

# Faces of Facebook: Privacy in the Age of Augmented Reality

Alessandro Acquisti, Ralph Gross, Fred Stutzman

Heinz College, Carnegie Mellon University

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- <http://www.heinz.cmu.edu/~acquisti/face-recognition-study-FAQ/>
- [acquisti@andrew.cmu.edu](mailto:acquisti@andrew.cmu.edu)

- In 2000, 100 billion photos were shot worldwide
- In 2010, 2.5 billion photos *per month* were uploaded by Facebook users alone
- In 1997, the best face recognizer in FERET program scored error rate of 0.54 (false reject rate at false accept rate of 1 in 1000)
- In 2010, the best recognizer scored 0.003 (almost three orders of magnitudes better)

# Background

- Face recognition is entering consumers products
  - Facebook has licensed Face.com technology to enable automated tagging
  - Microsoft has deployed face recognition on Kinect
  - Google has acquired Neven Vision, Riya, and PittPatt and deployed face recognition into Picasa
  - Apple has acquired Polar Rose, and deployed face recognition into iPhoto

# Background

- Someone asked during the Webinar: are there open source face recognizers?
- Answer: libface seems to be an example (<http://libface.sourceforge.net/file/Home.html>).  
However, we have not tested it

# Our focus: Converging technologies

- Increasing **public** self-disclosures through **online social networks** (especially photos)
- Continuing **improvements** in face recognizers' accuracy
- **Cloud** computing
- **Ubiquitous** computing
- **Statistical re-identification**

# Our questions

- Can we combine **publicly available** online social network data with **off-the-shelf** face recognition technology for the purpose of **large-scale, automated, real-time, peer-based...**
  1. **Individual re-identification, online and offline?**
  2. **Inference of additional, and potentially sensitive, personal data?**



# Agenda

- Three experiments
- Implications and limitations
- Extrapolations

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- **Three experiments**
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# Experiments

- Experiment 1: Online-to-Online Re-Identification
- Experiment 2: Offline-to-Online Re-Identification
- Experiment 3: Offline-to-Online Sensitive Inferences

# In a nutshell

## Un-Identified DB

- Profiles on Match.com, Prosper.com, etc.
- Photo repositories (e.g., Flickr)
- Open web cams
- CCTVs
- Your face on the street

## (Publicly available) Identified DB

- Personal Profiles on Facebook.com, LinkedIn, etc.
- Gov't or corporate databases
- Organizational rosters



[1]

[2]

[3]

[5]

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- Additional, sensitive inferences (e.g. sexual orientation, SSN, etc.)

# Identified DB in our experiments

- Facebook profiles
- Why?
  - Primary profile photos visible to all by default
    - ‘‘Facebook is designed to make it easy for you to find and connect with others. For this reason, your name and profile picture do not have privacy settings’’  
(Facebook Privacy Policy)
  - Most members use photos of themselves as primary profile image
  - Most members use real first and last names on their profiles

# Experiment 1

- Online to online
- We mined **publicly available images** from online social network profiles to re-identify profiles on one of the most popular dating sites in the US
  - We used PittPatt face recognizer (Nechyba, Brandy, and Schneiderman, 2007) for:
    - Face detection: automatically locating human faces in digital images
    - Face recognition: measuring similarity between any pair of faces to determine if they are of the same person

# Experiment 1: Data

- Facebook profiles: **Identified DB**
  - We downloaded primary profile photos for Facebook profiles from a North American city using a search engine's API (i.e., **without even logging on the Facebook itself**)
  - “Noisy” profile search pattern: Combination of search strategies (current location, member of local networks, fan of local companies/teams, etc.)

