DATA-PRODUCTS: CREATING, COMPOUNDING, AND AMPLIFYING NETWORK EFFECTS FROM CODE & A.I.

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Abstract

We are currently witnessing an unprecedented era of rapid and unparalleled company growth, driven by the exploitation of virtual spaces and network externalities, often without relying on proprietary networks. Organizations increasingly leverage software artifacts to create and amplify network effects, harnessing these externalities to a remarkable extent. Despite these advancements, there is a significant gap in our understanding and the absence of useful models to explain, harness, and optimize these phenomena. Such a model should facilitate continuous experimentation and enhancement while providing a strategic framework for exploiting network effects competitively.

This paper seeks to address these gaps by offering a clear differentiation between network externalities and network effects. It introduces the concept of *data-products* as software artifacts designed to activate network externalities and enhance network effects. Additionally, it distinguishes between network-agnostic and network-specific augmentations and proposes a graphical language for the strategic design of network effects. This comprehensive approach aims to provide a robust framework for understanding and strategically utilizing network effects in the competitive landscape.

1. INTRODUCTION

Network externalities, characterized by the latent capacity of a network to create economies of scale and in which demand-side economies of scale and scope become highly relevant, have generated significant attention in strategy, innovation management, information systems, and economics. This interest stems from their potential to generate what some see as exponential growth (Cusumano, 2022; Stummer et al. 2018). This growth is driven by the increasing value perceived by users as their number rises (Church & Gandal, 1992; Farrell & Saloner, 1985, 1986; Katz & Shapiro, 1985, 1986, 1992; Sheremata, 2004; Suarez, 2005).

The actual enabling of these externalities by artifacts resulting in network effects have been studied from many angles, particularly since the advent of platforms (Afuah, 2013; Van Alstyne, Parker, & Choudary, 2016); for example, their nature and consequences for user value (Cennamo & Santalo, 2013; Eisenmann, Parker, & Van Alstyne, 2011; Gawer, 2009; Majumdar & Venkataraman, 1998; McIntyre & Srinivasan, 2017; McIntyre, et al., 2021; Parker & Van Alstyne, 2005; Priem, Butler, & Li, 2013; Rochet & Tirole, 2003); the different types of network effects (Clements, 2004; McIntyre & Srinivasan, 2017), including data network effects (Gregory, Henfridson, Kaganer & Kyriakou, 2019); their effect on complements (Boudreau, 2012; Church, Gandal, Krause, & Canada, 2008; Clements & Ohashi, 2005); and the role artificial intelligence (AI) might play in data network effects (Gregory, et al., 2019). In sum, extant research has explored the subject and its impact from many perspectives.

Karhu, Heiskala, Ritala and Thomas (2024) draw a distinction between *network externalities*, which are considered exogenous to the context, and *network effects*, which are the result of strategic moves by firms to exploit externalities that happen to exist. Little attention has been devoted, however, to how or if network effects can be generated, enhanced, and compounded, possibly with software and increasingly AI in this process. This gap in understanding extends to the prerequisites for network effects to arise, including the necessity—or lack thereof—of a pre-existing community to catalyze such dynamics.

Addressing these inquiries is crucial for deepening our comprehension of growth dynamics at a granular level and illuminating aspects of competitive strategy, including the employment / exploitation of network effects to achieve market dominance. In a period marked by significant strides in generative AI, it is especially critical to explore how growth can be generated and stimulated solely through data and algorithms. This has substantial implications for not only facilitating but also driving value creation and capture. Network effects stem from social interactions, nowadays often created, moderated and enhanced by software, the mechanics of which have been insufficiently scrutinized; yet they are fundamental to the success of leading players such as Meta, Google, Amazon, or X, as well as emergent ones such as OpenAI.

The purpose of this paper is twofold. First, it delves into the mechanisms through which network effects are generated and amplified, framing them as a socio-technical construct synthesized through code and artificial intelligence. It introduces the concept of *data-products*, defined as software artifacts that can transform network externalities into network effects, thereby facilitating growth and value capture. Central to this work is the notion that network effects need to be enabled by artificial artifacts—*data-products*—and that these artifacts must be designed in ways that maximize network effects. An in-depth understanding of this underlying transformative mechanism is pivotal to this research. Subsequently, this research explores the influence and necessity of community engagement in the amplification of network effects as well as their diminishing effects as distance increases, as well as how data-products can mitigate this reduction. We propose an expanded classification of network effects, incorporating two novel types: augmentation effects and reputational effects, each manifesting in both direct and indirect forms. We contend that data-products act as essential components that endow platforms and products with network effects, which in turn could act as conduits for exponential growth.

By distilling these insights, this paper aims to contribute to a better understanding of how network effects are instantiated and enabled by data-products. It examines how current advances in AI allow new categories of network effects to appear, and offers a strategic framework for organizations to harness, align, and direct these multiplicative effects across diverse stakeholders, thereby collapsing network distance and even capitalizing on the networks of others. Ultimately, this paper examines a unique genre of growth—one propelled by a highly connected society capable of generating intelligent artifacts, where the boundaries between virtual and real have progressively faded.

2. CONCEPTUAL BACKGROUND

Prior to unveiling the proposed model, we provide an overview of the pertinent background concerning digitalization, artificial intelligence, and network effects. This foundational knowledge is essential to establish the causal relationships and arguments embedded within the model.

2.1 Digitalization and Artificial Intelligence

The impact of digital technologies revolves around the translation, total or partial, of capital for labor. This translation transforms the entire process (Zuboff, 1998), producing both organizational and societal impacts with feedback loops (Almirall, 2019). This translation can go beyond the task itself with impacts beyond productivity, such as when coordination tasks are translated into code (Bresnahan, 1997; Gurbaxani and Whang, 1991; Malone et al., 1989), transforming social dynamics.

While automation—substituting human tasks with programmed algorithms—has drawn significant attention due to its potential impact on jobs (Frey & Osborne, 2017), digital augmentation (Raisch & Krakowski, 2020) also plays a critical role by enhancing human capabilities, boosting productivity and efficiency (Agrawal, Gans & Goldfarb, 2018; Barro & Davenport, 2019; Daugherty & Wilson, 2018).

