Handwritten Digit Classification

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Classification

$k$-means

Boolean classification

Multiclass classification

Classification with random features
Handwritten digit classification

- goal is to automatically determine what a handwritten digit image is (i.e., 0, 1, ..., 8, or 9?)

![Handwritten digits: 6, 5, 4, 2]
images are $16 \times 16$ pixels, represented as $256$-vectors

values in $[0, 1]$ (0 is black, 1 is white)

images were first de-slanted and size normalized

our classifier is a function $\hat{f} : \mathbb{R}^{256} \to \{0, 1, \ldots, 9\}$ (called multiclass or in this case 10-way classification)

our guess is $\hat{y} = \hat{f}(x)$ for image $x$

our classifier is wrong when $\hat{y} \neq y$
Data set

- NIST data from US Postal Service
- training set has $N = 7291$ images
  - we’ll use this data set to develop our classifiers
- test set has $N^{\text{test}} = 2007$ images
  - we’ll use this data set to test/judge our classifiers
- we’ll look at error on training set and on test set
Outline

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Classification with random features
$k$-means

- start with a collection of image 256-vectors $x_1, \ldots, x_N$
- run $k$-means algorithm to cluster into $k$ groups, 10 times with random initial centroids
- use best of these 10 (in mean-square distance to closest centroid)
- centroids/representatives $z_1, \ldots, z_k$ can be viewed as images
Centroids, $k = 2$
Centroids, $k = 10$
Centroids, $k = 20$
Classification via \( k \)-means

- label \( k = 20 \) centroids by hand
- classify new image by label of nearest centroid
- classification error rate (on test set): 24%
### Classification via \( k \)-means

#### Confusion Matrix:

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Outline

Classification

\( k \)-means

Boolean classification

Multiclass classification

Classification with random features
a simpler problem: determine if an image \( x \) is digit \( k \) or not digit \( k \)
we use label \( y_i = 1 \) if \( x_i \) is digit \( k \) and \( y_i = -1 \) if not
classifier will have form

\[
\hat{y} = \text{sign}(w^T x + v)
\]

\( w \) is weight 256-vector, \( v \) is offset
we’ll use training set to choose \( w \) and \( v \), and test the classifier on test data set
Least squares Boolean classifier

- want $w, v$ for which $y_i \approx \hat{y}_i = \text{sign}(w^T x_i + v) = \text{sign}(\tilde{y}_i)$
- choose $w, v$ to minimize

$$\sum_{i=1}^{N} (\tilde{y}_i - y_i)^2 + \lambda \|w\|^2 = \|X^T w + v\|_2^2 - y^d\|^2 + \lambda \|w\|^2$$

- $X = [x_1 \cdots x_N]$ is matrix of training image vectors
- $y^d = (y_1, \ldots, y_N)$ is $N$-vector of labels
- $\lambda > 0$ is regularization parameter
Least squares Boolean classifier

classification error versus $\lambda$ for predicting the digit 0

Boolean classification
Weight vector
Outline

Classification

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Boolean classification

Multiclass classification

Classification with random features
10-way classification

- let $w_i$, $v_i$ be weight vector, offset for Boolean classification of digit $i$
- for image $x$, $\tilde{y}_i = w_i^T x + v_i$
- the larger $\tilde{y}_i$ is, the more confident we are that image is digit $i$
- choose $\hat{y} = \text{argmax}_i(\tilde{y}_i) = \text{argmax}_i(w_i^T x + v_i)$
- use the same regularization parameter $\lambda$ for each digit $i$
- choose $\lambda$ so that the total classification error on test set is small
multi-class classification error versus $\lambda$

with $\lambda = 50$, test classification error is about 13%
test confusion matrix

true ↓ predicted →

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Multiclass classification
Outline

Classification

\textit{k}-means

Boolean classification

Multiclass classification

Classification with random features
Doing even better

- in classes you’ll take later (AI, statistics), you’ll see (and construct) way better classifiers
- we’ll look at a simple example here
Generating random features

- generate a random $2000 \times 256$ matrix $R$ with entries $+1$ or $-1$
- scale $R$ by $1/\sqrt{256}$, so each row has norm 1
- create 2000 new features $\tilde{x}$ from original $x$ via
  \[ \tilde{x}_i = \max\{Rx, 0\} \]
- now do least squares classification with feature $2256$-vectors $(x_i, \tilde{x}_i)$
multi-class classification error versus $\lambda$

with $\lambda = 1$, test classification error is about 5%
Example

test confusion matrix

true \downarrow predicted \rightarrow

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