2021年ICM问题 D: 音乐的影响

音乐自古以来就是人类社会的一部分,是文化遗产的重要组成部分。为了理解音乐在人类 集体经验中所扮演的角色,我们被要求开发一种量化音乐进化的方法。当艺术家创作一首 新的音乐作品时,有许多因素会影响他们,包括他们与生俱来的独创性、当前的社会或政 治事件、获得新的乐器或工具的机会,或其他个人经历。我们的目标是了解和衡量以前制 作的音乐对新音乐和音乐艺术家的影响。

一些艺术家可以列出十几个或更多的其他艺术家谁,他们说影响了自己的音乐作品。也有人认为,影响可以衡量的程度之间的相似性歌曲的特点,如结构,节奏,或歌词。音乐有时会发生革命性的变化,提供新的声音或节奏,例如当一种新的音乐流派出现时,或者对现有的音乐流派(如古典音乐、流行音乐/摇滚音乐、爵士乐等)进行重新改造时。这可能是由于一系列小的变化,艺术家的合作努力,一系列有影响力的艺术家,或者社会内部的转变。

许多歌曲都有相似的声音,许多艺术家为音乐流派的重大转变做出了贡献。有时这些变化是由于一个艺术家影响另一个艺术家。有时,这是一种对外部事件(如世界重大事件或技术进步)作出反应的变化。通过考虑歌曲网络及其音乐特征,我们可以开始捕捉音乐艺术家之间的相互影响。或许,我们还可以更好地理解音乐是如何随着时间的推移在社会中演变的。

您的团队已被综合集体音乐协会(ICM)认定为

衡量音乐影响的模型。这个问题要求你研究艺术家和流派的进化和革命趋势。为此,ICM 向您的团队提供了多个数据集:

- 1) "影响力数据"代表了音乐影响者和追随者,正如艺术家自己所报道的,以及行业专家的意见。这些数据包含了过去90年中5854位艺术家的影响者和追随者。[1]
- 2) "完整音乐数据"提供 16 个可变条目,包括音乐特性,如舞蹈性、节奏、响度和键,以及 98340 首歌曲的艺术家名称和艺术家 id。这些数据用于创建两个摘要数据集,包括: [2]
 - a、 艺术家平均值"艺术家数据",
 - b、 是指跨年度"数据按年度"。

注: 这些文件中提供的数据是较大数据集的子集。这些文件仅包含解决此问题所需的数据。

为了开展这一富有挑战性的项目,ICM 协会要求您的团队通过对音乐艺术家的影响来探索音乐的演变,具体做法如下:

•使用影响数据集或其部分创建一个(多个)音乐影响定向网络,其中影响者与追随者相连。在这个网络中开发捕捉"音乐影响"的参数。通过创建你的定向影响者网络的子网络来探索音乐影响的子集。描述这个子网络。你的"音乐影响力"指标在这个子网络中揭示了什么?

- •使用完整的音乐数据和/或音乐特征的两个汇总数据集(包括艺术家和年份),以制 定音乐相似性的衡量标准。用你的标准衡量,流派内的艺术家比流派间的艺术家 更相似吗?
- •比较流派之间和流派内部的相似性和影响。一种体裁的区别是什么?体裁是如何随着时间的推移而变化的?某些体裁与其他体裁相关吗?
- •指出数据集中报告的相似性数据是否影响数据集,表明确定的影响者实际上影响了各自的艺术家。"影响者"真的会影响追随者创作的音乐吗?是一些音乐特征比其他特征更具"感染力",还是它们在影响某个艺术家的音乐方面都有相似的作用?
- •从这些数据中确定是否有可能意味着音乐进化中的革命(重大飞跃)的特征?在你的人际网络中,哪些艺术家代表革命者(重大变革的影响者)?
- •分析一个流派中随时间变化的音乐演变的影响过程。你的团队能否识别出能够揭示动态影响者的指标,并解释流派或艺术家是如何随着时间的推移而变化的?
- •你的作品如何表达音乐在时间或环境中的文化影响?或者,如何在网络中识别社会、政治或技术变化(如互联网)的影响?