Determining the viability of automating or augmenting tasks hinges on the concept of the technological frontier, which is the threshold at which technologies meet performance expectations. Dell'Acqua et al. (2023) demonstrate that the advantages of Large Language Models reverse when pushed beyond their technological frontier. The frontier is influenced by both technological capabilities and societal task tolerance for error—our indifference towards irrelevant ads or recommendations exemplifies a high tolerance, thus positioning these experiences within the technological frontier.

Artificial Intelligence displaces this frontier even further, especially with the advent of the last wave of generative AI. Endowing digital artifacts with an increasing capacity of performing actions labeled as "intelligent," we can not only create smarter products (Porter and Heppelmann, 2015) or augment human capacities by a higher multiplier, but also amplify human potential through technology in ways previously unimagined.

To fully grasp this phenomenon, it is necessary to understand its economic implications. Translating functions into code implies a significant reduction in marginal costs, often approaching zero as scalability increases. Coupled with the general trend of declining costs in information technology, this leads to increasing—or at least not decreasing—returns to scale over time, outcomes unattainable in the physical world. Cloud computing platforms such as AWS, Azure, and Google Cloud further enhance scalability to levels well beyond currently foreseeable demand. These economic traits not only drive the digitalization of current functions but also promote innovation by making previously impractical tasks viable and encouraging the development of new technologies that push the boundaries of digital capabilities and AI.

However, one facet that has been relatively overlooked is how digital transformation impacts tasks that automate or enhance social interactions. Such tasks share the economic benefits of digitalization but also have the unique ability to amplify social interactions and create new ones, generating social externalities, particularly network effects, which is the focal point of this paper.

2.2 Network Externalities and Network Effects

The concept of network effects, predicated on the notion of network externalities (Katz & Shapiro, 1985), is pivotal in understanding the value dynamics of products and services within a network. The foundational premise is that the utility a user derives from a product or service is contingent on the total number of users within that network. Thus, network externalities refer to the potential of a network to generate economies of scale due to its connectivity (Karhu, Ritala, & Thomas, 2024). However, the actual realization of these externalities depends on the existence of artifacts that enable them. One of the oldest examples of a platform is the telephone network, which, to summarize the analysis, "the telephone network is only valuable if many people you know are also connected to the network." While this basic observation is true, *it actually depends on the installed base having a physical telephone device*. Therefore, the value of a phone network also depends on the number of phones available, a physical artifact enabling connectivity. This value further increases with the existence of a phone directory—a data artifact—that provides visibility, thereby transforming network externalities into actual network effects.

Katz and Shapiro draw a distinction between direct and indirect network effects. Direct network effects occur when value increments are appreciated by the same cohort of users; this is evident in technologies that thrive on connectivity, such as telephone services, fax machines, and modern messaging apps such as WhatsApp. Here, a burgeoning user base directly translates to a broader spectrum of connectivity, thereby amplifying utility for each user.

In contrast, indirect network effects occur when an increase in "users" (or "complementors") enhances value for a different user group. This pattern was observable in the early iterations of the "Yellow Pages," where a multitude of advertisers attracted a substantial user base, thereby incrementing value for the advertisers. Similarly, in contemporary contexts, platforms such as Google harness indirect network effects, as a substantial user base attracts advertisers, who in turn increase the platform's value. Furthermore, indirect network effects can incentivize the addition of complementary products or services (Church & Gandal, 1992; Church et al., 2008; Katz & Shapiro, 1992; Rochet & Tirole, 2003, 2006; Schilling, 2002). This phenomenon is exemplified by the Microsoft Windows operating system and the proliferation of applications in the Apple App Store. In these instances, a significant number of users entice a variety of applications or apps, which enhances the platform's overall utility for users and developers alike.

The discussion around network effects has traditionally revolved around connectivity and the capacity to forge new connections, either connected directly or indirectly. However, the rise of digital platforms has introduced alternative mechanisms for capturing value from network interactions, leading to emergent types of network effects. The situation of "a computer in the middle of every transaction" (Varian, 2014, p.1), and in fact, of every interaction, opened new possibilities because data could be automatically gathered and processed by code, enjoying the economic characteristics of minimal and decreasing marginal costs, and what is perceived to be limitless scalability. This new paradigm has facilitated the emergence of data network effects, where an increase in users leads to improved functionalities and personalization, driven by enhanced data collection and analytics (Gregory, et al., 2019). Data network effects result in more functionality and better personalization as the number of users increases, thus the opportunity of data gathering and data learning increases together with other aspects (Cennamo & Santalo, 2013; Cennamo & Santaló, 2018; Himan, 2002; McIntyre & Srinivasan, 2017; Zhu & Iansiti, 2012; Zhu & Liu, 2018).

Afuah (2013) presaged these data network effects, going beyond network size and pointing at network structure and interaction feasibility as determinants. Uber is a prime example of this: having a large network of riders and drivers is not enough. To be feasible, a transaction requires both a rider and driver not only in close proximity to each other but also willing to accept the conditions. Under these lenses, data and learning effects become even more relevant, partially explaining why Uber extensively uses machine learning algorithms in its platform (Rosenblat, 2018). Gregory, et al. (2019) further explored data network effects with a model that highlights capabilities of the platform such as speed and accuracy of predictions together with data stewardship, platform legitimation, and user-centric design. However, the central question of how and if network effects of different types can be generated and enhanced is still unresolved.

In both the economics and platforms literatures, the terms *network externalities* and *network effects* have been viewed as interchangeable (Rietveld & Chsilling, 2021) with only subtle differentiation in the classification of direct and indirect reformulated as one-sided and two-sided market externalities in the platforms literature. Karhu et al. (2024) initiated a conversation to unpack the distinctions between these terms, something that we take up further next.

