UNIMORE
UNIVERSITÀ DEGLI STUDI DI MODENA E REGGIO EMILIA

Centro Interdipartimentale di Ricerca
Softech: ICT per le Imprese

Scene-driven Retrieval in Edited Videos using Aesthetic and Semantic Deep Features

Lorenzo Baraldi, Costantino Grana, Rita Cucchiara

Imagelab - University of Modena and Reggio Emilia, Italy

Outline

- **Introduction**
- Scene-driven retrieval with thumbnail selection
  - Scene detection
  - Semantic concept detection
  - Aesthetic ranking
- Experimental results

Introduction

Rick Steves' Rome: Eternally Engaging

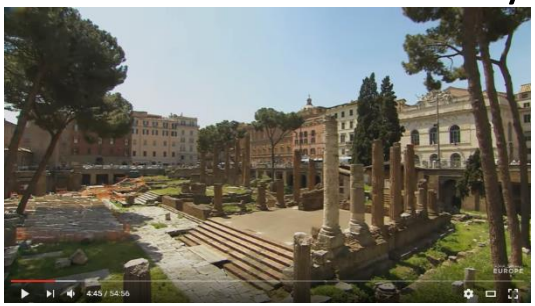
Rick Steves Europe

2 years ago • 293,358 views

In this hour-long travel special, we explore the "Eternal City" of Rome, a grand and ancient metropolis rich with exquisite art, ...

1 hour video
1 static thumbnail

Variety of topics: all should be searchable



...

Novelties of our work

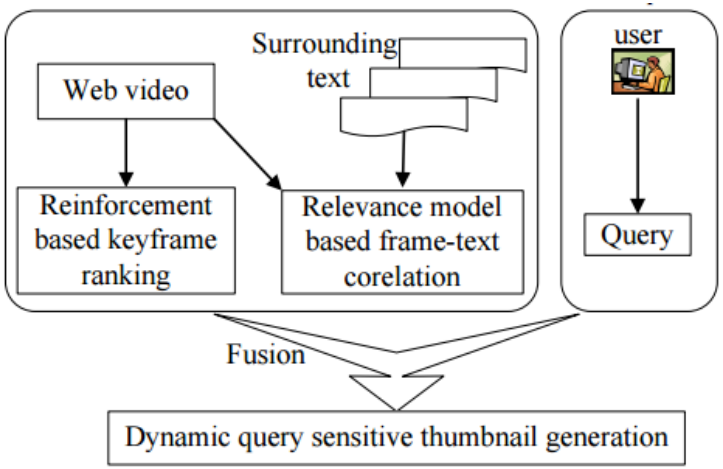
- Focus on collections of **long broadcast** videos
- Query-dependent, **semantically and aesthetically** valuable thumbnails
- Search with **finer granularity level**
- No manually provided annotations (description, tags)

Related works

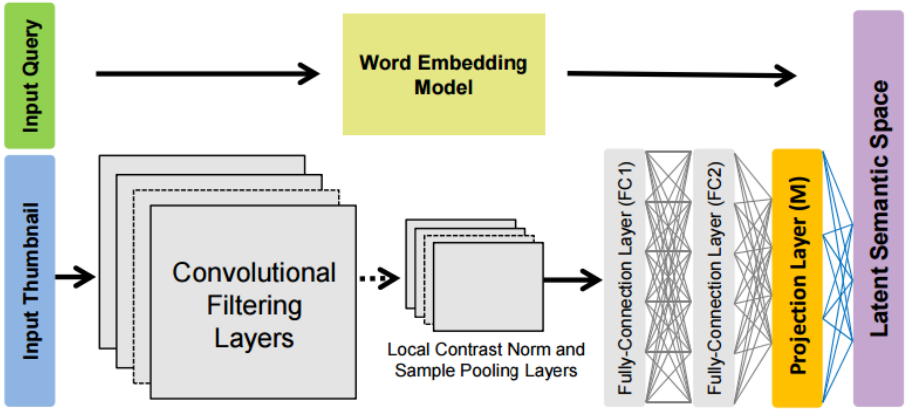
Thumbnails are *surrogates* for videos *[Craggs et al., 2014]*

- Thumbnails create an *intention gap* if not relevant

- C. Liu et al. (ICIP 2011) reinforcement + relevance model to compute query/thumbnail similarity



- W. Liu et al. (CVPR 2015) deeply-learned latent space to compute similarity between query and thumbnail

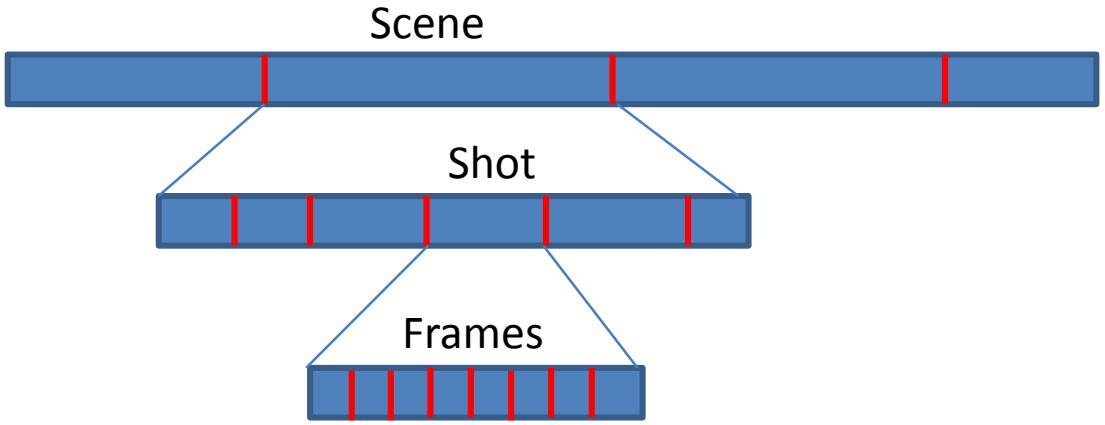


Outline

- Introduction
- **Scene-driven retrieval with thumbnail selection**
  - Scene detection
  - Semantic concept detection
  - Aesthetic ranking
- Experimental results

