Learning to Interpret Natural Language Commands through Human-Robot Dialog

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Commanding Robots

- Autonomous robots in human environments

- Simplest to interact with via natural language

Our Task

- Command a robot operating in an office environment
- Robot autonomously wanders by default
- Robot can navigate to rooms and deliver items

System Goals

- Require little initial data
  - More domain independent
- Reason using composition
  - “Alice’s office”
- Robust to lexical variation
  - “bring”, “deliver”, “take”
- Execute the **right** action
  - Perform clarifications with user

Closest Previous Work

- Service robot that accepts commands (Kollar, 2013)
- Semantics match spans of words to known actions/people/locations
- Can learn new referring expressions through dialog

Human	Go to Alice's office
Robot	Where is "Alice's office"?
Human	Room 3

- This system would explicitly match "Alice's office" to room 3

Closest Previous Work

- When system sees "Bob's office", will have to ask where that is
- Want to take advantage of compositionality instead
  - Reason about possessive marker "'s" and what entities "office" picks out
- Need a more powerful formalism for representing sentence semantics
  - Want to keep initial training data light

Helpful Previous Work

- Augment a semantic parser through conversation logs (Artzi, 2011)

Human	I would like to fly out of boston arriving to new york and back from new york to boston
System	Leaving boston (CONFIRM:*from(fl1,BOS)*) on what date? (ASK:*λx.departdate(fl1,x)*)

- Key idea for us: use known system semantic meanings to guess human utterance word meanings

Tag Token Sequence

token(s) — *syntax* : *semantics*

University of Washington Semantic Parsing Framework (SPF); (Artzi, 2011)
Known possibilities for each token stored in a lexicon
Use Combinatory Categorial Grammar (CCG)-driven parsing

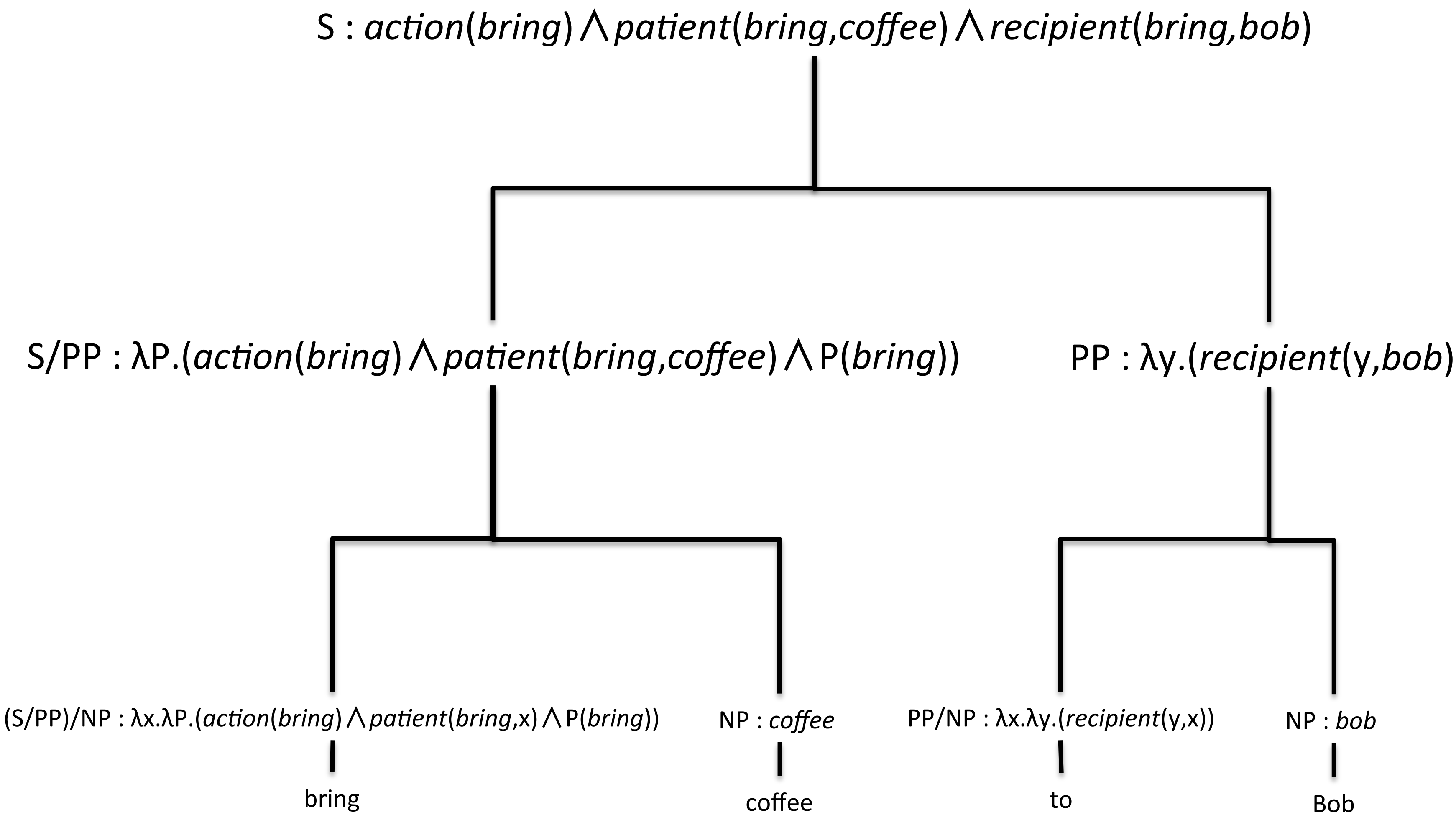
bring — (S/PP)/NP : $\lambda x.\lambda P.(\mathit{action}(\mathit{bring}) \wedge \mathit{patient}(\mathit{bring},x) \wedge P(\mathit{bring}))$

