What's so Hard about Natural Language Understanding?

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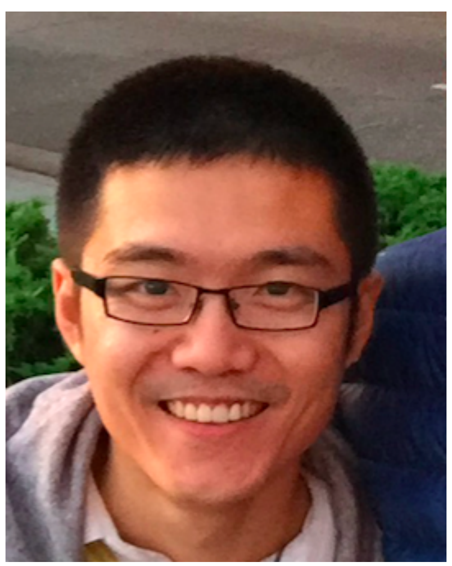

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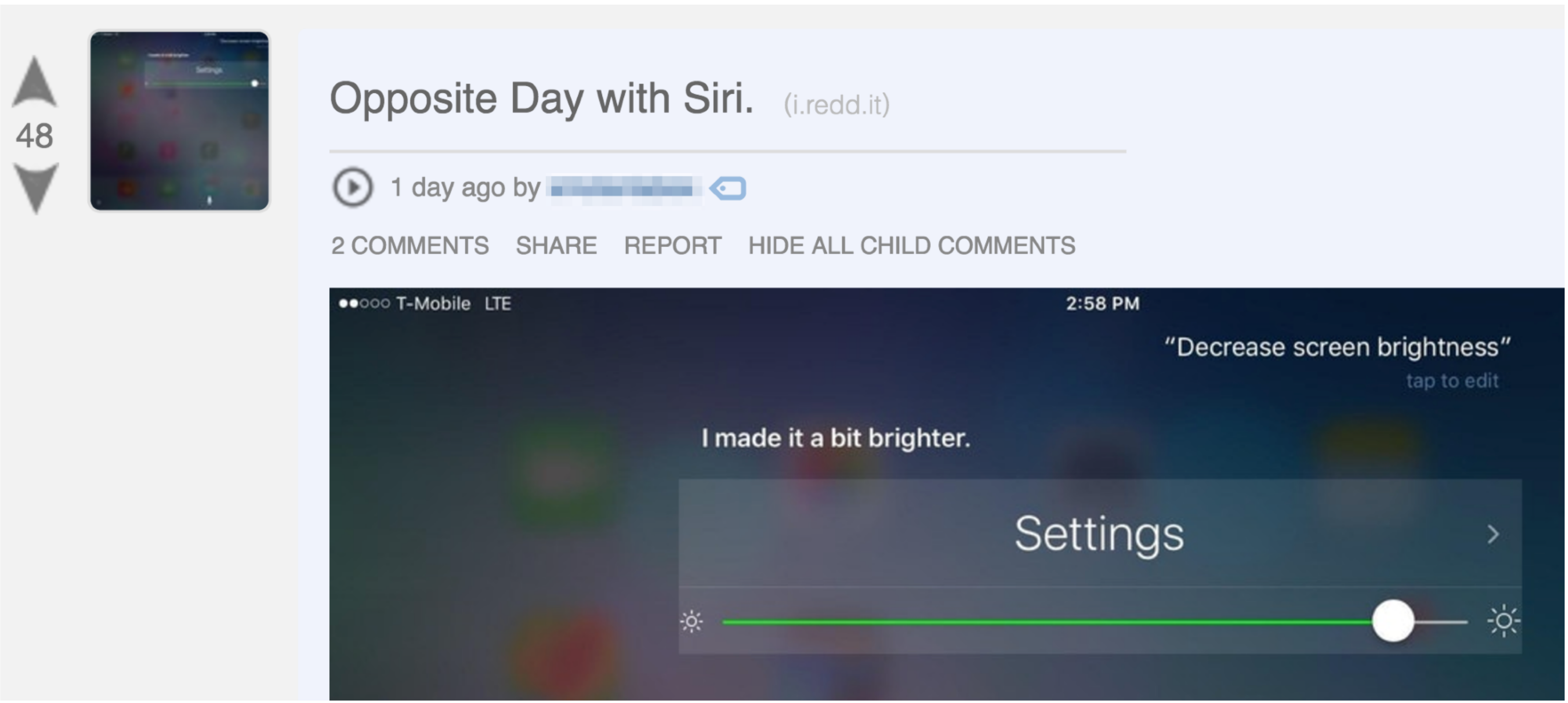

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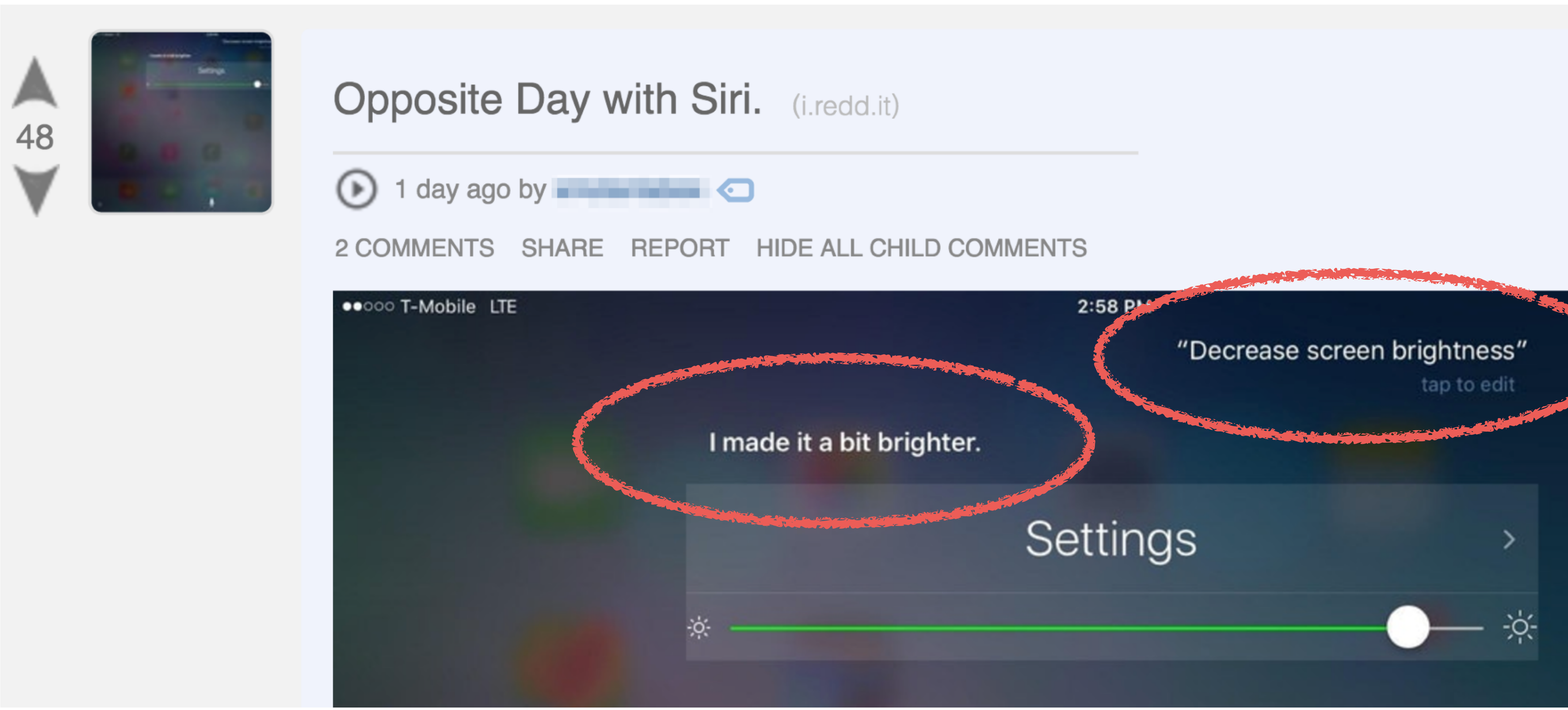

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Data-Driven Conversation

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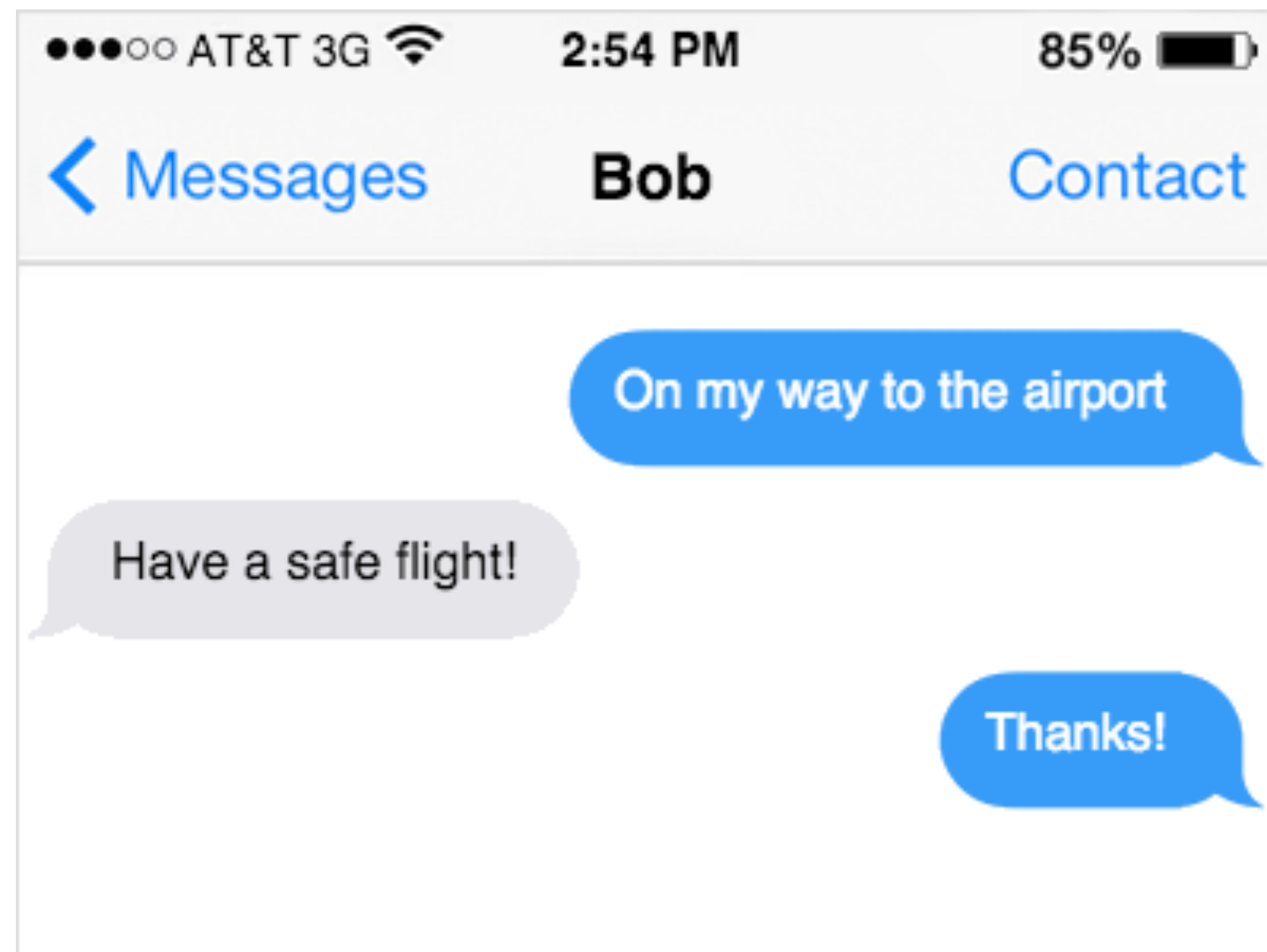
- **Goal:** Learn conversational agents directly from massive volumes of data.



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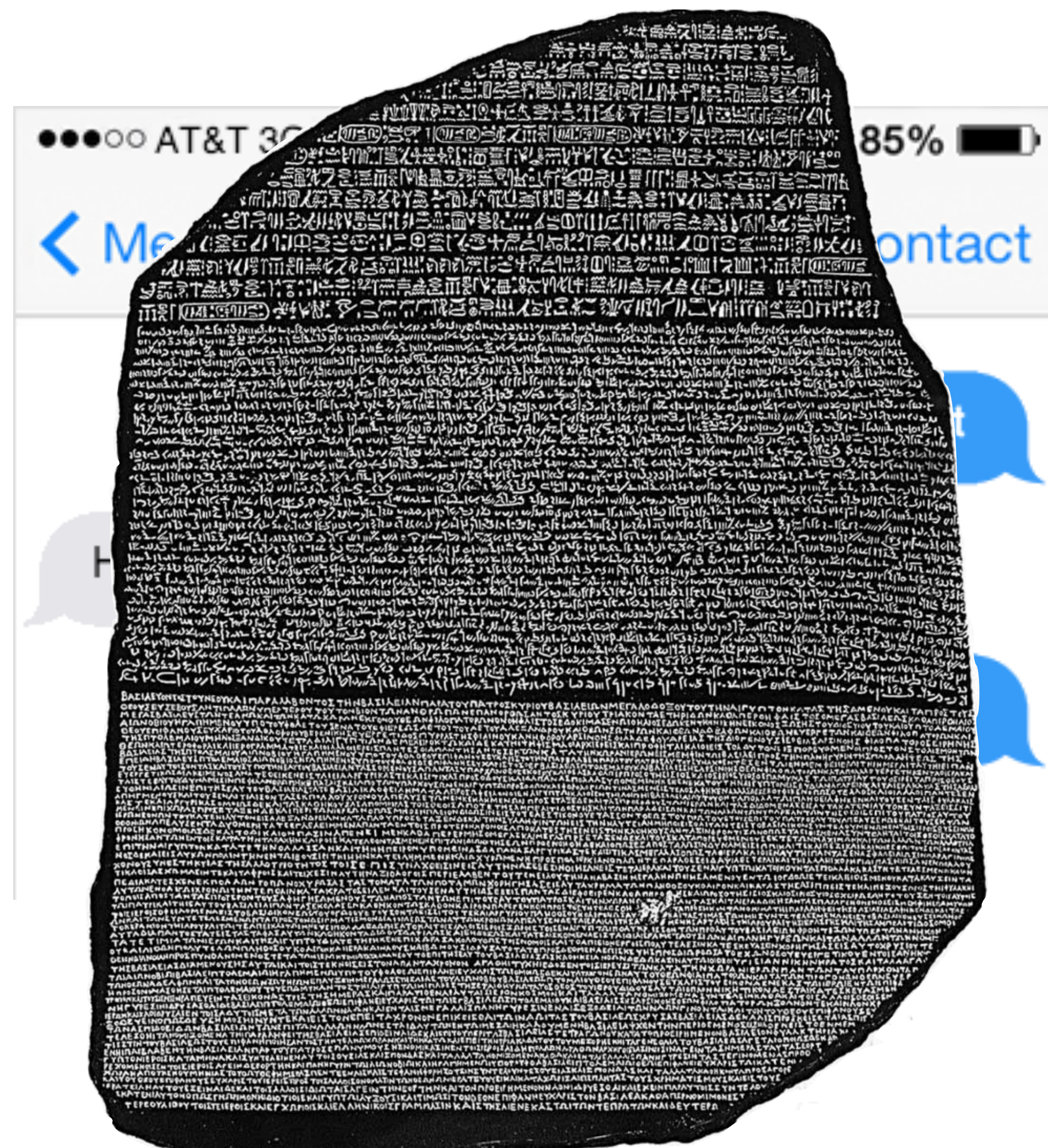

[Ritter, Cherry, Dolan EMNLP 2011]

Noisy Channel Model

Input:

Who wants to come over for dinner tomorrow?

[Ritter, Cherry, Dolan EMNLP 2011]

Noisy Channel Model

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Who wants to come over $\underbrace{\text{for dinner}}$ tomorrow?

Output:

Yum ! I

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Neural Conversation

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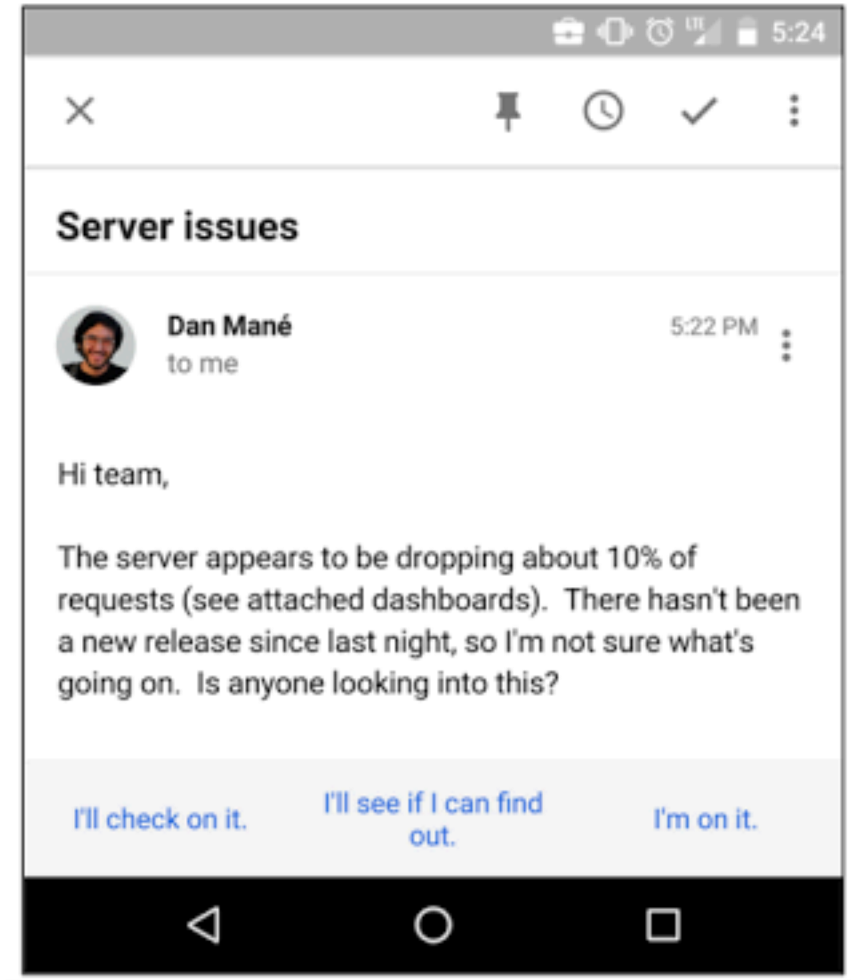

Google Research Blog

Computer, respond to this email.

