AIL 7024
Machine Learning
Sem 1, 2026-27

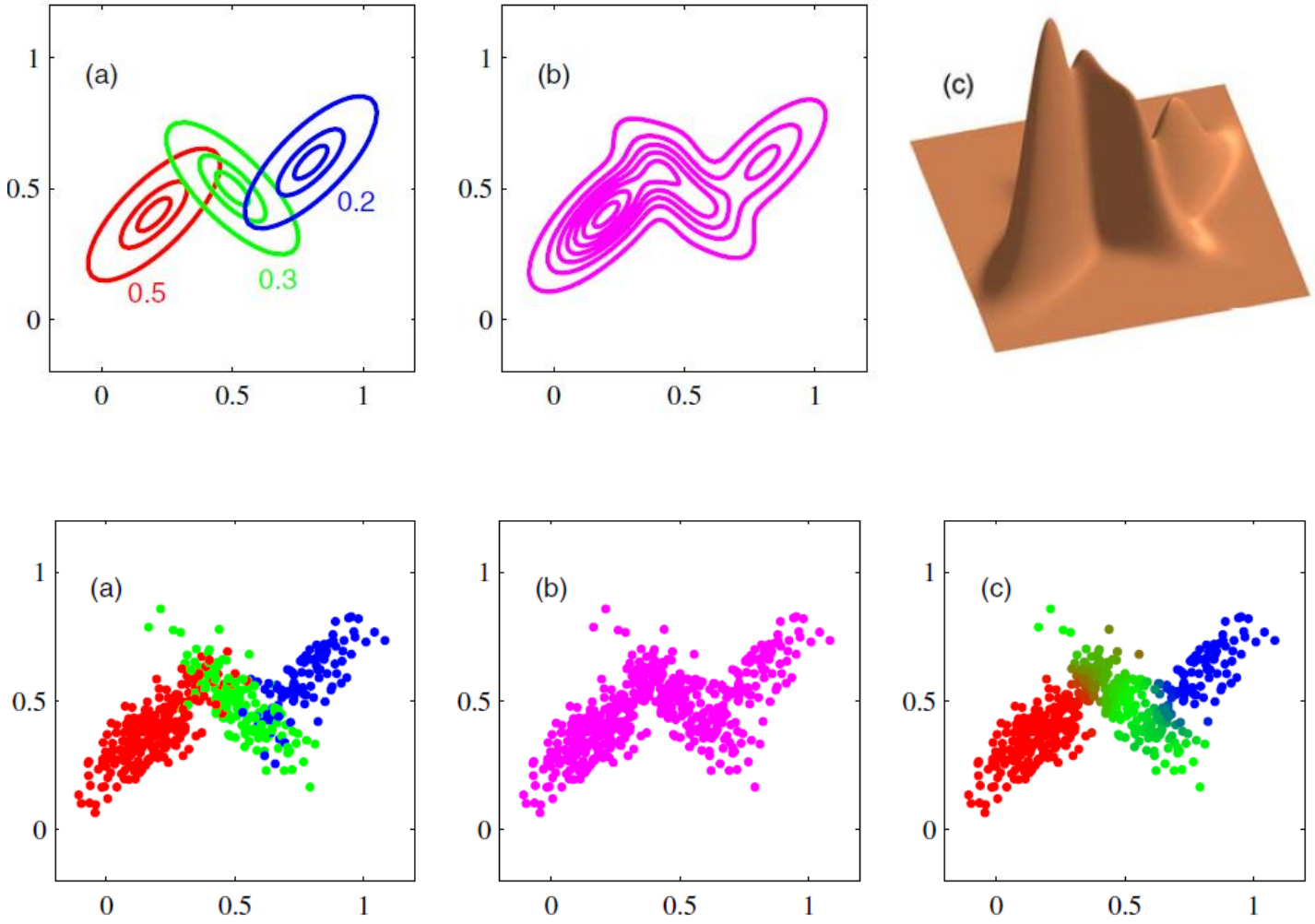
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Raunak P. Bhattacharyya, ScAI