coffee — NP : *coffee*

to — PP/NP : $\lambda x.\lambda y.(\mathit{recipient}(y,x))$

Bob — NP : *bob*

Construct Meaning Hierarchically



Tag Token Sequence – Missing Entry

bring —— (S/PP)/NP : $\lambda x.\lambda P.(\mathit{action}(\mathit{bring}) \wedge \mathit{patient}(\mathit{bring},x) \wedge P(\mathit{bring}))$

java —— ?

to —— PP/NP : $\lambda x.\lambda y.(\mathit{recipient}(y,x))$

Bob —— NP : *bob*

Given semantic form, can guess about missing token syntax/semantics

Human	bring java to bob
Robot	what should I bring to bob?
Human	coffee

S : $\mathit{action}(\mathit{bring}) \wedge \mathit{patient}(\mathit{bring},\mathit{coffee}) \wedge \mathit{recipient}(\mathit{bring},\mathit{bob})$

Tag Token Sequence – Missing Entry

bring —— (S/PP)/NP : $\lambda x.\lambda P.(\textit{action}(\textit{bring}) \wedge \textit{patient}(\textit{bring},x) \wedge P(\textit{bring}))$

java —— ?

to —— PP/NP : $\lambda x.\lambda y.(\textit{recipient}(y,x))$

Bob —— NP : *bob*

Given form:

$\textit{action}(\textit{bring}) \wedge \textit{patient}(\textit{bring},\textit{coffee}) \wedge \textit{recipient}(\textit{bring},\textit{bob})$

Lexicon entries that produce parts of this form:

bring :- (S/PP)/NP : $\lambda x.\lambda P.(\textit{action}(\textit{bring}) \wedge \textit{patient}(\textit{bring},x) \wedge P(\textit{bring}))$
bring :- (S/NP)/NP : $\lambda x.\lambda y.(\textit{action}(\textit{bring}) \wedge \textit{recipient}(\textit{bring},x) \wedge \textit{patient}(\textit{bring},y))$
coffee :- NP : *coffee*
Bob :- NP : *bob*

Candidates for 'java' lexical entry:

:- (S/PP)/NP : $\lambda x.\lambda P.(\textit{action}(\textit{bring}) \wedge \textit{patient}(\textit{bring},x) \wedge P(\textit{bring}))$
:- (S/NP)/NP : $\lambda x. \lambda y.(\textit{action}(\textit{bring}) \wedge \textit{recipient}(\textit{bring},x) \wedge \textit{patient}(\textit{bring},y))$
:- NP : *coffee*
:- NP : *bob*

Tag Token Sequence – Missing Entry

bring	(S/PP)/NP : $\lambda x.\lambda P.(\mathit{action}(\mathit{bring}) \wedge \mathit{patient}(\mathit{bring},x) \wedge P(\mathit{bring}))$
java	NP : *coffee*
to	PP/NP : $\lambda x.\lambda y.(\mathit{recipient}(y,x))$
Bob	NP : *bob*

With new lexicon entry, we can construct the correct semantic form

S : $\mathit{action}(\mathit{bring}) \wedge \mathit{patient}(\mathit{bring},\mathit{coffee}) \wedge \mathit{recipient}(\mathit{bring},\mathit{bob})$

Meeting System Goals

- Require little initial data
  - Bootstrap parser with 5 expressions, 105 words
- Handle composition used by speakers
  - Use CCG-driven semantic parsing (Artzi, 2011)
- Robust to lexical variation
  - Incrementally train parser to obtain new words
- Execute the **right** action
  - Use dialog to clarify meanings with user (Kollar, 2013)

Mechanical Turk Experiment

- Users given one navigation and one delivery goal
  - Train/test goals chosen at random from possibilities
- Chat with robot's dialog agent until goal is understood

Mechanical Turk Interface

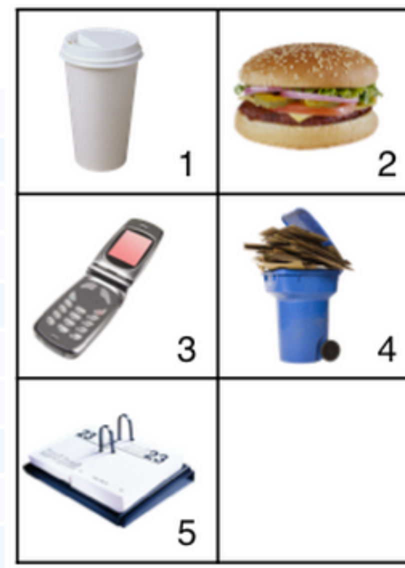
TASK TO COMPLETE

Dave Daniel wants the item in slot 5.

ROBOT	How can I help?
YOU	please bring the item in slot 5 to dave daniel
ROBOT	What should I bring to dave daniel?
YOU	a calander
ROBOT	I'm sorry, but I couldn't pinpoint what you meant by that.
ROBOT	What should I bring to dave daniel?
YOU	a day planner
ROBOT	I'm sorry, but I couldn't pinpoint what you meant by that.
ROBOT	What should I bring to dave daniel?
YOU	calendar
ROBOT	You want me to bring calendar to dave daniel?
YOU	yes
ROBOT	I thought so
ROBOT	Happy to help
YOU	

