Bayesian Estimation: Implications for Modeling Intensive Longitudinal Data

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Soon we will all be Bayesians…

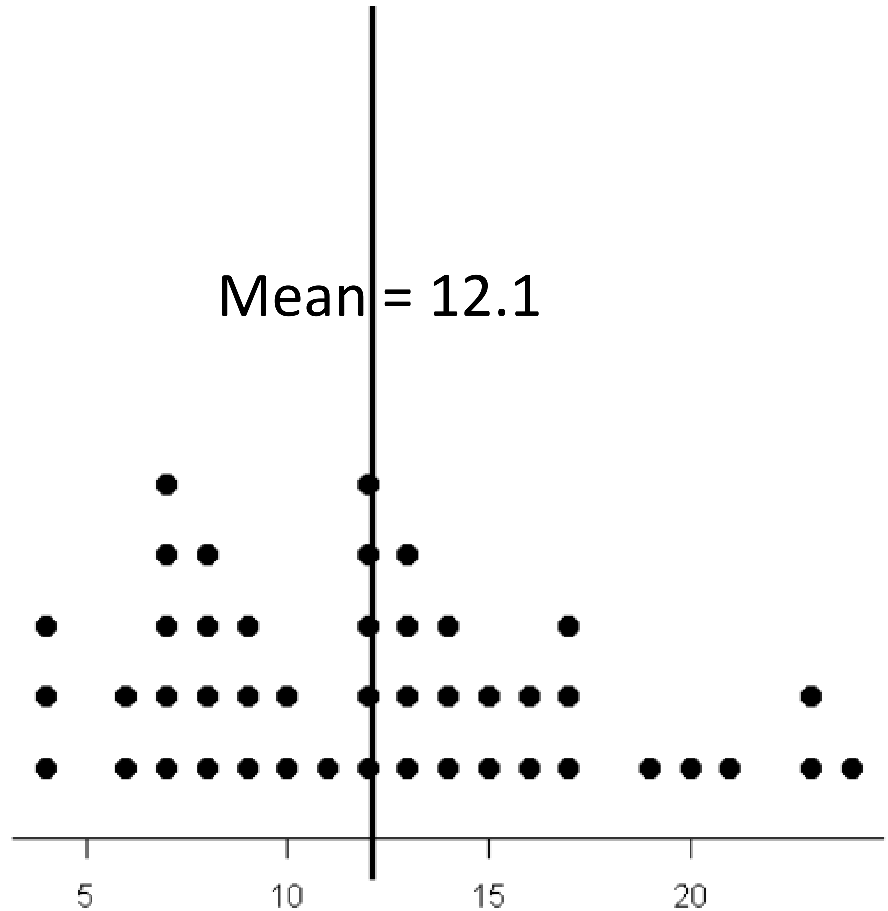
- Drawbacks of traditional Bayesian analysis are largely gone

- The use of non-informative priors is becoming common; skeptics, contrarians can no longer complain about the effects of priors on results.

- Difficulty of obtaining Bayesian results has been greatly reduced by the use of modern computational approaches, especially Markov Chain Monte Carlo simulation.

