Probabilistic Modeling of City-scale Image Collections

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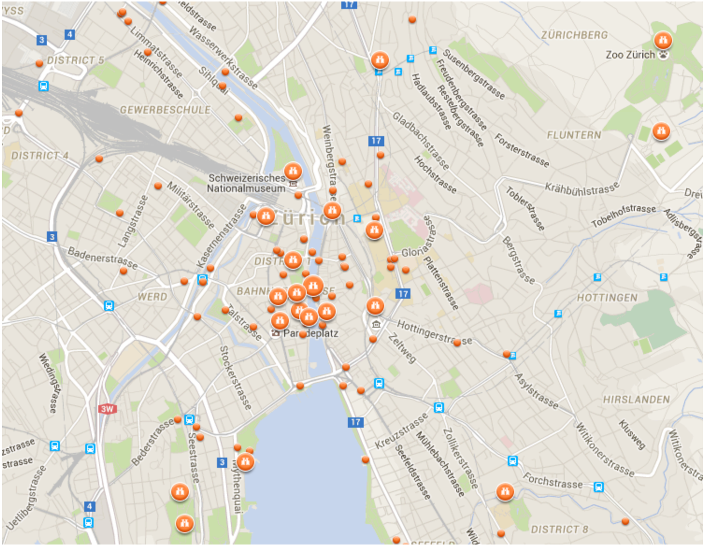
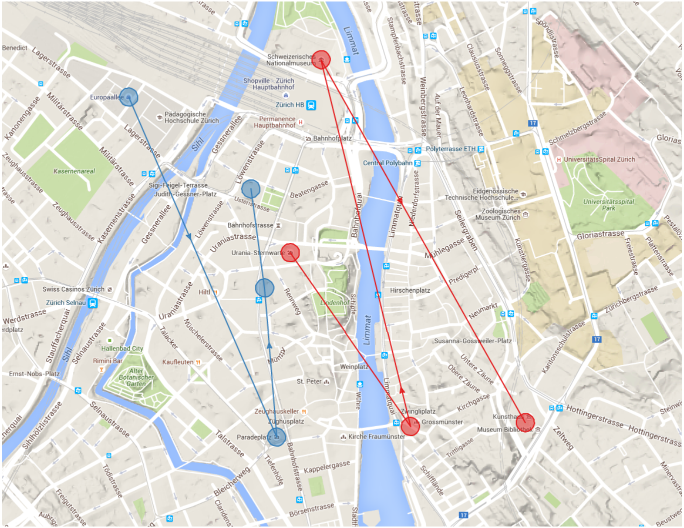
Outline

Popular Places in Zürich



Touristic Routes for 2 Day Trip

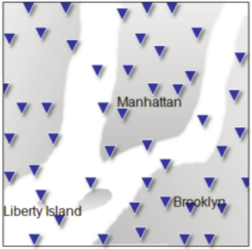


Related Work: Mapping the World's Photos

Representative photos for top landmarks in North America identified from Flickr data. Source: Kleinberg et al. (2009)

Related Work: Travel Route Recommendation Using Geotags in Photo Sharing Sites

- Kurashima et al. (2010) modeled photographer behavior by combining Markov and topic models in a probabilistic framework.



Highly photographed locations. Source: Kurashima et al. (2010)

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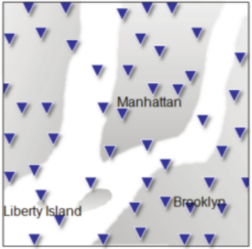

Highly photographed locations. Source: Kurashima et al. (2010)

$$P(l_t \mid l_{t-1})$$

$$\sum_{z \in \boldsymbol{Z}} P(z \mid h^u) P(l_t \mid z)$$

Markov and Topic models.

