Understanding User Booking Intent at Airbnb

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ABSTRACT

Airbnb, a renowned online marketplace for accommodations and experiences, has transformed the way people travel by offering unique and personalized stays in destinations worldwide. To provide a seamless and tailored experience, personalization plays a crucial role. Understanding user intent is essential for Airbnb's two-sided marketplace, benefiting both guests and hosts. We developed a deep-learning framework for understanding guest intent in the aspects of travel destination and dates, two of the most important aspects when guest plan for a trip. In this paper, we introduce the user intention platform overall design and implementation. Then we focus on three key applications of guest intent understanding at Airbnb. First, we explore destination recommendation for email marketing, where tailored suggestions can be provided to users based on their preferences. Secondly, we discuss how understanding guest intent can improve large area search, enabling users to find listings in broader regions that match their interests. Lastly, we delve into improving flexible date search with user date intent, allowing users to find accommodations that meet their desired travel dates.

KEYWORDS

machine learning; intent understanding; product development; e-commerce

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1 INTRODUCTION

Airbnb has revolutionized the travel industry by providing a platform that connects travelers with unique and personalized accommodations and experiences around the world. With a vast array of listings in diverse destinations, Airbnb strives to offer a seamless and tailored experience for both guests and hosts. Personalization is a key aspect of Airbnb's success, and understanding user intent plays a crucial role in achieving this level of customization. In recent years, there has been a growing recognition of the importance of user intent understanding in online marketplaces. By understanding the preferences and desires of users, platforms can deliver personalized recommendations, optimize search results, and enhance user satisfaction.

Airbnb, as a two-sided marketplace, places significant emphasis on understanding user intent to cater to the needs of both guests and hosts. For guests, understanding their intent enables Airbnb to recommend destinations, dates, prices, and other aspects that align with their preferences. This enhances the travel planning experience, attracts users to the platform, and increases booking conversions. Several key products can benefit from understanding guest intent: personalized destination recommendations for email marketing campaigns, flexible destination and date searches, homepage recommendation. For hosts, understanding guest intent also provides valuable insights into guest preferences and demands. By optimizing listings and offerings based on user intent, hosts can better align their properties with the desires of potential guests, resulting in improved satisfaction and increased bookings.

There are several challenges to understanding the intent of users:

- User intent usually is not explicit in the dynamics of user engagements. That is, even with the various user engagements with the platform, it's usually still a difficult task to understand user's intent.
- In Airbnb search, although users can specify their rough intention in search query, such as location, check in/check out dates, they are often not sufficient especially for certain search scenarios (large area search, flexible date search) and downstream applications (promotional emails, location suggestion).

- In practice, we can leverage the user engagement signals to generate features that implicitly indicate the user preference, which is the typical approach in search and recommendation ranking, it is often important to generalize the usage given user intent is widely involved in multiple applications.

This paper focuses on introducing the development of a deep-learning framework for understanding guest intent in the aspects of next travel destination and dates, two of the most critical factors when planning a trip. We begin by introducing the overall design and implementation of the user intention platform, highlighting the importance of guest intent understanding within Airbnb's ecosystem.

Next, three key production applications of user intent understanding are explored in detail. For context, we refer to *listing search* as the search interface where a location is given and a ranked list of Airbnb listings is returned in the search result page. We focus on applications that are either at the downstream of the listing search where user intent is not directly provided, or within the listing search where the intention is under a more ambiguous scenario. We elaborate location intention for two example applications in each category, and then share our approach on the intention beyond locations such as the date intention:

Firstly, the paper addresses the application of destination recommendation for email marketing. By leveraging guest intent understanding, tailored destination recommendations to individual users' preferences are provided for the downstream task, enhancing engagement and conversion rates for promotional emails and notifications.

Secondly, we introduce the improvement of large area search with guest intent understanding. Large area search or broad region search is a key product at Airbnb to provide recommendations to guests who are flexible on the geographical locations for their next trip. At the stage of a larger region location search, guests usually have not decided which specific location they'll be traveling to. Understanding the interests and preferences of guests based on guest past interactions and global travel interests enables the product to provide relevant listings in broader regions, helping users find accommodations that align with their desired experiences.

