COMP 790.139 (Spring 2017) Adv. Topics in NLP: Language Grounding for Robotics



Mohit Bansal

Class Info/Logistics

- COMP 790.139 'Language Grounding for Robotics'
- **3 UNITS**
- Instructor: Mohit Bansal (SN258, http://www.cs.unc.edu/~mbansal/)
- Time: Tuesdays 9.30am-12.00pm
- Room: FB008
- Office Hours: Tue 12.00-1.00pm (by appointment), SN258
- Course Webpage: <u>http://www.cs.unc.edu/~mbansal/teaching/robonlp-seminar-spring17.html</u>
 - **Course Email**: <u>nlpcomp790unc@gmail.com</u>

About Me

- Asst. Professor, CS, UNC (joined Fall 2016)
- Res. Asst. Professor, TTI-Chicago/UChicago, 2013-2016
- PhD, UC Berkeley, 2008-2013
- Research Interests:
 - Past: Syntactic parsing, coreference resolution, taxonomy induction, world knowledge and commonsense induction
 - Current: Multimodal and embodied semantics (i.e., language with vision and speech, for robotics); human-like language generation and Q&A/dialogue; interpretable and structured deep learning
- Office SN258
- Webpage: <u>http://www.cs.unc.edu/~mbansal/</u>, Email: <u>mbansal@cs.unc.edu</u>

Your Introductions

Please say your:

Name

- Department/degree/major
- Research interests (ML/AI/NLP/CV experience? Coding?)

▶ Fun fact ☺

(send me a few lines of intro at nlpcomp790unc@gmail.com)

About the Course (and its Goals)

- Research-oriented seminar course! We will read lots of interesting papers, brainstorm, and do fun novel projects!
- Basic NLP and machine learning (some deep learning) experience expected – check fall2016 NLP intro slides!
- We'll cover several latest research topics in NLP+robotics
- You will read papers in advance and write summaries
- You will present papers in class
- Brainstorm regularly and code + write up fun/novel projects!
- Some lecture(s) on academic/research quality paper writing

Prerequisites

- Graduate research-level class
- Some machine learning and coding experience is definitely expected!
- Moreover, some NLP and RL background is highly recommended
- Projects will require research and coding skills; summaries and paper presentation will require solid ML clarity

Expectations/Grading

- Paper presentation (15%)
- Paper written summaries (25%)
- Class participation, discussion and brainstorming (20%)
- Project reports and presentations (40%) (midterm = 15% and final = 25%)

Lateness Policy

- Written summaries are due *before class* by email to <u>nlpcomp790unc@gmail.com</u>
- First paper summary submission will have no late penalties.
- After that, for every week's summary submission, there will be a 25% value reduction per late day.
- Other lateness policies (for projects, etc.) will be sent via email during the semester

Collaboration Policy

- Paper summaries have to be written and submitted individually.
- Projects are encouraged to be done in pairs, with clearly outlined contributions from each team member
- But individual projects are fine too (e.g., if it relates to your current research)

Paper Presentation

- Lead discussion for 1-2 papers on a topic some week (may be done in pairs/groups depending on class size)
- Read related papers and present background to audience
- Present task and model details of given paper
- Present demo's of related code, etc.
- Ask interesting questions to initiate brainstorming
- Mention some next steps, future work, extension ideas!

Paper Written Summaries

- 0.5-1 page (per paper) write-up for every week's paper(s)
- Describe the task
- Summarize the method
- Explain the novelty
- Discuss the next steps or potential improvements

Class Participation and Brainstorming

- Audience students expected to take part in lively discussion every paper reading!
- After every topic gets completed (i.e., several papers in 2-3 weeks), we will have a brainstorming and 'idea-generation' session!
- Exact details to be announced soon but students expected to submit and discuss novel idea(s) on the whole general topic, e.g., new related task or dataset, new approach to existing task, combinations of tasks/approaches, etc.
- Don't hesitate to propose fancy ideas ②, but try to keep them grounded/feasible and think of how to approach them realistically (in terms of datasets, models, speed, memory, etc.)

