

# Big Social Media Organizing, Retrieving and Trusting Contents

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mm

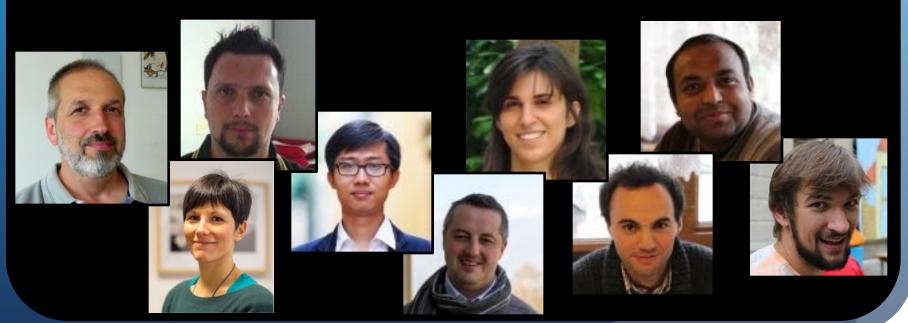
lab

# Acknowledgements

## The Multimedia Signal Processing and Understanding Lab (MMLab)

deals with relevant aspects of multimedia data processing, focusing on both theoretical and application-driven research issues.

Since media can be considered as the technological extensions of human capabilities, particular attention is paid to smart multimedia data management, analysis, transmission and protection, and to those applications where ambient intelligence can provide advanced services beyond human limitations.





### Outline

- Why social media are a good example of 'big data'
- Challenges of social media:
  - Making structured the unstructured
    - Event-based media structuring
    - Media Synchronization
    - Media Diversity
  - Making trustworthy the untrustworthy
    - Source and provenance detection
    - Manipulation detection and biasing
- Open problems in big social media research



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## What is "big"

- "Big" is a relative concept:
  - a data system is 'big' if the hw/sw used to capture and process it, is unable to do that in reasonable time/space <sup>1</sup>
  - what is "big" today can become treatable tomorrow...
    ... unless it continues to grow: in that case we have a problem!



# Is that big enough?...





# 'Big' does not only refer to size:

- Huge (and increasing) in volume
- Largely unstructured
- Largely diverse in content and format
- Partly untrustworthy
- Originating from different sources
- Used for indirect scopes (different from the application they have been collected for)



# 'Big' does not only refer to size: the 3V model

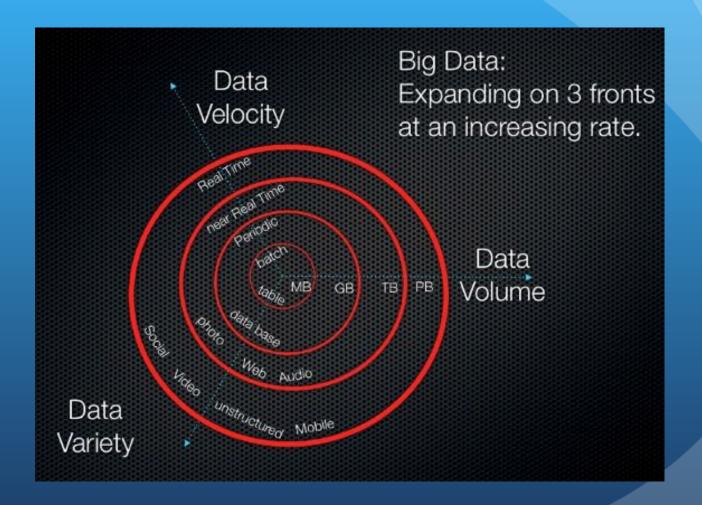
- According to Doug Laney (Gartner's Inc, 2001):
  - Big data is high-volume, -velocity and -variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making.

also known as the "3-Vs model"

- Later extended to many more Vs (2011), including:
  - Variability, Value, Veracity, Volatility, Vulnerability, Verification, ...
     from 3-Vs to 12-Vs and more



### The 3V model



Source: Diya Soubra's, The 3Vs that define Big Data, on Data Science Central



#### The 3 Vs of Social media

	Monthly active users	Average user activity	Data volumes and generated traffic	Data types
Facebook	2.1B	20 min/day	350 Mphoto/day 9M messages/h 100Mh video watched/day	Images, video, audio, text, graphics, links,
Youtube	1,57B	Avg. session 40'	5+ B shared videos today 5 B watched videos/day 300 h upload videos/min	Video and audio
Instagram	800M	8 likes/day 1 photo upld/week	40B photo shared 95M photo upld/day	Photos, stories
Twitter	330M	5 tweets/day	100M tweets+img/year	Mostly text but also images and video

<sup>+</sup> instant messaging, webcams, professional media, ...

Source: Salman Aslam, Omnicore Agency



### The other 'Vs'...

#### • Value:

- Facebook stock market valutation tops \$245 billion
- Annual revenue of Google for Youtube is around \$13 billion
- Instagram is expected to generate about \$5 billion in mobile advertising sales in 2018
- Twitter is currently valued at \$16 billion
- Value connected to content, users, ads, influencing

#### Variability and volatility:

- Contents can be modified, removed, linked, re-used, etc.
- No guarantee to find the same information the next day.



## The other 'Vs'...

- Veracity and Verification
  - Fake news are becoming a big problem in Social networks
  - Upload rate is overwhelming: impossible to check contents





### and the trends...

- Also trends are typical of big data
  - continuous growth (although rate tends to saturate)



Source: statista.com



### The challenges of Big Social Media

- Social Media are indeed big data
- Multimedia in general is today the killer application for systems and networks
  - Video is expected to cover 80% of total Internet traffic in 2019
- There is a dramatic direct and indirect value connected to media contents, BUT...
  - to make it (re-)usable and profitable, there is a need of structure, accessibility, trust, cross-linking, etc.
  - we will focus on two major challenges:
    - Making structured the unstructured
    - Making trustworthy the untrustworthy

A content-based perspective



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### Making structured the unstructured

- Structure is needed to make data easy to access, (re)use, retrieve, organize, summarize, present, ...
- Structure can be achieved through indexing, annotation, linking, time-stamping and any other instrument that allows capturing the relationships among pieces of content along some dimension (facet)
- We will focus on three concepts:
  - Event-based media structuring
  - Media synchronization
  - Media diversity



### Media vs. Semantics

#### What users need

Semantic search

Serch by Visual concept

Search by Example/Sketch

**SEMANTICS** 

**LABELS** 

**OBJECTS** 

**DESCRIPTIONS** 

RAW DATA

Connotation, context, relationships, actions

Annotated regions (general vs. specific)

Regions, blobs, partitions (segmentation)

Colors, textures, etc.

Media

What research mostly investigated so far



### Media vs. Semantics

**SEMANTICS LABELS BOTTOM-UP** From entro contentics semantics **OBJECTS DESCRIPTIONS RAW DATA** 

From antics semantics to content

TOP-DOWN



#### How to model semantics in media

#### Explicit Knowledge representation

- Taxonomies (description and classification of things)
- Ontologies (formal conceptualizations of domains)
- Events (formal conceptualizations of whatever is happening)

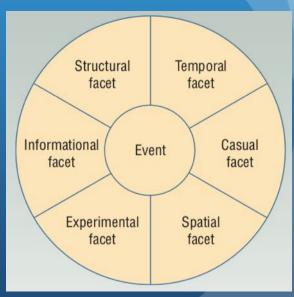
#### Human-based computation

- Relevance feedback (capture human semantics via interaction)
- Crowdsourcing (use collective intelligence)
- Gamification (use human intelligence 'concealed' by games)



#### Media and Events

- An interesting idea to put associate a semantic to media is using the concept of events
- Events have been widely used in information retrieval and successively applied to media retrieval
- Events are the way we organize our own memories, then they are a very natural way to organize media
- Events facets typically answer to questions such as:
  - What, Where, When, How, Who, ...



