Geographic information, texts and social media

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Plan of the talk

❖ Social Media and Geographic Information
❖ Extracting Geographic Information from Tweets
❖ An application in the Disaster Management domain
Social Media

❖ Key aspects:
  ❖ **Wide coverage** and continuously growing
  ❖ Temporally and **spatially** aware
  ❖ Allow for mining social behaviour, opinions, tendencies
  ❖ Metaphor: users as “active sensors” in an online environment
  ❖ Ubiquitous crowdsourcing, participatory sensor networks (Silva et al., 2013, Zhao et al., 2007)
Social Media as Sensor Networks

- Social Networks can therefore be viewed as sources of data about the physical world, with millions of users reporting about “what’s happening” around them

- Something that is happening = event

- Main application: event detection or discovery
  - Planned events such as cultural or sport events;
  - But also and especially: unplanned events such as demonstrations, crimes, accidents, natural disasters, etc.
Examples

- Tweet-SCAN (Capdevila et al., 2016) uses Twitter to discover events in the city of Barcelona.

- (Oostdijk et al., 2016) used Twitter to detect traffic incidences in the Netherlands.

- (Sakaki et al., 2010) used Twitter data to estimate earthquakes location.

- (Santos et al., 2017) used Instagram data to detect events in Manhattan.
Social Media and Geographic Information

- Localizing sensors (i.e. users) is critical

- How people tell their position?
  - **Exact location** (GPS coordinates) linked to the posted content (image, text)
  - **Place mention** (toponym) - only if text is admitted as content
  - **Origin** of user (profile information) - can be both an exact location or a place mention
Exact location

- Pro: best geolocalization
- Con:
  - Not all Social Media support it
    - At least Foursquare, Instagram and Twitter have support for geo-tagged content
  - GPS may be disabled on mobile devices for various reasons:
    - Privacy issues
    - Battery duration
  - Bad or no GPS signal; location not updated (resulting in an incorrect or imprecise geo-tag)
  - Geo-tagged content is less than 1% (Gonzalez et al., 2012) of all the published content
Place mention

Pro: widely used

(Hoang and Mothe, 2017): between 8.8% and 17.6% in various Twitter datasets

Microposts NEEL Challenge\(^1\): 20.79% of tweets had a Location marker

Con:

Potentially ambiguous

Toponym vs. non-toponym: ex. la Gave (de Pau) vs. gave (past form of the English verb to give)

Strictly geographic ambiguity: ex. Cambridge, UK vs. Cambridge, USA

Street names

Imprecise

Non-standard formatting: abbreviations, hashtags, etc. (BCN, #paris, #nuitblancheparis )

\(^1\) [http://microposts2016.seas.upenn.edu/challenge.html](http://microposts2016.seas.upenn.edu/challenge.html)
User origin

- **Pro:** even more widely used

- **Con:**
  - Highly imprecise
  - Users are moving
  - Users may talk about an event that they’re not involved in (but this may occur also with automated geo-tagging using GPS coordinates)
  - If specified in a textual way, same problems with toponyms
Extracting Geographic Information from Tweets
Geo-tagging Tweets

- Twitter is one of most popular social media, not only from the point of view of users but also from researchers
  - Rich context, relatively easy to analyze (text)
- But (as said before) geo-tagged content is extremely rare in Twitter
- In order to improve the effectiveness of any geographically-aware application based on Twitter, we need to geo-tag more data
Detecting placename mentions

Sub-task of Named Entity Recognition task

Wide-coverage NER tools: LingPipe, Stanford NER, GATE, etc. (Co-NLL accuracy ~90%)

However: not as accurate as on other categories of names (accuracy on GeoClef ~55%)

Problem: Inter-class ambiguity

Washington, president or place? (PER vs. LOC)

In Twitter: additional problem (hashtag, abbreviations, noisy text)
Detecting placename mentions

- Standard NER tools fail on Tweets
  - (Gelernter, 2011) studied the performance of the Stanford NER on a set of tweets related to the Christchurch earthquake, finding an accuracy of 34.4%
- (Ritter et al., 2011) introduced a NER tool specifically designed for tweets
  - https://github.com/aritter/twitter_nlp
- Most solutions try to normalize hashtags and abbreviations, exploiting clues in the text or external knowledge
  - For instance: #ParisFashionWeek -> Paris fashion week
  - CDMX -> Ciudad de México
Resolving place names

