1 November 2020
Fundamentals of Computer Vision

Assignment 2 260807622

1. **Gaussian Scale Space**
For the image and gaussian scale space, we use doublings scale starting at $\sigma_0 = 1$ up to $\sigma = 16$. We divide each doubling of scale into four steps that are equal on a log scale. This results in the following scales:

$$\sigma = 2, 2^{\frac{1}{4}}, ..., 2^{3/4}, 2, 4^{1/4}, ..., 16 \tag{1}$$

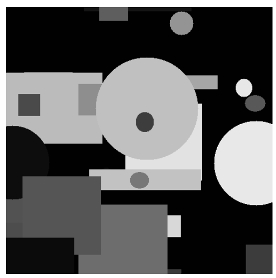


Figure 1: Synthetic image

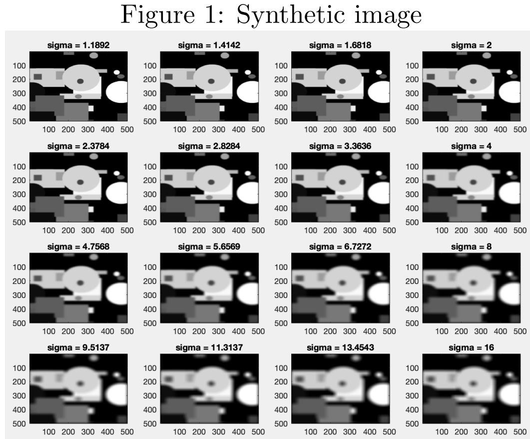


Figure 2: Gaussian Scale Space

2. **Harris-Stevens**
We applied the Harris Stevens operator to each level of the gaussian scale space. For lower scales, it appears that the operator detected edges more than it detected locally distinctive points. It go better at detecting such points for intermediate scales, where we can see clear high responses at corners. Finally, as we got the the large scales, the operator seemed to still highlight the locally distinctive points found in the intermediate scales, but this time it pinpointed them less accurately, as large blobs of high responses.

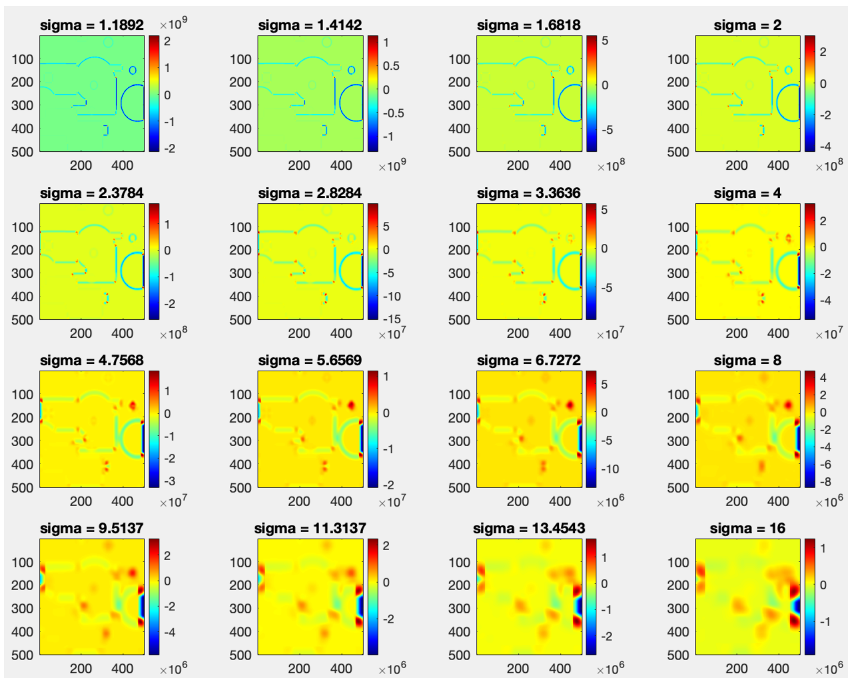


Figure 3: Harris-Stevens response

3. **Difference of Gaussians** In the below figure, we see that the zero crossing get thicker and more acute, easier to see, as we increase in scale.

