SAGE: Interactive State-aware Point-of-Interest Recommendation

Behrooz Omidvar-Tehrani, Sruthi Viswanathan, Frederic Roulland, Jean-Michel Renders

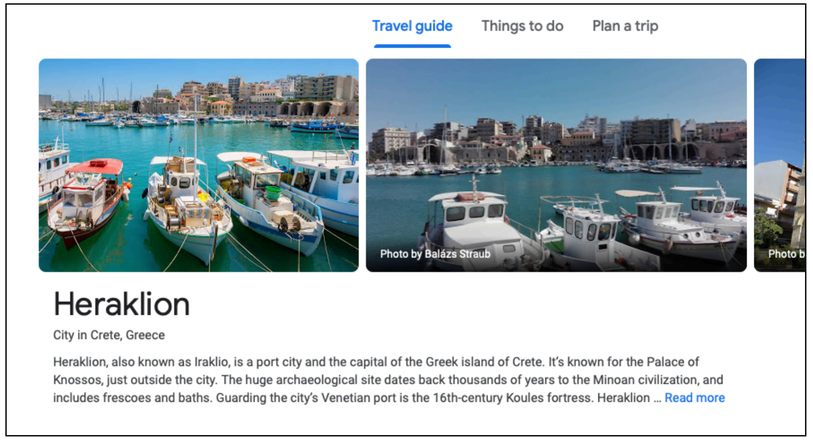
NAVER LABS Europe

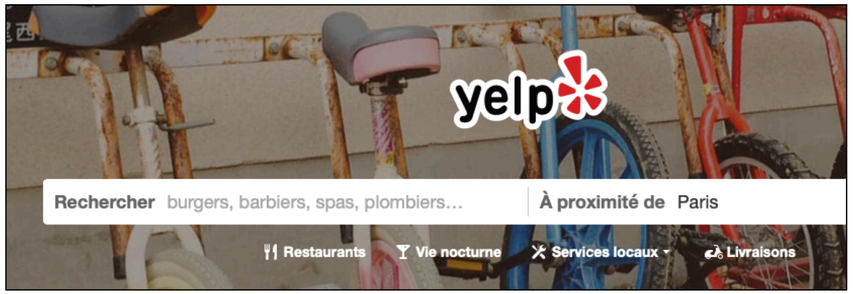
Workshop SUM'20: State-based User Modelling

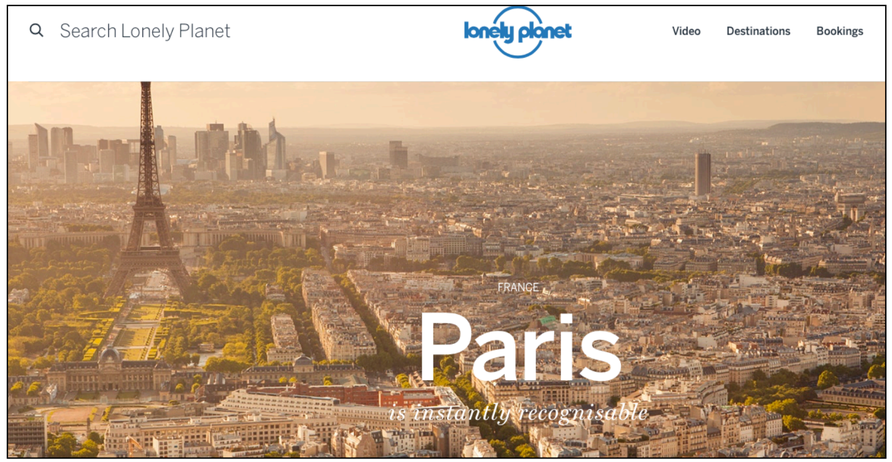
“What can I visit here?”

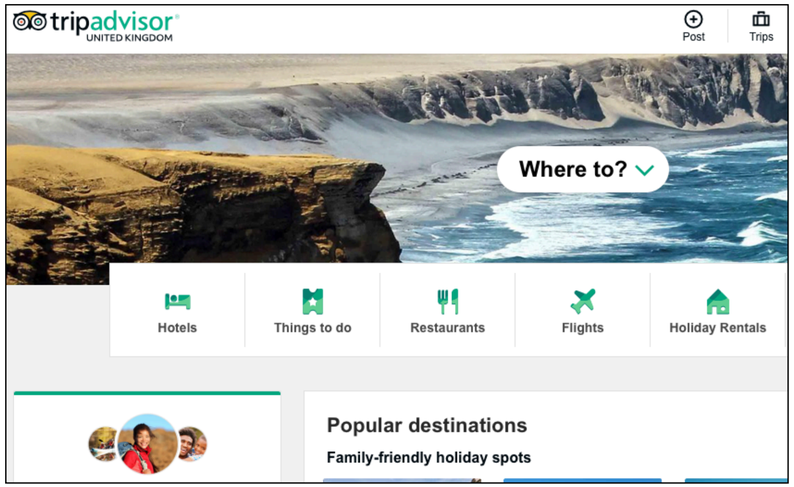
Off-the-shelf tools can already help!

