Networking data. A network analysis of Spotify's socio-technical related artist network

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Abstract

This is a case study of Spotify's related artist network of Dutch drum and bass artist Noisia, incorporating a critical perspective of data and streaming platforms, it argues that network theory can help deal with the deluge of online data by showing artists and music business professionals how to see relationships instead of mere isolated events. The case study applies network theory and methods within a data-critical context. Three core measures are employed to determine different kinds of powerful actors (as in artists on Spotify) in a particular network. The analysis uncovers how each actor is embedded in networked structures of relationships that provide opportunities, constraints, coalitions, and workarounds. The consequence of the network being algorithm-generated is also considered, as it was found that this creates a situation that differs from regular social networks.

Keywords: Digitization, music industry, Spotify, music streaming, network analysis, sociotechnical system, network centrality

1 Introduction

Since the late 1990's, digital technologies have become increasingly prominent and these very soon had large-scale implications for the music industry.[2] In today's fast-paced permanently connected society, social media and streaming platforms have become of paramount importance for the music industry. These platforms offer previously unknown possibilities to users, audiences and music professionals alike. The endless stream of data and data's associated metrics play a major role in the industry, influencing decisions at every level including what to play, who

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[2] See for example Rose & Ganz (2011); David (2010).

to contract, where to book, who, what and when to include or exclude. It has become fundamentally important for artists to understand what is happening online and where they fit in. The digital environment is relatively new and is constantly changing, and there are still many innovations taking place that impact the user (i.e. anyone using the platform) at any time. The amount of power and control available to any user is relative, as although online platforms enable access to data through figures and visualisations, it is not clear how use of such data realistically offers *insight* indeed merely having data does not confer power and knowledge. The insights must depend on applying a meaningful context or paradigm and the following proposes one such paradigm as a way to deal with data and online platforms namely through networks.

Just as we all shape and are shaped by our environment the same can be said of non-human elements. From a network perspective everything is embedded within the structures of relationships and in network terms all the elements or *actors* play a part as something that can 'bend space around itself' (Callon & Latour 1981: 286). This means all the actors effect (and are affected by) their environment. As opposed to a traditional, reductionist 'group think' that makes the situation appear like things are falling apart, thinking in network terms shows the world as a more diversified, complex and interesting place (Rainie & Wellman 2012: 56). Thinking in network terms thus offers more opportunity to explore the complex reality than approaches that focus on the individual. In music, this can be seen in the difference between claims that an artist's success is due to talent and hard work and acknowledging that the artist reached a certain point because of a collective effort; a result made possible not just by individual characteristics, but also by the relationship with the artist's own environment and ability to access tools that influenced the outcome. Although the idea of networks is not new, the way we are networked today is, and we can use new strategies and skills to address these networked structures that influence our relationships.

The main thesis of this article is that adopting a network perspective and methods of analysis can help music industry professionals in an increasingly fragmented networked society understand the current situation of the digitized music industry including dealing with information from online platforms and guiding decisions on what they offer. This view is examined through an empirical case study: a network analysis of the Dutch drum and bass act Noisia which has been active since the early 2000s, producing electronic music and best known for their drum and bass productions. Noisia are well respected worldwide for their technical skills and consistent quality of their sound design, producing, remixing and regularly collaborating with other artists such as the Prodigy, Foreign Beggars, Katy Perry, Skrillex and Korn. They have received over a dozen awards (for Best DJ, producer, album, track and more) and over time have established three independent record labels to release their own and other artists' music, especially after the major labels dropped out of the Dance genre in the Netherlands (Hitters & Van de Kamp 2010). As DJ's, they regularly perform throughout the world and although their music is part of a smaller sub-genre of Electronic Music, they have managed to become successful in their scene.

Emerging at the time of the digital paradigm shift for the music business and with their music being digital itself, Noisia are true 'digital natives'. As such, they have maintained an active presence on many online platforms, through which they have built a loyal and still growing online following. On Facebook, they have over half a million followers, their YouTube channel has 185.000 followers, Twitter has over 150.000, and around 80.000 individuals keep track of them on Instagram and Songkick. Music streaming platform SoundCloud counts 4 million followers, Spotify 127.000, and Deezer 73.000.

They are building presence on gaming platform Discord; currently with over 2000 members. The majority of Noisia's audience resides in the US and the UK, with London, as the birthplace of drum and bass (Fraser & Ettlinger 2008: 1648), the all-time top city.[3]

[3] The data and figures from this section come from the accumulated information from Flapper Management, Spotify, Deezer and Next Big Sound profile report, June 26, 2017.

When investigating online tracking and performance data, the example of Noisia is very suitable, given they have a large online fan-base spread across the world, which makes their data reliable for this analysis. The do-it-yourself ethos that came with the digital age made musicians and management more (if not entirely) responsible for choosing their own paths (Hracs 2015: 466, Hesmondhalgh & Baker 2011: 93). In this light, their situation is representative of many artists today who are not signed to any major label, and use the new -found possibilities of working and sharing their music online and releasing it by themselves or through small indie labels.

The case study presents an analysis of Noisia's network of related artists, as this appears on the music streaming platform Spotify. This network does not fit any strict social or technological framework, as it is a social algorithm generated network. Below is an exploration of how and why network theory and methods can help gain insight in this case, and more broadly for the music industry.

2 Data and the music industry

2.1 Digitization of the music industry

At first the music industry adapted slowly to the changing digital landscape. Around 2008 the music business started to find alternative ways of legal distribution and monetisation to deal with the new ways and scale of the production, circulation, access and engagement of music (Nowak & Whelan 2016: 2). In this post-download era, the most popular 'spaces of music consumption' (Prey 2015: 3) became on-demand music streaming platforms. Digital generally now accounts for half of all recorded music revenues (US $7.8 billion in 2016), of which streaming makes up the majority (56%) with Spotify as the leading platform (IFPI 2017). After years of decreasing revenues, since 2015 the industry has seen renewed growth, undoubtedly attributed to streaming services (ibid) and for this case study it is no different as the royalties Noisia earn from online services, such as those from Spotify are more than all the other sources combined.

Online music streaming platforms cater to the changed (social) environment of today, which is personal and connected, asynchronous and constantly evolving. A major difference between services like Spotify and previous forms of music consumption and distribution is unquestionably the data feedback loop they generate in real time. The audience, made up of loyal and active music consumers who had previously been casted as thieves in the download-era, are now perceived differently, becoming users and subjects whose activities can be monitored, influenced and monetized. The subsequent possibilities of tracking have resulted in a 'datafication of listening' (Prey 2015: 9; Prey 2016: 32), meaning that social action is now transformed into quantified data, making it possible to track behaviour through metrics and allowing for predictive analysis (Dijck 2014: 198). The resulting performance and tracking data from the platforms are partially fed back to the artist, offering them their own data pool of insights on digital music performance Even so it is questionable whether 'the data speaks for itself', and this needs further analysis.

2.2 Dataism, a sceptical approach

The term 'dataism' refers to *"a widespread belief in the objective quantification and potential tracking of all kinds of human social behaviour through online media technologies"* (Dijck 2014: 198). Dataism is a phenomenon that often goes together with a belief in the straightforward 'truth' of data. The endless flow of data being a 'treasure trove' that can easily be put to use by artists and their managers (Mombert 2015; Titlow 2017) using indispensable algorithms (often through third parties) to filter the incoming data flow (Hartnett 2017). Platforms propagate their user-friendly tools and dashboards, which are intended to be simple and insightful for non-analysts (Grow, Next Big Sound).

