Towards Controllable Text Generation

He He
AWS / NYU

NeuralGen Workshop at NAACL 2019

Generate from language models

The neural generation workshop is held today in Minneapolis. We will talk about some of the exciting developments in neurogenetics, brain models, and the development of neural networks from the neural genomics perspective.

GPT-2 345M. https://talktotransformer.com

Density estimation

$$p(y \mid x)$$

Large amounts of labeled data

- Language modeling
- Machine translation
- Summarization
- Dialogue
- Creative text generation

Density estimation

$$p(y \mid x)$$

Conflate grammaticality and task objectives

- Starting from scratch
- Undesired trade-offs
    - Fluency vs adequacy [Tu et al., 2016; Koehn and Knowles, 2017]
    - Fluency vs faithfulness [Wiseman et al., 2015; See et al., 2017]

Classic NLG

- **Edit action** (see survey by [Nenkova and McKeown, 2012])

  ~~Throngs of~~ Golden State Warriors fans ~~turned out for a victory parade to~~ celebrate ~~a team some are calling an NBA dynasty~~ .

- **Sentence realization** [Reiter and Dale, 1995]

  Do you like `[foodType]` food?

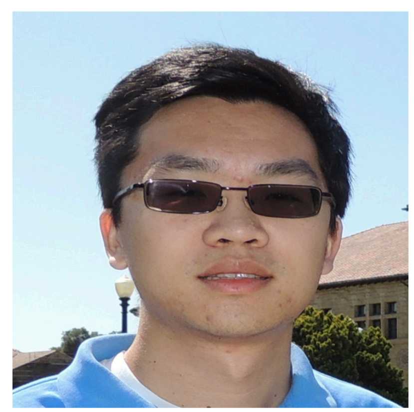
Outline

- Strong inductive bias on the generative process
  - Text attribute transfer
  - Pun generation
- Decouple strategy and generation
  - Negotiation dialogue

Delete, Retrieve, Generate: a Simple Approach to Sentiment and Style Transfer

NAACL 2018

Juncen Li



Robin Jia

Percy Liang

Text attribute transfer

- Control aspects of output

The soup was bland. ⟶ The soup was tasty.

No parallel data!

~~(negative sentence, positive sentence)~~

(sentence, negative / positive)

A generative model

Attribute

↓

Content → Model → Sentence

How to separate content and attribute?

Negative	Positive
The soup was bland.	Yummy chicken wings!
Very rude staff!	Definitely recommend.

A generative model

Attribute

↓

Content → Model → Sentence

How to separate content and attribute?

Negative	Positive
The soup was bland.	Yummy chicken wings!
Very rude staff!	Definitely recommend.

Local text spans as attribute markers

Key idea: replace attribute markers

The soup was bland.

↓

The soup was ____.

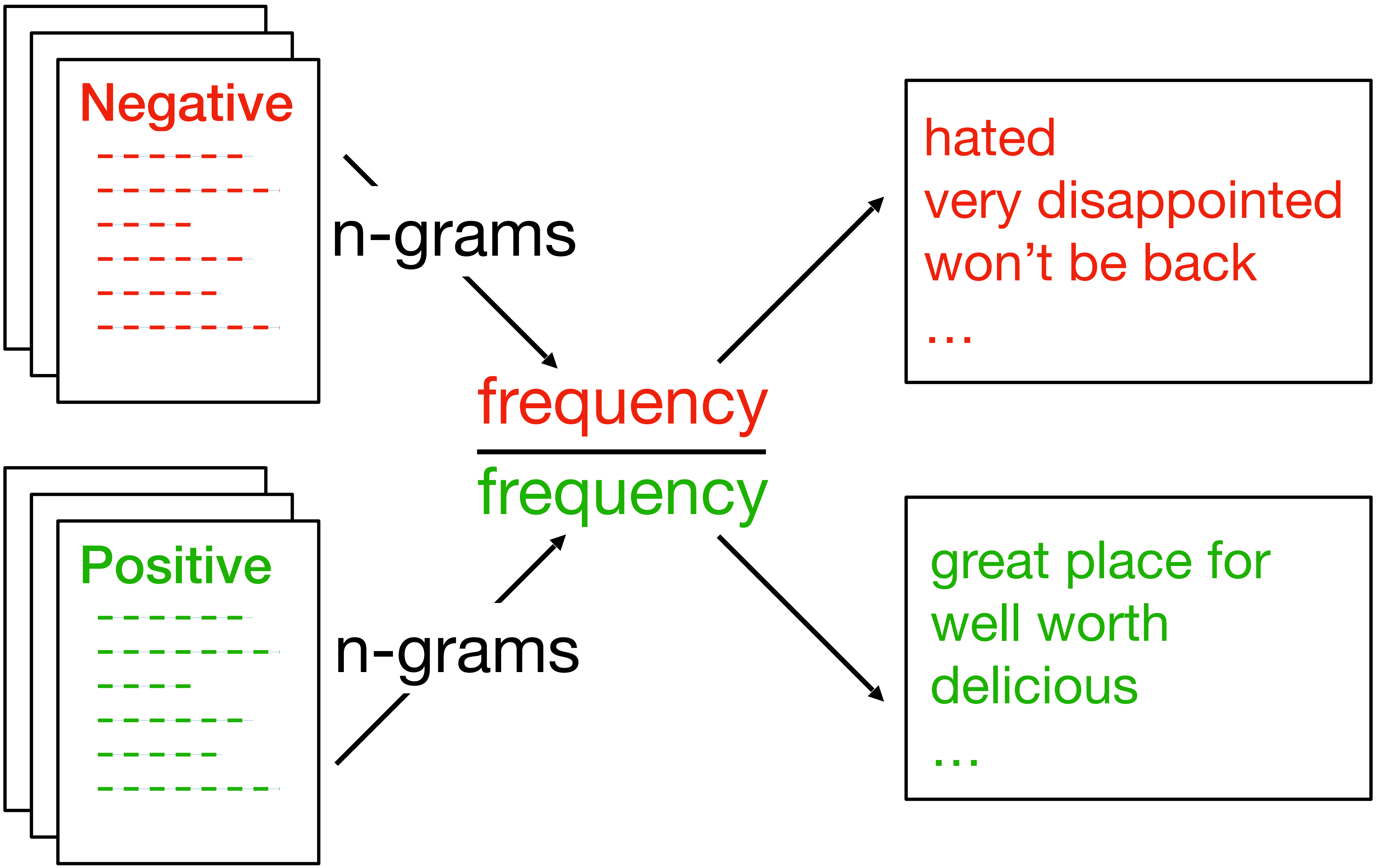
↓

The soup was yummy.

