Affect in Tweets and other research problems in NLP

Felipe Bravo-Marquez

Department of Computer Science, University of Chile & IMFD

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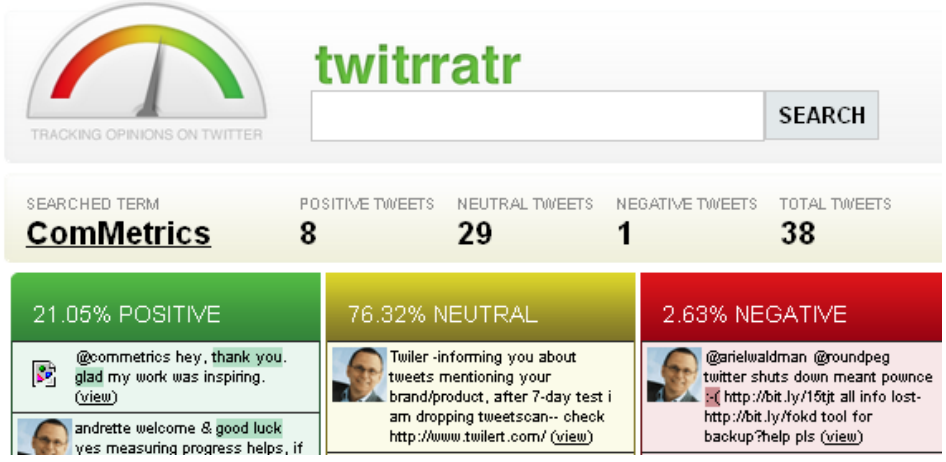
Social Media

- 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**, **#SweetAsBro**, **#yeahnah**, **:)** .

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.

Main Problem: Message-level Polarity Classification (MPC)

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

2. State-of-the-art solutions use **supervised** machine learning models trained from **manually** annotated examples [Kiritchenko et al., 2014].

Drawbacks of Supervised models for MPC

- **Label sparsity (LS)**: manual annotation is **labour-intensive** and **time-consuming**.
- **Concept drift**: the sentiment pattern can vary from one collection to another (domain-drift, temporal-drift).

A classifier trained from tweets annotated for one domain will **not necessarily** work on another one!

Examples of domain-Drift

1. For me the queue was pretty **small** and it was only a 20 minute wait I think but was so worth it!!! :D @raynwise
2. Odd spatiality in Stuttgart. Hotel room is so **small** I can barely turn around but surroundings are inhumanly vast & long under construction.

Solutions to MPC with LS

Using Prior Lexical Knowledge

- An opinion lexicon is a lists of terms labelled by sentiment.
- They are normally composed of positive and negative words such as **happy, wonderful** and **sad, bad**.
- Can be used for **unsupervised** sentiment classification [Thelwall et al., 2012], or as **low-dimensional** features [Kouloumpis et al., 2011].
- Informal Twitter words are **not** covered by most popular lexicons.
- The manual creation of a Twitter-oriented opinion lexicon is a **time-consuming** task.

Solutions to MPC with LS (2)

Distant Supervision

- Automatically **label** unlabelled data (**Twitter API**) using a heuristic method [Mintz et al., 2009].
- **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.

Research Problem

This thesis addresses the label sparsity problem for Twitter sentiment classification by automatically building **two type of resources**.

1. **Twitter-specific opinion lexicons**: we develop machine learning models to induce polarity lexicons from tweets.
2. **Synthetically labelled tweets**: we develop distant supervision methods based on **lexical knowledge** (we go beyond emoticons).

PLI from unlabelled Tweets

- We propose another supervised model for lexicon expansion referred to as the **tweet-centroid model (TCM)**.
- The words are represented by **high-dimensional vectors** based on the context's where they occur.
- In contrast to the previous approach the expansion is done from **unlabelled tweets**.
- It is inspired by the **Distributional Hypothesis** [Harris, 1954]: words occurring in the same **contexts** tend to have similar meanings.
- Or equivalently: "a word is characterized by the **company** it keeps".

