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Point of interest recommendations based on the anchoring effect in location-based social network services

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ABSTRACT

A point of interest (POI) recommender system (RS) is one of the representative research areas based on the location-based social network (LBSN). Most POI RS studies utilized various implicit information or social information to improve recommendation accuracy. However, majority of these studies overlooked the importance of users' initial check-in information. Users are affected by their first input data in online services, and this phenomenon is called the anchoring effect. In POI RSs, few studies have analyzed the association with the anchoring effect while other RS domains already verified this effect. In particular, a research area, including POI RS, that focuses on the importance of the initial input does not exist. In this paper, we propose a latent Dirichlet allocation (LDA) model based on the anchoring effect for POI RS. This model emphasizes the importance of initial check-in data and is called the anchor-LDA. Experimental results showed that the anchor-LDA outperformed existing LDA-based POI recommender algorithms. Furthermore, we validated the importance of initial check-in information on the LBSN.

1. Introduction

Location-based services (LBS) have become popular with the spread of smartphones. Moreover, most social network services (SNSs), such as Facebook[1] and Instagramm,[2] provide LBS to their users. For example, when a picture is taken with a smart phone, the location information is stored as its meta-data. In addition, when users upload content on SNSs, their location information is uploaded in the form of a tag. A location-based social network service (LBSN) is a special SNS focusing on the LBS (Cho et al., 2011). Popular LBSNs, such as Foursquare[3] and Gowalla,[4] first appeared more than a decade ago, and many researchers have widely utilized their data in various academic fields (Hsieh & Li, 2019; Huang et al., 2020; Kim et al., 2020; Zhang et al., 2020).

Although many studies have utilized data from LBSNs, it is still challenging to find a point of interest (POI) of a user due to the difficulty of obtaining POI preference information. Some existing studies have been based on matrix factorization (MF), which is one of the most famous algorithms in the field of recommender system (RS), as well as POI recommendations (Cheng et al., 2012; Gao et al., 2018; Li et al., 2015, 2016; Lian et al., 2014). MF has been widely used in studies that focus on solving data sparseness problems, because it allows the incorporation of additional implicit information into the sparse matrix (Hu et al., 2008; Lian et al., 2014). Furthermore, MF can be easily extended by taking into account social information (Ma et al., 2011), such as the relationship between users and the reviews of users in the LBSN (Gao et al., 2018; Li et al., 2016). However, users tend to be active on LBSNs when they are close to home. More than 99% of the check-in information of users originates from their home living area (Scellato et al., 2011; Yin et al., 2013). Therefore, we need a new approach for solving the data sparseness problem utilizing check-in information of the users and its meta-data not social information from LBSNs. Furthermore, a study is needed to recommend POI to users within their main activity area.

To address the issues mentioned above, it is not appropriate to use MF because the most common implicit preference for a POI in LBSNs is the number of visits or the probability distribution for that check-in location. In the case of an RS based on this preference measurement, the accuracy is higher when using algorithms based on a probability distribution such as the latent Dirichlet allocation (LDA) than when using MF (Kotzias et al., 2018). In addition, due to the high

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1 https://www.facebook.com/.
2 https://www.instagram.com/.
3 http://foursquare.com.
4 https://snap.stanford.edu/data/loc-gowalla.html.

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generality of the LDA, it can be applied in various research areas and guarantees excellent performance (Jin et al., 2005). Therefore, many studies have suggested methods of analyzing context information (Liu & Xiong, 2013; Xiong et al., 2020; Yin et al., 2013) or geographical information (Yin et al., 2015; Zhu et al., 2018), and applying them as weights to an LDA. Therefore, in this paper, we also use an LDA to propose a POI recommender algorithm with a distance-based weight.

Although many POI recommendation studies based on LDAs have been conducted, there is no study analyzing the importance of the initial check-in by the user (i.e., initial input). In LBSNs, the location of the user's first check-in is likely to be within his or her living area. Additionally, users are often influenced by their first input during decision making, and this cognitive bias is called the anchoring effect (Sherif et al., 1958). In the research field of decision making, some studies have been conducted based on anchoring effects (Cho et al., 2017; Stettinger et al., 2015), and there are also RS studies that have dealt with this phenomenon (Adomavicius et al., 2011; Wang & Benbasat, 2007). However, few studies have investigated whether this cognitive bias caused by the initial input affects LBSN data. In particular, no study has been conducted to analyze the importance of the user's initial input in any research area including LBSN. Therefore, we proposed a POI recommendation algorithm using the LDA with the weight of the initial check-in. Furthermore, we analyzed the importance of the initial check-in on LBSNs and the effect of the anchoring effect on POI recommendations.

The contributions of this paper are summarized as follows:

- We focused on finding the POI of users within their main activity area by using check-in data and its meta-data in LBSNs. Therefore, we experimented using only specific areas, such as San Francisco, Austin, and New York, from the LBSN dataset.
- The main goal of this paper is to propose a POI recommender algorithm applying an LDA that weights the initial check-in of users, and we call this algorithm an anchor-LDA. Also, we analyzed the effect of anchoring effect on POI recommendation through the anchor-LDA.
- The effectiveness of the anchor-LDA was verified through comparative experiments utilizing a Gowalla dataset. The experimental results showed that the anchor-LDA outperformed the previous POI recommendation algorithms based on the LDA.

The remainder of this paper is organized as follows. In Section 2, we introduce studies that focused on the anchoring effect and the importance of initial input and reviewed the existing POI RS studies based on MF and LDA. Section 3 describes the anchor-LDA in detail. We explain the comparative evaluation results in Section 4. Section 5 represents the benefits and limitation of our proposed system. Finally, Section 6 concludes this paper and presents future research direction.

2. Related works

In this section, we organized existing studies related to this study. First, we examined the research fields using the anchoring effect or emphasizing the importance of initial input. Next, we analyzed the existing POI RS studies based on MF or LDA and pointed out their problems.

