A Formal Language & Data Engineering Approach to Multi-Turn Dialogues

CS294S/W Fall 2020, Lecture 4

Giovanni Campagna
(Work done in collaboration with Sina Semnani, Ryan Kearns, Lucas Sato, Agata Foryciarz, Mehrad Moradshahi, Silei Xu & others in OVAL under supervision of Prof. Monica Lam)

(Genie Logo by SK Lim)

The “State of The Art” in VA Tools: Slot Elicitation

U: I want to make a restaurant reservation for Terun

A: For how many people?

U: 3 people

A: At what time?

U: 7pm

A: Ok, I’m going to make a restaurant reservation for 3 people at Terun at 7pm.

- One slot / parameter at a time
- Fixed, developer-provided questions per parameter
- **No error path**: if the user doesn’t answer the question, *tough luck*

Real World Dialogues [Budzianowski et al. 2018]

U: Could you give me information about a restaurant called Panahar?

A: Absolutely. Panahar is a more expensive Indian restaurant.
It is located at 8 Norfolk Street city centre. Their postal code is cb12lf.
Their phone number is 01223355012.

U: Could you book a table for me there on Friday?

A: Yes, I can, for how many people and what time on Friday?

U: There will be 4 of us and we would like to eat at 11:00.

A: Booking was unfortunately unsuccessful.
Can we try another day or time slot ?

U: Sure, how about 10:00?

Transaction (Slot-Filling) Dialogues

- A subset of *task-oriented dialogues* (participants trying to “do things”)
- **User** introduces the *transaction* & drives the conversation
- **Agent** provides answers & suggestions + elicits info to complete actions

- Superset of interactive search & Q&A (informational)
- Covers all dialogues that execute user-driven actions
  - Purchases
  - Reservations
  - Tickets
  - Simple customer support: changing/cancelling orders, paying bills, scheduling repairs/returns, etc.

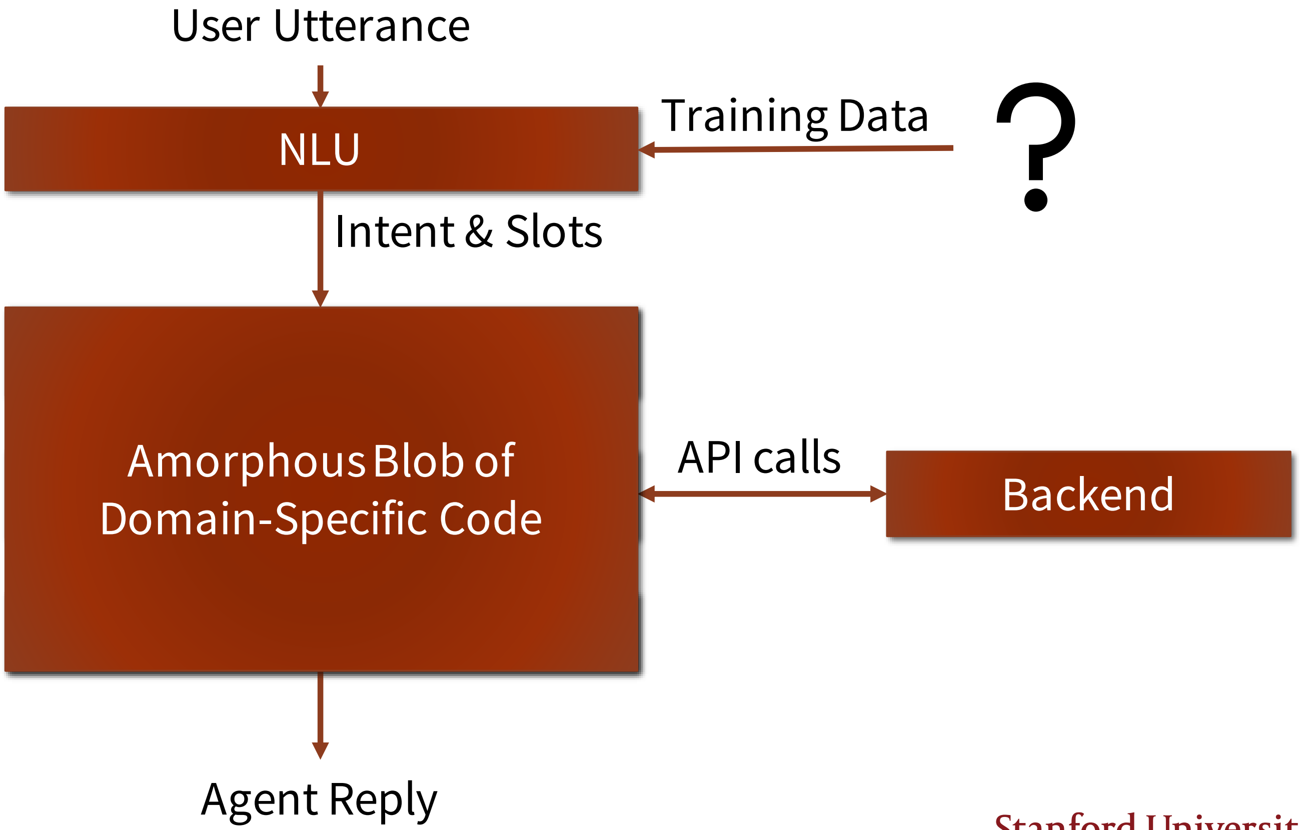
Challenges of Transaction Dialogues

- Carrying over of contextual information
- Multiple *slots* per turn
- Error correction and recovery

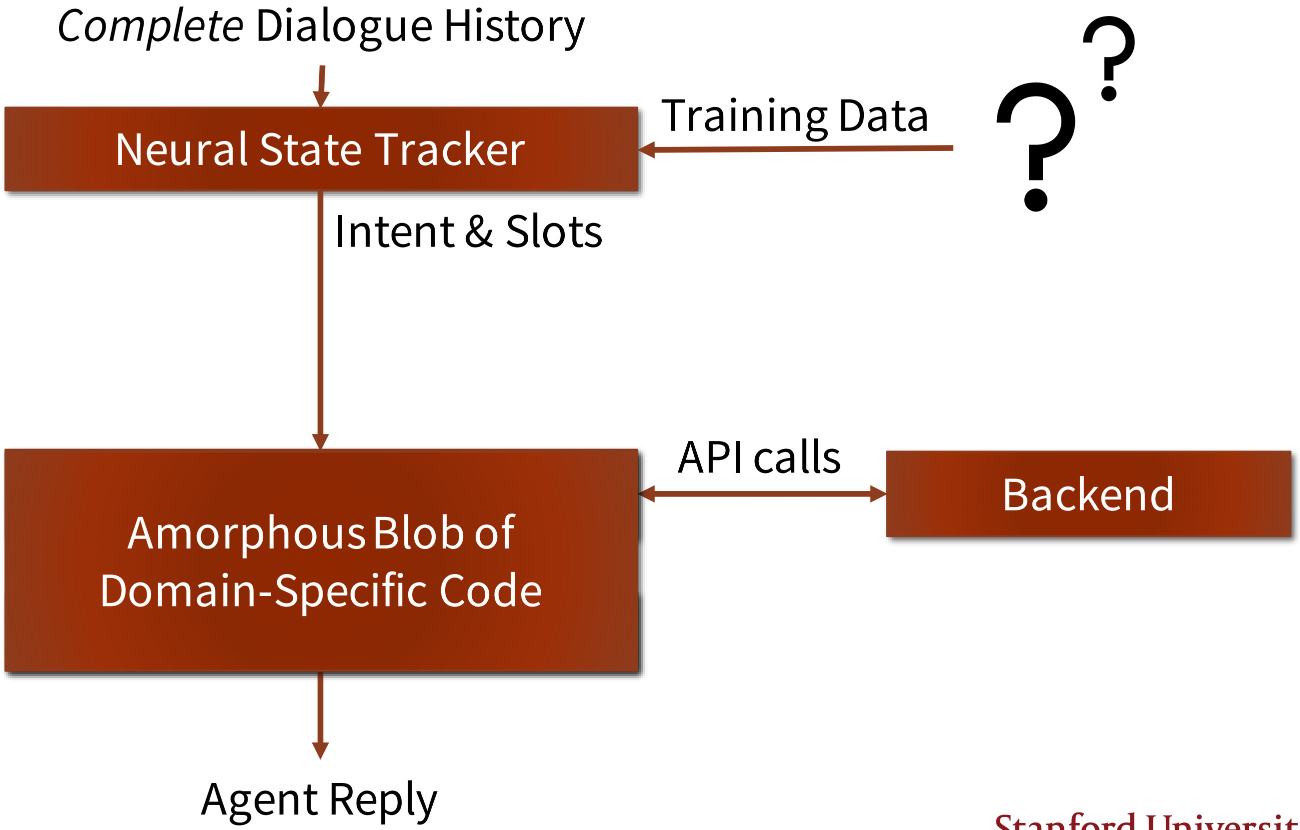
- Long studied field
- First notable work: **Dialogue State Tracking Challenge** (2011)

Can we solve transaction dialogues *once and for all?*

The Practical Modular Approach To Dialogues



The Academic Modular Approach To Dialogues



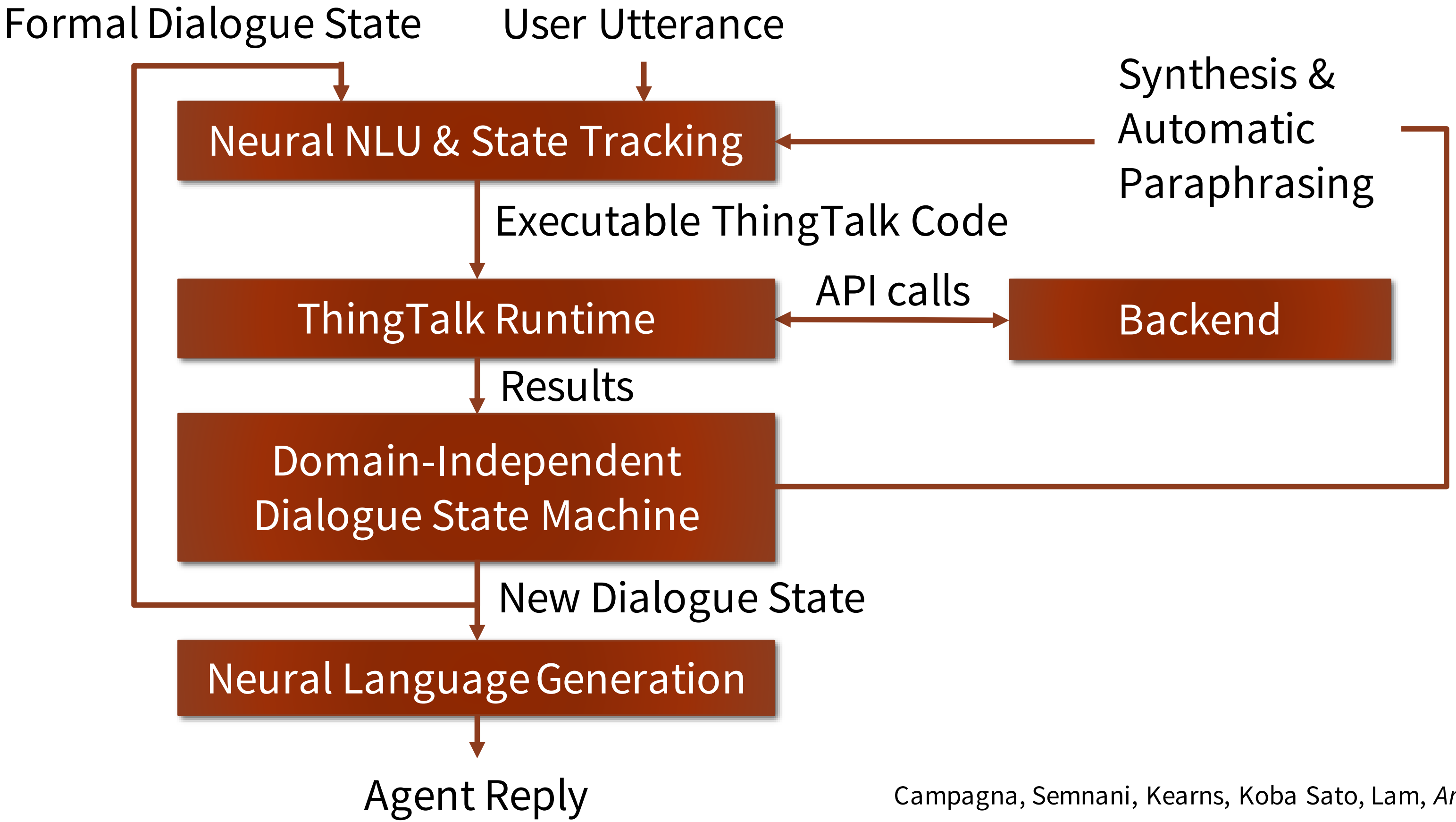
State of the Art: Manually Annotated Conversations

- Dialogues are vast, complex and very varied → **need a lot of data to train**

- Alexa: 10k employees, millions of manually annotated sentences

- *MultiWOZ* dataset [Budzianowski et al.]:
  - ~10k hand annotated dialogues in 5 domains
  - ~100k turns in total
- State of the art: about 55% *joint accuracy*
- About 30% of the errors are misannotations [Zhou and Small]

Our Approach


Formal Dialogue State
User Utterance
Neural NLU & State Tracking
Synthesis & Automatic Paraphrasing
Executable ThingTalk Code
ThingTalk Runtime
API calls
Backend
Results
Domain-Independent Dialogue State Machine
New Dialogue State
Neural Language Generation
Agent Reply

Campagna, Semnani, Kearns, Koba Sato, Lam, *ArXiv*

Key Insights

- Formal, *executable* representation for dialogue states
- State as input & output of neural network
- Domain-independent dialogue state machine to specify agent behavior
- Synthesis approach to training data

Lecture Outline

1. The last state machine for transaction dialogues
2. Combining language understanding & state tracking
3. How to specify a dialogue agent
4. From specification to a complete agent
5. Experimental results (and how to push them)

But First, A Bit of Terminology

- **Utterance**: each phrase said by the user or agent
- **Turn**: a pair of (agent, user) interactions
- **Dialogue**: well-formed sequence of turns
- **History**: sequence of all turns up to the current point
- **State**: formal representation of the dialogue, up to a certain point
  User state: right after the user speaks
  Result state: right after execution
  Agent state: right after the agent speaks
- **Abstract State**: family of states, as defined by the dialogue state machine

Lecture Outline

1. **The last state machine for transaction dialogues**
2. Combining language understanding & state tracking
3. How to specify a dialogue agent
4. From specification to a complete agent
5. Experimental results (and how to push them)

The High-Level Structure of Transaction Dialogues

U: I am looking for a restaurant. The restaurant should serve world food and should be in the centre.

