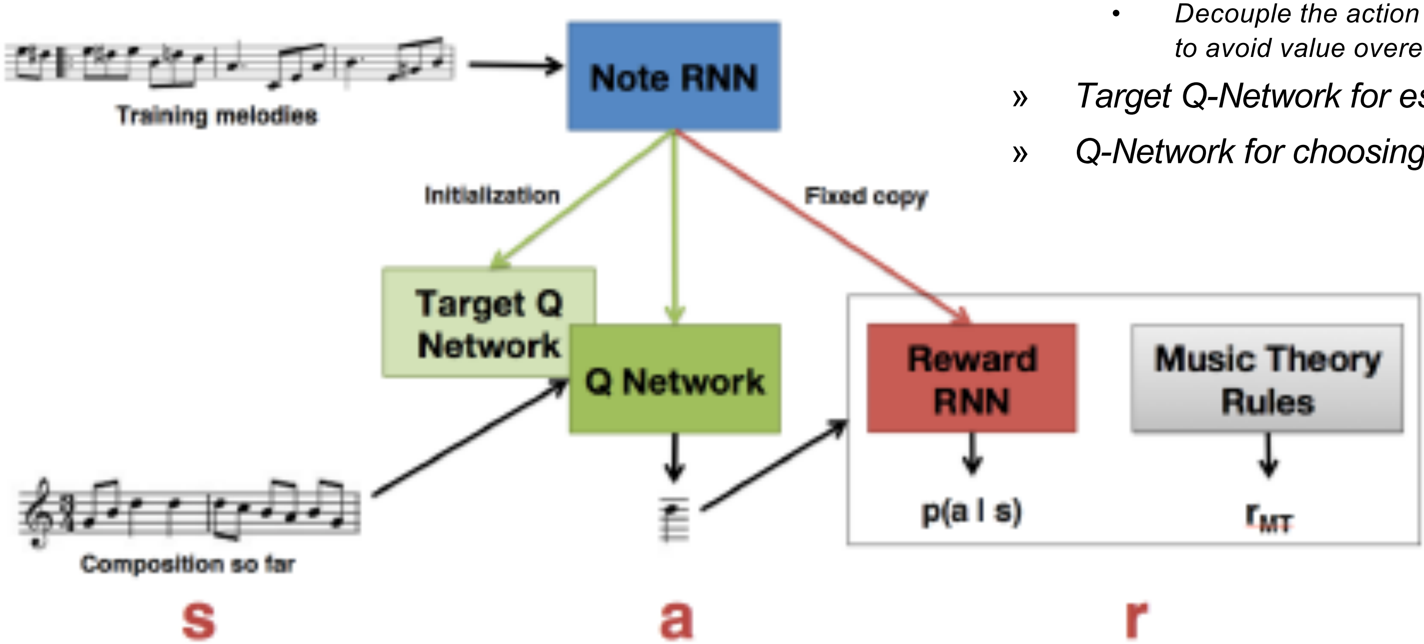
- *Reinforcement Learning implemented via Deep Learning ! (Deep Reinforcement learning)*
- *Double Deep Reinforcement Learning*
  - » *Double Q-Learning [Hasselt et al., 2015]*
    - *Decouple the action selection from the evaluation, to avoid value overestimation*
  - » *Target Q-Network for estimating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

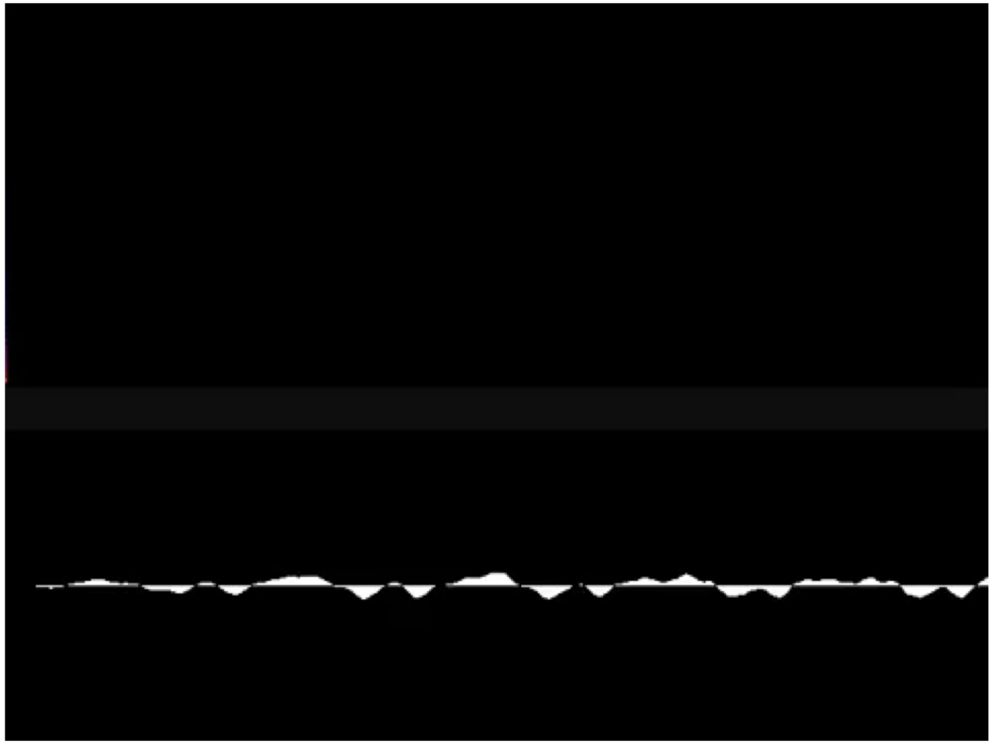


RL-Tuner – Results

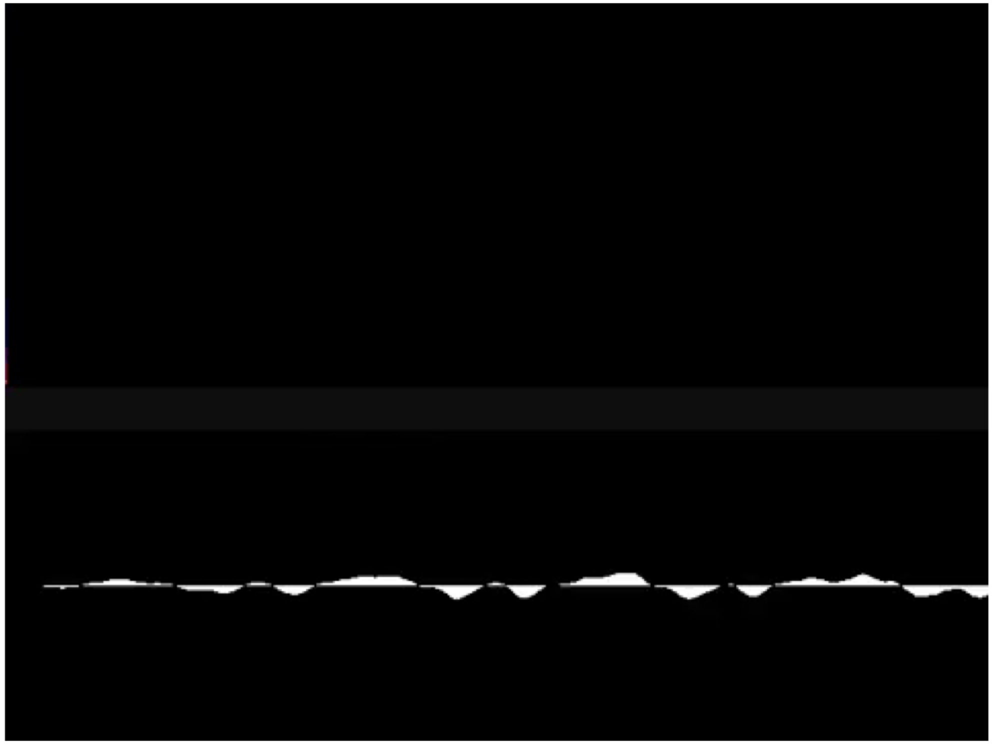
without with

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

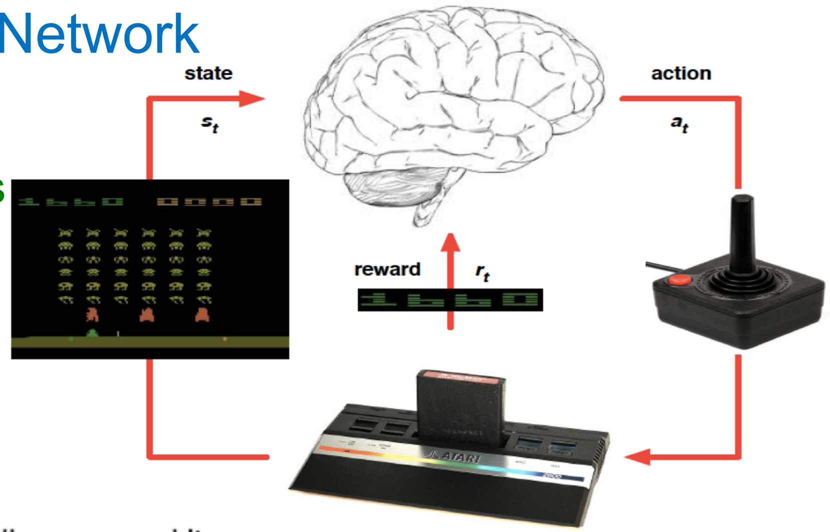


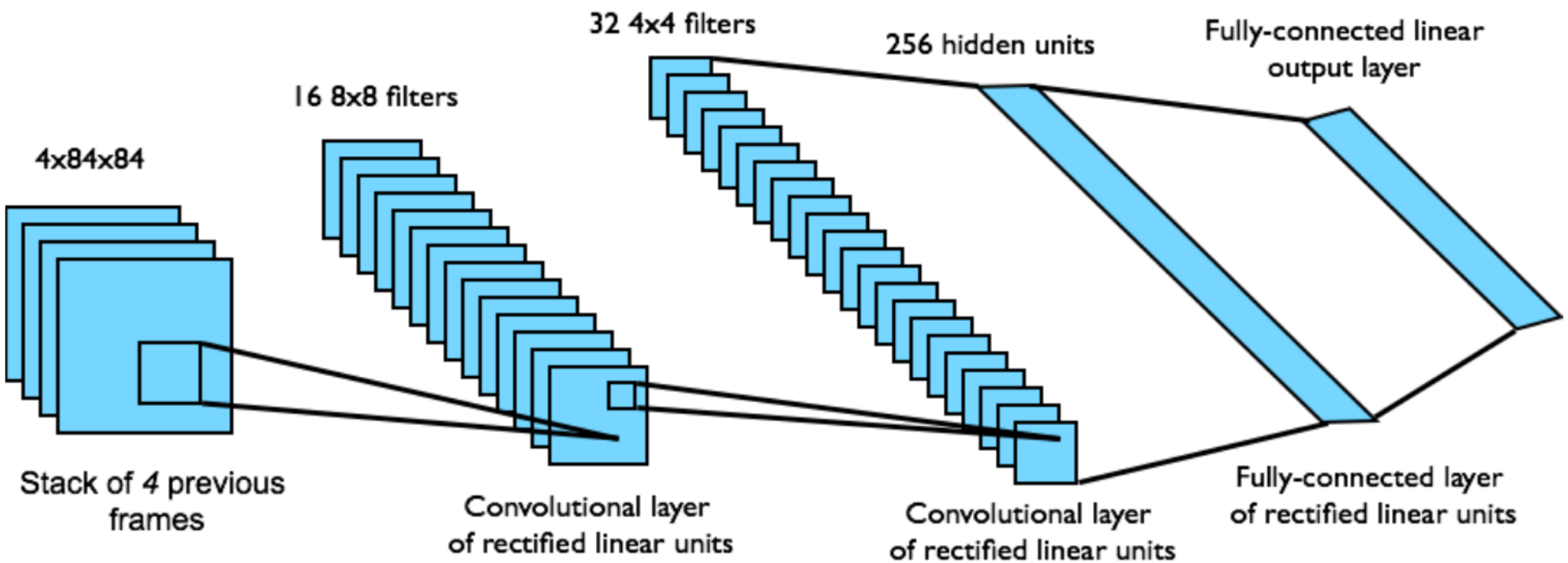
RL-Tuner

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:

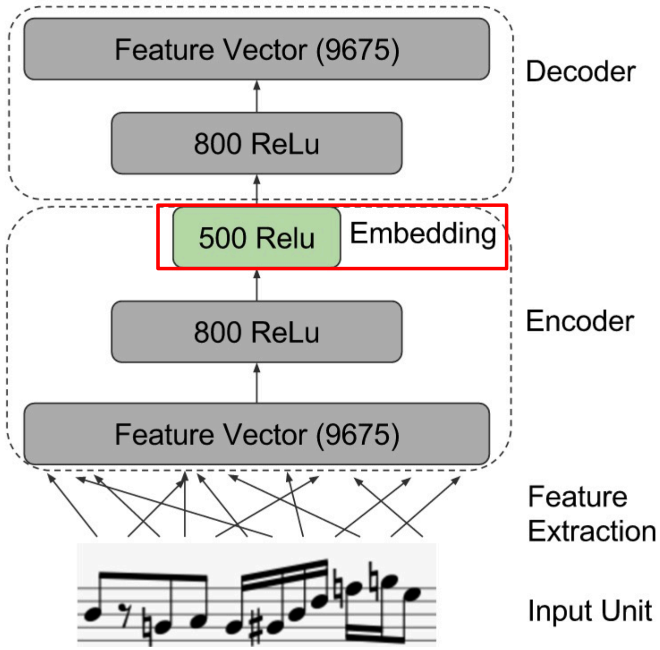
AlphaGo
[Silver et al., 2016]

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

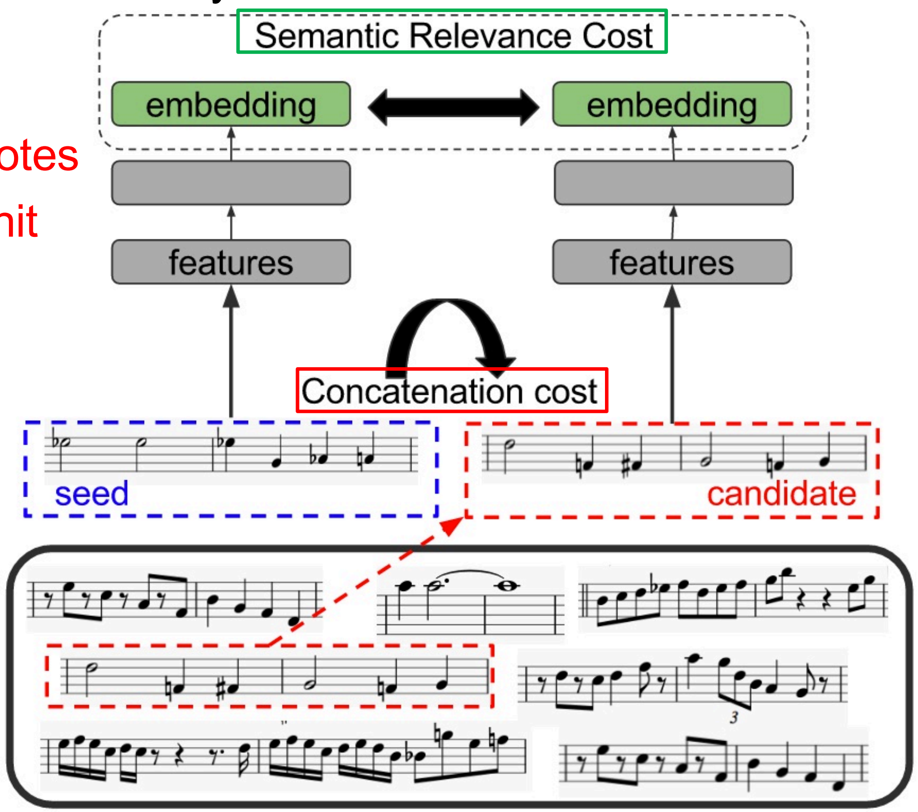


- *Top Down Approach*
  - Structure (Next Unit Features)
  - Fill (Select Best Fit Unit)

Unit Selection

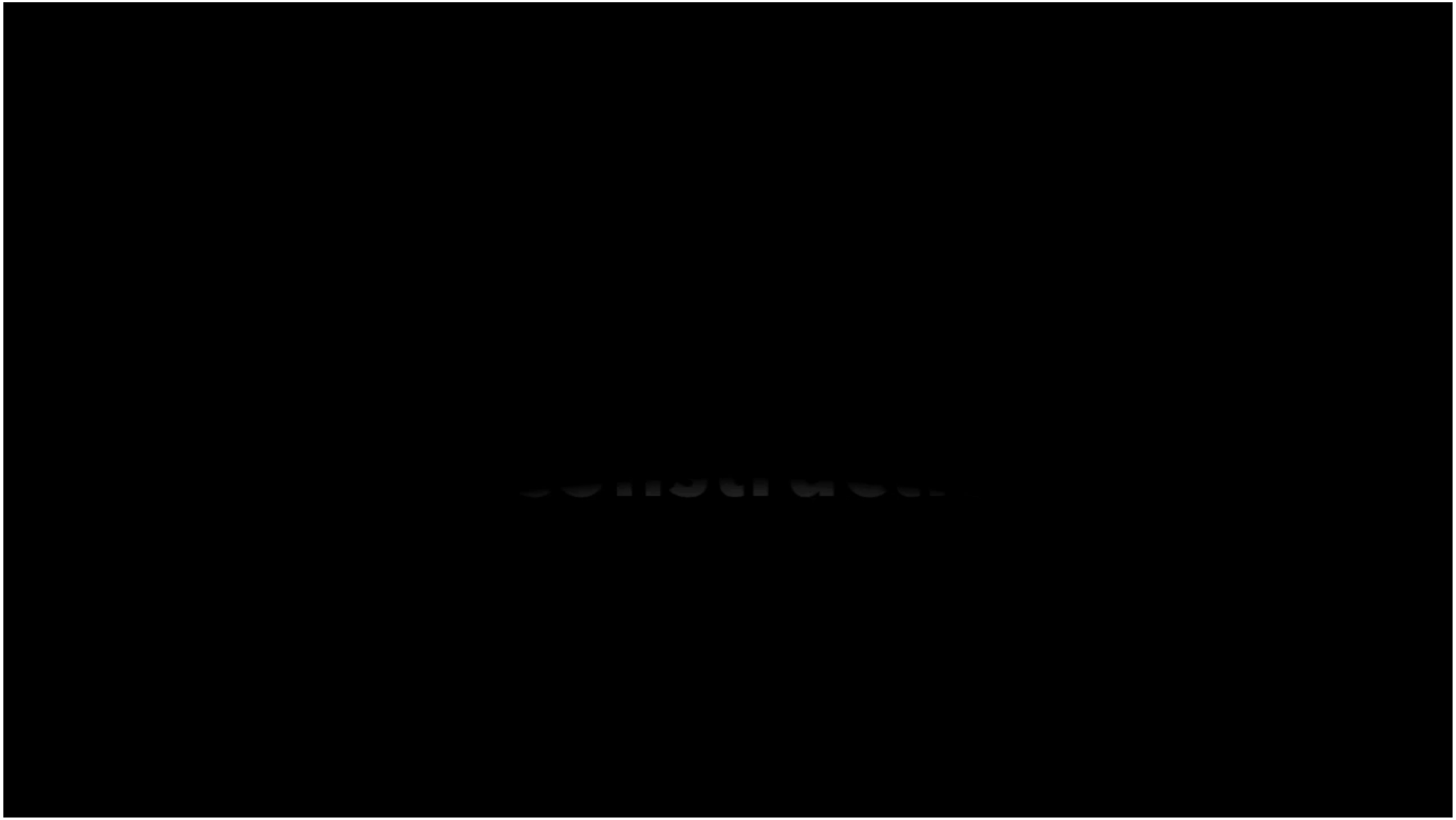
Unit Selection, based on:

- 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



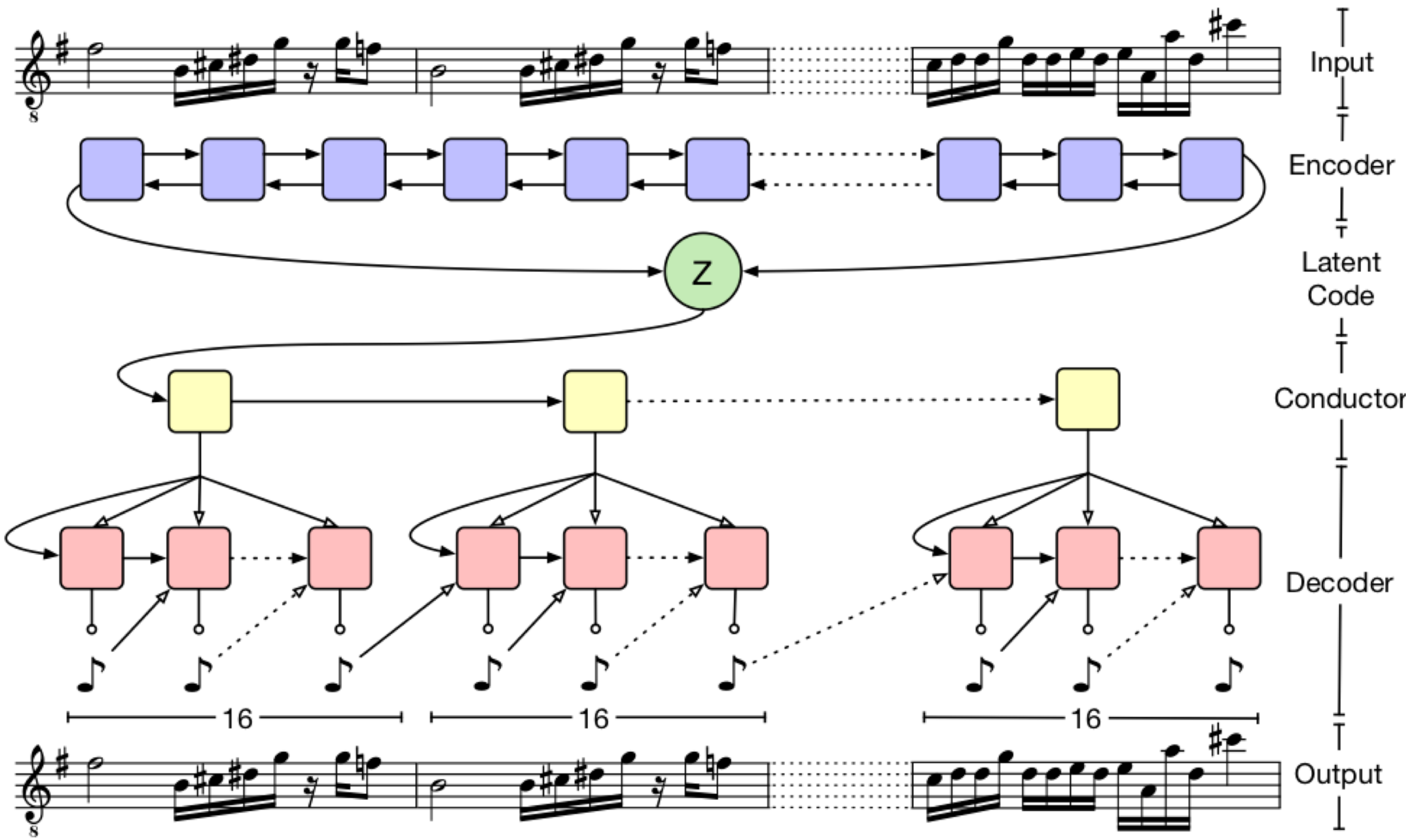
https://www.youtube.com/watch?v=BbyvbO2F7ug&feature=youtu.be

