

Understanding Behaviors that Lead to Purchasing: A Case Study of Pinterest

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ABSTRACT

Online e-commerce applications are becoming a primary vehicle for people to find, compare, and ultimately purchase products. One of the fundamental questions that arises in e-commerce is to characterize, understand, and model user long-term purchasing intent, which is important as it allows for personalized and context relevant e-commerce services.

In this paper we study user activity and purchasing behavior with the goal of building models of time-varying user purchasing intent. We analyze the purchasing behavior of nearly three million Pinterest users to determine short-term and long-term signals in user behavior that indicate higher purchase intent. We find that users with long-term purchasing intent tend to save and clickthrough on more content. However, as users approach the time of purchase their activity becomes more topically focused and actions shift from saves to searches. We further find that purchase signals in online behavior can exist weeks before a purchase is made and can also be traced across different purchase categories. Finally, we synthesize these insights in predictive models of user purchasing intent. Taken together, our work identifies a set of general principles and signals that can be used to model user purchasing intent across many content discovery applications.

1. INTRODUCTION

E-commerce has drastically changed traditional buyer-seller relationships, as well as the shopping process for many consumers [4]; today, consumers are able to browse and compare endless product catalogs, create wishlists, and enjoy powerful features such as search, personalization, and the benefits of social networks [5, 12, 21, 26]. As the complexity of online shopping behaviors has increased, it has become increasingly important to understand and characterize consumer online purchasing behavior. In particular, it is essential to un-

derstand how user activity might build up over time into purchase intent, and ultimately, a purchase. Here, purchase intent is defined as a predictive measure, at a given time, of subsequent purchasing behavior [23].

Understanding online purchase intent and its buildup over time is important because individuals spend large amounts of time and resources on online shopping—in the U.S. alone, e-commerce sales have reached over 350 billion USD per year and are expected to grow at around 15% annually [8]. Modeling and recognizing purchase intent is vital for providing better services, more usable e-commerce platforms, and improved personalization in content and search result rankings, as well as advertising.

However, there are several challenges in studying the purchase intent of online users. Generally, most prior work has examined short-term user activity and considered predicting whether a given user session will result in a purchase [18, 22, 29, 30, 32]. But the purchase intent of a consumer may slowly build up over time, and may not instantaneously lead to a purchase. Furthermore, traditional studies often examine user behavior on a single e-commerce platform, while users may use several different services and move across e-commerce platforms when deciding which product to purchase and where. Thus, what is missing from the picture is a cross-platform analysis of how user purchase intent varies over time. To this end, it is important to contrast the population of purchasing users with the population of non-purchasing users, and then also identify how purchasers' online behavior changes over time from the norm as a result of impending purchases.

Present work: Understanding cross-platform purchasing behavior. Here we perform a large-scale cross-platform longitudinal study of user purchase intent and how it builds and varies over time. We adopt the definition of purchase intent as a predictive measure of subsequent purchasing behavior [23] and estimate it by tracking anonymized user activity on a content discovery application. We identify four general classes of actions that users on content discovery applications engage in: closing-up on a piece of content, clicking through a link to an external website, searching for content, and saving content for later retrieval. We then analyze how engagement in these actions predicts users' future purchasing activity on a number of e-commerce platforms.

In particular, we study how the usage of Pinterest [17], a content discovery application, relates with future user shopping behavior. On Pinterest, users engage with visual bookmarks, called pins, which can be saved into collections of pins, called boards. In order for users to discover pins to

*Research partly done while at Pinterest.

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save to boards, users can search, closeup, and clickthrough on pins. We analyze the detailed activity traces of over two million Pinterest users over a one month time period and partner with external e-commerce sites in order to identify how Pinterest usage activity related to the future purchasing activity of those users.

We discover general cross-platform signals which characterize how purchase intent builds over time. While we created the dataset such that the number of active days in our observation period of purchasers and non-purchasers is the same, we surprisingly found that the total number of raw actions is slightly smaller for purchasers. In fact, we find that a trivial hypothesis that purchasers are simply more engaged users is not true, and our analyses reveal a much richer picture about the behavioral differences between the two populations. In particular, we find that purchasers engage in more high-effort actions. For example, purchasers tend to clickthrough on on-site content to visit external websites about 25% more, and engage in about 5% more saving behavior. On the other hand, purchasers tend to engage in about 5% fewer search and content closeup actions.

Users on Pinterest engage with a broad and diverse set of content, such as food and drinks, fashion, travel, gadgets, arts and crafts, as well as decorations and interior design. From analyzing the content users engage with, we find that users with purchase intent tend to disproportionately focus on content related to their purchase. In particular, we find a strong correlation between content engagement and purchasing behavior for content related to weddings, kids, travel, holidays, events, and health & fitness.

Importantly, in general we find that signals for purchase intent tend to slowly build up over time, and sharply increases about 3 to 5 days before a purchase. For example, we observe that about three days before the purchase, users with purchase intent start being more active. At that time we also observe that the number of searches and clickthrough actions to external websites sharply increases at the expense of browsing and content saving. Likewise, the focus on purchase content is frequently amplified about three days before the purchase, and on the day of purchase, users are on average nearly twice as likely to engage in commercial content (i.e., pins that are related to buyable products) of the same type as the category of the product they eventually buy.

To understand the dynamics of purchase intent over time and how it builds up, we formulate a prediction task aiming to detect whether a given user is going to make a purchase online k days or hours in the future. We find that purchasers can be identified with medium accuracy as early as 28-days before their purchase date. Again, we find that about three days before the purchase, users with purchase intent are easier to identify, with the last day being the easiest. By increasing the temporal resolution to hours, we find that behavioral characteristics of purchasers get very specific about three hours before the purchase and that such users can be relatively reliably identified. We further examine whether not just the purchase intent but also the category of purchase can be reliably modeled. Here we find that purchasers in weddings, home and decor, holidays, events, and cosmetics are easiest to identify.