# Experiment 1: Data

- Facebook profiles
  - Number of profiles: 277,978
  - Number of images: 274,540
  - Number of unique faces (“templates”) detected: 110,984



# Experiment 1: Data

- Dating site profiles: **Unidentified**
  - Profiles were members of one of the most popular dating sites in the US
  - Members use pseudonyms to protect their identities
  - However, facial images may make members recognizable not just by friends, but by strangers
    - **Unfeasible if done manually** (hundreds of millions of potential matches to verify), but quite **feasible using face recognition + cloud computing**

# Experiment 1: Data

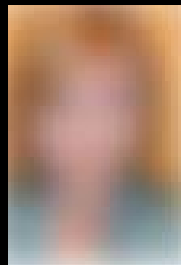
- Dating site profiles
  - Profile search pattern: Profiles within Urbanized Area of same North American city
    - Number of profiles: 5,818
    - Number of faces detected: 4,959

# Experiment 1: Approach

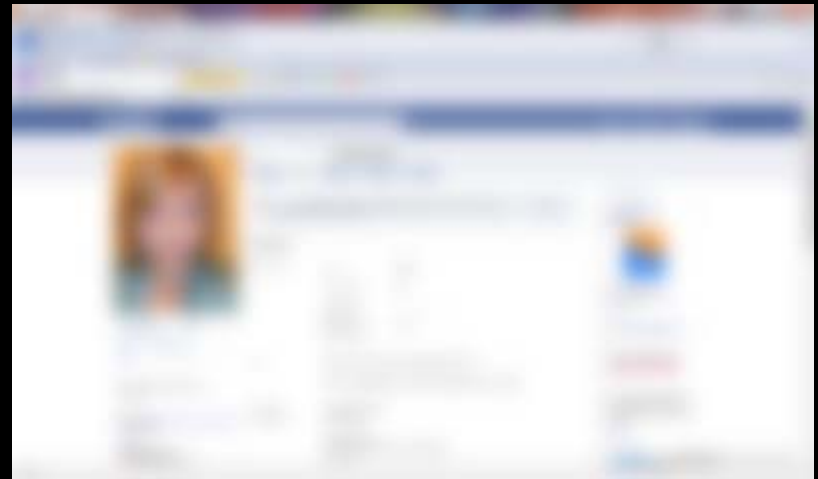
**Unidentified  
Database:  
Dating site Photos**



