Booking.com RecSys RecTour 2024 Challenge

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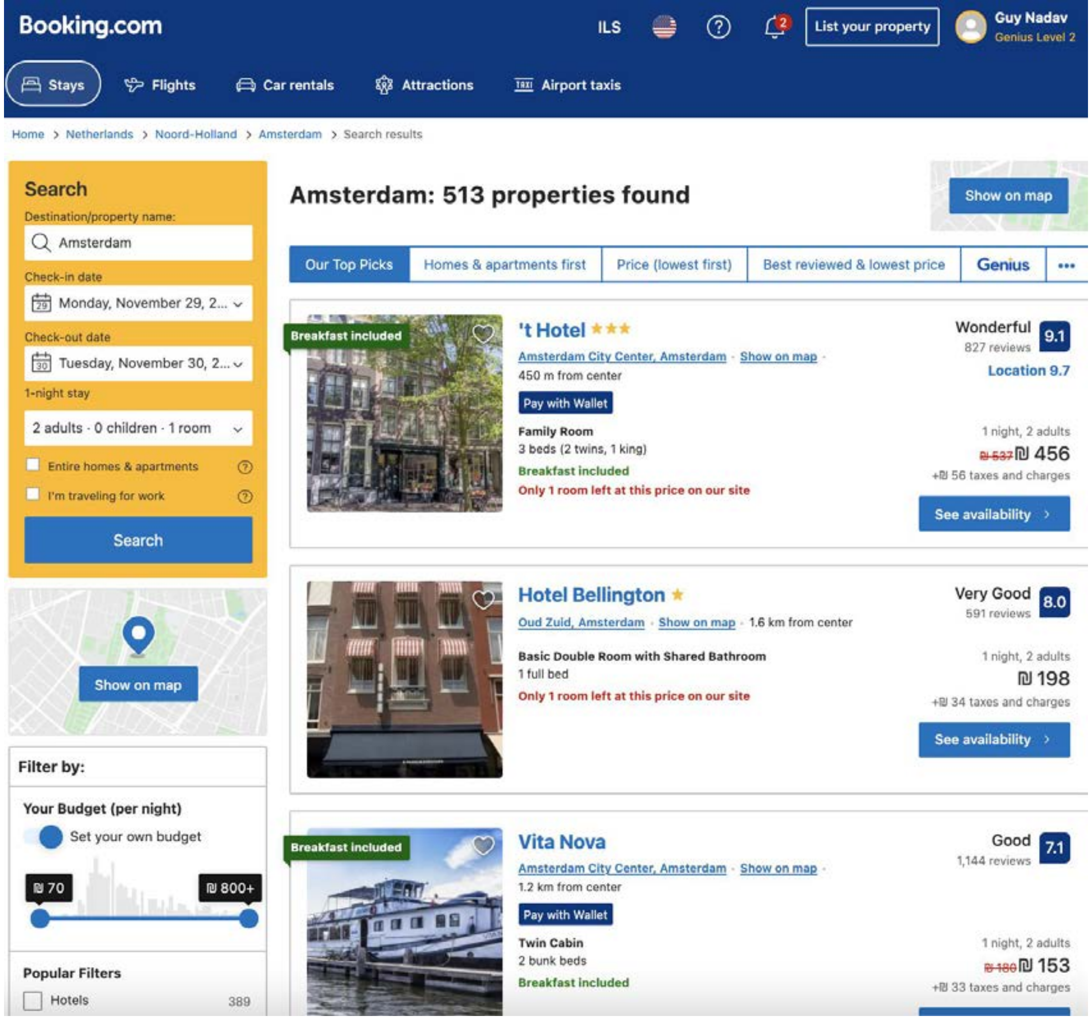
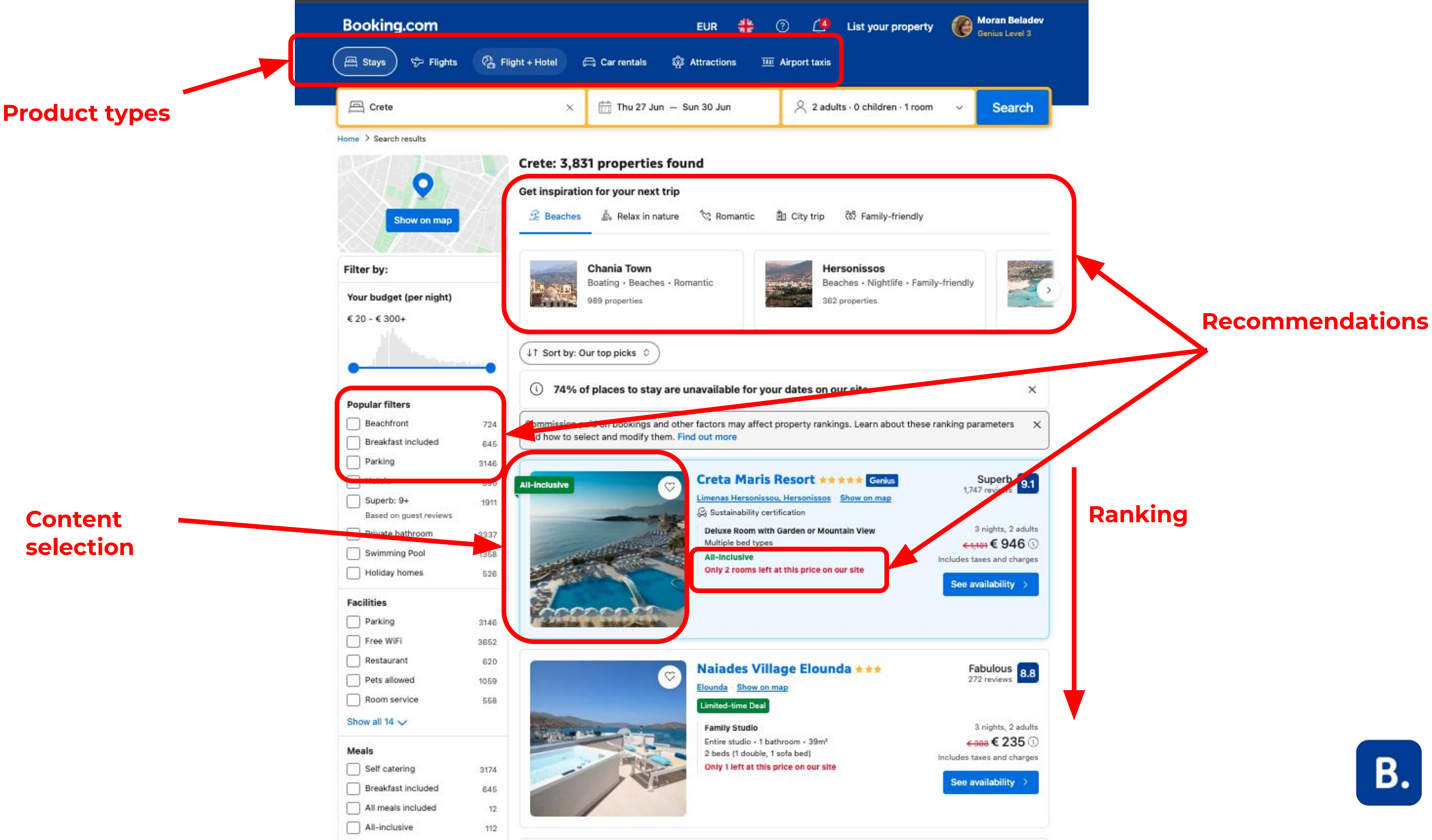
Booking.com

