VISUALIZATION FOR AI-ASSISTED COMPOSING
– SUPPLEMENTAL MATERIAL –

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1. INTRODUCTION

This document contains additional considerations and figures that did not fit into our main paper 'Visualization for AI-assisted Composing' due to the page limit. We explain the locus of control and the design considerations regarding note display, followed by a discussion of metrics. Additionally, we include the full description of our evaluation, as the main paper only contains a shortened version. This work started as a master's thesis [1] and was previously presented as late-breaking demo at ISMIR 2021 [2]. For the latest version of this document and other materials such as source code and live demo, see our GitHub repository [1]. For other research by our group, refer to our website [2].

2. LOCUS OF CONTROL – THE MANUAL VS. FULLY AUTOMATIC CONTINUUM

Composing music was a manual task for the most part of history. In the last century, algorithms became a new tool to create music automatically and there have been ongoing efforts to improve them. No matter which algorithm one uses, there will always be parameters or randomness involved that allows to generate different outputs with more or less direct control. More powerful generators often use neural networks, which are opaque to users.

Generating a whole composition in one try is difficult, as an AI cannot know what exactly a users wants. Users therefore have to try out different parameters and, for algorithms that make use of randomness, try multiple runs. When the result is not satisfactory, the user has to try again, with often uncertain knowledge of what to change.

Instead of this fully automatic approach, we propose to create a composition step by step. This idea has been around before [3], but has not yet been fully explored. Our main contribution is the combination of semi-automatic composition with visual parameter space analysis [3]. This combination allows to generate more samples for the user to choose from, as they do not have to listen through all, but can instead gain and keep an overview over tens or even hundreds of samples.

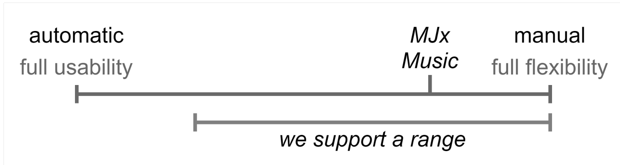

Figure 1. The locus of control that spans from fully manual to fully automatic. Our users can interact to a different degree, from simply selecting a random alternative to customizing every single note of a thoroughly chosen one, which means that our approach can lie within a broader range of the automatic-manual spectrum. See also similar spectra proposed by others [4–6].

In our main paper, we mention the artist MJx Music, who used AI to create an album by manually generating hundreds of AI-samples, listening to all, selecting the most interesting, and combining them into songs [4]. Figure 1 visualizes the locus of control of our approach and MJx Music's within a continuum that spans from fully automatic to fully manual. While automatic approaches could have the perfect usability, as the user cannot interfere, the fact that results are not perfect on the first try requires users to try many times, which can be considered bad usability.

3. PIPELINE

We now want to compare our workflow to the current fully automatic one. With an AI, the user interaction is usually limited to choosing parameters. When users are not happy with the result, they will change parameters and try again.

With our approach, the AI will produce multiple alternatives based on the current composition or an initial seed melody. Users can then interact with our visualizations to get an overview, find the most interesting sample, and adjust it, before adding it to the composition. Samples can be appended to the end, but also used as a fill-in that replaces any part of the composition. The steps for generation, analysis, and integration of samples are repeated until the com-

[1] github.com/visvar/vis-ai-comp
[2] visvar.github.io
[3] NLP4MuSA 2021 Invited Talk by Anna Huang (YouTube) youtu.be/vnRrGCB04WE?t=1293
[4] magenta.tensorflow.org/mj-hip-hop-ep

position is finished. This process results in a more personal composition, but also a better understanding of the AI. Figure 2 shows our general concept and simplified workflow and Figure 3 visually compares the automatic approach to ours in more detail.

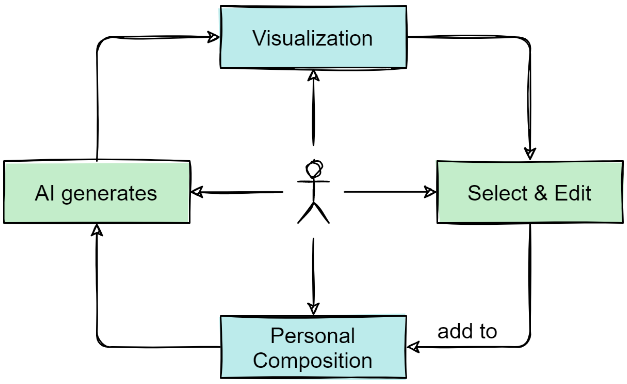

Figure 2. Simplified workflow of our approach. The loop start with an (optionally empty) composition, wherefore an AI generates alternative continuations or fill-ins. These are then visualized for the user to select and edit one, before being added to the composition, followed by the next iteration of the loop.

4. METRICS AND AGGREGATIONS

We use metrics to sort melodies and to produce overviews based on pairwise similarities. As our contribution focuses on the idea of visual support for AI-assisted composition, our metrics only serve as a set of examples that can and should be extended in the future. In general, any existing metric [7–9] that works on symbolic music can be used with our approach.

Our similarity function is calculated using the percentage of notes that start at the same time to represent the rhythm, while we take the percentage of common interval sizes between two consecutive notes in the same order as melody structure. Users can chose the weights and chose similarity based on more rhythmic or transposed samples.

Our study participants had many ideas on additional metrics, including number of notes, mean interval, tendency, contour, variance of rhythm, mean pause duration, distribution of notes, or more musical metrics like dissonance and harmonics.

5. STAFF NOTATION VS. PIANO ROLLS

We decided to not display melodies as staff notation, although there are frameworks [5] that we could integrate. Instead, we use piano rolls for two reasons: For editing notes, piano rolls are more easy to use and implement, as each pitch (C, C#) has its own row, allowing to simply drag notes around. In our visualizations, staff notation would lead to more complex visuals, especially for glyphs, and give different visual weight to naturals and accidentals, while notes of different durations would be harder to differentiate. We would of course welcome others to extend our concept or even our prototype (as it is open source) and add an optional staff mode.

[5] For example Verovio www.verovio.org

6. EVALUATION

As the complete discussion of our pair analytics study would have taken too much space in the main paper, we include the uncut version below. For explanations on setup and methods, please refer to the paper itself.

6.1 Methods and Participants

Composing music is a complex task and it usually takes a many hours to create a piece. There is also no objective measure for success, as that depends on current goals, inspiration, and more. As it is therefore hard to quantify success or efficiency, we decided that a quantitative evaluation was not helpful. Our design brings a lot of potentially unfamiliar technology to the musicians, such as machine learning, visualization, and dimensionality reduction. We therefore conducted a qualitative evaluation with domain experts, in our case composers. To avoid them having to learn using our design, we performed pair analytics, where experts and designers jointly analyze data, while the designers serve as technical assistants.

From acquaintances, we recruited five composers to participate in our study (P1 to P5). P1, P3, and P4 are currently pursuing a degree in composition for experimental music, P2 has a degree in composition and currently studies performance, and P5 studies a music instrument major but occasionally composes as well. P3 and P5 were accompanied by friends who spontaneously jumped in with additional comments.

