Mixed effects models in neurolinguistics: is there a way beyond univariate analysis?

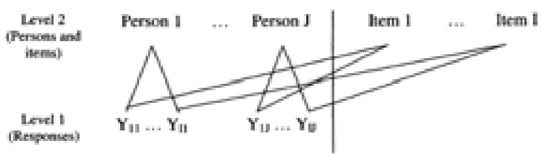
Marelli, Marco
University of Milano-Bicocca, Department od Psychology
piazza dell'Ateneo Nuovo, 1
20126, Milan, Italy
E-mail: m.marelli1@campus.unimib.it

Crippa, Franca
University of Milano-Bicocca, Department od Psychology
piazza dell'Ateneo Nuovo, 1
20126, Milan, Italy
E-mail: franca.crippa@unimib.it

Introduction

Mixed effects models have recently gained attention in psychological experimental research, even though their adoption is still not adequately extensive (Meyers and Beretvas, 2006). In most studies, multiple participants are presented multiple test items and their responses are recorded in terms both of reaction times (RT), *i.e.* the amount of time a subject takes for answering to each item, and of accuracy, that is the count of correct responses. This design clearly crosses each subject completely within each item, and each item is completely crossed among all subjects (Fig.1). The measurement scale is typically binary for evaluating correct answers, whereas it is continuous in the case of latency or, equivalently, reaction times (RTs). The most common approach for processing these two responses consists in a separate analysis, by prior averaging over subjects and then applying regression or Anova models, once again distinctively for items and subjects.

Figure 1: Complete crossed classification for items and subjects



This approach has raised several objections, in favour of a correct recognition of the data structure as a completely cross-classified one (Quené and van den Bergh, 2006; Baayen, 2008). This frame of mixed modelling with crossed random effects for items and subjects has so far shown to match psycholinguistic and neurolinguistic experiments adequately and results have produced a range of contributions, for instance in the theme of compound words processing and representation (Baayen, 2008; Crippa and Marelli, 2009).

Applications of univariate mixed models in neuro- and psycholinguistic: beyond fixed effects models

Our applications of mixed modelling have aimed so far at evaluating effects on compound words recognition either on accuracy and on latency in distinct analyses, according to the most recent literature on the theme. Compound nouns are morphologically complex elements generated from two (or more) existing words. Whether compounds are represented as a whole in the mind or accessed through their constituents is debated and no solution is fully confirmed by empirical data: dual-route models have been suggested, in which both a direct whole-word route and a parsing procedure can be employed during lexical access, and their efficiency is governed by frequency effects. In order to verify the latter theoretical view, lexical decision experiments with Italian compound nouns have been run to investigate frequency effects on word processing, in relation to the semantic and structural properties of compounds. Stimuli were either transparent or opaque (e.g., astronave, spaceship versus boccaporto, hatch) and head-final or head-initial compounds (e.g., astronave vs. capobanda spaceship versus ring-leader). The model can be extended in order to include several explanatory variables: the length in letters of the compound; its headedness, that is head-initial versus head-final compounds; semantic transparency and the frequency of the whole compound and of its constituents.

Under the methodological perspective, the basic multilevel model has been extended so as to reflect multiple random effects that are crossed, or mutually nested (Goldstein, 1999; Snijders & Bosker, 1999). Therefore, results can be jointly generalized to other participants and to other test items, due to the simultaneous inclusion of both random factors, for subjects and items, into the same analysis. Moreover, the general advantages of mixed-effects modelling (no assumptions of homoscedasticity or sphericity, robustness against mixing discrete and continuous predictors) also apply to models with crossed random effects.

The estimation procedures involving accuracy and Rts are distinct, therefore implying their independence. Latency or Reaction Time (RT), is a continuous variable and therefore can be estimated as the response in a regression model. In order to reduce its tipical asymmetry, the logarithmic transformation is usually applied, even if other density probability functions have been debated as better expressing the distributional shape of RTs:

$$Y_{ijk}^{RT} = \gamma_{0(00)} + \left(u_{0(j0)} + v_{0(0k)} + e_{(jk)}\right)$$

Three terms are in random part: the unique component of each participant $u_{0(j0)}$, of each test item $v_{0(0k)}$, and the residual component $e_{i(jk)}$. The latter corresponds to the deviation of each observation from its predicted value.