Sceptics on the other hand take a critical stance towards technology or big data and emphasize its limitations and generative characteristics. Some scholars point out its deceptive use and fallibility (Baym 2012), others the performative effect of technology shaping what they ought to be describing (Seaver 2012). This sometimes results in expressions of fear or predictions of dark futures (as in Schneier 2015; Harari 2016). Particularly useful here is the term 'socio-technical systems', introduced by Webster et al. (2016). While they specifically refer to recommendation systems, the idea applies to a wider range of data-driven platforms built and formed by humans, the systems being a product of both human and algorithmic effort, and they become 'cultural intermediaries'.[4] For these new cultural intermediaries are "machines (that) have been delegated ethics, values and duties and these are relentlessly, due to their mechanistic qualities, and silently prescribed back to the human," and by that, they play a role in regulating the cultivation of knowledge and taste (Webster et al. 2016). Such sceptic's ideas and concepts ensure we see the systems for what are but the daily reality is these systems are omnipresent, very welcome and useful. Network theory, with its long history of theoretical development, albeit deeply grounded in empirical practice, can help fill this gap.

3 Theoretical framework: networks

3.1 The new social operating system

Since its early days, the internet has typically created a decentralized, open and sharing culture and over time it has remained a network of networks, resembling an eco-system rather than a swiss watch (Rainie & Wellman 2012, Barabasí 2002). As a connected and asynchronous system, the internet allows its users to be more networked than before while being attuned to personal preferences. Societies, like computer systems, are observed to have networked structures that provide opportunities and constraints, rules and procedures (Rainie & Wellman 2012: 12). With this in mind, the current (digitised) music landscape needs a

[4] The term 'cultural intermediaries' was originally introduced by Pierre Bourdieu (1984), to describe the persons involved in the shaping of taste (such as critics, radio programmers), but did not include technical systems.

suitable perspective for today's society, a 'new logic' as it were to fit the information age: the logic of networks.

3.2 The logic of networks

While network-scientific jargon like *hubs*, *clusters*, *social ties* and indeed the word *network* itself are embedded in everyday language the fact that networks follow quantifiable internal rules and patterns is less well known. Often, there is a reliance on reductionist concepts that simplify environments, attributes or circumstances to an autonomous affair (Barabasí 2002: 6). Network explanations do not assume that environments, attributes or circumstances affect actors independently, nor do they assume the existence of groups (Marin & Wellman 2011: 11-13). The basic concept of network theory is that nothing happens in isolation: everything is linked to everything else (Barabasí 2002: 6). In this 'architecture of complexity' the linked components (usually called *actors*, and the links *ties)* show patterns of connections that are crucial to the behaviour of a system and can indeed be investigated, by representing them in networks (ibid).

Network theory has come a long way since the first abstract mathematical model of random distribution of connections (Erdős & Rényi 1959). Over time theory and models emerged that accounted for the appearance of highly connected subgroups -or *clusters*- (Granovetter 1986, Watts & Strogatz 1998), and later actors with an anomalously large number of ties, called *hubs* or *connectors,* which tend to dominate the structure of the network in which they appear (Barabasí 2002: 64). Findings like these indicate certain actors to be more 'central' than other.

Visualising and analysing a network can uncover how an actor is embedded in structures of relationships that provide opportunities, constraints, coalitions, and workarounds, as these properties are built into their construction (Barabási 2002: 12; Newman 2010: 2).

3.3 An additional network perspective

Generally, in social network theory, social networks take *humans* as their actors: the social units that form relations with each other. But *things* too, can express power relations or reinforce social inequalities (Latour 2005: 72). Latour's influential Actor Network Theory (ANT) builds on general network theory which equates humans and nonhumans both as actors without hierarchy a priori and describes how to explore their collective action (Latour 2005). Using ANT as a theory and methodology to supplement the more general social network theory, one can use social network theory to analyse socio-technical networks such as those encountered through streaming platforms. This ensures an openness to ambiguity that is so vital for any study dealing with social matters.

4 Methods

4.1 Data collection and processing

The principle source of information is the music streaming platform Spotify. On Spotify, the user is presented with a list of artists related to the artist whose page they visit (see figure 1). Under the tab 'RELATED ARTISTS' appears a more extensive list with a maximum of 20 related artists.[5]

As explained on the Spotify Community pages and the FAQ at "Spotify For Artists", related artists are determined by algorithms that look at what people listen to alongside that artist's music as well as "music discussions and trends happening around the internet" (Spotify Community, Spotify For Artists FAQ). The section cannot be changed manually but can be affected by online interaction with the artist's music, both on and outside the platform. The precise algorithm, and how it

[5] This feature has been renamed as 'Fans Also Like', medio 2018 on the Spotify desktop and mobile apps. The algorithm behind it does not seem to have changed, as the results appear to generate more or less the same network (some change is to be expected with the algorithm using the constant flux of user data.) It may be noticed that new name puts more emphasis on the listener (the 'fan') as the driving force behind it.

selects 'related artists,' is not publicly available, but the explanations make clear that user activity mainly determines who appear to be one artist's related artists.

Spotify provides related artists for any artist through their API. The use of a crawler (Rieder 2017) revealed the related artists, and artists related to those artists at two steps from the starting point (Noisia). This provided a data set of all the artists and their ties in this range and included for each of them a Spotify-provided attribute 'popularity': a value between 0 and 100, with 100 being the most popular on the platform, and 0 the least popular. The popularity value is calculated by the relationship between the popularity of all the artist's tracks and every other artist on the platform (Spotify for Developers). This revealed an aspect about Spotify's whole artist network, that will be covered later in this article.

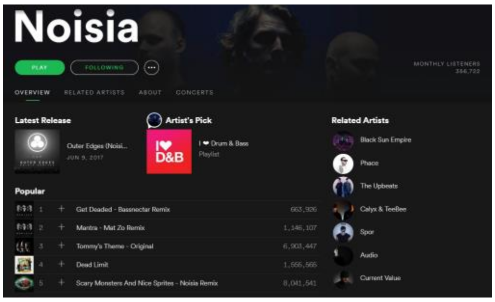

Figure 1: Screenshot of Noisia's profile on Spotify Premium on a desktop PC. Related artists presented on the right, or more extensively under the tab 'RELATED ARTISTS'.

Using this database, all the network graphs in this paper were built in Gephi, whose software renders statistics through built-in features and adds these measurements as attributes to the actors (the artists on Spotify). Three of those measurements have been used for the centrality analyses.[6]

[6] Algorithms for calculating centralities can differ; Gephi uses the ones by Brandes (2001).

4.2 Centrality measures

The network approach emphasises power and influence as inherently relational (Hanneman 2005). A prominent way to investigate these relations in a network is through the structural attribute of centrality. To determine an actor's centrality, we can refer to a handful of different concepts, of which three shall be treated: degree centrality, betweenness centrality and closeness centrality.

Degree defines the number of direct ties an actor has to other actors in the network. Actors with a high degree are highly visible, and tend to be seen as important, to have more influence, access to information or prestige (Borgatti et al. 2013: 166; Newman 2010: 169). High degree centrality means their position is advantageous in the exchange of information; more ties usually mean greater opportunities because the actor is believed to have more choices. Degree is also seen as important as an index of its potential activity (Freeman 1978: 211). Having high degree is a favoured position, because it gives the actor autonomy and makes them more independent of others (Hanneman 2005).

Closeness aims to define the most central actors in terms of the overall structure of the network. It measures the mean distance from an actor to every other actor. Gephi uses *inversed closeness*, so the highest values reflect the most central actors. The value is calculated by the sum of geodesic distances for a specific actor to *all* other actors. An actor that has a high closeness score is a short distance from most others. Having a high closeness, an actor will be able to obtain information (or whatever flows through the network) originating at a random actor potentially very quickly. When information flows through the network, the diffusion process tends to introduce distortion as the information has to pass every actor. For that reason, one expects information received by central actors to have higher fidelity on average. Thus, a high closeness would seem a significant advantage for an actor to the extent that it can avoid the control potential of others (i.e. their actions being controlled or mediated by others). Logically, shorter distances mean fewer transmissions and depending on the type of network, shorter times and lower costs, better access to information or more direct influence (Freeman 1978: 224; Borgatti et al. 2013: 173; Newman 2010: 183).