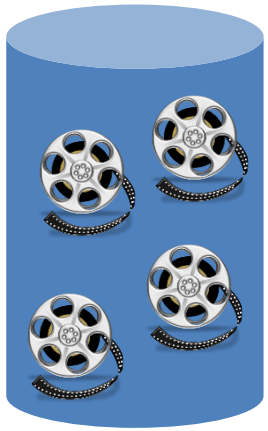
Overview

- Broadcast videos can be decomposed at three different levels:
  - **Frames**
  - **Shots**
    - Taken by a single camera
  - **Scenes**
    - Uniform semantic content



Overview

- Scene-based retrieval
- Given a query, return a ranked list of:



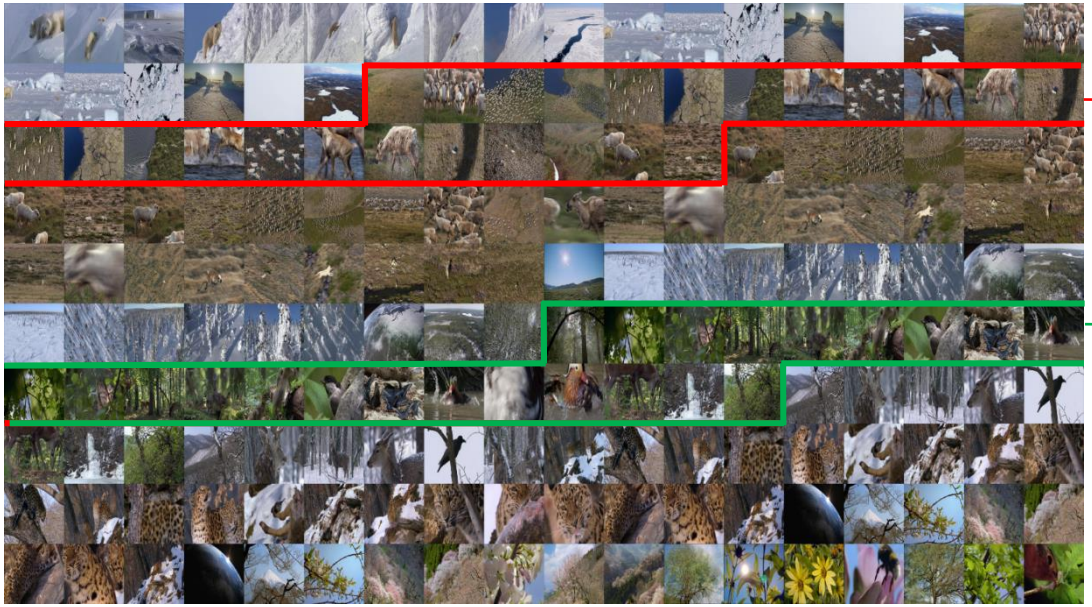
(video, scene, thumbnail)
(video, scene, thumbnail)
…
(video, scene, thumbnail)

Belongs to retrieved video
Should be **relevant for query**

Belongs to retrieved scene
Should be **relevant for query and aesthetically remarkable**

Scene detection

Group adjacent shots according to semantic coherence



Can not be identified with visual features

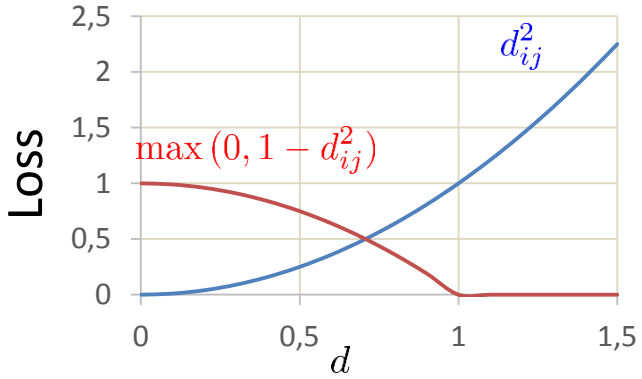
Can be identified with visual features only

Need of multi-modal features!

