DIGITAL MUSICOLOGY ASSIGNMENT 1

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ABSTRACT

In the realm of music generation, the emulation of human performance through computational algorithms poses a formidable challenge, encompassing nuances of timing, expression, and pitch distribution. This assignment [1] delves into the multifaceted problem of generating musical performances using computational methods, leveraging techniques from digital musicology. Through modeling approaches and empirical analyses, it seeks to unravel the underlying mechanisms governing musical expression and performance. The task A explores timing functions for specific pieces and general models across diverse time signatures, showcasing versatility and effectiveness. Results demonstrate variations in timing and pitch distribution across composers, eras, and performers. Insights from the analyses (Task B), coupled with class concepts, shed light on expressive timing, note onset distribution, and pitch characteristics, offering a deeper understanding of musical expression.

1. INTRODUCTION

Generating music presents a profound challenge, encompassing not just the reproduction of notes and melodies, but also the nuanced expression and timing that give music its emotive power and character. Computational methods offer a promising avenue for tackling this challenge, with implications ranging from aiding composers in exploring new creative directions to facilitating the learning and analysis of musical pieces.

In this context, this assignment explores the complex task of generating musical performances using computational methods. Drawing on insights from digital musicology, it seeks to discover the inherent mechanisms of timing, expression, and pitch distribution from musical performances. Through a combination of modeling techniques and empirical analyses, this study aims to discover the mechanisms that differentiate a computer-generated/robotic music from a human performance

2. MODEL

There is two timing different timing functions, used for single or multiple pieces analysis.

[1] https://github.com/JorisMonnet/DM_Assignement1

2.1 Model for a Specific Piece

This function calculates the tempo ratio between symbolic and performed onsets for each beat. It offers two modes of operation: either by specifying the paths to specific performance and symbolic annotation files, or by providing the folder path containing the piece. In the latter case, the onsets of all performances within the folder are averaged for each beat. Subsequently, the tempo of each onset is determined based on its duration. The output is a dictionary with beat numbers as keys and the corresponding ratio between symbolic and performed tempo as values. The resulting visualization is a line plot, as it focuses on individual beat ratios without considering meter changes within the piece. For an analysis based on meter changes, the following function can be utilized.

2.2 General Model

This function computes the tempo ratio between symbolic and performed onsets for each bar. Onsets are averaged within each bar for every time signature present in the piece or corpus of pieces. It accepts a folder name containing annotation files as input, accommodating high-level folder structures by searching for annotation files in subfolders. The output is a dictionary with different meters as keys, each associated with a list of averaged tempo ratios (one ratio per beat). This feature is particularly useful for pieces or corpora with varying time signatures. Additionally, the function allows for the selection of a specific meter if necessary, as demonstrated in the notebook. Moreover, it is optimized to efficiently handle large corpora, including the entire dataset, with minimal computing time (approximately 8 seconds). The function also accounts for cases where there are differing numbers of downbeats for the same time signature within the corpus, separating and visualizing them accordingly on the plot. Similar to the specific piece model, the plot function generates a line plot to facilitate comparison across different time signatures.

3. RESULTS

3.1 Task A

The timing function's versatility is showcased through four distinct graphical representations. Firstly, a single piece's tempo curve is depicted:

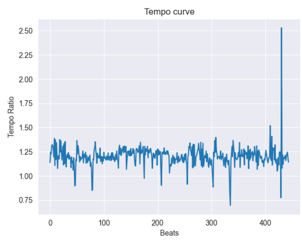
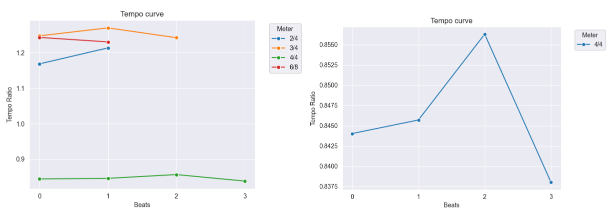


Figure 1: Tempo Curve for a Single Piece (Mozart, Piano Sonatas 11-3)

Following this, the tempo curves of multiple pieces are illustrated, with all their time signatures or only the 4/4.



