

Building Location Embeddings from Physical Trajectories and Textual Representations

**Laura Biester** Carmen Banea

Rada Mihalcea



{lbiester,carmennb,mihalcea}@umich.edu

#### Outline

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#### Overview

- Dense vector representations (embeddings) are commonly used in NLP to represent words, and have also been applied to locations
- We use location trajectories and text data to create embeddings
- To evaluate, we explore:
  - Surface level tasks to better understand what location embeddings encode

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 Downstream tasks to see if they can be used for predicting personal attributes

Liu, Xin, Yong Liu, and Xiaoli Li. "Exploring the Context of Locations for Personalized Location Recommendations." IJCAI. 2016.

Feng, Shanshan, et al. "Poi2vec: Geographical latent representation for predicting future visitors." Thirty-First AAAI Conference on Artificial Intelligence. 2017.

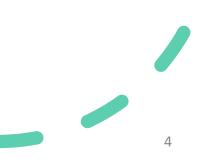
Solomon, Adir, et al. "Predict demographic information using word2vec on spatial trajectories." Proceedings of the 26th conference on user Modeling, adaptation and personalization. 2018.

Chang, Buru, et al. "Content-Aware Hierarchical Point-of-Interest Embedding Model for Successive POI Recommendation." IJCAI. 2018.

Sadilek, Adam, Henry Kautz, and Vincent Silenzio. "Modeling spread of disease from social interactions." Sixth International AAAI Conference on Weblogs and Social Media. 2012.

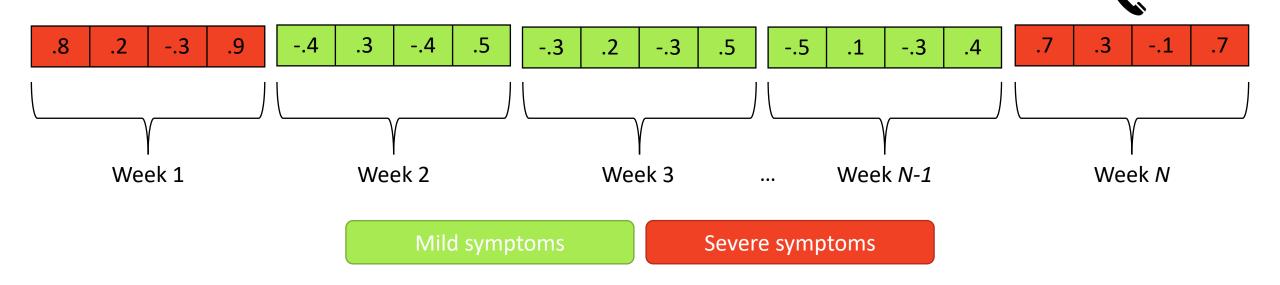
#### Research Questions

- 1. Do location embeddings encode meaningful semantic information?
- 2. What sources of data are most informative about locations?
- 3. Can location embeddings aid us in downstream tasks?



#### Example Use Case: Health Monitoring

- One downstream task is depression detection
- A possible application is individual-level monitoring for people who are in treatment for depression



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## Data Collection

#### Location Data

- Data consists of WiFi updates from connections to buildings at the University of Michigan
- Locations are tagged with Metadata
  - GPS position
  - Functionality 🔀

#### Pros and Cons of Wifi Data

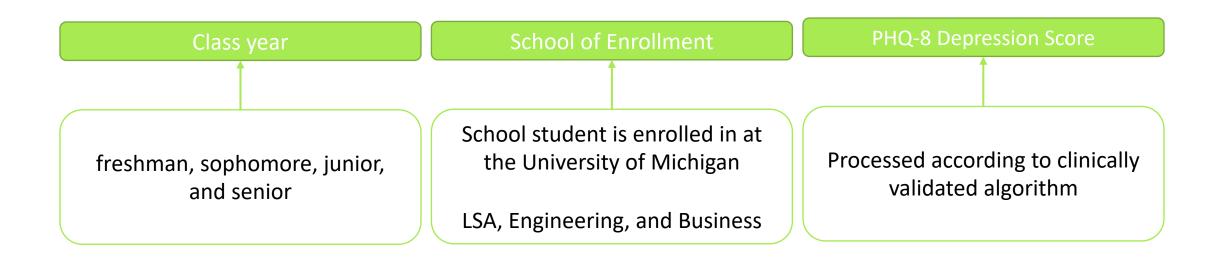
Pro

Con

- Locations are automatically discretized, unlike with GPS
- This data is likely available on most campuses
- We have no data when students are off campus
- Students can be connected to two access points at once