Noisia's network is built from one starting actor (the 'ego' Noisia) and is therefore an *egocentric network* (as opposed to a whole, or *socio-centric,* network) (Marin & Wellman 2011: 19). Usually, to investigate closeness centrality in egocentric social networks is uninformative. When building an egocentric network, the connections normally do not go further than the first-order zone: there is always one step from the ego to any other actor (the 'alter'). All geodesic distances from the ego to the alters would then be 1 by definition (Marsden 2002: 418). The case with this Spotify's network, however, differs for one, the network expands beyond first-order connection, as it incorporates to some extent artists that are also related to Noisia's related artists. Secondly, the network is based on user-generated data, and not Noisia's actual contacts, so it might be interesting to see what the closeness results bring for this socio-digital network and this is included it in the analysis.

Betweenness concerns the flow of information or other traffic and of the influence actors might have over that flow. Betweenness is a measure of how often a given actor falls along the shortest path between two other actors (Newman 2010: 186). More specifically, it is calculated for a given focal actor by computing, for each pair of actors other than the focal actor, what proportion of all the shortest paths from one to the other pass through the focal actor. These proportions are summed across all pairs and the result is a single value for each actor in the network. Betweenness centrality for an actor *j* is given by the formula *b*:

$$b_j = \sum_{i<k} \frac{g_{ijk}}{g_{ij}}$$

where g is the number of geodesic paths connecting *i* and *k* through *j*, and g_{ik} is the total number of geodesic paths connecting actors *i* and *k* (Borgatti et al. 2013: 174). High scoring betweenness-actors are the 'bridges' over which information tends to flow (Granovetter 1973). In general, they have a structurally advantaged position by being in between other actors; it has *"the capacity to broker contacts among* *other actors – to extract 'service charges' and to isolate actors or prevent contacts"* (Hanneman 2005). Betweenness is often useful as an index of the potential of a point for control of what flows through the ties (Freeman 1978: 224). It is important to realize that the centralities are not definitions of built-in properties of centrality but rather *hypotheses* about the potential consequences of centrality, either for the actor or the network in which they are embedded (Borgatti et al. 2013: 164).

5 Case study: results

The network graph seen below (figure 2) forms the network visualisation of Noisia's Spotify Related Artists. The overall network is shaped by *Force Atlas2*. This algorithm uses a formula for repulsion and attraction: without links, the actors repulse each other and spread. The ties work as springs that draw the actors together, aiming to produce a layout that shows visual densities that denote structural densities (Jacomy et al. 2014). The appearance of the actors (the artists, the dots) have been modified according to the popularity attribute as indicated by Spotify. The undirected network has 549 actors and 5634 ties. Every actor is an artist whose music can be found on Spotify and every tie is for when Spotify relates one artist to another, linking them to each other through their profile pages. The network consists of one component, meaning every actor is connected to the others within the network, directly or through others. Also, the actors are one-mode, because each of them are single type artists, meaning every actor could conceivably be connected to any other.

A first glance at this network already reveals basic information, such as who the artists in the network are, and who they are connected to. The names were observed of those that appear in Noisia's network, how 'big' they are in terms of Spotify popularity, and where they stand in this network: who seem central, and what names were seen on the outer edges. What particularly stands out in the visualisation (as opposed to tables and matrices of numbers and names) is the appearance, or the shape of the network.

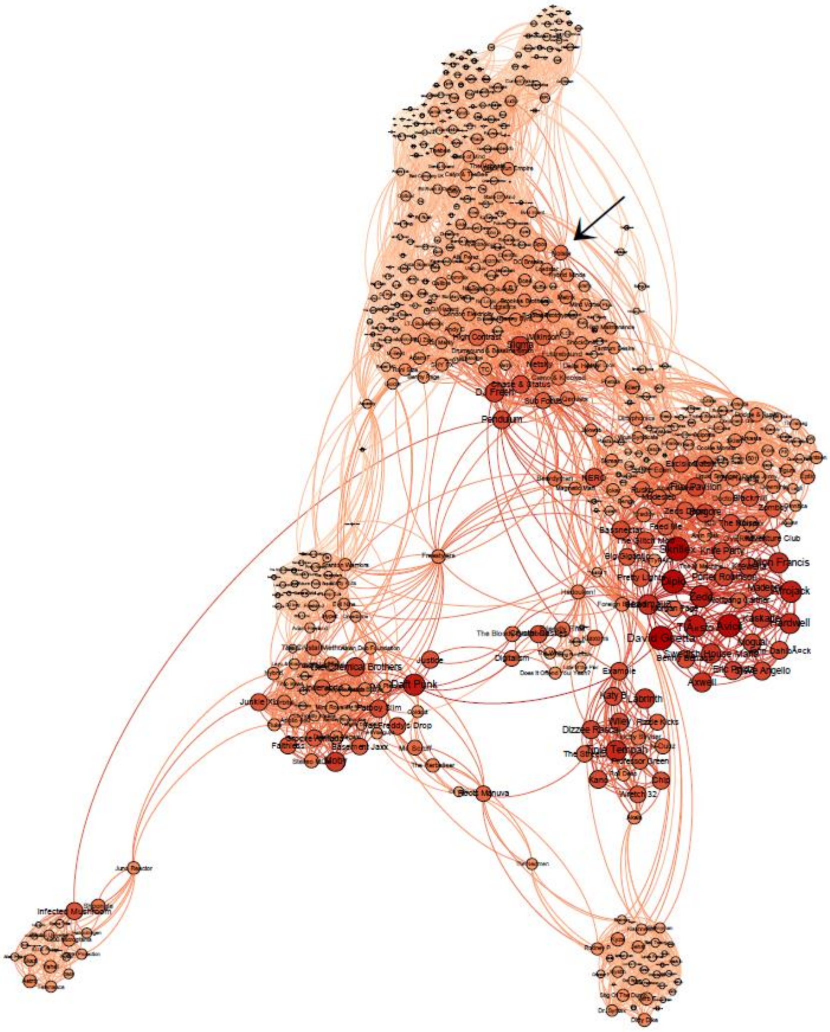

Figure 2: Network visualisation of Noisia's (arrow) Spotify Related Artists. The dots represent the actors (artists) and the ties between them represent a Related Artist link on Spotify. The size and colour of the dots represent popularity as indicated by Spotify.

The spread of the artists is quite expanded and shows some more densely knit areas that seem less connected to the rest. The densely knit areas are clusters of artists. Within those clusters the artists share many ties amongst themselves , their 'relatedness' apparently being very high. For example, in the cluster on the bottom left (shown in detail in figure 3), many ties between those artists can be observed, but as little as four ties link them to the rest of the network, coming from only two particular artists (Infected Mushroom and Juno Reactor). The other actors in this cluster might have a central role in their particular cluster, but without links to the other clusters, Noisia can be quite 'far' from these artists- or in Barabasi's (2002: 61) words, they would *"move in different worlds"*.

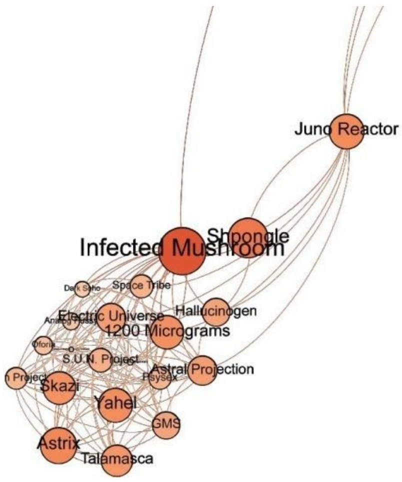

Figure 3: Detail of Noisia's Spotify related artists' network. One of the artists' clusters that appears on the bottom left.

Between those areas with high density are *structural holes*; areas with an absence of ties between the actors. Structural holes can be a source of inequality amongst actors, as they are associated with positional advantage or disadvantage (Hanneman 2005). The artist Magic Mushroom for example, is highly connected inside the cluster, but is also the only one that relates to Noisia's main cluster (through Pendulum, who is directly tied to Noisia). Typically, this position can therefore fulfil a gatekeeper role for their cluster, or a representative for others (ibid).

What follows is a discussion of the results of the ten actors most central in this network. Some of the aforementioned features will be covered later.

