**Chapter 1: The Problem and Its Background**

**1 Introduction**

Inappropriate expressions is something that is not within the bounds of what is considered appropriate or socially acceptable [YourDictionary, n.d.]. It is deﬁned as the propagation of offensive messages or remarks that in some circumstances are inappropriate, exhibit a lack of respect towards certain groups of people or are just rude in general [Vandersmissen, 2012]. This could be expressions containing swearing, unmoderated chatrooms where there’s no one supervising the conversation and barring unsuitable comments and sexual explicit comments [Inappropriate Content, [n.d.].

Classifying Inappropriate Content in English Text is important because many people who uses the internet can read inappropriate text content. Those inappropriate contents are very harmful to the readers, it can bully, harassment or etc. [Inappropriate Content, n.d.].

The algorithm to be use in this study is Bootstrapping as Semi-Supervised Learning. For Natural Language, it shows incorporating features derived from unlabeled data into a supervised model can provide substantial improvements, both in terms of reducing the error and the amount of labeled data required. Its results show that using word clusters and a new type of unlabeled data feature, mutual information statistics, can both boost performance [Liang, 2005].

**1.2 Background of the Study**

Sentiment classification aims to predict the sentiment polarity of a text [Lee et al., 2002] and plays a critical role in many Natural Language Processing (NLP) applications [Cheng et al., 2005; Cardie et al., 2005; Cui et al., 2006; Balahur et al., 2009]. Although supervised learning methods have been widely employed and proven effective in sentiment classification in the literature [Lee et al., 2002], they normally depend on a large amount of labeled data, which usually involves high cost in labor and time. To overcome this problem, various semi-supervised learning methods are proposed to effectively utilize a small scale of labeled data along with a larger amount of unlabeled data

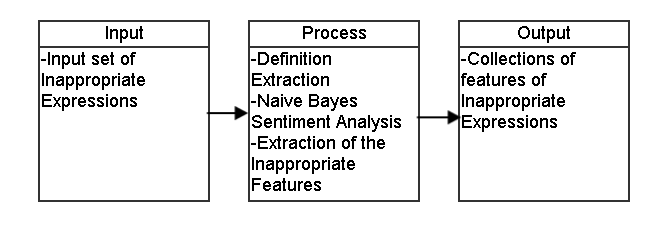
One specific open problems in semi-supervised learning is the co-training with linear separators which is known that the consistency problem is NP-hard. Even if one cannot solve the problem efficiently in general, a natural question is whether one can at least weaken the independence given the label assumption in a non-trivial way and still get an efficient algorithm for this class [Balcan and Blum, n.d.].

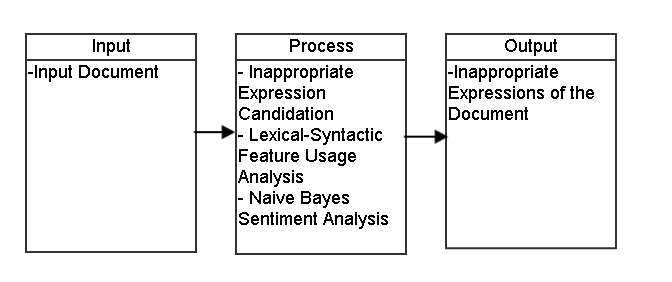
However, all the existing semi-supervised learning methods assume the balance between negative and positive samples in both the labeled and unlabeled data, and none of them consider a more common case where the class distribution is imbalanced, i.e., the number of positive samples is quite different from that of negative samples in both the labeled and unlabeled data. For clarity, the class with more samples is referred as the majority class (MA) and the other class with fewer samples is referred as the minority class (MI). In fact, semi-supervised learning on imbalanced classification is rather challenging: at least, there exist two basic issues to be solved. On the one hand, imbalanced classification requires a specifically-designed classification algorithm. Trained on the imbalanced labeled data, most classification algorithms tend to predict test samples as the majority class and may ignore the minority class. Although many methods, such as re-sampling [Bowyer et al., 2002], one-class classification [Duin and Juszczak, 2003], and cost-sensitive learning [Liu and Zhou, 2006], have been proposed to solve this issue, it is still unclear as to which method is more suitable to handle the imbalanced problem in sentiment classification and whether the method is extendable to semi-supervised learning. On the other hand, given the classification algorithm and the unlabeled data, which method is effective for capturing the inherent information in the unlabeled samples to improve the performances? Unfortunately, the issue of semi-supervised learning on imbalanced data sets has not been carefully studied in the literature.

