Latent Topic Modeling of Word Co-Occurrence Information for Spoken Document Retrieval

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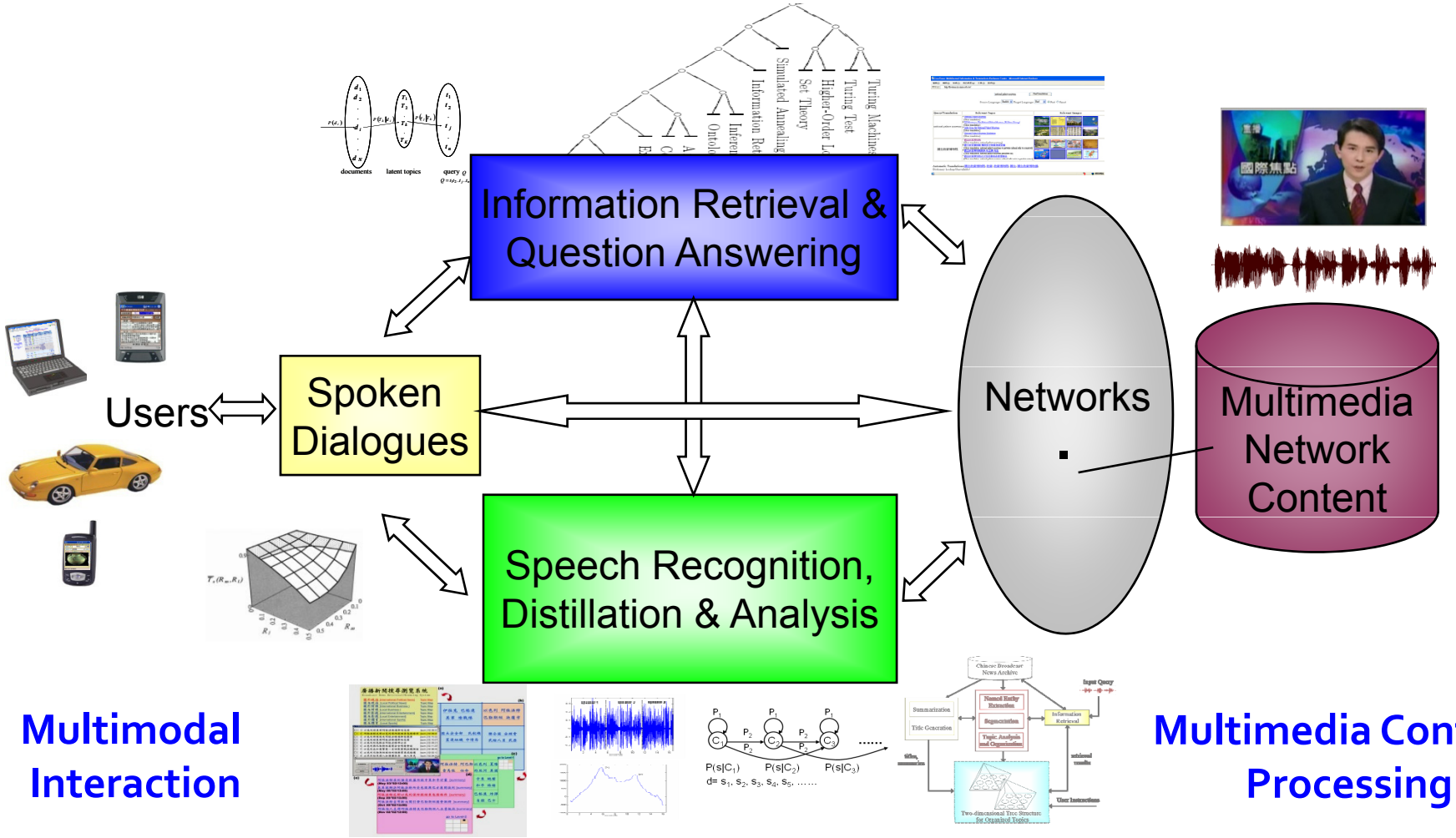
Outline

- Introduction
- Document Topic Models (DTM)
- Word Topic Model (WTM)
- Comparisons and Experiments on SDR
- Applications of WTM to Other Related Tasks
- Conclusions

Introduction

- Large volumes of multimedia associated with speech are now made available on the Internet
  - Speech is one of the most semantic (or information)-bearing sources
- Speech also is the most convenient means of communication between humans, or potentially between humans and machines
  - Especially helpful when using smaller hand-held devices with small screen sizes and limited keyboard entry capabilities
- Speech will be the key for multimedia information access in the near future

Multimodal Access to Multimedia in the Future



Multimedia vs. Text

- Written text documents are better structured and easier to browse through
  - Provided with titles and other structure information (e.g., hyperlinks)
  - Easily shown on the screen to glance through (with visual perception)

- Multimedia (Spoken) documents are just video (audio) signals
  - Users cannot efficiently go through each one from the beginning to the end during browsing, even if the they are automatically transcribed by automatic speech recognition
  - However, abounding speaker, emotion and scene information make them much more attractive than text
  - Better approaches for efficient organization and retrieval of multimedia (spoken) documents are highly demanded

Related Research Work and Applications

- Continuous and substantial efforts have been paid to (multimedia) speech recognition, summarization and retrieval in the recent past
  - Informedia System at Carnegie Mellon Univ.
  - AT&T SCAN System
  - The *Rough'n'Ready* System at BBN Technologies
  - The *SpeechBot* Audio/Video Search System at HP Labs
  - IBM Speech Search for Call-Center Conversations & Call-Routing, Voicemails, Monitoring Global Video and Web News Sources (TALES)
  - Google Voice Search (GOOG-411, Audio Indexing, Translation)
  - Microsoft Research Audio-Video Indexing System (MAVIS)
  - MIT Lecture Browser
  - NTT Speech Communication Technology for Contact Centers
  - Some Prototype Systems Developed in Taiwan

Key Technologies (1/2)

- Automatic Speech Recognition (ASR)
  - Automatically convert speech signals into sequences of words or other suitable units for further processing
- Spoken Document Segmentation
  - Automatically segment speech signals (or automatically transcribed word sequences) into a set of documents (or short paragraphs) each of which has a central topic
- Named Entity Extraction from Spoken Documents
  - Personal names, organization names, location names, event names
  - Very often out-of-vocabulary (OOV) words, difficult for recognition
    - E.g., "蔡煌郎", "九二共識", etc.
- Audio Indexing and Retrieval (Voice Search)
  - Robust representation of the spoken documents
  - Matching between (spoken) queries and spoken documents

Key Technologies (2/2)

- Summarization for Spoken Documents
  - Automatically generate a summary (in text or speech form) for each spoken document or a set of topic-coherent documents
- Title Generation for Multi-media/Spoken Documents
  - Automatically generate a title (in text/speech form) for each short document; i.e., a very concise summary indicating the themes of the documents
- Topic Analysis and Organization for Spoken Documents
  - Analyze the subject topics for (retrieved) documents
  - Organize the subject topics of documents into graphic structures for efficient browsing
- Information Extraction for Spoken Documents
  - Extraction of key information such as who, when, where, what and how for the information described by spoken documents

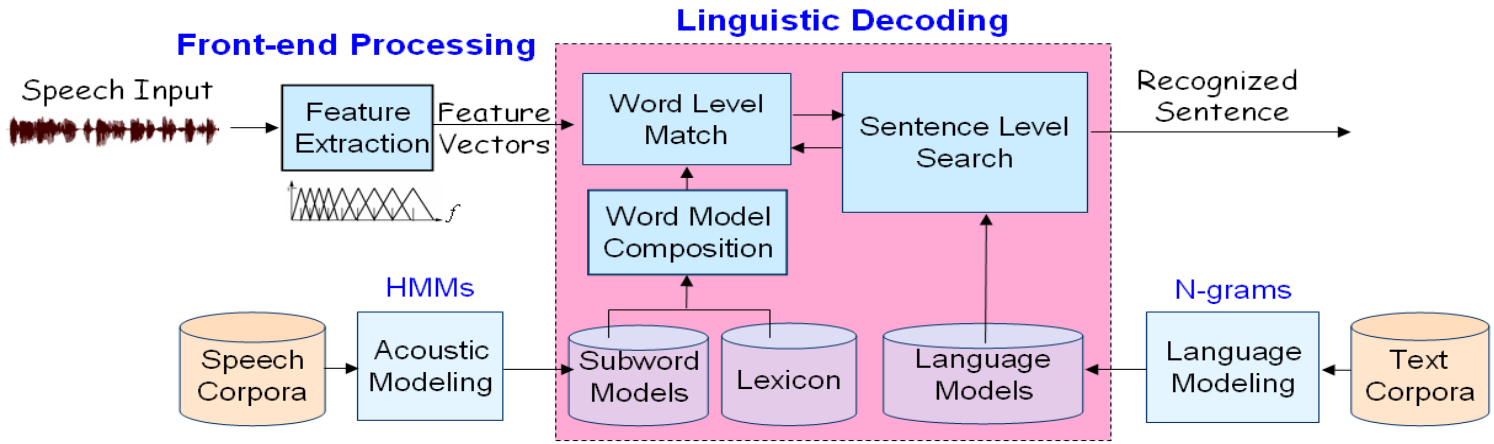
World-wide Speech Research Projects

- There also are several research projects conducting on related spoken document processing tasks, e.g.,
  - Rich Transcription Project[1] in the United States (2002-)
    - Creation of recognition technologies that will produce transcriptions which are more readable by humans and more useful for machines
  - TC-STAR Project[2] (Technology and Corpora for Speech to Speech Translation) in Europe (2004-2007)
    - Translation of speeches recorded at European Parliament, between Spanish and English, and of broadcast news by Voice of America, from Mandarin to English
  - "Spontaneous Speech: Corpus and Processing Technology" Project in Japan (1999-2004)
    - 700 hours of lectures, presentations, and news commentaries
    - Automatic transcription, analysis (tagging), retrieval and summarization of spoken documents

[1] http://www.nist.gov/speech/tests/rt/ [2] http://www.tc-star.org

Automatic Speech Recognition (ASR)