5.1 Centrality measures

Table 1 below shows the results for the actors most central presented per type of centrality. They form structural attributes to each artist. As this is an egocentric network with Noisia as the starting actor from which the network is built, high values for closeness and betweenness for Noisia is not surprising and of little informative value. For that reason, an 11th entry is added for closeness and betweenness, so we can address ten other actors ('alters'). Noisia's results are left in because their values will be addressed later on.

	artist	degree	artist	closeness centrality	artist	betweenness centrality
1	Gridlok	66	Noisia	0.402054292	Foreign Beggars	17283.04319
2	High Contrast	57	Sub Focus	0.393961179	Freestylers	16358.93998
3	Logistics	57	The Qemists	0.393961179	Noisia	14811.78684
4	Teebee	56	Pendulum	0.3856439127	Pendulum	13936.74676
5	Skynet	54	NERO	0.3848314607	Sub Focus	10150.11855
6	Dom & Roland	47	Dieselboy	0.3834849545	Infected Mushroom	9488.672452
7	London Elektricity	47	High Contrast	0.3832167832	deadmau5	7707.789186
8	Dillinja	46	Freestylers	0.379501385	Dieselboy	7030.578098
9	Current Value	46	Concord Dawn	0.3677852349	Example	6449.388223
10	Brookes Brothers	45	Foreign Beggars	0.3675385647	Hadouken!	6177.833136
11			Magnetic Man	0.363395	High Contrast	5447.221447

Table 1: Top central actors for 3 different centrality measures.

Overlap is visible mainly between the actors who are high in closeness and betweenness. Degree shows one actor (High Contrast) that reappears in the closeness and betweenness list. In relation to the rest of the network, table 2 gives an overview of the descriptive statistics of the centrality measures in the overall network. The standard deviation of closeness and betweenness reveal that, although their main actors might be similar, the variety amongst the actors for betweenness is quite big, which is not the case with closeness. This shows clearly in the visualisations of the centralities as well as we will see later on.

	degree	closeness centrality	betweenness centrality
count	549	549	549
mean	20.52459	0.281069	716.677596
std	9.19506	0.036227	1735.252999
min	2	0.218762	0
25%	14	0.251838	33.026142
50%	20	0.279165	172.105946
75%	26	0.305122	601.943473
max	66	0.402054	17283.04319

Table 2: Descriptive statistics for the overall network for three centrality measures.

Although the numbers on their own point to who the central actors are, in combination with a visual representation the top actors can be seen in context of the complete network. For that reason, there is an adjusted visualisation per category of the network in the sections below. Both the values and the visualisations help to investigate the centralities in Noisia's Spotify artists' network.

5.2 Degree centrality

In Noisia's network, degree centrality has a range from 66 ties (Gridlok) to 2 ties (Fat Freddy's Drop and Mighty Dub Catz) and Noisia themselves have a degree centrality of 27, not appearing in the top ten. The top degree actors are not evenly spread in the network (figure 4); they are all situated near to Noisia's position, in the densely knit upper area. For being in more or less the same cluster, this suggests there is a close relatedness amongst these top actors. The lower values are strikingly visible in the mid-right and bottom-left.

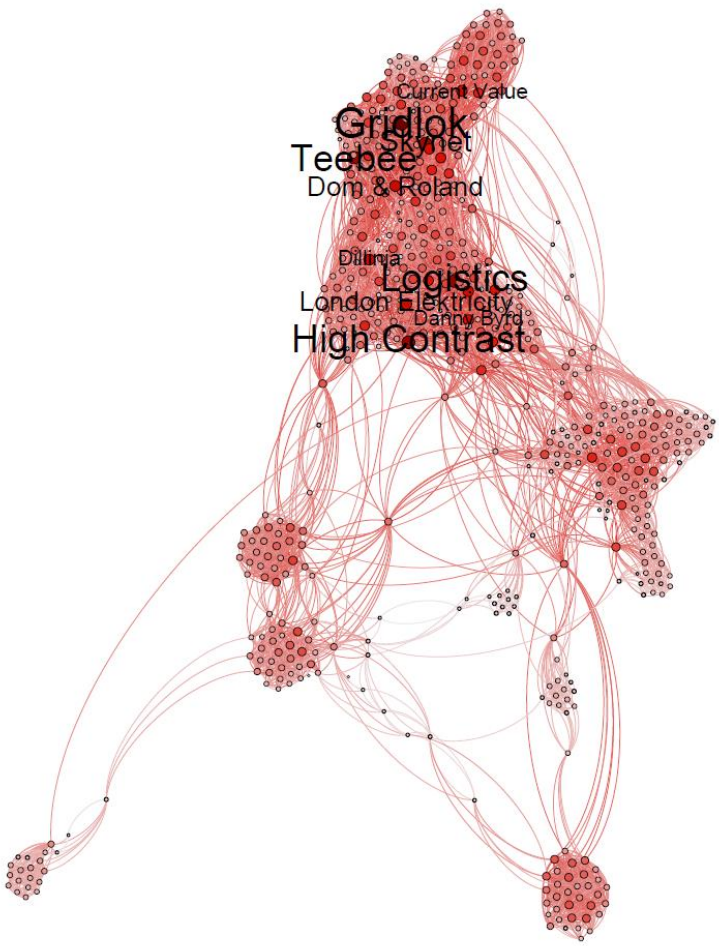

Figure 4: Noisia's Spotify Related Artist Network highlighting the top 10 actors with highest degree centrality. The size of the dots (small-large) are according to degree (low-high).

5.3 Closeness centrality

Closeness centrality relates to the actors most closely connected to others in the overall structure of network. Closeness centrality in this network ranges from 0.402054292 (Noisia) to 0.218762 (DJ IQ). As Noisia is our starting point, their values naturally appear at the top. This is not interesting as it is self-evident, and therefore Noisia will not be considered. The remaining top ten for closeness, are the actors with the smallest mean distance to others. As we can see in the next network graph (figure 5), the high closeness actors seem come from the centre of the graph, and fan out to the edges of the network to those actors with lowest closeness centrality; the actors with the highest closeness centrality are quite literally central.

5.4 Betweenness centrality

Betweenness centrality measures how often an actor falls on the shortest path between other actors. The range for betweenness in Noisia's network goes from 17283.043191 (Foreign Beggars) to 0.0 (for 5 actors). Noisia is #3 with a betweenness of 14811.78684. Again, this should ignore Noisia since having a high betweenness position is of little interest given they cannot be in between themselves. The next ten high betweenness actors are, therefore, highlighted in the visualisation of the network betweenness (figure 6).

This image is undoubtedly very different from the previous ones. The range of values are much larger, and the visualisation reflects this. The top betweenness actors stand out significantly because of these differences. The spread stands out as well: in this case the lower regions are included in the top ten as well, while with the other two centralities the central actors were closer to Noisia. The position of these high betweenness actors reflect what is characteristic for this measurement: high betweenness actors are called bridges as their position typically falls in between clusters of actors. The highlighted actors in the network graph show ties that connect otherwise much more separated clusters.

