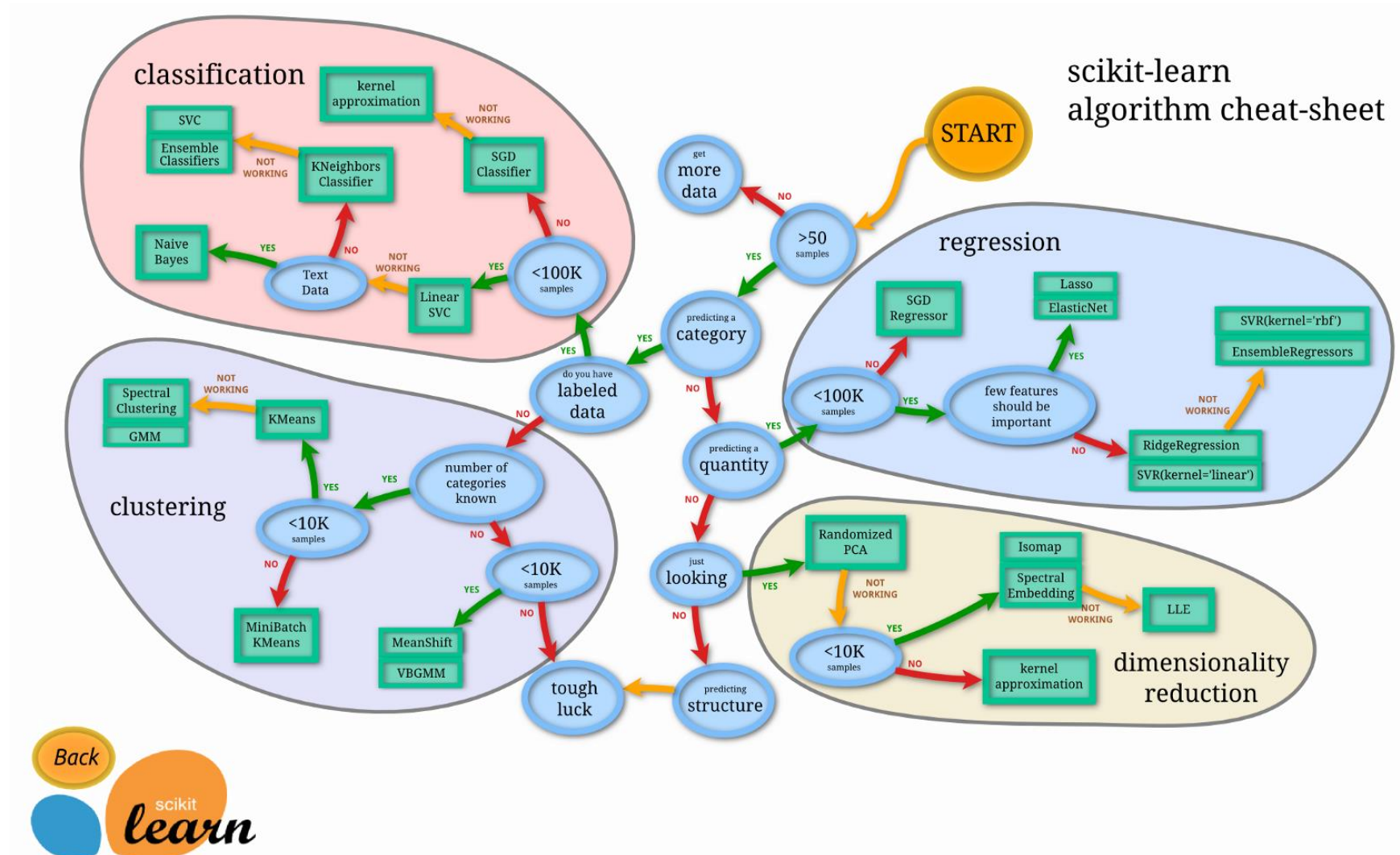


# Unsupervised learning 1

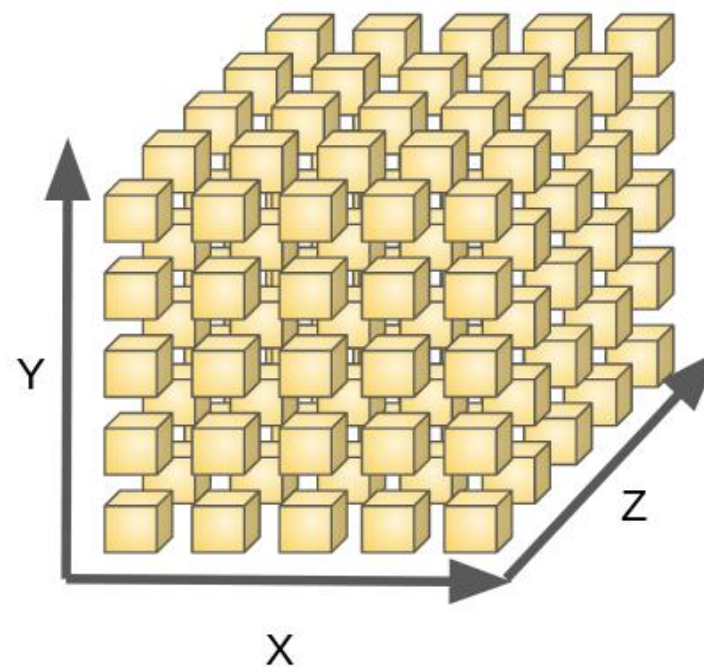
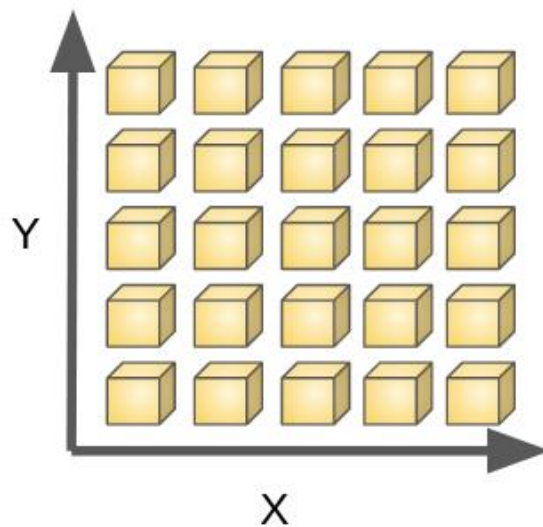