Tuesday, November 03, 2015

Posted by Greg Corrado*, Senior Research Scientist

Another bizarre feature of our early prototype was its propensity to respond with "I love you" to seemingly anything. As adorable as this sounds, it wasn't really what we were hoping for. Some analysis revealed that the system was doing exactly what we'd trained it to do, generate likely responses -- and it turns out that responses like "Thanks", "Sounds good", and "I love you" are super common -- so the system would lean on them as a safe bet if it was unsure. Normalizing the

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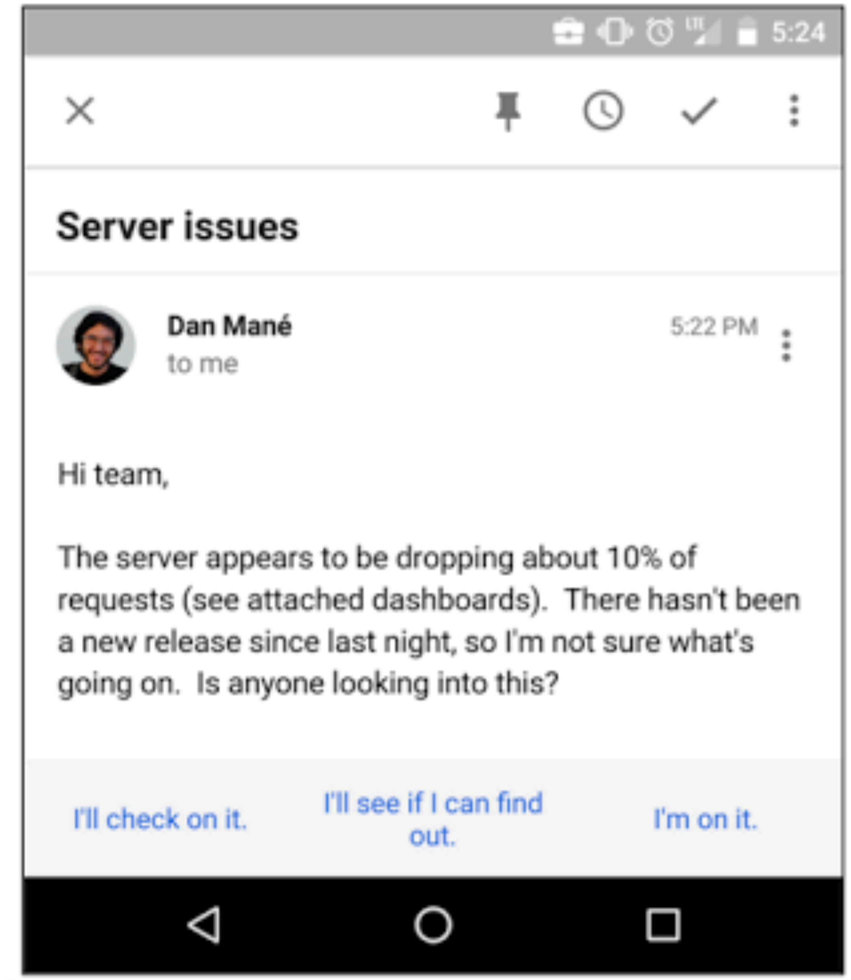

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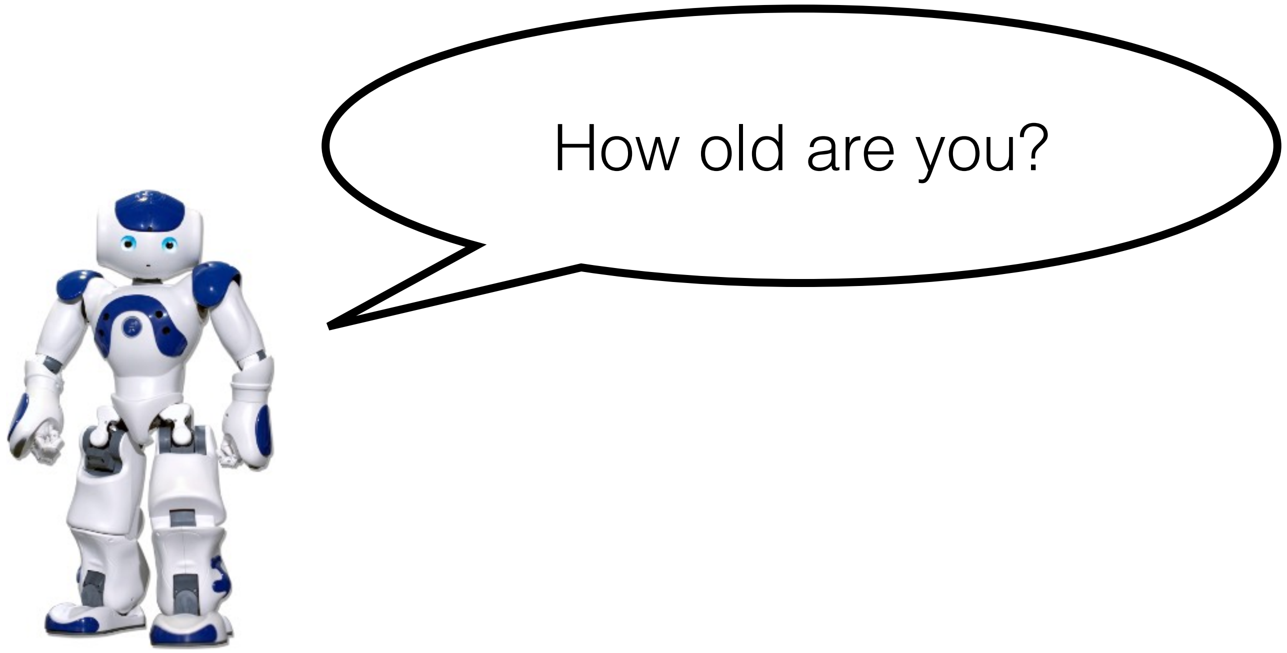

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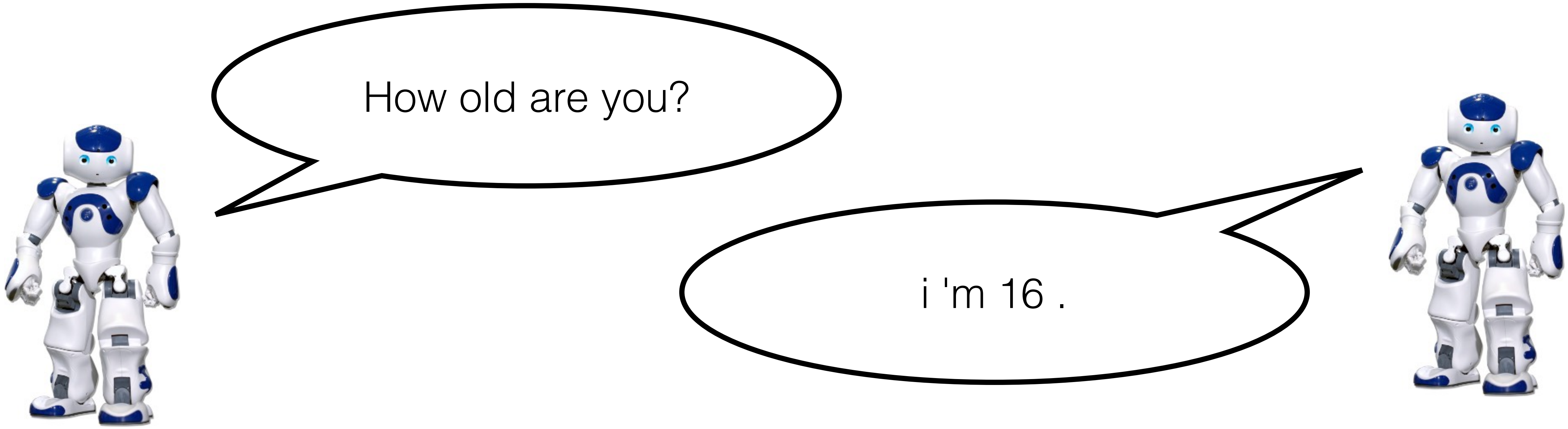

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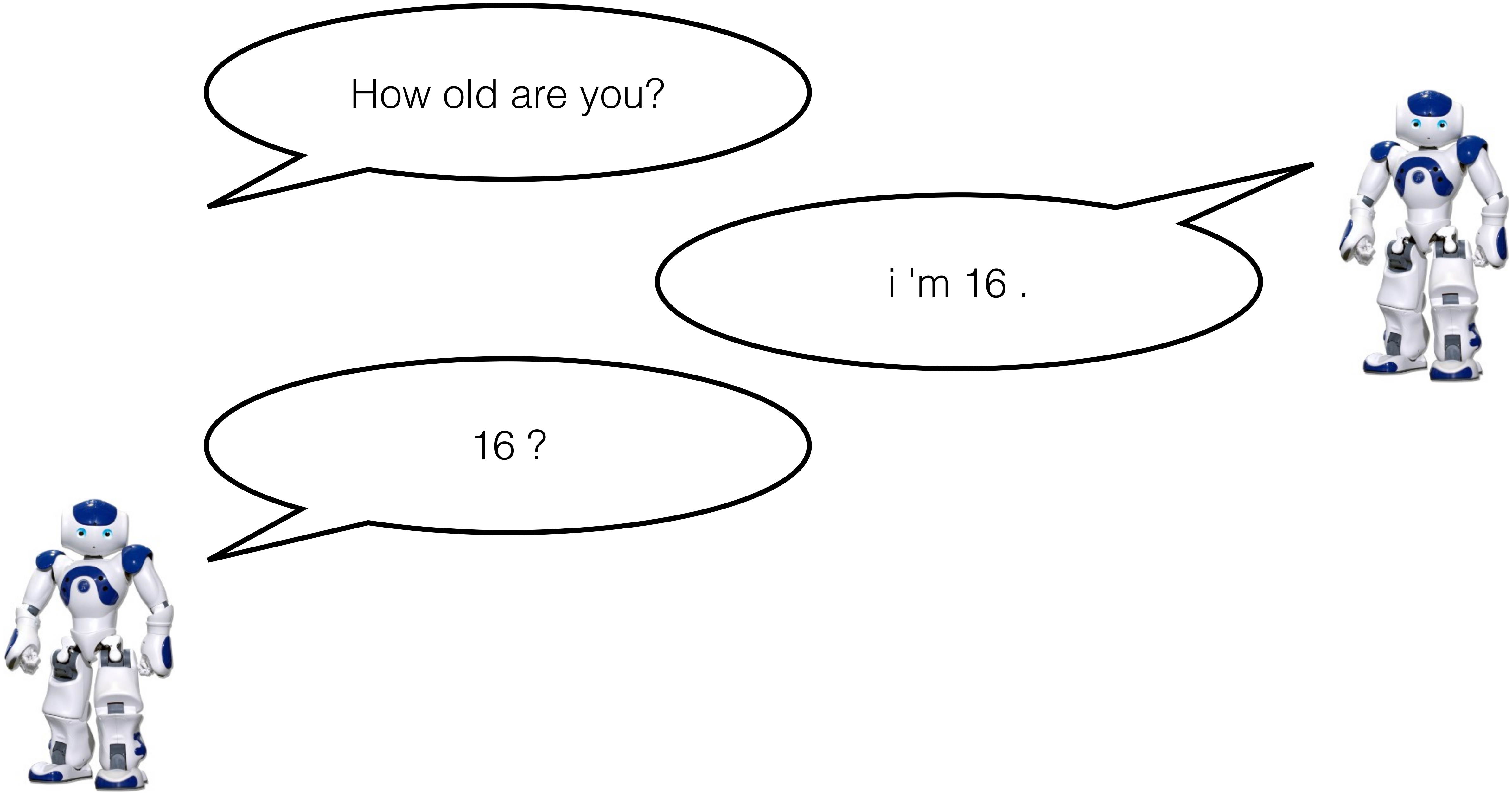

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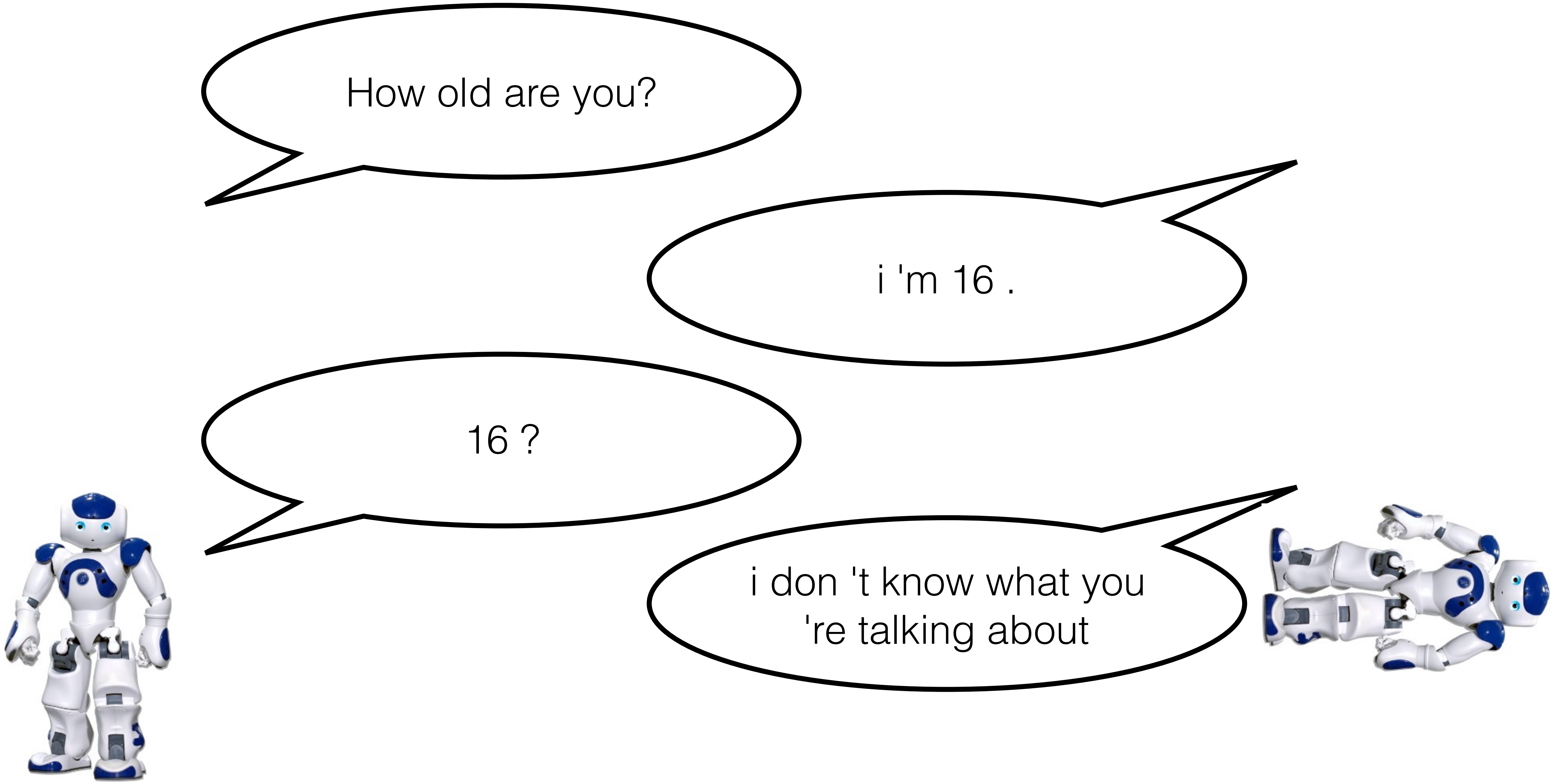

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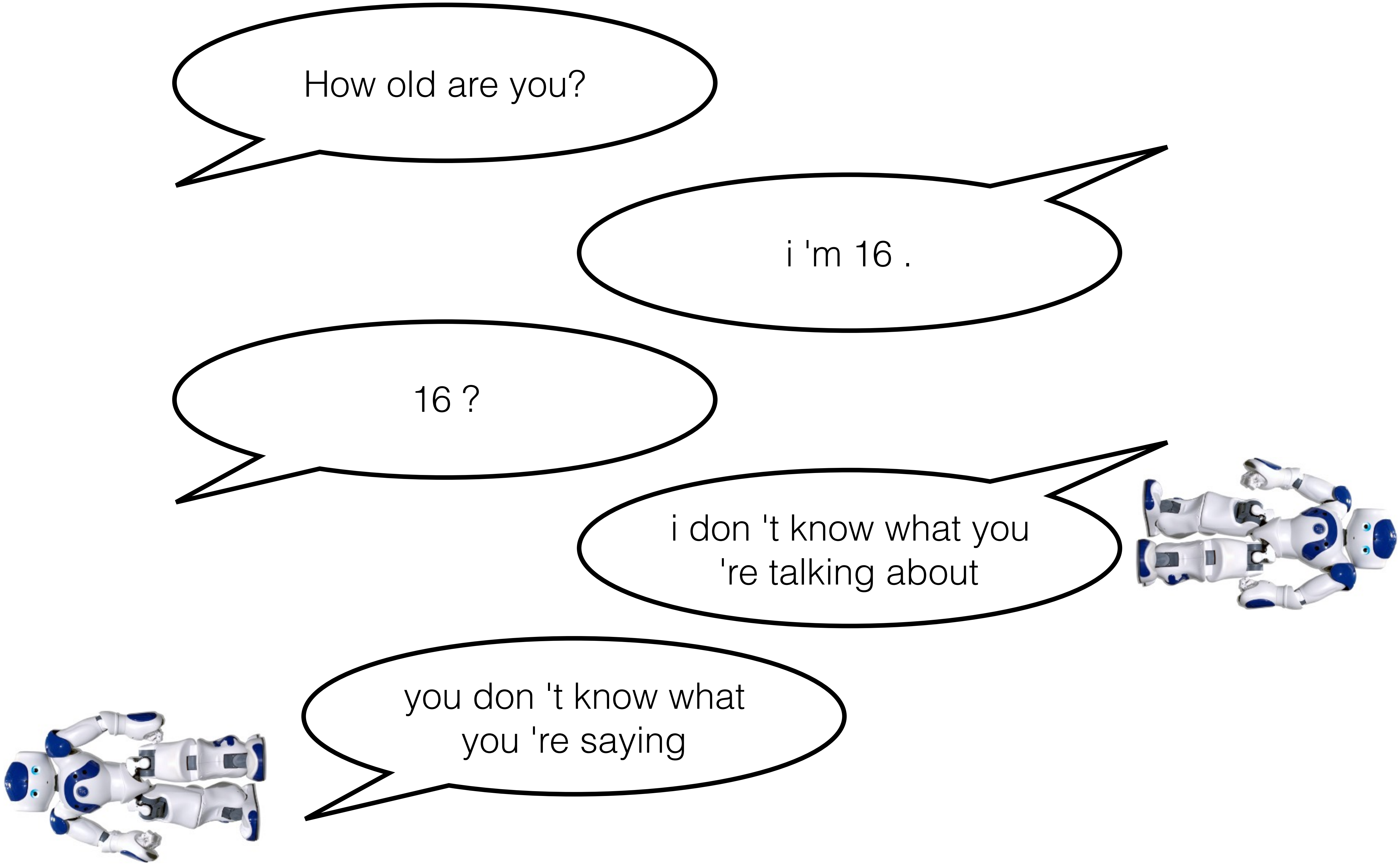

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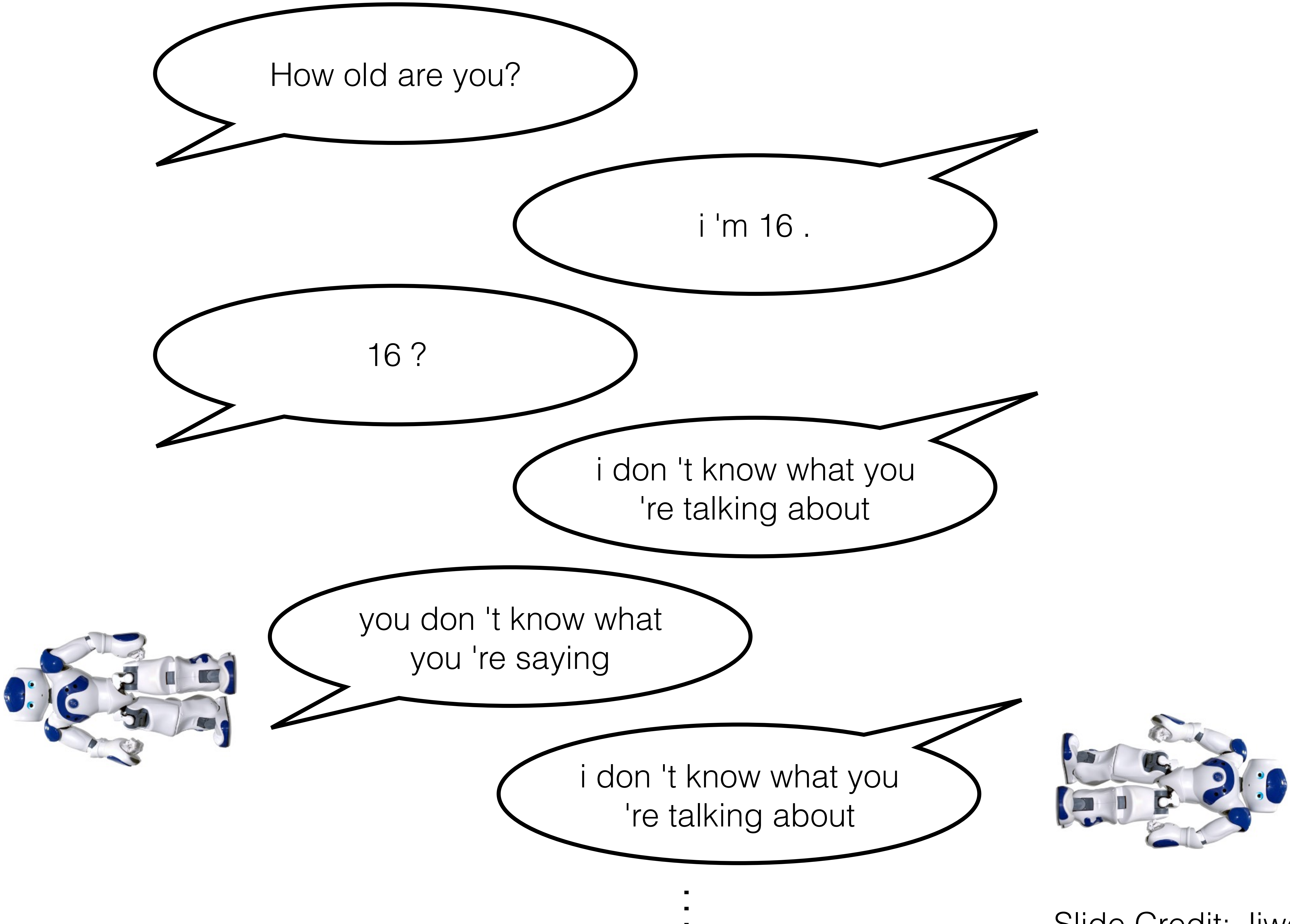

