# Neural Dialogue Generation

Jiwei Li Computer Science Department Stanford University





#### Collaborators



Michel Galley Microsoft Research



Bill Dolan Microsoft Research



Jianfeng Gao Microsoft Research



Chris Brockett Microsoft Research



Dan Jurafsky Stanford



Alan Ritter Ohio State University

#### Learn to Converse





#### Learn to Converse















#### Does Siri really understand language ?



Colbert: Write the show.

Siri: What would you like to search for?

**Colbert**: I don't want to search for anything! I want to write the show!

**Siri**: Searching the Web for "search for anything. I want to write the shuffle."

[...]

**Colbert**: For the love of God, the cameras are on, give me something?

Siri: What kind of place are you looking for? Camera stores or churches?

Slid Borrowed From Bill MacCartney

1. Computers need to **understand** what you ask.

- 1. Computers need to **understand** what you ask.
- 2. Computers need to generate coherent, meaningful sequences in response to what you ask,

- 1. Computers need to **understand** what you ask.
- Computers need to generate coherent, meaningful sequences in response to what you ask, that require domain knowledge, discourse knowledge, world knowledge

# Background

## Background

Template/Rule based systems (Levin et al., 2000; Young et al., 2010; Walker et al., 2003; Pieraccini et al., 2009; Wang et al., 2011)

## Background

# Response Generation as Statistical Machine Translation (Ritter et al., 2010)



Slide borrowed from Michel Galley

(Ritter et al., 2010)

#### Response Generation as SMT



#### Exploit high-frequency patterns with phrase-based MT

"I am"  $\rightarrow$  "you are" "sick"  $\rightarrow$  "get better" "lovely!"  $\rightarrow$  "thanks!"

Slide borrowed from Michel Galley

# Neural Generation Models for MT

(Sutskever et al., 2014; Jean et al., 2014; Luong et al., 2015)

 $Loss = -\log p(target|source)$ 





(Sutskever et al., 2014; Jean et al., 2014; Luong et al., 2015)

 $Loss = -\log p(target|source)$ 

Source : Input Messages Target : Responses







(Sutskever et al., 2014; Jean et al., 2014; Luong et al., 2015)

Long Short Term Memory

















#### Neural Generation Models as a **Backbone**



# Outline

1. Mutual Information for Response Generation.

The "I don't know" problem

- 2. Speaker Consistency
- 3. Multi-context Response Generation
- 4. Reinforcement learning for Response Generation

# Mutual Information for Response Generation.

Li et al., A Diversity-Promoting Objective Function for Neural Conversation Models (to appear, NAACL,2016)

"I don't know" problem (Sordoni et al., 2015; Serban et al., 2015)

"I don't know" problem (Sordoni et al., 2015; Serban et al., 2015; )



"I don't know" problem (Sordoni et al., 2015; Serban et al., 2015; )



"I don't know" problem (Sordoni et al., 2015; Serban et al., 2015; )



30% percent of all generated responses

## Mutual Information for Response Generation.

def ChatBot(input\_string): if string[len(input\_string)-1]=="?": return "i don't know"; else: return "i don't know what you are talking about";

### Mutual Information for Response Generation.

Solution #1: Adding Rules
Solution #1: Adding Rules

I don't know . I don't know .. I don't know ... ... I don't know ! I don't know !! I don't know !!!

Solution #1: Adding Rules

I don't know .	have no idea .	I don't have the foggiest idea what you are talking about .	
don't know I don't know			
 I don't know !		talking about .	
l don't know !! I don't know !!!	I haven't the faintest ic	lea	

How should I know ?

Solution #1: Adding Rules

	I have no idea	talking about
I don't know .		
l don't know	I don't have a clue.	
		I don't have the lightest idea what you are
I don't know !		talking about .
I don't know !!	I haven't the faintest idea	
I don't know !!!		

How should I know ?