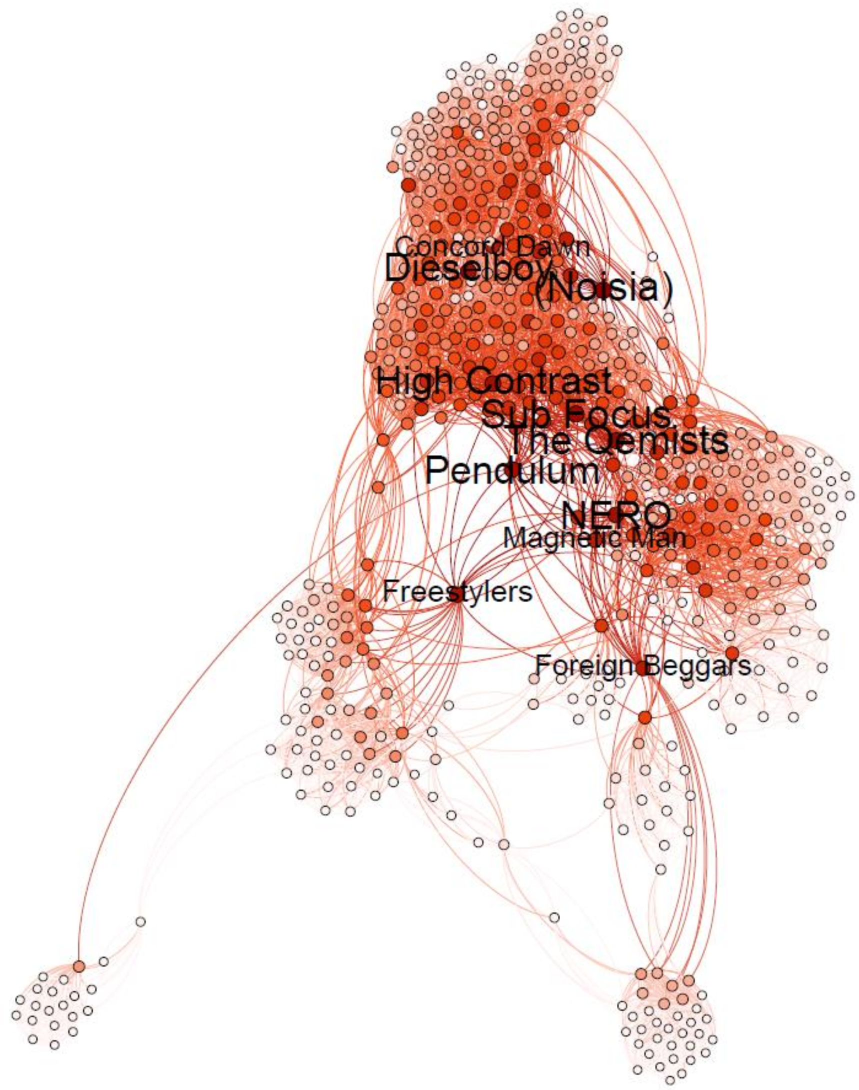

Figure 5: Noisia's Spotify Related Artist Network highlighting the top 10 actors with highest closeness centrality. The size of the dots (small-large) are according to closeness (low-high).

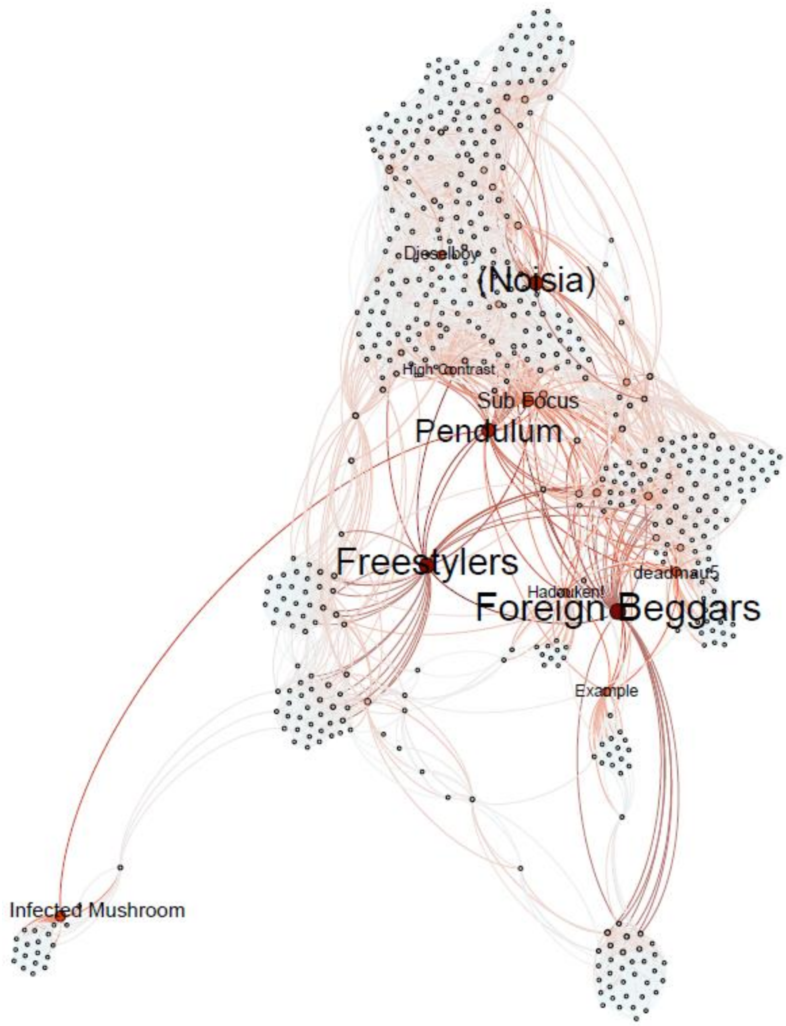

Figure 6: Noisia's Spotify Related Artist Network highlighting the top 10 actors with highest betweenness centrality. The size of the dots (small-large) according to betweenness (low-high).

The results from the different centrality measurements are far from identical and their usefulness equally varies. That 'being central' can be interpreted in different ways is clearly observed through the different kinds of centrality measures.

6 Network analysis

As argued before, the systems that provide the data play an important part in the outcome: they are socio-technical systems. Being built by humans with a certain idea in mind, they are intermediaries with their own ethics, values and duties. Spotify's Related Artists section, the starting point for the analysis, is therefore already laden with value and meaning in several ways. To make the connection between artists, Spotify constructs an image of the artists through endless data points, created by themselves and by their users. This process gives rise to a certain datafied construction of the artists; it creates a 'data double' (Lupton 2014).[7] Spotify then uses that data double to make their connections and predictions, causing the doubles to have their own social lives and materiality. Secondly, by making the related artists a prominent feature on a profile, Spotify assumes that users would find this interesting information. It may indeed be true that with so many users and so much behavioural information, there is a good chance that the linking of artists in this way *is* meaningful and wanted information yet it only has *a certain* meaning. Listener behaviour determined that the artists in the network are Noisia's related artists in this case. Alternatively, a network of related artists based on musical similarities, such as provided by Pandora Internet Radio does (Prey 2018), is probably just as effective. As Spotify is an important platform for artists to reach their audience and obtain revenue, the way they operate determines the possibilities to a certain extent. If an artist disagrees with the results, there is not much

[7] Lupton uses this term to refer to datafied constructions made by self-tracking, but the principle of 'a self' constructed by data applies here also. Other terms have been used as well, such as 'data shadow' (Andrejevic 2013) or 'data subject' (Ruppert 2011). I prefer the term 'double' as it highlights, in my perception, the fact that it is often treated as something complete and autonomous, often mistaken for the real thing.

that can be done, but the results will still affect the artists,[8] plainly what Spotify says is important.

The results need to be considered with this in mind. If one examines the clusters in the network (the more densely connected artists), it is evident they coincide roughly with different music genres. The visualisation below (figure 7) reveals the genres that can be associated with the clusters. This shows that Noisia's network is (unsurprisingly) dominated by electronic music, with some space for Rap and HipHop (central/bottom right). Even though Noisia collaborated with and remixed for musicians from the Pop and Metal genres in the Spotify network artists from those genres do not appear at all. In that way the network does not represent Noisia's actual artist network, but their data double's. The network is thus not less real but It is not a conventional social network where the relations are made by the artists themselves, but these artists are truly related in a way that the algorithm linked massive user-data points regarding their music and profile together.

What then, is Noisia's related artists' network? It is the interconnected artists on Spotify presented in a network graph. It is an imposed network, one that came into being not naturally by actual relations but determined by Spotify's algorithms that used data generated by user behaviour; a network of data doubles.[9] Keeping in mind the ambiguous nature of the source, there is a clear reason to take this network seriously. Even though we cannot always know what exactly is in the 'black box'[10] (the technology), we can use its outcomes to gain insight. To some extent, the black box needs to be trusted, because the streaming plat-

[8] For the related artists section, his can be painfully clear especially for artists that are new to the platform and on whom not much data is yet available. One artist by the name of 'Exodus Music' makes congregational worship music and reported on only having heavy metal bands in their Related Artists section (Spotify Community).

