CSE713
Pattern Recognition

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Paper Title

"Using Natural Language Processing to Classify Serious Illness Communication with Oncology Patients"

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Introduction

- Importance of serious illness communication (SIC) in patient-centered decision-making.
- Challenges in measuring and evaluating the quality of SIC.
- Potential of Natural Language Processing (NLP) for identifying and evaluating SIC documentation.

Objectives

- Develop NLP algorithms to identify and characterize SIC with oncology patients.
- Demonstrate the potential for using NLP-based metrics in oncology and other serious illness care settings.

What is Serious Illness Communication (SIC)?

- Importance of SIC for patient-centered decision-making.
- Impact on quality of life and goal-concordant care.
- SIC aims to address end-of-life care, prognosis, treatment options, and patient preferences.
- Inadequate SIC associated with psychosocial distress and incongruent end-of-life care.
- Need for evaluating SIC documentation as a core quality measure.

Challenges in SIC Documentation

- Underutilization and inconsistency of traditional forms of SIC documentation.
- Difficulty in tracking SIC across inpatient and outpatient settings.
- Limited ability of keyword-based approaches to capture nuanced documentation about patient priorities and prognostic communication.

Natural Language Processing (NLP) for SIC

- Overview of NLP as an efficient and accurate alternative for identifying SIC in electronic health records (EHR).
- Current approaches relying on keyword-based algorithms.
- Introduction of machine learning approaches for more accurate and automatic identification.
- Importance of expanding beyond keywords to capture critical SIC domains.
- Need for more sophisticated NLP approaches to capture nuanced SIC documentation.

Methods

- Collection of a weakly annotated dataset of free-text entries containing SIC documentation.
- Training of machine learning algorithms (Logistic Regression, XGBoost, BERT, Bio+Clinical BERT) to classify SIC documentation by domain and subdomain.
- Classification of SIC documentation by domain and subdomain.
- Characterization of features associated with each SIC subdomain.

Dataset and Schema

- Description of the dataset from the University of Pennsylvania Abramson Cancer Center.
- Structure of the "Serious Illness Conversation" note template for documenting SIC.
- Random split of the dataset for training and testing.

Prognosis Domains

Subdomain	Prompt	Responses	Comment
Prognostic Understanding (PU)	What is your understanding now of where you are with your illness?	*Overestimates prognosis; Accurate understanding of prognosis; Underestimates prognosis; No understanding of prognosis;*	"He knows he only has weeks to live."
Information Preferences (IP)	How much information about what is likely to be ahead with your illness would you like from me?	*Patient wants to be fully informed; Patient wants to be informed of big picture, but not details; Patient wants some information, but no "bad news"; Patient prefers information to be shared with ****	"She prefers weekly prognosis updates."
Prognostic Communication (PC)	Information shared with patient about prognosis	*Uncertain prognosis; Possibility of getting sick quickly; Limited time, may be as short as May never get stronger or regain function*	"He had questions about prognosis."

Goal Domains

Subdomain	Prompt	Responses	Comment
Main Goals (MG)	If your health situation worsens, what are your most important goals?	*Live as long as possible; Pursue every available treatment; Avoid hospitalizations/maximize time at home; Not be a burden/maintain independence; Be physically comfortable; Be mentally aware; Spent time with family*	"The patient wants to live to see his daughter's wedding."
Fears/Worries (FW)	What are your biggest fears and worries about the future with your health?	*Pain or other symptoms; Loss of control or dignity; Burdening others; Family concerns; Financial concerns*	"He worries about becoming dependent."
Strengths (ST)	What gives you strength as you think about the future with your illness?	*Friends/family; Faith/spirituality; Prior experience with adversity*	"Support of family and friends."

Serious Illness Communication Classifier Development and Evaluation

- Performance of machine learning algorithms on the test set (F1-score, precision, recall).
- Comparison of algorithms (Logistic Regression, XGBoost, BERT, Bio+Clinical BERT).
- Importance of selecting the appropriate algorithm for different SIC domains.

SIC classifier performance by SIC domain on the test set.

