

UNED Online Reputation Monitoring Team at RepLab 2013

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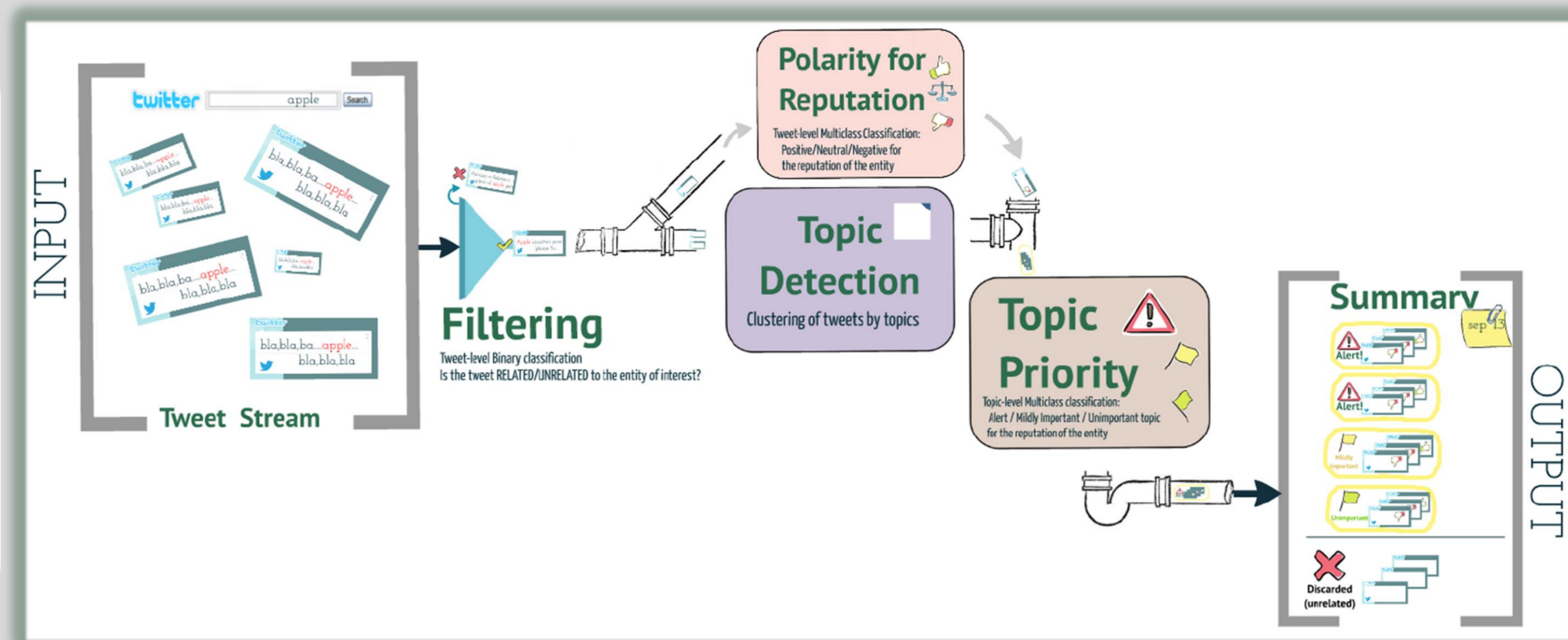
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Monitoring Task

Input: entity of interest + set of tweets + representative URL
Example: Apple Inc. + tweets containing "apple" + www.apple.com

- **Filtering:** Binary classification of tweets (related/unrelated)
- **Polarity for Reputation:** Classify each tweet according to its polarity for reputation (positive/negative/neutral)
- **Topic Detection:** Group tweets by topics
- **Topic Priority:** Rank topics, reputation alerts go first

Output: Monitoring summary (ranking of topics) for the reputation manager



RepLab 2013 Dataset

- 61 entities
- 4 domains: automotive, banking, universities, music
- For each entity: ~750 tweets for training
~1,500 tweets for test
- Languages: English and Spanish
- ~142,500 tweets
- ~372,800 manual annotations

Filtering Subtask

Filter Keywords

- Two-step classification algorithm
- Step 1: Automatic Keyword Discovery
Each term is classified as positive keyword / negative keyword / other
- Step 2: Automatic Tweet Classification
Tweets containing keywords are used to feed a binary BoW classifier that classifies the remaining tweets as related/unrelated

Instance-based learning + Heterogeneity-Based Ranking (HBR)

- Similar to the RepLab 2013 official baseline
- Each tweet in the test set is labeled as the most similar tweet in the training set
- Combination of rankings given by multiple text similarity measures
- Applicable to all the subtasks (Topic Detection, Polarity, Priority...)