**Identified Database:  
Facebook Photos**



**Re-Identified  
Individual**



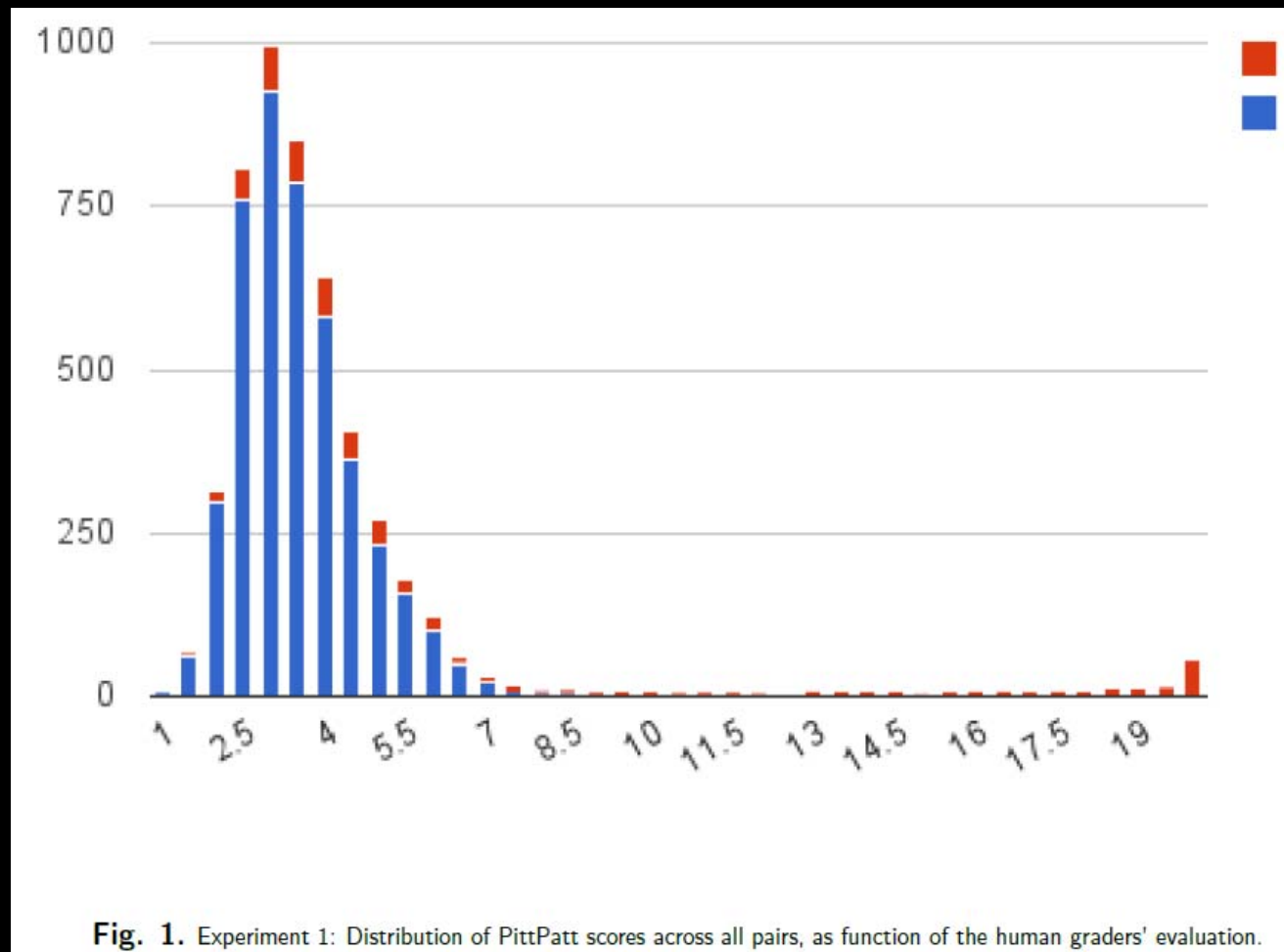
# Experiment 1: Evaluation

- More than 500 millions pairs compared by PittPatt on a cloud computing cluster
- We only considered the best matching pair for each dating site profile

# Experiment 1: Evaluation

- PittPatt produces matching scores between -1.5 (sure no match) and 20 (sure match)
- Crowdsourced to Amazon MTurkers validation of PittPatt's scores (*1=definitely a match, 2=likely a match, 3=unsure, 4=likely not a match, 5=definitely not a match*)
  - Inserted test pairs (sure matches; sure non-matches) to filter out “bad” human graders (also used various inter-coders reliability metrics)
  - At least 5 graders for each pair

# Experiment 1: Results



# Experiment 1: Results

- Mapping results onto profiles, we found:
  - Highly likely matches: **6.3%**
  - Highly likely + Likely matches = **10.5%**
  - I.e., about **1** out of **10** dating site's pseudonymous members likely identifiable

# Experiment 1: Comments

- In Experiment 1, we conservatively constrained ourselves to using **only a single Facebook** profile photo, and only considering the **top match** returned by the recognizer
  - However: Because an “attacker” can use more photos, and test more matches, ratio of re-identifiable individuals will dramatically increase
  - **See, in fact, Experiment 2**



# Experiment 2

- Offline to online
- We used publicly available images from a Facebook college network to identify students strolling on campus

