

Discovering themes in medical records of patients with psychogenic non-epileptic seizures

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ABSTRACT

Introduction Epileptic and psychogenic non-epileptic seizures (PNES) are common diagnostic problems encountered in hospital practice. This study explores the use of unsupervised machine learning in discovering themes in medical records of patients presenting with PNES. We hypothesised that themes generated by machine learning are comparable with the classification by human experts.

Methods This is a retrospective analysis of the medical records in the emergency department of patients (age >18 years) with PNES who underwent inpatient video-electroencephalography monitoring from May 2009 to June 2014 and received a final diagnosis of PNES. Prior to machine learning of written text, we applied a standardised approach in natural language processing to create a document-term matrix (removal of numbers, stop-words and punctuations, transforming fonts to lower case). The words were separated into tokens and treated as if existing within a bag-of-words. A probability of each word existing within a topic (theme) was modelled on multivariate Dirichlet distribution (R Foundation, V.3.5.0). Next, we asked four experts to independently provide a clinical interpretation of the generated topics. When the majority of (≥ 3) experts agreed, it was regarded as highly congruent. Interactive data are available on the web at (<https://gntem2.github.io/PNES/#topic=1&lambda=0.6&term=>).

Results There were 39 patients (74.4% women, median age 35 years with range 20–82). A total of 121 documents were converted to text files for text mining. There were 15 generated topics with 12/15 topics rated as highly congruent. The main themes were about descriptors of seizures and medication use.

Conclusions The findings from machine learning on PNES-related documentation provides evidence for the feasibility of applying machine-learning methodology to analyse large volumes of medical records. The topics generated by machine learning were congruent with interpretations by clinicians indicating this method can be used for screening of medical conditions among large volumes of medical records.

INTRODUCTION

Psychogenic non-epileptic seizures (PNES) are involuntary experiential and behavioural responses to a psychological process which

are not associated with abnormal electrical discharges in the brain.¹ PNES has some features similar to epileptic seizures (ES) and can be mistaken for ES by those who are not familiar with this condition.² The frequency of PNES misdiagnosed as epilepsy is as high as 30%,³ and in some cases diagnosis can be delayed by 7–9 years.^{4,5} As a result, patients with PNES are exposed to iatrogenic harms which might cause significant morbidity and mortality,⁶ as well as contribute to excessive utilisation of scarce medical resources.⁷

Many researchers have been evaluating different approaches to improve the diagnosis and classification of ES versus PNES.^{8–10} These approaches can improve the accuracy of visual discrimination of seizures short term and medium term.¹⁰ In hypothetical treatment scenarios, this newly learnt knowledge did not necessarily translate to logical decision-making in the use of medication for the management of PNES.¹¹ The lack of congruence between knowledge and clinical practice has led us to consider different approaches for understanding the thinking process at the time of the management of patients with PNES in the emergency department. We have chosen the emergency department as it is the first point of contact between the patients and the doctors in the hospital setting. One way of understanding the thinking at the time of the initial management is to employ a natural language-processing approach to analyse the written material by doctors working in the emergency department. Probabilistic topic modelling is a machine-learning method that generates topics or discovers themes among a collection of documents. This task is performed without the aid of an observer hence, the method is listed as unsupervised.^{12,13} We hypothesised that thematic analysis (topic modelling) permits an ‘unbiased’ approach to discover the themes documented in medical records



