Technical Report

Google Collab link:
https://colab.research.google.com/drive/1Gh6WriW9uZa0tpjCWZKPRrp7gBdgeZpw#scrollTo=O8kA_cRX0Q3n

Resources Referred:	URL
Tutorial for pytorch - Conducted by our Professors	
Reference for Gaussian Noise	https://discuss.pytorch.org/t/how-to-add-noise-to-mnist-dataset-when-using-pytorch/59745
#Auto Encoder creation. : Tutorial lectures.(Conducted by our professors)	
#Setting optimiser	https://pytorch.org/docs/stable/generated/torch.optim.Adam.html
Python related reference	https://realpython.com/python-zip-function/
Pixel Masking	https://stackoverflow.com/questions/68929785/how-to-apply-mask-to-image-tensors-in-pytorch

Database	Source
MNIST	PyTorch LIB
FashionMNIST	PyTorch LIB
VOCDetection	PyTorch LIB

Hyperparameter

Naming : 256-Autoencoder : (bottleneck dimension(256))

Noise/Masking	Model	NO of epochs	Learning rate	weight_decay	Optimiser	loss funtion	Dimensions
Noise	256-Autoencoder	15	1e-3	1e-5	Adam	MSELoss	256
Noise	128-Autoencoder	15	1e-3	1e-5	Adam	MSELoss	128
Noise	64-Autoencoder	15	1e-3	1e-5	Adam	MSELoss	64
Noise	32-Autoencoder	15	1e-3	1e-5	Adam	MSELoss	32
Noise	16-Autoencoder	15	1e-3	1e-5	Adam	MSELoss	16
Masking	20%-Masked-Data	15	1e-3	1e-5	Adam	MSELoss	256
Masking	40%-Masked-Data	15	1e-3	1e-5	Adam	MSELoss	256
Masking	60%-Masked-Data	15	1e-3	1e-5	Adam	MSELoss	256
Masking	80%-Masked-Data	15	1e-3	1e-5	Adam	MSELoss	256

Choice of best

Model	NO of epochs	Learning rate	weight_decay	Optimiser	loss funtion	Dimensions
256-Autoencoder	15	1e-3	1e-5	Adam	MSELoss	256

Reason for selecting 256-Autoencoder:

Minimum loss is seen across multiple loss is minimised maximum.

Refer to table:

Model	Epoch vs Loss
256-Autoencoder	Epoch:1, Loss:0.2390 Epoch:2, Loss:0.2055 Epoch:3, Loss:0.1874 Epoch:4, Loss:0.1644 Epoch:5, Loss:0.1608 Epoch:6, Loss:0.1711 Epoch:7, Loss:0.1541 Epoch:8, Loss:0.1565 Epoch:9, Loss:0.1632 Epoch:10, Loss:0.1582 Epoch:11, Loss:0.1514 Epoch:12, Loss:0.1564 Epoch:13, Loss:0.1549 Epoch:14, Loss:0.1728 Epoch:15, Loss:0.1556
128-Autoencoder	Epoch:1, Loss:0.2346 Epoch:2, Loss:0.2118 Epoch:3, Loss:0.2056 Epoch:4, Loss:0.1997 Epoch:5, Loss:0.1818 Epoch:6, Loss:0.1836 Epoch:7, Loss:0.1782 Epoch:8, Loss:0.1775 Epoch:9, Loss:0.1737 Epoch:10, Loss:0.1757 Epoch:11, Loss:0.1711 Epoch:12, Loss:0.1732 Epoch:13, Loss:0.1651 Epoch:14, Loss:0.1712 Epoch:15, Loss:0.1701

64-Autoencoder	Epoch:1, Loss:0.2493 Epoch:2, Loss:0.2305 Epoch:3, Loss:0.2132 Epoch:4, Loss:0.2026 Epoch:5, Loss:0.2013 Epoch:6, Loss:0.1896 Epoch:7, Loss:0.1892 Epoch:8, Loss:0.1903 Epoch:9, Loss:0.1917 Epoch:10, Loss:0.1867 Epoch:11, Loss:0.1866 Epoch:12, Loss:0.1834 Epoch:13, Loss:0.1890 Epoch:14, Loss:0.1878 Epoch:15, Loss:0.1791
32-Autoencoder	Epoch:1, Loss:0.2541 Epoch:2, Loss:0.2451 Epoch:3, Loss:0.2368 Epoch:4, Loss:0.2233 Epoch:5, Loss:0.2182 Epoch:6, Loss:0.2260 Epoch:7, Loss:0.2207 Epoch:8, Loss:0.2094 Epoch:9, Loss:0.2079 Epoch:10, Loss:0.2102 Epoch:11, Loss:0.2045 Epoch:12, Loss:0.2073 Epoch:13, Loss:0.2032 Epoch:14, Loss:0.2068 Epoch:15, Loss:0.2101
16-Autoencoder	Epoch:1, Loss:0.2549 Epoch:2, Loss:0.2503 Epoch:3, Loss:0.2452 Epoch:4, Loss:0.2384 Epoch:5, Loss:0.2351 Epoch:6, Loss:0.2275 Epoch:7, Loss:0.2306 Epoch:8, Loss:0.2277 Epoch:9, Loss:0.2241 Epoch:10, Loss:0.2221 Epoch:11, Loss:0.2187 Epoch:12, Loss:0.2117 Epoch:13, Loss:0.2139 Epoch:14, Loss:0.2161 Epoch:15, Loss:0.2109

Observation:

1) Loss value may increase, during our training, optimum loss (minimum loss) can be achieved with trying out various learning rates.
2) Architecture: For a vast dataset with many features, bigger dimension may yield smaller loss value.
3) Google Collab rocks!