Emotion analysis in dataset

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Abstract—We document a series of experiments on using a variety of natural language processing methods to classify emotions conveyed by sentences. In particular, we compare word categorizations, semantic similarity approaches and machine learning approaches. The machine learning approaches consist of classification models based on bag-of-words representations and convolutional neural networks applied on word embeddings. Our results indicate that machine learning approaches outperform string matching and semantic similarity with a considerable margin. Within the machine learning approaches, convolutional neural networks with word embeddings provide an improvement in accuracy of around 3-5 percentage points over bag-of-words models. The best accuracy on a hold-out validation set, around 93%, is achieved with a CNN approach using pre-trained word2vec embeddings. However, custom-trained word embeddings provide similar performance with less computational overhead.

Index Terms—natural language processing, text classification, sentiment analysis

I. GROUP INFO

Group 10

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Title: Emotion Analysis in Dataset

Github: https://github.com/MeriemLil/NLP_Project

II. INTRODUCTION

Emotions are feelings that caused by a situation person interact with. It is also associate with person's character, mood, personality and motivation. People express their feelings and emotions using verbally and non-verbally such as words, intonation of voice, facial expressions, gestures, and tears. Nowadays people tend to communicate their ideas, opinions, and feelings through social medias, Such as tweeter, facebook, instergram. People filled with lot emotions and they commonly use written text to express their emotions and feelings through social medias. Categorizing text into emotion types is known as emotion analysis. Sentiment analysis detect positive, negative, and neutral feelings from text and emotion analysis detect the types of feelings, emotion state, in the text [1].

Emotion analysis takes major role in some applications which use emotion recognition, and it is a growing research area. There are supervised and unsupervised approaches can be found in this research area. A novel unsupervised context-based approach represents in [2] to detect emotions from text in sentence level. Their approached does not need any existing manually created lexicons and they used semantic relation between words and emotion type. They fine tune scores using syntactic dependencies within the sentence structure and proves this model provide more accurate results than other unsupervised approaches. Research carried out in [3] paid their attention towards capturing semantic features in the text. Authors used distributional semantic model to calculate the semantic relatedness of the emotion in the text and they achieved accuracy of 71.79% without training or annotation of data use.

A lot of research had been carried out on sentiment analysis and emotion analysis problem in many different languages. Bag-of-words representations, first suggested by Luhn in the 1950s [4], are an important advance, and still a commonly applied tool for natural language processing tasks like text classification. In these models, text is represented as a sparse feature matrix, where features represents the occurrences of a given word in a text. Earlier approaches involved counting the occurrences of words. Later, improvements have been suggested that offset the number of occurrences of a word in a given text by the frequency of the word's occurrence in other texts in the corpus [5]. The most notable of these approaches is the term frequency–inverse document frequency (tf-idf) weighting.

In a seminal, of applying machine learning algorithms using a bag-of-words representation [6] propose the use of support vector regressions with the tf-idf matrix approach. Using this approach, they achieve notable improvements over the state-of-the-art benchmarks at the time. In a more recent example, [7] demonstrate their work on supervised machine learning approach to recognize the emotion types using emotion anno-tated dataset which combined news headlines, fairy tales and

blogs. They use bag of words and N-grams and proved that support vector machines classifier shows better performance and generalization than the other classifiers they used.

[8] introduce convolutional neural networkds for text categorization. Similar concepts are explored by e.g. [9], with a low complexity word level deep convolutional neural network for text categorization. [10] propose a new convolutional neural network that exploits from character to sentence level information to perform sentiment analysis of short texts. They found that combining small text with prior knowledge is effective.

Research in [11] introduce a new language representation model, BERT, a pretrained deep bidirectional representations from unlabeled text. They used conditioning on both information before and after a given word in all layers.BERT and successors inspired by it (see e.g. [12]), have massively improved the state-of-the-art in many language understandings tasks. For text classification, [13] used BERT provide general solution for BERT fine tuning in a text classification setting. Similarly, research on [14] improves the fine tuning of BERT using two effective mechanisms: self-ensemble and self-distillation.

In this research we are focusing on emotion analysis using word categorizations, semantic similarity approaches and machine learning approaches.

III. DATA AND METHODOLOGIES

A. Datasets and sources

Our main dataset of interest is a labeled dataset of 20 000 sentences with between 3 and 66 words. The dataset is provided by [15]. The sentences are labeled to convey one of six different emotions: fear, anger, joy, love, surprise and sadness. The dataset is collected following the approach of [16]. The sentences are tweets, and the emotion labels are hashtags at the end of the tweet. The sentences are preprocessed in that they contain no punctuation or special characters and all words are lowercase.