- Finding the most likely word sequence *W* in response to an input speech signal *O*



$$\hat{W} = \arg\max_{W} P(W \mid O)$$

$$= \arg\max_{W} \frac{p(O \mid W)P(W)}{P(O)}$$

Applying Bayes' Rule

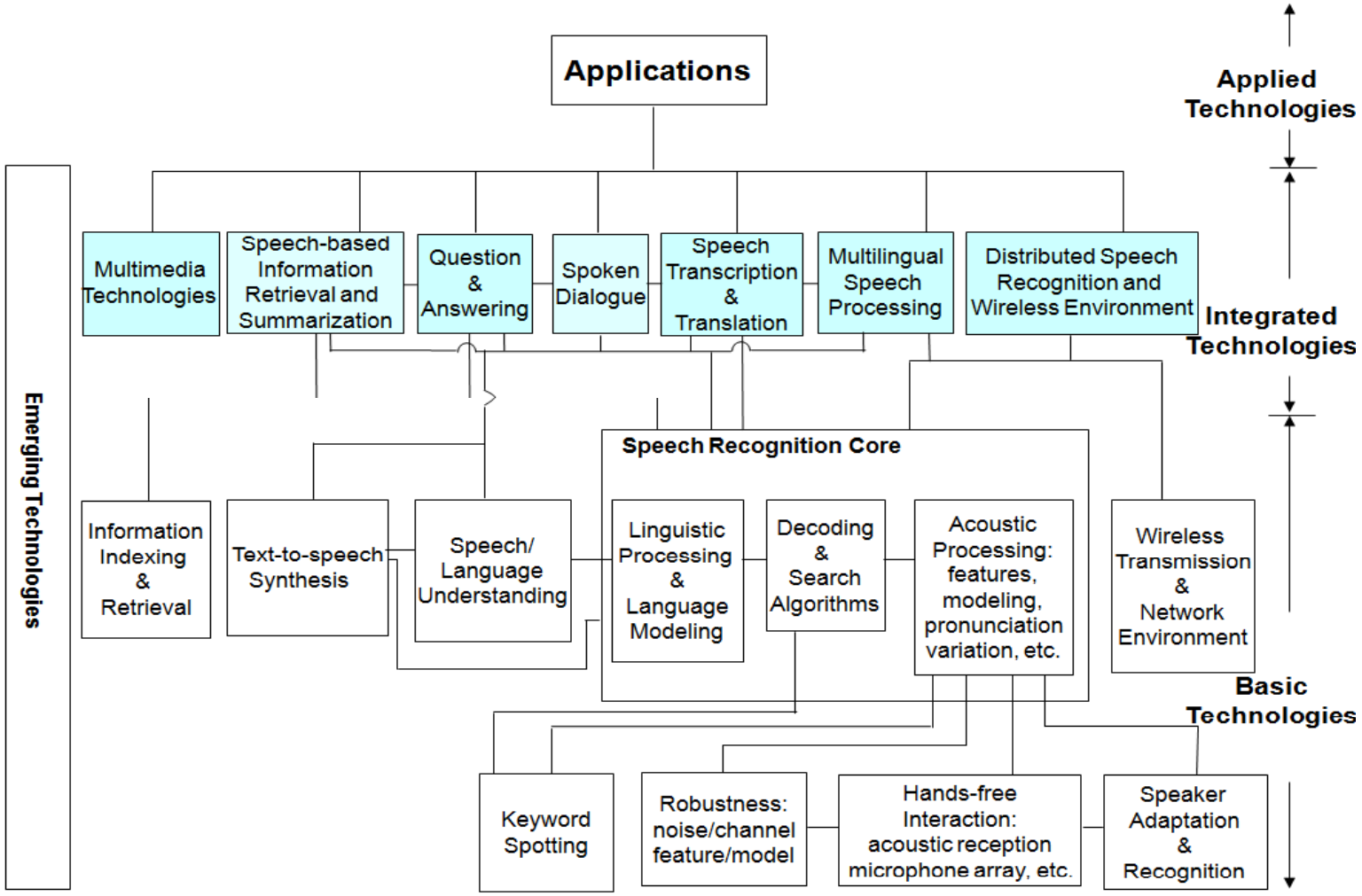
$$= \arg\max_{W} p(O \mid W)P(W)$$

Linguistic Decoding (Search)

Feature Extraction & Acoustic Modeling

Language Modeling

Related Research Areas of ASR



This slide was adapted from Prof. Lin-shan Lee's presentation

Broadcast Speech Transcription

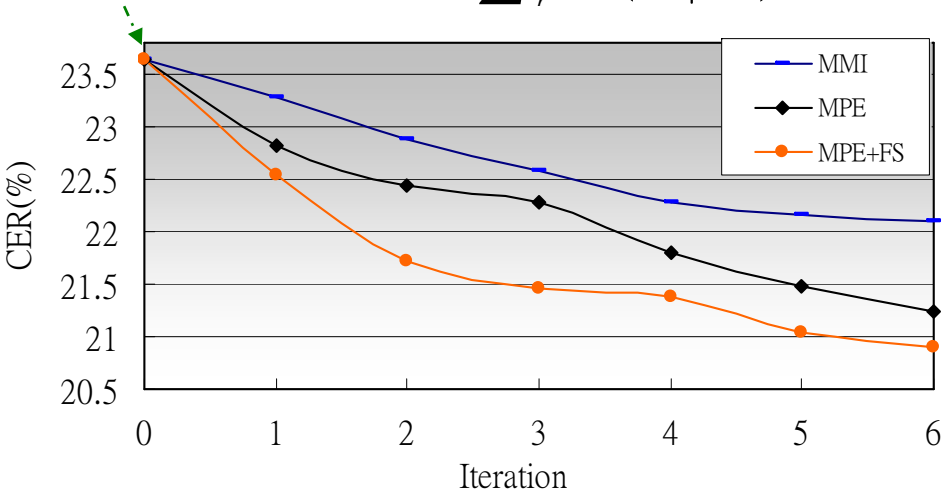
Automatic

根據 最新 但 雨量 統計
一 整天 下來
費 雪 以 試辦 兩 個 水庫 的 雨量
分別 是 五十 三 公里 和 二十 九 公厘
對 水位 上升 幫助 不 大
不過 就業機會 期間 也 多 在 夜間
氣象局 也 針對 中部以北 及 東北部 地區 發佈 豪雨 特 報
因此 還是 有 機會 增加 積水 區 的 降雨量
此外 氣象局 也 預測
華航 又 有 另 一道 鋒面 通過
水利署 估計 如果 這 波 鋒面 能 帶來 跟著 會 差不多 的 雨水
那 個 北 台灣 的 第二 階段 限水 時間
渴望 見到 五月 以後
公視 新聞 當時 匯率 採訪 報導

Manual

根據最新的雨量統計
一整天下來
翡翠石門兩個水庫的雨量
分別是五十三公厘和二十九公厘
對水位上升幫助不大
不過由於集水區降雨多在夜間
氣象局也針對中部以北及東北部地區發布了豪雨特報
因此還是有機會增加集水區的降雨量
此外氣象局也預測
八號又有另一道鋒面通過
水利署估計如果這波鋒面能帶來跟這回差不多的雨水
那麼北台灣的第二階段限水時間
可望延到五月以後
公視新聞張玉菁陳柏諭採訪報導

10 Iterations of ML training $F_{\mathrm{ML}}(\Lambda)=\sum_r P_\Lambda(O_r|W_r)$



Discriminative acoustic model training can further improve the ASR performance: (Relative Character Error Rate Reduction)
- MMI: 6.5% , MPE: 10.1%

$$F_{\mathrm{MPE}}(\Lambda,\Gamma)=\sum_r \sum_{W_i\in\mathbf{W}^r} \frac{p_\Lambda(O_r|W_i)P_\Gamma(W_i)A(W_i,W_r)}{\sum_{W_k\in\mathbf{W}^r} p_\Lambda(O_r|W_k)P_\Gamma(W_k)}$$

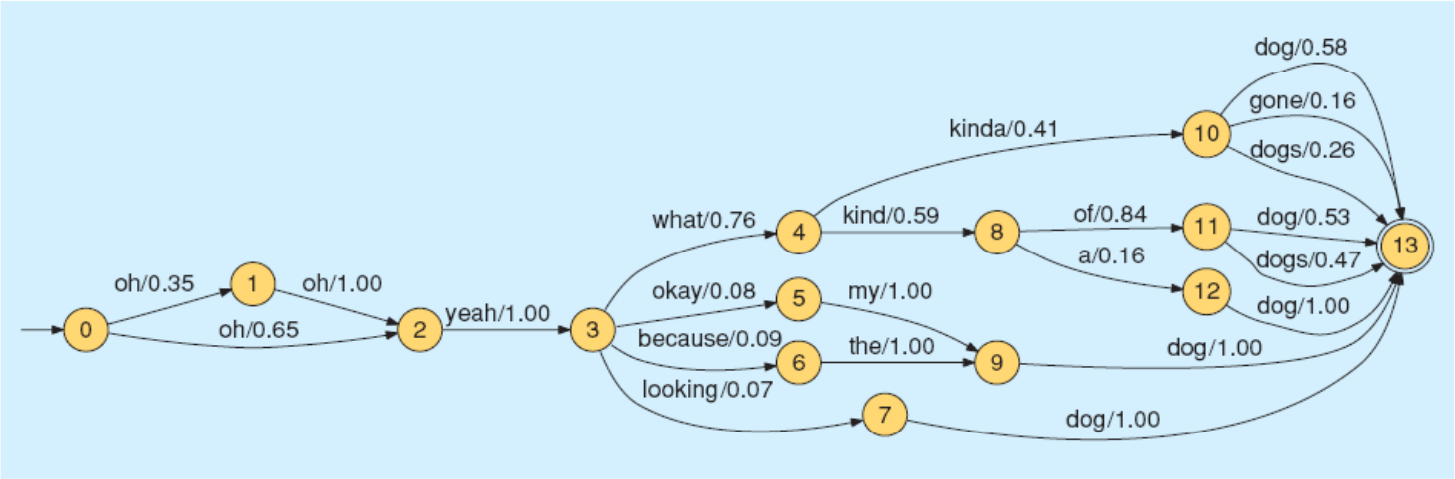
Task Definition for Voice Search

- Robustly Index spoken documents with speech recognition techniques
- Retrieve relevant spoken documents in response to a user query
  - Spoken Term Detection (STD)
    - Find "literally matched" spoken documents where all/most query terms should be present (much like Web search)
  - Spoken Document Retrieval (SDR)
    - Find spoken documents that are "topically related" to a given query

This talk focuses mainly on the document ranking models for SDR !

