

281 Live Session

Week 13 — 2023/4/12

Agenda

Non-Linear Classifiers

Basic CNN Architecture Types

Exercise – Face Classification Part 2

Modern Computer Vision Systems

Non-Linear Classifiers

13.1 Linear SVM, Implementation

13.2 Slack Variables

13.3 Nonlinear SVM

13.4 Neurons

13.5 Delta Rule

13.6 Sigmoidal Neurons

13.8 Hidden Layers

13.9 Xor With a Hidden Layer

13.10 Universal Approximation Theorem

13.11 Backpropagation

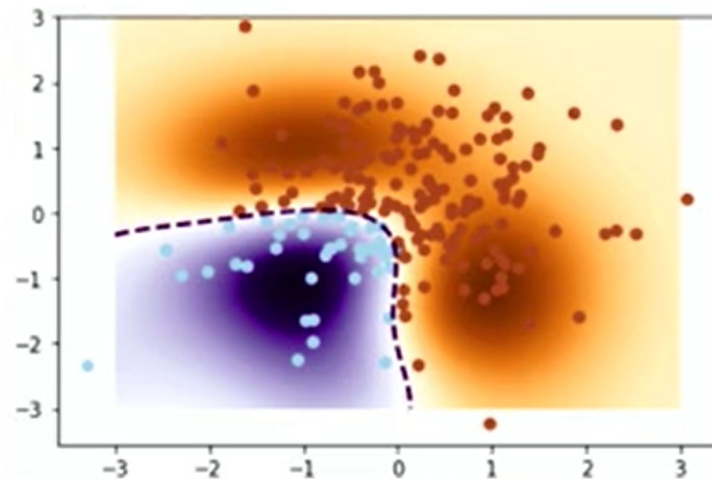
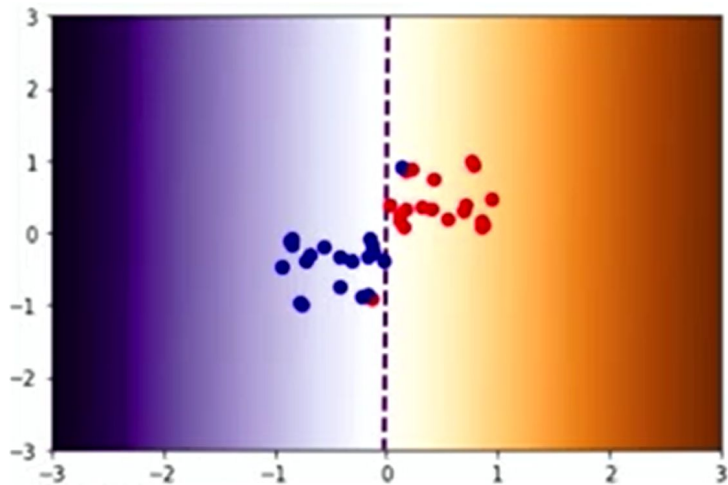
13.12 Convolutional Neural Networks

