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ARTIFICIAL INTELLIGENCE -BASED NATURAL DISASTER INTENSITY ANALYSIS USING MACHINE LEARNING TECHNIQUES

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ABSTRACT

Disaster management platforms such as emergency services provide valuable information for aiding disaster response during emergency events. Machine learning could be used to identify such information. There are numerous challenges when considering the use of social media data for emergency response, including issues of reliability, quantification of performance, deception, focus of attention, and translation of reported observations into a form that can be used to combine with other information. One problem became apparent during the earthquake in Haiti when thousands of technical volunteers from around the world suddenly attempted to provide responders with mapping capabilities, translation services, people and resource allocation, all via SMS at a distance. “To provide fast service these platforms was not equipped to handle this high volume and velocity of urgent information.” Despite the good will of field staff, their institutions' policies and procedures were never designed to incorporate data from outside their networks, especially at such an overwhelming flow. In addition, the organizations did not have the technical staff, or the analytical tools, to turn the flow of data into actionable knowledge. To address this limitation, we propose to use a domain adaptation approach, which learns classifiers from available dataset, with labeled data. Our approach uses the Linear SVC Algorithm, together with an Self-Training strategy. Experimental results on the task of identifying emergency messages classification relevant to a disaster of interest show that the domain adaptation classifiers.

1. INTRODUCTION

Natural disasters are inevitable, and the occurrence of disasters drastically affects the economy, ecosystem and human life. Buildings collapse, ailments spread and sometimes natural disasters such as tsunamis, earthquakes, and forest fires can devastate nations. When earthquakes occur, millions of buildings collapse due to seismological effects [1]. Many machine learning approaches have been used for wildfire predictions since the 1990s. A recent study used a machine learning approach in Italy. This study used the random forest technique for susceptibility mapping of wildfire [2]. Floods are the most devastating natural disaster, damaging properties, human lives and infrastructures. To map flood susceptibility, an assembled machine learning technique based on random forest (RF), random subspace (RS) and support vector machine (SVM) was used [3]. As the population is growing rapidly, people need to acquire land to live on, and as a result the ecosystem is disturbed horrifically, which causes global warming and increases the number of natural disasters. Populations in underdeveloped countries cannot afford damages disasters cause to infrastructures.

The aftermath of disasters leaves the humans in miserable situations, and sometimes the devastating effects cannot be detected; additionally, rescue operations cannot take place in most of the places and victims are unable to be identified due to geographical factors of the different areas. Disasters such as forest fires spread rapidly in dense areas, so firefighting is difficult to carry out; in this case, development of the strategy to predict such circumstances is crucial so that such disasters can be prevented beforehand. As the technologies are continuously improving, aviation systems have begun adopting smart technologies to develop unmanned aerial vehicles (UAVs) equipped with cameras, which can reach distant areas to identify aftereffects of natural disasters on human life,

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infrastructure, and transmission lines by capturing images and videos.

1.1 Problem statement

Temporally, the above problems arise at the stage when emergency responders and organizations begin engaging their organizational mechanisms to respond to the crises in question (Munro, 2011). For decades, these organizations have operated with a centralized command structure, standard operating procedures, and internal vetting standards to ascertain appropriate responses to emergencies. While not optimized to current expectations of speed, efficiency and knowledge, these mechanisms have been successful at bringing rescue, response and recovery to millions.

1.2 Objective

Towards optimizing current organizational mechanisms in terms of speed, efficiency and knowledge, machine learning algorithms have been used to help responders sift through the big crisis data, and prioritize information that may be useful for response and relief.

2. SYSTEM ANALYSIS

2.1 Existing System

During the Paris attacks in November 2015, eyewitnesses, or friends of eyewitnesses, shared information about gunfire and dangerous places through Twitter, to alert people within minutes after attacks in different places. Parisians also launched the hashtag #PorteOuverte (meaning “open door”) to offer, through Twitter, safety and refuge to those affected by the attacks.

