Sentiment Analysis with Incremental Human-in-the-Loop Learning and Lexical Resource Customization

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Problem Statement & Computational Solution

State of the art social media sentiment analysis suffers from various problems:

Table 1. Problems and suggested solutions in sentiment analysis.

Problem	Solution
Fixed models	Incremental models
Fixed vocabulary due to training data	Customizable lexicon features
Limited generalizability	Domain adaptation

Example: *I just tried out the new Rayn glasses they look* ***badass****.* **[negative]**

The above case will be classified as negative by simple lexicon based classifier as **"badass"** has a negative sentiment. However, in this context the word **"badass"** actually describes a very positive emotion as compared to its meaning in older days.

We have built **SAIL** (**S**entiment **A**nalysis and **I**ncremental **L**earning):

- GUI based tool that empowers users to perform domain and model adaptation
- Supports more insightful and interactive social media sentiment analysis

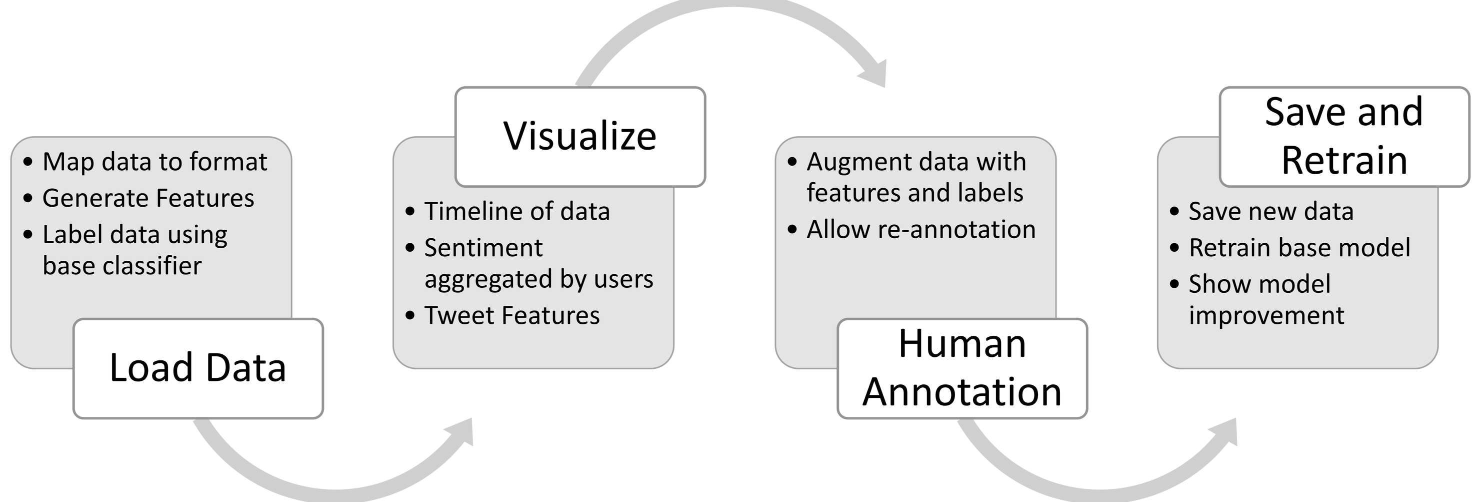

Fig 1. Workflow of analysis process of SAIL

Goals and Process

Building a robust sentiment classifier (positive/negative categorization) that can be dynamically updated with user intervention. Steps involved:

1. Convert raw, social media data into useful and high-quality training data.
2. Feature identification and model performance evaluation (in terms of accuracy).
3. Support domain specific classification via user customized lexicons.
4. Compare performance of fixed to incrementally updated classifiers.
5. Evaluate performance and usability on standard research twitter sentiment analysis dataset.
6. Made technology (SAIL) publicly available.

