Parkinson's disease cluster analysis

Pablo Martinez-Martin^a, Jesse Mu^b, Concha Bielza^c, Pedro Larrañaga^c

^aArea of Applied Epidemiology, National Centre of Epidemiology and CIBERNED, Carlos III Institute of Health, Madrid, Spain
^bDepartment of Computer Science, Boston College, Chestnut Hill, Massachusetts, USA
^cComputational Intelligence Group, Polytechnic University of Madrid, Madrid, Spain

Abstract

Background This is the background.

Methods These are methods. Findings These are findings.

Interpretation This is interpretation.

Funding This is funding.

1. Introduction

2. Methods

2.1. Statistical analysis

Out of the 951 patients in the study, we used listwise deletion to exclude 50 patients due to missing measurements in the variables of interest, resulting in 901 remaining patients. All symptoms were scaled to z-scores ($\mu=0$, $\sigma=1$) before clustering, and unscaled afterwards. Analysis was conducted in R 3.2.4 (www.r-project.org).

2.1.1. Cluster analysis

k-means was used for cluster analysis. We performed two analyses on the patients in the dataset: the first on the nine aggregate nonmotor symptom domains and the four motor symptoms, and the second on the 30 individual nonmotor symptoms collected with the four motor symptoms. Complete-linkage hierarchical clustering on the 30 nonmotor symptoms was also performed to observe the categorization of symptoms.

2.1.2. Determining k

Various formal measures were used to determine the optimal number of clusters for the dataset. First, the optimal k according to the Gap Statistic and the 1-standard-error method 1 was k = 4 (Figure 1). Second,

stability measures of the clValid R package² stability are 2, 6, and 8 (Figure 2), there appeared to be consensus that k = 4 is a locally-optimal number of clusters which supported the gap statistic result.

although the globally-optimal clusters reported from

Other cluster validation methods (SSE scree plot, minimum average silhouette width) generally suggested 2 clusters. As a consequence, k = 2,3,4 was tried, where k = 2,3 simply divided the data uninformatively into groups with varying levels of overall PD severity. Thus k = 4 was selected to offer a good blend of model fit, informativeness, and parsimony.

2.1.3. Interpretation

For the clustering on nonmotor domains, we displayed the distribution of each symptom for the four clusters using boxplots, which allowed us to visualize the center and spread of each cluster. Since the number of variables was larger for the clustering on the individual symptoms, we visualized results for the second analysis with a heatmap. Finally, for the hierarchical clustering on the symptoms themselves, we displayed results in a dendrogram and clustered the symptoms into four interpretable clusters.

For each symptom in both clusterings, we used one-way ANOVA to test the equality of symptom means across the clusters found, using Bonferroni correction for multiple testing with corrected p < 0.05 considered significant. Differences among pairwise clusters were tested post-hoc using Tukey's range test.

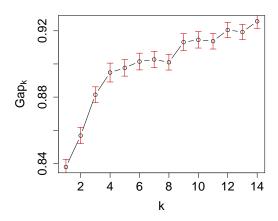


Figure 1: Plot of gap statistic versus number of clusters with k-means on 100 bootstrapped samples. Error bars are standard error. Per the method described in 1 , 4 is the smallest k such that $\operatorname{Gap}(k) \ge \operatorname{Gap}(k+1) - \operatorname{se}_{k+1}$.

3. Results

3.1. Clustering with nonmotor domains

k-means clustering on the nine nonmotor domains and the four motor symptoms found four clusters, available in Table 1 with boxplots in Figure 3. Cluster means for all symptoms were found to be statistically different, with specific pairwise differences noted in the table.

Cluster 1 (n = 406) patients were mildly affected in all domains.

Cluster 2 (n=189) patients were severely affected in nonmotor domains but mildly affected in motor domains (Nonmotor-Dom), cluster 3 (n=221) patients were severely affected in motor domains but mildly affected in nonmotor domains (Motor-Dom), and cluster 4 (n=88) patients were severely affected in all domains. Statistics for variables not used in the clustering were explored in Table 2.

3.2. Clustering with nonmotor symptoms

3.3. Hierarchical clustering on symptoms

Hierarchical clustering on the 30 nonmotor symptoms and the four motor symptoms produced the dendrogram in Figure 4. Predictably, symptoms in the same nonmotor domains tended to cluster together, with the exceptions of diplopia (domain 4), drowsiness (domain 2), and the symptoms in domain 9 (miscellaneous). Notably, tremor was the most dissimilar symptom, occupying a single branch at the top of the tree.