13.13 Conclusion

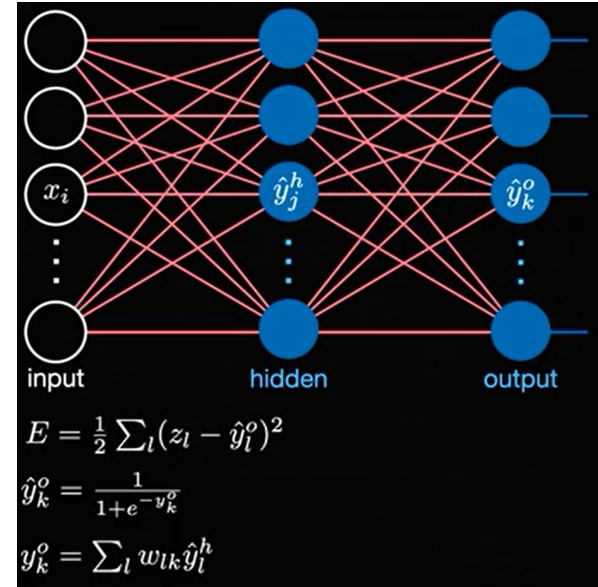
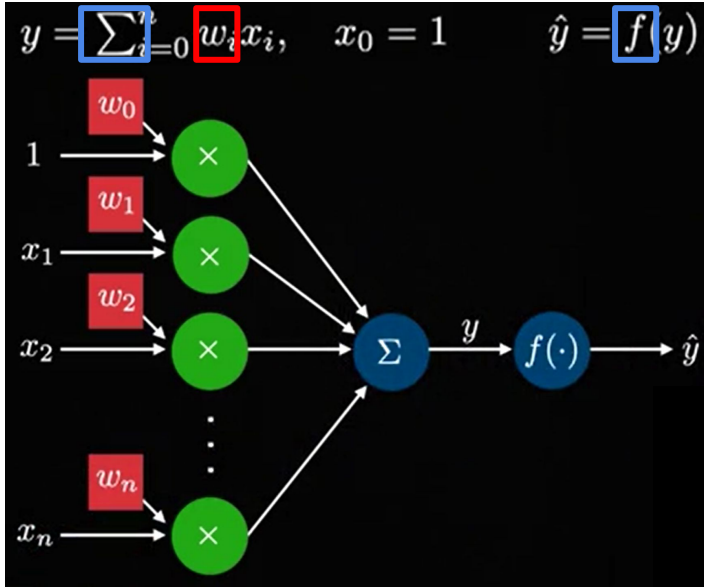
Intuition goals:

- Differences between linear and nonlinear SVMs
- What is a neuron? What functions can it perform?
- What is changing in a network on each iteration?
- What is an activation function? How do they work?

Linear vs Nonlinear SVMs



Neural Networks



$$E(\vec{w}) = \sum_{k=1}^m (z_k - f(\vec{x}_k^T \cdot \vec{w}))^2$$

$$\Delta w_i = \sum_{k=1}^m \alpha (z_k - f(\vec{x}_k^T \cdot \vec{w})) (x_{k,i}) (f'(\vec{x}_k^T \cdot \vec{w}))$$

Non-Linear Classifiers

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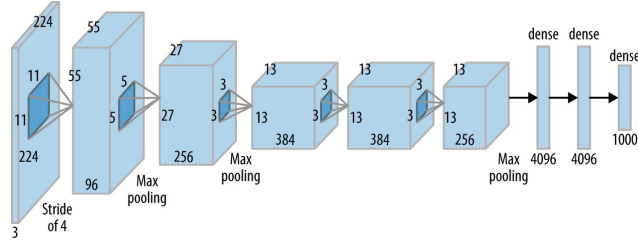
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Model Building Steps

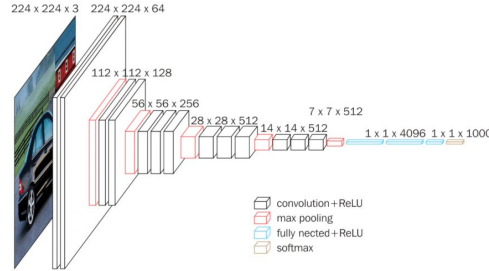
1. Inspect your data
 - Can it be standardized? Cleaned up? Augmented?
2. Split data into training, test, and validation set
3. Choose features to extract
 - What information do you need for training?
 - Are your features robust across all images?
4. Decide on a model
 - Linear? Nonlinear? Neural?
5. Define the error function
 - Usually quadratic
6. Define the gradient function
 - Usually the derivative of the error
7. Test a range of hyperparameters
8. Iterate!

AlexNet, VGGNet, & ResNet

AlexNet (original deep CNN)



VGGNet (fewer parameters)



ResNet (skip connections)

