Semantic structuring of video collections from speech: segmentation and hyperlinking

Anca Şimon

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Inria INVENTEURS DU MONDE NUMÉRIQUE UMR IRISA INSA RENNES cnrs

General context

- Size of world electronic data in 2013: 4.4 ZB (IDC report)
  ~ 9 ZB in 2015

… …

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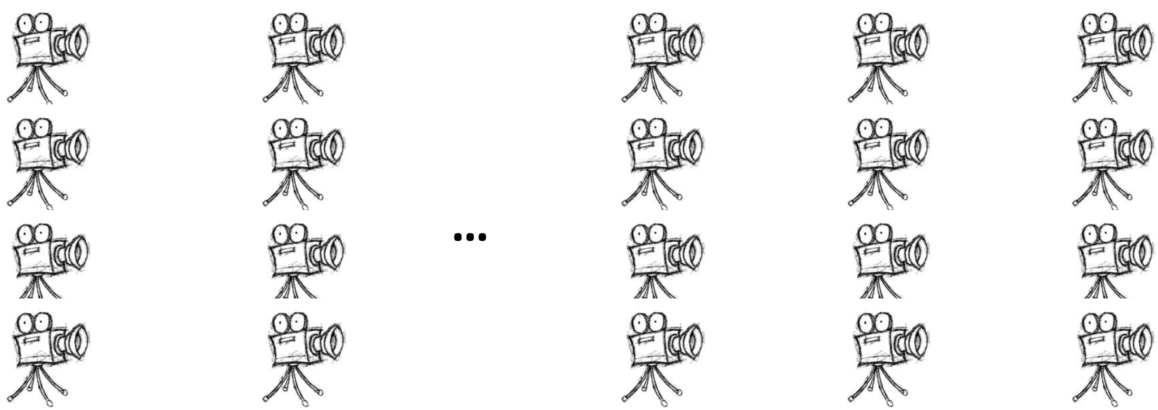
2500 BC
Pyramids of Giza

2015
The day of the defense



~ 2,600 cameras filming 24/7

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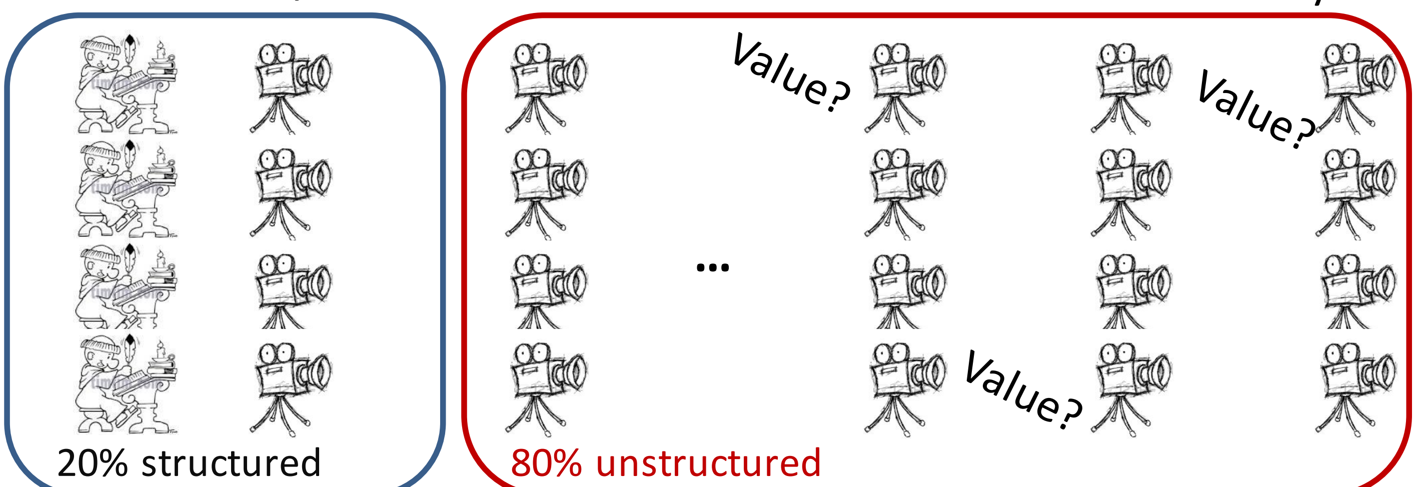

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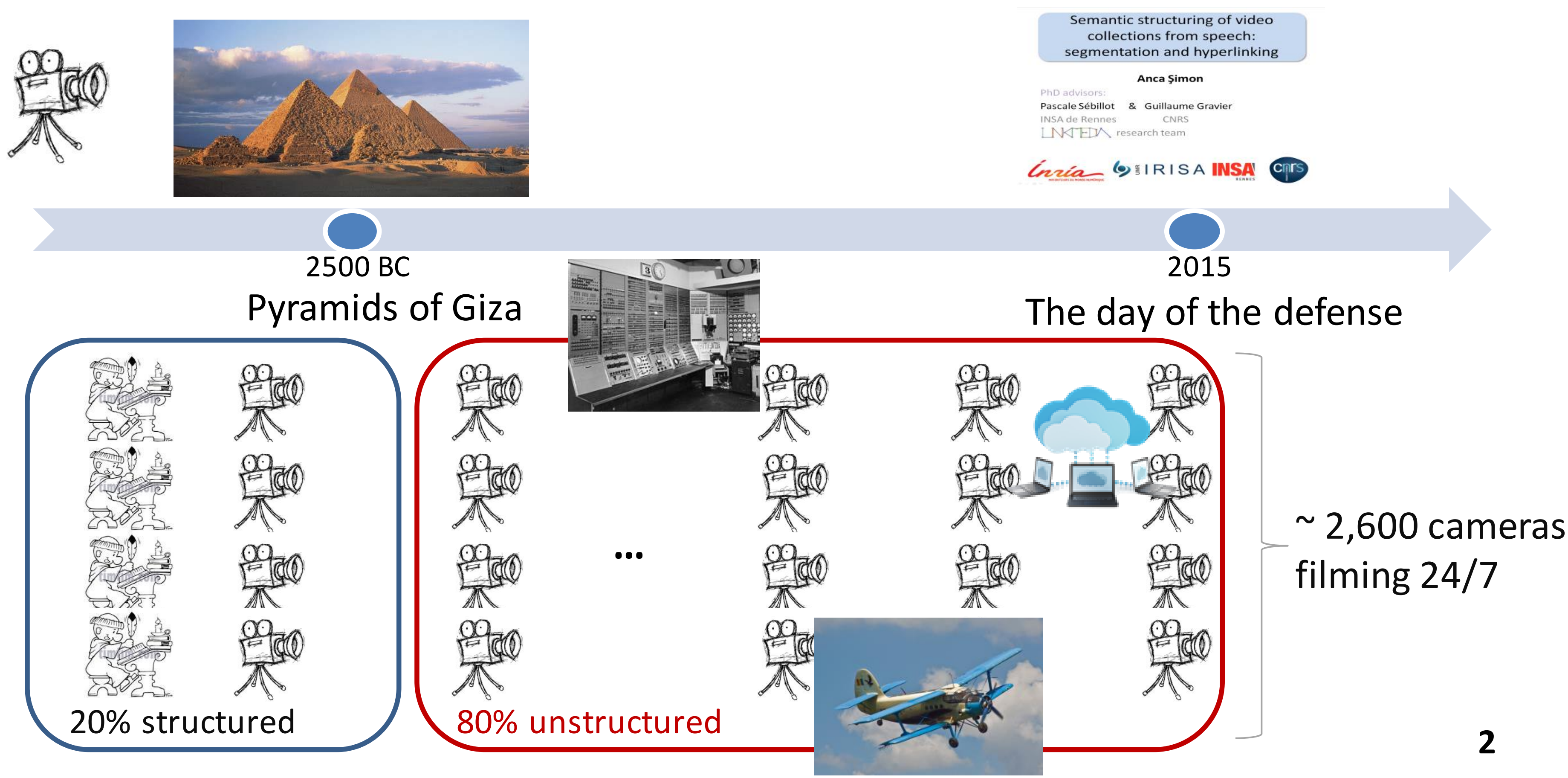
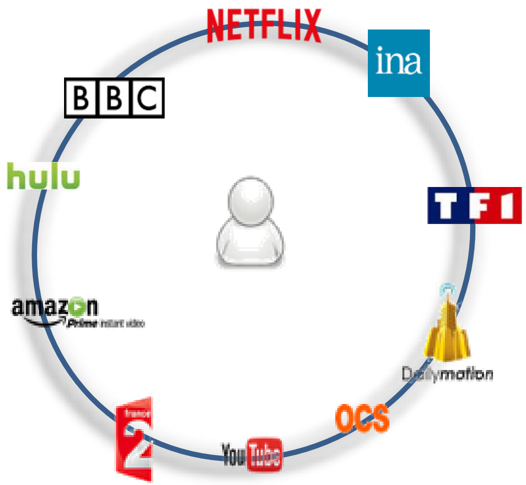


~ 90% of the internet traffic is video data

DIGITAL UNIVERSE

Audiovisual landscape



... INA archive > 5 million hours of programs;

Youtube > 300 hours of videos/minute;

Netflix subscribers > 60 million;

98.3% of French households have at least 1 TV ...

Watch what we want, when we want , on whatever device we want

Challenges:

- user centric model
- unstructured data
- heterogeneous content

Motivating examples

➢ Have access to points of interest in a video

…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2500 BC
Pyramids of Giza

80
Collosseum

1990
Hubble telescope

2015
The day of the defense

Motivating examples

- Study how a topic is presented by different TV shows

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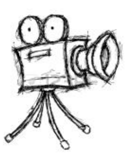
Pyramids of Giza

