EXPRESSIVE TIMING IN MUSIC PERFORMANCE

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ABSTRACT

This study aims to explore what expressive timing in music performances brings, by means of observing the distortion of the metrical grid in human performances. This is achieved by first developing a pipeline to translate symbolic time into performances metrics, by analysing where expressive timing is most likely to happen. On a second note, we examine the distribution of note onsets within measures in Mozart's *Piano Sonatas*. Finally, we explore the variability in timing across compositions by different composers, providing insights into the temporal nuances present throughout entire musical pieces.

1. INTRODUCTION

In the realm of music generation, one of the intriguing challenges lie in accurately capturing the nuances of human performance. Music, as a highly structured sequential data modality, exhibits complexity across various timescales, from the microscopic periodicity of waveforms to the macroscopic form of musical compositions spanning minutes. Capturing the temporal correlations inherent in this structure presents a formidable challenge due to their wide-ranging magnitudes [1].

Expressive timing, characterized by micro tempo fluctuations and distortions of the beat grid, such as accelerando to build tension or ritardando to emphasize phrase endings, plays a pivotal role in music performance. Numerous studies have delved into this phenomenon, shedding light on the nuanced deviations from strict metrical timing introduced by musicians [2, 3]. Musicians frequently diverge from exact notation, introducing intentional or unintentional irregularities stemming from inherent human psychological and motor intricacies [4, 5]. These deviations enrich the music with heightened expressiveness, augmenting its perceptual depth and individuality compared to generated music which is overly regular and sounds "robotic".

The initial objective entails examining this discrepancy between symbolic time and real human performance, aiming to devise a timing function establishing a mapping between the symbolic time and the performances metrics.

2. DATA

The data is sourced from the Aligned Scores and Performances (ASAP) dataset [1], which comprises 236 musical scores with 1067 performances from 15 composers.

For the analysis, the focus is on Mozart's *Piano Sonatas*. There are several reasons for this selection. As an initial step in a musicological analysis, a piece that is relatively familiar is more adapted. Additionally, these sonatas encompass the most common isochronous duple, triple, and quadruple meters (2/4, 3/4, 4/4) found in Western music, as seen in class. Selecting a piece that embodies these meters allows for establishing a direct connection between theoretical concepts and musical practice. Furthermore, delving into a well-known repertoire like Mozart's enables searching for other existing studies and resources, enriching the analysis with additional insights and perspectives.

3. METHODS

The main toolkit employed is music21, a Python-based toolkit designed for computer-aided musicology, to extract essential features from the dataset. These features include time signatures, beat timing and metrical positions of events. Specifically, the '*annotations.txt*' files are used, which contain detailed information about variations in timing across beats in both performed and unperformed renditions, to inform our timing function.

To create this function, a first round of observations are done on the human performances of the Mozart's *Piano Sonatas* corpus. For each performances, the relative time of each beat are gathered from MIDI annotations. Performances of the same sonata are then grouped together and cumulative distribution functions of discrepancies between notes duration and their mean for every beat in each sonata are created. To generate a performance, the original unperformed MIDI annotation is loaded and for each beat, a random sample is generated from the corresponding cumulative function and the original duration of the beat is modified accordingly. This method permits to get a mapping on any piece with the same time signatures as our corpus. Time signatures were separated to get the right number of beats per bar. The method was implemented for every time signature in the corpus (i.e. 2/4, 3/4, 4/4, and 6/8). There are two pieces in the corpus with a 4/4 time signature: the *Piano Sonata n°8 I. Allegro maestoso*, and

[1] `https://github.com/fosfrancesco/asap-dataset`

the *Piano Sonata n°12 II. Adagio*. Their beat's time duration in the measure follow a rather different pattern, that's why we decided to be able to choose between them. Also, since it is more intuitive to vary the beat when playing than varying each note's duration, the timing function uses beat duration rather than note duration. The final output of the timing function is the MIDI annotation file of the generated performance.

Metrical positions of the musical events are extracted from the MusicXML files, enabling the plotting of the distribution of note onset positions across measures for various time signatures (2/4, 3/4, 4/4, and 6/8), as depicted in Figure 4. Subsequently, to analyze the expressive timing, data is extracted from both performed and unperformed MIDI files, and the distributions are visualized in Figure 5. For the later visualization, a kernel density estimate (KDE) plot in continuous time is opted to reflect the continuous distribution of performed metrical positions, which contrasts with the symbolic time representation.

