CS 224S / LINGUIST 285
Spoken Language Processing

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Lecture 1: Introduction, ARPAbet, Articulatory Phonetics

Original slides by Dan Jurafsky

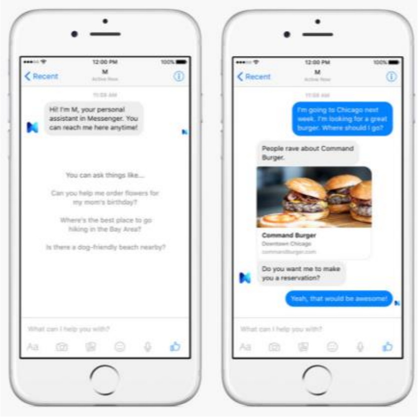
April 3, Week 1

- Course introduction
- Course topics overview
    - Speech recognition
    - Dialog / conversational agents
    - Speech synthesis (Text to speech)
    - Affect extraction
- Very brief history
- Articulatory Phonetics
- Course Logistics
- ARPAbet transcription

An exciting time for spoken language processing

Amazon Echo
2015

Google Home
2016



Hi! I'm M, your personal assistant in Messenger. You can reach me here anytime!

You can ask things like...

Can you help me order flowers for my mom's birthday?

Where's the best place to go hiking in the Bay Area?

Is there a dog-friendly beach nearby?

I'm going to Chicago next week. I'm looking for a great burger. Where should I go?

People rave about Command Burger.

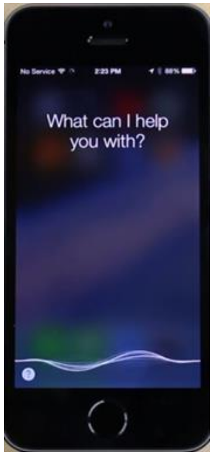
Command Burger
Downtown Chicago
commandburger.com

Do you want me to make you a reservation?

Yeah, that would be awesome!

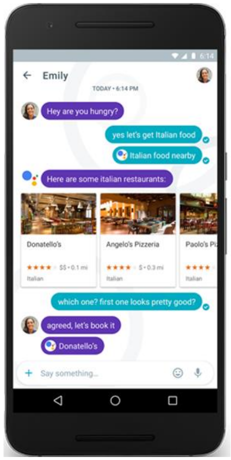
Facebook M
2015

Anki Cozmo
2016



What can I help you with?

Apple
Siri
2011



Emily

TODAY • 6:14 PM

Hey are you hungry?

yes let's get Italian food

Italian food nearby

Here are some italian restaurants:

Donatello's	Angelo's Pizzeria	Paolo's Pi
★★★★ $$ • 0.1 mi	★★★★ $ • 0.3 mi	★★★★
Italian	Italian	Italian

which one? first one looks pretty good?

agreed, let's book it

Donatello's

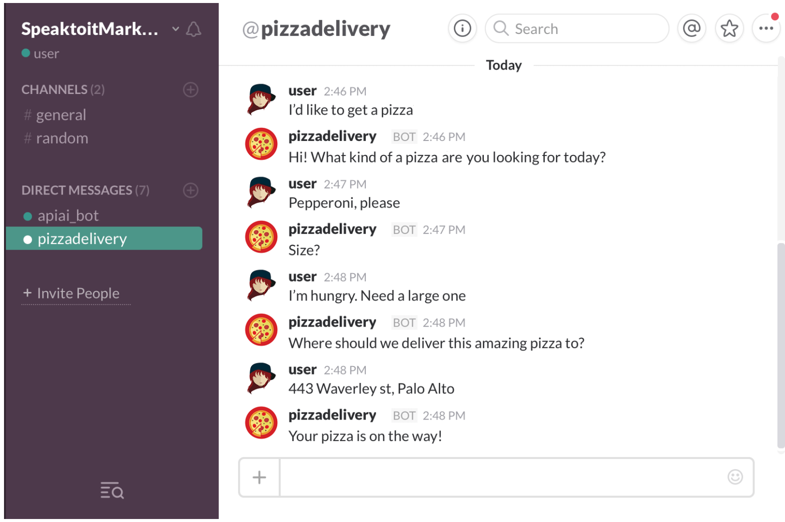
Google
Assistant
2016

Use the area below to ask me anything.

