HealthE: Classifying Entities in Online Textual Health Advice

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Abstract

The processing of entities in natural language is essential to many medical NLP systems. Unfortunately, existing datasets vastly under-represent the entities required to model public health relevant texts such as health advice often found on sites like WebMD. People rely on such information for personal health management and clinically relevant decision making. In this work, we release a new annotated dataset, HealthE, consisting of 6,756 health advice. HealthE has a more granular label space compared to existing medical NER corpora and contains annotation for diverse health phrases.

Additionally, we introduce a new health entity classification model, EP S-BERT, which leverages textual context patterns in the classification of entity classes. EP S-BERT provides a 4-point increase in F1 score over the nearest baseline and a 34-point increase in F1 when compared to off-the-shelf medical NER tools trained to extract disease and medication mentions from clinical texts. All code and data are publicly available on Github.

1. Introduction

Background and knowledge gap: Health information or health advice found on patient education sites (e.g., WebMD, Mayo Clinic, CDC website, American Diabetes Association) plays an important role in improving health literacy, medical information search, and patient empowerment Calixte et al. (2020); Masoni et al. (2013); Kubb et al. (2020). Entity classification from such online textual health advice can be essential to various downstream medical natural language processing (medNLP) tasks including but not limited to misinformation detection Swire-Thompson and Lazer (2019), medical dialogue systems Chintagunta et al. (2021), and patient-centric information tools Dai et al. (2020); Preum et al. (2017); Beaunoyer et al. (2017).

Unfortunately, off-the-shelf entity classifiers cover only a small subset of the entity classes commonly found in online textual health advice, e.g., disease, drug, side effects. They often overlook entities that are critical to computationally represent health advice, such as food, exercise, and physiological status unrelated to side effects. This is because existing works largely focus on the extraction of entities found in either technical content (i.e., electronic health record (EHR) notes and biomedical literature Neumann et al. (2019); Lee et al. (2020)) or layperson generated content (i.e., social media Derczynski et al. (2017)).
Most heat illnesses happen when you stay out in the heat too long. Exercising and working outside in high heat can also lead to heat illness. Older adults, young children, and those who are sick or overweight are most at risk. Taking certain medicines or drinking alcohol can also raise your risk.

Figure 1: Sample from the HealthE dataset with entities labeled from each class in the HealthE label space.

Our solution: To address this knowledge gap, we make the following contributions in this paper. We introduce a new annotated dataset and model for medical entity classification from public health related text targeting laypersons. The dataset, HealthE, contains 6,756 human-labeled health advice texts from numerous websites including WebMD, MedlinePlus, and several disease specific popular health websites. We explore the problem of health entity classification in this paper to classify entities into one of six classes: (i) Food / Nutrient, (ii) Disease / Condition, (iii) Medicine / Supplement / Treatment, (iv) Exercise, (v) Vitals / Physiological Status, and (vi) Other. The annotation format of HealthE is also compatible for medical named entity recognition (NER) task. Unlike existing medical NER tools, however, this class set is representative of public health related texts providing a more granular level of text annotation.

We also introduce Entity/Pattern S-BERT (EP S-BERT) for medical entity classification. EP S-BERT is a transformer-based architecture which leverages textual context patterns, as is commonly utilized in Entity Set Expansion Li et al. (2022); Yan et al. (2020), to predict health entity classes. EP S-BERT provides a 34% increase in F1 score over the nearest Medical NER baseline when used off-the-shelf, and a 4% increase in performance over the nearest baseline fine-tuned to HealthE.

2. Methods

2.1. Data Collection and Annotation

HealthE is a dataset of 6,756 textual health advice statements. A sample with annotation from all classes is highlighted in Figure 1. For each sample, objects or phrases were annotated as one of the displayed 6 classes. For example, in Figure 1, the entity “overweight” is labeled Physiological Status, which refers to symptoms, behaviors, organs, and general state of health/being. Other class names are generally self-explanatory, with full annotation details available in the appendix.

