CS 224S / LINGUIST 285
Spoken Language Processing

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Spring 2017

Lecture 11: Dialogue Acts, Information State, and Markov Decision Processes

Original slides by Dan Jurafsky

Outline

- Human dialogue considerations
- Information state
- Evaluation
- Markov decision processes

Linguistics of Human Conversation

- Turn-taking
- Speech Acts
- Grounding

Turn-taking

Dialogue is characterized by turn-taking.

A:

B:

A:

B:

…

So how do speakers know when to take the floor?

Adjacency pairs

Sacks et al. (1974)

- **Adjacency pairs:** current speaker selects next speaker
  - Question/answer
  - Greeting/greeting
  - Compliment/downplayer
  - Request/grant
- Silence inside the pair is meaningful:

A: Is there something bothering you or not?
(1.0)
A: Yes or no?
(1.5)
A: Eh
B: No.

Speech Acts

- Austin (1962): An utterance is a kind of action
- Clear case: performatives

  I name this ship the Titanic

  I second that motion

  I bet you five dollars it will snow tomorrow
- Performative verbs (name, second)
- Locutionary (what was said)
- Illocutionary (what was meant)
- Is there any salt?

5 classes of “speech acts”

Searle (1975)

Assertives: committing the speaker to something’s being the case

(suggesting, putting forward, swearing, boasting, concluding)

Directives: attempts by speaker to get addressee to do something

(asking, ordering, requesting, inviting, advising, begging)

Commissives: Committing speaker to future course of action

(promising, planning, vowing, betting, opposing)

Expressives: expressing psychological state of the speaker about a state of affairs

(thanking, apologizing, welcoming, deploring).

Declarations: changing the world via the utterance

(I resign; You’re fired)

More Illocutionary acts: Grounding

- Why do elevator buttons light up?
- Clark (1996) (after Norman 1988)

  Principle of closure. Agents performing an action require evidence, sufficient for current purposes, that they have succeeded in performing it
- What is the linguistic correlate of this?

Grounding

- Need to know whether an action succeeded or failed
- Dialogue is also an action
  - a collective action performed by speaker and hearer
  - Common ground: set of things mutually believed by both speaker and hearer
- Need to achieve common ground, so hearer must ground or acknowledge speakers utterance.

How do speakers ground? Clark and Schaefer

- Continued attention:
  - B continues attending to A
- Relevant next contribution:
  - B starts in on next relevant contribution
- Acknowledgement:
  - B nods or says continuer (uh-huh) or assessment (great!)
- Demonstration:
  - B demonstrates understanding A by **reformulating** A's contribution, or by **collaboratively completing** A's utterance
- Display:
  - B repeats verbatim all or part of A's presentation

A human-human conversation

C_1:	. . . I need to travel in May.
A_1:	And, what day in May did you want to travel?
C_2:	OK uh I need to be there for a meeting that's from the 12th to the 15th.
A_2:	And you're flying into what city?
C_3:	Seattle.
A_3:	And what time would you like to leave Pittsburgh?
C_4:	Uh hmm I don't think there's many options for non-stop.
A_4:	Right. There's three non-stops today.
C_5:	What are they?
A_5:	The first one departs PGH at 10:00am arrives Seattle at 12:05 their time. The second flight departs PGH at 5:55pm, arrives Seattle at 8pm. And the last flight departs PGH at 8:15pm arrives Seattle at 10:28pm.
C_6:	OK I'll take the 5ish flight on the night before on the 11th.
A_6:	On the 11th? OK. Departing at 5:55pm arrives Seattle at 8pm, U.S. Air flight 115.
C_7:	OK.

Grounding examples

Display:

C: I need to travel in May

A: And, what day in May did you want to travel?

Acknowledgement

C: I want to fly from Boston

A: mm-hmm

C: to Baltimore Washington International

Grounding Examples (2)

- Acknowledgement + next relevant contribution

  And, what day in May did you want to travel?

  And you're flying into what city?

  And what time would you like to leave?

- The and indicates to the client that agent has successfully understood answer to the last question.

Grounding negative responses From Cohen et al. (2004)

- System: Did you want to review some more of your personal profile?
- Caller: No.
- System: Okay, what's next?

Good!

- System: Did you want to review some more of your personal profile?
- Caller: No.
- System: What's next?

Bad!

