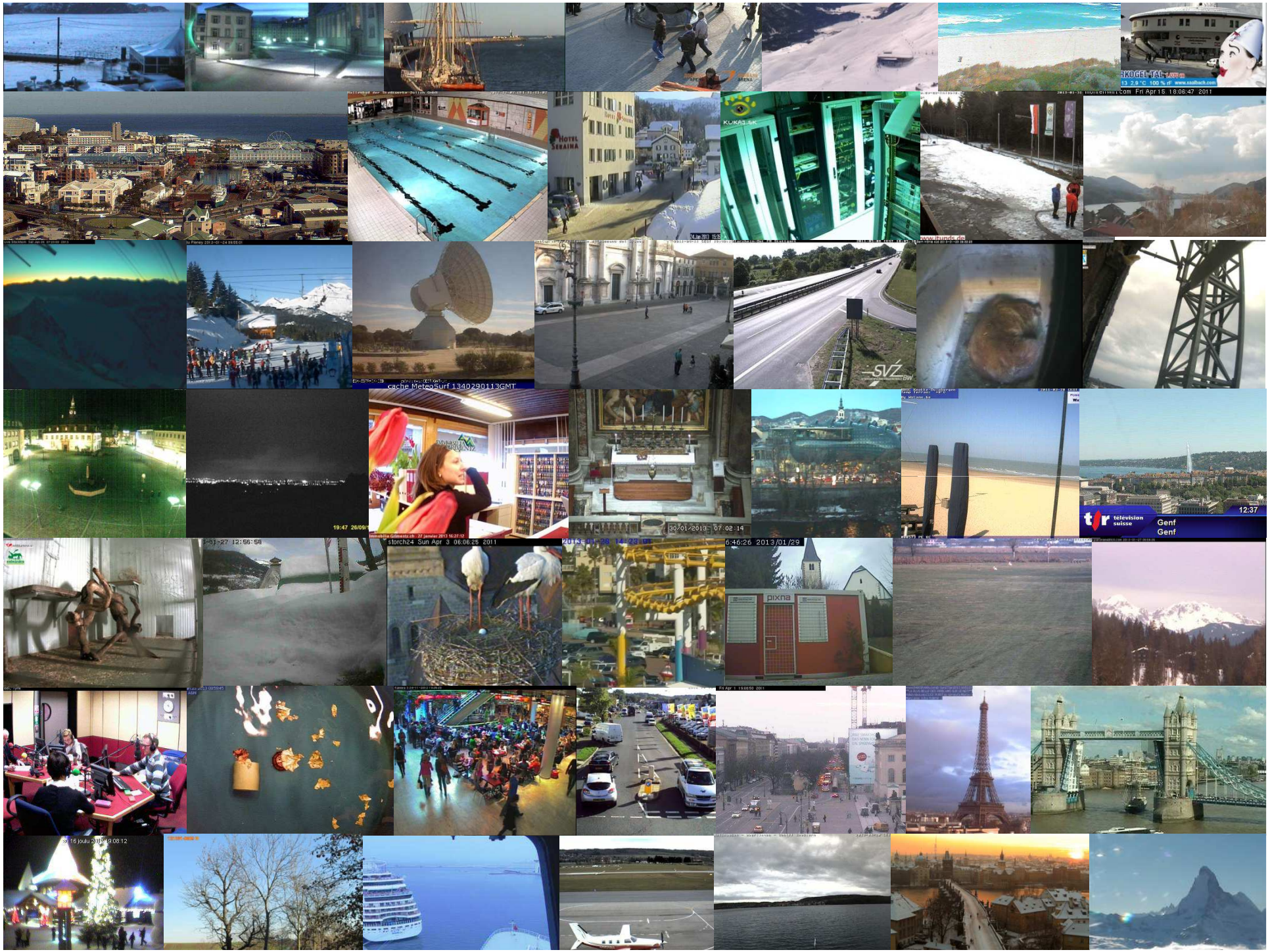
ETH zürich

webcamaze – Amazing Webcams

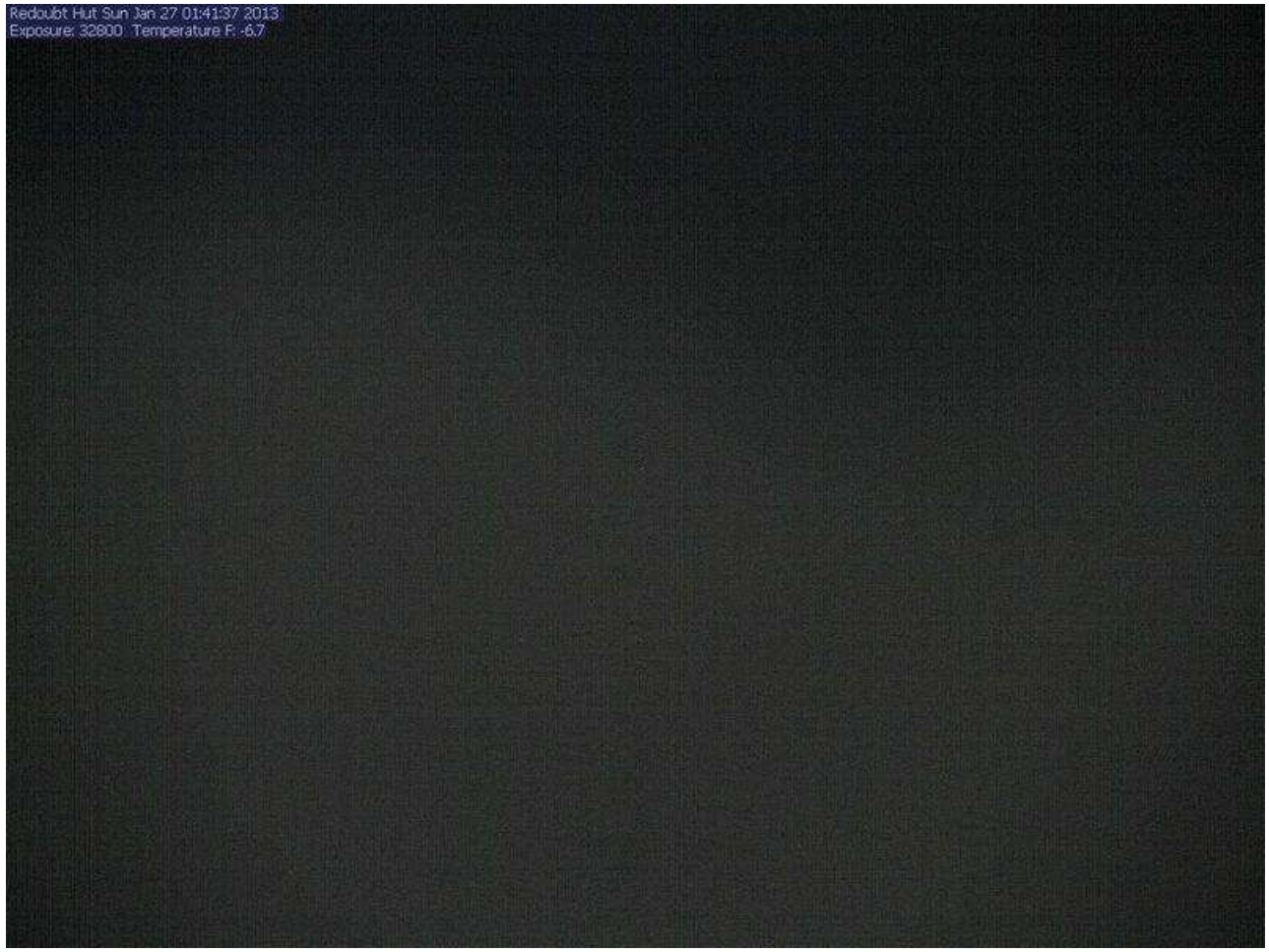
Helmut Grabner

ETH Zurich, Computer Vision Lab
upicto GmbH

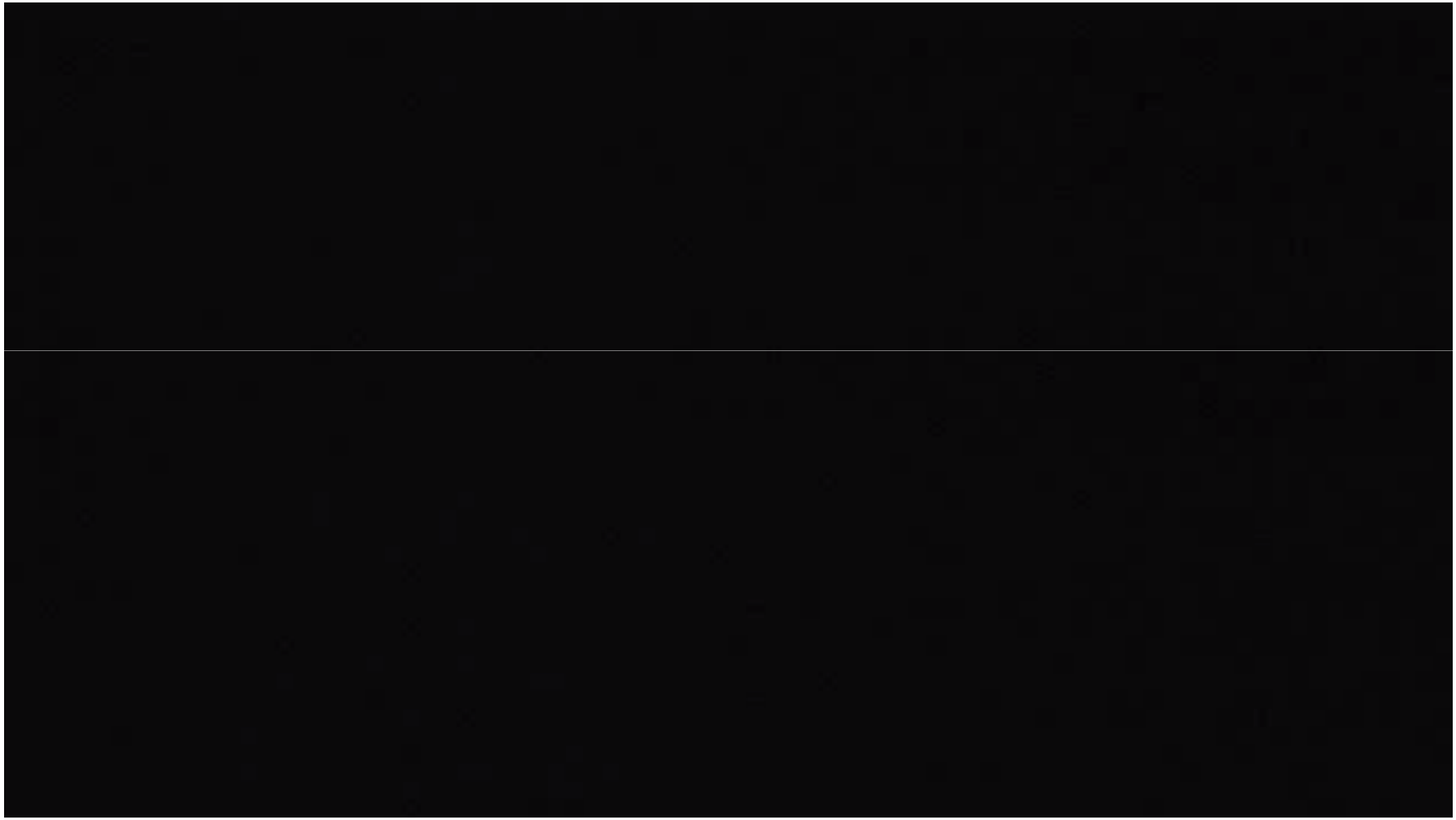
Webcams – Eyes of the Internet


KOGEL-TAL
www.kuhnds.de
cache MeteoSurf 1340290113GMT
19:47 26/09/
30/01/2013 07:02:14
12:37
tsr télévision suisse
Genf
Genf
storch24 Sun Apr 3 06:06:25 2011
6:46:26 2013/01/29
pixna

The Most Common Image Worldwide



Example Sequence



Images are Overwritten – What a pity!