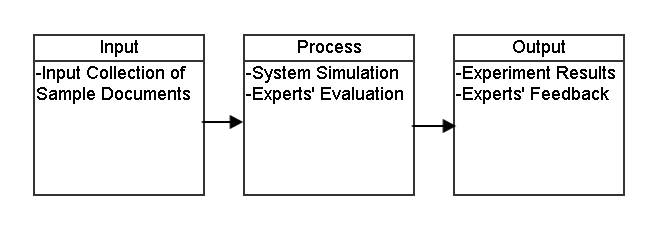
**1.3 Conceptual Framework**

**1.3.1 Conceptual Framework of the System**

a.Training Phase:

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b. Simulation Phase:

**1.3.2 Conceptual Framework of the Study**

**1.4 Statement of the Problem**

The study aims to design, develop and evaluate the system which will help to recognize Inappropriate Expressions from a document. The people who are in knowledgeable in English language are the respondents in this study. In addition to this, the researchers aim to seek answer to this problem:

What is the performance analysis of Sentiment Analysis based on the following:

1. Accuracy

2. Specificity

3. Harmonic Mean

1. Precision
2. Recall

**1.5 Research Assumption**

**1.5.1 Research Assumptions of the System**

**A1.** The More the Training Data, The More the Accuracy

**1.5.2 Research Assumptions of the Study**

**1.6 Scope and Limitations**

**1.6.1 Scope and Limitation of the System**

The system will be deployed as a Java Application. The system will be dependent of the tools such as WordNet, SentiWordNet, and Stanford Part-of-Speech Tagger. The system that will be developed will be dependent on the Latest Java Virtual Machine and Runtime Environment.

**1.6.2 Scope and Limitations of the Study**

The study will focus on recognizing inappropriate expressions such as offensive and sexually explicit expressions on a document. This system will also check for the context in the sentence and the language that this system will only consider is in English language. The system will not deal with idiomatic inappropriate expressions.

**1.7 Significance of the Study**

Inappropriate Expressions Recognition using Bootstrapping as Semi-supervised Learning focuses on recognizing inappropriate expressions on a document. The system will benefit the following:

**Students** – these are people who have a whole society around technology because most of them routinely use chat and email to communicate with each other. The system will prevent receiving possible inappropriate expressions through the internet.

**Parents** – these are the people who are worrying so much about what their children do on the internet because some articles found on google are not appropriate for their child and contains inappropriate expressions like offensive and sexually explicit words.

**Natural Language Processing Researchers (NLP)** – These are the experts in Natural Language processing. The system will provide avenues for further improvement of the said topic.

**Future Researches** – These are the people who will conduct future research to improve the existing studies about Sentiment Analysis. They can add additional functions to the system.

**1.8 Definition of Terms**

Bootstrapping Algorithm– works by drawing many independent bootstrap samples, evaluating the corresponding bootstrap replications, and estimating the standard error of by the empirical standard error, denoted by B, where B is the number of bootstrap samples used.

Inappropriate Expressions – is something that is not within the bounds of what is considered appropriate or socially acceptable.

Natural Language Processing – is a field of computer science, artificial intelligence and computational linguistics concerned with the interactions between computers and human languages.

Offensive Language – the term that is applied to hurtful, derogatory or obscene comments made by one person to another person.

Part-of-Speech Tagger -  is a piece of software that reads text in some language and assigns parts of speech to each word (and other token), such as noun, verb, adjective, etc., although generally computational applications use more fine-grained POS tags like 'noun-plural'.