Taken together, our study provides one of the first windows into how usage patterns on content discovery applications relates to user long-term purchasing behavior on external e-commerce platforms, and how user purchase intent

builds up. In general, our work has many practical applications in that the identification of users with purchase intent can be used to improve personalization, search, and content ranking efforts. Applications can also focus on promoting commercial content (e.g., buyable pins, or pins from which a direct purchase can be made on Pinterest) towards the users who would be interested, i.e., users with identified purchase intent.

2. RELATED WORK

Research on the purchasing behavior of online shoppers has a long tradition and dates back to the early days of e-commerce on the Web [4, 24]. Studies have investigated how motivations, privacy/security considerations, as well as demographic factors, such as gender and age, determine online shopping behavior [5, 9, 10, 14, 16, 19, 26, 27, 28, 31, 33]. Our work here adds to this line of work by performing a longitudinal analysis of how long-term as well as short-term usage patterns of a content discovery application differ between populations of purchasers and non-purchasers.

Another line of related work focuses on using machine learning methods to predict purchasing behavior. Prior work has considered predicting the purchase propensity of a given user for a given product in a given time window [18, 22] as well as predicting whether or not a purchase will be made during the next visit to the website [32]. In terms of features used for making such predictions, prior research has investigated user demographics and interests [34], user purchase patterns [18], product characteristics [5], as well as detailed navigational click-stream and web search data [22, 29, 30, 32]. Purchasing intent has been especially well studied in the context of search engines in order to identify user search goals [1, 6, 11, 20, 25]. There are many similarities as well as differences with our work here. While the above studies often focus on short-term user behavior on a website and try to predict a user’s purchasing intent on that same website, our work here is different. We observe a user’s actions and activity on one application, and then aim to correlate behavior on that application with the user’s purchasing behavior on different, external websites. Also, our goal here is broader as we aim to understand how the use of content discovery applications relates to shopping behavior. In particular, we are not interested in just predicting whether a given usage session will result in a purchase, but rather aim to characterize how the overall behavior and usage of a content discovery application differs for online purchasers and how purchase intent builds up over time.

More recently, social media has opened a new avenue for research on the behaviors of online purchasers and several interesting problems have been studied. Works have focused on modeling correlations between users’ social media profiles and their e-commerce behaviors [35] as well as understanding the linguistic relationships between users’ purchasing intent and their social media posts [3, 7, 13, 15]. Another interesting aspect is the role of social networks in online shopping in terms of user-to-user communication [12] as well as the diffusion of product adoption in social networks [2, 21]. Our work adds to this line of work by performing a large-scale longitudinal study of the dynamics of user purchase intent across a number of e-commerce sites. In contrast to previous work, our user activity data is resolved down to single actions and we not only observe user posting behavior but also clicking, searching, and browsing. Taken together, our work

identifies a set of general principles and signals that can be used for modeling user purchasing intent across many social media and content discovery applications.

3. DATASET DESCRIPTION

Our analysis focuses on the behavior of users on Pinterest, a content discovery application founded in 2010. While the concept of boards and pins is unique to Pinterest, many of the actions surrounding these concepts are analogous to actions that can be taken by different content discovery applications, making our subsequent findings generalizable.

3.1 Mechanics of a Content Discovery Application

We characterize four broad classes of actions that users in many content discovery applications take. Example content discovery applications include YouTube and Instagram, and even traditional social networking applications such as Facebook and Twitter have features that allow them to be considered as content discovery applications. Here we use Pinterest as a concrete instance in our analysis.

On Pinterest, specifically, users can browse, zoom-in on, and save/bookmark images—referred to as pins. These pins can be collected into boards, which are then shared with other users of the service. The four classes of actions are as follows:

- **Search:** Nearly every content discovery application possesses search functionality that allows users to *discover* previously unseen content. For example, users can search YouTube for videos, and Twitter for tweets and other users. On Pinterest, users may enter search queries (e.g., “christmas ornaments”), and pins that are related to the search query are subsequently displayed.
- **Closeup:** Applications allow users to engage *on-site* with specific content to reveal more information; we call this action a closeup. For example, on Facebook, Twitter, and Instagram, users can closeup on a post to receive detailed information. On Pinterest, users may choose to closeup on a pin so that a higher resolution image with text information is displayed.
- **Clickthrough:** Content discovery applications also allow users to engage *off-site* with content; we call such actions clickthroughs. For example, on Facebook and Twitter, this translates to clicking on a link to an external news article, and on Pinterest, users can click on links to external sites such as recipe blogs or e-commerce sites.
- **Save:** Many content discovery applications allow users to bookmark or save content for later retrieval and viewing. For example, YouTube allows users to organize and save videos into playlists, and Twitter allows users to create curated lists of other Twitter users. On Pinterest, users save pins by collecting them in boards.

3.2 Pinterest Dataset Preparation

Our dataset focuses on the anonymized activity and purchase data of Pinterest users in the United States in May of 2015. Users who make online purchases on one of Pinterest’s external partner companies (e.g., wedding invitation and footwear retailers) are referred to as *purchasers*. These purchasers buy items that span across a broad spectrum of categories, ranging from fashion to sports.

Statistic	Value
Number of purchasers	1.3M
Number of non-purchasers	1.3M
Number of users (total)	2.6M
Number of actions (total)	0.5B
Time duration	28 days
Month when purchases were made	May 2015

Table 1: Dataset statistics.

