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Bibliographic information:
Poechhacker, Nikolaus, and Eva-Maria Nyckel. 2020. "Logistics of Probability: Anticipatory Shipping and the Production of Markets." In *Explorations in Digital Cultures*, edited by Marcus Burkhardt, Mary Shnayien, and Katja Grashöfer. Lüneburg: meson press. DOI: 10.14619/1716 <Online first version>.

LOGISTICS

CALCULATION

PERFORMATIVITY

PROBABILITY

LOGISTICAL MEDIA

PREDICTIVE ANALYTICS

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Nikolaus Poechhacker and Eva-Maria Nyckel

Predictive analytics is becoming increasingly important in various sectors of contemporary societies. At the same time logistical media have a profound impact on our everyday life. Both elements—the importance of logistical media and the growing impact of predictive analytics—are coming together in Amazon's method of anticipatory shipping. By shipping packages based on the probability of an upcoming order, the logic of logistics is changed in a profound way. Based on the analysis of Amazon's U.S. Patent No. 8,615,473 B2 (Spiegel et al. 2013), which describes the process of anticipatory shipping, we argue that this logistic of probability pre-assumes structures of desires and needs in the targeted community, while at the same time providing methods to realize these presumptions via the entanglement of anticipatory shipping with algorithmic logistical infrastructures and

a second logic of prediction: the recommender system. Connecting these two forms of prediction via common centers of calculation (Latour 1987), these media logics become entangled by predicting as well as producing their customers' demand at the same time and actively preparing the grounds for logistics of probability.

Prediction and explanation are exactly symmetrical. Explanations are, in effect, predictions about what has happened; predictions are explanations about what's going to happen. – John Searle

Introduction

Logistics is at the core of the global market's metabolism. Goods offered by small corner stores, supermarkets, department stores and online retailers often traveled the world from production facilities to the consumers. Since the end of World War II the management of the flow of goods, information and people, i.e., logistics, has become a major driving force of global capitalism. This global movement of things is to a large extent empowered by the accumulation and circulation of information and knowledge. Knowing existing and emerging markets for one's goods poses a competitive advantage in orchestrating logistical operations (Danyluk 2017). Logistics thereby has always been a matter of mathematics, particularly in operations research methods. However, with the emergence of digital marketplaces in the mid-1990s (Lehdonvirta 2012), the process of market anticipation is increasingly based on data science applications and the algorithmic recognition of patterns in customer transaction data. An important element of this transformation—particularly in light of global just-in-time markets and the detachment of production and consumption—is not just the ability to transport commodities all over the globe, but also the ability to compress time and space—"especially in facilitating the movement of goods and materials" (Danyluk 2017, 6). Data science's answer to this request is the utilization of predictive analytics for logistical systems.

On December 24, 2013, Amazon was granted the U.S. patent *Method and System for Anticipatory Package Shipping* (Spiegel et al. 2013). The patent describes methods for shipping commodities based on the calculated probability of (potential) customers ordering goods from Amazon: with anticipatory shipping, packages are sent "in anticipation of a customer ordering items in that package, but before such an order has actually occurred" (Spiegel et al. 2013, 5). The prediction of a (potential) purchase is thereby calculated by prior patterns in tracked interactions of customers with the e-commerce platform, including purchases and click-rates. As a result, the patent suggests that the process of shipping a package will no longer be initiated by a customer pressing the buy button, but by an algorithm that predicts future demands of customers in different regions. Through this utilization of predictive analytics for shipping goods, delivery time can further be reduced, which grants an important competitive advantage. However, this compression of time based on technological foresight creates new uncertainties. Predictive analytics, based on probabilities, can and will produce incorrect deliveries—in data science identified as false positives. A system of probabilistic logistical media must therefore integrate mechanisms of dealing with these uncertainties: the logic of commodity flows has to change in a profound way to deal with the *logistics of probability*. We argue in this paper that logistical prediction is based on two central elements. First, an infrastructural system that allows for the flexible re-routing of commodities, integrating false positives into the existing stream of goods. Second, a coupling of predictions of consumption events and the construction of markets. *Logistics of probability* pre-assumes structures of desire and demand in the targeted community, while at the same time providing methods to realize these presumptions via the entanglement of anticipatory shipping with Amazon's e-commerce portal and a second logic of prediction: Amazon's recommender system.