#### Event webs







**RELATED-**

**NEDIA-LINKS** 

Historical Royal weddings



Chelsea Flower Show May 2018

WHERE-LINK (events in same place, same time) Royal wedding London, 5.19.18

**Prince Harry** playing rugby

WHEN-LINK

in the past)

(related events

Subevent: Church



Subevent: Harry arriving

WHO-LINK (events with Harry & relatives)

Harry's mother accident







**SUBEVENT-LINKS** (parts of the

event)





www.glocal-project.eu



## Discovering events from media

- All of this is possible if there is a way to automatically associate media and events
  - This rises many research questions:
    - How is it possible to discover the event associated to a media item?
    - How is it possible to discover the event associated to a collection of media (e.g., a photo album)?
    - What is important in a media item to understand the associated event?
    - How is it possible to link media that share some facets?



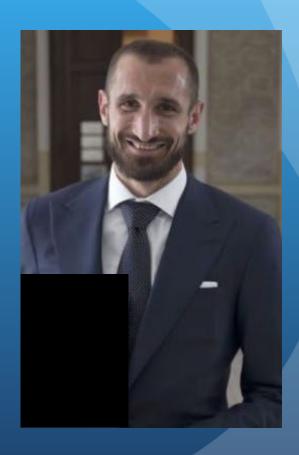
## The concept of Event Saliency

- Recently, we introduced the concept of event saliency
  - Identifying the parts of the image that reveal the event
  - Not as simple as visual saliency (typically based on appearance, color, contrast, position, etc.)
- Two major problems
  - Detecting the event saliency
    - Gamification experiments
    - Crowdsourcing experiments
  - Using the event saliency
    - Introducing saliency in media event detection

# Which events are those photos related to?







# Which events are those photos related to?









# A gamified event saliency detector

- An example of human computation using games
- EventMask is an adversarial game formulated as inversion problem:
  - We ask people to hide only what may reveal the event
  - 'Maskers' win if 'discoverers' cannot recognize the event
  - Earned points are inversely proportional to covered area
  - Players earn point in both hiding and discovering
- Event saliency map is generated combining maskers and discoverers results.

A.Rosani, G.Boato, F.De Natale, "EventMask: A game-based framework for event-saliency identification in images", IEEE Trans. on Multimedia, 2015

Dataset: http://mmlab.science.unitn.it/EventMaskDataset/



# Example of EventMask saliency

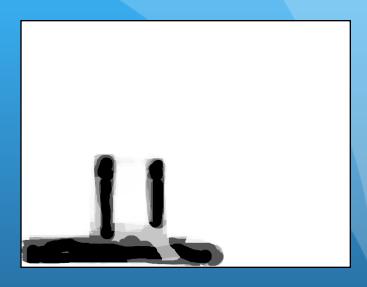
Original Image

Generated masks



**Event saliency** 

Traditional saliency











# Event saliency by crowdsourcing

- As an alternative, we used crowdsourcing for event saliency detection
  - Image fragments are generated by an agent, and micro-tasks consist in discovering the event
  - Reward is in form of micropayments
  - Mechanisms are used to prevent cheating

## Introduction to the Crowdsourcing Task ying out non-profit research at a university to build an event

We are carrying out non-profit research at a university to build an event retrieval system. By accepting this task, you agree that we may publish parts of your answers as part of our research study. We will NOT publish any information that could be linked to you. We do NOT use your worker ID, or any other information that links to you, during data analysis or storage. Your answers are used only by researchers for the purposes of gaining insight into general opinions concerning events related multimedia. Beyond the people who are doing research in this area, no other parties are allowed to use your answers.

#### Event Representation via a region



#### Questions

- (i) From these 8 possible events, which one do you think has been the one presented to you?
  - Option 1
  - Option :
    - Ontion
- (ii) Briefly explain, why did you choose the particular option in question i (open question)

Next



# Salient region extraction process

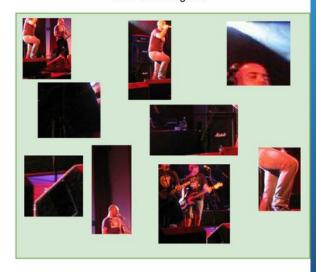




2. All region proposals

3. Filtered Regions





4. Event-salient Regions





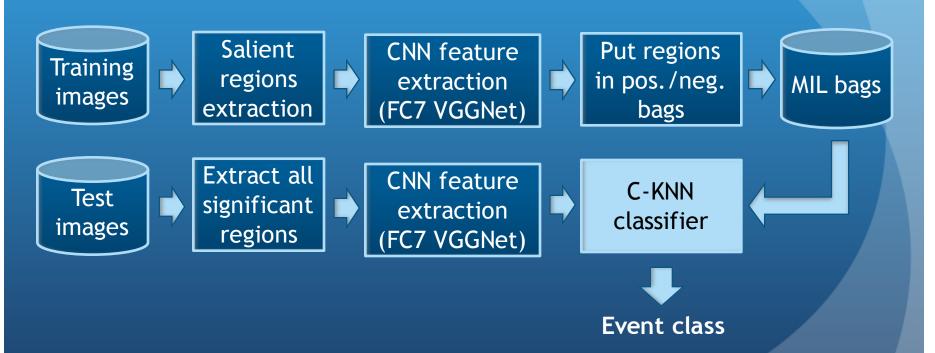




# Using saliency for event discovery from single image: MIL



 We adopt a Multiple-Instance-Learner to associate salient visual concepts to the relevant events



K.Ahmad, N.Conci, F.De Natale, "A saliency-based approach to event recognition", Signal Processing: Image Communications, 2017

# Using saliency for event discovery from single image: MIL



Results on different event detection datasets:

Method	Avg. Accuracy
Schinas et al 2012	0.334
Rosani et al 2015	0.459
Ahmad et al 2015	0.700
Ahmad et al 2016	0.858
Proposed	0.912

Method	Avg. Accuracy
Ahmad et al 2015	0.700
Rachmadi et al 2016	0.720
Proposed	0.771

USED

Method	Avg. Accuracy
Li et al 2007	0.734
Zhou et al 2014	0.944
Zhou et al 2016	0.950
Wang et al 2016	0.988
Proposed	0.983

**SED 2013** 

UIUC

#### SED

MediaEval Social Event Detection (SED) Task 2011-14 - www.mediaveal.org

K. Ahma, N.Conci, G.Boato, F.De Natale, USED: A large scale social event detection dataset, MMSys 2016 - <a href="http://loki.disi.unitn.it/~used/">http://loki.disi.unitn.it/~used/</a>

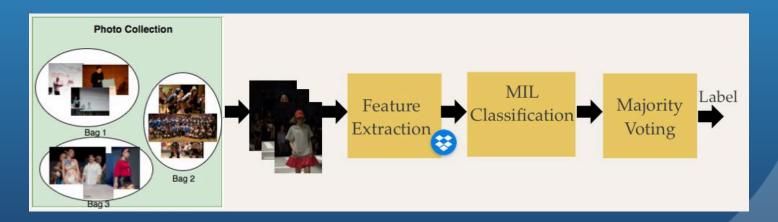
#### UIUC

L-J.Li, L.Fei-Fei, "What, where and who? Classifying event by scene and object recognition, ICCV 2007 - <a href="http://vision.stanford.edu/lijiali/event\_dataset/">http://vision.stanford.edu/lijiali/event\_dataset/</a>