Semi-supervised Learning – is a class of supervised learning tasks and techniques that also make use of unlabeled data for training – typically a small amount of labeled data with a large amount of unlabeled data.

Sentiment Analysis – refers to the use of natural language processing, text analysis and computational linguistics to identify and extract subjective information in source materials.

SentiWordNet - is a lexical resource for opinion mining. SentiWordNet assigns to each synset of WordNet three sentiment scores: positivity, negativity, objectivity.

Sexually explicit – presents sexual content without deliberately obscuring or censoring it.

WordNet - is a lexical database for the English language. It groups English words into sets of synonyms called synsets, provides short definitions and usage examples, and records a number of relations among these synonym sets or their members.

**Chapter 2: Review of Related Literature and Studies**

**2.1 Review of Related Literature**

**2.1.1 Inappropriate Expression**

Inappropriate Expression is something that is not within the bounds of what is considered appropriate or socially acceptable [YourDictionary, n.d.]. Inappropriate expression includes information that upset us or information that might lead or tempt us into unlawful or dangerous behavior. This could be content containing swearing, unmoderated chatrooms where there’s no one supervising the conversation and barring unsuitable comments and sexual explicit comments [Inappropriate Content, [n.d.]. Profanity is an offensive word or inappropriate language [Merriam-Webster Online Dictionary, 2014]. It is also called bad language, strong language, coarse language, foul language, bad words, vulgar language, lewd language, swearing, cursing, cussing, or using expletives. This use is a subset of a language's lexicon that is generally considered to be strongly impolite, rude or offensive. It can show a debasement of someone or something, or show intense emotion. Profanity in this sense takes the form of words or verbal expressions. In its older, more literal sense, the term profanity refers to offensive words, or religious words, used in a way that shows you do not respect God or holy things, or behavior showing similar disrespect [Longman Dictionary of Contemporary English, 2014].

**2.1.2 Bootstrapping Algorithm**

The Bootstrap algorithm works by drawing many independent bootstrap samples, evaluating the corresponding bootstrap replications, and estimating the standard error of by the empirical standard error, denoted by B, where B is the number of bootstrap samples used [Efron and Tibshirani, 1993].

With the bootstrap method, the basic sample is treated as the population and a Monte Carlo-style procedure is conducted on it. This is done by randomly drawing a large number of ‘resamples’ of size n from this original sample (of size n either) with replacement. So, although each resample will have the same number of elements as the original sample, it could include some of the original data points more than once, and some not included. Therefore, each of these resamples will randomly depart from the original sample. And because the elements in these resamples vary slightly, the statistic G\*, calculated from one of these resample will take on slightly different values. The central assertion of the bootstrap method is that the relative frequency distribution of these G\*’s is an estimate of the sampling distribution of G [The Original Bootstrap Method, n.d.].

**2.1.3 Semi-supervised Learning**

Semi-supervised learning is a class of supervised learning tasks and techniques that also make use of unlabeled data for training - typically a small amount of labeled data with a large amount of unlabeled data. Semi-supervised learning falls between unsupervised learning (without any labeled training data) and supervised learning (with completely labeled training data). Many machine-learning researchers have found that unlabeled data, when used in conjunction with a small amount of labeled data, can produce considerable improvement in learning accuracy [Wikipedia, n.d.].

Semi-Supervised Learning for Natural Language shows incorporating features derived from unlabeled data into a supervised model can provide substantial improvements, both in terms of reducing the error and the amount of labeled data required. Its results show that using word clusters and a new type of unlabeled data feature, mutual information statistics, can both boost performance. In addition, semi-Markov models can also increase performance modestly on the named-entity recognition (NER) task but in some cases hurts performance on the Chinese word segmentation (CWS) task [Liang, 2005].

**2.1.4 Naïve Bayes Classifier**

Naive Bayes has been studied extensively since the 1950s. It was introduced under a different name into the text retrieval community in the early 1960s, [Norvig and Russell et.al., 2003] and remains a popular (baseline) method for text categorization, the problem of judging documents as belonging to one category or the other (such as spam or legitimate, sports or politics, etc.) with word frequencies as the features. With appropriate preprocessing, it is competitive in this domain with more advanced methods including support vector machines [Karger et.al. 2003]. It also finds application in automatic medical diagnosis [Rish, 2001].