Purchasers and non-purchasers. Our sample dataset includes 1.3M unique users who purchased one or more items from partner companies in the month of May 2015. Each of these users was active on Pinterest at some point in the 28 days prior to a purchase (Table 1).

We find that the number of purchases made per user follows a heavy-tailed distribution with exponent 1.5 (Figure 1(a)). Less than 40% of users make more than one purchase in our observation period, and for these users we only consider a single randomly sampled purchase. We refer to the day on which this purchase takes place as the *purchase date*.

In subsequent analyses we compare the population of purchasers with the population of non-purchasers. For the purpose of this analysis we define *non-purchasers* to be users who do not purchase anything from one of Pinterest’s partner companies in the month of May 2015. (Note, however, that these users may have made purchases outside our observation window or while logged out of Pinterest.)

In general, we find that purchasers log on to Pinterest more frequently than non-purchasers. In order to conduct a more nuanced analysis that observes beyond such zero-order effects, we carefully match each purchaser with a non-purchaser by controlling for three potentially confounding factors: (1) registration month, to minimize sign-up cohort effects; (2) the number of days active 28 days prior to a purchase, so that similar long-term activity levels are maintained, and (3) gender, to minimize unrelated population-based effects, which we also minimize by considering only U.S.-based users. The benefit of matching is that we now have a paired and aligned population, which means that we can compare the dynamics of activity between each purchaser and her matched non-purchaser over time.

Time span. We refer to the 24 hour period of time prior to a purchase as day 0. Our analysis of user behavior spans the 28 day time period prior to purchase. In our analysis, N days prior to day 0 is referred to as day $-N$; thus, our analysis spans from day -27 to day 0.

3.3 User Activity Characteristics

To better understand user activity on Pinterest and how it varies in aggregate between purchasers and non-purchasers, we conduct an initial analysis of overall user activity.

We first examine overall activity levels by computing the number of days purchasers and non-purchasers are active within our 28-day dataset. A CCDF plot is shown in Figure 1(b). Cumulative density is practically identical between purchasers and non-purchasers, validating our matching process (as number of days active was used as a criteria for matching). More importantly, we observe that users in our dataset are, on the whole, regularly active. In fact, 50% of users are active at least 7 out of 28 days (i.e., approximately

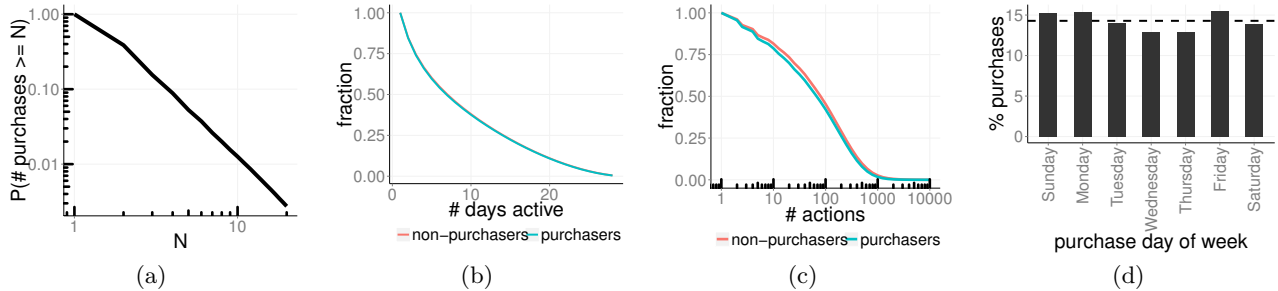


Figure 1: (a) CCDF of number of purchases made by purchasers in May 2015, capped at 20 purchases. (b) CCDF of number of days purchasers and non-purchasers are active in our analysis. Note that lines are identical. (c) CCDF of number of actions taken by purchasers and non-purchasers, capped at 10^4 actions. (d) Percentage of purchases made on any given day of the week.

every four days), and 25% are active 14 out of 28 days, i.e., approximately every other day.

Interestingly, we also notice that non-purchasers take slightly more actions than purchasers in aggregate (Figure 1(c)). Here, we define an action to be one of the four identified actions described in Sec. 3.1: search, closeup, clickthrough, or save. We also find that the amount of saved content, expressed as the number of saved boards and pins, is virtually identical between purchasers and non-purchasers (plots not shown for brevity). These observations are particularly interesting as they invalidate a trivial hypothesis that purchasers tend to be more engaged users. Moreover, these observations motivate our work because they suggest that on the surface purchasers seem to be no different from non-purchasers. In what follows, we develop a methodology that allows us to reveal a richer and more fine-grained picture about behavioral differences between the two populations.

4. DYNAMICS OF PURCHASE INTENT

Motivated by our observations, we now aim to develop a deeper understanding of how user purchase intent evolves over time, *i.e.*, how it builds up and ultimately results in an online purchase. Specifically, we examine user activity levels, types of actions taken, and content users interact with.

4.1 User Activity Level

In Section 3.3 we saw that in aggregate, purchasers are no more active than non-purchasers. However, we would expect that behavioral differences in activity emerge as the time of purchase approaches.

In order to see if such differences exist, we first note that seasonal cycles impact user online activity. To prevent such global changes from impacting our analysis, we compute the relative activity level of purchasers when compared to non-purchasers. We call this metric the *activity ratio* (AR) for each day d :

$$AR(d) = \frac{\% \text{ purchasers active on day } d}{\% \text{ non-purchasers active on day } d}. \quad (1)$$

Users are considered active on a certain day if they took at least one action on Pinterest on that day.