# Using saliency for event discovery from photo collections: MIL



- Even more challenging is the case of multiple images (photo collections, albums)
  - Annotation at collection-level only
  - Not every picture is relevant (e.g., close-ups, outliers)
- Again, MIL can provide superior performance



K.Ahmad, N.Conci, G.Boato, F.De Natale, "Event recognition in personal Photo collections via multiple instance learning-based classification of Multiple images", Journal of Electronic Imaging, 2017

# Using saliency for event discovery from photo collections: MIL



• Comparative results on PEC dataset<sup>1</sup>:

Method	Avg. Acc.	Method	Avg. Acc.
AgS [1]	0.4143	ShMM [1]	0.5571
Huang et al. [2]	0.7343	HAS [3]	0.8632
R-OS-PGM [4]	0.7428	SVM-CNN (Majority voting)	0.8230
MIL_SMO	0.9153	Our Approach	0.9527

<sup>&</sup>lt;sup>1</sup> L.Bossard, M.Guillamin, L.VanGool, "Event recognition in photo collections with a stopwatch HMM, ICCV, 2013

# Using saliency for event discovery: ensamble of deep models



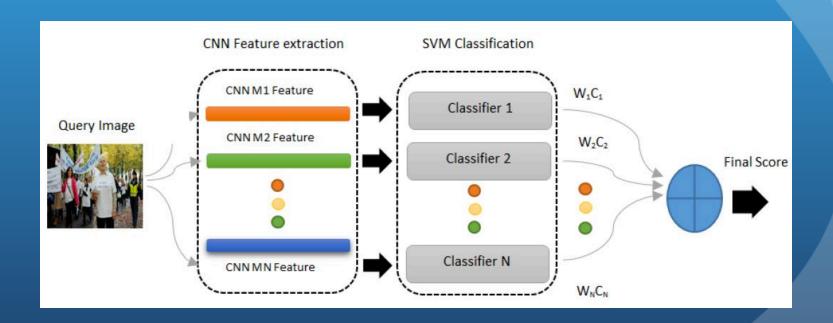
- Both object-related and background regions may contain useful information, complementing each-other
- We proposed a method based on the fusion of different classifiers, differently trained for the two areas
  - Object-level info coded by a network pre-trained on ImageNet dataset
  - Scene-level info coded by a network pre-trained on Places dataset
  - Different neural architectures are considered (AlexNet, VGGNet, GoogleNet, ResNet)
  - 3 different fusion models are considered (IOWA, PSO, GA)

K.Ahmad, M.L.Mekhalfi, N.Conci, F.Melgani, F.De Natale, "Ensemble of Deep Models for Event Recognition", ACM Trans. on Multimedia Computing Communications and Applications, 2018

# Using saliency for event discovery: ensamble of deep models



• Overview of the proposed scheme:



# Using saliency for event discovery: ensamble of deep models









Sample images for which training on background fails (theater event class)





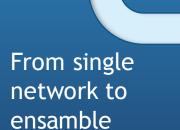


Sample images for which training on foreground fails (theater event class)

# Using saliency for event discovery: ensamble of deep models



CNN Model	Avg. Acc.	CNN Model	Avg. Acc.
AlexNet (ImageNet)	0.422	AlexNet (Places Dataset)	0.4154
VGGNet16 (ImageNet)	0.477	VGGNet16 (Places Dataset)	0.454
VGGNet19 (ImageNet)	0.479	VGGNet19 (Places Dataset)	0.4682
GoogleNet (ImageNet)	0.448	ResNet 50 (ImageNet)	0.3010
ResNet 152 (ImageNet)	0.3008	ResNet 101 (ImageNet)	0.3006



WIDER Dataset		UIUC Dataset			
Method	Avg. Acc.	Method	Avg. Acc.		
Baseline [1]	0.397	Baseline [2]	0.734		
Deep Channel Fusion [1]	0.424	Placess CNN [3]	0.941		
Reza et al. [4]	0.440	GoogleNet GAP [4]	0.950		
Zhou et al. [5]	0.530	Method in [5]	0.988		
Our Approach (IOWA)	0.5840	Our Approach (IOWA)	0.9854		
Our Approach (GA)	0.5826	Our Approach (GA)	0.9870		
Our Approach (PSO)	0.5908	Our Approach (PSO)	0.9887		
Our Approach (equal weights)	0.5593	Our Approach (equal weights)	0.9731		



### Structuring vs. Synchronization

- Another interesting problem is synchronization:
  - If there are multiple users taking part to the same event (possibly extended in time and space) how can we place their media into a single time scale?
    - Timestamp could be either unavailable or unreliable
    - Media could be captured from different perspectives, with different purposes, and with different devices
    - We could have images (single instant) and/or video (time span)
  - Also in this case, content can reveal a lot.





## Structuring vs. Synchronization

Synchronization of Multi-User Event Media (SEM) Dataset
Task in Mediaeval 2015



Jedía€val Benchmark













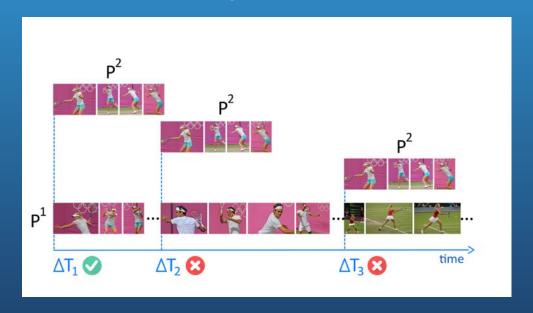
N.Conci, V.Mezaris, F.De Natale, M.Matton, "Synchronization of multi-user event media at MediaEval (SEM): Task description, datasets, and evaluation", Proc. MediaEval, 2014-2015

Dataset: http://mmlab.disi.unitn.it/MediaEvalSEM2014

# Automatic synchronization of multi-user photo collections



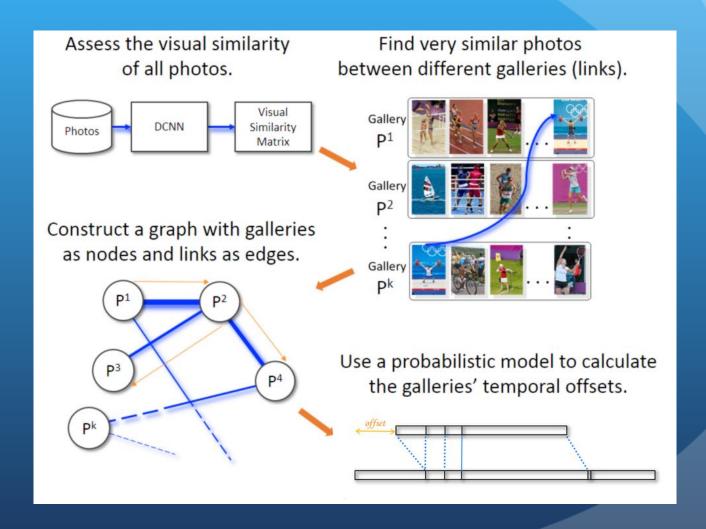
- Research question:
  - is it possible to find a common timeline for different sets of (possibly etherogeneous) media taken from a variety of users and devices, using content + metadata?



