

# Who you know or how you're known?

## The dual effect of professional collaboration and status connections on artistic careers in Dutch films.

Research Master in the Sociology of Arts, Media and Culture

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### Abstract:

*Research indicates the importance of networks on professional achievement. Particularly in the art world, two types of professional networks are significant: collaboration-based, in which artists choose whom to work with and symbolic networks, where others connect artist for comparison and evaluation. Understanding the interplay between these two connection types, and their relative effect on artistic careers, is the focus of this research.*

*For this study, I examine the Dutch film industry. I execute a two-staged research: first, I quantitatively map the professional networks between actors in Dutch films coming out in the cinema between 1997 and 2012. By analysing what positions actors have in a network on a specific point in their career through block modelling and sequence analysis, I find three ideal types of careers, with different amounts of career rewards: the long-term central, the long-term peripheral, and the sporadic career. Peripheral careers and sporadic careers in the centre of networks are evenly successful. Second, by making use of case studies of the ideal types emerging from the first analysis, I indicate how symbolic networks – the ways in which people talk and think about you – might differ for these actors. Findings indicate several dimensions on which symbolic network positions might differ: centrality, density and fragmentation. Further, I find these networks are multi-modal, transnational and span different fields of cultural production.*

### Keywords:

*Artistic careers; social network analysis; film production; evaluative practices; professional networks*

## Introduction

Research indicates the importance of networks on professional achievement (Granovetter, 1973; Burt, 1992). Particularly in the art world, two types of professional networks are significant: collaboration-based, in which artists choose whom to work with (Faulkner & Anderson, 1987; Uzzi & Spiro, 2005; Lutter, 2015) and symbolic networks, where others connect artist for comparison and evaluation (Braden, 2009; Jones, 2010). Understanding the interplay between these two connection types, and their relative effect on artistic careers, is the focus of this research.

For this study, I examine the Dutch film industry, which is characterized by collaboration-based production and individual aesthetic status—creating an ideal case for assessing the dual value of collaboration and symbolic networks. I have executed a sequential two-staged research: first, I quantitatively map the professional networks between actors in Dutch films coming out in the cinema between 1997 and 2012. By analysing what positions actors have in a network on a specific point in their career, I find three ideal types of careers, with different amounts of career rewards. Second, by making use of case studies of the ideal types that emerged from the first analysis, I indicate how symbolic networks—the ways in which people talk and think about you—might differ for these actors. Altogether, this project creates a complete picture of how professional and symbolic connections shape artistic careers. The formal research questions this article answers are: *To what extent do different artistic careers, shaped by historical trajectories through collaborative networks achieve different levels of success?* and *On what dimensions do symbolic networks differ for these different types of artistic careers and their respective success?*

## Relevance

This research is relevant in several ways. First, the idea of symbolic networks created by critics is a novel field of research on evaluative practices. The theoretical framework established in this article has wide-ranging applicability to other fields of cultural production. Particularly in fields where cultural production is still traditionally performed by singular individuals (literature, for example), the importance of exemplars for evaluation is essential for understanding our culture's beliefs in artistic quality. Moreover, this research provides some stepping stones to analyse these cultural frameworks into more detail.

Relatedly, a second theoretical contribution of this research is made to the academic tradition of Social Network Analysis (SNA). Although network analysis has been employed for some time (with the first graphic network performed around 1930) and has since acquired a strong empirical foundation (Bruggeman, 2008), the methodology is rarely used by social scientists to examine symbolic networks. A notable exception to this is Braden's work (2009), which uses network analysis to ascertain how curator-created connections influence the recognition of visual artists in

museum exhibitions. While such previous research examines symbolic networks, it lacks a comparison with traditional networks created through collaborative work. By understanding not only who you know (a staple of SNA) but also to whom you're compared, this research seeks to deepen understandings of social networks in general and explore what the role is of critic-created networks in cultural and artistic valuation.

Finally, this study contributes to a growing interest in collaboration and networks in artistic and general professional careers (Zuckerman, 2005). This emphasis on social capital for creating professional opportunities has received much social as well as scholarly attention (Bozionelos, 2015). Since contemporary careers involve considerable movement and uncertainty, a networked viewpoint may offer insight and strategy for optimizing long-term career development (Dobrow et al, 2012).

## Theoretical framework

### Success in creative careers

Creative careers are unique for a number of reasons. More than in other professions, artists function in "boundaryless" careers, which means creative actors move across different professional fields, as opposed to having a career within a specific, specialized domain (Jones, 2010). The uncertainty and highly skewed rewards in creative industries (see Caves, 2000), soothed by the intrinsic motivations artists identify for making art (see Hesmondhalgh and Baker, 2010), often leads to creative workers receiving less rewards than in other professions (Abbing, 2002). Another characteristic of creative careers is their dependence upon reputation: in a socially constructed art world (Becker, 1982) or market (Faulkner & Anderson, 1987) perceived success is reliant upon other's evaluation (Bourdieu, 1985). Two things can be learned from this: first, an artist's reputation is essential for career opportunities (Zuckermann, 2005) and subsequent success (Braden, 2009; Dubois & François, 2013). Note how reputation also extends beyond an artists' own agency, as Lang & Lang (1988) show for posthumous success of certain painter-etchers. Second, success stretches beyond the monetary rewards a worker receives in creative fields to include rewards such as contemporary recognition or, in some cases, historical renown.

Such conceptions of art worlds, theorized by Bourdieu (1983; 1985; 1993) as *fields of cultural production*, are defined as "a particular social universe endowed with particular institutions and obeying specific laws [...] where, in accordance with its particular laws, there accumulates a particular form of capital and where relations of force of a particular type are exerted" (1993, pp.164-165). Here Bourdieu distinguishes a world of art as a "field" apart from other professional fields, but also distinct from other fields of art: for every medium and art form, a specific field exists in which different rules and actors interact. In any of these fields, actors struggle for the scarce

rewards the field offers. In *fields of large-scale production*, rewards often take the form of monetary compensation (economic capital), whereas in fields of *restricted production*, in which fields abide more to the ‘art for art’s sake’-credo, can endow actors with cultural and symbolic capital (Bourdieu, 1985).

In both Bourdieu’s (1985) and Becker’s (1982) idea of an art world (see also Bottero & Crossley, 2011), collaborative actions are central to creating art. Pointing to experts as “*true producers of the value of the work*” (Bourdieu, 1983, p.263), Bourdieu describes how it is not the individual genius of the artist who solely creates the artwork, but rather how works come to be perceived as such by the interplay of different actors, institutions and rules of evaluation.

Again, a defining characteristic of fields of cultural production is success is not only measured by economic capital (although Bourdieu acknowledges this may be the end goal), but also by the symbolic position an artist acquires. This highest symbolic position is canonization or consecration: an artist has found his/her way into the annals of the history for a specific artistic field (Becker, 1982; Bourdieu, 1985; Allen & Lincoln, 2004). Therefore, when considering the levels of recognition for careers in cultural production, first is an artist’s reputation: the symbolic position he or she has within a specific field, which may, in some cases, transcend the boundaries of the field to larger social renown. Related to reputation are the concepts of “recognition” (which offers a slightly more *objective* connotation, as one can be “recognized” as important, without making a qualitative judgment of the reputation, see Lang & Lang, 1988), “prestige” (De Nooy, 2002; Verboord, 2003) and “valorization”, which is distinct from “consecration” (defined above) in its short-term duration (Allen & Lincoln, 2004; Braden, 2009)). However, reputation is inherently temporal—reputations change and may fade even over short periods of time. Consequently, in regards to long-term success, an artist needs to be *consecrated*, indicating a transcendence of normal transient recognition or as Bourdieu terms this “*a discontinuity in continuity*” (1991, p.120).

