Cultural Region	Chart Country	Country-of-Origin
African-Islamic	*UAE, Saudi Arabia, Turkey, South Africa	*Bahrain, *Morocco, Lebanon, *UAE, Saudi Arabia, Egypt, *Syria, South Africa, Iraq, Nigeria, Turkey, Algeria, Uzbekistan, Iran, Azerbaijan, *Kazakhstan, *Kuwait, Tunisia, Jordan, Palenstine, *Comoros, *Yemen, *Congo
Catholic-Europe	Croatia, Hungary, Poland, Austria, Belgium, Spain, France, Italy	France, Italy, Belgium, Spain, Austria, Croatia, Slovenia, Hungary, Poland, *Greece, Portugal
Confucian (Asia)	Not Applicable	South Korea, Japan
English-Speaking (Anglo-American)	Australia, Canada, *Ireland, United Kingdom, United States	United Kingdom, United States, Canada, Australia, *New Zealand, *Ireland
Latin America	Argentina, Brazil, Chile, Colombia, Guatemala, Mexico	Colombia, Philippines, *Puerto Rico, Argentina, Uruguay, Chile, *Panama, Venezuela, *Dominican Republic, Peru, *Jamaica, Brazil, Mexico, Guatemala
Orthodox-Europe	Russia, Ukraine	*Lithuania, *Kosovo, Bosnia and Herzegovina, Ukraine, Romania, Serbia, Bosnia, Belarus, Bulgaria, Russia, Armenia
Protestant-Europe	Switzerland, Germany, Denmark, Finland, Netherlands	Netherlands, Sweden, Norway, Germany, Switzerland, Denmark, Iceland, Finland, Estonia
West-South Asia	Not Applicable	Israel, Vietnam, Malaysia

Table 1. List of countries where charts were sampled from (Chart Country) and where sampled artists either resided in or originated from (Country-of-Origin). These were grouped according to Inglehart & Welzel's Cultural Map of the World (Cultural Region), following their macro-level orientation on Traditionalism and Secularity. Countries with '*' were not included in the original Cultural Map, but were categorized following the categories of their geographical neighbours.

(API) [1] , and obtained artists' country of residence/origin from the MusicBrainz API [2] . Through this method, we managed to obtain the country or residence for artists from 2942 songs, and manually searched for the country of residence or origin (if country of residence was unavailable) for the artists of the remaining 1921 songs, through a combination of databases from Google, Wikipedia, LastFM, and Popnable. For analyses, we labelled this variable as Country-of-Origin. We also obtained danceability, based on detrended fluctuation analysis [26], and spectral energy scores for each song through the Essentia [27] library.

Country-level indicators of economic development were obtained through Gross Domestic Product (GDP) per capita, percentage of migrants, and income inequality (Gini) from the World Bank Databank [3] . We also categorized countries according to their respective Inglehart-Welzel cultural regions [4] : African-Islamic, Catholic-Europe, Confucian, English-Speaking, Latin-America, Orthodox-Europe, Protestant-Europe, and West-South Asia. If the country was not officially categorized in this system, we approximated the category based on the categorization of its geographical neighbours. Country categorizations are in Table 1, and data is available on our online repository [5] .

2.2 Data Handling and Analysis

To construct the networks, we created undirected edge lists for each timepoint, consisting of nodes (song), weight: the number of times any two songs (or nodes) appeared on the same country's charts (denoted by W). In other words, for any given timepoint, we define a network G, where $G = (V, E)$. V refers to the set of unique songs in all charts, and E refers to the set of edges. W is the weighted adjacency matrix of the graph and is defined as follows for any pair of songs (i, j):

$$W_{ij} = \sum_{C_k \in C} Cooccur(C_k, i, j) \quad (1)$$

where $C = \{C_1, C_2, \dots, C_K\}$ is the set of all considered charts and C_k is a particular chart (for a particular country and month), *i.e.* the set of 100 songs that were most listened in this country during this month. $Cooccur$ is an indicator function which takes the value 1 if and only if song i and song j co-occur in C_k, and 0 otherwise. To assess the centrality of a node, we examined the eigencentrality (x) of a node i, which is written in Equation 2 as:

$$x_i = \frac{1}{\Lambda} \sum_{j \in V} W_{ij} x_j \quad (2)$$

Here, Λ refers to the largest eigenvalue of the matrix W. Centrality of a node (song) x_i takes into account the sum of centralities of its neighbors, which was a reason why we used this measure (as opposed to degree centrality, which relies only on the number of connections). Eigencentrality parameters (e.g., number of iterations) relied on igraph defaults obtained from arpack [28].