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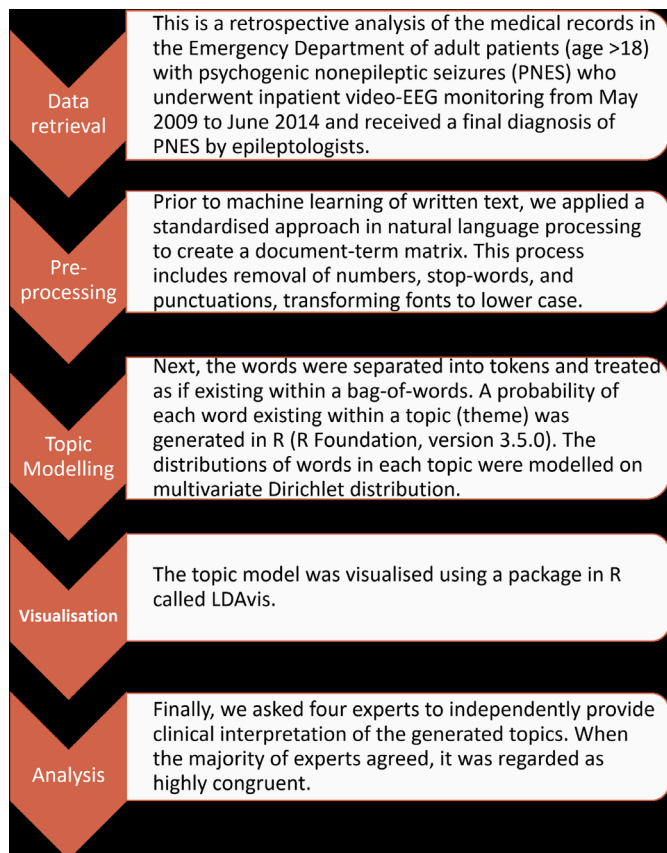


Figure 1 The flowchart illustrates the key steps in data collection and analysis. EEG, electroencephalograph.

in the emergency department on patients with PNES. We sought to explore the congruence between the topics generated by machine learning and interpretation by human experts.

METHODS

Subjects

We reviewed all medical records of patients who underwent inpatient video electroencephalography monitoring (VEM) from May 2009 to June 2014. This study included adult patients (age ≥ 18 years) with a final diagnosis of PNES. The consensus opinion of at least two epileptologists based on history, examination and investigations including the video-electroencephalograph was required for the final diagnosis. Those patients with a mix of both ES and PNES were excluded. The methodology was detailed in our previous publications.^{7 14}

Data retrieval, pre-processing and analysis

The medical records pertaining to clinical notes and observations during the emergency department visits were manually transcribed into plain text format. These documents were then compiled into a collection of documents (corpus). We used tm package (in R Foundation for Statistical Analysis V.3.5.0) for the pre-processing of the data.¹⁵ These steps included tokenisation where words in a sentence were separated so that they existed



Figure 2 Wordcloud of frequent words in documents. The size of the words represents the frequency of word appearance in documents. eeg, electroencephalograph; gcs, Glasgow Coma Scale; gtc, generalised tonic-clonic seizure; hopc, history of presenting conditions; loc, loss of consciousness; mas, Melbourne ambulance system; nad, no abnormality detected.

within a bag-of-words (unigram analysis). There was no importance placed with regards to the order of words in the documents. The words in the document-term matrix were further processed to enhance the accuracy of subsequent analysis. Phrases considered to be important were paired together. Additionally, a 'stop word' filter was used to remove common English words that provide little information (eg, 'I, he, am, was, don't and so on'). Next, we used the term frequency-inverse document frequency to prioritise important terms. This enhances the detection of meaningful terms and downweights common but unimportant terms that were not previously removed. Topic models were then generated from the corpus of these documents to extract 'hidden themes'. This step was performed using the Latent Dirichlet Allocation algorithm via the topicmodels package in R.¹⁶ Finally, the topics and words related to each topic were visualised using the LDAvis package for R (interactive data available on the web <https://gntem2.github.io/PNES/#topic=1&lambda=0.6&term=>).¹⁷ The clinical interpretations of the topics were provided by four experienced neurologists (US, TP, AF, HR). Each rater was asked to independently provide three possible interpretations of each topic. These interpretations had to be in the form of a single word; they were not asked to provide a description of the topic. If three or four experts provided a similar interpretation of a topic, it was considered to be highly congruent. When the agreement was found between two

Selected Topic:

Slide to adjust relevance metric:⁽²⁾ $\lambda = 0.6$

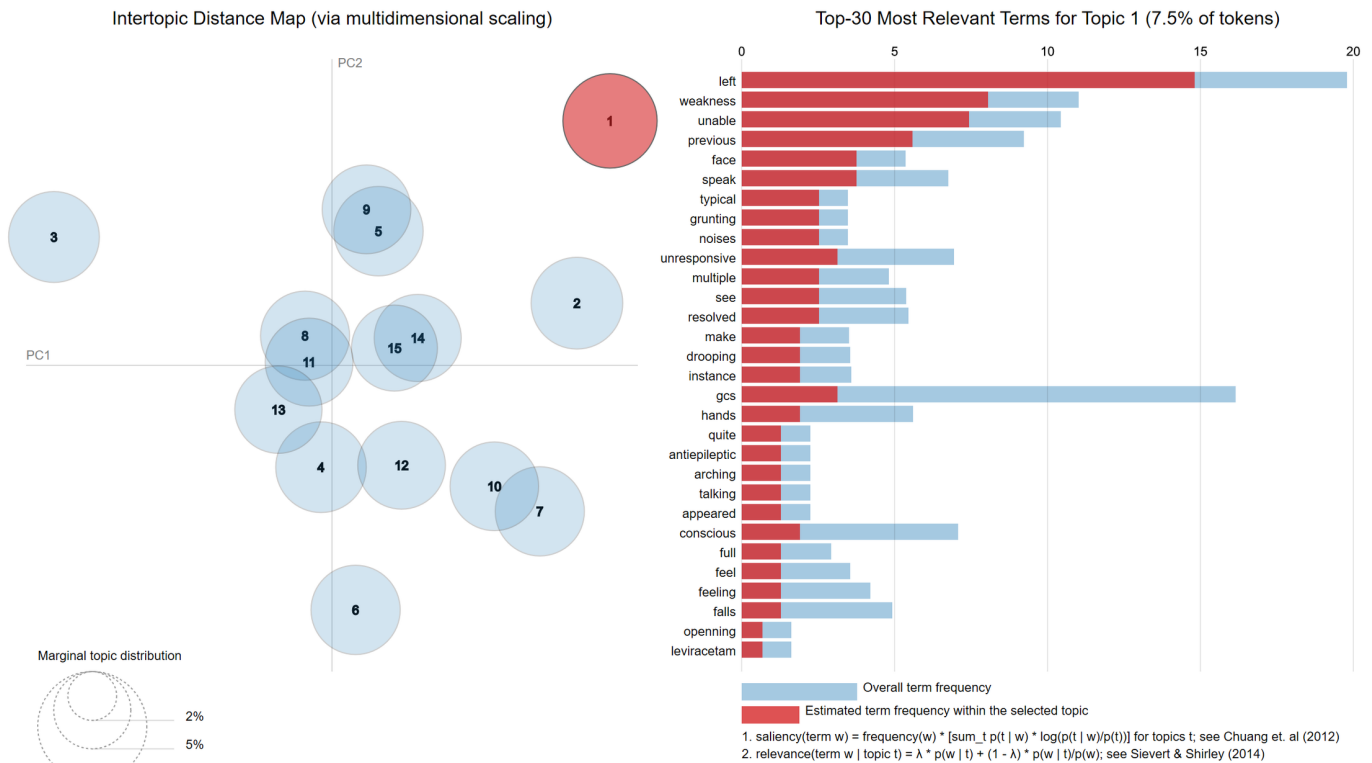


Figure 3 Topic model 1 and top 30 words belonging to this topic. The grouping of words in this topic suggests descriptions of the phenomenology of the clinical observation in the emergency department. The terms used to describe this topic by the raters in table 1 were: phenomenology (rater 1), semiology (rater 2), phenomenology (rater 3), semiology (rater 4). The raters were congruent in their interpretation of the theme of this topic

experts only, the results were rated equivocal. Figure 1 highlights the key steps in data collection and analysis.

RESULTS

A total of 39 patients fulfilled the inclusion criteria. Women constituted 74.4% of the cohort (29 cases). The median age of the cohort was 35 years (range 20–82) and the median duration of the condition was 3 years (range 1–432 months). A total of 121 documents were analysed and used in this analysis. Fifteen topics (themes) were generated based on analysis of the harmonic mean. Frequent words appearing in the document are displayed as wordcloud in figure 2. Words used in the description of ES were frequently observed among these patients with PNES and included ‘tonic’, ‘clonic’, ‘gtc’ (abbreviation for generalised tonic–clonic seizure), ‘phenytoin’, ‘midazolam’ and ‘clonazepam’. Words suggestive of PNES were used rarely (‘pseudoseizure’).

