Social Media Text Processing and Semantic Analysis for Smart Cities

MSc Dissertation Viva

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Agenda

1. Scope
2. Problem Statement
3. Goals
4. State of the Art
5. Framework
6. Exploratory Data Analysis
7. Text Analytics Experiments
8. Conclusions

Scope

- Instant connectivity 24/7
- Sharing of events, opinions and activities
- Many research areas have tried to exploit social media data
- Smart Cities and Intelligent Transportation Systems are also obvious candidates
- Information derived from such exploration may bring benefits to the cities' governance, traffic-flow management, etc.

Problem Statement

Mining social media data is a laborious and time-consuming process.

a) Social media platforms have their own specificities

b) The volume of data retrieved is overwhelming

c) Social media texts have several restrictions

Goals

1. Design and development of a framework for continuous collection of tweets from multiple bounding-boxes

2. Discovering of latent topics in the Twitter data

3. Travel-related classification of tweets using supervised learning

4. Aggregation and visualization of results

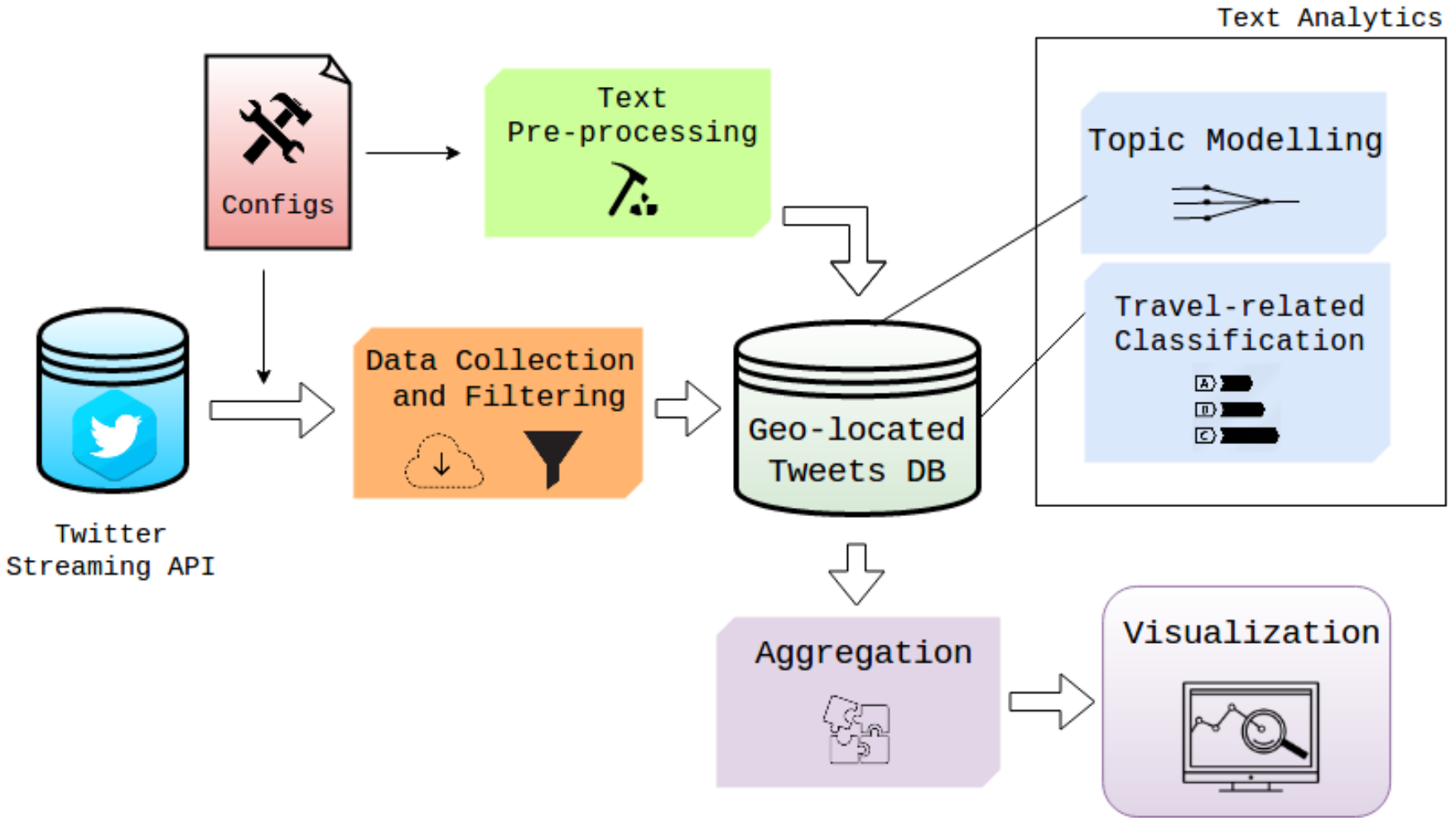
State of the Art

1. Lansley et al. (2016) depicted topic modelling over geo-located tweets in London and cross the results with geographic maps to identify land-use patterns

2. Maghrebi et al. (2016) classified travel-mode geo-located tweets using term-based search in Melbourne

3. Kuflik et al. (2017) performed multi-class transport classification over geo-located tweets from Liverpool

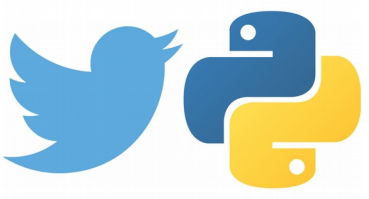
Architecture Overview



Data Collection

Twitter Streaming API allows three different collection heuristics:

- Term-based search
- Users' activity
- **Locations through bounding-box system**



Tweepy is an open-source Python library to acess the Twitter APIs

Data Filtering

The data retrieved has two inconsisitencies:

- A large amount of tweets in different languages comparative to the one spoken in the target city
- Tweets from the outside of the searching bounding-box are retrieved by the API

Text Pre-processing

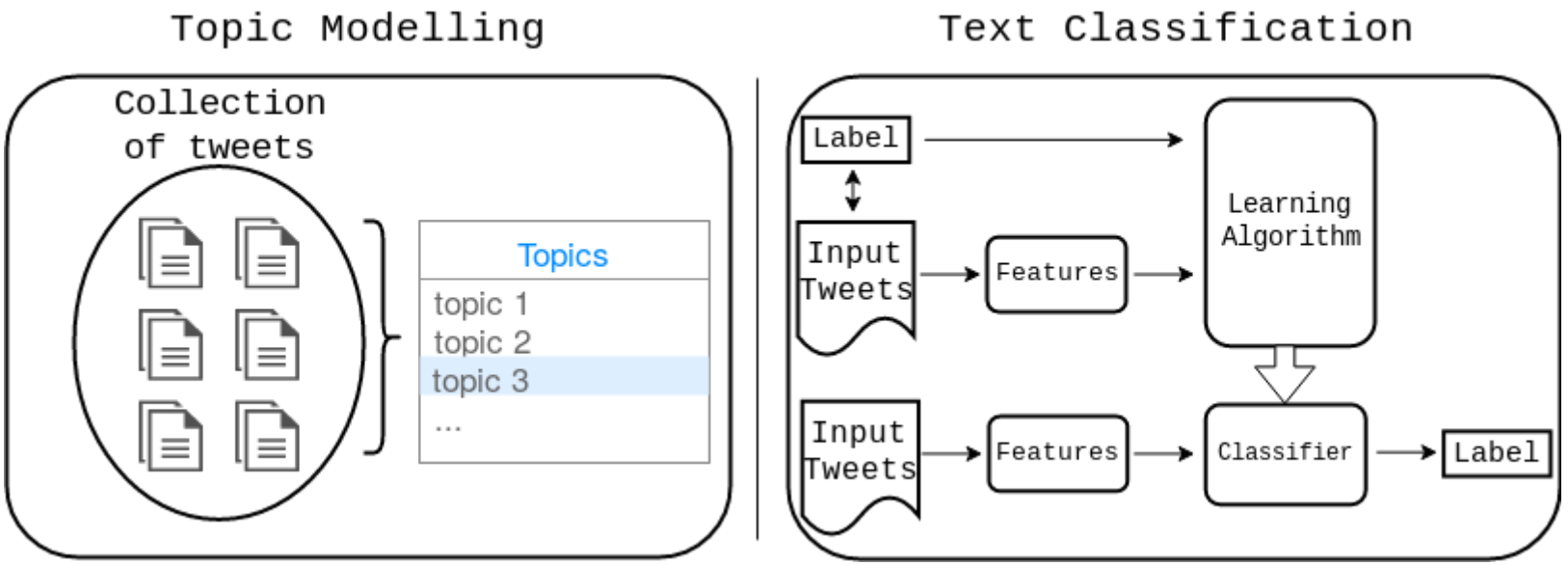
We apply a considerable group of text pre-processing operations to the messages

