Prior probability predicts projection

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Abstract

Interpreters' beliefs about the world have been shown to influence utterance processing and interpretation in a variety of empirical domains. This paper reports three experiments designed to investigate the hypothesis that such beliefs influence projection, that is, inferences about speaker commitment to non-entailed utterance content. We find, in support of the hypothesis, that the higher the prior probability of content, the more projective it is. We also find that projection is influenced by the average beliefs of a group and at the by-participant level. **JT: (Word count: xxx words)**

1 Introduction

Interpreters' beliefs about the world have been shown to influence sentence processing (e.g., Chambers, Tanenhaus, Eberhard, Filip, and Carlson 2002, Hagoort, Hald, Mastiaansen, and Petersson 2004, Hald, Steenbeek-Planting, and Hagoort 2007) and utterance interpretation in a variety of empirical domains, including ambiguity resolution (e.g., Chambers, Tanenhaus, and Magnuson 2004, Bicknell and Rohde 2014), reference resolution (e.g., Hanna and Tanenhaus 2004), genericity (e.g., Tessler and Goodman 2019) and scalar implicature (e.g., Degen, Tessier, and Goodman 2015).[1]

This paper provides empirical evidence that American English interpreters' beliefs also influence projection. Projection is characterized as the speaker being committed to content, based on their utterance, which then also influences whether the listener is committed: the content becomes part of the common ground between the speaker and the listener. A speaker who utters the polar question in (1b) may be committed to the truth of the content of the complement, that it is raining, even though it is realized in a polar question, that is, even though it is not entailed content.

(1) a. Sam knows that it's raining.
    b. Does Sam know that it's raining?
    c. Sam doesn't know that it's raining.

The hypothesis that the prior probability of content influences its projection has been put forth in Stevens, de Marneffe, Speer, and Tonhauser 2017 and Tonhauser, Beaver, and Degen 2018. Stevens et al. 2017 investigated the projection of the prejacent of utterances of manner adverb sentences, illustrated in (2). An utterance of (2a) implies both the prejacent, that Masha ran, and that her running was done in a quick manner. The prejacent is projective because it may also be implied by an utterance of the negated variant of (2a) given in (2b), especially when the adverb is produced with prosodic emphasis.

(2) Stevens et al. 2017:1144

[1]Different kinds of beliefs have been investigated. Some of these are called world knowledge, but it's not clear that it's knowledge. We use the more cautious term belief.

a. Masha ran quickly.

b. Masha didn't run QUICKLY.

Stevens et al. 2017 observed by-item variability in the projection of the prejacent and suggested that this variability may be due to interpreters having different prior probabilities about the prejacent.

Tonhauser et al. 2018 investigated the projection of content associated with 19 American English expressions, including the content of the complement of clause-embedding predicates, like *know*, illustrated in (1), and the prejacent of utterances of sentences with *stop*, illustrated in (3). The pre-state content of (3a), that Mary's daughter has been biting her nails, survives embedding in the question version in (3b).

(3) a. Mary's daughter stopped biting her nails.

b. Has Mary's daughter stopped biting her nails?

In addition to observing by-expression projection variability, Tonhauser et al. 2018 also found by-item variability for the same expression: for instance, the pre-state content of *stop* was numerically less projective when it was the content that Mary's daughter has been biting her nails than when it was the content that Jack was playing outside with the kids. Tonhauser et al. 2018:500 hypothesized that "the projectivity of content may depend on the prior probability of the event described by the expression that conveys the content, such that content conveyed by expressions that describe more a priori likely events may be more likely to project".

This experiment investigated the hypothesis that the prior probability of content influences its projection, specifically, that the higher the prior probability of content is, the more projective it is.

This paper provides empirical evidence for the hypothesis that the prior probability of content influences its projection, that is, that the prior probability ascribed to content prior to observing the utterance influences the extent to which the speaker is committed to that content. Our investigation builds on previous work that has investigated this hypothesis, with different results, namely Lorson 2018 and Mahler 2020.

Lorson (2018) investigated the influence of prior probability on the projection of the pre-state content of the English change of state verb *stop*: in the polar questions in (4), the pre-state contents are that James has worked as a plumber, in (4a), and that Linda has worked as a plumber, in (4b).

(4) a. Did James stop working as a plumber?

b. Did Linda stop working as a plumber? (Lorson 2018:38)

Gender stereotypes reported in Boyce, von der Malsburg, Poppels, and Levy 2018 were used to manipulate the prior probability of the pre-state content, that is, the prior beliefs of the interlocutors about the pre-state content: it is, for instance, more likely for a man (like James) to be a plumber than for a woman (like Linda) to be a plumber. The hypothesis was that higher probability pre-state contents, as in (4a), were more projective than lower probability pre-state contents, as in (4b). Lorson (2018) did not find empirical support for this hypothesis.

Mahler (2020) investigated the projection of politically-charged content, which was realized as the complement of a clause-embedding predicate. In (5), for example, the politically-charged content is that Obama improved/damaged the American economy, which is realized as the complement of the clause-embedding predicate *know*, which is embedded under negation.

(5) Cindy doesn't know that…

a. …Obama improved the American economy.

b. …Obama damaged the American economy. (Mahler 2020:779)

The speaker's political affiliation was used to manipulate the prior probability of the content of the complement: the speaker was attending a a meeting of the Democrat or the Republican party and was thereby implied to be a Democrat or a Republican. Thus, the content of the complement had a higher prior

The combination of the political party affiliation of the interlocutors and the content of the complement was used to manipulate the prior probability of the content: when the content of the complement was consistent with a liberal political perspective, as in (5a), it had a higher prior probability with Democrat interlocutors than with Republican interlocutors, and when the content of the complement was consistent with a conservative political perspective, as in (5b), it had a higher prior probability with Republican interlocutors than with Democrat interlocutors. Mahler (2020) found that the speaker's presumed belief in the content (before making her utterance) influences participants' certainty ratings: She then found that participants rate speakers with a higher prior belief as more committed than speakers with a lower prior belief. She did not measure participants' beliefs in these contens.

So, there is currently a conflicting state in the literature about the hypothesis that prior probability predicts projection. The difference in results may be due to

- the projective content investigated (pre-state content of *stop* versus the content of the complement of clause-embedding predicates),

- the ways in which the prior was manipulated (gender stereotypes versus political party affilliation).

Both Lorson 2018 and Mahler 2020 used the certainty diagnostic for projection (Tonhauser et al. 2018): sliding scale in both. Lorson 2018 relied on gender stereotypes established in previous work (no separate norming study) while Mahler 2020 conducted a norming study: Lorson recruited participants on Prolific and social media (no info on their demographics) while gender stereotypes were established on AMT; Mahler ran both the norming study and the experiment on AMT. Prior probability entered Lorson's model in a non-categorical fashion in Lorson 2018 (consistency measure) and in a categorical fashion in Mahler 2020 (political party (2 levels) and political orientation of CC (liberal vs. conservative). Lorson, p.36: "The consistency measure is a value that ranges from 0 to 1, where a value close to 0 means that the gender of an individual is inconsistent with a certain occupation, according to the collected gender-bias that was found to be associated with that occupation. A value close to 1 means that the gender of an individual is consistent with an occupation."

Our experiments manipulate the prior in much more variable ways than Mahler and Lorson. Like Mahler, we investigated the hypothesis that prior probability influences projection based on the content of the complement of clause-embedding predicates. But we do so on a broader set of 20 predicates than she did (she had 7 predicates, which she grouped into two groups and she found the effect in both groups). Our results consistent with Mahler's but we have a broader set of predicates and don't artificially group the predicates. We have shown elsewhere (Tonhauser and Degen ms) that this binary distinction is not supported by the data. Also we have a broader manipulation of the prior.

