Your Very First Reproducible Manuscript (Well, Maybe)

Alexandra Paxton[1] & Your Name Here[2]

[1] Department of Psychological Sciences, University of Connecticut

[2] University of Wherever You Are

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Correspondence concerning this article should be addressed to Your Name Here, Your Postal Address. E-mail: your@email.com

Abstract

This toy manuscript serves an example of how to write an APA-formatted reproducible manuscript in R using the papaja package.

Keywords: tutorial, papaja, reproducible manuscript, imaginary people, rapport, interaction

Word count: 885 [Manually update this with the automatic word count printout shown in the RStudio console after you compile]

Your Very First Reproducible Manuscript (Well, Maybe)

This document will be your very first reproducible manuscript. (Well, maybe. Even if it's not your very first reproducible manuscript, I hope you find it useful.) For this reproducible manuscript, we're going to be relying on the R package called `papaja` (Aust & Barth, 2020). While you don't need to use it to create a reproducible manuscript in R, it's designed specifically to create an APA-formatted manuscript—which, if you're in this workshop with me, might be standard formatting for your academic journals of choice.

Here, we're going to write up our formal report on the toy experiment that we've been working with throughout the rest of this tutorial.

The Present Study

The present study sought to investigate how conversational context and shared affective language influence rapport-building between strangers. Patterns of shared language have been shown to reflect a variety of individual and interpersonal dynamics, including rapport (for review, see Duran, Paxton, & Fusaroli, 2019). We focused on conversation *goals* as our context—specifically, whether dyads shared very positive things that happened to them in the past week or very negative things that happened to them in the past week. For shared affective language, we quantified the degree of similarity in partners' use of *positive or negative emotion words* during the conversation. In doing so, we investigate whether hallmarks of rapport are context-specific—that is, whether imaginary people tend to feel closer to one another if they are more similar in context-appropriate emotional dynamics.

Method

Participants

We recruited 80 individual imaginary volunteers to participate as 40 imaginary dyads of strangers. All imaginary pairs were confirmed to be strangers during the experiment debriefing. No participants or dyads were excluded from our sample for any reason.

At the time of running this imaginary experiment, no ethical body yet oversaw the treatment of random number generators; therefore, no formal ethical approval was obtained for the current imaginary study. However, we attempted to treat these imaginary randomly generated volunteers with as much care as possible.

Material and Procedure

We asked our imaginary individual participants of imaginary strangers to hold one of two kinds of conversations with one another: a *celebratory* conversation (in which they are each asked to share and discuss a very positive thing that happened to them in the last week) or a *commiseration* conversation (in which they are asked to share and discuss a very negative thing that happened to them in the last week). Dyads were randomly assigned to condition upon arrival. By chance, we had 15 dyads assigned to the celebratory condition and 25 dyads assigned to the commiseration condition. Each dyad's conversation was video- and audio-recorded.

Data Preparation and Analysis

Rapport. To track quantify rapport, we recruited two expert observers in interpersonal dynamics to serve as raters. We trained them to watch and listen to the recorded interactions while continuously rating rapport using a joystick-style method (cf. Sadler, Ethier, Gunn, Duong, & Woody, 2009), creating a time series of ratings between 0 and 1. We obtained a single rapport rating by taking the mean of the time series. Surprisingly, both raters demonstrated perfect agreement in their continuous ratings of rapport ($M_{overall} = 0.44$).

Shared Language. Each dyad's conversation was transcribed verbatim. Positive and negative words were identified using a simple bag-of-words approach (i.e., counting occurrences of words identified as positive or negative). Metrics of shared positive language and shared negative language were extracted by analyzing the correlation of turn-to-turn counts of negative and positive words between participants ($M_{negative} = 0.59$; $M_{positive} = 0.56$; see Figs. 1 and 2).

Data Analysis

We analyzed our data with an ANOVA predicting rapport with condition (`0` = commiseration condition; `1` = celebration condition), negative word similarity, positive word similarity, and all interactions. We used R (Version 4.2.1; R Core Team, 2020) and the R-packages *ggplot2* (Version 3.3.6; Wickham, 2016), *papaja* (Version 0.1.1; Aust & Barth, 2020), and *tidyverse* (Version 1.3.2; Wickham et al., 2019) for all data preparation, visualizations, and analyses[1].

