Re-Assessing the “Classify and Count” Quantification Method

Alejandro Moreo [0000−0002−0377−1025] and Fabrizio Sebastiani [0000−0003−4221−6427]

Istituto di Scienza e Tecnologie dell’Informazione
Consiglio Nazionale delle Ricerche
56124 Pisa, Italy
firstname.lastname@isti.cnr.it

Abstract. Learning to quantify (a.k.a. quantification) is a task concerned with training unbiased estimators of class prevalence via supervised learning. This task originated with the observation that “Classify and Count” (CC), the trivial method of obtaining class prevalence estimates, is often a biased estimator, and thus delivers suboptimal quantification accuracy. Following this observation, several methods for learning to quantify have been proposed and have been shown to outperform CC. In this work we contend that previous works have failed to use properly optimised versions of CC. We thus reassess the real merits of CC and its variants, and argue that, while still inferior to some cutting-edge methods, they deliver near-state-of-the-art accuracy once (a) hyperparameter optimisation is performed, and (b) this optimisation is performed by using a truly quantification-oriented evaluation protocol. Experiments on three publicly available binary sentiment classification datasets support these conclusions.

Keywords: Learning to quantify · Quantification · Prevalence estimation · Classify and count

1 Introduction

Learning to quantify (a.k.a. quantification) consists of training a predictor that returns estimates of the relative frequency (a.k.a. prevalence, or prior probability) of the classes of interest in a set of unlabelled data items, where the predictor has been trained on a set of labelled data items [13]. When applied to text, quantification is important for several applications, e.g., gauging the collective satisfaction for a certain product from textual comments [8], establishing the popularity of a given political candidate from blog posts [17], predicting the amount of consensus for a given governmental policy from tweets [4], or predicting the amount of readers who will find a product review helpful [5].

The rationale of this task is that many real-life applications of classification suffer from distribution shift [22], the phenomenon according to which the distribution $p_U$ of the labels in the set of unlabelled test documents $U$ is different from the distribution $p_L$ that the labels have in the set of labelled training documents $L$. It has been shown that, in the presence of distribution shift, the trivial strategy of using a standard classifier to classify all the unlabelled documents in $U$ and counting the documents that have been assigned to each class (the “Classify and Count” (CC) method), delivers poor class prevalence estimates. The reason is that most supervised learning methods are based on the IID assumption, which implies that the distribution of the labels is the same in $L$ and $U$. “Classify and Count” is considered a biased estimator of class prevalence, since the goal of standard classifiers is to minimise (assuming for simplicity a binary setting) classification error measures such as $(FP + FN)$, while the goal of a quantifier is to minimise quantification error.
measures such as $|FP - FN|$. (In this paper we tackle binary quantification, so FP and FN denote the numbers of false positives and false negatives, resp., from a binary contingency table.) Following this observation, several quantification methods have been proposed, and have been experimentally shown to outperform CC.

In this paper we contend that previous works, when testing advanced quantification methods, have used as baselines versions of CC that had not been properly optimised. This means that published results on the relative merits of CC and other supposedly more advanced methods are still unreliable. We thus reassess the real merits of CC by running extensive experiments (on three publicly available sentiment classification datasets) in which we compare properly optimised versions of CC and its three main variants (PCC, ACC, PACC) with a number of more advanced quantification methods. In these experiments we properly optimise all quantification methods, i.e., (a) we optimise their hyperparameters, and (b) we conduct this optimisation via a truly quantification-oriented evaluation protocol, which also involves minimising a quantification loss rather than a classification loss. Our results indicate that, while still inferior to some cutting-edge quantification methods, CC and its variants deliver near-state-of-the-art quantification accuracy once hyperparameter optimisation is performed properly. We make available all the code and the datasets that we have used for our experiments.

2 “Classify and Count” and its variants

In this paper we use the following notation. We assume a binary setting, with the two classes $\mathcal{Y} = \{\oplus, \ominus\}$ standing for Positive and Negative. By $x$ we denote a document drawn from a domain $\mathcal{X}$ of documents; by $L \subset \mathcal{X}$ we denote a set 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 the sample to quantify on. By $p_y(\sigma)$ we indicate the true prevalence of class $y$ in sample $\sigma$, by $\hat{p}_y(\sigma)$ we indicate an estimate of this prevalence, and by $\hat{p}^y_M(\sigma)$ we indicate the estimate of this prevalence as obtained via quantification method $M$. Of course, for any method $M$ it holds that $\hat{p}^\oplus_M(U) = (1 - \hat{p}^\ominus_M(U))$.