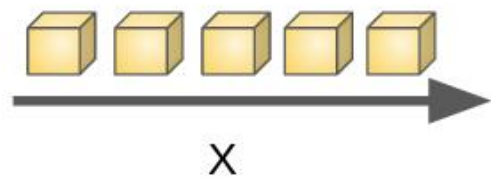
Dimensionality reduction og data visualisering

- PCA

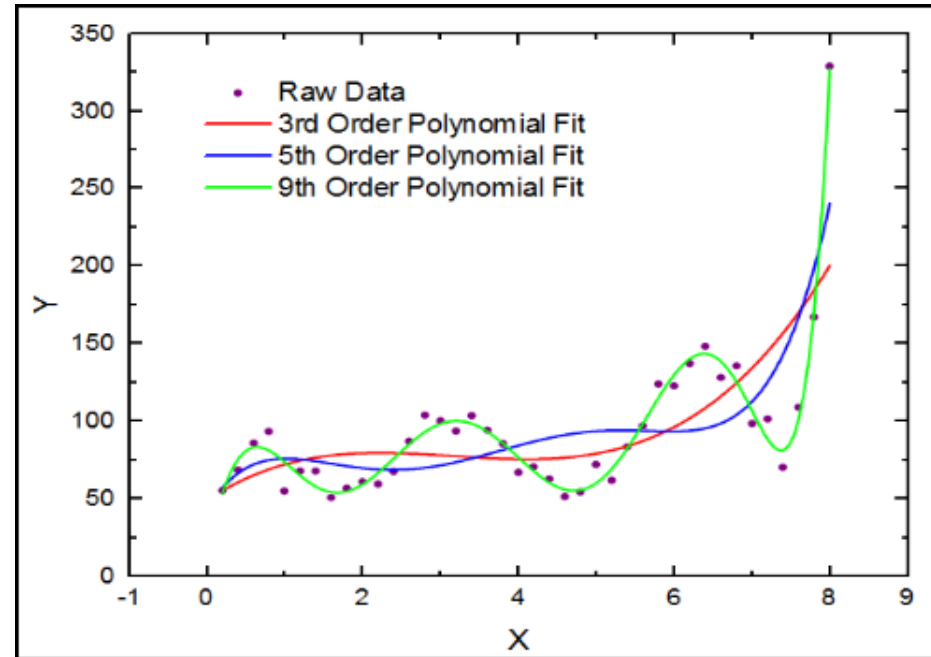
# Hvor er vi ? Dimensionality reduction..