A: Unfortunately, I could not find a restaurant that serves that kind of food in that area.

U: What expensive restaurants are there?

A: The Cambridge Chop House is expensive and it’s British food. Is that okay?

U: No. Try looking for a restaurant that serves Korean food.

A: I found the Little Seoul restaurant. Would you like me to make a reservation?

Search

U: Yes, a table for 2.

A: I would be happy to reserve for you, what day and time are you looking for?

U: Thank you, I need a reservation for 2 people at 13:15 on Monday.

Action Slot Fill

A: gg3dcufd is your confirmation code, may I help you with anything else?

U: No that was everything. Thanks

Execution

Beyond Restaurant Reservations

U: I would like to watch a movie.

A: What movie would you like? Do you like comedy?

U: I prefer action movies

A: How about Spiderman?

U: Sure I like that

A: Opening Netflix…

U: Hey Genie, order me a grande latte

A: Where would you like to pick it up?

U: Stanford & El Camino

A: Alright, ordering 1 grande latte from Starbucks. That will be $3.65 + tax. It will be ready in 10 minutes.

U: I need to buy new shoes.

A: Are you looking for sneakers or leather shoes?

U: Probably a new pair of Nikes

A: How about the new Air Jordans? They are $299 on nike.com

<Picture>

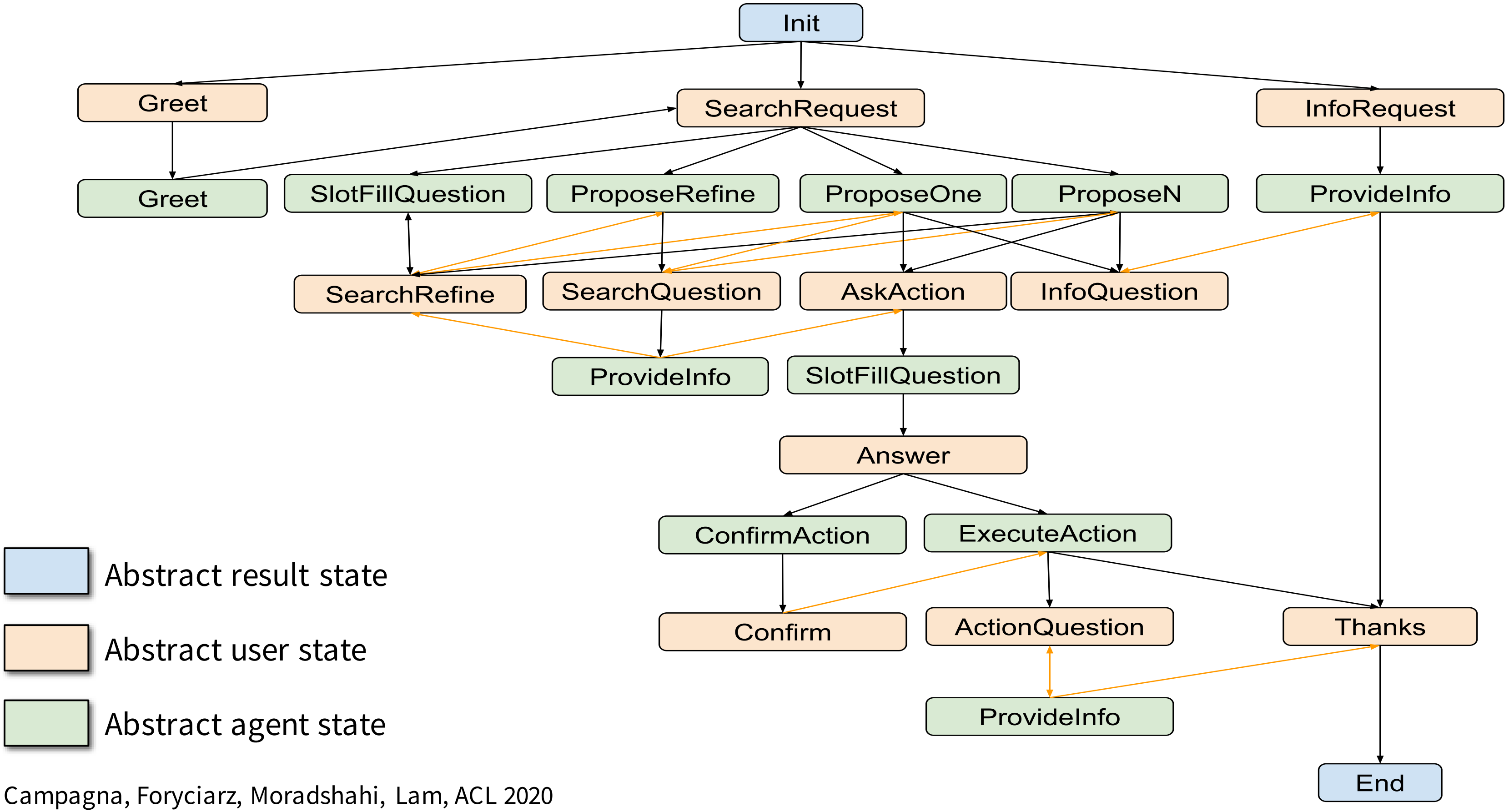
U: They look cool! I’ll take them.

A: Would you like them shipped at your usual address?

U: Yes please

A: Alright, payment is processing. With 2-day standard shipping, they will arrive Tuesday.

A State Machine For Transaction Dialogues



Campagna, Foryciarz, Moradshahi, Lam, ACL 2020

Transaction Dialogues in Practice

- All dialogues look the same - so why do people pay for *skill developers*?

- In Alexa (& DialogFlow, Rasa, Watson, LUIS…): **dialogue tree**
- Replace *dialogue act* (domain indep.) with *intent* (domain dep.)
- Write lots of sentences for each intent
- Hard-code the agent behavior for each intent

- Conflates:
  - *Semantics* (what it means)
  - *Policy* (what to do with it)
  - *Execution* (how to do it)

Concrete State Representation

- Previously: *domain* + *abstract dialogue act* + *slots*
- Slot: "latest mention of an entity from the user"
- **Ill-defined**

U: I'm looking for an Italian restaurant.

```
[ food = "Italian" ]
```

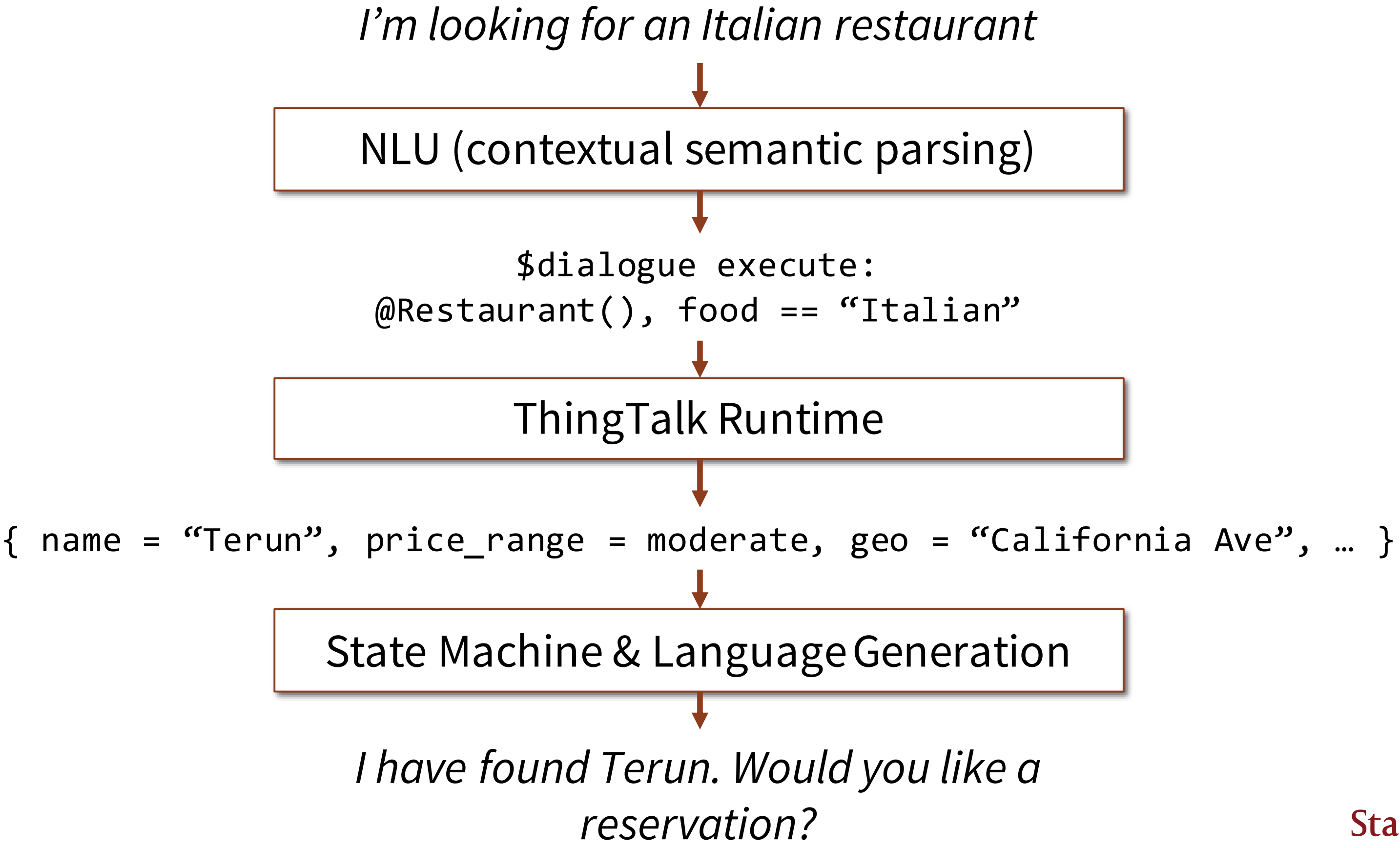
A: I found Terun. Would you like a reservation?

U: Yes please!

```
[ food = "Italian", name = ??? ]
```

- Contrast: formal **ThingTalk executable semantics**
  - Straightforward denotational semantics through relational algebra
  - It either gives you the answer, or it doesn't!

The Restaurant Example



I’m looking for an Italian restaurant

NLU (contextual semantic parsing)

```
$dialogue execute:
@Restaurant(), food == “Italian”
```

ThingTalk Runtime

```
{ name = “Terun”, price_range = moderate, geo = “California Ave”, … }
```

State Machine & Language Generation

I have found Terun. Would you like a reservation?

The Language of Dialogue States (User Side)

```
$dialogue @org.thingpedia.dialogue.transaction.execute ;

now => @com.yelp.Restaurant(), food == “italian” => notify
#[results=[
  { name = “Terun”, price_range = moderate, … },
  …
];

now => @com.yelp.Restaurant(), food == “italian” &&
   price_range == enum(cheap) => notify;

now => @com.yelp.make_reservation(restaurant=$?, …);
```

The Language of Dialogue States (Agent Side)

```
$dialogue @org.thingpedia.dialogue.transaction.sys_rec_one ;

now => @com.yelp.Restaurant(), food == “italian” => notify
#[results=[
  { name = “Terun”, price_range = moderate, … },
  …
];

now => @com.yelp.make_reservation(restaurant=$?, …);

now => @com.yelp.make_reservation(restaurant=“Terun”, …)
#[confirm=enum(proposed)];
```

Quiz 1

How do we know that this representation is sufficient?