For community detection, we used the modularity metric, which identifies nodes with statistically higher numbers of connections (edges) than random chance levels, and partitioning the interconnected nodes according to the boundaries of these 'above random' interconnections [29]. We used Clauset et al's fastgreedy function ('cluster_fast_greedy' [30]) that repeatedly combines lower-level communities to maximize modularity, for a bottom-up determination of the number and structure of communities. These analyses were conducted through the igraph package [31] in R [32].

For statistical analyses, we fitted separate χ^2 tests and ordinary least squares (OLS) or linear mixed effects (LME)

[1] https://developers.deezer.com/api
[2] https://musicbrainz.org
[3] https://databank.worldbank.org/source/world-development-indicators
[4] https://www.worldvaluessurvey.org/
[5] https://osf.io/uyh6d/

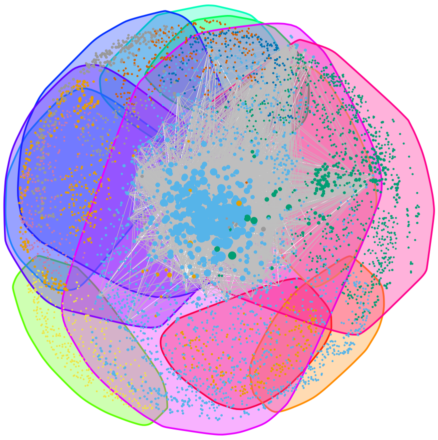

Figure 1. Network visualization using the Kamada-Kawai force-directed algorithm. Songs are represented by nodes, and node size corresponds to eigencentrality. Communities are displayed through colors. A version with node labels (titles and artists) is available on our online repository.

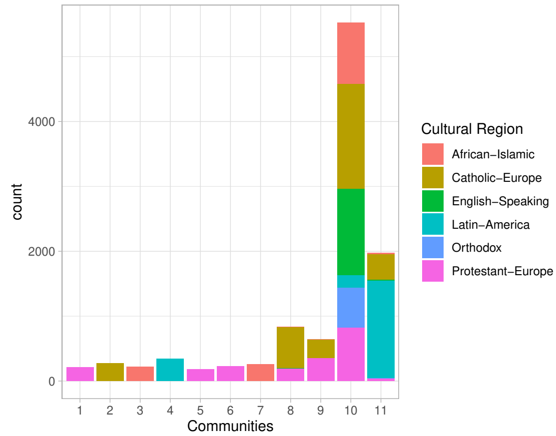

Figure 2. Visualizing culture-of-consumption: the distribution of charts that make up each Community, categorized by cultural region. Community 10 (C10) for example, comprises 5807 songs that are in charts from all 6 cultural regions sampled in this study.

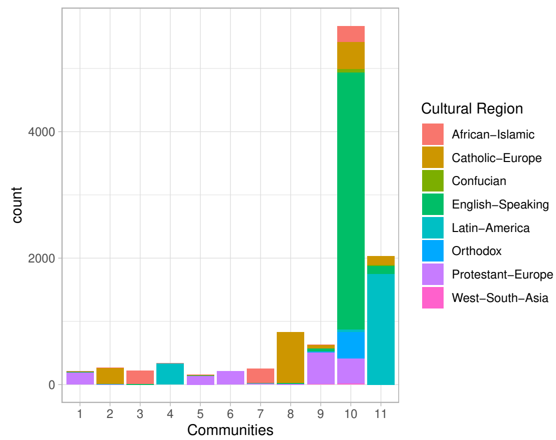

Figure 3. Visualizing culture-of-origin: the distribution of artists' countries for each Community, categorized by cultural region. Community 10 (C10) for example, comprises 5807 songs, of which 4707 are from the English-Speaking (Anglo-American) cultural region.

regression models [33] predicting node (song) eigencentrality from Community (OLS), cultural region (LME), economic development (LME), and danceability/spectral energy features (LME). For LME models, random intercepts were included for country-of-consumption (countries' charts), and random slopes were included for danceability and spectral energy by country where applicable. Degrees of freedom were estimated using Satterthwaite approximation. All categorical variables were deviation coded to examine the relative effect of a specific cultural region against the mean of all regions.