An obvious way to solve quantification is by aggregating the scores assigned by a classifier to the unlabelled documents. We first define two different aggregation methods, one that uses a “hard” classifier (i.e., a classifier $h_\oplus : \mathcal{X} \rightarrow \{0,1\}$ that returns binary decisions, 0 for $\ominus$ and 1 for $\oplus$) and one that uses a “soft” classifier (i.e., a classifier $s_\oplus : \mathcal{X} \rightarrow [0,1]$ that returns posterior probabilities $Pr(\oplus|x)$, representing the probability that the classifier attributes to the fact that $x$ belongs to the $\oplus$ class). Of course, $Pr(\ominus|x) = (1 - Pr(\oplus|x))$. The classify and count (CC) and the probabilistic classify and count (PCC) methods then consist of computing

$$p^{CC}_\oplus(U) = \frac{\sum_{x \in U} h_\oplus(x)}{|U|} \quad \quad p^{PCC}_\oplus(U) = \frac{\sum_{x \in U} s_\oplus(x)}{|U|}$$

Two popular, alternative quantification methods consist of applying an adjustment to the $\hat{p}^{CC}_\oplus(U)$ and $\hat{p}^{PCC}_\oplus(U)$ estimates. It is easy to show that, in the binary case, the true prevalence $p_\oplus(U)$ is such that

$$p_\oplus(U) = \frac{\hat{p}^{CC}_\oplus(U) - FPR_h}{TPR_h - FPR_h} \quad \quad p_\oplus(U) = \frac{\hat{p}^{PCC}_\oplus(U) - FPR_s}{TPR_s - FPR_s}$$

where $TPR_h$ and $FPR_h$ (resp., $TPR_s$ and $FPR_s$) here stand for the true positive rate and false positive rate that the classifier $h_\oplus$ (resp., $s_\oplus$) has on $U$. The values

\[1\] [https://github.com/AlexMoreo/CC]

\[2\] Consistently with most mathematical literature, we use the caret symbol (') to indicate estimation.
of TPR\textsubscript{h} and FPR\textsubscript{h} (resp., TPR\textsubscript{s} and FPR\textsubscript{s}) are unknown, but can be estimated via k-fold cross-validation on the training data. In the binary case this amounts to using the results that \( h_{\oplus}(x) \) (resp., \( s_{\oplus}(x) \)) obtains in the k-fold cross-validation (i.e., when \( x \) ranges on the training documents) in equations

\[
\begin{align*}
\text{TPR}_{\text{h}} &= \frac{\sum_{x \in \oplus} h_{\oplus}(x)}{|\oplus|} \\
\text{FPR}_{\text{h}} &= \frac{\sum_{x \in \ominus} h_{\oplus}(x)}{|\ominus|} \\
\text{TPR}_{\text{s}} &= \frac{\sum_{x \in \oplus} s_{\oplus}(x)}{|\oplus|} \\
\text{FPR}_{\text{s}} &= \frac{\sum_{x \in \ominus} s_{\oplus}(x)}{|\ominus|}
\end{align*}
\] (3)

We obtain \( \hat{p}_{\text{ACC}}(U) \) and \( \hat{p}_{\text{PACC}}(U) \) estimates, which define the adjusted classify and count (ACC) \[11\] and probabilistic adjusted classify and count (PACC) \[3\] quantification methods, resp., by replacing TPR\textsubscript{h} and FPR\textsubscript{h} (resp., TPR\textsubscript{s} and FPR\textsubscript{s}) in Equation 2 with their estimates from Equation 3.

3 Quantification and parameter optimisation

3.1 Unsuitable parameter optimisation and weak baselines

The reason why we here reassess CC and its variants we have described above, is that we believe that, in previous papers where these methods have been used as baselines, their full potential has not been realised because of missing or unsuitable optimisation of the hyperparameters of the classifier on which the method is based.

Specifically, both CC and its variants rely on the output of a previously trained classifier, and this output usually depends on some hyperparameters. Not only the quality of this output heavily depends on whether these hyperparameters have been optimised or not (on some held-out data or via k-fold cross-validation), but it also depends on what evaluation measure this optimisation has used as a criterion for model selection. In other words, given that hyperparameter optimisation chooses the value of the parameter that minimises error, it would make sense that, for a classifier to be used for quantification purposes, “error” is measured via a function that evaluates quantification error, and not classification error. Unfortunately, in most previous quantification papers, researchers either do not specify whether hyperparameter optimisation was performed at all \[9,11,14,15,17,19,26,27\], or leave the hyperparameters at their default values \[1,3,10,16,21\], or do not specify which evaluation measure they use in hyperparameter optimisation \[8,12\], or use, for this optimisation, a classification-based loss \[2,25\]. In retrospect, we too plead guilty, since some of the papers quoted here are our own.

All this means that CC and their variants, when used as baselines, have been turned into weak baselines, and this means that the merits of more modern methods relative to them have possibly been exaggerated, and are thus yet to be assessed reliably. In this paper we thus engage in a reproducibility study, and present results from text quantification experiments in which, contrary to the situations described in the paragraph above, we compare carefully optimised versions of CC and its variants with a number of (carefully optimised versions of) more modern quantification methods, in an attempt to assess the relative value of each in a robust way.

