Spoken Language Understanding

EE596B/LING580K -- Conversational Artificial Intelligence

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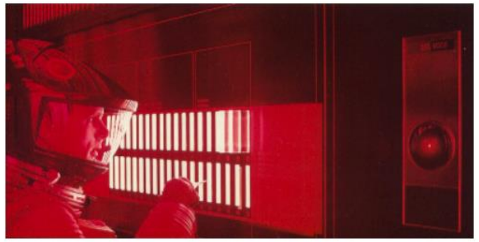
“Can machines think?”

A. M. Turing (1950) – Computing Machinery and Intelligence

“Nevertheless I believe that at the end of the century the use of words and general educated opinion will have altered so much that one will be able to speak of machines thinking without expecting to be contradicted.”

Sci-fi vs. Reality

HAL



David Bowman: Open the pod bay doors, HAL.

HAL: I'm sorry, Dave, I'm afraid I can't do that.

David: What are you talking about, HAL?

HAL: I know that you and Frank were planning to disconnect me, and I'm afraid that's something I cannot allow to happen.

Siri (2011)

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?

example from Andrew McCallum

Language Understanding

- Goal: extract **meaning** from natural language
- Ray Jackendoff (2002) – "Foundations of Language"
  - *"meaning" is the "holy grail" for linguistics and philosophy*
- **Spoken** Language Understanding (SLU)
  - self-corrections
  - hesitations
  - repetitions
  - other irregular phenomena

Terminology: NLU, NLP, ASR, TTS

- **N**atural **L**anguage **P**rocessing
- **N**atural **L**anguage **U**nderstanding
- **A**utomatic **S**peech **R**ecognition
- **T**ext-**T**o-**S**peech

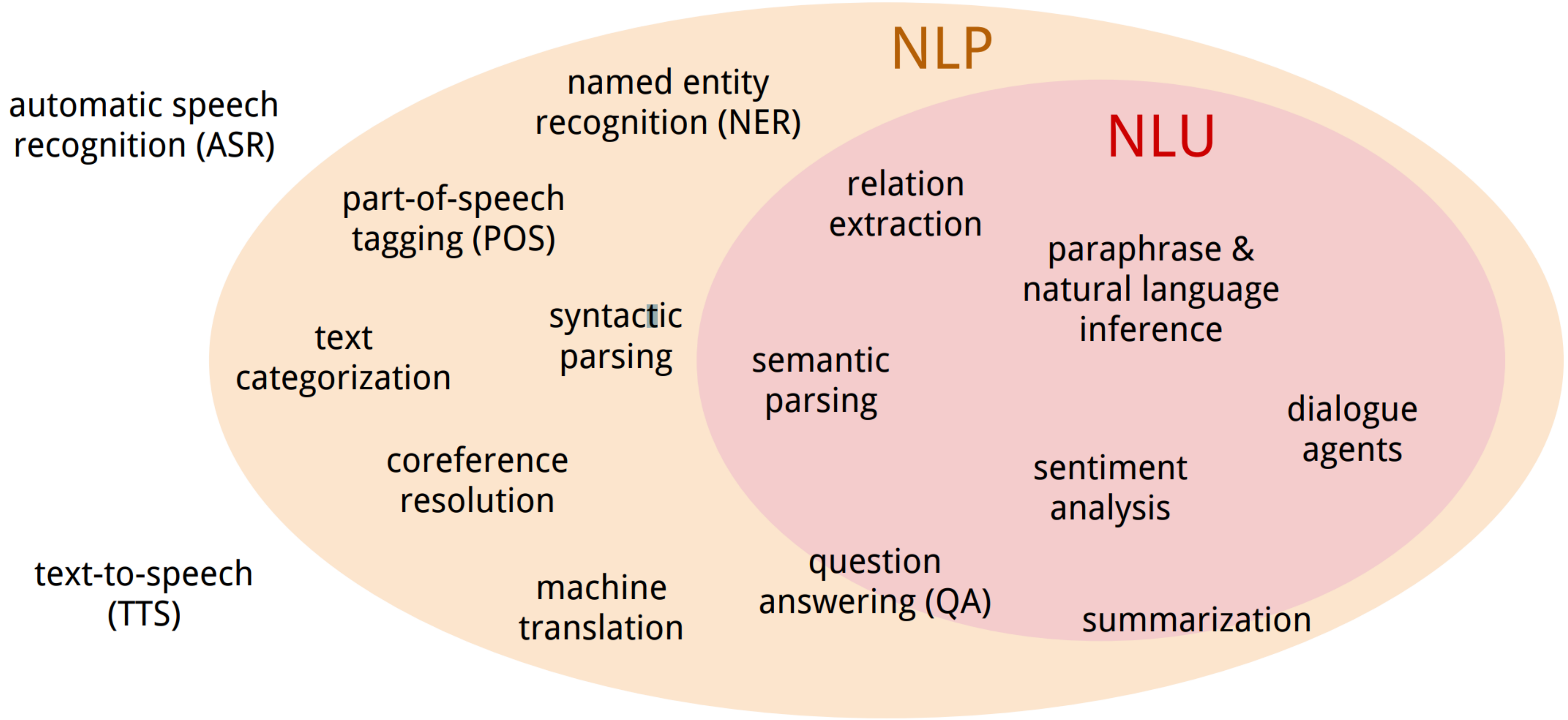


Figure from: Bill MacCarteny – "Understanding Natural Language Understanding" (July 16, 2014)

Early SLU systems

- Historically, early SLU systems used **text-based NLU**.
- S control: ASR generates a sequence of word hypotheses.
  - Knowledge Source (KS): acoustic, lexical, language knowledge
- NLU control: text-based NLU
  - KS: syntactic and semantic

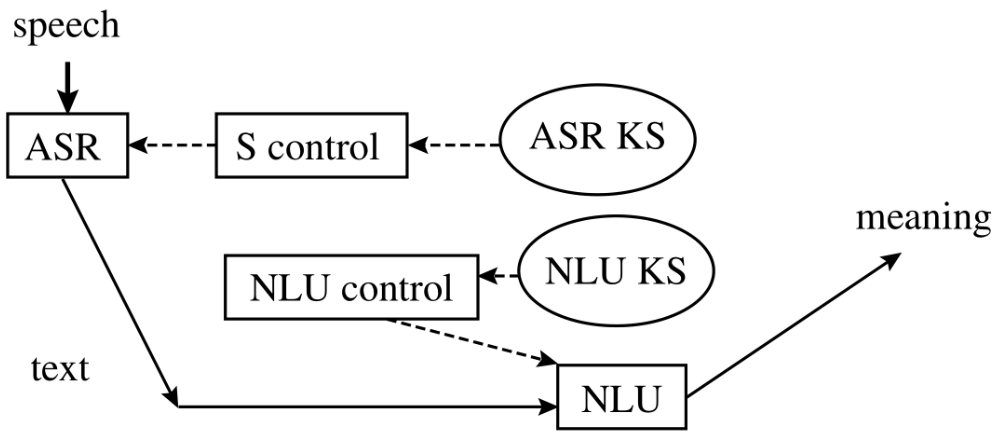


Figure 2.1 Scheme of early SLU system architectures

Figure from: Gokhan Tur and Renato De Mori (2011) – “Spoken Language Understanding”.

Meaning Representation Language (MRL)

- Programming Languages
  - syntax: legal programming statements
  - semantics: operations a machine performs when a syntactically correct statement is executed
- An MRL also has its own *syntax* and *semantics*
- Coherent with a *semantic theory*
- Crafted based on the desired capability of each application
- Two widely accepted MRL framework
  - FrameNet: https://framenet.icsi.berkeley.edu/fndrupal/
  - PropBank: https://propbank.github.io/

Frame-based SLU

Frame-based SLU

- The structure of the semantic space can be represented by a set of ***semantic frames***.
- Each frame contains several typed components called ***slots***.
- Goal: choose correct semantic frame for an utterance and fill the slots based on the utterance.

```
<frame name="ShowFlight" type="Void">
    <slot name="topic" type="Topic">
    <slot name="flight" type="Flight">
</frame>
<frame name="GroundTrans" type="Void">
    <slot name="city" type="City">
    <slot name="type" type="TransType">
</frame>
<frame name="Flight" type="Flight">
    <slot name="DCity" type="City">
    <slot name="ACity" type="City">
    <slot name="DDate" type="Date">
</frame>
```


Table from: Gokhan Tur and Renato De Mori (2011) – "Spoken Language Understanding".

Frame-based SLU: Example

- Show me flights from Seattle to Boston on Christmas Eve.

<ShowFlight>
 <**topic** type="Freeform">FLIGHT</**topic**>
 <**flight** frame="*Flight*" type="Flight">
  <**DCity** type="City">SEA</**DCity**>
  <**ACity** type="City">BOS</**ACity**>
  <**DDate** Type="Date">12/24</**DDate**>
 </**flight**>
</ShowFlight>

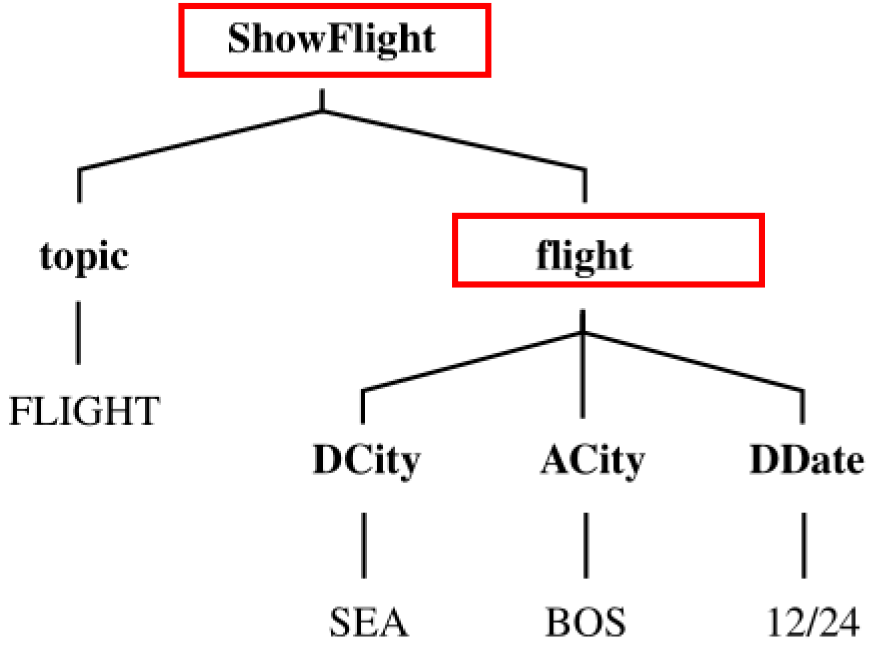


Table from: Gokhan Tur and Renato De Mori (2011) – "Spoken Language Understanding".

Simpler Frame-based SLU

- Some SLU systems do not allow any sub-structures in a frame.
- *attribute-value pairs / keyword-pairs / flat concept*

[**topic**: FLIGHT] [**DCity**: SEA] [**ACity**: BOS][**DDate**: 12/24]

Figure 3.4 The attribute-value representation is a special case of the frame representation where no embedded structure is allowed. Here is an attribute-value representation for "Show me the flights from Seattle to Boston on Christmas Eve" (Wang *et al.*, © 2005 IEEE)

Figure from: Gokhan Tur and Renato De Mori (2011) – "Spoken Language Understanding".