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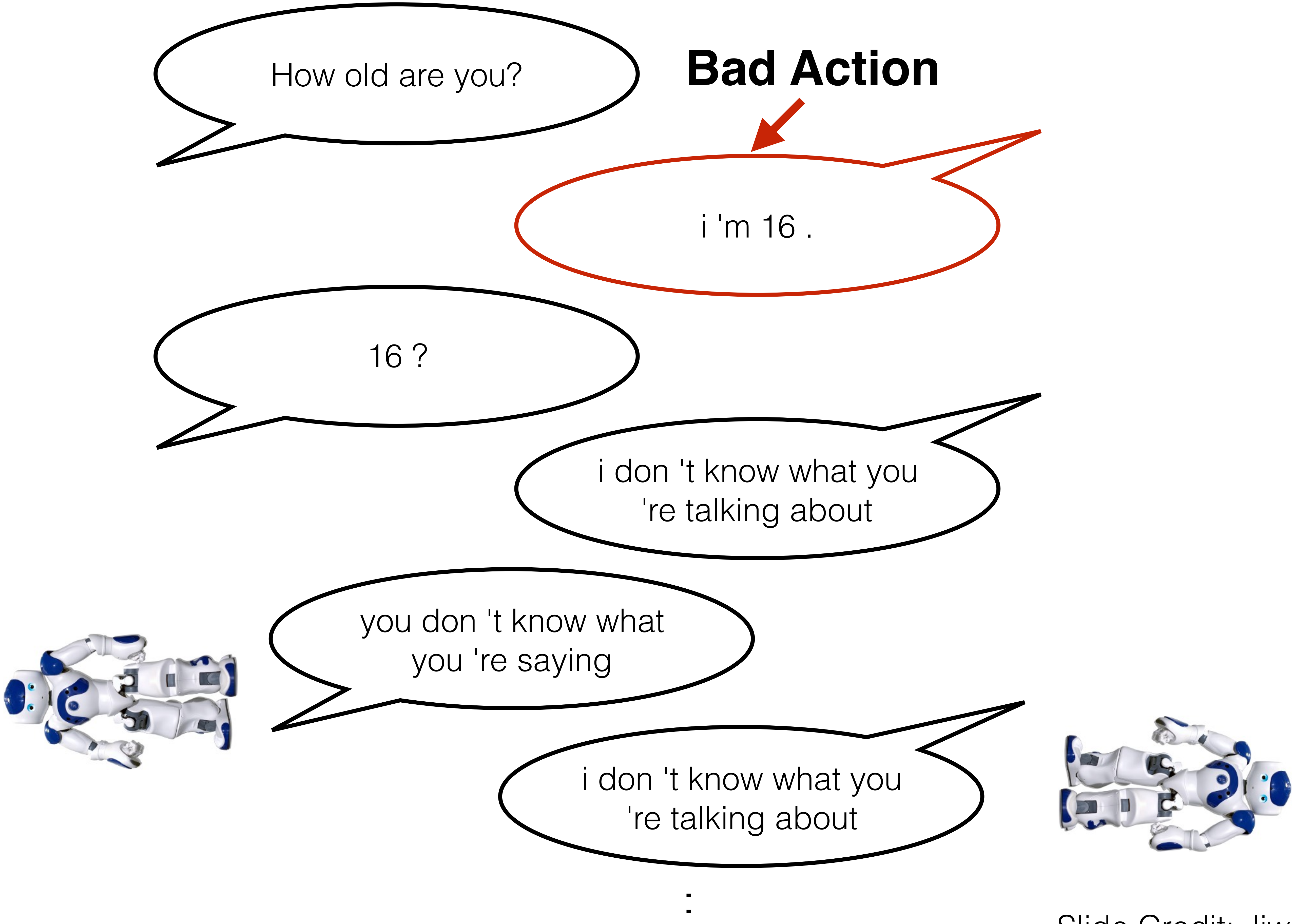

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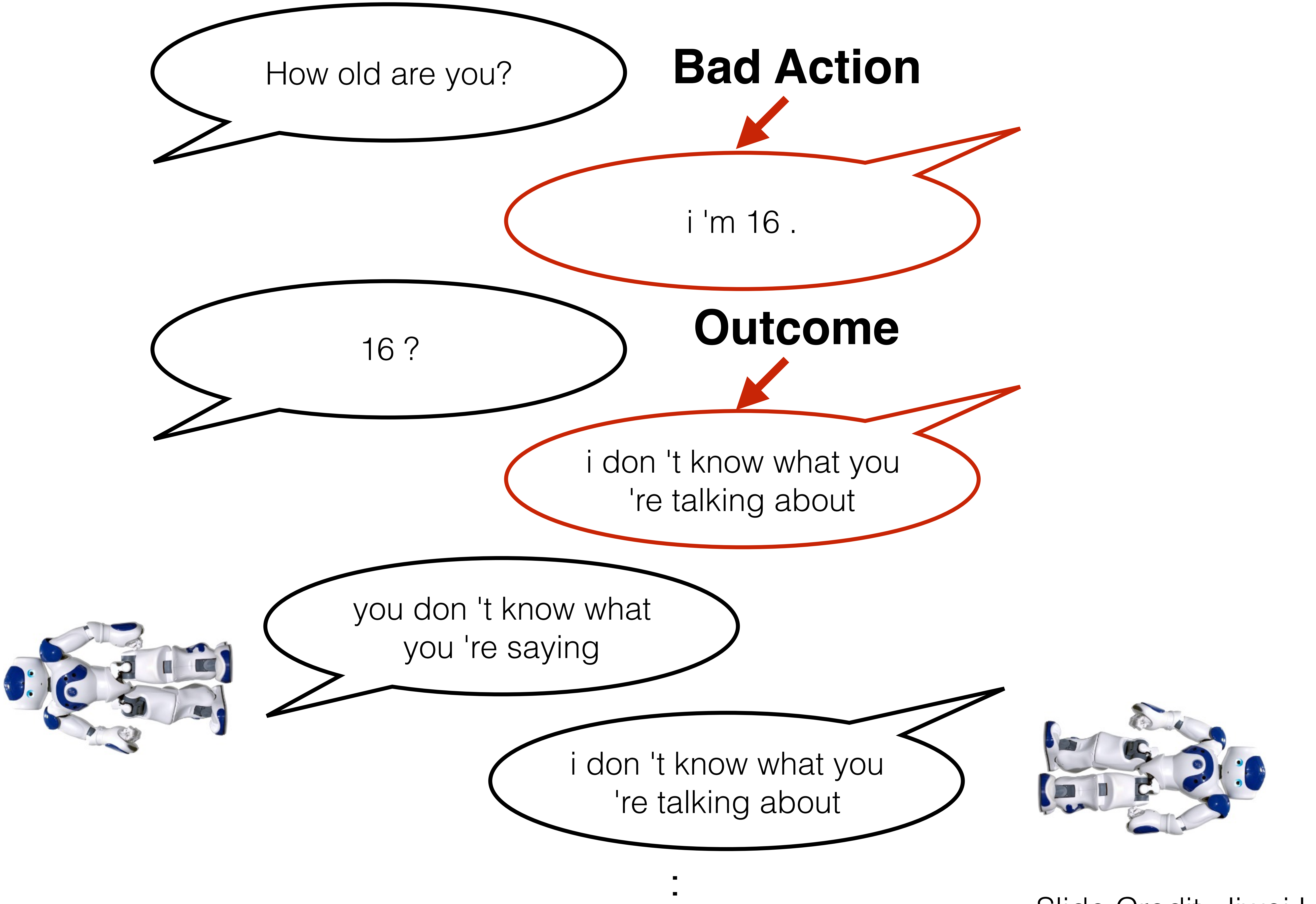

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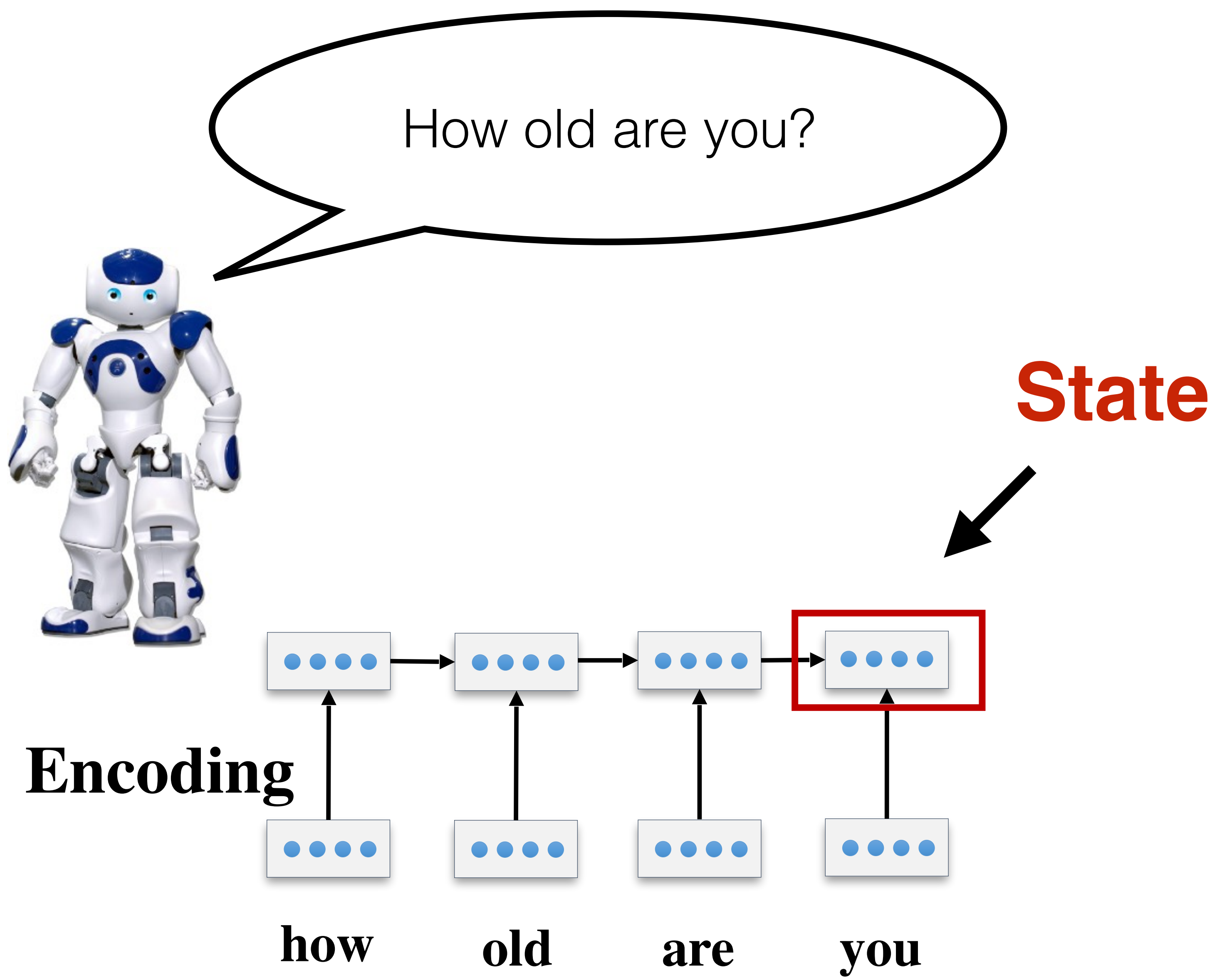
Deep Reinforcement Learning

[Li, Monroe, Ritter, Galley, Gao, Jurafsky EMNLP 2016]



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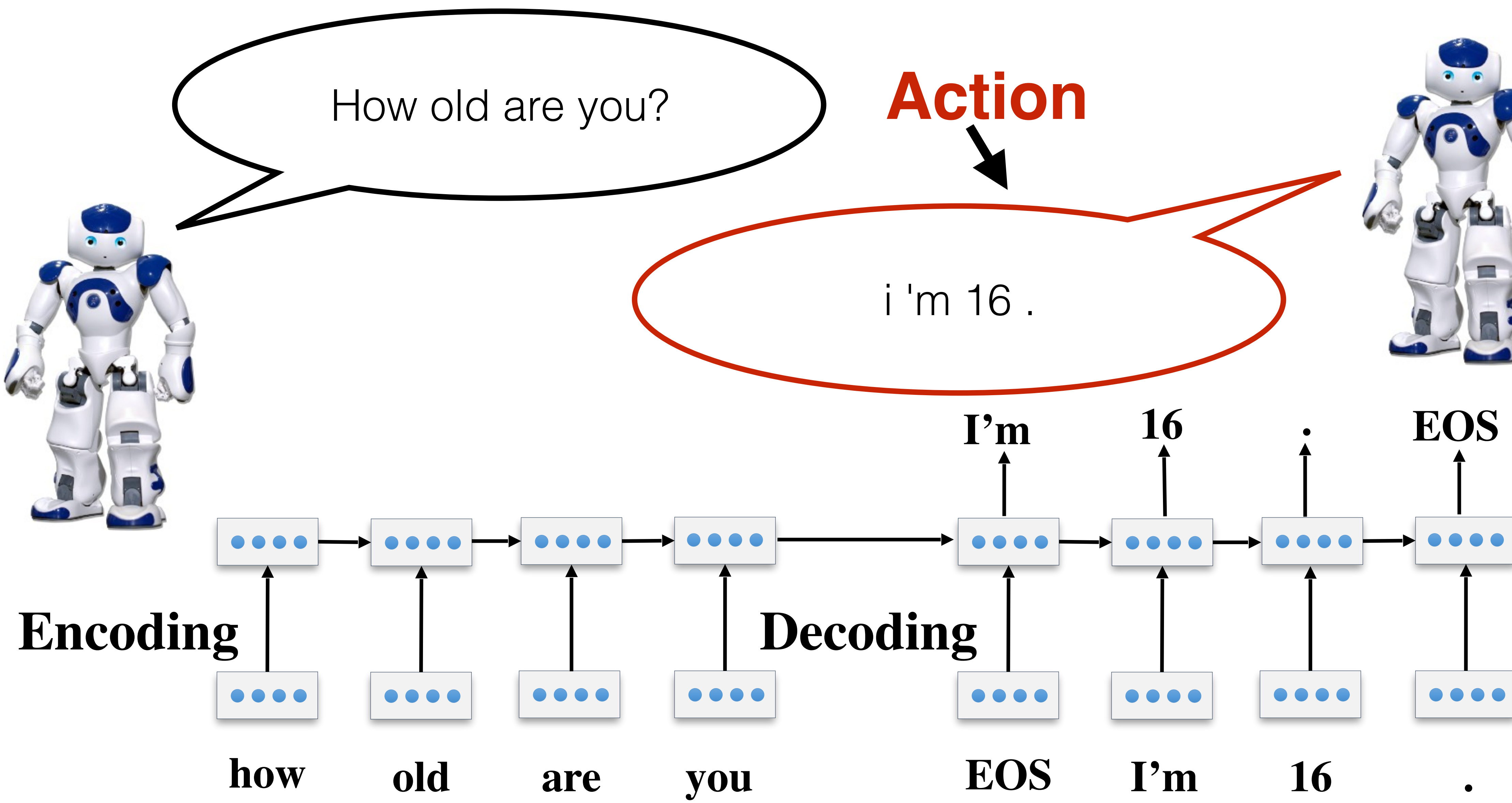


Learning: Policy Gradient

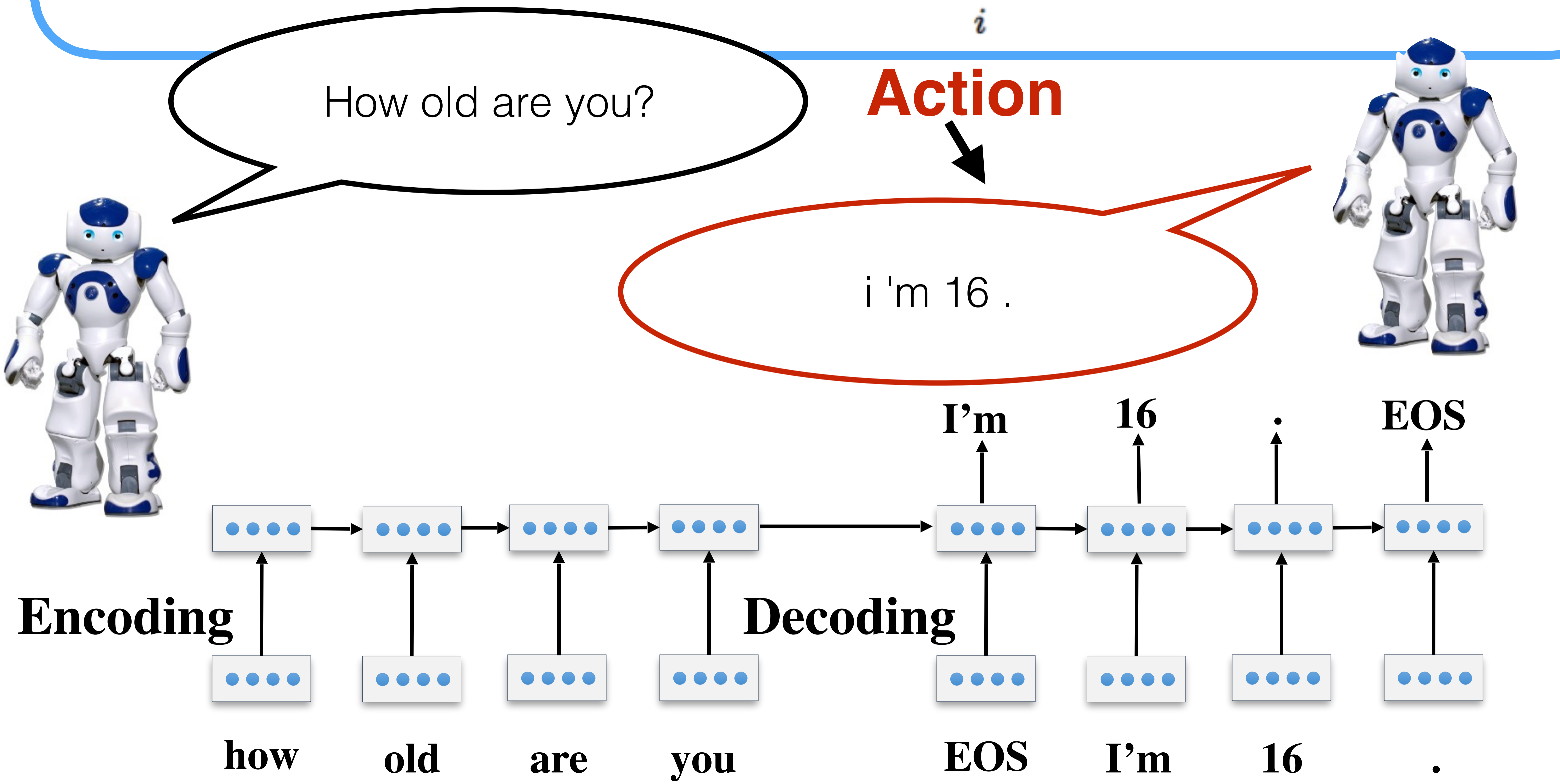
REINFORCE Algorithm (Williams,1992)

$$J(\theta) = \mathbb{E}[R(s_1, s_2, ..., s_N)]$$

$$\nabla J(\theta) = \nabla \log p(s_1, s_2, ..., s_N) R(s_1, s_2, ..., s_N)$$

What we want to learn

$$\nabla J(\theta) = \nabla \log \prod_i \boxed{p(s_i|s_{i-1})} R(s_1, s_2, ..., s_N)$$



Q: Rewards?

