# A Unified Account of the Effects of Distinctiveness, Inversion, and Race in Face Recognition

by Tim Valentine

(The Quarterly Journal of Experimental Psychology, 1991, 43A (2) 161-204)

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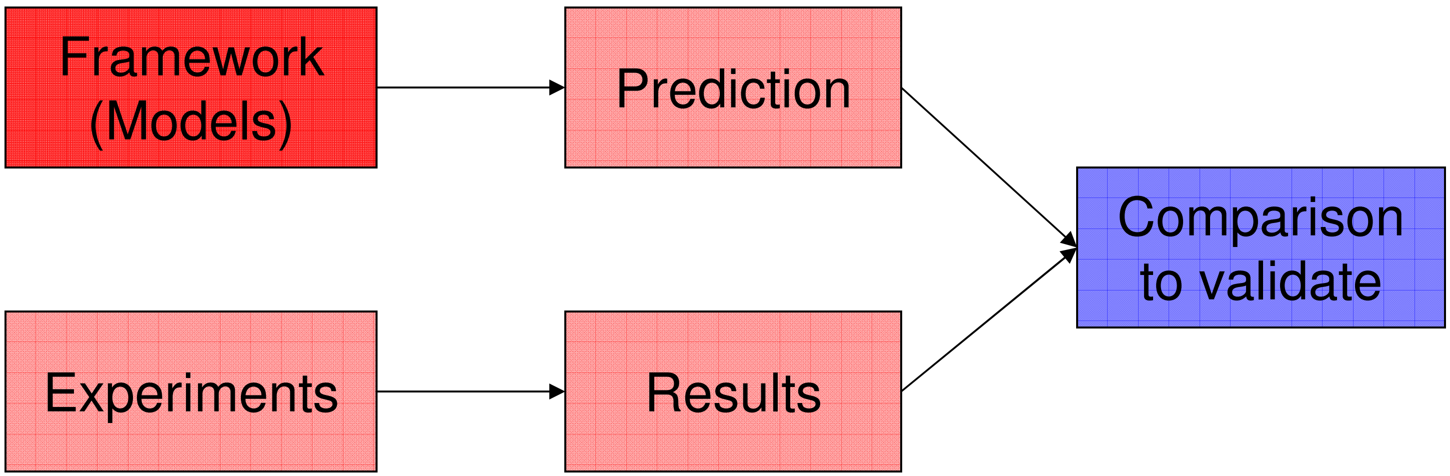
# Outline

- Previous works
- The proposed Framework
- Prediction
- 5 Experiments
- Discussion

# Overview



Framework (Models)
Prediction
Experiments
Results
Comparison to validate

# Terminology

- Distinctiveness
- Inversion – Orientation
- Race
- Classification task
- Recognition task
- Typical
- Familiar

# Previous works – Distinctiveness

- Two component theory
  - Light et al. (1979)
  - A distinctive face is more likely to access a specific memory
- Familiarity Information
  - Bartlett et al. (1984)
  - Presentation of a distinctive face results in a greater increment in familiarity.
- The prototype hypothesis
  - Valentine and Bruce (1986), Perkins (1975), Rhodes, Brennan, and Carey (1987)
    - Faster in recognition task but slower in classification.
    - Supported by caricature.
    - Similar to face schema theory by Goldstein and Chance's (1980)

# Previous works - Inversion

- Diamond and Carey (1986)
  - Dog experts.
  - the effect is large
    - (1) when the exemplars have a common configuration but subtle differences.
    - (2) the observers have sufficient expertise. (rigidity)