The study consisted of two parts, roughly oriented towards the two user types explained in Section Design. At the beginning of each parts, we showed a short video explaining the visualizations and interactions, to give participants a quick overview and allow for questions. We recorded the screen and spoken words throughout the whole study with consent. After both parts, we concluded the study with a semi-structured interview to further inquire about general thoughts. The whole study took about 11 hours, on average 2.2 hours per participant. See our supplemental material for more.

6.2 Part 1 — Interactive Composition

All participants started with recording and editing a short melody. They were interested in how the AI would react to their melodies, especially P3: *"I was curious, so I put in some short and some long notes"*. Next, we generated some continuation for their melody.

We showed our icicle plot as first visual representation of the samples. Participants found it helpful *"when generating many samples, [this] can help when you can see faster what samples are interesting and which are not"* (P4). Furthermore, P1 found it helpful to see all *"paths"* together and being able to view a selected path in a separate

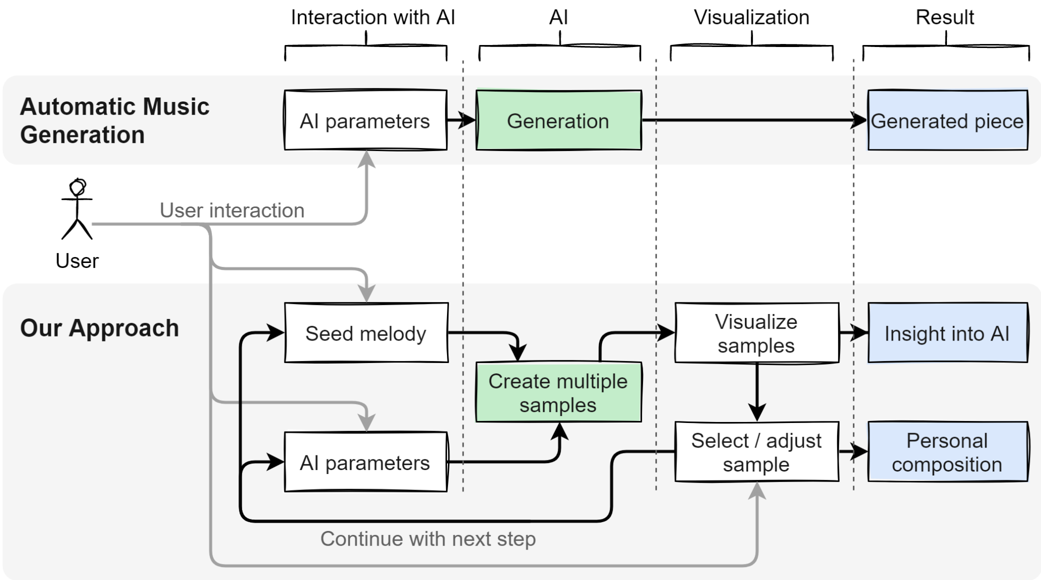

Figure 3. Comparison between a fully automatic generation and our human-in-the-loop approach in more detail.

piano roll. We found, that the icicle plot led to faster decision because participants found interesting samples just by looking at them: *"for example, I can see that these [points to two samples] are very interesting"* (P5), *"can I hear this one? [skips multiple samples]"* (P3). One participant found an increasing level of complexity of the samples by looking at the icicle plot. Especially P4 and P5 liked this representation due to the detailed piano rolls, for example, since it helped P5 find perfect fifths in melodies.

After the icicle plot, the participants used the node-link diagram and its possibility to sort samples to inspect and select continuations. Participants liked sorting samples by metrics: *"I think it's good to sort by intervals [...] essential when selecting a melody with specific characteristics"* (P1), and even found the idea helpful when using different metrics: *"I can imagine for complex music and many samples [...] and having an rough idea [sorting] can help using parameters"* (P4), *"[If] I was composing with dissonance and then sorting by dissonance would have helped"* (P3), *"Harmonic structure [tonic, subdominant ...] and then I generate multiple continuations and sort by these harmonics"* (P1).

We also found that sorting helps being more efficient *"when generating many samples, can help when you see more quickly which samples are interesting and which are not"* (P4).

We saw a similar strategy as with the icicle plot: Participants did not listen to all melodies and instead filtered visually. They also adapted melodies after choosing: *"[listens to just a few samples] Let's take this one and edit it a bit more"* (P3).

Especially P1 preferred the node-link diagram over the icicle plot, while other participants found it practical because of the sorting function (P4) but preferred the more detailed piano roll (P4, P5) in the icicle plot.

While composing with our tool, P3 repeatedly asked where the recently added samples began within the composition. We proposed using our provenance visualization, which showed the difference between added notes by the AI and edited notes, which helped P3 and was comfortable: *"where was the last note? [switching to provenance] This visual is very comfortable"* (P3). But we also found that the provenance visualization helped in the intended way when P5 said to their friend *"look at what I have done"* and the friend responded *"and what did you do?"*, prompting P5 to analyze the notes' origins.

In general, participants found our visualizations helpful and could *"filter visually"* (P5) instead of listening to all samples. Especially P4 mentioned that the visualizations would be even more helpful for complex compositions and save time when using AI as inspiration.

We especially focused on how participants selected samples, either for listening or to directly add them to their composition. Participants often already had some idea for what they were looking for, such as setting a contrast (P1), wanting *"to hear the most randomness"* (P2), or variations and less randomness (P4), where our visualization and color helped. For example, P1 and P2 looked for *"red ones"* (higher temperature), while P4 was taking a closer look at the melodies' structure: *"This is interesting and is a bit similar [...] edit it to link the composition and the added sample to have one (similar) musical idea"*. Similar to P4, P5 was looking for variations and had an idea for what to look for and found a melody: *"this last part is not satisfactory, but it is the only one that goes down"* (P5). Participants sometimes did not like samples (*"I liked the first part, but the second was not good"*(P2)) and edited them after adding to the composition (P5) or even discarded all to *"[...] change something on my own"* (P3).

We also inspected the usage of the AI, how it helped, and how participants interacted with it. While all participants were interested in what the AI would respond, P4 was hesitant and unsure when to use the AI. P4 was unsatisfied, (*"This is not so good [...] somehow I didn't like* *that"* (P4)) and tried to edit a part multiple times without success until we suggested to use the fill-in, which inspired P4 and led to further progress.

Most of the time, we suggested appropriate temperature ranges, but P5 surprised us and directly said: *"now I want something that is further away [...] OK then I'm choosing a higher temperature"* (P5), before choosing a range of 0.9 to 1.4.

Overall, participants made interesting comments in this interactive composition part on how the AI affected their composition style and what they would try in the future. Some participants stated that this AI would *"break with classic theory"* (P1) and suggest melodies *"we can not calculate"* (P3), as direct suggestions or only inspiration (P2) in combination with our visual approach on inspecting them: *"As human caught in own preferences [...] AI produces parts we would have not even tried [...] If we think about something we would throw it away, but if we see and hear it, it could be interesting"* (P4), *"good if I have no progress and then use it either take a part or to get inspired"* (P1), *"[If] not following a melodic tonal line [...] how do I chose the notes [...] and [the AI] can be helpful"* (P3). In contrast, P3 missed a long-term structure when composing part by part, which requires users to think about a structure on their own.

