Mixed effects models

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<https://cambiotraining.github.io/stats-mixed-effects-models/materials/06-significance-and-model-comparison.html>

1. Pseudoreplication
   1. *n* will be wrong (sample size)
   2. deal with by random effects
2. Fixed effects
   1. Point estimate
   2. Fixed means
3. Random effects
   1. Chosen at random from a larger set of possible categories kind of weather word in general if you want some sort of guiding principles are helping you to decide whether a variable should be treated as a random effect when you're modelling in in order to be around effect has to be that you cannot fit around them effect for a continuous variable the whole point of fitting around him effect is because you have not independence in the data is a variable is not creating an independence don't bother fitting around the set for it very good rules of thumb they're not necessarily always true but they are very good rules of thumb this concept of exchangeability which is that the specific categories or clusters that you've got don't really matter it could have been different clusters without really changing your research question or your experimental design I'm going to unpack all of these with an example this categorical clustering variable is not something you want to directly interested in so it wasn't like part question original for example in the you know the children in high schools example in their educational attainment we weren't really interested in the differences between classrooms and between schools they just happens to be that creating that structure at all and then another good for some is in order to sort of correctly or in order to have a good quality fitting model your family affection have at least 5 categories in it so let's talk about this with a very silly example
4. Example on dragons
   1. Random effect
   2. Random effect needs to be categorical
   3. Non-independence: creates clusters, groups
   4. Exchangeable: the specific groups do not matter
   5. Not interested in it directly
      1. Does not have to be true
   6. There are 5+ levels/groups
      1. You can estimate and fit a model, but the estimates are likely not to be reliable
      2. Do not NOT include mountain variable
5. If you are interested in mountain directly, then that becomes a fixed effect
   1. Intelligence ~ wingspan + mountain + (1|id)
6. Exam scores
   1. Textbooks
   2. Exam board
   3. GSE grades
      1. Schools as random effect
      2. Not independent (students from same school similar to each other within a school)
   4. Based on research question whether you have random and fixed effects
7. Agriculture
   1. Crop yield
   2. Year
      1. Year is random effect because less interested in year
      2. But year could be fixed effect if you are interested in year
      3. But if year included because those who did experiments needed more replicates
      4. Time is tricky
      5. But definitely needs to be included
         1. Not good to have model where year is not included at ALL
8. Covariate vs confound
   1. Predictor
   2. Random effect
   3. Fixed effect
9. Random effect vs covaroiate of no interest
   1. As a fixed covariate of interest so you never run what's called people in ancova an analysis of covariance all of those were fixed effects still you weren't doing around affects model you want to make bold but still doing and linear model it just so happened that you had decided to treat one of those predicted variables as the new society we weren't interested in mathematically it is treated the same way like whether you care about that variable or not whether it's a confounder or a variable of direct interest models software is going to is going to think of them identity it's not it doesn't actually make a difference between a covariate no interest and fixed affected interests that's a an artificial so calling something an cover is actually just giving it special label what's happening over the left is no different so fundamentally even if you got it something as a covariate no interest whether it be categorical continuous if you've got it in as a fixed facts it doesn't create it so when we go over or if we throw in a nuisance dummy variable or if we we treat them as fixed it doesn't actually so the examples textbook example right like if i had if i didn't care directly about example but i need that there were three different examples i could
   2. Exam board can be nuisance variable and can be fixed effect
   3. Nuisance variable can be continuous
      1. Nuisance is fixed effect
   4. Random effect not a fixed effect
   5. Random effect must be categorical
10. Nested random effects
    1. Patient in hospitals similar to each other
11. Random intercepts and slope
    1. Same slope for each mountain range
    2. Intercept changing
12. Random slope and intercepts
    1. Slope is now changing between mountains
13. Random slope and random intercepts
    1. Both differ
14. If you fit this as a fixed effect those are not drawn from a global mean
    1. There is no shrinkage
15. If you fit this as a random effect
    1. Those are drawn from a global mean
       1. There IS shrinkage
16. Look sweet so we probably want random insects what would be a disappointing well here what we've got random slopes would be is that the rate of the degree to which our fixed predictor drink affect our response variable is different between people so some people are going to be more affected by alcohol or by caffeine and others random slopes would be now biologically plausible however with 24 participants and only three observations from each person we might actually struggle with statistical power or model may fail from imagine things earlier with this smaller data set 2 separate random events we may see issues hence the question I want very list for time reasons but there is another example the answer is given on the slides but if you want to think about this if you want to ask me about this if you know you don't follow the logic example this is not official example well I said designed it such that it wouldn't make sense to have random intercepts and if you want a little thinking exercise feel free to think through this slide and if you don't get where that's coming from that is not alright
