

Feed-forward and Convolutional Neural Networks

Introduction and Usecase

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Acknowledgements

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- ▶ Data Machines (www.datamachines.io)
- ▶ DARPA

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Outline

1. Just enough theory/background
2. Feed forward neural networks
3. Convolutional neural networks
4. Use case: Mask fusion for image manipulation localization

About This Talk

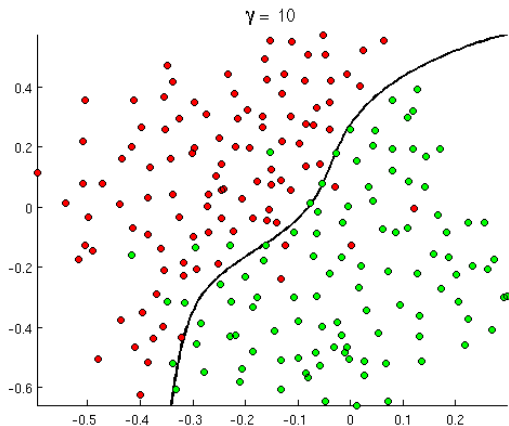
Goals:

- ▶ Give you nodding familiarity and ample pointers
- ▶ Leave you a starter code-base

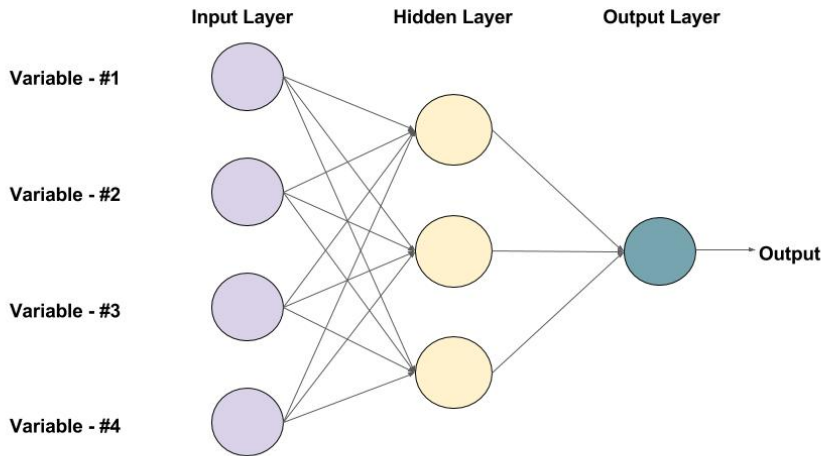
This talk lightly assumes:

- ▶ some familiarity with Python
- ▶ knowledge of general data science concepts

Supervised Models Are Function Approximators



The Feed Forward Neural Network



An example of a Feed-forward Neural Network with one hidden layer (with 3 neurons)

Neurons

Neurons take in the outputs of upstream neurons (or raw data).

They multiply that by a matrix of **weights**.

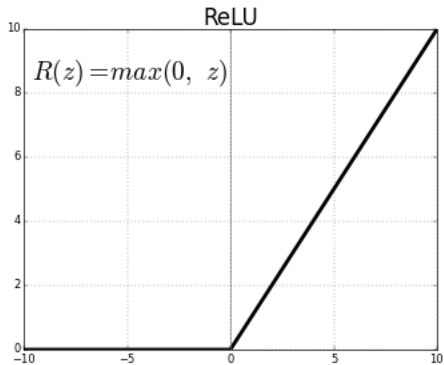
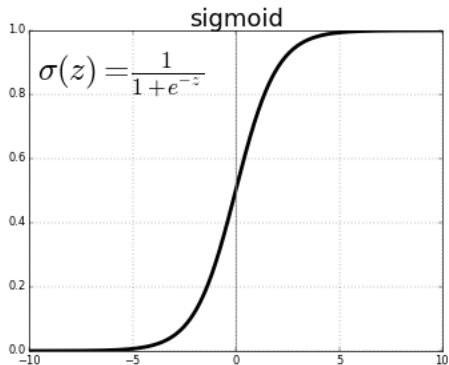
Add a **bias** term.

And pass that entire sum through an **activation function**.