Lastly, the paper introduces on enhancing flexible date search with user date intent prediction. By comprehending guests' preferred travel dates, Airbnb could further optimize search results, enabling users to find accommodations that meet their specific scheduling needs.

Through the development and implementation of the user intention platform that powers downstream products, we aim to enhance personalization, improve user experiences, and foster mutually beneficial interactions within its vibrant marketplace. By leveraging advanced deep-learning techniques and data-driven approaches, Airbnb is committed to continuously improving its understanding of user intent and delivering exceptional value to both guests and hosts.

2 RELATED WORK

User representations and intent understanding plays a crucial role in enhancing the performance and personalization of search and recommendation systems [7][4][5]. In recent years, researchers have focused on integrating user intent understanding techniques into these systems to deliver more personalized and relevant experiences.

In search systems, user intent study has been considered crucial in better personalizing user search experiences. [6] considered user queries and clicks in sequences to capture user information needs. [1] proposed a deep intent-aware recommender system that incorporates user intent understanding to improve recommendations. Their model captures user intent by considering both explicit signals, such as search queries, and implicit signals, such as browsing patterns. By integrating intent understanding into the recommendation process, the model generates more accurate and personalized recommendations. Recent research proposed implicit detection of intentions using pre-search context by monitoring the documents visited prior to performing a search [3]. [11][9][2] investigated intent-aware diversification techniques in search systems to address the challenge of presenting diverse yet relevant search results. They proposed a method that combines user intent understanding with diversification algorithms to balance the need for relevance and diversity in search results. By considering user intent, the system provides a more comprehensive search experience. [8] proposed to model query intent by incorporating feedback from users, which was proven to have improvements on exploratory searches. The line of work demonstrates that intent understanding is crucial for personalizing search systems. Challenges still remain in the case of online searches in online accommodation platforms like Airbnb. The lack of explicit context for user booking motives, sparsity of user engagement and conversions, scalability and real-time predictions are complex problems that inspires our exploration of intent understanding to improve booking at Airbnb.

3 AIRBNB USER INTENT PLATFORM

The goal of the user intent framework is to be able to understand and predict user interests on different aspects such as destination (location), date, price, etc. In this section, we introduce the goal of the user intent platform through problem definition, data collection, and model architecture.

3.1 Problem definition

We define user's intention on Airbnb as the guest's preference distribution on various facets over time. These facets include:

- Geo, Date, Price
- Amenities, Categories, Room Types, Trip Types
- New / Existing listing Preferences

Therefore, the user intent platform provides predictions on various aspects of user preferences and flexibility by leveraging user's engagement signals, Airbnb listing signals, context signals. The output of the platform are twofold: 1) direct prediction of the aspects of intent (geo, date, price, etc), and 2) the user intent embeddings from the underlying models. The intention platform, with models that captures guests' preference over various facets over time, in other words, their flexibility, can be leveraged to enhance a guest's experience on Airbnb for and beyond search ranking, including the contextual relevance of the destination location, expanding the location boundaries on prompts or preferences, understanding the guest's preferences before booking and applying them at the right time on the search journey, and ensuring a trustworthy and satisfactory trip outcome, can aid in faster and more precise matching.

3.2 Data collection

To support various recommendation tasks within the framework, a unified training dataset is created. This dataset encompasses multiple aspects related to user intent, including next travel destination, next travel date, next travel length, next booked listing, next booking price, next category, and days to book the next listing. Additionally, the framework is designed to accommodate future tasks beyond the ones mentioned.