The Tweet Centroid Model (TCM)

- We treat a **whole tweet** as a word's context.
- We model tweets as **vectors** using standard NLP features.
- We use high-dimensional **unigrams** $\overrightarrow{tb}$ and low-dimensional **word-clusters** $\overrightarrow{tc}$ to form the feature space.
- The word cluster are trained from a corpus of tweets using the **Brown clustering** algorithm [Brown et al., 1992].

The Tweet Centroid Model (TCM) (2)

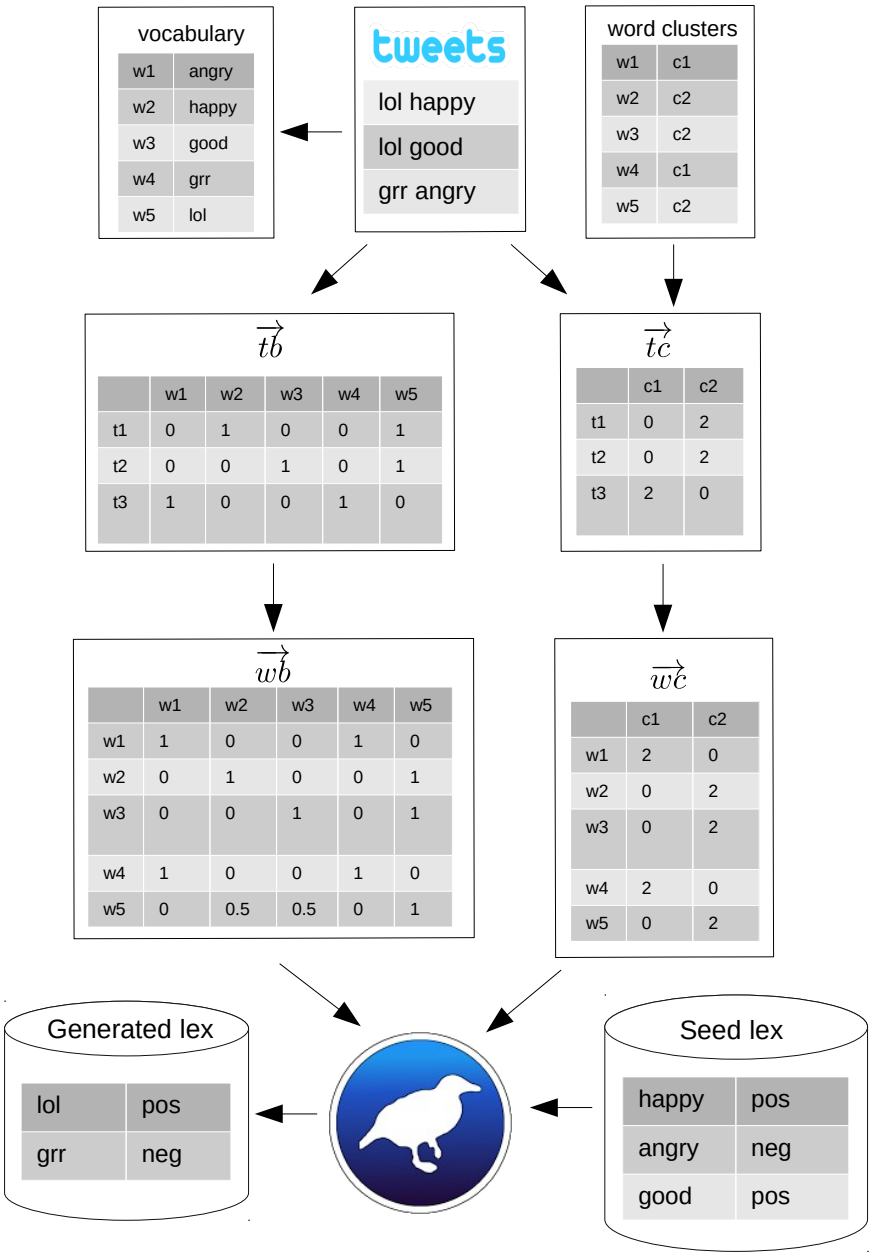
- The **word-tweet set** $\mathcal{M}(w)$ is the set of tweets from a corpus $\mathcal{C}_U$ in which the word w is observed (posting list in IR):

$$\mathcal{M}(w) = \{m : w \in m\} \tag{1}$$

- The TCM word vector $\overrightarrow{w}$ is the **centroid** of all tweet vectors in $\mathcal{M}(w)$.

