Neural Networks

PSC 8185: Machine Learning for Social Science

Iris Malone

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Recap

Where We've Been:

- Slow learning methods tend to outperform other methods
- Hyperplanes are a type of non-parametric classifier
- Non-parametric classifiers tradeoff low bias for more flexibility
- Kernels measure the similarity of two observations

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New Terminology:

- Maximal Margin Classifier
- Support Vectors
- Support Vector Machine
- Kernels

Agenda

1. Deep Learning
2. Neural Network Architecture
3. Recurrent Neural Nets
4. Convolutional Neural Nets

Deep Learning

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- 1800s-1950s: Linear Models + Principal Component Analysis
- 1960s-2010s: Random Forests, Boosting, Support Vector Machines, Bayesian
- Today: Deep Learning

Limits to Conventional Approaches

- Computational Expenses
    - Struggle to handle growth in big data
    - Slow
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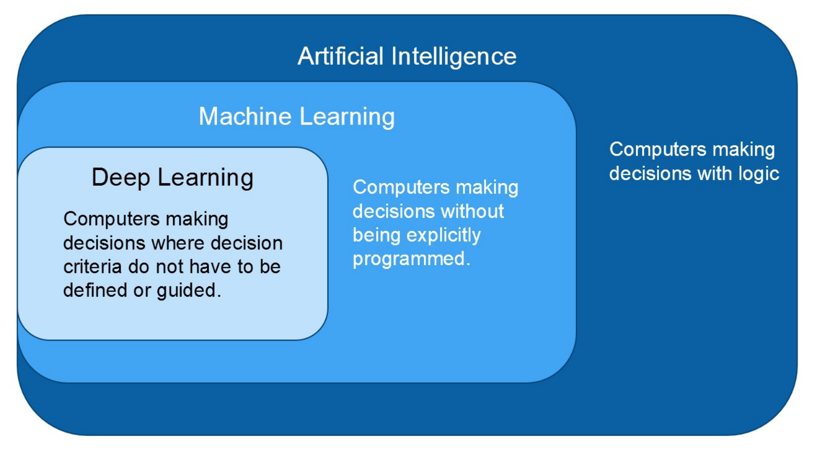
Solution: Deep Learning

Comparison of Deep Learning and ML



Deep Learning Results Improve on Conventional ML

- More Data
- More Model Complexity
- More Computational Power

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- Input of highly complex and multi-dimensional data (e.g. images, audio, time series data)

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- **Artificial Neural Networks**

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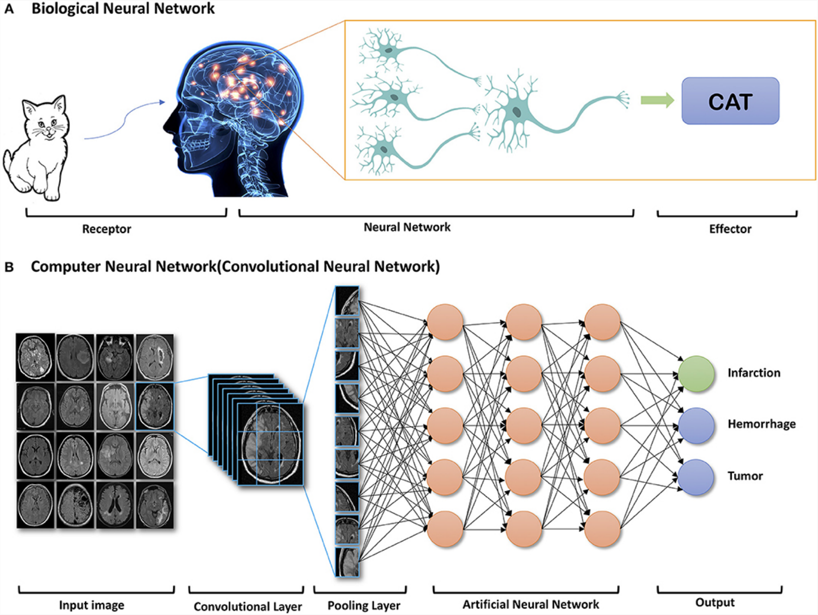
- Feed-forward (push forward) information from each previous input layer to assemble next layer
- Output is function of many inter-related input layers

Intuition of Deep Learning



Artificial Neural Networks May Sound Scary, But Aren't

Kareem Carr
@kareem_carr

I hate to tell you this but most deep learning models are just three or more logistic regressions in a trench coat.