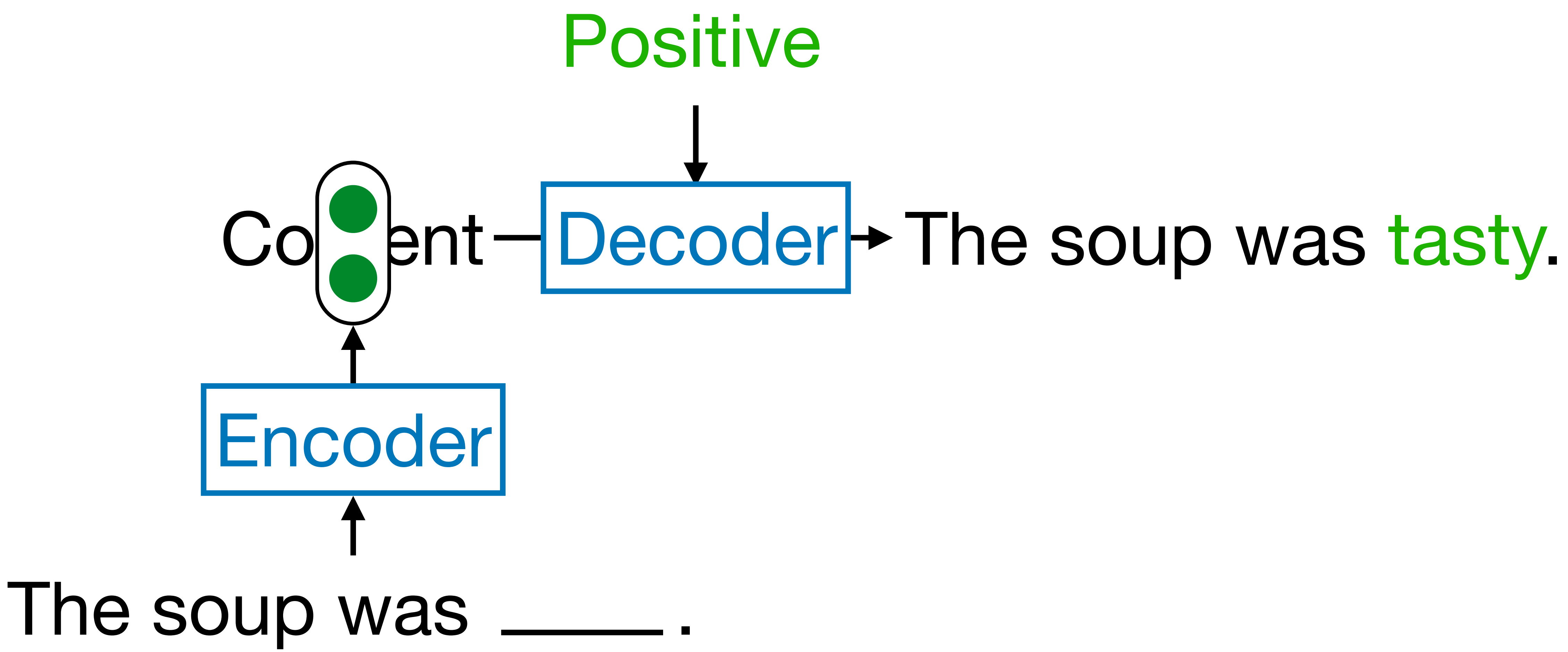
1. **Delete** source attribute markers

2. **Replace** them with target attribute markers

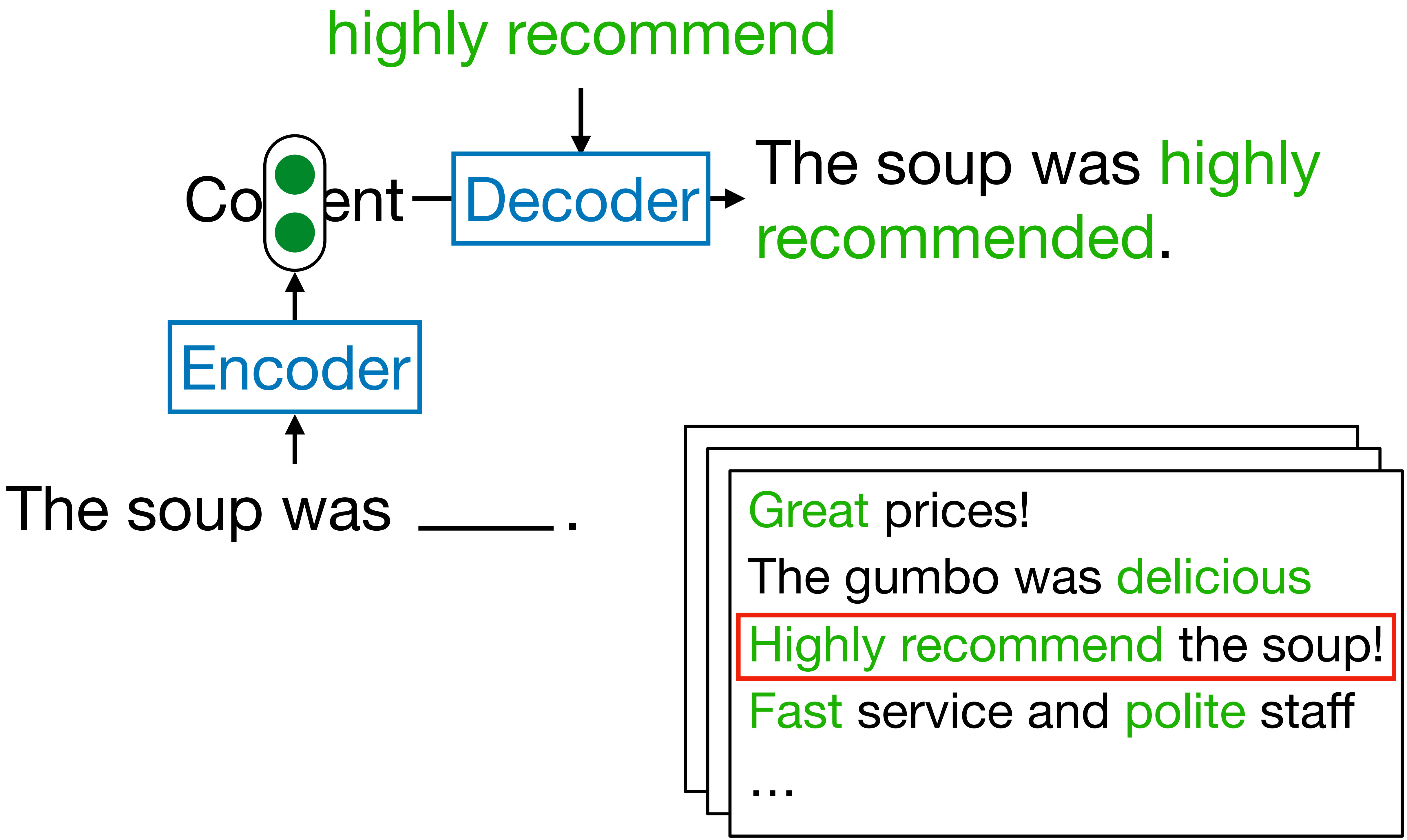
Extract attribute markers



Delete and generate



Delete, retrieve, generate



Train / Test

- Train
  - negative → negative

The soup was ____.

noise(bland)

The soup was bland.