"Humanizing" (as random timing jitters) is utilized to make computational music performance sound less "robotic" [6]. To better comprehend "humanizing" timing, a shift is made from a micro-level analysis of measure-by-measure timing to a comprehensive view of entire musical pieces. In particular, we aim to analyse the variability in timing, by using the standard deviations of performed and unperformed versions' note onset positions in metrics as a proxy. The study initiates with the performed and unperformed versions of Mozart's *Fantasia K. 475* and *Piano Sonatas*.

Broadening the scope to include various composers, the same methodology is then applied to assess the whole provided dataset. This expanded analysis offers a macroscopic perspective on expressive timing, potentially offering insights concerning rhythmic freedom, structural diversity, and stylistic elements among famous composers.

All the code can be accessed on GitHub [2].

4. RESULTS

4.1 Timing Function

Taking a look at the analysis of relative beat duration for performed *Piano Sonatas*, for example at the performances of Bogdanovitch and Jia on the *Piano Sonata n°8 I. Allegro maestoso*, several point can be noted. Firstly, both pianist tend to play faster than the unperformed version, which can be verified by looking at the box-plot on Figure 1. The mean of relative beat duration for each position is around 0.9, which indicates that the pianist are playing a slightly above 120BPM tempo, which is given by the unperformed MIDI files. Secondly, the outliers indicates both pianist tendency to sometimes distort the metrical grid on some beat positions; while they both seem to slow down on the first downbeat and the last upbeat (respectively, on position 1 and 4), Jia tends to accelerate the second downbeat (on position 3), while Bogdanovitch slows it, except on one occurrence. Interestingly enough, Jia also seems to slow more often on the first upbeat (position 2) than Bogdanovitch, which seems to play more evenly.

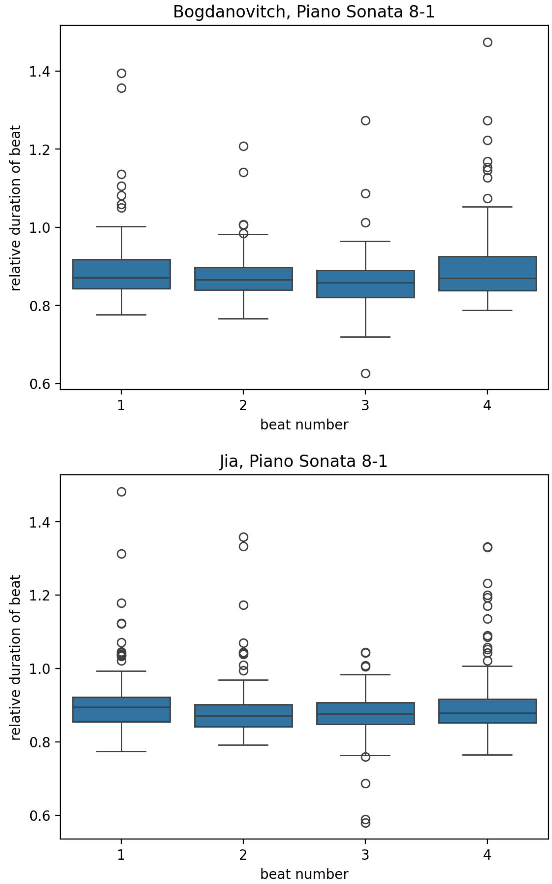

Figure 1. Relative duration of the beat, depending on its position in the measure, for performed *Piano Sonata n°8 I. Allegro maestoso*

Taking another example, *Piano Sonata n°12 I. Allegro*, performed by Wuu, Figure 2 shows that all beat position seems to be slowed at a same rate, and a notifiable outlier can also be seen on the second position.

As said previously, the timing function samples from various performances to give an artificially performed MIDI file. Applying the same analysis on the generated file, it is interesting to note what the generated file of the *Piano Sonata n°8 I. Allegro maestoso* takes from both Bogdanovitch and Jia. Figure 3 shows the typical slowing on position 1 and 4, while taking Bogdanovitch's on position 3 and Jia's tendencies on position 2. The generated file of *Piano Sonata n°12 I. Allegro* clearly follows Wuu's pattern of expressive timing, as also seen on Figure 3, notably with the outlier on the second position.

