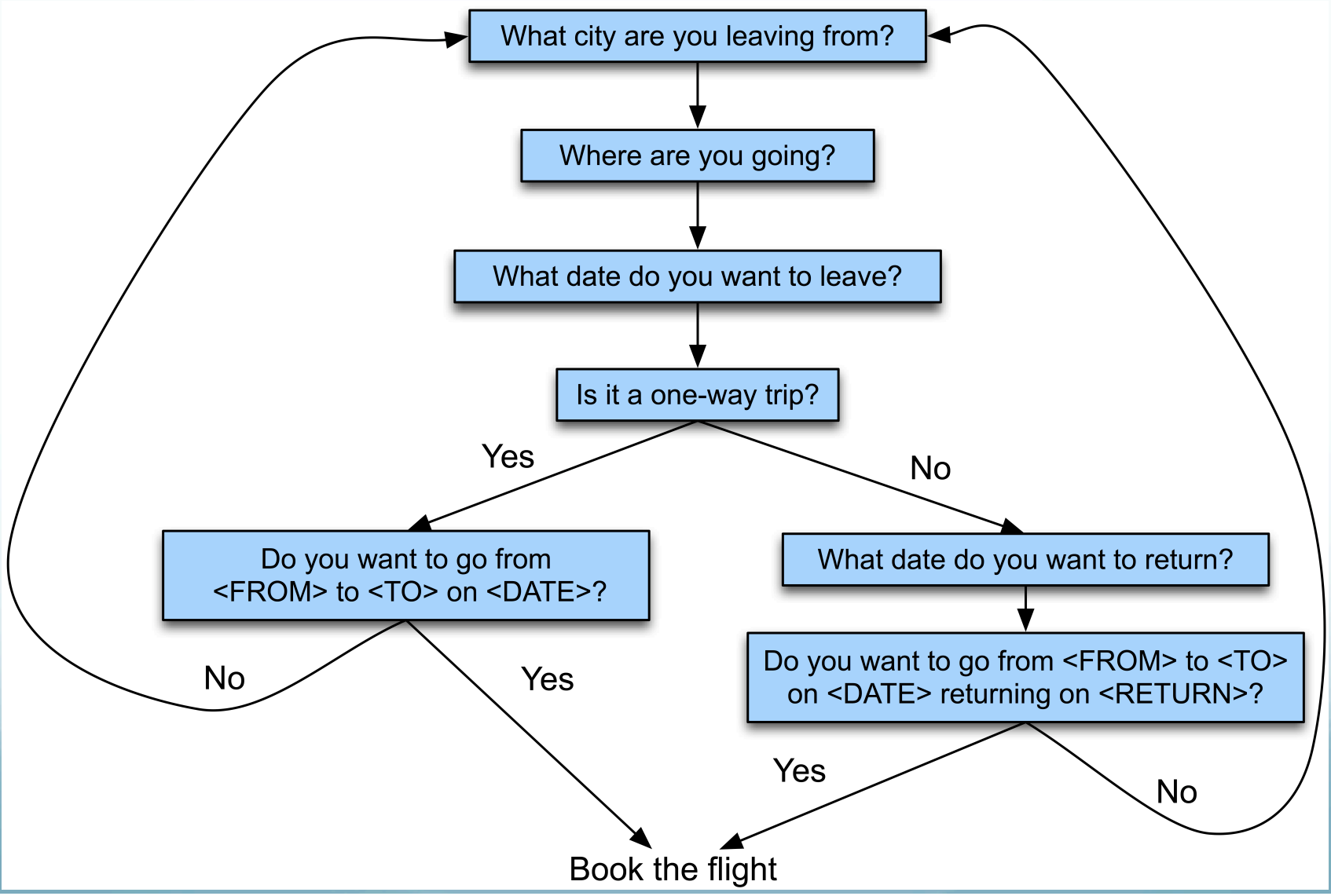
Dialogue Management

Ling575
Discourse and Dialogue
May 18, 2011

Dialog Management Types

- Finite-State Dialog Management
- Frame-based Dialog Management
  - Initiative
  - VoiceXML
  - Design and evaluation
- Information State Management
  - Dialogue Acts
    - Recognition & generation
- Statistical Dialogue Managemant (POMDPs)

