Economically-Efficient Sentiment Stream Analysis

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Sentiment Analysis

- Definition
  - Automatically extraction of opinions, sentiments, attitudes, and emotions expressed in text messages (i.e., Twitter).
- Motivation
  - It allows us to track products, brands and people to determine whether they are viewed positively or negatively.
- Problem
  - Content is created almost at the same time the event is happening in the real world.
    - Keeping track of sentiment streams is useful for advertising.

Sentiment Streams and Advertising

Superbowl 2013

Sentiment Streams and Advertising

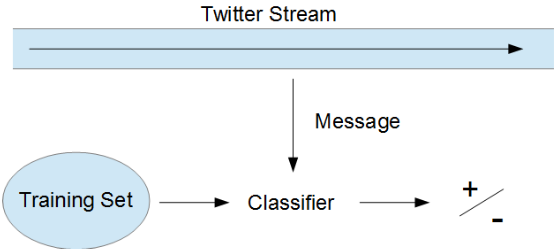
and yesterday ... Brazil 1 $\times$ Germany 7

PlayStation Brasil @PlayStation_BR · 2 h
#SeFosseNoPLAY era apertar o Reset e começar outra!
#BRA vs #GER pic.twitter.com/wMtwpsGNFF

Just hit the reset button and start again
#BRA vs #GER

Classifying Sentiment Streams

- Classifiers may be used to distinguish sentiments in the text.



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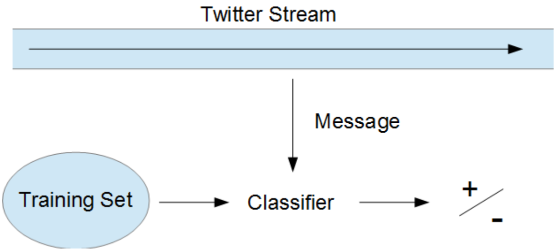
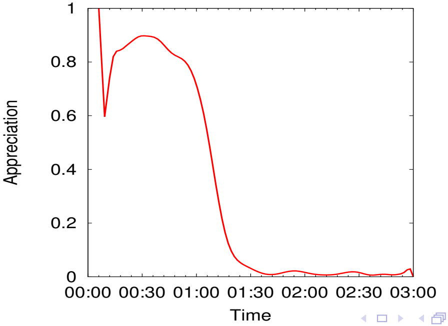
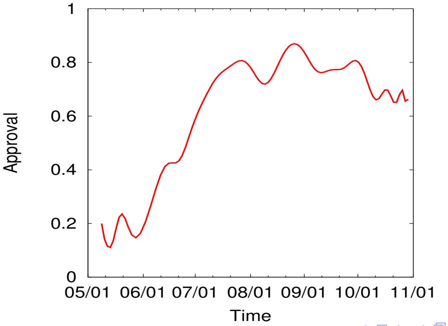


- Sentiments may change with time.

Sports (WC 2010)

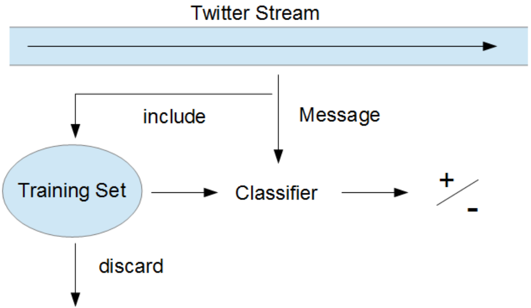


Elections (Brazil 2010)



Classifying Sentiment Streams

- Effective classification requires:
  - Updating the training-set to mitigate drifts.
  - Updating the classifier accordingly.



