CS388: Natural Language Processing
Lecture 22: Grounding

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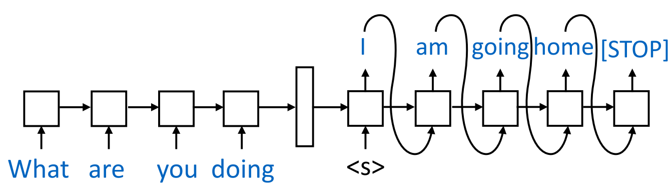
Administrivia

- Final project feedback out
- Project 2 graded soon

Recall: Seq2seq Chatbots



- Just like conventional MT, can train seq2seq models for this task
- Why might this model perform poorly? What might it be bad at?
- Hard to evaluate:

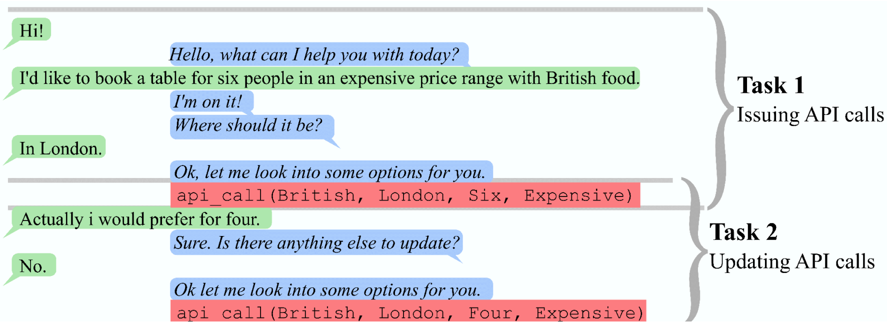
System	BLEU
RANDOM	0.33
MT	3.21
HUMAN	6.08

Recall: Lack of Diversity

- Solution: mutual information criterion; response R should be predictive of user utterance U as well
- Standard conditional likelihood: $\log P(R|U)$
- Mutual information: $\log \frac{P(R,U)}{P(R)P(U)} = \log P(R|U) - \log P(R)$
- log P(R) can reflect probabilities under a language model

Li et al. (2016)

Recall: Task-Oriented Dialogue

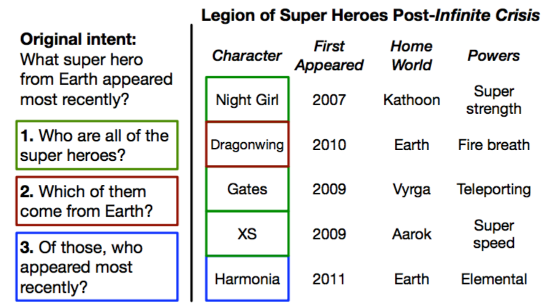


- Using either wizard-of-Oz or other annotations, can collect static traces and train from these

Bordes et al. (2017)

Recall: QA as Dialogue

- Dialogue is a very natural way to find information from a search engine or a QA system
- Several recent datasets on this topic, but tough to collect a static dataset for an interactive application



Character	First Appeared	Home World	Powers
Night Girl	2007	Kathoon	Super strength
Dragonwing	2010	Earth	Fire breath
Gates	2009	Vyrga	Teleporting
XS	2009	Aarok	Super speed
Harmonia	2011	Earth	Elemental

Iyyer et al. (2017)

This Lecture

- Example grounding applications
- Image captioning / VQA
- Grounding with interaction

Basic Grounding Examples

History

- Miller and Johnson-Laird (1976) — Language and Perception
- Harnad (1990) — Symbol grounding problem
  - How do we connect “symbols” to the world in the right way?

In a pure symbolic model the crucial connection between the symbols and their referents is missing; an autonomous symbol system, though amenable to a systematic semantic interpretation, is ungrounded. In a pure connectionist model, names are connected to objects through invariant patterns in their sensory projections, learned through exposure and feedback, but the crucial compositional property is missing; a network of names, though grounded, is not yet amenable to a full systematic semantic interpretation. In the hybrid system proposed here, there is no longer any autonomous symbolic level at all; instead, there is an intrinsically dedicated symbol system, its elementary symbols (names) connected to nonsymbolic representations that can pick out the objects to which they refer, via connectionist networks that extract the invariant features of their analog sensory projections.