- GOAL: Spot some “cool” images – automatically

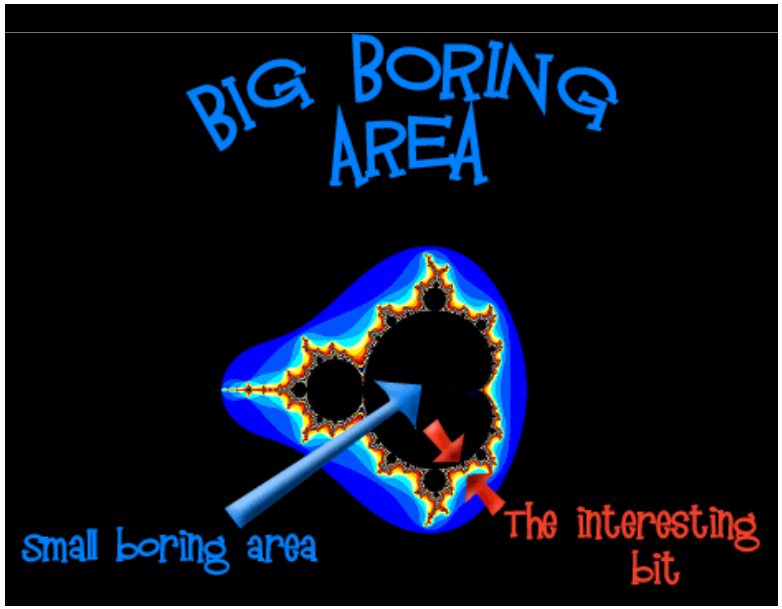
[BTW: Webcam Art by Kurt Caviezel]

"In the right time at the right spot"

KURT CAVIEZEL

Challenges

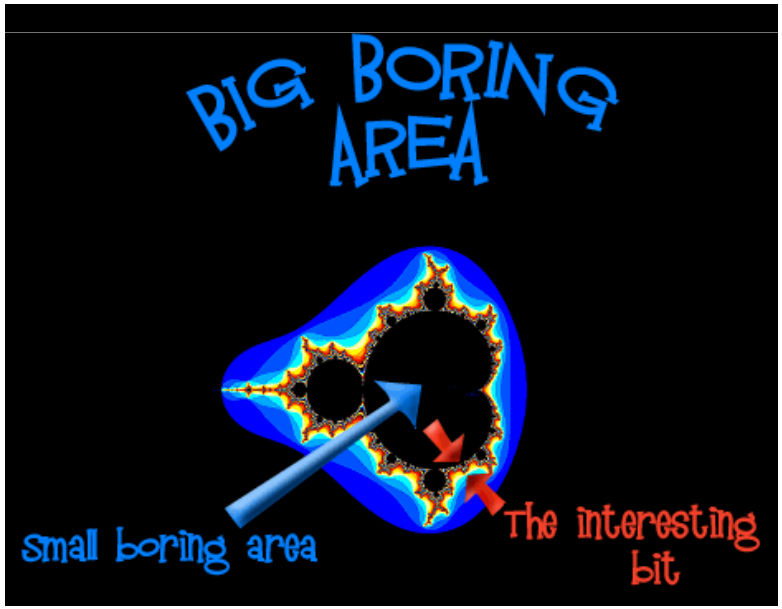
❶ Enormous amount of data



❷ What do we (humans) find interesting?

Challenges

❶ Enormous amount of data



❷ What do we (humans) find interesting?

What is “Interesting”

- (highly) subjective
  - prior knowledge
  - context
  - personal favor
  - semantics
  - etc.

What is “Interesting”

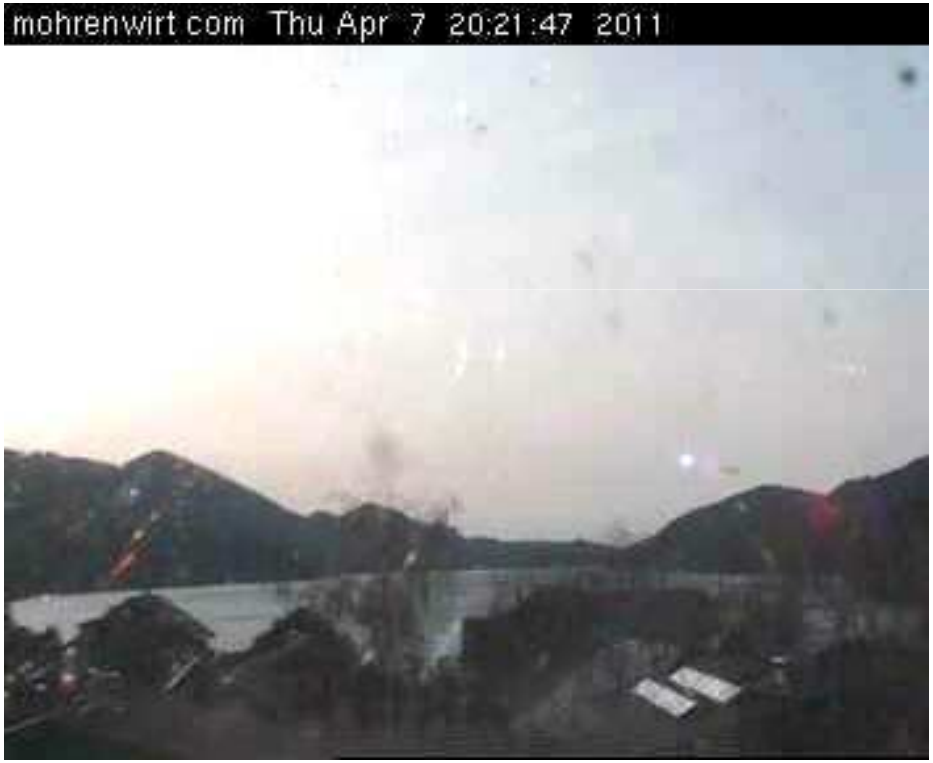
What is “Interesting”

What is “Interesting”

> 20 Years

What is “Interesting”

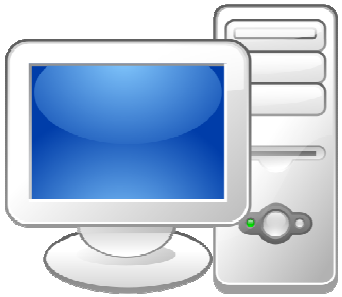
- Interestingness in image sequences
  - Sequence specifies the context



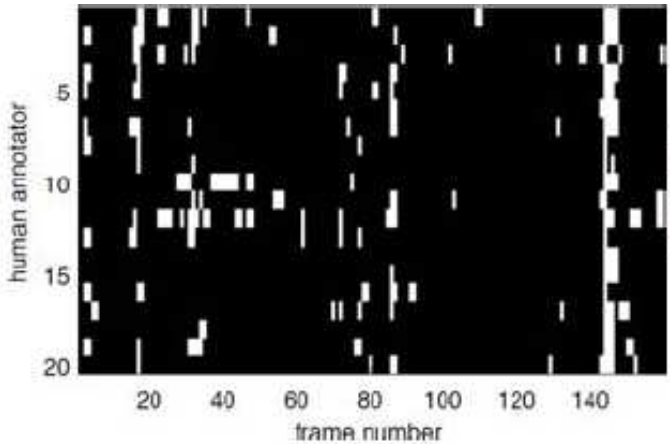
[H. Grabner, F. Nater, M. Druey, and L. Van Gool, Visual Interestingness in Image Sequences, ACM MM’13]

Outline

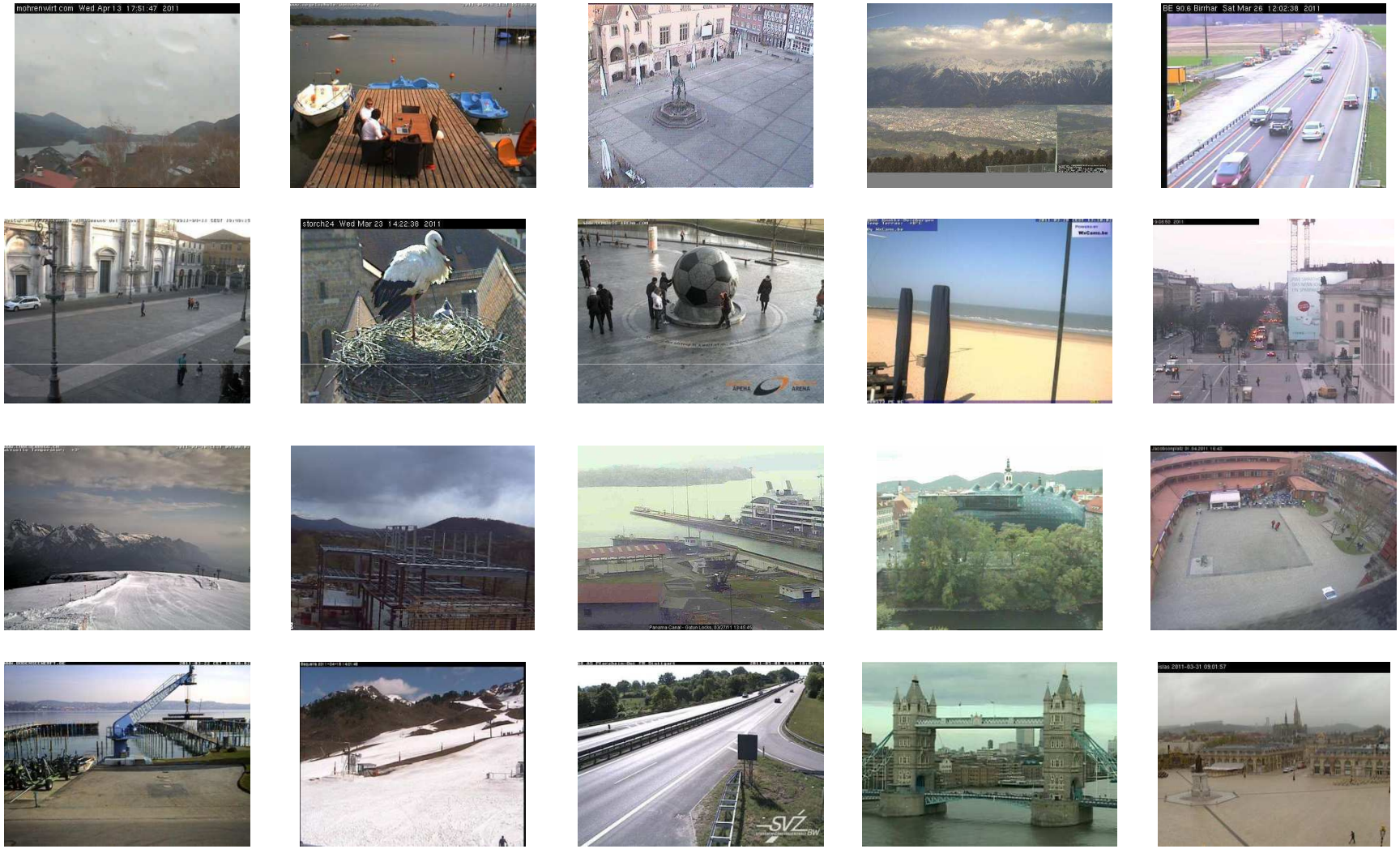
- Human consensus baseline of visual interestingness
- Computational approach