Research Questions

1. Effort:
   - How to reduce labeling effort?
2. Accuracy:
   - How to select messages to be kept and discarded?

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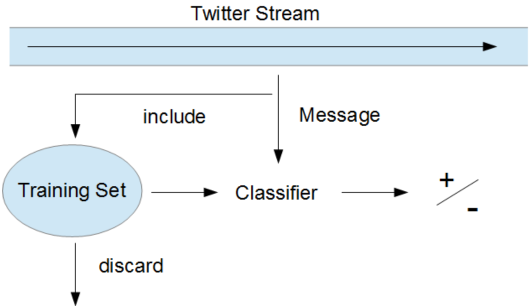
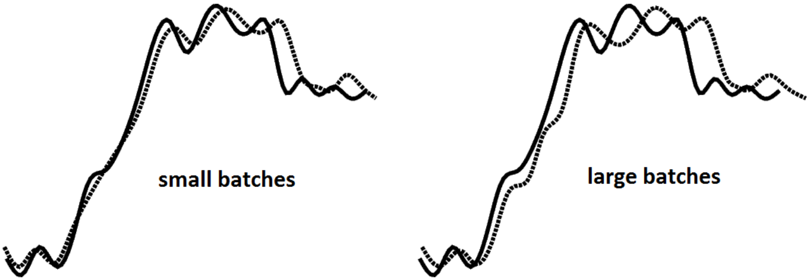
Batch Mode

- Instead of updating the training set on an instance-basis
    - Wait for a batch of b messages.
    - A similarity parameter δ controls the messages in the batch that must be labeled.



Batch Mode

- Trade-off between accuracy and labeling effort
  - Accuracy and effort decrease with batch size.
- However, there is locality of reference:
  - Messages appearing closer in time tend to be similar to each other (i.e., retweets).
  - Possible reduction without compromising accuracy.

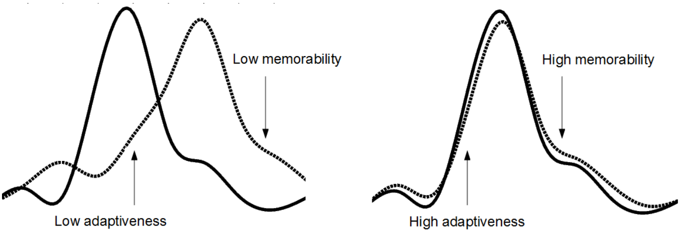


Research Questions

1. Effort:
   - How to reduce labeling effort?
2. Accuracy:
   - How to select messages to be kept and discarded?

Dealing with Drifts

- Two properties are necessary in order to produce classifiers that are robust to drifts:
  - Adaptiveness:
    - The ability to adapt itself to drifts.
  - Memorability:
    - The ability to recover itself from drifts.

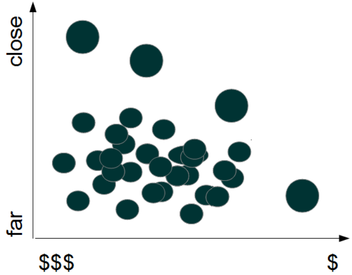


Dealing with Drifts

- Two properties are necessary in order to produce classifiers that are robust to drifts:
  - Adaptiveness:
    - The ability to adapt itself to drifts.
    - The training-set must contain fresh messages.
  - Memorability:
    - The ability to recover itself from drifts.
    - The training-set must contain pre-drift messages.
- Improving both properties simultaneously may lead to a conflict-objective problem.
  - Improve adaptiveness may hurt memorability, and vice-versa.

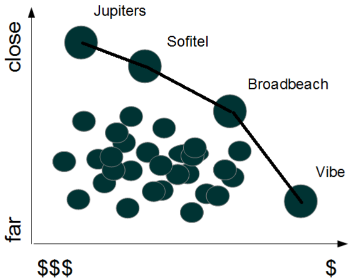
Pareto Efficiency

Example: hotels in Gold Coast.



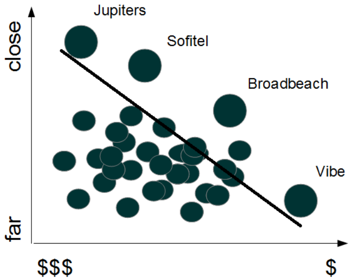
Pareto Efficiency

Pareto frontier.



Compensation — Kaldor-Hicks Principle

Region of compensation.

