Advanced NLU & Dialog Models

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Spoken Dialog Systems
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Roadmap

- Advanced NLU
- Advanced Dialog Models
  - Information State Models
  - Statistical Dialog Models

Learning Probabilistic Slot Filling

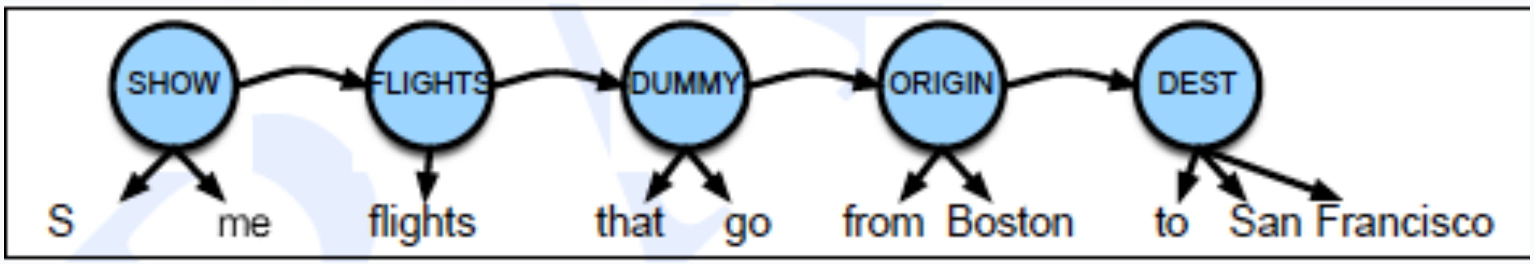
- Goal: Use machine learning to map from recognizer strings to semantic slots and fillers
- Motivation:
  - Improve robustness – fail-soft
  - Improve ambiguity handling – probabilities
  - Improve adaptation – train for new domains, apps
- Many alternative classifier models
  - HMM-based, MaxEnt-based

HMM-Based Slot Filling

- Find best concept sequence C given words W
- C^{*}= argmax P(C|W)
-     = argmax P(W|C)P(C)/P(W)
-     = argmax P(W|C)P(C)
- Assume limited M-concept history, N-gram words
  - = $$\prod_{i=2}^{N} P(w_i \mid w_{i-1} \ldots w_{i-N+1}, c_i) \prod_{i=2}^{N} P(c_i \mid c_{i-1} \ldots c_{i-M+1})$$

Probabilistic Slot Filling

- Example HMM



Advanced Dialog Management

Information State Models

- Challenges in dialog management
  - Difficult to evaluate
    - Hard to isolate from implementations
    - Integration inhibits portability
  - Wide gap between theoretical and practical models
    - Theoretical: logic-based, BDI, plan-based, attention/intention
    - Practical: mostly finite-state or frame-based
    - Even if theory-consistent, many possible implementations
  - Implementation dominates

Why the Gap?