### Creative careers and networks

With recent sociological and to some extent cultural economic inquiry adapting a relational approach to the analysis of art worlds and artistic careers (see Lamont, 2012; Dekker, 2015), it makes sense to further theorize sites of cultural production (and reception, for that matter) as networks (Bottero & Crossley, 2011). Though there are many ways through which art worlds can be understood as networks, in this research I specifically focus on two forms: professional, collaboration-based networks and symbolic networks. In the first, networks are based in practice, consisting of people working together and employing social capital. The latter, symbolic networks, are larger frameworks individuals employ when evaluating a person’s position within a field. Below I discuss both network types, starting with professional networks.

Much academic work considers the role of social capital in creative careers, i.e., how social connections provide career opportunities (e.g., Faulkner & Anderson, 1987; Bielby & Bielby, 1994; Rossman, Esparza & Bonacich, 2010). This concept is frequently researched through social network analyses. While social networks are not explicitly theoretical (López & Scott, 2000), the conception of networks as “*patterns of relations that are crucial for the flows of information, influence [and] goods*” (Bruggeman, 2008; p.2) proves useful in understanding the ways in which art worlds function. Given growing concerns about individualistic and narrow approaches within statistical methodology, network analysis ability to include relationships may offer a more valid model of socially constructed fields (e.g. Crossley, 2015). Most work on social networks in creative fields can be divided in two theoretical arguments (Lutter, 2014):

First, scholars argue familiarity—i.e., the recurrence of specific collaborations—enhances chances of artistic success, as frequent collaborations provide artists with reliable, trusted connections. Coleman (1988) describes how frequent collaborations enhance creative environments, as recurrent cooperation demonstrates trust, shared norms and complimentary behaviour. Familiar networks thus ease the exchange of reliable and important information (Rost, 2011). Moreover, the recurrence of collaborations can also answer market uncertainty, as previous successful collaborations often serve as predictors of future success (Faulkner & Anderson, 1987; Podolny, 1994). Uzzi and Spiro (2005) empirically research this idea by looking at the (financial) success of Broadway musicals. They find seasons in which the production of musicals are more clustered (i.e., team members increasingly collaborate together), chances of financial success increase. The authors interpret this increased success as a sign frequent collaborations create higher quality musicals, indicating creativity is nurtured by clustered networks. Yet, there is a limit to this creative flow-argument, as Uzzi & Spiro (2005) find a certain threshold for clustering after which the success diminishes: “*high levels of connectivity homogenize the pool of creative material, [...], decreasing artists’ ability to break out of conventional ideas or styles that worked in the past but that have since lost their market appeal*” (Uzzi & Spiro, 2005; p.493).

Second, scholars indicate heterogeneity of relations improves success and performance (Lutter, 2015). Granovetter’s *strength of weak ties* argument is the most well-known version of this idea: weak connections with individuals from different social groups offer a greater amount of new opportunities. In network analysis, Burt (1992) formalized this idea by employing the terms *brokerage* and *structural holes*. Here, individuals who bridge gaps between otherwise disconnected groups are in a position of power; these individuals function as a broker, deciding what information (or other resources) flow from one group to another.

In literature on creative careers, an in-between position is believed to affect success in

multiple ways. The most clear explanation is found in the interplay of creativity and innovation (Perretti & Negro, 2006; Stark, 2009; Uzzi & Spiro, 2005). When creative workers collaborate with individuals from different backgrounds, they are exposed to other practices and forced to solve divergences and incongruities. As creative industries rely on constant innovation (Bourdieu, 1993; Lazeretti, 2012), multi-disciplinary collaboration may yield better results than heterogeneity. Another explanation employs a reception perspective, where chances of success may increase with the introduction of multiple, diverse audiences. For example, consider the higher success rate of academic papers co-authored by authors from different institutions (Abramo, D'Angelo and Solazzi, 2001). The heterogeneity argument, however, can also work reversely: Van Venrooij and Schmutz (2010) find artists defying a simple genre classification have less chance of success than those who fit neatly in one genre. Hsu (2006) reports similar findings on films spanning genres, where only in certain cases is it perceived as positive to bridge specific genres.

### Boundaries, classifications and symbolic relations

Extending recent network studies researching relations between certain groups and their respective field conventions, there is now the possibility to enter a new domain: that of the symbolic networks. Previous ideas on entrepreneurship and creativity note an artist's transgression of certain conventions can be theorized as spanning different and previously unconnected networks; yet, such connections needn't be the product of social relations alone. Rather, there are *symbolic boundaries* also being crossed. Lamont and Molnár define these boundaries as "*conceptual distinctions made by social actors to categorize objects, peoples, practices, and even time and space*" (2002; p.168). Symbolic boundaries structure our perception of cultural fields and, consequently, categorization (or "classification", see De Nooy, 1991) processes greatly impact the reputation and long-term career outcomes of artists (Jones, 2010).

Any evaluative practice carries a level of categorization. In order to create judgement, one must typify what is actually being evaluated (Lamont, 2012). Categorization processes, however mundane, aren't natural or inherent to the entity being evaluated, but rather the result of boundary work at the symbolic level. Our shared understandings, repeated in practice and reified by institutions (Douglas, 1986; Baumann, 2001), provide the idea certain things belong to a specific category, while others do not. Categorization processes bear with them the classification of objects among hierarchical; any category relates to another one from which it is distinguishable along certain socially-delineated hierarchy.

Symbolic boundaries, and the categorization processes they structure, function as one of the main sites of struggle in Bourdieu's (1985) conception of any field of cultural production. As these boundaries are subject to constant change, members of these fields compete for the ability to alter

them by performing *boundary work*, and thereby strengthening or elevating their position in the specific field. Different kinds of actors—artists, critics, audiences—are thus in constant struggle to define what is *legitimate* in the field. Legitimacy, in this framework, is the collective construction of a social reality, that members of that specific field believe to be “*consistent with cultural beliefs, norms and values that are presumed to be shared*” (Johnson, Dowd & Ridgeway, 2006; p.57). By being able to influence what is considered legitimate, actors are able to alter what others believe *should* be, adding a normative component to the evaluation. A standard example of this struggle is artists who distinguish themselves from their predecessors by actively going against previous works and practices. Such is an active form of boundary work, in which the artists try to change what is considered legitimate, i.e., their *new* way of creating art or the previous “old-fashioned” one (see Dubois & François, 2013).

What we can learn here is categorization, legitimation and reputation-building processes are interlinked. Where categorization deals primarily with the evaluation of who belongs to what group, these judgements in themselves carry a certain legitimacy: by defining who belongs where, we also indicate worth and level of acceptance. Such positioning in turn influences the reputation an artist has within specific fields (Bourdieu, 1993; Baumann, 2007). De Nooy (1991) offers an example of this in literature, finding authors need categorization into certain legitimate groups through critical discourse in order to gain a favourable reputation.