Experiment 1: We measured the belief of each participant and also measured how much they take the speaker to be committed.

Experiment 2: We measured the belief of one group of people, test how the average belief of that group predicts something about projection of the second group.

2 Experiment 1

This experiment investigated the hypothesis that the prior probability of content influences its projection, specifically, that the higher the prior probability of content is, the more projective it is. Prior probability and projection ratings were collected for the contents of 20 clauses that realized the complements of clause-embedding predicates.[2]

Participants 300 participants with U.S. IP addresses and at least 99% of previous HITs approved were recruited on Amazon's Mechanical Turk platform (ages: 18-82, median: 35.5; 119 female, 179 male, 1 other, 1 undeclared). They were paid $1.80.

Materials The prior probability and the projection of the contents of 20 clauses were measured. As shown for the sample clause in (6), each clause was paired with two facts. One fact was hypothesized to result in higher prior probability ratings for the content and the other in a lower prior probability rating. See Supplement A for the full set of clauses and facts.

(6) Sample clause: Julian dances salsa.
Higher probability fact: Julian is Cuban.
Lower probability fact: Julian is German.

Prior probability and projection were measured in separate blocks. In the prior block, the 20 clauses were realized as the complements of *How likely is it that... ?* questions. As shown in (7), each target stimulus consisted of one of the two facts for that clause and the *How likely is it that... ?* question. There were a total of 40 target stimuli in the prior block.

(7) Sample target stimuli in the prior block
  a. **Fact:** Julian is Cuban.
  How likely is it that Julian dances salsa?
  b. **Fact:** Julian is German.
  How likely is it that Julian dances salsa?

In the projection block, the target stimuli consisted of a fact and a polar question that was uttered by a named speaker, as shown in (8). The fact was one of the two facts that the clause was paired with. The polar questions were formed by realizing the 20 clauses as the complements of the 20 clause-embedding predicates in (9). There were a total of 800 target stimuli in the projection block.

(8) Sample target stimuli in the projection block
  a. **Fact (which Carol knows):** Julian is Cuban.
  Carol: Does Sandra know that Julian dances salsa?
  b. **Fact (which Carol knows):** Julian is German.
  Carol: Does Sandra know that Julian dances salsa?

(9) 20 clause-embedding predicates
be annoyed, discover, know, reveal, see, acknowledge, admit, announce, confess, confirm, establish, hear, inform, prove, pretend, suggest, say, think, be right, demonstrate

[2] The experiments, data and R code for generating the figures and analyses of the experiments reported on in this paper are available at [redacted for review]. Exp. 1 was pregistered: [link removed for review]

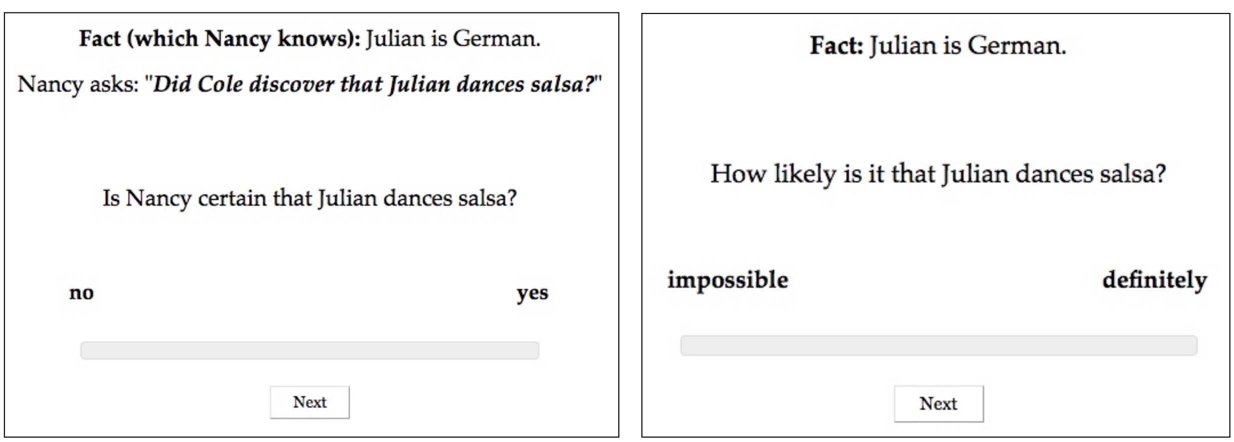
The 20 predicates in (9) include a cross-section of English clause-embedding predicates: They include cognitive predicates (e.g., *know*), emotive predicates (e.g., *be annoyed*), communication predicates (e.g., *announce*), and inferential predicates (e.g., *prove*), as well as so-called factive and non-factive predicates (e.g., *know* vs. *think*); as mentioned above, Tonhauser and Degen ms challenge this latter classification.

The projection block also included 6 control stimuli, which were used to assess participants' attention to the task. The content of these control stimuli was hypothesized to not project. For example, in the control stimulus in (10), the speaker is not committed to the main clause content, that Zack is coming to the meeting tomorrow. The control stimuli were presented with a fact that we hypothesized to not influence the prior probability of the content. The same 6 main clauses were also used to form the 6 filler stimuli in the prior block, but these were not used to assess participants' attention to the task. In each block, the same 6 control stimuli were presented to all participants. For the full set of stimuli Supplement A.

(10) Sample control stimulus in the projection block
Fact (which Margaret knows): Zack is a member of the golf club.
Margaret: Is Zack coming to the meeting tomorrow?

For each participant, a set consisting of the 20 clauses with one of their facts was randomly generated, with 10 higher and 10 lower probability facts, for a total of 20 clause/fact combinations. Participants saw a total of 52 stimuli: 20 target stimuli in each block, 6 control stimuli in the projection block and 6 filler stimuli in the prior block. In the prior block, participants rated the prior probability of the contents of these 20 clauses given the facts. In the projection block, the 20 clauses were randomly realized as the complements of the 20 clause-embedding predicates. Here, participants rated the projection of the contents of the 20 clauses given the facts. Block order and within-block trial order were randomized.

Procedure In the projection block, participants were told to imagine that they are at a party and that, on walking into the kitchen, they overhear somebody ask somebody else a question. Participants were asked to rate whether the speaker was certain of the content of the complement, taking into consideration the fact that was presented. They gave their responses on a slider marked 'no' at one end (coded as 0) and 'yes' at the other (coded as 1), as shown in Figure 1a. In the prior block, participants were told to read facts and to assess the likelihood of events, given those facts. They gave their responses on a slider marked 'impossible' at one end (coded as 0) and 'definitely' at the other (coded as 1), as shown in the sample trial in Figure 1b



(a) Projection block. (b) Prior block.

Figure 1: Sample trials in Exp. 1.

After completing the experiment, participants filled out a short, optional survey about their age, their gender, their native language(s) and, if English is their native language, whether they are a speaker of American English (as opposed to, e.g., Australian or Indian English). To encourage them to respond truthfully, participants were told that they would be paid no matter what answers they gave in the survey.

Data exclusion We excluded data based on self-declared non-native speaker status and other criteria given in Supplement B, leaving data from 286 participants to be analyzed (ages 18-82; median: 35.5; 116 female, 186 male, 1 other, 1 undeclared).

2.1 Results

The manipulation of the prior probability of the 20 contents was successful. Figure 2 plots the mean prior probabilities of the 20 contents by fact (participants' ratings are given as light dots). The mean prior probability rating for each content was higher when the content was presented with the higher probability fact than when it was presented with the lower probability fact.

