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The Value of Data and Its Impact on Competition

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Abstract

Common regulatory perspective on the relationship between data, value, and competition in online platforms has increasingly centered on the volume of data accumulated by incumbent firms. This view posits the existence of "data network effects", where more data leads to product improvements, which in turn leads to additional users and more data. In particular, this has raised concerns around incumbent data advantage creating an insurmountable barrier to entry and leading to winner-take-all outcomes in online platforms.

However, this perspective generally does not reflect the value of data in practical settings. More recent work across economics, management science, and engineering shows that there are a variety of factors that impact the value of data and that implications for competition are much more complex and subtle. The framework in this paper presents four key factors – data quality, scale and scope of data, and data uniqueness – that can influence the value that firms can derive from data.

Applying the framework to Netflix, Waymo, and the online advertising industry provides compelling evidence that incumbent data advantage, while generating value for innovation and for the consumer experience, does not necessarily lock out competitors and is not determinative of success. These examples illustrate that data can often serve as a catalyst for innovation that benefits both consumers and the broader ecosystem. The extent to which data accumulation can provide actual incremental value, and whether this is a cause for concern in enabling healthy competition, requires a case-by-case evaluation using the framework, as these factors depend significantly on the domain and context.

I. Overview

Debate on competition policy in digital markets has increasingly focused on data as the centerpiece of arguments. A recent government-initiated investigation into possible changes to the UK's competition framework, for example, reported that accumulation of data by incumbent firms is a significant barrier to market entry and could lead to increased concentration in digital markets (Furman *et al.*, 2019).

This view tends to focus on the volume of data accumulated (i.e., "more is better") and emphasizes the "feedback loop" generated by data, where more data leads to product improvements, which in turn leads to additional users and more data – eventually leading to increased revenues and market share for incumbent firms. Borrowing on the theory of network effects, this has led to discussions around "data network effects" and how data accumulation can lead to winner-take-all outcomes in online platforms. This perspective, however, generally does not reflect the value of data in practical settings. While common regulatory perspective often assumes a superlinear increase in value as a function of data volume, research demonstrates that this is typically not the case.

The most recent work across economics, management science, and engineering offers some nuance in understanding the value of data and implications for competition. Firms typically face diminishing returns to data value, and depending on the context and complexity of the domain, additional data may not necessarily confer learning across other users of the product. For example, Netflix discovered that there were rapidly diminishing returns to data in driving improvements in their recommendation algorithm, beyond a modest threshold. Similarly, Waymo, with all the data it has collected over the past decade, continues to face challenges associated with the long tail of scenarios its autonomous cars encounter on the road. Waymo's challenge is further compounded due to localized learning: learnings from the tail in one city generally do not transfer to other cities due to specifics such as traffic rules, weather, and geographic terrain.

While both Netflix and Waymo have made significant investments in developing the capabilities and infrastructure required to leverage data at petabyte-scale, neither has been able to avoid competition. In fact, both firms have seen increasing levels of competition and innovation in their respective markets. In the case of Netflix, the new entry of firms such as Disney, HBO, and Apple into content streaming demonstrates that Netflix's incumbent data advantage did not lock out competitors. Similarly, Waymo is compelling evidence of robust competition and innovation amidst significant scale and scope of data. Even in online advertising, which is frequently cited as an example where data accumulation by incumbents has led to insurmountable barriers to entry, there is nuance required in assessing data value and data is often not the sole determinant of success.

What appears to be needed is a practical and realistic framework to assess the actual value of data and its impact on competition. This paper lays out such a framework, integrating ideas from the economics, management science, and engineering literature. The framework focuses on four key characteristics of data – quality, scaling, scope, and uniqueness. The extent to which data accumulation can provide actual incremental value and whether this is a cause for concern in enabling healthy competition can be evaluated on a case-by-case basis using the framework described.

II. Literature Review

A. Concerns regarding data as a barrier to entry and data network effects

Over the past decade, economists, practitioners, and regulators have voiced concerns regarding market failures that might arise due to the accumulation of data (Carriere-Swallow and Haksar, 2019; Furman *et al.*, 2019; Schweitzer and Welker, 2019; de Corniere and Taylor, 2020; Tirole, 2020). In particular, several works have claimed that there is a self-reinforcing data feedback loop: better access to data helps firms improve upon their product, leading to more users, which in turn leads to additional data (Farboodi *et al.*, 2019; Ichihashi, 2020). This has raised regulatory concerns with regards to "big data" as a significant barrier to entry, potentially resulting in winner-take-all markets in data-intensive industries, and allowing incumbent firms to leverage their data resources in order to enter and capture adjacent markets (Stucke and Grunes, 2015; Rubinfeld and Gal, 2017).

More recently, this has extended to the notion that certain markets are characterized by “data network effects” (Gregory *et al.*, 2020). Markets are characterized by “network effects” when the value of a network to a user depends on the number of other users on the network (Rohlfs, 1974). Network effects have also been at the forefront of discussions on competition in online markets, where discourse has centered around network size being determinative of the outcome of a winner-take-all system and potentially leading to market failure (Church and Gandal, 1992; Besen and Farrell, 1994; Sheremata, 1997). Extending this to data, some have claimed that the strength of data network effects depends mainly on data volume and could potentially lead to market failure in industries where incumbents have access to a large volume of data (Abrahamson, 2014; Prufer and Schottmüller, 2017).

However, even with traditional network effects, more recent literature suggests that network size is just one factor in determining the strength of network effects (Kokkoris and Lianos, 2010; Afuah, 2013; Koh *et al.*, 2014; Hagiu and Rothman, 2016; McIntyre and Srinivasan, 2017; Zhu and Iansiti, 2019; Iansiti, 2021). Claims regarding remedial failure as a consequence of network effects often rely on strict assumptions and fail to consider that its strength depends on a wide variety of factors, including network structure and the presence of multi-homing (Aldrich and Kim, 2007; Choi, Kim and Lee, 2010; Zhu *et al.*, 2019; Jullien and Sand-Zantman, 2021). The same is true for data network effects, where theory has often relied on simplistic assumptions and has not been translated into a rigorous economic model nor established empirically (Lerner, 2014; Tucker and Wellford, 2014; Kennedy, 2017; Auer *et al.*, 2019).

B. Additional nuance in characterizing the value of data and data network effects

Recent literature suggests that there are a variety of factors, beyond data volume, that must be considered in order to understand the value of data and implications for competition. These factors include the ways in which data can drive product improvements, how learnings from data transfer across users, and whether competitors are excluded from using similar data (Tucker, 2019; de Corniere and Taylor, 2020; Cappa *et al.*, 2021).