E.Sansone, K.Apostolidis, N.Conci, G.Boato, V.Mezaris, F.De Natale, "Automatic Synchronization of Multi-user Photo Galleries", IEEE Trans. on Multimedia, 2017

# Automatic synchronization of multi-user photo collections

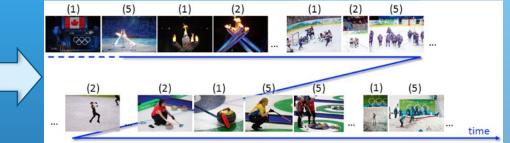




# Automatic synchronization of multi-user photo collections







Method	Vancouver		London		NAMM15		TDF14		Average and standard deviation across all datasets		
	P(%)	A(%)	P(%)	A(%)	P(%)	A(%)	P(%)	A(%)	P(%)	A(%)	H(%)
[24]	61.8	81.6	33.3	88.6	50.0*	73.5*	25.0	80.6	43.9 ± 17.6	$81.1 \pm 6.2$	55.5 ± 15.9
[31]	94.1	79.2	47.2	87.5	_	-	-	-	$70.7 \pm 33.2$	$83.4 \pm 5.9$	$73.6 \pm 17.2$
[34]	5.0	65.0	15.0	92.0	2	2	-	-	$10.0 \pm 7.1$	$78.5 \pm 19.1$	$17.6 \pm 11.6$
[33]	91.2	72.8	61.1	71.3	77.9*	90.4*	9.4	79.3	$61.4 \pm 37.0$	$78.5 \pm 8.7$	$62.7 \pm 31.8$
[35]	-	-	-	-	40.0	78.0	5.0	92.0	$22.5 \pm 24.5$	$85.0 \pm 9.9$	$31.2 \pm 30.6$
[37]	94.1	76.0	61.1	65.6	83.3	90.8	12.5	84.5	$62.8 \pm 36.2$	$79.2 \pm 10.9$	$64.0 \pm 30.1$
[36]	35.0	86.0	25.0	89.0	44.5*	82.4*	15.6	83.2	$30.0 \pm 12.5$	$85.2 \pm 3.0$	$43.2 \pm 13.7$
[38]	97.1	86.0	63.9	75.0	50.0*	71.5*	21.9	90.8	$59.6 \pm 30.9$	$80.8 \pm 9.1$	$64.5 \pm 23.0$
[36] modified (inception3a)	5.9	93.4	5.6	73.5	47.1	85.0	9.4	73.2	$17.0 \pm 20.1$	$81.3 \pm 9.8$	$24.7 \pm 24.1$
[38] modified (inception3a,exact)	85.3	56.3	47.2	74.6	88.9*	88.7*	65.6	84.6	$73.1 \pm 20.9$	$76.1 \pm 14.4$	$72.7 \pm 14.1$
[38] and [36]	8.8	54.7	19.4	67.4	58.8	66.8	25.0	80.6	$28.0 \pm 21.6$	$67.4 \pm 10.6$	$36.5 \pm 19.8$
Proposed (inception3a,exact,MRF)	97.1	83.7	75.0	84.3	83.3*	93.4*	65.6	73.7	$80.3 \pm 13.3$	$83.8 \pm 8.0$	$81.7 \pm 9.4$



### Structuring vs. Diversity



#### edia Eval Benchmark 2015

MediaEval Benchmarking Initiative for Multimedia Evaluation

The "multi" in multimedia: speech, audio, visual content, tags, users, context

#### **Retrieving Diverse Social Images Task**





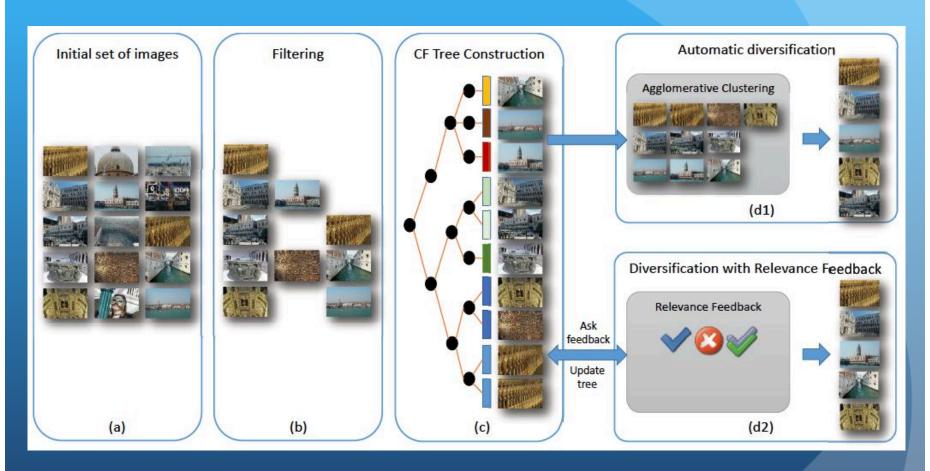
B.lonescu, A.Popescu, M.Lupu, H.Muller, "Retrieving Diverse Social Images", Proc. MediaEval, from 2013 to 2107 (5 editions)

Winner of 2014 Edition

D-T.Dang-Nguyen, G.Boato, F.De Natale, G.Giacinto, L.Piras, "Retrieval of Diverse Images by Pre-filtering and Herarchical Clustering", Proc. MediaEval, 2014



### Achieving diversity with RF



D-T.Dang-Nguyen, L-Piras, G.Giacinto, G.Boato, F.De Natale, "Multimodal retrieval with diversification and relevance feedback for tourist attraction images", ACM TOMM, 2017



### Diversity by RF: Some results

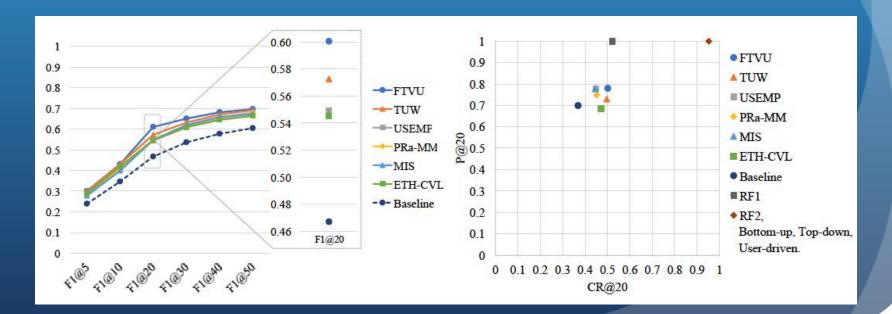


(a) Results from Flickr.



(b) Results without relevance feedback. (c) Results with relevance feedback.







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Fake news in the 18th century

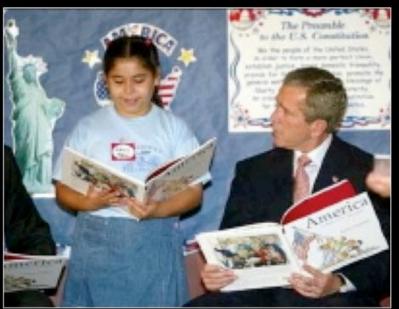




Fake news in the 18th century







Fake news today







Fake news today



### Media impact on perception

 Modified data may influence people opinions and even alter their attitudes in response to the represented event



How is your feeling if I say that this image reports the status of a polluted area?