2015
The day of the defense

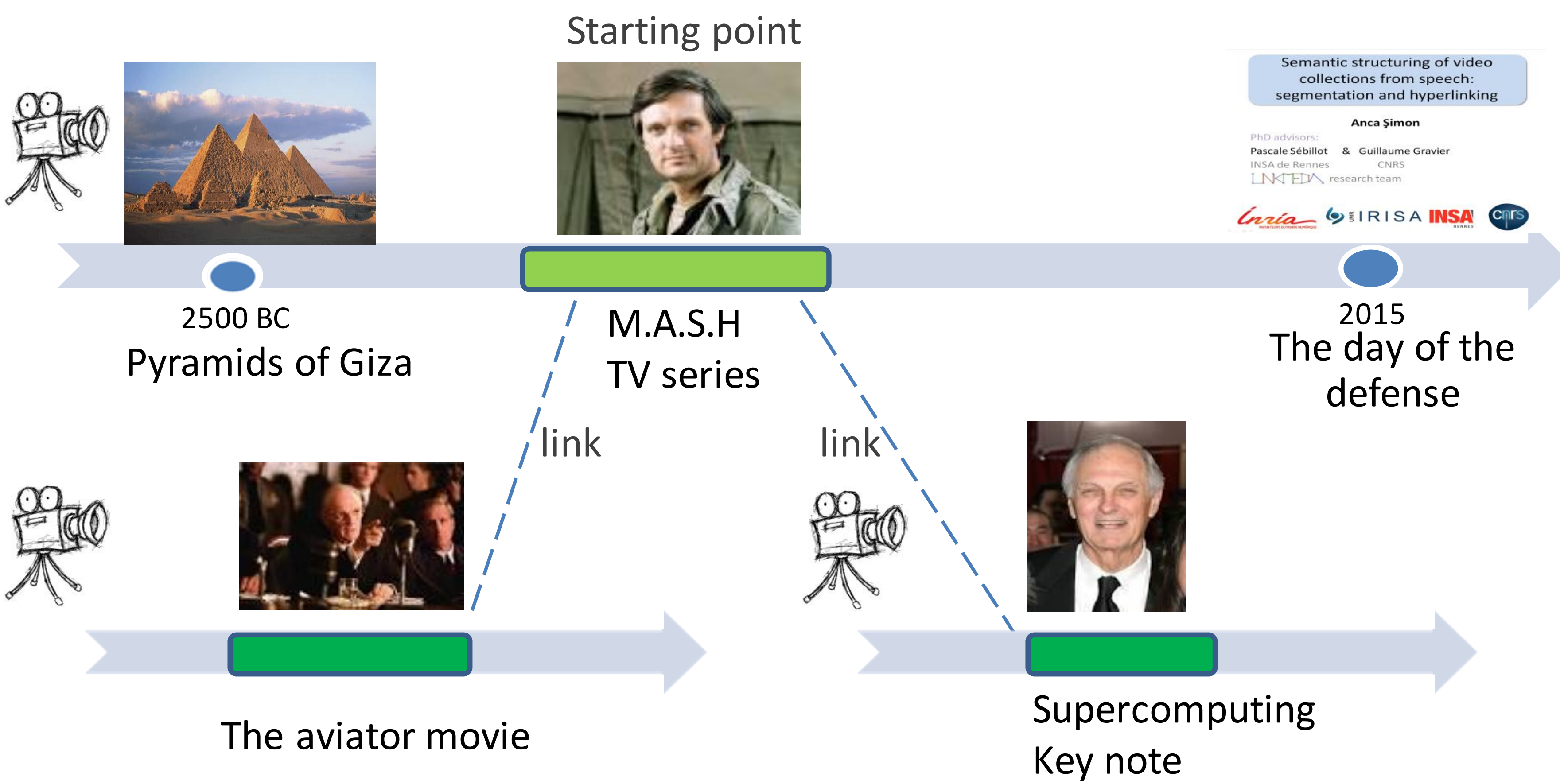


2500 BC
Pyramids of Giza

2015
The day of the defense

Motivating examples

➢ Discover *interesting* and *unexpected* information starting from a video fragment



Research questions

1. How to *structure* audiovisual content?

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Provide automatic and generic techniques for *topical structuring* of TV shows.

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Research questions

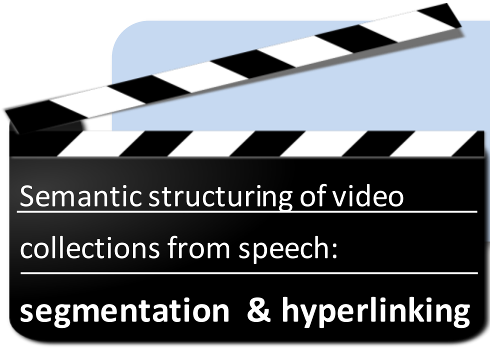
1. How to *structure* audiovisual content?

Provide automatic and generic techniques for *topical structuring* of TV shows.

- challenging data: automatic TV show transcripts (ASR system)

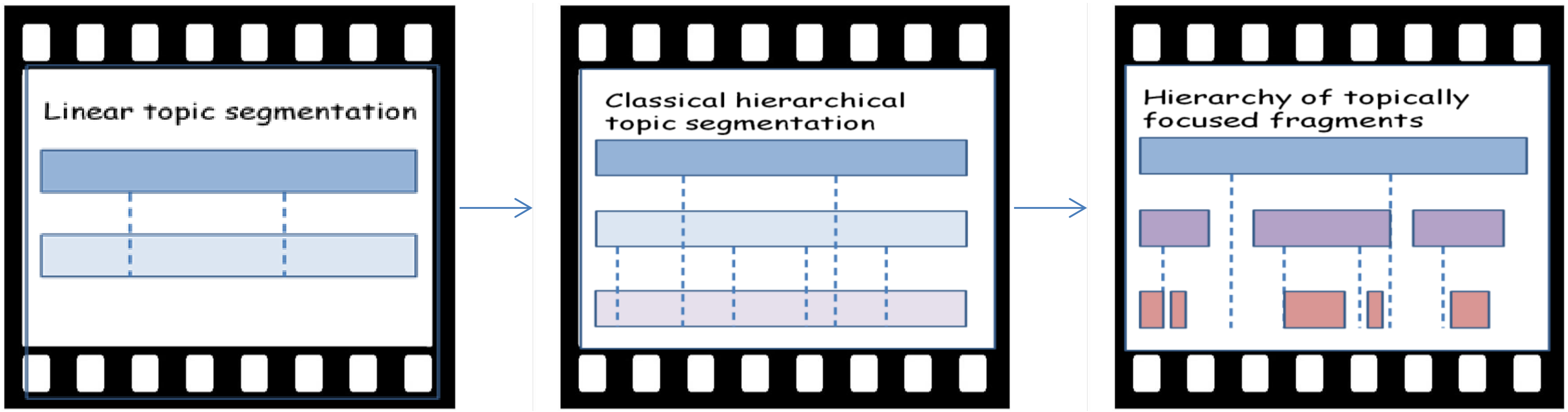
2. How to *exploit* structured content?

Study the implications of the topical structure in the context of *video hyperlinking.*

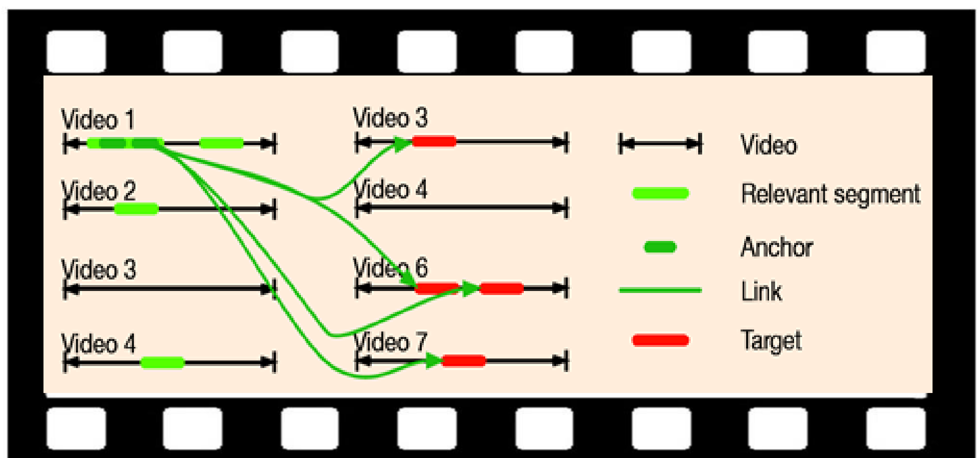


Outline

Thesis contributions in a nutshell



- Anchor and target generation
- Link justification & diversity control



MediaEval benchmark initiative
Search & Anchoring & Hyperlinking

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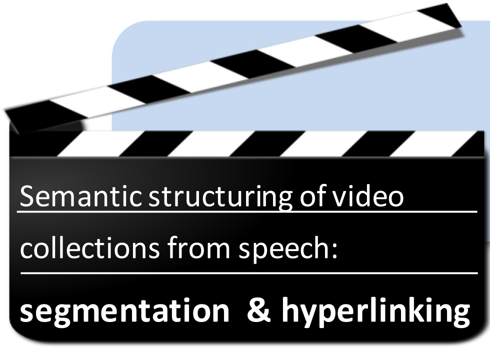

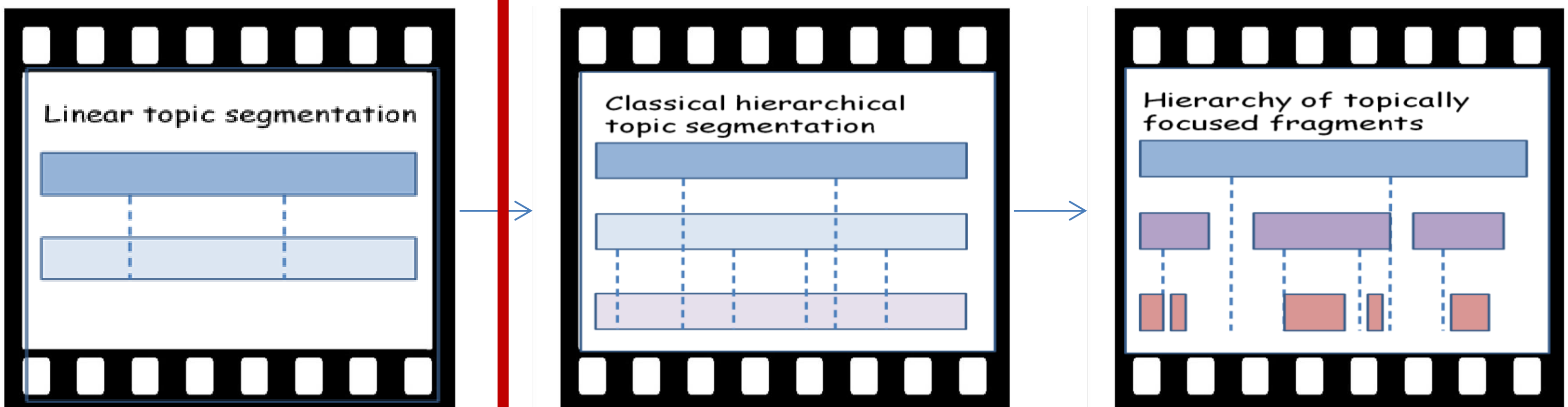

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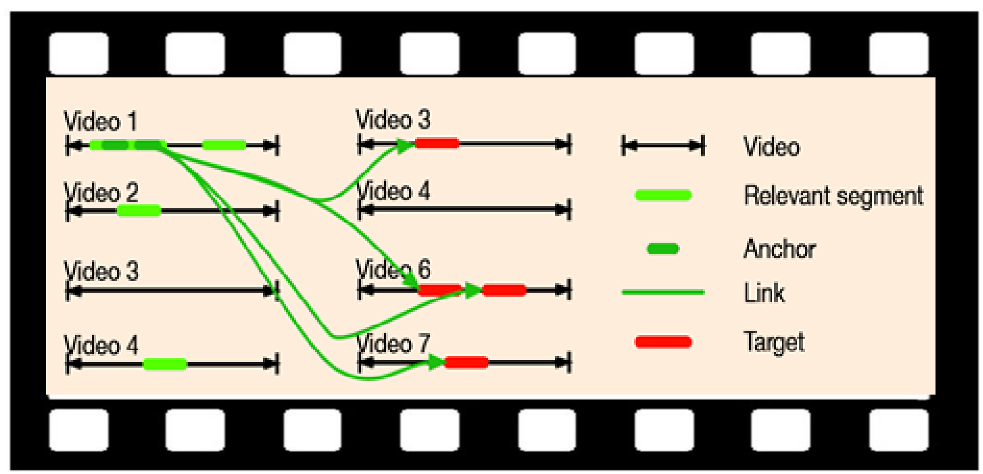

MediaEval benchmark initiative

Search & Anchoring & Hyperlinking

Linear topic segmentation

Divide data into topically coherent segments.