There exist many *POI search and recommendation* services on the web.









What is missing?

▶ Cold start and data sparsity

What if no check-in data is available to form recommendations? (e.g., new comer, privacy concerns)

▶ State integration

The state is not limited to contextual features such as time and location, but also situational features such as the user's mindset at the time of receiving recommendations. For instance, different POIs should be recommended in case the user is hungry, or in case he/she is seeking some personal relaxation time (i.e., me time).

▶ Interpretation of interactions

Users need to be inside the loop and interact with the system to gradually build their intent. The challenge with multi-shot recommendation systems is that it is not clear how user interactions with the system should influence the user state and the recommendation strategy.

▶ Explainability

Users may not trust in what they get from the recommender due to the cold start problem and interactions with the system. Hence it is of critical importance to let users know why they receive certain POIs as recommendation results.

SAGE is an interactive state-aware POI recommendation system based on look-alike groups.

Example: tourist visiting Pompidou neighborhood

User clicks on a yellow POI.

- group of visitors who post very few photos, have many friends, check in actively, and tend to visit historical landmarks on weekday afternoons.
- group of visitors who have many friends (i.e., social visitors like her), and tend to visit coffee shops.
- group of visitors who post many photos, highlight many pins (i.e., ideas to visit POIs), and tend to visit Asian Food restaurants.

- group of visitors who have many friends and visit restaurants on evenings.
- group of visitors who post very few photos and visit Modern Art Museums .
- group of visitors with many check-ins who visit shopping centers.

