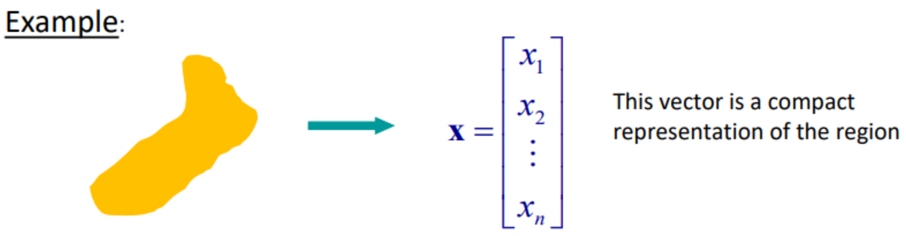
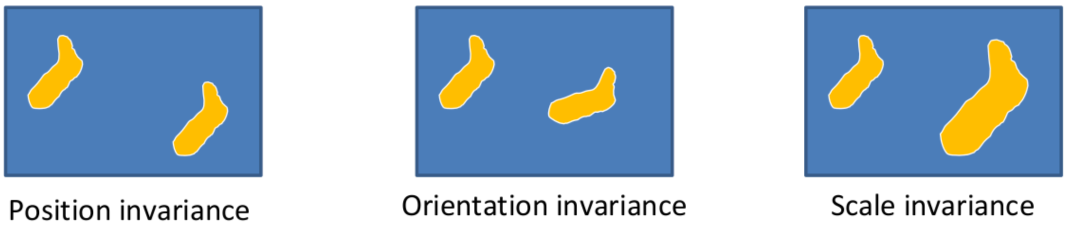
6.1 Shape descriptors

The main objective of region description is to obtain a mathematical representation of a segmented region from an image consisting of a vector of features $\mathbf{x} = [x_1, \ldots, x_n]$.


Example:
$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$
This vector is a compact representation of the region

In this notebook we will see a branch of region description called **shape analysis**. Shape analysis aims to construct this feature vector using only shape features (e.g., size, perimeter, circularity or compactness).

Depending on the application, it could be needed that the used descriptor be **invariant** to the position in the image in which the regions appears, its orientation, and/or its size (scale). Some examples:



This notebook **covers simple shape descriptors of regions** based on their area, perimeter, minimal bounding-box, etc (sections 6.1.1 and 6.1.2). We will also study **if these descriptors are invariant to position, orentation and size** (section 6.1.3). Let's go!

Problem context - Number-plate recognition

So here we are again! UMA called for us to join a team working on their parking access system. This time, they want to upgrade their obsolete number-plate detection algorithm by including better and more efficient methods.

Here is where our work starts, we are going to **apply shape analysis to each of the characters** that can appear on a license plate, that is, numbers from 0 to 9, and letters in the alphabet. The idea is to **produce a unique feature vector** for each character that could appear on a plate (e.g. $\mathbf{x}^\mathbf{0}$, $\mathbf{x}^\mathbf{1}$, $\ldots$, $\mathbf{x}^\mathbf{A}$, $\mathbf{x}^\mathbf{B}$, etc.) so it could be later used to **train an automatic classification system** (we will see this in the next chapter!).

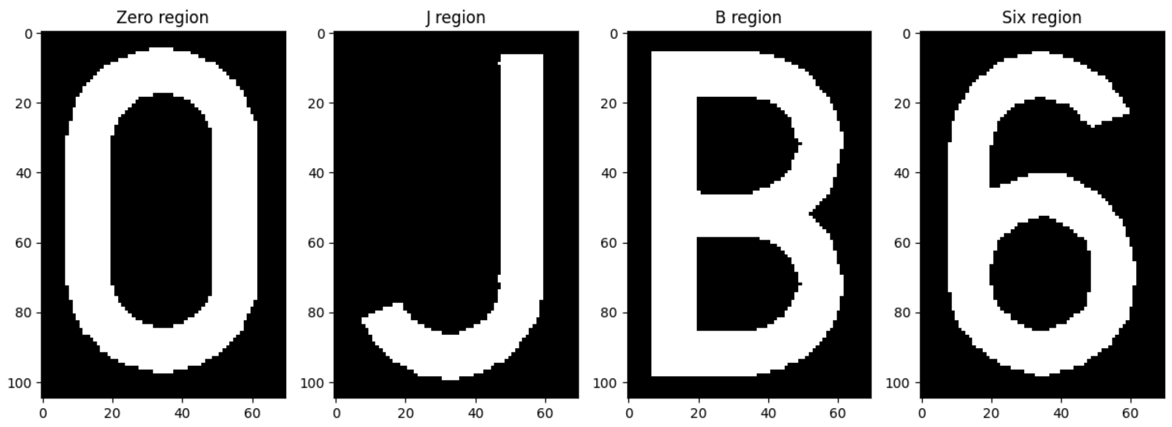
In [1]:
```
import numpy as np
import cv2
import matplotlib.pyplot as plt
import matplotlib
matplotlib.rcParams['figure.figsize'] = (15.0, 8.0)

images_path = './images/'
```

Initial data

UMA's parking security team have sent us some segmented plate characters captured by their camera in the parking. They have binarized and cropped these images, providing us with regions representing such characters as white pixels. These cropped images are `region_0.png` (region with a zero), `region_6.png` (region with a six), `region_B.png` (region with a B), and `region_J.png` (region with a J).

Let's visualize them!

In [2]:
```
# Read the images
zero = cv2.imread(images_path + 'region_0.png',0)
J = cv2.imread(images_path + 'region_J.png',0)
B = cv2.imread(images_path + 'region_B.png',0)
six = cv2.imread(images_path + 'region_6.png',0)

# And show them!
plt.subplot(141)
plt.imshow(zero, cmap='gray')
plt.title('Zero region')

plt.subplot(142)
plt.imshow(J, cmap='gray')
plt.title('J region')

plt.subplot(143)
plt.imshow(B, cmap='gray')
plt.title('B region')

plt.subplot(144)
plt.imshow(six, cmap='gray')
plt.title('Six region');
```



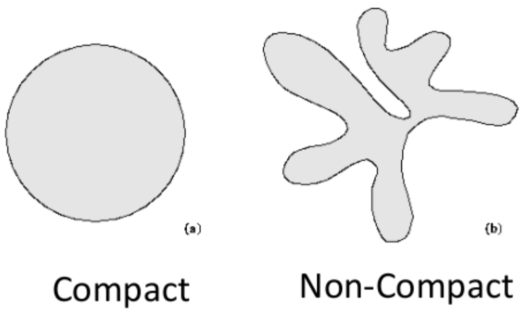
6.1.1 Compactness

The first feature we are going to work with is **compactness**:

$$\textbf{compactness} = \frac{area}{perimeter^2}$$

\[5pt]

As you can see, this feature associates the area with the permeter of a region. Informally, it tells how *rounded* and *closed* is a region. The most compact shape is the circle, with $\textbf{compactness} = 1/(4\pi)$.



OpenCV pill

OpenCV uses contours for analysing shapes. A contour is a list of points that defines a region. We can obtain the contours of a region using `cv2.findContours()`.

ASSIGNMENT 1: Computing compactness

What to do? Complete the function bellow, named `compactness()`, which computes the compactness of an input region.

For that, we are going to use the `cv2.findContours()` function, which takes as input:

- A binary image (containing the region as white pixels).
- Contour retrieval mode, it can be:

        - `RETR_EXTERNAL` : only returns the external contour
        - `RETR_LIST` : returns all contours (e.g. the character 0 would contain two contours: external and internal)
        - `RETR_CCOMP` : returns all contours and organize them in a two-level hierarchy. At the top level, there are external boundaries of the components. At the second level, there are boundaries of the holes.

- Method: controls how many points of the contours are being stored, this is for optimization purposes.

        - `CHAIN_APPROX_NONE` : stores absolutely all the contour points.
        - `CHAIN_APPROX_SIMPLE` : compresses horizontal, vertical, and diagonal segments and leaves only their end points.
        - `CHAIN_APPROX_TC89_L1` : applies an optimization algorithm.

And returns:

- a list containing the contours,
- and a list containing information about the image topology. It has as many elements as the number of contours.

For simplicity, we are going to take into account **only the external boundary** (as if the regions have not holes), so the second output is not relevant.