Results

For clarity and flow, all analyses are reported in Table 1, but to demonstrate how to programmatically call results, we will include significant *p*-values in the text as well. Two main effects significantly predicted rapport: negative word similarity (p = .017) and condition (p = .001). The interaction between negative word similarity and positive word similarity also significantly predicted rapport (p < .001). No other main or interaction terms reached statistical significance.

Discussion

Here, we explored the effects of similarity of emotional language patterns within specific emotion-inducing interaction contexts on perceived rapport between stranger dyads. In so doing, we provided an opportunity to learn how to create reproducible manuscripts with R markdown and `papaja` (Aust & Barth, 2020).

[1] The `cite_r()` function is a helper function from `papaja` (Aust & Barth, 2020) that will identify any references in the `.bib` file that begin with the prefix `R-`. This is a helpful shortcut to ensuring that all of your software tools are properly attributed in your manuscript.

Limitations and Future Directions

Of course, the present work is not without limitations, which we see as opportunities for future studies. The most important limitation of the work is our chosen population—that is, imaginary participants who contributed simulated data. As such, we must conduct experiments with non-imaginary participants in order to identify whether these observed effects hold in non-simulated experimental contexts.

References

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Table 1

Results from our statistical model

Effect	$\hat{\eta}^2_G$	90% CI	F	df	df_{res}	p
Negative word similarity	.165	[.018, .358]	6.34	1	32	.017
Positive word similarity	.015	[.000, .146]	0.49	1	32	.487
Condition	.317	[.111, .499]	14.84	1	32	.001
Negative word similarity × Positive word similarity	.321	[.115, .503]	15.14	1	32	$< .001$
Negative word similarity × Condition	.015	[.000, .033]	0.49	1	32	.488
Positive word similarity × Condition	.005	[.000, .103]	0.17	1	32	.687
Negative word similarity × Positive word similarity × Condition	.049	[.000, .213]	1.65	1	32	.208