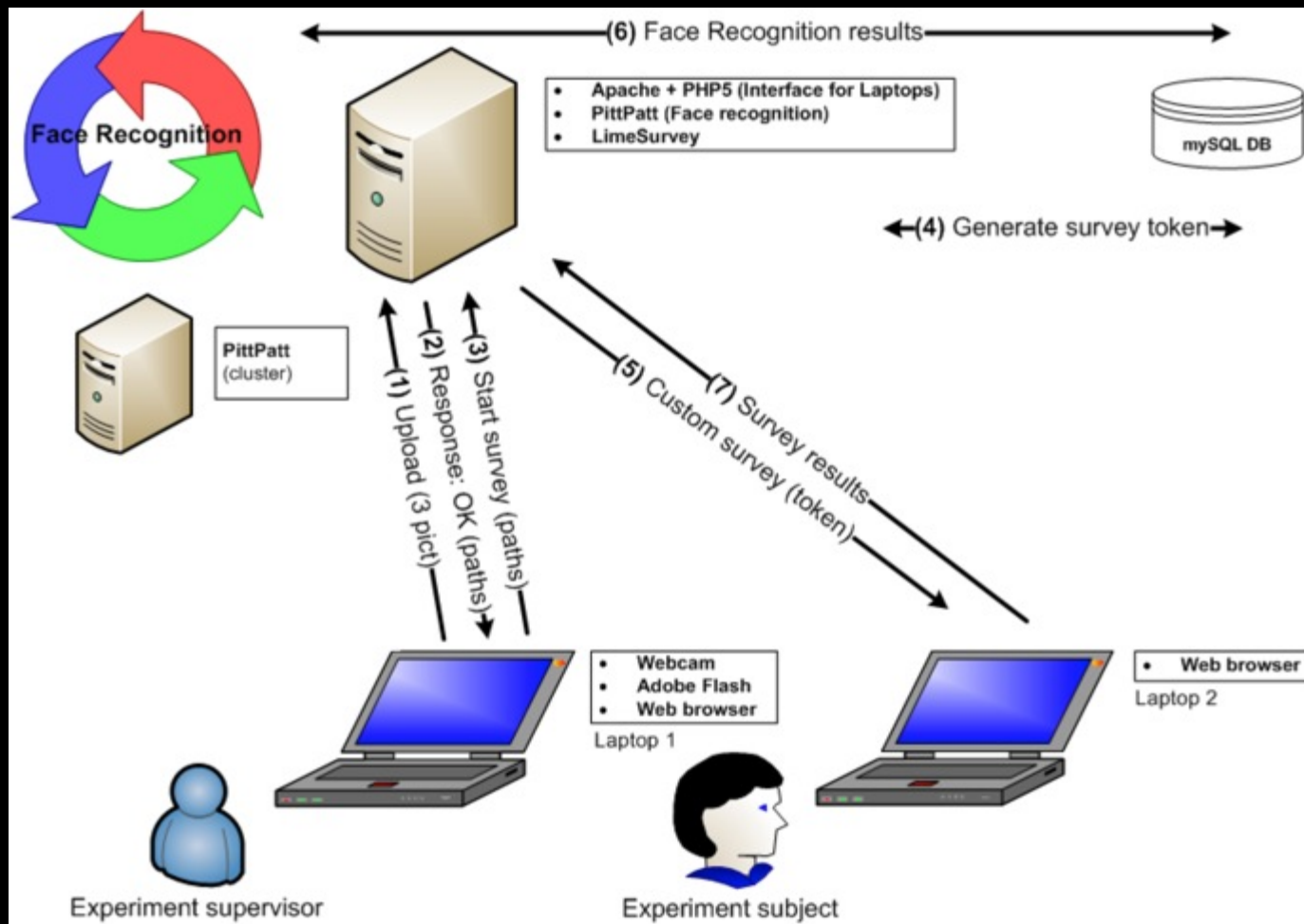
# Experiment 2: Data

- College photos
  - We used a webcam to take 3 photos per participant
  - Photos gathered over two days in November
- Facebook profiles photos
  - Number of profiles: 25,051
  - Number of images: 261,262
  - Number of faces detected: 114,745

# Experiment 2: Process

- We asked individuals walking by a campus building to stop and have their picture taken
- Then, we asked them to answer an online survey about Facebook usage
- In the meanwhile, face matching was taking place on an cloud computing service
- The last page of the survey was populated dynamically with the best matching pictures found by recognizer
- Participants were asked to select photos in which they recognized themselves within the top 10 matches produced by the recognizer

