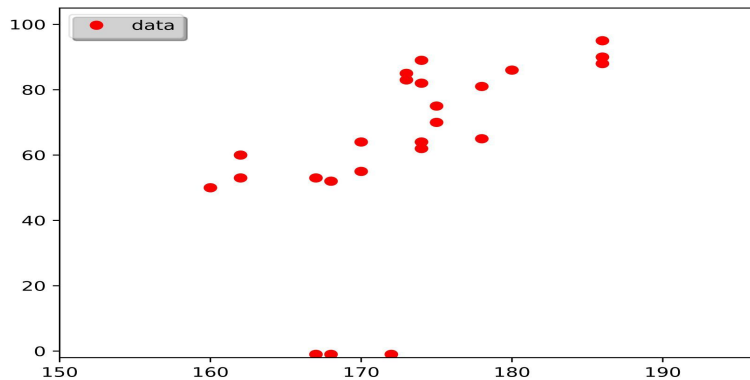


Pattern Recognition

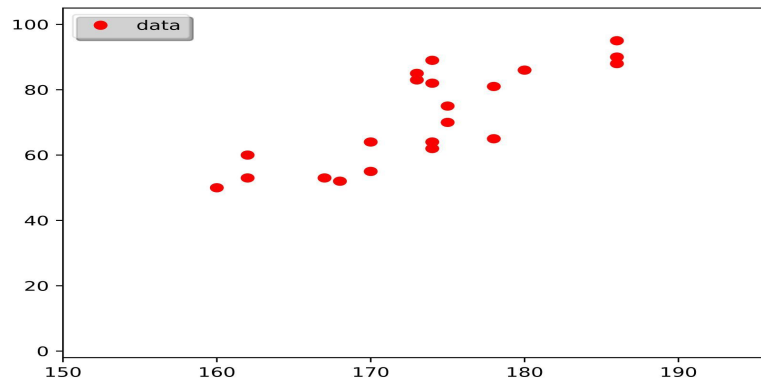
Project1

Warm-up

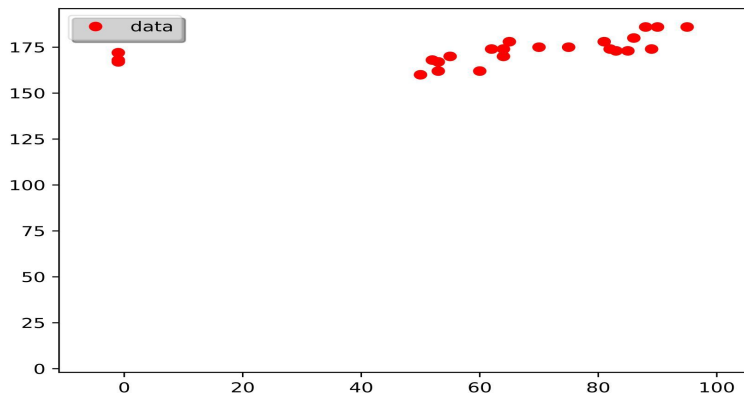
Task 1: Plots



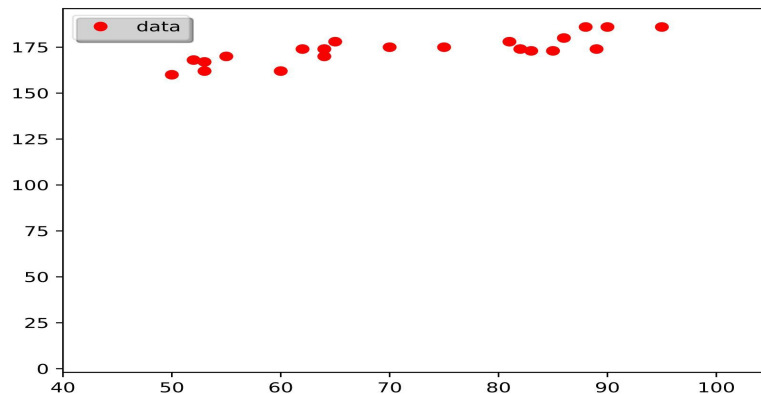
Plot height vs weight



Plot height vs weight(non-negative)