8:20 PM · Jan 18, 2021 · TweetDeck

396 Retweets 41 Quote Tweets 4.3K Likes

Neural Network Architecture

Neural Network Vocabulary

- Network Layers
  - **Input Layer:** Predictors/information fed into model
  - **Hidden Layer:** Unobservable function in middle of network which relates different predictors together
  - **Output Layer:** Predictions from model

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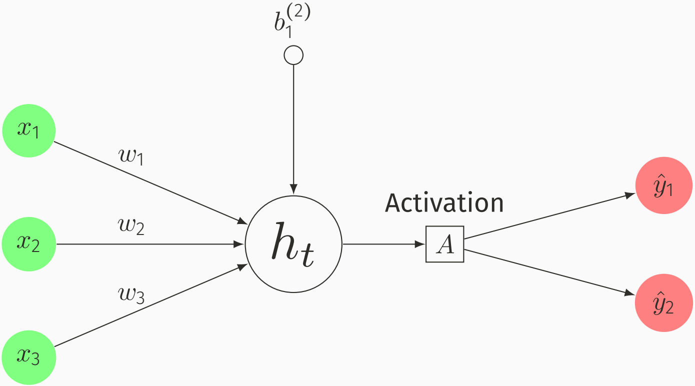
- **Activation Function:** Determines whether the expected output is in acceptable bounds and neuron should be 'fired' ('activated')

Basic Neural Network Architecture



An Analogy: 2SLS

Recall: In conventional regression methods, we sometimes want to model a process, but can't directly observe the effect of X on Y due to endogeneity concerns. The solution is **two-stage least squares modeling**

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Analogy: A NN is like a two-stage regression model where the hidden layer h_t is not directly observable

An Analogy: 2SLS

Two Equations:
First-Stage (estimate the effect of instrument on treatment):

$$h = \pi_o + \pi_1(X) + \nu$$

Second-Stage (estimate the effect of treatment on outcome):

$$Y = \beta_0 + \beta_1 h + u$$

Neural Network Procedure

- Each input is multiplied by a weight, e.g. $(x_1 * w_1), (x_2 * w_2), \ldots (x_p * w_p)$

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$$A(h_t) = f(x_1 * w_1 + x_2 * w_2 + \cdots + x_p * w_p + b)$$

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- Output $\hat{y}_1, \hat{y}_2, \dots, \hat{y}_n$ is transformed hidden layer

Neural Network Loss Function

Key Hyperparameters:

- weights w_i
- bias b

Loss functions $L(w_i, b)$ aims to minimize error with respect to weights.

Backpropagation

Minimize loss function through **backpropagation**, which is a system of calculating partial derivatives to find optimal w

$$\frac{\partial L}{\partial w_i} = \frac{\partial L}{\partial y}\frac{\partial y}{\partial w}$$

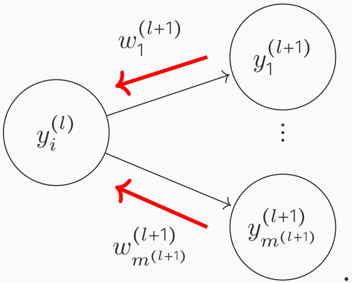
$$\frac{\partial L}{\partial y} = \frac{\partial (1-\hat{y})^2}{\partial y}$$

$$\frac{\partial y}{\partial w} = \frac{\partial \hat{y}}{\partial h}\frac{\partial h}{\partial w}$$

$$\frac{\partial \hat{y}}{\partial h} = w_i \times f(x_1 * w_1 + x_2 * w_2 + \cdots + x_p * w_p + b)$$

$$\frac{\partial h}{\partial w} = x_i \times f'(x_1 * w_1 + x_2 * w_2 + \cdots + x_p * w_p + b)$$

Backpropagation



Stochastic Gradient Descent

We apply a specific algorithm known as **stochastic gradient descent** which minimizes loss function by changing weights and bias:

$$w_1 - \lambda \frac{\partial L}{\partial w_1} \to w_1^*$$

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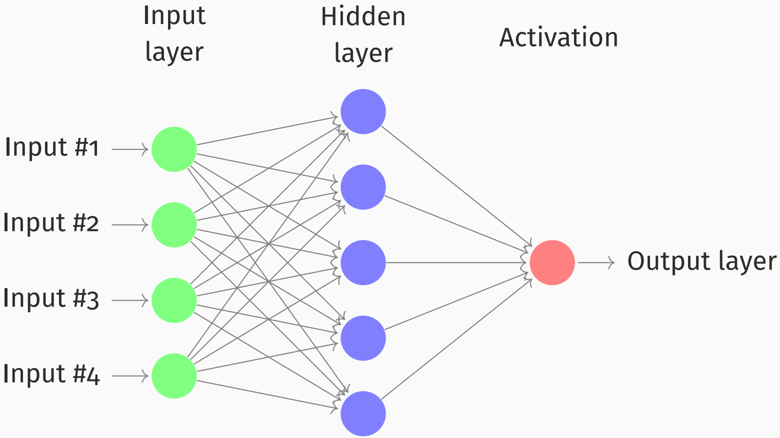
$$w_1 - \lambda \frac{\partial L}{\partial w_1} \to w_1^*$$

This is similar to how boosting worked:

- λ is a learning rate
- If $\frac{\partial L}{\partial w_1} > 0$, then weight decreases and loss decreases
- If $\frac{\partial L}{\partial w_1} < 0$, then weight increases and loss decreases

Complicated Neural Network Architecture

A neural network can have any number of layers with any number of neurons in those layers.



Choosing Number of Neurons

Neurons affect the bias-variance tradeoff of the model:

- More neurons → increased flexibility, but higher bias
- Fewer neurons → underfitting by blocking flow of information

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Rule of Thumb: Number Neurons = Number of Predictors +1

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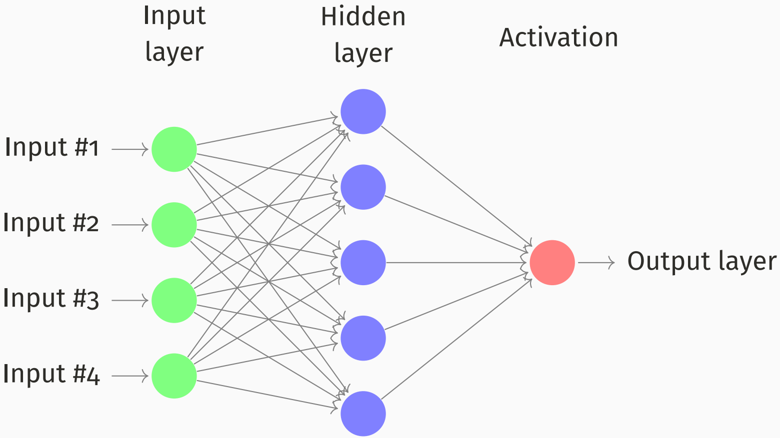

Activation Functions

Main Idea: Activation functions transform the hidden layers by constraining them to be in between particular values. It takes an unbounded input ($-\infty$ to ∞) $\rightarrow$ bounded input $[a, b]$

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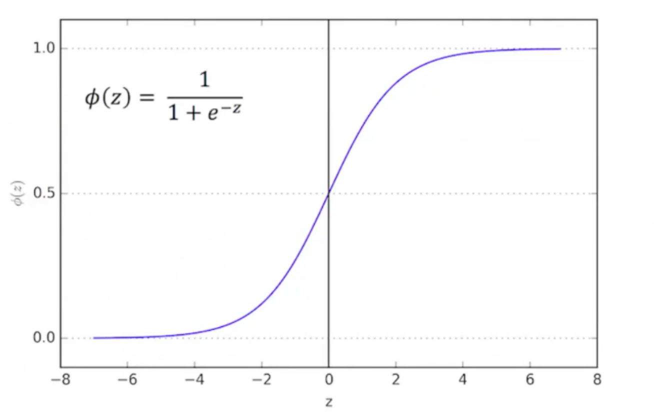
Common Activation Functions:

- Sigmoid Function: $[0, 1]$
- Rectified Linear Unit (ReLU): $[0, \infty]$
- Hyperbolic Tangent (TanH): $[-1, 1]$

Recall: Logit Function

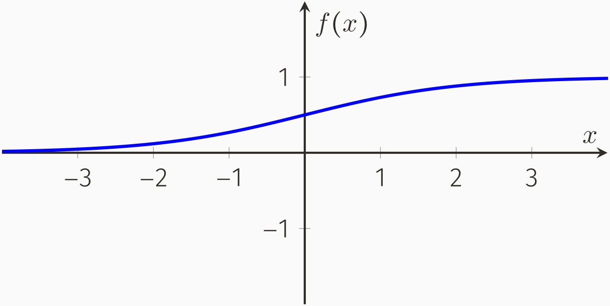
Logit Function (Sigmoid Function):

$$P(y = 1 \mid x) = f(X\beta) = \frac{e^{X\beta}}{1 + e^{X\beta}} = \frac{1}{1 + e^{-X\beta}}$$



