The emergence of Gricean maxims in goal-oriented interaction
(or, how Pragbot learned to play well with others)

Max Bodoia, Adam Vogel, and Christopher Potts

SUBTLE MURI review, Penn, October 12, 2012
Plan

1. Release 2 of the Cards corpus (1,266 transcripts; \(\approx 260,000\) words)
2. Grounded interpretation in the Cards world
3. Decision-theoretic agents:
   - Listener bot
   - Dialogue bot
   - And presenting, at last, a true Pragbot
Pragmatics and the question under discussion

(10) Traveler Are there aisle seats available on the 7:30 flight?
Agent There are seats available. (That’s all that matters.)

(11) What is our world like?

... Seats available? ...

Aisle seats? Window seats? ...
## Task oriented dialogue corpora

<table>
<thead>
<tr>
<th>Corpus</th>
<th>Task type</th>
<th>Domain</th>
<th>Task-orient.</th>
<th>Dialogues</th>
<th>Format</th>
</tr>
</thead>
<tbody>
<tr>
<td>Switchboard</td>
<td>discussion</td>
<td>open</td>
<td>very loose</td>
<td>2,400</td>
<td>aud/txt</td>
</tr>
<tr>
<td>SCARE</td>
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<td>3d world</td>
<td>tight</td>
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</tbody>
</table>

(See also Blaylock & Allen, ‘Generating artificial corpora for plan recognition’)
The Cards Corpus

http://CardsCorpus.christopherpotts.net/

Included:

- The transcripts in CSV format
- Python classes for working with the transcripts
- Examples of the Python classes in action
- R code for reading in the corpus as a data frame
- **All the annotations used in the work described here**
Gameboard

Yellow boxes mark cards in your line of sight.

You are on 2D

Task description: Six consecutive cards of the same suit

The cards you are holding

Move with the arrow keys or these buttons.
Scenario

Gather six consecutive cards of a particular suit (decide which suit together), or determine that this is impossible. Each of you can hold only three cards at a time, so you’ll have to coordinate your efforts. You can talk all you want, but you can make only a limited number of moves.
Version 1 numbers

- 744 transcripts
- Game length mean: 414.44 actions (median 325.50, sd 261.88)
- Actions:
  - Card pickup: 11,027
  - Card drop: 7,202
  - Move: 255,734
  - Utterance: 23,532
    - Utterance length mean: 5.84 words (median 5, sd 5.08)
    - Total word count: 137,323
    - Total vocabulary: 4,004 (3,453 if card references are normalized)
Version 2 numbers

- 1,266 transcripts
- Game length mean: 373.21 actions (median 305, sd 215.20)
- Actions:
  - Card pickup: 19,157
  - Card drop: 12,325
  - Move: 371,811
  - Utterance: 45,805
    - Utterance length mean: 5.69 words (median 5, sd 4.74)
    - Total word count: 260,788
    - Total vocabulary: 3,398 (assumes regularized card references)
Constants and points of variation

Constants

- Task description (‘six consecutive cards of the same suit’)
- Max cards in hand: 3

Randomness

- Players’ initial positions
- All card positions
Constants and points of variation

Systematic variation (highlights)

- Some games are infeasible because areas of the board are walled off.
- Most games are symmetric: the players each have the same line of sight and number of moves.
- Around 500 games are asymmetric: one player has a very limited number of moves but infinite line-of-sight; the other has a large number of moves but very limited line of sight.
- There are a few different game boards, in a few different sizes.
- The number of moves each player has varies from 100 to 600; these values result in very different play.
## Task oriented dialogue corpora

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<td>2d grid</td>
<td>tight</td>
<td>1,266</td>
<td>txt <strong>in context</strong></td>
</tr>
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Task oriented dialogue corpora

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Chief selling points for Cards:

- Pretty large.
- Controlled enough that similar things happen often.
- Very highly structured — the only corpus whose release version allows the user to replay all games with perfect fidelity.
Interpreting locative expressions

Example (Players establishing a basic search strategy)

Player 2: where are you?
Player 2: I am on the left side in the middle.
Player 1: i’m on the right side in the middle
Player 2: want to split left and right?

