Hiking is the Best Hobby for Research

Rating Inference for Custom Trips from Enriched GPS Traces

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Agenda

- Motivation
- Definition and Background
- Problem statement and scope
- Similarity-based trip rating inference framework
- ML-based trip rating inference framework
- Experimental settings and results
- Key take-aways

The real motivation (hobby-driven research)

Research motivation

- **GPS-enabled devices** allow us to pinpoint our location and generate a large amount of data that traces our movements along trips.
- **Custom trips** are designed to cater to travelers’ specific desires and user preferences for personalized tourism experience.
- Since the custom trip is usually new in the system, **no rating** can be shown to the user. As a result, the **rating inference** of custom trips has emerged as an important feature in tourism applications and location-based services.
- This paper aims to determine **which representation feeds best to the machine learning algorithms** and achieves higher accuracy for rating inference.
- Apart from **trip recommendations**, rating inference in this paper can be considered a **second opinion for custom trips** defined by users.

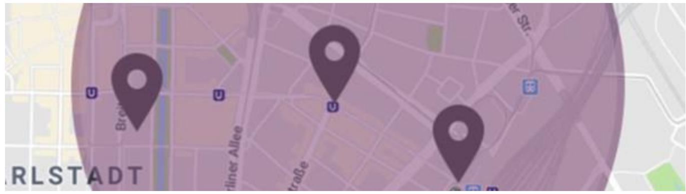
Custom trip

Stockach
Herdwangen-Schönach
Wilhelmsdorf
Horgenzell
Salem
Markdorf
Tettnang
Reichenau
Konstanz (Constance)
Altnau
Müllheim
Weinfelden
Romanshorn
A
B

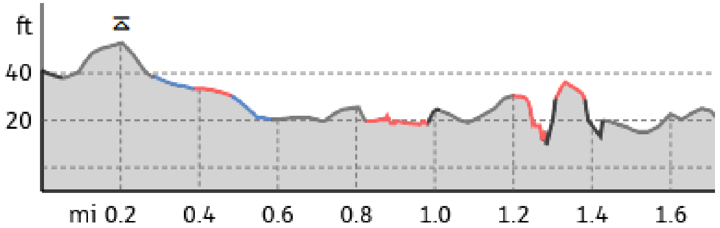
Enriched GPS traces along with the trip

- **Trip location**

- **Closeness to POIs**



- **Trip elevation**



- **Closeness to places where users take pictures**

Multi-criteria ratings for trips

- Multi-criteria ratings consider different factors simultaneously. For example, one hiking route would have various attributes for ratings, such as Condition, Difficulty, Technique, Quality of Experience, and Landscape.

Condition	★★★☆☆
Difficulty	★★☆☆☆
Technique	★★★★☆
Quality of Experience	★★★★☆
Landscape	★★★☆☆

Problem statement and scope

- The user designs a custom trip
- This trip contains enriched GPS traces
- There are different rating criteria for this trip

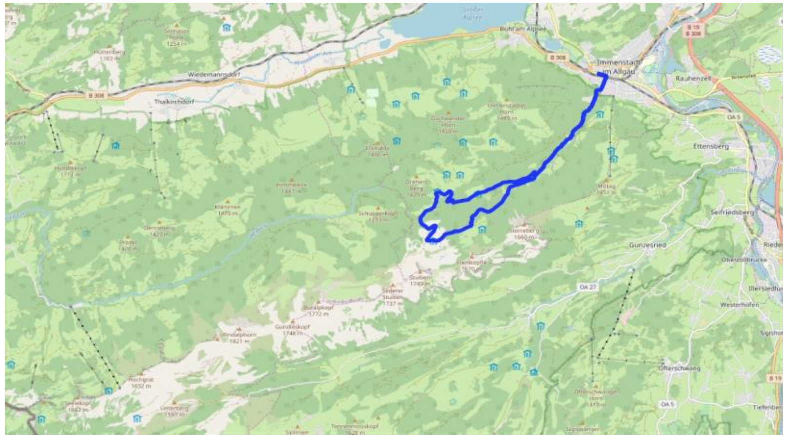
- We want to infer/predict
- The rating of each criterion for this custom trip

