# The Role of Polarity in Inferring Acceptance and Rejection in Dialogue

Julian J. Schlöder and Raquel Fernández Institute for Logic, Language & Computation University of Amsterdam



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## Introduction

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- But frequently, this is non-trivial.
  - (1) A: I never did care for him, in the James Bond movies. B: I was never into those movies, either.
  - (2) A: This is a very interesting design. B: It's just the same as normal.

Examples from the AMI Meeting Corpus and the Switchboard corpus.

## **Polarity Particles**

Even when the responding utterance seems trivial, determining its dialogue function is not.

- (3) A: But it's uh yeah it's uh original idea. B: Yes it is. → acceptance.
- (4) A: a banana is not it's not really handy . B: Yes it is.  $\rightsquigarrow$  rejection.
- (5) A: It's not very well advertised.B: No, it's not. → acceptance.

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- (5) A: It's not very well advertised. B: No, it's not. → acceptance.

We focus on the apparent ambiguity of these responses and arrive at a wider theory on logical polarity

We need to look at proposal and response, determine their polarity and specify how these polarities interact.

#### Talk Outline

- Some observations on properties of acceptance and rejection.
- A formal model to account for polarity effects.
- Heuristics to operationalize the model.
- Experimental results in a machine learning experiment.

#### **Observations**

## Rejections

There is a body of work on computational disagreement detection, drawing on observations from, i.a., conversation analysis.

Rejections are dispreferred moves, as such they tend to:

- Be longer.
- Start with hedges.
  - well, actually, I mean, perhaps. . .
- Contain more disfluencies
  - repetitions, hesitations, filled and unfilled pauses...
- P. Brown & S. Levinson, Politeness: Some universals in language usage, Cambridge University Press, 1987.
- M. Galley, K. McKeown, J. Hirschberg, E. Shriberg. Identifying agreement and disagreement in conversational speech: Use of bayesian networks to model pragmatic dependencies. ACL 2004.
- S. Germesin & T. Wilson. Agreement detection in multiparty conversation. Proceedings of the 2009 international conference on multimodal interfaces.
- A. Misra & M. Walker. Topic independent identification of agreement and disagreement in social media dialogue. SIGDIAL 2013.

## **Logical Polarity**

Logical polarity has not been explored in computational approaches.

Formal semantics has seen renewed interest in polarity particles and negation.

- (6) Sue failed the exam.
  Yes she did. / No she didn't.
- (7) Sue did not pass the exam. No she didn't. / Yes she did.

Farkas, Roelofsen. 2013. Polar initiatives and polar particle responses in an inquisitive discourse model.

#### **Parallelism**

The relative nature of acceptance and rejection is also reflected in sentential parallelisms.

- (8) A: It's still working. B: It is.
- (9) A: It's a fat cat. B: It is not a fat cat.
- → The key observation: When the polarities of proposal and response align, it is an agreement move, if they differ, disagreement.

## **Formal Model**

# **Relative Polarity**

We consider pairs of a proposal P and its response R.

We assign a polarity, either positive or negative, to both proposal and response.

- - ► Polarity signature of *P*−*R*: positive-positive or negative-negative.
- misaligned polarities → rejecting force.
  - ► Polarity signature of *P*−*R*: positive-negative or negative-positive.

# **Absolute Polarity**

Disregarding proposal polarity, there are absolute acceptance / rejection moves.

- (10) A: Ah, that's not the ecological part, yeah.
  - B: That's true. → absolute positive
- (11) A: We can't make a docking station anyway.
  - B: That's not true. → absolute negative

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- (11) A: We can't make a docking station anyway.
  - B: That's not true.  $\rightsquigarrow$  absolute negative
- Agreement Acts signal agreement.
  - I hereby agree.
- Rejection Acts signal disagreement.
  - I hereby disagree.

#### Formal Model

Assume a proposal P is on the table.

The next move R accepts P iff  $P \wedge R$  is consistent.

- R ≡ ⊤: absolute agreement.
- $R \equiv \bot$ : absolute rejection.
- $R \equiv P$ : relative agreement.
  - ightharpoonup P positive ightharpoonup default case; signature positive-positive.
  - ightharpoonup P negative ightharpoonup reverse case; signature negative-negative.
- $R \equiv \neg P$ : relative rejection.
  - ightharpoonup P positive ightharpoonup default case; signature positive-negative.
  - ightharpoonup P negative ightharpoonup reverse case; signature negative-positive.
- $\equiv$  is truth-conditional equivalence.

#### **Heuristics**

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- Local indicators for acceptance and rejection, inspired by previous work.
  - ▶ Utterance length.
  - ▶ absolutely, okay, agree, true,...
  - but, well, actually, umm...
  - 'Yeah, but'

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- Local indicators for acceptance and rejection, inspired by previous work.
  - Utterance length.
  - ▶ absolutely, okay, agree, true,...
  - but, well, actually, umm...
  - 'Yeah. but'
- Indicators to determine proposal polarity and response polarity.
  - Indicators are polarity particles and negation indicators
  - not, never, nobody...
  - ▶ Tag questions need special treatment.
  - ▶ The contrast particle but cancels polarity particles.
  - By default, an utterance has positive polarity.
  - Syntactic parallelisms.

# **Experiment**

# Setup

#### We extract datasets from the AMI and SWB corpora:

- The AMI is annotated with adjacency pairs which are marked as POS or NEG; we take all these where the first-part is marked as a proposal.
- The SWB is annotated with acceptance and rejection acts; we assign each of these the preceding utterance of the other speaker, if marked as a proposal.
- We filter out responses that are 'Yeah.', in both copora these are 100% acceptances.

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	acceptances	rejections	total P-R
SWB	4534 (97%)	145 (3%)	4679
AMI	7405 (91%)	697 (9%)	8102

#### **Featuresets**

#### Based on our heuristics we have the featuresets:

- LOCAL FEATURES: Cuewords, length of the response
- LOCAL POLARITY: Polarity of the response,
  - positive or negative.
- RELATIVE POLARITY: Polarity signature of the pair.
  - positive-positive
  - negative-negative
  - positive-negative
  - negative-positive
- SENTENTIAL PARALLELISM: Repetition of a negated syntactic pattern.

#### Results

- Task: Retrieval of rejections.
- Classifier: Bernoulli-distributed Naive Bayesian classifier from scikit-learn.
- The classifier was developed on the AMI dataset.
- Method: Cross-validiation, 10x AMI, 5x SWB.
- Unigram baseline: all words that appear 5 times or more.

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	AMI			SWB		
Feature sets	Precision	Recall	F1	Precision	Recall	F1
Unigrams	35.61%	28.97%	31.66	24.20%	12.93%	16.63
Local + Local Polarity	44.13%	64.12%	52.24	20.80%	82.46%	33.00
Local + Relative Polarity	58.08%	61.63%	59.75	49.12%	72.93%	58.49
Loc. + Rel. + Parallel.	58.23%	64.04%	60.96	n/a	n/a	n/a

- → Logical polarity helps significantly.
- → Relative polarity widespread in actual dialogue.

## **Summary**

- Discerning agreement from disagreement requires making inferences—we have studied how logical polarity helps this process.
- Inspired by recent formal work we have developed a framework that can be operationalized.
- Both absolute and relative polarities occur in actual spoken language.
- We have confirmed that the proposal-response polarity signature is important for disagreement retrieval.

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## Thank you!