#5 Limitation – Structure

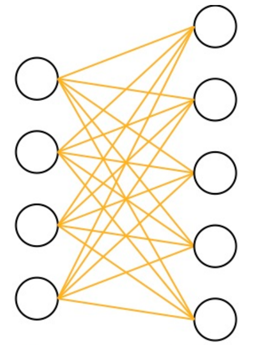
- No Sense of Direction
- No Structure

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

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



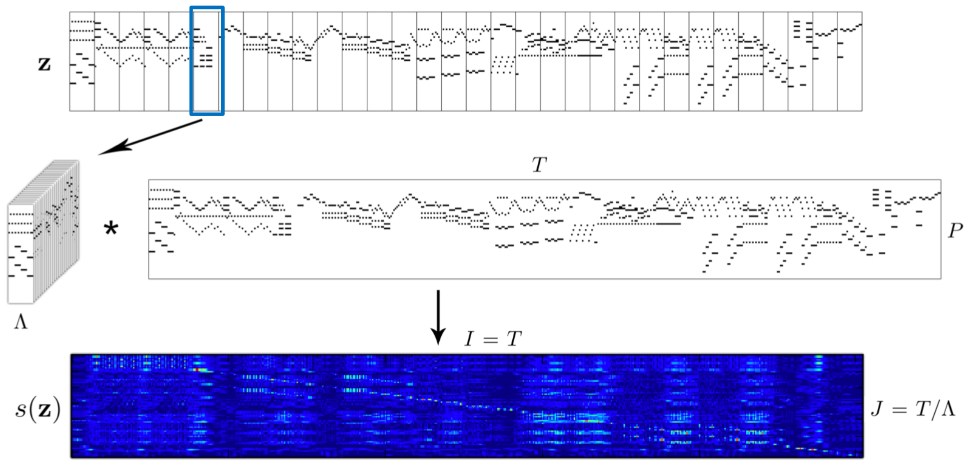
#5 Limitation – Structure – #2 Solution – Structure Imposition



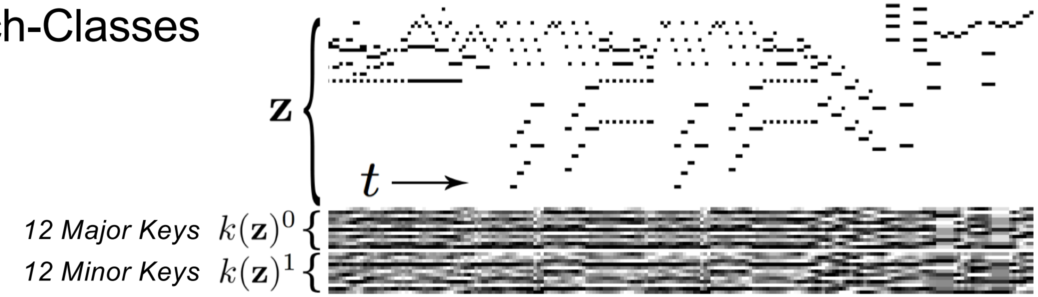
- Constrained sampling, C-RBM [Lattner et al., 2016]
- Convolutional Restricted Boltzmann Machine (RBM)
- Combination of:
  – Input Manipulation guided by Gradient Descent of current sample
    » to impose Higher-Level Structure/Constraints:
      - Structure
      - Tonality
      - Meter
  – Sampling 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

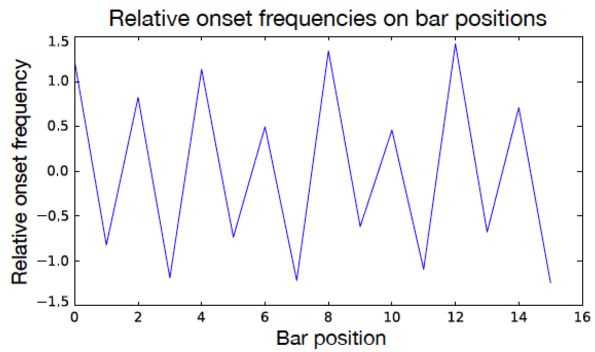
- Structure (Repetition Structure, Ex: AABA)
  - » Self-Similarity Matrix
  - » For each Music Slice



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



- 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)*

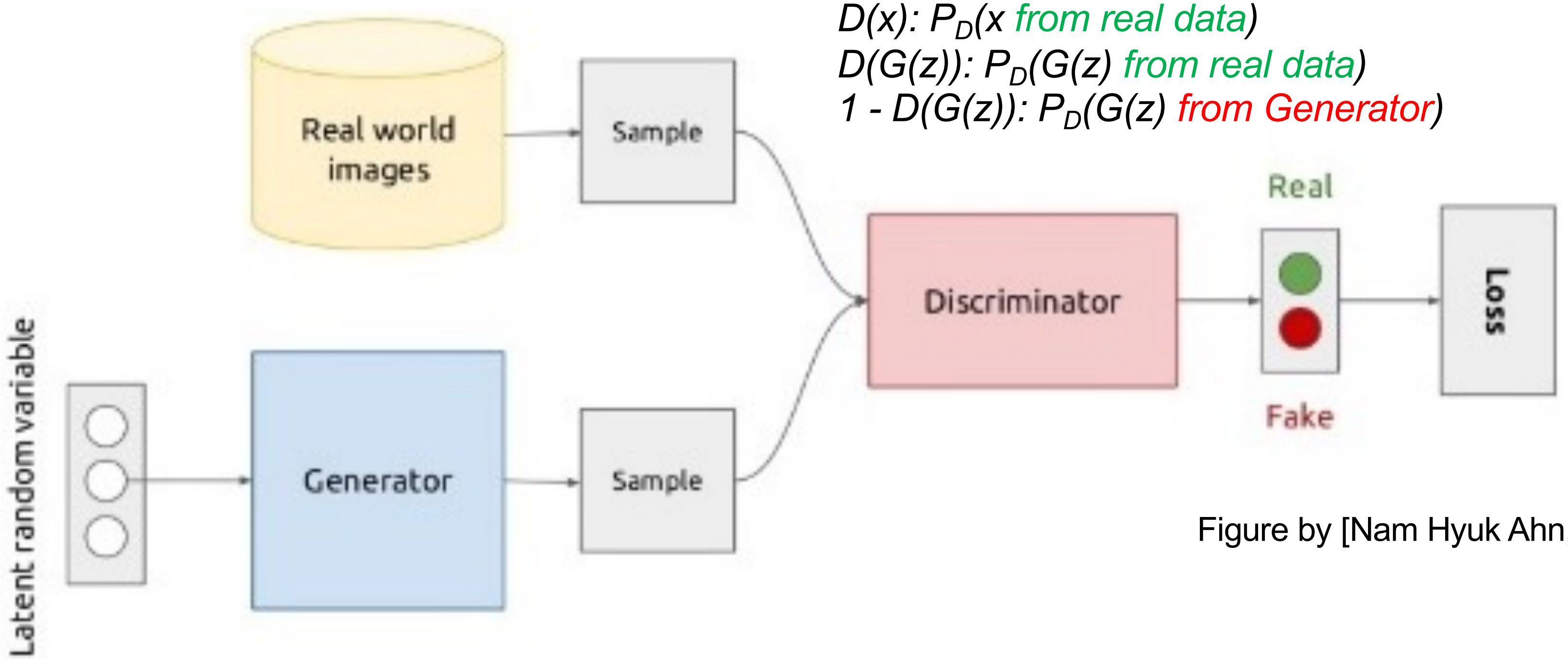
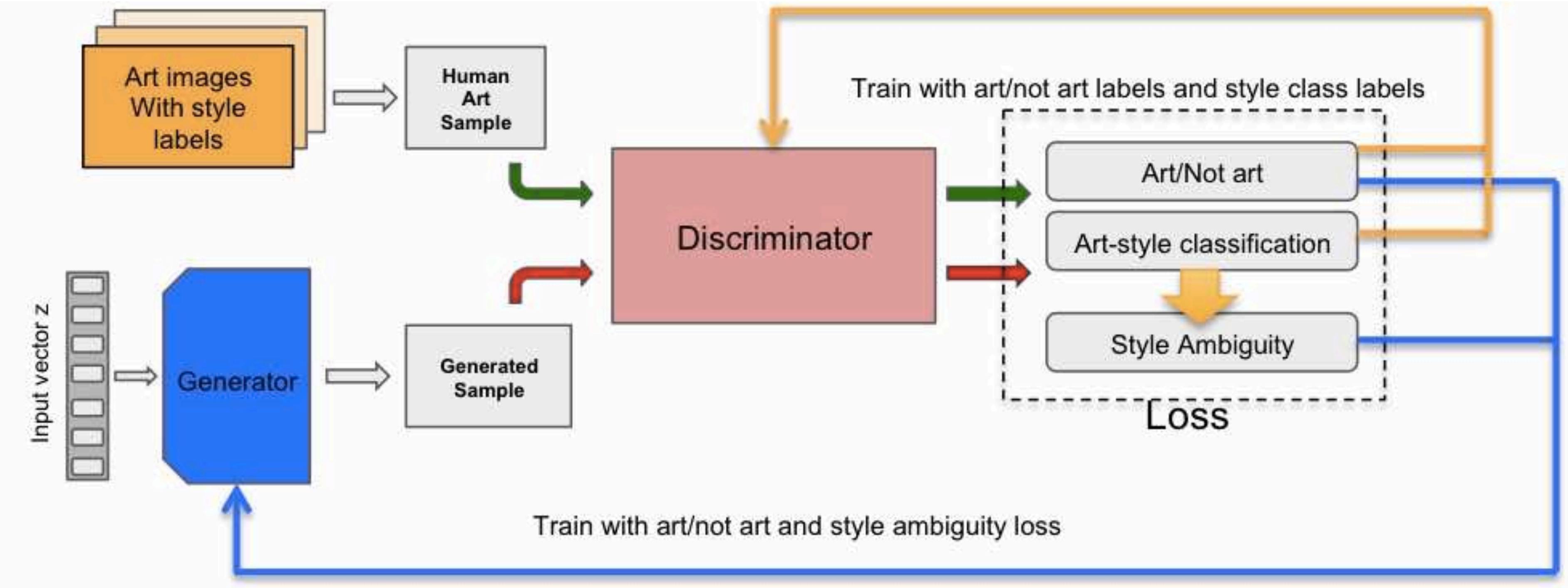