- Lowercasing
- Lemmatization
- Tokenization
- Transformation of repeated characters
- Punctuation removal
- Cleaning of *metadata* and numerical symbols in the text
- Stop and short words removal

Text Analytics

Two different approaches in the implementation of the text analytics modules:

- Unsupervised approach – Topic Modelling
- Supervised approach – Text Classification



Topic Modelling - Example

Topic 1:

20 most frequent words
paulo, vai, hoje, dia, jogo, ser, melhor, time, vamo, brazil, todo, santo, brasil, gol, cara, aqui, agora, corinthiam, ano, palmeiro, vem

Documents:
382,479 tweets in São Paulo

Topic 1 has the label “Sports and Games”

Topic 2:

20 most frequent words
paulo, brazil, sao, santo, vila, just, parque, posted, photo, shopping, paulista, centro, bernardo, jardim, cidade, avenido, praia, santa, campo, academia

Documents:
86,519 tweets in São Paulo

Topic 2 has the label “Tourism and Places”

Travel-related Classification

What is a travel-related tweet?

- “estou ficando acostumada ver o nascer do sol de **dentro de um ônibus** ou **estação de trem**”
- “**train** is quicker they said , get the **train** they said”

We opt for using a supervised learning approach using a combination of word-embeddings and bag-of-words

This approach required two important tasks:

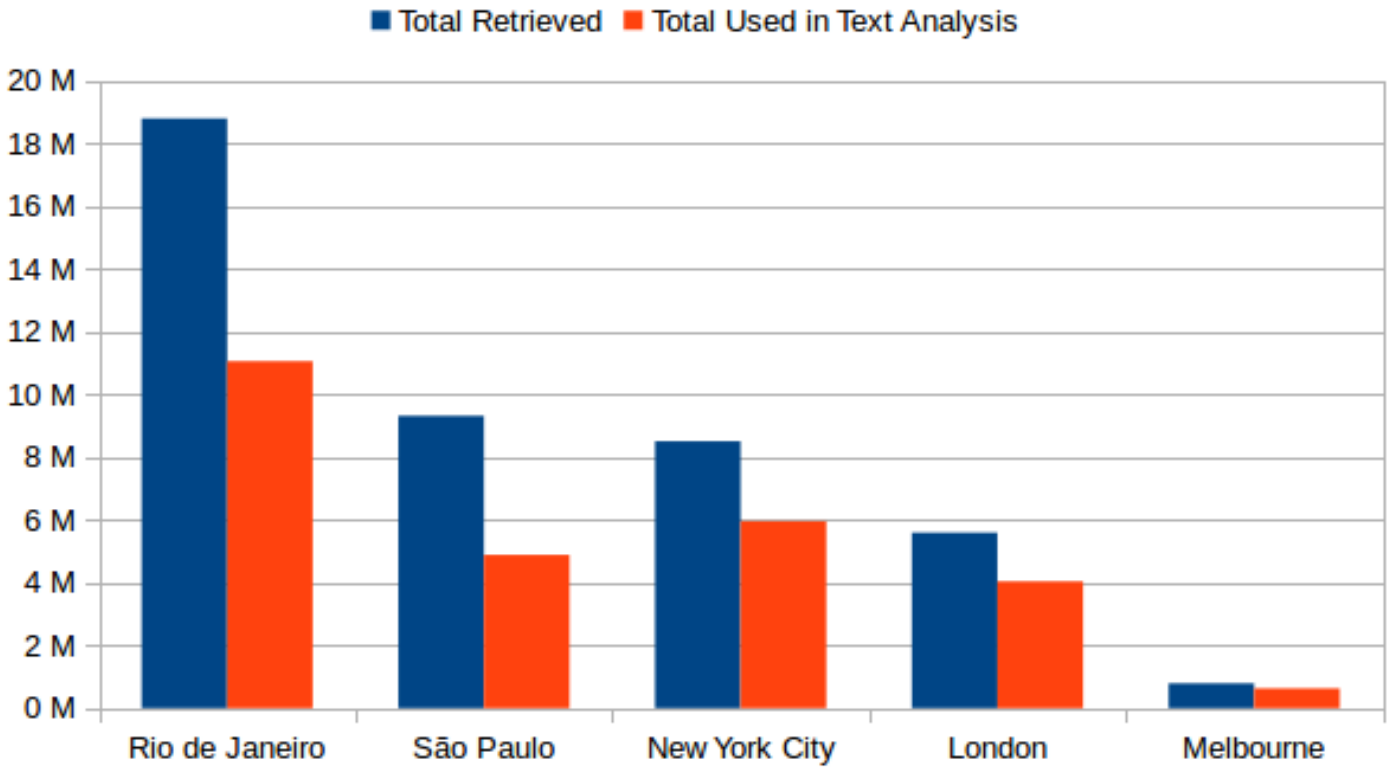
- Features extraction
- Construction of gold-standard datasets due to the lack of travel-related datasets in open-source repositories

Exploratory Data Analysis

We decided to test our framework in 5 cities over the world: **Rio de Janeiro**, **São Paulo**, **New York City**, **London** and **Melbourne**

We collected a total 43 million tweets over 3 months from March 12 to June 12, 2017

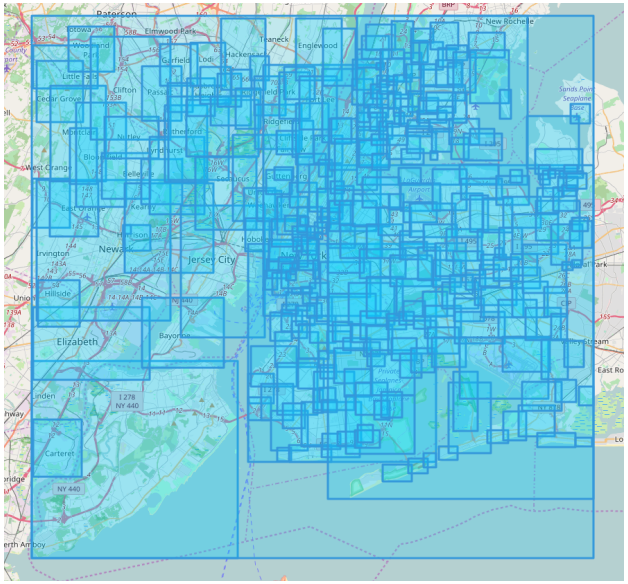
Total volume of tweets collected in each city