2.1. Anchoring effect

The anchoring effect is a cognitive bias, in which the initial piece of information, called an anchor, unduly influences subsequent decisions of the user. This term first appeared in psychophysics (Sherif et al., 1958); however, many studies in the field of computer science, such as decision-making (Cho et al., 2017; Stettinger et al., 2015) and RSs (Adomavicius et al., 2011; Benbasat & Wang, 2005; Wang & Benbasat, 2007), in which user behavior analysis is a challenging issue, have also used it. Our study focuses mainly on the impact of the initial check-in in an LBSN and regards this information as an anchor. Therefore, we also analyzed the importance of the initial input in research areas, such as information retrieval (IR) (Miyanishi et al., 2013; Yu et al., 2003) and RS (Averjanova et al., 2008; Negre, 2015). In Table 1, we classified the existing studies based on the anchoring effect in various fields, such as decision-making, information retrieval, and recommender system areas, and analyzed whether the initial input was used as the anchor in their studies

Many decision-making studies exploited the concept of the anchoring effect to discover elements, such as the first decision-maker (Stettinger et al., 2015) and visualization (Cho et al., 2017), that help users make decisions quickly. Stettinger et al. (2015) conducted a user study to verify that the conclusion of the primary decision-maker had the most significant impact on subsequent users' choices. They found that a large number of users' decisions had a positive effect on other users' decisions. Furthermore, additional descriptions of the reasons for the users' choices could help improve the satisfaction of the user in the decision-making process. Cho et al. (2017) validated that optical factors also influence a user's decisions by using a visual analytics (VA) system containing the design of coordinated and multiple views. Their VA system design included several visual anchors for the representations related to geography and time that influence users' decisions. Based on their VA system, they collected interaction logs between users and visual interfaces as well as survey results from users and analyzed the anchoring effect on users' decision-making process. However, in this area, initial inputs was not used as an anchor.

In the field of IR, an initial query set plays a role in reducing the scope for finding relevant results among a wide range of web browsing data (Yu et al., 2003) or SNS data (Miyanishi et al., 2013). More specifically, assuming that the top ranked document set generated by the initial query is relevant, an IR system expands the query using terms from those documents and re-ranks the documents. From the perspective of the anchoring effect, they considered the results generated by the initial query, not the initial input of the users (i.e., initial query), as an anchor.

In RS studies, the anchoring effect tends to be utilized to analyze the impact of the results generated by an RS on the users (Adomavicius et al., 2011; Benbasat & Wang, 2005; Wang & Benbasat, 2007). Benbasat and Wang (2005) found that the initial trust of a user in an RS affects the continuous adoption of the RS in the future. Although they did not mention the anchoring effect directly, the bias of the users they found in their RS study is closely related to this effect. Furthermore, they evolved their RS by adding an explanation feature for the recommendation results, which helps to improve the initial trust of the user in the RS (Wang & Benbasat, 2007). Adomavicius et al. (2011) assumed three cases of the anchoring effect of the RS and validated them through laboratory experiments. First, they found a strong correlation between the biased initial set rating values and the preference of users in the RS. Furthermore, they analyzed the effect of the RS results at the point of purchase of the user and the impact of an accurate RS on the preferences of users. However, The above RS studies did not view the initial input of the users as an anchor.

In RS, it is difficult to obtain the preferences of new users. Therefore, many RSs require users to specify their initial preferences to obtain precise recommendations. For example, various web services that provide media contents, such as Netflix,[5] collect information about users' preferences and tastes when they first join the systems. In addition, in the RS academic field, Averjanova et al. (2008) allow new users to enter an initial preference in the first step of their RS. In a pipelined architecture with multiple RSs, the initial input is increasingly important, and it is used to supplement the rest of the data (Negre, 2015).

[5] https://www.netflix.com/.

Table 1
Existing studies based on anchoring effect in various fields.

Domain	Studies	Anchor	Role of anchor	Initial input
Decision-making	Stettinger et al. (2015)	The decision of the primary decision-maker	Helping uses make decisions quickly	×
	Cho et al. (2017)	The first visual factors that the user encounters		×
Information retrieval (IR)	Yu et al. (2003)	Document set generated by an initial query set	Re-ranking the documents by expanding queries based on the anchor	△
	Miyanishi et al. (2013)			△
Recommender systems (RS)	Benbasat and Wang (2005)	First confidence in the results of the RS	Continuous adoption of the RS in the future	×
	Wang and Benbasat (2007)			×
	Adomavicius et al. (2011)	Biased initial rating	Affecting actual preference of the users	×
	Netflix	Initial preference	For the precise recommendation	✓
	Averjanova et al. (2008)			✓
	Proposed	Initial check-in	For the precise recommendation	✓

As mentioned above, several decision-making, IR, and RS studies have proved that the anchoring effect influences the users' judgment. However, there is little research on how this cognitive bias impacts POI RS. In addition, few LBSN studies related to POI RS have regarded the initial input as a major element despite its importance in the RS.

2.2. Point of interest recommendation based on a location-based social network service

An LBSN contains various types of implicit information, such as check-in, geographical, temporal, context, and social information, that are easy to apply to MF and LDA. Therefore, several POI RS studies have utilized mainly MF (Cheng et al., 2012; Gao et al., 2018; Li et al., 2015, 2016; Lian et al., 2014) and LDA (Kotzias et al., 2018; Liu & Xiong, 2013; Xiong et al., 2020; Yin et al., 2013; Zhu et al., 2018).

MF is one of the most common algorithms in RSs. Most domains of RSs have exploited this algorithm because of its effectiveness and efficiency. In particular, many POI RS studies used MF because it is a good algorithm to apply to implicit information (Hu et al., 2008) or social information (Ma et al., 2011). Some studies quantified the importance of geographical information by finding the representative location of a vast number of POIs (Cheng et al., 2012; Li et al., 2015; Lian et al., 2014). Cheng et al. (2012) focused on measuring the importance of geographical information. First, they found several center POIs through all the check-in information of users. Then, they measured the geographical influence using a method of weighting the check-ins close to the center called the multi-center Gaussian model (MGM) based on the Gaussian distribution. Finally, they combined the MGM and MF to design a recommender algorithm. Lian et al. (2014) exploited the weighted MF by considering the influence of POIs as well as user behavior. They augmented the latent factors derived through an implicit user feedback matrix with activity area vectors of users and influence area vectors of POIs. The former calculates the possibility that the user is likely to visit a specific location in the future. The latter estimates the degree to which the POI affects the corresponding area. Li et al. (2015) calculated a geographical influence score using the distance between two POIs as an element of a weight matrix (i.e., geographical influence matrix). They determined the latent factors using the POI ranking value, not the check-in frequency, to convert a sparse matrix into a dense one. Additionally, they incorporated the weight matrix and the ranking based matrix.