6.3 Part 2 — Exploring the AI's suggestions

As mentioned above, all participants where interested in analyzing the AI in the first part as well, as they wanted to *"try different start melodies"* (P2, P3), which made for a good transition into the second part, which focused less on composing and more on understanding the AI.

Since our goal in the second part was to evaluate the analysis potential, all participants recorded a melody and then generated 50 to 80 continuations to analyze with our visualizations. First, we introduced the scatterplot as an overview over all melodies. All participants agreed that the scatterplot, and our approach as a whole, could be used to compose (P1, P3, P4, P5), or as inspiration (P2). For example, they saw that they could *"select and adjust samples [...] and transpose some to fit"* (P1). *"want to do something complex [like notes around a contour, it] would be unbelievably costly [...] but have [the] structure in mind and build that with help of AI"* (P4), *"[combining variation with structure] is laborious by hand [but here you] can see similarities/characteristics [and then you] can use 200 [AI variations and] select some [of them] and combine"* (P4). Furthermore, P1 found all additional glyphs helpful and told us these could *"extend the intuitive analysis of composers [... and] could lead to a different style"* (P1) in composing. The participants were *"not used to look at the data"* (P2, P3) and these kinds of visualizations (*"This analysis was new for me"* (P1)), but most of learned quick and found the scatterplot interesting: *"It is very interesting as an analysis tool, even independent from the AI"* (P1). Especially P1 was very interested in all the analysis possibilities, and mentioned that to P1's knowledge, the lack of analysis is a huge downside to algorithmic composition that works with chance: *"I did see that really rarely and this is a shortcoming ... when composing with the computer"* (P1)

P1 surprised us, when he told us how their professor answered the question *"how to select the best samples"*: *"you could generate as often as you like and listen to all and decide while listening intuitively"*. This strategy was not satisfactory for P1: *"you would listen to all and have no overview"*. Our scatterplot provides such an overview (P1) and shows its need for selecting the best samples in the current music composition.

Again, we evaluated how users select neighborhoods in the scatterplot and found that the color, which encoded temperature, was impacting their decision. For example, P2 *"clicked there because of the color [...] ones with higher temperature and lower temperature"* and investigated *"how the melodies varied"* based on temperature (P3). Especially interesting to us was when P5 changed the similarity metric to rhythm only and detected that *"these all should have the original rhythm"*. Furthermore, P5 used this insight to look for further samples in the same cluster, to stick to the original rhythm. To investigate the samples further, P5 clicked on an outlier sample: *"why is this separate?"* (P5).

Next, we proposed using starglyphs for comparing melodies directly without clicking on them: *"Starglyphs were interesting [...] we can compare [the samples] faster [...] they show time component and pitch component"* (P1).

The piechart glyphs that represent chroma occurrences helped P3 select a melody sample, when they were looking for something that contrasts the composition and was calm: *"this has less pitches [...] I would assume that more colors means crazier"*. Some participants tested very experimental melodies as input, while P5 tried a tonal G Major melody and found this glyph type helpful for investigating whether all samples only contain G Major pitches: *"I bet that all samples will only have seven different colors"*.

While analyzing, P5 just looked through samples and searched for perfect fourths, as their melody contained a lot of these. We proposed using histogram glyphs and looking for big spikes of intervals with size five. P5 directly compared all of the samples in the scatterplot and found that there were not many perfect fourths in the melodies: *"I am interested in finding melodies with perfect fourths [showing occurrences of interval glyph] We can directly see [...] there is almost nothing"* (P5). Other participants used this glyph to select samples *"when I have a structure in mind [such as a rising line]"* (P1), which showed more positive intervals than negative, or to investigate the extreme melodies with many larger intervals: *"I am curious about the extremity I can see"* (P2). P2 also found histogram glyph more intuitive than starglyphs, because they showed less data at the same time, while other participants (P1, P4) missed the temporal aspect.

As a contrast to the statistical glyphs, we then presented our piano roll glyphs that show the melody directly. All participants were able to use this glyph to compare the melodic structure of the samples and find common pattern in clusters, like melodic bows, and differences and randomness when moving further away within the scatterplot: *"I can see the same musical structure (melodic bows) [...] and further away it turns different"* (P1), *"I can imagine the movement of the sound"* (P2), *"many of them have the same or similar melody structure"* (P4), *"now I'm interested in the melody structure [uses piano roll glyph] You can see here it goes up and down [...] and here we can't see any structure"* (P5).

Participants P1, P4, and P5 additionally found a relationship between temperature, shown through the color of piano rolls, and the structure (Figure 4): Low temperature samples had a clearer structure and were often similar, while high temperature samples showed large jumps and less structure and were sometimes called *"crazy"* (P4): *"The blue ones (low temp) have clearer structure while red ones are jumpier without that much connection"* (P1), *"Yes I can see the randomness"* (P2).

We found that the piano roll was more intuitive compared to other glyph types and would be a good default, because it shows the melody directly, so composers could imagine how they sound: *"For me [the piano roll glyph] is very intuitive, I can directly imagine how they approximately could sound like"* (P4). Although most participants found the piano roll helpful in the first place, especially for short melodies (P4), P1 found the statistical glyphs more interesting, because the encoded information that users cannot directly see when listening or looking at the piano roll.

For all statistical glyphs, P4 mentioned that using these statistics might always miss some information, but could help especially with longer samples, when other representations, like a piano roll, would fail. In comparison to the overall positive and interested feedback, P2 stated that, for them personally, using only statistical data for glyphs would be interesting for music analytics but not composing.

After exploring the data with our scatterplot, we showed the correlation matrix to our participants, none of whom were familiar with such a representation. Similar to the scatterplot, P3 mentioned that the correlation could also be interesting for selecting melodies for composing, especially when using different metric combinations, even further than our proposed metrics.

Especially P5 found that *"this [correlation] is fantastic [...] This would make analysis much easier' even without using the AI"*. After investigating some metric combinations, P5 surprised us and found a pattern regarding the similarity and the temperature, where the correlation between an arbitrary metric and the similarity would always be the opposite to when combining the metric with temperature (Figure 5). So if the average note duration would increase with increasing similarity, the average note duration would decrease with increasing temperature, which shows a negative correlation between temperature and similarity itself.

Participants mentioned that the scatterplot and correlation matrix *"can be very useful for not just composers but also music theorists [...] for analysis and further development"* (P3) and that it would be *"very good for analysis, even without AI"* (P5) and therefore interesting for own compositions (P1).

Although P2 did not find the visualizations as helpful (*"Unless we can't hear, we cannot say [how it sounds] as a composer"* (P2)), the evaluation showed that visualization helped other participants compose and analyze the AI (*"this tells me that this AI was created to create harmonics [...] and does not look for intervals, structure"* (P5)) and they would use it with other generative processes (P1) or without AI as well.

In general, participants had a lot of ideas for additional metrics to sort and investigate in node-link diagram, scatterplot, and correlation matrix. These ideas include number of notes, mean interval, tendency, contour, variance of rhythm, mean pause duration, distribution of notes, or more musical metrics like dissonance and harmonics.

6.4 Concluding Interview

We concluded our study with a short semi-structured interview. In the following, we summarize our participants' feedback on each talking point.