3. DATA-PRODUCTS GENERATING NETWORK EFFECTS

In this article, we underscore the importance of distinguishing between network effects and network externalities. As hinted at above, network externalities are described as outcomes stemming from the network's design and its potential capabilities, which can give rise to network effects when utilized effectively. Hence, a network that enhances connectivity, such as the telephone network or a widely used instant messaging service, possesses network externalities that are attributable to both its design features and its scale. The clearest instance of this is connectivity: a network that facilitates global user interconnectivity benefits from its size. Yet, for this potential to be realized, a facilitating “tool” must be employed, such as a traditional telephone device, which then defines the scope and magnitude of the resulting network effects. For instance, while a traditional telephone permits only one-on-one conversations, a contemporary video-conferencing application enables multi-person, broadcast, and group interactions, thus generating varying types of network effects within the same underlying network. Currently, this same pattern is replicated in platforms such as WhatsApp, Messenger, and broadly in various social networking services.

As mentioned above, network effects in the phone network cannot exist without the telephone device itself. The telephone and the phone network are the products that enable and create network effects. Similarly, the simplest network effect in a software platform is represented by a messaging service, such as WhatsApp. Again, in this case communication is enabled by a software product that creates a virtual “wall” and a message inbox for each user, together with a main page listing all users. In Twitter, we can find content message boxes, as in many other social networks. Like the telephone, these software products enable and create the network effects that power the growth of the platform, increasing its value for its users and third parties. These dynamics are not limited to social networks; to some extent, we can also witness these constructs in platforms such as Amazon, connecting buyers and sellers, enabling ratings and comments or even in services such as Google Maps or ChatGPT.

We define these software products enabling network effects as *data-products* because they are based on data produced by or gathered from users: messages in the case of WhatsApp, posts in the case of Twitter, Facebook, Instagram or TikTok, or comments and ratings in the case of Amazon. What changed in these new products is the nature of the artifact enabling connectivity. All these modern versions of the old-fashioned telephone are created with software that both utilizes user data and transmits user data.

The distinct nature of data-products confers upon them the characteristic advantages of software: notably, their marginal cost approaching zero, and their scalability only limited by the underlying Internet infrastructure.

This first iteration of data-products offered a “new” product to social network users: Web2.0 content, built on users’ own data and redirected to them via either an explicit feed—forwarded by users—or an implicit feed—the feed provided by the platform (Villarroel, 2008). However, we can also find data-products built around collected data instead of user data. Recommender systems (Resnick & Varian, 1997) are a prime example of this. Movilens built one of the first recommenders based on the expressed opinions and ratings of movie viewers. Nowadays, recommenders are widely used everywhere, from social networks to e-commerce, movie streaming platforms, and newspapers. The critical point to underscore is the intentional design and construction of these data-products, whether they serve the purpose of facilitating connections or attracting third parties, which are instrumental in generating and sustaining network effects.

This understanding implies that there is ample opportunity for innovation in the design of new data-products. These can be strategically designed, developed, refined, and combined to not only create and amplify network effects but also to synergize and multiply them, as we will explore below. Moreover, a multitude and diversity of data-products can co-exist in the same platform, providing a wide range of options, aggregating or even compounding their value. In fact, in almost any social platform, we can find a data-product enabling user generated content, another one suggesting content either from the user’s network, suggested to the user, or a combination of both, and another one feeding ads to users, and recently others augmenting user capabilities through generative AI. Thus, we see that data-products can be developed and tailored with the intention to produce network effects, adjusting them to maximize their effect in the platform.

The implications for management and design strategies are profound, suggesting that there is significant potential for competitive advantage through the thoughtful design and orchestration of network effects in the digital economy.

***Proposition 1a**. Network externalities are only materialized as network effects when enabled by artifacts such as data-products, purposely designed around data.*

***Proposition 1b**. The greater the functionalities enabled by data-products, the broader the network effects they realize.*

3.1 Surfacing and Creating Affordances

Organizations can design data-products to surface network externalities such as connectivity by allowing network users to connect to each other in various ways, depending on the functionalities embedded in the data-product. However, they can also design these data-products to enable new affordances that can take advantage of the existing network. One of these new affordances with which we are all familiar is user-content. By facilitating users' creation and publication of content in a variety of ways, these data-products also take advantage of the network with new affordances not directly endowed in its design. Tik-Tok, YouTube, X (Twitter) and Facebook exemplify platforms in which user-generated content is the primary vector of value, distributed in a variety of ways. An increase in the size of the network correlates to contributed content enhancing its value for the network as a whole. This is an example of an affordance created by the data-product beyond surfacing the ones latent in the network.

Enabling the generation and dissemination of content represents the most common novel affordance generating network effects. However, a myriad of others exist and warrant further investigation, such as the creation of user groups, events, and so forth. User groups in particular showcase the dynamics of two-sided or multi-sided network effects. For instance, third-party entities might offer exclusive discounts or integrate payment applications for these groups, as seen in platforms such as WeChat.

These new affordances, therefore, are not solely confined to enhancing the utility of the network through increased connectivity, but also through the creation of new forms of interaction and engagement. By examining them in more depth, we uncover the potential for software products to not just connect users, but to create new ecosystems of value that can be monetized and leveraged in diverse ways, suggesting a rich avenue for future research and application in the field of management and network economics.

> ***Proposition 2****. Data-products surface and generate affordances that catalyze increased network effects.*

3.3 Amplification of Network Effects

The concept of affordances created serves as a point of departure for discussing how data-products can be employed not only to *enable* but to *amplify* network effects. Take Instagram as an illustrative example. The platform primarily allows users to share images or videos as posts or "stories." Yet, the content on Instagram is not merely shared; it is augmented. A suite of filters, emojis, and editing tools empower users to elevate a mundane photo into something distinctive. This enhancement becomes almost a necessity, spurred by a competitive drive for artificial reputation, setting a new standard for content quality.

Photo enhancements are a ubiquitous method of augmenting network effects. However, this is just one of many tactics. For instance, the short video format and the advanced editing capabilities present on TikTok represent another layer of amplification. The amplification of network effects is not confined to content creation but extends to content delivery. Social platforms curate user feeds, promoting certain content over others, which can precipitate bursts of popularity for some content creators—this curation acts as another layer of amplification that can counteract the diminishing effect of user distance.

Thus, network effects are not merely enabled by technological artifacts, especially software artifacts such as data-products. They can be strategically designed and molded to enhance the data used to generate them, whether this data is user-contributed or collected from users. This enhancement bolsters their impact and the consequent utility to users, whether they belong to the same user group or a different one.

