Music Recommendation Software's Impact on New Artists

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Max McCullough

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

Advisor

Pedro A. P. Francisco, Department of Engineering and Society

I. Introduction

Today, music is something that nearly everyone can have unrestricted access to enjoy and listen to. But it is easy to forget just how long-ago music was something that could only be enjoyed on special occasions. What caused this shift was the introduction of mobile listening devices and eventually the focus of this paper, music streaming services. Since their inception, these streaming services have had music recommendation systems built into them. Because music has become such an integral part of many people's everyday lives, they often do not think about how their music is being provided and what is affecting the choices they make about listening. This is important because the music we listen to has effects on the people that produce that music, as listening to a specific artist could provide a source of income for someone who has risked everything to find a career in making music. In this paper I would like to ask the question: How has the introduction of music recommendation software affected new artists' ability to gain popularity?

My reasoning for covering into this topic comes from the fact that although the services available today for listening to music work quite well, I want to investigate the details of how this type of software works and more importantly how they are affecting new artists in today's musical landscape. This means the function of these systems will be reviewed to make sure that there are not any sources of bias or inequality they are causing that are not known to the music world. This is particularly important because in recent years over two-thirds of music is streamed on the top three streaming platforms, so if one of these platforms is exhibiting bias in some form it will have a huge impact on the types of music that people listen to (MIDiA, 2021). To get a full understanding of my answer to this question I will break this into multiple parts. First, I will go over a brief history of music recommendation software and how it came about. Particularly focusing on how they started off and how they have evolved since then. Then, I will proceed into my research methods and talk about the framework that I will use to defend my claim. Finally in the main body of this paper I will go over the state of music distribution before and after the introduction of music recommendation systems as we know them today. This will also include a section on what exactly the listening data shows over time and what the future of this technology has the potential to fix.

II. Background and Significance

Music has been around for thousands of years; it may even be a part of what differentiates humans from animals. Throughout the history of music, the way that people listened to music can be combined into three distinct eras, the first of which I will not be focusing on in this paper. This is the time when people were only able to listen to music being played in a live setting or from memory. After that, is the short-lived period in the middle where music was recorded and stored on storage devices where it could be played on a speaker. Finally, in the modern era, where in 1999 the music industry was changed forever, by the introduction of the first online music streaming service called Napster (Dowling, 2019). This meant that for a small fee every month or initially even free, people could listen to all the music available on Napster whenever they wanted. Although this was the first music streaming service, it already had the next big innovation in music listening technology embedded in it: music recommendation software. This is because even at the time where there were very few other competitors in this space, adding a music recommendation feature to this streaming service was an obvious choice as it wasn't too technically challenging.

Music recommendation software is a kind of software based on the broader category of recommendation software that can provide listeners with music recommendations tailored specifically to them based on similar artists. This may seem like a difficult thing to do especially when trying to do it on the first-ever music streaming platform. But recommendation software was not completely new for the time as it was invented in 1979 by Elain Rich (Dowling, 2019). All Napster and the following platforms had to do was make the technique work with their unique streaming platform. The specific recommendation technique that is used today is called collaborative filtering. “In collaborative filtering recommender systems user’s preferences are expressed as ratings for items, and each additional rating extends the knowledge of the system and affects the system’s recommendation accuracy” (Elahi, Ricci, & Rubens, 2016).

Now, with a base level understanding of the technology being addressed in this paper I would like to discuss the main human actors involved in this paper, the new artists. In the past, the music industry has been dominated by large music production companies that had connections with radio companies. The larger artists worked with companies to produce physical copies of their music and play on national radio. All of this meant that the barrier to entry was very high at the time. The introduction of online streaming lowered that barrier quite a bit. The issue with that is that even if new music is publicly available on streaming platforms, it must get recommended to become popular. By looking at how music recommendation software has affected new artists I can identify if these systems are creating a flatter landscape of income for musicians so more people can pursue their dream of becoming full-time musicians.