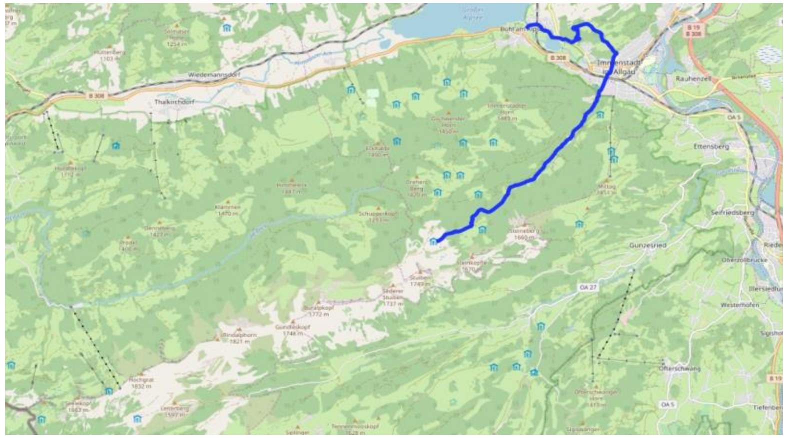
Our similarity-based solution

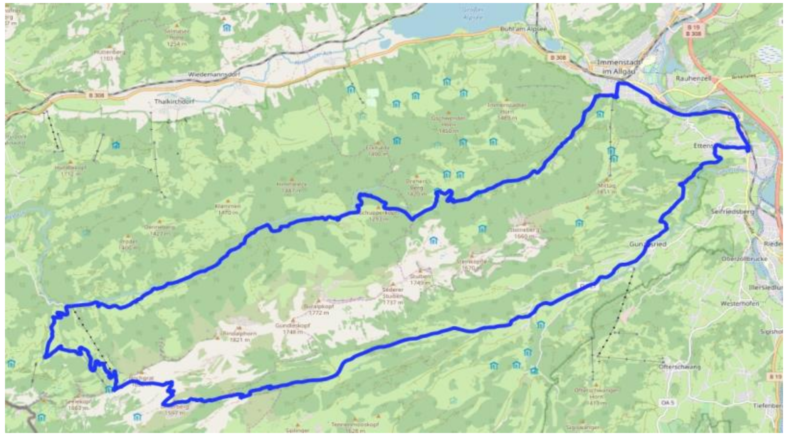
Proposed in 2019

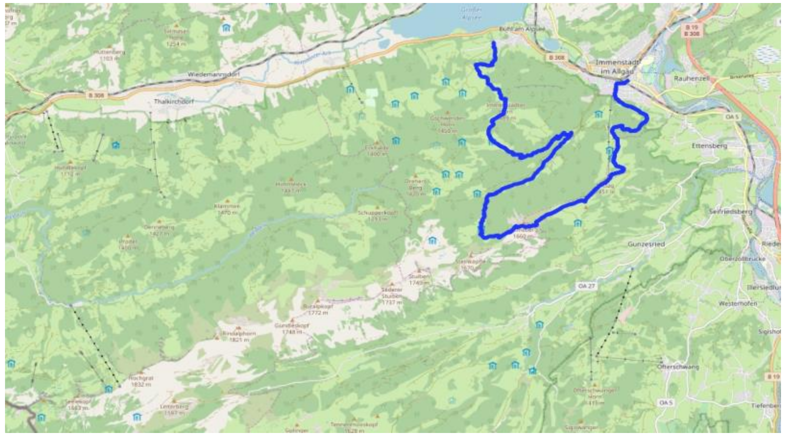
Theodoros Chondrogiannis, Mouzhi Ge: Inferring ratings for custom trips from rich GPS traces, LocalRec at 27th ACM SIGSPATIAL, Chicago, Illinois, USA, November 5, 2019.