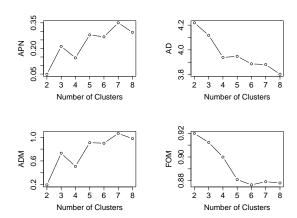


Figure 2: Average proportion of non-overlap (APN), average distance (AD), average distance between means (ADM), and figure of merit (FOM) stability measures 3,4 . Statistics should be minimized; notice the local optima at k = 4 for APN, AD, and ADM.

4. Discussion

k-means clustering on this Parkinsons' Disease data set reveals clusters that confirm previous findings in the field, mainly van Rooden et al. and the identification of four subtypes of Parkinson's disease: mild, nonmotor-predominant, motor-predominant, and severe. van Rooden's work was done with a separate dataset using a different modeling method (expectation-maximization), and this investigation independently confirms these subtype classifications. Unlike van Rooden, mean disease durations differences do exist between subtypes 1 (mild) and 4 (severe), likely due to further development of the disease, although the differences between 2 and 3 (nonmotor/motor predominated) subtypes are insignificant (Table ??), suggesting different developmental paths of the disease.

Overall, little information was found in pdonset, durat_pd, or current age, according to Tables ?? and ??. Mean ages were similar for subgroups 1, 2, and 3 (p > 0.05), but different for the severe subtype 4, which makes sense given that patients in 4 also have longer disease durations. Specifically, clusters 1 and 4 seem to be phenotypically quite similar, except at different stages of disease progression, given cluster 4's higher age and durat_pd scores.

However, clusters 2 and 3 clearly show different disease progression, one in the motor direction, and one in the nonmotor. Both groups have similar age, pdonset, and durat_pd scores, but differ wildly in symptomatic expression. Cluster 2 is dominated by a high prevalence of nonmotor symptoms, such as nms_d2, nms_d3,

Table 1: Summaries of clustering on nonmotor domains. Bold indicates the highest score for that symptom out of the four clusters.

Cluster	1	2	3	4
n	406 (44.9%)	189 (20.9%)	221 (24.4%)	88 (9.7%)
Nonmotor (Domains)				
Cardiovascular (0–24)	$0.7(1.6)^{24}$	$2.3(2.9)^{134}$	$1.1(2.0)^{24}$	7.0 (6.0) ²³⁴
Sleep/fatigue (0–48)	$4.3 (4.8)^{234}$	$14.9 (8.2)^{134}$	$6.9 (6.3)^{124}$	21.0 (10.0) ¹²³
Mood/cognition (0–60)	$3.1(4.5)^{234}$	$16.1 (14.0)^{134}$	$6.6(8.1)^{124}$	23.4 (14.3) ¹²³
Perception/hallucination (0–36)	$0.5(1.7)^{24}$	$1.9(3.5)^{134}$	$0.8(2.0)^{24}$	8.6 (6.9) ¹²³
Attention/memory (0–36)	$2.8 (4.2)^{24}$	$8.9(8.1)^{134}$	$3.2(4.4)^{24}$	15.6 (11.1) ¹²³
Gastrointestinal (0–36)	$2.8(3.9)^{234}$	$8.8(7.1)^{134}$	$4.1 (4.7)^{124}$	14.6 (9.6) ¹²³
Urinary (0–36)	$4.5(5.9)^{234}$	$12.4 (9.7)^{134}$	$6.1 (6.4)^{124}$	20.3 (9.9) ¹²³
Sexual function (0–24)	$1.5(3.1)^{24}$	$6.4(7.4)^{134}$	$2.5 (4.1)^{24}$	9.0 (9.7) ¹²³
Miscellaneous (0–48)	$3.9 (4.7)^{24}$	$13.2 (8.6)^{13}$	$5.2(5.8)^{24}$	14.0 (9.5) ¹³
Motor				
Tremor	$1.9(1.8)^{34}$	$1.6(1.9)^{34}$	4.3 (2.8) ¹²⁴	$3.5(3.8)^{123}$
Bradykinesia	$1.5(0.9)^{234}$	$2.1(1.1)^{134}$	$3.6(0.9)^{124}$	4.0 (1.5) ¹²³
Rigidity	$1.5(0.9)^{234}$	$1.8 (1.1)^{134}$	$3.3 (0.9)^{124}$	3.8 (1.4) ¹²³
Axial	$1.8(1.6)^{234}$	$3.3(2.1)^{134}$	$4.3 (2.4)^{124}$	7.4 (2.9) ¹²³

¹ Significant difference with cluster 1 (p < 0.05)

nms_d7, and nms_d9. Cluster 3, however, is dominated by a high prevalence of motor symptoms, while most motor symptoms are similar to the mild cluster 1. Of note is that the tremor population mean is the highest cluster mean, even higher than the severe subtype 4. This motor-dominant cluster may thus overlap with Ma's tremor dominant/slow progression cluster 6.