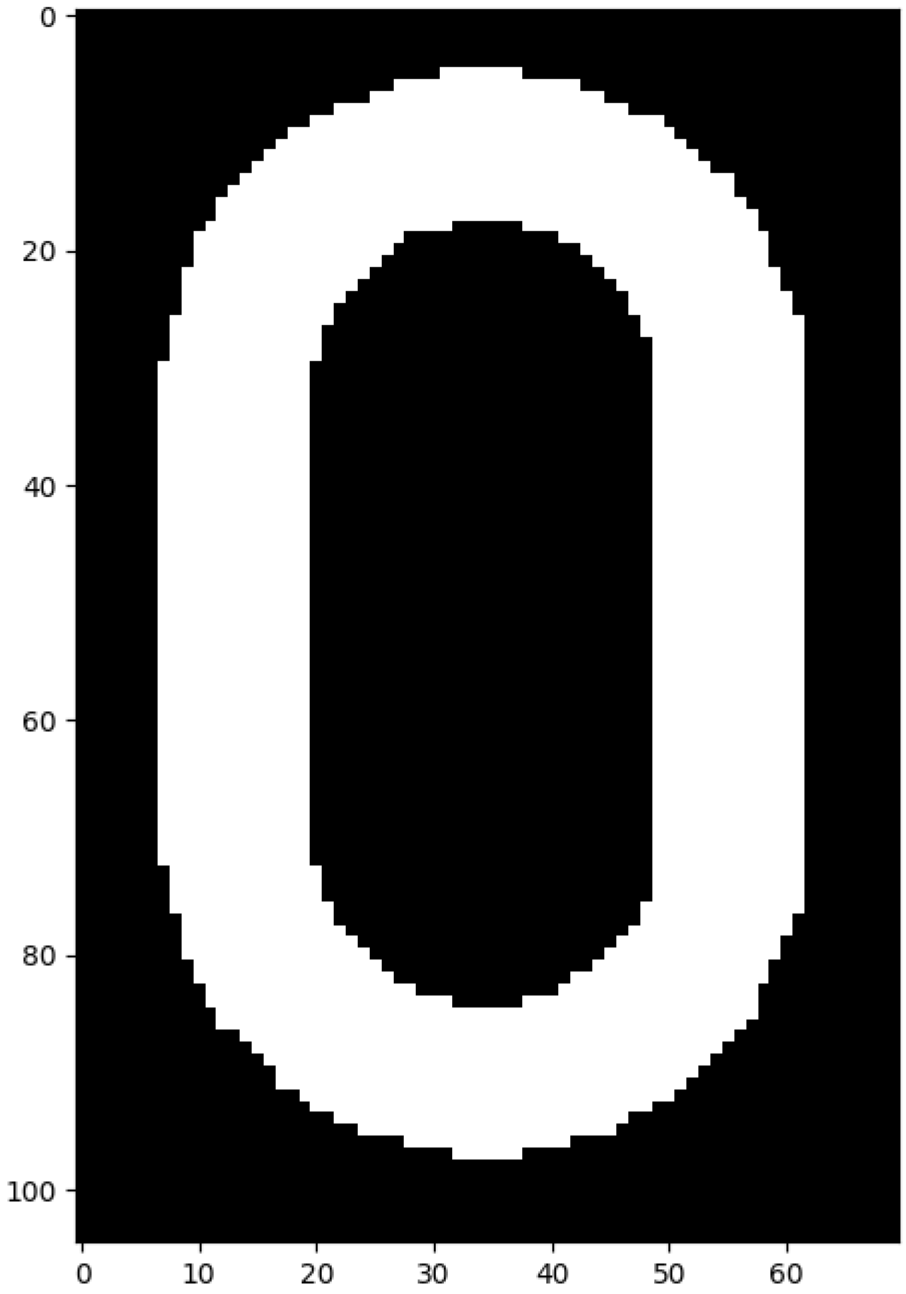
Having the contours, you can obtain the **area** and the **perimeter** of the region through `cv2.contourArea()` and `cv2.arcLength()` . Both functions take the contours of the region as input.

Note: Use `cv2.RETR_EXTERNAL` and `cv2.CHAIN_APPROX_NONE` .

In [3]:
```
# Assignment 1
def compactness(region):
    """ Compute the compactness of a region.

        Args:
            region: Binary image

        Returns:
            compactness: Compactness of region (between 0 and 1/4pi)
    """
    plt.imshow(region,cmap='gray')
    plt.show()
    # Get external contour
    contours,_ = cv2.findContours(region, cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_NC
    cnt = contours[0] # We only have 1 CONECTED EXTERNAL contour, so there's onl

    img_contours = np.zeros(region.shape)
    # draw the contours on the empty image
    cv2.drawContours(img_contours, contours, -1, (255,255,255), 1)
    plt.imshow(img_contours,cmap='gray')
    plt.show()

    # Calcule area
    area = cv2.contourArea(cnt)

    # Calcule perimeter
    perimeter = cv2.arcLength(cnt,True)

    print("Area:",area)
    print("Perimeter:", perimeter)

    # Calcule compactness
    compactness = area/(perimeter**2)

    return compactness
```

You can use next code to **test if the results are right**:

In [4]:
```
# Read the images
zero = cv2.imread(images_path + 'region_0.png',0)
J = cv2.imread(images_path + 'region_J.png',0)
B = cv2.imread(images_path + 'region_B.png',0)
six = cv2.imread(images_path + 'region_6.png',0)

# And show their compactness!
print(" Compactness of 0: ", round(compactness(zero),5), "\n",
      "Compactness of J: ", round(compactness(J),5), "\n",
      "Compactness of B: ", round(compactness(B),5), "\n",
      "Compactness of 6: ", round(compactness(six),5))
```


0
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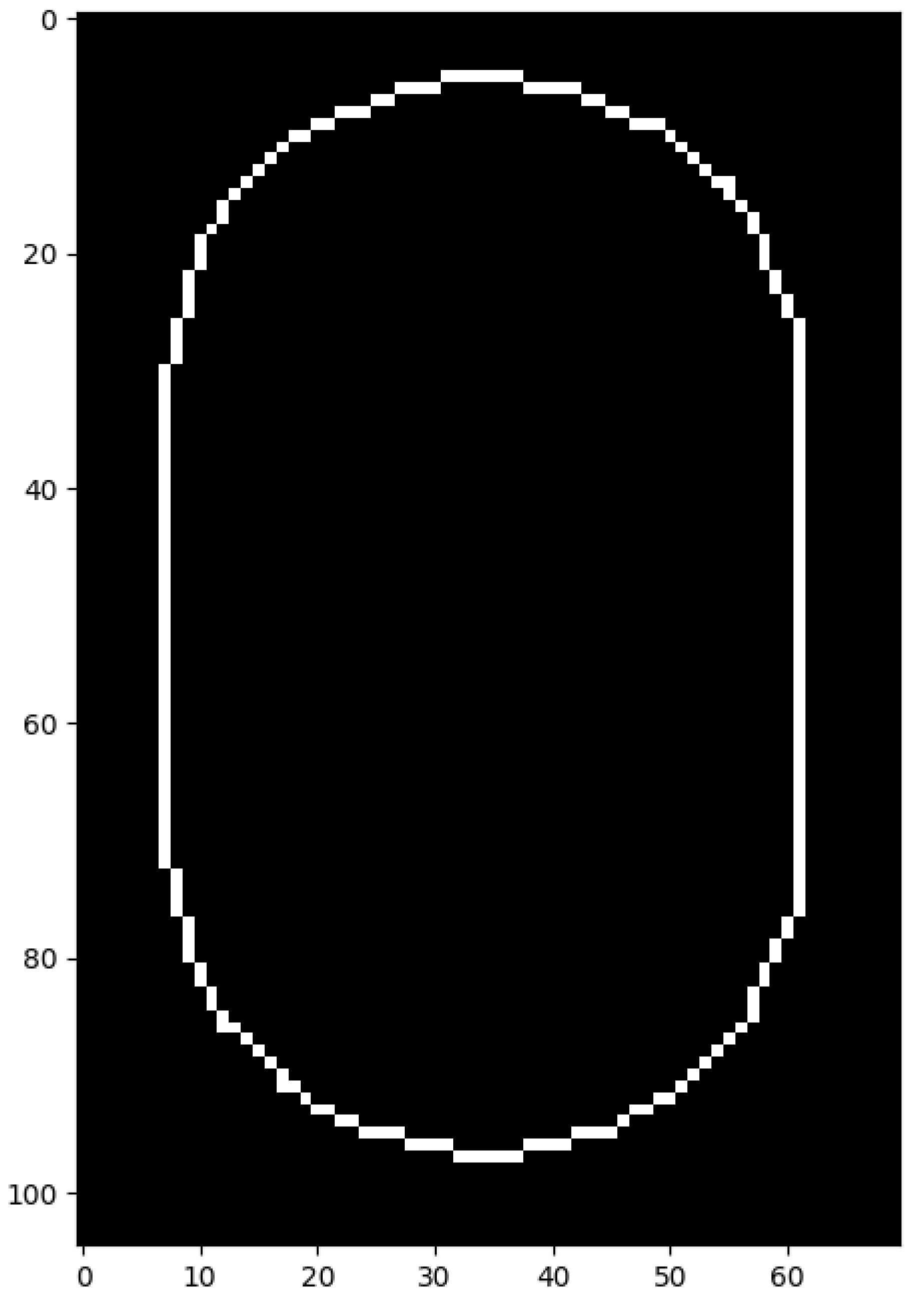
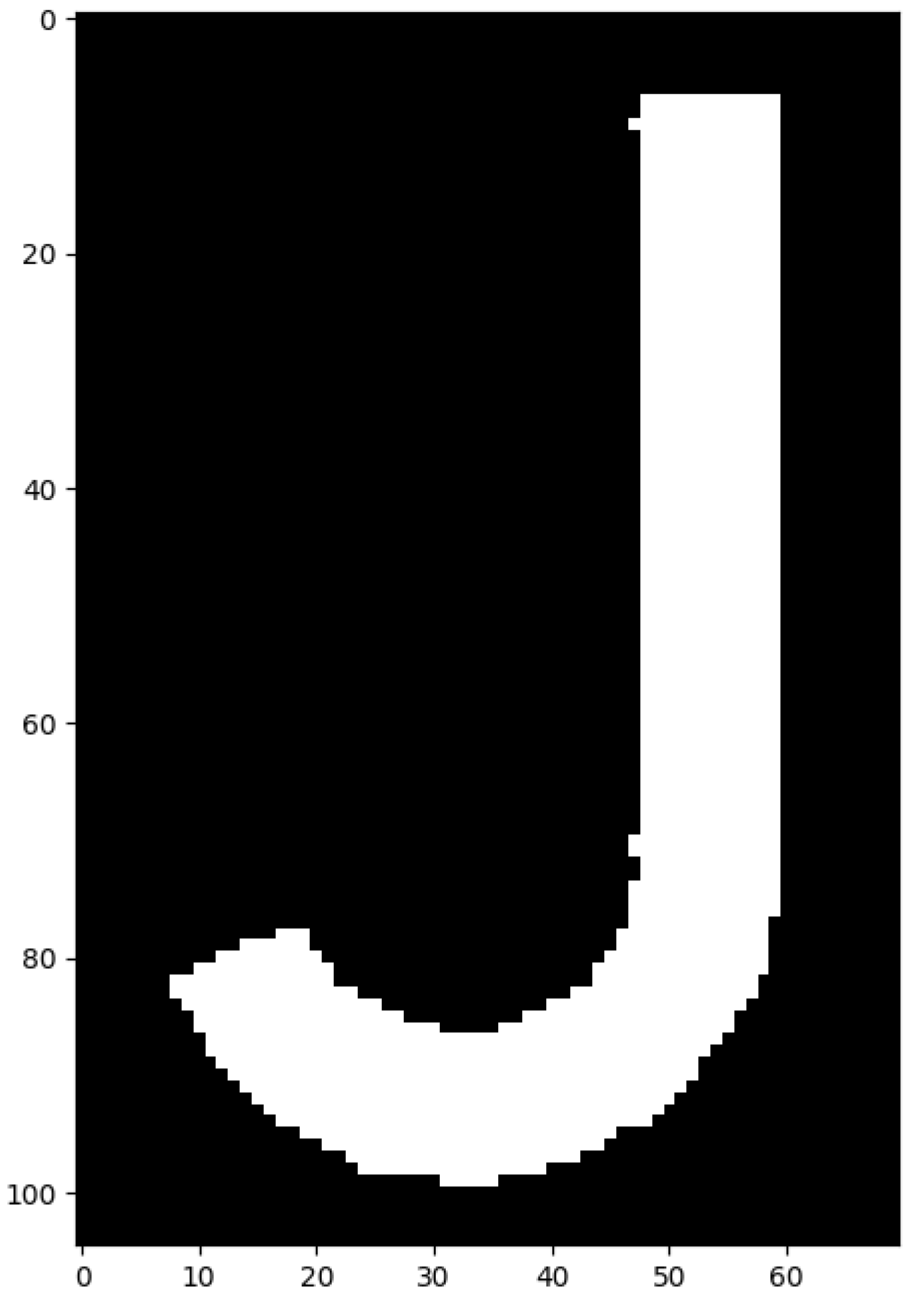
100
0
10
20
30
40
50
60



```
Area: 4307.0
Perimeter: 255.68123936653137
```