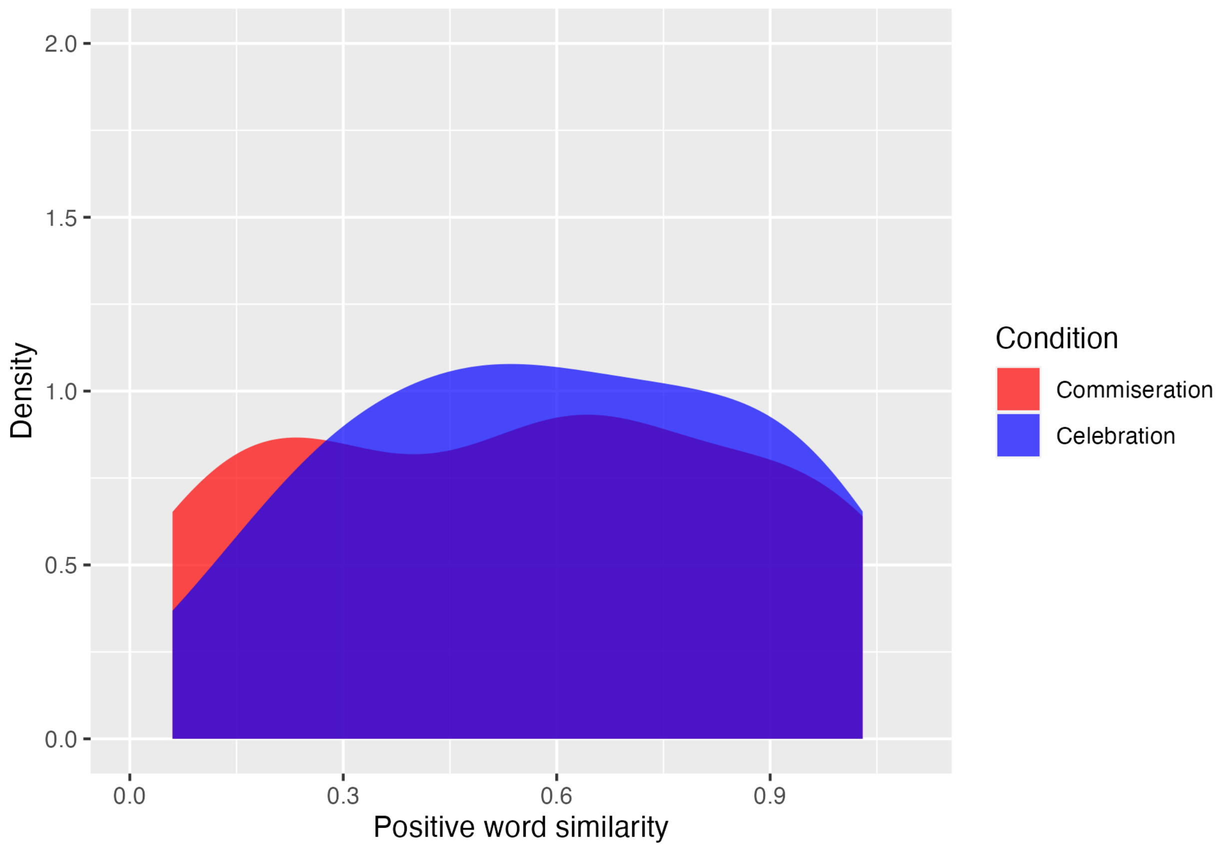

Figure 1. Positive word similarity by condition.

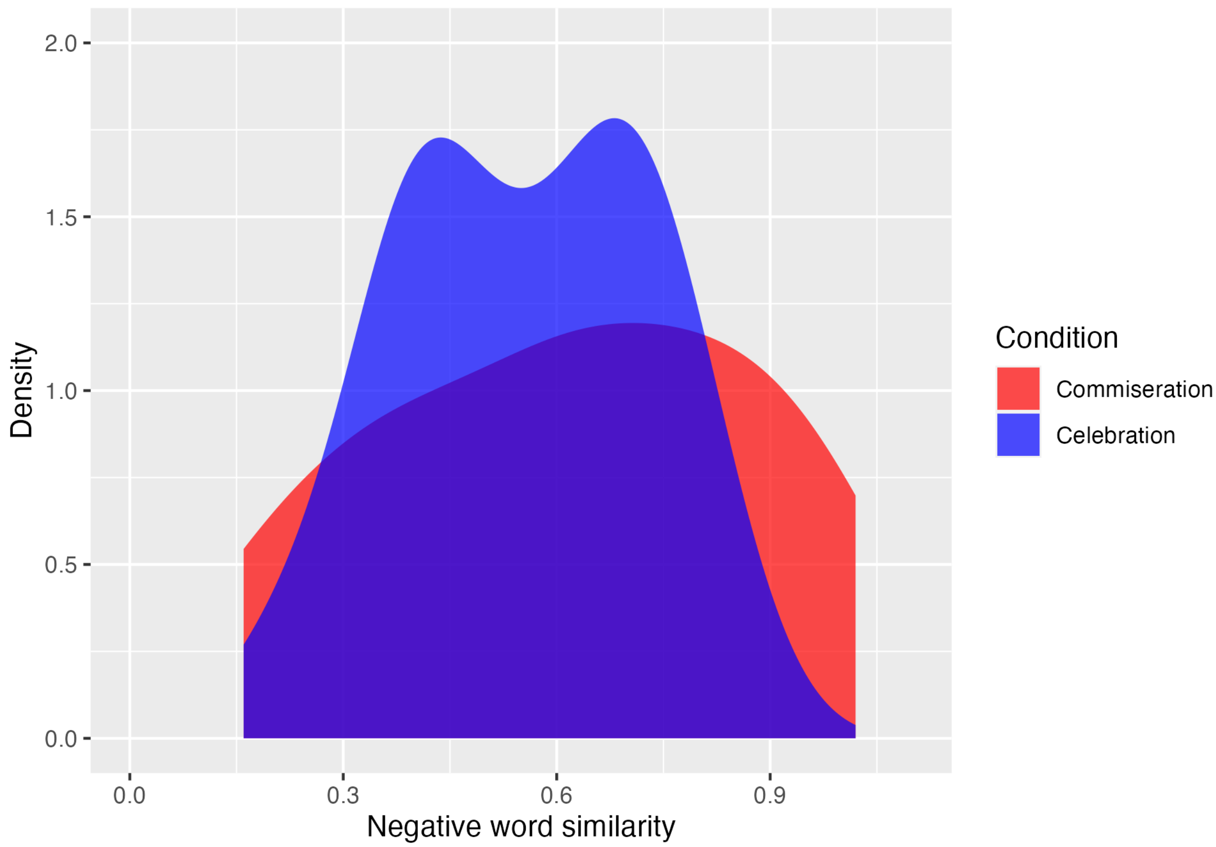

Figure 2. Negative word similarity by condition.