Generally, given stable pdonset scores and predictably increasing durat_pd scores for clusters 1 and 4, Ma et al's rapid disease progression/late onset and tremor dominant/slow progression clusters 6 were mostly not found in this dataset, save for the tremordominant motor cluster.

The most important nonmotor symptoms in determining these clusters were nms_d2 (sleep) and nms_d3 (mood/cognition), which echo findings of Fereshtehnejad's longitudinal study ⁷ and are similar to Sauerbier's identification of sleep dominant and cognitive dominant clinical NMS subtypes ⁸. Compared to Erro et al. ⁹, nonmotor/motor dominant subtypes were indeed found, but an additional subgroup with relatively severe levels of both motor and nonmotor symptoms were found. Erro's benign subtype groups possibly overlap with the mild cluster 1 found in this investigation.

4.1. Nonmotor subtype: clustering and modeling

Nonmotor symptoms nms_d2 and nms_d3 became critical not only in classification trees distinguishing between the various symptoms but in the nonmotorpredominant subgroup itself. In k-means subdivision of the nonmotor-dominant subtype where k=2 and k = 3, opposite trends were confirmed with nms_d2 and nms_d3 symptoms. Similarly, in the 2 and 4 vs rest decision tree (Figure ??), nms_d2 and nms_d3 nodes were used to differentiate various categories of nomotordominant patients. When k = 3, the subtype with the highest nms_d2 scores and lowest nms_d3 scores had by far the highest axial scores, nms_d6 (gastrointestinal) scores, and nms_d7 (urinary) scores. Thus subtype 3 of the nonmotor-dominated group could include patients falling into the cognitive/depression-dominant or autonomic dominant subtypes.

Despite the variety in symptomatic expression in this nonmotor group, what seems most consistent is the presence of nms_d9 (miscellaneous) nonmotor symptoms, as it is used as the root node of the 2 vs all decision tree (Figure ??) and the 2 and 4 vs rest decision tree (Figure ??).

It remains to be seen whether these classification models, especially the one-vs-all decision trees, are use-

² Significant difference with cluster 2 (p < 0.05)

³ Significant difference with cluster 3 (p < 0.05)

⁴ Significant difference with cluster 4 (p < 0.05)

[†] Another footnote.

Table 2: Cluster statistics for variables not used in the analysis

	1	2	3	4
Age	62.7 (9.7)	64 (9)	65 (10.2)	70.5 (8.9)
Sex	0.4(0.5)	0.5(0.5)	0.3(0.5)	0.4 (0.5)
PD_Onset	56 (10.6)	55.2 (10.1)	56.9 (11.1)	58.2 (11.4)
PD_Duration	6.7 (4.8)	8.7 (5.7)	8 (5.5)	12.3 (8.1)
CISI_Total	5.7 (3.2)	9.2 (3.9)	9.7 (3.5)	14.8 (5.1)
Surgery	0 (0.2)	0.1 (0.2)	0 (0.2)	0 (0.1)

¹ Significant difference with cluster 1 (p < 0.05)

ful in clinical practice.

4.2. New conclusions

First, the longitudinal analysis gives more insight into the clusters found when clustering on nms_d{1-9}. According to Figure ??, most symptoms are highly correlated, with PD duration, but notably, mood/cognition symptoms (nms9, nms10, nms12) and tremor are not correlated highly with PD duration. The differences in disease progression can be seen by the corresponding graphs, Figures ?? and ??. In both graphs, what is interesting is that Subtype 2 (Nonmotor-Dominant) starts at higher scores for nms_9 and nms_10, thus indicating that these patients' subtype is can be determined early in PD duration from depressive symptom score. Similarly, when examining Subtype 3 (Motor-dominant) in Figure ??, the mean tremor score is substantially higher from PD onset. Interestingly, Subtype 4 (Severe) generally starts at lower tremor and motor scores during disease onset (Figure ??), but then rises sharply, exceeding other Subtypes. More evidence that tremor is a unique motor symptom is located in Figure ??, where it is the most distant symptom from all other symptoms.

When examining all 30 symptoms, more evidence is given that the previously-discovered Subtype 2 (Nonmotor-Dominant) may be primarily characterized by high depressive symptoms. By graphing the 30 subtypes attached to the original clustering, as in Figure ??, the mean scores of nms8, nms9, and nms10 for Subtype 2 are substantially higher than Subtypes 1 and 3.

Indeed, PCA on the 30 nonmotor symptoms identifies the second-most prominent component as a general mood/cognition component, and *k*-means clustering on the 30 symptoms only (Figure ??) divides the 1000 patients into four slightly different groups, a mild, average, depression-dominant, and severe group.