Returning to our idea of cultural field as a network, it now makes more sense to divide this into two distinct networks. First, as previously discussed, there is the network created through social capital, in which people collaborate (i.e., network connections are created and fostered by individuals in practice). Here, people know each other and use their connections strategically. However, as discussed regarding symbolic boundaries and categorization, there is a second network of symbolic relations. Symbolic networks are socially constructed networks, consisting of symbolic connections between actors but created by someone other than the actor for the purpose of evaluating and assessing an actor’s field position. This definition differs from previous work, which uses actual symbols in the creation of social networks (Ansell 1997). As such, it is more related to Jones’ (2010) definition of symbolic networks, which focuses on perceived similarities between actors in a specific field. However, I argue the emphasis on *perceived similarities* is myopic: networks may vary enormously in what are the shared basics of comparison<sup>1</sup>, artists can also be contrasted for

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<sup>1</sup> In categorization processes, a perceived similarity is required to categorize entities along the same lines (Lamont, 2012) indicating a symbolic network only exists with (at least some) consensus actors belong to the same grouping and therefore can be compared. As such, Jones’ (2010) emphasis on perceived similarities is important. Yet, I hypothesize a less specific focus on *similarities*, as these symbolic networks may also be broader than the field itself (e.g., Plato’s influence on the 1999 movie *The Matrix* is often used in its critical evaluation, demonstrating cross-field comparison).

example.

Making a distinction between symbolic and collaboration-based networks doesn't mean they completely differ. Bourdieu (1985) describes a homology between the social structure of a field and its governing symbolic rules. There is "*a close correspondence between the social topography and the cognitive structure of cultural fields, that is the mental maps actors have of social positions and their organizational and cultural correlates.*" (Anheier, Gerhards & Romo, 1995; pp.860-861). Giuffre (2001) empirically finds a match in both mental maps and social topography in the US photography field circa 1980s. Her work compares the network of social relations photographers cultivate with how these artists symbolically connect through critics' reviews. Giuffre offers three explanations: first, critics' perceptions of style are based on the artist's social relations. Second, mental maps might "force" artists to work together, where stylistic connections influence with whom photographers work and relate. Finally, external influences, such as political or economic considerations, may influence the formation of both network types.

### Exemplars

In this research, I analyse symbolic networks by focusing on the connections critics make when creating evaluative comparisons. Previous studies scrutinize the relation between symbolic boundaries and success by researching reputation and classification processes in which certain stylistic qualities are ascribed to artists (De Nooy, 1991; Hsu, 2006; Van Venrooij & Schmutz, 2010). Extending such research, this study follows earlier work by Braden (2009) and Jones (2010) by focusing on connections made in evaluation. As such, I research not *how* someone is known, nor *who* someone knows, but *with whom* someone is compared. Below I detail how such comparative connections may function in evaluative practices.

Comparison has long been understood as essential for creating evaluative judgment. To determine value, one usually uses an ideal example for comparison. Indeed, the word "canon" is from the Greek for "measuring stick", indicating those who are "canonized" serve as ideals for which all others are measured. Kant (2009 [1790]) already deals with the idea of understanding the particular in light of the universal—i.e., judging an object in comparison with an ideal "universality" or what the object ought to be. This universality is further theorized by Arendt (1982) as the exemplary function certain high-status ideas or objects accrue for cultural comparison and evaluation. When evaluating, Arendt argues, we compare the evaluated object with a perfect example abstractly created in our thoughts, which she terms *exemplars*. Exemplars function solely within a community that understands their associations: only through shared understanding can specific objects gain exemplary function (Arendt, 1982). This process is comparable to the earlier described processes of categorization (Lamont, 2012), in which we can conceive of the exemplar as a



tool to assess where someone or something is positioned on a certain scale. Dekker (2015) understands the concept of “exemplary validity” as an indispensable tool for assessing the qualities of specific goods, such as the arts, where objective criteria are ambiguous (see also Karpik, 2010). Particularly for uncertain determinations, exemplars emerge as benchmarks for comparisons (Zuckerman, 1999; Dekker 2015).

Exemplars for symbolic networks only successfully function as a method of market coordination if understood by members of those markets (Dekker, 2015). Consequently, using an exemplar is not a random or unique occurrence. Rather, pre-existing, shared exemplars are used to describe an evaluative framework. The use of exemplars indicates an attempt to evaluate an object within larger conceptions of the field. Connections to exemplars, then, are the foundation of the *symbolic network*, with those exemplars repeatedly and broadly used in a central, strong network position. Altogether, it is useful to understand symbolic networks precisely as networks because of the relational nature of evaluation within a field.

Drawing on previous findings on *social* networks in fields of cultural production, the application of network theory to *symbolic* networks creates four points of connection that may impact artistic careers. First, *repeated* connections, i.e., recurrent connections to exemplars serve to classify an artist, reducing the cognitive effort required to freshly evaluate, and therefore strengthen and broaden the artist’s position in the field. Similarly, in previous work (Braden, Teekens, and Punt, forthcoming), I found repeated critical connections to older generations of painters greatly enhanced artistic reputation because connections with predecessors served to position an artist within art history.

Second, *diversity* in an actor’s symbolic network might also nurture his or her reputation as being wide-ranging. Giuffre (2001), in her study on *mental maps*, finds photographers evaluated through mixed symbolic classifications have greater chances of achieving “superstardom”, opposed to those evaluated among a restricted number of groups. Applying this to symbolic connections, comparisons to diverse others may indicate versatility, signalling a range of interpretation and appreciation, which can enhance reputation. As discussed earlier, there is also danger in too much diversity, resulting in exclusion from the *mental map*. Hsu (2006) describes this about movies spanning multiple genres:

*“When producers target multiple positions, they increase the total size of the market that they have the potential to appeal to and glean resources from. When producers bridge multiple positions, however, audiences have more difficulty interpreting their identities and become more likely to ignore producers. Moreover, audiences are likely to disapprove of the broad-*

*aiming producers who do gain their attention because of poor fit with their expectations and preferred tastes.” (p.444)*

Zuckerman (1999) uses the term “*categorical imperative*” to indicate the necessity of categorization for artistic reputation. Research on symbolic networks furthers the idea of categorical imperative by offering a mechanism for artistic classification, not by researching classification via genres or conventions, but rather by examining who symbolically bridges mental gaps in a field’s understanding and history.

Third, *symbolic connections* are directed. For example, “*with Interstellar, Christopher Nolan is following in the footsteps of Stanley Kubrick*”, clearly Nolan is the evaluation subject and Kubrick serves as exemplar on which Nolan is judged. Nolan is assessed and categorized, whereas Kubrick has achieved a position beyond, indicating “*canonization*”. Differentiating between these positions enables analysis of not only how symbolic connections frame newer artists, but also a nuanced understanding of consecration processes in action.

Finally, examining *symbolic networks* allows, at a network-level, greater understanding of the symbolic role extraneous actors play. Whereas previous analyses mainly focus on connections between a specific sample of artists, a symbolic network lends itself to illustrating how many others also play a supporting role in evaluation. Moreover, networks allow for cross-field examples; how important would, for instance, Shakespeare be in the evaluation of Hollywood movies? Such connections signify issues of legitimacy for both specific actors, as well as the field itself—particularly when exemplars are borrowed from other, more legitimate fields (DiMaggio, 1987).

## Collaborative networks

### Research setting

To examine the role of networks on artistic careers, I study actors in the Dutch film industry. Where film industries in general are characterized by collaborations in production (Caves, 2006), Ebbers and Wijnberg (2012) note how this project-based nature is even more present in the Dutch film industry, due to its relatively small size. Indeed, there are on average around 30 feature films released annually in the Netherlands, although recently the success of Dutch cinema is increasing (see Figure 1). As such, the Dutch film industry can be conceived as a peripheral niche-market in which connections play a large role in the realization of new films (Ebbers & Wijnberg, 2012). This small scale offers two advantages to answer this research question: first, the industry is strongly characterized by these project-based collaborations, and second, it allows me to analyse the complete image of artistic careers through this field.