$$w_j = \sum_{t \in \mathcal{M}(w)} \frac{x_j^{(t)}}{|\mathcal{M}(w)|} \tag{2}$$

Tweet-centroid Model



Datasets

Dataset	STS	ED
#tweets	1,600,000	2,500,000
#positive words	2015	2639
#negative words	2621	3642
#neutral words	3935	5085
#unlabelled words	36,451	67,692
#unigram attributes	45,022	79,058
#word-clusters attributes	993	999

Word-level 3-class polarity classification performance

AUC			
Dataset	Unigrams	Brown Clusters	Concatenation
STS	0.77 ± 0.01	$\mathbf{0.79} \pm \mathbf{0.01}$ +	$\mathbf{0.79} \pm \mathbf{0.01}$ +
ED	0.78 ± 0.01	0.79 ± 0.01 +	$\mathbf{0.80} \pm \mathbf{0.01}$ +

Message-level classification performance

AUC			
Dataset	Baseline	STS	ED
Sanders	0.78 ± 0.04	0.80 ± 0.04 +	**0.83** $\pm$ **0.04** +
6-human	0.79 ± 0.03	0.82 ± 0.03 +	**0.83** $\pm$ **0.02** +
SemEval	0.78 ± 0.02	0.82 ± 0.02 +	**0.84** $\pm$ **0.02** +

Other Applications of TCM

- Multi-Label Classification of Emotions.

Other Applications of TCM

Transfer Learning for PLI

- What if we don't have a seed lexicon?
- We can train a **message-level classifier** f_M from a corpus of sentiment annotated tweets $\mathcal{C}_L$ and deploy it on words found in a **corpus of unlabelled tweets** represented by tweet centroids.
- Tweets are represented by **sparse vectors** using unigrams, Brown clusters, and POS tags.
- Note that tweets and words reside in the **same feature space**.

AUC		
Source Dataset	PMI-SO	TCM
Sanders	0.757	**0.864**
6HumanCoded	0.861	**0.930**
SemEval	0.858	**0.916**

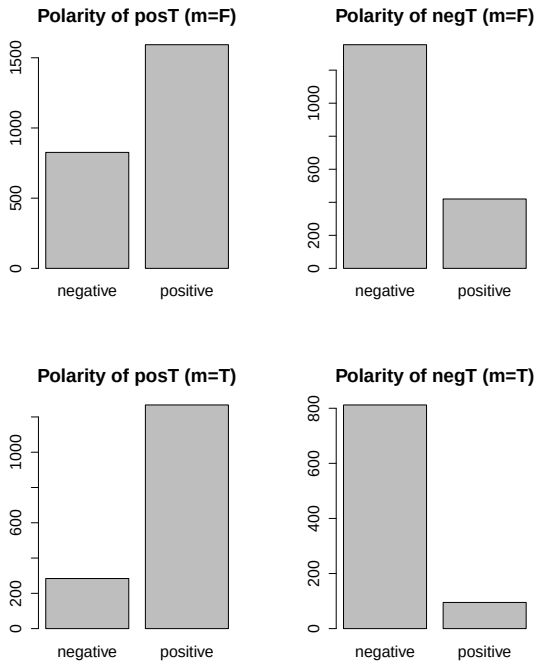
Table: Word-level Polarity Classification Results for the AFINN lexicon.

Lexical-based Distant Supervision

- Lexicons showed to be **useful features** for MPC.
- But we **still need labelled tweets** for training a message-level classifier.
- We will try to **directly use** lexical knowledge for training message-level classifiers.
- We propose two **distant supervision** models: **Partitioned Tweet Centroids** and **Annotate-Sample-Average (ASA)**.
- Proposed methods generate positive and negative training instances by **averaging** tweets containing words with the **same** polarity.