Social information is one of the main features of LBSNs frequently used in POI recommendations. Gao et al. (2018) and Li et al. (2016) extended the friend set to solving data sparseness problems and improving the recommendation accuracy. The former study (Li et al., 2016) categorized three types of friends, based on their characteristics in the LBSN: social friends, location friends, and neighboring friends. Social friends meant social relationships on the LBSN. Location friends were a set of friends who had also checked-in a specific location at which the user visited, and neighboring friends corresponded to the number of friends living around the user's home. The latter study (Gao et al., 2018) defined 5-tuple tensors and applied it to tensor factorization by using check-in information, social information, and temporal information. Among all tensors, social information consisted of two tensors. They computed the closeness between two users based on a Gaussian radial basis function. In addition, they measured the preferences of the user's friends for POIs where the users checked-in and used this as a tensor.

In POI RSs, most studies measured the POI preference of users through the frequency or probability distribution based on user check-in information (Liu & Xiong, 2013). Recently, Kotzias et al. (2018) proved that recommender algorithms based on probability distribution such as LDA outperformed MF in RS using the frequency of items as a measure of the users' preference. They experimented with the datasets of Gowalla, Twitter[6] (including geo-located tweets), Reddit,[7] and Last.fm.[8] Therefore, the LDA is a more suitable algorithm than the MF in an LBSN-based POI RS.

The LDA was primarily used to find key topics in a document (Blei et al., 2003). Thus, many POI RS studies also exploited the LDA to analyze the context information on LBSNs, such as a profile or a review by the user (Xiong et al., 2020), and the summary or category description related to the POI (Liu & Xiong, 2013; Yin et al., 2013). Liu and Xiong (2013) found interesting topics for users in their check-in history and relevant topics for POIs through textual information. After deriving the scores for two topic distributions, a matching score was defined to measure the similarity between them. Then, they calculated the preference of a user for a POI through this score and the popularity of the POI. Final recommendation results were provided through the Probabilistic MF (PMF) based on the preference value derived from the LDA. Yin et al. (2013) proposed a location–content-aware LDA (LCA-LDA) to learn the POI of users within their activity history. They solved the data sparsity problem through content information related to the POI, not just user check-in information. The LCA-LDA derived not only the co-occurrence pattern of POIs but also a word co-occurrence pattern of contents to compute the individual interest of users. They also quantified famous local places in a particular area, such as local attractions. Considering the preferences of the users and the locations, the RS can recommend new places that users have never visited as well as POIs near their home area. Xiong et al. (2020) found that users trust social information on communication-based social networks (CBSNs), such as Twitter and Facebook, more than on LBSNs. Based on this evidence, they introduced a method of mixing LBSN data and CBSN data. First, they built a heterogeneous network using the accounts of Foursquare users linked to Twitter or Facebook accounts. They proposed a heterogeneous information-based LDA (HI-LDA) by utilizing reviews from friends on CBSN and check-in information on LBSN.

Compared to other SNSs, the most distinctive feature of the LBSN is that it provides geographical information. Thus, most POI RS studies

[6] https://twitter.com/.
[7] https://www.reddit.com.
[8] https://www.last.fm/.

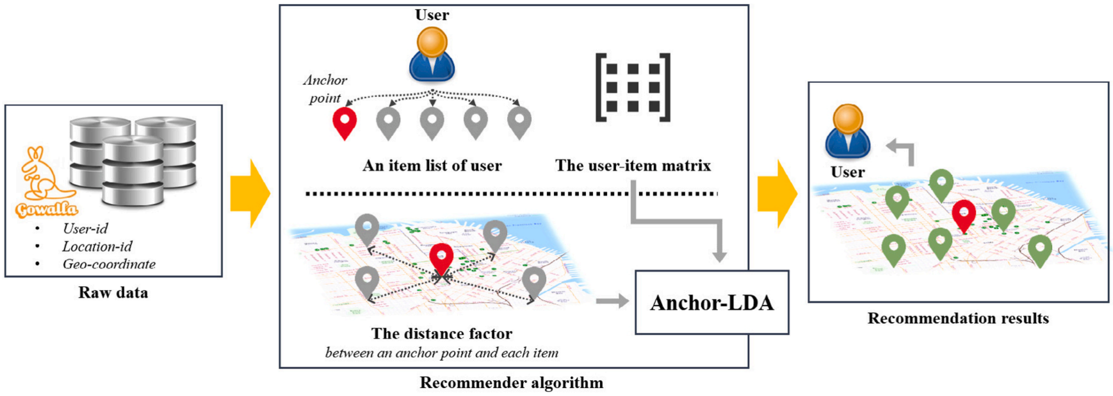

Fig. 1. Architecture framework of point of interest recommender system based on an anchor-LDA.

utilized this feature (Yin et al., 2015; Zhu et al., 2018). Yin et al. (2015) proposed a location-aware LDA (LA-LDA) model that considers the location of users and items (i.e., POI). The LA-LDA consists of two components, a user LA-LDA (ULA-LDA) and an item LA-LDA (ILA-LDA). In the case of the ULA-LDA, the model provided recommendations by weighting the POIs close to the users' homes. The ILA-LDA, on the other hand, recommended items located in a similar area as the location of the POIs. The LA-LDA incorporated these two LDA models and provided users with final recommendations. Zhu et al. (2018) quantified the impact of POIs based on the distance to users' homes. First, they utilized a Density-based spatial clustering of applications with noise (DBSCAN) algorithm to remove noise POIs and extract only the critical POIs needed for recommendations. Then, they found three types of scoring functions based on user interest, location distance, and time-aware popularity to quantify the predictive preferences of POIs. Among these, we focused on the analysis of the location-based scoring function, which is most relevant to this paper. After measuring the distances between the users' home and all POIs, they calculated the score of the POIs at the current location of the users based on the measured distance value.

Almost all existing POI RS studies based on LDA or MF focused on improving the effectiveness of recommendations using implicit information. However, the improvement of accuracy was marginal compared to the cost incurred by the data expansion and data pre-processing. In this study, the anchor-LDA considers only the initial check-in of the user as the main factor; therefore, the time complexity is much lower than in other studies. In addition, this anchor-LDA study is the first study to apply the anchoring effect to POI recommendations.