Depending on whether learnings from data are “within-user” or “across-user”, data network effects may not occur (Hagiu and Wright, 2020a). Across-user learning refers to when a firm is able to improve its product for each customer based on the learning across data from all customers. This may result in network effects in specific scenarios – for example, when it is combined with continued product improvements (Hagiu and Wright, 2020b). On the other hand, while within-user learning can improve the experience for individual users and generate switching costs, it does not result in a network effect as learning is localized to each user. Other factors that affect data value include a firm’s position along its “learning curve” (the rate of progress in deriving learning from additional data) and the properties of that learning curve.

For data to provide a sustainable competitive advantage, they must provide accurate, actionable insights that can be utilized by firms to drive learning in real-world scenarios (Lambrecht and Tucker, 2015; Athey, 2017). Data must also be inimitable and rare, resulting in learnings that rivals are unable to easily replicate (Lerner, 2014; Lambrecht and Tucker, 2015). In practice, this occurs infrequently, as data are non-rival in consumption, have low production costs, and are often either available open source or can be acquired by new entrants through data markets (Varian, 2018; Jones and Tonetti, 2020). The fact that customers frequently multi-home across several digital services further weakens data barriers to entry.

C. Engineering literature on value of data

Engineering literature provides a particularly useful lens in understanding the economics of data in real-world applications. In general, machine learning research has shown that using more data to train and optimize an algorithm can lead to improvements in performance (Banko and Brill, 2001; Halevy, Norvig and Pereira, 2009). This has been particularly true in the case of deep learning, where model performance continues to increase as a function of the size of the dataset in tasks such as machine translation, speech recognition, and computer vision (Hestness *et al.*, 2017; Kaplan *et al.*, 2020; Bahri *et al.*, 2021).

However, the same research also shows that the extent to which data can result in a sustainable competitive advantage depends heavily on the domain and application. Model "learning curves" (how model performance increases as a function of dataset size) generally consist of three regions: (i) the "small data" or "cold start" region; (ii) the "power-law" region; and (iii) the "irreducible error" region (Hestness *et al.*, 2017). In the "cold start" region, models find it challenging to learn from the small number of training samples available, so any additional data that can be acquired to form a minimum viable corpus are highly valuable. In the "power-law" region, each additional data point helps to improve the performance of the algorithm. Crucially, there are diminishing returns to data in this region, the steepness of which is defined by a power-law exponent. In applications such as machine translation, as an approximation, model performance has been found to improve with the square root of the number of data points. Finally, the model enters the "irreducible error" region, where additional data do not help to improve performance.

While the steepness and characteristics of the learning curve (e.g., when each region occurs) are context-dependent and must be tested empirically, they are crucial in understanding data value and implications for competition. In one example, research conducted by Amazon found no empirical evidence of a version of data network effects in retail product forecasting, where increasing the number of products did not result in substantial improvements across various lines of merchandise, beyond a small threshold (Bajari *et al.*, 2019).[1] Other research has shown that in domains such as news personalization and video recommendations, model performance saturates rapidly with additional data (Takács *et al.*, 2008; Larson *et al.*, 2018; Claussen, Peukert and Sen, 2019).

The time-dependency of data also impacts the extent to which data are valuable. Depending on the domain, the relevancy of data can diminish over time due to shifts in customer tastes and behaviors (Chiou and Tucker, 2017; Li and Ching, 2020; Valavi *et al.*, 2020). As a result, a current dataset of bounded size can obtain similar, or better, performance compared to a much larger volume of historical data (Valavi *et al.*, 2020). In a domain where data is highly time-dependent, "stocks" of historical data are therefore less valuable than continuous data "flows". Relatedly, there has been an increasing amount of research on *data quality and relevance* as opposed to *data quantity*, which shows that whether – and the extent to which – data are valuable is context-dependent. Individual data points have varying degrees of contribution to algorithm performance, and in the case of mislabeled data, or data drawn from a different distribution, they can even harm performance (Ghorbani and Zou, 2019; Jia *et al.*, 2019; Ghorbani, Kim and Zou, 2020; Swayamdipta *et al.*, 2020).

Recent work has also continuously advanced techniques that can be used to replicate learnings with smaller sets of data, further reducing barriers to entry. Techniques such as synthetic data generation, and transfer and few-shot learning can help firms achieve a high level of performance with a limited set of context-specific data (He *et al.*, 2008; Pan and Yang, 2010; Torrey and Shavlik, 2010; Snell, Swersky and Zemel, 2017; Xu *et al.*, 2019; Brown *et al.*, 2020).

D. A hybrid approach to assessing the value of data and its competitive advantage

It is clear that there is complexity and nuance in assessing the value of data and implications for competition. The current regulatory perspective, which focuses on data volume and a simplistic view of data network effects,

[1] In another dimension, Amazon found that increasing the number of time periods a product was for sale resulted in increased forecast performance for that specific product (with diminishing returns).