Figure by [Nam Hyuk Ahn, 2017]

#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…



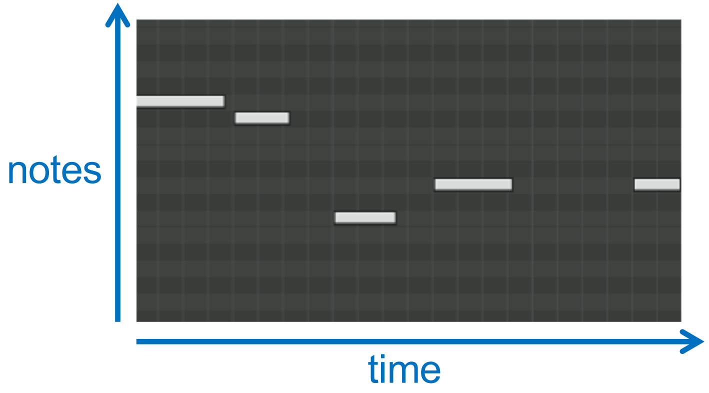
Creative Adversarial Networks (CAN) – Ex. of Paintings Generated

Table 1: Artistic Styles Used in Training

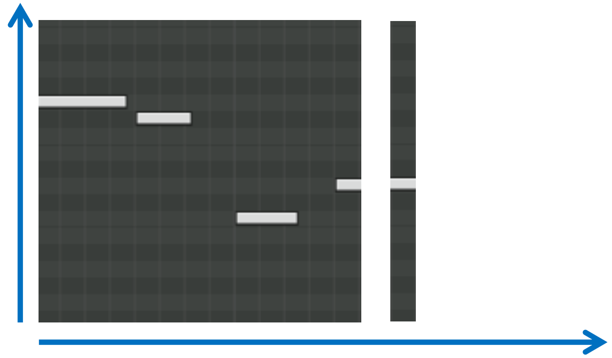
Style name	Image number	Style name	Image number
Abstract-Expressionism	2782	Mannerism-Late-Renaissance	1279
Action-Painting	98	Minimalism	
Analytical-Cubism	110	Naive Art-Primi	
Art-Nouveau-Modern	4334	New-Realism	
Baroque	4241	Northern-Renai	
Color-Field-Painting	1615	Pointillism	
Contemporary-Realism	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

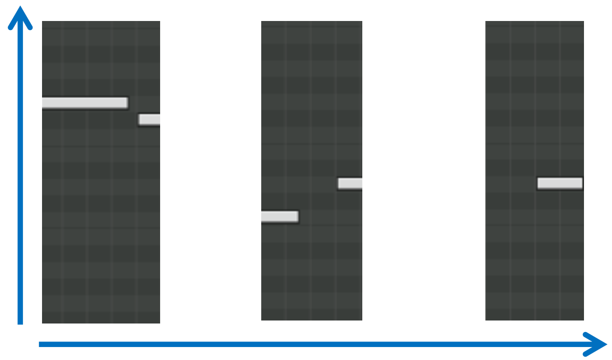
- Instantiation of Notes
  - Feedforward Models
    - » Global/One shot



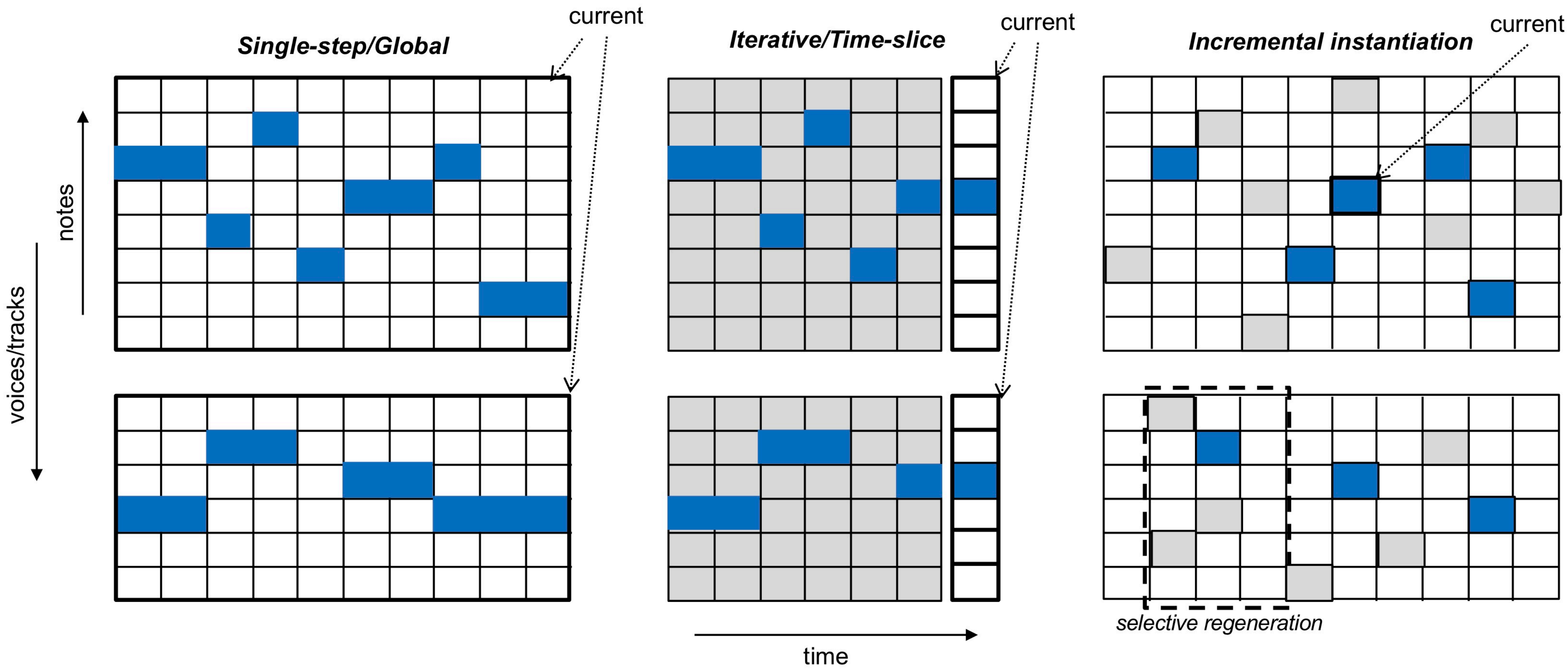
  - Recurrent Models
    - » Note by Note
    - » Following Time Steps



  - ?
    - » Arbitrary Part/Direction

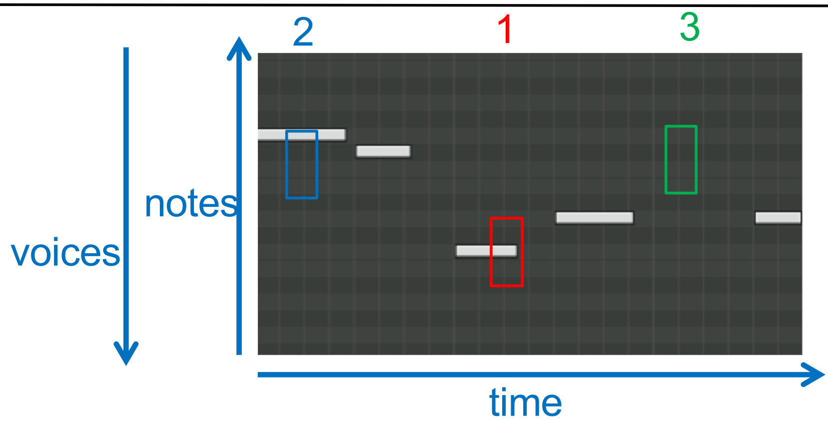


#7 Limitation – Incrementality



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

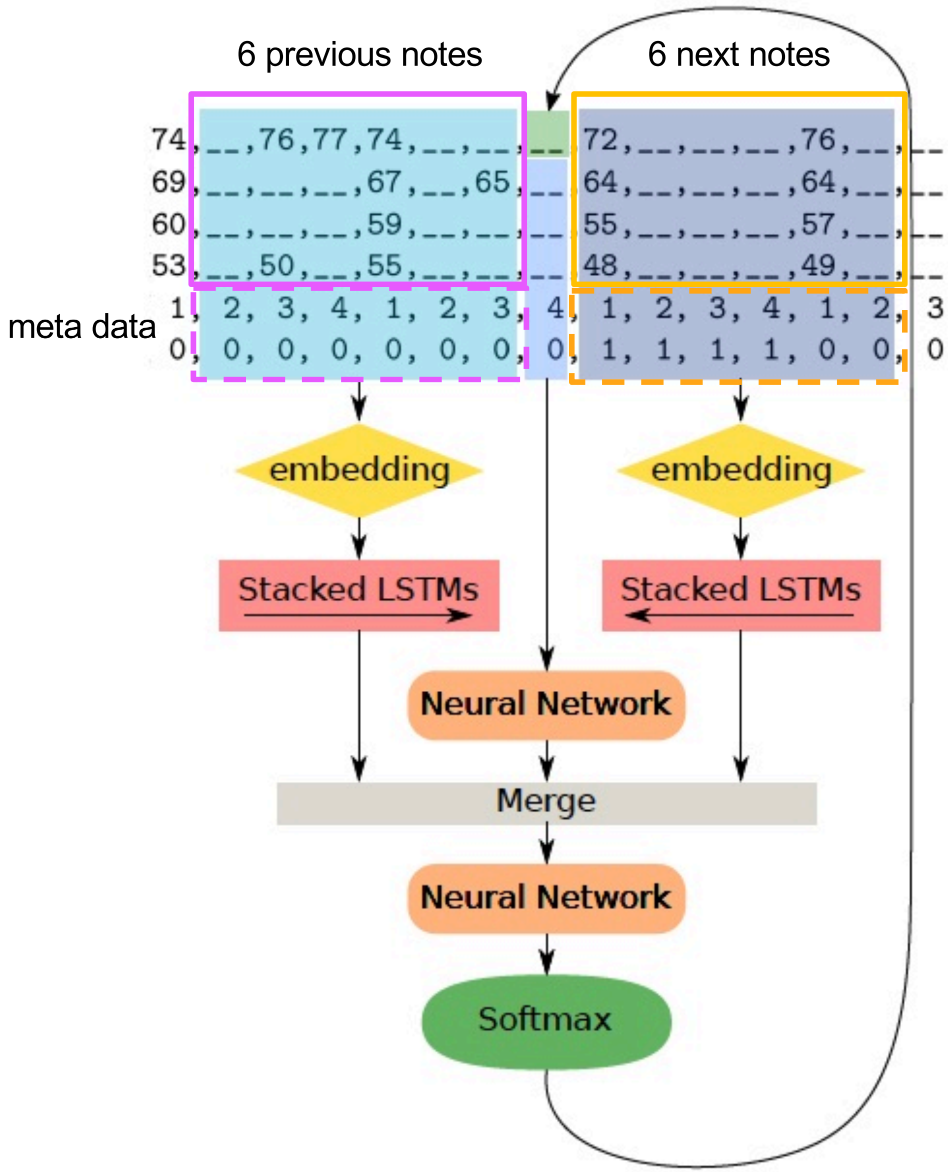
- Incremental Sampling
  - Iterative
  - Pseudo-Gibbs Sampling
  - Iterative
  - « Random »