The training data is collected from four different groups:

- User demographic data: This includes information about the user's demographics.
- User location: Data related to the user's location, including country, city, and other geographical representations.
- Locale/language: The language preferences and locale of the user, enabling personalized recommendations based on their language and cultural preferences.
- Search context features: This group encompasses various contextual factors that influence user intent, such as the current month, day of the week, and specific events or holidays occurring during the booking period.
- Booking activity features: additionally, the training data includes user booking history, consisting of details such as the booked listing, booked listing value, booked listing location, booked listing category, and the check-in/check-out dates. Additional information such as the booking nights, number of guests, and the timestamp of the booking is also captured.
- User view engagement features: User view history, specifically the listings viewed by the user in the past week, is considered in the training data as well. This includes details like the viewed listing ID, viewed listing price, viewed listing location, viewed listing category, and the review rating/count of the viewed listing. The timestamp of the viewing activity is recorded.

To ensure a comprehensive dataset, user's booking and view history are collected. The view history is collected from the day of booking t_0 minus k days $t_0 - k$ to $t_0 - 1$. This means that for each booking event, there are seven training examples available. Additionally, the view history and the context features are adjusted to simulate training examples for the time period before users started searching on Airbnb.

All continuous features in the dataset are bucketized and converted into categorical features. For categorical features with a large vocabulary size, hashing techniques are applied to organize them into manageable buckets. It is important to note that both booking history and view history are updated daily, allowing for the generation of static recommendations within a one-day time window.

By collecting and structuring this comprehensive dataset, the framework enables effective training and modeling of user intent understanding.

3.3 Model Architecture

The model architecture, as shown in Fig.1, utilizes transformer [10] blocks and fully connected networks (FCNs) as standard design components. The combination of Transformer and FCN serves as the user encoder, generating user embeddings as the output. One advantage of this structure is that it allows for customization of task heads tailored to different use cases. This customization can be achieved either by retraining the model with additional tasks or by reusing the pretrained user embeddings as input to the customized task heads.

Below we highlight several key considerations of the design:

- **Input to the Transformer block**: The booking or view history is represented as an ordered sequence (time series) of tuples containing listing IDs, timestamps (ts), and listing metadata. The time differences between the current booking example and the history event timestamps are bucketized into predefined ranges. Each bucket is then converted into a positional embedding. Additionally, metadata features such as price and review ratings are bucketized and converted into embeddings. These embeddings (listing ID, position, and metadata features) are transformed with different operations choices (summation, concatenation, etc.) and fed into the Transformer block.
- **Next destination head**: This head utilizes a softmax layer to classify the user embedding into one destination from a predefined vocabulary of geographical locations. The vocabulary consists of the top K destinations worldwide, sorted by the number of bookings within that destination. By tying the destination embedding between the softmax layer and the input layer, the model can leverage destination information from the booking/view history. This head can have two variants: a dateless head and a dated head, with the latter incorporating date queries as side inputs for cases where users specify travel dates.
- **Next travel date/trip lengths**: Users are classified into predefined date buckets (e.g., every 7 days) for travel dates. Instead of predicting the exact number of nights, the model predicts the range of nights, such as < 3 days, 3 days to 1 week, 1 week to 1 month, and > 1 month. This approach accounts for the possibility of a multimodal distribution, where users may initially consider staying for different durations. Two variants of this head are available: a locationless head and a location-aware head. The latter incorporates location queries from users, specifically for flexible search use cases.
- **Next booking price value**: Similar to the travel date/nights, the model predicts the price range of the next booking instead of the exact price. For example, the price ranges can be defined as [0, 50], [50, 80], [80, 120], [120, 200], [200, 200+]. Four variants of this head are possible: dated and location-aware, dated and locationless, dateless and location-aware, and dateless and locationless.