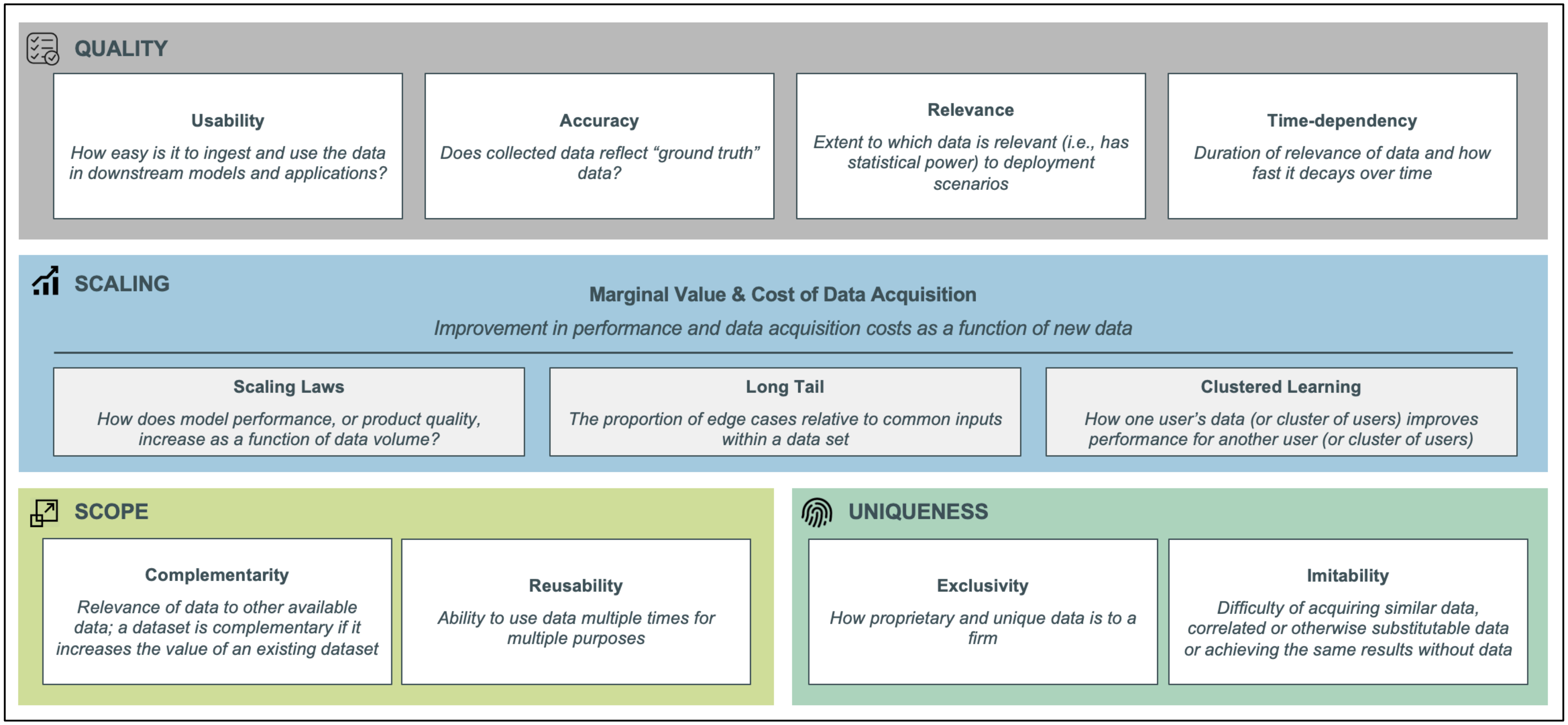
is inadequate in providing practitioners and regulators a realistic assessment of the circumstances in which data can provide a sustainable competitive advantage.

A practical framework needs to merge concepts found across economics, management science, and engineering literature and must be applied on a case-by-case basis, depending on the context and domain, in order to determine the true value of data.

III. Framework for Assessing the Value of Data and Its Impact on Competition

The value of data, and the extent to which data can confer competitive advantage, depends on four key dimensions: (i) data quality, (ii) how data value and costs scale with additional data, (iii) scope and boundaries within and across which data can add value, and (iv) uniqueness of data access and data-enabled learning. Figure 1 below outlines a framework incorporating these dimensions.

Figure 1: Value of Data Framework



A. Data Quality

Data by themselves are not inherently valuable if they are not *usable*. In order to provide value, data first need to be collected, cleaned, and processed for downstream usage. The complexity of data collection and ensuring data usability has continued to increase in recent years with the scale and diversity of data collected, with issues ranging from data discovery (finding the necessary data and serving to those who require it) to data integrity (Panzer-Steindel, 2007; Talmon, 2020; Dixit, 2021). There are also considerations and processes specific to making data usable for machine learning systems. For example, data must first be labeled in order to train a supervised machine learning algorithm,[2] and in the case of data dispersion – where multiple relevant datasets are stored in unique formats – data must be joined into a dataset suitable for machine learning.

Data quality is also determined by how *accurate* and *relevant* data are for the task at hand, as measured by the extent to which data reflect ground truth labels and can improve model performance in real deployment scenarios. In the context of machine learning systems, mislabeling of data occurs frequently, can be difficult to identify at scale, and negatively impacts model performance (Northcutt, Athalye and Mueller, 2021). Data collected for training, and how they are labeled, ultimately determines the output of machine learning systems and quality of user experience. Non-relevant, low-quality data can cause "data cascades," where data issues lead to compounding events causing negative downstream effects that result in technical debt (Sambasivan *et al.*, 2021). While data cascades are prevalent, machine learning practices have traditionally undervalued data quality and have instead focused more on data volume and model development.

The duration of data relevancy and how fast it decays over time – referred to as *time-dependency* – is also crucial in understanding the value of data, particularly in domains with rapidly shifting user preferences and trends (e.g., social media, streaming platforms). Loss of data relevancy can lead to deterioration in model performance and business value. For example, Facebook discovered that using stale machine learning models significantly impacted performance for a wide set of algorithms the firm deployed, including one designed to ensure community integrity (as adversaries constantly come up with new ways to display objectionable content). Algorithms that power the News Feed and Ads Ranking were also impacted significantly by stale models, with the impact being "measured in hours" for the latter (Hazelwood *et al.*, 2018).[3] In such cases, a limited but current set of data can result in similar, or even better, performance than a large amount of historical data, and increasing data volume by incorporating older datasets may even hurt performance (Valavi *et al.*, 2020).

The usability, accuracy, relevance, and time-dependency of data significantly influence the degree to which firms can gain value from data and implications for competition. Each provides an additional dimension to consider beyond data volume and requires a case-by-case evaluation depending on the domain.

Dimensions of data quality include:

- <u>Usability</u>: how easy is it to ingest and use the data in downstream models and applications?
- <u>Accuracy</u>: does collected data reflect "ground truth" data? For example, mislabeled data will hurt performance for machine learning models.
- <u>Relevance</u>: extent to which data are relevant (i.e., has statistical power) to deployment scenarios.
- <u>Time-dependency</u>: duration of relevance of data and how fast it decays over time.

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[2] Supervised learning algorithms rely on an expert-labeled dataset of the outcome (Y) based on the features (X). The objective is for the algorithm to match these labels as best as possible using the features. For example, a supervised learning approach to classifying cats vs. dogs would require each picture being labeled appropriately (as either cat or dog). Other approaches include unsupervised learning, which attempts to identify patterns in the features without labels, and reinforcement learning, where an agent learns to interact with the environment and aims to maximize the reward it receives through an iterative process of exploration and exploitation.

[3] The deterioration of performance, in this case, was due to the combination of leveraging stale data and models (i.e., not being able to explore new models and parameters).

B. Data Scaling

In considering data volume and its implications for value and competition, there must be an assessment of how additional data can transfer into real-world learnings (e.g., improvements in algorithm performance, product quality and user experience, revenue and costs). In practical deployments, additional data rarely result in an exponential increase in algorithm performance and face diminishing returns to scale.