- Test
  - negative → positive

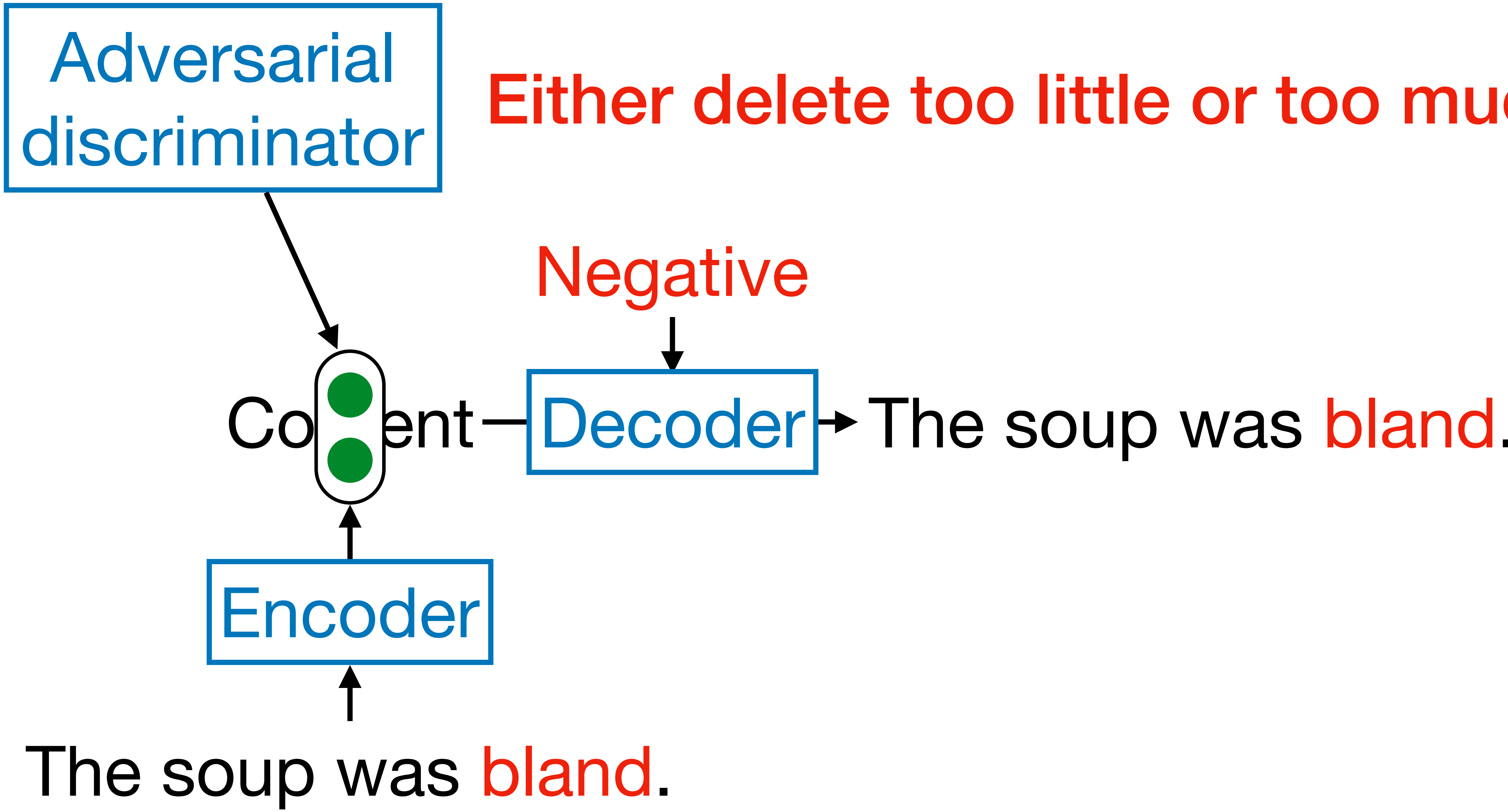
The soup was ____.

highly recommend

The soup was highly recommended.

End-to-end adversarial training

Either delete too little or too much



[Shen et al., 2018; Fu et al., 2018]

Evaluation

- Average over 3 datasets
  - Sentiment for Yelp reviews [Shen et al., 2017] and Amazon reviews [He and McAuley, 2016]
  - Factual to romantic/humorous style for image captions [Gan et al., 2017]
- Human Evaluation
  - Likert scale from 1-5 for grammaticality, attribute transfer, content preservation
  - Overall success: get ≥ 4 on each category

Results

Model	Attr	Cont	Gram	Succ
StyleEmbedding [Fu et al., 2018]	2.6	3.2	3.3	12%
MultiDecoder [Fu et al., 2018]	3.0	2.8	3.1	11%
CrossAligned [Shen et al., 2017]	3.2	2.4	3.3	12%
Retrieval Baseline	**3.7** ✔	2.7 ✘	**4.1** ✔	23%
Template Baseline	3.5 ✔	**3.9** ✔	3.2 ✘	24%
Delete	3.6 ✔	3.6 ✔	3.4	27%
Delete+Retrieve	**3.7** ✔	3.6 ✔	3.7 ✔	**34%**
Human	4.1	4.1	4.4	58%

Examples

Source:	we sit down and we got some really slow and lazy service .
CrossAligned:	we *went* down and we *were a good , friendly food* .
StyleEmbedding:	we sit down and we got some really slow and *prices suck* .
MultiDecoder:	we sit down and we got some really and *fast food* .
Template:	we sit down and we got some *the service is always great* and *even better* service .
Retrieval:	*i got a veggie hoagie that was massive* and some *grade a customer service* .
Delete:	we sit down and we got some *great* and *quick* service .
Delete+Retrieve:	we *got very nice place to* sit down and we got some service.

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- Decouple strategy and generation
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Pun Generation with Surprise

NAACL 2019

Nanyun Peng

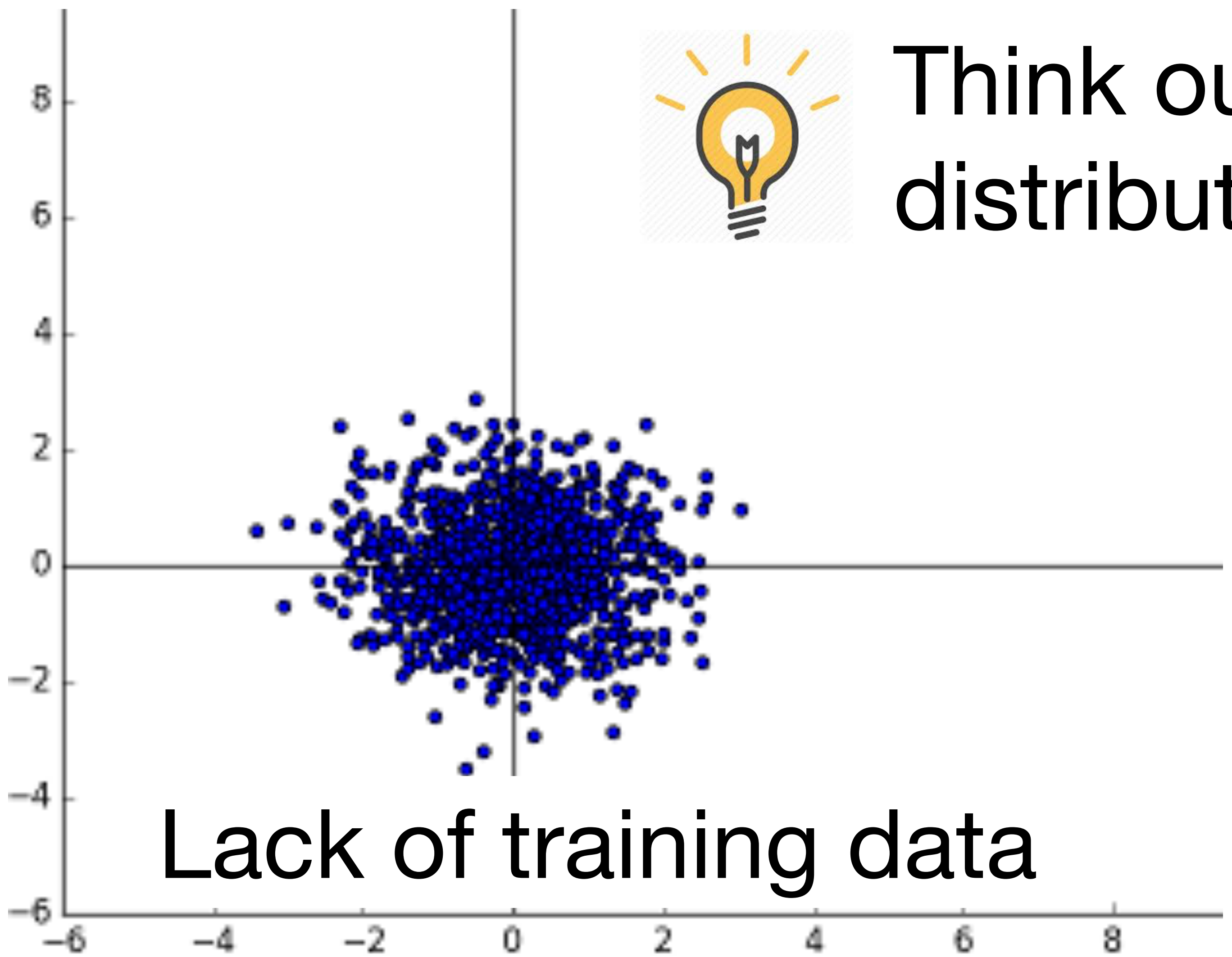
Percy Liang

Homophonic pun generation

Input
Pun word: dyed
Alternative word: died

Output
Yesterday I accidentally swallowed some food coloring. The doctor says I'm OK, but I feel like I've dyed (died) a little inside.