| Approach | Accuracy | Reliability | Sensitivity | F(R,S) | Rank (out of 76 runs) |
|---------------------------------------------|----------|-------------|-------------|--------|-----------------------|
| RepLab 2013 Best System | 0.91 | 0.73 | 0.45 | 0.49 | 1 |
| Filter Keywords (Tweet Classification Step) | 0.86 | 0.43 | 0.38 | 0.34 | 19 |
| RepLab 2013 Official Baseline | 0.87 | 0.49 | 0.32 | 0.33 | 21 |
| Instance-based Learning + HBR | 0.87 | 0.47 | 0.33 | 0.30 | 27 |
| Filter Keywords (training: same entity) | 0.84 | 0.67 | 0.26 | 0.25 | 42 |
| Filter Keywords (training: other entities) | 0.50 | 0.17 | 0.29 | 0.14 | 61 |

Polarity for Reputation Subtask

Semantic Graphs for Domain-specific Affective Lexicon Adaptation

- SentiSense
Affective Lexicon of 5,496 words and 2,190 synsets from WordNet labeled with emotional categories
- Domain-specific Lexicon Adaptation
For each domain, WordNet concepts are extracted from the training data. The graph is generated upon semantic relations between concepts. Emotional categories are propagated using SentiSense as seed.
- Polarity Classification
Tweets represented as a Vector of Emotional Intensities (VEI) feed a Machine Learning classifier.

| Approach | Reliability | Sensitivity | F(R,S) | Accuracy | Rank (out of 68 runs) |
|---------------------------------------------------------------------------|-------------|-------------|--------|----------|-----------------------|
| RepLab 2013 Best System | 0.48 | 0.34 | 0.38 | 0.69 | 1 |
| SentiSense (training: same entity) | 0.36 | 0.10 | 0.15 | 0.62 | 21 |
| SentiSense + Domain-specific Adaptation (training: same entity) | 0.33 | 0.11 | 0.14 | 0.62 | 22 |
| Instance-based Learning + HBR | 0.32 | 0.29 | 0.30 | 0.59 | 26 |
| RepLab 2013 Official Baseline | 0.32 | 0.29 | 0.30 | 0.58 | 28 |
| SentiSense + Domain-specific Adaptation (training: same entity, balanced) | 0.34 | 0.12 | 0.16 | 0.58 | 31 |

Topic Detection Subtask

LDA-based Clustering

- Based on Twitter-LDA and Topics over Time models
- Transfer learning: target tweets + background tweets to establish the right number of clusters

Term Clustering

- Step 1: Term Clustering
- Learned similarity function (content-based, meta-data, time-aware features)
- Hierarchical Agglomerative Clustering
- Step 2: Tweet clustering
- Assigns tweets according to maximal term overlap (highest Jaccard similarity).

Wikified Tweet Clustering

- Representation: Tweets are linked to Wikipedia pages/entities
- Clustering: Jaccard similarity over Wikipedia entities

| Approach | Reliability | Sensitivity | F(R,S) | Rank (out of 34 runs) |
|----------------------------------------------------------|-------------|-------------|--------|-----------------------|
| Wikified Tweet Clustering | 0.46 | 0.32 | 0.33 | 1 |
| LDA-based Clustering (all entities background tweets) | 0.30 | 0.22 | 0.24 | 5 |
| Term Clustering | 0.42 | 0.21 | 0.23 | 7 |
| LDA-based Clustering (entity-specific background tweets) | 0.34 | 0.16 | 0.21 | 16 |
| Instance-based Learning + HBR | 0.15 | 0.22 | 0.17 | 21 |
| RepLab 2013 Official Baseline | 0.15 | 0.22 | 0.17 | 22 |

Full Monitoring Task

| Filtering | Topic Detection | Topic Priority | F-1* | Rank (out of 26 runs) |
|---------------------------------------------|----------------------------------------------------------|-------------------------------|------|-----------------------|
| Filter Keywords (Tweet Classification Step) | Wikified Tweet Clustering | Baseline | 0.19 | 1 |
| Baseline | LDA-based Clustering (all entities background tweets) | Baseline | 0.18 | 2 |
| Filter Keywords (Tweet Classification Step) | Term Clustering | Baseline | 0.17 | 3 |
| Baseline | LDA-based Clustering (entity-specific background tweets) | Baseline | 0.17 | 4 |
| Instance-based Learning + HBR | Instance-based Learning + HBR | Instance-based Learning + HBR | 0.16 | 13 |
| Filter Keywords (training: other entities) | Wikified Tweet Clustering | Instance-based Learning + HBR | 0.12 | 14 |
| Filter Keywords (training: all entities) | Wikified Tweet Clustering | Baseline | 0.11 | 15 |
| Filter Keywords (training: all entities) | Term Clustering | Baseline | 0.11 | 16 |

* F-1 = Harmonic Mean({R,S} x {Filtering, Topic Detection, Topic Priority})

Conclusions

- **Full Task.** Large room for improvement. Filtering is crucial for the overall performance of a monitoring system.
- **Filtering.** Use entity-specific training data when available: +78% F(R,S), +68% accuracy for Filter Keywords.
- **Polarity for Reputation.** Different from traditional sentiment analysis. Domain-adaptive affective lexicons less competitive than other RepLab submissions.
- **Topic Detection.** Three approaches perform competitively w.r.t. other RepLab submissions.
- **Topic Priority (future work).** Challenging due to the difficulty of combining dissimilar and imperfect signals (computed automatically): polarity, novelty, centrality, etc.