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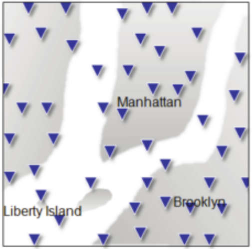

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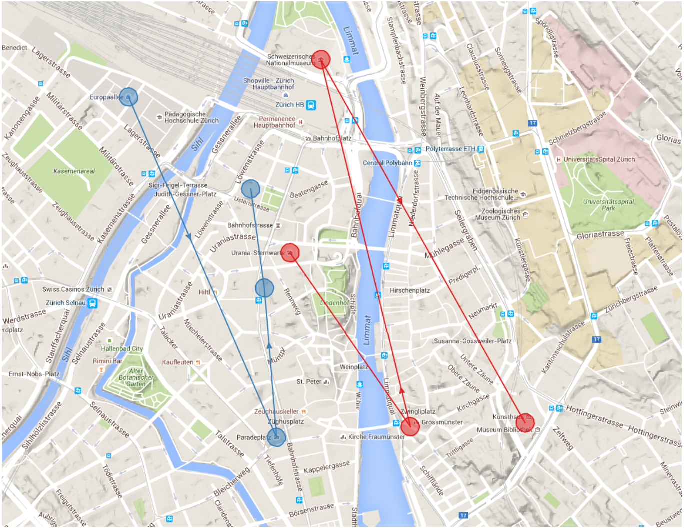
Markov and Topic models.

Routes from the model.

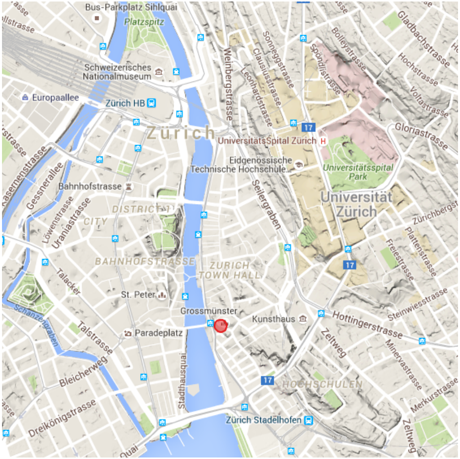
Source: Kurashima et al. (2010)

