Embedding Spatial and Semantic Contexts for **Geo-Entity Typing** in **Smart City** Applications

Basel Shbita, Binh Vu, Fandel Lin, Craig A. Knoblock

USC Information Sciences Institute, Marina del Rey, CA

WebAndTheCity

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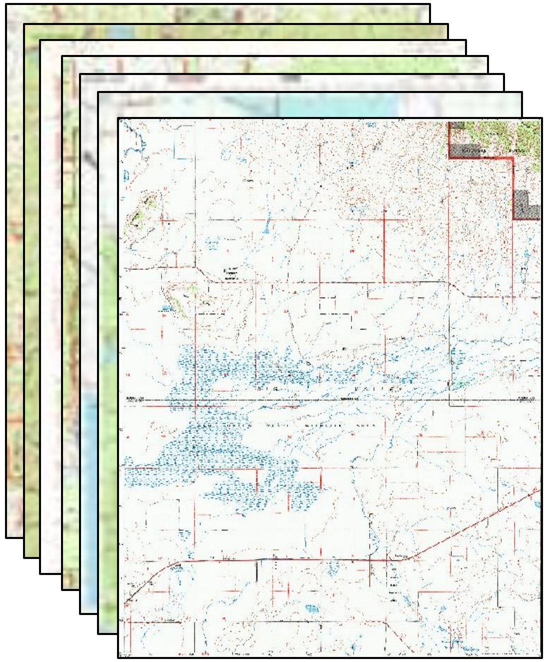
Agenda

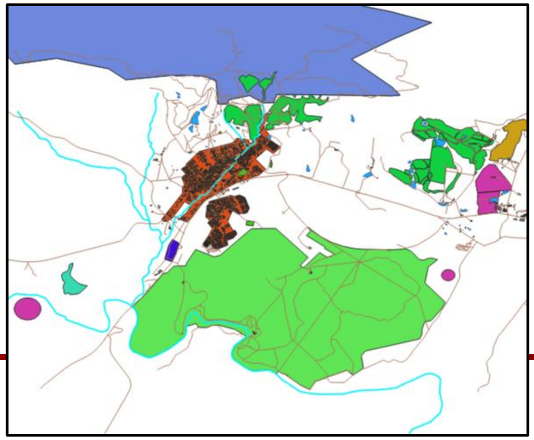
- Intro
- Problem
- Challenges
- Approach
- Evaluation & Discussion
- Related Work
- Future Directions
- Conclusions

Intro

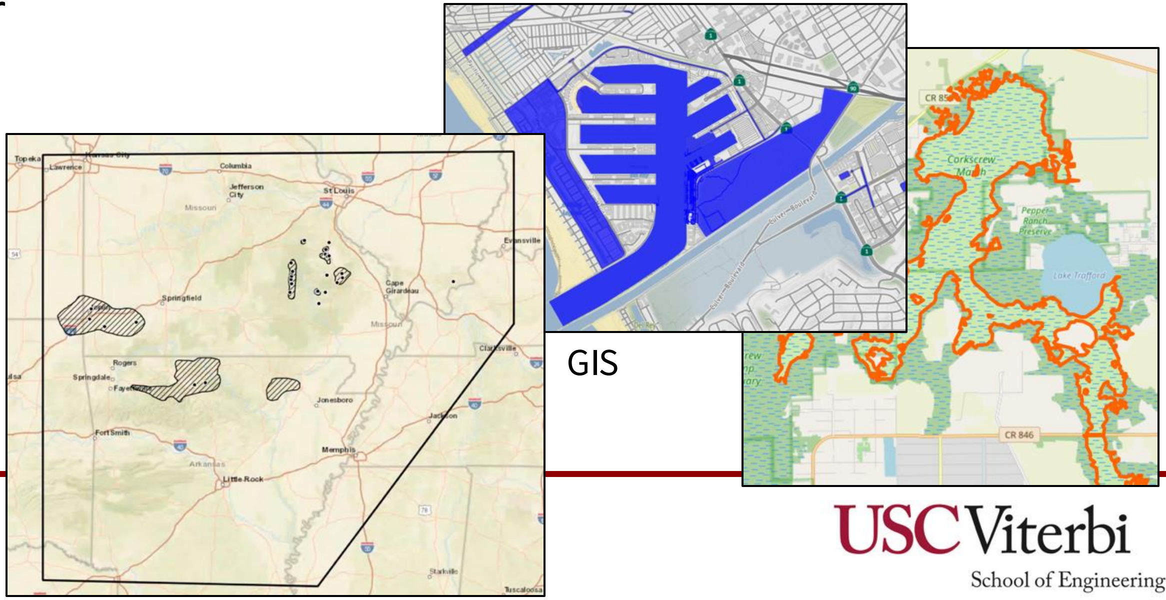
- Digitized Geo-Data
  - Rich sources of information
  - understanding human & environmental systems
  - describing human & natural activities
  - Labor-intensive to analyze
  - Often require grounding & additional contextual information
    - e.g., demographics, geology, stratigraphy, other