Finite-State Management



Pros and Cons

- Advantages
  - Straightforward to encode
  - Clear mapping of interaction to model
  - Well-suited to simple information access
  - System initiative
- Disadvantages
  - Limited flexibility of interaction
    - Constrained input – single item
    - Fully system controlled
    - Restrictive dialogue structure, order
  - Ill-suited to complex problem-solving

Frame-based Dialogue Management

- Finite-state too limited, stilted, irritating
- More flexible dialogue

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DEPARTURE TIME	"When would you like to leave?"
ARRIVAL TIME	"When do you want to arrive?"

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- System may have multiple frames
  - E.g. flights vs restrictions vs car vs hotel
  - Rules determine next action, question, information presentation

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- Prompts:
  - Open prompt: ‘How may I help you?’
    - Open-ended, user can respond in any way
  - Directive prompt: ‘Say yes to accept call, or no o.w.’
    - Stipulates user response type, form

Initiative, Prompts, Grammar

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  - System must recognize suitable input
    - Restrictive vs open-ended

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

Figure 24.10 Operational definition of initiative, following Singh et al. (2002).

Dialogue Management: Confirmation

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  - "Error spirals" of sequential errors
    - Highly problematic
  - Recognition, recovery crucial
- Confirmation strategies can detect, mitigate
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  - Implicit confirmation:
    - Include input information in subsequent prompt

Confirmation Strategies

- Explicit:

S:	**Which city do you want to leave from?**
U:	Baltimore.
S:	**Do you want to leave from Baltimore?**
U:	Yes.
U:	I'd like to fly from Denver Colorado to New York City on September twenty first in the morning on United Airlines
S:	**Let's see then. I have you going from Denver Colorado to New York on September twenty first. Is that correct?**
U:	Yes

Confirmation Strategy

- Implicit:

U:	I want to travel to Berlin
S:	**When do you want to travel to Berlin?**
U2:	Hi I'd like to fly to Seattle Tuesday Morning
A3:	**Traveling to Seattle on Tuesday, August eleventh in the morning. Your full name?**

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- Implicit:
  - Pro: more natural, efficient; Con: less easy to correct

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- Strategies: Progressive prompting
  - Initially: ‘rapid reprompting’: ‘What?’, ‘Sorry?’
  - Later: increasing detail

- Progressive prompting

System:	When would you like to leave?
Caller:	Well, um, I need to be in New York in time for the first World Series game.
System:	<reject>. Sorry, I didn't get that. Please say the month and day you'd like to leave.
Caller:	I wanna go on October fifteenth.

VoiceXML

- W3C standard for simple frame-based dialogues
  - Fairly common in commercial settings
- Construct forms, menus
  - Forms get field data
    - Using attached prompts
    - With specified grammar (CFG)
    - With simple semantic attachments

Simple VoiceXML Example

```
<form>
  <field name="transporttype">
     <prompt>
        Please choose airline, hotel, or rental car.
     </prompt>
     <grammar type="application/x=nuance-gsl">
       [airline hotel "rental car"]
     </grammar>
  </field>
  <block>
    <prompt>
     You have chosen <value expr="transporttype">.
    </prompt>
  </block>
</form>
```

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  - Ill-suited to more complex problem-solving
    - Form-filling applications

Dialogue Manager Tradeoffs

- Flexibility vs Simplicity/Predictability
  - System vs User vs Mixed Initiative
  - Order of dialogue interaction
  - Conversational “naturalness” vs Accuracy
  - Cost of model construction, generalization, learning, etc

Dialog Systems Design

- User-centered design approach:
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  - Iteratively test on users:
    - Redesign prompts (email subdialog)
    - Identify need for barge-in

SDS Evaluation

- Goal: Determine overall user satisfaction
  - Highlight systems problems; help tune
- Classically: Conduct user surveys

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

Figure 24.14 User satisfaction survey, adapted from Walker et al. (2001).

