POP2PIANO: POP AUDIO-BASED PIANO COVER GENERATION

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ABSTRACT

The piano cover of pop music is widely enjoyed by people. However, the generation task of the pop piano cover is still understudied. This is partly due to the lack of synchronized {Pop, Piano Cover} data pairs, which made it challenging to apply the latest data-intensive deep learning-based methods. To leverage the power of the data-driven approach, we make a large amount of paired and synchronized {Pop, Piano Cover} data using an automated pipeline. In this paper, we present Pop2Piano, a Transformer network that generates piano covers given waveforms of pop music. To the best of our knowledge, this is the first model to directly generate a piano cover from pop audio without melody and chord extraction modules. We show that Pop2Piano trained with our dataset can generate plausible piano covers.

Index Terms— Piano Cover, Music Arrangement, Transformer, Music Synchronization

1. INTRODUCTION

Piano cover refers to a musical piece in which all musical elements of an existing song are recreated or arranged in the form of a piano performance. Piano covers of pop music are one of the widely enjoyed forms of music. For example, people use them for music education purposes, and piano cover creators have millions of subscribers on media such as Youtube.

In order for a human to create a piano cover, it is necessary to recognize all musical elements such as melodies, chords or moods from the original audio and reinterpret them into musically appropriate piano performances. Therefore, making a piano cover is not an easy task even for humans as it is a creative task and requires musical knowledge.

There were studies on arranging given pop audio to other instruments [1, 2]. They used multiple external modules to extract explicit musical information, such as melodies and chords, from the original audio. However, in addition to this information, piano covers can be made under the influence of various implicit musical characteristics like the atmosphere of the music and the composer's arrangement style. So we believe that the research on end-to-end conversion between audio and piano covers can also be considered valuable.

Meanwhile, Deep learning has been reported to have excellent performance in modeling high-dimensional music audio data. To the best of our knowledge, however, there has been no deep learning study on piano cover modeling using waveforms from pop music directly. We suspect that this is due to the absence of large amounts of synchronized {Pop, Piano Cover} data for such modeling,

and also because it is practically difficult for humans to create sufficient amounts of data for deep learning.

In this study, we introduce a study on the Transformer-based piano cover generation model Pop2Piano, which generates a piano performance (MIDI) from the waveform of pop music. Our contribution is summarized as follows:

- We propose a novel approach to piano cover generation. For this, We build 300-hour of synchronized {Pop, Piano Cover} dataset, called Piano Cover Synchronized to Pop Audio (PSP), and introduce the preprocessing system used to make this dataset.
- We design Pop2Piano, a Transformer network that generates piano covers from given audio. It does not use a melody or chord extractor but uses the spectrogram itself as an input. It also controls the covering style using the arranger token.
- We upload a list of data and preprocessing codes to reproduce the PSP dataset, and release an executable Pop2Piano demo on Colab¹.

2. RELATED WORK

2.1. Automatic Music Transcription

The task most similar to this work in terms of the form of data is automatic music transcription (AMT). AMT is the task of estimating note information of a performance from the waveforms of musical instruments. In the piano AMT, [3, 4, 5] used architectures combining CNN for feature extraction and RNN for modeling note onset and offset and frame. [6] used the Transformer model (T5-small [7]), and they used the spectrogram of the piano audio as input to the encoder and generated a MIDI sequence as the output of the decoder.

Multi-instrument AMT is the task of estimating note information for each instrument from the mixed sounds of several instruments. Cerberus [8] is a multi-instrument AMT for a determined set of musical instruments using an RNN structure. MT3 [9] has a structure similar to [6], but it shows that multi-instrument AMT is possible by mixing datasets for several instruments.

AMT has yielded promising results when there is a large synchronized instrument-audio dataset. [3, 4, 5, 6] were trained using MAESTRO [10], the 200-hour synchronized piano MIDI-audio dataset. And [8, 9] obtained strong performance using Slakh2100 [11], the 150-hour multi-instrument MIDI-audio dataset. Since the task of piano cover generation is similar to AMT in the sense of input and output, in this study, we build a 300-hour synchronized piano cover dataset and use it for training.

