CS 224S/LING 281
Speech Recognition, Synthesis, and Dialogue

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Lecture 14:

Dialogue: MDPs

and

Speaker Detection

Outline for today

- MDP Dialogue Architectures
- Speaker Recognition

Now that we have a success metric

- Could we use it to help drive learning?
- In recent work we use this metric to help us 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
    - 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

Modeling a dialogue system as a probabilistic agent

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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

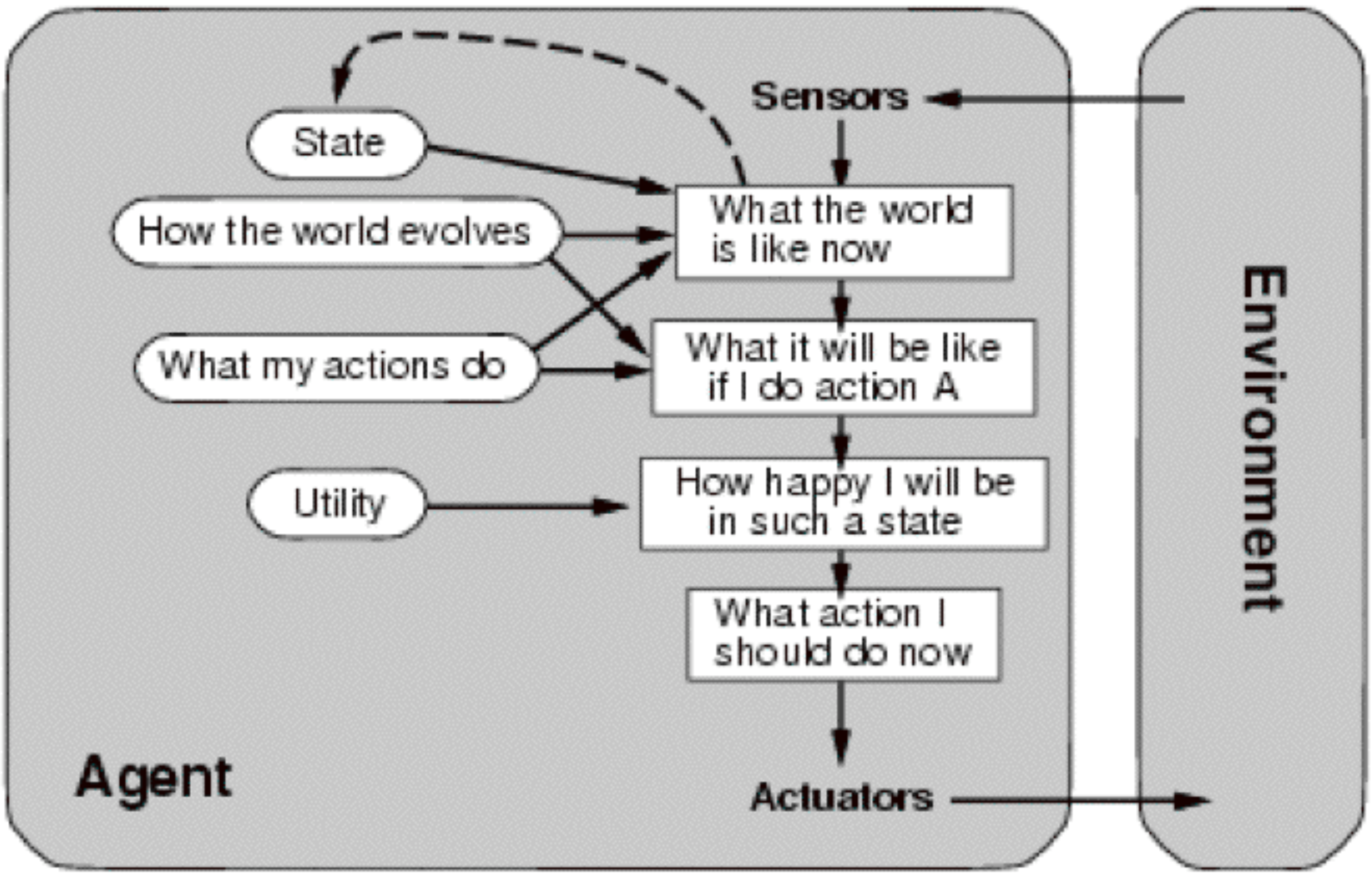
- A utility function
  - maps a state or state sequence
  - onto a real number
  - describing the goodness of that state
  - I.e. the resulting “happiness” of the agent
- Principle of Maximum Expected Utility:
  - A rational agent should choose an action that maximizes the agent’s expected utility

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:

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

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))

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 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 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

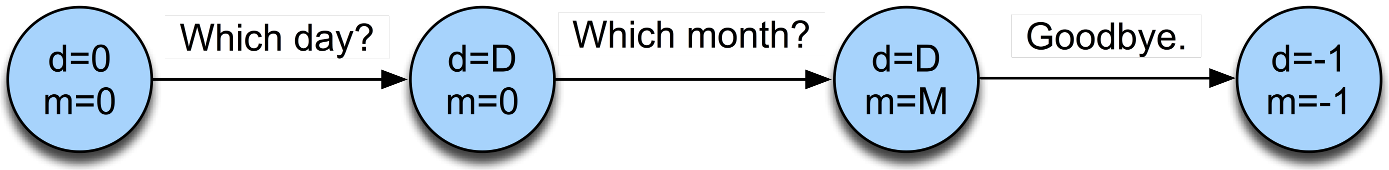
- a_d: a question asking for the day
- a_m: a question asking for the month
- a_{dm}: a question asking for the day+month
- a_f: a final action submitting the form and terminating the dialogue

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

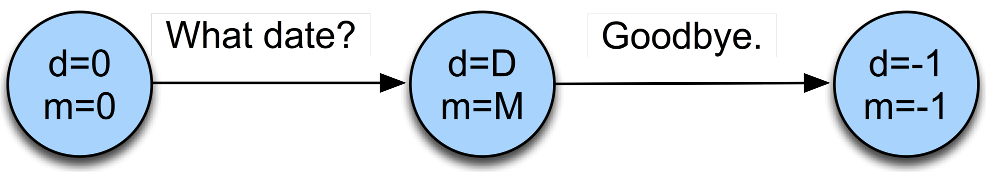
2 possible policies

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

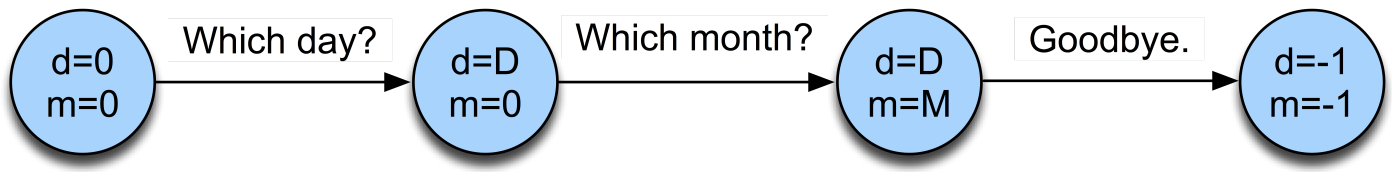
P_o=probability of error in open prompt

2 possible policies

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

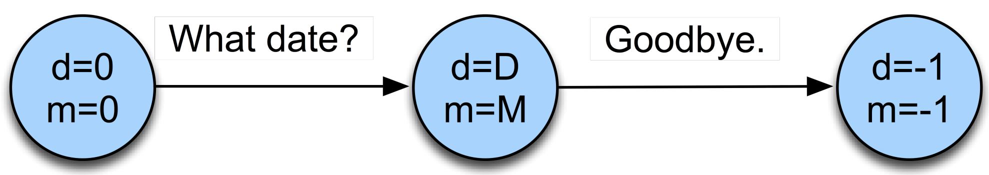
$$p_o - p_d > \frac{w_i}{2w_e}$$

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

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

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

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(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

