Inter-Annotator Agreement in Sentiment Analysis: 
Machine Learning Perspective 

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Abstract 
Manual text annotation is an essential part of Big Text analytics. Although annotators work with limited parts of data sets, their results are extrapolated by automated text classification and affect the final classification results. Reliability of annotations and adequacy of assigned labels are especially important in the case of sentiment annotations. In the current study we examine inter-annotator agreement in multi-class, multi-label sentiment annotation of messages. We used several annotation agreement measures, as well as statistical analysis and Machine Learning to assess the resulting annotations. 

1 Introduction 
Automated text analytics methods rely on manually annotated data while building their heuristics. Although manually annotated texts comprise a small part of a data set, learning algorithms extrapolate the results to the remaining part of the data set and beyond it. At the same time, development of annotation schemes and methods and their implementation attract considerably less research attention than building electronic resources or development of Machine Learning techniques. In this work, we study multi-class sentiment annotation of a new data set. The texts have been collected from an online health forum; three annotators annotated each text. Annotators could assign each text with one or more sentiment labels; 4 labels were predefined (facts, gratitude, encouragement, confusion) and could be supplemented by other sentiment labels, if annotators deemed the four given labels insufficient to cover sentiments found in the text. Our results show that metrics estimating inter-annotator agreement can be effectively used in deciding of sentiment categories and establishing annotation protocols. We apply Machine Learning (ML) techniques to compare human and automated recognition of sentiment labels. 

2 Related Work 
Inter-annotator agreement of multi-class sentiment annotations was analyzed in (Steinert, 2017). The author worked with 3255 German documents collected from social networks. Texts were 50 words in average, thus limiting topics and sentiments conveyed by individual messages. Six annotators annotated the documents with one of the following labels: Neg, Neut, Pos, No Sent, Undecided, and Irrelevant. Each document was annotated by three participants. Cohen kappa was used to estimate inter-annotator agreements between each pair of all the six annotators. The best kappa was 0.747 and the worst kappa was 0.480. The final message labels were selected by a majority voting algorithm. 

Manual annotations and automated annotations were compared by Emi Ishita et al. (2010). The authors worked with 1,783 sentences collected from written statements of hearings held by a U.S. Senate Committee. Four annotators could annotate a sentence into 10 possible labels; each sentence obtained 3 labels on average; the obtained agreement was 0.30. Then a k-NN algorithm was applied to classify the sentences; it obtained F-score = 0.4. Then human annotations were evaluated in the same way as the automated classification, i.e. obtaining F measures against the final annotation called “ground truth”. The best F-measure for human annotation was 0.70.
600 sentences collected from English-language Spine-health forum were manually annotated by 60 Master’s students, who were not health professionals (Melzi et al., 2014). Annotators used 6 basic emotions (Ekman, 1992): anger, disgust, fear, joy, sadness and surprise. Each sentence was annotated by two annotators. The inter-annotation coefficient Kappa was 0.26. 150 sentences from the same corpus were annotated by two health professionals. The agreement between health professional annotators and non-professionals was moderate, 0.46. The authors nevertheless proceeded with machine learning experiments; their best F-score was equal to 0.65.

150 topics from 115 documents (from the Blog Track at TREC 2008) were annotated in (Bermingham and Alan, 2009). An average of 3.6 annotators worked with each topic. Annotators’ agreement was evaluated by Krippendorf alpha (Hayes and Krippendorf, 2007). Unlike Cohen and Fleiss kappa, the measure can assess agreement among a variable number of annotators and accepts non-annotated examples. The value of 0.4219 was obtained for sentence-level annotation for 5-class annotation; the authors considered such agreement as moderate. Bermingham and Alan emphasized necessity of further studies of different levels of annotations, i.e., sentence, paragraph and document levels.

3 The Data Set and Annotation

The data set. To build this data set, we collected messages posted on Introduction and IVF/FET/IUI Cycle Buddies sub-forums of InVitroFertilization.ca forum\(^1\). The structure of the posted discussions is similar to those posted on other online forums: a participant starts discussion by posting the first message; other participants join discussion by replying on the initial post or the following messages, thus creating coherent online conversations. The Introduction sub-forum contained 2,913 discussions, whereas the IVF/FET/IUI Cycle Buddies contained 3,771 discussions. The number of messages in a single discussion varied considerably: from hundreds to only a few messages.