[9] Also, Rieders crawler of the network incorporated certain decisions, such as how big he allows the network to be. With different ranges, the network could be larger or smaller, influencing the results as well.

[10] According to Latour, *"paradoxically, the more science and technology succeed, the more opaque and obscure they become"* (1999, 304). The 'black box' is commonly referred to as those obscured internal workings of systems that are often a mystery to the user, who only focuses on input and/or output.

form has proven its worth by becoming an important platform for musicians and listeners. Nevertheless, there is a need to know *about* the black box, to acknowledge that it might serve purposes beyond the user's (like Spotify's needs). Additionally, there is the mediating role of technology, the possibility that even by providing this information, Spotify could be shaping the way artists relate to each other and what users listen to. The way Spotify implements Related Artists pushes artists to consider the suggested artists as related, and we thereby might treat them that way. Likewise, seeing an actor having a prominent position in the network, will make us approach them in this manner.

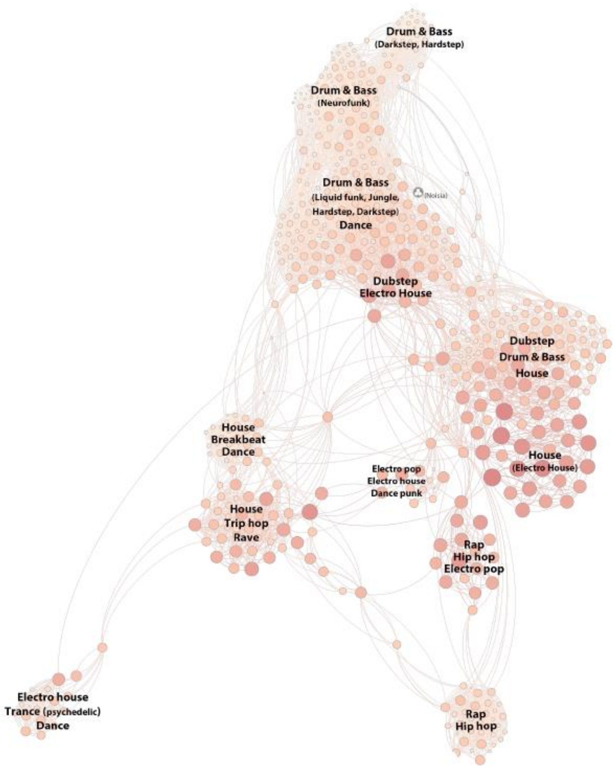

Figure 7: Genre clusters in Noisia's Spotify Artist Network.

6.1 Centrality analysis: degree centrality

By means of centrality analysis, one can examine possibilities and restrictions of actors in the network. Each centrality measure has its own characteristics and will be addressed separately.

Having a high degree means the artist is highly visible on Spotify, which means the artist is often linked with the profiles of other artists. Other possibilities include the artists appearing as a suggestion to the user as something they would be interested in. The actors from this top ten are probably well-known by any one of the actors in this network and their fans. In a way the score reflects the most prestigious or popular artists of Noisia's network. If we compare these names with the first network graph (figure 2), which reflects Spotify's overall popularity, we notice there is a difference. With regard to *all* Spotify's artists, in Noisia's network, the most popular ones appear at the centre-right (the 'House cluster') (see figure 7). It makes sense that the results differ, because drum and bass is a less mainstream sub-genre of Electronic Music than House, which overall has a bigger audience. Even so, when looking at Noisia, the position of important actors in this personal network would be more meaningful to them, as they would be less interested in the 'whole', where they play a relatively marginal role. In their network, the high degree actors such as Gridlok, High Contrast and Logistics, are most likely the important, highly esteemed ones in the genre, more so than for example Tiësto or David Guetta, who are more popular on Spotify.

High degree centrality in Noisia's network gives the artists an advantageous position with regard to connections and information that are interesting for Noisia. Even when we approach the artists as data doubles, this idea still stands. Degree information is valuable for example if one was looking for certain information or to form a collaboration. Artists with a high degree position might be the ones to connect to, as they are the prestigious artists in the network. Another reasons to pursue these artists would be if Noisia would want to release their own information (such as news or a new track) getting support from these other actors would be meaningful as their opinion would likely be held in high regard and therefore influential in their network. A downside is that because the high degree actors have great access to information and options because of their many connections, it would be harder to influence them since they are less dependent on others because of their position and do not need the influence of others to succeed. Even so, all top central actors are situated close to Noisia's position in this network, in the top clusters, indicating these actors are all closely connected: they are either directly related to Noisia through Spotify, or through one or a few ties. Their structural closeness is visible when we take a closer look: there are for example many 2-distant-paths (a separation of two ties/one actor) between Noisia and Gridlok (the #1 degree actor), meaning there is only one other artists profile separating the two and they share much the same audience and are visible in each other's network. As noted before these high degree actors are probably well known to the audience because of their visible position so to learn that these names hold each other in high esteem might not exactly be news. To know exactly who are given linked in this way by Spotify probably is. It is likely that based on real-life connections, the artists themselves would name very different artists but Spotify's data shows, which artists *users* hold in high regard and find important as made clear by their listening behaviour, all of which could add a deeper insight into the connections Noisia already has and is familiar with.

6.2 Centrality analysis: closeness centrality

The top closeness actors are the ones that have the shortest distance from all others in the network. Their position in this Spotify network means that we can quickly reach these artists through other artists profiles. Since we are dealing with an ego network, starting from Noisia, it is not surprising that Noisia is close to Noisia. It explains the fanning out of high to low closeness actors as well, as the low closeness actors have been rendered only through connections by other profiles, further away from the starting point of Noisia's profile. The names in the rest of the top ten, then, are logically found closely related to Noisia.

Since the network is egocentric, we would expect all the actors high in closeness to be *directly* tied to Noisia, but there are actually two actors in the top ten who are not: High Contrast and Magnetic Man. By expanding the network two steps beyond Noisia's directly related artists, the centrality of all the actors shifted. When looking at closeness, it gave more weight to some artists outside Noisia's direct ties. In terms of this particular network, it shows some artists 'further away' as having a more closely connected position. Because of this, we could attempt to approach it as if it were a whole network and see what that brings.

Usually, high closeness indicates a high likelihood of the actor for being in close connection to the network actors. An actor with a high closeness position, is never far away from the others in a network and thus would be able to avoid potential control by others for having their own quick access to information or people. A high position would account for more direct influence than others. However, we are not dealing with personal, 'physical' relationships between the artists and this network. The question arises how a high closeness artist in the Spotify Related Artists Network can for example, exercise control over another actor. Control, in this case, is exercised by the data of large amounts of users, unknowingly forming ties by using the platform. Noisia would not be able to cut a tie to refrain another actor from information (in that way 'exercise their power'). Noisia, nor any other central actor, has little, if any, control over the ties. The powerful and efficient tools of short transmission time and direct influence associated with closeness, would only be applicable if this network of Noisia's data double resembles the real artist's network, which would have to be assessed separately. Additionally, the standard deviation is small (table 2), as we see visually reflected in figure 5. The range of high scoring actors is quite large (visible as the many big, (dark)orange dots), and the closeness scores overall show little variance− something closeness suffers from in general (Borgatti et al. 2013: 173). This suggests that to occupy a position with high closeness is not unique, which limits its usefulness.

6.3 Centrality analysis: betweenness centrality

High betweenness actors are the 'bridges' in the network over which information tends to flow. In our network, this means a high betweenness actor is an artist profile that often appears between two other profiles. What stands out in these results (figure 5.5), is that beside a few of the actors that are central or important in other terms (for instance having high degree), we also find actors that in other cases hold relatively marginal positions in the network. This points towards the idea that 'smaller players' can be important bridges. Compared to closeness centrality, the difference between higher and lower scoring actors is much bigger: the top ten unquestionably stands out. That Noisia appears high in these lists is again of little surprise, because with the data coming from an egocentric design, by definition all pairs of actors are connected either directly or indirectly via the ego (Marsden 2002: 410). The next top ten betweenness actors will be the interesting ones in this case.