User & Agent Dialogue Act Labels

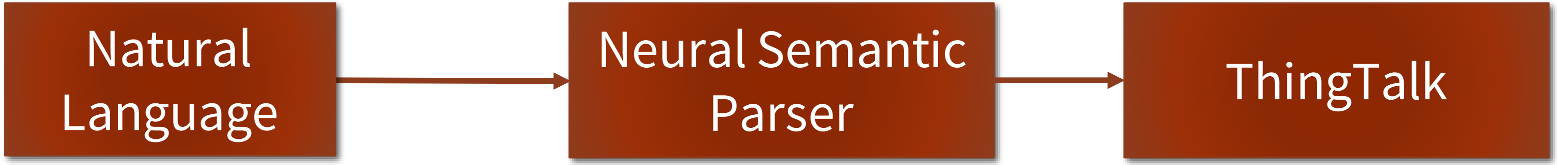
- greet
- execute
- learn_more
- ask_recommend
- cancel
- end

- sys_greet
- sys_search_question(param)
- sys_generic_search_question
- sys_slot_fill(param)
- sys_recommend_one
- sys_recommend_two
- sys_recommend_three
- sys_propose_refined_query
- sys_learn_more_what
- sys_empty_search_question(param)
- sys_empty_search
- sys_action_success
- sys_action_error
- sys_anything_else
- sys_goodbye

Lecture Outline

1. The last state machine for transaction dialogues
2. **Combining language understanding & state tracking**
3. How to specify a dialogue agent
4. From specification to a complete agent
5. Experimental results (and how to push them)

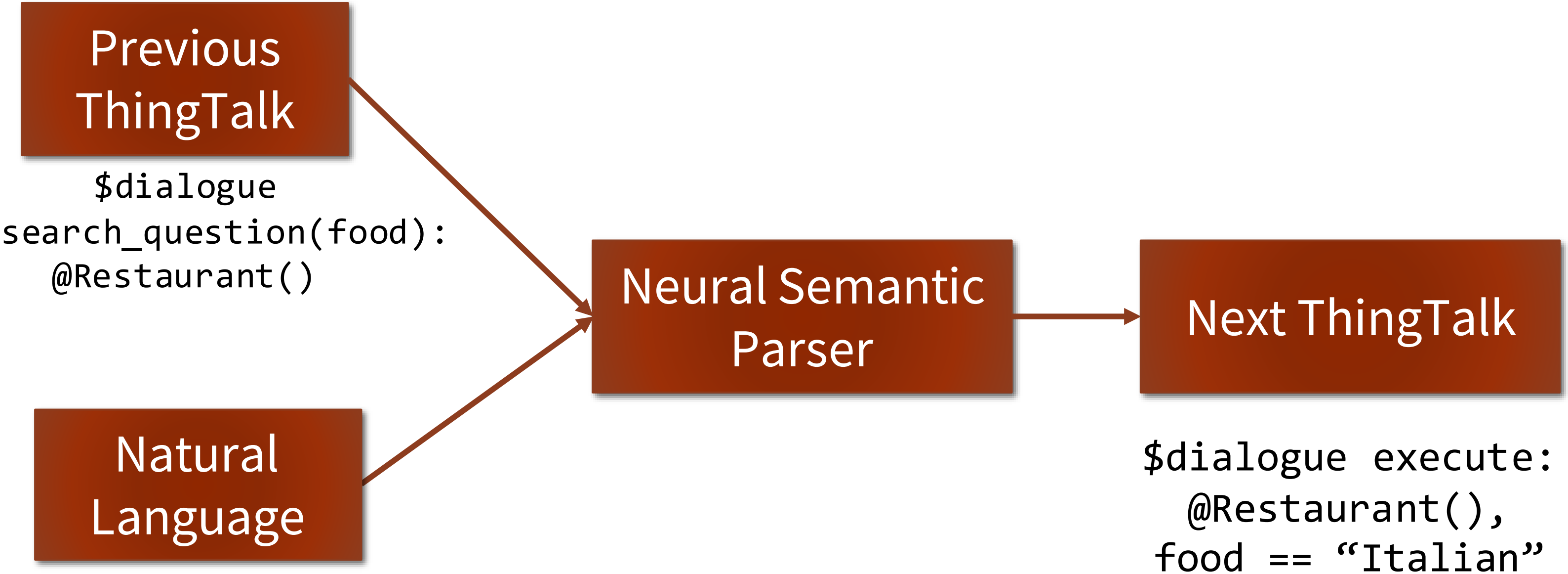
You’ve Seen This Picture Before



I’m looking for an Italian restaurant

```
$dialogue execute:
 @Restaurant(),
food == “Italian”
```

Adding The Dialogue State

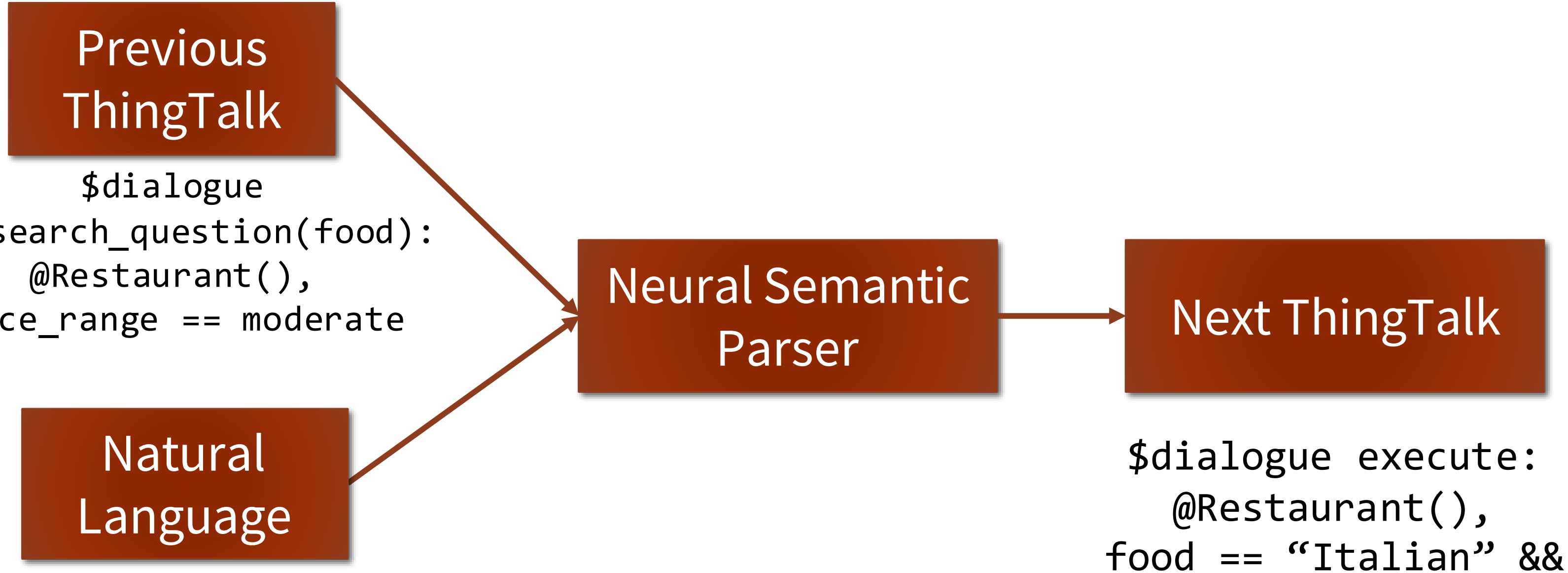


```
$dialogue
sys_search_question(food):
@Restaurant()
```

I'm looking for an Italian restaurant

```
$dialogue execute:
@Restaurant(),
food == “Italian”
```

Adding The Dialogue State

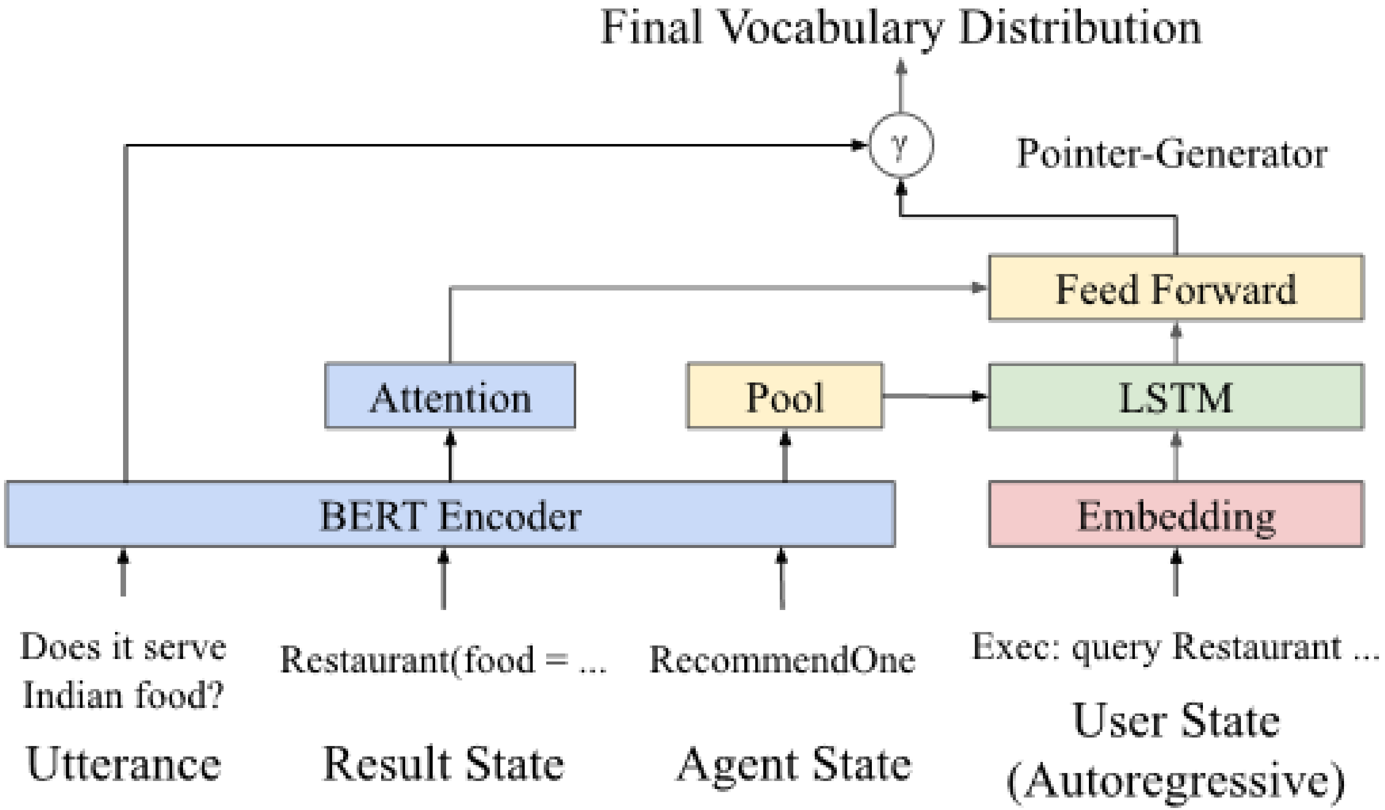


```
$dialogue
sys_search_question(food):
@Restaurant(),
price_range == moderate
```

I'm looking for an Italian restaurant

```
$dialogue execute:
@Restaurant(),
food == “Italian” &&
price_range == moderate
```

The Neural Model (BERT-LSTM)



Quiz 2

What are the advantages & disadvantages of the contextual NLU model vs. training with the full dialogue history?