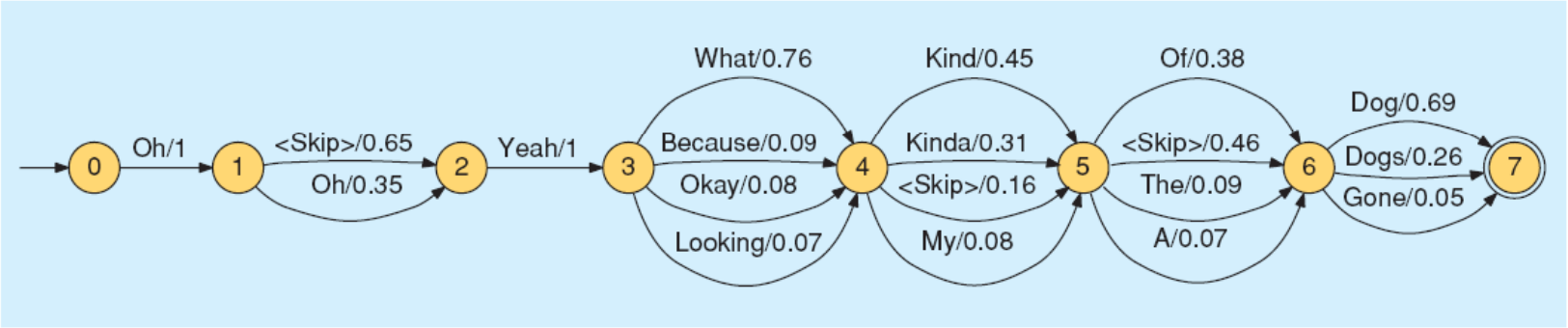
Robust Indexing: 1-bset Sequences vs. Lattices (1/3)

- Use of 1-best ASR output as the transcription to be indexed is suboptimal due to the high WER, which is likely to lead to low recall
- ASR lattices do provide much better WER, but the position information is not readily available (uncertainty of word occurrences) ?
- An example ASR Lattice



Robust Indexing: 1-bset Sequences vs. Lattices (2/3)

- Confusion/Consensus Networks (CN, also called "Sausages") derived from the Lattice
  - Group the word arcs in the lattice into several strictly linear lists (clusters) of word alternatives



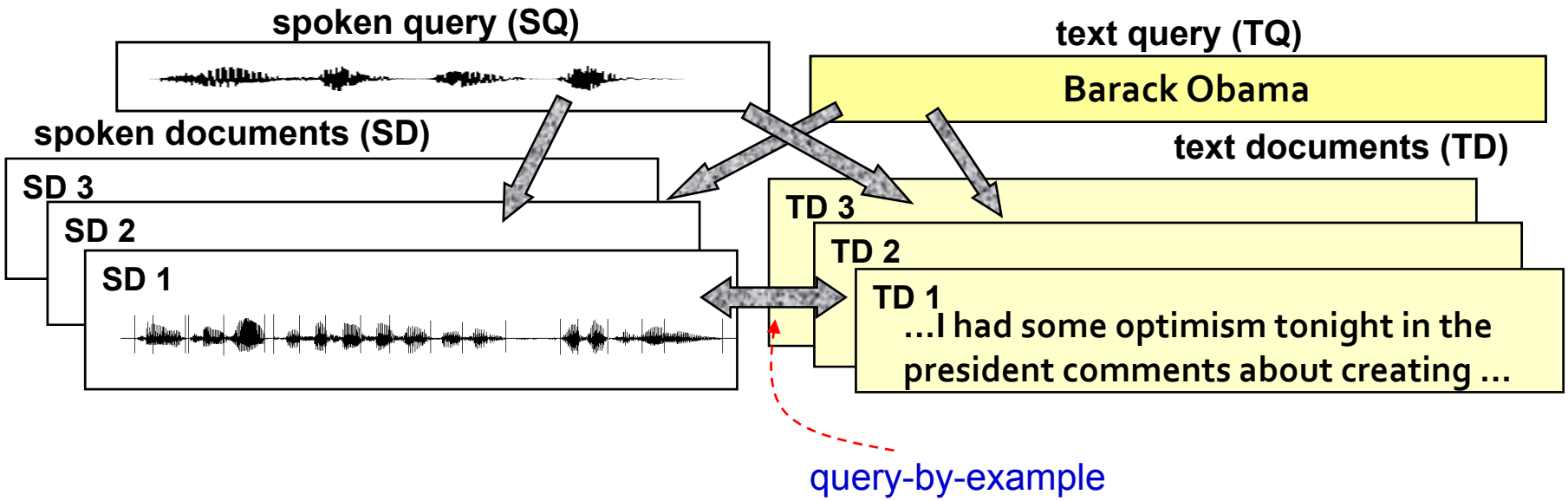
  - L. Mangu, E. Brill, A. Stolcke, "Finding consensus in speech recognition: word error minimization and other applications of confusion networks," *Computer Speech & Language* 14(4), 2000

Robust Indexing: 1-bset Sequences vs. Lattices (3/3)

- Position-Specific Posterior Probability Lattices (PSPL)
  - Position information is crucial for being able to evaluate proximity when assigning a relevance score to a given document
  - Estimate the posterior probability of a word w at a specific position l in the lattices $P(w,l \mid LAT)$ of spoken queries and documents

0		1		2		3		4		5		6		7	
Oh	1.0	**Yeah**	.65	**What**	.46	**Kind**	.27	Dog	.26	EOS	.34	**EOS**	.44	EOS	.16
—		Oh	.35	Yeah	.35	What	.27	**Of**	.23	**Dog**	.29	Dog	.09	—	
		—		Because	.06	Kinda	.19	Kind	.16	Dogs	.13	Dogs	.06		
				Okay	.05	The	.06	Kinda	.11	Of	.13	—			
				Looking	.05	My	.05	Dogs	.05	A	.03				
				—		Dog	.05	EOS	.05	Gone	.02				
						.....	...	.....	...	—					

Scenarios for Spoken Document Retrieval (SDR)



- SQ/SD is the most difficult
- TQ/SD is studied most of the time
  - This research investigates using (Xinhua) text news to retrieve relevant (Voice of America) broadcast news
    - "query-by-example"
    - Useful for news monitoring and tracking

Language Modeling (LM) Approaches

- LM approaches have been introduced to IR (and SDR), and demonstrated with good success

$$P_{\mathrm{LM}}\left(D|Q\right)=\frac{P\left(Q|\mathrm{M}_{\mathrm{D}}\right)P\left(D\right)}{P\left(Q\right)}\propto P\left(Q|\mathrm{M}_{\mathrm{D}}\right)$$

  - A probabilistic framework for ranking documents given a query
  - Each document is viewed as a language model for generating the query
  - Those documents with higher query-likelihoods are more relevant to the query

LM for SDR: Two Matching Strategies

- Literal Term Matching: Each document offers a *n*-gram (usually unigram) distribution for observing a query word

$$P_{\text{Unigram}}\left(Q|\text{M}_D\right)=\prod_{i=1}^{L}\left[\lambda\cdot P\left(w_i|\text{M}_D\right)+\left(1-\lambda\right)\cdot P\left(w_i|\text{M}_C\right)\right]$$

- Concept Matching: Each document as a whole consists of a set of shared latent topics with different weights -- A document topic model (DTM)
  - Each topic offers a unigram (multinomial) distribution for observing a query word

$$P_{\text{PLSA/LDA}}\left(Q\mid\text{M}_D\right)=\prod_{i=1}^{L}\left[\sum_{k=1}^{K}P\left(w_i\mid T_k\right)P\left(T_k\mid\text{M}_D\right)\right]$$

  - PLSA (Probabilistic Latent Semantic Analysis) and LDA (Latent Dirichlet Allocation) are the two good examples
    - Mainly differ in inference of model parameters (fixed & unknown vs. Dirichlet distributed)

Word Topic Models (WTM)

- Each word of language is treated as a word topic model (WTM) for predicting the occurrences of other words

$$P_{\mathrm{WTM}}\left(w_i \mid \mathrm{M}_{w_j}\right)=\sum_{k=1}^{K} P\left(w_i \mid T_k\right)P\left(T_k \mid \mathrm{M}_{w_j}\right)$$

- The relevance measure between a query and a document can be expressed by

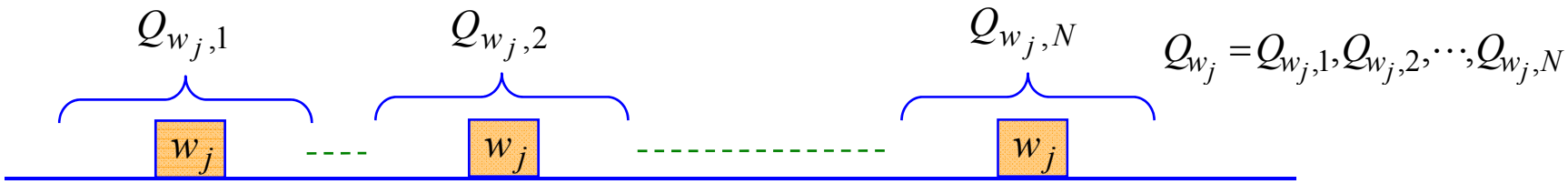
$$P_{\mathrm{WTM}}\left(Q\middle|D\right)=\prod_{i=1}^{L}\left[\sum_{w_j \in D} P_{\mathrm{WTM}}\left(w_i\middle|\mathrm{M}_{w_j}\right)P\left(w_j\middle|D\right)\right]$$

  - A spoken document can be viewed as a composite WTM
  - WTM is a kind of LM for translating words in the document to words in the query
  - $P\left(w_j\middle|D\right)$ is estimated according to the frequency of w_j in D

Can we model topic al information using other units beyond "documents" ?

Unsupervised Training of WTM

- The WTM $P_{\mathrm{WTM}}\left(w_i \mid \mathrm{M}_{w_j}\right)$ of each word can be trained with maximum likelihood estimation (MLE)
  - By concatenating those words occurring within a context window around each occurrence of the word, which are assumed to be relevant to the word, to form the training observation



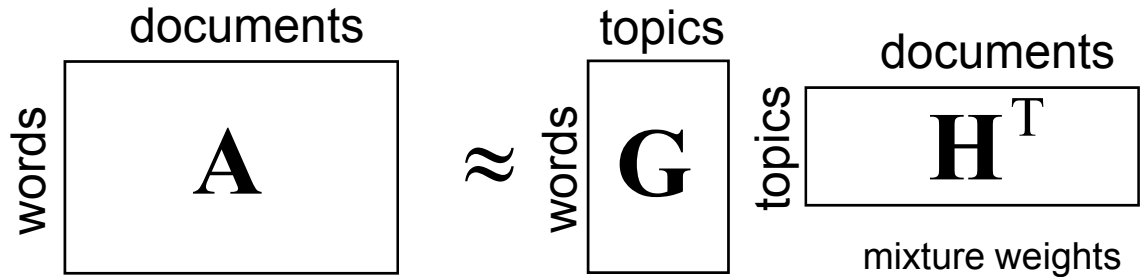
$$\log L_{\mathbf{w}} = \sum_{w_j \in \mathbf{w}} \log P_{\mathrm{WTM}}\left(Q_{w_j} \middle| \mathrm{M}_{w_j}\right) = \sum_{w_j \in \mathbf{w}} \sum_{w_i \in Q_{w_j}} c\left(w_i, Q_{w_j}\right) \log P_{\mathrm{WTM}}\left(w_i \middle| \mathrm{M}_{w_j}\right)$$