Touristic Paths

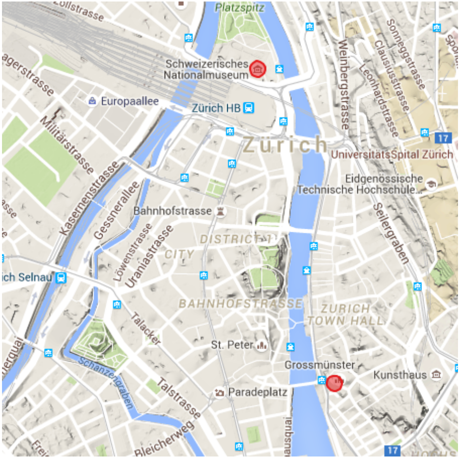


Focus: Sets of Locations to Visit

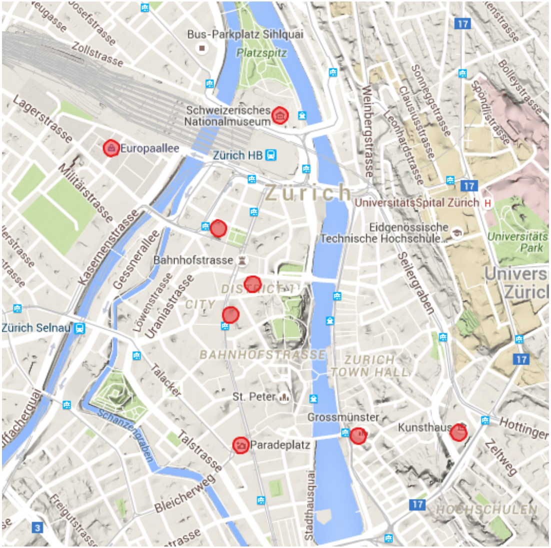
Good Sets of Locations



Diverse Sets of Locations



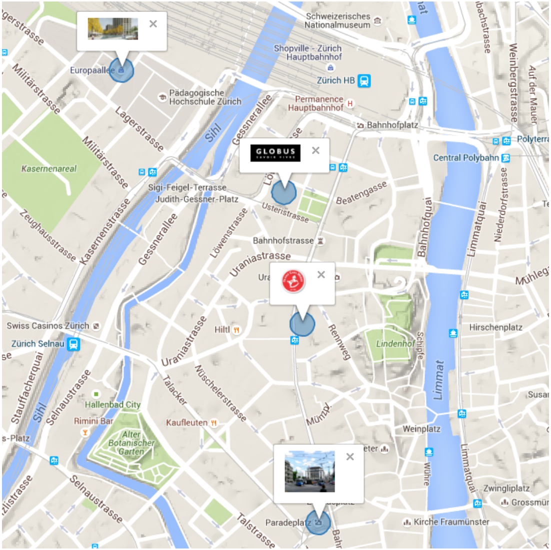
Diverse Sets of Locations



Diversity and Submodularity

- $F(\{\text{ETH} \mid \text{Framünster}\}) \geq F(\{\text{ETH} \mid \text{UZH, Framünster}\})$.
- Maximizing $F(S)$ for S of fixed size implies adding locations of different types $\rightarrow$ Diversity.

Complementary Sets of Locations



Complementarity and Supermodularity

- Suppose a function $F(S)$ that counts 1 for each pair of repeated location types in S.
- For example, $F(\{\text{ETH, UZH, Fraumünster}\}) = 1$, $F(\{\text{ETH, Fraumünster}\}) = 0$.
- Maximizing $F(S)$ for S of fixed size implies adding locations of the same types $\rightarrow$ Complementarity.

Goal

Model tourist behavior as probability distributions over sets of locations visited.

Probabilistic Submodular Models

- Probabilistic Submodular Models (PSMs) are a class of distributions over the powerset of a set V of the form

$$P(S) = \frac{\exp F(S)}{Z}$$

for all $S \subseteq V$, where F(S) is submodular or supermodular.

- Inference in these distributions is hard. Exact computation of Z is #P-complete.
- Inferences has been recently studied by Djolonga and Krause (2015) and Gotovos et al. (2015).

Learning PSMs

- We applied these distributions to a dataset of geotagged photographs.
- Tschiatschek et al. (2016) studied learning a PSM from data, i.e. estimating the model parameters.
- Noise Contrastive Estimation was used as an alternative for learning the PSM.

Noise Contrastive Estimation

- Transform the task of estimating a distribution into a supervised classification task.
- Noise samples $\mathcal{N}$ are drawn from a known normalized distribution P_n and contrasted with the data samples $\mathcal{D}$ assumed to come from a distribution P_d.

Outline

Submodular Model for Diversity

- This is the general form of the Facility Location Diversity (FLID) model proposed by Tschiatschek et al. (2016).
- A submodular function for diversity,

$$F(S) = u(S) + D(S)$$

  where $u(S)$ aggregates the utility of the items in S and $D(S)$ quantifies the diversity of the items in S.
- The corresponding PSM is:

$$P(S) = \frac{1}{Z} \exp\left(u(S) + D(S)\right)$$

Aggregating Utility

- A modular function
$$u(S) = \sum_{i \in S} u_i$$
where u_i represents the utility of each item i in the ground set V.
- For example, the utility of a location could be the number of users that have taken photos of it.

Quantifying Diversity

- A submodular function

$$D_d(S) = \max_{i \in S} w_{i,d} - \sum_{i \in S} w_{i,d}$$

where w_i quantifies the contribution of item i to some concept d related to the diversity of the set.

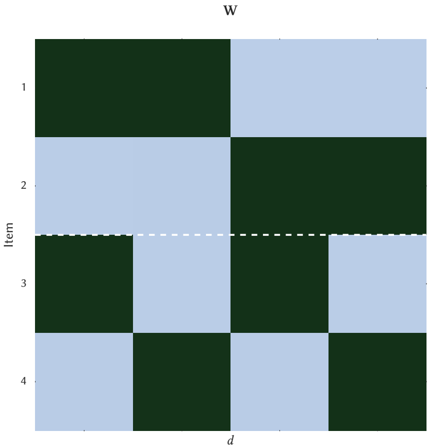
- For example, for the concept "is a museum" locations may have binary weights $w_d \in \{0, 1\}$. Then a set with many museums is penalized with a negative value of $D_d(S)$

Quantifying Diversity

- A submodular function

$$D(S) = \sum_{d=1}^{L} \left(\max_{i \in S} w_{i,d} - \sum_{i \in S} w_{i,d} \right)$$

  where w_i quantifies the contribution of item i to some concept d related to the diversity of the set.
- FLID aggregates L dimensions, where each represents one of these concepts.