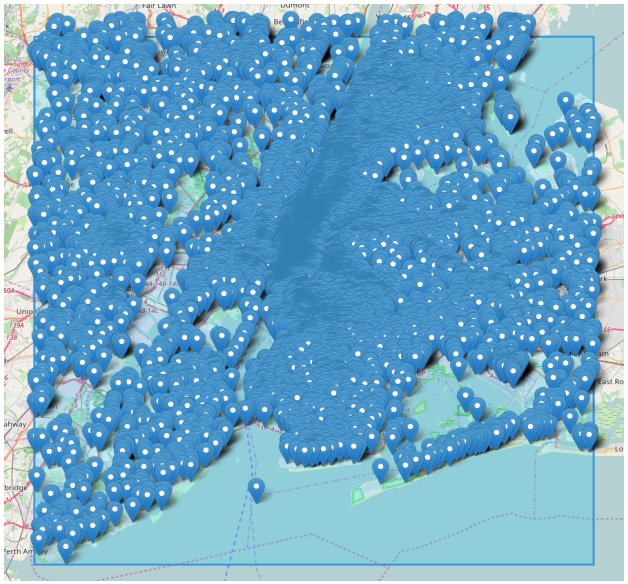
Geographical Statistics

> 70% of geo-located tweets correspond to areas/regions

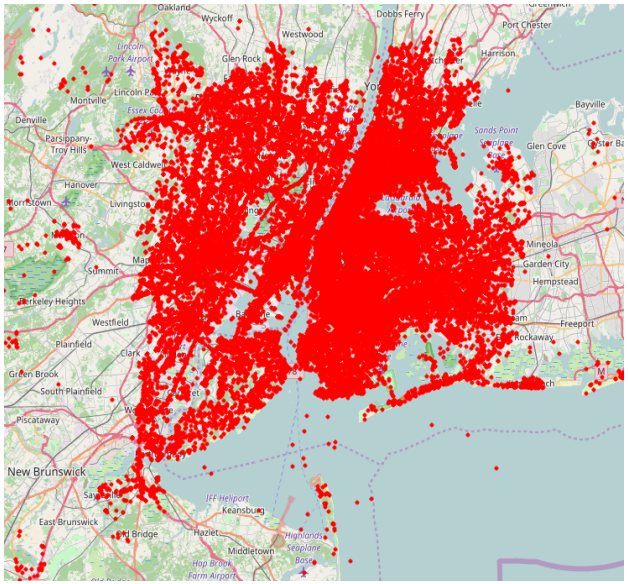
Many studies do not report this fact



Bounding-boxes of variable size



Fixed places

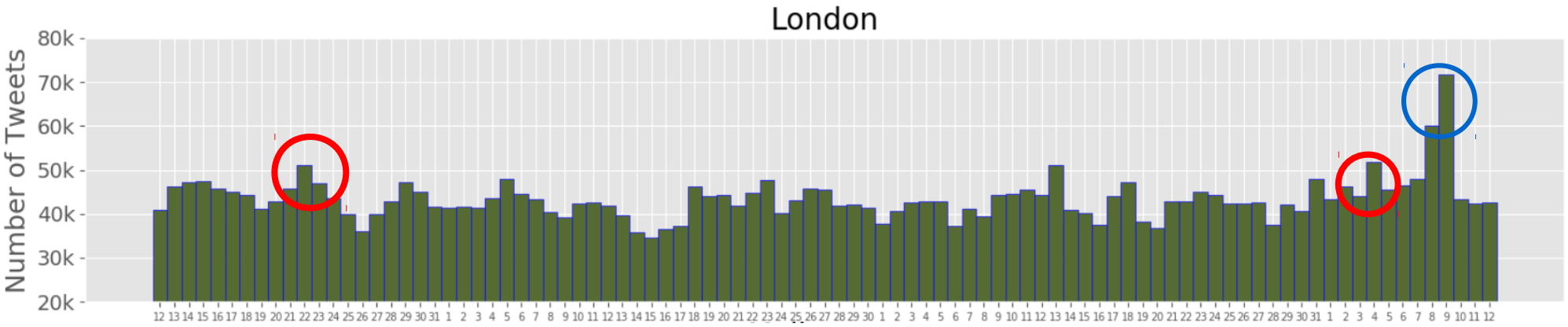


Precise coordinates

Temporal Frequencies

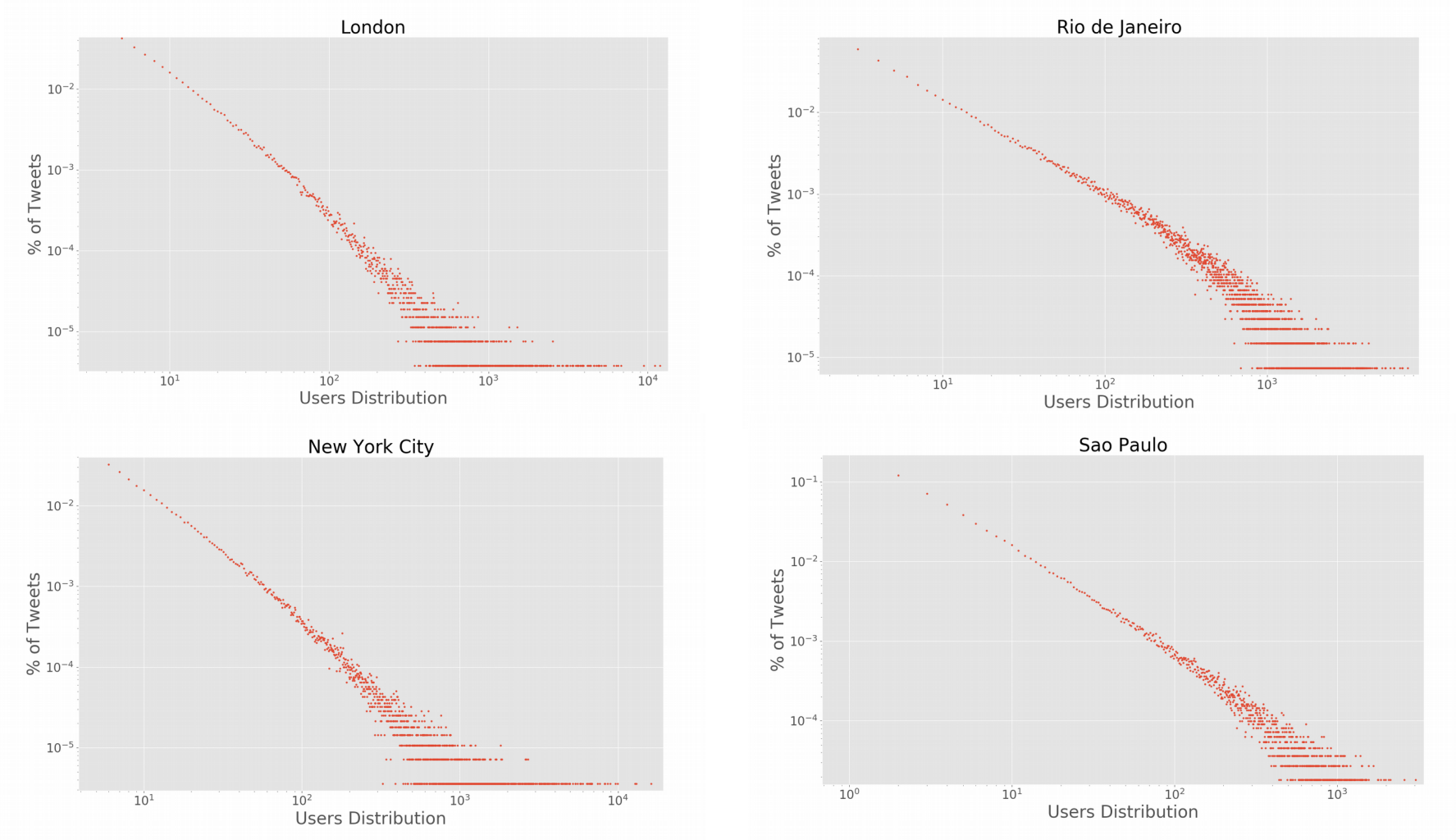
- Daily and hourly distributions of geo-located tweets allow the identification of potential remarkable events

red – Westminster attack and London Bridge attack
blue – UK General Elections 2017



Users Distribution

- User-tweets distributions are similar to a power-law distributions



Topic Modelling in Brazil

6.6M geo-located tweets for Rio de Janeiro and 2.7M geo-located tweets for São Paulo

Text pre-processing operations – all previous mentioned

Features and Model parametrization:

- Train over 20 iterations - Lansley et al. (2016)
- 5, 10, 20, 25, 50 latent topics
- Bag-of-words:
  - Dictionary limited to the 10,000 most frequent words
  - Words beloging to a maximum of 40% of documents
  - Word minimal frequency - 10

Topic Modelling in Brazil

High number of overlap terms between topics – 5, 10, 20 and 25.

