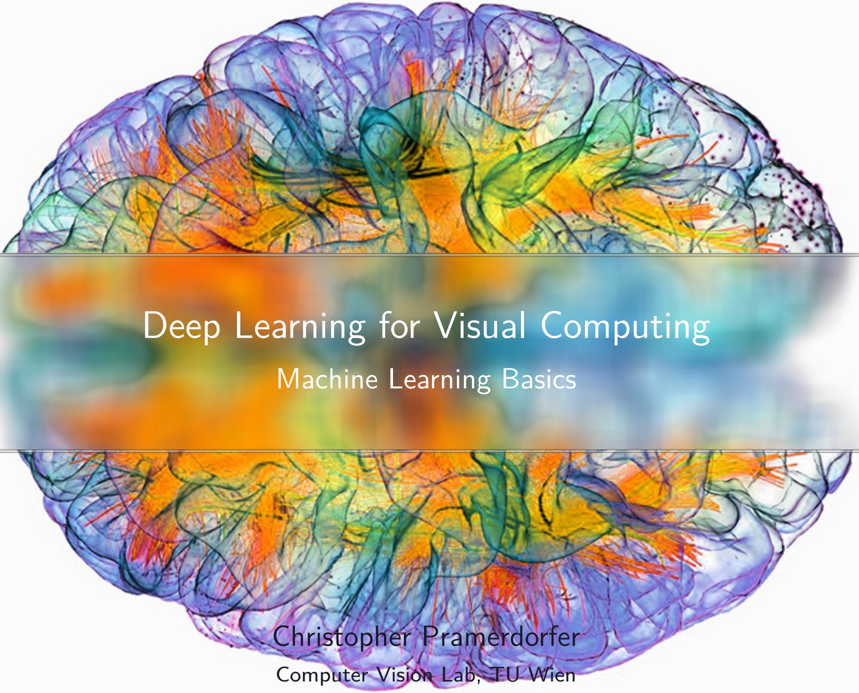

Deep Learning for Visual Computing

Machine Learning Basics

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Image by Neuroscape Lab

Topics

Machine learning motivation

Image classification via machine learning

- Approach
- How algorithms learn
- Simple example : k nearest neighbors

Statistical learning theory

Hyperparameter selection

Motivation

Let's build an image classifier

- Should support the classes {dog, cat}
- Using the CIFAR10 dataset

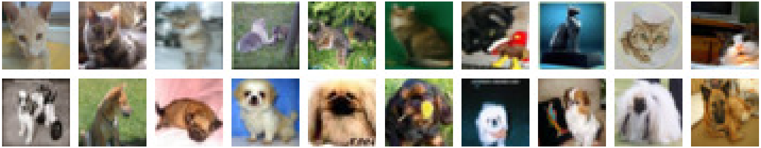


Image from cs.toronto.edu

Motivation

How can we write an algorithm for this purpose?

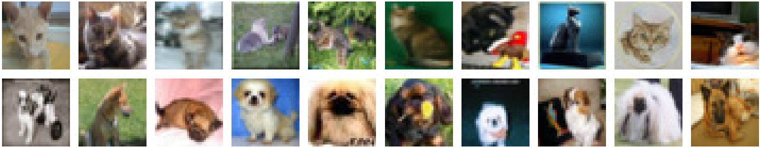


Image from cs.toronto.edu

Motivation

We cannot!

- No obvious unique and reliable features
- Not clear how to represent and use them

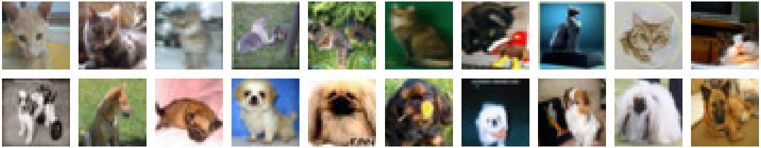


Image from cs.toronto.edu

Motivation

We can classify images easily

But we cannot describe formally how to do so

- Thus the standard `if {} else {}` approach fails

This applies to most vision problems

Motivation

Machine Learning (ML) to the rescue!