try what's the forecast?
see more

I've added a few interests to my notebook

Microsoft
Cortana
2014



user 2:46 PM
I'd like to get a pizza

pizzadelivery BOT 2:46 PM
Hi! What kind of a pizza are you looking for today?

user 2:47 PM
Pepperoni, please

pizzadelivery BOT 2:47 PM
Size?

user 2:48 PM
I'm hungry. Need a large one

pizzadelivery BOT 2:48 PM
Where should we deliver this amazing pizza to?

user 2:48 PM
443 Waverley st, Palo Alto

pizzadelivery BOT 2:48 PM
Your pizza is on the way!

Slack Bot API
2015

LVCSR

- Large Vocabulary Continuous Speech Recognition
  - ~64,000 words
  - Speaker independent (vs. speaker-dependent)
  - Continuous speech (vs isolated-word)

Current error rates

Ballpark numbers; exact numbers depend very much on the specific corpus

Task	**Vocabulary**	**Word Error Rate %**
Digits	11	0.5
WSJ read speech	5K	1
WSJ read speech	20K	1
Broadcast news	64,000+	4
Conversational Telephone	64,000+	6

Why is conversational speech harder?

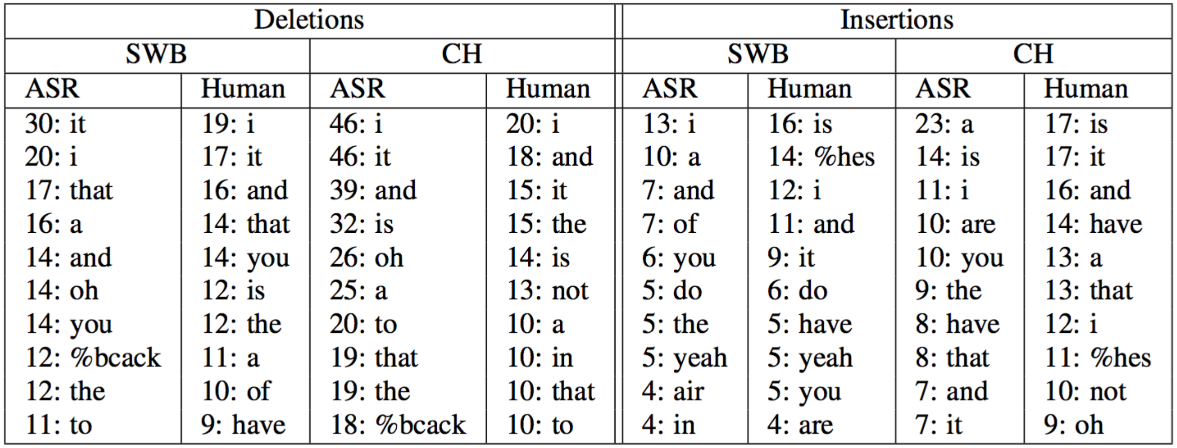
- A piece of an utterance without context
- The same utterance with more context

HSR versus ASR

Task	Vocab	ASR	Hum SR
Continuous digits	11	.5	.009
WSJ 1995 clean	5K	3	0.9
WSJ 1995 w/noise	5K	9	1.1
SWBD 2004	65K	~6	3-4?

