Not that much power: Linguistic alignment is influenced more by low-level linguistic features rather than social power

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Abstract

Does the social power status of people influence how others speak towards them? Previous studies said yes, but they overlooked the effect low-level linguistic features. We find that after controlling for low-level features (*utterance length*), the effect of power on alignment vanishes or is reversed.

Introduction

- The *social power* of interlocutors influences how they align (coordinate, accommodate) towards each other.
- Qualitative evidence: interviewers & interviewees (Willemyns et al., 1997), teachers & students (Jones et al., 1999) etc.
- Quantitative evidence: admins & non-admins in Wikipedia talkpages, judges & lawyers in supreme-court dialogues (Danescu-Niculescu-Mizil et al., 2012).
- **A widely accepted conclusion**: people align their language use more towards interlocutors of higher power (e.g., admins, judges) than those of lower power (e.g., non-admins, lawyers).
- **However**, previous studies overlooked the **low-level features** that could also affect alignment, e.g., lexical information density, syntactic surprisal, temporal clustering (Jaeger and Snider, 2008, 2013; Xu and Reitter, 2018; Mysln and Levy, 2016), which casts doubt on the conclusion.
- **Our work**: A two-step model analysis on how reliably social power affects alignment:
  - Step 1, a basic model to replicate Danescu-Niculescu-Mizil et al. (2012)'s findings.
  - Step 2, an extended model that includes *utterance length* on top of the basic model, aiming to examine whether the effect of social power still exists.

Experiment 1: Basic Model

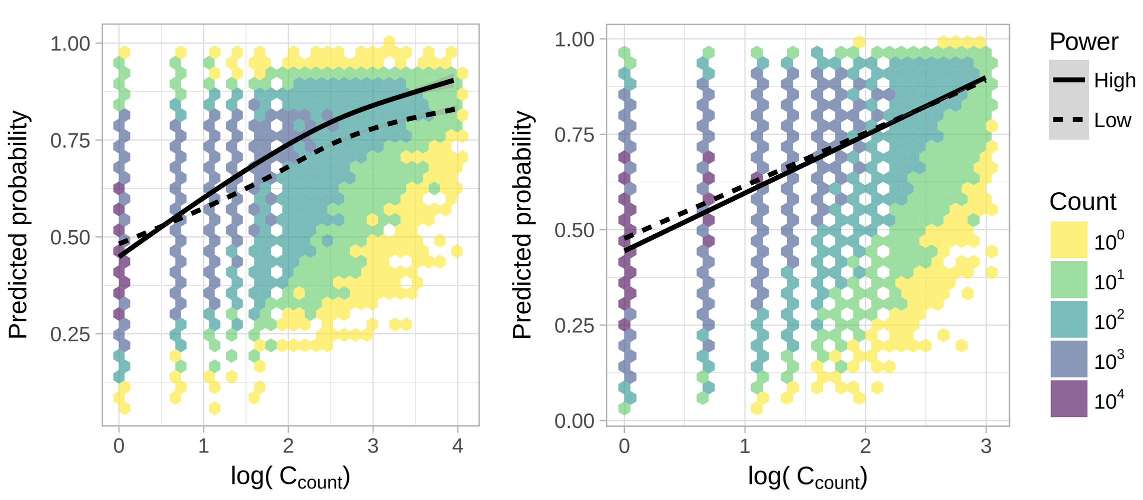
- Alignment is the impact of using certain linguistic elements in the preceding utterance (*prime*) on their chance to appear again in the following utterance (*target*).
- In the language of generalized linear models (GLM), we use the occurrence of linguistic markers in *target* as the response variable, and their occurrence in *prime* as the predictor.

$$\begin{aligned}\mathrm{logit}(m) &= \ln\frac{p(m \text{ in } target)}{p(m \text{ not in } target)}\\ &= \beta_0 + \beta_1 C_{\text{count}} + \beta_2 C_{\text{power}}\\ &+ \beta_3 \mathbf{C_{count} * C_{power}}\end{aligned} \tag{1}$$