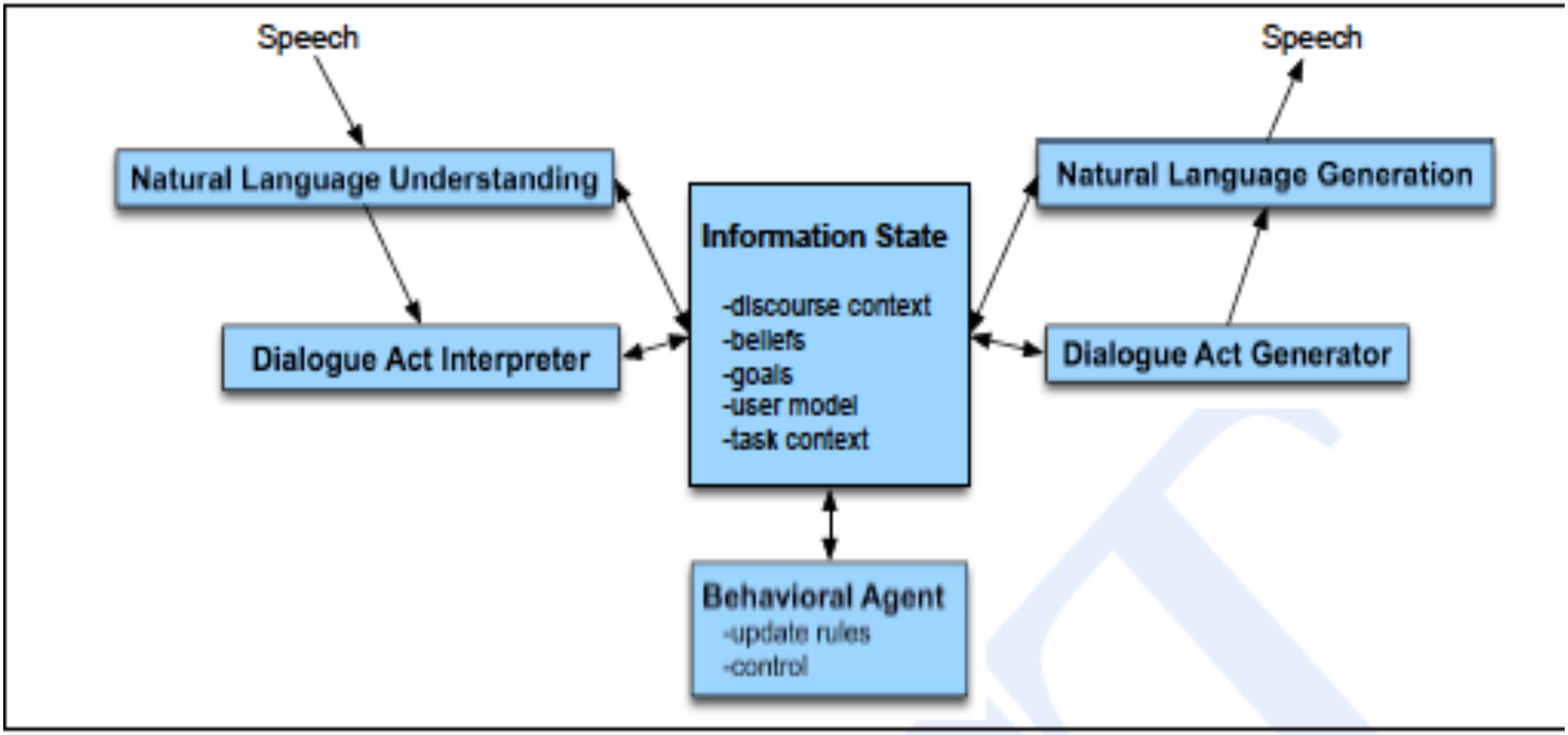
- Theories hard to implement
  - Underspecified
  - Overly complex, intractable
    - e.g. inferring all user intents
- Theories hard to compare
  - Employ diff't basic units
  - Disagree on basic structure
- Implementation is hard
  - Driven by technical limitations, optimizations
  - Driven by specific tasks
- Most approaches simplistic
  - Not focused on model details

Information State Approach

- Approach to formalizing dialog theories
- Toolkit to support implementation (Trindikit)
  - Designed to abstract out dialog theory components
- Example systems & related tools

Information State Architecture

- Simple ideas, complex execution



Information State Theory of Dialog

- Components:
  - Informational components:
    - Common context and internal models (belief, goals, etc)
  - Formal representations:

  - Dialog moves: recognition and generation
    - Trigger state updates
  - Update rules:
    - Describe update given current state, moves, etc
  - Update strategy:
    - Method for selecting rules if more than one applies
      - Simple or complex

Example Dialog

- S: Welcome to the travel agency!
- U: flights to paris
- S: Okay, you want to know about price. A flight. To Paris. Let's see. What city do you want to go from?