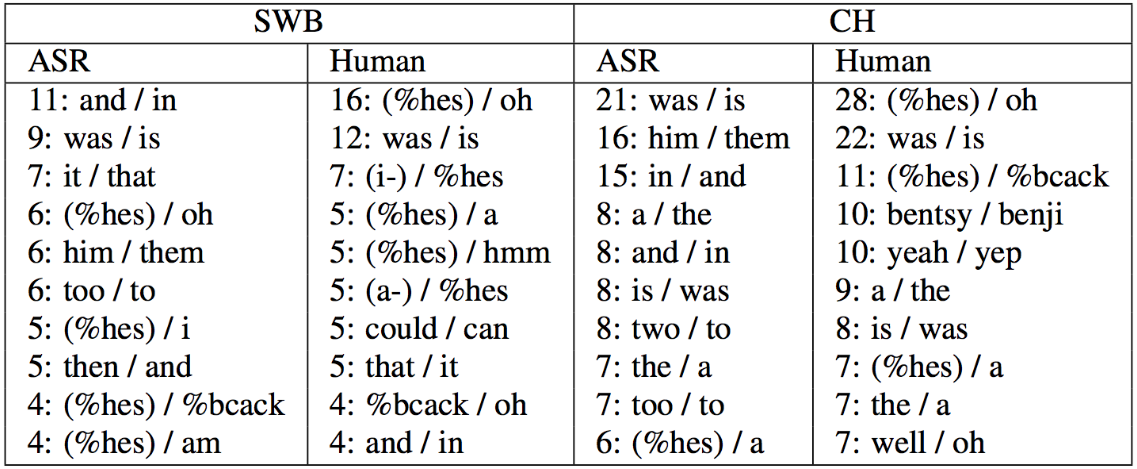
- Conclusions:
  - Gap increases with noisy speech
  - These numbers are rough, take with grain of salt
  - We are overfitting to the benchmark datasets

HSR versus ASR



Deletions				Insertions			
SWB		CH		SWB		CH	
ASR	Human	ASR	Human	ASR	Human	ASR	Human
30: it	19: i	46: i	20: i	13: i	16: is	23: a	17: is
20: i	17: it	46: it	18: and	10: a	14: %hes	14: is	17: it
17: that	16: and	39: and	15: it	7: and	12: i	11: i	16: and
16: a	14: that	32: is	15: the	7: of	11: and	10: are	14: have
14: and	14: you	26: oh	14: is	6: you	9: it	10: you	13: a
14: oh	12: is	25: a	13: not	5: do	6: do	9: the	13: that
14: you	12: the	20: to	10: a	5: the	5: have	8: have	12: i
12: %bcack	11: a	19: that	10: in	5: yeah	5: yeah	8: that	11: %hes
12: the	10: of	19: the	10: that	4: air	5: you	7: and	10: not
11: to	9: have	18: %bcack	10: to	4: in	4: are	7: it	9: oh

Table 3: Most frequent deletion and insertion errors for humans and ASR system on SWB and CH.



SWB		CH	
ASR	Human	ASR	Human
11: and / in	16: (%hes) / oh	21: was / is	28: (%hes) / oh
9: was / is	12: was / is	16: him / them	22: was / is
7: it / that	7: (i-) / %hes	15: in / and	11: (%hes) / %bcack
6: (%hes) / oh	5: (%hes) / a	8: a / the	10: bentsy / benji
6: him / them	5: (%hes) / hmm	8: and / in	10: yeah / yep
6: too / to	5: (a-) / %hes	8: is / was	9: a / the
5: (%hes) / i	5: could / can	8: two / to	8: is / was
5: then / and	5: that / it	7: the / a	7: (%hes) / a
4: (%hes) / %bcack	4: %bcack / oh	7: too / to	7: the / a
4: (%hes) / am	4: and / in	6: (%hes) / a	7: well / oh

Table 2: Most frequent substitution errors for humans and ASR system on SWB and CH.

(Saon et al, 2017)

Why accents are hard

- A word by itself

- The word in context

So is speech recognition solved? Why study it vs just use some API?

