

Nearest neighbor classification

DSE 220

Worksheet 1 # 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11

Outline

- ① Nearest neighbor classification
- ② k -nearest neighbor
- ③ Choosing the features and distance function

The problem we'll solve today

Given an image of a handwritten digit, say which digit it is.



\Rightarrow 3

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\Rightarrow 3

1 0
→ 8 4
7
1

More examples:



The machine learning approach

Assemble a data set:



The **MNIST** data set of handwritten digits:

- **Training set** of 60,000 images and their labels.
- **Test set** of 10,000 images and their labels.

And let the machine figure out the underlying patterns.

Nearest neighbor classification

$x^{(i)}$: i^{th} image

Training images $x^{(1)}, x^{(2)}, x^{(3)}, \dots, x^{(60000)}$

Labels $y^{(1)}, y^{(2)}, y^{(3)}, \dots, y^{(60000)}$ are numbers in the range 0 – 9

$y^{(i)}$: label
 $\{0, 1, \dots, 9\}$

1 4 1 0 1 1 9 1 5 4 8 5 7 2 6 8 0 3 2 2 6 4 1 4 1
8 6 6 3 5 9 7 2 0 2 9 9 2 9 9 7 2 2 5 1 0 0 4 6 7
0 1 3 0 8 4 1 1 1 5 9 1 0 1 0 6 1 5 4 0 6 1 0 3 6
3 1 1 0 6 4 1 1 1 0 3 0 4 7 5 2 6 2 0 0 9 9 7 9 9
6 6 8 9 1 2 0 8 6 7 0 8 5 5 7 1 3 1 4 2 7 9 5 5 4
6 0 1 0 1 8 7 8 0 1 8 7 1 1 2 9 9 1 0 8 9 9 7 0 9
8 4 0 1 0 9 7 0 7 5 9 7 3 3 1 9 7 2 0 1 5 5 1 9 0
6 6 1 0 7 5 5 1 8 2 5 5 1 8 2 8 1 4 3 5 8 0 9 0 9
4 3 1 7 8 7 5 2 1 6 5 5 4 6 0 5 5 4 6 0 3 5 4 6 0
5 5 1 8 2 5 5 1 0 8 5 0 3 0 4 7 5 2 0 4 3 9 4 0 1

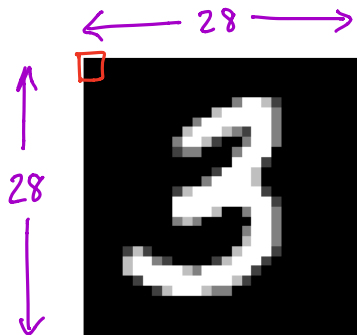


How to **classify** a new image x ?

- Find its **nearest neighbor** amongst the $x^{(i)}$
- Return $y^{(i)}$

The data space

How to measure the distance between images?

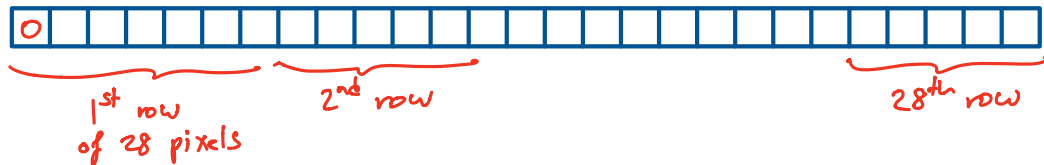


0 — black
255 — white

MNIST images:

- Size 28×28 (total: 784 pixels)
- Each pixel is grayscale: 0-255

Stretch each image into a vector with 784 coordinates:

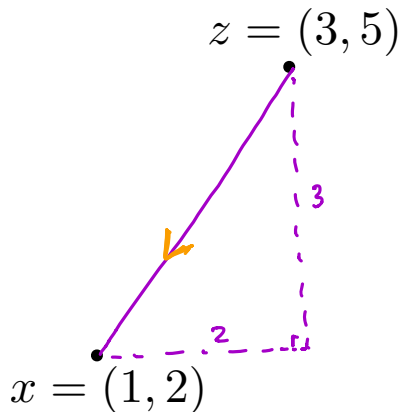


- Data space $\mathcal{X} = \mathbb{R}^{784}$
- Label space $\mathcal{Y} = \{0, 1, \dots, 9\}$

The distance function

$$x = \begin{pmatrix} 1 \\ 2 \end{pmatrix} \quad z = \begin{pmatrix} 3 \\ 5 \end{pmatrix}$$

Remember Euclidean distance in two dimensions?



$$\sqrt{2^2 + 3^2} = \sqrt{13}$$

$\|x - z\|$
Euclidean dist between
x and z

$$= \sqrt{(x_1 - z_1)^2 + (x_2 - z_2)^2}$$

} same as the length of $\underbrace{x - z} = \begin{pmatrix} -2 \\ -3 \end{pmatrix}$

Euclidean distance in higher dimension

Euclidean distance between 784-dimensional vectors x, z is

$$\|x - z\| = \sqrt{\sum_{i=1}^{784} (x_i - z_i)^2}$$

Here x_i is the i th coordinate of x .