Scene detection

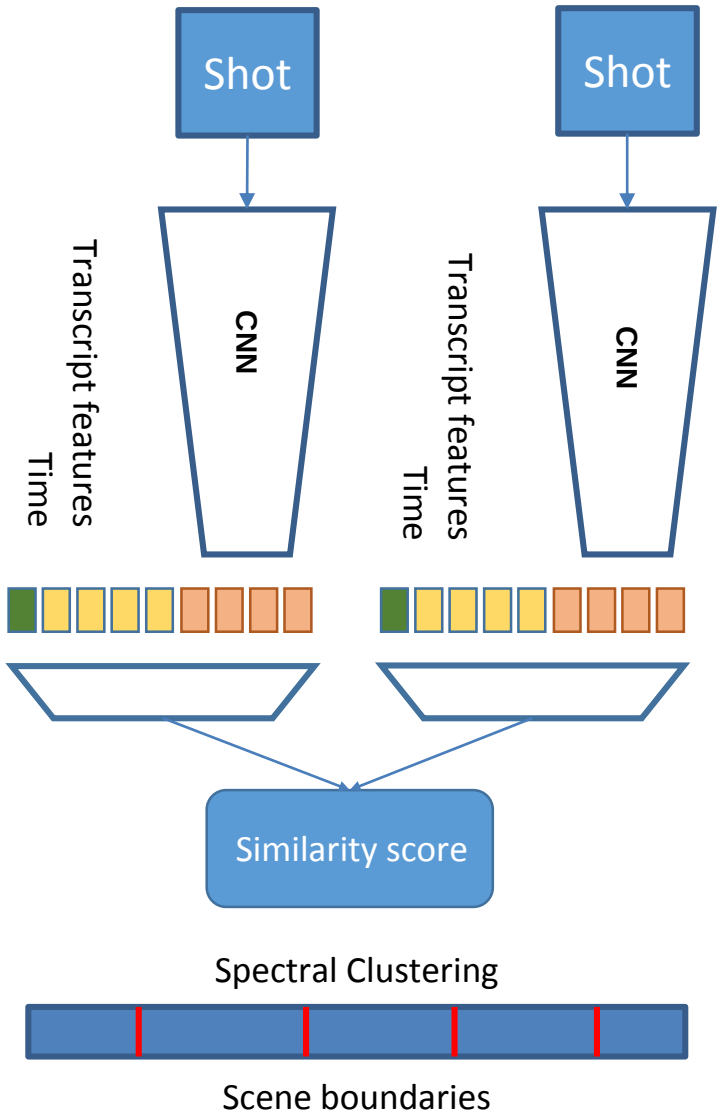
Shot clustering according to learned similarity metric.

A Siamese DN is trained to predict whether two shots should belong to the same scene.

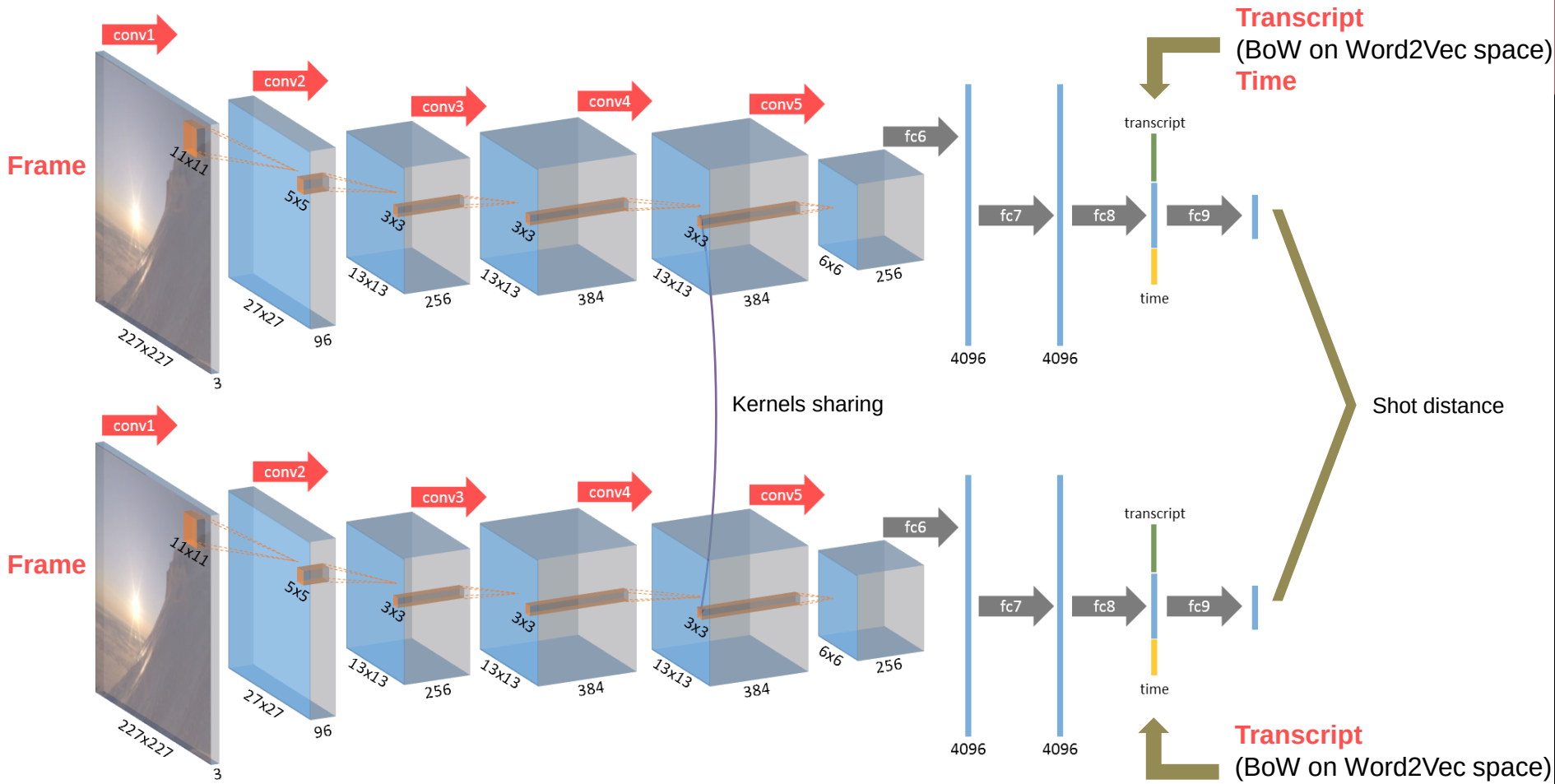


At test phase: spectral clustering

[Baraldi, Grana, Cucchiara; ACM MM 2015]