### Media impact on perception

 Modified data may influence people opinions and even alter their attitudes in response to the represented event



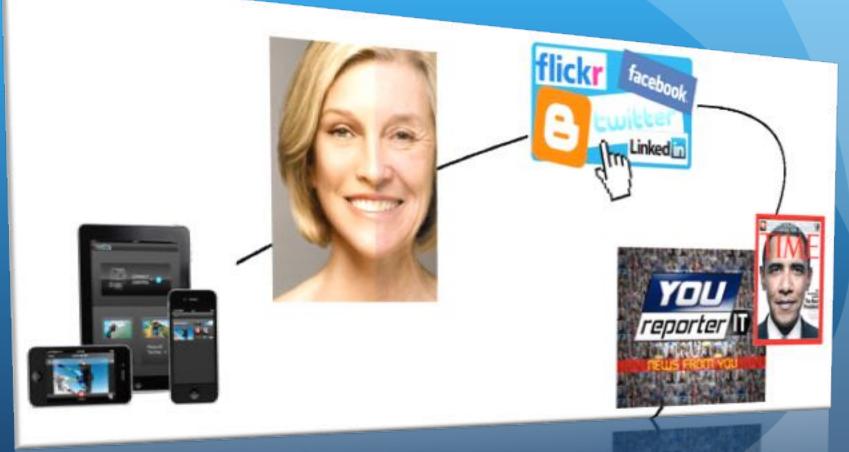


and now?...

 it is important to be able to automatically verify the authenticity and the integrity of digital images in order to guarantee their trustworthiness.



## Media impact on perception



Social media do the rest of the job: fast and large scale propagation (viral media) of modified multimedia content, potentially carrying a distorted semantic message



#### Multimedia forensics

- We refer to multimedia forensics as the set of methodologies that allow revealing information about the "history" of a media item from the instant of capturing to its current publication
  - Identifying the device (and possibly the person) that captured the media
  - Determining possible tampering (from simple image processing to complex and multiple manipulation)
  - Discriminating between real and computer generated media (or parts of)



#### Multimedia forensics is not a wizard





#### Source identification

• Acquisition devices leave unique traces (fingerprints) on the media, such as guns do it on bullets

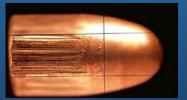














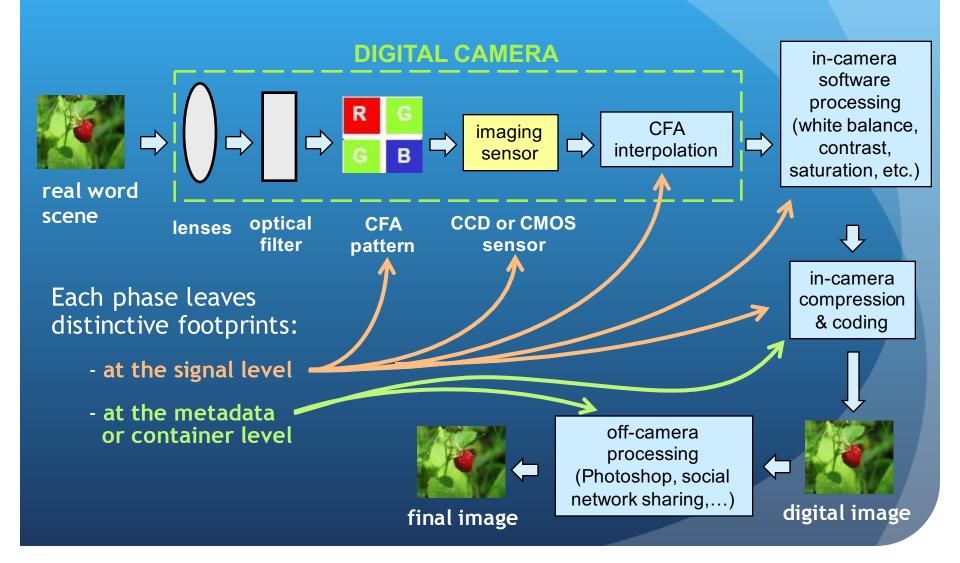


#### Source identification

- Source identification uses such traces to link media contents to a particular (class of) acquisition device(s)
- The problem can be solved at different levels:
  - Identifying the class of the device (e.g., scanner-vs-camera)
  - Identifying the specific device (e.g., Canon-vs-Nikon)
  - Identifying the brand/model of the device (e.g., SN\_X-vs-SN\_Y)



#### Source traces

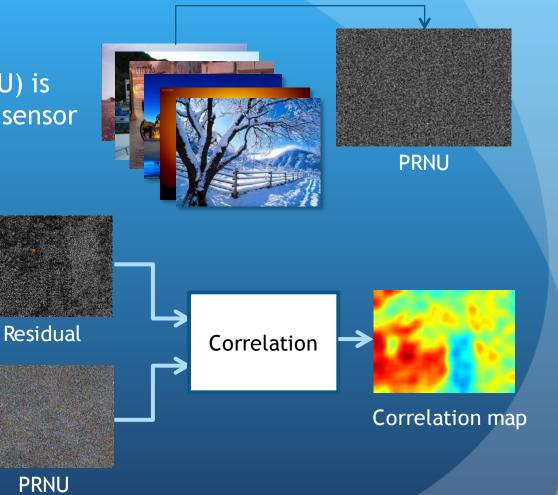




#### Source traces: PRNU

Photo Response Non
 Uniformity Noise (PRNU) is
 typical of a CCD/CMOS sensor

Denoising



M.Chen, J.Fridrich, M.Goljan, J.Lukas, "Determining Image Origin and Integrity Using Sensor Noise," in IEEE Trans. on Information Forensics and Security, 2008

# Example 1: detecting photo owner on Social Networks





Who is the author of this fake?













**BOB** 









**ALICE** 

**JOHN** 







JOHN











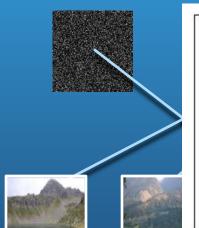


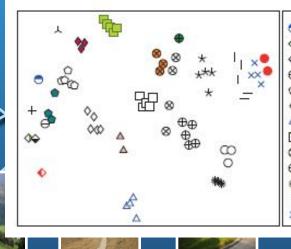
Canon Alpha SX710 HS

Panasonic DMC-LX100S Lumix

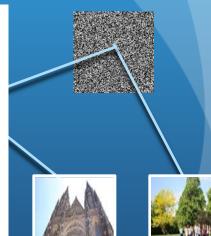
Sony Alpha 3000

Kodak PIXPRO AZ251





Agfa 505-X Agfa 530s Agfa DC-504 + Agfa DC-733s Agfa DC-830i 人 Canon A640 → Canon Ixus 55 Canon Ixus 70 Casio Z150 ♦ Fuji J50 A Nikon D200 △ Nikon D70/D70s Nikon S710 Panasonic FZ50 Olympus µ 1050 Pentax A40 Pentax W60 ⊕ Praktica DCZ5.9 ♣ Ricoh GX100 Rollei 7325XS O Samsung L74 Samsung NV15 - Sony H50 Sony W170 × Sony T77



Q-T.Phan, G.Boato, F.De Natale "Image Clustering by Source Camera via Sparse Representation", MFSec 2017

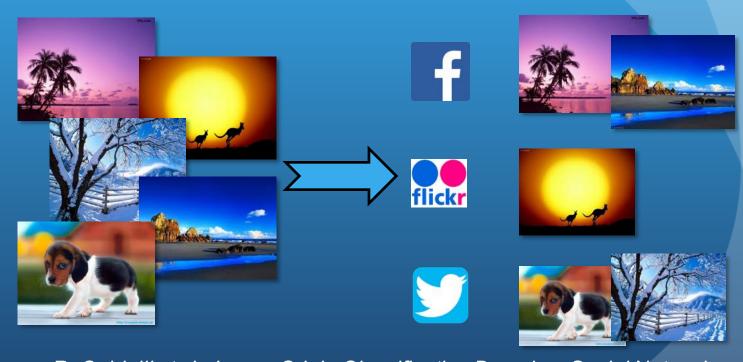
Q-T.Phan, G.Boato, F.De Natale, "Robust Image Clustering based on Sparse Representation of Camera Fingerprint", submitted to IEEE TIFS



