

Toward Spontaneous Speech Recognition and Understanding

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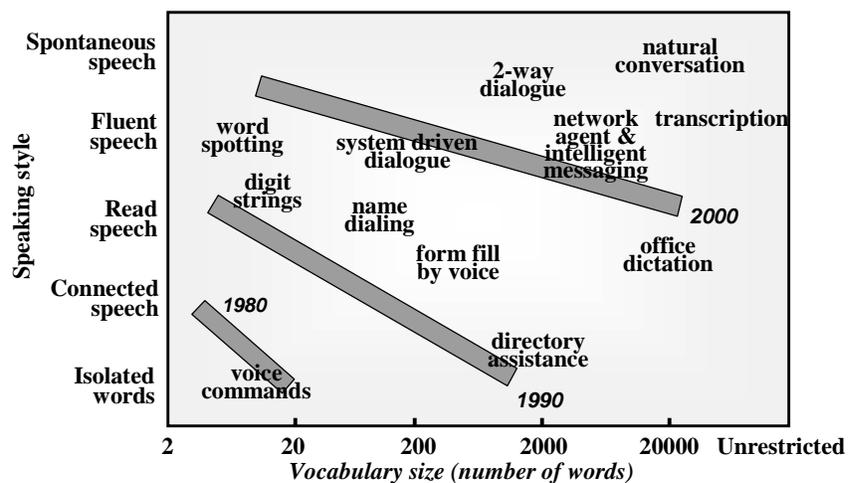
Outline

- Fundamentals of automatic speech recognition
- Acoustic modeling
- Language modeling
- Database (corpus) and task evaluation
- Transcription and dialogue systems
- Spontaneous speech recognition
- Speech understanding
- Speech summarization

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Speech recognition technology



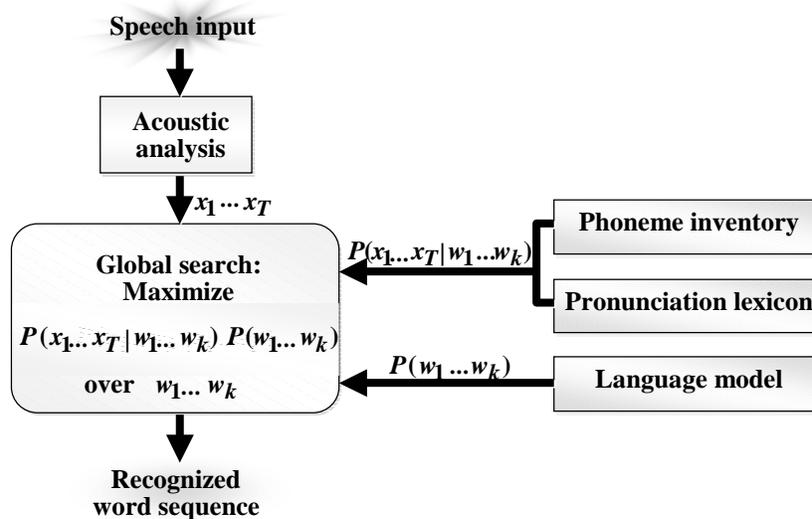
Categorization of speech recognition tasks

	Dialogue	Monologue
Human to human	(Category I) Switchboard, Call Home (Hub 5), meeting task	(Category II) Broadcasts news (Hub 4), lecture, presentation, voice mail
Human to machine	(Category III) ATIS, Communicator, information retrieval, reservation	(Category IV) Dictation

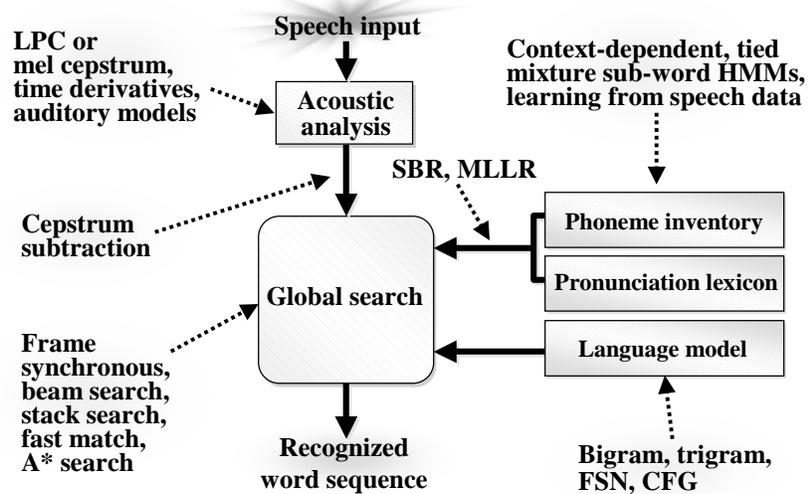
Major speech recognition applications

- **Conversational systems** for accessing information services
 - Robust conversation using wireless handheld/hands-free devices in the real mobile computing environment
 - Multimodal speech recognition technology
- Systems for **transcribing, understanding and summarizing** ubiquitous speech documents such as broadcast news, meetings, lectures, presentations and voicemails

Mechanism of state-of-the-art speech recognizers

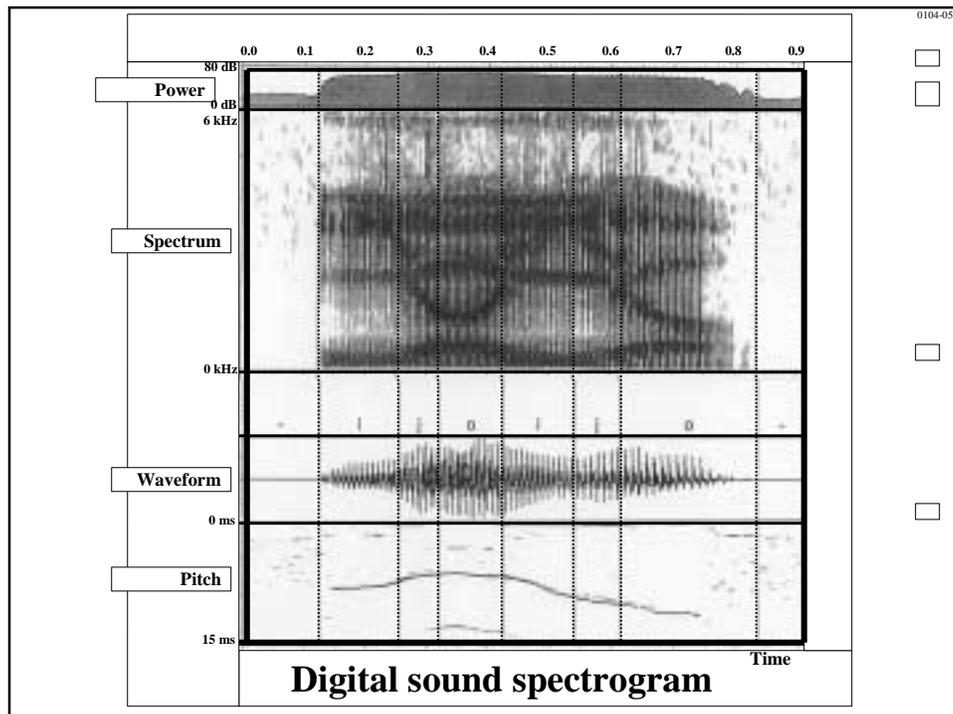


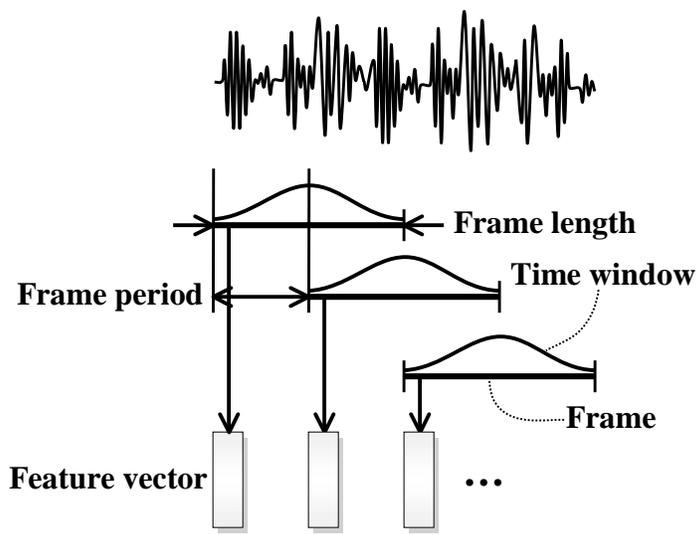
State-of-the-art algorithms in speech recognition