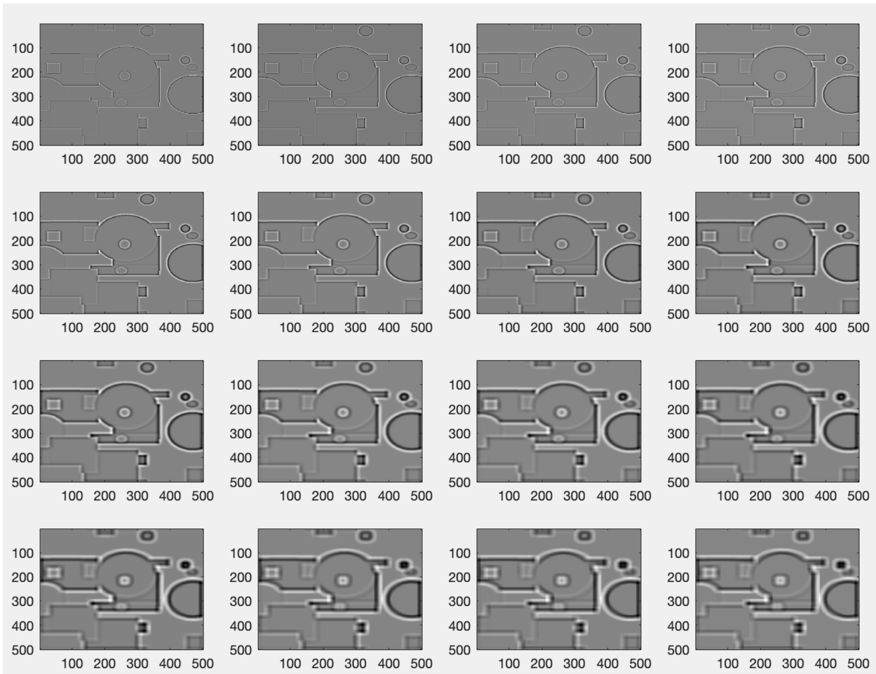


Figure 4: Difference of Gaussians scale space

4. **SIFT Keypoint Detection** We see that the algorithm implemented does detect most keypoints, although it also detects a lot of edges. We can distinguish the scale of the red circle which correspond to a keypoint being detected from a larger scale DoG.

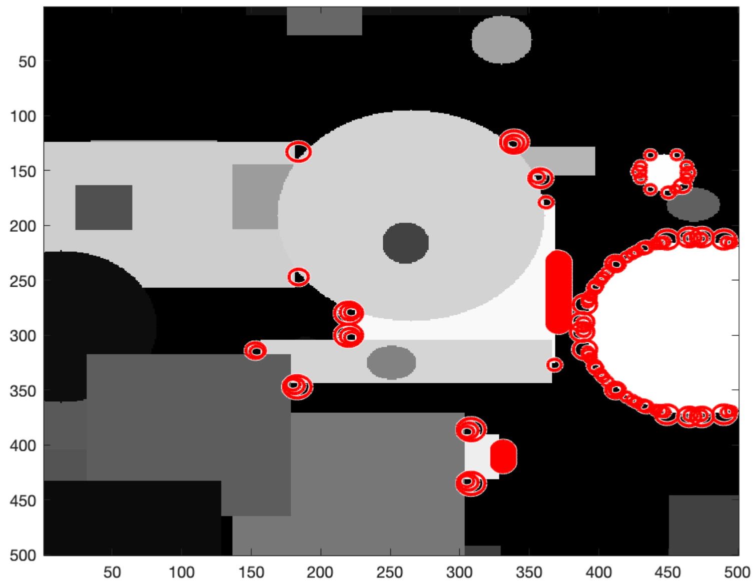


Figure 5: Brute force through DoG scale space for SIFT keypoints

5. **Hessian Constraint** We see that using the Hessian constraint, the keypoints found (in blue) are more accurate and show less edges detected, i.e., more corners than edges. An apparent problem, however, is the many sift keypoints found along the boundary of circles.

