Acquiring and Exploiting Lexical Knowledge for Twitter Sentiment Analysis

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21 September,2016

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Te Whare Wānanga o Waikato

Social Media

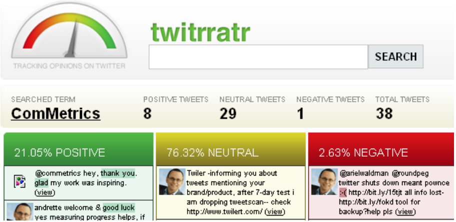
- Microblogging services are increasingly being adopted by people in order to access and publish information.
- **Twitter**: Massively used Microblogging platform where users post messages (a.k.a **tweets**) limited to 140 characters.
- Tweets use a unique **informal dialect** including many abbreviations, 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.

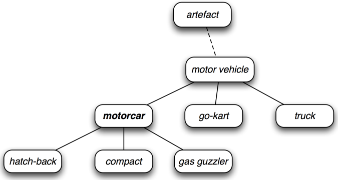
Research Problem

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).

Previous work on Polarity Lexicon Induction (PLI)

- The acquisition is normally done by exploiting **relations** between a **small seed lexicon** and **unknown words** from a **knowledge** resource.
- Two type of resources can be used: a **semantic network** (structured) such as **WordNet**, or a **corpus of documents** (unstructured).



PLI using Semantic Networks

- Methods based on WordNet expand the seed words using semantic relations such **synonyms** and **antonyms**, [Hu and Liu, 2004, Kim and Hovy, 2004].
- Hypothesis: synonyms have the **same** polarity and antonyms have the **opposite**.
- In [Kamps et al., 2004] a **graph** was created using WordNet **adjectives** as vertices and the **synonym** relation as edges.
- Words are expanded by its **relative distance** from the two seed terms **good** and **bad**.
- In [Esuli and Sebastiani, 2005, Esuli and Sebastiani, 2006] the authors take the **dictionary definitions** of the seed words to train a word-level classifier.
- As semantic networks cover a fixed vocabulary, they **cannot** capture informal Twitter words.

Corpus-based PLI

- Corpus approaches exploit **statistical patterns** observed in document corpora (e.g.**tweets**).
- Turney et.al proposed an unsupervised measure called **PMI semantic orientation** (PMI-SO) [Turney and Littman, 2003].
- It is calculated as the difference between the point-wise mutual information **PMI** of the word with a positive and a negative variable y.

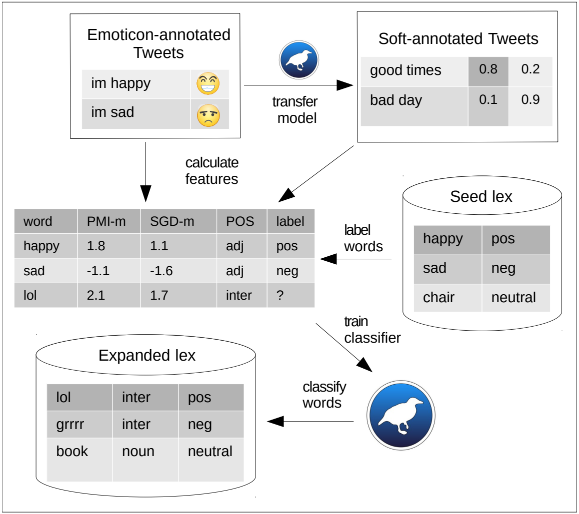
$$\text{PMI-SO}(w) = log_2 \left(\frac{\text{count}(w \wedge y = pos) \times \text{count}(y = neg)}{\text{count}(y = pos) \times \text{count}(w \wedge y = neg)} \right)$$

- For Twitter PLI these variables correspond to message-level labels obtained using **EAA** [Mohammad et al., 2013, Zhou et al., 2014]
- The approach suffers from the same limitations as **EAA** for MPC.

Word-sentiment Associations for PLI

- We propose a **supervised framework** for **PLI** based on **sentiment-annotated tweets**.
- The tweets are labelled in an **automatic fashion** (EAA and transfer model).
- Each expanded word has a **probability distribution**, describing how positive, negative, and neutral it is.
- All the entries of the lexicon are associated with a corresponding **part-of-speech** tag.
- This is useful for word **disambiguation** e.g., fine can be an adjective or a noun.
- These properties are inspired by **SentiWordnet**.