1. Globus in Bahnhofstrasse

2. Opera house

3. Globus Am Bellevue

4. Landesmuseum

FLID

$$P(S) = \frac{1}{Z} \exp\left(\sum_{i \in s} u_i + \sum_{d=1}^{L} \left(\max_{i \in S} w_{i,d} - \sum_{i \in S} w_{i,d}\right)\right)$$

- Learning can be performed efficiently, in $\mathcal{O}(|\mathcal{D} \cup \mathcal{N}| L\kappa)$ where $\kappa = \text{argmax}_{S \in \mathcal{D} \cup \mathcal{N}} |S|$.

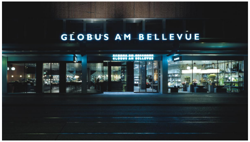
Outline

A Different Perspective

1. Globus in Bahnhofstrasse

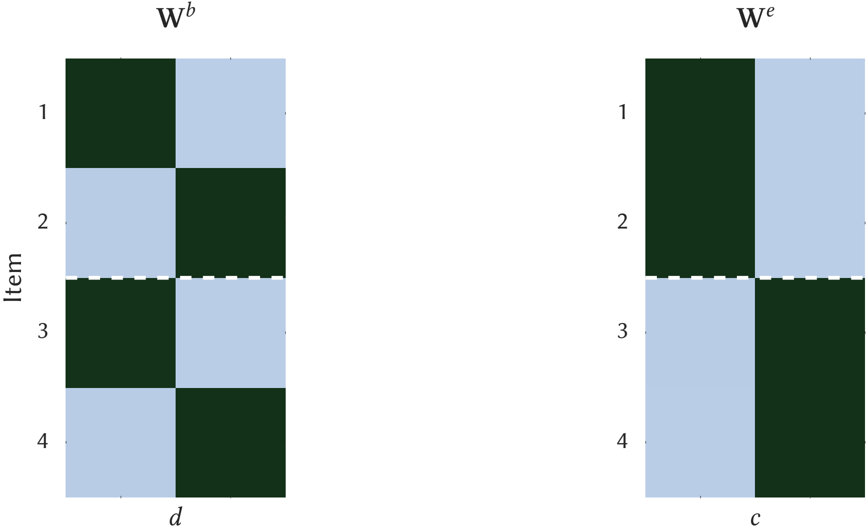
2. Landesmuseum

3. Globus Am Bellevue



4. Opera house

Quantifiying Complementarity

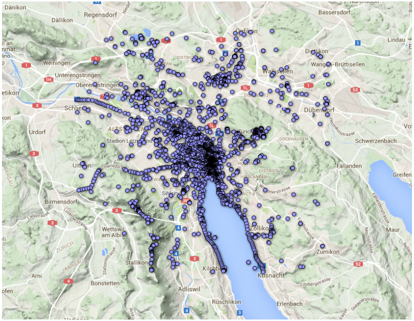


- We propose extending FLID with a supermodular term.

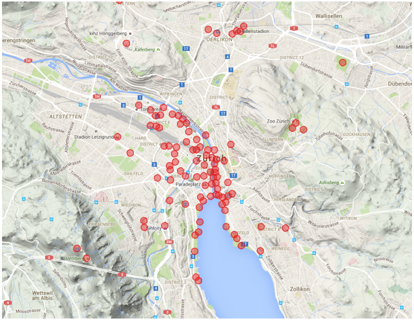
$$P(S) = \frac{1}{Z}\exp\left(u(S) + D(S) - \sum_{c=1}^{K}\left(\max_{i\in S} w_{i,c}^{e} - \sum_{i\in S} w_{i,c}^{e}\right)\right)$$

- Learning complexity is only increased by a factor of K.