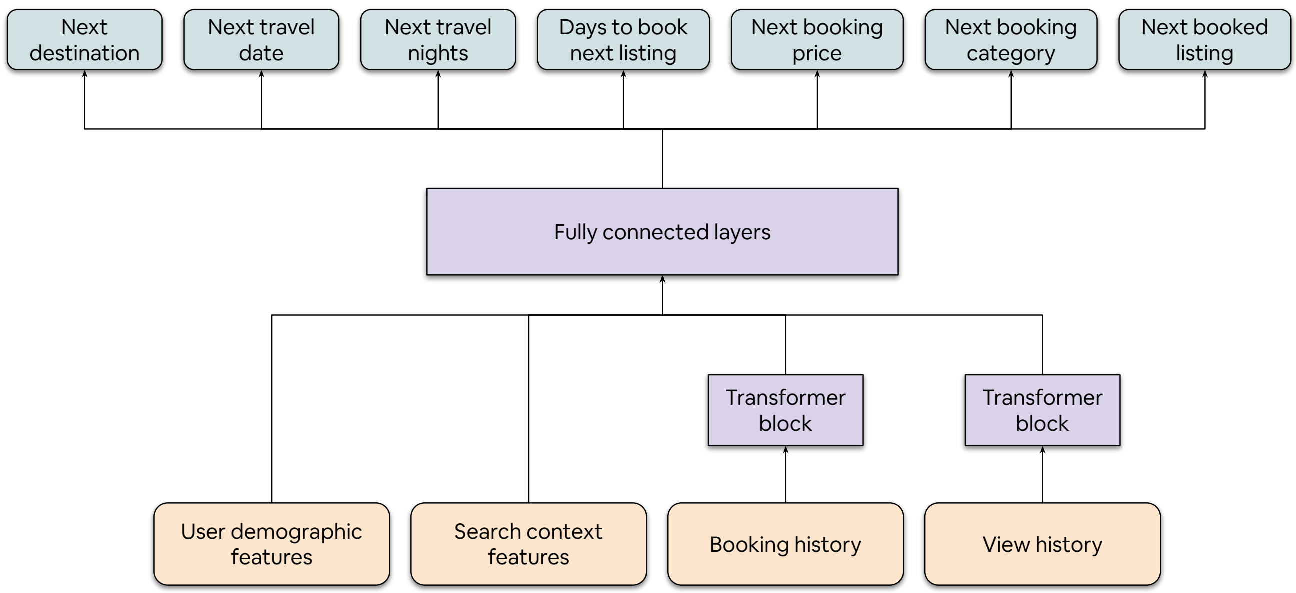

Figure 1: Model architecture of user intention prediction

- **Next booked listing**: The label for this head can be the listing ID or the listing clusters that aggregates listings based on business requirements. Additionally, listings can be preclustered based on location or listing embeddings, transforming the problem into a classification task.
- **Days to book next listing**: In addition to predicting the exact number of days or checkin and checkout dates, the model predicts the range of query lead days (refers to the number of days between the query date and the check in date), such as 0 to 3 days, 3 to 7 days, 7 to 14 days, 14 to 30 days, 1 to 3 months, etc.

  By incorporating these components and variations, the model architecture facilitates the prediction of user intentions in various aspects of the booking process, enabling Airbnb to deliver personalized recommendations and enhance the overall user experience.

4 USER INTENTION UNDERSTANDING APPLICATIONS

In the following subsections, we'll introduce the applications of the user intention model. The user intention platform could power these downstream applications as it provides a comprehensive understanding based on the aspects mentioned: location, date, etc. Intent prediction helps especially in the cases where users may be flexible on their travel destinations and dates, where the original recommendations or search results may have less information to work with when recommending listings to guests.

4.1 Promotional/Abandon Email/Landing Page Optimization

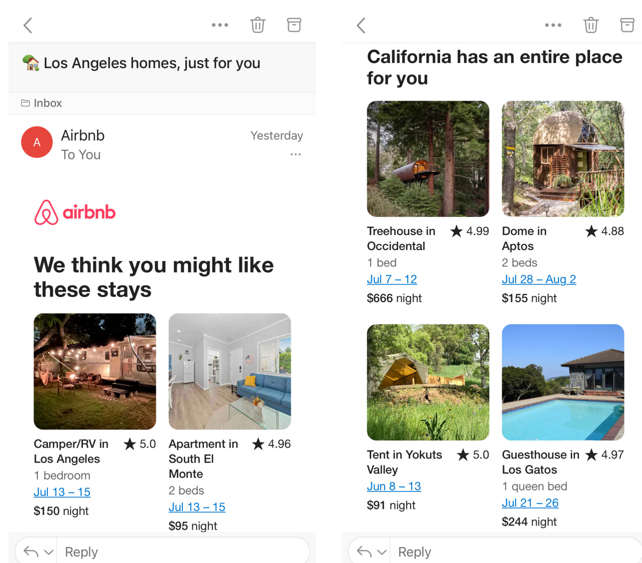

Figure 2: Email notification to recommend potential listings users may be interested in booking.