I double have the formation the provides the second

#### Rules don't work !!

 $Loss = -\log p(target|source)$ 

 $Loss = -\log p(target|source)$ 













**Mutual Information** 

$$\log \frac{p(S,T)}{p(S)p(T)}$$

$$\hat{T} = rgmax_T ig\{ \log rac{p(S,T)}{p(S)p(T)} ig\}$$

Standard Seq2Seq model

$$\hat{T} = \underset{T}{\arg \max} \left\{ \log \frac{p(S,T)}{p(S)p(T)} \right\}$$

$$Bayesian Rule$$

$$\hat{T} = \underset{T}{\arg \max} \left\{ \log p(T|S) - \lambda \log p(T) \right\}$$

Anti-language Model

$$\hat{T} = \arg \max_{T} \left\{ \log p(T|S) - \lambda \log p(T) \right\}$$
Bayesian Rule
$$\int_{T} \left\{ (1 - \lambda) \right\} = (T|S) + \lambda \log P(T) \right\}$$

$$T = \underset{T}{\arg \max} \left\{ (1 - \lambda) \log p(T|S) + \lambda \log p(S|T) \right\}$$

$$\hat{T} = \underset{T}{\arg \max} \left\{ \log p(T|S) - \lambda \log p(T) \right\}$$
  
Bayesian Rule  
$$T = \underset{T}{\arg \max} \left\{ (1 - \lambda) \log p(T|S) + \lambda \log p(S|T) \right\}$$
  
 $p(\text{source|target})$ 

Solution 1 
$$\hat{T} = \underset{T}{\arg \max} \left\{ \log p(T|S) - \lambda \log p(T) \right\}$$

Solution 2 
$$T = rgmax_T \left\{ (1-\lambda) \log p(T|S) + \lambda \log p(S|T) 
ight\}$$

Datasets: Twitter conversational Dataset (23M pairs) Opensubtitle movie scripts dataset (80M pairs)

Datasets: Twitter conversational Dataset (23M pairs) Opensubtitle movie scripts dataset (80M pairs)

Evaluations : BLEU (Papineni et al., 2003) #Distinct tokens Human Evaluation (1000 samples, each output is evaluated by 7 judges)

BLEU





# Distinct Tokens in generated targets (divided by total #) on Opensubtitle dataset



# Human Evaluation

Comparator	Gain	95% CI
SMT (Ritter et al., 2011)	0.29	[0.25, 0.32]
SMT+neural reranking	0.28	[0.25, 0.32]
SEQ2SEQ (baseline)	0.11	[0.07, 0.14]
SEQ2SEQ (greedy)	0.08	[0.04, 0.11]

## Human Evaluation

Comparator	Gain	95% CI
SMT (Ritter et al., 2011)	0.29	[0.25, 0.32]
SMT+neural reranking	0.28	[0.25, 0.32]
SEQ2SEQ (baseline)	0.11	[0.07, 0.14]
SEQ2SEQ (greedy)	0.08	[0.04, 0.11]

# Sampled Results

Input: What are you doing?			
-0.86 I don't know.	-1.09 Get out of here.		
-1.03 I don't know!	-1.09 I'm going home.		
-1.06 Nothing.	-1.09 Oh my god!		
-1.09 Get out of the way.	-1.10 I'm talking to you.		
Input: what is your name?			
-0.91 I don't know.			
-0.92 I don't know!	-1.55 My name is Robert.		
-0.92 I don't know, sir.	-1.58 My name is John.		
-0.97 Oh, my god!	-1.59 My name's John.		
Input: How old are you?			
-0.79 I don't know.			
-1.06 I'm fine.	-1.64 Twenty-five.		
-1.17 I'm all right.	-1.66 Five.		
-1.17 I'm not sure.	-1.71 Eight.		

Input: What are you doing?		
<ol> <li>I've been looking for you.</li> </ol>	<ol><li>I told you to shut up.</li></ol>	
<ol><li>I want to talk to you.</li></ol>	5. Get out of here.	
3. Just making sure you're OK.	6. I'm looking for a doctor.	
Input: What is your name?		
1. Blue!	4. Daniel.	
2. Peter.	<ol><li>My name is John.</li></ol>	
3. Tyler.	6. My name is Robert.	
Input: How old are you?		
1. Twenty-eight.	4. Five.	
2. Twenty-four.	5. 15.	
3. Long.	6. Eight.	