3. Problem formulation

In this study, we consider the user behavior of check-ins on a LBSN and propose an anchor-LDA for a POI RS. In the following subsections, we first describe the architecture framework of the anchor-LDA to explain our concept. Next, we study the distance effect on check-ins, and present our findings. We then summarize the notations and introduce our model with its generative process.

3.1. Architecture framework

Fig. 1 shows our architecture framework of the POI RS. We propose an anchor-LDA mainly based on the information extracted from the LBSN dataset, especially the distance factors between an anchor point (i.e., initial check-in) and each check-in location. The anchor-LDA is the first POI recommender algorithm to apply the anchoring effect. Finally, according to the anchor-LDA, our POI RS can provide the appropriate recommendation results for the users.

As shown in Fig. 1, we utilized Gowalla for a dataset of POI on the LBSN. Users on an LBSN check-in to places they visit, leaving digital footprints consisting of user-id, location id, geo-coordinates, and timestamp. In our experiments, we disregard the timestamp as our focus is not on discovering sequential patterns of check-ins. By collecting all the check-in records, we can construct a user-item matrix, in which each row corresponds to a unique user, and each column corresponds to an item. In our settings, the item becomes the location id which is a unique number for each place. We use the user-item matrix to understand user preferences over check-ins, which lead to the POI recommendations.

Each check-in is driven by the user's interest, which is not directly specified by the user. An RS tries to infer the implicit interest from past behaviors. Our POI RS starts with finding latent interests of each user, and we rely on the LDA for finding latent topics. The LDA was originally proposed in natural language processing (NLP) and has been widely used beyond extracting topics in a corpus of documents. By treating a document as a user and a word as an item (or location id in our setting), one can build an RS, which can effectively predict even unseen items for a given user. Since its introduction, the LDA has been extended and adapted in many ways including in RSs. One of the earliest works (Jin et al., 2005) applied an LDA to discover the hidden semantic relationships among items underlying the item-attribute co-occurrence data. Inspired by Jin et al. (2005) and the following approaches, we use LDAs to find hidden *topics* underlying the user-place co-occurrence data, and have the pure-LDA as one of our baselines. As the pure-LDA model does not consider the geo-coordinates, we further extend the LDA and introduce a novel variant that deals with the distance factors between an anchor point and each item. An anchor point means an initial check-in location of the user, which affects all distance factors. We call our LDA model an anchor-LDA and use this model as a recommender algorithm. Our POI RS based on the anchor-LDA provides the user with recommendation results that reflect the anchoring effect focused on the initial check-in location of the user.

3.2. Distance effect

In this section, we investigate how each check-in is affected by its distance from the anchor point. For this study, we use check-ins from the Gowalla dataset from San Francisco and compute the distance between the anchor point and each check-in place users visited. The initial check-in point for each user becomes the anchor point for that user. Fig. 2 is a histogram of the distances between the check-ins and their anchor points, which shows that the majority of check-ins are made near the anchor points. Observing the exponential decay in Fig. 2, we fit this histogram to the exponential distribution of the distance function. The shape of the decay is determined by a parameter that is the inverse of the average distance. Note that our interest is finding the anchoring effect, not finding the optimal probability distribution; this will be part of future work.

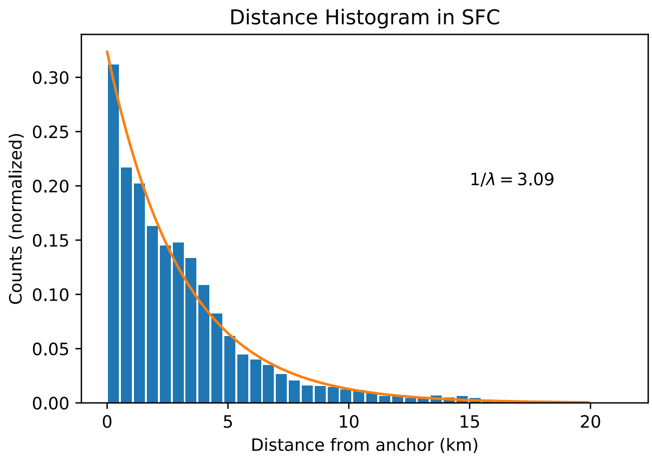

Fig. 2. Distance (km) distribution between each check-in and its anchor point.

Table 2
Notations used in the paper. Each notation can have a subscript for the user index and a superscript for identifying the index of check-in collections.

	Symbol	Description
Dimensions	$\mathcal{U}$	Set of users
	$\mathcal{V}$	Set of items (places)
	U	Total number of users (row)
	V	Total number of items (column)
	k	Total number of latent topics
LDA-notations	$\boldsymbol{\alpha}$	Dirichlet prior
	$\boldsymbol{\theta}$	Topic distribution
	z	$k \times 1$ Topic indicator
	w	Index of sampled word
	$\boldsymbol{\beta}$	Topic to word distribution
Distance factor	$\boldsymbol{\alpha_w}$	Beta distribution parameter
	$\boldsymbol{p}$	Bernoulli parameter
	c	Bernoulli RV $c \in \{0,1\}$
	$\boldsymbol{h}$	Anchor point (loc-id) in set $\mathcal{V}$
	λ	Exponential distribution parameter

3.3. Notations

Table 2 summarizes the notations used throughout this paper. Our notations try to follow the notations from LDAs (Blei et al., 2003), making the necessary distinctions along the way. We consider a finite set of users and a finite set of places (or items to be more general) of sizes U and V respectively. Dimensionality k of the Dirichlet distribution is assumed to be known and fixed, and we control it as a hyperparameter. Other hyperparameters include Dirichlet prior $\boldsymbol{\alpha}$ and beta distribution parameter $\boldsymbol{\alpha_w}$, a 2-by-1 sized vector. A user's check-in can be described by one of two factors: (i) pure interest, or (ii) distance proximity. For pure interest, the *topic* is borrowed from the LDA with all the notations used in Blei et al. (2003). For the distance factor, we assume each user has his or her own anchor point h, which is one of the places in the set $\mathcal{V}$. When check-ins are affected by distance proximity, we assume it follows the exponential distribution with parameter λ that decays with respect to the distance from the given user's anchor point. For each check-in, one of the two factors are selected through a Bernoulli trial, in which each user has its own Bernoulli parameter p sampled from the beta distribution. The subscript in the user specific notations denotes the corresponding user, which we have omitted in Table 2. The superscript m corresponds to each element from the collection of a given user, which has also been omitted in Table 2. More details are given in the following section.