$$\begin{bmatrix} \text{PRIVATE} & = & \begin{bmatrix} \text{BEL} & = & \{\} \\ \text{AGENDA} & = & \langle\rangle \\ \text{PLAN} & = & \left\langle \begin{array}{l} \text{findout}(?\text{x.dept-month}(\text{x})), \\ \text{findout}(?\text{x.dept-day}(\text{x})), \\ \text{findout}(?\text{x.class}(\text{x})), \\ \text{consultDB}(?\text{x.price}(\text{x})) \end{array} \right\rangle \\ \text{TMP} & = & \ldots \\ \text{NIM} & = & \ldots \end{bmatrix} \\ \text{SHARED} & = & \begin{bmatrix} \text{COM} & = & \{\text{dest-city}(\text{paris}),\text{how}(\text{plane})\} \\ \text{ISSUES} & = & \langle ?x.\text{dept-city}(x),\ ?x.\text{price}(x)\ \rangle \\ \text{QUD} & = & \langle ?x.\text{dept-city}(x)\rangle \\ \text{PU} & = & \ldots \\ \text{LU} & = & \langle \text{ask}(\text{sys},\ ?x.\text{dept-city}(x)),\ \ldots\rangle \end{bmatrix} \end{bmatrix}$$

Example Update Rule

U-RULE: **accommodateQuestion**(Q, A)

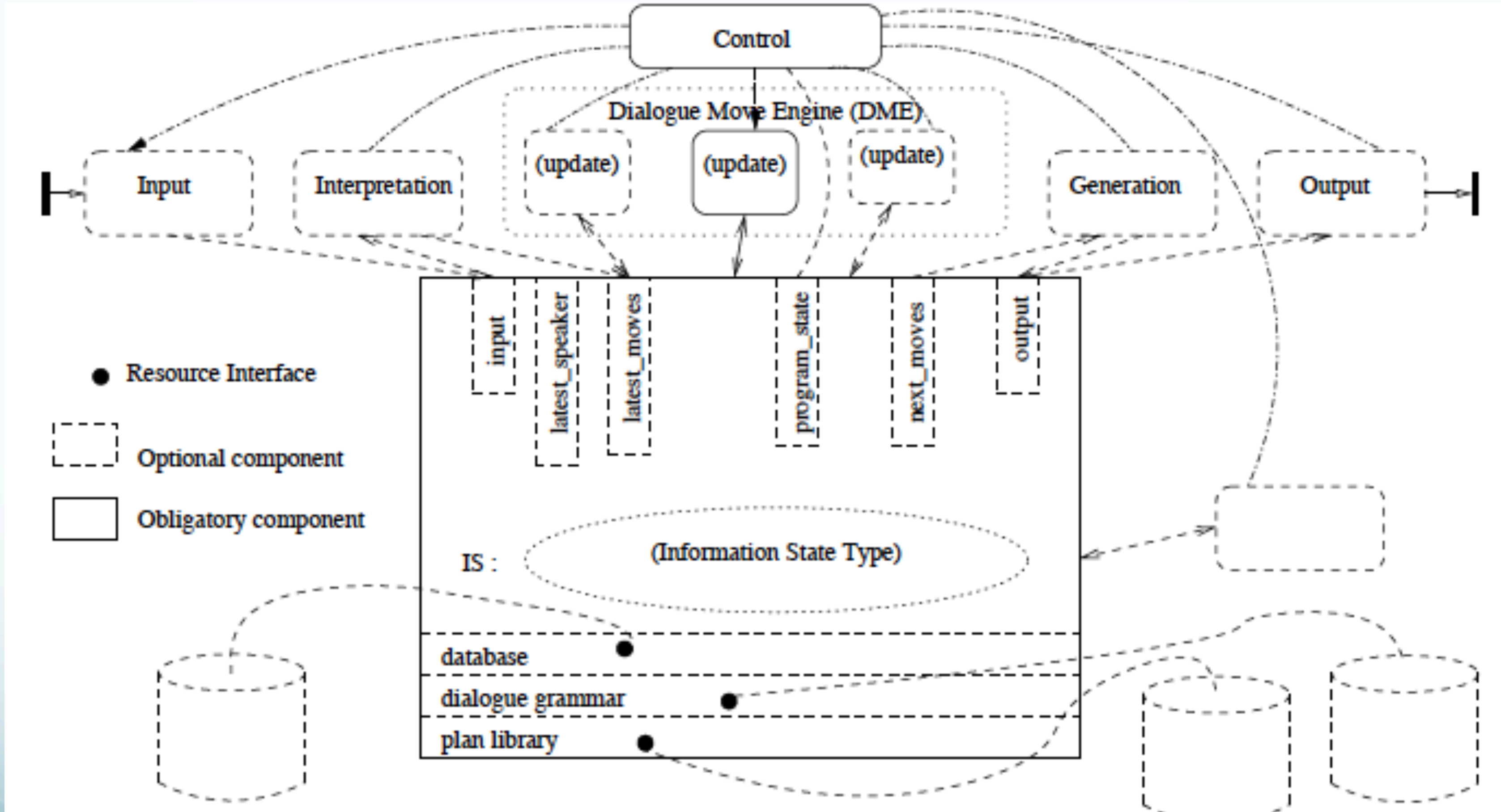
$$
\text{PRE: } \begin{cases} \text{in}(\textsc{shared.lu},\ \text{answer}(\text{usr}, A)), \\ \text{in}(\textsc{private.plan},\ \text{findout}(Q)) \\ \text{domain} :: \text{relevant}(\ A, Q\ ) \end{cases}
$$