Figure 2(a) shows the activity ratio in the 28 days before purchase. Recall that we match purchasers with non-purchasers based on the number of days active in the 28 days before a purchase is made. If the intent to purchase

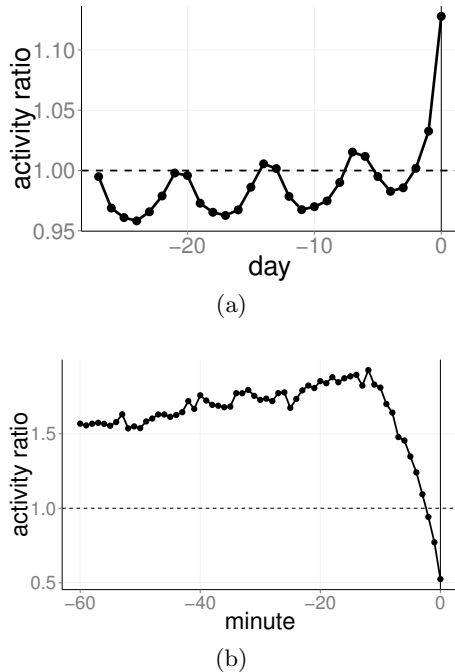


Figure 2: (a) Activity ratio of purchasers over time by day. Dashed line indicates comparable activity levels between purchasers and non-purchasers. (b) Activity ratio computed by minute.

did not impact user activity, we should see comparable levels of activity between purchasers and non-purchasers throughout the entire time duration analyzed, *i.e.*, the activity ratio should remain at approximately 1 throughout the entire time span. However, we instead observe interesting phenomena. First, we note that purchaser activity follows a weekly cycle, peaking on the purchase date’s day of week, meaning that purchasers are more likely to be on Pinterest on the day of week in which a purchase takes place. Figure 1(d) shows that while there is some variation, overall, purchases take place at every day of the week. In contrast, non-purchaser activity peaks only on weekend days, explaining the cyclic nature of the figure.

Second, we observe a slow but significant buildup of user activity. In fact, we notice a sharp increase in activity levels

in the three days right before a purchase—in particular, on the day of purchase, the activity ratio is 1.2, meaning that on that day, purchasers are 20% more likely to be active on Pinterest. The phenomenon of signals for purchase intent increasing sharply 3-5 days before a purchase is one that we observe multiple times throughout our analysis.

The fact that purchasers are more active on Pinterest closer to the purchase date remains true even when we closely zoom in to the period of time right before a purchase. To confirm this, we examine the ratio of users active on the site minutes before a purchase is made (Figure 2(b)). Here we compute activity ratio, where we compare the number of purchasers and non-purchasers active on a given *minute* as opposed to a day. We observe that purchasers are increasingly likely (nearly 2 times as likely) to visit Pinterest as the purchase time approaches, with a sharp but natural dropoff to account for time spent on the e-commerce site when actually making the purchase.

From our analysis of purchaser activity levels over time, we can conclude that in aggregate, purchasing intent can be reflected via a user’s activity on a content discovery application. In short, as purchase intent increases and manifests itself as a purchase, purchasers are more likely to be active on a relevant content discovery application. This observation, however, raises the question: How exactly might a purchaser’s specific behavior on the application change as a result of increasing purchase intent?

4.2 Types of User Actions

On many online applications, users can take different actions, which represent varying levels of effort. We would expect that the distribution over actions that purchasers take changes as the purchase time approaches.

We consider the four types of actions that users can take on social applications, as discussed in Section 3.1: search, closeup, clickthrough, and save. Note that on Pinterest, all these actions are taken by users intentionally, as opposed to passive actions such as viewing a pin that is recommended on a user’s home page. Among these four types of actions, searching and clickthroughing are typically used to browse and examine content. Both clickthroughing and saving are considered actions that suggest higher levels of engagement in specific content.

To determine the extent to which each user prioritizes each type of action, we compute an *action score* (AS) for each user u , day d , and action type a , defined as follows:

$$AS(u, d, a) = \frac{\# \text{ actions } u \text{ took on day } d \text{ of type } a}{\# \text{ actions } u \text{ took overall on day } d}. \quad (2)$$

For each action type a , we can then compare the action scores of purchasers and non-purchasers for each day d by computing an *action score ratio* (ASR):

$$ASR(d, a) = \frac{\text{avg}_{u \in \text{purchasers}} AS(u, d, a)}{\text{avg}_{u \in \text{non-purchasers}} AS(u, d, a)}. \quad (3)$$

Long-term behavior. Figure 3 plots the action score ratio for each action type over time (with day 0 being the day of purchase). As with our earlier analyses, if purchasers used Pinterest in the same manner as non-purchasers, one would expect the ASR to remain at approximately 1 at all times, for all action types. However, again we see that this is not the case; throughout the entire time period, purchasers have a higher save and clickthrough ASR, and a lower closeup and

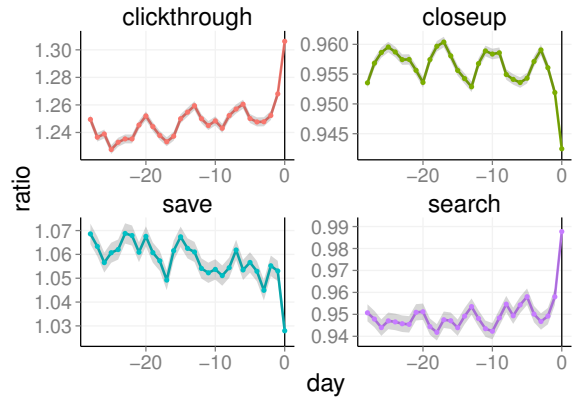


Figure 3: Action score ratios for each day. Shaded area represents standard error.

search ASR. As saves and clickthroughs are actions that suggest higher engagement with specific content, we conclude that purchasers are as a whole more focused on specific content, rather than casually interacting with many different types of content. We next take note of the substantially higher overall clickthrough ASR (1.25 average), when compared with the save ASR (1.06 average), which suggests that examining content is a stronger potential signal of long-term purchase intent than saving content.