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¹https://sweetcocoa.github.io/pop2piano_samples

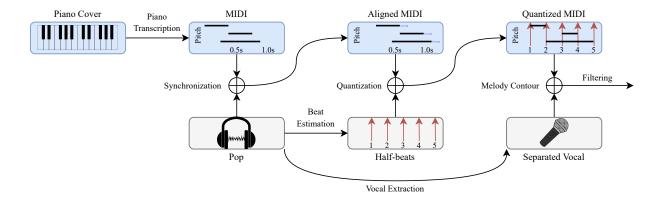


Fig. 1. A preprocessing pipeline for synchronizing and filtering paired {Pop, Piano Cover} audio data.

Although AMT and this study have similarities in converting a given audio into musical notes, there is an important difference in that AMT has a single correct answer, and the piano cover generation task does not. For example, the monophonic vocal of the original song may be expressed as a monophonic note sequence in the piano cover, but may also be performed as *voicing* (the simultaneous vertical placement of related notes at the same time) or *doubling* (playing the same notes in different octaves at the same time). The harmony of the original song may appear as the accompaniment of various textures in the piano cover, and these textures may also vary depending on the atmosphere of the original song or the style of the arranger.

2.2. Audio-based Instrument Cover

Most audio-based instrument cover studies have used external modules to get melodies and chords from the audio. Song2Guitar [1] generated guitar cover from pop audio. They used modules to extract melodies, chords and beats respectively. Then, a guitar tab score was generated by statistically modeling the fingering probability. In [2], They extracted melodies, chords, and choruses using external modules. Then, a piano score was generated using rule-based methods. Unlike them, our study, Pop2Piano, uses only a beat extractor and generates piano notes from pop audio directly.

3. DATASET

The main bottleneck in modeling raw waveform pairs is a long range of dependencies, as they are computationally challenging to learn the high-dimensional semantics of music. An alternative to that is a method of training short-length waveform segments in pairs. However, in the case of using this method {Pop, Piano Cover} pairs should be synchronized. If it is not synchronized, there is a high possibility that the correct answer label is not included in the given audio segment. And since the collected data was not synchronized, we designed the preprocessing pipeline to obtain synchronized {Pop, Piano Cover} data. See Fig 1 for overview.

3.1. Preprocessing

3.1.1. Synchronizing Paired Music

First, we convert piano cover audio into MIDI, using the piano transcription model [5]. Second, we roughly align piano MIDI with pop

audio. We obtain a warping path using *SynctoolBox* [12] and then use it to modify the note timings of MIDI via linear interpolation. This provides a simple synchronization between the piano cover and pop audio. Third, The note timings are quantized into 8th-note units. After extracting beats from pop audio using *Essentia*², the onset and offset of each note in MIDI are quantized to the nearest 8th-note beat. If the onsets and offsets of the quantized notes are the same, the offset is moved to the next beat. In this way, the entropy of data can be lowered by changing the time unit of a note from continuous-time (seconds) to quantized time (beats).

3.1.2. Filtering Low Quality Samples

There are cases where the data pairs are unsuitable for various reasons, such as the difference in musical progress or having different keys from the original song. To filter out these cases, all data with a melody chroma accuracy [13] of 0.15 or less, or an audio length difference of 20% or more are discarded. Melody chroma accuracy is calculated between the pitch contour of the vocal signal extracted from the audio and the top line of the MIDI.

We use *Spleeter* [14] to separate the vocal signal. Then, to get the melody contours of pop music, the f0 sequence of the vocal is calculated using *Librosa* [15] *pYIN* [16]. The sample rate is 44100 and the hop length is 1024, and the time resolution is about 23.21ms.

3.2. Piano Cover Synchronized to Pop Audio (PSP)

We collect 5989 piano covers from 21 arrangers and corresponding pop songs on YouTube. We then synchronized and filter {Pop, Piano Cover}. As a result, a total of 4989 tracks (307 hours) are left, which are used as a training set, PSP. Note that the piano cover included in the PSP is unique, but the original song is not. This will help the model train separately the style of the piano cover according to the arranger conditions and the acoustic characteristics of the given audio.

4. MODEL

The Pop2Piano model is a Transformer architecture. For each training step, A style token and a log-Mel spectrogram of 4-beat audio which is sampled randomly from the dataset are used as the input, and corresponding synchronized midi messages are used as the target for the decoder. An overview of this process is shown as Fig 2.