3. RESULTS

3.1 Descriptive statistics of detected Communities

A total of 11 Communities (C1-11) were detected from the network. Of which, Communities 10 (C10) and 11 (C11) had substantial amounts (5807 and 2056 songs respectively), but the other Communities ranged between sizes of 179 (C5) to 832 (C8). Due to space concerns we report only the results on cultural regions in this paper, but contingency tables and lists describing the country-of-consumption of the charts and country-of-origin of the artists' are available on our online repository [6]. Figure 1 displays a visualization of the network using a Kamada-Kawai layout [34].

We then tested the Communities' association with country-of-consumption (that the Top 100 chart was from) and country-of-origin of the artist. These were grouped according to their cultural region, described in Table 1. We observed a significant association between Communities and songs' culture-of-consumption, $\chi^2(50, 10681) = 15433, p < .001$, and between Communities and artists' culture-of-origin, $\chi^2(35, 10459) = 16253, p < .001$. Figures 2 and 3 visualize the cultural make-up by culture-of-consumption and culture-of-origin. For the most part, with the exception of C10, we find the relative consistency between culture-of-consumption and culture-of-origin, suggesting that the artists residing or originating from a specified cultural Community were largely listened to (popular) within the same cultural Community. For example, C1 comprised charts from the Netherlands, and a majority (87.6%) artists were of Dutch origin. Other Communities represented a linguistic cultural sphere over several countries: in C8, French-origin artists comprised 88.7% of the Community, which was largely split amongst Belgian (36.4%), French (39.3%), and Swiss (27.8%) Top100 charts. However, for C10, we observed that Anglo-American artists' formed the majority (70.1%), but consumption was spread out over all cultural regions and all 30 countries.

[6] `https://osf.io/uyh6d/`

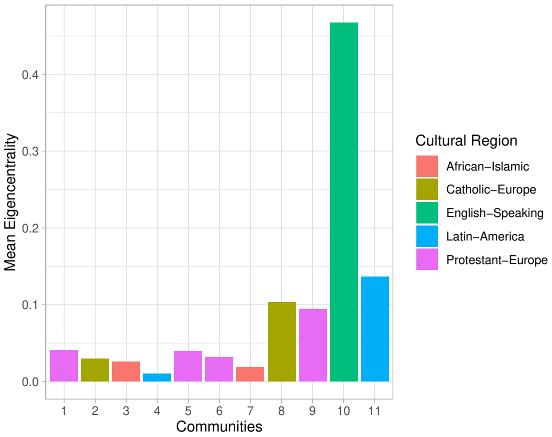

Figure 4. Mean eigencentrality of songs in each Community. Colors denote the most common culture-of-origin for artists in that Community.

3.2 Cross-cultural popularity (eigencentrality)

An OLS model ($R^2 = 0.36, F(10, 11033) = 614, p < .001$) with eigencentrality as the outcome variable, Communities as the predictor, and C1 as the reference level, found that, C2 ($\beta = -0.19, t = -4.15, p < .001$), C3 ($\beta = -0.20, t = -4.01, p < .001$), C4 ($\beta = -0.25, t = -6.10, p < .001$), C5 ($\beta = -0.16, t = -2.87, p = .004$), C6 ($\beta = -0.18, t = -3.69, p < .001$), and C7 ($\beta = -0.19, t = -4.15, p < .001$) showed significantly lower eigencentrality (than the average across Communities), and C10 ($\beta = 1.17, t = 72.08, p < .001$), and C11 ($\beta = 0.14, t = 6.92, p < .001$) showed significantly higher eigencentrality. These suggest that C2-7 had songs with cross-cultural popularity significantly lower than the Grand mean, and C10 and C11 had songs with cross-cultural popularity significantly above the Grand mean. These results are visualized in Fig 4.

