# Object recognition

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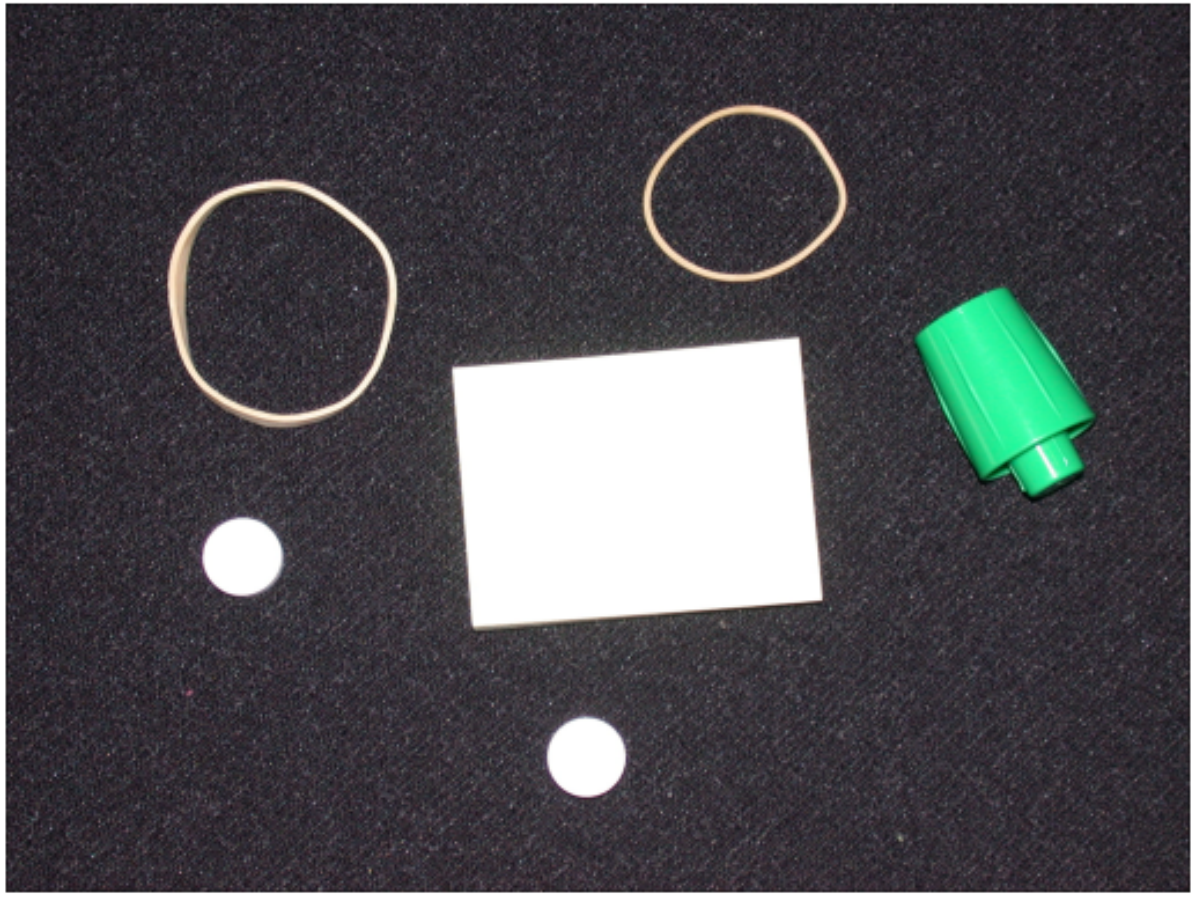
# Detection of round objects



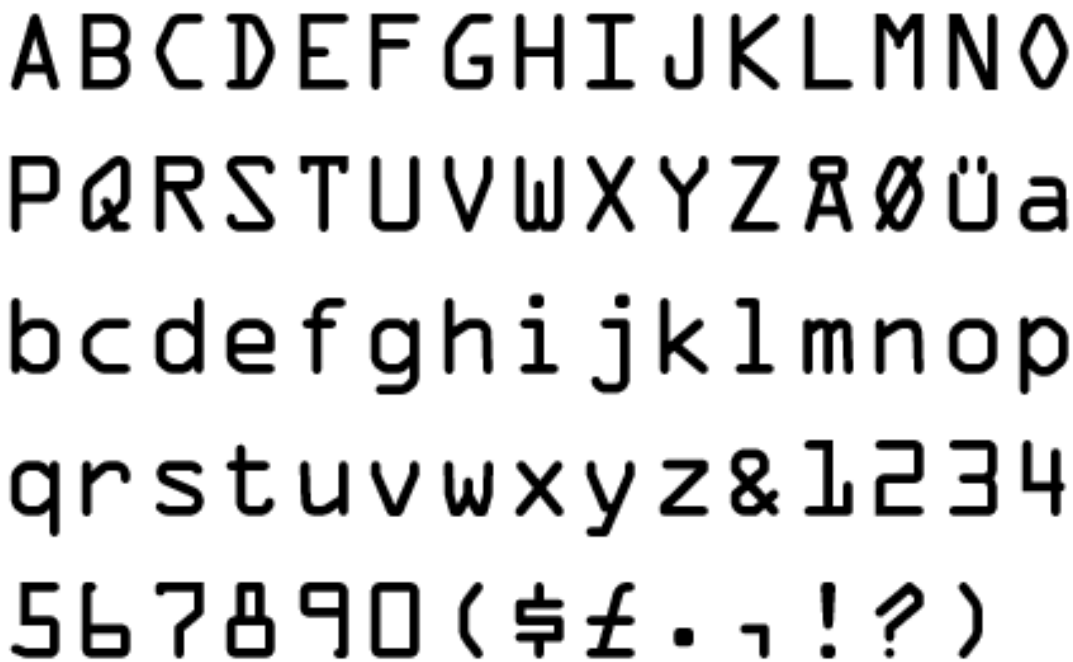
http://www.mathworks.se/products/image/examples.html?file=/products/demos/s

# Bottle recognition





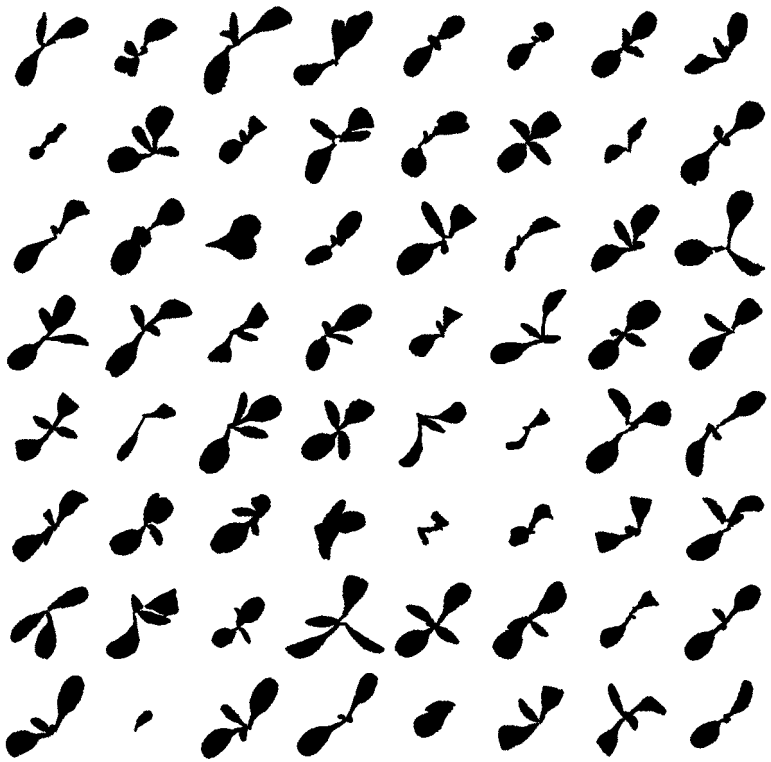
# Optical character recognition (OCR)



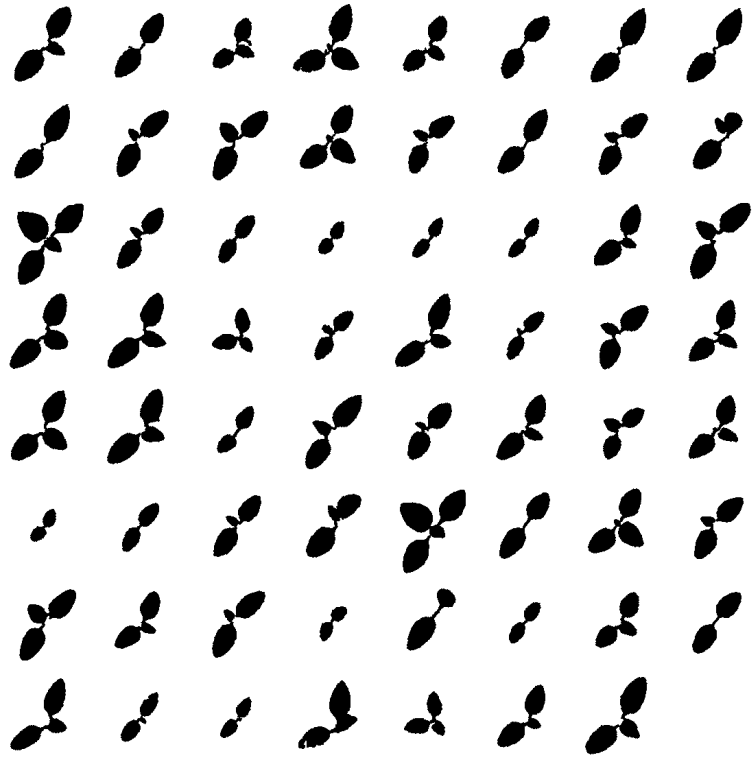

http://www.identifont.com/similar?25H

# Plant recognition

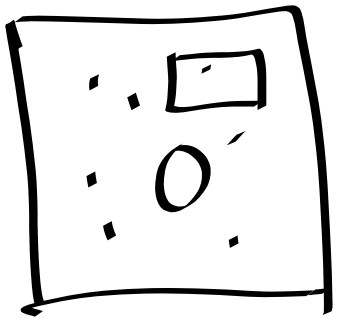
Cornflower (BBCH12)



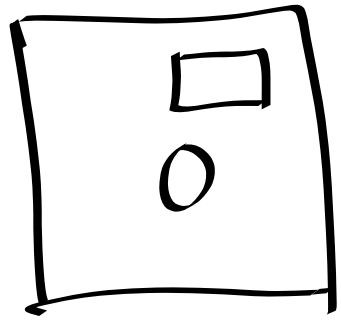
Nightshade (BBCH12)



