Urban Perception Extraction From Texts Shared on Social Media: Framework and Applications

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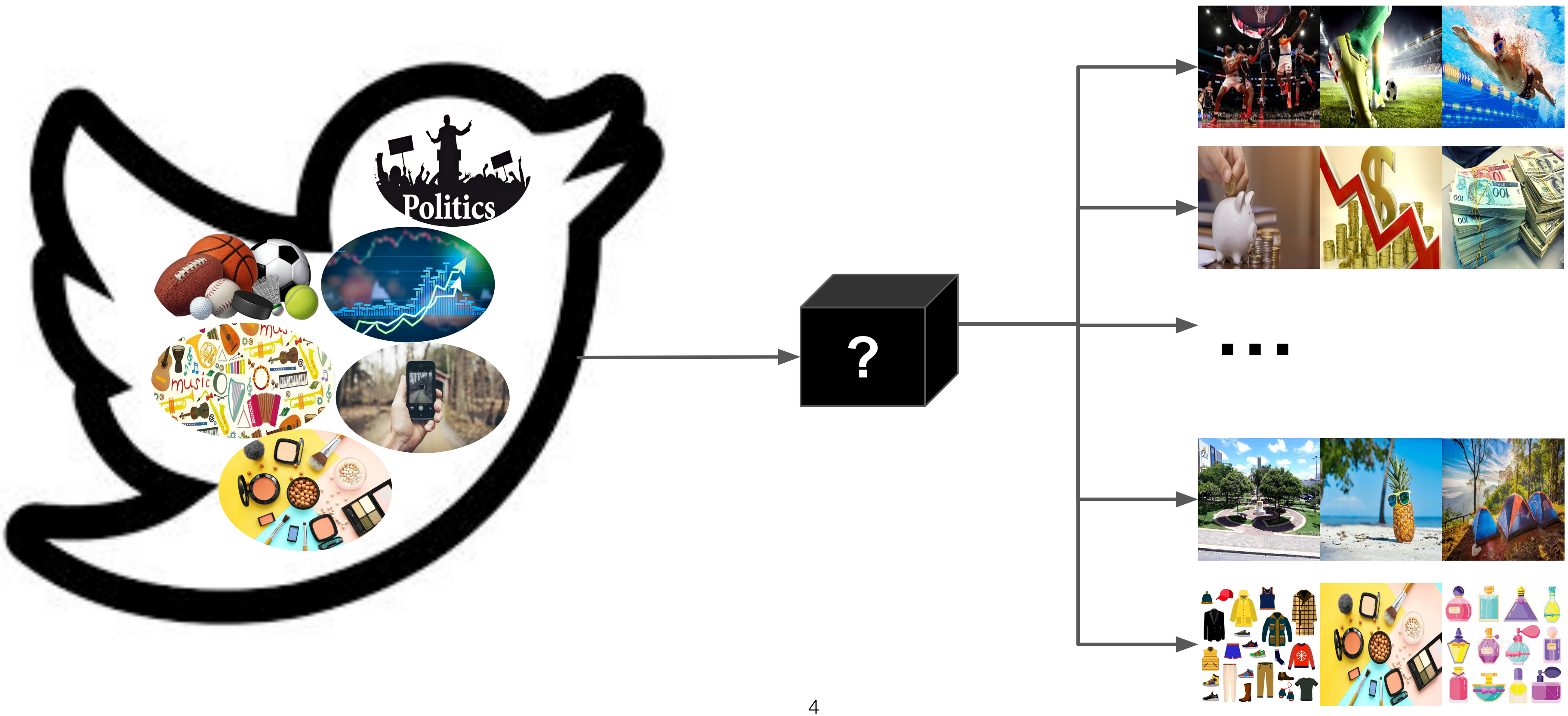
Campinas