3.2 Quantification-oriented parameter optimisation

In order to perform quantification-oriented parameter optimisation we need to be aware that there may exist two types of parameters that require estimation and/or optimisation, i.e., (a) the hyperparameters of the classifier on which the quantification method is based, and (b) the parameters of the quantification method itself.
The way we perform hyperparameter optimisation is the following. We assume that the dataset comes with a predefined split between a training set $L$ and a test set $U$. (This assumption is indeed verified for the datasets we will use in Section 4.) We first partition $L$ into a part $L_{Tr}$ that will be used for training purposes and a part $L_{Va}$ that will be used as a held-out validation set for optimising the hyperparameters of the quantifier. We then extract, from the validation set $L_{Va}$, several random validation samples, each characterised by a predefined prevalence of the $\oplus$ class; here, our goal is allowing the validation to be conducted on a variety of scenarios characterised by widely different values of class prevalence, and, as a consequence, by widely different amounts of distribution shift. In order to do this, we extract each validation sample $\sigma$ by randomly undersampling one or both classes in $L_{Va}$, in order to obtain a sample with prespecified class prevalence values. We draw samples with a desired prevalence value and a fixed amount $q$ of documents; in order to achieve this, in some cases only one class needs to be undersampled while in some other cases this needs to happen for both classes. We use random sampling without replacement if the number of available examples of $\oplus$ (resp. $\ominus$) is greater or equal to the number of required ones, and with replacement otherwise. We extract samples with a prevalence of the $\oplus$ class in the set $\{\pi_1, ..., \pi_n\}$; for each of these $n$ values we generate $m$ random samples consisting of $q$ validation documents each. Let $\Theta$ be the set of hyperparameters that we are going to optimise. Given the established grid of value combinations $\theta_1, ..., \theta_n$ that we are going to test for $\Theta$, for each $\theta_i$ we do the following, depending on whether the quantification method has its own parameters (Case 1 below) or not (Case 2 below):

1. If the quantification method $M$ we are going to optimise requires some parameters $\lambda_i$ to be estimated, we first split $L_{Tr}$ into a part $L_{Tr}^{Tr}$ and a part $L_{Tr}^{Va}$, training the classifier on $L_{Tr}^{Tr}$ using the chosen learner parameterised with $\theta_i$, and estimate parameters $\lambda_i$ on $L_{Tr}^{Va}$. Among the variants of CC, this applies to methods ACC and PACC, which require the estimation of (the hard or soft version of) TPR and FPR. Other methods used in the experiments of Section 4 and that also require some parameter to be estimated are HDy and QuaNet (see Section 4.3.2).

2. If the quantification method $M$ we are going to optimise does not have any parameter that requires estimation, then we train our classifier on $L_{Tr}$, using the chosen learner parameterised with $\theta_i$, and use quantification method $M$ on all the samples extracted from $L_{Va}$.

In both cases, we measure the quantification error via an evaluation measure for quantification that combines (e.g., averages) the results across all the validation samples. As our final value combination for hyperparameter set $\Theta$ we choose the $\theta_i$ for which quantification error is minimum.

Note that, in the above discussion, each time we split a labelled set into a training set and a validation set for parameter estimation / optimisation purposes, we could instead perform a $k$-fold cross-validation; the parameter estimation/optimisation would be more robust, but the computational cost of the entire process would be $k$ times higher. While the latter method is also, from a methodological standpoint,

\footnote{Note that this is similar to what we do, say, in classification, where the different hyper-parameter values are tested on many validation documents; here we test these hyper-parameter values on many validation samples, since the objects of study of text quantification are document samples inasmuch as the objects of study of text classification are individual documents.}

\footnote{Note that we do not retrain the classifier on the entire $L_{Tr}$. While this might seem beneficial, since $L_{Tr}$ contains more training data than $L_{Tr}^{Tr}$, we need to consider that the estimates TPR$_h$ and FPR$_h$ have been computed on $L_{Tr}$ and not on $L_{Tr}^{Tr}$.}
Table 1. The three datasets used in our experiments; the columns indicate the class prevalence values of the $\oplus$ and $\ominus$ classes, and the numbers of documents contained in the training set $L$ and the test set $U$.

| Dataset | $\oplus$ | $\ominus$ | $L_{Tr}$ | $L_{Va}$ | $U_{Tr}$ | $U_{Va}$ | $U$ |
|---------|---------|---------|--------|--------|--------|--------|-----|
| IMDB    | 0.500  | 0.500  | 25,000 | 10,000 | 25,000 |
| Kindle  | 0.917  | 0.083  | 3,821  | 2,292  | 1,529  | 21,592 |
| HP      | 0.982  | 0.018  | 9,533  | 5,720  | 3,813  | 18,401 |

an option, in this paper we stick to the former method, since the entire parameter optimisation process is, from a computational point of view, already very expensive.

4 Experiments

In order to conduct our experiments we use the same datasets and experimental protocol as used in [7]. Specifically, we run our experiments on three sentiment classification datasets, i.e., (i) IMDB, the popular Large Movie Review Dataset [20]; (ii) Kindle, a set of reviews of Kindle e-book readers [7], and (iii) HP, a set of reviews of the books from the Harry Potter series [7]. For all datasets we adopt the same split between training set $L$ and test set $U$ as in [7]. The IMDB, Kindle, and HP datasets are examples of balanced, imbalanced, and severely imbalanced datasets, since the prevalence values of the $\oplus$ class in the training set $L$ are 0.500, 0.917, 0.982, resp. Some basic statistics from these datasets are reported in Table 1.

We refer the reader to [7] for more details on the genesis of these datasets.

In our experiments, from each set of training data we randomly select 60% of the documents for training purposes, leaving the remaining 40% for the hyperparameter optimisation phase; these random splits are stratified, meaning that the two resulting parts display the same prevalence values as the set that originated them. In this phase (see Section 3.2) we use $n = 21$, $m = 10$, and $q = 500$, i.e., we generate $m = 10$ random samples of $q = 500$ documents each, for each of the $n = 21$ prevalence values of the $\oplus$ class in $\{0.00, 0.05, ..., 0.95, 1.00\}$.