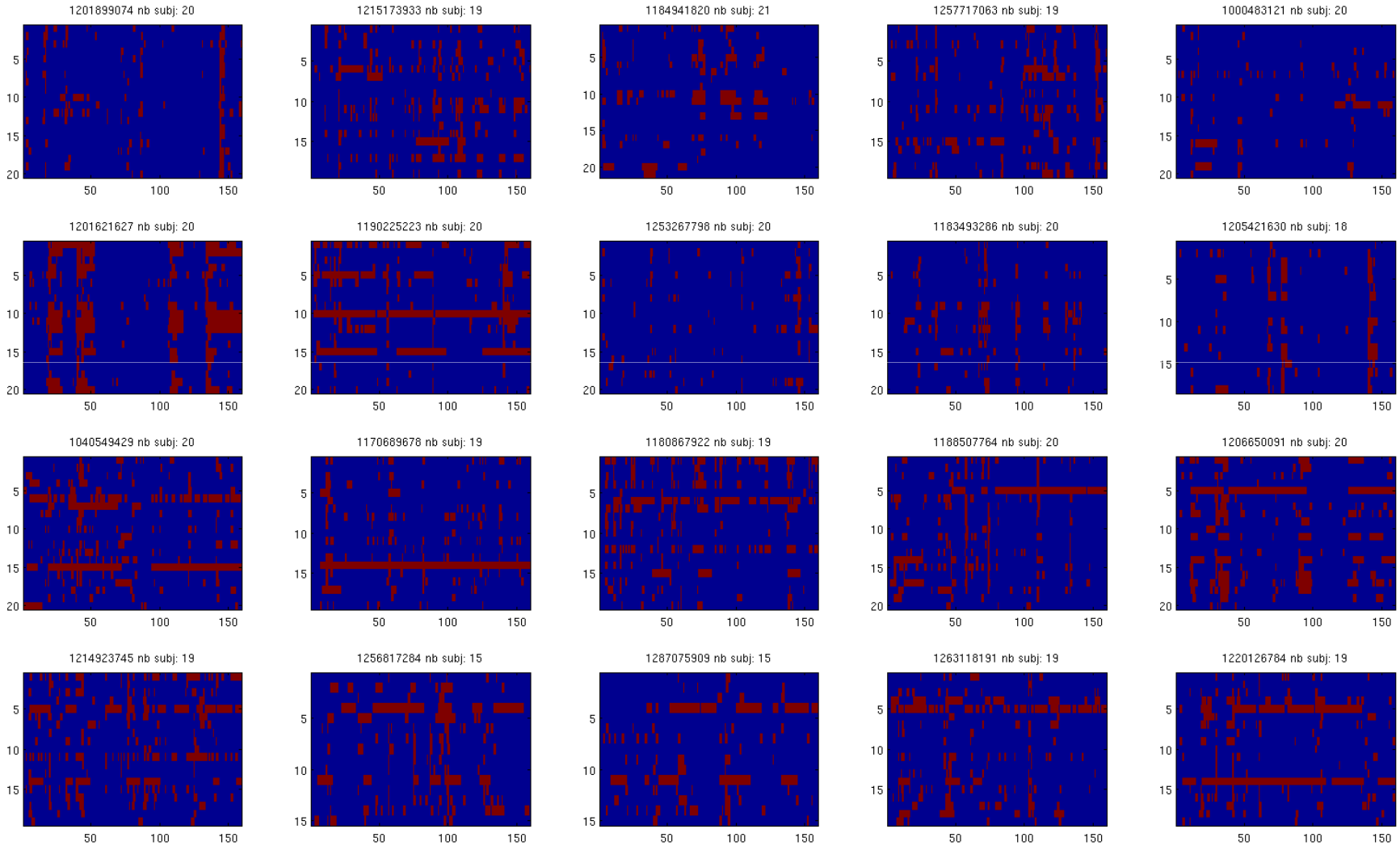
Human Consensus Baseline


human annotator
5
10
15
20
20
40
60
80
100
120
140
frame number

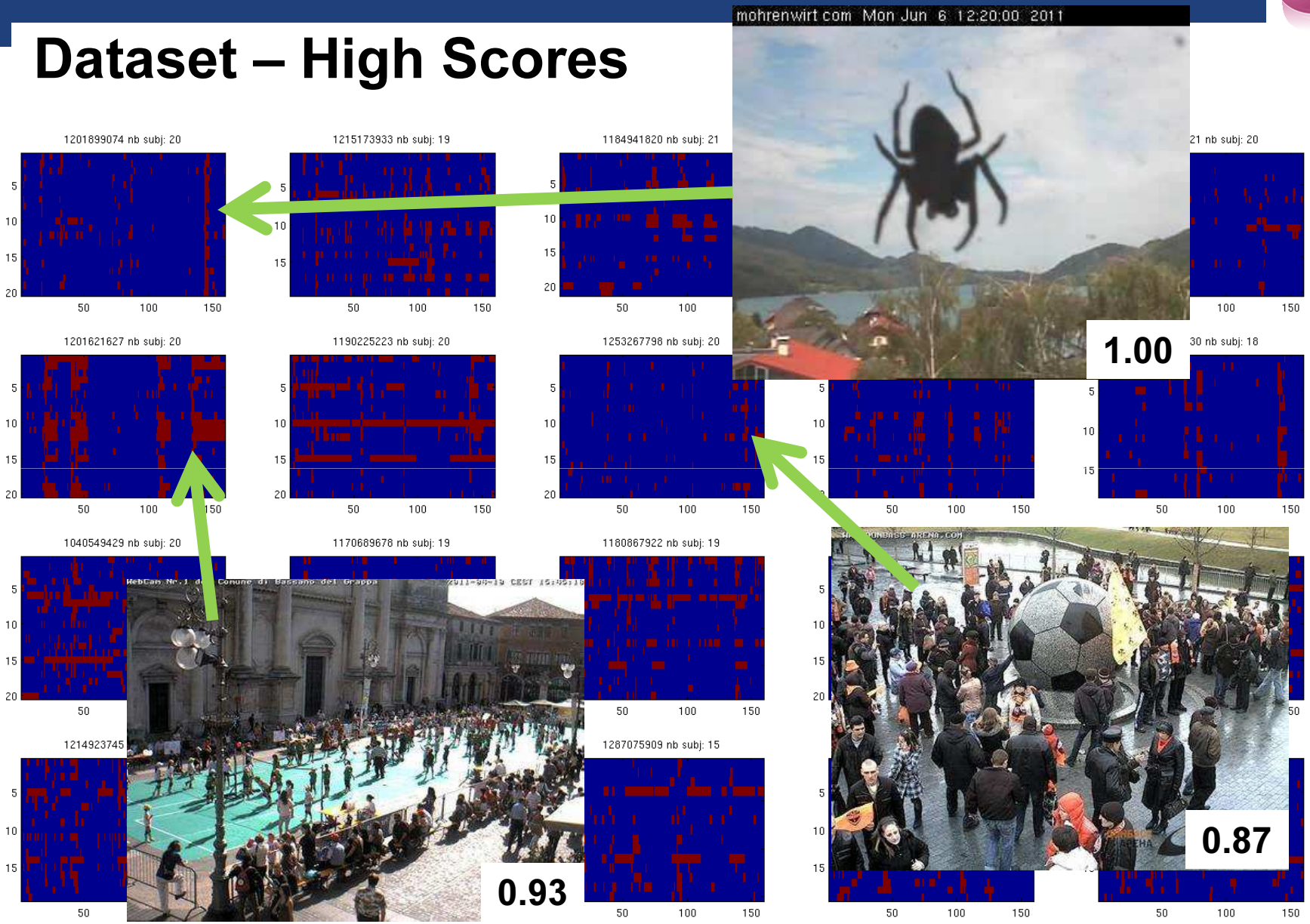
Dataset – 20 Sequences



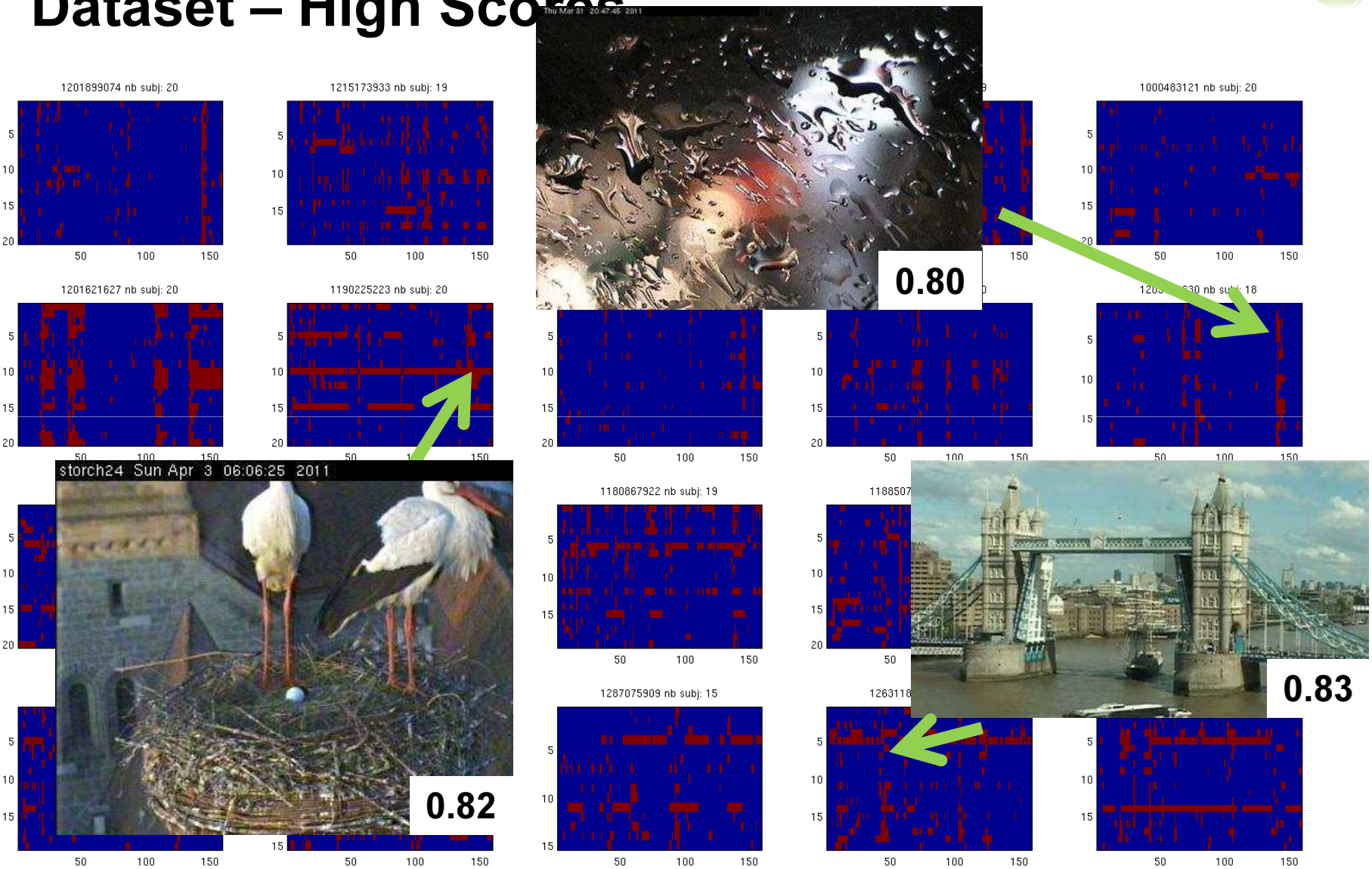
Dataset – Annotations



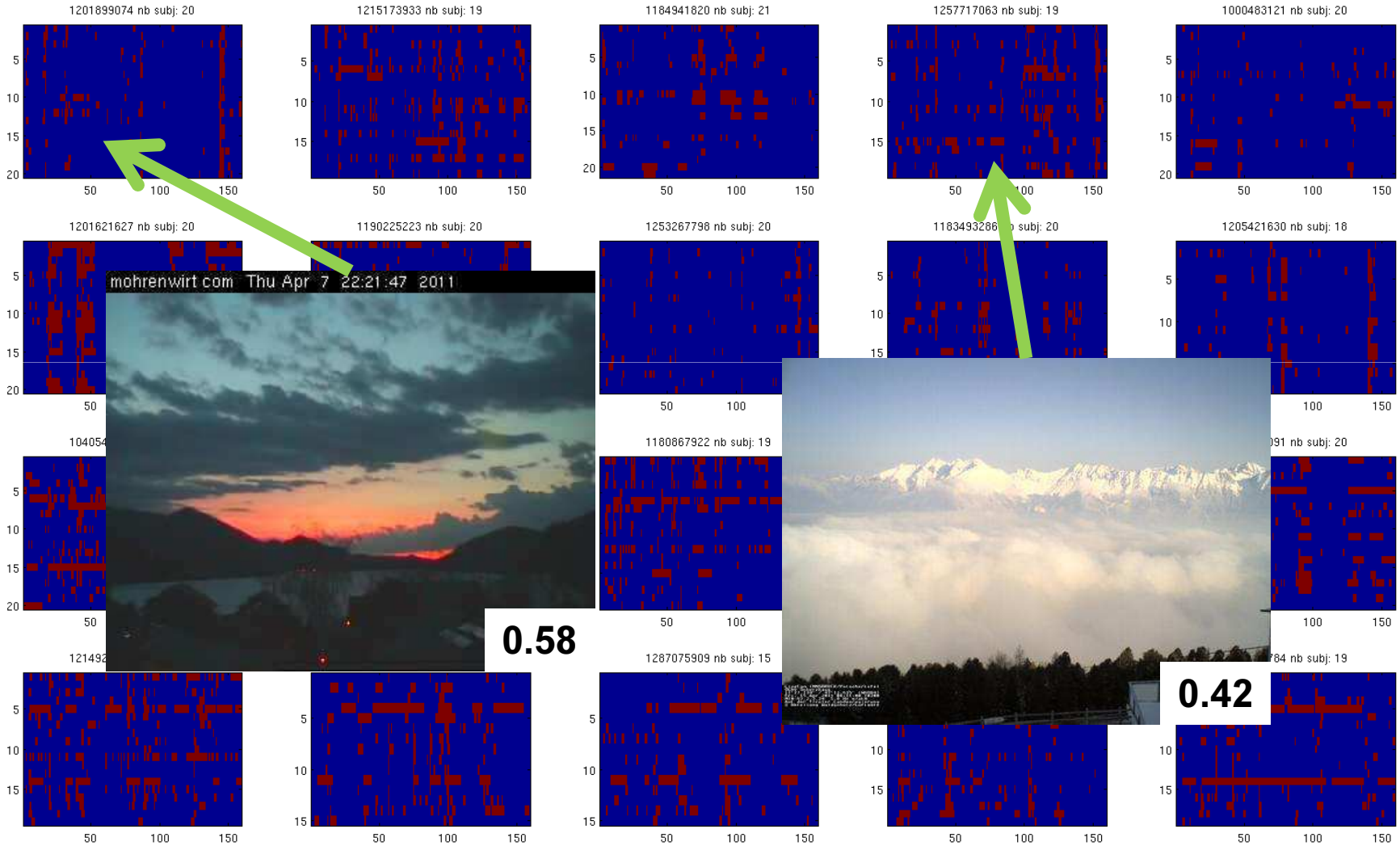
Dataset – High Scores



Dataset – High Scores

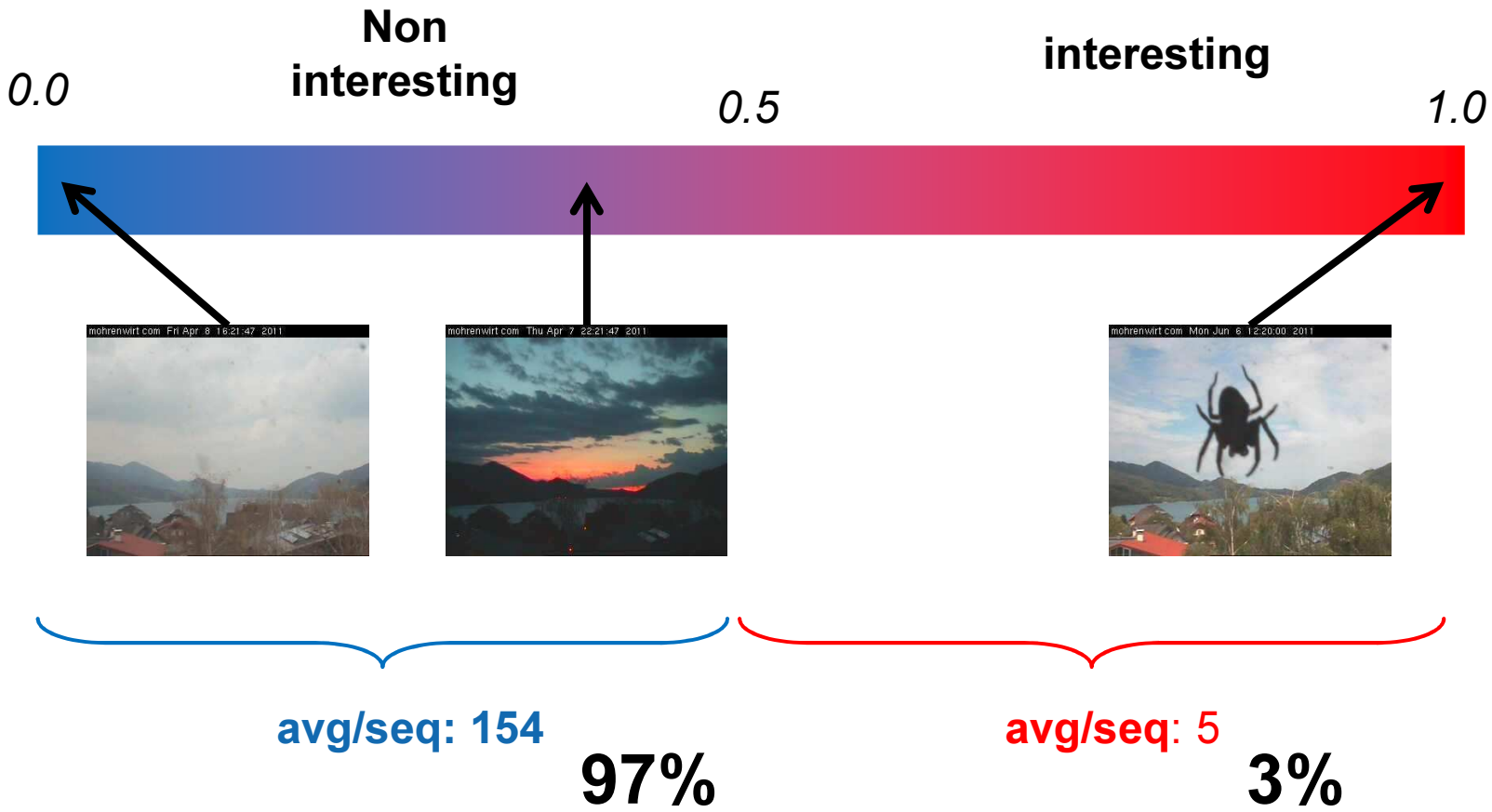


Dataset – Medium Scores



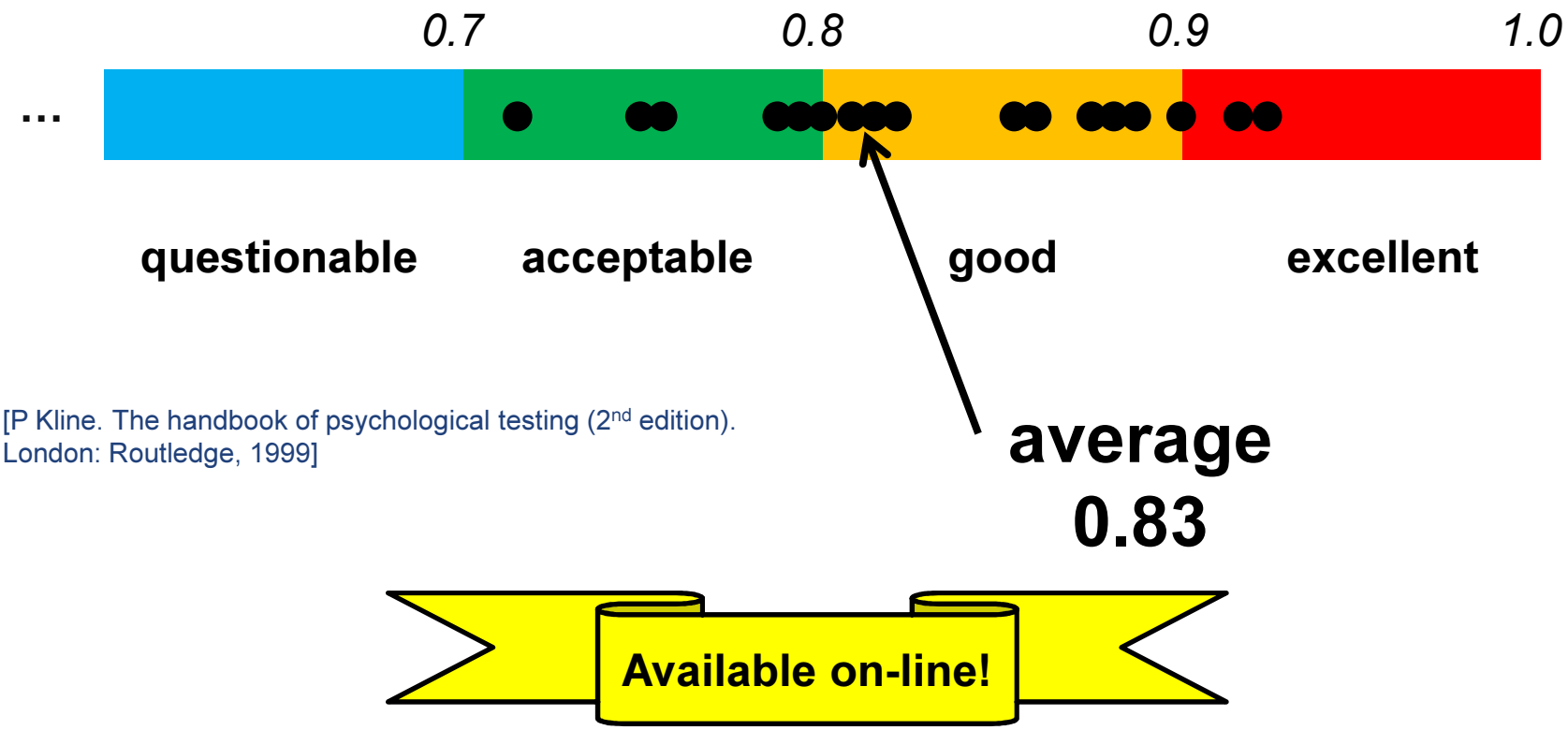
Dataset – Statistics

Human Consensus Baseline



Dataset – Consistency

Standardized Cronbach's Alpha

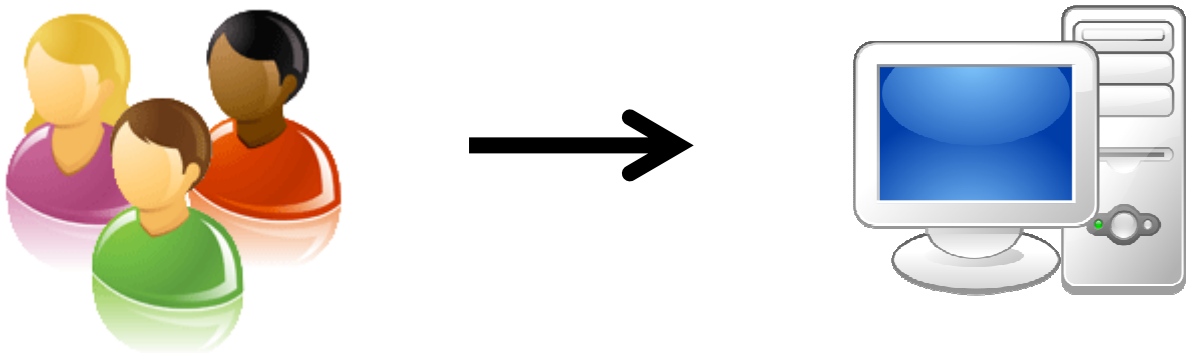


[P Kline. The handbook of psychological testing (2nd edition). London: Routledge, 1999]

Available on-line!

Human Consensus Baseline – Conclusion

- The human consensus base-line gives a solid ground and can be used to
  - build computational models and
  - evaluate them.



Psychological View

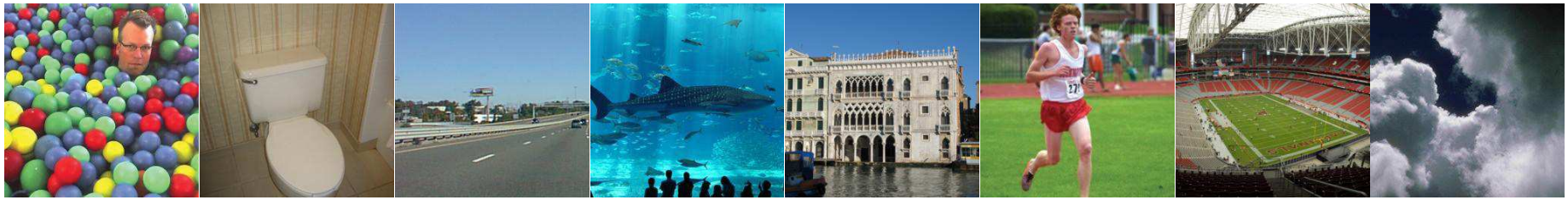
- **Daniel Berlyne** (1924-1976)
- Mid-50s: Interest relevant for human learning

