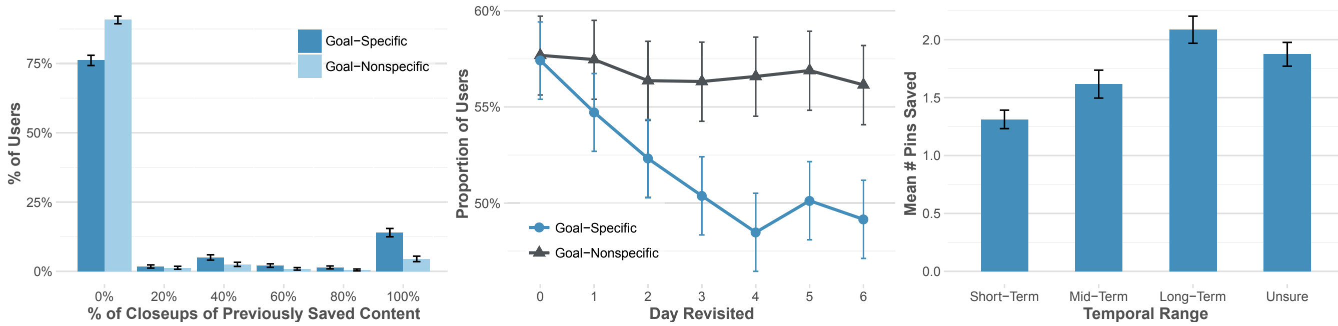


(a) Closeups of Previously Saved Content (b) Likelihood of Revisiting Pinterest (c) Amount of Content Saved

Figure 2: (a) The distribution of the proportion of closeups that were of content a user previously saved is bimodal for goal-specific users, suggesting that these users are either primarily looking for new content, or referring to past saved content. (b) Goal-specific users are less likely to revisit Pinterest on subsequent days. (c) Users with short-term goals save the least pins, while those with long-term goals save the most.

five minutes however, while both groups viewed fewer pins overall, the number of categories goal-specific users viewed decreased more than for goal-nonspecific users (6.2 vs. 8.3 , $t(3138)=12.0$, $p<10^{-3}$, $d=0.43$), suggesting increased specificity in what goal-specific users are looking for. Further, despite viewing fewer pins, goal-specific users did not click through on pins significantly less (0.58 vs. 0.53 clickthroughs, n.s.), while goal-nonspecific users did (0.52 vs. 0.42 clickthroughs, $t(3053)=3.4$, $p<0.01$, $d=0.12$). In other words, rather than switching to casual browsing, goal-specific users appear to be more strongly focusing on their goals over time.

But while goal-specific users spend more time on Pinterest, which may indicate greater engagement, are they more likely to return in the near future? As Figure 2b shows, initially, the likelihood of using Pinterest again on the same day is similarly high (71%) for both goal-specific and goal-nonspecific users. However, on subsequent days, goal-specific users are less likely to visit Pinterest (e.g., 50% vs. 56% on the third day, $\chi^2=16.0$, $p<10^{-3}$), suggesting that goal-specific users' visits may be driven by a particular need, while goal-nonspecific users' visits may be more habitual. Comparing gender, goal-specific female users were more likely to return in the near future than goal-specific male users (e.g., 52% vs. 40% on the third day, $\chi^2=7.8$, $p<0.05$).

Past behavior suggests future goal specificity. Past behavior can predict future intention [3]. While intent can vary from session to session, an individual's goals may persist over longer periods of time. Looking at activity from the past 24 hours prior to the current session, we find that while goal-specific users are not any more likely to have visited Pinterest, they tended to have been browsing less content (311 vs. 263 views, $t(5432)=2.4$, $p<0.05$, $d=0.06$) and viewing pins in fewer categories (controlling for the number of viewed pins, 7.9 vs. 8.4 categories, $V>10^6$, $p<10^{-3}$, $r=0.14$). Thus, goal-specific behavior can be reflected in past sessions, and can inform behavior in future sessions.