Historical Topographic Maps



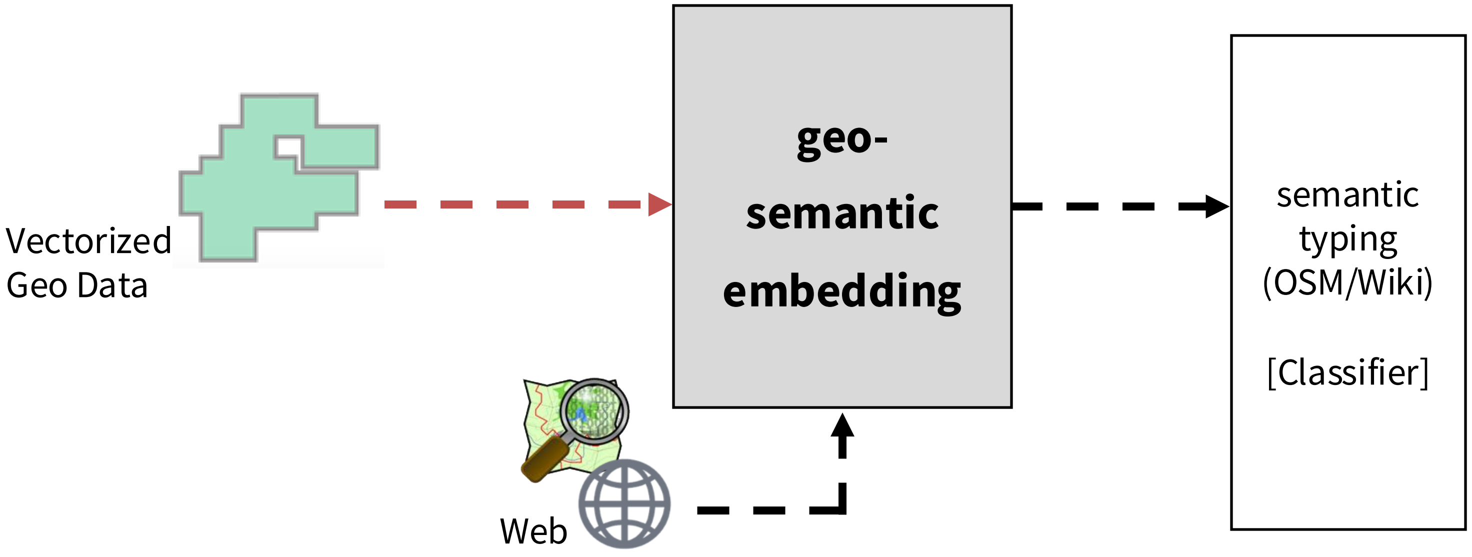
Remote Sensing Data



GIS

Problem

- Embed geospatial data into high-dimensional vector space
  - Preserve its semantic meaning & relationships between entities
  - enabling semantic typing/labeling of geospatial entities
  - Downstream tasks such as Smart City apps



Vegetation	Natural	wood, scrub, heath, meadow, grassland, tundra
	Artificial	forest, shrubbery, grass, orchard, vineyard, farmland
Water	Natural	water, wetland, mud, glacier, reef
	Artificial	salt pond, aquaculture, basin
Bare	Natural	bare rock, scree, shingle, sand, beach, shoal
	Artificial	quarry, landfill

Challenges

waterway

?

```
─ waterway
  ├── canal [5748]
  ├── dam [2425]
  ├── ditch [37754]
  ├── drain__waterway [7044]
  ├── river__waterway [16925]
  └── stream [799887]
```

water

?

```
─ water
  ├── basin [1870]
  ├── lake [3214]
  ├── pond [6835]
  ├── reservoir [4176]
  └── river__water [1570]
```

building

?

```
─ building
  ├── apartments [31601]
  ├── commercial [3875]
  ├── house [118030]
  ├── industrial [3223]
  ├── residential [19763]
  ├── retail__building [4109]
  ├── school [2400]
  └── warehouse [1098]
```

"Everything is related to everything else.
But near things are more related than distant things."

-Waldo R. Tobler

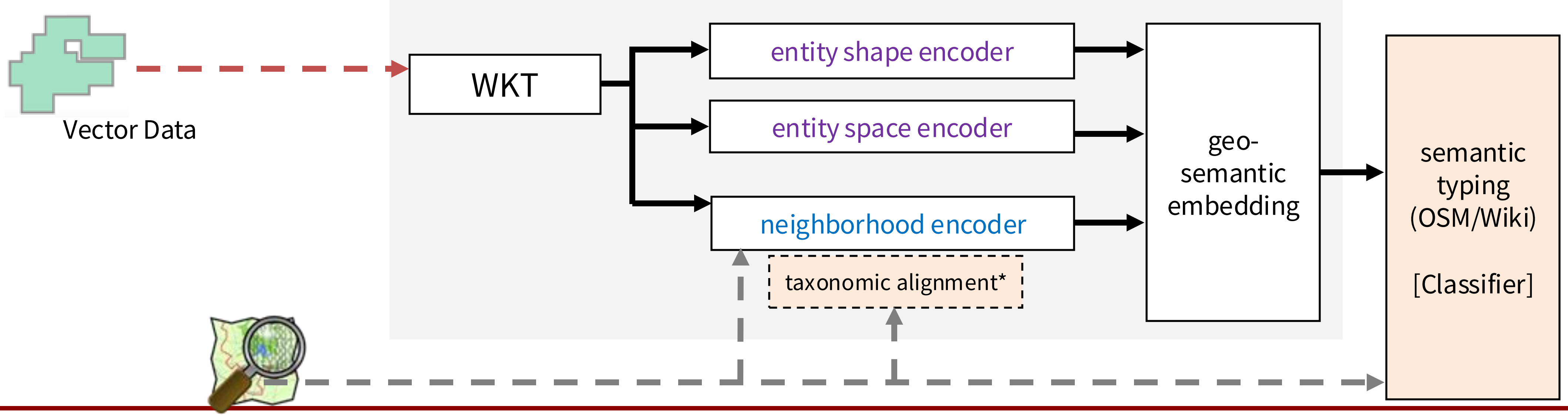
Approach

- Method to embed:
  - Geometric attributes (shape)
  - Spatial attributes (area, length)
  - Neighborhood context (nearby geo-entities)

geospatial

semantic

to generate a representation that can learn & infer properties about geo-entities



Approach – cont’d

- Data

OpenStreetMap

- Nodes - dots used to mark locations
- Ways - connected line of nodes
- Relation - used to create more complex shapes

CA OSM Snapshot

	index	0
0	node_tagged	1000170
1	node_untagged	133590505
2	way_untagged	4029438
3	way_tagged	9017322
4	relation_untagged	84613
5	relation_tagged	68462

	shp_type	count
0	Polygon	4876318
1	LineString	4176529
2	Point	1000170
3	MultiPolygon	12694
4	GeometryCollection	1364