Model learning curves, or *scaling laws*, are typically comprised of three regions: a "small data" or "cold start" region, a "power-law" region, and an "irreducible error" region (Hestness *et al.*, 2017). Once a firm is past the "small data" region and overcomes the cold start problem, it falls into the "power-law" region, which exhibits diminishing returns to data, until performance finally plateaus in the "irreducible error" region. These regions, in turn, inform how much value can be derived from data. In the "cold start" region, any additional data are particularly valuable as models find it challenging to learn from the small number of training samples available. In the "power-law" region, there are diminishing returns to data, the steepness of which is generally defined by a power-law exponent that must be tested for empirically.[4] Finally, the model enters the "irreducible error" region, where additional data do not help to improve performance.

Scaling law dynamics are, in part, driven by the fact that data often follow a *long-tailed* distribution, which has implications for marginal data value and cost of data acquisition. Depending on the domain, and the extent to which data are long-tailed, firms may face diseconomies of scale where the economics of data get worse over time relative to new entrants. This is because the marginal value of an additional data point diminishes quickly as it becomes more difficult to find a unique, and thus valuable, data point in the tail. In comparison, the cost of acquiring, processing, and maintaining data found in the tail may plateau, or decrease at a slower rate, as more time and resources are spent dealing with edge cases. In particular, it is becoming clear that long-tailed distributions are common in machine learning (Zhang *et al.*, 2016; Van Horn *et al.*, 2017; Liu *et al.*, 2019).

The economics of data depend not only on the length of the tail, but also the coverage required of the tail. This requirement is heavily dependent on the domain and product specifications – for example, development of fully autonomous vehicles requires complete coverage of the tail in order to create a functional product (in which case, data in the tail are both highly valuable and costly to collect), whereas recommendation engines may require less coverage of the tail in order to deploy a high-quality product.

Finally, the extent to which *clustered learning* can occur informs the strength of learning effects and the value of data points in the long tail. A "cluster" typically contains observations that are correlated along a dimension (e.g., segment of users with similar tastes, or in a similar geographic region). Clustered learning then enables transferability of learnings across data points in a cluster, or from one cluster to other clusters. For example, in autonomous vehicle development, transferability can be limited as learnings from one city may not inform learnings in other cities due to differences in traffic rules, weather, and geographic terrain. At the extremes, learning can either be "across-user" (where data from an individual user inform learning across all users) or "within-user" (where learning is limited to only that individual user). However, in most applications, there will be gradations between those two points, where learning can transfer across clusters of correlated data points.

In assessing the value of data and implications for competition, it is therefore crucial to assess the length of the tail and coverage required, and the extent to which learnings are clustered. These dynamics ultimately manifest as scaling laws, and while their shape and characteristics are context-dependent and must be tested for empirically, they are key in understanding the value of data.

[4] This assumes that the model, and model parameters, are fixed. In real-world deployments, learning curves can be closer to linear in this region with significant engineering effort, through an iterative process of adding high-quality data and model development.

Dimensions of scaling include:

- Scaling Laws: how does model performance, or product quality, increase as a function of data volume?
- Long Tail: proportion of edge cases relative to common inputs within data. The extent to which data are long-tailed will impact the economics of data (marginal value and costs of data acquisition).
- Clustered Learning: how one user's data (or cluster of users) improve model performance, or product quality, for another user (or cluster of users).

C. Data Scope

Data scope defines the boundaries within and across which data can be used to derive value. Data are typically more valuable if it is *complementary* to other types of data and if it can be *reused* across a diverse set of use cases.

Combining complementary datasets – sometimes referred to as data "recombination" – can generate significant performance improvements for machine learning tasks (Jia and Liang, 2016). Recently, this has particularly been true in recommendation systems, where models such as graph neural networks have been used to leverage diverse types of data. Pinterest, for example, uses graph neural networks for recommendations, incorporating the graph structure inherent to its platform (e.g., pins and boards as *nodes*, membership of pins to corresponding boards as *edges*), as well as both visual and textural features, to obtain significant improvements in performance (Ying *et al.*, 2018). Similarly, Netflix utilizes a diverse set of data for its recommendation algorithms, with inputs including movie metadata, user demographics, and viewing context (Netflix Technology Blog, 2012).

However, while data recombination can be valuable, it is not guaranteed to result in performance improvements. In the context of machine learning, the practical issue of data dispersion must be addressed, where different formats of data – often stored in different places – must first be combined into a dataset that can be used to train machine learning algorithms (Paleyes, Urma and Lawrence, 2020). Ultimately, the data being combined must be relevant to the task at hand and there must be meaningful interaction, and complementarity, between the data to provide benefits.

The non-rival nature of data also allows firms to *reuse* the same data across many different use cases. For example, location data can be utilized for several different purposes: Google uses location information not just to improve search results and personalize advertisements, but to drive research in epidemiology, natural disaster response, and infrastructure planning (Google AI Blog, 2019). Multiple firms can also collaborate and use the same data simultaneously, which can drive innovation and efficiency for consumers (Jones and Tonetti, 2020). For example, both Netflix and Waymo have previously released large datasets to the public, demonstrating how firms can utilize the non-rival nature of data to drive innovation in their ecosystems.

Dimensions of scope include:

- Complementarity: relevance of data to other available data; a dataset is complementary if it increases the value of an existing dataset.
- Reusability: ability to use data multiple times for multiple purposes.

D. Data Uniqueness

Data value is further defined by the extent to which they are *exclusive* and *imitable*. If data are not proprietary or do not result in learnings that are unique to a firm, they cannot provide a sustainable competitive advantage.

In practice, data that are useful for driving product improvements are often possible for companies to acquire or emulate as data are non-rival and have low production costs (Lambrecht and Tucker, 2015; Varian, 2018; Jones and Tonetti, 2020). Firms have utilized open-source data and data markets in order to acquire data, and new entrants can often collect similar data resources to incumbents as customers frequently multi-home across services. For instance, data on social interaction are not unique to Facebook, but are also available on Twitter or LinkedIn (among others), and are tailored to each platform (for example, LinkedIn obtains social interaction data that are more specific, and valuable, for its platform).

Even when data are exclusive, however, it may not lock out competitors if data are *imitable* and there are multiple routes to replicate the learnings from data (Lambrecht and Tucker, 2015). Ultimately, users do not select a product based on the amount of data a firm has access to; instead, adoption is determined by the learnings from data and how they translate into a better user experience. Both Uber and Lyft disrupting the taxi industry, and Tinder disrupting online dating, are examples where a superior product experience enabled new entrants to overtake incumbents, without initial access to a large volume of data.