ML algorithms are able to learn from data

Learning from data

- Performance of algorithm improves with experience
- Algorithm improves as it sees more cat and dog images

Motivation

ML is central in modern Computer Vision

DL is branch of ML

- Important ML concepts also apply to DL
- Why we review them in this lecture

Image Classification via ML
Approach

Show $(\text{image}, \text{label})$ pairs to ML algorithm

Algorithm somehow learns to predict labels for unseen samples

Finite number of different labels

- We have a classification problem (vs. regression)

We have samples and target labels

- Called supervised learning (vs. unsupervised learning)

Images are points in D-dimensional space

- Stack image rows/columns to obtain vector $\mathbf{x}$
- D is usually large (CIFAR10 : $D = 32 \cdot 32 \cdot 3 = 3072$)

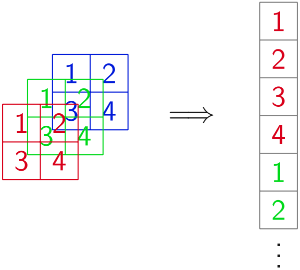


Image Classification via ML
How Algorithms Learn

Assuming $D = 2$ and three classes (colors)

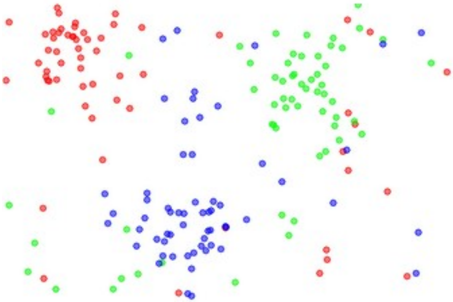


Image from cs231n.github.io

Discriminative models learn decision boundaries

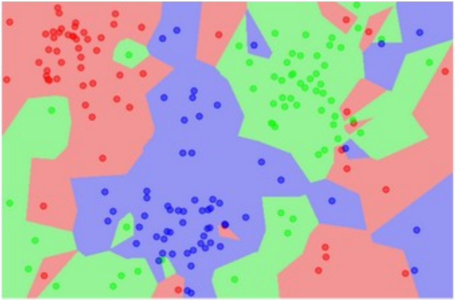


Image from cs231n.github.io

Ideally such models are probabilistic

- Measure of uncertainty

Let w encode the class label, e.g. $w \in \{\text{cat}, \text{dog}\}$

Such models compute $\Pr(w|\mathbf{x})$

- Conditional probability of w given $\mathbf{x}$
- Probability for every class given image $\mathbf{x}$

Decision boundaries where $\arg\max_w \Pr(w|\mathbf{x})$ changes

Generative models learn class-conditional densities $\Pr(\mathbf{x}|w)$

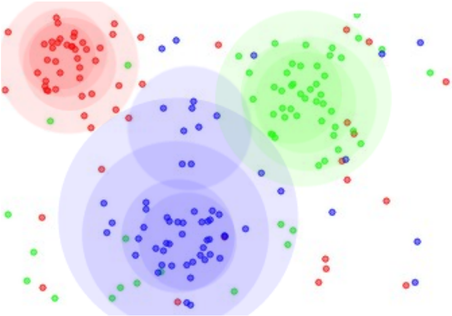


Image adapted from cs231n.github.io

Classification from $\Pr(\mathbf{x}|w)$

- Compute $\Pr(\mathbf{x}|w)\,\Pr(w)$ for all w
- Assign class where product is maximal

Or to obtain $\Pr(w|\mathbf{x})$

- Compute $\Pr(\mathbf{x}|w)\,\Pr(w)$ for all w
- Divide each product by sum over all products

$\Pr(w)$ is fraction of training samples with class w

This is Bayes' rule in action

$$\Pr(w|\mathbf{x}) = \frac{\Pr(\mathbf{x}|w)\Pr(w)}{\Pr(\mathbf{x})} = \frac{\Pr(\mathbf{x}|w)\Pr(w)}{\sum_w \Pr(\mathbf{x},w)} = \frac{\Pr(\mathbf{x}|w)\Pr(w)}{\sum_w \Pr(\mathbf{x}|w)\ \Pr(w)}$$

Don't remember this stuff?