In order to evaluate a quantifier over a wide spectrum of test prevalence values, we use essentially the same process that we have discussed in Section 3.2 for hyperparameter optimisation; that is, along with [7,11], we repeatedly and randomly undersample one or both classes in the test set $U$ in order to obtain testing samples with specified class prevalence values. Here we generate $m = 100$ random testing samples of $q = 500$ documents each, for each of the $n = 21$ prevalence values of the $\oplus$ class in $\{0.00, 0.05, ..., 0.95, 1.00\}$.

4.1 Evaluation measures

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

$$AE(p, \hat{p}) = \frac{1}{|\mathcal{Y}|} \sum_{y \in \mathcal{Y}} |\hat{p}_y - p_y|$$
$$RAE(p, \hat{p}) = \frac{1}{|\mathcal{Y}|} \sum_{y \in \mathcal{Y}} \frac{|\hat{p}_y - p_y|}{p_y}$$

where $\mathcal{Y}$ is the set of classes of interest ($\mathcal{Y} = \{\oplus, \ominus\}$ in our case) and the sample $\sigma$ is omitted for notational brevity. 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 both all \( p_y \)'s and \( \hat{p}_y \)'s via additive smoothing, i.e., we take 
\[
\hat{p}_y = \frac{\epsilon + p_y}{\sum_{y \in Y} (\epsilon + p_y)},
\]
where \( p_y \) denotes the smoothed version of \( p_y \) and the denominator is just a normalising factor (same for the \( \hat{p}(y) \)'s); following [11], 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 [3] 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 recently been argued [28], the most satisfactory evaluation measures 
for quantification.

### 4.2 Data processing

We preprocess our documents by using the stop word remover and default tokeniser 
available within the scikit-learn framework\(^6\). In all three datasets we remove all 
terms occurring less than 5 times in the training set and all punctuation marks, and 
lowercase the text. As the weighting criterion we use a version of the well-known 
tfidf method, i.e.,

\[
tfidf(f, x) = \log(#(f, x) + 1) \times \frac{|L|}{|x' \in L : #(f, x') > 0|}
\]  

(5)

where \( #(f, x) \) is the raw number of occurrences of feature \( f \) in document \( x \); weights 
are then normalised via cosine normalisation.

Among the learners we use for classification (see below), the only one that does 
not rely on a tfidf-based representation is CNN. This learner simply converts all 
documents into lists of unique numeric IDs, indexing the terms in the vocabulary.
We pad the documents to the first 300 words.

### 4.3 The quantifiers

We here describe all the quantification systems we have used in this work.

#### 4.3.1 CC and its variants.

In our experiments we generate versions of CC, ACC, PCC, and PACC, using five different learners, i.e., support vector machines (SVM), logistic regression (LR), random forests (RF), multinomial naive Bayes (MNB), and convolutional neural networks (CNN). For the first four learners we 
rely on the implementations available from scikit-learn, while the CNN deep 
neural network is something we have implemented ourselves using the pytorch 
framework\(^7\). The setups that we use for these learners are the following:

- SVM: We use soft-margin SVMs with linear kernel and L2 regularisation, and 
  we explicitly optimise the \( C \) parameter (in the range \( C \in \{10^i\} \) with \( i \in \{-4, -3, \ldots, 4, 5\} \)) that determines the tradeoff between the margin and the 
  training error (default: \( C = 1 \)). We also optimise the \( J_\oplus \) and \( J_\ominus \) “rebalancing” 
  parameters, which determine whether to impose that misclassifying a \( \oplus \) document 
  has a different cost than misclassifying a \( \ominus \) document (in this case one 
  sets \( J_\oplus = \frac{p_\oplus(L)}{p_\ominus(L)} \) and \( J_\ominus = 1 \), or not (in this case one sets \( J_\oplus = J_\ominus = 1 \), which 
  is the default configuration) [23].

- LR: As in SVM, we use L2 regularisation, and we explicitly optimise the rebalancing parameters and the regularisation coefficient \( C \) (default values are as in SVM).

\(^6\) [http://scikit-learn.org/](http://scikit-learn.org/)
\(^7\) [https://pytorch.org/](https://pytorch.org/)
– **RF**: we optimise the number of estimators in the range \(\{10, 50, 100, 250, 500\}\), the max depth in \(\{5, 15, 30, \text{max}\}\) \(^8\) and the splitting function in \{Gini, Entropy\} (default: (100, max, Gini)).

– **MNB**: We use Laplace smoothing, and we optimise the additive factor \(\alpha\) in the range \(\{0.00, 0.05, \ldots, 0.95, 1.00\}\) (default: \(\alpha = 1\)).

– **CNN**: we use a single convolutional layer with \(\gamma\) output channels for three window lengths of 3, 5, and 7 words. Each convolution is followed by a ReLU activation function and a max-pooling operation. All convolved outputs are then concatenated and processed by an affine transformation and a sigmoid activation that converts the outputs into posterior probabilities. We use the Adam optimiser (with learning rate \(1E^{-3}\) and all other parameters at their default values) to minimise the balanced binary cross-entropy loss, set the batch size to 100, and train the net for 500 epochs, but we apply an early stop after 20 consecutive training epochs showing no improvement in terms of \(F_1\) for the minority class on the validation set. We explore the dimensionality of the embedding space in the range \(\{100, 300\}\) (default: 100), the number of output channels \(\gamma\) in \(\{256, 512\}\) (default: 512), whether to apply dropout to the last layer (with a drop probability of 0.5) or not (default: “yes”), and whether to apply weight decay (with a factor of \(1E^{-4}\)) or not (default: “no”).