给 ICM 协会写一份单页的文档,说明通过网络了解音乐影响的价值。考虑到这两个问题数据集仅限于某些流派,以及随后两个数据集共用的艺术家,您的工作或解决方案将如何随着更多或更丰富的数据而改变?建议进一步研究音乐及其对文化的影响。

来自音乐、历史、社会科学、技术和数学等领域的跨学科、多元化团体 ICM 协会期待着您的最终报告。

总页数不超过 25 页的 PDF 解决方案应包括:

- •一页总结表。
- •目录。
- •您的完整解决方案。
- 向 ICM 协会提交一页文件。
- •参考文献列表。

注: 2021 年新增! ICM 竞赛现在有 25 页的限制。提交内容的所有方面均计入 25 页的限制: 摘要表、目录、解决方案主体、图像和表格、一页文档、参考列表和任何附录。

附件

我们为此问题提供以下四个数据文件。提供的数据文件仅包含用于解决此问题的数据。

1. 影响 data.csvfull\ u music\ u 数据.csvdata\u 作者 艺术家.csvdata.csv 文件 2. 3. 4.

数据描述

1. 影响 数据.csv

(数据以 utf-8 编码,以便处理特殊字符):

- **影响者 id**:给被列为影响者的人的唯一标识号。(数字串)
- **影响者姓名:** 追随者或行业专家给出的有影响力艺术家的名字。(字符串)
- **影响者\主要\流派:** 最能描述有影响力的艺术家创作的大部分音乐的流派。(如果可用)(字符串)
- **影响者\活动\启动**:这位有影响力的艺术家开始他们音乐生涯的十年。(整数)
- **跟随者 id:** 一个唯一的识别号,给予被列为追随者的艺术家。(数字串)
- **跟随者姓名**: 跟随有影响力艺术家的艺术家的姓名。(字符串)
- **主要流派**:最能描述下列艺术家创作的大部分音乐的流派。(如果可用)(字符串)
- **从动静启动**:以下艺术家开始他们音乐生涯的十年。(整数)

2. 全音 数据.csv 三。数据来源 艺术家.csv4 数据来源 年份.csv

Spotify"完整音乐数据"、"艺术家数据"、"年份数据"中的音频功能:

- 艺术家姓名:演唱曲目的艺术家。(数组)
- **艺术家 id**: 影响中给出的相同唯一标识号 数据.csv 文件。(数字串)

音乐特点:

- **舞蹈性**:根据音乐元素的组合(包括节奏、节奏稳定性、拍子强度和整体规律性)来 衡量一个曲目适合跳舞的程度。值 0.0 是最不可跳舞的,值 1.0 是最可跳舞的。(浮 动)
- **能量**:表示对强度和活动的感知的量度。值 0.0 表示强度/能量最小,值 1.0 表示强度/能量最大。通常,充满活力的音轨感觉很快,很响,很吵。例如,死亡金属具有很高的能量,而巴赫前奏曲在音阶上得分较低。感知特征包括动态范围、感知响度、音色、发生率和总熵。(浮动)
- **原子价**:描述音轨所传达的音乐积极性的量度。值 0.0 是最负的,值 1.0 是最正的。 高价音轨听起来更积极(例如。
 - 快乐的,欢快的,愉悦的),而带有低价的音轨听起来更消极(例如悲伤的,沮丧的,愤怒的)。(浮动)
- **速度**:以每分钟拍数(BPM)为单位的曲目的总估计速度。在音乐术语中,节奏是给定乐曲的速度或节奏,直接来自平均节拍持续时间。(浮动)
- **响度**: 音轨的总响度,单位为分贝(dB)。值的典型范围为-60到0db。响度值是整个音轨的平均值,用于比较音轨的相对响度。响度是声音的质量,是身体力量(振幅)的主要心理关联。(浮动)
- **模式**音阶:一个音轨的情态(大调或小调)的表示,音阶的音阶类型,它的旋律内容是从音阶派生出来的。主要由1表示,次要由0表示。