For inputs X , weight matrix W , bias b , and activation function f :

Neuron output = $f(WX + b)$

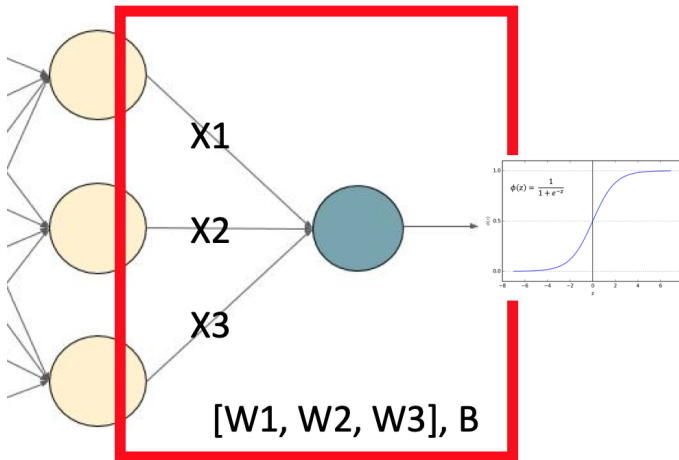
Activation Functions



Understanding a Neuron

Hidden Layer

Output Layer



Learning/Estimation/Function Approximation

Remember: The point is (flexible) function approximation.

In this case, approximation is optimization with respect to a **loss function**.

We **learn** the weights and biases via stochastic gradient descent.

What is Keras?

Light wrapper over TensorFlow.

<https://keras.io>

APIs allow simplicity and still power.

Great for **using** neural networks, even very complex ones.

Poor for research **on** neural networks.

Setup

`pip install keras`

– it brings along TensorFlow, numpy, etc
(that was easy)

Setup for GPU usage

Code Example: Iris Classification

Sepal Length	Sepal Width	Petal Length	Petal Width	Species
7.0	3.2	4.7	1.4	versicolor
...
...
5.9	3.0	5.1	1.8	virginica

A Simple Model

```
model = Sequential()

model.add(Dense(3, input_dim=4))
model.add(Dense(5))
model.add(Dense(3, activation='sigmoid'))

optimizer_details = SGD(lr=0.01, decay=1e-6)
model.compile(loss='binary_crossentropy',
              optimizer=optimizer_details)

model.fit(X_train, Y_train, epochs=20)
```

Hyperparameters and Overfitting

Hyperparameters:

- ▶ Number of layers
- ▶ Number of neurons in each layer

Strategies to avoid overfitting:

- ▶ Premature halting
- ▶ Dropout
- ▶ Regularization

Visit <http://playground.tensorflow.org> to see how hyperparameters affect outcomes in real models of toy data.

Pragmatics

- ▶ Start with an overly expressive model
- ▶ Track measure(s) of interest on test data; terminate upon plateau
- ▶ Match the problem type, output layer, and loss function

Problem Type	Output Layer	Loss Function
Regression	1-unit Linear	Mean Squared Error
Binary Classification	1-unit Sigmoid (softmax)	Binary Crossentropy
k-Class Classification	k-unit Sigmoid (softmax)	Categorical Crossentropy

Applicability

Q: When might you use a feed-forward neural network for regression or classification?

A: Probably never.

Image Classification with Neural Networks

Where **do** people get value out of neural nets?

Image Classification with Neural Networks

Where **do** people get value out of neural nets?

Images are arrays: Height by Width by 3 (RGB)

Why not “unwrap” them then use a set of fully connected layers?

- ▶ Tons of parameters
- ▶ Pixel location is relative

Convolutional Neural Network (CNN)

Conv Nets solve those problems by:

- ▶ Parameter sharing
- ▶ Looking at an image hierarchically

Idea:

- ▶ Find a set of micro-pictures that roughly capture the content across patches of all images (convolution)
- ▶ Then, let a single pixel represent its neighborhood, dropping the rest of the information (pooling)
- ▶ Repeat, generating a hierarchical view

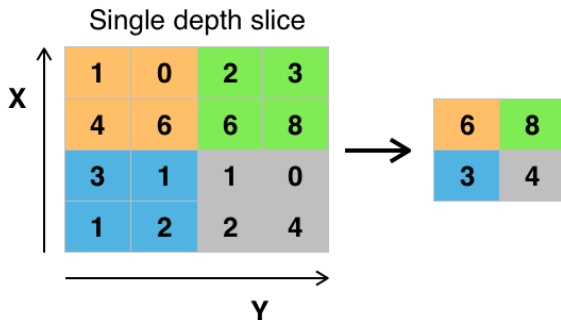
Convolutional Filters

“Find a set of micro-pictures that roughly capture content in every patch of all images”