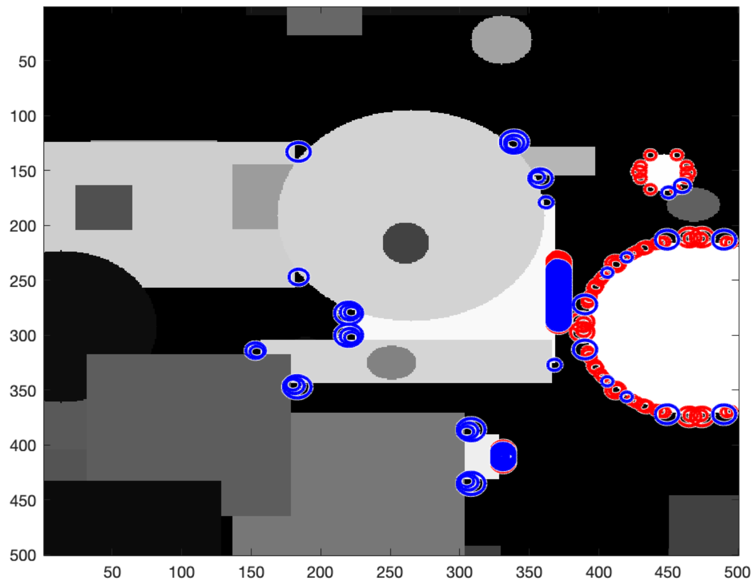


Figure 6: Keypoints under Lowe's condition (in blue)

6. **SIFT Feature Dominant Orientation** If we disregard the large density of horizontal edges near the edge on the right and those corresponding to circle boundary keypoints, and thus concentrate on keypoints located on actual corners, we see that while a few keypoints show a dominant orientation which correspond to the dominant gradient direction, some of them show dominant gradient direction that seem mis-oriented. Also note that most keypoints have multiple dominant orientations, as we've kept orientation bins which had a count larger than 80% of the dominant orientation bin count.

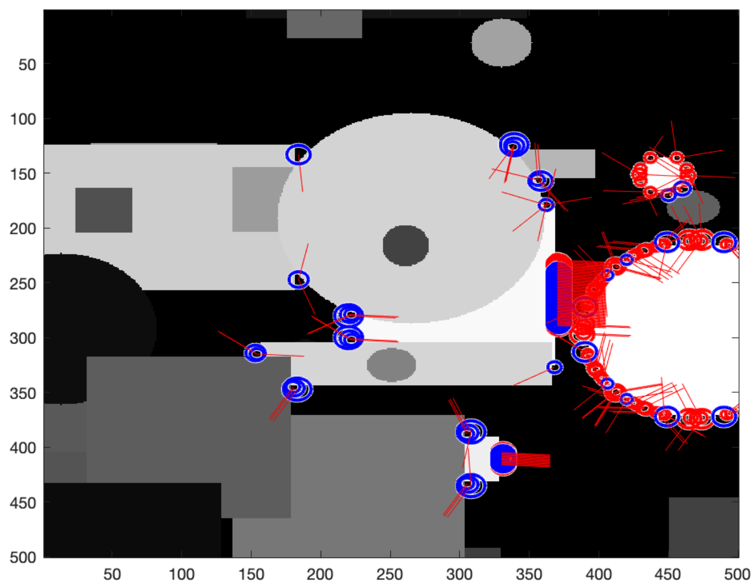


Figure 7: SIFT orientation assignment

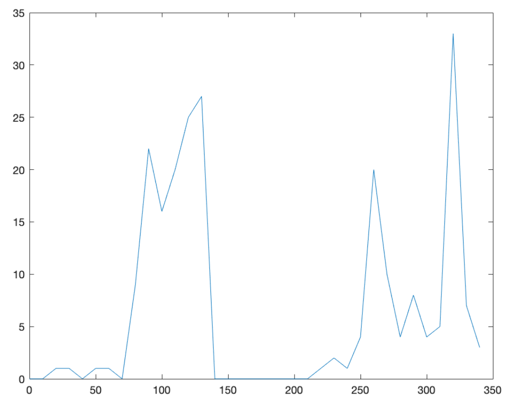


Figure 8: Orientation Histogram for keypoint at (126, 338)

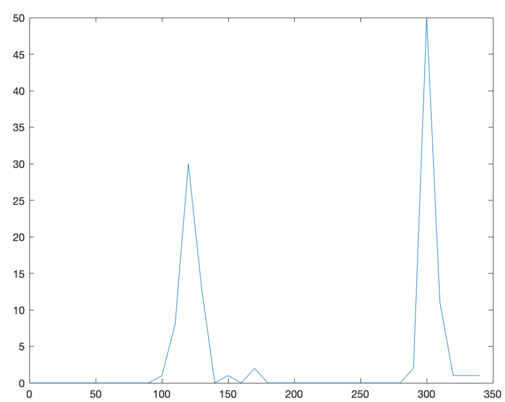


Figure 9: Orientation Histogram for keypoint at (361, 427)

7. **Scale Invariance** With the image resized with factor 0.6, we see that most of the keypoints which were not edge points are scale invariant. We will also note that while vertical/horizontal edge keypoints appear to have been detected less than in the original image, there is a large amount of keypoints that were detected around the circle boundary on the right.