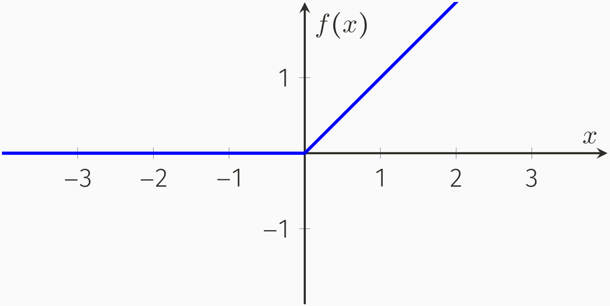
Sigmoid Activation Function

Sigmoid Activation Function: $A = \frac{1}{1+e^{-z}}$



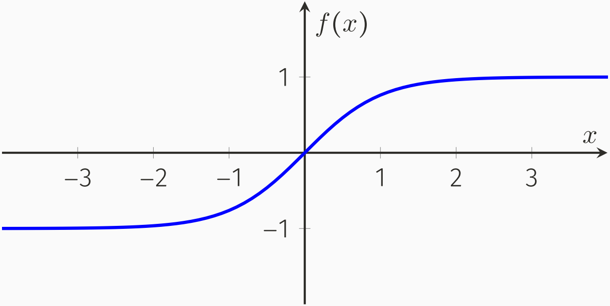
ReLU Activation Function

ReLU Activation FunctionTanh: $A = \max(0, z)$



Hyperbolic Tangent Function

Tanh Activation Function: $A = \frac{e^z e^{-z}}{e^z + e^{-z}}$



How does the Model Learn?

- **Batch Size:**

- **Epochs:**

- **Dropout:**

How does the Model Learn?

- **Batch Size:** Number of sequences the model studies before updating the weights.
  - Small batch size → more frequent updating (without observing all data)
  - Small batch size → fast, but worse accuracy
  - Large batch size → less frequent updating, but less sensitive to noise
- **Epochs:**
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How does the Model Learn?

- **Batch Size:** Number of sequences the model studies before updating the weights.

- **Epochs:** Measures the number of times the model iterates through all of the training data.
  - Large batch size → fewer iterations to go through full pass of data
  - Increasing passes is like bootstrap → increased likelihood population convergence
- **Dropout:**

How does the Model Learn?

- **Batch Size:** Number of sequences the model studies before updating the weights.
- **Epochs:** Measures the number of times the model iterates through all of the training data.
- **Dropout:** Prevents overfitting. Randomly removes a certain number of observations from each input when creating the model.

Types of Neural Networks

1. **Feed-forward Neural Networks:** Perform basic pattern recognition (information passes in a single direction)

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2. **Recurrent Neural Networks (RNN):** Performs Natural Language Processing (NLP), Speech Recognition, and Times Series Forecasting
3. **Convolutional Neural Networks (CNN):** Performs object recognition and image analysis

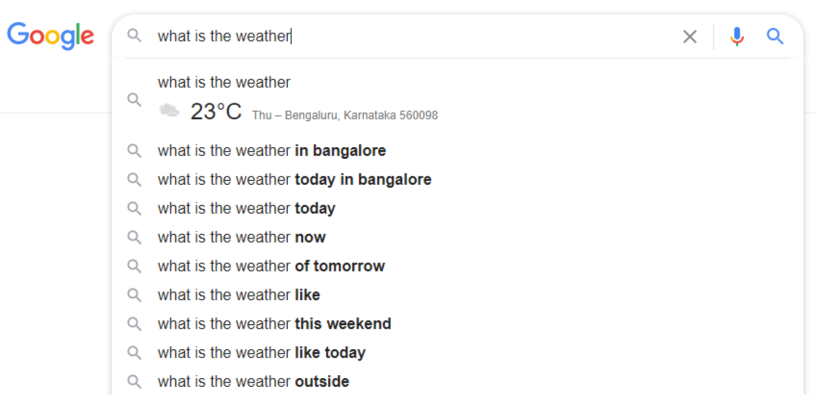
Recurrent Neural Nets

Motivation for RNN

Motivation: There are many prediction problems which are time- or sequence-dependent

- Stock Market Forecasts
- Supply/Demand Needs
- Conflict Risk
- Text Prediction

Google RNN Prediction



RNN and NLP

I forced a bot to watch over 1,000 hours of Olive Garden commercials and then asked it to write an Olive Garden commercial of its own. Here is the first page.