- Here, C_{count} is the number of marker m in *prime*. C_{power} is a binary predictor indicating the power status of *prime* speaker (*high* vs. *low*).
- A linguistic marker m is one of the 14 LIWC[1] categories: adverbs, articles, auxiliary verbs, certainty, conjunctions, discrepancy, exclusive, inclusive, impersonal pronouns, negations, personal pronouns, prepositions, quantifiers, and tentativeness.
- Datasets: Wikipedia talk-page corpus (*Wiki*) and a corpus of United States supreme court conversations (*SC*) (compiled by Danescu-Niculescu-Mizil et al. (2012)).
- **Results**: z scores of β_3 are shown in Table 1. Slopes of C_{count} are visualized in Figure 1.

Marker	$C_{\text{count}} * C_{\text{power}}$ SC	Wiki
adv	**6.16*****	-0.40
art	**4.60*****	1.27
auxv	**5.81*****	-0.83
certain	**1.94**†	**2.84****
conj	**6.79*****	0.39
discrep	**8.03*****	0.25
excl	**2.94****	**2.16***
incl	**5.24*****	**2.15***
ipron	**10.22*****	**1.90**†
negate	**5.49*****	**3.11****
ppron	1.29	-1.13
prep	**6.87*****	-0.19
quant	**4.14*****	-0.04
tentat	**4.52*****	-0.78

Table 1: Wald's z-score and significance level (*** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$, and † for $0.05 < p < 0.1$) of the interaction term, $C_{\text{count}} * C_{\text{power}}$.



a: Supreme Court b: Wikipedia

Figure 1: The predicted probability against C_{count}, grouped by C_{power}. Divergent slopes indicate significant interaction: high power speakers have larger slopes than low power ones.

- Therefore, we have replicated the previous finding from Danescu-Niculescu-Mizil et al. (2012): significant β_3 of $C_{\text{count}} * C_{\text{power}}$ indicates that the β of C_{count} depends on C_{power}, i.e., the strength of alignment varies with the power levels of speakers (*high* vs. *low*).
- **However**, this affirmative finding is **not** safe, because only one predictor, C_{power}, is included in the model, which we will show in Experiment 2.

Experiment 2: Extended Model

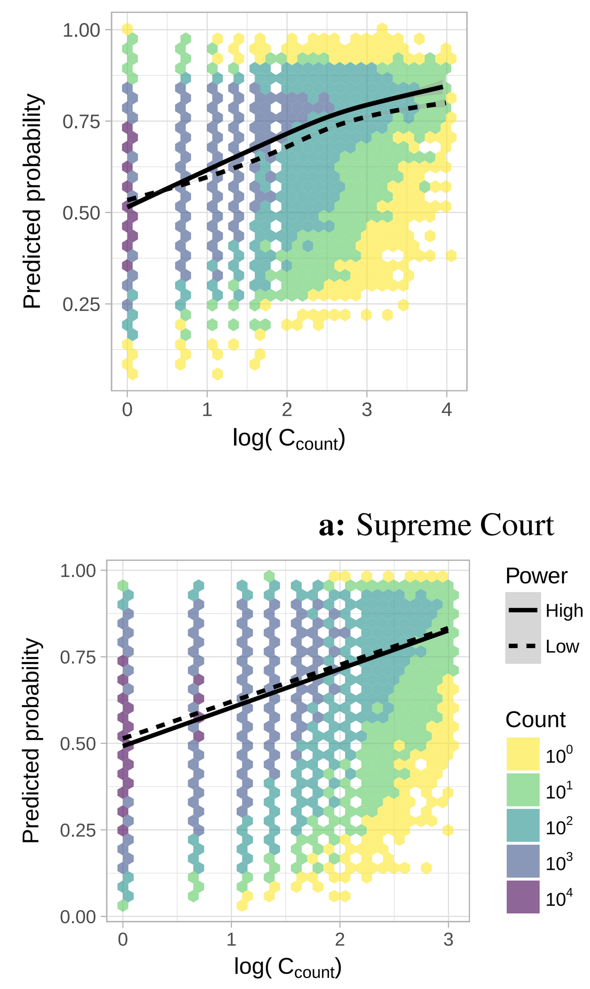
- Does the interaction term $C_{\text{count}} * C_{\text{power}}$ remain significant *after* including other predictors that represent low-level linguistic features?
- We add **utterance length** (number of words) as an additional predictor to the model, C_{pLen}.

