

# Agenda

- HW5 graded
- HW6 due next Tuesday
- Schedule changes
- IGERT
- Winter Storm

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- · Questions, comments, concerns?
- Text-to-Speech (TTS)

# Speech Synthesis/Text-to-Speech (TTS)

IP notice

- · The following slides are from Dan Jurafsy, Richard Sproat, and other researchers as noted on the slides
- · As presented in the Speech Synthesis lectures at the LSA Summer Institute

# TTS: Outline

- · From words to strings of phones
- · Dictionaries
- Letter-to-Sound Rules ("Grapheme-to-Phoneme Conversion")
- Prosody
- Linguistic Background
- Producing Intonation in TTS
- Stress/accent
- TTS Systems
- Diphone synthesis
- Unit selection synthesis

**Computational Linguistics 1** 

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# From words to phones

#### Two methods:

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- · Dictionary-based
- Rule-based (Letter-to-sound=LTS, grapheme-to-phoneme = G2P)
- Early systems, all LTS
- MITalk was radical in having 'huge' 10K word dictionary

Slide from Dan Jurafsky

Modern systems use a combination

# Pronunciation Dictionaries: CMU CMU dictionary: 127k words http://www.speech.cs.cmu.edu/cgi-bin/cmudict Some problems: Has errors Only American pronunciations No syllable boundaries · Doesn't tell us which pronunciation to use for which homophones (no POS tags) Doesn't distinguish case The word US has 2 pronunciations [AH1 S] and [Y UW1 EH1 S] Computational Linguistics 1

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# Dictionaries aren't sufficient

#### Unknown words (OOVs)

- Increase with the (sqrt of) number of words in unseen text
  Black et al (1998) OALD on 1st section of Penn Treebank:
- · Out of 39923 word tokens,



- · So commercial systems have 4-part system:
  - · Big dictionary
  - · Names handled by special routines · Acronyms handled by special routines (previous lecture)
  - Machine learned g2p algorithm for other unknown words

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# Names

#### Methods:

- · Can do morphology (Walters -> Walter, Lucasville)
- · Can write stress-shifting rules (Jordan -> Jordanian)
- Rhyme analogy: Plotsky by analogy with Trostsky (replace tr with pl)
- · Liberman and Church:
- for 250K most common names, got 212K (85%) from these modified-dictionary methods, used LTS for rest.
- · Can do automatic country detection (from letter trigrams) and then do country-specific rules Can train g2p system specifically on names
- · Or specifically on types of names (brand names, Russian names, etc)

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# Acronyms

- · We saw in the text normalization lecture
- · Use machine learning to detect acronyms
  - EXPN
  - ASWORD

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- LETTERS
- · Use acronym dictionary, hand-written rules to augment

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# Letter-to-Sound Rules · Earliest algorithms: handwritten Chomsky+Halle-style rules: $c \rightarrow [k] / \_ {a,o}V$ ; context-dependent ; context-independent

- $c \rightarrow [s]$
- · Rules apply in order
- "christmas" pronounced with [k]
- But word with ch followed by non-consonant pronounced [ch] · e.g., "choice'
- English famously evil
- · in terms of pronunciation and stress rules

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# Modern method: Learning LTS rules automatically

- Induce LTS from a dictionary of the language
- Black et al. 1998
- · Applied to English, German, French
- Two steps:
- alignment
- · (CART-based) rule-induction

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- Letters: checked
- Phones: ch \_ eh \_ k \_ t
- Black et al Method 1: P: K EY K ε
  - First scatter epsilons in all possible ways to cause letters and phones to align
- Then collect stats for P(phone|letter) and select best to generate new stats

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L: c a k e

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# $p(p_i|l_j) = \frac{\operatorname{count}(p_i, l_j)}{\operatorname{count}(l_j)}$

- This iterated a number of times until settles (5-6)
- This is EM (expectation maximization) alg