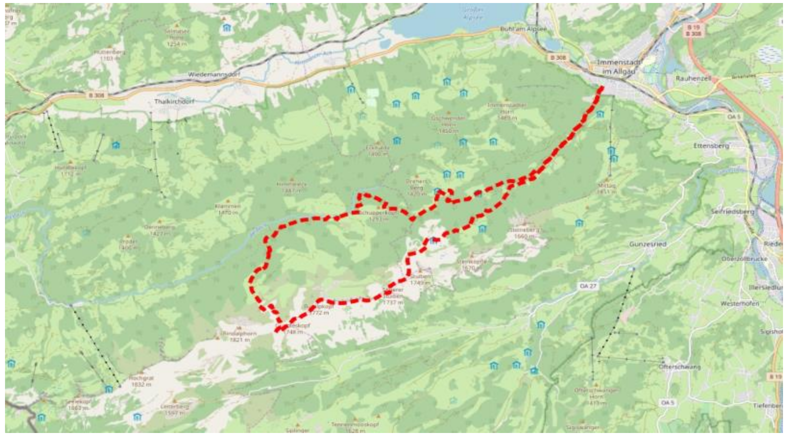
Hiking routes



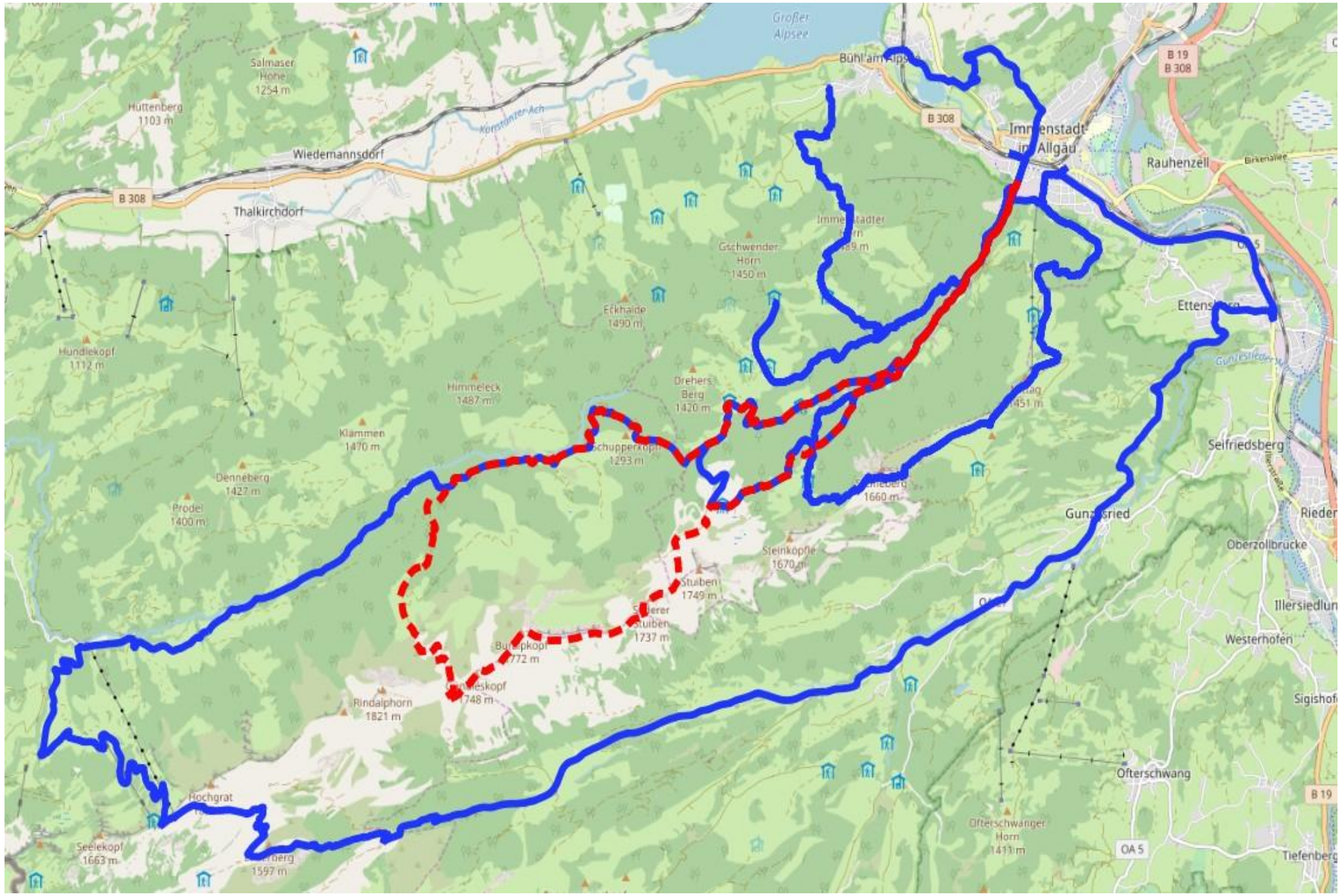








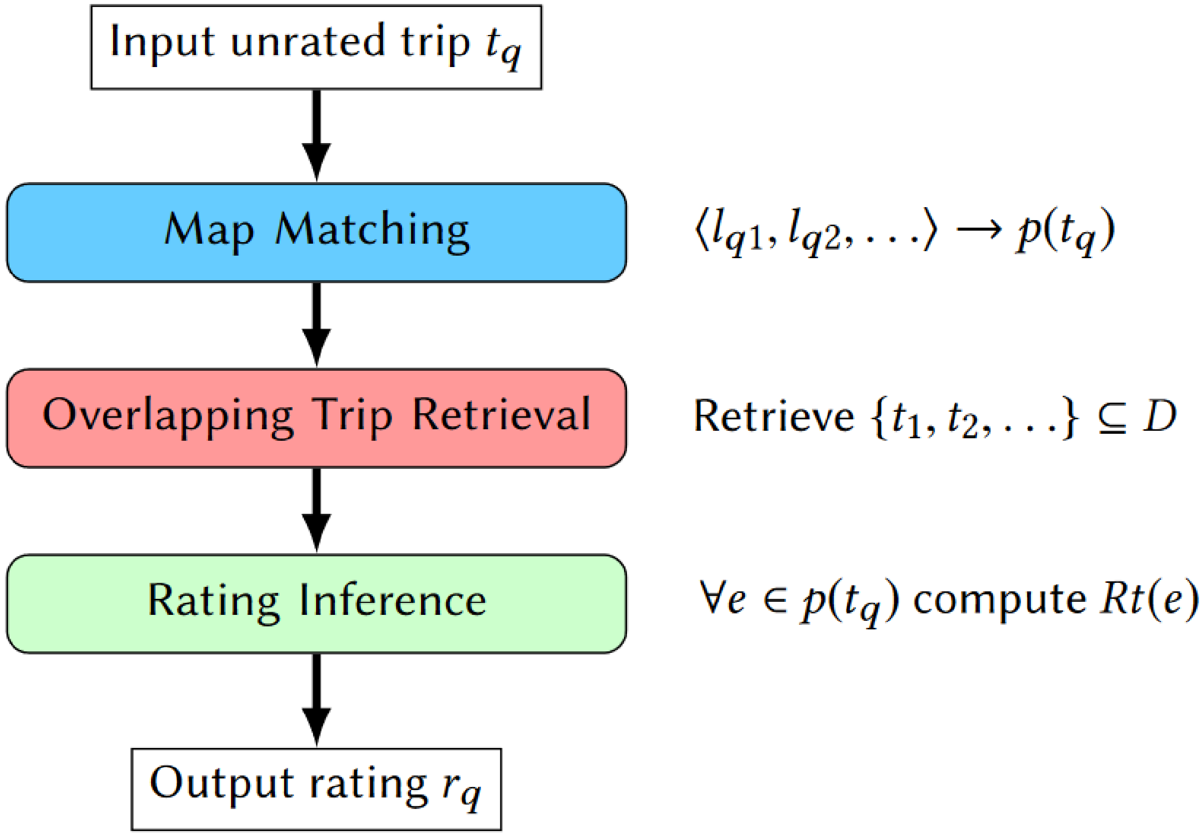
Hiking routes with overlaps



Recap and intuition

- Users design their own routes
- Applications
  - hiking trails
  - running/training routes
- **Problem:** what is the rating of such a route?
- **Idea:** Consider the ratings of overlapping routes to infer a rating for the new route

Trip rating inference similarity-based framework



Map Matching

- Map all rated trips to segments of the underlying spatial network (preprocessing)
- Map the unrated trip to a segment of the underlying spatial network (query processing)

$$\langle (x_1, y_1), \dots, (x_n, y_n) \rangle \longrightarrow \langle e_1, \dots, e_m \rangle$$

GPS Trace　　　　List of edges

Overlapping Trip Retrieval

- Overlap: how much of the query trip is overlapping with some already rated trip

$$Ol(t_i, t_j) = \frac{\sum_{\forall e \in p(t_i) \cup p(t_j)} \ell(e)}{\ell(p(t_j))}$$

- Inverted index
  - Edge $e \rightarrow$ List of trips that contain e
  - Retrieval cost is linear to the size of the query trip

Rating Inference (Step 1)

- Edge rating inference

$$Rt(e) = \sum_{\forall t_i \in T_e} r_i \cdot \frac{Ol(t_i, t_q)}{\sum_{\forall t_j \in T_e} Ol(t_j, t_q)} \mid T_e = \{t_i \mid t_i \in D \wedge e \in p(t_i)\}$$

  - T_e is the set of trips that cross e

- The rating of and edge e depends on
  - the rating of each trip that cross e
  - the overlap of each trip that cross e with t_q

Rating Inference (Step 2)

- The rating of the trip is given by the weighted sum of the ratings of its edges

$$r_q = \sum_{\forall e \in p(t_q)} Rt(e) \cdot \frac{\ell(e)}{\ell(E_q)}$$

  - E_q is the set of edges that have been rated from the previous step

- Note: our approach considers only segments that overlap with at least one existing trip.