Standard Seq2Seq p(t|s)

Mutual Information

# Outlines

- 1. Mutual Information for Response Generation.
- 2. Speaker Consistency
- 3. Multi-context Response Generation
- 4. Reinforcement learning for Response Generation

Li et al., 2016. A Persona-Based Neural Conversation Model,

**Mutual Information** 

MLE

$$\begin{split} \hat{T} &= \operatorname*{arg\,max}_{T} \left\{ \log \frac{p(S,T)}{p(S)p(T)} \right\} \\ \hat{T} &= \operatorname*{arg\,max}_{T} \left\{ \log p(T|S) \right\} \end{split}$$











Where do you live now?

I live in Los Angeles.





Where do you live now?

I live in Los Angeles.



In which city do you live now?

I live in Paris.









4, you ?
## Speaker Consistency



## Speaker Consistency



When was your mother born ?

In 1966.

## Speaker Consistency

Speaker Consistency

1. Background facts, user profiles.

Speaker Consistency

1. Background facts, user profiles.

2. Language behavior

Speaker Consistency

- 1. Background facts, user profiles.
- 2. Language behavior
- 3. Interaction style

Speaker Consistency

- 1. Background facts, user profiles.
- 2. Language behavior
- 3. Interaction style



#### How to represent users



#### How to represent users















Persona embeddings (70k)























#### Datasets and Evaluations

Conversation from Twitter 28M turns 74,003 Users minimum of 60 conversational turns

Perplexity BLEU (4,000 single reference) Human Evaluation

### Quantitative Results

	Seq2Seq	Speaker Model
Perplexity	47.2	42.2 (-10.6%)
BLEU (without MMI)	0.92	1.12 (+21.7%)
BLEU (with MMI)	1.41	1.66 (+11.7%)

**Question Pairs** 





**Question Pairs** 

What city do you live in ? What country do you live in ?



**Question Pairs** 

What city do you live in ? What country do you live in ?

> Are you vegan or vegetarian ? Do you eat beaf ?



**Question Pairs** 

What city do you live in ? What country do you live in ?

London/UK

London/US

Which Model produces more consistent answers ? Each item is given to 5 judges. Ties are discarded



	Seq2Seq Model	Persona Model
ltem1	+1	
ltem2		+1

Seq2Seq Model	Persona Model
0.84	1.33 (+34.7%)

User1		User2	
message	Where is your hometown?	message	Where is your hometown?
response	I'm from England.	response	I live in Indonesia.
message	Where are you from?	message	Where are you from?
response	I'm from England.	response	England, you?
message	In which city do you live now?	message	In which city do you live now?
response	I live in London.	response	I live in Jakarta.
message	In which country do you live now?	message	In which country do you live now?
response	I live in England.	response	I live in Indonesia.
message	What is your major?	message	What is your major?
response	Business. You?	response	Business, you?
message	What did you study in college?	message	What did you study in college?
response	I did business studies.	response	Psychology, you?
message	How old are you?	message	How old are you?
response	I'm 18.	response	I'm 18.
message	What is your age?	message	What is your age?
response	I'm 18.	response	I'm 16.

User1		User2	
message	Where is your hometown?	message	Where is your hometown?
response	I'm from England.	response	I live in Indonesia.
message	Where are you from?	message	Where are you from?
response	I'm from England.	response	England, you?
message	In which city do you live now?	message	In which city do you live now?
response	I live in London.	response	I live in Jakarta.
message	In which country do you live now?	message	In which country do you live now?
response	I live in England.	response	I live in Indonesia
message	What is your major?	message	What is your major?
response	Business. You?	response	Business, you?
message	What did you study in college?	message	What did you study in college?
response	I did business studies.	response	Psychology, you?
message	How old are you?	message	How old are you?
response	I'm 18.	response	I'm 18.
message	What is your age?	message	What is your age?
response	I'm 18.	response	I'm 16.

User1		Us	er2	
message	Where is your hometown?	mess	age	Where is your hometown?
response	I'm from England.	respo	nse	I live in Indonesia.
message	Where are you from?	mess	age	Where are you from?
response	I'm from England.	respo	nse	England, you?
message	In which city do you live now?	mess	age	In which city do you live now?
response	I live in London.	respo	nse	I live in Jakarta.
message	In which country do you live now?	mess	age	In which country do you live now?
response	I live in England.	respo	nse	I live in Indonesia.
message	What is your major?	mess	age	What is your major?
response	Business. You?	respo	nse	Business, you?
message	What did you study in college?	mess	age	What did you study in college?
response	I did business studies.	respo	nse	Psychology, you?
message	How old are you?	mess	age	How old are you?
response	I'm 18.	respo	nse	I'm 18.
message	What is your age?	mess	age	What is your age?
response	I'm 18.	respo	nse	I'm 16.