$$
\text{EFF: } \begin{cases} \text{del}(\textsc{private.plan},\ \text{findout}(Q)) \\ \text{push}(\textsc{shared.qud},\ Q) \end{cases}
$$

Implementation

- Dialog Move Engine (DME)
  - Implements an information state dialog model
  - Observes/interprets moves
  - Updates information state based on moves
  - Generates new moves consistent with state
- Full system requires: DME+
  - Input/output components
  - Interpretation: determine what move made
  - Generation: produce output for ‘next move’
  - Control system to manage components

Trindikit Architecture



Multi-level Architecture

- Separates types of design expertise, knowledge
- Domain & language resources → Domain system
- Dialog theory → Abstract DME
  - IS, update rules, etc
- Software Engineering → Trindikit
  - basic types, control

Dialogue Acts

- Extension of speech acts
  - Adds structure related to conversational phenomena
    - Grounding, adjacency pairs, etc
- Many proposed tagsets
  - We'll see taxonomies soon

Dialogue Act Interpretation

- Automatically tag utterances in dialogue
- Some simple cases:
  - **YES-NO-Q:** Will breakfast be served on USAir 1557?
  - **Statement:** I don't care about lunch.
  - **Command:** Show me flights from L.A. to Orlando
- Is it always that easy?
  - Can you give me the flights from Atlanta to Boston?
  - Yeah.
    - Depends on context: Y/N answer; agreement; back-channel

Dialogue Act Recognition

- How can we classify dialogue acts?
- Sources of information:
  - Word information:
    - *Please, would you*: request; *are you*: yes-no question
    - N-gram grammars
  - Prosody:
    - Final rising pitch: question; final lowering: statement
    - Reduced intensity: *Yeah:* agreement vs backchannel
  - Adjacency pairs:
    - Y/N question, agreement vs Y/N question, backchannel
    - DA bi-grams

Detecting Correction Acts

- Miscommunication is common in SDS
  - Utterances after errors misrecognized >2x as often
    - Frequently repetition or paraphrase of original input
- Systems need to detect, correct
- Corrections are spoken differently:
  - Hyperarticulated (slower, clearer) -> lower ASR conf.
  - Some word cues: ‘No’,’ I meant’, swearing..
- Can train classifiers to recognize with good acc.

Statistical Dialog Management

New Idea: Modeling a dialogue system as a probabilistic agent

- A conversational agent can be characterized by:
  - The current knowledge of the system
    - A set of states S the agent can be in
  - a set of actions A the agent can take
  - A goal G, which implies
    - A success metric that tells us how well the agent achieved its goal
    - A way of using this metric to create a strategy or policy π for what action to take in any particular state.

What do we mean by actions A and policies π?

- Kinds of decisions a conversational agent needs to make:
  - When should I ground/confirm/reject/ask for clarification on what the user just said?
  - When should I ask a directive prompt, when an open prompt?
  - When should I use user, system, or mixed initiative?

A threshold is a human-designed policy!