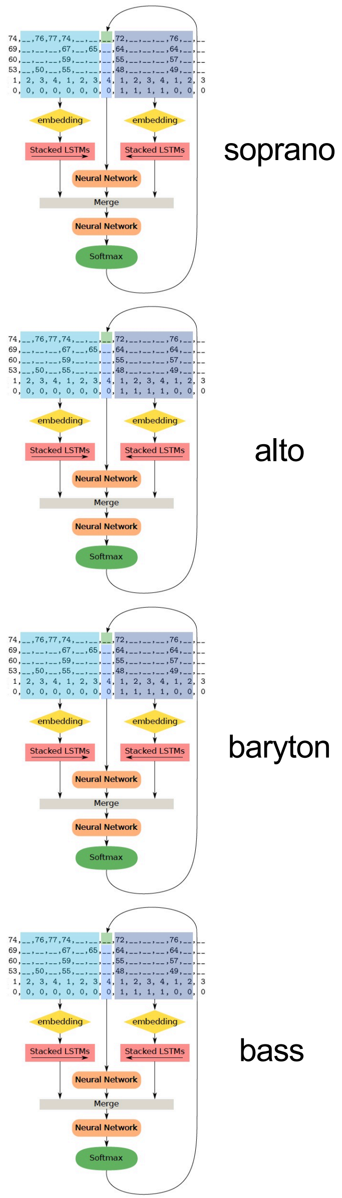
- Bach Chorales
  - 4 voices

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

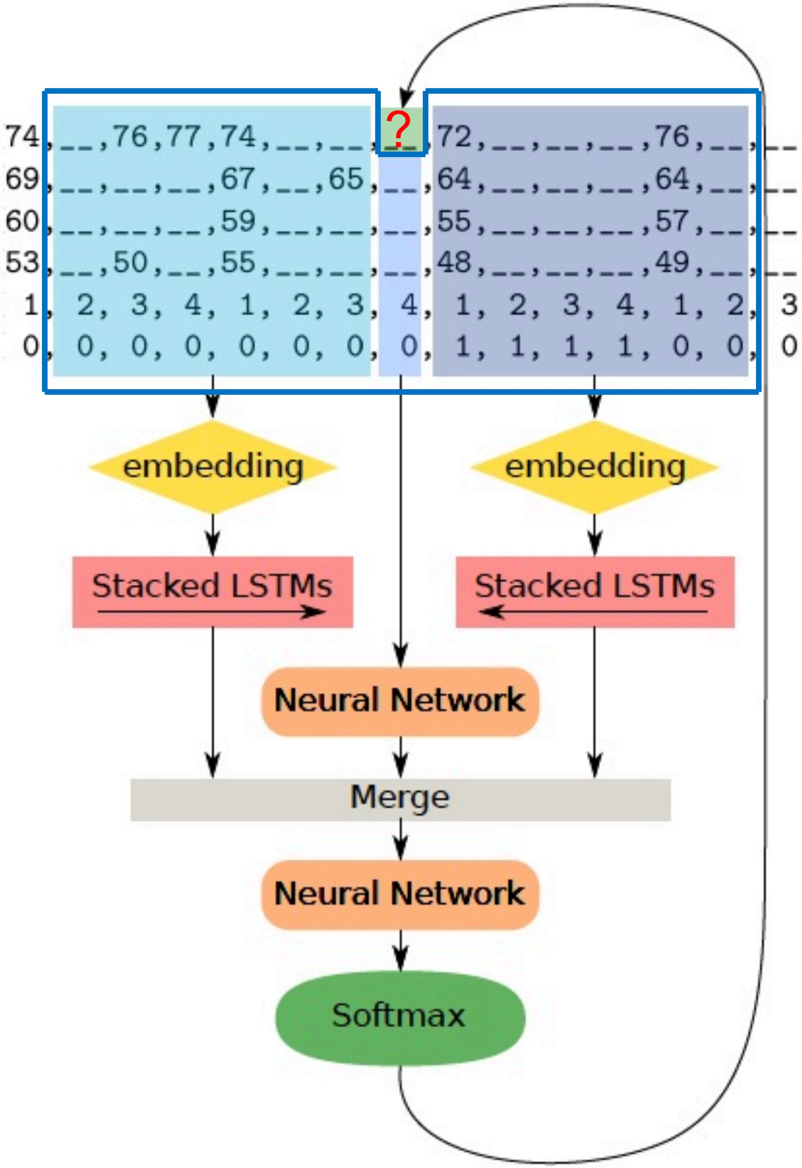


6 previous notes
6 next notes
74,__,76,77,74,__,__,__,__,72,__,__,__,76,__,__
69,__,__,__,67,__,65,__,64,__,__,__,64,__,__
60,__,__,__,59,__,__,__,55,__,__,__,57,__,__
53,__,50,__,55,__,__,__,48,__,__,__,49,__,__
meta data
1, 2, 3, 4, 1, 2, 3, 4, 1, 2, 3, 4, 1, 2, 3
0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1,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

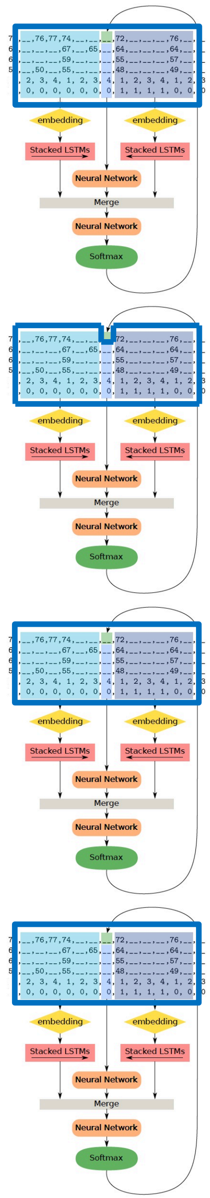


soprano
alto
baryton
bass

DeepBach



alto



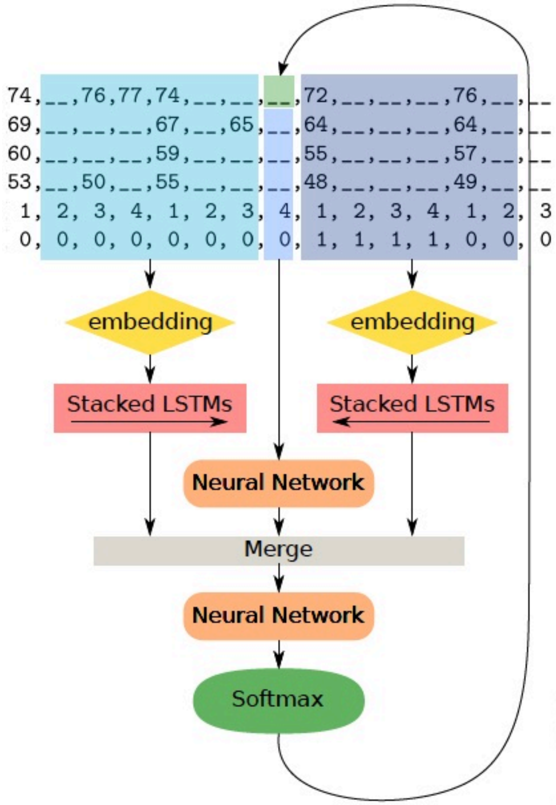
soprano

alto

baryton

bass

DeepBach



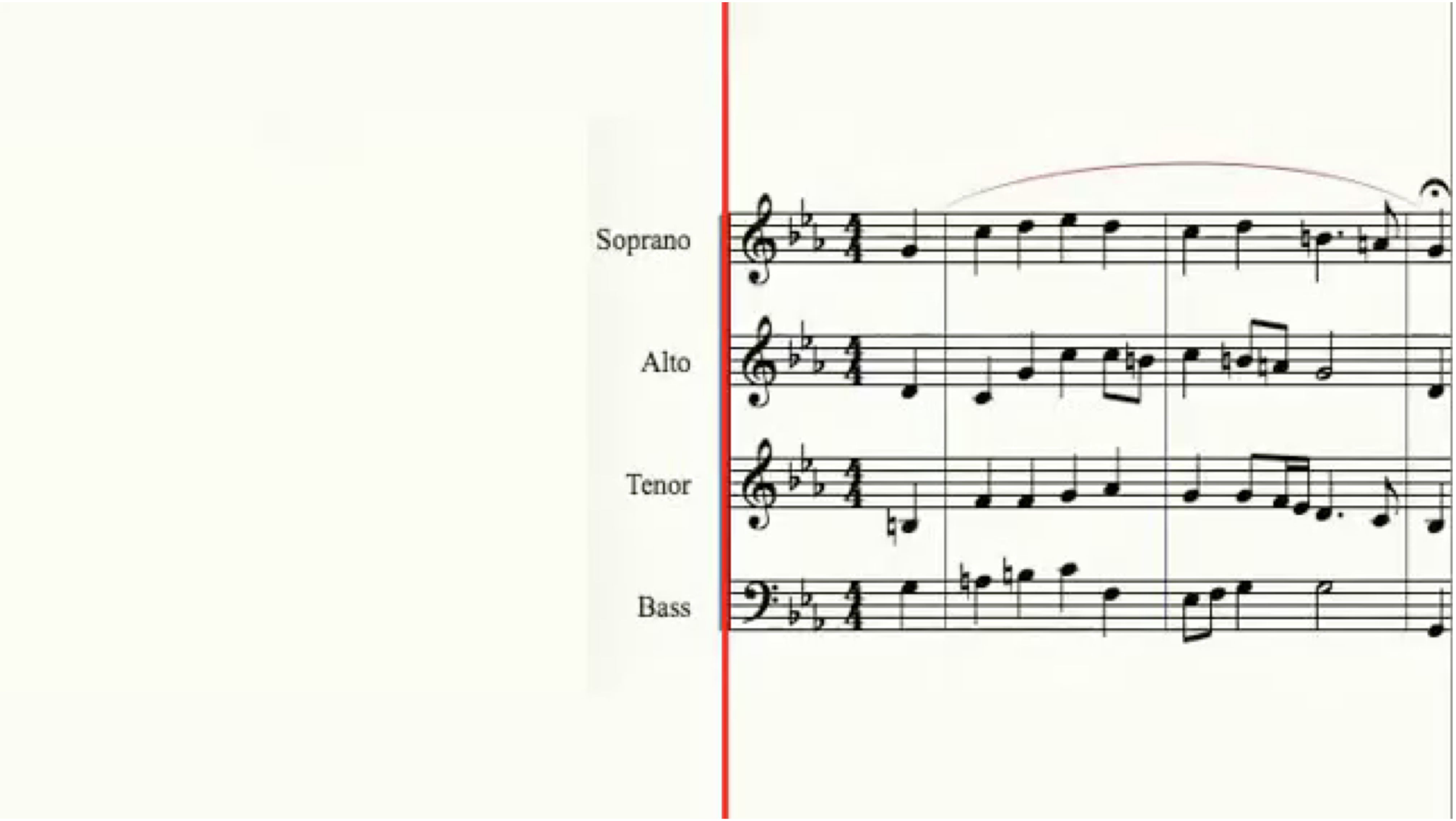
74,__,76,77,74,__,__,__,72,__,__,__,76,__,__
69,__,__,__,67,__,65,__,64,__,__,__,64,__,__
60,__,__,__,59,__,__,__,55,__,__,__,57,__,__
53,__,50,__,55,__,__,__,48,__,__,__,49,__,__
1, 2, 3, 4, 1, 2, 3, 4, 1, 2, 3, 4, 1, 2, 3
0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0
embedding
embedding
Stacked LSTMs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