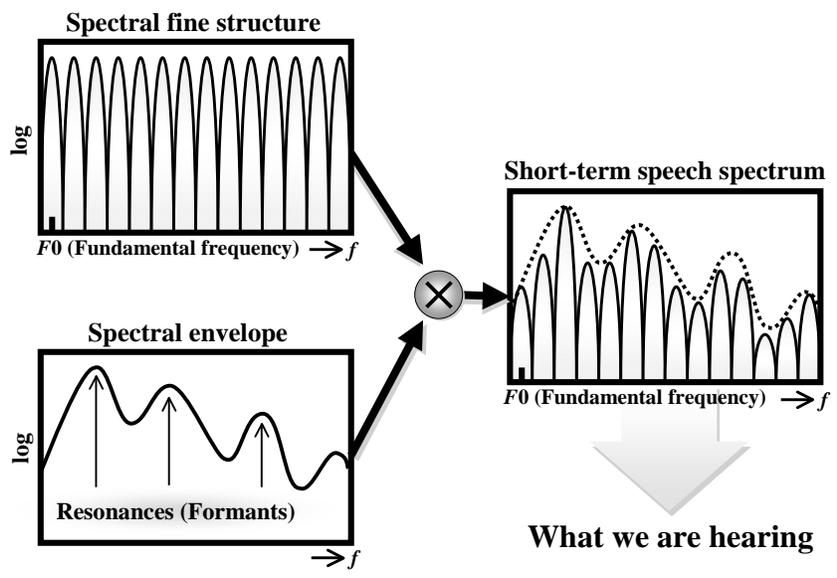
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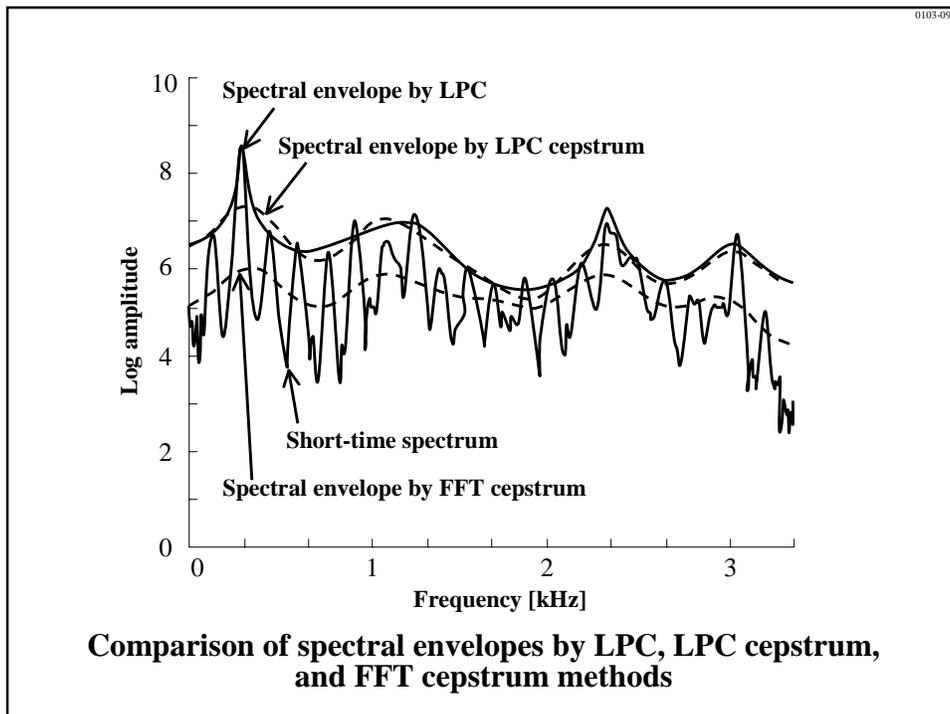
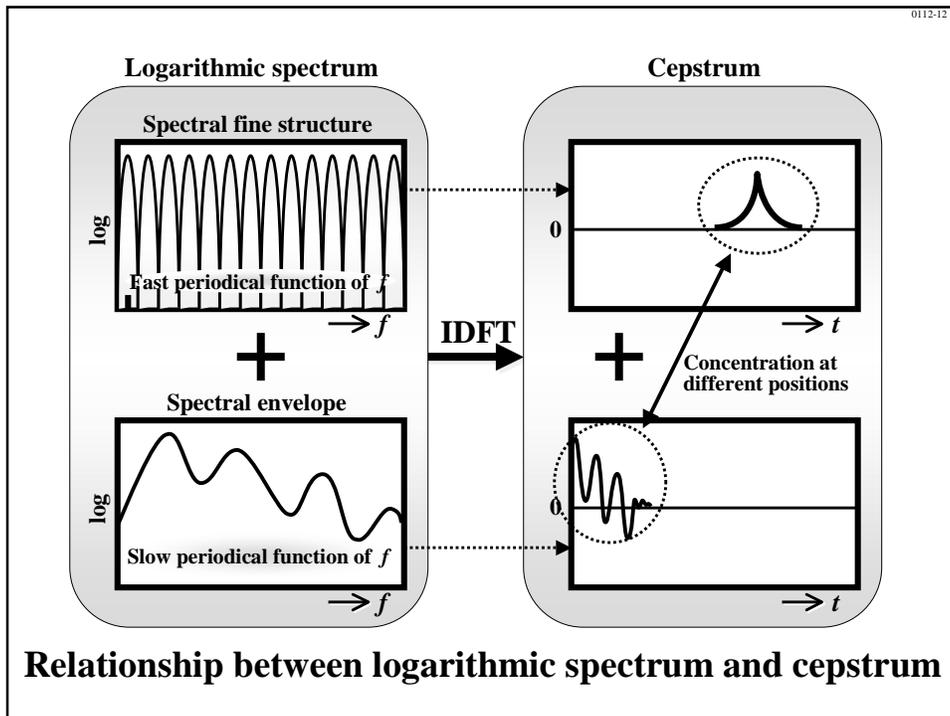


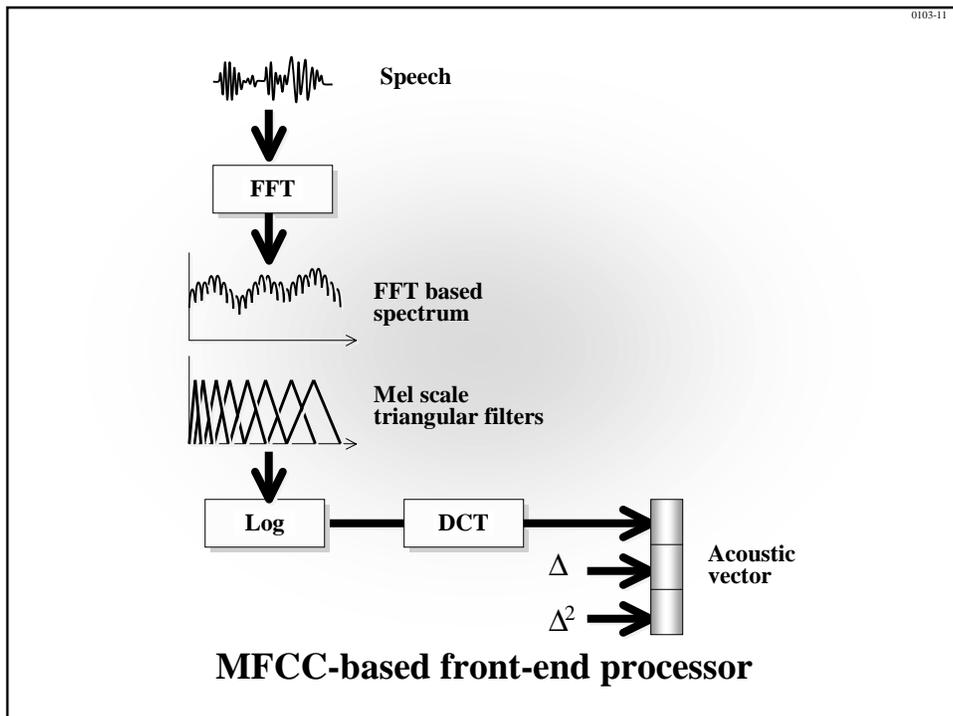
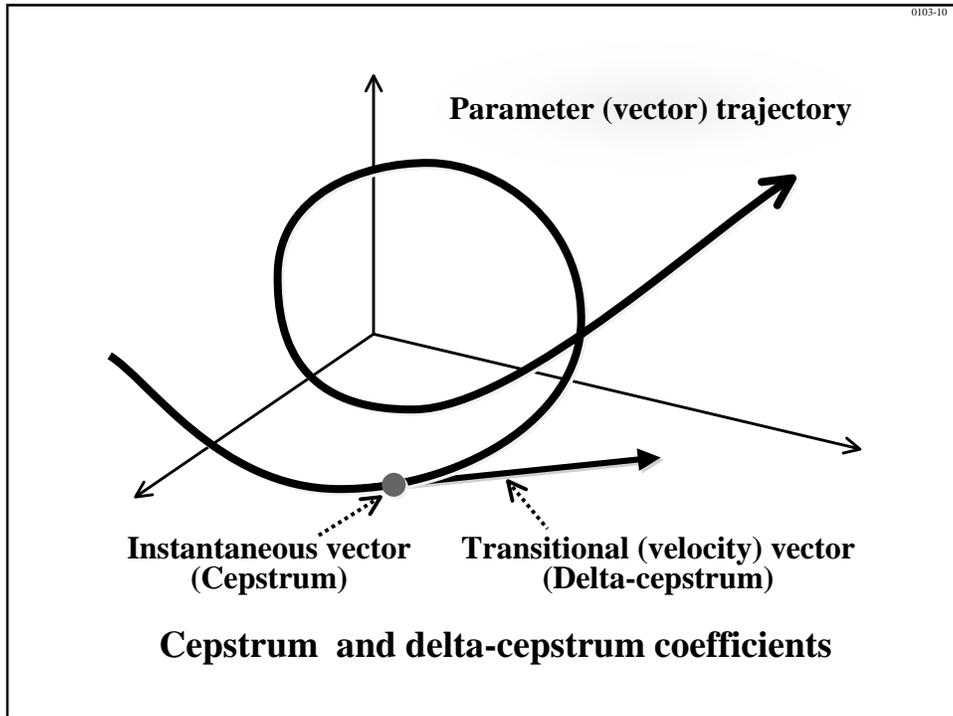


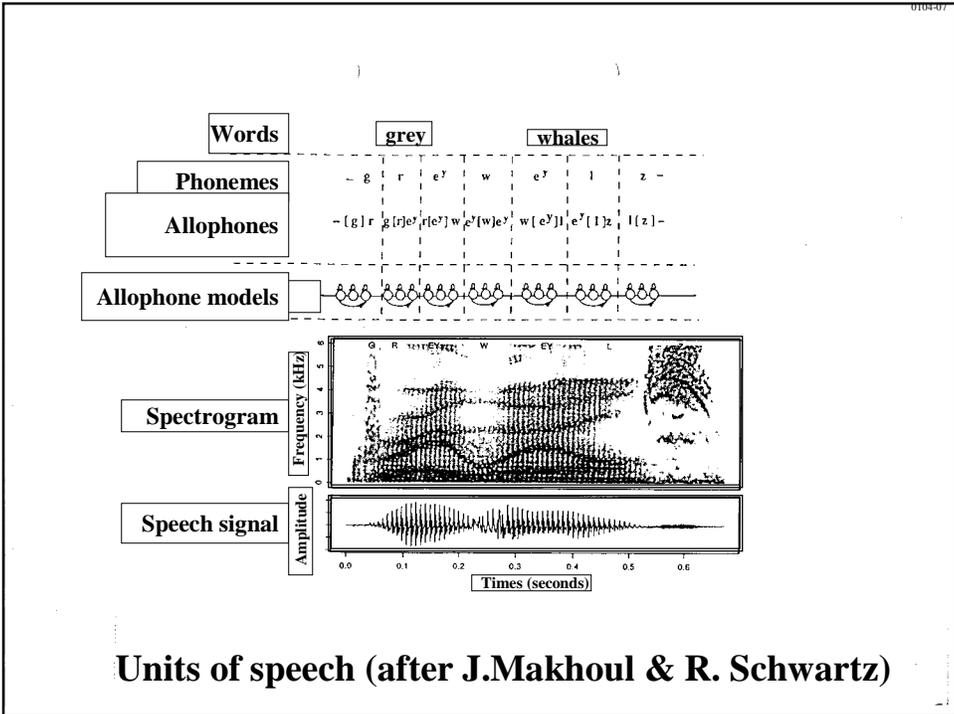
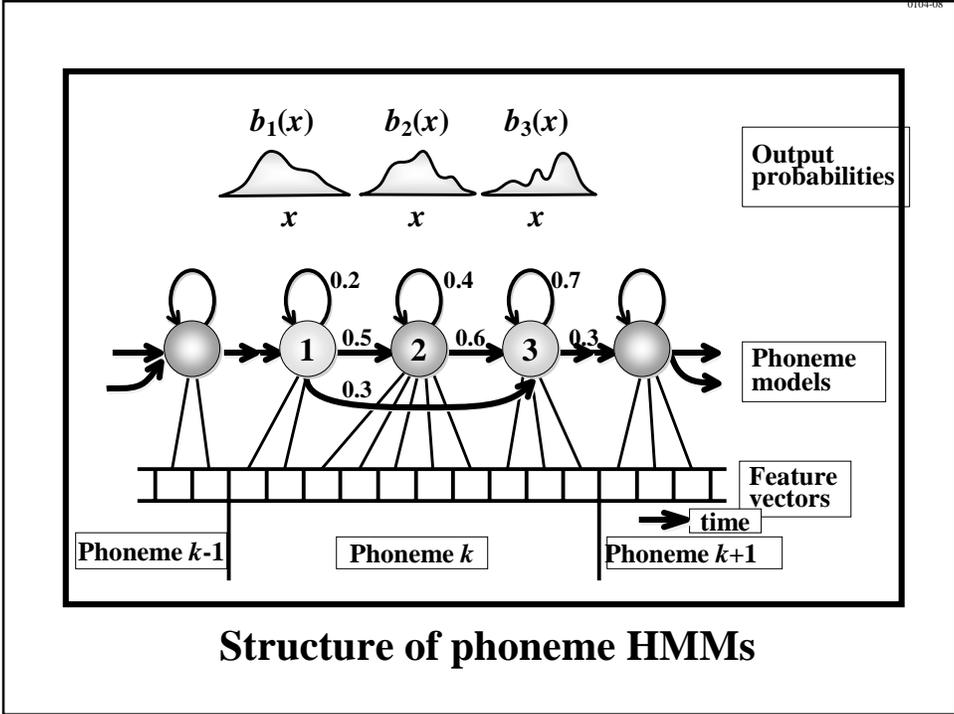
Feature vector (short-time spectrum) extraction from speech



