COMPOSE & EMBELLISH: WELL-STRUCTURED PIANO PERFORMANCE GENERATION VIA A TWO-STAGE APPROACH

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ABSTRACT

Even with strong sequence models like Transformers, generating expressive piano performances with long-range musical structures remains challenging. Meanwhile, methods to compose well-structured melodies or lead sheets (melody + chords), i.e., simpler forms of music, gained more success. Observing the above, we devise a two-stage Transformer-based framework that COMPOSEs a lead sheet first, and then EMBELLISHes it with accompaniment and expressive touches. Such a factorization also enables pretraining on non-piano data. Our objective and subjective experiments show that COMPOSE & EMBELLISH shrinks the gap in structureness between a current state of the art and real performances by half, and improves other musical aspects such as richness and coherence as well.

Index Terms— symbolic music generation, Transformers, autoregressive models, seq2seq models, transfer learning

1. INTRODUCTION

Recent years have witnessed a multitude of research works on leveraging Transformers [1] for symbolic music generation. Generating piano performances emerged as a quintessential arena for such studies, for the rich musical content and texture piano playing can entail without having to deal with the complicated orchestration of instruments. Thanks to Transformers’ outstanding capability of modeling long sequences containing complex inter-token relations, generating several minutes-long expressive piano music end-to-end has been made possible [2, 3, 4]. Though these works all claimed to have improved upon their predecessors in creating repetitive structures, a central element of music, it has been repeatedly shown that they fail to come up with overarching repetitions and musical development that hold a piece together [5, 6, 7]. On the other hand, a line of research that tackles simpler forms of music, e.g., melodies or lead sheets (melody + chords) has seen promising results in composing well-structured pieces [8, 9, 10]. A reasonable conjecture then follows: Could it be too demanding for a monolithic model to generate virtuosic performances end-to-end, as it has to process local nuances in texture or emotions, and the high-level musical flow, all at once?

Therefore, in this paper, we split piano performance generation into two stages, and propose the COMPOSE & EMBELLISH framework that rests on performant prior works [4, 5]. The COMPOSE step writes the lead sheet that sets the overall structure of a song, while the EMBELLISH step conditions on the lead sheet, and adds expressivity to it through accompaniment, dynamics, and timing. Through experiments, we strive to answer the following research questions:

• RQ #1: Can the two-stage framework compose better-structured piano performances than an end-to-end model, without adversely impacting diversity of musical content?
• RQ #2: Does being able to pretrain the COMPOSE step with larger amounts of non-piano data bring performance gains?
• RQ #3: How well does the EMBELLISH step follow the structure of music generated by the COMPOSE step?

Fig. 1 demonstrates our improvement over a state of the art [4]. We open-source our implementation1 and trained model weights.2 Readers are encouraged to listen to samples generated by our framework.3

2. RELATED WORK

For expressive piano performances, [2] and [3] showed respectively that relative positional encoding and beat-based music representation enhance generation quality. [4] designed a more compact representation and utilized memory-efficient attention to fit entire performances into a Transformer. [6] directly addressed musical structure with a multi-granular Transformer, but weakened expressivity by abstracting timing and dynamics away. Bar-level blueprints [12] and musical themes [13] may help to maintain long-range structure, but neither of these systems are capable of unconditioned generation. On composing melodies or lead sheets, researchers used note-level repeat detection and modeling [8], phrase tokens [5], hierarchical generative pipeline [9], and bar-level similarity relations [10] to induce repetitive structures. Out of these, [5] is the most straightforward one that avoids potential error propagation between multiple components, and is hence adopted by our framework.

1Code: github.com/s1SeanWU/Compose_and_Embellish
2huggingface.co/s1SeanWU/compose-and-embellish-pplk7
3Generated samples: bit.ly/comp_embel
3. METHOD

3.1. Input Sequences

We represent a polyphonic musical piece or performance with a sequence of tokens $X$. To encode the expressiveness of a performance, besides chord progression and onset time/pitch/duration of notes, $X$ also contains the velocity (i.e., loudness) of each note, as well as beat-level tempo changes. Any existing method that extracts the monophonic melody line (e.g., the skyline algorithm [14]) may then be applied to $X$. Using the chord progression in $X$ and the extracted melody, we additionally leverage a structure analysis algorithm [15] based on edit similarity and A* search to capture repetitive phrases (in a form like $A_1 A_2 A_3 ...$) of the piece. The melody, chords, and structure information would constitute a lead sheet of the piece, denoted by $M$. Typically, $M$ is much shorter for having less notes, and the expressive aspects being discarded. For both $X$ and $M$, there exists a mapping $\text{bar}(t)$ that gives the index of the bar the $t^{th}$ token belongs to. With the mappings, we may segment $X$ and $M$ into $\{X(1), ..., X(B)\}$ and $\{M(1), ..., M(B)\}$, where $B$ is the piece’s number of bars. The segmented sequences will be used in our model.