Outdooractive dataset

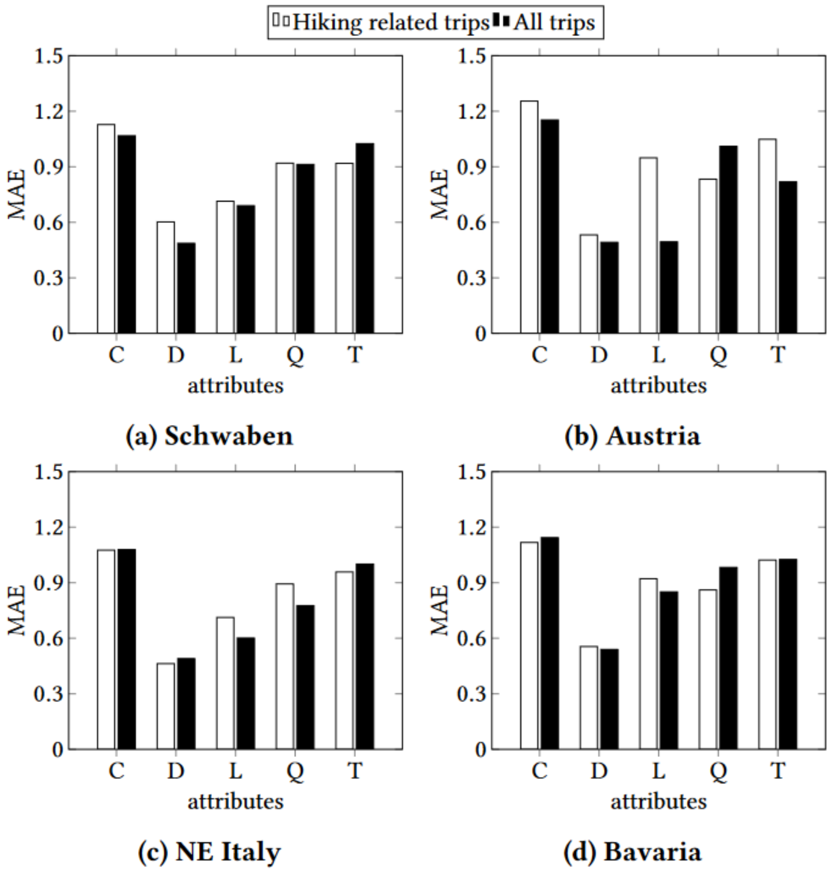
Evaluation Setup

- Hiking Trails from Outdooractive
- Five attributes rated betweem [1,6]
- (Condition, Difficulty, Landscape, Quality, Technique)

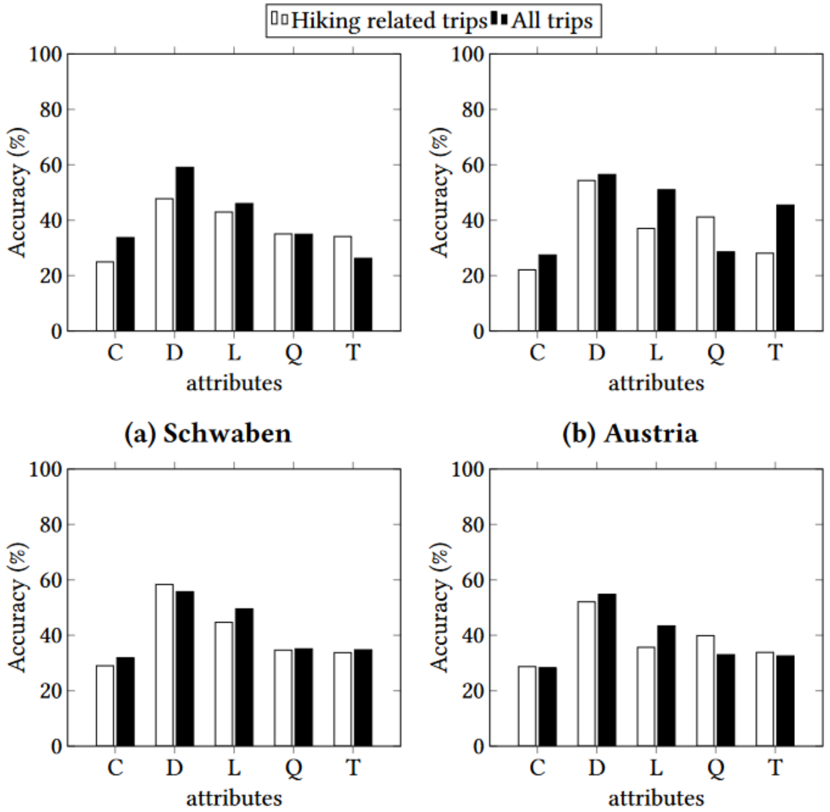
network	nodes	edges	trips (all)	trips (hiking)
Swabia	491213	630094	544	353
Austria	2484861	3033885	516	260
NE Italy	1467754	1884450	696	419
Bavaria	3045179	3928652	1346	754

The average overlap of each unrated trip with already rated trips was 48.6% for Swabia, 14.1% for Austria, 22.4% for NE Italy, and 15.5 % for Bavaria.