TV show

ASR: textual transcripts of the speech

...	La France de la débrouille	Le soutien scolaire privé	...

<u>Difficulties</u>:

- automatic transcripts ≠ written text
- subjectivity of the concept of topic
- evaluation

<u>Objective</u>:

- provide a solution for topic segmentation that is:
  - \+ generic
  - \+ robust

Topic segmentation
-lexical cohesion-based techniques-

- Exploit words distributions or lexical chains (Hearst 1997, Morris and Hirst 1991)

Key notion: significant change in vocabulary → topic change

1. Local methods: locally detecting the *lexical disrupture*

(Hearst 1997, Hernandez et al. 2002, Ferret et al. 1998, Claveau et al. 2011)

- Drawbacks: selecting the window size; choosing the threshold to decide if a frontier should be placed;

2. Global methods: globally measuring the *lexical cohesion*

(Choi 2000, Reynar 1994, Utiyama et al. 2001, Eisenstein et al. 2008)

- Drawbacks: potential oversegmentation; need the number of segments a priori;

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Can they be reconciled?

Reconciling lexical cohesion & disrupture

Propose :

1. A segmentation criterion that combines both cohesion and disrupture
2. The corresponding algorithm for topic segmentation

(similar concept: Malioutov and Barzilay, 2006)

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Starting point: Utiyama and Isahara (2001) global algorithm TextSeg

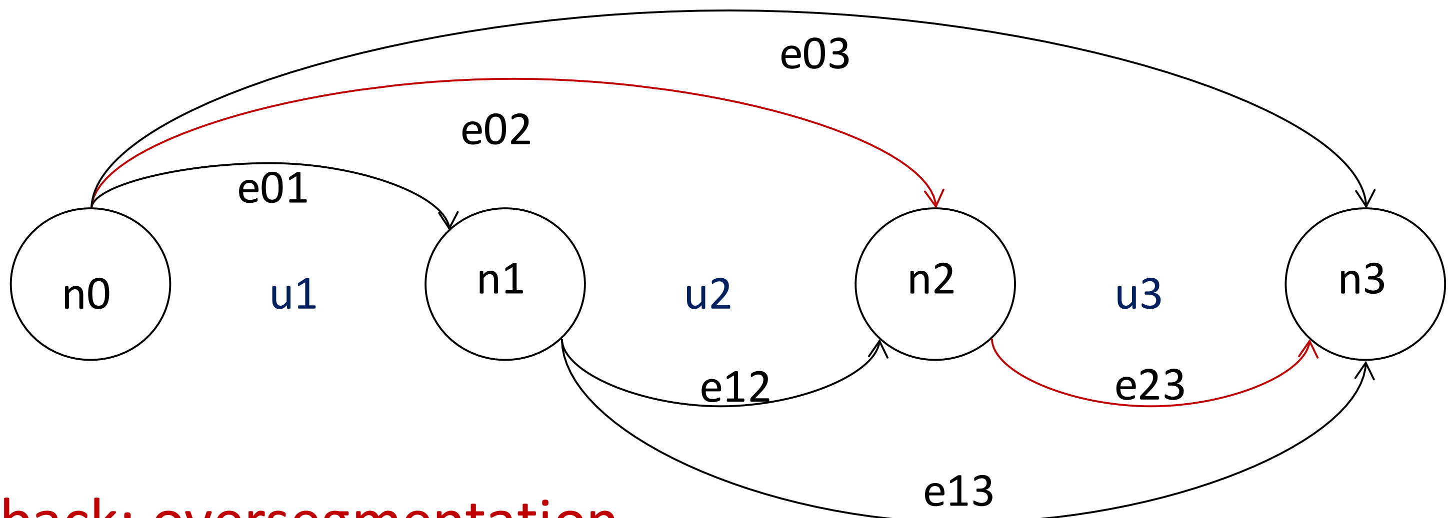
- State-of-the-art
- Domain independent
- Can deal with topical segments of highly varying lengths
- Provides an efficient graph based implementation

Statistical model TextSeg

Find the most probable segmentation among all possible ones, assuming that segments are mutually independent:

$$\hat{S} = arg \max_{S} \sum_{i=1}^{m} \ln(P[W_i|S_i]) - \alpha ln(n)$$

Probabilistic graph-based segmentation:



Drawback: oversegmentation

Introduction of the lexical disruption
MSeg

Assume a Markovian hypothesis between the segments in order to take into account, for each segment, the previous one:

$$\hat{S} = arg \max_{S} \sum_{i=1}^{m} \ln(P[W_i|S_i]) - \lambda \sum_{2}^{m} \Delta(W_i, W_{i-1}) - \alpha ln(n)$$

Disruption computation: Δ

- Cosine similarity, cross probabilities ($P[W_i \mid S_{i-1}]$ and $P[W_{i-1} \mid S_i]$)
- Weights: TF-IDF, Okapi

Experiments

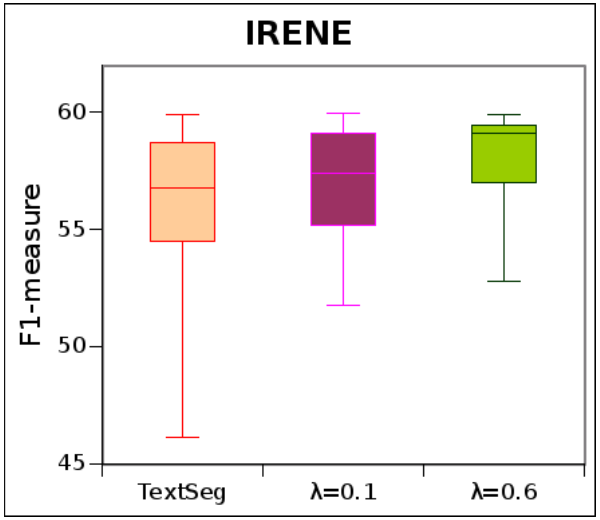
Corpora

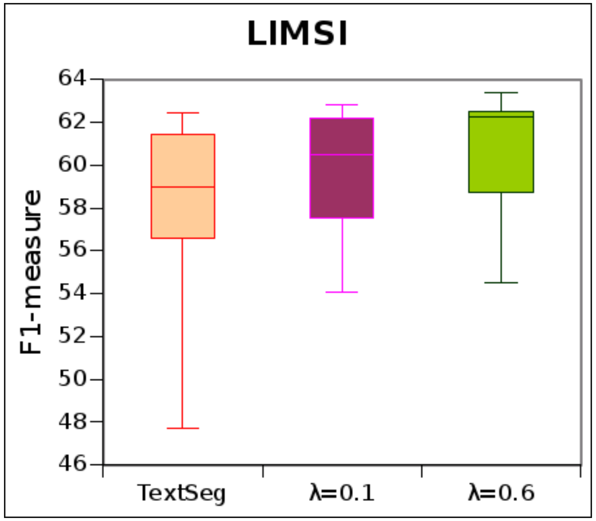
1. TV news transcripts (IRENE and LIMSI ASR systems)
    - 56 news programs (~1/2 hour each, reports duration ~ 2-3 min.)
    - Reduced number of word repetitions
    - IRENE has WER higher that that of LIMSI by ~ 6 points
    - TreeTagger: data lemmatized
    - Groundthruth: manual annotation
2. Choi's artificial data set
3. Medical textbook

Evaluation

- Recall, precision, F1-measure
- Tolerance: 10 sec.

Results: TextSeg vs. MSeg

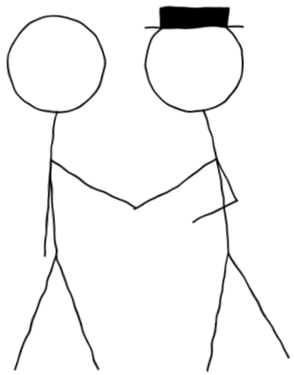




Corpus	F1 gain	Confidence interval 95% TextSeg (λ=0)	MSeg (λ≠0)
IRENE (WER 36%)	0.3	[54.4,57.6]	[56.92,59]
LIMSI (WER 30%)	**0.86**	[56.7,60.2]	[59.44,61.95]
REFERENCE (6)	**0.77**	[70.39,72.29]	[71.7,73.29]
IRENE(6)	0.2	[56.81,60.94]	[59.51,63.43]
LIMSI(6)	**0.5**	[64.27,68.64]	[67.7,71.56]

λ is the importance given to the disruption
α controls the contribution of the prior model

Lessons learned

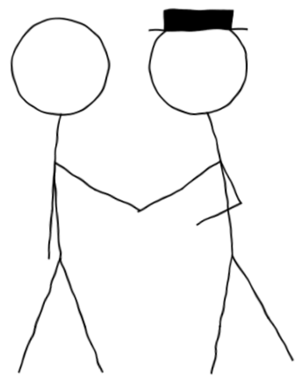


Lexical cohesion

Lexical disruption

- overcome challenges characteristic to local and global methods
- diminish the influence of the prior model
- eliminate wrong hypothesis
- impact of disruption is bigger on longer segments
- automatic transcripts ≠ written text
- automatic transcripts ≠ manual transcripts
- deal with abrupt vs. smooth topic changes
- BoW model looses semantic information

Lessons learned



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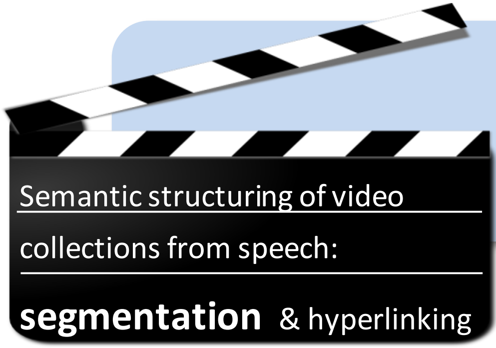