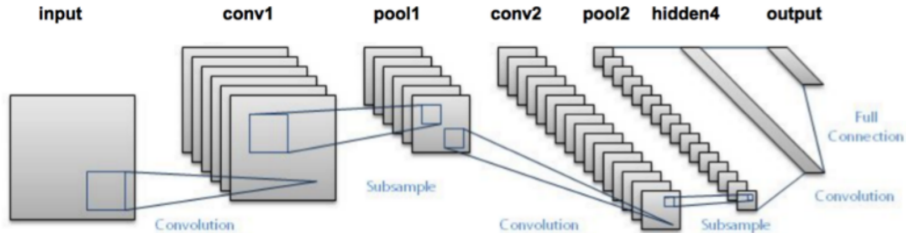


Pooling Operation

“Let a single pixel represent how much each filter matches the surrounding patch”



Repeat for Hierarchical Image Description



To learn:

- ▶ filters (which are just weights and biases with structure)
- ▶ weights and biases for hidden/output layers

A Tiny Example: Model Setup

```
from keras import Sequential
from keras.layers import Conv2D, MaxPooling2D, Dense
from keras.layers import Flatten
from keras.optimizers import SGD

model = Sequential()
model.add(Conv2D(32, kernel_size=(5, 5),
input_shape=input_shape))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Flatten())
model.add(Dense(50, activation='relu'))
model.add(Dense(num_classes, activation='softmax'))
```


A Tiny Example: Model Fitting

```
model.compile(loss=categorical_crossentropy,  
              optimizer=SGD(lr=0.01),  
              metrics=['accuracy'])
```

```
model.fit(x_train, y_train,  
         batch_size=batch_size,  
         epochs=epochs,  
         verbose=1)
```

Some Pragmatics

- ▶ Are your images special?
 - ▶ This is unlikely; consider fine-tuning an existing model.
- ▶ Are your images all the same size?
 - ▶ Either resize or consider pyramidal layers.
- ▶ Are your images large? Or many of them?
 - ▶ You likely need a GPU

A Challenging Use Case

Program Challenge: Write software that identifies altered images

Researchers write analytics that output scores and masks

My team tries to **fuse** the masks into a single, optimal mask.

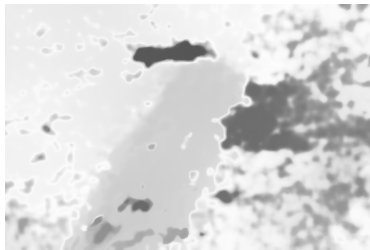
Example Data



Example Data



Example Data



Mask Fusion: Some Intuition

- ▶ Spatial smoothing
- ▶ Handle missing data
- ▶ Lightly parameterized – modest data
- ▶ Output is same shape as input image

Approach

- ▶ Large filters for spatial smoothing
- ▶ Not too deep a model (fewer parameters)
- ▶ Sized all images to 128x128, resize output back to original shape
- ▶ Missing data placeholder to -1

Eventually: Added information from an image segmentation model.

Example Autoencoding Setup

```
mod = Sequential()  
# Encoder Layers  
mod.add(Conv2D(18, (4,4), input_shape=(256, 256, 27)))  
mod.add(BatchNormalization())  
mod.add(MaxPooling2D((4,4), padding='same'))  
# Decoder Layers  
mod.add(UpSampling2D((4,4)))  
mod.add(Conv2D(1, (4,4), activation='sigmoid'))
```

Results

Short Version: Better than the best single analytic by a large margin.

Resources

- ▶ Keras: <https://keras.io>
- ▶ Keras tutorial: <https://elitedatascience.com/keras-tutorial-deep-learning-in-python>
- ▶ Intro to CNNs: <https://towardsdatascience.com/simple-introduction-to-convolutional-neural-networks-cdf8d3077bac>
- ▶ Mathy intro to CNNs: <https://arxiv.org/pdf/1511.08458.pdf>
- ▶ Advanced CNN architectures:
https://slazebni.cs.illinois.edu/spring17/lec04_advanced_cnn.pdf
- ▶ Hyperparameter tuning: <http://playground.tensorflow.org>

Questions?

Code and slides: https://github.com/nhdanneman/intro_to_dl

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