The results of the topic modelling are displayed on the web to allow user interaction (<https://gntem2.github.io/PNES/#topic=1&lambda=0.6&term=>). The user can query the topic by clicking on the topic number or number under the tab ‘Selected Topic’. By hovering over words, the topics in which the terms exist will appear. Screenshots of the web display are available

as figures 3 and 4. Table 1 summarises the interpretation of each topic independently by the four experts. Agreement among the experts was observed in 12/15 topics. An example of agreement on a topic is illustrated in figure 3. The grouping of words in this topic suggests a description of the clinical observation in the emergency department. The terms used to describe this topic were phenomenology (rater 1), semiology (rater 2), phenomenology (rater 3), semiology (rater 4). For the remaining 3/15 topics, the agreement was equivocal (topics 5, 8 and 9). An example of a topic with a lack of agreement among the raters is illustrated in figure 4. The grouping of words in this topic suggests a description of the type of movement and that these movements have been occurring over months. The terms used to describe this topic were background history (rater 1), type of movement (rater 2), seizure-valproate (rater 3), conscious state (rater 4).

Table 2 provides the frequent terms observed in the 15 topics and the percentage of tokens (words). The data for topics 1 and 5 are the same as those in figures 3 and 4. It is recommended that the reader visit the interactive web page to explore the relationship among words as well as their appearances in the topic. For example, the term ‘status’ appears in topics 3, 5 and 12, and ‘ambulance’

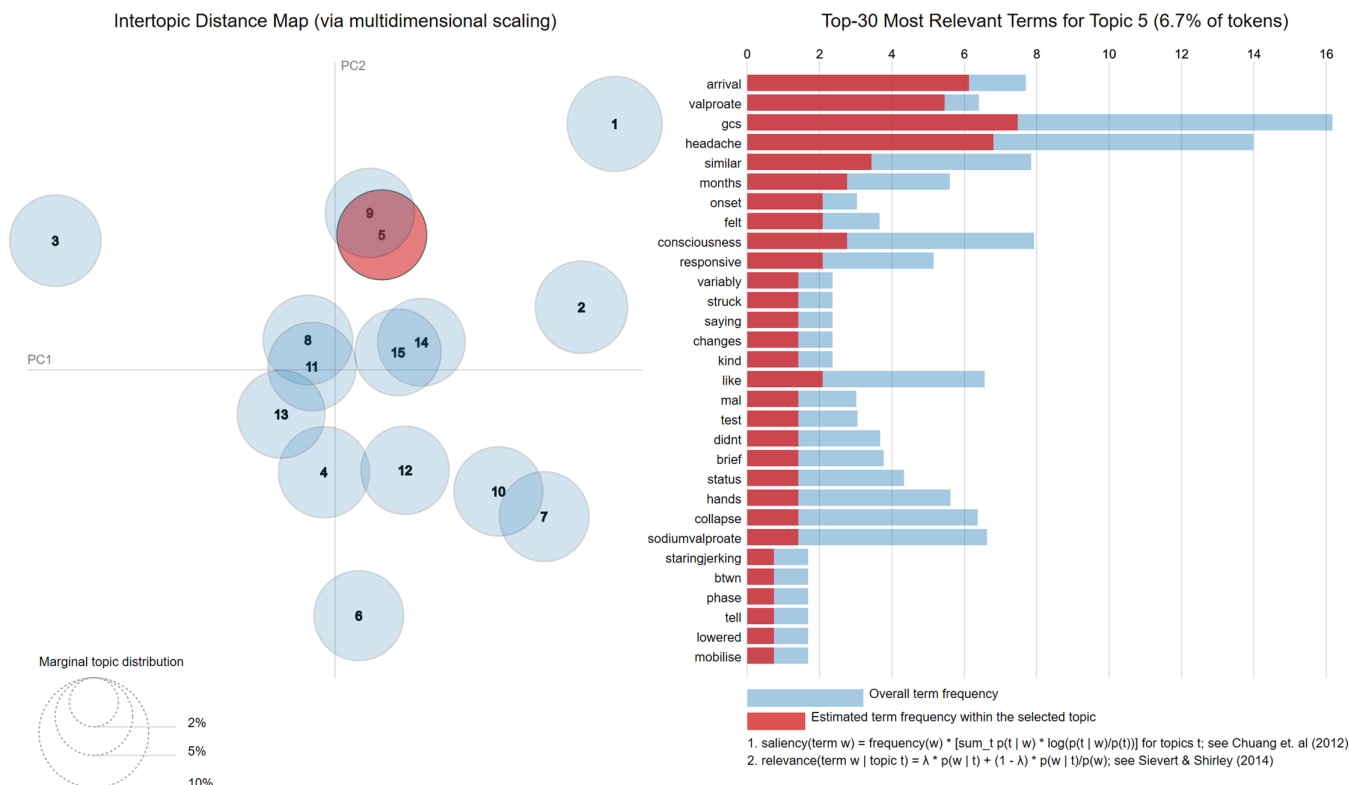
Selected Topic: Slide to adjust relevance metric:⁽²⁾ $\lambda = 0.6$ 