III. Methodology

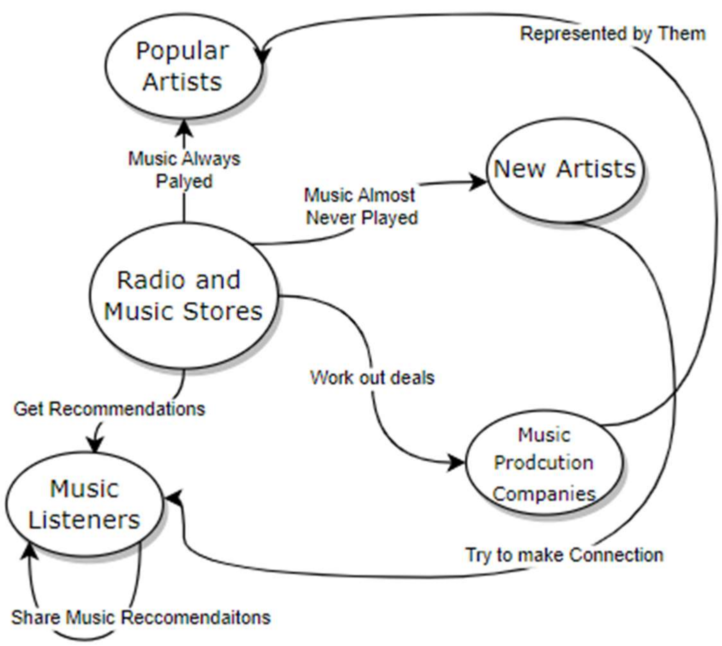
To address the effect that music recommendation software has had on new artists' ability to gain traction in the music industry I will focus on the change over time from before and after the introduction of this type of software. The best tool that I have for breaking down this problem is Actor-Network Theory. Actor-Network theory is known for its ability to apply to sociotechnical issues that experienced a change over time. In my case, there is a critical point, the introduction, that I can use to compare. In my research I have created two actor networks that represent before and after the introduction of these systems and compare their differences to expose the reasons new artists are being affected by music recommendation systems. A potential counterargument to using this approach could be that the method may provide too much of a binary observation of what happened because the truth is that this technology was not 100% adopted overnight. And it still is not completely adopted today (Backus, 2021). There was a distinct introduction of a new non-human actor, the recommendation systems, that I am focusing on. I believe that this is the best way to simplify this problem to extract what was directly caused by music recommendation systems and not just music streaming services. Additionally, In the following pages, I will show a visual representation of the Actor-Networks to provide a better understanding of how the music industry was affected. This is something that Bruno Latour, one of Actor-Network theory's most well-respected champions, advocated for in his work "Where are the Missing Masses?" (Latour, 1992). Although my diagrams will be relatively simple compared to the complexity of the music industries they will touch on the most important actors and give you a better representation of the ideas that I hope to convey in the following pages.

IV. Results and Discussion

In this section, I will discuss the state of the Actor-Network before the introduction of music recommendation systems to give you a baseline for what has changed for new artists. To construct this Actor Network, much of the information for the state of the music industry came from Paul Lopes' "Innovation and Diversity in the Popular Music Industry from 1969 to 1990" (Lopes, 1992).