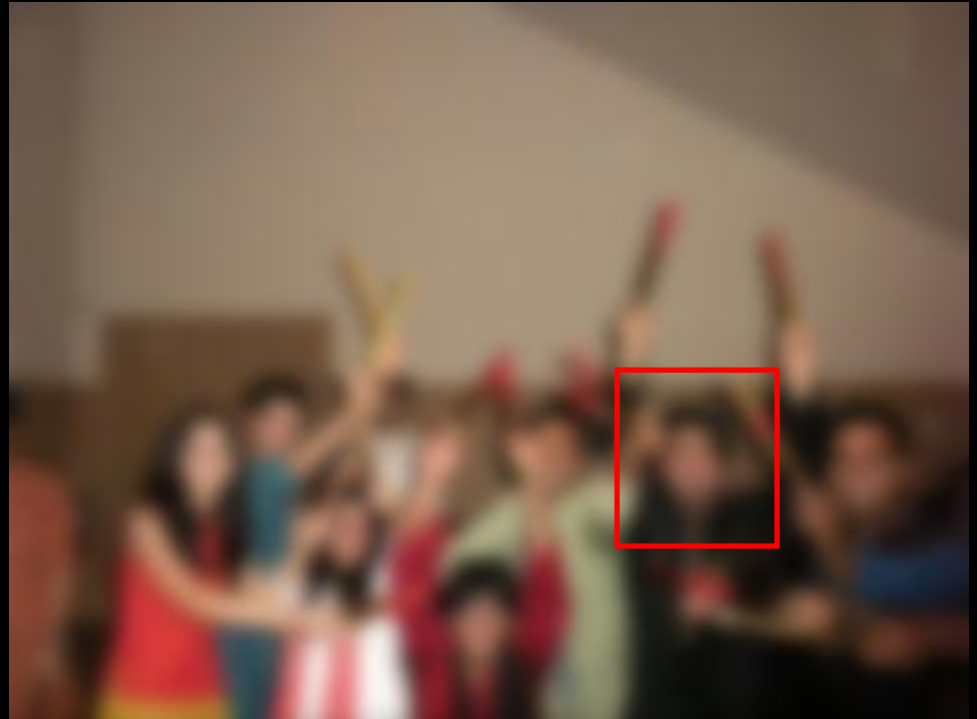
# Experiment 2: Approach



# Experiment 2: Examples



Campus shot  
**Unidentified**



Facebook image  
**(Possibly) identified**

# Experiment 2: Results

- 93 subjects
  - Based on survey's results, we know that all were students and all were Facebook members
- For 31.18% of subjects we matched the correct Facebook profile
  - .... including a subject who told us he did not have a photo on FB
  - Average computation time per subject: less than three seconds

# What we have shown so far



+



=



# What we had done before (Acquisti and Gross 2009)



+



SSDI Death Index Search Results

#	Name	SSN	Last Residence Zip	Last Residence State	Date of Birth	Date of Death
1	ACQUISTI, GREGORY J	000000000	00000	00	0000-00-00	0000-00-00
2	ACQUISTI, GREGORY J	000000000	00000	00	0000-00-00	0000-00-00
3	ACQUISTI, GREGORY J	000000000	00000	00	0000-00-00	0000-00-00
4	ACQUISTI, GREGORY J	000000000	00000	00	0000-00-00	0000-00-00
5	ACQUISTI, GREGORY J	000000000	00000	00	0000-00-00	0000-00-00
6	ACQUISTI, GREGORY J	000000000	00000	00	0000-00-00	0000-00-00
7	ACQUISTI, GREGORY J	000000000	00000	00	0000-00-00	0000-00-00
8	ACQUISTI, GREGORY J	000000000	00000	00	0000-00-00	0000-00-00
9	ACQUISTI, GREGORY J	000000000	00000	00	0000-00-00	0000-00-00
10	ACQUISTI, GREGORY J	000000000	00000	00	0000-00-00	0000-00-00