Furthermore, machine learning research shows continual progress in areas that allow for easier replicability of learnings from data, allowing firms to achieve high algorithm performance with limited amounts of data. State-of-the-art techniques include generation of synthetic data using generative adversarial networks, and transfer learning and few-shot learning, which allow models to be trained on a large dataset and subsequently fine-tuned on a smaller set of task-specific data (Snell, Swersky and Zemel, 2017; Xu *et al.*, 2019; Brown *et al.*, 2020). These advancements – while relatively new – serve to further minimize barriers to entry.

In cases where data are truly exclusive and inimitable, they can provide significant value and competitive advantage. However, data are often not as uniquely valuable as is commonly assumed. When data, or the learnings from data, are easily imitable by competitors, they cannot provide a sustainable long-term advantage.

Dimensions of uniqueness include:

- Exclusivity: how proprietary and unique data are to a firm.
- Imitability: difficulty of acquiring similar data, correlated or otherwise substitutable data, or achieving the same results without data.

IV. Case Studies

In this section, I apply the concepts described in the framework above and describe two case studies that illustrate markets where data are a crucial component, yet market leaders with a large accumulation of data continue to face robust competition and innovation. The first case study describes Netflix, which is facing increased competition from new market entrants despite its significant incumbent data advantage.[5] The other case study details Waymo, which despite possessing significant scale and scope of data, also faces competition in its goal to develop a fully autonomous vehicle. These two case studies illustrate that incumbent data advantage does not necessarily lock out competitors, and that nuance is required in evaluating the value of data.

Lastly, I also discuss data value in the context of online advertising, which is often used as an example to demonstrate that data accumulation and "big data" lead to winner-take-all outcomes. I describe two regimes of data used in online advertising, segmented by time-dependency, and show that it is challenging to conclude that data volume alone is determinative of success in online advertising.

A. Netflix

Since its earliest days as a DVD-by-mail rental service, Netflix has leveraged data and data-enabled learning to enhance and personalize the user experience. Now, with over 200 million users across more than 190 countries, Netflix relies on a sophisticated software and data infrastructure capable of processing petabytes of data per day in real time. These data are used to train algorithms that influence all aspects of its business, from recommending content to users to negotiating license agreements.

[5] The Appendix contains additional details on Netflix for each dimension of the value of data framework.

As a premium video streaming business, Netflix relies on relatively weak network effects. While it was able to provide value to consumers quickly by acquiring a critical mass of movies and TV shows, the same is true for competitors. Network effects are further weakened by prevalent multi-homing on both sides: Netflix procures content from production studios that often offer their content across multiple streaming platforms, and many Netflix users also tend to multi-home across streaming services, in part due to low switching costs.

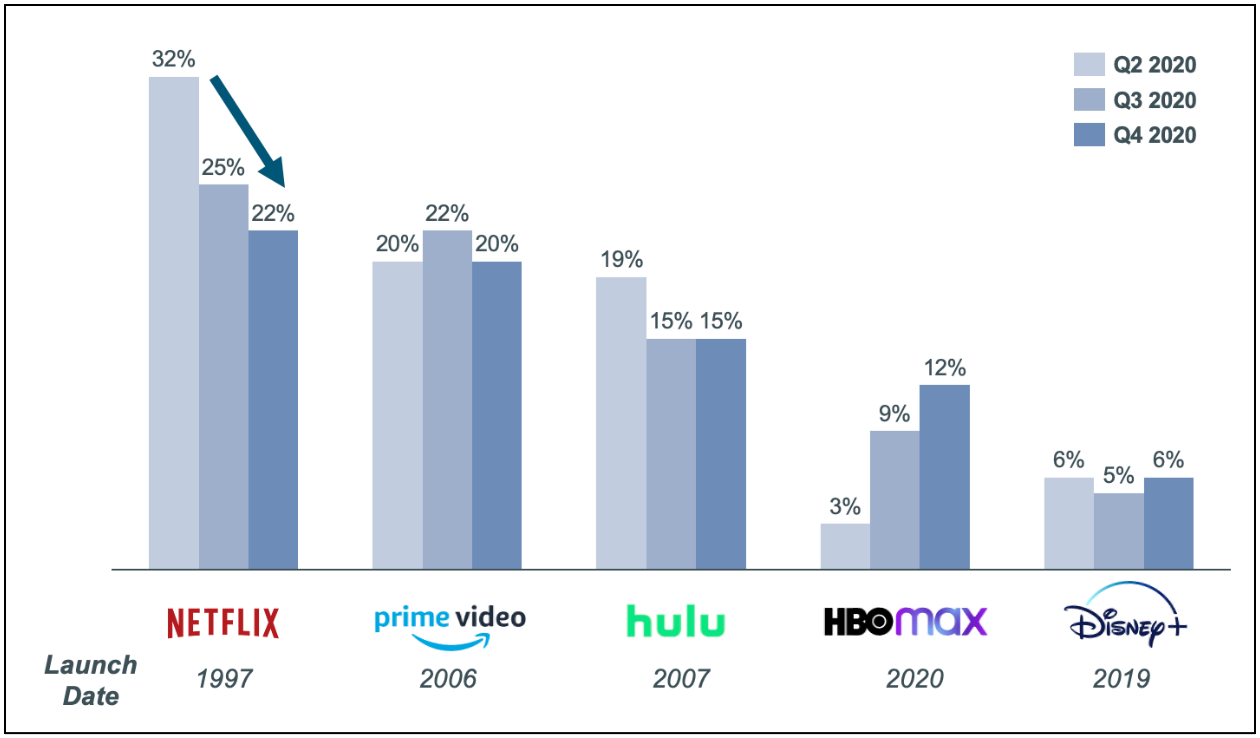
In the absence of strong network effects, Netflix has continuously invested in harnessing learning effects: developing infrastructure to collect and process high quality data, increasing the scalability of its algorithms and the extent to which clustered learning can occur,[6] and expanding data scope. However, despite the firm's early focus on data and data-enabled learning, Netflix has not been able to avoid competition.

There are many reasons for sustained competition in premium video streaming services. First, there are limits to scaling of data value in the video streaming industry, where marginal value of data saturates rapidly while content and user acquisition costs continue to incur significant costs (Amatriain, 2014). Second, competitors have been able to imitate Netflix's learnings from data, tailored to their own platform, after reaching a critical mass of content. Lastly, the competitive advantage that Netflix can derive from stocks of historical data is further weakened by time-dependency, where the relevancy of streaming data decays significantly with time (Hardesty, 2019).

This is well-illustrated by the competitive landscape in the video streaming market. A number of firms offer competitive options in the video streaming space, including Amazon and Hulu. New market entrants are common: in recent years, multiple firms including Disney, HBO, Comcast, and Apple have entered the market, leading to a substantial decrease in market share for Netflix. In the year 2020 alone, Netflix saw its global market share fall from 29% to 20% (Frankel, 2021) and its share of streaming activity fell from 32% to 22% from Q2 to Q4 2020, largely as a result of new market entrants (Reelgood for Business, 2021).