- Interpretation of results is much more in line with the way we actually think

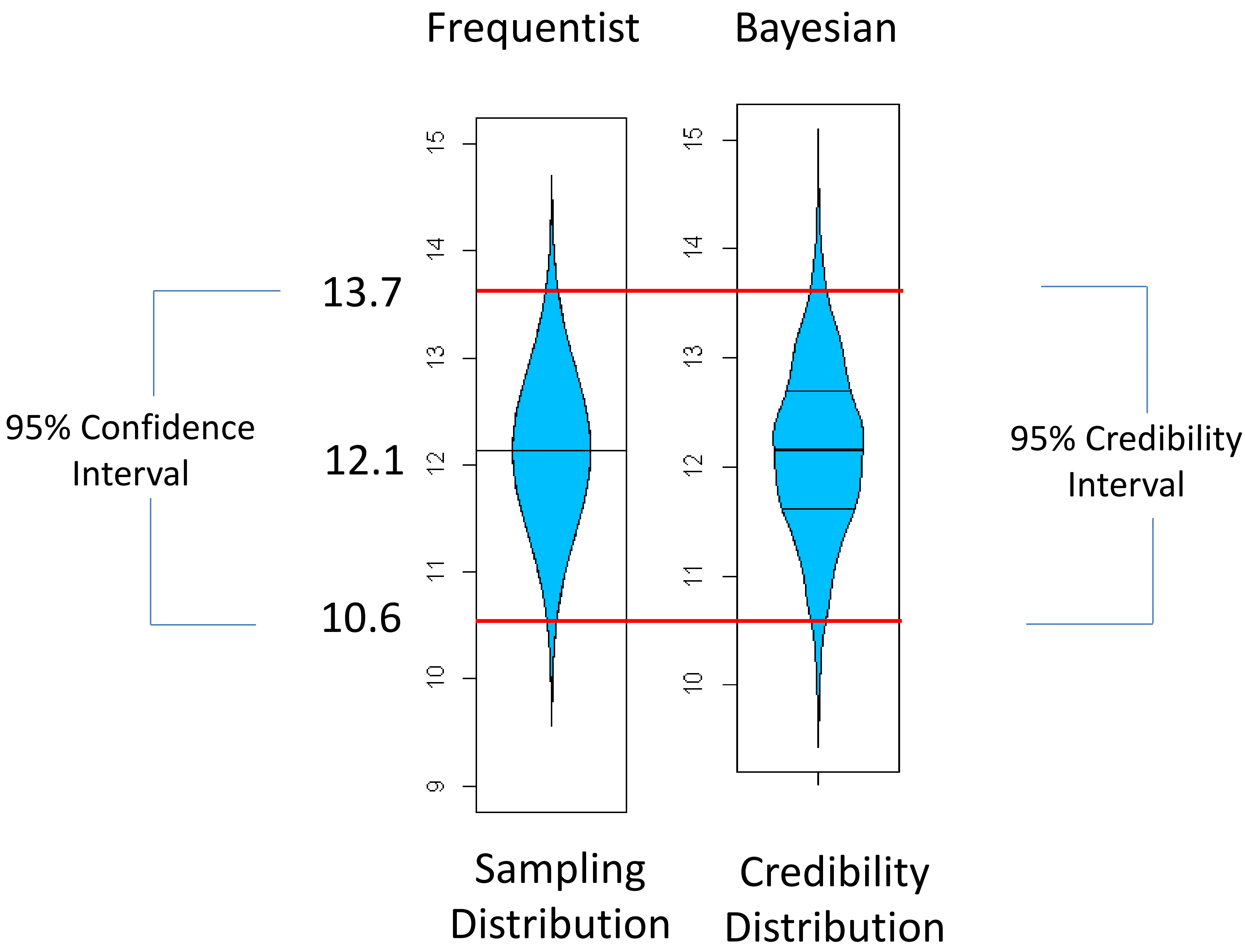
Example: Conformity scores from experiment (N=47)



Relationships Between Source Status, Authoritarianism, and Conformity in a Social Influence Setting[1]

JAMES C. MOORE, JR. AND EDWARD KRUPAT
York University, Toronto and Rutgers University

Source: Moore (1971), available in Companion to Applied Regression (car) R package



Frequentist
Bayesian
13.7
12.1
10.6
95% Confidence Interval
95% Credibility Interval
15
14
13
12
11
10
9
Sampling Distribution
Credibility Distribution

Recently published and retracted because of failure to account for random effects

Research Article

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Psychological Science
1–7

DOI: 10.1177/0956797615609900
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Women's Preference for Attractive Makeup Tracks Changes in Their Salivary Testosterone