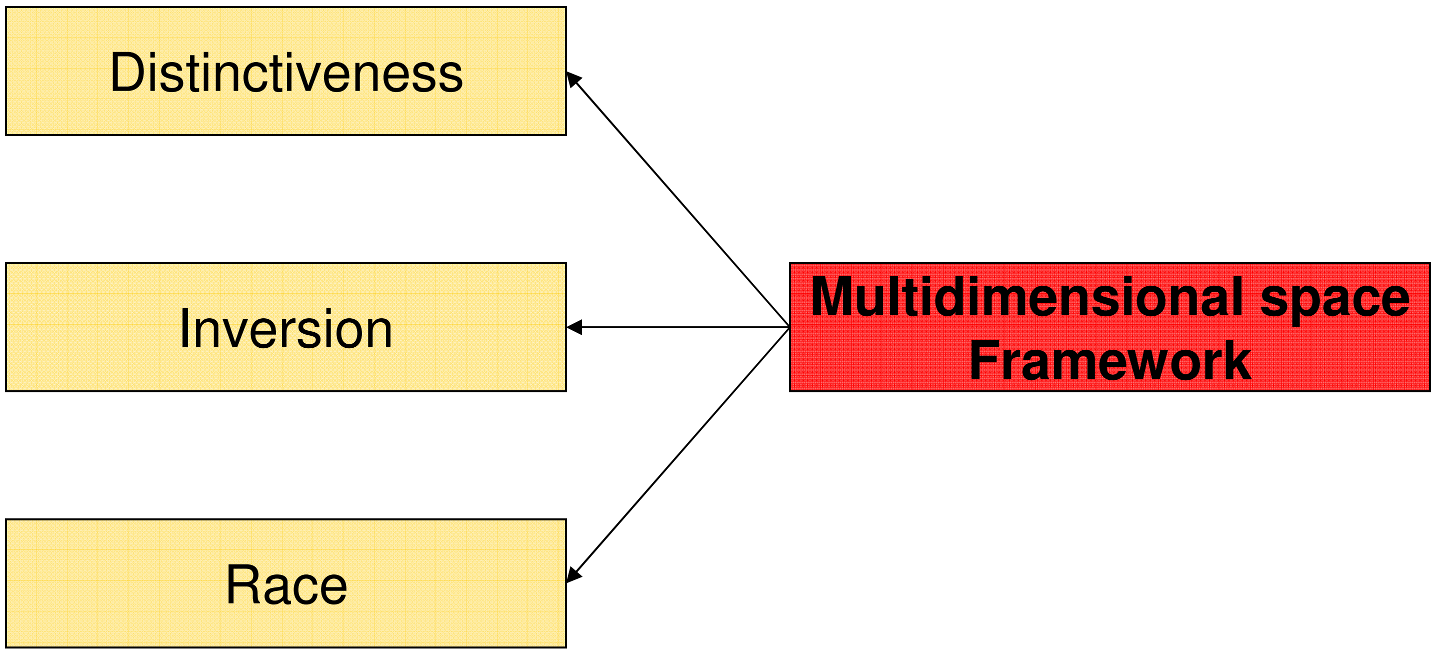
# Previous works - Race

- Adults recognize other-race faces less accurately than own-race faces.
  - Young children –with equal accuracy. More flexible.
  - Same as the effect of inversion.

# Previous works

- They are based on the role of knowledge of the population of faces previously encountered.
- And so on…