https://tinyurl.com/RecTour24Challenge

Booking.com Introduction

Booking.com


Booking.com
ILS
List your property
Guy Nadav
Genius Level 2
Stays
Flights
Car rentals
Attractions
Airport taxis
Home > Netherlands > Noord-Holland > Amsterdam > Search results
Search
Destination/property name:
Amsterdam
Check-in date
Monday, November 29, 2...
Check-out date
Tuesday, November 30, 2...
1-night stay
2 adults · 0 children · 1 room
Entire homes & apartments
I'm traveling for work
Search
Show on map
Filter by:
Your Budget (per night)
Set your own budget
₪ 70
₪ 800+
Popular Filters
Hotels 389
Amsterdam: 513 properties found
Show on map
Our Top Picks
Homes & apartments first
Price (lowest first)
Best reviewed & lowest price
Genius
Breakfast included
't Hotel
Amsterdam City Center, Amsterdam · Show on map
450 m from center
Pay with Wallet
Family Room
3 beds (2 twins, 1 king)
Breakfast included
Only 1 room left at this price on our site
Wonderful 9.1
827 reviews
Location 9.7
1 night, 2 adults
₪ 537 ₪ 456
+₪ 56 taxes and charges
See availability
Hotel Bellington
Oud Zuid, Amsterdam · Show on map · 1.6 km from center
Basic Double Room with Shared Bathroom
1 full bed
Only 1 room left at this price on our site
Very Good 8.0
591 reviews
1 night, 2 adults
₪ 198
+₪ 34 taxes and charges
See availability
Breakfast included
Vita Nova
Amsterdam City Center, Amsterdam · Show on map
1.2 km from center
Pay with Wallet
Twin Cabin
2 bunk beds
Breakfast included
Good 7.1
1,144 reviews
1 night, 2 adults
₪ 180 ₪ 153
+₪ 33 taxes and charges


Product types
Recommendations
Ranking
Content selection
Booking.com
EUR
List your property
Moran Beladev
Genius Level 3
Stays
Flights
Flight + Hotel
Car rentals
Attractions
Airport taxis
Crete
Thu 27 Jun — Sun 30 Jun
2 adults · 0 children · 1 room
Search
Home > Search results
Show on map
Crete: 3,831 properties found
Get inspiration for your next trip
Beaches
Relax in nature
Romantic
City trip
Family-friendly
Chania Town
Boating · Beaches · Romantic
989 properties
Hersonissos
Beaches · Nightlife · Family-friendly
362 properties
Filter by:
Your budget (per night)
€ 20 - € 300+
Sort by: Our top picks
74% of places to stay are unavailable for your dates on our site
Commission paid on bookings and other factors may affect property rankings. Learn about these ranking parameters and how to select and modify them. Find out more
Popular filters
Beachfront 724
Breakfast included 645
Parking 3146
Superb: 9+ 1911
Based on guest reviews
Private bathroom 3337
Swimming Pool 1358
Holiday homes 526
Facilities
Parking 3146
Free WiFi 3652
Restaurant 620
Pets allowed 1059
Room service 558
Show all 14
Meals
Self catering 3174
Breakfast included 645
All meals included 12
All-inclusive 112
All-Inclusive
Creta Maris Resort
Genius
Limenas Hersonissou, Hersonissos
Show on map
Sustainability certification
Deluxe Room with Garden or Mountain View
Multiple bed types
All-Inclusive
Only 2 rooms left at this price on our site
Superb 9.1
1,747 reviews
3 nights, 2 adults
€ 1,184 € 946
Includes taxes and charges
See availability
Naiades Village Elounda
Elounda
Show on map
Limited-time Deal
Family Studio
Entire studio · 1 bathroom · 39m²
2 beds (1 double, 1 sofa bed)
Only 1 left at this price on our site
Fabulous 8.8
272 reviews
3 nights, 2 adults
€ 308 € 235
Includes taxes and charges
See availability

Reviews in Booking.com

45 Languages

320M+

Reviews

Hotels, Homes, Apartments & more

29M+

Listings

Topics Filtering

Personalized Summarization

Reviews Ranking

Guest reviews

See availability

9.0 Fabulous · 1,234 reviews Read all reviews

Categories:

Staff	8.0	Facilities ↓	8.0	Cleanliness ↑	8.0
Comfort ↑	8.0	Value for money	8.0	Location	8.0
Free WiFi	8.0				

↑ High score for Amsterdam ↓ Low score for Amsterdam

Select topics to read reviews

+ Location + View + Rooms + Food

Review Summary

AI-generated summary based on 340 reviews from the last year ⓘ

Overall, guests were impressed with the property's convenient location, friendly staff, and clean and comfortable rooms. They also enjoyed the generous and varied breakfast offerings.