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- Criteria:
  - Maximize task success
    - Measure task completion: % subgoals; Kappa of frame values
  - Minimize task costs
    - Efficiency costs: time elapsed; # turns; # error correction turns
    - Quality costs: # rejections; # barge-in; concept error rate

PARADISE Model

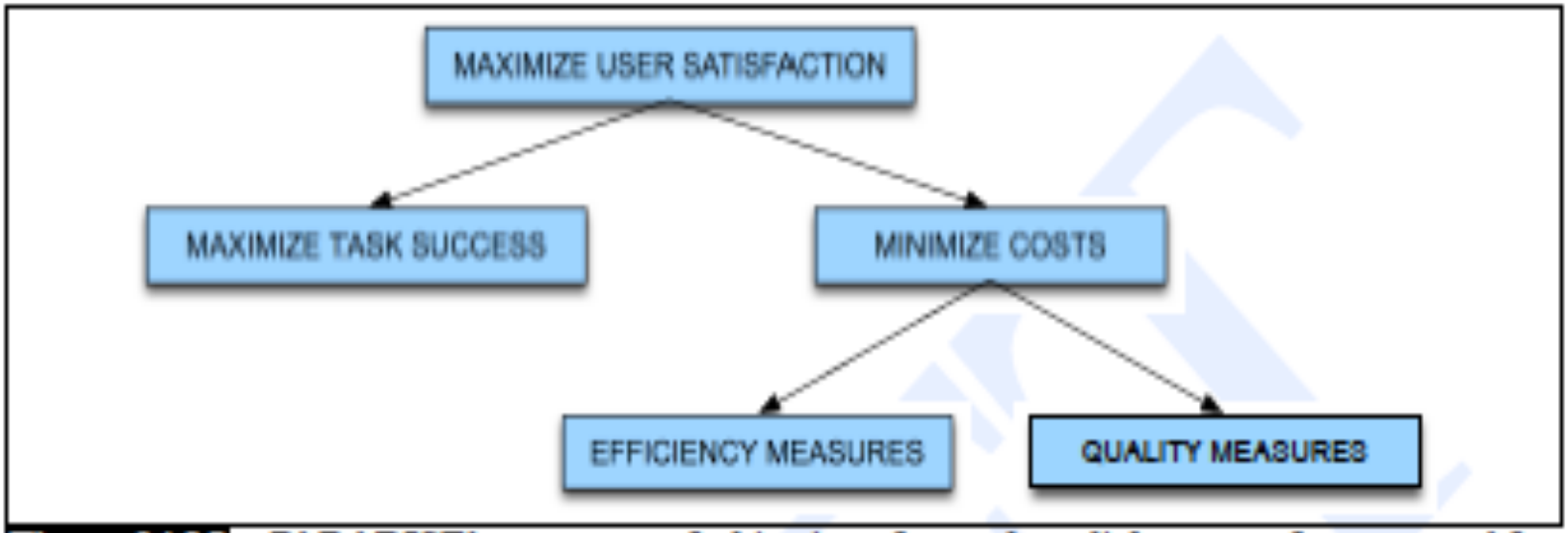

Figure 24.15 PARADISE's structure of objectives for spoken dialogue performance. After Walker et al. (1997).