Spectral structure of speech







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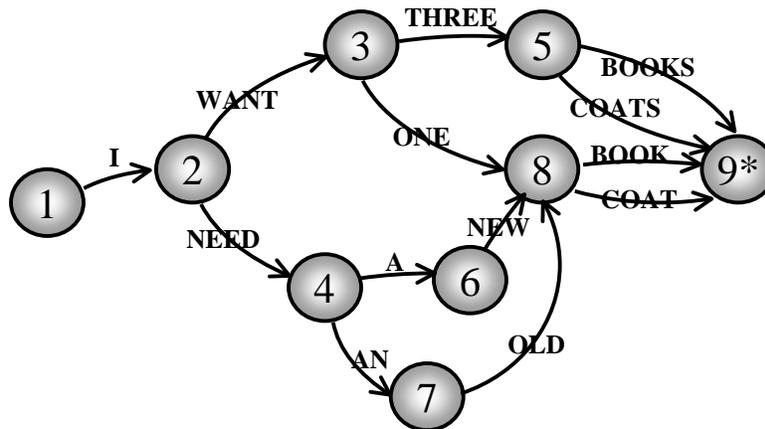
Language model is crucial !

- Rudolph the red nose reindeer.
- Rudolph the Red knows rain, dear.
- Rudolph the Red Nose reigned here.



- This new display can recognize speech.
- This nudist play can wreck a nice beach.

1. I	5. ONE	9. BOOKS	13. OLD
2. WANT	6. A	10. COAT	
3. NEED	7. AN	11. COATS	
4. THREE	8. BOOK	12. NEW	



An example of FSN (Finite State Network) grammar

Syntactic language models

- Rely on a formal grammar of a language.
- Syntactic sentence structures are defined by rules that can represent global constraints on word sequences.
- Mainly based on context-free grammars.
- Very difficult to extend to spontaneous speech.

Problems of context-free grammars

- **Over generation problem:** not only generates correct sentences but also many incorrect sentences.
- **Ambiguity problem:** the number of syntactic ambiguities in one sentence becomes increasingly unmanageable with the number of phrases.
- **Suitability for spontaneous speech is arguable.**

→ Stochastic context-free grammars

Statistical language modeling

Probability of the word sequence $w_1^k = w_1 w_2 \dots w_k$:

$$P(w_1^k) = \prod_{i=1}^k P(w_i | w_1 w_2 \dots w_{i-1}) = \prod_{i=1}^k P(w_i | w_1^{i-1})$$

$$P(w_i | w_1^{i-1}) = N(w_1^i) / N(w_1^{i-1})$$

where $N(w_1^i)$ is the number of occurrences of the string w_1^i in the given training corpus.

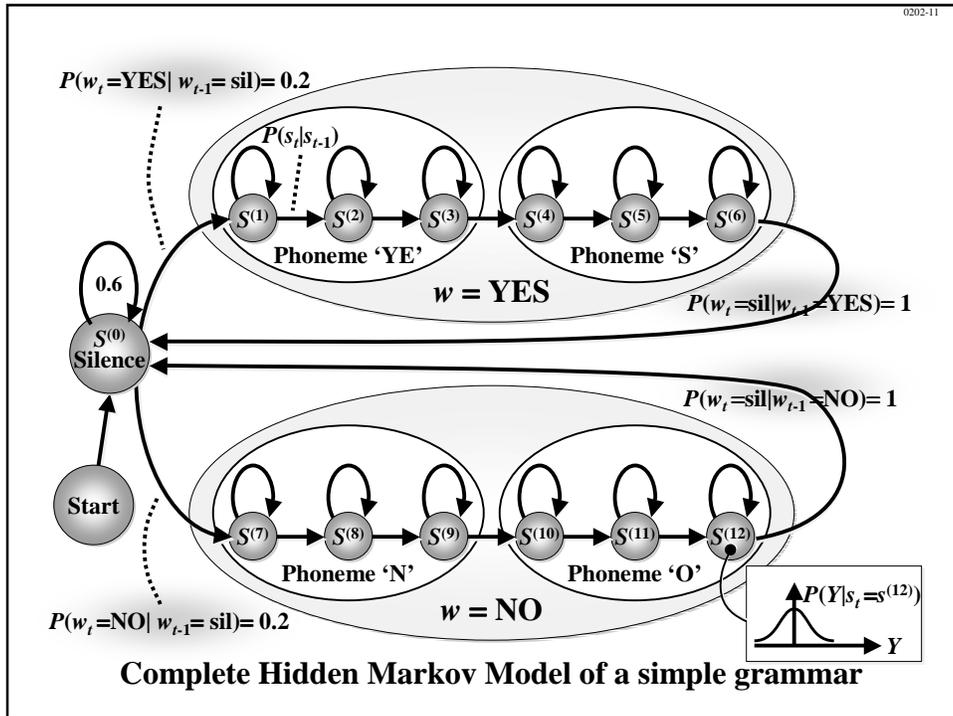
Approximation by Markov processes:

Bigram model $P(w_i | w_1^{i-1}) = P(w_i | w_{i-1})$

Trigram model $P(w_i | w_1^{i-1}) = P(w_i | w_{i-2} w_{i-1})$

Smoothing of trigram by the deleted interpolation method:

$$P(w_i | w_{i-2} w_{i-1}) = \lambda_1 P(w_i | w_{i-2} w_{i-1}) + \lambda_2 P(w_i | w_{i-1}) + \lambda_3 P(w_i)$$



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- ## Variations of N -gram language models
- Various smoothing techniques
 - Word class language models
 - N -pos (parts of speech) models
 - Combination with a context-free grammar
 - Extend N -grams to the processing of long-range dependencies
 - Cache-based adaptive/dynamic language models

Good-Turing estimate

For any n -gram that occurs r times, we should pretend that it occurs r^* times as follows:

$$r^* = (r+1) \frac{n_{r+1}}{n_r}$$

where n_r is the number of n -grams that occur exactly r times in the training data.

Katz smoothing algorithm

Katz smoothing extends the intuitions of the Good-Turing estimate by adding the combination of higher-order models with lower-order models.

$$P_{Katz}(w_i|w_{i-1}) = \begin{cases} C(w_{i-1}w_i)/C(w_{i-1}) & \text{if } r > k \\ d_r C(w_{i-1}w_i)/C(w_{i-1}) & \text{if } k \geq r > 0 \\ \alpha(w_{i-1})/P(w_i) & \text{if } r = 0 \end{cases}$$

$$\text{where } d_r = \frac{\frac{r^*}{r} - \frac{(k+1)n_{k+1}}{n_1}}{1 - \frac{(k+1)n_{k+1}}{n_1}} \quad \text{and} \quad \alpha(w_{i-1}) = \frac{1 - \sum_{w_i:r>0} P_{Katz}(w_i|w_{i-1})}{1 - \sum_{w_i:r>0} P(w_i)}$$

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Spontaneous speech corpora

- **Spontaneous speech variations: extraneous words, out-of-vocabulary words, ungrammatical sentences, disfluency, partial words, repairs, hesitations, repetitions, style shifting,**
- **“There’s no data like more data” – Large structured collection of speech is essential.**
- **How to collect *natural* data?**
- **Labeling and annotation of spontaneous speech is difficult; how do we annotate the variations, how do the phonetic transcribers reach a consensus when there is ambiguity, and how do we represent a semantic notion?**

Spontaneous speech corpora (cont.)

- How to ensure the corpus quality?
- Research in automating or creating tools to assist the verification procedure is by itself an interesting subject.
- Task dependency: It is desirable to design a task-independent data set and an adaptation method for new domains → Benefit of a reduced application development cost.

Main database characteristics (Becchetti & Ricotti)

Name	Quantities				No. units
	No.CD	No.hours	Giga-bytes	No. speakers	
TI Digits	3	~14	2	326	>2,500 numbers
TIMIT	1	5.3	0.65	630	6,300 sentences
NTIMIT	2	5.3	0.65	630	6,300 sentences
RM1	4	11.3	1.65	144	15,024 sentences
RM2	2	7.7	1.13	4	10,608 sentences
ATIS0	6	20.2	2.38	36	10,722 utterances
Switchboard (Credit Card)	1	3.8	0.23	69	35 dialogues
TI-46	1	5	0.58	16	19,136 isol. words
Road Rally	1	~10	~0.6	136	Dialogues/sentences
Switchboard (Complete)	30	250	15	550	2,500 dialogues
ATC	9	65	5.0	100	30,000 dialogues
Map Task	8	34	5.1	<256	128 dialogues
MARSEC	1	5.5	0.62	-	53 monologues
ATIS2	6	~37	~5	351	12,000 utterances
WSJ-CSR1	18	80	9.2	>124	38,000 utterances

Further database characteristics (Becchetti & Ricotti)

Name	Transcription		Speech style	Recording environment	SR kHz	Sponsor
	Based on:	TA				
TI Digits	Word	No	Reading	QR	20	TI
TIMIT	Phone	Yes	Reading	QR	16	DARPA
NTIMIT	Phone	Yes	Reading	Tel	8	NYNEX
RM1	Sentence	No	Reading	QR	20	DARPA
RM2	Sentence	No	Reading	QR	20	DARPA
ATIS0	Sentence	No	Reading spon.	Ofc	16	DARPA
Switchboard (Credit Card)	Word	Yes	Conv. spon.	Tel	8	DARPA
TI-46	Word	No	Reading	QR	16	TI
Road Rally	Word	Yes	Reading spon.	Tel	8	DoD
Switchboard (Complete)	Word	Yes	Conv. spon.	Tel	8	DARPA
ATC	Sentence	Yes	Spon.	RF	8	DARPA
Map Task	Sentence	Yes	Conv. spon.	Ofc	20	HCRC
MARSEC	Phone	-	Spon.	Various	16	ESRC
ATIS2	Sentence	No	Spon.	Ofc	16	DARPA
WSJ-CSRI	Sentence	Yes	Reading	Ofc	16	DARPA

Entropy: Amount of information (Task difficulty)

- Yes, No 1 bit ($\log 2$)

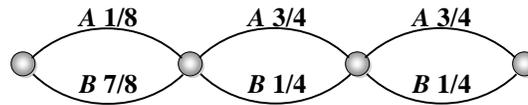
- Digits
 - * 0 ~ 9 : 0.1 3.32 bits ($\log 0.1$)