3.2. Data Representation

Our token vocabulary is designed based on Revamped MIDI-derived Events (REMI) [3]. In a full performance $X$, a $\text{BAR}^{*}$ token appears whenever a new musical bar begins. $\text{SUBBEAT}^{*}$ tokens indicate timepoints within a bar, in 16th note ($\frac{1}{8}$) resolution. Each note is represented by three tokens: $\text{PITCH}^{*}$ (A0 to C8), $\text{DURATION}^{*}$ (32 levels). Moreover, $\text{TEMPO}^{*}$ (32~224 bpm) tokens set the pace, and $\text{CHORD}^{*}$ tokens (12 roots $\times$ 11 qualities) provide harmonic context. The two above may appear as frequently as every beat. For lead sheets $M$, we take the mean tempo, and place only one $\text{TEMPO}^{*}$ token at the very beginning. We also omit $\text{VELOCITY}^{*}$ of each note. To add structure information to $M$, we refer to [5]: At a phrase’s starting bar, we put $\text{PHRASE}^{*}$ (8 possible letters) and $\text{REPSTART}^{*}$ (16th to 16th repetition) right after $\text{BAR}$. At the phrase’s ending, $\text{PHRASE}^{*}$ and $\text{REPEnd}^{*}$ close that bar. An $\text{EOS}$ token ends the entire lead sheet. Other tokens types are the same as in $X$. By our construction, the vocabulary size for both $X$ and $M$ is about 370.

3.3. Models and Objectives

Fig. 2 is a birds-eye view of our COMPOSE & EMBELLISH framework. It is made up of two generative models: the lead sheet model (COMPOSE) $p(M)$, and the performance model (EMBELLISH) $p(X|M)$. While being trained independently, the two models work in tandem during inference. For the lead sheet model, we simply factorize $p(M)$ into $\prod_t p(m_t | M_{<t})$. It can complete a lead sheet autoregressively given a start token, i.e., $[\text{TEMPO}^{*}]$.

For $p(X|M)$, we follow the conditioned generation case in CP Transformer [4], and interleave one-bar segments from $M$ and $X$ as $\{M(1), X(1), M(2), X(2), \ldots\}$. This way, when generating the performance for a bar, the completed lead sheet of that bar is always the closest piece of context the model may refer to, thereby encouraging it to stay faithful to $M$. Mathematically, $p(X|M)$ can be factorized as $\prod_t p(x_t | X_{<t}; M(\leq \text{bar}(t)))$. For the model to distinguish interleaved segments, we place $\text{TRACK}_M$ and $\text{TRACK}_X$ in front of each of $M(1)$ and $X(1)$ respectively. At inference time, we would move on the next bar whenever $\text{TRACK}_M$ is generated. Both models minimize the negative log-likelihood ($-\log p(\cdot)$) of the sequences. One can use any type of sequence decoder for both models. Due to the long sequence length (mostly >1k) of our data, our choice is Transformers with a causal attention mask.

Since the models are trained separately, we may pretrain the lead sheet model on a larger amount of data ($D_p$ in Fig. 2) extracted from, e.g., various multitrack pieces. These pieces, though not played only by the piano, or at all, still likely feature a well-structured melody that is either sung or played by another instrument. Then, we just need to finetune it on the piano performance dataset that $p(X|M)$ is trained on ($D_t$) to align their domain.

4. EXPERIMENTS

4.1. Datasets and Preprocessing

We adopt the full Lakh MIDI Dataset (LMD-full) [16] as the pretraining dataset ($D_p$) for our lead sheet model. The LMD-full contains over 100k multitrack MIDIs with various instrument combinations in each of them. The dataset for finetuning our leadsheet model and training our performance model ($D_t$) is Pop1K7 compiled in [4]. It features about 1,700 transcribed piano performances of Western, Japanese, and Korean pop songs.