The dataset has a predefined split into training, test and validation samples, with 16 000, 2 000 and 2 000, respectively. Because the semantic similarity and string matching approaches do not employ any predictive modeling, in these sections we use the all 20 000 sentences to measure prediction accuracy. For the machine learning approaches, we use the training set for model training, the test set for model selection and hyperparameter tuning, and reserve the validation dataset as a final benchmark, to ensure a fair comparison accross approaches.

In addition, we use pre-trained, 300-dimensional word2vec embeddings from [17] and pre-trained fastText embeddings from [18]. Both datasets consist of 300-dimensional word embeddings, with embeddings for 3 and 1 million english words, respectively. For the string matching, we use the Harvard General Inquirer dataset, which contains categorizations for around 11 000 english words.

B. Harvard Inquirer and String Matching

The first method we explore is to categorize each word in Harvard General Inquirer [19] to each emotion type. We use a filtering technique to this categorization. To identify words related to love emotion, we include Harvard General Inquirer words with that are labeled Affil label and exclude words associated with Negative label. The categories used for all six labels is reported in Table X. We store this information into a database and then compute the occurrences of words associated with each label for each sentence and predict the label of a sentence to be the category with the highest number of words.

C. Empath Client Categories

The next method we explore is to use the Empath Client [20], a text analyzing tool with a pre-buildt category set. We identify categories related to each sentence using the Empath client. Then for all the identified categories, we compute empath category similarity with each label using the concept of lowest common hypernymy. We then associate each category provided by the Empath client with the emotion that has the highest similarity. Then, we use the label assigned to each category of a sentence to identify the label that has the highest number of occurrences. The emotion is predicted to be this label. The empath client categorization has a category for each of our labels as well, so we also experiment using only the exact emotion category.

D. Semantic Similarity

asd

E. SentiStrength Sentiment Scores

As part of the project specification, we also use the SentiStrength client [21], to compute sentiment scores. These can be potentially be used as an additional feature in any approach to distinguish between the negative and positive emotions. However, intuitively, the more difficult task is distinguishing between different positive emotions and between different negative emotions. For this purpose, the sentiment scores are unlikely to provide added benefit. Considering this, and the fact that the simple approaches perform quite poorly, we do not explore the effects of these sentiment scores onto the accuracy of different models. Sentiment scores are still delivered as part of the project database, as suggested in the project specification.

F. Bag-of-Words Models

G. Convolutional Neural Networks

1) Model architecture: We replicate the convolutional neural network architecture used in [8]. The architecture is outlined in fig. 1. Sentences are represented as $n \times k$ matrices of word vector embeddings, where n refers to the length of the sentences and k to the dimension of the word vectors.
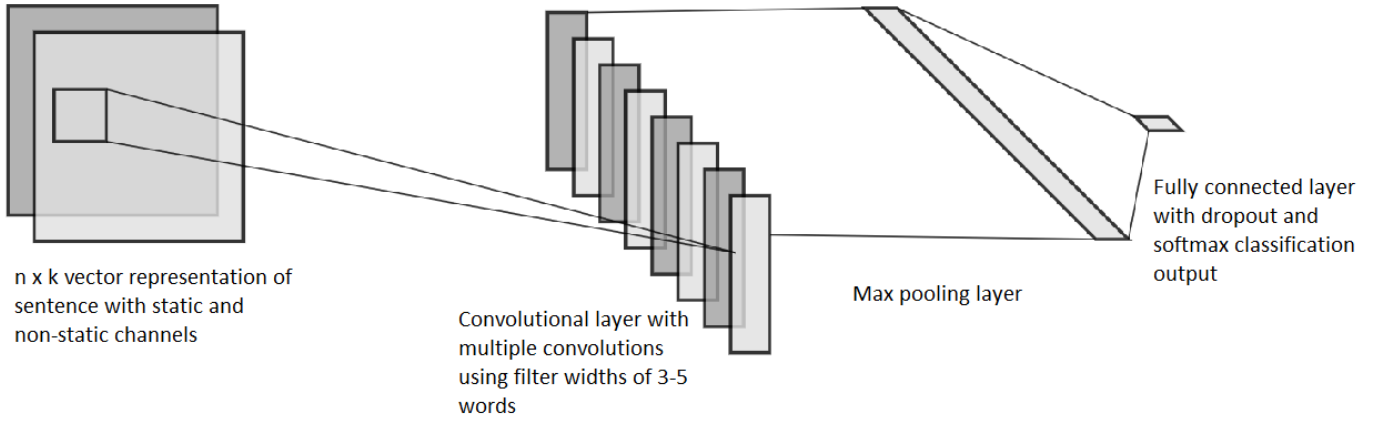
n x k vector representation of sentence with static and non-static channels