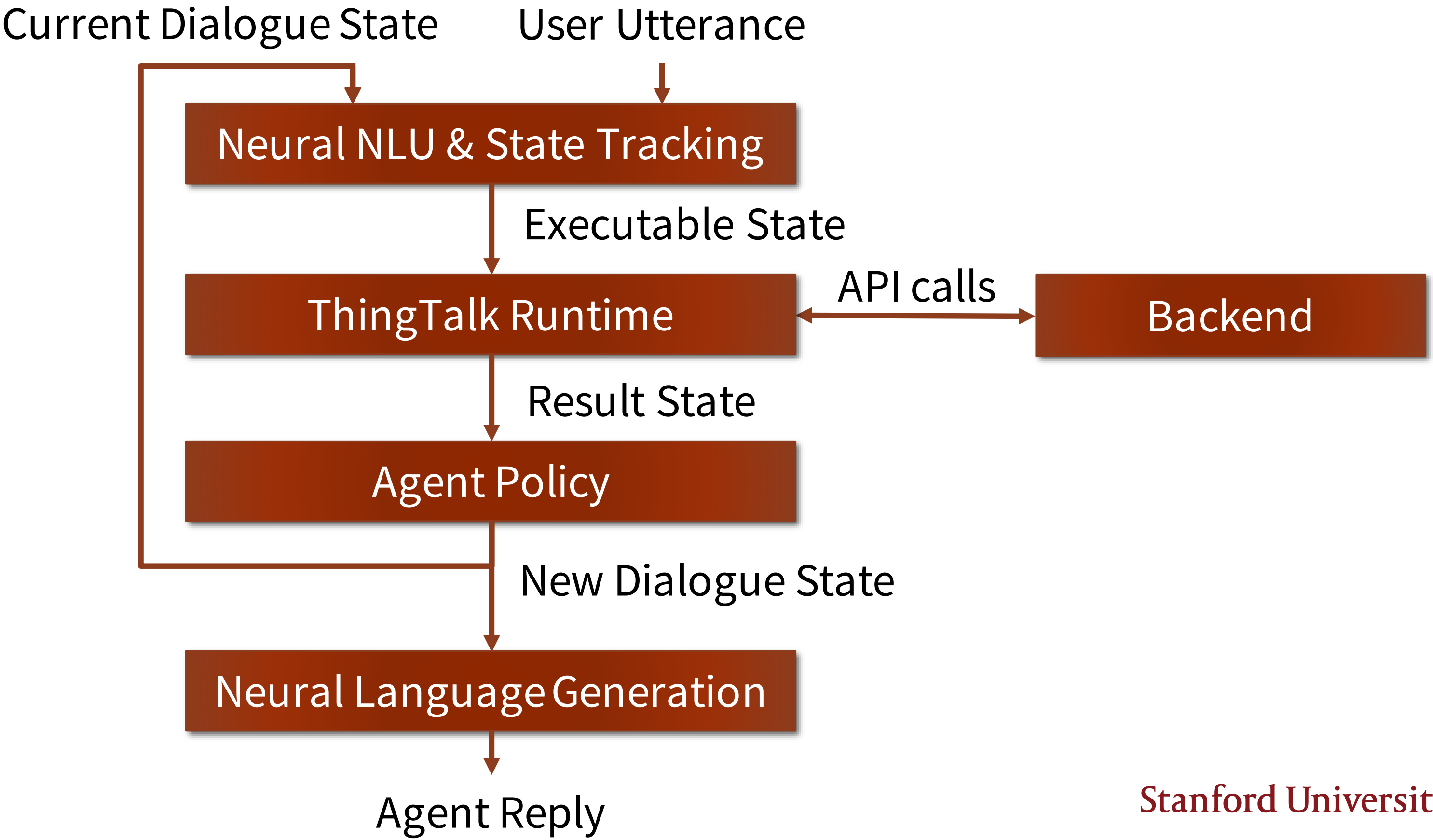
Pros & Cons of Contextual NLU

- Positive: **Minimal information to disambiguate input**
  - Formal state removes “extra” information
  - Controllable amount of history to show to network
  - Reduces needed training data
- Positive: **Formal guarantees of agent behavior**
  - Can prevent “bad states” with tools of formal verification
- Negative: **Difficult to capture uncertainty**
  - Hard sample of one dialogue state as output of the network
  - Inherent ambiguity must be expressed in formalism
  - Statistical ambiguity is lost

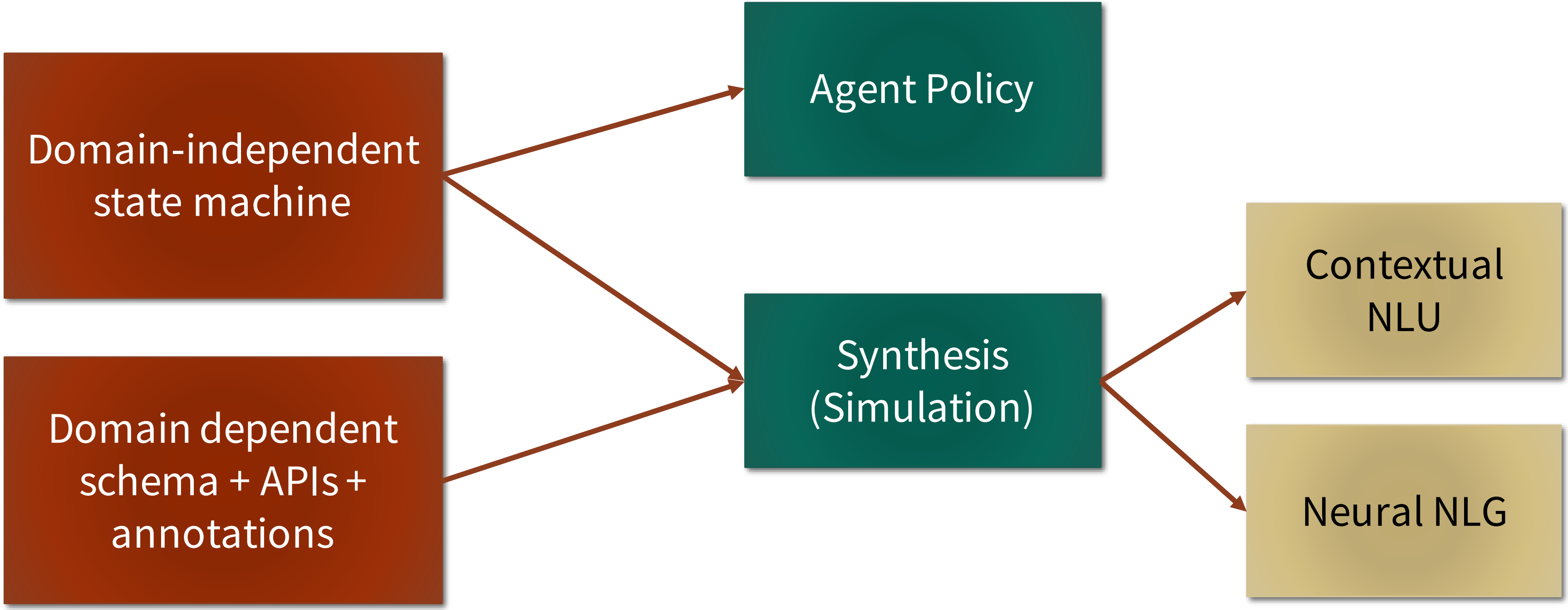
Lecture Outline

1. The last state machine for transaction dialogues
2. Combining language understanding & state tracking
3. **How to specify a dialogue agent**
4. From specification to a complete agent
5. Experimental results (and how to push them)

The Dialogue Agent, Again



Specifying The Dialogue Agent



Domain-independent state machine

Domain dependent schema + APIs + annotations

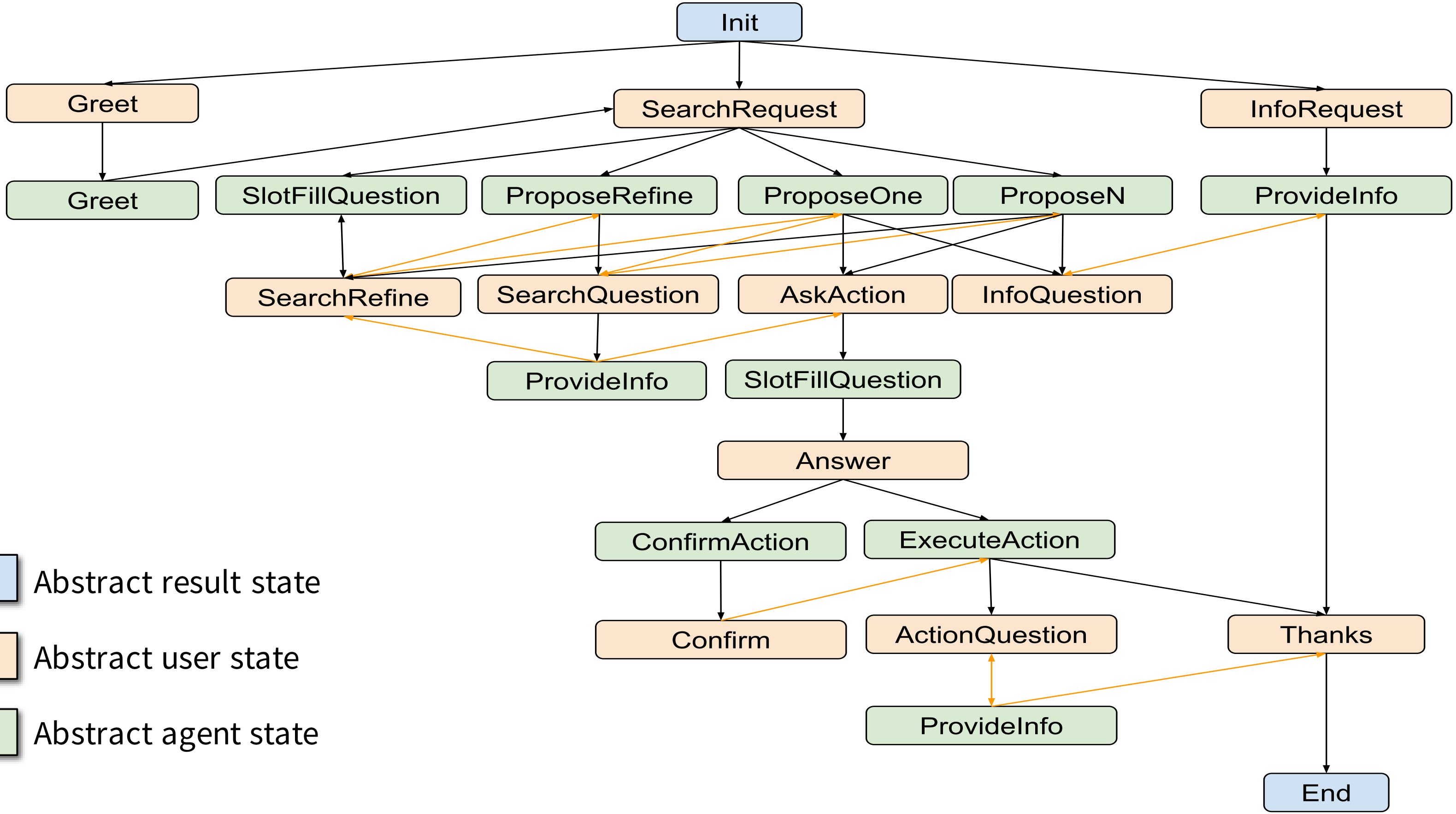
Agent Policy

Synthesis (Simulation)