We use different algorithms to extract melodies from $D_p$ and $D_t$. For $D_p$, we leverage the open-source code\footnote{github.com/gunnazaki/lyrics-melody} from [17], which searches for the instrument track whose note onset times align best with those of the song’s lyrics, and regards that track as the melody.\footnote{Songs without lyrics annotations are not considered.} For $D_t$, we employ the skyline algorithm [14], which keeps only the
Table 1. Summary of datasets used in our experiments. The numbers in the last three columns are averages across a dataset.

| Repr. | # songs | # bars / song | # bars / phrase | # tokens / song |
|-------|---------|---------------|-----------------|----------------|
| LMD-full (D_p) | M | 14,934 | 89.6 | 8.64 | 1,356 |
| Pop1K7 (D_I) | M | 1,591 | 104.5 | 8.74 | 5,379 |
| CP | 2,081 |

highest-pitched note from each set of simultaneous onsets. This simple heuristic has been shown to have a nearly 80% accuracy on identifying pop songs’ melodies [18]. We then perform structure analysis [15] on the extracted melodies and discard songs with phrase spanning >32 bars. The statistics of the processed datasets are displayed in Table 1. CP representation [4] for D_I is made for baselining purpose. 10% of each dataset is reserved for validation.

4.2. Model Implementation Details

Our lead sheet model p(M) is parameterized by a 12-layer Transformer [1] (512 hidden state dim., 8 attention heads, 41 million trainable parameters) with relative positional encoding proposed in [19]. With a batch size of 2, we can set maximum sequence length to 2,400 (longer than 98% & 90% of songs in D_p & D_I, respectively) on an RTX3090-Ti GPU with 24G memory. We use Adam optimizer with 200 steps of learning rate warmup to a peak of 1e−4, followed by 500k steps of cosine decay. We keep a checkpoint after each epoch.

In each epoch, a random 3,072 token-long crop of interleaved X segments (see Sec. 3.3 for explanation) of each song is fed to the former with Performer [20] attention (38 mil. trainable parameters). With a batch size of 2, we can set maximum sequence length to 2,400, due to its low memory overhead.

4.3. Baselines and Ablations

We select Compound Word (CP) Transformer [4] as our baseline, as pointed out by [10]. For our COMPOSE & EMBELLISH framework, to examine whether (1) pretraining on D_p, and (2) adding structure (phrase) tokens contribute to its success, we test three ablated versions without either, or both, of them.

Additionally, we sample single-bar, and single-phrase, excerpts from the real data and repeat such excerpts to the song’s length (in # bars), to see how naive repetitions would compare to the models.

4.4. Objective Evaluation

We utilize a set of metrics that can be computed on a song’s notes, or its synthesized audio, to evaluate the intra-song structureness, diversity, and general quality of the generated music.

- **Structureness Indicators (SI)**: proposed first by [5], this metric takes the minimum value from a specific timescale range (e.g., all 10~20 seconds long segments) of the fitness scape plot [11] (see Fig. 1 for examples) computed on the audio of a song. This value represents the extent to which the most salient repetitive segment in that timescale range is repeated throughout the entire song. We set the timescales ranges to 4~12, 12~32, and over 32 seconds to capture the short-, medium-, and long-term structureness (denoted as SI_short, SI_mid, and SI_long respectively).
- **Percentage of Distinct Pitch N-grams in Melody (DN)**: following the popular dist-n [23] metric used in natural language generation to evaluate the diversity of generated content, we compute the percentage of distinct n-grams in the pitch sequence of the skyline extracted from each full performance. We regard 3~5, 6~10, and 11~20 contiguous notes as short, medium, and long excerpts, and compute DN_short, DN_mid, and DN_long accordingly.
- **Pitch Class Histogram Entropy (H):** proposed in [5] to see if a model uses primarily a few pitch classes (i.e., C, C#, B, Bb, B♭, 12 in total), or more, and more evenly, of them, hence leading to a higher harmonic diversity. The subscripts denote whether histograms are accumulated over 1-, or 4-bar segments.
- **Grooving Similarity (GS):** used also in [5]. It calculates the pairwise similarity of each bar’s groove vector g (binary, indicating which sub-beats have onsets) as 1 − HammingDistance(g_0, g_1). All bar pairs (a, b) are involved, not just adjacent ones. Higher GS suggests more consistent rhythm patterns across the song.

We generate 100 songs with each model to compute the metrics. Due to high computation cost of fitness scape plots, we only sample 200 songs from real data (D_I) for comparison.

