CS5670: Computer Vision

Image Classification

Some Slides from Fei-Fei Li, Justin Johnson, Serena Yeung
http://vision.stanford.edu/teaching/cs231n/
Announcements

• One more project to go – Project 5: Neural Radiance Fields
  • Tentative release date: Thursday, April 20
  • Tentative due date: Wednesday, May 3

• In-class Final Exam during the last lecture: Tuesday, May 9
Third Place
Jinzhao Kang and Xianglin Chen
Second Place
Wenqi Xiao and Zhuoyi Li
First Place
Last time: intro to recognition + classification

• Different problems: **image classification**, object detection

• Initial classification idea: k Nearest Neighbors
Image Classifiers in a Nutshell

- Input: an image
- Output: the class label for that image
- Label is generally one or more of the discrete labels used in training
  - e.g. \{cat, dog, cow, toaster, apple, tomato, truck, ... \}

```python
def classifier(image):
    # Do some stuff
    return class_label;
```

\[ f(\text{Cat}) = \text{“Cat”} \]

\[ f(\text{Dog}) = \text{“Dog”} \]

\[ f(\text{Toaster}) = \text{“Toaster”} \]
Image classification demo

https://cloud.google.com/vision/docs/drag-and-drop

See also:
https://aws.amazon.com/rekognition/
https://www.clarifai.com/
https://azure.microsoft.com/en-us/services/cognitive-services/computer-vision/
The Semantic Gap

What we see

What the computer sees
Variation Makes Recognition Hard

- The same class of object can appear very differently in different images.
The Problem is Under-constrained

• Distinct realities can produce the same image...
• We generally can’t compute the “right” answer, but we can compute the most likely one...
• We need some kind of prior to condition on. We can learn this prior from data:

\[ f(x) = \arg \max_{\ell_x} P(\ell_x | \text{data}) \]
Images As High-Dimensional Vectors

• An image is just a bunch of numbers
• Let’s stack them up into a vector
  • Our training data is just a bunch of high-dimensional points now
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  • Our training data is just a bunch of high-dimensional points now

• Divide space into different regions for different classes
Images As High-Dimensional Vectors

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- Let’s stack them up into a vector
  - Our training data is just a bunch of high-dimensional points now

- Divide space into different regions for different classes

The Space of All Images
Images As High-Dimensional Vectors

- An image is just a bunch of numbers
- Let’s stack them up into a vector
  - Our training data is just a bunch of high-dimensional points now
- Divide space into different regions for different classes
  
  or
- Define a distribution over space for each class

The Space of All Images

- Toasters
- Cats
How high-dimensional is an image?

Let’s consider an iPhone X photo:
- 4032 x 3024 pixels
- Every pixel has 3 colors
- 36,578,304 pixels (36.5 Mega pixels)

In practice, images sit on a lower-dimensional manifold.

Think of image features and dimensionality reduction as ways to represent images by their location on such manifolds.
Image Features and Dimensionality Reduction

• How high-dimensional is an image?
  • Let’s consider an iPhone X photo:
    • 4032 x 3024 pixels
    • Every pixel has 3 colors
    • 36,578,304 pixels (36.5 Mega pixels)

• In practice, images sit on a lower-dimensional manifold

• Think of image features and dimensionality reduction as ways to represent images by their location on such manifolds

Side Note:
This also lets us deal with images of different sizes, crops, etc.
Training & Testing a Classifier

• Collect a database of images with labels
• Use ML to train an image classifier
• Evaluate the classifier on test images
Training & Testing a Classifier

Training

Training Images

Image Features

Training

Training Labels

Learned Classifier

Dataset: ETH-80, by B. Leibe
Slide credit: D. Hoiem, L. Lazebnik
Training & Testing a Classifier

Training

Training Images

Training Labels

Image Features

Training

Learned Classifier

Testing

Test Image

Image Features

Learned Classifier

Prediction

Dataset: ETH-80, by B. Leibe
Slide credit: D. Hoiem, L. Lazebnik
Classifiers

- Nearest Neighbor
- kNN ("k-Nearest Neighbors")
- Linear Classifier
- Neural Network
- Deep Neural Network
- ...
First idea: Nearest Neighbor (NN) Classifier

- **Train**
  - Remember all training images and their labels

- **Predict**
  - Find the closest (most similar) training image
  - Predict its label as the true label
CIFAR-10 and NN results

Example dataset: **CIFAR-10**
- **10 labels**
- **50,000** training images
- **10,000** test images.

airplane
automobile
bird
cat
deer
dog
frog
horse
ship
truck
CIFAR-10 and NN results

Example dataset: **CIFAR-10**

- **10 labels**
- **50,000 training images**
- **10,000 test images.**

For every test image (first column), examples of nearest neighbors in rows.