Lastly, we observe that the actions that purchasers take relative to non-purchasers change over time. Clickthrough ASR, for example, increases noticeably from 1.26 to 1.30 in the three days right before purchase and peaks on the purchase date itself. In contrast, in the 28 days prior to purchase date, the clickthrough action scores of non-purchasers remain relatively constant (plot not shown). We observe similar behavior for searches, while the amount of save and closeup actions drops in the last three days before the purchase. Over 28 days, search action ratios increase and save action ratios decrease very slightly for all users, but the corresponding increase and decrease among searches and saves for purchasers in the three days before purchase is much more prominent, which results in the trends observed in Figure 3.

We find it especially intriguing that many of the temporal changes in ASR occur surrounding the purchase date. In fact, the spikes in ASR on the date of purchase suggest that purchaser behavior does change right before a purchase.

Short-term behavior. To further examine temporal trends in behavior, we next focus on just the 24 hours before the purchase. Figure 4 plots the ASR per hour for this time frame. Here we immediately observe that the spikes in clickthrough and search ASR seen on day 0 (Figure 3) spike even more sharply as the purchaser approaches the hour of purchase (Figure 4). For example, the likelihood that purchasers will engage in clickthrough actions increases from 30% at the start of the day to 50% at the time of purchase. We furthermore observe an interesting unimodal pattern for closeups, where the ASR peaks within 8 to 15 hours before purchase.

Most interesting is the fact that for several hours before a purchase, purchasers are *more* likely to conduct search actions. In the majority of our analysis we found that differences between purchaser and non-purchaser behavior are

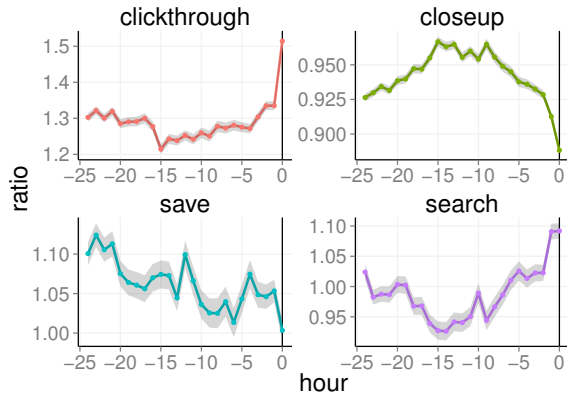


Figure 4: Action score ratios for the hours before a purchase. Shaded area represents standard error.

amplified towards the date of purchase, but in this case, recall from Figure 3 that purchasers are actually *less* likely to search for content in the long-term. This shows that searching is most likely to provide direct utility for purchasers in the short term.

From our analysis of different action types taken by users on Pinterest, we conclude that there exist two overarching characteristics in the behavior of purchasers. First is an increased investment in specific content over a lengthy period of time. Second is a sharp increase in searching for and browsing through content on the purchase date relative to the purchasers’ behavior on other days. Put together, we can conclude that purchasers seek out content over time in a more frequent and more focused manner than their non-purchaser counterparts.

4.3 Content Users Interact With

Our above conclusions motivate our next question: What types of content do purchasers seek out over time, and how might this reflect upon their purchase intent? We aim to examine whether purchasers are more likely to focus on content relating to their future purchases.

On Pinterest, specifically, all content falls under one of 32 predetermined high-level categories, ranging from “Women’s fashion” to “Travel” to “Weddings”. Using these high-level categories, we can characterize the topicality of pins users engage with. Similarly, by examining the category of pins that are owned by Pinterest’s partner companies, we also assign a category to each partner company by finding the most common category of the pins owned by the partner company. We find that all partner companies fall within 10 high-level categories.

For each purchaser, we then compare her level of interaction in her purchase category with the average non-purchaser’s level of interaction in that category. Specifically, let

$$I(u, d, c) = \frac{\# \text{ actions } u \text{ takes in category } c \text{ on day } d}{\# \text{ actions taken in total on day } d}. \quad (4)$$

$I(u, d, c)$ (*category interaction score*) is the fraction of actions taken by a user u on day d that fall under some category c . Here, we define an action to be a closeup, save, or clickthrough, all of which are actions that involve interacting with a single pin. We define an action to be taken in a certain category c if the pin interacted with belongs to that

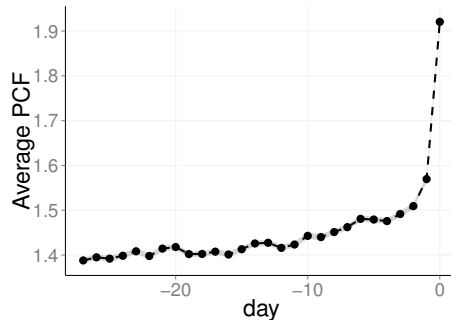


Figure 5: Average purchase category focus (PCF) score for purchasers active on Pinterest, by day. Shaded area represents standard error.

category. We can define for each purchaser p , category c , and day d the *purchase category focus* (PCF) score:

$$PCF(p, d, c) = \frac{I(p, d, c)}{\text{avg}_{u \in \text{non-purchasers}} I(u, d, c)}. \quad (5)$$

The PCF score directly evaluates the relative amount of interaction a purchaser devotes to her purchase category as compared to a baseline user. If purchasers were not more focused on their purchase category than the average user, one would expect the average PCF over time to be 1.