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**!!

TCM for message-level classification

- TCM can be used as a **distant supervision** model for MPC.
- We use a **word-level** classifier f_W trained with TCM vectors calculated from $\mathcal{C}_U$ labelled by a **polarity lexicon** $\mathcal{L}$ (AFINN).
- The classifier is deployed on the target tweets represented by **sparse vectors**.
- The number of labelled words for training f_W is **limited** to the number of words from $\mathcal{L}$.
- TCM is **not capable** of exploiting large collections of unlabelled tweets for producing training datasets larger than the size of $\mathcal{L}$.

Partitioned TCM

- We propose a modification of our method for **increasing** the number labelled instances it produces.
- The word-tweet set $\mathcal{M}(w)$ for each word from the lexicon ($w \in \mathcal{L}$) is **partitioned** into smaller disjoint subsets $\mathcal{M}(w)_1, \ldots \mathcal{M}(w)_z$ of a fixed size determined by a parameter p.
- We calculate one tweet centroid vector $\overrightarrow{w}$ for **each partition** labelled according to $\mathcal{L}$.

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**.

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%)
LAA	681,531	(34.1%)	294,177	(14.7%)	975,708	(48.8%)
TCM	1537	(0.05%)	951	(0.08%)	2488	(0.12%)
TCM (p=5)	276,696	(13.8%)	149,989	(7.5%)	426,684	(21.3%)
TCM (p=10)	138,596	(6.9%)	75,390	(3.8%)	213,986	(10.7%)
TCM (p=20)	69,518	(3.5%)	38,044	(1.9%)	107,563	(5.4%)
TCM (p=50)	32,231	(1.6%)	17,950	(0.9%)	50,181	(2.5%)
TCM (p=100)	14,338	(0.7%)	8357	(0.4%)	22,695	(1.1%)

TCM for MPC

	6HumanCoded		Sanders		SemEval	
EAA	0.805 ± 0.005	= -	0.800 ± 0.017	= +	0.802 ± 0.006	= -
LAA	0.809 ± 0.001	+ =	0.778 ± 0.002	- =	0.814 ± 0.000	+ =
TCM	0.776 ± 0.004	- -	0.682 ± 0.024	- -	0.779 ± 0.008	- -
TCM (p=5)	0.834 ± 0.002	+ +	0.807 ± 0.008	= +	0.833 ± 0.002	+ +
TCM (p=10)	0.845 ± 0.003	+ +	**0.817** ± 0.006	+ +	0.841 ± 0.002	+ +
TCM (p=20)	**0.850** ± 0.003	+ +	0.815 ± 0.011	+ +	**0.844** ± 0.003	+ +
TCM (p=50)	0.844 ± 0.004	+ +	0.785 ± 0.010	- +	0.836 ± 0.004	+ +
TCM (p=100)	0.829 ± 0.003	+ +	0.752 ± 0.019	- -	0.821 ± 0.004	+ +

Table: Message-level Polarity Classification Results. Best results per column are given in bold.

Annotate-Sample-Average (ASA)

- Partitioned TCM can generate **very large** training datasets.
- TCM instances are obtained by averaging tweets containing **the same word**.
- What if we average random tweets containing **different words** with the same polarity?
- What if we can define the **number of instances** to generate?
- This could be useful for creating **compact and balanced** training datasets.

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 discarded if the flag *m* is set, and will be simultaneously added to both **posT** and **negT** otherwise.
- Tweets are likely to contain words with the **opposite polarity**: we believe that unsetting the flag will produce instances with better **generalisation** properties.
- **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).