- Neural networks (connectionism) help us connect symbolic reasoning to sensory inputs

Grounding

- Tie language to something concrete in the world
  - Percepts: *red* means this set of RGB values, *loud* means lots of decibels on our microphone, *soft* means these properties on our haptic sensor…
  - Higher-level percepts: *cat* means this type of pattern in an image
  - Effects on others: *go left* means the robot turns left, *speed up* means increasing actuation

Colors

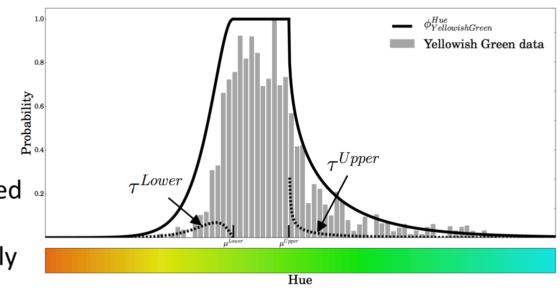
- What color is this?

- What about this?

McMahan and Stone (2014)

Colors

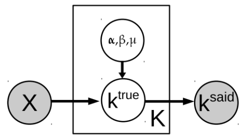
- When we say “yellowish-green”, what does that mean?
- Color descriptions governed by perception as well as *availability*: how commonly it is used (yellowish green vs. chartreuse)



McMahan and Stone (2014)

Colors

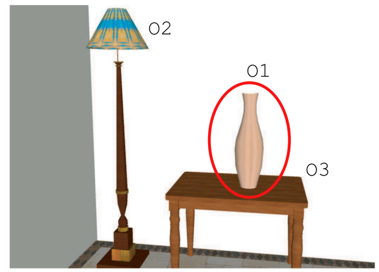
- $P(k_{true} \mid X)$: distribution parameterized in HSV space as follows: there are certain ranges where a color can "definitely apply", others where it can apply



- $P(k_{said} \mid k_{true})$: captures availability; prior towards common colors
- Model combines language / reasoning with basic perception — characteristic of grounding

McMahan and Stone (2014)

Spatial Relations



Golland et al. (2010)

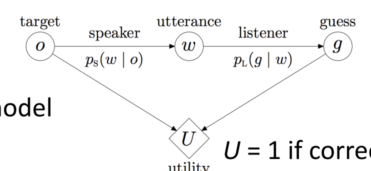
- How would you indicate O1 to someone with relation to the other two objects? (not calling it a vase, or describing its inherent properties)
- What about O2?
- Requires modeling listener — "right of O2" is insufficient though true

Spatial Relations

Golland et al. (2010)

- Grice (1975)
  - Maxim of quality: say something true
  - Maxim of quantity: be as informative as required but no more
  - Maxim of relation: be relevant
  - Maxim of manner: avoid ambiguity
- Maximize expected utility given listener model

$$\mathrm{EU}(\mathrm{S},\mathrm{L}) = \sum_{o,w,g} p(o)p_{\mathrm{S}}(w|o)p_{\mathrm{L}}(g|w)U(o,g)$$



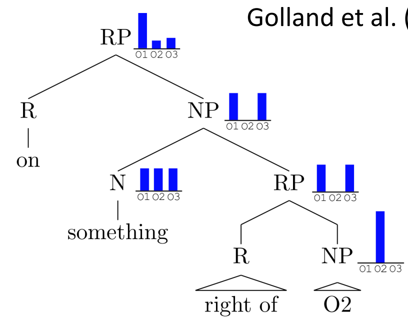
U = 1 if correct, else 0

- Say something which has a high probability of evoking the right response in the listener

Spatial Relations

Golland et al. (2010)

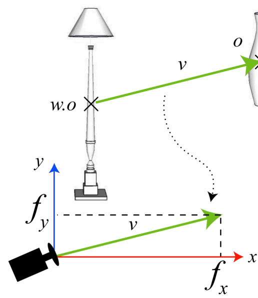
- Listener model:
  - Syntactic analysis of the particular expression gives structure
  - Rules (O2 = 100% prob of O2), features on words modify distributions as you go up the tree



Spatial Relations

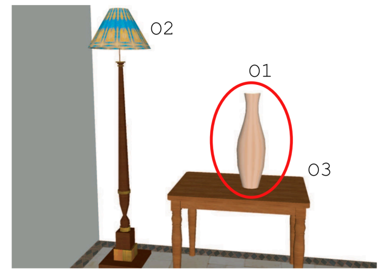
- Objects are associated with coordinates, features map lexical items to distributions (“right” modifies the distribution over objects to focus on those with higher x coordinate)
- Language -> spatial relations -> distribution over what object is intended