4.2 Temporal Range

Temporal range corresponds to when a user anticipates a goal will be accomplished. Goals may be oriented towards the shorter-term future (e.g., tomorrow), or the longer-term future (e.g., the end of the week, perhaps on an indefinite timescale) [14]. Understanding temporal range allows us to understand the urgency of a visit – users looking for recipes to make right away may behave differently from users who are looking for recipes to use sometime in the future, who in turn are likely to behave differently from users who save recipes with little intention of making them. Thus, we asked Pinterest users if they planned to take action on what they were doing on Pinterest in the short-term (defined as within two days), the medium-term (within three to seven days), the long-term (a week or more), or if they were unsure of taking (or not intending to take) action. In this section, we focus on comparing users with short-term goals, long-term goals and those unsure of taking action; observations for users with medium-term goals tend to fall between users with short-term and long-term goals.

Temporal range varies significantly. In contrast to goal specificity's bimodality, temporal range is relatively varied on Pinterest. A third of all users had short-term goals, and another third was unsure of taking action (Figure 1b). Male users were significantly more likely than female users to be unsure of taking action (46% vs. 28%, $\chi^2=55.6$, $p<10^{-3}$). Relating temporal range to specific motivations, a majority of users with long-term goals were looking for ideas or inspiration (56% of users with long-term goals), while users with short-term goals were either looking for ideas or wanting to make something (41% and 26% respectively).

Temporal range correlates with goal specificity. Long-term goals tend to be more abstract and less specific, while shorter-term goals tend to be more concrete and more specific [35]. 49% of goal-specific users planned to act in the short-term (Figure 1b), while 52% of goal-nonspecific users were unsure of taking action. In fact, goal specificity correlates positively with having short-term goals (Pearson's $r=0.42$, $t(5931)=35.8$, $p<10^{-3}$), and negatively with both having long-term goals ($r=-0.31$, $t(5931)=2.4$, $p<0.05$) and being unsure about taking action ($r=-0.45$, $t(5931)=39.9$, $p<10^{-3}$).

Nonetheless, being goal-specific does not necessarily imply taking action in the short-term (e.g., a user may be looking for a coffee table for their new home), and conversely, having short-term goals does not imply being goal-specific (e.g., a user may be looking for something to do during the weekend, but not decided on exactly what). Thus, to isolate the effect of temporal range, we have to disentangle the effects of goal specificity. As such, while this and the previous subsections report differences in one dimension, we also performed regression analysis using both temporal range and goal specificity to ensure that any observations reported are not due to interactions between them.

Users with short-term goals also have greater task-focus, and look at more past saved content but save less new content. Where greater goal specificity suggests that users know what they want, shorter temporal range suggests that users want to do something soon. Given the implication of greater urgency in the latter case, users with short-term goals may also exhibit greater task focus in their activity on Pinterest. Though temporal range does not have a significant effect on either the number of searches or the average search query length, users with short-term goals were more likely to click through to a pin than other users (0.96 vs. 0.70 click-throughs, $t(3183)>6.9$, $p<10^{-3}$, $d=0.20$), even after controlling for goal specificity. Users with short-term goals also viewed pins in fewer categories overall, after controlling for the number of pins viewed (8.6 vs. 9.1 categories, $V>10^5$, $p<10^{-3}$, $r=0.19$). Thus, users with short-term goals are more discriminative about the content they examine but examine it in greater detail.

Similarly to our analysis of goal specificity in the previous section, we also study the effect of temporal range on how users save content and reference past saved content. When a user looks up information they previously saved, they likely intend to use that information right away. As such, we might expect that users with short-term goals are more likely to reference past saved content. At the same time, given that short-term goals indicate a sense of immediacy, users may also be less likely to save new content, being less likely to be thinking about the long-term future.

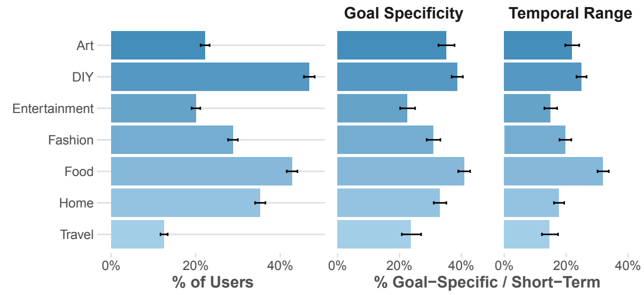
In addition to users with short-term goals being most likely to report looking up previously seen pins as their motivation for visiting, we find that they are more likely to view closeups of pins they previously saved (20% of closeups are of previously saved pins), or boards that they own (79% of boards viewed are their own) than users with long-term goals (10% and 57% respectively, $t>6.3$, $p<10^{-3}$, $d>0.30$). Like goal-specific users, users with short-term goals can also be divided into those looking for new content or referring to past saved content. Users unsure of taking action are least likely to look at closeups of previously saved pins and their own boards (6% for closeups, 50% for boards, $t>3.6$, $p<0.05$, $d>0.16$).