While logistics has always been invested in predicting markets and demand to some extent, anticipatory shipping operates on a different level. The prediction does not target the demand of a whole region for a certain type of product— the aggregation is scaled down much more. Subject to prediction are singular product purchases, resulting in packages of only some items to be distributed within the logistical infrastructure of Amazon. Instead of shipping larger amounts of goods to meet anticipated demand, singular connections between shipping and (probable) purchase are constructed and afforded through technological advances, making it necessary to integrate different strategies of distribution that show greater flexibility. The production of prediction (Mackenzie 2015) is relying on the "total media link on a digital base" (Kittler 1999, 2)—the digital, allowing the connection of everyone and everything with everything and everyone else. Through this, a control of commodity flows and the entanglement of digitally constructed demand and supply are enabled via algorithmic logistical media.

Algorithmic Logistical Media

The term *logistical media* was coined by John D. Peters, who particularly stresses the infrastructural role of media. The job of logistical media is—in Peters' words—"to organize and orient, to arrange people and property, often into grids" (Peters 2015, 37). For Peters, the work of media itself can be understood as fundamentally logistical.[1] In connection to this understanding of logistical media, and taking into account that logistical infrastructures are increasingly managed through computational systems of code, media theorist Ned Rossiter (2016) defines logistical media as a coupling of infrastructure and software, having an inherent governing power: "If infrastructure makes worlds, then software coordinates them" (Rossiter 2016, xv). While Kittler stated that "media determine our situation" (Kittler 1999, XXXIX), Rossiter further specifies this as logistical media, specifically "software coupled with infrastructure [,] determines our situation" (Rossiter 2016, 121). In other words, he describes logistical media as infrastructures that make the flow of materials possible on the one hand, and the operational logic that controls the flow of goods on the other:

> Logistical media—as technologies, infrastructure, and software—coordinate, capture, and control the movement of people, finance, and things. Infrastructure makes worlds. Logistics governs them. (Rossiter 2016, 4–5)

Algorithms and software are therefore substantial elements in organizing and arranging the capacities of infrastructures to order and influence the ways in which they interact with the world. However, logistical infrastructure is a larger system that is full of frictions, which are intentional parts of this system (Gregson, Crang, and Antonopoulos 2017). The seemingly seamless flow of goods is the result of many interruptions, where distributed spaces are used for storing, repackaging, and relocating cargo. Distribution centers are spaces of intended friction, as "logistics

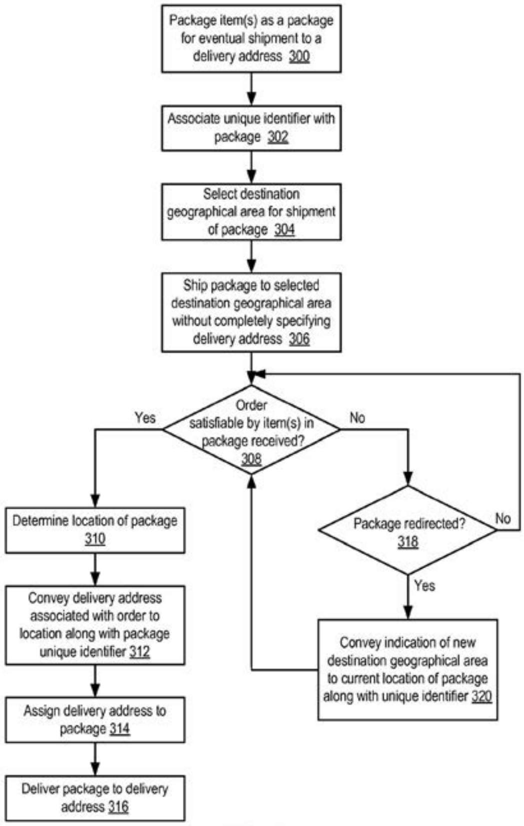
1 It is important to note here that Peters argues against an understanding of media that just structure and coordinate logistical operations. Instead he considers media operations as inherently logistical.

