

New Perspectives on Digital Media Integrity

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NOTRE DAME INITIATIVE FOR
GLOBAL DEVELOPMENT



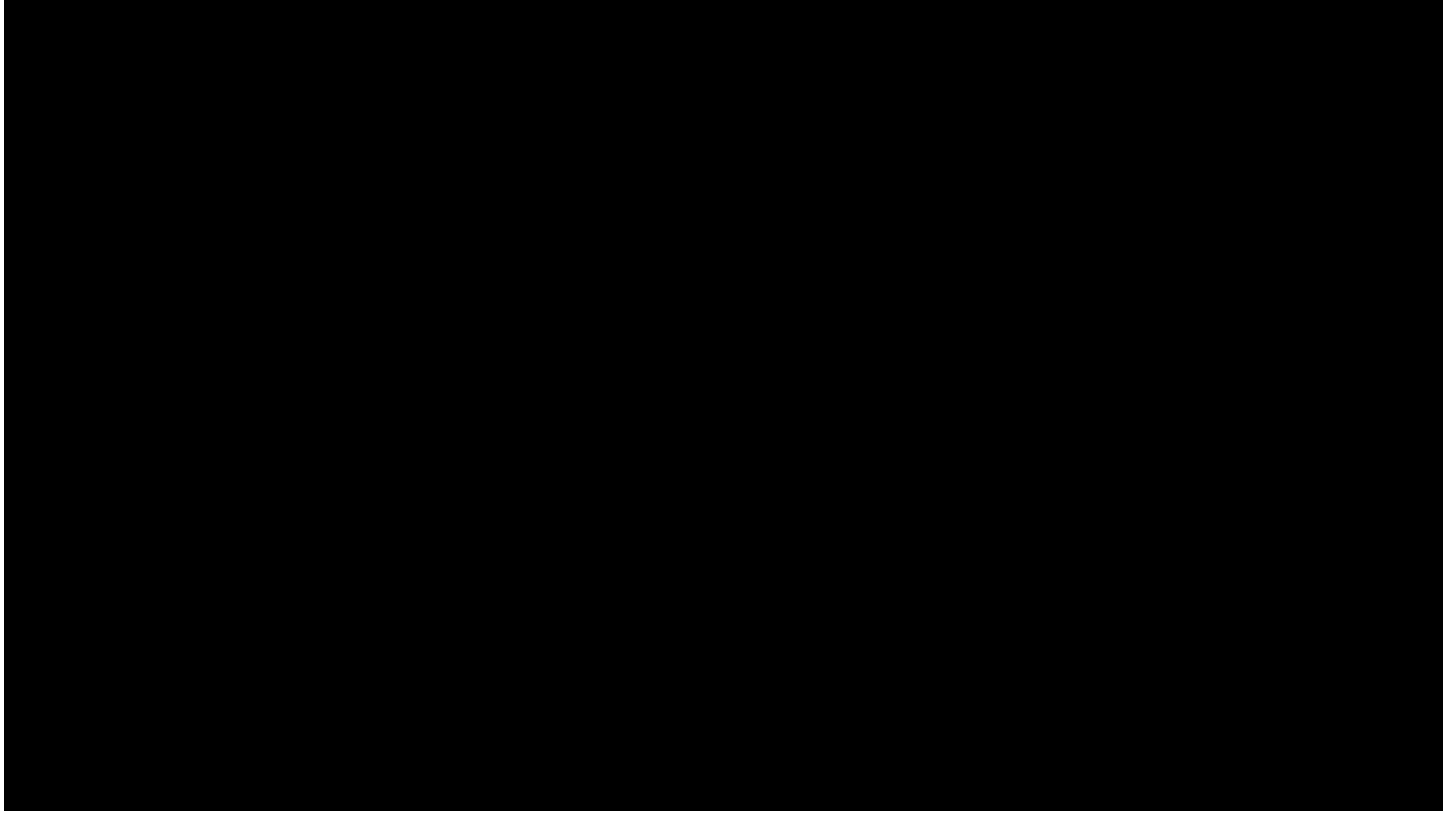
“The battle for the mind of North America
will be fought in the video arena”

Brian Oblivion, *Videodrome*

Videodrome (1983)



Deep Fakes

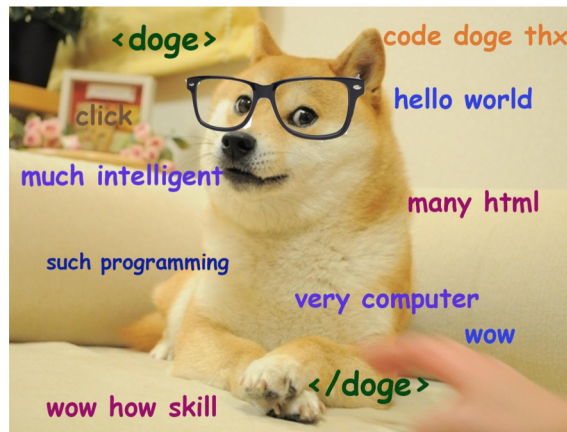


ISIS Execution Videos (Fake)



The Intersection of Politics and Entertainment: Internet Memes

What is a Meme?