Technical Challenges

- Extra-grammaticality
  - not as well-formed as written language
  - people are in general less careful with speech than with writing
  - no rigid syntactic constraints
- Disfluencies
  - false starts, repairs, hesitations are pervasive
- Speech recognition errors
  - ASR is imperfect (4 miles, for miles, form isles, for my isles)
- Out-of-domain utterances

Evaluation Metrics

- Sentence Level Semantic Accuracy (SLSA)

$$SLSA = \frac{\text{\# of sentences assigned the correct semantic representation}}{\text{\# of sentences}}$$

Evaluation Metrics

- Slot Error Rate (SER) / Concept Error Rate (CER)
  - inserted: present in the SLU output, absent from the reference
  - deleted: absent from the SLU output, present in the reference
  - substituted: aligned to each other, differ in either the slot labels or the sentence segments they cover

$$SER = \frac{\text{\# of inserted/deleted/substituted slots}}{\text{\# of slots in the reference semantic representations}}$$

- reference: [**topic**: FLIGHT] [**DCity**: SEA] [**ACity**: BOS] [**DDate**: 12/24]
- inserted: [**topic**: FLIGHT] [**DCity**: SEA] [**ACity**: BOS] [**DDate**: 12/24] [**Class**: Business]
- deleted: [**topic**: FLIGHT] [**ACity**: BOS] [**DDate**: 12/24]
- substituted: [**topic**: FLIGHT] [**DCity**: SEA] [**ACity**: BOS] [**DDate**: 12/25]

Evaluation Metrics

- Slot Precision/Recall/F1 Score
  - Precision and recall can be traded off with different operation points.
  - Recall-precision curve is often reported in SLU evaluations.

$$Precision = \frac{\text{\# of reference slots correctly detected by SLU}}{\text{\# of total slots detected by SLU}}$$

$$Recall = \frac{\text{\# of reference slots correctly detected by SLU}}{\text{\# of total reference slots}}$$

$$F_1 = \frac{2 \times (Precision \times Recall)}{Precision + Recall}$$

- End-to-end Evaluation
  - e.g., task success rate

Knowledge-based Approaches

- Many advocates of the knowledge-based approach believe that general linguistic knowledge is helpful in modeling domain-specific language.
- How to inject the domain specific semantic constraints into a domain-independent grammar?

Semantically Enhanced Syntactic Grammars

- low-level **syntactic non-terminals** -> **semantic non-terminals**

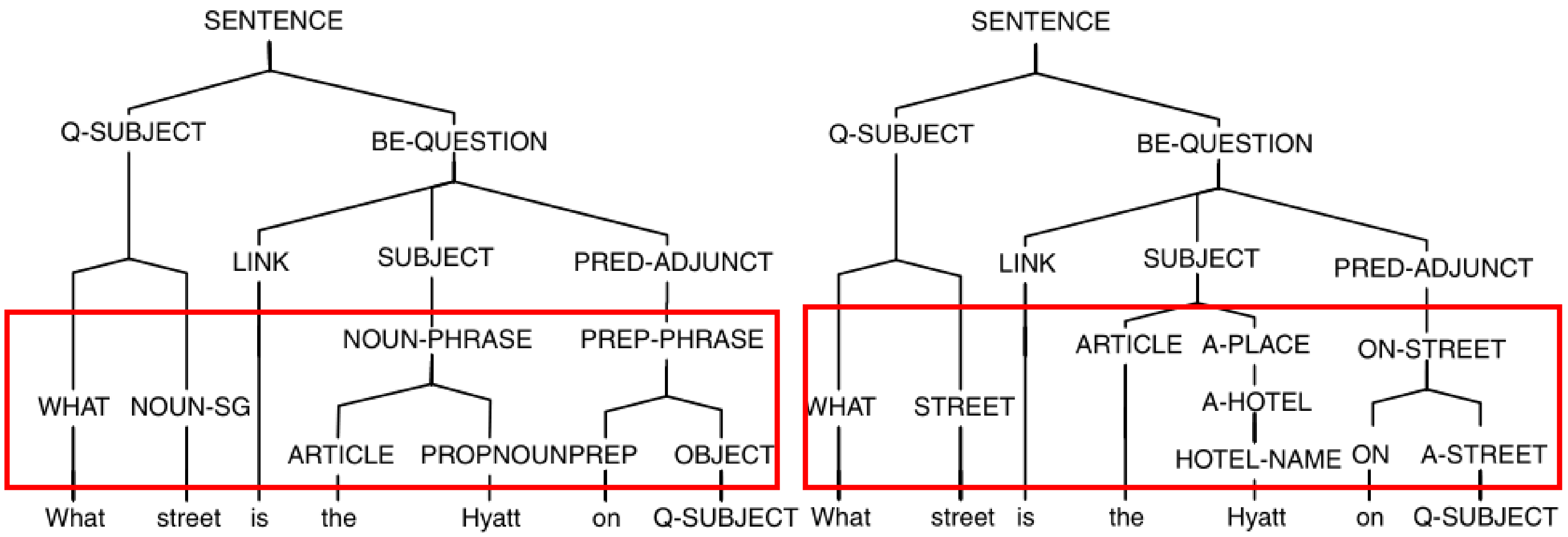


Figure 3.7 TINA parse tree with syntactic rules only (left) and with lower-level syntactic rules replaced by domain-dependent semantic rules (right) (The second tree is reproduced from Seneff (1992) (© 1992 Seneff))

Figure from: Gokhan Tur and Renato De Mori (2011) – "Spoken Language Understanding".

Semantic Grammars

- Directly models the domain-dependent semantics
- Phoenix (Ward, 1991) for ATIS
  - 3.2K non-terminals
  - 13K grammar rules

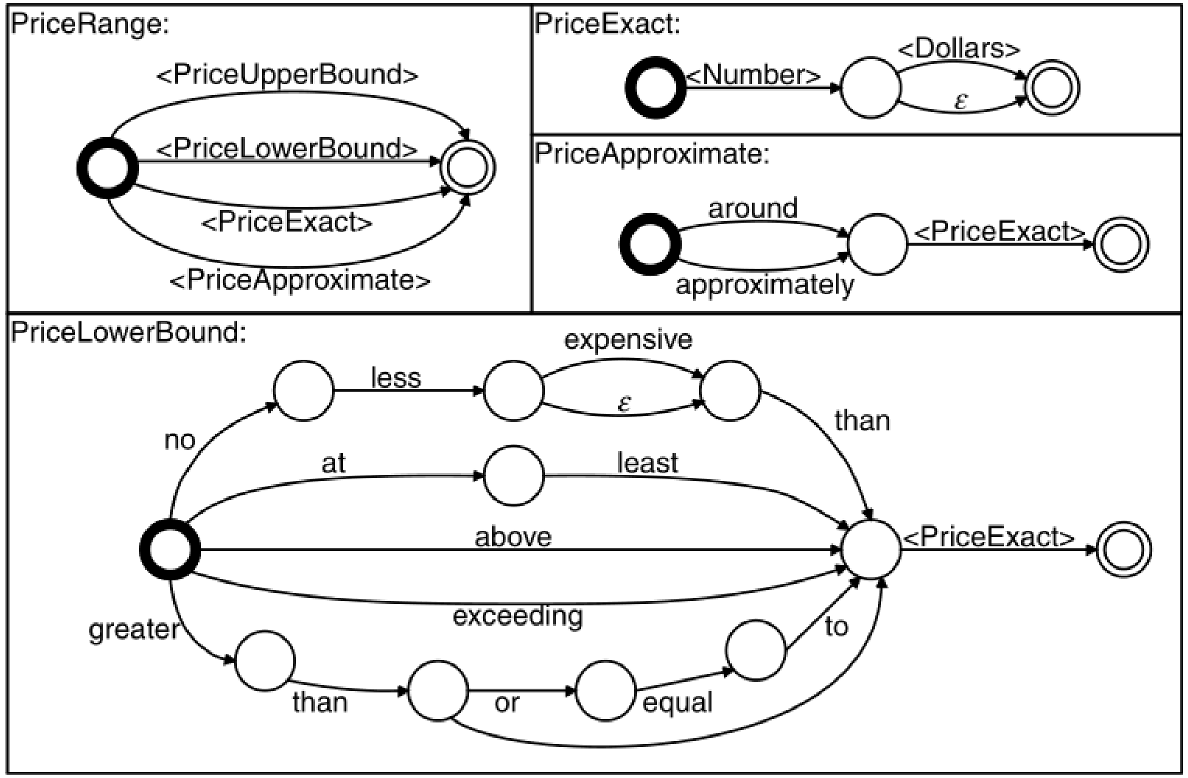


Figure 3.8 Recursive transition network for "PriceRange," together with three sub-nets called by it: "PriceExact", "PriceApproximate" and "PriceLowerBound." The arc labels in angular brackets indicate calls to sub-networks

Figure from: Gokhan Tur and Renato De Mori (2011) – "Spoken Language Understanding".

Knowledge-based Approach

- Advantage:
  - no or less dependent on labeled data
  - almost everyone can start writing a SLU grammar with some basic training
- Disadvantage
  - grammar development is an error-prone process (simplicity vs. coverage)
  - it takes multiple rounds to fine tune a grammar
  - scalability

Data-driven Approaches

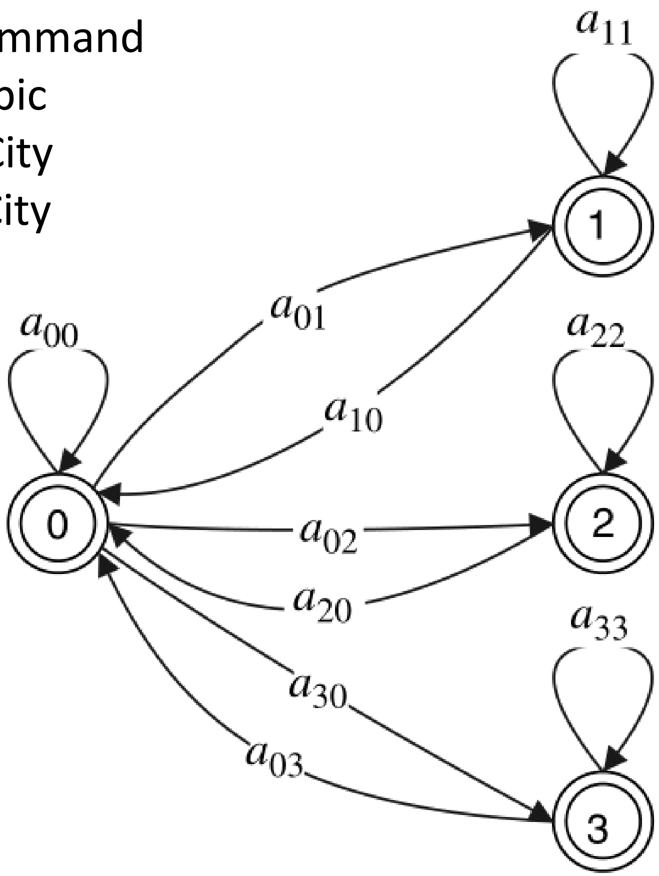
- Word sequence W
- Meaning representation M