Note that since unperformed MIDI is based on a 120BPM tempo, the resulting generated performance is also based on that same tempo, but inputting in the function another unperformed MIDI with another tempo, for example 100BPM, yields a generated performance which

[2] `https://github.com/cindytangch/expressive-timing-in-music-performance`

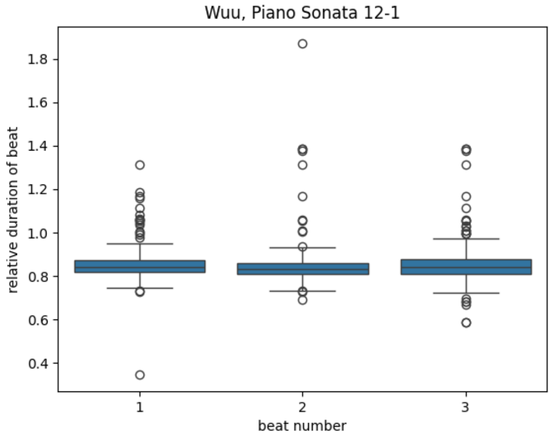

Figure 2. Relative duration of the beat, depending on its position in the measure, for performed *Piano Sonata n°12 I. Allegro*

will also be at 100BPM, which is why the performances are generated with regard to beat duration, and therefore, BPM doesn't change with the expressive performance. This is also clearly seen on Figure 3, by observing that the mean of the box-plots are around 1.0.

4.2 Note Onset Position in Measure

In symbolic time, one would anticipate note onsets occurring at each 1/4 location (i.e., 0, 0.25, 0.5, 0.75, 1,...) in 2/4, 3/4, and 4/4 time signatures, and at each 1/8 location (i.e., 0, 0.125, 0.25, 0.625, 0.75, 0.875, 1,...) in a 6/8 time signature. As illustrated in Figure 4, the majority of note onsets indeed align with these expected positions within the measure. However, an intriguing observation emerges in the 6/8 time signature, where there are no note onsets at the x.875 positions. One hypothesis could be that since these positions directly follows a strong beat, this events is reinforced in importance by giving it more space, which is done by not adding any onset directly after the strong beat, and probably making it span various events.

Moreover, beyond these locations, we also notice some note onsets occurring at other positions, such as x.33 or x.88. One hypothesis to explain these deviations is that the composer deliberately introduced offbeat onsets to infuse their music with elements of surprise and introduce new expressive dimensions.

By examining the frequency counts of note onsets, a consistent pattern emerges. The predominant onset location is consistently at 0, corresponding to the downbeat, followed by the midpoint of the measure, and subsequently by the quarter positions, and so forth. This suggests a recurring structure where the meter appears to be recursively divided by two. This recurring pattern of strong-weak-medium-weak structure, as referred in the D. Huron's book '*Sweet Anticipation: Music and the Psychology of Expectation*' [7], is commonly observed in 4/4 time signatures according to the author. Furthermore, this structure aligns with the theory of metrical hierarchy expounded in the works of C. Palmer and C. L. Krumhansl, in 1990 [8], and subsequently modeled by M. Rohrmeier in 2020 [9].

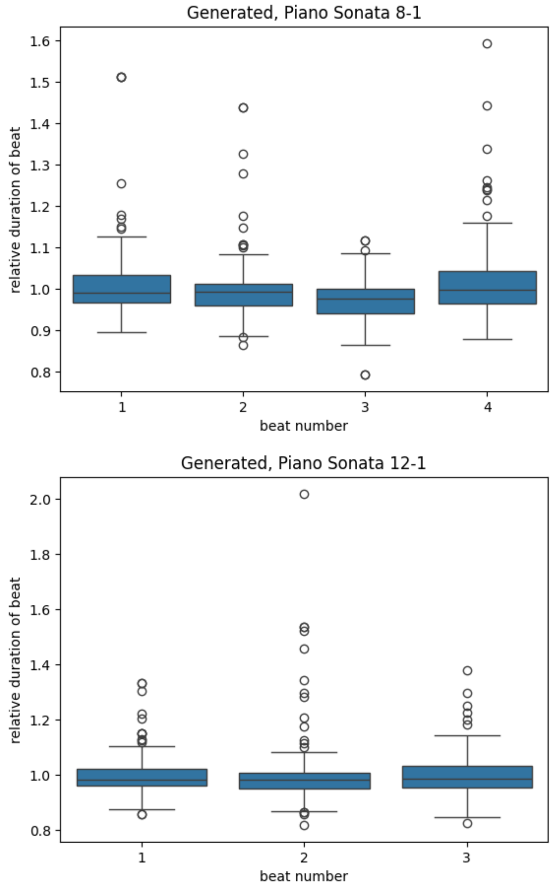

Figure 3. Relative duration of the beat, depending on its position in the measure, for generated MIDI files

Upon analyzing the human performance illustrated in Figure 5, we observe the anticipated strong-weak-medium-weak structure, albeit with less pronounced curves compared to the unperformed pieces. The distribution of onsets appears to follow a Gaussian pattern around the expected onset points. Additionally, we also observe additional onset positions, such as at 0.33 or 0.66 in 2/4 and 6/8 time signatures, contributed by various performers.

