# APS360 Fundamentals of AI

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Lecture 8; May 30, 2019

# Agenda

Last Class:

- Convolutional Neural Networks

Today:

- CNN Architectures
- Fully Convolutional Networks
- Neural Network Debugging
- Train/Test Split

# CNN Architectures

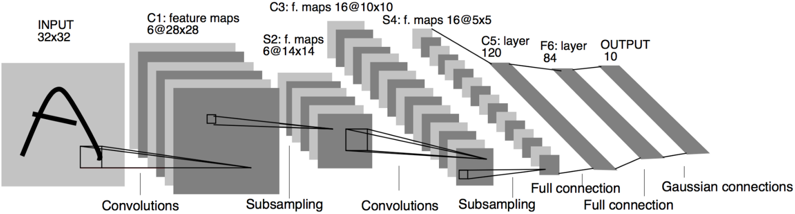
# Named Architectures

- LeNext
- AlexNet
- VGG
- ResNet

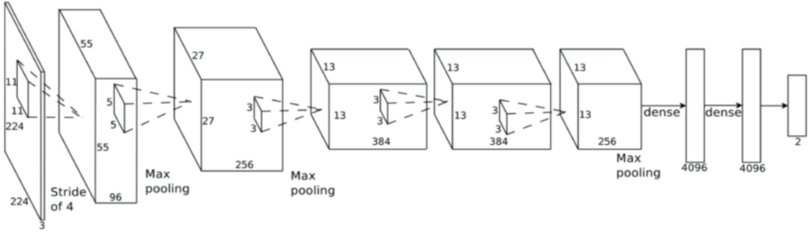
You should know:

- How do we interpret CNN figures?
- How were these architectures different from the previous?
- What new idea was introduced?

# LeNet

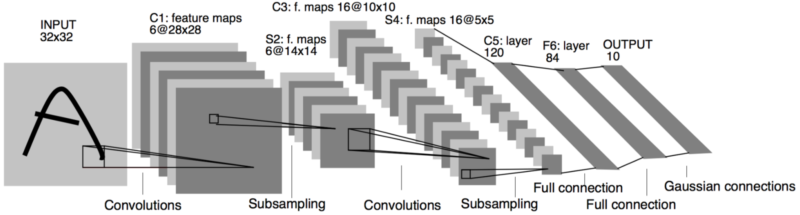

INPUT
32x32
C1: feature maps
6@28x28
S2: f. maps
6@14x14
C3: f. maps 16@10x10
S4: f. maps 16@5x5
C5: layer
120
F6: layer
84
OUTPUT
10
Convolutions
Subsampling
Convolutions
Subsampling
Full connection
Full connection
Gaussian connections

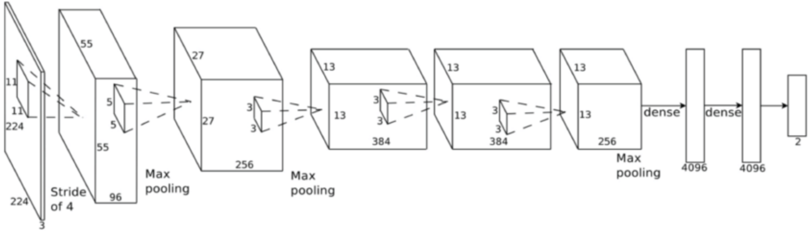
# AlexNet



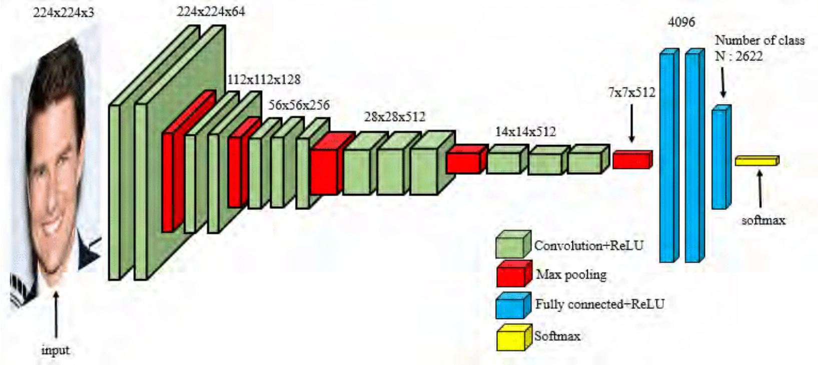

```
import torchvision.models
alexNet = torchvision.models.alexnet(pretrained=False)
```

