

Tweet Sentiment Quantification: An Experimental Re-Evaluation

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Abstract. Sentiment quantification is the task of estimating the relative frequency (or “prevalence”) of sentiment-related classes (such as **Positive**, **Neutral**, **Negative**) in a sample of unlabelled texts; this is especially important when these texts are tweets, since most sentiment classification endeavours carried out on Twitter data actually have quantification (and not the classification of individual tweets) as their ultimate goal. It is well-known that solving quantification via “classify and count” (i.e., by classifying all unlabelled items via a standard classifier and counting the items that have been assigned to a given class) is suboptimal in terms of accuracy, and that more accurate quantification methods exist. In 2016, Gao and Sebastiani carried out a systematic comparison of quantification methods on the task of tweet sentiment quantification. In hindsight, we observe that the experimental protocol followed in that work is flawed, and that its results are thus unreliable. We now re-evaluate those quantification methods on the very same datasets, this time following a now consolidated and much more robust experimental protocol, that involves 5775 as many experiments as run in the original study. Our experimentation yields results dramatically different from those obtained by Gao and Sebastiani, and thus provide a different, much more solid understanding of the relative strengths and weaknesses of different sentiment quantification methods.

Keywords: Learning to quantify · Quantification · Prevalence estimation · Sentiment analysis · Sentiment quantification · Twitter

1 Introduction

Quantification (a.k.a. *supervised prevalence estimation*, or *learning to quantify*) is the task of training a predictor that estimates the relative frequency (a.k.a. *prevalence*, or *prior probability*) of the classes of interest in a sample of unlabelled data items, where the data used to train the predictor are a set of labelled data items [16]. Quantification finds applications in fields (such as the social sciences [17], epidemiology [19], market research [8], and ecological modelling [2]) that are inherently interested in aggregate (rather than individual) data, but also in other fields as diverse as resource allocation [13] and word sense disambiguation [5].

In the realm of textual data, one important domain to which quantification is applied, is sentiment analysis. In fact, as argued in [9], many applications of sentiment classification are such that the final goal is not determining the class label (e.g., **Positive**, or **Neutral**, or **Negative**) of an individual text (say, a blog post, a response to an open question, or a comment on a product), but is that of determining the relative frequency of each class of interest in a set of unlabelled texts. In a 2016 paper, Gao and Sebastiani [15] have argued that, when the objects of analysis are tweets, the *vast majority* of sentiment classification endeavours actually have

quantification as their final goal, since hardly anyone who engages in sentiment classification of tweets is interested in the sentiment conveyed by a specific tweet.

Driven by this consideration, [15] presented an experimental comparison of 8 important quantification methods on 11 Twitter datasets annotated by sentiment, with the goal of assessing the strength and weaknesses of the various methods for tweet sentiment quantification. That paper became then influential¹ and, to date, the largest comparative experimentation on sentiment quantification for Twitter and a standard reference on this problem.

In this paper we argue that the experimental results obtained in [15] are unreliable, as a result of the fact that the experimental protocol used in that paper is flawed. We thus engage in a reproducibility study and present new experiments in which we re-test all 8 quantification methods originally tested in [15] (plus some additional ones that have been proposed since then) on the same 11 datasets used in [15], this time using a now consolidated and much more robust experimental protocol. These new experiments (that are 5775 times larger in size than the ones of [15]) yield results dramatically different from those obtained in [15], and thus give us a new, more reliable picture of the relative merits of the various methods on the tweet sentiment quantification task.

The rest of this paper is structured as follows. In Section 2 we discuss experimental protocols for quantification, and argue why the one used in [15] is, in hindsight, flawed. In Section 3 we present the new experiments we have run, briefly discussing the quantification methods and the datasets we use, and explaining in detail the experimental protocol we use. Section 4 discusses the results and the conclusions that they allow to draw, also pointing at how they differ from the ones of [15].

We make all the code we use for our experiments available²; together with the fact that the authors of [15] made available (in vector form) all their 11 datasets³, this allows our experiments to be easily reproduced by other researchers.

2 Experimental Protocols for Quantification

2.1 Notation

In this paper we use the following notation. By \mathbf{x} we indicate a document drawn from a domain \mathcal{X} of documents, while by y we indicate a class drawn from a set of classes (a.k.a. *codeframe*) $\mathcal{Y} = \{y_1, \dots, y_{|\mathcal{Y}|}\}$. Given $\mathbf{x} \in \mathcal{X}$ and $y \in \mathcal{Y}$, a pair (\mathbf{x}, y) thus denotes a document with its class label. Symbol σ denotes a *sample*, i.e., a nonempty set of (labelled or unlabelled) documents drawn from \mathcal{X} . By $p_\sigma(y)$ we indicate the true prevalence of class y in sample σ , by $\hat{p}_\sigma(y)$ we indicate an estimate of this prevalence⁴, and by $\hat{p}_\sigma^M(y)$ we indicate the estimate of this prevalence as obtained via quantification method M . By $D(p, \hat{p})$ we denote an evaluation measure for quantification. By L we denote a sample of labelled documents, that we typically use as a training set, while by U we denote a sample of unlabelled documents, that we typically use as a sample to quantify on. We take a *hard classifier* to be a function $h : \mathcal{X} \rightarrow \mathcal{Y}$, and a *soft classifier* to be a function $s : \mathcal{X} \rightarrow [0, 1]^{|\mathcal{Y}|}$, where $s(\mathbf{x})$ is a vector of $|\mathcal{Y}|$ *posterior probabilities* (each indicated as $\Pr(y|\mathbf{x})$), such that $\sum_{y \in \mathcal{Y}} \Pr(y|\mathbf{x}) = 1$; $\Pr(y|\mathbf{x})$ indicates the probability of membership in y of item \mathbf{x} as estimated by s . By $\delta_\sigma(y)$ we denote the set of documents in sample σ that have been assigned to class y by a hard classifier.