Figure 1

Actor-Network Pre-Music Recommendation Software



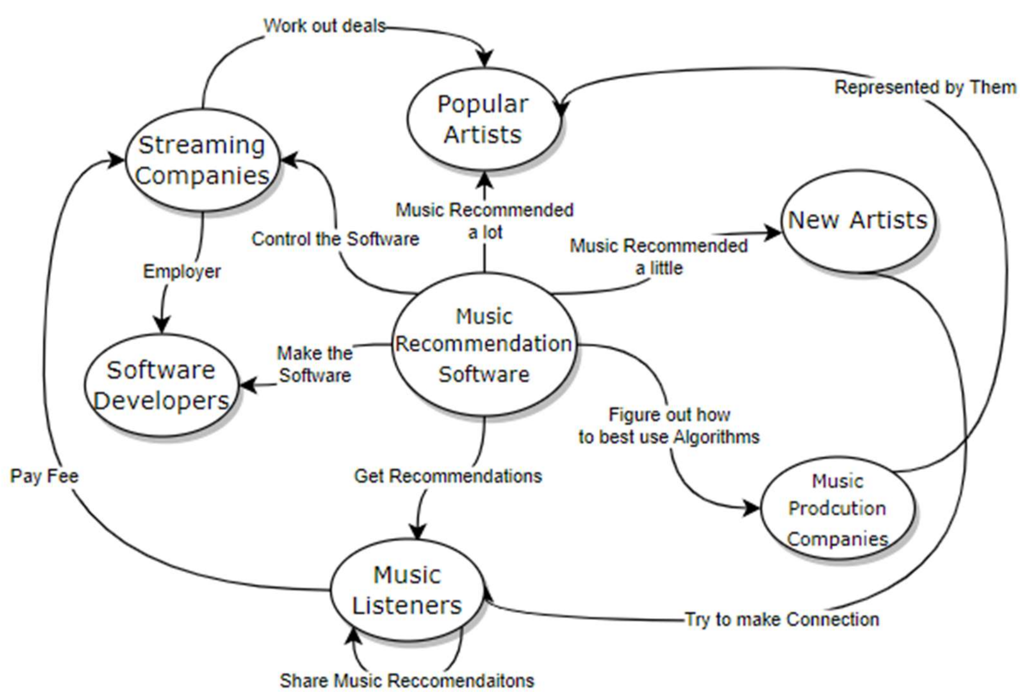
The first point of interest is the relationship between radio stations, music listeners, and record companies forced more people to listen to the mass most popular music of the time without any real alternatives. The reason why people were influenced into listening to more popular music from the big production companies was that most people's main source of new music was the radio. Even if the people of the time wanted to try to reach out and buy a record, they were relatively limited in how much they could try listening to it before paying the considerably high price to buy a whole vinyl or CD. This was particularly true in the 1960s and 1970s when record companies had a stronger hold on their contracts with major musicians. In the 1980s and 1990s production companies focused less on promoting a smaller number of major artists and transitioning to a looser approach where they would seek out new talent and promote it (Verboord & Brandellero, 2018). The effects that radio had on the listener were still quite strong and limited their options for the exploration of new music. It is this very relationship that caused such a massive need for some new technology to come in to solve the problem of the average music listener. Many music stores and small artists tried to come up with ways to fill this missing gap, but it seems like the main issue was the technology to solve this problem was just not available at the time.

The next conclusion that I drew from this Actor-Network and my research is that before music recommendation software the music industry was significantly less dynamic. It was true from everything from the ability for music production companies to switch which artists they were producing to how fast an artist could release their music. For example, today, it is much more common for artists to release singles. There have even been examples where very popular artists will release a new song just because they had a specific connection with a current event, and they feel that a song needs to be released right now. That is not something that would have been possible before music recommendation systems. The reason for this was simply a matter of the technology that music production companies were working with at the time. Recording equipment has also become less expensive to purchase (Recording Connection, 2022). Releasing a single was not something that made a lot of sense unless it was only on the radio because they had to make physical copies to get it out to the public. Additionally, if a record company wanted to start working with new artists it would take much longer for them to record music, produce physical copies, and get them distributed to a significant number of people. The main counterargument to this point is that radio stations did provide a significant boost in speed of distribution compared to physical copies but the issue of finding newer smaller artists remained. In conclusion, the music industry before the introduction of music recommendation software left a big hole to be filled by the right innovative technology. In the next section, I will discuss the changes to the Actor-Network and what those mean for new musicians.

The goal of this section is to analyze the main changes to the Actor-Network that happened when music recommendation systems were first introduced at the end of the 1990s. This Second Actor-Network below will serve as a visual guide in this section.

Figure 2

Actor-Network Post-Music Recommendation Software



Looking at this new Actor-Network the most obvious new feature is that the center has changed from radio and music stores to music recommendation software. The barrier of entry that music stores and radio stations present is now almost completely gone. One obvious concern about the new Actor Network is the lack of radio and music stores in this model. The reason for this is that the focus of this paper is on smaller people, and they don’t typically interact with those two actors.