<table>
<thead>
<tr>
<th>airplane</th>
<th>automobile</th>
<th>bird</th>
<th>cat</th>
<th>deer</th>
<th>dog</th>
<th>frog</th>
<th>horse</th>
<th>ship</th>
<th>truck</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Image" /></td>
<td><img src="image2.png" alt="Image" /></td>
<td><img src="image3.png" alt="Image" /></td>
<td><img src="image4.png" alt="Image" /></td>
<td><img src="image5.png" alt="Image" /></td>
<td><img src="image6.png" alt="Image" /></td>
<td><img src="image7.png" alt="Image" /></td>
<td><img src="image8.png" alt="Image" /></td>
<td><img src="image9.png" alt="Image" /></td>
<td><img src="image10.png" alt="Image" /></td>
</tr>
</tbody>
</table>

Slides from Andrej Karpathy and Fei-Fei Li
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**k-nearest neighbor**

- Find the k closest points from training data
- Take **majority vote** from K closest points
What does this look like?
What does this look like?
What does this look like?
How to Define Distance Between Images

L1 distance:

\[ d_1(I_1, I_2) = \sum_p |I_1^p - I_2^p| \]

Where \( I_1 \) denotes image 1, and \( p \) denotes each pixel.

<table>
<thead>
<tr>
<th>test image</th>
<th>training image</th>
<th>pixel-wise absolute value differences</th>
</tr>
</thead>
<tbody>
<tr>
<td>56 32 10 18</td>
<td>10 20 24 17</td>
<td>46 12 14 1</td>
</tr>
<tr>
<td>90 23 128 133</td>
<td>8 10 89 100</td>
<td>82 13 39 33</td>
</tr>
<tr>
<td>24 26 178 200</td>
<td>12 16 178 170</td>
<td>12 10 0 30</td>
</tr>
<tr>
<td>2 0 255 220</td>
<td>4 32 233 112</td>
<td>2 32 22 108</td>
</tr>
</tbody>
</table>

\[ \rightarrow 456 \]
Choice of distance metric

- Hyperparameter

\[ d_1(I_1, I_2) = \sum_p |I_1^p - I_2^p| \]

\[ d_2(I_1, I_2) = \sqrt{\sum_p (I_1^p - I_2^p)^2} \]

- Two most commonly used special cases of \( p \)-norm

\[ \|x\|_p = (|x_1|^p + \cdots + |x_n|^p)^{\frac{1}{p}} \quad p \geq 1, x \in \mathbb{R}^n \]
K-Nearest Neighbors: Distance Metric

L1 (Manhattan) distance

\[ d_1(I_1, I_2) = \sum_p |I_1^p - I_2^p| \]

L2 (Euclidean) distance

\[ d_2(I_1, I_2) = \sqrt{\sum_p (I_1^p - I_2^p)^2} \]

Hyperparameters

• What is the **best distance** to use?
• What is the **best value of k** to use?

• These are **hyperparameters**: choices about the algorithm that we set rather than learn

• How do we set them?
  • One option: try them all and see what works best
Setting Hyperparameters

**Idea #1:** Choose hyperparameters that work best on the data

| Your Dataset |
Setting Hyperparameters

**Idea #1:** Choose hyperparameters that work best on the data

**BAD:** $K = 1$ always works perfectly on training data

- [Your Dataset]
Setting Hyperparameters

**Idea #1:** Choose hyperparameters that work best on the data

**BAD:** $K = 1$ always works perfectly on training data

Your Dataset

**Idea #2:** Split data into **train** and **test**, choose hyperparameters that work best on test data

train | test
Setting Hyperparameters

**Idea #1**: Choose hyperparameters that work best on the data

BAD: K = 1 always works perfectly on training data

Your Dataset

**Idea #2**: Split data into train and test, choose hyperparameters that work best on test data

BAD: No idea how algorithm will perform on new data

| train  | test  |
Setting Hyperparameters

**Idea #1:** Choose hyperparameters that work best on the data

BAD: $K = 1$ always works perfectly on training data

---

**Idea #2:** Split data into **train** and **test**, choose hyperparameters that work best on test data

BAD: No idea how algorithm will perform on new data

---

**Idea #3:** Split data into **train**, **val**, and **test**; choose hyperparameters on val and evaluate on test

**Better!**
Setting Hyperparameters

Idea #4: Cross-Validation: Split data into folds, try each fold as validation and average the results