Would you prefer this approach over your current workflow? Would you use it occasionally to get inspiration?

None of the participants preferred our approach over their current workflow, but many could image using it for inspiration or certain tasks.

Do you prefer piano rolls over classic sheet music as representation? As we only used piano rolls instead of staff notation for representing notes, we were interested whether our participants missed the latter. All but P2 were familiar with piano rolls and had prior experience, but would not generally prefer it, only depending on the situation and intended piece.

Did visualization help understand and interact with the AI? Did they help find good samples more efficiently compared to only listening?

All participants found the visualizations helpful for comparing, filtering, and selecting melody samples, and helpful for beginners, even when P2 had problems imaging the sound of a melody by its visuals. Most participants mentioned that it takes some time to get used to the visualizations and statistics, as this approach was new to them in the music domain.

Do you think Human-AI collaborative composition is a step in the right direction? All participants, as artists, do not think Human-AI is always the right direction because of lack of trust in the AI, no need, or expressing the own creativity, but most participants see the potential of this field and would be interested in specific scenarios.

If everything would be perfect, would you use this regularly? What needs to change or be added? If everything would be perfect and easily accessible as a website, all our participants would use it depending on the situation. While some would change the source of generation, others would use our approach to get some inspiration, to compose a starting melody to elaborate further, or as a fill for a part of a current composition via interpolation.

7. HIGH-RESOLUTION AND ADDITIONAL FIGURES

The following images were already presented in the paper, but captions are more detailed and images larger.

Figure 4 shows the gridified similarity-based scatterplot with piano roll glyphs and temperature as color coding. This was used to investigate variations of the composition. In Figure 5, we showed the negative correlation between temperature and similarity. Figure 6 and Figure 7 show a simple node-link diagram of the general data structure, not focused on music samples. This symbolizes the general idea and structure behind our icicle plot and the node link diagram. We show an overview of our implemented prototype in Figure 8, where some views are active at the same time. The node-link diagram in Figure 9 shows the structure idea from Figure 7. Figure 12 shows the provenance of the notes and explains the five classes. Last, Figure 13 explains all of our four glyph types and provides a use case and possible insights.

The following images are not contained in the paper:

Figure 10 shows a similarity-based scatterplot with 200 samples, using our weighted similarity function, allowing users to investigate clusters and outliers. We also show a different example for our correlation view in Figure 11. The positive correlation between temperature and distinct pitches is shown.

We also edit an image from our evaluation in Figure 14, where the user liked the visuals and we compared it to art.

8. REFERENCES

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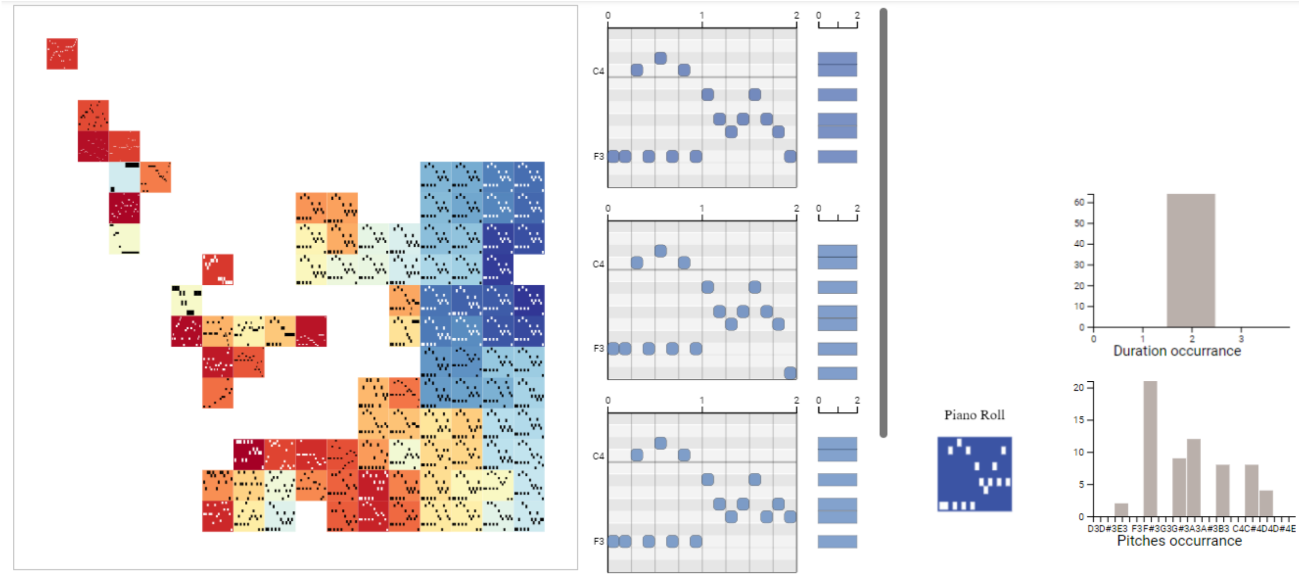

Figure 4. Similarity based scatterplot with piano roll glyphs. Colors encode temperature. We can see the similarity of melodic structures on the right and different kinds of structures further away from them. The color also shows a nice temperature flow, indicating how temperature impacts the melodic structure.

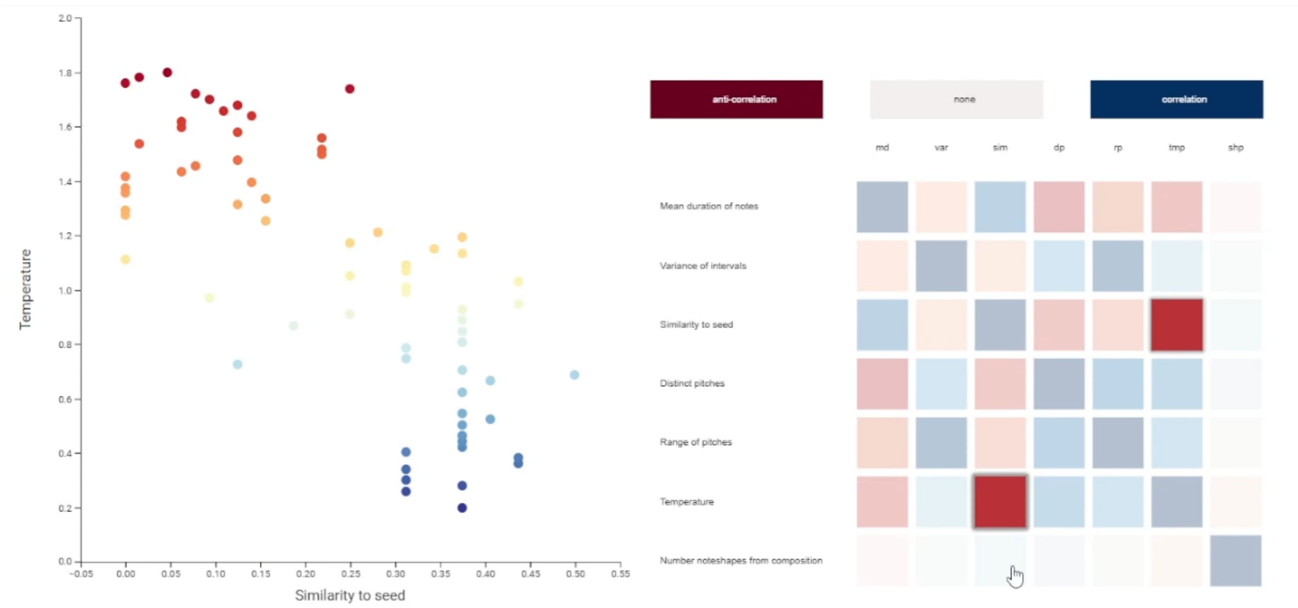

Figure 5. Negative correlation between temperature and similarity, which underlines the statement that temperature controls randomness.