Figure 4 Topic model 5 and top 30 words belonging to this topic. The grouping of words in this topic suggests descriptions of the type of movement and that these movements have been occurring over months. The terms used to describe this topic by the raters in table 1 were: background history (rater 1), type of movement (rater 2), seizure-valproate (rater 3), conscious state (rater 4). The raters did not agree in their interpretation of the theme of this topic.

appears in topics 2, 7, 8 and 11, but 'arching' only appears in topic 1.

DISCUSSION

In this proof-of-concept study, we have demonstrated the use of unsupervised machine-learning methods to identify different themes in medical records of patients with PNES. The majority of these themes were interpreted as congruent by four experts. This method is efficient in gaining quick comprehension of the medical records. Furthermore, topic models provide an insight into the thinking process of health professionals at the time of initial management. While the method is applied to a small dataset from the scanned medical records here as proof of concept, it is scalable to large volumes of medical data available in electronic medical records and for any disease process. The topics generated by machine learning were congruent with interpretations by clinicians indicating this method can be used for screening of medical conditions among large volumes of medical records in clinical practice.

Natural language processing (NLP), also described as text mining, is a way of converting unstructured text into a structured format paving the way for automated analysis.

With the increasing use of electronic medical records, the need for NLP to handle large volumes of medical information has also risen.¹⁸ There are three main approaches adopted in NLP. The machine-learning approach involves fully automated text processing, whereas the rule-based approach depends on predefined rules by experts. The hybrid approach is a combination of the two methods.¹⁹

The topic modelling approach has been previously adopted by medical researchers to identify patterns of comorbid medical conditions,²⁰ detect medication non-compliance using posts in patient forums,²¹ describe public health information from the social media,²² cluster analysis of large biomedical datasets²³ and predict inpatient clinical order patterns.²⁴ The method used in this study assigns words to topics (themes) based on the probability of membership of the topic but the clinical interpretation of the topic is still needed. We approached this by asking four experts to assign meaning to the collection of words in each topic. This aspect of the work can be prone to bias as different experts can interpret the collection of words in different ways or use various words to convey a similar meaning. For example, the terms 'phenomenology' and 'semiology' were used to describe observations on seizures. A drawback of topic modelling

