Problem Set I

- 1. (20%) Prove the properties of convolution. For all continuous function f, g, and h, the following axioms hold. Please make sure to lay out all key steps of your proof for full credits.
 - Associativity: (f * g) * h = f * (g * h)
 - Distributivity: f * (g + h) = f * g + f * h
 - Differentiation rule: (f * g)' = f' * g = f * g'
 - Convolution theorem: $\mathcal{F}(g * h) = \mathcal{F}(g)\mathcal{F}(h)$, where \mathcal{F} denotes Fourier transform
- 2. (25%) Frequency smoothing:
 - (a) Compute Fourier transform of the given image lenaNoise.PNG by using numpy.fft.fft2 in Python, and then center the low frequencies (e.g., by using fftshift).
 - (b) Keep different number of low frequencies (e.g., 7^2 , 15^2 , 31^2 and the full dimension), but set all other high frequencies to 0.
 - (c) Reconstruct the original image (ifft2) by using the new generated frequencies in step (b).

Submit the code and include the restored images with different number of low frequencies in your report.

- 3. (55%) Implement gradient descent algorithm for image denoising with total variation model explained in class. All codes and a two-page report including problem description, a concrete optimization objective function, and experimental results (a denoised image and a convergence graph that generated by your best-tuned parameters) with discussions should be submitted.
 - With the given image Einstein.jpeg, generate different noisy images with additive Gaussian noises at different variance ($\sigma = 0.001, 0.01, 0.1$).
 - Test your denoising program on the generated noisy images.
 - The forward / backward difference for computing image gradient is given in Dx / Dxt. Feel free to use it, or use the python function provided by scipy.ndimage.
 - The convergence graph is a plot of your objective function $E(u^k)$ along with all iterations.
 - A detailed class note of deriving total variation, computing gradient term, and gradient descent algorithm can be downloaded from Canvas.