- Could we learn what the right action is
  - Rejection
  - Explicit confirmation
  - Implicit confirmation
  - No confirmation
- By learning a policy which,
  - given various information about the current state,
  - dynamically chooses the action which maximizes dialogue success

Another strategy decision

- Open versus directive prompts
- When to do mixed initiative

- How we do this optimization?
- Markov Decision Processes

Review: Open vs. Directive Prompts

- Open prompt
  - System gives user very few constraints
  - User can respond how they please:
  - "How may I help you?" "How may I direct your call?"
- Directive prompt
  - Explicit instructs user how to respond
  - "Say yes if you accept the call; otherwise, say no"

Review: Restrictive vs. Non-restrictive gramamrs

- Restrictive grammar
  - Language model which strongly constrains the ASR system, based on dialogue state
- Non-restrictive grammar
  - Open language model which is not restricted to a particular dialogue state

Kinds of Initiative

- How do I decide which of these initiatives to use at each point in the dialogue?

Grammar	Open Prompt	Directive Prompt
Restrictive	*Doesn't make sense*	System Initiative
Non-restrictive	User Initiative	Mixed Initiative

Goals are not enough

- Goal: user satisfaction
- OK, that's all very well, but
  - Many things influence user satisfaction
  - We don't know user satisfaction til after the dialogue is done
  - How do we know, state by state and action by action, what the agent should do?
- We need a more helpful metric that can apply to each state

Utility

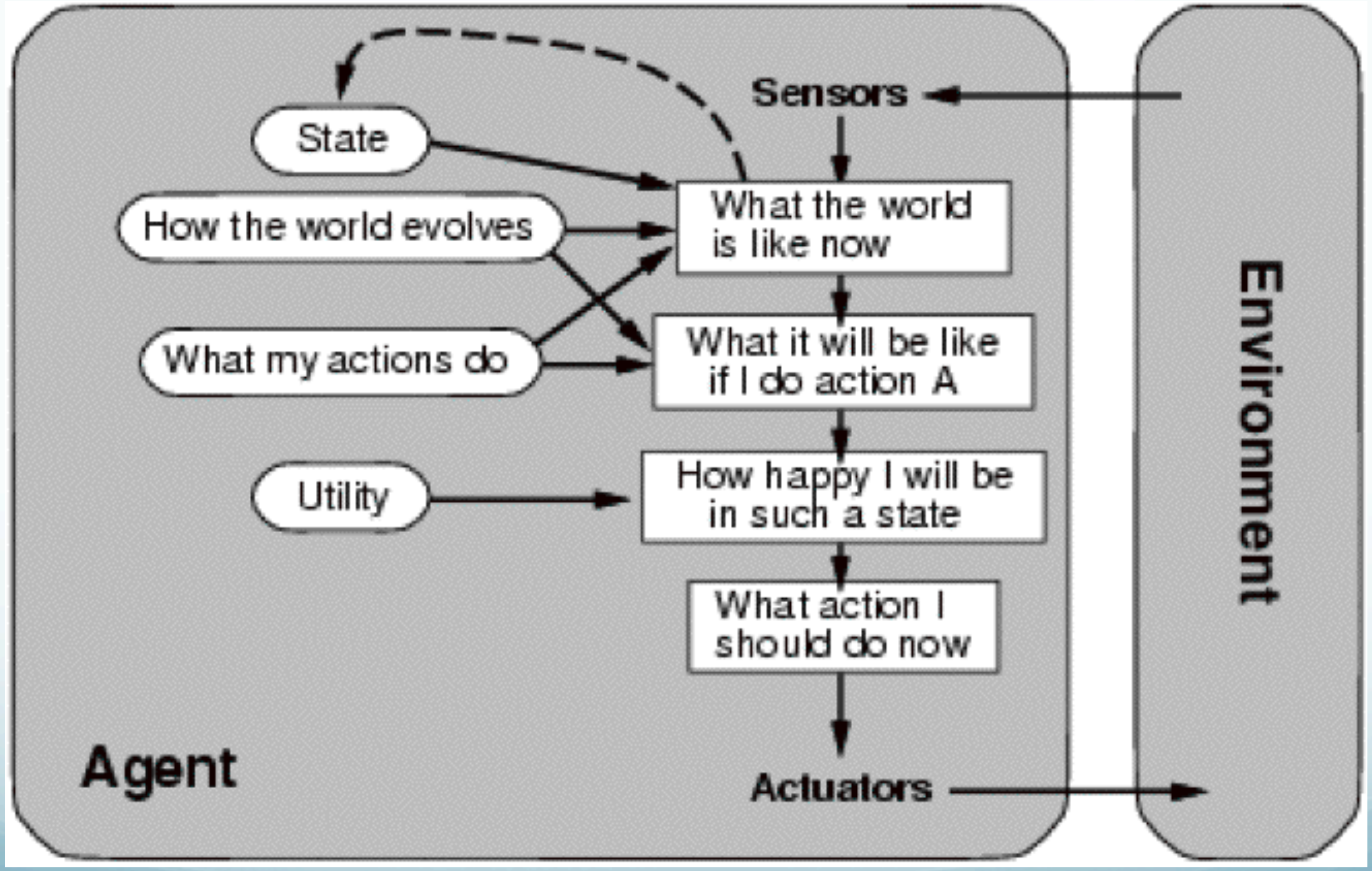
- A utility function
  - maps a state or state sequence
  - onto a real number
  - describing the goodness of that state
  - I.e. the resulting "happiness" of the agent
- Principle of Maximum Expected Utility:
  - A rational agent should choose an action that maximizes the agent's expected utility