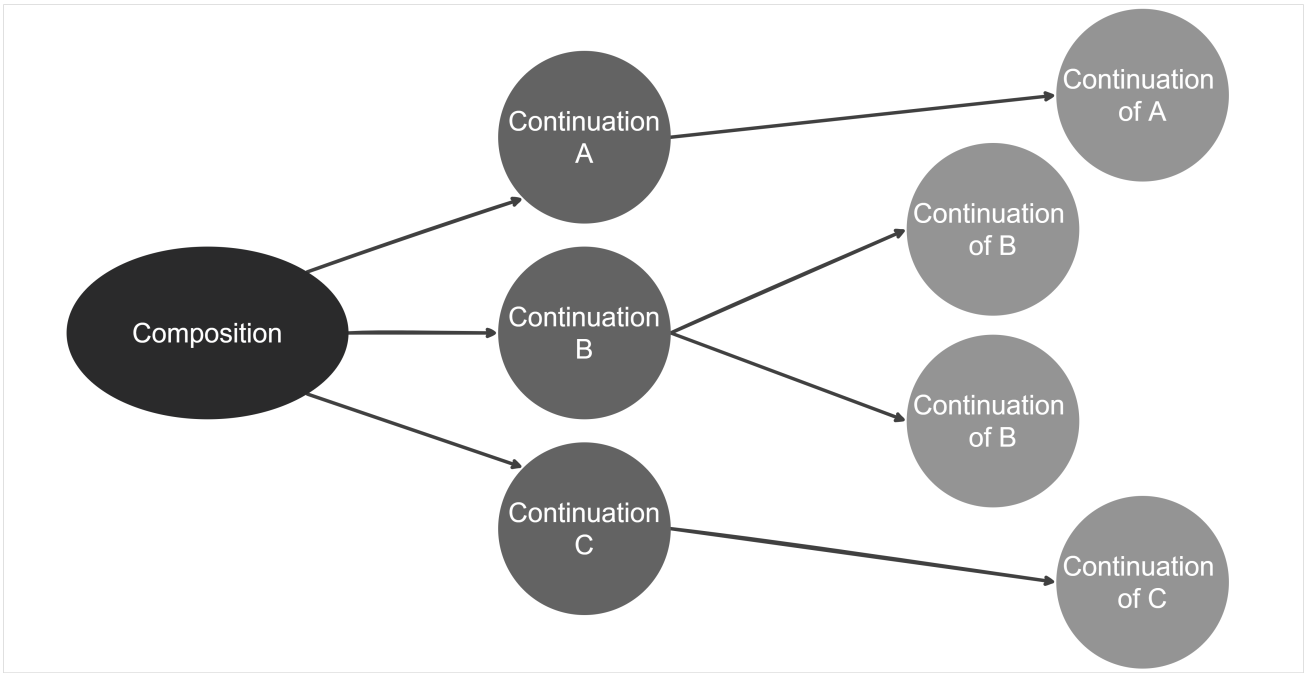

Figure 6. Tree structure with two layers of continuations shown as basic node-link visualization.

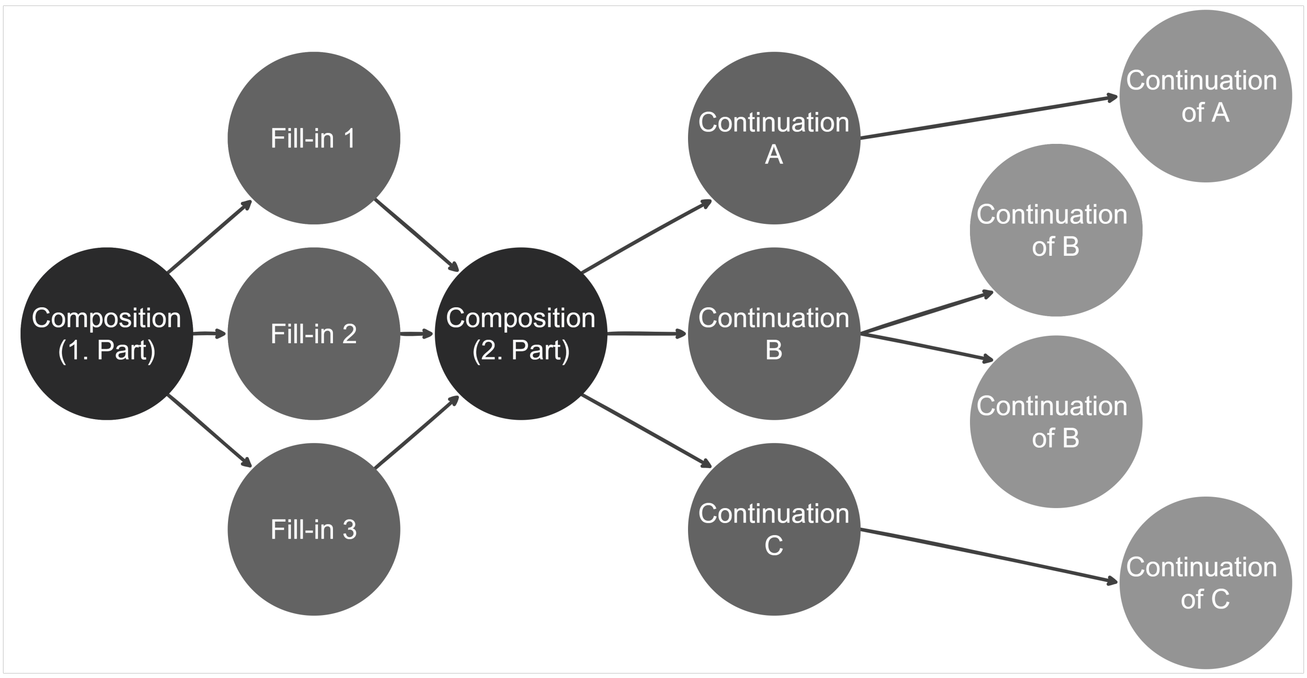

Figure 7. Graph structure with one fill-in and two layers of continuation as basic node-link visualization. Composition is split in two parts as result of the fill-in.