October 27, 2021

Natural Language Understanding
NLU

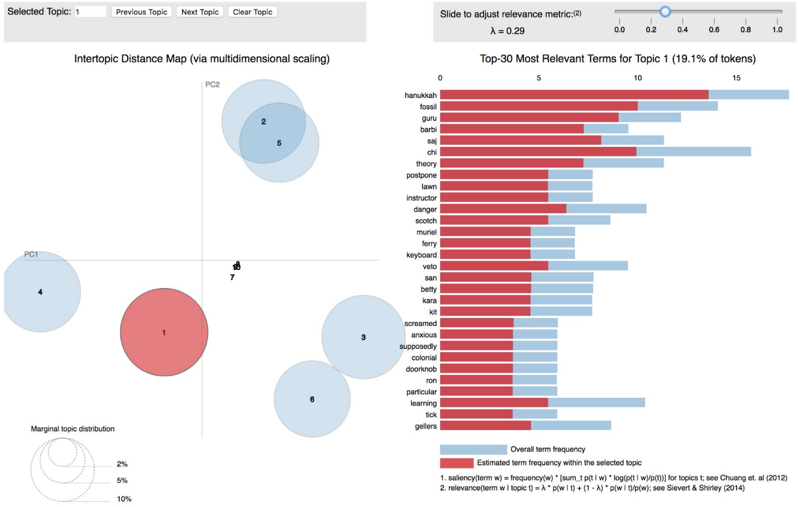
Extract useful urban perceptions using social media content to help better understanding urban areas and leverage new services and applications

Problem 1: How can we extract urban perceptions from social media data (natural language texts)?



Attempt 1: Keyword-Based Topic Modeling (2016)

- Define a subset of keywords related to urban perceptions.
- Using a Topic Modeling approach (e.g., LDA), we could group data into topics and identify the most relevant words for each topic

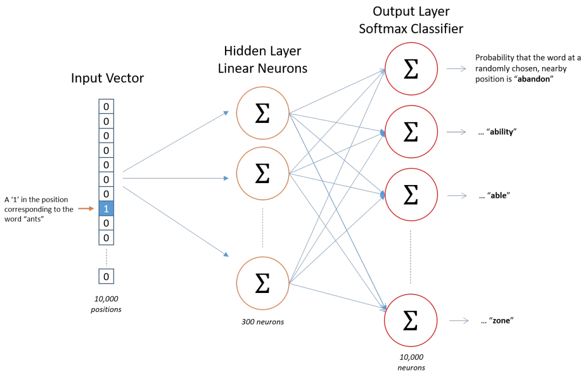


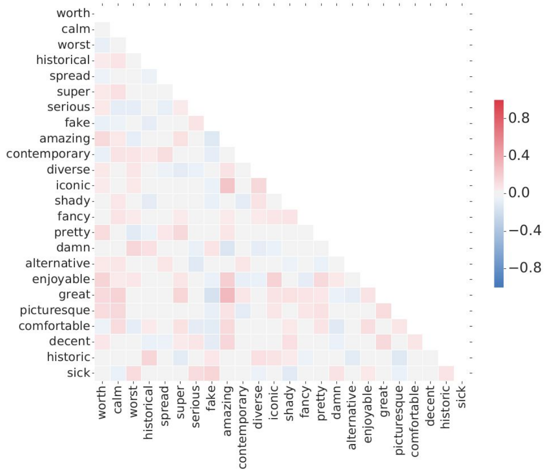
Problem: some words can be used in different contexts: shooting, crime, great, etc. Thus, a huge amount of extracted data was not related to urban perception.

shooting

Attempt 2: Unsupervised Learning

- Using a Word2Vec model, trained with users' reviews shared on crowdsourcing systems, to estimate the similarity of a tweet as the corpus





Problems:

- Small corpus (54,612)
- Noisy data
- Hard to distinguish among urban perceptions (traffic, safety, etc)

A considerable amount of extracted data still was not related to urban perception.

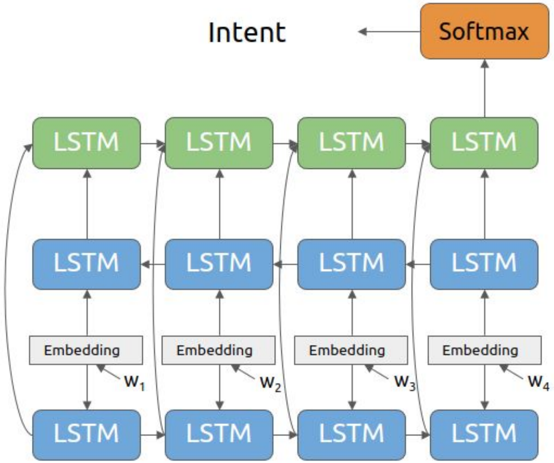
Attempt 3.1: Intent Recognition

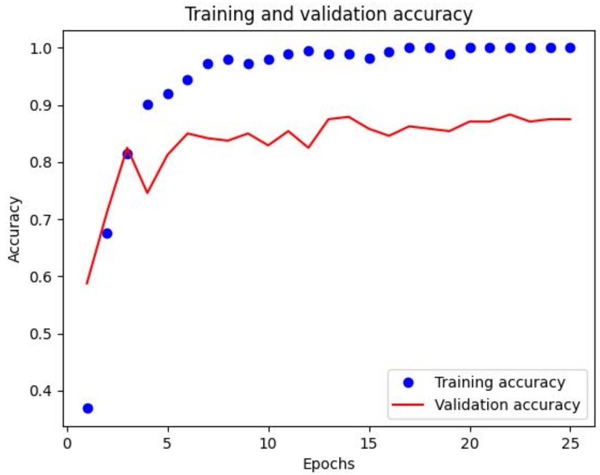
- Manually label a tweet data set to train a supervised model