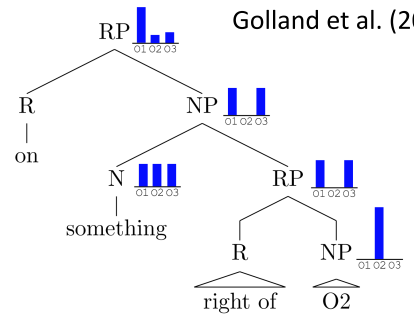
Golland et al. (2010)



Spatial Relations

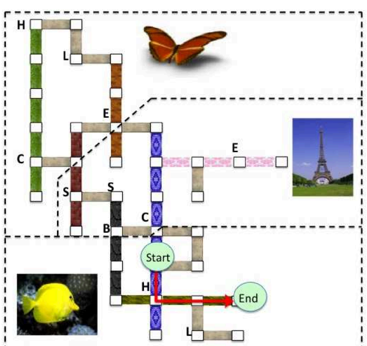
Golland et al. (2010)





- Put it all together: speaker will learn to say things that evoke the right interpretation
- Language is grounded in what the speaker understands about it

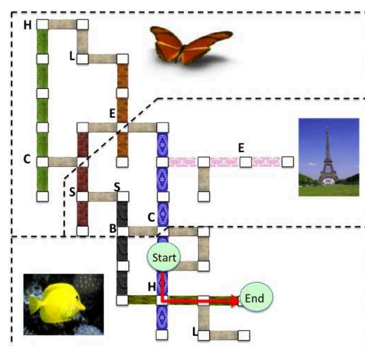
Instruction Following



- Want to be able to follow instructions in a virtual environment
- “Go along the blue hall, then turn left away from the fish painting and walk to the end of the hallway”

MacMahon et al. (2006)

Instruction Following



Instruction: “Go away from the lamp to the intersection of the red brick and wood”

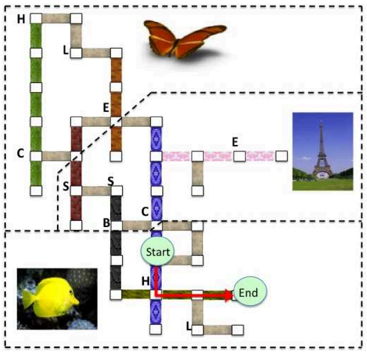
Basic: Turn ( ) ,
Travel (steps: 1)

Landmarks: Turn ( ) ,
Verify (left: WALL , back: LAMP , back: HATRACK , front: BRICK HALL) ,
Travel (steps: 1) ,
Verify (side: WOOD HALL)

- Basic plans derived directly from supervision
- “Landmarks” plans — things that should be true after each step (which may show up in the language)

Chen and Mooney (2011)

Instruction Following



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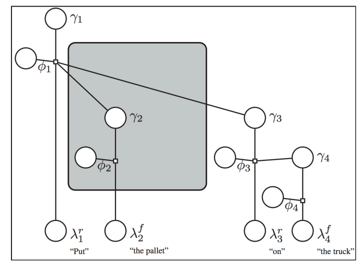
- Train semantic parser on (utterance, action) pairs
- Language is grounded in actions in the world

Chen and Mooney (2011)

Instruction Following

$EVENT_1(r = \texttt{Put},$
$\quad l = OBJ_2(f = \texttt{the pallet}),$
$\quad l2 = PLACE_3(r = \texttt{on},$
$\qquad l = OBJ_4(f = \texttt{the truck})))$

(a) SDC tree



(a) Robotic forklift

Commands from the corpus
- Go to the first crate on the left and pick it up. - Pick up the pallet of boxes in the middle and place them on the trailer to the left. - Go forward and drop the pallets to the right of the first set of tires. - Pick up the tire pallet off the truck and set it down

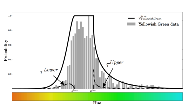
(b) Sample commands

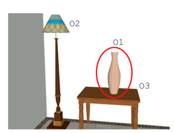
- "Spatial description clauses" -> "grounding graphs"

Tellex et al. (2011)

Connections to Semantic Parsing

- Each grounding framework requires mapping natural language to something concrete (distribution in color space, object, action sequence)
- Sometimes looks like semantic parsing, particularly when language -> discrete output
- Using linguistic structure to capture compositionality is often useful





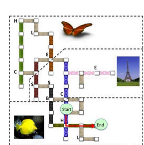


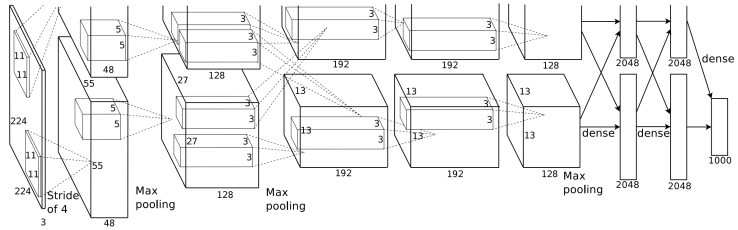
Image Captioning

How do we caption these images?