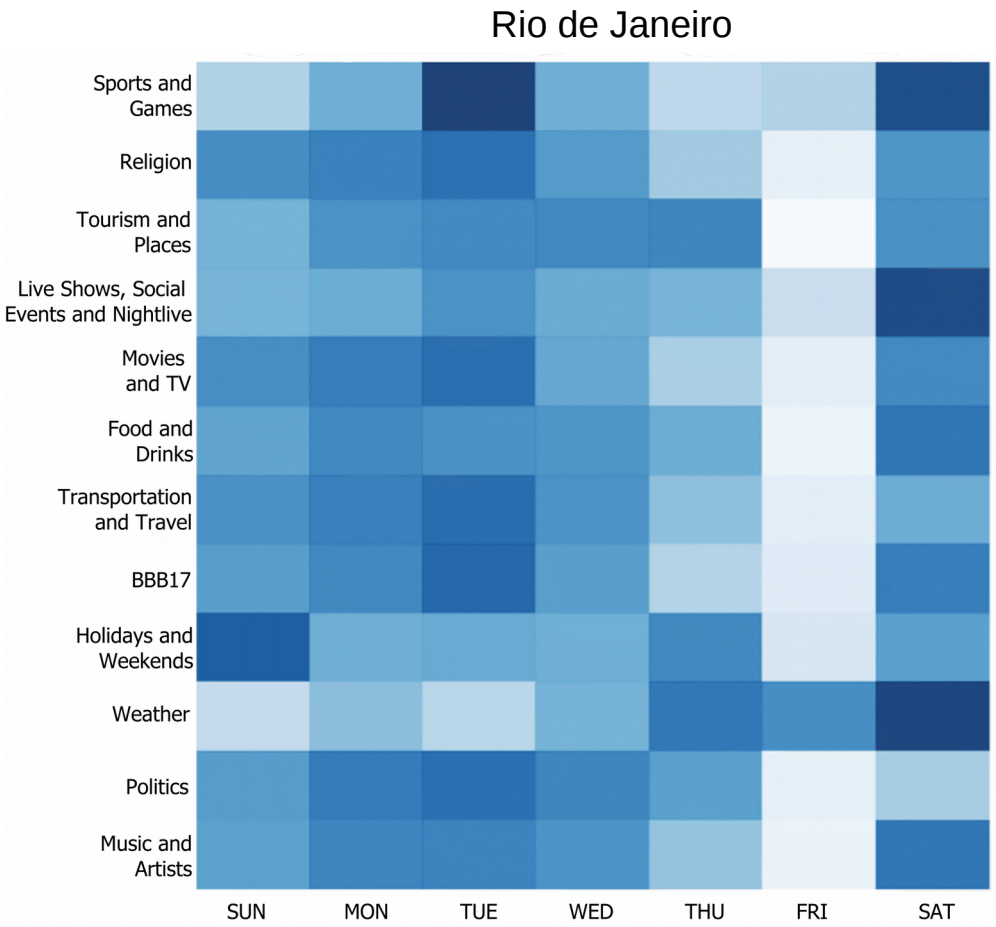
Final experiment model - 50 latent topics

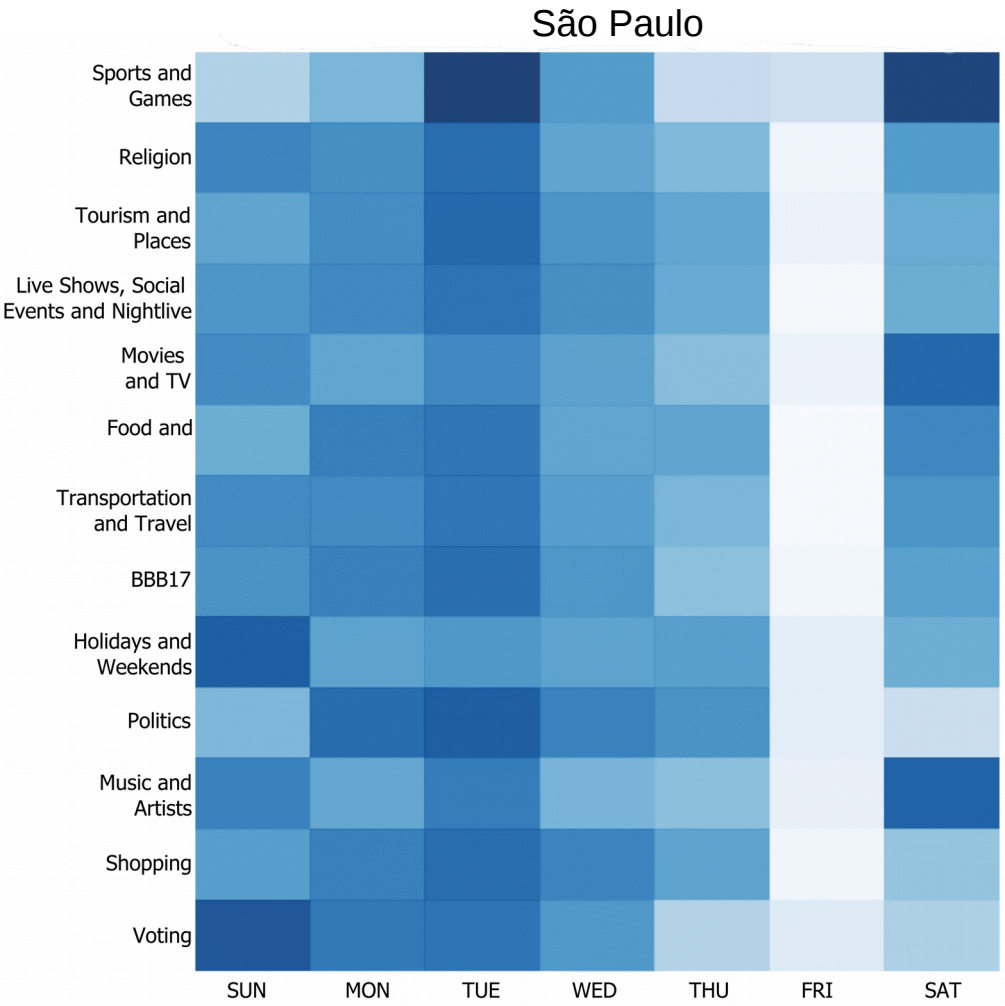
Results:

- Topics labelling using a pre-defined taxonomy - Lansley et al. (2016)
- Such topics were impossible to label according to the taxonomy
  - For instance, “Academic Activities”, “BBB17”, “Relationships and Friendship”
- Overlapping of words between topics -> Topics Aggregation
  - For instance, “European Football *vs* Brazilian Football”
- 29 different topics, in which 2 are unique in each city

Topic Modelling in Brazil

Temporal Distribution of the Latent Topics





Topic Modelling in Brazil

Latent Topics Word Cloud

Travel-related Classification

Features and Models parametrization:

- Bag-of-embeddings:
  - Context window of 2
  - Embeddings of 50, 100 and 200 dimensions
- Bag-of-words:
  - Dictionary limited to the 3,000 most frequent words
  - Words beloging to a maximum of 60% of documents
  - Word minimal frequency – 10
- Combination of both group of features.