#### Also social media leave traces

- Multimedia data phylogeny
  - Trace the history of the data (source, manipulations, sharing)





R. Caldelli et al., Image Origin Classification Based on Social Network Provenance, IEEE Trans. on Information Forensics and Security, 2017 I. Amerini et al., Tracing images back to their social network of origin: a CNN-based approach, IEEE WIFS, 2017

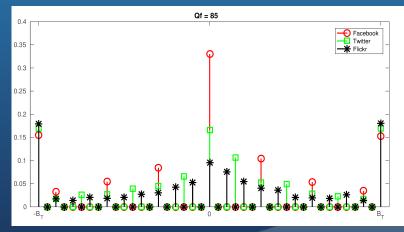
# Example 1: detecting social media provenance



- Uploading an image on a Social Network: the process alters images
  - Resize
  - Rename
  - Meta-Data deletion/editing
  - Re-Compression
  - NEW JPEG file Structure



E.g., histogram of DCT coefficients allows recognizing different social networks





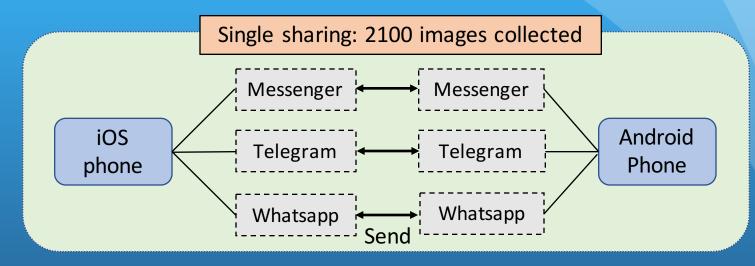
# Example 2: detecting instant messaging app provenance

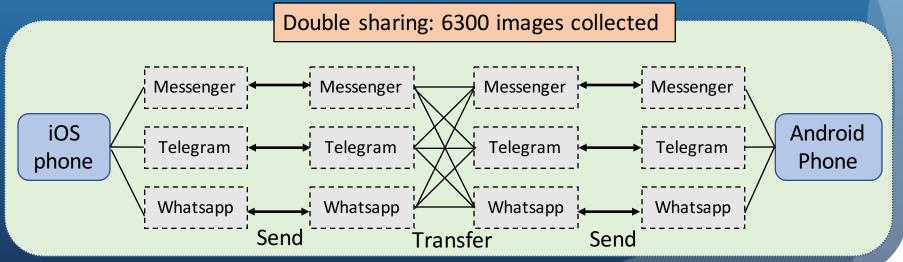
- Considered messaging apps: Messenger, Whatsapp, Telegram
- Two mobile phones of different operating systems: Android and iOS
- Original images are taken from VISION dataset: various resolutions and qualities.
- Features:
  - Histogram of DCT coefficients
  - Additional information from JPEG headers
- Extension to double sharing scenarios.

Q-T.Phan, C.Pasquini, G.Boato, F.De Natale "Identifying image provenance: an analysis of mobile instant messaging apps", IEEE MMSP 2018

# Example 2: detecting instant messaging app provenance









# Image provenance detection: mobile instant messaging apps

- APP and OS / LAST APP and LAST OS can be reliably identified in single / double sharing scenarios.
- The PREVIOUS APP can be reliably revealed based on the information of the LAST APP or LAST APP + LAST OS.

	Scenario	Accuracy
APP	Single sharing	100
APP + OS	Sillare silalilla	100
LAST APP		94
LAST APP + LAST OS		89
PREVIOUS APP   LAST APP	Double sharing	77
PREVIOUS APP   LAST APP + LAST OS		80





- Verifying not only images but also their context
  - Image is original, but its use is not consistent



Real photo captured April 2011 by WSJ BUT heavily tweeted during Hurricane Sandy (29 Oct 2012)



### Verification task @ MediaEval

- Given a post (image+metadata), return a decision (fake, real, unknown)
   on whether the information presented by the post reflects the reality
  - Photos from past events reposted as being associated to current event
  - Digitally manipulated photos
  - Artworks presented as real imagery







C.Boididu, S.Papadopoulos, S.Middleton, G.Boato, D-T.Dang-Nguyen, M.Riegler, "Task: Verifying Multimedia Use", Proc. MediaEval, 2016
C.Lago, Q-T.Phan, G.Boato, "Image forensics in online news", IEEE MSSP 2018





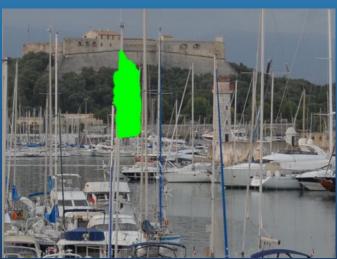




























Manipulation detection



Manipulation localization



Forgery map

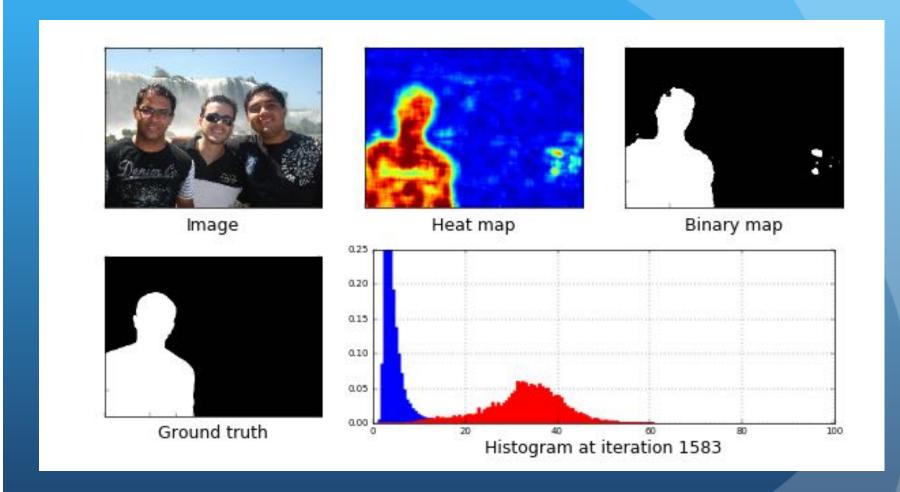


## Tampering detection

- Pixel-level traces
  - CFA, PRNU, etc. consistency
  - Filtering detection (linear, non linear, contrast, color, ...)
- Scene-level traces
  - Physical and geometric distortion (perspective coherence)
  - Light direction and shadows coherence
- Format-level traces
  - Multiple JPEG compression
  - Other encoding
- Semantic-level traces
  - Date, place, time coherence



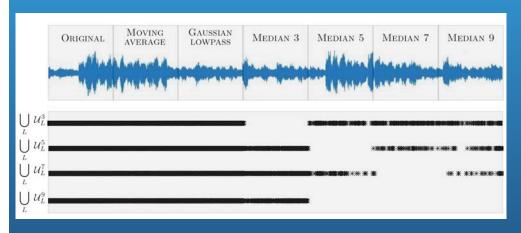
### Pixel level traces

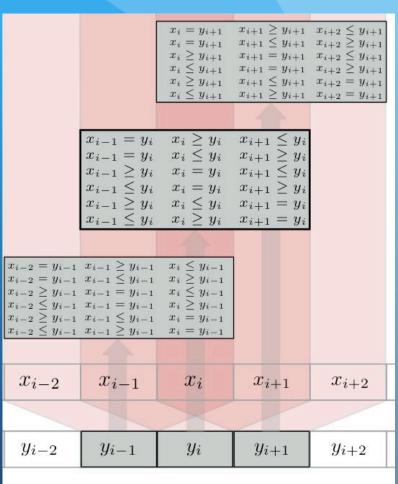


D.Cozzolino, G.Poggi, L.Verdoliva, "Recasting residual-based local descriptors as convolutional neural networks: an application to image forgery detection", IH&MMSec 2017