Email marketing campaigns are a crucial aspect of reaching and engaging with users in the highly competitive travel industry. With millions of users around the world, Airbnb relies on email campaigns to connect with its user base, promote relevant offerings, and ultimately drive bookings. These campaigns serve as an essential touchpoint for communicating with users and influencing their travel decisions. By leveraging the power of user intention understanding, we further enhance the effectiveness and impact of the email marketing efforts, providing a personalized and tailored experience to each individual user. 2 shows example promotional email notifications to users after their initiated search on Airbnb.

The rich understanding of guest next travel destination allows Airbnb to curate and deliver highly personalized recommendations in its email campaigns, ensuring that the content aligns perfectly with the unique interests and desires of each recipient. The impact of user intention understanding on email marketing campaigns is evident in the results achieved. As shown in Table 1, we observed a positive impact on key metrics for *bookings from new guests that were not canceled*, it increased by 1.1% in an online A/B test setting, indicating that personalized recommendations based on user intent are driving more successful bookings from guests who haven't booked before with the platform. In addition, user intention understanding helps to increase email action rates, such as click-through rates and conversions. The *email action rate* which measures user engagement with the email content, increased by 2.2%, showcasing the effectiveness of delivering personalized recommendations aligned with user intent. By incorporating user preferences, previous booking history, and intent into the email content, Airbnb creates highly targeted and compelling messages. This tailored approach resonates with recipients, increasing the likelihood of them taking action, whether it's clicking on links to explore listings, making a booking, or sharing the email with others.

The positive impact of user intention understanding on email marketing campaigns highlights the effectiveness of this approach in delivering personalized and engaging experiences to Airbnb users. These results demonstrate the power of understanding user intent and delivering relevant recommendations in email campaigns, ultimately contributing to the overall success of Airbnb's marketing strategies.

Models	Geo top1 acc	City top1 acc
Most recent	0.228	0.179
Intent model	0.326	0.237

Table 1: Offline results for abandon email with user intent model.

Metrics	Results
Bookings New Guest That Were Not Canceled	+1.1%
Email Action Rate	+2.2%

Table 2: Results of online A/B test metrics for abandon email with user intent model.

The results presented in 2 provide quantitative evidence of the positive impact of user intention understanding in Airbnb's email marketing campaigns. The increased bookings from new guests and improved email action rates demonstrate the effectiveness of personalized recommendations aligned with user intent. These results reinforce the importance of leveraging user intention understanding to drive successful email marketing campaigns and enhance the overall user experience.

4.2 Large area searches

Large area search refers to the process of guests exploring accommodations and destinations within a broader geographical region rather than focusing on specific cities or neighborhoods. This type of search allows users to cast a wider net and discover potential travel options across a larger expanse. By expanding the search scope beyond individual locations, users can explore diverse destinations and find accommodations that align with their desired travel experiences. 3 illustrates the concept of large area search (a *Europe* search). In the figure, instead of targeting a single city, the search area includes all areas within the map boundry of Europe. This approach enables users to discover listings and destinations that may be outside their usual search parameters, opening up new possibilities for travel experiences, especially for users who are flexible on the destination for their next trip.