- 4 collative variables:
  - **Novelty**
  - **Uncertainty**
  - **Conflict**
  - **Complexity**

[D. Berlyne, Conflict, arousal, and curiosity. McGraw-Hill, 1960]

Human Study on Single Images

- Memorability dataset…



[P. Isola, J. Xiao, A. Torralba, A. Oliva. *What makes an image memorable?* CVPR, 2011]

- …with additional annotations
  - Human annotates (Mechanical Turk)
  - > 900 features (e.g., indoor, enclosed space, aesthetic, famous place, etc.)

[P. Isola, D. Parikh, A. Torralba, A. Oliva. *Understanding the intrinisc memorability of images*, NIPS, 2011]

Correlation with Memorability

Abstract

Artists, advertisers, and photographers are routinely presented with the task of creating an image that a viewer will remember. While it may seem like image

...

not. Contrary to popular belief, unusual or aesthetically pleasing scenes do not tend to be highly memorable. This work represents one of the first attempts at

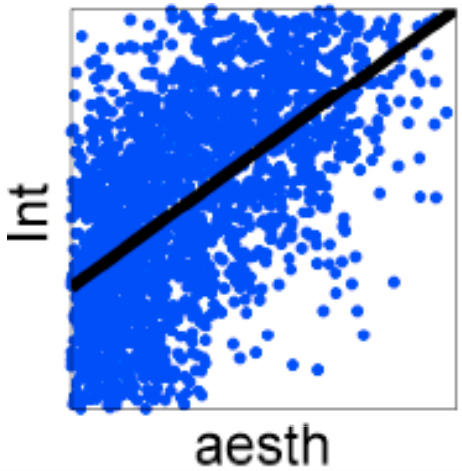
...