  - $\mathbf{W}$: the set of words in the language

  - WTM was trained to optimize its prediction power over the observation

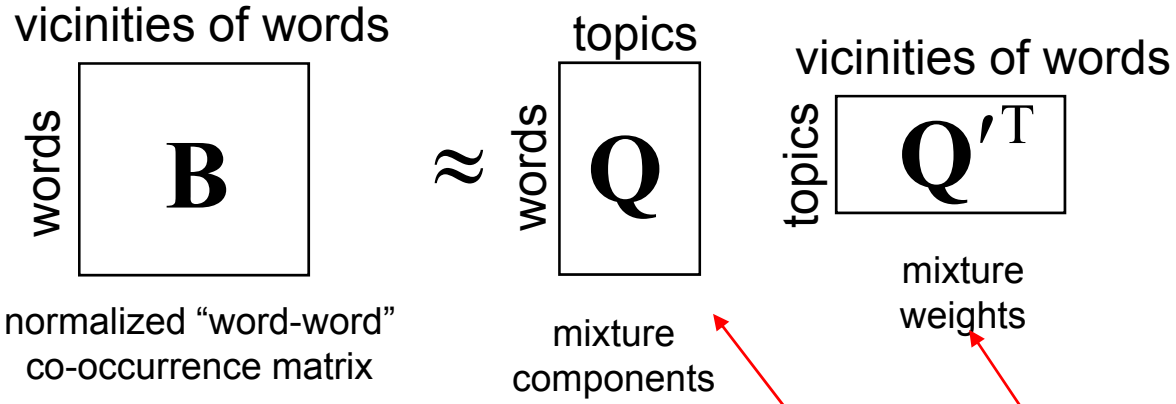
Comparison Between WTM and DTM -- Probabilistic Matrix Decompositions

PLSA/LDA



$$P_{\text{PLSA/LDA}}\left(w_i \mid \mathrm{M}_D\right) = \sum_{k=1}^{K} P\left(w_i \mid T_k\right) P\left(T_k \mid \mathrm{M}_D\right)$$

WTM



$$P_{\text{WTM}}\left(w_i \mid \mathrm{M}_{w_j}\right) = \sum_{k=1}^{K} P\left(w_i \mid T_k\right) P\left(T_k \mid \mathrm{M}_{w_j}\right)$$

Comparison Between WTM and DTM -- Spoken Document Retrieval

- Experiments were conducted on the TDT-2 spoken document collection (~50h broadcast news stories, 16 test queries)
  - Results were measured by Mean Average Precision (*m*AP)

PLSA		LDA		WTM		WTM-L	
TD	SD	TD	SD	TD	SD	TD	SD
0.627	0.568	0.641	0.570	0.636	0.573	0.644	0.574

  - PLSA, LDA and WTM (8 topics) are all trained without supervision (without using additional query-document relevance information)
    - PLSA or LDA maximizes the collection likelihood
    - WTM maximizes the likelihood of words in each word's vicinity
  - WTM-L: Further assume the parameters of WTM follow Dirichlet distributions

$$\hat{P}_{\mathrm{DTM/WTM}}(w_i \mid \mathrm{M}_D) = \rho_1 \cdot P_{\mathrm{DTM/WTM}}(w_i \mid \mathrm{M}_D) + \rho_2 \cdot P(w_i \mid \mathrm{M}_D) + (1-\rho_1-\rho_2) \cdot P(w_i \mid \mathrm{M}_C)$$

Supervised Training of WTM

- Maximum Likelihood Estimation (MLE)
  - Maximize the log-likelihood of an outside training set of (~800) query exemplars generated by their relevant documents

$$\log L_{\mathbf{Q}_{TrainSet}} = \sum_{Q \in \mathbf{Q}_{TrainSet}} \sum_{D_r \in \mathbf{D}_{R \text{ to } Q}} \log P_{\text{WTM}}\left(Q \middle| \text{M}_{D_r}\right)$$

- Minimum Classification Error Training (MCE)
  - Given a training query exemplar, we can instead minimize the following error function

relevant document

irrelevant document

$$E(Q, D_r, D_{irr}) = \frac{1}{|Q|}\left[-\log P_{\text{WTM}}\left(Q \middle| \text{M}_{D_r}\right) + \max_{D_{irr}} \log P_{\text{WTM}}\left(Q \middle| \text{M}_{D_{irr}}\right)\right]$$

Other irrelevant documents for the training query can be into consideration

  - Further converted to a loss function with a Sigmoid operator
  - Corresponding parameters of WTM then are updated with a generalized probabilistic descent (GPD) procedure

Results of Supervised Training

	WTM				PLSA				Unigram	
	MIX-8		MIX-32		MIX-8		MIX-32			
	TD	SD	TD	SD	TD	SD	TD	SD	TD	SD
MLE	0.689	0.617	0.735	0.686	0.675	0.592	0.683	0.626	0.633	0.566
MCE	0.700	0.631	0.760	0.710	0.679	0.608	0.685	0.628	0.646	0.581

- For WTM, if training query-relevant document pairs were available, significantly better results could be achieved by either MLE or MCE
- PLSA and Unigram LM (i.e., the simple literal term matching model) can also be trained with supervision
- Notice also that, MCE seems to provide additional performance gains over MLE

Results of Various Vector Space Approaches

- Here we also list the results of retrieval using three popular vector space approaches

VSM		LSA		SVM	
TD	SD	TD	SD	TD	SD
0.555	0.512	0.551	0.531	0.580	0.532

  - SVM (Support Vector Machine) treats IR as a classification problem
    - A set of 11 heterogeneous features is used to represent each spoken document given an input query
    - SVM was trained by leveraging the relevance information of the outside training query exemplars
  - All LM-based retrieval approaches are significantly better than these vector space approaches

WTM Applied to Other Related Tasks

- Language Modeling in Speech Recognition

$$P\left(w_i \middle| H_{w_i}\right) = \sum_{j=1}^{i-1} P_{\text{WTM}}\left(w_i \middle| \text{M}_{w_j}\right) P\left(w_j \middle| H_{w_i}\right)$$
$$= \sum_{j=1}^{i-1} P\left(w_j \middle| H_{w_i}\right) \sum_{k=1}^{K} P\left(w_i \middle| T_k\right) P\left(T_k \middle| \text{M}_{w_j}\right)$$

$$P\left(w_j \middle| H_{w_i}\right) = \phi_j \prod_{s=1}^{i-j-1} \left(1 - \phi_{j+s}\right)$$

- Extractive Spoken Document Summarization

$$P\left(D \middle| S\right) = \prod_{i=1}^{L} \left[\sum_{w_j \in S} P_{\text{WTM}}\left(w_i \middle| \text{M}_{w_j}\right) P\left(w_j \middle| S\right) \right]$$
$$= \prod_{i=1}^{L} \left[\sum_{w_j \in S} P\left(w_j \middle| S\right) \sum_{k=1}^{K} P\left(w_i \middle| T_k\right) P\left(T_k \middle| \text{M}_{w_j}\right) \right]$$

- For both tasks, WTM has preliminarily demonstrated good results as compared to existing approaches

Chen et al., "A probabilistic generative framework for extractive broadcast news speech summarization," *IEEE Transactions on Audio, Speech and Language Processing* 17(1), *2009*

Conclusions

- Multimedia information access (over the Web) using speech will be very promising in the near future
  - Speech is the key for multimedia understanding and organization
  - Several task domains still remain challenging
- This research presented a word topic modeling (WTM) approach for spoken document retrieval
  - Simple and easy to implement
- Various model inference techniques were studied for WTM and other document topic models (DTMs)
  - Given an outside training set of query exemplars with relevance labels, the LM-based retrieval models can be steadily improved

Thank You !

IBM's Research Activities in Speech Translation and Speech-based Multimedia Content Access

Speech Translation

- **Speech-to-text: driven by foreign broadcast monitoring and information retrieval**

  E.g., DARPA GALE program

  1. ASR, MT
  2. Broad domain coverage, formal languages
  3. Large amount of training corpus
     - Hundreds of hours speech, hundreds of millions of words in training data
  4. Rich computation resources
     - Servers, supercomputers
  5. Allow response delay: minutes
  6. Not dialog systems
  7. Typical applications: intelligence, media companies

IBM TALES project

- **Speech-to-speech: for cross-lingual communication**

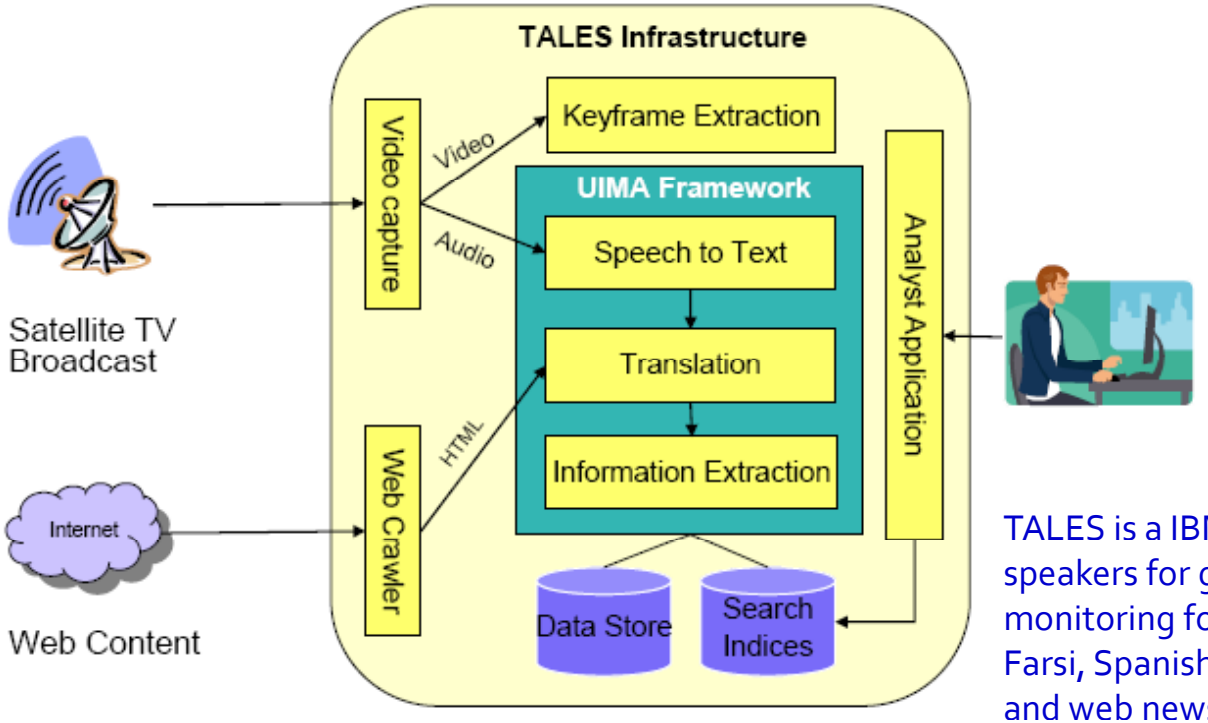
  E.g. DARPA TransTac program

  1. ASR, MT, TTS
  2. Relative narrow domain coverage, conversational colloquial languages
  3. Often have to deal with low resource languages and rapid development for such new languages
     - Much less data available
  4. Very limited computation resources
     - Laptops, PDAs
  5. Need real-time
  6. Interactive dialog systems: allow repeats, confirmation
  7. military, law enforcement, hospitals, business travelers, service industry

IBM MASTOR project

IBM TALES (Translingual Automatic Language Exploitation System) Project (1/2)

TALES Base Capabilities



TALES is a IBM solution for English speakers for global news monitoring for Arabic, Chinese, Farsi, Spanish, and English video and web news sources.