Nearest neighbor classification

Training images $x^{(1)}, \dots, x^{(60000)}$, labels $y^{(1)}, \dots, y^{(60000)}$

1 4 1 0 1 1 9 1 3 4 8 5 7 2 6 8 0 3 2 2 6 4 1 4 1
8 6 6 3 5 9 7 2 0 2 9 9 2 9 9 7 2 2 5 1 0 0 4 6 7
0 1 3 0 8 4 1 1 1 5 9 1 0 1 0 6 1 5 4 0 6 1 0 3 6
3 1 1 0 6 4 1 1 1 0 3 0 4 7 3 2 6 2 0 0 9 9 7 9 9
6 6 8 9 1 2 0 8 6 7 2 8 5 5 7 1 3 1 4 2 7 9 5 5 4
6 0 1 0 1 8 7 5 0 1 8 7 1 1 2 9 9 1 0 8 9 9 7 0 9
8 4 0 1 0 9 7 0 7 5 9 7 3 3 1 9 7 2 0 1 5 5 1 9 0
6 6 1 0 7 5 5 1 8 2 5 5 1 8 2 8 1 4 3 5 8 0 9 0 9
6 3 1 7 8 7 5 2 1 6 5 5 4 6 0 5 5 4 6 0 3 5 4 6 0
5 5 1 8 2 5 5 1 0 8 5 0 3 0 4 7 5 2 0 4 3 9 4 0 1



To classify a new image x :

- Find its nearest neighbor amongst the $x^{(i)}$ using **Euclidean distance in \mathbb{R}^{784}**
- Return $y^{(i)}$

How accurate is this classifier?

Accuracy of nearest neighbor on MNIST

Training set of 60,000 points.

- What is the error rate on training points?

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(One that picks a label 0 – 9 at random?)

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- What test error would we expect for a *random classifier*?
(One that picks a label 0 – 9 at random?) **90%**.
- Test error of nearest neighbor: **3.09%**.

309 test pts were incorrectly classified

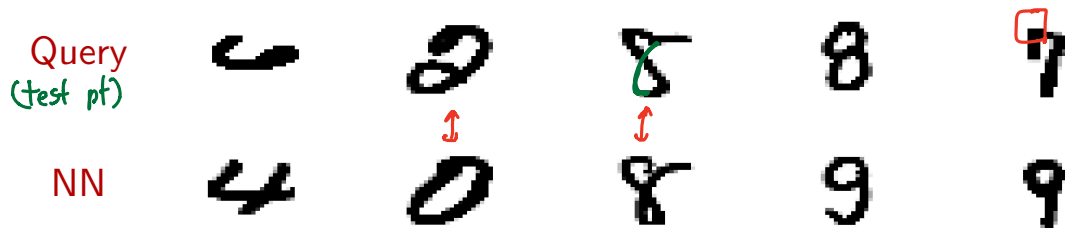
Examples of errors

Test set of 10,000 points:

- 309 are misclassified
- Error rate 3.09%

confidence-rated prediction
probability estimation

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Ideas for improvement: (1) k -NN (2) better distance function.

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	Test error (%)	3.09	2.94	3.13	3.10	3.43	3.34

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① Hold-out set.

- Let S be the training set.
- Choose a subset $V \subset S$ as a *validation set*.
- What fraction of V is misclassified by the k -nearest neighbors in $S \setminus V$?

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$|V|$ matters in determining
error bar on our estimate

② Leave-one-out cross-validation.

- For each point $x \in S$, find the k -nearest neighbors in $S \setminus \{x\}$.
- What fraction are misclassified?

Cross-validation

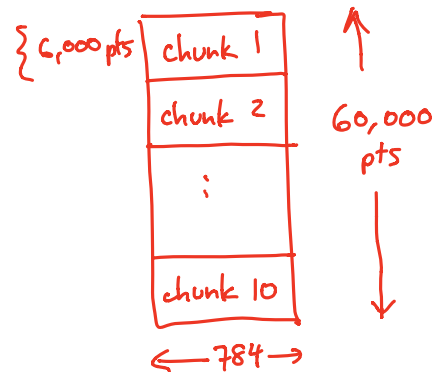
m-fold cross-validation

How to estimate the error of k -NN for a particular k ?