Scene detection



Training on ILSVRC12 (1.2 million images, 978 object classes)

Fine-tuning with Places Dataset (2.5 million immages, 205 scene categories)

Fine-tuning with BBC Planet Earth (12 million shot pairs)

[Baraldi, Grana, Cucchiara; ACM MM 2015]

Outline

- Introduction
- Scene-driven retrieval with thumbnail selection
  - Scene detection
  - **Semantic concept detection**
  - Aesthetic ranking
- Experimental results

Semantic Concept Detection

Hypothesis:

- *In broadcast videos (documentaries, news, educational footage, …) speaker describes what the video shows*

Video transcript suggests semantic concepts

- No ontologies
- No pre-defined concept list
- No user queries

“Semantic Concept Detection” is the task of extracting concepts defined in the transcript in frames → shots → scenes

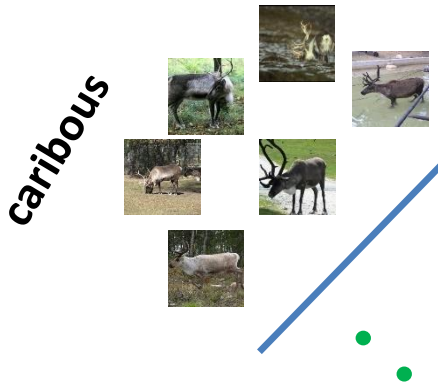
Semantic Concept Detection

Every year three million caribou migrate across the arctic tundra. The immensity of the herd can only be properly appreciated from the air.

Video transcript

Most similar category
In semantic space

(caribou)



Probabilistic SVM classifier
on CNN features

IMAGENET

40.000 categories
(1000 images per class on avg)

$P(s, u)$

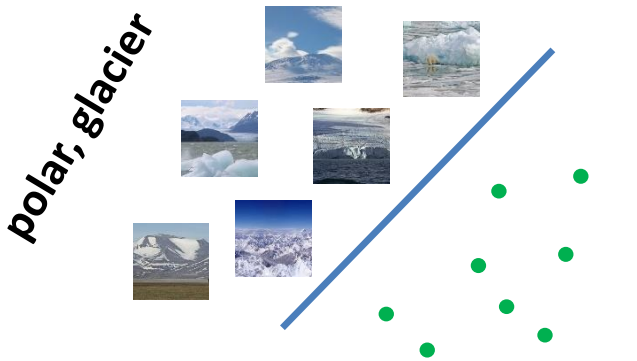
Probability that shot s
contains “caribou”

Semantic Concept Detection

Imagine our world without sun. Male emperor penguins are facing the nearest that exists on Plane earth, winter in Antarctica

Video transcript

Most similar category
In semantic space
(polar, glacier)



IMAGENET

40.000 categories
(1000 images per class on avg)

Probabilistic SVM classifier
on CNN features

$P(s, u)$

Probability that shot s
contains “polar/glacier”