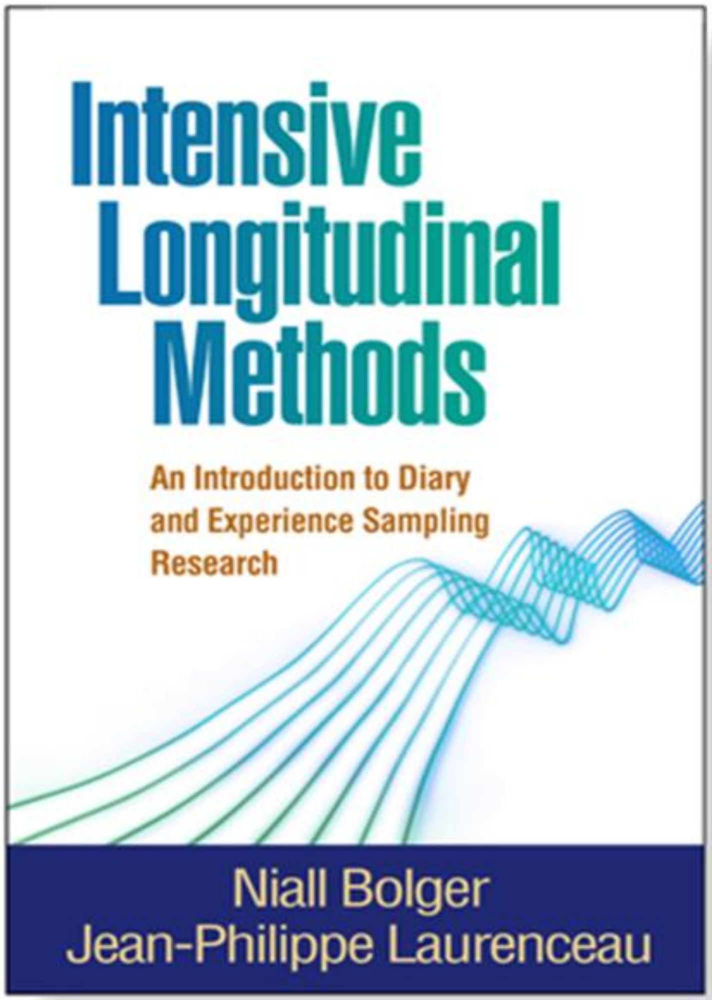
Claire I. Fisher, Amanda C. Hahn, Lisa M. DeBruine, and Benedict C. Jones
Institute of Neuroscience & Psychology, University of Glasgow

Published online: November 2, 2015

Retracted : February 3, 2016

The problem: in multilevel modeling on within-subjects data, you need to allow for person-to-person heterogeneity

Example from Bolger & Laurenceau (2013)



Guilford Press
Methodology in the Social Sciences Series

www.intensivelongitudinal.com

B & L (2013) chapter 6: categorical outcomes

Dataset: Convenience sample of 61 opposite-sex couples

- <u>Independent Variable</u>: Morning reports of anger/irritability by the female partner
- <u>Dependent Variable</u>: Evening reports of conflict by the male partner: 0 = no conflict, 1 = conflict.

Data Matrix

categoricaldata.sav [DataSet4] - IBM SPSS Statistics Data Editor

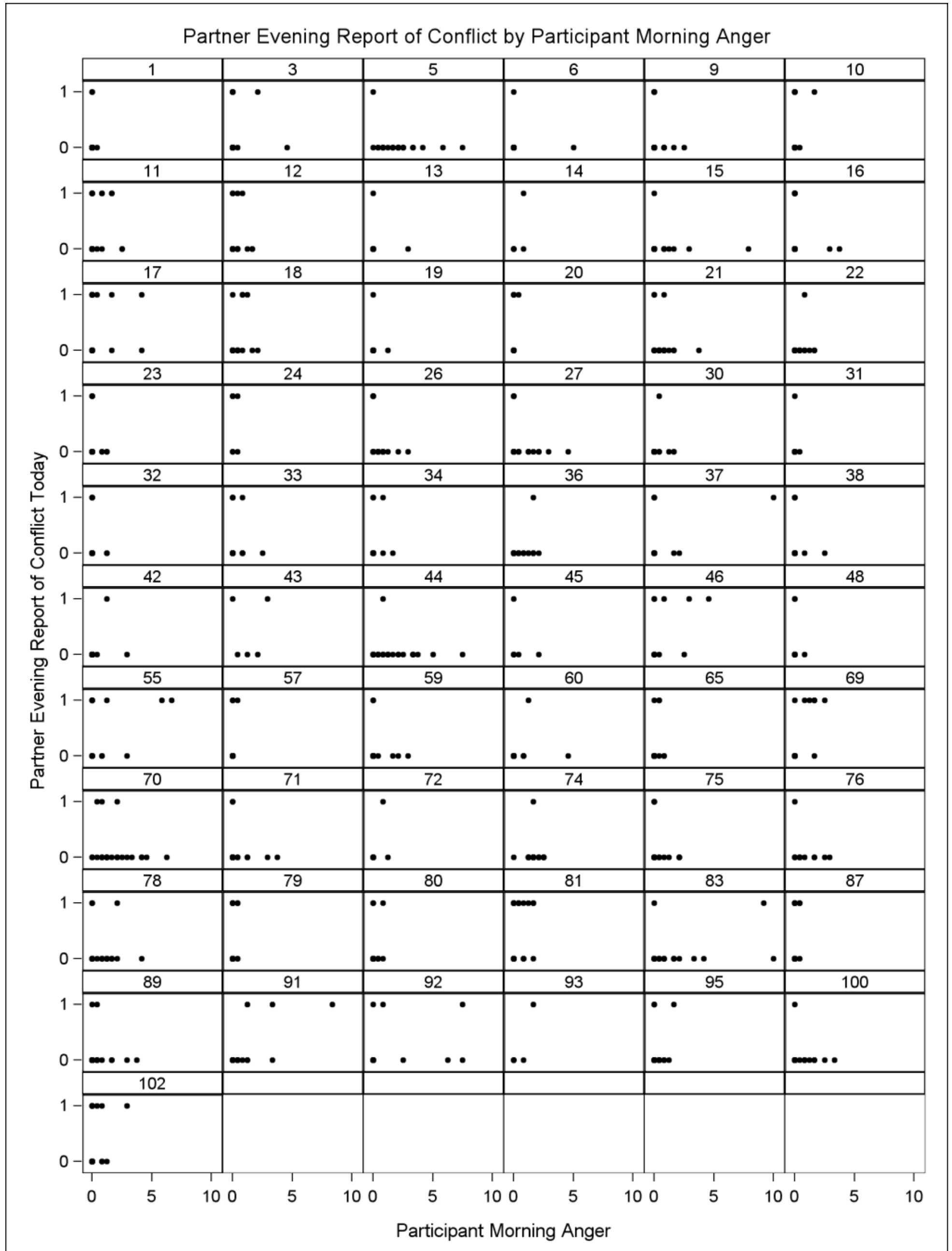
File Edit View Data Transform Analyze Direct Marketing Graphs Utilities Add-ons Window Help