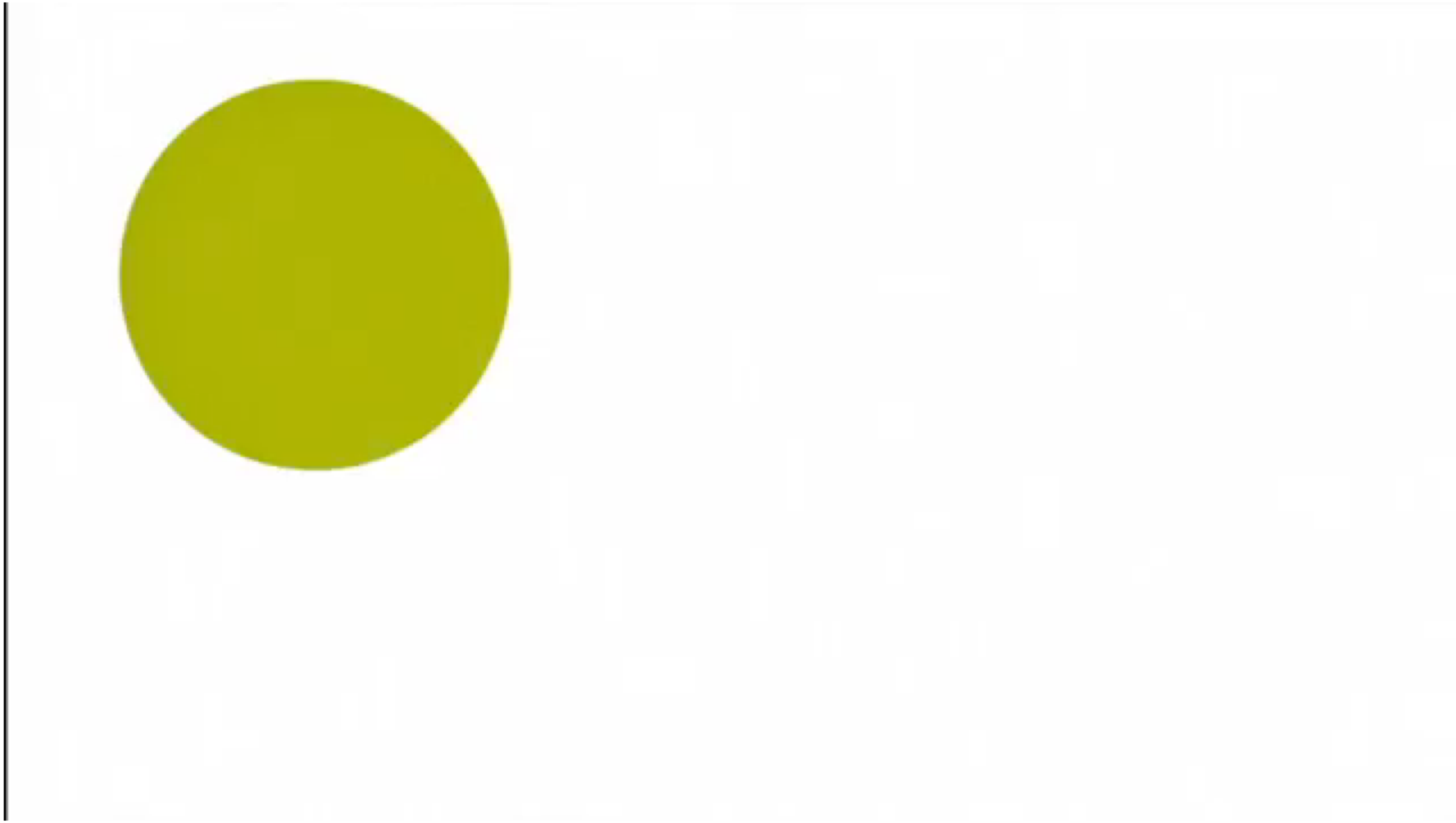
Soprano
Alto
Tenor
Bass

DeepBach – Demo



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

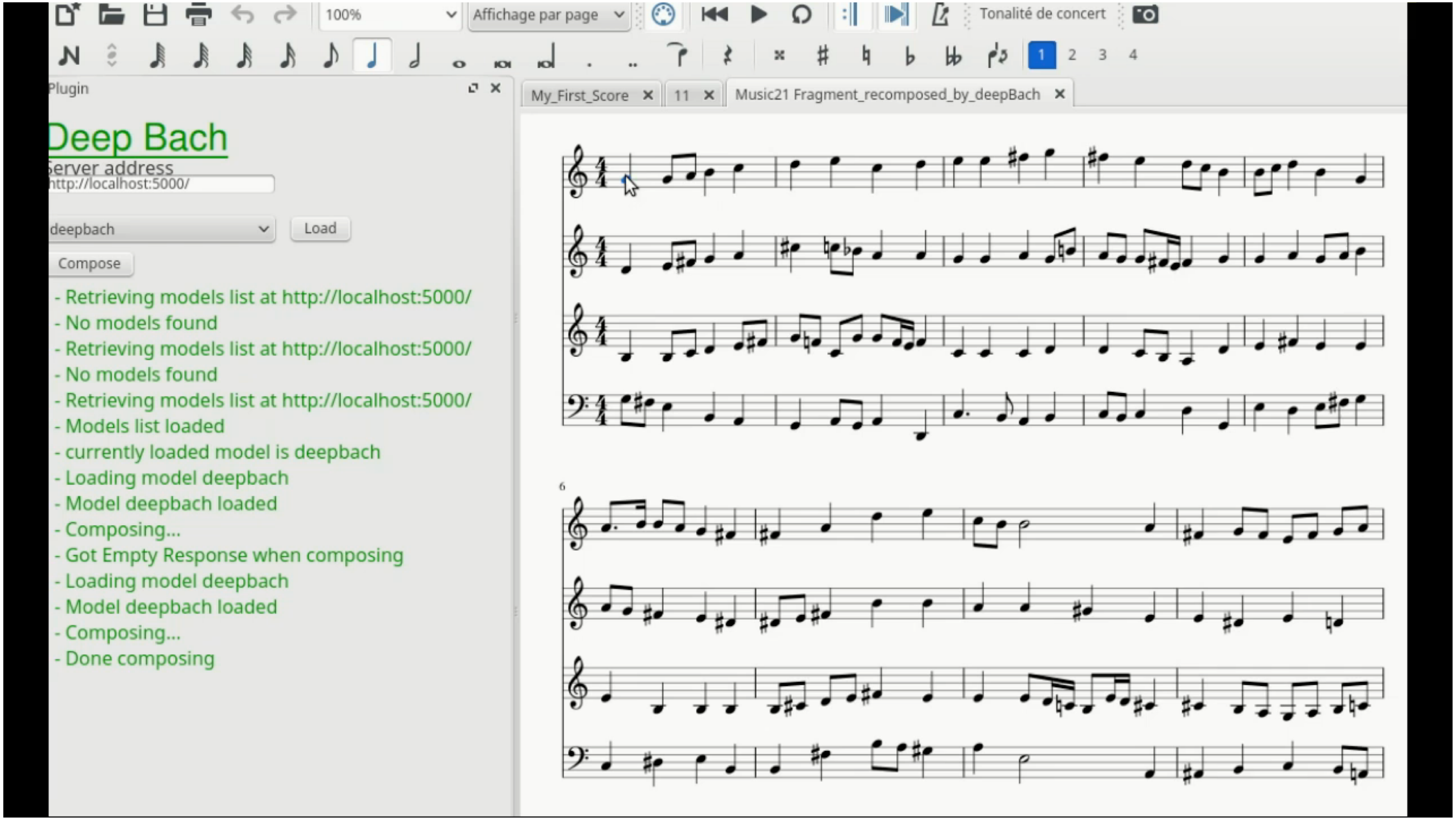
Turing Bach Test



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

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

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



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

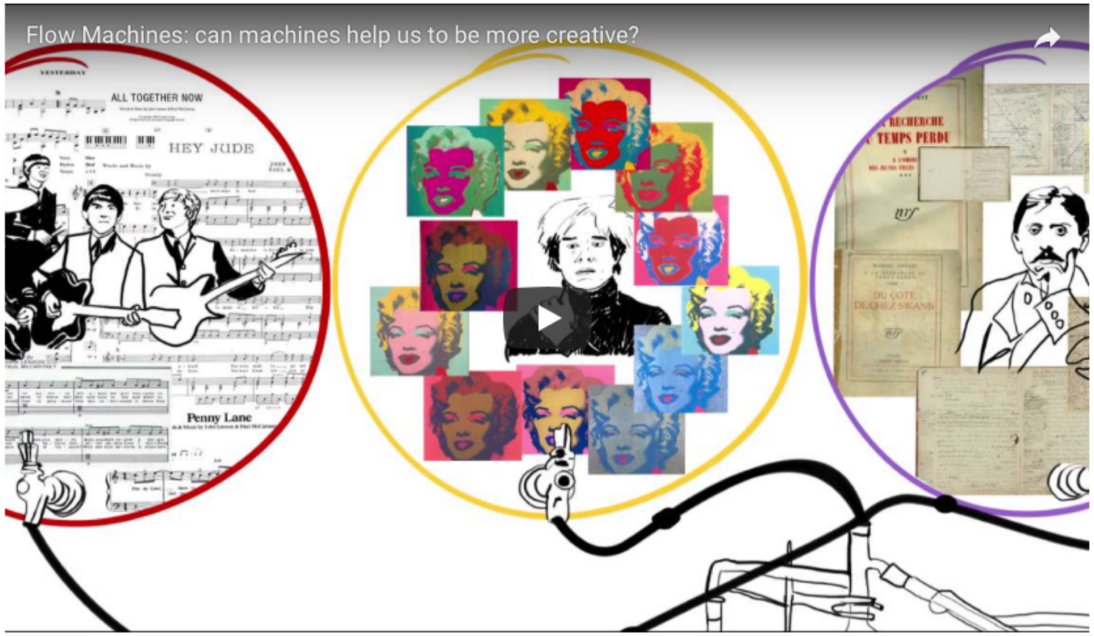
vs Assistant for Human Artists (Composers, Arrangers, Instrumentists…)

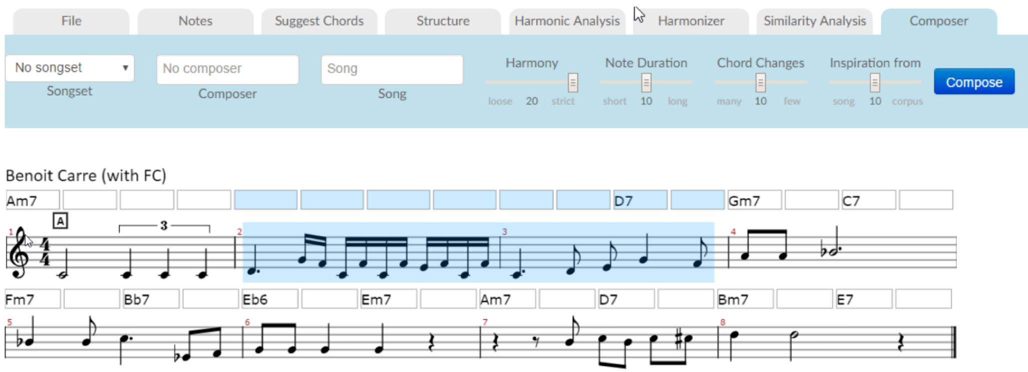
Flow Machines Project [Pachet et al., 2012]