# Alignment

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- · Some alignments will turn out to be really bad.
- These are just the cases where pronunciation doesn't match letters:
- Dept d ih p aa r t m ah n t
- CMU s iy eh m y uw
- · Lieutenant I eh f t eh n ax n t (British)
- Also foreign words

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These can just be removed from alignment training

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# **Building CART trees**

Build a CART tree for each letter in alphabet (26 plus accented) using context of +-3 letters

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- # # # <mark>c</mark> h e c -> ch

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#### Add more features $\mathsf{LANG=Russian} \quad \mathsf{I}_{\mathsf{i}\mathsf{-}\mathsf{3}} \quad \mathsf{I}_{\mathsf{i}\mathsf{-}\mathsf{2}} \quad \mathsf{I}_{\mathsf{i}\mathsf{-}\mathsf{1}} \quad \mathsf{I}_{\mathsf{i}} \quad \mathsf{I}_{\mathsf{i}\mathsf{+}\mathsf{1}} \quad \mathsf{I}_{\mathsf{i}\mathsf{+}\mathsf{2}} \quad \mathsf{I}_{\mathsf{i}\mathsf{+}\mathsf{3}}$ POS=NNP y # # # # J u r a f s k € AXR AE1 F ? JH p<sub>i-3</sub> p<sub>i-2</sub> p<sub>i-1</sub> Even more: for French liaison, we need to know what the next word is, and whether it starts with a vowel French six • [s iy s] in j'en veux six • [s iy z] in six enfants · [s iy] in six filles Computational Linguistics 1 Slide from Dan Jurafsky 17



# **Defining Intonation**

- · Ladd (1996) "Intonational Phonology"
- "The use of suprasegmental phonetic features... Suprasegmental = above and beyond the segment/phone
- F0

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- · Intensity (energy)
- Duration
- · ...to convey sentence-level pragmatic meanings"
- i.e., meanings that apply to phrases or utterances as a whole, not lexical stress, not lexical tone.

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# Three aspects of prosody

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- Prominence: some syllables/words are more prominent than others
- · Structure/boundaries: sentences have prosodic structure · Some words group naturally together

From Ladd (1996)

- · Others have a noticeable break or disjuncture between them
- Tune: the intonational melody of an utterance.

Graphic representation of F0 400 350 300 F0 (in Hertz) 250 200 150 100 50 legumes are a good source of VITAMINS time (F0 is not defined for consonants without vocal fold vibration.) tational Linguistics 1 Slide from Jennifer Venditti

ress rbitr ccen tona	is a sary) le t is a t is a tiona	e is the place structural ( ocation for property of I prominer	cement of property r an acce of a word nce in ore	f pitcl of a int to in <u>c</u> der to	h acce word occu ontex o 'higi	nts — it ma r, if thei <u>t</u> — it is hlight' ir	irks a potential re is one. a way to mark nportant words in the
(x)					(x)		(accented syll)
(x) x					(x) x		(accented syll) stressed syll
(x) x x			x		(x) x x		(accented syll) stressed syll full vowels
(x) x x x	x	x	x x	x	(x) x x x x	X	(accented syll) stressed syll full vowels syllables

# Stress vs. Accent

- The speaker decides to make the word vitamin more prominent by accenting it.
- · Lexical stress tell us that this prominence will appear on the first syllable, hence Vltamin.
- · So we will have to look at both the lexicon and the context to predict the details of prominence
- · I'm a little surPRISED to hear it CHARacterized as upBEAT

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# Which word receives an accent?

- · It depends on the context.
- · For example, the 'new' information in the answer to a question is often accented, while the 'old' information usually is not.
- Q1: What types of foods are a good source of vitamins?
  A1: LEGUMES are a good source of vitamins.
- · Q2: Are legumes a source of vitamins?
- · A2: Legumes are a GOOD source of vitamins
- Q3: I' ve heard that legumes are healthy, but what are they a good source of ?
- · A3: Legumes are a good source of VITAMINS.
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From Ladd (1996)

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# Phrasing sometimes helps disambiguate

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Temporary ambiguity:

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When Madonna sings the song is a hit.