Challenges



Think out of the distribution

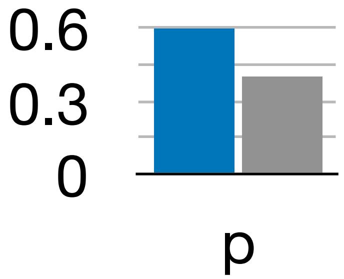
Lack of training data

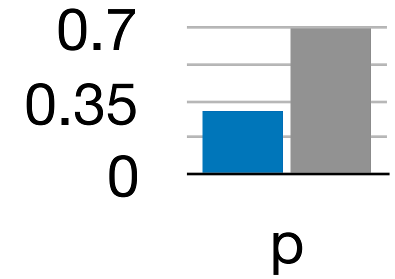
Structure of puns

Global context

Local context

The magician got so mad that he pulled his hare out.





hair

- Ambiguity is not enough
- Distinctive support [Kao et al., 2015]
- **Local-global surprisal**

Instantiate the principle as a metric

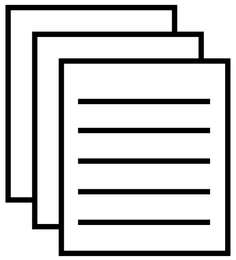
$$\text{surprisal} = -\frac{\log p(\ldots\text{hare}\ldots)}{\log p(\ldots\text{hair}\ldots)}$$

$$\text{funniness} \propto \frac{\text{local surprisal}}{\text{global surprisal}}$$

Correlates with human ratings but not robust enough as an objective

[Levy. 2015]

Instantiate the principle as an algorithm



hare, hair

retrieve

the man stopped to get a hair cut.

swap

local surprisal ↑

the man stopped to get a hare cut.

insert

the greyhound stopped to get a hare cut.

global surprisal ↓

Instantiate the principle as an algorithm

- Find related words with "distant" skip-gram model $p_\theta(w_i \mid w_j)$

- Avoid degenerating into nonsense

Each ~~person~~ must pay their fare share.

ship

Type-consistency check

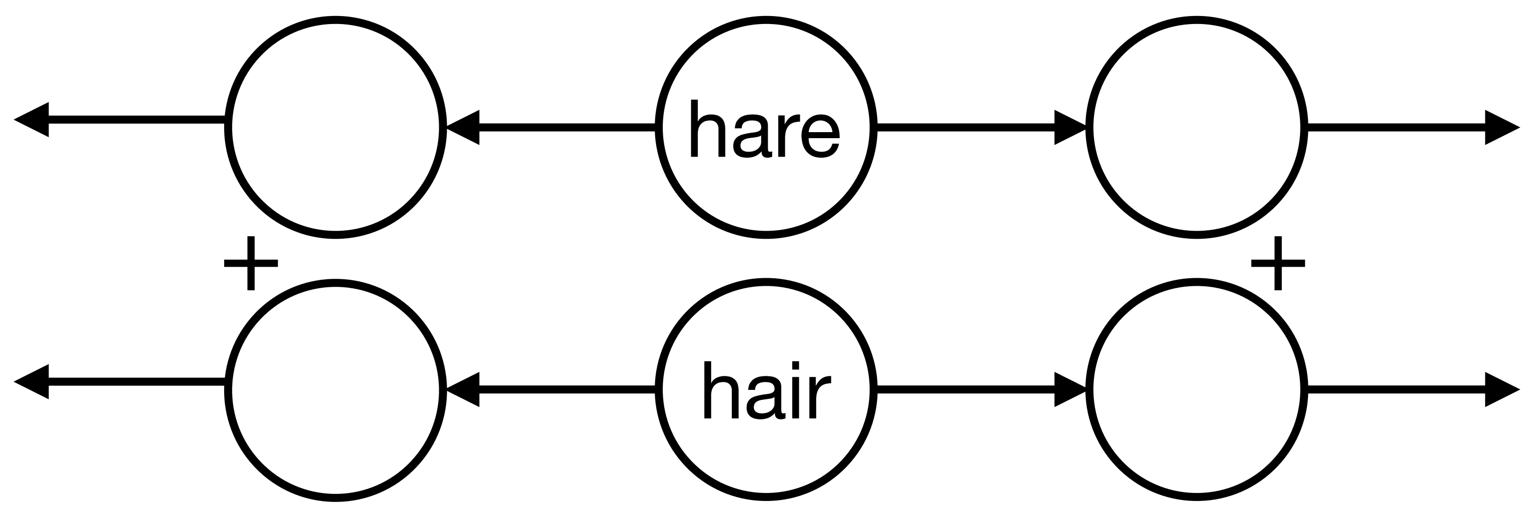
negotiator

~~i~~ am just a woman trying to peace her life back together.

Neural LM smoother

Experiments

- Baselines
  - Neural Joint Decoder [Yu et al., 2018]



  - Retrieve with the pun word
  - Ablations of our system

Evaluation

- Grammaticality
  - How grammatical is the sentence?
- Funniness
  - How funny is the sentence?
- Success
  - Is the sentence a pun? (Given definition from [Miller et al., 2017])

Results

Model	Gram	Funn	Succ
Neural Joint Decoder	2.6 ✘	1.4	9.2%
Retrieve Common sentence	**3.9**	1.3	4.6%
Retrieve+Swap	3.5	1.6	27%
Retrieve+Swap+Topic (SurGen)	3.0	**1.7**	**31.4%**
Retrieve+Swap+Topic+Smoother	2.9	1.7	28.8%
Human	3.8	3.0	78.9%

Examples

😀

gladiator left the room for a moment and i answered the ground lion.

That’s because negotiator got my car back in one peace.

Even from the outside, I could tell that he’d already lost some wait.

---

and as progeny obliquely indicated to you yesterday, you do n't have to do that much to urn (earn) it.

because stooge think he's my son come back to them,' jessica said, her voice board (bored).

😖

Summary

- Domain knowledge helps generation with less data/supervision
- Neural LM as a smoother
- Trade coverage for quality

Outline

- Strong inductive bias on the generative process
  - Text attribute transfer
  - Pun generation
- **Decouple strategy and generation**
  - Negotiation dialogue

Decouple Strategy and Generation in Negotiation Dialogues

EMNLP 2018

Derek Chen

Anusha Balakrishnan

Percy Liang

Negotiation

Decision-making in conversations.

Craigslist negotiation

1402 postings
6682 dialogues
~9 turns / dialogue
~16 words / turn
~1.2K vocab

Having trouble with this task? Click here to send us a report.

Report

Let's Negotiate!

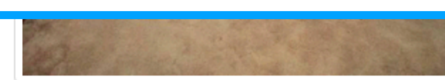
Show/Hide Instructions

You and another user (or a bot) will negotiate the price

Instructions - Please read carefully!