# Feature based object recognition



Input image

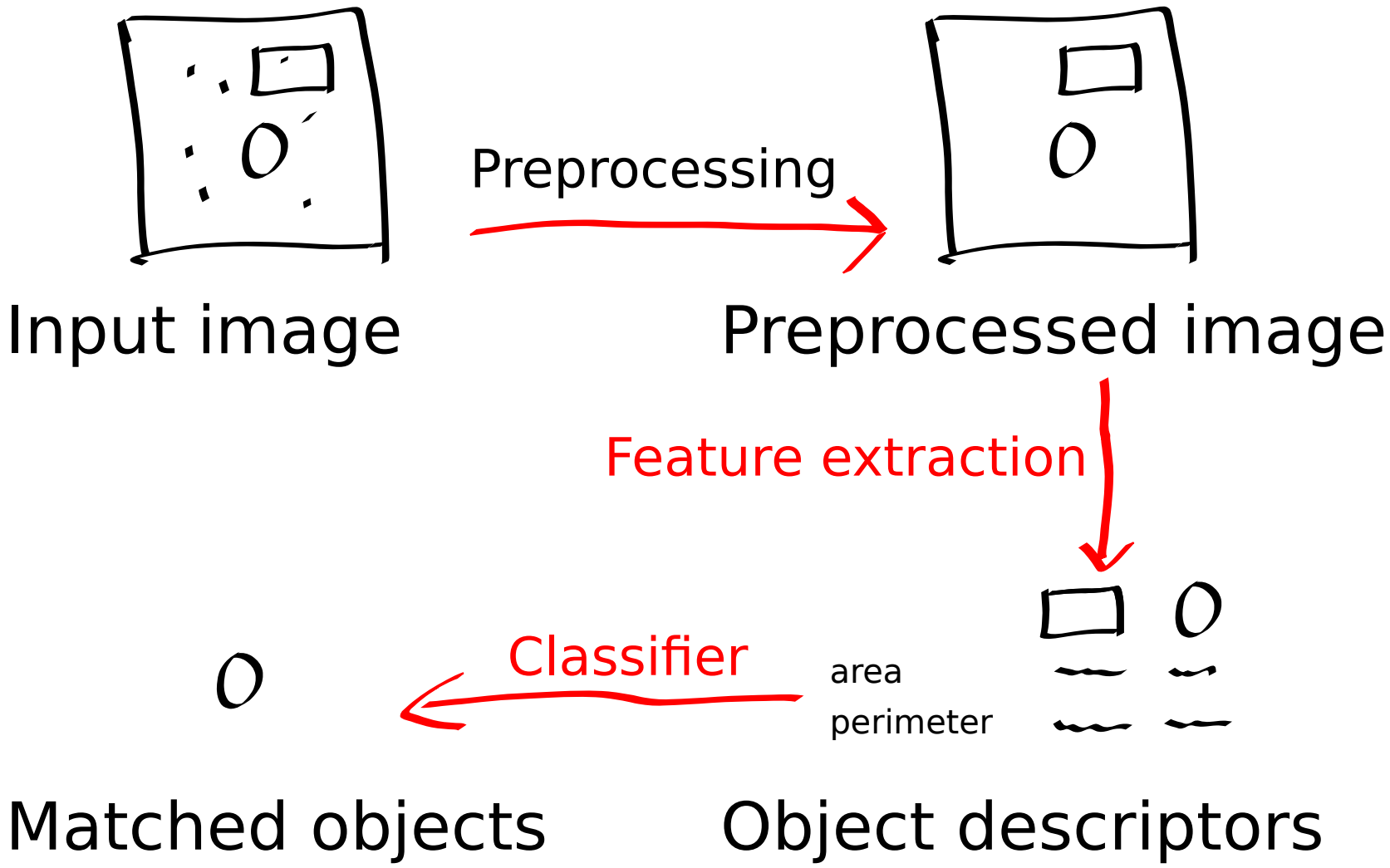


Preprocessed image

Matched objects


Object descriptors

# Feature based object recognition



# Example: Circle detection

Features:

- area
- perimeter

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Combination

$$\frac{4\pi \cdot \text{area}}{\text{perimeter}^2}$$

# Example: Circle detection

Features:

- area
- perimeter

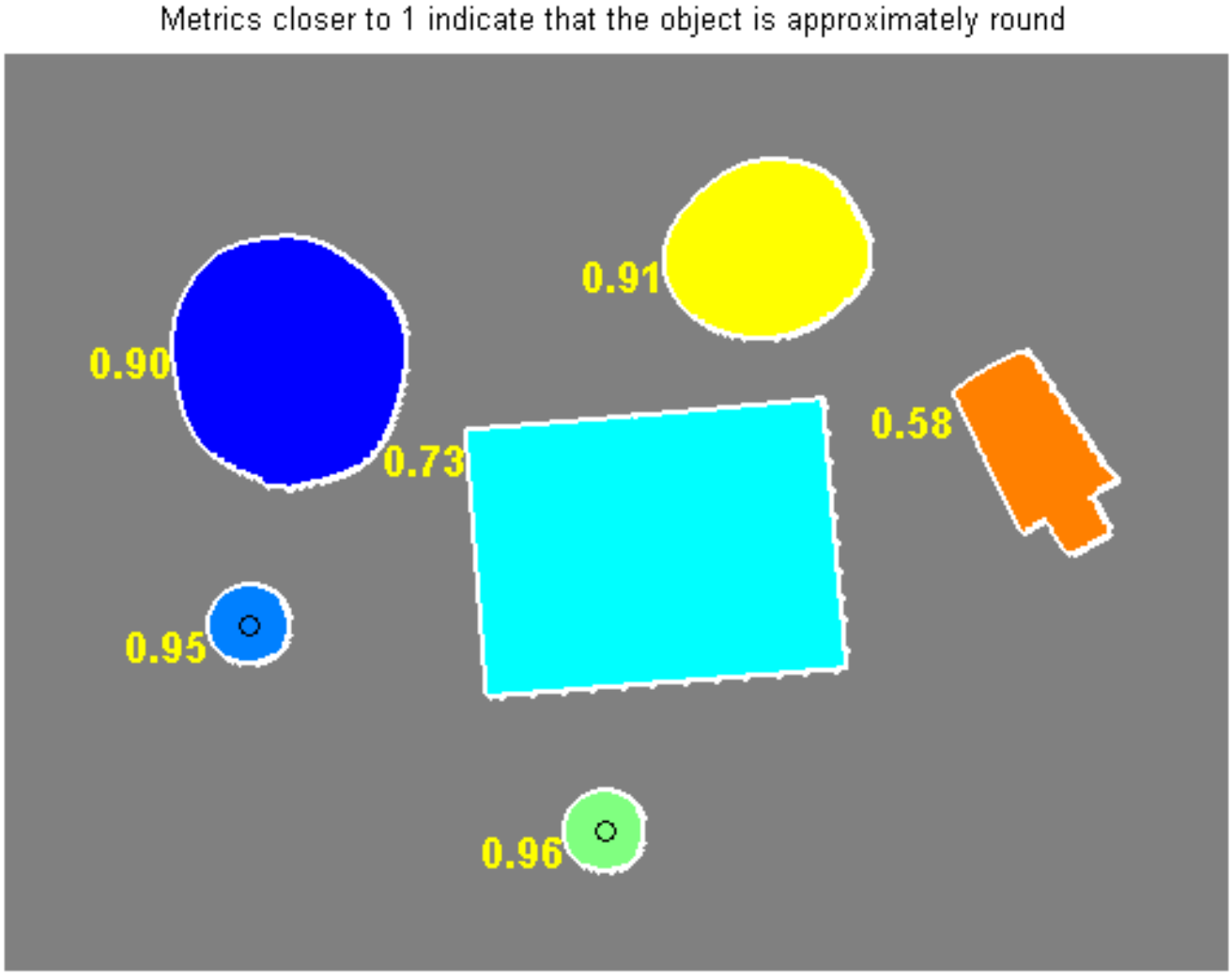
Combination

$$\frac{4\pi \cdot \text{area}}{\text{perimeter}^2}$$

Maximum value for a circle

$$\frac{4\pi \cdot \pi r^2}{(2\pi r)^2} = \frac{4\pi \cdot \pi r^2}{4\pi^2 r^2} = 1$$