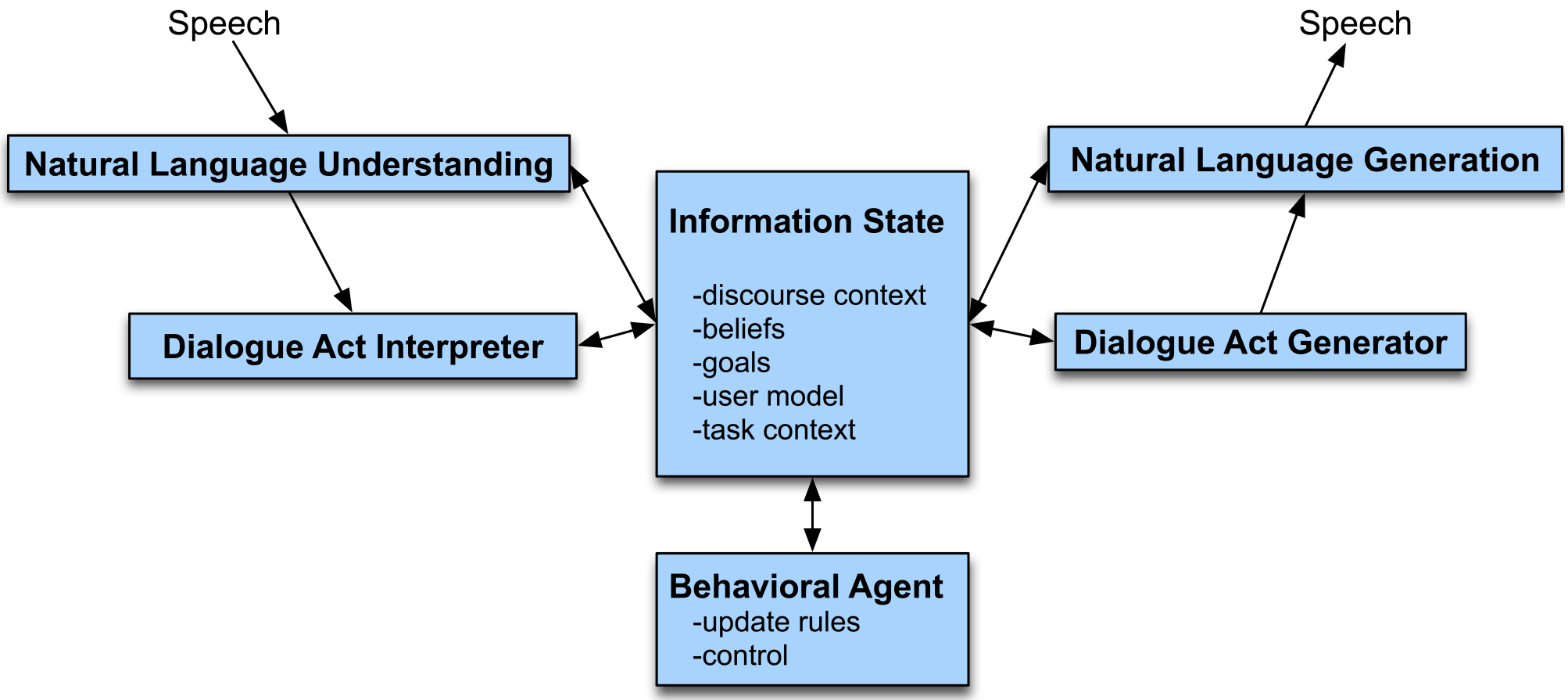
Information-State and Dialogue Acts

- For more than just form-filling
- Need to:
  - Decide when the user has asked a question, made a proposal, rejected a suggestion
  - Ground a user's utterance, ask clarification questions, suggest plans
- Need models of interpretation and generation
  - Speech acts and grounding
  - More sophisticated representation of dialogue context than just a list of slots

Information-state architecture

- Information state
- Dialogue act interpreter
- Dialogue act generator
- Set of update rules
  - Update dialogue state as acts are interpreted
  - Generate dialogue acts
- Control structure to select which update rules to apply

Information-state



Dialog acts

- Also called “conversational moves”
- An act with (internal) structure related specifically to its dialogue function
- Incorporates ideas of grounding
- Incorporates other dialogue and conversational functions that Austin and Searle didn’t seem interested in

Verbmobil task

- Two-party scheduling dialogues
- Speakers were asked to plan a meeting at some future date
- Data used to design conversational agents which would help with this task
- (cross-language, translating, scheduling assistant)

Verbmobil Dialogue Acts

THANK	thanks
GREET	Hello Dan
INTRODUCE	It's me again
BYE	Allright, bye
REQUEST-COMMENT	How does that look?
SUGGEST	June 13th through 17th
REJECT	No, Friday I'm booked all day
ACCEPT	Saturday sounds fine
REQUEST-SUGGEST	What is a good day of the week for you?
INIT	I wanted to make an appointment with you
GIVE_REASON	Because I have meetings all afternoon
FEEDBACK	Okay
DELIBERATE	Let me check my calendar here
CONFIRM	Okay, that would be wonderful
CLARIFY	Okay, do you mean Tuesday the 23rd?

Dialog Act Markup in Several Layers (DAMSL): forward looking function

STATEMENT	a claim made by the speaker
INFO-REQUEST	a question by the speaker
CHECK	a question for confirming information
INFLUENCE-ON-ADDRESSEE	(=Searle's directives)
OPEN-OPTION	a weak suggestion or listing of options
ACTION-DIRECTIVE	an actual command
INFLUENCE-ON-SPEAKER	(=Austin's commissives)
OFFER	speaker offers to do something
COMMIT	speaker is committed to doing something
CONVENTIONAL	other
OPENING	greetings
CLOSING	farewells
THANKING	thanking and responding to thanks

DAMSL: backward looking function

AGREEMENT speaker's response to previous proposal
- ACCEPT accepting the proposal
- ACCEPT-PART accepting some part of the proposal
- MAYBE neither accepting nor rejecting the proposal
- REJECT-PART rejecting some part of the proposal
- REJECT rejecting the proposal
- HOLD putting off response, usually via subdialogue