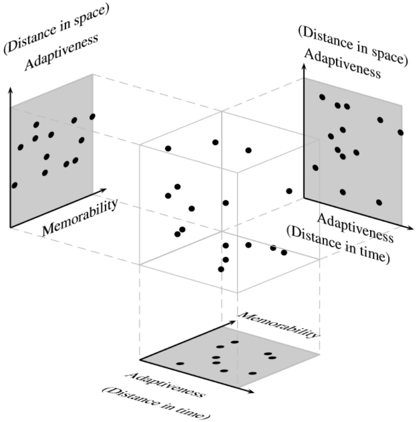


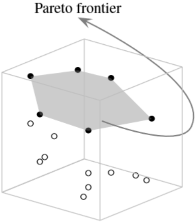
Utility Measures

- Distance in space:
  - How similar message t_j is to the newest message t_n.
  - $U_s(t_j) = \frac{|\mathcal{R}(t_n) \cap \mathcal{R}(t_j)|}{|\mathcal{R}(t_n)|}$
- Distance in time:
  - How fresh is the message.
  - $U_t(t_j) = \frac{\gamma(t_j)}{\gamma(t_n)}$.
    - $\gamma(t_j)$ returns the time in which message t_j arrived.
- Random permutation of messages:
  - $U_r(t_j) = \frac{\alpha(t_j)}{|\mathcal{D}_n|}$
    - $\alpha(t_j)$ returns the position of t_j in the shuffle.
    - $\mathcal{D}_n$ is the training set at time step n.

Utility Measures

1. At each time step *n*:
   1. Place candidate messages in the utility space.
   2. Select messages in the Pareto frontier.



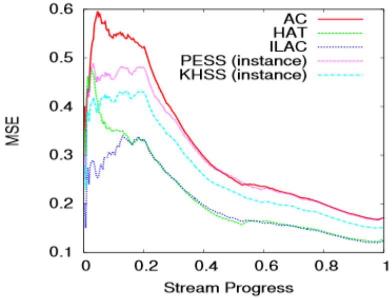


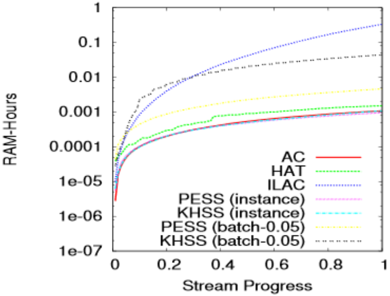
Evaluation

- Measures used:
  - Mean Squared Error.
  - RAM-Hours:
    - A GB of RAM deployed for 1 hour execution.
- Labeling Effort:
  - Different batch sizes and δ values.
- Three datasets:
  - Brazilian elections 2010.
  - World Cup 2010.
  - Person of the Year 2010 (Assange vs. Zuckerberg)
  - Baselines:
    - AC – Active Classifiers (KDD 2011)
    - HAT – Hoeffding Adaptive Trees (JMLR 2011)
    - ILAC – Incremental Lazy Classifiers (SIGIR 2011)

Evaluation

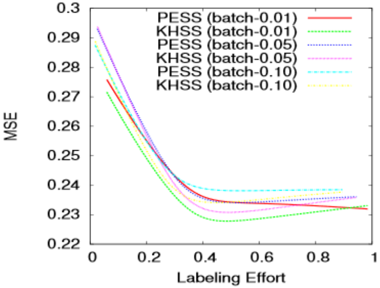
- MSE and RAM-Hours

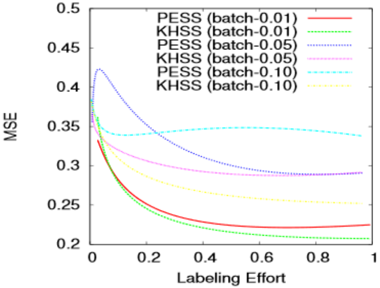




Evaluation

- MSE and Labeling Effort





Conclusions

- Sentiment analysis on Twitter streams.
  - Limited computing and training resources.
  - Sentiment drifts.
- Efficiency and accuracy.
  - Incremental classifiers.
  - Pareto efficiency and compensation principle.
- Our results.
  - 50% reduction in terms of labeling effort without impact on accuracy.
- Future work includes:
  - Other utility measures.
  - Other application scenarios.

Thank you!

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