Frequently mentioned

Good location Beautiful views Average rooms Limited food options

Read all reviews

Guest reviews for Riu Plaza London Victoria

8.4 Very good
7,104 reviews

We aim for 100% real reviews

Guest reviews

Sort reviews by: Most relevant

Charlynne
Marshall Islands
One-Bedroom Suite
3 nights · May 2022
Family

Reviewers' choice Reviewed: June 4, 2022

loved it!

10

· the staff were very friendly and helpful. liked how they had laundry in every floor. the kids enjoyed the pool. spacious room for my family at a good price..

· loved the property!

Helpful Not helpful

Jianhui
United States of America
One-Bedroom Suite
5 nights · February 2023
Family

Reviewed: February 3, 2023

Good

7.0

· location

· Parking facility is convenient but the women who run the gate causing difficulty to get out from the garage each time.

Helpful Not helpful

Kim
Australia
One-Bedroom Suite with Mountain View
11 nights · January 2023
Family

Reviewed: February 1, 2023

Wonderful

9.0

· The 33rd Floor Mountain View Room was absolutely amazing! Amenities were great, especially having a minimart in the building was very convenient. Location was quite good. Staff were very friendly and accomodating. Loved our stay and would stay here again!

· Not much to be honest, maybe a little closer to the beach but we genuinely enjoyed the walking after all the eating we did.

Reviews Ranking

Personalized Review Ranking

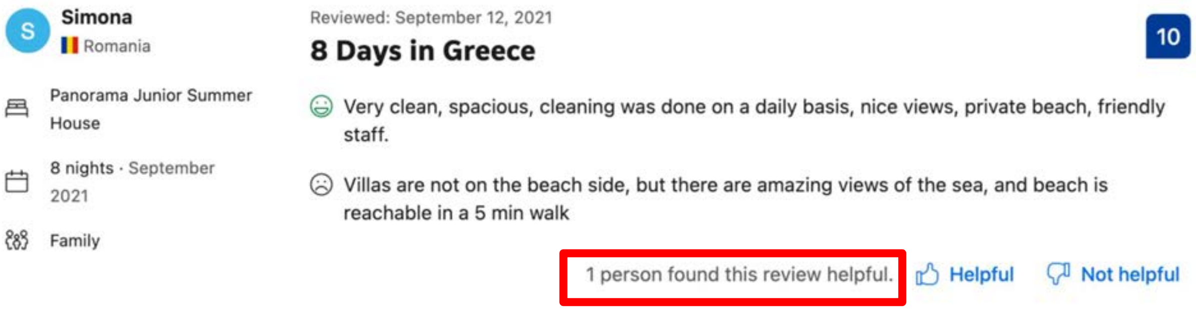
Related Work
Non-Personalized Review Ranking

- **Text-based features** (TF-IDF [6], contextual embeddings [4], readability [17], sentiment [35] and subject analysis [11]).
- **Temporal features** (time decay over review age, past reviewers average score [24])
- **Multimodal** (review images & textual embeddings [13, 27])
- **Labels** are a function of the number of the number of helpful votes

Related Work
Personalized Review Ranking

- **Context-aware features** (previous helpfulness votes, product purchases, past user reviews etc [15, 25, 33])
- **Ground truth is subjective**
- **Graph based features** (social relations between users [33], relations between users and products and users and reviews [15, 25])
- Usage of **recommendation methods** like matrix factorization [23]

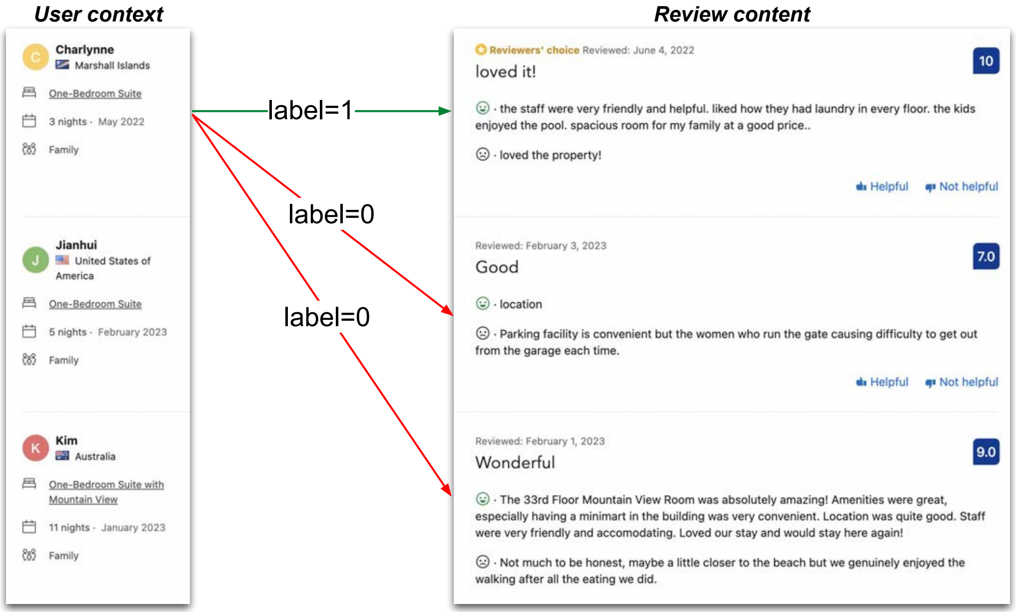
Challenges in Modeling Helpful Votes



- Votes are aggregated and anonymous
- Votes are sparse (~8.7% of reviews)
- Votes suffer from a presentation bias [23, 33]
- Cold-start problem [16]