# Example: Circle detection continued

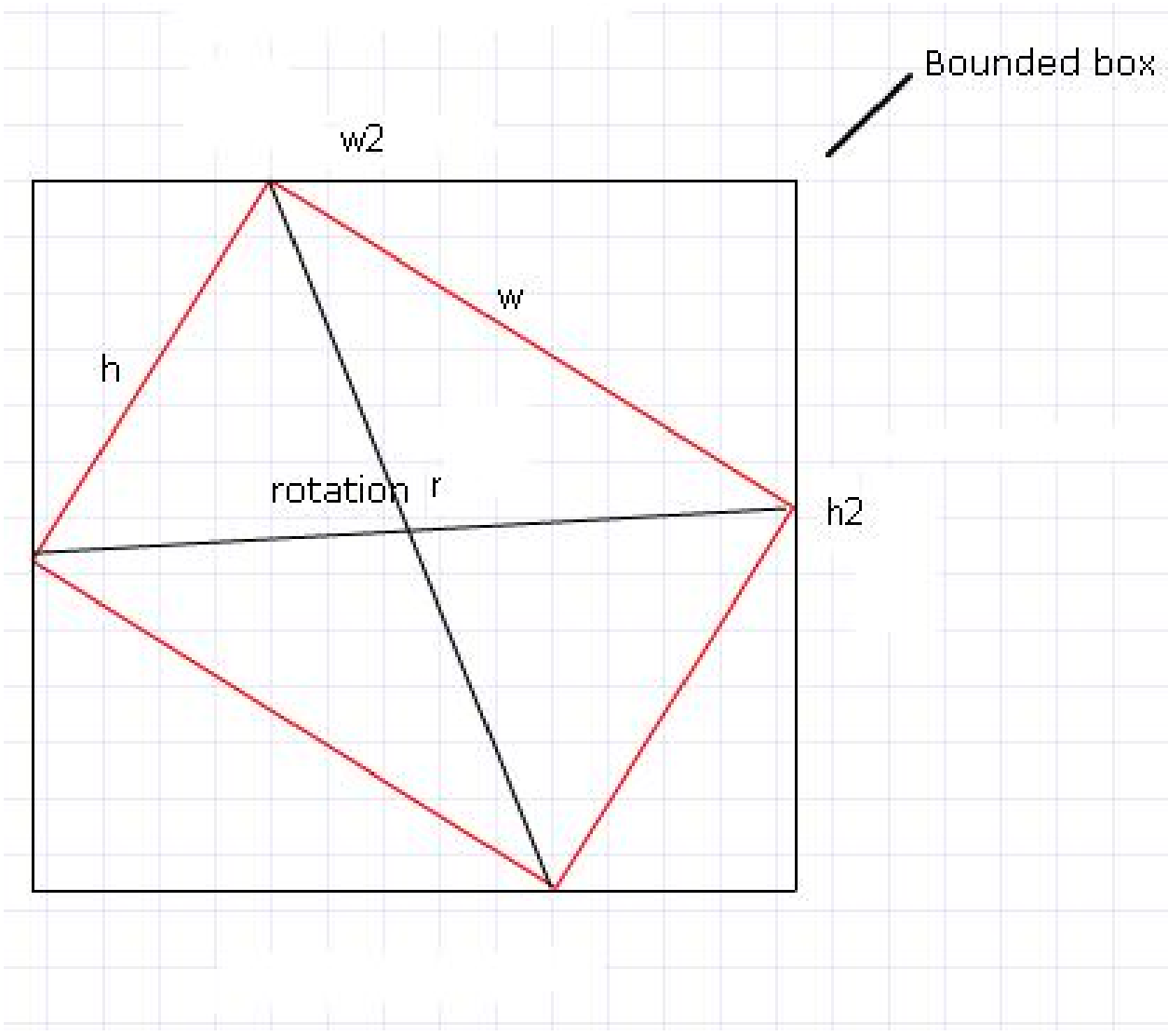



http://www.mathworks.se/products/image/examples.html?file=/products/demos/s

# Parameter types

Reconstructive
Descriptive

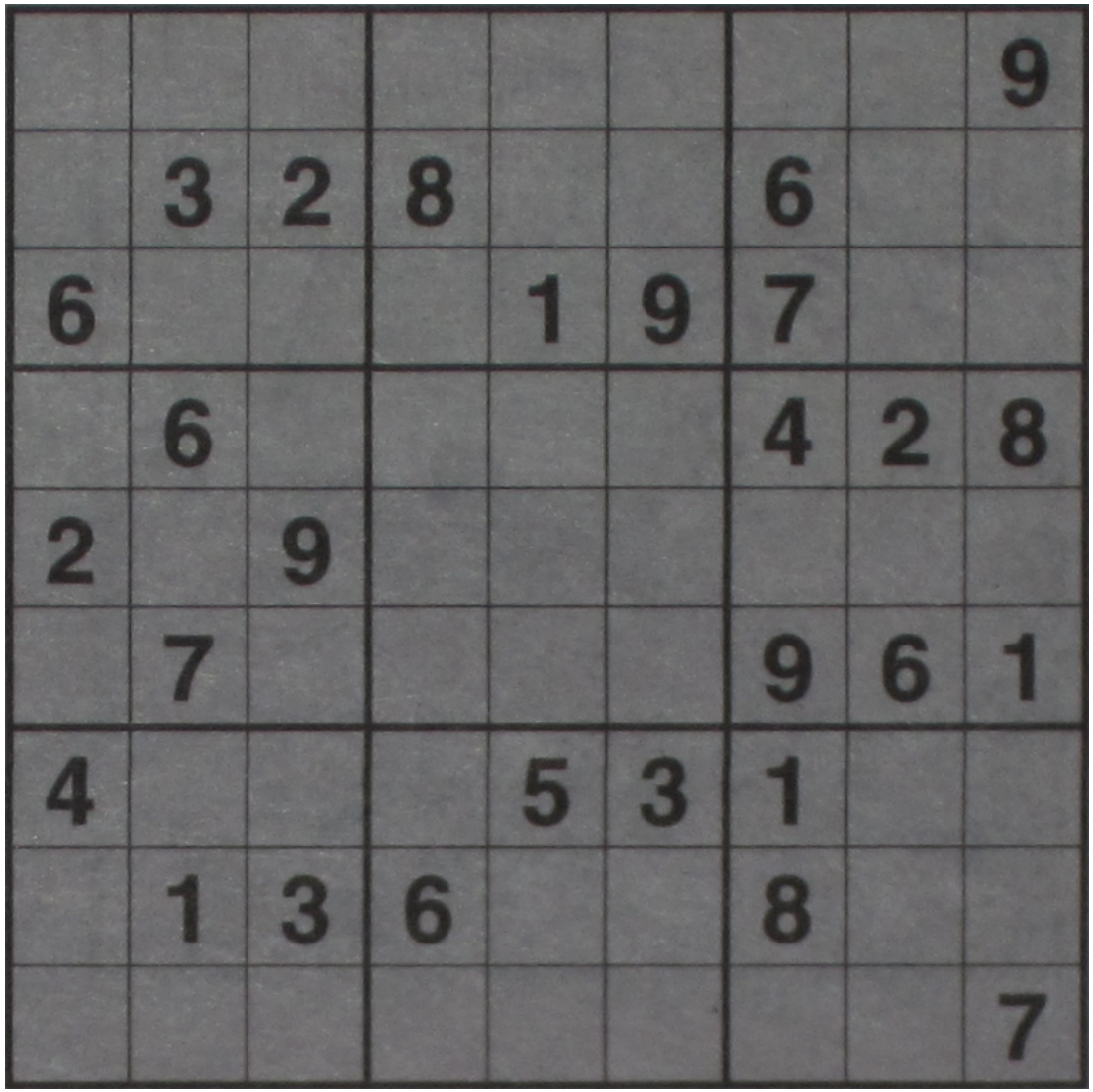
# Example: Height and width of bounding box



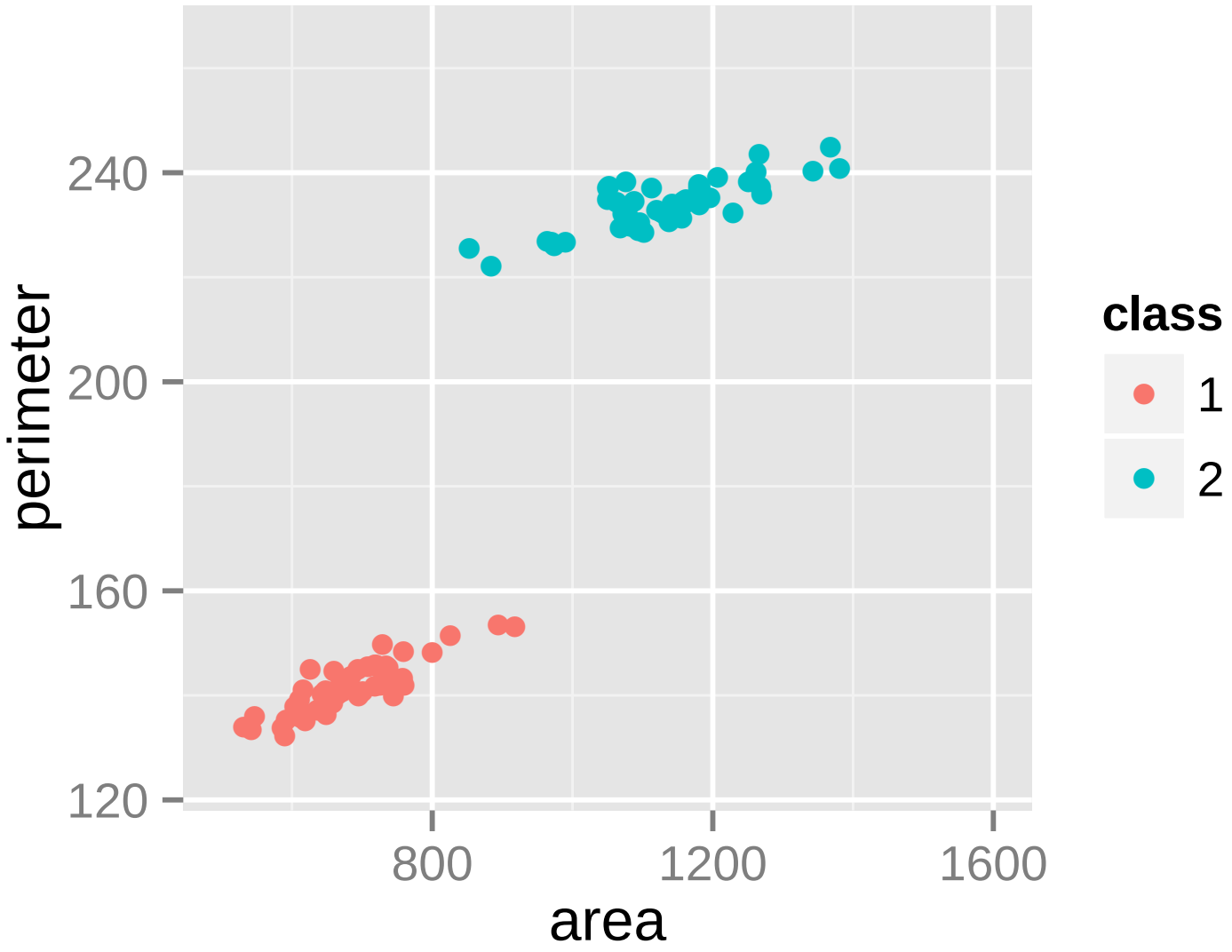
# Desired properties of features

- Discriminative power (determined by the classification task)
- Invariant to
  - Translation
  - Scale
  - Rotation