# Framework



Distinctiveness
Inversion
Race
Multidimensional space Framework

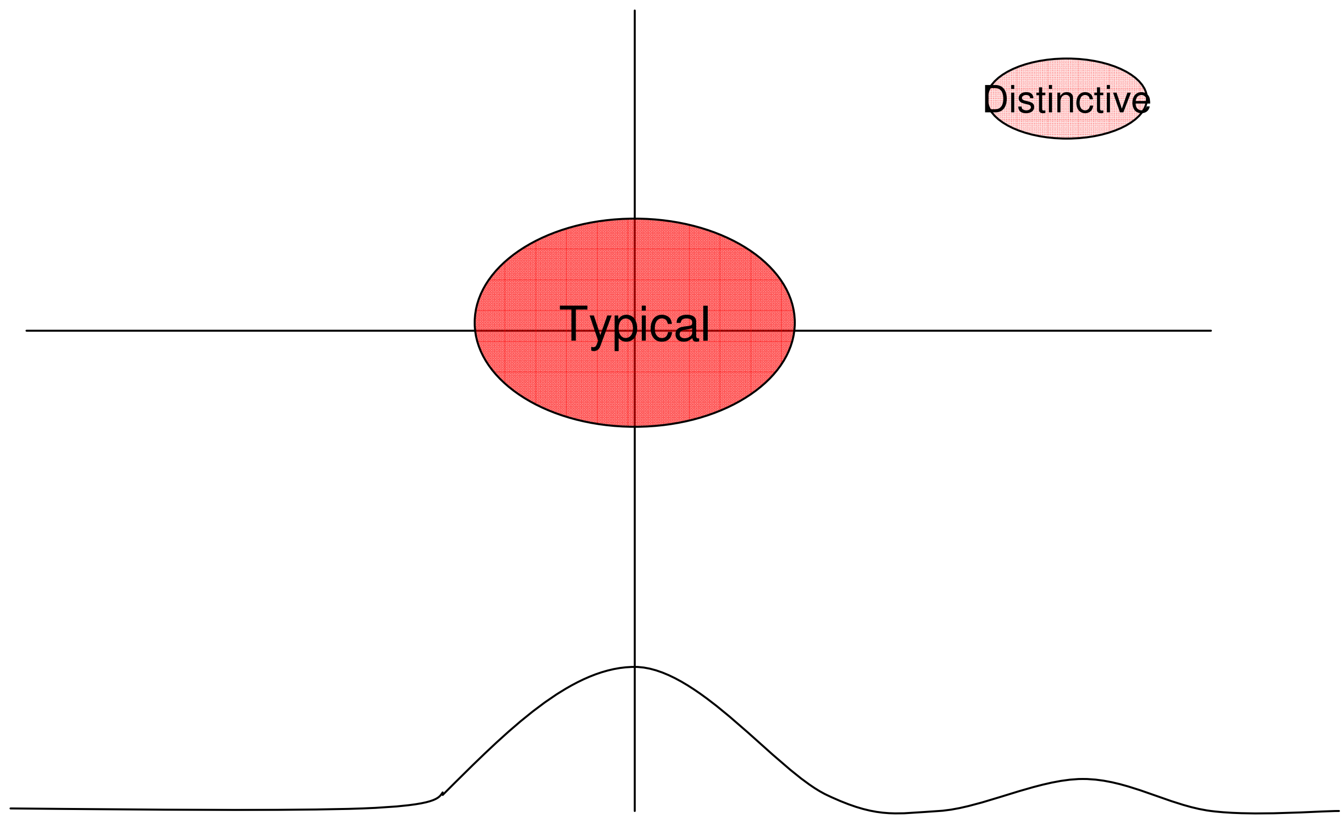
# Framework

- Faces are assumed to be encoded as points in a multidimensional space.
- Two models.
  - Norm-based coding model.
    - Faces are encoded by reference to an abstracted norm or prototype
  - Exemplar-based model
    - A norm is not abstracted and only specific faces are stored.

# Framework

- Assumption
  - A location in a Euclidean m-dim space provides an appropriate metaphor for the mental representation of a face.
- The origin – central tendency of the dimensions.
  - Typical faces are around it.
  - The density of points will decrease as the distance from it.
- Familiarity – an implicit knowledge from a lifetime's experience.

# Framework



# Framework

- Norm-based coding model
  - In terms of their deviation from the origin. (norm) and the density.
  - Recognition process
    - Feature extraction
    - similarity check

# Framework

- Exemplar-based model
  - Points rather than vectors.
    - Actually, a point is a vector.
  - The origin plays no part.
  - Exemplar density.

# Framework

- Two models differ in
  - the role of an abstracted norm and
  - the use of a vector- or distance- based measure of similarity.
- Basically, however, they are same

# Prediction – Distinctiveness Recognition

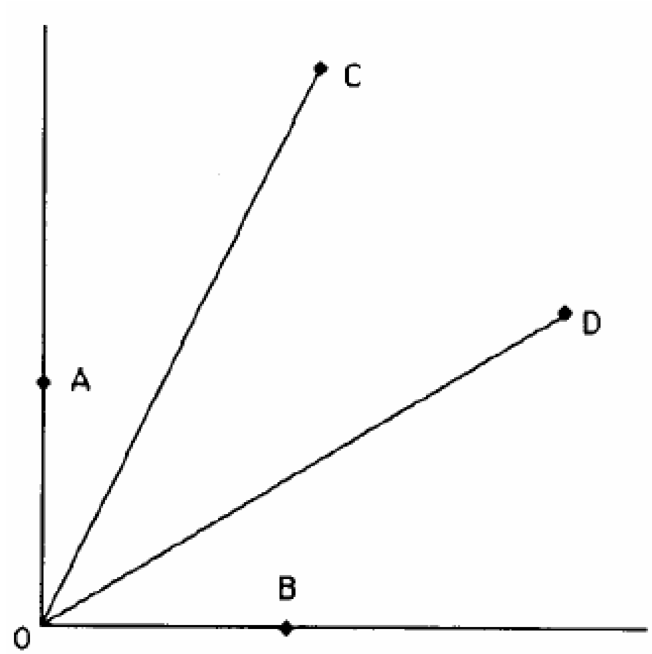
- Distinctive & Familiar face
  - much closer to the target than other faces.
  - The error is small
  - So, it can be identified accurately and rapidly.
- Typical & Familiar face
  - Close to the center.
  - Close to the target but still close to another.
  - Slower and more error.