Final Task

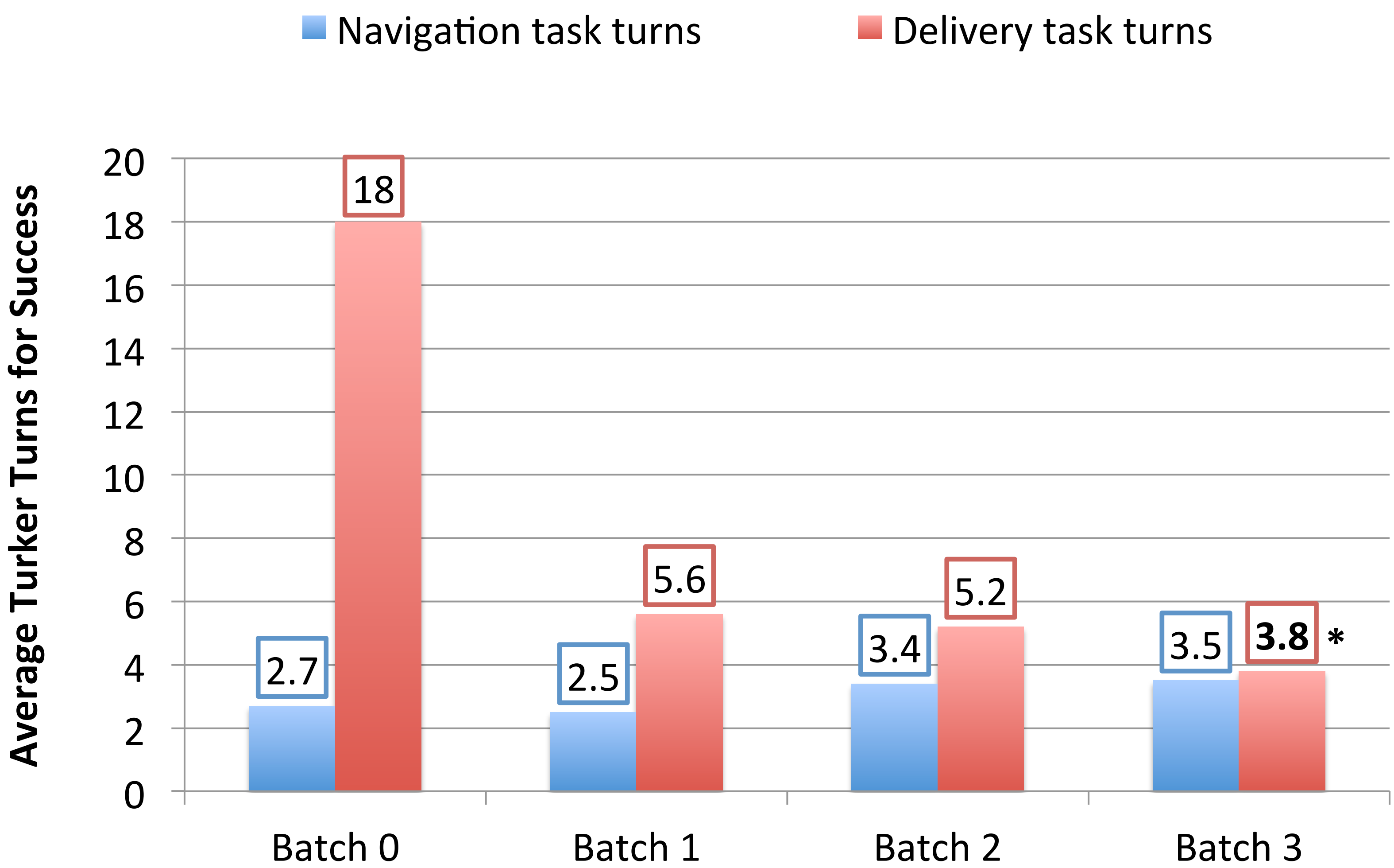
Items available to robot:



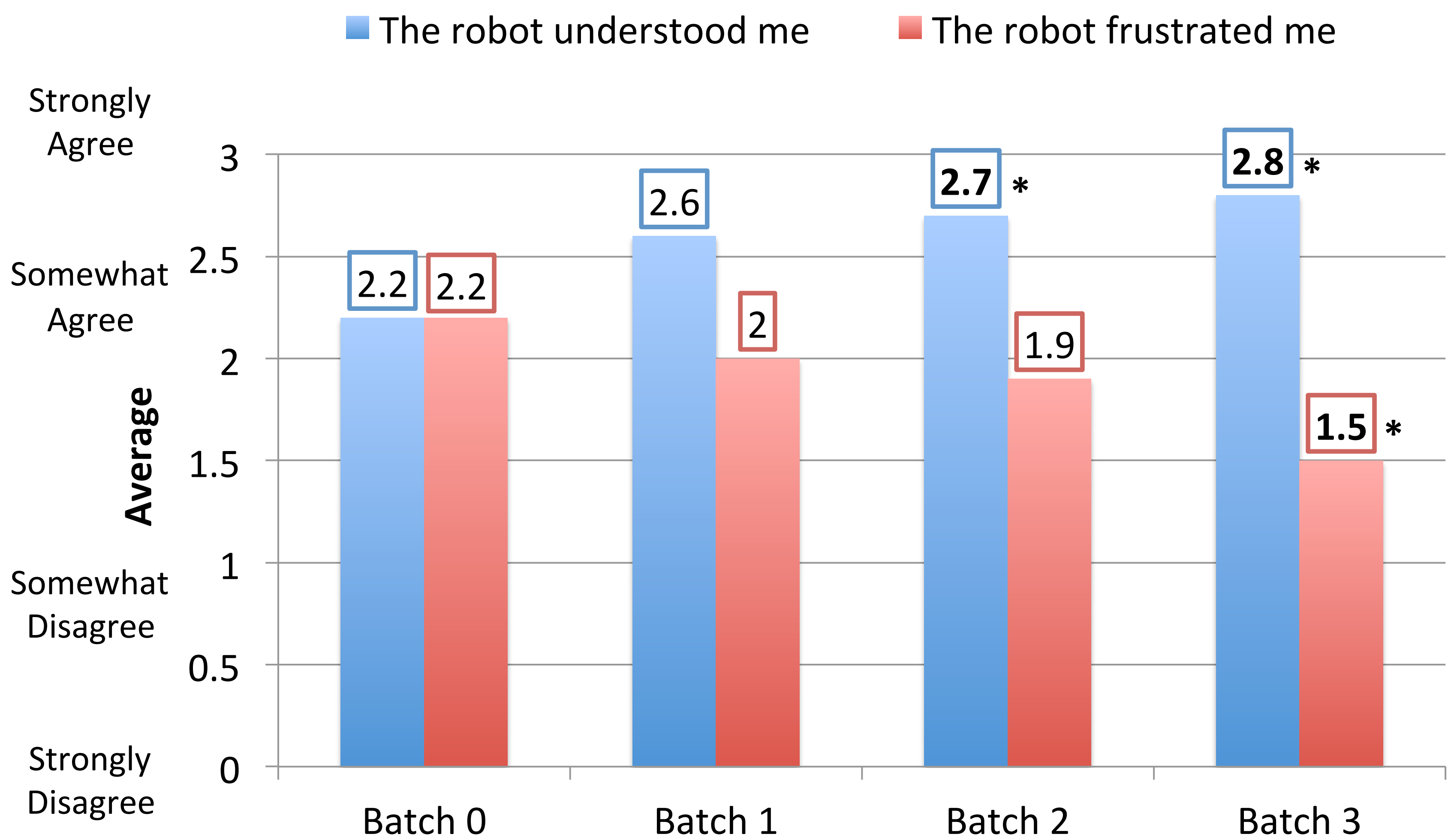
Large-Scale Experiment

- Tested in 4 phases
- ~50 users received test goals, ~50 train goals
  - Unique users in each phase
- System incrementally trained via train goal conversations only

