Data Article

Dataset for modeling Beck’s cognitive triad to understand depression

Shreekant Jere∗, Annapurna P. Patil, Ganeshayya I. Shidaganti, Shweta S. Aladakatti, Laxmi Jayannavar

a MS Ramaiah Institute of Technology, Bengaluru, India Affiliated to VTU, Belagavi, India
b Dayananda Sagar University, Bengaluru, India

A R T I C L E   I N F O

Article history:
Received 9 September 2021
Revised 22 September 2021
Accepted 23 September 2021
Available online 25 September 2021

Keywords:
Cognitive triad
Depression
Sentiment classification

A B S T R A C T

This article presents data to model Beck’s cognitive triad to understand the subjective symptoms of depression, such as negative view of self, future, and world. The Cognitive Triad Dataset (CTD) comprises 5886 messages, 600 from the Time-to-Change blog, 580 from Beyond Blue personal stories, and 4706 from Twitter. The data were manually labeled by skilled annotators. This data is divided into six categories: self-positive, world-positive, future-positive, self-negative, world-negative, and future-negative. The Cognitive Triad Dataset was evaluated on two subtasks: aspect detection and sentiment classification on given aspects. The dataset will aid in the comprehension of Beck’s Cognitive Triad Inventory (CTI) items in a person’s social media posts.

© 2021 The Author(s). Published by Elsevier Inc. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/)

∗ Corresponding author.
E-mail address: shrikantjere@gmail.com (S. Jere).

https://doi.org/10.1016/j.dib.2021.107431
2352-3409/© 2021 The Author(s). Published by Elsevier Inc. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/)
Specifications Table

| Subject | Health psychology |
|---------|-------------------|
| Specific subject area | Beck’s cognitive theory |
| Type of data | Text |
| How data was acquired | The data from Tweeter was extracted using the Twitter API. Data from the Time-to-Change blog and Beyond Blue personal stories are manually collected. |
| Data format | Raw and analyzed. |
| Parameters for data collection | The Tweeter API was utilized to capture tweets using filter keywords related to cognitive triad aspects. The keywords related to self, future, and world include (“I”, “myself”, “me”), (“future”, “from now”, “look forward”, “turn out”, “am going to”, “are going to”, “won’t”, “will”), and (“world”, “globe”, “people”, “he”, “she”, “it”, “they”, “nobody”, “others”, “obstacle”) respectively. |
| Description of data collection | The data from Tweeter was extracted using the Twitter API. The filter keywords related to cognitive triad aspects were used in the Tweeteer API to capture tweets. The data from the Time-to-Change blog were manually collected. The GitHub code was used to generate simulated data that resembles cognitive patterns found in the Beyond Blue personal stories. The data were manually labeled by skilled annotators. The data includes messages from 798 adult Tweeters and 42 adult Time-to-Change blog users from all over the world. |
| Experimental factors | Data were preprocessed by deleting duplicate Tweets, incomplete Tweets, and Tweets shorter than four words, removing punctuations and stop words from the text, and deconstructing multi-word hashtags into individual words. |
| Data source location | Twitter, Time-to-Change blog and Beyond Blue personal stories. |
| Data accessibility | Raw data can be retrieved from the Mendeley repository [2] [1]. The source code is available online at https://github.com/bctriad/code. |

Value of the Data

• Patients may under- or over-report their symptoms during traditional clinical interviews, depending on the actual or perceived implications for a mental health disorder diagnosis. Intelligent mental disorder understanding systems trained with CTD can overcome these limitations and effectively test for depression.

• The CTD presents 6-ary cognitive triad labels to understand the CTI-items associated with statements in a person’s social media messages. 6-ary labels include self-negative, future-negative, world-negative, self-positive, future-positive, and world-positive.

• The data can be utilized to train a sentiment analysis model, which can then be used for initial screening of depression based on the client’s recent interactions with the clinical chatbot or their social media data.

• The labeled text data can be used to train machine learning models for sentiment analysis and aspect detection tasks. The aspect-based sentiment classification model on CTD can assist psychologists in identifying the cognitive triad aspect-sentiment pairs (self, negative), (world, negative), (future, negative)) from the social media messages of the individual.

1. Data Description

Beck [2] determined three factors responsible for depression: faulty information processing (errors in logic), cognitive triad (negative thinking about world, self, and future), and negative self-schemas. Critical evaluation of Beck’s theory is provided in Alloy et al. [3] and Butler et al. [4]. This section highlights the cognitive triad which, can be modeled using sentiment analysis. The Cognitive Triad Inventory (CTI) comprises items [5] related to a view of the self, the world, and the future, as shown in Table 1.