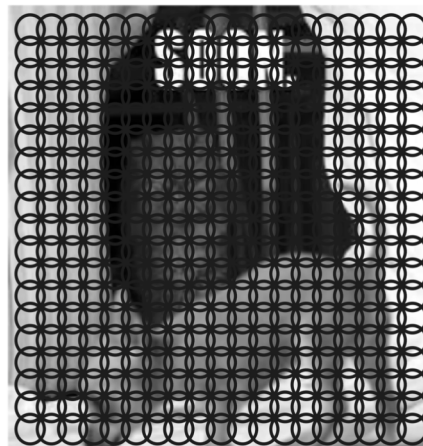
Forstall and Scheirer, *Quantitative Intertextuality*, Springer-Nature 2019

Memes, Visual Style, and Semantic Analysis

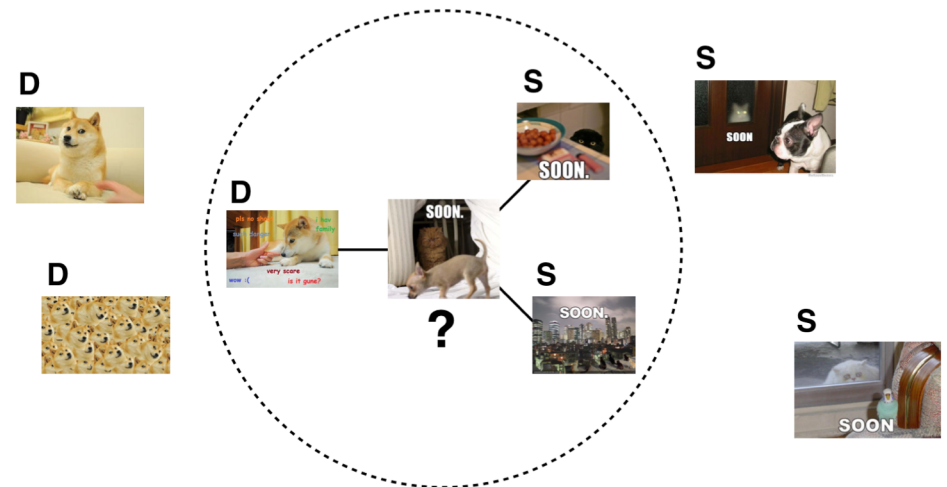
A naive approach:



Original



Dense grid of HOG descriptors



K-Nearest Neighbors

Related Work

Memes as Cultural Artifacts

L. Shifman, *Memes in Digital Culture*, MIT Press, 2014.

Visual Style in Computer Vision

J. Jupp and J. Gero, "Let's look at style: Visual and spatial representation and reasoning in design," In: S. Argamon, K. Burns, S. Dubnov (eds.) *The Structure of Style: Algorithmic Approaches to Understanding Manner and Meaning*. Springer-Verlag, 2010.

Q. Wu, H. Cai, P. Hall, "Learning graphs to model visual objects across different depictive styles," ECCV, 2014.

Y. Lee, A. Efros, M. Hebert, "Style-aware mid-level representation for discovering visual connections in space and time," IEEE ICCV, 2013.

Empirical Effects of Manipulated Media

Shen et al., "Fake images: The effects of source, intermediary, and digital media literacy on contextual assessment of image credibility online," *New Media & Society*, 21 (2), 2018.

Memes and Political Interference

Brazil



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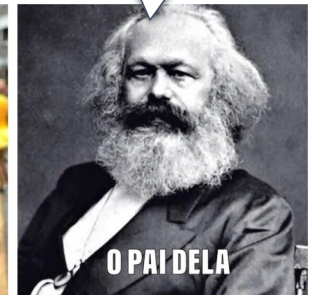
Bolsonaro's actual fraudulent
employee: his brain



The girl you
like



Her
father



Her
brother



The guy
she likes



Her ex



You



Brazil

That's it, Messi, I'm not your supporter for nothing...

É isso aí Messi, sempre fui teu fã e não é a toa.