[6] In 2016, Netflix transitioned from local models (for each geographic region) to a global model for its recommendation engine, which allowed it to better leverage clustered learning and offer improved recommendations to users in new markets, as well as users with niche tastes. Additional details are found in the Appendix.

Figure 2: Subscription Video on Demand Streaming Share, Top Five Platforms, Q2-Q4 2020[7]



It is clear that Netflix's incumbent data advantage has not been able to lock out competitors in the video streaming market. Instead, in order to remain competitive and attract customers, firms have had to continuously innovate on content and provide a more personalized user experience tailored to their platforms. Disney Plus, as a platform that has a lot of repeat viewing and a mix of short and long form content, is working to identify characteristics that define repeat viewing behavior (e.g., story arcs, protagonists); taking into account the specific context of the user's experience (for example, recommending a short if that appears to be the user's current "mood"); and using natural language processing to analyze closed caption files to understand the "aboutness" of content and its emotional arcs (Forbes Insights Team, 2020). On the other hand, HBO Max is taking an alternative approach to personalization. While algorithms are still used to recommend content, human curation is heavily emphasized, with pockets of the platform dedicated to content recommended by curators ranging from WarnerMedia editors to celebrities (Alexander, 2020).

This competitive innovation has resulted in a diverse set of capabilities and experiences across video streaming platforms, providing a wider range of options to consumers. In the video streaming market, it is this innovation that attracts users and data to each platform in the first place, whereas large volumes of data and data network effects have a limited role in foreclosing competition.

B. Waymo

Waymo first started as an experimental self-driving car project inside Google's X lab in January 2009. Through the spinoff and transition to a subsidiary under Alphabet in 2016, Waymo has continued to focus on its goal of bringing autonomous vehicles to market.

[7] Figures adapted from *Q3 2020 Video Streaming Report* and *Q4 2020 VOD Streaming Report* (Santos, 2020; Reelgood for Business, 2021).

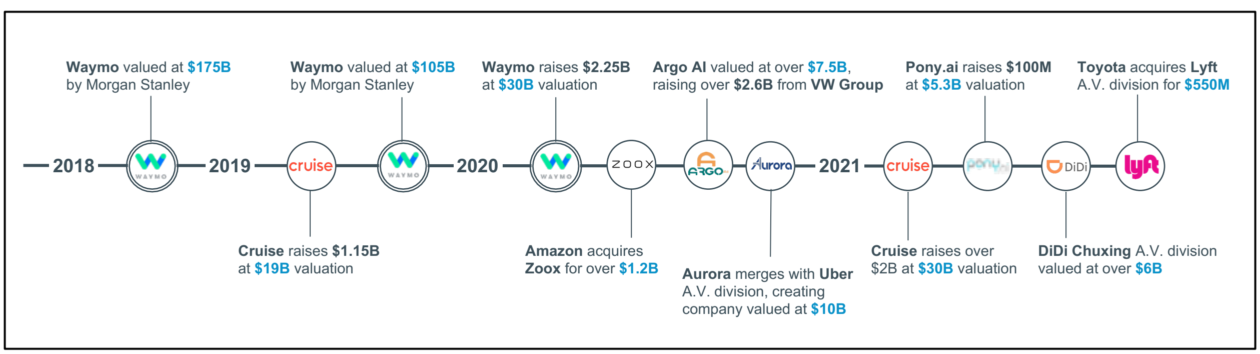
Waymo relies significantly on machine learning algorithms to power key components of autonomous driving across perception, prediction, and planning. As such, data are essential in the development of fully autonomous vehicles. To collect data to train its neural networks, Waymo vehicles have driven over 20 million miles on public roads across 25 cities and have generated petabytes of data daily through the suite of lidar, radars, and high-resolution cameras equipped on its vehicles (Waymo, 2020b; Wiggers, 2020). In addition to real world driving, Waymo also utilizes computer simulations to expand the scale and complexity of the data that it collects. A simulation enables for more miles to be driven (more than 20 million miles are driven per day inside Waymo's simulation software) and helps to accelerate the velocity of learning by introducing edge cases and testing experimental scenarios. By April 2020, Waymo had driven over 15 billion miles in simulation (Waymo, 2020a).

However, more than a decade after inception, despite the immense amount of data and learnings generated from millions, and billions, of miles on public roads and in simulation, Waymo has not been able to avoid competition and a fully autonomous vehicle remains some time away (Abuelsamid, 2018). One key technical challenge has revolved around the long tail of scenarios a vehicle encounters on the road, as autonomous vehicles require full coverage of edge cases (i.e., it is not acceptable for an autonomous vehicle to succeed in 99% of scenarios and fail in the other 1%, as compared to, for example, searches on Google or music recommendations on Spotify). Learning from the tail is further complicated by limited clustered learning: in many cases, learnings from one city do not transfer to others due to differences in traffic rules, weather, and geographic terrain.

Thus, in autonomous driving, the limits of scaling of data value are primarily driven by the long tail of scenarios, the coverage required across the entirety of the tail, and the limited transferability of learnings from edge case to edge case (localized learning). Due to these factors, there is a decreasing marginal utility to data, as the majority of data collected represents common scenarios that the software has already learned how to perceive, predict, and plan around. On the other hand, costs associated with collecting, processing, and utilizing additional data will generally stay flat, as the system must be tailored to deal with each edge case.

These challenges, and the amount of competition and innovation in the autonomous driving space, is reflected in Waymo's valuation over time. While Waymo holds a first-mover advantage and has collected more data than nearly all of its competitors, its valuation has been falling relative to these competitors in recent years. Between 2018 and 2020, Waymo's valuation fell from \$175 billion to \$30 billion. At the same time, competitors have continued to receive external funding, and in many cases have seen their valuations rise. For example, in January 2021, GM's Cruise raised \$2 billion at a valuation of over \$30 billion.

Figure 3: Funding and Valuation of Autonomous Driving Companies, 2018 – 2021



Data are clearly crucial in developing autonomous vehicles. The long tail of scenarios, however, along with the requirement of full coverage of the tail, means that the relative advantage that Waymo derives from data can become smaller over time in comparison to competitors. Thus, despite Waymo's advantage in the scale and scope of data collected over the past decade, it is clear that this data advantage has not locked out competitors. There has been an enormous amount of competition and innovation in the space, as seen by competitors such as Cruise and Argo AI. Interestingly, competition around data has continued to become more open in nature, with firms starting to release large, high-quality datasets into the open (e.g., Waymo Open Dataset, Argo AI Argoverse) in order to spark innovation in the research and development of autonomous vehicles.