0
20
40
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0
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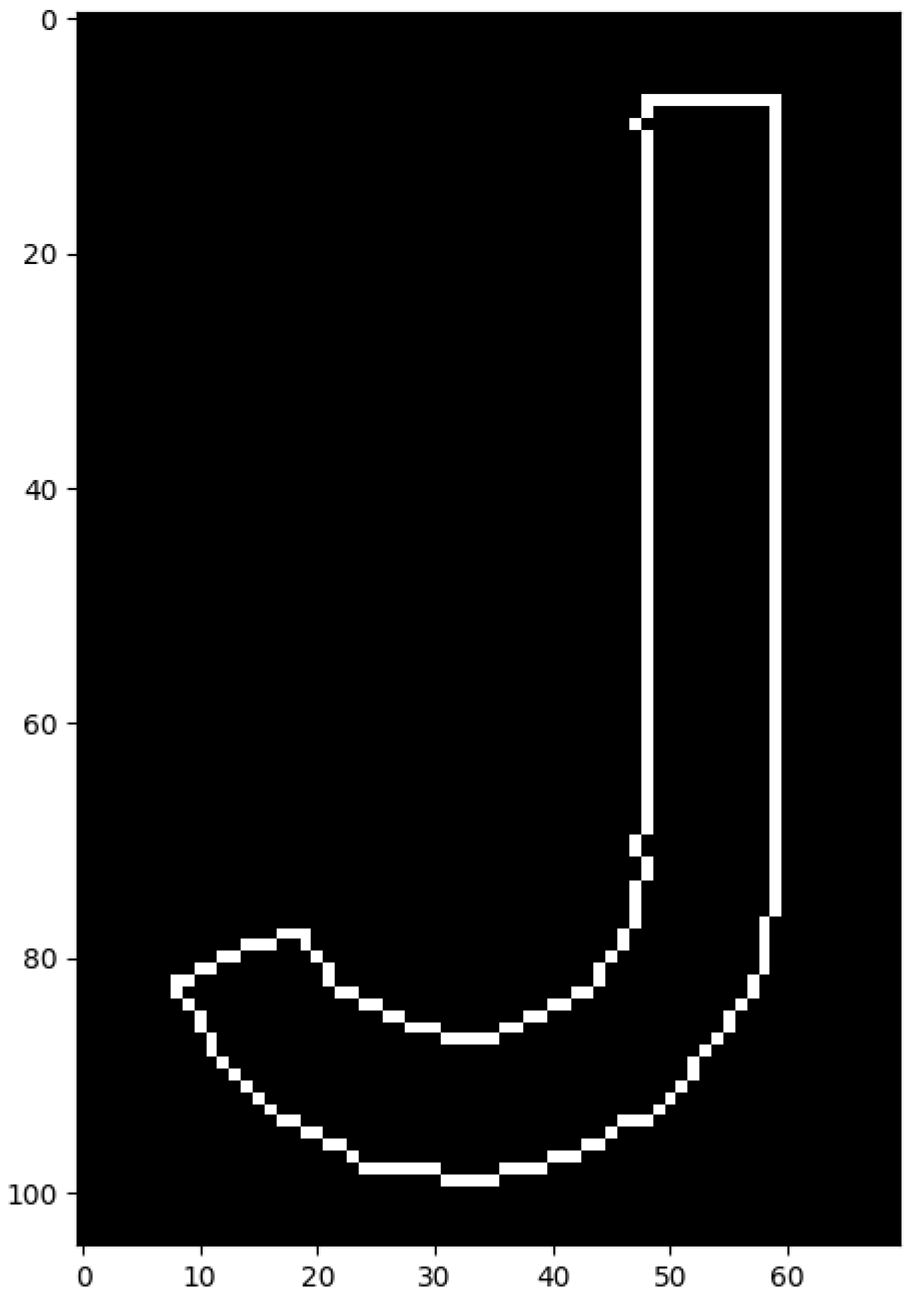
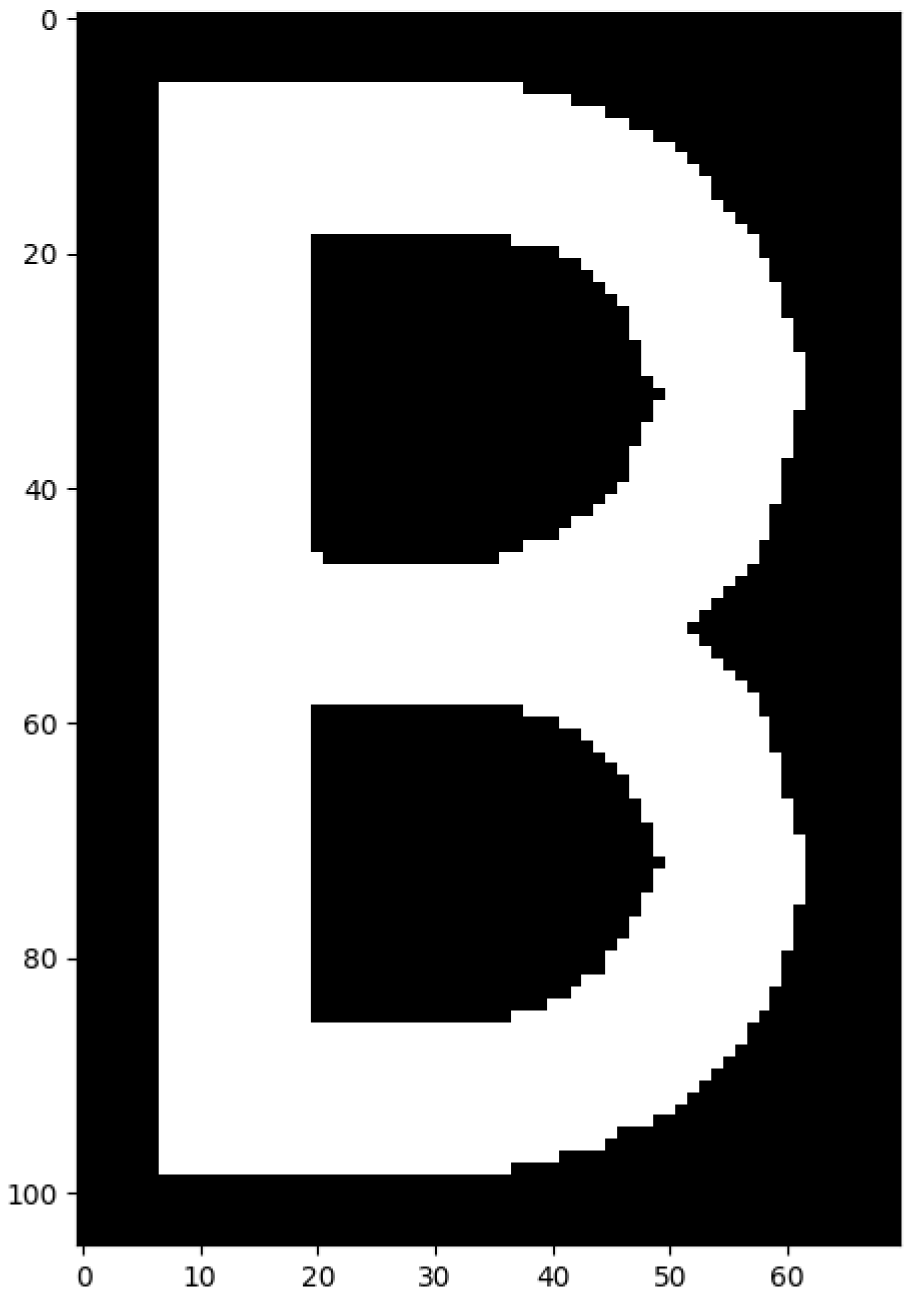
30
40
50
60



```
Area: 1386.0
Perimeter: 276.3675310611725
```