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- Allows prediction of accuracy on new dialog w/Q&A

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- Real tasks require:
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- Information state models include:
  - Information state
  - Dialogue act interpreter
  - Dialogue act generator
  - Update rules
  - Control structure

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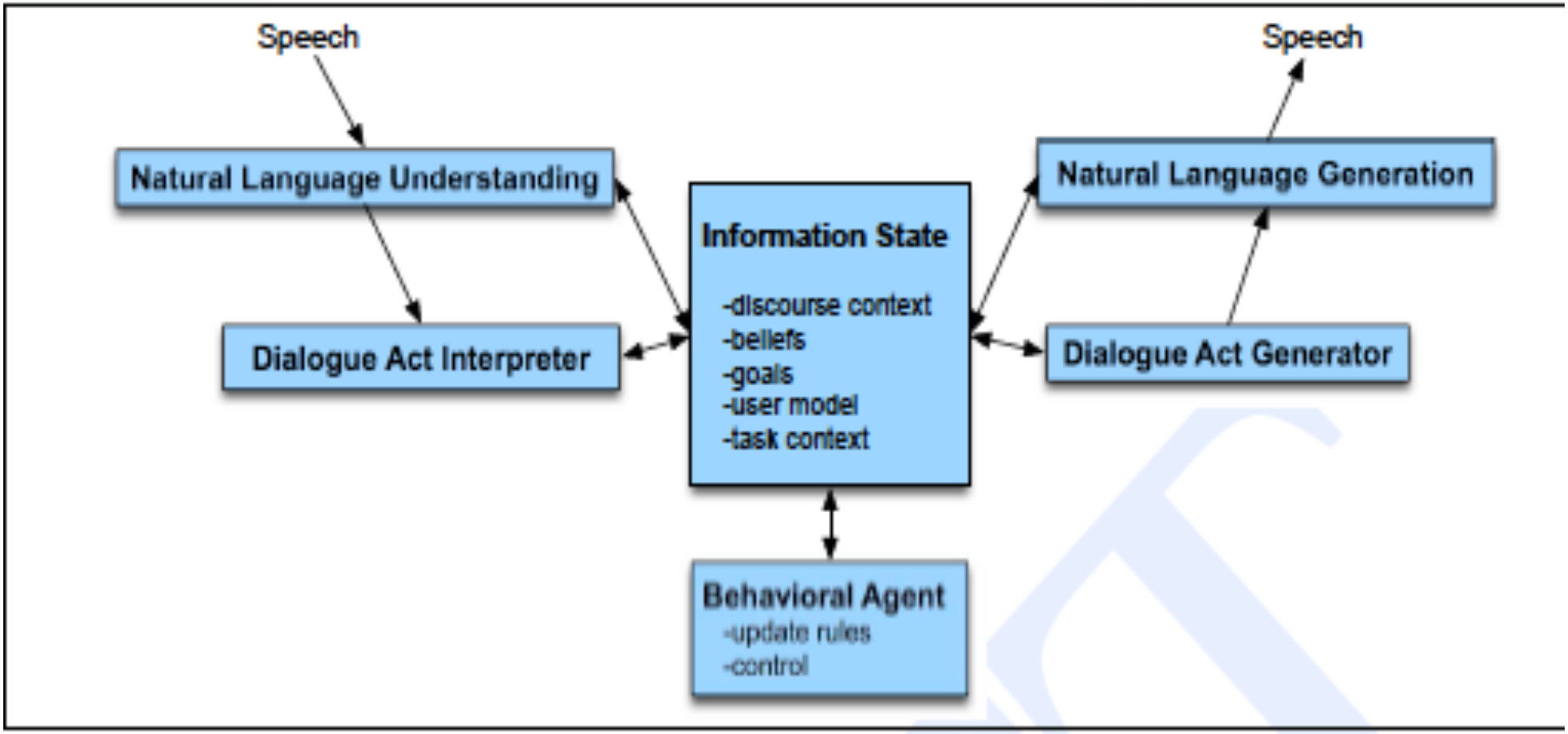
      - Add information to context, grounding state

Information State Architecture

- Simple ideas, complex execution



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  - Conversation acts:
    - Add turn-taking and argumentation relations

Verbmobil DA

- 18 high level tags

Tag	Example
THANK	*Thanks*
GREET	*Hello Dan*
INTRODUCE	*It's me again*
BYE	*Allright bye*
REQUEST-COMMENT	*How does that look?*
SUGGEST	*from thirteenth through seventeenth June*
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?*
DIGRESS	*[we could meet for lunch] and eat lots of ice cream*
MOTIVATE	*We should go to visit our subsidiary in Munich*
GARBAGE	*Oops, I-*

Figure 24.17 The 18 high-level dialogue acts used in Verbmobil-1, abstracted over a total of 43 more specific dialogue acts. Examples are from Jekat et al. (1995).