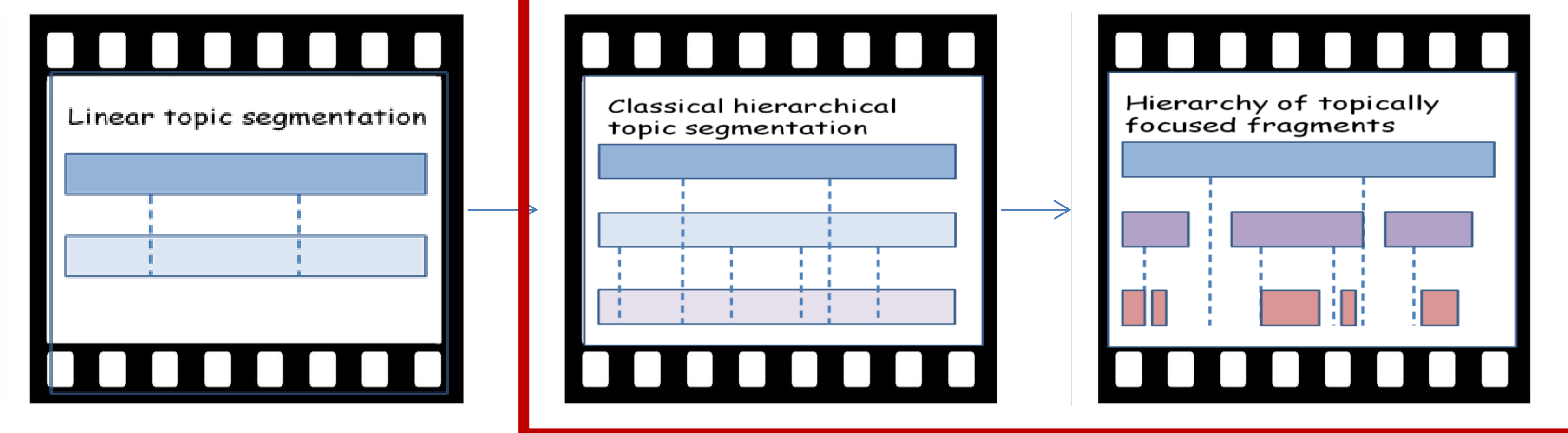

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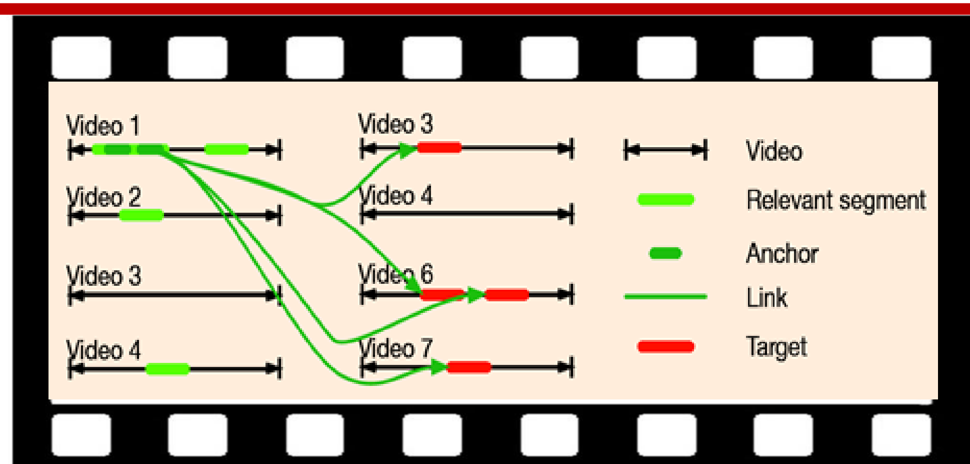

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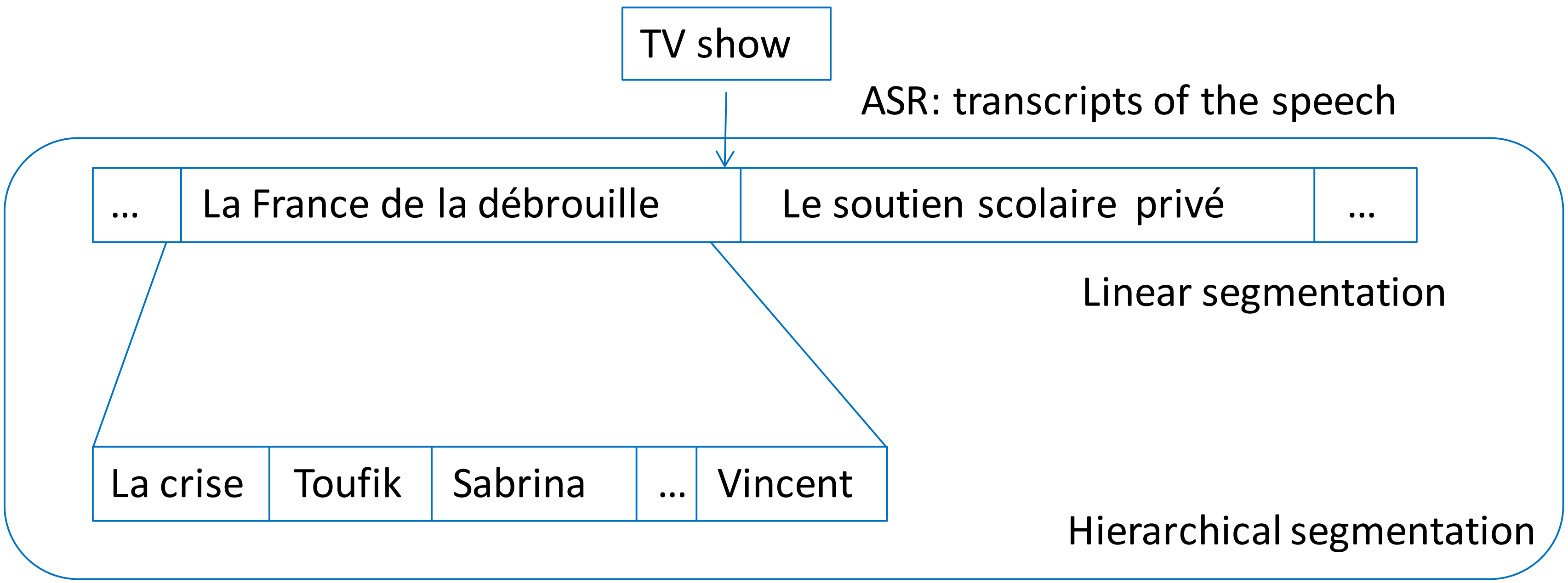
Hierarchical topic segmentation

Discourse structure often displays a hierarchical form

(Grosz and Sidner 1986, Eisenstein 2009, Carroll 2010, etc.)



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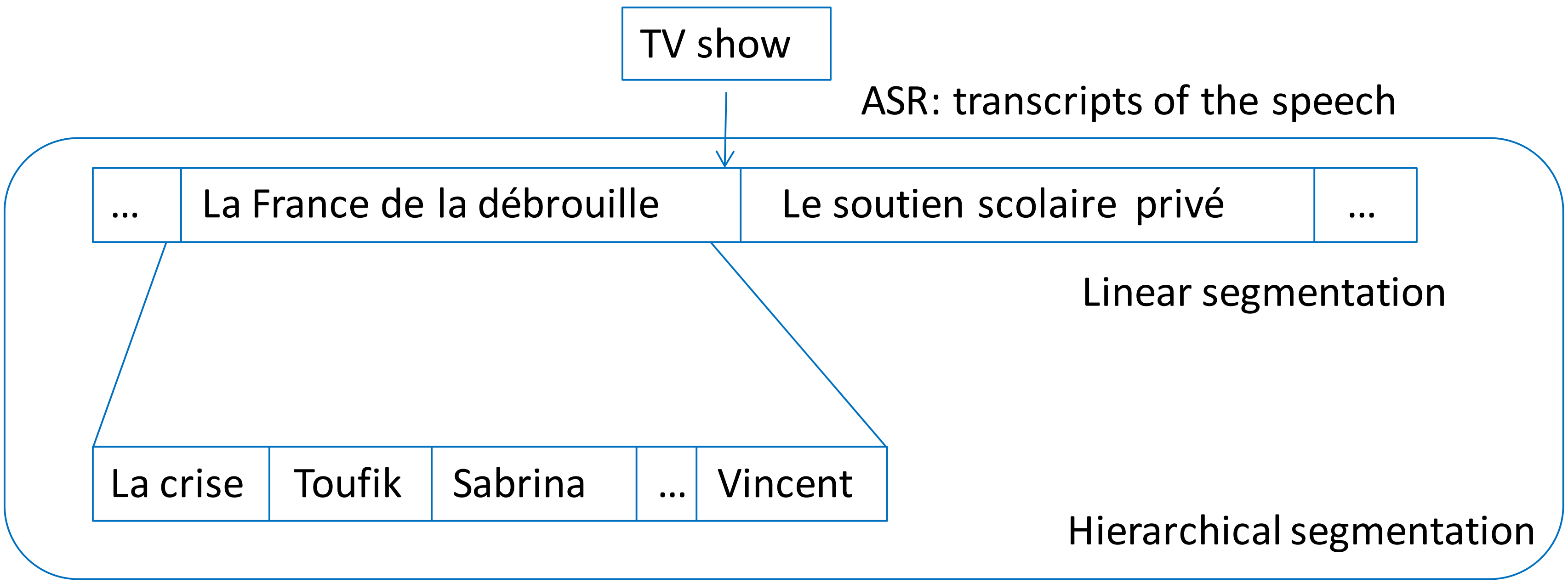

<u>Difficulties</u>:
- automatic transcripts ≠ written text
- number of words available
- subjectivity of the concept of topic and sub-topic
- evaluation

Existing solutions for hierarchical segmentation

1. Recursive application of a linear segmentation technique

(Guinaudeau 2011, Carroll 2010)

- Drawbacks: decide when to stop; errors from one level get propagated to another one

2. Obtain directly the hierarchical structure

(Moens and Busser 2001, Eisenstein 2009, Kazantseva, 2014)

- Drawbacks: need information about the granularity level; expected segment durations

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How well do they work?

Classical measures have limitations

Segmentation results

Method	F1-measure					
	TV shows				Wikipedia	
	Manual (4)		Automatic (7)		(66 articles)	
	coarse	fine	coarse	fine	coarse	fine
Eisenstein	100	**28.3**	100	**21.2**	18.15	**27.94**
(recursive) TextSeg	100	**30.6**	95.24	**27.11**	33.6	**37.7**
(recursive) MSeg	100	**31**	95.24	**27.47**	33.6	**40.2**

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Need something new…

➢leverage the **burstiness** phenomenon in word occurrences:

if a word appears once it is more likely to appear again, instead of independently

(Rasmus, 2005)

Proposed approach

1) Leverage the burstiness phenomenon in word occurrences

- Bursty words: characterized by long inter-arrival times followed by short inter-arrival times;
- Non-bursty words: exhibit inter-arrival times with smaller variance.

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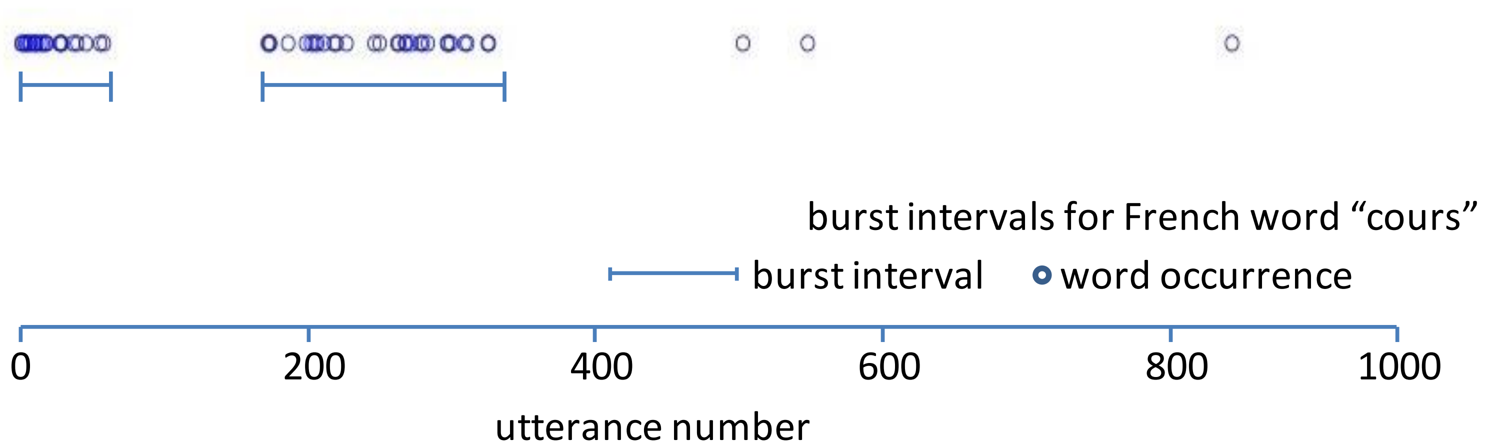