Since we perform hyperparameter optimisation via grid search, the number of validations (i.e., combinations of hyperparameters) that we perform amounts to 20 for SVMs, 20 for LR, 40 for RF, 21 for MNB, and 16 for CNN.

In the following, by the notation \(M^{l_m}\) we will indicate quantification method \(M\) using learner \(l\) whose parameters have been optimised using measure \(m\) (where \(M^{0}\) indicates that no optimisation at all has been carried out). We will test, on all three datasets, all combinations in which \(M\) ranges on \{CC, ACC, PCC, PACC\}, \(l\) ranges on \{SVM, LR, RF, MNB, CNN\}, and \(m\) ranges on \{A, \(F_1\), AE\}, where \(A\) denotes vanilla accuracy, \(F_1\) is the well-known harmonic mean of precision and recall, and AE is absolute error. We stick to the tradition of computing \(F_1\) with respect to the minority class, which always turns out to be \(\ominus\) in all three datasets (this means that, e.g., the true positives of the contingency table are the documents that the classifier assigns to \(\ominus\) and that indeed belong to \(\ominus\)).

Note that PCC requires the classifier to return posterior probabilities. Since SVMs does not produce posterior probabilities, for PCC\(_{\text{SVM}}\) and PACC\(_{\text{SVM}}\) we calibrate the confidence scores that SVMs return by using Platt’s method \([24]\).

### 4.3.2 Advanced quantification methods

As the advanced methods that we test against CC and its variants, we use a number of more sophisticated systems that have been top-performers in the recent quantification literature.

– We use the Saerens-Latinne-Decaestecker method \([6,27]\) (SLD), which consists of training a probabilistic classifier and then exploiting the EM algorithm to iteratively shift the estimation of \(p_y(U)\) from the one that maximises the likelihood on the training set to the one that maximises it on the test data. As the underlying learner for SLD we use LR, since (as MNB) it returns posterior probabilities (which SLD needs), since these probabilities tend to be (differently from those returned by MNB) well-calibrated, and since LR is well-known to perform much better than MNB.

– We use methods SVM(KLD), SVM(NKLD), SVM(Q), SVM(AE), SVM(RAE), from the “structured output learning” camp. Each of them is the result of
instantiating the SVM\textsubscript{perf} structured output learner [18] to optimise a different loss function. SVM(KLD) [10] minimises the Kullback-Leibler Divergence (KLD); SVM(NKLD) [9] 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). We also add versions that minimise AE and RAE, since these latter are now, as indicated in Section 4.1, the evaluation measures for quantification considered most satisfactory, and the two used in this paper for evaluating the quantification accuracy of our systems. We optimise the $C$ parameter of SVM\textsubscript{perf} in the range $C \in \{10^i\}$, with $i \in \{-4, -3, \ldots, 4, 5\}$. In this case we do not optimise the $J_{\oplus}$ and $J_{\ominus}$ “rebalancing” parameters since this option is not available in SVM\textsubscript{perf}.

– We use the HDy method of [15]. The method searches for the prevalence values that minimise the divergence (as measured via the Hellinger Distance) between two cumulative distributions of posterior probabilities returned by the classifier, one for the unlabelled examples and the other for a validation set. The latter is a mixture of the distributions of posterior probabilities returned for the $\oplus$ and $\ominus$ validation examples, respectively, where the parameters of the mixture are the sought class prevalence values. We use LR as the classifier for the same reasons as discussed for SLD.

– We use the QuaNet system, a “meta-”quantification method based on deep learning [7]. QuaNet takes as input a list of document embeddings, together with and sorted by the classification scores returned by a classifier. A bidirectional LSTM processes this list and produces a quantification embedding that is then concatenated with a vector of predictions produced by an ensemble of simpler quantification methods (we here employ CC, ACC, PCC, PACC, and SLD). The resulting vector passes through a set of fully connected layers (followed by ReLU activations and dropout) that return the estimated class prevalence values. We use CNN as the learner since, among the learners we use in this paper, it is the only one that returns both posterior probabilities and document embeddings (we use the last layer of the CNN as the document embedding). We set the hidden size of the bidirectional LSTM to 128 + 128 = 256 and use two stacked layers. We also set the hidden sizes of the fully connected layers to 1024 and 512, and the dropout probability to 0.5. We train the network for 500 epochs, but we apply early stopping with a patience of 10 consecutive validations without improvements in terms of mean square error (MSE). Each training epoch consists of 200 quantification predictions, each of which for a batch of 500 randomly drawn documents at a prevalence sampled from the uniform distribution. In our case, validation epochs correspond to 21 quantification predictions for batches of 500 documents randomly sampled to have prevalence values 0.00, 0.05, \ldots, 0.95, 1.00. We use Adam as the optimiser, with default parameters, to minimise MSE. In order to train QuaNet, we split (using a 40%/40%/20% stratified split) the training set $L_{Tr}$ in three sets $L_{CTr}^{\oplus}$, for training the classifier; $L_{CTr}^{\ominus}$, for training QuaNet; and $L_{QVa}^{\oplus}$, for validating QuaNet. When optimising QuaNet we do not explore any additional hyperparameter apart from those for the CNN.