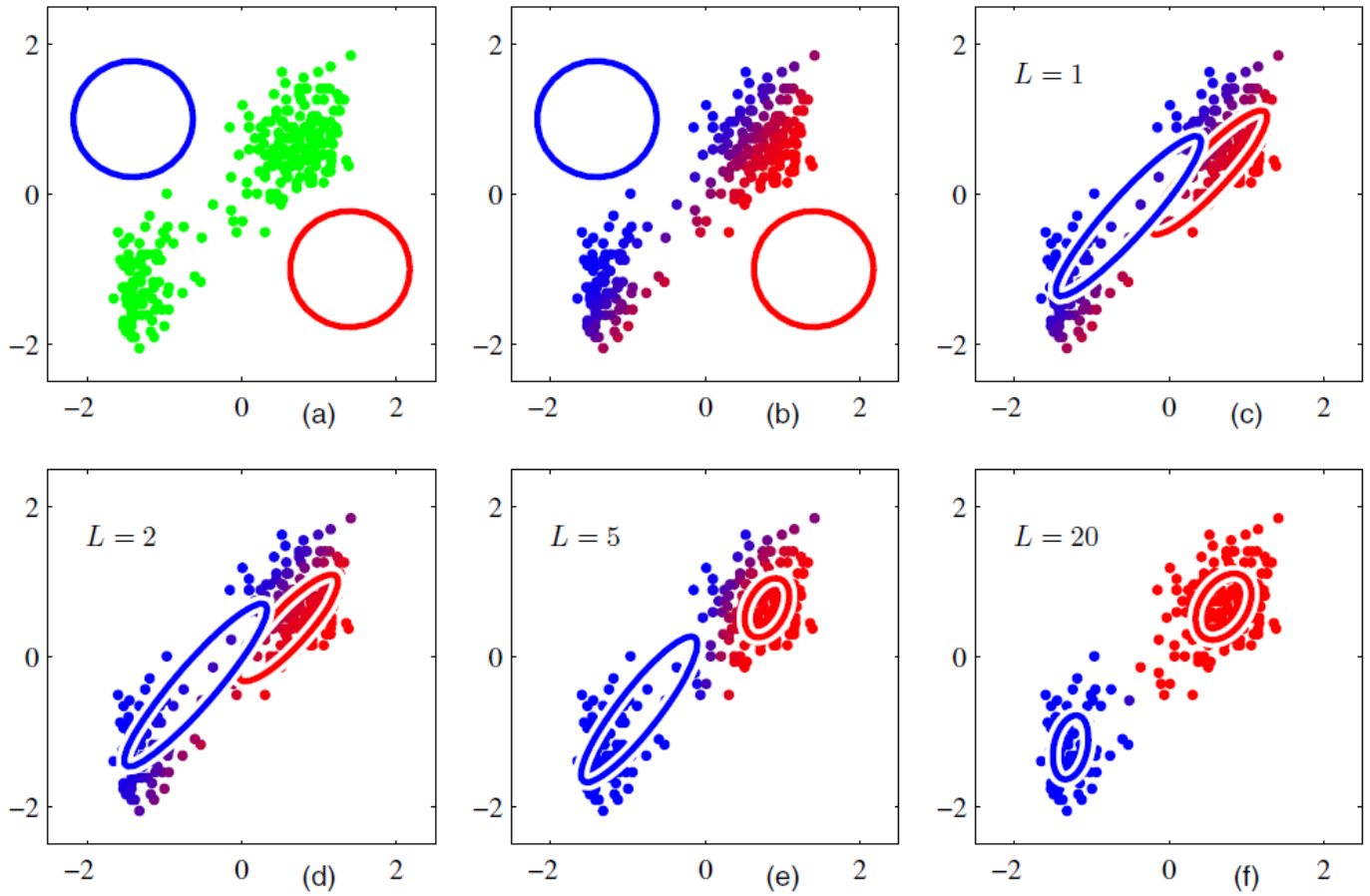
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MOG with Latent Variables