Summary

- The Linguistics of Conversation
- Basic Conversational Agents
  - ASR
  - NLU
  - Generation
  - Dialogue Manager
- Dialogue Manager Design
  - Finite State
  - Frame-based
  - Initiative: User, System, Mixed
- VoiceXML
- Information-State
  - Dialogue-Act Detection
  - Dialogue-Act Generation
- Evaluation
- Utility-based conversational agents
  - MDP, POMDP

Part II: Speaker Recognition

Speaker Recognition tasks

- Speaker Recognition
  - Speaker Verification (Speaker Detection)
    - Is this speech sample from a particular speaker

      Is that Jane?
  - Speaker Identification
    - Which of this set of speakers does this speech sample come from

      Who is that?
    - Related tasks: Gender ID, Language ID

      Is this a woman or a man?
- Speaker Diarization
  - Segmenting a dialogue or multiparty conversation

    Who spoke when?

Speaker Recognition tasks

- Two Modes of Speaker Verification
  - Text-dependent (Text-constrained)
    - There is some constraint on the type of utterance that users of the system can pronounce
  - Text-independent
    - Users can say whatever they want

Slide adapted from Chu, Bimbot, Bonastre, Fredouille, Gravier, Magrin-Chagnolleau, Meignier, Merlin, Ortega-Garcia, Petrovska-Delacretaz, Reynolds

Introduction (cont.)

- Two Cases of Speaker Identification
  - Closed Set
    - A reference model for the unknown speaker may not exist
  - Open Set
    - An additional decision alternative, “the unknown does not match any of the models”, is required

Slide adapted from Chu, Bimbot, Bonastre, Fredouille, Gravier, Magrin-Chagnolleau, Meignier, Merlin, Ortega-Garcia, Petrovska-Delacretaz, Reynolds

Speaker Verification

- Basic idea: likelihood ratio detection
  - Assumption: A segment of speech Y contains speech from only one speaker
  - Hypothesis test:

    H0: Y is from the hypothesized speaker S

    H1: Y is not from the hypothesized speaker S
  - A likelihood ratio (LR) test given by

$$\frac{p(Y|H0)}{p(Y|H1)} \begin{cases} > \Theta, \text{ accept H0,} \\ < \Theta, \text{ accept H1,} \end{cases}$$

Slide adapted from Chu, Bimbot, Bonastre, Fredouille, Gravier, Magrin-Chagnolleau, Meignier, Merlin, Ortega-Garcia, Petrovska-Delacretaz, Reynolds

Speaker ID

Log-Likelihood Ratio Score

- We determine which hypothesis is true using the ratio:

$$\frac{p(X \mid H_0)}{p(X \mid H_1)} \begin{cases} \geq \text{threshold}, & \text{accept } H_0 \\ \leq \text{threshold}, & \text{reject } H_0 \end{cases}$$

$$\Lambda(X) = \log[p(X \mid \lambda_C)] - \log[p(X \mid \lambda_{\overline{C}})]$$

$$\Lambda(X) \begin{cases} \geq \text{threshold}, & X \text{ generated by } \lambda_C \\ < \text{threshold}, & X \text{ generated by } \lambda_{\overline{C}} \end{cases}$$

- We use the *log-likelihood ratio score* to decide whether an observed speaker, language, or dialect is the target

Statistical Modeling (cont.)

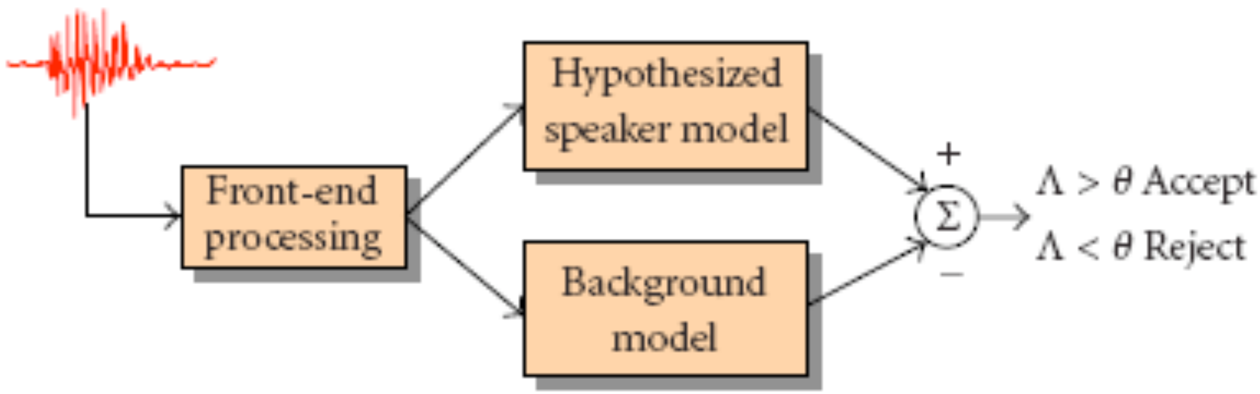


FIGURE 5: Likelihood-ratio-based speaker verification system.

Slide adapted from Chu, Bimbot, Bonastre, Fredouille, Gravier, Magrin-Chagnolleau, Meignier, Merlin, Ortega-Garcia, Petrovska-Delacretaz, Reynolds

How do we get H1?

- Pool speech from several speakers and train a single model:
  - a universal background model (UBM)

- Main advantage :
  - a single speaker-independent model (λ_{bkg}) can be trained once for a particular task and then used for all hypothesized speakers in that task

Slide adapted from Chu, Bimbot, Bonastre, Fredouille, Gravier, Magrin-Chagnolleau, Meignier, Merlin, Ortega-Garcia, Petrovska-Delacretaz, Reynolds

How to compute P(H|X)?