(a) Multiple Pieces (Mozart, Piano Sonatas)

(b) Multiple Pieces in 4/4 Meter (Mozart, Piano Sonatas)

Lastly, the tempo curves encompassing the entire dataset are exhibited:

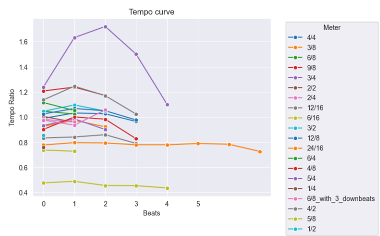


Figure 3: Tempo Curve for Multiple Pieces (Full Dataset)

The dictionaries returned by these timing functions, particularly the general one, serve as maps to correlate unperformed onsets with performed ones. This mapping can be further utilized to generate music that emulates human performance. This demonstrates the broader application of the timing function beyond this task.

We observe differences for the same time signatures between Composers, Eras and performers. There is even a 6/8 with 3 downbeats in the dataset or several irregular meters. There are all handled by the timing function.

3.2 Task B

In Task B, we selected the Mozart Piano Sonatas subcorpus from the asap-dataset [1].

3.2.1 Distribution of Note Onsets

For this part we analyzed pieces 11-3 in 2/4 time signature, 12-1 in 3/4 time signature, and 12-2 in 4/4 time signature. In addressing the distribution of note onsets on metrical locations, we excluded notes that are tied to the preceding note, thereby focusing solely on the 'true' onset notes—those that mark the beginning of a sound event. To explore the distribution of onset notes in different time signatures, we constructed both Kernel Density Estimate (KDE) plots and frequency plots for each piece of music. The KDE plot provides a smoothed continuous estimation of the onset distribution, revealing the probability density of onsets at different metrical positions. In contrast, the frequency plot displays the relative occurrence of each onset, offering a direct view of the rhythmic patterns across measures.

In the analysis of different time signatures, the x-axis represents the beats within a single measure. For 2/4 time, there are two beats per measure; for 3/4 time, there are three beats; and for 4/4 time, there are four beats. We have set the minimum unit of analysis at 0.5 beats, which is equivalent to an eighth note.

In the 2/4 time signature, the density plot shows a con-

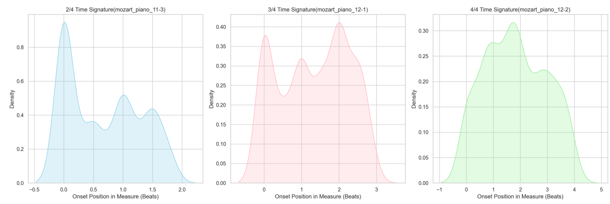


Figure 4: Note Onset Distribution in Different Time Signatures (Frequency Plot)

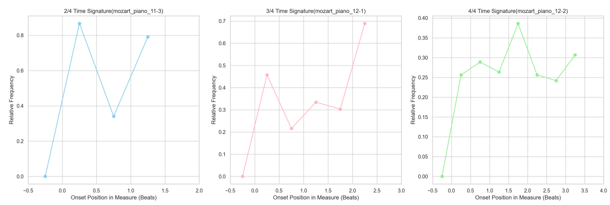


Figure 5: Note Onset Distribution in Different Time Signatures (Kernel Density Estimate Plot)

centration of note onsets at the first beat of each measure, highlighting the strong downbeat characteristic of this time signature. Additionally, there's a smaller peak at the midpoint of the second beat. The frequency plot align with this feature indicating a rhythmic emphasis.

For the 3/4 time signature, the density plot is more dispersed and we can observe a prominent peak at the first beat and the third beat in both plots. The peak at the first beat is consistent with the expected stress on the downbeat in 3/4 time. The peak at the third beat could indicate a specific compositional choice to place emphasis on the final beat of the measure, possibly to lead into the next measure or to highlight a musical phrase.