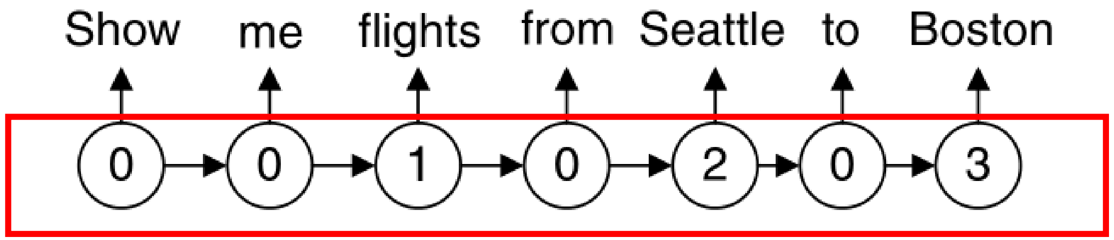
$$\hat{M} = \arg\max_{M} \boxed{P(M \mid W)} = \arg\max_{M} \boxed{P(W \mid M)} P(M)$$

- Generative Model
  - P(M): semantic prior model
  - P(W|M): lexicalization / lexical generation / realization model
- Discriminative Model
  - P(M|W)

Hidden-Markov Model (HMM)

- State 0: command
- State 1: topic
- State 2: DCity
- State 3: ACity





$$\Pr(M) = \pi_0 a_{00} a_{01} a_{10} a_{02} a_{20} a_{03} a_{30}$$

$$\Pr(W \mid M) = b_0\,(\text{Show}) \times b_0\,(\text{me}) \times b_1\,(\text{flights}) \times b_0\,(\text{from}) \times b_2\,(\text{Seattle}) \times b_0\,(\text{to}) \times b_2\,(\text{Boston})$$

Figure from: Gokhan Tur and Renato De Mori (2011) – “Spoken Language Understanding”.

Conditional Random Field (CRF)

- Word sequence $x_1, \ldots, x_n$
- Meaning representation (state sequence) $y_1, \ldots, y_n$

$$P(\mathbf{y} \mid \mathbf{x}; \Lambda) = \frac{1}{Z(\mathbf{x}; \Lambda)} \exp \left\{ \sum_k \lambda_k f_k (\mathbf{y}, \mathbf{x}) \right\}$$

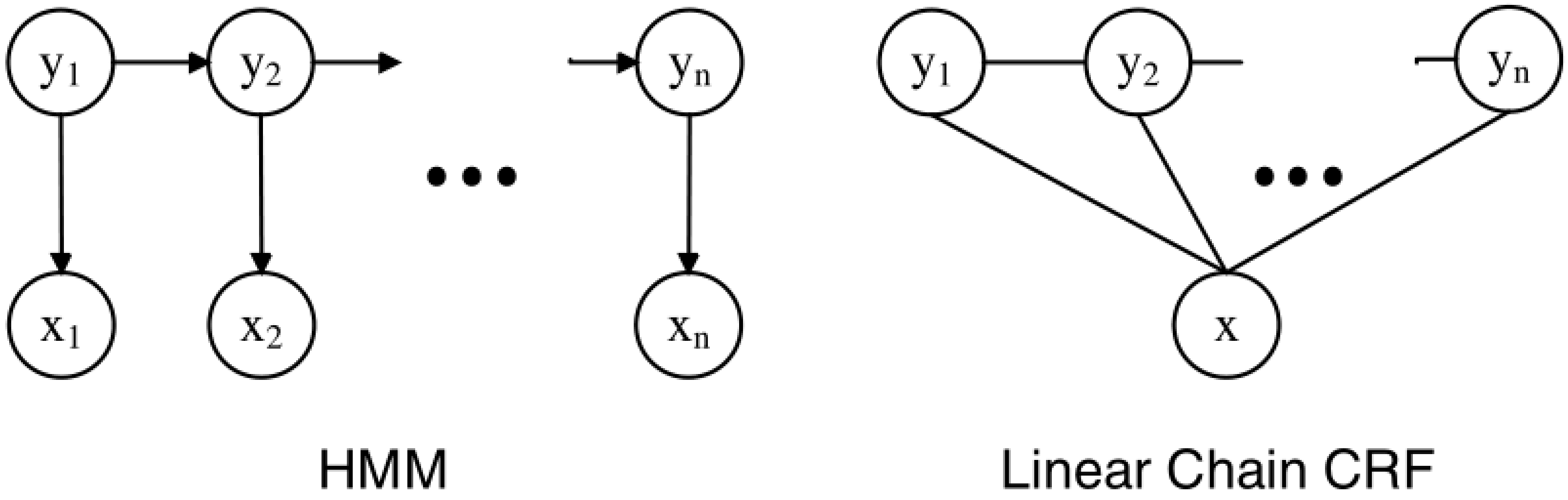


Figure from: Gokhan Tur and Renato De Mori (2011) – "Spoken Language Understanding".

Intent Classification

Machine-initiative Systems

- Interaction is completely controlled by the machines.
  - *Please say collect, calling card, or third party.*
- Commonly known as Interactive Voice Response systems(IVR)
  - Now widely implemented using established and standardized platforms such as VoiceXML.
- A primitive approach, a great commercial success

Utterance Level Intents

- AT&T's **H**ow **M**ay **I** **H**elp **Y**ou system

HMIHY: How may I help you?
User: Hi, I have a question about my bill (*Billing*)
HMIHY: OK, what is your question?
User: May I talk to a human please? (*CSR*) (Customer Service Representative)
HMIHY: In order to route your call to the most appropriate department can you tell me the specific reason you are calling about?
User: There is an international call I could not recognize (*Unrecognized_Number*)
HMIHY: OK, I am forwarding you to the human agent. Please stay on the line.

Figure 4.2 A conceptual example dialogue between the user and the AT&T HMIHY system

Figure from: Gokhan Tur and Renato De Mori (2011) – "Spoken Language Understanding".

Intent Classification

- Task: Classify users' utterances into predefined categories
- Speech utterance X_r
- M semantic classes: $C_1, C_2, \dots, C_M$

$$\hat{C}_r = \arg\max_{C_r} P(C_r|X_r).$$

- Significant freedom in utterance variations
  - *I want to fly from Boston to New York next week*
  - *I am looking to fly from JFK to Boston in the coming week*

Evaluation Metrics

- Accuracy / Precision / Recall / F1 Score
- End-to-end evaluation
  - Cost savings
  - Customer satisfaction

Intent Classification vs. Frame-based SLU

- Less attention to the underlying message conveyed
- Heavily rely on statistical methods
- Fit nicely into spoken language processing
  - less grammatical and fluent
  - ASR errors
- Out-of-domain utterances are still challenging
  - *I want to book a flight to New York next week*
  - *I want to book a restaurant in New York next week*

Dialog Act

- A **Speech Act** is a primitive abstraction or an approximate representation of the illocutionary force of an utterance. (Austin 1962)
  - asking, answering, promising, suggesting, warning, or requesting
- Five major classes (Searle, 1969)
  - Assertive: commit the speaker to something is being the case
    - suggesting, concluding
  - Directive: attempts by the speaker to do something
    - ordering, advising
  - Commissive: commit the speaker to some future action
    - planning, betting
  - Expressive: express the psychological state of the speaker
    - thanking, apologizing
  - Declaration: bring about a different state of the world
    - *I name this ship the Titanic*

Named Entity Recognition

What is a Named Entity?

- Introduced at the MUC-6 evaluation program (Sundheim and Grishman, 1996) as one of the *shallow understanding* tasks.
- No formal definition from a linguistic point of view.
- Goal: extract from a text all the word strings corresponding to these kinds of entities and from which a unique identifier can be obtained without resolving any reference resolution process.
  - New York city: yes
  - the city: no

Entity Categories

1. ENAMEX
   - ORGANIZATION: named corporate, governmental, or other organizational entity
   - PERSON: named person or family
   - LOCATION: name of politically or geographically defined location (cities, provinces, countries, international regions, bodies of water, mountains, etc.)
2. TIMEX
   - DATE: complete or partial date expression
   - TIME: complete or partial expression of time of day
3. NUMEX
   - MONEY: monetary expression
   - PERCENT: percentage

Technical Challenges

- Segmentation ambiguity
  - [Berkeley University of California]
  - [Berkeley] [University of California]
- Classification ambiguity
  - John F. Kennedy: PERSON vs. AIRPORT

Approaches

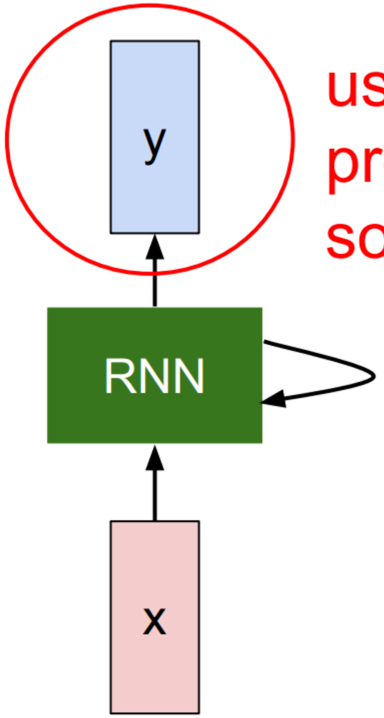
- Rules and Grammars
- Word Tagging Problem

Sentence	*show*	*flights*	*from*	*Boston*	*To*	*New*	*York*	*today*
Slots/Concepts	O	O	O	B-dept	O	B-arr	I-arr	B-date
Named Entity	O	O	O	B-city	O	B-city	I-city	O

Break (15min)

Recurrent Neural Networks for SLU

Recurrent Neural Networks



usually want to predict a vector at some time steps

$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

new state

old state

input vector at some time step

some function with parameters W

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

$$y_t = W_{hy}h_t$$

Figure from: Hannaneh Hajishirzi, EE 511 Winter 2018 – “Introduction to Statistical Learning”.