- fold 1
- fold 2
- fold 3
- fold 4
- fold 5
- test

Useful for small datasets, but not used too frequently in deep learning
Hyperparameter Tuning

Example of 5-fold cross-validation for the value of k.

Each point: single outcome.

The line goes through the mean, bars indicated standard deviation.

(Seems that $k \approx 7$ works best for this data)
Recap: How to pick hyperparameters?

• Methodology
  • Train and test
  • Train, validate, test

• Train an initial model
• Validate to find hyperparameters
• Test to understand generalizability
kNN – Complexity and Storage

• N training images, M test images

• Training: $O(1)$
• Testing: $O(MN)$

• We often need the opposite:
  • Slow training is ok
  • Fast testing is necessary
k-Nearest Neighbors: Summary

• In **image classification** we start with a **training set** of images and labels, and must predict labels on the **test set**

• The **K-Nearest Neighbors** classifier predicts labels based on nearest training examples

• Distance metric and K are **hyperparameters**

• Choose hyperparameters using the **validation set**; only run on the test set once at the very end!
Problems with KNN: Distance Metrics

- terrible performance at test time
- distance metrics on level of whole images can be very unintuitive

(all 3 images have same L2 distance to the one on the left)
Problems with KNN: The Curse of Dimensionality

• As the number of dimensions increases, the same amount of data becomes more sparse.

• Amount of data we need ends up being exponential in the number of dimensions.

Animation from https://www.cs.cornell.edu/courses/cs4780/2018fa/lectures/lecturenote02_kNN.html
Linear Classifiers
Linear Classification vs. Nearest Neighbors

- Nearest Neighbors
  - Store every image
  - Find nearest neighbors at test time, and assign same class
Linear Classification vs. Nearest Neighbors

• Nearest Neighbors
  • Store every image
  • Find nearest neighbors at test time, and assign same class

• Linear Classifier
  • Store hyperplanes that best separate different classes
  • We can compute continuous class score by calculating (signed) distance from hyperplane

We can interpret this as a linear "score function" for each class.
Score functions

class scores

Slide adapted from Andrej Karpathy and Fei-Fei Li http://vision.stanford.edu/teaching/cs231n/
Parametric Approach

\[ f(x, W) \]

10 numbers, indicating class scores

[32x32x3] = 3072
array of numbers 0...1
(3072 numbers total)

Slide adapted from Andrej Karpathy and Fei-Fei Li http://vision.stanford.edu/teaching/cs231n/
Parametric Approach: Linear Classifier

\[ f(x, W) = Wx \]

10x1 \rightarrow 10x3072 \rightarrow 3072x1

[32x32x3] = 3072
array of numbers 0...1

parameters, or “weights”

10 numbers, indicating class scores

Slide adapted from Andrej Karpathy and Fei-Fei Li http://vision.stanford.edu/teaching/cs231n/
Parametric Approach: Linear Classifier

\[ f(x, W) = Wx + (b) \]

- \([32 \times 32 \times 3] = 3072\) array of numbers 0...1
- 10 numbers, indicating class scores
- Parameters, or “weights”
Linear Classifier

Define a score function

\[ f(x_i, W, b) = Wx_i + b \]

- Data (image)
- "weights"
- "bias vector"
- "parameters"
- Class scores

Slide adapted from Andrej Karpathy and Fei-Fei Li http://vision.stanford.edu/teaching/cs231n/
Interpretation: Algebraic

Example with an image with 4 pixels, and 3 classes (cat/dog/ship)

Slide adapted from Andrej Karpathy and Fei-Fei Li http://vision.stanford.edu/teaching/cs231n/
Interpretation: Geometric

• Parameters define a hyperplane for each class:

\[ f(x_i, W, b) = Wx_i + b \]

• We can think of each class score as defining a distribution that is proportional to distance from the corresponding hyperplane
**Interpretation: Template matching**

- We can think of the rows in $W$ as templates for each class.