$$\begin{aligned}\mathrm{logit}(m) &= \ln\frac{p(m \text{ in } target)}{p(m \text{ not in } target)}\\ &= \beta_0 + \beta_1 C_{\text{count}} + \beta_2 C_{\text{power}} + \beta_3 C_{\text{pLen}}\\ &+ \boldsymbol{\beta_4 C_{count} * C_{power}}\\ &+ \beta_5 C_{\text{count}} * C_{\text{pLen}}\\ &+ \beta_6 C_{\text{power}} * C_{\text{pLen}}\\ &+ \beta_7 C_{\text{count}} * C_{\text{power}} * C_{\text{pLen}}\end{aligned} \tag{2}$$

- Our goal: to examine whether β_4 remains significant and in same direction as β_3 in Experiment 1.
- **Results**: Full model coefficients are shown in Table 2.

Table 2: Model coefficients of all terms in Equation 2. Notice that the β_4 of $C_{\text{count}} * C_{\text{power}}$ is **negative** in SC and **non-significant** in Wiki

Corpus	Predictor	β	z
SC	Intercept	0.360	2.40*
	C_{count}	0.213	26.92***
	C_{power}	-0.060	-3.39***
	C_{pLen}	0.080	13.03***
	$\mathbf{C_{count} * C_{power}}$	**-0.103**	**-9.95*****
	$C_{\text{count}} * C_{\text{pLen}}$	-0.066	-15.35***
	$C_{\text{power}} * C_{\text{pLen}}$	0.231	25.25***
	$C_{\text{count}} * C_{\text{power}} * C_{\text{pLen}}$	0.036	4.79***
Wiki	Intercept	0.330	1.40
	C_{count}	0.149	31.11***
	C_{power}	-0.074	-10.52***
	C_{pLen}	0.179	40.80***
	$\mathbf{C_{count} * C_{power}}$	**0.001**	**0.14**
	$C_{\text{count}} * C_{\text{pLen}}$	0.022	6.13***
	$C_{\text{power}} * C_{\text{pLen}}$	0.042	5.52***
	$C_{\text{count}} * C_{\text{power}} * C_{\text{pLen}}$	-0.010	-1.61