Long Short Term Memory (LSTM)

- h_t in RNN servers 2 purpose
  - make output predictions
  - represent the data sequence processed so far
- The LSTM cell split these two roles into two separate variables
  - h_t: make output predictions
  - C_t: save the internal state

$$\tilde{C} = \tanh(W_{cx}X_t + W_{ch}h_{t-1} + b_c)$$
$$C_t = gate_{forget} \cdot C_{t-1} + gate_{input} \cdot \tilde{C}$$
$$h_t = gate_{out} \cdot \tanh(C_t)$$

LSTM Gates

- Forget gate: what part of the previous cell state will be kept
- Input gate: what part of the new computed information will be added to the cell state C_t
- Output gate: what part of the cell state C_t will be exposed as the hidden state

$$\tilde{C} = \tanh(W_{cx}X_t + W_{ch}h_{t-1} + b_c)$$
$$C_t = gate_{forget} \cdot C_{t-1} + gate_{input} \cdot \tilde{C}$$
$$h_t = gate_{out} \cdot \tanh(C_t)$$

$$gate_{forget} = \sigma(W_{fx}X_t + W_{fh}h_{t-1} + b_f)$$
$$gate_{input} = \sigma(W_{ix}X_t + W_{ih}h_{t-1} + b_i)$$
$$gate_{out} = \sigma(W_{ox}X_t + W_{oh}h_{t-1} + b_o)$$

Gated Recurrent Unit (GRU)

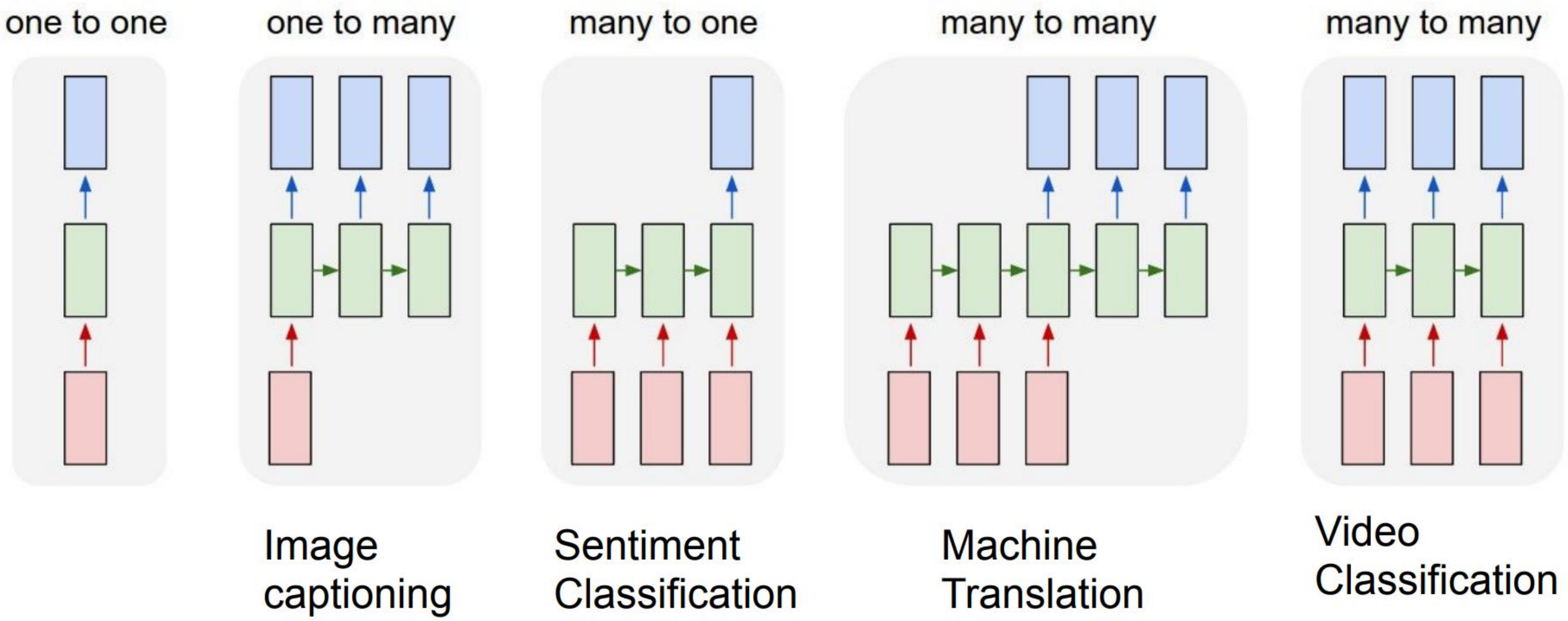
- No separate cell
- Two gates
  - Reset gate: what part of the previous state will be kept
  - Update gate: how much the unit updates the state

$$h_t = (1 - gate_{update}) \cdot h_{t-1} + gate_{update} \cdot \tilde{h_t}$$

$$\tilde{h}_t^j = \tanh\left(W\mathbf{x}_t + U\left(\mathbf{r}_t \odot \mathbf{h}_{t-1}\right)\right)^j$$

$$gate_r = \sigma(W_{rx}X_t + W_{rh}h_{t-1} + b)$$
$$gate_{update} = \sigma(W_{ux}X_t + W_{uh}h_{t-1} + b)$$

Recurrent Neural Networks



Intent Classification

HMIHY: How may I help you?
User: Hi, I have a question about my bill (*Billing*)
HMIHY: OK, what is your question?
User: May I talk to a human please? (*CSR*)
HMIHY: In order to route your call to the most appropriate department can you tell me the specific reason you are calling about?
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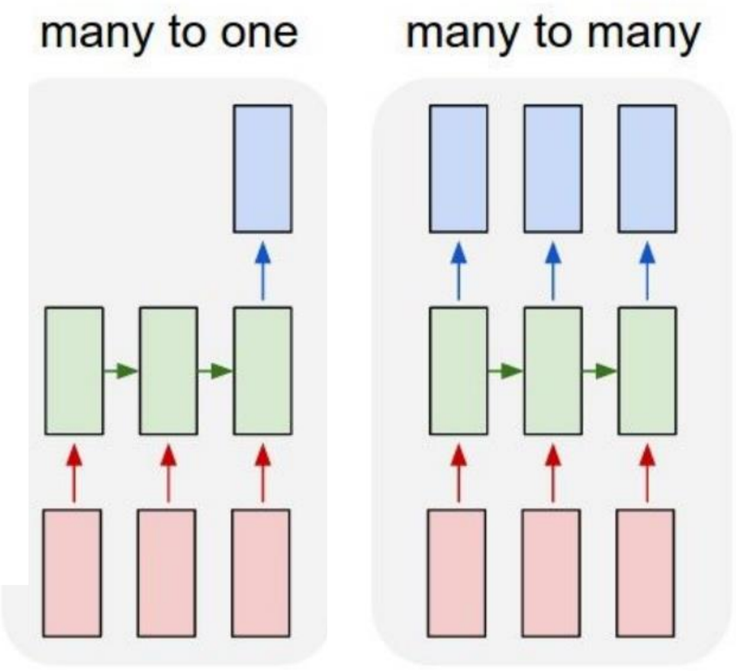


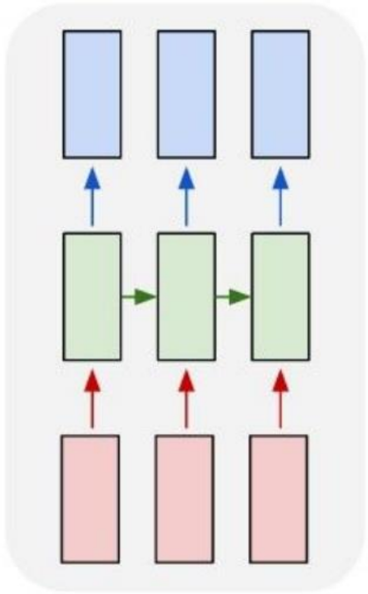
Slot Filling Task

- in/out/begin (IOB) representation

Sentence	*show*	*flights*	*from*	*Boston*	*To*	*New*	*York*	*today*
Slots/Concepts	O	O	O	B-dept	O	B-arr	I-arr	B-date
Named Entity	O	O	O	B-city	O	B-city	I-city	O
Intent	*Find_Flight*							
Domain	*Airline Travel*							

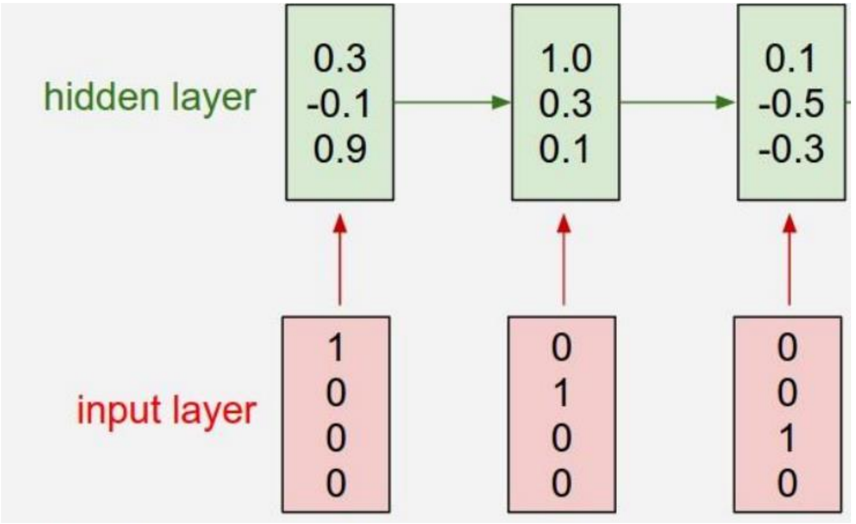
ATIS utterance example IOB representation

many to many



How to represent a word?

- Vocabulary: [how, about, sports, <unk>]
- One-hot encoding



how about sports

Pre-trained Word Embedding

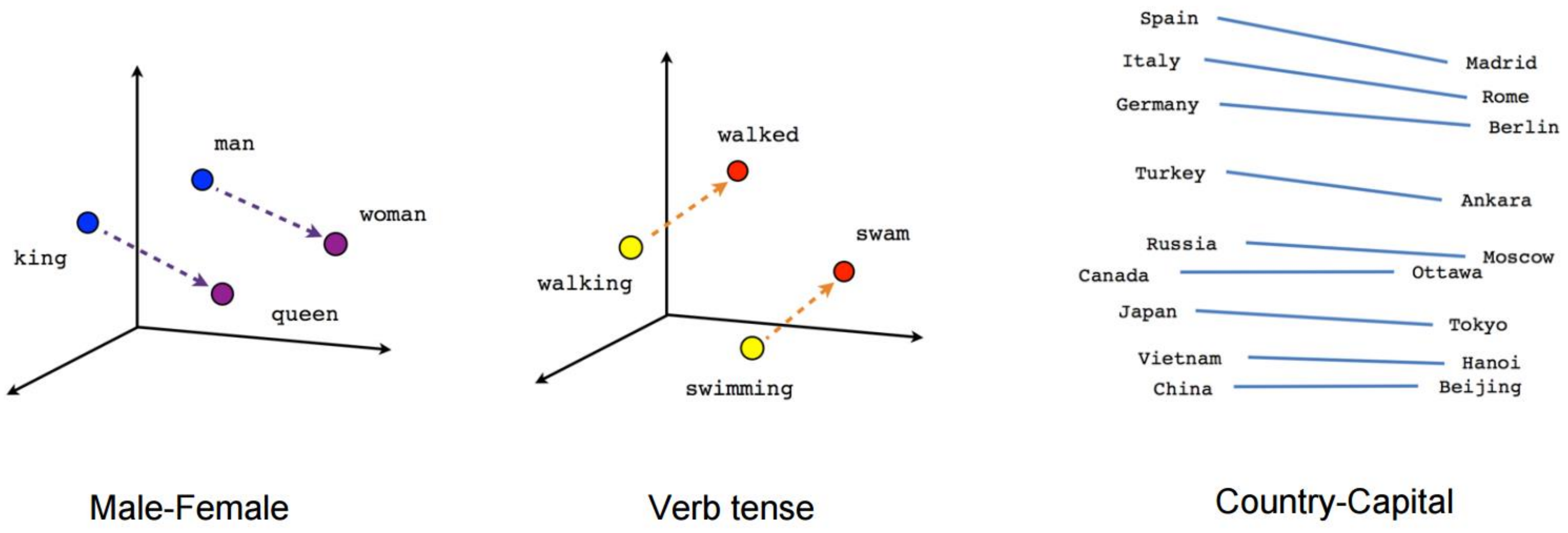


Figure from: https://www.tensorflow.org/tutorials/word2vec

SLU in Alexa Skills Kit

Creating an Alexa Skill

Figure from: Jeff Blankeburg and Alexa Evangelist (2017) – “Build an Alexa Skill using AWS Lambda”.