C. Online Advertising

Online advertising is often cited as an industry where data accumulation by incumbents has created an insurmountable barrier to entry. This is sometimes argued to be caused by "network effects" associated with the scale and scope of data collected (Newman, 2014; Stucke and Grunes, 2015).

However, the reality is that understanding the value of advertising data is complex. Ultimately, the value of advertising data depends on many factors including data quality, complementarity with other existing data, how data drive improvements in personalization, and, in turn, when increased personalization translates into increased ad effectiveness (Arnold *et al.*, 2018; Dobson, 2018). This value can be significantly less than is often assumed in regulatory discussions. In one example, research demonstrated that for a national apparel retailer, incorporating additional data such as demographics and ad exposure data provided essentially no performance improvements, while other types of data such as purchase history and retail-defined customer categories provided only minor improvements (Johnson, Lewis and Reiley, 2017). In fact, in this case, *reducing* data volume by removing purchase data prior to a customer's first ad exposure increased performance substantially more than adding new data.

Furthermore, the impact of advertising data on competition is also complex. In the context of targeted advertising, data can be thought to fall into one of two separate regimes depending on its degree of time-dependency. The first regime consists of stable, low time-dependency data, which are used to infer consumer characteristics that change slowly, or predictably, with time. Such characteristics include socio-demographic factors (e.g., age, race, education) and chronic health conditions (e.g., diabetes, hypertension). As this type of data has very stable time-dependency and can be identified across various points in time, it is generally not unique to specific platforms. For example, demographic and user interest data can be acquired from a variety of sources, including data providers such as comScore and Nielsen.[8] Other firms, from news publishers to smaller online stores, can also infer similar data on consumer characteristics to guide targeted advertising (Computer and Communications Industry Association, 2019). Due to this lack of exclusivity, possessing a large stock of low time-dependency data typically does not provide a sustainable competitive advantage, especially as much of the data collected are duplicative and do not provide new insight on consumer characteristics. Research has also shown that low time-dependency data are often less valuable for targeted advertising compared to data that reveal short-term trends in user behavior (Yan *et al.*, 2009; He *et al.*, 2014).

The second regime encompasses highly time-dependent data. Examples of such data include geo-location information for targeting consumers in a particular area and customer purchase intent data. While this type of data can be quite valuable for advertisers, it also has rapidly decaying utility, and data that are no longer relevant can fail to deliver returns on ad spending (McKenna, 2017; Oakes, 2020). For example, once a customer leaves a certain geographic location, data that may have enabled hyperlocal advertisements can immediately lose most of their value. As a result, with high time-dependency data, continuous flows of data can be significantly more valuable than a large stock of historical data, which reduces any competitive advantage that incumbents may have due to data accumulation. In addition, high time-dependency data may also not be exclusive. Location data is frequently accessed by many applications on a consumer's phone and consistently available to a wide range of advertisers

[8] For example, see https://www.comscore.com/Products/Activation/Audience-Targeting-Solution and https://www.nielsen.com/us/en/solutions/capabilities/audience-segments/ for comScore and Nielsen data.

(Almuhimedi *et al.*, 2015). Advertisers can also acquire location data through marketplace vendors such as Foursquare, which further lowers the exclusivity of such data.[9]

Finally, across both regimes, there is a limit to how much data value can scale. Advertising data faces diminishing marginal utility, as the long tail of data generally contains information on thinner segments of the market that attract fewer advertisers (Arnold *et al.*, 2018). In some cases, joining together diverse datasets, including granular consumer-level information, may not improve the performance of targeted advertisements as the data may not be complementary (Johnson, Lewis and Reiley, 2017). This can also be true for data collected *across* multiple products or services, as data generated for each product are generally specific to that product and may hold limited complementarity with other existing data.

Based on these factors, it is difficult to conclude that the success of platforms in online advertising is solely due to the scale and scope of data accumulated. Their success is more likely due to a confluence of factors, including not only the value of data collected, but also innovation in product development, a competitive pricing strategy, and extensive sales efforts.

V. Conclusion

While common regulatory perspective on the relationship between data, value, and competition tends to focus on the volume of data accumulated by incumbents and posits the existence of data network effects, more recent work across economics, management science, and engineering shows that there are a variety of factors that impact the value of data and that implications for competition are much more complex and subtle.

The framework in this paper presents four key factors – data quality, scale and scope of data, and data uniqueness – that can influence the value that firms can derive from data. Understanding data value and its likely impact on competition requires a careful case-by-case evaluation, as these factors depend significantly on the domain and context. These factors also illustrate that the volume of data accumulated, by itself, does not determine data value. Applying the framework to Netflix, Waymo, and the online advertising industry provides compelling evidence that incumbent data advantage, while generating value for innovation and for the consumer experience, does not necessarily lock out competitors and is not determinative of success. As these case studies show, data serve as a catalyst for innovation that benefits both consumers and the broader ecosystem.

[9] See https://foursquare.com/products/audience/ for Foursquare's offerings.

VI. Appendix: Details on Case Study

A. Netflix

Since its earliest days, Netflix recognized the importance of using data to personalize the user experience. With the pivot towards online streaming in 2007, Netflix started to leverage an increasingly diverse set of data to personalize content for users. The company now provides personalization for over 200 million subscribers spread across more than 190 countries, and at the core of Netflix sits a sophisticated software and data infrastructure that collects, processes, and deploys petabytes of data daily. Netflix uses this data to train algorithms to influence virtually every aspect of its business, including recommending content to users, optimizing the signup process, and negotiating license agreements.

However, despite Netflix's significant investment in data, it has faced significant competition in the video streaming market. In recent years, multiple firms including Disney, HBO, Comcast, and Apple have entered the market, leading to a substantial decrease in Netflix's market share. The following discusses Netflix's investments in assuring data quality, increasing the scope in which data is deployed, and enhancing data scalability to show how the firm's investments in data have driven innovation and have benefited customers. However, at the same time, the case study explores the limits to scaling data value, as well as how competitors have been able to imitate Netflix's data-driven learnings.

1) Data Quality

Netflix has invested significantly in developing infrastructure and processes to enable real-time *usability* of data. In order to effectively capture and use the trillions of data events that are generated on the platform daily, Netflix developed its "Keystone Stream Processing Platform" as the firm's data backbone, allowing data to be collected, processed, and aggregated in real time (Netflix Technology Blog, 2018b). Data collected includes video viewing metadata, user interface interactions, performance data, and troubleshooting records.