Original

Manipulation to
claim support

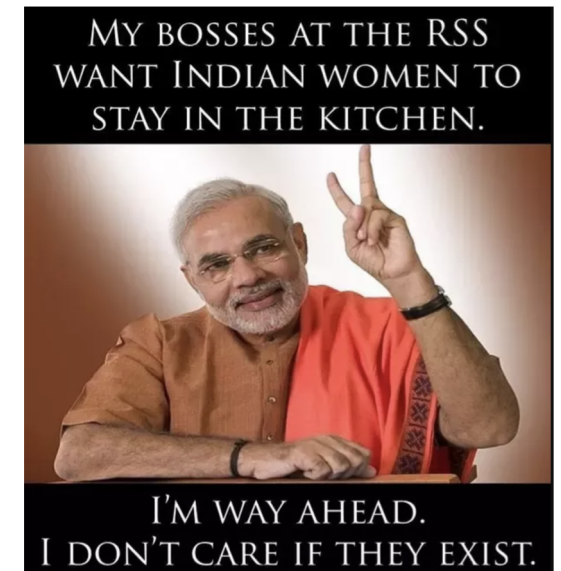
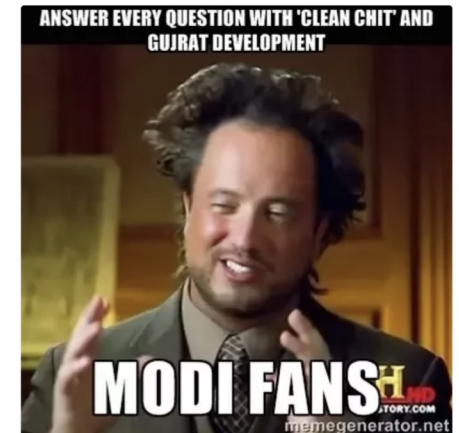
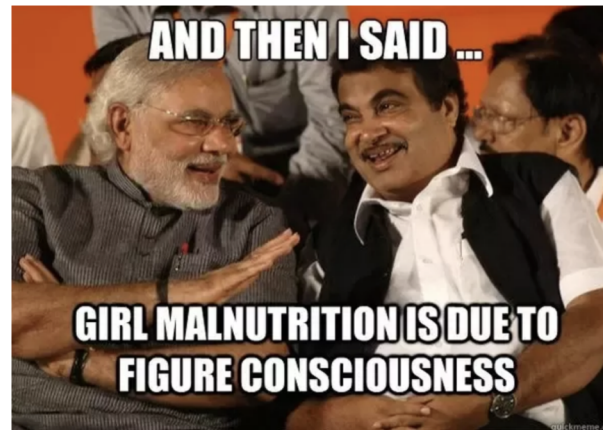
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A Federal University 'class'
We don't want to pay for it!



Image repurposing

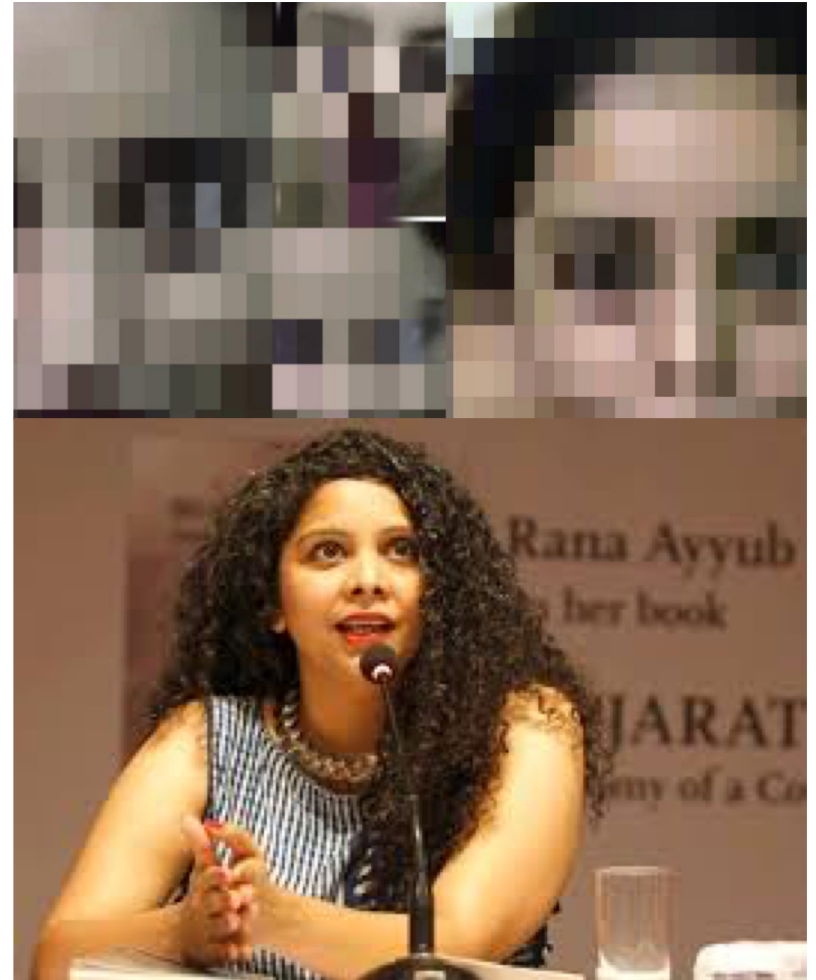
India



Deep Fakes as a Political Tool

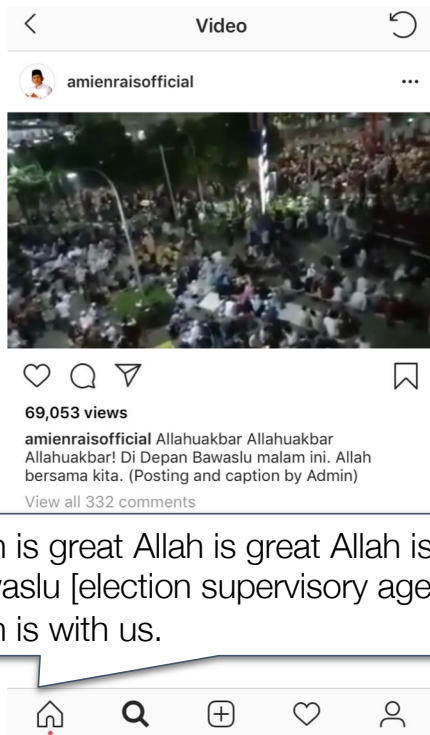
2018: BJP supporters target investigative journalist Rana Ayyub with a doctored pornographic video containing her face

https://www.huffingtonpost.co.uk/entry/deepfake-porn_uk_5bf2c126e4b0f32bd58ba316



Credit: Huffington Post and Facebook

Indonesia



015 KRAMAT JATI DKE JAHAMTA

TENGAH JAHAMTA TENGAH

01 H. JOKO WIDODO (P.K.) KH. MA'RUF AMIN

02 PRABOWO SUBANTO KH. SAIFUL KHAN

127

127

DIRUBAH?????