Due to budgetary limitations, we restricted the number of annotated discussions. We selected 65 medium length discussions, with 10-20 posts in each discussion. Those discussions yielded in total 1000 posts. The messages were comparatively long, 126 words on average.

Annotation procedure. We adopted four labels from a label set proposed in (Sokolova and Bobicev, 2013); the label set was further analyzed in (Navindgi et al., 2016). We used three sentiment labels: confusion, encouragement and gratitude and the label facts for neutral factual information. We discarded the label endorsement that was created as combination of two labels facts and encouragement (Bobicev et al., 2015). Navindgi et al. (2016) demonstrated that this label confused machine learning algorithms and was not recognized properly.

As one message often conveyed > 1 sentiment, the resulting sentiment mosaic posed challenges to both one label and multi-labeled post annotation:

- one label annotation can be directly mapped into a multi-class classification problem; however, deciding on one sentiment label will artificially restrict annotators’ choices, thus, leaving side important information about message sentiment and their annotation.
- multi-labeled annotation represents diversity of sentiments in individual posts; however, mapping multitudes of labels into multi-label machine learning is not a trivial task.

In this study, we have decided to combine the two approaches: first, allow multiple labels for one post; then generalize the received annotations into one label per post.

Preliminary text annotation. In the annotation guidelines we presented three sentiment labels and one for neural/factual information as default labels and then suggested that for each message annotators can indicate as many sentiments as they considered appropriate. Although the annotators were allowed to attach any number of any labels, in many cases they assigned only one predefined label per post: approx. 85% of the assigned labels were from the predefined set. New labels suggested by the annotators are reported in Table 1.

The final text annotation. To choose one label for each post based on all the labels assigned by annotators, we had to resolve the following situations: (1) All three annotators assigned the same label for a post; no other labels were assigned; that ideal case happened in 326 posts. (2) All three annotators assigned the same label for a post; however, other, non-matching labels were assigned too; in this case, the label indicated by all three annotators was selected as the final one: 297

\(^1\) www.ivf.ca
posts. (3) All three annotators assigned same two labels for a post; no other labels were assigned; it happened for 26 posts; one annotator indicated the importance of the labels; we used this information and assigned the label she indicated first. (4) Of all labels attached to the post by all annotators only one label was used twice; this label was selected as the final one: 214 posts (5) Two or even three labels were used twice in annotation of the same post; in this case we kept the label marked as the most important; it happened for 95 posts; in four cases the most important label was not repeated by other annotators; we did not use these posts in the experiments. (6) All the annotators attached different labels to a post. This happened for 14 posts. Those posts remained ambiguous without the final label.

Figure 1 reports labels assigned by annotators after we merged the additional labels. The first annotator tended to use more neutral labels whilst the second annotator attached more labels with sentiments. This problem was discussed in (Melzi et al., 2014) as health forums are about health problems, diagnosis, treatment, etc. Thus, some annotators, by empathy, associated negative emotion to factual information about diseases, symptoms and diagnoses.

In general, the first annotator attached fewer labels (average labels per post is 1.17; 83% of posts annotated with only one label); the second and the third annotators attached more labels (average labels per post is 1.35, 68% of posts annotated with only one label).

Table 1: New sentiments of 1st, 2nd and 3rd annotators.

| Sentiment  | 1st | 2nd | 3rd |
|------------|-----|-----|-----|
| support    | 473 |     |     |
| cheering   | 158 |     |     |
| worry      | 124 |     |     |
| uncertainty| 115 |     |     |
| compassion | 53  | 96  | 17  |
| hope       | 37  | 238 | 19  |
| optimism   | 125 |     |     |
| dislike    | 92  |     |     |
| excitement | 20  |     |     |
| concern    | 81  |     |     |
| sadness    | 38  |     |     |
| joy        | 5   |     |     |
| happiness  | 36  | 3   |     |
| disappointment| 13 | 3   | 2   |
| sadness    | 9   | 12  |     |
| frustration| 7   |     |     |

Figure 1: The ratio of labels used by all three annotators in the order: 1st, 2nd, 3rd.

4 Assessment of Inter-Annotator Agreement

Several inter-annotators metrics were proposed for inter-annotator agreement evaluation. Per cent of agreement is the easiest and the most straightforward measure. The measure is often criticized (it does not differentiate between categories) but still it gives a basic approximation of annotators’ agreement. As we have multiple labels per post, inter-annotator agreement was calculated for each label separately and the average for these four labels. The same situation is for three annotators. The pairwise agreement calculated for each pair of the annotators and the average are presented in Table 2.