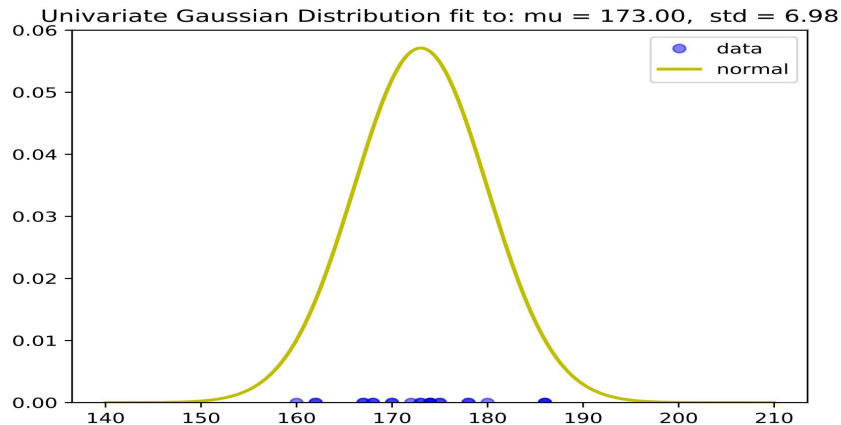


Plot weight vs height



Plot weight vs height(non-negative)

Task 2: Plot a Normal distribution



Mean: 173.00

Standard Deviation: 6.98

$$f(x \mid \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

Task 3: Fitting a Weibull Distribution

2 parameter Weibull distribution:

$$f(x|\kappa, \alpha) = \frac{\kappa}{\alpha} \left(\frac{x}{\alpha}\right)^{\kappa-1} e^{-\left(\frac{x}{\alpha}\right)^{\kappa}}$$

where κ and α are the shape and scale parameters respectively.

Task: Fit Weibull distribution to the interest in the word 'myspace' over time using Maximum Likelihood Estimate.

Log-likelihood of the Weibull Distribution (as given):

$$L(\alpha, \kappa | D) = N(\log \kappa - \kappa \log \alpha) + (\kappa - 1) \sum_i \log d_i - \sum_i (d_i/\alpha)^{\kappa}.$$

Task 3: Fitting a Weibull Distribution

Newton's formula for simultaneous equations:

$$\begin{bmatrix} \kappa^{\text{new}} \\ \alpha^{\text{new}} \end{bmatrix} = \begin{bmatrix} \kappa \\ \alpha \end{bmatrix} + \begin{bmatrix} \frac{\partial^2 L}{\partial \kappa^2} & \frac{\partial^2 L}{\partial \kappa \partial \alpha} \\ \frac{\partial^2 L}{\partial \kappa \partial \alpha} & \frac{\partial^2 L}{\partial \alpha^2} \end{bmatrix}^{-1} \begin{bmatrix} -\frac{\partial L}{\partial \kappa} \\ -\frac{\partial L}{\partial \alpha} \end{bmatrix}$$

D : Set of N data samples

Components of partial derivatives with D

$$\sum_{i=1}^N \log(d_i)$$

$$\sum_{i=1}^N \left(\frac{d_i}{\alpha}\right)^{\kappa} \log\left(\frac{d_i}{\alpha}\right)$$

$$\sum_{i=1}^N \left(\frac{d_i}{\alpha}\right)^{\kappa}$$

$$\sum_{i=1}^N \left(\frac{d_i}{\alpha}\right)^{\kappa} \left(\log\left(\frac{d_i}{\alpha}\right)\right)^2$$

Task 3: Fitting a Weibull Distribution

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Task: Fit to h instead of D

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Task 3: Fitting a Weibull Distribution

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Components of partial derivatives with D