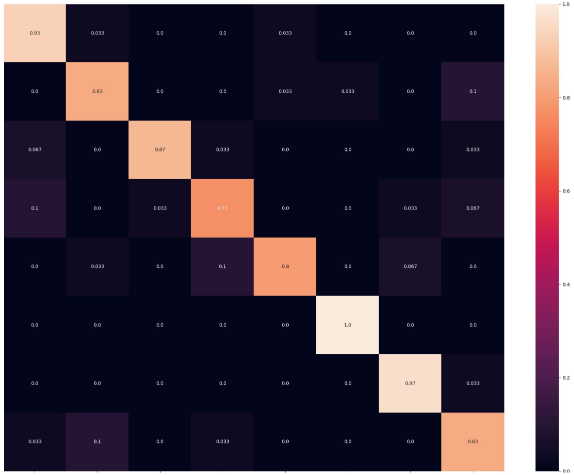
  8 categories (intents); 1,200 samples; 150 for each intent; 120/30 for training/testing

- Create a RNN model (BiLSTM + LSTM)

Problems:
- Slow
- Monolingual
- Performance?

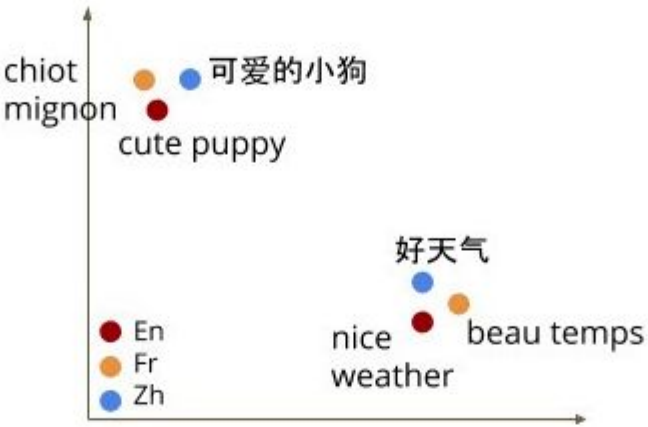




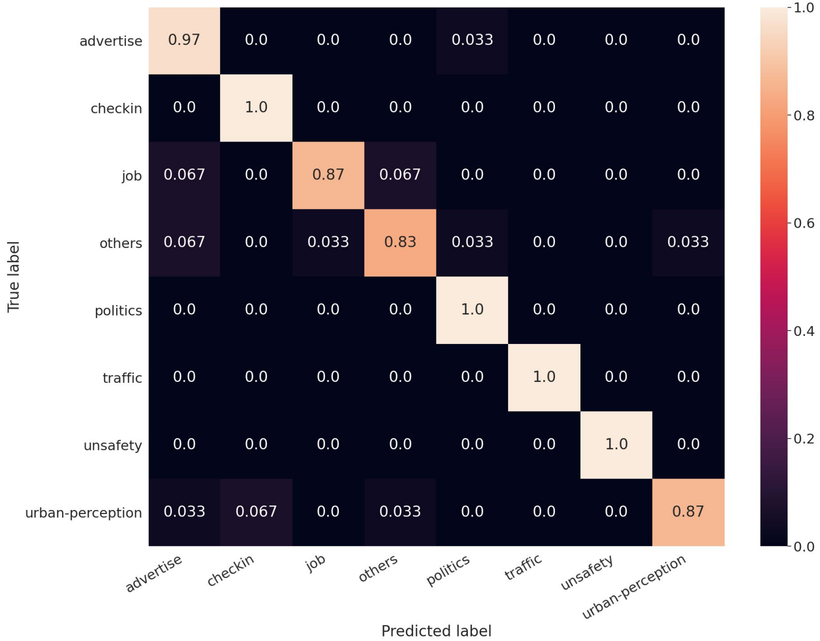


Attempt 3.2: Intent Recognition

- **LaBSE**: Language-Agnostic BERT Sentence Embedding
- Combined with a fast classifier, e.g., Logistic Regression