Samples were collected from various online sources of information pertaining to health and general well-being including WebMD, Medline Plus, CDC, COVID Protocols, Yahoo! Health, MayoClinic, as well as 8 mobile health applications. For a detailed view of the distribution of health advice topics from which entities were extracted, please refer to Section B in the appendix.
2.2. Entity/Pattern S-BERT

*EP S-BERT* is based on the Sentence-BERT (S-BERT) architecture Reimers and Gurevych (2019) which outputs a single vector representation for a given textual input. The choice to use S-BERT, a sequence encoder, as opposed to a word embedding model is motivated by the large quantity of multi-token entities (e.g. “exposure to nature”, “drinking enough fluids”, “ringing in the ears”) found in HealthE. We additionally use S-BERT to encode the context patterns of a given entity. Encoding entity context helps classify multi-meaning context-dependent entities. For example, if we wish to classify the entity “liver” without any context, it is not apparent whether it refers to animal liver that someone may eat, or the organ. However, if we observe that “liver” occurs within patterns such as “beef or chicken”, “chicken will help”, “kidneys, dairy”, it becomes apparent that we should classify “liver” as FOOD. To generate the context embedding for an entity $E$, we consider the set of advice texts $C = \{h_1, h_2, \ldots, h_n\}$ where $h_i$ is an advice text in HealthE containing $E$. $C$ is processed by replacing all entity tokens $E$ with a mask token $[\text{MASK}]$, leaving only the entities’ context. Formally, this transforms a given health advice statement into $h_i = \{t_1, t_2, \ldots, [\text{MASK}], \ldots, t_n\}$, retaining all tokens $t_i$ except those pertaining to the entity $E$. Finally, we embed each text in $C$ using S-BERT and use the mean of all context embeddings as the entity pattern embedding. The concatenation of the entity and pattern embeddings are then fed into a linear classifier. A visualization of this pipeline is shown in Figure 2.

![End-to-End health entity classification pipeline for our model EP S-BERT](image)

**Figure 2:** End-to-End health entity classification pipeline for our model EP S-BERT.

### Table 1: HealthE Data Distribution

| Class | Number of Samples |
|-------|-------------------|
| MED   | 2011              |
| DIS   | 1162              |
| FOOD  | 905               |
| PHYS  | 871               |
| EXER  | 215               |
| OTH   | 254               |

3. Experiments and Results

3.1. Baselines and Related Works

In this study we compare 6 baseline methods to our approach *EP S-BERT*. Each of our entity classification baselines, namely GLoVe Pennington et al. (2014), BERT Devlin et al. (2018), Bio+Clinical BERT Alsentzer et al. (2019) and S-BERT, are used to produce embeddings for a given input entity which is then fed into a linear classification head.

Additionally, to identify the capability of off-the-shelf Medical NER tools to extract entities of HealthE, we run two experiments using SciSpacy Neumann et al. (2019) and BioBERT NER Lee et al. (2020). We note this is not a one-to-one comparison with *EP S-BERT*, which is fine-tuned to the HealthE label space, but rather an illustration of the limitations of existing Medical NER models.
Table 2: Mean F1 score for each class over a 5-fold cross validation as well as the weighted average (W/AVG) across all classes. The medical NER models (i.e., SciSpacy and BioBERT NER) only overlap with two classes in the HealthE label space.

| Model               | DIS | MED | FOOD | EXER | PHYS | OTH | W/AVG |
|---------------------|-----|-----|------|------|------|-----|-------|
| GloVE               | 0.78| 0.85| 0.88 | 0.77 | 0.71 | 0.40| 0.79  |
| BERT                | 0.77| 0.83| 0.83 | 0.78 | 0.70 | 0.41| 0.77  |
| Bio+Clinical BERT   | 0.80| 0.84| 0.79 | 0.71 | 0.71 | 0.39| 0.77  |
| S-BERT              | 0.79| 0.86| 0.87 | 0.84 | 0.71 | 0.36| 0.80  |
| SciSpacy            | 0.59| 0.44|-     | -    | -    | -   | 0.51  |
| BioBERT NER         | 0.28| 0.29|-     | -    | -    | -   | 0.28  |
| EP S-BERT           | 0.81| 0.89| **0.92**| **0.88**| 0.75 | 0.49| **0.84**|
| EP S-BERT + DA      | **0.84**| **0.90**| **0.90**| **0.84**| **0.78**| **0.57**| **0.85**|

and the datasets on which they are trained (i.e. clinical note and PubMed data).

Given that S-BERT is not trained on any health data, we additionally evaluate EP S-BERT with domain adaptation training using TSDAE Wang et al. (2021). We select TSDAE since it is a denoising autoencoder designed for use with the S-BERT model. This experiment, **EP S-BERT + DA**, first enters a round of domain adaptive training on an additional 40k unlabeled health texts scraped from the sources described in Section 2.1 before being fine-tuned to HealthE. This pre-disposes EP S-BERT to intermediate level health texts, which should better prepare it for understanding uncommon health terminology such as medication or treatment names.

