Finding a link between emotions and actionability of a tweets

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***Abstract*—The research aimed to find actionable tweets tweeted from March 9 2021 to March 8 2022 by the Public of Calgary as with the help of these tweets, the City of Calgary can pinpoint problems they should act upon. The problem arises because we could not find any efficient methods to filter these actionable tweets. The current method used by the City of Calgary to find problems they can act upon requires a lot of human interaction and time. Instead of spending all these resources to find problems, I believe these resources are better spent solving the problems. I believe that tweets conveying a fearful emotion are more likely to be actionable. I found a strong correlation of 0.694 between the number of fearful tweets per month to the number of actionable tweets in a month. Additionally, I found out that a tweet which was labelled fearful has a 0.5 probability to be actionable.**

***Index Terms*—actionability, emotional analysis, pipelines**

I. Introduction

I am not proposing an entirely new method of finding actionable tweets, but a result which could reduce the amount of resources spent by City of Calgary on finding problems using tweets. I believe if we can find a relation between emotions and actionability of a tweet we can reduce the workload of City of Calgary to find these problems. As the concept of finding emotions of a tweet comparatively easier, because we have more resources available online. The aim of this paper is to shows that there is a link between emotions and actionability of a tweet.

The paper covers the data I used and the methodology I implemented using Pearson correlation and conditional probability which helped me find a link between the emotion and actionability of a tweet. Additionally, I also cover several types of threats to validity according to the paper [10] by Robert Feldt as the paper focus on an observation without a rigourous scientific proof. Lastly, I talk about work related to my paper which shows the peculiarity of my observation.

A. What is actionability?

A piece of information is actionable if the knowledge could be implemented/used by the users for whom it was intended to engage. In our case, we are trying to find tweets which could be useful for the City of Calgary to find the concerns of its citizens.

B. Why actionability is important?

Professor Elena [1] talks about actionable knowledge in depth. To summarize, the study describes actionable knowledge as a link between the academic and the practical field, as the results from a theoretical study are only useful if they can be applied to the practical field. In our case, a tweet with all its data is only useful to us if it can be used in the practical field, or if the problem can be acted upon by the City of Calgary.

C. What is a pipeline?

The pipelines are a great and easy way to use models for inference. These pipelines are objects that abstract most of the complex code from the library, offering a simple API dedicated to several tasks, including Named Entity Recognition, Masked Language Modeling, Sentiment Analysis, Feature Extraction and Question Answering. [4].

II. Data

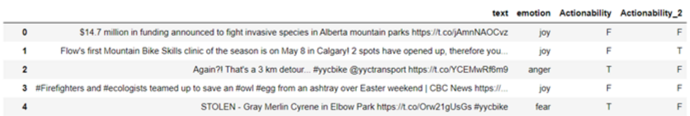
A. Dataset for research

We collected data from March 9 2021 to March 8 2022 for the explotary study. The dataset is a collection of tweets tweeted by the citizens of Calgary talking about issues related to the running of the city. As our goal is to find actionable tweets with the help of emotion analysis, all the tweets in the dataset have been annotated with emotions with the help of pipelines. The original database consisted of 10,000 tweets and their emotions. I randomly selected 2000 tweets out of the database and distributed them into 2 files which were later annotated by 2 research assistants each. The emotions were removed from both files so they would not affect the annotations. After appending both the files and adding emotions, I was left with a rough total of 1000 tweets (figure 1).

B. Dataset used for Testing Validity C

Aside from this main dataset, I had a few other datasets like the one which contains tweets based on the clusters : biking, pedestrian_safety, drinking_in_parks etc. The original dataset was divided into clusters by another research assistant Navid using several clustering techniques around the second week of

May and majorly consists of joyful tweets as more than 250 out of the total 650 tweets are joyful.



	text	emotion	Actionability	Actionability_2
0	$14.7 million in funding announced to fight invasive species in Alberta mountain parks https://t.co/jAmnNAOCvz	joy	F	F
1	Flow's first Mountain Bike Skills clinic of the season is on May 8 in Calgary! 2 spots have opened up, therefore you...	joy	F	T
2	Again?! That's a 3 km detour... #yycbike @yyctransport https://t.co/YCEMwRf6m9	anger	T	F
3	#Firefighters and #ecologists teamed up to save an #owl #egg from an ashtray over Easter weekend | CBC News https://...	joy	F	F
4	STOLEN - Gray Merlin Cyrene in Elbow Park https://t.co/Orw21gUsGs #yycbike	fear	T	F

Fig. 1. Main Dataset

III. Methodology

A. How do we find emotion of a tweet?

There are several pipelines which help us find the emotions of a tweet using the power of Machine learning. The popular pipelines can be easily implemented by importing them from the transformers library (figure 1). I used the Twitter Roberta base emotion pipeline [2] to label emotions for my dataset as it was specifically trained to label tweets with emotions in a dataset, and as it is one of the most popular models for emotions labelling with 162,458 downloads last month, I deduced it's also relatively accurate.. As a result, all the tweets in my dataset were labelled with one of the 6 emotions: sadness, anger, fear, surprise, joy, and love. Alongside the emotions, the pipeline also gave an emotional score to the emotion of every tweet which represented how sure the model is about the given emotion.

