What is automated facial age estimation

How old are these people?

Estimated Age: 46  
True Age: ??

Estimated Age: 26  
True Age: 32

Estimated Age: 16  
True Age: 32
For the most accurate algorithm, 67% of estimates are accurate within 5 years with a Mean Absolute Error (MAE) of 4.3 years.
Age Estimation Accuracy & Error by Age Group

<table>
<thead>
<tr>
<th>Age Group</th>
<th>Num Images</th>
<th>B30D</th>
<th>B31D</th>
<th>E30D</th>
<th>E31D</th>
<th>E32D</th>
<th>F30D</th>
<th>K10D</th>
<th>P30D</th>
<th>Q10D</th>
</tr>
</thead>
<tbody>
<tr>
<td>0–17</td>
<td>1605807</td>
<td>2.6</td>
<td>3</td>
<td>5.3</td>
<td>5.4</td>
<td>5.3</td>
<td>18.6</td>
<td>21</td>
<td>6.1</td>
<td>10.9</td>
</tr>
<tr>
<td>18–55</td>
<td>3781607</td>
<td>4.9</td>
<td>4.5</td>
<td>5.5</td>
<td>5.5</td>
<td>4.6</td>
<td>5.6</td>
<td>6.6</td>
<td>7.6</td>
<td>7</td>
</tr>
<tr>
<td>56–100</td>
<td>785287</td>
<td>6.2</td>
<td>5.8</td>
<td>13.9</td>
<td>14</td>
<td>9</td>
<td>14.7</td>
<td>14</td>
<td>16.7</td>
<td>10.9</td>
</tr>
</tbody>
</table>

Mean Absolute Error (years)
Results:
All algorithms estimate age more accurately on males than females.
Face Recognition Accuracy By Age Group
Identification miss rates by age group

- Older ➔ [56,120]
- Parents ➔ [31,55]
- Young ➔ [20,30]
- Teen ➔ [14,19]
- Pre ➔ [9,13]
- Kid ➔ [4,8]
- Baby ➔ [0,3]

Visa images:
Enrolled size, \(N = 19972\)
Mated searches = 19972
Non-mated searches = 203082

One-to-many “miss rate”
FNIR when threshold set to produce a false positive in only 1 in 100 non-mate searches (FPIR = 0.01)
Identification miss rates by age group, algorithm
Accuracy = \( F(Age, Ageing) \)

- Baby \( \leftarrow [0,3] \) \quad \text{Mean time lapse} = 1.6
- Kid \( \leftarrow [4,8] \) \quad \text{Mean time lapse} = 3.0
- Pre \( \leftarrow [9,13] \) \quad \text{Mean time lapse} = 3.9
- Teen \( \leftarrow [14,19] \) \quad \text{Mean time lapse} = 2.7
- Young \( \leftarrow [20,30] \) \quad \text{Mean time lapse} = 2.0
- Parents \( \leftarrow [31,55] \) \quad \text{Mean time lapse} = 2.1
- Older \( \leftarrow [56,120] \) \quad \text{Mean time lapse} = 2.2
Accuracy by age group :: Summary

» Using visa photographs, younger people, especially but not limited to children, are more difficult to recognize.

» Lifelong trend to be more easily recognized. This is a big effect, larger than other drivers in face recognition.

» Two effects:
  • **Repeatability**: Older people more easily recognized as themselves.
  • **Distinguishability**: Older people more easy to distinguish from others.
Face Visa Data :: Accuracy(Age, ΔT)

- Age of Subject at Enrollment (Years)
  - < 10
  - 10 ≤ < 20
  - 20 ≤ < 30
  - 30 ≤ < 42
  - 42 ≤ < 56
  - 56 ≤ < 100

- Time Between Verification and Enrollment
  - < 1 YR
  - < 2 YR
  - < 3 YR
  - < 5 YR

- Mean Matching Score (Proprietary Scale)
Face Visa Data :: Accuracy(Age, ΔT)

Age of Subject at Enrollment (Years)

- < 10
- < 20
- < 30
- < 42
- < 56
- < 100

Time Between Verification and Enrolment
- < 1 YR
- < 2 YR
- < 3 YR
- < 5 YR

Mean Matching Score
(Proprietary Scale)

CONCEPTUAL ISSUANCE
RE-ISSUANCE PLOT
(DUMMY VALUES)

THRESHOLD
Face Ageing
Quantification + Relevance

Patrick Grother + Mei Ngan
Information Access Division
National Institute of Standards and Technology

NTIA Meeting, Washington, DC
Thursday, November 6, 2014
Ageing: Permanent Appearance Change