- See slide 21

For example, assume that

- Classifier says $\Pr(\mathbf{x}|\text{cat}) = 0.03$ and $\Pr(\mathbf{x}|\text{dog}) = 0.022$
- We know that $\Pr(\text{cat}) = 0.4$ and $\Pr(\text{dog}) = 0.6$

We obtain

- $\Pr(\mathbf{x}|\text{cat}) \Pr(\text{cat}) = 0.0120$
- $\Pr(\mathbf{x}|\text{dog}) \Pr(\text{dog}) = 0.0132$
- $\Pr(\text{cat}|\mathbf{x}) = 0.48$ and $\Pr(\text{dog}|\mathbf{x}) = 0.52$

So we cannot be sure whether image shows cat or dog

Discriminative models are more popular

- CNNs are discriminative and probabilistic

Different discriminate models/algorithms differ in

- Decision boundary properties (e.g. linear)
- How boundaries are computed

Models vs. algorithms

- Model specifies boundary properties
- Algorithm specifies how to compute boundaries

Linear SVMs and logistic regression are both linear models

- But training and prediction algorithms differ

In practice, both terms often used interchangeably

See "Computer Vision Models" book for details

- Available at computervisionmodels.com
- Highly recommended

Simple ML algorithm

Simply store the training set (images as vectors $\mathbf{x}$)

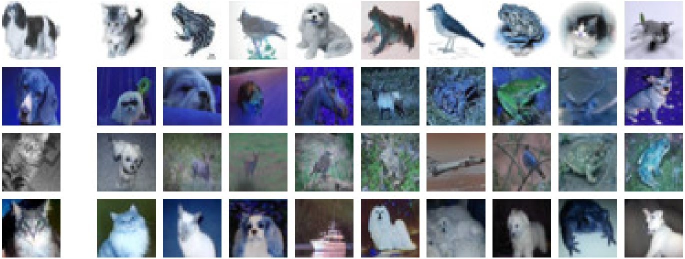
Classify new image using labels of k nearest training samples

Need distance measure between two images $\mathbf{x}_1, \mathbf{x}_2$

$$\text{L1 distance} \quad : \quad \sum_{i=1}^{D} \left| x_i^1 - x_i^2 \right|$$

$$\text{L2 (Euclidean) distance} \quad : \quad \sum_{i=1}^{D} \sqrt{\left(x_i^1 - x_i^2 \right)^2}$$

Resulting cat vs. dog classifier



Looks like our classifier does not work so well

How can we quantify algorithm performance?

- Need a suitable performance measure

Accuracy is popular for classification

- Let algorithm predict labels for dataset
- Compare predictions and true (ground truth) labels
- Accuracy is fraction of correctly classified samples

Measure $1 -$ accuracy is called error rate

What happens if we test on training data with $k = 1$?

Must test algorithm on data unseen during training!

- Want to assess its ability to generalize to unseen data
- Indicates how well it will perform in real world

Need two disjoint datasets

- Training set for learning
- Test set for assessing performance

How can this even work?

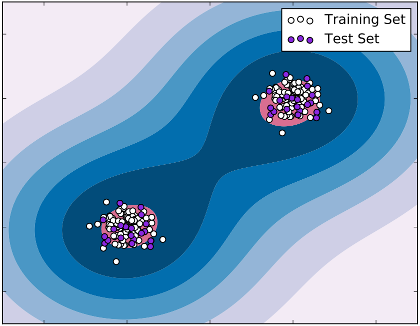
- We show the algorithm some data
- It should then perform well on different data

Proper training and test sets are highly correlated

- Both reflect problem we want to solve
- Implies relationship between training and test accuracy

Samples of both sets generated by same underlying distribution

- So sets also have similar distribution



Algorithm Performance

Statistical Learning Theory

In our case, the underlying distribution

- Is distribution of *all* images that capture problem
- All possible cat and dog images (of certain size)

We clearly don't know how this distribution looks like

- But we can sample from this distribution
- By taking photos of cats and dogs

Can only collect so many samples

- Distributions more or less dissimilar
- Test error equal or greater than training error

Distributions of sets dissimilar to underlying distribution

- Problem known as dataset bias
- Test set performance generally upper bound

Two factors determine algorithm performance

- Ability to minimize training error
- Ability to minimize gap between training and test error

Related to two main challenges in ML

- Unable to reach low training error (underfitting)
- Gap between training and test error too large (overfitting)

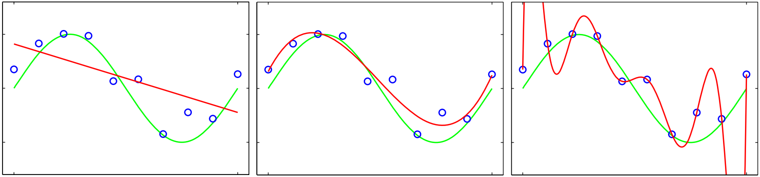


Image adapted from [1]