3.4. Anchor-LDA

In this section, we provide the details of our model, which extends the LDA-based model by incorporating the user-specific preference *topic* that is borrowed from the LDA and the distance proximity for which we rely on the distance-based probability function. the anchor-LDA assumes that check-ins are affected by one of two factors, *distance* or *topic*. Specifically, we assume that each user has an anchor point that bounds the area of check-in locations. This anchoring effect corresponds to the distance factor. The topic factor is adopted from the LDA, in which the topic determines the selection of words (or items: location id in our setting). The overall process can be considered as a mixture of two subprocesses (i.e., topic, distance). The mixture is created through 2-stage generative process shown below. This generative process is flexible enough to capture the two phenomena. Later in the experiments, we show how this mixture approach outperforms the weighted LDA, in which all check-ins are affected by *topic* and *distance* simultaneously. Fig. 3 represents the plate diagram of our anchor-LDA model.

- **Initialization**
  1. For each user $u \in \mathcal{U}$, sample the anchoring effect Bernoulli parameter, the anchor point, and the $k \times 1$ topic distribution.
     $\boldsymbol{p}_u \sim \text{Beta}(\boldsymbol{\alpha_w})$,
     $\boldsymbol{h}_u \sim \text{Unif}(\mathcal{V})$,
     $\boldsymbol{\theta}_u \sim \text{Dirichlet}(\boldsymbol{\alpha})$.
  2. Have a probability density function of exponential distribution for sampling venues with respect to the distance from anchor point.
  3. Let $\boldsymbol{\beta}_{ij}$ in $k \times V$ matrix $\boldsymbol{\beta}$ describe the probability of choosing jth item given ith topic.
- **Generating Check-ins**
  Let M_u be the total number of selections[9] of user u from the (location id) set $\mathcal{V} = \{1, \ldots, V\}$.
  1. **Stage 1:** For each mth selection of user u, determine one of the two effects from Bernoulli trial, where the Bernoulli parameters are $\boldsymbol{p}_u$.
     $c_u^m \sim \text{Bernoulli}(\boldsymbol{p}_u)$, where $m \in \{1, \ldots, M_u\}$, and the $c_u^m \in \{0, 1\}$ determines one of the two cases in Stage 2.
     $$\text{if} \quad c_u^m = \begin{cases} 0 & \text{,then goto Stage 2-a (topic)} \\ 1 & \text{,then goto Stage 2-b (distance)} \end{cases}$$
  2. **Stage 2**: For each selection from Stage 1, choose a check-in place following the corresponding generative process with respect to $\mathbf{c}_u^m$
     (a) Stage 2-a (topic-based sampling)
     Choose a location id following the generative process of LDA (refer to Blei et al., 2003 for details)
     $\mathrm{w}_u^m \sim \mathrm{p}(\mathrm{w}_u^m|\boldsymbol{\theta}, \boldsymbol{\beta})$.
     (b) Stage 2-b (distance-based sampling)
     Choose a location with respect to the distance from anchor point and exponential distribution
     $\mathrm{w}_u^m \sim \mathrm{p}_{dist}(\mathrm{w}_u^m|\lambda) \propto \mathrm{p}_{exp}(dist(\mathrm{w}_u^m, h_u)|\lambda)$,
     where function $dist(a, b)$ returns the distance between place a and place b.

[9] For the purposes of data generation, M_u can be sampled from for example a Poisson distribution. This is not relevant in an instance where M_n is specified in the data.

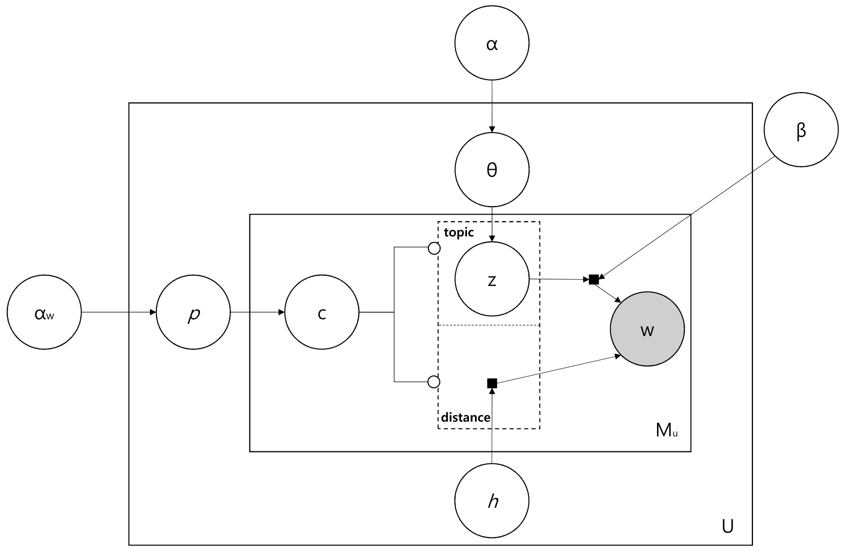

Fig. 3. Plate diagram of the anchor-LDA.

The overall generative process consists of two stages. Stage 1 determines one of the two factors through a Bernoulli trial. All users have their own Bernoulli parameters, which reflect the probability of the indicator variable being 1 (success). We tie the indicator variable to each of the two factors. When the indicator variable $c = 0$, we generate a check-in with respect to the sampled topic from the LDA; when $c = 1$, we generate a check-in by sampling places with respect to the probability distribution function we defined. Hence, when a user has p close to 0 for his or her Bernoulli parameter, the check-in place is more likely to be sampled from the generative process of the LDA and vice versa. We believe this user-specific parameter p reflects real-world scenarios adequately, as some users are less affected by travel distances while other users are more affected by location proximity when visiting places.