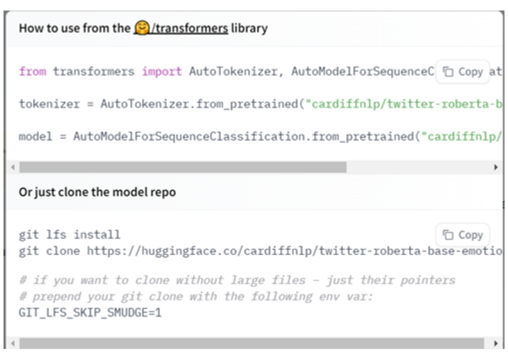


Fig. 2. Using transformers library to import the pipeline.

B. Finding the link between emotions and actionability if both of the markers considers the tweet actionable:

Firstly, I worked on finding the Pearson correlation coefficient between the number of emotional tweets per week and the number of actionable tweets per group where a group consists of 15 tweets. I found correlations for the dataset multiple times after shuffling the data points so that the resulting correlation would not be a coincidence in the dataset. I found the average correlation after 1000 shufflings and got good results for 2 emotions, i.e., the average R for number of joyful tweets and actionable tweets was -0.25. Additionally, I got r = 0.30 between fearful tweets and the other variable discussed. We had a total of 67 data points for the correlation which is a large number of observations and according to the paper [5], the resulting Pearson should be close to the actual correlation.

Finding p-value:

Additionally, I also calculated the p-value[12] [13] for my result as that is a quantative way to calculate the precision of my results, I started by calculating the t-value as the p-value we calculate using correlation is somewhat inaacurate while we can calculate a really accurate t-value and furthermore, calculate a precise p-value using the t-value. I got both tailed p-value **0.0094** which is less than 0.01, hence we are 99% certain our result is correct. Though, this correlation coefficient does not prove that fearful tweets have a link to actionable tweets. It only states that if the number of fearful tweets increase then the most likely number of emotional tweets will also increase.

R* value between no. of emotional tweets and no. of actionable tweets. (Considering one of the markers consider the Tweet actionable)	
fear correlation	0.30
anger correlation	-0.01
joy correlation	-0.25
love correlation	-0.05
sadness correlation	0.046

*R - Pearson Correlation Coefficient

The table above states that we have a moderate correlation between number of fearful tweets and actionable tweets and number of joyful tweets and actionable tweets, the reason the results are interesting is because the other emotions have no correlation with actionability at all while having the same characteristics (like number od tweets etc.) as joyful and fearful tweets.

Why actionability by 1 marker is not consider correct in the methodology?

I had atleast 2 annotators annotating a tweet being actionable or not, so I had the option to set an criteria for a tweets being actionable, I concluded even if one of the markers thinks the tweet is not Actionable, there is most likely a reason for the tweet being marked as Not Actionable and at that point, both the markers should discuss within themselves and conclude the annotation .

Why Pearson Correlation?

In the field of statistics, we mainly deal with 3 types of correlation: Pearson, Kendall and Spearman. The paper [6] below studies in-depth about all these correlations and concludes that for bivariate normal distribution*, the Pearson product moment correlation (Pearson correlation for short) consistently results a larger statistical power. Since the bivariate normal distribution is optimal for the Pearson's correlation coefficient, as the intervals between the datapoints are consistent. *Bivariate normal distribution is a distribution of data is made of two independent random variables. Eg: count of emotional tweets and count of actionable tweets [7].

Filtering out only the tweets with a high emotional score:

We also have information about how precise an emotion is, which is also called an emotional score. I filter out all the tweets with an emotion score of ¡ 0.99, as this way we can weed out tweets which the algorithm is not certain about. This reinforced my earlier observation, as the correlation coefficient for fearful tweets represents a moderate correlation.

```
fear coorelation:      0.3164
anger coorelation:     -0.020
joy coorelation:       -0.249
love coorelation:      -0.049
sadness coorelation:   0.0365
surprise coorelation: -0.019
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Fig. 3. R-values for tweets with a high emotional score and marked actionable by both markers

C. Why are we not using causation?

The results we got from correlation only showcase that if we have more fearful tweets then we are also likely to have more actionable tweets. In a perfect world, we would like to prove a causation relationship between the two relationships but that's a herculean task as the algorithms at our disposal can only find causation between variables in its domain but fails if the true reason for causation is outside the set domain. So instead of aiming for causation, we are aiming to find other factors which can show a link between emotion and the actionability of a tweet.

D. Probability a tweet being actionable given its emotion:

One other factor is probability which can give us more information about a specifically given tweet. We found that the Probability that a tweet is actionable given that the tweet is fearful = P(A—F) = 0.49. We got this result on a dataset of 1025 tweets where the number of tweets for the 3 most frequent emotions: joy, fear and anger were 570, 226 and 151 respectively while the total number of actionable tweets were 240.
Additionally, the number of tweets which were actionable and fearful were 111, meaning in this given dataset 46.25 percent of the actionable tweets were fearful while only 22 percent of the total tweets were fearful. So, we can confidently say that majority of actionable tweets were marked to show fearful emotions.

P(tweet is actionable given it's emotion	
Probability that a tweet is actionable if it is fearful	0.491
Probability that a tweet is actionable if it is joyful	0.136
Probability that a tweet is actionable if it is angry	0.218
Probability that a tweet is actionable if it is sad	0.285

Table 3

E. Discussion

The only moderate correlation I observed was the correlation between the number of fearful tweets and actionable tweets, this agrees with what Lily A.Gutnik, A. Forogh Hakimzada are talking about in paper [14]. More specifically the paper talks about how humans are more likely to take less risks and think logically when they are indduced with fear, though it does not talk about a direct link with actionability which should explain the moderate correlation. Additionally, [15] states that compared to negative mood, positive mood negatively affects the use of rule-based decision strategies in a dominated choice task, which aligns with our results as joyful tweets had a negative correlation. Though, the interesting part was that no other emotion had any significant link with actionability.

IV. Testing validity of the solution

A. Following the solution with a different pipeline to find emotions

To check the internal validity[10] of the data, which is making sure there are no other factors that have caused the outcome, factors that we do not have control over or have not measured. The first thing I worked on finding the relation between the emotion and actionability of a tweet using a different pipeline to find the emotions. In the original process, I used the Roberto emotion pipeline [2] while now I have implemented the distillery [3] pipeline. Unlike Roberto [2] distillery is not specialized in the emotions of a tweet but is still popular with over half a million downloads which shall speak for its credibility. Additionally, the average emotion score for the dataset using both pipelines ranges from 0.81 to 0.83. We find 2 noteworthy correlations, Firstly, the number of fearful tweets per week and number of actionable tweets per week, with r = 0.30 and the correlation efficiency of the number of joyful tweets per week and number of actionable tweets per week = -0.23. The results are exactly what we had expected, hence using a new pipeline gives us similar results. Moreover, if we look that the probability of a tweet being actionable given its emotion. P(actionable—fearful) = 0.51 which states that 50% of the fearful tweets were actionable.

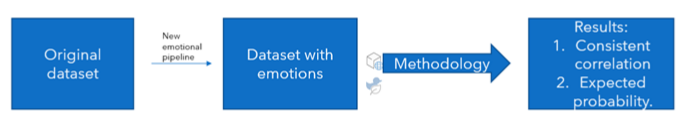


Fig. 4. Flowchart of the process

Surprising Result:

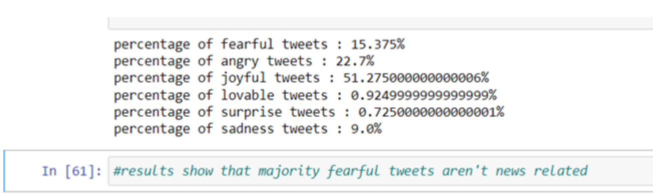
The database was filled with joyful tweets, most likely due to the new pipeline. It marked 1365 as joyful from a total of 2000 tweets which comes to 68.25 percent compared to 55 percent with the Roberto emotion pipeline [2]. Though even if we remove 15 percent of the joyful tweets while working with the distilbert pipeline [3] to even out the percentages, the r value for the joyful emotion still remains high. But when we look at more details, we found out that out of 278 fearful tweets roughly 139 were actionable (51 percent) while out of 1365 joyful tweets only 198 tweets actionable (14 percent). Thus,even with an overwhelming amount of joyful tweets, the observations still hold.

B. Implementing the proposed solution on a new dataset