Rows of $W$ in $f(x_i, W, b) = W x_i + b$
Hard Cases for a Linear Classifier

Class 1:
First and third quadrants

Class 2:
Second and fourth quadrants

Class 1:
1 <= L2 norm <= 2

Class 2:
Everything else

Class 1:
Three modes

Class 2:
Everything else
Linear Classifier: Three Viewpoints

**Algebraic Viewpoint**

\[ f(x, W) = Wx \]

**Visual Viewpoint**

One template per class

**Geometric Viewpoint**

Hyperplanes cutting up space
So far: Defined a (linear) score function \( f(x, W) = Wx + b \)

Example class scores for 3 images for some \( W \):

- Airplane: \(-3.45\)  
- Automobile: \(-0.87\)  
- Bird: \(0.09\)  
- Cat: \(2.9\)  
- Deer: \(4.49\)  
- Dog: \(8.02\)  
- Frog: \(3.78\)  
- Horse: \(1.06\)  
- Ship: \(-0.36\)  
- Truck: \(-0.72\)  

How can we tell whether this \( W \) is good or bad?
Recap

• Learning methods
  • k-Nearest Neighbors
  • Linear classification

• Classifier outputs a **score function** giving a score to each class
• How do we define how good a classifier is based on the training data? (Spoiler: define a **loss function**
## Linear classification

### Output scores

<table>
<thead>
<tr>
<th></th>
<th>Cat</th>
<th>Car</th>
<th>Frog</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>airplane</td>
<td>-3.45</td>
<td>-0.51</td>
<td>3.42</td>
<td></td>
<td></td>
</tr>
<tr>
<td>automobile</td>
<td>-8.87</td>
<td>6.04</td>
<td>4.64</td>
<td></td>
<td></td>
</tr>
<tr>
<td>bird</td>
<td>0.09</td>
<td>5.31</td>
<td>2.65</td>
<td></td>
<td></td>
</tr>
<tr>
<td>cat</td>
<td>2.9</td>
<td>-4.22</td>
<td>5.1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>deer</td>
<td>4.48</td>
<td>-4.19</td>
<td>2.64</td>
<td></td>
<td></td>
</tr>
<tr>
<td>dog</td>
<td>8.02</td>
<td>3.58</td>
<td>5.55</td>
<td></td>
<td></td>
</tr>
<tr>
<td>frog</td>
<td>3.78</td>
<td>4.49</td>
<td>-4.34</td>
<td></td>
<td></td>
</tr>
<tr>
<td>horse</td>
<td>1.06</td>
<td>-4.37</td>
<td>-1.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ship</td>
<td>-0.36</td>
<td>-2.09</td>
<td>-4.79</td>
<td></td>
<td></td>
</tr>
<tr>
<td>truck</td>
<td>-0.72</td>
<td>-2.93</td>
<td>6.14</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### TODO:

1. **Define a loss function** that quantifies our unhappiness with the scores across the training data.

2. Come up with a way of efficiently finding the parameters that minimize the loss function. *(optimization)*
Loss functions

Suppose: 3 training examples, 3 classes.
With some \( W \) the scores \( f(x, W) = Wx \) are:

<table>
<thead>
<tr>
<th></th>
<th>cat</th>
<th>car</th>
<th>frog</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.2</td>
<td>1.3</td>
<td>2.2</td>
<td></td>
</tr>
<tr>
<td>5.1</td>
<td>4.9</td>
<td>2.5</td>
<td></td>
</tr>
<tr>
<td>-1.7</td>
<td>2.0</td>
<td>-3.1</td>
<td></td>
</tr>
</tbody>
</table>

A loss function tells how good our current classifier is.

Given a dataset of examples

\[ \{(x_i, y_i)\}_{i=1}^{N} \]

Where \( x_i \) is image and \( y_i \) is (integer) label.