Project

- This is a 'Reading, Coding, and Writing' class!
- Students will pick (early) their favorite topic among latest cutting-edge research topics covered in class
- And will try a novel idea (implementing + extending or original) -- I am happy to discuss details!
- Midterm and final report + presentation (and possibly some updates)
- Might be in pairs/groups depending on final class size
- Use conference style files and aim for conference-quality papers
- Will have some lecture(s) on research-quality paper writing

Reference Books

- SLP2: D. Jurafsky & James H. Martin. "Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics and Speech Recognition". Prentice Hall, Second Edition, 2009.
- SLP3: Some draft chapters of the third edition are available online at <u>https://web.stanford.edu/~jurafsky/slp3/</u>
- FSNLP: Chris Manning and Hinrich Schütze, Foundations of Statistical Natural Language Processing, MIT Press. Cambridge, MA: May 1999. <u>http://nlp.stanford.edu/fsnlp/</u>
- ML Background: Andrew Ng's Coursera Machine Learning course <u>https://www.coursera.org/learn/machine-learning</u>
- Reinforcement Learning: Sutton & Barto Book: Reinforcement Learning: An Introduction. <u>https://webdocs.cs.ualberta.ca/~sutton/book/the-book.html</u>

Course Syllabus/Topics (tentative)

- interpreting and executing verbal instructions for navigation, articulation, manipulation, assembly, skill learning, etc.
- human-robot collaboration and dialogue for learning new subactions, mediating shared perceptual basis, referring expression generation, etc.
- grounding and language learning via dialogue-based and interactive games.
- automatic language generation for embodied tasks.
- grounded reinforcement learning.
- grounded knowledge representations (mapping language to world).
- machine learning models (structured and deep), datasets, and metrics for embodied language.

Question answering



Question answering

Google	Wha	it was the	U.S. popu	Ilation whe	en Bernie Sa	nders was	born?	Ŷ	Q
	All	News	Images	Videos	Shopping	More -	Search tools		
	About	t 1,620,000	results (0.67	seconds)					
	Un	ited State	es of Amer	ica / Popu	lation (1941)		* * * *		-
	1 194	33.4	millic	n				North Pacific Ocean	
							Feedba	ck	

Question answering

Google	whic	h countrie	es border t	he black	sea			୍
	All	Maps	Images	News	Shopping	More •	Search tools	

About 2,710,000 results (0.81 seconds)

This major inland sea is bordered by six countries — **Romania** and **Bulgaria** to the west; **Ukraine**, **Russia**, and **Georgia** to the north and east; and **Turkey** to the south. Additionally, it is impacted by another 10 nations through the five major rivers that empty into the Black Sea, the largest of which is the Danube River.



Black Sea Geography - College of Earth, Ocean, and Environment https://www.ceoe.udel.edu/blacksea/geography/index.html University of Delaware -

About this result . Feedback

Machine Translation



Yaha maśīna anuvāda kā ēka udāharaņa hai

Sentiment Analysis



Sentiment Analysis with Python NLTK Text Classification

This is a demonstration of **sentiment analysis** using a NLTK 2.0.4 powered **text classification** process. It can tell you whether it thinks the text you enter below expresses **positive sentiment**, **negative sentiment**, or if it's **neutral**. Using **hierarchical classification**, *neutrality* is determined first, and *sentiment polarity* is determined second, but only if the text is not neutral.

Analyze Sentiment

Language

english 🖨

Enter text

Analyze

It always amazes me how Universal never cares to create anything remotely clever when it comes to their animations, and so once again they come up with a harmless little story that wants to be cute and funny (which it is sometimes) but is only bound to be quickly forgotten.

Enter up to 50000 characters

Sentiment Analysis Results

The text is neg.

The final sentiment is determined by looking at the classification probabilities below.