- **钥匙**:轨道的估计总关键点。整数使用标准的音高类表示法映射到音高。E、g.0=C, $1=C\sharp/D$, 2=D,依此类推。如果未检测到密钥,则密钥的值为-1。(整数)

人声类型:

- **声学**: 轨道是否声学的置信度(无技术增强或电放大)。如果值为 1.0,则表示音轨 具有很高的可信度。(浮动)
- 工具性: 预测曲目是否不包含人声。"哦"和"啊"的声音在这种情况下被视为乐器。说唱或口语曲目显然是"有声的"。"工具性"(instrumentalness)值越接近 1.0,轨迹不包含声音内容的可能性就越大。大于 0.5 的值表示仪器轨迹,但当值接近 1.0 时,置信度更高。(浮动)
- **活泼**: 检测曲目中是否有观众。较高的活跃度值表示实时执行轨迹的概率增加。如果值高于 0.8,则轨迹很有可能处于活动状态。(浮动)
- **言语:** 检测音轨中是否存在口语。像录音(例如脱口秀、有声读物、诗歌)这样的讲话越专一,属性值就越接近 1.0。大于 0.66 的值描述了可能完全由口语组成的音轨。介于 0.33 和 0.66 之间的值表示可能包含音乐和语音的曲目,可以是分段的,也可以是分层的,包括说唱音乐等情况。低于 0.33 的值很可能表示音乐和其他非语音类曲目。(浮动)
- **明确的**:检测曲目中的显式歌词(真(1)=是,它有;假(0)=否,它没有或未知)。 (布尔值)

说明:

- 持续时间\u ms: 磁道的持续时间(毫秒)。(整数)
- 人气:这首歌的流行程度。该值将介于 0 和 100 之间,其中 100 最受欢迎。流行度是通过算法计算出来的,在很大程度上是基于这首歌的总播放次数和最近播放的次数。一般来说,现在播放频率更高的歌曲会比过去播放频率更高的歌曲更受欢迎。重复曲目(例如,单曲和专辑中的同一曲目)是独立评分的。艺术家和专辑的受欢迎程度是从歌曲受欢迎程度数学推导出来的。(整数)
- **年**: 轨道发布的年份。(从1921年到2020年的整数)
- **发布日期**: 轨道发布的日历日期,主要采用 yyyy-mm-dd 格式,但日期的精度可能会有所不同,有些仅给出 yyyy。
- **歌名(删)**:磁道的名称。(字符串)软件被运行以删除歌曲标题中任何潜在的显式单词。
- **计数**: 特定艺术家在完整音乐中所代表的歌曲数 数据.csv 文件。(整数)

叫这些数据是从 AllMusic.com

²¹这些数据来自 Spotify 的 API

2021 ICM

Problem D: The Influence of Music

Music has been part of human societies since the beginning of time as an essential component of cultural heritage. As part of an effort to understand the role music has played in the collective human experience, we have been asked to develop a method to quantify musical evolution. There are many factors that can influence artists when they create a new piece of music, including their innate ingenuity, current social or political events, access to new instruments or tools, or other personal experiences. Our goal is to understand and measure the influence of previously produced music on new music and musical artists.

Some artists can list a dozen or more other artists who they say influenced their own musical work. It has also been suggested that influence can be measured by the degree of similarity between song characteristics, such as structure, rhythm, or lyrics. There are sometimes revolutionary shifts in music, offering new sounds or tempos, such as when a new genre emerges, or there is a reinvention of an existing genre (e.g. classical, pop/rock, jazz, etc.). This can be due to a sequence of small changes, a cooperative effort of artists, a series of influential artists, or a shift within society.

Many songs have similar sounds, and many artists have contributed to major shifts in a musical genre. Sometimes these shifts are due to one artist influencing another. Sometimes it is a change that emerges in response to external events (such as major world events or technological advances). By considering networks of songs and their musical characteristics, we can begin to capture the influence that musical artists have on each other. And, perhaps, we can also gain a better understanding of how music evolves through societies over time.