Therefore, microblogging data from Twitter like platforms are seen to have intrinsic value for both responder organizations and victims, due to their growing ubiquity, communications rapidity, and cross-platform accessibility.

a) Disadvantages of Existing System

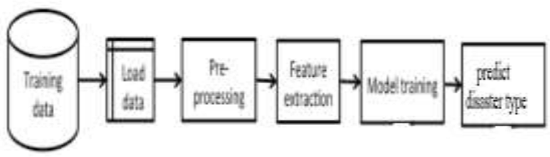
- One problem became apparent during the earthquake in Haiti when thousands of technical volunteers from around the world suddenly attempted to provide responders with mapping capabilities, translation services, people and resource allocation, all via SMS at a distance.
- Despite the good will of field staff, their institutions' policies and procedures were never designed to incorporate data from outside their networks, especially at such an overwhelming flow. In addition, the organizations did not have the technical staff, or the analytical tools, to turn the flow of data into actionable knowledge.

2.2 Proposed System

We propose to use a domain adaptation approach, which learns classifiers from available dataset, with labeled data. Our approach uses the Linear SVC Algorithm, together with an Self-Training strategy. Experimental results on the task of identifying emergency messages classification relevant to a disaster of interest show that the domain adaptation classifiers.

3. SYSTEM DESIGN

3.1 System architecture



The automatic classification of tweets begins with the manual classification of a dataset which serves as the ground truth for evaluating the performance of two machine classifying algorithms, Naive Bayes (NB) and Support Vector Machine (SVM). The following sub-sections describe the dataset and the approach used in the study.

3.2 Data Source

Habagat hit the Philippine's capital Manila and its neighboring provinces last August 1-8, 2012. The monsoon brought about eight days of torrential rain and thunderstorms which caused flooding in several areas and consequently caused massive damages and loss of properties and lives. At the onset of the Habagat until its aftermath, subscribers of Twitter used this social medium to send relevant or personal messages to their intended recipients. A

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sample of Habagat tweets were collected by the researchers of Ateneo de Manila University using the Twitter API. The sample has a total of 612,622 tweets, of which 373,771 are unique tweets and 238,851 are retweets. Unique tweets are the original messages that are sent by the author of a tweet which can be viewed by his or her followers and followees. Retweets on the other hand are messages received by a subscriber and are forwarded to another user or set of users.

3.3 Manual Classification

From the collected Habagat tweets, a sample of 4,000 tweets was randomly selected. Annotators initially classified the randomly selected tweets as to whether they are encoded in English, Tagalog, combination of English-Tagalog or other languages or dialects. The annotators further classified the English tweets as informative or uninformative based on the given definitions. Informative tweets are tweets that provide useful information to the public and are relevant to the event, while uninformative tweets are tweets that are not relevant to the disaster and these do not convey enough information or are personal in nature and may only be beneficial to the family or friends of the sender.

3.4 Information Extraction

Using conditional probability and Bayes' theorem, information can be extracted from the statistics of manually classified tweets. Conditional probability is defined as $P(A|B) = P(A \cap B)/P(B)$, provided $P(B) > 0$. Bayes' theorem , also known as Bayes' rule or Bayes' law, is a result in probability theory that relates conditional probability. If A and B denote two events, P(A|B) denotes the conditional probability of A occurring, given that B occurs [22]. Bayes theorem is mathematically defined as:

$$P(A|B) = P(B|A)\,P(A)/P(B)$$

where:

P(A) is the prior probability or marginal probability of A.

It is ‖prior‖ in the sense that it does not take into account any information about B

P(A|B) is the conditional probability of A, given B

P(B|A) is the conditional probability of B given A

P(B) is the prior or marginal probability of B, and acts as a normalizing constant

In the context of this study, *P(A)* is the probability of a tweet being informative, while *P(B)* is the probability of a tweet being unique. Therefore, information of the probabilities of tweets being informative or not informative, given that these are unique or are re tweets were then extracted.