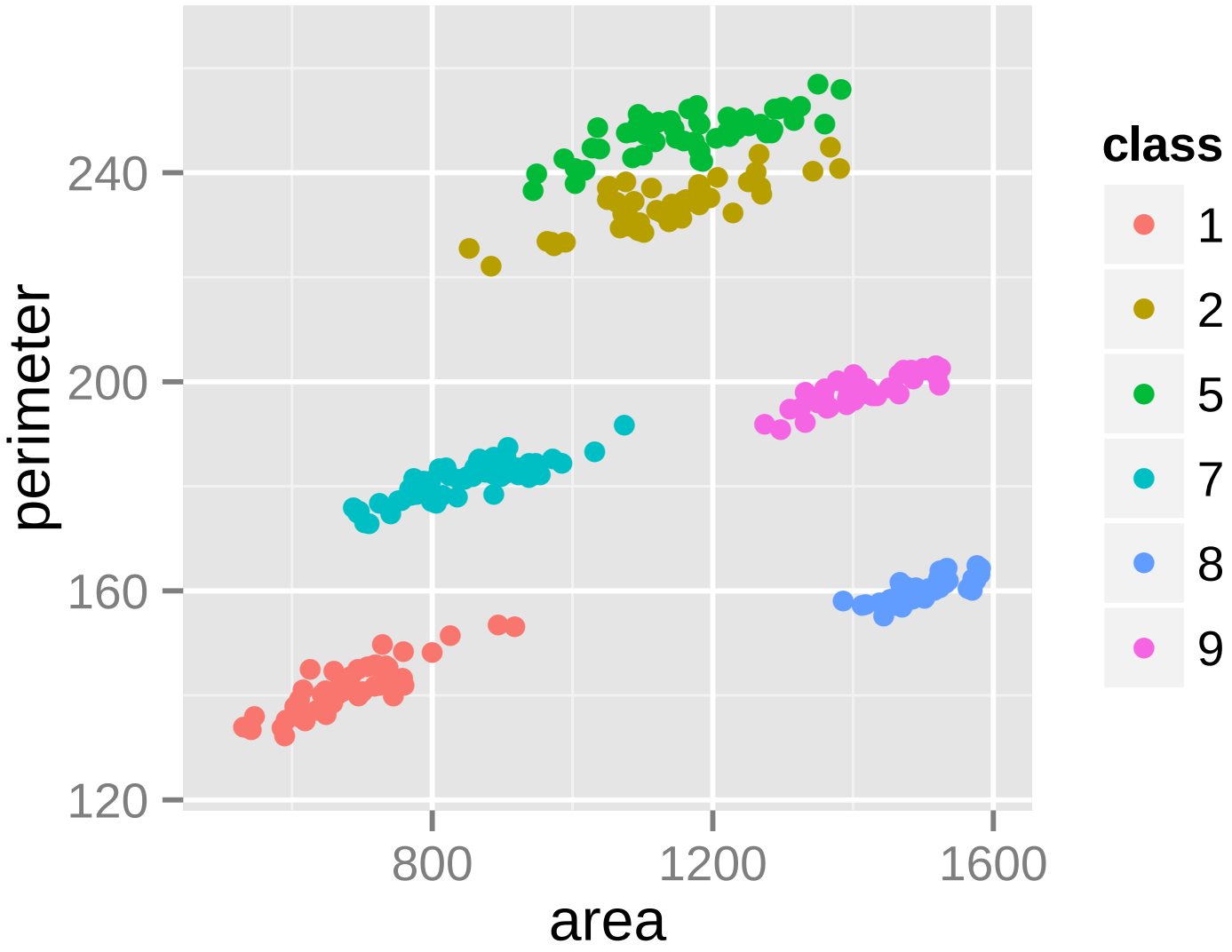
# Case: Digit recognition



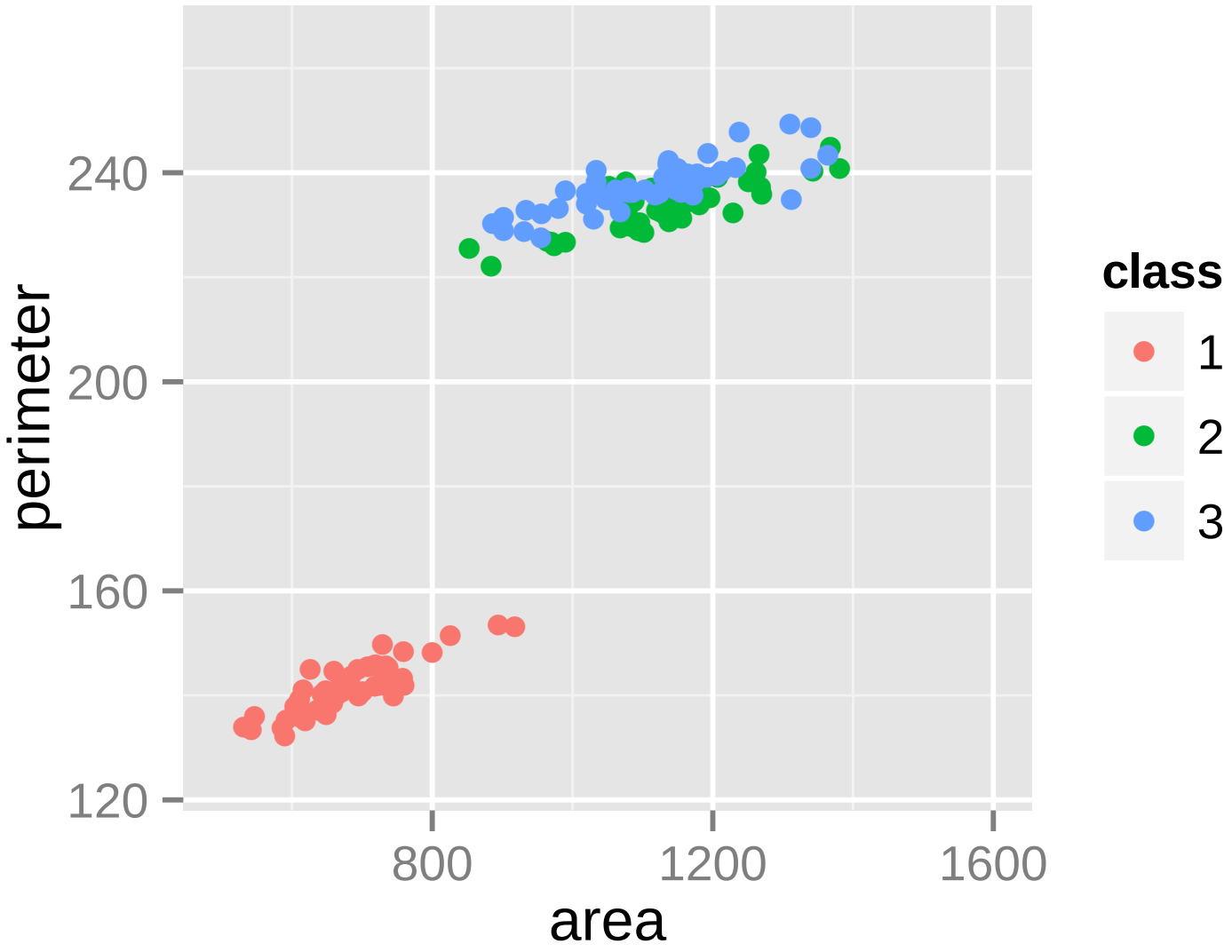
# Feature space



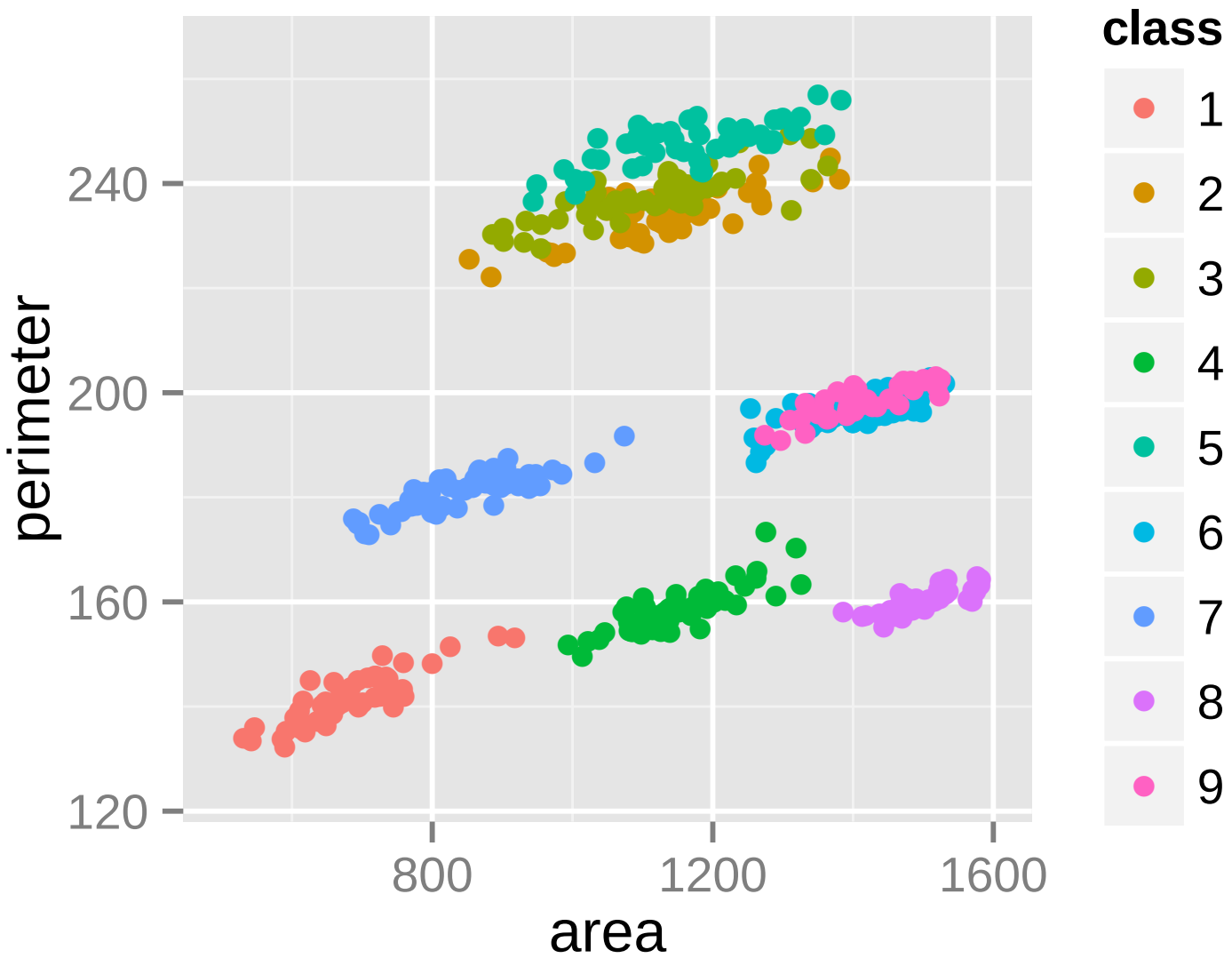
# Feature space



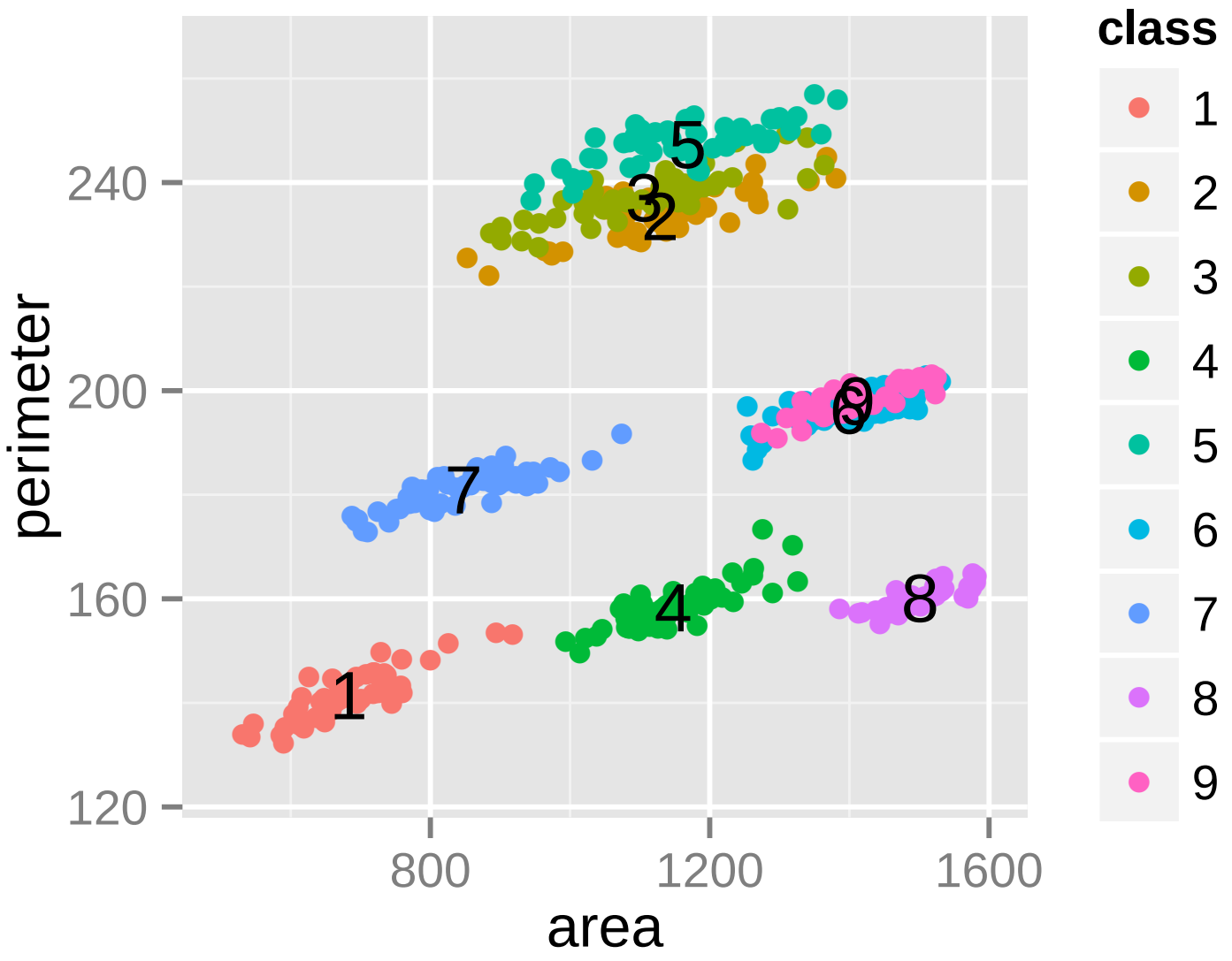
# Feature space



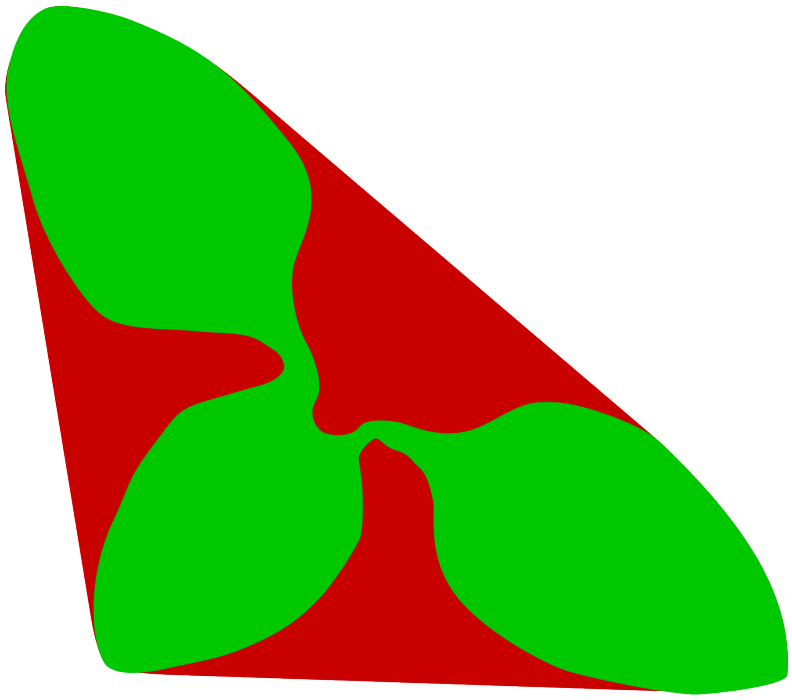
# Feature space



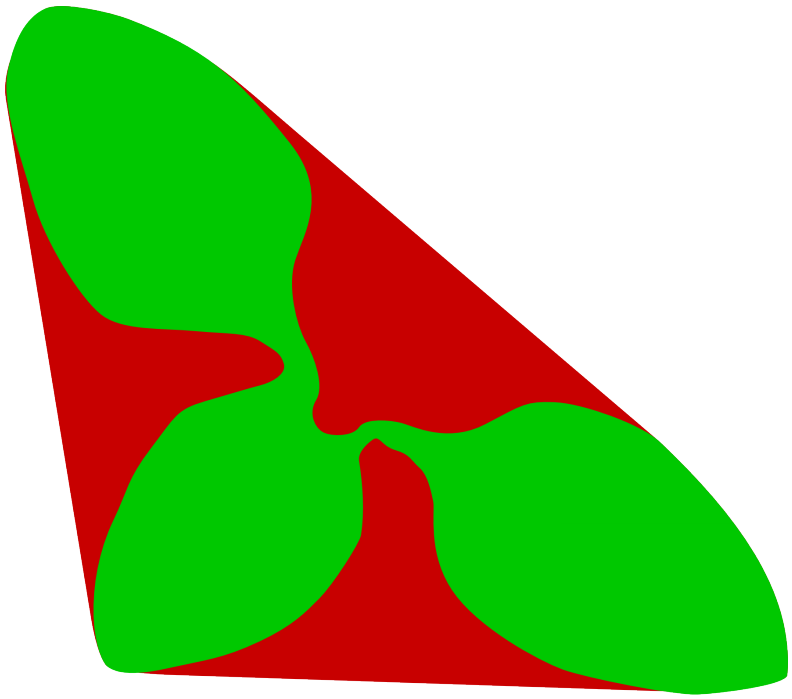
# Feature space



# Feature example

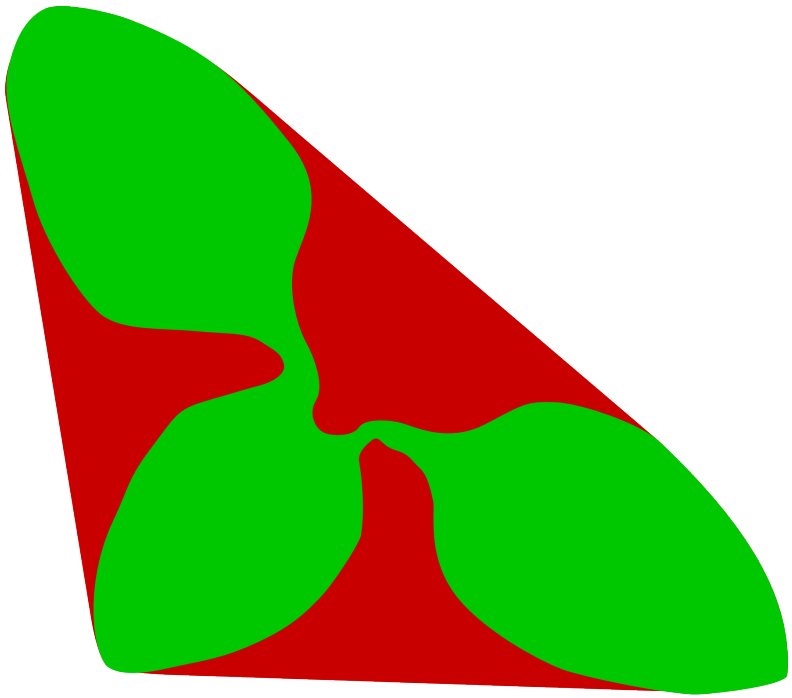


# Feature example

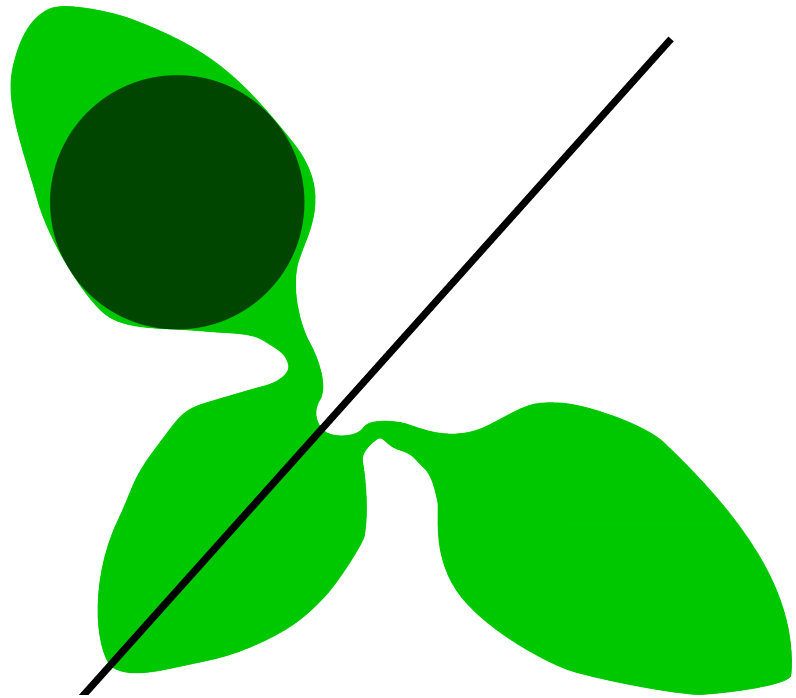


Convex hull

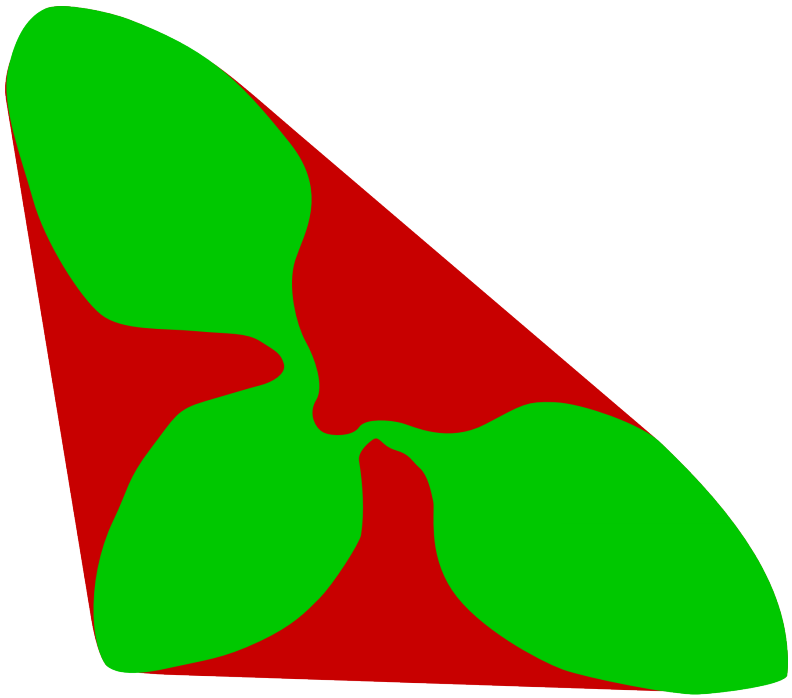
# Feature example



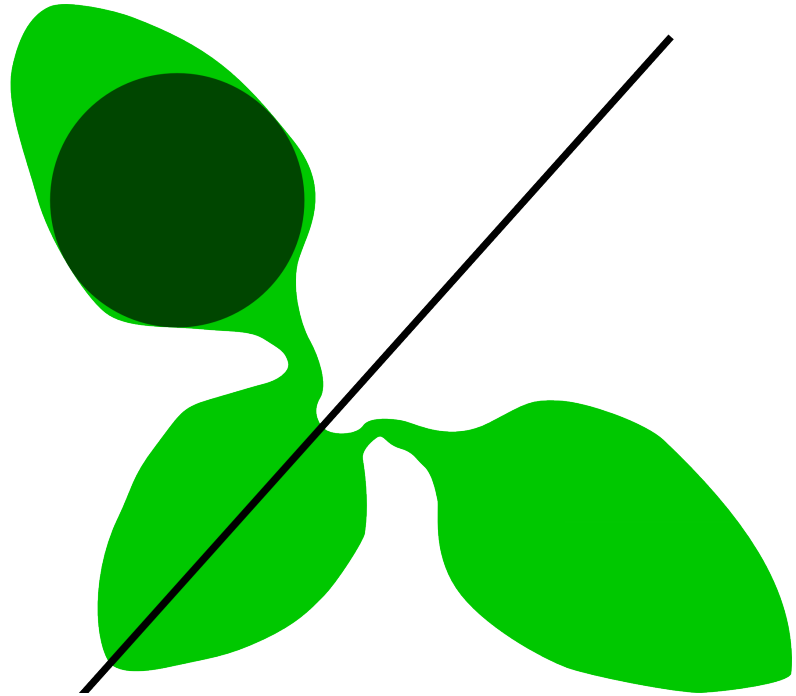
Convex hull



# Feature example



Convex hull



Max ferret, symmetry, ...

# Raw moments

$I(x, y)$ intensity of image at location $x$, $y$

$$M_{ij} = \sum_x \sum_y x^i \cdot y^j \cdot I(x, y)$$