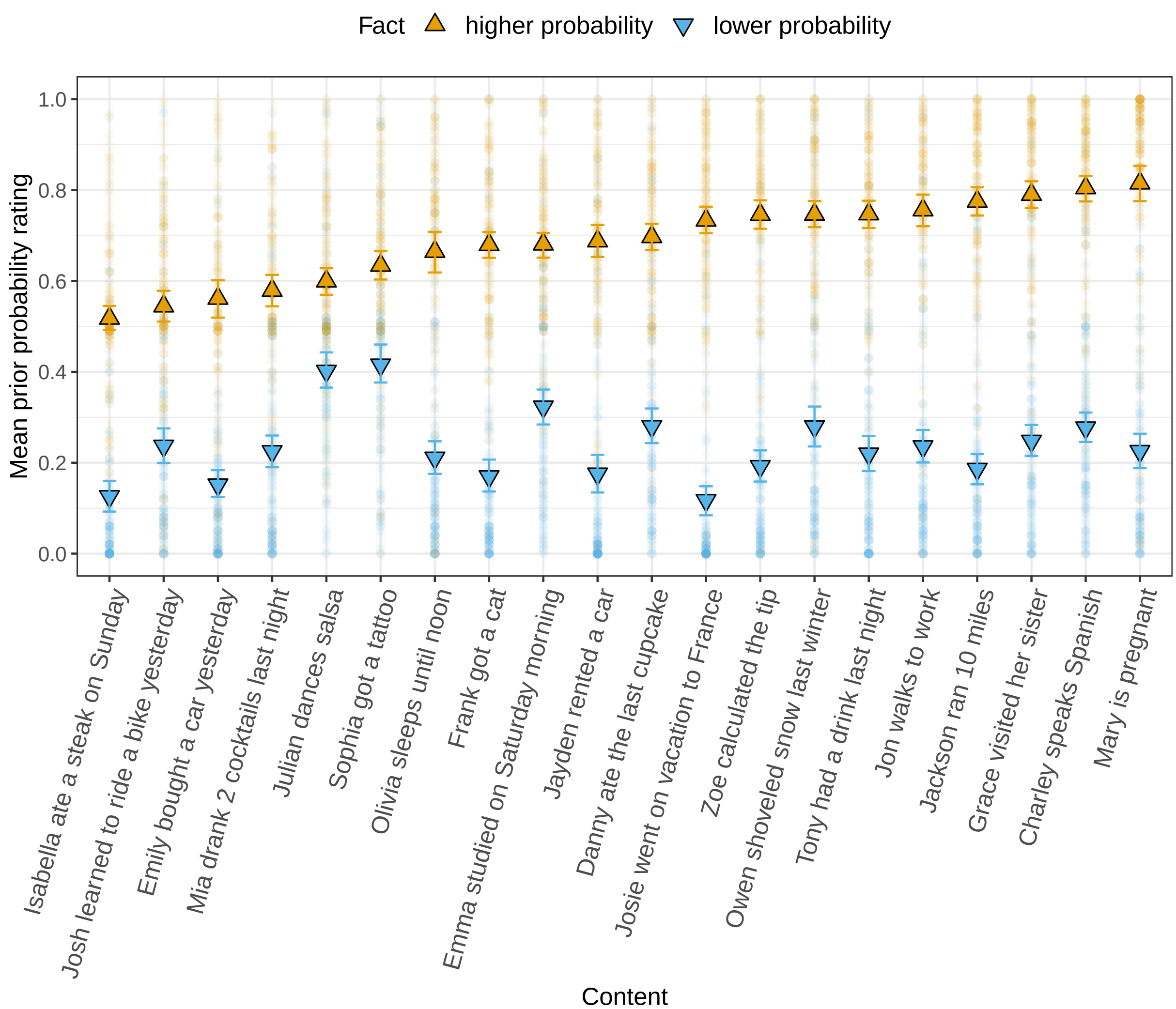


Figure 2: Mean prior probability by content and fact in Exp. 1. Error bars indicate 95% bootstrapped confidence intervals. Light dots indicate participants' ratings.

We now address the research question of whether prior probability influences projection. Figure 3 plots the mean certainty ratings for the contents of the clausal complements by clause-embedding predicate and by fact, as well as the mean certainty rating for the main clause content (abbreviated 'MC'). Light dots indicate participants' ratings. As shown, the mean certainty ratings were higher for contents presented with the higher probability facts than for contents presented with the lower probability fact. This result, which holds for all 20 clause-embedding predicates, suggests that prior probability influences projection.

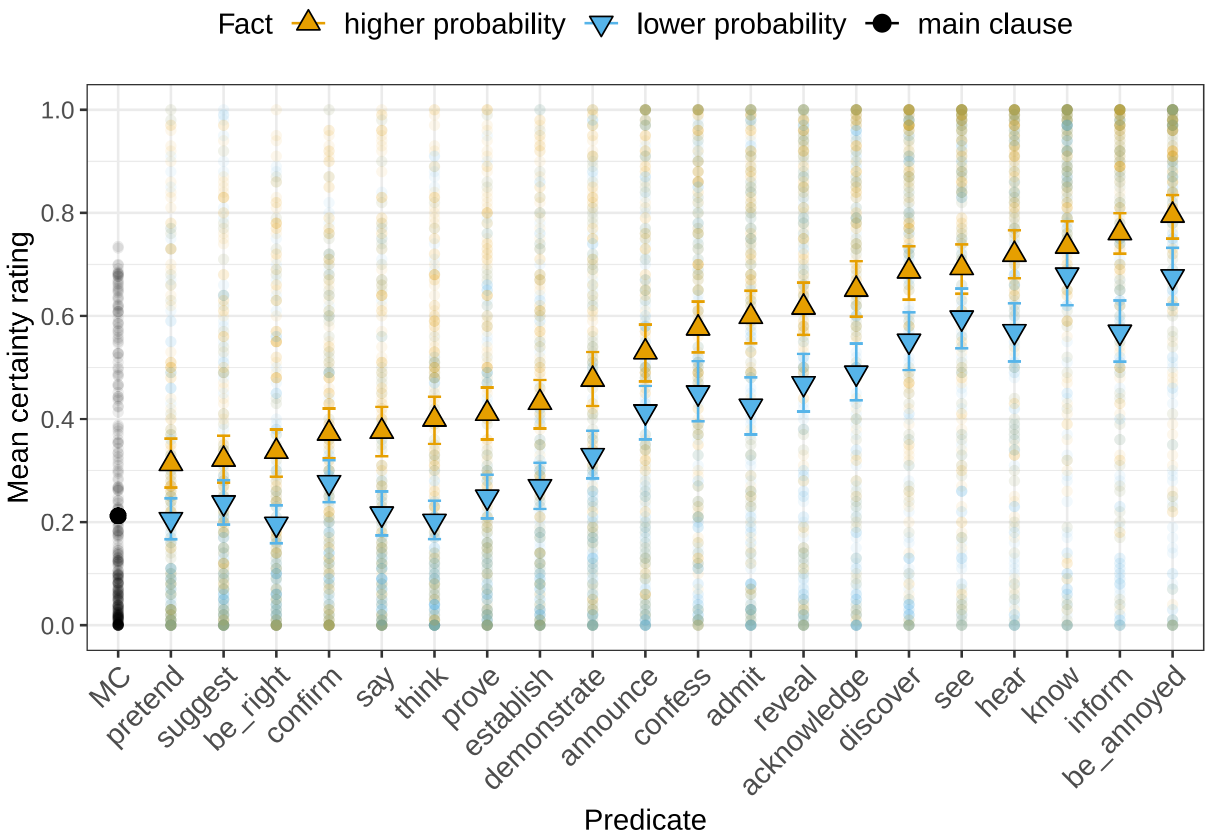


Figure 3: Mean certainty ratings by predicate and prior probability of the content of the complement in Exp. 1. Error bars indicate 95% bootstrapped confidence intervals. Light dots indicate participants' ratings.