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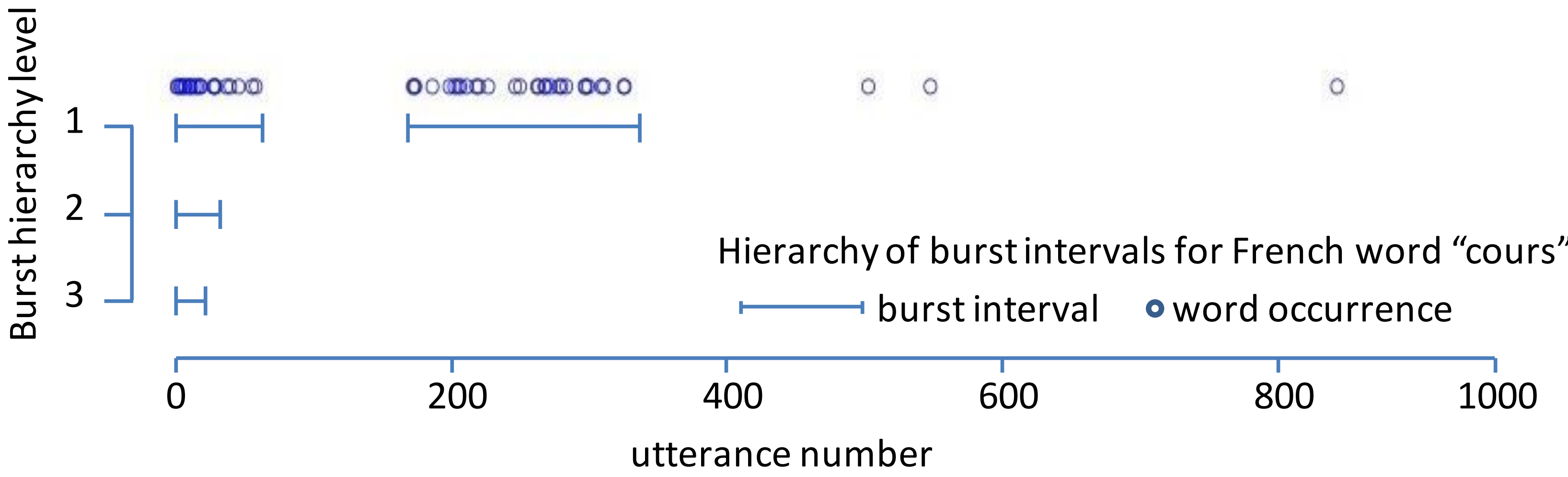
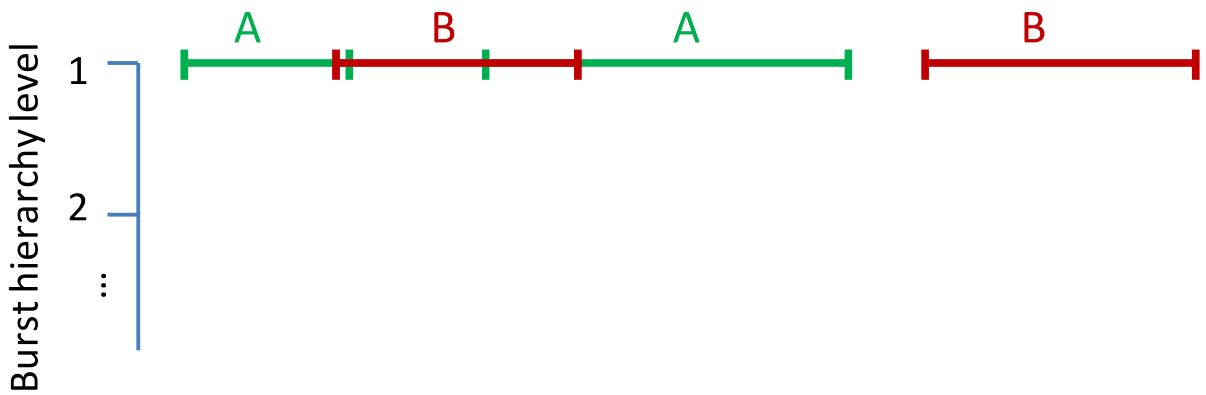


Proposed approach

2) Agglomerative clustering of burst intervals



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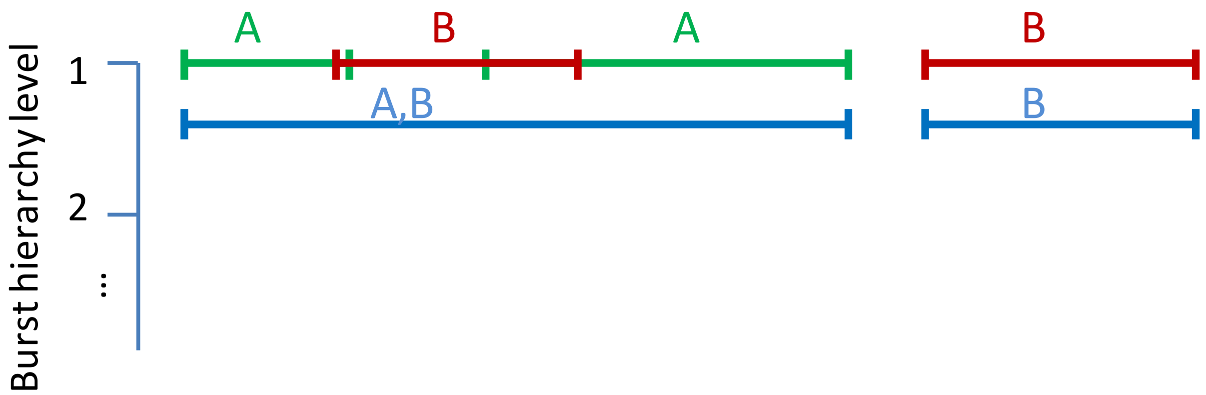

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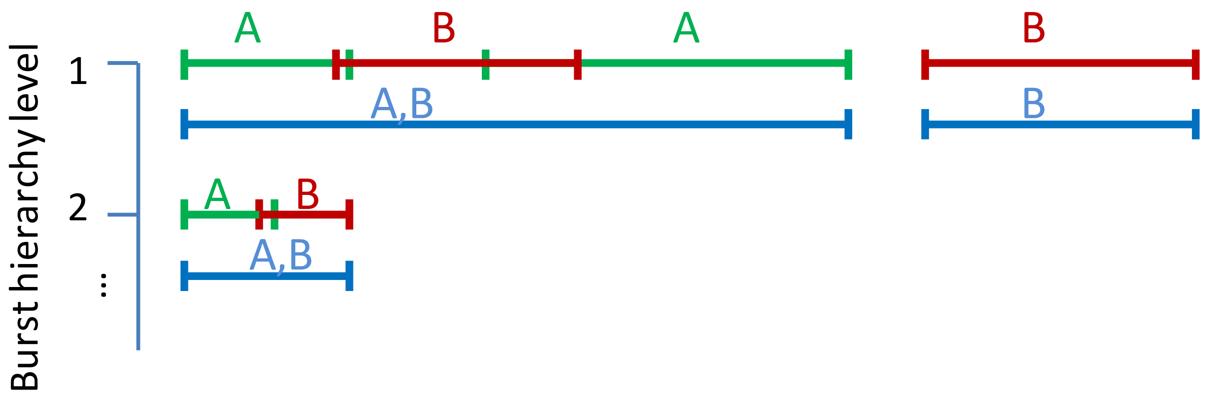

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Result: *a hierarchy of topically focused fragments*

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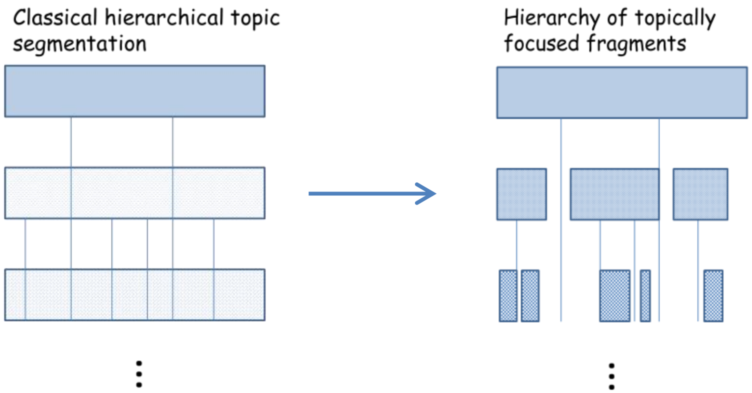

Hierarchy of topically focused fragments

Automatic transcript: *Castle in the country*
[start time: 0.01 -> end time: 29.23]

⋮

0.01 -> 10.5
(place, ballroom, color, king, royal, rock, tweed, palace, etc.)

0.01- > 1.50
(royal, tweed, site, ballroom, palace, etc.)

2.29- > 3.21
(build, prosperous)

…

7.43- > 8.35
(friend, Picasso)

…

0.01 -> 0.10
(ballroom)

0.18 -> 1.50
(royal, site, tweed, palace)

1.33 -> 1.50
(royal, palace)

Experiments

Corpora

1. TV shows, manual and automatic transcripts
    - 7 episodes of a report show (Envoyé Spécial) (~2 hour each)
    - 3 levels of topic hierarchy (manual annotation)
2. Medical textbook
    - 227 chapters and 1136 sections
    - 2 levels of topic hierarchy
3. Wikipedia articles
    - 66 articles
    - 4 levels of hierarchy

Evaluation

M1: proportion of topical fragment belonging to a unique reference segment
M2: proportion of reference segments with at least one matching topical fragment

Comparison to dense segmentation

Corpus	Level	HTFF		Eisenstein (HierBayes)	
		M1	M2	M1	M2
TV shows manual transcripts	Level1 (coarse)	**0.75**	1	0.51	1
	Level2	**0.56**	0.74	0.15	1
	Level3 (fine)	**0.47**	0.17	--	--
Medical textbook	Level1 (coarse)	0.82	0.89	0.22	1
	Level2 (fine)	0.71	0.64	0.06	1
Wikipedia articles	Level1 (coarse)	**0.22**	0.97	0.29	1
	Level2	**0.62**	0.66	0.42	1
	Level3	0.69	0.29	--	--
	Level4 (fine)	0.49	0.06	--	--

HTFF: provide a better topical focus (M1);
the topic coverage at lower levels is smaller (M2)
HierBayes: segments usually do not belong to a unique topic;

Lessons learned: topic segmentation

- Question the fundamental aspects:
  - When is it worth to segment?
  - Can we actually find the segments in the groundthruth?