Table 1 Clinical interpretation of the 15 topics by four raters

Topic	Rater 1	Rater 2	Rater 3	Rater 4	Rater 1	Rater 2	Rater 3	Rater 4	Rater 1	Rater 2	Rater 3	Rater 4	Rater 1	Rater 2	Rater 3	Rater 4	Interpreted theme 3
1	Phenomenology of seizure	Semiology	Seizure phenomenology	Semiology	Phenomenology of seizure	Semiology	Seizure phenomenology	Semiology	Phenomenology of seizure	Semiology	Seizure phenomenology	Semiology	Phenomenology of seizure	Semiology	Seizure phenomenology	Seizure phenomenology	Conscious state
2	Post-ictal phenomenology	Findings on examination	Examination	Semiology	History of event	Findings on examination	Left-sided weakness	Semiology	History of event	Findings on examination	Left-sided weakness	Semiology	History of event	Findings on examination	Anxiety	Severity	Severity
3	Phenomenology	Type of movement	Tonic-clonic seizure	Generalised	Phenomenology	Type of movement	Tonic-clonic seizure	Semiology	Phenomenology	Type of movement	Tonic-clonic seizure	Semiology	Phenomenology	Awareness	Tonic-clonic seizure	Semiology	Semiology
4	Phenomenology	Treatment	Seizure-phenytoin	Medication	Phenomenology	Awareness	Seizure-phenytoin	Semiology	Phenomenology	Awareness	Seizure-phenytoin	Semiology	Phenomenology	Awareness	Seizure-phenytoin	Severity	Severity
5	Background history	Type of movement	Seizure-valproate	Conscious state	Background history	Awareness	Seizure-valproate	Medication	Background history	Awareness	Seizure-valproate	Medication	Background history	Awareness	Seizure-valproate	Recurrence	Recurrence
6	Treatment	Treatment	Anti-epileptic medications	Medication	Post-ictal signs	Treatment	Anti-epileptic medications	Generalised	Post-ictal signs	Treatment	Anti-epileptic medications	Generalised	Post-ictal signs	Treatment	Anti-epileptic medications	Severity	Severity
7	Phenomenology	Post-ictal phase	Post-ictal	Recurrence	Treatment	Treatment	Post-ictal midazolam	Semiology	Treatment	Treatment	Post-ictal midazolam	Semiology	Treatment	Examination findings	Post-ictal behaviour	Conscious state	Conscious state
8	Consciousness	Comorbidity	Vasovagal	Semiology	Consciousness	Treatment	Confusion	Semiology	Consciousness	Treatment	Confusion	Semiology	Consciousness	Treatment	Fever	Severity	Severity
9	Preceding seizure history	Treatment	Headache	Semiology	Preceding seizure history	Differential diagnosis	Syncope	Medication	Preceding seizure history	Differential diagnosis	Syncope	Medication	Preceding seizure history	Awareness	Keppra	Recovery	Recovery
10	History prior to seizure	Responsiveness	Blackout	Conscious state	History prior to seizure	Responsiveness	Tremor	Semiology	History prior to seizure	Responsiveness	Tremor	Semiology	History prior to seizure	Responsiveness	Headache	Recovery	Recovery
11	History prior to seizure	Ambulance assessment	Ambulance assessment	Semiology	History prior to seizure	Awareness	Fall	Conscious state	History prior to seizure	Awareness	Fall	Conscious state	History prior to seizure	Awareness	Conversion	Post-ictal	Post-ictal
12	Phenomenology of seizure	Clinical features	Observations in resuscitation bed	Semiology	Phenomenology of seizure	Type of movements	Observations in resuscitation bed	Generalised	Phenomenology of seizure	Type of movements	Observations in resuscitation bed	Generalised	Phenomenology of seizure	Awareness	Observations in resuscitation bed	Severity	Severity
13	Consciousness	Diagnosis	Airway assessment	Semiology	Consciousness	Duration	Agitation	Recovery	Consciousness	Duration	Agitation	Recovery	Consciousness	Investigations	Assault	Provoked	Provoked
14	Treatment	Post-ictal phase	Post-ictal	Semiology	Phenomenology	Treatment	Post-ictal	Medication	Phenomenology	Treatment	Post-ictal	Medication	Phenomenology	Responsiveness	Post-ictal	Post-ictal	Post-ictal
15	Consciousness	Airway management	History	Conscious state	Pre-ictal history	Investigations	History	Conscious state	Pre-ictal history	Investigations	History	Conscious state	Pre-ictal history	Awareness	History	Recovery	Recovery

The raters provided three possible interpretations for each topic. Shading represents congruent themes. PNES, psychogenic non-epileptic seizures.