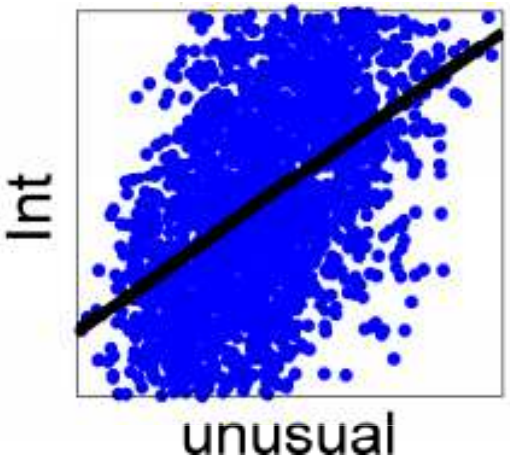
(a) (b) ↑U ↓M (c) ↓U ↑M (d) (e) ↑A ↓M (f) ↓A ↑M (g) (h) ↑m ↓M (i) ↓m ↑M

[P. Isola, D. Parikh, A. Torralba, A. Oliva. *Understanding the intrinisc memorability of images*, NIPS, 2011]

Correlation with “Interestingness”

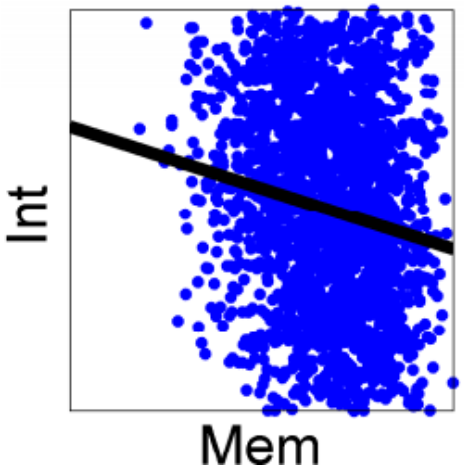
corr: 0.59

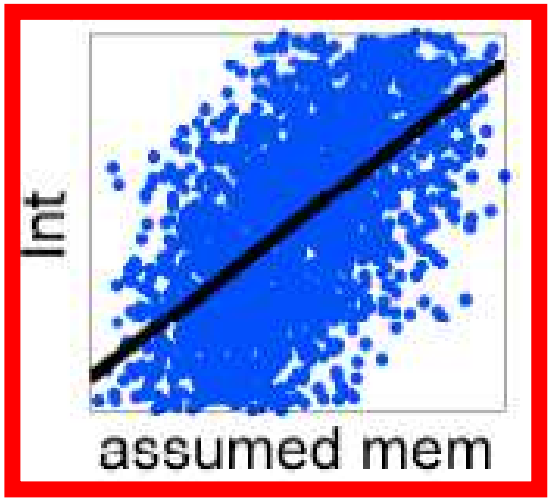




corr: 0.51

corr: -0.17

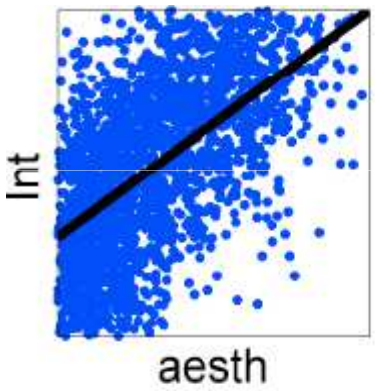




corr: 0.63

[M. Gygli, H. Grabner, H. Riemenschneider, F. Nater, and L. Van Gool, The Interestingness of Images, ICCV’13]

A new Concept: Interestingness

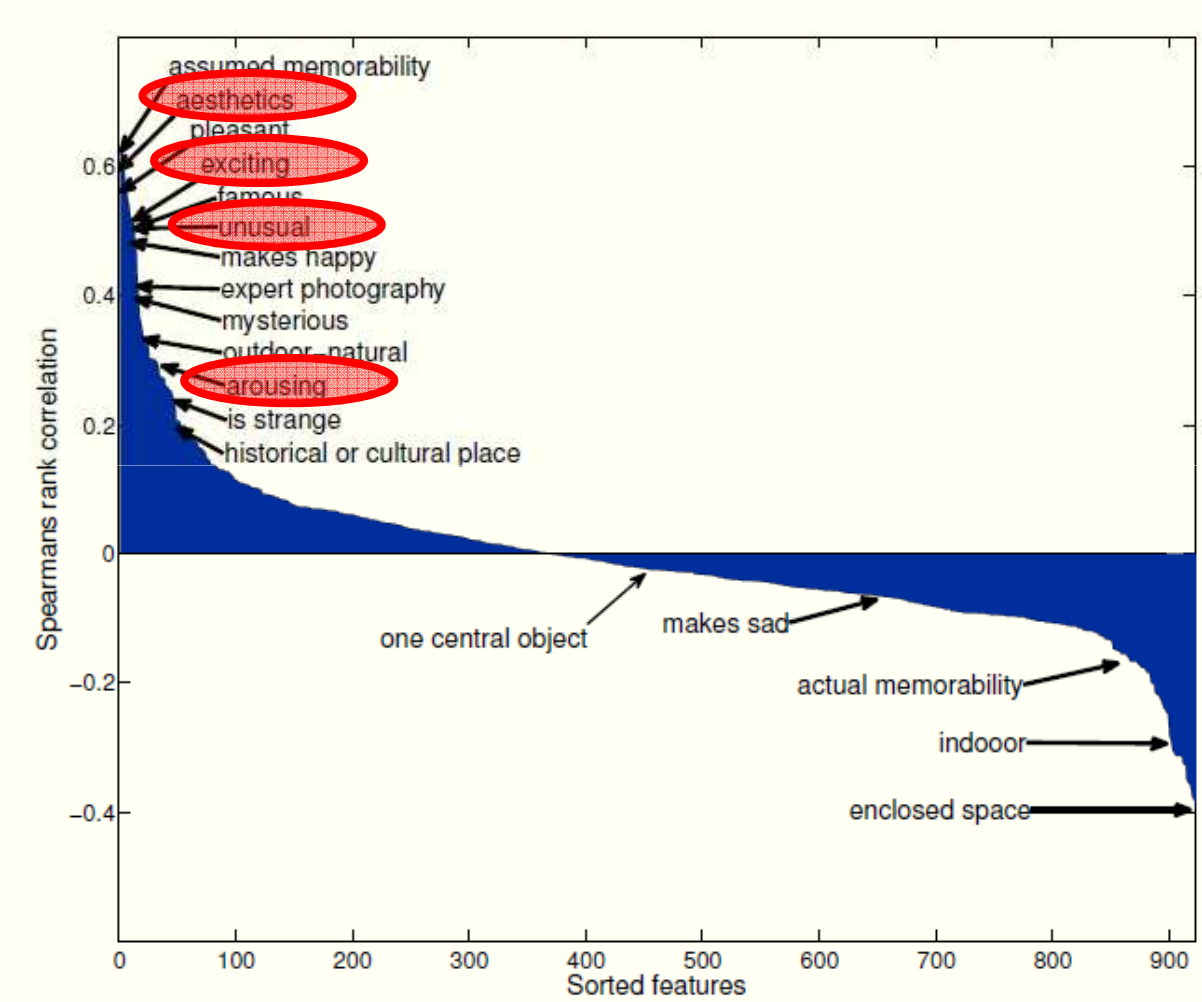


corr= +0.59

↑ aesth ↓ int ↓ aesth ↑ int

[M. Gygli, H. Grabner, H. Riemenschneider, F. Nater, and L. Van Gool, The Interestingness of Images, ICCV'13]

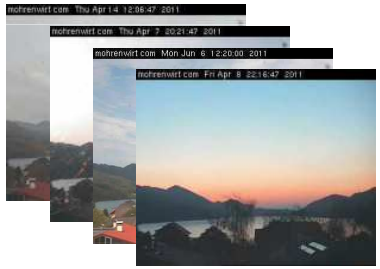
Correlation with Interestingness



[M. Gygli, H. Grabner, H. Riemenschneider, F. Nater, and L. Van Gool, The Interestingness of Images, ICCV'13]

Computational Approach: Overview

Image Sequence



Interestingness Cues

- → emotion
- → complexity
- → novelty
- → learned

Ranking

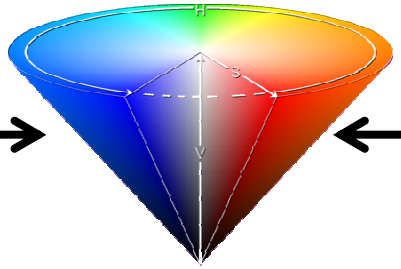
high

...

low

Combination and Context Regularizations

Cues for Interestingness: Emotion

Image ⟷  ⟷ Arousal ⟷ Emotions

[P. Valdez and A. Mehrabian. Effects of color on emotions. Journal of Experimental Psychology: General,123(4):394-409, 1994]

[P. Lang, M. Bradley, and B. Cuthbert. International affective picture system (IAPS): A effective ratings of pictures and instruction manual. Technical Report A-8. University of Florida, 2008]

High scoring samples

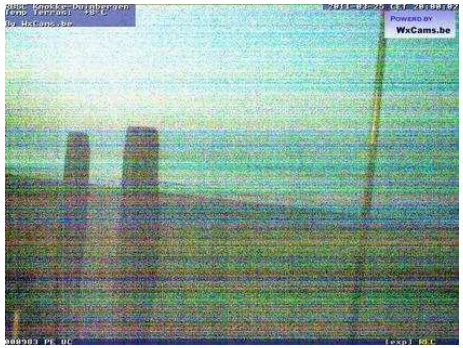
Cues for Interestingness: Complexity

Image ⟷

⟷ # Bytes ⟷ Complexity

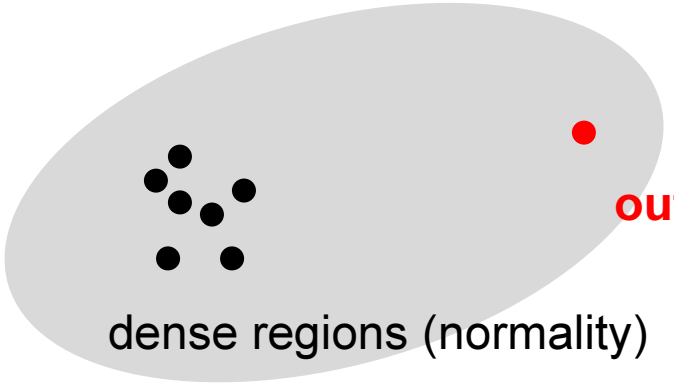
Compression

High scoring samples



Cues for Interestingness: Novelty

Image ⟷



⟷ **Novelty**

[M. Breunig, H. Kriegel, R. Ng, and J. Sander. LOF: Identifying density-based local outliers. In Proc. ACM SIGMOD Int. Conf. on Management of Data, 2000]

[H. Zhong, J. Shi, and M. Visontai. Detecting unusual activity in video. In Proc. CVPR, 2004]

High scoring samples

Cues for Interestingness: Learned

Features & Machine Learning

Image ⟷ ⟷ **Interestingness**

[J. Machajdik and A. Hanbury. Affective image classification using features inspired by psychology and art theory. In Proc. ACM MM, 2010.]

[S. Dhar, V. Ordonez, and T. Berg. High level describable attributes for predicting aesthetics and interestingness. In Proc. CVPR, 2011]

[P. Isola, J. Xiao, A. Torralba, and A. Oliva. What makes an image memorable? In Proc. CVPR, 2011]

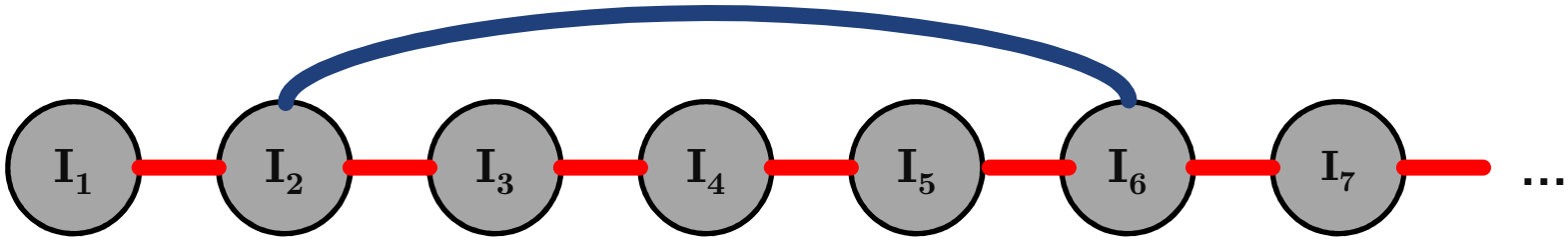
High scoring samples

Combination & Context Regularization

- Linear Model

$$\mathbf{s} = \mathbf{w}^{\mathbf{T}} \left[\mathbf{x}^{(\mathbf{emotion})}, \mathbf{x}^{(\mathbf{novelty})}, \mathbf{x}^{(\mathbf{learned})}, \mathbf{x}^{(\mathbf{complexity})}\right]^{\mathbf{T}}$$