The 4/4 time signature plot shows a distinct peak around the third beat. The third beat in 4/4 is often used to provide a counterbalance to the first beat which may explain the higher number of onsets.

3.2.2 *Expressive Timing*

We chose Piano Sonatas 12-1 by Mozart as Q2 in task B. The time signature of this music is 3/4, which means there are three beats in each measure. The unperformed version lasts for 342.5 seconds, whereas the performed version, by TET01 lasts for 278.7 seconds. So, on average, the performed version was played faster then the original score.

To extract expressive timing in the metrical grid, we created the distribution of sound duration of each beat as violin plots. Figure 6 shows the distribution of sound duration by each beat. According to this graph, on average, the shape of the distribution area is almost the same in each beat, and each beat has almost the same length as outlier.

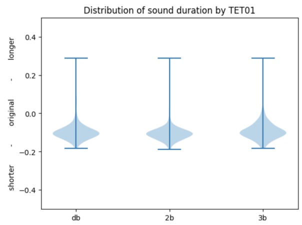


Figure 6: Distribution of sound duration of the performance by TET01 in the four parts and comparison with the unperformed version

However, we expect that the expressive timing can be changed based on the position in the music, so we divided the whole music into four parts, which have 171, 171, 171, and 173 notes, respectively. Figure 7 show each beat's sound duration distribution in each part.

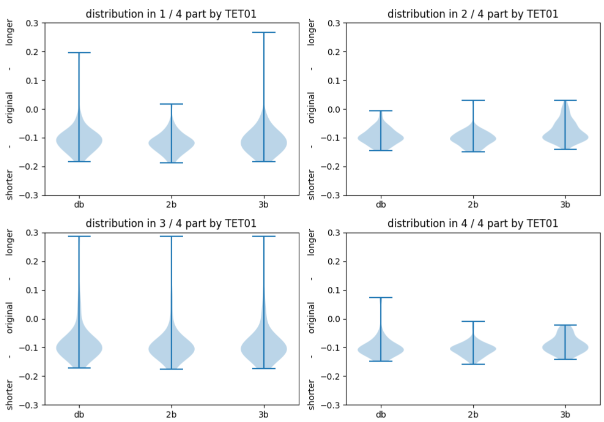


Figure 7: Distribution of sound durations compared to the unperformed version in four parts

The first graph of 7 represents the distribution of the sound duration in the first part. In the first part, the shape of the distribution is almost the same, but the outlier notes exist in the downbeat and the third beat. In the second part. Each beat does not have a specific outlier. The modes of each beat's distribution are almost the same. In the third part, the shape of the distribution area of each note's sound duration is also almost the same. Moreover, each note has outlier, which are mostly the same length as each other. In the last part, the shape of the distribution area of the third beat is different from others. The distribution of the third beat is higher on the graph than the other beats.

3.2.3 *Pitch Analysis*

We want to talk about how can we quantitatively analyze and compare the characteristics of pitch distribution in the works of different composers and musical periods. So we have categorized musicians by period, and the categorization results are as follows.

Period	Composer
Baroque (1600-1750)	Bach
Classical (1750-1820)	Haydn and Mozart
	Beethoven
Romantic (1820-191)	Chopin and Liszt
	Schumann and Brahms
	Tchaikovsky and Rachmaninoff
	Schubert
Impressionist (1875-1925)	Debussy
20th Century and Modern	Prokofiev and Ravel
	Scriabin
	Balakirev and Glinka

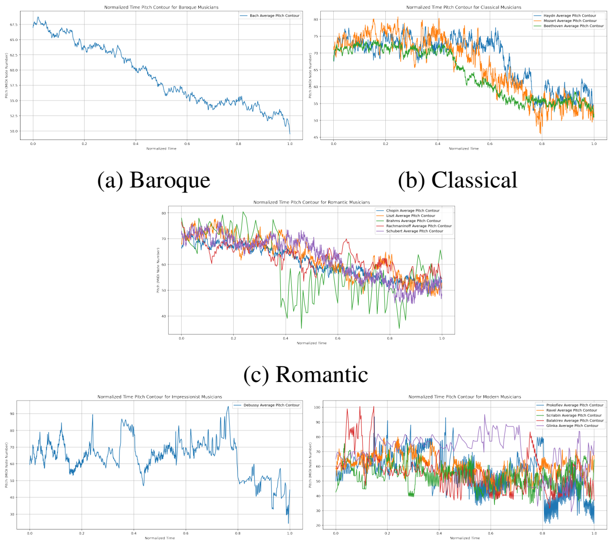
Table 1: Composers of Different Historical Periods in Western Classical Music [2]

