Emotion classification from text (chat)
Course Project, CS-725
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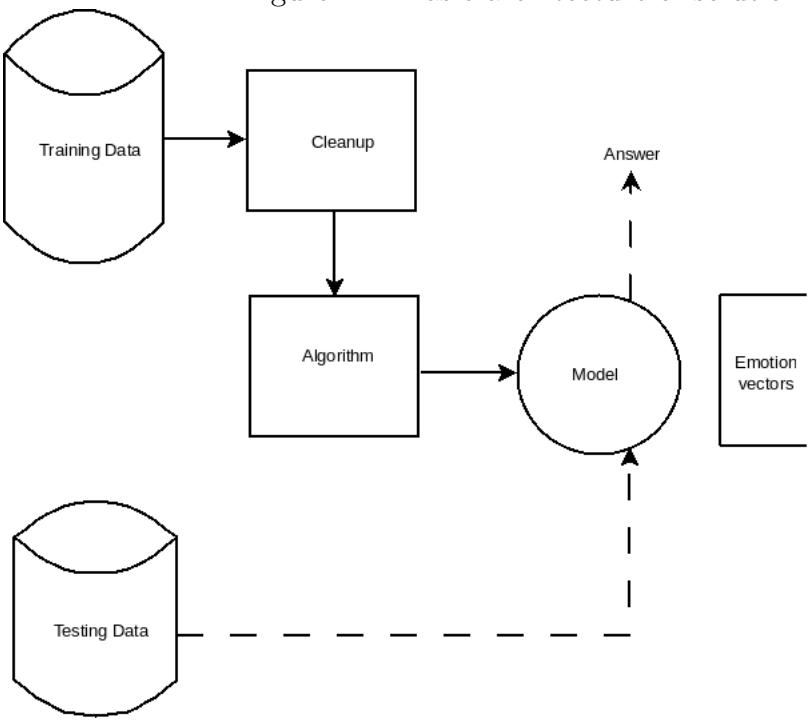
Chapter 1

Project Initialization

1.1 Feasibility

- We wish to create a system, which having been trained from sentences annotated with emotions portrayed, is capable of predicting the emotion for a new sentence.
- We will be closely following the paper Taner Danisman and Adil Alpkocak titled **Feeler: Emotion Classification of Text Using Vector Space Model**.
- We will need to build a lexicon, which is basically an ordered set of all *good* words in the training data.
- For each sentence we will build a weight vector of all terms in the lexicon.
- The weights are calculated using the **tf-idf** technique.
- For each emotion class we take the mean of all vectors within it.
- We will be utilizing python for developing the application and be using **nltk** for text clean up, stemming etc.
- Estimated time to develop the project would be a month.

Figure 1.1: Basic architecture of solution



1.2 Dataset

- The paper mentions the ISEAR dataset, which is composed of around 15000 annotated sentences.

1.3 Scope

- At its core, the idea is to find median vectors corresponding to each emotion (joy, sadness, anger, ...) and then find the cosine similarity of the new vector composed from test input with the former. The highest similarity vector will be the winner.
- Other than implementing their proposed solution, we will also try to incorporate methods like bayesian classification and neural networks and analyse the results.
- If time permits, we will build some application around our system.

Chapter 2

Submission 1

2.1 Project Description

2.1.1 Problem Statement

Text written by a person can help us determine what emotion he is portraying. Other such modalities can be facial cues, body language etc. In this project we will try to predict the emotion using information from a sentence input by a user. This can have applications in chatting programs, movie reviews etc. Consider the following scenarios:

Sentence	**Emotion**
•A close person lied to me	Sadness
•A colleague asked me for some advice and as he did not have enough confidence in me he asked a third person.	Sadness
•I got a present today.	Joy

Table 2.1: Some examples

2.1.2 Basic Details

- We wish to implement a system capable of predicting the emotion portrayed, given a sentence. The predicted classes will be limited to **anger, joy and sadness**.