Travel-related Classification in Brazil

7.7M geo-located tweets, during a period of 1 month, from March 12 to April 12, 2017

Training and Test datasets:

- Semi-automatic labeling approach
- Queries using terms of Maghrebi et al. (2016)
  - For instance, “carro”, “trem”, “ônibus”
- Balanced training set composed by 2,000 positive and 2,000 negative examples
- Existence of unknown terms in the test dataset
  - For instance, “Busão” and “Uber”
- Test dataset - 71 travel-related tweets and 929 non-related.

Travel-related Classification in Brazil

Results:

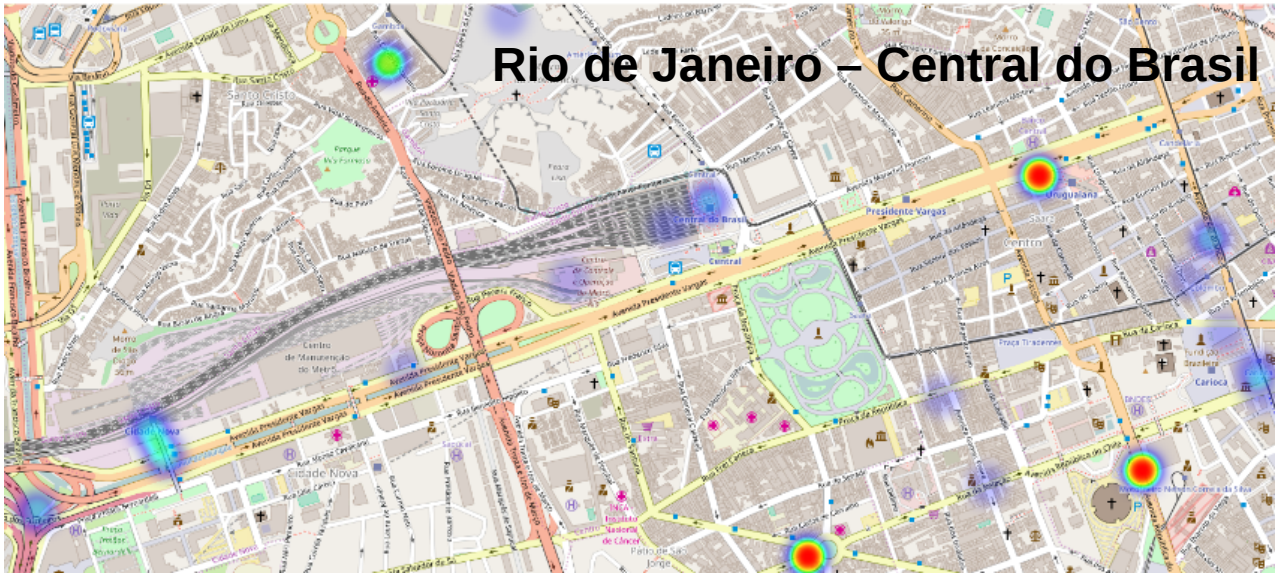
Best model – **Linear SVM**

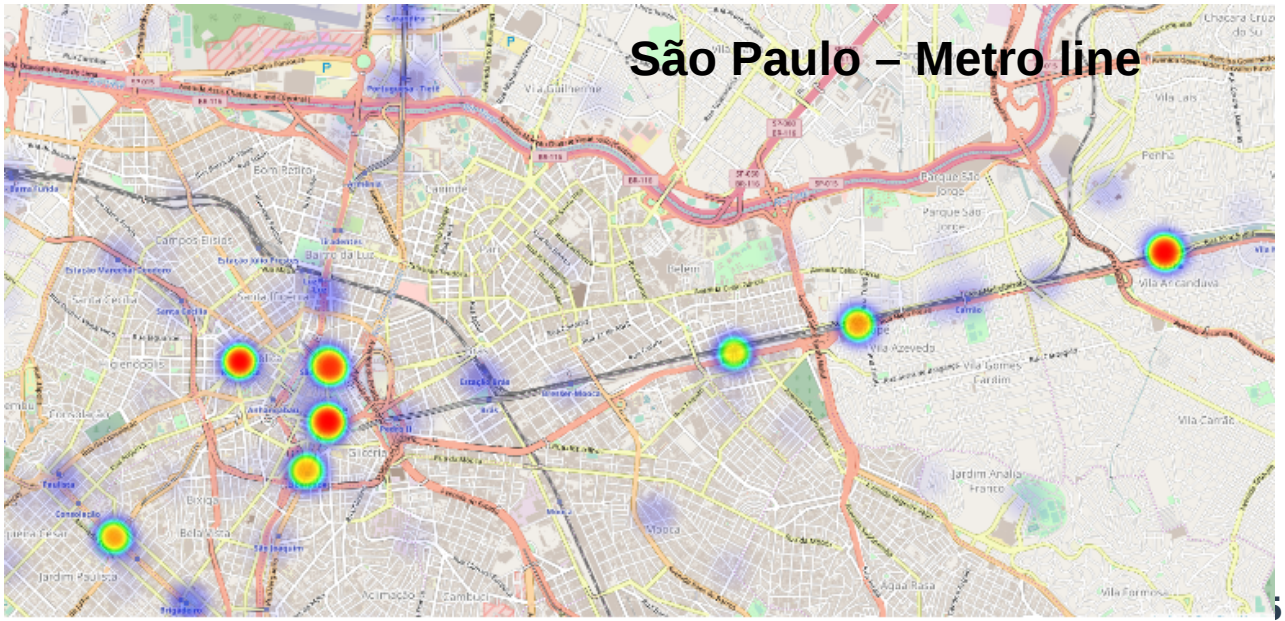
F1-score – **0,8548**

AUC - **0,97**

Group of features - **BoW + BoE (100)**

37,300 travel-related tweets





Travel-related Classification in NYC

4M geo-located tweets in New York City, during a period of 2 months, from March 12 to May 12, 2017

Training and Test datasets:

- Two-phase approach - polysemy of English terms
  - For instance, “walk” and “train”
- Balanced training set composed by 1,686 positive and 1,686 negative examples
- Balanced travel-mode classes in the positive examples
- Inclusion of ambiguous geo-located tweets in the set of negative examples

Travel-related Classification in NYC

Training Strategy:

k-fold cross-validation - 10 iterations

Preliminary Results:

Best Classifier - **Logistic Regression** with **BoE (200) + BoW**

Classifier	Features	F1-score
Linear SVM	BoE (200)	0,87089
	BoW	0,96962
	BoE (200) + BoW	**0,98170**
Logistic Regression	BoE (100)	0,87447
	BoW	0,97222
	BoE (200) + BoW	**0,98324**
Random Forests	BoE (100)	0,82394
	BoW	**0,97764**
	BoE (50) + BoW	0,96701