- Need to know what's going on in the images — objects, activities, etc.

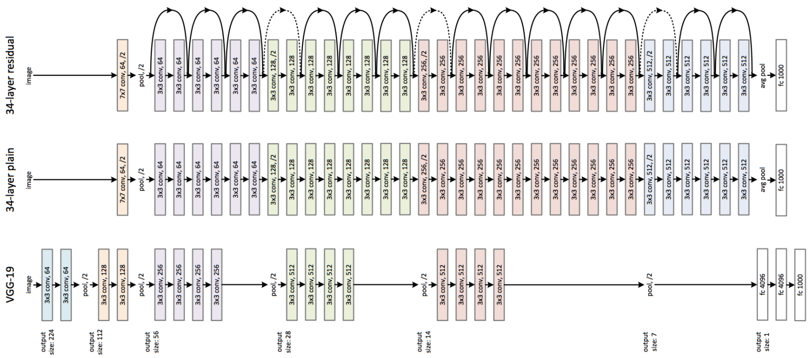
ImageNet models

- Train on ImageNet to do object classification



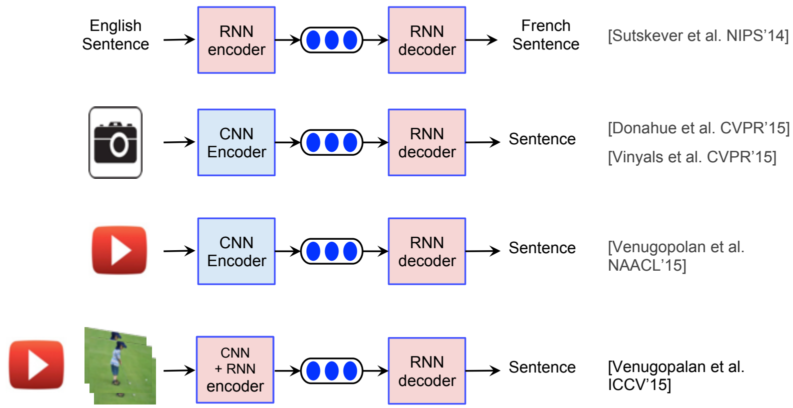
- Last layer is just a linear transformation away from object detection — should capture high-level semantics of the image, especially what objects are in there

ImageNet models



- Many architectures for this: VGG, ResNet, DenseNet, etc. — all end in fully-connected layers

Images -> Text



What's the grounding here?

food

a close up of a plate of ___

a dirt road

a couple of bears walking across ____

- What are the vectors really capturing? Probably some objects, but maybe not deep relationships

Simple Baselines

- Simple baselines work well!
- D-*: condition on detections only
- MRNN: take the last layer of the CNN, feed into RNN
- k-NN: use last layer of ImageNet model, find most similar train images based on cosine similarity with that vector

LM	PPLX	BLEU	METEOR
D-ME†	18.1	23.6	22.8
D-LSTM	14.3	22.4	22.6
MRNN	13.2	25.7	22.6
k-Nearest Neighbor	-	26.0	22.5
1-Nearest Neighbor	-	11.2	17.3

Table 1: Model performance on testval. †: From (Fang et al., 2015).

D-ME+DMSM	a plate with a sandwich and a cup of coffee
MRNN	a close up of a plate of food
D-ME+DMSM+MRNN	a plate of food and a cup of coffee
k-NN	a cup of coffee on a plate with a spoon

D-ME+DMSM	a black bear walking across a lush green forest
MRNN	a couple of bears walking across a dirt road
D-ME+DMSM+MRNN	a black bear walking through a wooded area
k-NN	a black bear that is walking in the woods

D-ME+DMSM	a gray and white cat sitting on top of it
MRNN	a cat sitting in front of a mirror
D-ME+DMSM+MRNN	a close up of a cat looking at the camera
k-NN	a cat sitting on top of a wooden table