¹ At the time of writing, paper [15] and paper [14] (a shorter and earlier version of [15]) have 101 citations altogether on Google Scholar.

² <https://github.com/AlexMoreo/TweetSentQuant>

³ http://alt.qcri.org/~wgao/data/SNAM/tweet_sentiment_quantification.zip

⁴ Consistently with most mathematical literature, we use the caret symbol ($\hat{\cdot}$) to indicate estimation.

Quantification may be seen as the task of approximating a *true distribution* p across the classes in a codeframe $\mathcal{Y} = \{y_1, \dots, y_{|\mathcal{Y}|}\}$ by means of a *predicted distribution* \hat{p} ; in other words, in quantification one needs to generate estimates $\hat{p}(y_1), \dots, \hat{p}(y_{|\mathcal{Y}|})$ of the true (and unknown) class prevalence values $p(y_1), \dots, p(y_{|\mathcal{Y}|})$, where $\sum_{y \in \mathcal{Y}} \hat{p}(y) = \sum_{y \in \mathcal{Y}} p(y) = 1$. In this paper we consider a ternary sentiment quantification task (an example of *single-label multiclass quantification*) in which the codeframe is $\mathcal{Y} = \{\text{Positive}, \text{Neutral}, \text{Negative}\}$, where these three class labels will be indicated, for brevity, by the symbols $\{\oplus, \odot, \ominus\}$; all the 11 datasets discussed in Section 3.3 use this codeframe.

2.2 The APP and the NPP

There are two main experimental protocols that have been used in the literature for evaluating quantification; we will here call them the *artificial-prevalence protocol* (APP) and the *natural-prevalence protocol* (NPP).

The APP consists of taking a standard dataset, split into a training set L of labelled items and a set U of unlabelled items, and conducting repeated experiments in which either the training set prevalence or the test set prevalence of a class are artificially varied via subsampling (i.e., by removing random elements of a specific class until the desired prevalence values are obtained). For instance, in the binary quantification experiments carried out in [12], given codeframe $\mathcal{Y} = \{y_1, y_2\}$, repeated experiments are conducted in which examples of either y_1 or y_2 are removed at random from the test set in order to generate predetermined prevalence values for y_1 and y_2 in the sample U thus obtained. In this way, different samples can be generated, each characterised by a different prevalence of y_1 (e.g., $p_U(y_1) \in \{0.00, 0.05, \dots, 0.95, 1.00\}$) and, as a result, by a different prevalence of y_2 . This can be repeated, thus generating multiple random samples for each pair of class prevalence values. Analogously, random removal of examples of either y_1 or y_2 can be performed on the training set, thus bringing about training sets with different values of $p_L(y_1)$ and $p_L(y_2)$.

This protocol has been criticised because it may generate samples exhibiting class prevalence values very different from the ones of the set from which the sample was extracted, i.e., class prevalence values that are hardly plausible. As a result, one may resort to the NPP, which consists instead of conducting experiments on “real” datasets only, i.e., datasets consisting of a training set L and a test set U that have been sampled IID from the data distribution.

The experimentation conducted by Gao and Sebastiani on tweet sentiment quantification [15] is indeed an example of the NPP, since it relies on 11 “original” datasets of tweets annotated by sentiment, i.e., no extraction of samples at pre-specified values of class prevalence was performed. However, the authors of [15] failed to realise that, while in classification an experiment involving 11 different datasets probably counts as large and robust, this does not hold in quantification. The reason is that, since the objects of quantification are sets of documents inasmuch as the objects of classification are individual documents, *testing a quantifier on 11 sets of documents is as robust an experiment as testing a classifier on 11 documents*. Unfortunately, finding a large enough set of datasets sampled IID from the data distribution is very problematic; this indicates that the APP is probably the only way to go for evaluating quantification.⁵ Indeed, most recent quantification works (e.g., [7,20,23]) adopt the APP, and not the NPP.

⁵ An example set of experiments that use the NPP protocol on a large enough set of test sets is the one reported in [11], where the authors test quantifiers on $52 \times 99 = 5148$ binary test sets. This results from the fact that, in using the RCV1-v2 test collection, they consider 99 classes and bin the RCV1-v2 791607 test documents in 52 bins of 15212 documents each on average. However, it is not always easy to find test collections with

As a result, we should conclude that the experimental protocol followed in [15] is flawed, and that the results of that experimentation are thus unreliable. We thus re-evaluate the same quantification methods that [15] tested (plus some other more recent ones) on the same datasets, this time following the by now consolidated and much more robust APP; in our case, this turns out to involve 5775 as many experiments as run in the original study.