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

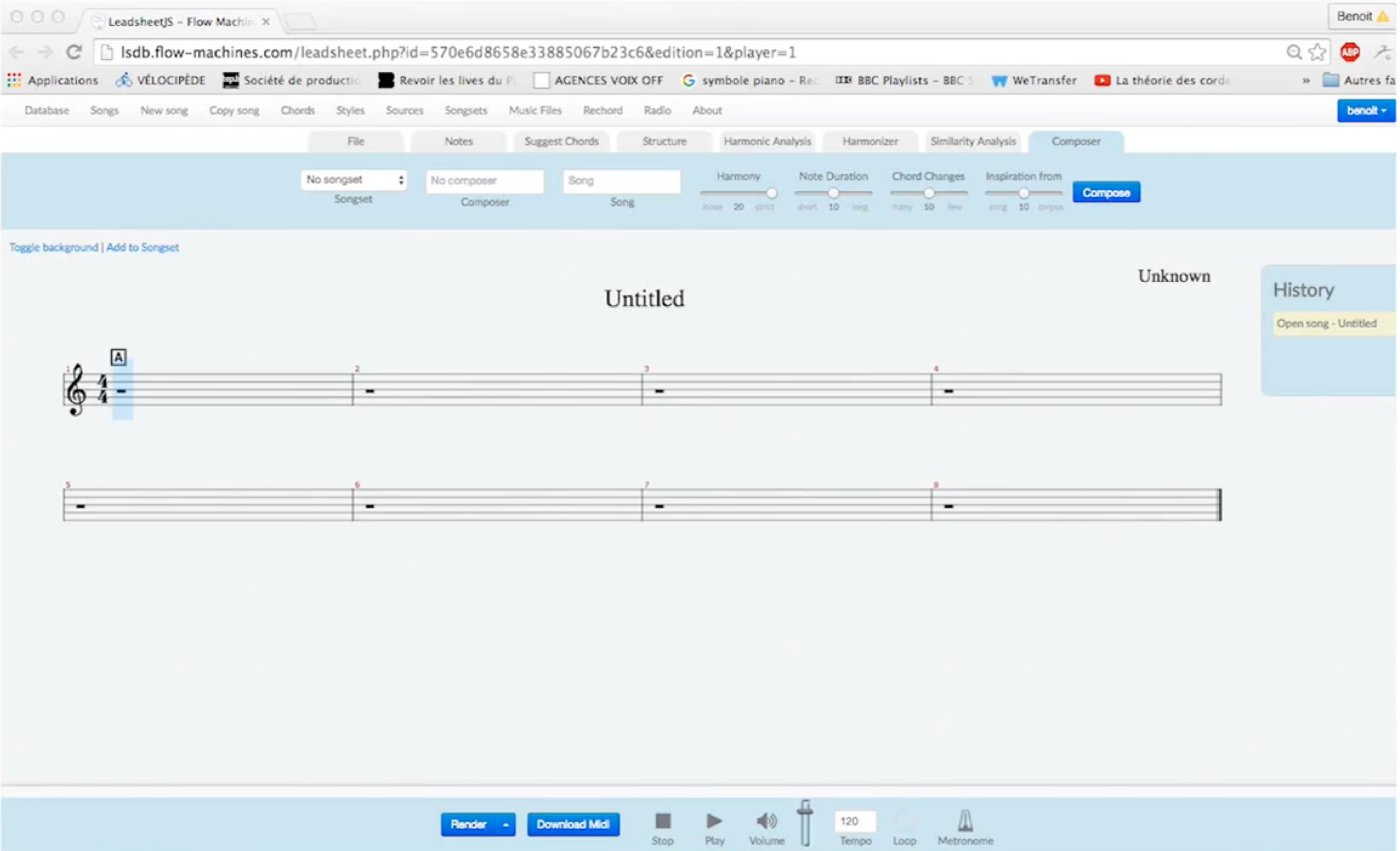
Flow Machines collaborate with musicians to compose the future.

Flow Machines are AI music-making.





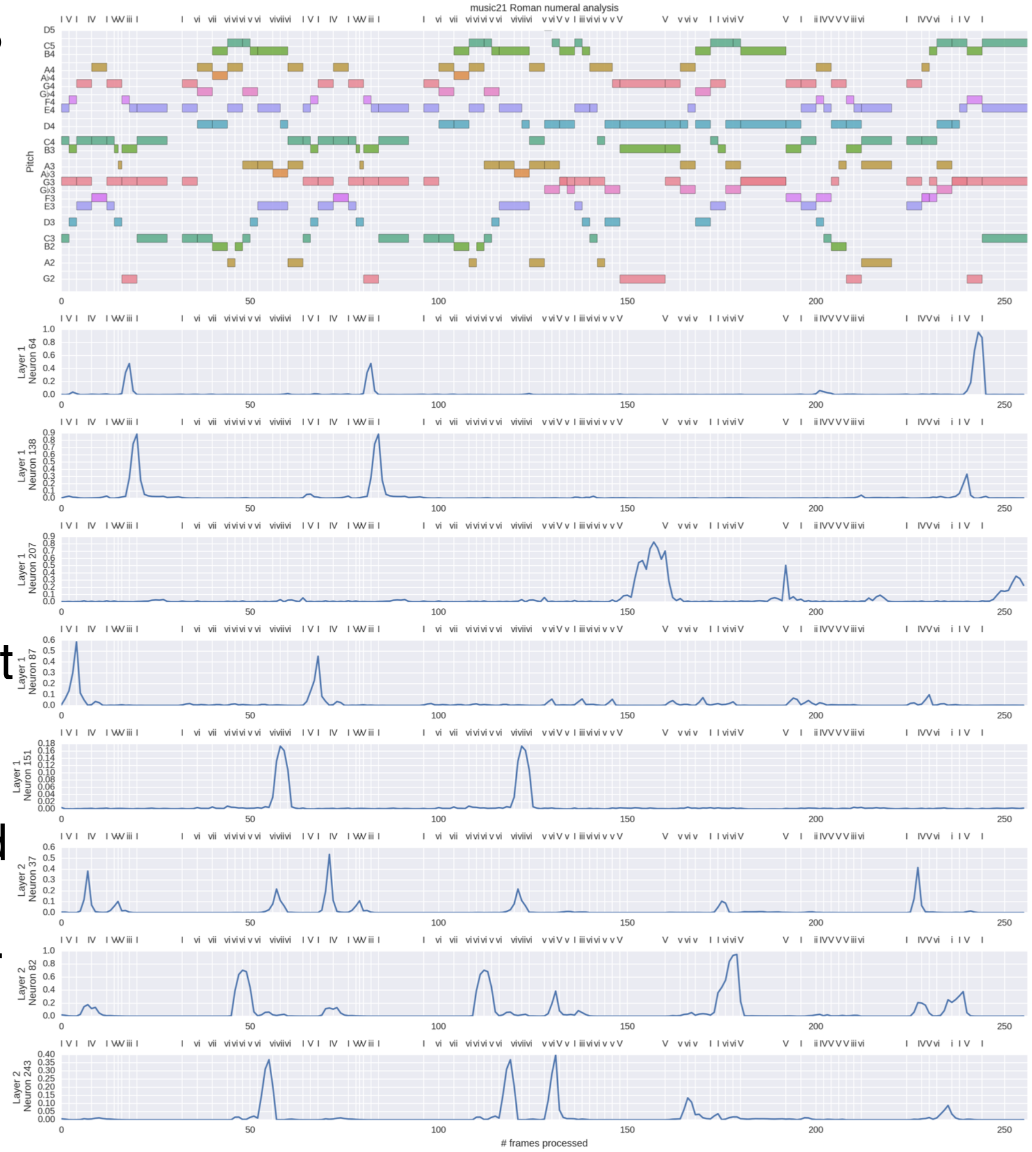
FlowComposer – Demo



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

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

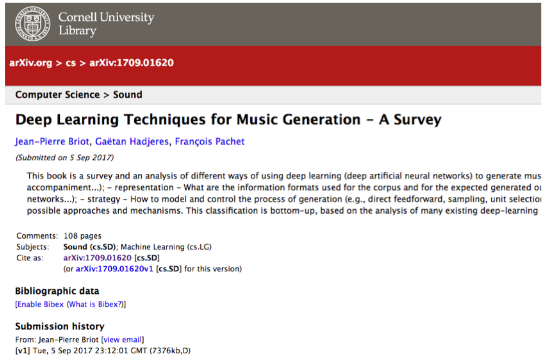
- Ex: BachBot correlation analysis [Liang, 2016]



- 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.



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arXiv.org > cs > arXiv:1709.01620

Computer Science > Sound

Deep Learning Techniques for Music Generation – A Survey

Jean-Pierre Briot, Gaëtan Hadjeres, François Pachet

(Submitted on 5 Sep 2017)

This book is a survey and an analysis of different ways of using deep learning (deep artificial neural networks) to generate mus
accompaniment...); – representation – What are the information formats used for the corpus and for the expected generated o
networks...); – strategy – How to model and control the process of generation (e.g., direct feedforward, sampling, unit selectio
possible approaches and mechanisms. This classification is bottom-up, based on the analysis of many existing deep-learning

Comments: 108 pages
Subjects: **Sound (cs.SD)**; Machine Learning (cs.LG)
Cite as: arXiv:1709.01620 [cs.SD]
(or arXiv:1709.01620v1 [cs.SD] for this version)

Bibliographic data

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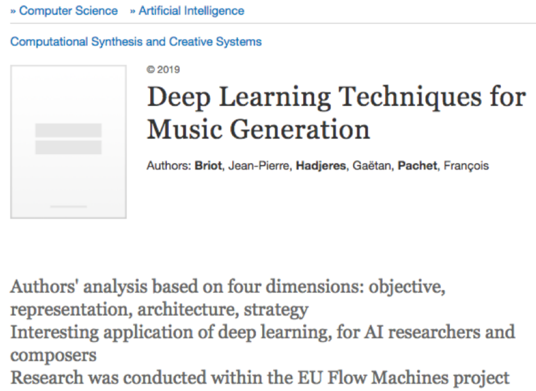
J.-P. Briot, G. Hadjeres, F. Pachet, Deep Learning Techniques for Music Generation, Computational Synthesis and Creative Systems Series, Springer Nature, 2019.



» Computer Science » Artificial Intelligence

Computational Synthesis and Creative Systems

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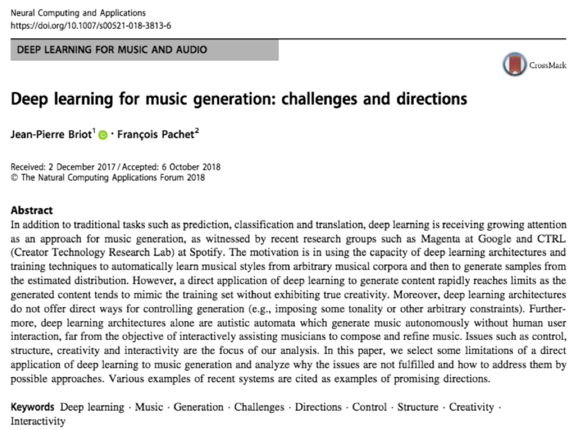
Deep Learning Techniques for Music Generation

Authors: **Briot**, Jean-Pierre, **Hadjeres**, Gaëtan, **Pachet**, François

Authors' analysis based on four dimensions: objective, representation, architecture, strategy
Interesting application of deep learning, for AI researchers and composers
Research was conducted within the EU Flow Machines project

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.