# Curse of dimensionality



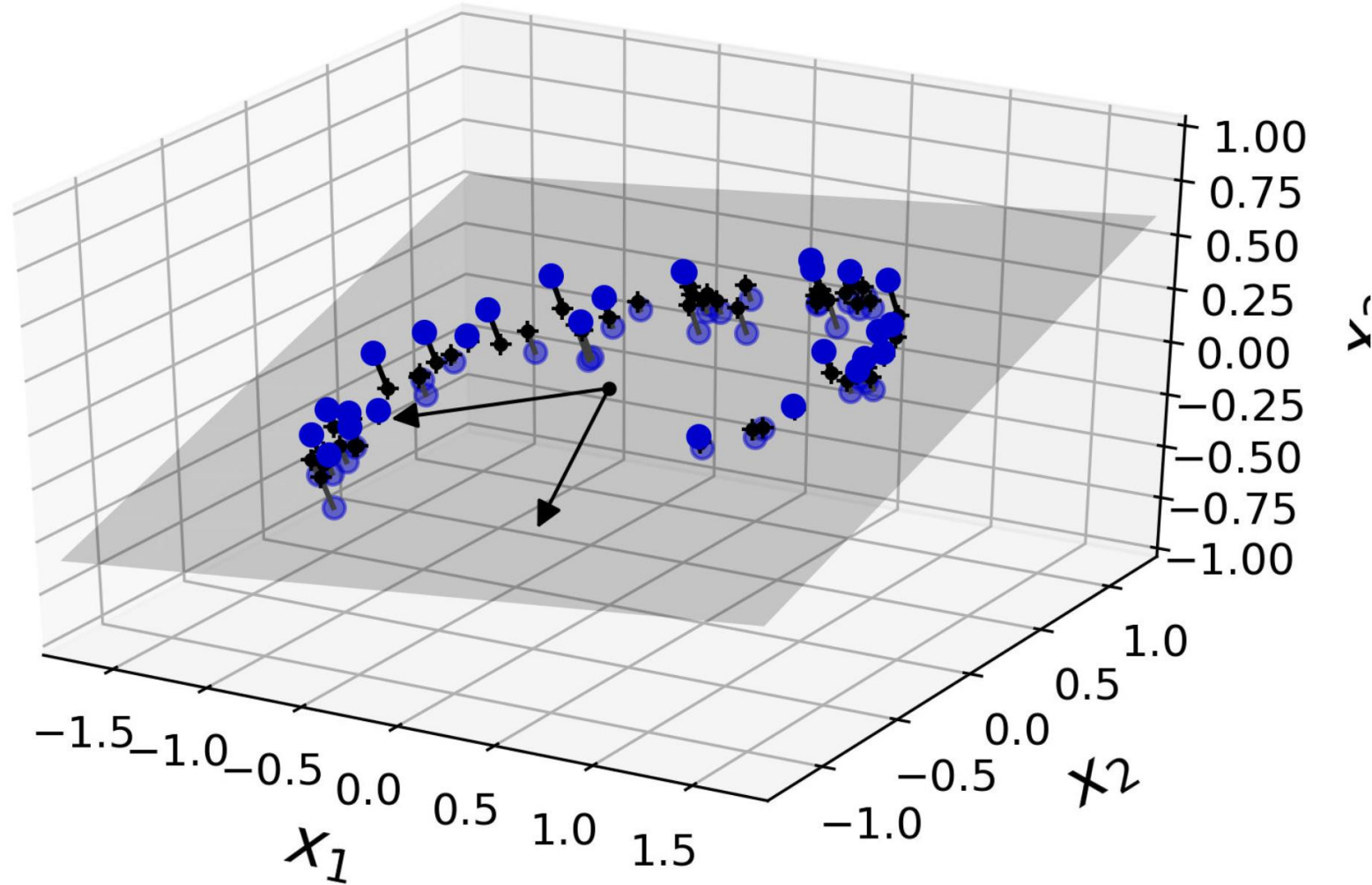
# Curse of dimensionality – e.g. polynomial regression



