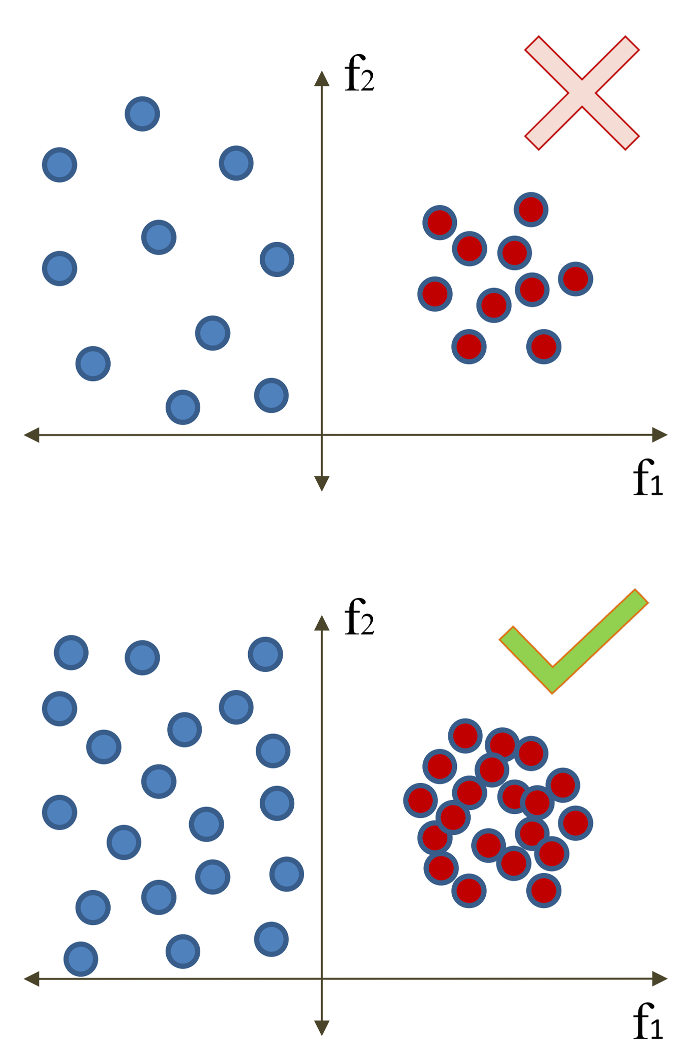
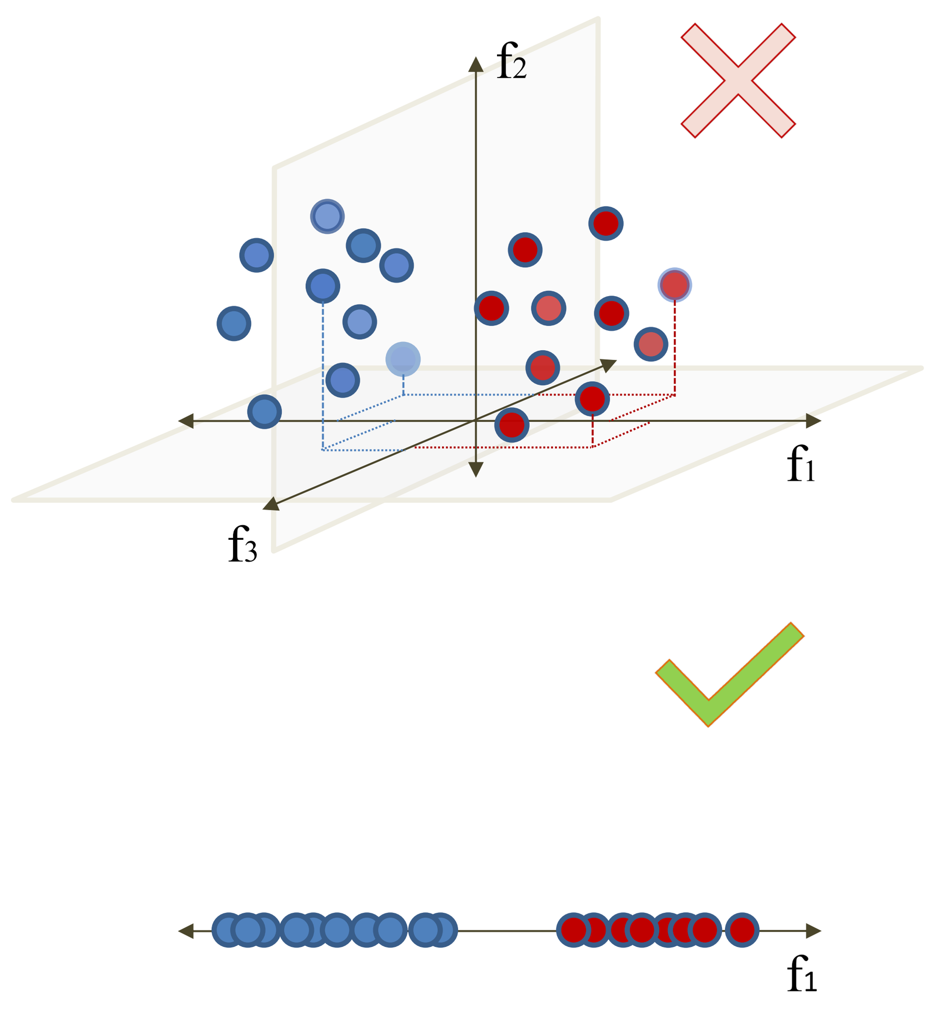
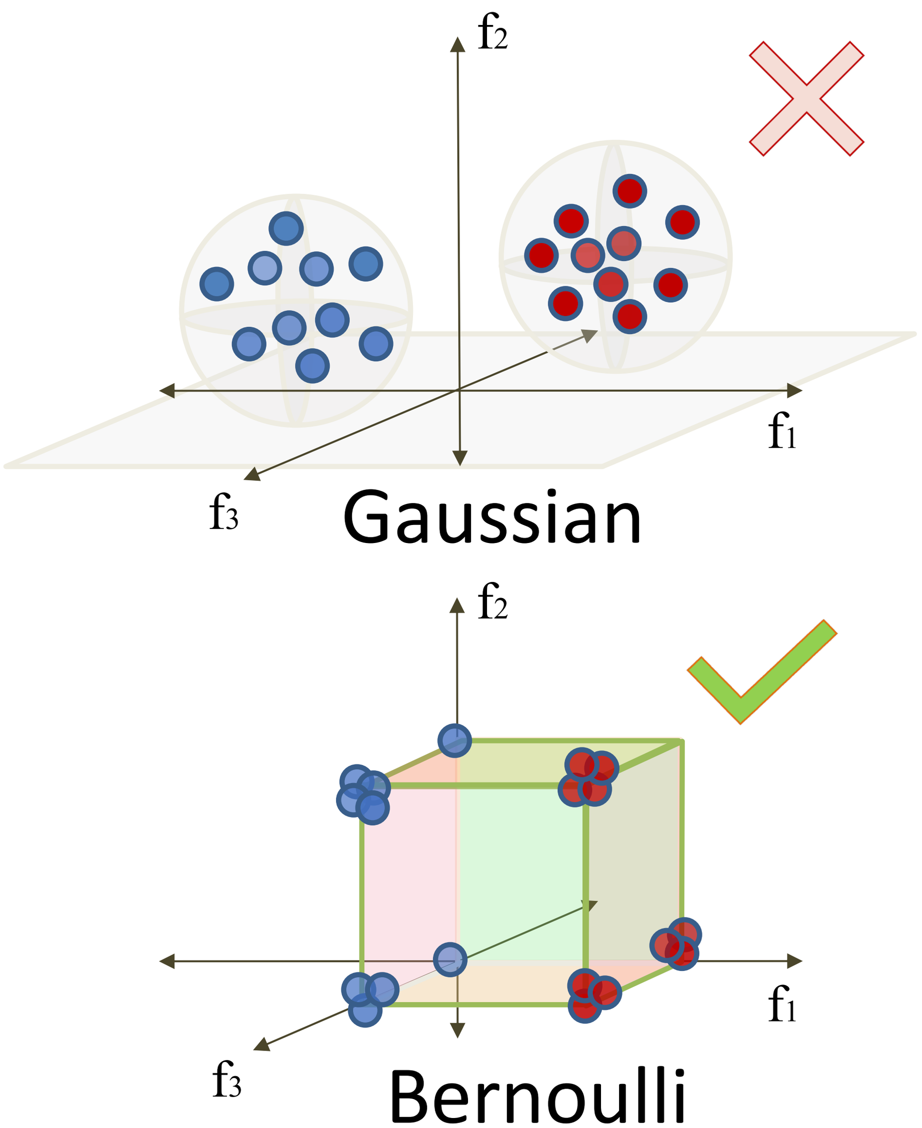
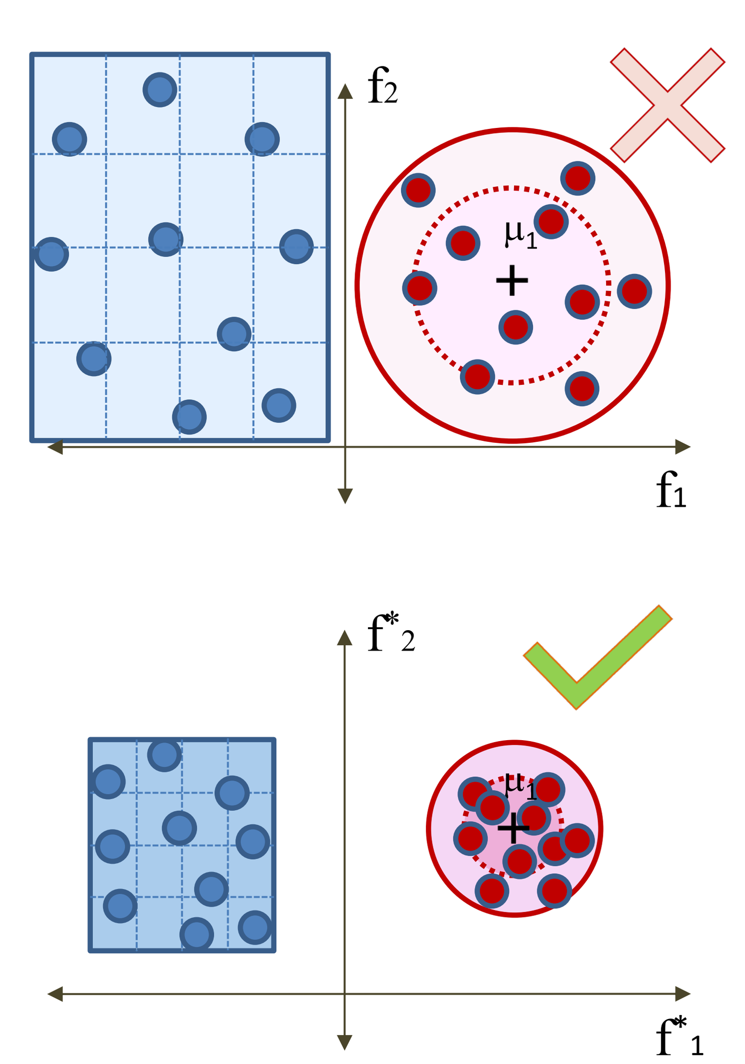
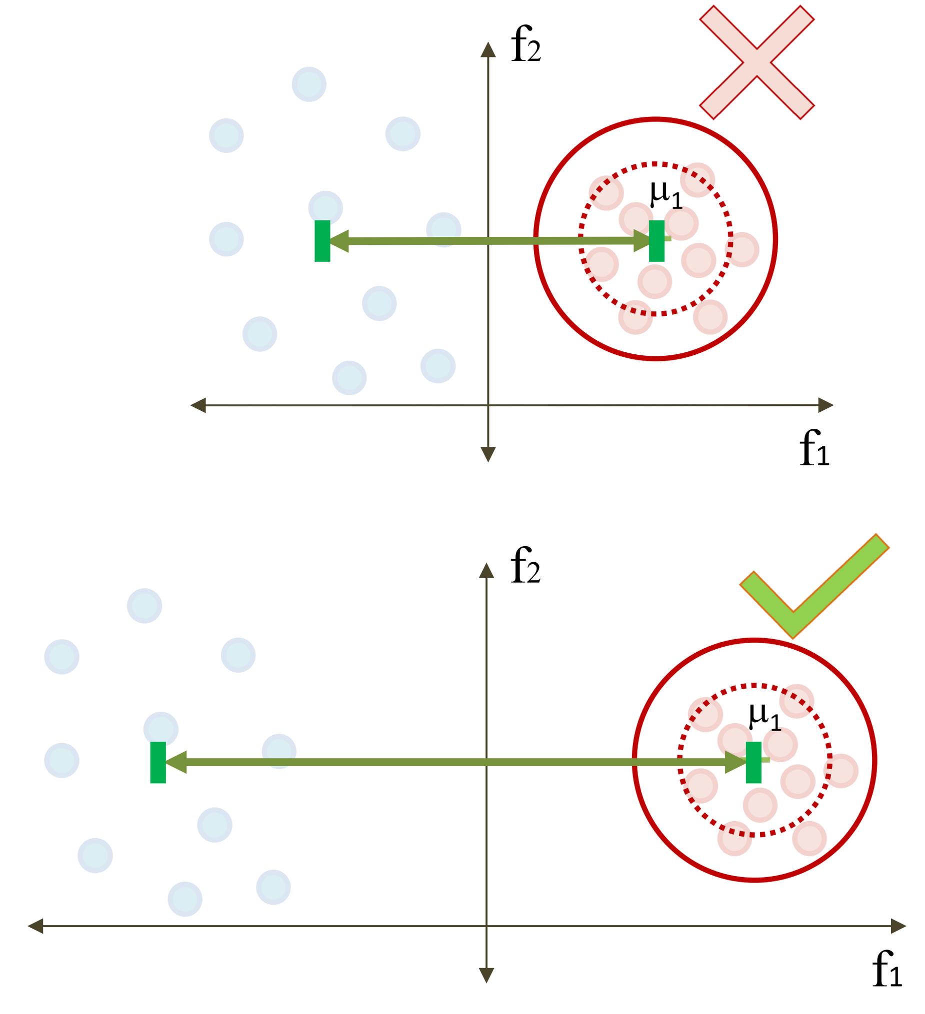
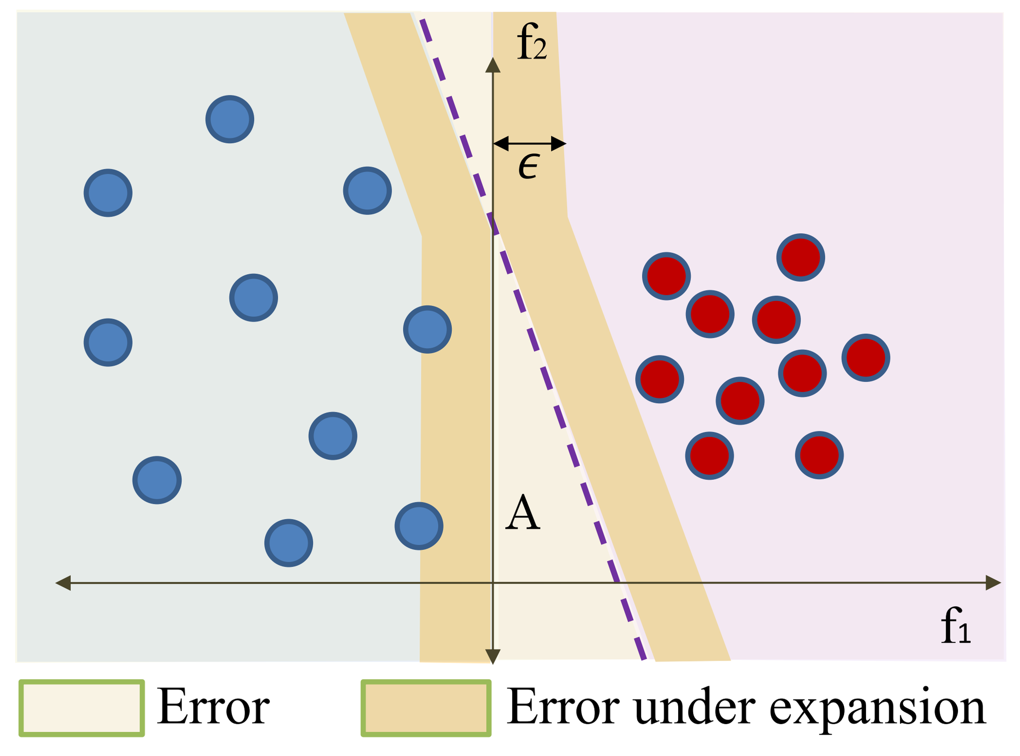