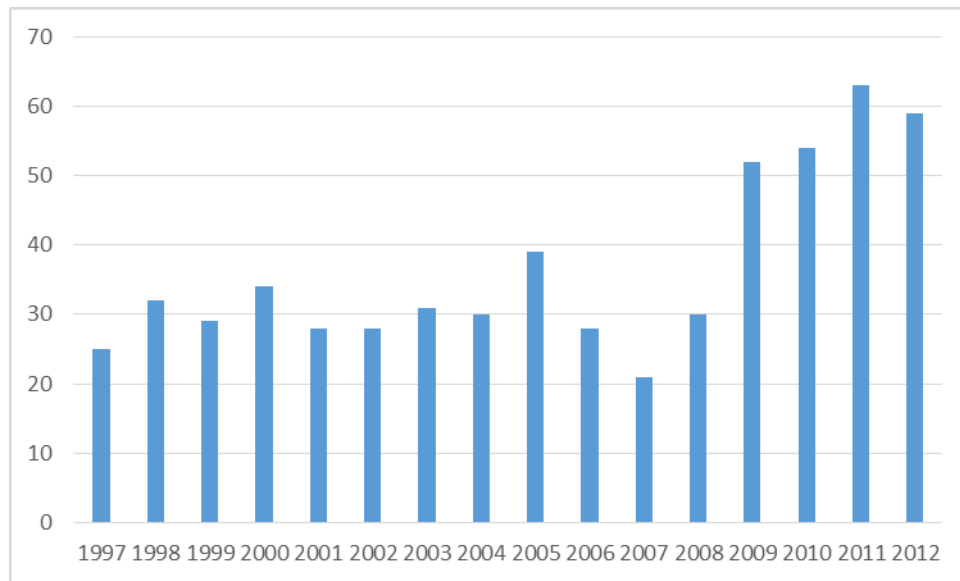


Figure 1 - Number of Dutch films and documentaries released annually<sup>2</sup>

## Data

I gathered data on Dutch movie production through the Internet Movie Database, a well-known public database containing information on practically all professionally-produced movies. IMDb gained popularity as data source among academic researchers, who benefit from the website open sourced offering of data (Rossman et al, 2010). As IMDb has a restricted policy on altering content, research finds IMDb provides valid and trustworthy information (Hsu, 2006; Lutter, 2015).

My sample of movies was constructed by indexing all the feature films<sup>3</sup> on IMDb that were listed as created in The Netherlands, contained some Dutch-spoken parts, and were released between 1997 and 2012. The two different conditions were necessary to exclude foreign films that Dutch production companies worked on, and to exclude any foreign film that included the Dutch language (the most frequent example being Belgian films). From this sample of movies (N=531), the title, release data and the entire list of acting cast was compiled, resulting in a sample of 6382 actors. For the analysis of artistic careers, I restricted the analysis to only those actors appearing in more than two films during the time frame, as the term artistic career implies temporal movement, which cannot be found if an actor only appeared in a movie once or twice. This decreases the number of analysed actors to 777.

I gathered information on the amount of cinema-visitors and box-office of this sample of movies in the Annual Reports of the Nederlandse Vereniging van Bioscoopexploitanten en Filmdistributeurs<sup>2</sup>. These periodicals also bracketed the boundaries of my sample: they start

<sup>2</sup> Based on annual reports data from: <http://film-bioscoopbranche.nl/periodicals/JRV>.

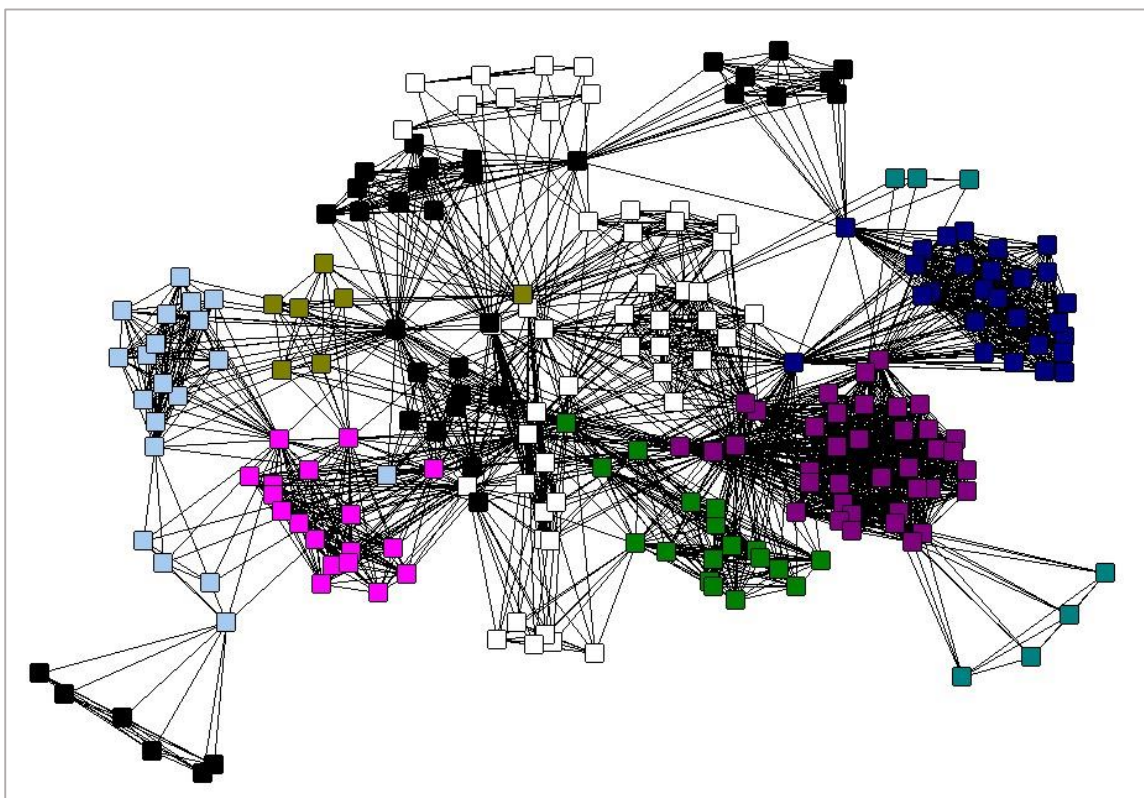
<sup>3</sup> Several categories, such as television series, video games and pornography were not included in the sample.

providing data on box-office for *all* released movies in 1997, and stop systematic presentation of data again in 2012.

### Methodology

Given the exploratory nature of this research and lack of prior work on the interaction of collaborative and symbolic networks, I offer no hypotheses. Rather, I follow Guiffre (1999) in quantitatively establishing ideal types from similar patterns or “sequences” of network connections in my research sample and then determining the career success of these different types.

Several analytical steps were taken to find out how careers, networks and success are related to each other. From the lists of actors who appeared in each movie, I created an artist-by-movie matrix, containing information on what actor appeared in what movie. These artist-by-movie matrices were transposed into an artist-by-artist matrix through network software Ucinet (Borgatti, Everett & Freeman, 2002). For each year, I created a network of actors, with ties between those actors who starred in a movie together, thus resulting in 16 different networks. Figure 2 illustrates an example of a yearly network. Colouring of the nodes signal to which cluster actors were assigned during analysis.