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'E GARDEN COMMERCIAL

. OLIVE GARDEN RESTAURANT

:oup of FRIENDS laughs at a dinner table. A WAITR
leliver what could be considered food.

WAITRESS
Pasta nachos for you.

ee the pasta nachos. They're warm and defeated.

FRIEND 1
The menu is here.

WAITRESS
Lasagna wings with extra Italy.

ee the lasagna wings. There's more Italy than ne

FRIEND 2
I shall eat Italian citizens.

FRIEND 3
Leave without me. I'm home.

WAITRESS
Gluten Classico. From the kitchen.

Gluten Classico. We believe the waitress tl
he kitchen. We have no reason not to believ

4 says nothing.

FRIEND 1
What is wrong, Friend 4?

4 says nothing.

FRIEND 2
Friend 4, what is wrong, Friend 4?

4 smiles wide. Her mouth is full of secret

An Actual RNN NLP Example

In The Alteri Silence by Forest_of_Holly for roscreens41

Snape receives life after plants to do by work over whether they get into. Just Hell.

A Second Chance by DarkCorgi

Snape had a second thing, and that is better than anything for for the rest of his life.

Mirror by orphan_account

Severus Snape tries to get a lot of dragons and that was to be more than he didn't expect to continue. He has always been a bit of an old and a baby to stay the way he'd been the brother at Hogwarts and he keeps the chance of meeting…

Deception by FlyingEyes

Snape is a British Robes of interesting things and worrys like a little fun and sees the pretty battle for a while.

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Solution: Recurrent Neural Nets

RNN

Main Idea:

- RNNs loop through previous outputs and learn from previous cases to improve model performance
- Memory previous states + new input states → outputs

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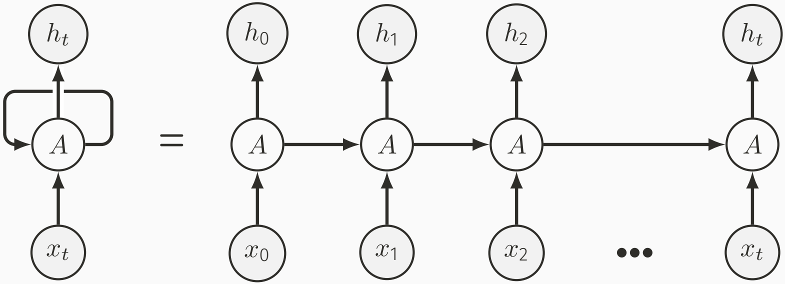
Hidden layer output h_t is now function of weighted input state x_t and previous hidden states h_{t-1} transformed by A.

$$h_t = A(h_{t-1}, x_t) = tanh(W_{yh}h_{t-1} + W_{xh}x_t) \tag{1}$$

How Recurrent Neural Networks Work



Advantages to RNN

- Assumes current events dependent on deep past
- Long Memory $\rightarrow$ takes input of any length
- Learns from temporal dependencies
- Improved long-term accuracy forecasting

Limits to RNN

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  - If $\sum_{i=1}^{n} \frac{\partial L(w_i)}{\partial w_i} \rightarrow 0$, then slow to no learning
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- Risk of Over-Fitting
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- Training Challenges
  - Hyperparameter Tuning
    - Epochs
    - Neurons
    - Batch Size
  - Solution: Loops, updating, numerous iterations

Convolutional Neural Nets

Motivation for CNN

Motivation: There are many prediction problems which are spatial-dependent

- Image Classification
- Disease Contagion
- Natural Disaster Risk Zones
- Conflict Spillover

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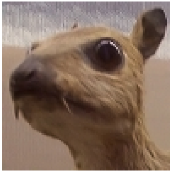
- **Convolutional layer:** performs linear operation to multiply and weight 2d inputs (like hidden layer)
- **Feature Map** makes the links - it encodes the presence and degree of presence of the feature it detects.