KIDUL DALEM PASIRAN

015 KRAMAT JATI DKE JAHAMTA

TENGAH JAHAMTA TENGAH

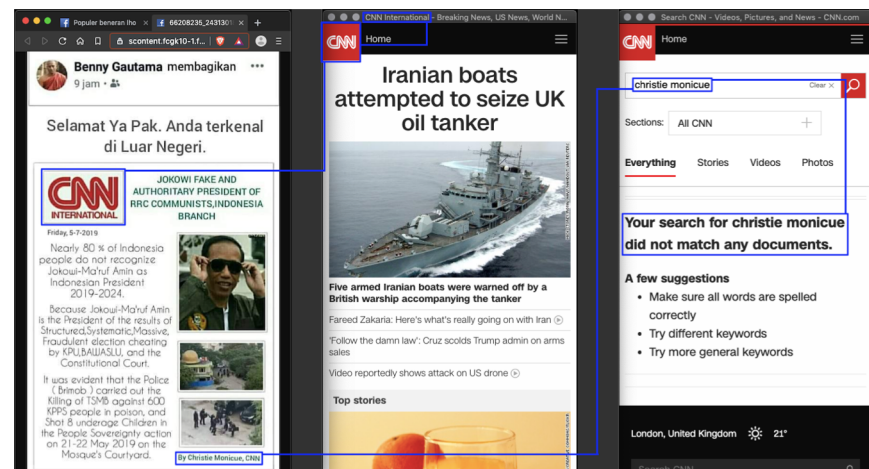
01 H. JOKO WIDODO (P.K.) KH. MA'RUF AMIN

02 PRABOWO SUBANTO KH. SAIFUL KHAN

127

127

ANGKA YANG TERTUKAR



Case Study: 2019 Indonesian Elections

Indonesian Presidential Election Overview

Direct general election

Fourth presidential election

Rematch of 2014 (five year terms)

Joko Widodo re-elected with over 55% of the vote



A voting station in Samarinda, East Kalimantan © BY-SA 4.0 Ezagren

The Candidates

Joko “Jokowi” Widodo

- Incumbent
- PDI-P candidate (center-left party)
- Appealed to younger voters
- “Man of the people”

Prabowo Subianto

- Challenger
- Gerindra candidate (right populist party)
- Strongly Islamic
- Military background (Ties to Suharto dictatorship)



Indonesian Election Aftermath

Prabowo claims a count fraud

Protests/Riots in Jakarta May 21-22, 8 dead

Indonesia restricts access to social media

<https://www.straitstimes.com/asia/se-asia/old-age-poor-health-caused-deaths-of-poll-administrators-indonesia-government>



Survey of the Meme-space

Millions of images collected during the course of the election

Twitter

- ~170,000 images from 14 different sources

Instagram

- ~1.9 million images from 20 different sources

The Data

Image sources identified by our partner in Indonesia, CekFakta

Images span from May 31st, 2018 to May 31st, 2019

Collected from 2 users and 12 popular hashtags (Twitter)



Buzzer Accounts

Social media propaganda

Firms use fake accounts to generate “buzz”