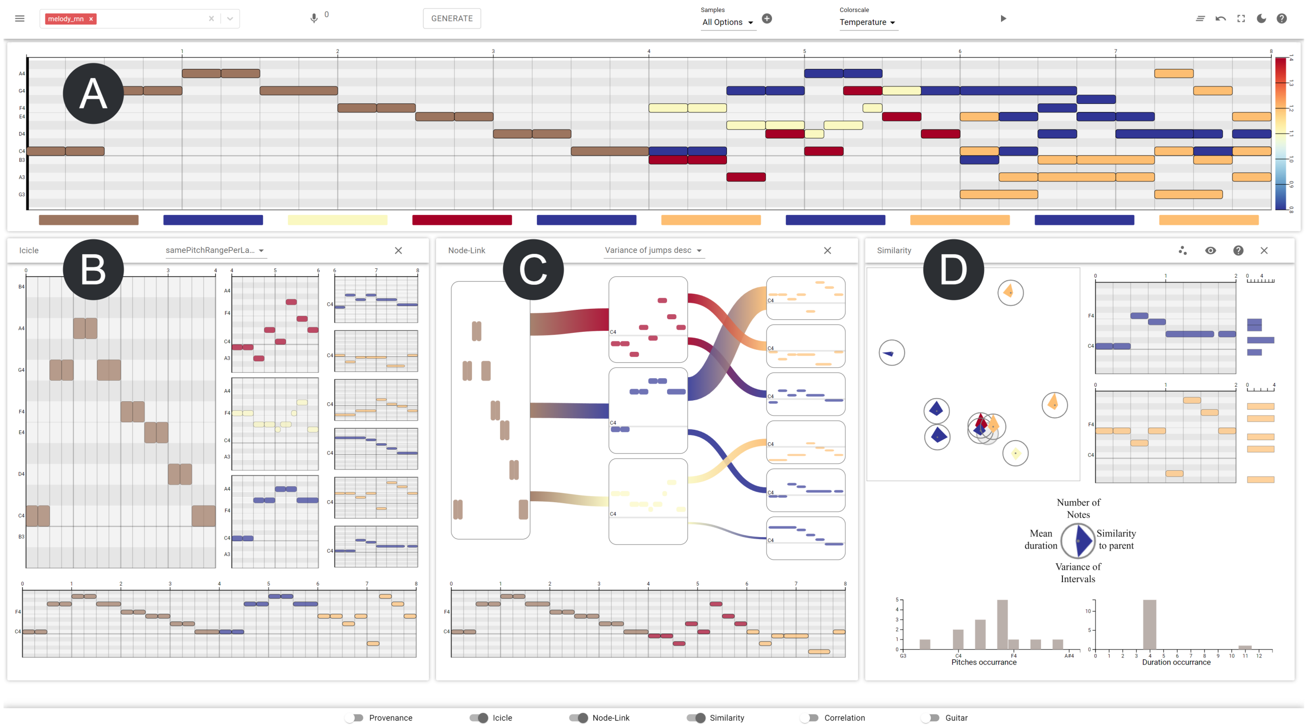

Figure 8. An Overview of our design with three active and one inactive view. The colors of notes show the temperature of the melody sample. (A) Piano roll to show and edit composition is always active and gets larger if only Provenance or nothing is active. (B) Icicle plot and (C) Node-Link diagram visualize the tree structure and melody samples via piano rolls. Samples in the Node-Link diagram are sorted by variance of interval sizes in descending order. The user can select path by clicking a node, which is visualized in the detailed piano roll below. (D) Similarity-based scatterplot as overview of all samples represented as starglyphs. We can directly see that the outlier on the left is a melody with a few and mostly longer notes and smaller variety of intervals which could represent a calm melody. Additionally the occurrence histograms only shows pitches from C Major and mostly quarter notes for the selected melodies, which often occur in the composition as well.

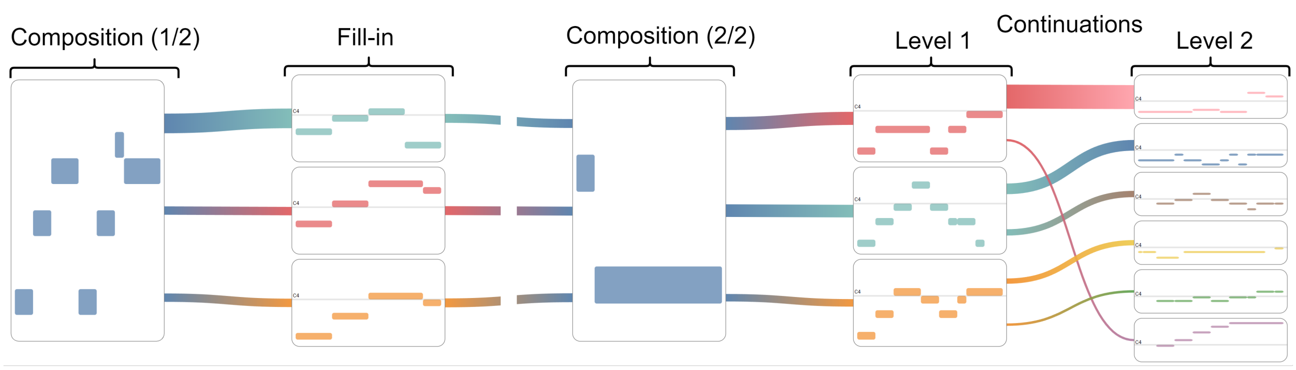

Figure 9. Node-link diagram shows one fill-in level, splitting the composition in two parts, and two levels of continuations. Colors help differentiate between melody samples. Nodes in the same level are sorted by variance of intervals descending, which is also encoded in the link width.