4. IMPLEMENTATION

4.1 Machine Learning Algorithms for Classification

a) Supervised Learning

Supervised learning was used in training the machine to classify a tweet as informative or not informative. Supervised learning is a training in which the class attribute values for the dataset are known (labeled data) before running the algorithm [24]. Supervised learning builds a model that maps x to y;

where **x** is a vector and *y* is the class attribute. A model is generated when the supervised learning algorithm is run on a training set, which maps the feature values (**x**) to the class attribute values (*y*). After training, the model is tested on a dataset which will predict class attributes. In the context of this study, **x** = vector of features and *y* {informative, uninformative}.

In order to minimize bias related to the sampling of data, the stratified 10-fold cross validation was used to estimate the performance of the model. In a 10-fold cross validation, the dataset is randomly split into 10 mutually exclusive subsets (DS1, DS2...DS10) of approximately equal sizes and with proportional representation of the tweet classes. Using the data set, the classification model is trained and tested 10 times, with the 9-folds used as the training data set and the remaining 1-fold as the testing data set. The algorithms Naive Bayes and Support Vector Machine (SVM) were compared in terms of the different metrics of evaluation.

Naive Bayes' and Support Vector Machine are two

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of the most commonly used machine learning algorithms for classification. Naive Bayes classifier is robust and has a good performance in several real-world classification tasks. A Naive Bayes classifier is a simple probabilistic classifier basedon Bayes' theorem (from Bayesian statistics) with strong (naive) independence assumptions [25]. In simple terms, a Naive Bayes classifier assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature [26]. Support Vector Machine is a learning method used for binary classification. The basic idea is to find a hyperplane which optimally separates the *d*-dimensional data into its two classes [26]. However, since example data is often not linearly separable, SVM incorporates the notion of a kernel induced feature space which projects the data into a higher dimensional space where the data is more easily separable [27].

b) Evaluation of the Machine Learning Algorithms:

In this study, accuracy, recall, precision, area under curve (AUC) and F-measure were used as metrics in the empirical evaluation of the classification algorithms Naive Bayes and Support Vector Machine. Table I presents the description of each metric of evaluation, as described in Rapid miner.

Table I: Metrics of Evaluation

Metric	Description
Accuracy	Relative number of correctly classified examples or in other words percentage of correct predictions.
AUC	AUC is the Area Under the Curve of the Receiver Operating Characteristics (ROC) graph which is a technique for visualizing, organizing and selecting classifiers based on their performance.
Precision	Relative number of correctly as positive classified examples among all examples classified as positive
Recall	This parameter specifies the relative number of correctly as positive classified examples among all positive examples
F-measure	This parameter is a combination of the *precision*and the *recall*i.e. *f=2pr/(p+r)*where *f*,*r*and *p*are *f*-

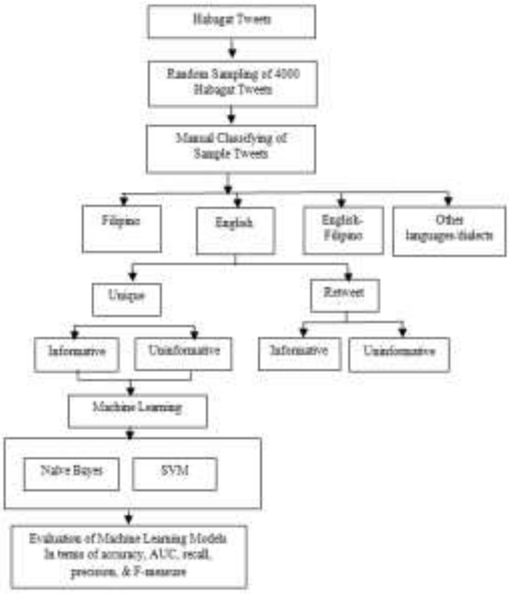

Figure: Methodology Structure

5. RESULTS AND DISCUSSION

5.5 Manual Classification of Habagat Tweets

From the 4000 tweets randomly selected, there were 1,563 English tweets, 1,393 Tagalog tweets, 913 tweets using a combination of English and Filipino and 121 tweets using other languages or dialects. Table III presents a summary of the manually classified English tweets.
Based on the labeling of the annotators, the computed ICC or multi-rater Kappa coefficient is 0.671, which apparently is substantial [33][34][35] or there is a good level of agreement among the annotators in classifying whether a tweet is informative or not.