- In the last ~5 years
  - Dramatic reduction in LVCSR error rates (16% to 6%)
  - Human level LVCSR performance on Switchboard
  - New class of recognizers (end to end neural network)
- Understanding how ASR works enables better ASR-enabled systems
  - What types of errors are easy to correct?
  - How can a downstream system make use of uncertain outputs?
  - How much would building our own improve on an API?
- Next generation of ASR challenges as systems go live on phones and in homes

Speech Recognition Design Intuition

- Build a statistical model of the speech-to-words process
- Collect lots and lots of speech, and transcribe all the words.
- Train the model on the labeled speech
- Paradigm: Supervised Machine Learning + Search

Dialogue (= Conversational Agents)

- Personal Assistants
    - Apple SIRI
    - Microsoft Cortana
    - Google Assitant
- Design considerations
    - Synchronous or asynchronous tasks
    - Pure speech, pure text, UI hybrids
    - Functionality versus personality

Paradigms for Dialogue

- **POMDP**
  - Partially-Observed Markov Decision Processes
  - Reinforcement Learning to learn what action to take
  - Asking a question or answering one are just actions
    - "Speech acts"
- **Simple regular expressions and slot filling**
  - Pre-built frames
    - Calendar
      - Who
      - When
      - Where
  - Filled by hand-built rules
    - ("`on (Mon|Tue|Wed…)`")

Paradigms for Dialogue

- **POMDP**
  - Exciting Research
  - Implemented in no commercial systems
- **Simple regular expressions and slot filling**
  - State of the art used most systems
- **Reusing new search engine technology**
  - Intent recognition / semantic parsing
- **Neural network chatbots**
  - Recent research, not really dialog yet

Extraction of Social Meaning from Speech

- Detection of student uncertainty in tutoring
  - Forbes-Riley et al. (2008)
- Emotion detection (annoyance)
  - Ang et al. (2002)
- Detection of deception
  - Newman et al. (2003)
- Detection of charisma
  - Rosenberg and Hirschberg (2005)
- Speaker stress, trauma
  - Rude et al. (2004), Pennebaker and Lay (2002)

Conversational style

- Given speech and text from a conversation
- Can we tell if a speaker is
  - Awkward?
  - Flirtatious?
  - Friendly?
- Dataset:
  - 1000 4-minute “speed-dates”
  - Each subject rated their partner for these styles
  - The following segment has been lightly signal-processed:

Speaker Recognition tasks

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

      Is that Jane?
  - Speaker Identification
    - Which of these speakers does this 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?

Applications of Speaker Recognition

- Speaker Recognition:
  - Speaker verification (binary decision)
    - Voice password
    - Telephone assistant
  - Speaker identification (one of N)
    - Criminal investigation
- Diarization
  - Transcribing meetings

TTS (= Text-to-Speech) (= Speech Synthesis)

- Produce speech from a text input
- Applications:
  - Personal Assistants
    - Apple SIRI
    - Microsoft Cortana
    - Google Assistant
  - Games
  - Airport Announcements

TTS Overview

- Main Commercial Algorithm
  - Google TTS
- Collect lots of speech (5-50 hours) from one speaker, transcribe very carefully, all the syllables and phones and whatnot
- To synthesize a sentence, patch together syllables and phones from the training data.
- Parametric synthesis shows recent gains
- First end to end neural systems in 2016

History: foundational insights 1900s-1950s

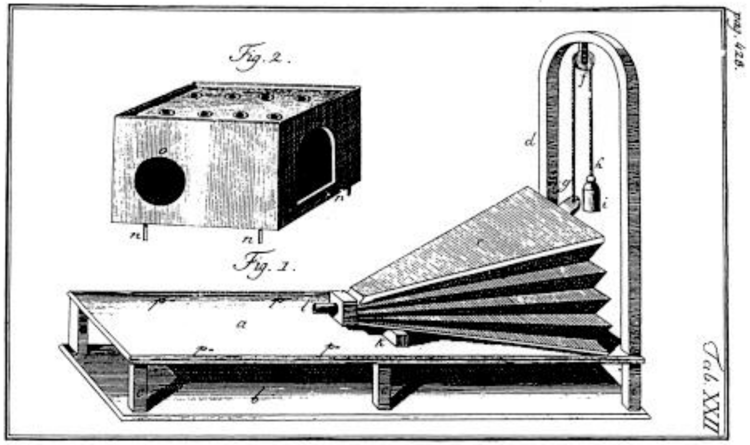
- Automaton:
  - Markov 1911
  - Turing 1936
  - McCulloch-Pitts neuron (1943)
    - http://marr.bsee.swin.edu.au/~dtl/het704/lecture10/ann/node1.html
    - http://diwww.epfl.ch/mantra/tutorial/english/mcpits/html/
  - Shannon (1948) link between automata and Markov models
- Human speech processing
  - Fletcher at Bell Labs (1920’s)
- Probabilistic/Information-theoretic models
  - Shannon (1948)