0
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40
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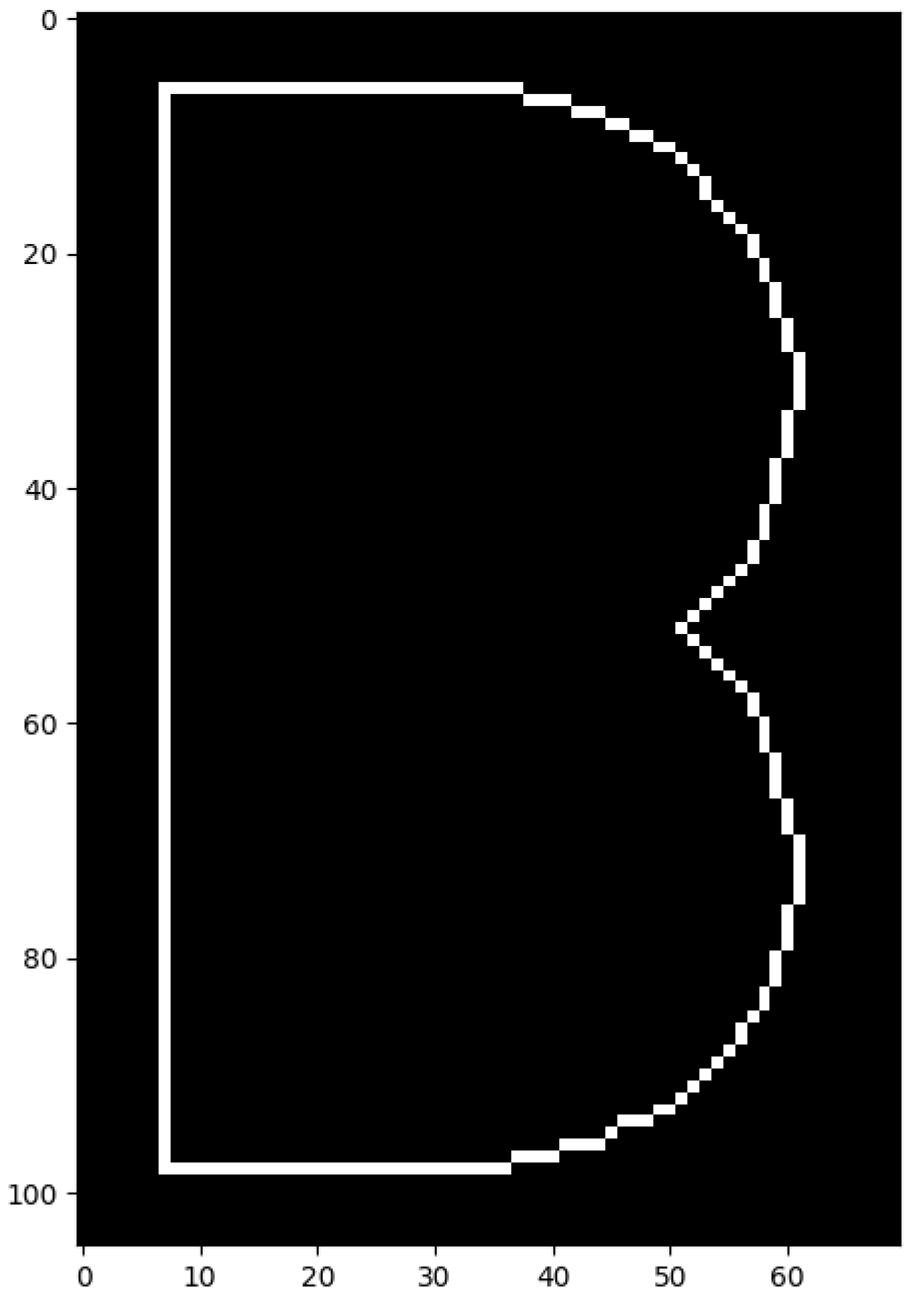
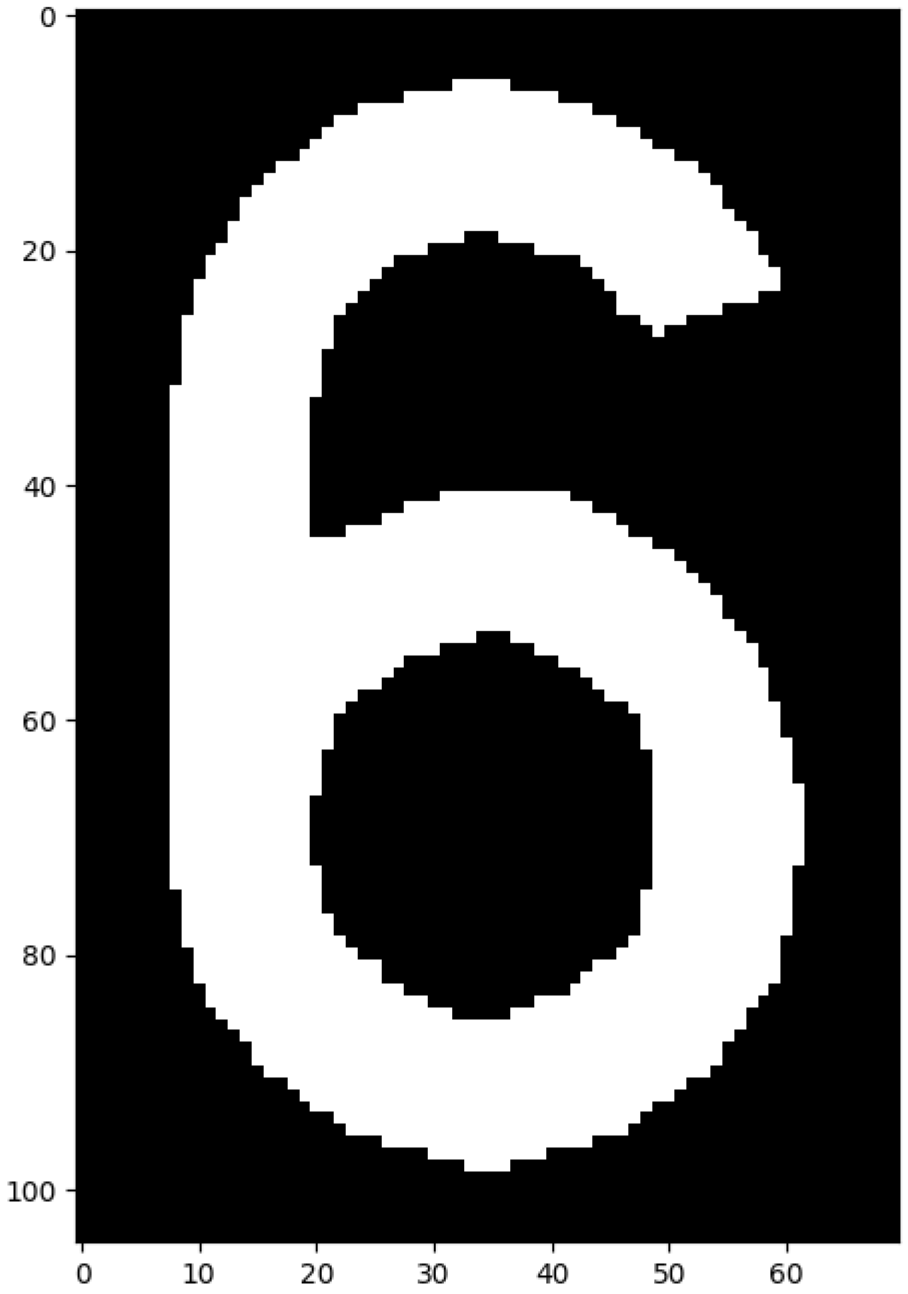
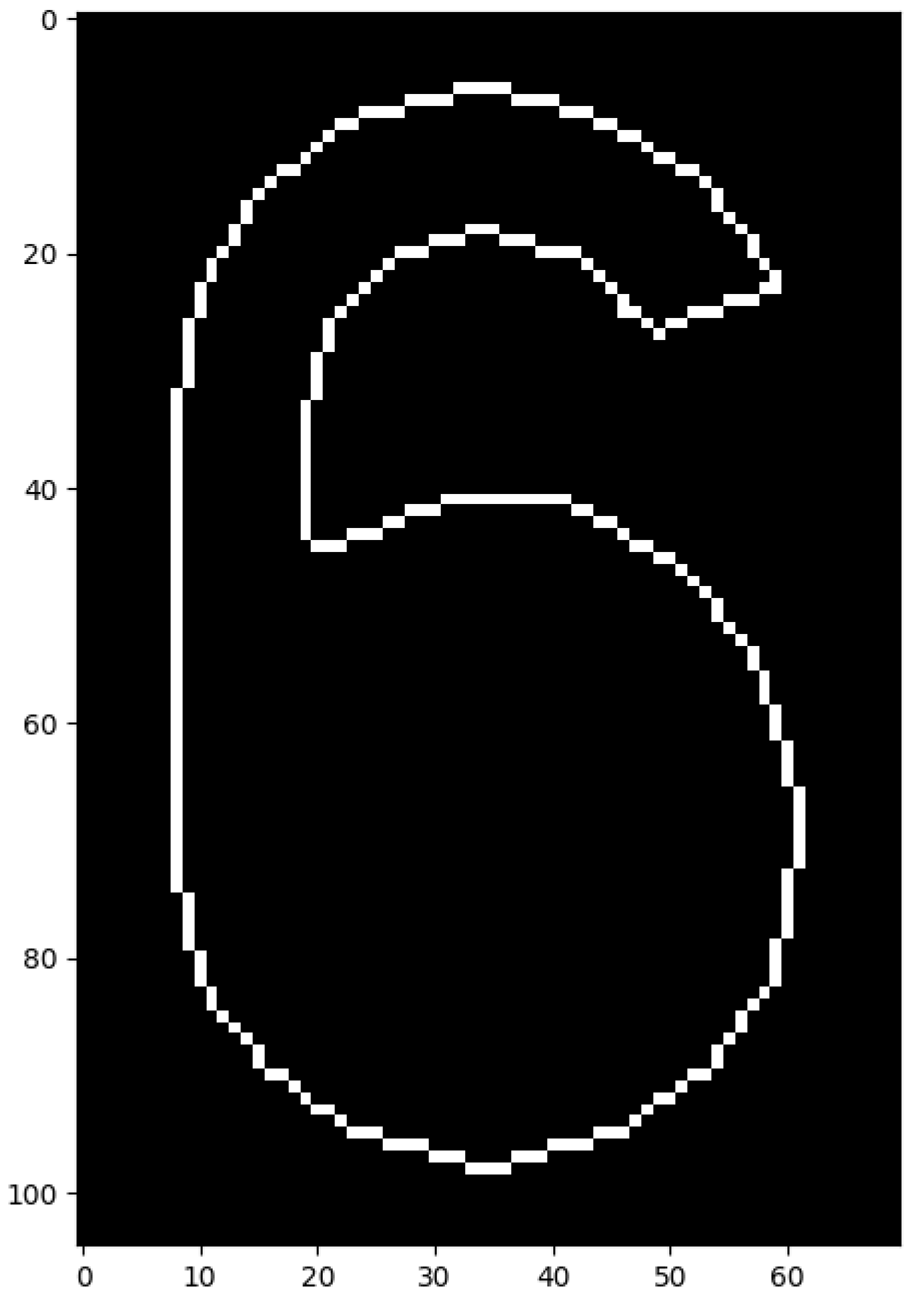
80
100
0
10
20
30
40
50
60



```
Area: 4498.0
Perimeter: 281.53910398483276
```