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Task: Fit to h instead of D

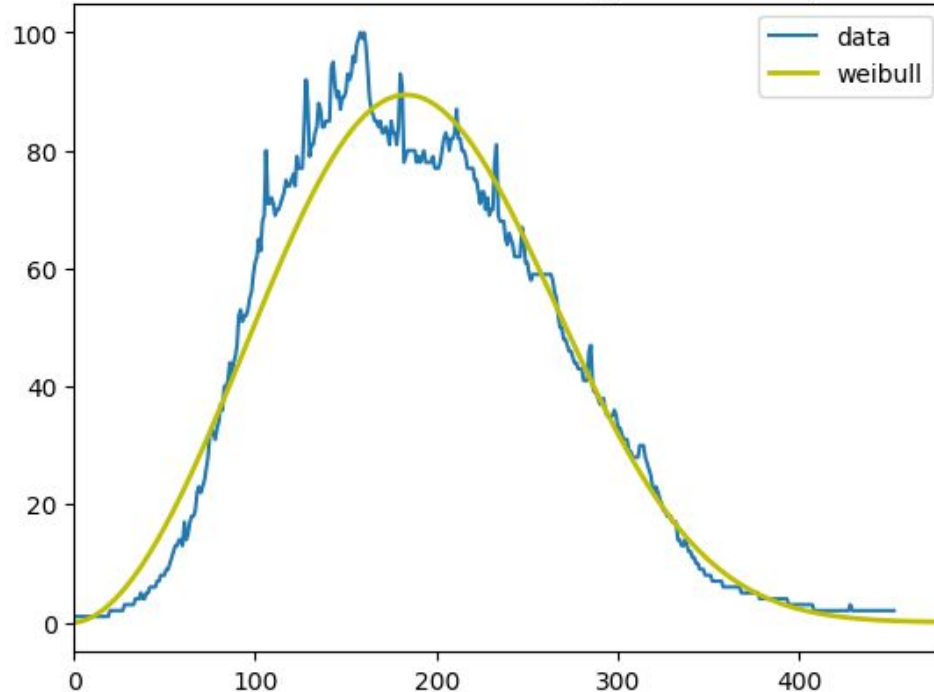
h : Set of n entries in histogram of D

Components of partial derivatives with h

$$\begin{aligned} & \sum_{i=1}^n h_i \log(i) \\ & \sum_{i=1}^n h_i \left(\frac{i}{\alpha}\right)^{\kappa} \log\left(\frac{i}{\alpha}\right) \\ & \sum_{i=1}^n h_i \left(\frac{i}{\alpha}\right)^{\kappa} \\ & \sum_{i=1}^n h_i \left(\frac{i}{\alpha}\right)^{\kappa} \left(\log\left(\frac{i}{\alpha}\right)\right)^2 \end{aligned}$$

Task 3: Fitting a Weibull Distribution

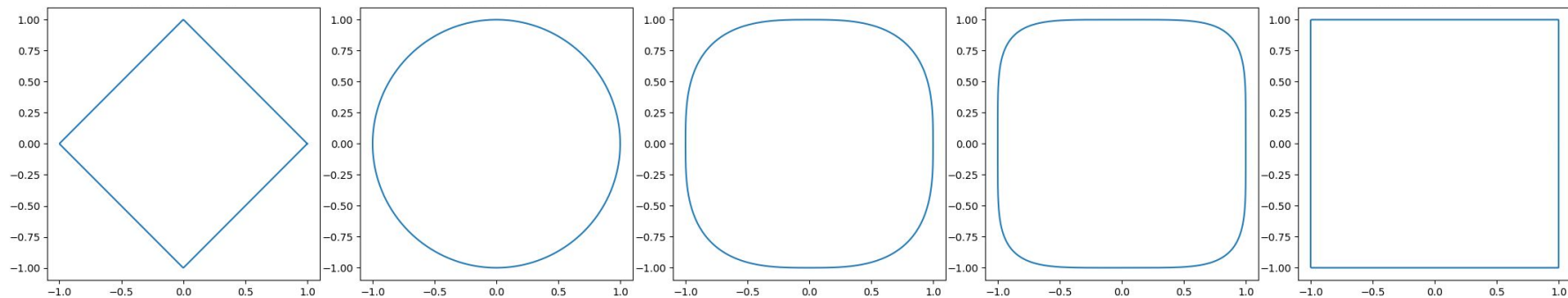
Univariate Weibull Distribution fit to: $\kappa = 2.80$, $\alpha = 214.47$



Interpretation:

1. κ equal to 2 indicates linear growth in interest while that between 3 and 4 indicates a symmetric distribution. 2.8 might mean a faster rate in growth of interest and a slower fall.
2. $\alpha = 214.47$ indicates that 63.2% of the data (time instances from start) has falls within 214.47 time instances.

