THE PRIMARY CARE COMPANION FOR CNS DISORDERS

Supplementary Material

- Article Title: Phenotyping of Review-Of-Systems Responses to Differentiate Functional Seizures From Epilepsy
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UCLA Medical Center

Neurological Services

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REVIEW OF SYSTEMS

Please place a checkmark if you currently have any of the following symptoms. (Disregard the bold headings in quotes on the left. They are for administrative purposes only):

1. "constitutional"	fever	weight loss	fatigue				
2. "eyes problems"	blurred vision	double vision	loss of vision				
4 1	eye pain	eye redness	eye dryness				
3. "ear/nose/throat"	trouble hearing	ringing in ear(s)	dizziness (vertigo)				
	loss of balance	ear pain	ear discharge				
	hoarseness	trouble swallowing	slurred speech				
4. "cardiovascular"	chest pain	irregular heart beat	fast heart beat				
	limb swelling	limb pain on walking	fainting				
5. "respiratory"	trouble breathing	chronic cough	coughing blood				
6. "gastrointestinal"	indigestion	heart burn	abdominal pain				
	nausea	vomiting	regurgitation				
1	diarrhea	constipation	bloody stools				
7. "genitourinary"	incontinence	pain on urination	blood in urine				
8. "musculoskeletal"	muscle pain	muscle cramp	muscle twitches				
	loss of muscle bulk	neck pain	back pain				
	joint pain	joint stiffness	joint swelling				
9. "skin & breast"	numbness	tingling	discoloration				
	hair loss	nail changes	sweating changes				
10. "neurologic"	headache	face pain	face numbness				
	weakness	tremors	clumsiness				
	blackouts	trouble with memory	trouble concentrating				
11. "psychiatric"	hallucinations	feeling depressed	trouble sleeping				
	suicidal thoughts	inappropriate crying	inappropriate laughing				
12. "hematologic/lymphatic"	abnormal bleeding	nose bleeds	lumps or swellings				
13. "allergic/immunologic"	skin rash	joint pain	dry eyes &/or dry mouth				
14. "endocrine"	excessive thirst	heat or cold intolerance	excessive urination				
Person completing questionnarie		Relationship to patient					
For office use: This questionnaire may be co later be made to this information by a signed	mpleted by the patient, relatives or a and dated statement by the treating	ancillary staff <u>provided that it is signed an c</u> 7 physician, designating location of the info	lated by the treating physician. (Reference ma rmation, date obtained and any subsequent				
changes./	· · ·						
Physician's Signature		Date					

Supplementary Figure 2. Methods

In KM, the number of clusters, *k*, is pre-selected and the algorithm is initiated by *k*-data points from *n*-patients being randomly selected as initial medoids [1]. The percent of responses that differs from that medoid is called the Hamming distance [2]. The other (*n-k*) patients are assigned to each medoid based on the minimum Hamming distance. With these assignments, a new set of *k*-medoids are set based on the median response within each cluster. K-medoids is preferred over k-means for categorical data. The algorithm of assignment to clusters is repeated iteratively until convergence. We evaluated KM for pre-defined *k* ranging from 2 to 70. The upper limit of 70 was chosen to facilitate statistical identifiability of representing 78 ROS symptoms into a slightly smaller number of clusters. Validation data was assigned to the closest medoid using a Hamming distance.

In LCA, the number of latent classes, *k*, also is pre-selected and the algorithm is initiated by data points being randomly assigned to *k*-clusters [3]. Cluster membership was determined based on a sequential expectation-maximization (EM) algorithm. In the expectation (E)-step, the expected cluster sizes and assignments are calculated conditional on the definitions of how each symptom probabilistically contributes to the likelihood that each patient lies within each cluster. In the maximization (M)-step, those definitions are modified to maximize the likelihood of the expected cluster assignments determined in the E-step. The E and M steps are applied sequentially until convergence in the MDLV toolbox [4]. Within this convergence method, cluster membership is probabilistic, whereas after convergence, patients were assigned greedily the cluster with highest probability of membership. We varied *k* from 2 to 70, similar to KM. Validation data was assigned to the cluster with the highest membership probability. Supplementary Table 1. Exact performance of each method evaluated using leave-one-out cross-validation. Confidence intervals estimated with binomial exact statistics or, for the area under the receiver operating curve (AUC), the Wald method. Abbreviations: Logistic regression based on individual symptoms (LR), LR with recursive feature elimination (LR-RFE), k-medoids (KM), principal component analysis (PCA), independent component analysis (ICA), latent class analysis (LCA), density-based spatial clustering of applications with noise (DBSCAN), estimate (Est), confidence interval (CI), predictive value (PV).

	Accuracy		Sensitivity		Specificity		ES-PV		DS-PV		AUC	
Method	Est (%)	95% CI	Est (%)	95% CI	Est (%)	95% CI	Est (%)	95% CI	Est (%)	95% CI	Est (%)	95% CI
LR	76	72-81	88	84-92	35	25-45	82	78-87	46	34-58	62	53-69
LR-RFE	75	71-80	91	87-94	24	15-33	80	76-85	42	28-56	64	55-72
Total	79	75-84	97	95-99	17	9-25	80	75-85	64	44-84	72	65-78
КМ	78	74-83	97	95-100	13	6-21	79	75-84	60	40-80	69	61-76
PCA	79	74-83	85	81-90	55	45-66	87	82-91	53	42-63	74	66-80
ICA	47	41-52	35	30-41	87	79-94	90	84-96	28	22-34	67	60-74
LCA	80	76-85	96	93-98	28	19-39	82	77-86	65	50-80	72	65-79
DBSCAN	77	67-87	100	100-100	0	0-0	77	73-82	-	-	69	61-76

In DBSCAN, we eschew the concept of pre-defining the number of clusters and summarizing a cluster by a central point or pattern of responses [5]. Instead, we pre-define an epsilon, ε , and a minimum number of points, *m*, needed to define a cluster. We randomly select data points and assign any data points within a Hamming distance of ε to the same cluster. We extend the definition of that cluster by iteratively extending the cluster to include all data points within ε of the points within the presumptive cluster. This iterative process stops when there are no more points within ε of the points within the presumptive cluster and the cluster is maintained if it includes at least *m* points. If the cluster is too small, the data points are assigned to the "outlier" cluster. This process of cluster determination is repeated for each data point. We vary ε from the minimum non-zero to maximum observed Hamming distance in the dataset. We vary *m* from 2 to the entire size of the entire dataset, minus one point. If validation data was within ε of data within a cluster, then it was assigned to that cluster but otherwise it was considered an "outlier."

In PCA and ICA, the hypothesis is that the 78 ROS symptoms can be summarized using a lower number of components based on patterns in similar responses across multiple symptoms. Components are interpreted as combinations of similar symptoms that may be more interpretable than individual symptoms (e.g. a pain component including musculoskeletal, joint, and head pain). In PCA, the first component is determined based on the single vector that maximizes the variance of the data when projected onto that vector [6]. Each subsequent component is determined based on the vector perpendicular to all prior components that maximizes the remaining variance of the projected data. In ICA, the components are initialized with the PCA components [7]. These components are modified

iteratively by the FAST ICA algorithm to maximize the statistical independence of components

[7], as compared to the requirement of being perpendicular. This tends to lead to a sparse

representation of the data. Validation data was projected onto these learned components and

did not contribute to the determination of components.

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