- Context Regularization
  - Temporal neighboring images ⇨ similar interestingess Score
  - Visually similar images ⇨ similar interestingess Score



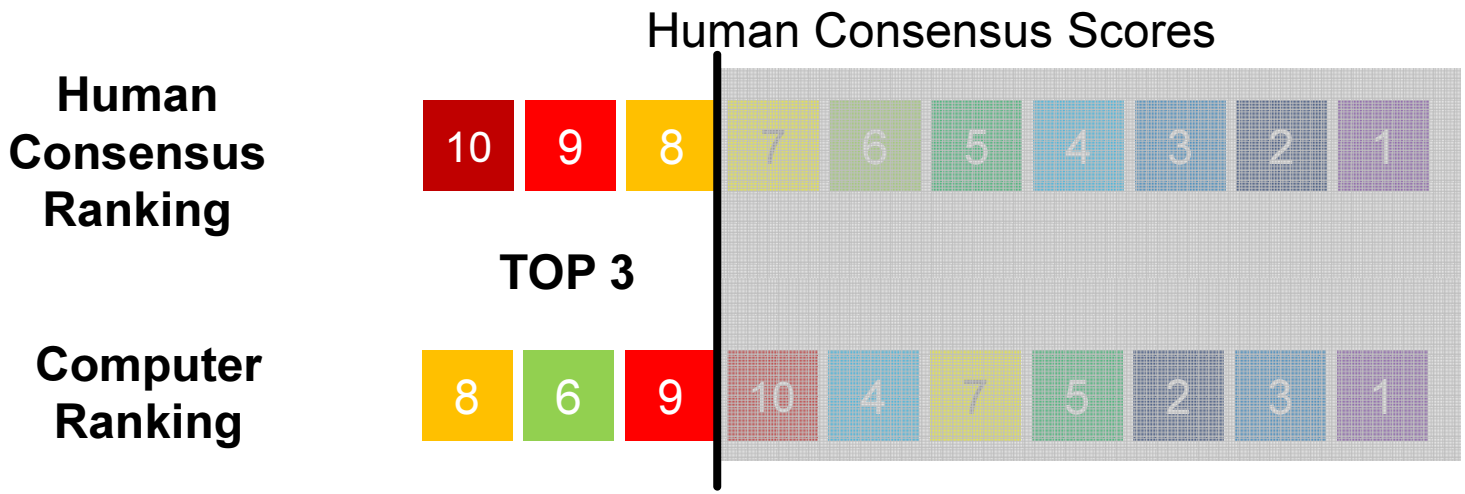
[F. Nater, H. Grabner, and L. Van Gool. Temporal relations in videos for unsupervised activity analysis. In Proc. BMVC, 2011.]

[V. Jain and E. Learned-Miller. Online domain adaption of a pre-trained cascade of classifiers. In Proc. CVPR, 2011.

[X. Zhu, Z. Ghahramani, and J. Lafferty. Semi-supervised learning using gaussian fields and harmonic functions. In Proc. ICML, 2003.]