*Figure 2 – Yearly network of actors collaborating in Dutch movie productions, 2003.*

Following Guiffre (1999), I use block modelling and sequence analysis to longitudinally analyse the positions actors occupy in these networks. Block modelling is a method that allows the researcher to group actors together based on a shared number of connections to other actors in that network.

This method is based on the idea of structural equivalence, meaning two people have the same network position when tied to exactly the same persons (Lorrain & White, 1971). However, finding only such strict structural equivalence is not the main goal of block modelling; rather, it forces all users in a network into one of the blocks, leading to blocks with members more structurally equivalent to each other than to members of the other group.

To perform block modelling, I used the CONCOR method from Ucinet. This software divides networks (and subnetworks) in as many desired parts to find different levels of structural equivalence. To remain consistent in my block modelling procedures, I used the following rules—mostly concerned with density of the blocks—when fragmenting the networks: first, I divide the network in two parts, to subsequently slice both up in two smaller pieces. In most cases, the result were four blocks with similar density scores (between 0,2 and 0,6). Then, I also split these blocks, which oftentimes resulted in the emergence of one or two strongly interconnected cliques (with densities over 0,8), and/or a smaller sparser group (with a density below 0,5). To remain consistent, I didn't split the network of any year in more than 11 partitions. The following typology of blocks emerged:

- *A Blocks*: blocks within the centre of the network that consistently retain lower density scores (below 0,5) after double-partitioning.
- *B Blocks*: highly interconnected groups, with a (density scores > 0,75) within the centre of the network, indicating strong collaboration.
- *C Blocks*: groups at the outskirts the network, nevertheless connected to the main group. Density in these groups ranged between 0,4 and 1.
- *Z Blocks*: groups outside of the network. These are thus collaborations that occurred without any cooperation from anyone from the *main* (largest) network.
- *X Blocks*: actors not appearing in any movie in that year were assigned an *X* block score.

This block modelling analysis resulted in each actor having a specific score in a specific year – indicating which block (s)he belonged to. The result is thus a list of scores per year of actors' positions, enabling us to compare how the sequence of these network positions influence box-office success. The method of choice here is sequence analysis (Abbott, 2001). Sequence analysis is a method that incorporates time into statistical analysis; instead of only looking at certain variables as if they are static at a certain point in time, sequence analysis is interested in the fluidity of certain events. As such, it has proven a useful method in explaining careers, among other cultural events (Abbott & Tsay, 2000).

I use the TraMineR package in R for sequence analysis. This program performs both tasks necessary for sequence analysis: it can both create distance matrices, to calculate how different

each artist's sequence is from another's *and* cluster artists together based on these distance matrices. It thus provides a twofold method of distinguishing ideal types of sequences and forcing actors in groups based on these types.

To determine how dissimilar two sequences are, I use optimal matching analysis. This method calculates the difference of two sequences based on the steps—and the costs of those steps—needed to change one in the other. There are two kinds of operations the program can take: first, it can transform one event into another, and second, it can insert or delete an event into the chain. Each of these steps has a different cost, (i.e. changing an A into a B might “cost” 2 points, whereas deleting any event might only be 1 point), which enables the algorithm to calculate what the “cheapest” way is to transform one sequence into another. Previously, these costs were devised by the researcher (one of the more *random* parts of optimal matching (Abbott & Tsay, 2000)), but an alternative is proposed by Gabadinho et al. (2011), which uses the probability of a transition from one state into any other as the basis to automatically generate this transformation cost matrix. This matrix is then used to create a distance matrix: a symmetrical matrix with actors on both axes. The scores in the cells are the “costs” of changing the sequence of actor A into actor B, with higher scores indicating more dissimilar career sequences.

The final step is hierarchically clustering these distance networks, in order to cluster the more similar actors together. To do this, TraMineR uses the Ward method of hierarchical clustering. From this clustering, five “overall” types of sequences were retrieved. Cluster 1 contains the longest and most consistent of careers, with members appearing most frequently in A and B blocks. Cluster 2 is characterized by longer careers that are mostly in C-blocks, indicating actors in this cluster mostly operate at the periphery of the world of movie production. Clusters 3 and 4 both feature more sporadic careers, with actors appearing in both A and B blocks – theoretically these sequences are similar, but the algorithm distinguished them, based on the start of their careers. Actors in these cluster have not been able to consistently tie together with others blocks, but do manage to keep making a number of movies. Cluster 5 encompasses the most inconsistent of all careers: here, we find a more scattered group of sequences, that have in common nothing but their variation.

## Results

To find out to what extent these different artistic careers achieve different forms of success, I have a measurement of the economic success of different artists. As information on personal and professional salaries are almost impossible to acquire, I use box office success of the movies one plays in as a proxy of short-term success. As such, this measurement shouldn't be seen as the amount of money an actors individually has earned, but rather as an indicator of what (s)he's worth.

Table 1 shows the results of an ANOVA-test, comparing the group means of actors in the five different clusters.

Table 1. Results of ANOVA analysis, comparing the group means of box-office success for the five different clusters.

Cluster	Group means of box-office success (€ x1.000)	Std. Deviation	N
1	10.283	8.231	214
2	4.971	5.293	101
3	4.569	4.283	132
4	5.868	6.738	184
5	3.246	3.713	146

F=34,566

Significance=.000

df=776

This comparison shows there is a significant difference between the five group means. In other words, we find significant differences in short-term success for actors with different career trajectories.

The Scheffe test (Table 2) compares the differences between the groups. Here, it becomes clear members from cluster 1 consistently score higher than all other groups. Maybe unsurprisingly, the artists that have the longest and most consistent careers in block A and B positions are the most successful, with group means of this cluster being almost twice or even three times higher than those of the other groups. Furthermore, significant differences are present between clusters 4 with cluster 5. We thus find that actors with more sporadic careers, that do once in a while appear in the A and B blocks, are generally more successful than the more “random” careers. This can be interpreted as a result of cultural classification: individuals that follow a more generic career path will have more success than those that do not fall into a specific category of a profession.

Table 2. Results of a Post Hoc Scheffé Test, comparing group means of box-office success of five clusters of actors<sup>4</sup>.

Cluster (I)	Cluster (J)	Mean differences (€ x 1.000) (I-J)	Sig.
1	2	5.312	***
	3	5.714	***
	4	4.415	***
	5	7.036	***
2	1	-5.312	***
	3	402	
	4	-897	
	5	1.724	
3	1	-5.714	***
	2	-402	
	4	-1.299	
	5	1.323	
4	1	-4.415	***
	2	897	
	3	1.299	
	5	2.622	**
5	1	-7.036	***
	2	-1.724	
	3	-1.323	
	4	-2.622	**

\*p<.05,\*\* p<.01,\*\*\*p<0.001

Maybe the most surprising finding of this F-test is that the differences between clusters 2 and 3-4, and between clusters 2 and 5 are not significant. Cluster 2, containing artists having somewhat steady careers in movies, albeit in the outskirts of the film networks, are not reaping the benefits of their more steady careers.