ANSWER answering a question

UNDERSTANDING whether speaker understood previous
- SIGNAL-NON-UNDER. speaker didn't understand
- SIGNAL-UNDER. speaker did understand
  - ACK demonstrated via continuer or assessment
  - REPEAT-REPHRASE demonstrated via repetition or reformulation
  - COMPLETION demonstrated via collaborative completion

A DAMSL Labeling

[info-req,ack]	A_1:	And, what day in May did you want to travel?
[assert, answer]	C_2:	OK uh I need to be there for a meeting that's from the 12th to the 15th.
[info-req,ack]	A_2:	And you're flying into what city?
[assert,answer]	C_3:	Seattle.
[info-req,ack]	A_3:	And what time would you like to leave Pittsburgh?
[check,hold]	C_4:	Uh hmm I don't think there's many options for non-stop.
[accept,ack]	A_4:	Right.
[assert]		There's three non-stops today.
[info-req]	C_5:	What are they?
[assert, open-option]	A_5:	The first one departs PGH at 10:00am arrives Seattle at 12:05 their time. The second flight departs PGH at 5:55pm, arrives Seattle at 8pm. And the last flight departs PGH at 8:15pm arrives Seattle at 10:28pm.
[accept,ack]	C_6:	OK I'll take the 5ish flight on the night before on the 11th.
[check,ack]	A_6:	On the 11th?
[assert,ack]		OK. Departing at 5:55pm arrives Seattle at 8pm, U.S. Air flight 115.

Conversation Acts
Traum and Hinkelman (1992)

Act Type	Sample Acts
turn-taking	take-turn, keep-turn, release-turn, assign-turn
grounding	acknowledge, repair, continue
core speech acts	inform, wh-question, accept, request, offer
argumentation	elaborate, summarize, question-answer, clarify

Generating Dialogue Acts

- Two examples
  - Confirmation
  - Rejection

Confirmation

- Errors: Speech is a pretty errorful channel
  - Humans use grounding to confirm that they heard correctly
  - ASR is way worse than humans!
- Dialog systems need to do even more grounding and confirmation than humans
  - Users are confused when system doesn't give explicit acknowledgement signal.

    Stifelman et al. (1993), Yankelovich et al. (1995)

Explicit confirmation

S: Which city do you want to leave from?

U: Baltimore

S: Do you want to leave from Baltimore?

U: Yes

Explicit confirmation

U: I'd like to fly from Denver Colorado to New York City on September 21st in the morning on United Airlines

S: Let's see then. I have you going from Denver Colorado to New York on September 21st. Is that correct?

U: Yes

Implicit confirmation: display

U: I'd like to travel to Berlin

S: When do you want to travel to Berlin?

U: Hi I'd like to fly to Seattle Tuesday morning

S: Traveling to Seattle on Tuesday, August eleventh in the morning. Your name?

Implicit vs. Explicit

- Complementary strengths
- Explicit: easier for users to correct systems' s mistakes (can just say "no")
- But explicit is cumbersome and long
- Implicit: much more natural, quicker, simpler (if system guesses right).

Implicit and Explicit

- Early systems: all-implicit or all-explicit
- Modern systems: adaptive
- How to decide?
  - ASR system can give confidence metric.
  - This expresses how convinced system is of its transcription of the speech
  - If high confidence, use implicit confirmation
  - If low confidence, use explicit confirmation

Computing confidence

- Simplest: use acoustic log-likelihood of user's utterance
- More features
  - Prosodic: utterances with longer pauses, F0 excursions, longer durations
  - Backoff: did we have to backoff in the LM?
  - Cost of an error: Explicit confirmation before moving money or booking flights

Rejection

- “I’m sorry, I didn’t understand that.”
- Reject when:
  - ASR confidence is low
  - Best interpretation is semantically ill-formed
- Might have four-tiered level of confidence:
  - Below confidence threshhold, reject
  - Above threshold, explicit confirmation
  - If even higher, implicit confirmation
  - Even higher, no confirmation

Automatic Interpretation of Dialogue Acts

- How do we automatically identify dialogue acts?
  - Given an utterance:
    - Decide whether it is a QUESTION, STATEMENT, SUGGEST, or ACK
- Perhaps we can just look at the form of the utterance to decide?

Can we just use the surface syntactic form?

YES-NO-Qs have auxiliary-before-subject syntax:

Will breakfast be served on USAir 1557?

STATEMENTs have declarative syntax:

I don't care about lunch

COMMANDs have imperative syntax:

Show me flights from Milwaukee to Orlando on Thursday night

Surface form != speech act type

	Surface form	Speech act
Can I have the rest of your sandwich?	Question	Request
I want the rest of your sandwich	Declarative	Request
Give me your sandwich!	Imperative	Request

Dialogue Act ambiguity

Can you give me a list of the flights from Atlanta to Boston?