Relation: 10052899

Version #1

Changeset #74650407

Tags

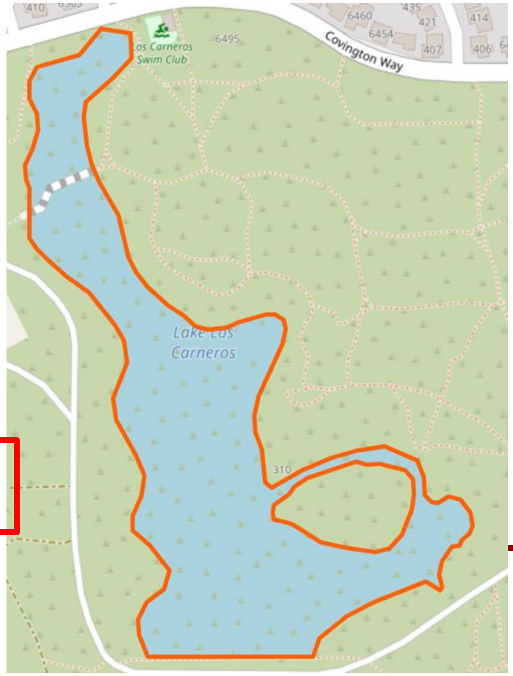
ele	22
gnis:county_id	083
gnis:created	06/13/2000
gnis:feature_id	1871851
gnis:state_id	06
type	multipolygon
natural	water
water	reservoir

Members

▾ 2 members

Way 23145279 as outer

Way 726021752 as inner



Approach – cont'd

- but, OSM data is
  - Inconsistent across regions
  - Varying-granularity
  - Noisy

WIKIDATA

sidewalk (Q177749)

pedestrian path along the side of a road

pavement | footpath | footway | platform

Statements

subclass of	thoroughfare

Statements

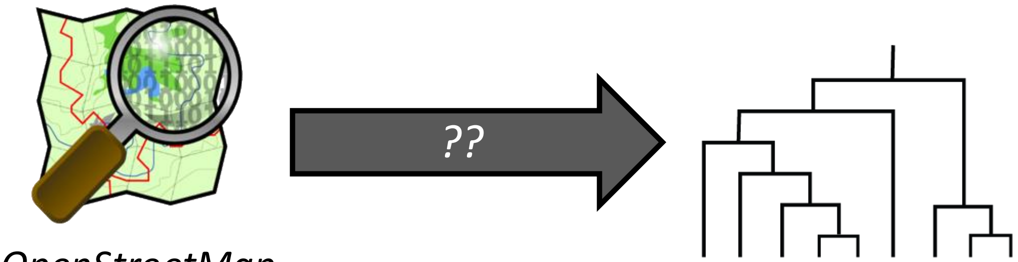
subclass of	public space
	line construction
	axis of communication
	geographical feature

OSMonto - An Ontology of OpenStreetMap Tags

Mihai Codescu*, Gregor Horsinka*, Oliver Kutz
Till Mossakowski*,**, Rafaela Rau*

* DFKI GmbH Bremen, Germany
** Research Center on Spatial Cognition, SFB/TR 8, University of Bremen, Germany

OUTDATED



OpenStreetMap data/dump

2024 IEEE 18th International Conference on Semantic Computing (ICSC)

Automatically Constructing Geospatial Feature Taxonomies from *OpenStreetMap* Data

Basel Shbita
Information Sciences Institute
Department of Computer Science
University of Southern California
Marina del Rey, California
shbita@usc.edu

Craig A. Knoblock
Information Sciences Institute
Department of Computer Science
University of Southern California
Marina del Rey, California
knoblock@isi.edu

Approach – cont’d

- use taxonomy-constructor as an auxiliary tool to
  - Generate a lightweight taxonomy from OSM tag data

OpenStreetMap data/dump


```
<way id="232250107" visible="true" vers
2019-05-06T23:22:23Z" user="Enock4seth"
  <nd ref="5058536215"/>
  <nd ref="1797433673"/>
  <nd ref="4992821222"/>
  <tag k="highway" v="tertiary"/>
  <tag k="name" v="Nana Kana Street"/>
</way>
<way id="244376453" visible="true" vers
2015-04-02T14:55:17Z" user="sidneys" ui
  <nd ref="2517024878"/>
  <nd ref="2517024879"/>
  <nd ref="2517024880"/>
  <nd ref="2517024881"/>
  <nd ref="2517024878"/>
  <tag k="building" v="industrial"/>
</way>
<way id="244376454" visible="true" vers
2015-04-02T13:43:25Z" user="sidneys" ui
```


construct base terminology
frequent non-informative
infrequent informative

```
{'apartments',
 'building',
 'driveway',
 'highway',
 'house',
 'residential',
 'service'}
```

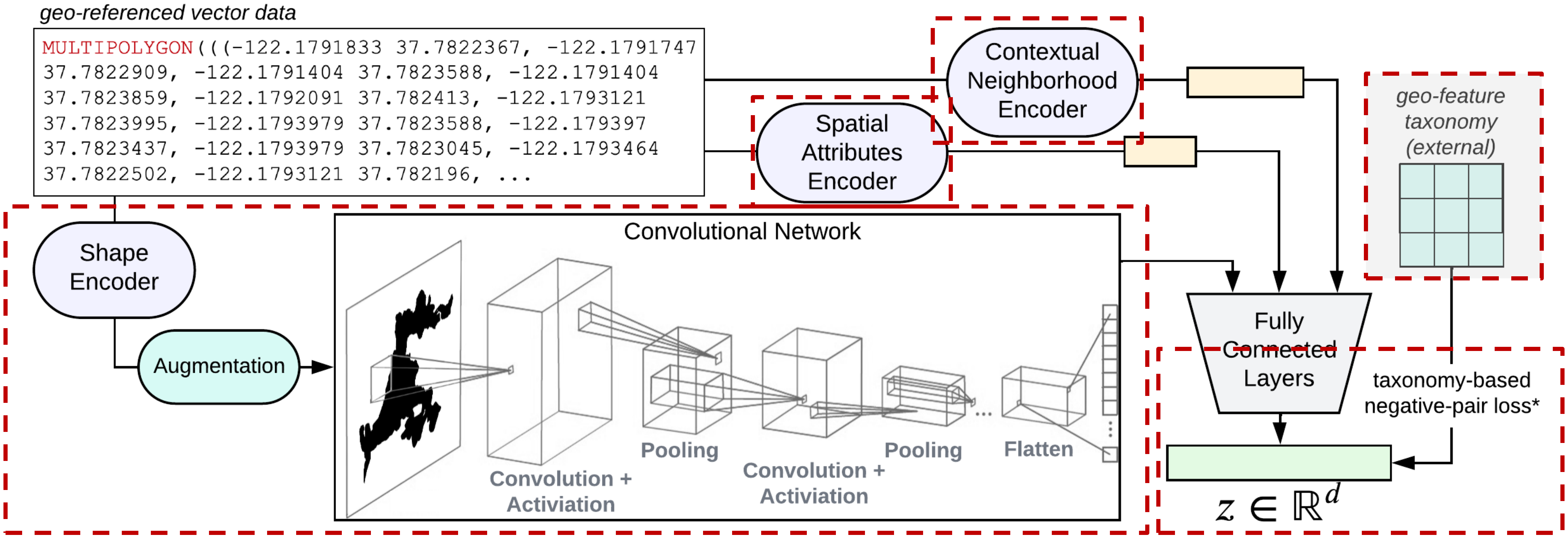
count parent-child relations
path frequency