Naive Bayes classifiers are highly scalable, requiring a number of parameters linear in the number of variables (features/predictors) in a learning problem. Maximum-likelihood training can be done by evaluating a closed-form expression [Norvig and Russell, 2003], which takes linear time, rather than by expensive iterative approximation as used for many other types of classifiers.

**2.2 Review of Related Studies**

**2.2.1 Sentiment Analysis in Classifying Offensive Language**

The researchers introduced the study of bullying to the NLP Community. Bullying, in both physical and cyber worlds (the latter known as cyberbullying), has been recognized as a serious national health issue among adolescents. One is being bullied or victimized when he or she is exposed repeatedly over time to negative actions on the part of others. There are wide ranges of emotions expressed in bullying traces. After manually inspecting a number of bullying traces in Twitter, our domain experts identified seven most common emotions such as anger, embarrassment, empathy, fear, pride, relief and sadness. Analyzing Social Media to Detect Cyber Bullying using Sentiment Mining found that “sentiment analysis is the task of finding the opinions of people about specific textual entities. The decision making process of people is usually affected by the opinions formed by domain authorities and the proliferation of online discussions [Bi, n.d.].

Sentiment Analysis has the potential to identify victims who pose high risk to themselves or others, and to enhance the scientific understanding of bullying overall Victims usually experience negative emotions such as depression, anxiety and loneliness. In extreme cases such emotions are more violent or even suicidal. Detecting at risk individuals via sentiment analysis enables potential interventions. In addition, social scientists are interested in sentiment analysis on bullying traces to understand participants’ motivations [Bellmore et.al, 2012].

The Lexical Syntactical Feature (LSF) approach from the research Detecting Offensive Language in Social Media to Protect Adolescent Online Safety is to identify offensive contents in social media, and further predict a user’s potentiality to send out offensive contents. It includes two phases of offensive detection. Phase 1 aims to detect the offensiveness on the sentence level and Phase 2 derives offensiveness on the user level. In Phase 1, the researchers apply advanced text mining and natural language processing technique to derive lexical and syntactic features of each sentence. Using these features, we derive an offensive value for each sentence. In Phase 2, we further incorporate user-level features where we leverage research on authorship analysis. The system consists of pre-processing and two major components: sentence offensiveness prediction and user offensiveness estimation. During the pre-processing stage, user’s conversation history is chunked into posts, and then into sentences. During sentence offensiveness prediction, each sentence’s offensiveness can be derived from two features: its word’s offensiveness and the context. The researchers use lexical feature to represent words’ offensiveness in a sentence, and syntactic feature to represent context in a sentence. Words’ offensiveness nature is measured from two lexicons. For the context, we grammatically parse sentences into dependency sets to capture all dependency types between a word and other words in the same sentence, and mark some of its related words as intensifiers. The intensifiers are effective in detecting whether offensive words are used to describe users or other offensive words. During user offensiveness estimation stage, sentence offensiveness and users’ language patterns are helped to predict user’s likelihood of being offensive. Experimental result shows that the LSF sentence offensiveness prediction and user offensiveness estimate algorithms outperform traditional learning based approaches in terms of precision, recall and f-score. It also achieves high processing speed for effective deployment in social media [Chen et.al, n.d.].

Very few other research teams are working on the detection of cyber bullying. A misbehavior detection task was offered by the organizers of CAW 2.0, but only one submission was received. It is determined that a baseline text mining system (using bag of words approach) was significantly improved by including sentiment and contextual features. Even with the combined model, a support vector machine learner could only produce a recall level of 61.9% [Hong et. al., 2009].