Devlin et al. (2015)

Simple Baselines

System	Unique Captions	Seen In Training
Human	99.4%	4.8%
D-ME+DMSM	47.0%	30.0%
MRNN	33.1%	60.3%
D-ME+DMSM+MRNN	28.5%	61.3%
k-Nearest Neighbor	36.6%	100%

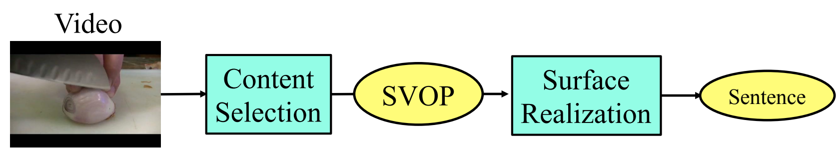
Table 6: Percentage unique (Unique Captions) and novel (Seen In Training) captions for testval images. For example, 28.5% unique means 5,776 unique strings were generated for all 20,244 images.

- Even from CNN+RNN methods (MRNN), relatively few unique captions even though it's not quite regurgitating the training

Devlin et al. (2015)

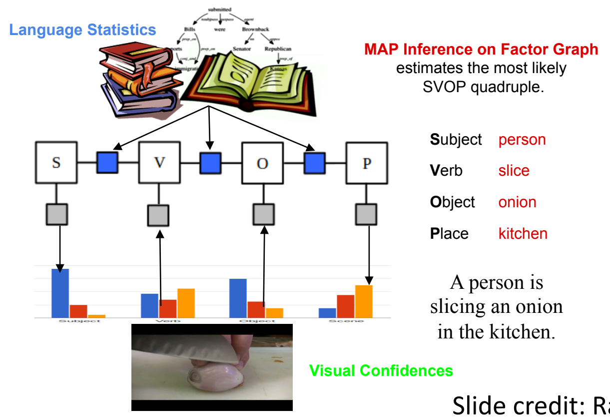
Video Captioning

- Generate an NL video description by training a suite of SVM-based visual recognizers and composing their outputs into a coherent sentence using a graphical model (Krishnamoorthy et al., 2013; Thomason et al., 2014)



Slide credit: Ray Mooney

Video Captioning



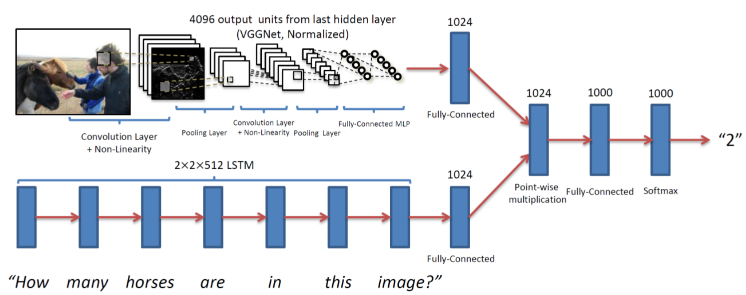
Slide credit: Ray Mooney

Visual Question Answering

- Answer questions about images
- Frequently much more metaphorical, require compositional understanding of multiple objects + activities in the image

Agrawal et al. (2015)

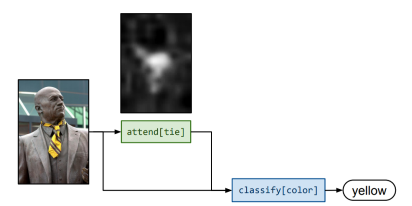
Visual Question Answering



- CNN processing of the image, RNN processing of the language
- What could go wrong here?

Neural Module Networks

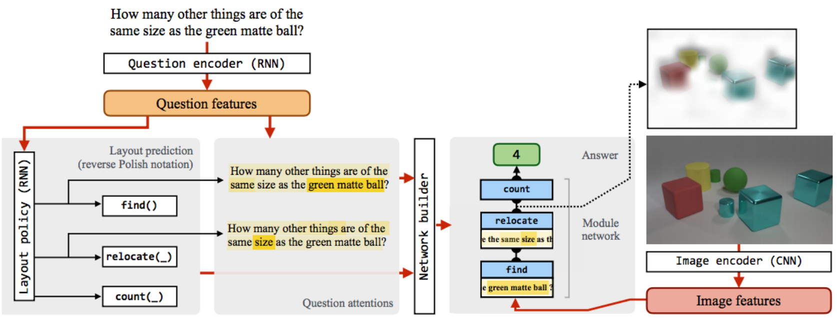
- Integrate compositional reasoning + image recognition
- Have neural network components like `classify[color]` whose use is governed by a parse of the question



(a) NMN for answering the question *What color is his tie?* The `attend[tie]` module first predicts a heatmap corresponding to the location of the tie. Next, the `classify[color]` module uses this heatmap to produce a weighted average of image features, which are finally used to predict an output label.