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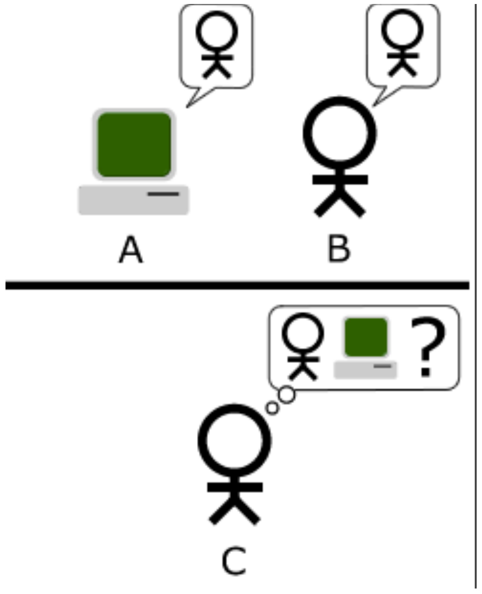
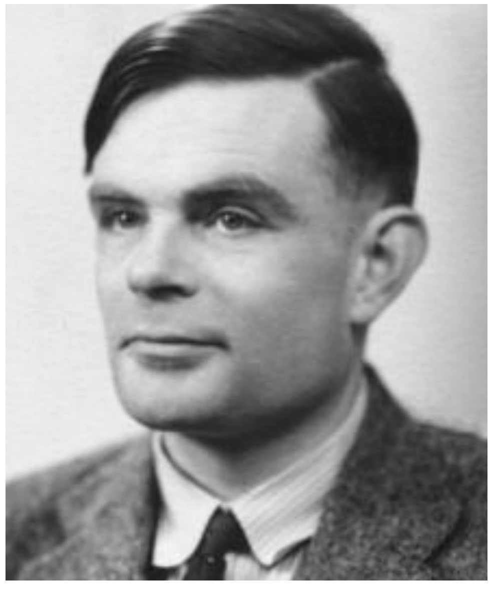
A: Turing Test





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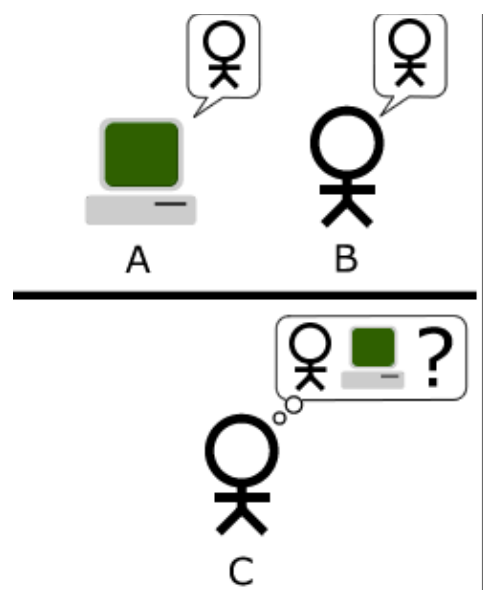
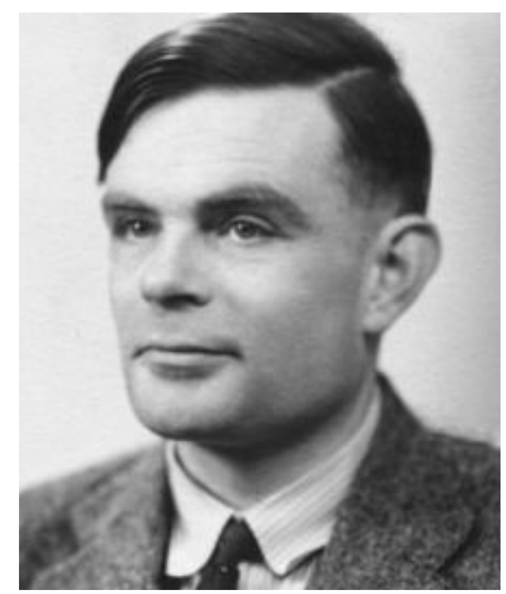
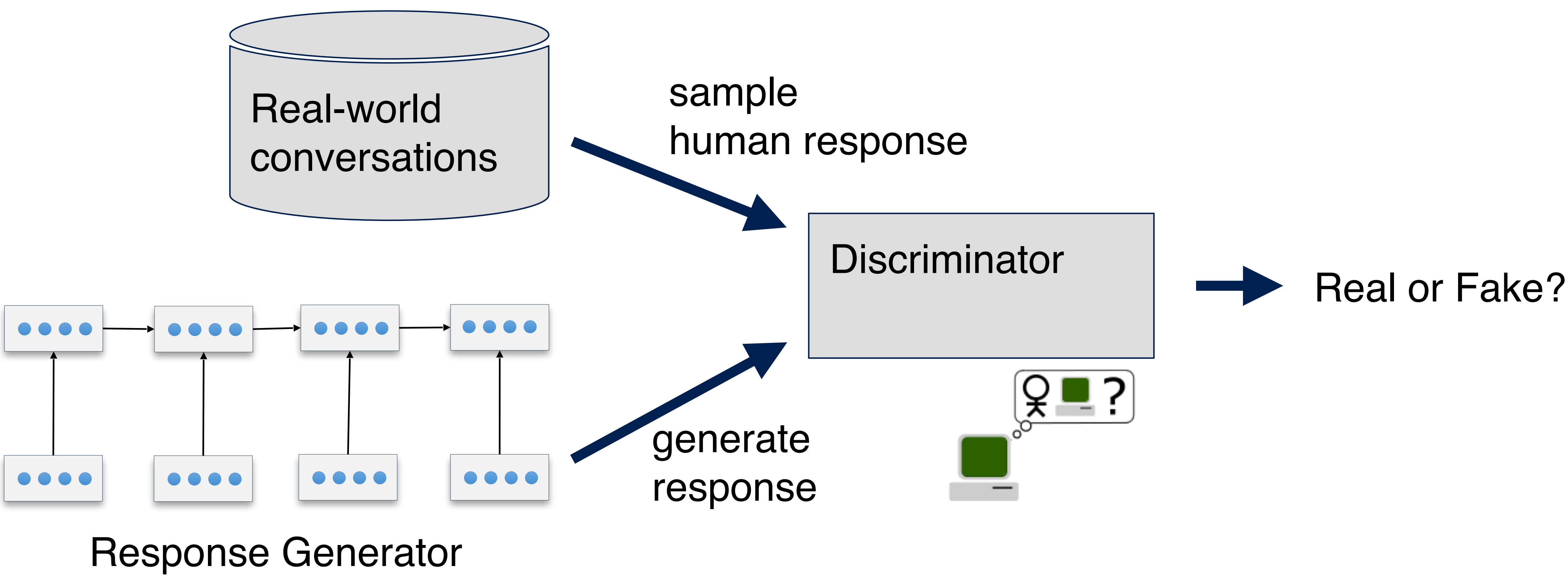




Adversarial Learning
(Goodfellow et al., 2014)

Adversarial Learning for Neural Dialogue [Li, Monroe, Shi, Jean, Ritter, Jurafsky EMNLP 2016]



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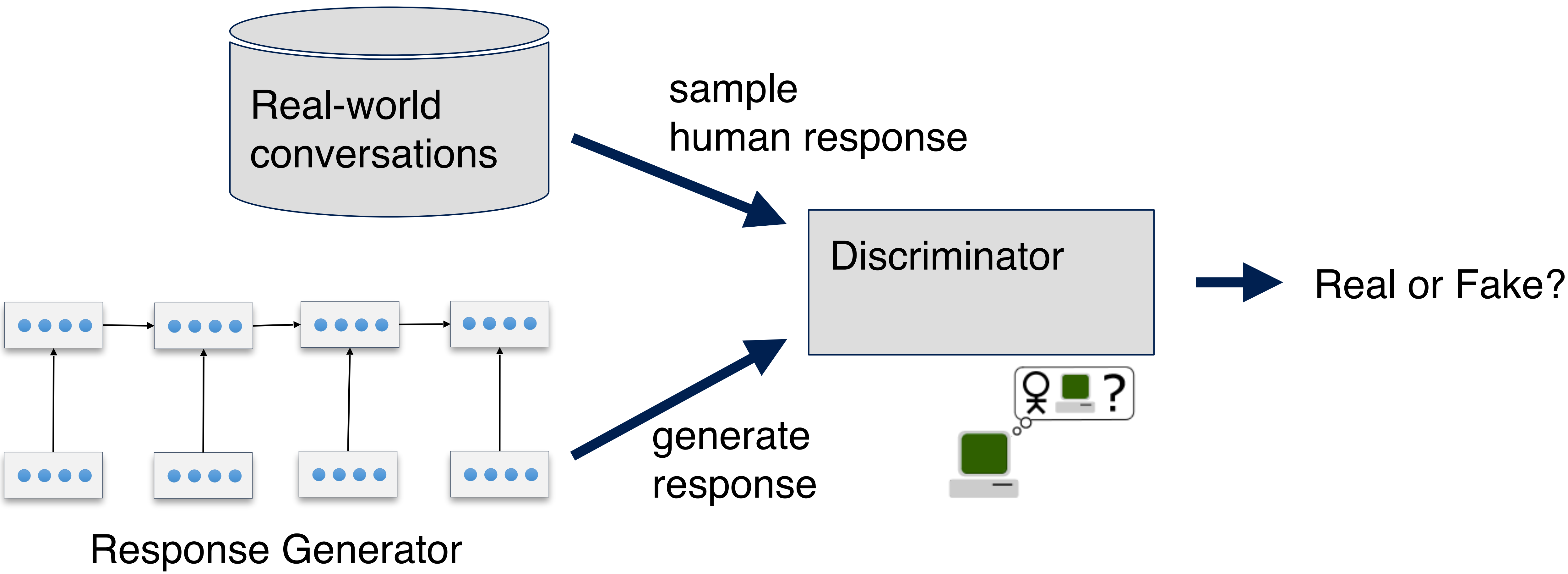
(Alternate Between Training Generator and Discriminator)



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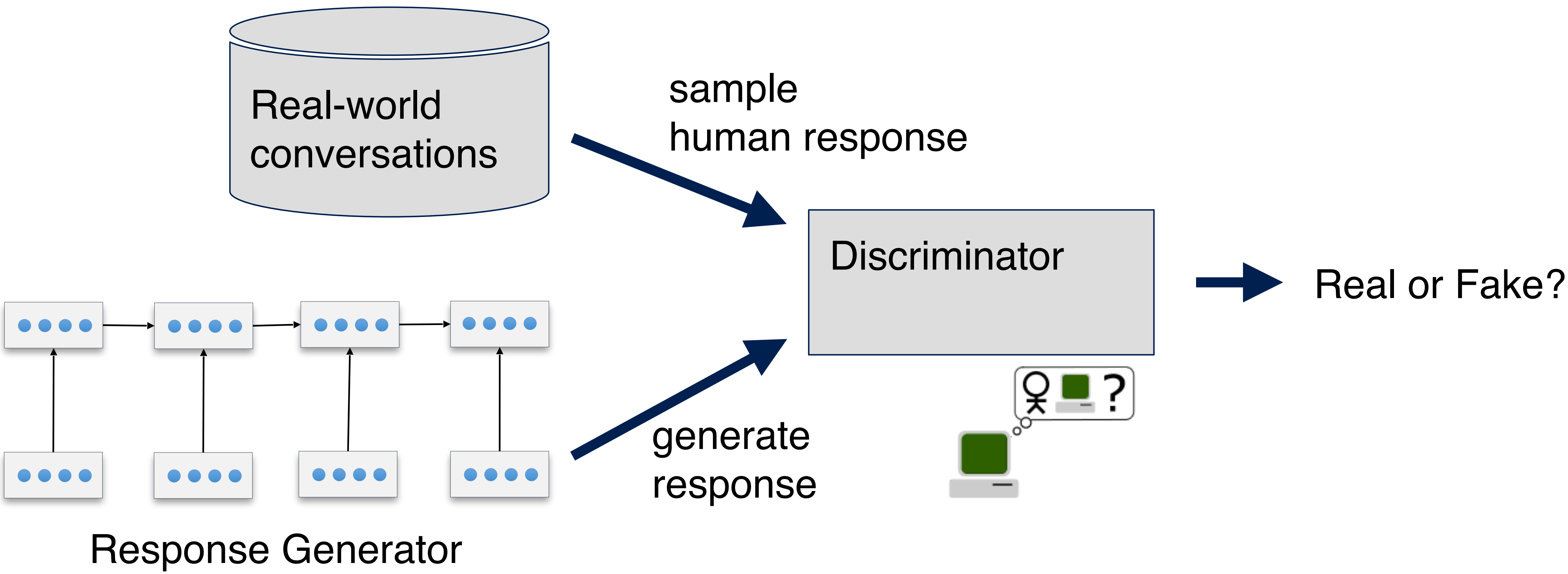

REINFORCE Algorithm (Williams,1992)

Adversarial Learning Improves Response Generation

Human Evaluator:

vs vanilla generation model

Adversarial Win	Adversarial Lose	Tie
62%	18%	20%

Machine Evaluator:
[Bowman et. al. 2016]

Adversarial Success (How often can you fool a machine)

Adversarial Learning	8.0%
Standard Seq2Seq model	4.9%

Slide Credit: Jiwei Li

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Really Natural Language Understanding?

Learning from **Distant Supervision** [Mintz et. al. 2009]

1) Named Entity Recognition

Challenge: highly ambiguous labels
[Ritter, et. al. EMNLP 2011]

2) Relation Extraction

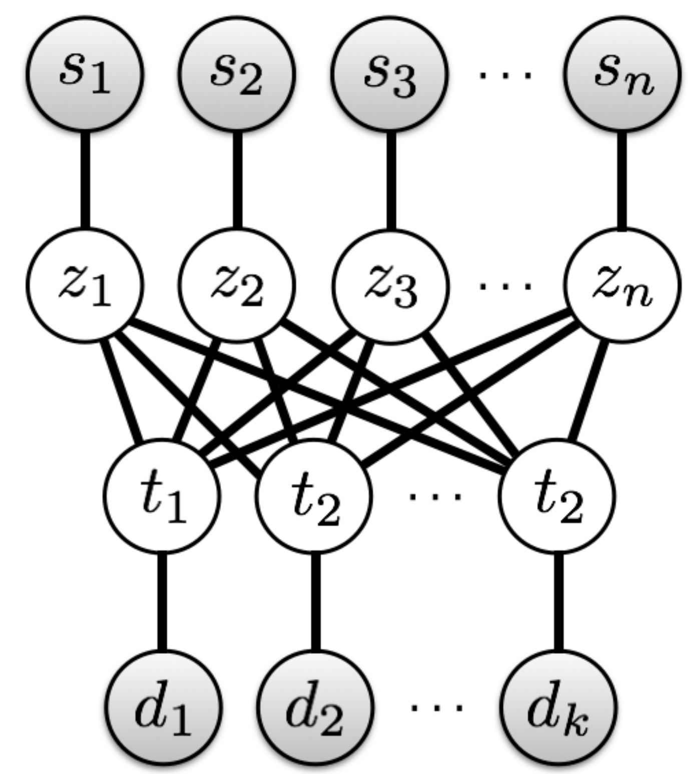
Challenge: missing data
[Ritter, et. al. TACL 2013]

3) Time Normalization

Challenge: diversity in noisy text
[Tabassum, Ritter, Xu, EMNLP 2016]

4) Event Extraction

Challenge: lack of negative examples
[Ritter, et. al. WWW 2015]
[Konovalov, et. al. WWW 2017]



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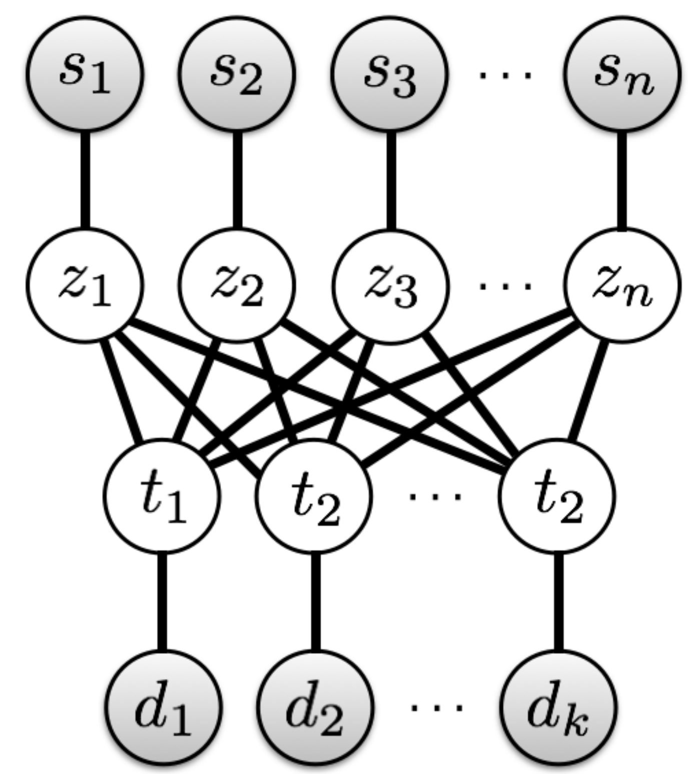

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Time Normalization

[Tabassum, Ritter, Xu EMNLP 2016]

State-of-the-art time resolvers

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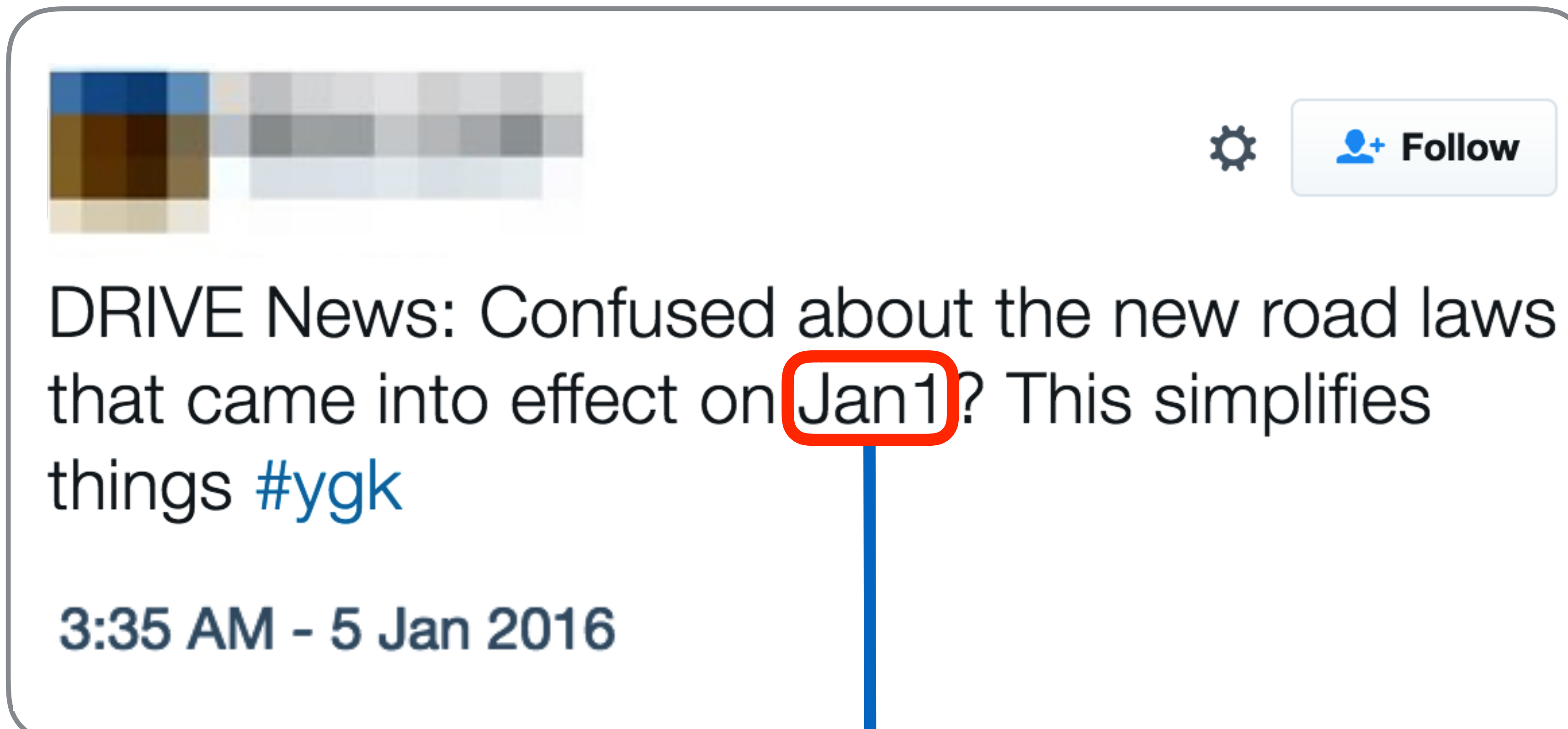
- HeidelTime
- SUTime
- UWTime



1 Jan 2016

Time Normalization

[Tabassum, Ritter, Xu EMNLP 2016]

Distant Supervision
(no human labels or rules!)