parent	child	counter
building	house	15
highway	service	14
building	residential	33
highway	residential	22
building	apartments	2
service	driveway	5

build taxonomy
conflict resolution

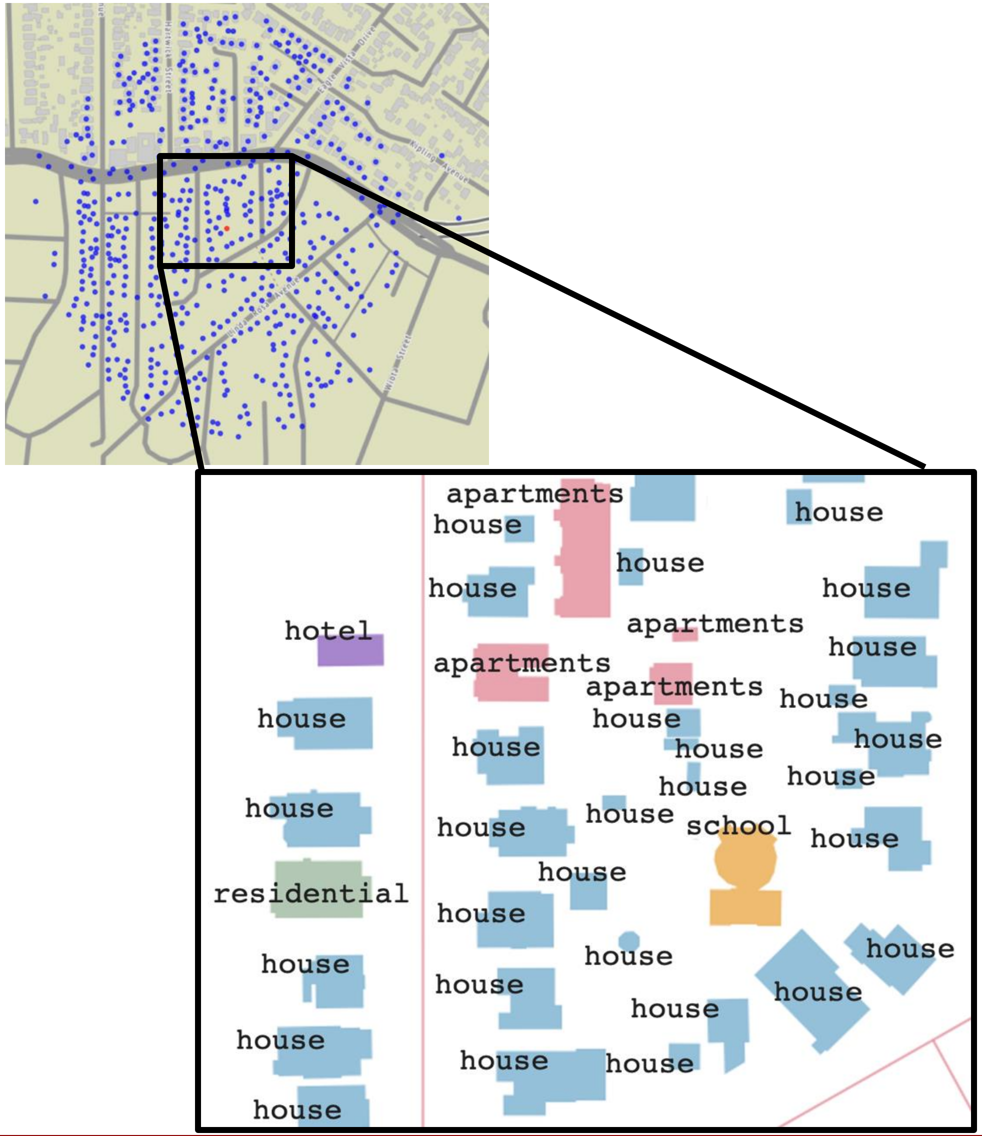
```
OSM
├── building
│   ├── apartments
│   ├── house
│   └── residential__building
└── highway
    ├── residential__highway
    └── service
        └── driveway
```

Approach – cont'd

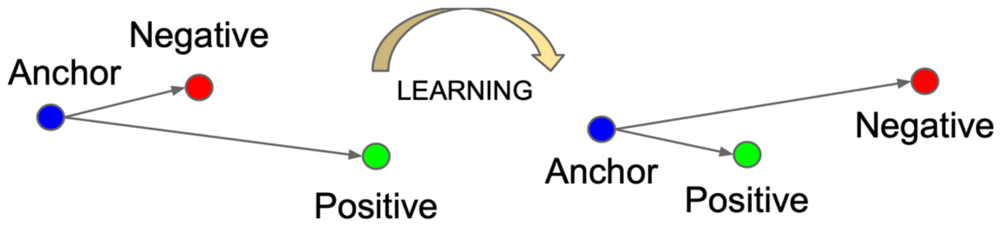


Approach – cont’d

house	414
residential__building	57
primary	29
apartments__building	28
residential__highway	21
service	11
commercial__building	8
retail__building	6
hotel__tourism	6
platform	4
alley	3
hotel__building	2
school__building	2
tertiary	2
industrial__building	1
steps	1
warehouse	1
restaurant	1
turning_circle	1
motorway_link	1
place_of_worship	1
driveway	1
school__amenity	1