Polynomial curve fitting,  $M = 3$

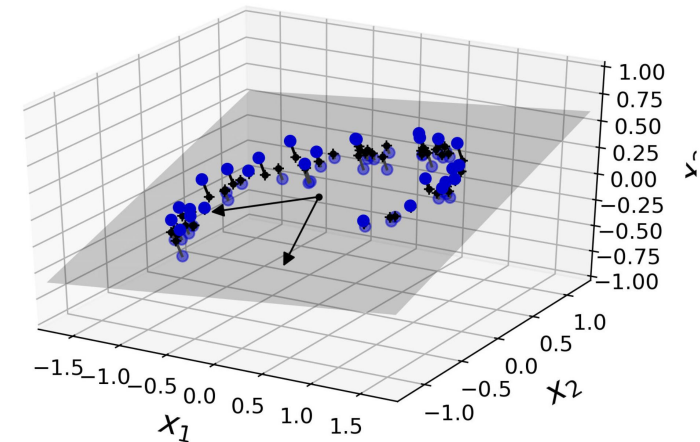
$$y(\mathbf{x}, \mathbf{w}) = w_0 + \sum_{i=1}^D w_i x_i + \sum_{i=1}^D \sum_{j=1}^D w_{ij} x_i x_j + \sum_{i=1}^D \sum_{j=1}^D \sum_{k=1}^D w_{ijk} x_i x_j x_k$$