There exists, therefore, a significant managerial domain not only in the coordination, aggregation, and compounding of network effects, but also in their enhancement and amplification, particularly with AI becoming a common technology.

> ***Proposition 3***. *The more data-products are combined with A.I. and digital tools, the greater amplification of network effects will be realized.*

The following sections will delve into the intricacies of these dynamics, shedding light on the mechanics of the process.

3.4 Anatomy of a Data-Product

Data-Products constitute the technological backbone of platforms and social networks, catalyzing network effects in the process as discussed above. The first iteration of data-products presented a novel offering to social network users, user generated content disseminated through their networks via both explicit and implicit feeds. However, data-products may also be constructed around data gathered from user interactions as in the case of recommendations or some kind of social reputation.

As a thought experiment, consider a simple example of how these network effects work. The same piece of content that we all create in a social network perhaps has little value in and of itself, but its value increases with the number of users that see and like it. Therefore, the more users in the network, the greater the potential value of user-generated content packaged and distributed as a data-product that acts as an enabler. The value for a user of a network is therefore related to the size of the network (this will be a traditional direct network externality), but also to the number of pieces of content generated by users of this network, which is also but not exclusively related to the number of users. The new addition that data-products bring is that they are artifacts created with code. Therefore, new network effects can be created by building new data-products, delivering actual growth.

But this is merely the surface layer. Data-Products that harness network effects to transform value and drive growth, capturing users' attention and aspirations, tap into their fullest potential. To precisely grasp data-products and their capabilities, we must dissect their components. We suggest that data-products consist of five core elements:

1) **Data gathering (input)**. The foundation of data-products is data, serving as the primary resource. This data can be user-generated, gathered, or constructed based on reputational elements such as "likes."
2) **Amplification**. The simplest form of data amplification are filters such as the ones Instagram, movie effects, music and editing tools. But data amplification also refers to prediction when a data-product uses a recommender or generation in the case of generative AI.
3) **Generated Data feed (output).** This concerns the delivery mechanism, which involves predicting user preferences, whether favorable or unfavorable, thereby providing relevant content that extends well beyond the user's network, mitigating the diminishing effect of distance in network effects.
4) **User data feed (output)**. Users can also explicitly consume the data-product through subscriptions, discovery mechanisms, or forwarding the output explicitly. In this form users explicitly generate network effects.
5) **Data & learning loops**. Data-products can be endowed with data-loops aimed at extracting insights and learning, producing better predictions.

Not all incarnations of data-products necessarily embody all five components, yet many—especially those that are more advanced or employed in mature applications—do integrate several of these elements. Additionally, data products are often compound such as in the case of posts and the associated comments. Let us now examine each of these components in detail.

Data gathering (input)

Data serves as the cornerstone of data-products. It can be actively supplied or generated by users, with user-created content being the most evident form of such data. The rise of new-generation social networks like TikTok or Twitch has introduced novel types of user-generated content, including videos and dynamic comment feeds. The underlying concept remains consistent: users generate data, shaping it purposefully for consumption by others.

Data can also be implicit, collected from user interactions. This was the case of recommender systems, that collected first from explicit feedback of users (Netflix or Movilens) but lately turned to implicit feedback (e.g. movies that we watch, particularly the ones that we watch for a significant amount of time). Social networks leverage this kind of implicit feedback, including likes or the links users click on, to craft complex user profiles that inform and refine the data feed. This dual nature of data collection, both explicit and implicit, forms the backbone of data-products, enabling them to become more sophisticated and personalized as they evolve.

Amplification

Data-Products incorporate a digital component that either modifies or enriches the data in the case of user-generated data, or introduces a new feature such as a payment system or a prediction based on A.I.. For instance, our photographs were engaging prior to the advent of Instagram, but the introduction of Instagram's filters elevated them to a new level of appeal. Videos were entertaining before TikTok, but TikTok's editing capabilities have made them significantly more engaging, capturing the attention of a vast user base. These instances illustrate how software and increasingly A.I. can enhance data—in this case, content—in a manner that amplifies its impact and, consequently, its value to users and network effects.

Not all enhancements brought about by amplification elements are overt. At times, they may be understated or arise from imposing certain limitations. X (Twitter), for instance, by initially restricting posts to 140 characters, necessitated brevity and clarity in communication.

The amplification is not confined to the alteration of existing content; it can also serve as a catalyst for new content creation. The introduction of "stories," ephemeral short videos, necessitated the creation of content tailored to this transient medium of communication. More traditional functions align with this trend as well, such as payment services like WeChat Pay or mini-programs that facilitate the splitting of bills. The potential for data transformation is dependent on the capabilities of the technology, highly enhanced with the new wave of generative A.I. and contingent upon the digital context. The more digitalized the context, the broader the scope for creating data-products. At the far end of the spectrum lies the Metaverse, where, within the digital realms constructed by platforms, the possibilities for what can be achieved are nearly boundless.

Generated Data Feed (output)

The mere creation of a digitally enhanced or triggered data-product is not sufficient to catalyze growth. It is the social aspect, particularly the capability of sharing these products that unleashes the network effects intrinsic to data-products. This sharing mechanism is especially evident in social networks, where content is disseminated to other users based on its perceived relevance. An A.I.-driven feed that adeptly channels digitally enhanced content to users who will value it sets off a domino effect of sharing. This not only magnifies the content's value in proportion to the network's size but also amplifies the network's overall value.

However, the act of sharing that underpins network effects can manifest in more nuanced ways beyond simple content distribution facilitating sharing with tools such as copying. Take, for example, functionality-based data-products like a bill-splitting feature. Such a product promotes network effects through its sharing capability but also by facilitating new user acquisitions eager to utilize this function, thereby extending its reach beyond the initial network. Consequently, the network may evolve into the default mode of settling payments.

Standardization emerges as a potent strategy for engendering lock-in effects—enhanced switching costs—which in turn, can secure market dominance. Data-products can initiate, drive, or facilitate this process, transforming the network's scale and its functional offerings into a competitive moat.