works through this known friction. There is purposeful pausing, or interruption, of flow that is most visible in the spatialities of storage that are critical to the achievement of coordination" (Gregson, Crang, and Antonopoulos 2017, 390). These distribution centers are stations where the flow and relocation of cargo in the network of connected spaces are coordinated by code, creating a code/space conflation (Kitchin and Dodge 2011). Big retailers and the logistics industry are building large "network[s] of fulfillment centers capable of dispatching goods almost anywhere in the world" (Danyluk 2017, 9). Walmart, for example, created a huge network of distribution centers, where 90% of the stock is turned over every day (LeCavalier 2016). As a result, networks of dispatch and fulfillment centers enabled logistical networks to operate as just-in-time (JIT) systems, reducing extensive stock-hold inventories. With JIT, cargo containers function as storage on the road and in steady motion (Hirsch 2013).

Amazon, as one example for these developments, also relies heavily on this specific setup of logistical infrastructures. Amazon 's marketplace is not limited to an e-commerce website but also includes fulfillment centers (i.e., Amazon 's distribution centers), the identifiable packages, the stored goods, and the workers carrying, packaging and labeling these goods. Software logic and a material infrastructure are managing all of these activities at the same time. The calculation of markets needs logistical infrastructures. In the case of anticipatory shipping, however, the logic that guides and organizes the flow of goods through the material infrastructure takes a specific form. As the patent formulates it:

> That is, at a given time, numerous speculatively shipped packages [...] may be propagating through a shipping network. When an order is placed, a closest-proximity package [...] may already be at or close to a hub [...] closest to the delivery address of the order, and thus may be available within, e.g., a day of the order placement. (Spiegel et al. 2013, 15)

Anticipatory shipping does not just need to predict consumption but also to control, track, and redirect flows of commodities. Thus, a system of constant flow of commodity with fine-grained tracking is necessary. It is not the flow of commodities that must be seamless, but the flow of data streams, RFID codes, and location trackers. Logistical media does not only include the flow of goods: it also entails the very organization of immutable mobiles, combinable in multiple ways to make it possible to apply the logic of logistics.



[Fig. 1] Flow diagram of anticipatory shipping (Source: Spiegel et al. 2013, 1)

As Latour argues, "the logistics of immutable mobiles is what we have to admire and study" (Latour 1987, 237). The algorithmic logic is thereby dependent on a structured environment that enables such predictions. This logic, based on predictive analytics, comes with uncertainties in the form of probabilities and false positives. The logic of Amazon's algorithmic logistics has to take that into account and develop risk management procedures. Anticipatory shipping can therefore be seen as part of this code/space production with its constant flow of commodities. As the patent describes, methods of accounting for false predictions are an integral part of the vision called anticipatory shipping.

> In one embodiment, a speculatively shipped package [...] may reach its destination geographical area before any corresponding customer

> order occurs. Depending on the common carrier, such a package [...] may be redirected to a different geographical area in response to actual or forecasted customer demand in that area. (Spiegel et al. 2013, 16)

When an order is placed in the corresponding area, different mechanisms of re-labeling and shipping the package come into place. As it is outlined in the patent for anticipatory package shipping, Amazon's logistics is influenced by the predicted probability that a customer in a specific region will order a specific package. The package is shipped to the region by analyzing collected user data such as former purchases, search histories, wish lists, and shopping carts as well as the duration of the user's mouse cursor resting on certain products on the website. In the best case scenario, a customer in the area places an order.

Amazon's anticipatory shipping is a system governed by an assemblage of digital media working as "logistical devices of tracking and orientation," organizing movement in time and space as well as registering data traces (Peters 2015, 7). The system can be understood as a logistical, operational logic as it was described by Rossiter (2016) and Peters (2015), which requires its own massive logistics infrastructure. This infrastructure allows for the alignment of predicted desires derived from user data with the flow of products. A material infrastructure with planned frictions and interruptions as moments of possible intervention is combined with a corresponding flow of data in order to enable a constant flow of goods to make predictions possible, i.e., reducing the costs of false predictions. Logistics not only governs worlds but also makes predictions less risky.