The Cognitive Triad Dataset is used to understand the CTI-items associated statements in a person’s social media messages. 6-ary classes include \(C_6 = \{\text{self-negative (sneg)}, \text{world-negative}\)
Table 1

CTI items and expected answers from depressed person.

| CTI items                                                                 | Aspect (Subscale) | Expected answer from depressed person (Binary Yes/No class) | Expected answer from depressed person with Scale 1–7 (Higher scores indicate true views and lower scores indicate false views) |
|---------------------------------------------------------------------------|-------------------|-------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------|
| Everything in the future will turn out perfectly for me.                 | Future            | No                                                          | False view                                                                                                                 |
| I believe some things are going really well for me a couple of years from now. | Future            | No                                                          | False view                                                                                                                 |
| I can do many things right.                                              | Self              | No                                                          | False view                                                                                                                 |
| I think when I grow older, I will be happy.                              | Future            | No                                                          | False view                                                                                                                 |
| I value myself.                                                          | Self              | No                                                          | False view                                                                                                                 |
| A lot of good things are going to happen to me in the future.            | Future            | No                                                          | False view                                                                                                                 |
| I do a lot of different things well.                                     | Self              | No                                                          | False view                                                                                                                 |
| I want to think about the positive stuff that is going to happen to me in the future. | Future            | No                                                          | False view                                                                                                                 |
| I am a loser.                                                            | Self              | Yes                                                         | True view                                                                                                                   |
| I dislike myself.                                                        | Self              | Yes                                                         | True view                                                                                                                   |
| I am a really good person.                                               | Self              | No                                                          | False view                                                                                                                 |
| I do my schoolwork properly.                                             | Self              | No                                                          | False view                                                                                                                 |
| I will fix my issues.                                                    | Future            | No                                                          | False view                                                                                                                 |
| There is nothing left in my life that I can look forward to.             | Future            | Yes                                                         | True view                                                                                                                   |
| No matter what happens to me, my family doesn’t care.                   | World             | Yes                                                         | True view                                                                                                                   |
| My worries and problems will never go away.                              | Future            | Yes                                                         | True view                                                                                                                   |
| I am faced with several obstacles.                                       | World             | Yes                                                         | True view                                                                                                                   |
| Lots of bad things happen to me.                                        | World             | Yes                                                         | True view                                                                                                                   |
| I feel guilty of several things.                                         | Self              | Yes                                                         | True view                                                                                                                   |
| I have personality issues.                                               | Self              | Yes                                                         | True view                                                                                                                   |

Table 2

6-ary CTD statistics.

| Corpus                  | sneg | wneg | fneg | spos | wpos | fpos |
|-------------------------|------|------|------|------|------|------|
| Tweet                   | 797  | 768  | 784  | 793  | 787  | 777  |
| Time to Change          | 106  | 102  | 103  | 102  | 90   | 97   |
| Beyond Blue             | 95   | 90   | 93   | 97   | 107  | 98   |
| Total                   | 998  | 960  | 980  | 992  | 984  | 972  |

(wneg), future-negative (fneg), self-positive (spos), world-positive (wpos), future-positive (fpos)). We collected data from Tweet, Time-to-Change blog, and Beyond Blue personal stories and used the majority vote for our dataset with the gold standard. The statistics for the 6-ary dataset is provided in Table 2. For cognitive aspect detection, CTD classes are reduced to ternary classes (self, world, future). CTD statistics for cognitive aspects are given in Table 3. For sentiment classification, CTD classes are decreased to binary classes (positive, negative). Table 4 shows the CTD statistics for sentiment classification. Word clouds for self-negative, world-negative, future-negative, self-positive, world-positive, and future-positive labels are provided in Figs. 1–6. A word cloud is a depiction of text data in which the size of each word signifies its frequency or relevance.
Table 3
CTD statistics on cognitive aspects.

| Corpus        | Self | World | Future |
|---------------|------|-------|--------|
| Tweeter       | 1590 | 1555  | 1561   |
| Time to Change| 208  | 192   | 200    |
| Beyond Blue   | 192  | 197   | 191    |
| Total         | 1990 | 1944  | 1952   |

Table 4
CTD statistics on cognitive sentiments.

| Corpus        | Negative | Positive |
|---------------|----------|----------|
| Tweeter       | 2349     | 2357     |
| Time to Change| 311      | 289      |
| Beyond Blue   | 278      | 302      |
| Total         | 2938     | 2948     |

Fig. 1. Word cloud for self-negative label.