- For text-independent speaker recognition, the most successful likelihood function has been GMMs

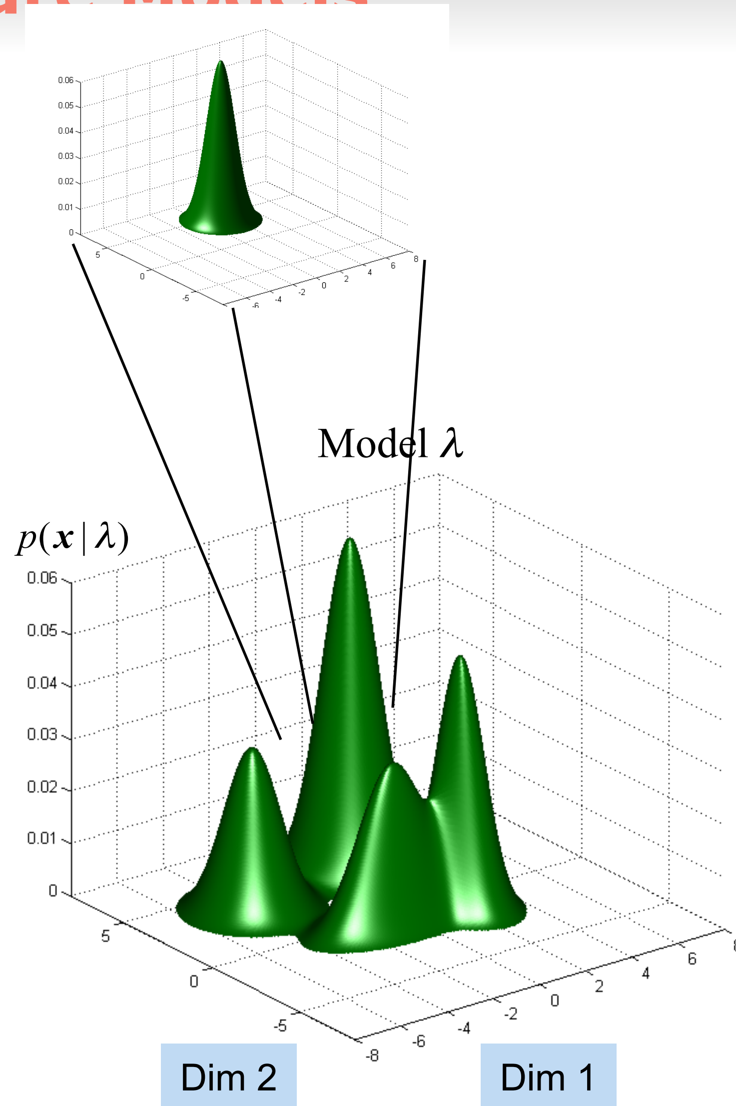
Slide adapted from Chu, Bimbot, Bonastre, Fredouille, Gravier, Magrin-Chagnolleau, Meignier, Merlin, Ortega-Garcia, Petrovska-Delacretaz, Reynolds

Recognition Systems

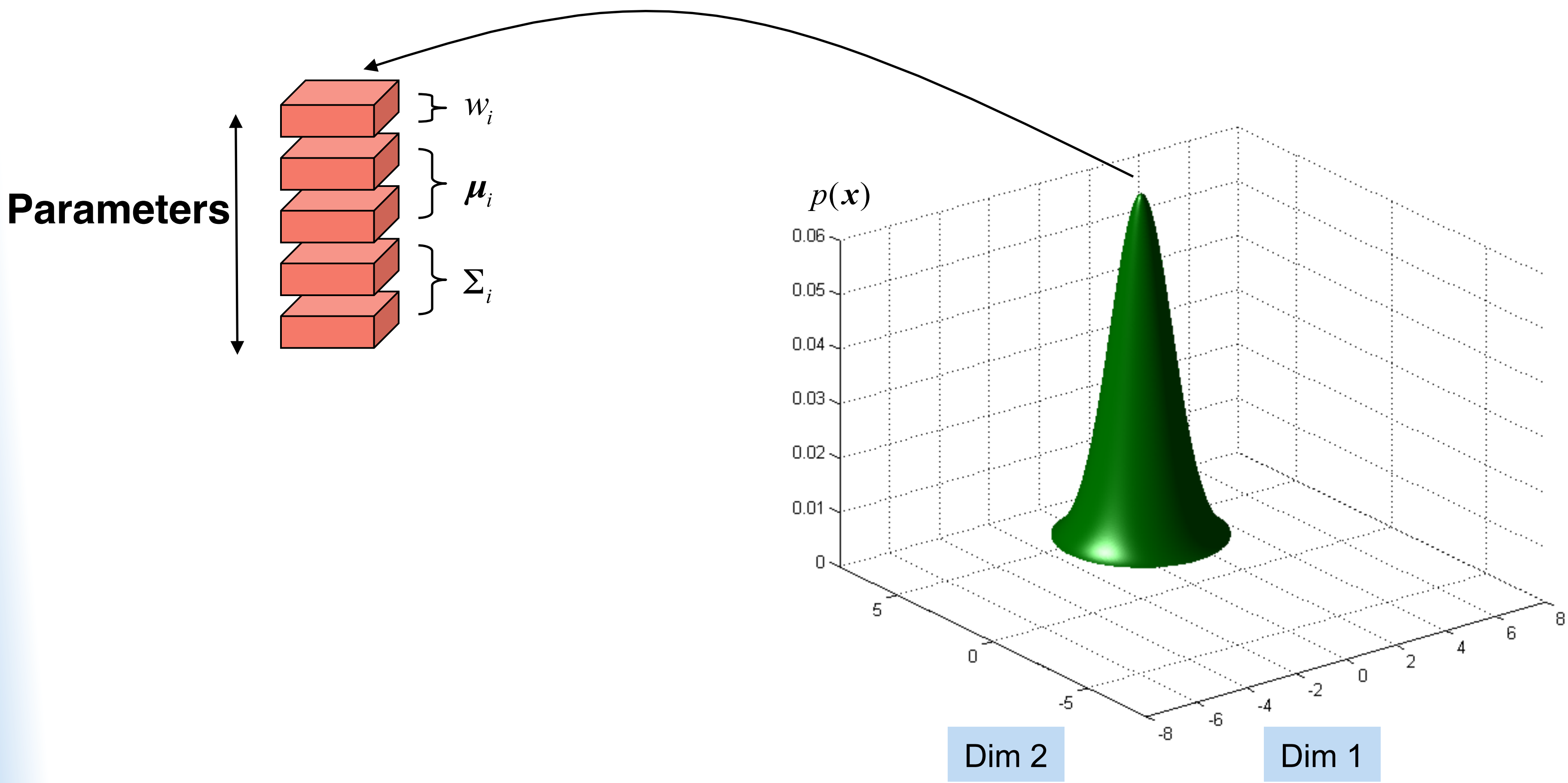
Gaussian Mixture Models

- A Gaussian mixture model (GMM) represents features as the weighted sum of multiple Gaussian distributions