 - * $\left\{ \begin{array}{l} 0 : 0.91 \\ 1 \sim 9 : 0.01 \end{array} \right.$ 0.722 bits

 - ($0.91 \log 0.91 + 0.09 \log 0.01$)

Test-set perplexity

Vocabulary: A, B Test sentence: ABB



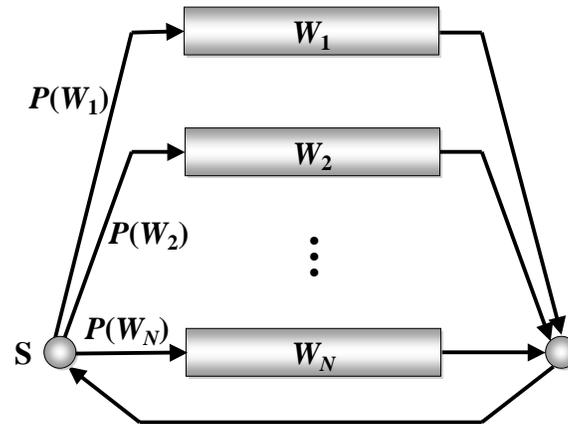
Test sentence entropy: $\log 8 + \log 4 + \log 4 = 7$ bit
(ABB)

Entropy per word: $7 / 3 = 2.33$ bits

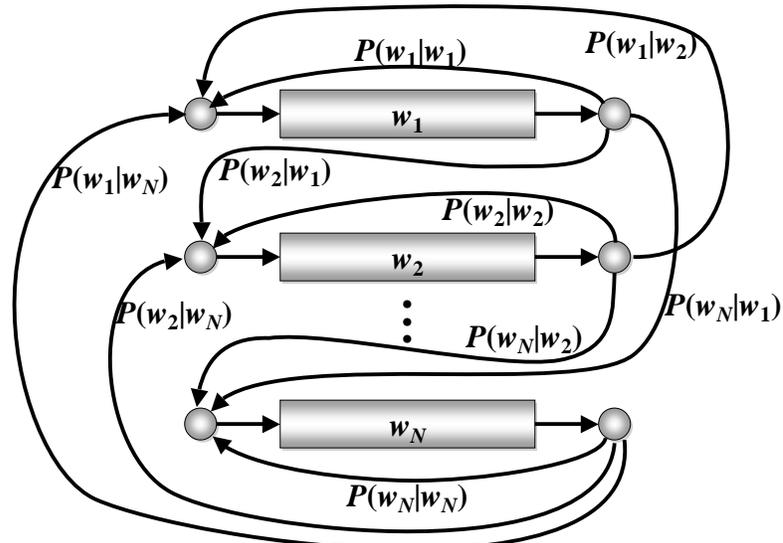
Test-set perplexity (branching factor): $2^{2.33} = 5.01$

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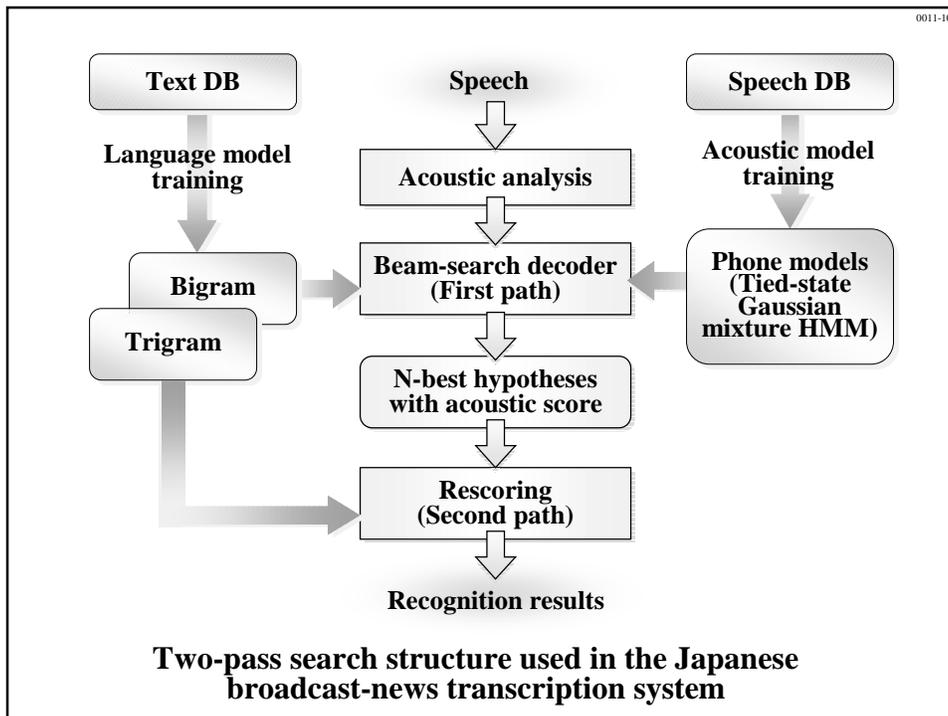
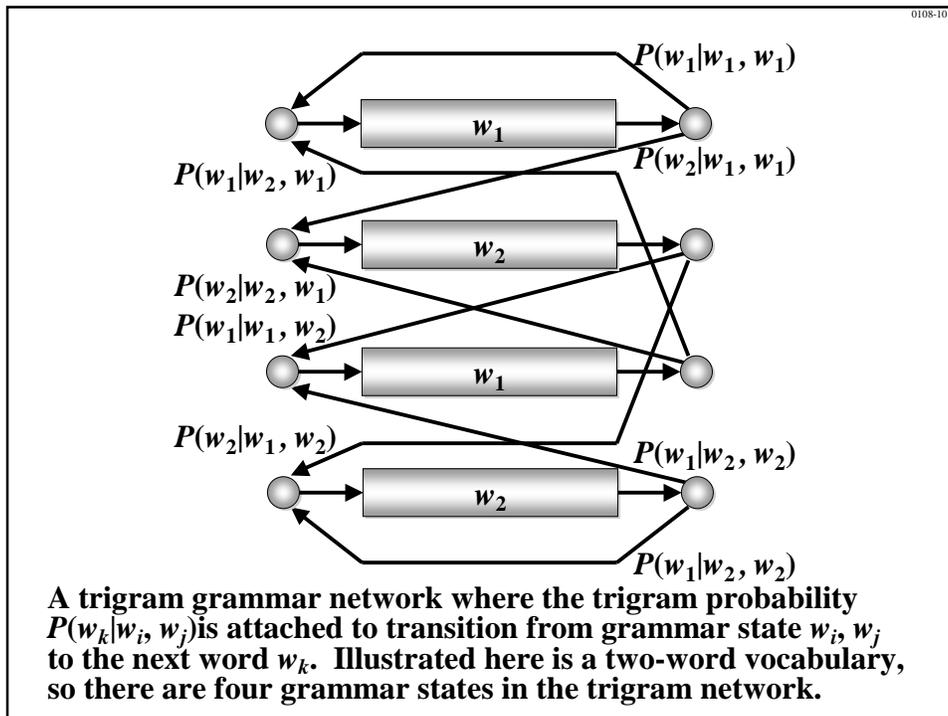
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A unigram grammar network where the unigram probability is attached as the transition probability from starting state S to the first state of each word HMM.

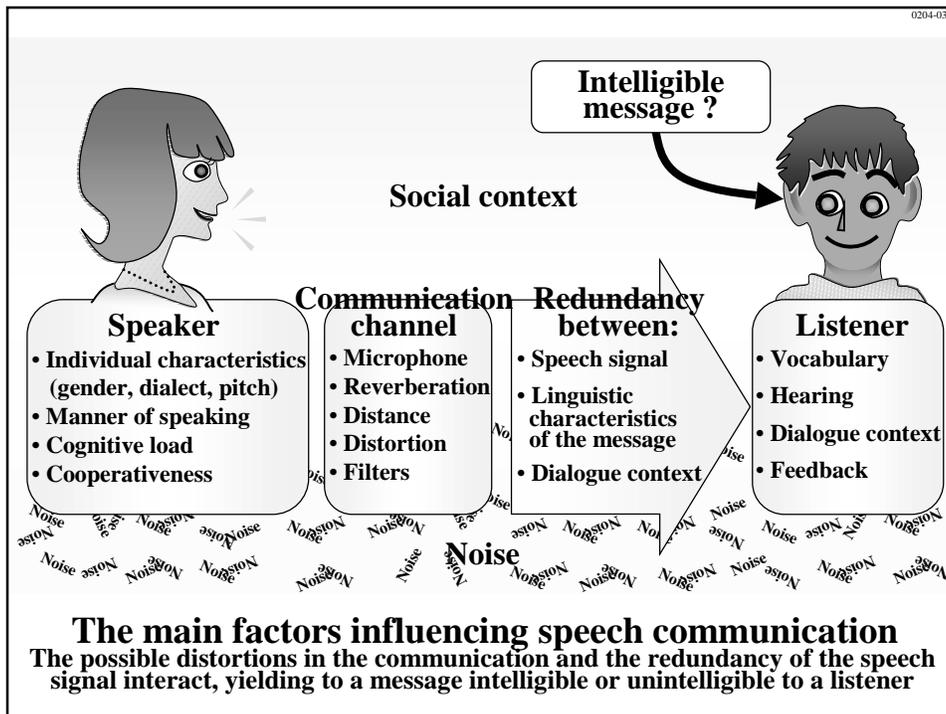


A bigram grammar network where the bigram probability $P(w_j|w_i)$ is attached as the transition probability from word w_i to w_j .