Convolutional layer with multiple convolutions using filter widths of 3-5 words

Max pooling layer

Fully connected layer with dropout and softmax classification output

Fig. 1. CNN model architecture

All sentences are zero-padded to length n. [1] Then a set of 1-dimensional convolutions are applied on the sentences. For each sentence, a feature c_i is generated by the convolution

$$c_i = f(w * x_{i:i+h-1} + b) \qquad (1)$$

where h refers to the length of the convolution window, w are the filter weights of the convolution operation, b is an added bias term, and f is a non-linear activation function. A feature map c is then an $n-h+1$-dimensional vector of these features.

Equation (1) describes only one feature map produced by one convolution filter, while the model can consist of an arbitrary number of these feature maps. Then, for each feature map, max-pooling is applied, such that the largest feature value c_{i-max} is selected. This operation produces a vector of final features with dimension equal to the number of feature maps used. These features are then connected to the final, 6-dimensional softmax output with a fully connected layer.

For regularization the original paper uses dropout on the penultimate layer. Dropout is a commonly used regularization method in neural networks. It hides each of the final features from the output layer with some probability p, preventing the co-adaptation of the different features. In addition, we experiment with another common method of avoiding overfitting; an l_2-norm regularization across the layer weights. The l_2 regularization penalizes large weight vectors, preventing overfitting. Finally, following [8], we also constrain the l_2 - norms of the weight vectors w to be a maximum of a fixed size s. Note that the norm-constraint is most often applied to prevent an exploding gradients problem rather than to prevent overfitting.

Something on the different modes of the model.....

2) Word Embeddings: The purpose of using word embeddings in the CNN model is to provide a k dimensional numerical representation that can be input to the neural network. The

general idea of these embedding model is to identify useful word embeddings by training a shallow neural network on a word prediction task using a large text corpus. Model training positions word vectors in the k-dimensional vector space such that similarities between word vector embeddings represent the semantic similarity between the words.

In [8], pre-trained Word2Vec embeddings from [17], [22] are used. In addition to replicating this approach, we consider a few alternatives. First, we test pretrained fastText embeddings from [18], [23]. Second, we explore explore training our own word2vec and fastText embeddings using the papers cited above.

[22] apply two approaches to training a word2vec model, a continuous bag-of-words (CBOW) model and a continuous skip-gram model. The idea for the CBOW model is to train a shallow neural network to predict a current word in a sentence given a pre-specified window of words around it. The skip-gram model instead predicts the words around a given word wihin a pre-specified range in the sentence. The pre-trained word2vec vectors that we use in the experiments are trained using the skip-gram architecture. For our custom-trained embeddings, we instead use the CBOW model to provide a comparison.

FastText [18] is proposed as an extension to the word2vec model. The fastText model introduces subword information, in the form of character n-grams, by representing words as the sum of the vector representations of its n-grams. This means that or example if $n = 3$, then the word $what$ is represented by: $< wh, wha, hat, he > n$-grams and the sequence $< what >$ itself. The authors in [18] argue that this allows to incorporate the internal structure of words and to produce more reliable representations for rare words.

3) Hyperparameters and training: For the custom-trained word2vec and fastText models, we use a maximum distance between predicted words of five and early stopping on a generic word analogy evaluation task. Since this is a secondary objective, we do not explore alternative setups or model

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[1] A similar architecture is proposed in [9], but one where sentences are not padded to a fixed length. Note that, the application of max-pooling is likely to make the zero-padding inconsequential.

tuning for the word embedding task, and focus on tuning the CNN instead. As for the dimension of the word embeddings, we experiment with 50-, 100- and 300-dimensional word embeddings for the custom-trained word embeddings. With the pre-trained embeddings, we are restricted to the commonly available 300-dimensional word embeddings.

For all CNN models, we use sentence length $n = 70$ and convolution windows h of 3, 4 and 5. following the original paper. We use a rectified linear unit (ReLU) activation function for the convolutions, and a softmax activation for the output layer. The original paper uses Adadelta [24] optimization, but we achieve faster convergence with an Adam [25] update rule. We train using mini-batches of 50 sentences, a learning rate of 10^{-3} and the cross-entropy loss function. We also employ early stopping based on the models cross-entropy loss on the test dataset.