Maximum Expected Utility

- Principle of Maximum Expected Utility:
  - A rational agent should choose an action that maximizes the agent's expected utility
- Action A has possible outcome states $Result_i(A)$
- E: agent's evidence about current state of world
- Before doing A, agent estimates prob of each outcome
  - $P(Result_i(A)|Do(A),E)$
- Thus can compute expected utility:

$$EU(A|E) = \sum_i P(Result_i(A)|Do(A),E)U(Result_i(A))$$

Utility (Russell and Norvig)



Markov Decision Processes

- Or MDP
- Characterized by:
  - a set of states S an agent can be in
  - a set of actions A the agent can take
  - A reward r(a,s) that the agent receives for taking an action in a state

A brief tutorial example

- Levin et al (2000)
- A Day-and-Month dialogue system
- Goal: fill in a two-slot frame:
  - Month: November
  - Day: 12th
- Via the shortest possible interaction with user

What is a state?

- In principle, MDP state could include any possible information about dialogue
  - Complete dialogue history so far
- Usually use a much more limited set
  - Values of slots in current frame
  - Most recent question asked to user
  - Users most recent answer
  - ASR confidence
  - etc

State in the Day-and-Month example

- Values of the two slots day and month.
- Total:
  - 2 special initial states s_i and s_f.
  - 365 states with a day and month
  - 1 state for leap year
  - 12 states with a month but no day
  - 31 states with a day but no month
  - 411 total states

Actions in MDP models of dialogue

- Speech acts!
  - Ask a question
  - Explicit confirmation
  - Rejection
  - Give the user some database information
  - Tell the user their choices
- Do a database query

Actions in the Day-and-Month example

- a_d: a question asking for the day
- a_m: a question asking for the month
- a_{dm}: a question asking for the day+month
- a_f: a final action submitting the form and terminating the dialogue

A simple reward function

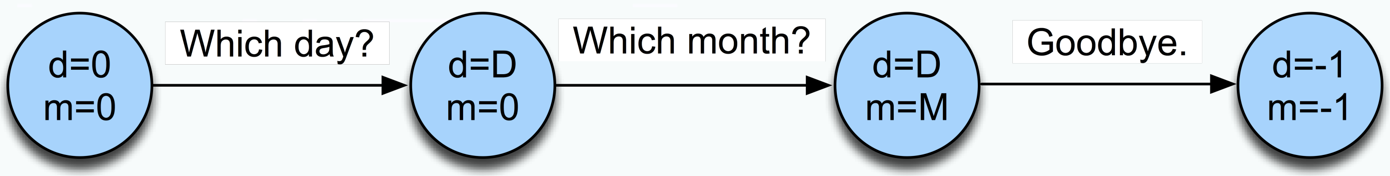
- For this example, let's use a cost function
- A cost function for entire dialogue
- Let
  - N_i=number of interactions (duration of dialogue)
  - N_e=number of errors in the obtained values (0-2)
  - N_f=expected distance from goal
    - (0 for complete date, 1 if either data or month are missing, 2 if both missing)
- Then (weighted) cost is:
- $C = w_i \times N_i + w_e \times N_e + w_f \times N_f$