– We also report results for Maximum Likelihood Probability Estimation (MLPE), the trivial baseline for quantification which makes the IID assumption and thus simply assumes that $p_\oplus(U)$ is identical to the training prevalence $p_\oplus(L)$ irrespectively of the set $U$.

Note that ACC, PACC, HDy, and QuaNet need to estimate their own parameters on a validation set, which means that their performance depends on exactly which documents this set consists of. In order to mitigate the impact of this random choice,
for these methods we run each experiment 10 times, each time with a different random choice. The results we report are the average scores across these 10 runs.

### 4.4 Results

Tables 2, 3, and 4 report the results obtained for CC, ACC, PCC, and PACC. At first glance, the results do not seem to give any clearcut indication on how the CC variants should be optimised. However, a closer look reveals a number of patterns. One of these is that SVM and LR (the two best-performing classifiers overall) tend to benefit from optimised hyperparameters, and tend to do so to a greater extent when the loss used in the optimisation is quantification-oriented. Somehow surprisingly, not all methods improve after model selection in every case. However, there tends to be such an improvement especially for ACC and PACC. A likely reason for this is the possible existence of a complex tradeoff between obtaining a more accurate optimisation) becomes a reasonable quantifier if it learns to pay equal importance to one. A possible reason is that any classifier (with or without hyperparameter optimisation) becomes a reasonable quantifier if it learns to pay equal importance to positive and negative examples, i.e., if the errors it produces are unbiased towards the majority class, and only when corrected via an adjustment (ACC or PACC) they deliver results comparable to those obtained for other learners.

CNN works well on average almost in all cases, and seems to be the least sensitive learner to model selection.

In order to better understand whether or not, on average and across different situations, CC and its variants benefit from performing model selection using a quantification-oriented loss, we have submitted our results to a statistical significance test. Table 5 shows the outcome of a two-sided t-test on related sets of scores,
Table 3. Same as Table 2 but with ACC instead of CC.

|         | IMDB     | KINDELE | HP     |
|---------|----------|---------|--------|
|         | AE  | RAE   | AE  | RAE  | AE  | RAE  |
| ACCUVM  | 0.023 | 1.081 | 0.068 | 2.958 | 0.341 | 17.350 |
| ACCUVM+ | 0.019  | (-17.6%) | 0.889 | (-18.0%) | 0.593 | (-47.0%) |
| ACCUVM- | 0.007  | (-79.9%) | 0.181 | (-74.4%) | 0.161 | (-82.5%) |
| ACCUVF  | 0.022  | (-5.2%) | 1.151 | (-6.3%) | 0.052 | (-22.9%) |
| ACCUVF+ | 0.016  | (-4.1%) | 0.515 | (-5.6%) | 0.196 | (-23.1%) |
| ACCUVF- | 0.009  | (-79.9%) | 0.311 | (-76.9%) | 0.090 | (-81.7%) |
| ACCVF   | 0.020  | (+21.2%) | 0.933 | (+63.9%) | 0.069 | (+6.6%) |
| ACCVF+  | 0.013  | (+13.8%) | 0.896 | (+57.4%) | 0.057 | (+7.9%) |
| ACCVF-  | 0.018  | (+10.8%) | 0.859 | (+45.3%) | 0.005 | (+71.1%) |
| AECNN   | 0.034  | (+38.7%) | 1.254 | (+46.2%) | 0.136 | (+4.1%) |
| AECNN+  | 0.021  | (+31.7%) | 0.643 | (+38.8%) | 0.180 | (+13.4%) |
| AECNN-  | 0.019  | (+42.7%) | 0.526 | (+58.1%) | 0.155 | (+13.4%) |
| AECNNF  | 0.019  | (+43.0%) | 0.554 | (+58.8%) | 0.197 | (+44.2%) |
| AECNNF+ | 0.049  | (+3.5%) | 2.316 | (+11.9%) | 0.453 | (+2.2%) |
| AECNNF- | 0.051  | (+4.4%) | 2.479 | (+7.0%) | 0.188 | (-59.9%) |
| AECNNF+ | 0.049  | (+0.5%) | 2.044 | (-3.8%) | 0.197 | (-58.3%) |
| AECNNF- | 0.051  | (+3.9%) | 2.591 | (-11.9%) | 0.213 | (-54.9%) |
| AECNNF+ | 0.021  | 1.082 | 0.074 | 1.596 | 0.173 | 10.642 |
| AECNNF- | 0.019  | (-8.2%) | 0.811 | (-25.0%) | 0.064 | (-12.7%) |
| AECNNF+ | 0.049  | (+9.1%) | 1.067 | (+1.4%) | 0.061 | (-17.4%) |
| AECNNF- | 0.023  | (+9.1%) | 1.072 | (-0.9%) | 0.068 | (-7.8%) |

Table 4. Same as Table 2 but with PCC instead of CC.