Contextual NLU

Neural NLG

Reminder: The Transaction Dialogue State Machine

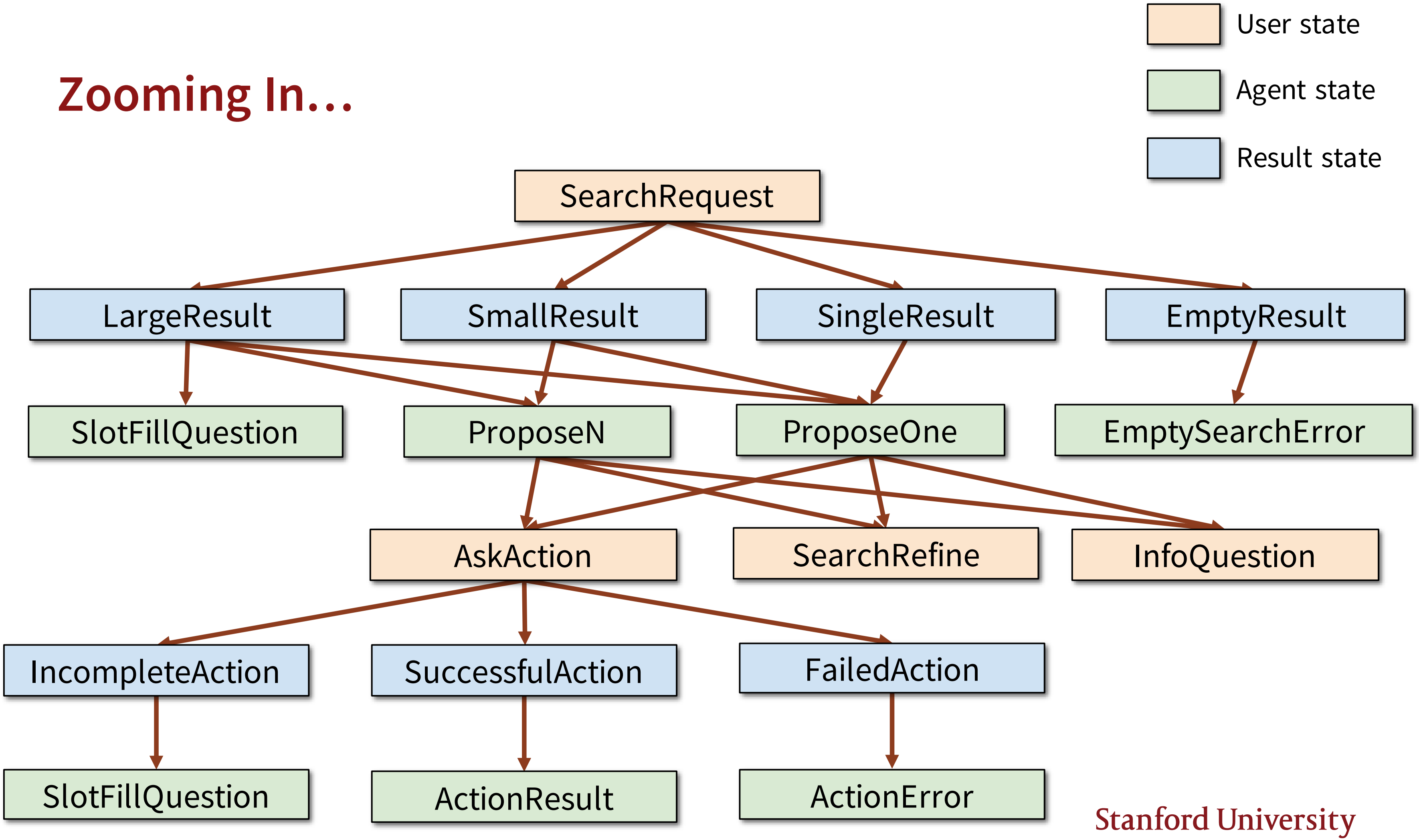


🟦 Abstract result state

🟧 Abstract user state

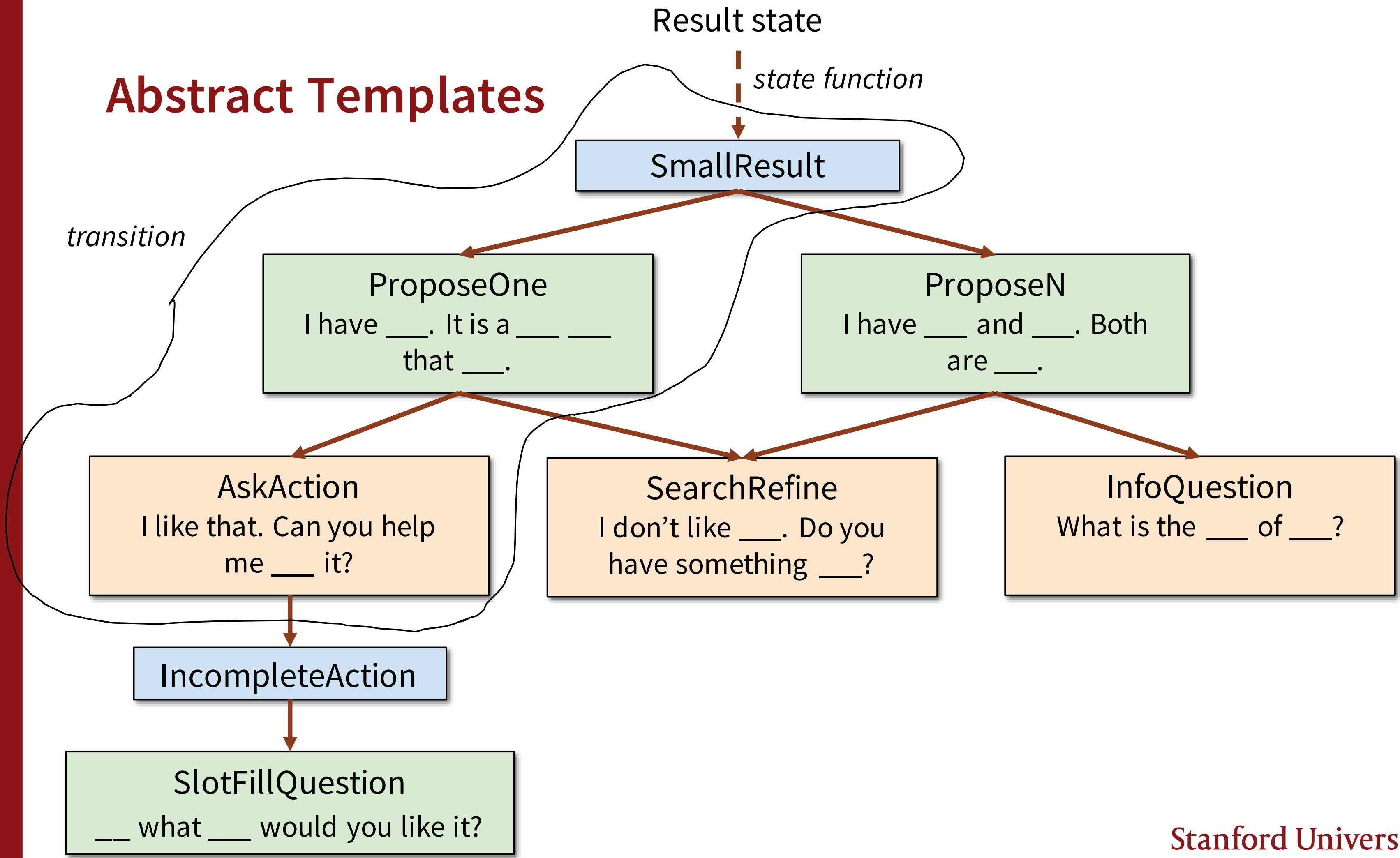
🟩 Abstract agent state

Zooming In…



Stanford University

Abstract Templates



Result state

state function

transition

SmallResult

ProposeOne
I have ___. It is a ___ ___ that ___.

ProposeN
I have ___ and ___. Both are ___.

AskAction
I like that. Can you help me ___ it?

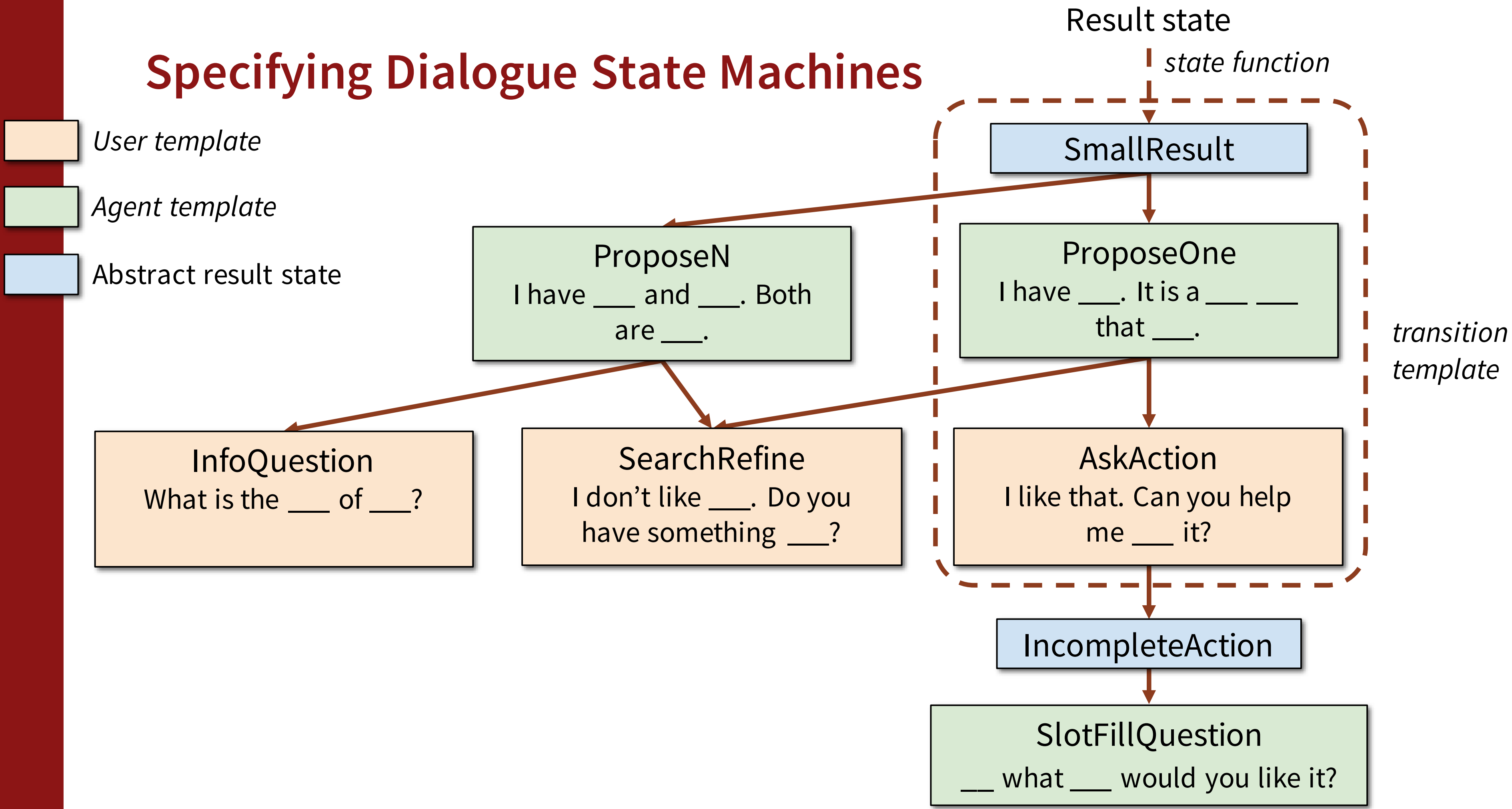
SearchRefine
I don't like ___. Do you have something ___?

InfoQuestion
What is the ___ of ___?

IncompleteAction

SlotFillQuestion
__ what ___ would you like it?

Specifying Dialogue State Machines



🟧 *User template*

🟩 *Agent template*

🟦 Abstract result state

Result state

state function

SmallResult

ProposeN
I have ___ and ___. Both are ___.

ProposeOne
I have ___. It is a ___ ___ that ___.

transition template

InfoQuestion
What is the ___ of ___?

SearchRefine
I don’t like ___. Do you have something ___?

AskAction
I like that. Can you help me ___ it?

IncompleteAction

SlotFillQuestion
__ what ___ would you like it?

Specifying Dialogue State Machines

State function: map dialogue state (ThingTalk code + result) to *abstract state*

Transition templates: triple of (*abstract state, agent act, user act*)
+ validation code

Agent templates: express agent act as sentence + target state

User templates: express user act as sentence + target state

The Transaction Dialogue State Machine

State function: function(state) { if (state.current.result !== null) return StateResult ; … }

Transition templates:

StateResult: ProposeOne → AskAction

StateResult: ProposeOne → SearchRefine

StateResult: ProposeN → InfoQuestion

Agent templates

ProposeOne = [“I have” | “I found”] Name [“Would you like to” CorefAction “?” | InfoPhrase]

ProposeN = [“I have” | “I found”] Name “and” Name “Both are”
    [AdjectiveSlot | PassiveVerbSlot]

User templates

AskAction = [“I like that” | “Sounds good”] “Can you help me” CorefAction “?”

InfoQuestion = [“Can you tell me the”] Param “of” Name “?”

Specifying A Skill

Database Schema

Restaurant

- name: “Curry Prince”, “Pizza Express”, …
- area: “north”, “south”, “east”, …
- price: “cheap”, “moderate”, “expensive”
- food: “Italian”, “Chinese”, “Indian”, …
- address
- phone
- postcode

API Actions

Make Reservation

- book_people: 1 … 7
- book_day: “Monday”, “Tuesday”, …
- book_time: 7:00, 8:00, …
- confirmation_number

Referring To Slots In Natural Language

DOMAIN:

[“restaurant”, “food place”]

Slot “food”:

- NOUN: [“food”, “cuisine”]
- ADJECTIVE: [“*$value*”]
- HAS-NP: [“*$value* food”, “*$value* cuisine”]
- VERB: [“serves *$value* food”]

what <NOUN> does this <DOMAIN> have?
what <NOUN> would you like?

what food does this restaurant have?
what cuisine would you like?