3 Experiments

3.1 Quantification methods

We now briefly describe the quantification methods used in [15], that we also use in this paper.

The simplest quantification method (and the one that acts as a lower-bound baseline for all quantification methods) is the above-mentioned *Classify and Count* (CC), which, given a hard classifier h , comes down to computing

$$\hat{p}_U^{\text{CC}}(y_i) = \frac{|\{\mathbf{x} \in U | h(\mathbf{x}) = y_i\}|}{|U|} = \frac{\sum_{y_j \in \mathcal{Y}} C_{ij}^h}{|U|} \quad (1)$$

where C_{ij}^h indicates the number of documents classified as y_i by h and whose true label is y_j . CC is an example of an *aggregative* quantification method, i.e., a method that requires the (hard or soft) classification of all the unlabelled items as an intermediate step. All the methods discussed in this paper are aggregative.

The *Adjusted Classify and Count* (ACC) quantification method [13] derives from the observation that, by the law of total probability, it holds that

$$\Pr(\delta(y_i)) = \sum_{y_j \in \mathcal{Y}} \Pr(\delta(y_i) | y_j) \cdot \Pr(y_j) \quad (2)$$

where $\delta(y_i)$ denotes the set of documents that have been assigned to class y_i by the hard classifier h . Equation 2 can be more conveniently rewritten as

$$\frac{\sum_{y_j \in \mathcal{Y}} C_{ij}^h}{|U|} = \sum_{y_j \in \mathcal{Y}} \frac{C_{ij}^h}{\sum_{y_x \in \mathcal{Y}} C_{xj}^h} \cdot p_U(y_j) \quad (3)$$

Note that the leftmost factor of Equation 3 is known (it is the fraction of documents that the classifier has assigned to class y_i , i.e., $\hat{p}_U^{\text{CC}}(y_i)$), and that $\frac{C_{ij}^h}{\sum_{y_x \in \mathcal{Y}} C_{xj}^h}$ (which represents the disposition of the classifier to assign y_i when y_j is the case), while unknown, can be estimated by k -fold cross validation on L . Note also that $p_U(y_j)$ is unknown (it is the goal of quantification to estimate it), and that there are $|\mathcal{Y}|$ instances of Equation 2, one for each $y_i \in \mathcal{Y}$. We are then in the presence of a system of $|\mathcal{Y}|$ linear equations in $|\mathcal{Y}|$ unknowns (the $p_U(y_j)$'s); ACC thus consists of estimating these latter (i.e., computing $\hat{p}_U^{\text{ACC}}(y_j)$) by solving, via the known techniques, this system of linear equations.

CC and ACC use the predictions generated by the hard classifier h , as evident by the fact that both Equations 1 and 3 depend on factors of type C_{ij}^h . Since most classifiers can be configured to output “soft predictions” in the form of posterior probabilities $\Pr(y|\mathbf{x})$ (from which hard predictions are obtained by choosing the y

such a large amount of classes and annotated data, and this limits the applicability of the NPP. It should also be mentioned that, as [4] found, the vast majority of the 5148 RCV1-v2 binary test sets exhibit very little shift, which makes the testbed used in [11] unchallenging for quantification methods.

for which $\Pr(y|\mathbf{x})$ is maximised),⁶ and since posterior probabilities contain richer information than hard predictions, one can generate probabilistic versions of the CC and ACC methods [3] by replacing “hard” counts C_{ij}^h with their expected values, i.e., with $C_{ij}^s = \sum_{(\mathbf{x}, y_j) \in U} \Pr(y_i|\mathbf{x})$.

One can then define *Probabilistic Classify and Count (PCC)* as

$$\hat{p}_U^{\text{PCC}}(y_i) = \frac{\sum_{\mathbf{x} \in U} \Pr(y_i|\mathbf{x})}{|U|} = \frac{\sum_{y_j \in \mathcal{Y}} C_{ij}^s}{|U|} \tag{4}$$

and *Probabilistic Adjusted Classify and Count (PACC)*, which consists in estimating $p_U(y_j)$ (i.e., computing $\hat{p}_U^{\text{PACC}}(y_j)$) by solving the linear system

$$\frac{\sum_{y_j \in \mathcal{Y}} C_{ij}^s}{|U|} = \sum_{y_x \in \mathcal{Y}} \frac{C_{ij}^s}{\sum_{y_x \in \mathcal{Y}} C_{xj}^s} \cdot p_U(y_j) \tag{5}$$

The fact that PCC is a probabilistic version of CC is evident from the similarity between Equations 1 and 4, which only differ for the fact that the hard classifier h of Equation 1 is replaced by a soft classifier s in Equation 4; the same goes for ACC and PACC.

A further method that [15] uses is *Expectation Maximisation for Quantification (EMQ [24])*, which consists of training a probabilistic classifier and then using the EM algorithm to update the posterior probabilities that the classifier returns to and re-estimate the class prevalence values, in an iterative, mutually recursive way [6].