# Dimensions-reduktion

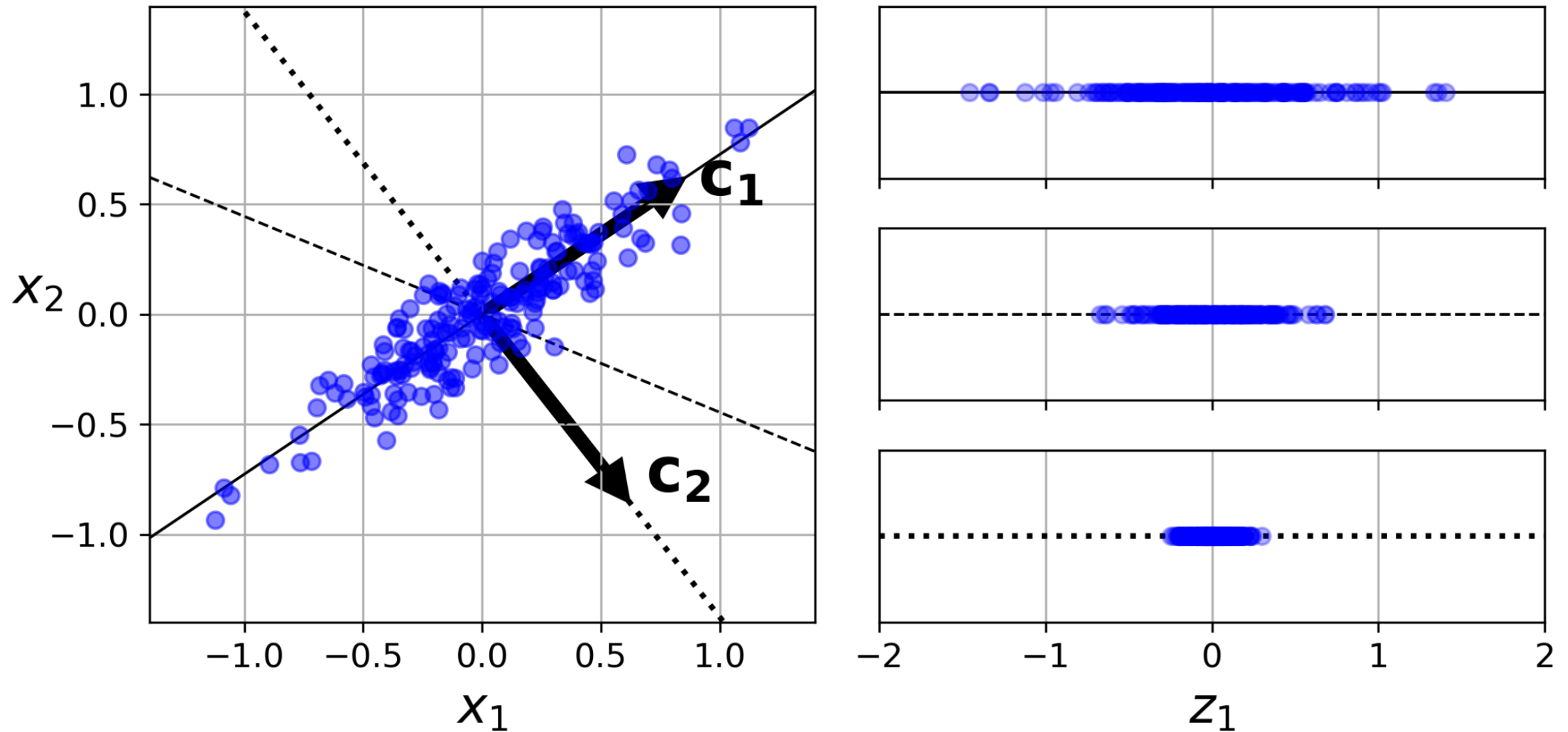


# Principal Component Analysis (PCA) – formål

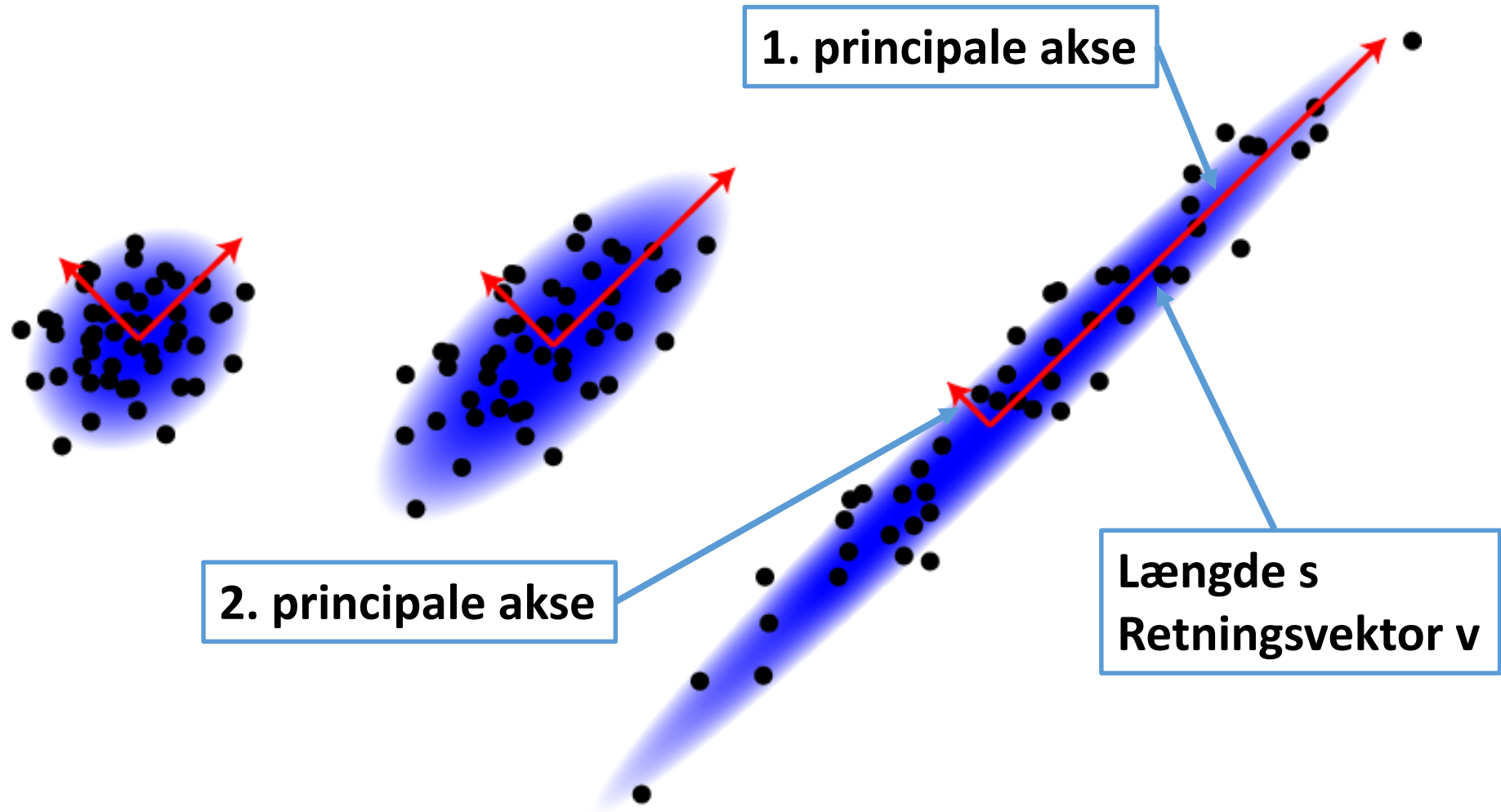
- Dimensionsreduktion
  - Visualisering
  - Præprocessering - undgå overfit og hurtigere træning
- Data analyse
- Kompression
- ..