- Being able to detect mentions of places is not enough
- The toponyms may be ambiguous
- Resolving a toponym: to assign to a toponym the right referent, selected among a set of places with the same name
  - This allows to assign geographical coordinates
  - Key for the NLP – GIS bridge
- The ambiguity of a toponym depends on the world knowledge that a system has
Dealing with ambiguity

Factors that modify the risk of ambiguity:

- Geographical scope of an application: if the application is monitoring a small region, the less the risk of ambiguity

- Detail of the resource used as inventory of placenames:
  - OpenStreetMap > GeoNames > (Wiki | DB)pedia
Talking resources...

- OpenStreetMap has also polygons
- GeoNames provides only the center coordinates
- Quattroshapes has boundaries for various administrative regions, with GeoNames IDs

http://quattroshapes.com/#preview
Ambiguity and Frequency

- Most frequent toponyms tend to be less ambiguous than those rarely used
- Street names are particularly ambiguous

Probability of finding an ambiguous toponym at Frequency F

\[ P(F) = \frac{|T_{amb,F}|}{|T_F|} \]

(Buscaldi and Magnini, 2010)
Resolving toponym ambiguity (from GIR)

Existing methods can be subdivided into three broad categories:

- **Map-based**
  - They need geographical coordinates

- **Knowledge-based**
  - They need resources providing clues for the disambiguation

- **Data-driven** or supervised
  - They need a large enough set of labelled data
  - Many names occurring only once (impossible to estimate their probabilities)
Exploiting geographical context

The right referent is the one with minimum average distance (geographical or conceptual) from the context locations.

“One hundred years ago there existed in England the Association for the Promotion of the Unity of Christendom. ... A Birmingham newspaper printed in a column for children an article entitled "The True Story of Guy Fawkes," ... An Anglican clergyman in Oxford sadly but frankly acknowledged to me that this is true. ... A notable example of this was the discussion of Christian unity by the Catholic Archbishop of Liverpool, ...”
The “Steinberg hypothesis”

- These methods cannot be applied in Twitter because of the lack of context toponyms.
- Among all the tweets containing a toponym in Microposts 2016 collection, 68.8% contained just only one toponym.
- (Overell, 2009) formulated the Steinberg hypothesis (based on the famous New Yorker drawing by Steinberg):
Testing the Steinberg hypothesis

- Number of mentions wrt distances from Trento of places in the Trento newspaper “L’Adige” (Buscaldi and Magnini, 2010)
Resolving toponym ambiguity in Tweets

- The “Steinberg hypothesis” may help in disambiguating toponyms in Tweets
- Need to take into account additional context:
  - Mention of places in the history of the user
  - User origin
  - Size of places
- (Zhang and Gelernter, 2014) found the following best features:
  - Population of place in gazetteer entry.
  - Number of alternative names within an entry, and among matching entries.
  - Other location expressions mentioned in the tweet
Geo-tagging without place names

- Technique introduced by (Paraskevopoulos and Palpanas, 2015)
- Idea: use tweets that are geo-tagged with precise coordinates to build a signature corresponding to an event taking place at the same coordinates
- Tweets that are not geo-tagged but have words contained in a signature derived from geo-tagged data are tagged with the same location
- Ideal for narrow, focused scope

**INPUT:** A training set of timestamped and geotagged tweets, a timestamped query-tweet ($Q_t$) that is not geotagged.

**OUTPUT:** The most eligible candidate location.

```
1: for all $i \in \{\text{candidate geolocations: Geolocs}\}$ do
2:     for all $t \in \{\text{time intervals}\}$ do
3:         $Doc_{it} \leftarrow$ all tweets in location $i$ at time interval $t$
4:         $kwVector_{it} \leftarrow$ create vector of $Doc_{it}$ keywords and their weights
5:         $kwVector_{Qt} \leftarrow$ create vector of $Q_t$ keywords and their weights
6:         $location \leftarrow \text{argmax}_{i \in \text{Geolocs}} \{\text{similarity between } kwVector_{it} \text{ and } kwVector_{Qt}\}$
7:     return $location$
```