Contrasting with goal specificity which does not significantly influence how much users save, users with short-term goals save fewer pins than users with long-term goals or who are unsure about taking action (1.3 vs. 2.1 and 1.9 pins saved respectively, $t>4.3$, $p<10^{-3}$, $d>0.14$). Notably, users with long-term goals, being the most future-oriented, saved the most. Users with long-term goals were also more likely than users with short-term goals to state collecting or organizing as their motivation for visiting Pinterest (16% vs. 10%, $\chi^2=24.9$, $p<10^{-3}$).

In sum, users with short-term goals tend to look up information to use immediately, while those with long-term goals or who are unsure of taking action appear to be more future-oriented, and more likely to save what they find.

Users with short-term goals spend more time using the service. One might expect that an action taken in the short term suggests shorter deadlines, and thus a more rapid work pace [6, 22], which would suggest that short-term goals lead to shorter sessions. In contrast, we find that a greater proportion of users with short-term goals spend more than half an hour using Pinterest than those with long-term goals (48% vs. 42%, $\chi^2=13.7$, $p<10^{-3}$). Importantly, these differences remain significant even when controlling for goal specificity. We also might expect that users with long-term goals may be more likely to return at a future date to continue working towards their goals. However, unlike goal specificity, temporal range has no significant effect on return visits in the next seven days.

Older people realize goals in the short-term; younger people are less certain. Prior research also suggests that people adjust their time horizons with increasing age, as they increasingly perceive their future time as being more limited, and that conversely, younger people are more likely to expend time exploring their options [7]. Indeed, age is positively correlated with having short-term goals ($r=0.03$, $p<0.05$), and negatively correlated with being unsure about taking action ($r=0.05$, $p<10^{-3}$). In other words, older users are more likely to focus on accomplishing short-term goals, and younger users



(a) Category Distribution (b) Intent by Category

Figure 3: (a) Surveyed users were most interested in food and drink or DIY. (b) Intent differs by category. For example, users interested in food and drink tend to be the most goal-specific and most likely to have short-term goals.

think less about a goal's timeframe for completion. We note that there are no significant differences with respect to goal specificity.

5. CATEGORY AND INTENT

In this section, we analyze how intent and behavior varies by category. As a case study, we consider recipe-finding on Pinterest, which lets us study in greater detail how intent may further influence category-specific behaviors (e.g., the type of food users look for).

5.1 Overall Categorical Differences

Food and DIY are the most popular categories on Pinterest. As Figure 3a shows, food and drink and DIY were the two most popular categories, corroborating prior market studies (e.g., [18]). Looking deeper at the specific motivations users have in each category, users interested in these categories are also more likely to be planning to make something (17% and 14% respectively), than if they were interested in other categories. Across all categories however, looking for ideas and inspiration was still the most common motivation ($\geq$38%), and this was most pronounced among users interested in home and decor – over half (52%) were looking for ideas in this category. Boredom as a motivating factor was cited most commonly among users looking for entertainment (27%). And where surveyed male users were more interested in art and design, female users were more interested in food and drink, DIY, home decor, and fashion ($\chi^2>34.3$, $p<10^{-3}$).

Category moderates goal specificity and temporal range. Depending on the category of interest, goals may be more actionable and shorter term (e.g., finding recipes), or less actionable and longer-term (e.g., planning a vacation). Examining goal specificity, users interested in food and drink or DIY were most likely to be goal-specific (40% and 39% of users are goal-specific respectively, Figure 3b), and those interested in travel or entertainment less goal-specific (24% and 23% respectively).