Approach – cont'd

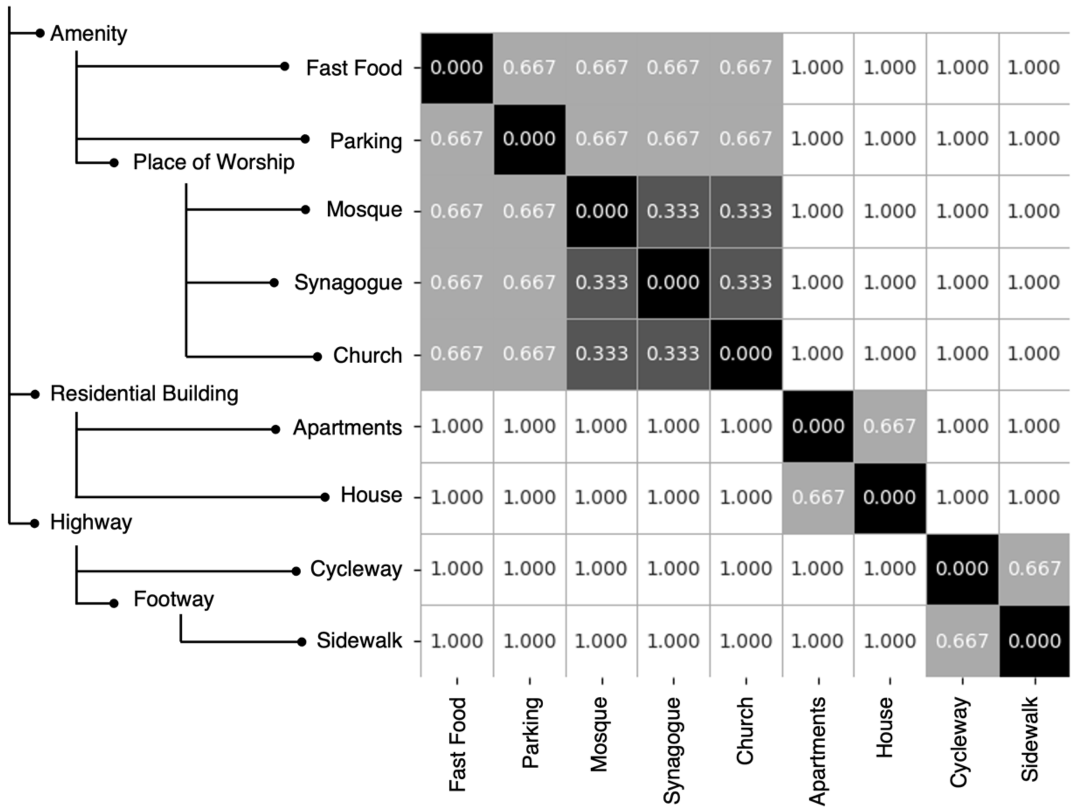


$$L_q = -\log \frac{\exp(sim(e_q, e_+)/\tau)}{\sum_{i=0}^{K} \exp(sim(e_q, e_i) \cdot w_{q,i}/\tau)}$$

$$w_{i,j} = \frac{d_{tree} - d_{i,j}}{d_{tree}}$$

Normalized
Temperature-scaled
Cross Entropy Loss

```
class NTXentLossWithTaxonomy(NTXentLoss):
    def __init__(self, taxonomy_matrix, *args, **kwargs):
        super().__init__(*args, **kwargs)
        self.taxonomy_matrix = taxonomy_matrix
    def compute_weights(self, a2, n, labels)
    def _compute_loss(self, pos_pairs, neg_pairs, indices_tuple, labels)
```



Evaluation

- 8-fold SVC on embeddings

Data: 2k+ instances → 11 WD classes

16k+ instances → 18 OSM tags

Training: 200k CA OSM dump (2.3 tags avg)