- process training dataset, for all locations
- and for all time intervals
- process non-geotagged tweet $Q_t$
- identify location of tweet $Q_t$
An application in the disaster management domain
Not only event detection

- Many applications that exploit the spatial data are focused exclusively on the detection of ongoing events.
- Tweets provide more context that is worth to be analyzed.
  - Going beyond counting the number of tweets in a certain place.
- Applying NLP techniques such as sentiment analysis to geo-tagged data has many potential interesting applications.
Social Media and Disaster Management

HURRICANE SANDY

At its peak, Instagram users uploaded Sandy-related photos at a rate of:

TEN every SECOND

Facebook mentions of "Hurricane Sandy" and "Frankenstorm" increased by 1,000,000%

Top 5 Shared Terms on Facebook:

1. we are ok
2. power
3. damage
4. hope everyone is ok
5. trees

FEMA tweeted to its Twitter followers:
"Phone lines may be congested during/after #Sandy. Let loved ones know you’re OK by sending a text or updating your social networks."

23 RED CROSS STAFFERS monitored 2.5 MILLION Sandy-related social media postings

4,500 They tagged 4,500 of them for officials to follow up on, providing aid for those in need

http://mashable.com/2013/05/21/social-media-disaster-response/IKxYUNzazgq0
Social Media and Disaster Management

Question: are we able to select tweets that are related to “interesting” categories (such as help requests) and filter out the “noisy” categories (sarcasm, etc.)?

From: Parsons et al., Thematically Analysing Social Network Content During Disasters Through the Lens of the Disaster Management Lifecycle
Case Study: the 2014 Genoa flood

Total annotations:
8922 subj
499 pos
3519 neg
1019 iro
6033 users

Problem: evaluation
Evaluating subjectivity accuracy

- Manual annotation of 75 sources
  - News (59.2%)
    - @ScoopSquareGE,
      - @MeteoWeb_eu,
      - @infoitinterno, @ITnewsGE,
      - @TopTrendIT…
  - Personal accounts (40.8%)
    - @Miti_Viglieri, @mauneobux,
      - @LaRouge_DOC, …
Indirect evaluation - relevant items

- Subset of relevant **hashtags**, **toponyms** and **topics**:
  - #allertameteo, #protezionecivile, #alluviononege, ...
  - Montoggio, Sturla, Fereggiano, ...
  - “Ondata di piena”, “Invaso dal fango”, “esonda ...”
Indirect evaluation - relevant items

- acqua, deraglia un freccia
- allagamenti e paura
- allerta massima
- allerta meteo
- alluvione in corso
- croce rossa
- crolla muraglione
- danni enormi
- danni ingenti
- deraglia un treno
- emanata allerta
- esce dai binari
- esonda il bisagno
- esonda lo scrivia
- esondano i fiumi
- esondano il bisagno
- esondano i torrenti
- esonda un torrente
- evacuate 16 famiglie
- fa paura
- frana improvvisa
- ho paura
- invaso dal fango
- livello di allerta
- mancato allarme
- meteo da allerta
- momenti di ansia
- morto e dispersi
- morto e gravi
- morto foto
- nuova alluvione
- nuovo alluvione
- ondata di piena
- piani alti
- prestare massima attenzione
- protezione civile
- rubano nei negozi
- sciacalli in azione
- situazione critica
- situazione drammatica
- tanta paura
- trascinate da acqua
- trascinate dall'acqua
- travolge auto
- trovato il corpo
- usate l'auto
- uscite di casa
- uscite da casa

- #allerta2
- #allertameo
- #allertameo2
geneva
- #allertameog
- #allertameolig
- #alluvione
- #alluvionege
- #angelidelfango
- #arpal
- #bisagno
- #busalla
- #campoligure
- #chiaravagna
- #crocerossa
- #emergenza24
- #emergenze

- #entella
- #feregiano
- #forzagenovarisorgidalfango
- #genovaalluvione
- #iononrischio
- #maltempo
- #molassana
- #montoggio
- #noncefangochetenga
- #ovada
- #polcevera
- #protezionecivile
- #stura
- #voltri
Detecting trending items

