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Review Article

Artificial Intelligence Augmented Counseling - A Model

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Abstract

Sentiment analysis of texts produced by patients undergoing mental health counseling can be used in the process of diagnosing a variety of conditions. An artificial intelligence driven approach to assisting mental health counselors in the process if diagnosing conditions, SenSym™, based on DSM-5 guidelines, translates sentiments into symptoms. The SenSym™ model replaces initial in-person meetings between patients and counselors, with the analysis of text items created by patients. By extracting patients' sentiments from text, the system prepares an initial evaluation, ready to be audited by a clinician. SenSym™ is scalable and can potentially reduce clinicians' case load considerably, by automatically analyzing conditions of multiple simultaneous patients.

Keywords: Natural Language Processing; Artificial Intelligence; Sentiment Analysis; Time Series Analysis; Association Rules; DSM-5; Cosine Similarity

Introduction

Advances in natural language processing (NLP) have reached the point at which text-based conversations can be conducted between a software application and a human, and a computer program can extract sentiments expressed in the conversation. Such sentiment analysis tasks are discussed by Elik Hari Muktafin, Pramono, and Kusrini [1]. While there is still a lot of work needed to fully simulate human-to-human conversations, there have been several successes in some areas. Most notable are situations when the topic is very well defined and constrained, and the expectation is limited to the exchange of useful and relevant information. These include customer service chatbots in the retail industry [2], higher education [3] and initial forays into healthcare [4].

The model proposed here, uses artificial intelligence (AI) and sentiment analysis in assisting human counselors in the process of diagnosis of a variety of disorders. Despite current and expected advances in AI and NLP, a psychological barrier must be overcome before fully entrusting human patients solely in the care of software. However, given that drivers and passengers are already trusting AI with their transportation needs (ground and air), AI-based counseling will eventually earn public trust as well.

Not all those seeking professional counseling have access to one, and if they do, there are additional factors that impact access to needed care: transportation, geographical location, cost of lengthy meeting schedules, time availability, and other. The model proposed here attempts to mitigate some of these obstacles and assist patients while improving diagnosis efficiency.

The sentiment to symptom mapper (SenSym™) model

A key element in SenSym™ (Figure 1) is that it replaces the initial set of meetings between patient and counselor, with a set of journal entries written by the patient. Rather than scheduling (and paying) for in-person consultations, a software application analyses the journal entries and extracts sentiments about certain areas of interest such as social norms, personal character traits, physical appearance, finances, self-esteem, and so on. Over a predetermined period, the patient writes a journal, using a web-based writing environment, which stores the entries on a HIPAA-compliant, secure cloud platform. Journal entries do not need to be made at a particular frequency or time of day. Every journal entry is written in free form. The patient can choose to write about the events of the day, an event from the past, random thoughts, a poem, bullet points of ideas, or any other form of writing the patient chooses for a given entry. Each journal entry is added to the corpus of documents for that patient and is immediately passed on to the sentiment analyzer. Currently the only supported language is English.

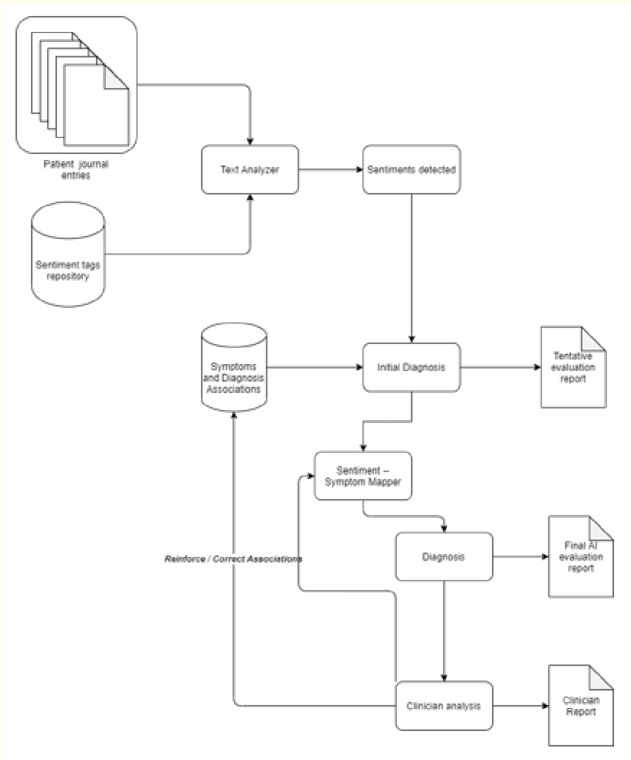

Figure 1: SenSym™ - Diagnosis based on sentiment analysis.

The system produces obvious and some less obvious descriptive statistics, like words frequency, part-speech-tagging, and other proprietary metrics used by SenSym™ to explore the raw data (patients journal entries). The clinician can configure several system settings related to the sensitivity of sentiment extractions, size and number of documents that can trigger the production of interim reports, and a variety of metrics associated with DSM-5 compliance [5].

Once sentiments are extracted from the patient's journal, a proprietary algorithm maps the sentiments onto a set of predefined associations with known conditions, stored in a proprietary repository, compliant with DSM-5. The sentiments extracted are used to generate an initial, tentative evaluation report on the patient's conditions. This report serves two purposes:

- Generate an alert if obvious symptoms are detected (e.g., imminent self-harm).
- Used as part of a system audit, necessary to continuously improve the algorithms.

The result of the comparison between predefined symptoms-diagnosis associations and detected symptoms is used by another proprietary algorithm to generate a more refined patient evaluation report. This concludes phase 1 of SenSym™, which produces an artificial intelligence driven, automated diagnosis.