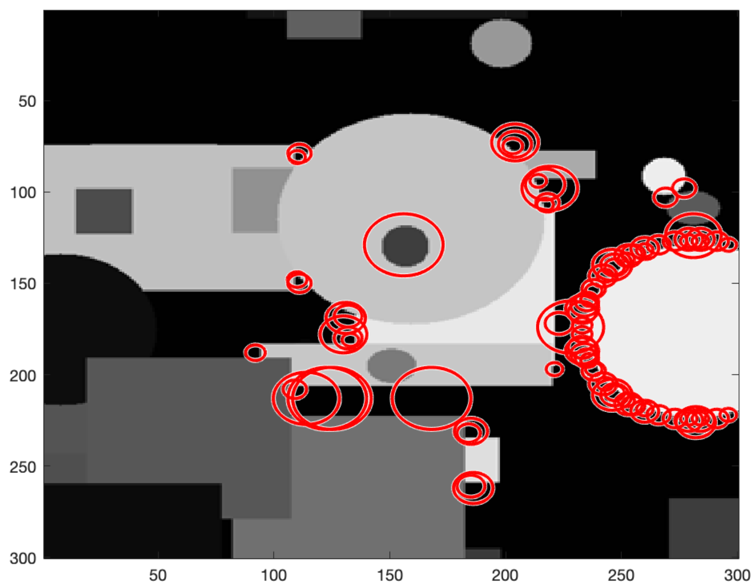


Figure 10: SIFT keypoints for image resized by 0.6

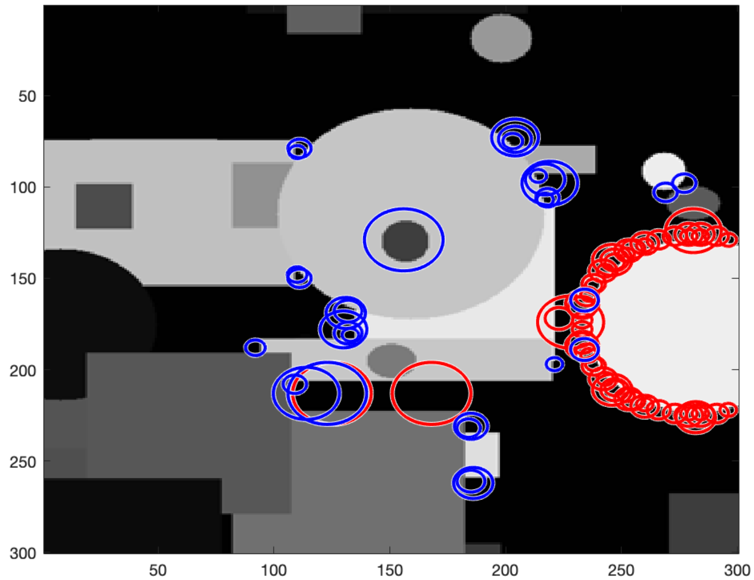


Figure 11: SIFT keypoints with Hessian correction for image resized by 0.6

8. Non-synthetic image results: Bobby Fischer