- Extraction of trending* (hashtags | toponyms | topics) for each hour

\[ Pr(X = k) = \frac{\lambda^k e^{-\lambda}}{k!} > \epsilon \]

- The key is to model \( \lambda \) to capture the expected frequency of an item

- With enough data, it is possible to model the frequency over the same period (week, hour, etc.) of the year

- In our test, the threshold \( \epsilon \) was set to 0

- \( \lambda \) was set to the estimated frequency during the previous hour
Indirect evaluation

- plot precision (# relevant trending / # trending)

**Precision**

![Graph showing precision over time]

<table>
<thead>
<tr>
<th>Hashtags</th>
<th>Toponyms</th>
<th>Topics</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>0.160</td>
<td>1.000</td>
</tr>
<tr>
<td>Subj</td>
<td>0.197</td>
<td>0.875</td>
</tr>
<tr>
<td>Neg</td>
<td>0.254</td>
<td>0.625</td>
</tr>
<tr>
<td>Pos</td>
<td>0.208</td>
<td>0.188</td>
</tr>
<tr>
<td>Iro</td>
<td>0.322</td>
<td>0.313</td>
</tr>
</tbody>
</table>

Mean Average Precision
Qualitative analysis

- Most of the positive tweets (82 out of 493 - ~16%) came from the same account (spam?):
  

- Many false positives for irony but also some good answers: “Ragazzi tranquilli #Renzi ha detto che non ci lascerà soli”

- Negative tweets may convey different emotions:
  
  - Fear: “Basta guardare fuori per avere paura”
  - Rage: "In tre anni non è stato fatto nulla, amministrazioni delinquenti”
  - Sadness: "Mi viene da piangere”

- Some features may change polarity (meaning) depending on the context:
  
  - “Coraggio Genova!!!” vs. “Salite ai piani alti!!!”
  - “Speriamo bene” vs. “Stiamo bene”
Geographical aspects

The narrow scope of the study limited also the ambiguity of the involved toponyms.

Only 13 toponyms in the collection, all with only one possible referent.

In most cases they were written correctly, with the only problems related to the use of hashtags and incorrect capitalization.

Less than 190 tweets were geo-tagged (GPS coordinates).
Future plans: project NaDiA

Zone to be monitored

Extracting related flux

Meteorological alert

Signalling relevant situations
Seine dataset

We collected 45,831 tweets related to the spring 2016 flood in France (annotating…)

- <tweet id="736542320611446784" authorid="@rdvavecdamenat" time="2016-May-28 14:59" loc="Mirebeau, France">ça va être costaud les orages cette après-midi sur le Poitou fort risque d’inondations locales à prévoir #Vienne86</tweet>

- <tweet id="735868225506947072" authorid="@AuCoeurMeteo" time="2016-May-26 18:20">#Inondations locales à #StMalo sous un orage diluvien...https://twitter.com/Meteovilles/status/735867818781069312 ...</tweet>

- <tweet id="735850798316441600" authorid="@KeraunosObs" time="2016-May-26 17:11">Inondations locales en #Bretagne à Plougasnou dans le #Finistère lors des #orages de l’après-midi via @LeTelegrammepic.twitter.com/HZtrRK5sQg</tweet>
Conclusions

- Social Media are a rich source of information with spatial and temporal markers
- Most of the geographic information is coded using text (toponyms)
- Resolving toponyms may be a major problem - or not, depending on the scale of the application
  - GIR-derived Algorithms and techniques often lack context to be effective at the same level
  - Need to exploit the network to enrich context (where possible)
- NER algorithms need to adapt to the writing style of social media
Selected Bibliography

- Thi Bich Ngoc Hoang, Josiane Mothe: Location Extraction from Tweets, Information Processing and Management, in Press (2017)
- Pavlos Paraskevopoulos, Themis Palpanas: Fine-Grained Geolocalisation of Non-Geotagged Tweets, Advances in Social Networks Analysis and Mining (ASONAM), 2015
- Nelleke Oostdijk, Ali Hürriyetoglu, Marco Puts, Piet Daas, Antal van den Bosch: Information extraction from social media: A linguistically motivated approach. TALN 2016, Paris