- Each Gaussian *state i* has a
  - Mean $\boldsymbol{\mu}_i$
  - Covariance Σ_i
  - Weight w_i



Recognition Systems
Gaussian Mixture Models



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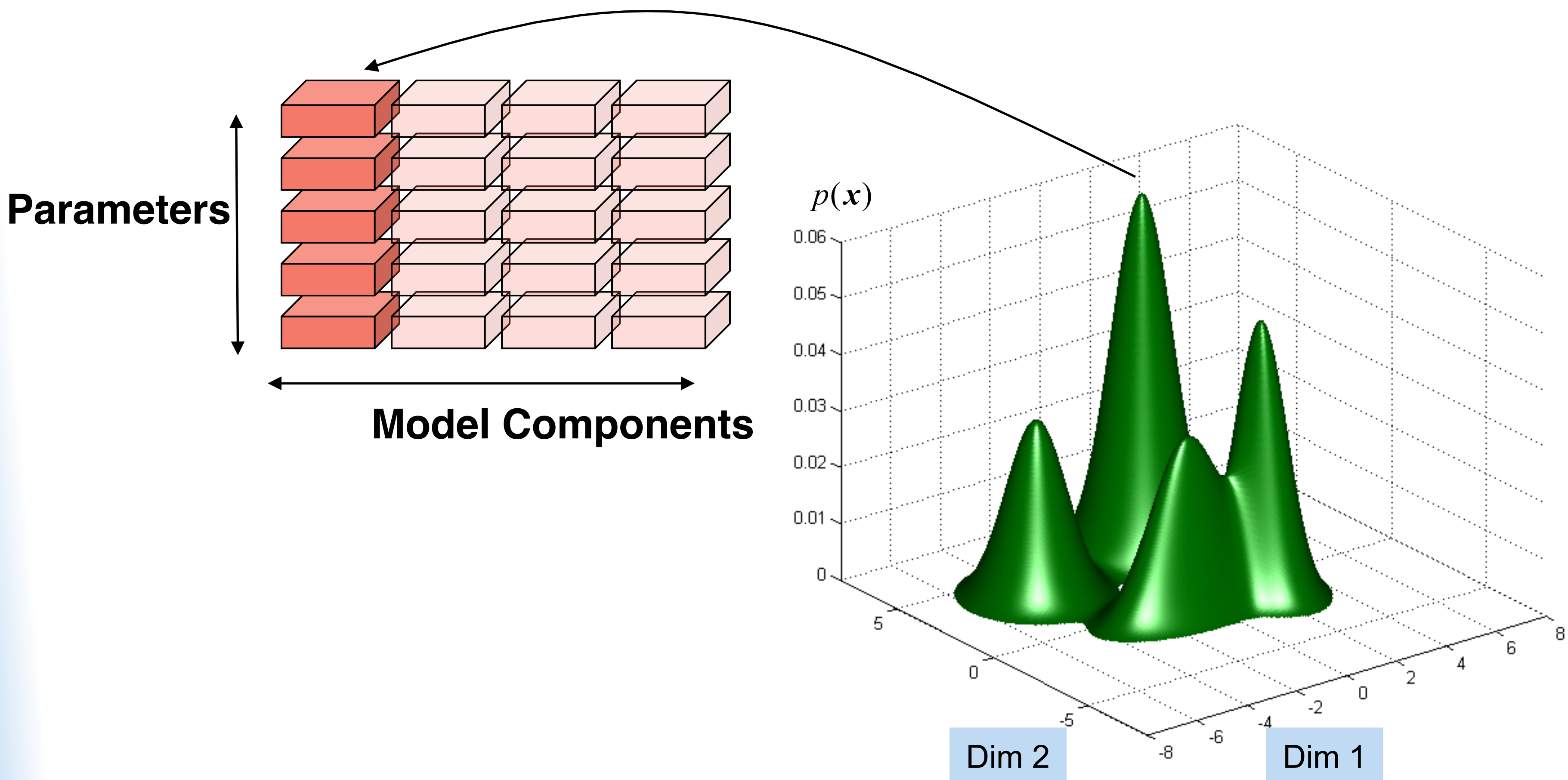
Recognition Systems

Gaussian Mixture Models



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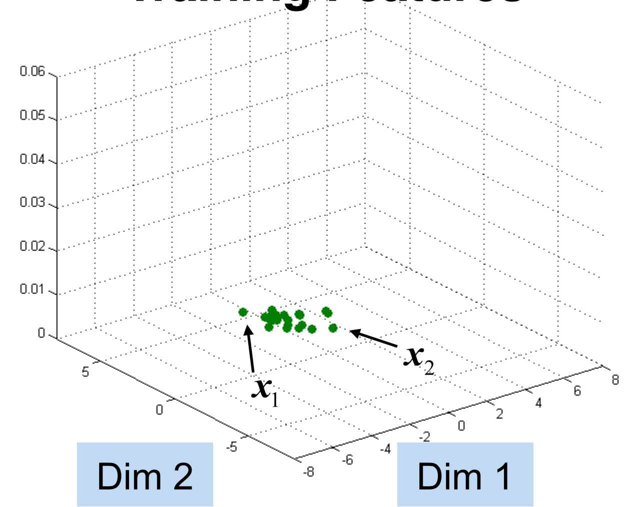
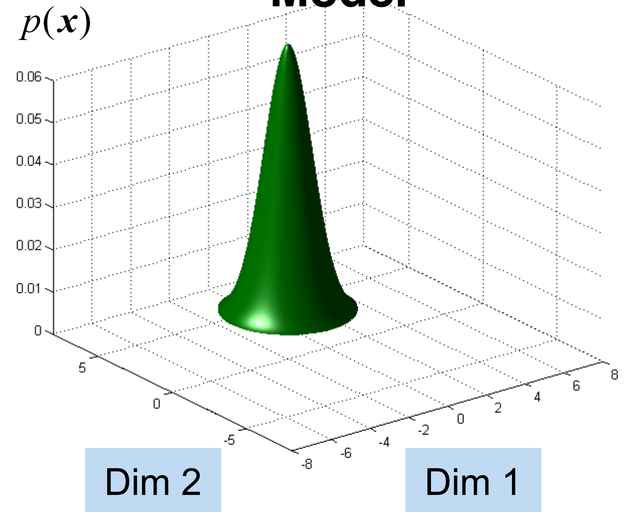
GMM training

- A recognition system makes decisions about observed data based on a knowledge of past data
- During *training*, the system learns about the data it uses to make decisions
  - A set of features are collected from a certain language, dialect, or speaker
  - A *model* is generated to represent the data