4.3 Variability in Timing

4.3.1 Mozart Fantasia K.475 vs. Piano Sonatas

Mozart's *Fantasia K.475* has a much lower standard deviation between performed and unperformed versions' note onset positions in metrics compared to his other *Piano Sonata* series as shown in Figure 6.

To explain it, one perspective is the inherent qualities of works' nature and form. One consideration is that *Fantasias* are usually more free and improvisational, not as constrained by traditional musical forms. As for the poignant and contrasting *Fantasia K. 397*, composed in Vienna in 1782, the Massins believed that it represents "the archetype of Mozartian improvisation, with the erce pathos of its opening [...] and its recitative effects" [10]. which might lead to a more delicate and coherent handling of rhythm, resulting in lower timing variability. In contrast, *Sonatas* might place more emphasis on structural contrast and variation, potentially leading to higher timing variability.

Another possible view is that the creation of the *Fantasia* might have been Mozart's attempt to explore or express specific emotions. This might have led to less flexibility in performance to adhere to Mozart's emotional intentions.

4.3.2 *Overview of all composers and styles*

From the Figure 7, we can see that when it comes to the performed and unperformed version's standard deviations of the note onset positions, Beethoven's compositions are characterized by a high median deviation, long boxes, long whiskers, and the presence of multiple outliers. These attributes suggest that performers might adopt a broad spectrum of interpretive choices when playing his pieces, potentially due to the technical and expressive freedoms inherent in Beethoven's music. Another explanation would be some Beethoven' compositions are technically demanding, this difficulty can lead musicians to adjust the timing to execute complex passages. As one article says, the techniques that have been observed the weakening or by-passing of cadential points, the shifts of cadential emphasis, the underlining of distant relationships, the massive concentration of harmonic meaning upon a single tone—all of these can generate more powerful harmonic leverage than was customary in the music of Beethoven's predecessors and contemporaries in the Classic era, a leverage that creates intense harmonic thrusts and broad trajectories. As we follow his harmonic path, often tortuous, often unclear, we sense something of the same struggle, the same wrestling with materials that comes across in his treatment of melody, rhythm, and texture. Indeed, these elements tend to reinforce each other in Beethoven's music; as we have seen, there are expressive and rhetorical complements to Beethoven's searching harmonic procedures [11].

Similarly, Scriabin's works are distinguished by the most extensive range of standard deviation we defined and the highest median among the composers compared.

Chopin's works are depicted with several discrete outliers. One explanation for this is Chopin frequently employed rubato, which can introduce significant variability in timing. No composer has suffered more from the misuse of Tempo Rubato than Chopin. The contemporary practice of it which passes for "interpretation", or "individuality", but too often degenerates into mere distortion, is the result of prolonged misunderstanding of it, in spite of the testimony of Chopin's contemporaries and of Chopin himself [12].

On the contrary, Bach's compositions display the least timing variability, as depicted by the short boxes. This conveys a strong uniformity in timing throughout the majority of his works. This could be attributed to the clearer emotional content and structure of his music or to the well-established interpretive traditions that guide performances of his works. Another similar example is Rachmaninoff, his works' plot is characterized by a low median deviation, compact boxes, and short whiskers.

5. DISCUSSION

This study represents our first experience into applying computational methods to extract and analyze real pieces of music, offering a practical application of the theoretical concepts covered in the class lectures. By delving into the nuances of expressive timing and exploring the underlying metrical structures, we gain valuable insights into how and where these elements manifest in actual musical performances. Moreover, this endeavor provides us with hands-on experience in discovering the various methods used to encode music and getting familiar with the available tools to analyse these pieces.