- This looks like an INFO-REQUEST.
- If so, the answer is:
  - YES.
- But really it's a DIRECTIVE or REQUEST, a polite form of:

Please give me a list of the flights…

- What looks like a QUESTION can be a REQUEST

Indirect speech acts

Utterances which use a surface statement to ask a question

Utterances which use a surface question to issue a request

Dialogue Act ambiguity

- What looks like a STATEMENT can be a QUESTION:

Us	OPEN-OPTION	**I was wanting to make some arrangements for a trip that I' m going to be taking uh to LA uh beginnning of the week after next**
Ag	HOLD	**OK uh let me pull up your profile and I' ll be right with you here. [pause]**
Ag	CHECK	And you said you wanted to travel next week?
Us	ACCEPT	**Uh yes.**

DA interpretation as statistical classification: Features

- Words and Collocations:
  - Please or would you: good cue for REQUEST
  - Are you: good cue for INFO-REQUEST
- Prosody:
  - Rising pitch is a good cue for INFO-REQUEST
  - Loudness/stress can help distinguish yeah/AGREEMENT from yeah/BACKCHANNEL
- Conversational Structure
  - Yeah following a proposal is probably AGREEMENT; yeah following an INFORM probably a BACKCHANNEL

An example of dialogue act detection: Correction Detection

- If system misrecognizes an utterance, and either
  - Rejects
  - Via confirmation, displays its misunderstanding
- Then user has a chance to make a

  correction
  - Repeat themselves
  - Rephrasing
  - Saying “no” to the confirmation question.

Corrections

- Unfortunately, corrections are harder to recognize than normal sentences!
  - Swerts et al (2000): corrections misrecognized twice as often (in terms of WER) as non-corrections!!!
  - Why?
    - Prosody seems to be largest factor: **hyperarticulation**
    - Liz Shriberg example:
      - "NO, I am DE-PAR-TING from Jacksonville"

A Labeled dialogue (Swerts et al)

	Turn	Corr Type
S	On which day of the week do you want to leave?	
S	Sorry, I didn't hear anything from you. Please tell me your departure date	
U	*Um tomorrow*	NA
S	You can say the departure date. For example, you can say 'today' or 'tomorrow'. Or you can say 'Monday', 'Tuesday', 'Wednesday'...	
U	*Tomorrow*	REP
S	You can say the departure date. For example, you can say 'today' or 'tomorrow'. Or you can say 'Monday', 'Tuesday', 'Wednesday'...	
U	*Saturday*	PAR
S	Do you want to leave on Saturday?	
U	Yes	
S	What time do you want to leave?	
U	Eight o'clock A M	
S	Do you want to leave around ten oclock p-m	
U	*Eight o'clock*	OMIT
S	Do you want to leave around ten oclock p-m	
U	*No*	OMIT
S	What time do you want to leave?	
U	*Eight o'clock A M*	ADD

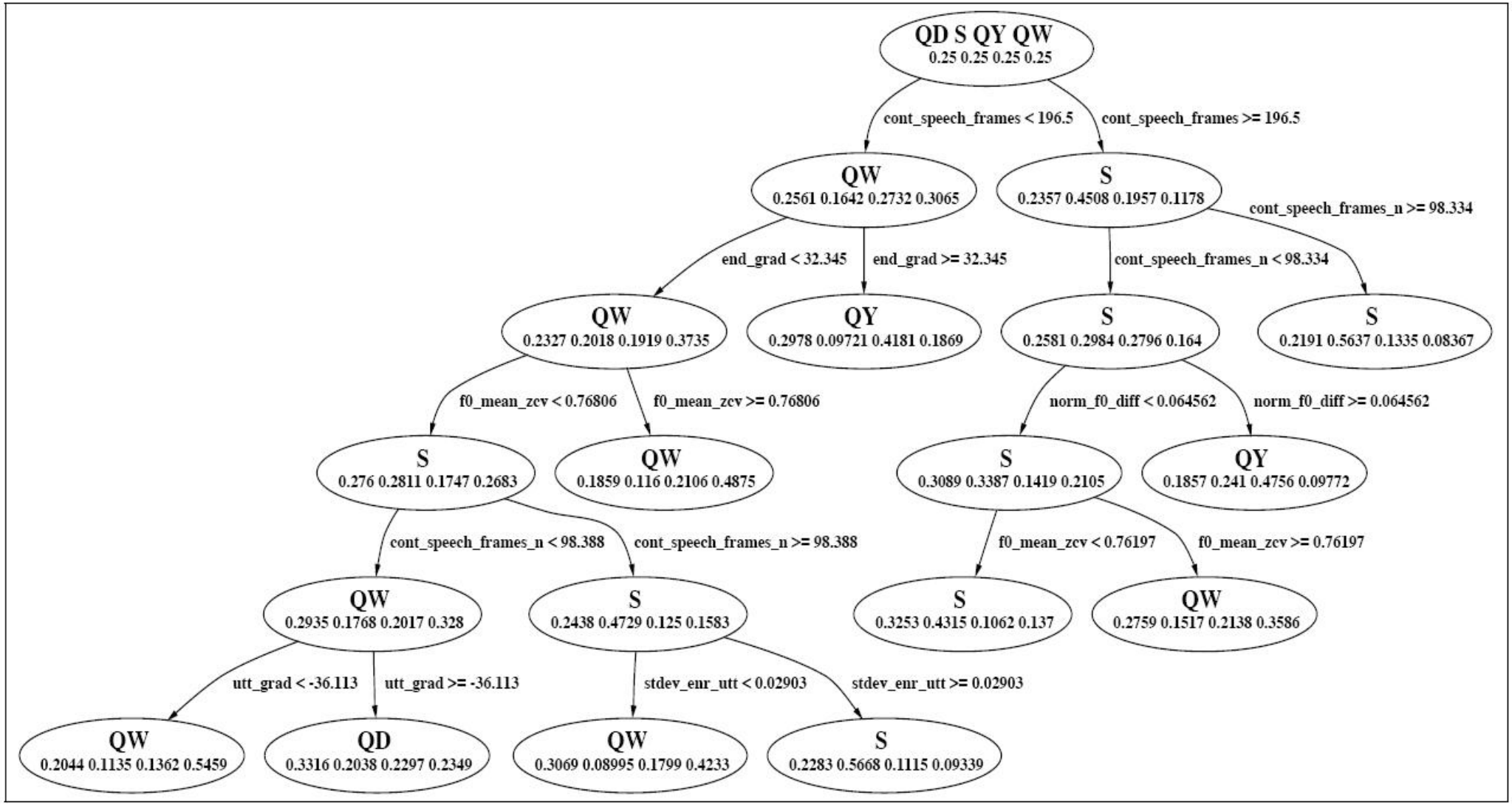
Machine learning to detect user corrections: features