Subjectivity

- neutral: 0.3
- polar: 0.7

Polarity

- pos: 0.2
- neg: 0.8

Natural Language Generation: Summarization





Natural Language Generation: Conversation/Dialogue



Natural Language Generation: Image Captioning

C 🛈 www.cs.toronto.edu/~nitish/nips2014demo/results/8832804.html

Results

Tags

- authors
- scones
- luncheon
- breakfast
- seder

Nearest Caption in the Training Dataset

a man cuts a cake while children sit around at the table , looking on .

Generated Captions

- two people at a table with a cake .
- the two people are having a meal that is in a party.
- a man and two children in a blue table with a cake .
- a man sitting at a table with a bunch of cake on it .
- a man and woman sitting at a table with cake at a party .



<u>back</u>

Natural Language Generation: Visual Question Answering



What color are her eyes? What is the mustache made of?



How many slices of pizza are there? Is this a vegetarian pizza?



Is this person expecting company? What is just under the tree?



Does it appear to be rainy? Does this person have 20/20 vision?

Automatic Speech Recognition



Task-based instructions, e.g., navigation, grasping, manipulation, skill learning



Task-based instructions, e.g., navigation, grasping, manipulation, skill learning



Navigation Instruction Following



Place your back against the wall of the "T" intersection. Go forward one segment to the intersection with the blue-tiled hall. This interesction [sic] contains a chair. Turn left. Go forward to the end of the hall. Turn left. Go forward one segment to the intersection with the wooden-floored hall. This intersection conatains [sic] an easel. Turn right. Go forward two segments to the end of the hall. Turn left. Go forward one segment to the intersection containing the lamp. Turn right. Go forward one segment to the empty corner.

Figure 1: An example of a route instruction-path pair in one of the virtual worlds from MacMahon, Stankiewicz, and Kuipers (2006) with colors that indicate floor patterns and wall paintings, and letters that indicate different objects. Our method successfully infers the correct path for this instruction.

Learning to interpret natural language navigation instructions from observations. Chen and Mooney. AAAI 2011. Weakly supervised learning of semantic parsers for mapping instructions to actions. Artzi and Zettlemoyer. TACL 2013. Listen, Attend, and Walk: Neural Mapping of Navigational Instructions to Action Sequences. Mei, Bansal, and Walter. AAAI 2016

Navigation + Manipulation Instructions



(a) Robotic forklift

(b) Sample commands

Figure 1: A target robotic platform for mobile manipulation and navigation (Teller et al., 2010), and sample commands from the domain, created by untrained human annotators. Our system can successfully follow these commands.



(a) Object groundings

(b) Pick up the pallet

(c) Put it on the truck

Figure 4: A sequence of the actions that the forklift takes in response to the command, "Put the tire pallet on the truck." (a) The search grounds objects and places in the world based on their initial positions. (b) The forklift executes the first action, picking up the pallet. (c) The forklift puts the pallet on the trailer.

Understanding Natural Language Commands for Robotic Navigation and Mobile Manipulation. Tellex, Kollar, Dickerson, Walter, Banerjee, Teller, and Roy. AAAI 2011.

Navigation Dialogue



Fig. 1. A user gives a tour to a robotic wheelchair designed to assist residents in a long-term care facility. (Left) The guide provides an ambiguous description of the kitchen's location. (Right) When the robot is near one of the likely locations, it asks the guide a question to resolve the ambiguity.

Navigation Instruction Generation



Fig. 4. Participants' field of view in the virtual world used for the human navigation experiments.



Fig. 8. Examples of paths from the SAIL corpus that ten participants (five for each map) followed according to instructions generated by humans and by our method. Paths in red are those traversed according to human-generated instructions, while paths in green were executed according to our instructions. Circles with an "S" and "G" denote the start and goal locations, respectively.

Utterance

Assembly Instruction Execution

Scene

Move the block that is currently located closest to the top left corner to the bottom left of the table, slightly higher than the block in the bottom right corner.

Error:

7.29 Block lengths



Error:

Move the block closest to the top left corner so it is above half a block length to the right of the blocks near the lower left corner of the table.

0.94 Block lengths

Table 6: Above are two commands and the worlds they applyto. Below we see the prediction error of our best model.

