Modelling Political Disaffection from Twitter Data

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Twitter

- Main **microblogging** platform
  - instant publication of short textual contents
- **Tweet →** 140 characters
- Widespread in Italy too

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![Diagram showing Italian internet users, Hearsay knowledge of Twitter, Weekly Twitter users, and Daily Twitter users.]

- **Italian internet users**: 28.6 M people (100%)
- Hearsay knowledge of Twitter: 25.3 M people (88.6% of internet users)
- Weekly Twitter users: 4.7 M people (16.5% of internet users)
- Daily Twitter users: 1.24 M people (4.4% of internet users)

December 2012
Textual classification

- We would like to classify millions of texts
  - Rule-based approach: rules defined by experts (keywords, regular expressions)
    - Inaccurate, hard to define
  - Supervised machine learning
    - They need a training set to learn how to classify new texts
    - Every text is transformed in a sequence of numerical features

- Recent problem: Sentiment Analysis → it recognizes the sentiment expressed by the author of the text
- Many applications, both industrial and academic
Measuring collective feelings

- One of the first works is O’Connor et al. (2010), who measured economic trust through Sentiment Analysis on Twitter.

- For which phenomena is this possible?
- How much are these measures valid? Do they work in Italy too?
Goals of this work

- Hypothesis: can political disaffection be measured through massive tweet classification?
  - It is a relevant phenomenon, especially in Italy
  - Lot of interest (academics and practitioners)
Political disaffection

- How to define a “disaffected” tweet?

- According to domain experts, it must:

  1. have a politic-related topic → topic detection
  2. have negative sentiment → sentiment analysis
  3. refer to all politicians

```
Tweet
  Is political? [No] Discarded
  [Yes]
  Is negative? [No] Discarded
  [Yes]
  Is general? [No] Discarded
  [Yes] Politically Disaffected Tweet
```
Training Set

- 28,340 tweets labelled by 40 political science students
  - From April to June 2012
  - 3 labelers for every text
- We keep in the dataset only tweets with unanimous “politic” label
- For other labels we measure agreement with Krippendorff $\alpha$:
  - “negative” $\rightarrow$ 0.78 $\rightarrow$ reliable labels ✓
  - “generic” $\rightarrow$ 0.41 $\rightarrow$ too noisy labels ×

\[
\begin{array}{|c|c|c|}
\hline
& \text{negative} & \text{non negative} \\
\hline
\text{politic} & 7'965 & 4'544 \\
\hline
\text{not politic} & 15'831 & \\
\hline
\end{array}
\]
1 – Topic Detection: politics

- Time-robust classifier
  - Training Set extension: 17,388 news titles (January-October 2012)

- Best feature extraction:
  - 5-grams of characters
  - tf-idf
  - Discard terms with less than 4 occurrences
45’728 points with 78’642 features

SMO SVM-solver, k-Nearest Neighbor, Random Forest, kernels are too time consuming

We employed online algorithms:
- ALMA, Passive-Aggressive, PEGASOS, OIPCAC

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Accuracy</th>
<th>F-Measure</th>
<th>Global time</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALMA</td>
<td>0.88 ± 0.01</td>
<td>0.87 ± 0.01</td>
<td>13.5 ± 1</td>
</tr>
<tr>
<td>PA</td>
<td>0.89 ± 0.01</td>
<td>0.89 ± 0.01</td>
<td>10.6 ± 0.1</td>
</tr>
<tr>
<td>PEGASOS</td>
<td>0.88 ± 0.01</td>
<td>0.88 ± 0.01</td>
<td>1103 ± 10</td>
</tr>
<tr>
<td>OIPCAC</td>
<td>0.89 ± 0.001</td>
<td>0.89 ± 0.01</td>
<td>5911 ± 52</td>
</tr>
</tbody>
</table>

Other algorithms were tested, but with worst results (i.e. Naive Bayes)

We selected Passive-Aggressive: good results, low costs
2 – Sentiment Analysis: feature extraction

- Different approaches have been tested:
  - n-grams of characters, words, n-grams of words
  - boolean presence, term frequency, tf-idf, fuzzy match between n-grams
- Best: **term frequency of single words**
- Adjustments:
  - Fraction of uppercase words as a feature
  - **Features of synonyms were joined together**
To improve the quality of our approach, we eliminated the target of the sentiment.