- Lexical information (no, correction, I don't, swear words)
- Prosodic indicators of hyperarticulation
  - increases in F0 range, pause duration, word duration
- Length
- ASR confidence
- LM probability
- Various dialogue features (repetition)

Prosodic Features

- Shriberg et al. (1998)
- Decision tree trained on simple acoustically-based prosodic features
  - Slope of F0 at the end of the utterance
  - Average energy at different places in utterance
  - Various duration measures
  - All normalized in various ways
- These helped distinguish
  - Statement (S)
  - Yes-no-question (QY)
  - Declarative question (QD) (“You’re going to the store?”)
  - Wh-question (QW)

Prosodic Decision Tree for making S/QY/QW/QD decision



Dialogue System Evaluation

- Always two kinds of evaluation
  - Extrinsic: embedded in some external task
  - Intrinsic: evaluating the component as such

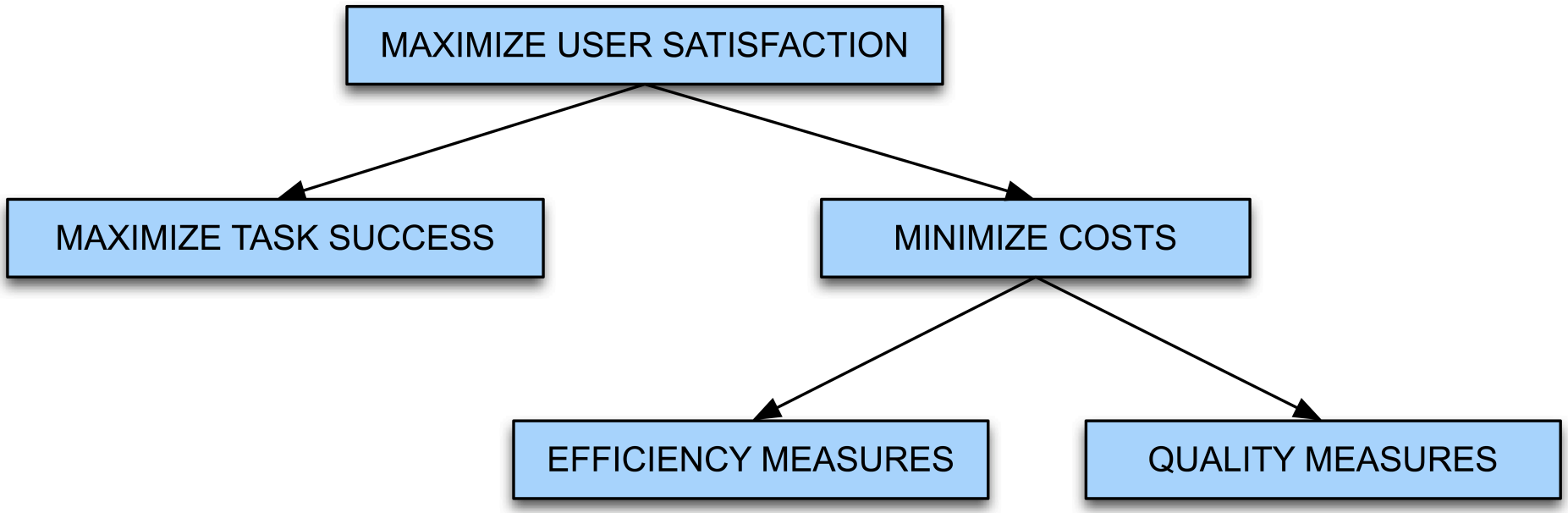
- What constitutes success or failure for a dialogue system?