0
20
40
60
80
100
0
10
20
30
40
50
60



```
Area: 3217.5
Perimeter: 334.4924215078354
 Compactness of 0:  0.06588
 Compactness of J:  0.01815
 Compactness of B:  0.05675
 Compactness of 6:  0.02876
```

Expected output (using `CHAIN_APPROX_NONE`):

```
Compactness of 0:  0.06588
Compactness of J:  0.01815
Compactness of B:  0.05675
Compactness of 6:  0.02876
```

Thinking about it (1)

Excellent! Now, **answer the following questions:**

- Why `region_0.png` have the greatest compactness?

Because its shape is the most similar to a circle, which is the shape with the greatest compactness.

- Could we differentiate all characters using only this feature as feature vector?

  Probably not. 0 and B have similar compactness, and this also happens with many other chracters (for example, the O). Similar thing with 6 and G. So, if we wanted to accurately differentiate characters we would need additional features and shape descriptors.

- Is compactness invariant to position, orientation or scale?

  Yes, it is; to all of them. It is invariant to position and orientation as it is dimensionless (nothing matters except for the relation between area and perimeter). Scaling affects both perimeter and area proportionally, and compactness is the quotient between area and perimeter, so the relationship between the two variables, which is what compactness represents, would remain the same.

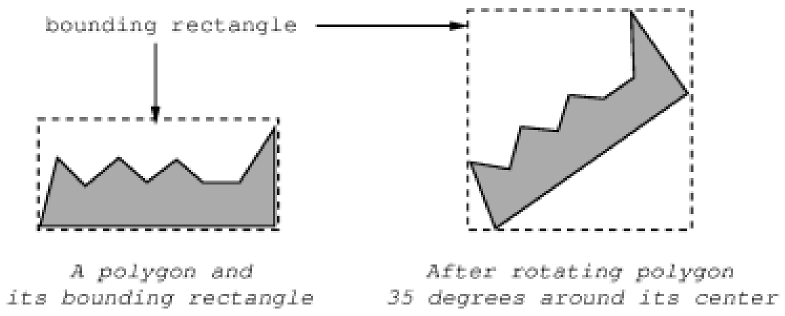
6.1.2 Extent

Another shape descriptor is **extent** of a shape:

$$\textbf{extent} = \frac{area}{bounding\,rectangle\,area}$$

\[5pt]

This feature associates the area of the region with the area its bounding rectangle. A **bounding rectangle** can be defined as the minimum rectangle that contains all the pixels of a region whose bottom edge is horizontal and its left edge is vertical.


bounding rectangle
A polygon and its bounding rectangle
After rotating polygon 35 degrees around its center

The shape with the highest extent value is the rectangle, with $extent = 1$, while the lowest one is an empty region so $extent = 0$.

ASSIGNMENT 2: Time to compute the extent

Complete the function `extent()`, which receives the `region` to be described as input and returns its `extent`.

Tip: compute the bounding rectangle using cv2.boundingRect(), which also takes the contours as input.

In [5]:
```python
def extent(region):
    """ Compute the extent of a region.

        Args:
            region: Binary image

        Returns:
            extent: Extent of region (between 0 and 1)
    """

    # Get external contour
    contours,_ = cv2.findContours(region,cv2.RETR_CCOMP,cv2.CHAIN_APPROX_SIMPLE)
    cnt = contours[0]

    # Calcule area
    area = cv2.contourArea(cnt)

    # Get bounding rectangle
    _,_,w,h = cv2.boundingRect(cnt)

    # Calcule bounding rectangle area
    rect_area = w*h

    # Calcule extent
    extent = float(area)/rect_area

    return extent
```

You can use next code to **test if the obtained results are correct**:

In [6]:
```python
# Read the images
zero = cv2.imread(images_path + 'region_0.png',0)
J = cv2.imread(images_path + 'region_J.png',0)
B = cv2.imread(images_path + 'region_B.png',0)
six = cv2.imread(images_path + 'region_6.png',0)

# And show their extent!
print("Extent of 0: ", round(extent(zero),5), "\n",
      "Extent of J: ", round(extent(J),5), "\n",
      "Extent of B: ", round(extent(B),5), "\n",
      "Extent of 6: ", round(extent(six),5))
```

```
Extent of 0:  0.84203
 Extent of J:  0.2866
 Extent of B:  0.87937
 Extent of 6:  0.64068
```

Expected output (using `CHAIN_APPROX_NONE`):

```
Extent of 0:  0.84203
Extent of J:  0.2866
Extent of B:  0.87937
Extent of 6:  0.64068
```

Thinking about it (2)

Now, **answer the following questions:**

- Why `region_B.png` have the greatest extent?

  Beacuse its shape resembles the most to the rectangle, which is the shape with the greatest extent.

- Is extent invariant to position, orientation or scale? If not, how could we turn it into a invariant feature?