Fig. 2. Word cloud for world-negative label.

Fig. 3. Word cloud for future-negative label.
2. Experimental Design, Materials and Methods

The cognitive triad dataset is evaluated for aspect detection and sentiment classification using popular machine learning and deep learning models. Data were preprocessed by deleting duplicate Tweets, incomplete Tweets, and Tweets shorter than four words, removing punctuations and stop words from the text, and deconstructing multi-word hashtags into individual words. In the preliminary work, Decision Tree, Random Forest, Naive Bayes, SVM [6], and RNN-Capsule [7] models are evaluated for aspect extraction and sentiment classification on the cognitive triad dataset. The baseline machine learning models are implemented using scikit-learn. The RNN-capsule model is implemented using PyTorch and run on a single GPU (NVIDIA GeForce RTX 3080 Ti). By default, we trained the model for 28 epochs with a batch size of 32. We employed pre-trained GloVe for the word embedding. In numerous trials, we chose the best validation performance and presented the testing performance in experimental results. Table 5 compares various models on CTD for aspect extraction task. The results of accuracy and an F1-score are
very close for Random Forest and Support Vector Machine. The RNN Capsule model has a maximum accuracy of 96.17% and an F1-score of 96.02%. Table 6 provides the comparison of various models on CTD for the sentiment classification task. The results of accuracy and F1-score are very close for Decision Tree and Support Vector Machine. The Random Forest model has the highest accuracy of 81.58% and an F1-score of 81.56% among machine learning models. The RNN Capsule model has a maximum accuracy of 88.87% and an F1-score of 88.55% for the sentiment classification task. Table 7 gives the performance of various models on CTD for sentiment classification task on the self aspect. The results of accuracy and F1-score are very close for Random Forest and Support Vector Machine. The RNN Capsule model has a maximum accuracy of 83.67% and an F1-score of 83.72% for the sentiment classification task on the self aspect. Table 8 provides the performance of various models on CTD for sentiment classification task on the future aspect. The Random Forest model has the highest accuracy of 83.62% and an F1-score of 84.11% among machine learning models. The RNN Capsule model has a maximum accuracy of 90.06% and an F1-score of 89.89% for the sentiment classification task on the future aspect. Table 9 gives the performance of various models on CTD for sentiment classification task on the world aspect. The Random Forest model has the maximum accuracy of 86.60% and an F1-score of 86.59% for the sentiment classification task on the world aspect. Table 10 provides the performance

| Table 5 | Performance of aspect extraction on CTD. |
|---------|------------------------------------------|
| Model   | Accuracy | Precision | Recall | F1-score |
| Decision Tree | 70.25 | 70.28 | 70.42 | 70.35 |
| Random Forest | 76.58 | 76.65 | 76.74 | 76.69 |
| Naive Bayes | 54.33 | 61.77 | 54.18 | 57.73 |
| Support Vector Machine | 77.25 | 77.84 | 77.35 | 77.59 |
| RNN-Capsule | 96.17 | 96.86 | 95.20 | 96.02 |

| Table 6 | Performance of sentiment classification on CTD. |
|---------|------------------------------------------|
| Model   | Accuracy | Precision | Recall | F1-score |
| Decision Tree | 76.25 | 76.29 | 76.14 | 76.21 |
| Random Forest | 81.58 | 81.61 | 81.51 | 81.56 |
| Naive Bayes | 64.83 | 70.31 | 65.65 | 67.90 |
| Support Vector Machine | 77.83 | 79.03 | 78.16 | 78.59 |
| RNN-Capsule | 88.87 | 89.62 | 87.50 | 88.55 |

| Table 7 | Performance of sentiment classification on self aspect. |
|---------|------------------------------------------|
| Model   | Accuracy | Precision | Recall | F1-score |
| Decision Tree | 73.11 | 73.12 | 73.00 | 73.06 |
| Random Forest | 77.13 | 77.27 | 76.97 | 77.12 |
| Naive Bayes | 67.08 | 69.89 | 66.36 | 68.08 |
| Support Vector Machine | 75.38 | 76.55 | 74.97 | 75.75 |
| RNN-Capsule | 83.67 | 83.44 | 84.00 | 83.72 |

| Table 8 | Performance of sentiment classification on future aspect. |
|---------|------------------------------------------|
| Model   | Accuracy | Precision | Recall | F1-score |
| Decision Tree | 81.88 | 82.18 | 82.01 | 82.09 |
| Random Forest | 83.62 | 84.40 | 83.83 | 84.11 |
| Naive Bayes | 68.73 | 76.59 | 69.46 | 72.85 |
| Support Vector Machine | 80.40 | 81.49 | 80.65 | 80.07 |
| RNN-Capsule | 90.06 | 90.28 | 89.04 | 89.89 |
Table 9
Performance of sentiment classification on world aspect.