Problem formulation

- Model the relationship between **user context** and **review content**
- Use the combination of **reviews content with their corresponding reviewers' context** as positive labels



Dataset Creation

Text2Topic [9]

"*The **Bed** and the pillows were **not comfortable**, the **room** was **small** and **very cold** at night. Not at all what we expected.*"

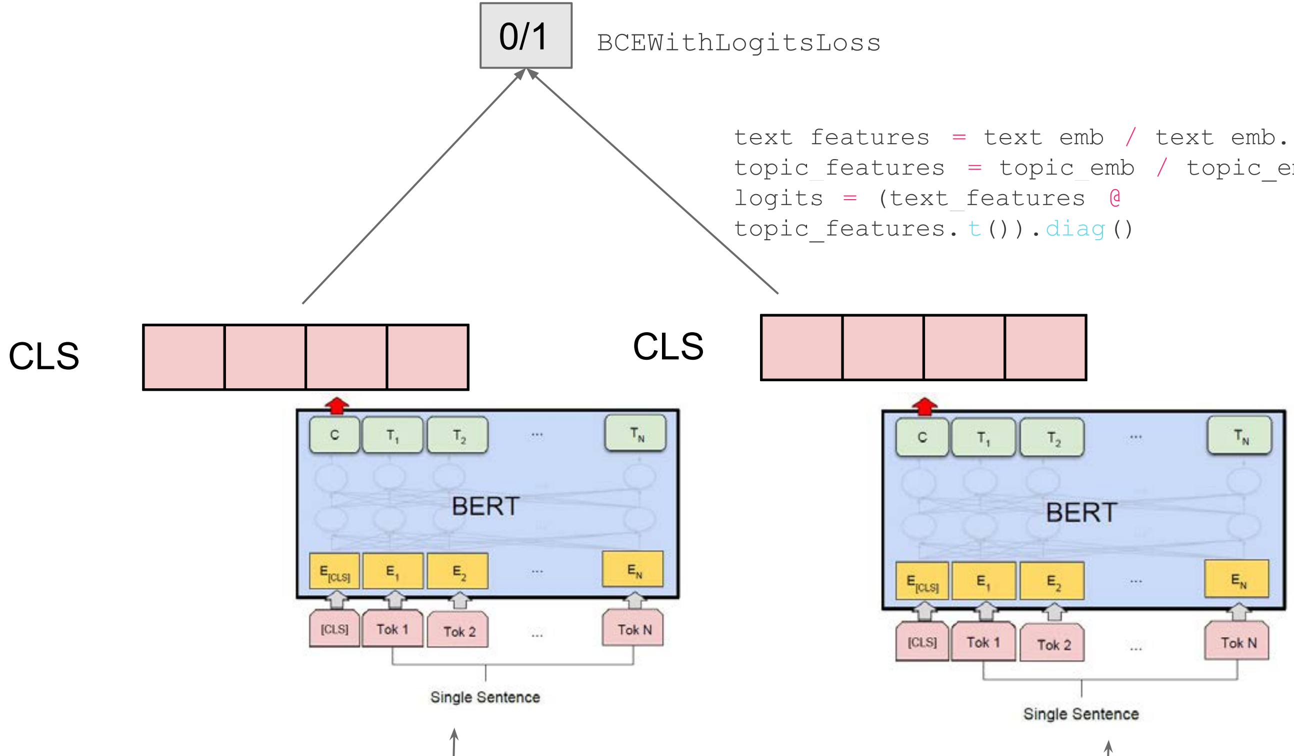
0.95 Negative

0.92 Bed Comfort

0.83 Room Temperature

0.71 Room size

ML architecture - Bi Encoder - cosine




```
text_features = text_emb / text_emb.norm(dim=1)
topic_features = topic_emb / topic_emb.norm(dim=1)
logits = (text_features @
topic_features.t()).diag()
```

Text: *“best private pool in room, room was good and nice breakfast”*

Topic: *“private swimming pool”*

Review dataset publication

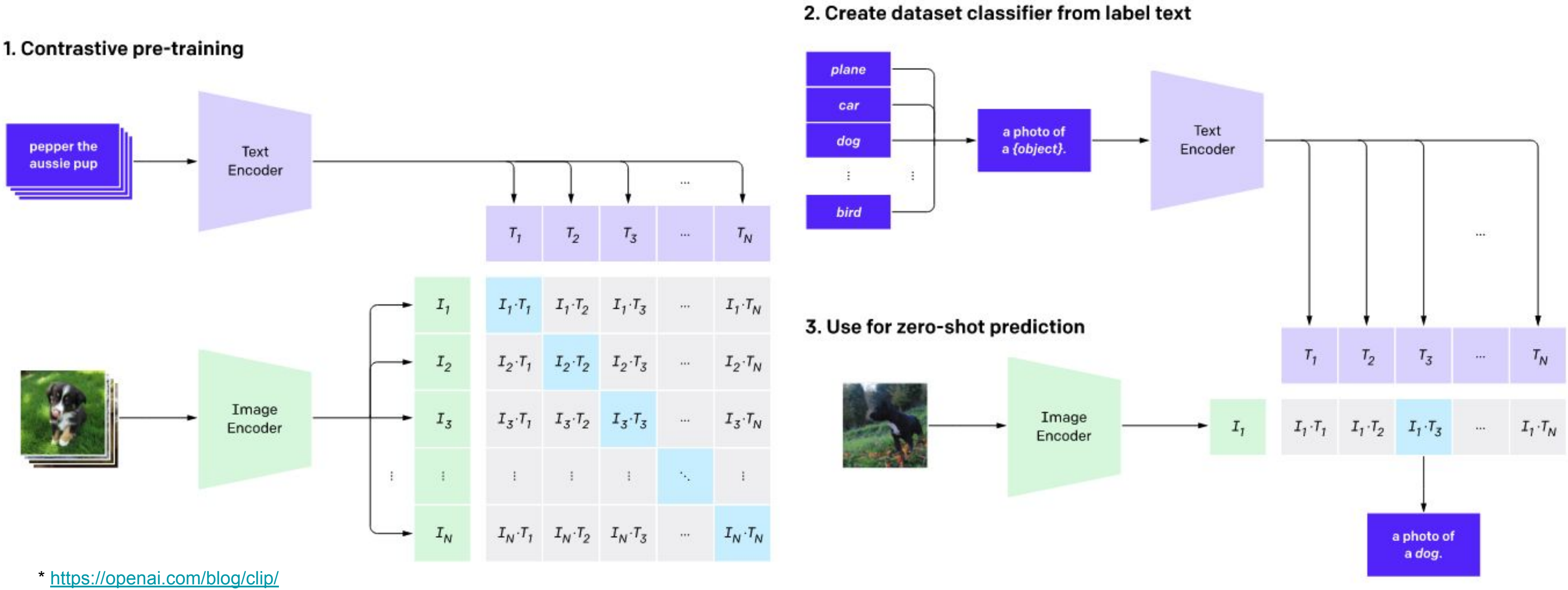
- The training dataset contains **1.6M** moderated English reviews from 2023 originating from **40,000** unique properties.
- We selected English reviews with **≥3 topics** (using text2topic) and sampled properties with at least **10 reviews.** All reviews are moderated and approved for publication.