Example (Players seeking to exchange cards)

Player 2: ok i am going to drop a card for you
Player 1: ok, where at?
Player 2: i am at the very bottom right in front of the long skinny corridor across the bottom
Player 2: right at the opening on the left side
Variation

bottom
bottom left
left middle
I’m dead center
in the middleish
i’m inside the dead-end hallway
in the small box at the left center
I am in the middle toward the bottom.
far right, 7 blocks up from the bottom
I am in the middle just under the C room
i’m in the narrow room in the upper left
im inside the sideways C at the top left
The bottom left corner above the second line
I am two squares away from the upper left corner
I am just to the left of the C room in the middle.
I am in the long rectangle towards the bottom center
I am 2 spaces off the top 3 from left wall in the center
bottom right corner inside the box just below the single black square
i am at the very bottom right in front of the long skinny corridor across the bottom
Annotations

Player 2,23804,CHAT_MESSAGE_PREFIX,[where are you?]_{sem=where(you); engagesGoal=search}

Player 2,20236,CHAT_MESSAGE_PREFIX,hello, [where are you located?]_{sem=where(you); engagesGoal=search}

Player 2,13931,CHAT_MESSAGE_PREFIX,[where are you P?]_{sem=where(you); engagesGoal=meet}

Player 1,204774,CHAT_MESSAGE_PREFIX,[where are you exactly]_{sem=exactly(where(you)); engagesGoal=card}

(a) Questions.

Player 2,31931,CHAT_MESSAGE_PREFIX,I am [on the left side in the middle]_{sem=located(Player 2; @left middle); answers=23804}

Player 1,69058,CHAT_MESSAGE_PREFIX,hi....i am [in the lower right corner of the center of the board]_{sem=located(Player 1; @middle<bottom right>)); answers=20236}

Player 1,22344,CHAT_MESSAGE_PREFIX, i am [on the left bottom corner]_{sem=located(Player 1; @bottom left corner); answers=13931}

i’m [at the very very top right]_{sem=located(Player 1; @precise top right); answers=imp(where(you)); engagesGoal=card}

(b) Answers.

Table: Some of the 599 annotated locative answers, with associated questions.
## Annotations

<table>
<thead>
<tr>
<th>Text</th>
<th>Domain</th>
<th>Semantics</th>
</tr>
</thead>
<tbody>
<tr>
<td>middle box towards the right up top</td>
<td>middle</td>
<td>approx;right</td>
</tr>
<tr>
<td>3 left of the c</td>
<td>BOARD</td>
<td>4.8;5.4;6.4</td>
</tr>
<tr>
<td>to middle box</td>
<td>BOARD</td>
<td>middle;room</td>
</tr>
<tr>
<td>on the left bottom corner</td>
<td>BOARD</td>
<td>bottom;corner;left</td>
</tr>
<tr>
<td>in the bottom you see the opening on the bottom row</td>
<td>BOARD</td>
<td>bottom;entrance</td>
</tr>
<tr>
<td>in the center towards the bottom</td>
<td>BOARD</td>
<td>approx;bottom;middle</td>
</tr>
<tr>
<td>middle right</td>
<td>BOARD</td>
<td>middle;right</td>
</tr>
</tbody>
</table>

### Table: Example answer annotations. (Showing just three of the 27 columns in the extracted annotations file.)

<table>
<thead>
<tr>
<th>Word</th>
<th>Count</th>
<th>Word</th>
<th>Count</th>
<th>Word</th>
<th>Count</th>
<th>Word</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>BOARD</td>
<td>547</td>
<td>corner</td>
<td>91</td>
<td>hall</td>
<td>31</td>
<td>U_room</td>
<td>2</td>
</tr>
<tr>
<td>right</td>
<td>227</td>
<td>approx</td>
<td>77</td>
<td>room</td>
<td>18</td>
<td>T_room</td>
<td>2</td>
</tr>
<tr>
<td>middle</td>
<td>195</td>
<td>SQUARE</td>
<td>71</td>
<td>sideways_C</td>
<td>11</td>
<td>deadend</td>
<td>2</td>
</tr>
<tr>
<td>top</td>
<td>183</td>
<td>precise</td>
<td>68</td>
<td>loop</td>
<td>7</td>
<td>wall</td>
<td>1</td>
</tr>
<tr>
<td>left</td>
<td>178</td>
<td>entrance</td>
<td>59</td>
<td>reverse_C</td>
<td>3</td>
<td>sideways_F</td>
<td>1</td>
</tr>
<tr>
<td>bottom</td>
<td>169</td>
<td>C_room</td>
<td>35</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Table: Semantic lexicon with token counts.
**Table:** The rightmost seven columns of the gameboard. The blank spaces correspond to walls (undefined values). The counts table shows an outlier four rows from the bottom.
Heatmaps