SAIL Overview

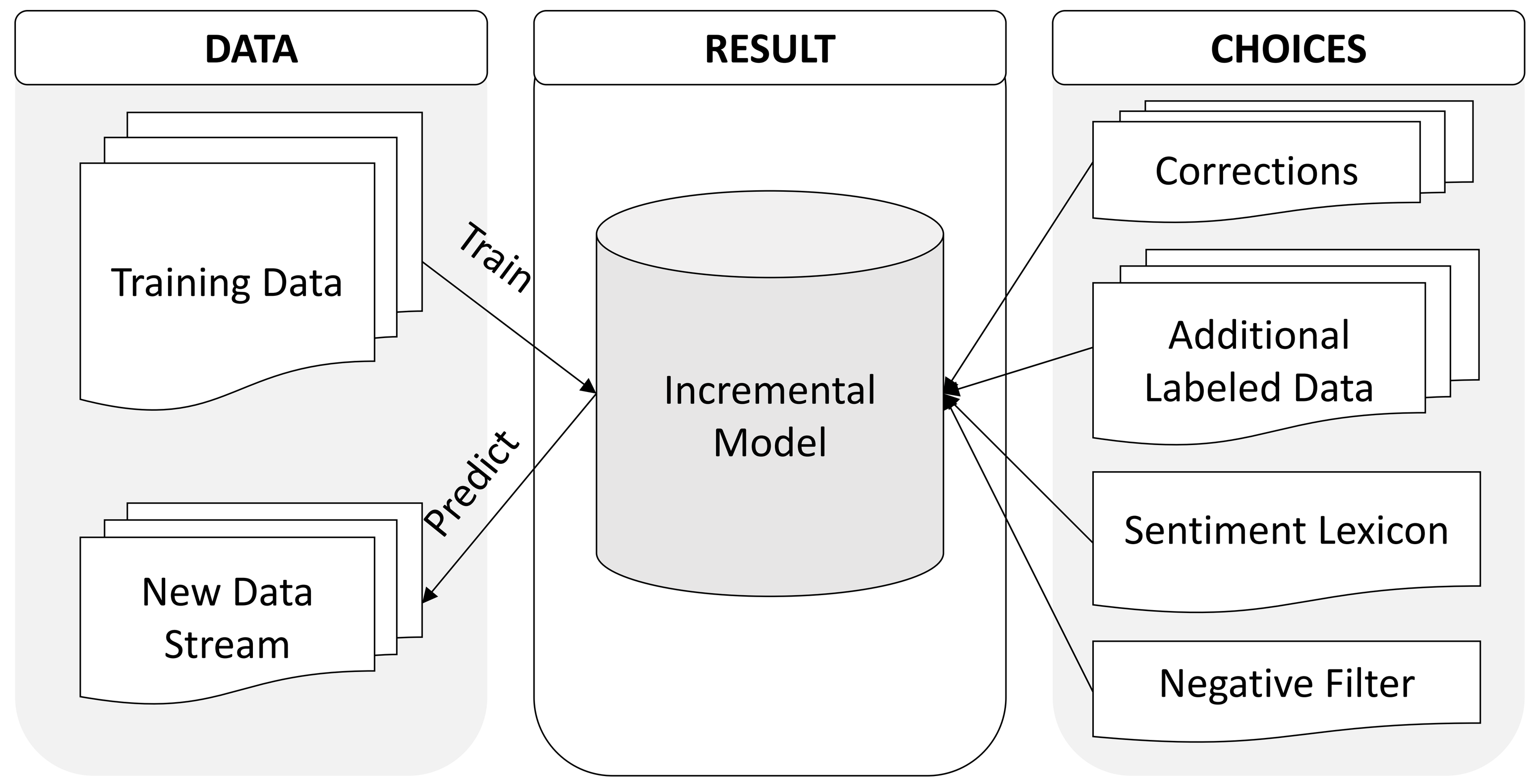

Fig 2. SAIL overview: Incremental learning and prediction with adjustable lexical resources and additional labeled data.

Data Preprocessing and Feature Extraction

Each tweet is normalized by converting each mention of a Hashtag, URL, Mention, Emoticon and Quotes into _HASH, _URL, _MENTION, _EMO, _DQ respectively. It is then converted into a vector with the following features:

a) **Meta:** Count of hashtags, emoticons, URLs, mentions, double quotes
b) **POS:** Count of parts of speech extracted using the ark-tweet-nlp tool
c) **Word:** Presence of the top 10,000 unigram & bigram with at least three occurrences per class
d) **Sentiment lexicon:** Count of positive and negative words matching a widely used sentiment lexicon, which the user can edit;
e) **Negative filter:** A user generated list of words, hashtags and usernames that represent false positives w.r.t. the sentiment lexicon, and hence are omitted from consideration for feature d).

Model Training and Incremental Learning

Stochastic Gradient Descent (SGD) algorithm with log loss was used to incrementally train our model using Weka. Incremental learning helps in improving models using new data with lower computational costs. SGD performs much better than using static SVM model on prediction task.

Table 2 Prediction accuracy depending on training algorithm and feature sets

Features considered			Accuracy (F1)	
Meta	POS	Word	SVM	SGD
X	X		70.50%	70.40%
X	X	X (N=2K)	85.70%	85.60%
X	X	X (N=20K)	86.60%	**87.50%**

Baseline v/s Domain Aligned Model

Baseline model is trained on SEMEVAL 2013 Task 2 tweets using only positive and negative labels on which the SGD model achieves an F-1 score of **80%**. It gives **~50%** accuracy on a domain specific data. Using a domain specific model we get close to **75%** accuracy.

Human-in-the-loop incremental learning

Incremental training of the baseline model leads to improvement in cross validation accuracy. This model was trained incrementally on 2 batches of data and the cross validation accuracy improved by 2-4 %.