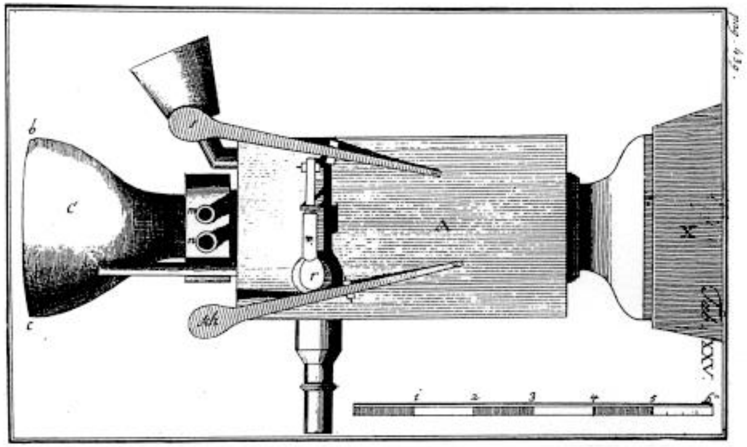
Speech synthesis is old!

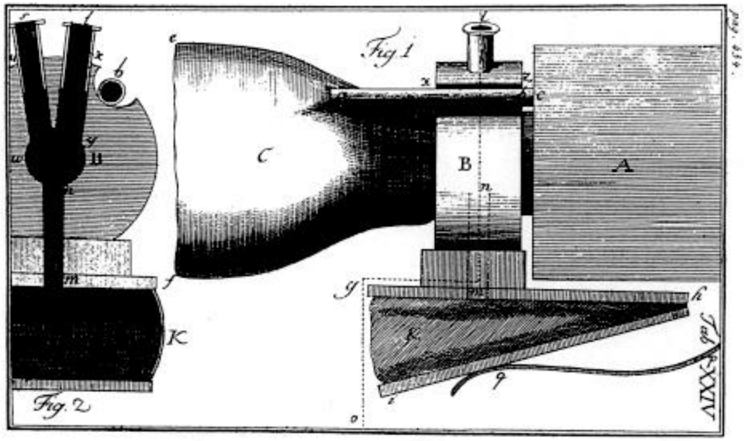
- Pictures and some text from Hartmut Traunmüller's web site:
  - http://www.ling.su.se/staff/hartmut/kemplne.htm
- Von Kempeln 1780 b. Bratislava 1734 d. Vienna 1804
- Leather resonator manipulated by the operator to try and copy vocal tract configuration during sonorants (vowels, glides, nasals)
- Bellows provided air stream, counterweight provided inhalation
- Vibrating reed produced periodic pressure wave

Von Kempelen:

- Small whistles controlled consonants
- Rubber mouth and nose; nose had to be covered with two fingers for non-nasals
- Unvoiced sounds: mouth covered, auxiliary bellows driven by string provides puff of air