A final note on the results of this analysis is the finding that A and B blocks, which in Giuffrè's (1999) research proved to be of such different relevance for the career success of photographers, do not seem to have such differing impacts on artistic careers in the film world. One explanation for this might be found in the fact that the film world, by its nature, is a more collaborative environment than more individualistic fields as photography. Therefore, it can be explained that there isn't this individual penalty on working in too close groups, but rather that group collaborations are an essential part of making movies. My results do replicate Giuffrè's (1999) findings that careers have to become steady and have to anchor themselves in one of these A or B blocks. However, these

<sup>4</sup> An OLS regression analysis using the clusters as dummy variables, including the number of films an actor appeared in as a control variable provides the same results. For reasons of space, these tables aren't included in this paper. (For Master's Thesis, it is appended).



results indicate a conception of these networks as a core-periphery model (Cattani & Ferriani, 2008), in which careers remaining at the periphery of the network are less successful.

## Mapping symbolic networks

### Data and Methodology

In the first component, this research focuses on collaborative networks, providing five distinct career sequences in the Dutch movie industry. Three distinct career types were distilled, which can be described as the long-term central career, long-term peripheral career and a sporadic career. In the following, I explore how these different career types may entail differing *symbolic networks*. By using a case study from each career type, I inductively identify dimensions on which these networks differ. Table 3 provides an overview of the three selected cases, their career type, and career trajectory.

Table 3. Case study sequences and descriptives

Name	Type	Sequence	Number of reviews in sample
Bas Keijzer	1	A A X B B A B A C A	50
Juliette van Ardenne	2	C C C X B X C C	28
Lies Visschedijk	3	B X B X X A B	39

To map the symbolic networks present in discourse surrounding an actor’s career, I use two methods of sampling film reviews. First, I collected three general film reviews (one each from the *Volkscrant*, *NRC* and *Het Parool*<sup>5</sup>) for every movie in which my case study actor appeared. In this way, I created a general framework of their critical evaluation. Thereafter, I used a search query to retrieve all articles containing the actor’s name during 1997 to 2012, which were published in Dutch news outlets. From these, all articles mentioning one of the films in relation to the actor were also included in the sample. Overall, I created three databases of critical reviews for the actors.

All reviews were coded manually as follows: all *entities* mentioned in the texts (in semantic analysis, “entities” describes objects, as opposed to other words (Fairclough, 2003)) are listed, including a code of their nature (i.e., an actor, film, etc.), and connections to other entities. Additionally, sentences mentioning entities are included. Coding resulted in two different lists: one list of entities (nodes in the network) and their nature; and an *edge list* containing the connections between these entities and the strength of the connection. Together, these lists form the basis of the different networks depicted in Figures 3-5. Nodes are coloured to indicate the category they belong in.

<sup>5</sup>Following sampling techniques used by Berkers, Janssen & Verboord (2013) and Kersten (2014) for film reviews in Dutch quality newspapers.

## Results

### Juliette van Ardenne—Type 2

Actress Juliette van Ardenne was selected as case study for the long-term, but peripheral career trajectory. Her career is a perfect example of this type, as she consistently plays in movies aimed specifically at Dutch children, most notably the series of films titled *Zoop!*. Although children's movies are quite successful for Dutch box-office terms (Kanzler, 2014), the actress still hasn't found entry into the centre of the network.

Van Ardenne's symbolic network is depicted in Figure 3. The network basically exists out of 4 components (Director Paul Verhoeven functioning as a symbolic bridge between two further unconnected groups in the largest component), indicating a scattered symbolic network. Juliette van Ardenne's position is in the centre of the *Zoop!*-network, together with a number of co-actors. In this position, four media products (three *Zoop!*-movies and a series) strongly connect these actors and crew members together. She is embedded in a dense network surrounding these movies. Furthermore, she is connected to a network surrounding *New Kids Nitro*, although she isn't connected to anyone else but the movie itself. The other components of the network are thus movies the actress played in, but where she plays no role in the symbolic evaluation: her name isn't mentioned at all when reviewers write about these films.

Another more general finding about the symbolic evaluation of Dutch film that becomes clear in this network is the influence of Hollywood cinema. Van Ardenne herself compared to both Natalie Portman and Jennifer Connelly (albeit due to a self-expressed wish to follow in the footsteps of those actresses, and not necessarily an other-created connection). Furthermore, we find for example *The Big Lebowski*, Spielberg's *Indiana Jones*, and the series *The Sopranos*, and *The West Wing* functioning as nodes in the network. This indicates the researcher has to adopt a broader frame of analysis, for further analysis of symbolic networks, to indicate how transnational exemplars might affect the evaluation of an artist or product.

### Lies Visschedijk—Type 3

Lies Visschedijk's symbolic network (Figure 4) is different from the previous network in two main ways: first, it is wholly interconnected, with no components lying outside of the network. Second, the network is more dense than that of Van Ardenne. Lies Visschedijk, the case study for the shorter, sporadic career trajectory found in the sequence analysis, seemingly contradictory at first sight, is found in a more dense and embedded network. The logical explanation for this is that the actress isn't really contributing to the creation and sustenance of these networks, but rather is part of a network that will continue to exist without her.

Visschedijk's appearance in two very successful Dutch productions, *Alles is Liefde*, and *Gooische Vrouwen*, is the key reason for her position in this dense symbolic network. These two

movies featuring some of the most recognized names in Dutch film (e.g. Linda de Mol and Carice van Houten) are also evaluated by reviewers by their *star power*: the renowned cast is mentioned in practically all reviews. This indicates Lies Visschedijk, a name generally less recognized, might not benefit as much from these connections, but rather has to struggle among these names for acknowledgement. Any symbolic connection created in reviews thus has to be understood from a larger perspective: while for Visschedijk these connections to bigger names could be detrimental for long-term success, as it doesn't allow her to differentiate, in another instance such connections could be beneficial by ranking someone along these stars. This case shows that an essential part in understanding this interplay between symbolic connections and recognition thus firstly lies in the collaborative networks someone appears in, and that a connection only gains worth in comparison to the larger context of the surrounding symbolic network.

Principally, there are two basic types of comparison that appear in all these symbolic networks. First, we have the film product comparison that focuses on the contents of the movie: for instance, a review of the movie *Alles is Liefde* is titled: "*Love Actually meets Makkers Staakt Uw Wild Geraas*" [NRC, 2007]. In this review, the writer notes how the movie is a remake of *Love Actually*, but infused with elements of the classical Dutch Sinterklaas holiday movie. These connections are thus used to place the films contents into context. The other connection is personal in nature, and occurs for instance when a reviewer writes "... *Visschedijk, with her Elisabeth Taylor-like blue eyes is more attractive than...*" [De Pers, 2011]. Within personal connections I found two other main distinctions, namely between directors (and sometimes writers) and actors. In accordance with auteur theory (Sarris, 1962), directors play a central role in symbolic networks, as their works and oeuvres being compared to others in reviews. These case studies indicate that further exploration of different comparisons might be useful for understanding an artist's career, as it shows what the focus of evaluative frameworks is: is it the content, or the creators (and if so, which?) that produces our evaluation.