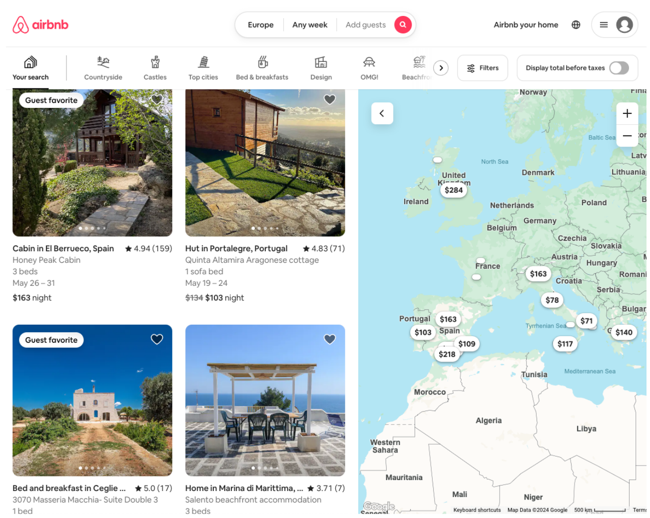

Figure 3: Example of a "Europe" search, where the destination location is a very wide area.

Large area search presents unique challenges due to the potentially vast number of listings within the specified area. Without a comprehensive understanding of the potential locations that users are interested in, the ranking of search results could be irrelevant to the true intent of users in terms of destination, leading to a suboptimal search experience. To overcome these challenges, we leverage user intention understanding to improve large area search and provide more meaningful and personalized recommendations.

One major challenge in large area search arises from the sheer volume of listings within the specified area. With numerous cities, neighborhoods, and accommodations to choose from, it becomes crucial to narrow down the options to those that are truly relevant to the user. Without a clear understanding of the user's preferences and intent, it can be challenging to rank the listings in a way that aligns with the user's desired travel experience.

To address this challenge, we employ a two-step process for large area search. First, a geographical location (geo) query retrieves the geos (cities or regions) that fall within the bounding box of the large area specified by the user. This initial step helps narrow down the search to a manageable set of potential locations.

The second step utilizes user intention understanding to generate destination recommendations. The user intention model is trained to generate k geo destination recommendations based on the user's historical booking patterns, preferences, and browsing behavior. This model takes into account factors such as the user's previous destinations, preferred travel dates, and other relevant signals.

In the search ranking process for large area searches, the destination recommendations generated by the user intention model play a crucial role. The search ranking algorithm boosts the visibility of listings from the recommended destinations, ensuring that they are presented prominently to the user. By incorporating these recommendations into the ranking process, we increase the chances of presenting listings that are more relevant to the user's intent and desired travel destinations.

By leveraging user intention understanding, Airbnb enhances the large area search experience by providing more personalized and meaningful recommendations. The combination of the geo query, user intention model, and search ranking algorithm helps narrow down the options, prioritize relevant listings, and improve the overall relevance of the search results. This approach ensures that users are presented with listings that align with their desired travel experiences within the specified large area, enhancing their ability to find accommodations that meet their preferences and needs.

4.3 Exploration on Intentions beyond Location: Flexible Date Searches

Flexible date or dateless searches allow guests to find accommodations based on their next travel date bucket and desired length of stay (nights bucket). Figure 4 shows two ways for a flexible date search on Airbnb: by selection different trip lengths, month of planned travel, the range of the travel month ahead. Flexible date search is a valuable feature that empowers guests to customize their travel plans by providing a more relaxed approach to selecting travel dates. The relaxation of search dates potentially presents users with more relevant listings which users may not be aware of in dated search due to inventory and availability. The success of this product helps drive guest bookings for those who may be flexible on travel dates, and also attracts user engagement on long-term interest to listings presented to them, either by wishlisting, saving or sharing to friends for a future travel, since it helps presenting users with more available listings outside of a specific date range.