SenSym™ is not presuming to replace a human clinician but assist the clinician by simplifying the diagnosis tasks. Since all AI-driven evaluations are for internal use only (clinicians, software developers), the patient is presented with an official evaluation prepared and certified by a licensed professional. The clinician reserves the right to corroborate SenSym™'s findings, dispute them, or entirely overwrite them. This decision, stemming from human intelligence is necessary feedback to the artificial intelligence modules. A proprietary reinforcement learning algorithm is employed to improve the AI, using feedback from the human clinician.

The SenSym™ system consists of multiple modules, each based on a combination of proprietary algorithms. The central idea in several algorithms is presented here, omitting intellectual property protected elements.

Algorithm 1 - Text analyzer

Text analysis is performed at the journal entry level, as well as the corpus level, the collection of journal entries created by one patient. The algorithm (Algorithm 1) is implemented continuously, as new journal entries are created. Thus reports, analysis, and plots can be generated over time to enable detection of trends, using time series analysis tools. The use of relevant time-series analysis and associated methods, is surveyed by Kaushik., *et al.* [6].

Algorithm 2 - Sentiment detection

Sentiment detection is using a word frequency approach, coupled with syntax analysis, to extract sentiments. Parts of speech are identified in each sentence and paragraph and their positions and frequency are converted to vectors (Algorithm 2). The sentiment tags are also converted to vectors (of similar dimension) using a proprietary approach. The two sets of vectors are then matched, using cosine similarity. The method and reasoning for its use, is corroborated by Wijewickrema, Petras, and Dias [7].

```
for each journal
    for each journal entry
        identify journal entry type
        identify mood entities
        identify action entities
        identify event entities
        identify predefined marker(*) entities
        sentiments <- detectSentiments(entities)
        symptoms <- detectSymptoms(sentiments)
        generate statistics for journal entry
        visualize journal entry statistics
    end
    match symptoms with DSM symptoms-diagnostic associations
    generate statistics for entire journal
    visualize statistics for entire journal
    generate tentative evaluation reports
end
```

Algorithm 1: Text analyzer.

```
function detectSentiments(entities, sentimentTags)
    entityVecSet <- convertToVectors(entities)
    sentTagsVecSet <- convertToVectors(sentimentTags)
    sentiments <- cosineSimilar(entityVecSet, sentTagsVecSet)
    return sentiments
end
```

Algorithm 2: Sentiment detection.

Algorithm 3 - Symptoms and diagnosis mapping

The translation of sentiments into symptoms and consequently into a diagnosis, is the essence of the clinician-patient interaction. At the core of this approach, there is framework of association rules and an implementation of the apriori algorithm (Algorithm 3), as argued in a model proposed by Kim and Chung [8]. In SenSym™, the traditional format of an association rule: if conditions then outcome is replaced with: conditions contributes to outcome.

```
function detectSymptoms(sentiments)
    calculate sentiment frequencies
    symptomRules <- apriori(sentiments, support=0.001, confidence=0.5)
    confidence, support, lift <- calculateRulesMetrics(symptomRules)
    optimalRules <- optimizeRules(symptomRules, confidence, support, lift)
    return symptomRules
end
```

Algorithm 3: Symptoms and diagnosis mapping.

Thus, at the core of the module that detects symptoms from a given set of sentiments, there is a method that implements the apriori algorithm, then choose the rules with support and confidence level above a predetermined threshold.

Algorithm 4 - Diagnosis

SenSym™ empowers clinicians by assisting in the monitoring of multiple patients simultaneously. The AI-based diagnosis framework attempts to generate information and evaluation reports, similar in nature to what the clinician would have collected by individually meeting and conversing with each patient (Algorithm 4).

```
function diagnosis (symptoms)
        conditions <- searchRelevantDSM5Rules(symptoms)
        patientDiagnosis <- interpret(conditions)
        return patientDiagnosis
end
```

Algorithm 4: Diagnosis.

The detected symptoms are then fed into another module, which generates diagnosis according to DSM-5 guidelines, as outlined, for example, in Hong and Tan [9].

Upon computing the AI-driven diagnosis, SenSym™ generates a final evaluation report, which is ready to be reviewed and analyzed by a human clinician.

Implementation and reports

SenSym™ is being built using a variety of open-source development tools, combined with implementation of proprietary algorithms. The Python-based Natural Language Toolkit (NLTK) is used to build sentiment classifiers. Training, visualizations, and transformer-based pipelines are implemented in spaCy. A similar use of spaCy is described by Shelar, Kaur, Heda, and Agrawal [10]. Currently in a prototyping stage, all user-facing web-based components are developed in Python, using the Django framework. The journal entries are stored as collections of documents in a MongoDB database.

A clinician-configurable system can generate reports at a variety of stages and formats as desired by a particular practice. They include patient-oriented reports, like tentative diagnostic reports, results of statistical analysis of the journal entries, as well as system functionality and performance. The reports include quantitative data, analytic data, and visualizations in the form of graphic plots. Reports can be viewed on demand by the clinician, but are also automatically generated, to support the monitoring of large numbers of patients simultaneously.

Conclusion

SenSym™ a model for augmenting mental health clinicians' ability to diagnose patients' conditions, was described. The instantly recognizable benefit of SenSym™ is that multiple patients can be monitored and (tentatively) diagnosed and tracked simultaneously. In fact, the scalability of the system is capped only by the availability of computing resources. Since the clinician can monitor many patients simultaneously, several configurable monitoring metrics, and is subscribed to the stream of journal entries, continuous autonomous assessment can follow its course if desired. Conversely, due to the ability to generate interim reports and alerts, the clinician can intervene anytime and take charge of the diagnostic process. SenSym™ © 2021 Isac Artzi, developed by Isac Artzi, is currently in the prototype and proof of concept phase.

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