|         | IMDB     | KINDELE | HP     |
|---------|----------|---------|--------|
|         | AE  | RAE   | AE  | RAE  | AE  | RAE  |
| PCCUVM  | 0.101 | 9.460 | 0.255 | 14.514 | 0.375 | 20.158 |
| PCCUVM+ | 0.100 | (-0.4%) | 9.517 | (+0.6%) | 0.283 | (+10.9%) |
| PCCUVM- | 0.510 | (+0.9%) | 9.425 | (-0.4%) | 0.251 | (-1.8%) |
| PCCUVF  | 0.100 | (-0.4%) | 9.484 | (+0.2%) | 0.254 | (-6.0%) |
| PCCUVF+ | 0.212 | 11.564 | 0.356 | 20.405 | 0.464 | 24.608 |
| PCCUVF- | 0.091 | (-25.5%) | 8.563 | (-26.0%) | 0.279 | (-21.5%) |
| PCCUVF+ | 0.092 | (-25.0%) | 8.606 | (-25.6%) | 0.172 | (-51.0%) |
| PCCUVF- | 0.079 | (-35.3%) | 7.348 | (-36.5%) | 0.154 | (-56.6%) |
| PCCVF   | 0.199 | 18.860 | 0.576 | 21.592 | 0.461 | 24.267 |
| PCCVF+  | 0.198 | (-0.7%) | 18.753 | (-0.6%) | 0.368 | (-2.0%) |
| PCCVF-  | 0.195 | (-2.1%) | 18.495 | (-2.2%) | 0.372 | (-0.9%) |
| PCCVF+  | 0.196 | (-1.4%) | 18.560 | (-1.6%) | 0.366 | (-2.5%) |
| PCCVF-  | 0.174 | 19.928 | 0.478 | 24.762 | 0.498 | 25.453 |
| PCCVF+  | 0.169 | (-1.7%) | 15.663 | (-1.7%) | 0.355 | (-20.3%) |
| PCCVF-  | 0.167 | (-2.2%) | 15.617 | (-2.0%) | 0.380 | (-20.4%) |
| PCCVF+  | 0.160 | (-6.4%) | 14.907 | (-6.4%) | 0.380 | (-20.4%) |
| PCCVF-  | 0.110 | 9.994 | 0.111 | 10.448 | 0.257 | 18.368 |
| PCCVF+  | 0.115 | (-4.8%) | 9.933 | (-1.0%) | 0.154 | (-39.2%) |
| PCCVF-  | 0.099 | (-10.3%) | 9.377 | (-6.2%) | 0.111 | (-5.5%) |
| PCCVF+  | 0.145 | (+31.3%) | 11.146 | (+11.5%) | 0.145 | (+33.8%) |

across datasets and learners, from which we can compare pairs of model selection methods. The test reveals that optimising AE works better than optimising A or than using default settings (O). The test does not clearly say whether optimising AE or F1 is better, but it suggests that PACC (the strongest CC variant) works better when optimised for AE than when optimised for F1.

Finally, Table 7 compares the CC variants against more recent state-of-the-art quantification systems. Columns AE and RAE indicate the error of each method for each dataset. Columns rAE and fRAE show the rank positions for each pair (dataset, error) and, in parentheses, the rank position each method would have obtained in case the CC variants had not been optimised.

Interestingly, although some advanced quantification methods (specifically: SLD and HDy) stand as the top performers, many among the (supposedly more sophisticated) quantification methods fail to improve over CC’s performance. At a glance, most quantification methods tend to obtain lower ranks when compared with properly optimised CC variants. Remarkable examples of rank variation include CC and
Table 5. Same as Table 2 but with PACC instead of CC.

Table 6. Two-sided t-test results on related samples of error scores across datasets and learners. For a pair of optimization measures X vs. Y, symbol \( \triangleright \) (resp. \( \triangleright \) ), indicates that method X performs better (i.e., yields lower error) than Y, and that the difference in performance, as averaged across pairs of experiments on all datasets and learners, is statistically significant at a confidence score of \( \alpha = 0.001 \) (resp. \( \alpha = 0.05 \)). Symbols \( \leq \) and \( < \) have a similar meaning but indicate that X performs worse (i.e., yields higher error) than Y. Symbol \( \sim \) instead indicates that the differences in performance between X and Y are not statistically significantly different, i.e., that \( p\text{-value} \geq 0.05 \).

ACC with SVM and LR: when evaluated on Kindle and HP, they climb several positions (up to 25), often entering the group of the 10 top-performing methods. In the most extreme case, ACC\(_{AE}\) moves from position 28 (out of 29) to position 3 once properly optimised for quantification.