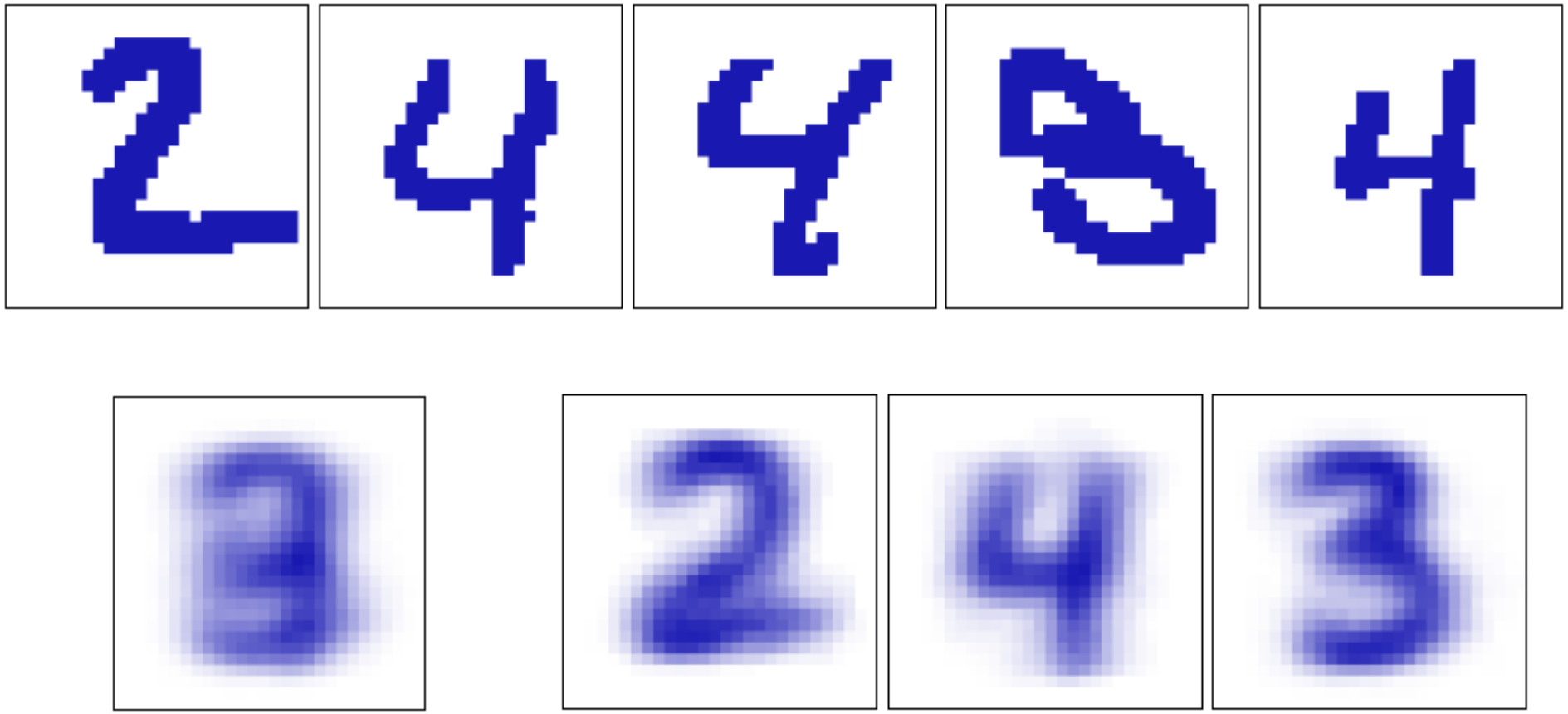
From Bishop PRML: 2,23, 9.5

EM for Old Faithful Dataset



From Bishop PRML: Fig 9.8

MoB to model MNIST



From Bishop PRML: Fig 9.10

PPCA

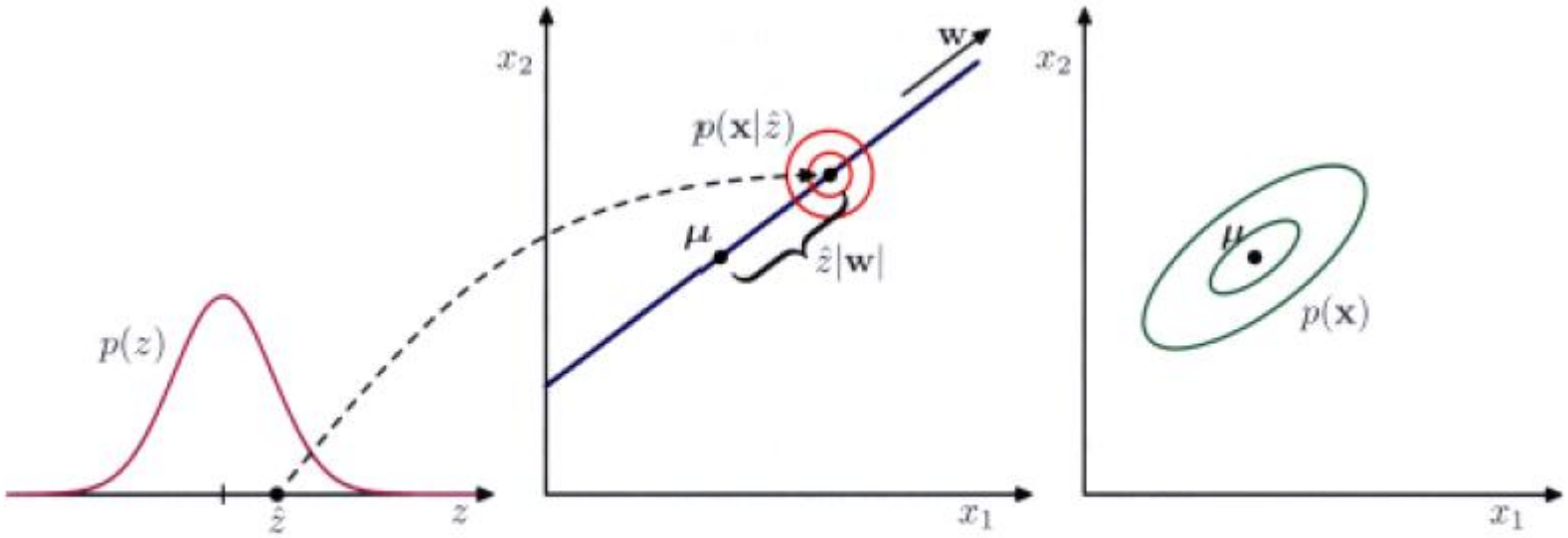


Figure 12.9 An illustration of the generative view of the probabilistic PCA model for a two-dimensional data space and a one-dimensional latent space. An observed data point $\mathbf{x}$ is generated by first drawing a value $\hat{z}$ for the latent variable from its prior distribution $p(z)$ and then drawing a value for $\mathbf{x}$ from an isotropic Gaussian distribution (illustrated by the red circles) having mean $\mathbf{w}\hat{z} + \boldsymbol{\mu}$ and covariance $\sigma^2\mathbf{I}$. The green ellipses show the density contours for the marginal distribution $p(\mathbf{x})$.

