Generowanie muzyki przy pomocy modelu transformer-GAN trenowanego metodą polityki gradientu

Music generation with transformer based generative adverserial network trained using policy gradient methods

Transformer

Attention is all you need

Attention Is All You Need

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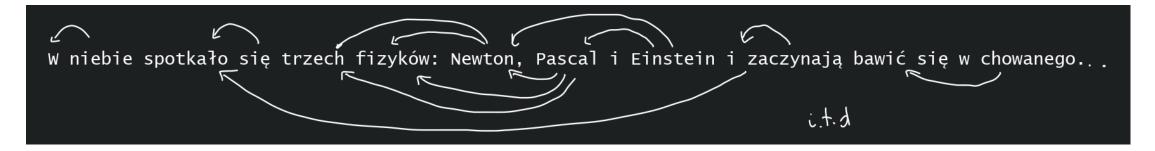
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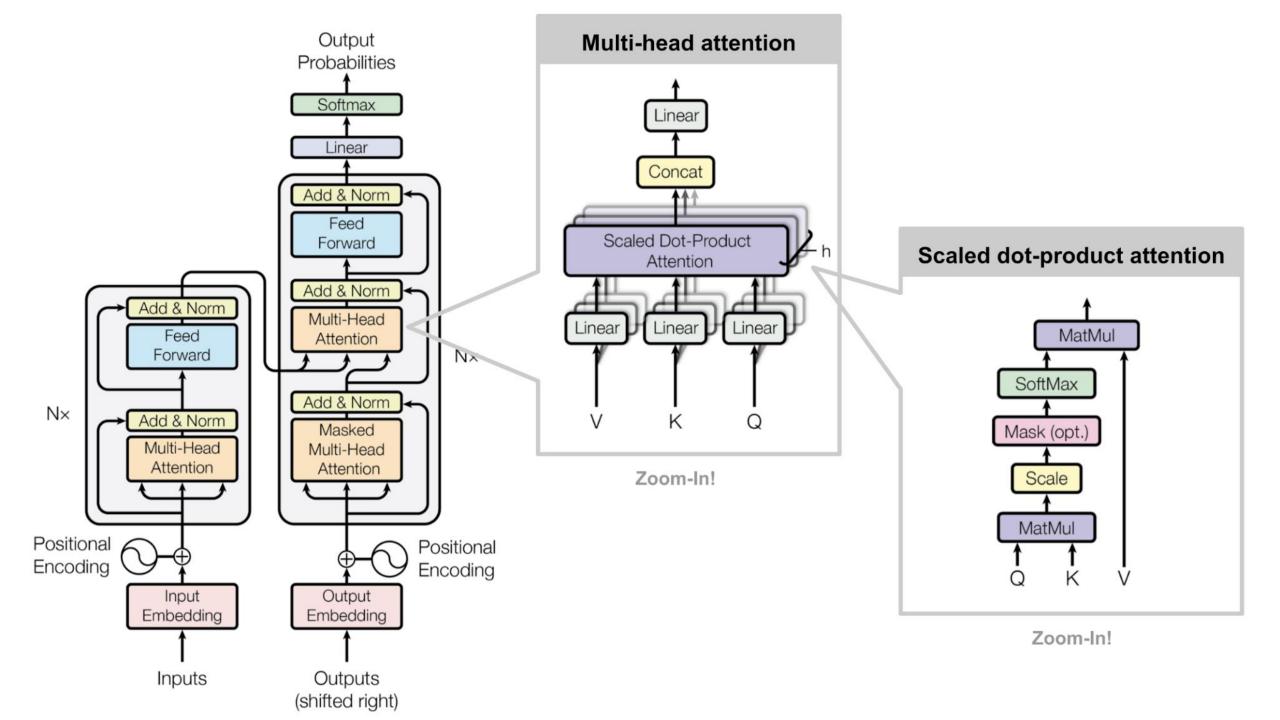
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Mechanizm uwagi (attention)



RNN, LSTM, GRU

W niebie spotkało się trzech fizyków: Newton, Pascal i Einstein i zaczynają bawić się w chowanego.