#### Personal Data

### For downstream tasks, we use data from a **survey** and the **university administration**, including:



#### Location-Related Text Data



#### How do people *express themselves* in different locations?

🚫 r/uofm · Posted by u/StardustNyako 11 months ago 🧧

I'm a transfer who accidently signed up for a Baits II room and now can't back out

#### Housing

Trying to do the room swap thing but no hits so far lol any advice or comfort? I'm a sophomore so most of my classes will be on Central so a 20 min bus ride isn't super great on paper but ehhhh

Any input is much appreciated.

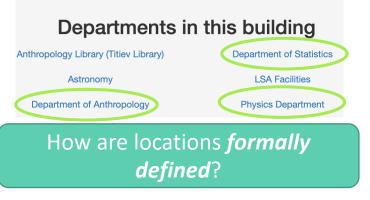
EDIT: Also kinda worried about the socialing aspect since I want to make friends

How do people *informally describe* locations?

#### West Hall



Address: 1085 UNIVERSITY AVE ZIP: 48109 Locate on the map



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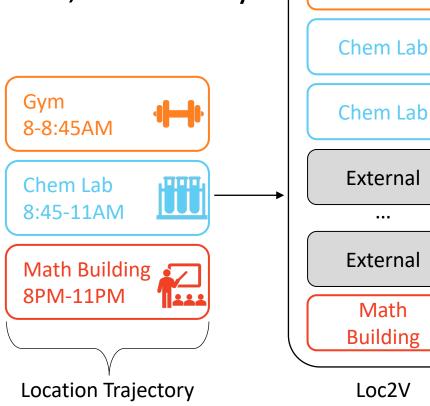
## Methodology

Gym

#### Trajectory-Based Vectors (Loc2V)

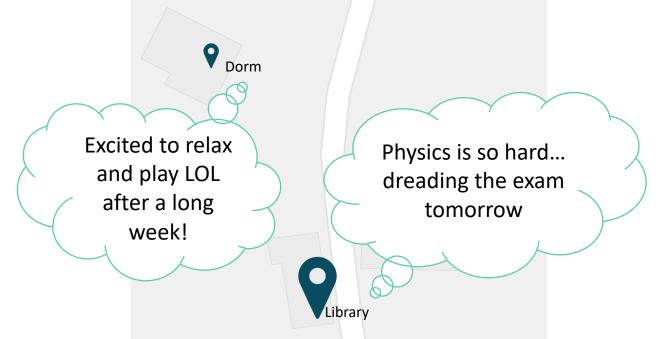
- Traditional word2vec input: sentences
- Our word2vec input: sequence of locations, ordered by time visited
- For each hour, record one location
  - This is the location with the longest time spent in that hour
- Provides a precise meaning to adjacent locations in a sequence

What can we learn from how people **physically interact** with the world?



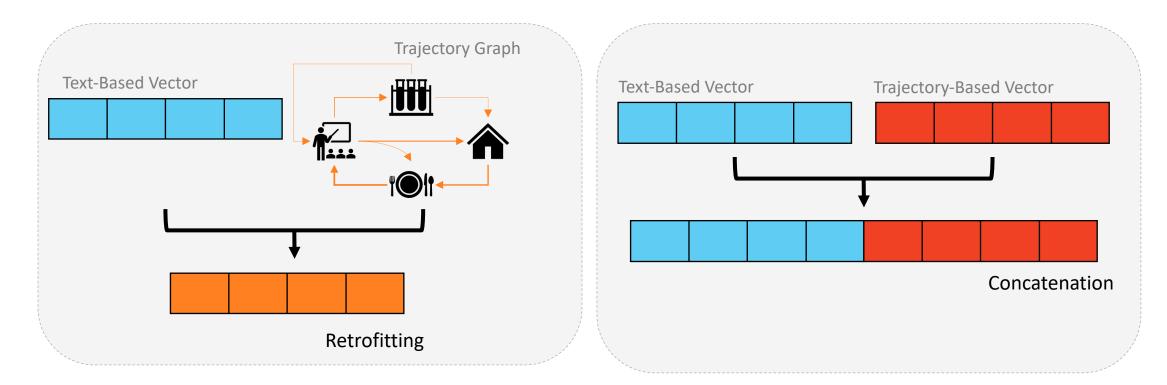
#### Text-Based Representations

- Collect datasets that link locations to text
- Create a **weighted average** of pretrained GloVe embeddings
- Weight embeddings using term frequency-inverse document frequency (TFIDF)



What can we learn from **what people say** in and about physical spaces?