Buzzers use upwards of 250 fake accounts each

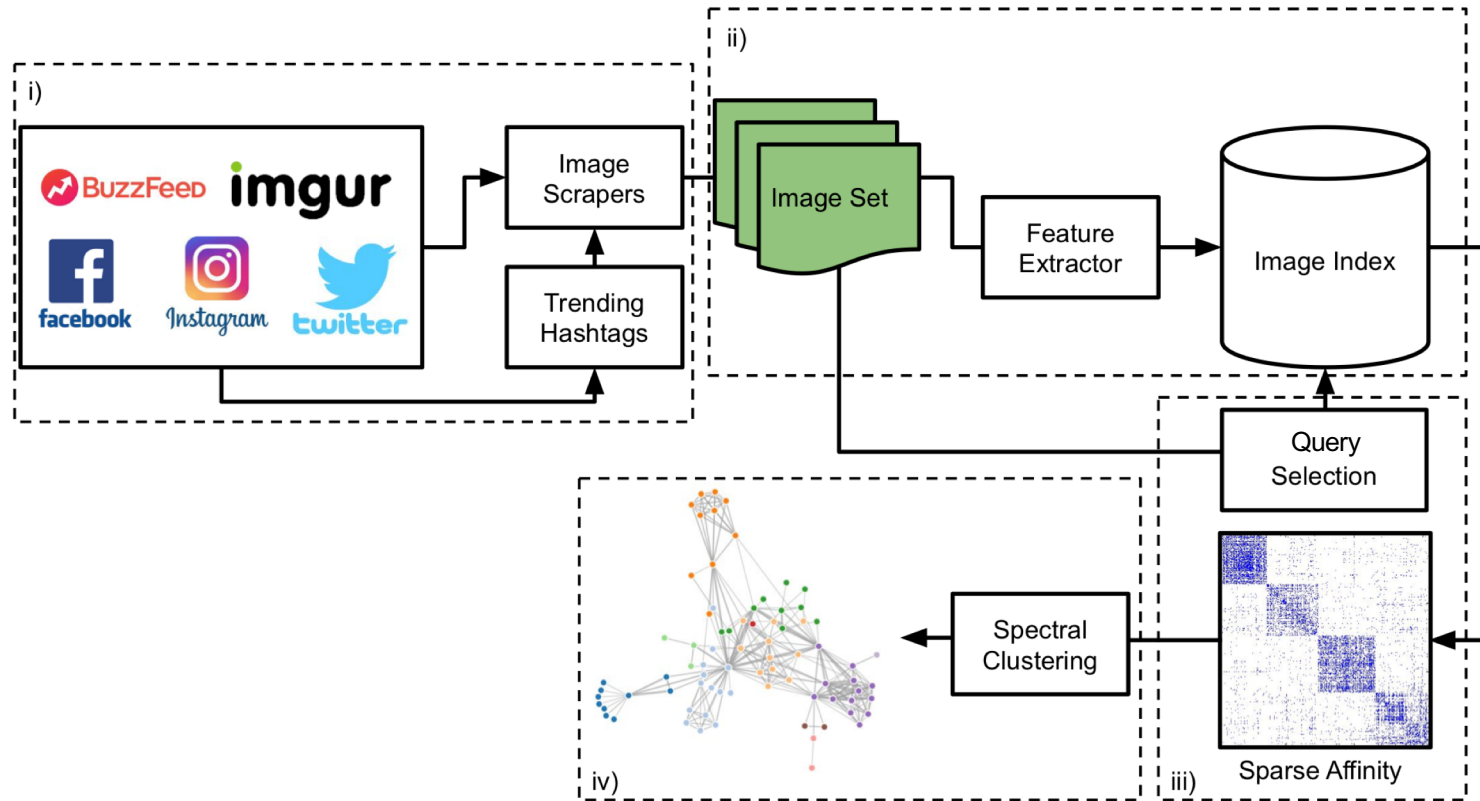
<https://www.reuters.com/article/us-indonesia-election-socialmedia-insigh/in-indonesia-facebook-and-twitter-are-buzzer-battlegrounds-as-elections-loom-idUSKBN1QU0AS>

Finding Trending Memes: Motif Mining

Objectives for an early warning system

- Real-time processing pipeline with content flagging
- Assess meme landscape with respect to political actors
- Allow humans to gauge the threat of violence
- Scale to the order of billions of images per day
- Match composite images to other composite and donor images

Motif Mining Pipeline



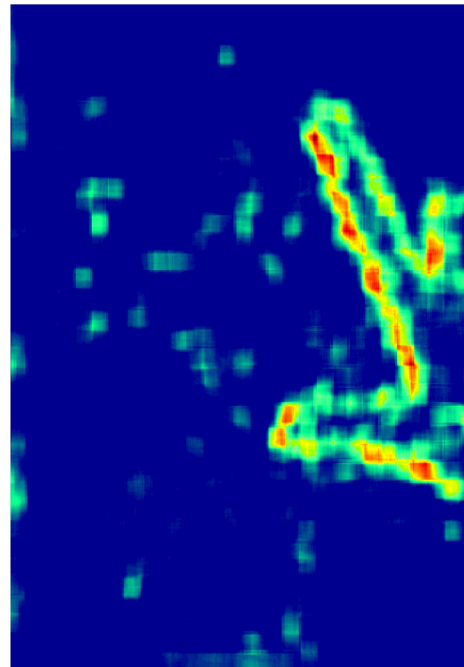
Query Selection: Detecting Edited Objects

Use meme images to search for related meme content

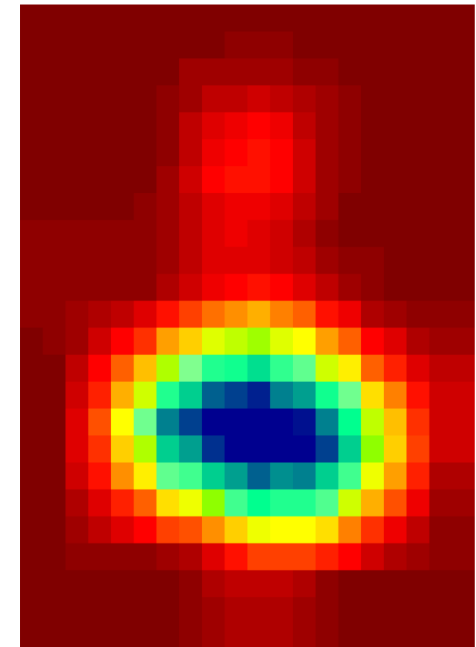
- Option 1: Randomly sample images from known buzzers
- Option 2: Detect new memes via the identification of edits