- Go in a different direction:
  - Propose something new
  - ✓ HTFF - a new representation

- Use of topic segmentation in NLP-related applications:
  - TextSeg, Mseg: target generation
  - HTFF: decide when to stop a segmentation; compression; summarization; anchor generation;

Semantic structuring of video collections from speech: segmentation & **hyperlinking**

Outline

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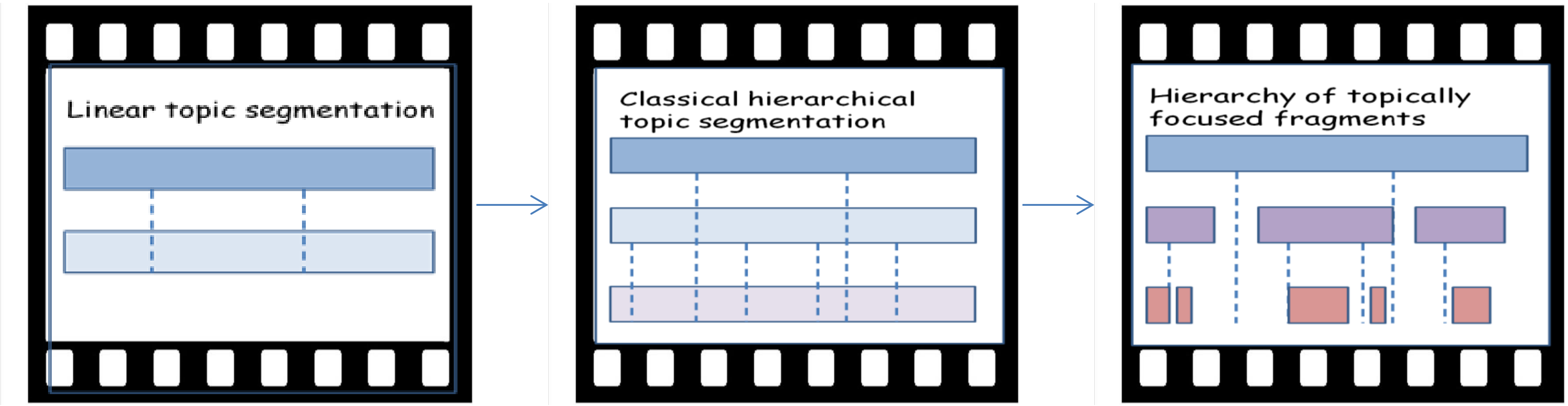
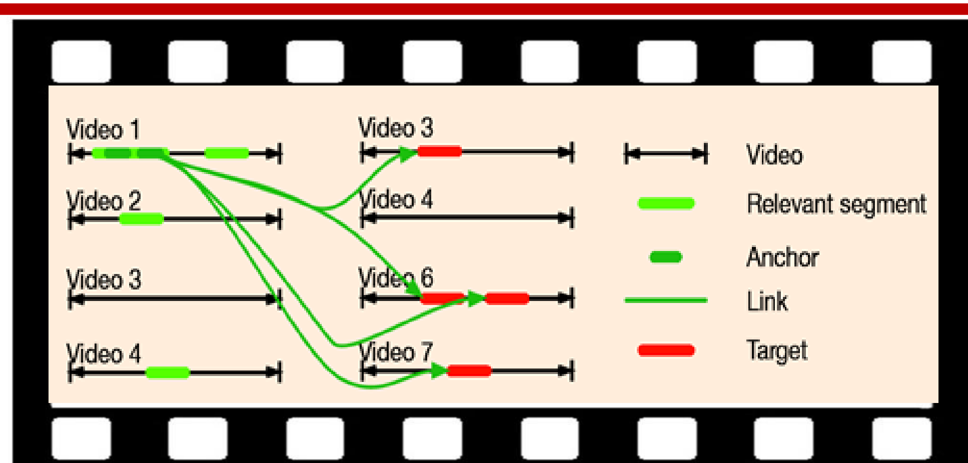


- Anchor and target generation
- Link justification & diversity control

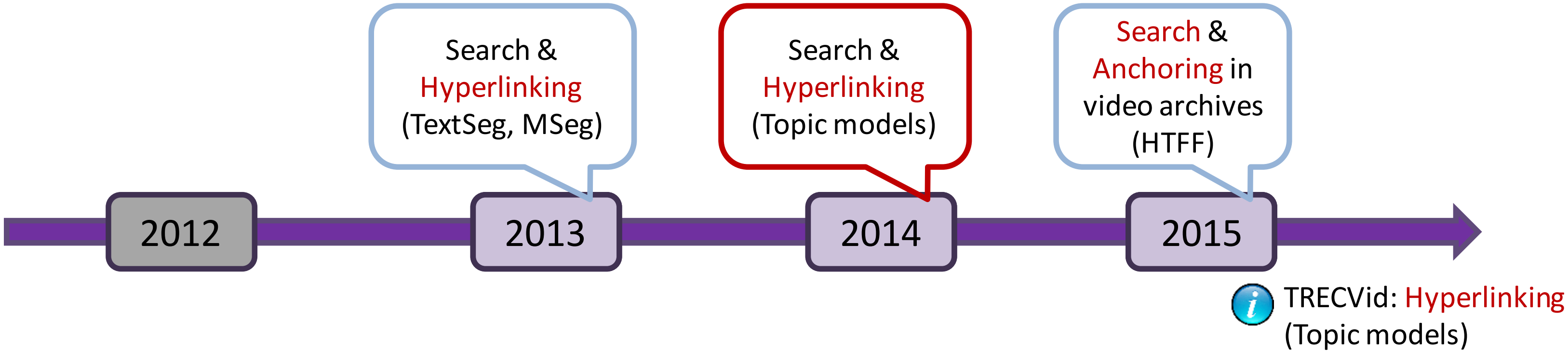


MediaEval benchmark initiative

Search & Anchoring & Hyperlinking

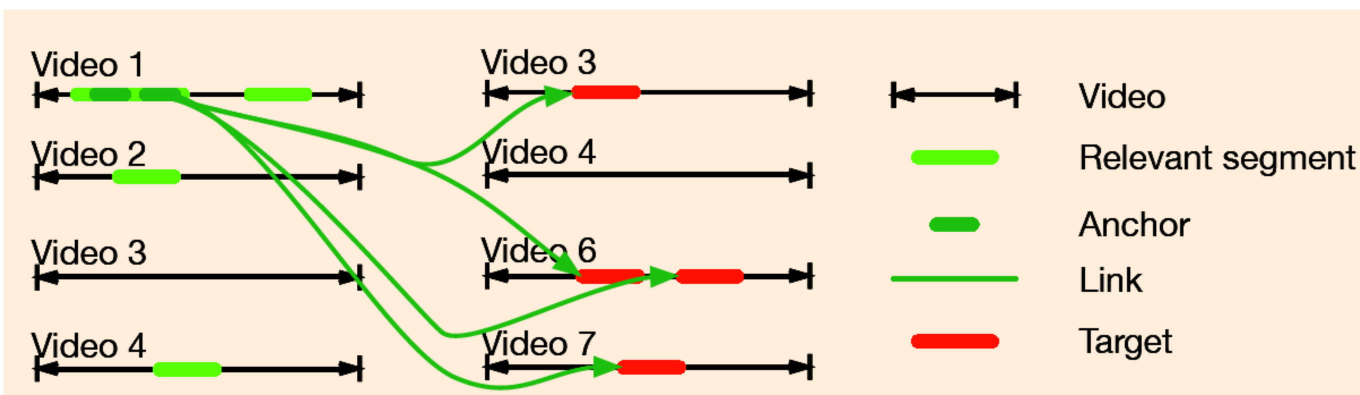
Context

MediaEval benchmarking initiative: Search and Hyperlinking task



Use case

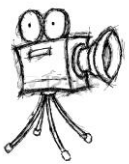
Text query
- speech cue
- visual cue



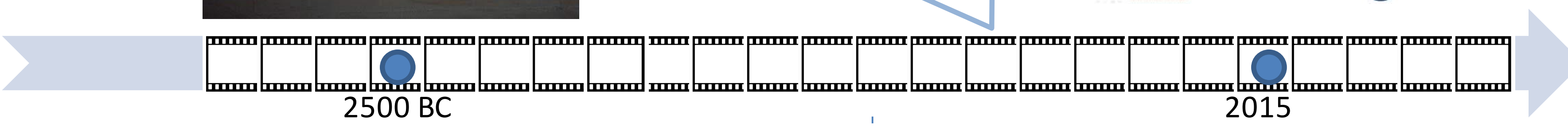
Video hyperlinking

A two-step approach:

1. Segmentation



-Fixed-length segments
-Video shots
-Topic segments
-Utterances



2500 BC

Pyramids of Giza

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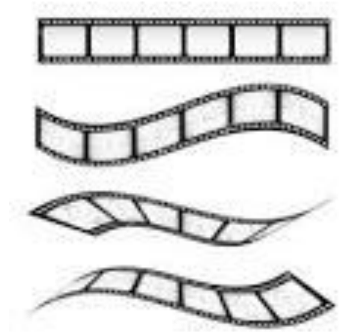
Potential targets



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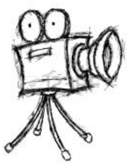
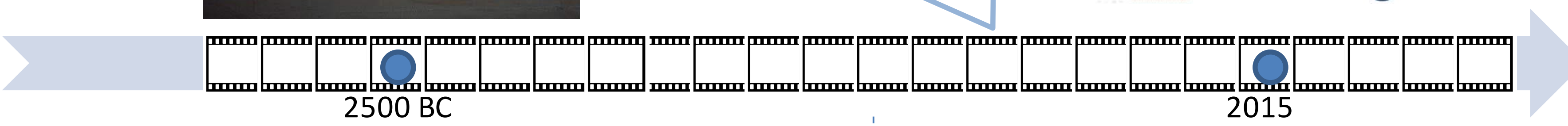
A two-step approach:

1. Segmentation



-Fixed-length segments
-Video shots
-Topic segments
-Utterances

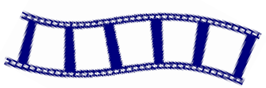


Pyramids of Giza

The day of the defense

2. Target selection

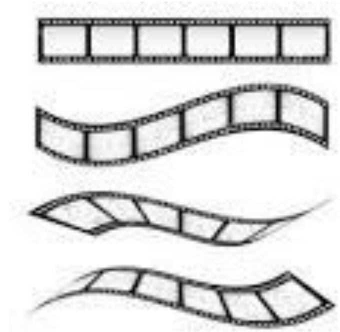
Anchor



comparison & selection

-Language via transcripts (entities, prosody)
-Visual content (concepts)
-Metadata

Potential targets



What about diversity?

Direct comparison in vector space with cosine similarity!

Targets very similar to the anchor

- near duplicates
- timeline events
- … but no diversity and no serendipity

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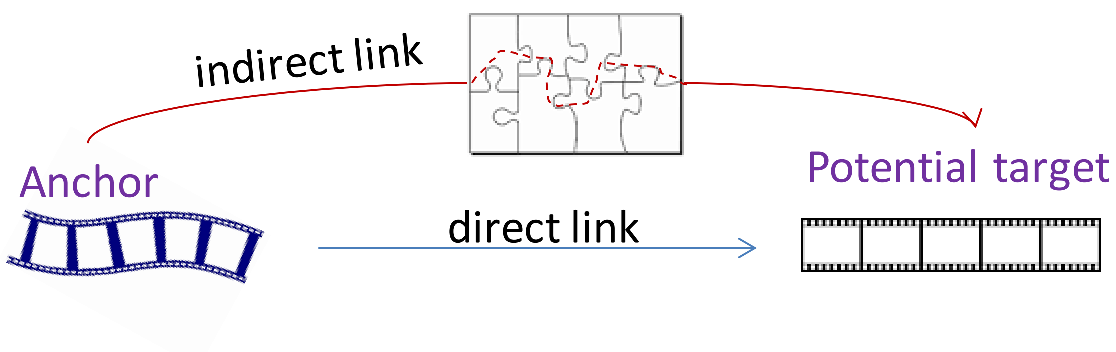
<u>Solution</u>: Indirect comparison



+ link anchor-target pairs with few words in common

What about diversity?