Task 4: p-Norm



$p = 1$

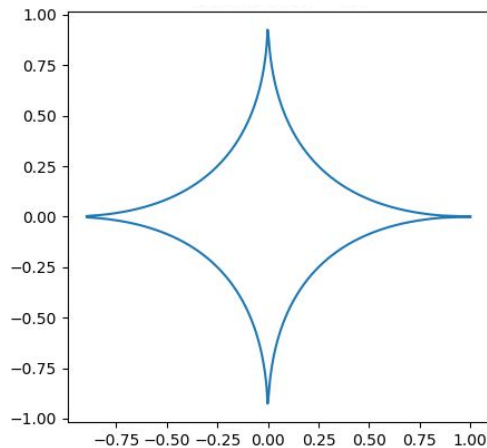
$p = 2$

$p = 3$

$p = 5$

$p = \infty$

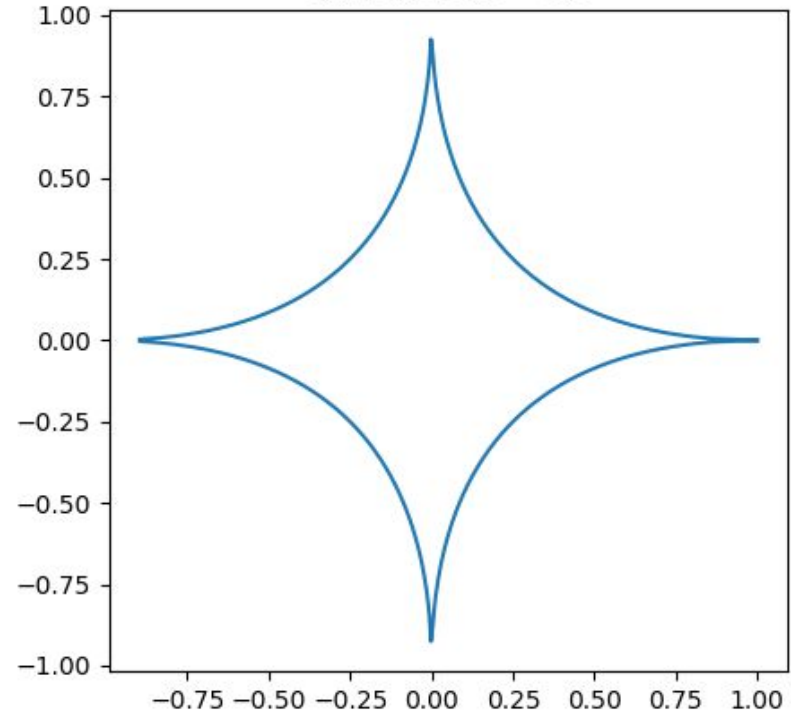
$$\|x\|_p := \left(\sum_{i=1}^n |x_i|^p \right)^{\frac{1}{p}}$$



$p = 1/2$

Task 4: Is it actually norm with $p = 1/2$?

1. $d(\mathbf{x}, \mathbf{y}) \geq 0 \wedge d(\mathbf{x}, \mathbf{y}) = 0 \Leftrightarrow \mathbf{x} = \mathbf{y}$
2. $d(\mathbf{x}, \mathbf{y}) = d(\mathbf{y}, \mathbf{x})$
3. $d(\mathbf{x}, \mathbf{z}) \leq d(\mathbf{x}, \mathbf{y}) + d(\mathbf{y}, \mathbf{z})$