# Q: What is new in AlexNet (compared to LeNet)?



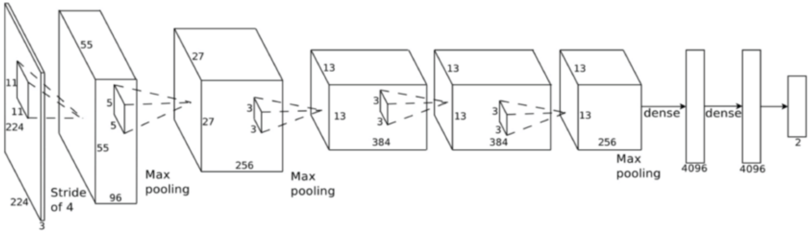



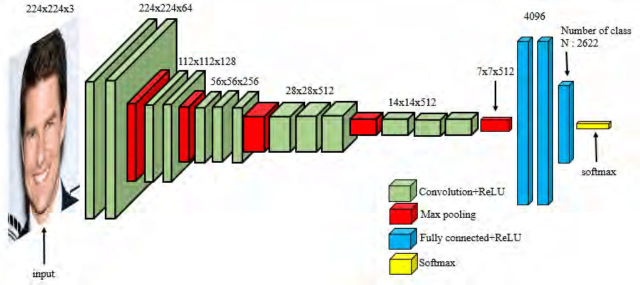
# VGG



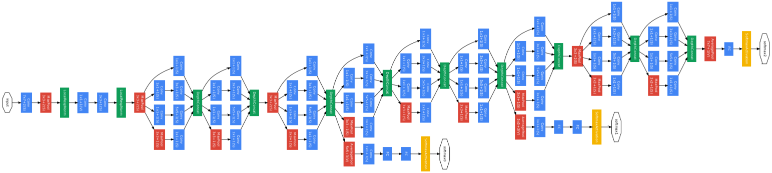

```
# There are many VGG versions
vgg16 = torchvision.models.vgg.vgg16(pretrained=False)
vgg19 = torchvision.models.vgg.vgg19(pretrained=False)
```

# Q: What is new in VGG (compared to AlexNet)?



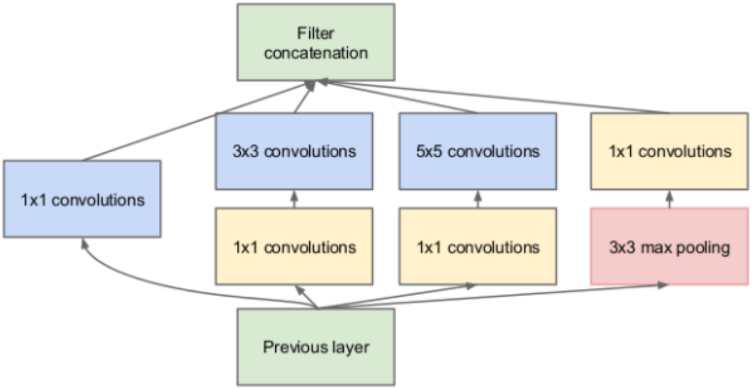
# GoogLeNet (Inception)



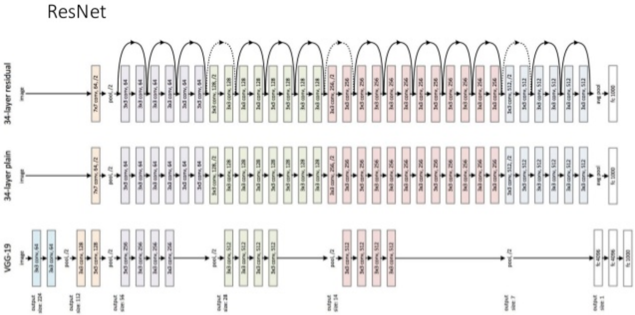
```
torchvision.models.inception.inception_v3(pretrained=False)
```

Q: What is new in GoogLeNet that we haven't seen yet?

# Inception Module



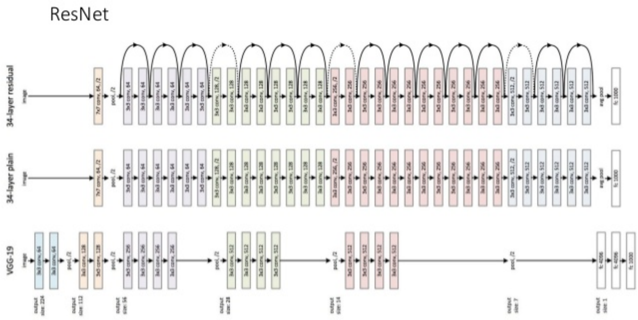
# ResNet




```
torchvision.models.resnet.resnet18(pretrained=False)
torchvision.models.resnet.resnet152(pretrained=False)
```

Q: What is new in ResNet that we haven't seen yet?

# ResNet

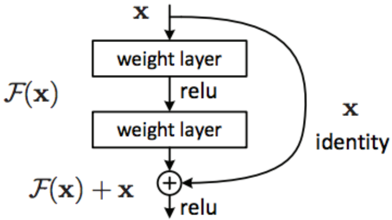



```
torchvision.models.resnet.resnet18(pretrained=False)
torchvision.models.resnet.resnet152(pretrained=False)
```

Q: What is new in ResNet that we haven't seen yet?