Bag-of-embeddings do not have the desired impact on this classification

Travel-related Classification in NYC

***Leave-one-group-out* strategy:**

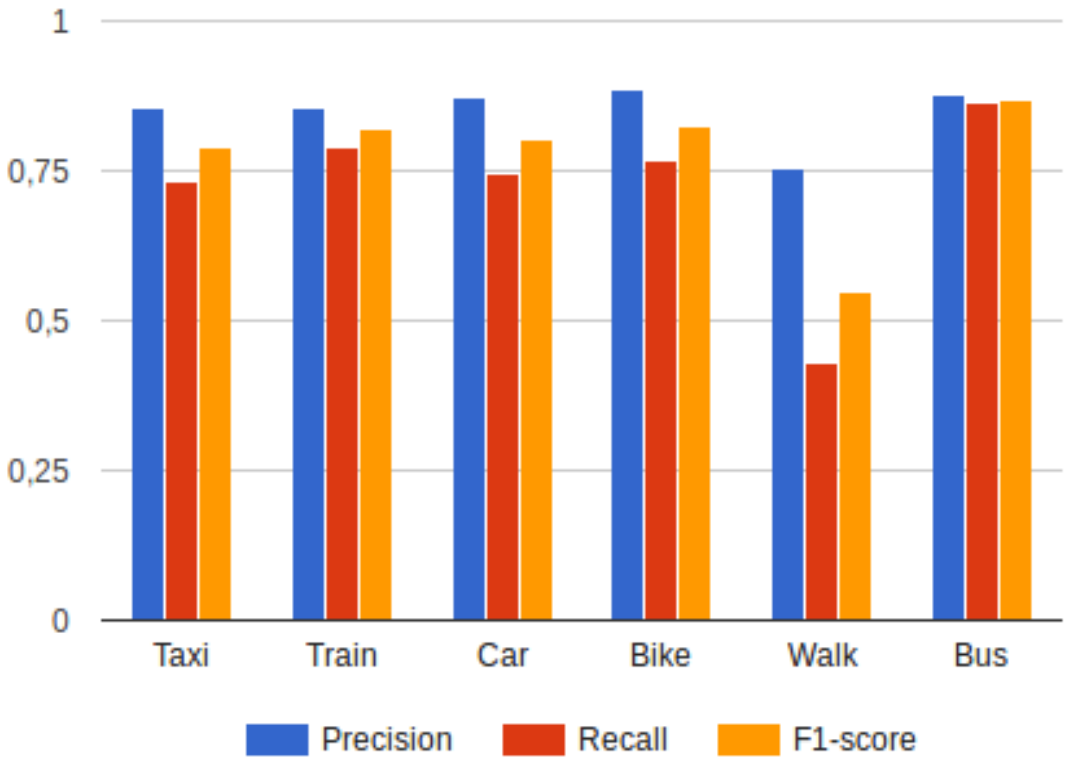
- Hiding one travel-mode class at a time from the training
- Compare classifiers using BoW and BoE features separately
- 10-fold cross-validation

Classifier	Features	Mean F1-score
Random Forests	BoW	0,12629
	BoE (50)	**0,78447**
Logistic Regression	BoW	0,12629
	BoE (50)	**0,80219**
Linear SVM	BoW	0,12203
	BoE (200)	**0,81289**

Travel-related Classification in NYC

***Leave-one-group-out* strategy:**

- Results of the classifier for each of the hidden classes using embeddings of 200 dimensions



Conclusions

Main Results

1. Continuous collection of geo-located tweets from multiple bounding-boxes in parallel and in compliance with Twitter API usage limits
2. Tackling of the Twitter Streaming API inconsistencies and filtering noisy tweets
3. Implementation standard text pre-processing methods for social media texts
4. Content analysis using topic modeling and comparative characterization among different bounding boxes (e.g. cities)
5. Travel-related classification of tweets using supervised learning
6. Word embeddings from geo-located tweets
7. Study the impact of word embeddings in travel-related classification
8. Creation of gold-standard data for travel-related supervised learning
9. Aggregation and visualization of results

Contributions

A) Technical Contributions

i) Design and implementation of a framework in Python to collect geo-located tweets

ii) The framework allows the monitoring of multiple bounding-boxes (cities and regions)

B) Applicational Contributions

i) First large scale study with respect to topic modelling and geo-located tweets in Brazil

ii) Application of word embeddings to text classification tasks in the context of smart cities and ITS

C) Scientific Contributions

i) Empirical studies on the applicability of word embeddings in travel-related text classification

ii) Creation of novel resources for the research community on Smart Cities and ITS

Publications

i. Transportation in Social Media: an automatic classifier for travel-related tweets. In *Portuguese Conference on Artificial Intelligence (EPIA)*, 2017. Published.

ii. Classifying Travel-related Tweets Using Word Embeddings. In *IEEE 20th International Conference on Intelligent Transportation Systems (IEEE ITSC)*, 2017. Under review.

iii. Characterizing Geo-located Tweets in Brazilian Megacities. In *IEEE Third International Smart Cities Conference (IEEE ISC2)*, 2017. Under review.

Future Work

1. Extend text analytics experiments to all cities
2. Intrinsic evaluation of word embeddings trained from geo-located tweets
3. Aspect-based sentiment analysis
4. Train travel-related classifier with deep neural networks
5. Multi-class classification of travel modes
6. Correlation analysis of social-media-based activities and official traffic data

References

- David M Blei, Andrew Y Ng, and Michael I Jordan. Latent dirichlet allocation. *Journal of machine Learning research*, 3(Jan):993–1022, 2003.
- Tomas Mikolov, Wen-tau Yih, and Geoffrey Zweig. Linguistic regularities in continuous space word representations. In *Hlt-naacl, volume 13*, 2013.
- Quoc Le and Tomas Mikolov. Distributed representations of sentences and documents. In *Proceedings of the 31st International Conference on Machine Learning (ICML-14)*, pages 1188–1196, 2014.
- Guy Lansley and Paul A Longley. The geography of twitter topics in London. *Computers, Environment and Urban Systems*, 58:85–96, 2016.
- Tsvi Kuflik, Einat Minkov, Silvio Nocera, Susan Grant-Muller, Ayelet Gal-Tzur, and Itay Shoor. Automating a framework to extract and analyse transport related social media content: The potential and the challenges. *Transportation Research Part C: Emerging Technologies*, 77:275–291, 2017.
- Mojtaba Maghrebi, Alireza Abbasi, and S Travis Waller. Transportation application of social media: Travel mode extraction. In *Intelligent Transportation Systems (ITSC)*, 2016 IEEE 19th International Conference on, pages 1648–1653. IEEE, 2016.

Social Media Text Processing and Semantic Analysis for Smart Cities

Thank you

Framework

The framework may contemplate the following requirements:

a) Collection of multiple bounding-boxes (cities, regions or countries)

b) Flexibility

c) Scalability

d) Almost real time

Database

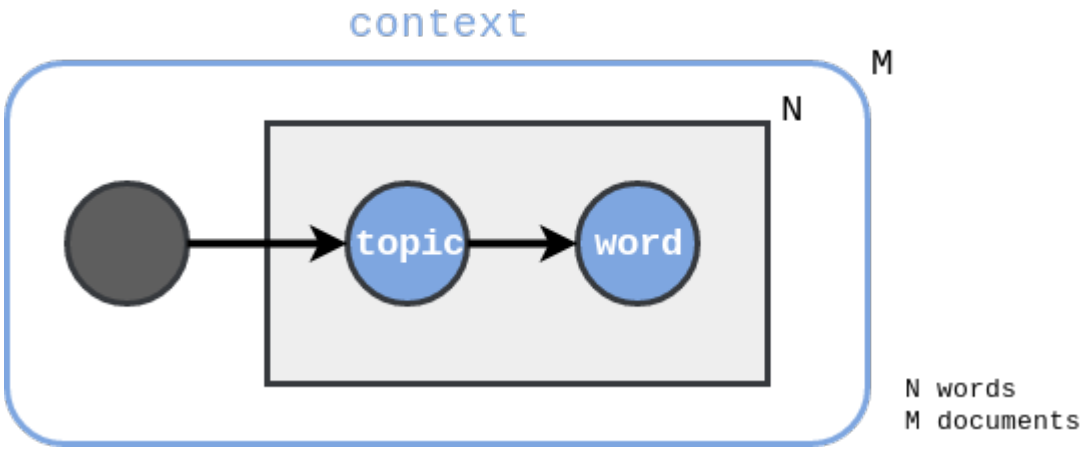
- Tweets are retrieved in JSON-like format;

- MongoDB is a NoSQL software to store collections/schemas of this data format;
- The overwhelming amount of tweets makes conventional querying operations to perform poorly;
- On the contrary, MongoDB has high performance regarding the querying system.
- Nonetheless, this software allows easier and quickly deployment and scalability.