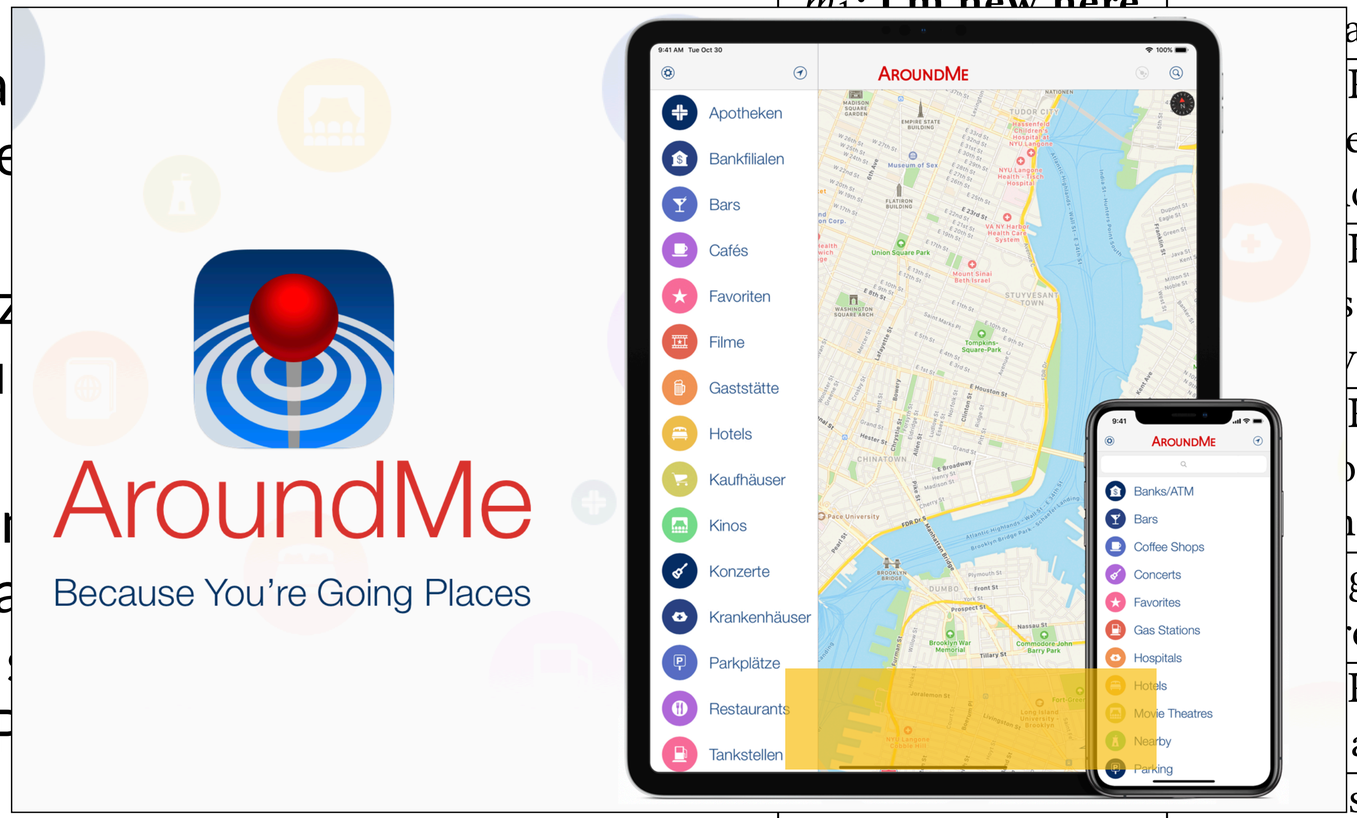
Core assumptions in SAGE

1. We assume that the user is in an **exploratory setting.**

2. We conjecture that **look-alike user data** is a good proxy to gain user preferences.

Exploratory setting

- A core concept in a
  recommendation se
- It is often materializ
  features such as cu
- An additional dimen
  mindsets, i.e., actua
  the user. Mindsets
  interestingness of P
  on user's intent.



Mindset label	Description
m_1: I'm new here	towards touristic POIs about the attractions in the city.
	POIs which haven't been efore by the user and are on (seldom visited)
	POIs related to physical s like swimming pools, yms, and mountains
	POIs related to activities oneself and be pursued solo d and relax
	getting faster access elated POIs nearby
	POIs such as museums, and cultural landmarks
m_7: **hidden gems**	small intriguing local POIs that are highly rated but not necessarily popular

Mindsets

- A mindset m is a tuple **m** = ⟨label, func()⟩, where label provides a short description of the mindset, and func() defines semantics of POI interestingness.

$$m.func(P, \mu) = \frac{\sum_{f_i(P) \in \mathcal{F}} b_{i,m} w_{i,\mu} f_i(P)}{\sum_{f_i(P) \in \mathcal{F}} b_{i,m} w_{i,\mu}}$$

Priors in mindsets

- Priors reflect the importance of a utility function for a mindset. The weights, on the other hand, are user-centric parameters and reflect the importance of a utility function for the user.

	popularity	**prestige**	**recency**	**coverage**	**surprisingness**	**diversity**	**size**
m_1: **I'm new here**	**0.25**	**0.25**	**0.10**	**0.15**	0.00	**0.25**	0.00
m_2: **surprise me**	**0.25**	**0.20**	0.00	0.00	**0.25**	**0.20**	**0.10**
m_3: **let's workout**	**0.35**	**0.40**	0.00	**0.25**	0.00	0.00	0.00
m_4: **me time**	**0.20**	**0.20**	0.00	**0.20**	0.00	**0.20**	**0.20**
m_5: **I'm hungry**	0.00	**0.40**	**0.20**	**0.40**	0.00	0.00	0.00
m_6: **let's learn**	**0.30**	**0.30**	0.00	**0.20**	0.00	**0.20**	0.00
m_7: **hidden gems**	**0.30**	**0.30**	**0.15**	0.00	0.00	0.00	**0.25**

Utility functions

- We measure the interestingness of POIs using POI utility functions.
- A more interesting POI has higher chances to be recommended to the user.
- A POI utility function $f : 2^P \rightarrow [0,1]$ returns a value between 0 and 1 which reflects the extent of interestingness for one or several POIs.