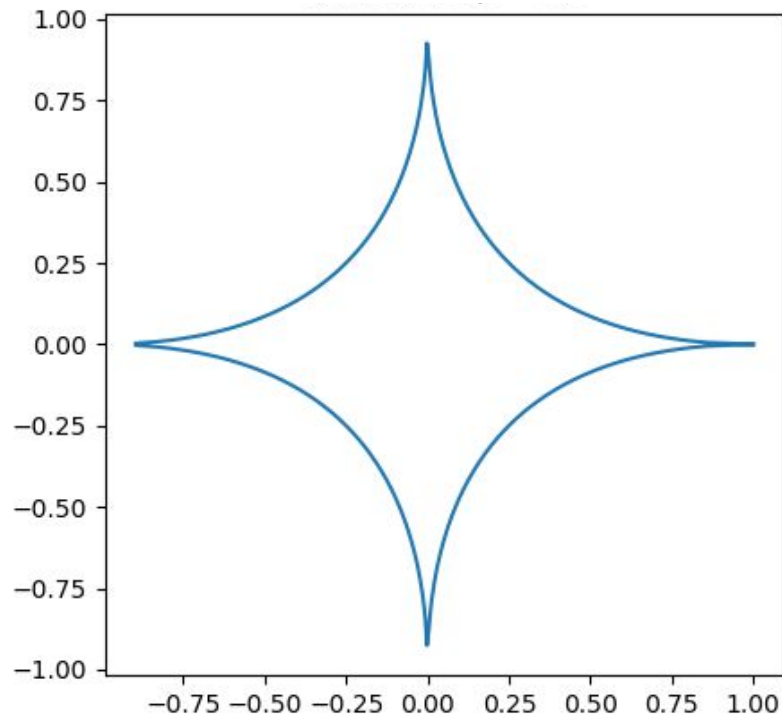


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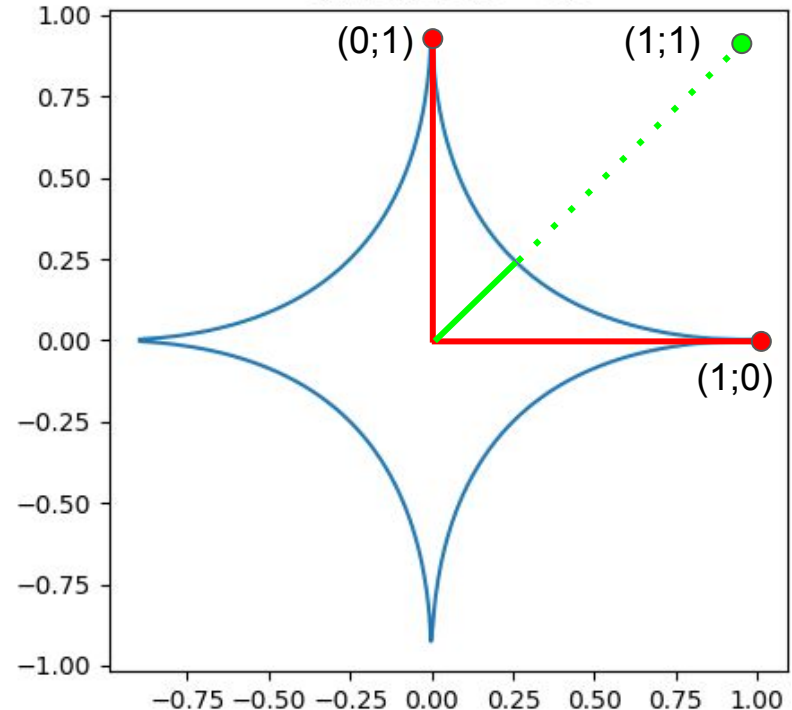


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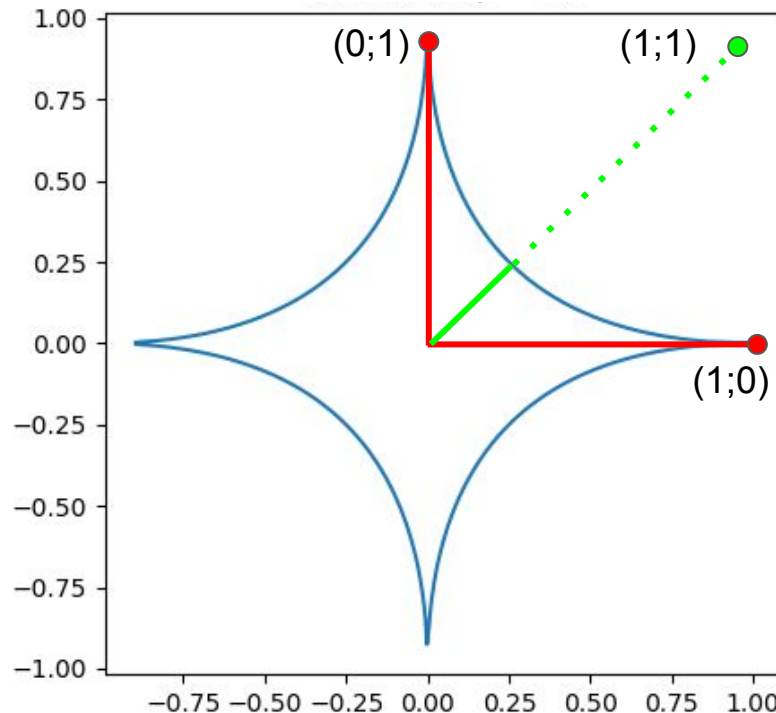
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$$\|(1; 1)\| \leq \|(1; 0) + (0; 1)\|$$

$$\|(1; 1)\| = 2^{1/p} = 4$$

$$\|(1; 0)\| = \|(0; 1)\| = 1$$



Is it actually norm with $p = 1/2$?