Your team has been identified by the **Integrative Collective Music (ICM) Society** to develop a model that measures musical influence. This problem asks you to examine evolutionary and revolutionary trends of artists and genres. To do this, your team has been given several data sets by the ICM:

- 1) "influence_data" ¹ represents musical influencers and followers, as reported by the artists themselves, as well as the opinions of industry experts. These data contains influencers and followers for 5,854 artists in the last 90 years.
- 2) "full_music_data" provides 16 variable entries, including musical features such as danceability, tempo, loudness, and key, along with artist_name and artist_id for each of 98,340 songs. These data are used to create two summary data sets, including:
 - a. mean values by artist "data_by_artist",
 - b. means across years "data by year".

¹ These data were scraped from AllMusic.com

² These data were obtained from Spotify's API

Note: DATA provided in these files are a subset of larger data sets. These files **CONTAIN THE ONLY DATA YOU SHOULD USE FOR THIS PROBLEM**.

To carry out this challenging project, the ICM Society asks your teams to explore the evolution of music through the influence across musical artists over time, by doing the following:

- Use the *influence_data* data set or portions of it to create a (multiple) directed network(s) of musical influence, where influencers are connected to followers. Develop parameters that capture '*music influence*' in this network. Explore a subset of musical influence by creating a subnetwork of your directed influencer network. Describe this subnetwork. What do your 'music influence' measures reveal in this subnetwork?
- Use *full_music_data* and/or the two summary data sets (with artists and years) of music characteristics, to develop measures of music similarity. Using your measure, are artists within genre more similar than artists between genres?
- Compare similarities and influences between and within genres. What distinguishes a genre and how do genres change over time? Are some genres related to others?
- Indicate whether the similarity data, as reported in the *data_influence* data set, suggest that the identified influencers in fact influence the respective artists. Do the 'influencers' actually affect the music created by the followers? Are some music characteristics more 'contagious' than others, or do they all have similar roles in influencing a particular artist's music?
- Identify if there are characteristics that might signify revolutions (major leaps) in musical evolution from these data? What artists represent revolutionaries (influencers of major change) in your network?
- Analyze the influence processes of musical evolution that occurred over time in one genre. Can your team identify indicators that reveal the dynamic influencers, and explain how the genre(s) or artist(s) changed over time?
- How does your work express information about cultural influence of music in time or circumstances? Alternatively, how can the effects of social, political or technological changes (such as the internet) be identified within the network?

Write a **one-page document** to the ICM Society about the value of using your approach to understanding the influence of music through networks. Considering the two problem data sets were limited to only some genres, and subsequently to those artists common to both data sets, how would your work or solutions change with more or richer data? Recommend further study of music and its effect on culture.

The ICM Society, an interdisciplinary and diverse group from the fields of music, history, social science, technology, and mathematics, looks forward to your final report.

Your PDF solution of no more than 25 total pages should include:

- One-page Summary Sheet.
- Table of Contents.
- Your complete solution.
- One-page document to ICM society.
- References list.

Note: New for 2021! The ICM Contest now has a 25-page limit. All aspects of your submission count toward the 25-page limit: Summary Sheet, Table of Contents, Main Body of Solution, Images and Tables, One-page Document, Reference List, and any Appendices.

Attachments

We provide the following four data files for this problem. THE DATA FILES PROVIDED CONTAIN THE ONLY DATA YOU SHOULD USE FOR THIS PROBLEM.

- 1. influence data.csv
- 2. full music data.csv
- 3. data by artist.csv
- 4. data by year.csv

Data Descriptions

1. influence data.csv

(Data is encoded in utf-8 to allow for handling of special characters):

- **influencer_id**: A unique identification number given to the person listed as influencer. (string of digits)
- **influencer_name**: The name of the influencing artist as given by the follower or industry experts. (string)
- **influencer_main_genre**: The genre that best describes the bulk of the music produced by the influencing artist. (if available) (string)
- **influencer_active_start**: The decade that the influencing artist began their music career. (integer)
- **follower_id**: A unique identification number given to the artist listed as follower. (string of digits)
- **follower name**: The name of the artist following an influencing artist. (string)
- **follower_main_genre**: The genre that best describes the bulk of the music produced by the following artist. (if available) (string)
- **follower_active_start**: The decade that the following artist began their music career. (integer)