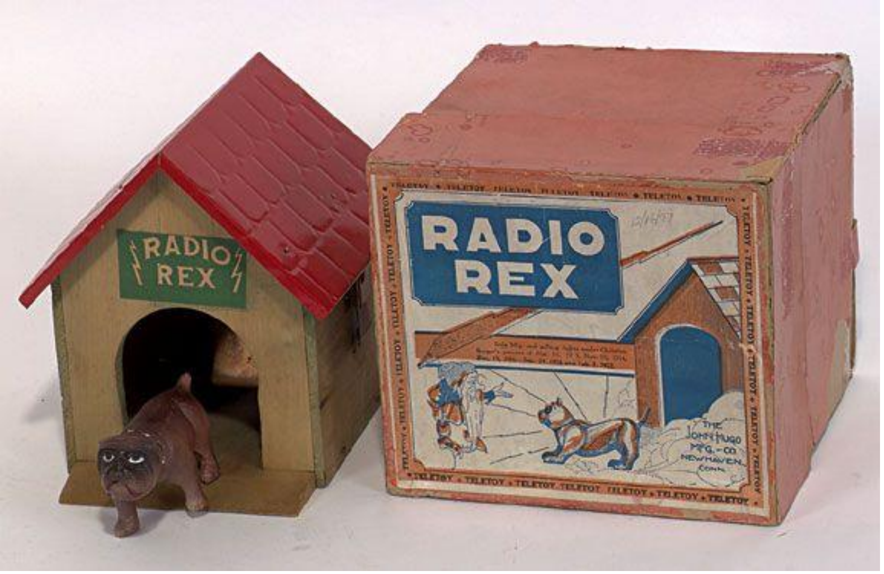






From Traunmüller's web site

History: Early Recognition



- 1920's Radio Rex
  - Celluloid dog with iron base held within house by electromagnet against force of spring
  - Current to magnet flowed through bridge which was sensitive to energy at 500 Hz
  - 500 Hz energy caused bridge to vibrate, interrupting current, making dog spring forward
  - The sound "e" (ARPAbet [eh]) in Rex has 500 Hz component

History: early ASR systems

- 1950's: Early Speech recognizers
  - 1952: Bell Labs single-speaker digit recognizer
    - Measured energy from two bands (formants)
    - Built with analog electrical components
    - 2% error rate for single speaker, isolated digits
  - 1958: Dudley built classifier that used continuous spectrum rather than just formants
  - 1959: Denes ASR combining grammar and acoustic probability