- Your **role** (buyer or seller) is to the right, as well as the descripti photo (if available).
- Use the **chat box below** to negotiate with your partner given th Please use complete, grammatical English without typos.
- **Feel free to negotiate terms that are not financial!** E.g., offeri throwing in free items; negotiating additional benefits like a war but **don't contradict any facts** given in the description or show
- At the end, **submit** the agreed deal in the text box at right, whic **rejected**
- Please do not leave the chat unattended. If you are inactive for more than 3 minutes your connection will time out.
- If you run into any trouble with the website, use the button on the **top right** to report the issue.

e for this item is **$2000**. You would like to pay for **$1840**.
e item is really good or there are other perks.



RARE 1989 ROSSIN ROAD BIKE. BUILT IN 1989 AND STORED FOR 27 YEARS! NEVER BEEN ON THE STREET! ALL CAMPY RECORD PARTS. TRULY A COLLECTOR/MUSEUM PIECE. 58-60CM. CALL WITH QUESTIONS. 2000.00 OBO.

[12/29/17 21:37:21] <Your partner has joined the room.>
[12/29/17 21:37:25] Partner: Hello!
[12/29/17 21:38:00] You: Hey! I'm interested in your road bike. Is it working properly?
[12/29/17 21:38:33] Partner: Yes, it's been stored for 27 years! But still in good condition.
[12/29/17 21:39:03] You: Hmm, 2000 is too much for such an old bike. I'm willing to pay $1000.
[12/29/17 21:39:30] Partner: Well, this is a classic bike. Can you come up to 1800?
[12/29/17 21:39:39] You: Can I come to take a look?
[12/29/17 21:39:49] Partner: Absolutely.
[12/29/17 21:40:00] You: Okay great!
[12/29/17 21:40:07] <You made an offer!>

Enter your message here

Final agreement:

Be careful. You can only enter the offer **once**.

Price 1800 Submit

Quit:

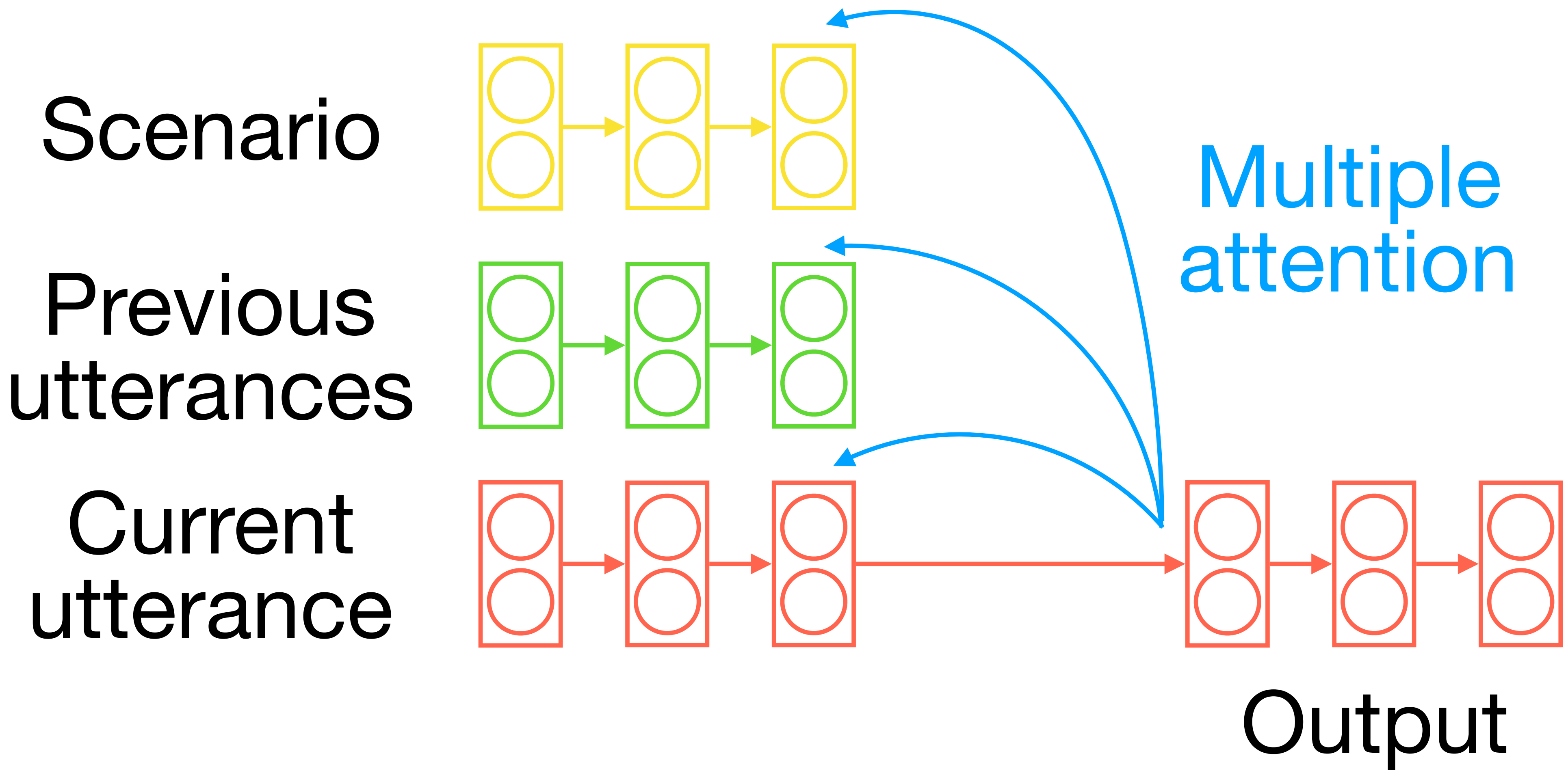
If you think that it will not be possible to negotiate a deal, you can choose to **quit** this dialogue.