Table 2: Per cent inter-annotator agreement for the four labels and three annotators. A1, A2, A3 are the annotators; the labels are: lab1 (encouragement), lab2 (facts), lab3 (confusion), lab4 (gratitude).

| lab1 | lab2 | lab3 | lab4 |
|------|------|------|------|
| A1 vs A2 | 73%  | 72%  | 85%  | 88%  |
| A2 vs A3 | 73%  | 70%  | 83%  | 93%  |
| A1 vs A3 | 78%  | 74%  | 81%  | 87%  |
| average | 74.6% | 71.8% | 82.7% | 89.1% |

The average agreement is 79.6%; it shows a strong agreement. Agreement between pairs of the three annotators is almost uniform; we cannot say that some are better than others.

Comparing agreement per labels we see that lesser agreement was reached on encouragement and facts. This may be explained by the specific of the text: participants often asked to tell success stories to encourage them fighting with health issues. Thus, factual stories of illness and following
recovery were frequently perceived as encouragement.

Inter-annotator agreement is often evaluated by Cohen’s kappa ($\kappa$), Fleiss’ kappa ($K$), Krippendorf’s alpha ($\alpha$) (Artstein, Poesio, 2008). Cohen’s kappa and Fleiss kappa are Chance-Corrected Coefficients which means that they measure above chance agreement. The general formula for these coefficients is:

$$ k = (A_o - A_e)/(1 - A_e) $$

where $A_o$ is observed agreement and $A_e$ is expected agreement by chance if the annotators pick the labels randomly.

Cohen $k$. In case of Cohen $k$ the expected agreement $A_e$ is calculated basing on the assumption that random assignment of categories to the items is governed by prior distributions that are unique to each coder, and which are observed from their actual distribution. Cohen $k$ is applied to two annotators only, thus we calculated it for each pair of our annotators (Table 3)

|       | lab1 | lab2 | lab3 | lab4 | average |
|-------|------|------|------|------|---------|
| A1 vs A2 | 0.48 | 0.41 | 0.50 | 0.47 |         |
| A1 vs A2 | 0.46 | 0.34 | 0.51 | 0.56 |         |
| A1 vs A2 | 0.53 | 0.40 | 0.49 | 0.44 |         |
| average | 0.49 | 0.38 | 0.50 | 0.49 |         |

The average Cohen’s $k = 0.46$ shows moderate agreement.

Fleiss $k$ is generalization to more than two annotators; expected agreement is calculated on the basis on the assumption that random assignment of categories to items, by any annotator, is governed by the distribution of items among categories in the actual world (Table 4).

|       | lab1 | lab2 | lab3 | lab4 | average |
|-------|------|------|------|------|---------|
| Fleiss $k$ | 0.48 | 0.38 | 0.49 | 0.48 | 0.46    |
| observed | 0.75 | 0.72 | 0.83 | 0.89 | 0.80    |
| expected | 0.51 | 0.55 | 0.66 | 0.79 | 0.63    |

Krippendorf’s alpha ($\alpha$) is an agreement coefficient based on assumptions that expected agreement is calculated by looking at the overall distribution of judgments without regard to which coders produced these judgments. It applies to multiple coders, and it allows missing values. As in previous cases $\alpha$ is calculated for each label and then averaged in Table 5.

|       | lab1 | lab2 | lab3 | lab4 | average |
|-------|------|------|------|------|---------|
| $\alpha$ | 0.48 | 0.38 | 0.49 | 0.48 | 0.46    |

The average agreement is equal to 0.46 in all calculated metrics which is similar to 0.48 reported in (Bobicev, Sokolova, 2017) and is considered as moderate in (Artstein, Poesio, 2008).

In the current study, there was no considerable difference between the results of the inter-annotator metrics. Nevertheless, we conjecture that pairwise metrics can serve for the detection of the best annotator. For example, Nowak and Roger (2010) identified the best and the worst annotators (among 11 annotators) by calculating correlation between their labels and the final labeled set.

On the other hand, we can calculate annotator agreement per label and then use the result as an indicator of the label identification difficulty: labels with the best agreement are the easiest to detect and, vice versa, the worst agreement shows labels with the most problems for the annotators. Finally, annotator agreement can be used in analysis of the label sets and annotation instructions in order to improve annotation process and resolve annotation difficulties.