1 :

	id	time	time7c	pconf	lpconf	lpconfc	amang	amangc	amangcb	amangcw	va
1	1	2	-1.88	0	0	-.157	.42	-.07	-.47	.40	
2	1	3	-1.73	0	0	-.157	.00	-.49	-.47	-.02	
3	1	4	-1.58	0	0	-.157	.00	-.49	-.47	-.02	
4	1	5	-1.43	0	0	-.157	.00	-.49	-.47	-.02	
5	1	6	-1.28	1	0	-.157	.00	-.49	-.47	-.02	
6	1	7	-1.13	0	1	.843	.00	-.49	-.47	-.02	
7	1	8	-.99	0	0	-.157	.00	-.49	-.47	-.02	
8	1	9	-.84	0	0	-.157	.00	-.49	-.47	-.02	
9	1	10	-.69	0	0	-.157	.00	-.49	-.47	-.02	
10	1	11	-.54	0	0	-.157	.00	-.49	-.47	-.02	
11	1	12	-.39	0	0	-.157	.00	-.49	-.47	-.02	
12	1	13	-.25	0	0	-.157	.00	-.49	-.47	-.02	
13	1	14	-.10	0	0	-.157	.00	-.49	-.47	-.02	
14	1	15	.05	0	0	-.157	.00	-.49	-.47	-.02	
15	1	16	.20	0	0	-.157	.00	-.49	-.47	-.02	
16	1	17	.35	1	0	-.157	.00	-.49	-.47	-.02	
17	1	18	.49	0	1	.843	.00	-.49	-.47	-.02	
18	1	19	.64	0	0	-.157	.00	-.49	-.47	-.02	

Dataset available at www.intensivelongitudinal.com

Scatterplots for each dyad



Output from Bolger & Laurenceau, 2013, chapter, 6

Model Term	Coefficient (SE)	*t*	*p*	95% *CI* Lower	95% *CI* Upper
Intercept	-1.87 (0.10)	-19.21	<0.001	-2.06	-1.68
amamgcw	0.21 (0.07)	3.17	0.002	0.08	0.34
amangcb	-0.18 (0.20)	-0.90	0.37	-0.58	0.22
lpconfc	0.86 (0.18)	4.80	<0.001	0.51	1.22
time7c	-0.17 (0.06)	-2.61	0.009	-0.29	-0.04