Training Features



Model



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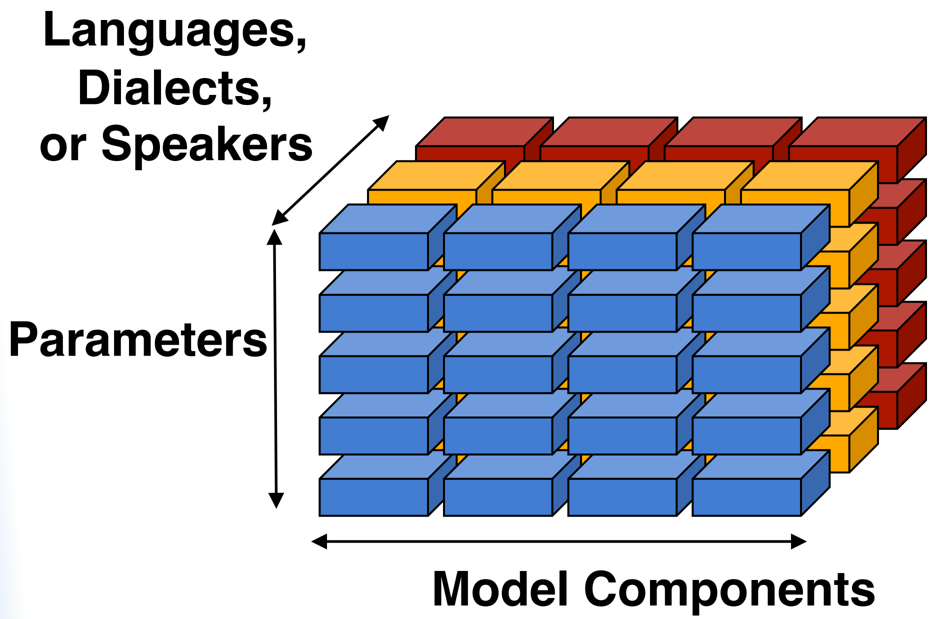
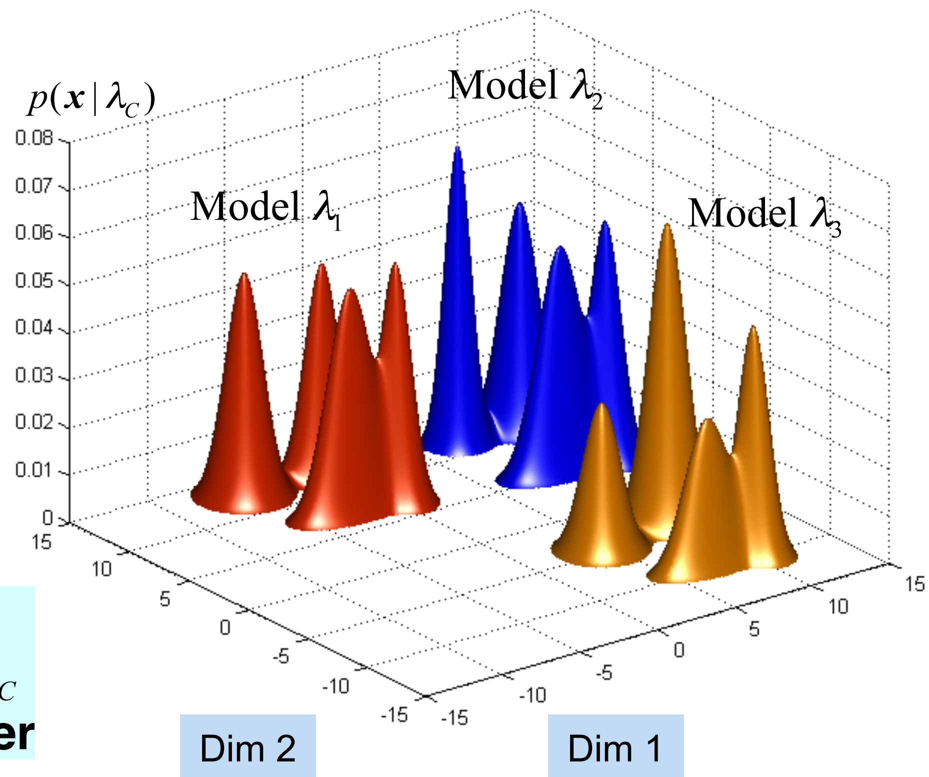
Recognition Systems

Language, Speaker, and Dialect Models





In LID, DID, and SID, we train a set of *target models* λ_C for each dialect, language, or speaker

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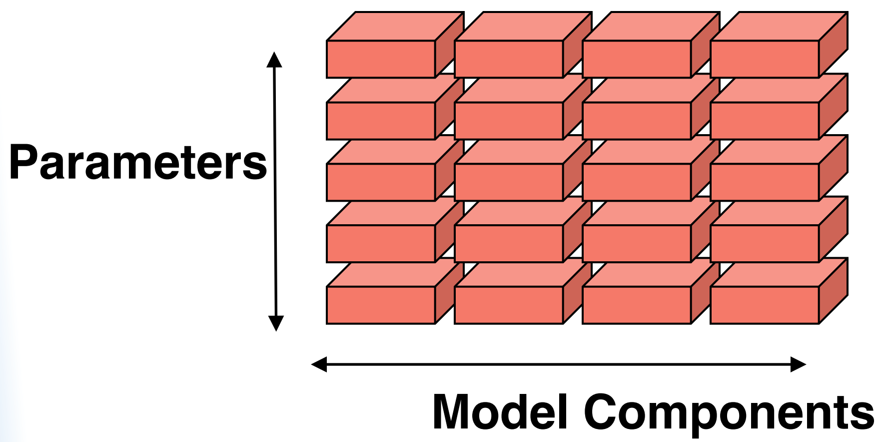
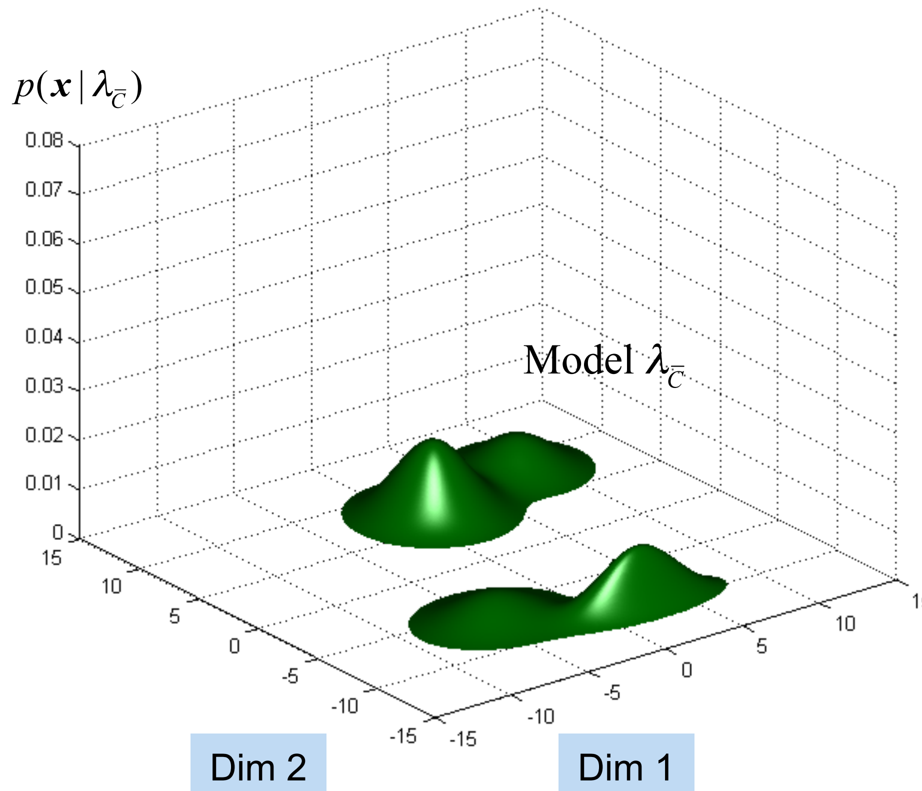
Recognition Systems
Universal Background Model