Answers to each item by every subject are denoted by Y_{ijk}^{A}, where *i* indexes the *j x k* observations, *j* and *k* being the total number of subjects and items respectively. The distribution of Y_{ijk}^{A} is binomial (e.g. yes-no or correct-incorrect responses), with *p* specifying the probability of a correct answer given by subject *k* to item *j*. The empty model for accuracy, with no explanatory variables, is:

$$ln\left(\frac{p}{1-p}\right) = \gamma_{0(00)} + \left(u_{0(j0)} + v_{0(0k)} + e_{(jk)}\right)$$

where *ln(p/(1-p))* is the logit of the probability of a correct answer. The grand mean, γ_{000}, adds to a random part (in parentheses), that once again expresses the total variation as the additive result of three components: differences between participants, differences between test items and the residual variation nested under the combination of participants and test items. Fixed factors of interest can be included into a random intercept model:

$$ln\left(\frac{p}{1-p}\right) = \gamma_{0(00)} + \sum \gamma_{s(00)} X_s + \left(u_{0(j0)} + v_{0(0k)} + e_{(jk)}\right)$$

that can be extended to a random coefficient one and to more complex equations, that incorporate relevant interactions. The extensions of the null models to include covariates and their interactions obviously apply both to dichotomous and continuous models.

Deveoplments in software programs for crossed classified data has allowed one to face the analysis in simpler operative terms, when estimating in separate sessions Rts by means of linear mixed models and in the case of logistic mixed models, for estimating accuracy. Different software deals with cross random models. Detailed procedures for psycho- and neurolinguistic applications in the univariate case have been provided in the R environment, with the specification of functions like lmer (Baayen, 2008). In line with the author's recommendations, completely crosses mixed models with participants and items as random effects were applied in studies for participants' accuracy and latency at responding to neuropsychological items. Some applications, namely on the position and the mental representation of nominal compounds, have proved also in our research practice the existence of differences between participants and between items, respectively, that can be highlighted and subsequently explained by appropriate covariates, referring to the items characteristics in our angle (Tab.1).

Table 1: Mixed effects model estimation in experiments on the mental representation of nominal compound: random part and evaluation of the difference between the null and the fixed effects model

Ln Reaction Time	*Effect*	*Variance*	*Standard deviation*
Random	Subject (intercept)	0.0056281	0.07502
	Item (intercept)	0.0145000	0.120416
	Residual	0.0266233	0.16317
Evaluation(2 log(lh)	Chi-sq=38.319	Df=8	Pr(>Chisq)= 6.572e-06

Number of observations: 1756, 48 items, 42 subjects

Considering accuracy and latency relation in a bivariate analysis

We move from the consideration that the independence assumed in the applications aforementioned between Rts and accuracy do not always applies. In fact, it has been often observed a relation between them, and the understanding and interpretation of various psycho- and neuro-linguistic issues could benefit from a coherent statistical frame, inclusive of their interdependence too.

In case of a standard multilevel model, multivariate response data are conveniently incorporated by creating an extra level below the original level 1 units to define the multivariate structure. To define a bivariate model, as in our interests, the observation, that stands at a level 1 in the univariate analysis, as a level 2 unit and the measurements for the two responses as a level 1 repeated measures. In order to simplify the bivariate expression, dummy variables, set as basic covariates, indicates which response variable is present:

$$y_{si}=\beta_{01}z_{1si}+\beta_{02}z_{2si}+s_{01}z_{1i}+s_{02}z_{2i};\ z_{1si}=\begin{cases}1\ if\ RT\\0\ if\ accuracy\end{cases}$$

$$z_{2si} = 1 - z_{1si};\ var(s_{1s}) = \sigma_{s1},\ var(s_{2s}) = \sigma_{s2},\quad cov(s_{1s}s_{2s}) = \sigma_{s12}$$

Further explanatory variables are defined by multiplying the dummy variables aforementioned by level 2 explanatory variables (Goldstein, 1995). It should be underlined that there is no level 1 variation because its role lies only in the definition of the bivariate structure. The level 2 variances and covariances are the residual between- student-and-item variances. The previous expression can be extended to the case of a mixture of a binary response, accuracy, and a continuous response, RT. The expression the becomes

$$y_{si}=\delta_s exp\left\{1 + exp\left[\left(-X_1\beta_1\right)_{si} + s_{1i}\right]\right\}^{-1} + \delta_s e_{1si} + (1-\delta_1)[\left(X_2\beta_2\right)_{si} + s_{2i} + e_{2i}];\ \delta_s = 1\ if\ binary, \delta_s = 0\ if\ continuous$$

For our purposes, we are moving towards the adoption of the previous bivariate model, that is a mixture of a dichotomous and a continuous model, since it would allow us to investigate accuracy and latency simultaneously and therefore it would provide us with a more precise estimations of fixed and random effects. To this purpose, at present we are facing some issues, the first and most evident consisting in the specification of the model for completely crossed classified data structures instead of nested structures. Preliminary applications, still under revision, in the R environment have led us so far to the specification of the mixture model and the estimation of main effects, whereas interactions still poses some questions.