<http://reveal-mklab.iti.gr/reveal/>

Detecting Image Edits

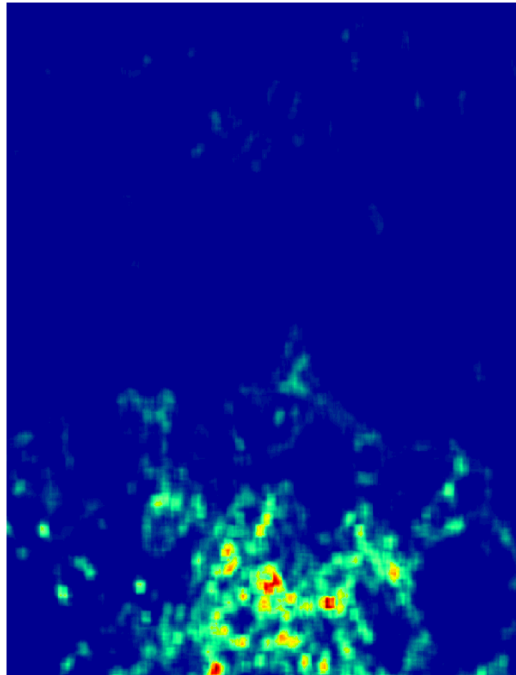


Farid 2009

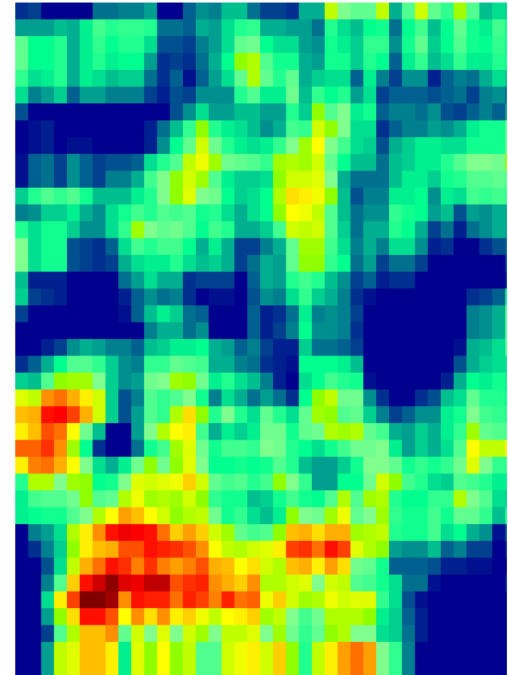


Iakovidou et al. 2018

Detecting Image Edits

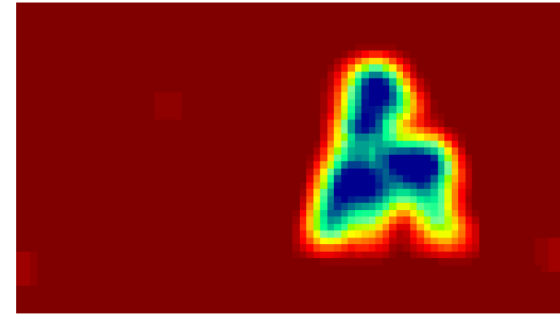


Farid 2009

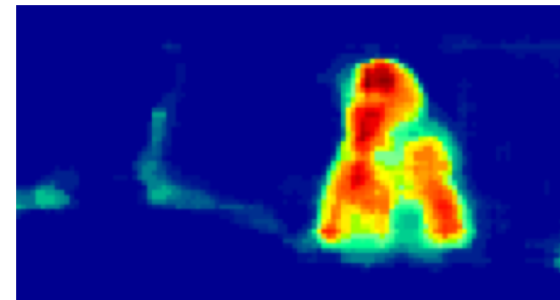


Weihai et al. 2009

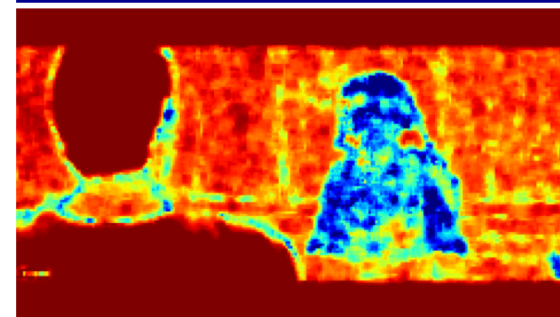
Detecting Deep Fakes



Iakovidou et al. 2018

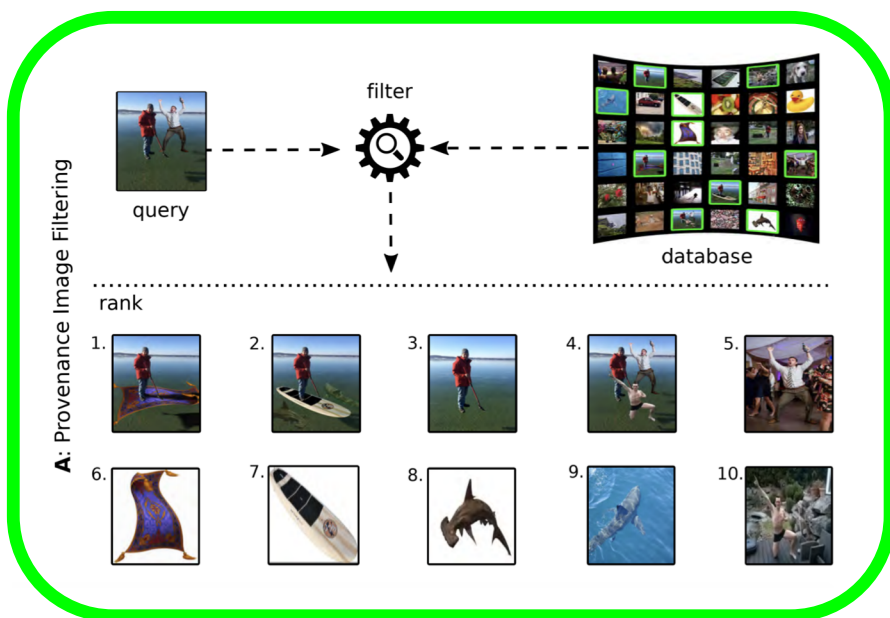


Mahdian et al. 2009

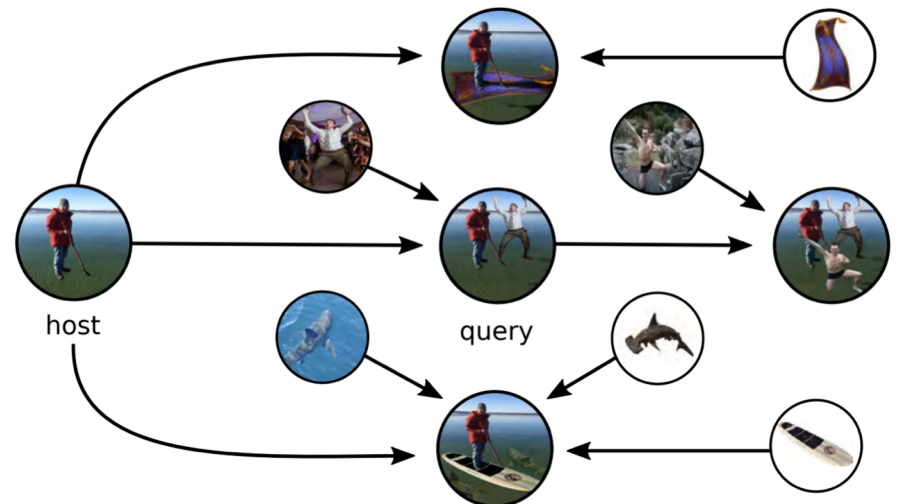


Wei-hai et al. 2009

Adapting a provenance pipeline to motif mining