Reasons for Dialogue System Evaluation

1. A metric to compare systems
   - can't improve it if we don't know where it fails
   - can't decide between two systems without a goodness metric
2. A metric as an input to reinforcement learning:
   - automatically improve conversational agent performance via learning

PARADISE evaluation

- Maximize Task Success
- Minimize Costs
  - Efficiency Measures
  - Quality Measures
- PARADISE (PARAdigm for Dialogue System Evaluation) (Walker et al. 2000)



Task Success

- % of subtasks completed
- Correctness of each questions/answer/error msg
- Correctness of total solution
  - Error rate in final slots
    - Generalization of Slot Error Rate
- Users' perception of whether task was completed

Efficiency Cost

Polifroni et al. (1992), Danieli and Gerbino (1995)
Hirschman and Pao (1993)

- Total elapsed time in seconds or turns
- Number of queries
- Turn correction ration: number of system or user turns used solely to correct errors, divided by total number of turns

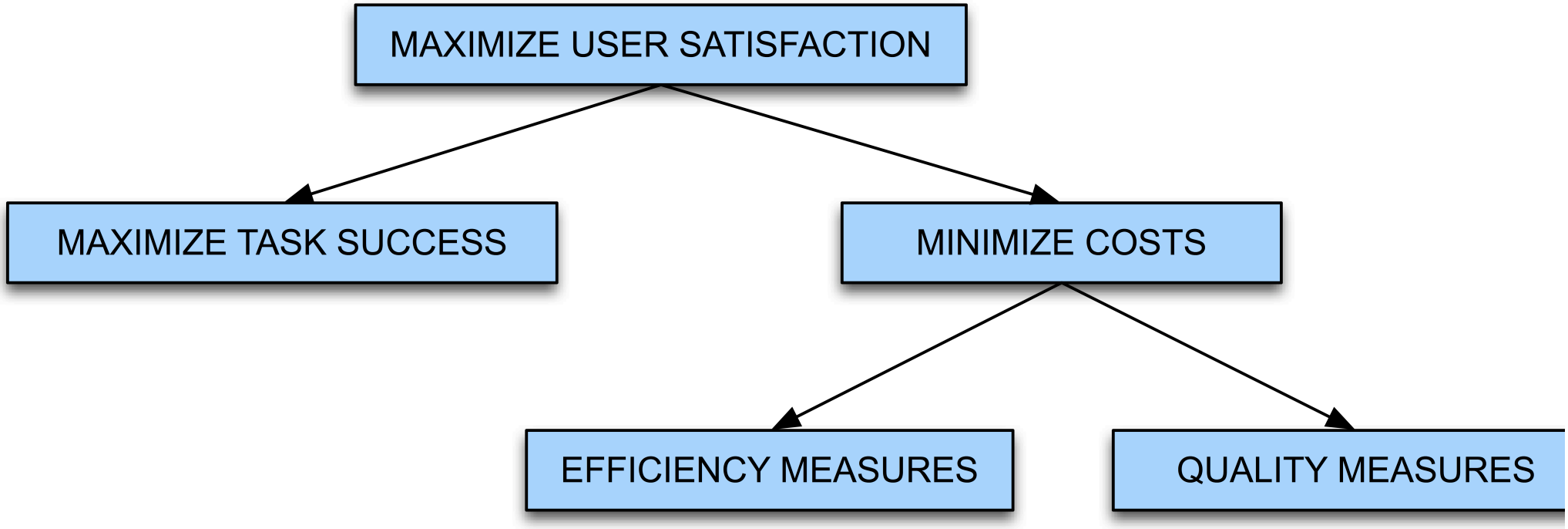
Quality Cost

- # of times ASR system failed to return any sentence
- # of ASR rejection prompts
- # of times user had to barge-in
- # of time-out prompts
- Inappropriateness (verbose, ambiguous) of system's questions, answers, error messages

Concept accuracy:

- “Concept accuracy” or “Concept error rate”
- % of semantic concepts that the NLU component returns correctly
- I want to arrive in Austin at 5:00
  - DESTCITY: Boston
  - Time: 5:00
- Concept accuracy = 50%
- Average this across entire dialogue
- “How many of the sentences did the system understand correctly”
- Can be used as either quality cost or task success

PARADISE: Regress against user satisfaction



Regressing against user satisfaction

- Questionnaire to assign each dialogue a "user satisfaction rating": this is dependent measure
- Set of cost and success factors are independent measures
- Use regression to train weights for each factor

Experimental Procedures

- Subjects given specified tasks
- Spoken dialogues recorded
- Cost factors, states, dialog acts automatically logged; ASR accuracy,barge-in hand-labeled
- Users specify task solution via web page
- Users complete User Satisfaction surveys
- Use multiple linear regression to model User Satisfaction as a function of Task Success and Costs; test for significant predictive factors

Slide from Julia Hirschberg

User Satisfaction: Sum of Many Measures

- Was the system easy to understand? (TTS Performance)
- Did the system understand what you said? (ASR Performance)
- Was it easy to find the message/plane/train you wanted? (Task Ease)
- Was the pace of interaction with the system appropriate? (Interaction Pace)
- Did you know what you could say at each point of the dialog? (User Expertise)
- How often was the system sluggish and slow to reply to you? (System Response)
- Did the system work the way you expected it to in this conversation? (Expected Behavior)
- Do you think you'd use the system regularly in the future? (Future Use)

Performance Functions from Three Systems

- ELVIS User Sat.= .21* COMP + .47 * MRS - .15 * ET
- TOOT User Sat.= .35* COMP + .45* MRS - .14*ET
- ANNIE User Sat.= .33*COMP + .25* MRS -.33* Help