²https://essentia.upf.edu/

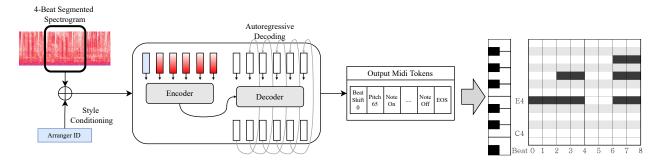


Fig. 2. The architecture of our model is an encoder-decoder Transformer. Each input position for the encoder is one frame of the spectrogram. We concatenated an embedding vector representing a target arranger style to the spectrogram. Output midi tokens are autoregressively generated from the decoder.

4.1. Inputs and Outputs

Pop2Piano uses a log-Mel spectrogram of pop audio as an encoder input. The sampling rate is 22050, the window size is 4096, and the hop size is 1024. In addition, the arranger token, which indicates who arranged the target piano cover, is embedded and appended before the first frame of the spectrogram. Each step of the decoder output is chosen from the following types of tokens:

Note Pitch [128 values] Indicates a pitch event for one of the MIDI pitches. But only the 88 pitches corresponding to piano keys are actually used.

Note On/Off [2 values] Determines whether previous Note Pitch events are interpreted as note-on or note-off.

Beat Shift [100 values] Indicates the relative time shift within the segment quantized into 8th-note beats(half-beats). It will apply to all subsequent note-related events until the next Beat Shift event. We define the vocabulary with Beat Shifts up to 50 beats, but because time resets for each segment, In practice we use only about 10 events of this type.

EOS, PAD [2 values] Indicates the end of the sequence and the padding of the sequence.

This dictionary is inspired by [6, 9]. For a detailed example of this token's interpretation, See Fig 3. For each input, the model autoregressively generates outputs until an EOS token is generated in the decoder. To generate a piano cover of pop audio of arbitrary length, in the inference stage, the audio is sequentially cropped by 4 beats and used as input to the model, then generated tokens (except for EOS) are concatenated. After that, the relative beats of the generated tokens are converted into absolute time using the absolute time information of the beat extracted from the original song and then converted into a standard MIDI file.

4.2. Architecture

The Pop2Piano model architecture is T5-small [7] used for [9]. It is a Transformer network with an encoder-decoder structure. The number of learnable parameters is about 59M. Unlike [9], the relative positional embedding of the original T5 is used instead of the absolute positional embedding. Additionally, A learnable embedding layer is used for embedding the arranger style.

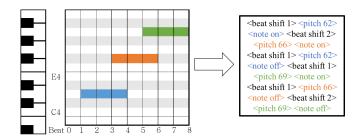


Fig. 3. An example of piano tokenization, the beat shift token means a relative time shift from that point in time.

5. EXPERIMENT

In this experiment, we check whether Pop2Piano trained with PSP (Pop2Piano_{PSP}) can generate a plausible piano cover and verify that it follows a specific arranger's style.

5.1. Training Setup

We train the model 2000 epoch with a batch size of 32, and the input audio is randomly extracted from the dataset with 4-beat length audio. The neural network is optimized using the AdaFactor[17] optimizer and its learning rate is 0.001.

5.2. Generation Result

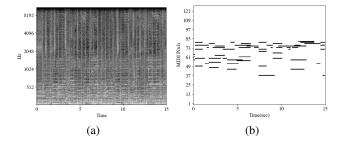


Fig. 4. (a) A Melspectrogram of an input pop audio. (b) A piano roll of output MIDI notes corresponding to input audio.

Fig 4 is an example of a piano cover generated using arbitrary pop music as an input. The generated sample can be listened to on

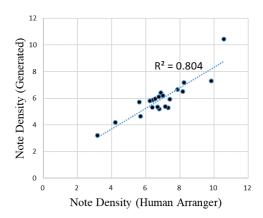


Fig. 5. The dots represent the note density of the piano cover generated by being conditioned with that arranger. The unit is the number of notes per second.