Random effect covariances	Estimate (SE)	*Z*	*p*	95% *CI* Lower	95% *CI* Upper
Level-2 (between-person)					
Intercept	0.21 (0.10)	2.09	0.037	0.08	0.54
AR1 Diagonal	0.97 (0.04)	24.52	<0.001	0.90	1.05
AR1 Rho	-0.10 (0.06)	-1.69	0.09	-0.20	0.02

Frequentist vs. Bayesian Results

Frequentist (Random Intercept Only)

Model Term	Coefficient (SE)	*t*	*p*	95% *CI* Lower	95% *CI* Upper
Intercept	-1.87 (0.10)	-19.21	<0.001	-2.06	-1.68
amamgcw	0.21 (0.07)	3.17	0.002	0.08	0.34

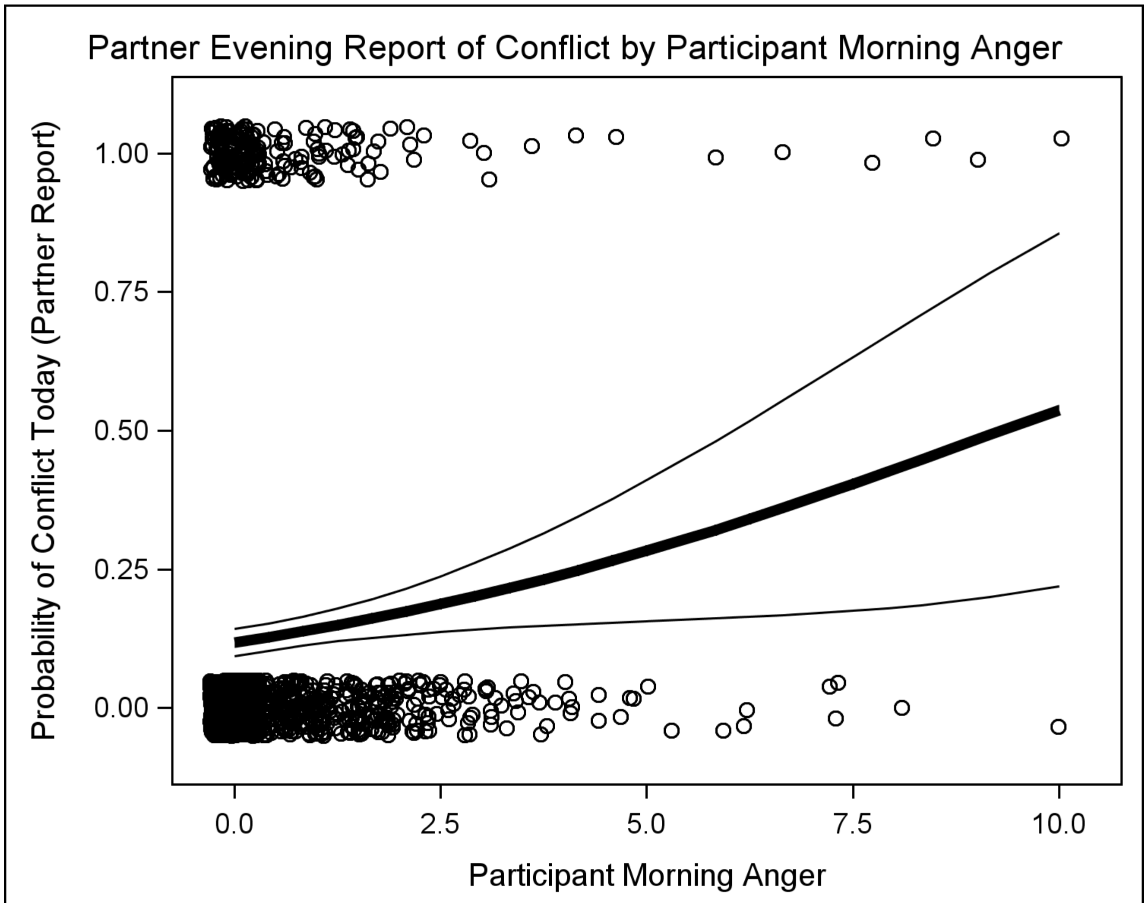
Using R package lme4

Bayesian (Random Intercept Only)