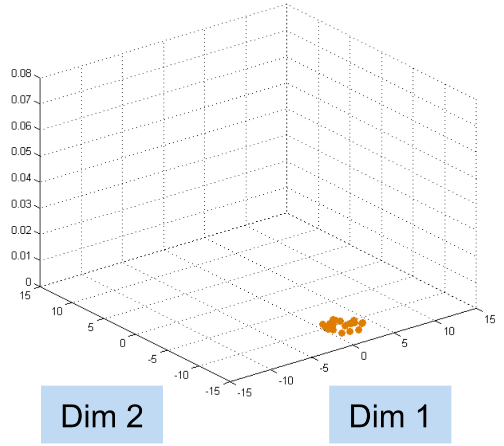
We also train a *universal background model* $\lambda_{\bar{C}}$ representing all speech

Recognition Systems
Hypothesis Test

- Given a set of *test observations*, we perform a hypothesis test to determine whether a certain class produced it

$$H_0: \quad X_{test} \text{ is from the hypothesized class}$$
$$H_1: \quad X_{test} \text{ is not from the hypothesized class}$$

$$X_{test} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \cdots, \boldsymbol{x}_K\}$$



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Recognition Systems

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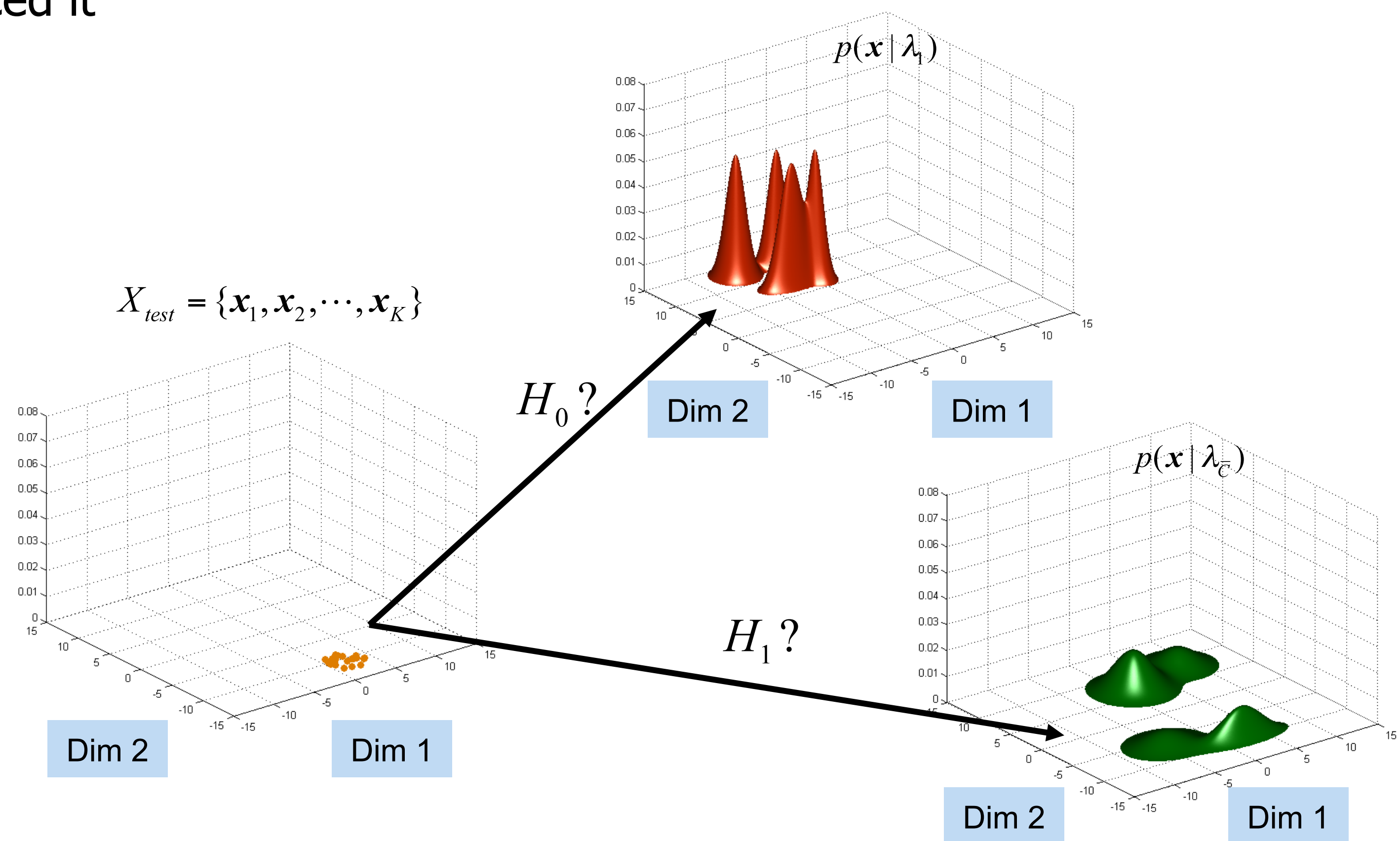