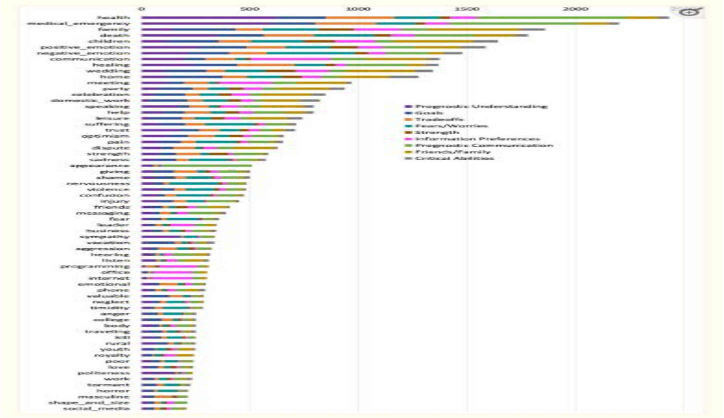
Prognosis	Recall	Precision	F1-score
Logistic Regression (baseline)	0.81	0.85	0.83
XGBoost	0.85	0.86	0.86
BERT	0.80	0.64	0.71
Bio+Clinical BERT	0.86	0.80	0.83
Goals	**Recall**	**Precision**	**F1-score**
Logistic Regression (baseline)	0.91	0.89	0.90
XGBoost	0.92	0.91	0.91
BERT	0.80	0.90	0.84
Bio+Clinical BERT	0.88	0.92	0.90

Logistic Regression SIC classifier performance by SIC subdomain on the test set.

Prognosis	Recall	Precision	F1-score
Prognostic Understanding	0.58	0.64	0.61
Information Preferences	0.44	0.42	0.43
Prognostic Communication	0.57	0.63	0.60
Goals	**Recall**	**Precision**	**F1-score**
Main Goals	0.52	0.68	0.59
Fears/Worries	0.62	0.40	0.49
Strengths	0.75	0.58	0.65
Critical Abilities	0.70	0.71	0.71
Tradeoffs	0.60	0.65	0.63
Friends/Family	0.47	0.27	0.35

Serious Illness Communication Subdomain Characterization

- Identification of the most informative n-grams and Empath categories associated with each SIC subdomain.
- Visualization of associated features using WordCloud.
- Distribution of Empath categories across subdomains.



Algorithms

- Logistic Regression: Learns a logit regression model to explain the relationship between features and classes.
- XGBoost: Gradient descent algorithm that predicts residual errors and minimizes loss for class prediction.
- BERT: Pretrained deep bidirectional representations fine-tuned using a masked language model.
- Bio+Clinical BERT: BERT model initialized from BioBERT and fine-tuned using clinical notes.

Results

- Overview of the study's findings on the identification and classification of SIC documentation.
- Distribution of comments by subdomain.
- Predictive performance of machine learning algorithms on test set.
- Comparison of F1-scores, precision, and recall for prognosis and goals domains.
- Performance of the SIC classifier and identification of informative features.

Limitations

- Semi-structured Epic EHR modules.
- Replicability in other settings.
- Free-text clinical notes.
- Discrimination between relevant and irrelevant text.
- Performance in population-level datasets.
- Limited number of clinicians at one institution.
- Generalizability.
- Patient preferences evolution.
- SIC across gender, race, ethnicity, and culture.

Future Work

- Enhance discrimination within each SIC domain to improve classifier performance in free-text clinical notes.

- Test and validate the algorithm's ability to identify and classify SIC in undifferentiated clinical notes.

- Further explore the performance of algorithms on longer free-text entries.

Discussion

- Importance of accurate and scalable identification of SIC in the EHR.
- Evaluation of the developed NLP algorithm's performance.
- Potential for further improvement and exploration in classifying SIC in free-text clinical notes.

Conclusion

- Successful development of an NLP algorithm for classifying SIC documentation.
- Potential for utilizing NLP-based metrics in measuring and improving the quality of oncology care.
- Future work to enhance algorithm performance, expand applications, and integrate into clinical practice.
- Future directions and implications for research in serious illness communication.

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