Quantification methods **SVM(KLD)**, **SVM(NKLD)**, **SVM(Q)**, belong instead to the “structured output learning” camp. Each of them is the result of instantiating the SVM_{perf} structured output learner [18] to optimise a different loss function. SVM(KLD) [11] minimises the Kullback-Leibler Divergence (KLD); SVM(NKLD) [10] minimises a version of KLD normalised via the logistic function; SVM(Q) [1] minimises the harmonic mean of a classification-oriented loss (recall) and a quantification-oriented loss (RAE). Each of these learners generates a “quantification-oriented” classifier, and the quantification method consists of performing CC by using this classifier.

From the “structured output learning” camp we also consider **SVM(AE)** and **SVM(RAE)**, i.e., variants of the above that minimise AE and RAE, since these latter are, for reasons discussed in Section 3.2, the evaluation measures used in this paper for evaluating the quantification accuracy of our systems. We consider SVM(AE) only when testing according to AE, and we consider SVM(RAE) only when testing according to RAE; this obeys the principle that a sensible user, after deciding the evaluation measure to use for her experiments,⁷ would instantiate SVM_{perf} with that measure, and not with others.

3.1.1 Underlying classifiers. Consistently with [15], as the classifier underlying CC, ACC, PCC, PACC, and EMQ, we use one trained via L2-regularised logistic regression. The reasons of this choice are the same as described in [15], i.e., the fact that logistic regression is known to display very good classification accuracy across a variety of application domains, and that a classifier trained via LR returns posterior probabilities that tend to be fairly well-calibrated, a fact which is of fundamental importance for methods such as PCC, PACC, and EMQ.

⁶ If a classifier natively outputs classification scores that are not probabilities, the former can be converted into the latter via “probability calibration”; see e.g., [22].

⁷ Quantification is a task in which deciding the right evaluation measure to use for one’s application is of critical importance; in fact, [25] argues that some applications demand measures such as AE, while the requirements of other applications are best mirrored in measures such as RAE.

As specified above, the classifier underlying SVM(KLD), SVM(NKLD), SVM(Q), SVM(AE), SVM(RAE), is one trained via SVM_{perf}.

3.2 Evaluation measures

As the measures of quantification error we use *Absolute Error* (AE) and *Relative Absolute Error* (RAE), defined as

$$\text{AE}(p, \hat{p}) = \frac{1}{|\mathcal{Y}|} \sum_{y \in \mathcal{Y}} |\hat{p}(y) - p(y)| \quad (6)$$

$$\text{RAE}(p, \hat{p}) = \frac{1}{|\mathcal{Y}|} \sum_{y \in \mathcal{Y}} \frac{|\hat{p}(y) - p(y)|}{p(y)} \quad (7)$$

where \mathcal{Y} is the set of classes of interest ($\mathcal{Y} = \{\oplus, \odot, \ominus\}$ in our case). Note that RAE is undefined when at least one of the classes $y \in \mathcal{Y}$ is such that its prevalence in U is 0. To solve this problem, in computing RAE we smooth all $p(y)$'s and $\hat{p}(y)$'s via additive smoothing, i.e., we take $\underline{p}(y) = \frac{\epsilon + p(y)}{\epsilon|\mathcal{Y}| + \sum_{y \in \mathcal{Y}} p(y)}$, where $\underline{p}(y)$ denotes the smoothed version of $p(y)$ and the denominator is just a normalising factor (same for the $\hat{p}(y)$'s); following [13], we use the quantity $\epsilon = \frac{1}{2|U|}$ as the smoothing factor. We then use the smoothed versions of $p(y)$ and $\hat{p}(y)$ in place of their original non-smoothed versions in Equation 7; as a result, RAE is always defined.

The reason why we use AE and RAE is that from a theoretical standpoint they are, as it has been recently argued [25], the most satisfactory evaluation measures for quantification. This means that we do not consider other measures used in [15], such as KLD, NAE, NRAE, and NKLD, since [25] has shown them to be less adequate, as evaluation measures for quantification, than AE and RAE.

3.3 Datasets

The datasets on which we run our experiments are the same 11 datasets on which the experiments of [15] were carried out, and whose characteristics are described succinctly in Table 1. As already noted at the end of Section 1, the authors of [15] make these datasets available already in vector form; we refer to [15] for a fuller description of these datasets. In the experiments described in this paper we discard all features that occur in fewer than 5 training documents.

As mentioned in Section 2.2, for each of the 13 datasets we here extract multiple samples from the test set, according to the following protocol. For each different triple $(p_{\oplus}, p_{\odot}, p_{\ominus})$ of class prevalence values such that each class prevalence is in the finite set $P = \{0.00, 0.05, \dots, 0.95, 1.00\}$, we extract m random samples of q documents each; in these experiments we use $m = 25$ and $q = 100$. For each label $y \in \{\oplus, \odot, \ominus\}$ the extraction is carried out via sampling without replacement.⁸

It is easy to verify that there exist $|P|(|P| + 1)/2 = 231$ different triples with values in P .⁹ Our experimentation of a given quantification method M on a given dataset thus consists of training M on the training tweets L_{Tr} , using the validation tweets L_{Va} for optimising the hyperparameters, and testing the trained system on each of the $25 \cdot 231 = 5775$ samples extracted from the test set U .

⁸ here it is possible to always use sampling without replacement because each test set contains at least $q = 100$ documents for each label $y \in \{\oplus, \odot, \ominus\}$. If a certain test set contained fewer than $q = 100$ documents for some label $y \in \{\oplus, \odot, \ominus\}$, for that label and that test set it would be necessary to use sampling with replacement.