Original Songs	Arranger	Average MCA
$POP909_F$	Human	0.395
PSP	Human	0.3493
$POP909_F$	Pop2Piano _{PSP}	$\textbf{0.402} \pm \textbf{0.021}$

Table 1. Average Melody Chroma Accuracy (AMCA) of humanmade and generated piano covers. The piano covers of Pop2Piano are generated for all 21 arrangers of PSP, and its standard deviation according to arrangers are shown in the table.

the link³. The original song is a complex audio signal mixed with various sounds such as vocals, bass, and percussion. Nevertheless, it can be seen that the generated piano cover shows the vocal melody line of the original song as stacked notes, and also includes a plausible accompaniment that follows the harmony of the original song. Also, various piano cover samples generated by Pop2piano can be listened to with the original song on the demo page.

Additionally, we would like to confirm whether the generated piano cover not only plausibly followed the original song but also covered it in the style of the arranger we designated. However, the cover style is very implicit, so there are few ways to evaluate quantitatively. Inspired by the difference in note densities among arrangers, we measure the note densities of the piano cover generated by Pop2Piano_{PSP} to indirectly verify whether it generates a piano cover in the target arranger's style. As a result, Fig 5 shows that the generated piano cover follows the note density of the target arranger with high linearity of $R^2=0.804$.

We also calculate the MCA used in 3.1.2 for generated piano covers, showing that they have a similar level of MCA to the dataset even in training without explicit melodies. See Table 1. Note that a higher MCA doesn't necessarily mean a better piano cover. Therefore, a study on how to evaluate the generation result of a piano cover will also be a good follow-up study.

5.3. Subjective Evaluation

We measure the subjective quality of the generated piano covers by evaluating their naturalness. Since there is no prior study pub-

(%)	GT_F	Ours	Baseline
vs GT _F	-	29.6	22.24
vs Ours	70.4	-	36
vs Baseline	77.76	64	-
MOS	3.771	3.216	2.856

Table 2. The winning rate and Mean Opinion Score(MOS) according to the piano cover model. "Ours" denotes Pop2Piano_{PSP}, "Baseline" denotes Pop2Piano_{POP909}.

licly available, we use a Pop2Piano network trained with POP909 (Pop2Piano_{POP909}) as a baseline model. The comparison with this model indicates how the PSP dataset affected the performance of the Pop2Piano model.

POP909 [18] is a piano MIDI dataset of 909 Chinese pop songs. There are separate melody, bridge, and accompaniment tracks in this dataset, but we merge all the tracks for the consistency of the experiment. Like PSP, we synchronize {Pop, Piano Cover} pairs through our preprocessing pipeline. After filtering, 817 tracks remain. In the remaining part of this paper, this preprocessed POP909 dataset is denoted as $POP909_F$.

We conduct a user study. There are 25 participants and no professional musicians are included. Participants do not know which model has made each piano cover. We select 10-seconds from the beginning of the chorus of 25 songs that are not included in the training dataset. For each song, a piano cover made by a human arranger is used as GT. However, since GT also needs to be synchronized with the original song, the synchronization pipeline is applied and that data is denoted as GT_F . After listening to the original song and piano covers, the participants evaluate how naturally the given piano cover arranged the original song with 1-5 points.

In the listening evaluation, 70% of participants prefer the piano cover generated by Pop2Piano_{PSP} to Pop2Piano_{POP909}. In MOS analysis between Pop2Piano_{PSP} and Pop2Piano_{POP909}, using paired one-sided Wilcoxon test, we reject H_0 at 99% confidence intervals $(0.222, \inf)$ with p=3.34e-05. See Table 2.

5.4. Limitation

We recognize that some improvements can be made to our model. For instance, Pop2Piano uses only four-beat length audio for the context of input. Therefore, features such as melody contour or texture of accompaniment have less consistency when generating longer than four-beat. Also, time quantization based on eighth note beats prevents the model from generating piano covers with other rhythms such as triplets, 16th notes, and trills.

6. CONCLUSION

We present Pop2Piano, a novel study on generating pop piano covers directly from audio without using melody or chord extraction modules based on a Transformer network. We collect PSP, 300 hours of paired {Pop, Piano Cover} datasets, to train the model. And we design a pipeline that synchronizes them in a form suitable for training neural networks. We open-source the list of data and code needed to reproduce the PSP. We show and evaluate that Pop2Piano_{PSP} can generate plausible pop piano covers and also can mimic the style of a specific arranger.

³https://sweetcocoa.github.io/pop2piano_samples/fig_on_paper.html

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