Semantic Concept Detection

Visual concepts

plain · steppe · grassland · reach · forest

Visual concepts

cloud · plateau · mountain · side · sun

Visual concepts

grass · mammal · hog · pig · work

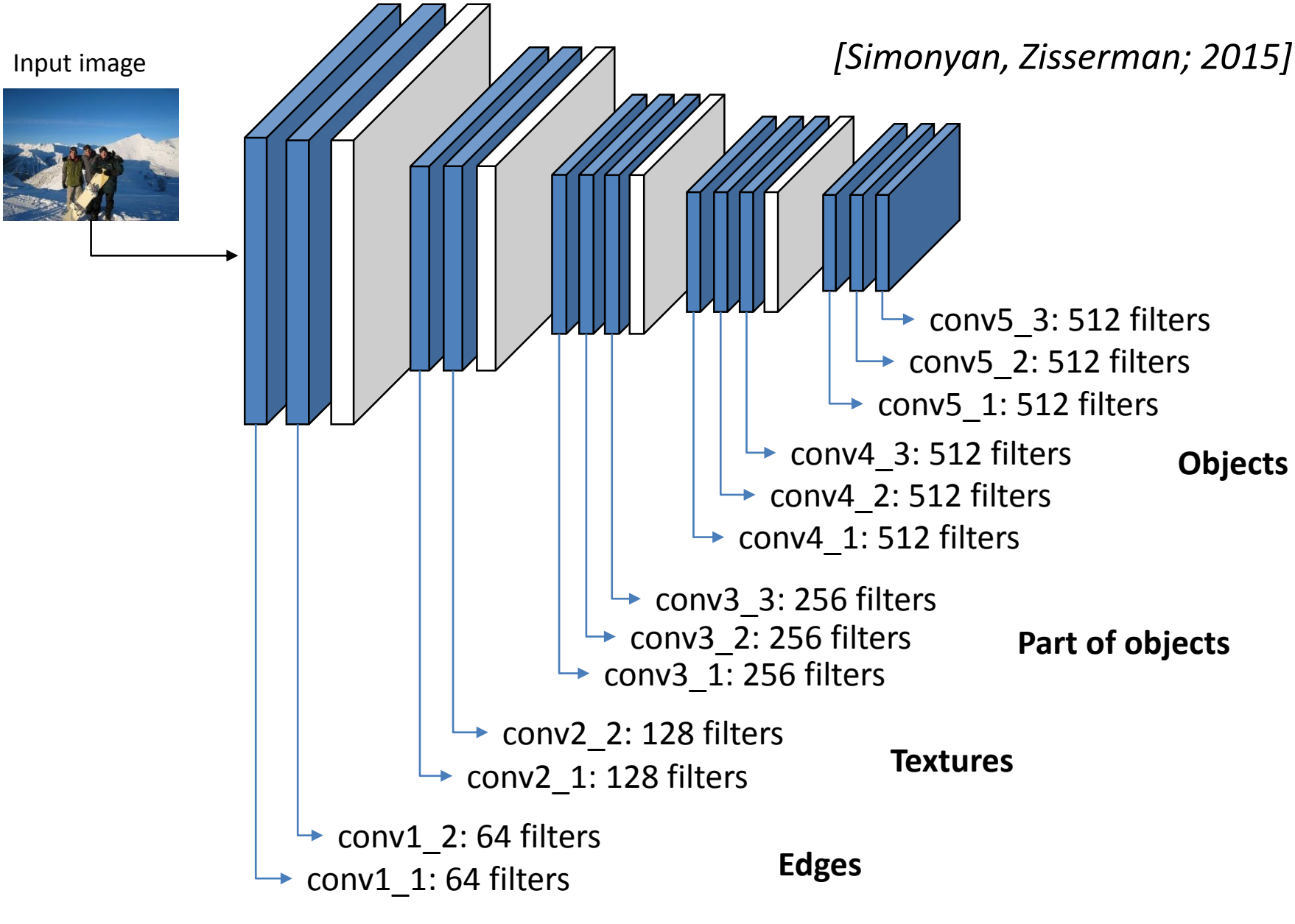
Visual concepts

animal · elephant · water · grass · hole

Outline

- Introduction
- Scene-driven retrieval with thumbnail selection
  - Scene detection
  - Semantic concept detection
  - **Aesthetic ranking**
- Experimental results