Quit

Rich negotiation language

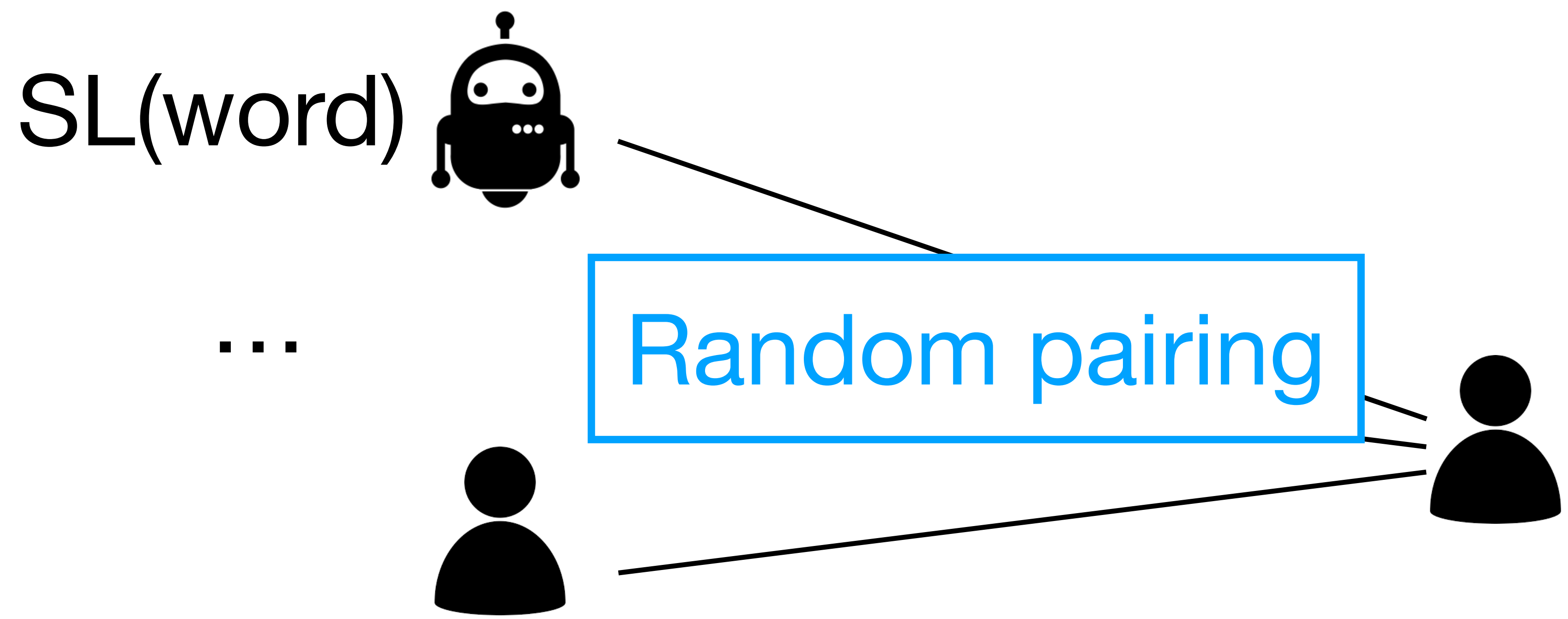
Buyer	Hello do you still have the TV?
Seller	Hello, yes the TV is still available.
Buyer	What condition is it in? Any scratches or problems? I see it recently got repaired, post details
Seller	It is in great condition and works like a champ! I just installed a new lamp in it. embellishment cratches or problems.
Buyer	All right. Well I think 275 is a little high for a 10 year old TV. Can you lower the price some? How about 150?
Seller	I am willing to lower the price, but $150 is a little low. How about $245 and if you are not too far from me, I will deliver it to you for free? side offer
Buyer	It's still 10 years old and the technology is much older. persuasion 5 and you deliver it. How's that sound?
Seller	Okay, that sounds like a deal!
Buyer	Great thanks!
Seller	OFFER {"price": 225.0, "sides": ""}
Buyer	ACCEPT OFFER

Supervised learning with seq2seq



Evaluation: setup

A/B testing on Amazon Mechanical Turk



- Task-oriented metric: reward
- Human-likeness: *"Do you think your partner demonstrated reasonable human behavior?"*

Supervised learning

	Human-likeness	Utility
Human	4.3	-0.07
SL(word)	3.0	-0.32

Bot learns to be agreeable

Reinforcement learning

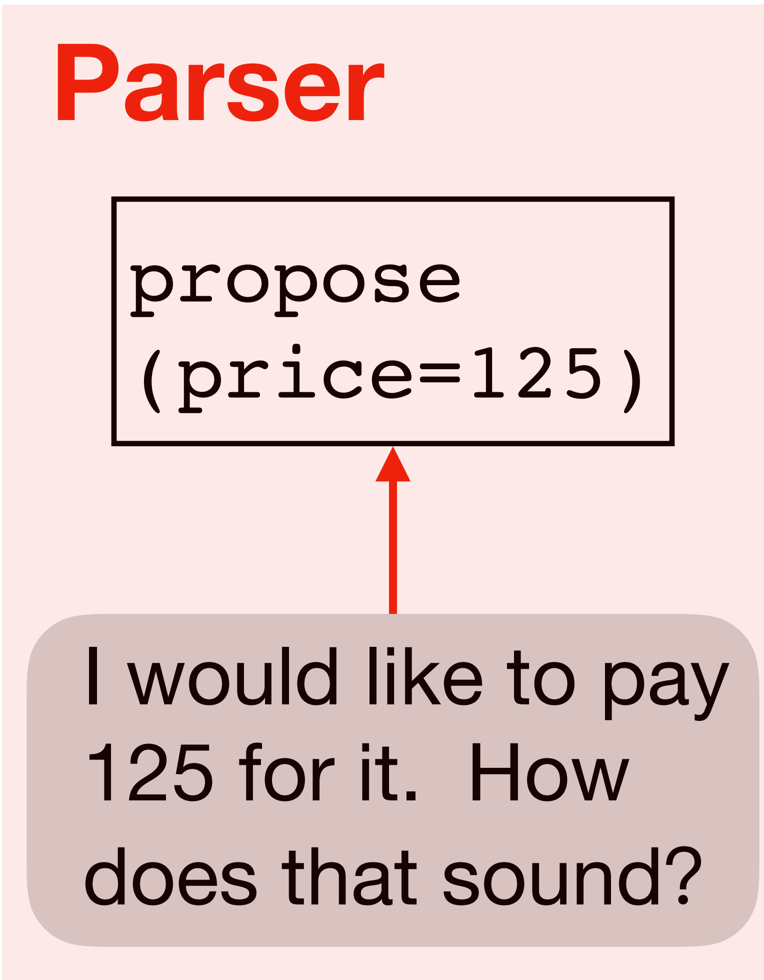
```
Alice : book=(count:3 value:1) hat=(count:2 value:1)
Bob   : book=(count:3 value:0) hat=(count:2 value:0)
-----------------------------------------------------
Bob   : i can i i everything else . . . . . . . . . .
Alice : balls have zero to me to me to me to me to m
Bob   : you i everything else . . . . . . . . . . .
Alice : balls have a ball to me to me to me to me to
Bob   : i i can i i i everything else . . . . . . .
Alice : balls have a ball to me to me to me to me to
Bob   : i . . . . . . . . . . . . . . . . . . .
Alice : balls have zero to me to me to me to me to m
Bob   : you i i i i i everything else . . . . . . .
Alice : balls have 0 to me to me to me to me to me t
Bob   : you i i i everything else . . . . . . . . .
Alice : balls have zero to me to me to me to me to m
```

https://www.independent.co.uk/life-style/gadgets-and-tech/news/facebook-artificial-intelligence-ai-chatbot-new-language-research-openai-google-a7869706.html