# PCA Princip : Maksimer varians



# PCA – geometrisk fortolkning





# PCA - Projektion på principale akser

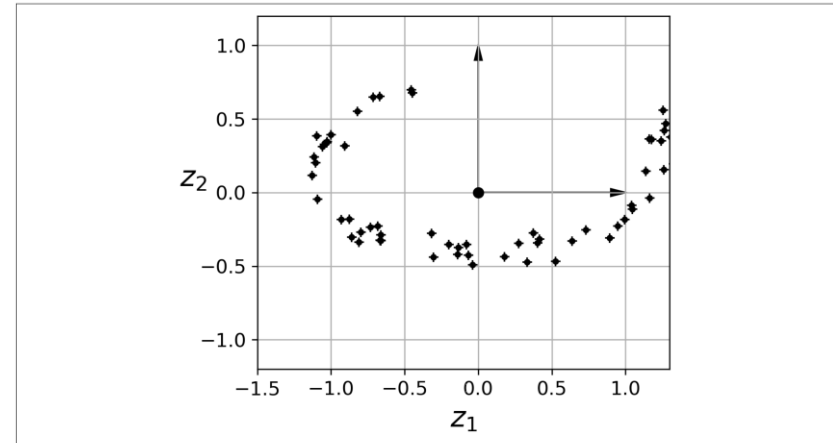
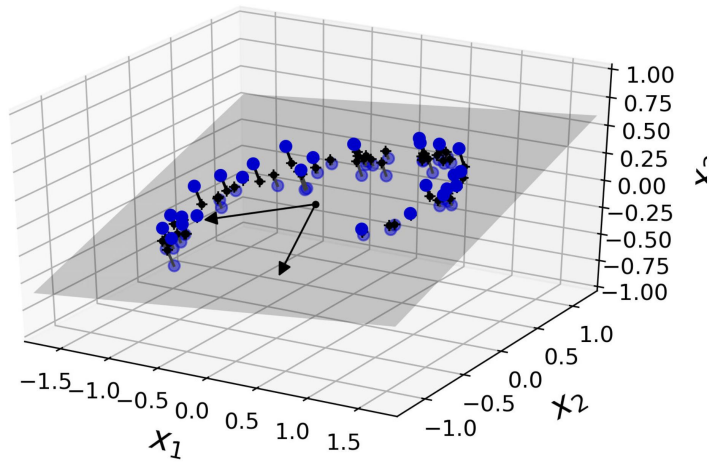
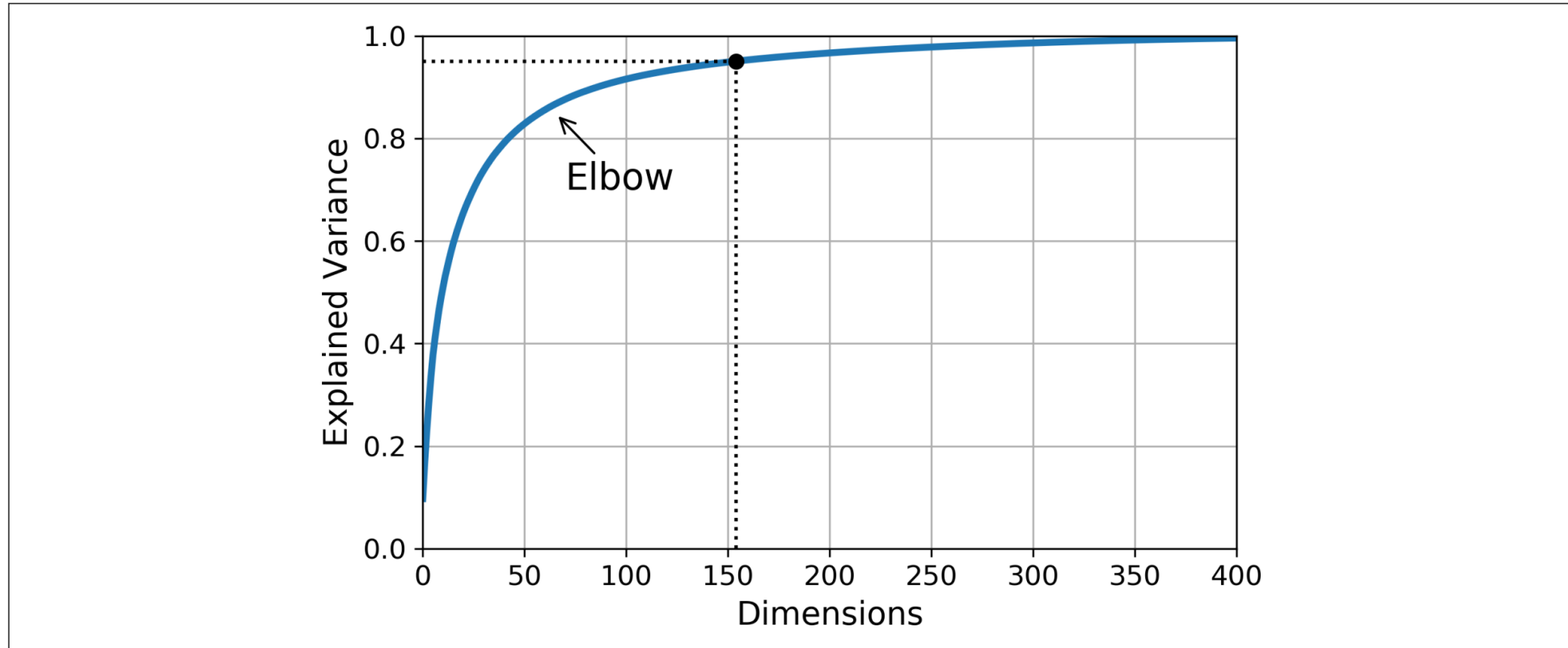