Andreas et al. (2016), Hu et al. (2017)

Neural Module Networks



- Can also learn these structures with reinforcement learning

Andreas et al. (2016), Hu et al. (2017)

Visual Question Answering

- In many cases, language as a prior is pretty good!
  - "Do you see a…" = yes (87% of the time)
  - "How many…" = 2 (39%)
  - "What sport…" = tennis (41%)
- Balanced VQA: remove these regularities by having pairs of images with different answers

Goyal et al. (2017)

Understanding VQA

- "Attentive Explanations: Justifying Decisions and Pointing to the Evidence," Park et al., InterpML, NIPS-2017.

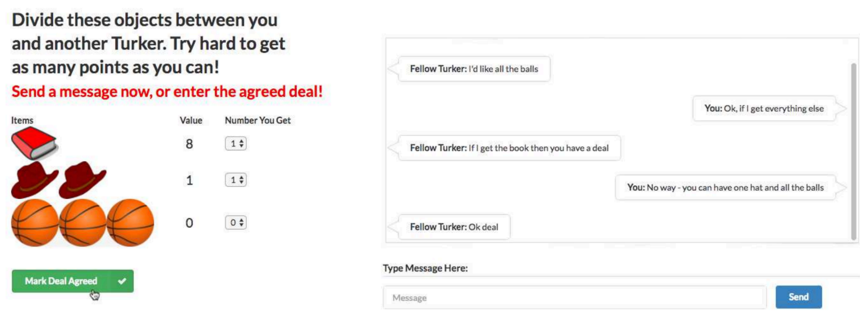
Q: What is the person doing? A: Skiing

Explanation: "Because he is on a snowy hill wearing skis"

Slide credit: Ray Mooney

Grounding Language in Interaction

Grounding in Interaction

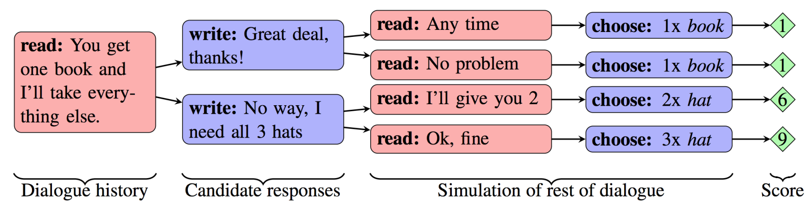


- Corpus of dialogues — can train a model on these to learn to negotiate

Lewis et al. (2017)

Grounding in Interaction

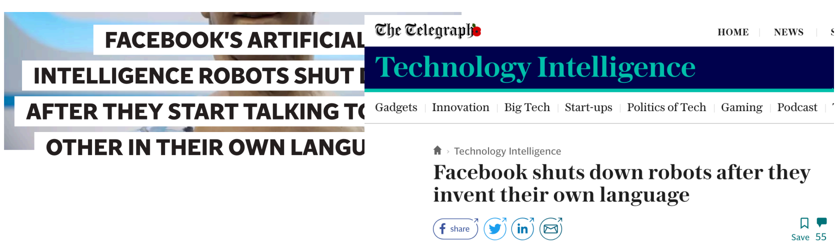
- Same issues as other dialogue systems: system may prefer generic choices, like accepting the offer, instead of negotiating harder
- Instead: do self-play rollouts, train with reinforcement learning to maximize reward and not likelihood of human utterances



Lewis et al. (2017)

Grounding in Interaction

- Interleave self-play with supervised learning, otherwise the messages stop looking like real English



- When two systems talk to each other, they remap what words mean and completely change the grounding

Lewis et al. (2017)

Grounding in Interaction

- Less direct form of grounding: we understand the language used based on the effects it produces in the other agent (whether human or machine) and in the final reward
- More "symbolic" than grounding percepts like color, but still about interacting with the world!

Lewis et al. (2017)

Takeaways

- Lots of problems where natural language has to be interpreted in an environment and can be understood in the context of that environment
- Image recognition: particularly large area of research featuring big neural networks (but they sometimes learn to cheat)
- More complex environments/robots/simulations/tasks -> more complex dialogue to be learned over time!