| Model                  | Accuracy | Precision | Recall | F1-score |
|------------------------|----------|-----------|--------|----------|
| Decision Tree          | 79.65    | 80.03     | 79.80  | 79.91    |
| Random Forest          | 86.60    | 86.60     | 86.58  | 86.59    |
| Naïve Bayes            | 69.73    | 76.56     | 69.01  | 72.59    |
| Support Vector Machine | 80.89    | 81.68     | 80.67  | 81.17    |
| RNN-Capsule            | 86.05    | 86.80     | 84.46  | 85.61    |

Table 10
Performance of aspect based sentiment classification on cognitive ⟨aspect, sentiment⟩ classes.

| Model                  | Accuracy | Precision | Recall | F1-score |
|------------------------|----------|-----------|--------|----------|
| Decision Tree          | 52.65    | 53.31     | 52.65  | 52.62    |
| Random Forest          | 58.64    | 59.05     | 58.52  | 58.26    |
| Naïve Bayes            | 44.65    | 46.75     | 44.15  | 42.17    |
| Support Vector Machine | 60.54    | 61.69     | 60.35  | 60.58    |
| RNN-Capsule            | 85.71    | 85.99     | 85.69  | 85.84    |

of aspect based sentiment classification on cognitive ⟨aspect, sentiment⟩ classes. The Support Vector Machine has the highest accuracy of 60.54% and an F1-score of 60.58% among machine learning models. The RNN Capsule model has a maximum accuracy of 85.71% and an F1-score of 85.84% for the sentiment classification task.

Ethics Statement

The data presented in this article is being distributed in accordance with the Twitter developer policy (https://developer.twitter.com/en/developer-terms/policy), Beyond Blue terms of use (https://www.beyondblue.org.au/general/terms-of-use), and Time-to-Change privacy policy (https://www.time-to-change.org.uk/privacy-policy).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT Author Statement

Shreekant Jere: Conceptualization, Methodology, Data curation, Investigation, Writing – original draft; Annapurna P. Patil: Investigation; Ganeshayya I. Shidaganti: Writing – original draft; Shweta S. Aladakatti: Writing – review & editing; Laxmi Jayannavar: Investigation.

Acknowledgments

The authors acknowledge the support received from the Research Centre, Department of Computer Science and Engineering, M S Ramaiah Institute of Technology, Bengaluru, India.

References

[1] S. Jere, A. Patil, Cognitive triad dataset: understanding Beck's cognitive triad mechanism in an individual from social media interactions, Mendeley Data V1 (2021), doi:10.17632/wb2n39sgbp.1.
[2] M.D. William E. Powles, Beck, Aaron T. Depression: Causes and Treatment. Philadelphia: University of Pennsylvania Press, 1972. Pp. 370. $4.45, Am. J. Clinical Hypnosis 16 (4) (1972) 281–282, doi:10.1080/00029157.1974.10403697.

[3] L. Alloy, L. Abramson, W.C. Whitehouse, M. Hogan, N. Tashman, D. Steinberg, D.T. Rose, P. Donovan, Depressogenic cognitive styles: predictive validity, information processing and personality characteristics, and developmental origins, Behav. Res. Therapy 37 (6) (1999) 503–531.

[4] S.G. Hofmann, et al., The efficacy of cognitive behavioral therapy: a review of meta-analyses, Cogn. Therapy Res. 36 (2012) 427–440.

[5] E.E. Beckham, et al., Development of an instrument to measure Beck’s cognitive triad: the cognitive triad inventory, J. Consult. Clin. Psychol. 54 (1986) 566–567.

[6] W. Medhat, A. Hassan, H. Korashy, Sentiment analysis algorithms and applications: a survey, Ain Shams Eng. J. 5 (2014) 1093–1113.

[7] Y. Wang, A. Sun, J. Han, Y. Liu, X. Zhu, Sentiment analysis by capsules, in: Proceedings of the 2018 World Wide Web conference, WWW ’18, International World Wide Web Conferences Steering Committee, Republic and Canton of Geneva, CHE, 2018, pp. 1165–1174, doi:10.1145/3178876.3186015.