2 possible policies

Strategy 1 is better than strategy 2 when improved error rate justifies longer interaction:

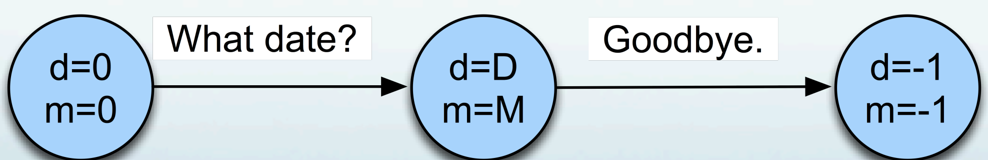
$$p_o - p_d > \frac{w_i}{2w_e}$$

Policy 1 (directive)



$c_1 = -3w_i + 2p_d w_e$

Policy 2 (open)



$c_2 = -2w_i + 2p_o w_e$

That was an easy optimization

- Only two actions, only tiny # of policies
- In general, number of actions, states, policies is quite large
- So finding optimal policy π^* is harder
- We need reinforcement learning
- Back to MDPs:

MDP

- We can think of a dialogue as a trajectory in state space

$$s_1 \rightarrow_{a1,r1} s_2 \rightarrow_{a2,r2} s_3 \rightarrow_{a3,r3} \cdots$$

- The best policy π^* is the one with the greatest expected reward over all trajectories
- How to compute a reward for a state sequence?

Reward for a state sequence

- One common approach: discounted rewards
- Cumulative reward Q of a sequence is discounted sum of utilities of individual states

$$Q([s_0, a_0, s_1, a_1, s_2, a_2 \cdots]) = R(s_0, a_0) + \gamma R(s_1, a_1) + \gamma^2 R(s_2, a_2) + \cdots,$$

- Makes agent care more about current than future rewards; the more future a reward, the more discounted its value

The Markov assumption

- MDP assumes that state transitions are Markovian

$$P(s_{t+1} \mid s_t, s_{t-1}, \ldots, s_o, a_t, a_{t-1}, \ldots, a_o) = P_T(s_{t+1} \mid s_t, a_t)$$

Expected reward for an action

- Expected cumulative reward Q(s,a) for taking a particular action from a particular state can be computed by Bellman equation:

$$Q(s,a) = R(s,a) + \gamma \sum_{s'} P(s'|s,a) \max_{a'} Q(s',a')$$

- Expected cumulative reward for a given state/action pair is:
  - immediate reward for current state
  - + expected discounted utility of all possible next states s'
  - Weighted by probability of moving to that state s'
  - And assuming once there we take optimal action a'

What we need for Bellman equation

- A model of p(s' |s,a)
- Estimate of R(s,a)
- How to get these?
- If we had labeled training data
  - P(s' |s,a) = C(s,s' ,a)/C(s,a)
- If we knew the final reward for whole dialogue R(s1,a1,s2,a2,...,sn)
- Given these parameters, can use value iteration algorithm to learn Q values (pushing back reward values over state sequences) and hence best policy

Final reward

- What is the final reward for whole dialogue R(s1,a1,s2,a2,…,sn)?
- This is what our automatic evaluation metric PARADISE computes!
- The general goodness of a whole dialogue!!!!!

