

# An interactive timeline for Speech Database Browsing

Benoit Favre

SRI – STAR Lab Seminar Series  
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# Who am I?

- Benoit Favre
  - PhD “Automatic Speech Summarization”, at LIA
  - Postdoc at ICSI until March 2008 (sentence segmentation)
  - favre@icsi.berkeley.edu
- Former lab: *Laboratoire Informatique d’Avignon* (LIA)
  - <http://www.lia.univ-avignon.fr> – English coming soon
  - Speech group (~10 permanent and 20 PhD students)
    - Dialogue systems (Renato De Mori)
    - Speaker id/diarization (Alize toolkit, Jean-François Bonastre)
    - STT: French and resource-sparse languages
    - Voice/Language pathologies



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# Outline

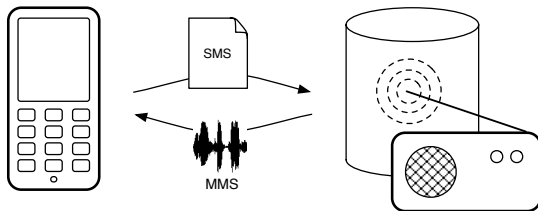
- 1 Introduction
- 2 Speech Database Browsing
  - Context
  - Interactive timeline
- 3 Prototype
  - Demo
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- 4 Conclusion

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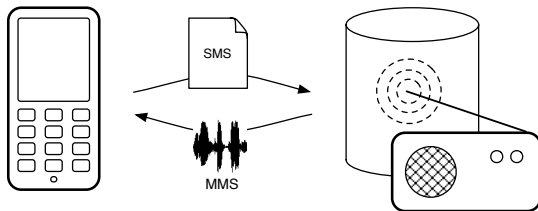
# Application context: spoken information retrieval

- SMS: text based query (eg. “baseball results”)
- Generate a **spoken summary** of the news
- Audio delivered by MMS



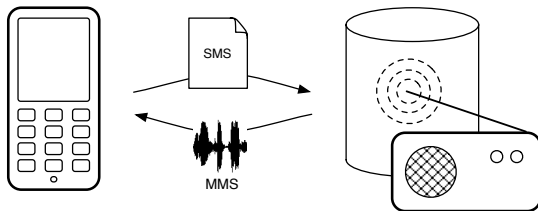
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# Approaches

- Knowledge rich
  - Database of information items
  - Text generation
  - Speech synthesis
- Open domain (data driven)
  - Collect broadcast news (or/and other sources)
  - Select informative segments (sentences)
  - Segment playback
- Hybrid
  - Fill the knowledge base from collected BN
  - Contextualize the segment playback with speech synthesis
  - ...

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# From text to speech summarization

- Rich transcription
  - Acoustic segmentation, diarization
  - Speech-to-text transcript
  - Information extraction
- Summarization by sentence selection
  - Impact of STT errors (and other RT errors)
  - Require accurate sentence boundaries
  - Perception of “cut-and-paste”
- Audio only features
  - Speaker state and identity
  - Emphasis
  - Speech quality

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# My work at LIA

- Setup a rich transcription processing chain
  - Speeral toolkit for STT
  - Alize platform for diarization
  - Word lattice based NE tagging
  - CRF based Sentence Segmentation
- Build and evaluate a text summarization system
  - MMR-LSA summarization system
  - Document Understanding Conference (DUC) evaluation
  - Impact on audio: simulate ASR
- Study possible user interactions
  - Speech database browsing
  - Interactive timeline
- Next PhD student: Audio only features



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# Constraints

- Continuous audio archives (BN, Meetings...)
  - “Decades” of recordings
  - Multiple sources
- Why isn't “raw” summarization suitable?
  - Reintroduce context
  - Track the source
- Information retrieval → exploration
  - Structure discovery
  - Temporal vs Topical structure
- Speech is bound to time
  - Wait to hear more
  - No static representation

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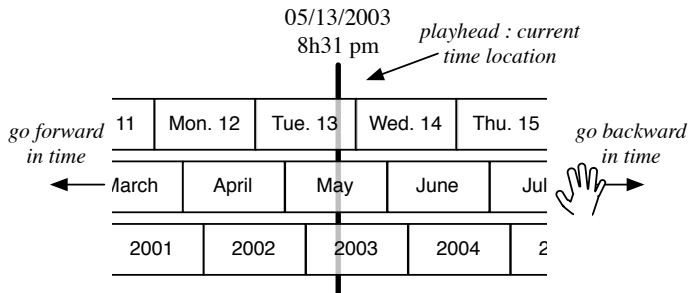
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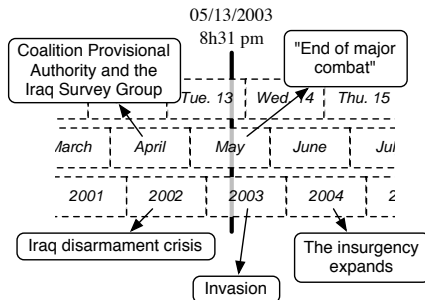
# Multiscale playhead