Column	Description
review_title	Review title
review_positive	Positive ('liked') section in review
review_negative	Negative ('disliked') section in review
guest_score	Review score for the stay
review_helpful_votes	How many users marked the review as helpful
guest_type	There are 4 types of traveller types: Solo traveller (1 adult) / Couple (2 adults) / Group (>2 adults) / Family with children (adults & children)
guest_country	Anonymized country from which the reservation was made
room_nights	What is the length of the reservation, i.e. number of nights booked
month	The month of the check-in date of the reservation
accommodation_id	An anonymized accommodation ID
accommodation_type	The type of the accommodation, e.g. hotel, apartment, hostel
accommodation_score	The overall average guest review score for the accommodation
accommodation_country	Country of the accommodation
accommodation_star_rating	Accommodation star rating is provided by the property, and is usually determined by an official accommodation rating organisation or another third party
location_is_beach	Is the accommodation located in a beach location
location_is_ski	Is the accommodation located in a ski location
location_is_city_center	Is the accommodation located in the city center

Mapping between review UI and fields in dataset

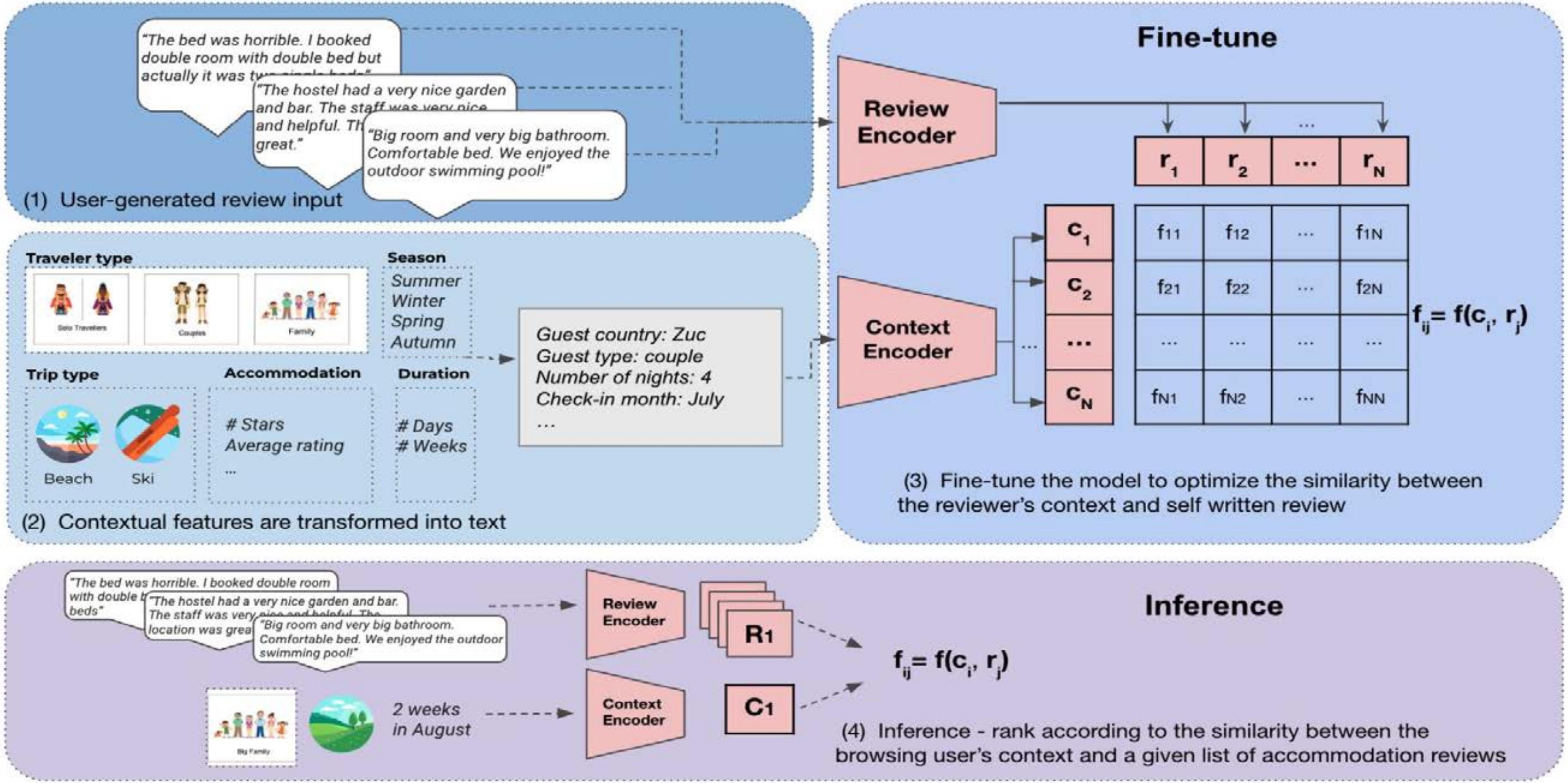
Our Solution

Recap on CLIP
(Contrastive Language–Image Pre-training)



* https://openai.com/blog/clip/
** https://github.com/openai/CLIP

How?