Topic Modelling

Latent Dirichlet Allocation (LDA) - Blei et al. [1]

- Generative probabilistic model;
- Aims to find the latent topics present in a collection of documents;
- Two distinct distributions:
  - Distribution of words over topics;
  - Distribution of topics over documents.
- We use the Python's LDA library to implement this text analytics module.



Bag-of-words

Bag-of-words (BoW)

Majority of studies focus on conventional techniques

Frequency-term based text representation

Dictionary size and words belonging to documents can be limited

Messages

(1) I was in an uber yesterday.

(2) You like donuts.

Bag-of-words Representation

(1)	1	1	1	1	1	1	0	0	0
(2)	0	0	0	0	0	0	1	1	1

Dictionary

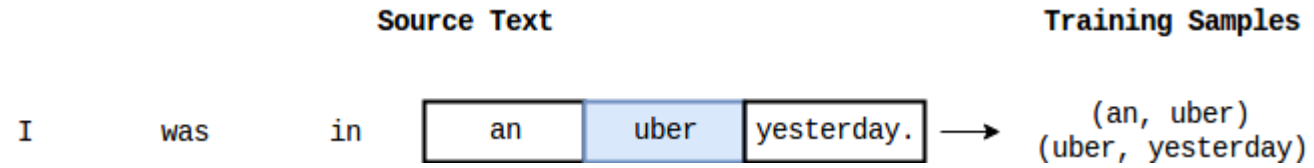
```
[
      "I",
    "was",
     "in",
     "an",
   "uber",
"yesterday",
    "You",
   "like",
  "donuts"
]
```

Word Embeddings

Word Embeddings

- Continuous representation of text into multi-dimensional vectors
  - *Words or phrases* are mapped to vectors of real numbers;
- Model uses:
  - Neural network
  - Context in which the word appears (surronding words, i.e. words behind and ahead)

Word Embeddings - The Fake Task



Learning of statistics from the number of times each pairing shows up.

Word Embeddings Libraries

- ***Word2vec* – Mikolov et al. (2013)**
  - Input of a collection of pre-processed tweets
  - Training of word embeddings is automatic
  - The model outputs the matrix of weights for each word in the dictionary
- ***Paragraph2vec*, a.k.a. *doc2vec* – Le and Mikolov (2014)**
  - Similar to *word2vec*
  - Each document has a label passed into the embeddings matrix
  - Labels -> tweets *ids*
- **Gensim is a Python library which has both embeddings' models**

Aggregation and Visualization

Aggregation

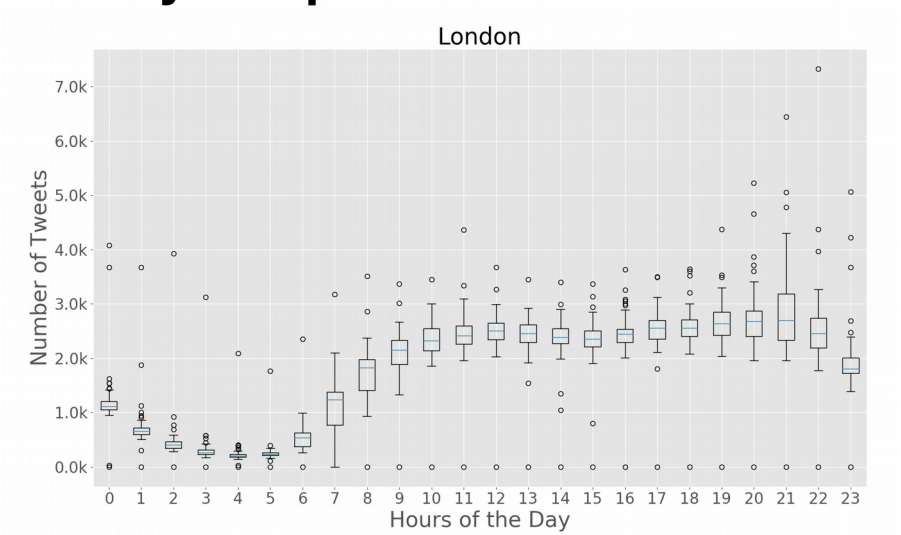
- MongoDB provides inner frameworks that allow aggregation of data
- These aggregation operations are easier and quickly because they are performed using a map-reduce paradigm
- Aggregation of results are made periodically

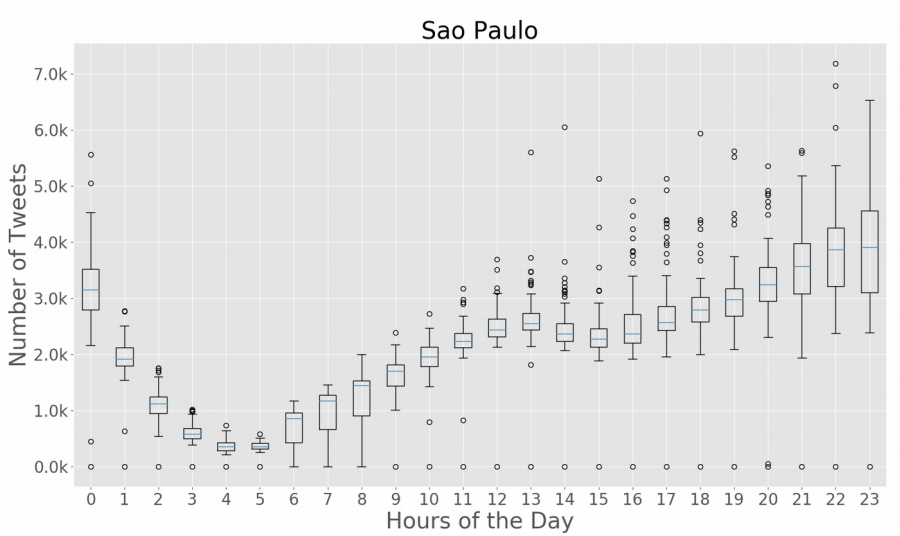
Visualization

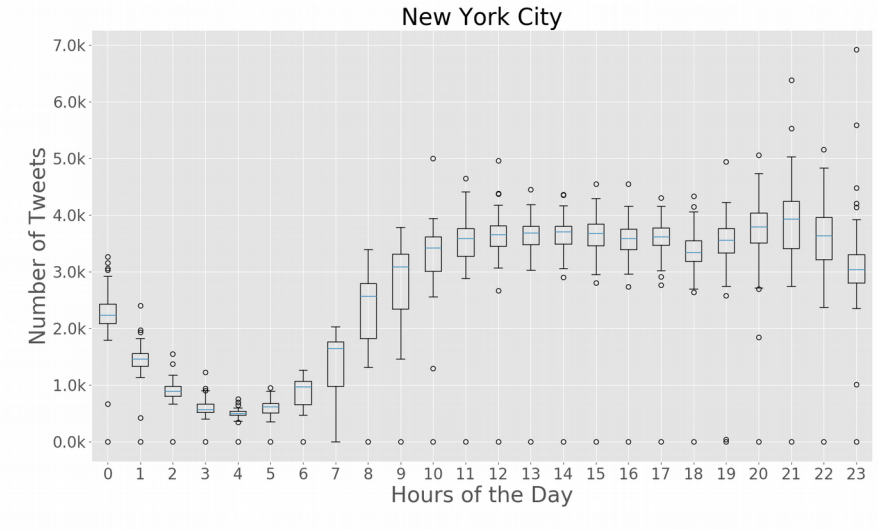
- Plotly is a Python library to produce graphical visualizations of data
- The library allows local storage of these visualizations in HTML files
- By exploring the embedding functionality of HTML5 we can demonstrate on-time visualizations