Recommendations and the Production of Markets

A central issue with capitalist modes of production in the logistical revolution is "the disjuncture between production and distribution, or supply and demand" (Bonacich and Wilson 2008, 4). Production and consumption are detached from each other, making the issue of connecting these two aspects of each market a major problem that contemporary capitalism is facing. This issue becomes even more pressing if anticipatory shipping enacts a reality that has not yet been realized—logistic action has to be connected with emerging demand. Here the detachment is not just between production and consumption but also between delivery and locally confined consumption. The market is the mediating instance, and identifying potential customers is part of this mediation function. However, there are manifold studies arguing that we should understand markets by looking into socio-material market practices on the one hand and theories and models about those markets on the other, which are rather performative than descriptive to the exchange of values; they are "an engine, not a camera" (MacKenzie 2006).

Along the lines of MacKenzie's argument, we can understand recommender systems as market devices that have the distinct aim of segmenting the market by identifying "smaller homogenous markets in response to differing product preferences" (Smith 1956, 6). Following Callon's (1998) conception of markets as practical achievements of heterogeneous actors, Amazon's recommender algorithm is one important actor in the constitution of the market. Algorithmic configurations that couple demand and supply are not independent of markets, but are actively shaping them (Callon and Muniesa 2005). Recommender systems can be conceptualized as algorithmic configurations calculating relations between users and items, but also between users and other users as well between items—each with its different inscribed ideas about social configurations (Pöchhacker et al. 2017). As such, the algorithms are identifying and classifying items to be sold as well as different kinds of users. Based on these identifications, the supply is shaped accordingly. The e-commerce platform is using recommender algorithms to pre-configure its online market.

> Algorithmic configurations calculate encounters differently, depending on the way in which they perform these operations; each concrete market corresponds to a particular mode of organization (and calculation) of the connection between singular supplies and demands. (Callon and Muniesa 2005, 1242)

As Callon and Muniesa argue, algorithmic configurations are technical instruments within an assemblage of marketing techniques, including cookies, click-through rates, etc., that relate people to things and, as a result, construct an economic space (Cluley and Brown 2015). Nevertheless, in this digital marketing mode, segmentation is no longer driven by theories about identity-related demand. The construction of the user through clustering and segmentation based on data tracks is a form of what Zwick and Dholakia (2004) call "narrating consumers." As a result, "the market, in a sense, does not exist outside of traces consumers leave within databases" (Cluley and Brown 2015, 115). Market segmentation then becomes rather an exercise of modulating consumer *dividuals* (Deleuze 1992) with existing supply than matching existing demands with variable supply (Zwick and

Denegri Knott 2009). Calculative marketing becomes a matter of fluid reorganization and reconstruction of the individual based on changing patterns and variables (Danna and Gandy 2002; Gandy 2001).

Recommender systems as intermediaries (see also Morris 2015) are reorganizing a complex and massive amount of goods. Instead of creating ads, recommendations are creating visibility by assembling personalized forms of offers. This is, ultimately, a data-driven structuring of consumer choices. Recommendation algorithms are thereby reducing complexity, which helps consumers navigate the enormous number of offered goods. Selective visibility reduces the number of goods taken into consideration and enables exploration of prior unknown items at the same time. However, this reduction in complexity does not come without side effects. By doing so, these intermediaries are also predicting the user's taste, as well as performing it (see also Beer and Burrows 2013). MacKenzie (2006) defines the strongest form of performativity as a process in which reality is adapted to the applied model. In the case of machine learning techniques used in recommender systems, however, one can argue that the model and reality are co-shaping each other dialectically. One does not exist without the other, but the model and the observation are interdependent, where the recommender system creates a projection of past behavior in the future (Kaiser 2015), pre-forming market interactions as the basis for further recommendations as well as speculative shipping. As Nigel Thrift (2004) argues, with the introduction of information technologies, the flexibility of configurations increases and becomes an object of experimentation and constant change itself. Following Thrift, this kind of prediction is a flexible and ever-adapting form of matching supply and demand—and therefore continually changing the basis for performing markets.