BOARD(top & right); $H: 5.68$
### Heatmaps

<table>
<thead>
<tr>
<th>BOARD(top &amp; right); $H$: 5.68</th>
<th>BOARD(precise &amp; top &amp; right); $H$: 4.4</th>
<th>middle(top &amp; right); $H$: 5.27</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1" alt="Heatmap Image" /></td>
<td><img src="image2" alt="Heatmap Image" /></td>
<td><img src="image3" alt="Heatmap Image" /></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>BOARD(left); $H$: 6.82</th>
<th>BOARD(bottom); $H$: 6.54</th>
<th>BOARD(precise &amp; bottom); $H$: 6.05</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image4" alt="Heatmap Image" /></td>
<td><img src="image5" alt="Heatmap Image" /></td>
<td><img src="image6" alt="Heatmap Image" /></td>
</tr>
</tbody>
</table>
Heatmaps

- BOARD(middle); $H: 7.37$
- BOARD(middle & bottom); $H: 6.1$
- BOARD(entrance & bottom); $H: 5.48$
- BOARD(C_room); $H: 6.49$
- BOARD(loop); $H: 4.72$
- BOARD(hall); $H: 7.02$
Experimental result (Potts 2012, WCCFL)

Specificity hypotheses (informal versions)

1. When the players need to meet up or direct each other to specific cards, their answers will tend to be more specific.

2. When the players are developing a general search strategy, their answers will tend to be less specific.

Example (search)
Player 1: on the left

Example (card)
Player 1: at the very top right corner
Experimental result (Potts 2012, WCCFL)

Specificity hypothesis (experimental version)

Answers to questions annotated as engagesGoal=search will tend to have higher entropy ($H$) than answers to questions annotated as engagesGoal=card or engagesGoal=meet.

Example (search)
Player 1: on the left

BOARD(left); $H$: 6.82

Example (card)
Player 1: at the very top right corner

BOARD(precise & top & right); $H$: 4.4
Experimental result (Potts 2012, WCCFL)

Specificity hypothesis (experimental version)

Answers to questions annotated as engagesGoal=search will tend to have higher entropy ($H$) than answers to questions annotated as engagesGoal=card or engagesGoal=meet.

(a) The full annotated set.  
(b) Symmetric games only.  
(c) Asymmetric only.

Figure: The distribution of entropy values relative to task types.
Decision-theoretic agents

- The previous result supports the idea that people’s answers are goal-oriented, a version of the general question-driven model of pragmatics that we began with.

- But what does it mean to be goal-oriented?

- And how does cooperative linguistic behavior emerge from the goals?

- More generally: to what extent do general Gricean pressures on rational communication emerge from basic decision-theoretic considerations?
### Outline

<table>
<thead>
<tr>
<th>What we want</th>
<th>How we get it</th>
</tr>
</thead>
<tbody>
<tr>
<td>Semantic representations</td>
<td>Linear classifiers</td>
</tr>
<tr>
<td>Grounded language interpretation</td>
<td>As in the previous section</td>
</tr>
<tr>
<td>Decision-theoretic agents</td>
<td>Partially Observable Markov Decision Processes (POMDPs)</td>
</tr>
<tr>
<td>Language as a representation for planning</td>
<td>Generalizing from human behavior in the corpus</td>
</tr>
<tr>
<td>Modeling others beliefs</td>
<td>Add others’ beliefs to the state space</td>
</tr>
</tbody>
</table>
Simplified cards scenario