Figure 5 plots the average PCF for the 28 days prior to purchase. We make several observations. First, the average PCF remains noticeably above the baseline of 1 for the entire time duration. In other words, purchasers are already predisposed to interacting with content in their purchase category, well before a purchase is made. We also observe a steady rise in the PCF throughout the entire 4 week period, in which the PCF increases from 1.4 to 1.5. Most interestingly, we observe a sharp increase in the last three days before the purchase. Overall, PCF provides a reliable signal for growing user purchase intent, both as a long-term signal as well as a useful short-term signal.

Per-category PCF. Thus far we only examined the interaction of all purchasers with their purchase category, in aggregate. Thus, a natural follow-up question is: How does the purchase category focus (PCF) differ between categories? In particular, we are interested in understanding how much more engaged are purchasers in specific categories.

To answer this question, we compute the average PCF for purchasers, split by purchase category (Figure 6). We observe that for the vast majority of categories, the average PCF remains above 1, which means that purchasers are generally more focused on their purchase category.

We next observe that overall PCF levels vary widely between different categories. Purchasers in specialized categories, such as “Holidays & Events” and “Weddings” have a higher overall PCF, whereas broader categories with more general appeal, such as “Food & Drink” and “Women’s Fashion” have lower overall PCF scores. The PCF score can therefore be considered comparatively as a measure of how much general appeal (to purchasers and non-purchasers alike) a category may have; higher PCF scores overall mean that those who interact with that category may be that much more inclined to make a purchase.

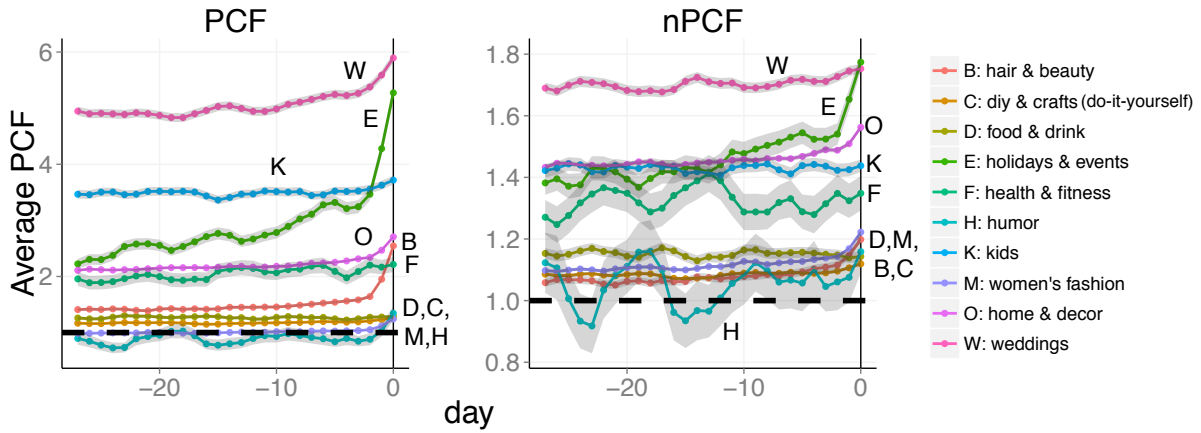


Figure 6: Left: Average purchase category focus (PCF) scores for purchasers in each purchase category. Right: Average normalized purchase category focus (nPCF) scores for purchasers in each purchase category. Shaded area represents standard error.

Furthermore, we also observe that while many categories experience a spike in PCF right before the purchase date, this behavior differs across category. “Holidays & Events” and “Hair & Beauty”, for example, experience a more dramatic spike, whereas “DIY Crafts” barely experiences a spike at all. One explanation is that there may exist a correlation between the size of a spike in PCF on the purchase date and the tendency for users to make an impulse or sudden purchase in that category. For example, one may decide, after browsing for a short while on Pinterest, to purchase a Christmas card or a hair curler on a whim, but because DIY projects can span a lengthy period of time and may require pre-planning, it is less likely that a brief online browsing session will be sufficient to determine what to purchase.

While PCF is a good measure to gauge a purchaser’s focus on her purchase category in comparison with the global population, an important question remains unanswered: What happens when we compare how interested a purchaser is in her purchase category with users on Pinterest who we already know are interested in that category? To compare these two types of users, we introduce the *interest-normalized purchase category focus* (nPCF) score:

$$nPCF(p, d, c) = \frac{I(p, d, c)}{\text{avg}_{u \in \text{interested}_{np}} I(u, d, c)}, \quad (6)$$

where *interested_{np}* is the set of non-purchasers who interacted with category *c* on Pinterest on day *d*. In essence, *nPCF* allows us to determine whether interested purchasers might be even more interested in their purchase category than interested non-purchasers.

Figure 6 plots the nPCF over time. Here, an nPCF score of 1 would indicate that interested purchasers are approximately as focused on their purchase category as non-purchasers interested in that purchase category are. Surprisingly, we see that across the board, even within only the population of users who are already interested in their purchase category, purchasers are even more focused on their purchase category than average. They are in fact extra dedicated to their purchase category, which further highlights the potential effectiveness of targeted advertising efforts.

In summary, our analysis here shows that 1) users with purchase intent focus on content related to their purchase,

and increasingly so as the purchase date approaches, and that 2) the extent to which purchase intent is expressed varies by category.

5. MODELING PURCHASE INTENT

Our analysis thus far points to noticeable differences in the online behavior of purchasers, which grow slowly over weeks and are amplified in the days right before a purchase. To better understand the dynamics of how purchase intent grows over time, we build on the insights and signals developed in Section 4 to formulate the following general prediction task: Can we identify purchasers based on their behavior *k* days before purchase?

Here, we are interested in seeing how predictive performance might change over time, or by category, to reflect purchase intent. If purchasers are easy to identify (predictive performance is high) then their behavior is very different from users with no purchasing intent. Similarly, if purchasers are hard to identify (low predictive performance), then their purchasing intent is also low since the activity patterns closely match those of non-purchasers.