And then we first illustrated the pitch distribution in the works of composers from various historical periods. Subsequently, we calculated the information entropy values of these periods in terms of pitch distribution. In the end, by conducting significance tests, we robustly substantiated that there are indeed noticeable differences in the pitch distribution of works from different historical periods.

The distribution results have been shown in Figure8 and we can do some analysis from it. In periods leading up to Impressionism, compositions often began with higher pitches and gradually transitioned to lower ones. However, during the Romantic and Modern eras, there was a noticeable shift towards greater pitch diversity. Romantic pieces, for instance, showed intricate variations within their descending trends, while Modern composers like Prokofiev embraced a wider range of pitch use which makes a departure from the more uniform approach of contemporaries.

Calculating information entropy (Table2) to assess the diversity of pitch use across different musical eras also shows that pitch diversity was richest during the Romantic and Modern periods, and least varied during the Baroque period. Moreover, significance tests confirm substantial differences in pitch distribution across these periods (Table3).

[2] Some composers' styles span multiple musical periods or genres. The categorization here reflects the most widely recognized association according to various sources.



(a) Baroque (b) Classical

(c) Romantic

(d) Impressionist (e) Modern

Figure 8: Average pitch distribution for each period

Musical Period	Entropy
Baroque	5.31
Classical	5.71
Romantic	5.93
Impressionist	5.54
Modern	5.92

Table 2: Entropy values for different musical periods.

Group 1	Group 2	t-statistic	p-value
Baroque	Classical	-53.821604	0.0
Baroque	Romantic	-50.674402	0.0
Baroque	Impressionist	-9.526888	6.06e-21
Baroque	Modern	-8.250351	1.77e-16
Classical	Romantic	-1.427682	0.153
Classical	Impressionist	3.386300	0.000727
Classical	Modern	16.212631	2.79e-58
Romantic	Impressionist	3.659086	0.000262
Romantic	Modern	16.457593	4.89e-60
Impressionist	Modern	4.589199	4.70e-06

Table 3: Statistical T-test Results

4. DISCUSSION/CONCLUSION

4.1 Task A

In this dataset, it can be confidently affirmed that the function operates effectively across various scenarios, regardless of the time signature or downbeat pattern. Its primary advantage lies in its ability to consistently return dictionaries even during intermediate stages, thereby enhancing flexibility for implementing different functionalities, such as selecting specific time signatures. The modeling of onsets leverages insights gained from lectures on meter and rhythm, particularly in its adept handling of irregular downbeat patterns within ostensibly "regular" meters, such as in the case of 6/8 time signatures.

4.2 Task B

4.2.1 *Distribution of Note Onsets*

In 3/4 and 4/4 time signatures, we observe that the peaks are not predominantly on the first beat, as might be typically expected. This could be attributed to notes that are tied over from the end of the previous measure which we learnt from the course. Such ties can create a sense of anticipation and add expressiveness to the music. To ascertain this hypothesis, we extended the distribution to two measures in the 4/4 time signature. This allows us to observe any extended patterns or cycles in the rhythm that might not be apparent within a single measure.

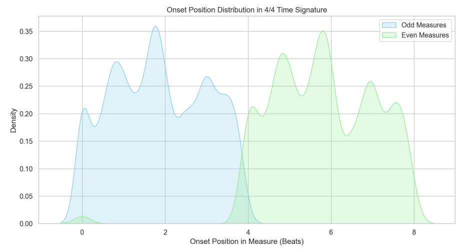


Figure 9: Note Onset Distribution of the 4/4 time signature over two measures

The plot indicates that the start of even measures has fewer new note onsets, possibly due to notes being sustained, or tied, from the end of odd measures. This results in a smoother transition across measures and explains why there's a stronger peak at the third beat. Such a pattern suggests that tied notes may contribute to a sense of continuity and flow in the music.