*Both players must find the ace of spades.*
Semantic representations

- Utterances are bags of words (for now). No preprocessing (yet) for spelling correction, lemmatization, etc.
- Assign semantic tags using log-linear classifiers trained on the corpus data.
- Binary classifiers for semantic tags and a multi-class classifier for domain tags.
- Micro-averaged F1 (10-fold cross-validation) is 81.9% — but the real test is how well it works in the extrinsic (bot vs. bot) evaluation I describe later.
Grounded language interpretation

“in the bottom you see the opening on the bottom row”
\[ \Rightarrow \]
BOARD(entrance & bottom); \( H: 5.48 \)

“in the top right of the middle part of the board”
\[ \Rightarrow \]
middle(top & right); \( H: 5.27 \)

“i’m in the center”
\[ \Rightarrow \]
BOARD(middle); \( H: 7.37 \)
Agent framework

We want our agent to:

- Make moves that are likely to lead it to the card.
- Change its behavior based on observations it receives.
- Respond to locative advice from the other player.
- Give locative advice to the other player.

Modeling the problem as a POMDP allows us to train agents that have these properties.
POMDPs

- \( S \): states
- \( b_0 \): initial belief state (distribution over \( S \))
- \( A \): actions
- \( O \): observations
- \( T \): distributions \( P(s'|s, a) \)
- \( \Omega \): distributions \( P(o|s, a) \)
- \( R \): rewards \((S \times A) \mapsto \mathbb{R}\)
Approximate solutions take us (only) part of the way

- An exact solution specifies the value of every action at any reachable belief state.

- In practice, only approximate solutions are tractable. We used the PERSEUS solution algorithm.

- Even approximate solutions are generally only possible for problems with < 10K states.

<table>
<thead>
<tr>
<th>Card location</th>
<th>Agent location</th>
<th>Partner location</th>
<th>Partner’s card beliefs</th>
</tr>
</thead>
<tbody>
<tr>
<td>$231 \times 231 \times 231 \times 231$</td>
<td>$\approx 50K$</td>
<td>$\approx 12M$</td>
<td>$\approx 3B$</td>
</tr>
</tbody>
</table>

**Table:** Size of the state-space for the one-card game.
Language as a representation for planning

- Divide the board up into \( n \) regions, for some tractable \( n \)
- Generate this partition using our locative phrase distributions.
- \( k \)-means clustering in locative phrase space.

<table>
<thead>
<tr>
<th>Class</th>
<th>(0,0)</th>
<th>(0,1)</th>
<th>...</th>
<th>(9,6)</th>
<th>(9,7)</th>
<th>(9,8)</th>
<th>(9,9)</th>
<th>...</th>
<th>(17,23)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BOARD(bottom;entrance)</td>
<td>0</td>
<td>0</td>
<td>.01</td>
<td>.03</td>
<td>.04</td>
<td>.05</td>
<td>.04</td>
<td>.12</td>
<td>0</td>
</tr>
<tr>
<td>BOARD(middle;top)</td>
<td>0</td>
<td>0</td>
<td>.02</td>
<td>.02</td>
<td>.03</td>
<td>.02</td>
<td>.02</td>
<td>.07</td>
<td>0</td>
</tr>
<tr>
<td>middle(middle)</td>
<td>0</td>
<td>0</td>
<td>.02</td>
<td>.07</td>
<td>.08</td>
<td>.09</td>
<td>.10</td>
<td>.02</td>
<td>0</td>
</tr>
<tr>
<td>BOARD(bottom;corner;right)</td>
<td>0</td>
<td>0</td>
<td>.03</td>
<td>.06</td>
<td>.05</td>
<td>.06</td>
<td>.07</td>
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<td></td>
<td>0</td>
<td>0</td>
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<td>0</td>
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<td>...</td>
</tr>
</tbody>
</table>
Clusters induced

Figure: 12-cell clustering.
Clusters induced

Figure: 14-cell clustering.
Clusters induced

Figure: 16-cell clustering.
Clusters induced

Figure: 18-cell clustering.
Listener Bot

- $S$: all combinations of the player’s region and the card’s region
- $b_0$: initial belief state (distribution over $S$)
- $A$: travel actions for each region, and a single search action
- $O$: {AS seen, AS not seen}
- $T$: distributions $P(s'|s, a)$, except travel actions fail between nonadjacent regions
- $\Omega$: distributions $P(o|s, a)$; travel actions never return positive observations; search actions return positive observations only if the player’s current region contains the AS
- $R$: small negative for not being on the card, large positive for being on it. No sensitivity to the other player.
Listener Bot example
Listener Bot example
Listener Bot example
Listener Bot example