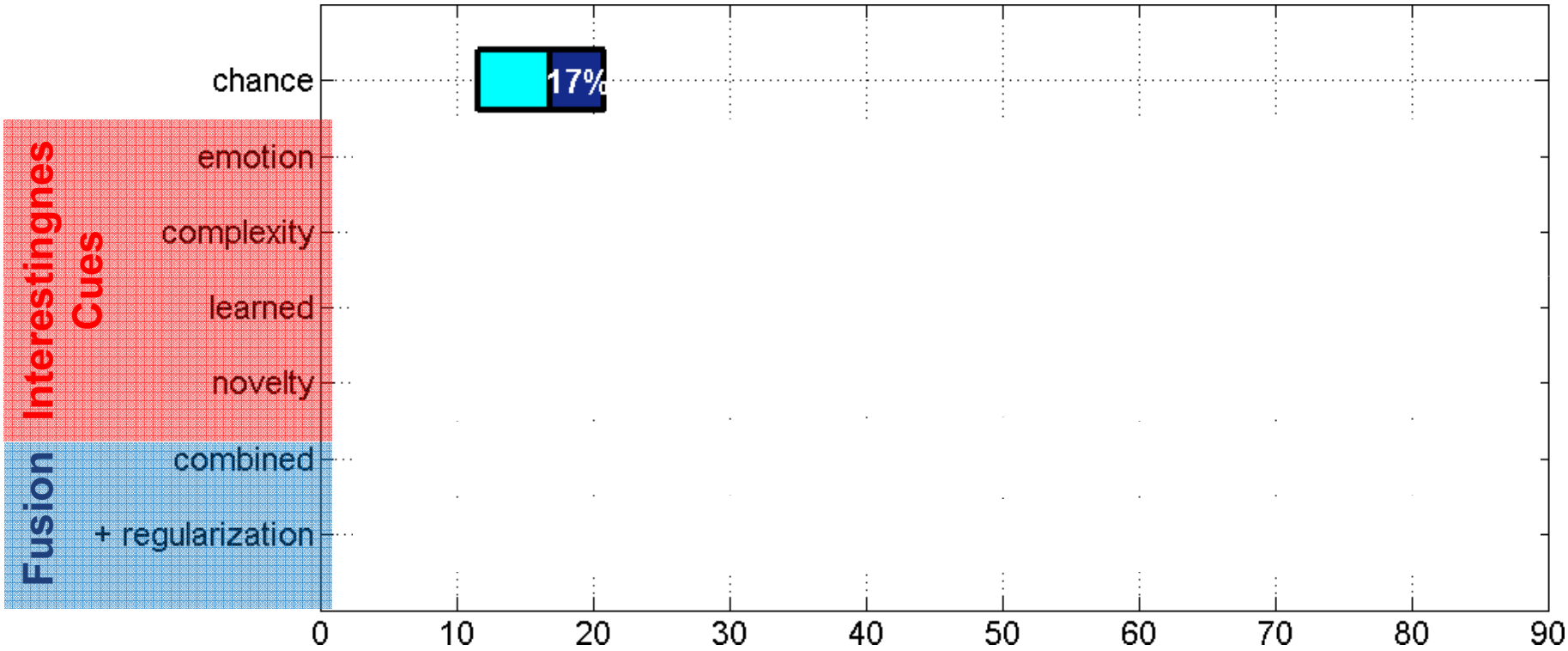
Results

- Evaluation: Top_3 Score



$$Top_3 = \frac{8 + 6 + 9}{10 + 9 + 8} = 0.6$$

Results: Box-plot of Top_3 for the 20 Sequences



Low Ranked Images

High Ranked Images

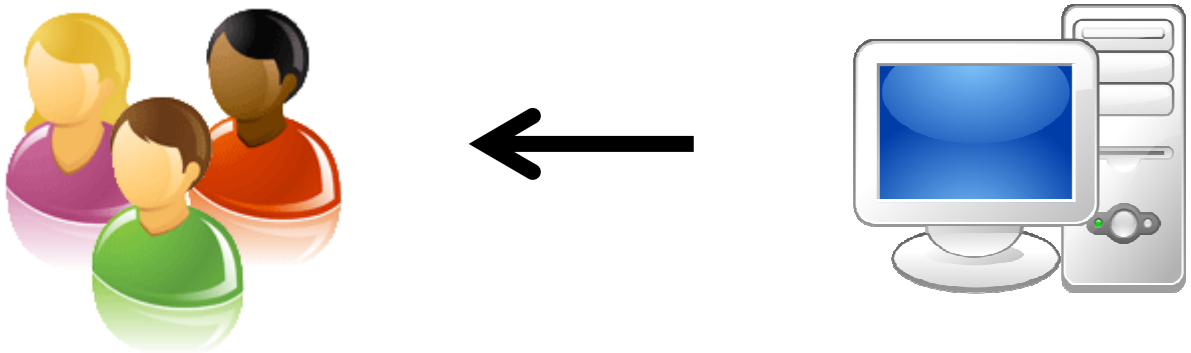
Failures

False Positives

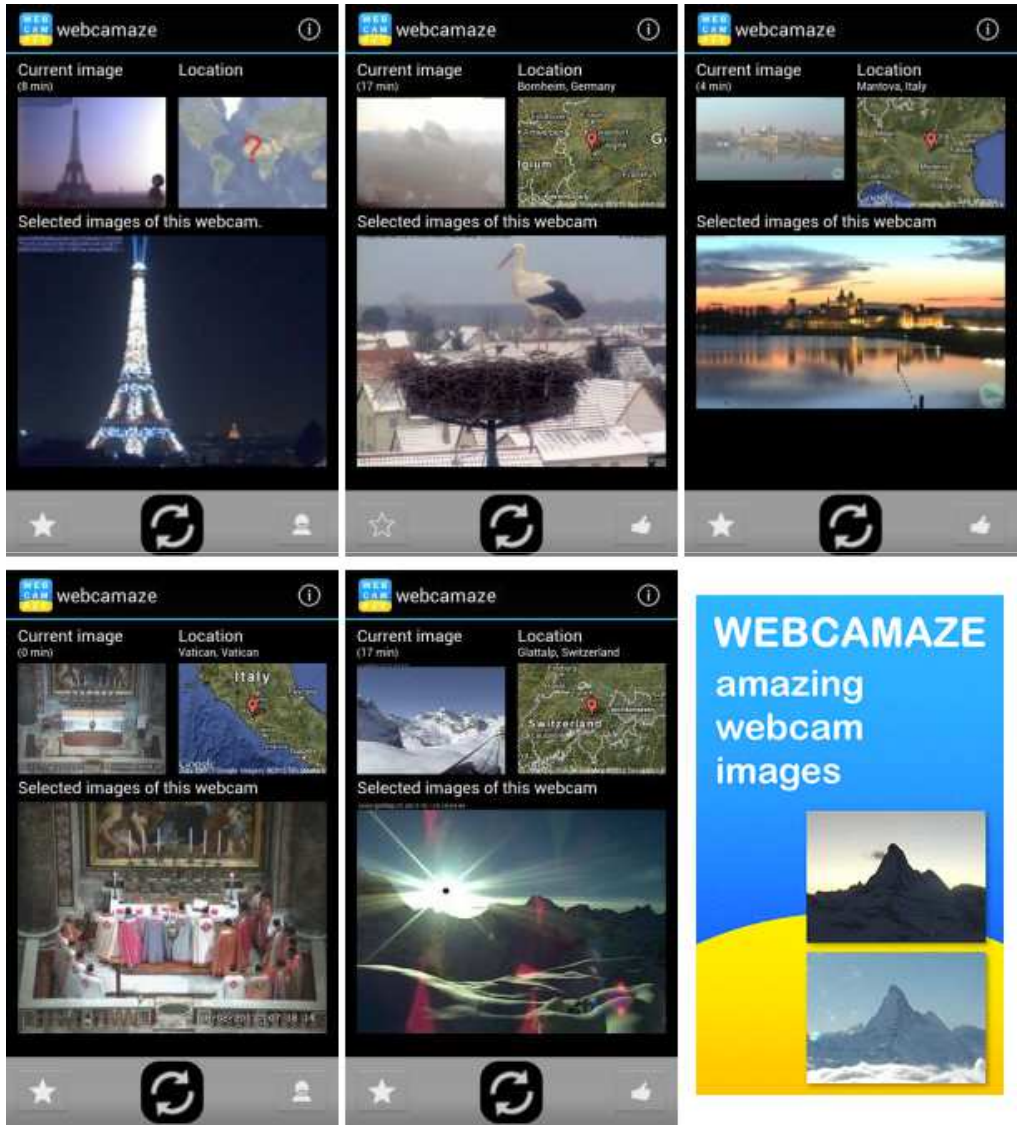
Misses

Computational Approach – Conclusion

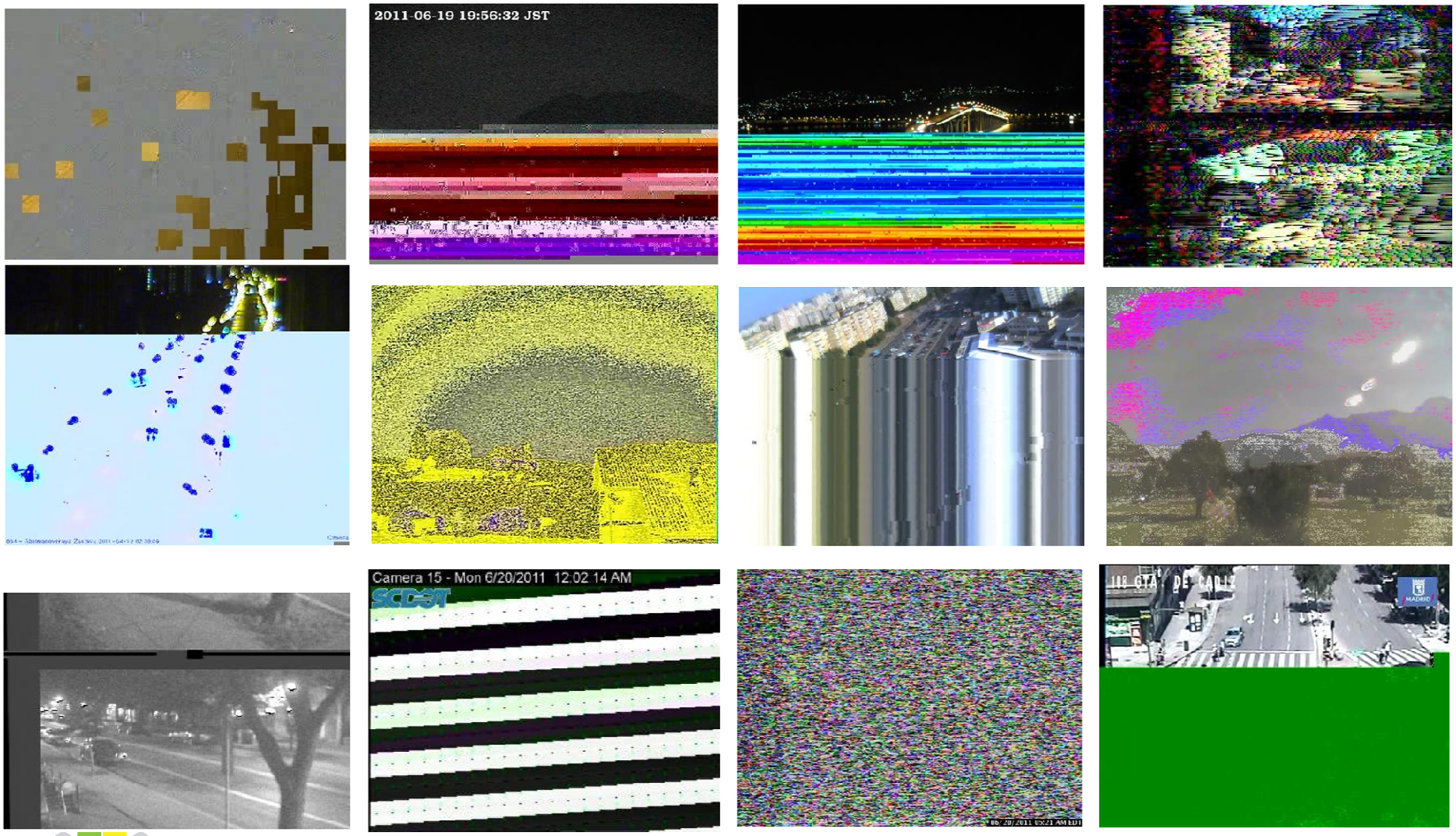
- We have demonstrated – while still remaining far from a semantic interpretation – a number of basic cues and their straight forward combination already let us mimicking human interest responses.



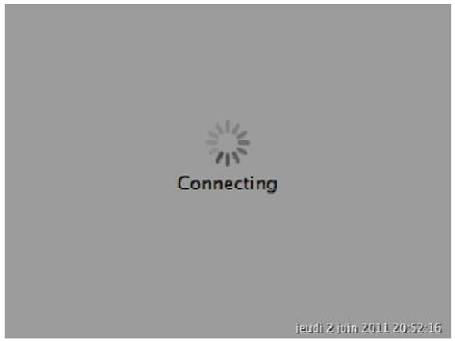
www.webcamaze.com



Automatically Detected Interesting Images

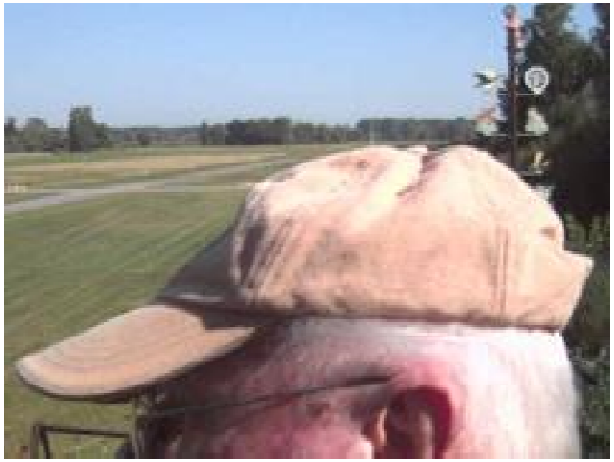


Automatically Detected Interesting Images



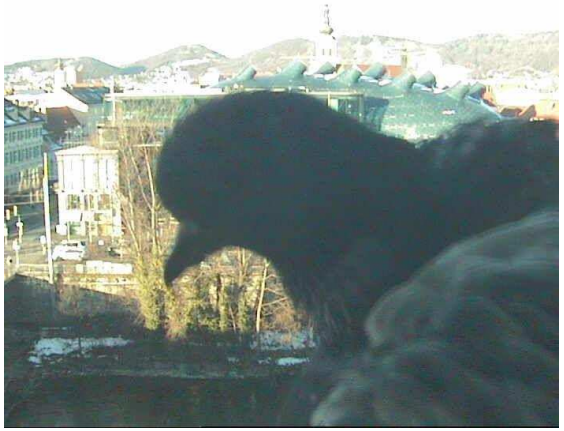
Automatically Detected Interesting Images

Automatically Detected Interesting Images



Automatically Detected Interesting Images

Automatically Detected Interesting Images



Automatically Detected Interesting Images

Automatically Detected Interesting Images

Other Applications…

- Make a long and boring video short and interesting

Original (40 s)

Other Applications…

- Make a long and boring video short and interesting

Original (40 s)

↓

Shortened (6 s)

Other Applications…

- Make a long and boring video short and interesting

6 s (86 % reduced)

Other Applications…

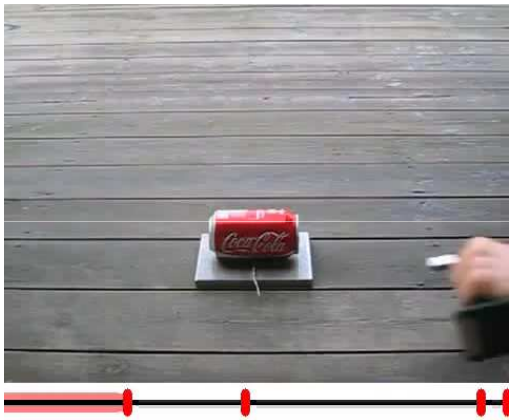
- Make a long and boring video short and interesting

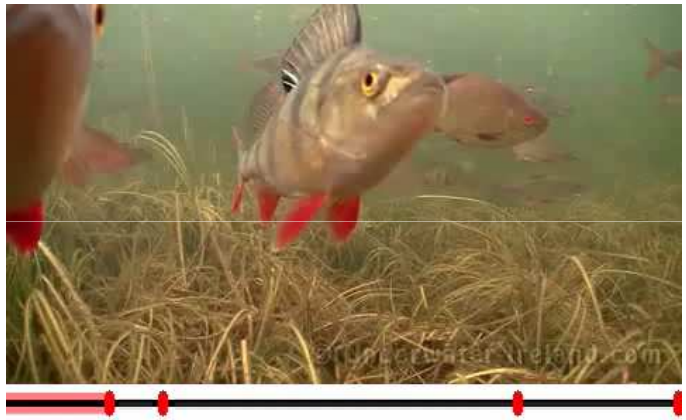
15 s (66 % reduced)

Other Applications…

- Make a long and boring video short and interesting

www.snaplife.tv





Summary

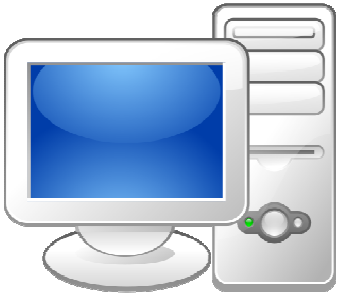
Make a long and boring talk short and interesting

Summary

What cases human interest?

User Study, Analysis

Approach it computationally



Application(s)

Thanks!

Fabian Nater

Michael Gygli

Michel Druey

upicto

ETH zürich

University of Zurich UZH

Thank you!

upicto

www.upicto.com

CVL Computer Vision Lab

WEB CAM AZE

GET IT ON Google play

www.webcamaze.com

Thank you!

upicto

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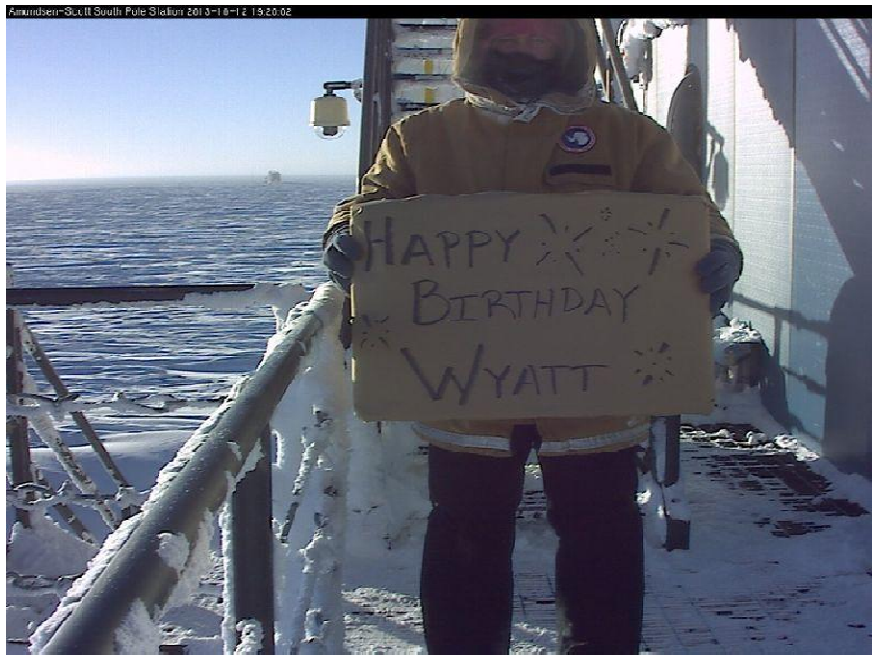

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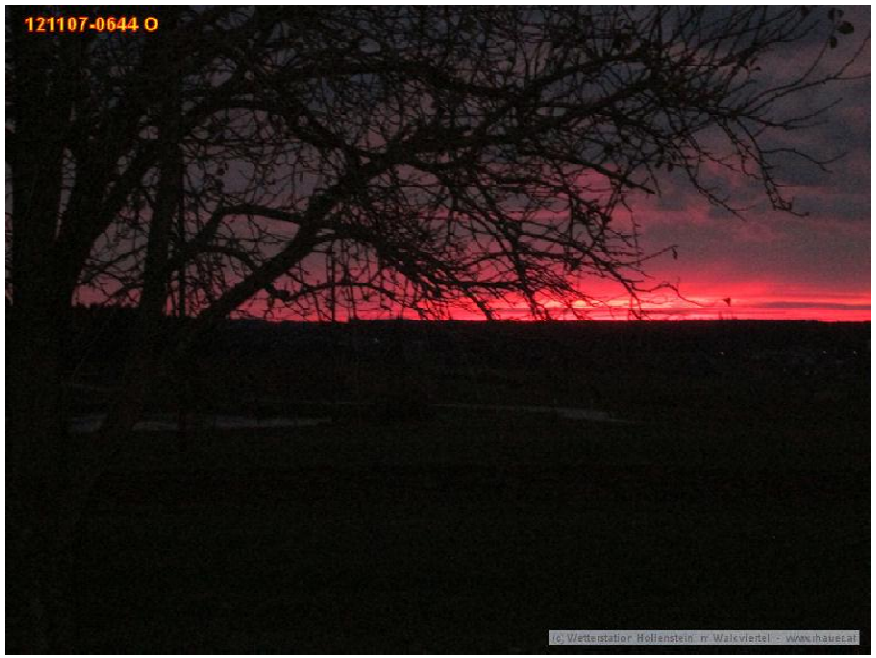