Methodology



Ground-Truth word polarities

- The expansion requires a **seed lexicon** with words labelled by sentiment.
- We create a meta-lexicon by taking the **union** of existing hand-made lexicons.
- We discard all words where a **polarity clash** is observed.

	Positive	Negative	Neutral
AFINN	564	964	0
Bing Liu	2003	4782	0
MPQA	2295	4148	424
NRC-Emo	2312	3324	7714
Seed Lexicon	3730	6368	7088

Table: Lexicon Statistics

Word-level Features

- We prepend a **POS-tag** prefix to each word in order to differentiate **homographs** exhibiting different POS-tags and use the POS tag as a nominal feature.
- We calculate two types of associations for each word: **Stochastic Gradient Descent** (SGD-SO), and **PMI Semantic Orientation** (PMI-SO).
- We calculate associations from **hard** and **soft** message-level labels.

The SGD-SO association

- This SGD-SO association is calculated by incrementally training a **linear support vector machine** from the collection of **hard-labelled** tweets.
- We use **stochastic gradient descent** (SGD) online learning process.

$$\frac{\lambda}{2}||w||^2 + \sum[1 - y(\mathbf{xw} + b)]_+. \quad (1)$$

- We use a squared loss function over the log odds $z = \log_2(\frac{pos(d)}{neg(d)})$ for **soft-annotated** tweets.

$$\frac{\lambda}{2}||w||^2 + \sum(z - (\mathbf{xw} + b))^2. \quad (2)$$

The PMI-SO association

- The second association for **hard-annotated** tweets corresponds to the **PMI semantic orientation** (PMI-SO).

$$\text{PMI-SO}(w) = log_2 \left(\frac{\text{count}(w \wedge y = 1) \times \text{count}(y = -1)}{\text{count}(y = 1) \times \text{count}(w \wedge y = -1)} \right) \quad (3)$$

- For soft-annotated tweets:

$$\text{PMI-SO}'(w) = log_2 \left(\frac{\sum_{d \in C(w)} \text{pos}(d) \times \sum_{d \in C} \text{neg}(d)}{\sum_{d \in C} \text{pos}(d) \times \sum_{d \in C(w)} \text{neg}(d)} \right) \quad (4)$$

Feature Visualisation

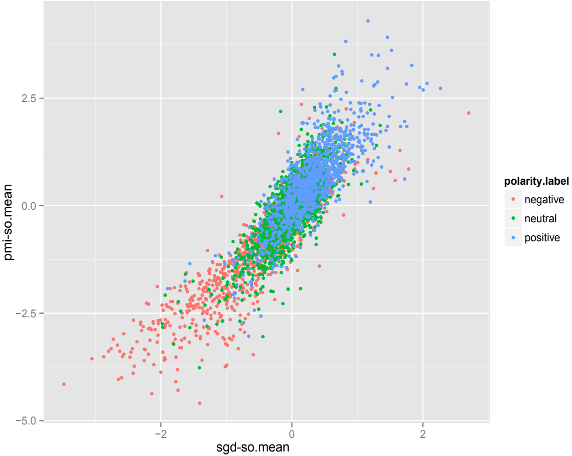


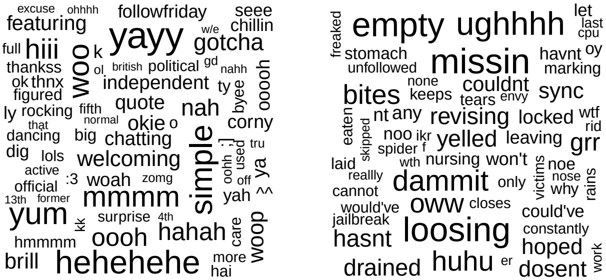
Figure: PMI-SO vs SGD-SO scatterplot.

Word-level Classification Results using RBF SVMs

Weighted AUC		
Dataset	PMI-SO	ALL FEATURES
ED.EM	0.62 ± 0.02	$\mathbf{0.65} \pm \mathbf{0.02}$ +
STS	0.64 ± 0.02	$\mathbf{0.66} \pm \mathbf{0.01}$ +
ED.SL	0.63 ± 0.02	$\mathbf{0.65} \pm \mathbf{0.02}$ +

Table: World-level classification performance.