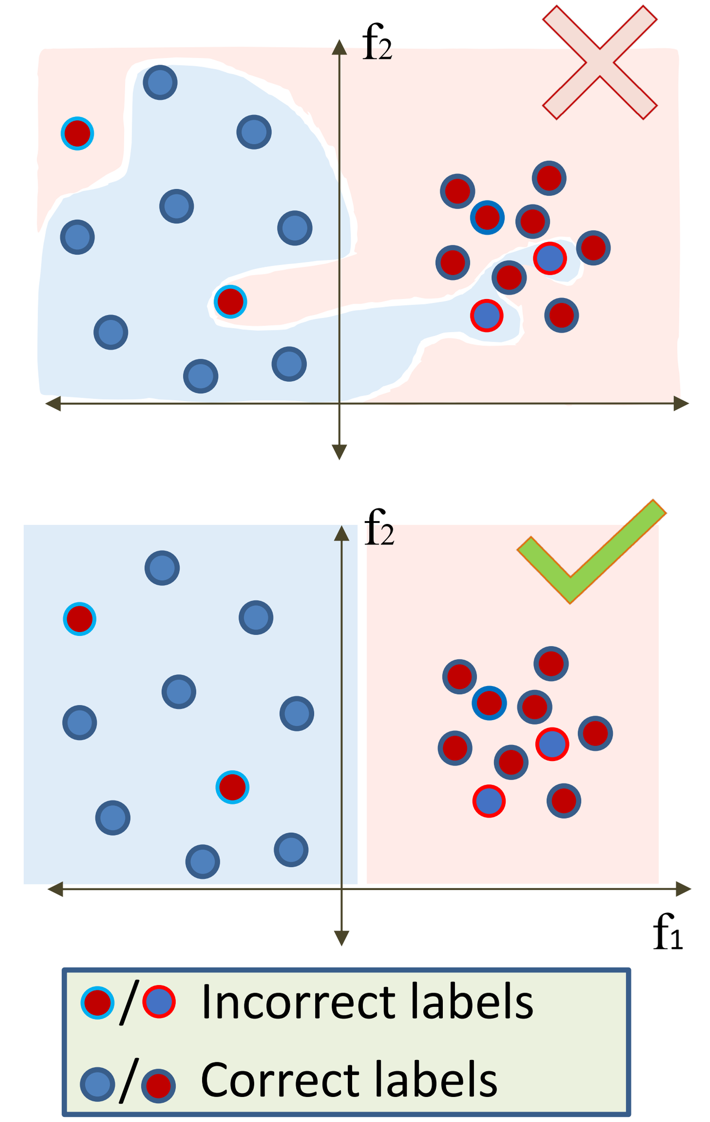
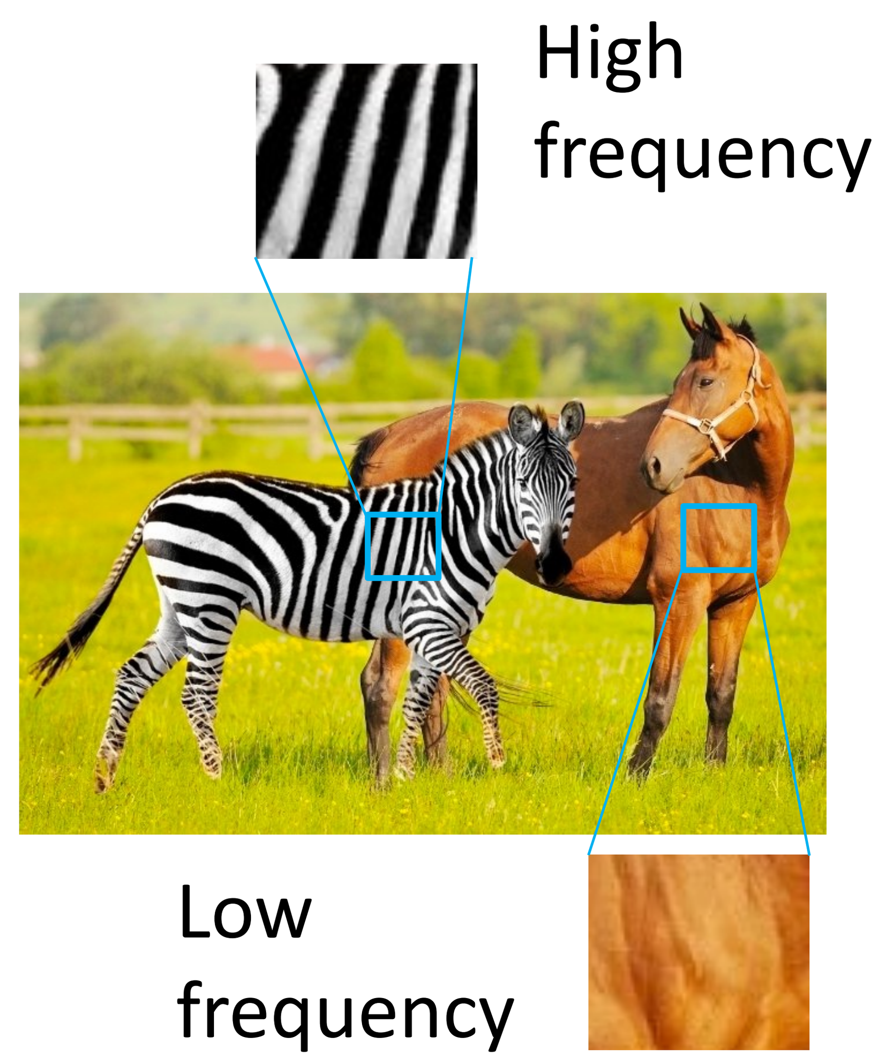
	Number of Training Samples ↑	Number of Features/ Dimensionality ↓	Types and Properties of Distribution	Density ↑	Separation ↑	Concentration ↓	Label Noise and Label Granularity	Domain specific
Illustration								
Main results	○ Significantly larger quantity is needed for adversarial vs. standard generalization ○ Robustness is harder on imbalanced data	○ High-dimensional datasets are more prone to adversarial examples ○ More challenges in generalizing robust solutions	○ Certain distribution types are more optimal ○ Distributions with symmetry and low variance are more optimal for robustness	○ Adversarial examples from low density regions are more transferable ○ Can defend by projecting to high density regions	○ Optimal-transport-based separation defines adversarial risk's lower bound ○ Local classifiers are inherently robust on well-separated data	○ Concentration worsen with high dimensionality ○ Evaluating the concentration of empirical datasets provides an estimate of attainable robustness	○ Using refined labels, e.g., "cat" instead of "animal", improves robustness ○ Training with multiple tasks boosts robustness	○ CNNs are vulnerable to attacks on high frequency components ○ Diverse image frequencies boosts robustness