3.2. Results

For each experiment, we report mean F1 score calculated over five-fold cross validation in Table 2. For each individual class, we report the F1 of the positive class only, as well as the weighted-F1 of the overall model. EP S-BERT outperforms all baselines on the health entity classification task, highlighting the value of context pattern utilization. Additionally, we see a slight increase in performance from domain adaptation, specifically on the more medically-relevant topics such as DIS, MED and PHYS. This is to be expected as the standard S-BERT model is not trained on any health/medical specific texts.

We also observe the Medical NER models struggling to classify DIS and MED entities in HealthE. We suspect that this is largely due to differing label spaces between HealthE and the medical corpora on which the Medical NER models were trained. For example, in the advice sample “You may also need this test if other tests, such as a blood glucose test, show you have low blood sugar,” HealthE has **low blood sugar** labeled as DIS because it is a condition, whereas SciSpacy only extracts the chemical **Glucose**. This label shift from existing Medical NER corpora marks an important distinction of HealthE as a general health advice corpus.

4. Conclusion and Future Work

Existing Medical NER tools perform poorly on HealthE, requiring new solutions to understand the unique HealthE label space. We show that transformer-based models perform well at entity classification and gain a significant performance boost from the encoding of entity context. The use of context/pattern
embeddings is inspired by the low-resource task of Entity Set Expansion, a task under which HealthE could also be explored in future works. Future works may explore this problem in the context of medical NER by including a non-entity token label for all non-labeled tokens. Also, the performance increase from domain adaption highlights the potential for explicit integration of medical knowledge bases.

References

Emily Alsentzer, John R. Murphy, Willie Boag, Wei-Hung Weng, Di Jin, Tristan Naumann, and Matthew B. A. McDermott. Publicly available clinical BERT embeddings. *CoRR*, abs/1904.03323, 2019. URL http://arxiv.org/abs/1904.03323.

Elisabeth Beaunoyer, Marianne Arsenault, Anna M Lomanowska, and Matthieu J Guitten. Understanding online health information: Evaluation, tools, and strategies. *Patient education and counseling*, 100(2):183–189, 2017.

Rose Calixte, Argelis Rivera, Olutobi Oriyote, William Beauchamp, and Marlene Camacho-Rivera. Social and demographic patterns of health-related internet use among adults in the united states: a secondary data analysis of the health information national trends survey. *International Journal of Environmental Research and Public Health*, 17(18):6856, 2020.

Bharath Chintagunta, Namit Katariya, Xavier Amatriain, and Anitha Kannan. Medically aware gpt-3 as a data generator for medical dialogue summarization. In *Machine Learning for Healthcare Conference*, pages 354–372. PMLR, 2021.

Enyan Dai, Yiwei Sun, and Suhang Wang. Ginger cannot cure cancer: Battling fake health news with a comprehensive data repository. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 14, pages 853–862, 2020.

Leon Derczynski, Eric Nichols, Marieke van Erp, and Nut Limsoopatham. Results of the wnut2017 shared task on novel and emerging entity recognition. In *Proceedings of the 3rd Workshop on Noisy User-generated Text*, pages 140–147, 2017.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. *CoRR*, abs/1810.04805, 2018. URL http://arxiv.org/abs/1810.04805.

Christian Kubb, Heather M Foran, et al. Online health information seeking by parents for their children: systematic review and agenda for further research. *Journal of Medical Internet Research*, 22(8):e19985, 2020.

Jinhyuk Lee, Wonjin Yoon, Sungdong Kim, Donghyeon Kim, Sunkyu Kim, Chan Ho So, and Jaewoo Kang. Biobert: a pre-trained biomedical language representation model for biomedical text mining. *Bioinformatics*, 36(4):1234–1240, 2020.

Yinghui Li, Shulin Huang, Xinwei Zhang, Qingyu Zhou, Yangning Li, Ruiyang Liu, Yumbo Cao, Hai-Tao Zheng, and Ying Shen. Automatic context pattern generation for entity set expansion, 2022. URL https://arxiv.org/abs/2207.08087.

