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# EXTREME CLUSTER ANLYSIS AND UNDERSTANDING WHY SOME PEOPLE FALL

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## SUMMARY

A third of older people (≥65 years) fall each year. A fall can start a downward spiral that ends with early death. Predicting why older people will fall depends on multiple risk-factors. For prediction models derived from around 100 people, validated accuracy plateaus at around 75% (Kappa=0.45). We incorporated new biomechanical measures of gait stability and mobility along with traditional risk-factors. A new approach for building prediction models was used. Significant clusters of extreme performance in the tails of interacting risk-factors were identified. The selected clusters predicted future falls in 96 older people with 90% validated accuracy (Kappa=0.80).

## INTRODUCTION

Fall prediction models use multiple risk-factors to determine who is likely to fall, and the most appropriate interventions. Many risk-factors have been investigated including but not limited to: (i) biomechanical (gait stability and static sway), (ii) psychological (including fear of falling and depressive symptoms), (iii) physiological (such as poor eye sight and decreased leg strength), (iv) mobility related (such as walking speed and activity levels), and (iv) falls history.

Many methods have been used to combine risk-factors including discriminant analysis [1-6], linear or logistic regression [7, 8], classification trees [9-11], and support vector machines [12].

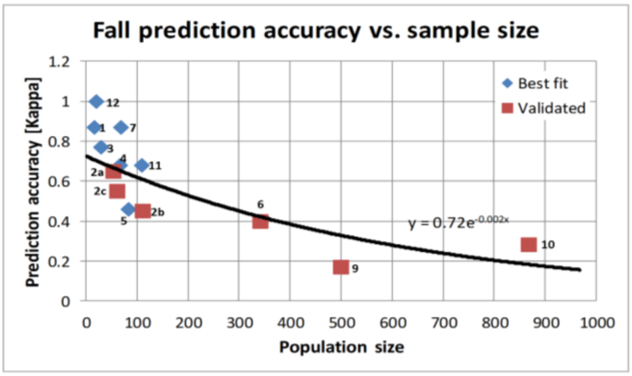


**Figure 1: Funnel effect, performance drops with sample size. Numbers refer to references cited in text.**

Performance measures, population sizes and validation methods vary widely, making comparisons between studies difficult. Performance may be measured as accuracy, sensitivity, specificity, odds ratio or relative risk.

## METHODS

Risk-factors were collected from 96 older people, aged 74 to 93 years. Accelerometers were attached to the head and sacrum to acquire biomechanical measures of gait stability and mobility. Falls were followed up over 12 months.

Extreme cluster analysis is a new method. Risk-factors were analysed for the presence of extreme clusters of (F) or non-fallers (NF). Local anomalies in the tails of up to three interacting risk-factors were identified; cluster boundaries were determined by Equation 1. Clusters were then ranked according to the probability of not occurring by chance. Cluster chance was determined by the hyper-geometric probability density function with Bonferroni adjustment for the number of combinations of measured risk-factors tested.

$$CPower_{NF} = \frac{nC_{NF}^{k}/(nC_F + 1)}{nD_{NF}/(nD_F + 1)}$$

**Equation 1: Cluster power for non-fallers (*NF*), is a modified odds ratio. Cluster (*C*) boundaries are set to maximize the concentration of the number (*n*) of *NF* to fallers (*F*) relative to the underlying distribution (*D*).**

The top ranked clusters g' (Figure 2) were used to make a decision tree. The decision tree was tested for over-fitting using 10-fold cross over validation, and bootstrapped 1000 times. Median and 95% ranges for classification performance were measured using accuracy, sensitivity, and Cohen's Kappa.

If sufficient data were available we also converted some published performance measures to Cohen's Kappa for comparative purposes. Kappa incorporates aspects of accuracy from the confusion matrix and adjusts for unbalanced group sizes [13]. Perfect prediction models have a Kappa of 1; models equal to chance have a Kappa of zero.

## RESULTS AND DISCUSSION

A comparison between different published falls prediction models (Figure 1) demonstrates performance drops with population size. The line of best-fit might suggest that many fall prediction models would perform little better than chance for larger populations. For populations of around 100 participants, validated accuracy plateaus at around 75%, Kappa=0.45.

Validated models (Figure 1, squares) either had an events per variable ratio of greater than the recommended 10 [14] or used 10-fold cross over validation [2]. Cross over validation reduces the likelihood of over-fitting the smaller data sets with too many risk-factors. Leave-one-out cross over validation was not considered sufficient because it did not detect over-fitting in a model that used 25 risk-factors to fit a data set with 9 fallers [7].

At 12 months, 35 people reported falls (F) and 61 were non-fallers (NF). The top cluster (Figure 2) contained 32 NF and 2 F. The adjusted probability ($p$=0.0012) of this cluster occurring by chance was low. The top cluster combined stable lateral hip movements while walking with a correlate of walking speed. The reason this subgroup were identified as non-fallers is because they had both fast and stable gait.

The analysis shows that in our sample different risk-factors were important for different people. For example, a fear of falling was only important when combined with poor visual contrast sensitivity and poor lateral stability while walking.

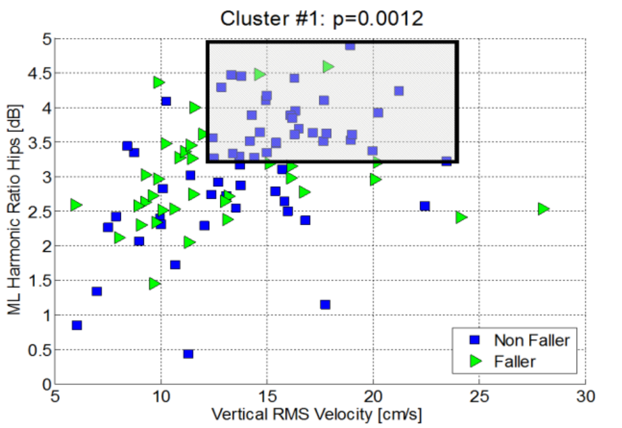


**Figure 2: A cluster containing 32 non-fallers (94% pure) forms the first two nodes of a classification tree.**

Extreme cluster analysis identified another 107 significant clusters. From these, the top 8 risk-factors were identified and used to form a classification tree. Risk-factors selected were biomechanical, mobility related, psychological, and physiological: (i) poor ML hip stability while walking, (ii) low RMS VT velocity, (iii) High postural sway on foam, (iv) low RMS ML hip displacement, (v) a fear of falling, (vi) poor visual contrast sensitivity, (vii) poor anterioposterior head control, (viii) high ML/VT Head Jerk.

The classification tree had good 10-fold cross over validated performance: Kappa 0.8 (0.73 to 0.84), accuracy 90% (87% to 92%), sensitivity to fallers 89% (83 to 91%), specificity to non-fallers 92% (92 to 93%). However, as shown in Figure 1, it is unlikely a Kappa of 0.80 can be replicated for the general population. In a small sample population all significant combinations of risk-factors that may result in a fall are not present. Without external validation using an independent data set we cannot know how applicable all identified clusters are to the general population.

## CONCLUSIONS

Fall prediction models may be improved by incorporating biomechanical measures of gait stability and mobility.

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