Stage 2 is divided into case (a) and case (b), in which case (a) corresponds to the LDA and case (b) corresponds to the generative process with anchoring effect. For case (a), check-in places are sampled with respect to the topic to item (place) distribution $\boldsymbol{\beta}$, where the topic distribution and topic indicator are sampled following the generative process of LDA. The anchoring effect in case (b) restricts the travel distance of each check-in from the anchor point. Inspired by the previous work in RS (Averjanova et al., 2008; Negre, 2015) , we set the initial check-in point for each user as the anchor point. By observing the travel distances from each user's anchor place as in Fig. 2, we use the exponential distribution for the probability distribution function. We sample check-in places with respect to the probability distribution function given the anchor point of each user.

3.5. Variational inference

We now describe the variational inference for the model presented above. Variational inference is most often used to infer the posterior distribution over the latent variables, which cannot be easily analytically solved. The main idea behind variational inference is to choose a family of distributions over the latent variables defined by a set of free variational parameters to approximate the posterior distribution. Variational inference achieves the closest approximation to the true posterior by minimizing the Kullback–Leibler (KL) divergence between the variational distribution and the posterior distribution. To accomplish this goal, we define the following variational distribution under mean field assumptions.

$$q(\boldsymbol{p},\boldsymbol{\theta},c,\mathrm{z}|\boldsymbol{\rho},\boldsymbol{\gamma},\boldsymbol{\tau},\boldsymbol{\phi}) = q(p|\rho)q(\theta|\boldsymbol{\gamma})\prod_{m=1}^{M} q(c|\boldsymbol{\tau})q(\mathrm{z}|\boldsymbol{\phi}), \tag{1}$$

where variational distributions $q(\boldsymbol{\theta}|\boldsymbol{\gamma})$ and $q(\mathrm{z}|\boldsymbol{\phi})$ are carried over from Blei et al. (2003). Just as in the previous work, $q(\boldsymbol{\theta}) \sim Dir(\boldsymbol{\gamma})$ and $q(\mathrm{z}) \sim Multinomial(\boldsymbol{\phi})$. Additional variational distributions are required in our proposed model to capture the mixture of the two phenomena. While the preexisting terms are responsible for the latent *topics*, the additional parameters account for the user's preference over distance when selecting places and the choice of the two for a given check-in. We posit two variational distributions as follows: $q(p) \sim Beta(\rho)$ and $q(c) \sim Binomial(\tau)$. These added terms in Eq. (1) also reflects how the LDA has been extended to capture the distance effect.

Minimizing the KL-divergence is equivalent to maximizing the evidence lower bound (ELBO), where the KL-divergence cannot be directly minimized. Using Jensen's inequality, we can bound the log-likelihood as follows.

$$\log p(\mathrm{w}|\boldsymbol{\alpha},\boldsymbol{\beta}) \geq \mathbb{E}_q[\log p(\boldsymbol{p},\boldsymbol{\theta},c,\mathrm{z},\mathrm{w}|\boldsymbol{\alpha},\boldsymbol{\beta})] - \mathbb{E}_q[\log q(\boldsymbol{p},\boldsymbol{\theta},c,\mathrm{z})], \tag{2}$$

where variational parameters have been omitted for simplicity. By rewriting the lower bound of Eq. (2) to $\mathcal{L}(\boldsymbol{\rho},\boldsymbol{\gamma},\boldsymbol{\tau},\boldsymbol{\phi};\boldsymbol{\alpha},\boldsymbol{\beta})$, we can derive that the difference between the log-likelihood and the lower bound is equivalent to the KL divergence between the variational probability and the true posterior. Hence, optimal variational parameters can be obtained by maximizing the ELBO: $\mathcal{L}(\boldsymbol{\rho},\boldsymbol{\gamma},\boldsymbol{\tau},\boldsymbol{\phi};\boldsymbol{\alpha},\boldsymbol{\beta})$.

By taking the derivatives of $\mathcal{L}(\boldsymbol{\rho},\boldsymbol{\gamma},\boldsymbol{\tau},\boldsymbol{\phi};\boldsymbol{\alpha},\boldsymbol{\beta})$ with respect to each of the variational parameters and setting them to 0, we obtain a closed form of the update equations, which is provided below:

$$\boldsymbol{\phi}^m_{u,i} \propto \boldsymbol{\beta}_{i,\mathrm{w}^m_u} \exp(\mathbb{E}_q(\boldsymbol{\theta}_{u,i}|\boldsymbol{\gamma}_{u,i})), \tag{3}$$

where u denotes the user, and i denotes the ith topic. We normalize $\boldsymbol{\phi}^m_u$ to sum to 1.

$$\boldsymbol{\gamma}_u = \boldsymbol{\alpha} + \sum_{m=1}^{M} \boldsymbol{\phi}^m_u. \tag{4}$$

One can easily verify that Eqs. (3) and (4) follow the update equations in Blei et al. (2003). The update equations for $\{\boldsymbol{\tau}\}$ and $\{\boldsymbol{\rho}\}$ are as follows:

$$\boldsymbol{\tau}^m_{u,0} \propto \sum_{i=1}^{k} \boldsymbol{\phi}^m_{u,i}\boldsymbol{\beta}_{i,\mathrm{w}^m_u}, \tag{5}$$

$$\boldsymbol{\tau}^m_{u,1} \propto \mathrm{p}_{dist}(\mathrm{w}^m_u|\lambda), \tag{6}$$

$$\boldsymbol{\rho}_u = \boldsymbol{\alpha}_w + \sum_{m=1}^{M} \boldsymbol{\tau}^m. \tag{7}$$

Table 3
Statistics of check-ins from San Francisco (SFC), Austin (ATX), and New York City (NYC).

Dataset	Users (U)	Places (V)	Total check-ins
Gowalla-SFC	2056	11,462	89,815
Gowalla-ATX	4181	18,435	200,926
Gowalla-NYC	2171	19,130	83,099

For each check-in of a given user, τ_u^m computes how likely the mth check-in of user u would happen with respect to each of the two factors. These $\{\tau_u\}$ are later collected to obtain ρ_u in Eq. (7). These variational parameters are updated iteratively until the lower bound reaches convergence, while the parameters β and λ are simultaneously being updated.

4. Experimental results

To validate our POI RS based on the anchor-LDA, we conducted a comparative experiment with various LDA-based algorithms using a Gowalla dataset.