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Alexa Skills Kit

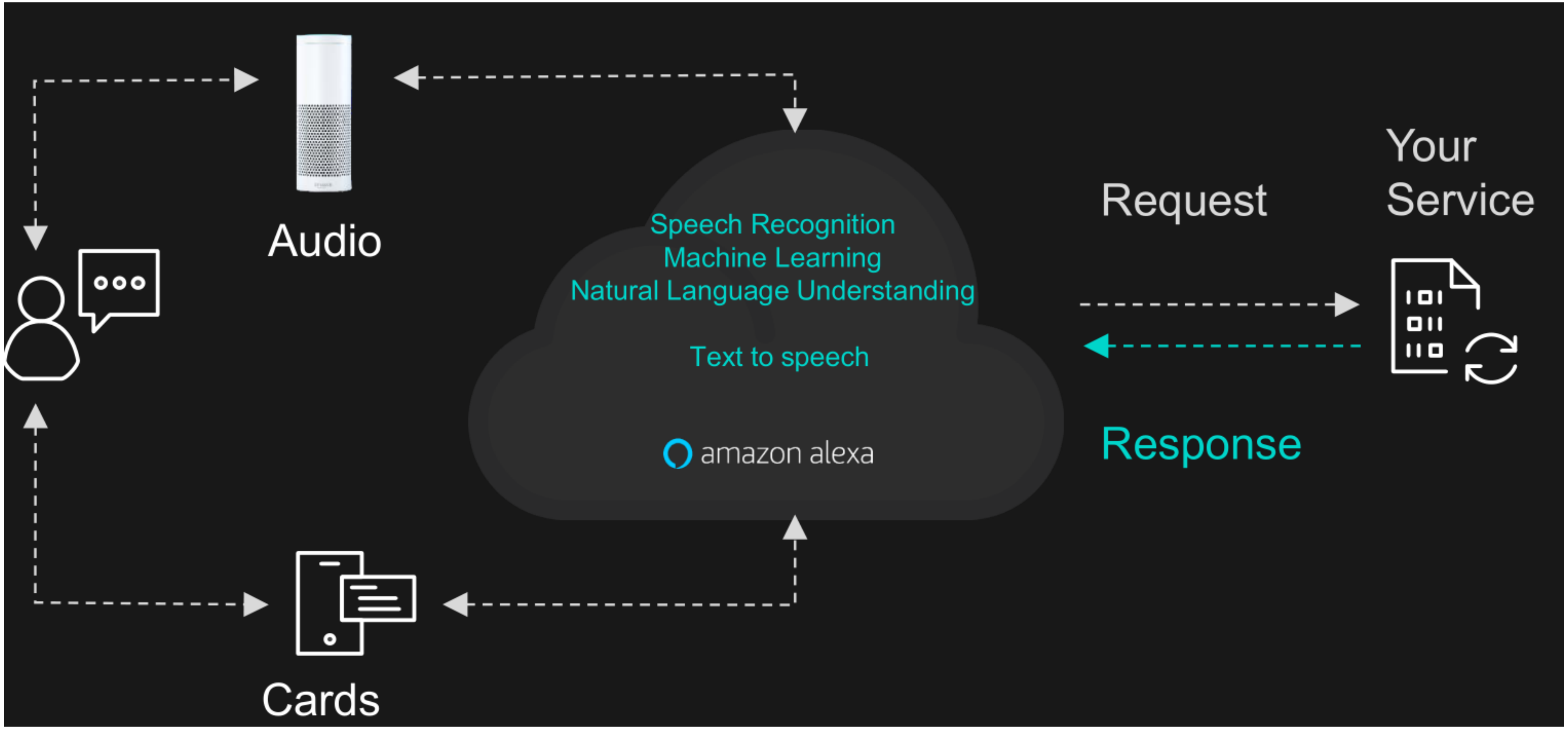


Figure from: Jeff Blankeburg and Alexa Evangelist (2017) – “Build an Alexa Skill using AWS Lambda”.

Alexa Skills Kit: Signal Processing

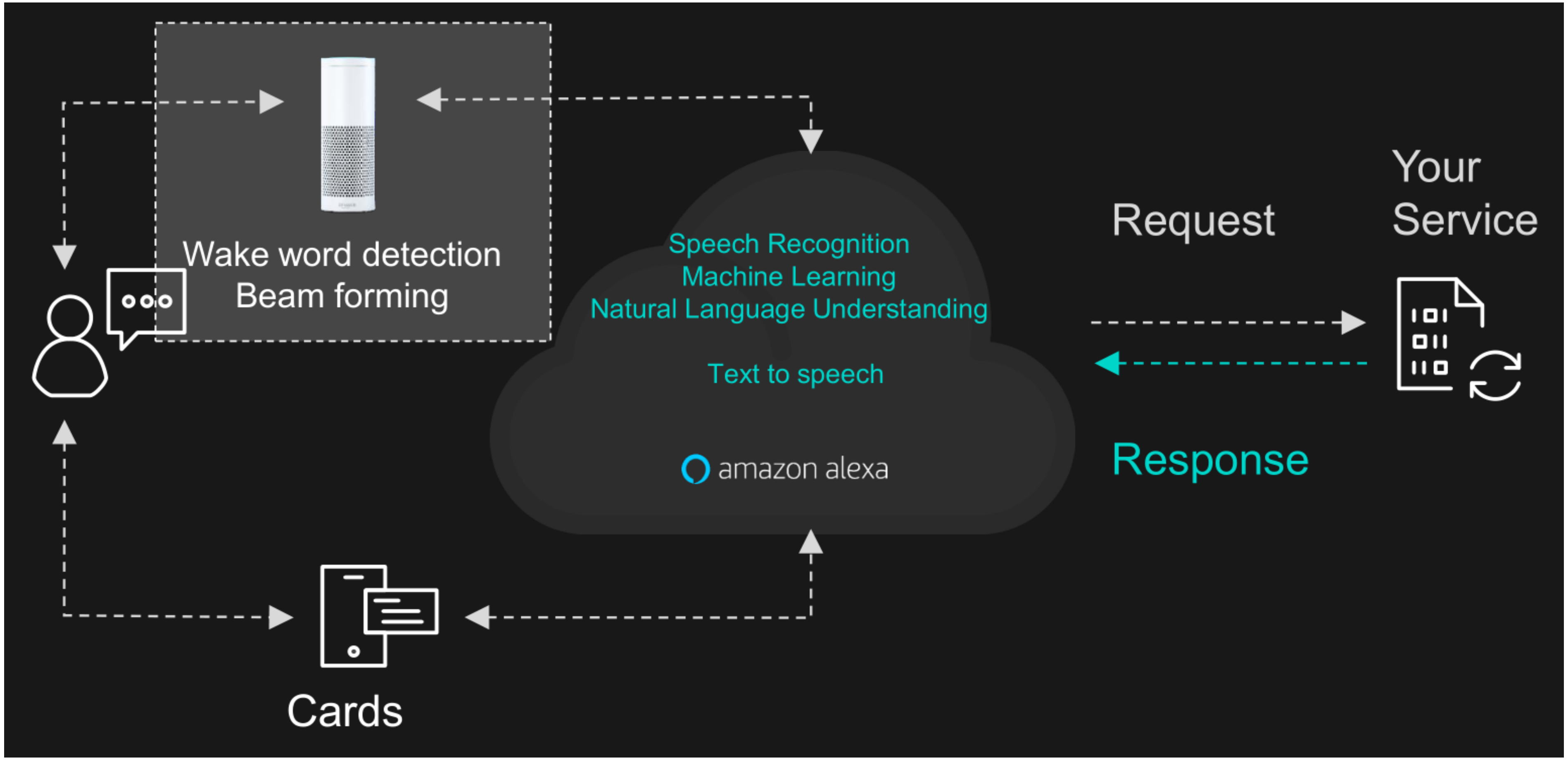
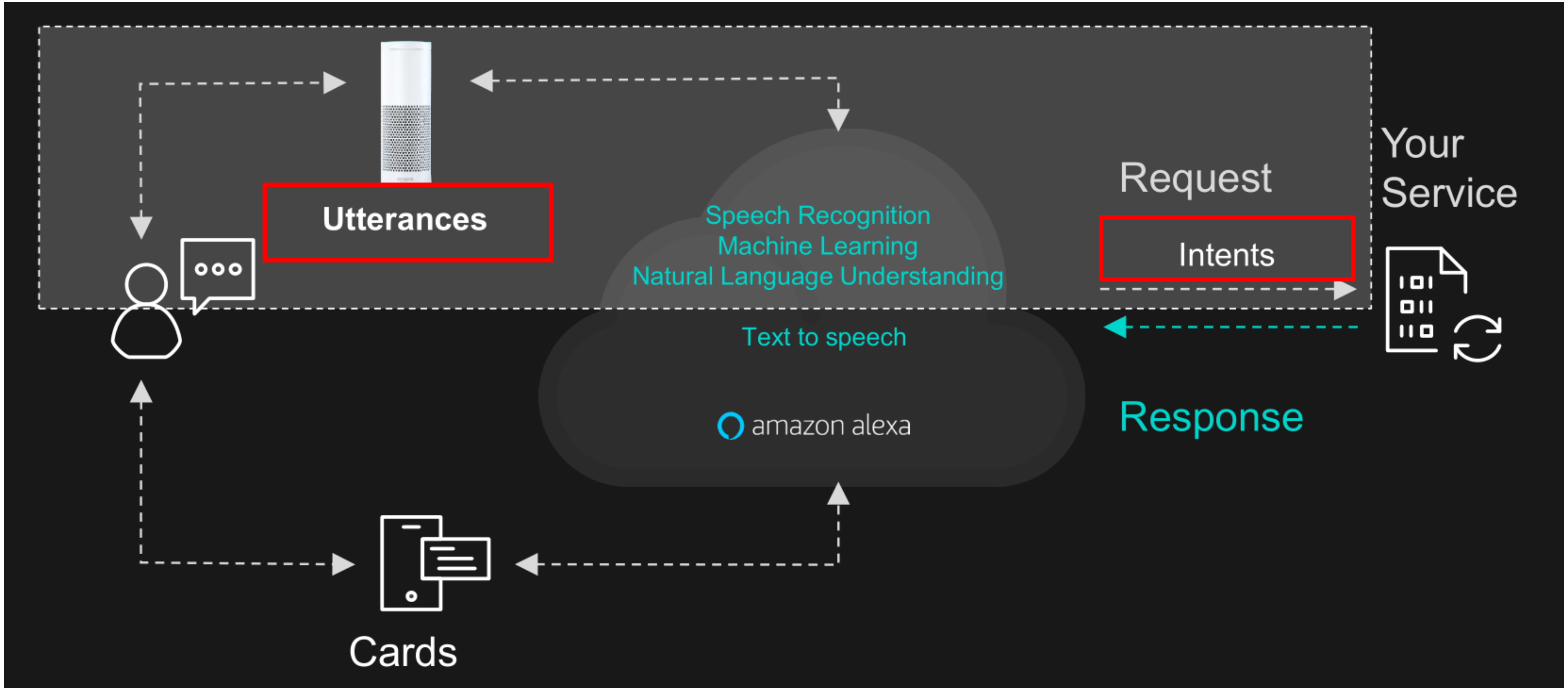


Figure from: Jeff Blankeburg and Alexa Evangelist (2017) – “Build an Alexa Skill using AWS Lambda”.