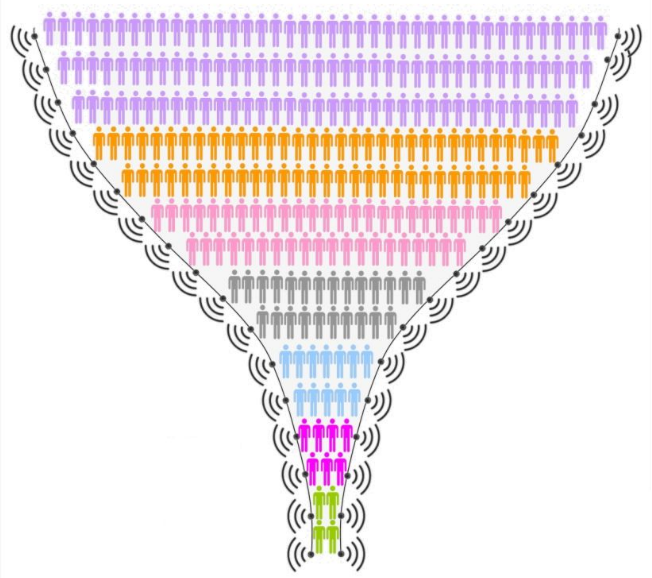


Multilingual Embedding Space



Problem 2: Only a small part of collected tweets are geotagged (~10%) and some of them, mainly those related to traffic and unsafety, are posted by news agencies

Million of tweets

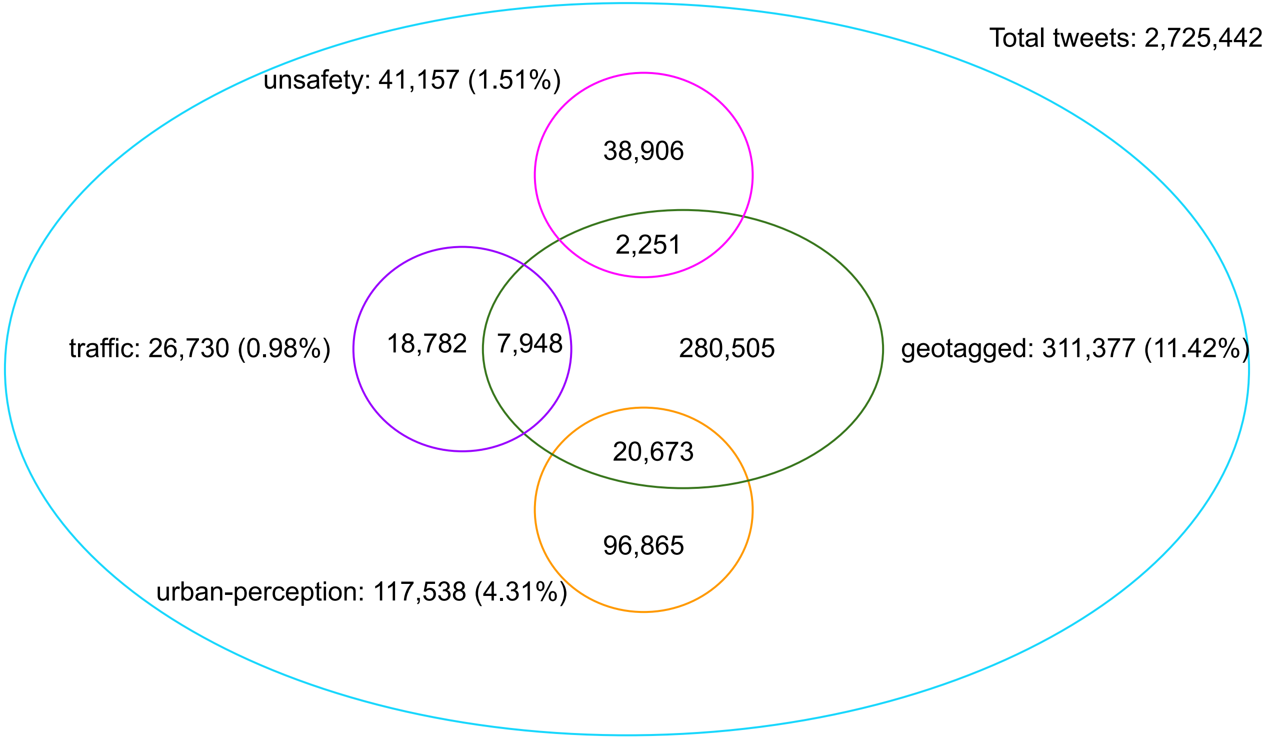


A few thousand of tweets

Hypothesis: If there is an address in the text, we can use NER to get it and applying a geocoding algorithm to obtain the most likely geolocation