4 settings

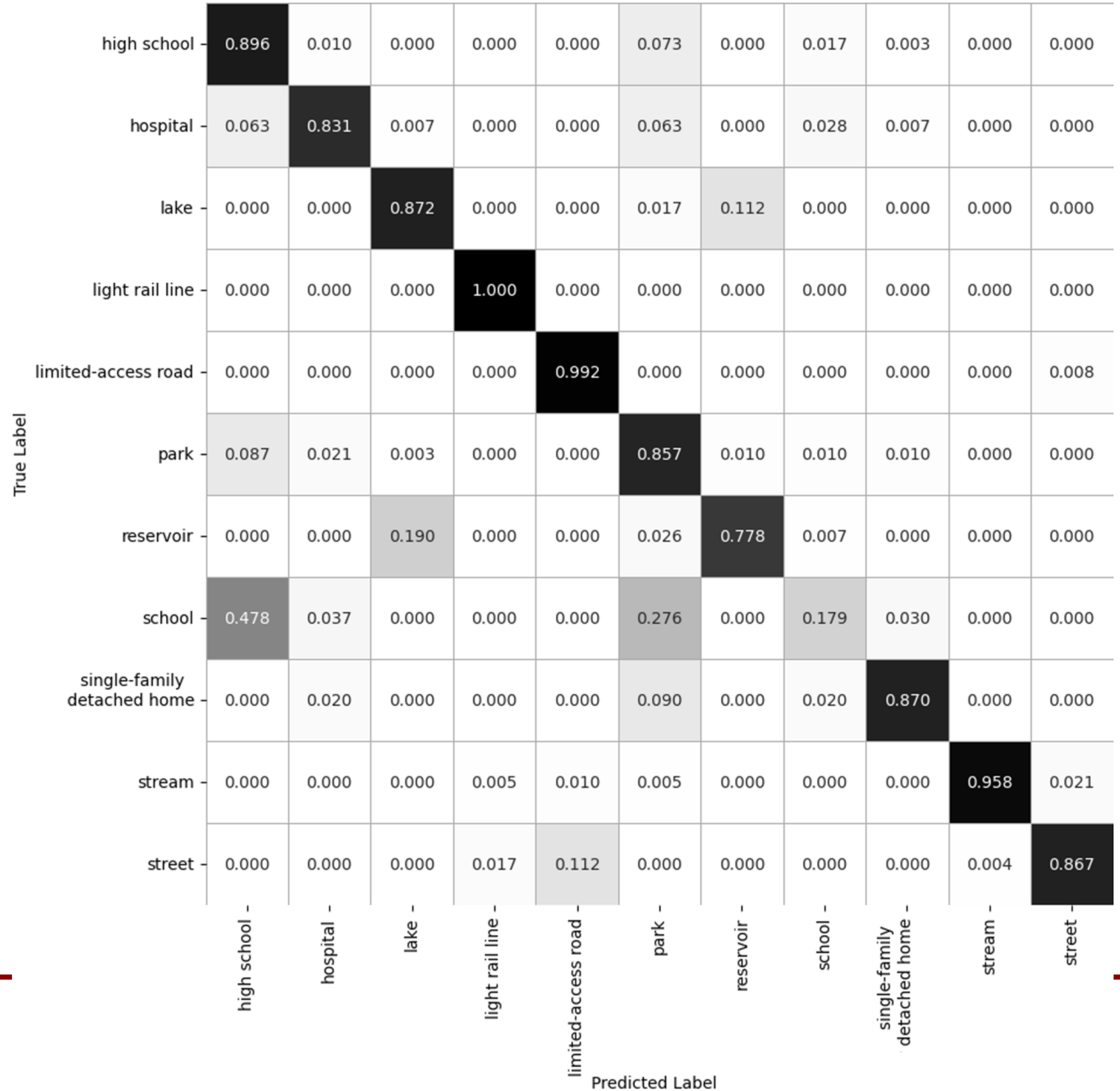
WIKIDATA

OpenStreetMap

Setting		WD-2k			OSM-16k		
		Precision	Recall	F_1	Precision	Recall	F_1
1	Ours$_{\texttt{shape}}$	0.497	0.506	0.501	0.473	0.512	0.492
2	Ours$_{\texttt{shape+spatial}}$	0.506	0.545	0.525	0.491	0.536	0.513
3	Ours$_{\texttt{full}}$	**0.850**	0.823	0.836	**0.877**	0.725	0.794
4	Ours$_{\texttt{full w/taxonomy}}$	0.849	**0.852**	**0.850**	0.858	**0.854**	**0.856**
	GPT-3.5-Turbo	0.198	0.209	0.121	0.145	0.063	0.026
SotA	GeoVectors	0.819	0.834	0.826	0.833	0.815	0.824

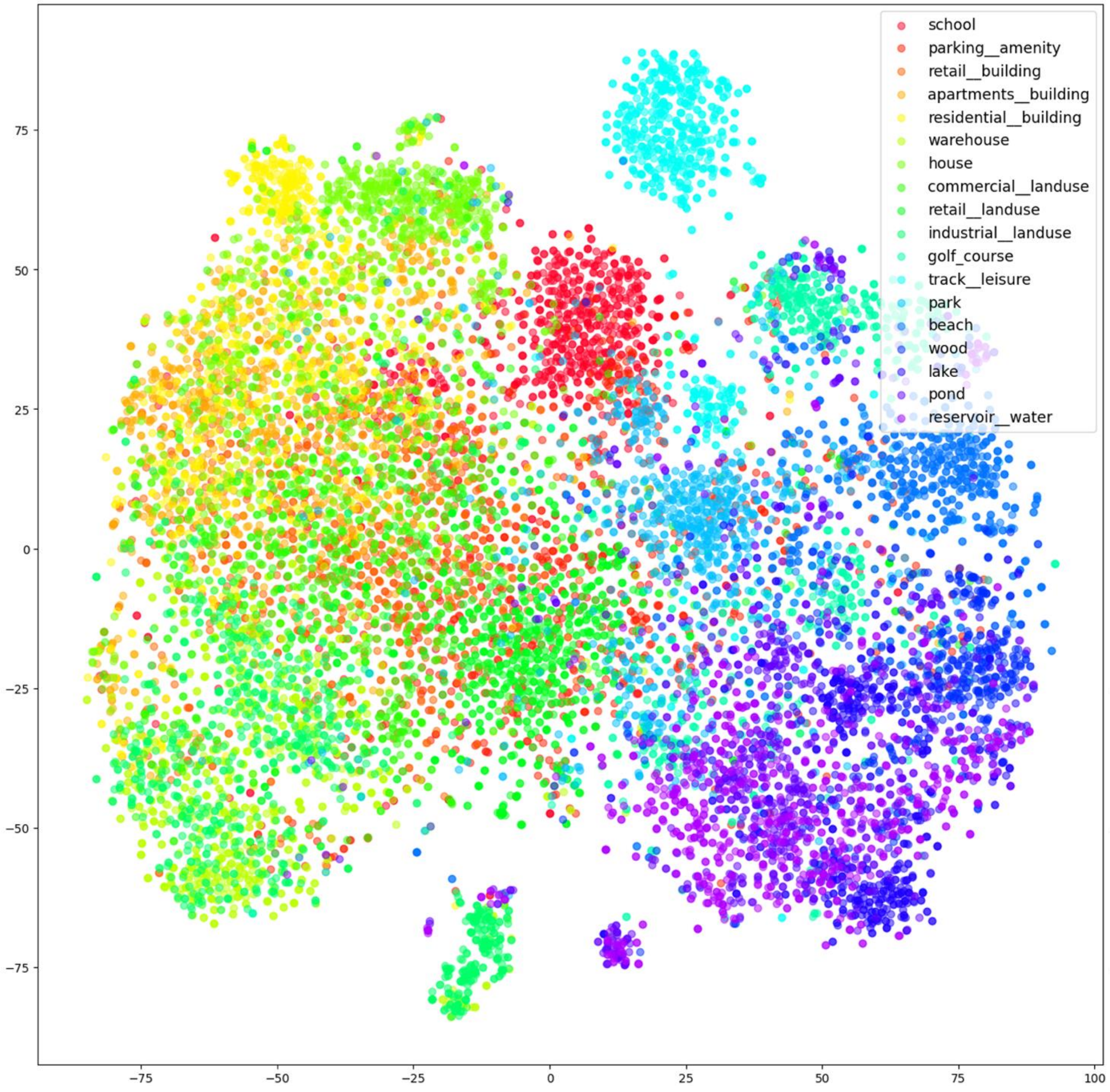
Evaluation – cont'd

	Precision	Recall	F_1	Support
high school	0.725	0.896	0.802	289
hospital	0.881	0.831	0.855	142
lake	0.834	0.872	0.852	179
light rail line	0.975	1.000	0.987	192
limited-access road	0.891	0.992	0.938	238
park	0.745	0.857	0.797	286
reservoir	0.838	0.778	0.807	153
school	0.615	0.179	0.277	134
single-family detached home	0.906	0.870	0.888	100
stream	0.995	0.958	0.976	192
street	0.972	0.867	0.917	241