Experimental results (MAE)



Experimental results (Accuracy)



(a) Schwaben

(b) Austria

(c) NE Italy

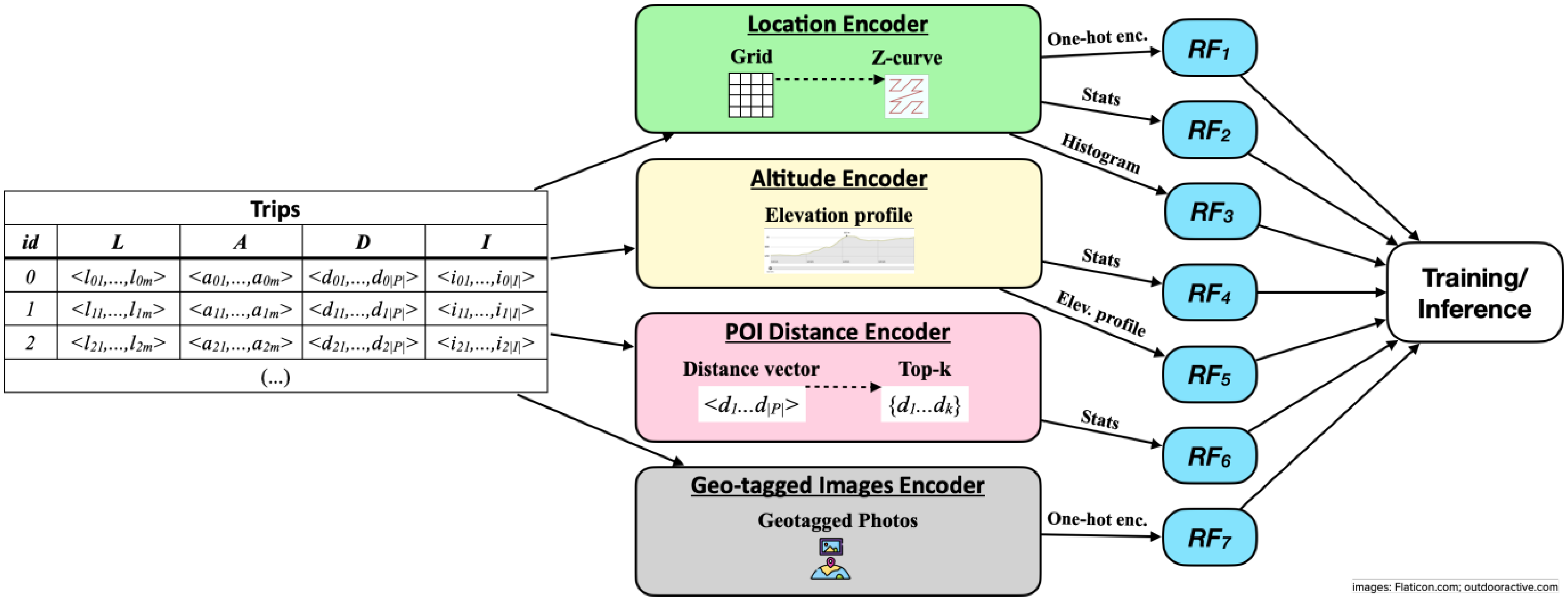
(d) Bavaria

Our machine leaning based solution

Proposed in 2023

Theodoros Chondrogiannis, Mouzhi Ge: Rating Inference for Custom Trips from Enriched GPS Traces using Random Forests, LocalRec at 31st ACM SIGSPATIAL, Hamburg, Germany, November 13, 2023.

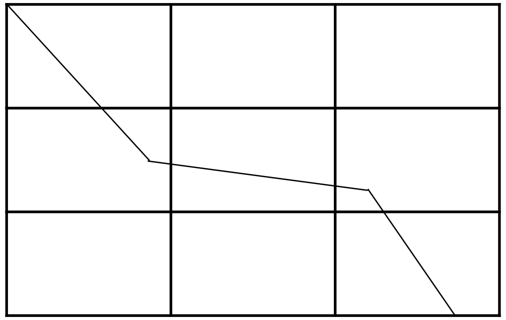
Trip rating inference ML-based framework



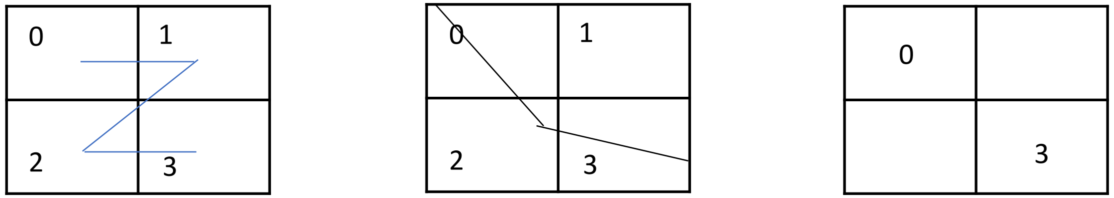
We want to use machine learning to do the rating inference, but the focus of this work is not ML model selection, it is feature engineering and encoding selections, given the enriched GPS traces are complex.