MUSIC TRANSFORMER: GENERATING MUSIC WITH LONG-TERM STRUCTURE

Cheng-Zhi Anna Huang* Ashish Vaswani Jakob Uszkoreit Noam Shazeer Ian Simon Curtis Hawthorne Andrew M. Dai Matthew D. Hoffman Monica Dinculescu Douglas Eck Google Brain

Music Transformer

Poza użyciem architektury transformera w celach generacji muzyki, artykuł używa metody uwagi nazywanej "Relative Attention" czyli wzbogacony tradycyjny algorytm. Polega on na dodaniu możliwości patrzenia na relatywną pozycje tokenu w sekwencji.

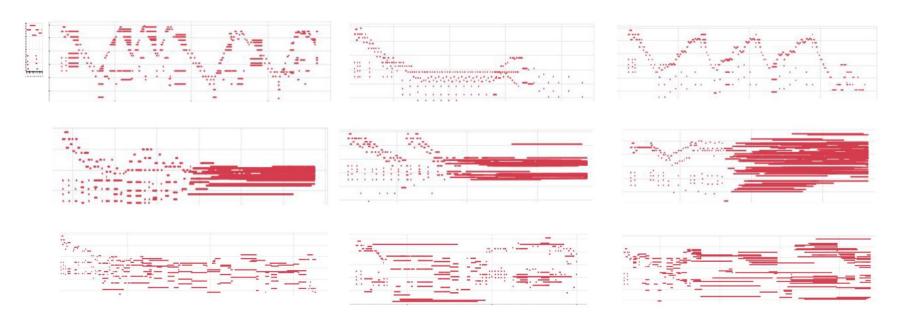


Figure 4: Comparing how models continue a prime (top left). Repeated motives and structure are seen in samples from Transformer with relative attention (top row), but less so from baseline Transformer (middle row) and PerformanceRNN (LSTM) (bottom row).

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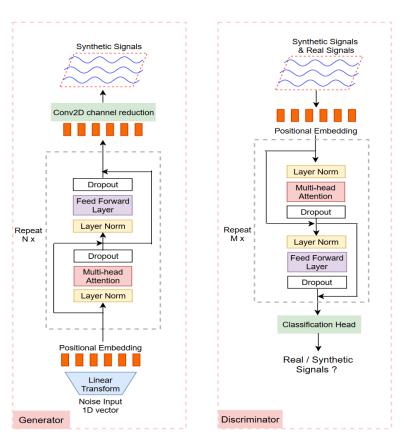
TTS-GAN: A Transformer-based Time-Series Generative Adversarial Network

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TTS-GAN

Architektura i trening sieci



Random Input

Generator

Generated Data

Discriminator

Classification real or generated?

Training

Training

Trening odbywa się w następujący sposób: z losowego szumu generator nadbudowuje syntetyczne dane, które następnie są przekazywane do dyskryminatora razem z prawdziwymi danymi z odpowiednimi oznaczeniami. Oba modele poprawiają sobie wagi. Trening odbywa się do momentu, w którym dyskryminator nie jest w stanie odróżnić prawdziwych danych od sztucznie wygenerowanych.

Fig. 1: TTS-GAN model architecture

Trenowanie przy pomocy gradient polityki

SeqGAN

SeqGAN: Sequence Generative Adversarial Nets with Policy Gradient

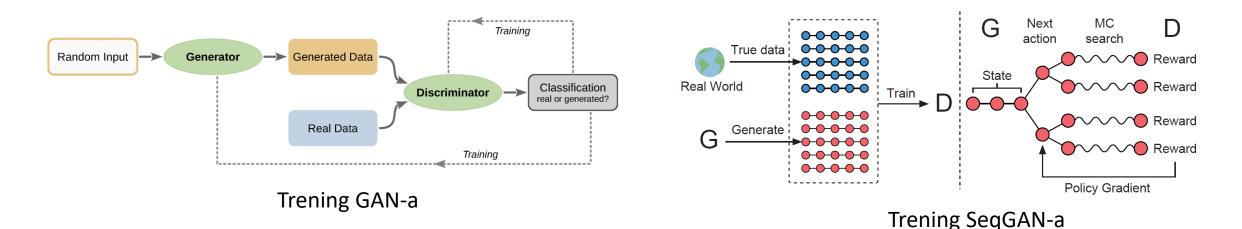
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Problem:

Typowy GAN jest trenowany według schematu przedstawionego na rysunku. Niestety w naszym przypadku bloczek *Random Input,* jest sekwencyjne losowanym wektorem na podstawie poprzednich tokenów, co uniemożliwia przeprowadzenie gradientu.