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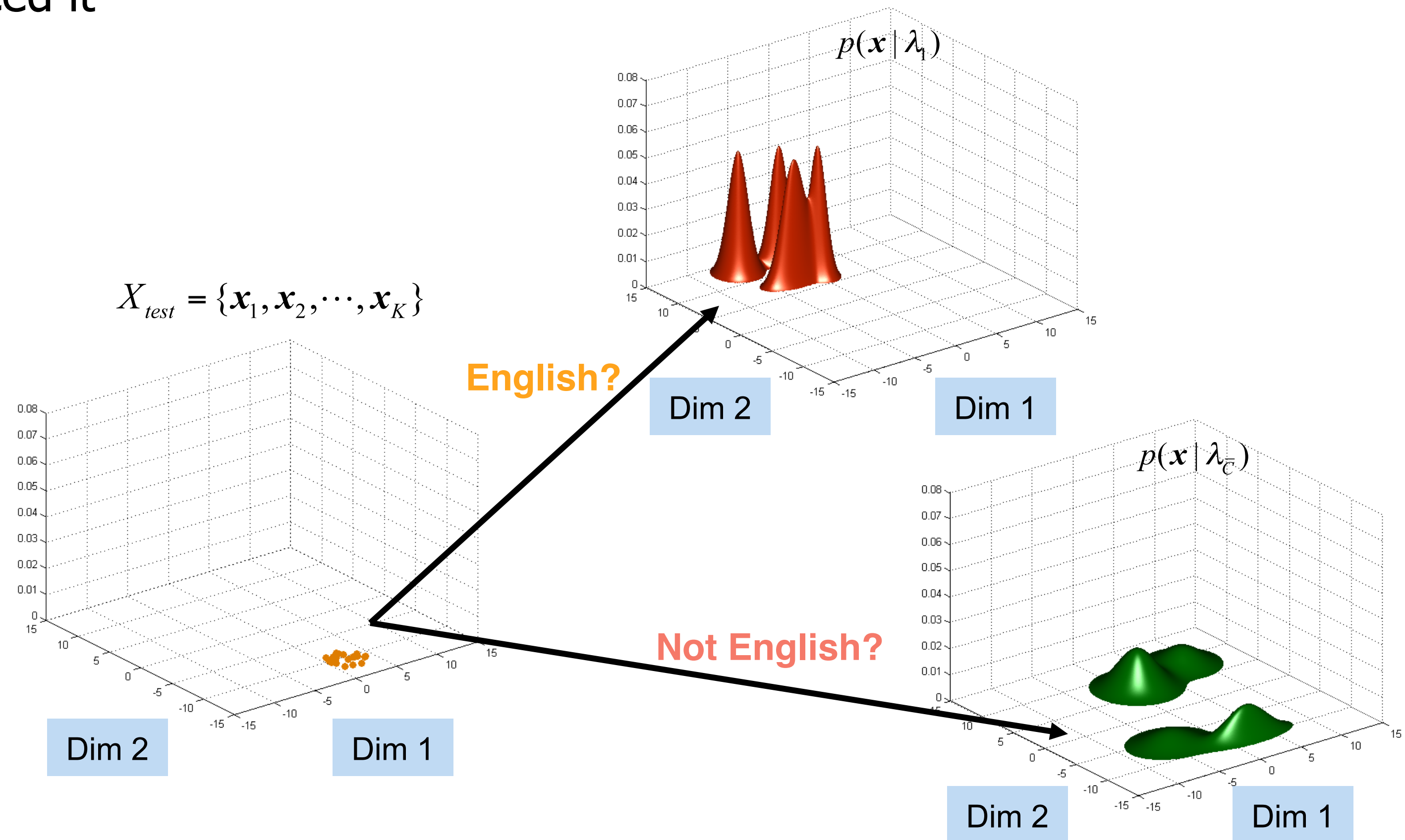

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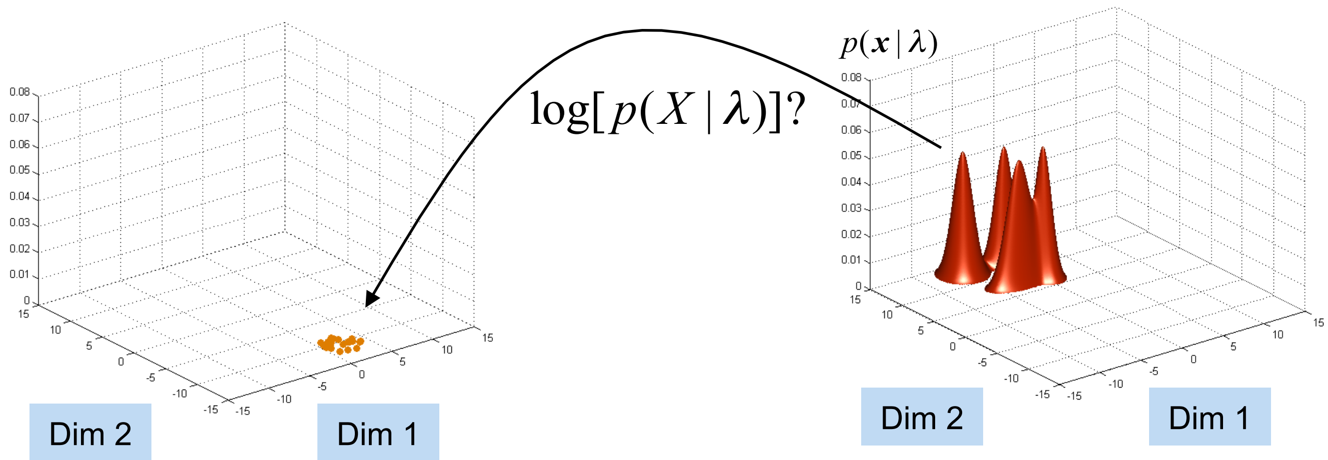
Recognition Systems
Log-Likelihood Computation

- The observation log-likelihood given a model λ is:



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Gaussian mixture models

- For a *D*-dimensional feature vector $\vec{x}$, the mixture density used for the likelihood function is defined as follows:

$$p(\vec{x} \mid \lambda) = \sum_{i=1}^{M} w_i p_i(\vec{x}) \qquad \sum_{i=1}^{M} w_i = 1,$$

- Gaussian densities $p_i(\vec{x})$, each parameterized by a *D* × 1 mean vector $\vec{u}_i$ and a *D* × *D* covariance matrix Σ *i*:

$$p_i(\vec{x}) = \frac{1}{(2\pi)^{D/2} \mid \Sigma_i \mid^{1/2}} e^{-(1/2)(\vec{x}-\vec{\mu}_i)' \sum_i^{-1} (\vec{x}-\vec{\mu}_i)}$$

- Collectively, the parameters of the density model are denoted as $\lambda = (w_i, \vec{u}_i, \Sigma_i)$, *i* = (1, . . . ,*M*)

Slide adapted from Chu, Bimbot, Bonastre, Fredouille, Gravier, Magrin-Chagnolleau, Meignier, Merlin, Ortega-Garcia, Petrovska-Delacretaz, Reynolds