Features used for learning. Based on our insights from Sections 3 and 4 we identify five general classes of features that can be extracted in any content discovery application, including Pinterest. Note that here, none of the computed features rely on prior knowledge of whether a user is a purchaser, and can be computed on an individual basis.

- **Demographics (4 features):** Demographic information used most frequently in computational advertising. It forms a useful baseline because it contains static, infrequently changing information. We include gender and geographic region as well as long-term user profile information, namely the number of boards and pins created by a user to date (Sec. 3).
- **Activity (2 features):** In Sec. 4.1 we observed that activity levels of purchasers change as the purchase date approaches. We formalize this as two features: the number of days active in the previous 7 days and the number of actions taken in a day.

- **Action-type (2 features):** We also observed that a user’s mix of actions changes as the purchase date approaches (Sec. 4.2). We capture this via each user’s action ratio across each of the four action types, as well as platform usage information (*e.g.*, mobile, desktop).
- **Content (2 features):** Sec. 4.3 showed that purchase intent is revealed through the type of content users interact with. We capture this signal by computing category interaction scores as seen in Eq. (4). We do not include PCF scores, as they indicate knowledge of a purchase category. We instead include category interaction scores, normalized by a user’s activity level, from a set of approximately 500 LDA-trained topics, which Pinterest uses internally as sub-categories.
- **Temporal (3 features):** Throughout Sec. 4 we observed consistent temporal dynamics where purchase intent can build slowly over time. Thus, we include temporal features based on Action-type and Content features, which compare each user’s feature values at a given time with earlier feature values. Specifically, we compare feature values with the values 3 days prior. We also compare feature values between the last two quarters of a day. Finally, we compare the current day’s feature values with the feature values from the entire week prior.

5.1 Modeling Purchasing Intent Over Time

We first aim to understand how well we can identify purchasers as their day of purchase approaches. Our goal is to use changes in classification performance by day to understand changes in user purchasing intent.

We proceed as follows. We train multiple classifiers, one for each day before a purchase. For each day k , we sample 250K purchasers and 250K non-purchasers who were active on Pinterest on that day and our goal is to determine whether a given user is a purchaser (that is, whether the user will engage in e-commerce activity k days in the future). Note that user populations may differ between classifiers, because different subsets of users are active on different days. For each of the 28 days in our analysis we train a separate logistic regression classifier and report the 10-fold cross validated AUC ROC score. A random baseline has a score of 0.50 under this setup.

Figure 7 plots the results over time. We immediately observe that throughout the entire analysis duration, the ROC AUC remains above the random baseline, ranging from approximately 0.62 to 0.66. These results confirm that there exist long-term differences in the online behavior of purchasers, and that these differences provide a non-random signal in identifying them weeks before the purchase. We also note a sharp increase in classification performance in the 3 days preceding the purchase, which parallels the way signals of purchase intent (*e.g.*, activity of purchasers) also pick up in the last three days, as shown in Section 4. As with Figure 4.1, we also observe weekly patterns in our results. Overall, our results suggest that purchase intent slowly builds up over time and significantly increases in the last three days right before purchase.

Next, we focus on user purchase intent dynamics in the 12 hours right before purchase. Our aim is to better understand the extent to which purchaser behavior deviates right before a purchase is made. Here we predict whether a user active in a given hour prior to purchase is a purchaser.

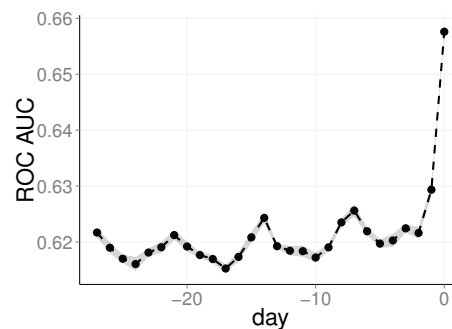


Figure 7: The ROC AUC for predicting whether a given user is a purchaser. Shaded area represents standard error.

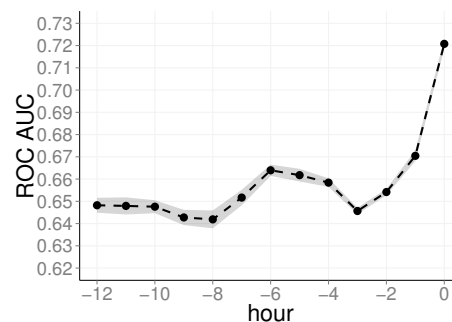


Figure 8: The ROC AUC for predicting whether a given user active on a certain hour is a purchaser.

Figure 8 displays the results. We observe that performance increases significantly as the purchase time approaches. In fact, the ROC AUC for the hour right before the time of purchase is 0.72 (up from 0.65). This result demonstrates that strong short-term differences in online behavior of purchasers exist shortly before a purchase is made.

Overall, we conclude that purchase intent builds slowly over time and starts getting stronger approximately 3 days before the time of purchase. Interestingly, we also observe that last few hours before a purchase, shoppers become easier to identify.

5.2 Importance of Different Signals

To better understand the role that different behavioral signals play in the buildup of purchase intent, we examine separate models trained on different groups of features. We focus on two prediction tasks: identifying purchasers active on day 0, and identifying purchasers active on hour 0.