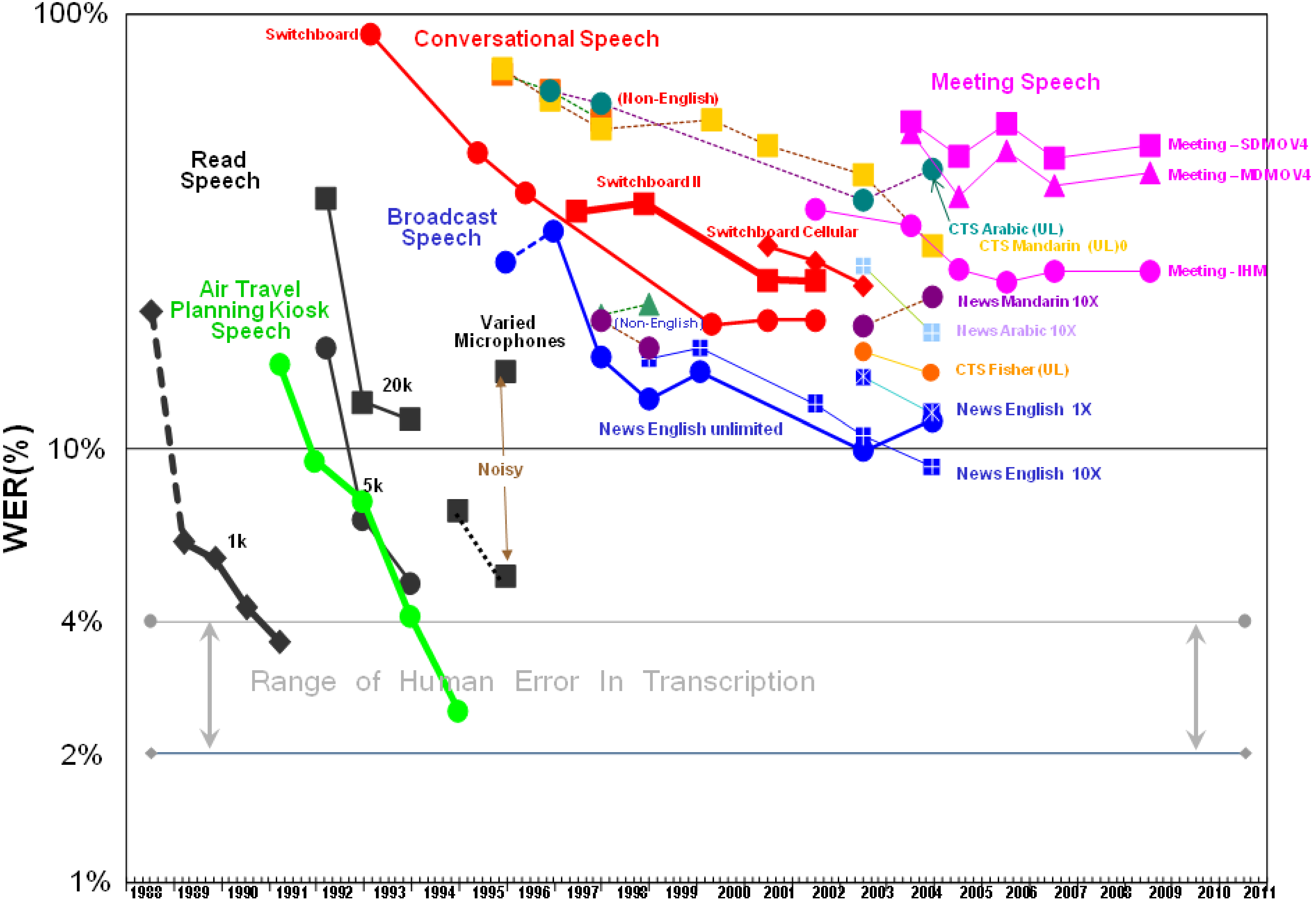
History: early ASR systems

- 1960’s
  - FFT - Fast Fourier transform (Cooley and Tukey 1965)
  - LPC - linear prediction (1968)
  - 1969 John Pierce letter “Whither Speech Recognition?”
    - Random tuning of parameters,
    - Lack of scientific rigor, no evaluation metrics
    - Need to rely on higher level knowledge

ASR: 1970’s and 1980’s

- Hidden Markov Model 1972
  - Independent application of Baker (CMU) and Jelinek/Bahl/Mercer lab (IBM) following work of Baum and colleagues at IDA
- ARPA project 1971-1976
  - 5-year speech understanding project: 1000 word vocab, continous speech, multi-speaker
  - SDC, CMU, BBN
  - Only 1 CMU system achieved goal
- 1980’s+
  - Annual ARPA “Bakeoffs”
  - Large corpus collection
    - TIMIT
    - Resource Management
    - Wall Street Journal

NIST STT Benchmark Test History – May. '09



Course Logistics

Course Logistics

- http://www.stanford.edu/class/cs224s
- Homeworks released and due on Wednesdays
- Gradescope for homework submission
- Piazza for questions. Email staff only for personal/confidential questions
- Project poster session tentatively June 7 (during class time)

Admin: Requirements and Grading

- Readings:
  - Selected chapters from
    - Jurafsky & Martin. Speech and Language Processing.
      - Will mix chapters from 2nd and in progress 3rd editions
    - A few conference and journal papers
- Grading
  - Homework: 40%
    - 4 assignments. Will use Python, Tensorflow, and command line tools
  - Course Project: 50%
    - Group projects of 3 people
  - Participation: 10%

Necessary Background

- Foundations of machine learning and natural language processing
  - CS 124, CS 224N, CS 229, or equivalent experience
- Mathematical foundations of neural networks
  - Understand forward and back propagation in terms of equations
- Proficiency in Python
  - Programming heavy homeworks will use Python and Tensorflow