Key Technologies

- Speech recognition
- Statistical machine translation
- Information extraction (Named entity and relationship detection - optional)
- UIMA framework
- OmniFind search engine

http://domino.research.ibm.com/comm/research_projects.nsf/pages/tales.index.html

Adapted from the presentation slides of Dr. Yuqing Gao's at ISCSLP2008

IBM TALES (Translingual Automatic Language Exploitation System) Project (2/2)

TALES Demo

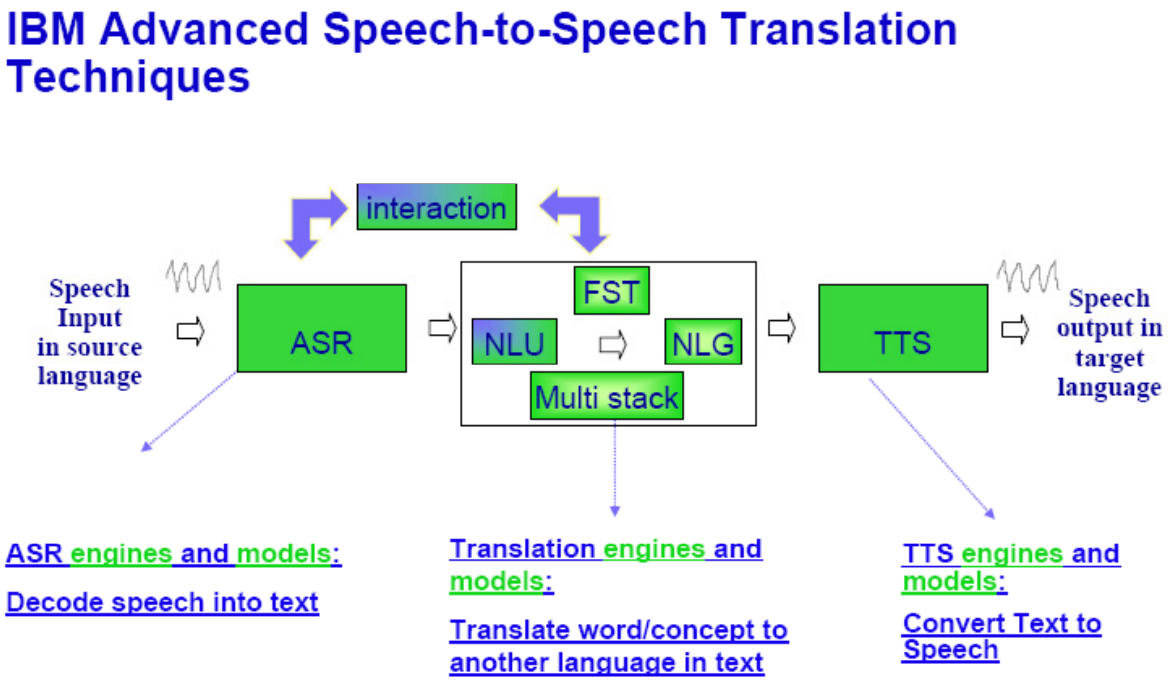
Foreign Broadcast Video Monitoring and Search

- UIMA-based multi-lingual search technology:
  - Speech-to-Text
  - Machine Translation (English, Arabic, Chinese, Spanish)
  - Advanced Text Analysis (language identification and translation, named entity extraction and translation)
  - Cross-lingual Information Retrieval

Foreign Web Site Translation and Search

IBM Mastor (Speech-to-Speech Translation) Project (1/2)

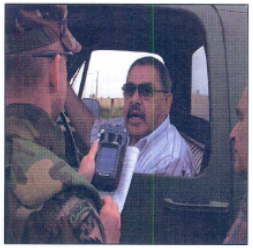
- MASTOR is a two-way, free form speech translator that assists human communication using natural spoken language for people who do not share a common language



IBM Mastor (Speech-to-Speech Translation) Project (2/2)

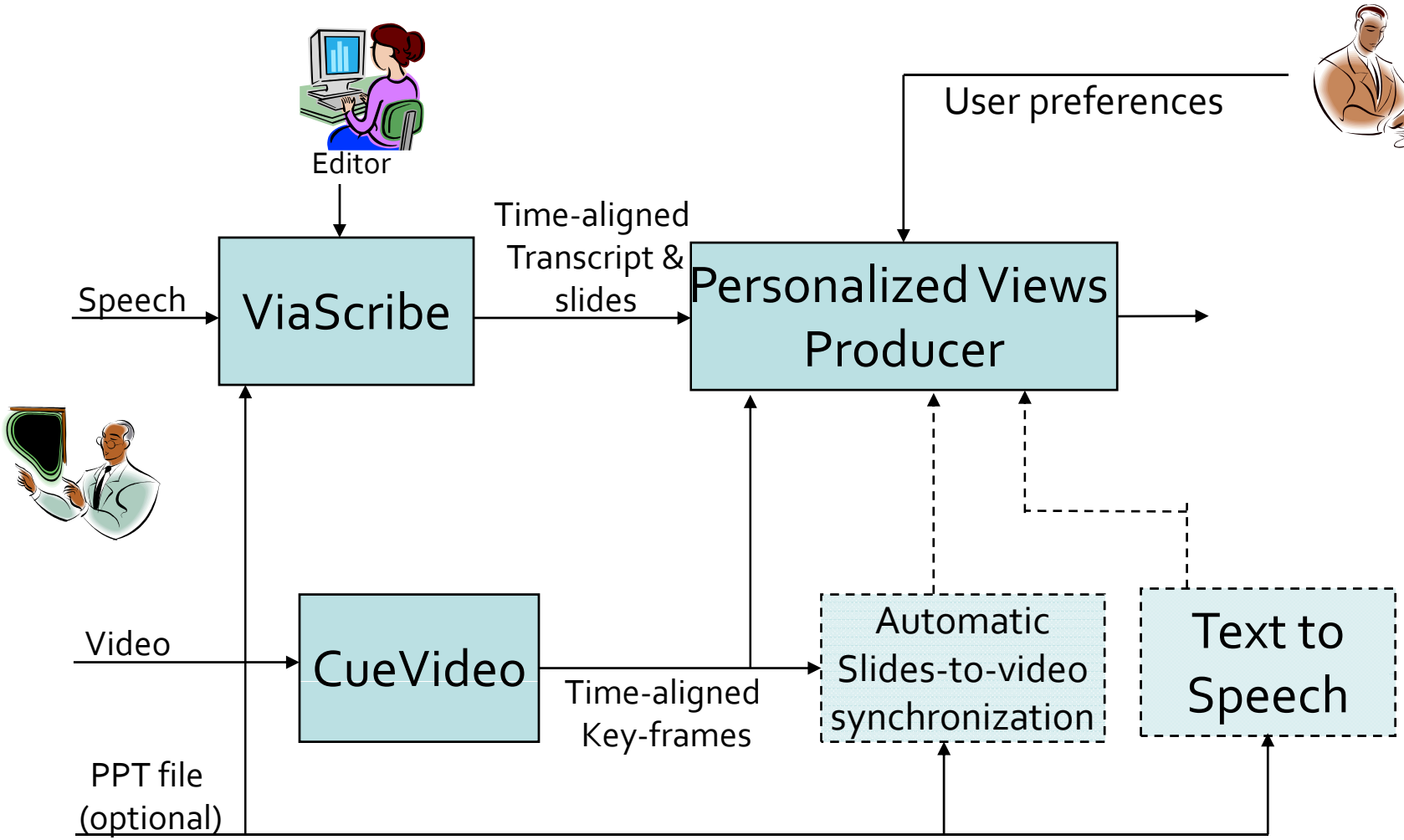
Laptop systems
- hands-free, eyes-free function