REFERENCES

BAAYEN, R.H. (2008): *Analyzing Linguistic Data. A Practical Introduction to Statistics Using R*. Cambridge: Cambridge University Press.

CRIPPA, F., MARELLI, M. (2009): Mixed-effects modeling for items and subjects in psycholinguistics: an application, *Classification and data analysis 2009, Book of short papers*, *Padova: Cleup*, pp.465-468.

MEYERS, J.L. and BERETVAS, S.N. (2006): The Impact of Inappropriate Modeling of Cross-Classified Data Structures. *MMultivariate Behavioral Research, 41, 473-497.*

QUENE', H. and VAN DEN BERGH, H (2008): Examples of Mixed-Effects Modeling with Crossed Random Effects and With Binomial Data. Journal of Memory and Language, 49, 413-425.

RASBASH, J. and GOLDSTEIN, H. (1994). Efficient analysis of mixed hierarchical and crossed random structures using a multilevel model. *Journal of Behavioural Statistics, 19:337-350.*

ABSTRACT

Mixed effects models have recently gained some attention in psycho- and neurolinguistics applied research, eve n though their adoption is still not extensive enough (Meyers and Beretvas, 2006). In particular, psycho- and neurolinguistics data have a specific structure where subjects and items are reciprocally nested. Each subject i s crossed within each item, since every person is studied at answering each item, and all items are asked to a ll subjects. The evaluation of an answer is typically binary (correct or incorrect), while the time needed for an swering, namely latency or reaction time (RT), is traditionally processed by prior averaging. These data are th en analysed by means of Anova models, once again for items and subjects separately.

Several objections have been raised to this approach, and the nested reciprocal relation between items and su bjects has been correctly recognised as a completely cross-classified structure (Quenẽ and van den Bergh, 200 6; Baayen, 2008). This frame of multilevel mixed modeling with crossed random effects for items and subjects has so far shown to match psycholinguistic and neurolinguistic experiments and results have produced sound contributions, for instance in the theme of compound words processing and representation (Crippa & Marelli, 2009). Further applications have endorsed this approach and hint a possible extension from univariate to biva

riate mixed effects models. The application of bivariate models would be particularly indicated in psycho- and neurolinguistics, in which both accuracy and speed measures are usually considered, as aforementioned, as re sponses in two distinct equations. A bivariate approach would enable one to take into account the correlation betw

een the two dependent variables, while respecting the cross classified structure of the data.

Mixed-effects regression models are a powerful tool for linear regression models when your data contains global and group-level trends. This article walks through an example using fictitious dataâ€¦Â First Try: Fixed-Effect Linear Regression. There are clear positive correlations between exercise and mood, though the model fit is not great: exercise is a significant predictor, though adjusted r-squared is fairly low. By the way, I love using R for quick regression questions: a clear, comprehensive output is often easy to find. reg1 <- lm(Mood ~ Exercise, data = data). summary(reg1). 1 Introduction to Multivariate Models. Beyond univariate models â€¢ Consider the following AR(2) process for ination (yt). Yt = a1Ytâˆ'1 + a2Ytâˆ'2 + Îµt Îµt âˆ¼ W N.Â Notice that for any noninvertible process with determinant that does not vanish on the unit circle there is an invertible process with identical autocovariance structure. Wold Decomposition Any zero-mean stationary vector process Yt admits the following representation. Yt = C(L)Îµt + Îºt. This study reviews fixed and mixed effects models for univariate and multivariate meta-analysis. In addition, the study discusses specialized software that facilitates the statistical analysis of meta-analytic data. â€¦ HLM Input for Mixed Model Multivariate Analyses of SAT Coaching Data from Kalaian and Raudenbush (1996).Â There are many different effect sizes and the effect size used in a meta-analysis should be chosen so. that it represents the results of a study in a way that is easily interpretable and is comparable across studies. In a sense, effect sizes should put the results of all studies â€œon a common scaleâ€ so that they can be readily. interpreted, compared, and combined. It is important to distinguish the effect size estimate in a study from. Models and frameworks in neurolinguistics today. Influences: Linguistics, psychology, clinical work, neuroimaging, computer simulation. Clusters of influence.Â known as Studies in Neurolinguistics, edited by Whitaker and Whitaker in the 1970s, as follows: even though the eld of neurolinguistics is frankly interdisciplinary, there is a common theme of the relationships between language and the brain (Whitaker & Whitaker, 1976, p. xi). A similar description, although more focused on functional aspects, can be found in the introductory description of Brain and Language, one of the most inuential journals in this eld