# Phrasing sometimes helps disambiguate

Slide from Jennifer Venditti

Slide from Jennifer Venditti

#### Temporary ambiguity:

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When Madonna sings  $\ensuremath{\%}$  the song is a hit.

When Madonna sings the song % it's a hit.

[from Speer & Kjelgaard (1992)]

# by the second second

















# Predicting Pitch Accent: Factors

#### · Part of speech

- · Content words are usually accented
- Function words are rarely accented
- Of, for, in on, that, the, a, an, no, to, and but or will may would can her is their its our there is am are was were, etc. · But it's not just function/content

  - Contrast

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- Legumes are poor source of VITAMINS No, legumes are a GOOD source of vitamins I think JOHN or MARY should go No, I think JOHN AND MARY should go
- List intonation
- Information status
- Syntactic structure

POS of next word

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• POS

Stress of current, previous, next syllable

Predicting Pitch Accent: Other Features

Unigram probability of word

· POS of previous word

- · Bigram probability of word
- · Position of word in sentence

### Predicting Pitch Accent: State-of-the-art

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- · Hand-label large training sets
- · Use CART, SVM, CRF, etc to predict accent
- · Lots of rich features from context
- Classic lit:

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Hirschberg, Julia. 1993. Pitch Accent in context: predicting intonational prominence from text. Artificial Intelligence 63, 305-340

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# Predicting Boundaries: Features

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- Intonation phrase boundaries
- · Intermediate phrase boundaries
- · Full intonation phrase boundaries
- · Based just on punctuation and clauses?

Police also say | Levy's blood alcohol level | was twice the legal limit ||

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### Predicting Boundaries: More Features

· Length features:

- Phrases tend to be of roughly equal length
- · Total number of words and syllables in utterance
- Distance of juncture from beginning and end of sentence (in words or syllables) Neighboring POS, punctuation
- Syntactic structure (parse trees)
- · Largest syntactic category dominating preceding word but not succeeding word · How many syntactic units begin/end between words
- · Other:
  - · English: boundaries are more likely between content words and function words
  - · Type of function word to right
  - · Capitalized names
  - # of content words since previous function word

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# **TTS Intonation Prediction**

- Predict duration
- Predict F0

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# TTS: Outline

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     ("Grapheme-to-Phoneme Conversion")
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# 

# Waveform Synthesis in Concatenative TTS Diphone Synthesis Unit Selection Synthesis Target cost Unit cost



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# **Diphone TTS Architecture**

#### Training:

- Choose units (kinds of diphones)
- Record 1 speaker saying 1 example of each diphone
- · Mark the boundaries of each diphones,
- cut each diphone out and create a diphone database
- Synthesizing an utterance:
- Grab relevant sequence of diphones from database
- · Concatenate the diphones, doing slight signal processing at
- boundariesUse signal processing to change the prosody (F0, energy, duration) of selected sequence of diphones

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# Diphones

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- · Mid-phone is more stable than edge
- Need O(phone<sup>2</sup>) number of units
- Some combinations don't exist (hopefully)
- ATT (Olive et al. 1998) system had 43 phones
  - 1849 possible diphones
    Phonotactics ([h] only occurs before vowels), don't need to keep diphones across silence
  - Only 1172 actual diphones
- May include stress, consonant clusters
- So could have more
- Lots of phonetic knowledge in design
- Database relatively small (by today's standards)
   Around 8 megabytes for English (16 KHz 16 bit)

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Can it be automatically found?