Wykorzystanie polityki gradientowej zaciągniętej z działu RL, pozwala na policzenie gradientu, traktując ciąg dyskretnych tokenów, jako ciąg przyszłych akcji dla danego stanu, maksymalizowania szansa na "oszukanie" modelu dyskryminatora.



Music Generation

For music composition, we use Nottingham dataset as our training data, which is a collection of 695 music of folk tunes in midi file format. We study the solo track of each music. In our work, we use 88 numbers to represent 88 pitches, which

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https://github.com/samim23/obama-rnn
http://www.iro.umontreal.ca/~lisa/deep/data
```

correspond to the 88 keys on the piano. With the pitch sampling for every 0.4s⁷, we transform the midi files into sequences of numbers from 1 to 88 with the length 32.

To model the fitness of the discrete piano key patterns, BLEU is used as the evaluation metric. To model the fitness of the continuous pitch data patterns, the mean squared error (MSE) (Manaris et al. 2007) is used for evaluation.

From Table 4, we see that SeqGAN outperforms the MLE significantly in both metrics in the music generation task.

Algorithm 1 Sequence Generative Adversarial Nets

```
Require: generator policy G_{\theta}; roll-out policy G_{\theta}; discriminator
     D_{\phi}; a sequence dataset \mathcal{S} = \{X_{1:T}\}
 1: Initialize G_{\theta}, D_{\phi} with random weights \theta, \phi.
 2: Pre-train G_{\theta} using MLE on S
 3: \beta \leftarrow \theta
 4: Generate negative samples using G_{\theta} for training D_{\phi}
 5: Pre-train D_{\phi} via minimizing the cross entropy
 6: repeat
        for g-steps do
           Generate a sequence Y_{1:T} = (y_1, \dots, y_T) \sim G_\theta
           for t in 1:T do
              Compute Q(a = y_t; s = Y_{1:t-1}) by Eq. (4)
           end for
           Update generator parameters via policy gradient Eq. (8)
13:
        end for
14:
        for d-steps do
           Use current G_{\theta} to generate negative examples and com-
15:
           bine with given positive examples S
           Train discriminator D_{\phi} for k epochs by Eq. (5)
16:
17:
        end for
        \beta \leftarrow \theta
19: until SeqGAN converges
```

GETMusic: Generating Music Tracks with a Unified Representation and Diffusion Framework

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https://github.com/microsoft/muzic

Artykuł ten pokazuje innowacyjne podejście do generacji muzyki, ponieważ zamiast tradycyjnych sekwencyjnych modeli używa modeli dyfuzyjnych. Pliki muzyczne są reprezentowane jako struktura 2D, gdzie osią Y jest ilość ścieżek dźwiękowych, a osią X kolejne timestamy.

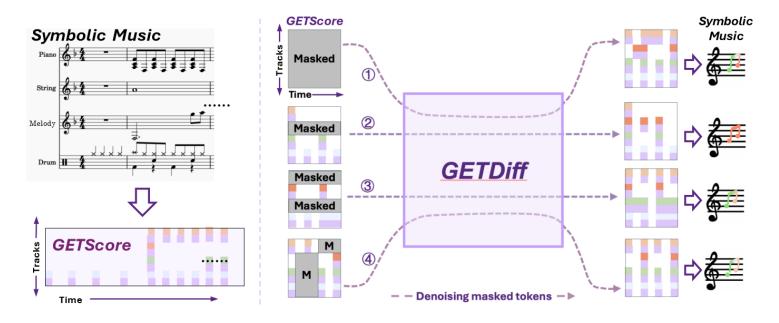
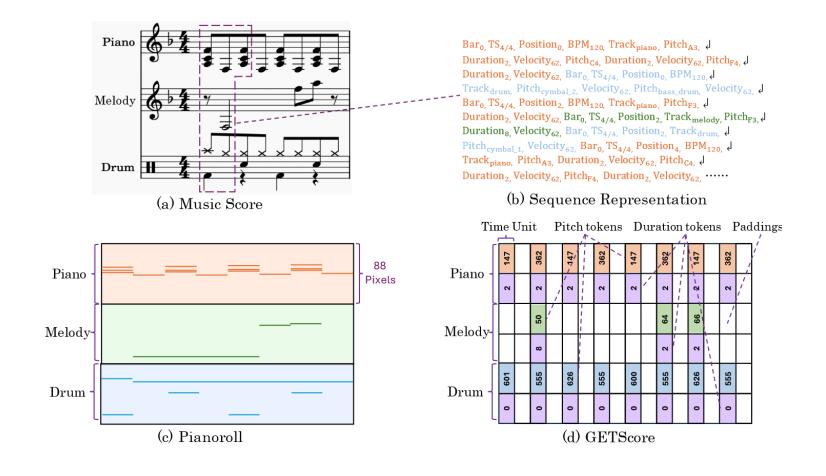