# Prediction – Distinctiveness Recognition

- Distinctive & Unfamiliar
  - The density of points around it is low.
  - Error is small.
  - Rejected more accurately and more quickly.
- Typical & Familiar
  - The density of points around it is high.
  - It is close to the familiar faces. -> error.

# Prediction – Distinctiveness Recognition

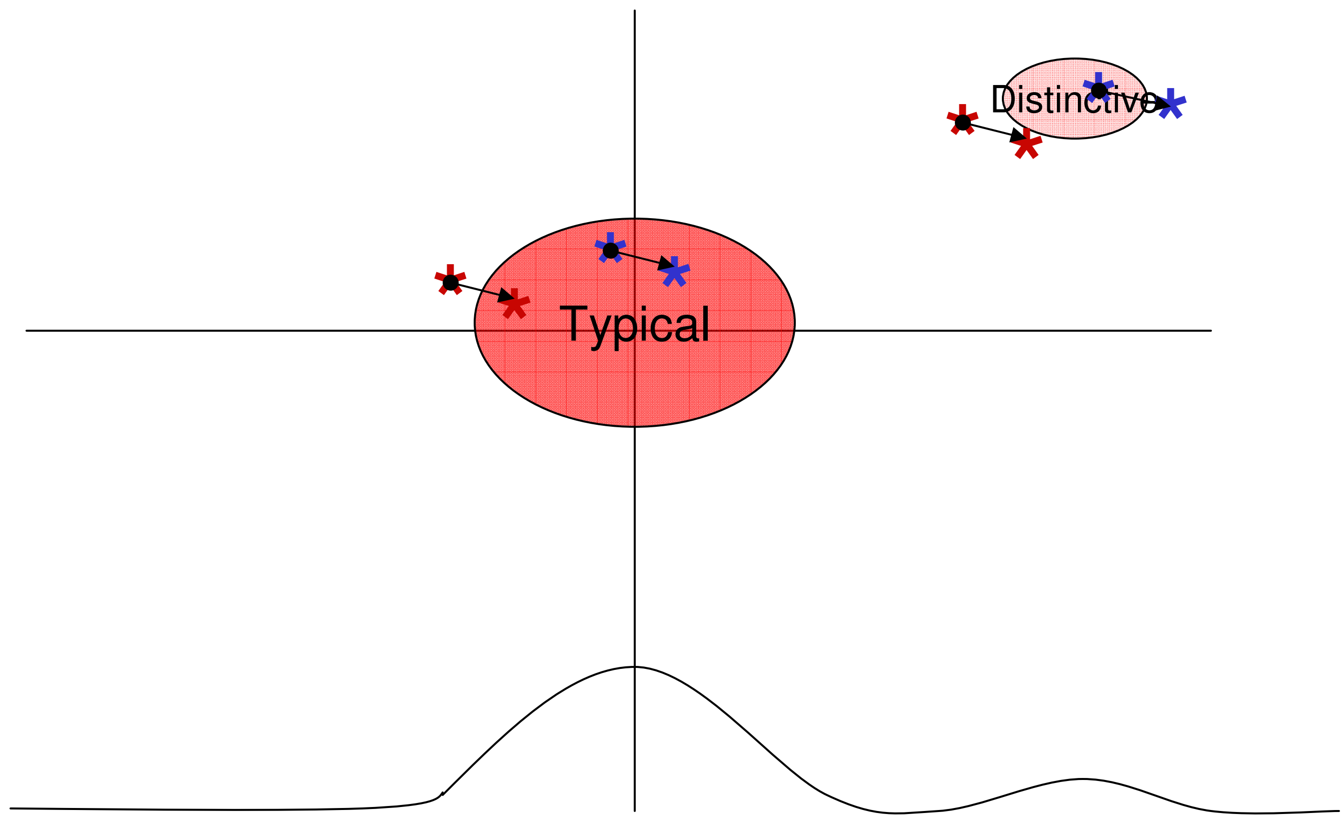
- The difference in exemplar density > the opposite effect
  - Different metric.
- This is the reason why feature extraction is important.