4.1. Data and setting

We used three datasets from Gowalla (Cho et al., 2011) in the experiments to evaluate the performance of the proposed method, which were utilized in many recent studies related to LBSN (Hsieh & Li, 2019; Huang et al., 2020; Kim et al., 2020; Zhang et al., 2020). Gowalla is one of the earliest LBSN platforms that enables users to check-in to places they visit. The dataset contains check-ins from February 2009 to October 2010. Most check-ins in Gowalla came from major cities in the US. For our experiments, we selected San Francisco (SFC), Austin (ATX), and New York City (NYC) from the West Coast, Central, and East Coast respectively. Throughout our experiments, we use check-ins from *active* users who have checked-in to at least 10 different places within a city. Repeated check-ins from the same user in the same location have been removed. In other words, the user-item matrix is a binary matrix, where 1 represents the existence of a check-in.

Table 3 provides the basic statistical features of the datasets from the three cities. One interesting finding is that the total number of check-ins in Austin was nearly 2.5 times as high as in NYC, whereas the NYC population is much larger than the Austin population. We found that Gowalla was an Austin based company which later was acquired by Facebook in 2012.

4.2. Experimental setup

We conducted a series of experiments on the datasets from the three major cities and compared the performance of our proposed model to other baselines. In this study, we only utilized check-in and geo-coordinate information in LBSN. Therefore, we decided on the baselines considering only this information, not other implicit information, such as pure-LDA (Blei et al., 2003), weight-LDA, and the LDA mixture with mean coordinates (Cho et al., 2011; Yin et al., 2015; Zhu et al., 2018). For each baseline and the anchor-LDA, we predicted the unobserved check-ins based on the existing check-in records. Each dataset in Table 3 was divided into training data and test data using 10-fold cross validation, while we ensured the inclusion of the initial check-in for each user in the training data.

pure-LDA. A pure-LDA model predicts unobserved check-ins through inferred latent topic distributions of each user and the estimated topic-to-place distributions (Blei et al., 2003). The inference and learning use only the user-item matrix collected from the observed check-ins with no information on geo-coordinates of each check-in. This simplest approach for predicting new check-ins can be easily adopted from a conventional recommendation system with a user-item relationship. The performance improvement over this baseline will show how worth it is to incorporate geo-coordinates for POI RS.

weighted-LDA. If the check-ins in the LBSN are in fact affected by the distance from the anchor point, we need to further investigate whether the distance factor affects all check-ins or only some cases of check-ins. The former corresponds to the weighted-LDA; the latter corresponds to the mixture model of the two components: distance and topic, which is our proposed model. In the weighted-LDA, the topic to place distribution β is re-weighted with respect to the distance function. Each user will have its own weighted-β, in which the weights are proportional to the distance function that decays with respect to the distance from the anchor point. As described above in Section 3.2, we found that each check-in is bounded by the anchor of given user. This phenomenon leads us to add this baseline to the series of experiments.

anchor-LDA. We compare the predictive performance of our model to the two baselines we described above. The main difference between our model and the weighted-LDA is how we handle the distance factor. The anchor-LDA assumes the check-in is driven by one of the two factors, which are topic or distance. In the generative process of the anchor-LDA, check-ins are generated from the mixture of two components. When the *topic* component is chosen, a check-in is generated with respect to the sampled topic defying the distance from the anchor point. When the *distance* component is chosen, a check-in is generated bounded by the anchor point regardless of the user's topic distribution. The weighted-LDA, on the other hand, assumes every check-in is affected by distance between the current place and the anchor point.

LDA mixture with mean coordinates. This baseline is quite similar to our proposed model, and the only difference lies in how we define the anchor. Our proposed model defines each user's anchor as the initial point of check-ins. To verify that the initial check-in point is effective enough to become an anchor point, we compare it to the exact same model with anchor points set as the mean coordinates for each user. In fact, the mean of geo-coordinates in LBSN has been widely used in the previous works (Cho et al., 2011; Yin et al., 2015; Zhu et al., 2018), in which the mean of the geo-coordinates for each user were used as home locations. We verify whether initial check-ins are more informative than the whole collection of coordinates by comparing the performance of our model with this baseline.

4.3. Evaluation on predictive tasks

Each check-in record in Gowalla contains the user id, location id, the time of check-in and the GPS coordinates in latitude and longitude. While we use the time of the check-ins to find the first check-in of each user, the actual time of the check-in is not considered in our experiments. All repeated check-ins have been discarded so that user only contains unique items (places). We perform a 10-fold cross validation to evaluate the predictive performance on 10% of the datasets for each of the three major cities.

Tables 4, 5, and 6 summarize the predictive performances on the datasets from the three cities. We measure recall and precision at K. Recall and precision at K sort the predicted items from most likely to least likely and compute the recall and precision scores on top-K items. In an RS, users mostly focus on top-K items neglecting the items on the bottom of the page. Hence, recall and precision at K have been widely used as a performance metric in RSs. The anchor-LDA clearly outperforms the other baselines in terms of recall and precision with various settings of K.

The results of the weighted-LDA, LDA-mixture, and anchor LDA in Table 4 reveal the importance of incorporating geo-coordinate information into the POI RS model. These three models achieve better performance than the pure-LDA. Even the weighted-LDA, the simplest model of the three, when compared to the pure-LDA, yields an increase of 9.4%, and 5.1% in terms of recall and precision at K = 100, respectively. In Table 4, it can also be seen that the LDA-mixture model performs better than the weighted-LDA, and the anchor-LDA achieves

Table 4
Comparison of recall (R) and precision (P) at K with the Gowalla SFC dataset.

Methods		GoSFC: (R)ecall and (P)recision @ K			
		100	200	300	400
pure-LDA	R	0.203	0.288	0.345	0.387
	P	0.0078	0.0057	0.0046	0.0040
weighted-LDA	R	0.222	0.297	0.351	0.393
	P	0.0082	0.0058	0.0047	0.0041
LDA-mixture /w mean coordinates	R	0.226	0.303	0.361	0.403
	P	0.0085	0.0059	0.0048	0.0040
anchor-LDA	R	**0.237**	**0.328**	**0.391**	**0.438**
	P	**0.0087**	**0.0064**	**0.0052**	**0.0045**

Table 5
Comparison of recall (R) and precision (P) at K with the Gowalla ATX dataset.