4.2.2 *Expressive Timing*

In this music, the third beat is often more flexible than the other beats because the shape of the distribution of the third beat is longer vertical on the graph compared to other shapes(Figure 6). This flexibility can encourage us to feel happiness, playfulness, sprightliness, and mental yearning, depending on the major or minor [2].
The first and the third parts have a certain number of outlier notes, especially in the first part; the downbeat and the third beat are likely to be expressive because the beats have flexibility. Also, the third part has outlier notes in all beats, which have almost the same length. So, we checked the specific features throughout the third part, shown in Figure10. The characteristic part in the third part exists from 150[s] to 165[s]. This characteristic part has patterns that include a firm and flowing rhythm, which can express the dignified, vigorous and happy, playful, respectively [2].

4.2.3 *Pitch Analysis*

Despite these differences in diversity and style, the overarching principle of beginning with higher pitches

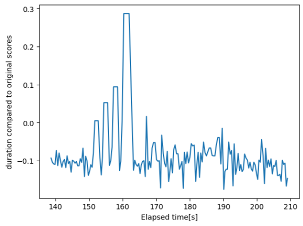


Figure 10: Fluctuation of the sound duration compared to the unperformed version in the third part

and transitioning to lower ones reflects a common tension-release mechanism [3, 4] in Western music. This way of starting with high pitches and going to low ones shows a common method in writing music. It matches well with Schenkerian analysis, which sees many pieces of music as moving downwards from high to low pitches [5]. This analysis highlights that many musical works fundamentally follow a descending trajectory from high to low pitches, considered the backbone of musical structure and illustrated a deep-rooted adherence to this pattern across various periods.
This analysis reminds me of the concepts regarding pitch we've learned in class. Even though the pitch changes over time, the existence of the pitch spiral and octave equivalence principles suggests that these variations harmoniously coexist within a piece, enriching the emotional and historical expression. Through this framework, pitches, though varied, are organized to maintain harmony and effectively reflect changes in emotions and periods.
However, due to the limited number of musicians in some periods, the representativeness of these samples for entire periods is questionable. Additionally, the volume of works by individual composers varies which means that the dataset may not fully support an analysis of pitch variation across all music periods. It is also important to note that some composers' works were not included in the analysis due to issues with the XML files, further limiting the breadth of our dataset. Consequently, while informative, our conclusions might not be entirely reliable.

4.2.4 Conclusion

This assignment has underscored the lesson that a comprehensive understanding of music cannot be achieved through quantitative analysis alone; it must be augmented with music theory to truly grasp the intricacies of a piece.

5. AUTHOR CONTRIBUTION

Task A: Joris Monnet
Task B 1a: Yiwei Liu
Task B 1b: Yutaka Osaki
Task B 2: Xingyu Pan
Report: All
Code Cleaning: Joris Monnet
Notebook: All

6. REFERENCES

[1] F. Foscarin, A. McLeod, P. Rigaux, F. Jacquemard, and M. Sakai, "ASAP: a dataset of aligned scores and performances for piano transcription," in *International Society for Music Information Retrieval Conference (ISMIR)*, 2020, pp. 534–541.

[2] K. Hevner, "Experimental studies of the elements of expression in music," *The American Journal of Psychology, 48(2)*, pp. 246–268, 1936.

[3] . C. P. A. V. Barchet, J. M. Rimmele, "Tensemusic: An automatic prediction model for musical tension," *Plos one*, 2024.

[4] F. L. . C. L. Krumhansl, "Modeling tonal tension," *Music perception*, pp. 329–366, 2007.

[5] E. Wen, "Tonal analysis: A schenkerian perspective," *Journal of Music Theory Pedagogy*, p. 261, 2020.