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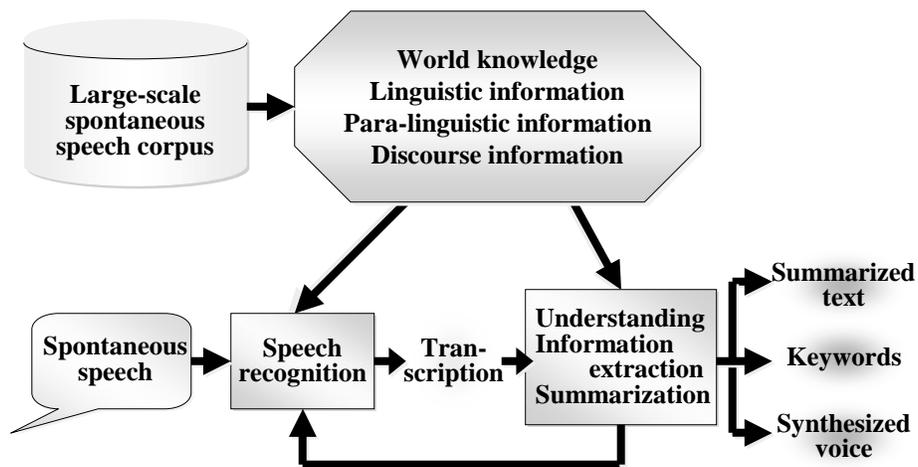
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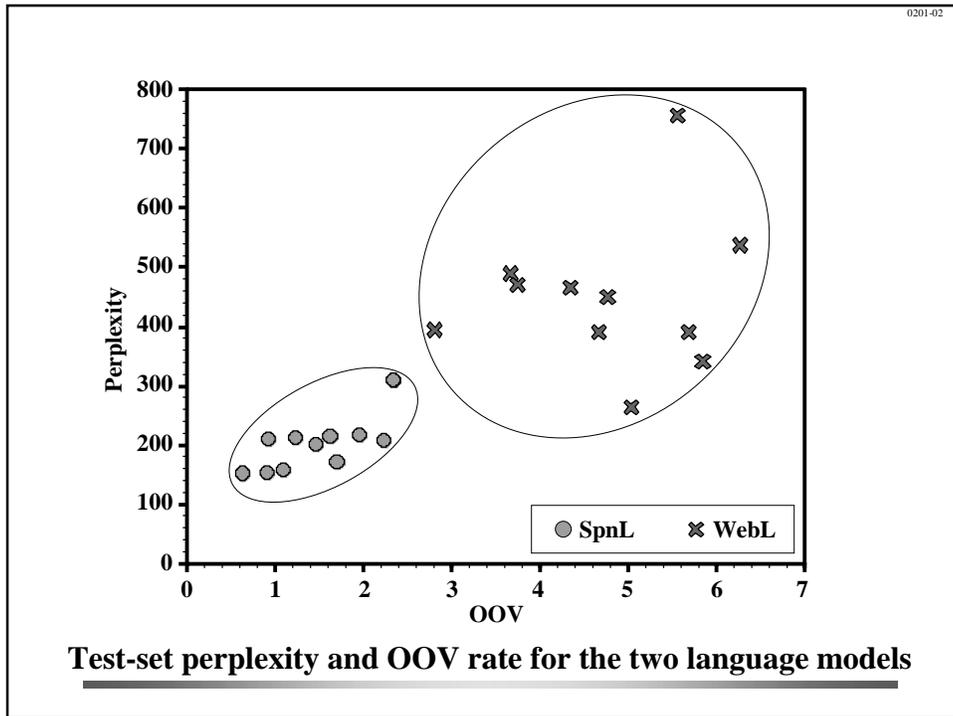
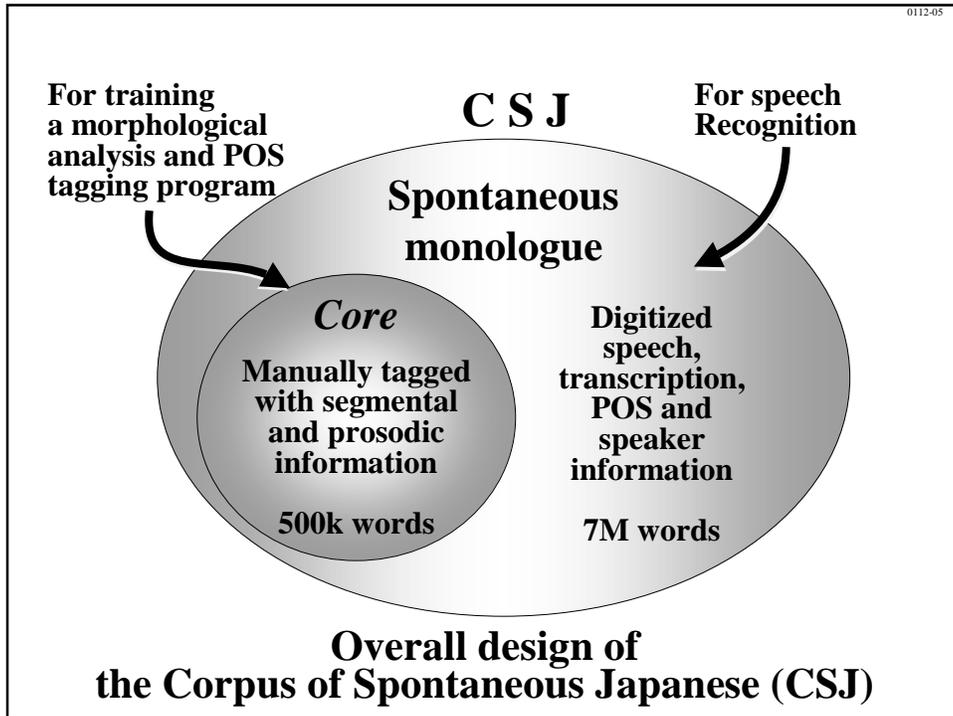


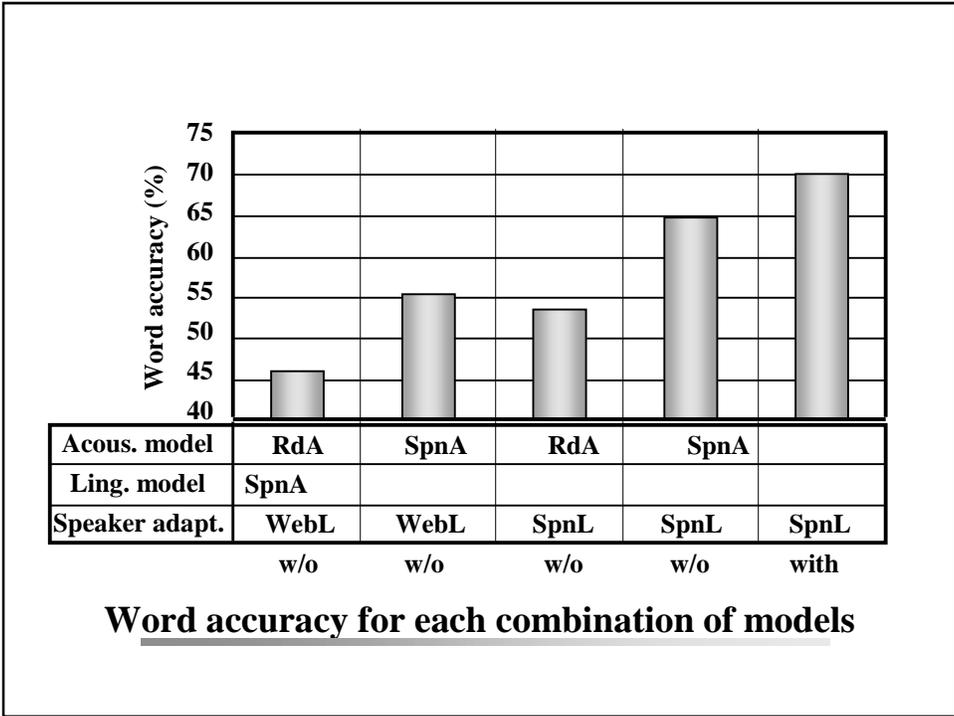
Difficulties in (spontaneous) speech recognition

- **Lack of systematic understanding in variability**
 - Structural or functional variability**
 - Parametric variability**
- **Lack of complete structural representations of (spontaneous) speech**
- **Lack of data for understanding non-structural variability**

Overview of the Science and Technology Agency Priority Program “Spontaneous Speech: Corpus and Processing Technology”





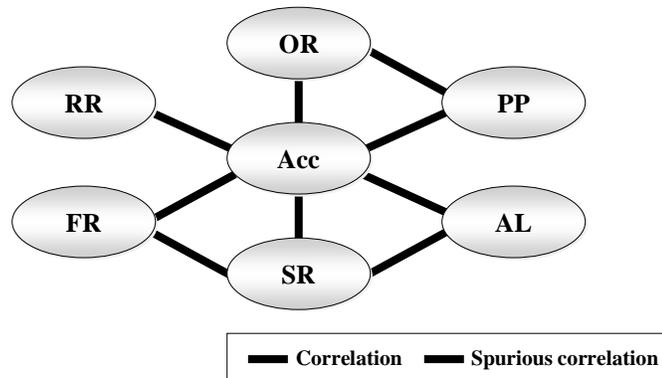


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**Mean and standard deviation
for each attribute of presentation speech**

	Acc	AL	SR	PP	OR	FR	RR
Mean	68.6	-53.1	15.0	224	2.09	8.59	1.56
Standard deviation	7.5	2.2	1.2	61	1.18	3.67	0.72

Acc: word accuracy (%), AL: averaged acoustic frame likelihood,
 SR: speaking rate (number of phonemes/sec), PP: word perplexity,
 OR: out of vocabulary rate, FR: filled pause rate (%),
 RR: repair rate (%)



Acc: word accuracy, OR: out of vocabulary rate,
 RR: repair rate, FR: filled pause rate,
 SR: speaking rate, AL: averaged acoustic frame likelihood,
 PP: word perplexity

Summary of correlation between various attributes

Linear regression models of the word accuracy (%) with the six presentation attributes

Speaker-independent recognition

$$\text{Acc} = 0.12\text{AL} - 0.88\text{SR} - 0.020\text{PP} - 2.2\text{OR} + 0.32\text{FR} - 3.0\text{RR} + 95$$

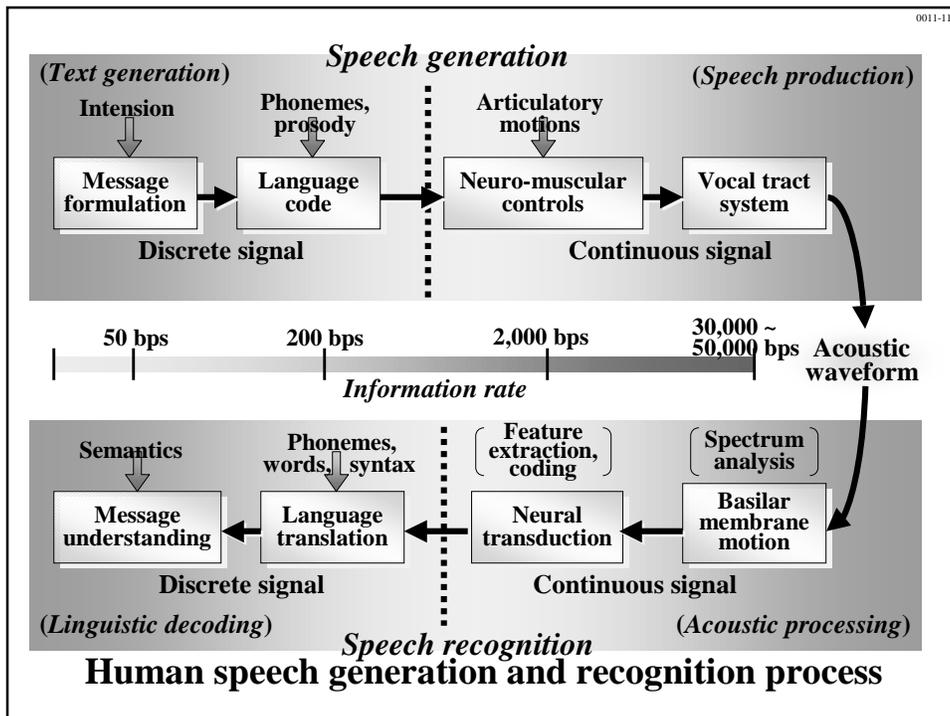
Speaker-adaptive recognition

$$\text{Acc} = 0.024\text{AL} - 1.3\text{SR} - 0.014\text{PP} - 2.1\text{OR} + 0.32\text{FR} - 3.2\text{RR} + 99$$

Acc: word accuracy, SR: speaking rate,
 PP: word perplexity, OR: out of vocabulary rate,
 FR: filled pause rate, RR: repair rate