For the input mode, we introduce. The full set and ranges of the hyperparameters that we tune is reported in able VI. The original paper uses a set of 100 convolutions. We treat the number of convolutions as a hypermeter, and experiment with from 50 to 250 convolutions. Note that the number of convolutions is applied for each of the three window lengths resulting in a total of $3 * number of feature maps$ convolutions. We explore

IV. RESULTS AND DISCUSSION

A. Word categorizations and semantic similarity

TABLE I
WORD CATEGORIZATIONS AND SEMANTIC SIMILARITY ACCURACIES

Classifier	Accuracy
Harvard String Matching	0.336
Empath Client	0.160
Empath Client with exact categories	0.183
Semantic Similarity - One synset	0.269
Semantic Similarity - All synset	0.240

B. Model selection for bag-of-words

Table II reports the accuracies on the test dataset used for model selection.

C. Validation set performance of best models

Table III reports the accuracies on the test dataset used for model selection.

V. OVERALL DISCUSSION AND RELATED LITERATURE

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As mentioned in the introduction, the state of the art for text classification tasks has moved beyond word level embedding representations considered here. For example, [11], [12] and [13] employ pre-trained bidirectional encoder representations to achieve state-of-the-art results in sentence classification.

TABLE II
MAXIMUM ACCURACY ON THE TEST DATASET ACROSS DIFFERENT BAG-OF-WORDS SETUPS

parameter	value	score
vectorizer	CountVectorizer	0.886
	TfidfVectorizer	0.888
stopwords	nltk	0.888
	none	0.878
	sk	0.884
lemmatize	0	0.888
	1	0.886
max features	100	0.396
	500	0.728
	1000	0.865
	2000	0.880
	3000	0.886
classifier	DecisionTreeClassifier	0.866
	GradientBoostingClassifier	0.849
	LogisticRegression	0.878
	MultinomialNB	0.859
	RandomForestClassifier	0.888
	SVC	0.876

TABLE III
VALIDATION AND TEST SET ACCURACIES FOR BEST MODELS

Classifier	Accuracy	
	Validation	Test
MultinomialNB	0.681	0.694
LogisticRegression	0.872	0.864
RandomForestClassifier	0.899	0.89
CNN fastText pretrained	0.925	0.928
CNN Word2Vec own	0.928	0.929
CNN fastText own	0.928	0.931
CNN Word2Vec pretrained	0.930	0.928

However, constructing a replication and a fair comparison of these models is beyond the scope of this study. [2]

Our results indicate that the starting point vectors are not of massive importance in tuning to the tasks, as different embedding representations achieve very similar test and validation set performance. Further exploring alternative models and hyperparameters for pre-training the word vectors might nonetheless be an interesting exercise but is beyond the scope

[2]There is a minimal, unofficial implementation of BERT [11] embeddings on the dataset we study [15] available at Kaggle by the dataset author. This implementation appears to slightly exceed the validation accuracy of the best CNN model studied here by around 0.3 percentage units.

TABLE IV
VALIDATION PRECISION AND RECALL FOR BEST MODELS

Classifier	Metric	
	Precision	Recall
MultinomialNB	0.734	0.681
LogisticRegression	0.875	0.872
RandomForestClassifier	0.898	0.899
CNN fastText pretrained	0.926	0.925
CNN Word2Vec own	0.93	0.928
CNN fastText own	0.928	0.928
CNN word2vec pretrained	0.930	0.930

of this paper. An important aspect of this observation, is the fact that the pretrained embeddings are quite large in size, while custom embeddings trained on the emotions dataset are much smaller. Furthermore, because model performance with embeddings trained on the emotions dataset is very close in performance to the pretrained embeddings, the custom models provide a lightweight alternative for model serving.

In terms of the generalizability of the results, it is important to note, however, that the emotions dataset contains very homogenous sentences across the training, test and validation datasets. This causes the vocabulary of the custom word embeddings to be much smaller than the pretrained word embeddings. Therefore the model is more likely to suffer in performance on out-of-distribution sentences. [3]

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VI. Conclusion

conclude.

VII. Latex examples

To be removed.

A. Equations example

$$a + b = \gamma \qquad (2)$$

Use "(2)", not "Eq. (2)" or "equation (2)", except at the beginning of a sentence: "Equation (2) is . . ."