Mechanical Turk Dialog Turns



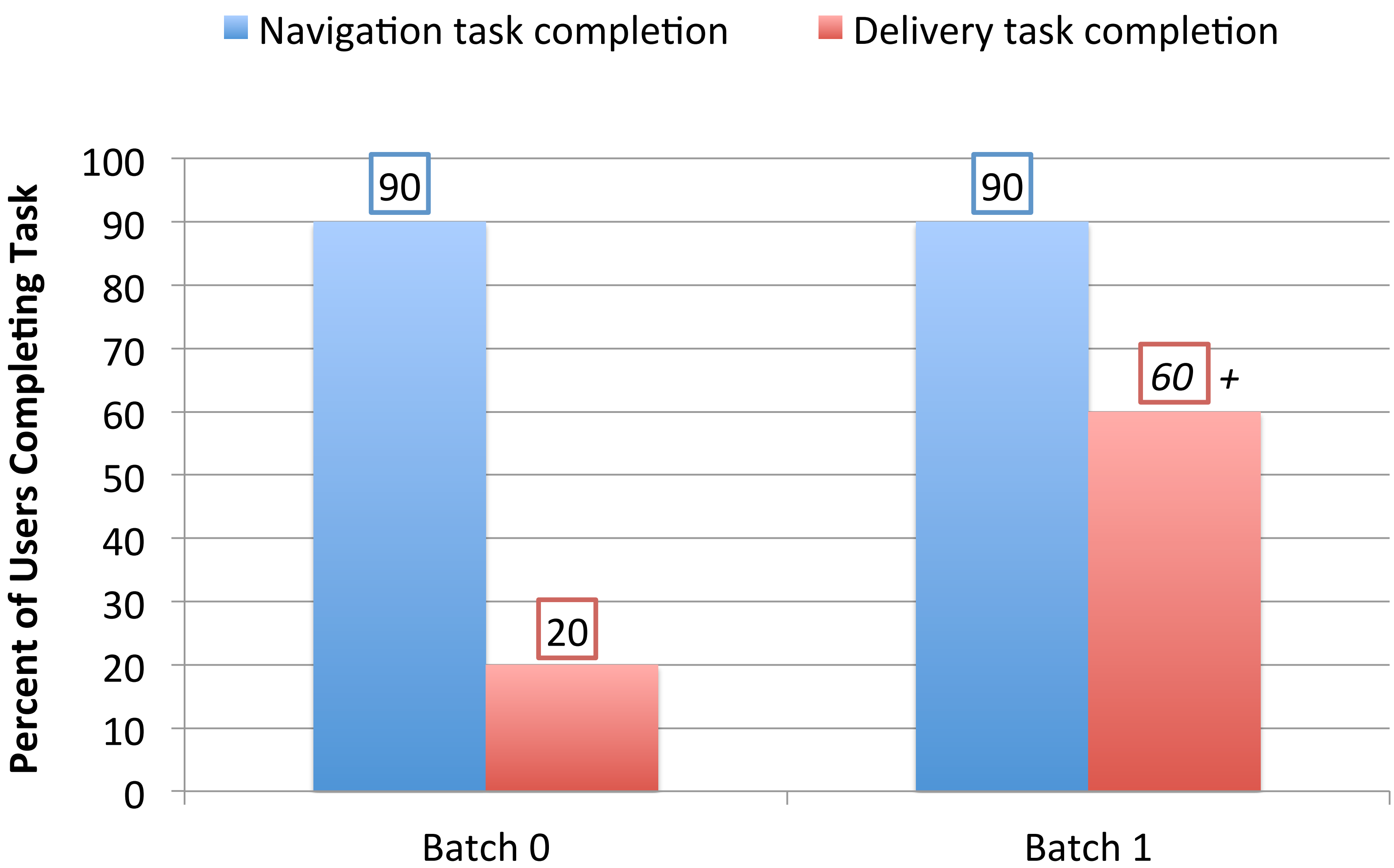
Mechanical Turk Survey Responses



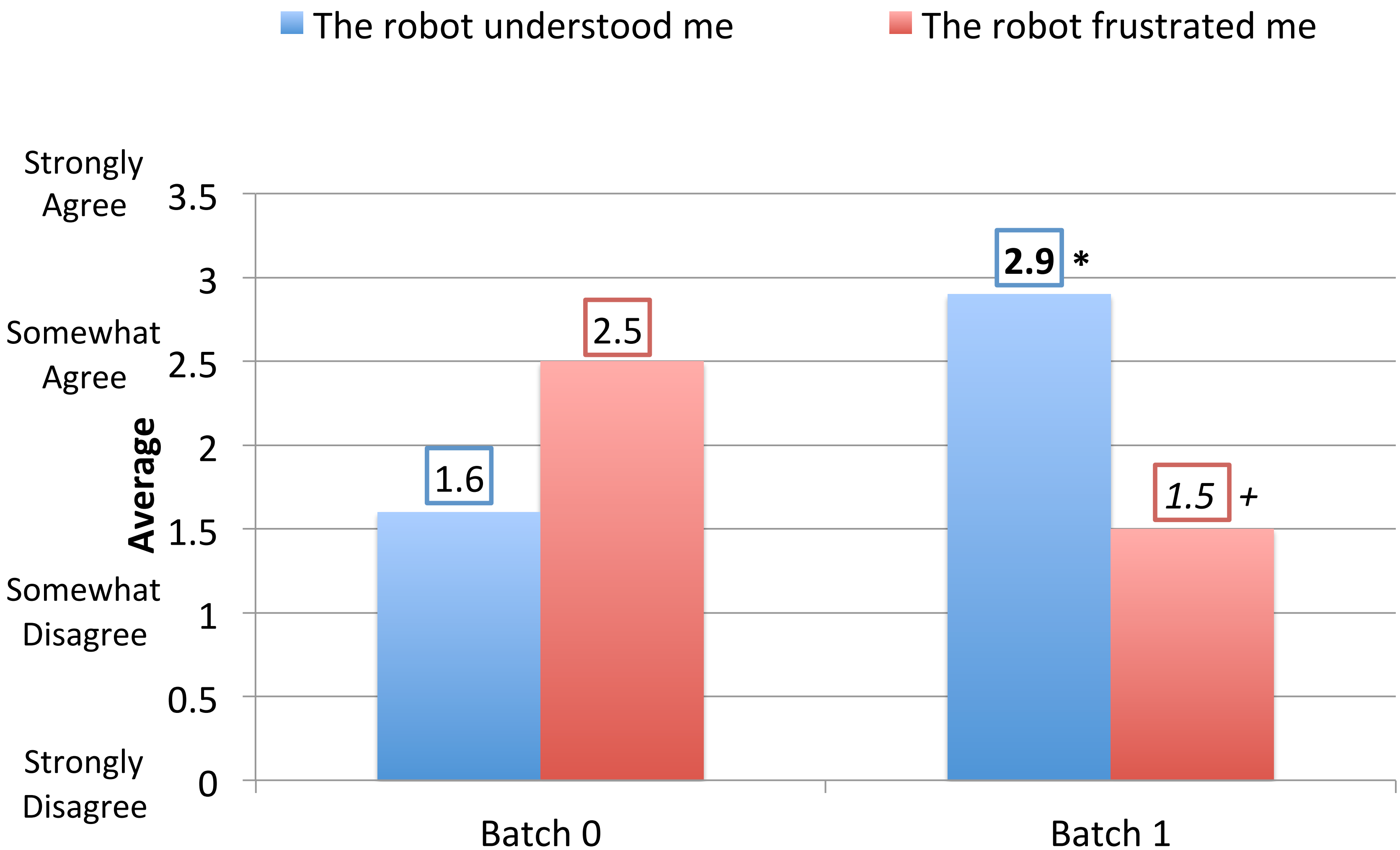
Robot Experiment

- Same setup, but real robot and fewer users
  - Users type to robot to mimic Mechanical Turk setup
- 10 users in initial test batch
- System interacted freely with people on the floor for four days as training (34 conversations in total)
- 10 users in the second test batch, after retraining

Office Robot Dialog Completion



Office Robot Survey Responses



Conclusions

- Lexical acquisition reduces dialog lengths for multi-argument predicates like delivery
- Causes users to perceive the system as more understanding
- Leads to less user frustration
- Allows improving language understanding without large, annotated corpora

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Related Work

- Command processing has taken many forms
- Specify tasks step-by-step (Meriçli, 2014)
  - Assumes particular words in particular order
- Specify low-level action sequences (Misra, 2014; Tellex, 2011)
  - Uses a parser trained on a huge corpus
- Map language to action specifications (Matuszek, 2013)
  - Cannot learn new words/expressions

Future Work

- Perceptual grounding (`blue’,`left of’)
- Predicate invention (`ruddy’)
- Learning a multi-objective dialog policy that trades off learning and user satisfaction