Figure 1: The overview of GETMusic, involving a novel music representation "GETScore" and a discrete diffusion model "GETDiff." Given a predefined ensemble of instrument tracks, GETDiff takes GETScores as inputs and can generate any desired target tracks conditioning on any source tracks (①, ②, and ③). This flexibility extends beyond track-wise generation, as it can perform zero-shot generation for any masked parts (④).

Podejście jest o tyle innowacyjne, że muzyka jest reprezentowana jako obrazek, a nie sekwencja dyskretnych tokenów.



Museformer: Transformer with Fine- and Coarse-Grained Attention for Music Generation

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Museformer

Podobnie jak Music Transformer, ten model próbuje rozwiązać problem z ilością tokenów, które w algorytmie attention, każdy inny token ma brać pod uwagę. Ten artykuł wprowadza nowy rodzaj algorytmu nazywany "fine- and coarse-grained attention (FC-Attention)". Podstawową ideą FC-Attention jest to, że zamiast bezpośrednio zwracać uwagę na wszystkie tokeny, co powoduje złożoność kwadratową, token określonego taktu zwraca uwagę tylko na takty związane ze strukturą, które są niezbędne do generowania muzyki strukturalnej (uwaga drobnoziarnista), a w przypadku innych taktów token zwraca uwagę tylko na ich tokeny podsumowujące, aby uzyskać skoncentrowane informacje (uwaga gruboziarnista). Aby to osiągnąć, najpierw podsumowujemy lokalne informacje każdego taktu w kroku podsumowania, a następnie agregujemy drobnoziarniste i gruboziarniste informacje w kroku agregacji.

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Google: Magenta



Magenta Studio 2.0

Magenta Studio has been upgraded to more seamlessly integrate with Ableton Live. It is a collection of music creativity tools built on Magenta's open source models, using cutting-edge machine learning techniques for music generation.

AUGUST 24, 2023

JUNE 21, 2023



The 2023 I/O Preshow – Composed by Dan Deacon (with some help from MusicLM)

A look into Dan Deacon's creative process for the 2023 Google I/O preshow.



The Wordcraft Writers Workshop: Creative Co-Writing with Al

We invited 13 professional writers to explore the limits of co-writing with LaMDA and foster an honest and earnest conversation about the rapidly changing relationship between technology and creativity.

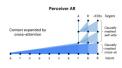
DECEMBER 1, 2022



The Chamber Ensemble Generator and CocoChorales Dataset

We combine Coconet and MIDI-DDSP into a system called the Chamber Ensemble Generator, which we use to make a giant dataset of four-part Bach chorales called

SEPTEMBER 30, 2022



namber Ensemble Generato

Autoregressive long-context music generation with Perceiver AR

We generate music with clear long-term coherence and structure in both symbolic and audio domains, by attending to inputs spanning up to several minutes.

JUNE 16, 2022



DDSP-VST: Neural Audio Synthesis for All

DDSP-VST is a neural audio synthesizer for your digital audio workstation, powered by DDSP.

JUNE 8, 2022