Xu, Campagna, Li, Lam, CIKM 2020

Referring To Slots In Natural Language

DOMAIN:

["restaurant", "food place"]

Slot "food":

- NOUN: ["food", "cuisine"]
- ADJECTIVE: ["*$value*"]
- HAS-NP: ["*$value* food", "*$value* cuisine"]
- VERB: ["serves *$value* food"]

<ADJECTIVE> <DOMAIN>
<DOMAIN> that <VERB>
<DOMAIN> with <HAS-NP>
<DOMAIN> that has <HAS-NP>

Italian restaurant, *Italian food place*
restaurant that serves Italian food
restaurant with Italian food
restaurant that has Italian cuisine

Xu, Campagna, Li, Lam, CIKM 2020

Specifying The Domain For A Transaction Dialogue

Query (Schema)

Restaurant [“restaurant”, “food place”]

- id : Entity(Restaurant)
- geo : Location
  [“address”, “in #”, “near #”, “around #”]
- price : Enum(cheap, moderate, expensive)
  [“# -ly priced “, “#”]
- rating : Number [min=1, max=5]
  [“rated #”]
- cuisines : Array(Entity(Cuisine))
  [“# food”, “serves # food“]
- …

Actions

MakeReservation
[“reserve #”, “book #”]

- restaurant : Entity(Restaurant)
- book_people : Number [min=1]
  [“for #”, “for # people”]
- book_day : Date [“for #”]
- book_time : Time [“at #”, “for #”]
- confirmation_number : String
  [“confirmation number”]

In ThingTalk Syntax

```
class @com.yelp {
   query restaurant(out id: Entity(com.yelp:restaurant),
                    out food: String
                    #[canonical={
                       base=[“cuisine”, “food”],
                       property=[“# cuisine”, “# food”]
                    }]
                    #[prompt=[“what would you like to eat”]],
                    …);
   action make_reservation(in req restaurant: Entity(com.yelp:restaurant),
                           in req book_day : Date
                           #_[canonical={
                              base=[“day”, “date”],
                              preposition=[“for #”, “on #”]
                            }], …)
}
```

Stanford University

The General Form of Transactional Domains

- One query + one or more actions
  - Query: the subject of the discourse
  - Actions: what you can do with it

- Query with `id` parameter of `Entity` type
- Query must have the same name as the Entity type
- Other parameters are the properties of the object
  - Some are searchable (`#[filterable=true]`)

- Actions have one parameter with the same type as the query ID
  - Ties query and actions together

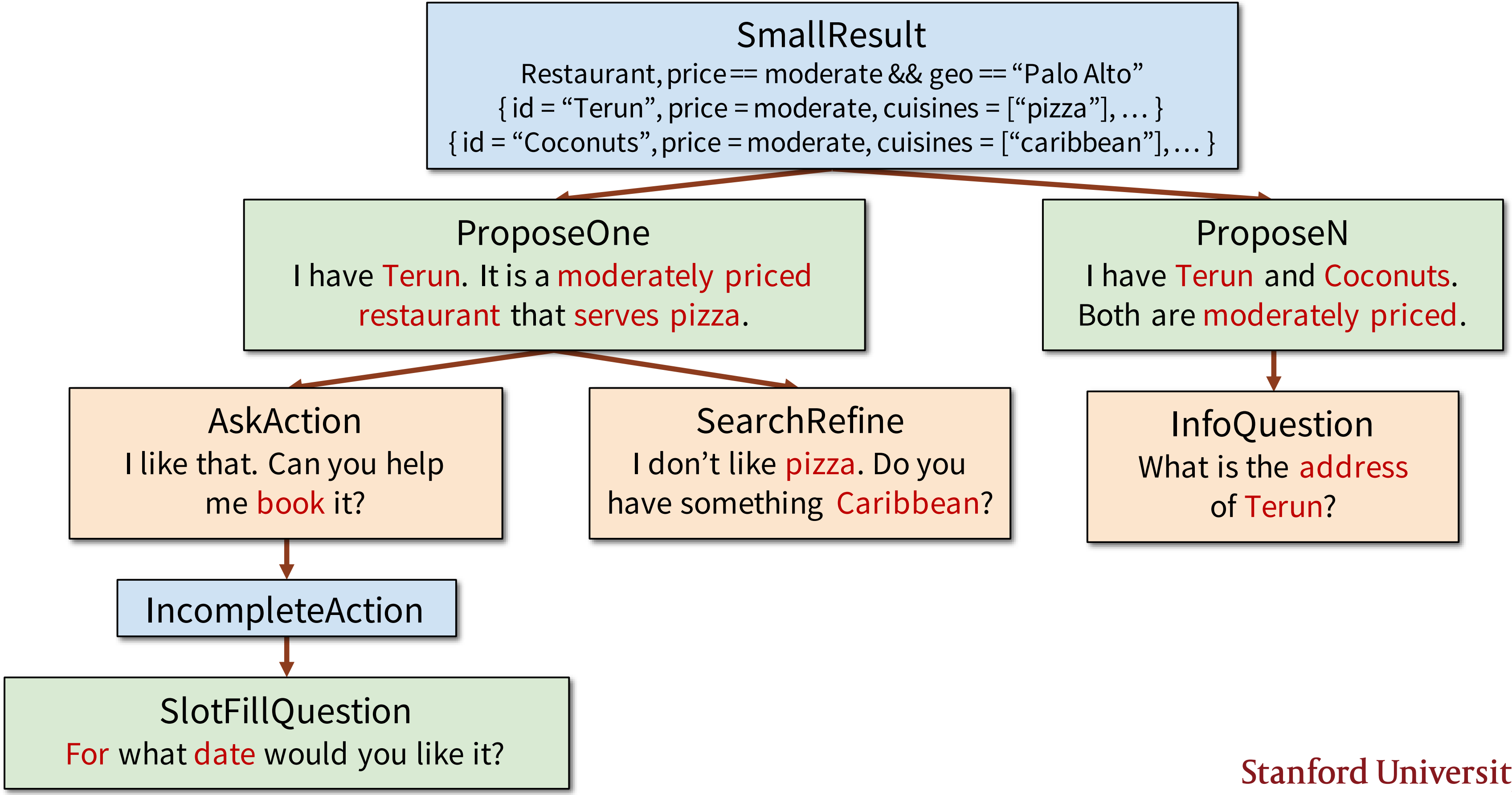
Concretely Doing Things: The Backend

```
const Tp = require(‘thingpedia’);

module.exports = class extends Tp.BaseDevice {
    get_restaurant() {
        // return the content of the database
        // to perform the query
        return …;
    }

    do_make_reservation({ restaurant, book_day, … }) {
        // call the API to make it happen!
    }
}
```

Putting It All Together



SmallResult

Restaurant, price == moderate && geo == “Palo Alto”

{ id = “Terun”, price = moderate, cuisines = [“pizza”], … }

{ id = “Coconuts”, price = moderate, cuisines = [“caribbean”], … }

ProposeOne

I have Terun. It is a moderately priced restaurant that serves pizza.

ProposeN

I have Terun and Coconuts. Both are moderately priced.

AskAction

I like that. Can you help me book it?

SearchRefine

I don’t like pizza. Do you have something Caribbean?

InfoQuestion

What is the address of Terun?

IncompleteAction

SlotFillQuestion

For what date would you like it?

Quiz 3

What are examples of dialogues that cannot be expressed as transactions?

Designing State Machines (For Your Projects)

1. State with few manually written dialogues
2. Annotate fully
3. Collapse into abstract states, agent acts and user acts (on paper)
4. Draw the state machine (on paper)
5. Separate domain-independent & domain-dependent parts
6. Code the state machine in Genie
7. Generate a sample dataset
8. Observe, refine, iterate

Designing State Machines (For Your Projects)

- Write state function
  - Given concrete state of the dialogue, capture abstract state
  - Ideally, should work for *all* possible states
- Write agent templates
  - Both sentence & formal state
- Given agent sentence, write as many user templates as meaningful
  - Templates will depend on the specifics of the agent sentence!
  - Capture **pragmatics**: why is the user saying something?
  - Collapse or distinguish meaning accordingly
  - OK to write *a little* nonsense
- Helpful to look at existing human-human conversations

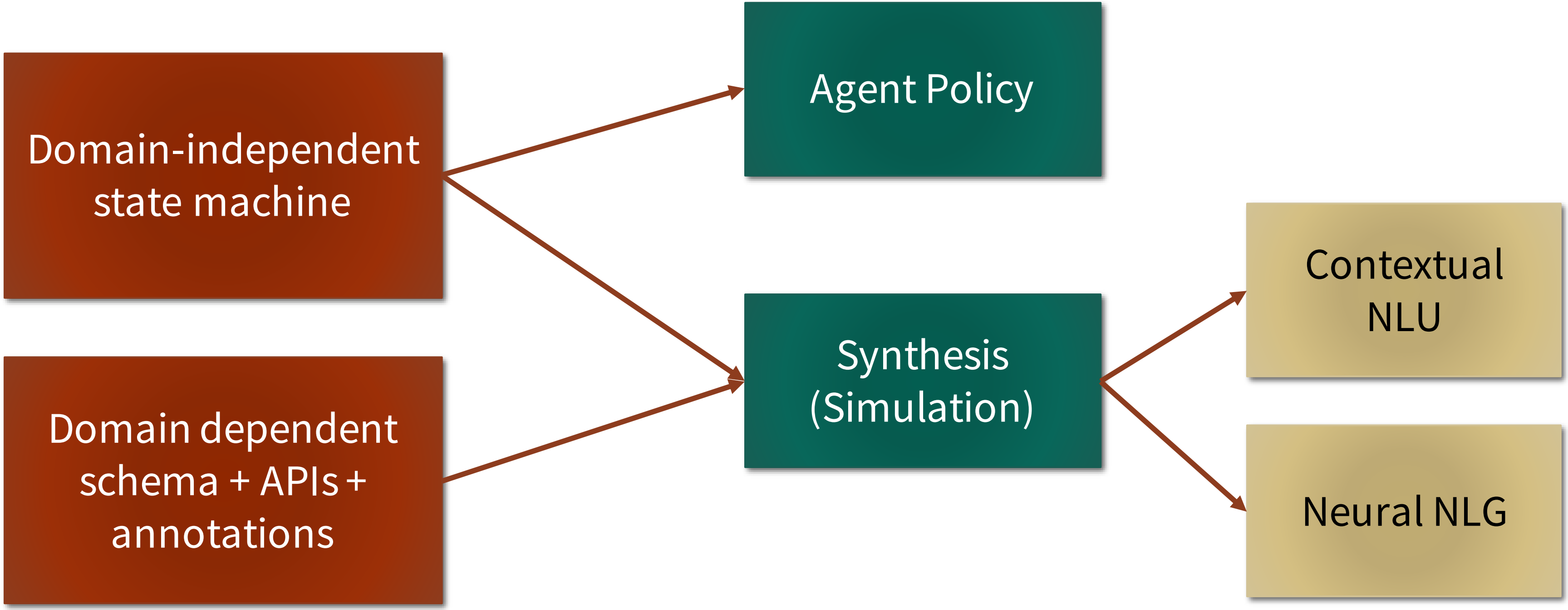
Tips & Tricks for Dialogue Design

- Be *transparent* to your users
  - It’s an incomplete information game
  - Reveal as much as possible of what you know
- Let the user be in the charge
  - The customer is always right

Lecture Outline

1. The last state machine for transaction dialogues
2. Combining language understanding & state tracking
3. How to specify a dialogue agent
4. **From specification to a complete agent**
5. Experimental results (and how to push them)

Reminder: Specifying The Dialogue Agent


Domain-independent state machine
Domain dependent schema + APIs + annotations
Agent Policy
Synthesis (Simulation)
Contextual NLU
Neural NLG

Training the NLU

- Step 1: synthesize as many dialogues as possible
  - Enumerate many possible next states
  - Simulate execution
  - Iterate until enough dialogues generated
- Step 2: extract one *training sample* per turn
  - Old state + user utterance + new state

Constructing the Agent Policy

- Dialogue state from execution with real policy
  - Sample *transition*
  - Sample *agent template*
  - Output: *state after agent speaks* + *synthetic utterance*
- (Future) neural NLG to improve synthetic utterance

Quiz 4

How do you compare the Genie way to write the agent vs. dialogue trees?

Lecture Outline

1. The last state machine for transaction dialogues
2. Combining language understanding & state tracking
3. How to specify a dialogue agent
4. From specification to a complete agent
5. **Experimental results (and how to push them)**

Experiment 1: Quality of Synthesis (Domain Transfer)

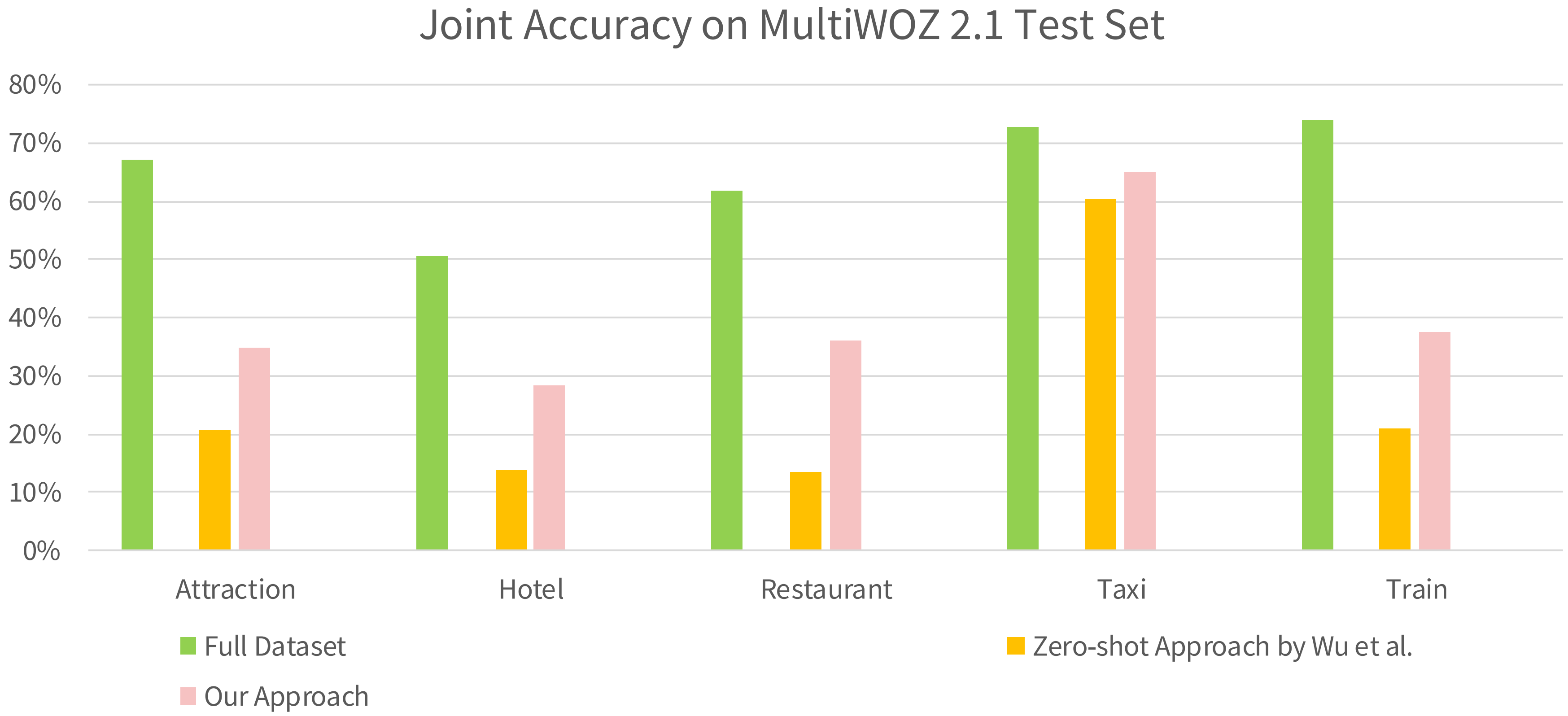
- **MultiWOZ 2.1 benchmark** [Budzianowski et al. 2018, Eric et al. 2019]
  - ~10k hand annotated dialogues in 5 domains
  - Annotation: Domain + Slot: not mentioned / value / don’t care