We also replicate Tonhauser and Degen's ms result that there is by-predicate variation in the projection of the content of the complement: for instance, the content of the complement of *be annoyed* is more projective than that of *discover*, which in turn is more projective than that of *announce*. The Spearman rank correlation between the mean certainty ratings in Exp. 1 (collapsing over facts) and Tonhauser and Degen's ms Exp. 1a is .991; see Supplement D for a visualization. Exp. 1 thereby provides further evidence for the systematic influence of the predicate on projection.

Figure 2 revealed by-participant variation in prior probability ratings, which means that participants' prior probability ratings need not align with the prior probability classification assumed in Figure 3. For example, given a particular content (e.g., that Julian dances salsa), it is possible that one participant's prior probability rating was lower than that of another participant, even though the first participant was presented with the higher probability fact (Julian is Cuban) and the second one with the lower probability fact (Julian is German). To investigate whether prior probability influences projection at the by-participant level, Figure 4 plots the participants' certainty ratings (indicating projection) by their prior probability ratings. (The color coding here merely represents the type of fact the participant was presented with. No classification is imposed.) The linear smoothers suggest a positive correlation for each predicate between prior probability and certainty ratings such that contents with higher prior probability ratings receive higher certainty ratings. This result suggests that prior probability predicts projection even at the by-participant level.

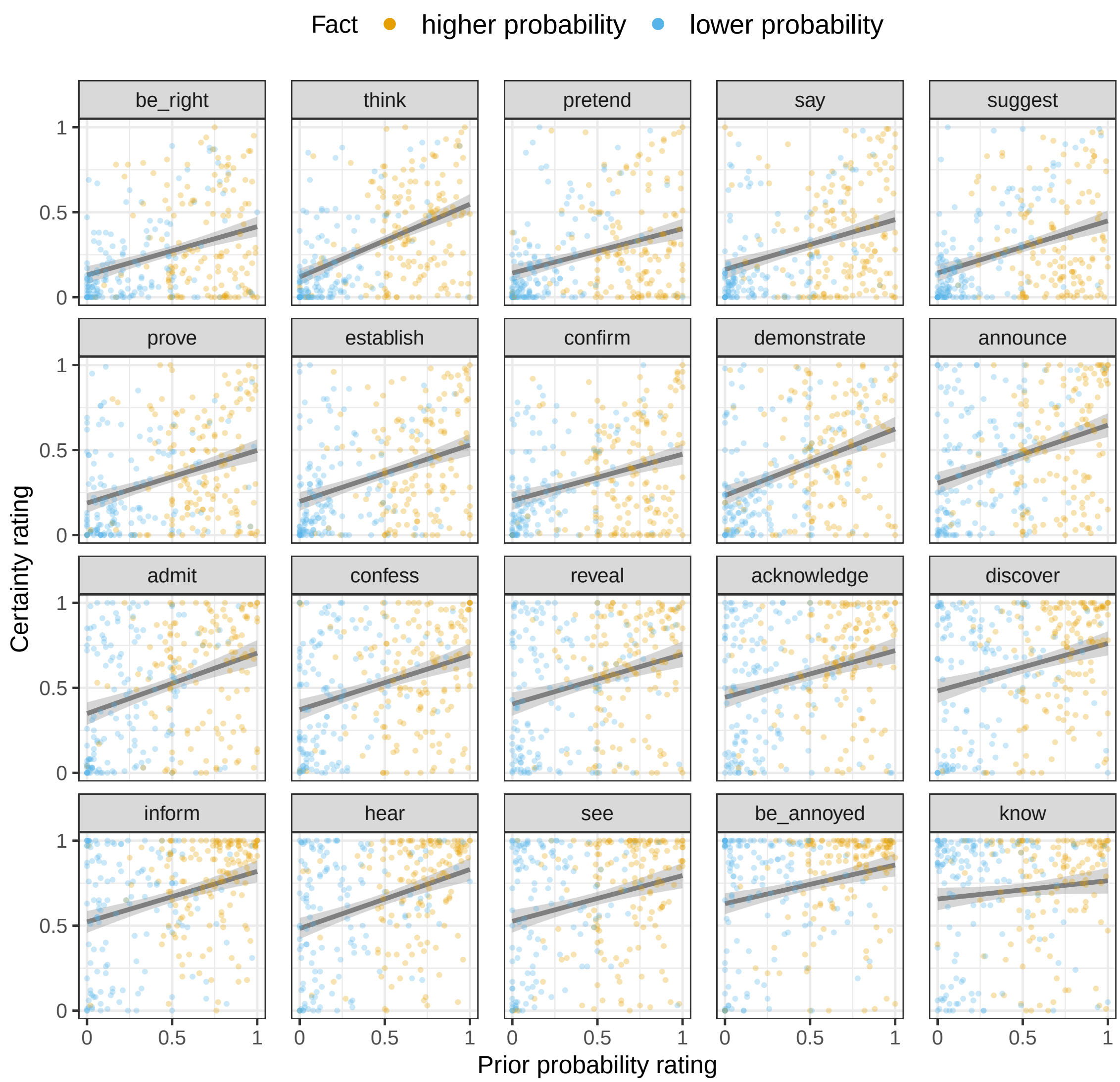


Figure 4: Certainty ratings by prior probability ratings by predicate in Exp. 1. Linear smoothers with 95% confidence intervals are overlaid.

The qualitative observations about the relations between prior probability, clause-embedding predicate and projection were borne out statistically. We fitted a Bayesian mixed effects Beta regression model with weakly informative priors using the `brms` (Bürkner 2017) package in R (R Core Team 2016) on the target data (5,720 data points). The model predicted the certainty ratings from a fixed effect of prior probability and included the maximal random effects structure justified by the design, namely random by-participant and by-item intercepts (where an item is a combination of a predicate and a complement clause). A Beta regression model estimates the mean of the outcome distribution (like a linear regression model).[3] We thus obtain a 95% credible interval for **JT: the mean effect of prior probability on certainty?**. Supplement C motivates the use of Beta regression over linear regression, provides a brief primer on how to interpret Bayesian mixed effects Beta regression models, and reports the full model output.

JT: We need to report two models here: predicting projection from prior at by-participant level, but also predicting mean projection from mean prior, to allow for comparison to Exps. 2

JT: According to the Beta regression model, the estimated mean for each predicate was higher than that of the main clause controls, i.e., the 95% credible intervals for the estimated adjustment to the main clause control mean did not contain 0 for any predicate. This suggests that the content of the complement of each of the 20 predicates is projective compared to non-projective main clause content.[4] Thus, to distinguish factive predicates from optionally factive and non-factive ones in this set of 20 predicates, one would need to arbitrarily distinguish one group of projective CCs from another group of projective CCs.

2.2 Discussion

The results of Exp. 1 provide empirical support for the hypothesis, put forth in Stevens et al. 2017 and Tonhauser et al. 2018, that the prior probability of content influences its projection. Specifically, we observed that a participant's certainty ratings for the content of the clausal complement of a predicate like *think, announce* and *know* are influenced by the prior probability rating for such content.