Centroid coordinates in terms of raw moments

$$\bar{x} = \frac{M_{10}}{M_{00}} = \frac{\sum_x \sum_y x \cdot I(x, y)}{\sum_x \sum_y I(x, y)}$$

$$\bar{y} = \frac{M_{01}}{M_{00}} = \frac{\sum_x \sum_y y \cdot I(x, y)}{\sum_x \sum_y I(x, y)}$$

`http://en.wikipedia.org/wiki/Invariant_Moments`

# Central moments

Place object centroid in $(0, 0)$
This makes central moments invariant to translation.

$$\mu_{pq} = \sum_x \sum_y (x - \bar{x})^p \cdot (y - \bar{y})^q \cdot I(x, y)$$

# Central moments from raw moments

$$
\begin{aligned}
\mu_{20} &= \sum_x \sum_y (x - \bar{x})^2 \cdot (y - \bar{y})^0 \cdot I(x, y) \\
&= \sum_x \sum_y (x^2 - 2x \cdot \bar{x} + \bar{x}^2) \cdot I(x, y) \\
&= \sum_x \sum_y x^2 \cdot I(x, y) - 2 \cdot \bar{x} \cdot \sum_x \sum_y x \cdot I(x, y) \\
&\qquad + \bar{x}^2 \sum_x \sum_y I(x, y) \\