## Filtering traces





C.Pasquini, G.Boato, N.Alajlan, F.DeNatale, "A deterministic approach to detect median filtering in 1D data", IEEE Trans. On Information Forensics and Security, 2016



## Filtering traces

a Respect, Monsleur Eddy In Nº2398 LE MITO-ELL ACADEMOUE

Dans were numéro de 21 extebre, une er tique de l'ultime opus d'Eddy Mitchell m'a fait coorir à la médiathèque pour vérifier les-écrits de Mrue Sorbie Delassein. Après une écuate attentive de l'album, je me suis précipité chez mon disquain:..

Notez bien que le n'achète nos systèmatique ment Eddy Mitchell, mais j'ai trouvé dans or disque un résumé babile du parcours du chunteur : entre crooner et rockeur, il nous balance son humour en demi-teinte sor des hurmorie bien trouvées (Pierre Panadiamondis) et des rythases d'enfer (« En garde à vue »). Je ne connais pus vos goûts madame S. D. mais je vous conseille de réécouter d'une oreille un eu plus attentive ce « come back » et como disaient Otis et Aretha : respect, Monsieur Serge Lelièvre (internet) « Une façon claire, juste

#### NY2798 CONSTRUER OU CONSTRUBE

Tai lu avec besucoun d'attention l'article d

M. Derús Olivernes et je trouve enfin quelqu'un qui one traiter de façon chire, juste et objective le problème des retraites en France. Dans cet cian d'hypocrisie généralisée qui noie comsouhaitons qu'enfin nos responsables poli tiques, syndicalistes et médiatiques retrouvent

Jacones Ballé, 33170 Gradignan

#### Inacceptable!

Quels directeurs des programmes (tous), proches de l'Eglise catholique, se sont permis du 1º au 5 novembre ser le service public latoue », d'imposer à des millions de téléspectateurs - dont un grand nombre out pris leurs distances avec la religion - une senzone de « reportages » complaisants auprès d'une unauté de bonnes accurs confites dans propagande, cette catéchisation télévisuelle mériterait à tout le moins une réprimande du CSA. A quand une semaine consacrée au culte protestant, israélite, musulman, à celui les mormons, des Témoins de Jéhovah, des néliens ou, tout bonnement et en toute le gique, su quotidien des agnostiques et des Jean Bérard (internet) 40 LE NOUVEL OBSERVATEUR

LES PLIS DE L'ACTUALITÉ

#### Algérie : les blessures toujours ouvertes

Plus de quarante ans ans après l'in-dépendance, comme le dit Claudine Denis Marchand précise que, se trou vant à Alger en 1962, il a pu consta Romes, «in guerre d'Alpéric et l'axil restent ter l'absence totale d'assistance de la une blessure intime pour tous crux qui les ont vécus et aucune analyse rationnelle uc France lorsqu'il s'est agi d'aider at rapatriement des pieds-noirs. « Grateat en render comptte. Il v a. tout simple. qui embarquaient à cette époque étaient ment, le souverair de l'Algèrie, quittée défi-silivement il y a quarante-lant ans. (...) Je les plus humbles. Ces gens devaient quit ter leur lagement sons gnasiment rier conducts rectifier l'issusse partiale que sous enstorier e Ce lecteur nous moroche dounez (volontairement?) des "Français" d'avoir parlé de «l'Etat terfionnaire» l'Algérie. Il y avait asssi de passeres gens, Pour lui, ec'est honteux. Vous oublies ballottis par l'Histoire, aut s'aut pas comd'ailleurs les nambreuses exactions des pris grand-chose aux manipulations politi-circus sies uns et des autres, mais qu'on "maquisants" : c'était encure plus qu'iune guerre (...) ». Non, nous n'oublions rien a supripules aisément puisque leur seule mais, comme l'a rappelé Jean Darriel, « fa consiction residuit dans ort attachement d lanture est peut-être le procédé le plu un pays où ils étaient nés. Leur tort? N'avoir pas su porter un evai regard sur la novant pour le bourreau ». oncie réalité du pays, ne pas avoir fait l'ef-fort de comprendre que leur mode de pan-Et dans cette guerre il y a une autre catégorie de victimes, celles des harsée et de vie viétaient pas auversels (...). kis, qui pour beaucoup pavent encor-D'avoir ainsi, par leur comportement irresponsable, participé à un des plus même si, comme le souligne Jean Peyrondet, « c'est grâce à l'homeur de lamentables et effrojebles malentendes de certains officiers and out desober and l'Histoire contemporaine qui en retour les a écraboniles. Est-ce cela être d'extrême ontres que quelques milliers de harkis (...) and foi embarquer pour la métropoir droite? Je ne pense pas que ma contribu d échapper aux massacres du FLNs tion suit publiée dans votre courrier des les Cette guerre, on refusait de l'appeler par son nom. On parlait des «évèseteurs, ear elle ne correspond pas au bien

penser attendir nur le sujet'a. Et bien, si mentira, comme en atteste le ténsoignage Madame, nous la publions car, quoi que vous pensiez, nous avons chris ce dossier longtemps refoulé d'une élève infirmièr Lucie Marsol, témoin d'une rixe entre kössé place á des témoigrages similaires. Algériers et de la mort de l'un d'eux dans Relisez la page 34. Jean-Philippe Delchambre, lui, voul'indifférence génésale : « "Ne vous occu-pez pas de ço. partez, laissez ces gens-là se drait faire partager son sentiment de dibrouller." D'autres abroses se terrififrustration en taut qu'ancien rapatrié rent, is n'écoutais also, Autourd'hui en pour qui aucun engagement n'a été core, je suis que je porterais secours au teens: « En 2007, nous avons en droit à some homme, si c'était à refaire (...) Qu'est-il devenu? Une mère, une seu une fensme le pleare-t-elle?» Nimes à la résile de M. Estrosi, promettast formellement un désendettement via un moretoire. Le temps basse, nous Jean-Marcel Bourgereau sommes disormais à près d'un demi-siè-cle de l'indépendance de l'Algéric. La

course contre la mantre va s'imposer dans

la double perspective de cette villèbration et de la présidentielle de 2012. L'houre de

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« Derrière les plis de l'actualisé »

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#### « Une façon claire, juste

N72798 CONSERVER OU CONSTRURE C'est dans les prochains jours que l'éle

ministre de Lionei Jospin devrait annonum le lancement de sa propre fondation, Ecologe d'Averier, hébergaie comme besucoup d'autre par l'Institut de France, qui réunit quai Con-les cinq grandes Académies, dont les immst. tels en habit... vert. Une « panger fondationitiques, syndicalistes et médiatiques retrouvent

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bissé place à des témoigrages similaires. Relisez la page 34. Jean-Philippe Delchambre, lui, voudrait faire partager son sentiment de frustration en tant qu'ancien rapatrié pour qui aucun engagement n'a été term: «En 2007, nous avens en droit à Nimes à la visite de M. Extrosi, promet-tant formellement un désendettement via un moratoire. Le tentes basse, nous sommes désormais à près d'un demi-sié-cle de l'indépendance de l'Algérie. La course contre la mantre vo s'imposer dans la double perspective de cette celébration et de la présidentielle de 2012. L'Irone de régler les comptes avesi ... «