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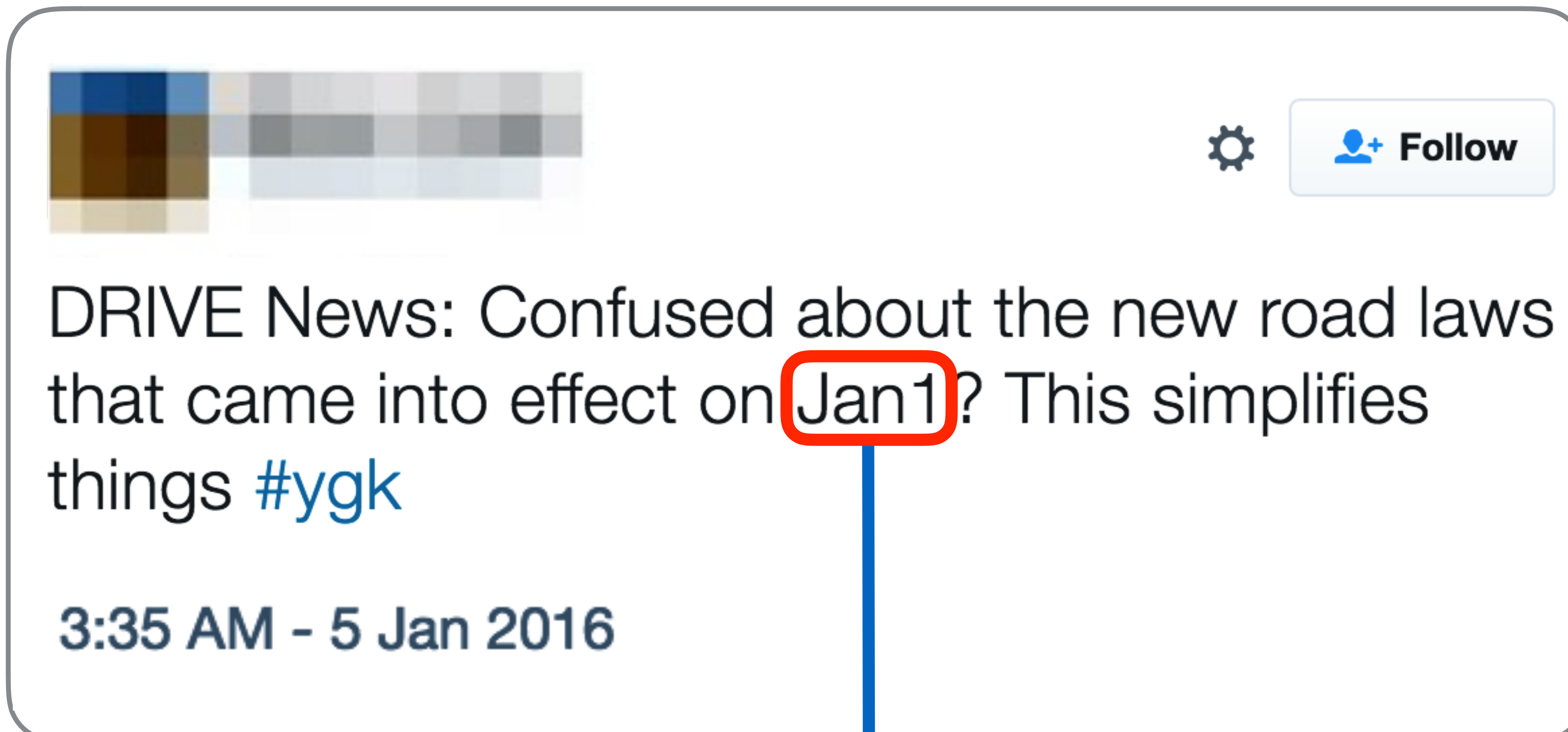

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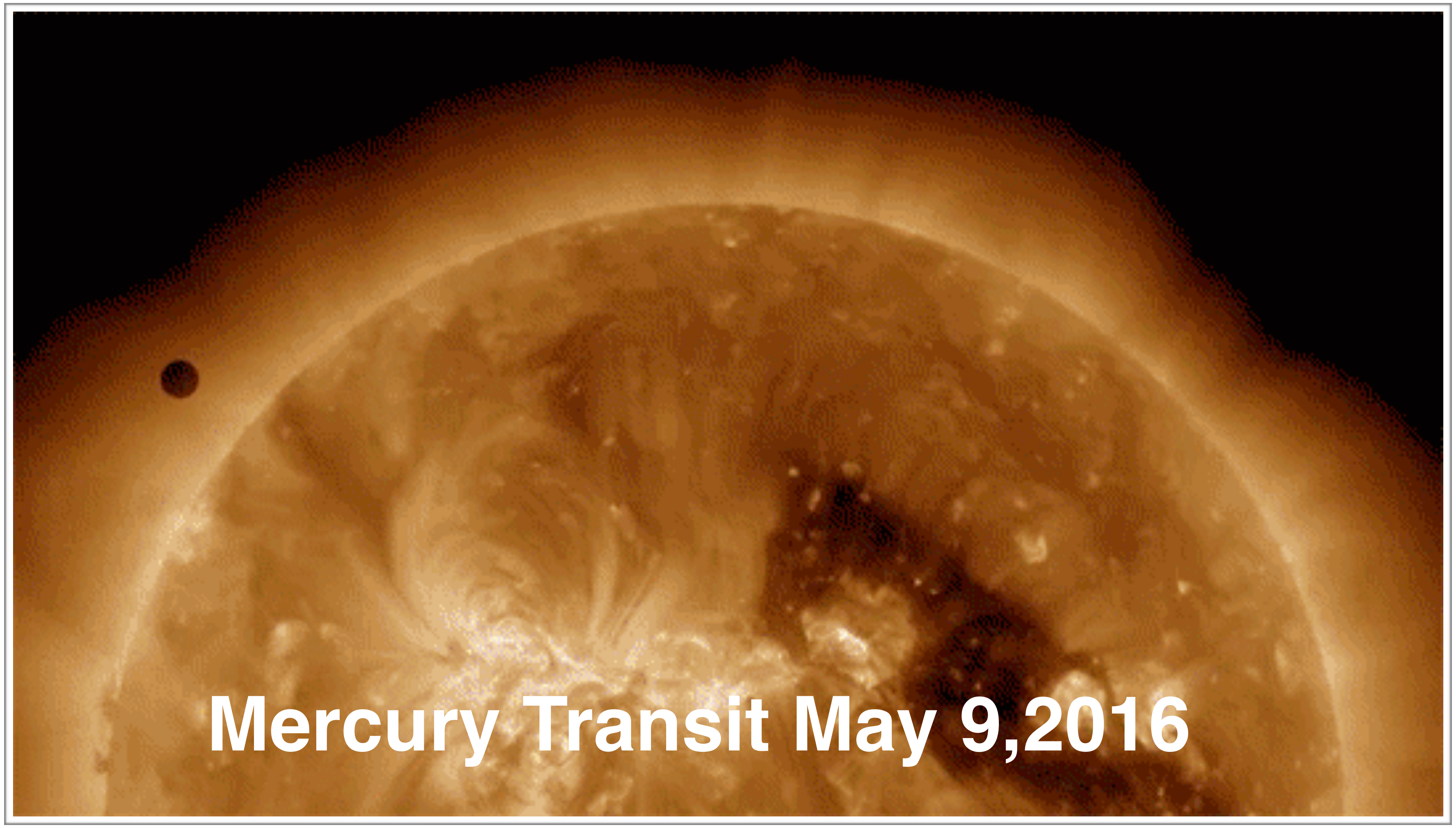

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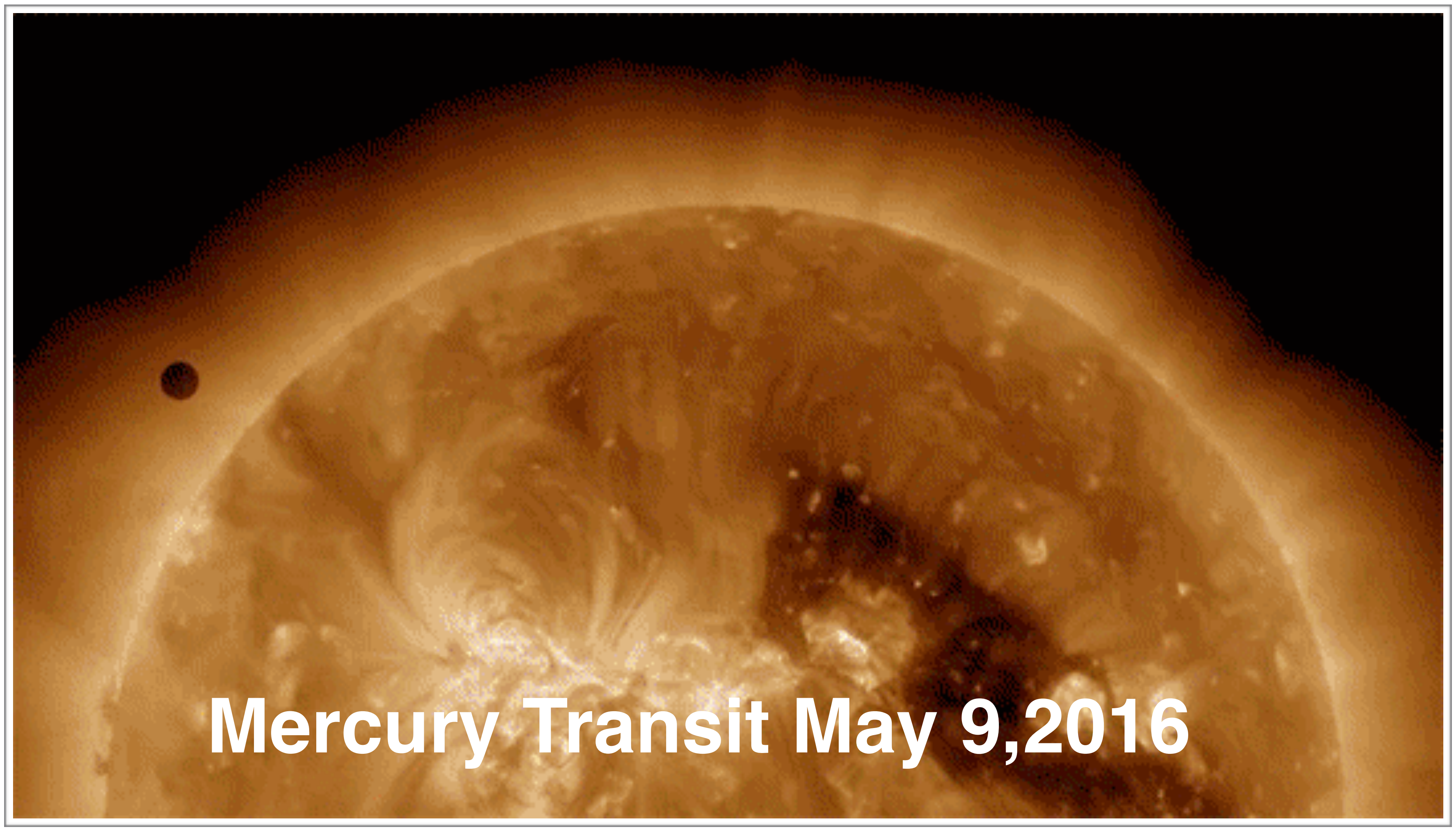
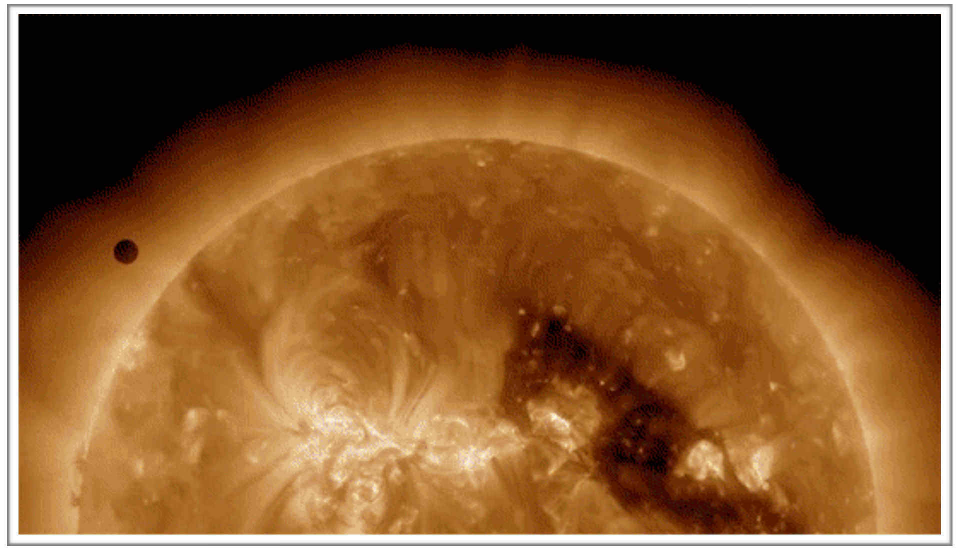


Distant Supervision Assumption

Mercury Transit
May 9,2016



8 May

Follow

Mercury will make a rare transit across the sun tmrw morning (Mon). If you're able to catch it, don't miss out -- and use a solar filter!

10:28 PM - 8 May 2016

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7:30 PM - 8 May 2016

9 May

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Paul from Creators Hand Photography captured a shot of today's Mercury transit, along with a larger sunspot that... fb.me/7jaxf4rfC

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i didn't get to see mercury transit today because of this horrible weather 😤

3:54 PM - 9 May 2016

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I watched this event yesterday by a small telescope with all the precautions, but this transit of Mercury is great!

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Mercury passes between Earth and the sun only about 13 times a century.
It was yesterday! May 9th #lagalaxiaensmira

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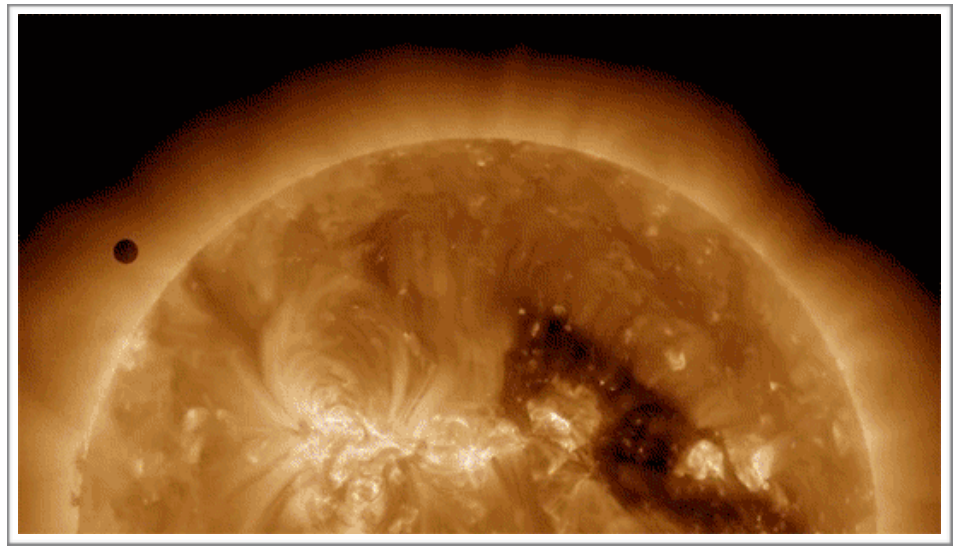

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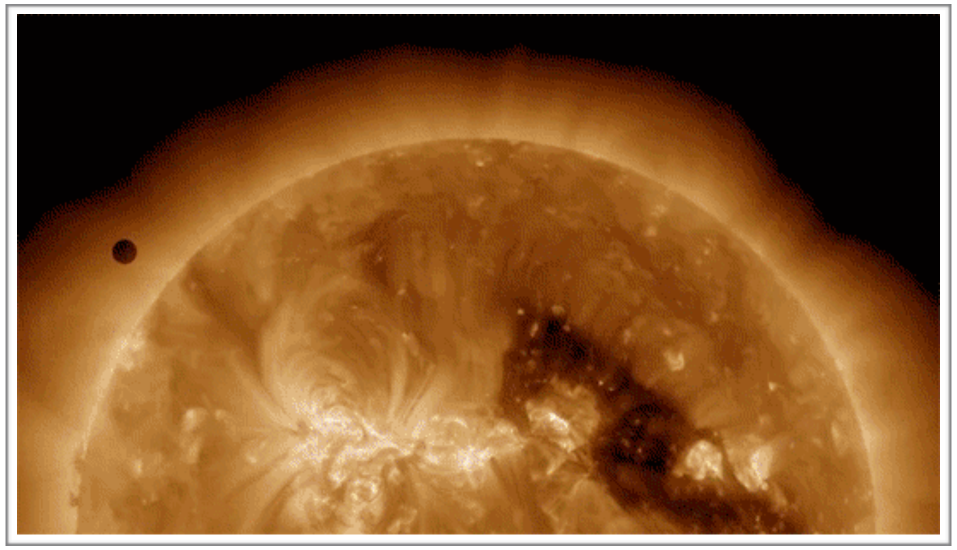

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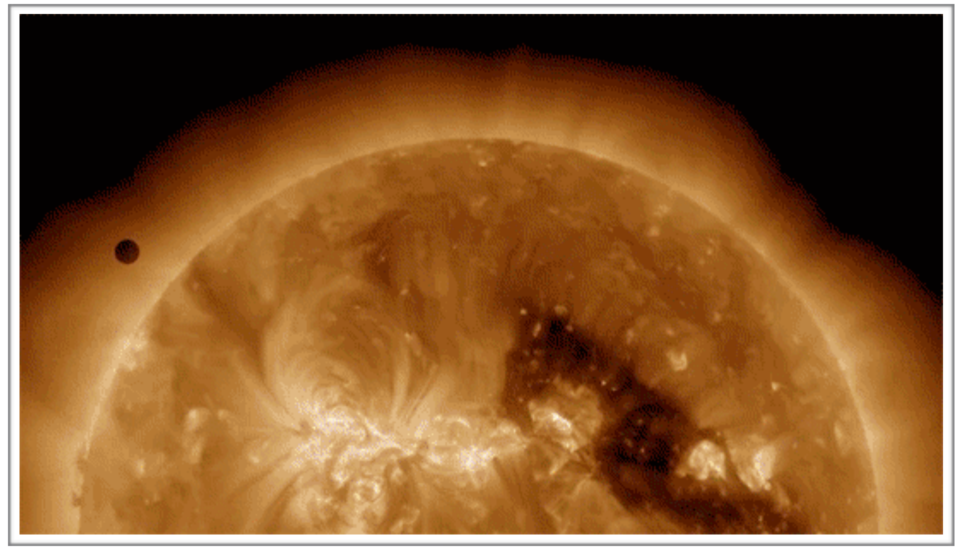

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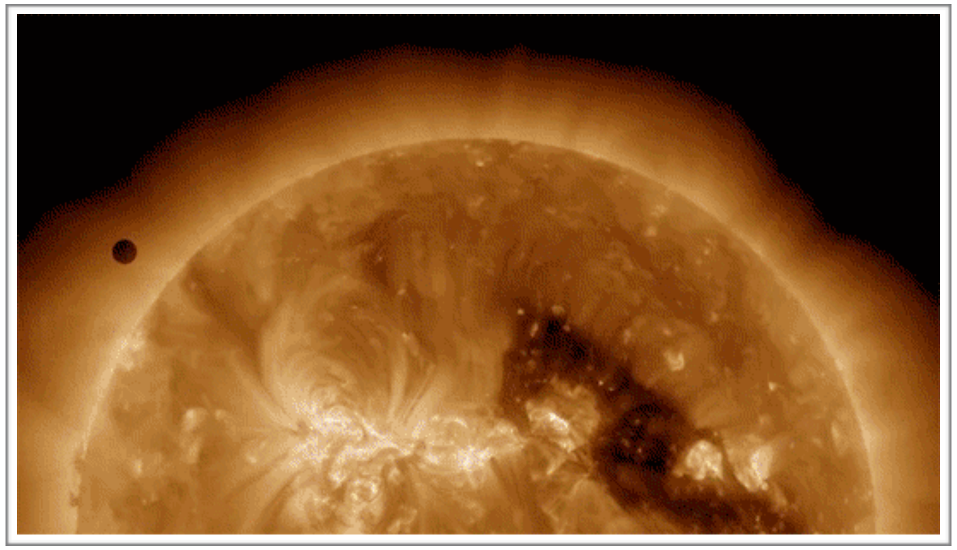

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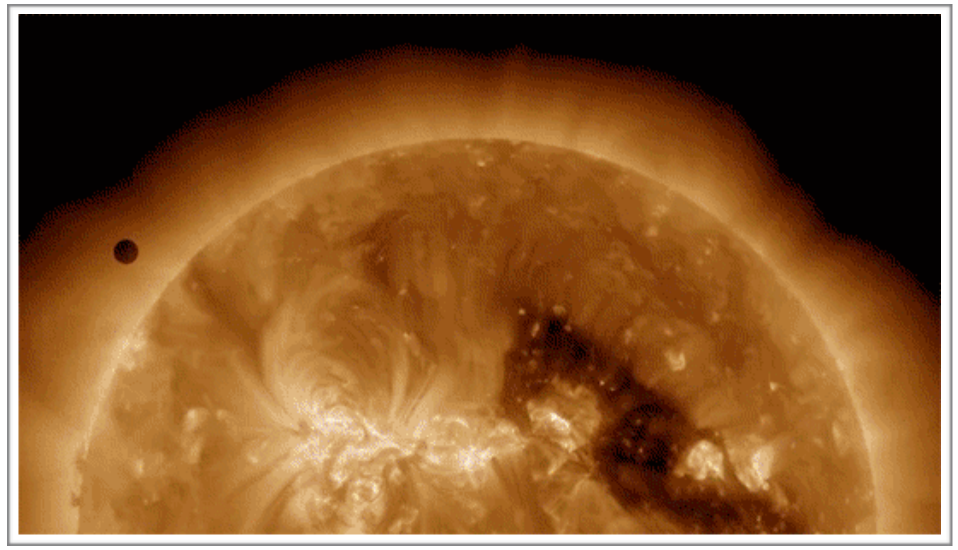

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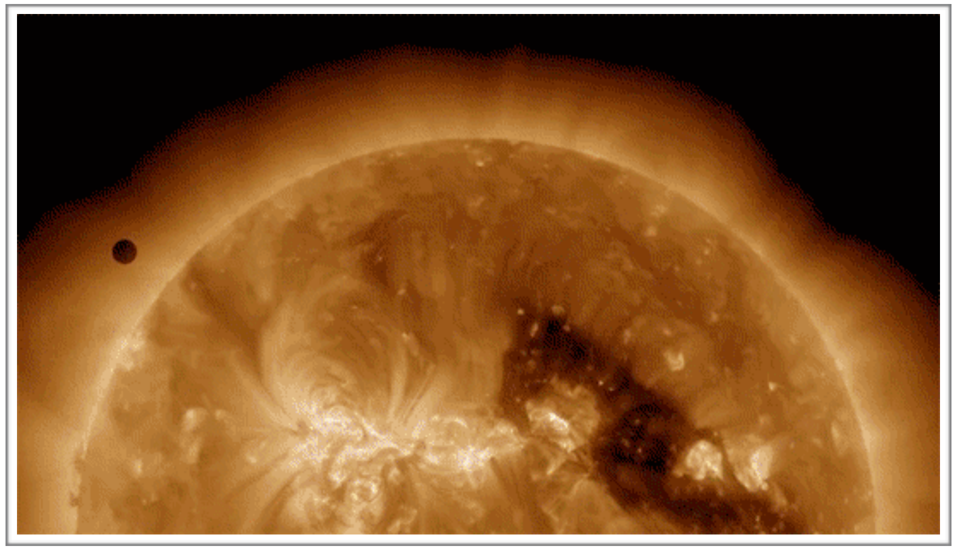
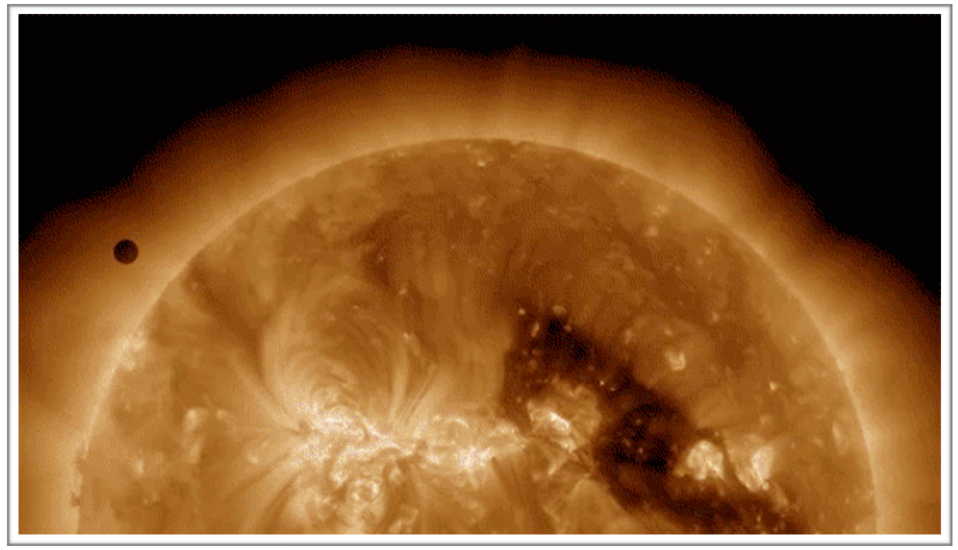
May 9,2016