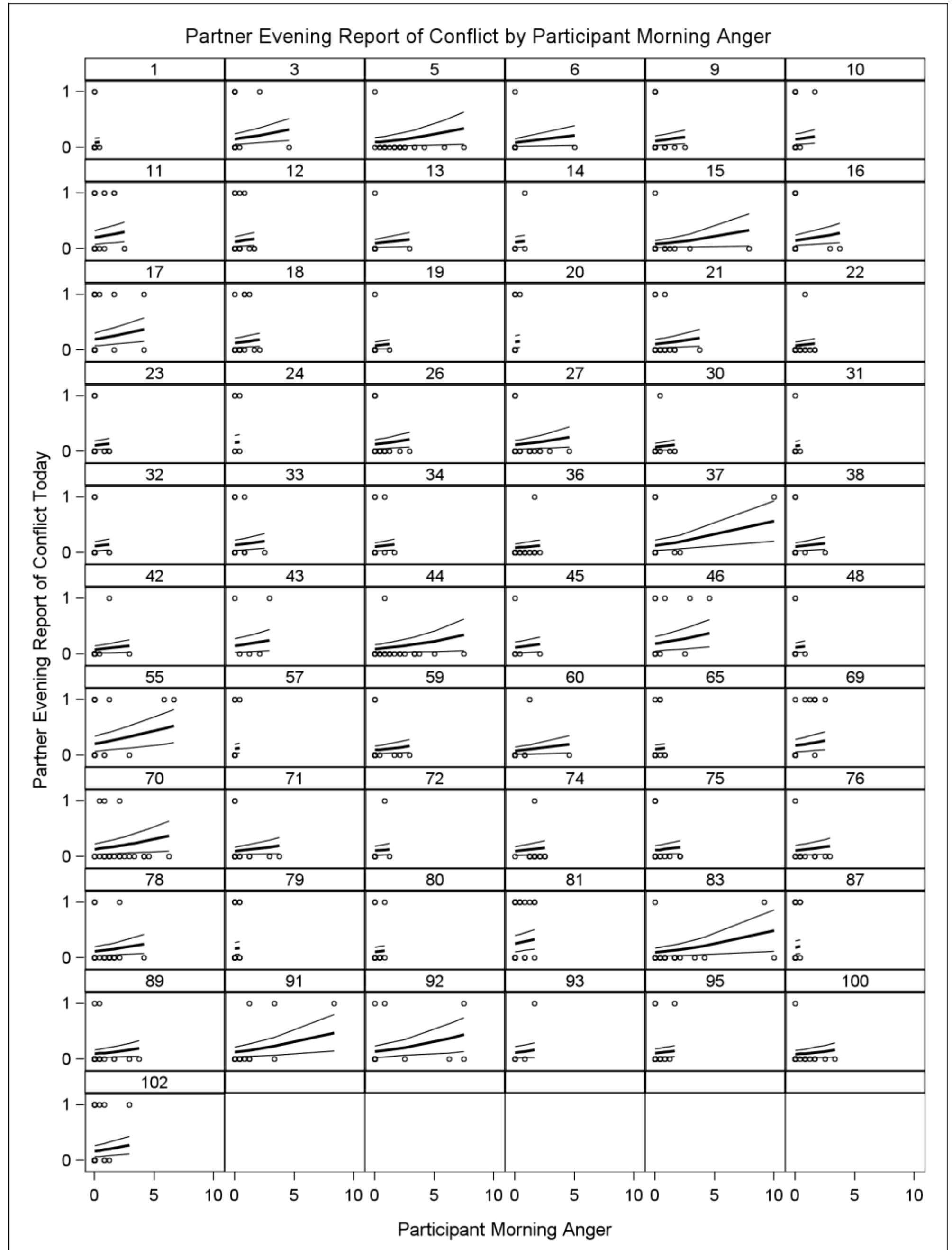
Model Term	Coefficient (SE)	*t*	*p*	95% *CI* Lower	95% *CI* Upper
Intercept	-1.92 (0.11)			-2.14	-1.70
amamgcw	0.21 (0.07)			0.08	0.35

