Combining Biclustering with Probabilistic Predictive Models to Develop Personalised Tests for Early Detection of Dementia

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Introduction and background

- Dementia is a significant health challenge for the elderly population.
- Early detection of dementia is difficult and lacks appropriate diagnostic tools an accessible tool for tracking memory condition needed
- The Famous Faces Test (FFT) is a potential tool for dementia detection. It involves naming photos of famous people and recalling their names or selecting from a list.
- This research aims to introduce personalisation to the FFT using data science.

udrev Hepbi Marylin Monro Elizabeth Taylor Madonna Example prompt

for the

recognition task

Example prompt for the recall task



Methods

- **Data**: FFT results on recall and recognition tasks of over 300 individuals, information about the participants, collected via questionnaires, and the test items [1]
- **Population**: cognitively normal Dutch adults aged ≥ 60

Individual differences and biclustering

• Information-Theoretic Co-Clustering - comparing 2 sets of features, based on mutual information [2,3].

Modelling

- Aim: generate a personalised set of *n* faces based on patient characteristics.
- 3 probabilistic classifiers compared: Logistic Regression, SVM, Gaussian Naïve Bayes.
- Comparison in two settings: with and without bicluster membership as an additional feature.
- Multi-label classification using separate binary models per face.
- Optimal items derived by aggregating models and selecting items with probability scores around some threshold.

-1.6

-1.4

- 1.2

- 1.0

0.8

- 0.6

- 0.4





Are there individual differences in the FFT performance?

Sports, 2010	Singers/ Musicians, Film/ Theatre	Politics, male	Politics	dutch, Singers/ Musicians	Singers/ Musicians 1960
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Males interested in sports, soccer, and cycling, who have few visits from friends or family.	1.	1,688 (84,27)	0.652 (34,31)	1.054 (34,37)	1,093 (34,53)	0.897 (34,35)	0.677 (34,37)
People married or in a relationship , reporting emotional loneliness.	2-	0.831 (25,27)	0.91 (25,31)	1.166 (25,37)	1.051 (25;53)	1.171 (25,35)	0.516 (25,37)
Younger participants, born in NL, interested in soccer, music, and sports, reporting social loneliness.	3-	1,302 (64,27)	1,296 (64,31)	0.788 (64,37)	0,943 (64,53)	0.95 (64,35)	1,147 (64,37)
Retired participants, not in soccer or cycling .	4-	0.253 (35,27)	0.591 (35,31)	1.121 (35,37)	1,212 (35,53)	1.03 (35,35)	1.214 (35,37)
Female participants, (ex-) smoke rs who have hyper cholesterol , not interested in cycling or soccer .	5-	0.671 (37,27)	1,442 (67,31)	0.871 (37,37)	0.799 (37,53)	1.129 (37,35)	1.323 (67 <i>,</i> 37)
Relatively younger participants, not retired and not interested in politics , reporting social loneliness.	6-	1.546 (26,27)	1.756 (26,31)	1,109 (26,37)	0.357 (26,53)	1.264 (26,35)	0.522 (26,37)
Retired individuals who are divorced or separated.	7	0.904 (50,27)	0.818 (50,31)	0.897 (50,37)	1,144 (50,53)	0.942 (50,35)	<u>1,252</u> (50,37)
People not interested in music or soccer .		0.341 (24,27)	0.715 (24,31)	1.778 (24,27)	0.596 (24,53)	1.314 (24,35)	0.386 (24,37)
Relatively older male participants with more years of education , not divorced or separated , interested in politics but not in film and theatre , who have lower weight	9	0.816 (38,27)	0.151 (38,31)	1.477 (88,37)	1.461 (53,55)	0.7 (38,35)	0.48 (38,37)



- Logistic regression consistently outperformed the other candidate models.
 - Bicluster information had a modest but **positive effect** on results, increasing accuracy by an average of 2.8 percentage points.
- The results and performance metrics should be viewed through the prism of the application - for example, at 10 faces, accuracy is around 90% for recall.



Cluster informativeness (mutual information score δ_{kl}) graph with descriptions derived with feature selection. A darker shade corresponds to a bicluster having more correct answers.

- Evidence of **individual differences in FFT recall task** performance.
- Participants and items tend to form groups.
- Visualisation of **cluster informativeness** with correlated features (feature selection).
- Existence of meaningful biclusters indicates individual differences.

Model "in action"

- An example prediction of a set of 10 faces that a person is the most likely to name correctly.
- Participant (from the test set): a 65-year-old woman, interested in music and, moderately, politics, but not in soccer or cycling.
- Output: 10 faces in reality, she indeed recalled all of their names correctly.



Limitations

- Small sample size.
- Data from a specific population.
- Need for further verification in different countries.
- Crucial next steps: testing on early stage dementia patients, consultation with experts and practitioners.

Conclusion and practical implications

- There are individual differences in FFT performance and individualised FFT sets can be generated.
- Adaptive tools for early dementia detection with adjustable difficulty and interest matching on the individual level can benefit patients and practitioners.
- Biclustering visualisation and probability estimates enhance the solution's **interpretability**.
- Adding bicluster membership information can improve classification results of probabilistic classifiers.

References

[1] van den Elzen, E. H. T., Brehmer, Y., Van Deun, K., & Mark, R. E. (2023). Stimulus material selection for the Dutch famous faces test for older adults. Frontiers in Medicine, 10. https://doi.org/10.3389/FMED.2023.1124986 [2] Govaert, G., & Nadif, M. (2018). Mutual information, phi-squared and model-based co-clustering for contingency tables. Advances in Data Analysis and Classification, 12(3), 455-488. https://doi.org/10.1007/S11634-016-0274-6 [3] Role, F., Morbieu, S., & Nadif, M. (2019). CoClust: A Python Package for Co-Clustering. Journal of Statistical Software, 88(7). https://doi.org/10.18637/jss.v088.i07