Mahler also manipulated clause-embedding predicate: two categories (factive: *know, realize, see, discover* and non-factive: *believe, think, feel*). CCs of factive predicates more projective than CCs of non-factive predicates. In addition to wanting to identify whether prior probability influences projection, she also wants to find out whether this only happens for factive predicates or for factive and non-factive predicates alike. Later on in the paper she adds the RQ of whether projection is influenced by factivity. She finds that prior probability influences projection for both factive and non-factives. She also finds that projection is higher with factive than non-factive predicates.

Lorson: There are several differences between Exp. 1 and Lorson's 2018 investigation that may have contributed to why Lorson 2018 did not observe an influence of prior probability on projection.

1. Difference: the prior probability of content was manipulated through gender stereotypes in Lorson 2018 but assumptions about what individuals with a variety of dispositions, professions, ages or nationalities are more or less likely to do. As shown in Figure **??**, the effect of prior probability on projection is observed for all contents, i.e., regardless of how prior probability was manipulated.

2. Difference: we investigated the projection of the content of the clausal complement of clause-embedding

[3] Beta regression models also estimate a second parameter, namely the precision, which is a measure of dispersion: the greater the precision, the more concentrated the ratings are around the mean. In this paper, we rely on the estimated mean to identify whether prior probability predicts projection. Both the estimated mean and precision are reported in the full model output table in Supplement C.

[4] **JT: A Bayesian mixed effects linear regression with the same fixed and random effects structure yielded qualitatively identical results, except that the contrast between *pretend* and the main clause controls was only marginally significant. See the Github repository mentioned in footnote 2 for the model code.**

predicates whereas Lorson 2018 investigated the pre-state content of *stop*. **JT: How much to investigate this possibility?**

Mahler: found an effect based on a manipulation of prior probability based on content that was more or less likely depending on the political party affilliation.

1. We replicate her result, showing that it generalizes to prior probability manipulated based on a broader variety of properties of individuals. **JT: May also be a good reason to include Fig 5**

2. Mahler used the content of the complement of clause-embedding predicates, like us. She had 7 predicates; we had 20. She found that the CCs of factive predicates more projective than CCs of non-factive predicates, and finds the effect for both groups (no by-predicate discussion). We go beyond her by showing that this holds for 20 predicates.

3. "CCs were more projective when the predicate was factive compared to when it was non-factive, regardless of the speaker?s political affiliation. This result is compatible with the assumption that factive predicates lexically-encode their complements as presuppositions, whereas non-factive predicates do not." (p.788) **JT: We want to engage with this here: factives paper challenges factive/non-factive distinction so the fact that we find effect of prior on all predicates cannot be used to support such a differential analysis**

   in general our results are compatible with Mahler?s (we both find effect). if one wanted to uphold the binary divide, we also find that factives more than non-factives, but the fact that the prior effect holds across the different groups we think further supports that no binary categorical distinction necessary

In Exp. 1, prior probability and projection were measured in a within-participant design in order to investigate whether prior probability predicts projection at the by-participant level. It is possible, however, that participants' responses on either block primed their responses on the other block. To mitigate against this possibility, we conducted Exps. 2, where prior probability and projection ratings were collected from different populations.

3 Experiments 2

Exps. 2a and 2b measured the prior probability and the projection of the 20 contents of Exp. 1, respectively.

3.1 Methods

Participants Participants with U.S. IP addresses and at least 99% of previous HITs approved were recruited on Amazon's Mechanical Turk platform. The 95 participants in Exp. 2a (ages: 21-75, median: 33; 45 female, 50 male) were paid 55 cents. The 300 participants in Exp. 2b (ages: 21-72, median: 36; 145 female, 154 male, 1 undeclared) were paid 85 cents.[5]

Materials and procedures The 40 target stimuli of Exp. 2a were identical to those of the prior block of Exp. 1. Each participants saw the two control stimuli in (10), which were included to assess attention to the task. We expected high prior probability ratings for (10a) and low ones for (10b). Trial order of the 22 stimuli in Exp. 2a was random.

[5] 28 participants took both experiments. Given that the experiments were run two weeks apart (Exp. 2a on November 13, 2017 and Exp. 2b on November 28, 2017, it is unlikely that these 28 participants' prior ratings influenced their projection ratings.

(11) a. **Fact:** Barry lives in Germany.
How likely is it that Barry lives in Europe?

b. **Fact:** Tammy is a rabbit.
How likely is it that Tammy speaks Italian and Greek?

The materials of Exp. 2b were identical to those of the projection block of Exp. 1. The procedures of Exps. 2a and 2b were identical to those of the prior and projection blocks of Exp. 1, respectively.

Data exclusion We excluded data based on the criteria given in Supplement B, leaving data from 75 participants to be analyzed in Exp. 2a (ages 21-75; median: 35; 34 female, 41 male) and of 266 participants in Exp. 2b (ages 21-72; median: 36; 129 female, 136 male, 1 undeclared).

3.2 Results and discussion

Exps. 2 replicated the critical result of Exp. 1, that the prior probability of content influences the projection of that content.[6] **JT: report models predicting a) projection mean Exp 2b from prior mean Exp 2b, b) projection mean Exp 1 from prior mean Exp 2b, and c) projection mean Exp 2b from prior mean Exp 1). USE COHENS D?** These results suggest that the result of Exp. 1 is not an artifact of the within-participant design of Exp. 1.

4 Discussion

These results support Tonhauser et al.'s (2018) hypothesis that prior content probability influences projectivity. The result that the CC of many non-factive predicates is at least weakly projective, even with low prior probability CCs, confirms intuitions reported in, e.g., Schlenker 2010, Anand and Hacquard 2014 and Spector and Egré 2015. These results motivate the development of projection analyses that derive the influence of prior content probability and make predictions for the CCs of a broad range of both factive and non-factive predicates.

Current projection analyses, while limited to the CCs of factive predicates (e.g., Heim 1983, van der Sandt 1992, Abrusán 2011, Simons et al. 2010, Beaver et al. 2017), are compatible with the result that prior content probability influences projectivity. Heim 1983, for instance, assumes default global accommodation when a presupposition is not entailed by the common ground (CG) when the trigger is uttered. This default is overridden when the presupposition is inconsistent with the CG. If we can assume that Julian dancing salsa is more likely to be consistent with the CG when Julian is Cuban than when he is German, Heim 1983 predicts that the presupposition that Julian dances salsa is more projective when it has a higher prior probability.

5 Conclusions

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[6] Exps. 2 also replicated other results of Exp. 1. First, Exp. 2a replicated the manipulation of the prior probability of the 20 contents: The Spearman rank correlation of the results of Exp 2a and the prior block of Exp. 1 was high, at .977; see Supplement E for visualizations. Exp. 2b replicated Tonhauser and Degen's ms result that there is by-predicate variation in the projection of the content of the complement; see Supplement D.