Skip connections to make very deep neural networks

# ResNet Basic Block (Skip Connections)




```
# normal layer application:
next_activation = layer(activation)
# residual layer application
next_activation = activation + layer(activation)
```

# Skip Connections

- Made it easier to train deeper neural networks
- Information about weight updates are passed **backwards** from the output towards the input
- Difficult for information to propagate to the earlier layers

Note: You don't need to know the math behind why skip connections are better

# Fully Convolutional Networks

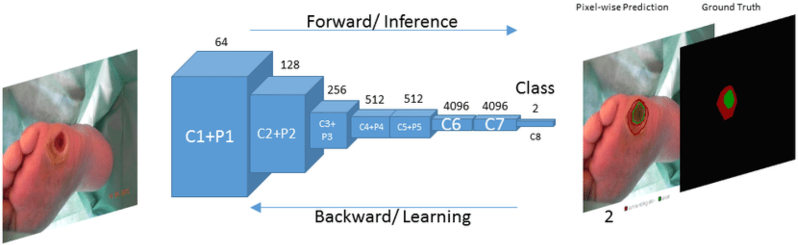



Image from "Fully Convolutional Networks for Diabetic Foot Ulcer Segmentation"

Q: How is this network different from what we have seen so far?

# Why avoid fully connected layers?

- So that the neural network can (theoretically) take arbitrary dimension images as input

# Instead of fully connected layers..

- Use a convolution layer with the same kernel size as hidden unit size and no padding
- Use global average-pooling

# Neural Network Debugging

# Why Debugging Neural Networks is Hard

- Most bugs are invisible and manifest only in **poor performance**
- How do you know whether poor performance is due to:
  - a bug
  - poor architecture/hyperparameter choice
  - data quantity/quality
  - something else?

Please make sure you flip through the reading:

`http://josh-tobin.com/assets/pdf/troubleshooting-deep-neural-networks-01-19.pdf`

Slides 1-34, 46-47, 52-75 (for now, there are more useful information here later)

# Steps to building a neural network

1. Start with a simple model
2. Get your training code to run without syntax and runtime errors
3. Get your code to overfit on a small subset of the training set (single batch)
4. Actual training

# 1. Simple Model

- Start with something like `LargeNet` modified to fit the new problem
- Some number of convolutions, then 1 or 2 fully-connected layer(s)

# 2. Common Runtime Errors

- Labels out of order
- Incorrect shapes for tensors
- Incompatible types of tensors (`float32` vs `float64` vs `long`)
- Incorrect pre-processing of images (not scaling the pixels to the range `[0, 1]`, or normalize to mean 0, std 1)
- Incorrect input to the loss function (pre-softmax vs post-softmax)
- Forgetting `optimizer.zero_grad()` cleanup step
- **Learning rate too high**

Recommended solutions for some of these in:

`http://josh-tobin.com/assets/pdf/troubleshooting-deep-neural-networks-01-19.pdf`

# 3. Overfit on a batch

Q: What does overfitting on a small data set achieve?

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Q: What does overfitting on a small data set achieve?

- "Quickly" = maybe ~100 iterations
- Check that your learning rate isn't too **low** or too **high**
- You can use the `Adam` optimizer:
  `optim.Adam(model.parameters(), lr=learning_rate)`
  - Adam generally trains faster than SGD
  - Usually the go-to optimizer for modern practitioners

Questions?

# Train/Test Split Strategies for Lab 3

# Proposed Strategy #1

Strategy:

- Each student has three sets of gesture images submitted
- Place two of those sets in the training/validation set
- Place one of those sets in the test set

Q: What do you think about this strategy?

# Proposed Strategy #2

Strategy:

- Randomly split the images into training, validation and test

Q: What do you think about this strategy?

# Proposed Strategy #3

Strategy:

- Split **students** into training/validation and test
  - If a student is in the test set, then all images generated by that student is in the test set.
- Hand pick which students are in which set

Q: What do you think about this strategy?

# Take-away

- Data splitting is hard
- You will need to make some trade-offs, especially with limited data
- Be honest when reporting what you did, and explain your choices

# Other thoughts: Recommend use ImageFolder

Sample code:

```
from google.colab import drive
drive.mount('/content/gdrive')
# Upload data
!unzip '/content/gdrive/My Drive/train_data.zip'
images = datasets.ImageFolder(root='train_data/', transform
images = list(images)
```

# Other thoughts: Saving the AlexNet output

I don't think anyone is there yet, but when you get there. . .

- Don't compute AlexNet features every time during training!
- Save the features for each input image
- When training your model, start with the saved features (rather than the image pixels)

# Lab Today

- I will be there too
- Walk-through of lab 2 code
- Office Hour Monday 4pm-5pm