“by the middle of the top hallway”

\[
\text{BOARD}(\text{middle} \land \text{top})
\]
Listener Bot example
Listener Bot example

(by the middle of the top hallway)
Listener Bot example

"by the middle of the top hallway"
ListenerBot home movies

- “in the room on the left of the board”
- “in the top west corner”
- “in the top entrance to the middle room”
- “in the middle of the top hallway”
- “on the right ... the right of the middle room that is”
- “in the middle of the right hallway”
- “in the corner”
- “at the entrance to the main room”
- “halfway up”
DialogBot (Baby Pragbot?)

DialogBot is a strict extension of Listener Bot:

- The set of states is now all combinations of
  - both players’ positions
  - the card’s region
  - the region the other player believes the card to be in
- The set of actions now includes dialogue actions.
- (The player assumes that) a dialogue action $U$ alters the other player’s beliefs in the same way that $U$ would impact his own beliefs.
- Same basic reward structure as for Listenerbot, except now also sensitive to whether the other player has found the card.
DialogBot and ListenerBot play together

**DialogBot beliefs:**
ListenerBot's position

**DialogBot beliefs:**
ListenerBot's beliefs

**ListenerBot beliefs:**
ListenerBot's position

**ListenerBot beliefs:**
ListenerBot's beliefs
DialogBot and ListenerBot play together

DialogBot beliefs:
ListenerBot’s position

DialogBot beliefs:
ListenerBot’s beliefs
DialogBot and ListenerBot play together

**DialogBot beliefs:**
ListenerBot’s position

**ListenerBot beliefs:**
ListenerBot’s beliefs
DialogBot and ListenerBot play together

DialogBot beliefs:
ListenerBot’s position

DialogBot beliefs:
ListenerBot’s beliefs
DialogBot and ListenerBot play together

DialogBot beliefs:
ListenerBot’s position

DialogBot beliefs:
ListenerBot’s beliefs
DialogBot and ListenerBot play together

DialogBot beliefs

DialogBot beliefs: ListenerBot’s position

ListenerBot beliefs

DialogBot beliefs: ListenerBot’s beliefs
DialogBot and ListenerBot play together

**DialogBot beliefs**

**ListenerBot beliefs**

**DialogBot beliefs:** ListenerBot’s position

**DialogBot beliefs:** ListenerBot’s beliefs
DialogBot home movies

- Right player finds the card on the top:
  - Players’ card beliefs
  - Players’ beliefs about other players’ card beliefs
  - Players’ beliefs about other players’ locations

- Right player finds the card in the middle:
  - Players’ card beliefs
  - Players’ beliefs about other players’ card beliefs
  - Players’ beliefs about other players’ locations
Emergent pragmatics

Quality

- The Gricean maxim of quality says roughly “Be truthful”.
- For DialogBot, this emerges from the decision problem: false information is (typically) more costly.
- DialogBot would lie if he thought it would move them toward the objective.

Quantity and Relevance

- The Gricean maxims of quantity and relevance for informative, timely contributions.
- When DialogBot finds the card, he communicates the information, not because he is hard-coded to do so, but rather because it will help the other player find it.
Experimental results

<table>
<thead>
<tr>
<th></th>
<th>Success rate</th>
<th>Moves (overall)</th>
<th>Moves (successful)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ListenerBot &amp; ListenerBot</td>
<td>58.4%</td>
<td>18.90</td>
<td>14.20</td>
</tr>
<tr>
<td>ListenerBot &amp; DialogBot</td>
<td>60.9%</td>
<td>19.37</td>
<td>15.45</td>
</tr>
<tr>
<td>DialogBot &amp; DialogBot</td>
<td>90.9%</td>
<td>19.26</td>
<td>16.12</td>
</tr>
</tbody>
</table>

**Table:** Test pairs of agents from 197 random initial states.
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- Thus, a bot that reasoned to this level might be truly worthy of the name Pragbot.