## Designing a Conversational Travel Recommender System Based on Data-Driven Destination Characterization

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## Problem

Recommend global cities for traveling

## Challenges

- Large item space
- Intangible items
- No ratings available
- Expert-based characterization of items is very costly
- High-stakes recommendation
- Complex decision making



## **Destination Characterization**

#### **Collect City Data**

- From Foursquare, via official API
- 180 cities on all continents
- Download of all venues in the city
- Analyze distribution
- · Enrich cities with cost and climate data



Heatmap of New York City Venues

Table 1. Raw values of exclipitally cities	Table	1:	Raw	values	of	exem	plary	citie
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City	Venues	Arts	Food	Nightlife	Outdoors	Cost Index	Temperature	Precipitation
Rome	36,848	1,995	12,264	2,063	3,482	69.03	15.7°C	798mm
Mexico City	213,612	12,158	83,225	16,780	19,330	34.18	15.9°C	625mm
Cologne	16,163	966	4,107	1,144	2,127	67.36	10.1°C	774mm
Penang	50,647	2,193	21,389	1,686	5,273	43.98	25.7°C	1,329mm
Cordoba	3,636	246	1,282	427	379	55.11	17.8°C	612mm

## **Destination Characterization**

### **Cluster Analysis**

- Normalize raw data by number of venues
- Normalize feature values using min-max
- Compare k-mean, k-medoids, hierarchical clustering
- Determine cluster quality using silhouette width
- **Best result:** Hierarchical clustering with 5 clusters



Normalized Values of Centroid Cities



Linus W. Dietz (TUM) | RecTour 2019





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## Evaluation



Independent variable: Critiquing vs. non-critiquing baseline

**Dependent variables:** 

- Time to result
- Clicks
- Self assessment of the importance of Food, Arts & Entertainment, Outdoors, and Nightlife
- ResQue Questionaire
  - 1. The travel destinations recommended to me by CityRec matched my interests
  - 2. The recommender system helped me discover new travel destinations
  - 3. I understood why the travel destinations were recommended to me
  - 4. I found it easy to tell the system what my preferences are
  - 5. I found it easy to modify my taste profile in this recommender system
  - 6. The layout and labels of the recommender interface are adequate
  - 7. Overall, I am satisfied with this recommender system
  - 8. I would use this recommender system again, when looking for travel destinations

## Results



Variable	Baseline	Critiquing	р	W	Significance
(Q1) Interest match	3.58	3.88	0.043	645	*
(Q2) Novelty	3.44	3.75	0.118	705	ns
(Q3) Understanding	3.46	3.77	0.073	673.5	ns
(Q4) Tell prefs.	3.73	3.90	0.328	775	ns
(Q5) Modify profile	3.24	3.48	0.17	723.5	ns
(Q6) Interface	4.15	3.62	0.009	1,044	**
(Q7) Satisfaction	3.66	3.92	0.037	649	*
(Q8) Future use	3.49	3.67	0.166	724	ns
Time to results	60.92s	184.07s	<0.001		* * *
Clicks	6.32	21.35	<0.001		* * *
PCC Food	-0.11	-0.01	0.341		ns
PCC Arts	0.05	0.38	0.066		ns
PCC Outdoors	0.02	0.45	0.024		*
PCC Nightlife	0.2	0.57	0.028		*

Significance levels: \* *p* < 0.05; \*\* *p* < 0.01; \*\*\* *p* < 0.001

## Conclusions

Recommendation accuracy > User effort

Critiquing system did better in capturing user preferences

#### **Future work**

Evaluate destination characterization

Compare different user interaction paradigms

Sources available https://github.com/divino5/cityrec-prototype

# Try out CityRec http://cityrec.cm.in.tum.de/