Experimental Setup: Data and Clustering



Geotagged photos from Flickr.



Top photographed locations.

Experimental Setup: Completing Sets

- Geotagged photos were grouped by user and day they were taken.
- Each group represents a set. Test sets are constructed by taking out one element at a time.
- For example, if the original set is *{Fraumünster, Grossmünster, Hauptbahnhof}*, the test sets are:
  - *{Fraumünster, Hauptbahnhof}*
  - *{Grossmünster, Hauptbahnhof}*
  - *{Fraumünster, Grossmünster}*
- The test set is $S = \{l_1, \ldots, l_n\} \setminus \{l_t\}$.

Experimental Setup: Baselines

- Modular

$$\operatorname*{argmax}_{i \notin S} u_i$$

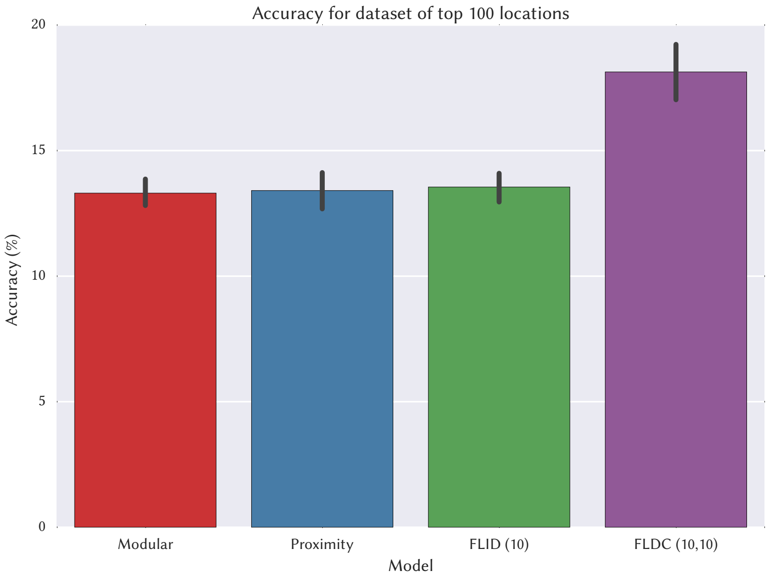
- Proximity

$$\operatorname*{argmin}_{i \notin S} \sum_{j \in S} d(i, j)$$

- FLID

$$\operatorname*{argmax}_{i \notin S} P_{\mathrm{FLID}}(S)$$

Results - Sets



Experimental Setup: Baselines with Paths

- The test path is $S_n = [l_1, \ldots, l_{t-1}, l_{t+1}, \ldots, l_n]$.
- Markov model

$$\operatorname*{argmax}_{i \in V} P(i \mid l_{t-1}) P(l_{t+1} \mid i)$$

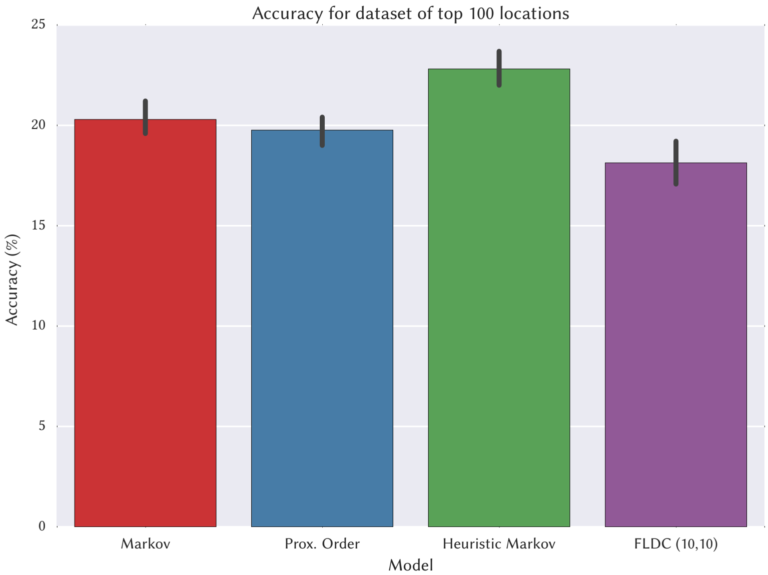
- Heuristic Markov model

$$\operatorname*{argmax}_{i \notin S_n} P(i \mid l_{t-1}) P(l_{t+1} \mid i)$$

- Proximity ordered model

$$\operatorname*{argmin}_{i \notin S_n} d(i, l_{t-1}) + d(i, l_{t+1})$$

Results - Paths



Outline

How to Generalize?