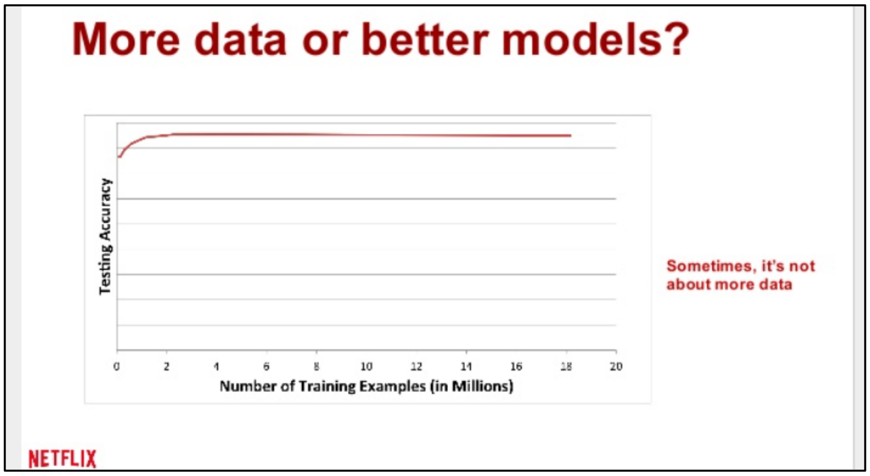
Netflix also spends considerable effort in optimizing the *relevance* of data that it uses to train its algorithms. For example, in 2017, Netflix shifted from a star-based rating system to a simpler "thumbs-up" model (Roettgers, 2017). One primary reason for this shift was the recognition that star-based ratings were not necessarily good predictors of what users were interested in watching – for example, "users would rate documentaries with 5 stars, and silly movies with just 3 stars, but still watch silly movies more often than those high-rated documentaries" (Roettgers, 2017). The "thumbs-up" feedback model provided a clearer link to personalization and resulted in an over 200% increase in ratings collected (Netflix, 2017). This was also part of a broader shift at Netflix, from relying solely on the billions of ratings it had collected in its early days of personalization, to recognizing that certain types of data are more relevant than others (i.e., implicit user behaviors matter more than explicit ratings).

While Netflix has spent considerable effort to increase the relevancy of the data it collects, it operates in an industry where this relevancy also decays rapidly over time. Netflix's catalog of videos is updated constantly and viewership tends to decay rapidly after movies are newly released. Research from competing video streaming service, Amazon Prime Video, confirms that users are far more likely to watch a recent release than a highly rated classic (Hardesty, 2019). Due to this *time-dependency* of data, effectively capturing a real time flow of data generated on the platform ("data flows") is far more valuable to Netflix than a large volume of historical data ("data stock") that will continue to decay in value with time.

2) Scale Effects

Content recommendation is a core use case for Netflix. For recommendations, however, data faces significantly diminishing returns. In 2014, Xavier Amatriain, Netflix Director of Algorithms Engineering, showed that the performance of Netflix's in-production recommendation algorithm showed no improvement after just 2 million training examples (Amatriain, 2014).

Figure 4: Netflix Recommendation System Scaling[10]



This rapid saturation in performance is, in part, due to Netflix's long tail of content. On one hand, this content is extremely valuable for Netflix and its viewers, and Netflix devotes significant effort to increase customer engagement by promoting the full extent of its video catalog in recommendations (Gomez-Uribe and Hunt, 2016). On the other hand, the cost of acquiring long tail content will likely continue to incur significant costs for Netflix (in comparison to, for example, YouTube, where long tail content emerges organically as it is community driven).

These challenges were further compounded by limited *clustered learning* across users in individual regions. Initially, Netflix divided member countries into groups based on geographic region, language, culture, and video availability. In 2016, Netflix announced a pivot towards a single global model leveraging over 2000 "taste micro-clusters," which defines groups of users with shared viewing interests. This transition allowed Netflix to offer better recommendations to users in new markets, as well as users with niche tastes:

> "Another example of what our global recommendation system means for members around the world comes from the global community of health-conscious foodies, who are very interested in learning about food and the industry around it …
>
> The percentage of members from each country in this community is actually relatively small. So if we were relying just on the data from a single country (especially a new one with a smaller number of members), our personalized recommendations would suffer as a result. By leveraging data from across the world and countries of all sizes, our global algorithms are able to tap those insights to make recommendations for this food conscious community that are more accurate and robust." (Netflix, 2016)

3) *Scope*

Netflix initially relied exclusively on user ratings to train its recommendation algorithms (Roettgers, 2017). By 2012, however, Netflix was using data inputs ranging from video metadata to external social data for training its recommendation algorithm, which resulted in a significant improvement relative to relying solely on user ratings (Netflix Technology Blog, 2012). More recently, Netflix has experimented with deep learning models

[10] Excerpt from "10 Lessons Learned from Building ML Systems" (Amatriain, 2014).

in order to make contextual recommendations by leveraging sequential context about the user (e.g., country, device, time, content consumed) to predict what the user will engage with next based on their current context. In particular, combining this with discrete time variables (e.g., day of week) and continuous time variables (i.e., timestamps) resulted in a more than 40% improvement over traditional matrix factorization techniques (Basilico, 2019).

Netflix has also continuously expanded the scope in which data drives value by *reusing* data across use cases. Netflix now uses user viewing history not just to drive personalized recommendations, but also to personalize the artwork that individual users see (Netflix Technology Blog, 2017). Other examples include utilization of historical movie metadata to inform its content production; using factors such as viewing history, connection speed, device preference to improve the user streaming experience; and optimizing the sign up experience based on users' device, location, payment methodology, and more (Netflix Technology Blog, 2018a, 2020).

4) Uniqueness

Ultimately, however, competitors have been able to imitate the data that Netflix collects and the learnings enabled by that data. While Netflix's data is proprietary and exclusive to Netflix, competitors such as Hulu, Amazon Prime Video, and Comcast Peacock have been able to obtain a critical mass of content and thus obtain data that is most valuable for its own platforms in order to power their algorithms. For example, Disney Plus, as a platform that has a lot of repeat viewing and a mix of short and long form content, has invested in identify characteristics that define repeat viewing behavior (e.g., story arcs, protagonists) and taking into account the specific context of the user's experience (Forbes Insights Team, 2020). Other platforms have also invested significantly in developing sophisticated data pipelines and recommendation engines – for example, Amazon Prime Video recognized the importance of time-dependency early on and optimized their neural network training procedure to take into account data freshness (Hardesty, 2019).

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