- The project is inspired from the paper mentioned in section 1.1.
- The paper details the use of **Vector Space Models** (VSM) to implement the solution.
- We will be using our dataset, comprising sentences annotated with emotions to train the model. The trained model will then be presented with the test data in form of a vector and the most probable emotion will be displayed as output.
- Later, if time permits, we will implement some form of application to showcase the prowess of our project.

2.2 Papers

The paper implemented is mentioned in 1.1.

2.3 Dataset

The dataset used is mentioned in 1.2. The dataset has around 15000 sentences. We will use $2/3^{rd}$ of the dataset for training and cross validation and the rest for testing.

2.4 Method

- As mentioned in section 2.1.2, in line with the paper, we will be using VSM for out initial implementation.
- Put simply, we will have representative vectors for each of our emotion classes, **joy, anger and sadness**. Then we will transform our input sentence in the same way we found our representative vectors and find the cosine similarity with each of them.
- These similarities will be used to calculate probabilities of the input being in some emotion class and the most probable class will be output.
- The vectors will comprise of weights in terms of **tf-idf** frequencies. We could simply use word frequency instead but:

- **tf-idf** was chosen to provide weights as some words occur sparsely in the document, but provide definitive information about the emotion being portrayed. For example, the word *devil* occurring in a sentence tips the scale towards negative emotion.
- Had we chosen only frequencies, this could pollute the result.
- Similarly, some words occur very frequently like *cat*, but do not provide much information. Frequentistically speaking these words will get higher weight.
- **tf-idf** balances these disparities by multiplying the term frequency with inverse document frequency. The latter meaning the ratio of total number of documents and the number of documents containing that term.
- For low frequency words, the **idf** will be high and vice-versa.

2.4.1 High level algorithm

Training

- The training set is cleaned, in that:
  - Stop words are removed, after comparing with standard stop word lists.
  - Apostrophes are expanded.
  - Words are reduced to their root using some stemming technique.
- We build a lexicon from $2/3^{rd}$ of the above cleaned data.
- Each term in the vector corresponds to a term in our lexicon. The lexicon is an ordered set of all words in the cleaned dataset.
- We build document vectors using weights assigned to each term. These weights are calculated using the **tf-idf** technique. These weights are further normalized.

$$w_{ki} = c(t_k, d_i) = \frac{tf_{ik} log(N/n_k)}{\sqrt{\sum_{k=1}^{n} (tf_{ik})^2 [log(N/n_k)]^2}}$$

where,
$t_k = k^{th}$ term in document d_i

tf_{ik} = frequency of the word t_k in document d_i
$idf_k = \log(\frac{N}{n_k})$, inverse document frequency of word t_k in entire dataset.
n_k = number of documents with word t_k.
N = total number of documents in the dataset.

- Now each emotion class is a set of the corresponding vectors, calculated as above. We then find the mean of all these vectors to find a representative vector of the said class.
- Finally, we'll get s vectors corresponding to the distinct emotion classes.

Testing

- Each input sentence is cleaned, and transformed into a vector with weights calculated using **tf-idf** technique.
- The similarity is calculated as:

$$\text{sim}(Q, E_j) = \sum_{k=1}^{n} w_{kq} * E_{kj}$$

where,
Q is query vector,
E_j is an emotion vector.

- Answer is calculated as:

$$\text{VSM}(Q) = \text{argmax}_j(\text{sim}(Q, E_j))$$

2.5 Submission on 21^{st}

We plan to complete the implementation of the paper along with relevant testing and output metrics, outlined above. We will complete the code for text cleaning and VSM.

2.6 Final submission

- Complete implementation of VSM.

- Implement some bayesian model using bigram, trigram or ngram approach and check the variation in results.
- If time permits, we'll develop some applications to showcase the model.

2.7 Team Members

Name	**Roll No**
Ravi Shankar Mondal **(leader)**	133059003
Srikrishna Khedkar	143050055
Saurabh Jain	143050048
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Table 2.2: Team members