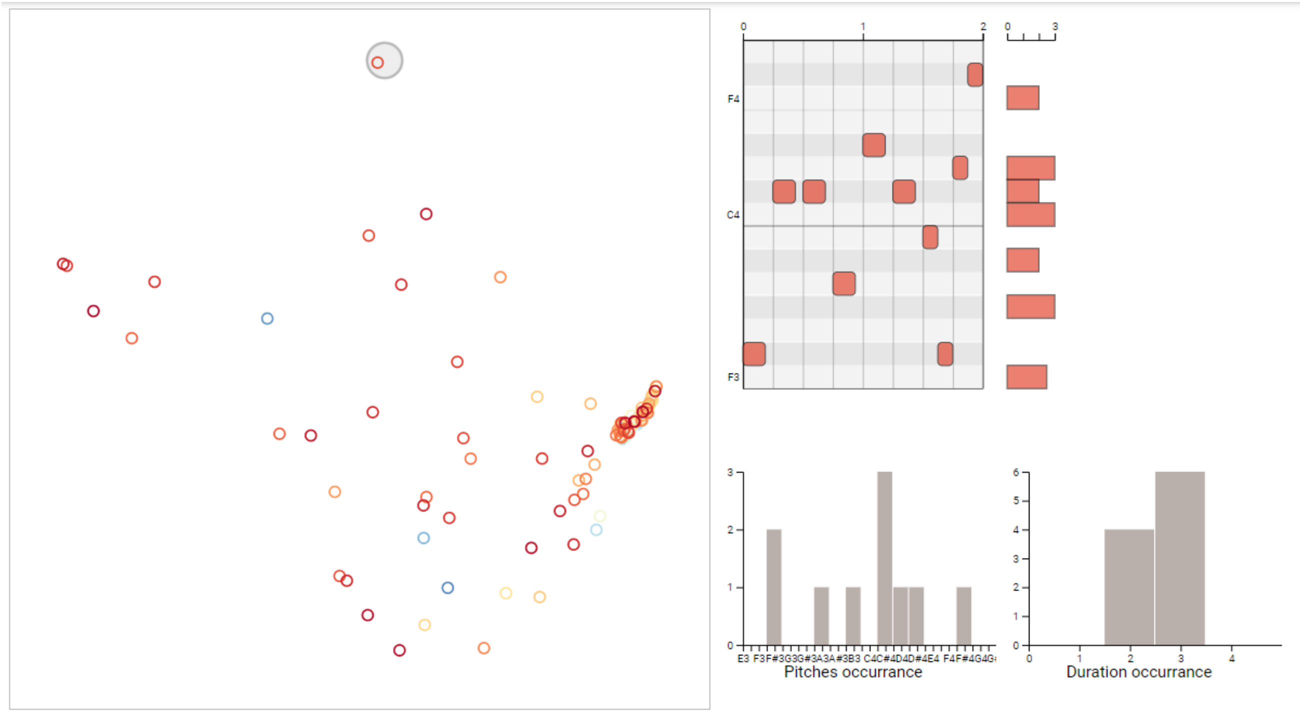

Figure 10. Similarity-based scatterplot showing 200 samples at the same time. Similarity is calculated with 85% Rhythm and 15% Melody. Colors represent the temperature. The highlighted outlier at the top shows a rhythm with many 2 and 3 step notes and some pauses, while the primer rhythm only contained only 2 step notes and no pauses, indicating the dissimilarity shown in the scatterplot. The large cluster on the right shows samples with the same rhythm as the primer, while the slight curve could show the dissimilarity of the melody part in our weighted similarity function. Samples close to the cluster often showed slight changes of the rhythm like a few longer, shorter, or missing notes.

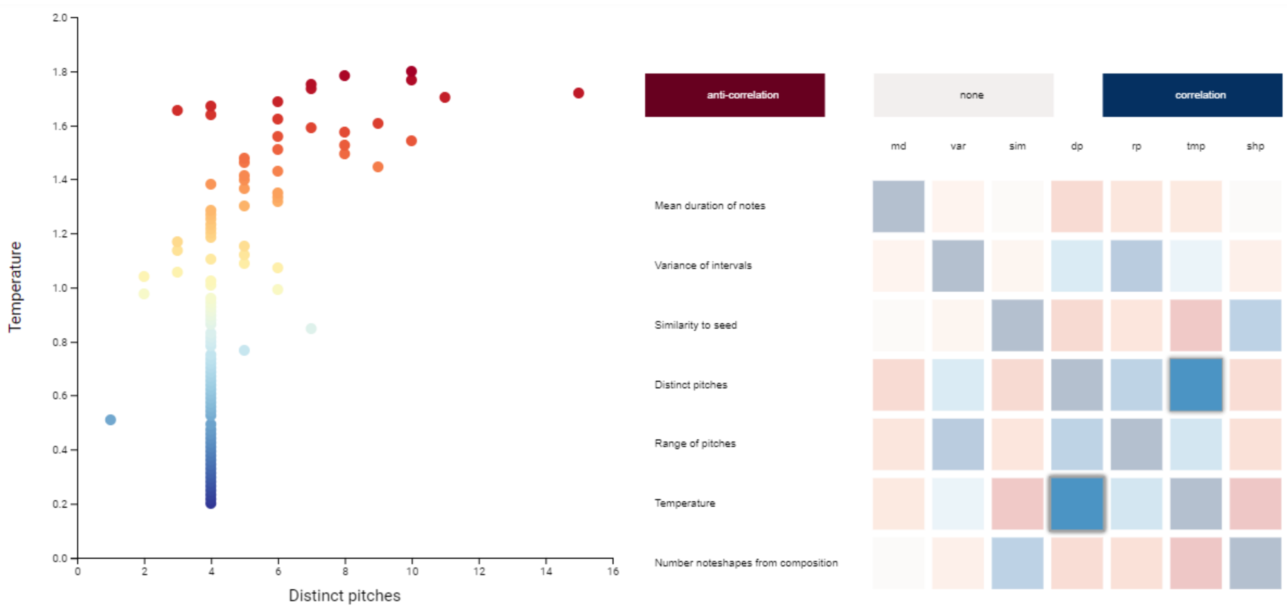

Figure 11. Right: A correlation matrix shows the correlations between pairs of metrics. Metric pairs showing a correlation are encoded with blue, negative (anti) correlations with red. Left: The scatterplot shows pitch range (X axis) and temperature (Y axis and color). There seems to be a positive correlation: the higher the temperature, the larger the range of pitches. We can directly see that there is a positive correlation between variance of interval sizes and range of pitches.

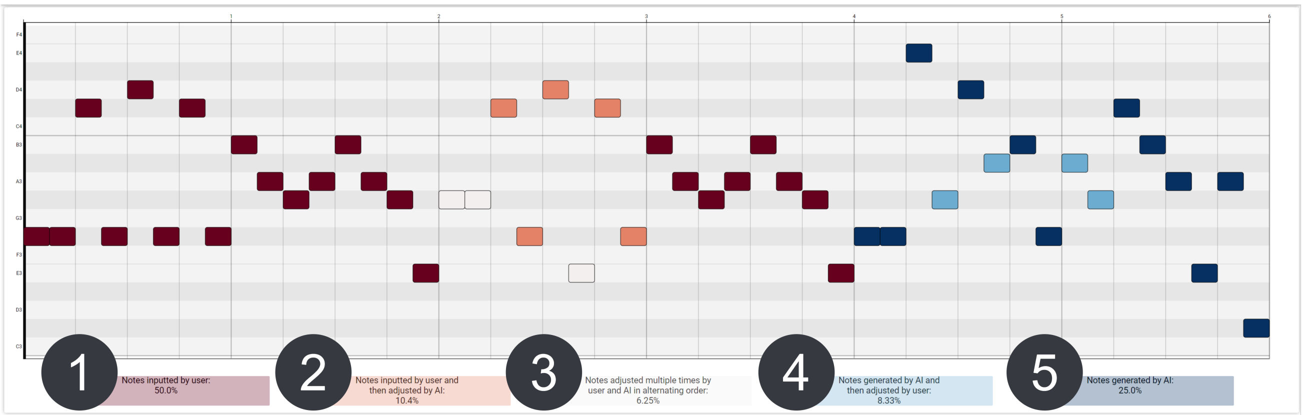

Figure 12. Provenance of notes: color indicates in how far notes were created and edited by the user (red) and the AI (blue). Provenance classes: 1) completely human-created notes, 2) human-created but AI-adapted notes (fill-in), 3) notes changed by both parties multiple times, 4) AI-generated but user-updated notes, and 5) AI-generated, unedited notes. We can see that the user composed 50%, the AI 25% without the other parties influence, but the remaining 25% are shared.

