WaveNet - Generative Music Production

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WaveNet in General

- Developed by DeepMind in London
- Generate raw speech Signals with subjective naturalness never before reported in the Field of Text-to-Speech (TTS) (Oord et al., 2016)
- Performance improvement by over 50% (van den Oord and Dieleman, 2016)
- Advantage : One Model for different Purposes

WaveNet in General

- Architecture based on Dilated Causal Convolutions
- WaveNets provide a generic and flexible Framework for many Applications relying on Audio generation :
    - Text-to-Speech
    - Music generation
    - Speech enhancement
    - Voice conversion
    - Source separation

Source : (Oord et al., 2016)

Model Explanation - Theoreticaly

- Generative Model operating on raw Audio Waveform
- Joint probability of a Waveform is factorised as a Product of conditional Probabilities
- Each Audio Sample is therefore conditioned on the Samples at all previous Timesteps
- Conditional Probability Distribution is modelled by a Stack of Convolutional Layers
- No pooling Layers in Network
- Output of the Model has the same Time Dimensionality as the Input

Source : (Oord et al., 2016)

Model Explanation - Visual

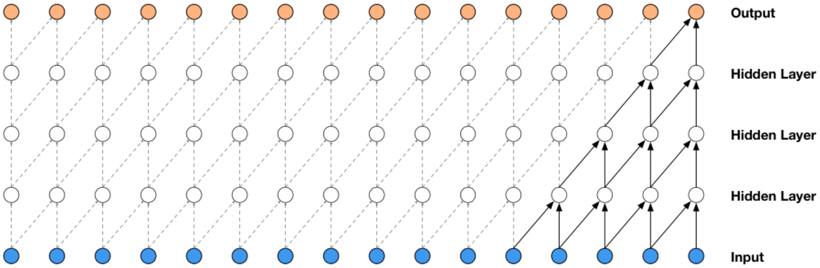


Figure : Visualization of a Stack of causal Convolutional Layers
Source : (Oord et al., 2016)

Model Explanation - Causal Convolutions

- Main Ingredient of WaveNet are Causal Convolutions
- Based on that, the Model cannot violate the Ordering in which the Data is modeled
- Predictions emitted by the Model at Timestep t cannot depend on any of the future Timesteps
- At Training, Conditional Predictions for all Timesteps can be made in parallel (all Timesteps of Ground Truth x are known)

Source : (Oord et al., 2016)

Model Explanation - Causal Convolutions

- At the Generation of the Outputs with the Model, Predictions are sequential :
  after each Sample is predicted, it is fed back into the Network to predict the next Sample
- Models with Causal Convolutions do not have recurrent Connections, they are typically faster to train than RNNs
- Problem of Causal Convolutions is : they require many Layers, or large Filters to increase the Receptive Field

Source : (Oord et al., 2016)

Model Explanation - Dilated Convolutions

- A Dilated Convolution is a Convolution where the Filter is applied over an area larger than its length by skipping Input Values with a certain step
- It is equivalent to a Convolution with a larger Filter derived from the original Filter by dilating it with zeros, but significantly more efficient
- Similar to pooling or strided Convolutions, but here the Output has the same Size as the Input
- Stacked Dilated Convolutions enable Networks to have very large receptive Fields with just a few Layers

Source : (Oord et al., 2016)

Model Explanation - Visual

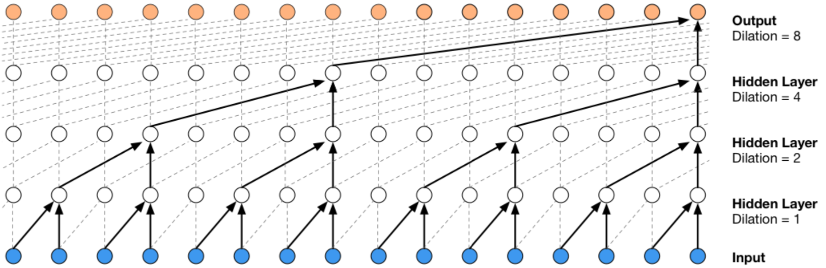


Figure : Visualization of a stack of Dilated Causal Convolutional Layers
Source: (Oord et al., 2016)

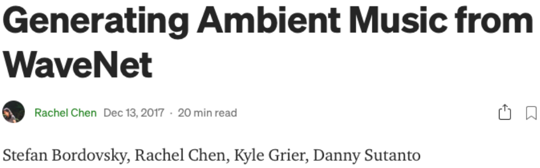
Music Production with WaveNet

- "WaveNets can be used to model any audio signal"
- Unlike the TTS experiments Networks were not conditioned on an Input Sequence telling it what to play (such as a musical score)
- Instead : simply let it generate whatever it wanted to
- Fact that directly generating Timestep per Timestep with Deep Neural Networks works at all for 16kHz Audio is really surprising

Source : (van den Oord and Dieleman, 2016)

Implementation Example

Let's have a look at the Results Chen written down in following Article :



Generating Ambient Music from WaveNet

Rachel Chen Dec 13, 2017 · 20 min read

Stefan Bordovsky, Rachel Chen, Kyle Grier, Danny Sutanto

Source : Medium (Chen, 2017)

Implementation Example - Prerequisites

- The Model trained on Tensorflow Implementation of WaveNet
- 150 000 Steps at a default of 0.001 Learning Rate
- They use Amazon Web Services' p2.xLarge EC2 Instance to train the WaveNet Model with a GPU
- 118 500 Steps trained in approximately 3.5 days (then the AWS Costs get to high) :
  - With each Step taking roughly 2.5 seconds
  - Their Notebooks took approximately 1 Minute just to train one Step

Source : Medium (Chen, 2017)

Implementation Example - Some Results

- Based on Happy Music from YouTube the Model Results are :
  - ▸ 9950 steps
  - ▸ 10800 steps
  - ▸ 14450 steps
  - ▸ 25650 steps

Source : Medium (Chen, 2017)

Implementation Example - Challenges

- Very much Iterations are needed in order to achieve approximately good Results
- The Model requires at least 20 000 Steps to generate something somewhat recognizable
- And around 80 000 Steps for something somewhat coherent
- Learning on local Machines takes very long for only semi good results

Source : Medium (Chen, 2017)

Implementation Example - Chances

- Scientist at DeepMind implemented a Model playing Piano :
  - WaveNet Piano example (van den Oord and Dieleman, 2016)
- Advantage is, that they input exactly one Instrument
- WaveNet achieves good results on simple Inputs
- Complex Inputs require a lot of Learning Steps

Wrap up

- WaveNet is basically a good Model for generating Music
- Good Results can be achieved quickly with individual Instruments
- If whole songs are used as Input, the Model has to make significantly more Learning Steps
- This extensive learning is very Computationally, Time-Consuming and Costly

Bibliography

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Oord, A. v. d., Dieleman, S., Zen, H., Simonyan, K., Vinyals, O., Graves, A., Kalchbrenner, N., Senior, A., and Kavukcuoglu, K. (2016). Wavenet: A generative model for raw audio.

van den Oord, A. and Dieleman, S. (2016). Wavenet: A generative model for raw audio.