Validation Dataset

- Tweets from October to December 2017 in Chicago, IL



Attempt 1: Slot Filling

Sentence:	Show	flights	from	Boston	to	New	York	today
Slots:	O	O	O	B-dept	O	B-arr	I-arr	B-date
Named Entity:				city start: 18 end: 23		city start: 28 end: 35		date start: 37 end: 41

- Manually label a data set to train a supervised model to predict address entities (POI, City, State, Country, Neighborhood, Avenue/Road/Street)
    - 1,200 samples

- Create a RNN model (BiLSTM)

Attempt 2: spaCy Library

Requirements

```
pip install spacy
python -m spacy download en_core_web_sm
```

Code:

```
import spacy

nlp = spacy.load('en_core_web_sm')

# print(spacy.explain("GPE"))

sentence = "Show flights from Boston to New York today"

doc = nlp(sentence)

for ent in doc.ents:
    print(ent.text, ent.start_char, ent.end_char, ent.label_)
```

Output

```
Boston 18 24 GPE
New York 28 36 GPE
today 37 42 DATE
```

Labels*

```
CARDINAL: Numerals that do not fall under another type
DATE: Absolute or relative dates or periods
EVENT: Named hurricanes, battles, wars, sports events,
etc
FAC: Buildings, airports, highways, bridges, etc
GPE: Countries, cities, states
LANGUAGE: Any named language
LAW: Named documents made into laws
LOC: Non-GPE locations, mountain ranges, bodies of water
MONEY: Monetary values, including unit
NORP: Nationalities or religious or political groups
ORDINAL: "first", "second", etc.
ORG: Companies, agencies, institutions, etc
PERCENT: Percentage, including "%"
PERSON: People, including fictional
PRODUCT: Objects, vehicles, foods, etc. (not services)
QUANTITY: Measurements, as of weight or distance
TIME: Times smaller than a day
WORK_OF_ART: Titles of books, songs, etc
```

Result

intent	Non-geotagged		Geotagged	
	Has entity	Has not entity	Has entity	Has not entity
traffic	**4,594**	14,188	**4,206**	3,742
unsafety	**10,039**	28,867	**1,205**	1,046
urban-p.	**18,402**	78,463	8,600	12,073

Problem 2.1: Geocoding

Attempt 1: Geocoder library (Multiple different geocoding provider such as Google, Bing, OSM & so on)

Requirements

```
pip install geocoder
## Installing Nominatim:
## http://nominatim.org/release-docs/latest/admin/Installation/
```

Code:

```
import geocoder

g = geocoder.osm(“11 Wall Street, New York”)

print(g.json)
```

Output

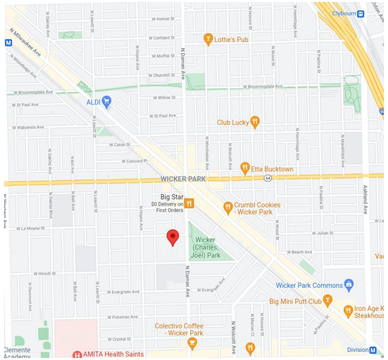
```
{
    "x": -74.010865,
    "y": 40.7071407,
    "addr:country": "United States of America",
    "addr:state": "New York",
    "addr:housenumber": "11",
    "addr:postal": "10005",
    "addr:city": "NYC",
    "addr:street": "Wall Street"
}
```

Example: urban-perception

Input

```
text = “Ending my year in Wicker Park [FAC]. The hipster part of
town where the amount of skinny jeans and man…
https://t.co/tweet_code”

fetch = “wicker park, Chicago, il”
```



Output


```
Output =
{
        'accuracy': 0.7456954929675734,
        'address': 'Wicker Park, Chicago, Cook County,
Illinois, 60622, United States',
        'bbox': {
                'northeast': [41.9178018, -87.6681551],
                'southwest': [41.8978018, -87.6881551]
        },
        'city': 'Chicago',
        'confidence': 7,
        'country': 'United States',
        'country_code': 'us',
        'county': 'Cook County',
        'importance': 0.7456954929675734,
        'lat': 41.9078018,
        'lng': -87.6781551,
        'neighborhood': 'Wicker Park',
        'ok': True,
        ...
        'quality': 'neighbourhood',
        'raw': {...}
}
```