Figure 12: Chess legend Bobby Fisher

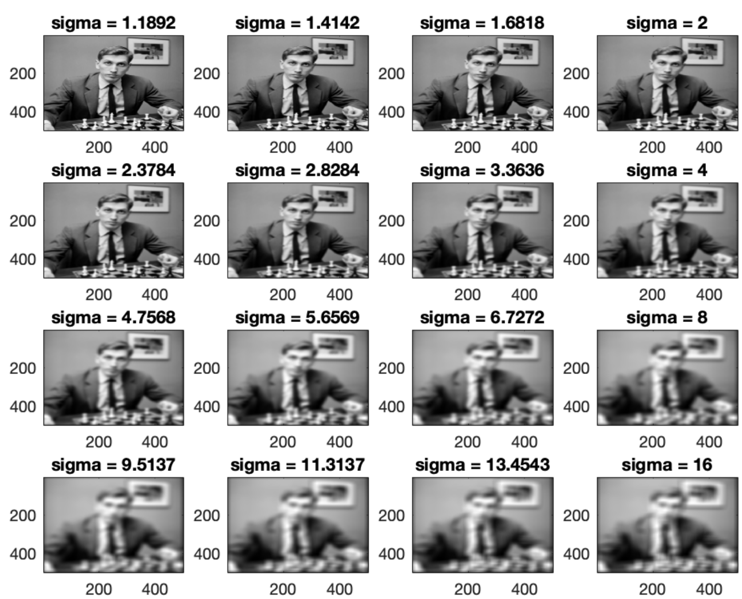


Figure 13: Bobby Fischer Gaussian Scale Space

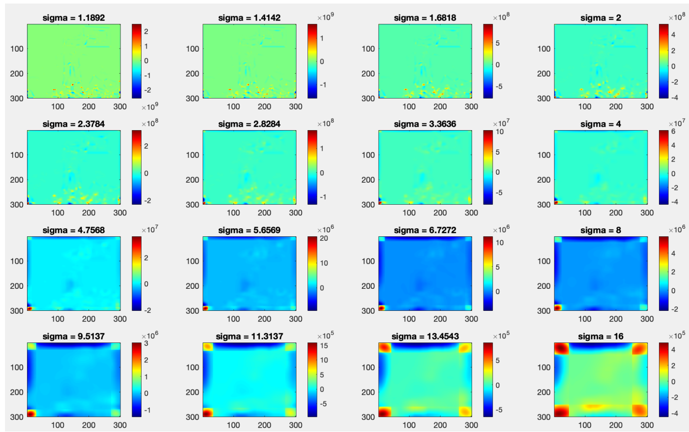


Figure 14: Harris Stevens response

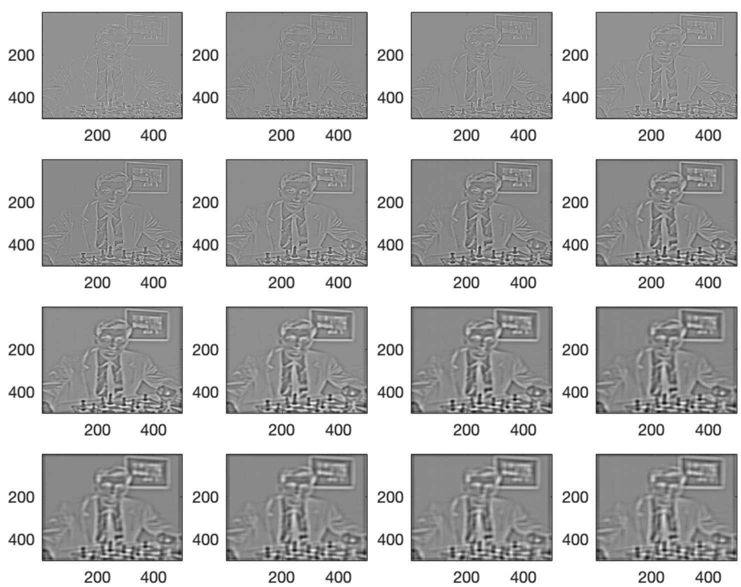
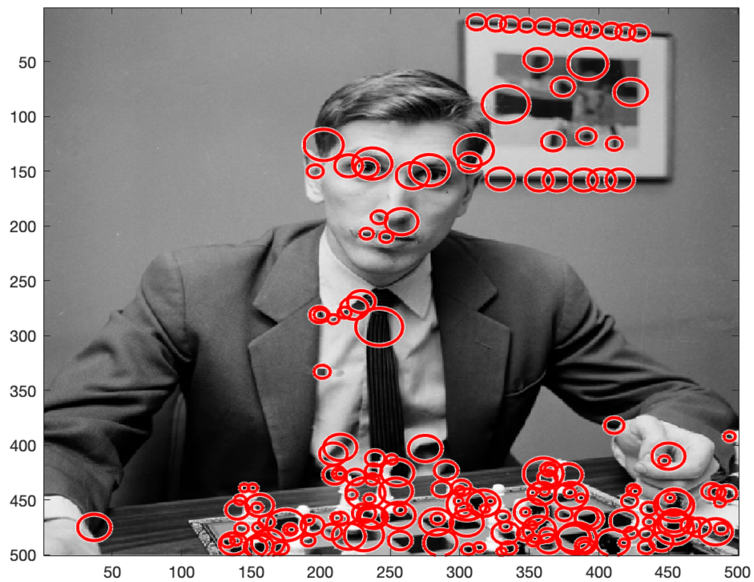