One limitation of the visual representation of the Actor-Network is that you cannot see the quantities of each of the actors. This does play a big role in how they interact with each other so I will spend this section pointing out what is missing from that discrepancy. One issue with the current state of recommendation systems is that they are mostly controlled by a select few companies. As stated at the beginning of this paper there are only three main companies that control two-thirds of the music that people stream (MIDiA, 2021). These companies include Spotify, Apple Music, and Amazon Music in descending order of popularity. The reason for such dominance in who controls who has the music is the number of musicians that they can get on their platforms. If people are going to sign up for a music streaming service, they want to get the best service with the greatest number of different artists. This has led to the top couple of companies having massive control over that. Even though the top three music streaming companies control most of that market. Spotify has the largest share by quite a bit. This is a double-edged sword for new artists in the music industry. It means that they only must upload their new music to a select few streaming platforms to make their music available to the public. Still, there will not be very much diversity in how the songs are recommended. So, all the pressure for how these systems recommend music is on Spotify, Apple Music, and Amazon Music.

One of the most difficult portions of conducting research on this topic is gathering consistent data that covers the complete period that I am researching in this paper. But it is extremely important information to gather because it is the key to my main positive claim that I have about the introduction of music recommendation software. That is that in general music recommendation software has indeed been able to increase the diversity of music that the average music listener consumes. A metric that I will use to defend this claim is that the amount of hits that come from artists from foreign countries has increased significantly since the year 2000 (Verboord & Brandellero, 2018). What this means is that artists that were not traditionally listened to by demographics such as the United States have seen an increase in listening to music from outside their culture. These artists are new artists to those markets. This rise begun right around the year 2000 when the world of online music recommendations began. One could argue that this trend could have been caused by other factors such as the general increase in globalization in the last ten years. I would argue that even though that is true and likely is part of the reason for this trend in music listening preferences the root cause of the increase in globalization of music is due to music recommendation software.

In the previous sections, I have broken down the problem of how music recommendation has affected new artists in the music industry. As this technology has grown it has spread to have had a positive impact on the music that people listen to, giving people more options that are tailer to their preferences. Even with all the good things that this piece of technology has provided to its users there is still an area that music recommendation software still struggles with to this day. At this point in time, a song must have been listened to by a significant sample size for the modern-day music recommendation systems to have enough data to start recommending them.

If it does not meet this threshold, then it has no chance to make it to people's ears unless they go out and look for it. The solution to this problem is more difficult to solve than one might think because it involves that analyzation of the actual music itself. Machine learning algorithms that take advantage of digital signal processing techniques to find the similarity between different pieces of music so they can be recommended. Digital Signal processing, or DSP, is a type of technology involving the use of computers to break down the electronic signals used in music or other types of information to recognize patterns or disturbances (Schedl, 2019). This can be applied to any type of digital signal but in this case, it can be used to great success with digital audio files. Modern Research in this field has come a long way since the introduction of collaborative filtering. The main advantage of this technique is that music can be recommended to listeners without ever having been heard.

This technology may sound like it is the perfect solution to solve the current problems with music recommendation software. Unfortunately, we must return to one of the most important problems with music recommendation software and that is eliminating bias. The current form of machine learning still has a ways to go before doing this. The data that they are trained on can have problems that could go onto create issues for the recommendations that they provide (Nikki & Craig, 2020). Machine learning is one of the most heavily researched technologies of the current day so I suspect that it won't be too long before we will see these biases get reduced over time. That is why I think that it is a good idea to continue researching using machine learning along with digital signal processing to provide music recommendations because it may be the best bet of have a perfect music recommendation system that is without bias and can recommend songs without anyone having heard them before.

V. Conclusion

So, how has the introduction of music recommendation software affected new artists' ability to gain popularity? Music recommendation systems have created huge improvements for new artists trying to make it in the music industry. They have made it possible for their music to have a chance to break out even if the artist doesn't have a lot of money or isn't backed by a large production company. The case is not all good for new artists, the industry is still largely controlled by several massive companies and thus the power for controlling this has been concentrated in a select few of these music recommendation software types. This conclusion was drawn by looking at the change in the Actor-Network over time. Additionally, I looked at the data for how the diversity of music has changed over time to also help the conclusion. In my section about the future of technology, I went over how machine learning combined with new digital signal processing techniques could unlock a new way to recommend music that would avoid the problems that the music recommendation systems of today are not capable of handling. In the future, I think that it would be great for more research to be done on the potential impact that technology may have on the music industry. Particularly regarding new forms of bias elimination that this emerging technology could provide.

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