From Bishop PRML

PPCA in the limit of 0 variance: PCA

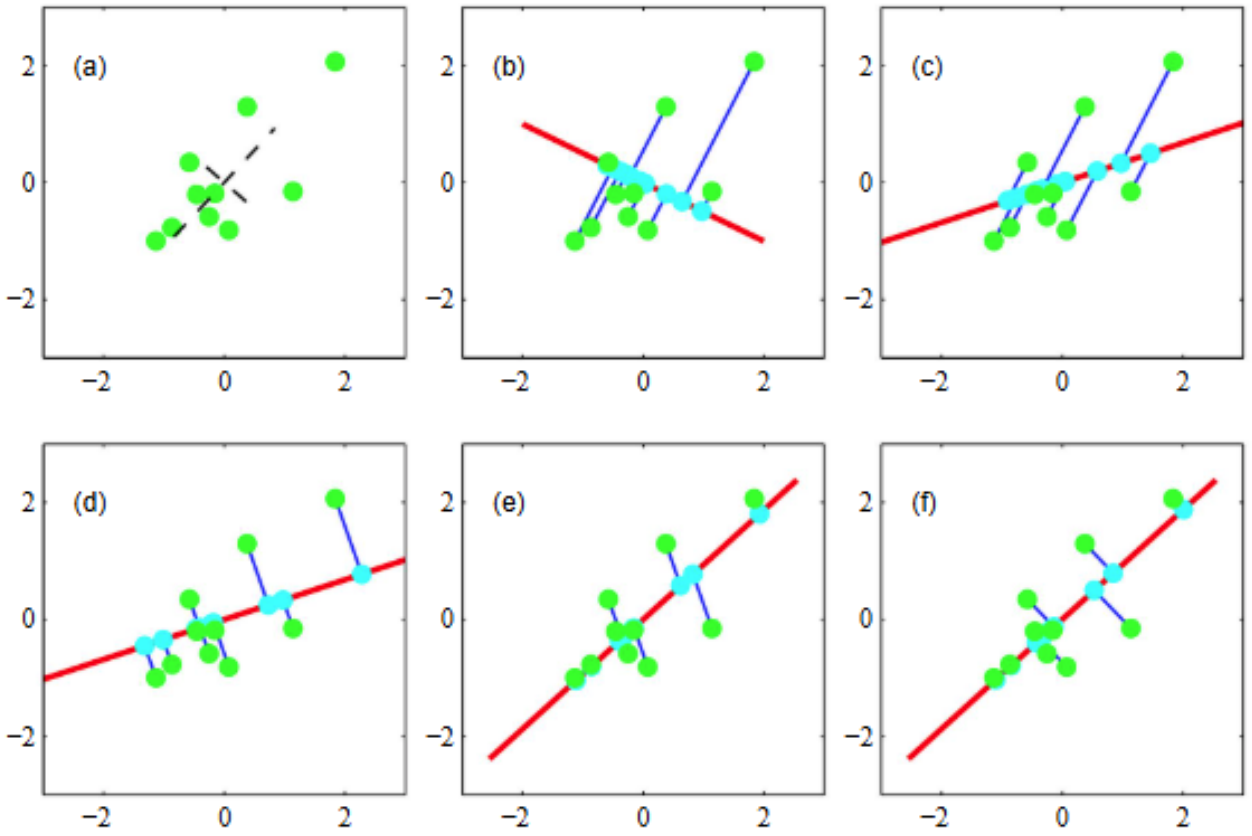


Figure 16.10 Synthetic data illustrating the EM algorithm for PCA defined by (16.70) and (16.71). (a) A set of data points shown in green, together with the true principal components (shown as eigenvectors scaled by the square roots of the eigenvalues). (b) Initial configuration of the principal subspace defined by $\mathbf{W}$, shown in red, together with the projections of the latent points $\mathbf{Z}$ into the data space, given by $\mathbf{ZW}^{\mathrm{T}}$, shown in cyan. (c) After one M step, $\mathbf{W}$ has been updated with $\mathbf{Z}$ held fixed. (d) After the successive E step, the values of $\mathbf{Z}$ have been updated, giving orthogonal projections, with $\mathbf{W}$ held fixed. (e) After the second M step. (f) The converged solution.

From Bishop DL