However, flexible date search also presents certain challenges. One of the primary challenges is the need to expand inventory to cater to the varying demand patterns across different time frames. Ensuring an adequate inventory of available accommodations for flexible date searches requires a comprehensive understanding of user intention and demand fluctuations. To tackle this challenge, we leverage the predictions generated by our user intention model

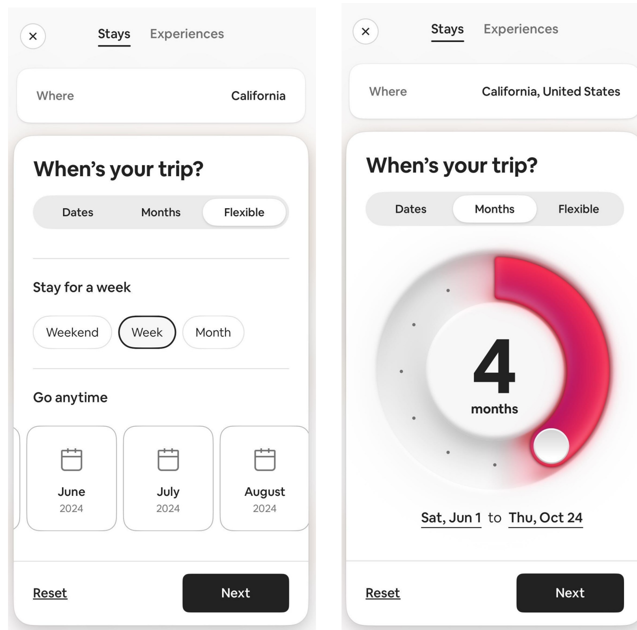

Figure 4: Flexible date search where guests can choose a more relaxed date to search.

regarding guest check-in and checkout dates. By utilizing this information, we can optimize the availability and presentation of accommodations to align with the desired travel time frames indicated by guests. This approach allows us to enhance the inventory selection and ensure a wider range of options and availability for guests with flexible travel dates.

To provide personalized recommendations for flexible date search, the user intention model was trained to predict guest query lead time, check-in and checkout dates. This model takes into account various factors such as historical booking patterns, historical user impression/click patterns, user preferences, and market trends. By understanding the guest's intention regarding their travel dates, the model helps provide more accurate and relevant recommendations.

The intention model's predictions are then incorporated into the listing ranking process. The search ranking algorithm boosts the visibility of listings that align with the guest's preferred travel time frame. By considering the guest's intended check-in and checkout dates, we ensure that the search results prioritize listings that are available and suitable within the desired time frame. This personalized ranking enhances the search experience, enabling guests to find accommodations that not only match their flexible travel dates but also meet their specific preferences and needs. Overall, flexible date search powered by user intention understanding offers guests greater control and flexibility in their travel plans. By providing a wider range of travel date options, personalized recommendations, and enhanced search rankings, we optimize the search experience for guests seeking flexible date accommodations.

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6 CONCLUSION

In this paper, we studied the challenge of user intent understanding in two-sided marketplace search and recommended systems at Airbnb for online accommodation booking. The model analyzes user behavior, preferences, and historical data to accurately predict user intentions, such as desired travel dates, preferred destinations, and accommodation preferences. This understanding of user intent allows us to tailor our recommendations and search experiences to better match individual user preferences and needs. The applications we introduced demonstrate the practical use of user intent understanding in different areas of the Airbnb platform. By leveraging the intent model, we optimize email marketing campaigns, landing page optimization, large area search, home page ranking, and flexible date search. These applications enable Airbnb to deliver personalized recommendations, enhance search results, and improve the overall user journey throughout the platform. By incorporating user intent understanding, we have observed positive results, including increased bookings from new guests, improved email action rates, and enhanced search relevancy. These outcomes validate the effectiveness of our approach in effectively understanding user intent and translating it into meaningful recommendations and personalized experiences.

Moving forward, there are several opportunities for further research and development. Expanding the capabilities of the intent model to incorporate additional user signals and contextual information can enhance the accuracy and granularity of our understanding of user intent. Additionally, continued analysis and optimization of the applications introduced in this paper will drive ongoing improvements in user engagement, conversion rates, and overall customer satisfaction.

In conclusion, the integration of user intent understanding in Airbnb has proven to be instrumental in providing a more personalized and tailored experience for our users. By leveraging the intent model, we have successfully improved recommendation relevance, search performance, and overall user satisfaction. We believe that user intent understanding will continue to play a vital role in driving innovation and advancements in the Airbnb platform, ultimately enhancing the travel experiences of millions of users worldwide.

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