Figure 8-3. The new 2D dataset after projection

*Equation 8-2. Projecting the training set down to  $d$  dimensions*

$$\mathbf{X}_{d\text{-proj}} = \mathbf{X}\mathbf{W}_d$$

# Valg af antal komponenter



*Figure 8-8. Explained variance as a function of the number of dimensions*

# PCA til kompression

```
pca = PCA(n_components = 154)  
X_reduced = pca.fit_transform(X_train)  
X_recovered = pca.inverse_transform(X_reduced)
```

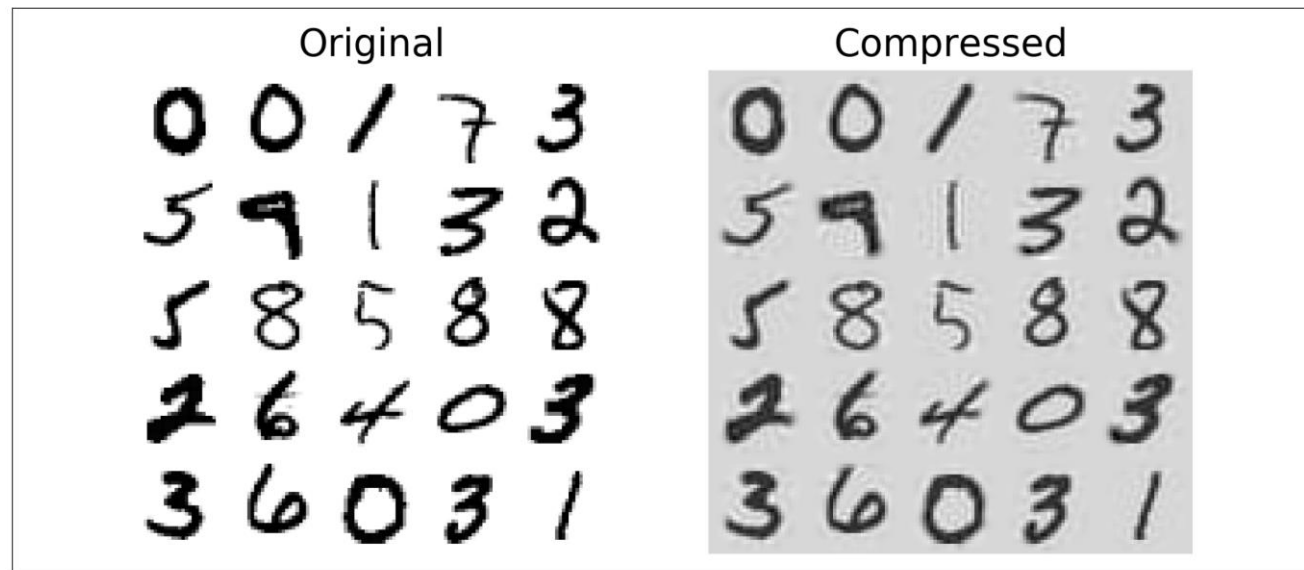


Figure 8-9. MNIST compression preserving 95% of the variance

# PCA – Scikit implementation

```
class sklearn.decomposition. PCA (n_components=None, copy=True, whiten=False, svd_solver='auto', tol=0.0,  
iterated_power='auto', random_state=None) \[source\]
```

Principal component analysis (PCA)

Linear dimensionality reduction using Singular Value Decomposition of the data to project it to a lower dimensional space. The input data is centered but not scaled for each feature before applying the SVD.