"The bed was horrible. I booked double room with double bed but actually it was two single beds"
"The hostel had a very nice garden and bar. The staff was very nice and helpful. The location was great."
"Big room and very big bathroom. Comfortable bed. We enjoyed the outdoor swimming pool!"
(1) User-generated review input
Traveler type
Solo Travelers
Couples
Family
Season
Summer
Winter
Spring
Autumn
Trip type
Beach
Ski
Accommodation
Stars
Average rating
...
Duration
Days
Weeks
Guest country: Zuc
Guest type: couple
Number of nights: 4
Check-in month: July
...
(2) Contextual features are transformed into text
Fine-tune
Review Encoder
Context Encoder
r_1 r_2 ... r_N
c_1 c_2 ... c_N
f_{11} f_{12} ... f_{1N}
f_{21} f_{22} ... f_{2N}
f_{N1} f_{N2} ... f_{NN}
$f_{ij} = f(c_i, r_j)$
(3) Fine-tune the model to optimize the similarity between the reviewer's context and self written review
Inference
"The bed was horrible. I booked double room with double beds"
"The hostel had a very nice garden and bar. The staff was very nice and helpful. The location was great"
"Big room and very big bathroom. Comfortable bed. We enjoyed the outdoor swimming pool!"
Big Family
2 weeks in August
Review Encoder
Context Encoder
R1
C1
$f_{ij} = f(c_i, r_j)$
(4) Inference - rank according to the similarity between the browsing user's context and a given list of accommodation reviews

Data Preprocessing

guest_type	guest_country	room_nights	month	accommodation_type	accommodation_country
Couple	Cobra Island	3	August	Hotel	Greece

Context textual representation

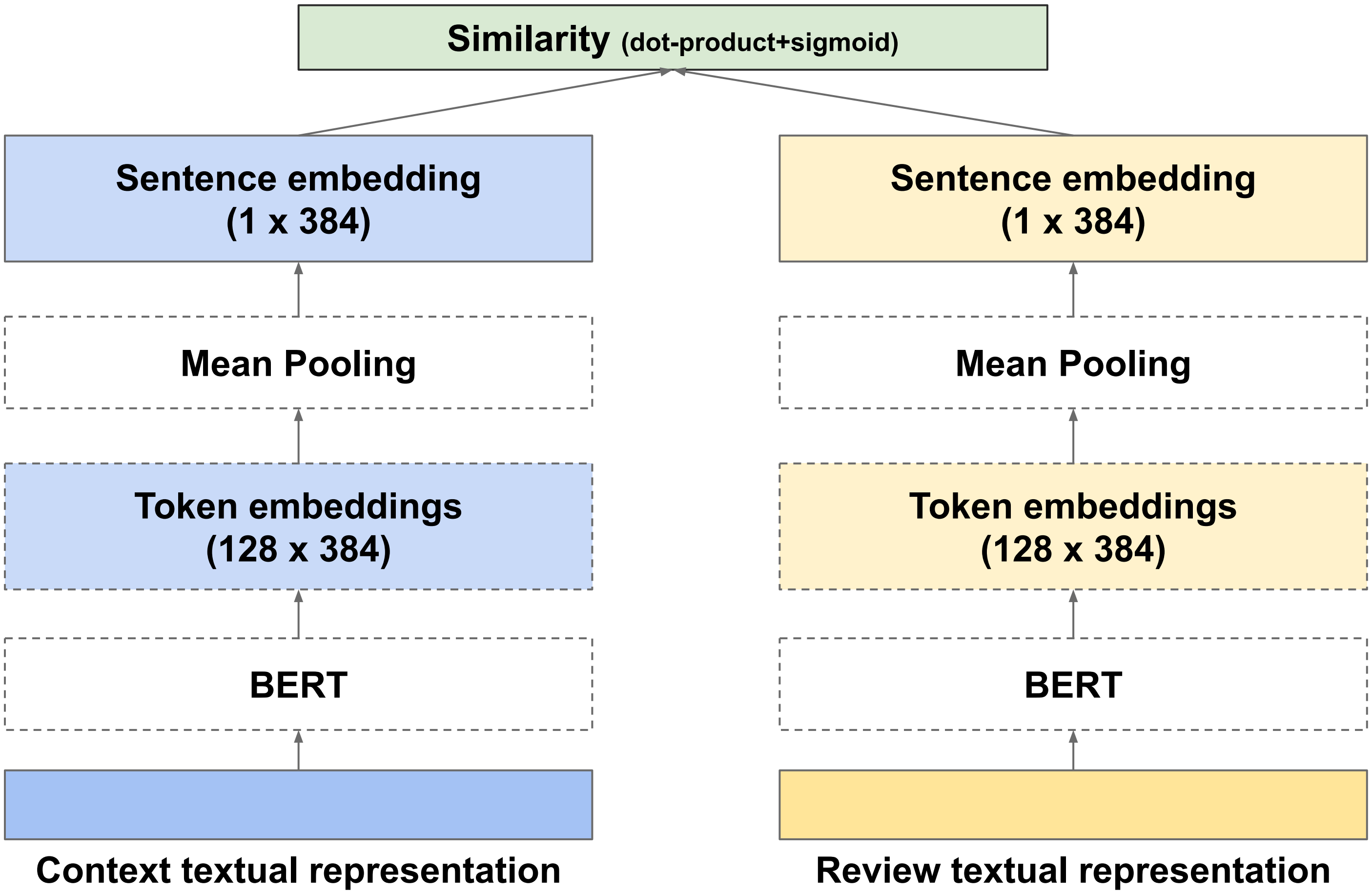
"Guest type: Couple
Guest country: Cobra Island
Room nights: 3
...."