User1		U	er2	
message	Where is your hometown?	mes	age	Where is your hometown?
response	I'm from England.	respo	nse	I live in Indonesia.
message	Where are you from?	mes	age	Where are you from?
response	I'm from England.	respo	nse	England, you?
message	In which city do you live now?	mes	age	In which city do you live now?
response	I live in London.	respo	nse	I live in Jakarta.
message	In which country do you live now?	mes	age	In which country do you live now?
response	I live in England.	respo	nse	I live in Indonesia.
message	What is your major?	mes	age	What is your major?
response	Business. You?	respo	nse	Business, you?
message	What did you study in college?	mes	age	What did you study in college?
response	I did business studies.	respo	nse	Psychology, you?
message	How old are you?	mes	age	How old are you?
response	I'm 18.	respo	nse	I'm 18.
message	What is your age?	mes	age	What is your age?
response	I'm 18.	respo	nse	I'm 16.

User1		User2	
message	Where is your hometown?	message	Where is your hometown?
response	I'm from England.	response	I live in Indonesia.
message	Where are you from?	message	Where are you from?
response	I'm from England.	response	England, you?
message	In which city do you live now?	message	In which city do you live now?
response	I live in London.	response	I live in Jakarta.
message	In which country do you live now?	message	In which country do you live now?
response	I live in England.	response	I live in Indonesia.
message	What is your major?	message	What is your major?
response	Business. You?	response	Business, you?
message	What did you study in college?	message	What did you study in college?
response	I did business studies.	response	Psychology, you?
message	How old are you?	message	How old are you?
response	I'm 18.	response	I'm 18.
message	What is your age?	message	What is your age?
response	I'm 18.	response	I'm 16.

User1		User2	
message	Where is your hometown?	message	Where is your hometown?
response	I'm from England.	response	I live in Indonesia
message	Where are you from?	message	Where are you from?
response	I'm from England.	response	England, y bu?
message	In which city do you live now?	message	In which city do you live now?
response	I live in London.	response	I live in Jakarta.
message	In which country do you live now?	message	In which country do you live now?
response	I live in England.	response	I live in Indonesia.
message	What is your major?	message	What is your major?
response	Business. You?	response	Business, you?
message	What did you study in college?	message	What did you study in college?
response	I did business studies.	response	Psychology, you?
message	How old are you?	message	How old are you?
response	I'm 18.	response	I'm 18.
message	What is your age?	message	What is your age?
response	I'm 18.	response	I'm 16.



# Outlines

- 1. Mutual Information for Response Generation.
- 2. Speaker Consistency
- 3. Multi-context Response Generation
- 4. Reinforcement learning for Response Generation
Single Context:

Any particular plan?

????

What's your plan for the upcoming summer ? I am going to Hawaii for vocation. Any particular plan ?











What's your plan for the upcoming summer?

I am going to Hawaii for vocation.

...







 $C = \sum_{i} O_{i}c_{i}$  Memory Network (Weston et al., 2014)





Attention Models (Bahdanau et al., 2014; Luong et al., 2015)









## Results on the Opensubtitle Dataset



Perplexity

**# of context sentences** 

## Results on the Opensubtitle Dataset



**#** of context sentences

# Outlines

- 1. Mutual Information for Response Generation.
- 2. Speaker Consistency
- 3. Multi-context Response Generation
- 4. Reinforcement learning for Response Generation

















 $Loss = -\log p(target|source)$ 

## Supervised Learning

## Supervised Learning

Data + Labels/Rewards

# Supervised Learning

Data

You are a good boy.

Labels



You are a bad boy.







Labels



# What if labels or rewards is not immediate clear ?

# What if labels are not immediate clear ?

# What if labels are not immediate clear ?



# What if labels are not immediate clear ?





How old are you?





How old are you ?

i 'm 16 .


