Spotify audio features from the "full_music_data", "data_by_artist", "data_by_year":

- **artist_name**: The artist who performed the track. (array)
- **artist_id**: The same unique identification number given in the influence_data.csv file. (string of digits)

Characteristics of the music:

- **danceability**: A measure of how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity. A value of 0.0 is least danceable and 1.0 is most danceable. (float)
- **energy**: A measure representing a perception of intensity and activity. A value of 0.0 is least intense/energetic and 1.0 is most intense/energetic. Typically, energetic tracks feel fast, loud, and noisy. For example, death metal has high energy, while a Bach prelude scores low on the scale. Perceptual features contributing to this attribute include dynamic range, perceived loudness, timbre, onset rate, and general entropy. (float)
- **valence**: A measure describing the musical positiveness conveyed by a track. A value of 0.0 is most negative and 1.0 is most positive. Tracks with high valence sound more positive (e.g. happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g. sad, depressed, angry). (float)
- **tempo**: The overall estimated tempo of a track in beats per minute (BPM). In musical terminology, tempo is the speed or pace of a given piece and derives directly from the average beat duration. (float)
- **loudness**: The overall loudness of a track in decibels (dB). Values typical range between -60 and 0 db. Loudness values are averaged across the entire track and are useful for comparing relative loudness of tracks. Loudness is the quality of a sound that is the primary psychological correlate of physical strength (amplitude). (float)
- **mode**: An indication of modality (major or minor), the type of scale from which its melodic content is derived, of a track. Major is represented by 1 and minor is 0.
- **key**: The estimated overall key of the track. Integers map to pitches using standard Pitch Class notation. E.g. 0 = C, 1 = C♯/D♭, 2 = D, and so on. If no key was detected, the value for key is -1. (integer)

Type of vocals:

- **acousticness**: A confidence measure of whether the track is acoustic (without technology enhancements or electrical amplification). A value of 1.0 represents high confidence the track is acoustic. (float)
- **instrumentalness**: Predicts whether a track contains no vocals. "Ooh" and "aah" sounds are treated as instrumental in this context. Rap or spoken word tracks are clearly "vocal". The closer the instrumentalness value is to 1.0, the greater likelihood the track contains no vocal content. Values above 0.5 are intended to represent instrumental tracks, but confidence is higher as the value approaches 1.0. (float)
- **liveness**: Detects the presence of an audience in a track. Higher liveness values represent an increased probability that the track was performed live. A value above 0.8 provides strong likelihood that the track is live. (float)

- **speechiness**: Detects the presence of spoken words in a track. The more exclusively speech-like the recording (e.g. talk show, audio book, poetry), the closer to 1.0 the attribute value. Values above 0.66 describe tracks that are probably made entirely of spoken words. Values between 0.33 and 0.66 describe tracks that may contain both music and speech, either in sections or layered, including such cases as rap music. Values below 0.33 most likely represent music and other non-speech-like tracks. (float)
- **explicit**: Detects explicit lyrics in a track (true (1) = yes it does; false (0) = no it does not OR unknown). (Boolean)

Description:

- **duration ms**: The duration of the track in milliseconds. (integer)
- **popularity**: The popularity of the track. The value will be between 0 and 100, with 100 being the most popular. The popularity is calculated by algorithm and is based, in the most part, on the total number of plays the track has had and how recent those plays are. Generally speaking, songs that are being played more frequently now will have a higher popularity than songs that were played more frequently in the past. Duplicate tracks (e.g. the same track from a single and an album) are rated independently. Artist and album popularity are derived mathematically from track popularity. (integer)
- year: The year of release of a track. (integer from 1921 to 2020)
- **release_date**: The calendar date of release of a track mostly in yyyy-mm-dd format, however precision of date may vary and some just given as yyyy.
- **song_title (censored)**: The name of the track. (string) Software was run to remove any potential explicit words in the song title.
- **count**: The number of songs a particular artist is represented in the full_music_data.csv file. (integer)