Using R package brms

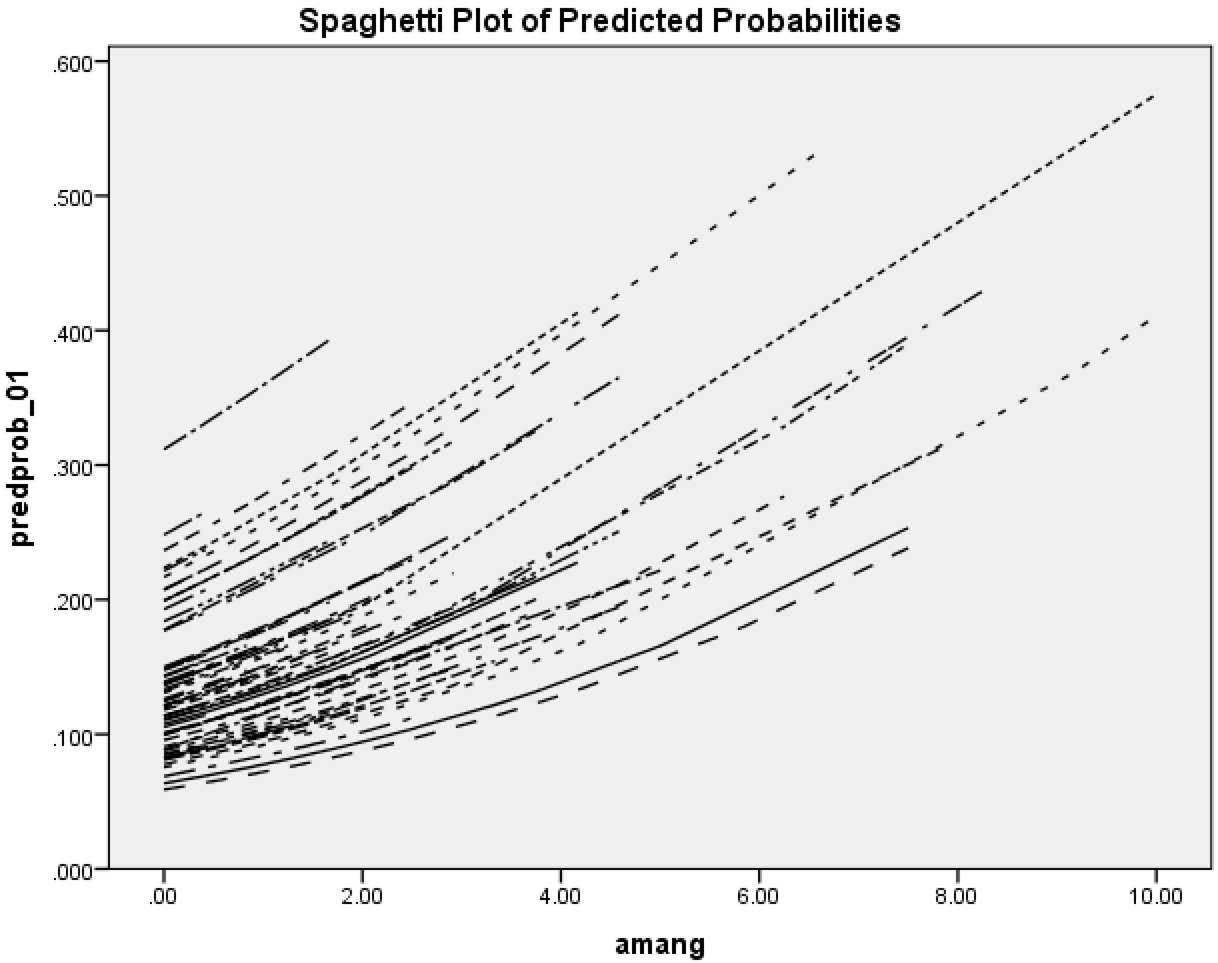
Predictions for average person (using fixed effect slope from random intercept, fixed slope model)



Model predictions for each dyad



Spaghetti Plot of Predictions



Frequentist vs. Bayesian Results

Frequentist (Random Intercept Only)

				95% *CI*	
Model Term	Coefficient (SE)	*t*	*p*	Lower	Upper
Intercept	-1.87 (0.10)	-19.21	<0.001	-2.06	-1.68
amamgcw	0.21 (0.07)	3.17	0.002	0.08	0.34