To work on conclusion validity[10], which means to be sure of the observation. I created a new dataset called dataset2 by sampling 300 random tweets from the original database containing 10,000 tweets. Moreover, I annotated dataset2 about whether the tweets were actionable or not. Though, as the data is marked actionable by only one marker the data is expected to have some differences. After following the proposed solution, the results reinforce our findings with the r-value of the number of fearful emotions per week and the number of actionable tweets per week being 0.26 which is surprisingly good result considering the tweets were only annotated by only 1 annotator. Moreover, P (tweet is actionable — given it's fearful) = 0.58. These results are similar to our expectations but one interesting thing I noticed while working with the dataset. Around 39/57 tweets were news related for fearful tweets while only 9/23 and 14/47 tweets were news related for sad and angry tweets respectively. Even though the labelling of a tweet being news was only done by one marker, the observation could be another reason for discrepancy as we have only worked with this database where a lot of fearful tweets are linked to news.

Further Research:

As further research, I found a database containing tweets related to news. It's called the 'cc news' database and can be found in the hugging face website datasets [9]. I sampled 4000 random tweets and found the emotion distribution using the bhadresh pipeline [3].



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percentage of fearful tweets : 15.375%
percentage of angry tweets : 22.7%
percentage of joyful tweets : 51.275000000000006%
percentage of lovable tweets : 0.9249999999999999%
percentage of surprise tweets : 0.7250000000000001%
percentage of sadness tweets : 9.0%

In [61]: #results show that majority fearful tweets aren't news related
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Fig. 5. Percentage of tweets conveying each emotion with a sample size of 4000

The results show us that the percentage of fearful tweets is not overwhelming and we can say that if a tweet is news related, it is not likely to be a fearful tweet.

C. Using a biased dataset with an overwhelming majority of one of the emotions

Testing my observation further for more conclusion validity I used the datasets with clusters involving biking, bike lanes, drinking in parks, pedestrian safety etc. All these clusters are filled predominantly with joyful tweets and the dataset contains roughly 500-700 tweets which is a particularly small dataset and 65 percent of the tweets are joyful while only 5 percent are fearful which is an extremely skewed dataset. The results show no significant correlation between any emotion and actionability and the probability of a tweets being actionable given its fearful is also only 10%. Hence, neither of the methodologies give us a results which could have happened due to the database being extremely skewed.

Distribution of actionable tweets	
Number of tweet that are actionable and fearful	3
Number of tweet that are actionable and joyful	25
Number of tweet that are actionable and angry	5
Number of tweet that are actionable and sad	0

Table 4

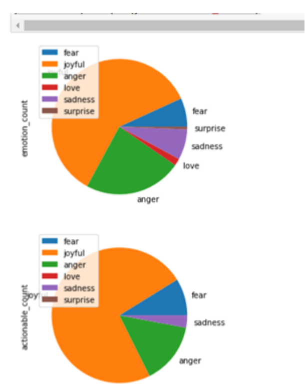

Fig. 6. Distribution of general and actionable tweets w.r.t. emotions

Figure 4 is a pie chart showing us the distribution of general tweets and actionable tweets with respect to the emotions. It is evident that majority of the actionable tweets are joyful though fearful tweets still have the ratio of tweets per actionable tweets.

V. Conclusion

After validating the solution by getting the desired results which were a high correlation coefficient of at least 0.64 between no. of fearful tweets and no. of actionable tweets alongside a high 0.5 probability of a tweet being actionable given that it is fearful for all examples. I beilieve that fearful tweets are more likely to be actionable as compared to the other tweets.

This study can help find actionable tweets more easily as instead of working with the entire set of the database we can filter the tweets showing fearful emotions and as roughly half of those tweets should be actionable, City of Calgary can reduce the time it takes for them to find problems for them to work on. Though, this means missing out on the other actionable tweets but that is something which can be improved upon.

VI. Related works:

A. Actionability of tweets

Paper [8] talks about finding actionable tweets in the situation of a disaster/crisis. The part of the paper concerns how they find these actionable tweets. They start by finding keywords which exploded in recent times using clustering analysis and manually checking if those keywords can help us find actionable tweets. Now, one can use models trained over specific domains to find actionable/useful tweets. Lastly, filter the output of the last step using characteristics or human effort to find actionable tweets.

B. Emotions of tweets

Paper [11] talks about different models of emotions like the Plutchick and Ekman model. It suggests that a mixture of keyword based, corpus based and Learning based approach gives us the best results to find the emotion of a tweet. The pipelines we have talked about implement this hybrid approach to find the emotion of a tweet. A peculiar thing about this approach is that we do not require internse human interaction to succesfully predict the emotions unlike actionability. So my aim was to bridge the gap by looking for relations between the two.

C. Need for study

The approach they discussed in the paper is a valid general approach, my findings could be used in parallel to this approach to find better results. As this was one of the most popular papers about finding actionable tweets, I believe my findings can help find actionable data by filtering the original data using emotions and only keeping fearful tweets. This in most cases cuts the data to 1/5ths of its original size while retaining 40% to 50% of the actionable tweets.

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