Loss over the dataset is a sum of loss over examples:

\[
L = \frac{1}{N} \sum_{i} L_i(f(x_i, W), y_i)
\]
Loss function, cost/objective function

• Given ground truth labels ($y_i$), scores $f(x_i, W)$
  • how unhappy are we with the scores?
• Loss function or objective/cost function measures unhappiness

• During training, **want to find the parameters $W$ that minimize the loss function**
Simpler example: binary classification

- Two classes (e.g., “cat” and “not cat”)
  - AKA “positive” and “negative” classes
Linear classifiers

• Find linear function (hyperplane) to separate positive and negative examples

\[ x_i \text{ positive: } x_i \cdot w + b \geq 0 \]
\[ x_i \text{ negative: } x_i \cdot w + b < 0 \]

Which hyperplane is best? We need a loss function to decide
What is a good loss function?

• One possibility: Number of misclassified examples
  • Problems: discrete, can’t break ties
  • We want the loss to lead to *good generalization*
  • We want the loss to work for more than 2 classes
Softmax classifier

- Interpret Scores as unnormalized log probabilities of classes

Squashes values into *probabilities* ranging from 0 to 1

\[
f(x_i, W) = Wx_i \quad \text{(score function)}
\]

\[
\frac{e^{f_{y_i}}}{\sum_j e^{f_j}}
\]

\[
P(y_i | x_i; W)
\]

Example with three classes:

\[
[1, -2, 0] \rightarrow [e^1, e^{-2}, e^0] = [2.71, 0.14, 1] \rightarrow [0.7, 0.04, 0.26]
\]
# Softmax classifier

**Example with an image with 4 pixels, and 3 classes (cat/dog/ship)**

<table>
<thead>
<tr>
<th>x_i</th>
<th>W</th>
<th>b</th>
<th>f(x_i; W, b)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.2</td>
<td>-0.5</td>
<td>0.1, 2.0</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>0.25</td>
<td>0.2, -0.3</td>
</tr>
<tr>
<td></td>
<td>1.5</td>
<td>1.3</td>
<td>2.1, 0.0</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>0</td>
<td>231</td>
</tr>
<tr>
<td>2</td>
<td>24</td>
<td>2</td>
<td>56</td>
</tr>
<tr>
<td></td>
<td>1.1</td>
<td></td>
<td>1.1, -96.8, 437.9, 61.95</td>
</tr>
</tbody>
</table>

Where $f(x_i; W, b)$ represents the score for each class.

Softmax "probabilities" calculated as:

$$e^{f_{x_i}} / \sum_{j} e^{f_{x_j}}$$

<table>
<thead>
<tr>
<th>Class</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cat</td>
<td>0.06</td>
</tr>
<tr>
<td>Dog</td>
<td>0.82</td>
</tr>
<tr>
<td>Ship</td>
<td>0.12</td>
</tr>
</tbody>
</table>
Cross-entropy loss

\[ f(x_i, W) = W x_i \] (score function)
Cross-entropy loss

We call $L_i$ cross-entropy loss

$$f(x_i, W) = Wx_i$$

(score function)

$$L_i = -\log \left( \frac{e^{f_{y_i}}}{\sum_j e^{f_j}} \right)$$

$f_{y_i}$ : score of correct class

$$L_i = -f_{y_i} + \log \sum_j e^{f_j}$$
Cross-entropy loss

We call $L_i$ cross-entropy loss

\[
f(x_i, W) = W x_i \quad \text{(score function)}
\]

\[
L_i = -\log \left( \frac{e^{f_{y_i}}}{\sum_j e^{f_j}} \right) \quad \text{i.e. we’re minimizing the negative log likelihood.}
\]

\[
L_i = -f_{y_i} + \log \sum_j e^{f_j}
\]
Losses

• Cross-entropy loss is just one possible loss function
  • One nice property is that it reinterprets scores as probabilities, which have a natural meaning

• SVM (max-margin) loss functions also used to be popular
  • But currently, cross-entropy is the most common classification loss
Summary

• Have score function and loss function
  • Currently, score function is based on linear classifier
  • Next, will generalize to convolutional neural networks
• Find W and b to minimize loss

\[ L = \frac{1}{N} \sum_i - \log \left( \frac{e^{f_{yi}}}{\sum_j e^{f_j}} \right) + \lambda \sum_k \sum_l W_{k,l}^2 \]

Average of cross-entropy loss over all training examples

Regularization term (will talk about this later)
Questions?