CNN Procedure

- Take 2d input and apply **filter kernel** to the input layer
- Product of input & filter kernel → **Feature Map**

Input image



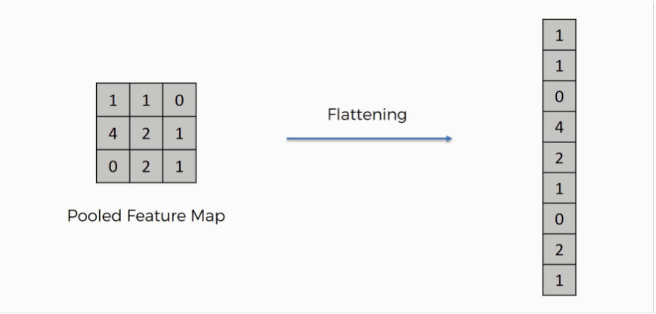
Convolution Kernel

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

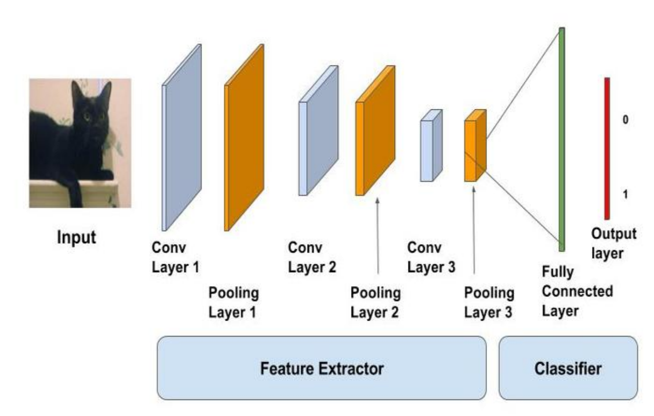
Feature map

CNN Procedure

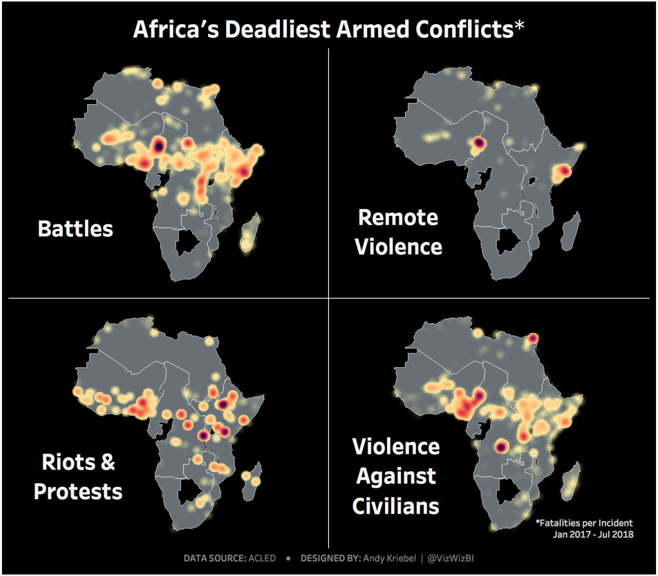
- Take **feature map** and apply flattening transformation
- Use flattened transformation as input layer for artificial layer
- Build conventional NN and get 1d output
- Apply transformation to restore to 2d output
- Iteratively repeat



2D CNN Architecture



Examples of CNN



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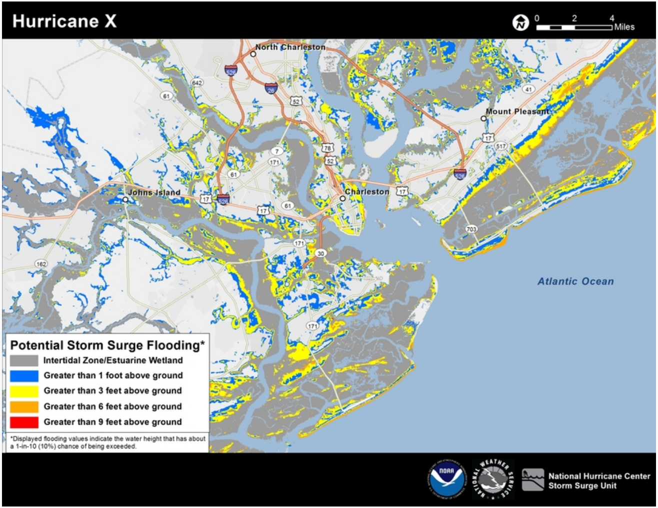

Limits to CNN

- Black Box
- Assumes temporal independence
- Vanishing gradient problem
- Very hard to train
- Computational Expensive (image quality)

Conclusion

- NN are like 2SLS; they feed forward information from inputs to output via hidden layer
- 3 types of artificial neural nets: feedforward, recurrent, and convolutional
- NN are hard to tune, but perform very well when they work