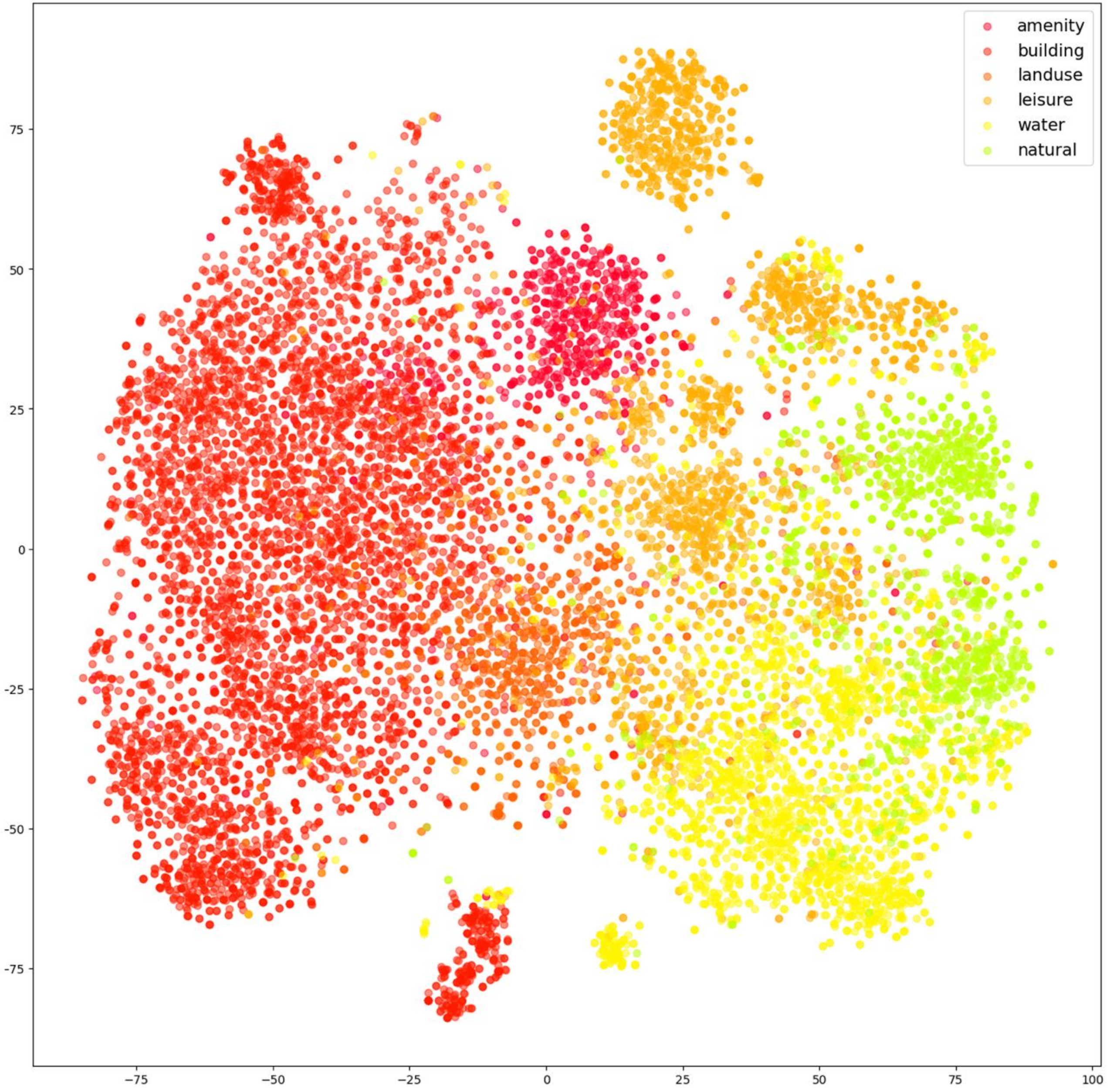


True Label \ Predicted Label	school	parking__amenity	retail__building	apartments__building	residential__building	warehouse	house	commercial__landuse	retail__landuse	industrial__landuse	golf_course	track__leisure	park	beach	wood	lake	pond	reservoir__water
school	0.791	0.028	0.042	0.043	0.029	0.007	0.015	0.018	0.000	0.007	0.000	0.007	0.010	0.000	0.002	0.000	0.001	0.002
parking__amenity	0.073	0.441	0.104	0.004	0.001	0.010	0.002	0.053	0.108	0.005	0.006	0.006	0.097	0.034	0.025	0.007	0.017	0.008
retail__building	0.015	0.050	0.556	0.102	0.061	0.048	0.004	0.105	0.028	0.022	0.000	0.002	0.005	0.001	0.000	0.000	0.000	0.000
apartments__building	0.032	0.005	0.114	0.558	0.208	0.018	0.010	0.040	0.000	0.010	0.000	0.000	0.002	0.000	0.002	0.000	0.000	0.000
residential__building	0.026	0.000	0.061	0.155	0.673	0.011	0.030	0.018	0.001	0.021	0.000	0.000	0.002	0.000	0.000	0.000	0.000	0.000
warehouse	0.008	0.012	0.060	0.019	0.016	0.658	0.010	0.039	0.003	0.168	0.002	0.000	0.002	0.000	0.000	0.000	0.000	0.002
house	0.026	0.002	0.027	0.098	0.170	0.015	0.628	0.024	0.000	0.005	0.000	0.000	0.001	0.000	0.002	0.000	0.000	0.002
commercial__landuse	0.027	0.049	0.349	0.092	0.055	0.065	0.029	0.261	0.016	0.048	0.000	0.000	0.005	0.001	0.001	0.000	0.001	0.001
retail__landuse	0.004	0.037	0.043	0.000	0.000	0.007	0.000	0.010	0.847	0.000	0.005	0.000	0.035	0.008	0.000	0.000	0.003	0.000
industrial__landuse	0.006	0.011	0.035	0.025	0.015	0.362	0.011	0.038	0.005	0.482	0.001	0.000	0.000	0.000	0.001	0.000	0.001	0.007
golf_course	0.001	0.007	0.000	0.000	0.000	0.001	0.000	0.000	0.010	0.000	0.863	0.003	0.055	0.010	0.019	0.003	0.008	0.020
track__leisure	0.002	0.005	0.000	0.000	0.000	0.001	0.000	0.000	0.011	0.000	0.002	0.937	0.027	0.004	0.002	0.000	0.005	0.002
park	0.020	0.070	0.003	0.000	0.003	0.009	0.006	0.002	0.043	0.000	0.053	0.008	0.665	0.053	0.020	0.007	0.020	0.016
beach	0.000	0.015	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.005	0.000	0.028	0.901	0.014	0.009	0.017	0.009
wood	0.005	0.020	0.000	0.000	0.002	0.000	0.000	0.000	0.004	0.000	0.037	0.004	0.025	0.018	0.748	0.028	0.027	0.083
lake	0.000	0.010	0.000	0.000	0.000	0.000	0.001	0.000	0.003	0.000	0.037	0.000	0.059	0.013	0.050	0.585	0.081	0.162
pond	0.000	0.044	0.002	0.000	0.001	0.000	0.002	0.000	0.009	0.002	0.011	0.007	0.041	0.016	0.044	0.039	0.710	0.071
reservoir__water	0.000	0.009	0.000	0.000	0.000	0.001	0.003	0.000	0.004	0.004	0.037	0.002	0.041	0.013	0.041	0.047	0.166	0.632

OSMTag	WikidataClass
amenity=police	police station
amenity=restaurant	restaurant
amenity=restaurant	business
amenity=school	academy school
amenity=school	community school
amenity=school	primary school