Figure 15: Difference of Gaussians Scale Space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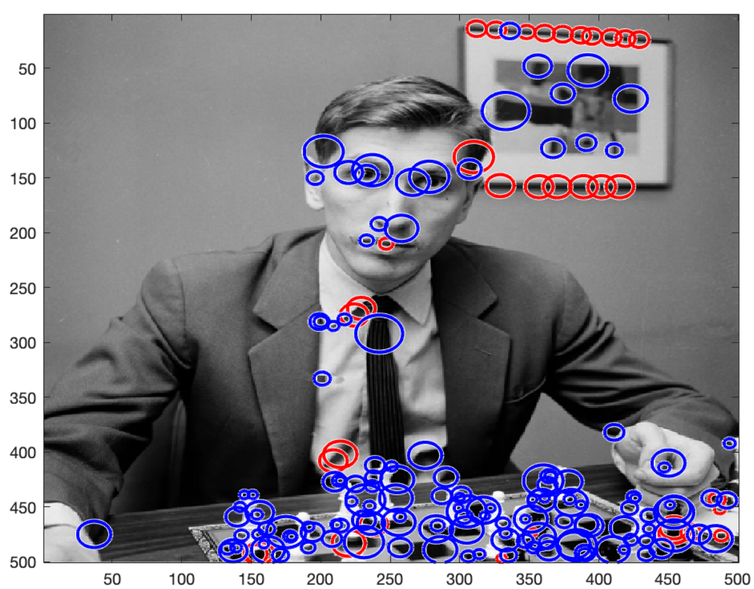
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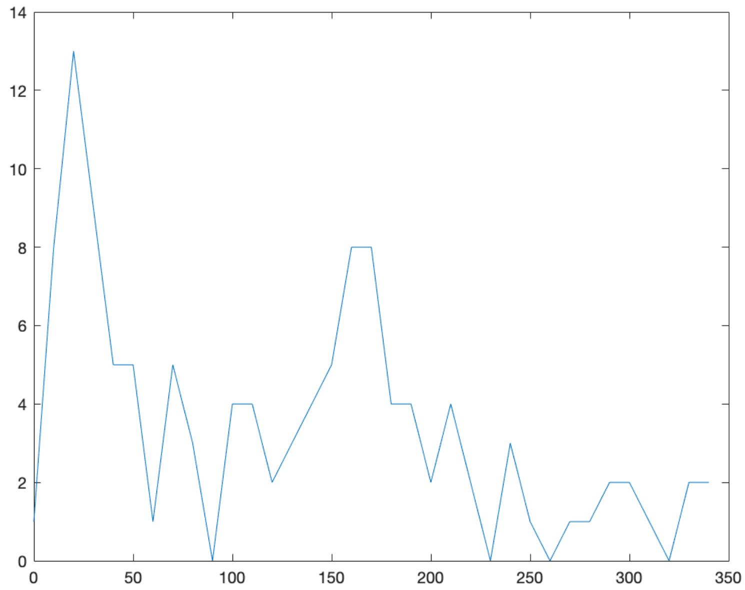
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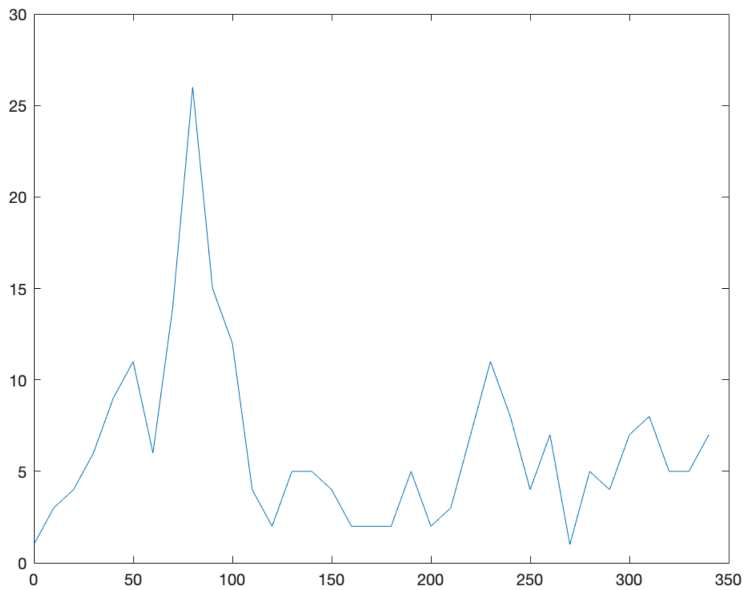
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