⁹ This results from the fact that, when $p_{\oplus}(\sigma) = 0.00$, there exist 21 different pairs $(p_{\odot}(\sigma), p_{\ominus}(\sigma))$ with values in P ; when $p_{\oplus}(\sigma) = 0.05$, there exist 20 different such pairs; ...; and when $p_{\oplus}(\sigma) = 1.00$, there exists just 1 such pair. The total number of combinations is thus $\sum_{i=1}^{21} i = \frac{21 \cdot 22}{2} = 231$.

Table 1. Datasets used in this work and their main characteristics. Columns L_{Tr} , L_{Va} , U contain the numbers of tweets in the training set, held-out validation set, and test set, respectively. Column “Shift” contains the values of distribution shift between $L_{Tr} \cup L_{Va}$ and U , measured in terms of absolute error.

Dataset	L_{Tr}	L_{Va}	U	Total	Shift
GASP	7,532	1,256	3,765	12,553	0.0094
HCR	797	797	798	2,392	0.0630
OMD	1,576	263	787	2,626	0.0171
Sanders	1,847	308	923	3,078	0.0020
SemEval2013	9,684	1,654	3,813	15,151	0.0270
SemEval2014	9,684	1,654	1,853	13,191	0.1055
SemEval2015	9,684	1,654	2,390	13,728	0.0417
SemEval2016	6,000	2,000	2,000	10,000	0.0070
SST	2,546	425	1,271	4,242	0.0357
WA	1,872	312	936	3,120	0.0208
WB	3,650	609	1,823	6,082	0.0023

3.4 Parameter optimisation

Parameter optimisation is an important factor, that could bias, if not carried out properly, a comparative experimentation of different quantification methods. As we have argued elsewhere [21], when the quantification method is of the aggregative type, for this experimentation to be unbiased not only it is important to optimise the hyperparameters of the classifier that underlies the quantification method, but it is also important that this optimisation is carried out using a quantification-oriented loss, and not a classification-oriented one.

In order to optimise a quantification-oriented loss it is necessary to test different hyperparameter settings on multiple samples extracted from the held-out validation set, in the style of the evaluation described in Section 3.3. In order to do this, for each combination of class prevalence values we extract, from the held-out validation set of each dataset, m samples of q documents each, again using class prevalence values in $P = \{0.00, 0.05, \dots, 0.95, 1.00\}$. Here we use $m = 5$ and $q = 100$; we use a value of m five times smaller than in the evaluation phase (see Section 3.3) in order to keep the computational cost of the parameter optimisation phase within acceptable bounds.

For each label $y \in \{\oplus, \odot, \ominus\}$ the extraction is carried out by sampling without replacement if the test set contains at least $p_y \cdot q$ examples, and by sampling with replacement otherwise.¹⁰

In the experiments we report in this paper the hyperparameter that we optimise is the C parameter (that determines the tradeoff between the margin and the training error) of both LR and SVM_{perf}; for this we carry out a grid search in the range $C \in \{10^i\}$, with $i \in [-4, -3, \dots, +4, +5]$. We optimise this parameter by using either the AE measure (the corresponding results are reported in Table 2) or the RAE measure (Table 3). We evaluate the former batch of experiments only in terms of AE and the latter batch only in terms of RAE, following the principle that, once a user knew the measure to be used in the evaluation, she would carry out the parameter optimisation phase in terms of exactly that measure.

In the following, by the notation M^m we will indicate quantification method M in which the parameters of the learner have been optimised using measure m (where M^\emptyset indicates that no optimisation at all has been carried out).

¹⁰ Unlike when extracting samples in the evaluation phase (see Section 3.3), it is here sometimes necessary to use sampling with replacement because, in some dataset, the validation set does not contain at least 100 documents per class.

4 Results

Table 2 reports AE results obtained by the quantification methods we have tested on the 11 datasets, while Table 3 does the same for RAE. The tables also report the results of a paired sample, two-tailed t-test that we have run, at different confidence levels, in order to check if other methods are different or not, in a statistically significant sense, from the best-performing one.

Table 2. Values of AE obtained in our experiments; each value is the average across 5775 values, each obtained on a different sample. **Boldface** indicates the best method for a given dataset. Superscripts † and †† denote the methods (if any) whose score are not statistically significantly different from the best one according to a paired sample, two-tailed t-test at different confidence levels: symbol † indicates $0.001 < p\text{-value} < 0.05$ while symbol †† indicates $0.05 \leq p\text{-value}$. The absence of any such symbol indicates $p\text{-value} \leq 0.001$.