Direct comparison in vector space with cosine similarity!

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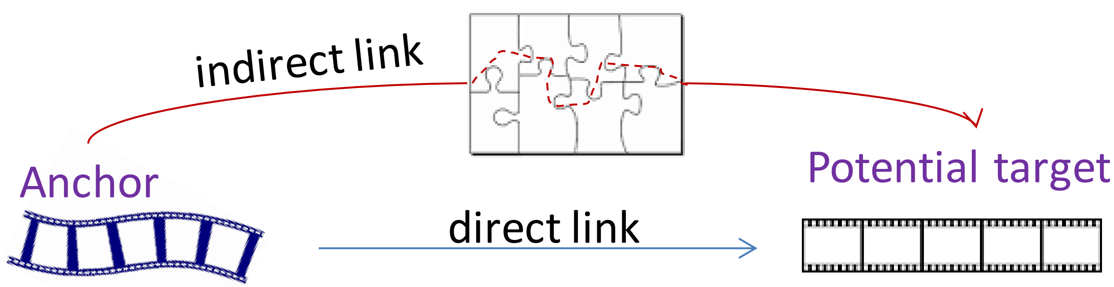
- near duplicates
- timeline events
- … but no diversity and no serendipity

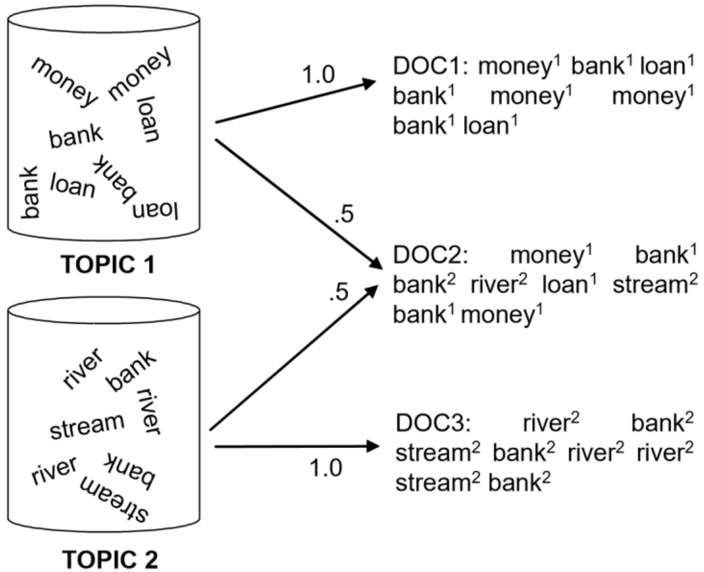
Solution: Indirect comparison via a hierarchy of topic models



+ link anchor-target pairs with few words in common
+ control diversity
+ link justification

LDA model

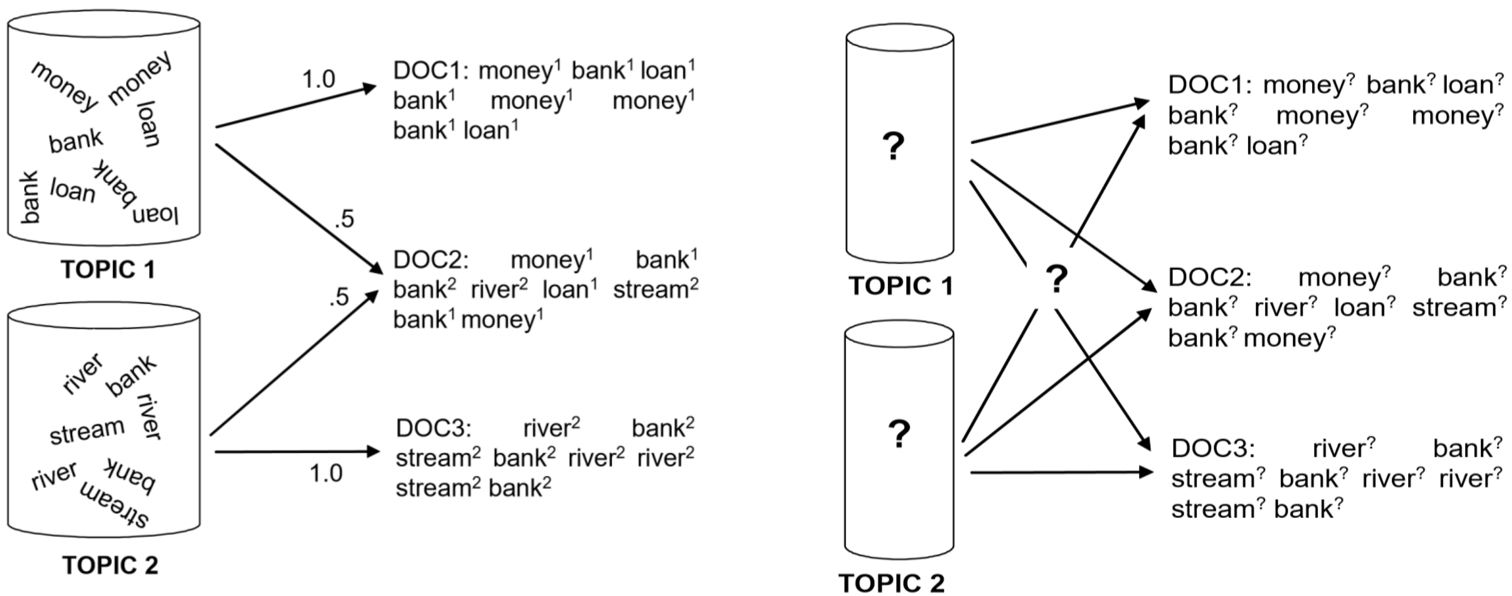
<u>Key idea:</u> there exist latent topics which uncover how words in documents have been generated



Steyvers and Griffiths, 2010

LDA model

<u>Key idea:</u> there exist latent topics which uncover how words in documents have been generated



Steyvers and Griffiths, 2010

LDA model

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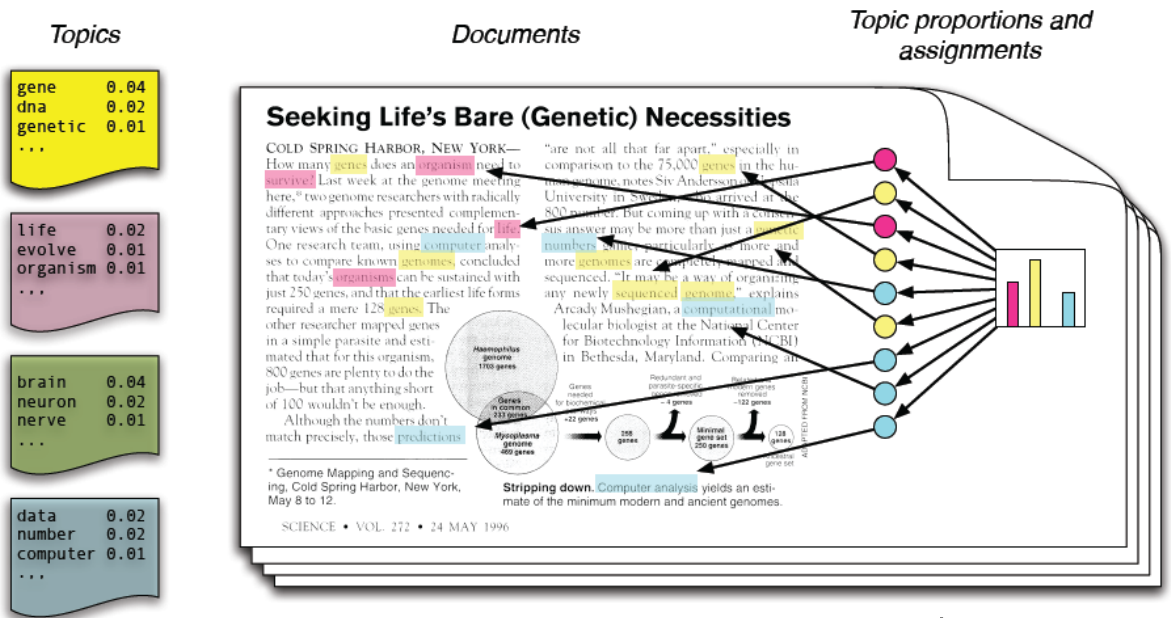

Blei, 2012

- Each topic: a probability distribution over words
- Each document: a mixture of topics

Leverage LDA for hyperlinking

Create a hierarchy of topics:

$$K \in \{50,100,150,200,300,500,700,1000,1500,1700\}$$

- Level 1, $K_1 = 50$, broad topics $z_i^1, i \in [1, K_1]$
- Level 10, $K_{10} = 1700$, fine-grained topics $z_i^{10}, i \in [1, K_{10}]$

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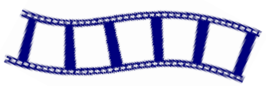
broad	fine-grained
z_3^1, K_1=50	z_{50}^{10}, K_{10}=1700
People	Referendum
Government	Minister
Tax	Scotland
Minister	Independence
Party	Alexander

$$\begin{array}{llllll}
z_1^1 & z_2^1 & z_3^1 \ldots & z_{50}^1 & & \\
z_1^2 & z_2^2 & z_3^2 \ldots & z_{50}^2 \ldots & z_{100}^2 & \\
\vdots & & & & & \\
z_1^{10} & z_2^{10} & z_3^{10} \ldots & z_{50}^{10} \ldots & z_{100}^{10} \ldots & z_{1700}^{10}
\end{array}$$

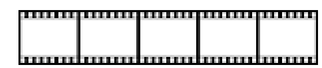
Changing the representation space

$$
\begin{array}{llllll}
z_1^1 & z_2^1 & z_3^1 \;\ldots\; z_{50}^1 & & & \\
z_1^2 & z_2^2 & z_3^2 \;\ldots\; z_{50}^2 \;\ldots\; z_{100}^2 & & & \\
\vdots & & & & & \\
z_1^{10} & z_2^{10} & z_3^{10} & \ldots\; z_{50}^{10} & \ldots\; z_{100}^{10} & \ldots\; z_{1700}^{10}
\end{array}
$$

Anchor



Potential target

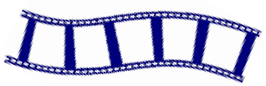


- New representation of an anchor/target segment

$$
x_l = (p(x \mid z_1^l) \ldots p(x \mid z_{K_l}^l))
$$

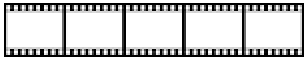
Changing the representation space

Anchor



$$\begin{array}{llllllll}
z_1^1 & z_2^1 & z_3^1 & \ldots z_{50}^1 & & & & \\
z_1^2 & z_2^2 & z_3^2 & \cdots z_{50}^2 & \ldots & z_{100}^2 & & \\
\vdots & & & & & & & \\
z_1^{10} & z_2^{10} & z_3^{10} & \ldots z_{50}^{10} & \ldots & z_{100}^{10} & \ldots & z_{1700}^{10}
\end{array}$$