For temporal range, users interested in food were most likely to have short-term goals (32%), and least likely to be unsure about taking action (30%). At the other end, users interested in home and decor or travel tended to have long-term goals (29% and 27%); users interested in entertainment were most likely to be unsure about taking action (52%). In other words, users looking for food or DIY-related content tended to be looking for something to make right away, while users interested in home and decor or travel were more likely to be looking for ideas and planning for the longer term.

Intent accentuates behavior differently in different categories. While many of our prior results hold within individual categories, intent affects specific behaviors differently in different categories.

Studying goal specificity, among users interested in DIY, those that were goal-specific made just over twice as many searches as those that were goal-nonspecific (1.0 vs. 0.4, $t(1902)=10.0$, $p<10^{-3}$, $d=0.38$). In contrast, among users interested in entertainment, goal-specific users made over three times as many searches (1.0 vs. 0.3, $t(360)=6.3$, $p<0.001$, $d=0.53$). Among users interested in food and drink, those that were goal-specific were more likely to reference past saved content than those that were goal-nonspecific (21% vs. 7% of closeups were of past content, $t>4.7$, $p<10^{-3}$, $d>0.42$), but this was not the case for users interested in fashion (11% vs. 8% for closeups, n.s.).

Differences also exist for temporal range. Among users interested in food and drink, those with long-term goals pinned almost twice as much as those with short-term goals (2.4 vs. 1.3, $t(840)=4.4$, $p<10^{-3}$, $d=0.27$). In contrast, among users interested in fashion, those with long-term goals did not pin significantly more (2.1 vs. 1.9, n.s.). Among users interested in food and drink or DIY, those with short-term goals were over twice as likely to be viewing closeups of past saved content compared to those with long-term goals (food and drink: 22% vs. 10% of closeups were of past content, DIY: 18% vs. 8%, $t>5.0$, $p<10^{-3}$, $d>0.32$). However, this was not the case for users interested in travel (9% vs. 9%, n.s.).

In summary, by examining individual categories of interest, we can discover subtle differences in the specific behaviors users engage in. In the case of the food and drink category, users may be likely to be looking up recipes saved in the past. In the case of travel or home decor, users are instead more likely to be engaging in more exploratory idea-finding and longer-term planning.

5.2 Recipes on Pinterest

One of the most common uses of Pinterest is to find recipes [18]. To study how intent influences recipe-finding behavior, we consider the subset of users who viewed a closeup of at least one recipe. We find that goal-specific users view more closeups of recipes than goal-nonspecific users (1.6 vs. 0.9 recipes, $d=0.50$, $t(762)=7.3$, $p<10^{-3}$), indicating that goal-specific users may be more interested in how to make the depicted food item. Users with short-term goals also view more recipe closeups than users with long-term goals (1.8 vs. 0.9, $d=0.30$, $t(230)=2.9$, $p<0.01$).

Intent may also affect the specific types of food that users look for. An examination of a recipe's ingredients reveals that the proportion of recipes that users view closeups of containing meat or seafood-related ingredients is highest among users with short-term goals (42% vs. 27% for users with long-term goals, $t(189)=3.2$, $p<0.01$, $d=0.34$). On the other hand, the proportion of recipes containing sugar is higher for goal-nonspecific users than for goal-specific users (39% vs. 27%, $t(295)=2.9$, $p<0.01$, $d=0.28$).

Together, these findings suggest that users with short-term goals are more likely to be looking for main courses to make, perhaps for dinner, and that users who are casually browsing are more likely to be looking for desserts to admire. Future work here may involve studying differences in recipe complexity and nutritional value. With regards to the latter, we observed a trend that users with short-term goals may view recipes with more sugar and salt than those with long-term goals. While these effects were not significant, they are suggestive of time discounting [13], or that users looking to make food in the short-term may be undervaluing the future health benefits of food with less salt or sugar.

6. PREDICTING INTENT

Thus far, we have described how goal specificity and temporal range affect user behavior. However, is it possible to use these behavioral signals to recover intent? If we can predict user intent near the beginning of their current session, we can alter the user interface and content to better serve that visitor's needs. In this section, we construct predictive models of intent, and study how performance and feature importance changes with the observation window and category, for both goal specificity and temporal range.