Madame, nous la publicos car, quei que vous pensiez, nous avons dans ce dossier

Denis Marchand précise que, se trou-vant à Alger en 1962, il a pu constater l'absence totale d'assistance de la France lorsqu'il s'est agi d'aider au rapatriement des pieds-noirs. « Conoui emberovaicut à cette étouve étaient les plus humbles. Ces gens desnient quit ter lear legement seus quasiment rien enscept, réagit Delcourt, même si avas ac scarlage has concevarie beiseur www.frm défis de l'après pêtrole. Reste que, c'est s' suis atterni par la psilimique sur les OGA siai pas escrie qu'un konhebertu nous sau. genge en nous traitant d'apprents sort torture est peut-être le procédé le plus lumilieut pour le victime, le plus déshonormal pour le bourreur »

Et dans cette guerre il y a une autre catégorie de victimes, celles des harkis, qui pour beaucoup payent encore même si, comme le souligne Jean Peyrondet, «c'est grâce à l'houveur de certains officiers qui out désobéi nux ordres que quelques milliers de harkis (...) ent pu embarquer pour la métropoir et échapper aux massacres du FLN+. Cette guerre, on refusait de l'appeler ments », comme en atteste le témoigrage longtemps refoulé d'une élève infirmiér Algèriens et de la mort de l'un d'eux dans l'indifférence générale : « "Ne vous ocu-pez pas de ça. partez, laissez ces gens-lá se débrouiller." D'autres tilmuses se tendirent, ie n'éconfais blus Autourd'hui eucore, je sais que je portevais secours au source homme, si c'était à refaire (...). Qu'est-il devenn? Une mère, une saur une femme le pleuro-t-elle?»

Jean-Marcel Boornereau

« Derrière les plis de l'actualité »



F.DeNatale, G.Boato, "Detecting morphological filtering of binary images", IEEE Trans. On Information Forensics and Security, 2017



## Light consistency traces

- When composing images, it is difficult to match lighting effects under which each image was taken
- Inconsistencies in lighting can be used to detect splicing



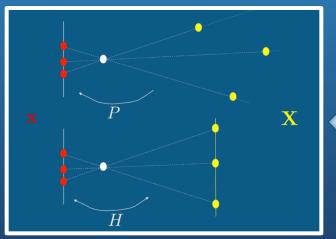


M.Johnson, H.Farid, "Exposing Digital Forgeries in Complex Lighting Environments", IEEE Transactions on Information Forensics and Security, 2007

## Perspective consistency traces









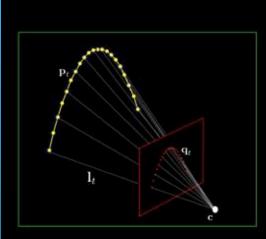
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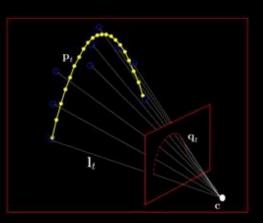
≠ H ALICE

V.Conotter, G.Boato, H.Farid, "Detecting photo manipulation on signs and billboards", IEEE ICIP, 2010

## Trajectory consistency traces







Geometric techniques
 can detect physically
 implausible trajectories
 of objects in video
 sequences

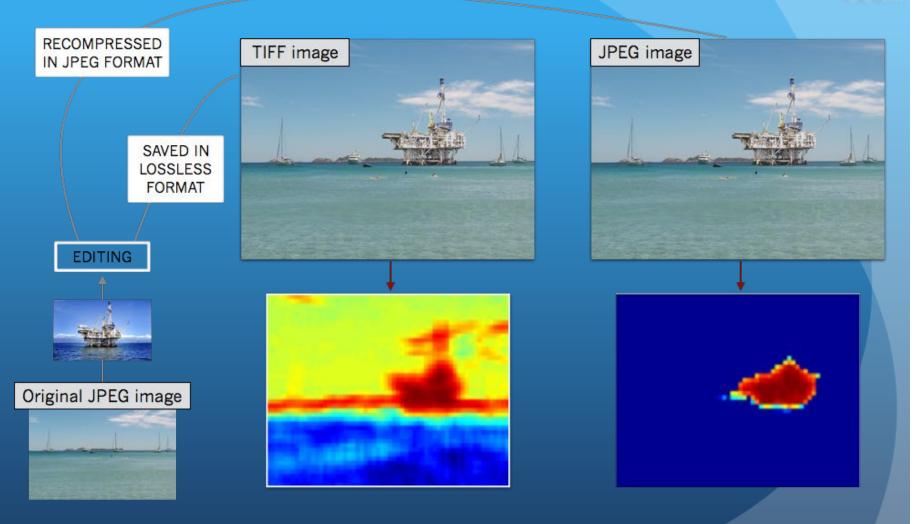




V.Conotter, J.O'Brien, H.Farid, "Esposing digital forgeries in ballistic motion", IEEE Trans. on Information Forensics and Security, 2012

## Compression traces





C.Pasquini, G.Boato, F.Pèrez-Gonzàlez, »Statistical Detection of JPEG Traces in Digital Images in Uncompressed Formats», IEEE Trans. on Information Forensics and Security, 2017



### Outline

- Why social media are a good example of 'big data'
- Challenges of social media:
  - Making structured the unstructured
    - Event-based media structuring
    - Media Synchronization
    - Media Diversity
  - Making trustworthy the untrustworthy
    - Source and provenance detection
    - Manipulation detection and biasing
- Open problems in big social media research



## The Challenges: Structuring multimedia information

- There is still a gap in our capability to capture media semantics
  - The new generation of neural networks are creating big expectations in research and industry, but...
  - ...there is not yet a sufficient knowledge about how they work and how to manage the relevant models
- Scalability and generalization are still unsolved problems (managing the amount and variety of data)
- There are a number of opportunities for applications
  - Using big social media to create new user apps in different domains (health&well-being, mobility, turism, safety, etc.)





#### Robustness & Security

 Current techniques are mostly at research level, additional effort needed to make them robust/usable in the wild

#### Adversarial approaches

- It's a cat and mouse game, as far as forensic techniques improve, also manipulations become smarter.
- Adversarial approaches mimic this process in advance

#### Generalization and Scalability

- Many specific techniques, no unique/standard framework
- Need to check ever increasing amounts of information, this requires computationally efficient approaches

## The challenges: Other (general) issues



- Availability of data
  - Only big players can fully access real data
  - The groundtruth is still a big problem
- ANNs are defeating the competitors
  - Current efforts are mostly focused on using neural approaches, is that the ultimate answer?
- Is there an upper limit in "big data"?
  - We are generating a lot of data, but what about information content?

## How much "information" is really out there?





Extract from first page of Google image search for query "Coliseum"



S. Mc Cann, "3D Reconstruction from Multiple Images", 2014

# How much "information" is really out there?





Source: hoppa.com

# How much "information" is really out there?



• 4 Million "likes" every minute on Facebook

Oxford Dictionary elected Word-of-the-Year
 2015 an emoji



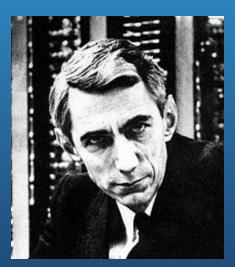


Frequency of use of "tears of joy" according to Oxford Dictionary



# Does big data mean also big information?

• Time for a new chapter of Information Theory?



Claude Shannon (1916-2001)