In the research Filtering Offensive Language in Online Communities using Grammatical Relations, mainly tackles the problem about how the offensive language can be removed in a user message. They analyze the offensive language in text messages posted in online communities, and propose a new automatic sentence-level filtering approach that is able to semantically remove the offensive language utilizing the grammatical relations among words. Their solution includes 3 steps. First, they analyzed the characteristics of offensive text content in user messages. Then, they introduced their filtering philosophy according to the summarized characteristics. Finally, they show how this philosophy is transformed into heuristic rules applicable in the filtering process. The overview idea of their filtering approach is shown in the presented Algorithm 1 in which the functions POS tagging ad TD generator generate Part-of-Speech tags and typed dependency relations, respectively. They also use existing NLP (Natural Language Processing) tools to implement these two functions. They also focused in the design of two other functions CreateRelTree and EstimateRelTree. In their research assume that the filtering is based on a comprehensive offensive lexicon containing all offensive words. Words do not appear in the lexicon are considered inoffensive. Experiments their dataset, comments from Youtube, show over 90% agreement in filtered results between the proposed approach and manual filtering approach [Xu and Sencun, 2010].

The researchers of Detecting Offensive Tweets via Topical Feature Discovery over a Large Scale Twitter Corpus in proposed a novel semi-supervised approach for detecting profanity-related offensive content in Twitter. They introduced an approach that exploits linguistic regularities in profane language via statistical topic modeling on a huge Twitter corpus, and detects offensive tweets using these automatically generated features. Their step by step processes are as follows: (a) Bootstrap between twitters and tweets based on a seed word set to obtain training tweets for topic model learning; (b) Topic models are learned via a generative LDA approach; (c) Tweets in a holdout testing set are processed in the same fashion as in (a); (d) Topic distributions are inferred for each testing tweet by the topic model learned in step (b); (e) Seed words are applied against each testing tweet, leading to a binary lexicon feature; (f) ML models are built and evaluated. The keyword matching technique has been shown to perform very well in the literature and achieved a TP of 69.7% with an FP of 3.77% in our experiment. While keeping the FP on the same level as the baseline, our approach had a TP of 75.1% over 4029 testing tweets using Logistic Regression, a significant 5.4% improvement over the baseline [Fan et.al, n.d.].

**2.1.2 Semi-supervised Sentiment Classification**

Generally, sentiment classification methods can be categorized into three types: unsupervised [Turney, 2002], supervised [Pang et al., 2002], and semi-supervised [Melville and Sindhwani, 2008]. Compared to supervised and unsupervised methods, semi-supervised methods for sentiment classification become more and more popular due to their making use of both the labeled and unlabeled data. This paper mainly focuses on semi-supervised methods for sentiment classification.

One kind of semi-supervised methods for sentiment classification is to utilize prior lexical knowledge in conjunction with the labeled and unlabeled data. For example, Document-Word Co-regularization for Semi-supervised Sentiment Analysis analyzed the sentiment of documents and words based on a bipartite graph representation of the labeled and unlabeled data while Li et al. [2009] employed some simple update rules to make use of tri-factorization of the term-document matrix. It is rather common that such methods require a high-quality lexicon with the polarity of words properly defined [Melville and Sindhwani, 2008].

Another kind of semi-supervised methods for sentiment classification is to employ some bootstrap techniques, such as self-training [Yarowsky, 1995] and co-training [Blum and Mitchell, 1998]. Among them, co-training has been proven more effective than self-training [Wan, 2009; Huang et.al, 2010]. The key issue of applying co-training is to find a suitable set of different views. For instance, Co-Training for Cross-Lingual Sentiment Classification regarded two different languages (i.e., English and Chinese) as two views [Wan, 2009] while Employing Personal/Impersonal Views in Supervised and Semi-supervised Sentiment Classification considered personal and impersonal texts as two views [Huang et.al, 2010]. This paper employs the co-training technique and generates different views from random feature subspaces. Among others, Mine the Easy and Classify the Hard: Experiments with Automatic Sentiment Classification integrated various methods, such as spectral clustering, active learning, transductive learning, and ensemble learning, in semi-supervised sentiment classification [Dasgupta and Ng, 2009]. To our best knowledge, no existing semi-supervised methods consider the class imbalance problem in sentiment classification.