Handheld System



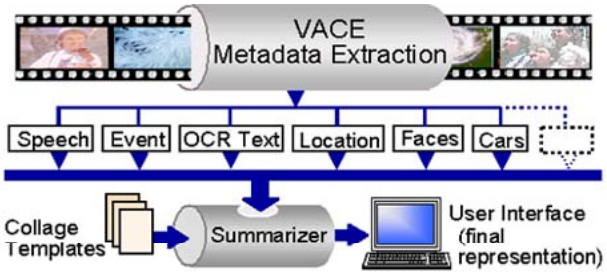
MASTOR Demo

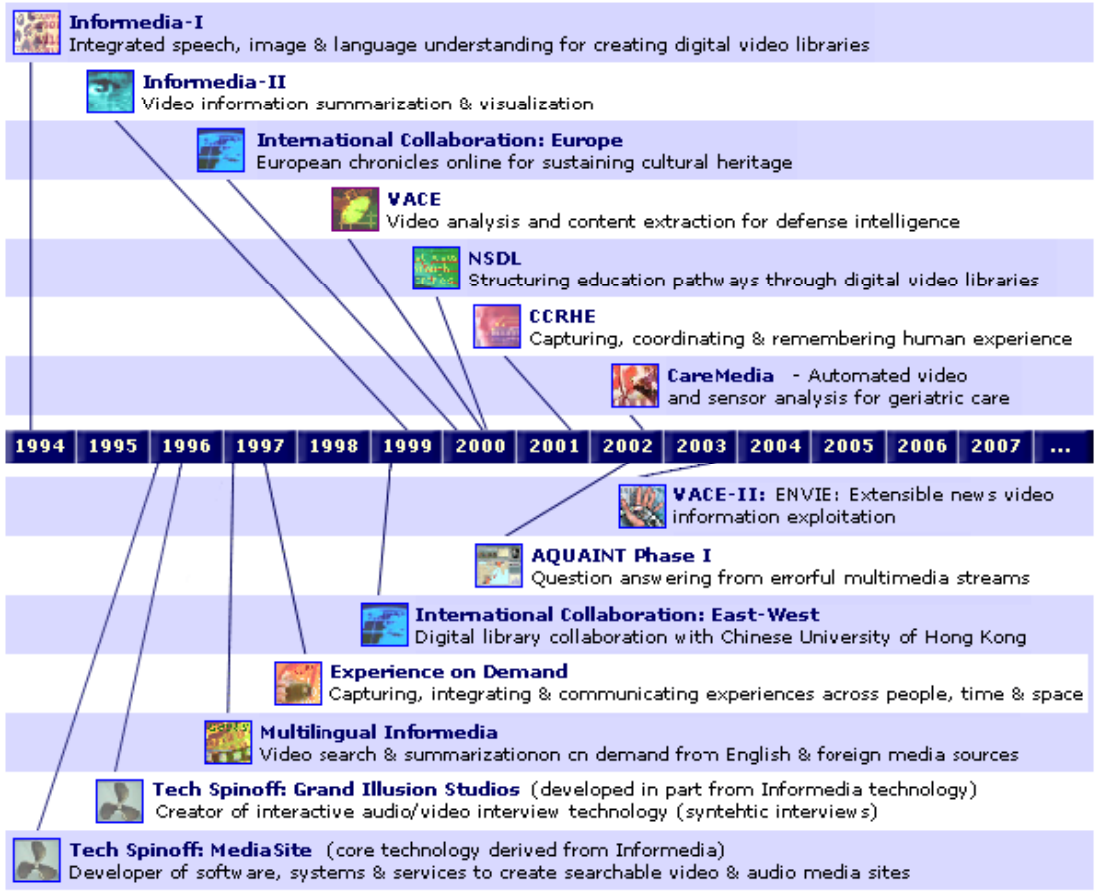
IBM's Audio-Visual Search Solutions



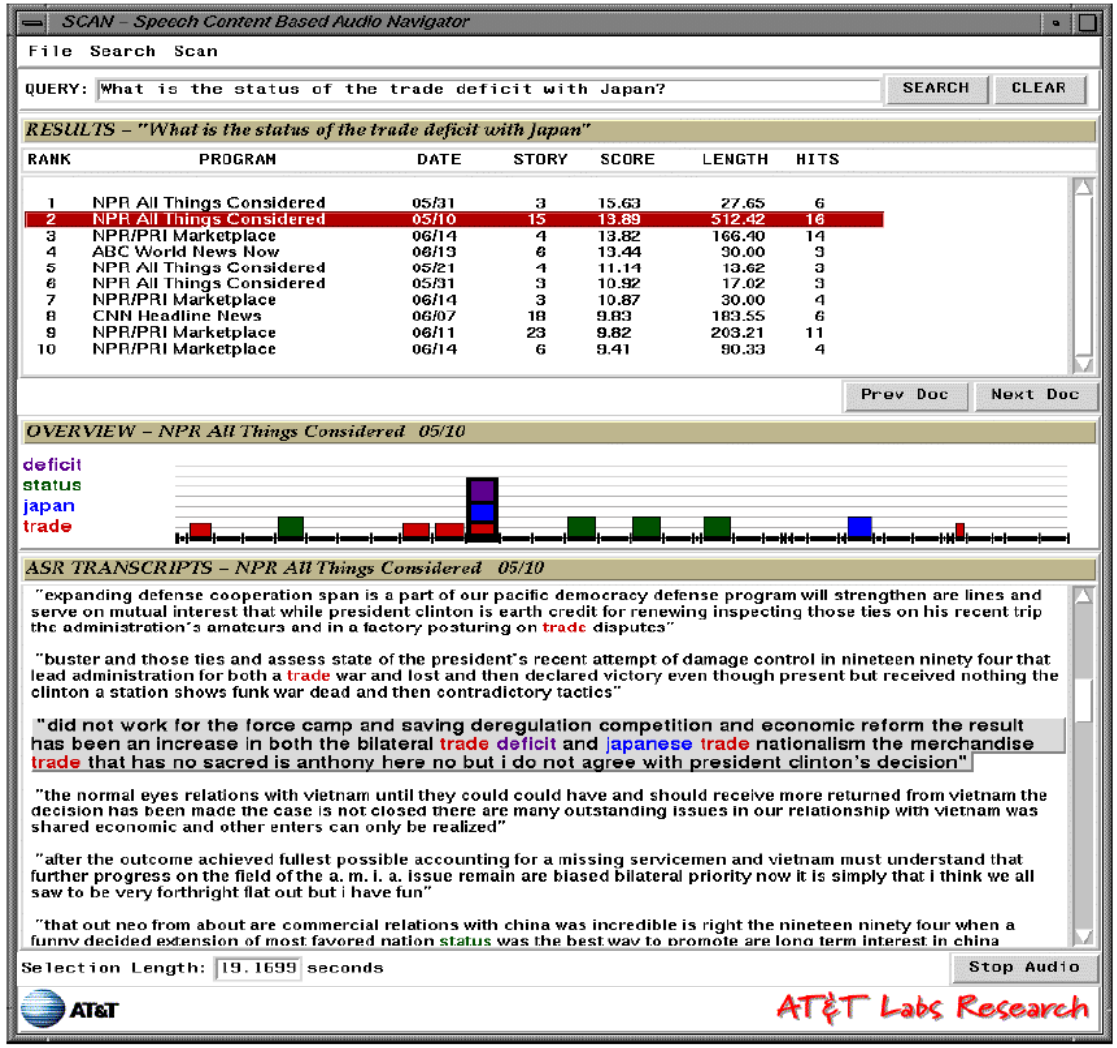
The Informedia System at CMU

- Video Analysis and Content Extraction (VACE)
  - http://www.informedia.cs.cmu.edu/





AT&T *SCAN* System

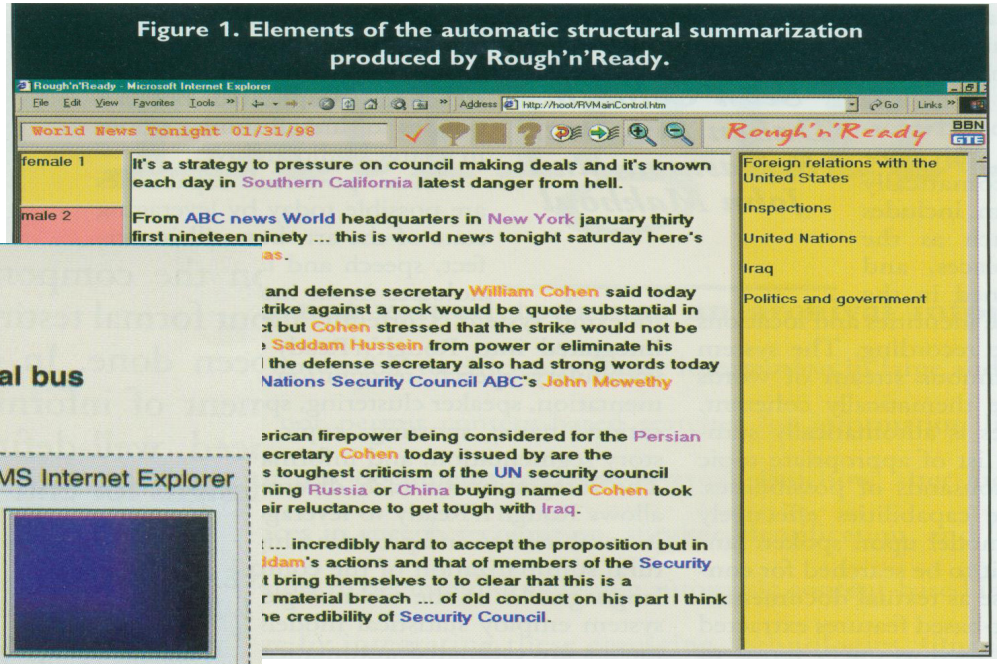


Design and evaluate user interfaces to support retrieval from speech archives

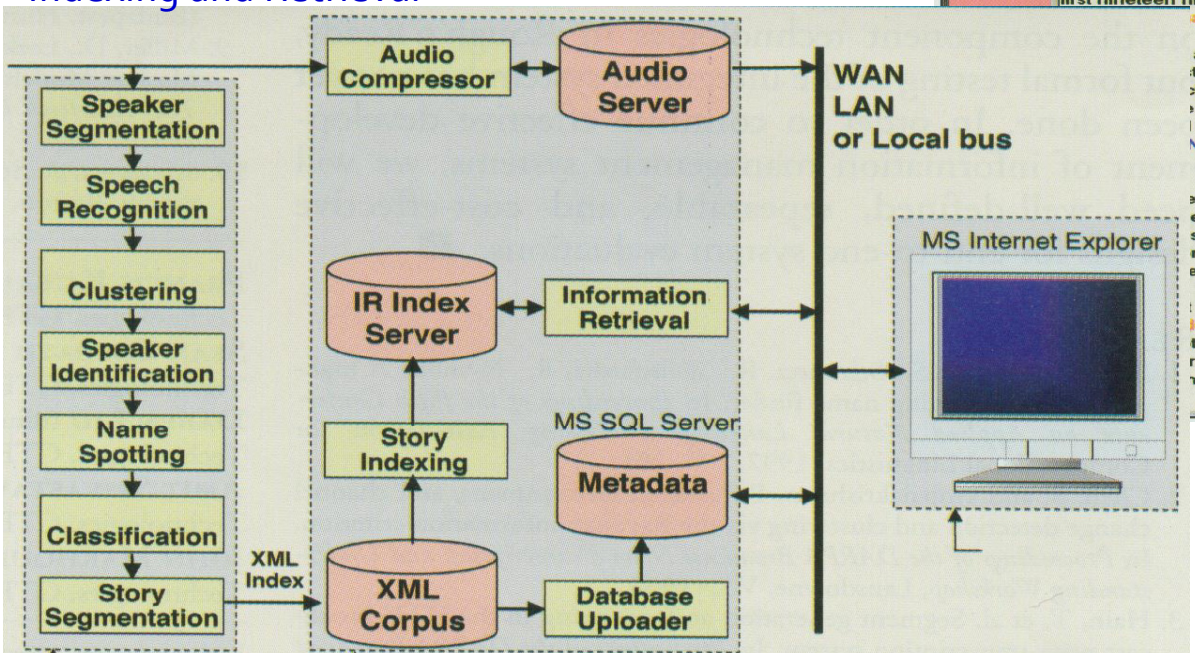
Julia Hirschberg,Fernando Pereira, Amit Singhal et al., "SCAN: designing and evaluating user interfaces to support retrieval from speech archives," SIGIR 1999

BBN *Rough'n'Ready* System

Automatic Structural Summarization for Broadcast News



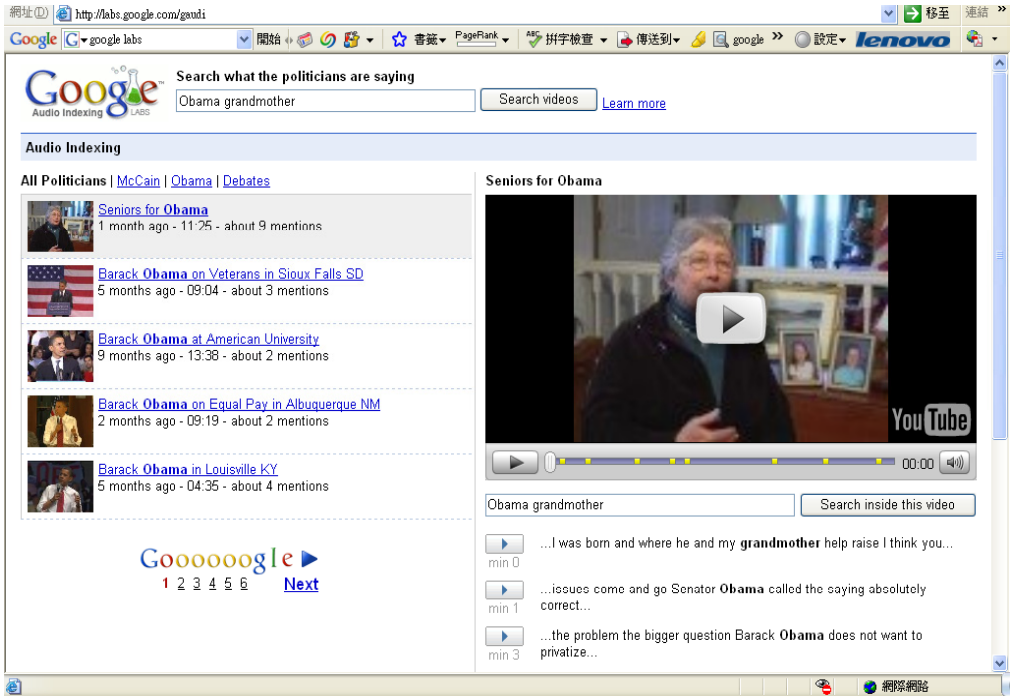
Distinguished Architecture for Audio Indexing and Retrieval



Google Voice Search

Google-411:
Finding and connecting to local business

Google Audio Indexing:
Searching what people are saying inside YouTube videos
(currently only for what the politicians are saying)



Hold the Phone: It's Google Voice and It's Free

Posted Mar 16, 2009

Google last week released Google Voice, an application offering a number of features for the telecommunications space.

