

Modelling Heterogeneity in the Trajectory of Duchenne Muscular Dystrophy

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Duchenne Muscular Dystrophy (DMD)

- A devastating muscle wasting condition that affects young boys, caused by a mutation in the dystrophin (DMD) gene [1–4].
- The expected life expectancy ranges from 20 to 40 years [3–5].
- The worldwide prevalence for this disease is 4.78 per 100,000 - very rare [1, 2].
- The DMD gene is the largest known gene in the human genome - a lot of variability in patient symptoms because a lot can go wrong [6, 7].

North Star Ambulatory Assessment (NSAA)

- A functional (motor ability) measure of disease severity - consists of integers between 0 and 34 [1–3, 8].
- Composed of 17 elements e.g. Walk, Stand, Jump etc.
- Each item is scored on an integer scale 0-2, which is then summed to give the NSAA [1].

The NSAA Component Integer Scale

0	Unable to perform task
1	Able to perform task with assistance
2	Able to perform task independently

The problem

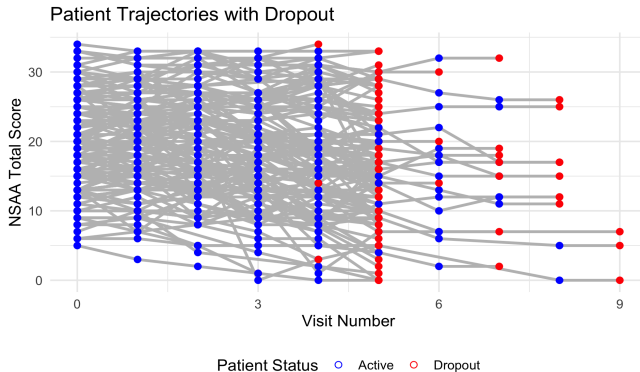


Figure 1: Individual placebo group patient trajectories, from a phase 3 trial [3]. Large cross-sectional and temporal variability in patient scores makes it hard to identify nuanced treatment effects.

Project Aim

Modelling Clinical Heterogeneity

Advise clinicians on how to better capture the differences in symptoms between patients.

How did I achieve this?

- Analysed a dataset of placebo group patients [3], and fitted a generalised least squares (GLS) model.
- Performed statistical diagnostics on the GLS model and interpreted estimated parameters.
- Specified an ideal clinical trial design (sample size and patient characteristics) through simulation - power analysis.
- Proposed a more stable and meaningful measurement - principal component analysis.

What is wrong with the NSAA?

- The NSAA assumes each component is equally important and useful at differentiating between patient severity.
- Easy & difficult elements of the NSAA are not particularly variable.
- “Jump”, “Hop”, “Climb Box Step” appear to be the most variable - most useful.

What is wrong with the NSAA?

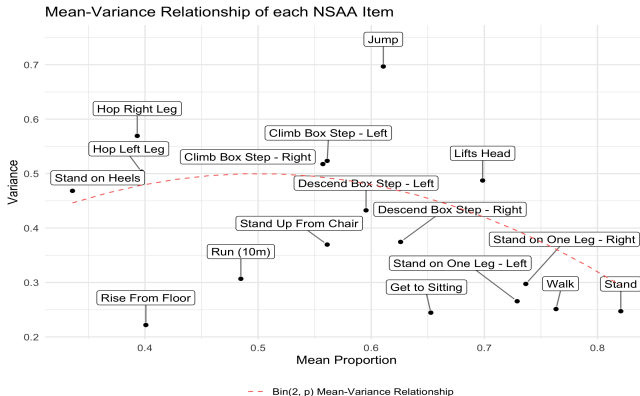


Figure 2: The mean-variance relationship of NSAA components (at baseline) is loosely aligned with the mean-variance relationship from a $\text{Bin}(2, p)$ - scaled Bernoulli.

What is wrong with the NSAA?

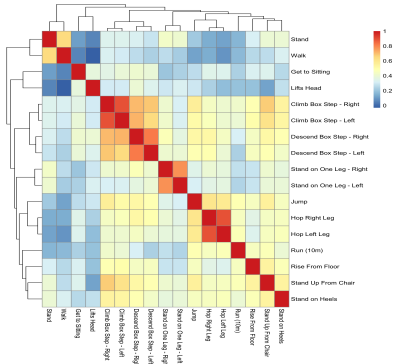


Figure 3: The heatmap and dendrogram illustrate correlations and clustering between certain activities.