&= M_{20} - 2 \cdot \bar{x} \cdot M_{10} + \bar{x}^2 \cdot M_{00} \\
&= M_{20} - 2 \cdot \frac{M_{10}}{M_{00}} \cdot M_{10} + \left( \frac{M_{10}}{M_{00}} \right)^2 \cdot M_{00} \\
&= M_{20} - \frac{M_{10}}{M_{00}} \cdot M_{10} = M_{20} - \bar{x} \cdot M_{10}
\end{aligned}
$$

# Object orientation

Covariance matrix

$$\mu'_{20} = \mu_{20}/\mu_{00} = M_{20}/M_{00} - \bar{x}^2$$
$$\mu'_{02} = \mu_{02}/\mu_{00} = M_{02}/M_{00} - \bar{y}^2$$
$$\mu'_{11} = \mu_{11}/\mu_{00} = M_{11}/M_{00} - \bar{x}\bar{y}$$

$$\text{cov}[I(x,y)] = \begin{bmatrix} \mu'_{20} & \mu'_{11} \\ \mu'_{11} & \mu'_{02} \end{bmatrix}.$$

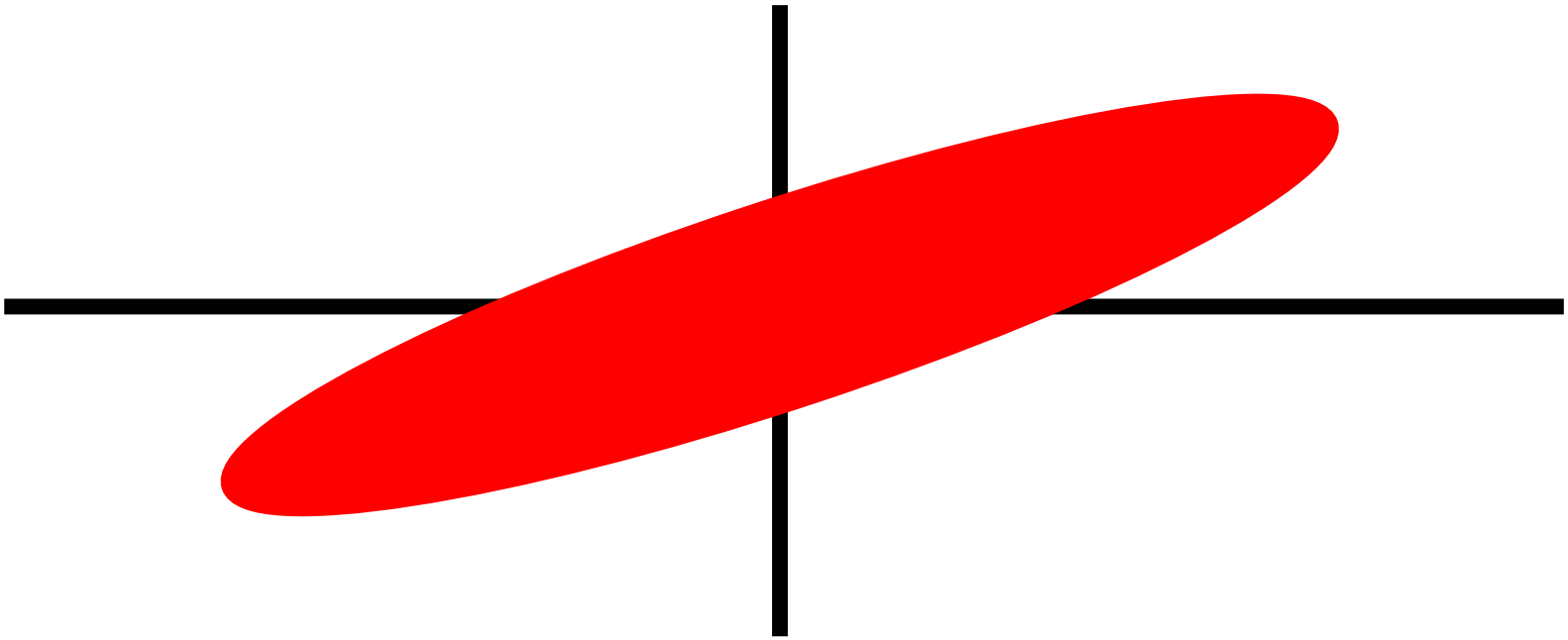
Orientation of largest eigenvalue (and of object)

$$\Theta = \frac{1}{2} \arctan\left(\frac{2\mu'_{11}}{\mu'_{20} - \mu'_{02}}\right)$$

