

Summarizing Behavioral Change Goals from SMS Exchanges to Support Health Coaches

Anuja Tayal
657111812
UIC, Chicago
atayal4@uic.edu

REVIEW

Objective

To reduce the risk of chronic health diseases by increasing physical activity and improve mental well being of the patients, the authors (Itika Gupta, Barbara Di Eugenio, Brian D Ziebart, Bing Liu, Ben S Gerber, Lisa K Sharp) in [1] promotes healthy behavior among patients by assisting health coaches to achieve SMART (Specific, Measureable, Attainable, Realistic and Time Bound) goals. The authors understood the conversations between the health coaches and the patients by extracting the goal of the physical activity and negotiate it with the patient via text messages to achieve SMART goals.

Through their work, authors proposed two goal extraction process by classifying the stage and dialogue acts and use it to identify goal attributes. To predict dialogue act, the authors use traditional and transformer based machine learning models.

Dataset

The authors in [1] collected two health coaching datasets with the added feature of viewing patient's past goals and use it to set future goals. Dataset 2 is available on request while Dataset 1 is not publicly available. Dataset 1 was collected for 4 weeks by a health coach who coached 28 patients with the help of Mytapp web based application. Each patient was provided with a Fitbit to track their progress which can be viewed by the health coach. On the other hand, for 2nd dataset, 28 patients were coached for 8 weeks by 3 health coaches.

The dataset was annotated with 2 goals of goal setting and goal implementation. In the goal setting stage, there were 5 stages mainly Goal identification, Goal refining, goal negotiation, solve barrier and anticipate barrier, while in goal implementation there was a follow-up stage instead of goal identification stage.

On the other hand, to identify the dialogue acts 12 tags were annotated mainly set question, choice question, propositional question, inform, answer, commissive, directive, feedback, apology, salutation, thanking and self correction.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

Domain specific SMART attributes were also annotated which consisted of 10 attributes- activity, time, location, measurable quantity amount, quantity distance, duration, days name, days number, repetition and attainability score.

Models

Goal Extraction

By predicting phase, SMART attributes and dialogue acts, and going through different phases of the goal setting stage, final goal summary was determined and extracted.

SMART Attributes Modeling

For modelling 10 SMART attributes, dataset 1 was trained with the help of sequential and non sequential classifiers of CRF, Structured Perceptron, Logistic Regression, SVM and Decision Trees. Different features of current word, left and right context words, POS tags, left and right context words, SpaCy based Named Entity Recognition model along with ELMo word embeddings.

Modeling Dialogue Acts

The authors modeled the different dialogue acts with the help of multi-class classification problem and trained a CRF model in addition to 5 different BERT models. Among all the models trained, ToD-BERT performed the best.

Modeling Phases

Similar to modeling SMART attributes, phases were identified by training different sequential and non sequential classifiers. Different attributes and their combinations- unigrams, present/absence of SMART attributes, distance of message from the top, message length, message sender, word2vec word embeddings were used among others. Among all the models trained, CRF performed the best with F1 macro score of 0.71.

Goal Summary Extraction

Different combinations of the SMART attributes, Phase and dialogue act prediction models were used to extract the summary of the goal.

Pros and Cons

I really liked that the authors proposed to solve a very difficult and challenging problem which affects the lifestyle of so many people. It is a common problem which everyone is facing. I also liked that the authors have calculated the inter-annotator agreement which is a measure of agreement between the annotators and also gives a confidence that the results can be reproduced. In addition, while modeling dialogue acts, to

support their hypotheses, the authors also performed statistical significant testing. I was really impressed with the human evaluation experiment performed which showed whether the goal summary is helpful for the health coaches and whether the goal summary generated helpful for the patients. The only thing I feel is that it would be very difficult to manage so many people in messaging kind of system. I am doubtful that its reachability would be less and whole system would be a little difficult to deploy. Also, different people would have different preferences, some people wont be motivated enough or become demotivated if they do not accomplish their goal. Also the answers generated should be more human like and have more empathy and at the same time push people to fulfill their goals.

Conclusion

With the increase in stress and physical inactivity, well being and physical activity is very important in daily life and for that pushing ourself is the way to go which the researchers proposes to successfully achieve it.

REFERENCES

- [1] Itika Gupta, Barbara Di Eugenio, Brian D. Ziebart, Bing Liu, Ben S. Gerber, and Lisa K. Sharp. 2021. Summarizing Behavioral Change Goals from SMS Exchanges to Support Health Coaches. In *Proceedings of the 22nd Annual Meeting of the Special Interest Group on Discourse and Dialogue*. Association for Computational Linguistics, Singapore and Online, 276–289.