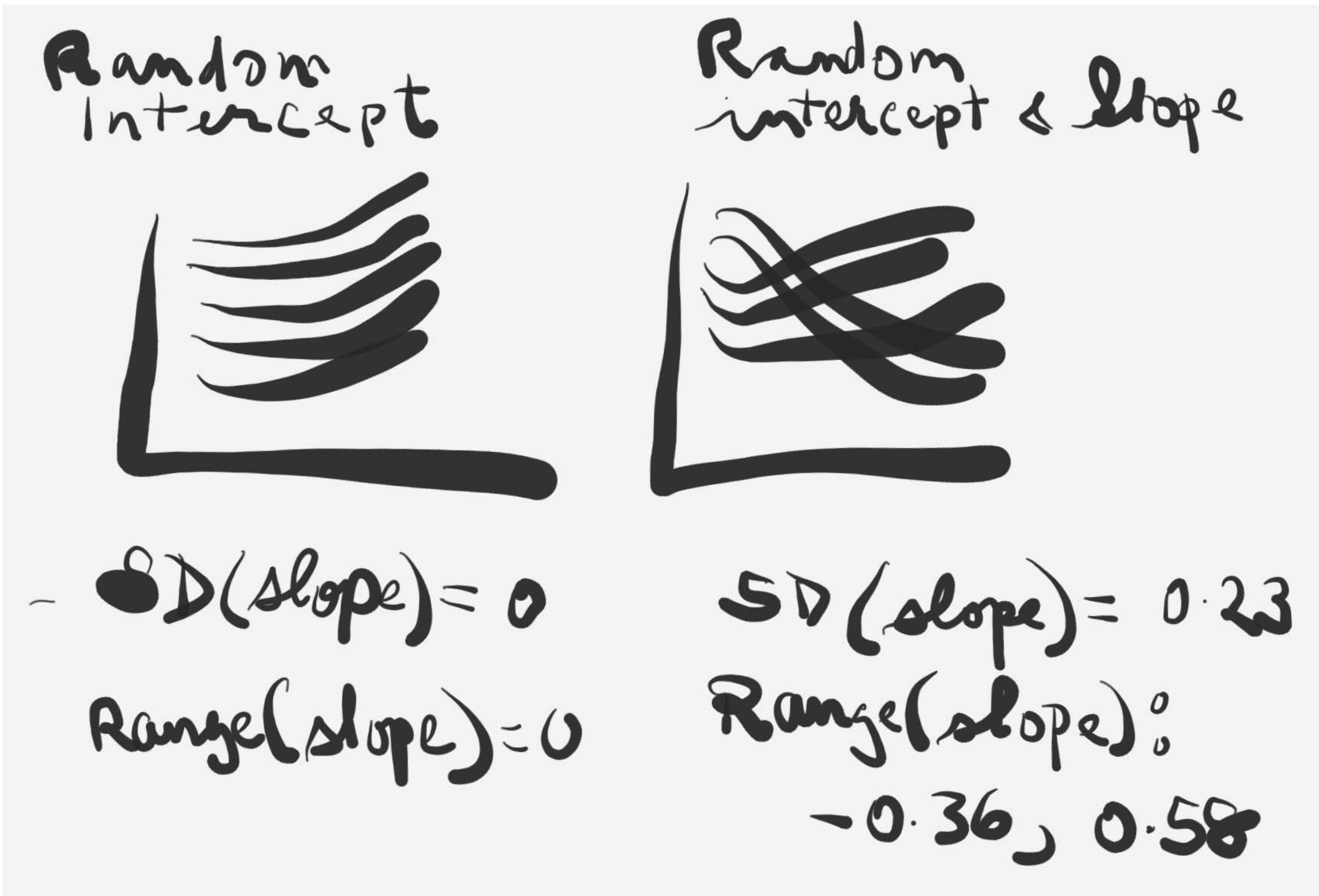
Using R package lme4

Bayesian (Random Intercept & Slope)

				95% *CI*	
Model Term	Coefficient (SE)	*t*	*p*	Lower	Upper
Intercept	-1.94 (0.12)			-2.19	-1.70
amamgcw	0.12 (0.13)			-0.17	0.34

Using R package brms

What you miss if you don't use Bayesian estimation



Sources for Bayesian Modeling

- 1. Krushke (2014): Doing Bayesian Data Analysis
- 2. McElreath (2015): Statistical Rethinking
- 3. Bürkner (2016) brms R package

Summary

- Bayesian estimates, when you use vague priors, are often very similar to frequentist estimates, but their interpretation is more intuitive.
- In multilevel modeling, Bayesian methods can find solutions in cases where frequentist methods can’t.
- When these solutions involve random effects, Bayesian estimation can show startlingly different results.