The Gaussian mixture model identified in Figure ?? fragments the previously-discovered clusters into more groups. Here, a wide variety of specialized subtypes of PD are displayed, including insomnia, urinary, motor, nonmotor, and depression-dominant groups, as well as the expected mild, average, and severe subtypes. It is likely that the previous analysis with only nms_d{1-9} combined most of those specialized groups into the more general nonmotor-dominant Subtype 2.

It's intuitive that a Depression-Dominant group emerges when clustering on nms{1-30}, since domain 3 consists of 5 separate measures. Thus, any high expression of depressive symptoms is magnified in clustering, since the symptoms are highly similar (Figure ??) and treated with equal weight. Once again reinforcing what was discovered previously, depressive symptoms have been shown to be very important in determining subtypes of PD.

5. Supplementary Material

6. References

- [1] Tibshirani R, Walther G, Hastie T. Estimating the number of clusters in a data set via the gap statistic. Journal of the Royal Statistical Society: Series B (Statistical Methodology) 2001;63(2):411–23
- [2] Brock G, Pihur V, Datta S, Datta S. clvalid: An r package for cluster validation. Journal of Statistical Software 2008;25(1):1-22. URL: https://www.jstatsoft.org/index.php/jss/article/view/v025i04. doi:10.18637/jss.v025.i04.
- [3] Datta S, Datta S. Methods for evaluating clustering algorithms for gene expression data using a reference set of functional classes. BMC bioinformatics 2006;7(1):397.
- [4] Yeung KY, Haynor DR, Ruzzo WL. Validating clustering for gene expression data. Bioinformatics 2001;17(4):309–18.
- [5] van Rooden SM, Heiser WJ, Kok JN, Verbaan D, van Hilten JJ, Marinus J. The identification of parkinson's disease subtypes us-

² Significant difference with cluster 2 (p < 0.05)

³ Significant difference with cluster 3 (p < 0.05)

⁴ Significant difference with cluster 4 (p < 0.05)

[†] Another footnote.

- ing cluster analysis: a systematic review. Movement Disorders 2010;25(8):969-78.
- [6] Ma LY, Chan P, Gu ZQ, Li FF, Feng T. Heterogeneity among patients with parkinson's disease: Cluster analysis and genetic association. Journal of the neurological sciences 2015;351(1):41– 5.
- [7] Fereshtehnejad SM, Romenets SR, Anang JB, Latreille V, Gagnon JF, Postuma RB. New clinical subtypes of parkinson disease and their longitudinal progression: a prospective cohort comparison with other phenotypes. JAMA neurology 2015;72(8):863–73.
- [8] Sauerbier A, Jenner P, Todorova A, Chaudhuri KR. Non motor subtypes and parkinson's disease. Parkinsonism & related disorders 2016;22:S41–6.
- [9] Erro R, Vitale C, Amboni M, Picillo M, Moccia M, Longo K, et al. The heterogeneity of early parkinsons disease: a cluster analysis on newly diagnosed untreated patients. PLoS One 2013;8(8):e70244.

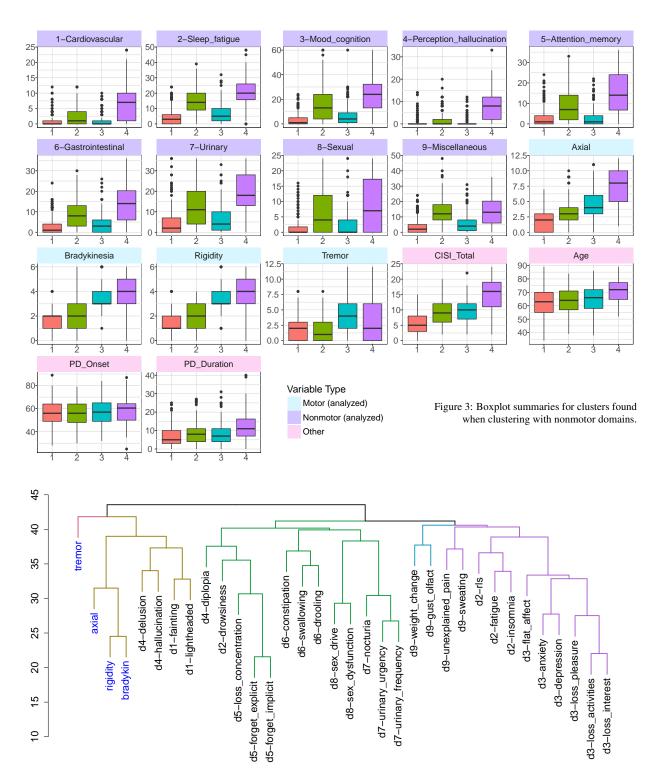


Figure 4: Hierarchical clustering of motor (blue) and nonmotor (black) symptoms. Symptoms are labeled with their name and corresponding domain number. Dendrogram colored with 4 clusters.