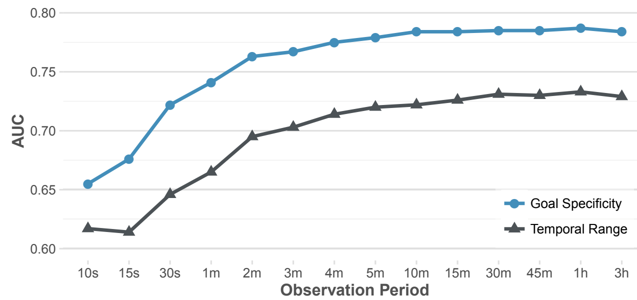


Figure 4: Observing just the first two minutes of a user's session results in robust prediction performance for goal specificity and temporal range, with prediction performance increasing the longer a session is observed.

Feature Set	Goal Specificity	Temporal Range
Demographics	0.56	0.54
+ Historical Activity	0.67 (0.66)	0.62 (0.61)
+ Current Activity	0.78 (0.77)	0.72 (0.71)

Table 1: Intent is best predicted by what a user is currently doing (i.e., current activity in the first ten minutes of a user session), but can still be predicted even before a user logs on (using demographics and historical activity). Shown are the performance improvements from incrementally adding these features, with AUC reported. Individual feature set performance is in parentheses.

Challenges in predicting intent. Several challenges exist in accurately predicting intent. First, intent is provisional and may change over time; models of planned behavior from prior work only explain up to 38% of the variance in observed behavior [42]. Further, if one seeks to predict intent in the minutes following a user logging on, there are few behavioral signals, if any at all. In the first two minutes of a user session on Pinterest, the median number of pins, closeups, content click-throughs, and searches are all zero. The impreciseness of how intent is defined coupled with data sparsity suggests that high performance is difficult to achieve.

Features. Based on our findings in our previous sections, we considered three broad classes of features:

- **Demographics**. Demographic factors such as gender, age, and location can affect intent [10]. For example, we found that women on Pinterest are more likely to be goal-specific, and other work also found gender effects on behavior on Pinterest [8]. Age can also influence users' future time perspective [21], and hence a goal's temporal range.
- **Current activity**. Behavior is directly influenced by intent, and affects how much time users spend on individual pieces of content, how much they search, and what categories of content they browse. Thus, we consider factors relating to the different actions users may take on Pinterest (e.g., searches, views, pins, closeups, and click-throughs), the time of day and day of week of the current session, as well as the categories (of which there are 33) within which these actions are taken.
- **Historical activity**. Past behavior may be indicative of future intent. For example, users who viewed less content in the past tended to be more goal-specific in the current session. Thus,

we measured user activity in the 24 hours prior to the current session, in addition to other longer-term features such as the days since a user signed up and the total number of pins a user saved over their lifetime.

Prediction tasks. With these features in mind, we considered two prediction tasks. After observing a user's behavior for a period of time, can we (a) predict whether their intent was goal-specific or not, and (b) whether they planned to take action in the short-term or the long-term? For the former prediction task, we used a balanced dataset of goal-specific or goal-nonspecific users, noting that the original dataset is already fairly balanced, and that users who reported being neither comprise a relatively small fraction of users. As exactly half of users are goal-specific, random guessing achieves classification accuracy of 50%. For the latter prediction task, we instead use a balanced dataset of users with either short-term or long-term goals. We also consider a multi-class setting of this prediction task which includes having mid-term goals or being unsure of taking action as possible outcomes. Using a random forest classifier, we performed ten-fold cross-validation, and primarily report the area under the ROC curve (AUC). All features were standardized.

Overall performance is robust. We obtain strong performance in predicting both goal specificity (AUC=0.78, F1=0.70) and temporal range (AUC=0.72, F1=0.67) after observing the first ten minutes from when a user logs in (Table 1). A logistic regression classifier gives empirically similar results. In the multi-class version of predicting temporal range, we also obtain comparatively robust performance (weighted F1=0.38, as compared to 0.14 when simply predicting the majority class).

Current activity is most predictive of intent. Given that user activity in the current session resulted directly from their stated intent, we expect that current activity alone would strongly predict intent. In fact, with current activity alone, we achieve performance almost equal to that of using all features (AUC=0.77, 0.71 respectively). In comparison, while demographic and historical activity are less predictive, they remain useful – demographics can provide a baseline estimate of what a new user is likely to do during their first visit, while historical activity can be used to estimate what a current user is likely to do the next time they visit the web site.