Next, we examined the eigencentrality of songs by the culture-of-origin of the artist. As one artist could have several songs across various countries' charts, we used a LME model, with random intercepts for country-of-consumption (Model $R^2_{marginal} = 0.42, R^2_{conditional} = 0.44$). As countries' economic situation may have also influenced their consumption preferences, GDP per capita was added as a control variable. We observed a significant effect of culture-of-origin ($F(7, 6166.9) = 778.73, p < .001$), but not GDP per capita ($F(1, 27.9) = 0.90, p = .350$). With African-Islamic culture as a reference level, we found that songs originating from artists in Catholic-Europe ($b = -0.11, t = -9.31, p < .001$), Latin America ($b = -0.11, t = -8.43, p < .001$), and Orthodox Europe ($b = -0.06, t = -3.73, p < .001$) cultures had eigencentrality significantly below the Grand mean, songs originating from artists in Confucian Asia ($b = 0.12, t = 4.49, p < .001$) and English-Speaking (Anglo-American) cultures ($b = 0.34, t = 34.93, p < .001$) had eigencentrality significantly above the Grand mean. This suggests that songs from Confucian Asian and Anglo-American artists appeared to be more popular cross-culturally.

3.3 Additional analyses

We fitted two LME models exploring possible factors behind cross-culturally song popularity. These include socioeconomic reasons, such as GDP, income inequality, and immigration, and musical reasons, where we focus on danceability and energy as measures of rhythmic and intensity arousal inherent in the song. For the socioeconomic model (Model $R^2_{marginal} = 0.05, R^2_{conditional} = 0.10$), only immigration, measured using 2015 migrant percentages within a country's population, significantly predicted the eigencentrality of the songs on its charts ($b = 0.01, t = 3.83, F(1, 20.1) = 14.67, p = .001$). However, we noted the possibility that Anglo-American cultures, that typically have higher migrant percentages, also have artists with songs that have higher cross-cultural popularity. As such, we repeated the analysis with the exclusion of these countries (USA, UK, Australia, Canada). While still significant, migrant percentages predicted eigencentrality to a smaller extent (Model $R^2_{marginal} = 0.03, R^2_{conditional} = 0.07; b = 0.007, t = 2.21, F(1, 16.9) = 4.90, p = .041$, suggesting that countries with larger migrant populations also consume songs that are more cross-culturally popular.

While both are used as measures of arousal, danceability (rhythmic arousal) and spectral energy (intensity arousal) are only weakly correlated on a song-level ($r = 0.043, p, .001$). The LME model (Model $R^2_{marginal} = 0.02, R^2_{conditional} = 0.12$) showed a significant effect of danceability ($F(1, 30.4) = 12.4, p = .001$) and spectral energy ($F(1, 26.9) = 16.3, p < .001$). Eigencentrality was negatively predicted by danceability ($b = -0.121, t = -3.52, p = .001$), but positively predicted by spectral energy ($b = 2.68, t = 4.04, p < .001$). In sum, after controlling for country-specific effects, the cross-cultural popularity of a song was negatively associated with its danceability but positively associated with energy.

4. DISCUSSION

Our network appears to model the cultural spread of music consumption amongst the 30 countries studied. The 11 Communities detected largely reflect cultural consumption, which to some extent, seems to quantify linguistic boundaries as a common denominator across cultures. C8 for example, comprises French music, and is consumed in countries where French is widely spoken: Belgium, France, and Switzerland. Similarly, C9 comprises German artists, and is most consumed in Austria, Germany, and Switzerland. However, C10 appears unique in that that is largely comprised of songs by Anglo-American artists, yet is common in charts from countries where English is not primarily spoken. This appears to go beyond the nation or language-based consumption patterns of the other Communities. Given the high eigencentrality scores associated with songs from these cultures, our results may thus be indicative of a disproportional popularity of English-medium songs in global music consumption.

This interpretation would be consistent with Bello and Garcia's [4] research on nationalism and cultural divergence in local charts in recent years. Our results show that many charts retain a large amount of songs by local or regional artists, and despite past research suggesting that American cultural hegemony in popular music might have decreased in recent years (see [1]), still contain strong Anglo-American music presences.