# Prediction – Distinctiveness Classification

- Typical faces are classified as a face faster than distinctive faces.
  - Based on density of points in norm-based coding model
    - The distance of norm is related to the density.
  - Based on exemplar density in exemplar-based model.
    - Faster classification – higher density.

# Prediction – Inversion Classification



# Summary for the frame.

- In a high-dimensional space.
  - Salient features are good for recognition
    - Distinctiveness and own-race
  - High density is good for classification
    - Typical and own-race
  - Salient features are robust against noise in recognition
    - Inversion is kind of noise.

# Experiment 1

- Distinctiveness Ratings (1-7)
  - 16 subjects
  - 64 faces (man, neutral full-face pose)

# Experiment 1

- Recognition Memory Task (different exposure time)
  - 20 subjects
  - Distinctiveness is not significant
  - Inversion (or with distinctiveness) is significant

TABLE 1

Mean A′ Scores, Hits,[a] False Positives[a] and Mean RT of Hits[b] and Correct Rejections[b] as a Function of Orientation and Distinctiveness (Experiment 1)

| | *Upright* | | *Inverted* | |
|---|---|---|---|---|
| | *Distinctive* | *Typical* | *Distinctive* | *Typical* |
| *A′* | 0.905 | 0.919 | 0.802 | 0.699 |
| Hits | 6.50 | 6.55 | 5.35 | 4.85 |
| F.P. | 1.00 | 0.70 | 1.75 | 2.70 |
| RT of hits | 1356 | 1595 | 1770 | 2050 |
| RT of C.R. | 1418 | 1723 | 1767 | 2208 |

# Experiment 2

- Recognition Memory Task (same exposure time)
  - 28 subjects
  - Distinctiveness is a little significant
  - Inversion (or with distinctiveness) is significant

**TABLE 2**

**Mean A′ Scores, Hits,[a] False Positives[a] and Mean RT of Hits[b] and Correct Rejections[b] as a Function of Orientation and Distinctiveness (Experiment 2)**

| | *Upright* | | *Inverted* | |
|---|---|---|---|---|
| | *Distinctive* | *Typical* | *Distinctive* | *Typical* |
| *A′* | 0.915 | 0.894 | 0.824 | 0.693 |
| Hits | 6.75 | 6.39 | 5.75 | 4.82 |
| F.P. | 1.0 | 1.14 | 1.93 | 2.75 |
| RT of hits | 1242 | 1471 | 1626 | 1851 |
| RT of C.R. | 1382 | 1647 | 1830 | 1910 |

# Experiment 3

- Distinctiveness and Familiarity Ratings
  - 18 subjects
  - 54 famous faces and 39 unfamiliar faces

# Experiment 3

- Familiar decision task (22 subjects)