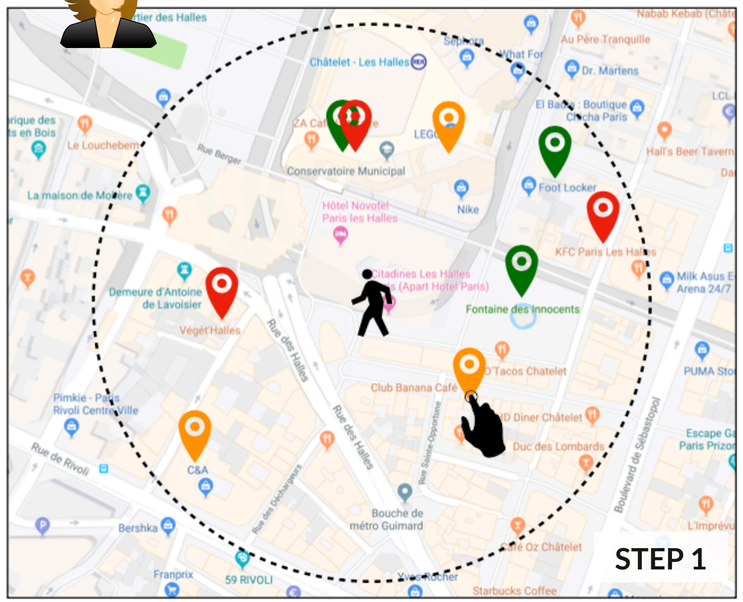
Utility function	Description
$popularity(P)$	normalized average number of check-ins of P.
$prestige(P)$	normalized average rating score of P.
$recency(P)$	inverse difference between the current date and the average insertion date of P.
$coverage(P)$	the area of a polygon induced by the geographical location of POIs in P normalized by the area of the city.
$surprisingness(P)$	normalized Jaccard distance between POI categories of P and POI categories of the bookmarked POIs by the user $\mathcal{P}_\mu$.
$diversity(P)$	normalized Jaccard distance between sets of POI categories in P.
$size(P)$	normalized average radius of POIs in P.

Look-alike user data

- There exist various publicly available POI datasets, such as Yelp, TripAdvisor, Foursquare, and Gowalla, structured as $D = \langle U, P \rangle$.
- To build look-alike relations in the POI dataset, we build "visitor groups" which aggregate a set of visitors with common demographics and/or POIs.
- A visitor group is a triple $g = \langle members, demogs, POIs \rangle$ where $g.members \subseteq U$, $\forall u \in g.members$, $\forall \langle a,v \rangle \in g.demogs$, $\langle a,v \rangle \in u.demogs$, and $\forall u \in g.members, \forall p \in g.POIs$, $\exists \langle p,t \rangle \in u.checkins$.

Example: tourist visiting Pompidou neighborhood

I look for "me time"



User clicks on a yellow POI.

"I'm hungry"

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Problem definition

- Given a user μ and his/her affiliated context c(μ) = ⟨loc, time⟩, a mindset m = ⟨label, func()⟩, a radius r, and integers k and k', the problem is to find top-k groups G and k' POIs for each group in G , such that the following conditions are met.

$$(i)\ \forall g \in G, \mathcal{P}_\mu \cap g.POIs \neq \emptyset$$

$$(ii)\ \forall g \in G, \forall p \in g.POIs, distance(p, c_\mu.loc) \leq r;$$

$$(iii)\ \Sigma_{g \in G} m.func(g.POIs, \mu) \text{ is maximized.}$$

Solution: SAGE

- SAGE is a session-based system which begins with an ambiguous user's intent for POI recommendation, and ends when he/she is satisfied with the resulting POIs.
- Each session consists of a finite sequence of iterations which captures interactions with the user. A new iteration begins by defining a **mindset** (which may remain the same as the previous iteration), which then results in **k relevant groups** and **k' POIs for each group**.
- At the end of each iteration, the user is free to bookmark some of the recommended POIs to be added to Pμ .

SAGE algorithm

Algorithm 1: SAGE Algorithm

Input: Visitors $\mathcal{U}$ and POIs $\mathcal{P}$, user context $c_\mu = \langle loc, time \rangle$, radius r, mindset m, number of groups k, number of POIs per group k'

Output: Groups G and their POIs P_G

1. $P \leftarrow nearby\_POIs(\mathcal{P}, c_\mu.loc, r)$
2. $H \leftarrow checkins\_of(P, c_\mu)$
3. $G^* \leftarrow mine\_groups(\mathcal{U}, H)$
4. $G \leftarrow maximize(\mu, G^*, k, m)$
5. **for** *each group* $g \in G$ **do** $P_G.append(top\_POIs(g, k'))$
6. **return** G, P_G

Mining look-alike groups

- Explainability is a crucial need in cold start settings.
- To address the challenge of explainability, we aim to find describable groups which identify a set of visitors checking in a set of POIs.
- For this aim, we employ Frequent Itemset Mining (FIM) technique.

Maximizing mindsets

- Not all groups are equally interesting to the user. We need to pick **k** groups out of all mined groups which are in line with the mindset requested by the user.
- The mindset function admits as input a set of POIs, and returns a value in the range [0, 1].
- Given a mindset m and a group g, we measure the utility of g regarding m's functionality as group_utility(g) = m.func(g.POIs).
- We employ a simple scalarization approach.