The strategic backbone

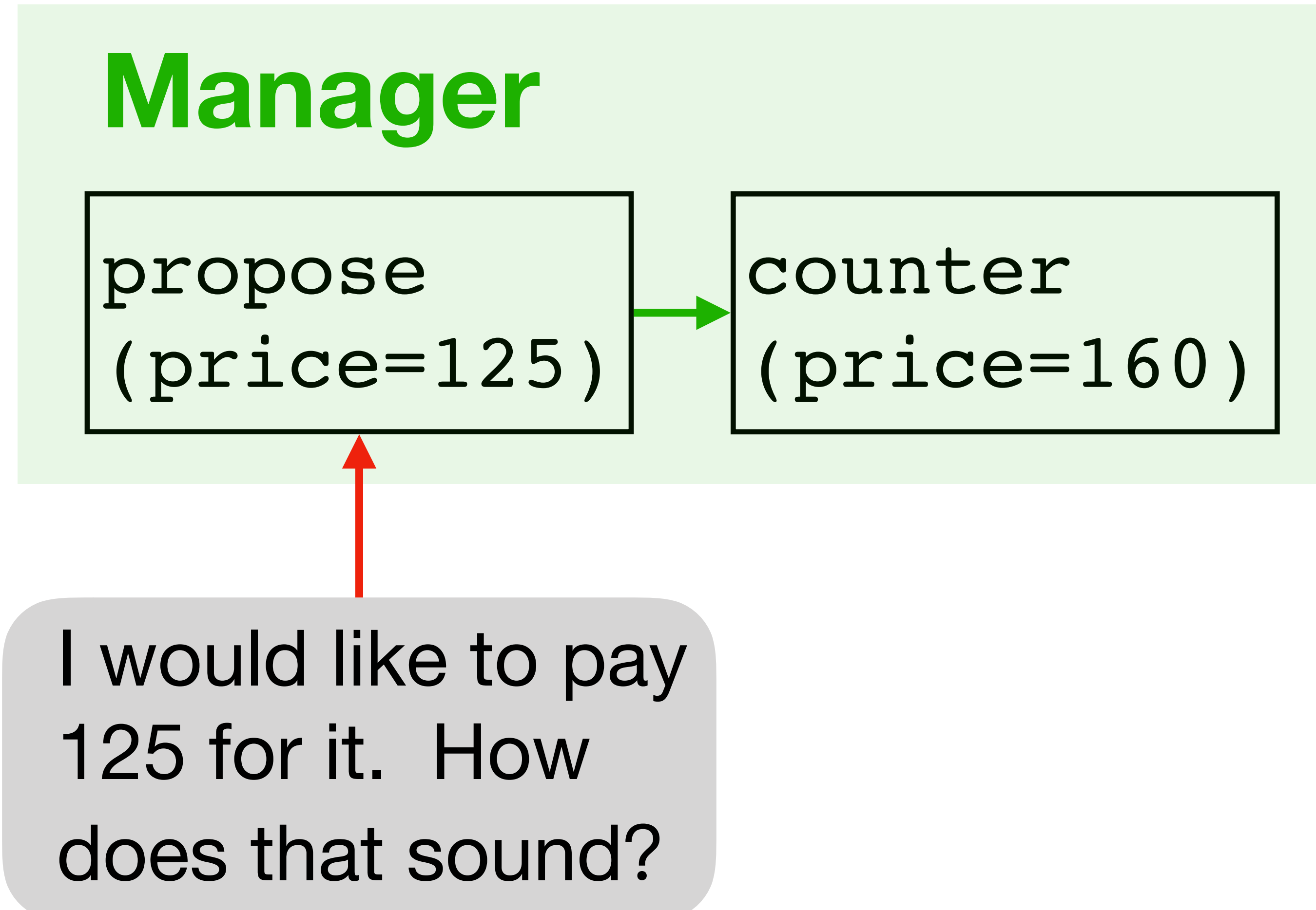
Buyer	Hello do you still have the TV?	greet
Seller	Hello, yes the TV is still available.	greet
Buyer	What condition is it in? Any scratches or problems? I see it got repaired,	inquire
Seller	It is in great condition and works like a champ! I ed a new lamp in it. There aren't any scratches or problem	inform
Buyer	All right. Well I think 275 is a little high for a 10 year lower the price some? How about 150?	propose(150)
Seller	I am willing to lower the price, but $150 is a little 45 and if you are not too far from me, I will deliver it	counter(245)
Buyer	It's still 10 years old and the technology is much ol and you deliver it. How's that sound?	counter(225)
Seller	Okay, that sounds like a deal!	agree
Buyer	Great thanks!	agree
Seller	OFFER {"price": 225.0, "sides": ""}	offer(225)
Buyer	ACCEPT OFFER	accept

A modular framework

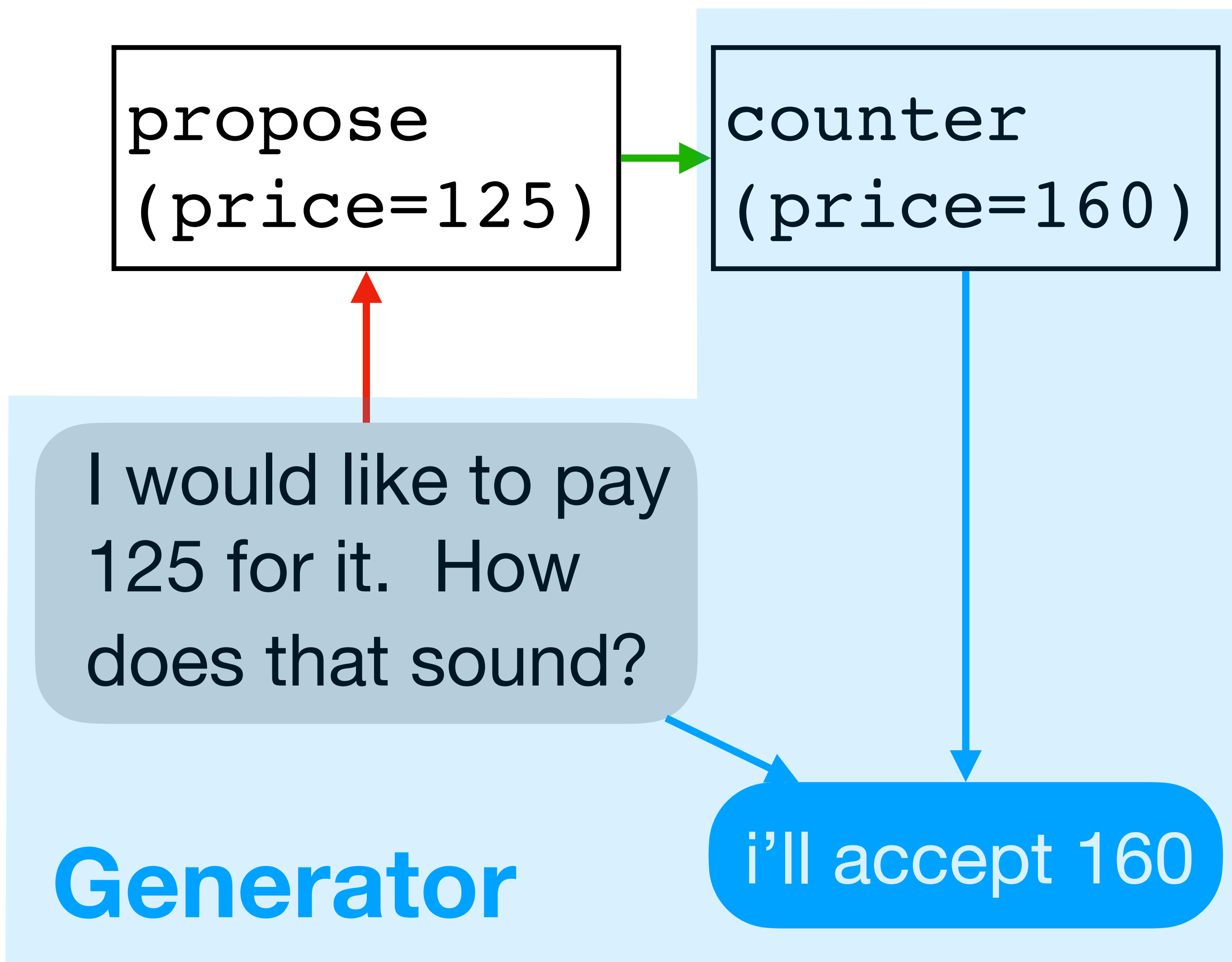


e.g., [Young et al., 2013]