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Word co-occurrence score

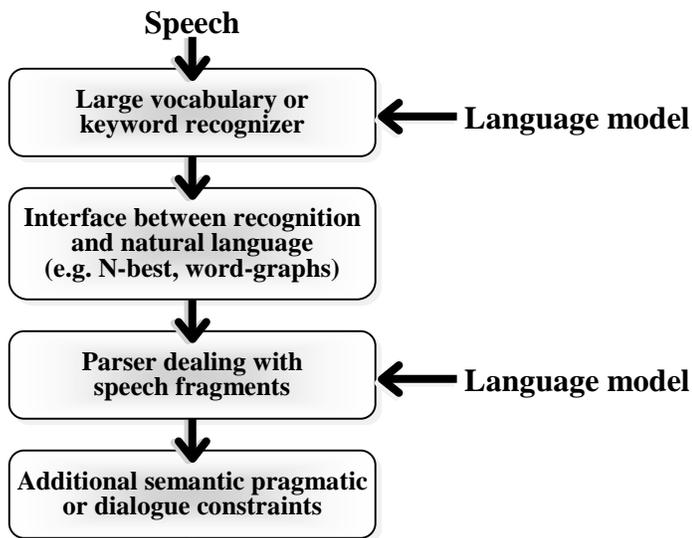
$P(W|M)$ is represented by word co-occurrences of nouns;

$$CoScore(w_i, w_j) = \log \frac{p(w_i, w_j)}{(p(w_i)p(w_j))^{1/2}}$$

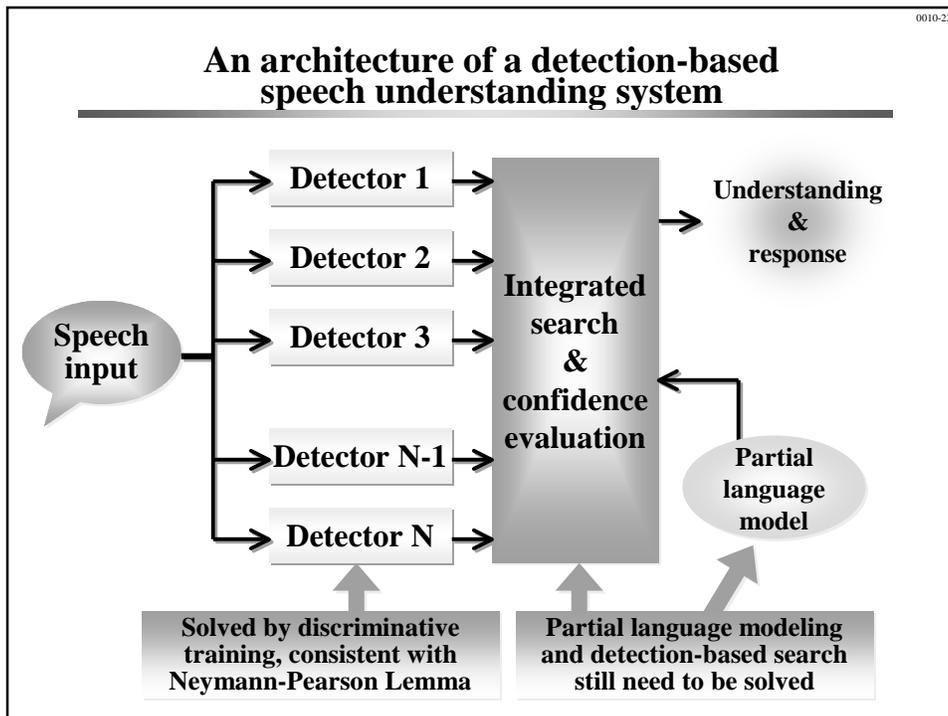
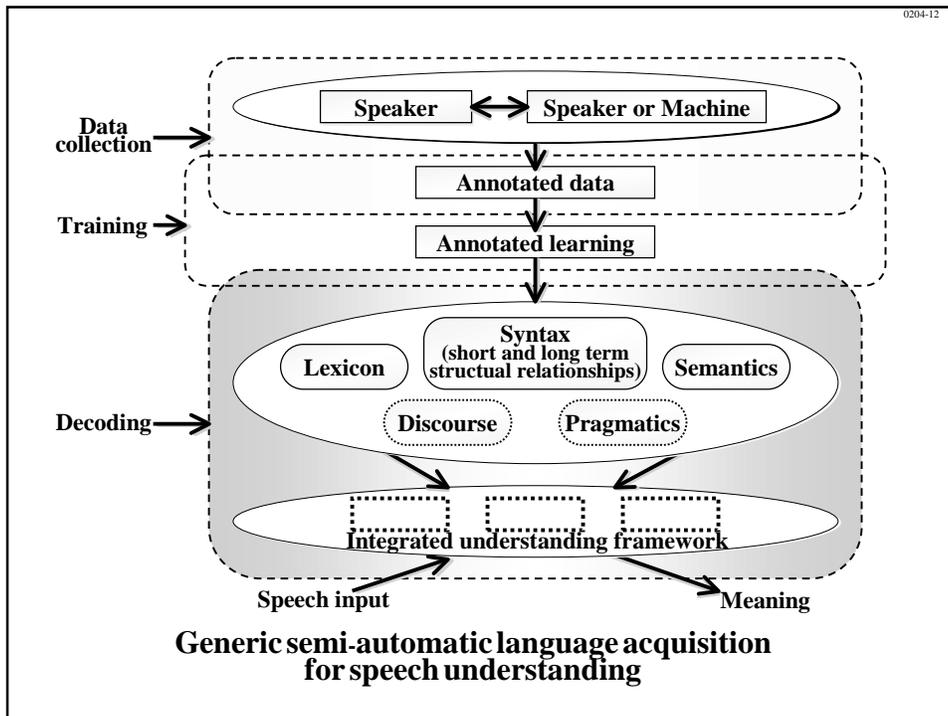
$p(w_i, w_j)$: probability of observing words w_i and w_j in the same news article

$p(w_i), p(w_j)$: probabilities of observing word w_i and w_j in all the articles

A square root term was employed to compensate the probabilities of the words with very low frequency.



Generic block diagram for spontaneous speech understanding



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Sayings

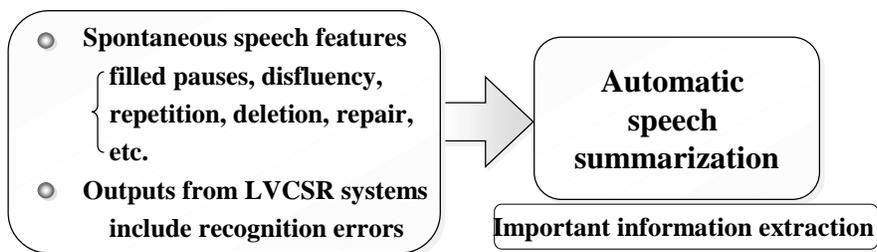
- **The shortest complete description is the best understanding – *Ockham***
- **If I had more time I could write a shorter letter – *B. Pascal***
- **Make everything as simple as possible – *A. Einstein***

From speech recognition to summarization

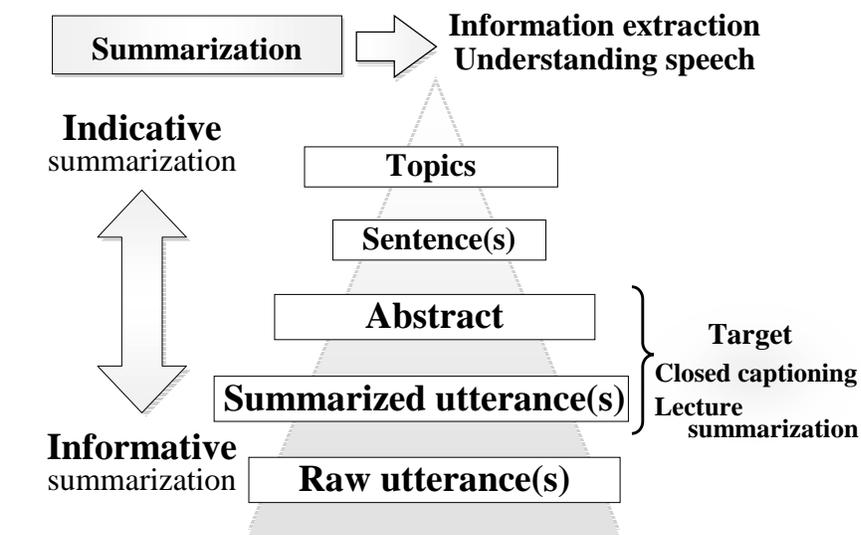
LVCSR (Large Vocabulary Continuous Speech Recognition) systems can transcribe **read speech** with 90% word accuracy or higher.

Current target

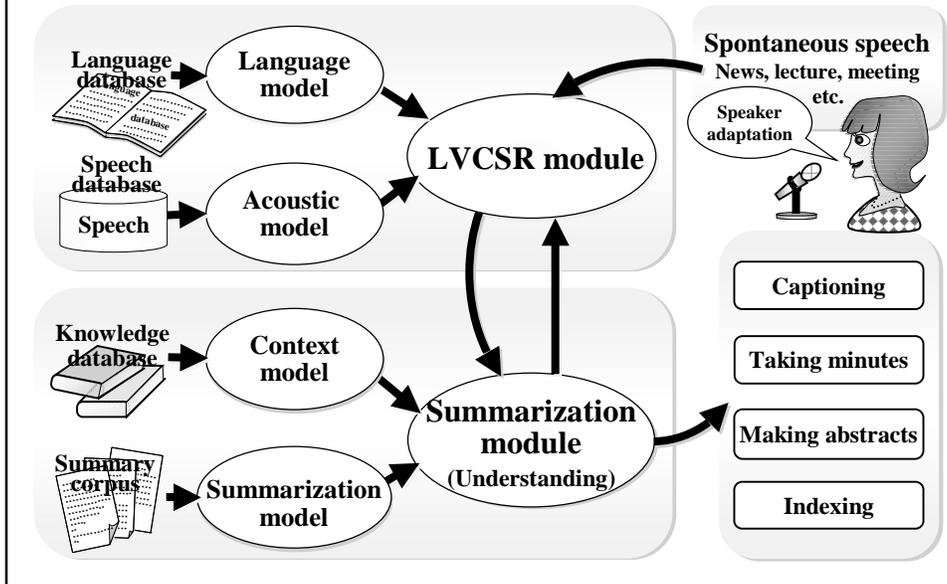
LVCSR systems for spontaneous speech recognition to generate closed captions, abstracts, etc.