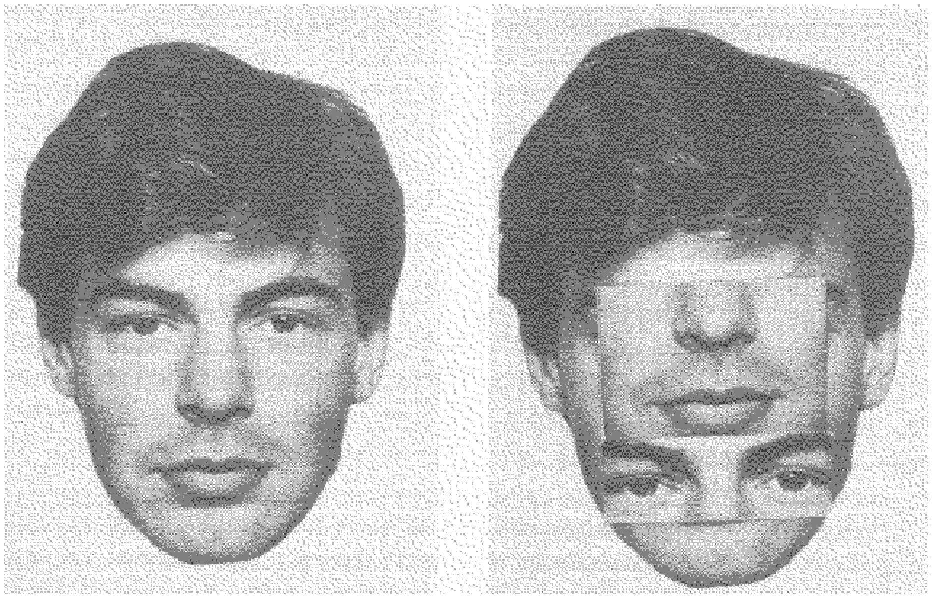
TABLE 3

Mean Latency and "Accuracy" of Responses in a Familiarity Decision Task as a Function of Orientation and Distinctiveness (Experiment 3)

| | *Upright* | | *Inverted* | | |
|---|---|---|---|---|---|
| | *Distinctive* | *Typical* | *Distinctive* | *Typical* | |
| Mean RT of correct familiar responses | 983 | 1076 | 1552 | 2312 | |
| Mean RT of correct unfamiliar responses | 1526 | 1698 | 2197 | 2372 | |
| Mean no. of correct familiar responses[a] | 7.5 | 7.3 | 5.0 | 3.0 | < 50% |
| Mean no. of familiar responses to "unfamiliar" faces[a] | 0.3 | 0.9 | 0.7 | 1.3 | |
| Mean *A′* of familiarity decisions | 0.975 | 0.944 | 0.865 | 0.715 | |

# Experiment 4 – classification

- (1) First rated, (2) face classification task.
- Not familiar faces (intact and jumbled).



# Experiment 4

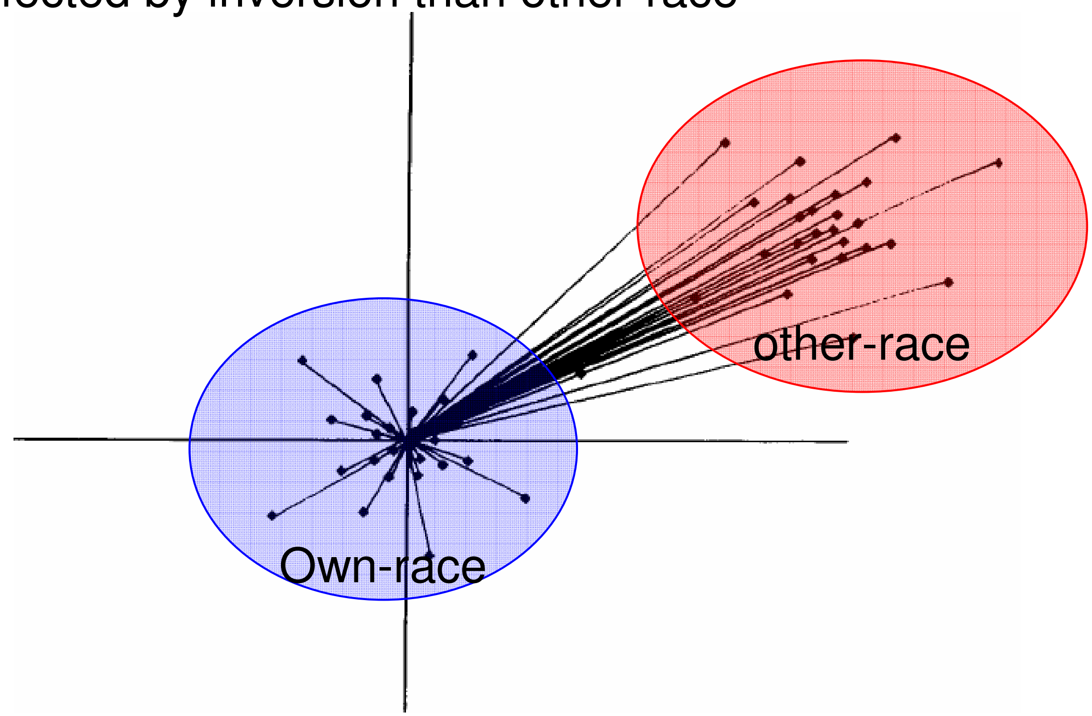
- The effect of distinctiveness reverses in a classification task.
  - Typical faces can be classified as a face more rapidly