- Is it possible to transfer knowledge about Zürich to Geneva?
- If new locations are identified, how can they be included in the model without learning it again?
- Our proposed solution: **Featurized representations**.

Featurized Facility Location Diversity and Complementarity

- Define a feature matrix for all items in V, i.e. $\mathbf{X} \in \mathbb{R}^{|V| \times M}$.
- Factorize the model parameters $\mathbf{u}, \mathbf{W}^b, \mathbf{W}^e$

$$\begin{aligned} \mathbf{u} &= \mathbf{X}\mathbf{a} \\ \mathbf{W}^{\mathbf{b}} &= \mathbf{X}\mathbf{B} \\ \mathbf{W}^{\mathbf{e}} &= \mathbf{X}\mathbf{E} \end{aligned}$$

- Model is then defined in the space of features, not items.

Experimental Setup: Locations

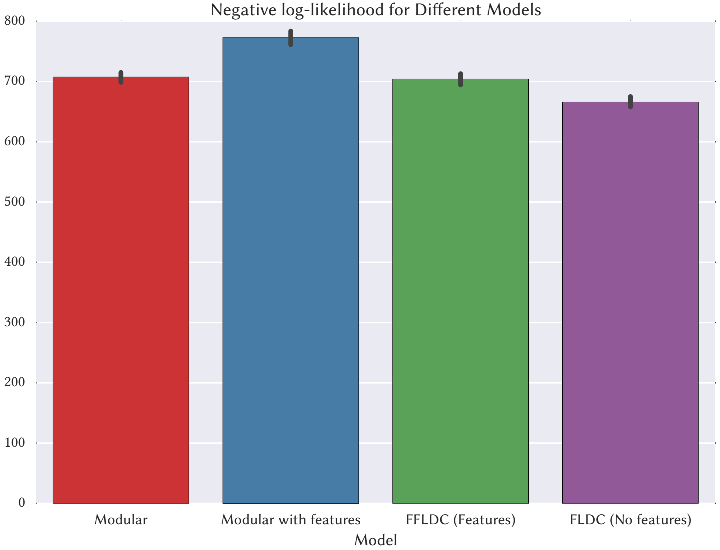
A smaller dataset with 10 locations.

- Hauptbahnhof
- Fraumünster
- Grossmünster
- Hallenstadion
- Prime tower
- Bürkliplatz
- Paradeplatz
- Bellevueplatz
- Rathaus
- Zoo

Experimental Setup: Features

- Is it a transit station? E.g. Hauptbahnhof, Bürkliplatz.
- Is it a church? E.g. Fraumünster.
- Is it a historic building? E.g. Grossmünster, Rathaus.
- Is it an indoors location? E.g. Prime tower, Hallenstadion.
- Normalized number of photographs n_p, $\sqrt{n_p}$ and $\sqrt[4]{n_p}$.
- Number of users per photograph.

Results - Negative Log-likelihood



Outline

Conclusions

- We have proposed an extension of FLID to model complementarity or attractiveness in sets.
- Experiments in a real world application show how this can improve the quality of the model.
- Recommendation of tourist locations can be modeled using PSMs with positive results. However, modeling of ordered sets is an important direction to explore.
- We have proposed an extension of FLID to generalize the model to unseen items through features.

References I

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References II

Tschiatschek, S., Djolonga, J., and Krause, A. (2016). Learning probabilistic submodular diversity models via noise contrastive estimation. In *Proc. International Conference on Artificial Intelligence and Statistics (AISTATS)*.