In contextualizing cross-cultural popularity in the socioeconomic conditions of a country, we found that migrant population, and not economic development (GDP) or income inequality (Gini coefficient), significantly predicted a country's consumption of cross-cultural popular songs. As many such artists are of Anglo-American origins, and Anglo-American countries typically have large migrant populations, we repeated this analysis after systematically excluding these countries. Despite a smaller observed effect, our findings remained consistent, in suggesting that migrant population is associated with wider consumption of cross-culturally popular songs. We speculate that a larger migrant population could indicate a more diverse population [35, 36]. If so, consumption patterns may be less subject to nationalistic tendencies, and the drive for local music in recent years may not have had as strong an effect in these Communities. One possibility could be that this creates a larger space and demand for music that is popular elsewhere, but caution that these interpretations are speculations, and more research is needed to uncover the antecedents of cross-cultural popularity.

We also examined cross-cultural popularity by analyzing song arousal. Following research by [22, 37] that found popular music comprised high intensity and strong rhythms, we show that intensity arousal appears to be more cross-culturally popular, but rhythmic arousal appeared inversely related to popularity. This suggests a conceptual differentiation between both arousal domains, and more research is needed to identify the distinct functions and qualities of both.

Regarding the high eigencentrality of artists from Confucian Asian cultures, we note however that this could be a result of sampling bias. Given that we did not examine charts from Confucian Asian cultures, the presence of artists with this cultural background would mean that they had to have a level of global visibility to appear in the charts we sampled. In our data, these mainly consisted of South Korean artists, like BTS and Blackpink. Nevertheless, that these artists had songs with larger-than-average eigencentrality, despite our sample not having any East Asian charts (where they would have had a natural advantage), is a testament to the success of the South Korean Hallyu movement. Yet, research has also suggested that this may be due to the hybridization of Korean popular music with American influences and trends [38].

One limitation of our research is in the narrow sample of countries included in the analysis. For validity, we chose only to focus on countries where Deezer occupies a sizeable market share, inevitably under-representing users in Asia. Secondly, some songs may be region-locked, in that users from Country A may not necessarily be able to listen to a song from Country B. However, we think that this affects only a minority of songs, and most songs appear to be accessible from different geographical regions; region specificity may not be a strong-enough limiter in preventing German artists (for example) from being played in the United States.

Next, we did not conceptually distinguish popularity from influence. Cross-cultural popularity (i.e., the consumption of foreign music) may not necessarily suggest cross-cultural influence (i.e., the pervasiveness of foreign aesthetics and values in local culture), and some of our arguments are built on the assumption that popularity reflects a certain amount of influence. A thorough distinction on mechanisms are beyond the scope of the current paper, but is an area that we feel is in need of more research. Finally, we had difficulties in differentiating country-of-origin from country-of-residence for the artists sampled. These issues were often technical, in that the databases we relied on did not necessarily specify these differences. Consequently, some issues on validity remain: an artists originating from Puerto Rico but residing in New York may be coded inconsistently. Nevertheless, we think our data is sufficient in supporting the broad claims on cross-cultural popularity made in this paper, but we defer to ethnomusicologists working in localized geographical areas for greater depth on the role of specific cultural influences within local societies.

5. CONCLUSION

Given that our aim was to empirically quantify the dynamics of cultural influence in music charts, we think that the findings demonstrate a limited usefulness of our method of using song co-occurence on countries' charts for network construction, to empirically examining the extent of a culture's influence. While we focused solely on music consumption and popularity, which at best can be considered just one aspect of influence, we nevertheless found convergence in our findings on Anglo-American musical influence, with evidence from sociological and anthropological literature: Anglo-American dominance remains unmatched in its prevalence around the world. Moving forward, we propose that our method of network construction can also be used to examine the dynamics of regional influences from within the other Communities. For example, C11 comprises songs mostly on Latin American charts, but shows that artists tend to be from Puerto Rico or Colombia, and these artists from these countries may thus have a stronger regional influence within this Community. Thus, even within these regional cultural spheres, artists may be concentrated within industries centered on a small number of countries, and this may be of interest to researchers. All supplementary materials are available on our online OSF repository [7], and we hope that this can be a resource for the music science community in researching the dynamics of cultural products and cross-cultural influence.