TABLE 4
Mean RTs to Classify Correctly Intact and Jumbled Faces, as a Function of Distinctiveness and Orientation (Experiment 4)

| | *Intact faces* | | | *Jumbled Faces* | | |
|---|---|---|---|---|---|---|
| | *Typical* | *Distinctive* | *Mean* | *Typical* | *Distinctive* | *Mean* |
| Upright | 683<br>(0.6) | 737<br>(1.9) | 710<br>(1.3) | 741<br>(0) | 738<br>(0.6) | 739<br>(0.3) |
| Inverted | 817<br>(1.3) | 860<br>(5.6) | 839<br>(3.5) | 866<br>(7.5) | 841<br>(5.0) | 855<br>(6.3) |
| Mean | 750<br>(0.9) | 798<br>(3.7) | | 803<br>(3.7) | 791<br>(2.8) | |

# Race

- In the norm-based coding model, other-race faces will be more difficult to recognize. This is straight forward.
- When it comes to the effect of inversion, own-race faces are analogous to distinctive faces.
  - More affected by inversion than other-race



# Race

- In the exemplar-based model
  - Better recognition rate for own-race. Again, own-race faces are analogous to distinctive faces.
  - It works if it is assumed that exemplar density is greater for other-race faces than for own-race faces.

# Experiment 5 – Race

- 20 Subjects are white.

- Race and Inversion – Recognition
  - Better recognition in own-race
  - Other-race is denser than own-race. (F.P. and RT)

**TABLE 5**

Mean A′ Scores, Hits,[a] False Positives[a] and Mean RT of Hits[b] and Correct Rejections[b] as a Function of Orientation and Race in a Recognition Memory Task

| | *Upright* | | *Inverted* | |
|---|---|---|---|---|
| | *White* | *Black* | *White* | *Black* |
| *A′* | 0.900 | 0.918 | 0.723 | 0.609 |
| Hits | 6.5 | 6.7 | 4.9 | 4.7 |
| F.P. | 1.2 | 0.9 | 2.3 | 3.6 |
| RT of Hits | 1222 | 1553 | 1685 | 1933 |
| RT of C.R. | 1502 | 1792 | 2002 | 2355 |

# Experiment 5 – Race

- Race and Inversion – Classification
  - Other-race is classified slowly.
    - Own-race is denser?
    - Density is greater but less densely clustered.

**TABLE 6**
Mean RTs to Classify Intact and Jumbled Faces, as a Function of Race and Orientation (Experiment 5)

| | *Intact Faces* | | | *Jumbled Faces* | | |
|---|---|---|---|---|---|---|
| | *White* | *Black* | *Mean* | *White* | *Black* | *Mean* |
| Upright | 611<br>(0.8) | 765<br>(3.1) | 688<br>(1.9) | 739<br>(4.7) | 707<br>(0) | 723<br>(2.3) |
| Inverted | 719<br>(1.6) | 843<br>(6.3) | 781<br>(3.9) | 796<br>(7.0) | 724<br>(0) | 759<br>(3.5) |
| Mean | 665<br>(1.2) | 804<br>(4.7) | | 768<br>(5.9) | 716<br>(0) | |

# Discussion

- The representation of faces in a multidimensional space.
  - Norm-based coding model and exemplar-based model.
- Inversion for typical faces is greater in recognition but not in classification.
- ‘Other-race’ is like ‘typical’ in recognition and like ‘distinctive’ in classification.
- Multi-norms might exist (separate norms)

# Discussion (HC)

- Experimental results are different. Depends on researchers.
- Is this model enough to explain all?
  - Race type or distinctiveness do not affect to recognition and classification, but features and density do.
  - Inversion is just one variation.
- The comparison between the prediction and the result.
  - Is it enough? It does not guarantee that human brain is using the model.
- The real problem is "How can we find those space?"