The ML Nitty Grittys

Details on general ML implementations

Today's Content

- Getting your data right
- Training Data vs. Testing Data
- Overfitting
- Error Functions
- Applications of machine learning

We need a little more context before talking about Deep Learning

- What are machine learning systems trying to accomplish?
- How do we set the data up most effectively?
- What problems might arise?

All machine learning systems try to learn the function

$$f(X) = Y$$

s.t. X is a matrix of data and Y is a vector (usually)

	X ₁ = Roses	X ₂ = Violets	Y=Poem Quality
Sample 1	Red	Blue	Good
Sample 2	Not Red	Not Blue	Bad

- Our ML system here is learning Poem Quality as a function of Word Choice
 - Our data here is Categorical, not continuous
 - Each column in the X-set is called a feature
- But this data isn't good enough, we haven't preprocessed it yet.

	X ₁ = Roses	X ₂ = Violets	Y=Poem Quality
Sample 1	Red	Blue	Good
Sample 2	Not Red	Not Blue	Bad

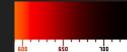
- First, we need to bound our sets. We need to establish the space that we are working in.
 - O What values can each feature take on?
 - Will each feature always appear in each sample?

	X ₁ = Roses (Red/Not Red)	X ₂ = Violets (Blue/Not Blue)	Y=Poem Quality (Good/Bad)
Sample 1	Red	Blue	Good
Sample 2	Not Red	Not Blue	Bad

- Then, we introduce a numeric scale
 - S.t. it levels each variable's importance
 - [0,1] scale, normalize each column vector, etc.
 - Why is a numerical scale necessary?

	X ₁ = Roses (1/0)	X ₂ = Violets (1/0)	Y=Poem Quality (1/0)
Sample 1	1	1	1
Sample 2	0	0	0

- Numeric scales are useful when
 - We are working with continuous functions
 - Roses are red...how red?



- We want to graphically represent our data
- We want to see patterns in the data easier by eye
- If you have categorical data, choose a numerical scale so that it makes sense!
 - Lower class = 0, upper class = 1, middle class = 2 doesn't
 make sense

- Ex: bird sanctuary website records data on user page visits
- Feature Selection
 - More data = Longer run time
 - Some data may be superfluous

Decomposition

 What if time is recorded in seconds but the patterns are hourly?

Aggregation

 What if you get a list of all login attempts but don't care about them as single data points?

Why do we pre-process the data?

 As we'll see, ML systems only learn to make decisions by minimizing their error from data

Why do we pre-process the data?

- As we'll see, ML systems only learn to make decisions by minimizing their error from data
- Inconsistent data = Inconsistent decisions
- Poorly scaled data = Poorly scaled decisions

Why do we pre-process the data?

- As we'll see, ML systems only learn to make decisions by minimizing their error from data
- Inconsistent data = Inconsistent decisions
- Poorly scaled data = Poorly scaled decisions
- Good data = Good decisions?

Training Data vs. Testing Data

- Once our data is processed, we need to split it into training data
 vs. testing data
 - o ???????
 - o ???????

Training Data vs. Testing Data

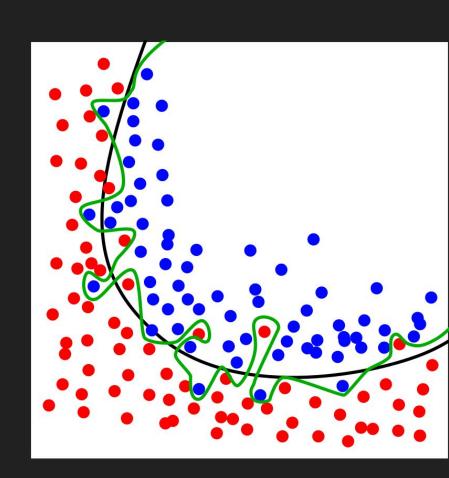
- Once our data is set up, we need to split it into training data vs. testing data
- Training Data What your machine learning system learns on
- Testing Data What your machine learning system checks its learning on
- Why do we need this?

Overfitting

- Any ML system conforms itself as best it can to your exact data
- In a perfect world, they will learn to generalize
- ML systems instead overfit to whatever data they are given
 - We did this last week with the buses

Overfitting

- More complex ML systems are more likely to overfit
- Less complex ML systems may not have the means to learn
- Training data that repeats specifics is more likely to be overfit on
 - Roses = red → Good Poem
 every time in training set?



Back to Training vs. Testing

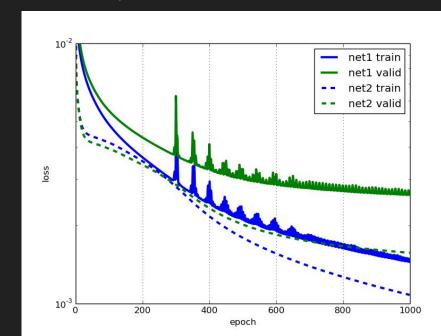
So we train on one set of data hundreds of times over

Hope that this will carry over to test data (which is a separate

set!)

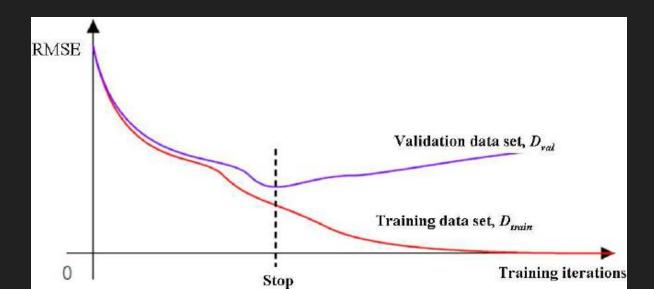
Overfit == Something's wrong?

No overfit == Everything's fine?



Early Stopping to avoid overfitting

- Often, the overfit will end up worsening the test results with enough iterations on the training data
- We'll talk about deep learning strategies for this later



Okay, but how does an ML system actually learn?

- Error functions!
 - Aka cost functions, loss functions
- We want to minimize the following I s.t.
 - f is our machine learning system
 - V is the error function
 - o p is the probability distribution of the data

$$I[f] = \int_{X imes Y} V(f(ec{x}),y) p(ec{x},y) \, dec{x} \, dy$$

Error Functions (in theory)

- Let's do an example error analysis given a classification task
 - X is the vector space of all possible inputs
 - Y is only from set [-1, 1]
 - Our error function V is the 0-1 Indicator Function
- Remember, we want to minimize I

$$I[f] = \int_{X imes Y} V(f(ec{x}),y) p(ec{x},y) \, dec{x} \, dy$$

So that's our I, how do we minimize it?

- We take the gradient of I (usually of V actually) and go towards the local minimum
 - We take the gradient of V rather than I since we may not know p
- More on this in the next lecture

$$I[f] = \int_{X imes Y} V(f(ec{x}),y) p(ec{x},y) \, dec{x} \, dy$$

Back to the real world

- Hopefully you can see how powerful this is
- We can minimize our prediction error on any type of data
 - Language can be made into data
 - Videos are data
 - Your logins are data
 - Motion is data
 - Blood tests are data
- Our error equation is general
 - Our data can be anything and these techniques will work

Machine Learning Applications today

- Self driving car
- Recommendations (Netflix, Youtube, etc.)
- Weather
- Fraud detection
- Looking at X-Rays
- Autonomous grocery store
- Crime prediction
- Autonomous military vehicles
- Automated investing (every thousandth of a second)