Dwight D Eisenhower

ALGORITHM X
- 0.647
- 0.601
- 0.599
- 0.579

ALGORITHM Z
- 0.595
- 0.578
- 0.565
- 0.548

**Green** indicates successful 1:1 authentication at FMR = 0.001.
**Red** indicates failure.

FACE AGEING → DECREASED SIMILARITY.
IS THERE AN ANALOGOUS EFFECT FOR OTHER MODALITIES?
The Brown Sisters
Photographed every year from 1975-2014

Photographs on exhibit at Museum of Modern Art, NYC

See Susan Minot’s text in NY Times Magazine Sunday Oct 3 2014
Ageing

Brown Sister #1

T ~ 5  T ~ 10  T ~ 20  T ~ 30  T ~ 40 Years

THREE LEADING COMMERCIAL FR ALGORITHMS

X

0.632  0.608  0.584  0.602  0.576

Y

3004  2954  2755  2845  2781

Z

0.622  0.616  0.613  0.517  0.426
Ageing

Brown Sister #2

T ~ 5  |  T ~ 10  |  T ~ 20  |  T ~ 30  |  T ~ 40 Years

FR
ALGORITHM X

| X | 0.648 | 0.601 | 0.600 | 0.610 | 0.605 |

| Y | 2863  | 2821  | 2758  | 2752  | 2824  |

| Z | 0.617 | 0.593 | 0.506 | 0.531 | 0.533 |
Ageing

Brown Sister #3

T ~ 5  T ~ 10  T ~ 20  T ~ 30  T ~ 40 Years

FR ALGORITHM

X  0.673  0.635  0.627  0.607  0.586

Y  2847  2649  2687  2637  2630

Z  0.610  0.511  0.524  0.595  0.472
Ageing
Brown Sister #4

<table>
<thead>
<tr>
<th>T ~ 5</th>
<th>T ~ 10</th>
<th>T ~ 20</th>
<th>T ~ 30</th>
<th>T ~ 40 Years</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.jpg" alt="Image" /></td>
<td><img src="image2.jpg" alt="Image" /></td>
<td><img src="image3.jpg" alt="Image" /></td>
<td><img src="image4.jpg" alt="Image" /></td>
<td><img src="image5.jpg" alt="Image" /></td>
</tr>
</tbody>
</table>

FR ALGORITHM

<table>
<thead>
<tr>
<th>X</th>
<th>Y</th>
<th>Z</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.652</td>
<td>3055</td>
<td>0.632</td>
</tr>
<tr>
<td>0.654</td>
<td>2795</td>
<td>0.516</td>
</tr>
<tr>
<td>0.603</td>
<td>2743</td>
<td>0.475</td>
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<tr>
<td>0.591</td>
<td>2847</td>
<td>0.524</td>
</tr>
<tr>
<td>0.578</td>
<td>2607</td>
<td>0.432</td>
</tr>
</tbody>
</table>
Verification over 40 years
The simplest conception of ageing is that:
• Accuracy = \( F(\text{Time-of-Enrollment} - \text{Time-of-Recognition}) = F(\Delta T) \)

And we all ageing “steadily”:
• Accuracy = \( a - b \Delta T \)  “if we’re lucky, or simplistic, linear ageing”

Inexorable change:  “It’s a one way street, and downhill at that”
• Accuracy = \( F(\text{monotone}(\Delta T)) \)
• Modulo cosmetics(?), botox(?), surgery(?) and ... photoshop

But at least it’s graceful:
• Accuracy = \( F(\text{slowly varying function}(\Delta T, n)) \)
• Absent injury, disease, abuse

But ... complications
• Unsteady ageing:  “Five years at 30 is not five years at 40”
  • Accuracy = \( F(\text{Age-at-Enrollment}; \Delta T) \)  or, simple Taylor expansion,
  • Accuracy = \( F(\text{Age-at-Enrollment}, \text{Age-at-Recognition}) \)
• Person-specific ageing:  “Some age better than others”
  • Accuracy_{i} = \( F_{i}(\text{Age-at-Enrollment}, \text{Age-at-Recognition}) \)  subscript i
Longitudinal Analysis

Quantifying Permanence Using Data from a Large-Population Operational System
Ageing :: Longitudinal data
Brad Wing

ALGORITHM E20A
0.617 0.578 0.532 0.541

ALGORITHM J20A
0.589 0.587 0.579 0.569

Green indicates successful 1:1 authentication at FMR = 0.001.
Red indicates failure.