  - COMP: User perception of task completion (task success)
  - MRS: Mean (concept) recognition accuracy (cost)
  - ET: Elapsed time (cost)
  - Help: Help requests (cost)

Slide from Julia Hirschberg

Evaluation Summary

- Best predictors of User Satisfaction:
  - Perceived task completion
  - mean recognition score (concept accuracy)
- Performance model useful for system development
  - Making predictions about system modifications
  - Distinguishing ‘good’ dialogues from ‘bad’ dialogues
  - As part of a learning model

Now that we have a success metric

- Could we use it to help drive learning?
- Learn an optimal policy or strategy for how the conversational agent should behave

New Idea: Modeling a dialogue system as a probabilistic agent

- A conversational agent can be characterized by:
  - The current knowledge of the system
    - Set of states S the agent can be in
  - 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 already a policy – a human-designed one!

- 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

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.

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 until 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

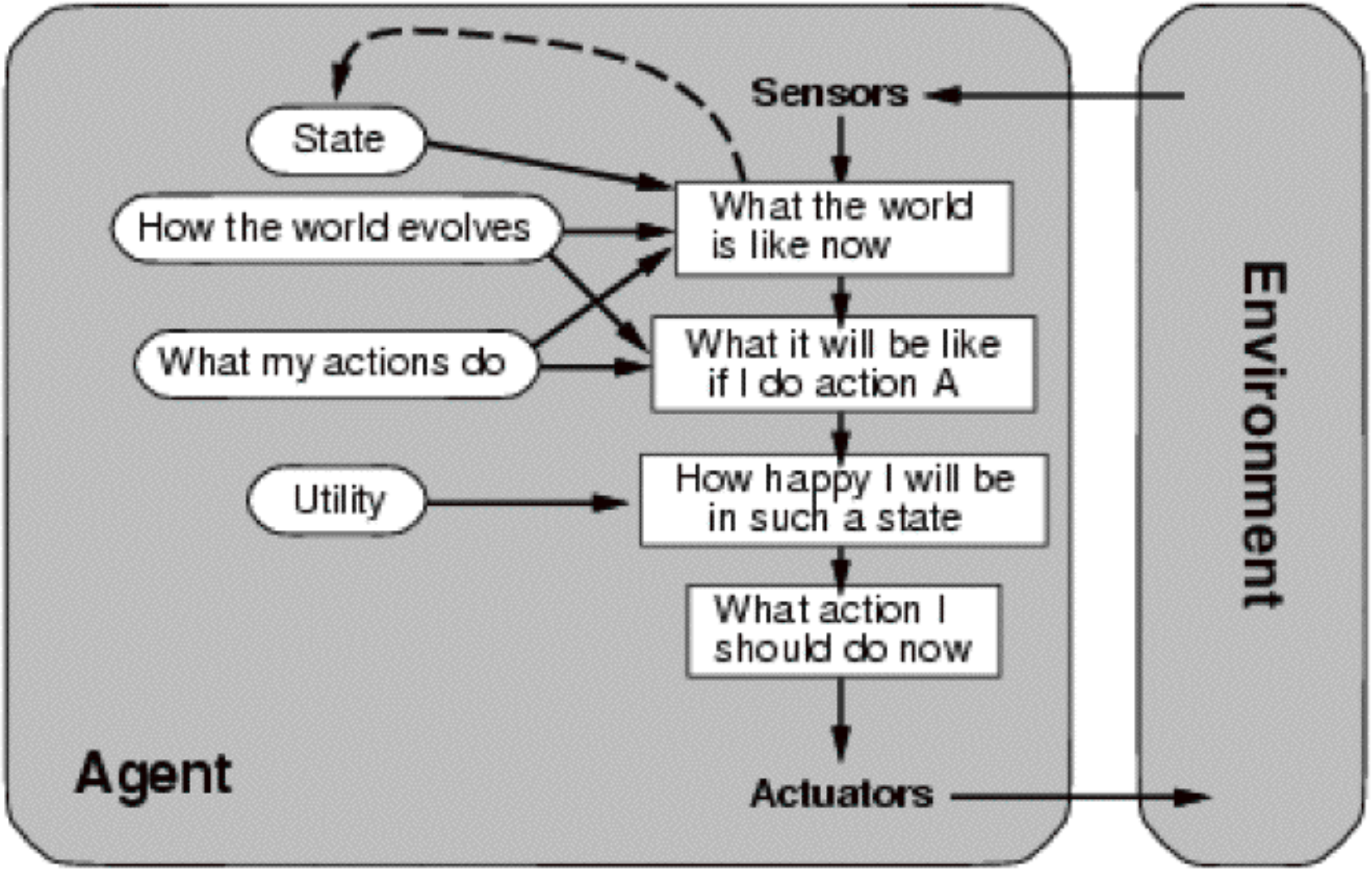
- A utility function
  - maps a state or state sequence
  - onto a real number
  - describing the goodness of that state
  - I.e. the resulting “happiness” of the agent
- Principle of Maximum Expected Utility:
  - A rational agent should choose an action that maximizes the agent’s expected utility