Performing Predictability

Anticipatory shipping, as described in Amazon's U.S. Patent No. 8,615,473 B2 (Spiegel et al. 2013), is not independent of the market construction process. What anticipatory shipping is predicting is a pre-configured market, co-shaped and highly influenced by Amazon's e-commerce platform and recommender system. It is widely acknowledged that the recommender system of Amazon is a central part of its business model (Smith and Linden 2017). Nevertheless, how are anticipatory shipping and recommender systems related to each other? Connecting these two forms of prediction via common centers of calculation (Latour 1987), these media logics become entangled by predicting as well as producing their customers' demand at the same time and actively preparing the grounds for the logistics of probability.

Centers of calculation, as Latour (1987) argues, are places where references or translations of the real world, such as questionnaires and maps, are collected and made combinable. This collection of the world's traces makes the actors inside these centers of calculation able to act at a distance, recombine different parts of the world, and therefore create new possibilities for interventions. However, being able to do so involves some effort. The projection used to describe the world becomes a single point of passage for all data collected. Distributed elements in the network of goods, dispatching and user interactions must be brought together in a common information ecology, developing standards and classifications (Bowker and Star 2000) and integrating the captured information in databases, making it comparable (Burkhardt 2015). In the case of Amazon's anticipatory shipping, the two forms of prediction—recommender algorithm and anticipatory shipping algorithm—do not exist independently from each other. Recommendations are based on customer data. The prediction of future purchases in a specific region, on the other hand, is based on this very database co-produced by the recommendation algorithms. Anticipatory shipping is, as the patent describes it, based on historical customer data.

> Specifically, in one embodiment, forecasting model [...] may be configured to forecast or predict customer demand for a given item. Forecasting model [...] may be configured to predict aggregate demand for items as well as demand within particular geographical areas. (Spiegel et al. 2013, 17)

Moreover:

> Demand may be predicted in various ways. For example, if a given customer has purchased a given item, other customers with similar historical shopping patterns (e.g., having purchased or browsed items similar to those of the given customer) may be more likely to purchase the given item, and in some embodiments forecasting model [...] may be configured to detect such possible correlations. (Spiegel et al. 2013, 18)

Following these descriptions, anticipatory shipping is not just based on purchases but also on browsing history, patterns in user ratings, and many more factors. Recommendations are placed on the e-commerce platform based on exactly these parameters. For their recommendation system, Amazon utilizes a method that allows the identification of not only the personal purchase history but also personalization based on group behavior identification. If you browse a certain item, the recommendation is based on the browsing history of other "dividuals": users who viewed this item also viewed that one. This, however, influences how actants are connected in a particular market. The recommender system becomes a calculative mode of market organization, including certain market participants and excluding others by default. Of course, this segmentation mechanism can be overcome by individual searches, but still, the interactions are highly pre-structured. The recommender algorithm, while not absolutely deterministic, shapes the market; it becomes a market device (Muniesa, Millo, and Callon 2007). Based on this market device, the anticipatory shipping is not based on an external phenomenon to be predicted but reproduces to some degree what the recommender system performed in the first place. Prediction of user choices in the form of a recommender pre-structures and co-produces the data sets that are used for predictions of purchases in anticipatory shipping. The anticipation of purchases is therefore not so much the analysis of an independent and objectively given world but rests on complex interactions between algorithmic selection, logistical media, and market choices of consumers.

While recommender algorithms are performing markets that are subsequently predicted in anticipatory shipping, the models of anticipatory shipping are also being stabilized by adjusting the reality of purchased goods to match the representation of the world created in the database of Amazon. False positives, or, more simply, incorrect predictions, are attempted to be "saved" via the e-commerce platform, by offering goods to customers close to the actual location of the shipped package.

> Using a shipping model […] may allow for increased predictability and flexibility of control of speculatively shipped packages already in transit, for example by selectively offering packages in transit to a customer depending on the proximity of those packages to the customer, or based on a customer's potential interest in items included in those packages. (Spiegel et al. 2013, 17)

Combining logistical media with digital marketplaces creates even stronger performed markets, making predictions more accurate without changing the model behind the anticipatory shipping method. Demand is not predicted but produced.