# Central moments from raw moments

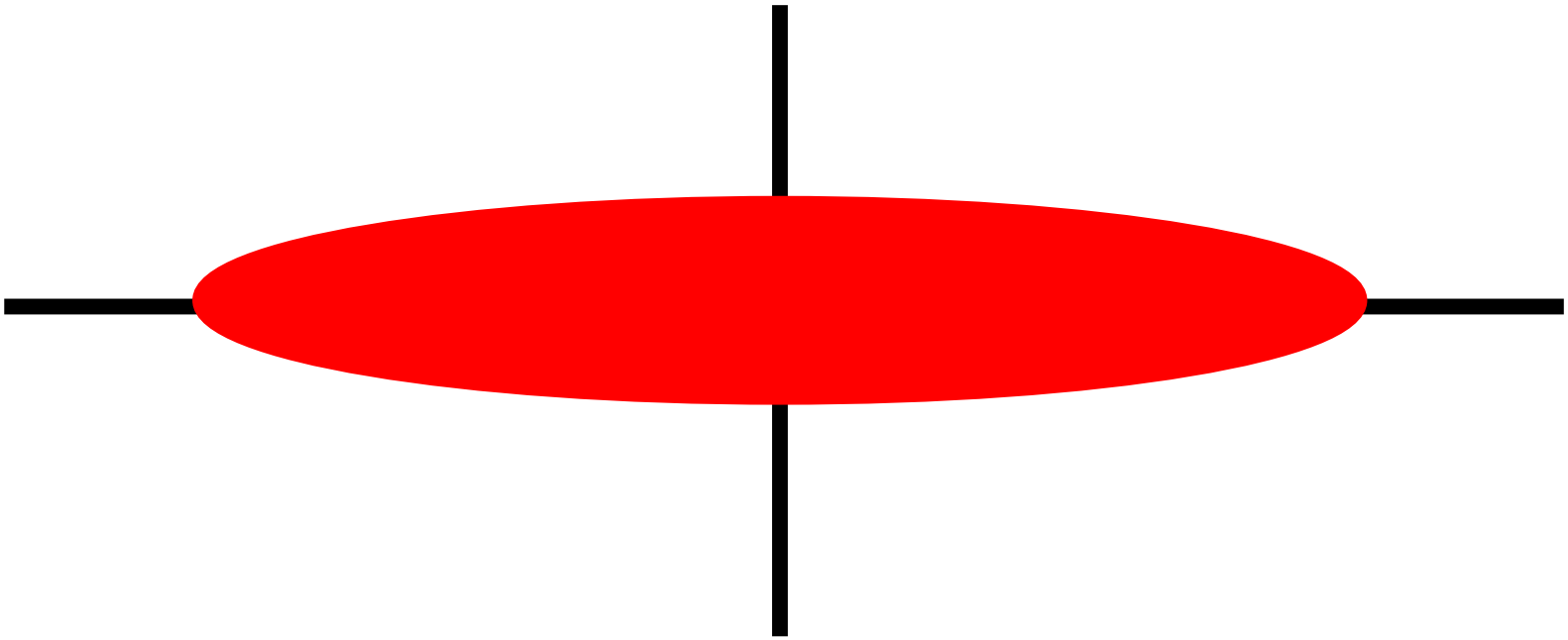
$$\mu_{00} = M_{00}$$
$$\mu_{01} = 0$$
$$\mu_{10} = 0$$
$$\mu_{11} = M_{11} - \bar{x}M_{01} = M_{11} - \bar{y}M_{10}$$
$$\mu_{20} = M_{20} - \bar{x}M_{10}$$
$$\mu_{02} = M_{02} - \bar{y}M_{01}$$
$$\mu_{21} = M_{21} - 2\bar{x}M_{11} - \bar{y}M_{20} + 2\bar{x}^2M_{01}$$
$$\mu_{12} = M_{12} - 2\bar{y}M_{11} - \bar{x}M_{02} + 2\bar{y}^2M_{10}$$
$$\mu_{30} = M_{30} - 3\bar{x}M_{20} + 2\bar{x}^2M_{10}$$
$$\mu_{03} = M_{03} - 3\bar{y}M_{02} + 2\bar{y}^2M_{01}$$

# Sign of central moment



`http://m.socrative.com/` + login with *hsm*

# Sign of central moment



`http://m.socrative.com/` + login with *hsm*

# Scale invariant moments

$$\eta_{ij} = \frac{\mu_{ij}}{\mu_{00}^{\left(1+\frac{i+j}{2}\right)}}$$

# Rotation invariant moments – Hu moments

$$
\begin{aligned}
I_1 &= \eta_{20} + \eta_{02} \\
I_2 &= (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \\
I_3 &= (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \\
I_4 &= (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \\
I_5 &= (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] \\
&\quad + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \\
I_6 &= (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \\
&\quad + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \\
I_7 &= (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] \\
&\quad - (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]
\end{aligned}
$$

# Hu moments

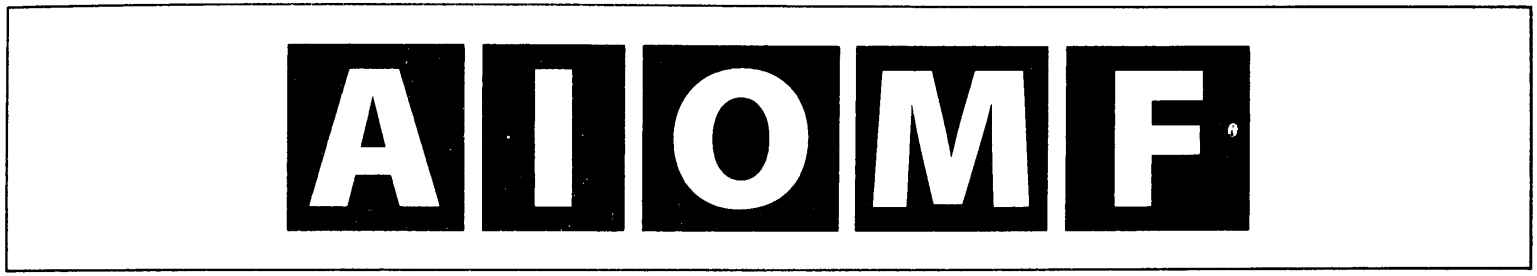



*Figure 8-9. Images of five simple characters; looking at their Hu moments yields some intuition concerning their behavior*

*Table 8-1. Values of the Hu moments for the five simple characters of Figure 8-9*

| | $h_1$ | $h_2$ | $h_3$ | $h_4$ | $h_5$ | $h_6$ | $h_7$ |
|---|---|---|---|---|---|---|---|
| A | 2.837e−1 | 1.961e−3 | 1.484e−2 | 2.265e−4 | −4.152e−7 | 1.003e−5 | −7.941e−9 |
| I | 4.578e−1 | 1.820e−1 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| O | 3.791e−1 | 2.623e−4 | 4.501e−7 | 5.858e−7 | 1.529e−13 | 7.775e−9 | −2.591e−13 |
| M | 2.465e−1 | 4.775e−4 | 7.263e−5 | 2.617e−6 | −3.607e−11 | −5.718e−8 | −7.218e−24 |
| F | 3.186e−1 | 2.914e−2 | 9.397e−3 | 8.221e−4 | 3.872e−8 | 2.019e−5 | 2.285e−6 |

Learning OpenCV, Bradski & Kaehler, 2008

# Hu moments

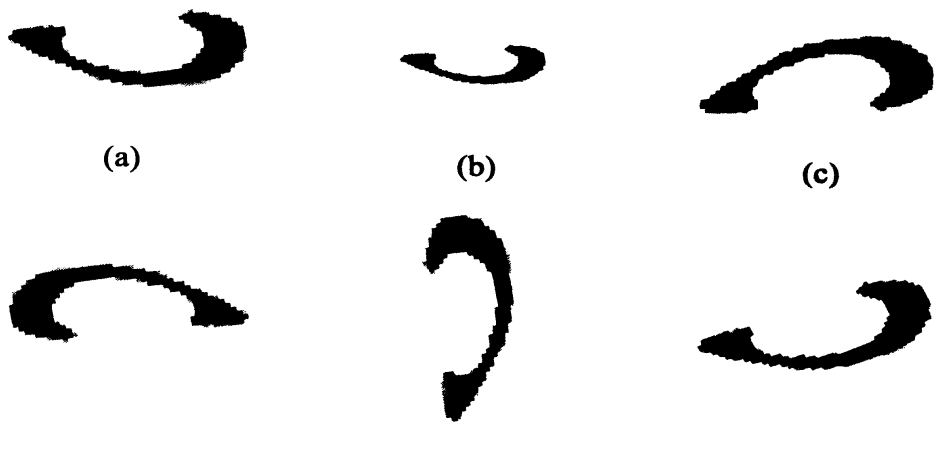



**FIGURE 7.5:** The Byzantine symbol "petasti" in various scaled and rotated versions, from (a) to (f).

Table 7.4: The invariant moments of Hu for the versions of the "petasti" symbol

| Moments | 0° | Scaled | 180° | 15° | Mirror | 90° |
|---|---|---|---|---|---|---|
| $\phi_1$ | 93.13 | 91.76 | 93.13 | 94.28 | 93.13 | 93.13 |
| $\phi_2$ | 58.13 | 56.60 | 58.13 | 58.59 | 58.13 | 58.13 |
| $\phi_3$ | 26.70 | 25.06 | 26.70 | 27.00 | 26.70 | 26.70 |
| $\phi_4$ | 15.92 | 14.78 | 15.92 | 15.83 | 15.92 | 15.92 |
| $\phi_5$ | 3.24 | 2.80 | 3.24 | 3.22 | 3.24 | 3.24 |
| $\phi_6$ | 10.70 | 9.71 | 10.70 | 10.57 | 10.70 | 10.70 |
| $\phi_7$ | 0.53 | 0.46 | 0.53 | 0.56 | −0.53 | 0.53 |