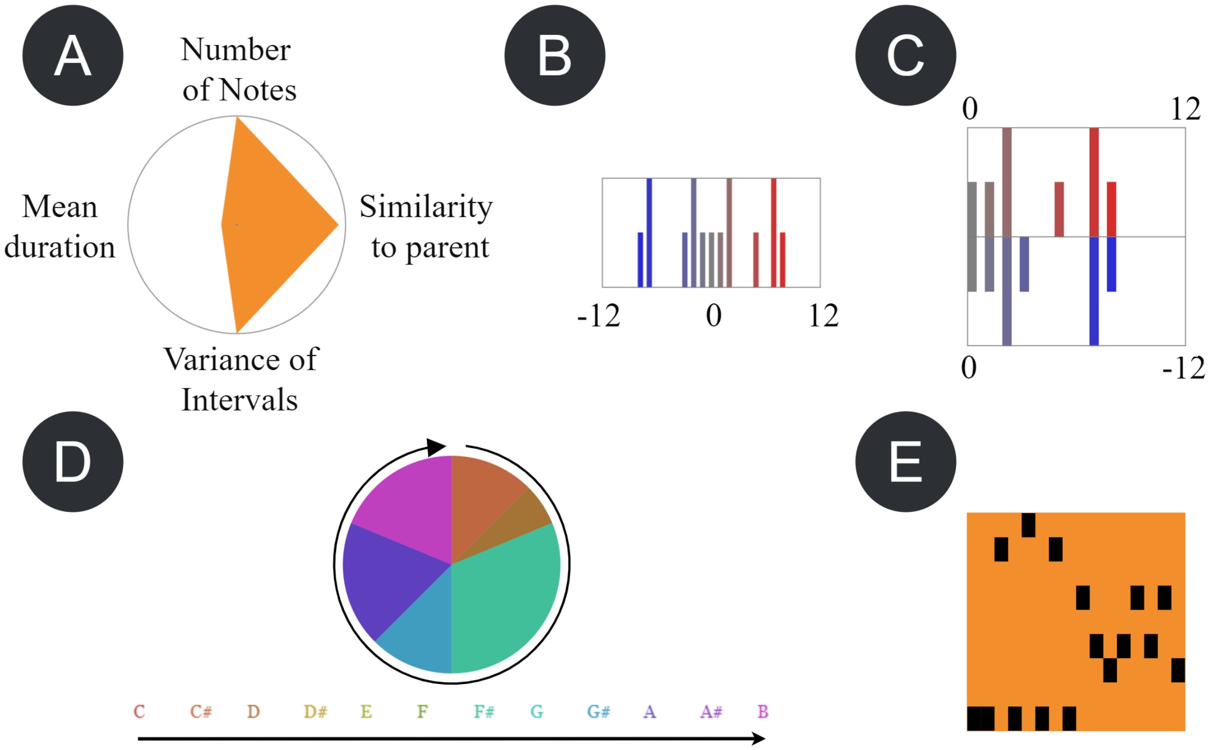

Figure 13. Comparison of our glyphs. (A) star glyph showing four metrics at the same time, (B, C) occurrences of intervals between consecutive notes, (D) chroma distribution of pitches, and (E) piano roll representation showing the melodic structure. We can directly see in (C), that the melody shows the same intervals in positiv and negativ most of the time, indicating the alternating structure or some kind of bow. The Glyph (C) show the one of the largest occurrences at seven steps, which indicates a perfect fifths. In Glyph (D) we can see that F# is the most used note, followed by B, A, C#, and G#, which indicates a F#-minor.

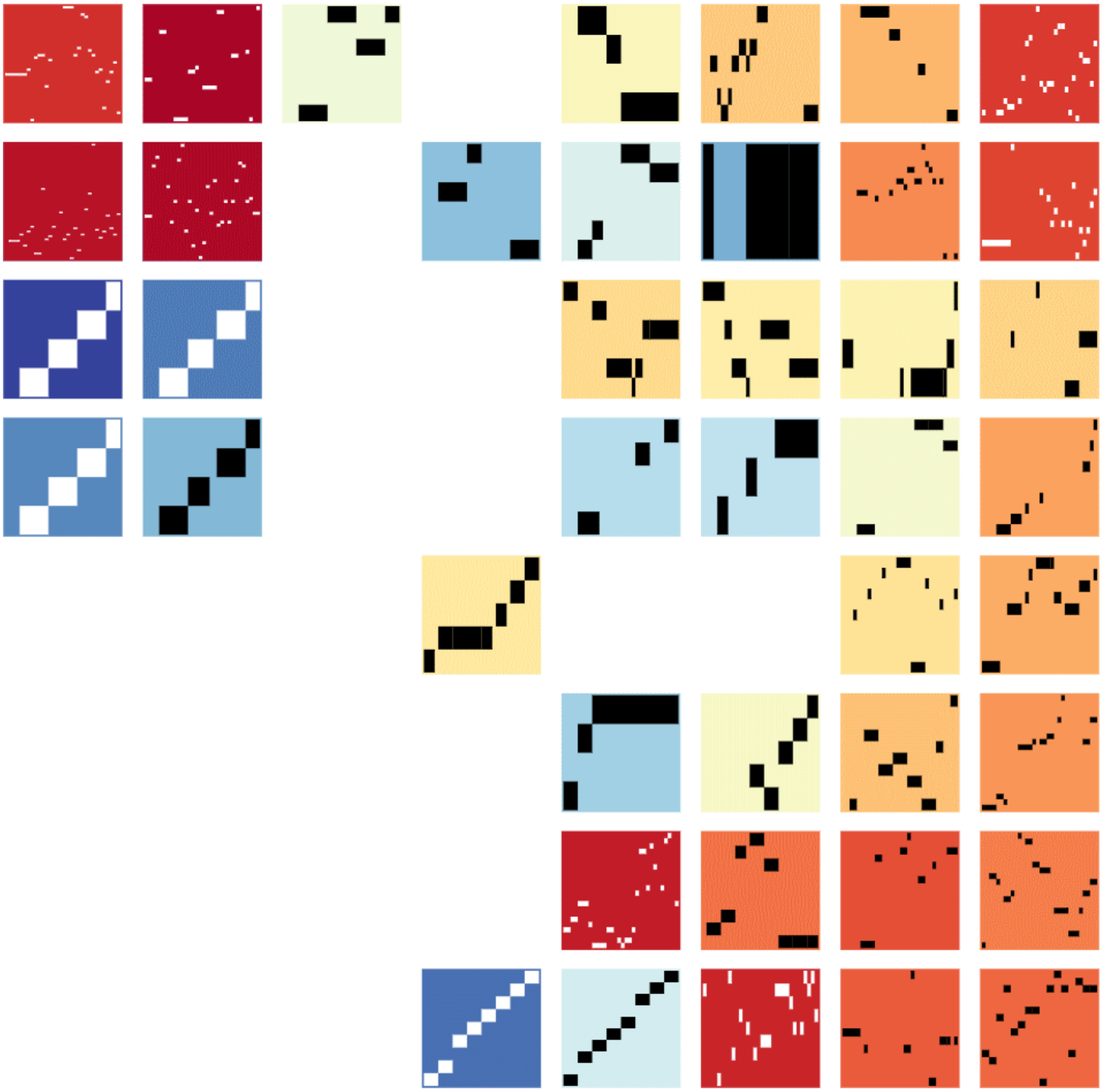

Figure 14. The gridified similarity-based scatterplot showing piano roll of different temperature. This image originated during our evaluation study and was liked by the participant for its visuals and we think of it as a kind of abstract art in itself.