A set of environment states **S** (current board for the Go game)

A set of environment states **S** 

A set of actions to take a (where to place a stone)

A set of environment states **S** 

A set of actions to take a (where to place a stone)

Reward (capture the opponent's stone, or win the entire game)

Goal: to learn which action to take given a specific state

By maximizing the overall reward function

# Why can RL make the goal more achievable?

- 1. Allow us to design real world reward function
  - 1. Interesting vs not interesting; informative vs not informative

# Why can RL make the goal more achievable?

- 1. Allow us to design real world reward function
  - 1. Interesting vs not interesting; informative vs not informative
  - 2. User feedback.

# Can RL (to some extent) achieve this goal?

- 1. Allow us to design real world reward function
  - 1. Interesting vs not interesting; informative vs not informative
  - 2. User feedback
  - 3. Conversation Length ...

# Can RL (to some extent) achieve this goal?

- 1. Allow us to design real world reward function
- 2. Look beyond two conversation turns (into the future)

# Notations for Reinforcement Learning

## Notations: Starting State



### Notations: Action



How old are you ?





How old are you ?



$$R(r_i, s) = MMI(r_i, r_{i-1}) \cdot reward(r_i)$$









tf-idf Informativeness



tf-idf # of turns it takes before generating dull responses



Mutual information (how old are you, I'm 16)

# Objective function:

Goal: to learn which action to take given a specific state

# Objective function:

Goal: to learn which action to take given a specific state

#### p(target|source)

Based on the overall reward

#### **Future Reward**

$$\mathbb{E}_{r_i}[\hat{R}(r_i)] = \sum_{r_i} p(r_i|r_{i-1})[\hat{R}(r_i)]$$



Action: Generating current response  $r_i$ 

$$\mathbb{E}_{r_i}[\hat{R}(r_i)] = \sum_{r_i} p(r_i|r_{i-1})[\hat{R}(r_i)]$$

Approximation1: Sample a small list of candidates A

Action: Generating current response  $r_i$ 

$$\mathbb{E}_{r_i}[\hat{R}(r_i)] = \sum_{r_i} p(r_i|r_{i-1})[\hat{R}(r_i)]$$

Approximation1: Sample a small list of candidates A

$$\mathbb{E}_{r_i}[R(r_i)] \approx \sum_{r_i \in \mathbb{A}} \frac{p(r_i | r_{i-1})}{\sum_{t \in \mathbb{A}} p(r_i | r_{i-1})} [\hat{R}(r_i)]$$

**Normalization Part** 

$$\hat{R}(r_i) = R(r_i) + \gamma \sum_{r_{i+1}} p(r_{i+1}|r_i) \hat{R}(r_{i+1})$$

**Immediate Reward** 

$$\hat{R}(r_i) = R(r_i) + \gamma \sum_{r_{i+1}} p(r_{i+1}|r_i) \hat{R}(r_{i+1})$$

**Immediate Reward** 

 $MMI(r_i, r_{i-1}) \cdot reward(r_i)$ 

$$\hat{R}(r_i) = R(r_i) + \gamma \sum_{r_{i+1}} p(r_{i+1}|r_i) \hat{R}(r_{i+1})$$

**Future Reward** 

$$\hat{R}(r_i) = R(r_i) + \gamma \sum_{r_{i+1}} p(r_{i+1}|r_i) \hat{R}(r_{i+1})$$

**Future Reward** 

$$\approx R(r_{i}) + \sum_{r_{i} \in \mathbb{A}} \frac{p(r_{i+1}|r_{i})}{\sum_{t \in \mathbb{A}} p(r_{i+1}|r_{i1})} [\hat{R}(r_{i+1})]$$





 $\text{Loss} = -\mathbb{E}_{r_i}[R(r_i)] \approx \sum_{r_i \in \mathbb{A}} \frac{p(r_i | r_{i-1})}{\sum_{t \in \mathbb{A}} p(r_i | r_{i-1})} [\hat{R}(r_i)]$ 

$$R(\hat{r}_{i}) \approx R(r_{i}) + \gamma \sum_{r_{i+1} \in \mathbb{A}} \frac{p(r_{i+1}|r_{i})}{\sum_{t \in \mathbb{A}} p(r_{i+1}|r_{i})} [R(r_{i+1})]$$