Again, because we deal with data generate by platform user-behaviour, and not the actual social network of the artists, we cannot say the artists themselves have control and influence over connections. With regard to betweenness, the #1, Foreign Beggars, cannot exercise power by for example isolating or preventing contacts on Spotify, as would be the case in a purely human social network. Even though none of the actors can actually control the relations, high positions still account for important actors that can function as bridges on the streaming platform: high betweenness actors appear often between artists pages on Spotify and thus connect their audiences. The bridge-actors in several cases could prove to be valuable ties for reaching out to other genres. If for example Noisia were interested in expanding their audience and genre-horizon, high betweenness could indicate which other artists already in their network, might prove a strategic ally. Based on the results, Foreign Beggars and Example can connect them to an audience of Rap and HipHop, Freestylers to House and Dance music and Infected Mushroom to Psychedelic Trance.

However, since Noisia have been productive for many years, collaborations with a lot of the artists in their network have in fact already taken place. Noisia has produced music together with certain artists and (as is very common in electronic music) remixed many others. An extensive collaboration between Noisia and the rap artists Foreign Beggars for example even led to the forming of supergroup 'I Am Legion'. Furthermore, they already have remixed for half of this betweenness top actors alone. The possibility that these ties and centralities appear in Noisia's Spotify related artists network could well be *because* they worked together in the past, which would reflect the effects of their musical choices. By collaborating with rap artists, they gained an audience that share an interest in both rap and electronic music, which makes them related artists. On the other hand, we do not find any Pop or Metal artists here, so Noisia's productions for pop artists (such as Robbie Williams and Katy Perry), or the collaborations with the metal band Korn did not result in bridging those audiences, at least not visibly so on Spotify. At this point, unexplored bridges might prove fruitful connections to new genres and their audiences, or the related artists network could be deployed to find artists beyond their network to really explore new audiences. For example, artists on the periphery might have little importance within the current network but can be effective in connecting to other networks and hence audiences.

This centrality analysis shows a more in-depth understanding of an artist on one of the most important music streaming platforms by looking at the relationships it identifies between musicians. The network shows us what artist group Noisia is perceived to belong to according to the data. As far as Spotify reveals, the related artists are based on user activity, so it tells us something also about audience perception; the artists in the network are the artists that share an audience. The different kind of central figures in the network can point towards important artists— maybe not a view founded on how the artists see themselves but one based on user behaviour data. If we include considerations about the importance of these actors in the real world, the data can be put to use beyond Spotify's streaming platform.

7 Discussion and conclusion

When it comes to data analysis, there is no shortage of help in accumulating numbers and showing timelines. Many services provide such intelligence on their own platform, and services that incorporate the results from several platforms are growing (e.g. SoundCharts, Next Big Sound, Chartmetric). A more fundamental question is the best way to approach data analytics and platforms in general, and other ways of analysing data that provides more insight than plain statistics. A key aspect is that platforms like Spotify are sociotechnical systems, making them function as cultural intermediaries. The digitisation of the music business has been caused by a wider technological advancement, driven by typical network concepts and methods, which led individuals to become more networked as well. For that reason, employing a network perspective to answer to the need of insight beyond statistics is to be recommended. Based on the findings, both theoretical and empirical, there is an answer to the main question of what possibilities network theory can provide music business professionals. That we live in a networked society is no surprise but to realise that networks are not random is less well known.

Networks follow internal rules and patterns that we can study and the theory of networks offers a way of approaching the world by thinking in relations, not in isolated units or groups. We can use it to make sense out of online platforms that themselves use typical network structures and ideas. Using network perspectives and analysis will usually not directly show one how to succeed or predict the future, but its value is beyond that; it provides guidance on where to look for answers (Marin & Wellman 2011: 21). Network theory provides the tools and methods to understand our complex systems of relationships. When the biases that come with datafication are taken into consideration, using network perspective when dealing with data and online platforms can indeed offer more control and power over one's activity.

A case study of Noisia's related artists has shown that caution is needed when we apply network analysis for algorithm provided data. This caution will reveal the biased nature of the data and makes us realise what the numbers *can* reveal. It allows us to bridge unproductive data scepticism and naive faith in numbers. Each investigated centrality measure reflects some important, powerful structural characteristic of the network: degree centrality demonstrated who the prominent actors in the network are, which can be useful when seeking reach or respect, for example. Closeness centrality highlighted the actors who have the shortest distance from all other actors in the network, but the value of this measurement is not likely to be that useful with so little variety in the results and because this was an egocentric network. Betweenness exposed the actors that fell along the shortest paths, or, the possible bridges of the network. They are not per se prominent actors, but possible connectors between for example audiences or genres. Importantly, we cannot blindly follow the theory behind the centrality measures, to say the centrality measures reveals possible opportunities and restrictions, when it comes to this network. An understanding and critical approach to data and the way it has been mediated by algorithms and platforms, an awareness of the black box as it were, is necessary to reasonably interpret the results. If the network resembled the real-life social network of Noisia, then the power and control possibilities make sense but that is not the case with this algorithm generated network. Investigating this particular network gives insight into the position Spotify places the artists and tells us a lot about how listener behaviour creates a datafied version of Noisia with its own reality and network. Since Spotify plays an increasingly important role in the way audiences discover music, it is valuable to gain insight into how the platform organises, categorises and links artists because that information is vital to potential success. The network analysis in the case study indicates one of those ways, and consequently reveals information on interesting relations Spotify draws for Noisia, both past and future.

8 Limitations and future work

However freely available or easily accessible much network data and tools are, it is to be noted that network theory is a complex area of study. Network analysis demands commitment to the subject and theory for the research to be useful. When proposing anyone to apply a network perspective to gain insight, thorough application and understanding probably demands specialised assistance. With regard to practical issues, one main limitation lies in the source of the data. Because Spotify is not completely transparent about the way the related artists are constructed, it cannot be completely determined what exactly flows through the ties. The analysis was made on the assumption that the decisive data source is user behaviour, based on reports on Spotify's platform, but how exactly this is assembled could not be verified. This adds uncertainty to the results.

Furthermore, while network perspective has become increasingly important to describe social dynamics in today's information age,[11] the fact remains that our interactions are not only typically, more fragmented, diverse and free than before, they are also more digital which can complicate things. The way we connect, communicate and exchange information indeed can be approached as embedded in networked structures, but the 'classical' constraints, rules and procedures are not always the same. In social network theory, *trust* for example is regarded as the primary currency (Rainie & Wellman 2012: 19). Much of the activity is aimed at gaining and building trust, because trust ensures relationship ties, which are necessary to thrive. But if one looks at a related artists network on Spotify, where does trust fit in when the ties are made or broken?

Trust does not have a place in the process of building relations constructed from big data, accumulated by machines. This fact signals a weakness in Latour's equalizing of all types of actors, human or non-human, in his actor-network-theory. When our socio-technical networks follow different rules to our usual social networks, there must be a difference, and such networks perhaps need another approach. It would be interesting to see how network theory can adapt to these developments.

This research aimed to engage in both qualitative and quantitative practice using methods and tools that go beyond any single approach. At an academic level, the results may add some insight into how to critically

[11] As described thoroughly in for example Barabási's "Linked" (2002), Castell's "Rise of the Networked Society" (2009) and Rainie & Wellman's "Networked: The New Social Operating System" (2012).

engage with theory and practice. What the research findings offer to music professionals is a concept of how to deal with our datafied surroundings, that have quite suddenly permeated the music industry. By looking at events as a collective effort and seeing that everything is connected, thinking in networked relations can help grasp some meaning amidst the current deluge of information.

9 References

Barabási, A.L. (2002) Linked: The New Science of Networks, Basic Books, New York.

Baym, N.K. (2013), "Data Not Seen: The Uses and Shortcomings of Social Media Metrics", First Monday, vol. 18, no. 10. Available at: https://firstmonday.org/ojs/index.php/fm/article/view/4873/3752 (15 April 2019)

Bilton C. & Leary, R. (2002) "What can managers do for creativity? Brokering creativity in the creative industries", International Journal of Cultural Policy, vol. 8, no. 1, pp. 49–64.