User Data Feed (output)

Data feeds can also be generated by the users of the network. This is the case of subscriptions (e.g., YouTube subscriptions, X (Twitter) and Instagram followers), content forwarded by users (e.g., Facebook) or direct discovery of content made by users while searching or navigating their own network. This user-driven model stands in contrast to algorithmically curated feeds that prioritize content relevance. Here, users are motivated not only to maximize their content's reach and foster community building but also to generate content that is of high quality and relevance, thereby increasing user engagement and network growth.

The potent generative capacity of these user-created feeds is evident on platforms like TikTok, YouTube, or Twitter. On these platforms, the feed is often correlated with reputational status and, in some cases, is tied to financial incentives. This link between the generative feed and tangible rewards further motivates users to produce content that resonates within their networks, perpetuating a cycle of creation, engagement, and amplification that is central to the growth and vibrancy of these digital ecosystems.

Data and Learning Loops

Data-Products possess the inherent capability to initiate and sustain data and learning loops, thus fostering a cycle of continuous improvement. A familiar manifestation of a data-product that activates such a loop is the solicitation of explicit feedback on content, typically through mechanisms like "likes", “forward” or "share." These interactions serve as tacit endorsements of content by the users, and the accumulation of these signals tailors the feed to enhance its relevance, thereby increasing the network's value for both current and potential users.

The generation of data and learning loops does not solely rely on explicit actions. Implicit user activities, such as watching YouTube videos, expanding tweets, viewing "stories," or simply conducting searches, can have analogous effects. Data and learning loops represent a symbiotic relationship: data availability is crucial for the learning process, and conversely, the application of new learnings—often in the form of refined algorithms—spurs the collection of fresh data. Without data, there is no learning, and without the application of new insights, data cannot evolve into its next iteration.

Summary of the Anatomy of a Data-Product

Figure 1 intends to diagrammatically depict the structure of a data-product, highlighting its various interrelated components. At the apex of the diagram, the Data-Product is named to identify its function within a social network—our example uses “posts” to represent a typical posting feature. Data-products can be interconnected and combined, forming more complex structures. An exemplar of such a compound data-product is “posts” integrated with their respective “comments,” illustrating how multiple elements can coalesce to form a more sophisticated system within the network architecture. This kind of schematic representation helps in understanding the multifaceted nature of data-products and their capacity for synergy in digital ecosystems.

***** Please insert Figures 1 and 2 about here *****

In Figure 2, a generic social network's implementation of posts is depicted, which serves as a foundational example of data-product integration. Within this compound data-product, the interconnection with the primary data-product—posts—is delineated. Notably, this compound structure, comprising both posts and comments, does not have an independent data feed, whether user-generated or otherwise, which means that only the primary data-product, the posts themselves, possess the "shareable" attribute. This framework underscores the adaptability of data-products within a social network, where various configurations beyond the prototypical model are conceivable and can be tailored to meet different network dynamics and user engagement strategies.

Proposition 4. *Data products harness network externalities with a deliberately modular structure. The better engineered and compounded, the stronger the generation and amplification of network effects.*

4. NETWORK EFFECTS REVISITED

Network effects, traditionally viewed in economics as equivalent to network externalities, have been foundational to our understanding of the value dynamics in networks and platforms. According to seminal work by Katz and Shapiro (1985, 1986, 1992) and Farrell and Saloner (1985), such effects occur when the utility of a product or service is dependent on the number of others using it.

Transposed into the realm of management, particularly in relation to platforms, these network effects are seen as a key driver of value—a value that escalates as the user base expands (Church & Gandal, 1992; Cusumano, Mylonadis, & Rosenbloom, 1992; Suarez, 2005). The modern interpretation of this concept, especially in the context of connectivity (Afuah, 2013; Van Alstyne, Parker & Choudary, 2016), posits that the addition of more users enhances the platform's worth by broadening the scope of interaction.

An additional categorization emerges concerning the nature of the network effects themselves. The increase in user numbers—and thus in content and interaction volume—carries implications that extend beyond mere connectivity. With the advent of AI and Big Data analytics, there is the potential to derive insights from this wealth of data, thereby refining models and enhancing their accuracy with increasing data volume (McAfee & Brynjolfsson, 2012; Varian, 2014). This shift from connectivity as the sole source of value underscores a new dimension of value creation: data-enabled learning. Gregory, et al. (2019) describe Data Network Effects as a phenomenon where more data does not simply enhance the learning but also facilitates more precise targeting of both users and content, affecting both direct and indirect network effects.

In this work we aim to present an alternative view in the line of thought of Karhu, Heiskala, Ritala and Thomas (2024) where network effects are purposely created by artifacts either exploiting network externalities or supporting and enhancing this exploitation. We refer to these artifacts as data-products in their digital form, but we must remember that they also do exist in physical form as telephones enabling the network externalities of a phone network or the yellow pages book enabling the network externalities of the affiliated network of vendors. However, in their digital form they take advantage of negligible marginal costs, high scalability and enabling technologies such as A.I., characteristics that enable network effects multipliers unseen before.

We present a topology of network effects based on five categories: connectivity, reputation, agglomeration, augmentation and data & learning effects and, three goals: network specific augmentation, network agnostic augmentation and fostering augmentation capabilities.

4.1 Exploiting Network Specific Externalities

Leveraging the inherent externalities of a specific network forms the simplest strategy to generate network effects. Through data-products that facilitate interactions among network participants, connectivity emerges as a fundamental and often highly valuable aspect—examples include communication platforms like WhatsApp, Messenger, and WeChat. Beyond communication, a multitude of avenues exist for creating network effects, encompassing diverse content forms like brief updates (Twitter), video sharing (YouTube), individual social profiles (Facebook), photographic content (Instagram), short video clips (TikTok), and professional networking (LinkedIn). Beyond content, a network can offer various functionalities such as employment opportunities, fan communities, group formations, gaming experiences, and even dating services. These services capitalize on a network's social ties and interactions in myriad ways, enhancing the network's value and dynamism. Nonetheless, the dimension of social interaction and connectivity is just one facet of social groups. The reputational aspects within social groups often translate into a power hierarchy that shapes their dynamics and interactions. These reputational elements, deliberately cultivated within the network, exploit network externalities, thereby inducing network effects that amplify both the network's worth for its users and its overall activity. Proxies for reputation are embedded in most platforms: Twitter's followers are seen as a measure of social importance often cited by the media, while on Facebook, Instagram, Tinder, Bumble, TikTok, and YouTube, the act of following, subscribing, or attracting "matches" serves a similar function.