= SSN



# Can you do 1+1? Experiment 3

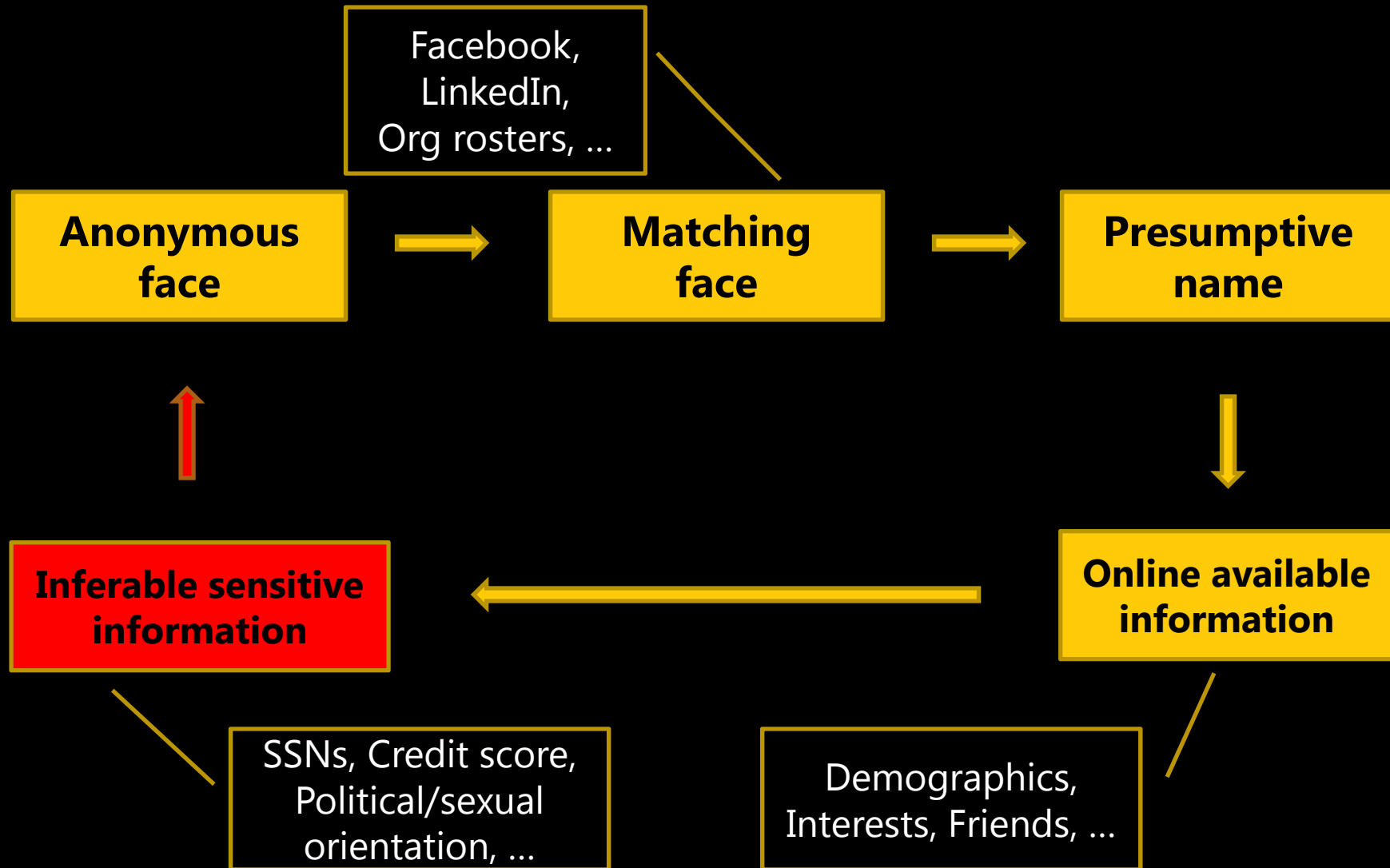


**27% of subjects' first 5 SSN digits identified with four attempts - starting from their faces**

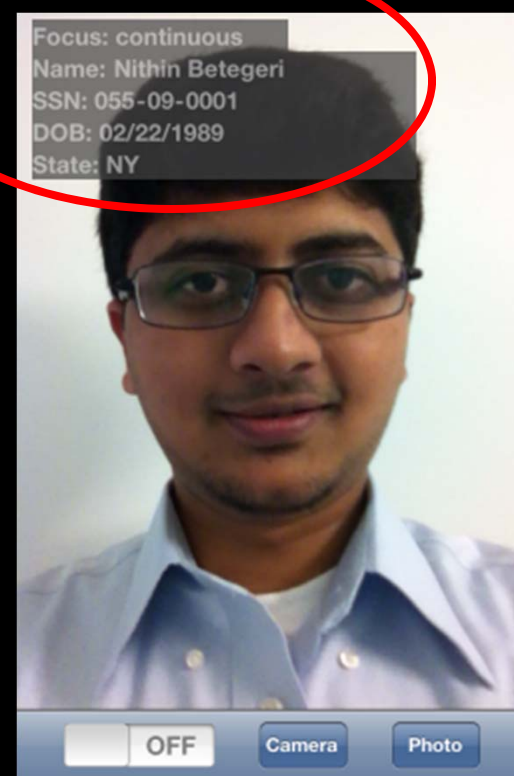
**SSN**

*I.e., predicting SSNs (or other sensitive information) from faces*

# Data "accretion"



# Privacy in the Age of Augmented Reality: Real time, peer-based, sensitive predictions



# Privacy in the Age of Augmented Reality: Real time, peer-based, sensitive predictions

- <http://money.cnn.com/video/technology/2011/10/05/t-ts-iphone-camera-id.cnnmoney/?iid=EL>
- <http://www.bbc.co.uk/news/magazine-15069858>
- [http://abclocal.go.com/kgo/story?section=news/7\\_on\\_your\\_side&id=8425742](http://abclocal.go.com/kgo/story?section=news/7_on_your_side&id=8425742)

# Agenda

- Three experiments
- **Implications and limitations**
- Extrapolations

# Scenarios and trade-offs

- Stranger in the street?
- Brick and mortar store?
- Large-scale real-time surveillance?



# Implications: Key themes

- Faces as conduits between online and offline data
- The emergence of PPI: “personally predictable” information
- The rise of visual, facial searches
- Democratization of surveillance
- Social network profiles as Real IDs
- *What will the future of privacy be in a world of augmented reality?*



# Limitations

- However: Face recognition of everyone/everywhere/all the time is **not** yet feasible
  - Data sources: Technical and legal availability
  - Accuracy: false positives and scope
  - Cooperative subjects
  - Computational costs
- That said, current technological and business trends suggest that current limitations will keep fading over time

# Agenda

- Three experiments
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# Data sources

- Mining publicly available data
- Hacking
- Search engines
- Private sector DBs of identified images, **selling data** or **providing identification** services to:
  - Individuals
  - Other companies
  - US government
  - Other governments