Among its offerings, the service allows users to place domestic calls for free from a PC, place low-cost calls internationally, switch phones during a call, record conversations, share voicemails, and transcribe voicemails to email or SMS with automatic recognition technology.

Google Voice is built on GrandCentral, a service that Google bought in the summer of 2007 and allows a user to tie all of her phones to one phone number. According to an email from Sara Jew-Lim, a member of the global communications team for Google, the automatic recognition engine was developed in-house and is the same engine used in Goog411, Google's business directory service, and in its mobile voice search products.

The launch of Google Voice is just another sign, like the launch of the Google mobile operating system (OS), Android phone, or Goog411, that Google is serious about making a name for itself in the telecommunications space. The move also suggests that Google is looking to include new modalities, like voice, in its search capabilities.

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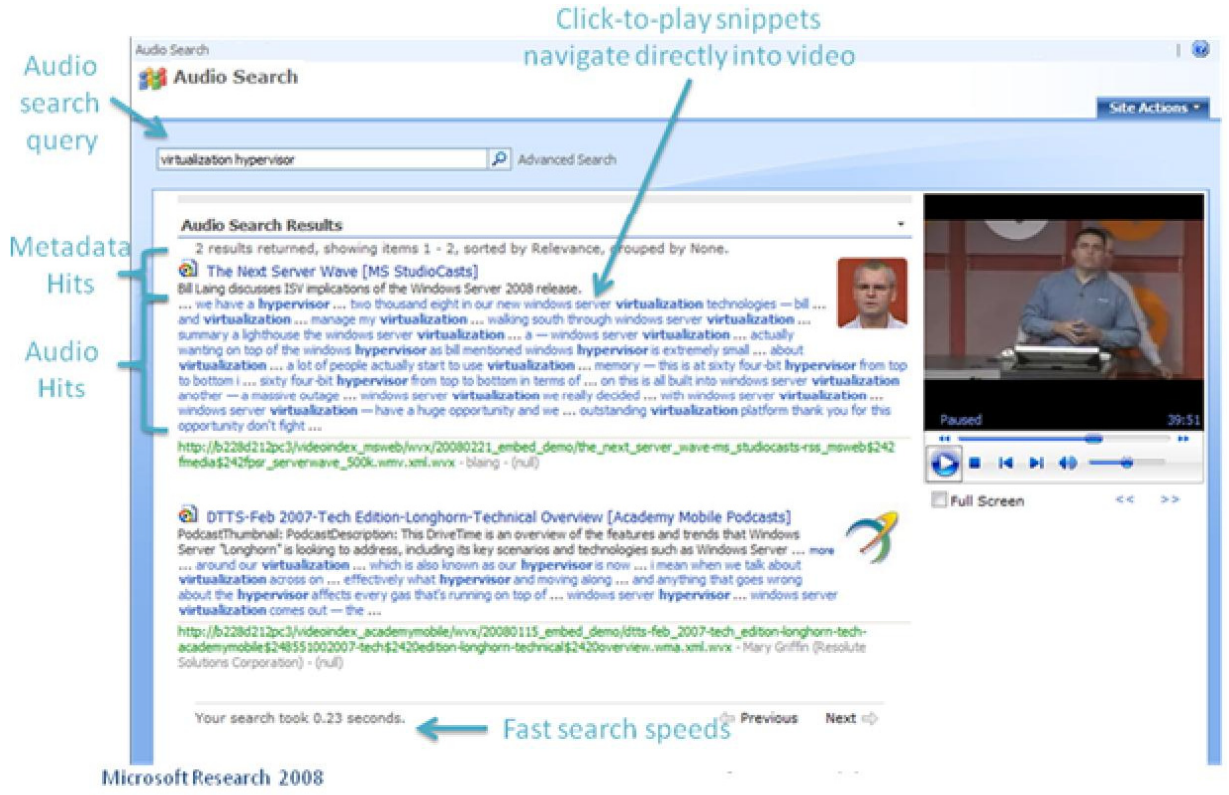
Microsoft Research Audio-Video Indexing System (MAVIS)

- MAVIS uses speech recognition technology to index spoken content of recorded conversations, like meetings, conference calls, voice mails, lectures, Internet videos



http://research.microsoft.com/en-us/projects/mavis/

Microsoft Launches Mobile Voice Search Application

Microsoft this week launched Microsoft Recite, a voice search application for Windows mobile devices.

The offering—which Microsoft calls "search technology for your voice"—allows users to capture, search, and retrieve spoken notes and reminders via voice commands.

"The idea behind Recite was to help make a busy mobile lifestyle easier by providing [users] an easy method for remembering, searching, and retrieving mental notes and reminders from their mobile phones using the sound of their voice—without navigating menus or tapping out text," writes Stathis Papaefstathiou, product unit manager at Microsoft, in an email to Speech Technology. "Just speak your mental note to store it and later, when you need the information, just search and retrieve the remembrance using your voice."

Microsoft Recite can store hundreds of spoken notes and uses voice pattern matching, which is based on speaker inflection, to analyze speech and search recordings.

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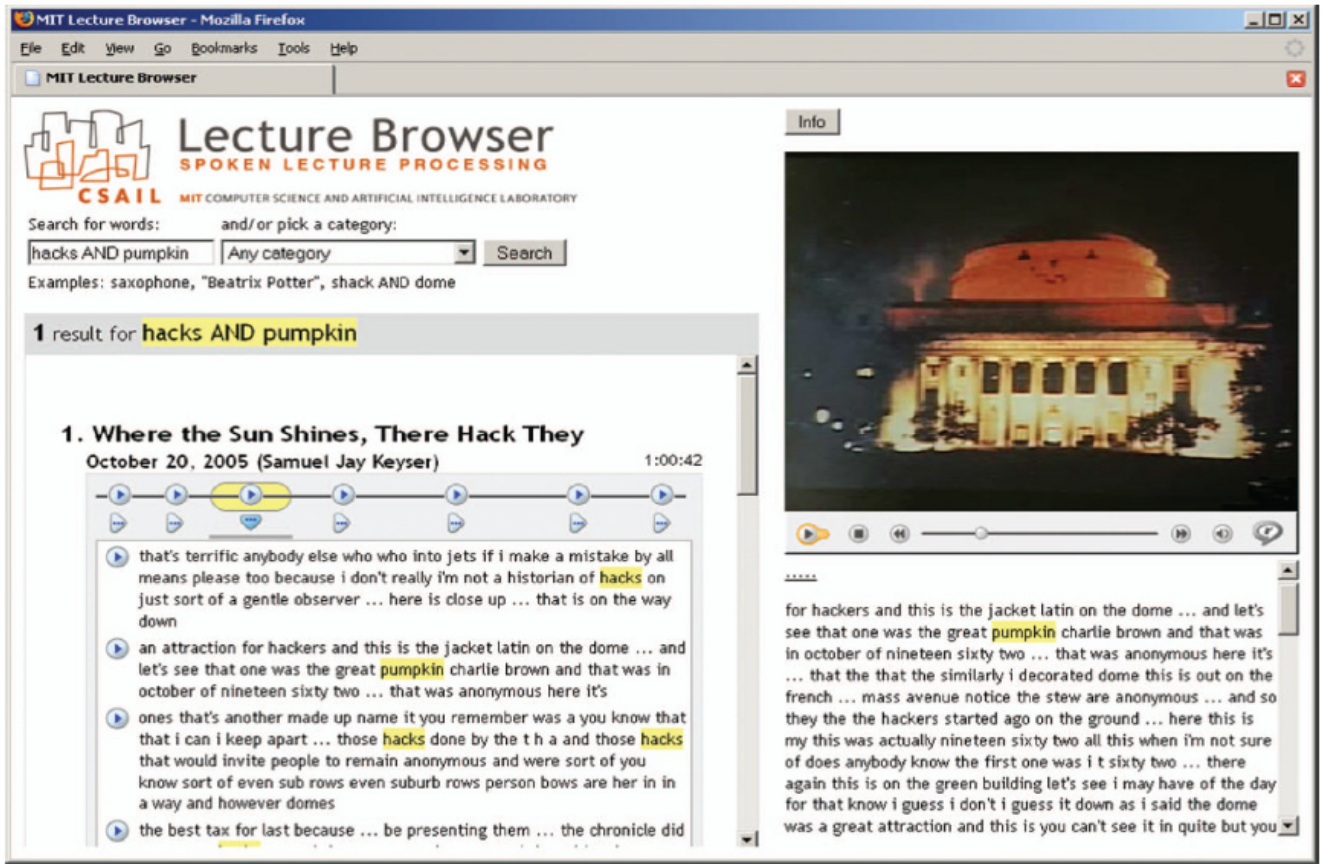
MIT Lecture Browser