	Methods tested in [15]								
	CC ^{AE}	ACC ^{AE}	PCC ^{AE}	PACC ^{AE}	EMQ ^{AE}	SVM(Q) ^{AE}	SVM(KLD) ^{AE}	SVM(NKLD) ^{AE}	SVM(AE) ^{AE}
GASP	0.103	0.057	0.137	0.059	0.036	0.119	0.114	0.109	0.136
HCR	0.131	0.081	0.159	0.080	0.073	0.150	0.143	0.138	0.157
OMD	0.122	0.079	0.129	0.081	0.071	0.141	0.124	0.139	0.116
Sanders	0.128	0.062	0.149	0.062	0.046	0.140	0.140	0.110	0.157
SemEval13	0.117	0.089	0.144	0.078	0.093	0.129	0.144	0.134	0.143
SemEval14	0.106	0.071	0.136	0.064	0.073	0.127	0.128	0.122	0.134
SemEval15	0.129	0.108	0.149	0.112	0.098	0.142	0.149	0.144	0.144
SemEval16	0.148	0.157	0.176	0.125	0.100	0.167	0.154	0.164	0.178
SST	0.115	0.082	0.138	0.079	0.052	0.136	0.113	0.128	0.125
WA	0.081	0.046	0.083	0.043	0.043††	0.111	0.100	0.063	0.071
WB	0.081	0.044	0.084	0.041	0.034	0.106	0.084	0.103	0.069

An important aspect that emerges from this table is that the behaviour of the different quantifiers is fairly consistent across our 11 datasets; in other words, when a method is a good performer on one dataset, it tends to be a good performer *on all datasets*. Together with the fact that we test on a large set of samples, and that these are characterised by values of distribution shift across the entire range, this allows us to be fairly confident in the conclusions that we draw from these results.

A second observation is that three methods (EMQ, PACC, and ACC) stand out, since they perform consistently well across all datasets and for both evaluation measures. In particular, EMQ is the best method for 8 out of 11 datasets (and is not different, in a statistically significant sense, from the best method on yet another dataset) when testing with AE, and for all 11 datasets when testing with RAE. PACC also fares very well, and is the best performer for 3 out of 11 datasets when testing with AE. The fact that both ACC and PACC tend to perform well shows that the intuition according to which CC predictions should be “corrected” by estimating the disposition of the classifier to assign class y_i when class y_j is the case, is valuable and robust to varying levels of distribution shift.

By contrast, these results show a generally disappointing performance on the part of all methods based on structured output learning, i.e., on the SVM_{perf} learner.

Table 3. As Table 2, but with RAE instead of AE.

	Methods tested in [15]								
	CC^{RAE}	ACC^{RAE}	PCC^{RAE}	$PACC^{RAE}$	EMQ^{RAE}	$SVM(Q)^{RAE}$	$SVM(KLD)^{RAE}$	$SVM(NKLD)^{RAE}$	$SVM(RAE)^{RAE}$
GASP	2.974	0.690	3.707	0.683	0.426	4.076	3.261	3.433	4.581
HCR	3.866	1.344	4.292	1.517	0.512	4.934	4.219	4.187	3.998
OMD	3.701	0.891	3.856	1.106	0.531	4.571	3.865	4.486	3.290
Sanders	3.255	1.042	3.772	1.076	0.249	4.408	3.596	3.550	3.741
SemEval13	3.169	1.209	3.730	1.111	0.465	4.007	3.726	3.945	3.594
SemEval14	3.149	0.892	3.728	0.928	0.343	4.033	3.545	3.754	3.380
SemEval15	3.638	2.054	4.079	2.128	0.844	4.414	4.032	4.274	3.850
SemEval16	4.641	2.676	5.244	2.650	1.222	5.433	4.887	5.263	5.196
SST	4.117	0.996	4.234	0.983	0.512	4.437	3.608	3.563	3.391
WA	2.549	0.753	2.645	0.827	0.273	3.520	2.830	1.413	2.064
WB	2.458	0.548	2.587	0.615	0.266	3.456	2.534	2.255	2.052

Note that the fact that SVM(KLD), SVM(NKLD), SVM(Q) optimise a performance measure different from the one used in the evaluation (AE or RAE) cannot be the cause of this suboptimal performance, since this latter also characterises SVM(AE) when tested on AE and SVM(RAE) when tested with RAE.

CC and PCC do not perform well either. If this was somehow to be expected for CC, this is surprising for PCC, which always performs worse than CC in our experiments, on all datasets and for both performance measures. It would be tempting to conjecture that this might be due to a supposedly insufficient quality of the posterior probabilities returned by the underlying classifier; however, this conjecture is implausible, since the quality of the posterior probabilities did not prevent EMQ from displaying sterling performance, and PACC from faring very well.

We now turn to comparing the results of our experiments with the ones reported in [15]. For doing this, for each dataset we rank in terms of their performance the 8 quantification methods used in both batches of experiments, and compare the rank positions obtained by each method in the two batches. The results of this comparison are reported in Table 4 (for AE) and Table 5 (for RAE).

Something that jumps to the eye when observing these tables is that our experiments lead to conclusions that are *dramatically different* from those drawn by the authors of [15]. First of all, EMQ now unquestionably emerges as the best performer, while it was often ranked among the worst performers in [15]. Conversely, PCC was the winner on most combinations (dataset, measure) in [15], while our experiments have shown it to be a bad performer. Other methods too see their merits disconfirmed by our experiments; in particular, ACC and PACC have climbed up the ranked list, while all other methods (especially SVM(KLD)) have lost ground.

The reason for the different conclusions that these two batches of experiments allow to draw is, in all evidence, the amounts of distribution shift which the methods have had to confront in the two scenarios. In the experiments of [15], this shift was moderate, since the only test sample used (which coincided with the entire test set) usually displayed class prevalence values not too different from the class prevalence values in the training set. This is shown in the last column of Table 1, where the shift between training set and test set (expressed in terms of absolute error) is reported

Table 4. Rank positions of the quantification methods in the AE experiments, and (between parentheses) the rank positions obtained in the evaluation of [15].