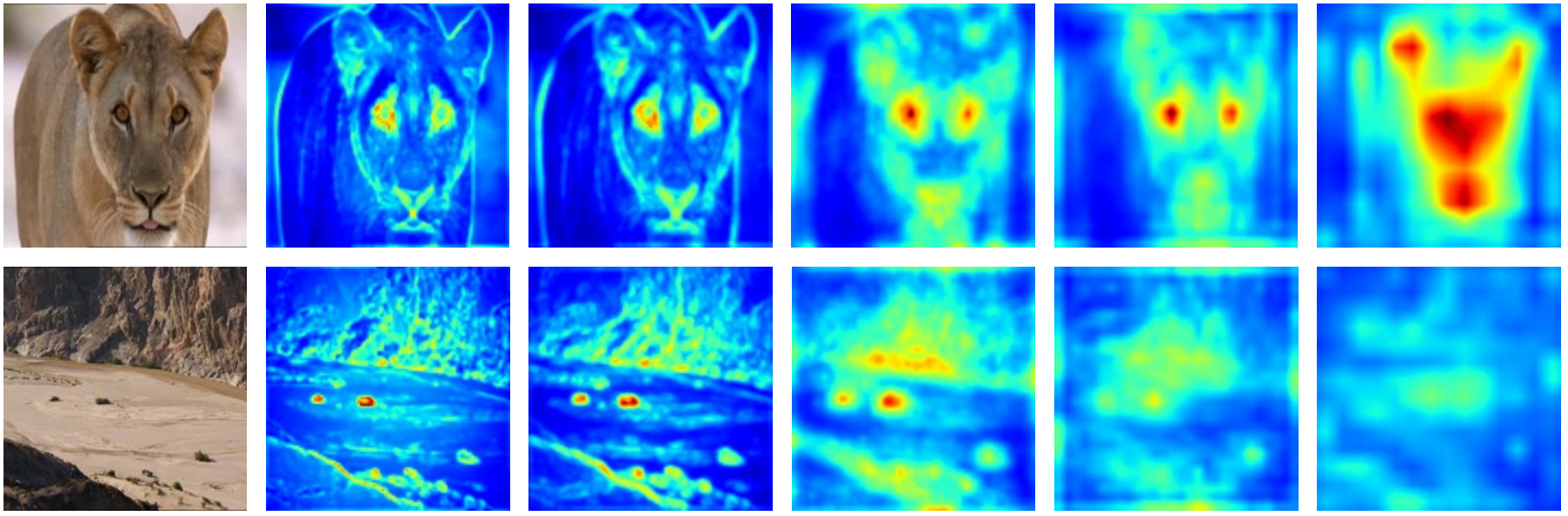
Aesthetic Ranking



Aesthetic ranking

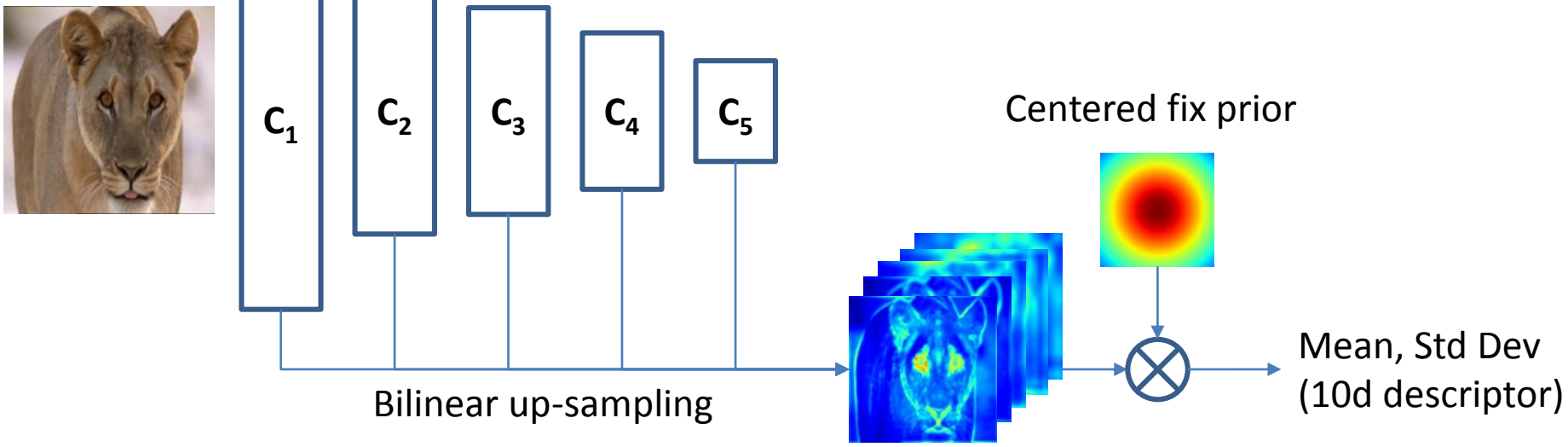
Learn a (linear) ranking model for aesthetics, with a small training set

- Pre-trained CNN
- Hypercolumn features [Hariharan et. al, 2015]
  - From ~4000 activation maps to 5!
  - Disregard information on classes, focus on level (edges vs patterns vs objects) and position



Input image | C_1 128 filters | C_2 256 filters | C_3 768 filters | C_4 1536 filters | C_5 1536 filters

Aesthetic ranking



Ranking model: Linear SVM Rank

- For each scene, dataset consists of thumbnail pairs:
  - (d_i,d_j) where d_i is ranked higher than d_j
- Equivalent to a linear SVM on pairwise difference vectors

$$\begin{aligned}
\underset{\mathbf{w},\epsilon}{\text{minimize}} \quad & \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i,j,k}\epsilon_{i,j,k} \\
\text{subject to} \quad & \forall(d_i,d_j) \in r_1^* : \mathbf{w}\phi(d_i) \geq \mathbf{w}\phi(d_j) + 1 - \epsilon_{i,j,1} \\
& \cdots \\
& \forall(d_i,d_j) \in r_n^* : \quad \mathbf{w}\phi(d_i) \geq \mathbf{w}\phi(d_j) + 1 - \epsilon_{i,j,n} \\
& \forall i,j,k : \epsilon_{i,j,k} \geq 0
\end{aligned}$$

Retrieval

Query *q* → **Match with most similar concept in semantic space** *u*

Rank scenes according to

$$R_{scene}(q) = \max_{s \in scene} \left(\alpha P(s,u) + (1-\alpha) \max_{d \in s} \mathbf{w}\phi(d) \right)$$

Shots of the scene

Probability that concept *u* appears in shot *s*

Aesthetic ranking of shot *s*

As thumbnail, select the one that maximizes $\mathbf{w}\phi(d)$

Outline

- Introduction
- Scene-driven retrieval with thumbnail selection
  - Scene detection
  - Semantic concept detection
  - Aesthetic ranking
- **Experimental results**

Evaluation

BBC Planet Earth dataset

- 11 videos, approximately 50 minutes each
- 4900 shots and 670 scenes
- 3802 unigrams

Annotation

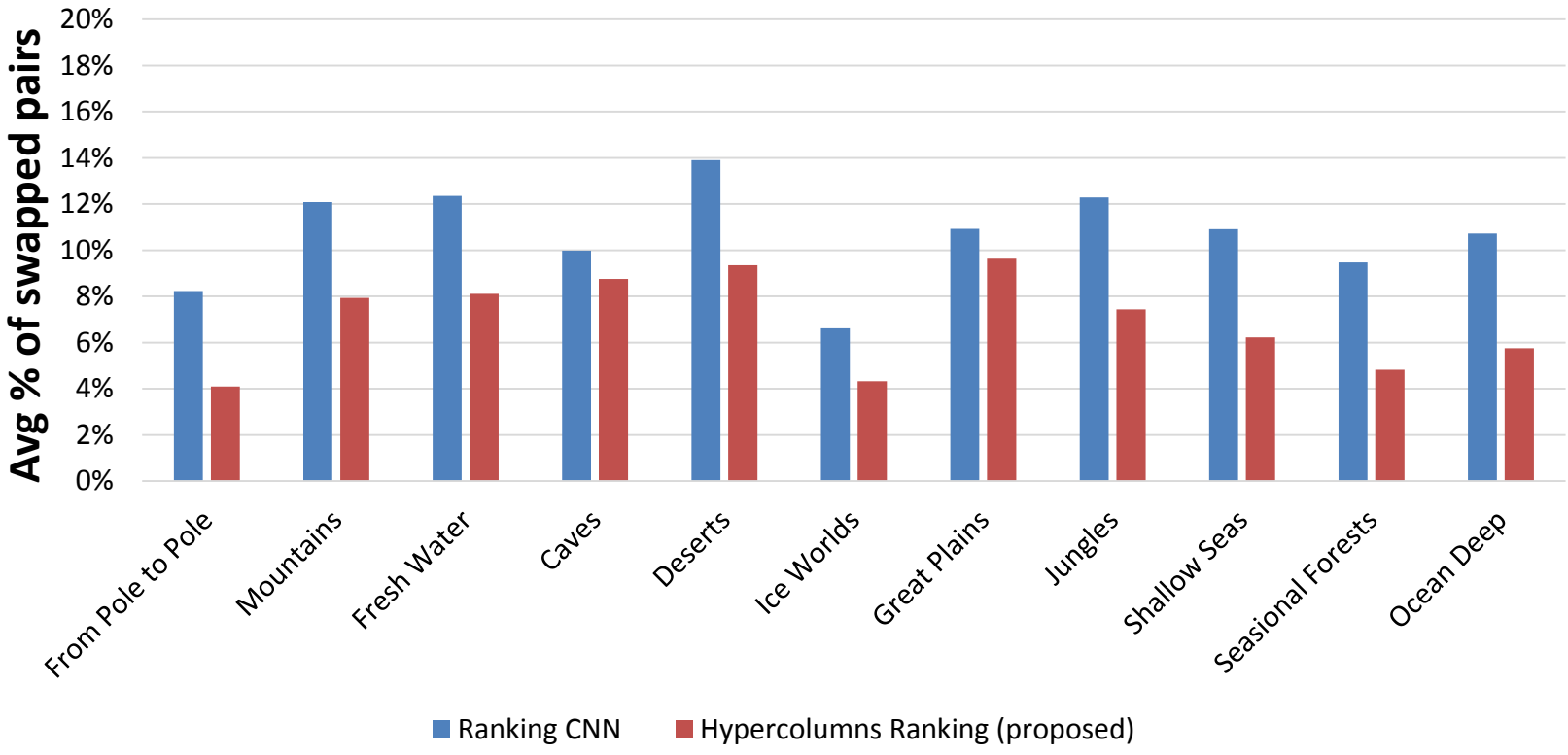
Three (paid) users asked to mark whether each key-frame was aesthetically relevant for its scene:

- Training pairs build according to the number of times a key-frame was selected

Thumbnail selection

Comparison with baseline: **Ranking CNN**

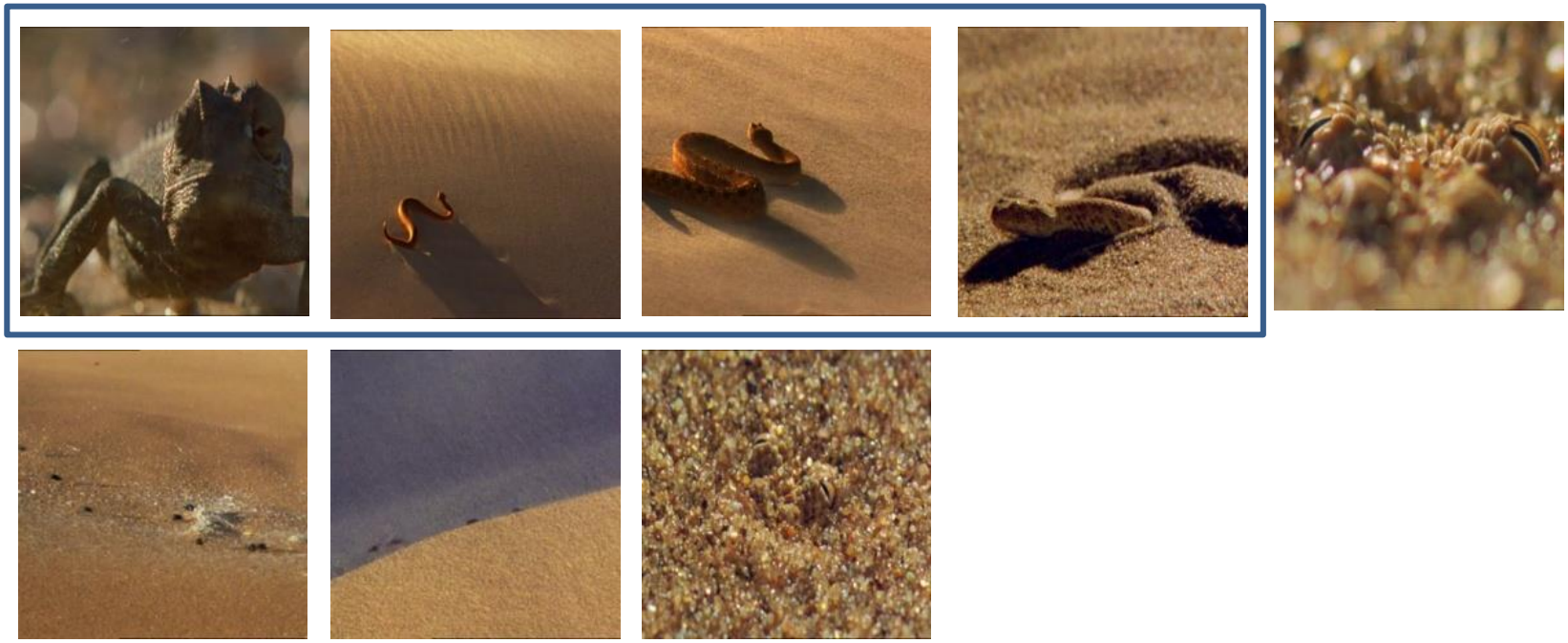
- Pre-trained VGG-16
- End-to-end learning with MSE



3,73% error reduction

Thumbnail selection

Ranking of a sample scene



Thumbnails with good quality and clearly visible object in the middle are preferred

Thumbnail selection

Ranking of a sample scene

Thumbnails with good quality and clearly visible object in the middle are preferred

Thumbnail selection

Ranking of a sample scene

Failure case:

Retrieval results (query “penguin”)

Shallow Seas

Probability: 0.78%

Being flightless, the returning penguins must cross the open beach on foot. Fur seals, that have come to the beach to breed are waiting for them... Fur seals normally live on krill, but these have now acquired an unexpected taste for blubber-rich penguins....