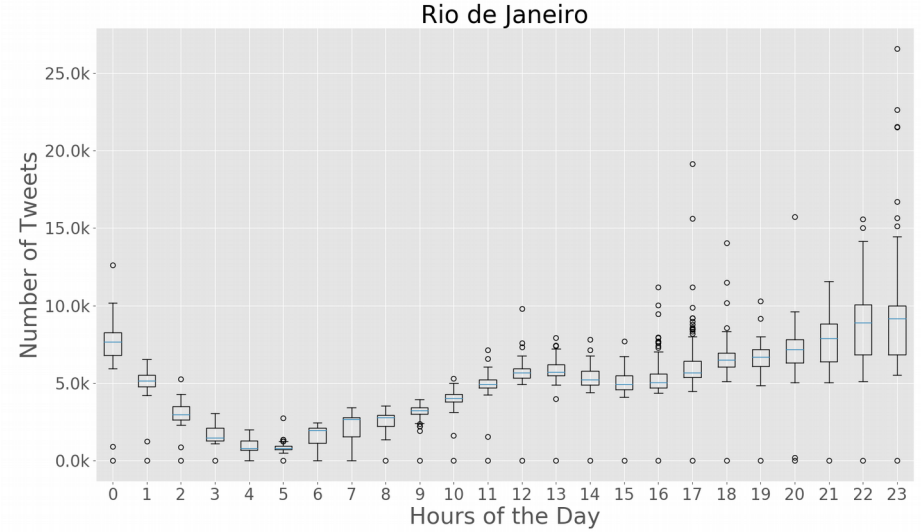
Temporal Frequencies

Hourly Frequencies





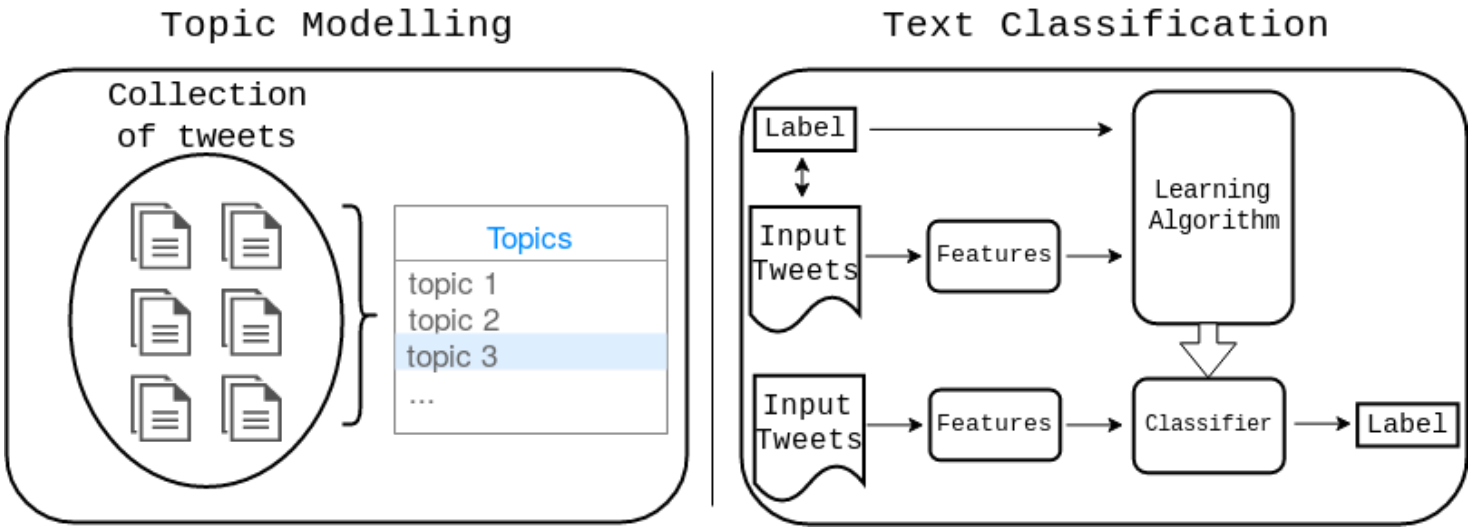




Text Analytics Experiments

Three experiments to text analysis

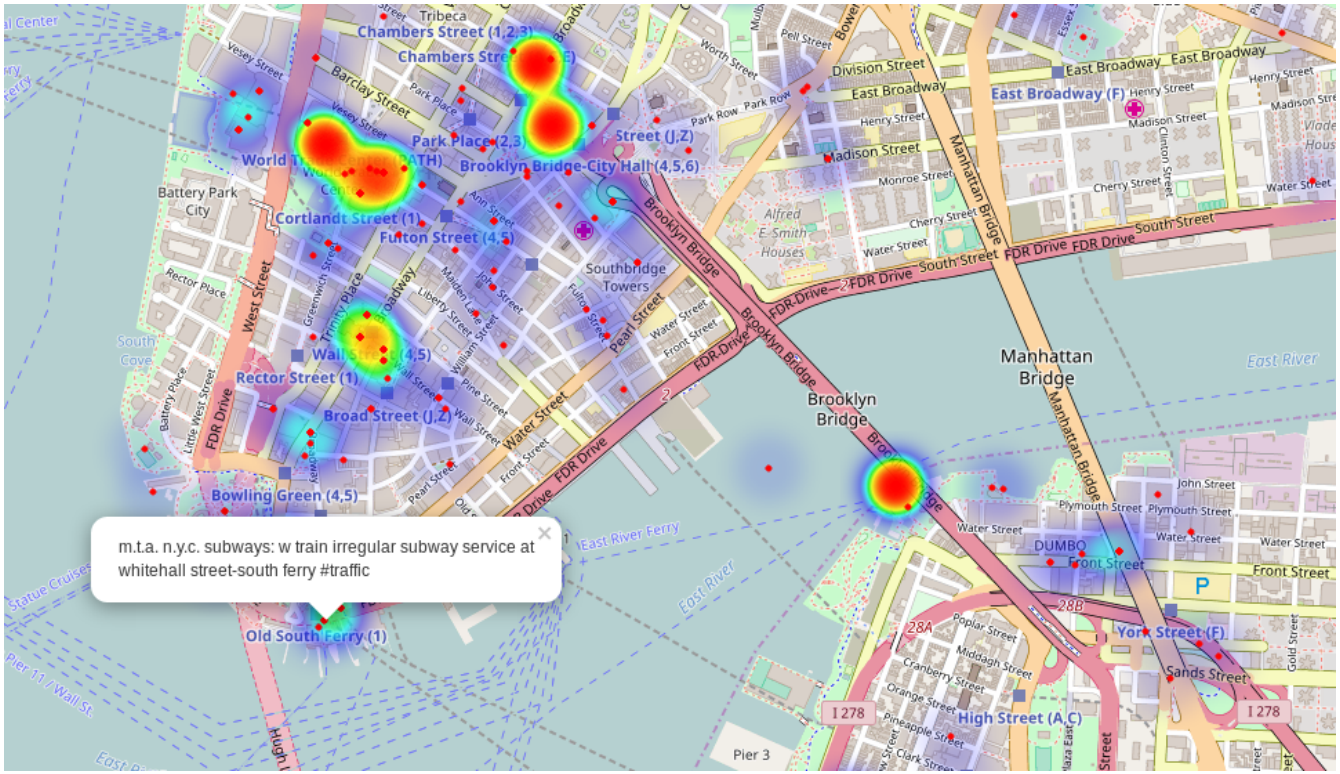
- Topic Modelling over Rio de Janeiro and São Paulo;
- Travel-related classification over Rio de Janeiro and São Paulo;
- Travel-related classification over New York City.



Travel-related Classification in NYC

Final model

- BoE with 200 dimensions
- Trained with all travel-mode classes together
- Dataset prediction, 300,000 travel-related tweets



South of Manhattan and over look at the Brooklyn Bridge.