Figure 3 - Juliette van Ardenne's Symbolic Network

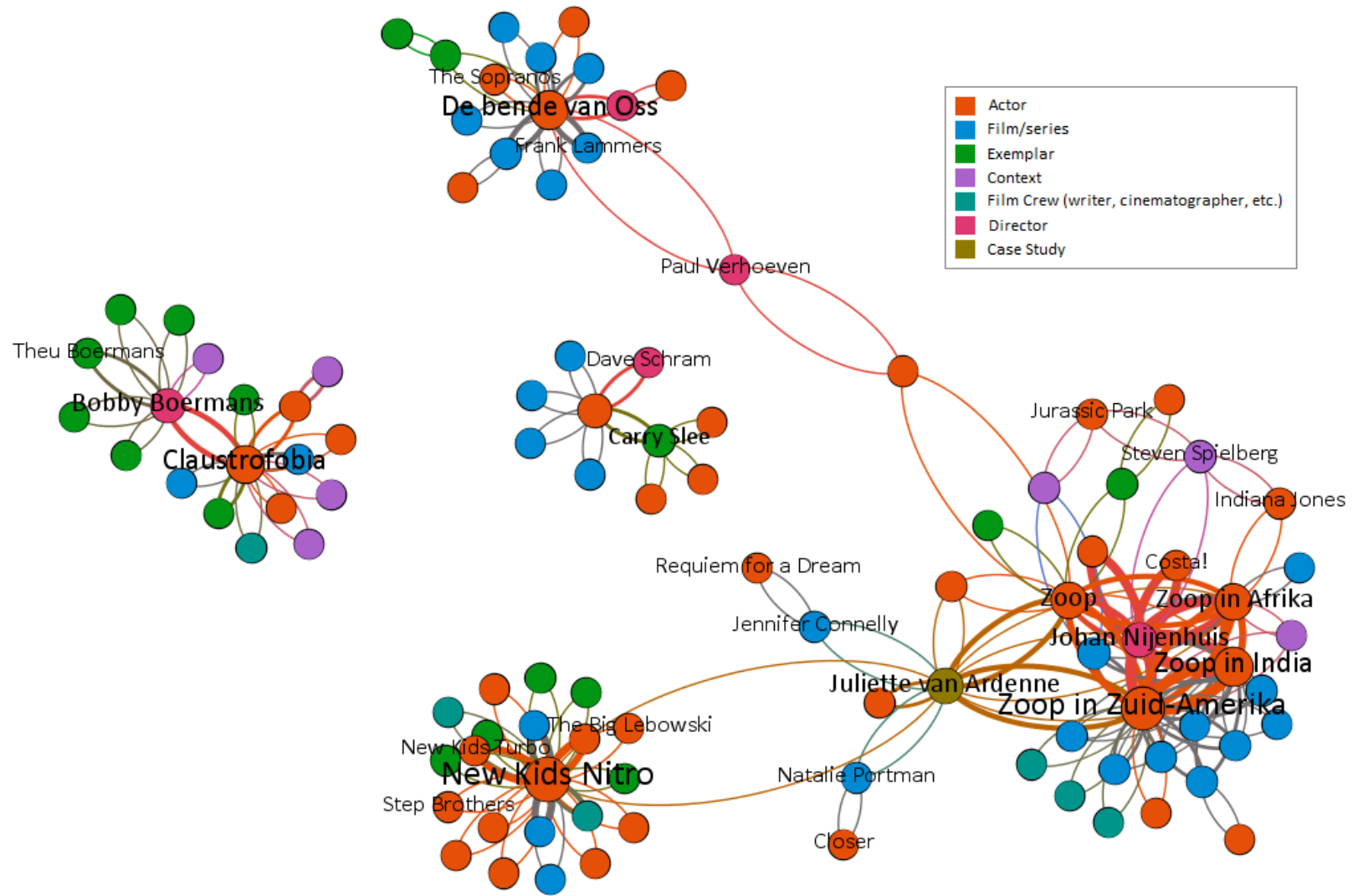
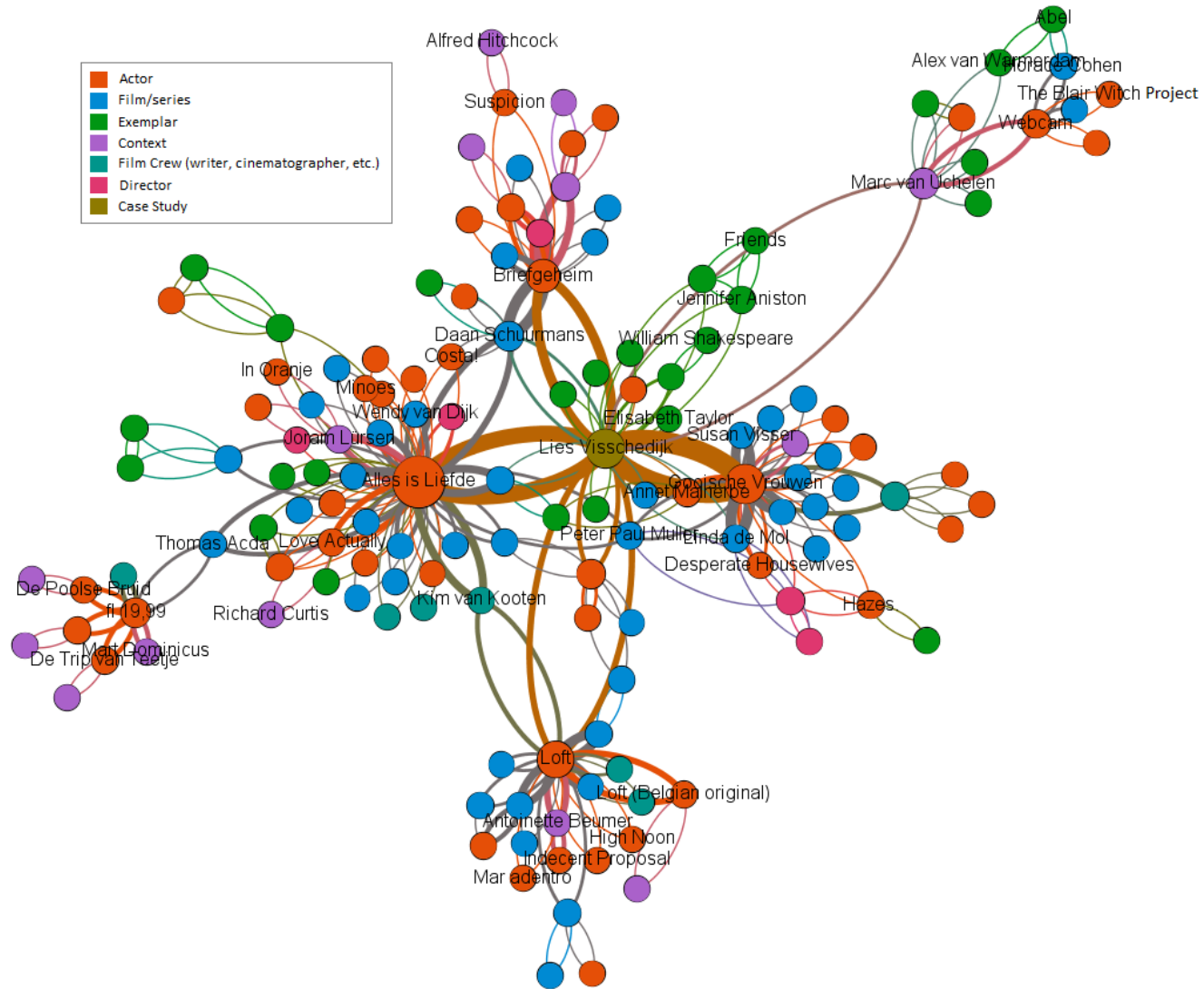


Figure 4 - Lies Visschedijk's Symbolic Network





### Bas Keijzer–Type 1

The last case study is the symbolic network of Bas Keijzer. As can be seen in Table 3, Keijzer's career belongs to the most successful type, consistently making appearances in both A- and B-block movies. Not surprisingly, the symbolic network (Figure 5) is also the largest network of my cases. Despite its overall size, the network is somewhat more fragmented than Visschedijk's: nodes are more scattered around instead of forming one cohesive whole. Apparently, the stability of Keijzer's career allows him to be part of different partitions of symbolic actors, without belonging to one specific sub-group.