  It is invariant to position (since it depends only on the area and bounding box, which are independent of position) and scale (it is a ratio of areas, so when scaled both increase proportionally, the ratio remains the same). It is not invairant to orientation, as the bounding box is painted relative to the base of the axes of the image rather than the object in question. This would be easily solved by using the objects eigenvectors as the base over which we would paint the bounding box (similar procedure to the invariance of orientation in the Harris detector).

6.1.3 Building a feature vector

Now that we can compute two different features, compactness (x_1) and extent (x_2), we can build a feature vector ($\mathbf{x}$) for characterizing each region by concatenating both features, that is, $\mathbf{x} = [x_1, x_2]$.

Before sending to UMA our solution for region description, let's see if these features are discriminative enough to differentiate between the considered characters.

ASSIGNMENT 3: Plotting feature vectors

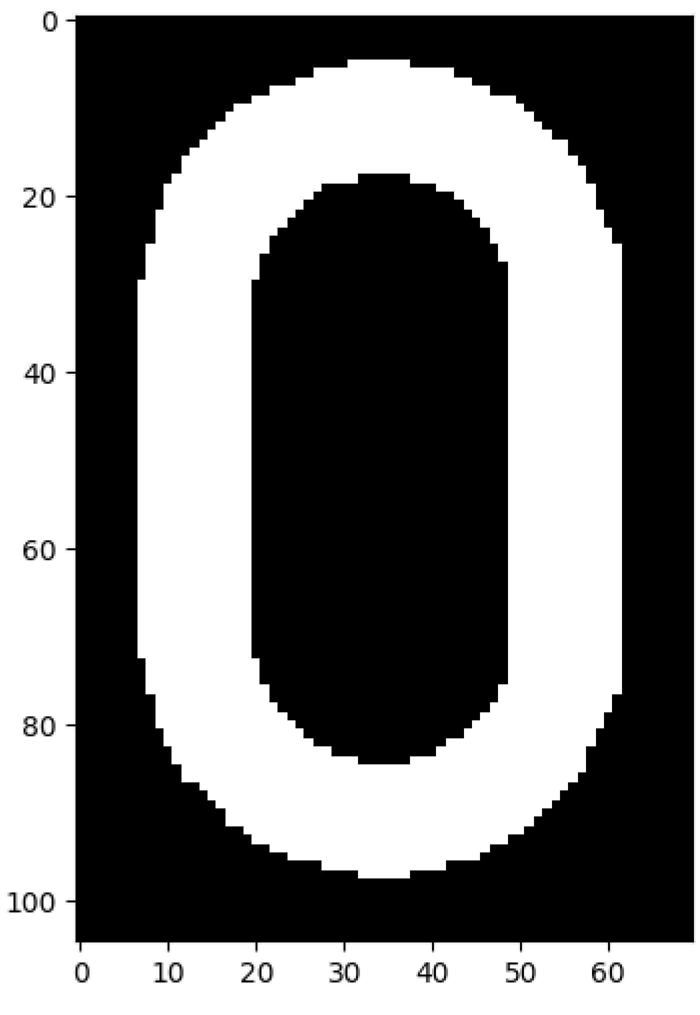
You task is to plot the feature vectors, computed by the functions `compactness()` and `extent()`, in a 2D-space called the **feature space!**. In such a space, the **x-axis represents the compactness** of a region and the **y-axis its extent**.

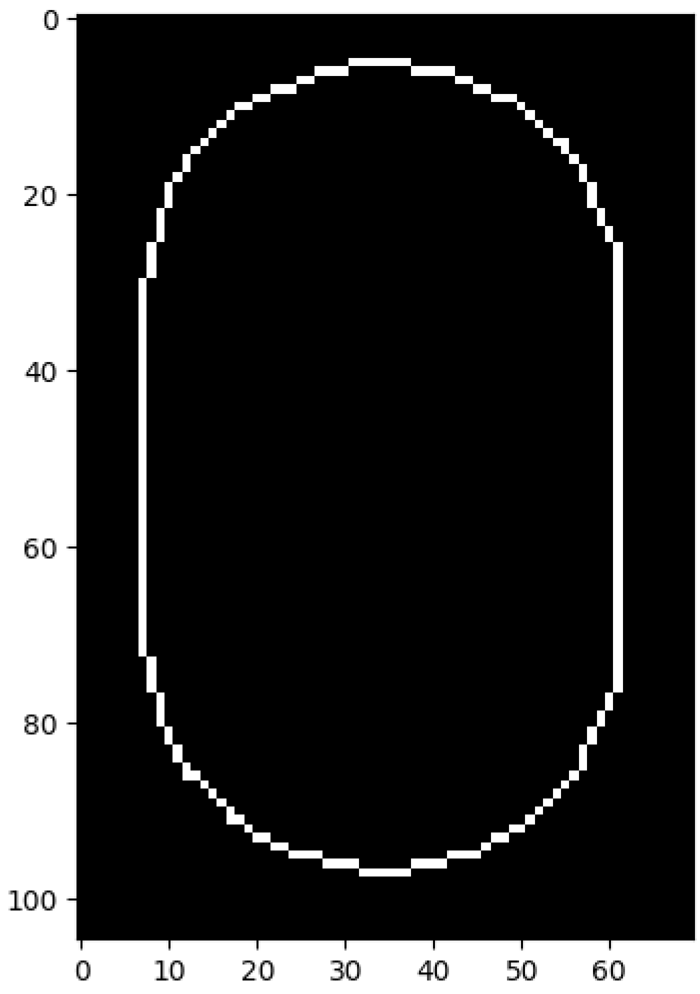
In this way, if the descriptions of the considered characters in this space don't appear close to each other, that means that they can be differentiated by relying on those features. **The problem appears if two or more characters have similar features** (their respective points are near). This tell us that **those features are just not enough** for automatically detect the plate characters.

Tip: intro to pyplot.

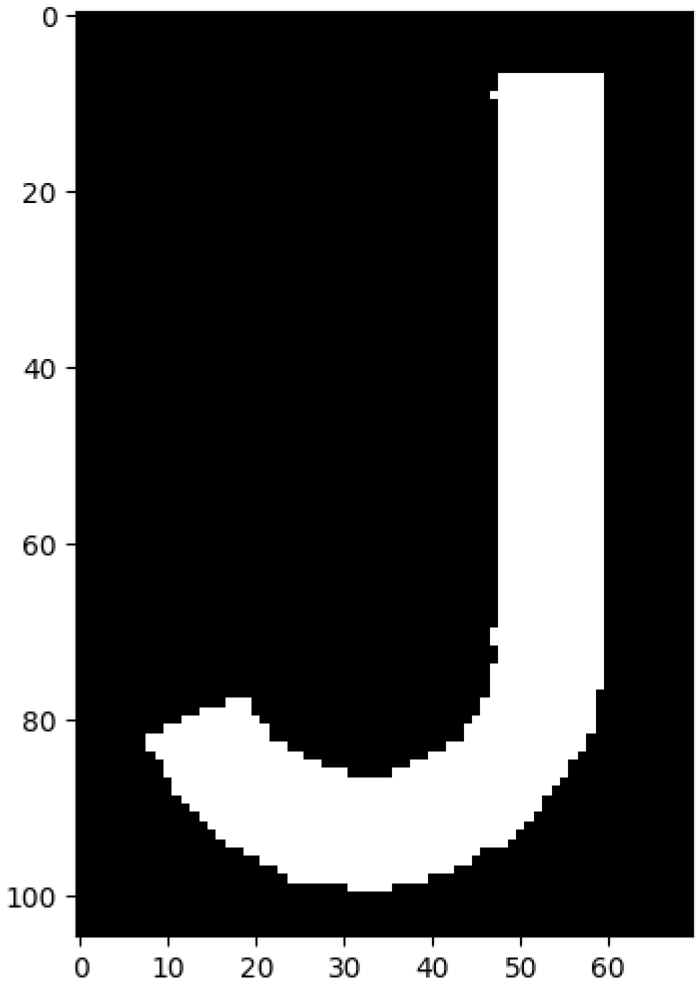
In [7]:
```python
# Assignment 3
matplotlib.rcParams['figure.figsize'] = (6.0, 6.0)

# Read the images
zero = cv2.imread(images_path + 'region_0.png',0)
J = cv2.imread(images_path + 'region_J.png',0)
B = cv2.imread(images_path + 'region_B.png',0)
six = cv2.imread(images_path + 'region_6.png',0)

# Build the feature vectors
x_zero = np.array([compactness(zero), extent(zero)])
x_J = np.array([compactness(J), extent(J)])
```

```
x_B = np.array([compactness(B), extent(B)])
x_six = np.array([compactness(six), extent(six)])

# Define the scatter plot
fig, ax = plt.subplots()
plt.axis([0, 1/(4*np.pi), 0, 1])
plt.xlabel("Compactness")
plt.ylabel("Extent")

# Plot the points
plt.plot(x_zero[0], x_zero[1], 'go')
plt.text(x_zero[0]+0.005,  x_zero[1]+0.05, '0', bbox={'facecolor': 'green', 'alp
plt.plot(x_J[0], x_J[1], 'ro')
plt.text(x_J[0]+0.005,  x_J[1]+0.05, 'J', bbox={'facecolor': 'red', 'alpha': 0.5
plt.plot(x_B[0], x_B[1], 'mo')
plt.text(x_B[0]+0.005,  x_B[1]+0.05, 'B', bbox={'facecolor': 'magenta', 'alpha':
plt.plot(x_six[0], x_six[1], 'bo')
plt.text(x_six[0]+0.005,  x_six[1]+0.05, '6', bbox={'facecolor': 'blue', 'alpha'
```





```
Area: 4307.0
Perimeter: 255.68123936653137
```