Results are shown in Table 2. First, we observe that demographics is a very bad predictor of user purchase intent. Content and overall activity have similar predictive performance. The types of actions that users take are the best individual predictors of purchasing behavior (0.63 AUC ROC for day 0 and 0.70 for hour 0). We see that features which represent *how* the user is using the application (Activity, Demographics, and Action-type) are collectively more predictive of user purchase intent than features that represent *what* the user is looking at (Content). However, we also note that *how* and *what* features seem to be somewhat orthogo-

Features	Day 0	Hour 0
Random Baseline	0.500	0.500
Demographics (d)	0.513 ± 0.0007	0.513 ± 0.0024
Activity (a)	0.591 ± 0.0008	0.625 ± 0.0015
Action-type (A)	0.633 ± 0.0008	0.698 ± 0.0020
Content (C)	0.577 ± 0.0008	0.617 ± 0.0020
Temporal (T)	0.544 ± 0.0007	0.581 ± 0.0019
d + a + A (<i>how</i>)	0.642 ± 0.0009	0.702 ± 0.0017
d + a + A + C + T	0.657 ± 0.0007	0.721 ± 0.0026

Table 2: Performance results (ROC AUC) for predicting whether a user is a purchaser based on user behavior at the purchase time.

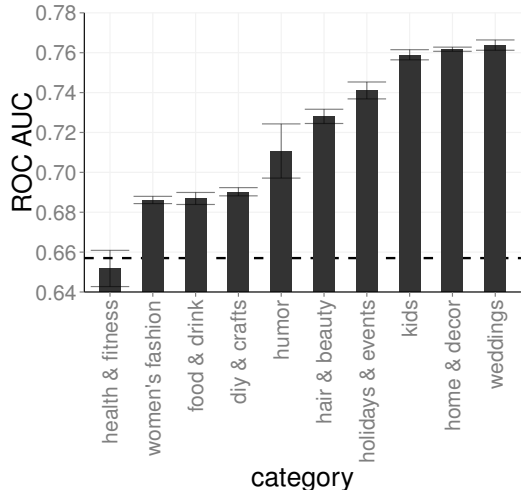


Figure 9: The ROC AUC for predicting whether a given user is a purchaser in a specific category. Error bars represent standard error. Dashed line represents baseline ROC AUC for predicting whether a given user is a purchaser in any category.

nal, as their combination gives best results (0.66 for Day 0, and 0.72 for Hour 0).

5.3 Modeling Per-Category Purchase Intent

Lastly, we consider modeling the intent of users to purchase products in a given product category. Here we formulate a task to predict whether a user will purchase an item in a specific category (e.g., Women’s Fashion) given her activity data on Pinterest.

As before, we only focus on users who are active on the purchase date for each category. We sample an equivalent number of non-purchasers and purchasers in each given category and build one binary classifier per category. Our goal here is to predict whether a user is a purchaser in a given product category.

Figure 9 gives the results. We note that in almost all cases, the ROC AUC is noticeably higher for our category-based classifiers than in our original day-based classifier described in Section 5.1. We interpret differences in ROC values between categories as an indication that purchase intent is easier to identify in some categories than in others. Several large and important categories (e.g., Weddings, Home & Decor) have respectable ROC AUCs, suggesting that in most

cases, category-based classification provides higher utility than general purchaser classification. Finally, we observe that although PCF scores were specifically excluded as a feature in all discussed prediction tasks, generally speaking, higher average PCF scores lead to higher ROC AUC scores in our category-based classification. In fact, the Spearman rank correlation coefficient between the PCF scores and the AUC ROC scores is 0.75, indicating a strong positive correlation. This demonstrates that the content viewed by users can be used to provide insights into their purchase decisions.

Taken together, our results show that purchase intent can be modeled both over time, as well as within a specific category. Our results are also an encouraging proof-of-concept that a user’s online activity in a content discovery application can be used as signals in determining the user’s inclination to purchase online.

6. DISCUSSION & CONCLUSION

In this paper we conducted a data-driven cross-platform analysis of the behavioral and usage patterns of purchasers with the goal of modeling time-varying user purchasing intent. We analyzed the purchasing behavior of over two million Pinterest users to determine short-term and long-term signals in user behavior that suggest strong purchase intent.

We found that users with long-term purchasing intent tend to save and clickthrough more on content. However, as users approach the time of purchase their activity gets more topically focused and actions shift from saves to searches. We also showed that purchase intent can be traced across different purchase categories. Overall, we found that purchase signals in online behavior can exist weeks before a purchase is made and are amplified in the last three days before purchase. Finally, we synthesized these insights into a predictive model of user purchasing intent.

Our study opens the door for many important applications. It provides a promising starting point in terms of identifying potential purchasers and better understanding their long-term behavior. Predictions based on our models show a clear path for identifying users with purchase intent. On Pinterest, this can be used to surface buyable pins only to users whose experience would be improved by their presence, *i.e.*, users with potential purchase intent. Buyable pins are pins that allow a user to purchase products directly from Pinterest’s interface. In general, the identification of users with purchase intent can also be used to improve personalization and search result ranking to provide increased value to users, *e.g.*, users with identified purchase intent in the wedding category can be shown other useful wedding-related content. Finally, our models allow us to better understand how purchasing intent forms around certain topics, as well as brands. Surfacing such analytic results can be very useful to commercial partners as well as to Pinterest itself.

There are also many fruitful avenues for future work. In particular, there is a large opportunity to study how user behavioral data can be used to recognize purchasers in content discovery applications. We believe that an in-depth textual analysis of the content that purchasers on such applications interact with can further increase our understanding of user purchasing intent. And last, further work is needed on how to recognize purchasers based on their online behavior; in particular, we are curious whether long-term behavioral differences exist between impulse shoppers, and shoppers who carefully make well-researched purchase decisions.

Taken together, our work identifies a set of general principles and signals that can be used for modeling user purchasing intent across many social media and content discovery applications. We hope that the present work will serve as a useful basis for future studies on the intersection of online user behavior and purchasing patterns.

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