Must select suitable algorithm capacity

- Ability to compute complex decision boundaries

Lower capacity

- May struggle to fit the training set (higher bias)
- More prone to underfitting, less prone to overfitting

Higher capacity

- May fit the training set too well (higher variance)
- Less prone to underfitting, more prone to overfitting

Test (generalization) error usually U-shaped function of capacity

- Decreases until some point, then increases again

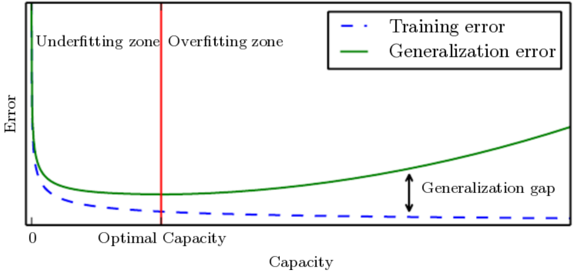


Image from [2]

Increasing training set size

- Increases performance as data reflect problem better
- Increases optimal capacity until adequate for problem

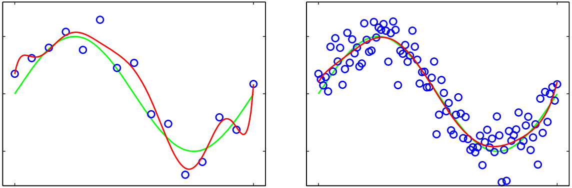


Image adapted from [1]

Capacity governed by k

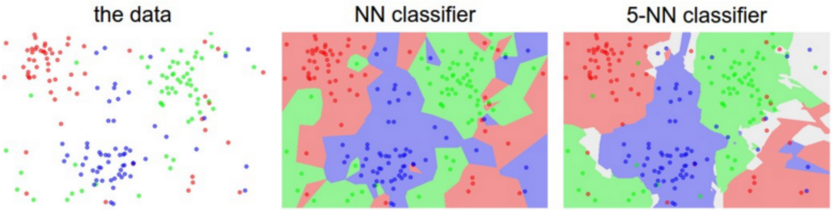


Image from cs231n.github.io

Hyperparameter Selection
Validation Sets

k is a hyperparameter

- Manually set, controls algorithm behavior

How should we set k?

- Depending on data, different k work best
- Must find good choice experimentally

For this purpose we

- Use part of training set as validation set
- Use this set to see how different k perform

Validation set is split away from training set

- Never use test set during training!

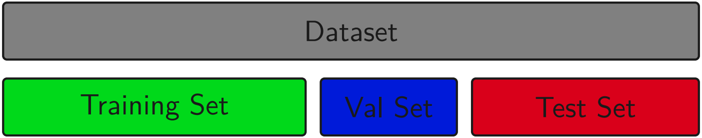
Usually 10% to 30% of training data used for validation

- Depends on dataset size, number of hyperparameters

Alternatively we can use cross-validation

- Usually not done in DL (takes too long)

We thus need three disjoint datasets



We cannot test all hyperparameter combinations

- Testing one combination can take long
- Number blows up if we have several hyperparameters
- Large and/or continuous intervals

Use an approximative search strategy

- Grid search
- Random search

For each hyperparameter

- Define search interval
- Sample from interval (often uniformly)

Test all sample combinations

(Repeat with smaller intervals based on previous results)

Define search interval for each hyperparameter

For each trial

- Randomly sample value from each interval
- Test sample combination

Hyperparameter Selection
Search Strategies

Random search usually works better

- Wastes less time on unimportant hyperparameters

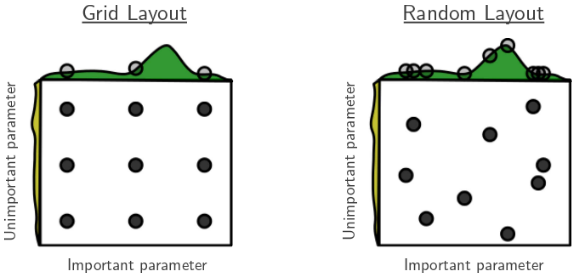


Image from [3]

Bibliography

[1] C. M. Bishop, *Pattern recognition*, , 2006.

[2] I. Goodfellow, Y. Bengio, and A. Courville, *Deep learning*, 2016.

[3] J. Bergstra and Y. Bengio, *Random search for hyper-parameter optimization*, Journal of Machine Learning Research, 2012.