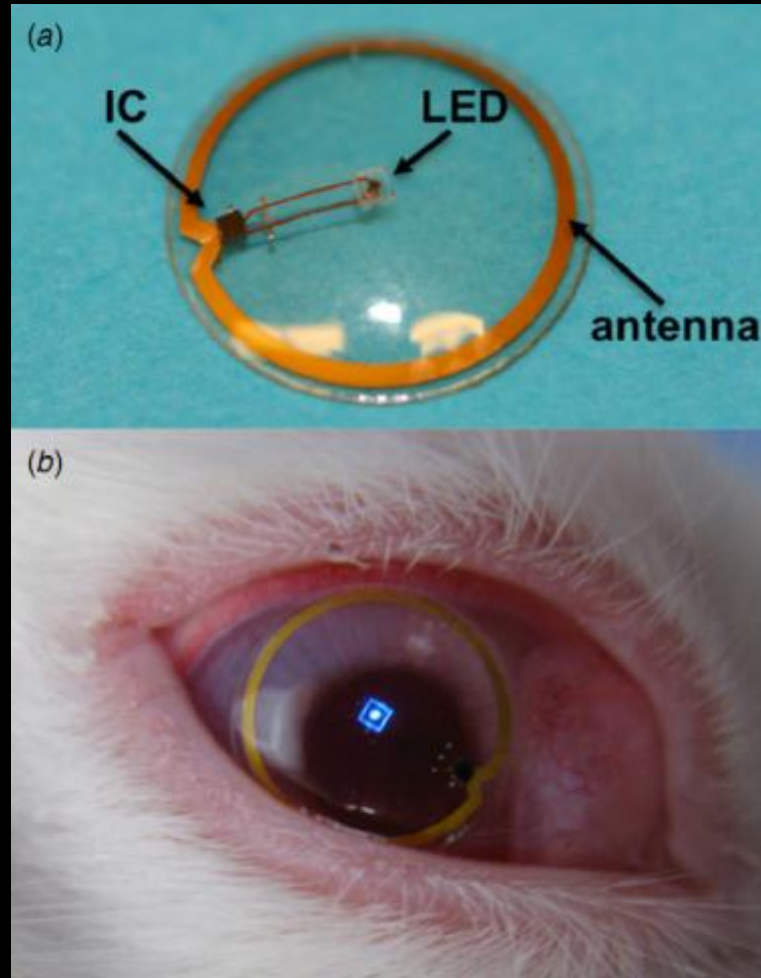
# Example: Facebook

- Facebook has implemented a verified identity policy, actively promotes tagging of its members, makes names and primary photo public to all by default
  - Other photos accessible by connected profiles, Facebook, 3<sup>rd</sup> party apps, ...
- Simple test based on FB's directory (accessible without login):
  - ~800 million users
  - Randomly sampled 1906 images
  - In 46% exactly one face detected (in 59.7% at least one face detected)
  - Estimated 90% of members using real names (CMU survey)
  - **Extrapolating: about 330 million uniquely identified faces publicly accessible**

# Accuracy

- Face recognition research is focusing on:
  - Lighting
  - Non-frontal shots
  - Facial hair
  - Metadata
  - [...]

# Cooperative subjects and ubiquitous devices



# Computational costs and extrapolations

- Today
  - 0.000108 seconds per pair comparison (does not include upload time)
  - Consider target population as including all US residents 14+ yro (about 280M)
  - Assume each person has one identified frontal photo available to public or to Web 2.0 providers
  - **Up to more than 4 hours to find a potential match**
  - **Cost: \$2/hr.**

# Computational costs and extrapolations

- In 2021
  - US 14+yro population about 300M
  - Assume Moore's law for cloud computing clusters
  - Merely pre-classify photos into male and female faces
  - **Fewer than 5 minutes to find a potential match**
  - **Or, 10 seconds using larger clusters (\$60/hr, assuming prices/per hour for clusters stay the same)**



# Extrapolations

- In short: false-positives and self-regulatory concerns currently restrain wider application of face recognition technologies
- Neither restraint is guaranteed in the long run

# Implications – cont'd

- Augmented reality combined with face recognition may also carry **deep-reaching behavioral implications**
  - Through natural evolution, human beings have **evolved mechanisms to assign and manage trust in face-to-face interactions**
  - Will we rely **on our instincts, or on our devices**, when mobile devices make their own predictions about hidden traits of a person we are looking at?

# Agenda

- Three experiments
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- **And more section: *Solutions?***

# Solutions?

- Ideal balance: Permit “good” usages of face recognition but stop “creepy” usages
- Problems:
  - Define good, creepy
  - Then, find out how to achieve that balance

# Solutions?

- What is *less* likely to work
  - Disrupting research on face recognition
  - Halting data collection
  - Blurring images
  - Self-regulation
    - Reliance on notice and consent
    - Do-not-identify me lists
    - “Trust me” models

# Solutions?

- What *may* be more likely to work
  - Regulate **usage**, not **collection**

# OECD Privacy Guidelines

- Openness (notice)
- Individual participation (consent)
- **Use limitation**
- **Purpose specification**
- Collection limitation
- Security safeguards
- Data quality
- Accountability

# For More Information

- Google/Bing: [economics privacy](#)
- Visit: <http://www.heinz.cmu.edu/~acquisti/economics-privacy.htm>
- Email: [acquisti@andrew.cmu.edu](mailto:acquisti@andrew.cmu.edu)