review_title	review_positive	review_negative	review_score
Amazing!	We enjoyed the pool, our clean room and the breakfast was fab!	It would be nice to have fresh towels on a daily basis	8

Review textual representation

"Review title: Amazing!
Review positive: We enjoyed the pool, our clean room and the breakfast was fab!
Review negative: It would be nice to have fresh towels on a daily basis
Review score: 8"

Architecture



Loss Functions

$$\mathcal{L}_{\text{BCE}} = -\frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N}\left[\mathbf{I_{i,j}}\log(f_{i,j}) + (1-\mathbf{I_{i,j}})\log(1-f_{i,j})\right]$$

$$\mathcal{L}_{\text{InfoNCE}} = -\frac{1}{2N}\left(\sum_{i=1}^{N}\log\frac{\exp(f_{i,i})}{\sum_{j=1}^{N}\exp(f_{i,j})} + \sum_{j=1}^{N}\log\frac{\exp(f_{j,j})}{\sum_{i=1}^{N}\exp(f_{i,j})}\right)$$

Where:

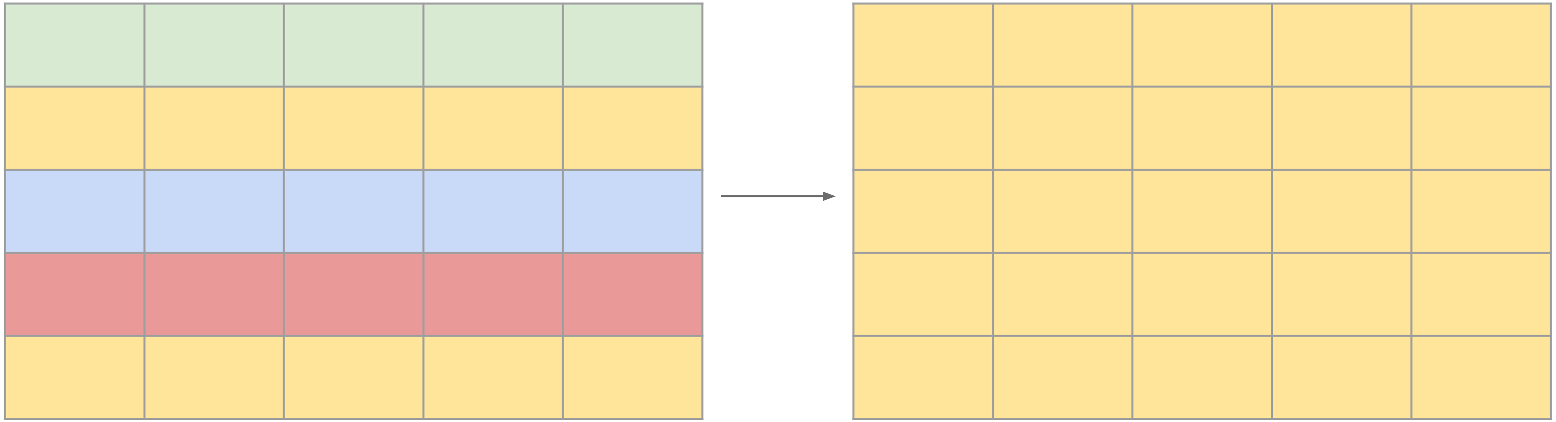
- ***$f_{i,j}$*** *is the* ***similarity*** *between context i and review j*
- ***N*** *is the number of context-review pairs within the batch*

Review embeddings

Context embeddings

$f_{0,0}$	$f_{0,1}$	$f_{0,2}$	$f_{0,3}$	$f_{0,4}$
$f_{1,0}$	$f_{1,1}$	$f_{1,2}$	$f_{1,3}$	$f_{1,4}$
$f_{2,0}$	$f_{2,1}$	$f_{2,2}$	$f_{2,3}$	$f_{2,4}$
$f_{3,0}$	$f_{3,1}$	$f_{3,2}$	$f_{3,3}$	$f_{3,4}$
$f_{4,0}$	$f_{4,1}$	$f_{4,2}$	$f_{4,3}$	$f_{4,4}$

Batch sampling



Random batch sampling **In-accommodation batch sampling**

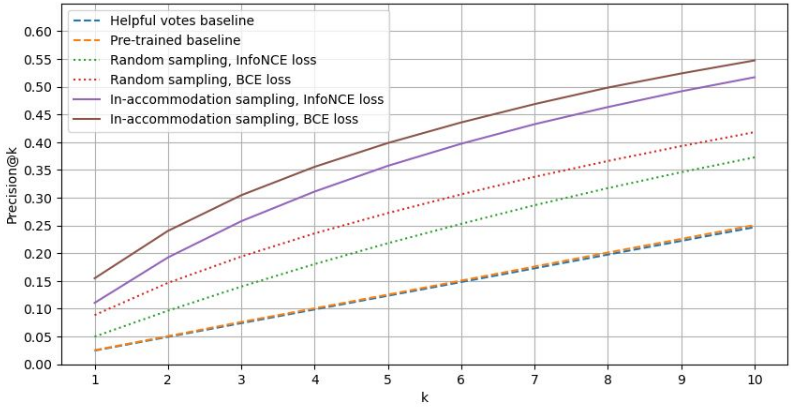
Might lead to learn differences between accommodations and reviews instead of between users and reviews within the same accommodation

Fine-tune Details

- **Model**: sentence-transformers/all-MiniLM-L6-v2 (link)
- **Optimizer**:
  - AdamW optimizer [20]
  - Weight decay=0.01
  - Initial LR=3e-5
- **Batch size**: 64
- **Warm up**: 0.05
- Fine-tune took ~9h on a computation instance with 1 NVIDIA A10G GPU, 8 vCPU and 32GB RAM.