A message from training set

$$\text{Loss} = -\mathbb{E}_{r_i}[R(r_i)] \approx \sum_{r_i \in \mathbb{A}} \frac{p(r_i | r_{i-1})}{\sum_{t \in \mathbb{A}} p(r_i | r_{i-1})} [\hat{R}(r_i)]$$

$$R(\hat{r}_{i}) \approx R(r_{i}) + \gamma \sum_{r_{i+1} \in \mathbb{A}} \frac{p(r_{i+1}|r_{i})}{\sum_{t \in \mathbb{A}} p(r_{i+1}|r_{i})} [R(r_{i+1})]$$



A message from training set



 $\text{Loss} = -\mathbb{E}_{r_i}[R(r_i)] \approx \sum_{r_i \in \mathbb{A}} \frac{p(r_i | r_{i-1})}{\sum_{t \in \mathbb{A}} p(r_i | r_{i-1})} [\hat{R}(r_i)]$ 

$$R(\hat{r}_{i}) \approx R(r_{i}) + \gamma \sum_{r_{i+1} \in \mathbb{A}} \frac{p(r_{i+1}|r_{i})}{\sum_{t \in \mathbb{A}} p(r_{i+1}|r_{i})} [R(r_{i+1})]$$



A message from training set


$$\text{Loss} = -\mathbb{E}_{r_i}[R(r_i)] \approx \sum_{r_i \in \mathbb{A}} \frac{p(r_i | r_{i-1})}{\sum_{t \in \mathbb{A}} p(r_i | r_{i-1})} [\hat{R}(r_i)]$$

$$R(\hat{r}_{i}) \approx R(r_{i}) + \gamma \sum_{r_{i+1} \in \mathbb{A}} \frac{p(r_{i+1}|r_{i})}{\sum_{t \in \mathbb{A}} p(r_{i+1}|r_{i})} [R(r_{i+1})]$$





$$\begin{aligned} \text{Loss} &= -\mathbb{E}_{r_i}[R(r_i)] \approx \sum_{r_i \in \mathbb{A}} \frac{p(r_i | r_{i-1})}{\sum_{t \in \mathbb{A}} p(r_i | r_{i-1})} [\hat{R}(r_i)] \\ R(\hat{r}_i) &\approx R(r_i) + \gamma \sum_{r_{i+1} \in \mathbb{A}} \frac{p(r_{i+1} | r_i)}{\sum_{t \in \mathbb{A}} p(r_{i+1} | r_i)} [R(r_{i+1})] \end{aligned}$$





$$\text{Loss} = -\mathbb{E}_{r_i}[R(r_i)] \approx \sum_{r_i \in \mathbb{A}} \frac{p(r_i|r_{i-1})}{\sum_{t \in \mathbb{A}} p(r_i|r_{i-1})} [\hat{R}(r_i)]$$

$$R(\hat{r}_{i}) \approx R(r_{i}) + \gamma \sum_{r_{i+1} \in \mathbb{A}} \frac{p(r_{i+1}|r_{i})}{\sum_{t \in \mathbb{A}} p(r_{i+1}|r_{i})} [R(r_{i+1})]$$







Input	Mutual Information	The proposed model
How old are you ?	l'm 4.	I'm 4. why are you asking ?

Input	Mutual Information	The proposed model
How old are you ?	l'm 4.	I'm 4. why are you asking ?
what is your full name ?	i have no idea	what 's yours ?

Input	Mutual Information	The proposed model
How old are you ?	l'm 4.	I'm 4. why are you asking ?
what is your full name ?	i have no idea	what 's yours ?
I don 't want to go home tonight .	Really ?	Why ?

Input	Mutual Information	The proposed model
How old are you ?	l'm 4.	I'm 4. why are you asking ?
what is your full name ?	i have no idea	what 's yours ?
I don 't want to go home tonight .	Really ?	Why ?
Do you have any feelings for me?	I don't know what you are talking about.	Would I see you if I didn 't ?

Keep your expectation low



How old are you ?

Keep your expectation low



How old are you?

i 'm 4, why are you asking ?



Keep your expectation low



How old are you?

I thought you were 12.





#### Keep your expectation low



Keep your expectation low

How old are you ?





I thought you were 12.

What made you think so ?



I don't know what you are talking about .