Alexa Skills Kit: Interaction Model



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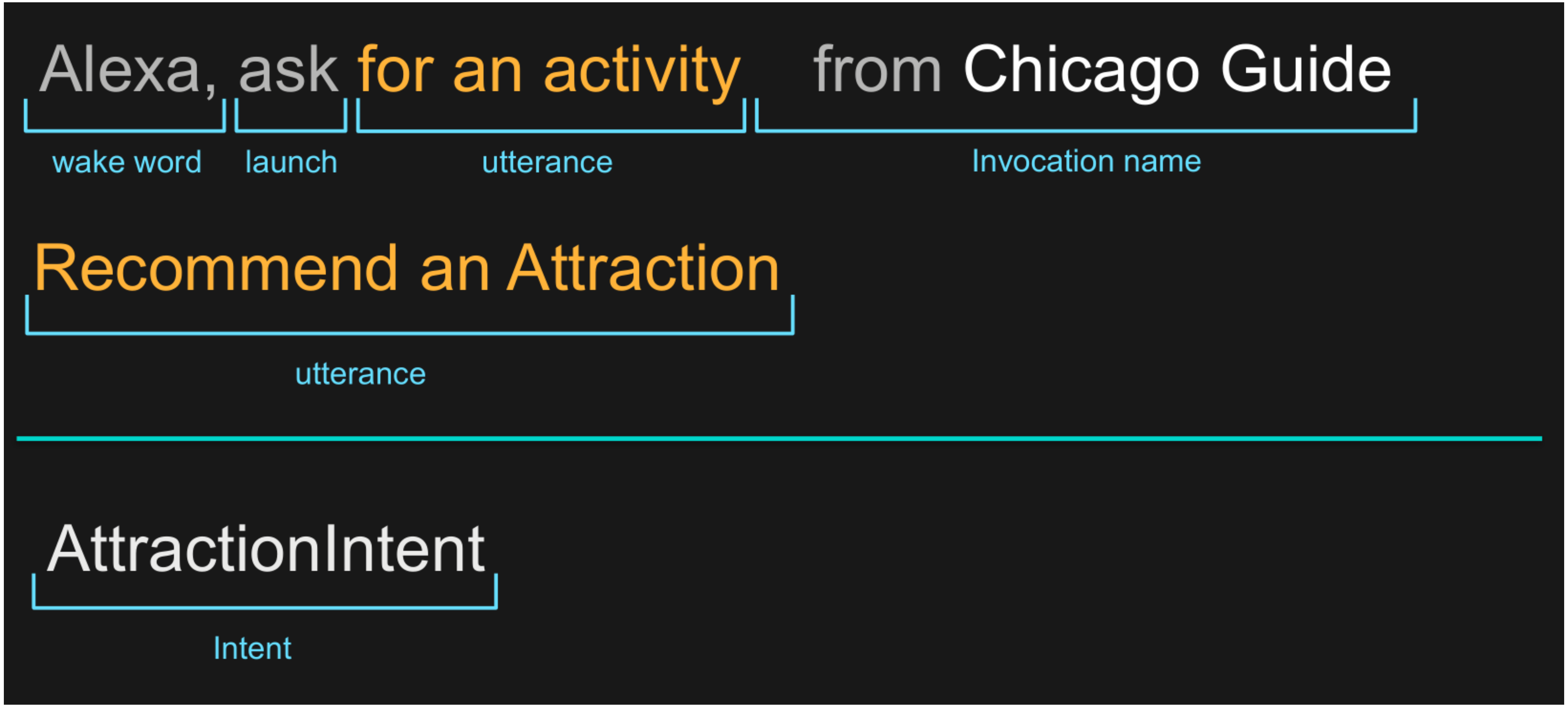
Intents



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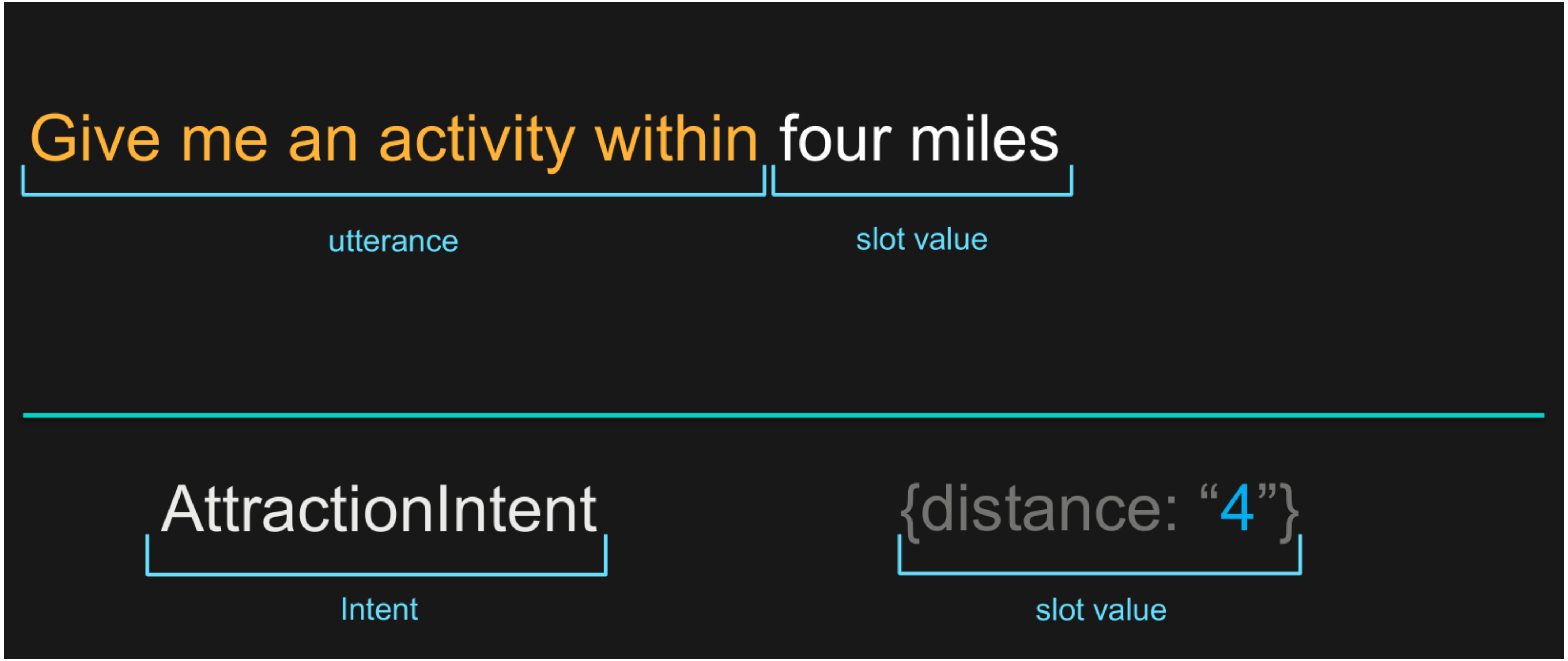
Built-in Slots



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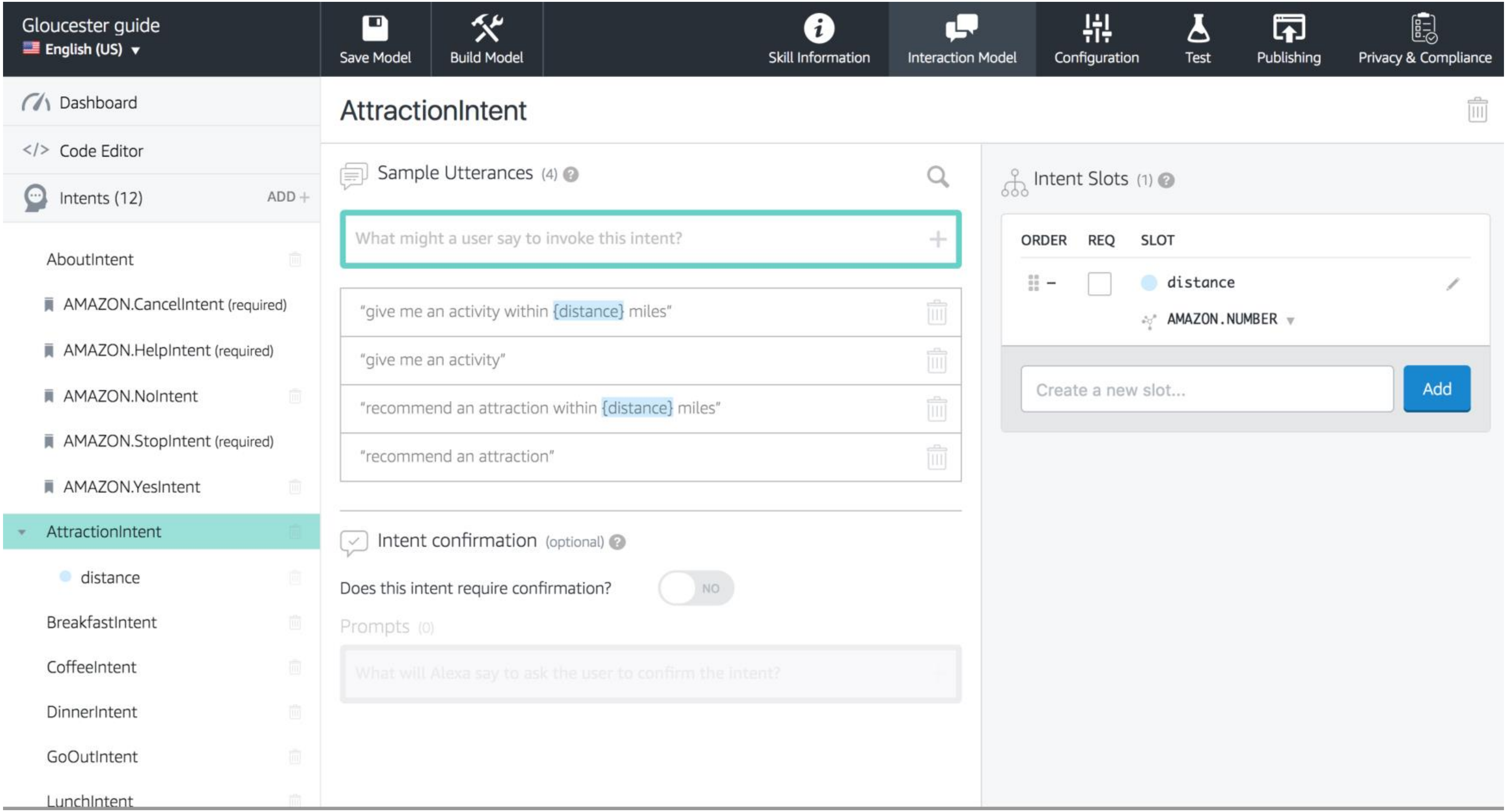