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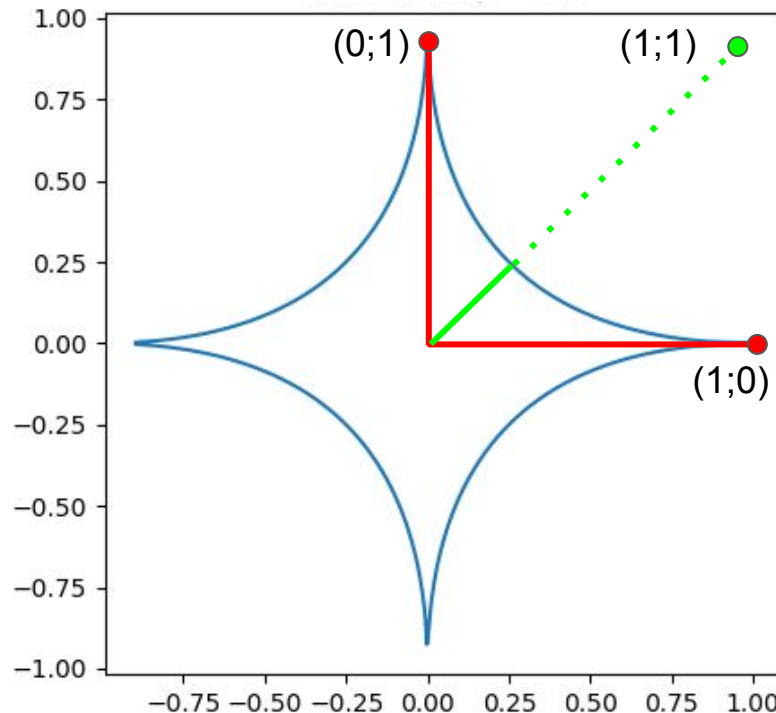
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$\|(1; 1)\| \not\leq \|(1; 0)\| + \|(0; 1)\|$

$$\|(1; 1)\| = 2^{1/p} = 4$$

$$\|(1; 0)\| = \|(0; 1)\| = 1$$



Task 5: How to identify the “foreground”

-Apply two Gaussian filters with different variance on a picture and subtract the results from each other.



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- Apply two Gaussian filters with different variance on a picture and subtract the results from each other.
- Discretize the result



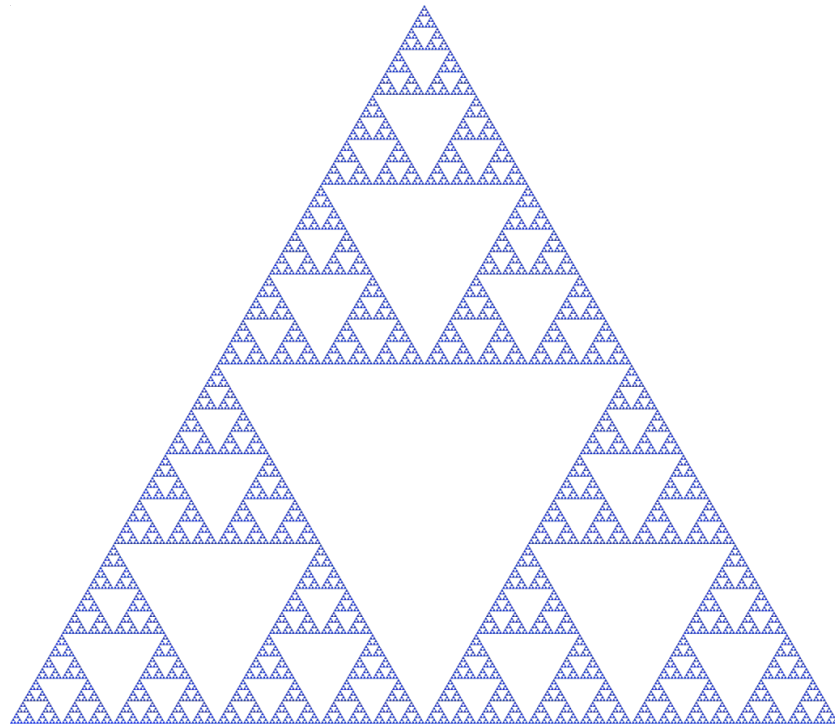
Task 5: How to identify the “foreground”

- Apply two Gaussian filters with different variance on a picture and subtract the results from each other.
- Discretize the result
- Use the closing operator to fill small holes in the result.