4.5. User Study

We recruit 15 subjects who are able to spend around half an hour to take part in our listening test. Each test taker is given three independent sets of music. There are three piano performances (full song, about 3~5 minutes long each) in each set, composed respectively by (1) a human composer, (2) COMPOSE & EMBELLISH, and (3) CP Transformer. To facilitate comparison, the three performances in a set share the same 8-bar prompt drawn from our validation split. Test takers are asked to rate each performance on the 5-point Likert scale, on the following aspects:

- **Coherence (Ch):** Does the music follow the prompt well, and unfold smoothly throughout the piece?
- **Correctness (Cr):** Is the music free of inharmonious notes, unnatural rhythms, and awkward phrasing?

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6Other model hyperparameters, hardware, optimizer settings, and check-point selection criterion are the same as those for the lead sheet model.

7Sampling hyperparameters (τ & p) for the ablated models are chosen in the same way as described in Sec. 4.2.
Table 2. Objective evaluation results. (All metrics are the closer to real data, the better. StDevs across individual songs follow ±.)

|                | Structureness (in %) | Melody-line Diversity | Quality |
|----------------|----------------------|------------------------|---------|
|                | S_mean | S_mid | S_long | D_N_short | D_N_mid | D_N_long | H_1 | H_4 | GS (%) |
| Naive repeats (1-bar) | 83.6 ± 8.3 | 88.3 ± 5.4 | 75.7 ± 11 | 1.2 ± 0.6 | 1.2 ± 0.6 | 1.3 ± 0.6 | 1.95 ± 0.4 | 1.95 ± 0.4 | 100 ± 0.0 |
| Naive repeats (1-phrase) | 75.5 ± 15 | 86.2 ± 6.8 | 73.9 ± 11 | 8.2 ± 4.8 | 10.0 ± 5.8 | 10.8 ± 6.5 | 1.96 ± 0.7 | 2.52 ± 0.2 | 83.1 ± 8.8 |
| CP Transformer [4] | 32.5 ± 3.5 | 29.9 ± 4.4 | 17.9 ± 6.3 | 82.0 ± 8.9 | 99.6 ± 0.7 | 100 ± 0.0 | 1.73 ± 0.2 | 2.49 ± 1.1 | 82.6 ± 9.3 |
| COMPPOSE & EMBELLISH & w/o struct | 36.8 ± 6.8 | 35.1 ± 7.7 | 25.8 ± 12 | 49.7 ± 19 | 69.9 ± 20 | 81.6 ± 17 | 1.99 ± 1.7 | 2.54 ± 17 | 81.0 ± 8.4 |
| o/p pretrain | 36.6 ± 7.5 | 33.1 ± 8.8 | 19.6 ± 10 | 53.2 ± 19 | 74.9 ± 18 | 87.9 ± 14 | 1.97 ± 2.2 | 2.49 ± 19 | 81.7 ± 9.6 |
| w/o struct & pretrain | 36.3 ± 6.0 | 34.1 ± 6.7 | 23.0 ± 8.4 | 52.5 ± 18 | 76.1 ± 16 | 89.0 ± 11 | 2.00 ± 2.2 | 2.57 ± 18 | 82.7 ± 8.7 |
| Real data | 43.8 ± 7.1 | 43.1 ± 8.4 | 34.8 ± 12 | 50.0 ± 14 | 74.1 ± 14 | 88.3 ± 11 | 1.96 ± 2.2 | 2.53 ± 15 | 75.3 ± 8.5 |

Table 3. Difference in structureness indicator scores between lead sheets and full performances.

| Lead sheet | Performance | Δ |
|------------|-------------|---|
| S_mean | S_mid | S_long | S_mid | S_long | | |
| C&E | 42.9 | 36.9 | 35.1 | 25.8 | −7.8 | −10.8 |
| w/o struct | 44.4 | 36.5 | 34.2 | 23.8 | −10.2 | −12.7 |
| w/o pretrain | 41.1 | 28.9 | 33.1 | 19.6 | −8.0 | −9.3 |
| w/o both | 41.3 | 31.3 | 34.1 | 23.0 | −7.2 | −8.3 |
| Real data | 43.6 | 36.6 | 43.1 | 34.8 | −0.5 | −1.8 |

Table 4. User study MOS results. (Coherence, Correctness, Structureness, Richness, Overall; SDs across individual data points follow ±.)

|                | Ch | Cr | S | R | O |
|----------------|----|----|---|---|---|
| CPT [4]        | 2.38 ± 0.9 | 2.49 ± 0.9 | 2.33 ± 0.9 | 2.64 ± 0.9 | 2.33 ± 0.9 |
| C&E (ours)     | 3.53 ± 0.9 | 3.11 ± 1.0 | 3.36 ± 1.2 | 3.29 ± 1.0 | 3.18 ± 0.9 |
| Real data      | 4.42 ± 0.7 | 4.13 ± 0.8 | 4.44 ± 0.8 | 4.24 ± 0.8 | 4.40 ± 0.7 |

- **Structureness (S):** Are recurring motifs/phanes/sections, and reasonable musical development present?
- **Richness (R):** Is the music intriguing and full of variations within?
- **Overall (O):** Subjectively, how much do you like the music?