	Methods tested in [15]							
	CC ^{AE}	ACC ^{AE}	PCC ^{AE}	PACC ^{AE}	EMQ ^{AE}	SVM(Q) ^{AE}	SVM(KLD) ^{AE}	SVM(NKLD) ^{AE}
GASP	4 (5)	2 (3)	8 (2)	3 (1)	1 (6)	7 (8)	6 (4)	5 (7)
HCR	4 (5)	3 (2)	8 (1)	2 (3)	1 (7)	7 (8)	6 (4)	5 (6)
OMD	4 (6)	2 (3)	6 (1)	3 (2)	1 (8)	8 (7)	5 (4)	7 (5)
Sanders	5 (5)	2 (4)	8 (2)	3 (3)	1 (6)	6 (8)	7 (1)	4 (7)
SemEval13	4 (7)	2 (5)	8 (1)	1 (6)	3 (8)	5 (4)	7 (3)	6 (2)
SemEval14	4 (8)	2 (2)	8 (6)	1 (1)	3 (3)	6 (7)	7 (5)	5 (4)
SemEval15	4 (4)	2 (3)	8 (1)	3 (2)	1 (7)	5 (8)	7 (6)	6 (5)
SemEval16	3 (3)	5 (4)	8 (1)	2 (7)	1 (5)	7 (8)	4 (2)	6 (6)
SST	5 (2)	3 (5)	8 (1)	2 (8)	1 (3)	7 (6)	4 (4)	6 (7)
WA	5 (6)	3 (5)	6 (2)	1 (1)	2 (3)	8 (8)	7 (7)	4 (4)
WB	4 (2)	3 (4)	5 (1)	2 (3)	1 (5)	8 (6)	6 (8)	7 (7)

for each dataset; the average value of this shift across all datasets is 0.0301, which is a very low value. In our experiments, instead, the quantification methods need to confront class prevalence values that are sometimes *very* different from the ones in the training set; this means that the quantification methods that have emerged in our experiments are the ones that are robust to possibly radical changes in these class prevalence values, while the ones that had fared well in the experiments of [15] are the methods that tend to perform well merely in scenarios where these changes are bland.

This situation is depicted in the plots of Figure 1. For generating these plots we have computed, for each of the $11 \times 5775 = 63525$ test samples, the distribution shift between the training set and the test sample, and we have binned these 63525 samples into bins characterised by the same amount of distribution shift (we compute distribution shift as the absolute error between the training distribution and the distribution of the test sample). The plots show, for a given quantification method and for a given bin, its quantification error measured (via AE in the top figure and via RAE in the bottom figure) as the average error across all samples in the same bin. The plots clearly show that, for CC, PCC, SVM(Q), SVM(KLD), and SVM(NKLD), this error increases, in a very substantial manner, as distribution shift increases.

The obvious conclusion is that these methods are not robust to high amounts of distribution shift, and that the reason why some of them were successful in the evaluation of [15] is that this latter confronted the methods with very low amounts of shift. In fact, it is immediate to note from Figure 1 that, when distribution shift equals 0.0301 (the average value of distribution shift that the experiments of [15] confronted), all quantification methods perform similarly. Conversely, our plots show that the quantification error of EMQ, PACC, and ACC remains fairly stable across the entire range of distribution shift values, and this is clearly the reason of their success in the evaluation we have presented here.