B. Some Common Mistakes

- The word "data" is plural, not singular.
- In your paper title, if the words "that uses" can accurately replace the word "using", capitalize the "u"; if not, keep using lower-cased.
- Be aware of the different meanings of the homophones "affect" and "effect", "complement" and "compliment", "discreet" and "discrete", "principal" and "principle".
- Do not confuse "imply" and "infer".
- The prefix "non" is not a word; it should be joined to the word it modifies, usually without a hyphen.
- There is no period after the "et" in the Latin abbreviation "et al.".
- The abbreviation "i.e." means "that is", and the abbreviation "e.g." means "for example".

Acknowledgment

[3] While we do not have an out-of-distribution labeled dataset available, unreported, hand-crafted tests support this intuition.

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APPENDIX A
ADDITIONAL TABLES

TABLE V
AVERAGE ACCURACY ACROSS DIFFERENT BAG-OF-WORDS SETUPS

parameter	value	score
vectorizer	CountVectorizer	0.719
	TfidfVectorizer	0.727
stopwords	nltk	0.725
	none	0.703
	sk	0.74
lemmatize	0	0.723
	1	0.723
max features	100.0	0.361
	500.0	0.631
	1000.0	0.830
	2000.0	0.844
	3000.0	0.845
classifier	DecisionTreeClassifier	0.702
	GradientBoostingClassifier	0.729
	LogisticRegression	0.733
	MultinomialNB	0.704
	RandomForestClassifier	0.744
	SVC	0.723

TABLE VII
BEST CNN MODEL BY MODE

	Metric		
name	mode	Accuracy	Loss
CNN Word2Vec own	multichannel	0.927	6.404
	non-static	0.929	6.44
	static	0.900	10.404
CNN fastText own	multichannel	0.921	9.463
	non-static	0.931	6.599
	static	0.770	25.254
CNN fastText pretrained	multichannel	0.928	6.326
	non-static	0.928	6.133
	static	0.908	8.786
CNN word2vec pretrained	multichannel	0.928	6.583
	non-static	0.927	6.668
	static	0.906	9.025

TABLE VI
CNN HYPERPARAMS

Hyperparameter	Values
dropout	0.4, 0.5, 0.55, 0.6, 0.7, 0.75, 0.8
mode	multichannel, non-static, static
number of feature maps	50, 150, 100, 250, 200
embeddings	ownfast, own, word2vec, fasttext
regularization	$0, 7*10^{-4}, 10^{-3}, 5*10^{-4}$
word dimension	50, 100, 300

TABLE VIII
HYPERPARAMETERS FOR THE BEST CNN MODELS

Hyperparameter	Metric			
	CNN fastText pretrained	*CNN Word2Vec own*	*CNN fastText own*	*CNN word2vec pretrained*
dev acc	0.928	0.929	0.931	0.928
dropout	0.5	0.75	0.75	0.7
num feature maps	100.0	150.0	100.0	100.0
regularization	0.0	0.001	0.001	0.0
word dim	300.0	50.0	50.0	300.0

TABLE IX
CONFUSION MATRICES

Classifier	Label											
	joy		*sadness*		*anger*		*fear*		*love*		*surprise*	
CNN Word2Vec own	664	32	525	26	254	16	196	34	158	30	60	5
	40	1264	25	1424	21	1709	16	1754	20	1792	21	1914
CNN fastText own	674	38	531	32	258	25	171	12	155	22	67	15
	30	1258	19	1418	17	1700	41	1776	23	1800	14	1904
CNN fastText pretrained	664	36	520	17	259	24	195	35	148	27	64	11
	40	1260	30	1433	16	1701	17	1753	30	1795	17	1908
CNN word2vec pretrained	673	36	524	29	255	15	189	27	156	23	64	9
	31	1260	26	1421	20	1710	23	1761	22	1799	17	1910
LogisticRegression	672	119	516	73	229	23	155	23	122	10	51	7
	32	1177	34	1377	46	1702	57	1765	56	1812	30	1912
MultinomialNB	683	364	514	268	93	3	60	3	12	0	0	0
	21	932	36	1182	182	1722	152	1785	166	1822	81	1919
RandomForestClassifier	659	72	508	43	241	21	185	36	142	21	62	10
	45	1224	42	1407	34	1704	27	1752	36	1801	19	1909

TABLE X
HARVARD GENERAL INQUIRER CATEGORY SELECTION

Label	Inclusion	
	Included	*Excluded*
surprise	Arousal	
joy	Positiv	Affil
love	Affil	Negativ
anger	Hostile	
sadness	Negativ	Hostile
fear	Weak	