Pattern Recognition, Theodoridis & Koutroumbas, 2006

# Hu moments – Interpretation

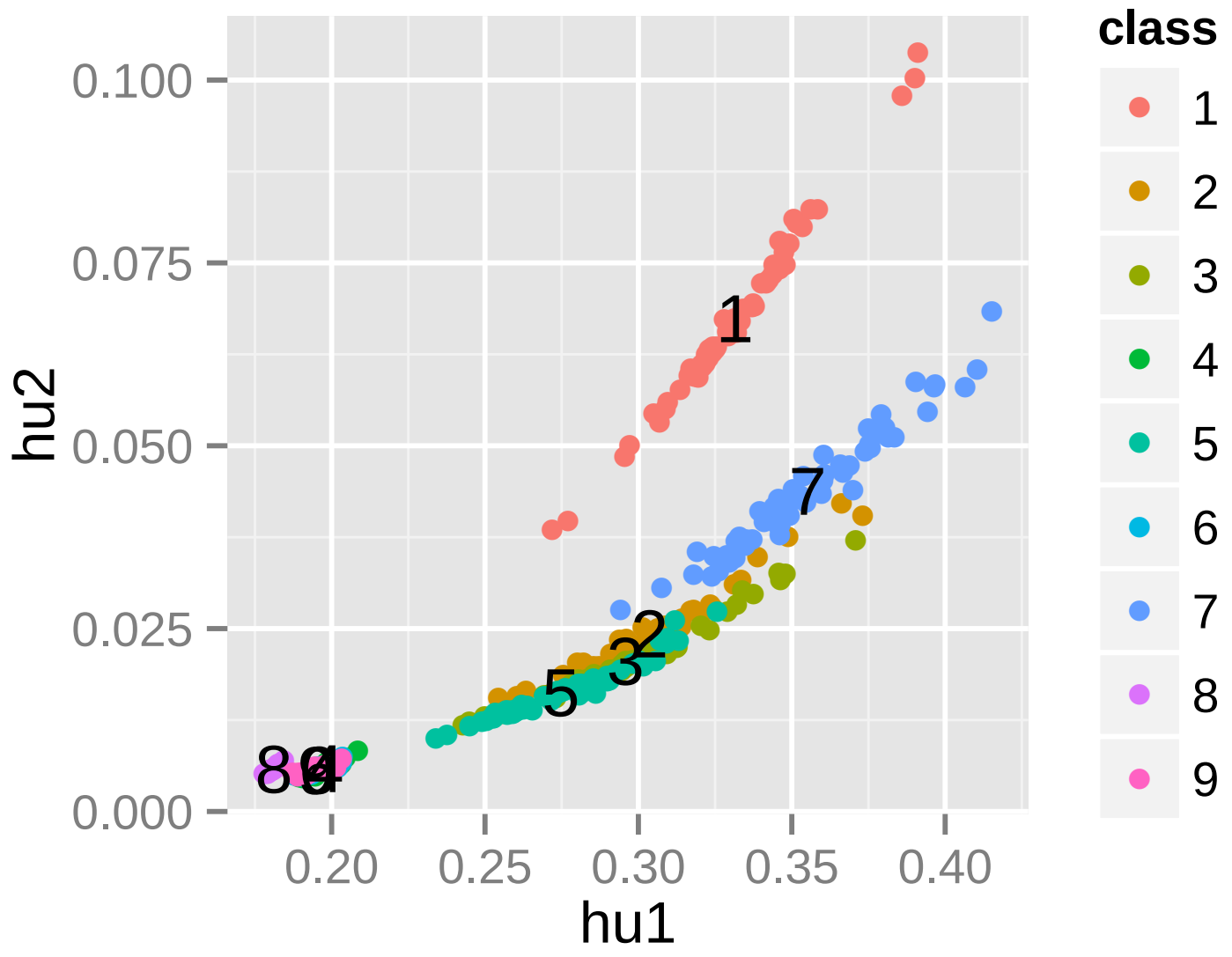
- $I_1$ Angular momentum
- $I_7$ Skew invariant, changes sign when object is mirrored

# Features from sudoku digits

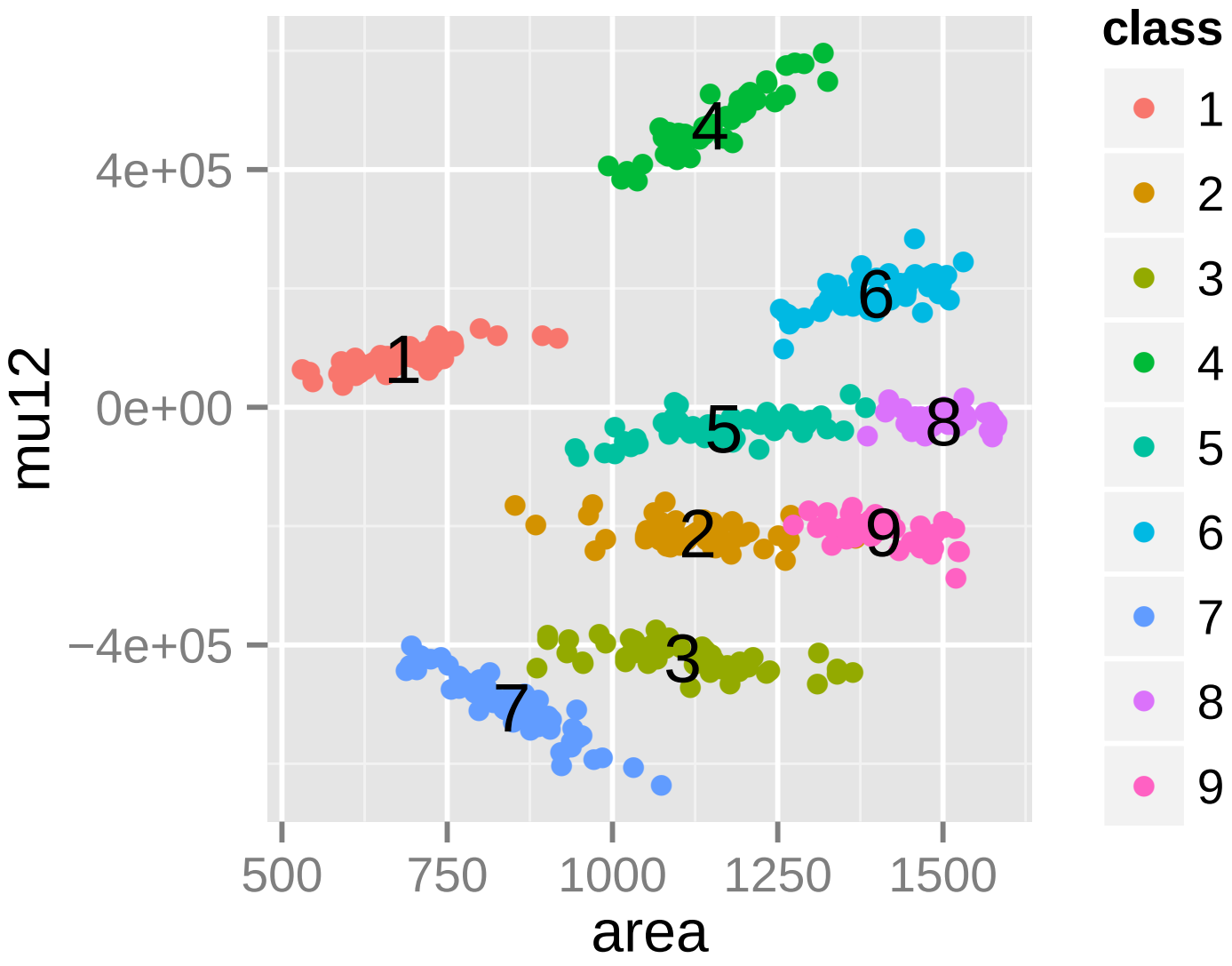
Some example data from digit recognition.
Now with better features

- area
- perimeter
- central moments
- Hu moments

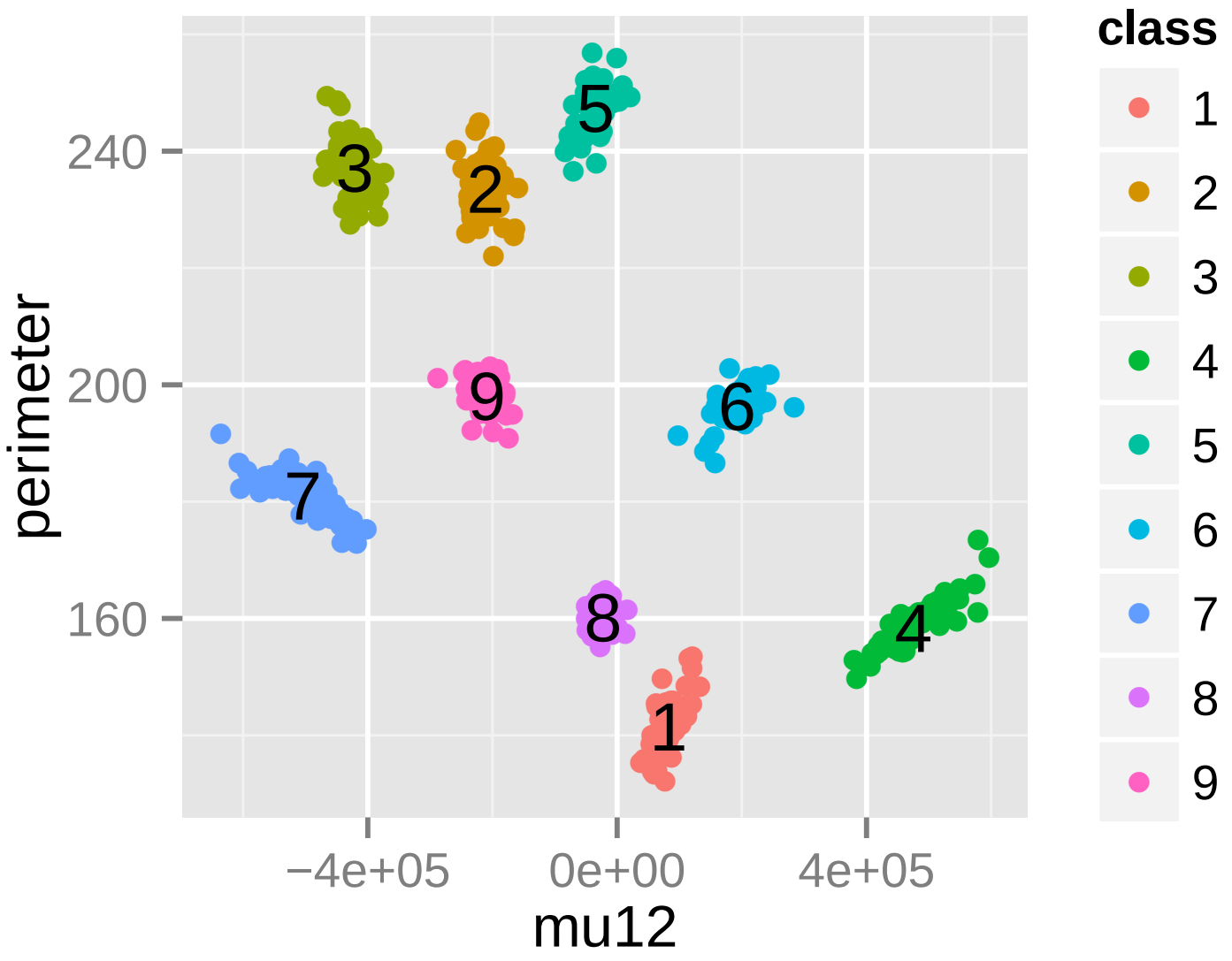
# Sudoku digits



# Sudoku digits



# Sudoku digits



# Features from sudoku digits

Some example data from digit recognition.
Now with better features

- area
- perimeter
- central moments
- *Hu moments* – Is not enough alone (6 vs. 9)

# Summary

- feature based object recognition can be used for several tasks
- features are derived from objects
- choosing good features are important