Annotate-Sample-Average (ASA): A New Distant Supervision Approach for Twitter Sentiment Analysis

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Social Media

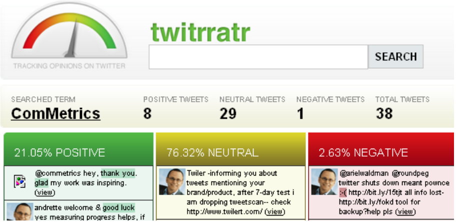
- Microblogging services are increasingly being adopted by people in order to access and publish information.
- **Twitter**: Massively used Microblogging platform where users post messages (a.k.a **tweets**) limited to 140 characters.
- Tweets use a unique **informal dialect** including many abbreviations, acronyms, misspelled words, hashtags, and emoticons, e.g., **lol**, **omg**, **hahaha**, **#hatemonday**, **:)** .

Sentiment Analysis and Social Media

- Twitter users tend to publish **personal opinions** regarding certain topics and news events.

    1. Hey @Apple, pretty much all your products are amazing. You blow minds every time you launch a new gizmo. That said, your hold music is crap.
    2. #windows sucks... I want #imac so bad!!! why is it so damn expensive :(@apple please give me free imac and I will love you :D

- Analysing the sentiment underlying these opinions has important applications in product **marketing** and **politics**.



Opinion Mining or Sentiment Analysis

- Application of **NLP** and **text mining** techniques to identify and extract subjective information from textual datasets.

Message-level Polarity Classification (MPC) of Tweets

- Automatically classify a tweet to classes **positive**, **negative**, or **neutral**.

- State-of-the-art solutions use **supervised** machine learning models trained from **manually** annotated examples [Kiritchenko et al., 2014].
- **The Label Sparsity Problem**: manual annotation is **labour-intensive** and **time-consuming**.

Distant Supervision

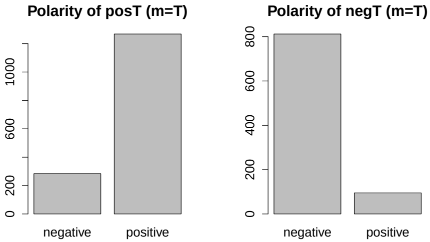
- The label sparsity problem can be addressed using **Distant Supervision**.
- Automatically **label** unlabelled data (**Twitter API**) using a heuristic method [Mintz et al., 2009].
- Unlabelled tweets are **cheap** to optain :)
- **Emoticon-Annotation Approach (EAA)**: tweets with positive **:)** or negative **:(** emoticons are labelled according to the polarity indicated by the emoticon [Read, 2005].
- The emoticon is **removed** from the content.
- Drawback: emoticons are **rarely** used in certain domains such as politics.

Lexicon-based Distant Supervision

- We propose a distant supervision method that builds **synthetically labelled tweets** based on **opinion lexicons** (we go beyond emoticons).
- An opinion lexicon $\mathcal{L}$ is a lists of terms labelled by sentiment.
- They are normally composed of positive and negative words such as **happy, wonderful** and **sad, bad**.
- Proposed method generate positive and negative training instances by **averaging** tweets containing words with the **same** polarity.
- Tweets are represented by **sparse feature vectors**.

Lexical Polarity Hypothesis

- A tweet containing a word with a certain polarity is more likely to express the **same polarity** than the **opposite** $p_d > 0.5$ (Bernoulli experiment).



- The opposite polarity may also be expressed due to the presence of **negation**, **sarcasm**, or other opinion words with the **opposite** polarity.

Why Averaging?

- Averaging multiple tweets with words with the same polarity **increases** the confidence of generating instances located in the **region** of the desired polarity.
- We assume that the average tweet will behave similarly to the **majority**.
- Probability that the **majority** of the tweets sampled from a collection of tweets with at least one word with the target polarity have the desired polarity:

$$P(M) = \sum_{i=\lfloor \frac{a}{2} \rfloor + 1}^{a} \binom{a}{i} p_d^i (1 - p_d)^{a-i}$$

	$p_d = 0.6$	$p_d = 0.7$	$p_d = 0.8$	$p_d = 0.9$
$a = 3$	0.648	0.784	0.896	0.972
$a = 5$	0.683	0.837	0.942	0.991
$a = 10$	0.633	0.850	0.967	0.998
$a = 50$	0.902	0.998	1	1
$a = 100$	0.973	1	1	1
$a = 500$	1	1	1	1
$a = 1000$	1	1	1	1

- $P(M) > p_d$, when $a \geq 3$ and $p_d \geq 0.5$. This is analogous to the **Condorcet's Jury Theorem**!!