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- Automatically tag utterances in dialogue
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    - Syntactic form: question; Act: request/command
  - Yeah.

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  - Yeah.
    - Depends on context: Y/N answer; agreement; back-channel

Dialogue Act Ambiguity

- Indirect speech acts

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

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  - Adjacency pairs:
    - Y/N question, agreement vs Y/N question, backchannel
    - DA bi-grams

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  - Identify dialogue acts in conversational speech
- Spoken corpus: Switchboard
  - Telephone conversations between strangers
  - Not task oriented; topics suggested
  - 1000s of conversations
    - recorded, transcribed, segmented

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- 1,155 conv labeled: split into train/test

Common Tags

- **Statement** & **Opinion**: declarative +/- op
- **Question**: Yes/No&Declarative: form, force
- **Backchannel:** Continuers like uh-huh, yeah
- **Turn Exit/Adandon:** break off, +/- pass
- **Answer :** Yes/No, follow questions
- **Agreement**: Accept/Reject/Maybe

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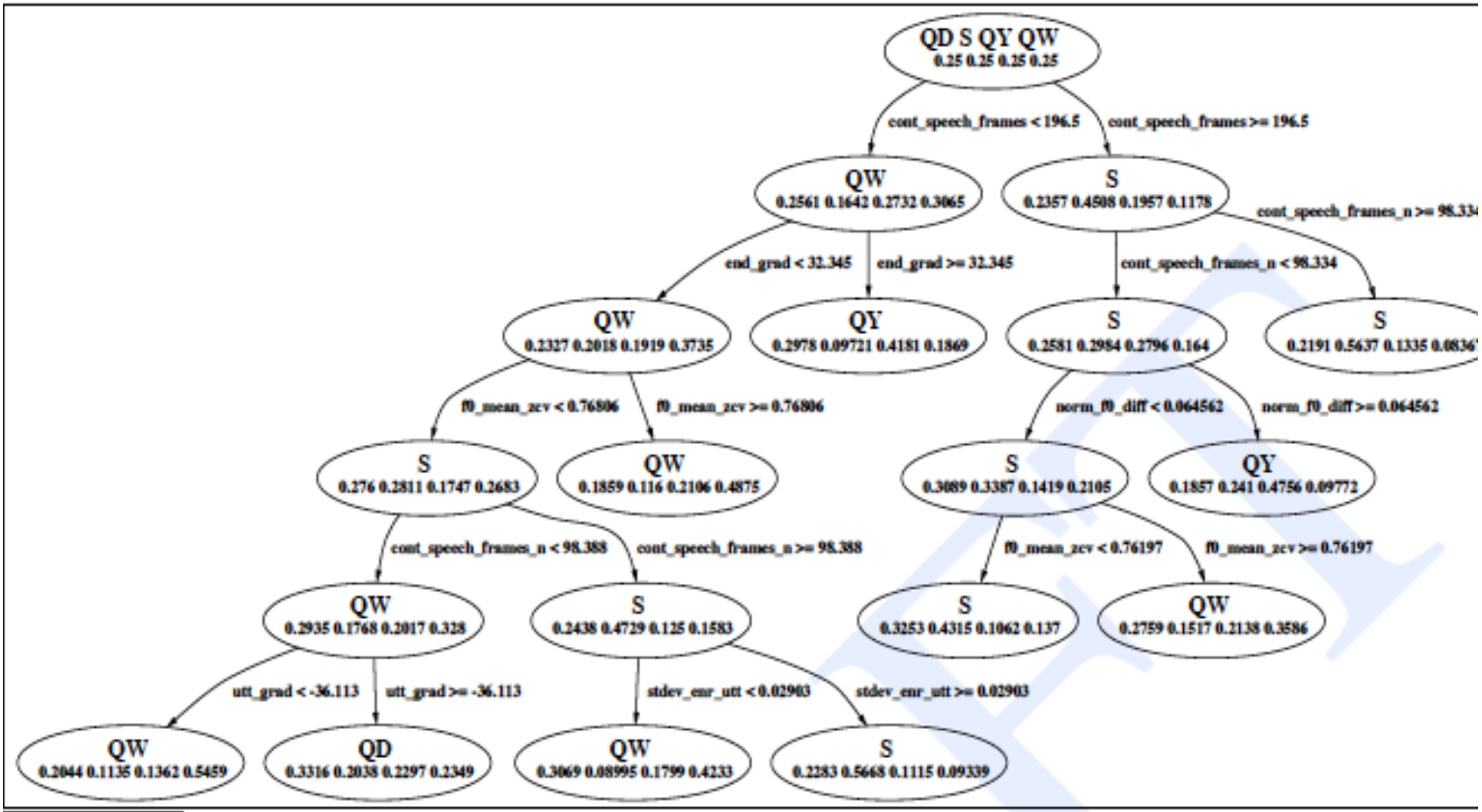
DA Classification - Prosody