5. RESULTS AND DISCUSSION

We run the metrics described in Sec. 4.4 on all our model variants and baselines. The results are shown in Table 2. First and foremost, we compare CP Transformer (abbr. as CPT henceforth) to the full COMPPOSE & EMBELLISH (C&E). On ST metrics, C&E sits right in the middle of CPT and real data, with its advantage over CPT increasing as the timescale goes up. Although CPT scores high on D_N’s, we should keep in mind that it is not trained to take extra care of the melody, and hence likely does not know some melodic content should be repeated. On the other hand, D_N’s scores of C&E are close to those of real data, and a lot better than the two excessively repetitive baselines. An affirmative answer to our RQ #1 may be given: C&E composes better-structured piano performances without sacrificing musical diversity within a piece. Worthwhile to note is that, despite the high D_N’s, CPT gets considerably lower H_1, H_4, and slightly higher GS (vs. C&E and real data), suggesting that its music may actually sound bland harmonically and rhythmically.

Next, we pay attention to the full vs. ablated versions of COMPPOSE & EMBELLISH. From Table 2, we may observe that variants not pretrained on D_0 suffer losses on S_mid and S_long. Some-what to our surprise is that w/o pretrain performs worse than w/o struct & pretrain. A possible explanation is that the introduction of structure-related tokens renders a larger amount training data necessary, as the concept of long-range repetition those tokens carry is less explicit than direct interactions between notes. Whether this reasoning holds, however, warrants further study. Despite worse longer-ST scores and higher D_N scores, we discover that, contrarily, the w/o pretrain variants are more prone to over-repetition (which we define to be: one bar of melody being exactly and consecutively repeated over 6 times, or two neighboring bars of melody repeated over 4 times)—5.5% of these two variants’ generations suffer from it, while only 2.5% of pieces by pretrained variants and 0.5% of real data do. We may now answer another yes to our RQ #2: pretraining the lead sheet model helps with not only the structureness, but also the quality consistency, of generated music.

Table 3 displays how much longer-range structureness slip after we feed generated lead sheets to our performance model. The performance model falls far short of real performances in terms of structureness, regardless of whose lead sheets it conditions on, while our best lead sheet model already performs structure-wise similarly to real data. (Lead sheet S_long of the full C&E model is significantly higher than that of the w/o pretrain variants with p < .01, reaffirming our answer to RQ #2.) To get a better sense our performance model’s issues, we check the melody mismatch [4] it achieves (i.e., the percentage of notes in a melody that a performance model copies and pastes into the performance; ideally 100%)—it gets >98% on lead sheets by all four variants. Hence, a reasonable response to our RQ #3 would be: The performance model follows the melody faithfully; but some aspects of repetitive structures come inherently with the accompaniment and expressive details, which cannot be captured even with effective melody conditioning.

The mean opinion scores (MOS) obtained from our user study is listed in Table 4. As expected, C&E holds significant advantage over CPT on all five aspects (p < .01 on 45 sets of comparisons). Coherence (Ch) and structureness (S) are what our model does particularly well, gaining >1 points over CPT. This indicates that explicit modeling of lead sheets helps C&E better glue generated music into one piece, as well as reuse and develop musical content. Nonetheless, the scores also corroborate (p < .01) that, by every criterion, our model still has a long way to go to rival real performances.

6. CONCLUSION

In this paper, we have introduced a two-stage framework, COMPPOSE & EMBELLISH, to generate piano performances with lead sheets as the intermediate output. Promising prior art [4, 5] were chosen and integrated to form our model backbone. We showed via objective and subjective study that our framework composes better-structured and higher-quality piano performances compared to an end-to-end model. Furthermore, pretraining the 1st-stage (i.e., lead sheet) model with extra data contributed to a sizable performance gain. Future endeavors may focus on redesigning the performance model to further close the gap between generated and real performances.
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