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In case of conflict in label, a discussion among the three annotators was necessary to resolve such differences. After thorough discussion, annotators agreed on a specific label for the tweet.

5.2 Extracted Information

Applying conditional probability and Bayes' theorem, information were extracted from the statistics of the manually classified tweets. Based on these statistics, uninformative tweets outnumbered informative tweets by a ratio of 65% to 35%. An actual example of an uninformative tweet is ―Stay safe evryone!!! #PrayForThePhilippines #TrustGOD".

The unique tweets are more likely uninformative (71.72%) and the unique tweets are more likely to be informative with the probability of 28.28%. It can also be noted that the probabilities of retweets being uninformative and informative are 49.22% and 50.78% respectively, which are relatively equal.

Though uninformative tweets tend to outnumber the informative tweets sent, the informative tweets are more likely to be retweeted (41.99%) than uninformative tweets (21.67%). Informative tweets that are retweeted imply the degree of significance and urgency of the situation, which then may provide information that may enhance the situational awareness of the public and disaster response units.

The results also suggest that the subscribers used Twitter to broadcast more of tweets that express their subjective messages and emotions regarding the Habagat event. These results seem to confirm the findings of Hughes and Palen on hurricanes[39], Starbird and Palen on flooding and wildfires[37] and Starbird and Palen on Haiti earthquake[40]. These studies revealed that users tweet to share information about the crisis, to express their opinions and feelings, and to help those in need of aid.

5.2 Evaluation of Machine Learning Algorithms:

Table IVpresents the results of the 10-fold cross validation for all folds for all the metrics of evaluation. Using the Kolomogorov-Smirnov and Shapiro Wilk for normality testing, the data is normally distributed and this is true to all the five evaluation metrics. The normality of these variables has also been validated by their Normal Probability Plots.

Since the data are normally distributed, parametric testing was performed. The parametric t-test was specifically used to determine the significant differences between Naive Bayes and SVM. Table Vpresents the results of the experimentation.

The paired t-test results shown in Table V demonstrate that there is a significant difference between Naive Bayes and SVM ($p<0.001$). This is true to all the five parameters namely, accuracy, AUC, precision, recall, and F-measure. In particular, SVM is significantly higher than Naive Bayes in accuracy, AUC, recall, and F-Measure, though Naive Bayes is significantly higher than SVM in precision. Table VI shows the mean values for the paired sample statistics.

	Informative Tweets	**Uninformative Tweets**	**Total**
Unique	315	799	1114
Retweets	228	221	449
Total	543	1020	1563

5.3 Evaluation of Machine Learning Algorithms

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Table IV: Results Of 10-Fold Validation

	ACCURACY		AUC		PRECISION		RECALL		F-MEASURE	
FOLD	NB	SVM	NB	SVM	NB	SVM	NB	SVM	NB	SVM
1	0.5940	0.8100	0.7200	0.9170	0.9696	0.8125	0.5963	0.8747	0.6400	0.8871
2	0.5550	0.7857	0.7200	0.8870	0.8571	0.7798	0.4900	0.9879	0.5902	0.8881
3	0.5696	0.7698	0.6300	0.8570	0.8111	0.7575	0.5443	0.9873	0.6515	0.8571
4	0.5550	0.8525	0.6420	0.8390	0.8000	0.7923	0.5000	1.0000	0.6154	0.8840
5	0.4695	0.8018	0.6730	0.8860	0.8510	0.8000	0.3924	0.9620	0.5254	0.8736
6	0.6216	0.7920	0.6950	0.8850	0.8346	0.7922	0.5456	0.9879	0.6660	0.8720
7	0.6339	0.8214	0.7300	0.9090	0.9024	0.8121	0.5679	0.9686	0.6917	0.8866
8	0.5766	0.8018	0.7720	0.9020	0.7333	0.8023	0.4625	0.9625	0.6160	0.8750
9	0.4640	0.7946	0.5310	0.8380	0.7567	0.7959	0.4074	0.9036	0.5238	0.8715
10	0.6036	0.8108	0.6000	0.8350	0.8442	0.8040	0.5568	0.9756	0.6667	0.8696
MEAN	0.5605	0.8007	0.6761	0.8840	0.8123	0.7940	0.4820	0.9663	0.6207	0.8753