Neural Computing and Applications
https://doi.org/10.1007/s00521-018-3813-6

DEEP LEARNING FOR MUSIC AND AUDIO

CrossMark

Deep learning for music generation: challenges and directions

Jean-Pierre Briot[1] · François Pachet[2]

Received: 2 December 2017 / Accepted: 6 October 2018
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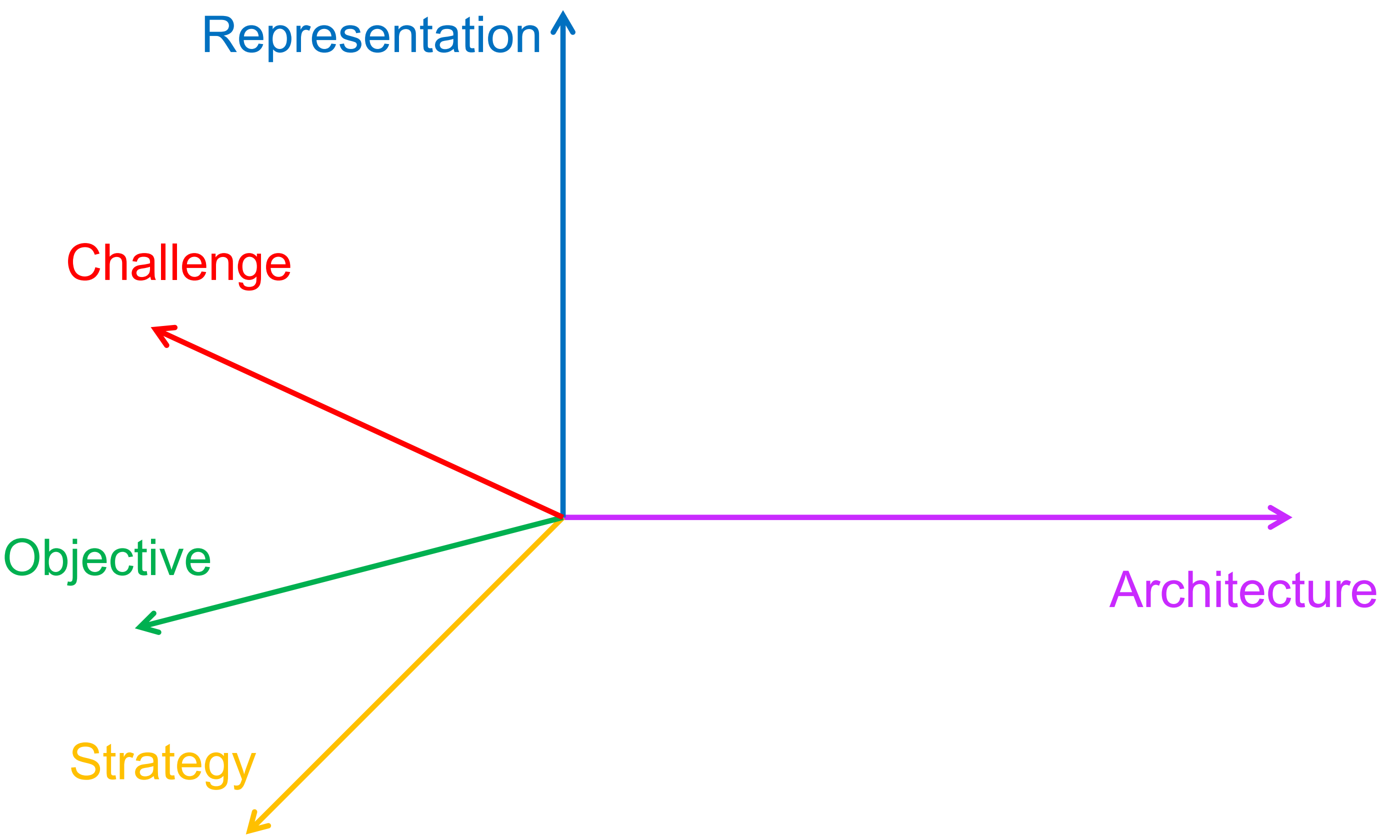
Abstract
In addition to traditional tasks such as prediction, classification and translation, deep learning is receiving growing attention as an approach for music generation, as witnessed by recent research groups such as Magenta at Google and CTRL (Creator Technology Research Lab) at Spotify. The motivation is in using the capacity of deep learning architectures and training techniques to automatically learn musical styles from arbitrary musical corpora and then to generate samples from the estimated distribution. However, a direct application of deep learning to generate content rapidly reaches limits as the generated content tends to mimic the training set without exhibiting true creativity. Moreover, deep learning architectures do not offer direct ways for controlling generation (e.g., imposing some tonality or other arbitrary constraints). Furthermore, deep learning architectures alone are autistic automata which generate music autonomously without human user interaction, far from the objective of interactively assisting musicians to compose and refine music. Issues such as control, structure, creativity and interactivity are the focus of our analysis. In this paper, we select some limitations of a direct application of deep learning to music generation and analyze why the issues are not fulfilled and how to address them by possible approaches. Various examples of recent systems are cited as examples of promising directions.

Keywords Deep learning · Music · Generation · Challenges · Directions · Control · Structure · Creativity · Interactivity

Survey/Analysis

4+1 dimensions



Objective

- Melody
  - Monodic

  - Polyphonic

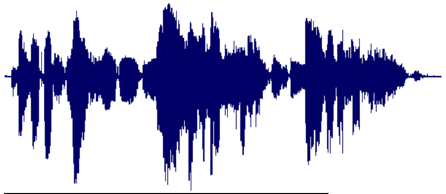
- Polyphony (Multiple Voices/Tracks)
- Accompaniment
  - Counterpoint
    - » Melody
    - » Melodies (Chorale)

  - Chords
- Melody + Harmony/Chords

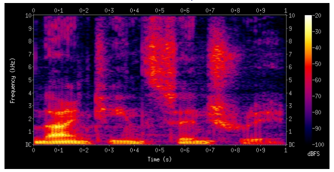
- Leadsheet

Representation

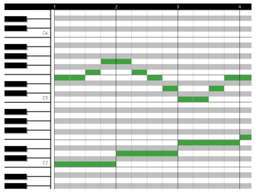
- Signal
  - Waveform



  - 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:|
```

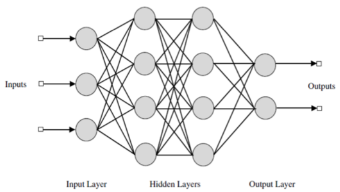
  - Chord

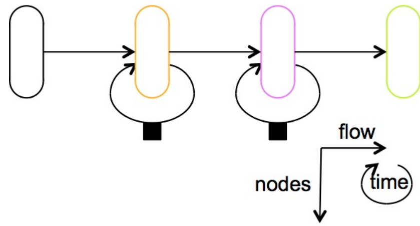
EbMaj7/G

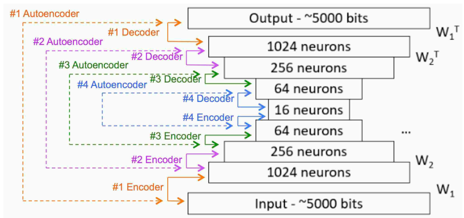
  - Lead sheet
  - Rhythm

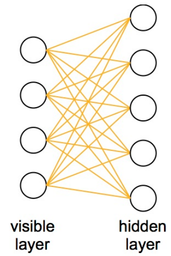
Architecture

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

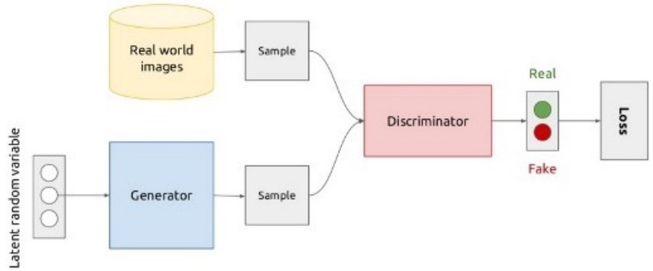




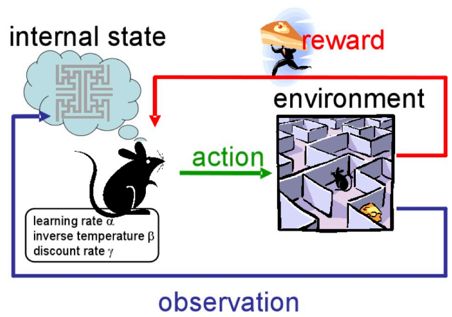




- Patterns
  - Convolutional
  - Conditioning
  - Generative Adversarial Networks (GAN)



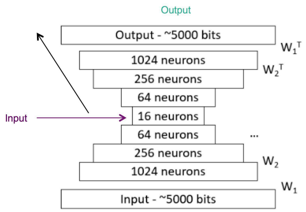
- Reinforcement Learning



- Compound
  - RNN Encoder-Decoder
  - …

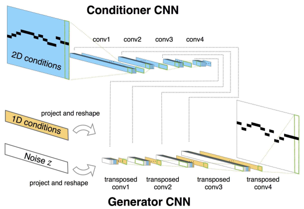
Strategy

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

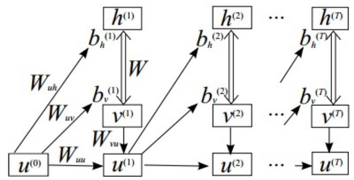


[Sun, 2016]

- Conditioning



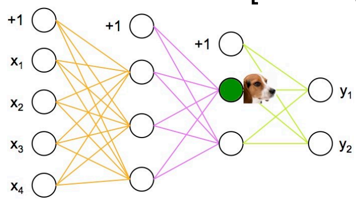
[Yang et al., 2017]



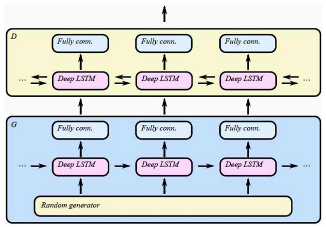
[Boulanger-Lewandowski et al., 2012]

- Sampling

- Input Manipulation

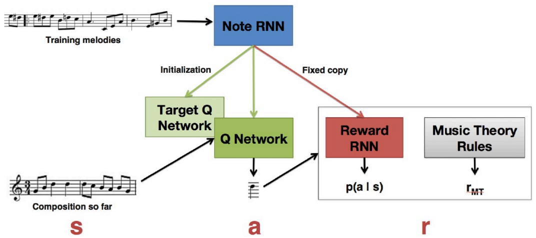


- Adversarial



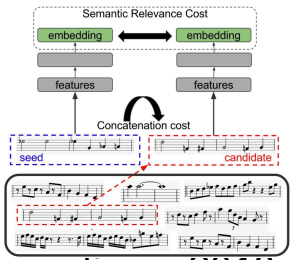
[Mogren, 2016]

- Reinforcement



[Jaques et al., 2016]

- Unit Selection



[Bretan et al., 2016]

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Thank You – Questions