Borgatti, S.P., Everett, M.G. & Johnson, J.C. (2013), Analyzing social networks, SAGE Publications Limited, Newbury Park.

Bourdieu, P. (1984) Distinction: A Social Critique of the Judgement of Taste. Routledge, Oxford.

Brandes, U. (2001) "A Faster Algorithm for Betweenness Centrality", The Journal of Mathematical Sociology, vol. 25, no. 2, pp. 163–177. doi:10.1080/0022250X.2001.9990249.

Callon, M. & Latour, B. (1981) "Unscrewing the big Leviathan: How actors macro-structure reality and how sociologists help them to do so", in Advances in Social Theory and Methodology: Toward an Integration of Micro- and Macro-Sociologies, eds. K. Knorr-Cetina & A.V. Cicourel, Routledge and Kegan, Boston, pp. 277-304.

Castells, M. (2009) The Rise of the Network Society, Wiley-Blackwell, Oxford.

David, M. (2010) Peer to Peer and the Music Industry: The Criminalization of Sharing, SAGE, Newbury Park.

Erdős, P. & Rényi, A. (1959) "On Random Graphs. I.", Publicationes Mathematicae, vol. 6, pp. 290–297.

Fraser, A. & Ettlinger, N. (2008) "Fragile Empowerment: The Dynamic Cultural Economy of British Drum and Bass Music", Geoforum, vol. 39, no. 5, pp. 1647–1647.

Freeman, L.C. (1978) "Centrality in Social Networks Conceptual Clarification", Social Networks, vol. 1, no. 3, pp. 215–239, doi:10.1016/0378-8733(78)90021-7.

Hanneman, R.A. & Riddle, M. (2005) Introduction to social network methods, University of California, Riverside CA.

Harari, Y.N. (2017) Homo Deus: A Brief History of Tomorrow, Vintage, New York.

Hartnett, K. (2017) "Best-ever Algorithm found for huge streams of data", Quanta Magazine online, 24 October 2017. Available at: https://www.quantamagazine.org/best-ever-algorithm-found-for-huge-streams-of-data-20171024 (29 October 2017).

Hesmondhalgh, D. & Baker, S. (2011) Creative Labour: Media Work in Three Cultural Industries, Routledge, London.

Hitters, E. & Van de Kamp, M. (2010) "Tune in, fade out: Music companies and the (re)evaluation of domestic music products in the Netherlands", Poetics, vol. 38, no. 2, pp. 461-480.

Hracs, B.J. (2015) "Cultural Intermediaries in the Digital Age: The Case of Independent Musicians and Managers in Toronto", Regional Studies, vol. 49, no. 3, pp. 461–475.

IFPI (2017) Global Music Report, IFPI, London. Available at: http://www.ifpi.org/downloads/GMR2017.pdf (15 April 2019).

Jacomy, M., Venturini, T., Heymann, S. & Bastian, M. (2014) "ForceAtlas2, a Continuous Graph Layout Algorithm for Handy Network Visualization Designed for the Gephi Software", PLoS ONE vol. 9 no. 6: e98679. https://doi.org/10.1371/journal.pone.0098679.

Konstan, J. A. & Riedl, J. (2012) "Recommender Systems: From Algorithms to User Experience", User Modeling and User Adapted Interaction, vol. 22, no. 1-2, 2012, pp. 101–123.

Latour, B. (1999) Pandora's Hope: Essays on the Reality of Science Studies. Harvard University Press, Cambridge (Mass.).

Latour, B. (2005) Reassembling the Social: An Introduction to Actor-Network-Theory. Oxford University Press, Oxford.

Marin, A., & Wellman, B. (2011) "Social Network Analysis - An Introduction", in: Handbook of Social Network Analysis, eds. J. Scott & P.J Carrington. SAGE, Los Angeles, pp. 11–25.

Marsden, P.V. (2002), "Egocentric and Sociocentric Measures of Network Centrality", Social Networks, vol. 24, no. 4, pp. 407–422, doi:10.1016/S0378-8733(02)00016-3.

Mombert, G. (2015) "Spotify unveils treasure trove of listener data to artists with fan insights portal", Digitaltrends.com. Available at: https://www.digitaltrends.com/music/spotify-fan-insights-portal/ (15 April 2019).

Newman, M.E.J. (2010) Networks: An Introduction. Oxford University Press, New York.

Nowak, R. & Whelan, A. (2014) "Editorial: A Special Issue of First Monday on the 15-Year Anniversary of Napster – Digital Music As Boundary Object", First Monday, vol. 19, no. 10, doi:10.5210/fm.v19i10.5542.

Prey, R. (2015) "Henri Lefebvre and the Production of Music Streaming Spaces", Sociologica, vol. 9, no. 3, pp. 1–22.

Prey, R. (2016) "Musica Analytica: The Datafication of Listening", Networked Music Cultures: Contemporary Approaches, Emerging Issues, eds. R. Nowak & A. Whelan, Palgrave Macmillan, New York, pp. 31-49.

Prey, R. (2018) "Nothing personal: algorithmic individuation on music streaming platforms" Media, Culture & Society, vol. 40, no. 7, pp. 1086–1100.

Rainie, H. & Wellman, B. (2012) Networked: The New Social Operating System, MIT Press, Cambridge (Mass.).

Rieder, B. (No Date), Spotify Artist Network. Digital Methods Initiative, online. Available at: http://labs.polsys.net/playground/spotify/ (15 April 2019).

Rose, J. & Ganz, J. (2011) "The MP3: A History Of Innovation And Betrayal", NPR, 23 March 2011. Available at: http://www.npr.org/sections/therecord/2011/03/23/134622940/the-mp3-a-history-of-innovati on-and-betrayal (28 July 2017).

Schneier, B. (2015) Data and Goliath: The Hidden Battles to Collect Your Data and Control Your World, W.W. Norton & Company, New York.

Seaver, N. (2012) "Algorithmic Recommendations and Synaptic Functions", Limn, UCLA 2. Available at: https://limn.it/algorithmic-recommendations-and-synaptic-functions/ (15 April 2019).

Spotify Community (no date) "Related artists" – how do Spotify decide what artists are related to a specific artist?" Spotify. User: Terkel_Mohl 2015-08-10. Available at: https://community.spotify.com/t5/Content-Questions/quot-Related-artists-quot-how-do-Spotify-decide-what-artists-are/td-p/1185597 (10 October 2017).

Spotify Fan Insights (no date), Spotify, online, Available at: https://artists.spotify.com/ (20 June 2017).

Spotify For Artists (no date) "How does Fans Also Like work?" Spotify, online. Available at: https://artists.spotify.com/faq/profile#can-i-create-and-edit-my-artist-playlists-using-spotify-for- artists (10 October 2017).

Spotify For Brands (no date) "You are what you stream", Spotify, online. Available at: https://spotifyforbrands.com/us/feature/streaming-habits/ (10 October 2017).

Spotify for Developers (no date) Spotify, online. Available at: https://developer.spotify.com/technologies/metadata-api/search/ (10 October 2017).

Titlow, J.P. (2017) "Spotify's Plan To Win Over Anxious Artists–And Win The Streaming War", Fast Company, online. Available at: https://www.fastcompany.com/3068915/spotify-artists-streaming-playlists-data (10 October 2017).

Van Dijck, J. (2014) "Datafication, Dataism and Dataveillance: Big Data between Scientific Paradigm and Secular Belief", Surveillance & Society, vol. 12, no. 2, pp. 197–208.

Watts, D.J & Strogatz, S.H. (1998) "Collective dynamics of 'small-world' networks", Nature, vol. 393, no. 6684, pp. 440-442.

Webster, J., Halford, S., Hracs, B. & Gibbins, N. (2016) "Towards a Theoretical Approach for Analysing Music Recommender Systems as Sociotechnical Cultural Intermediaries", WebSci '16, ResearchGate, Hannover, Germany.