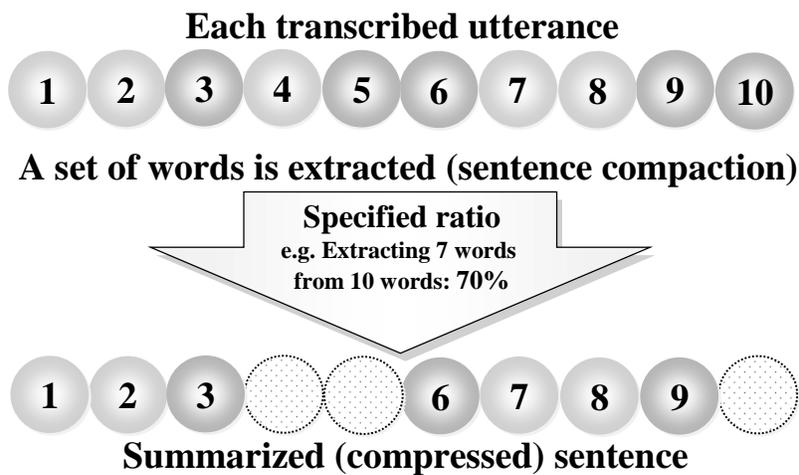
Summarization levels



Automatic speech summarization system

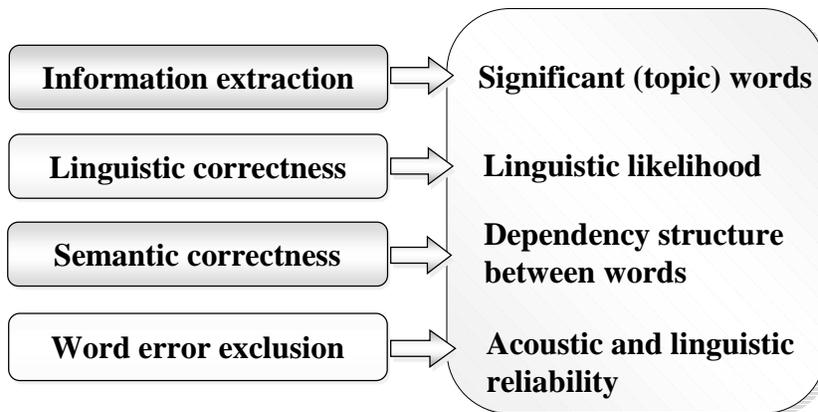


Approach to speech summarization utterance by utterance



Target of summarized speech

Maintaining original meanings of speech
as much as possible



Summarization score

Summarized sentence with M words $V = v_1, v_2, \dots, v_M$

Summarization score

$$S(V^M) = \sum_{m=1}^M \left\{ \begin{array}{l} L(v_m | \dots v_{m-1}) \\ + \lambda_I I(v_m) \\ + \lambda_C C(v_m) \\ + \lambda_T T_r(v_m) \end{array} \right\}$$

The equation is annotated with arrows pointing to the right, explaining each component:

- $L(v_m | \dots v_{m-1})$ is linked to **Linguistic score** (Trigram).
- $+ \lambda_I I(v_m)$ is linked to **Significance (topic) score** (Amount of information).
- $+ \lambda_C C(v_m)$ is linked to **Confidence score** (Acoustic & linguistic reliability).
- $+ \lambda_T T_r(v_m)$ is linked to **Word concatenation score** (Word dependency probability).

Linguistic score

Linguistic likelihood of word strings
(bigram/trigram)
in a summarized sentence

$$\log P(v_m | v_{m-2} v_{m-1})$$

Linguistic score is trained using a summarization corpus.

Word significance score

Amount of information

$$f_i \log \frac{F_A}{F_i}$$

f_i : Number of occurrences of u_i in the transcribed speech

u_i : Topic word in the transcribed speech

F_i : Number of occurrences of u_i in all the training articles

F_A : Summation of all F_i over all the training articles

$$(F_A = \sum_i F_i)$$

•Significance scores of words other than topic words and reappearing topic words are fixed.

Confidence score

Acoustic and linguistic reliability of a word hypothesis

Posterior probability

$$C(w_{k,l}) = \log \frac{\alpha_k P_{ac}(w_{k,l}) P_{lg}(w_{k,l}) \beta_l}{P_G}$$

$C(w_{k,l})$: Log posterior probability of $w_{k,l}$

k, l : Node index in a graph

$w_{k,l}$: Word hypothesis between node k and node l

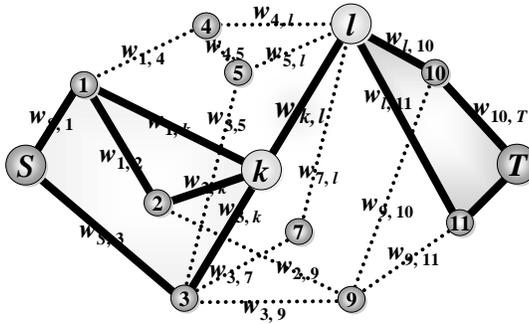
α : Forward probability from the beginning node S to node k

β : Backward probability from node l to the end node T

P_{ac} : Acoustic likelihood of $w_{k,l}$

P_{lg} : Linguistic likelihood of $w_{k,l}$

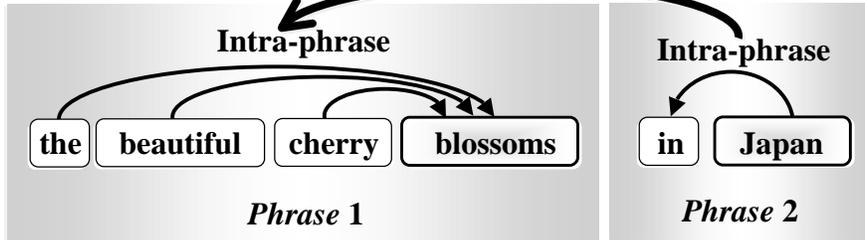
P_G : Forward probability from the beginning node S to the end node T



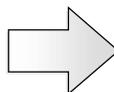
Word concatenation score

A penalty for word concatenation with no dependency in the original sentence

Inter-phrase



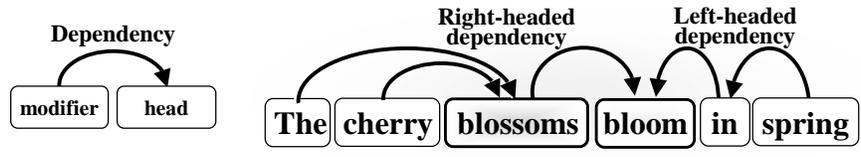
“the beautiful Japan”



Grammatically correct but incorrect as a summary

Dependency structure

Dependency Grammar

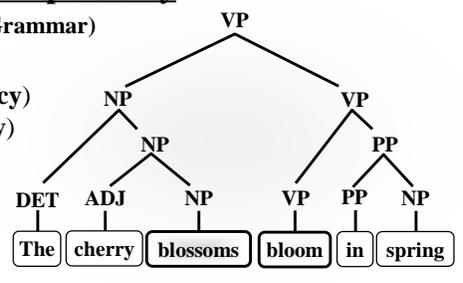


Phrase structure grammar for dependency

DCFG (Dependency Context Free Grammar)

- $\alpha \rightarrow \beta\alpha$ (Right-headed dependency)
- $\alpha \rightarrow \alpha\beta$ (Left-headed dependency)
- $\alpha \rightarrow w$

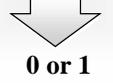
α, β : Non-terminal symbols,
 w : Terminal symbols



Word concatenation score based on SDCFG

Word dependency probability

If the dependency structure between words is deterministic,



0 or 1

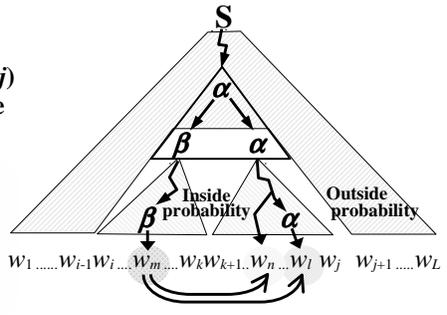
If the dependency structure between words is ambiguous,



SDCFG
(Stochastic DCFG)

The dependency probability between w_m and $w_l, d(w_m, w_l, i, k, j)$ is calculated using Inside-Outside probability based on SDCFG.

$$T(w_m, w_n) = \log \sum_{i=1}^m \sum_{k=m}^{n-1} \sum_{j=n}^L \sum_{l=n}^i d(w_m, w_l, i, k, j)$$

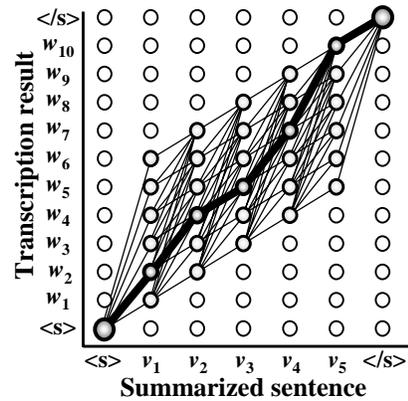


S: Initial symbol, α, β : Non-terminal symbol, w : Word

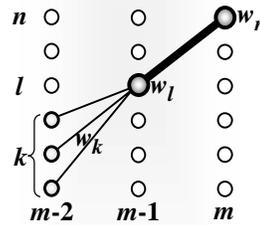
Dynamic programming for summarizing each utterance

Selecting a set of words maximizing the summarization score

Ex.: $\langle s \rangle w_2 w_4 w_5 w_7 w_{10} \langle s \rangle$



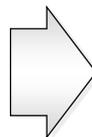
$$g(m, l, n) = \max_{k < l} \{g(m-1, k, l) + \log P(w_n | w_k w_l) + \lambda_I I(w_n) + \lambda_C C(w_n) + \lambda_T T_r(w_l, w_n)\}$$



Summarization of multiple utterances

The method of summarizing each utterance is extended to summarize a set of multiple utterances by adding a rule giving a restriction at utterance boundaries.

Original utterances having many informative words are preserved and utterances having few informative words are deleted or shortened.



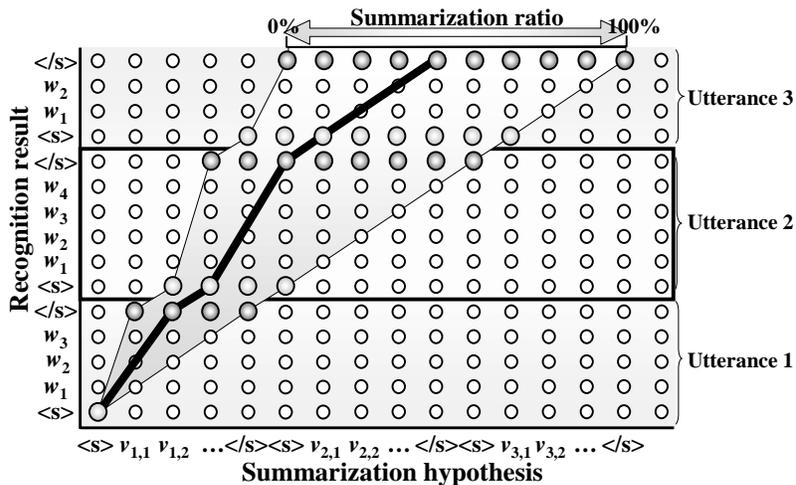
Important sentence extraction

+

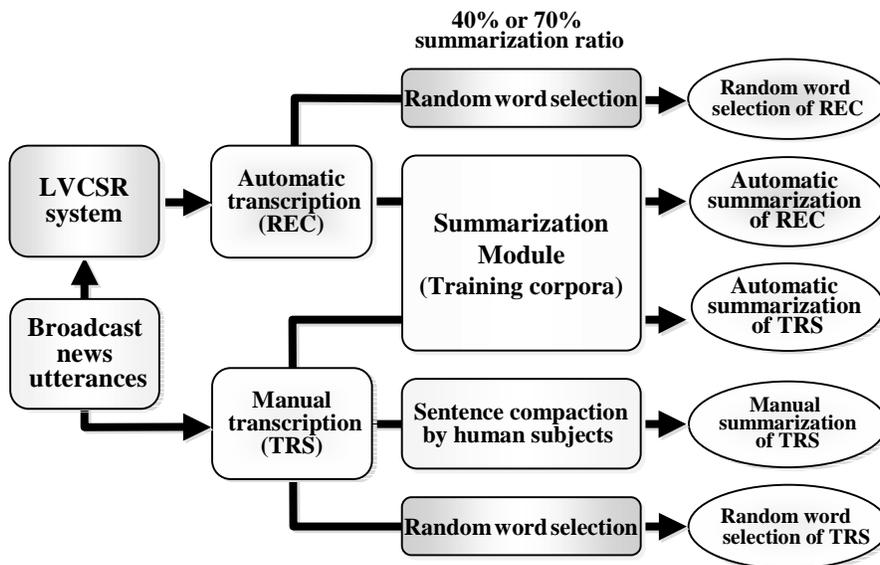
Summarization of each utterance

Dynamic programming for summarizing multiple utterances

- * Initial and terminal symbols cannot be skipped.
- * Word concatenation score is not applied to the utterance boundaries.