Methods		GoATX: (R)ecall and (P)recision @ K			
		100	200	300	400
pure-LDA	R	0.261	0.362	0.429	0.482
	P	0.0104	0.0076	0.0061	0.0052
weighted-LDA	R	0.264	0.365	0.432	0.486
	P	0.0105	0.0075	0.0061	0.0053
LDA-mixture /w mean coordinates	R	**0.268**	0.371	0.444	0.495
	P	**0.0107**	0.0077	0.0063	0.0053
anchor-LDA	R	0.267	**0.373**	**0.445**	**0.498**
	P	**0.0107**	**0.0078**	**0.0064**	**0.0054**

Table 6
Comparison of recall (R) and precision (P) at K with the Gowalla NYC dataset.

Methods		GoNYC: (R)ecall and (P)recision @ K			
		100	200	300	400
pure-LDA	R	0.197	0.243	0.282	0.309
	P	0.0043	0.0034	0.0029	0.0025
weighted-LDA	R	0.188	0.243	0.278	0.310
	P	0.0065	0.0044	0.0034	0.0029
LDA-mixture /w mean coordinates	R	0.207	0.264	0.310	0.341
	P	0.0070	0.0047	0.0038	0.0032
anchor-LDA	R	**0.228**	**0.287**	**0.327**	**0.361**
	P	**0.0077**	**0.0051**	**0.0041**	**0.0034**

the highest performance of the four. The anchor-LDA yields a performance improvement on average of 7.5% and 7.9% in terms of recall and precision, respectively, over the second-best performing model, the LDA-mixture with mean location. This is quite interesting as the LDA-mixture with the mean location model requires more information on geo-coordinates for computing the mean than does our proposed model, which only needs the initial geo-coordinates. Nonetheless, the anchor-LDA presents a better performance than the LDA-mixture with mean location model with comparably less geo-information. We believe this reflects the significance of the anchoring effect in check-ins.

The performance improvement on the ATX dataset (shown in Table 5) was not as significant as the other two cities. Like the other two datasets, the anchor-LDA shows the best performance of the four. However, the improvement was not as remarkable as with the other two datasets. We believe this is due to a unique characteristic of ATX dataset, as Austin is the city where Gowalla was founded. There could have been testing and promotion activities by Gowalla, which could have influenced the users' behavior.

The performance of the four models on the NYC dataset is presented in Table 6. The anchor-LDA clearly outperformed the other three baselines both in terms of recall and precision with relative improvement of 10.1–15.7% and 10–79% at $K = 100$, respectively, over the LDA-mixture with mean coordinates, the second best performing model and the pure-LDA. The results from all three datasets consistently present the robustness and the superior performance of the anchor-LDA. The improvement over the LDA-mixture with mean coordinates signifies the anchoring effect of the initial check-in.

Another observation from Tables 4, 5, and 6 is that the two LDA-distance mixture models with different approaches to the anchor point always perform better than the weighted-LDA, which assumes every check-in is affected by distance. This shows that check-ins can be affected by distance, but it is not always the case. Some check-ins can be made above the travel boundaries neglecting the travel distances within the same city. This observation supports our assumptions that check-ins are affected by two factors *topic*, and *distance* not simultaneously but exclusively. Our mixture approach reflects this assumption.

5. Discussion

Our POI recommender system has advantages from the perspectives of both a user and a service provider. First, from the user's point of view, we confirmed that the initial input has a positive effect on the user in the recommender system. In other words, We can improve user satisfaction with the recommendation results by using their initial inputs as the weight of the recommender algorithm. Therefore, we plan to extend the idea of anchoring effect on other recommender system domains. In addition, as our study only uses geo-coordinate information, the time complexity is low compared to other studies using various features of LBSN, such as social and temporal-sequential information. Thus, there is a benefit of reducing the overall cost of service from the standpoint of a service provider. Finally, our work can be applied to all SNSs that provide the location information to users, such as Gowalla, Foursquare, Facebook, and Instagram.

As shown in the experimental results, the low precision of the proposed method is our limitation. However, this problem arises due to the sparseness of our user-POI matrix derived from the LBSN dataset. In our experimental dataset, the density of matrices in Gowalla-SFC, Gowalla-ATX, and Gowalla-NYC are 0.0038, 0.0026, and 0.0020 respectively. As our method depends on the user's check-in behavior, it is sensitive to the density of the matrix. Due to the nature of data sparsity in LBSN datasets, previous studies have considered other factors to predict the user's future check-ins, which can improve predictive performance. Hsieh and Li (2019) investigated how social ties affect user's check-ins. Zhang et al. (2020) considered text descriptions, social ties, and temporal-sequential context for POI recommendation through a unified neural network framework. Huang et al. (2020) considered a social influence, temporal-sequential influence along with the distance influence in their probabilistic generative model. To conduct comparative experiments with them (Hsieh & Li, 2019; Huang et al., 2020; Zhang et al., 2020), we will propose a method to apply the anchoring effect on social and temporal information. In addition, our study is different from them in the experimental environment (i.e., preprocessing condition, settings of K in precision@K and recall@K). Therefore, we must conduct comparative experiments in the same environment for a fair comparison. As our work is focused on discovering the anchoring effect on user's check-in behavior, the problem of evaluating our model against these studies is left for future work.

6. Conclusion

In this paper, we proposed an LDA model that applied the anchoring effect to a POI RS and called this model the anchor-LDA. We focused on an anchor point, which is the initial check-in of the user, and measured the distances between this point and each location used as the main factor in the anchor-LDA. Our POI RS based on the anchor-LDA provided the user with recommendation results according to the distance factors and the latent preferences of the users. Based on the LBSN dataset, we conducted comparative experiments to validate the effectiveness of the anchor-LDA. The results of both precision and recall show that anchor-LDA outperformed the existing LDA-based recommender algorithms. Furthermore, we confirmed that the anchoring effect affects the interests of users on the LBSN.

In future work, we plan to verify whether an anchor point of other features on the LBSN, such as social information, not check-in information, is applicable to the anchor-LDA. Next, we will develop a version of the anchor-LDA model that generalizes the anchoring effect for the POI RS. In addition, we will find an appropriate probability distribution method for the anchor-LDA using additional data analysis.

CRediT authorship contribution statement

Young-Duk Seo: Methodology, Formal analysis, Investigation, Writing - review & editing, Visualization. **Yoon-Sik Cho:** Conceptualization, Software, Validation, Resources, Data curation, Writing - original draft, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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