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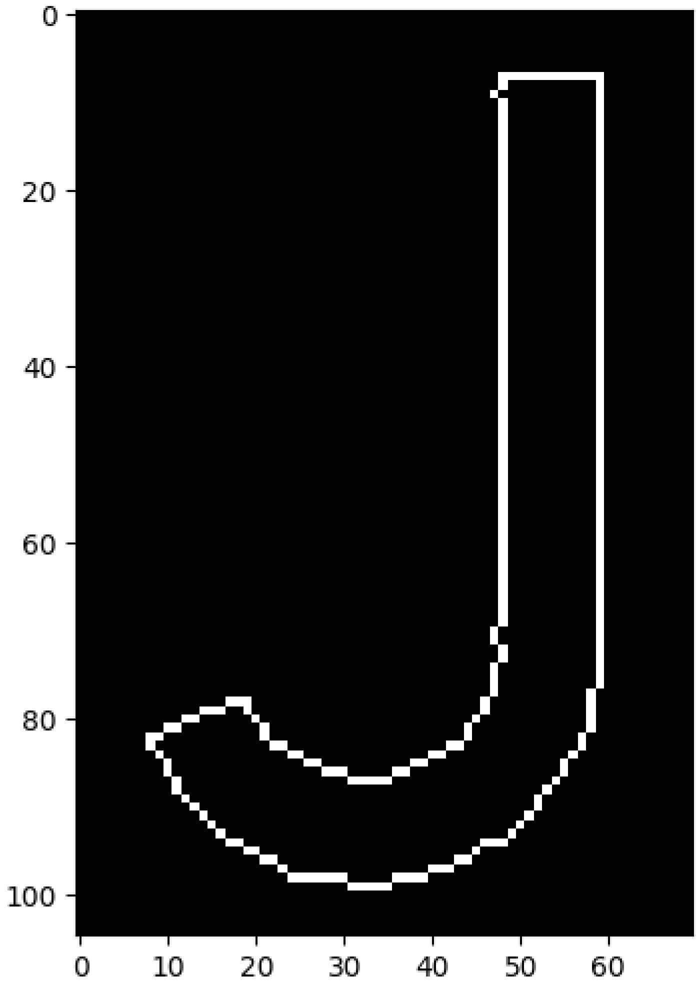
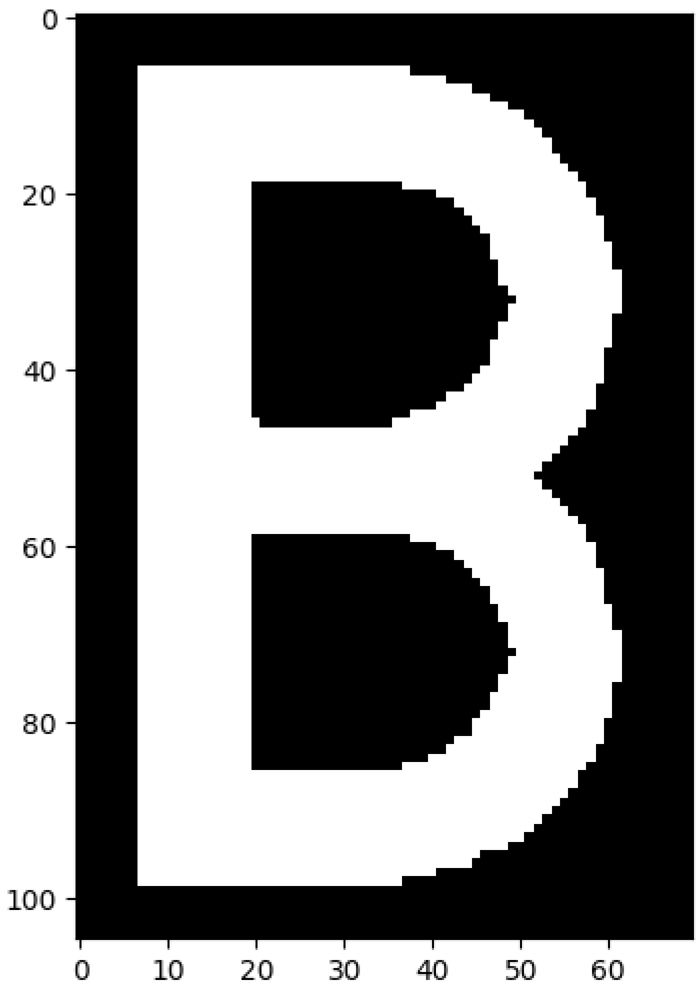
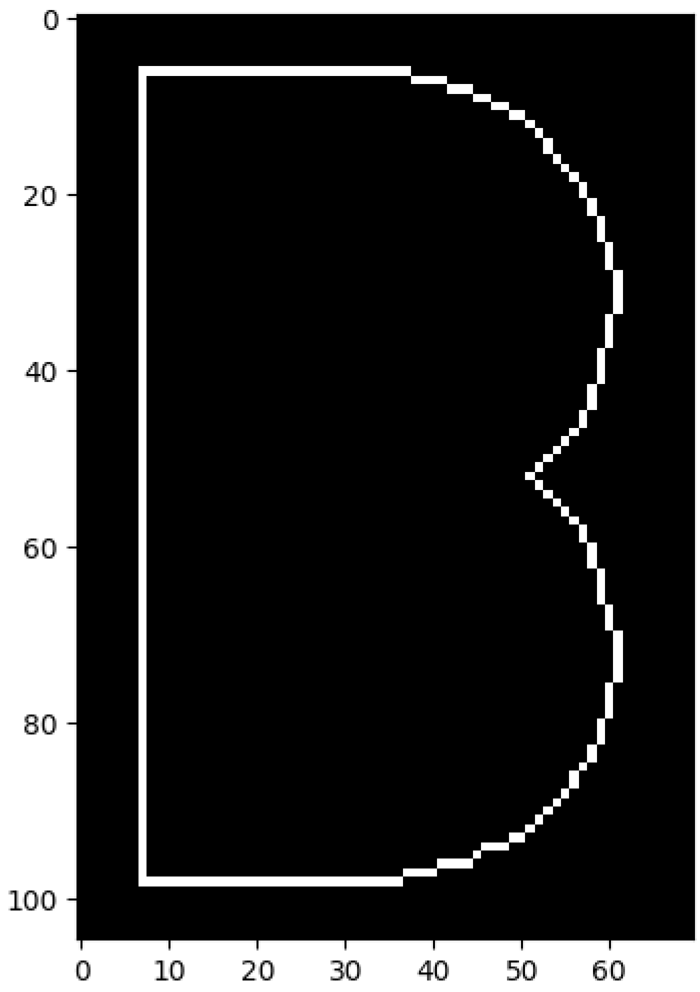