- Do we need all 17 items of the NSAA? Do they add value?
- Elements performed on left and right legs are highly correlated - symmetric vs asymmetric? [9, 10]
- Correlations and clustering between items that are similar e.g. “Jump” & “Hop”, “Stand” & “Walk”

Temporal Mean-Variance Relationship

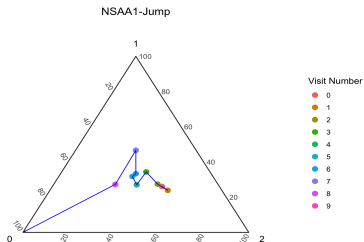


Figure 4: The proportion of 0s, 1s and 2s are near the centroid, thus are balanced through time.

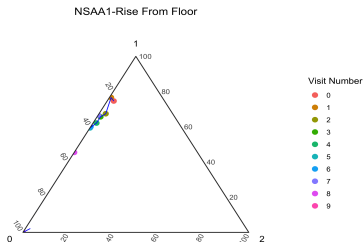


Figure 5: The proportion of 0s, 1s and 2s are biased towards the 0-1 edge, indicating a challenging task.

Principal Component Analysis (PCA)

- PCA is a statistical technique commonly used for condensing the most vital information in a dataset
- It linearly transforms the original variables into orthogonal directions of maximum variance - known as principal components or axes (PCs).
- PC1 the direction of largest possible variance in the dataset, PC2 is second largest possible and orthogonal to the first ...
- It can be shown that the principal components of any centred dataset matrix X comes from the eigendecomposition of its covariance matrix $\frac{1}{n}X^T X$ [11].

A PCA Solution

Proposed Solution

Linearly transform the current NSAA framework, which aggregates the marginal scores, using PCA.

- Perform PCA on the unstandardised baseline marginal scores from placebo group [3] - justification later.
- Use the coefficients/weights/loadings of PC1 to specify a new linear combination.
- We allow the higher utility items to have more influence on a patient's overall score.

The Weights

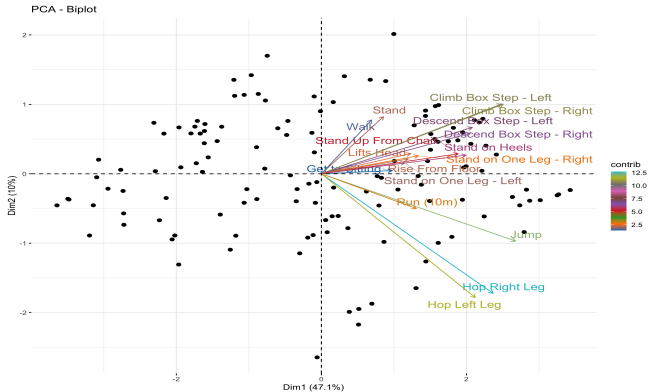


Figure 6: Diagrammatic representation of the weights of each variable onto PC1 (x-axis) and PC2 (y-axis). All items are positively weighted onto PC1, but not true for PC2.

Outcome

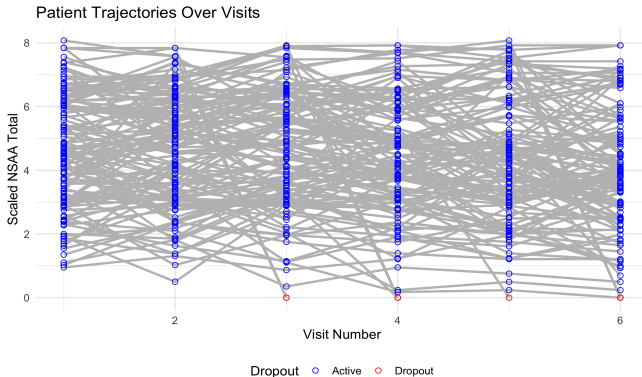


Figure 7: Scaled NSAA total is derived from projecting the marginal scores (at each visit) onto PC1 (i.e. matrix-vector multiplication). A significant reduction in cross-sectional variability. So, can detect more nuanced treatment effects. But no change in temporal variability.

Why Unstandardised? Why Baseline

- We argued that z-transformation (i.e. centre and divide by variance) was too harsh and removed the mean-variance relationships seen above - we claim this is useful.
- Also the unstandardised scores led to more time independent (stable) weights.
- A priori, we won't have future patient scores, so it is not possible to use the weights from each patient visit. Pragmatically, can only perform PCA on baseline scores to get a certain measurement.

Limitations & Further Work

- Treated the scores of each NSAA item as numerical values - are they not ordinal?
- PC1 only explained $\sim 47\%$ of the variance - a unidimensional measure might not be appropriate, in fact, 7 PCs were needed to explain 80% of the variability.
- We didn't explore other less stringent variance stabilising methods.
- We performed PCA independently on each visit - could be reason for time dependency in weights (recall there was dropout) - sequentially update weights using Kalman filter?
- We need to test versatility of new measurement.

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