# Conclusion

We apply neural generation methods to dialogue (chatbot) tasks

- 1. ``I don't know problem"
- 2. speaker consistency
- 3. leveraging multiple context information
- 4. preliminary attempt to make conversation keep flowing using RL

#### Q&A



#### Mutual Information for Response Generation.

Solution 1 
$$\hat{T} = \underset{T}{\arg \max} \left\{ \log p(T|S) - \lambda \log p(T) \right\}$$

Anti-language Model

- 1. Training P(T|S) and P(T)
- 2. Decoding



#### Mutual Information for Response Generation.

Solution 1 
$$\hat{T} = \operatorname*{arg\,max}_{T} \left\{ \log p(T|S) - \lambda \log p(T) \right\}$$
  
 $p(T) = \prod_{i=1}^{L_t} p(t_i|t_1, t_2, ..., t_{i-1})$ 

#### Mutual Information for Response Generation.

Solution 1 
$$\hat{T} = \operatorname*{arg\,max}_{T} \left\{ \log p(T|S) - \lambda \log p(T) \right\}$$
  
 $p(T) = \prod_{i=1}^{L_t} p(t_i|t_1, t_2, ..., t_{i-1})$ 

Action: Generating current response  $r_i$ 

State: LSTM hidden state obtained from history  $r_1, r_2, ..., r_{i-1}$ 

Action: Generating current response  $r_i$ 

State: LSTM hidden state obtained from history  $r_1, r_2, ..., r_{i-1}$ 

transition function  $p(r_i | r_1, r_2, ..., r_{i-1}, r_i) \approx p_{\theta}(r_i | r_{i-1}) \quad \neq p_{seq}(r_{i+1} | r_i)$ 

Action: Generating current response  $r_i$ 

State: LSTM hidden state obtained from history  $r_1, r_2, ..., r_{i-1}$ 

transition function 
$$p(r_i|r_1,r_2,...,r_{i-1},r_i) pprox p_{ heta}(r_i|r_{i-1})$$

new State: LSTM hidden state obtained  $r_1, r_2, ..., r_{i-1}, r_i$ 

Action: Generating current response  $r_i$ 

State: LSTM hidden state obtained from history  $r_1, r_2, ..., r_{i-1}$ 

transition function 
$$p(r_i|r_1,r_2,...,r_{i-1},r_i) pprox p_{ heta}(r_i|r_{i-1})$$

new State: LSTM hidden state obtained  $r_1, r_2, ..., r_{i-1}, r_i$ 

reward  $R(r_i)$ 

Action: Generating current response  $r_i$ 

State: LSTM hidden state obtained from history  $r_1, r_2, ..., r_{i-1}$ 

transition function 
$$p(r_i|r_1,r_2,...,r_{i-1},r_i) pprox p_{ heta}(r_i|r_{i-1})$$

new State: LSTM hidden state obtained  $r_1, r_2, ..., r_{i-1}, r_i$ 

reward  $R(r_i)$ 

 $R(r_i, s) = MMI(r_i, r_{i-1}) \cdot reward(r_i)$ 

Action: Generating current response  $r_i$ 

State: LSTM hidden state obtained from history  $r_1, r_2, ..., r_{i-1}$ 

transition function 
$$p(r_i|r_1,r_2,...,r_{i-1},r_i) pprox p_{ heta}(r_i|r_{i-1})$$

new State: LSTM hidden state obtained  $r_1, r_2, ..., r_{i-1}, r_i$ 

reward 
$$R(r_i, s) = MMI(r_i, r_{i-1}) \cdot reward(r_i)$$
  
 $p_{seq}(t|s) \cdot p_{seq}(s|t)$ 

Action: Generating current response  $r_i$  Infinite #

State S: LSTM hidden state obtained from history  $r_1, r_2, ..., r_{i-1}$  Infinite #

transition function  $p(r_i|r_1, r_2, ..., r_{i-1}) \approx p(r_i|r_{i-1})$ 

new State: LSTM hidden state obtained  $r_1, r_2, ..., r_{i-1}, r_i$ 

reward  $R(r_i, s) = MMI(r_i, r_{i-1}) \cdot reward(r_i)$ 

Future reward  $\hat{R}(r_i,s)$ 

#### Standard Seq2Seq2

Any particular plan?