How to select the words to be removed:

- **ontology-based filter**
2 – Sentiment Analysis: classification

- 12’476 points with 2’383 features

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</thead>
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<tr>
<td>ALMA</td>
<td>0.70 ± 0.03</td>
<td>0.75 ± 0.03</td>
<td>0.82 ± 0.3</td>
</tr>
<tr>
<td>PA</td>
<td>0.67 ± 0.06</td>
<td>0.71 ± 0.12</td>
<td>0.9 ± 10^{-3}</td>
</tr>
<tr>
<td>PEGASOS</td>
<td>0.69 ± 0.03</td>
<td>0.73 ± 0.05</td>
<td>76 ± 0.1</td>
</tr>
<tr>
<td>OIPCAC</td>
<td>0.71 ± 0.03</td>
<td>0.75 ± 0.02</td>
<td>121 ± 25</td>
</tr>
<tr>
<td>RF</td>
<td>0.72 ± 0.03</td>
<td>0.78 ± 0.03</td>
<td>2173 ± 48</td>
</tr>
</tbody>
</table>

- We select ALMA: good results, low costs
3 – Generic vs. Specific: rule-based approach

- Problem: select tweets related to all politicians
- Unhelpful training set labels
- Rules employed:

  Presence of keywords defined by domain experts

  Entities from at least three different political areas (identified through DBpedia ontologies)
Hypothesis:

Applying this classification system to Twitter, can we obtain a good measure of the diffusion of political disaffection in society?
Public Opinion Surveys

- Surveys are a courtesy of IPSOS
- We compute two indexes:

1. **Inefficacy**: fraction of Italians whose propensity to vote any political party is 1 on a 1 to 10 scale
   - This measure captures the **sentiment** of inefficacy perceived by citizens, symptom of political disaffection

2. **Non-vote**: fraction of Italians that will not vote
   - This measure captures the **behavior** and it is influenced by election proximity and “moral” perception of no-vote
We gather a random set of users active in October and we sample their followers.

We obtain 261’313 users representing:

- ~5% of Italian users and ~10% of active Italian users in October 2012.

We select only those active in April → 167’557 users.

We collect their tweets obtaining: 35’882’423 tweets.
Comparisons

- For each survey, we compute the ratio between disaffected tweets and political tweets in a fixed time window. We consider the following time windows:

  \[ \Delta_{14}^{14} \quad \Delta_{7}^{14} \quad \Delta_{1}^{7} \]

  Last two weeks  From 14 to 7 days before  Last week

- We compare these ratios with polls through Pearson correlation index
### Inefficacy:

<table>
<thead>
<tr>
<th>$\Delta_{\text{min}}^{\text{max}}$</th>
<th>$\rho$</th>
<th>95% Confidence Interval</th>
<th>P-Value for $\rho &gt; 0$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta_{1}^{14}$</td>
<td>0.7860</td>
<td>0.476-0.922</td>
<td>0.031%</td>
</tr>
<tr>
<td>$\Delta_{7}^{14}$</td>
<td>0.7749</td>
<td>0.454-0.917</td>
<td>0.042%</td>
</tr>
<tr>
<td>$\Delta_{1}^{7}$</td>
<td>0.6880</td>
<td>0.310-0.878</td>
<td>0.226%</td>
</tr>
</tbody>
</table>

### No-vote:

<table>
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<tr>
<th>$\Delta_{\text{min}}^{\text{max}}$</th>
<th>$\rho$</th>
<th>95% Confidence Interval</th>
<th>P-Value for $\rho &gt; 0$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta_{1}^{14}$</td>
<td>0.5579</td>
<td>0.190-0.788</td>
<td>0.567%</td>
</tr>
<tr>
<td>$\Delta_{7}^{14}$</td>
<td>0.5920</td>
<td>0.248-0.803</td>
<td>0.231%</td>
</tr>
<tr>
<td>$\Delta_{1}^{7}$</td>
<td>0.4433</td>
<td>0.049-0.718</td>
<td>3.00%</td>
</tr>
</tbody>
</table>
Interpretation

- Data seems to indicate a strong correlation between disaffected tweets and the diffusion of the political disaffection in society.
- We can hypothesize that the quantity of discussion about this phenomenon is connected with how much it will spread.
Further investigation

- Employing this Twitter sample, we analyse the disaffection peaks
- For each peak:
  1. we take news of that day
  2. we compare them with the tweets that characterize the peak
  3. we select the most similar news
Conclusions

- We find political disaffection on Twitter to be highly correlated with the indicator of political disaffection in the public opinion survey.

- We show the peaks in the time-series are often generated by external political events reported on the main newspapers.
Any Questions?