[7] https://osf.io/uyh6d/

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THREE RELATED CORPORA IN MIDDLE BYZANTINE MUSIC NOTATION AND A PRELIMINARY COMPARATIVE ANALYSIS

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ABSTRACT

The Middle Byzantine notation (MBn) is used to capture the plainchant melodies of eastern Orthodox Christian music from the middle of the 12th century until 1814. In the context of this research, we study the evolution of a subgenre of Byzantine music known as Heirmologic. We present three Heirmologic corpora spanning the periods before, during and after the 16th century. We discuss the challenges we faced during the digitisation process, and the steps we took to overcome them. For the analysis of the three corpora, we apply the three methods, namely notational texture, melodic arch similarity, and Jensen-Shannon distances of Markovian models, the second of which is novel and inspired by the idea of melodic arches [1, 2]. Through these methods, we aim at highlighting the differences of the corpora in order to obtain an outline of the evolution of the subgenre. We observe that the post-16th century Heirmologic pieces are more similar to the 16th century ones, while there is a greater difference with the pre-16th century pieces. This indicates that the 16th century constitutes a turning point in the melodic features of the Heirmologic subgenre.

1. INTRODUCTION

Byzantine music has a known history of 2000 years and it constitutes a part of the human world heritage [3]. Roughly, the first millennium is characterised as pre-notational period, while the second as notational period [4]. It was mainly developed in the Eastern Byzantine Empire and up to this day has been influencing the cultures of the Southeast and Eastern Europe, and parts of the Caucasus regions. It has also influenced, among others, the Western and the Slavic music [5, 6].

The Middle Byzantine notation (MBn) is used to capture the plainchant melodies of Byzantine music from the middle of the 12th century until 1814 [7]. At the moment of writing, the cataloged manuscripts of Byzantine music are numbered approximately 10,000, most of them written in MBn [8]. The absence of MBn corpora prevents the computational process of this music genre and makes impossible any cross-cultural research, what is described in [9, 10]. Previous attempts have been made to transcribe Byzantine music into staff notation, but they were rejected due to loss of the information that is rooted in the symbols' orthography [7].

We present three related corpora of MBn scores which are part of the Knowledge Representation presented in [11]. The corpora are available to MBn researchers as well as to the wider musicological community [12]. These corpora are used in a study to outline the evolution of the Heirmologic subgenre of Byzantine music that took place in the 16th century. For this reason, we present a preliminary comparative analysis of the corpora.

This paper is organised as follows. Section 2 introduces the Heirmologic subgenre that the pieces of the corpora belong to, the manuscripts that the corpora consist of, and the reason why we study them. It closes with the discussion on the challenges in the digitisation and how we dealt with them. Section 3 presents the methods we applied for the musicological analysis of the corpora. Section 4 presents the results of the analysis. This paper closes with section 5 which discusses our results.

2. THE THREE CORPORA

Byzantine music consists of three subgenres: Heirmologic, Sticheraric, and Papadic. The subgenre of a Byzantine music piece depends on the poetic form of its lyrics [1]. Generally, Byzantine music compositions of a hymn are influenced by (a) the subgenre that the hymn belongs and (b) the preceding compositions of the same hymn (different melodies using the same lyrics). Regarding point (b), Manuel Chrysaphes (15th century) in his treatise [14, pp. 44–47], states that new compositions of Hymns follow the music of the preceding compositions of these Hymns. Since music can be expressed as a series of viewpoints,

[1] Specifically, the Heirmologic music pieces (called *Heirmoi*) use lyrics that belong to the poetic form of *Kanon* [7, 13]. At a high level, a *Kanon* consists of a number of stanzas, some of which work as model melodies. These stanzas are called *Heirmoi* (singular: *Heirmos*). The remaining stanzas of *Kanon* follow the melodies of the *Heirmoi* [7]. The book that contains the Heirmoi is called Heirmologion.

we explore this observation and we model the similarity of the corpora through the distances of their respective viewpoints.

In the context of this research, we study the evolution of the Heirmologic subgenre. Using the Knowledge Representation (see section 2.5), we focus our attention on the Heirmologions of 16th century, and specifically the Karykis Heirmologion. This selection is not random. According to the existing historical research, in the 16th century a great change happened to the melodies of the Heirmologion [13, 15, 16]. In order to study the Karykis' Heirmologion and to evaluate its contribution to the tradition, we select the Heirmologions of pre-Karykis, Karykis and post-Karykis.

2.1 A representative sample of Heirmologion of pre-Karykis era

In our research we evaluate the contribution of Karykes' Heirmologion in the context of tradition. As a representative example of the previous tradition, the Heirmologion of manuscript 1101 from the Iveron (mount Athos) library was chosen. This Heirmologion was written somewhere between 1535-1540 by the monk Pachomius Rousanos [17].