Potential target



- New representation of an anchor/target segment

$$\boxed{x_l = (p(x \mid z_1^l) \ldots p(x \mid z_{K_l}^l))}$$

- 1st strategy: independent topic levels (IT)
- 2nd strategy: hard and soft links between topics

Independent levels

- Anchor segment x $\quad x_l = (p(x \mid z_1^l) \ldots p(x \mid z_{K_l}^l))$
- Target segment y $\quad y_l = (p(y \mid z_1^l) \ldots p(y \mid z_{K_l}^l))$

$$\boxed{Similarity(x, y) = \sum_l \alpha_l \log(x_l \cdot y_l)}$$

IT_k only level *k* $\quad \alpha_{\mathrm{k}} = 1, \alpha_{\mathrm{i \neq k}} = 0$

$IT_=$ equal weights $\quad \alpha_{\mathrm{k}} = 0.2, \forall k \in \{1,3,5,7,9\}$

$IT_<$ general<specific $\quad \alpha_1 = 0.1, \alpha_3 = 0.15, \alpha_5 = 0.2, \alpha_7 = 0.25, \alpha_9 = 0.3$

$IT_>$ specific<general $\quad \alpha_1 = 0.3, \alpha_3 = 0.25, \alpha_5 = 0.2, \alpha_7 = 0.15, \alpha_9 = 0.1$

Data

2013 & 2014 Search & Hyperlinking data

- BBC broadcast videos
- automatic speech transcripts (LIMSI)

Task considered: reranking targets

- Targets proposed by all the participants!
- Relevance judgments provided by turkers (AMT)

year	#hours of video	#anchors	avg. anchor duration (95% interval)	#targets (% relevant)	avg. target duration (95%interval)
2013	1,335	30	32.2 [13.4,51]	9,973 (29.9%)	83.38 sec. [82.58,84.18]
2014	2,686	30	22.9 [11.1,34.8]	12,340 (15.3%)	58.85 sec. [58.1,59.58]

Relevance assessment

- Baseline: direct cos-similarity (DirectH)
- Measures: relevance (P@10);
  tolerance to irrelevance (P@10_tol)

	2013		2014	
method	P@10	P@10_tol	P@10	P@10_tol
DirectH	0.61	0.25	0.41	0.19
IT_{50}	0.65	**0.44***	0.26	0.18
IT_{150}	0.57	**0.34***	0.37	**0.25***
IT_{300}	0.61	**0.35***	0.34	**0.26***
IT_{700}	0.64	**0.34***	0.31	0.21
IT_{1500}	0.59	**0.32***	0.32	0.24
$IT_{Comb=}$	0.66	**0.35***	0.27	0.22
$IT_{Comb<}$	0.67	**0.37***	0.27	0.21
$IT_{Comb>}$	0.65	**0.35***	0.29	0.22

* Statistical significant values (paired t-test, $p<0.05$)

Diversity assessment

Success of a hyperlinking system:
cover potential (idiosyncratic) user interest & enable serendipity

Links differ between systems

System 1	System 2	% difference 2013	2014
IT_{700}	*DirectH*	93	86
IT_{700}	$IT_{Comb>}$	82	90
IT_{700}	*Hierarchy*	98	93
$IT_{Comb=}$	*Hierarchy*	94	95

AMT evaluation scenario at MediaEval

- 1 judgement/anchor-target pair
- yes/no relevance assessment
- description of potential targets

Diversity in the links

Design a new evaluation scenario:

- At least 3 assessments per anchor-target pair
- Each participant should do 5 tests
- Test for: relevance (same topic, related topic, same show);
  unexpectedness;
  interestingness;

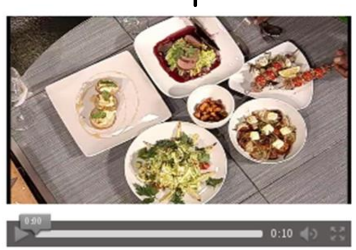
Clip A

Anchor:

Two video clips (B and C) that could be linked to video A are recommended to you that should encourage this further exploration. Please watch the two videos and answer the questions.

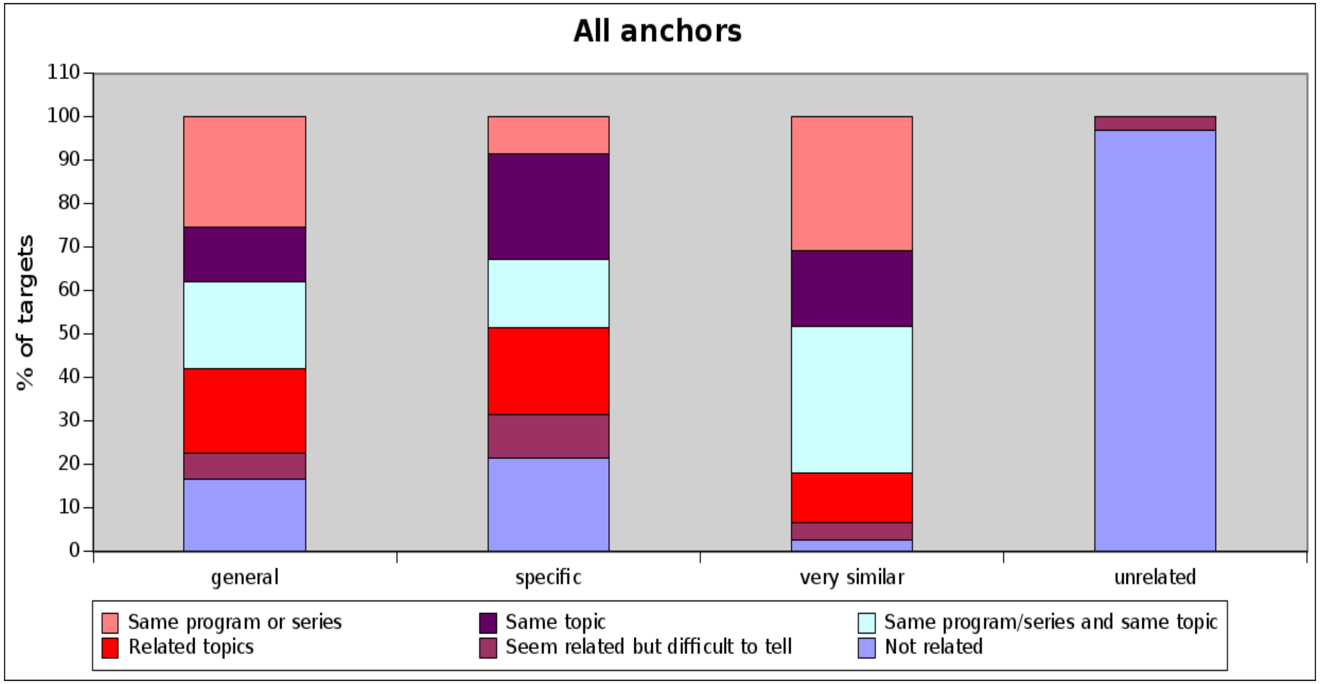
Targets:

Clip B



Clip C

Results for the new scenario

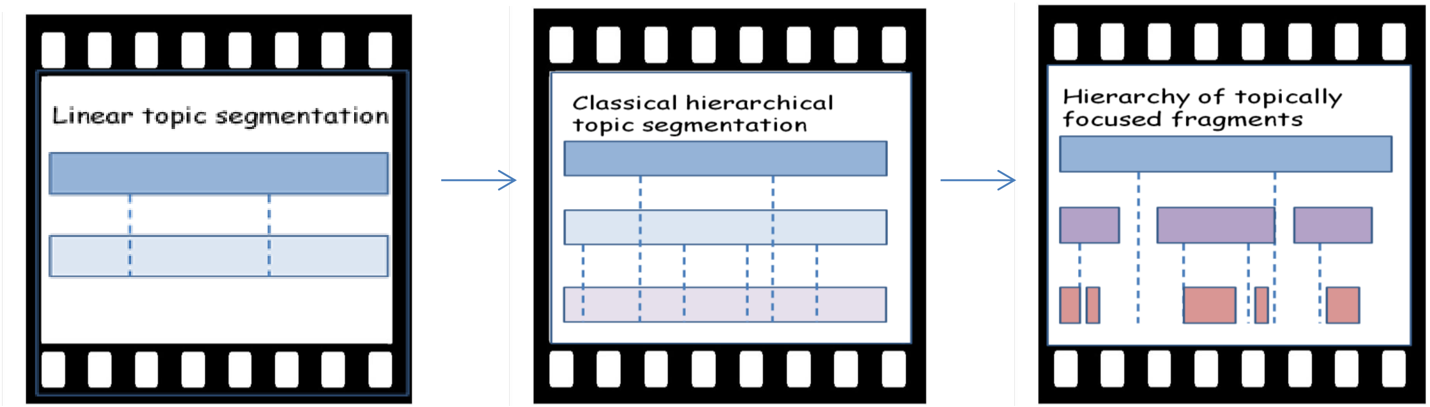


- Very similar targets:
  - same program/series and same topic (91% expected; 9% possibly)
  - most expected
- Specific topics:
  - same topic (47% expected; 53% possibly)
  - less expected

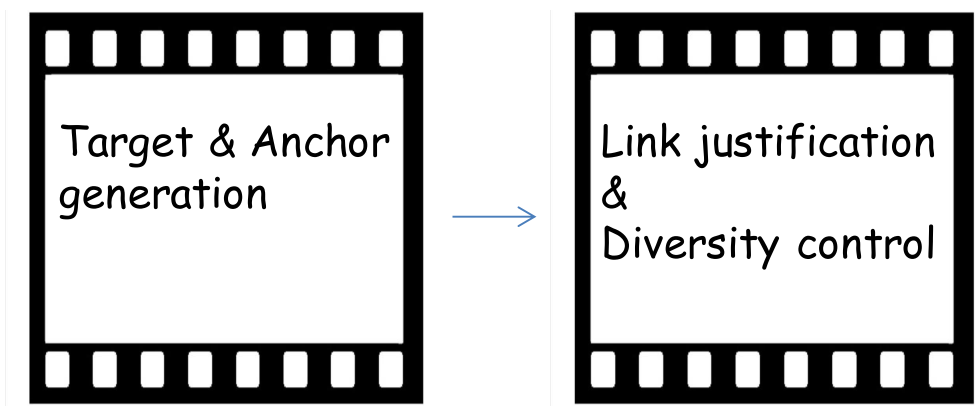
Conclusions & Perspectives

Answering the research questions

1.How to *structure* audiovisual content?



2. How to *exploit* structured content?



Answering the research questions

1.How to *structure* audiovisual content?

- ✓ EMNLP 2013
- ✓ TALN 2013
- ✓ RANLP 2015

2. How to *exploit* structured content?

✓ SLAM 2014, SLAM 2015, MediaEval 2013,2014,2015

Challenges:

✓ MediaEval(2013-2015), TRECVid 2015

➢ Collaborations: Sien Moens, Camille Guinaudeau, Rémi Bois, Ronan Sicre, Emmanuel Morin, Martha Larson

Perspectives