LONGITUDINAL ANALYSIS APPLIED TO ALGORITHM SCORE DATA
Quantify ageing :: Individual recognition scores over time

- Often, visually flat
- Considerable variance within subject
- Considerable variance between subjects
- Irregular sampling
- Imbalanced sampling
- Mixed effects models
  - Shared population part
  - Individual part

Trajectories indicate heterogeneity – intercepts (and gradients) vary with quality of the enrollment image cf. Doddington's ZOO
Quantifying permanence via mixed-effects regression

Model for the j-th score from the i-th eye

$$HD_{ij} = \pi_{0i} + \pi_{1i}T_{ij} + \epsilon_{ij}$$

Intercept is sum of population average term, the fixed effect, and an eye-specific random effect

$$\pi_{0i} = \gamma_{00} + \psi_{0i}$$

Slope is sum of population average term, the fixed effect, and an eye-specific random effect

$$\pi_{1i} = \gamma_{10} + \psi_{1i}$$

Subject to assumptions:

$$\epsilon_{ij} \sim N(0, \sigma^2)$$

$$\begin{bmatrix} \psi_{0i} \\ \psi_{1i} \end{bmatrix} \sim N \left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^2_0 & \sigma^2_{01} \\ \sigma^2_{10} & \sigma^2_1 \end{bmatrix} \right)$$

Permanence stated by the population wide rate at which scores are decreasing.

MIXED EFFECTS MODEL RESPECT IDENTITY INFORMATION. SIMPLE LINEAR REGRESSION, IN YELLOW, DOES NOT AND HAS OTHER PROBLEMS
Conclusions

- Brown sisters: existence proof that 1:1 face authentication is possible over thirty years
  - But scores become weaker.
  - Successful 1:N identification demands stronger scores

- No good long term face ageing studies. e-Passports and digital photography will change that... eventually.
  - And suitable longitudinal analysis methods are published (NIST, MSU)

- But, there’s a “so what” for some use cases:
  - Algorithms improve on a timescale shorter than ageing
  - Identity credentials are re-issued on a timescale shorter than ageing
    - But possibility to recycle old photos
  - Law enforcement + counter terrorism functions have no such luxury
Face In Video Evaluation (FIVE)
FR in Video :: Scope

Face In Video Evaluation (FIVE)

Goals

» Comparative accuracy of algorithms
» Absolute accuracy
» Comparative computational cost
» Iterative development with tech. providers
» Threshold calibration
» How to analyze + metrics → ISO/IEC 30137-2
» Failure analysis → ISO/IEC 30137-1

Out-of-scope

» Re-identification
» Anomaly detection
» Detection of un-coop, evasion
» Other modalities + non-human
Challenges for FR

» Pose
- Compound rotation of head to optical axis

» Resolution
- Range to subject
- Legacy camera
- Adverse compression for storage or transmission
- Motion blur

Surveillance Video Related to Boston Bombings
Off angle recognition: The problem for video

ISO standard tolerance for pristine imagery
S2S – V2S – S2V – V2V

Search = Mugshot

Enrolled = Video corpus, e.g. Youtube

Example applications:
1. Media search
2. Asylum re-identification

Patrick Grother, National Institute of Standards & Technology, USA
Example applications:
1. Identity clustering
2. Re-identification
Thanks

patrick.grother@nist.gov
# Time variation in three modalities

<table>
<thead>
<tr>
<th>Iris</th>
<th>Fingerprint</th>
<th>Face</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Healthy</strong>&lt;br&gt;• Blink occlusion&lt;br&gt;• Gaze direction&lt;br&gt;• Dilation varies with mood, consumption, ambient light&lt;br&gt;<strong>Cosmetic</strong>&lt;br&gt;• Contact lenses&lt;br&gt;• Glasses&lt;br&gt;<strong>Ageing</strong>&lt;br&gt;• Pupil constriction&lt;br&gt;• Palpebral aperture&lt;br&gt;<strong>Disease</strong></td>
<td><strong>Healthy</strong>&lt;br&gt;• Facial expression&lt;br&gt;• Mouth movement&lt;br&gt;• Head motion, head orientation&lt;br&gt;• Facial hair&lt;br&gt;<strong>Cosmetic</strong>&lt;br&gt;• Moisturizers&lt;br&gt;<strong>Ageing</strong>&lt;br&gt;• Arthritic fingers</td>
<td><strong>Healthy</strong>&lt;br&gt;• Facial expression&lt;br&gt;• Mouth movement&lt;br&gt;• Head motion, head orientation&lt;br&gt;• Facial hair&lt;br&gt;<strong>Cosmetic</strong>&lt;br&gt;• Makeup&lt;br&gt;<strong>Ageing</strong>&lt;br&gt;• Soft tissue folds&lt;br&gt;• Stoop – pitch forward</td>
</tr>
</tbody>
</table>