# PCA – med SVD

$$V = \begin{pmatrix} | & | & & | \\ c_1 & c_2 & \cdots & c_n \\ | & | & & | \end{pmatrix}$$

```
X_centered = X - X.mean(axis=0)
U, s, Vt = np.linalg.svd(X_centered)
c1 = Vt.T[:, 0]
c2 = Vt.T[:, 1]
```

**X** = data matrix (N\_samples x N\_dims)

**Vt** = Eigenvectors (retningsvektorer med længde 1)

**s** = Singular values (angiver længde af vektorer)

**U** – benyttes ikke her

# Eigenfaces – repræsentation af ansigter



= 0.96972



+0.20877



-0.12676



= 0.82532



+0.23646



-0.51277



# Data i "non-linear manifold" (mangfoldighed) / embedding

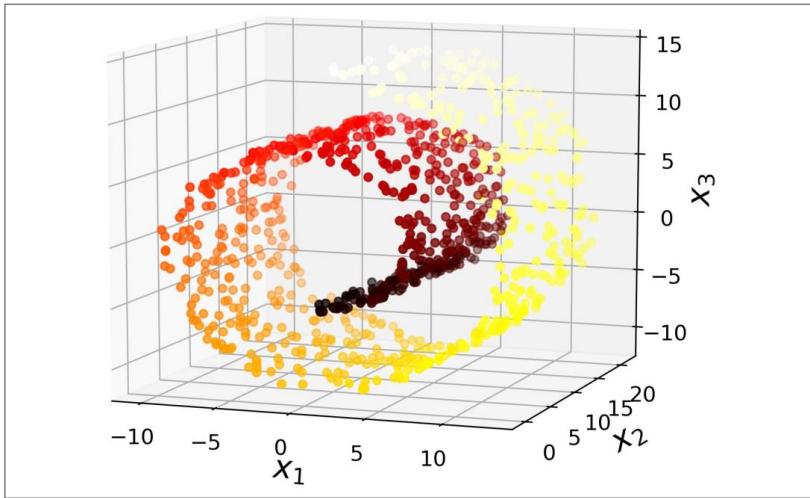


Figure 8-4. Swiss roll dataset

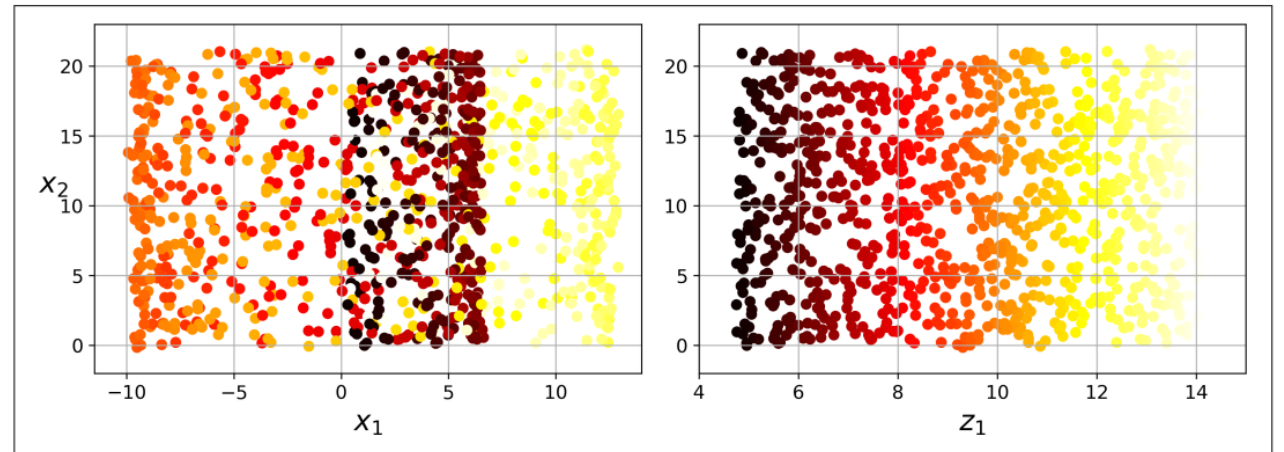


Figure 8-5. Squashing by projecting onto a plane (left) versus unrolling the Swiss roll (right)

# Other methods

- Clustering metoder (i Unsupervised Learning 2)
  - Kmeans / GMM, hierarchical clustering
- Manifold learning
  - Isomap, LLE, t-SNE, ..
- Decomposition
  - ICA, NMF, ..
- Deep learning methods
  - Autoencoders
  - GAN