Marco Masoni, Maria Renza Guelfi, Antonio Conti, and Gian Franco Gensini. Pharmacovigilance and use of online health information. *Trends in pharmacological sciences*, 34(7):357–358, 2013.
Mark Neumann, Daniel King, Iz Beltagy, and Waleed Ammar. Scispacy: Fast and robust models for biomedical natural language processing. *ArXiv*, abs/1902.07669, 2019.

Jeffrey Pennington, Richard Socher, and Christopher D. Manning. Glove: Global vectors for word representation. In *Empirical Methods in Natural Language Processing (EMNLP)*, pages 1532–1543, 2014. URL http://www.aclweb.org/anthology/D14-1162.

Sarah Masud Preum, Abu Sayeed Mondol, Meiyi Ma, Hongning Wang, and John A. Stankovic. Preclude: Conflict detection in textual health advice. In *2017 IEEE International Conference on Pervasive Computing and Communications (PerCom)*, pages 286–296, 2017. doi: 10.1109/PERCOM.2017.7917875.

Nils Reimers and Iryna Gurevych. Sentence-bert: Sentence embeddings using siamese bert-networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, 11 2019. URL https://arxiv.org/abs/1908.10084.

Briony Swire-Thompson and David Lazer. Public health and online misinformation: challenges and recommendations. *Annual review of public health*, 41:433–451, 2019.

Kexin Wang, Nils Reimers, and Iryna Gurevych. Tsdae: Using transformer-based sequential denoising auto-encoder for unsupervised sentence embedding learning. *arXiv preprint arXiv:2104.06979*, 4 2021. URL https://arxiv.org/abs/2104.06979.

Lingyong Yan, Xianpei Han, Ben He, and Le Sun. End-to-end bootstrapping neural network for entity set expansion. *Proceedings of the AAAI Conference on Artificial Intelligence*, 34(05):9402–9409, Apr. 2020. doi: 10.1609/aaai.v34i05.6482. URL https://ojs.aaai.org/index.php/AAAI/article/view/6482.
Appendix A. Data Annotation Details

A.1. Dataset

In this work, we use a combination of two datasets, namely Online Health Advice (OHA) and Preclude Preum et al. (2017). Both of these datasets contain textual health advice with entities (objects/phrases) annotated for the following six classes: (i) Food / Nutrient, (ii) Medicine / Supplement / Treatment, (iii) Disease / Condition, (iv) Exercise, (v) Vitals and Physiological Status, and (vi) Other. These classes are described in the annotation schema below.

A.1.1. Online Health Advice (OHA)

Collection: The Online Health Advice (OHA) dataset consists of 5,600 samples of textual health advice collected from four online sources of information pertaining to health and general well-being: WebMD, Medline Plus, CDC, and Covid Protocols.

Annotation: These health advice statements were first annotated for usefulness. We define a health advice statement to be useful if it conveys some information, directly mentioned or implied, that is actionable. 2,536 out of the 5,600 statements were annotated as useful. Human annotators then manually extracted entities from the useful advice statements and labeled them as one or more of the six classes described in Section A.2 (Annotation Details). For the purpose of this work, these annotations were simplified so that each entity is annotated as one and only one of the six classes.

A.1.2. Preclude

Collection: Preclude is an existing dataset consisting of 1,156 samples of textual health advice that primarily relate to food, exercise, lifestyle, and over-the-counter drugs. 790 of these advice statements came from WebMD, Yahoo! Health, MayoClinic, and Healthline.

Annotation: This dataset was originally annotated for medical conflict detection. 3 human annotators manually extracted entities from the advice statements and labeled them as positive, negative, or neutral. Then, for the purpose of this work, the manually extracted entities were then labeled by a human annotator as one the six classes described in Annotation Details.

A.2. Annotation Details

A health advice statement in the corpus can have several entities, each annotated for different classes. However, for the purpose of clearly describing the classes, only entities in the class in question are labeled in the following examples.

A.2.1. Food / Nutrient (FOOD)

Annotators were instructed to list objects or phrases that are food items or nutrients. Example advice statements from the dataset are listed below, in which labeled FOOD objects or phrases are in bold.

- Finding healthy food choices on the road can be an adventure. Don’t fill up on low-fiber foods at fast food chains, rest stops, or airports. Instead, pack a few high-fiber snacks for your trip to help keep you regular. Good choices include whole grain crackers, dried or fresh fruit, fresh vegetables, or whole grain cereals.