How to estimate p(s' |s,a) without labeled data

- Have random conversations with real people
  - Carefully hand-tune small number of states and policies
  - Then can build a dialogue system which explores state space by generating a few hundred random conversations with real humans
  - Set probabilities from this corpus
- Have random conversations with simulated people
  - Now you can have millions of conversations with simulated people
  - So you can have a slightly larger state space

An example

- Singh, S., D. Litman, M. Kearns, and M. Walker. 2002. Optimizing Dialogue Management with Reinforcement Learning: Experiments with the NJFun System. Journal of AI Research.

- NJFun system, people asked questions about recreational activities in New Jersey
- Idea of paper: use reinforcement learning to make a small set of optimal policy decisions

Very small # of states and acts

- **States**: specified by values of 8 features
  - Which slot in frame is being worked on (1-4)
  - ASR confidence value (0-5)
  - How many times a current slot question had been asked
  - Restrictive vs. non-restrictive grammar
  - Result: 62 states
- **Actions**: each state only 2 possible actions
  - Asking questions: System versus user initiative
  - Receiving answers: explicit versus no confirmation.

Ran system with real users

- 311 conversations
- Simple binary reward function
  - 1 if competed task (finding museums, theater, winetasting in NJ area)
  - 0 if not
- System learned good dialogue strategy: Roughly
  - Start with user initiative
  - Backoff to mixed or system initiative when re-asking for an attribute
  - Confirm only a lower confidence values

State of the art

- Only a few such systems
  - From (former) ATT Laboratories researchers, now dispersed
  - And Cambridge UK lab
- Hot topics:
  - Partially observable MDPs (POMDPs)
  - We don't REALLY know the user's state (we only know what we THOUGHT the user said)
  - So need to take actions based on our BELIEF , I.e. a probability distribution over states rather than the "true state"

Summary

- Utility-based conversational agents
  - Policy/strategy for:
    - Confirmation
    - Rejection
    - Open/directive prompts
    - Initiative
    - +?????
  - MDP
  - POMDP

Dialog State Tracking

- Developed as new Shared Task for SDS
- Goals:
  - Typical shared task:
    - Common data, resources, evaluation
    - To allow fair comparison, drive development
  - Reduce barrier to entry
    - Prior SDS shared tasks all full system development
      - Complex, many components
      - Domain-bound
  - Yield more general dialog management findings

Task

- At some time *t*,
  - Given prior dialog context, and
  - A set of possible dialog states N_t
    - Produce a probability distribution over states
- States?
  - Assignments of values to slots +
  - "REST" = None correct
- Ideal distribution?
  - Correct state = 1; all others 0

Context

- What can be in the context?
  - Almost anything
- Speech context:
  - Current, prior ASR results
  - Current, prior SLU results
    - Outputs, confidence scores, etc
- Interaction context:
  - Backend system database, etc
- How long? As much as desired

Data

- (2012, 2013)
- System data from 2010 Spoken Dialog Challenge
  - Pittsburgh bus information database and access
  - 4 participating dialog systems w/different behavior
  - Collected dialogs
- Logs transformed to per-utterance dialog acts: 9 slots
  - E.g. the next 61c from oakland to mckeesport transportation center
  - inform(time.rel=next),inform(route=61c),inform(from.neighborhood=oakland), inform(to.desc="mckeesport transportation center").
  - Also system-specific confidence/alt. hypotheses in n-best

Labeling & Evaluation

- Gold-standards created manually
  - By transcribers, crowdsourced state labeling (checked)

- Lots of evaluation measures:
  - Accuracy: per-turn, is top-ranked hyp correct?
  - AvgP: average score of correct hyp
  - MRR: mean reciprocal rank of correct hyp
  - L2: distance between output score vector, true one hot
  - Variants of ROC

Baselines

- Majority class:
  - Always guess “REST”
- Standard non-tracking approach:
  - Highest ranked SLU 1-best
    - Score = confidence score
- Note: Intrinsic evaluation only

Example Approach

- DNN system for Dialog State Tracking
  - Henderson, Thompson & Young 2013
- Straight-forward DNN approach
  - Inputs: Feature functions over context window
  - Outputs: probability distribution over states
- Features:
  - Score: variants of SLU confidence, ranks, confirm
  - User dialog acts, machine dialog acts, acts on values
- Results: All features useful, 10 turn context best