Gaussian mixture models

- Under the assumption of independent feature vectors, the log-likelihood of a model λ for a sequence of feature vectors $X = \{\vec{x}_1, \ldots, \vec{x}_T\}$ is computed as follows:

$$\log p(X \mid \lambda) = \frac{1}{T} \sum_t \log p(\vec{x}_t \mid \lambda)$$

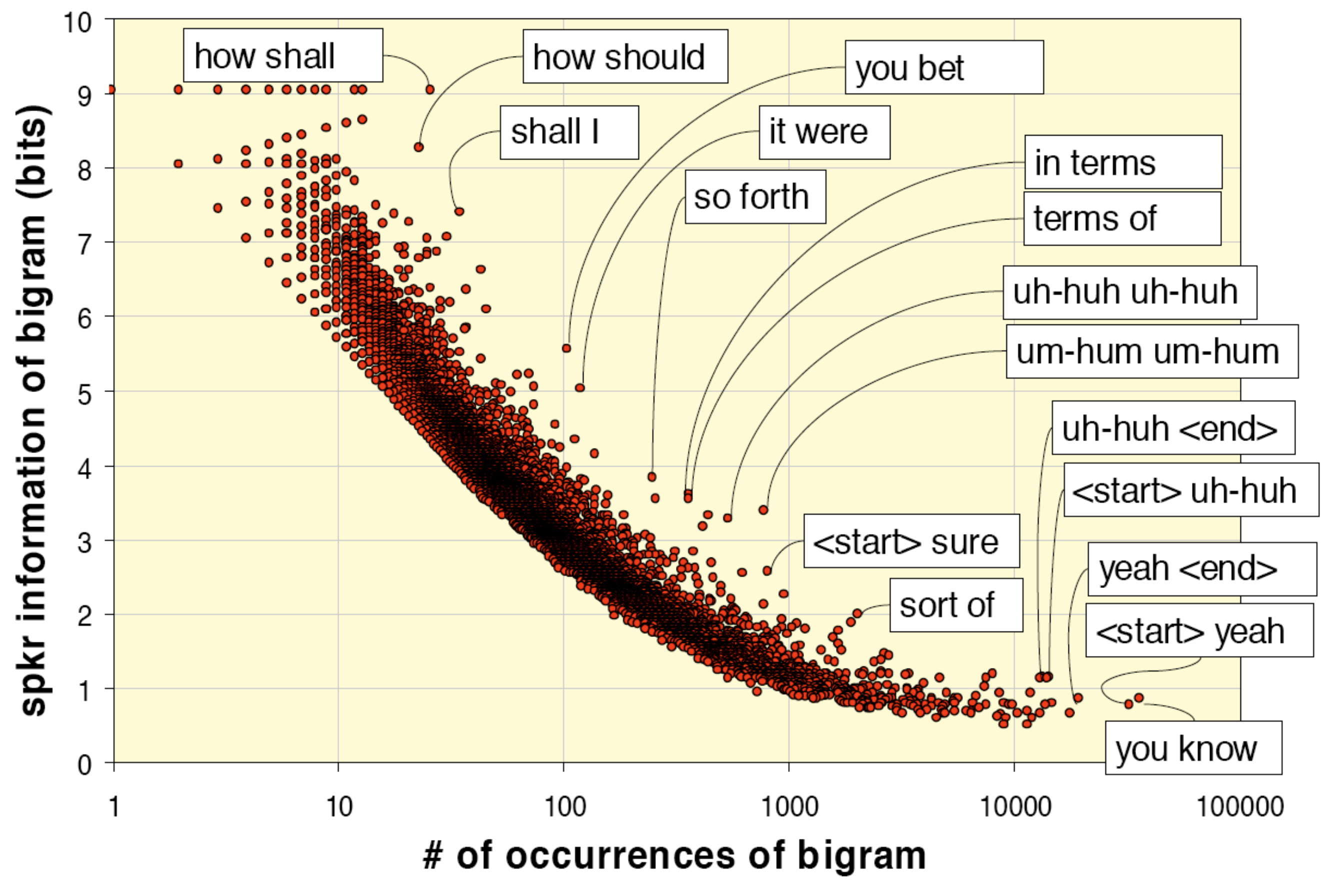
- GMMs are comptuationally inexpensive
  - For homework: single gaussian.
  - Real systems:
    - UBM background model: 512–2048 mixtures
    - Speaker's GMM: 64–256 mixtures

- Recent work:
  - Combining high-level information (such as speaker-dependent word usage or speaking style) with GMMs

Slide adapted from Chu, Bimbot, Bonastre, Fredouille, Gravier, Magrin-Chagnolleau, Meignier, Merlin, Ortega-Garcia, Petrovska-Delacretaz, Reynolds

Doddington (2001)

- Word bigrams can be very informative about speaker identity



Speaker diarization

- Tasks
  - Conversational telephone speech
    - 2 speakers
  - Broadcast news
    - Many speakers although often in dialogue (interviews) or in sequence (broadcast segments)
  - Meeting recordings
    - Many speakers, lots of overlap and disfluencies
- General 2-step algorithm
  - Segmentation into speakers
    - Detection of speaker-change (insert boundaries)
  - Clustering (MFCC)s of segments

Speaker diarization

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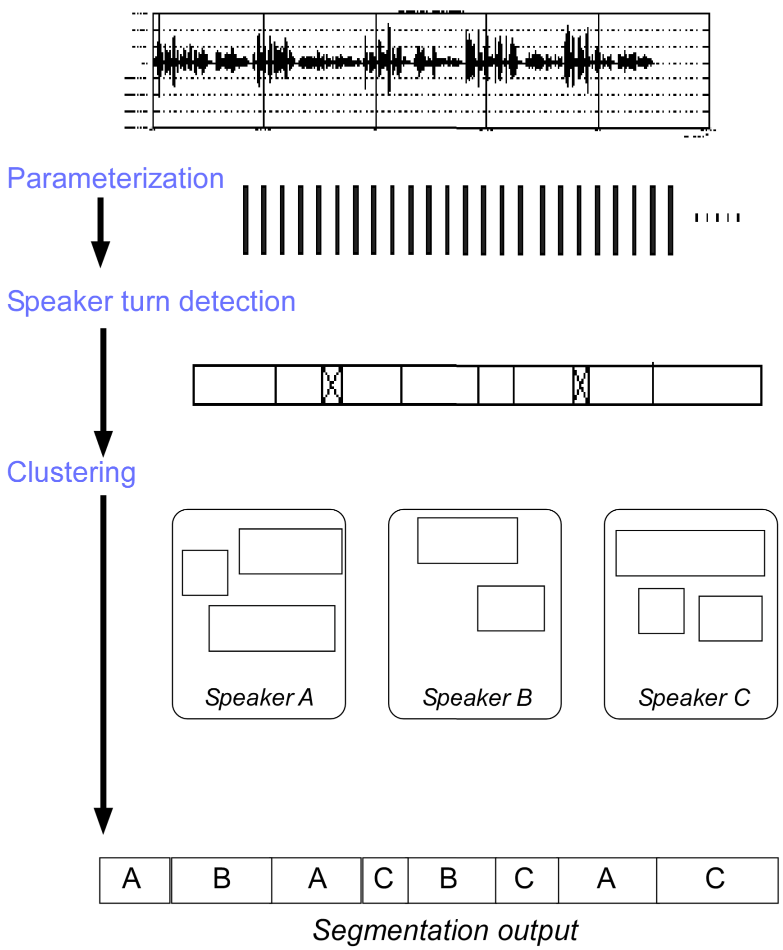

Picture from slide by Moraru, Besacier, Meignier, Fredouille, Bonastre

Outline for today

- MDP Dialogue Architectures
- Speaker Recognition