Shallow Seas

Probability: 0.75%

Penguins may be the featherweights by comparison, but they have razor sharp bills and a feisty character. The seal could easily lose an eye. The only safe way to grab a penguin is from behind... and the birds are well aware of that. Both animals are clumsy on this terrain. But the penguin has...

From Pole to Pole

Probability: 0.72%

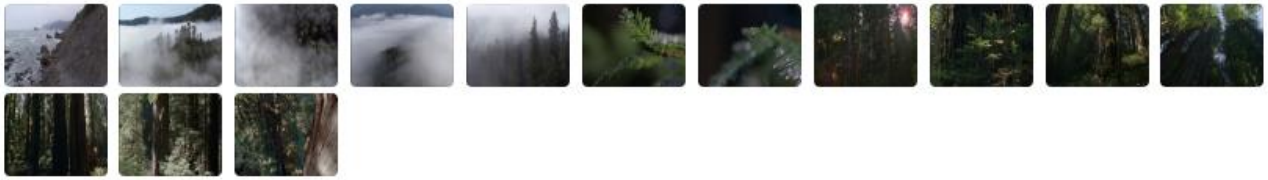
The penguins stay when all other creatures have fled because each guards a treasure a single egg resting on the top of its feet and kept warm beneath the downy bulge of its stomach. There is no food and no water for them and they will not see the sun again for four months. Surely, no greater ord...

Retrieval results (query “conifer”)

Seasonal Forests

Probability: 0.78%

The Pacific coast of North America. The land of hemlock, Douglas fir and giant redwood. Here, water is never locked-up in ice. And even if rains fail, the needles can extract moisture from the fogs that roll in from the sea. The sun's energy powers these forests not for one month, as it does...



Seasonal Forests

Probability: 0.70%

The American conifer forests may not be the richest in animal life, but their trees are extraordinary. This giant sequoia, a relative of the redwood, is the largest living thing on earth. Known as 'General Sherman', it's the weight of ten blue whales. Higher up in the nearby mountains, bristle-co...

Seasonal Forests

Probability: 0.64%

Trees. Surely among the most magnificent of all living things. Some are the largest organisms on earth, dwarfing all others and these are the tallest of them all. The deciduous and coniferous woodlands that grow in the seasonal parts of our planet are the most extensive forests on earth. Their shee...

Retrieval results (query “fall”)

Fresh Water

Probability: 0.62%

In their upper reaches mountain streams are full of energy. Streams join to form rivers, building in power, creating rapids....

Fresh Water

Probability: 0.58%

Fresh Water

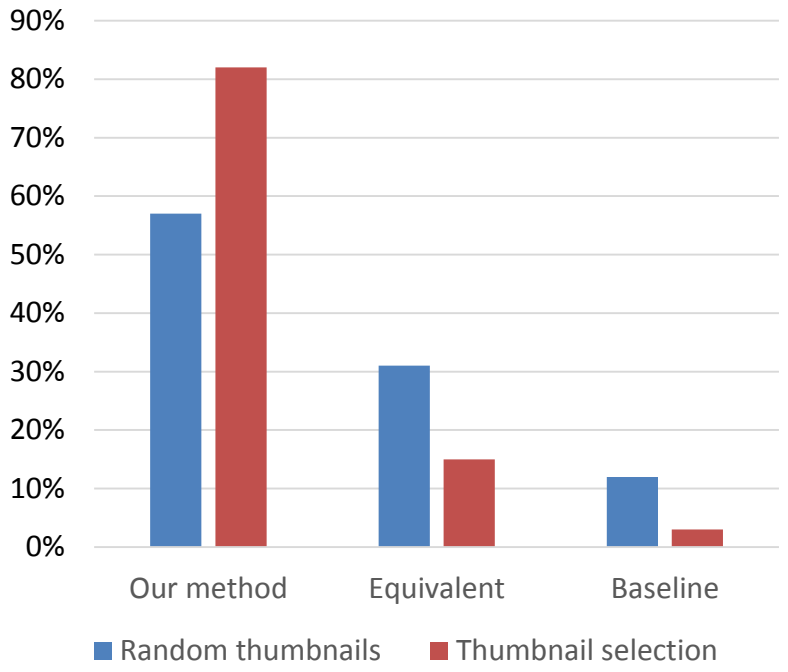
Probability: 0.53%

Moisture, rising as water vapour from the surface of the sea, is blown inland by wind. On reaching mountains, the moist air is forced upwards and, as it cools, it condenses into cloud and finally rain, the source of all Fresh Water. There is a tropical downpour here almost every day of the year...

Retrieval results

User study

- 12 undergraduate students
- 20 queries each
- Comparison with respect to the results of a full-text search inside text:
  - With random thumbnails
  - With thumbnail selection



Conclusions

- We proposed a video retrieval pipeline
  - Specifically designed for broadcast videos
  - Relies on temporal video segmentation (scenes)
  - Retrieval is carried out with semantic concept detection and aesthetic rankings.
  - Quantitative and qualitative evaluation

Thank you

Any questions?

lorenzo.baraldi@unimore.it, costantino.grana@unimore.it, rita.cucchiara@unimore.it

http://imagelab.ing.unimore.it

Thanks to "Educating City" Project funded by Italian MIUR National Technology Cluster program with UNIMORE, CNR, UNITN, RAI, ATI_CIttàedu, RCI, Almaviva