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| Psychology 111 | |  | |  |  | | | | | | | | |  | | |  | | | | |  | | | |  | | | |
| Winter 2021 | |  | |  |  | | | | | | | | |  | | |  | | | | |  | | | |  | | | |
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| Meeting time: MWF 9:00 - 10:00 in the ether | | | | | | | | | | | | |  | | |  | | | |  | | | | |  | | | |
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| Readings from Field "Discovering Statistics Using R" and various others | | | | | | | | | | | | | | | | | | | |  | | | | |  | | | |
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|  | Date |  | |  | Topic | | | | | | | | |  | | | Readings | | | | |  | | | |  | | | |
|  | January | 4 | |  | Overview, ANCOVA  We begin the term by reviewing the general linear model and the change into linear mixed models. | | | | | | | | | |  | | | F 11  Covar\_pdf | | | | |  | | | |  | | | |
|  |  | 6  8 | |  | MANOVA and matrix algebra  Matrix concepts are key to many multivariate analyses.  Homework 1 | | | | | | | | | | | | F 16 | | | | |  | | | |  | | | |
|  |  |  |  | | | |  | |  | |
|  |  | 11 | |  | Repeated Measures (ANOVA, MANOVA)  The majority of psych analyses use repeated measures. They were done improperly for years. We begin with using traditional ANOVA with or w/o corrections and the use of MANOVA to address those issues. | | | | | | | | |  | | | F 13, 14  UCLA handout | | | | |  | | | |  | | | |
|  |  | 13  15 | |  | Reapeated Measures (GLS)  With GLS, we solve the problem of lack of sphericity by modeling the complete covariance structure. This is the preferred solution for discrete IVs.  Homework 2 | | | | | | | | |  | | | UCLA handout | | | | |  | | | |  | | | |
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|  |  | 18 | |  | Linear Mixed Models, continuous IVs  In this section, we begin to cover true linear mixed models. They have many advantages including the ability to assume that the effect of an IV might vary across subjects, better handling of missing data, etc. | | | | | | | | | Bodo 2  F 19 | | | | | | | | | |  | | | |
|  |  | 20  22 | |  | Linear Mixed Models and what is a **random** effect  Also hierarchical models  Homework 3 | | | | | | | | |  | | | Bodo 2 | | | | |  | | | |  | | | |
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|  |  | 25 | |  | Random effects in general  More on what is and what isn’t a random effect | | | | | | | | | | | | F 19 | | | | |  | | | |  | | | |
|  |  | 27  29 | |  | LMMs, multiple random effects  Another important feature of LMMs is the ability to have multiple random effects. In our experimental work, that will often mean including random item effects, highly recommended.  Homework 4 | | | | | | | | |  | | |  | | | | |  | | | |  | | | |
|  | February | 1 | |  | GLMMs  Our final branch of the general models is to do repeated measures while relaxing the assumption of normally distributed data. I predict rapid growth in the use of these models, particularly with accuracy data. | | | | | | | | |  | | |  | | | | |  | | | |  | | | |
|  |  | 3  5 | |  | More GLMs  Homework 5 | | | | | | | | | | | | Bodo 2, Bates, et al | | | | |  | | | |  | | | |
|  |  | 8 | |  | | Classification models – Disc. Anal. | | | | | | | |  | | |  | | | | |  | | | |  | | | |
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|  |  | 10 | |  | Classification models – logistic regr. Signal detection Theory | | | | | | | | |  | | |  | | | | |  | | | |  | | | |
|  |  | 12 | |  | Homework 6 | | | | | | | | |  | | |  | | | | |  | | | |  | | | |
|  |  | 15  17  19 | |  | Structure – factor analysis  We will examine PCA and factor analysis as ways of finding structure and/or reducing the number of predictor variables.  Structure – factor analysis  Homework 7 | | | | | | | | |  | | | F17 | | | | |  | | | |  | | | |
|  |  | 22 | |  | Structure: Multidimensional scaling  We will cover other techniques for uncovering patterns in similarity and distance matrices. | | | | | | | | |  | | |  | | | | |  | | | |  | | | |
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|  |  | 24 | |  | Structure: clustering | | | | | | | | |  | | |  | | | | |  | | | |  | | | |
|  |  | 26 | |  | Homework 8 | | | | | | | | |  | | |  | | | | |  | | | |  | | | |
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|  | March | 1 | |  | Other clustering algorithms  Also keeping this week available as  Wiggle room | | | | | | | | |  | | |  | | | | |  | | | |  | | | |
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|  |  | 3  5  12 | |  | Categorical Data  Review, exam available  Go over exam | | | | | | | | | F18 | | |  | | | | |  | | | |  | | | |
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