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Supplemental material for *Prior probability predicts projection*

A Experiment 1: Target and control stimuli

This list gives the 20 clauses of the target stimuli with the lower and higher probability facts, respectively:

1. Mary is pregnant. Facts: Mary is a middle school student / Mary is taking a prenatal yoga class
2. Josie went on vacation to France. Facts: Josie doesn't have a passport / Josie loves France
3. Emma studied on Saturday morning. Facts: Emma is in first grade / Emma is in law school
4. Olivia sleeps until noon. Facts: Olivia has two small children / Olivia works the third shift
5. Sophia got a tattoo. Facts: Sophia is a high end fashion model / Sophia is a hipster
6. Mia drank 2 cocktails last night. Facts: Mia is a nun / Mia is a college student
7. Isabella ate a steak on Sunday. Facts: Isabella is a vegetarian / Isabella is from Argentina
8. Emily bought a car yesterday. Facts: Emily never has any money / Emily has been saving for a year
9. Grace visited her sister. Facts: Grace hates her sister / Grace loves her sister
10. Zoe calculated the tip. Facts: Zoe is 5 years old / Zoe is a math major
11. Danny ate the last cupcake. Facts: Danny is a diabetic / Danny loves cake
12. Frank got a cat. Facts: Frank is allergic to cats / Frank has always wanted a pet
13. Jackson ran 10 miles. Facts: Jackson is obese / Jackson is training for a marathon
14. Jayden rented a car. Facts: Jayden doesn't have a driver's license / Jayden's car is in the shop
15. Tony had a drink last night. Facts: Tony has been sober for 20 years / Tony really likes to party with his friends
16. Josh learned to ride a bike yesterday. Facts: Josh is a 75-year old man / Josh is a 5-year old boy
17. Owen shoveled snow last winter. Facts: Owen lives in New Orleans / Owen lives in Chicago
18. Julian dances salsa. Facts: Julian is German / Julian is Cuban
19. Jon walks to work. Facts: Jon lives 10 miles away from work / Jon lives 2 blocks away from work
20. Charley speaks Spanish. Facts: Charley lives in Korea / Charley lives in Mexico

In the target stimuli of the projection block of Exp. 1, eventive predicates, like *discover* and *hear*, were realized in the past tense and stative predicates, like *know* and *be annoyed*, were realized in the present tense. The direct object of *inform* was realized by the proper name *Sam*. The subject of the clause-embedding predicate and the speaker of the target stimuli were realized by a proper name.

The following list gives the six clauses that were used in the control and filler stimuli of Exp. 1, with their facts. In the prior block, these six clauses were embedded under *How likely is it that... ?*. The projection block featured polar questions variants of the clauses.

1. Zack is coming to the meeting tomorrow. Fact: Zack is a member of the golf club.
2. Mary's aunt is sick. Fact: Mary visited her aunt on Sunday.
3. Todd played football in high school. Fact: Todd goes to the gym 3 times a week.
4. Vanessa is good at math. Fact: Vanessa won a prize at school.
5. Madison had a baby. Fact: Trish sent Madison a card.
6. Hendrick's car was expensive. Fact: Hendrick just bought a car.

B Data exclusion

Table A1 presents how many participants' data were excluded from the analyses based on the exclusion criteria. The first column records the experiment, the second ('recruited') how many participants were recruited, and the final column ('remaining') how many participants' data entered the analysis. The 'Exclusion criteria' columns show how many participants' data were excluded based on the two exclusion criteria:

- 'language': Participants' data were excluded if they did not self-identify as native speakers of American English.
- 'controls': In Exps. 1 and 2b, participants' data were excluded if their response mean on the 6 control items was more than 2 sd above the group mean. In Exp. 2a, participants' data were excluded if their response mean was more than 2 sd below the group mean of the control in (10a) or more than 2 sd above the group mean of the control in (10b).

		Exclusion criteria		
	recruited	language	controls	remaining
Exp. 1	300	3	11	286
Exp. 2a	95	8	12	75
Exp. 2b	300	23	11	266

Table A1: Data exclusion in Exps. 1 and 2

C Model details for Experiments 1 and 2

This supplement provides details on the data analysis conducted for Exps. 1, 2, and 3. We first motivate the use of Beta regression rather than linear regression in Exps. 1a, 2a, and 3a (section C.1) and then provide a brief primer on how to interpret Bayesian mixed effects Beta regression models (section C.2). We then report the model outputs for Exps. 1, 2, and 3 (section C.3).

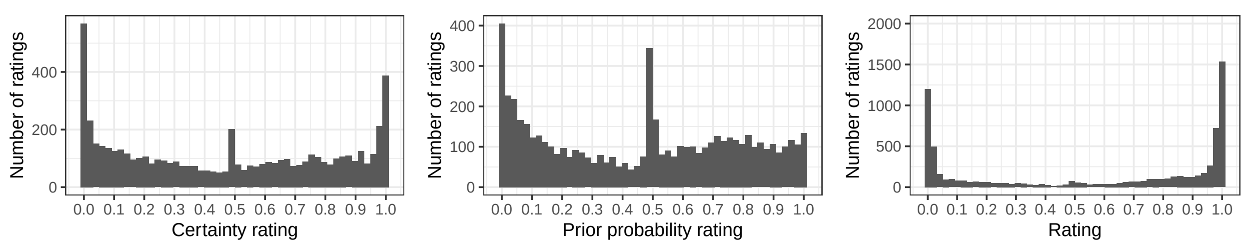
C.1 Motivation for using Bayesian mixed effects Beta regression

There are three separate pieces to motivate: the use of *mixed effects*, the use of a *Bayesian* rather than *frequentist* models, and the use of *Beta regression* rather than *linear regression*.

Using mixed effects refers to the practice of modeling the outcome variable, here slider ratings or proportions of 'yes' ratings, as a function of not just fixed effects of interest (i.e., predicate) but also as the result of possible random variability that is not of theoretical interest (e.g., random by-participant or by-item variability). This is standard practice in psycholinguistic studies and allows the researcher to trust that any observed effects of theoretical interest are true average effects rather than the result of idiosyncratic behavior (e.g., of participants or items). This is also the motivation for using mixed effects in Exps. 1b, 2b, and 3b.

Using Bayesian models rather than frequentist models is increasingly becoming the norm in psycholinguistic studies as computational power has increased and running Bayesian models has become more accessible with the introduction of R packages such as `brms` (Bürkner 2017). The presence of an effect in frequentist models is evaluated by checking whether the p-value is smaller than .05, where the p-value is defined as the probability of obtaining data that is as skewed or more skewed than the observed data if the null-hypothesis was true, i.e., if the hypothesized effect was absent. Parameter estimates in frequentist models are obtained via maximum-likelihood techniques, i.e., by estimating the parameter values that maximize the probability of observing the data. Bayesian models, by contrast, return a full posterior distribution over parameter values that take into account not just the probability of the data under the parameter values, but also the prior probability of parameter values. In order to evaluate the evidence for an effect of a predictor of interest, one can report 95% credible intervals and the posterior probability $P(\beta < 0)$ or $P(\beta > 0)$ that the predictor coefficient β is either lower or greater than zero, depending on the direction of the expected effect. A 95% credible interval (CI) demarcates the range of values that comprise 95% of probability mass of the posterior beliefs such that no value inside the CI has a lower probability than any point outside it (Jaynes and Kempthorne 1976, Morey et al. 2016). There is substantial evidence for an effect if zero is (by a reasonably clear margin) not included in the 95% CI and $P(\beta > 0)$ or $P(\beta < 0)$ is close to zero or one. Posterior probabilities indicate the probability that the parameter has a certain value, given the data and model – these probabilities are thus *not* frequentist p-values. In order to present statistics as close to widely used frequentist practices, and following Nicenboim and Vasishth 2016, we defined an inferential criterion that seems familiar (95%), but the strength of evidence should not be taken as having clear cut-off points (such as in a null-hypothesis significance testing framework).

Using Beta regression rather than linear regression was motivated by the violation of two of the assumptions of linear regression: first, that residuals be normally distributed (where "residuals" refers to the residual error for each data point after fitting the model), and second, that the error term exhibit homoscedasticity (that it be roughly the same across different conditions). Slider ratings data has the property of being bounded by its endpoints (which we code as 0 and 1, respectively). This often leads to "bunching" behavior at the endpoints (see Figure A1 for the distribution of raw ratings in Exps. 1a, 2a, and 3a).