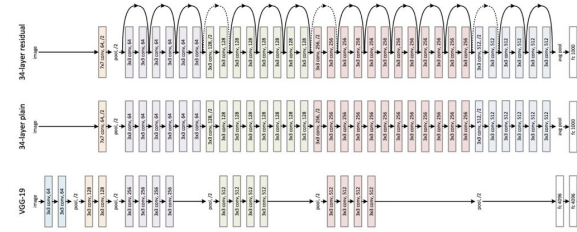
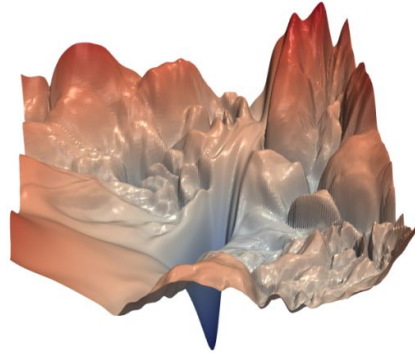
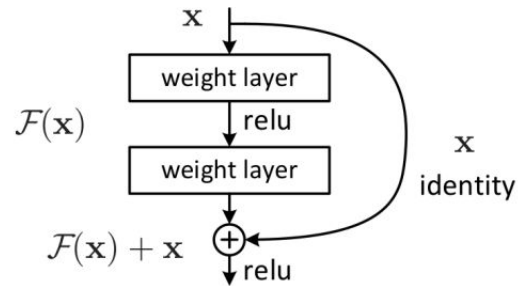


Figure 3. Example network architectures for ImageNet. Left: the VGG-19 model (61 (19.6 billion FLOPs) and 148 million parameters). Middle: the AlexNet model (218 (6.2 billion FLOPs) and 218 million parameters). Right: a plain network with 34 parameter layers (5.6 billion FLOPs) and 148 million parameters. Table 1 shows more details and other variants.

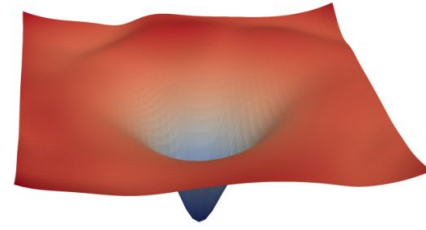
Benefits of Skip Connections

Addresses vanishing gradient problem

Can be combined using addition or concatenation

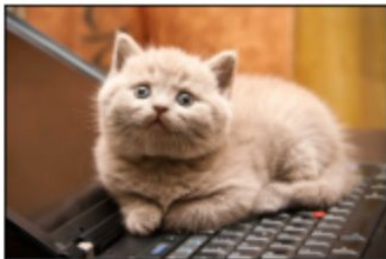


(a) without skip connections



(b) with skip connections

Exercise — Faces Part 2 (ResNet Features)



Modern Computer Vision Systems

Generative Adversarial Networks (GANs)

- Unsupervised learning (look ma, no labels!)
- Simultaneously learn the *generator* (makes images) and the *discriminator* (decides if images are fake or real)

Unsolved problems for GANs

- Unstable / hard to train reliably
- Not usually good at long-range correlations (eg earrings)



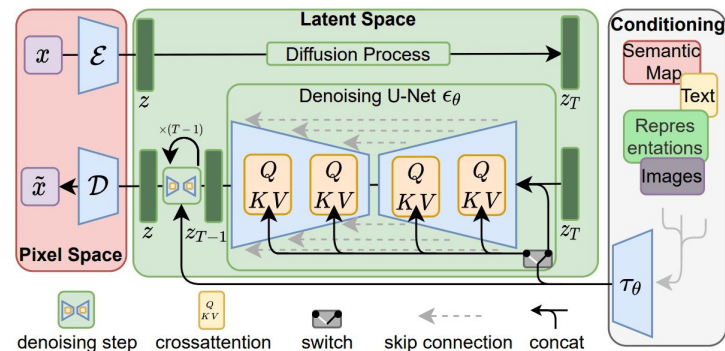
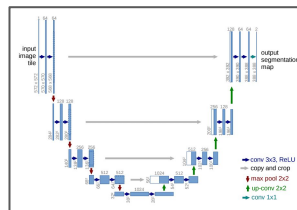
Modern Computer Vision Systems

Diffusion Models

- Similar to an auto-encoder, except using noise instead of down-sampling
- Can be used directly for denoising/superresolution
- Or, can be guided for image generation

Unsolved problems for Diffusion Models

- Structure vs texture limitations
- Difficult to control



Modern Computer Vision Systems

There is still significant work needed to improve the usefulness of these systems

- Robustness
- Data privacy
- Bias / ethics concerns
- Explainability



Upcoming ToDo's

Watch async lectures for unit 13

Course evaluations next week

Final project presentations next week (10 minutes!)

Written report due April 23rd