17. so summary we've had a good long chat this morning but this is the this will be the longest of the lecture bits especially random effects are awesome they allow us to cope with not independence in our data set without needing to split our data into lots of little subgroups they would in a video situation but whether or not we want to fit something as a random effect is going to depend on a few different factors it's not always clear cut we need to think both about the nature of that variable itself but also about our research context and the quality of the data other factors right and then when we do fix around them effects we can actually fit multiple random effects because the intercept sandal strike which we choose is also going to depend on our research question of what we think is so the cause materials they the 1st chapter or two is a lot of background stuff without many exercises there is a chapter that gives you some just more practise examples if you want to do or of this is it random is it fixed again feel free to do that with someone else do that so whatever you prefer but then the chapter the fitting mixed effects models chapters and it's like emphasise shows you how to use the enemies
18. MLE
19. MLE vs. REML
    1. MLE gived biased estimates of random effects
20. Deviance
    1. DVS is a more general of relative which just captures the difference between model and data that there will be some gap between what your model thinks is happening and what's actually happening in your data set now this is intentional we want there to be at least some previous because a model that has no gap at all is a massively over fitted model where we just got doctor dot between data points which isn't helpful 'cause the point in model is to simplify the tax at some degree right but we also don't want it to be too much so we can use deviance too compare models to each other to assess significance of models and a bunch of different ways so there exists so actually is is the log of the likelihood function so if you take the likelihood that you obtained your maximum likelihood estimation procedure the likelihood of that model if you log that you will get and then this slightly abstracted
    2. Saturated model
    3. Your proposed model
    4. Null model
       1. Intercept only
    5. Random effects from partial pooling
       1. Completely independently I'm actually always keeping the global effect in mind even as I produce the estimates for the individual clusters I'll show you what I mean let's use the dragon day set again but I'm going to add added artificially to the very real set of Dragons that exist previously the rest of Europe 2 attackers that have come from a sick mountain range F this ABCDE and my two Dragons from mountain range So what I could do is I could Pulis data together pseudo replicate and fit a single simple model Y equals beta therapist beaten by ex all of these data collectively
       2. Complete pooling
          1. Ignore everything and pool all data
       3. No pooling
          1. Just fixed effect of mountain
          2. Other mountain ranges forgotten
       4. Partial pooling
          1. Random and fixed effects for mountain
          2. Less overfitting
          3. Shrinkage = regularisation
    6. Summary
       1. Mini models we use Emily or rather switch off a century the same thing tiny tweaks the difference is only relevant or you get into the significance testing my favourite method of assessing the quality and significance of the model is by looking at the deviants and doing these likelihood ratio tests now the course materials admitted they will show you a couple of other methods which are also available to you and also valid again we're kind of what kind of into a realm here that even statisticians don't all completely agree with each other on people have different preferences in in how they should be assessing significance P values for mixed effects model on not straightforward like they offer and enable that's really the takeaway and you don't have to I will say that the chapter on significance testing in the course materials I suspect maybe one of those bits of resource that you need to come back to each time that you're trying to extract the values because it it's sort of a video useful reference just as much as it is teaching materials how I intended it when I wrote it so I hope that and then random effects we that we were thinking about this morning is very much like that you know into it X perimental design definition but what's actually different about random effects the thing that actually makes around effective from fixed back is that it is not just a point estimate of like the mean of the average relationship it is the entire distribution different and because we are estimating around them affect this way because we're estimating a distribution we're also it's all packaged into the same thing going on we're actually sharing information we're not treating each group like a completely distinct population we're thinking about them collectively and not sharing information that partial pooling shrinkage process is very very helpful for
    7. CONCEPT
       1. MLE for mixed effects models means you are estimating a mean and a variance