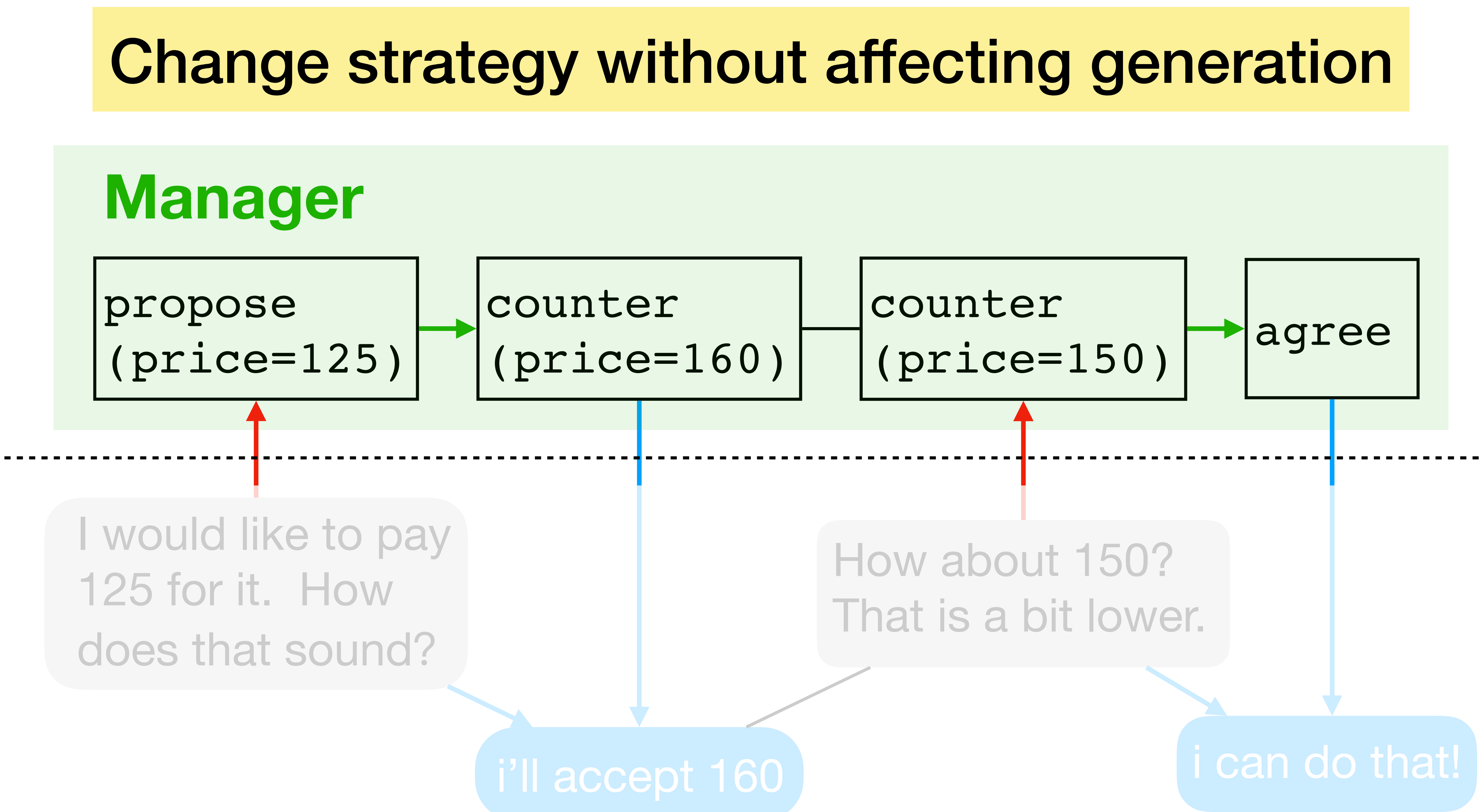
A modular framework



A modular framework

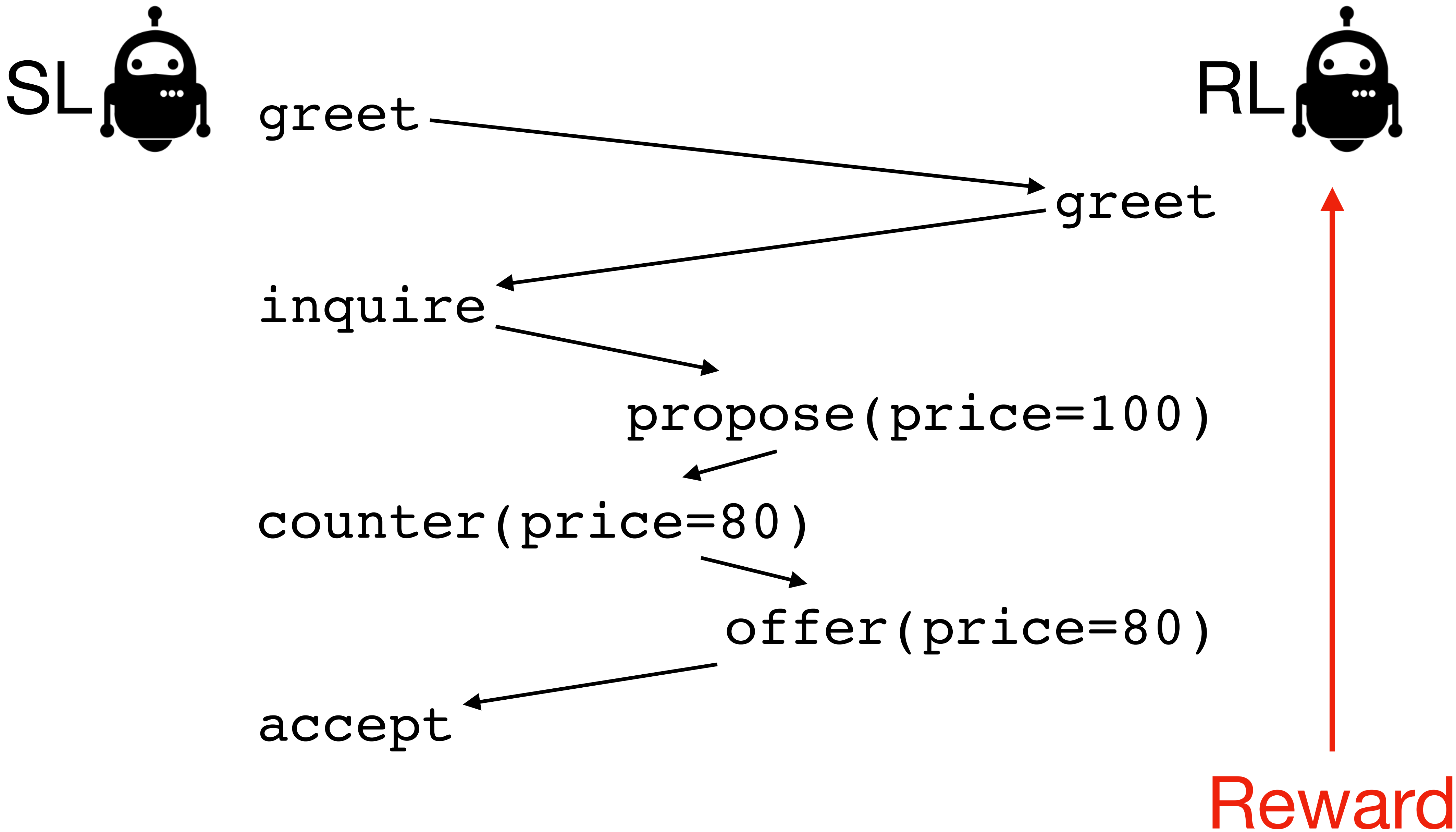


A modular framework



Reinforcement learning

Fixed | Policy gradient [Williams, 1992]



Reinforcement learning in the act space

	Human-likeness	Utility
Human	4.3	-0.07
SL(word)	3.0	-0.32
SL(act)	3.3	0.06
RL(word)	1.7	1.00
RL(act)	2.8	1.00

RL(act) avoids degeneracy during optimization

Summary

- Easier to learn actions than language
- Separate grammaticality from task objective optimization to avoid degeneracy
- Content planning -> sentence realization

Conclusion

- Need more than density estimation
- Reborn of old techniques in new context - structures help!
- Big (pretrained) LMs for grammaticality