TABLE V: Paired T-Test Results

		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of Difference Lower	Upper	T	df	Sig(2-tailed)
Pair 1	Accuracy (SVM-NB)	0.232400	0.05287630	0.0166577	0.164727	0.194727	13.952	9	<0.001
Pair 2	AUC (SVM-NB)	0.207000	0.05758700	0.0183095	0.166290	0.166290	11.346	9	<0.001
Pair 3	Precision (SVM-NB)	-0.308110	0.05148000	0.0164147	-0.077850	-0.077858	-2.566	9	<0.001
Pair 4	Recall (SVM-NB)	0.475670	0.06405660	0.0211157	0.414274	0.424171	11.981	9	<0.001
Pair 5	F-measure (SVM-NB)	0.252200	0.06027520	0.0190607	0.209481	0.289481	15.252	9	<0.001

Table VI: Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	NB_Accuracy	0.60172	10	0.5014710	0.0158579
	SVM_Accuracy	0.80207	10	0.0265764	0.0084042
Pair 2	NB_AUC	0.72350	10	0.0958443	0.0310821
	SVM_AUC	0.86880	10	0.0620767	0.0196304
Pair 3	NB_Precision	0.86546	10	0.0648431	0.0205052
	SVM_Precision	0.79652	10	0.0186738	0.0059052
Pair 4	NB_Recall	0.51856	10	0.0510700	0.0161498
	SVM_Recall	0.96747	10	0.0253584	0.0080190
Pair 5	NB_F-Measure	0.64702	10	0.0479798	0.0151726
	SVM_F-Measure	0.87349	10	0.0162222	0.0051299

Confusion matrices of SVM and Naive Bayes as shown in Table VII and Table VIII respectively. Using the same training data set for both algorithms, the SVM model achieved an average accuracy of 80%, while Naive Bayes had 57% average accuracy. This indicates that the SVM model returned 892 correct classifications out of 1,114 unique tweets while Naive Bayes model correctly classified only 633 tweets.

In terms of recall, the SVM model correctly classified 780 uninformative tweets and only 19 labeled uninformative tweets as informative resulting to a recall value of 97.62% for the uninformative class. For Naive Bayes, the model correctly classified 396 uninformative tweets over 799 uninformative tweets yielding a 49.56% recall value.

AUC is a measure of quality of a probabilistic classifier. A random classifier has an area under curve 0.5, while a perfect classifier has 1. Binary classifiers used in practice should therefore have an area somewhere in between, preferably close to 1 [41]. In this experiment, SVM demonstrated an average AUC of 0.884 which indicates that the classifier ranked positive examples higher than the negative examples.

6. CONCLUSION

classifying algorithms SVM and Naïve Bayes. With a 10-fold cross validation, SVM outperformed Naïve Bayes in terms of accuracy, recall, AUC and F-measure, while Naïve Bayes performed better in precision.

Future directions of the research will be the exploration of other features and weights to generate a word vector and investigate their effects on the evaluation metrics. Feature selection, parameter optimization and semantics will be another focus of the research and the evaluation of other machine learning algorithms on the basis of other metrics of evaluation other than accuracy, recall, precision, AUC and F-measure. It is also essential to determine the priority of evaluation metrics which will guide data mining researchers to choose an algorithm for specific operations. Multi-label classification of English and multi-lingual tweets is also imperative to the extraction of relevant information which can eventually aid in increasing situational awareness. A real-time system that can detect and filter information from the disaster-relevant tweets may then be developed for an effective and efficient disaster response management.

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