Expanded Lexicon



(a) (b)

Figure: Word clouds of positive and negative words using log odds proportions.

Message-level classification

	AUC		
Dataset	6HumanCoded	Sanders	SemEval
Seed.Lex	0.77 $\pm$ 0.03 = + -	0.77 $\pm$ 0.04 = + =	0.77 $\pm$ 0.02 = + -
SW	0.74 $\pm$ 0.03 - = -	0.7 $\pm$ 0.05 - = -	0.76 $\pm$ 0.02 = = -
SS	0.81 $\pm$ 0.02 + + =	0.78 $\pm$ 0.03 = + =	0.81 $\pm$ 0.02 + + =
STS	0.82 $\pm$ 0.02 + + =	**0.84** $\pm$ 0.04 + + +	**0.83** $\pm$ 0.02 + + +
ED.EM	0.82 $\pm$ 0.03 + + =	0.83 $\pm$ 0.04 + + +	0.81 $\pm$ 0.02 + + =
ED.SL	0.81 $\pm$ 0.02 + + =	0.83 $\pm$ 0.04 + + +	0.81 $\pm$ 0.02 + + =
ENS	**0.83** $\pm$ 0.02 + + =	**0.84** $\pm$ 0.04 + + +	**0.83** $\pm$ 0.02 + + +

Table: Message-level polarity classification performance. Best result per column is given in bold.

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)

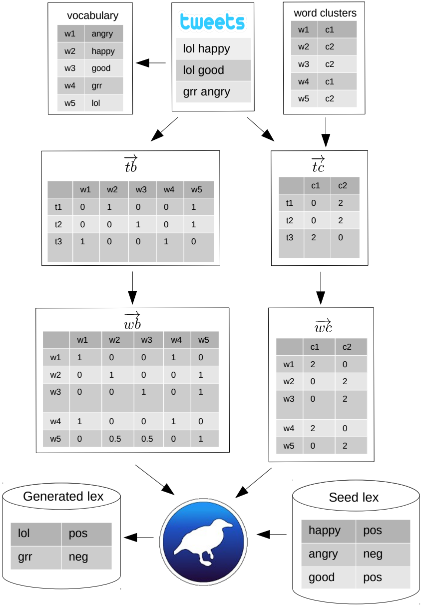
- The **word-tweet set** $\mathcal{M}(w)$ is the set of tweets from a corpus $\mathcal{C}_U$ in which the word w is observed (posting list in IR):

$$\mathcal{M}(w) = \{m : w \in m\} \tag{5}$$

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

$$w_j = \sum_{t \in \mathcal{M}(w)} \frac{x_j^{(t)}}{|\mathcal{M}(w)|} \tag{6}$$

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	$0.80 \pm 0.04 +$	**0.83** $\pm$ **0.04** $+$
6-human	0.79 ± 0.03	$0.82 \pm 0.03 +$	**0.83** $\pm$ **0.02** $+$
SemEval	0.78 ± 0.02	$0.82 \pm 0.02 +$	**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**

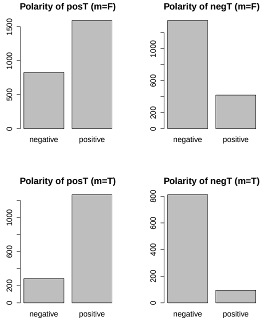
Table: Word-level Polarity Classification Results for the AFINN lexicon.

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	+ +	$\mathbf{0.817} \pm 0.006$	+ +	0.841 ± 0.002	+ +
TCM (p=20)	$\mathbf{0.850} \pm 0.003$	+ +	0.815 ± 0.011	+ +	$\mathbf{0.844} \pm 0.003$	+ +
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** $\pm$ 0.001	+ + + +	**0.812** $\pm$ 0.015	+ + + +	**0.840** $\pm$ 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.