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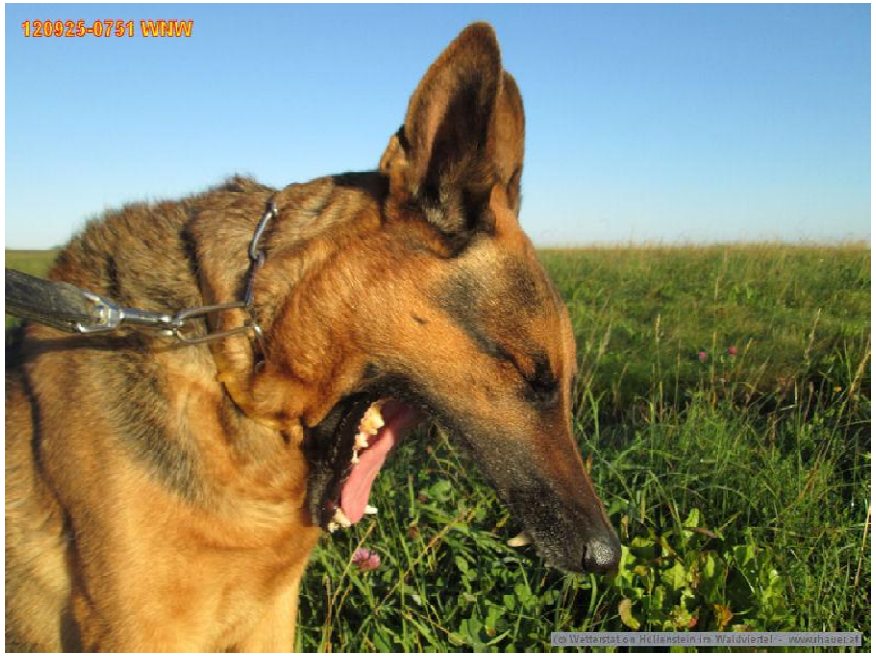

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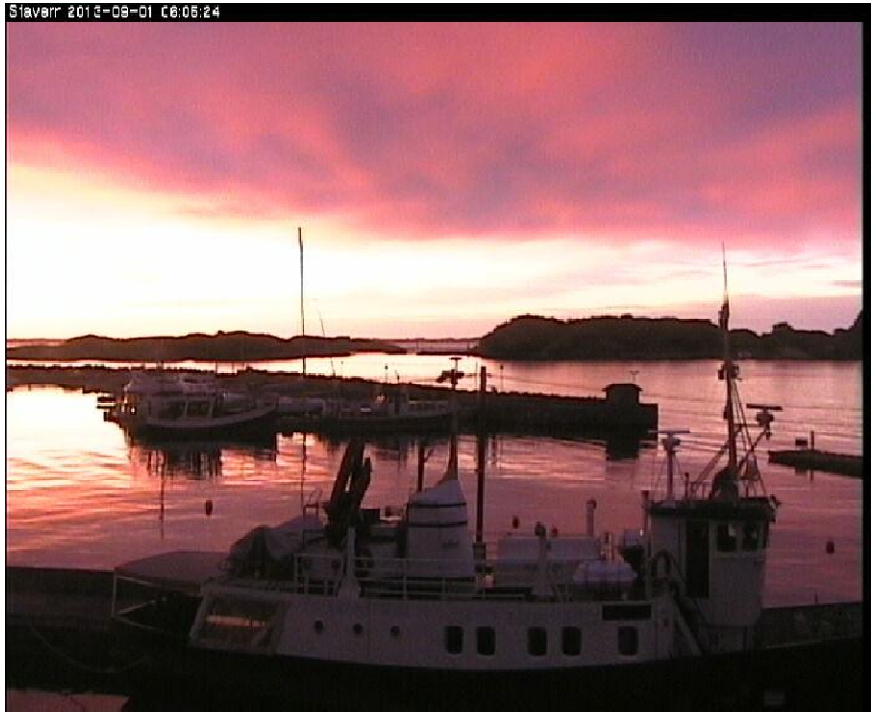

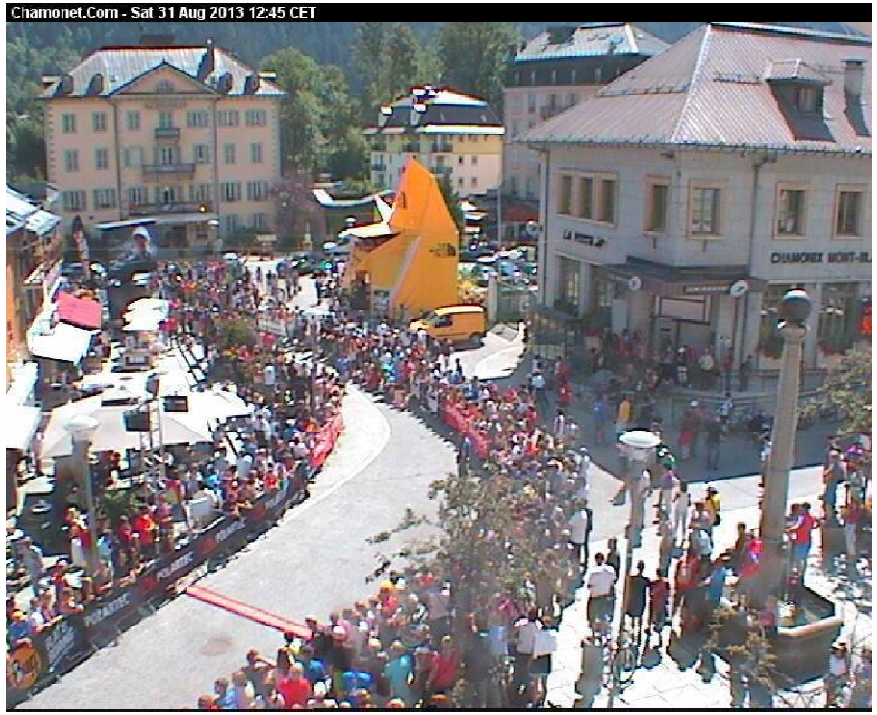

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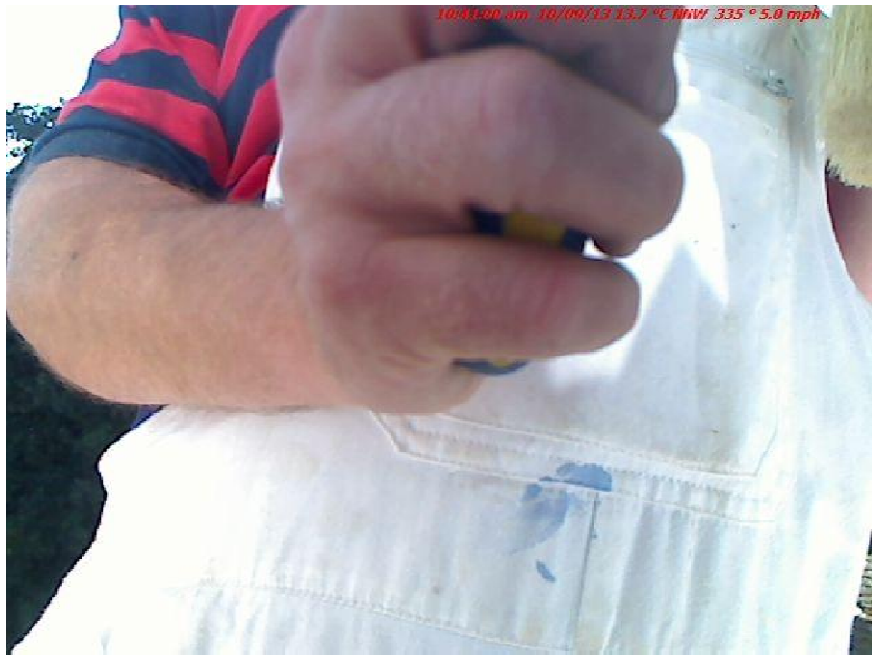

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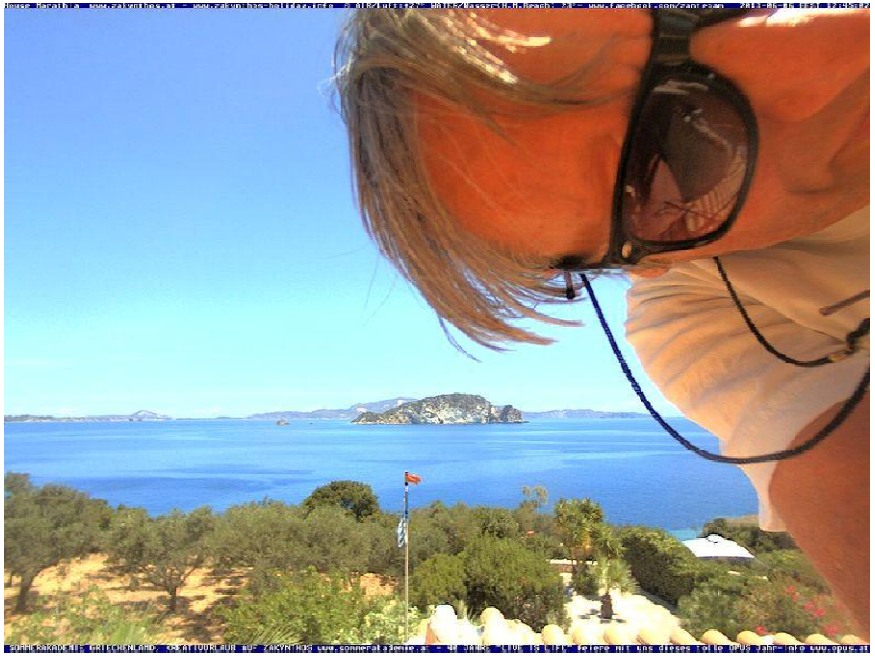

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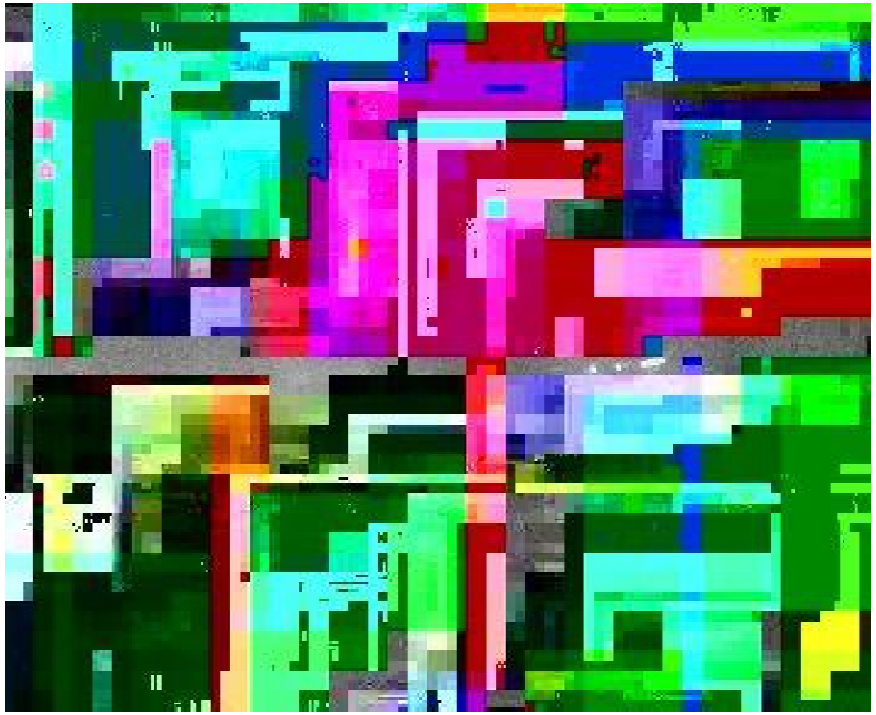

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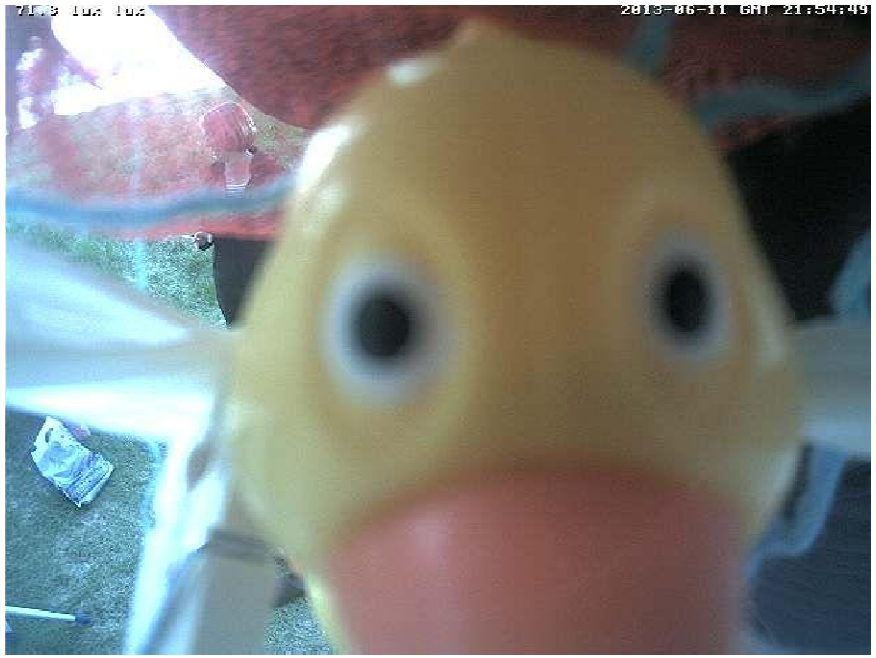

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