For both goal specificity and temporal range, search most strongly indicated intent. The mean number of words in search queries (AUC=0.66 and 0.59) and the number of search queries (0.65 and 0.58) were two of most individually predictive features, i.e., a greater number of more complex queries corresponds to a higher likelihood of being goal-specific or having short-term goals. Other measures of task focus also played a significant role, as did content category – viewed pins belonging to fewer categories (0.61) was also predictive of greater goal specificity, while viewing pins related to home and decor (0.62) was most predictive of having long-term goals.

Intent can be predicted quickly. As Figure 4 shows, while intent becomes easier to discern the longer a user's behavior is observed, performance remains relatively robust even when predictions are based on shorter durations of time. In just the first two minutes, performance for both goal specificity and temporal range are already substantial (AUC=0.76 and 0.70 respectively). Prediction remains possible even with shorter amounts of time (in 30 seconds, 0.72 and 0.65). Predictions can also be made before a user does anything by using only demographics and historical activity features (0.67 for goal specificity, 0.61 for temporal range).

Thus, not only can we guess a user's intent before they even log on, but we can quickly improve on our guess within minutes, and immediately adjust a user's experience to match their intent.

Predictibility varies by category. In the context of consumer research, prior work found that segmentation helped improve sales forecasts based on purchasing intent [31]. Similarly, if we know what category a user is interested in, we may be able to make better predictions about their intent. Here, our results are mixed. Training classifiers on individual categories, we find that intent is most predictable for food and drink (AUC=0.80 for goal specificity, 0.75 for temporal range), but least predictable for fashion (0.71 and 0.62).

7. DISCUSSION AND CONCLUSION

In this work, we presented a framework for characterizing the relationship between a person's intent and their behavior. Through a survey designed to clarify a user's intent that was followed by an observational study of subsequent behavior, we discovered significant differences in how users behaved depending on whether they were goal-specific or goal-nonspecific, or if they were planning to take action in the short-term, long-term, or take no action at all. Users differed in how focused their activity was, what content they looked at and at what level of detail, how long they spent on the site, and whether they would return soon. Intent also varied with gender and age, and by category. Finally, we used these behavioral signals to recover a user's intent.

Design implications. How may we apply these insights to the design of online platforms? First, our findings (e.g., on task focus) may be directly useful in similar content discovery and sharing services (e.g., Flickr or Netflix). Next, as goal-specific and goal-nonspecific users view content differently, recommender systems could prioritize showing specific, targeted content to goal-specific users, and more diverse content to goal-nonspecific users. Recommendations can also be tailored to specific categories – depending on whether a user looking for restaurants has short-term goals or long-term goals, a system might suggest either restaurants currently open nearby, or ones with higher ratings that accept reservations further away. Further, while goal-specific users may not return to a web site as often, they stay longer whenever they do, so providing specific goals (e.g., learning how to write a simple computer game like Pong) may encourage these users to visit more. When users have longer-term goals, sites could offer feedback or track progress towards the goal [11], for example, through providing checklists or email reminders. And as intent can be predicted quickly, content and interface changes can be made in real-time, with these predictions improving as a user continues to use the site.

Limitations and future work. Several limitations of this analysis exist. Measuring intent may influence a user's subsequent behavior [30]. Intent can also change [12] during a user session, but we partially mitigate this by primarily considering only the first ten minutes of a user session, and surveying intent right before the beginning of the session. Explicitly modeling how intent changes over time may improve predictions over longer user sessions. Surveyed users also tend to be more engaged or invested. Further, while we sought to present a broad overview of aggregate behavior on Pinterest, our results suggest that category-specific behaviors exist (e.g., in recipes) – their detailed study remains future work.

Our study in this work is limited to understanding goal specificity and temporal range on Pinterest, but we see our methods generalizing to other online settings. On social networks (e.g., Facebook), we could survey users' social support and self-presentation motivations [32], then observe and subsequently predict their posting and commenting behavior. More generally, by considering other aspects of intent such as difficulty and commitment, we may also predict if a user is likely to succeed in their goals [25].

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