However, our exploration has not been without its challenges. Notably, we encountered unexpected occurrences when analysing the performed MIDI files. For instance, while onset positions should theoretically fall within the range of beats per measure, we still detect onsets extending up to location 4 for 2/4, 3/4, and 6/8 time signatures in the Figure 5. The cause of this anomaly remains unclear; it may come from the data preprocessing steps, as there are multiple methods to generate MIDI files, we may not have employed the appropriate approach to extract the onset positions. Moreover, we often encounter discrepancies between the extracted time signatures from MIDI files with those from annotations.txt and MusicXML files.

Another challenge arises in interpreting the data after it has been acquired. We've come to understand that, in examining the variability in timing phase across various authors, we may observe similar data distributions among compositions from different composers; however, the stylistic expressions of their work can be significantly distinct. This realization underscores the necessity for a more insightful analysis, one that requires an extensive foundation in literature review and a thorough understanding of the musicological context.

6. CONCLUSION

The timing function produces changes in beat's durations to create a generated performance, according to how their durations were changed during a real performance of one of the pieces in the corpus.

The analysis of note onset positions within Mozart's *Piano Sonatas* reveals a strong-weak-medium-weak metrical structure, characteristic of compositions in 4/4 time signature.

Additionally, the exploration of standard deviations in note onset positions across various composers and their compositions unveils the nuanced interplay between musical expression, composer intention, structural complexity, and performer interpretation, underscores the beauty and complexity of classical music, making the study of its performance both a challenging and intriguing endeavor.

Ultimately, through the integration of psychological insights, computational modeling techniques, and music theory, we have gained a deeper comprehension of raw music data, enriching our understanding of musical timing expression and performance dynamics.

7. AUTHOR CONTRIBUTIONS

Initially, tasks were divided among the team members: R. Clerc focused on modeling the timing function, C. Tang on plotting the distribution of onset positions, S. Yang on studying timing variability, and O. Profeta on reviewing literature related to expressive timing. Each member starts by analyzing and drafting their respective sections of the report. Subsequently, all team members actively engaged in reviewing, providing feedback, and refining each section. This collaborative approach enabled each section to benefit from the diverse expertise of each team member.

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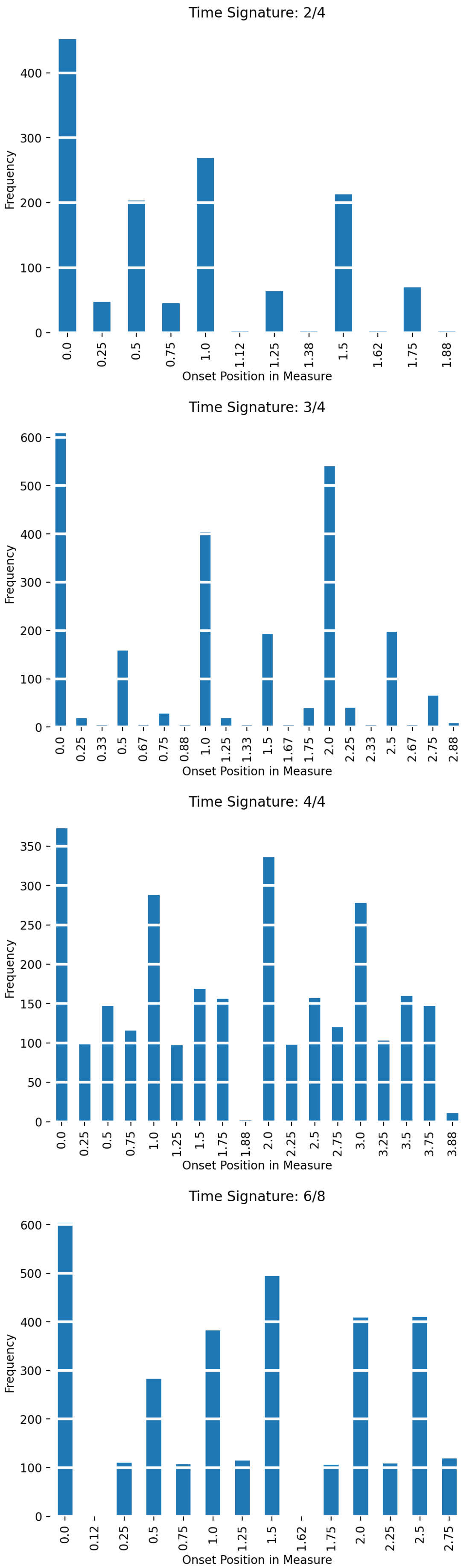

Figure 4. Distribution of note onsets positions in the measure for 2/4, 3/4, 4/4 and 6/8 time signature.