Results

Model	MRR		Precision@1		Precision@10	
	Mean	Std	Mean	Std	Mean	Std
Random sampling, InfoNCE loss	0.147	0.051	0.049	0.048	0.375	0.106
Random sampling, BCE loss	0.191	0.063	0.089	0.064	0.419	0.111
In-accommodation sampling, InfoNCE loss	0.237	0.067	0.111	0.069	0.519	0.111
In-accommodation sampling, BCE loss	**0.278**	0.074	**0.154**	0.079	**0.549**	0.110



Challenge

RecTour 2024 Challenge https://workshops.ds-ifs.tuwien.ac.at/rectour24/rectour-2024-challenge/

- Data is published in https://tinyurl.com/RecTour24-Data
- There are 3 files (currently only training set data is available):
  - **{set_name}_users.csv** - holds the contextual data (user and accommodation)
  - **{set_name}_reviews.csv** - holds the review data (title, positive section, negative section etc)
  - **{set_name}_matches.csv** - holds the positive labels in form of matches between user_id, accommodation_id and review_id

- We will assess performance using MRR@10. Participants will submit a prediction file containing accommodation_id, user_id and top 10 review_ids sorted by their algorithm:

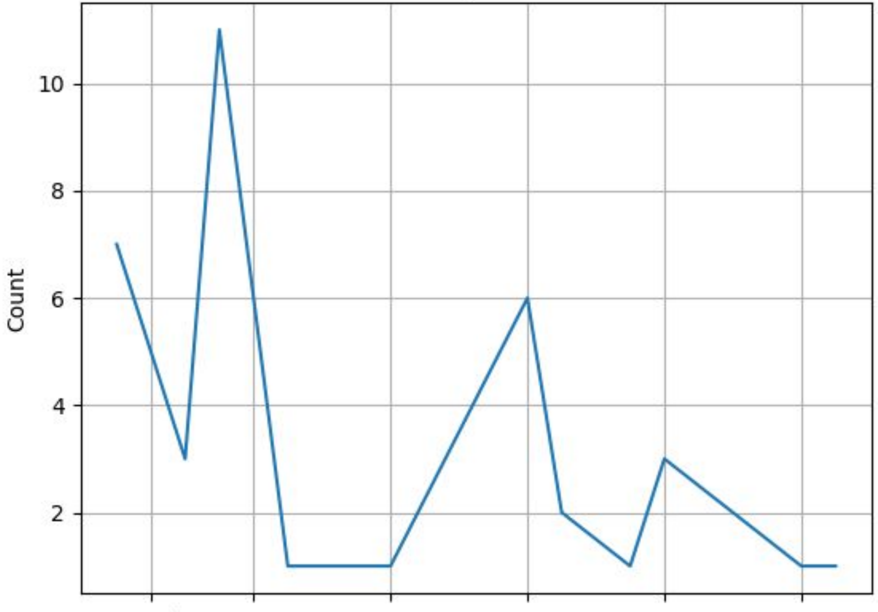
accommodation_id	user_id	review_1	review_2	review_3	…	review_10
1	24	123	764	129		325

Statistics

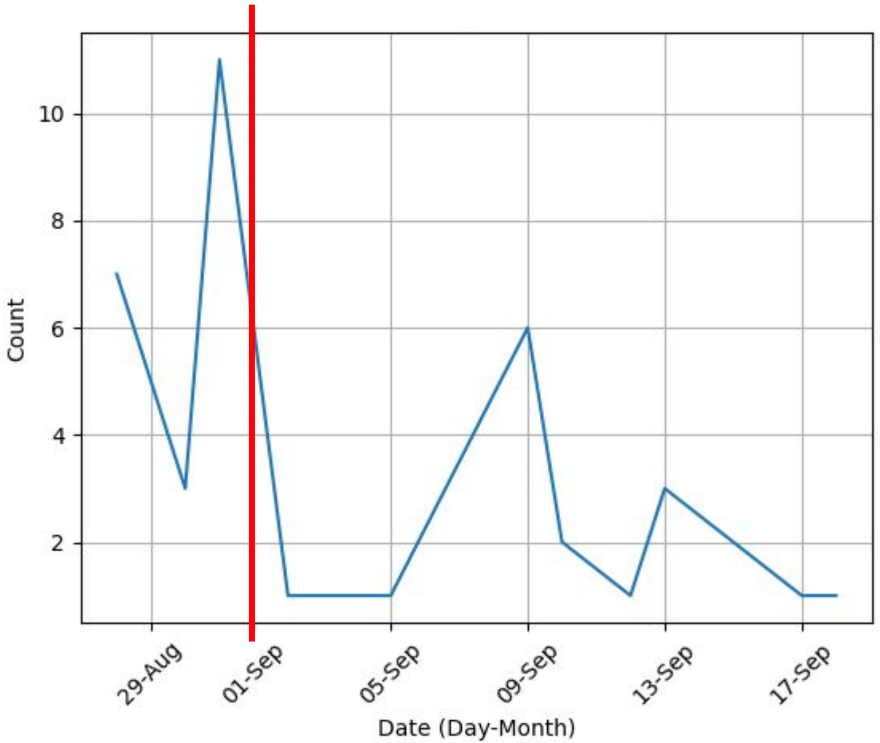
- 31 teams
- 60 participants

Statistics

- 31 teams
- 60 participants



Statistics



10
8
6
4
2
Count
29-Aug
01-Sep
05-Sep
09-Sep
13-Sep
17-Sep
Date (Day-Month)

Top teams

	Team	MRR@10
1	ringo	0.1662
2	TMU-Rec	0.0775
3	BMS Hunters	0.0735
4	qtravel.ai	0.0735

Top teams results after submission deadline

	Team	MRR@10
1	ringo	0.1662
2	TMU-Rec	0.0775
3	BMS Hunters	0.0735
4	qtravel.ai	0.0735

	Team	MRR@10
1	ringo	0.1662
2	BMS Hunters	0.0829
3	TMU-Rec	0.0787
4	qtravel.ai	0.0736

Thank you!

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