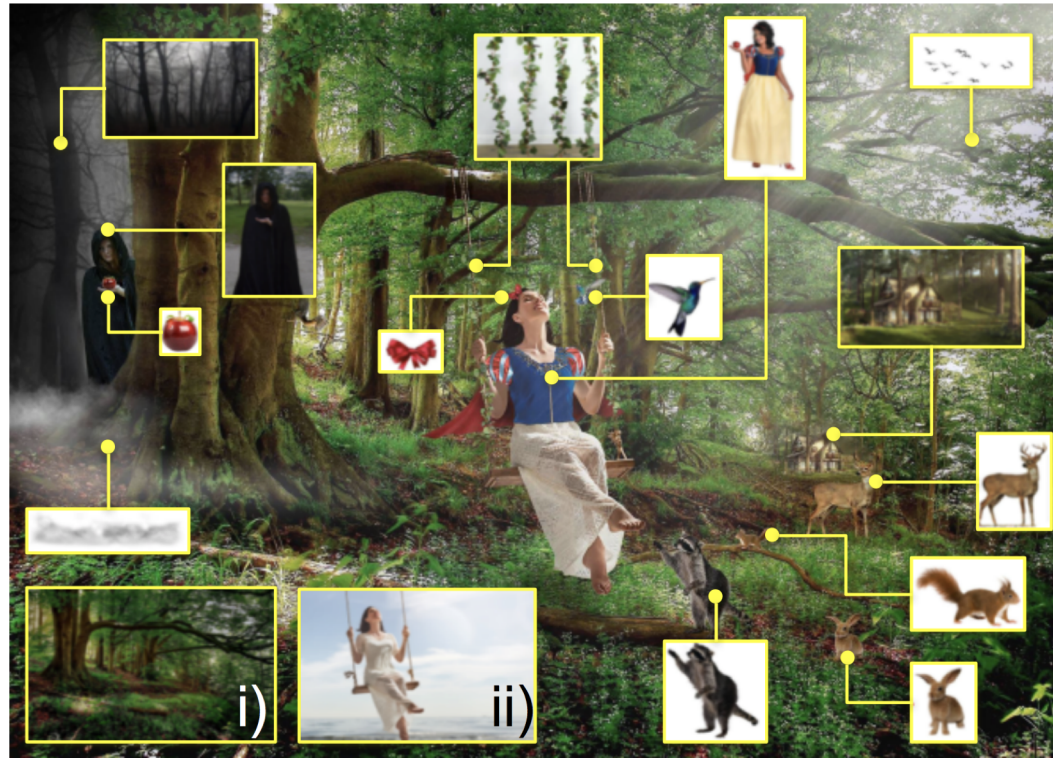


B: Provenance Graph Construction

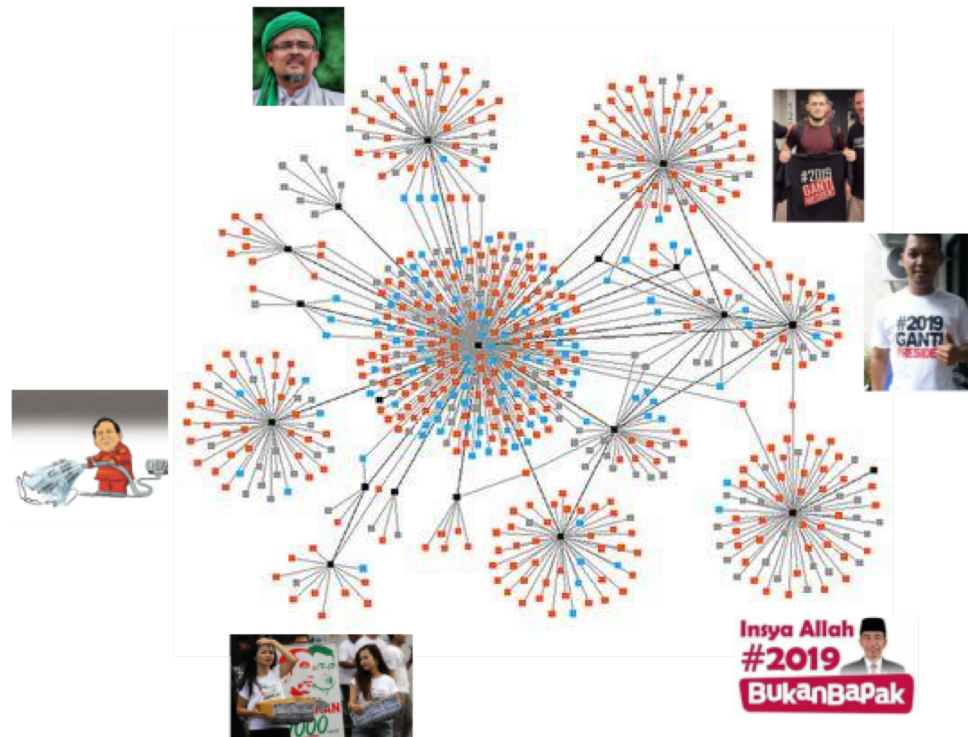


Moreira, D., et al. *Image Provenance Analysis at Scale*. IEEE T-IP, 2018

Add the ability to localize and match small objects



Add a spectral clustering stage

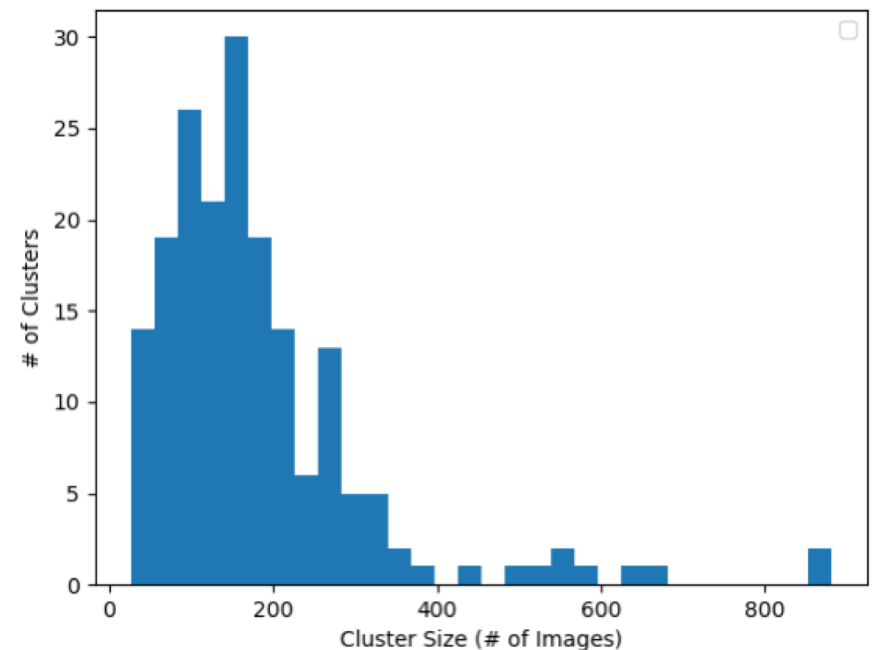


Motif Mining (Twitter Dataset)

- 174,328 images scraped from Twitter
- Image Index was built in 6.2 hours on a single GPU machine with 12 CPU cores
- 10,000 Random queries were performed for matrix generation in 6.5 hours
- **No deep learning was used**

Motif Mining (Twitter Dataset)

- 174328 total images
- 197 computed clusters
- Mean cluster size: 895 images
- Median cluster size: 156
- Minimum cluster size: 26
- Maximum cluster size: 36304



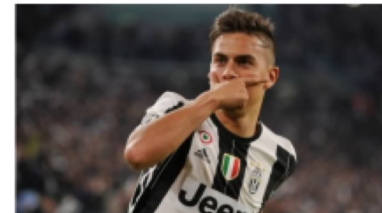
Automatic Motif Detection



Automatic Motif Detection



Automatic Motif Detection



Some Questions...

Q1: What capabilities do we still need for meme analysis?

Q2: What aspects of semantic analysis can improve the process?

Q3: What is a good process for data collection?

Q4: Who outside of the forensics community should we engage with?