Location Encoder

- We first impose a $n \times n$ grid over the space defined by the minimum bounding rectangle of all traces.



- One-hot encoding
- Z-order curve to first ID the grids
  - For each set of IDs the trip crosses, a vector that contains basic statistics, i.e., min, max, mean, and median values.
  - Histogram of n buckets



Altitude Encoder

<

- total ascent,
- total descent
- minimum altitude
- maximum altitude
- standard deviation of the elevation profile

>

POI Distance Encoder

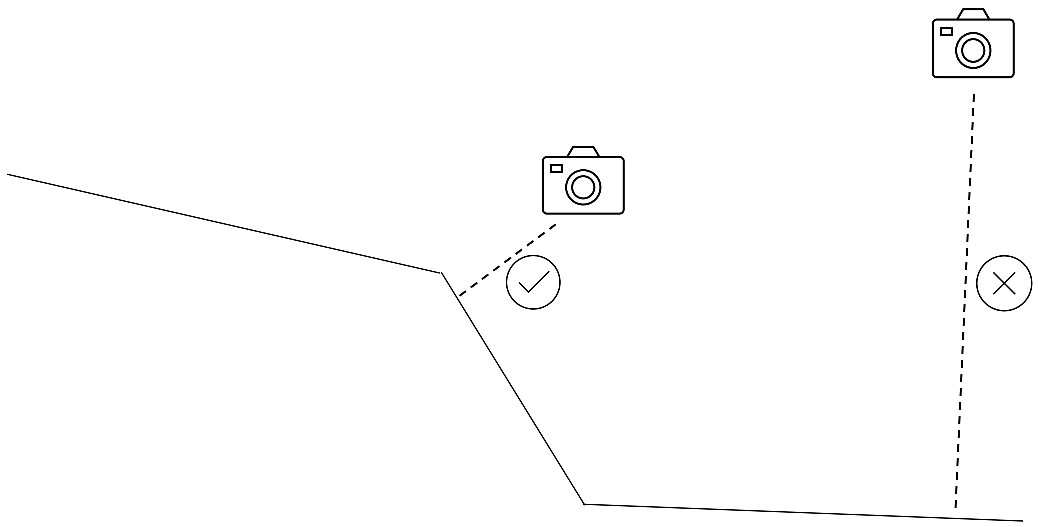
- A combination of two vectors
- Vector 1: Distances to all POIs

Plus

- Vector 2: Distances to a predefined set of POIs (k nearest POIs)

Geo-tagged Images Encoder

- A bit vector and the size equals to the number of images in I
- we set each bit associated with an image to 1 if the minimum distance between the trace and the image location is below a predefined threshold, e.g., 20 meters.



Datasets

- Trip data obtained from Outdooractive: www.outdooractive.com

network	trips	avg # points	avg length (km)
Hiking	1,813	496.05	12.207
Cycling	4,051	1489.86	49.617

- Elevation data for trip from Copernicus: www.copernicus.eu
- 181,185 POI data from www.kaggle.com/datasets/ehallmar/points-of-interest-poi-database
- 50,000 geotagged images from www.kaggle.com/datasets/habedi/large-dataset-of-geotagged-images

Encoding methods overview

One-hot Enc. Location encoder that imposes a grid and uses one-hot encoding to indicate which cells are crossed by the trip trace.

Grid Stats Location encoder that imposes a grid, determines the Z-order of the grid cells, and computes basic statistics of the numerical cell IDs.

Histogram Location encoder that imposes a grid, determines the Z-order of the grid cells, and computed a histogram.

Elevation Altitude encoder using statistics computed over the elevation profile.

POIs POI Distance Encoder that computes a vector of distances to a predefined set of POIs.