There are several reasons for choosing Rousanos' Heirmologion as a representative of the pre-Karykis era: (a) the Rousanos' Heirmologion follows the prevailing tradition of the subgenre, (b) it is dated close to Karykis' era, (c) Rousanos was a well-known lettered monk, who had a good knowledge of both notation and theory, so his manuscripts are considered reliable sources.

2.2 A representative sample of Karykis' Heirmologion

So far, no autograph of Karykis' Heirmologion has been identified. From various copies of the Karykis' Heirmologion, the Iveron 1167 was chosen for these analyses. This manuscript dates to the early 17th century.

2.3 A representative sample of Heirmologion of post-Karykis era

As a representative example of the post-Karykis tradition, we take the Balasis' Heirmologion of Sinai 1433 (Jerusalem). This Heirmologion was written in 1690 by Kosma the Macedonian [18]. In the period between the Balasis' and Karykis' Heirmologions, appeared also some other Heirmologion anthologies. However, based on the number of copies, Balasis' Heirmologion was especially popular among the post-Karykis' Heirmologions. Therefore, the next main tradition of the Heirmologion subgenre is considered to be that of Balasis. Regarding the choice of the copy, Kosmas the Macedonian was a peer of Balasis in music studies and his manuscripts are considered to be a reliable source [19].

2.4 Corpora

Having defined the previous and the next tradition of the Karykis' Heirmologion, it becomes possible to create three corpora that represent these traditions. Specifically, 128 Heirmoi were received from each Heirmologion. The sample is evenly distributed in terms of Echoi (modes): 16 Heirmoi per Echos. The same Heirmoi were taken from each corpus, i.e., the same text (lyrics) composed by different composers. This sample is approximately 25% of the number of Heirmoi contained in each Heirmologion.

2.5 Knowledge Representation

The Knowledge Representation we use is a tree structure capturing the viewpoints [20, 21] of the music piece. In our case, these viewpoints are the *syllable*, *interval*, *pitch*, and *voiced sign*. The *syllable* is the viewpoint that captures in a sequential form the syllables of the lyrics. The *interval* and *pitch* viewpoints capture the information that provides us with the Metrophonia [2] of the piece (i.e., basic melodic line without duration information). The *voiced sign* viewpoint captures the aspect of the notation that provides us with the Metrophonia. Naturally the tree captures the relations of the viewpoints and their sequence in the music piece. Exploiting the structure of the tree, the researcher can then perform a computational analysis of the properties of the music piece. Moreover, the researcher can post-process the tree to highlight specific properties of the music piece by reorganising the connections of the viewpoints. For more information see [11].

2.6 Digitisation challenges

During the process of digitisation of the music pieces, we were faced with a number of challenges. Firstly, notational errors in the manuscripts due to the scribe is a common issue. Such errors are identified through the Metrophonia of the notation and are corrected by comparing these excerpts containing the error with similar excerpts from other manuscripts. For the pre-Karykis Heirmologion (manuscript Iveron 1101), the following manuscripts were used for the corrections: Grottaferrata EgII [22], Sinai 1256 [23] and Iveron 1185 [24]; for Karykis Heirmologion (manuscript Iveron 1167) manuscripts Iveron 1154, Iveron 1155 and Iveron 1231 were used [24]; and for post-Karykis Heirmologion (manuscript Sinai 1433) manuscripts NLG 946, NLG 936 and NLG 967 were used [25]. All the imposed corrections are documented within the corpus (GitHub link).

Secondly, the signs of MBn are grouped into two main categories: Voiced signs and Voiceless signs. One of the uses of the latter is to group the former. Many times it does not seem clear which Voiced signs the Voiceless signs are grouping (e.g., Figure 1). This ambiguity particularly concerns the Heirmologions of Karykis' era and onwards. This problem does not have a unique solution and individual rules may apply. A general principle that we followed in our corpora was that Voiceless signs group all the Voiced signs in a syllable. Also, sometimes we juxtaposed the am-

[2] Although the interpretation of this notation remains an open question, the basic melodic line as evidenced by the signs (called Metrophonia) is unquestionable.