amenity=school	high school
amenity=school	private not-for-profit educational institution
amenity=school	public educational institution of the United States
amenity=school	school
amenity=school	school building
amenity=school	state school
amenity=studio	radio station
amenity=telephone	red telephone box
amenity=theatre	theatre
amenity=theatre	movie theater
amenity=university	private not-for-profit educational institution
amenity=university	public educational institution of the United States
artwork_type=sculpture	sculpture
artwork_type=sculpture	statue
artwork_type=statue	statue
artwork_type=statue	sculpture
building=church	church building
building=house	English country house



school
parking__amenity
retail__building
apartments__building
residential__building
warehouse
house
commercial__landuse
retail__landuse
industrial__landuse
golf_course
track__leisure
park
beach
wood
lake
pond
reservoir__water
75
50
25
0
-25
-50
-75
-75 -50 -25 0 25 50 75 100



amenity
building
landuse
leisure
water
natural
75
50
25
0
-25
-50
-75
-75 -50 -25 0 25 50 75 100

Related Work

- ML for Geospatial Classification (Castelluccio 2015, Klemmer 2023, Kaczmarek 2023, Xu 2022, Yan 2021)
  - Employ CNNs, GNNs, and GCNs for: building footprints & urban land-use classification
  - Do not address the incorporation of external (open) knowledge
- Geospatial Embedding Techniques (Tempelmeier 2021, Jenkins 2019, Li 2022)
  - Develop unsupervised embedding such as *GeoVectors* & *SpaBert*
  - Do not address shape or explicit spatial data for enhanced geo-entity representation
- OSM Embedding (Woźniak 2021)
  - Proposes embedding method for OSM regions using hexagonal grids
  - Does not address individual entities

Future Directions

- Advanced data modeling
  - More modalities
  - More data (e.g., rapidly changing geographies)
- Enhanced embedding techniques
  - Utilize textual information and deep learning attention mechanisms
  - Expand integration of textual data
- KG expansion
  - Apply & integrate with additional domains like archaeology & environmental sciences
- Dynamic semantic modeling
  - Create more sophisticated & evolving semantic models for accurate representation across multiple domains

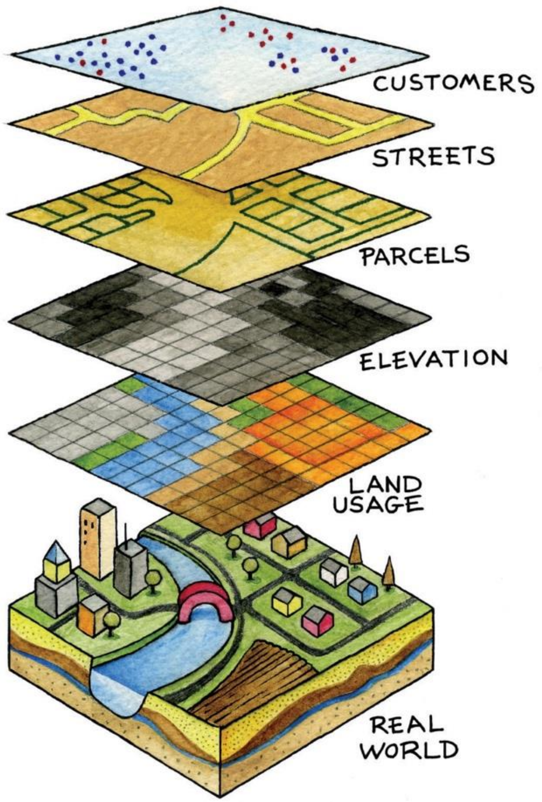


figure from *Essentials of Geographic Information Systems, Ch 7, Saylor Academy, 2012*

Conclusions

- Takeaways
  - Method for geo-referenced entity embedding on the web
    - self-supervised
    - leverages geometric, spatial, & semantic contexts
    - weighted contrastive learning
    - enables seamless semantic typing for integration on the web
      - fuels further discovery & enrichment

- Thanks for Listening!