This form of reputation accrues multiple advantages. Users with high reputational scores typically enjoy greater content visibility and the potential for their content to be "boosted" through likes and reposts. Moreover, some social networks financially compensate content creators, with potential earnings being substantial for those with large followings. The benefits extend beyond mere visibility, encompassing product placements, brand endorsements, appearances at social events, and other perks once exclusive to traditional celebrities.

These reputational mechanisms are intricately designed (Fogg 2003, 2009), and behavioral models like the "Hook" model (Eyal, 2014) exploit them to capture user attention. This model and its variants operate on four stages: a trigger, an action (like posting), a variable reward (likes or reposts), and an investment (time spent and reputation maintenance). Platforms often offer paid promotions to amplify these reputational elements while monetizing them.

As Afuah (2013) suggested, the value of reputational network effects scales with the size and activity level of the platform—the larger and more active it is, the more significant these effects become. They also play a role in anchoring users to the platform, attracting new ones, and stimulating activity, which in turn allows for better monetization and growth.

Visibility is a cornerstone of reputational dynamics. Reputation serves as a signal within society but is only effective when it's visible. Consequently, platforms meticulously curate the visibility of these elements, balancing the pursuit of popularity against the risk of quality compromise.

Reputational effects also manifest both as same-side and multi-sided. The same-side form is straightforward—the larger and more active the network, the more significant its reputation. However, these effects also appeal to a different group than the one that generates them, advertisers who target individuals with high reputational standing to enhance brand awareness.

Finally, agglomeration effects also exploit network externalities resulting in network effects. The concept is extensively examined within both economic and platform-based literature. Studies by Rosenthal and Strange (2020), Strange (2008), and Venables (2008) explore it from an economic viewpoint, while platform-focused discussions by Taeuscher and Rothe (2021), Cennamo (2018), and Cennamo, Ozalp, and Kretschmer (2018) consider the role of complementary actors known as 'complementors.' Agglomeration effects leverage the mechanism of preferential attraction, where the size and influence of a network are critical in drawing participants.

> ***Proposition 5****. Network specific externalities can be exploited by data-products generating network effects in three avenues, interaction, reputation and agglomeration, with each reinforcing the other to enhance the overall value and functionality of the network.*

4.2 Exploiting Network Agnostic Externalities

While leveraging a network's own externalities is common, network effects can also arise without a foundational network. This phenomenon was widely discussed in the case of the Wintel platform, which attracted consumers through an extensive array of software and hardware options, and with search engines, exemplified by the widespread usage of "Google it!" in place of the generic term 'search.' Similar cases are observed with Chrome or Android, and the recent surge in ChatGPT's popularity is a testament to such network effects.

Interestingly, these instances do not rely on an existing network. In many situations, they leverage external networks, as seen with OpenAI's ChatGPT, which benefited from users sharing their discoveries, applications, and novel uses across platforms like Twitter, Facebook, Instagram, and YouTube. This dynamic facilitated network effects for ChatGPT without the platform having a network of its own.

Instead of utilizing network-specific externalities, these cases capitalize on augmenting human capabilities in areas such as searching, processing, language, or image generation, which are network agnostic. They harness the power of other networks to spread and generate value, effectively utilizing the dissemination and generative capacities of external networks.

> ***Proposition 6****. the more significant the enhancement of human capacities provided by a data-product, the more potent the network effects it can foster. Furthermore, the relevance of these enhanced capabilities makes it easier for such products to leverage and benefit from other networks.*

4.3 A Taxonomy for Network effects and the Key Role of Augmentation

Thus far, our examination has centered on how data-products—artificial constructs—facilitate network effects through leveraging network externalities. A taxonomy outlining the five distinct categories of network effects that have been examined is provided in Table 1.

***** Please insert Table 1 about here *****

A detailed examination of these categories underscores that the conversion of network externalities into network effects is fundamentally a social process, underpinned by the creation and enhancement of affordances as well as the spread of information within and across various networks.

The genesis and intensification of new affordances are central to the network effects under discussion. This dynamic can broadly be interpreted as an augmentation process, one that extends human capabilities through, predominantly, digital tools. There is, however, a variance in the extent and focus of this augmentation. For categories such as connectivity, reputation, and agglomeration, the augmentation primarily takes place within the confines of a proprietary network. In contrast, when augmentation is a predominant feature, as observed with generative AI, it transcends these confines by utilizing pre-existing networks. The crucial distinction hinges on whether the affordances introduced by data-products are bespoke to the network's infrastructure or whether they are universal, applicable across any social structure.

This process is not binary but exists on a spectrum. For instance, we observe Twitter posts disseminated across LinkedIn, Facebook, Instagram, and even traditional media. Similarly, a universal tool like ChatGPT is now cultivating its network of complementors, including third-party GPT models and digital assistants, to amplify these synergistic effects.

***** Please insert Figure 3 about here *****

> ***Proposition** 7. The generation of network effects exploiting network externalities is a social process based on augmentation. The larger of this augmentation through the creation and amplification of affordances and their diffusion, the greater the magnitude of network effects.*

5. A STRATEGIC PERSPECTIVE ON NETWORK EFFECTS

In previous discussions, we have considered network effects as social externalities intricately woven by technological artifacts, which can be further enhanced through technological means. We have identified various categories of network effects, each catering to a spectrum of interests and creating value in the process.

Given the diverse array of network effects operating concurrently across multiple dimensions, it becomes imperative to adopt a strategic lens in understanding and leveraging these effects. This section aims to cultivate such a strategic viewpoint, presenting a graphical language to reflect about network effects and their implications.

We can find two predominant approaches in this strategic discourse: a static perspective, which determines the optimal combination of network effects for growth and engagement; and a dynamic perspective, which views network effects as competitive tools to establish and maintain market dominance. Both perspectives are critical in formulating how network effects can be harnessed and optimized for long-term strategic advantage. Therefore, to compete with network effects.