5 Experiments

We worked with the following sets of text:

1. 970 posts, each post identified with one label;
2. 326 posts with exact match of the labels assigned by the three annotators;
3. 297 posts with a principal match: all 3 annotators agreed on 1 label but other labels were added;
4. 214 posts with a partial agreement: two annotators selected one label which was considered the final one;

The complete set of 970 messages has the following distribution of labels: confusion: 146, encouragement: 494, gratitude: 69, facts: 261.

To estimate reliability of annotations (see Sec 4), we have run ML experiments on sets (1) – (3). We used several sets of features:

1. BOW – Bag of Words. All words from the whole corpus with the frequency at least 2; 3497 features.
2. SS – SentiStrength (Thelwall et al., 2012). All terms from SentiStrength lexicon which appear in our corpus.
3. SWN – SentiWordNet (Esuli, Sebastiani, 2006). All terms from SentiWordNet lexicon which appear in our corpus.
4. DM – DepecheMood (Staiano, Guerini, 2014). All terms from DepecheMood lexicon which appear in our corpus.
5. HA – HealthAffect (Sokolova, Bobicev, 2013). All terms from HealthAffect lexicon which appear in our corpus.

Note that SS, SWN, DM, HA showed reliable results in sentiment analysis studies (Bobicev et al., 2015). We applied Naive Bayes (NB), NB Text, NB multinomial, SVM machine learning algorithms in our experiments. To select the best results, we used 10-fold cross-validation and computed F-score (F). We used the majority class baseline. We run four experiments using the created sub-corpora. We run four experiments using the created sub-corpora (Table 6):

(1) 326 posts with exact match; baseline=0.536.
(2) 297 posts with agreement; baseline=0.362.
(3) 214 posts with partial agreement; baseline=0.283.
(4) All the 970 posts with one label; baseline=0.344.

The best result F=0.794 was obtained for the sub-corporus with exact match. For the whole corpus the best F-measure=0.571 was too obtained on the BOW feature set.

Table 8: Classification per label

| Class  | F-Measure |
|--------|-----------|
| confusion | 0.562   |
| facts    | 0.535   |
| gratitude | 0.441   |
| encouragement | 0.759 |

Feature selection Feature sets consisting of all words from the texts or from lexicons were comparatively large. We used Correlation-based Feature Subset Selection (Hall, 1999) which evaluates the worth of a subset of features by considering the individual predictive ability of each feature along with the degree of redundancy between them. We created a set of selected features from all 4 lexicons’ merged features and have run the same 6 experiments on them. The results are presented in Table 7. Feature selection improved the learning results: F measure for the whole set is 0.652 which is much better than 0.571 on BOW features.

F-measures for the individual labels are presented in Table 8. We used the feature selection results obtained on all the 970 posts with 1 label, i.e. experiment # 4 in Table 7. Encouragement was classified significantly better than other categories: F-score = 0.759; the lowest F-score= 0.441 was obtained for classification of gratitude.

Those results may be explained by imbalanced distribution of categories: almost half of posts were labeled by encouragement (i.e., 494 posts out of 970 posts) while gratitude had been assigned to the smallest number of posts (i.e., 69 out of 970). Thus, the automate method had enough training data to recognize encouragement, but not enough training data for recognition of gratitude.

Table 9: Inter-annotator agreement calculated for automated classification and final labels.

| label   | Per cent Agreement | Cohen kappa |
|---------|--------------------|-------------|
| confusion | 85.9               | 0.478       |
| facts    | 76.7               | 0.380       |
| gratitude | 93.2               | 0.405       |
| encouragement | 74.5               | 0.489       |

To compare automated classification and human annotation we calculated agreement between the results of automated analysis and the final set of labels used in the experiments. Cohen kappa is the worst for facts (0.380) and the best for encouragement (0.489) (Table 9). Thus, humans and
automated methods disagree more when they assign facts than when they assign encouragement.

6 Conclusions and Future Work

We have presented a study of multi-class sentiment annotation. We worked with a new data set of 970 texts collected from a health-related forum. To estimate the quality of annotations, we have applied several inter-annotation agreement metrics. We have shown how those metrics can be used in evaluation of sentiment categories and annotation schemes. Finally, we applied Machine Learning techniques to compare automated classification and human annotation of the same data.

Our future work will expand current studies to new data sets. We aim to investigate various protocols and procedures of generalization of sentiment annotations, and how those procedures affect Machine Learning sentiment classification.

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