Table 2 Top 30 most salient words for 15 topics

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8	Topic 9	Topic 10	Topic 11	Topic 12	Topic 13	Topic 14	Topic 15
Left	Lower	Clonic	Phenytoin	Arrival	Clonazepam	Episode	Small	Post	Episode	Ambulance	Twitching	Activity	Postictal	States
Weakness	Arm	Tonic	Fit	Valproate	Diazepam	Postictal	Limb	Right	Blackouts	Ceased	Neck	Seizure type	Sodium valproate	Period
Unable	Examination	Selfresolve	Limb	Gcs	Midazolam	Past	Brain	Body	Period	Csl	Prior	Stopped	Medication	Trolley
Previous	Without	Epilepsy	Blood	Headache	Gtc	Jerking	Fevers	Said	Epileptic	Drowsy	Discharge	Mas	Injuries	Airway
Face	Memory	Place	Arms	Similar	Describes	Injury	Admission	Levetiracetam	Floor	Head strike	Response	Reports	Contact	Frequent
Speak	Right	Etoh	Mas	Months	Loading	Hour	Developed	Came	See	Similar	Loc	Spontaneously	Slurred	Urine
Typical	Agitated	Level	Movements	Onset	Arrived	Examination	Supported	Found	Used	Confused	Insulin	Pseudo seizure	Stimuli	Disorder
Grunting	Falls	Room	Settled	Felt	Hour	Loc	Poor	Side	Triage	Regularly	Gtc	Intermittent	Generalised	Happened
Noises	Work	Anxious	Unconscious	Consciousness	Sats	Sitting	Description	Short	Beers	Better	Responsive	Guedel	Consciousness	Plns
Unresponsive	Associated	Aware	Reports	Responsive	Frothing	Shakes	Started	Woke	Become	Reassurance	Decision	Fingers	Unknown	Conversation
Multiple	Previous	Regained	Slurred	Variably	Fit	Duration	Mas	Sob	Tremor	Can	Tolerating	Call	Movements	Still
See	Ambulance	Times	Opening	Struck	Whole	Resus	Meds	Treated	Looked	Way	Blue	Xray	Red	Investigation
Resolved	Hold	Status	Holding	Saying	Phenytoin	Midazolam	Taking	Diagnosed	Two	Complaints	Slowly	Collapsed	Funny	Regain
Make	Earlier	State	Altered	Changes	Ground	Calling	Saw	Headache	Legs	Med	Commenced	Flat	Requiring	Fell
Drooping	Event	Total	Feeling	Kind	Lying	Behaviour	Vasovagal	Repeated	Turns	Conscious	Applied	Assault	Increase	Arrived
Instance	Ear	Ground	Fell	Like	Jerking	Displays	Drowsy	Syncope	Awake	Come	Lasts	Prolonged	Like	Conscious
Gcs	Worse	Meds	State	Mal	Fall	Legs	Self	Complained	Responding	Asked	Focal	Taken	Unresponsive	Gags
Hands	Claims	Pupils	Sitting	Test	Legs	Bit	Rolling	Looking	Became	Impression	Gastro	Fitted	Hands	Opens
Guite	Anxiety	Resists	Shakes	Didn't	Arms	Current	Depression	Maintained	Activity	Became	Drowsiness	State	Prior	Attempted
Antiepileptic	Combined	Handed	Leg	Brief	Cyanosis	Gcs	Alert	Associated	Arriving	Focal	Fitted	Meds	Arm	Agitation
Arching	Episode	Notify	Past	Status	Husband	Feel	Mouth	Move	Awake	Reactive	Hours	Squeezes	Spasm	Converse
Talking	Left	Disorientated	Shook	Hands	Violently	Recovery	Became	Loaded	Man	Dusky	Observed	Discs	Close	Never
Appeared	Move	Quiet	Injuries	Collapse	Returned	Collapse	Ground	Hours	Security	Equivocal	Resus	Aggressive	Investigate	Develops
Conscious	Weakness	Difference	Hips	Sodium valproate	Sounds	Focal	Confused	Leg	Interact	Daughter	Apnoea	Definitely	Note	Coryzal
Full	Fall	Rapid	Lots	Staring	Speaking	Nasal	Gcs	Total	Ordination	Labels	Gym	Verbal	Frustrated	Seat
Feel	Recovery	Support	Padded	Btwn	Sol	Slumped	Work	Duration	Headache	Stayed	Cuff	Phx	Occurred	Visible
Feeling	Unknown	Enroute	Lifting	Phase	Contractions	Surgery	Ambulance	Still	Mildly	Violent	Fists	Oblivious	Grazing	Drop
Falls	Epilepsy	Aura	Big	Tell	Pregnancy	Vitals	Light	Speak	Nature	Causing	Inflating	Sure	Breath	Pillow
Opening	Floor	Stop	Remembering	Lowered	Rash	Vomiting	Clonus	Consciousness	Far	Admissions	Protruding	Witness	Surrounding	Crushed
Levetiracetam	Fit	Immediately	Requested	Mobilise	Sats	Tpp	Circulation	Increased	During	Conversion	Saliva	Expression	Spincter	Ct brain

The words are ordered from top to bottom in terms of probability of belonging to the topic.

is that it is not a classification tool and cannot separate PNES from ES. Machine-learning methods for classification include generalised linear model, naive Bayes classification, tree-based approaches, support vector machine and neural network. These methods were not used here as they are not adept at evaluating the thematic structures of the documents we used in the study.