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:

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

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

  - (+ Some other things I'll come back to (gamma, state transition probabilities))

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
  - User's most recent answer
  - ASR confidence
  - *etc.*

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

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

State in the Day-and-Month example

- Values of the two slots day and month.
- Total:
  - 2 special initial state 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 the Day-and-Month example

ad: a question asking for the day

am: a question asking for the month

adm: a question asking for the day+month

af: 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)

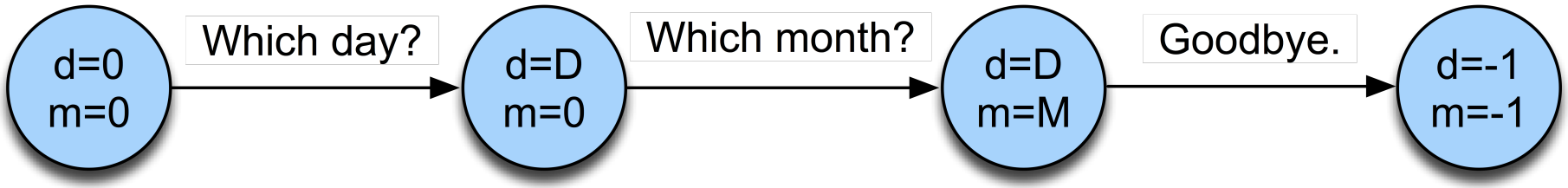
  N_f = expected distance from goal

  - (0 for complete date, 1 if either data or month are missing, 2 if both missing)
- Then (weighted) cost is:

$$C = w_i \times N_i + w_e \times N_e + w_f \times N_f$$

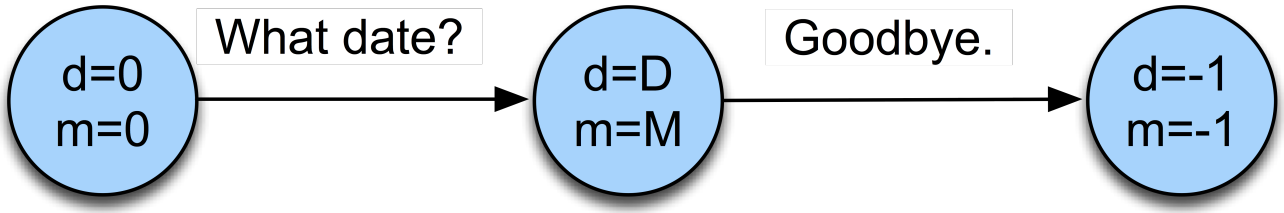
2 possible policies

Policy 1 (directive)



$c_1 = -3w_i + 2p_d w_e$

Policy 2 (open)



$c_2 = -2w_i + 2p_o w_e$

P_d=probability of error in directive prompt

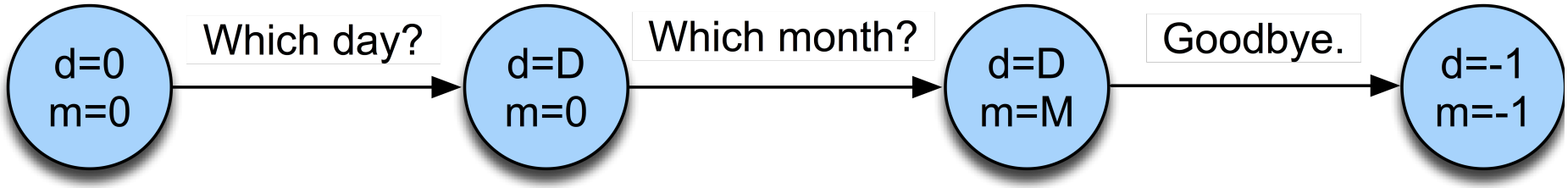
P_o=probability of error in open prompt

2 possible policies

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

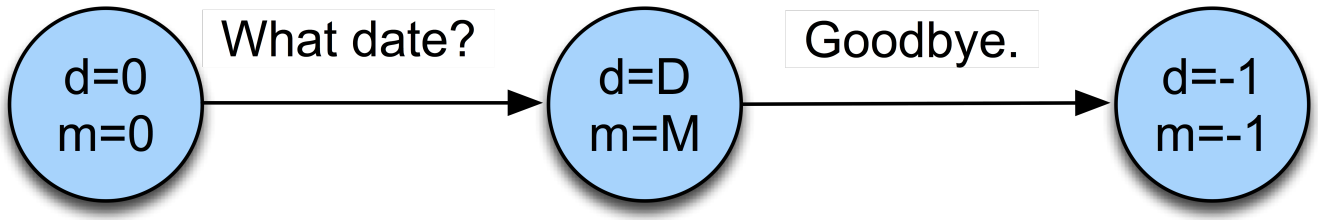
$$p_o - p_d > \frac{w_i}{2w_e}$$

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 leraning

Back to MDPs:

MDP

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

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

- 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

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

- Discount factor γ between 0 and 1
- 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 $R(s_1,a_1,s_2,a_2,\ldots,s_n)$
- 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 $R(s_1,a_1,s_2,a_2,\ldots,s_n)$?
- 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 MDP systems were built
- Current direction:
  - 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"