An interesting finding in this network can be seen around the film *Black Out*. The symbolic network around this movie consists of *exemplars* more than any other movie in these three networks, as it is consistently compared to directors as Quentin Tarantino and Dick Maas, and to *The Godfather* and *The Sopranos*. As such, the evaluation of this film seems to be symbolically loaded with the use of *exemplars*. It is precisely for this film for which Keijzer eventually was nominated for a *Gouden Kalf*—the annual awards given by the Dutch Film Institute—perhaps indicating that symbolic networks indeed enlarge chances for more long-term recognition. By putting the movie in the perspective of film history, reviewers can thus add value to the perception of an actor's performance.

Keijzer's network features quite some actors external to the film world. Next to films, Keijzer has an extensive career in theatre, and his endeavours in theatre are used when reviewing his performance in film productions. More specifically, Keijzer's career as theatre actor seems to revolve around Russian playwright Checkov, and some movie reviewers mention this in their evaluations, perhaps to add some weight to the persona of Keijzer. Although theatre is the medium seemingly creeping into film evaluations most (we also find Shakespeare in Figure 4), literature also provides some connections (a movie's camerawork being compared to Ronald Giphart's writing style). Another external type of exemplar is the historical person: Dutch footballer Johan Crujff appears twice in the network, Madonna is mentioned once, as well as more obvious examples, i.e. when Willem Barentsz is mentioned in a review of a movie based on his life.

## Conclusion and discussion

By entering into collaborations, artists find themselves occupying a certain position in a field, consisting of a network of other actors with differing levels of success and status. This study shows an artist's career can be typified by the sequence of different positions within these networks, and different ideal types of trajectories have different rates of success. Mapping out the yearly networks of all Dutch film productions released between 1997 and 2012, this research analyses the career trajectories of 777 Dutch actors—all the actors appearing in these films more than twice.

Through block modelling (following Giuffre, 1999) I was able to distinguish different structural positions an actor could occupy in a year, ranging from a position in a densely interconnected clique in the middle of the network to a position outside of the network entirely. Each actor was assigned a network position for each year in the sample, with sequence analysis facilitating longitudinal analysis of career trajectories. Three theoretically differing sequences of artistic careers were found: the steady, long-term career in A- and B-block network positions, the long-term career in peripheral positions in the network, and the sporadic career, with infrequent appearances in A- and B-blocks. Unlike Giuffre (1999), who finds a strong distinction between artists occupying positions in the A and B blocks, my analysis doesn't point to significant differentiation between these blocks. Explanations for this may be sought in the fact the world of *film production* is more collaborative than that of *photography*; the penalty for close collaboration in less individual environments, such as film, will be smaller. These different career types have different levels of success: I find the first type of artistic careers is on average more successful, but the second and third type aren't significantly different from each other. For box-office success, I find long-term careers aren't necessarily more rewarded, in case they are in the outskirts of the networks.

The second part of this research mapped out the symbolic networks of three case studies: Bas Keijzer (career type 1), Lies Visschedijk (type 2), and Juliette van Ardenne (type 3). An analysis of film reviews offered a picture of the symbolic networks used to evaluate their performance. These case studies allowed me to explore the dimensions on which symbolic networks differ, and already indicate a glimpse of how the relationship with collaborative networks and success would appear.

First, I find several dimensions relating to the position of an actor in his/her own symbolic network. Three dimensions that have directly to do with the structure of a network and an artist's position herein are an artist's *centrality*, a network's *density*, and *fragmentation*. An actor's centrality deals with the number of connections one has, and to how many different persons one is connected. The *density* is related to *centrality*, but deals more with the overall structure of the network. Denser networks indicate a person's position in that network isn't unique and therefore exchangeable: how important is an actor in the sustaining of that specific network? In case you are exchangeable, this might have detrimental effects for remembrance in the long run. The *fragmentation* of a network is interesting as it indicates whether or not you have enough *symbolic* power or influence to bind the networks together. In the example of Juliette van Ardenne, the symbolic network consists of different unconnected components, indicating that she performs no function in the evaluation of those movies.

Furthermore, three other characteristics of symbolic networks are distinguished. First, symbolic networks are *multi-modal* in nature, meaning that both films, individuals, institutions and



concepts function in it. Any quantitative analysis of these networks has to allow for a differentiation between these modes and their functioning in the networks. Second, this exploration of symbolic networks shows symbolic connections aren't restricted to the field of film production itself: not only do actors perform in other media types, but other sources of media are also frequently used to evaluate films. The third uncovered dimension is *trans-nationality*. In reviews of Dutch films, exemplars from specifically American films are used frequently. To analyse one specific national sub-field of production, one thus has to understand how much it is influenced by other, dominant fields, such as the world of Hollywood.

The exploratory nature of especially the second part provides stepping stones for further research. As such, the goal of uncovering dimensions that are vital to understanding symbolic networks hopefully provides the basis for a further, more quantitative and large-scale analysis on effects of symbolic networks<sup>6</sup>. There are several questions this research doesn't answer yet, which leaves room for discussion. For instance, how do these artistic careers and symbolic networks affect different forms of success? In this article, success is only defined by box-office scores (although results are—logically—similar for number of visitors), without leaving room for more long term recognition, for which symbolic networks might be of even greater importance. Moreover, I haven't created a formal overview of how collaborative networks and symbolic networks influence one another, apart from the finding that not all actors and directors appear in all symbolic networks. Also, the symbolic networks presented here are aggregations of reviews appearing during the course of several years, whereas they change over time. This article thus is only the beginning of uncovering the significance of symbolic networks in our understanding of the evaluation of artists.

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<sup>6</sup> Currently, I am working on creating a PhD-project with precisely this goal in mind. After a application for a NWO Humanities grant, I am currently applying for a project at the University of Amsterdam which will try to develop a quantitative and longitudinal method of analysing symbolic networks.

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## Master Thesis Appendix A.

Table I. OLS Regression analysis

	B	Std. Error	Beta	
Constant	-889.088	502.096		
Number of film appearances	1.103.805	64.769	0,590	***
<i>Career cluster~</i>				
Type 1	1.304.654	661.929	0,086	*
Type 2	-653.769	701.418	-0,033	
Type 3	407.414	640.161	0,023	
Type 4	1.101.923	589.454	0,133	***
R <sup>2</sup>		0,384		

\* $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .001$

~ Scores are in comparison to the dummy variable Type 5

This regression table shows that actors part of cluster 1 are still significantly more successful than members of other clusters, even when controlling for the number of film appearances (which logically is higher for actors who enjoy a longer and more steady career than others—the correlation isn't so high that the OLS regression gives false results, though). A surprising finding here is that actors from career type 4 have significantly higher success rates than group 5, when controlling for the number of films an actor appears in: the comparison of means in the Scheffe test was insignificant. For the research article, I prefer the F-test and Post Hoc Scheffe test, as they provide more information on the comparison between groups.