- Synchronous multiscale timeline
  - Slices representing years, months, days...
  - Dragging one slice synchronize the others
  - Easy “time travel” at every granularity
- Annotation



# Multiscale playhead

- Synchronous multiscale timeline
- Annotation
  - Need for structure information
  - Topic/Event labels
  - Example from Wikipedia (Iraq war)

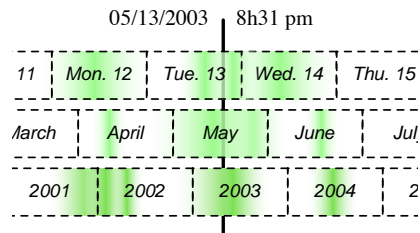


# Automatic Annotation

- Constraints
  - Reflect a user query
  - Highlight regions of interest
  - Interactive
- Approach
  - Relevance density (information retrieval)
  - Anchorage points (automatic summarization)

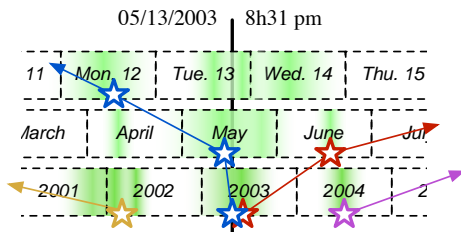
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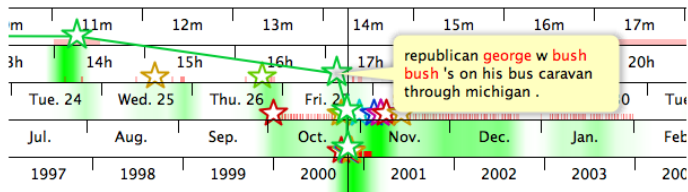
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Demo

# Screen capture (and demo if lucky)

Query: [Submit](#)Timeline ([Stop playing](#))

Oct 27, 2000 5:14:16 PM

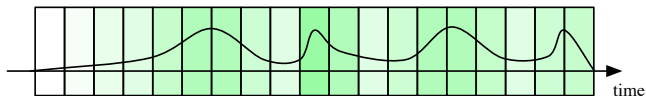
Summary (temporally sorted) - [Play summary \(70s\)](#) - [Download as mp3](#)Key-words : - [bush](#) - [george](#) - [al](#) - [gore](#) - [jeb](#) - [governor](#) - [president](#) - [bit](#) - [winner](#) - [brother](#)

# Information density

- $n$  highest-relevant sentences
- Okapi IR model [*Robertson et al*],

$$\frac{P(R|D, Q)}{P(\bar{R}|D, Q)} \sim \prod_w \frac{P_w(1 - \bar{P}_w)}{\bar{P}_w(1 - P_w)} \sim \sum_w \log f(w, D, \Lambda)$$

- Stop-word removal
- Context modeling (interpolation with neighboring sentences)



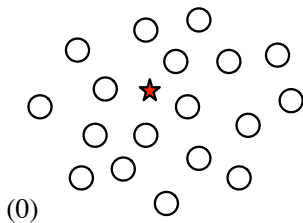


# Anchorage points: Maximal Marginal Relevance (MMR)

- Select the  $m$  highest-representative sentences
- Greedy sentence selection [Goldstein et al]

$$(\hat{\mathbf{s}})_{k+1} = \operatorname{argmax}_{\mathbf{s}_i \notin \operatorname{mmr}_k} \left( \lambda \operatorname{coverage}(\mathbf{s}_i, \mathbf{q}) - (1 - \lambda) \max_{\mathbf{s}_j \in \operatorname{mmr}_k} \operatorname{redundacy}(\mathbf{s}_i, \mathbf{s}_j) \right)$$

- Duration based stopping criterion

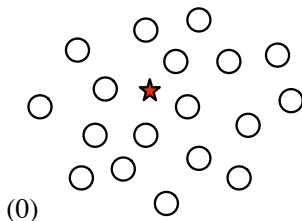


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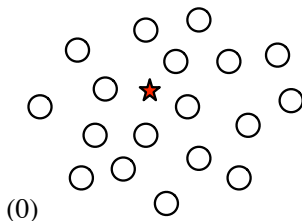


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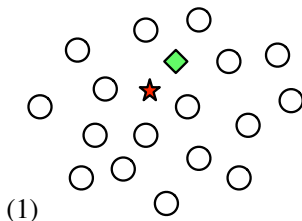


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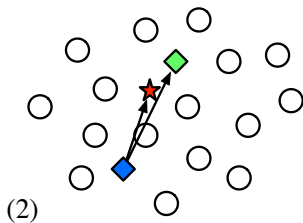


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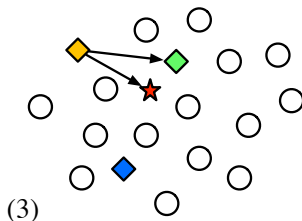


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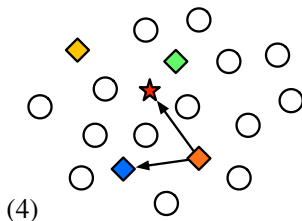