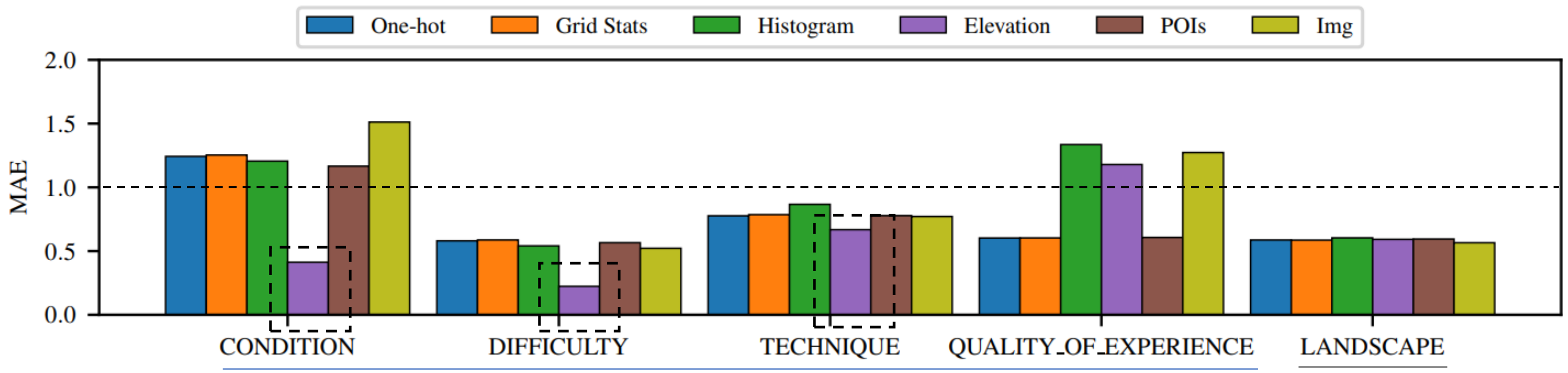
Img Geo-tagged Images Encoder that computes distances to a predefined set of geotagged images and uses one-hot encoding to indicate which images have been taken from location alongside the trip trace.

ML Model and Evaluation Metric

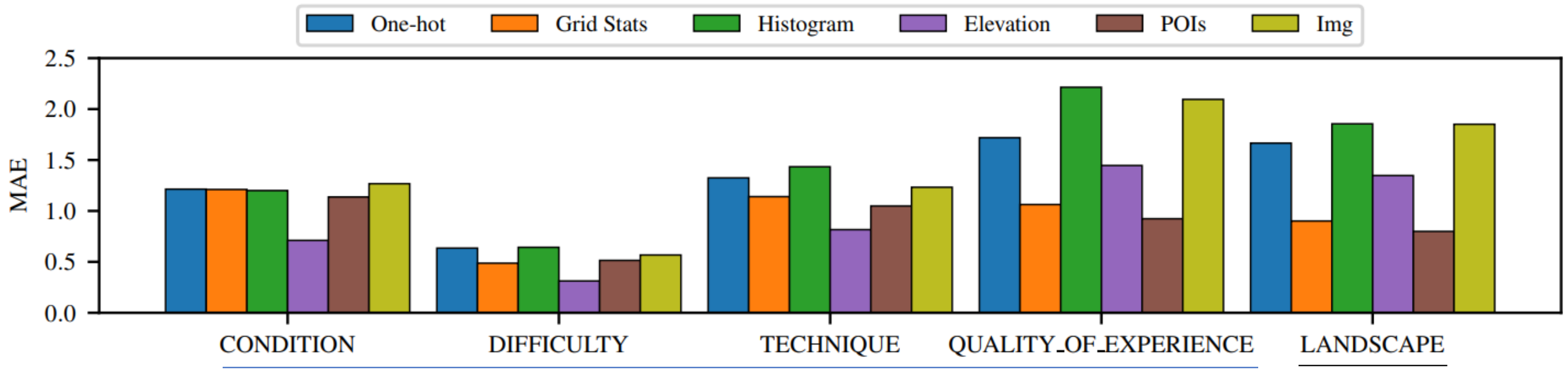
- Random forest
  - Our previous experiments demonstrated that Random Forest performs best in several similar rating inference scenarios. We used Random Forest classifier in this work.
- MAE, widely used for evaluating rating predictions, especially in recommender system research.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i|$$

Experimental Results



(a) Hiking data set



(b) Cycling data set

Take aways

- "One size fits all" encodings may lower the quality of multi-criteria rating inferences.
- Different encodings might be dynamically used to infer different rating criteria.
- The trip-oriented ratings are focused on the intrinsic features of the trip. Thus, the encoding of trip profiles can offer higher-quality rating inferences.
- User-oriented ratings focus on how users feel about the trip and user satisfaction.

Summary and Future Research

- Scope of this research: **encoding selection, not model selection**.
- The model may consider more **contextual factors**. For example, the context of a trip may include group dynamics, previous experiences, and cultural factors.
- Users would often like to know how the inference is made. In turn, users can be more confident in their trip decisions. Therefore, developing **transparent and explainable** models may increase user trust and satisfaction.
- Including **user feedback** to enhance user engagement is also critical. User feedback can be used to improve the model training and provide continuous improvement for implementing trip recommendations

Thank you and questions

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