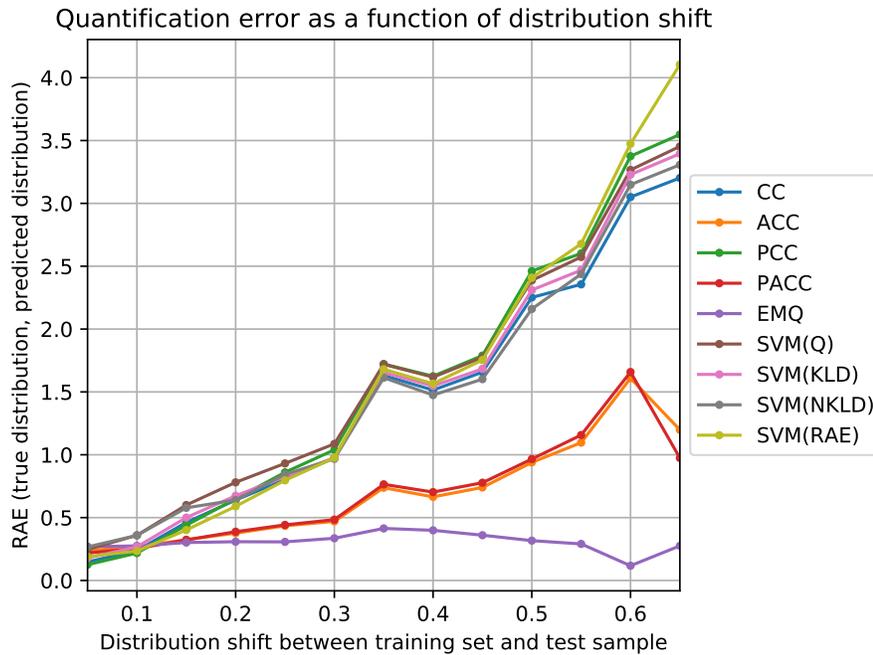
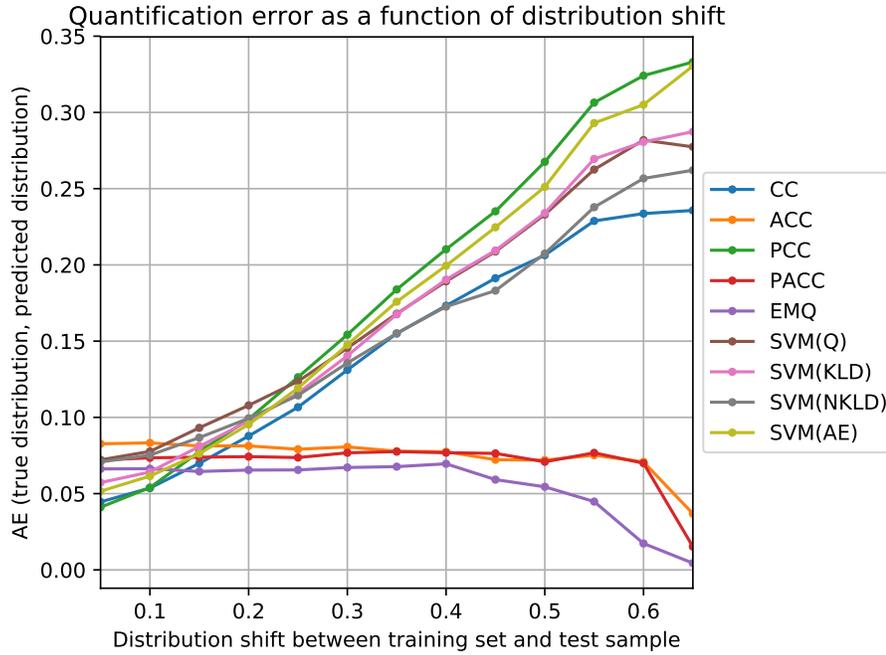


Fig. 1. Performance of the various quantification methods, measured in terms of AE (top) and RAE (bottom) – lower is better, as a function of the distribution shift between training set and test sample; the results are averages across all datasets and across all samples exhibiting the same amount of shift. (For better clarity the RAE results are actually displayed on a logarithmic scale.)

Table 5. Same as Table 4, but with RAE instead of AE.

	Methods tested in [15]							
	CC^{RAE}	ACC^{RAE}	PCC^{RAE}	$PACC^{RAE}$	EMQ^{RAE}	$SVM(Q)^{RAE}$	$SVM(KLD)^{RAE}$	$SVM(NKLD)^{RAE}$
GASP	4 (5)	3 (4)	7 (3)	2 (2)	1 (6)	8 (8)	5 (1)	6 (7)
HCR	4 (4)	2 (2)	7 (1)	3 (3)	1 (7)	8 (8)	6 (5)	5 (6)
OMD	4 (6)	2 (3)	5 (1)	3 (2)	1 (8)	8 (7)	6 (4)	7 (5)
Sanders	4 (5)	2 (4)	7 (1)	3 (3)	1 (6)	8 (8)	6 (2)	5 (7)
SemEval13	4 (7)	3 (3)	6 (1)	2 (4)	1 (8)	8 (6)	5 (2)	7 (5)
SemEval14	4 (4)	2 (2)	6 (8)	3 (3)	1 (6)	8 (7)	5 (1)	7 (5)
SemEval15	4 (3)	2 (5)	6 (1)	3 (2)	1 (4)	8 (8)	5 (6)	7 (7)
SemEval16	4 (3)	3 (5)	6 (2)	2 (7)	1 (4)	8 (8)	5 (1)	7 (6)
SST	6 (3)	3 (5)	7 (1)	2 (6)	1 (2)	8 (7)	5 (4)	4 (8)
WA	5 (5)	2 (4)	6 (2)	3 (1)	1 (3)	8 (8)	7 (7)	4 (6)
WB	5 (2)	2 (4)	7 (1)	3 (3)	1 (5)	8 (6)	6 (8)	4 (7)

5 Conclusions

The results of our experiments show that a re-evaluation of the relative merits of different quantification methods on the tweet sentiment quantification task was necessary. We have shown that the experimental protocol used in the evaluation previously conducted in [15] was faulty, and that this led the authors of this study to conduct their evaluation on a radically insufficient amount of test data points. We have then conducted a re-evaluation of the same methods on the same datasets according to a more robust, and now accepted, experimental protocol, which has lead to an experimentation 5775 times larger than the one of [15]. This experimentation has proven necessary for at least two reasons. The first reason is that some of the evaluation functions (such as KLD and NKLD) that had been used in [15] are now known to be unsatisfactory, and their use should thus be deprecated in favour of functions such as AE and RAE. The second reason, and probably the most important one, is that the results of our re-evaluation have radically disconfirmed the conclusions originally drawn by the authors of [15]. In particular, our experiments do justice to the EMQ method, which had obtained fairly bland results in the experiments of [15], and which now emerges as the true leader of the pack.

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