5.1 A Language for Network effects

Network effects hinge on the creation and amplification of interactions. Consequently, a language designed to express network effects needs the capacity to accurately portray these dynamics. A graphical language, with its visual expressiveness, is particularly well-suited for this task, surpassing other forms of representation.

We introduce a visual representation for network effects that has undergone several years of refinement and testing within an educational setting. This tool aids not only in mapping the interactions within existing platforms or ecosystems but also serves as a strategic device to contemplate their competitive positioning in relation to other platforms. For illustrative purposes, we will utilize a generic social networking platform, a type of tool with which we are all widely acquainted.

***** Please insert Figure 4 about here *****

The initial phase in modeling our hypothetical social networking platform involves delineating the distinct stakeholder groups present. In this scenario, we've identified three key groups: users (notated as 'users'), advertisers ('ads'), and game developers ('games').

After pinpointing these groups, we assign network effects intrinsic to the group itself rather than to specific interactions. Agglomeration and reputation effects, denoted by 'A' and 'R' respectively, can be described using a formula like +Em. A sign (positive '+' or negative '-') indicates the nature of the effect, with a negative sign possibly indicating a crowding-out effect. 'E' signifies the type of network effect, with 'A' for Agglomeration, 'R' for Reputation, 'C' for Connection, 'DL' for Data and Learning, and 'Ag' for Augmentation. 'm' signifies a multiplier, which can be an approximation or derived experimentally.

The subsequent step is mapping the network effects within and between these groups. Arrows annotated with brief descriptors (essentially labels for the data-products) visualize these connections. If a data-product facilitates same-side network effects—like a messaging feature for users—an arrow loops back to the originating group. These effects can also be positive or negative and are expressed using the same formulaic language.

Interactions between data-products, like posts and comments, are visualized with arrows that begin and end on the same element, indicating a reinforcing effect.

Cross-group interactions are depicted with arrows pointing from one group to another. For instance, a data-product that enables advertisers to micro-target users would be represented by an arrow pointing from 'ads' to 'users'. Such targeting can be symmetrical—as in game developers inviting users to play, with users reciprocating—or asymmetrical, like advertisers targeting users without direct reciprocation.

Finally, when depicting augmentation, an additional outward-pointing arrow is included, extending beyond the platform's boundary. This signifies that the augmentation's utility spans beyond the immediate network, relevant also in other networks.

This tool serves not only to represent and evaluate existing network effects and their interplay but also to theorize about potential effects and determine their prospective influence and cumulative impact. In the classroom, it has been extensively utilized as a strategic aid for devising and refining ideas on the optimal design, alignment, and compounding of network effects to maximize efficacy.

6. CONCLUSION

This research introduces a new perspective on network effects, describing how network externalities are materialized as network effects through a social process enabled but also expanded through technological artifacts. This perspective shifts the focus from the aftermath effects to the origin and dynamics of these phenomena. It identifies the technological artifact as the deliberate creator of targeted outcomes, which implies that technology holds the power to not only facilitate and magnify existing network effects but also to generate new ones as desired. As technological capabilities advance, so too does the potential to create and enhance network effects.

We delved into the social dynamics that underpin network effects, recognizing that data-products, when integrated within social dynamics, can significantly transform them by establishing new social proxies for reputation, by augmenting and amplifying human capacities for social interaction. Within this framework, we elaborated a taxonomy for network effects, directed to enhancing connectivity, establishing reputations, fostering agglomeration, augmenting human capacities, and supporting these new functionalities with data and learning effects. This taxonomy integrates as actors of network effects categories previously not taken into account such as the role of Influencers, YouTubers or TikTokers and the network effects resulting from augmentation and the resulting generativity exemplified by platforms like Google or ChatGPT.

We evolved this taxonomy into a model where augmentation is the driver of network effects situated in the social space in a continuum from specific networks to the utilization of the publicly available ones.

Furthermore, we proposed a strategic approach to understanding and leveraging network effects, acknowledging their variety and the opportunities they present for tailored, ad-hoc development. To that extent we provided a graphical language for depicting, analyzing and designing network effects and examined both a static strategic viewpoint, aimed at boosting efficiency and the multiplier effect of network effects, and a dynamic strategic perspective, which considers how to harness network effects competitively, recognizing the pursuit of attention as a finite resource resulting in a zero-sum game that can be played on scale or scope.

Throughout the paper, we show that network effects are social constructs synthesized by artificial products that have incorporated certain human and social functions. As technology progresses, enhancing our ability to augment social environments, network effects will also evolve augmenting our social capabilities. With the advent of generative A.I., we stand on the cusp of a bold new chapter in the evolution of network effects.

This work aims to catalyze further research inquiries, especially regarding the design and strategic alignment of network effects, as well as the competitive dynamics they engender. The implications for management and strategy in the context of network effects are profound and warrant extensive exploration to understand how organizations can navigate and influence these powerful social mechanisms.

In conclusion, the study of network effects, as deliberate social constructs powered by technological advancements, presents an expansive field for academic inquiry and practical application. It challenges us to reconsider how we engage with technology, each other, and the collective dynamics that shape our digital and social landscapes.

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TABLES

	Key element	Description	Effect	Mechanism
Connectivity	Connection	Harness social connection for interaction, content creation and distribution, visibility, groups, …	The larger the network the higher the potential for social connection and interaction and the higher the value for the same and other groups	**Exploits own network externalities** with functionalies and affordances that trigger network effects
Reputation	social reputation	Builds on and creates visibility and reputation in social groups	The larger the network the more relevant social reputation in this network and the value for the same and other groups	**Exploits own network externalities** with artificial reputational & visibility construcs (e.g. followers)
Agglomeration	preferential attraction	Builds on the preferential attraction to larger and more relevant social groups	The larger and more relevant a network and its complementors are the higher its capacity to attract members of the same/other group	**Exploits own network externalities.** Visibility of network size and influence are key
Data and Learning	Artificial Intelligence	Gathers data and with A.I. enables better predicitons that drive more data	The larger and significant the data gathered the better the predictions and the larger the value for the same and other groups	**Develops internal capabilities** through data and A.I.
Augmentation	augmentation	Increases human capacities with generative A.I., search or digital tools	The larger the increase and the more common, the higher the value and need to adopt it	**Exploits own and other network externalities** augmenting human capacities and triggering network effects