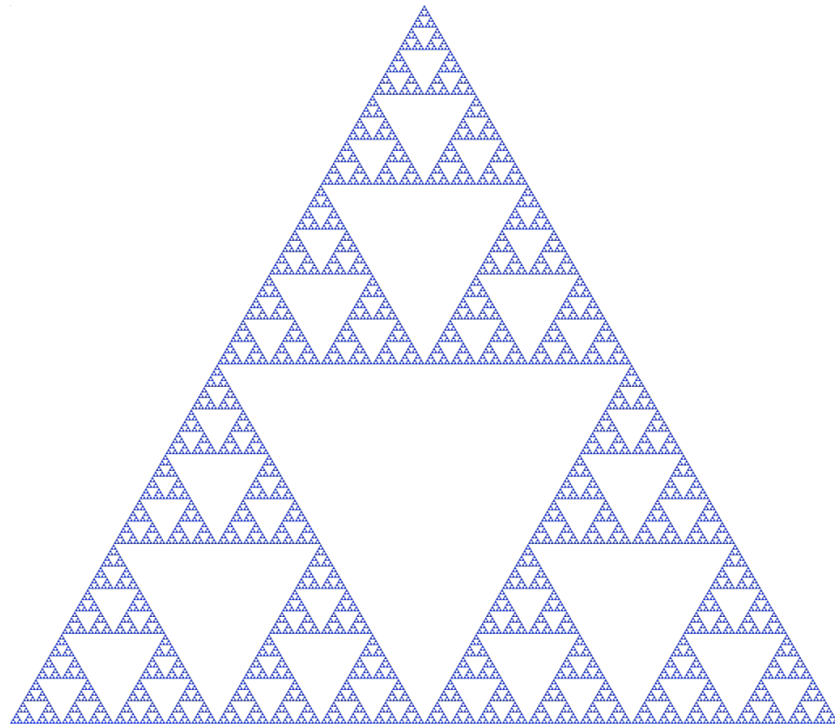
Task 5: The fractal dimension

- Idea to determine the dimension of fractals, like the Sierpiński Triangle



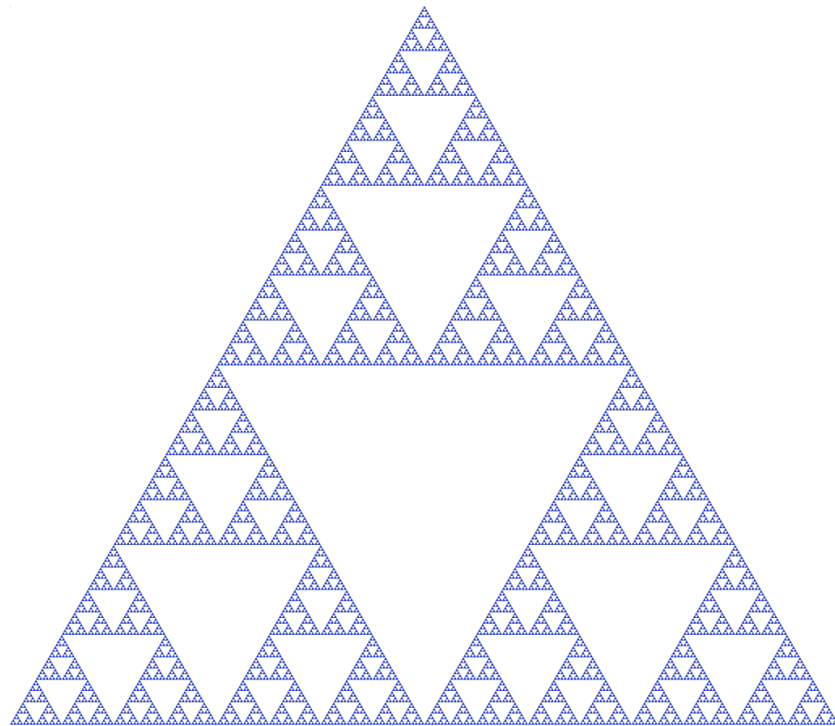
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- Can also be applied to define the dimension of objects in a picture.



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- Idea to determine the dimension of fractals, like the Sierpiński Triangle
- Can also be applied to define the dimension of objects in a picture.
 - via box counting



Task 5: Results



Fractal Dimension: 1.590



Fractal Dimension: 1.867