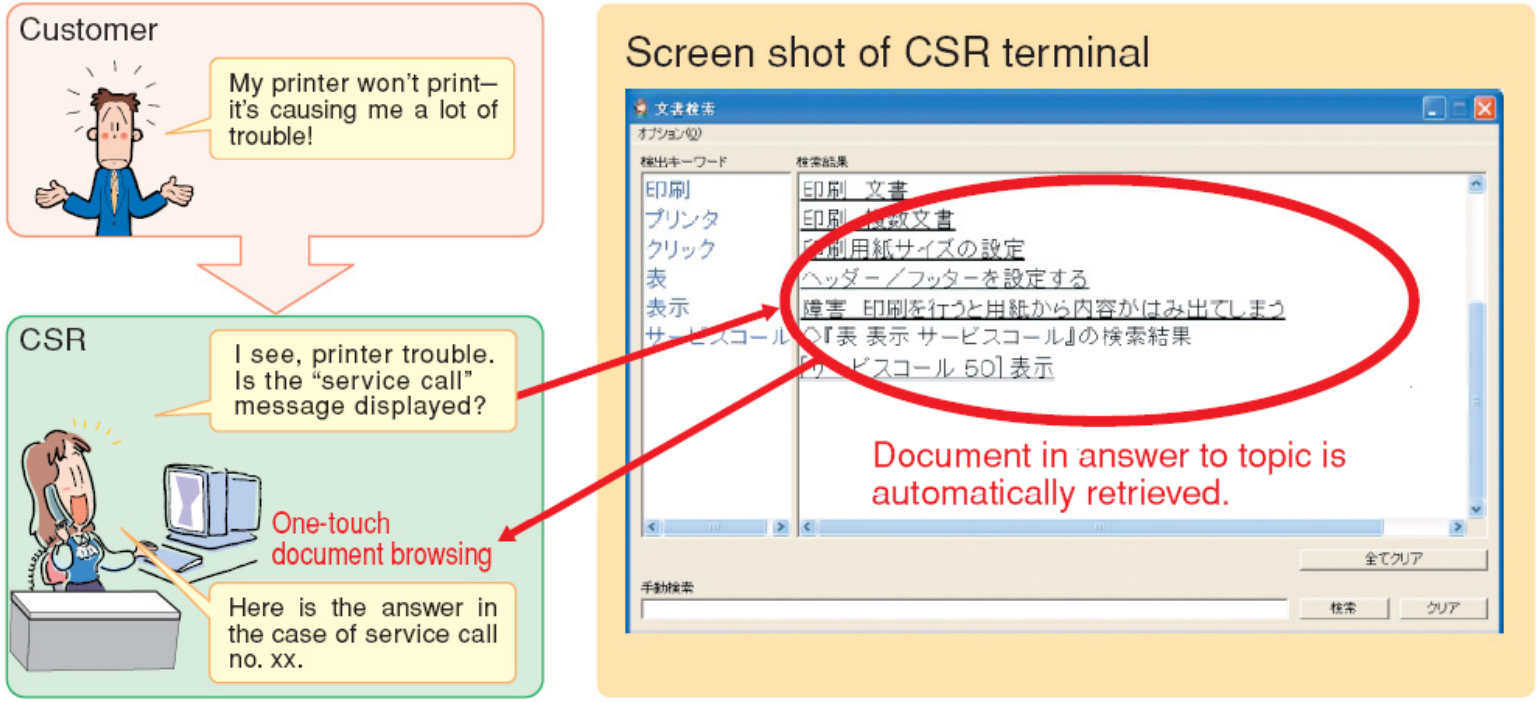
- Retrieval and browsing of academic lectures of various categories



http://web.sls.csail.mit.edu/lectures

NTT Speech Communication Technology for Contact Centers

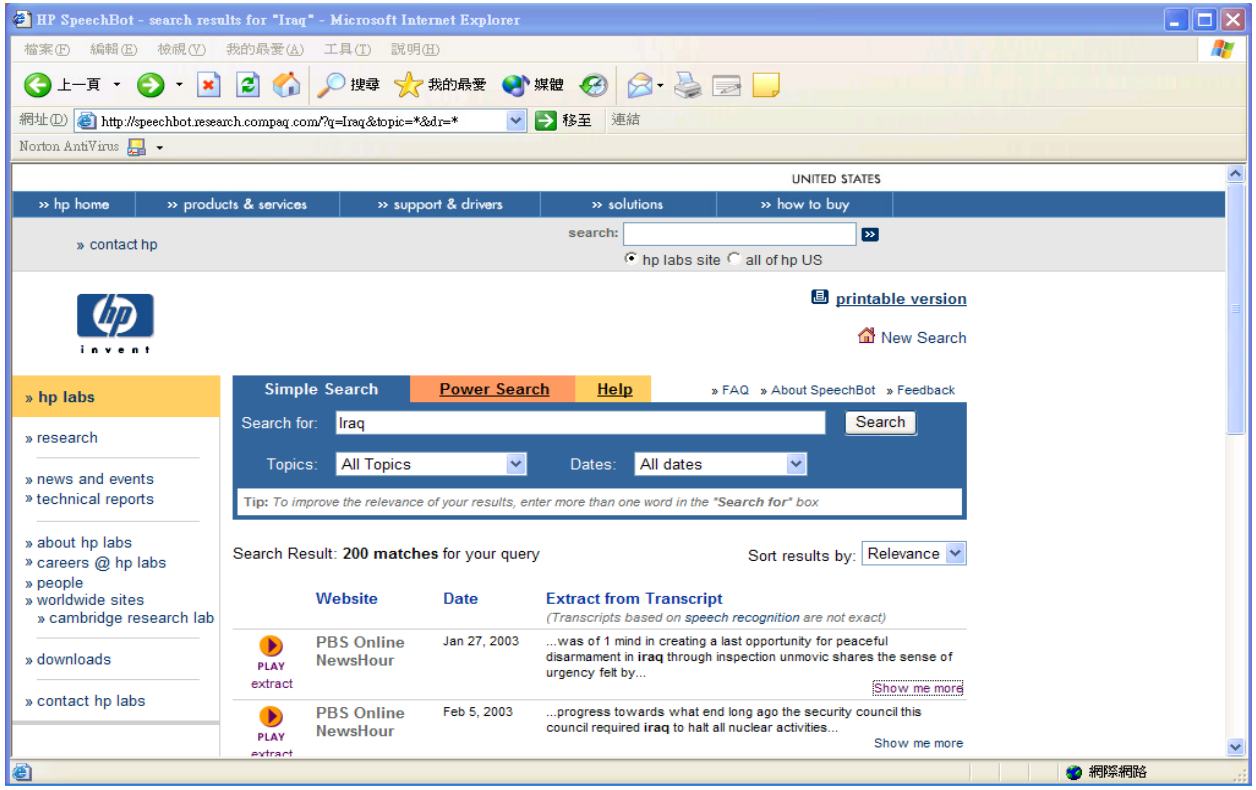
Automatic document-retrieval by speech recognition



– CSR: Customer Service Representative

SpeechBot Audio/Video Search System at HP Labs

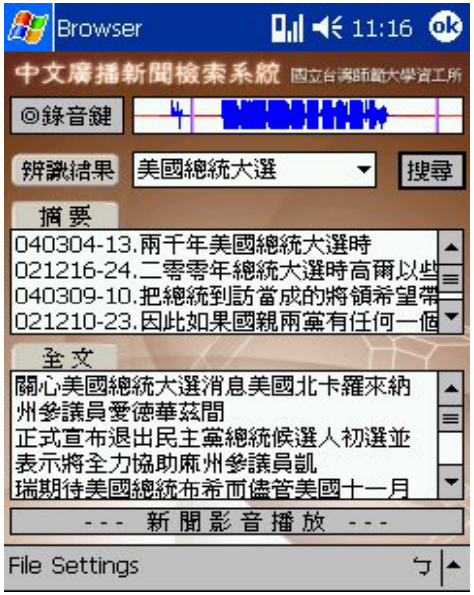
- An experimental Web-based tool from HP Labs that used voice-recognition to create seachable keyword transcripts from thousands of hours of audio content



Some Prototype Systems Developed in Taiwan

NTU Broadcast News Retrieval and Browsing System (Prof. Lin-shan Leee), 2004~

NTNU PDA Broadcast News Retrieval System (Dr. Berlin Chen), 2003~2004



Detailed Statistics of the TDT-2 Collection

No. of spoken documents	2,265 stories, 46 hrs of audio		
No. of distinct text test queries	16 Xinhua text stories (Topics 20001~20096)		
	Min.	Max.	Mean
Document length (characters)	23	4841	287
Query length (characters)	183	2623	533
No. of relevant documents per query	2	95	29

WTM vs. Other LMs

- If the context window for modeling the vicinity information of WTM is reduced to one word (S=1), WTM can be either degenerated to:
  - A unigram model as the latent topic number K is set to 1
  - Or, viewed as analogous to a bigram model (as K=V), or an aggregate Markov model (as 1<K<V)
- WTM is also close in spirit to the word class based model (WCBM) as well, by relating the latent topics of the former to the word classes of the latter
  - WTM differs from WCBM in that WTM disregards word order information and leverages word co-occurrence statistics from longer text spans
  - Whereas most of WCBM approaches are based purely on modeling word bigram sequences

WTM vs. IBM Translation Model (1/2)

- WTM

$$P_{\mathrm{WTM}}(Q|D)=\prod_{i=1}^{L}\left[\sum_{w_j\in D}P_{\mathrm{WTM}}\left(w_i\middle|\mathrm{M}_{w_j}\right)P(w_j|D)\right]=\prod_{i=1}^{L}\left[\sum_{w_j\in D}\sum_{k=1}^{K}P(w_i|T_k)P\left(T_k\middle|\mathrm{M}_{w_j}\right)P(w_j|D)\right]$$

$$=\prod_{i=1}^{L}\left[\sum_{k=1}^{K}P(w_i|T_k)\sum_{w_j\in D}P\left(T_k\middle|\mathrm{M}_{w_j}\right)P(w_j|D)\right]$$

$$=\prod_{i=1}^{L}\left[\sum_{k=1}^{K}P(w_i|T_k)\hat{P}(T_k|\mathrm{M}_D)\right]$$

⇐ WTM has the same document ranking form as PLSA/LDA

  - Both unsupervised and supervised training

- IBM Translation Model

$$P_{\mathrm{IBM}}(Q|D)=\prod_{i=1}^{L}\left[\sum_{w_j\in D}P_{\mathrm{TRANS}}(w_i|w_j)P(w_j|D)\right]$$

  - Supervised training (e.g., using title-document corresponding relationships)

WTM vs. IBM Translation Model (2/2)

- Compare WTM with IBM Translation Model (IBM-1)
  - Supervised training: using outside training query exemplars

WTM (MIX-8)		WTM (MIX-32)		IBM-1	
TD	SD	TD	SD	TD	SD
0.689	0.617	0.735	0.686	0.700	0.645

WTM vs. PLSA: Language Model Adaptation

- Tested on broadcast news transcription task

		CER (%)		PP	
Baseline (Background Trigram Model)		15.22%		752.49	
		WTM		PLSA	
Adaptation Corpus	No. Latent Topic	CER (%)	PP	CER (%)	PP
Texts	16	14.77	566.10	14.83	588.51
	32	14.69	553.88	14.73	571.46
	64	14.60	540.62	14.58	552.80
	128	14.44	524.15	14.53	527.41
	256	14.38	508.29	14.47	510.20
Automatic Transcripts	16	14.87	574.60	14.99	591.21
	32	14.90	568.76	14.92	580.80
	64	14.85	564.56	14.82	569.93
	128	14.81	563.25	14.87	562.45
	256	14.96	567.53	14.92	565.85