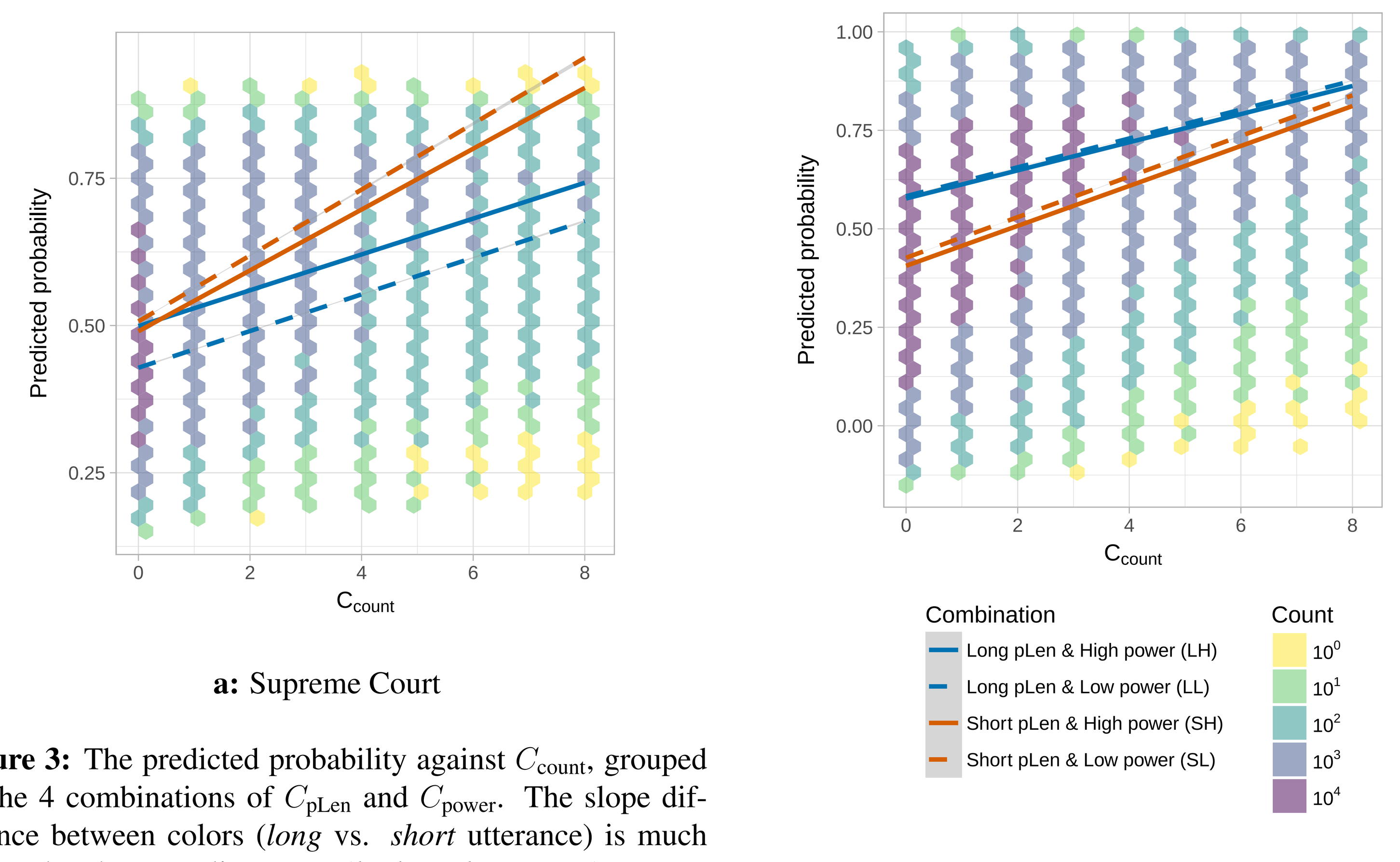


a: Supreme Court

b: Wikipedia

Figure 2: The predicted probability against C_{count}, grouped by C_{power}. Notice that the differences in slopes (between *high* power and *low* power) are much smaller than Figure 1.

- **Surprisingly**, the coefficient of $C_{\text{count}} * C_{\text{power}}$ is negative in SC, and non-significant in Wiki, which is inconsistent with the positive coefficients in Experiment 1.
- Further illustration of how the interaction $C_{\text{count}} * C_{\text{power}}$ diminishes after including C_{pLen} to the model: cluster C_{pLen} to two discrete values, *long* and *short*, and then plot the regression lines grouped by the combination of C_{pLen} and C_{power} (shown in Figure 3).



a: Supreme Court

b: Wikipedia

Figure 3: The predicted probability against C_{count}, grouped by the 4 combinations of C_{pLen} and C_{power}. The slope difference between colors (*long* vs. *short* utterance) is much bigger than between line-types (*high* vs. *low* power).

- Thus, C_{pLen} is a more determinant factor of alignment than C_{power}.

Discussion and Conclusions

- Our findings suggest that the previously reported effect of power on linguistic alignment is not reliable. Instead, alignment is more sensitive to certain low-level features (e.g., utterance length).
- We do not deny the existence of accommodation caused by social perception, but we want to emphasize the difference between the priming-induced alignment and the intentional accommodation.
- The dynamics of LIWC categories in probability space is more likely to be a case of automatic alignment, rather than accommodation. Therefore, we suggest future work on social aspects of language use should consider higher levels of linguistic elements.

Acknowledgements

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[1] Linguistic Inquiry and Word Count, https://liwc.wpengine.com/