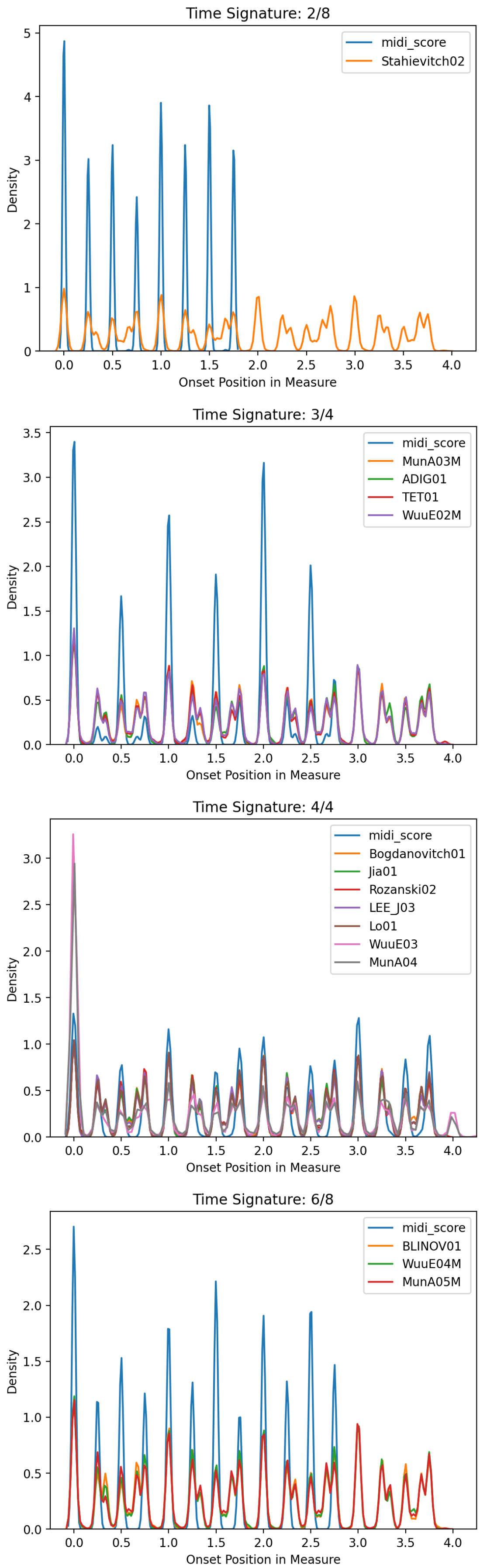

Figure 5. Kernel density estimation of note onsets positions in measure for 2/4, 3/4, 4/4 and 6/8 time signature, for performed and unperformed performances. The blue curves represent the unperformed ones, and the remaining curves are the different performed versions.

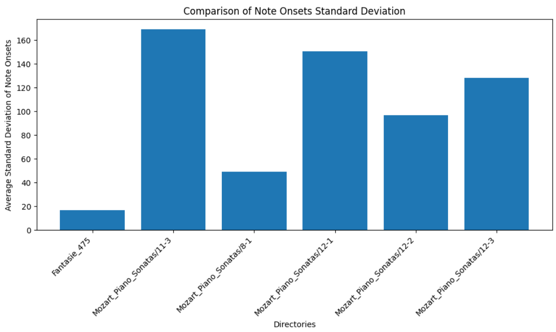

Figure 6. Comparison between the standard deviation between performed and unperformed versions' note onset positions of Mozart's Fantasia and Piano Sonatas.

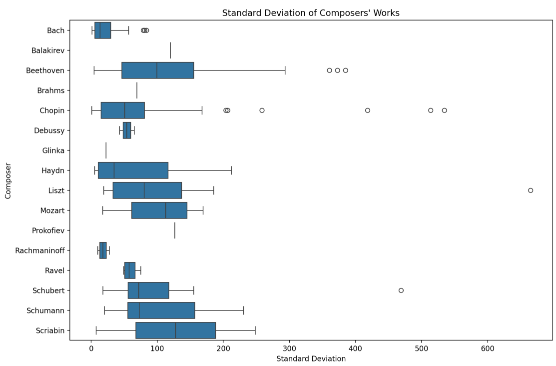

Figure 7. Timing variability in compositions across different composers by visualizing the standard deviation between performed and unperformed versions' note onset positions.