Semi-Supervised Learning for Semantic Relation Classification using Stratified Sampling Strategy explores several key issues in semi-supervised learning based on bootstrapping for semantic relation classification. The application of stratified sampling originated from statistics theory to the selection of the initial seed set contributes most to the performance improvement in the bootstrapping procedure. In addition, the more strata the training data is divided into, the better performance will be achieved. However, the augmentation of the labeled data using the stratified strategy fails to function effectively largely due to the unbalanced distribution of the confidently classified instances, rather than the stratified sampling strategy itself [Kong et.al, 2009].

Semi-supervised Learning for Relation Extraction integrate the advantages of SVM bootstrapping in learning critical instances and label propagation in capturing the manifold structure in both the labeled and unlabeled data, by fir­st bootstrapping a moderate number of weighted support vectors through a co-training procedure from all the available data, and then applying label propagation algorithm via the bootstrapped support vectors [Li et.al, 2008].

Open Problems in Efficient Semi-supervised PAC Learning address semi-supervised learning for imbalanced sentiment classification. It adopts under-sampling to generate multiple sets of balanced initial training data and then propose a novel semi-supervised learning method based on random subspace generation which dynamically generates various subspaces in the iteration process to guarantee enough variation among the involved classifiers. Evaluation shows that semi-supervised method can successfully make use of the unlabeled data and that dynamic subspace generation significantly outperforms traditional static subspace generation [Balcan and Blum, n.d.].

**2.3 Synthesis of the Study**

Lexical Syntactic features play a big role in the recognition of determining inappropriate expressions. The said features help in identifying the usage in the sentence level, and then how it affects the person related in the expressions. Bootstrapping approach for learning has been proven to be effective in learning, and modeling of linguistic data, though it is preferred to have forms of supervision rather than being unsupervised. There is a need for learning, modeling, clustering, and resampling techniques for the features of inappropriate expressions to further model the inappropriate language, in which it contains inappropriate expressions, thus coming up with a bootstrapping methodology.

**Chapter 3 – Research Methodology**

**3.1 Research Method Used**

The method used by the researchers in developing the study is experimental method of research that describes and analyzes variable to know he occurrence of a particular event. The researchers of this study conducted a pre-test and post-test about the implementation of the system. In this method, researches and studies were used to come up with the expected result.

**3.2 Research Paradigm**

The researchers would implement positivist way of approach. This is because Sentiment Analysis requires a lot of testing and observational analysis to ensure accurate and better result compare to the other Sentiment’s. Series of testing and analysis of the system will be done to get the result with the highest level of accuracy.

In this way, the researchers will have the series of data that will act as empirical evidence and later will be used to analyze the system accuracy and performance level.

**3.3 System Architecture**

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In the Training phase there is a Learning Module. The learning module input consists of a file that contains lists of words that is deemed as Inappropriate. The learning module evaluates the Inappropriateness with basis of its polarity value in the Sentiment Corpus (which will be implemented via SentiWordnet) and the polarity of the definition of the word, in which it will be extracted via WordNet with the implementation of naïve bayes model. The Inappropriate expression back propagation will be done by extracting the features in the definition that made the input inappropriate, and will be collected to the inappropriate expression features knowledge base. The synset resampling gets the synsets of the word and will undergo to the phases undergone by the original word. The training module repeats this per word in the collection until all are evaluated and there are no more synsets to be resampled.

In the Analyzer Module, There will be an input of a document. A document will undergo preprocessing. The preprocessing phase consists of sentence splitting, tokenization, and Part-of-Speech Tagging. After undergoing preprocessing, for each sentence there will be a search for candidates in inappropriate expressions, which will be based on the collected features in the knowledge base. Then the sentence will undergo to the Relational Inference Analyzer, where it determines the inappropriateness of the candidate words based each words’ Lexical Syntactic Features and its relations to the other existing words in the same sentence. If the analyzer determines the sentence has an inappropriate sense, then, the sentence will be scored by a polarity analyzer, which is based on naïve bayes model. The results will determine the inappropriateness of the sentence. If the sentence is determined as inappropriate, the analyzer will list down the candidate inappropriate expressions inside it.