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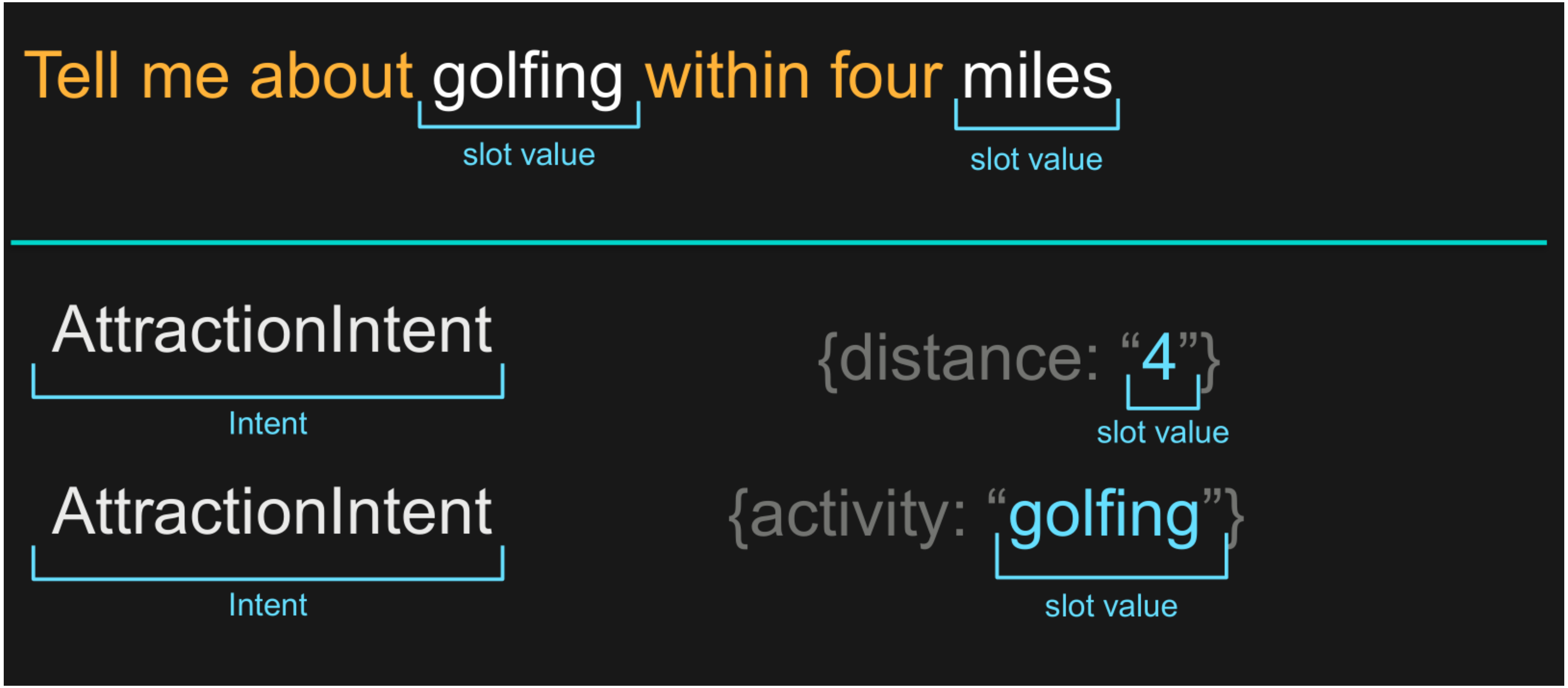
Custom Slots



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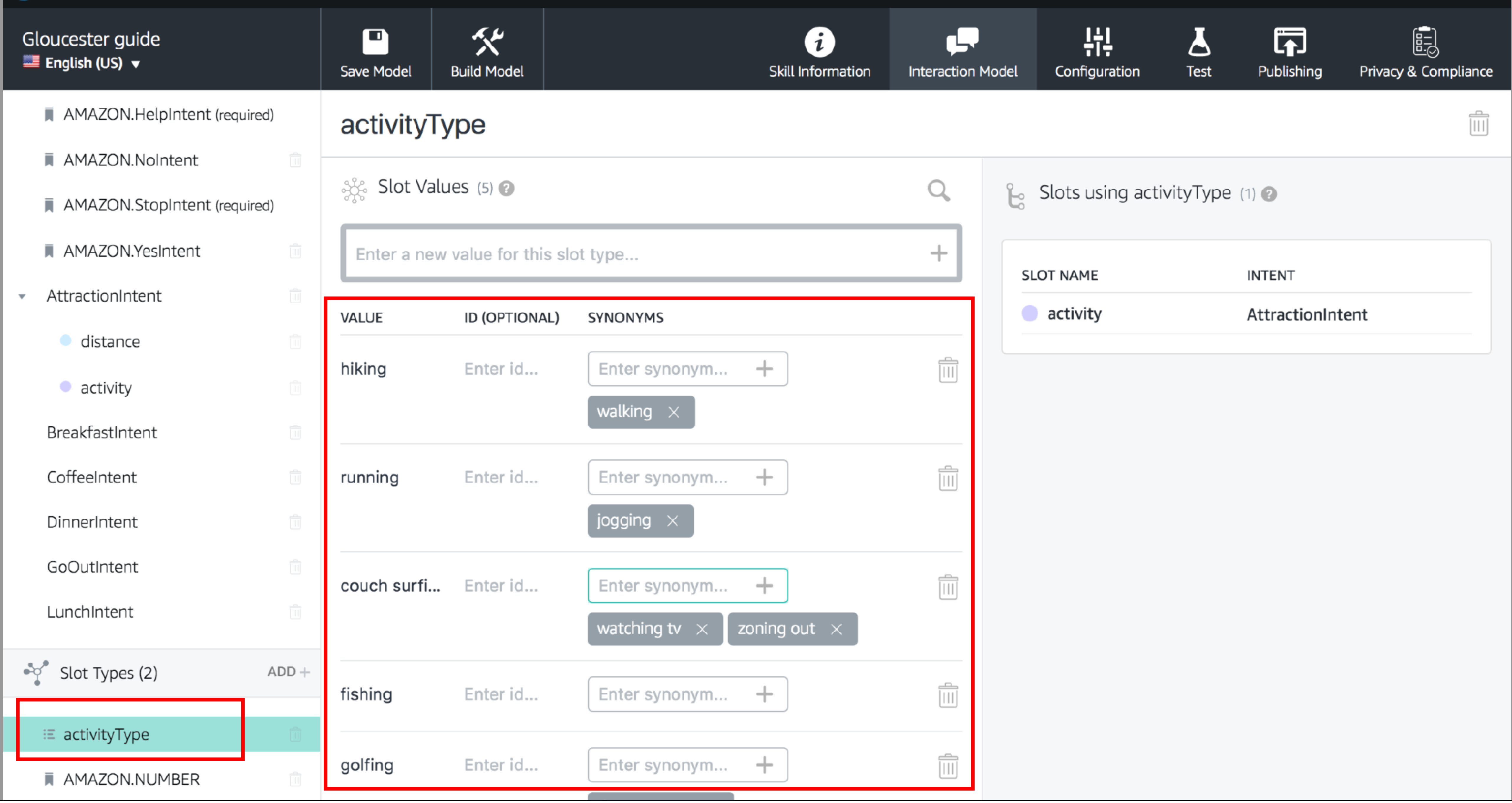

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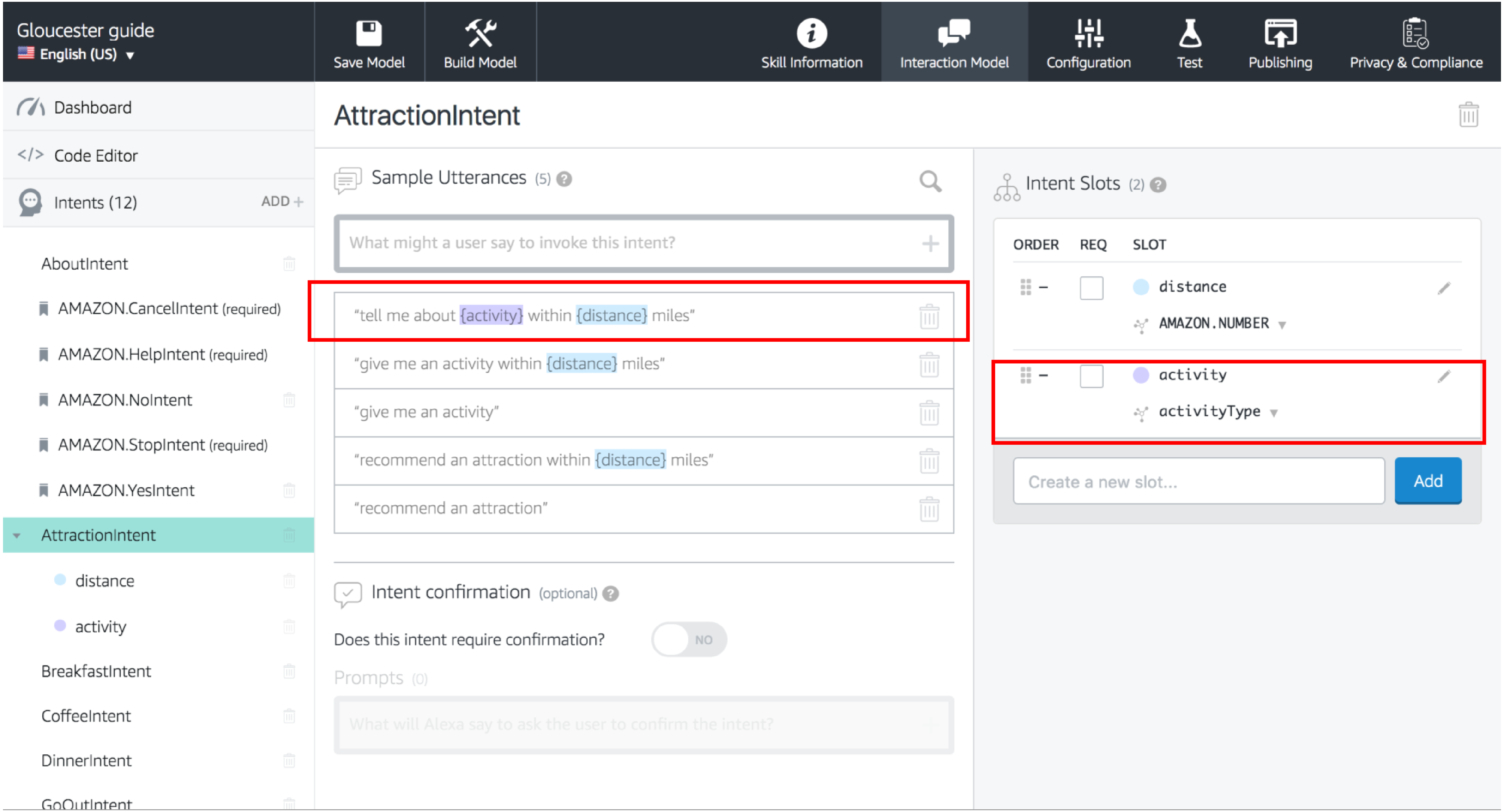

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How Do I Receive My Slot?

```
myDistance = this.event.request.intent.slots.distance.value

myActivity = this.event.request.intent.slots.activity.value
```

Figure from: Jeff Blankeburg and Alexa Evangelist (2017) – “Build an Alexa Skill using AWS Lambda”.