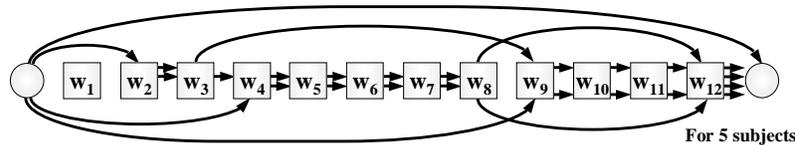
Evaluation experiments



Word network of manual summarization results for evaluation

Manual summarization results are merged into a network.

- The network approximately expresses all possible correct summarization including subjective variations.



Summarization accuracy is defined as the word accuracy based on the word string, extracted from the word network, that is most similar to the automatic summarization result.

$$\text{Summarization accuracy} = \{ \text{Len} - (\text{Sub} + \text{Ins} + \text{Del}) \} / \text{Len} * 100 [\%]$$

Len: number of words in the most similar word string in the network

Sub: number of substitution errors

Ins: number of insertion errors

Del: number of deletion errors

Examples of automatic summarization for manually transcribed CNN news - 1

- Transcription:**
It's sulfur, and as Ed Garsten reports in today's edition of tech trends, the petroleum industry is proposing a cleanup.
- Automatic summarization (30-40% summarization ratio) :**
sulfur Ed Garsten reports tech petroleum __ proposing cleanup.
- The most similar word string in the manual summarization network:**
Ed Garsten reports tech trends industry proposing cleanup.
- Automatic summarization (50-70% summarization ratio):**
sulfur Ed Garsten reports in today's edition tech trends petroleum industry is proposing cleanup.
- The most similar word string in the manual summarization network :**
Sulfur, Garsten reports in today's tech trends the industry is proposing cleanup.

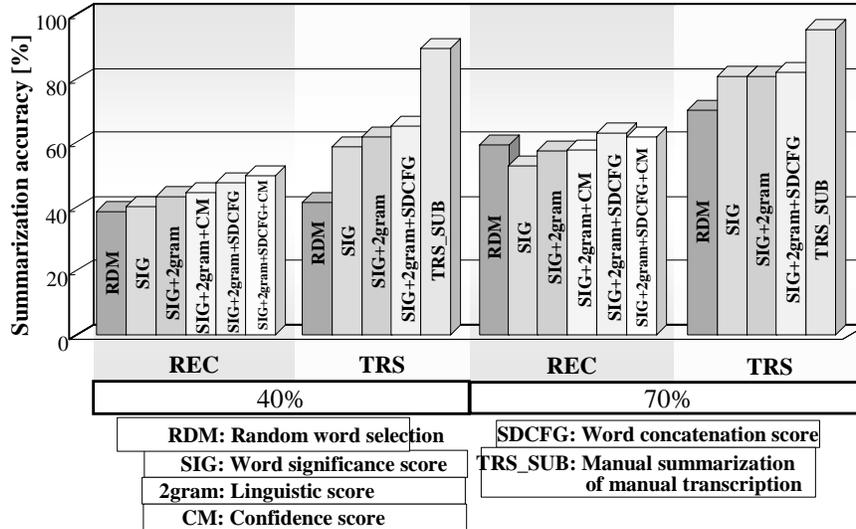
Examples of automatic summarization for manually transcribed CNN news - 2

- **Transcription:**
We are dealing with something of such a massive uh size and potential impact, um that a lot of people wisely are saying hands off.
- **Automatic summarization (20-40% summarization ratio) :**
We're dealing something __ impact lot of people saying hands __.
- **The most similar word string in the manual summarization network :**
We're dealing something such impact lot of people saying hands off.
- **Automatic summarization (50-70% summarization ratio) :**
We're dealing with something of a size and impact, a lot of people wisely are saying hands __.
- **The most similar word string in the manual summarization network :**
We're dealing with something of such size and impact, a lot of people wisely are saying hands off.

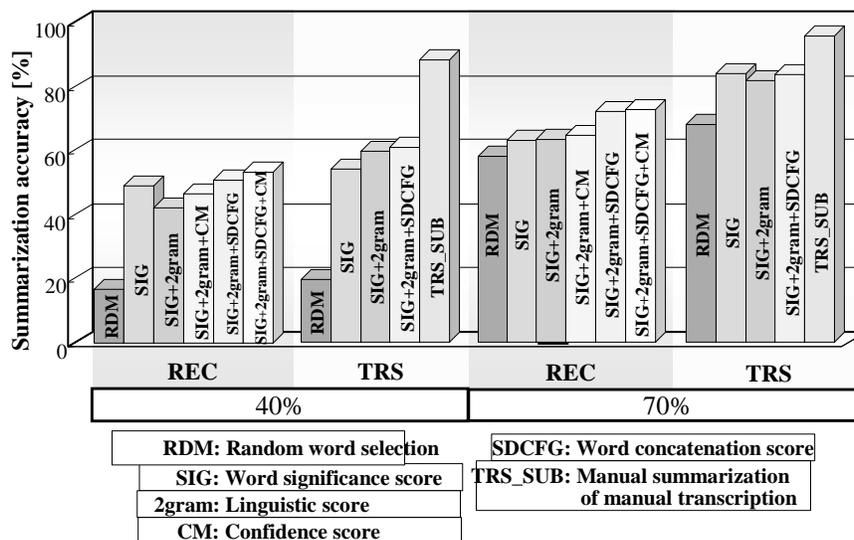
Examples of automatic summarization for recognized CNN news (80% recognition accuracy)

- **Recognition result:**
*Vice president Al Gore says the government has a plan to avoid the inevitable prospect of increased airplane crashes and fatality **(is)***
- **Automatic summarization (40% summarization ratio) :**
***(Gore)** the government has a plan to avoid the increased airplane crashes*
- **The most similar word string in the word network:**
<INS> the government has a plan to avoid the increased airplane crashes
- **Automatic summarization (70% summarization ratio) :**
Vice president Al Gore says the government has a plan to avoid increased airplane crashes
- **The most similar word string in the word network:**
*Vice president Al Gore says the government has a plan to avoid **(the)** increased airplane crashes*

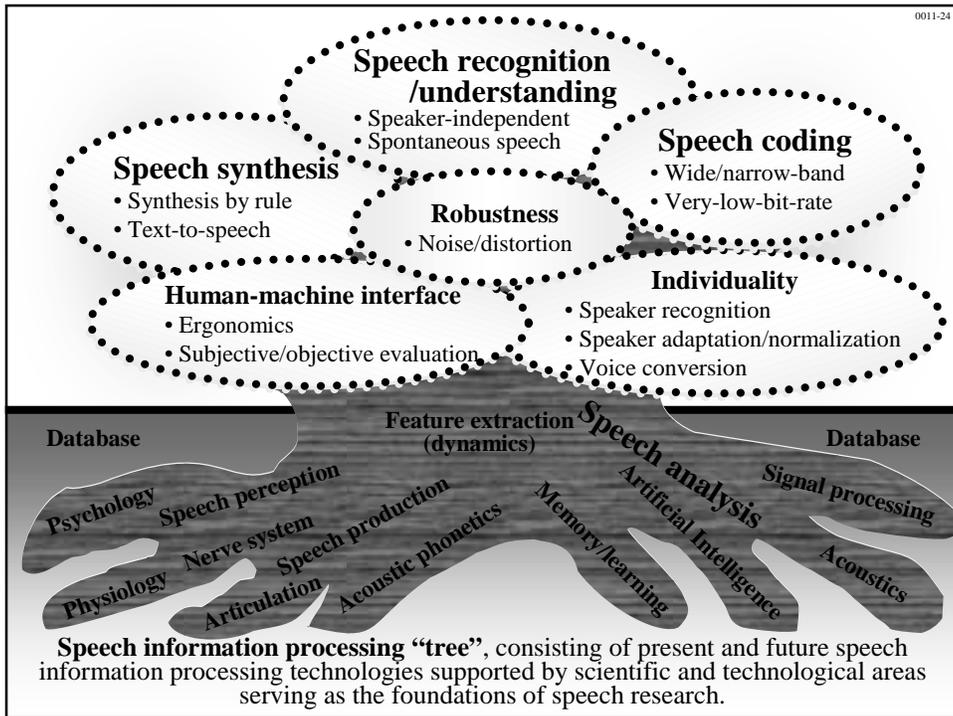
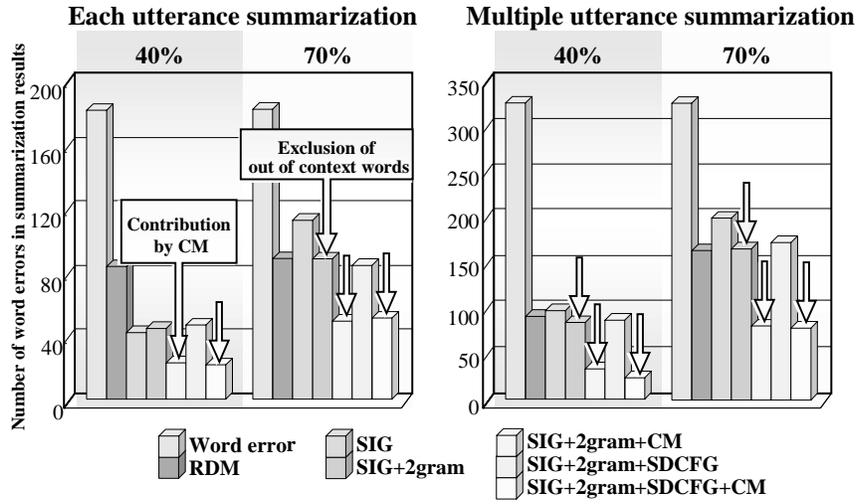
English news speech summarization (Each utterance summarization)



English news speech summarization (Multiple utterance summarization)



Recognition error reduction



Summary

- ***Speech recognition technology* has made significant progress with many potential applications.**
- **How to model and recognize *spontaneous speech* is one of the most important issues.**
- **Construction of a large-scale *spontaneous speech corpus* is crucial.**
- **Paradigm shift from recognition to *understanding* is needed.**
- ***Speech summarization* is attractive as information extraction and speech understanding.**

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