**3.4 Population Frame and Sample Size**

**3.5 Description of the Respondents**

**3.6 Sampling Technique**

**3.7 Instrumentation**

Instrumentation refers to the tools or means by which researchers attempt to measure variables or items of interest in the data collection process. The study utilizes experiments to test its effectiveness on recognition of inappropriate expressions. The researchers will be using experiment paper to identify the results of the tests conducted.

Table 1: Each document is tested in system and by the expert per sentence

|  |  |  |
| --- | --- | --- |
| Sentences | Inappropriate | |
| System | Expert |
| 1 |  |  |
| 2 |  |  |
| 3 |  |  |
| 4 |  |  |
| 5 |  |  |
| 6 |  |  |
| 7 |  |  |
| 8 |  |  |
| 9 |  |  |
| 10 |  |  |

**\***Sampling Methodology is Purposive Random Sampling

Table 1 is where the answers for the sentence analysis is recorded for each input. The expert labeled each input as yes, if the input is inappropriate, or no if it is not. The researchers also did the same for the system. Based from the results, each sentences was classified into the following:

\* TP (True Positive) – expert and system both determined the input is inappropriate

\* FP (False Positive) – System determined the input is inappropriate present, the expert indicated it’s not

\* TN (True Negative) – both the expert and the system indicated that the input is not inappropriate

\* FN (False Negative) – system indicated that the input is not offensive, the expert indicated it is inappropriate

Table 2: Input Scoring

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Sentence | TP | FP | TN | FN |
| 1 |  |  |  |  |
| 2 |  |  |  |  |
| 3 |  |  |  |  |
| 4 |  |  |  |  |
| 5 |  |  |  |  |
| 6 |  |  |  |  |
| 7 |  |  |  |  |
| 8 |  |  |  |  |
| 9 |  |  |  |  |
| 10 |  |  |  |  |
| Total |  |  |  |  |
| Average |  |  |  |  |

Table 2 is where each input will be labeled as true positive, false positive, true negative, and false positive. This scoring will be used for the evaluation of data per document in which the following metrics is used: Precision: the percent of identified inputs that is inappropriate. Recall: the percent of inappropriate expressions correctly identified. Specificity: rate of the results without the condition, which have a negative test result. F- measure: the weighted harmonic mean of precision and recall. We used F- measure which gives equal weight to precision and recall.

Table 3: Averaging of Results per Document

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Document | Ave. TP | Ave. FP | Ave. TN | Ave. FN |
| 1 |  |  |  |  |
| 2 |  |  |  |  |
| 3 |  |  |  |  |
| 4 |  |  |  |  |
| 5 |  |  |  |  |
| 6 |  |  |  |  |
| 7 |  |  |  |  |
| 8 |  |  |  |  |
| 9 |  |  |  |  |
| 10 |  |  |  |  |
| Total |  |  |  |  |
| Average |  |  |  |  |

Table 3 is where each document’s average true positive, average false positive, true negative, and false positive. This scoring will be used for the evaluation of data as overall system performance in which the following metrics is used: Precision: the percent of identified inputs that is inappropriate. Recall: the percent of inappropriate sentences correctly identified. Specificity: rate of the results without the condition, which have a negative test result. F- measure: the weighted harmonic mean of precision and recall. We used F- measure which gives equal weight to precision and recall.

**3.8 Data Gathering Procedure**

**3.9 Statistical Treatment**

The performance of the Sentiment Analysis will be measured through the use of the Harmonic Mean, or f-measure. The f-measure is the weighted average of the values of the Precision and Recall. By multiplying the values by 2 and dividing it by the sum of the Precision and Recall, we can get the harmonic mean of the system. A high F1 score will imply a good performance of the system. The formula for the Harmonic mean is as follows:

Where:

­­ F = F-measure

P = Precision – Percentage of identified comments that is inappropriate.

R = Recall – Percentage of inappropriate expressions correctly identified.

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