Alexa Skills Kit: Requests and Responses

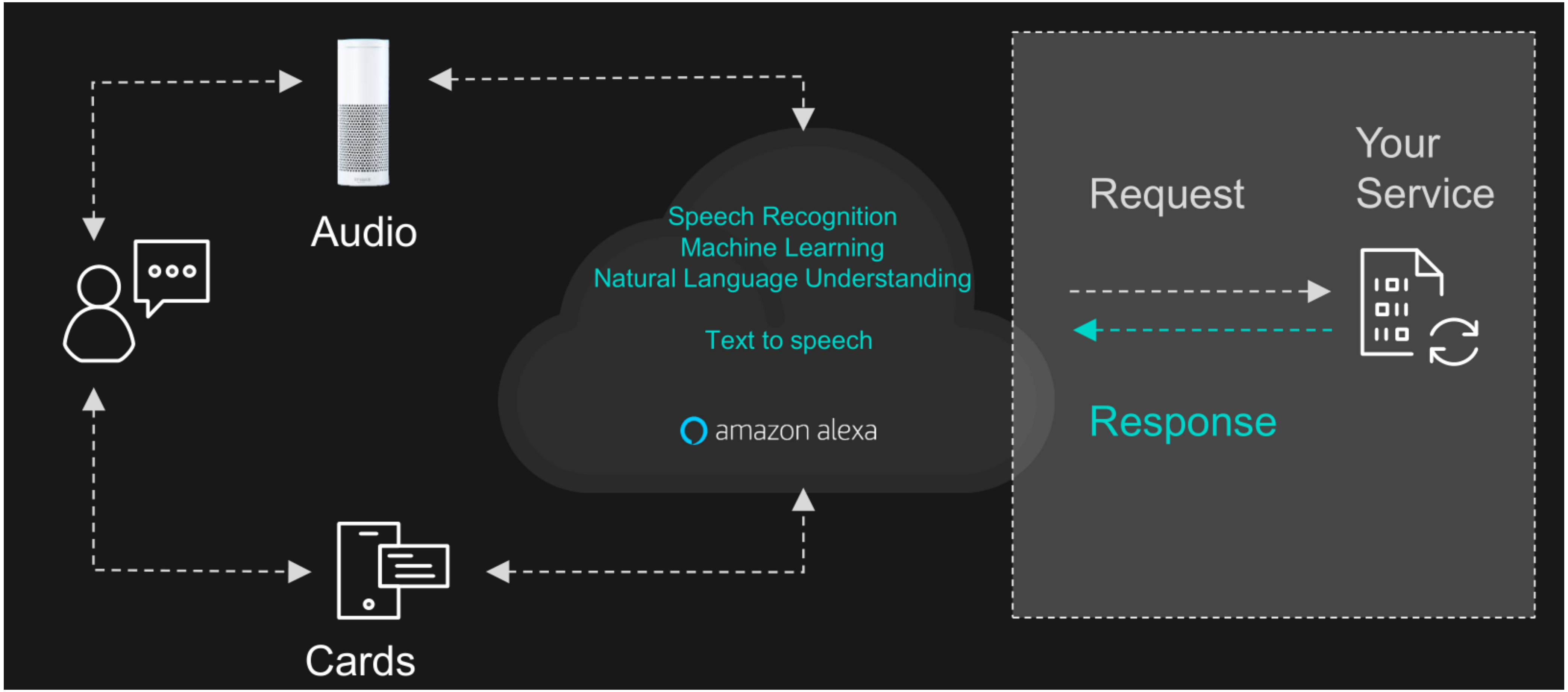

Figure from: Jeff Blankeburg and Alexa Evangelist (2017) – “Build an Alexa Skill using AWS Lambda”.

Alexa Skills Kit: Output

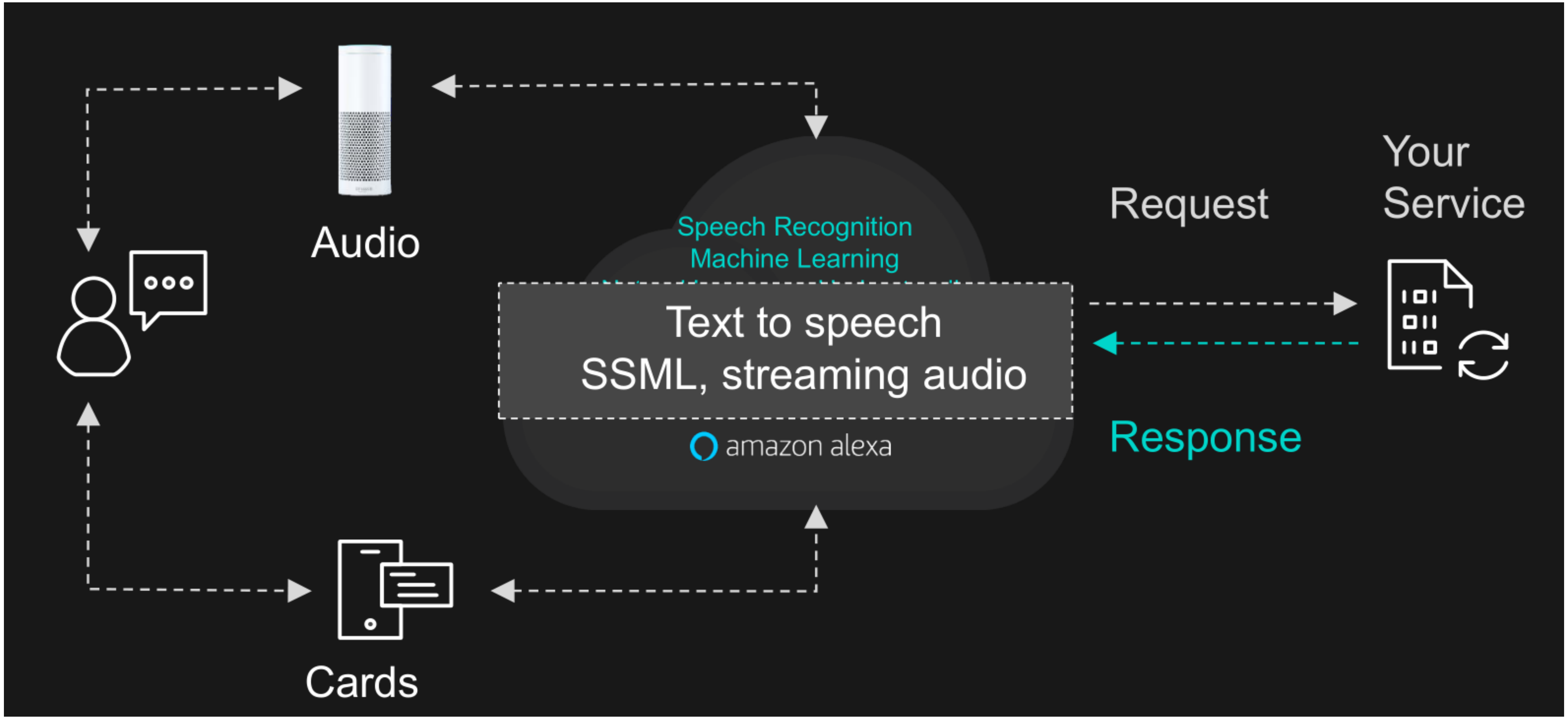

Figure from: Jeff Blankeburg and Alexa Evangelist (2017) – “Build an Alexa Skill using AWS Lambda”.

Lab 1 Updates

Lab 1 Updates

- Walkthrough for Task 1
- Task 2 is simplified (you don’t need to write codes)

Lab Checkoff and Report

- This course requires everyone to join a team and work together on the final project.
  - Collaboration is important!
- On Thursday, you will need to checkoff Lab 1 as a team.
  - You are encouraged to work together on labs and learn from each other
- Please submit a lab report as a team as well

Paper Presentation

Topics

- The presentation should focus on 1-2 relevant topics and cover several papers.
- Example topics:
  - Language Understanding
  - Dialog Management
  - Language Generation
  - Dialog Model Theory
  - Linguistic Analysis
  - End-to-end Systems
  - Reinforcement Learning
  - …

Where to find papers?

- Journals
  - IEEE/ACM Transactions on Audio, Speech and Language Processing (TASLP)
  - Transactions of the Association for Computational Linguistics (TACL)
  - Dialogue & Discourse
- Conferences & Workshops
  - Special Interest Group on Discourse and Dialogue (SIGdial)
  - INTERSPEECH
  - ACL, EMNLP, NAACL, EACL, COLING
  - ICML, NIPS, ICLR

Format

- 10% of your final grade
- Each team leads a discussion
  - Week 6 (May 1): 2 teams
  - Week 7 (May 8): Guest Lecture
  - Week 8 (May 15): 2 teams
  - Week 9 (May 22): 1 team + Project Consulting Session
- 50min presentation & discussion
- All team members need participate in the presentation.

ConvAI Challenge

2nd ConvAI Challenge

- http://convai.io/
- Persona-Chat
- Pre-defined Bot profile
- April 6 – Sept 1

Persona 1	**Persona 2**
I like to ski	I am an artist
My wife does not like me anymore	I have four children
I have went to Mexico 4 times this year	I recently got a cat
I hate Mexican food	I enjoy walking for exercise
I like to eat cheetos	I love watching Game of Thrones

[PERSON 1:] Hi
[PERSON 2:] Hello ! How are you today ?
[PERSON 1:] I am good thank you , how are you.
[PERSON 2:] Great, thanks ! My children and I were just about to watch Game of Thrones.
[PERSON 1:] Nice ! How old are your children?
[PERSON 2:] I have four that range in age from 10 to 21. You?
[PERSON 1:] I do not have children at the moment.
[PERSON 2:] That just means you get to keep all the popcorn for yourself.
[PERSON 1:] And Cheetos at the moment!
[PERSON 2:] Good choice. Do you watch Game of Thrones?
[PERSON 1:] No, I do not have much time for TV.
[PERSON 2:] I usually spend my time painting: but, I love the show.

Example dialog from the PERSONA-CHAT dataset. Person 1 is given their own persona (top left) at the beginning of the chat, but does not know the persona of Person 2, and vice-versa. They have to get to know each other during the conversation.

Upcoming Deadlines

- April 3 (today): Team registration
- April 5: Lab 1 checkoff (in class)
- April 10: Lab 1 report (canvas)