- Training set:
  - 4 annotated domains
  - Synthesized data for the 5th domain
  - *Domain adaptation*: convert dialogues of similar domains
- Test set with new domain (existing test data)

- Evaluation metric: *Joint Accuracy* (all slots correct given partial dialogue)

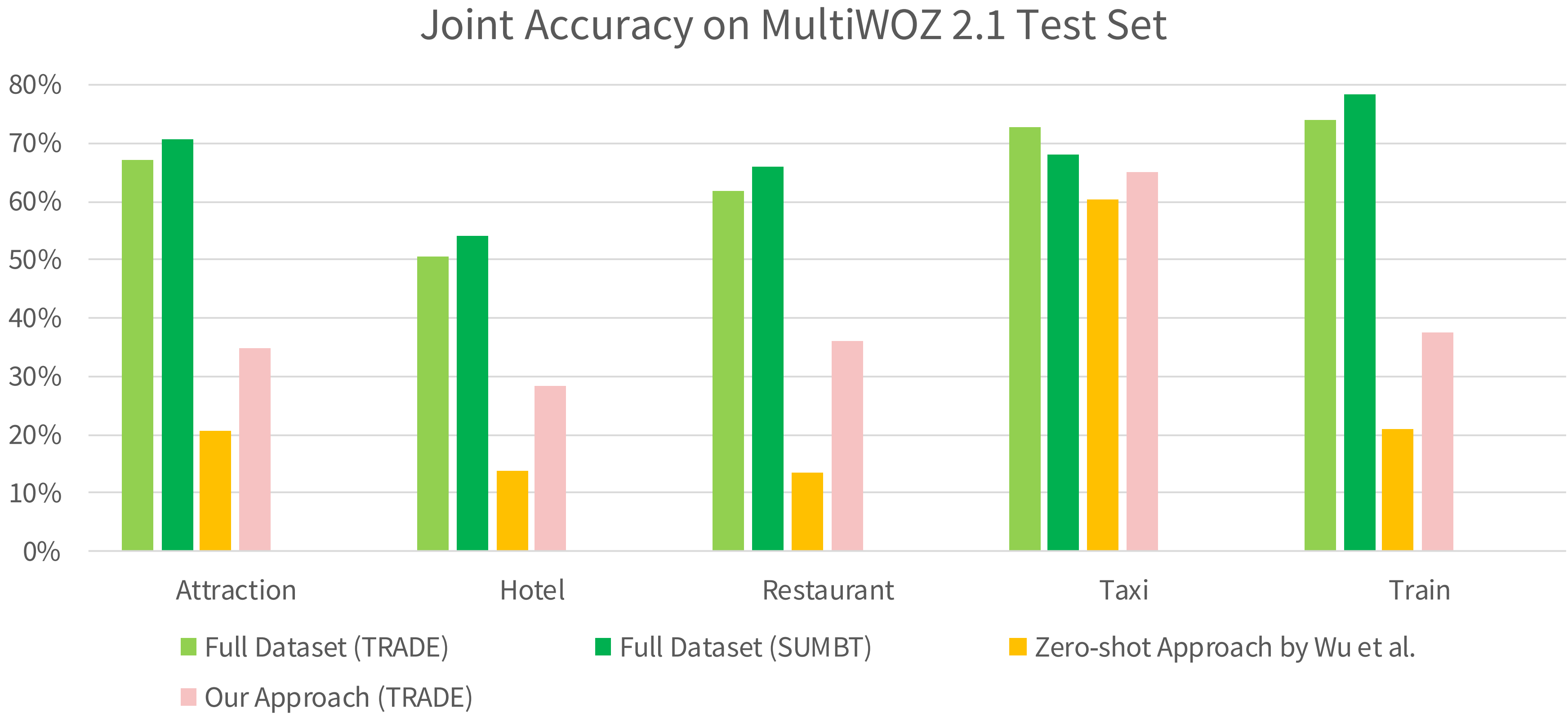
- Models:
  - TRADE [Wu et al. 2019] – fully trained RNN + ptr-gen
  - SUMBT [Lee et al. 2019] – pretrained BERT + ontology match

Zero-Shot Transfer Learning (TRADE)