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Concatenating diphones: junctures
If waveforms are very different, will perceive a click at the junctures
So need to window them
Also if both diphones are voiced
Need to join them pitch-synchronously
That means we need to know where each pitch period begins, so we can paste at the same place in each pitch period.
Pitch marking or epoch detection: mark where each pitch pulse or epoch occurs
Finding the Instant of Glottal Closure (IGC)
(note difference from pitch tracking)

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# **Prosodic Modification**

- Modifying pitch and duration independently
- Changing sample rate modifies both:
   Chipmunk speech
- · Duration: duplicate/remove parts of the signal
- · Pitch: resample to change pitch

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# Summary: Diphone Synthesis

- · Well-understood, mature technology
- Augmentations
   Stress
- Stress
   Onset/coda
- Demi-syllables

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- Problems:
- · Signal processing still necessary for modifying durations
- Source data is still not natural
  Units are just not large enough; can't handle word-specific effects, etc.

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# Problems with Diphone Synthesis

slide from Alan Black

- Signal processing methods leave artifacts, making the speech sound unnatural
- Diphone synthesis only captures local effects
- But there are many more global effects (syllable structure, stress pattern, word-level effects)

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# Unit Selection Synthesis Generalization of the diphone intuition Larger units From diphones to sentences Many many copies of each unit to hours of speech instead of 1500 diphones (a few minutes of speech) Little or no signal processing applied to each unit Unlike diphones

## 

# Unit Selection Intuition Given a big database For each segment (diphone) that we want to synthesize Find the unit in the database that is the *best* to synthesize this target segment What does "best" mean? Target cost: Closest match to the target description, in terms of Phonetic context F0, stress, phrase position

- Join cost: Best join with neighboring units
   Matching formants + other spectral characteristics
  - Matching rormants + other spe
     Matching energy
  - Matching energy
     Matching F0

$$C(t_1^n, u_1^n) = \sum_{i=1}^n C^{target}(t_i, u_i) + \sum_{i=2}^n C^{join}(u_{i-1}, u_i)$$

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# Targets and Target Costs

- A measure of how well a particular unit in the database matches the internal representation produced by the prior stages
- · Features, costs, and weights
- · Examples:
- · /ih-t/ from stressed syllable, phrase internal, high F0, content word · /n-t/ from unstressed syllable, phrase final, low F0, content word
- /dh-ax/ from unstressed syllable, phrase initial, high F0, from function word "the"

slide from Paul Taylor



**Target Costs** 

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# How to set target cost weights

- · What you REALLY want as a target cost is the perceivable acoustic difference between two units
- · But we can't use this, since the target is NOT ACOUSTIC yet, we haven't synthesized it!
- · We have to use features that we get from the TTS upper levels (phones, prosody)
- · But we DO have lots of acoustic units in the database. We could use the acoustic distance between these to help set the WEIGHTS on the acoustic features.

slide from Paul Taylor

# Join (Concatenation) Cost Measure of smoothness of join

- · Measured between two database units (target is irrelevant)
- · Features, costs, and weights
- · Comprised of k subcosts:
- Spectral features
- F0 Energy Join cost

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$$C^{j}(u_{i-1}, u_{i}) = \sum_{k=1}^{p} w_{k}^{j} C_{k}^{j}(u_{i-1}, u_{i})$$

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# Join costs

## Hunt and Black 1996

- If u<sub>i-1</sub>==prev(u<sub>i</sub>) C<sup>c</sup>=0
- Used

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- · MFCC (mel cepstral features)
- Local F0
- · Local absolute power
- · Hand tuned weights

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# Join costs

- . The join cost can be used for more than just part of search
- · Can use the join cost for optimal coupling (Isard and Taylor 1991, Conkie 1996), i.e., finding the best place to join the two units.
- · Vary edges within a small amount to find best place for join · This allows different joins with different units
- · Thus labeling of database (or diphones) need not be so accurate

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- Quality is far superior to diphones
- Natural prosody selection sounds better
- Disadvantages:
- Quality can be very bad in places
   HCI problem: mix of very good and very bad is quite annoying
- Synthesis is computationally expensive
- Can't synthesize everything you want:
- Diphone technique can move emphasis
- Unit selection gives good (but possibly incorrect) result

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# HMM Synthesis

Unit selection (Roger)

Unit selection (Nina)

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   Text-to-Movies: xtranormal.com

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