#### Combining Trajectories and Text



#### Combine vector and graph to get a completely new vector

#### Concatenate two vector representations

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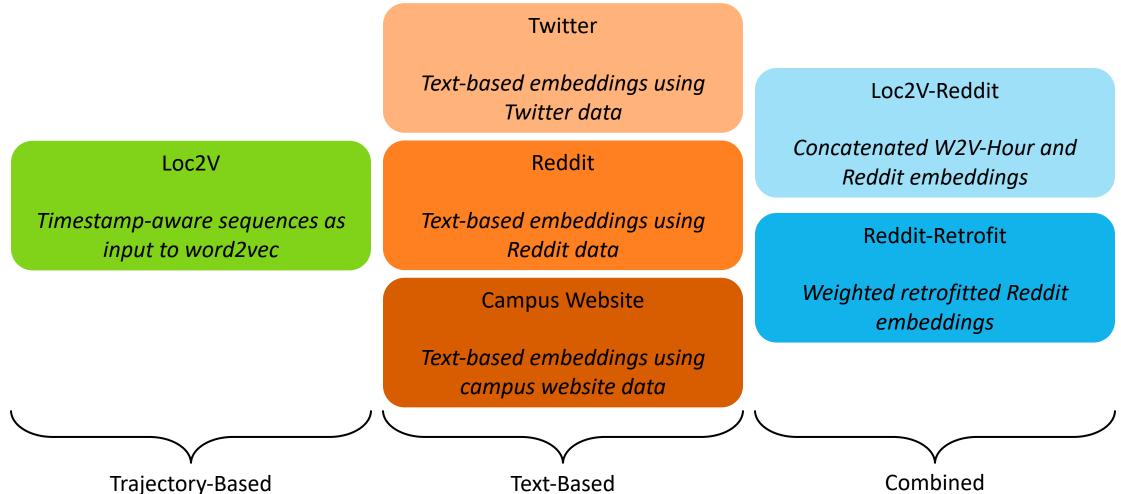
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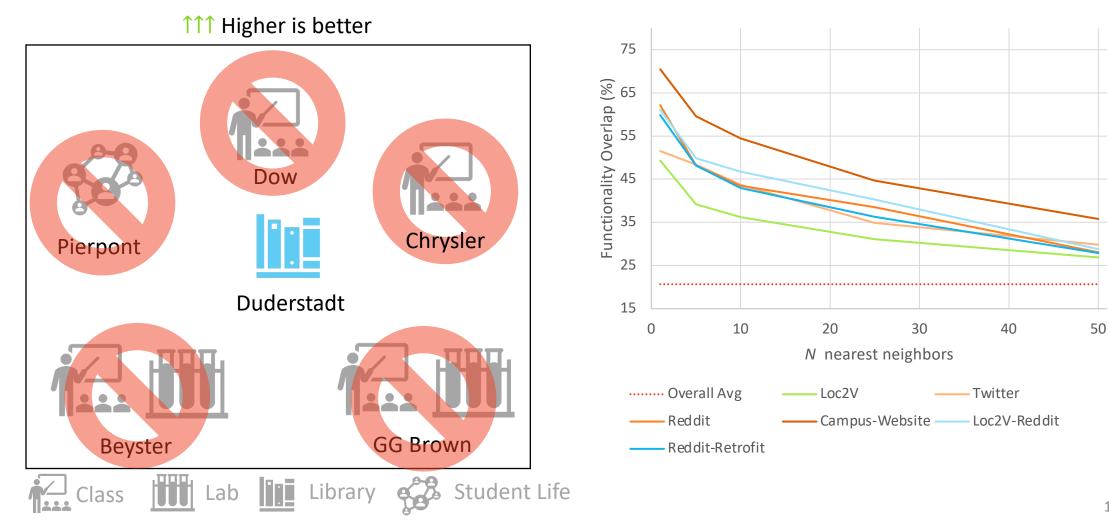
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## Experiments