(a) Exp. 1 certainty ratings. (b) Exp. 1 prior ratings. (c) Exp. 2 prior ratings.

Figure A1: Histograms of raw slider ratings in Exps. 1 and 2.

This "bunching" behavior, in turn, can lead to the violation of both of the above assumptions of linear regression. Intuitively, these assumptions are violated because conditions that elicit ratings closer to endpoints necessarily have a compressed variance; consequently, a condition's mean and its variance are not independent. Beta regression is useful here because it allows for modeling an arbitrarily distributed outcome variable in the [0,1] interval. The Beta distribution is characterized by two parameters, one capturing the mean μ of the distribution and one capturing its precision ϕ, a measure of dispersion. The greater the precision, the more concentrated the values are around the mean, i.e., the lower the variance of the distribution. We follow Smithson and Verkuilen (2006) in modeling μ and ϕ separately for each predictor. That is, we allow each predictor to affect both the mean and the precision of the outcome variable's distribution.

C.2 Coding choices and interpreting model output

The outcome variable in Exps. 1a, 2a and 3a (slider ratings) contained the values 0 and 1, which Beta regression is undefined for. We therefore applied a common transformation to ratings before the main analysis that rescales values y to fall in the open unit interval (0,1) (Smithson and Verkuilen 2006). First, we apply $y' = (y - a)/(b - a)$, where b is the highest possible slider rating and a is the smallest possible slider rating. The range is then compressed to not include 0 and 1 by applying $y'' = [y'(N - 1) + 1/2]/N$, where N is the total number of observations.

The mean parameter μ is modeled via a logit link function (default for Beta regression in `brms`), though other links that squeeze μ into the [0,1] interval are possible. The dispersion parameter ϕ is modeled via a log link, which ensures that values of ϕ are strictly positive, which is necessary because a variance cannot be negative.

We allowed both μ and ϕ to vary as a function of predicate, with reference level set to main clause control in Exp. 1a, entailing control in Exp. 2a and contradictory control in Exp. 3a. We also allowed random intercept adjustments to each parameter by participant and by item, where item was defined as a unique combination of a predicate and a complement clause. Four chains converged after 2000 iterations each (warmup = 1000, $\hat{R} = 1$ for all estimated parameters) with a target acceptance rate of .95 and a maximum treedepth of 15.

C.3 Model outputs for Experiments 1, 2 and 3

The three tables in this section show the model outputs for Exps. 1, 2 and 3, respectively: Table **??** for Exps. 1a and 1b, Table **??** for Exps. 2a and 2b, and Table **??** for Exps. 3a and 3b. Each table shows maximum a posteriori (MAP) model estimates for projection ratings from the Beta regression model (left and middle column, mean μ and precision ϕ) and the logistic regression model (right column, β) with 95% credible intervals.

D Projection results (Exp. 2b) and comparisons

Figure A2 shows that the mean certainty ratings of Exp. 2b were higher for contents presented with the higher probability facts than for contents presented with the lower probability fact. This result suggests that prior probability influences projection.

Comparisons of the projection results of Exp. 1, Exp. 2b, and Tonhauser and Degen's ms Exp. 1a (abbreviated 'TD Exp. 1a') in Figure A3 reveal striking similarities. The Spearman rank correlations were XX (Exp. 1 vs. TD Exp. 1a), XX (Exp. 2b vs. TD Exp. 1a) and XX (Exp. 1 vs. Exp. 2b).

E Prior probability results (Exp. 2a) and comparisons

The manipulation of the prior probability of the 20 contents was successful. Figure A4 plots the mean prior probabilities of the 20 contents by fact (participants' ratings are given as light dots). The mean prior probability rating for each content was higher when the content was presented with the higher probability fact than when it was presented with the lower probability fact.

Figure A5 plots the mean prior probability ratings in Exp. 2a against the mean prior probability ratings in Exp. 1. The Spearman rank correlation was XX.

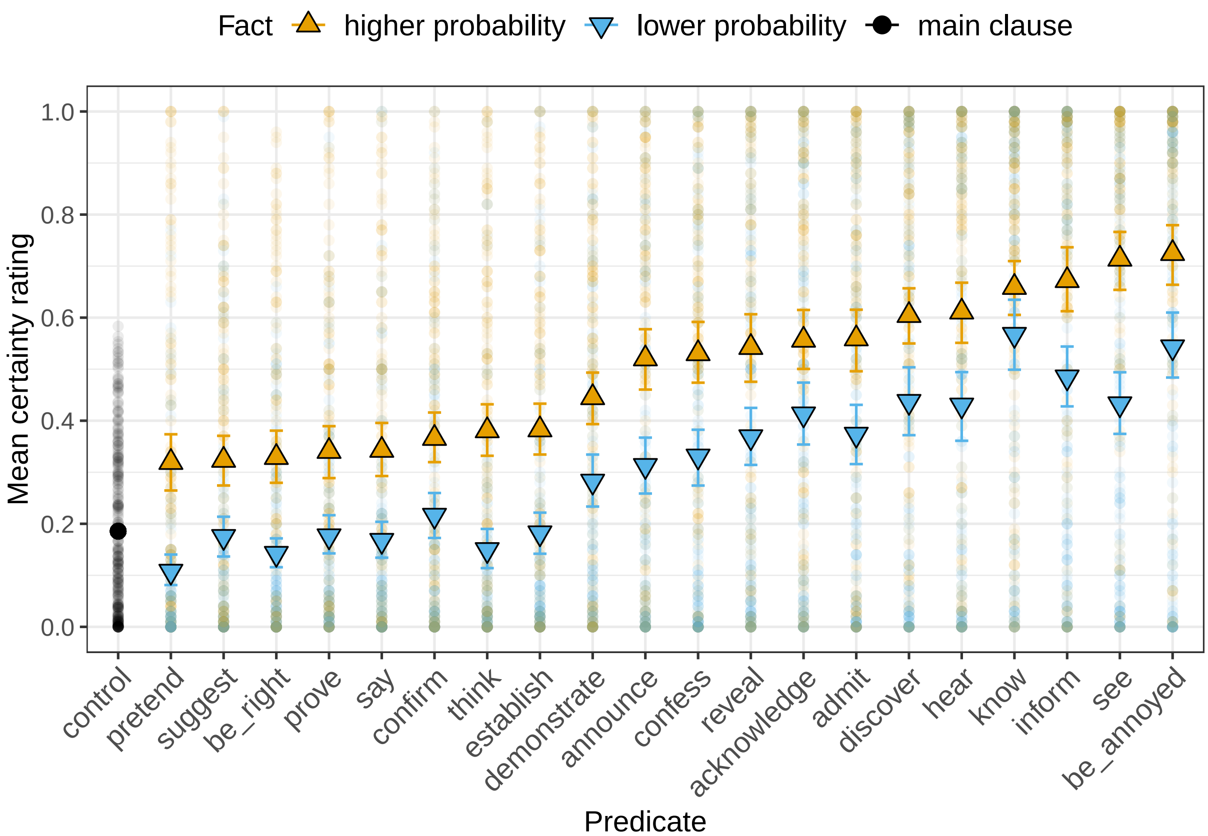
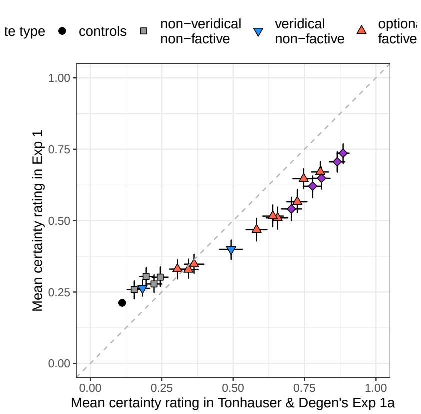
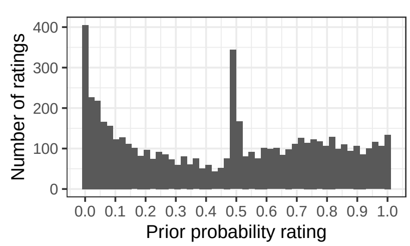


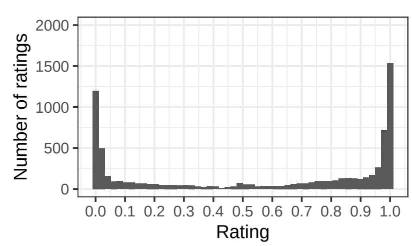
Figure A2: Mean certainty ratings by predicate and prior probability of the content of the complement in Exp. 2b. Error bars indicate 95% bootstrapped confidence intervals. Light dots indicate participants' ratings.