Recipes: Bakebot (<u>http://projects.csail.mit.edu/video/research/robo/bakebot_final.mp4</u>)



Fig. 3 Architecture of the BakeBot system. The NL system processes the plain text recipe, producing a high-level plan which is sent to the robot. For each instruction in the high-level plan, the motion planner assembles a motion plan and executes it on the PR2 robot.

Recipes: Tell Me Dave (<u>http://tellmedave.cs.cornell.edu/</u>)



Fig. 1. Natural Language Instructions to sequence of instructions for a given new environment. Our approach takes description in natural language and sequences together robotic instructions that are appropriate for a given environment and task. Note that the NL instructions are often ambiguous, and are incomplete, and need to be grounded into the environment.

Recipes: Tell Me Dave (<u>http://tellmedave.cs.cornell.edu/</u>)



Take some coffee in a cup.

Add ice cream of your choice.

Finally, add raspberry syrup to the mixture.

Fig. 4. **Robot Experiment.** Given the language instruction for making the dessert 'Affogato': '*Take some coffee in a cup. Add icecream of your choice. Finally, add raspberry syrup to the mixture.*', our algorithm outputs a sequence that the PR2 executes to make the dessert. (Please see the video.)

Recipes: RoboBarista (<u>http://robobarista.cs.cornell.edu/</u>)



Fig. 5. Screen-shot of Robobarista, the crowd-sourcing platform running on Chrome browser. We have built Robobarista platform for collecting a large number of crowd demonstrations for teaching the robot.

RoboBarista: <u>http://robobarista.cs.cornell.edu/</u>



Fig. 10. **Examples of transferred trajectories** being executed on PR2. On the left, PR2 is able to rotate the 'knob' to turn the lamp on. In the third snapshot, using two transferred trajectories, PR2 is able to hold the cup below the 'nozzle' and press the 'lever' of 'coffee dispenser'. In the last example, PR2 is frothing milk by pulling down on the lever, and is able to prepare a cup of latte with many transferred trajectories.

Learning New Actions by Situated Human-Robot Dialogue



Figure 1: An example setup and dialogue. Objects are marked with labels only for the illustration purpose.

Back to the Blocks World: Learning New Actions through Situated Human-Robot Dialogue. She, Yang, Cheng, Jia, Chai, Xi. SigDial 2014.

Learning To Interpret Language Commands via Dialogue

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	To whom should I bring something?
YOU	dave daniel
ROBOT	What action did you want me to take involving dave daniel?
YOU	5
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	

DIRECTORY

People:

Alice Ashcraft; Secretary Francis ("Frannie") Foster Robert ("Bob") Brown Carol Clark, PhD Dave Daniel, PhD George Green; Intern Evelyn ("Eve") Eckhart Mallory Morgan; Director Peggy Parker, PhD Walter Ward; Supervisor

Items available to robot:



Figure 3: The Mechanical Turk interface for the delivery task. This abridged conversation is from a Turker in training batch 0, when the system had access to only the seed lexicon. Because of this conversation, the agent learned that "calender" and "planner" mean "calendar" during retraining.



Figure 5: Left: Robot platform (Segbot) used in experiments. **Right:** Segbot architecture, implemented using Robot Operating System (ROS).

Learning Language Games Through Interaction



Figure 1: The SHRDLURN game: the objective is to transform the start state into the goal state. The human types in an utterance, and the computer (which does not know the goal state) tries to interpret the utterance and perform the corresponding action. The computer initially knows nothing about the language, but through the human's feedback, learns the human's language while making progress towards the game goal.

Collaborative Referring Expression Generation by Dialogue





(b) An example of the robot's internal representation of the shared environment.



(c) An example of collaborative referential process.

Collaborative Models for Referring Expression Generation in Situated Dialogue. Fang, Doering, and Chai. AAAI 2014.

Next Week

- Website will be updated with initial paper list very soon
- Once paper list is up, start volunteering for paper presentation!
- We might do pairs/groups of students depending on class size
- Project details and dates will be announced soon