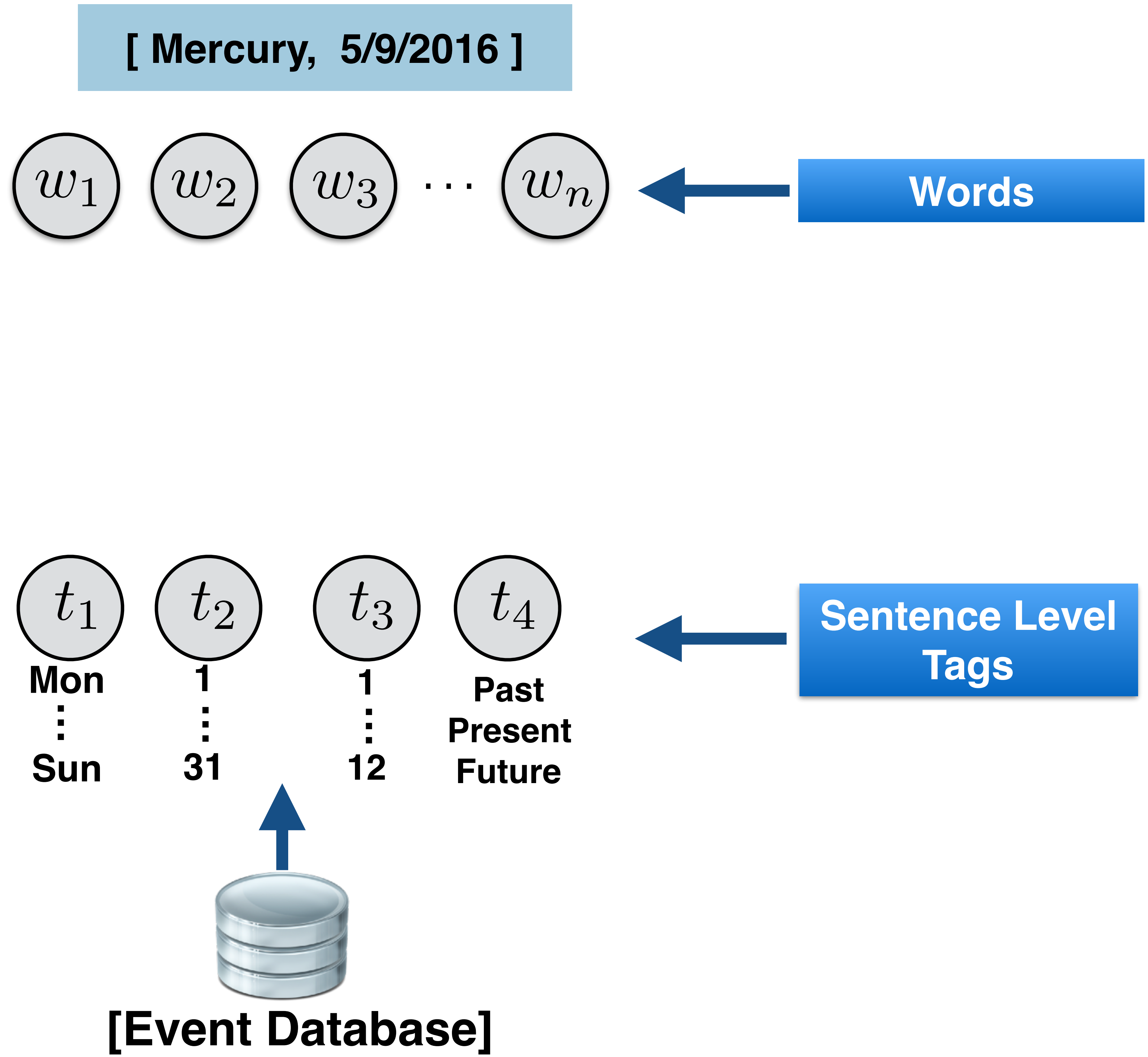


Distant Supervision Assumption

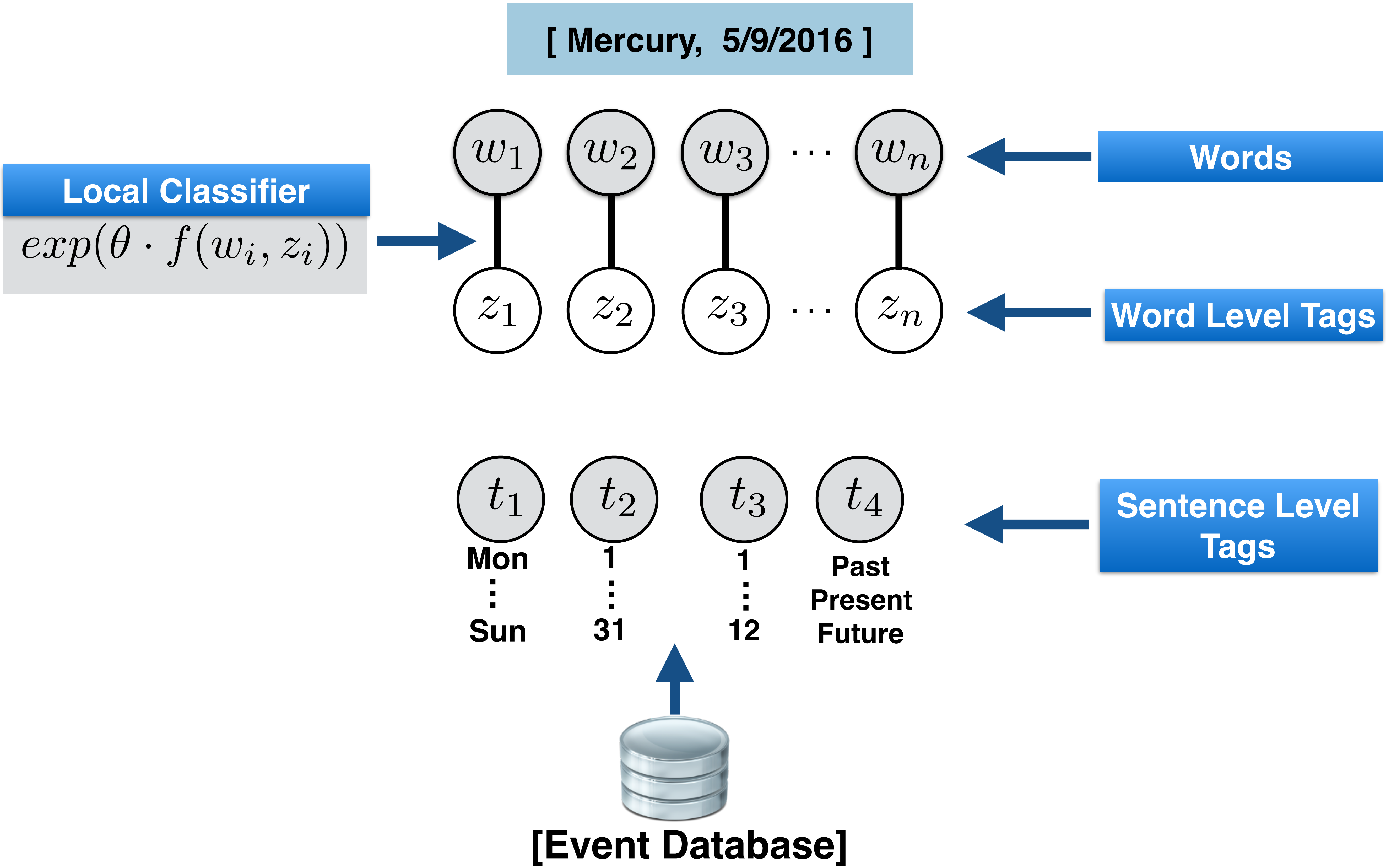
Mercury Transit
May 9,2016



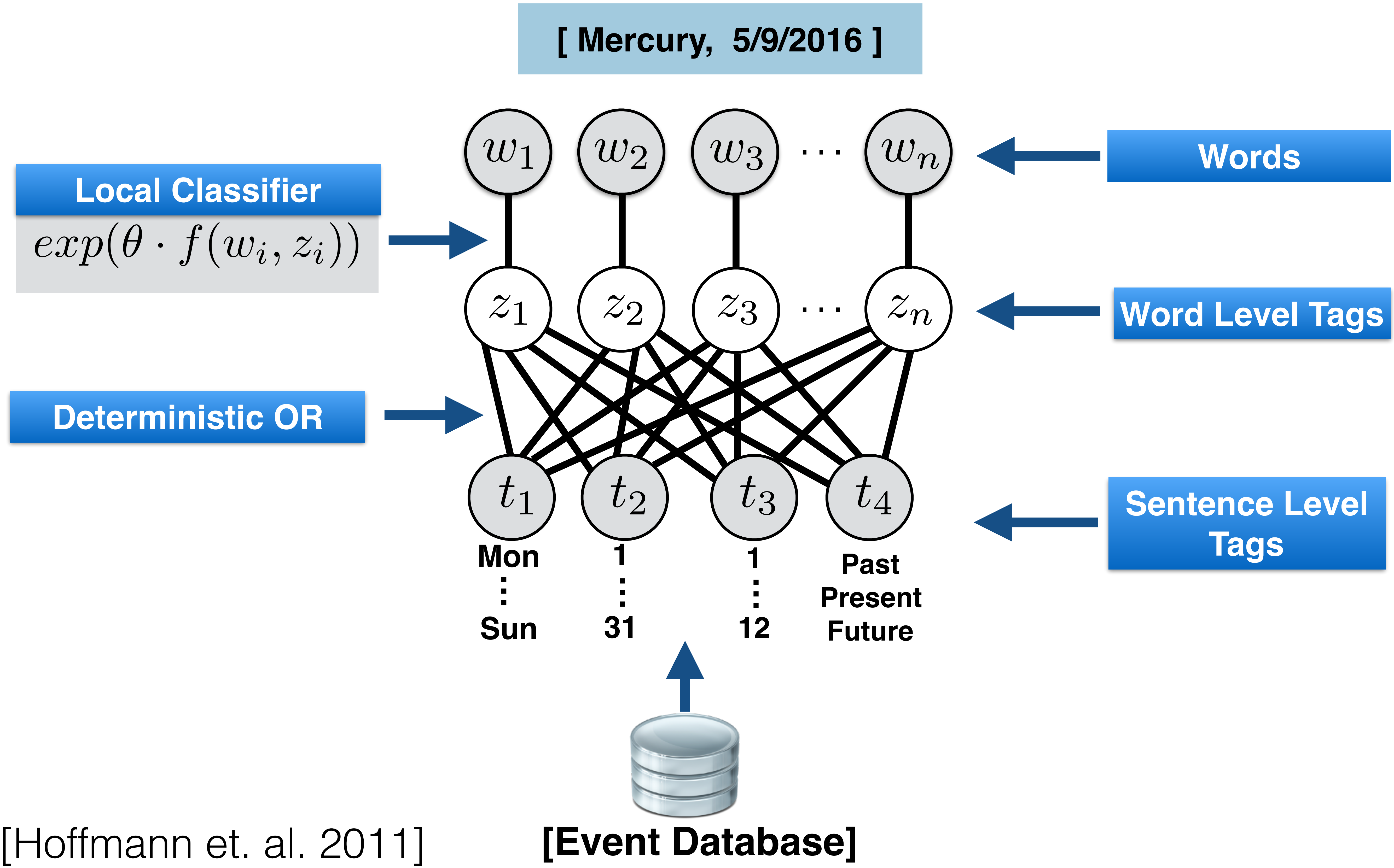
Multiple Instance Learning Tagger



Multiple Instance Learning Tagger

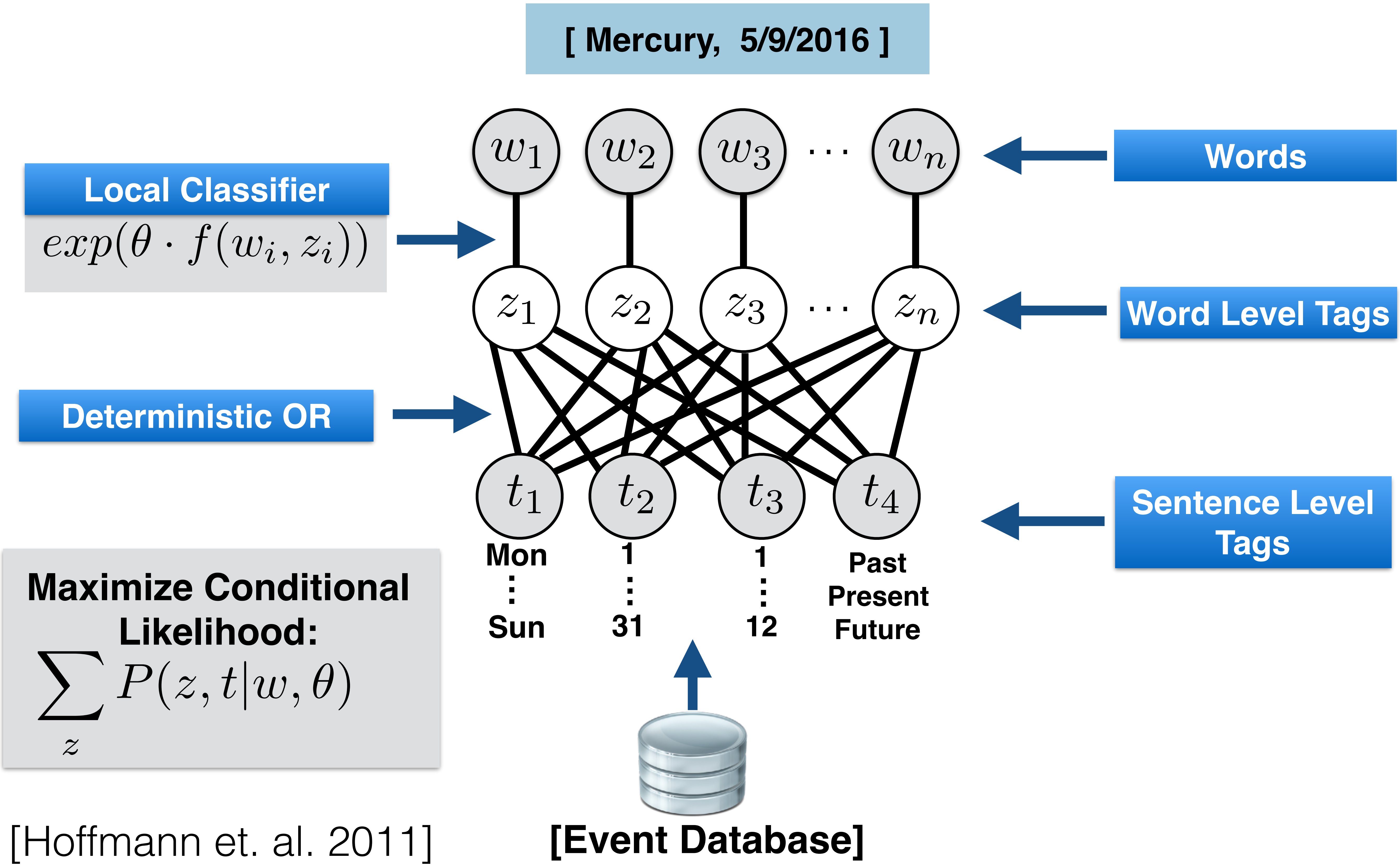


Multiple Instance Learning Tagger



[Hoffmann et. al. 2011]

Multiple Instance Learning Tagger



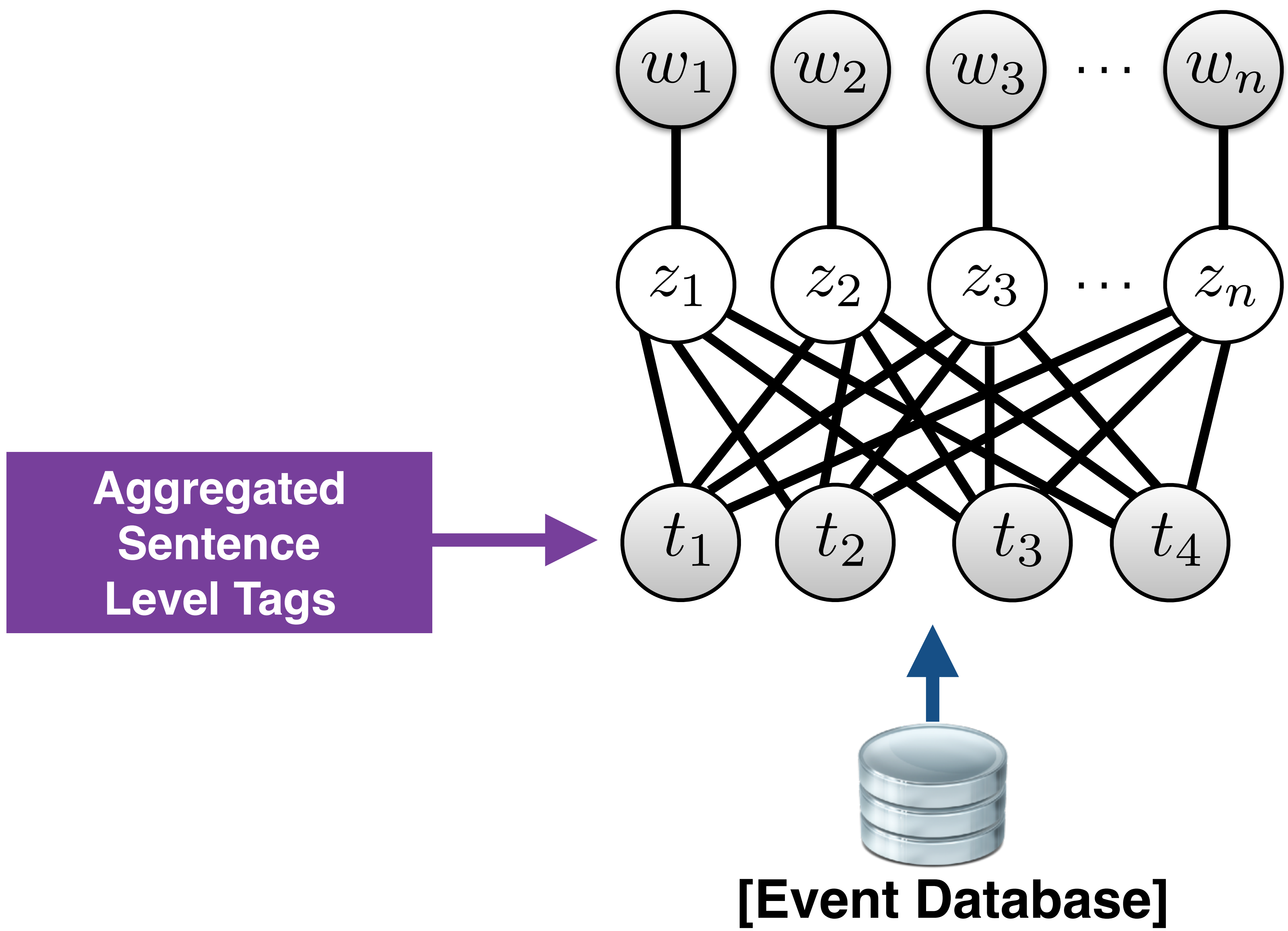
[Hoffmann et. al. 2011]

Missing Data Problem

Sentence Level Tags:

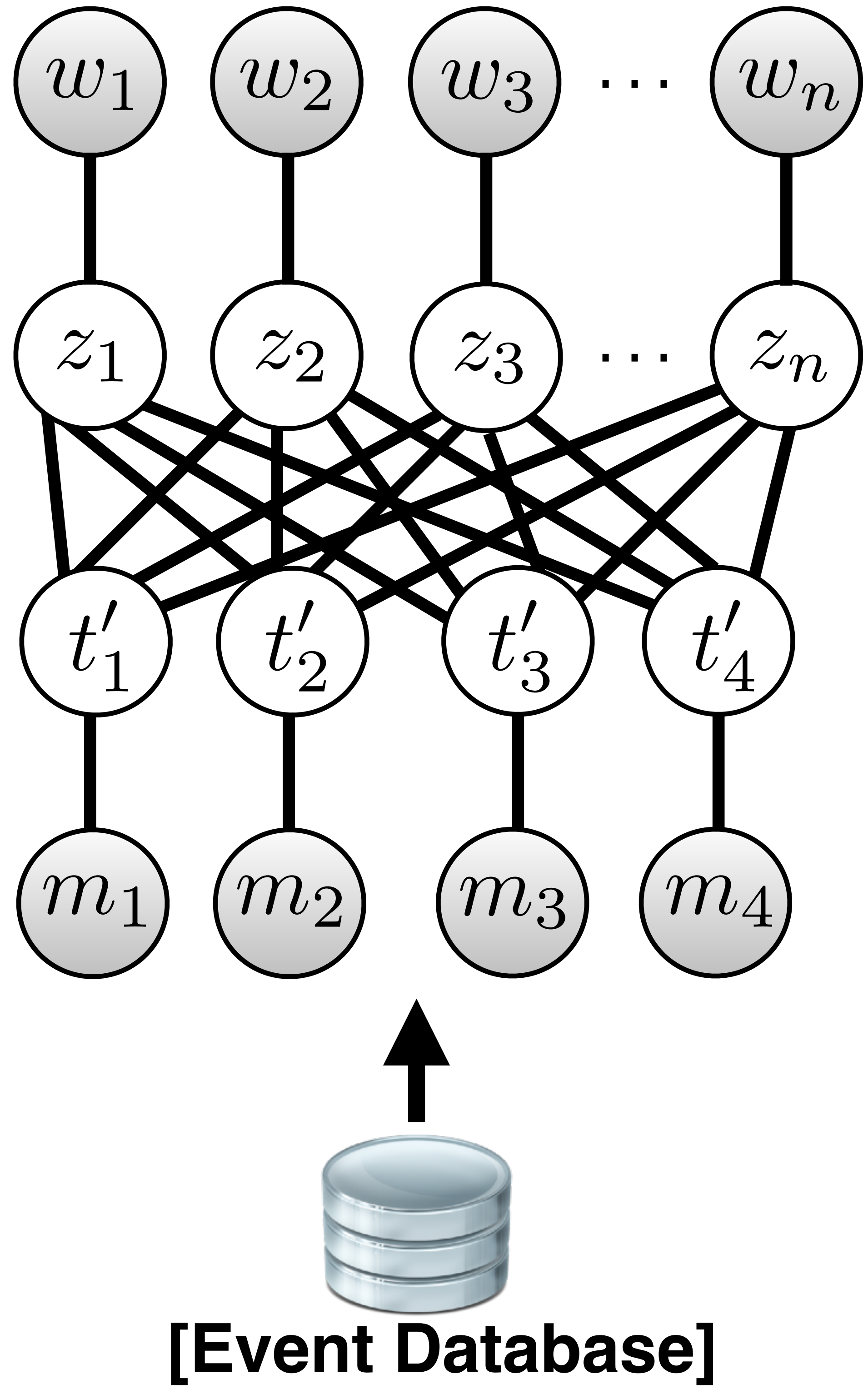
- ✔ TL = Future
- ✘ MOY= May
- ✘ DOM=9
- ✔ DOW= Mon

Missing Data Extension



Missing Data Extension

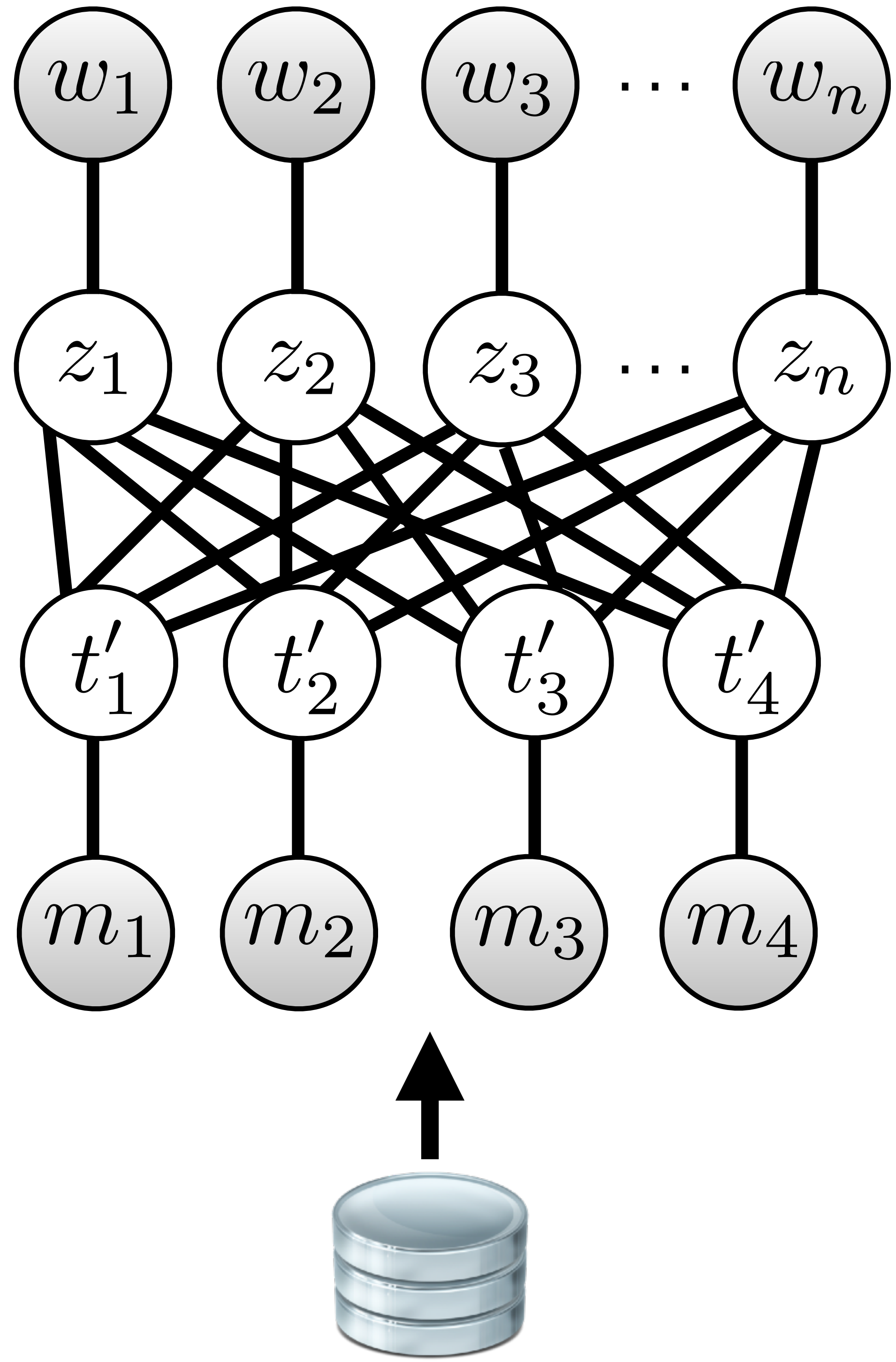
Missing Data Problem
In Distant Supervision
[Ritter, et. al. TACL 2013]



Missing Data Extension

Missing Data Problem
In Distant Supervision
[Ritter, et. al. TACL 2013]

Mentioned in Text



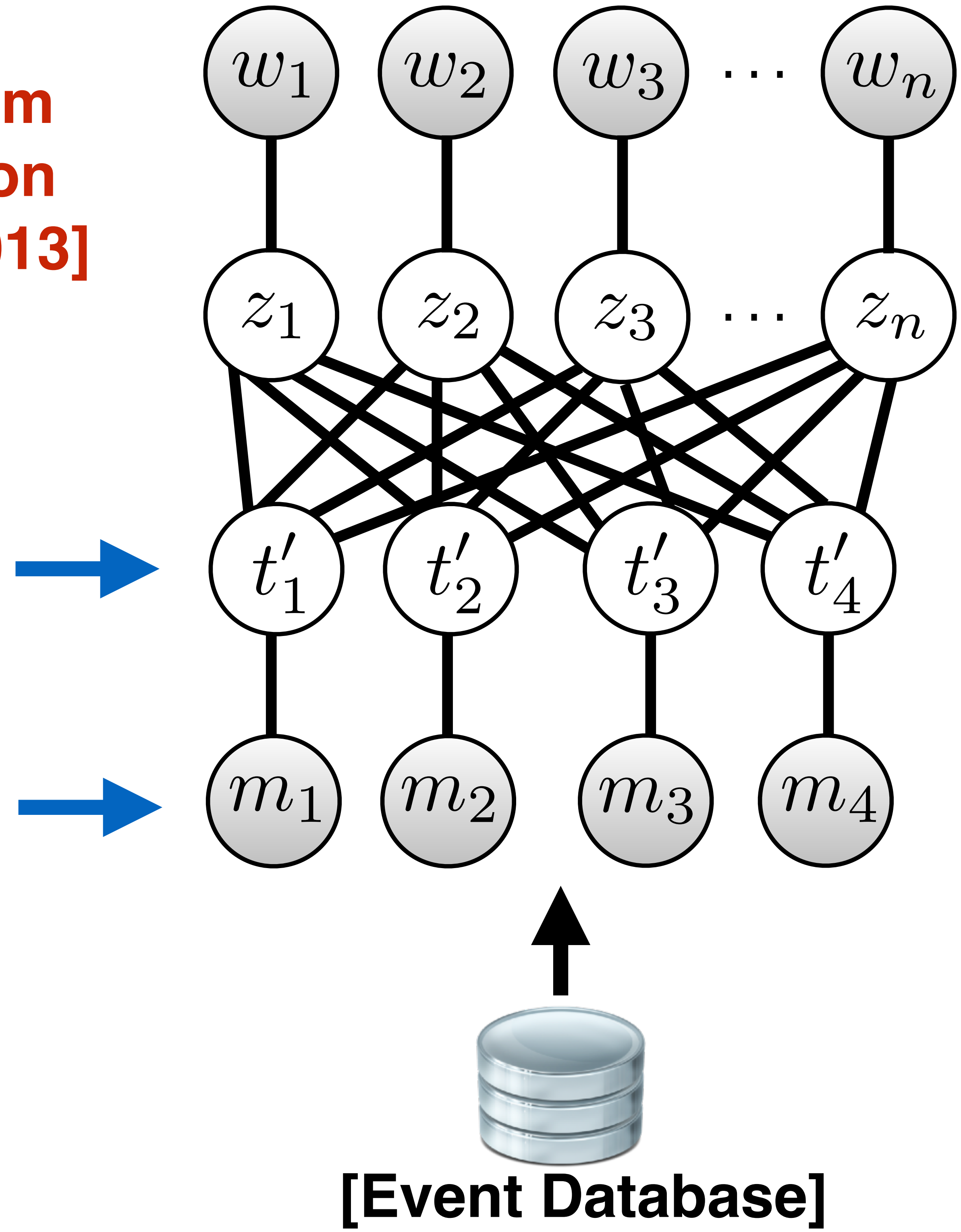
[Event Database]

Missing Data Extension

Missing Data Problem
In Distant Supervision
[Ritter, et. al. TACL 2013]

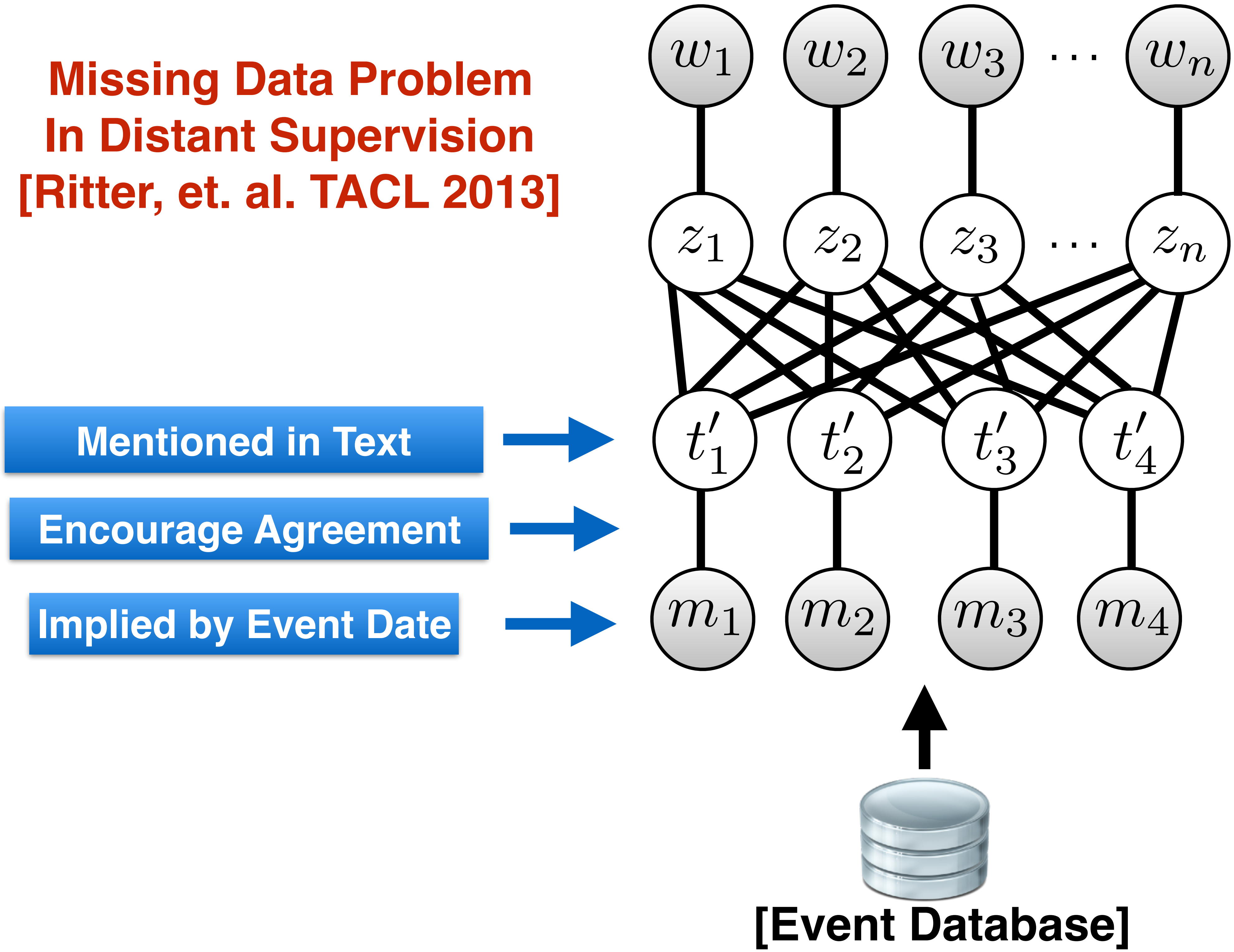
Mentioned in Text

Implied by Event Date



Missing Data Extension

Missing Data Problem
In Distant Supervision
[Ritter, et. al. TACL 2013]

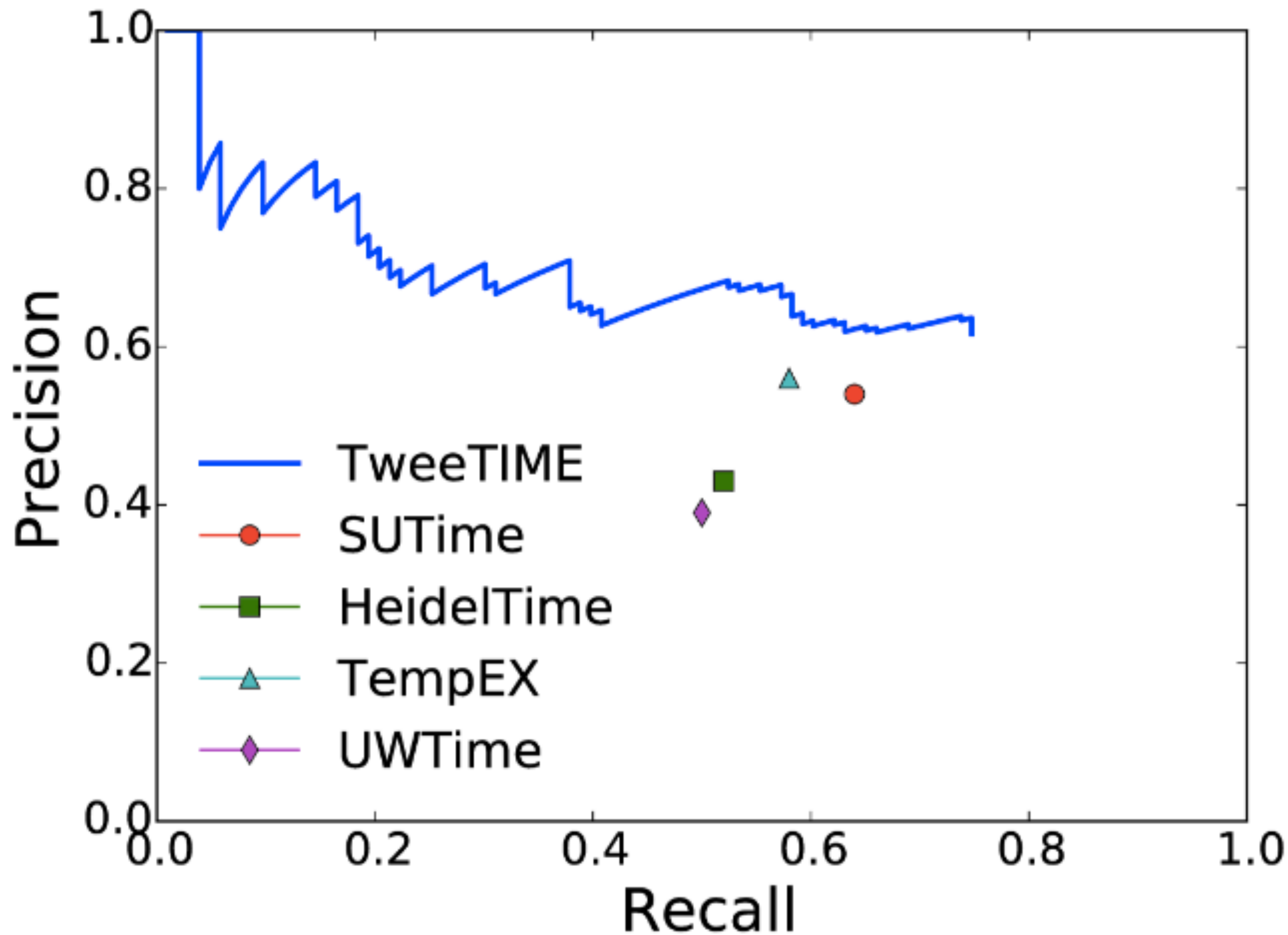


Example Tags

Word	Im	Hella	excited	for	tomorrow
Tag	NA	NA	Future	NA	Future

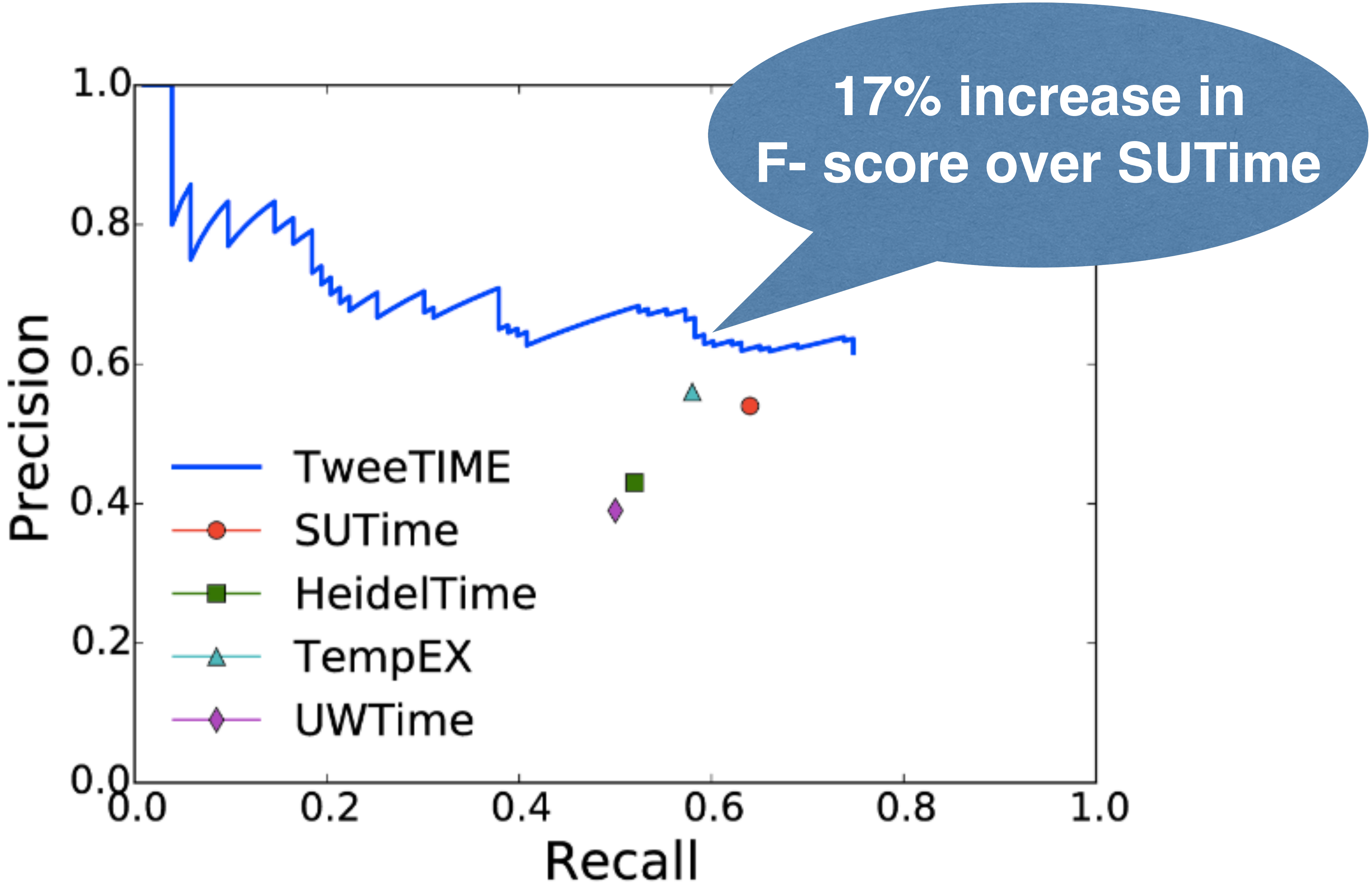
Word	Thnks	for	a	Christmas	party	on	fri
Tag	NA	NA	NA	December	NA	NA	Friday