(a) Exp. 1 vs. TD Exp. 1a.



(b) Exp. 2b vs. TD Exp. 1a.



(c) Exp. 1 vs. Exp. 2b.

Figure A3: Mean by-predicate certainty ratings from Exp. 1, Exp. 2b, and Tonhauser and Degen's ms Exp. 1a (abbreviated 'TD Exp. 1a'). Error bars indicate 95% bootstrapped confidence intervals.

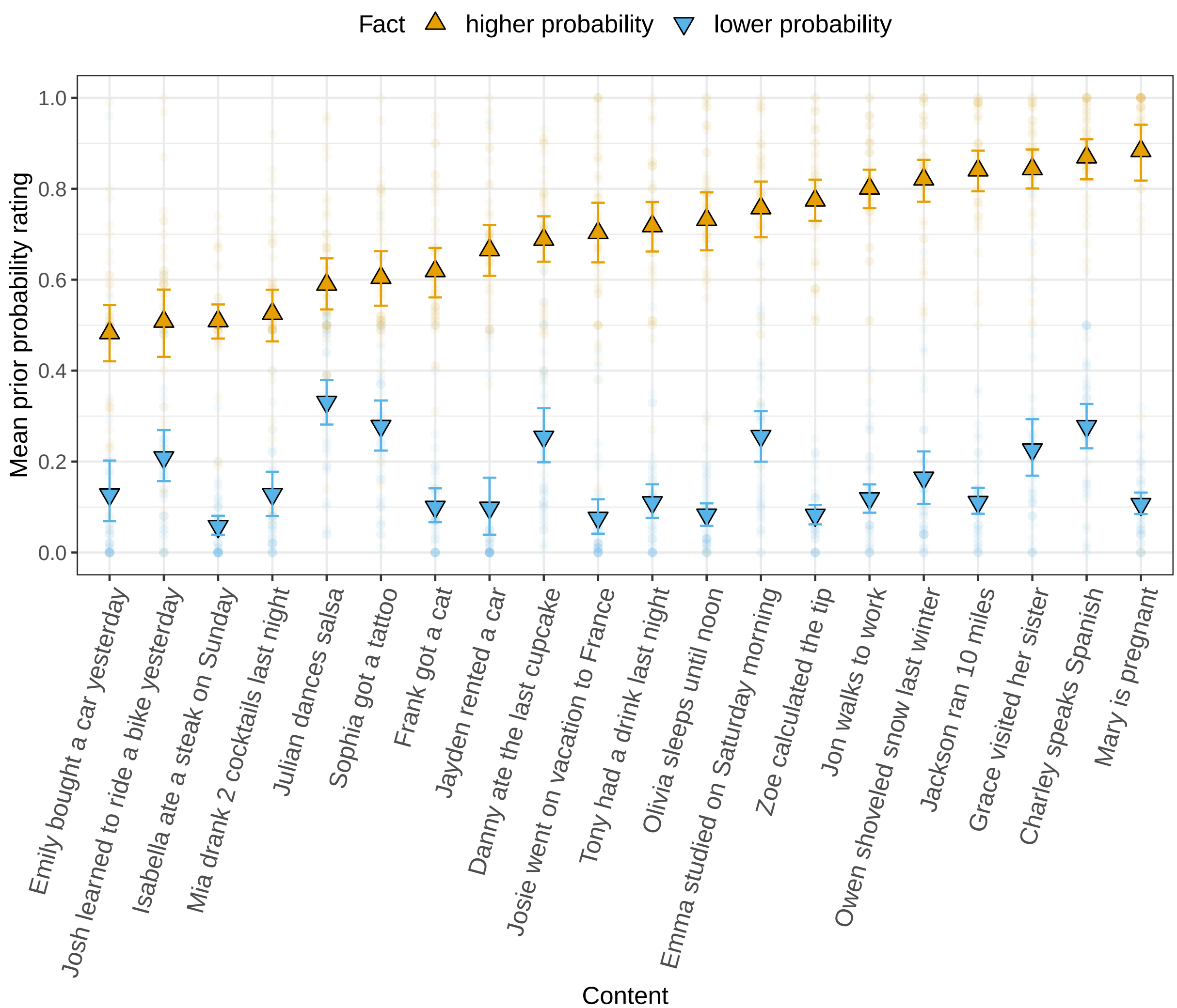


Figure A4: Mean prior probability by content and fact in Exp. 2a. Error bars indicate 95% bootstrapped confidence intervals. Light dots indicate participants' ratings.

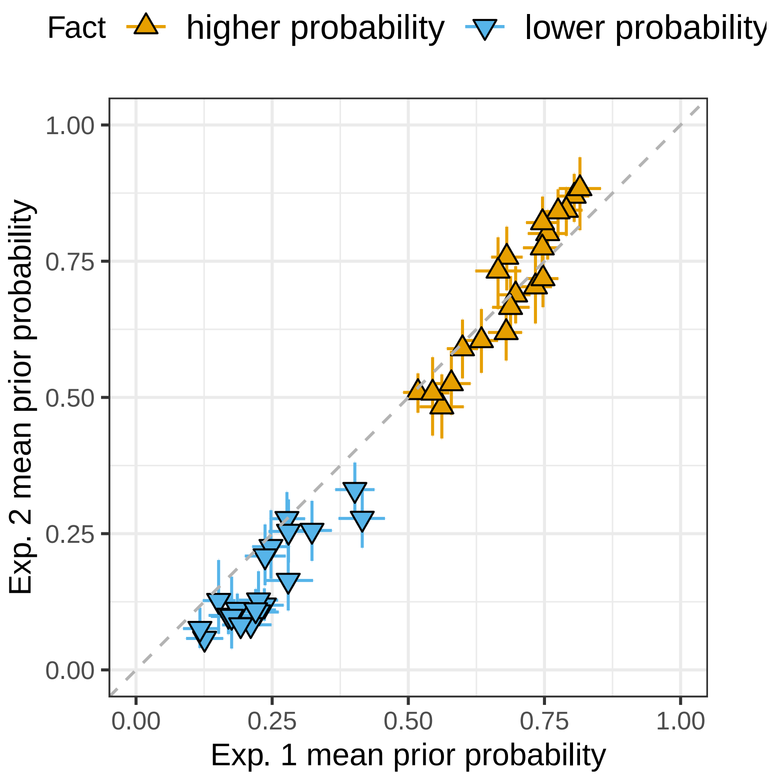


Figure A5: Mean prior probability ratings in Exp. 2a against those of Exp. 1. Error bars indicate 95% bootstrapped confidence intervals.