ASA results

	6HumanCoded		Sanders		SemEval	
EAA_U	0.805 ± 0.005	= = - -	0.800 ± 0.017	= = + +	0.802 ± 0.006	= + - -
EAA_B	0.809 ± 0.001	= = = =	0.795 ± 0.016	= = + +	0.798 ± 0.007	- = - -
LAA_U	0.809 ± 0.001	+ = = =	0.778 ± 0.002	- - = =	0.814 ± 0.000	+ + = =
LAA_B	0.809 ± 0.001	+ = = =	0.778 ± 0.003	- - = =	0.813 ± 0.001	+ + = =
ASA ($a = 1$, $m = T$)	0.806 ± 0.003	= = - -	0.786 ± 0.007	- - + +	0.808 ± 0.002	+ + - -
ASA ($a = 5$, $m = T$)	0.809 ± 0.002	= = = =	0.787 ± 0.005	- = + +	0.810 ± 0.003	+ + - -
ASA ($a = 10$, $m = T$)	0.804 ± 0.001	= - - -	0.776 ± 0.008	- - = =	0.806 ± 0.003	+ + - -
ASA ($a = 50$, $m = T$)	0.756 ± 0.003	- - - -	0.697 ± 0.005	- - - -	0.763 ± 0.002	- - - -
ASA ($a = 100$, $m = T$)	0.729 ± 0.002	- - - -	0.672 ± 0.006	- - - -	0.739 ± 0.002	- - - -
ASA ($a = 500$, $m = T$)	0.696 ± 0.003	- - - -	0.642 ± 0.008	- - - -	0.707 ± 0.005	- - - -
ASA ($a = 1000$, $m = T$)	0.690 ± 0.004	- - - -	0.637 ± 0.008	- - - -	0.701 ± 0.006	- - - -
ASA ($a = 1$, $m = F$)	0.793 ± 0.005	- - - -	0.762 ± 0.016	- - - -	0.787 ± 0.007	- - - -
ASA ($a = 5$, $m = F$)	0.837 ± 0.004	+ + + +	0.807 ± 0.010	= = + +	0.833 ± 0.003	+ + + +
ASA ($a = 10$, $m = F$)	**0.845** ± 0.001	+ + + +	**0.812** ± 0.015	+ + + +	**0.840** ± 0.003	+ + + +
ASA ($a = 50$, $m = F$)	0.815 ± 0.003	+ + + +	0.759 ± 0.006	- - - -	0.810 ± 0.004	+ + - -
ASA ($a = 100$, $m = F$)	0.781 ± 0.003	- - - -	0.720 ± 0.007	- - - -	0.779 ± 0.004	- - - -
ASA ($a = 500$, $m = F$)	0.723 ± 0.002	- - - -	0.670 ± 0.008	- - - -	0.729 ± 0.005	- - - -
ASA ($a = 1000$, $m = F$)	0.712 ± 0.002	- - - -	0.665 ± 0.007	- - - -	0.721 ± 0.005	- - - -

Table: AUC measure for different distant supervision models. Best results per column are given in bold.

Conclusions

- The methods developed in this thesis can be used to **acquire** and **exploit** lexical knowledge for Twitter sentiment analysis under **label sparsity conditions**.
- We proposed two methods (Word Sentiment Associations and TCM) for building Twitter-specific **opinion lexicons** (acquisition of lexical knowledge).
- These methods could be used to create **domain-specific** lexicons.
- They could also be used to study the **dynamics** of opinion-words.
- We proposed two **distant supervision methods** (TCM and ASA) that outperformed LAA and EAA for MPC.
- TCM is a **unified model** for message-level and word-level sentiment classification.

Post PhD Projects

1. AffectiveTweets: and open source project for analyzing affect from social media posts (it has been used in around 30 publications and its website receives around 10 unique visits per day). `https://affectivetweets.cms.waikato.ac.nz/`
2. WekaDeepLearning4j: `https://deeplearning.cms.waikato.ac.nz/`
3. Emotion Intensity Detection (WASSA 2017 and SemEval 2018): `https://competitions.codalab.org/competitions/17751`
4. Time-evolving word vectors.
5. Bias in word vectors.
6. Multi-prototype word vectors for polysemous words.
7. Māori loanwords on Twitter.

Questions?

Thanks for your Attention!

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