Prediction of Demand, Demands of Prediction

The technology of anticipatory shipping has not been adopted by many companies yet but promises its wide application in the future. While Amazon is often considered a key player of a technological avant-garde, others have started to adopt and adapt these methods as well.[2] However, anticipatory shipping comes with specific requirements and demands that have to be met. Predictive analytics is not a detached technology that can be applied at any time and place, but it must be embedded in a whole algorithmic ecology (Beer 2017). Although it has often been described as such, “the algorithm” is not a mystical and powerful actor by itself (Ziewitz 2016). The power of algorithmic systems is neither inherent to the term digital, nor is it exclusively a question of culture. In the case of Amazon’s anticipatory shipping, effective prediction is based on and enabled by two crucial elements.

First, we have to account for the entanglement of digital and material infrastructures. Prediction in its probabilistic nature requires methods and procedures to account for false positives. In the case of Amazon, a dense network of sensors, RFID chips and digital communication channels for fine-grained surveillance of shipped commodities is combined with a material infrastructure with planned frictions, interruptions and pauses that enable the re-routing of goods accordingly. Without such an infrastructural network, false predictions would become costly—and prediction a bit less likely. Material infrastructure is a defining element enabling the revolution of logistics (Vahrenkamp 2012) but also for organizing social life as such (Graham and Marvin 2001). However, what increasingly holds these infrastructures together is a network of digital communication channels, coordinating flows of goods and integrating heterogeneous sites in a logistical network. Prediction relies on the coupling of digital and material infrastructures controlled from a common center of calculation.

Second, predictions of social systems are hardly ever based on observations that are unaffected by the process of prediction. In the case of Amazon’s anticipatory shipping, predicting demand is based on the same data sets that are used to produce recommendations, and thereby creating demands. Thus, recommendations become a powerful tool to construct markets and connect demand and supply—recommendations are

2 In Germany, *Blue Yonder* is an important player in artificial intelligence solutions for retail, implementing predictive analytics to forecast demand for several companies (see for example: www.blue-yonder.com/en/customers/otto-price-replenishment-optimization, accessed June 21, 2019)

affirmatively creating what they are predicting in the first place. This has profound effects on the production of prediction as well as the production of knowledge in digitized societies. Inquiries into these interdependencies of digital culture are therefore necessary to understand epistemic and technologic practices of applied predictive analytics. Yet, this entails technical questions of computability of actions as well as cultural ideas of similarity and group behavior of consumers.

In order to account for the social power of machine learning in societies that increasingly rely on algorithms as *knowledge machines*, the affordances and necessities formulated by these applications need to be understood. Interactions with algorithmic systems are stabilized by a wider network of actors, databases, data workers, protocol interfaces, and so on. The complex matter of implementing predictive analytics in logistical media can produce profound economic and political impacts. Anticipatory shipping promises to reduce delivery times tremendously, which results in competitive advantage. However, this advantage is not open to everyone. Amazon is able to stabilize and enable predictions because of its power to shape markets and control supply chains in a wide network of dispatch and fulfillment centers, and to integrate false predictions into a constant flow of goods. Yet, this utilization of machine learning in logistical business is not necessarily available for all competitors, only to the ones with comparable capabilities to combine big marketplaces with highly controlled logistic infrastructures. In a more recent development, Amazon even started to establish its own package delivery service (Soper 2017) and the controversial partner program “Amazon Flex” (Matsakis 2019) to strengthen its independence from companies such as UPS and FedEx and to make this assemblage even stronger. As such, predictive analytics as a market device is available for the big players and stabilizes their position within increasingly consolidated markets—a development that could lead to a monopolization of (online) trade, putting pressure on competitors and consumers alike. These developments call for an ongoing investigation of technology-driven shifts in (online) markets. To do so, however, we have to accept that “we have never been modern” (Latour 1993). Instead of approaching these questions only from a technological or economic perspective, a broad disciplinary portfolio of approaches is needed to understand the techno-political hybrids that shape contemporary markets. This includes at least dialogue and collaboration with computer scientists for a deep understanding of algorithmic phenomena in contemporary societies. Without an interdisciplinary approach, our explorations into digital cultures might come to a certain end, providing us with neither predictions nor explanations.

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