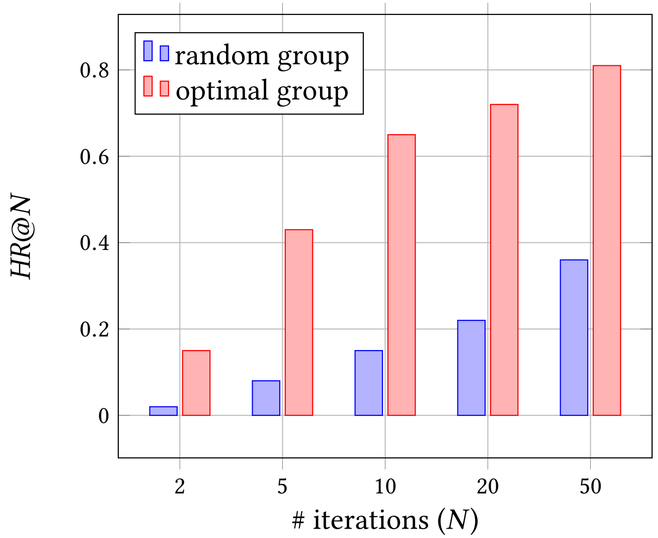
Experiments

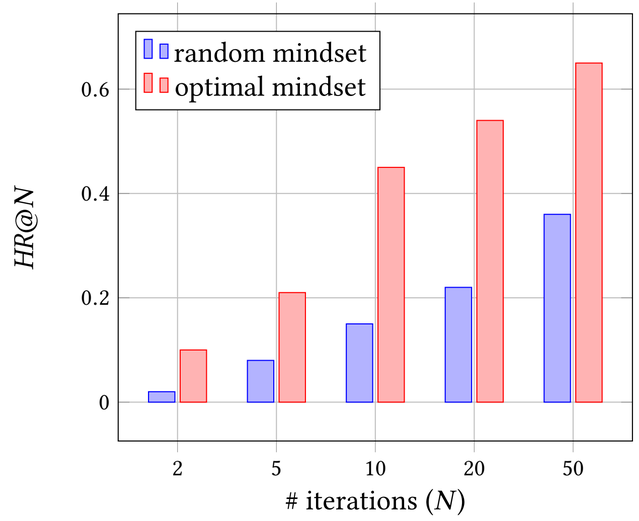
- In this work, we use Gowalla dataset, collected from a popular LBSN with 36, 001, 959 check-ins of 319, 063 visitors over 2, 844, 076 POIs.
- We evaluate the overall algorithmic behavior of SAGE by simulating interaction sessions and reporting the Hit Ratio measure.
- We also evaluate the user-centered aspects of SAGE using an extensive user study.

Simulation study

- To remove the influence of human decisions from the exploratory process, we simulate interactions (by picking a random user μ in Gowalla, and a random check-in from μ.checkins as μ's actual state) and report the Hit Ratio HR@N for each simulated session.

$$HR@N = \sum_{i=1}^{S} (\mathbb{1}_{j=1}^{N}(i, j, \mu))/S$$





User study (1)

- We perform an extensive between-subject user study in Amazon Mechanical Turk to measure the effectiveness of employing look-alike groups and mindsets in SAGE.
- We recruited 753 participants in AMT to answer different questions about the functionality of our proposed system.
- We compare SAGE with a baseline, i.e., Google Map Explore, an interactive POI exploration and recommendation system. For a given region, the participant observes the results of SAGE and the baseline side-by-side, and should decide which set of POI recommendations he/she finds more useful. We found out that 59% of the participants prefer SAGE over its competitor.

User study (2)

- Moreover, we perform an independent study by describing an intuitive contextual state (e.g., “an evening in Paris”) and a mindset to the participant, and asking his/her opinion about the usefulness of SAGE’s output.
- **Viewpoint 1:** The group-based results are relevant to the selected mindset.
- **Viewpoint 2:** The groups help the participant understand why he/she receives the POIs as recommendation results.
- For both viewpoints, we observe that the supremacy of the agreement vote is statistically significant (72.97% for v1 and 72.65% for v2).

Conclusion

- We present SAGE, an interactive state-aware POI recommendation system based on look-alike groups, which tackles the common challenges of cold start, interactivity, state-awareness, and explainability.
- We introduce the notion of “mindsets” which extends the scope of user state, and captures actual situation and intents of the user.
- In an extensive set of experiments, we show that SAGE achieves a Hit Ratio higher than 50% only after 10 iterations. We also showed the effectiveness of look-alike groups and mindsets for POI recommendation in an extensive user study.

Thanks.

For questions and more:
omidvar.info

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