Table 1. Taxonomy of network effects

FIGURES

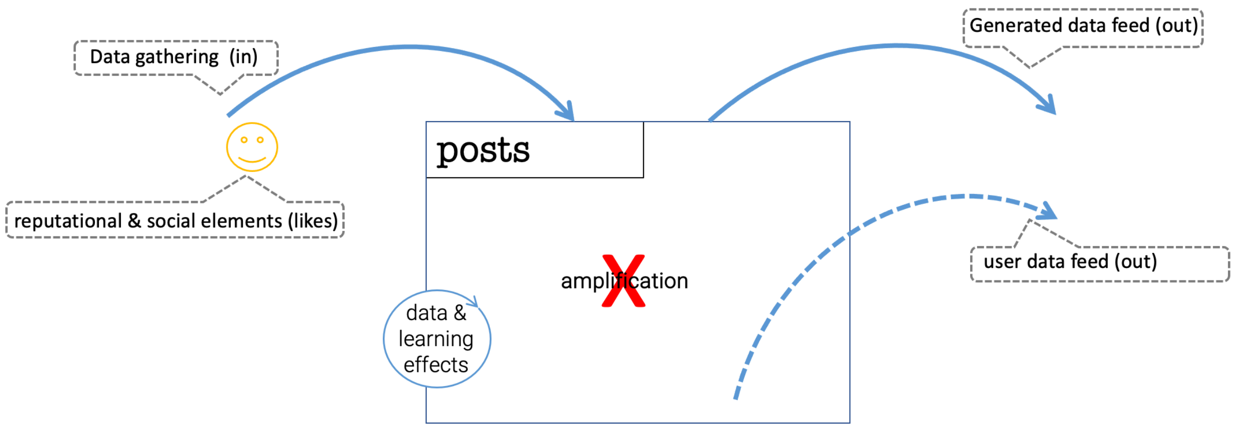

Figure 1. Anatomy of a data-product

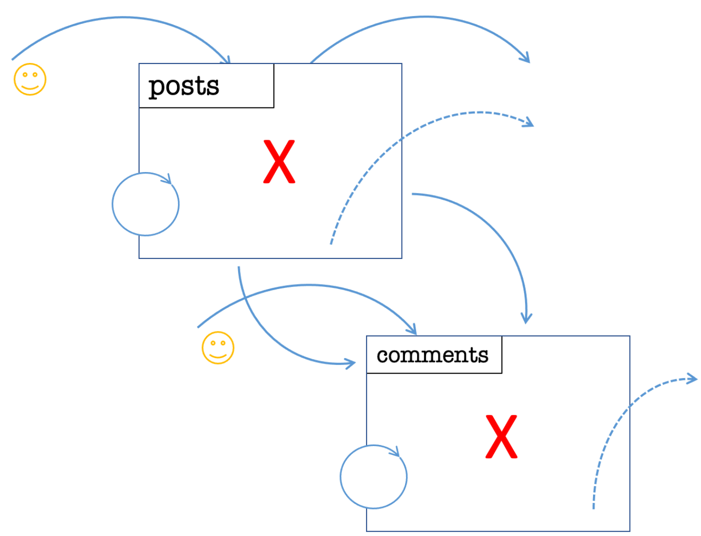

Figure 2. Compound data-product. Post with comments.

Figure 3. The key role of augmentation and diffusion.

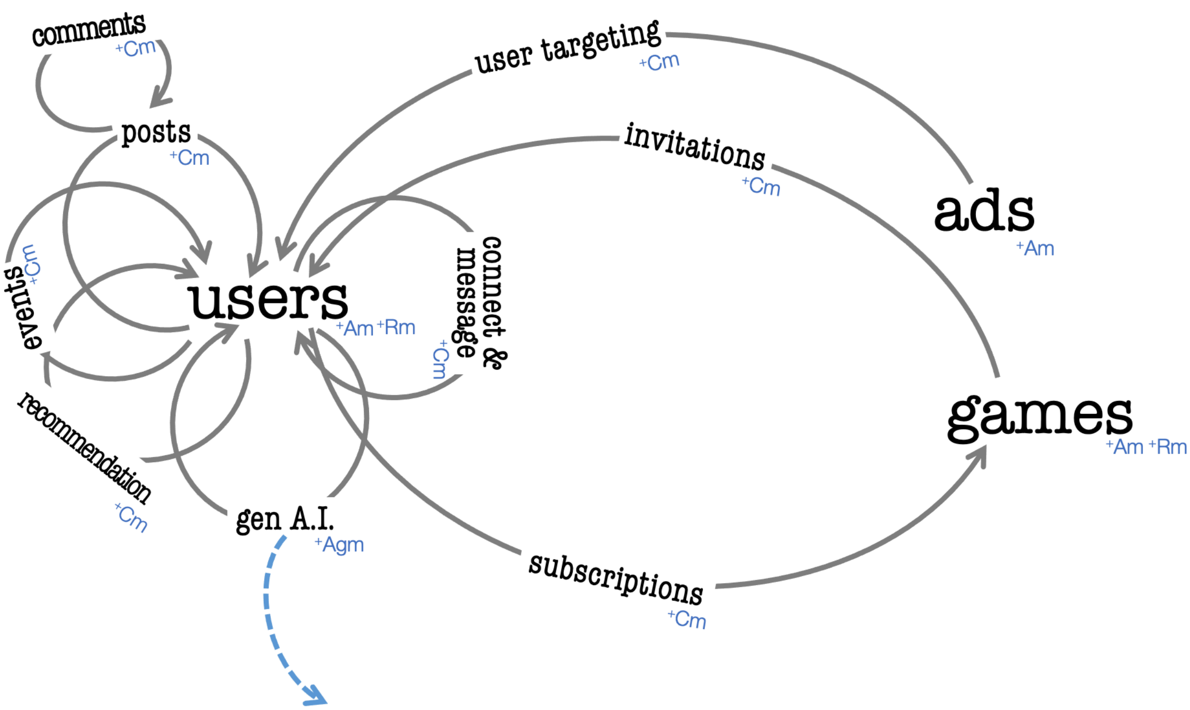

Figure 4. A language for network effect, social networking platform