Campagna, Foryciarz, Moradshahi, Lam, ACL 2020

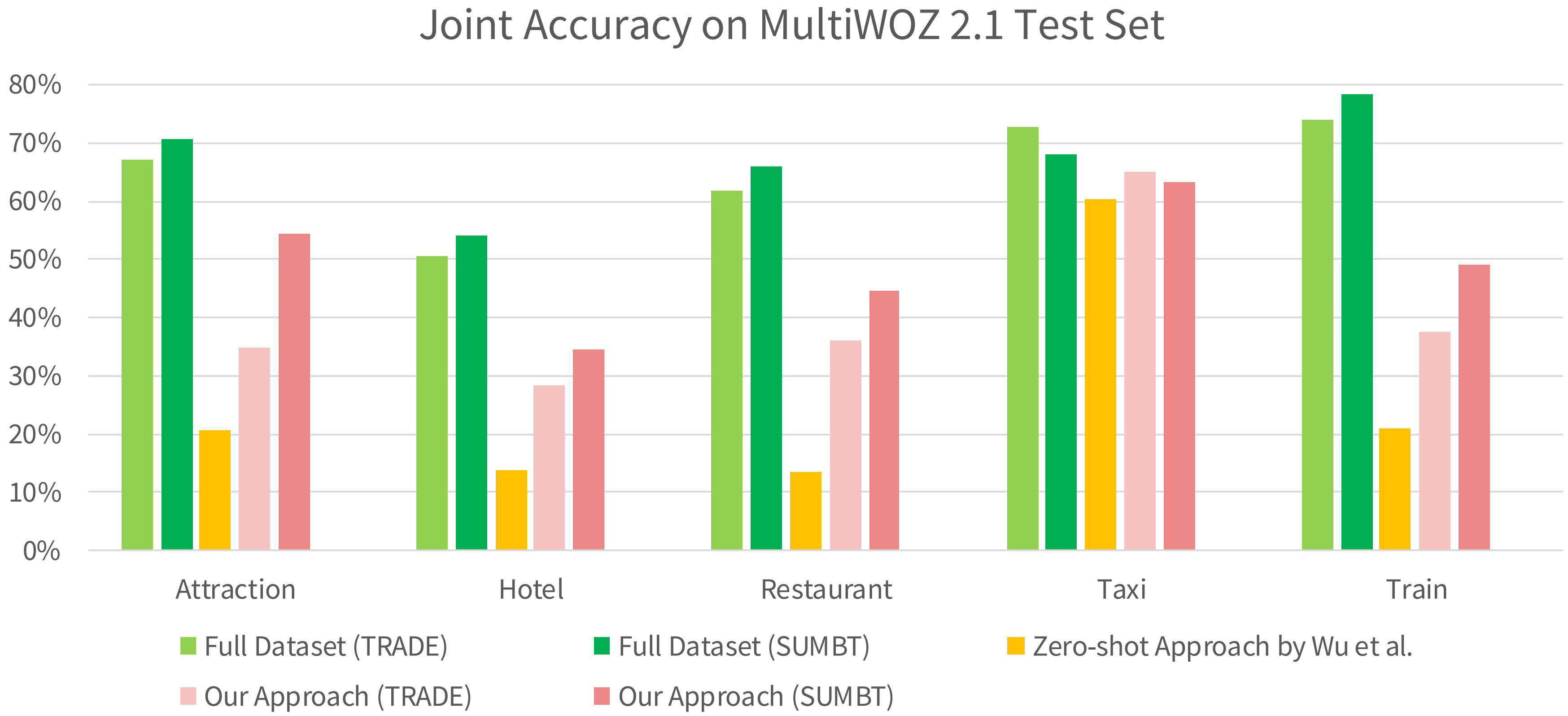
Zero-Shot Transfer Learning



Campagna, Foryciarz, Moradshahi, Lam, ACL 2020

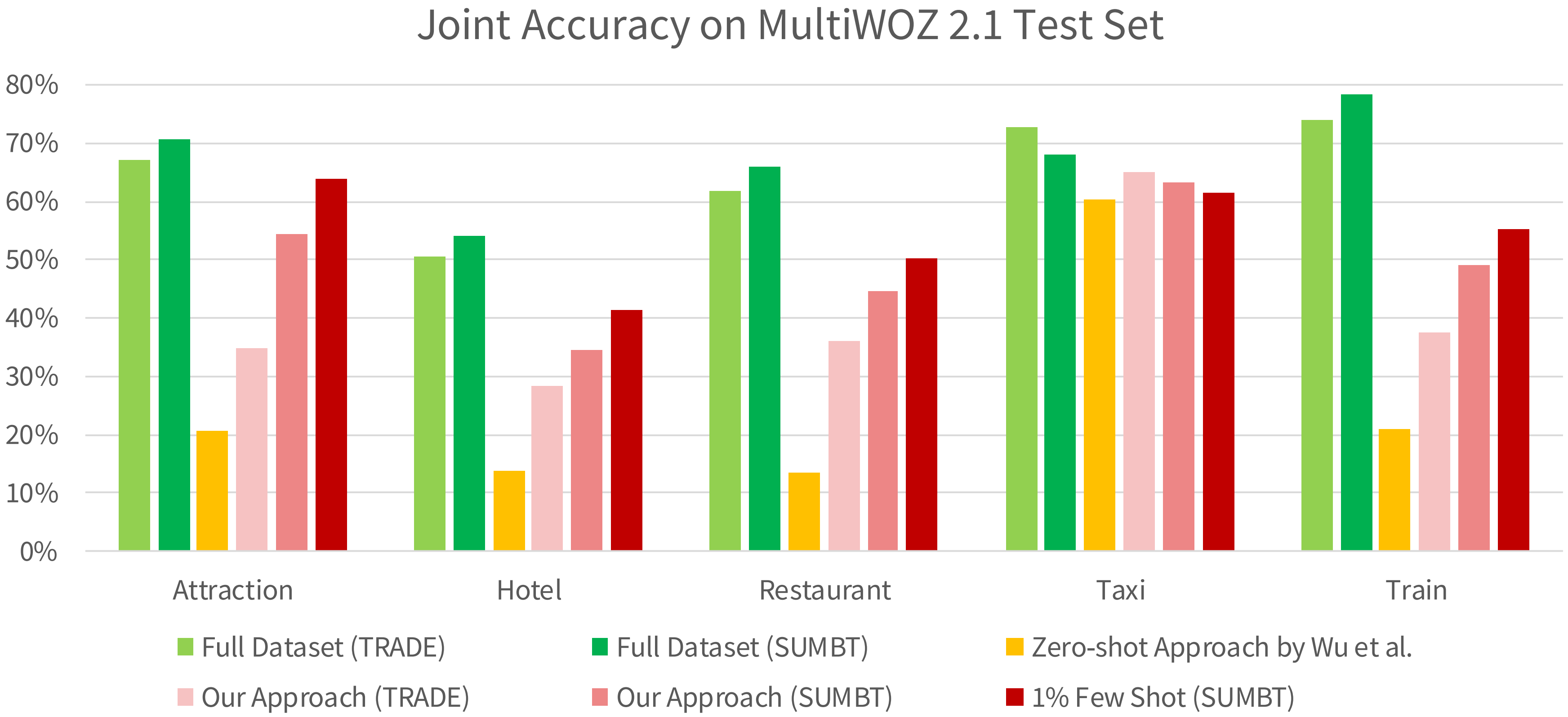
Stanford University

Zero-Shot Transfer Learning



Campagna, Foryciarz, Moradshahi, Lam, ACL 2020

Zero- and Few-Shot Transfer Learning

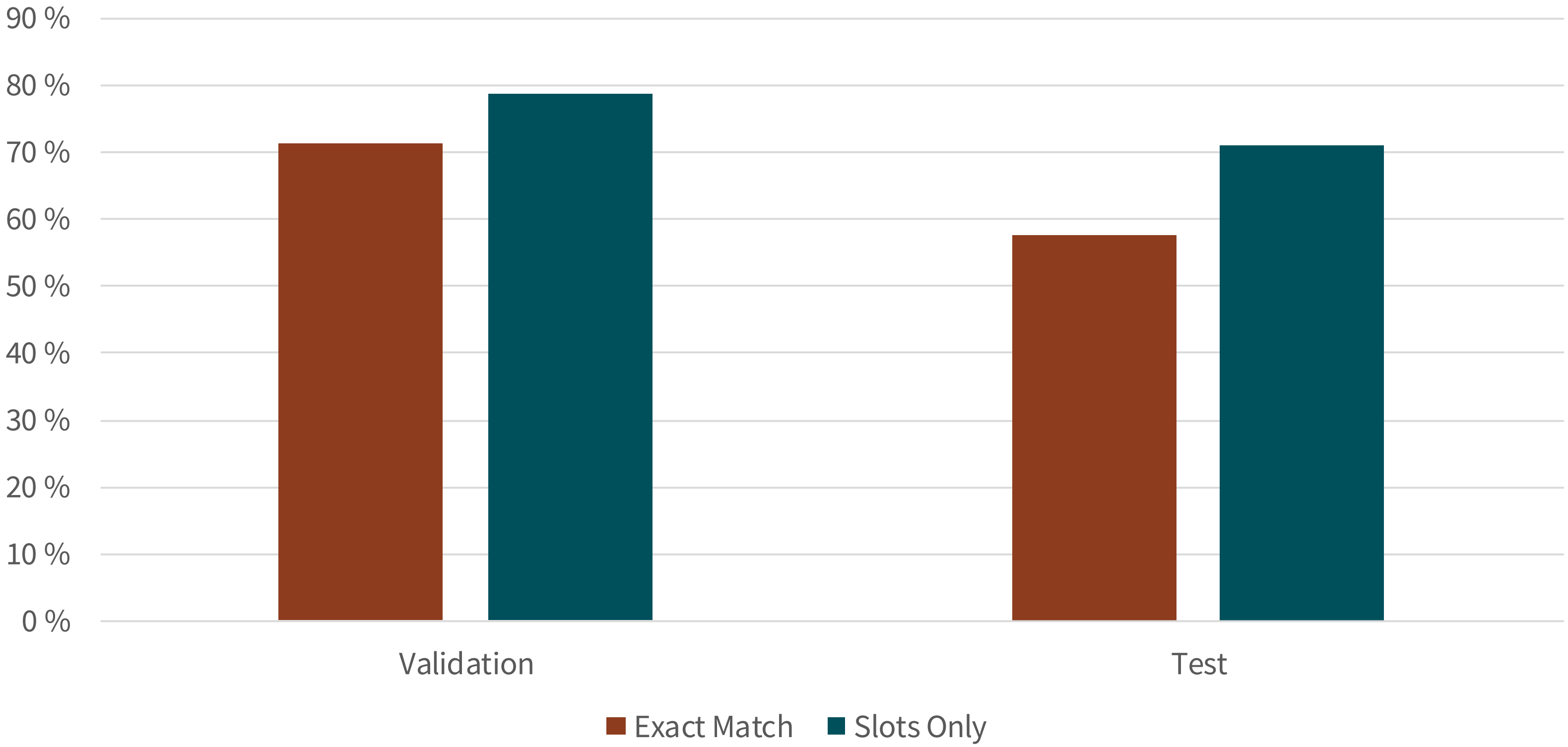


Campagna, Foryciarz, Moradshahi, Lam, ACL 2020

Experiment 2: Performance of Contextual Semantic Parsing

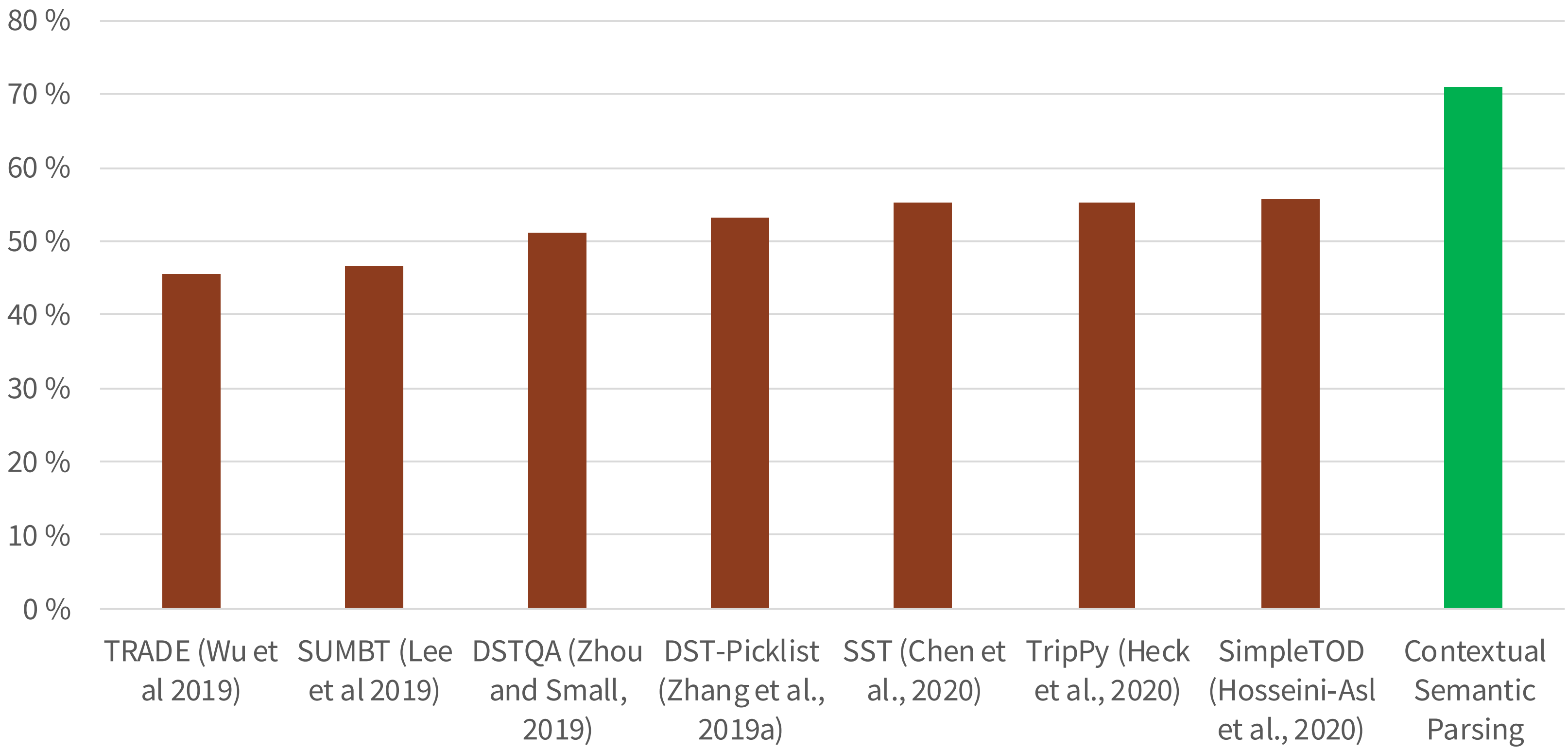
- Experimental setting: **MultiWOZ 2.1 dev and test**, *reannotated*
  - Add dialogue states for agent, correct annotations
- Training set: synthesized + ~1k turns few-shot (**2%** of original training)
- Evaluation metric: *Turn-By-Turn Accuracy* (correct next state given current)
  - Measures the ability to continue the dialogue
- Model: BERT-LSTM

Results



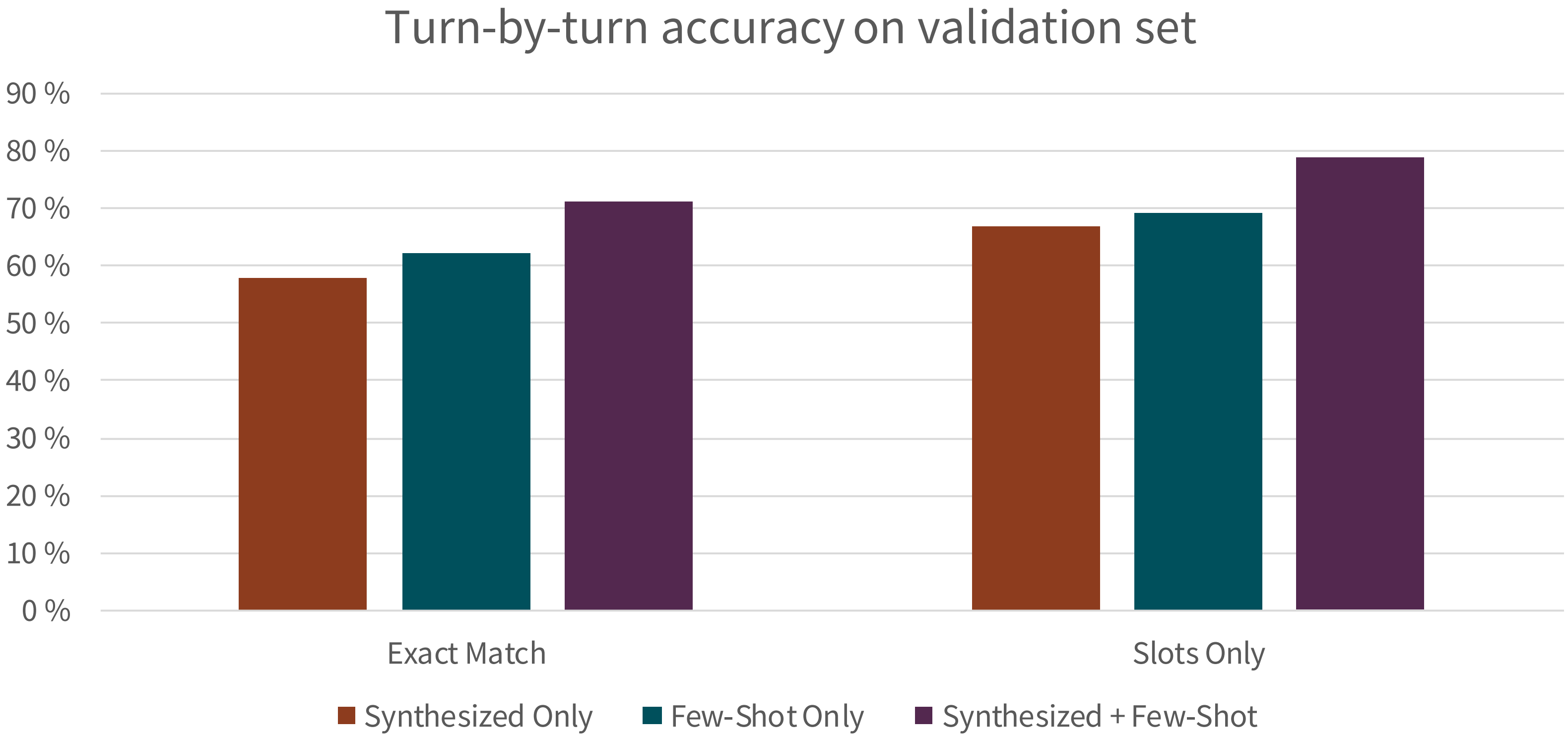
Campagna, Semnani, Kearns, Koba Sato, Lam, *ArXiv*

Contextual Semantic Parsing vs Dialogue State Tracking



Campagna, Semnani, Kearns, Koba Sato, Lam, *ArXiv*

Ablation Study



Campagna, Semnani, Kearns, Koba Sato, Lam, *ArXiv*

Takeaways

- Synthesized data is a **cheap** and **effective** way to build training sets
  - Easy to obtain with a general *state machine* + few domain templates
  - **+21% accuracy** over zero-shot SOTA in DST

- Contextual semantic parsing is a better way to build a dialogue agent
  - Needs more precise annotations than DST (agent state)
  - But easy to obtain with synthesized and few shot
  - **+14% accuracy** turn by turn compared to DST

Recap: Dialogues The Genie Way™

- Formal, executable state representation
- Contextual NLU for state tracking: (current state , user input) → new state
- Data engineering of both agent and user at the same time
  - Domain-independent state machine factored out
  - A lot more state transitions possible
  - Domain-specific in the form annotations (generated in the future?)

Quiz 4 (Open Ended)

How hard is it
to write new dialogue state machines?