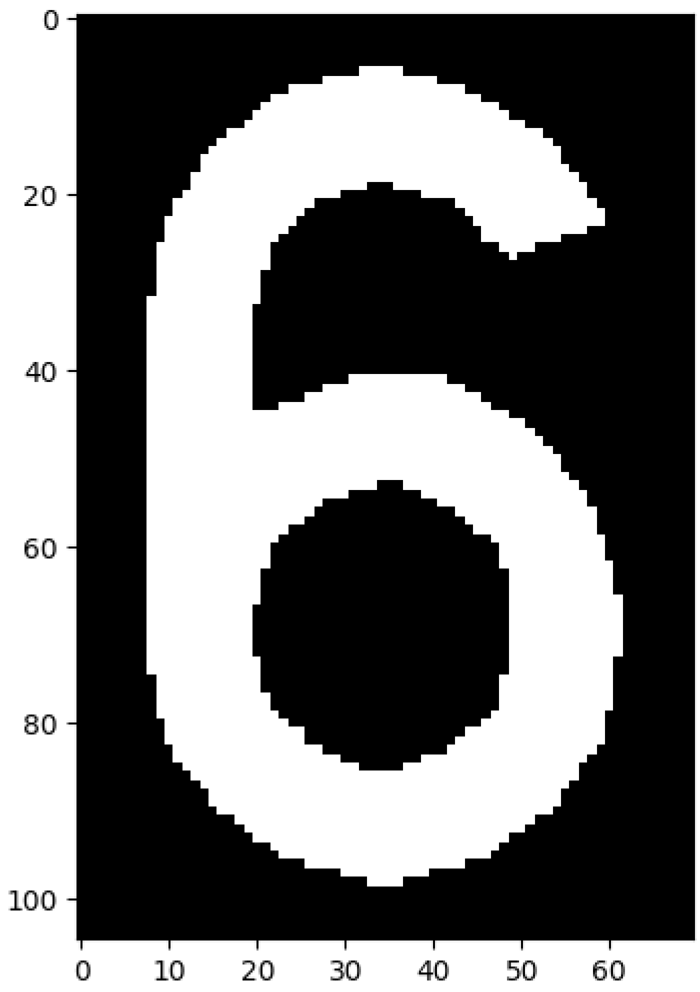
0
20
40
60
80
100
0
10
20
30
40
50
60

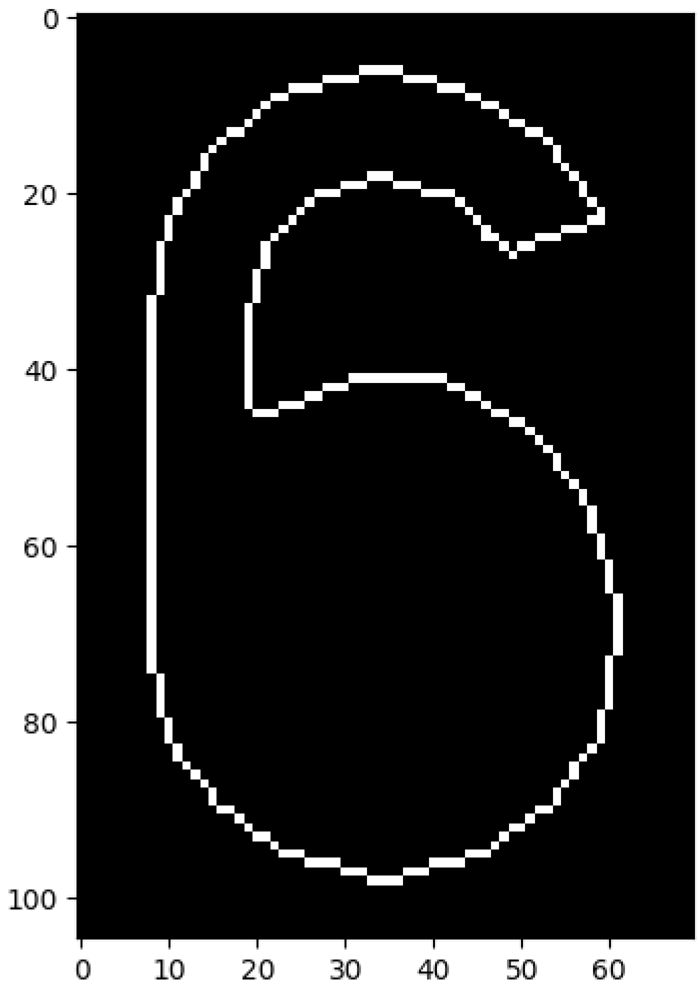
```
Area: 1386.0
Perimeter: 276.3675310611725
```





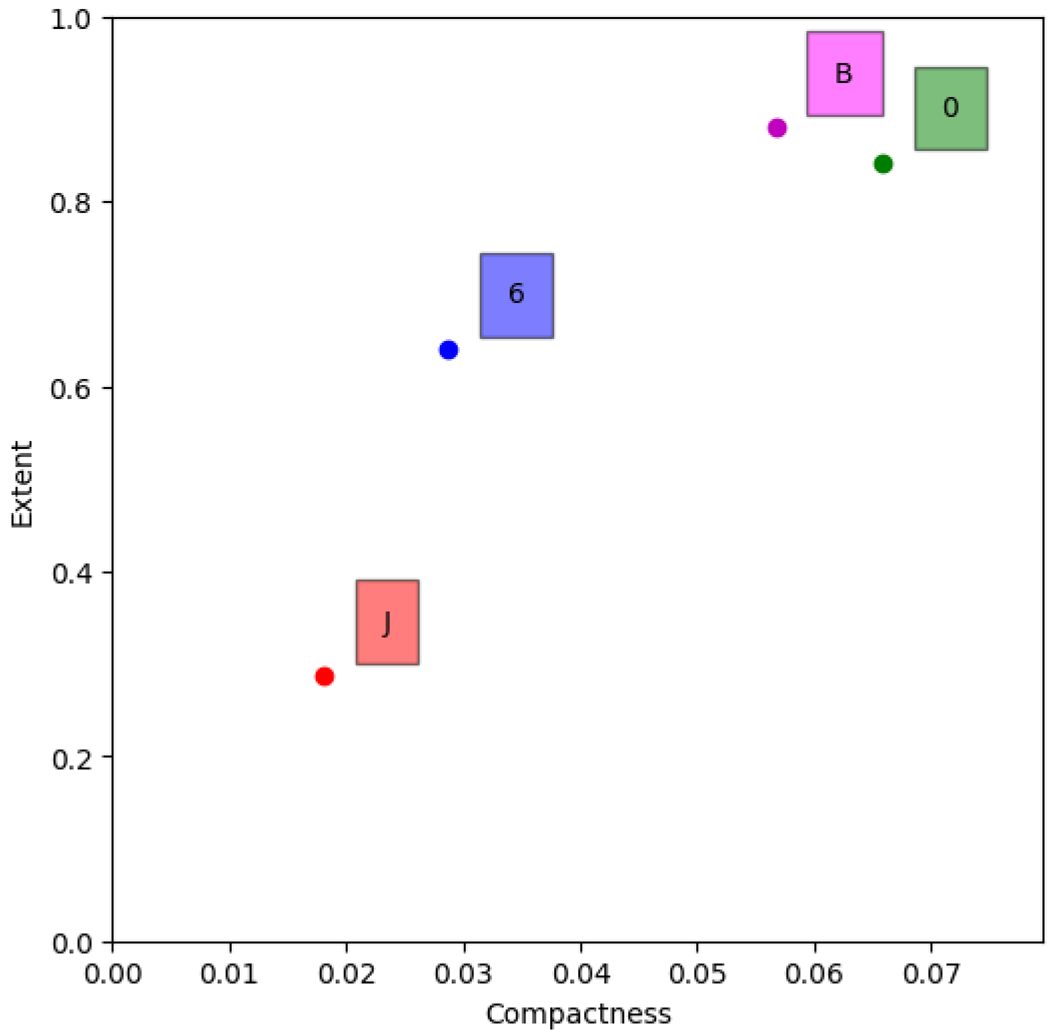
```
Area: 4498.0
Perimeter: 281.53910398483276
```


0
20
40
60
80
100
0
10
20
30
40
50
60


0
20
40
60
80
100
0
10
20
30
40
50
60

```
Area: 3217.5
Perimeter: 334.4924215078354
```

```
Out[7]:  Text(0.033757159783557804, 0.6906810035842295, '6')
```



Thinking about it (3)

What do you think?

- Are they discriminative enough?

  For 6 and J, it is discriminative enough. However, for B and 0 it is not. Both characters are too close to each other in the feature space to be able to differentiate if a character would be a B or a 0.

- If your answer is no, how could we handle this problem?

  We could add more shape descriptors to the feature vector. For instance, we could include metrics like aspect ratio, convexity, or solidity, which capture different aspects of the shape. Another approach would be to use invariant moments (Hu moments would be the way to go here), which can provide unique characteristics without relying on shape alone.

OPTIONAL

Surf the internet looking for **more shape features**, and try to find a pair of them working better than compactness and extent.

SOLIDITY

*- **Description**: ratio of an object's area to the area of its convex hull (the smallest convex shape that can contain the object).*
*- **Formula**:* $\text{Solidity} = \frac{\text{Object Area}}{\text{Convex Hull Area}}$
*- **Purpose**: It is useful for identifying shapes with **irregular contours or holes**. For instance, a shape with indentations or holes will have a lower solidity compared to a convex or hole-free shape.*
*- **Invariance**: Solidity is invariant to position, orientation, and scale.*

ASPECT RATIO

*- **Description**: proportion between the width and the height of the minimum bounding box that contains the shape.*
*- **Formula**:* $\text{Aspect Ratio} = \frac{\text{Bounding Box Width}}{\text{Bounding Box Height}}$
*- **Purpose**: It helps to differentiate elongated shapes from more compact or square-like shapes. This can assist in distinguishing between characters such as **B** and **0** if one is wider than the other.*
*- **Invariance**: Aspect Ratio is invariant to position and scale, but **not** to orientation.*

These two descriptors can provide additional discrimination compared to compactness and extent:
- Solidity helps in detecting shapes with irregular edges, holes, or concavities, which compactness alone does not distinguish.
- Aspect Ratio provides information about the elongation of the shape, which can be useful for distinguishing between similar shapes with different proportions.
This combination is beneficial in scenarios where compactness and extent are not sufficiently discriminative, such as in differentiating characters or shapes with more specific geometric configurations.

END OF OPTIONAL PART

OPTIONAL

Take an image of a car plate, apply the thechniques already studied in the course to improve its quality, and binarize it. Then, extract some shape features and check where the numbers/letters are projected in the feature space.

END OF OPTIONAL PART

Conclusion

Great work! You have learned about:

- what is the aim of region descriptors,
- the ideas behind two simple shape descriptors: compactness and extent, and
- to build a vector of features and analyze its discriminative power.

Unfortunately, it seems that those two features are not enough to differentiate the plate characters, so let's try more complex descriptors in the next notebook!

Extra work

Surf the internet looking for **more shape features**, and try to find a pair of them working better than compactness and extent.