This study provides useful insights into how doctors in the emergency department view or conceptualise seizures among patients presenting with PNES. This approach allows one to postulate that the clinicians were considering the diagnosis of ES rather than PNES. This was inferred from the frequent use of descriptive semiological terms of ES such as ‘tonic’ and ‘clonic’ in the documents. Furthermore, ‘epilepsy’, ‘epileptic’ and ‘GTC’ (implying generalised tonic–clonic seizure) appeared more often in topics (2, 3, 6, 10, 12), whereas ‘pseudoseizure’ featured only once in topic 13 indicating the focus of doctors was ES. Topic 1 is a collection of terms describing the seizure semiology, but descriptions of terms relating to PNES such as ‘arching’ appeared only once. Other typical terms used in the description of PNES such as ‘pelvic thrusting’, ‘eye closure’, ‘head-shake’, ‘asymmetry’ and ‘asynchrony’ were not observed at all. This view is consistent with the frequent mention of antiepileptic medications used in the treatment of seizure and status epilepticus; these medications include phenytoin, clonazepam, diazepam and midazolam (topic 6 on acute treatment). The frequent use of the term ‘loading’ is a likely reference to intravenous loading of phenytoin in status epilepticus and appeared in topics 6 and 14. Aligned with that, ‘status’ appeared in topics 3 and 5 suggesting that the doctors were considering the diagnosis of status epilepticus. Misdiagnosis of non-epileptic psychogenic status as true status epilepticus leads to inappropriate interventions resulting in considerable morbidity, healthcare utilisation cost and even mortality.⁷ These observations raise the need to improve education on seizure diagnosis among medical professionals.^{8–10} Related to this matter is the need to document observations of these events in free-text form avoiding the use of jargon. This is a potential trap with electronic medical record whereby commonly used phrases are saved for repeated use. This situation may lead to homogenising of neurological descriptions.

What we have illustrated here is only one use of topic modelling with medical records in the setting of the emergency department. This approach does not have to be restricted to this location or neurological disorders. It can be used for other medical conditions and in any location. Furthermore, the method can also be applied to qualitative data from surveys or suggestions from team-building meetings.

Limitations

There are several limitations to this study. The unigram (bag-of-words) approach we adopted does not arrange words according to their meanings. In this approach, each word is treated equally and the relationships among

words are not explored. In order to overcome this limitation, we used word combinations when we considered the sequence of words to be important (example: ‘status epilepticus’). An alternative method is bigram approach. However, the package ‘topicmodels’ does not handle the bigram analysis.¹⁶ Additionally, the use of stop-word filter denotes that a negative meaning of the sentence may not be discovered in the themes (example: ‘no incontinence’ vs ‘incontinence’). At the time of the data acquisition, electronic medical records were not operational in our institution. The data were transcribed from scanned medical records. This task introduced a potential source of error with manual copying of texts. It is hoped that the introduction of electronic medical records will render the analysis of written text easier. Another limitation of this study is that we have only studied patients with PNES who had VEM. This approach was undertaken to ensure the analysis was related to patients with conformed PNES. The drawback of this approach is that patients with PNES who did not have VEM could not be captured. Hence, it is possible that more severe cases of PNES were included in the study introducing potential bias. Furthermore, our study did not include patients presenting with ES. As such the results cannot be directly extrapolated to all patients presenting with seizures.

CONCLUSIONS

Our study shows that unsupervised machine learning can be used to objectively and efficiently evaluate large chunks of unsorted medical data. This provides a good starting point for subsequent deeper analysis by highlighting key themes. Additionally, our study also has implications for the understanding of the thinking process of healthcare workers at the time of evaluating patients presenting with seizures. The analysis of a larger sample of patients presenting with ES and PNES would be useful to detect different topics between the two seizure types in order to design a way of improving the diagnosis based on the topic modelling approach.

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