- Features:
  - Duration, pause, pitch, energy, rate, gender
    - Pitch accent, tone
- Results:
  - Decision trees: 5 common classes
    - 45.4% - baseline=16.6%

Prosodic Decision Tree



DA Classification -Words

- Words
  - Combines notion of discourse markers and collocations:
    - e.g. uh-huh=Backchannel
  - Contrast: true words, ASR 1-best, ASR n-best
- Results:
  - Best: 71%- true words, 65% ASR 1-best

DA Classification - All

- Combine word and prosodic information
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$$d^* = P(d \mid d_{t-1}) \frac{P(d \mid f)}{P(d)} \prod_{i=2}^{N} P(w_i \mid w_{i-1} \ldots w_{i-N+1}, d)$$

- Slightly better than raw ASR

Integrated Classification

- Focused analysis
  - Prosodically disambiguated classes
    - Statement/Question-Y/N and Agreement/Backchannel
    - Prosodic decision trees for agreement vs backchannel
      - Disambiguated by duration and loudness

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    - True words: S/Q: 85.9%-> 87.6; A/B: 81.0%->84.7

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  - Substantial improvement for prosody+words
    - True words: S/Q: 85.9%-> 87.6; A/B: 81.0%->84.7
    - ASR words: S/Q: 75.4%->79.8; A/B: 78.2%->81.7
  - More useful when recognition is iffy

Many Variants

- Maptask: (13 classes)
  - Serafin & DiEugenio 2004
    - Latent Semantic analysis on utterance vectors
    - Text only
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- MRDA: Meeting tagging: 5 broad classes

Observations

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- Questions:
  - Whole utterance models? – more fine-grained
  - Longer structure, long term features

Detecting Correction Acts

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  - Utterances after errors misrecognized >2x as often
    - Frequently repetition or paraphrase of original input

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  - Some word cues: 'No',' I meant', swearing..
- Can train classifiers to recognize with good acc.

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  - Develops update rules for content planning, e.g.
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  - Develops update rules for content planning, i.e.
    - If user releases turn, system can do 'TAKE-TURN' act
    - If system needs to summarize, use ASSERT act
  - Identifies turn-taking as key aspect of dialogue gen.

Cue	Turn-taking acts signaled
um	KEEP-TURN, TAKE-TURN, RELEASE-TURN
<lipsmack>, <click>, so, uh	KEEP-TURN, TAKE-TURN
you know, isn't that so	ASSIGN-TURN

Figure 24.21 Language used to perform turn-taking acts, from Stent (2002).

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      - Sentence/prosodic features: longer, initial pause, pitch range
    - Cost of error:
      - Book a flight vs looking up information
- Markov Decision Process models more detailed