- A glass of red wine a day is good for you. The polyphenols in green tea, red wine and olives may also help protect you against breast cancer. The antioxidants may help protect you from environmental carcinogens such as passive tobacco smoke.
A.2.2. Medicine / Supplement / Treatment (MED)
Annotators were instructed to list objects or phrases that are a medicine, supplement, or treatment. Example advice statements from the dataset are listed below, in which labeled MED objects or phrases are in bold.

- This drug should not be used with the following medications because very serious interactions may occur: cisapride, dofetilide.
- Certain medical conditions that increase bone breakdown, including kidney disease, Cushing’s syndrome, and an overactive thyroid or parathyroid, can also lead to osteoporosis. Glucocorticoids, also known as steroids, also increase bone loss. anti-seizure drugs and long-term immobility because of paralysis or illness can also cause bone loss.

A.2.3. Disease / Condition (DIS)
Annotators were instructed to list objects or phrases that are the name of a disease or condition. Example advice statements from the dataset are listed below, in which labeled DIS objects or phrases are in bold.

- Has your doctor said you have high cholesterol? Then you know you need to change your diet and lifestyle to lower cholesterol and your chance of getting heart disease. Even if you get a prescription for a cholesterol drug to help, you’ll still need to change your diet and become more active for heart health. Start with these steps.
- See your health care provider if you think you have an ACL injury. Do not play sports or other activities until you have seen a provider and have been treated.

A.2.4. Exercise (EXER)
Annotators were instructed to list objects or phrases that are names or types of exercise. Example advice statements from the dataset are listed below, in which labeled EXER objects or phrases are in bold.

- See your health care provider if you think you have an ACL injury. Do not play sports or other activities until you have seen a provider and have been treated.
- “Once you can do stretching and strengthening exercises without pain, you can gradually begin running or cycling again. Slowly build up distance and speed.

A.2.5. Vitals / Physiological Status (VIT)
Annotators were instructed to list objects or phrases that are the name of a vital or physiological status. This class also encompasses symptoms, behaviors, organs, and general state of health/being. Example advice statements from the dataset are listed below, in which labeled VIT objects or phrases are in bold.

- If you or a loved one has signs of infection, talk to your doctor. Symptoms alone can’t tell whether klebsiella is the cause. So your doctor will test your spit, blood, urine, or other fluids to find out what type of bug is to blame.
- Ask your provider how often you should have your a1c level tested. Usually, testing every 3 or 6 months is recommended.

A.2.6. Other (OTH)
Annotators were instructed to list relevant objects or phrases that were not appropriate
for the other five categories. This category exists in order to be exhaustive and inclusive of medically relevant objects or phrases that do not fit into the other five categories, but still may be important. Example advice statements from the dataset are listed below, in which labeled OTH objects or phrases are in bold.

- Do not **puncture** the canister or expose it to **high heat** or **open flame**. Keep all medications away from children and **pets**.

- Getting enough quality slumber may lower your pain and fatigue. Limit caffeine and alcohol and avoid tobacco. Eat your last meal of the day several hours before you go to sleep. Keep your bedroom comfortable and free of **electronics**.

A sample of five advice statements with their labels contained in HealthE is provided in Table 3.

**Appendix B. Entity Topic Distribution**

To analyze the health topics covered by the full health advice dataset from which entities were extracted, we sample 500 advice statements and identify the article topic from which each statement was extracted. Figure 3 shows the distribution of health advice topics discovered in this analysis. We find that most entities come from samples providing advice about Arthritis, Hypertension, and Pregnancy.
Some people with type 2 diabetes can control their blood sugar with healthy food choices and physical activity. But for others, a diabetic meal plan and physical activity are not enough. They need to take diabetes medicines.

Knee, hip, and back problems may put a cramp in your walking plans. Ask your doctor or physical therapist for advice before lacing up your walking shoes. Other problems that might hinder walking include balance issues, muscle weakness, and other physical disabilities.

Your doctor may use x-rays to help confirm the diagnosis and rule out other types of arthritis. X-rays show how much joint damage has occurred.

Burns can lead to many complications, including infection and bone and joint problems. Because of this, it’s a good idea to always follow up with your doctor.

Older adults may be more sensitive to the side effects of this drug, especially dehydration and loss of salts in the blood (such as potassium, sodium).

Table 3: A sample of five health advice statements taken from HealthE with their associated labels. Each advice statement is accompanied by a unique identifier and each labeled health entity is listed in its respective category.
Figure 3: Entity Topic Distribution of Medical Advice Dataset