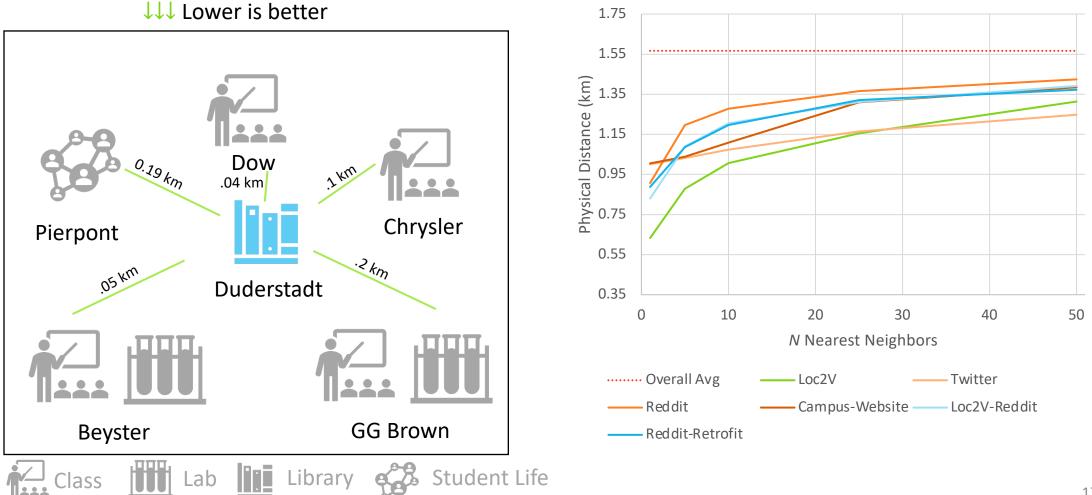
#### Six Embedding Models



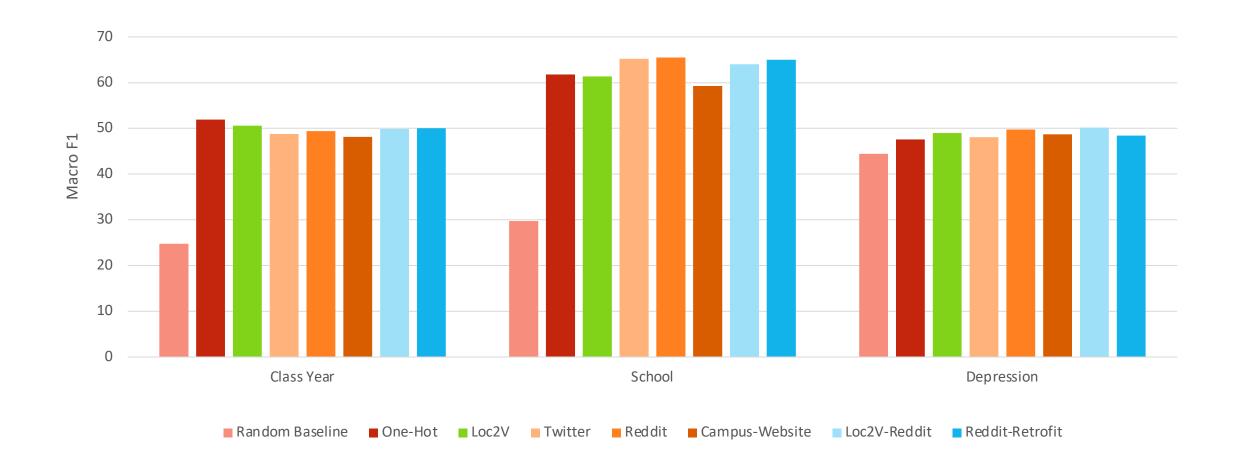
#### Functionality Overlap



#### Physical Distance Results



#### Downstream Task Results



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## Conclusions

### Do location embeddings encode meaningful semantic information?

Yes, all of our embedding methods encoded physical distance and functionality

# What types of data are most informative about locations?

Using **text data** tended to inform us more about **functionality** Using **location trajectories** tended to inform us more about **physical distance** On **downstream tasks**, results were **task dependent** 

# Can location embeddings aid us in downstream tasks?

When predicting **school and depression**, we saw slightly stronger performance with location embeddings

For other tasks requiring more **surface level information**, one-hot vectors led to better performance