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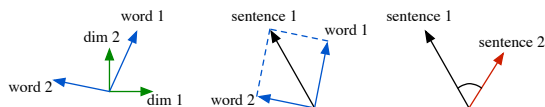


# Latent Semantic Analysis (LSA)

- Similarity between sentences (Generalized VSM)

*“Chris purchased a BMW”*

*“Mr. Jones bought a car”*



- Cooccurrence matrix (lexicon  $\times$  lexicon, sliding window)

- Train on a big corpus [*Peters et al*]
- Reduce the matrix by SVD,  $X^* = U\Sigma_k V^T$
- Project sentences,  $s^* = \Sigma_k^{-1} U^T s$
- Cosine similarity,  $\text{cosine}(a, b) = \frac{a \cdot b}{|a||b|}$

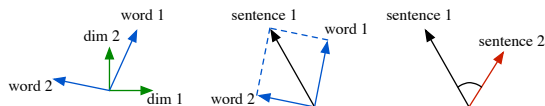


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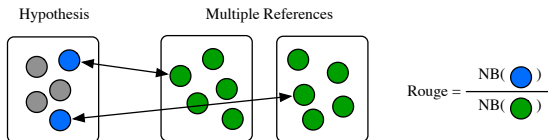
# Performance

- ESTER 2005 Evaluation (French BN)

<b>Task</b>	<b>Perf.</b>	<b>Measure</b>
Speech detection	99	$F_1$ -m
Speech+Music det.	92	$F_1$ -m
Music detection	54	$F_1$ -m
Diarization	19	%err
STT	22	WER
Sentence Segmentation	68	$F_1$ -m
Named Entities	63	$F_1$ -m

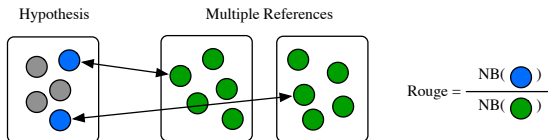
# Document Understanding Evaluation

- Multidocument, user oriented, text summarization
  - 50 topics, 25 newswire documents per topic
  - Human judgments (linguistic quality and responsiveness)
  - Automatic judgments (not a trivial at all)
- ROUGE
  - Recall in  $n$ -grams with a set of hand written summaries
  - Correlated with Human judgements



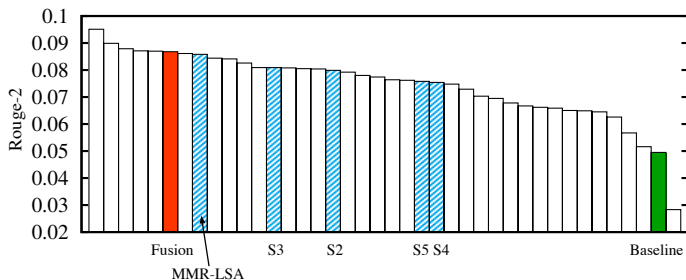
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# DUC Results on text documents

- LIA submission at DUC 2006, 2007
  - Fusion of up to 7 (sentence ranking) systems
  - A lot of heuristics, linguistic pre/post processing



# Simulating a spoken content

- Simulated STT on DUC documents
  - Uniform random errors
  - Worst case for a summarizer
- Conditions
  - Noisy: word errors appear in the summary
  - Cleaned: only sentence selection is affected

Degradation	WER	R2 Noisy		R2 Cleaned	
None	0.0	0.08407		0.08407	
Replace OOV	1.0	0.08255	-1.8%	0.08318	-1.0%
Remove OOV	1.0	0.08283	-1.4%	0.08279	-1.5%
Replace NE	10.4	0.06741	-19.8%	0.08029	-4.4%
Remove NE	10.4	0.07211	-14.2%	0.07991	-4.9%
Random errors	10.0	0.07440	-11.5%	0.08232	-2.0%

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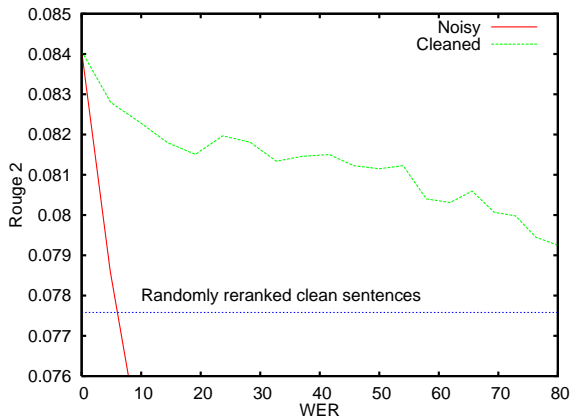
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## Rouge-2 / WER



Head-Baseline:  $Rouge2 = 0.049$

Random-Baseline:  $Rouge2 = 0.055$

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# Conclusion and future work

- Improving speech database browsing
  - Multi-scale interactive timeline
  - Annotation using IR and Automatic Summarization techniques
- Future work
  - Evaluation (ergonomics and relevance)
  - Topical dimension: representation, exploration
  - Label formulation
  - Timeline of discourse → Timeline of events
  - Indirect/Passive querying

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