5 Conclusions

One of the takeaway messages from the present work is that, when using CC and/or its variants as baselines in their research on learning to quantify, researchers should properly optimise these baselines (i.e., use a truly quantification-oriented protocol, which includes the use of a quantification-oriented loss, in hyperparameter optimisation), lest these baselines become strawmen. The extensive empirical evaluation we have carried out shows that, in general, the performance of CC and its variants improves when the underlying learner has been optimised with a quantification-oriented loss (AE). The results of our experiments are less clear about whether optimising AE or F\(_1\) (which, despite being a classification-oriented loss, is one that rewards classifiers that balance FPs and FNs) is better, although they indicate that optimising AE is preferable for PACC, the strongest among the variants of CC.
Table 7. Results showing how CC and its variants, once optimised using a quantification-oriented measure, compare with more modern quantification methods. **Boldface** indicates the best method. For columns AE and RAE, the best/worst results are highlighted in bright green/red; the colour for the other scores is a linearly interpolation between these two extremes. For columns \( t_{AE} \) and \( r_{RAE} \), green/red is used to denote methods which have obtained higher/lower rank positions once the CC variants have been optimised for AE, with respect to the case in which they have not been optimised at all. All scores are different, in a statistically significant sense, from the best one according to a paired sample, two-tailed t-test at a confidence level of 0.001.

| Method | IMDB | KINDLE | HP | IMDB | KINDLE | HP |
|--------|------|-------|----|------|-------|----|
|        | \( \text{AE} \) | \( \text{RAE} \) | \( \text{AE} \) | \( \text{RAE} \) | \( t_{AE} \) | \( r_{RAE} \) | \( \text{AE} \) | \( \text{RAE} \) | \( t_{AE} \) | \( r_{RAE} \) |
| CC | 0.065 | 0.981 | 0.100 | 7.555 | 0.119 | 10.993 | 20 (20) | 20 (20) | 13 (21) | 15 (21) | 8 (22) | 11 (20) |
| ACC | 0.020 | 0.984 | 0.099 | 3.129 | 0.108 | 7.225 | 7 (8) | 7 (6) | 6 (8) | 9 (9) | 5 (16) | 4 (15) |
| PCC | 0.100 | 0.484 | 0.254 | 14.461 | 0.186 | 20.607 | 25 (23) | 25 (23) | 24 (19) | 24 (20) | 21 (17) | 22 (18) |
| PAC | 0.022 | 1.363 | 0.059 | 2.333 | 0.114 | 7.497 | 6 (7) | 11 (7) | 3 (3) | 7 (7) | 7 (5) | 5 (3) |
| CC | 0.062 | 1.637 | 0.094 | 7.087 | 0.110 | 10.304 | 14 (14) | 15 (14) | 12 (26) | 14 (26) | 6 (29) | 10 (28) |
| ACC | 0.018 | 0.850 | 0.065 | 2.801 | 0.092 | 5.849 | 4 (3) | 5 (3) | 4 (20) | 8 (17) | 3 (28) | 3 (27) |
| PCC | 0.079 | 7.348 | 0.154 | 13.066 | 0.211 | 19.597 | 22 (25) | 22 (25) | 19 (22) | 22 (22) | 16 (21) | 20 (22) |
| PAC | 0.021 | 1.257 | 0.068 | 2.255 | 0.104 | 8.812 | 8 (3) | 10 (4) | 5 (4) | 6 (6) | 6 (3) | 5 (5) |
| CC | 0.079 | 1.487 | 0.464 | 23.721 | 0.500 | 25.487 | 23 (23) | 23 (23) | 29 (25) | 28 (24) | 29 (24) | 29 (23) |
| ACC | 0.019 | 0.554 | 0.197 | 6.057 | 0.499 | 25.436 | 5 (11) | 3 (11) | 21 (14) | 11 (10) | 27 (19) | 26 (19) |
| PCC | 0.196 | 18.565 | 0.360 | 21.088 | 0.462 | 24.379 | 28 (28) | 28 (28) | 25 (23) | 26 (23) | 24 (20) | 24 (21) |
| PAC | 0.020 | 0.914 | 0.081 | 3.286 | 0.140 | 10.067 | 6 (10) | 6 (10) | 10 (9) | 10 (8) | 10 (6) | 9 (7) |
| CC | 0.057 | 1.411 | 0.443 | 22.710 | 0.499 | 25.461 | 24 (22) | 24 (22) | 28 (29) | 27 (29) | 28 (26) | 28 (29) |
| ACC | 0.051 | 2.591 | 0.213 | 10.376 | 0.451 | 23.146 | 12 (12) | 12 (12) | 23 (27) | 23 (27) | 23 (27) | 23 (26) |
| PCC | 0.160 | 19.907 | 0.380 | 20.396 | 0.473 | 24.479 | 27 (27) | 27 (27) | 26 (28) | 25 (25) | 25 (25) | 25 (25) |
| PAC | 0.063 | 3.815 | 0.144 | 6.626 | 0.248 | 13.999 | 16 (13) | 13 (13) | 16 (17) | 12 (12) | 19 (10) | 17 (9) |
| CC | 0.074 | 6.613 | 0.109 | 8.591 | 0.343 | 19.008 | 21 (21) | 21 (21) | 14 (11) | 17 (14) | 20 (14) | 19 (14) |
| ACC | 0.023 | 1.072 | 0.068 | 1.309 | 0.174 | 10.810 | 10 (5) | 8 (5) | 6 (8) | 3 (3) | 13 (7) | 12 (8) |
| PCC | 0.145 | 11.116 | 0.148 | 14.017 | 0.156 | 16.644 | 26 (24) | 26 (24) | 17 (12) | 23 (18) | 11 (15) | 18 (16) |
| PAC | 0.018 | 0.830 | 0.069 | 1.367 | 0.165 | 8.829 | 2 (7) | 4 (9) | 7 (5) | 2 (2) | 12 (8) | 7 (6) |

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Re-Assessing the “Classify and Count” Quantification Method

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