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 ($a = 1$, $m = T$)	0.734 ± 0.005	+ = + +	0.721 ± 0.010	+ + + +	0.724 ± 0.004	+ + = +
ASA ($a = 5$, $m = T$)	0.745 ± 0.005	+ + + +	0.723 ± 0.010	+ + + +	0.722 ± 0.006	+ + = +
ASA ($a = 10$, $m = T$)	0.737 ± 0.003	+ = + +	0.703 ± 0.011	+ = - =	0.708 ± 0.007	+ - - =
ASA ($a = 50$, $m = T$)	0.693 ± 0.003	+ - - -	0.643 ± 0.004	+ - - -	0.639 ± 0.006	+ - - -
ASA ($a = 100$, $m = T$)	0.672 ± 0.004	+ - - -	0.620 ± 0.005	+ - - -	0.607 ± 0.006	+ - - -
ASA ($a = 500$, $m = T$)	0.638 ± 0.004	+ - - -	0.599 ± 0.008	+ - - -	0.563 ± 0.005	- - - -
ASA ($a = 1000$, $m = T$)	0.635 ± 0.004	+ - - -	0.594 ± 0.010	+ - - -	0.554 ± 0.003	- - - -
ASA ($a = 1$, $m = F$)	0.717 ± 0.007	+ - - =	0.691 ± 0.013	+ - - -	0.699 ± 0.008	+ - - -
ASA ($a = 5$, $m = F$)	0.755 ± 0.004	+ + + +	0.730 ± 0.008	+ + + +	0.735 ± 0.005	+ + + +
ASA ($a = 10$, $m = F$)	**0.761** ± 0.003	+ + + +	**0.735** ± 0.015	+ + + +	**0.742** ± 0.006	+ + + +
ASA ($a = 50$, $m = F$)	0.749 ± 0.004	+ + + +	0.673 ± 0.005	+ - - -	0.699 ± 0.009	+ - - -
ASA ($a = 100$, $m = F$)	0.717 ± 0.003	+ - - -	0.645 ± 0.006	+ - - -	0.664 ± 0.005	+ - - -
ASA ($a = 500$, $m = F$)	0.665 ± 0.002	+ - - -	0.621 ± 0.007	+ - - -	0.621 ± 0.004	+ - - -
ASA ($a = 1000$, $m = F$)	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

- 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.
- Future work: try **non-linear representations** on TCM (Auto-Encoders or RBM).

Conclusions

- 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.
- Future work: subjectivity, emotions, handle negations, non-linear representations and deep networks. Volunteers?

Publications

1. F. Bravo-Marquez, E. Frank, and B. Pfahringer *Positive, Negative, or Neutral: Learning an Expanded Opinion Lexicon from Emoticon-annotated Tweets*, In *IJCAI '15: Proceedings of the 24th International Joint Conference on Artificial Intelligence*. Buenos Aires, Argentina 2015.
2. F. Bravo-Marquez, E. Frank, and B. Pfahringer *From Unlabelled Tweets to Twitter-specific Opinion Words*, In *SIGIR '15: Proceedings of the 38th International ACM SIGIR Conference on Research & Development in Information Retrieval*. Santiago, Chile 2015.
3. F. Bravo-Marquez, E. Frank, and B. Pfahringer *Building a Twitter Opinion Lexicon from Automatically-annotated Tweets*, In *Knowledge-Based Systems*. Volume 108, 15 September 2016, Pages 65 -– 78.
4. F. Bravo-Marquez, E. Frank, and B. Pfahringer *Annotate-Sample-Average (ASA): A New Distant Supervision Approach for Twitter Sentiment Analysis*, In *ECAI'16: Proceedings of the biennial European Conference on Artificial Intelligence*. The Hague, Netherlands 2016.
5. F. Bravo-Marquez, E. Frank, and B. Pfahringer *From opinion lexicons to sentiment classification of tweets and vice versa: a transfer learning approach*, In *WI'16: Proceedings of the IEEE/WIC/ACM International Conference on Web Intelligence*. Omaha, Nebraska, USA 2016.
6. F. Bravo-Marquez, E. Frank, S. Mohammad, and B. Pfahringer *Determining Word–Emotion Associations from Tweets by Multi-Label Classification*, In *WI'16: Proceedings of the IEEE/WIC/ACM International Conference on Web Intelligence*. Omaha, Nebraska, USA 2016.

Questions?

Thanks for your Attention!
#ThankYouHeaps
#GraciasTotales

Acknowledgements

- University of Waikato Doctoral Scholarship
- Machine Learning Group at the University of Waikato

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