Annotate-Sample-Average (ASA)

- **Annotation**: every time a word from $\mathcal{L}$ is found, the tweet is added to sets **posT** or **negT** (depending on the polarity).
- Tweets with both positive and negative words will be simultaneously added to both **posT** and **negT**.
- This will produce instances with better **generalisation** properties: Tweets are likely to contain words with the **opposite polarity**.
- **Sample**: randomly sample with replacement a tweets from either **posT** or **negT** for each generated instance.
- **Averaging**: average and label sampled feature vectors.
- We create **balanced training datasets** with size equal to 1% of the size of the source corpus ($20,000$ in our experiments).

Baselines

Emoticon-Annotation Approach (EAA)

- Labels tweets with positive or negative emoticons according to the emoticon's polarity after removing the emoticon from the message.
- Tweets containing both positive and negative emoticons are **discarded**.

Lexicon-annotation approach (LAA)

- Uses a given polarity lexicon $\mathcal{L}$.
- Tweets with at least one positive word and no negative word are labelled **positive**.
- Tweets with at least one negative word and no positive word are labelled **negative**.

We compare balance and unbalanced versions of each baseline!

Instances Generated by Distant Supervision Models

We use 10 collections of 2 million tweets as source corpora.

	Avg. Positive	(%)	Avg. Negative	(%)	Avg. Total	(%)
EAA	130,641	(6.5%)	21,537	(1.1%)	152,179	(7.6%)
EAA_B	21,537	(1.1%)	21,537	(1.1%)	43,074	(2.2%)
LAA	681,531	(34.1%)	294,177	(14.7%)	975,708	(48.8%)
LAA_B	294,177	(14.7%)	294,177	(14.7%)	588,354	(29.4%)
ASA	10,000	(0.5%)	10,000	(0.5%)	20,000	(1%)

Testing Datasets

	Positive	Negative	Total
6HumanCoded	1340	949	2289
Sanders	570	654	1224
SemEval	5232	2067	7299

Table : Message-level polarity classification datasets.

ASA results

	6HumanCoded		Sanders		SemEval	
EAA_U	0.576 ± 0.007	= - - -	0.506 ± 0.018	= - - -	0.591 ± 0.018	= - - -
EAA_B	0.735 ± 0.008	+ = + +	0.709 ± 0.018	+ = = =	0.711 ± 0.006	+ = - =
LAA_U	0.729 ± 0.004	+ - = +	0.711 ± 0.003	+ = = +	0.725 ± 0.002	+ + = +
LAA_B	0.719 ± 0.002	+ - - =	0.703 ± 0.004	+ = - =	0.712 ± 0.002	+ = - =
ASA ($a = 1$)	0.717 ± 0.007	+ - - =	0.691 ± 0.013	+ - - -	0.699 ± 0.008	+ - - -
ASA ($a = 5$)	0.755 ± 0.004	+ + + +	0.730 ± 0.008	+ + + +	0.735 ± 0.005	+ + + +
ASA ($a = 10$)	**0.761** ± 0.003	+ + + +	**0.735** ± 0.015	+ + + +	**0.742** ± 0.006	+ + + +
ASA ($a = 50$)	0.749 ± 0.004	+ + + +	0.673 ± 0.005	+ - - -	0.699 ± 0.009	+ - - -
ASA ($a = 100$)	0.717 ± 0.003	+ - - -	0.645 ± 0.006	+ - - -	0.664 ± 0.005	+ - - -
ASA ($a = 500$)	0.665 ± 0.002	+ - - -	0.621 ± 0.007	+ - - -	0.621 ± 0.004	+ - - -
ASA ($a = 1000$)	0.653 ± 0.003	+ - - -	0.619 ± 0.007	+ - - -	0.613 ± 0.002	+ - - -

Table : Macro-averaged F1 measure for different distant supervision models. Best results per column are given in bold.

Conclusions & Future Work

- ASA is a powerful distant supervison method that creates **compact and balanced** training datasets.
- It outperformed EAA and LAA!
- It could potentially used for domain-specific sentiment analysis.

Future Work

- Try ASA with other type of word-level labels: subjectivity, emotions.
- Design a mechanism for handling negations with ASA.
- Try non-linear representations with ASA such as paragraph embeddings.

Questions?

Thanks for your Attention!

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