Evaluation

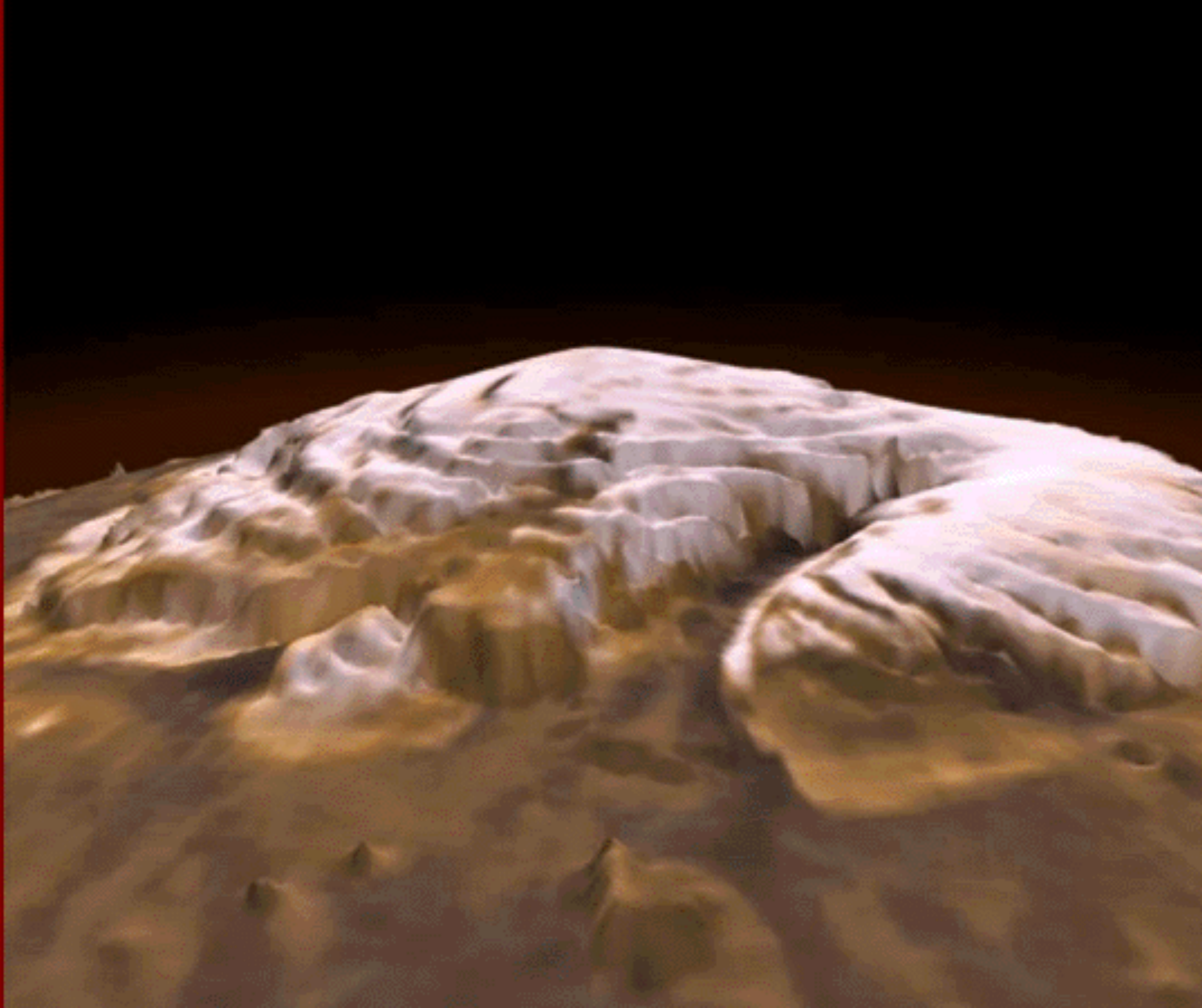


Precision
Recall
TweeTIME
SUTime
HeidelTime
TempEX
UWTime
0.0
0.2
0.4
0.6
0.8
1.0

Evaluation


17% increase in
F- score over SUTime
Precision
Recall
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
TweeTIME
SUTime
HeidelTime
TempEX
UWTime

Following the Water: The Mars Exploration Program



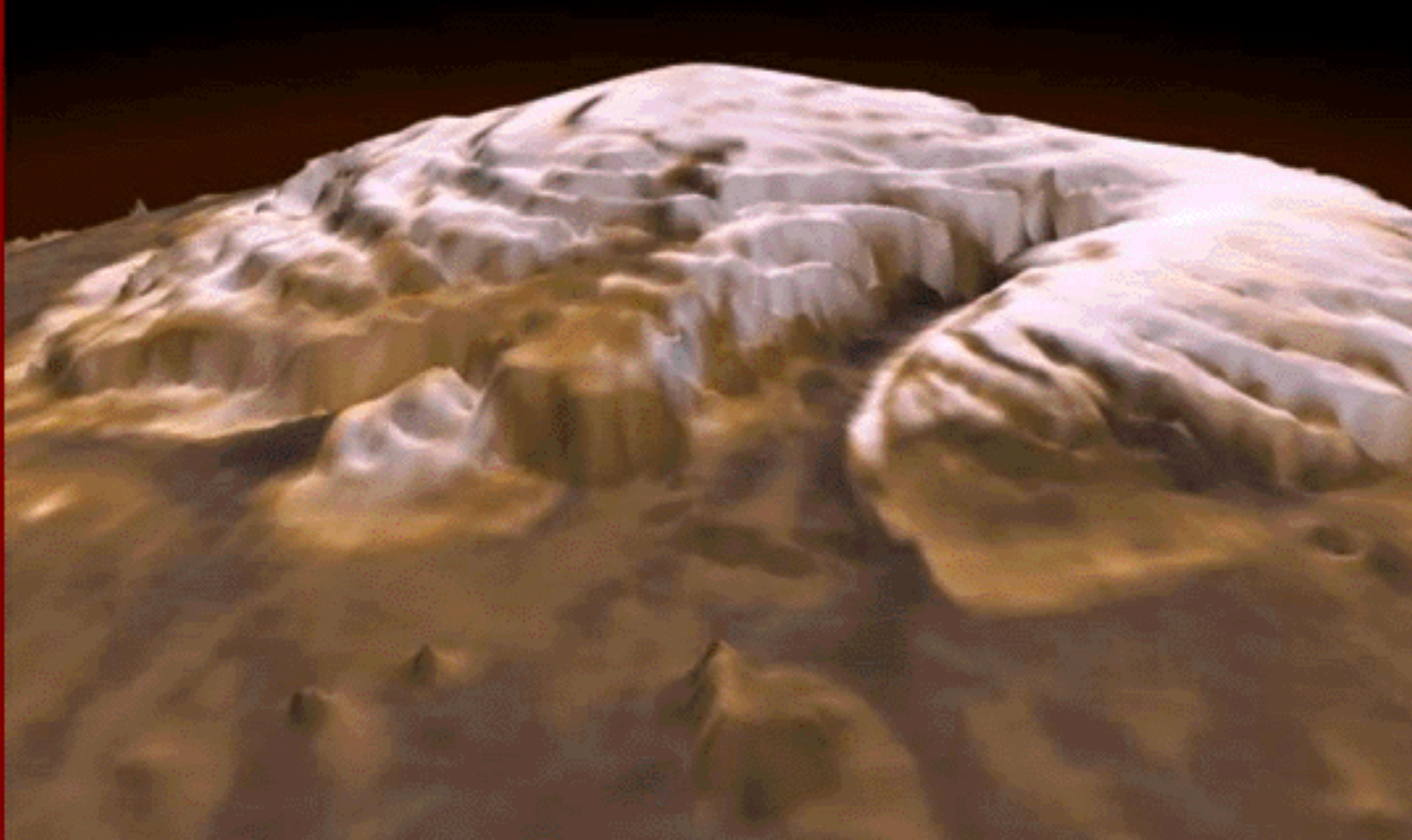
Orlando Figueroa, Director

Dr. Jim Garvin, Lead Scientist

Mars Exploration Program
NASA

Following the Water:
Program

Where can we find NLU?



Orlando Figueroa,
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Dr. Jim Garvin,
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Mars Exploration
Program
NASA

Following the Water:
Program

Where can we find NLU?
Follow the data!

Orlando Figueroa,
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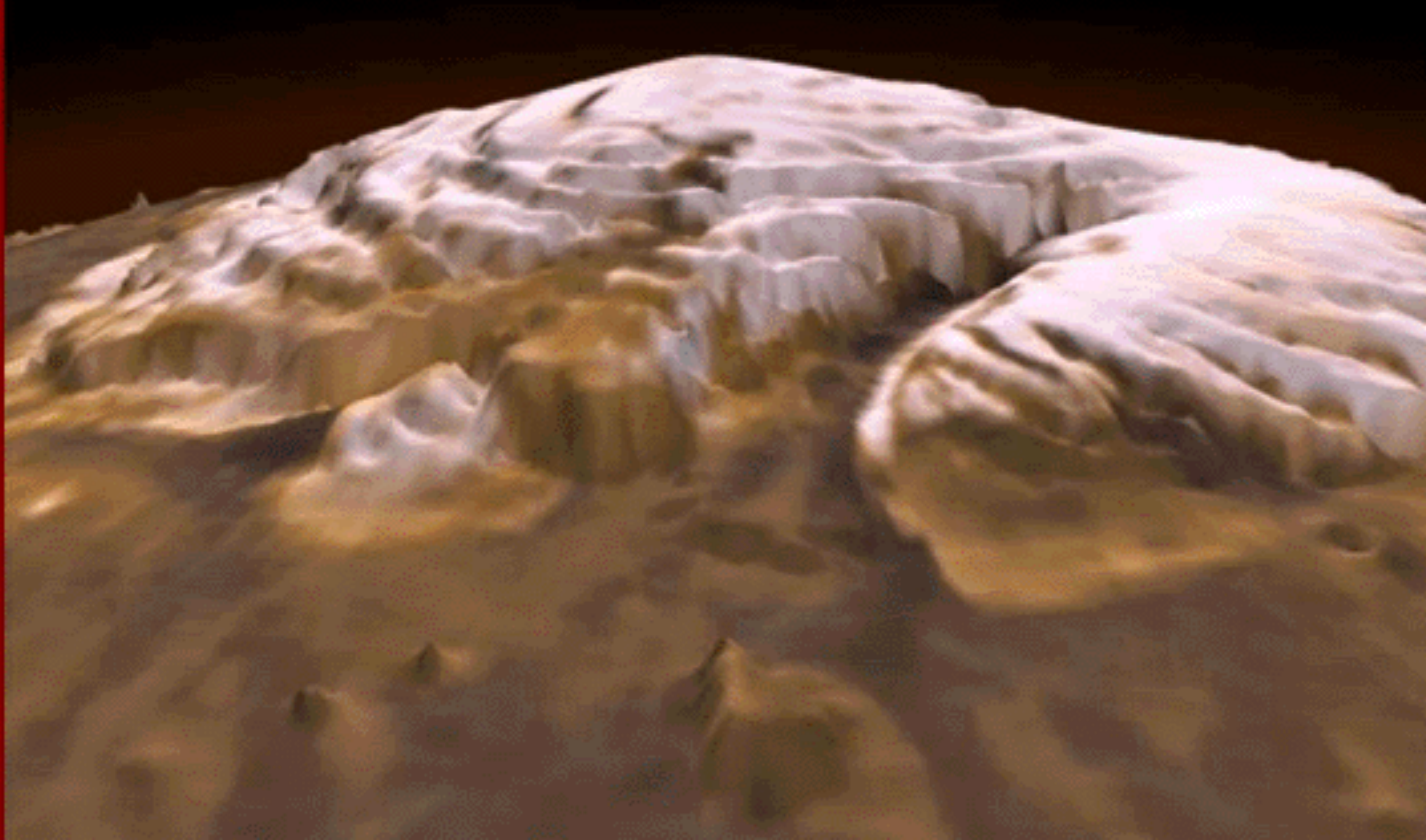
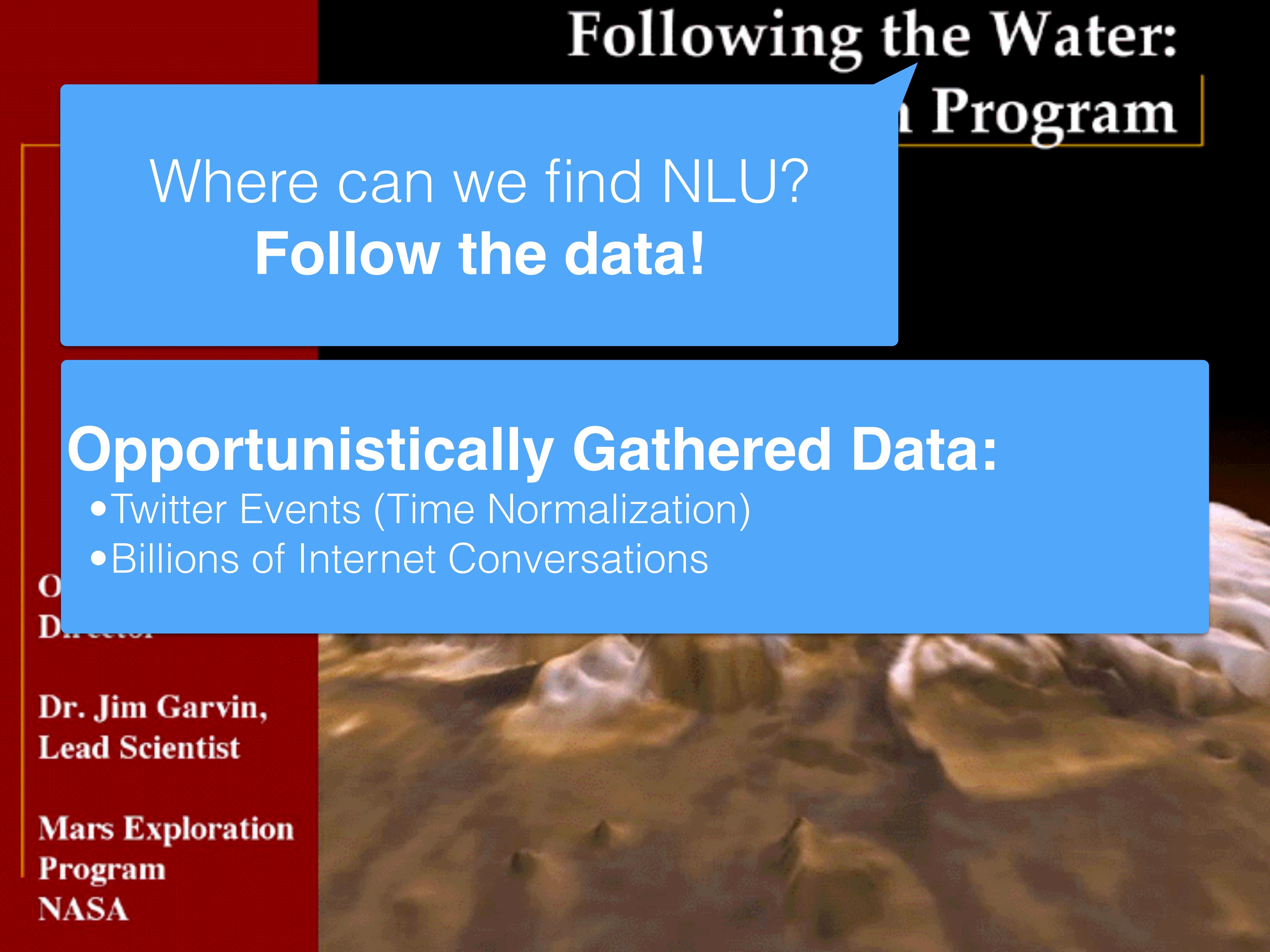
Mars Exploration
Program
NASA



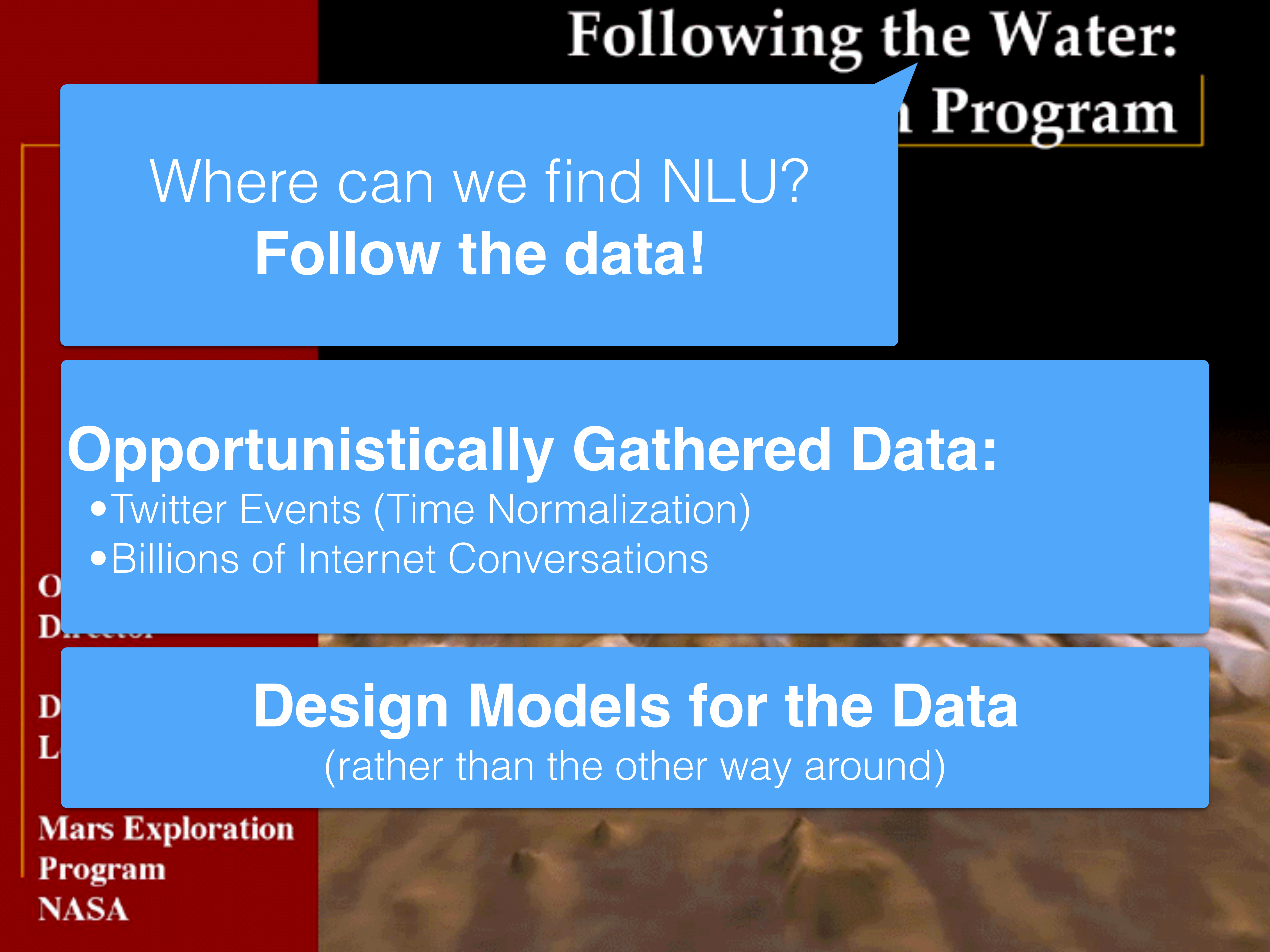


Where can we find NLU?

Follow the data!

Opportunistically Gathered Data:

- Twitter Events (Time Normalization)
- Billions of Internet Conversations


Following the Water:
Program
Where can we find NLU?
Follow the data!
Opportunistically Gathered Data:
•Twitter Events (Time Normalization)
•Billions of Internet Conversations
Design Models for the Data
(rather than the other way around)
Mars Exploration
Program
NASA

Following the Water:

...n Program

Where can we find NLU?

Follow the data!

Opportunistically Gathered Data:

- Twitter Events (Time Normalization)
- Billions of Internet Conversations

Design Models for the Data

(rather than the other way around)

Mars Exploration Program
NASA

Thank You!