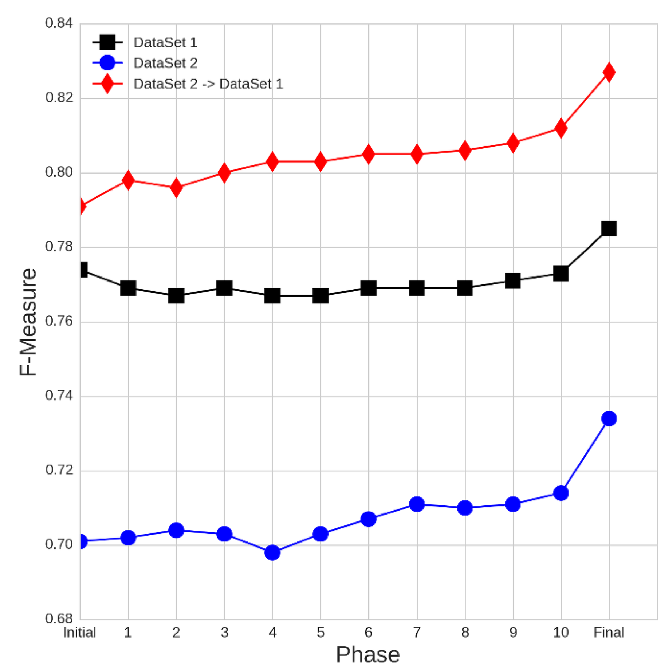

Fig 3. Accuracy gain from incremental learning with additional labeled data.

Exploration and Customization

SAIL is available as a Java based open source tool which uses incremental learning to customize trained models.

The software package comes with model pre-trained using SEMEVAL 2013 Task 2 data using positive, negative class labels.

We provide a GUI-based technology that supports the prediction of standard sentiment classes and allows for a) relabeling predictions or adding labeled instances to retrain the weights of a given model, and b) customizing lexical resource to account for false positives and false negatives. The tool supports interactive result exploration and model adjustment.

SAIL can be used by the humanities research community to utilize advances in online learning to improve sentiment analysis and annotation using machine assisted methods.

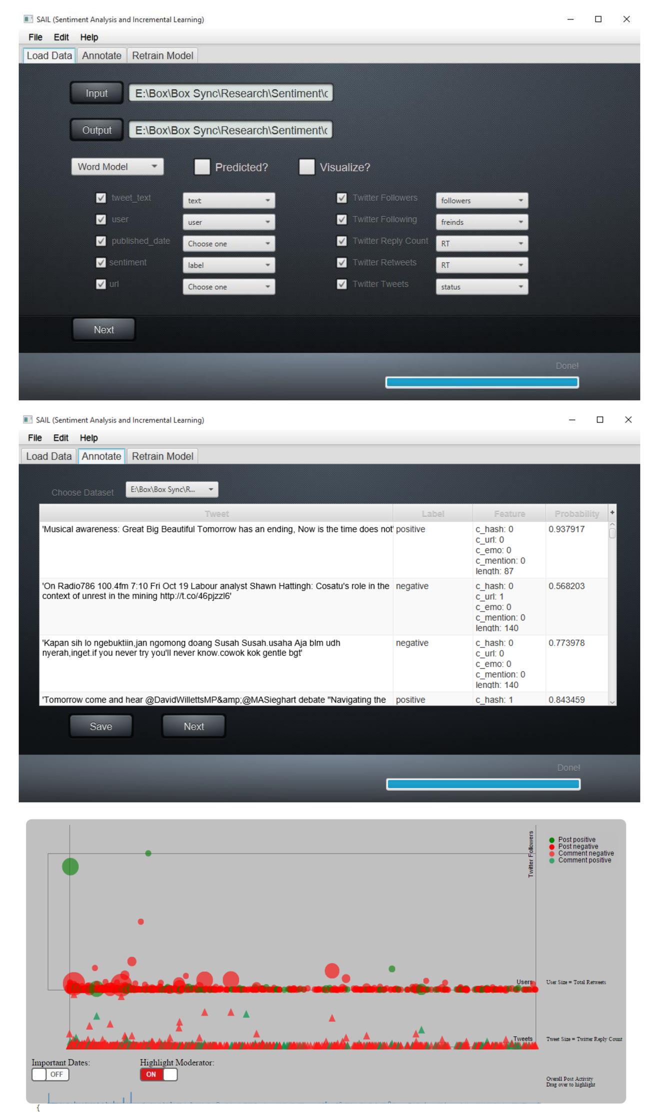

Fig 4. SAIL input and annotation interface(above 2), and user based temporal sentiment visualization (below)

User based temporal sentiment visualization

With relevant properties of tweets like number of followers, retweets etc. SAIL allows the user to see a temporal visualization of authors and posts. Each author is identified via the aggregate sentiment of all their tweets. This can be useful for exploring phases of a discourse in more detail.

Conclusion

We have leveraged advancements in sentiment analysis and incremental machine learning research to design, implement and test a practical and end-user friendly solution for large scale sentiment prediction. Our solution allows for prediction improvement and domain adaptation through a human in the loop approach. We are making our solution publicly available (https://github.com/uiuc-ischool-scanr/SAIL) to empower people with no machine learning background to replicate our approach and get better sentiment analysis results.

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