10-fold cross-validation

- Divide the training set into 10 equal pieces.
Training set (call it S): 60,000 points
Call the pieces S_1, S_2, \dots, S_{10} : 6,000 points each.
- For each piece S_i :
 - Classify each point in S_i using k -NN with training set $S - S_i$
 - Let ϵ_i = fraction of S_i that is incorrectly classified
- Take the average of these 10 numbers:

$$\text{estimated error with } k\text{-NN} = \frac{\epsilon_1 + \dots + \epsilon_{10}}{10}$$



*set
hyperparameters
e.g. k*

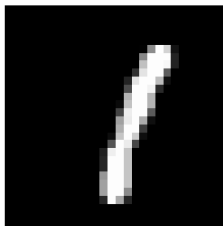
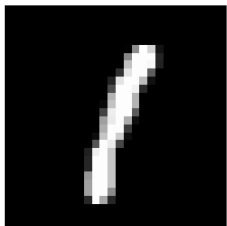
*classifier
(parameters)*

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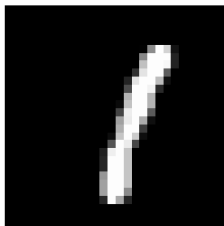
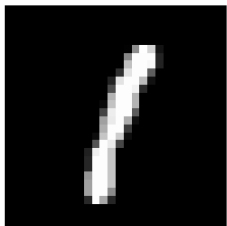
Another improvement: better distance functions

The Euclidean (ℓ_2) distance between these two images is very high!



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| |

Much better idea: distance measures that are invariant under:

- Small translations and rotations. e.g. *tangent distance*.
- A broader family of natural deformations. e.g. *shape context*.

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Much better idea: distance measures that are invariant under:

- Small translations and rotations. e.g. *tangent distance*.
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Test error rates:	ℓ_2	tangent distance	shape context
	3.09	1.10	0.63

Related problem: feature selection

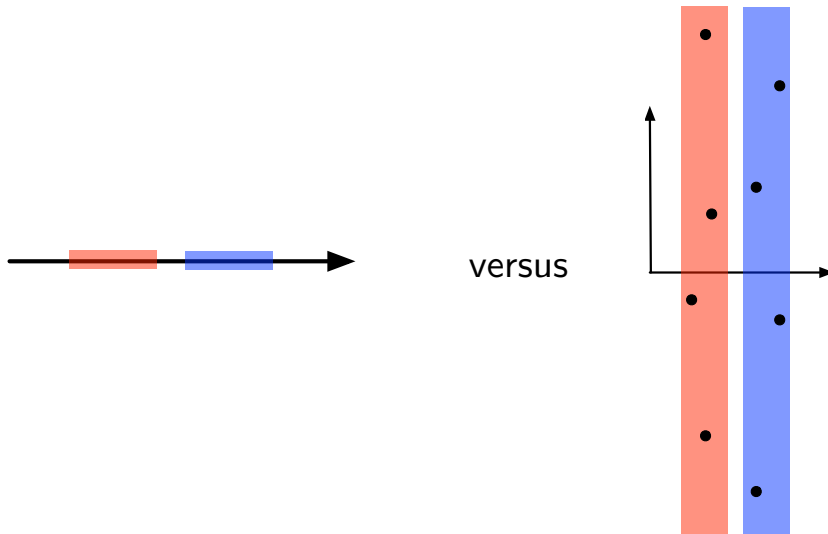
Feature selection/reweighting is part of picking a distance function.

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Algorithmic issue: speeding up NN search

Naive search takes time $O(n)$ for training set of size n : slow!

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There are data structures for speeding up nearest neighbor search, like:

- ① Locality sensitive hashing
- ② Ball trees
- ③ K -d trees

These are part of standard Python libraries for NN, and help a lot.

Example: k -d trees for NN search

A hierarchical, rectilinear spatial partition.

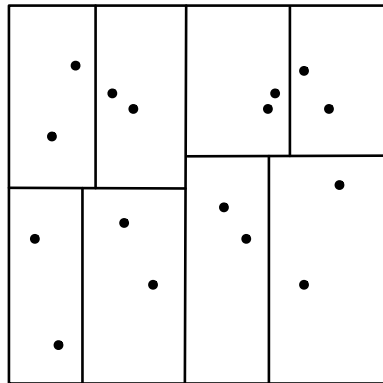
For data set $S \subset \mathbb{R}^d$:

- Pick a coordinate $1 \leq i \leq d$.
- Compute $v = \text{median}(\{x_i : x \in S\})$.
- Split S into two halves:

$$S_L = \{x \in S : x_i < v\}$$

$$S_R = \{x \in S : x_i \geq v\}$$

- Recurse on S_L, S_R



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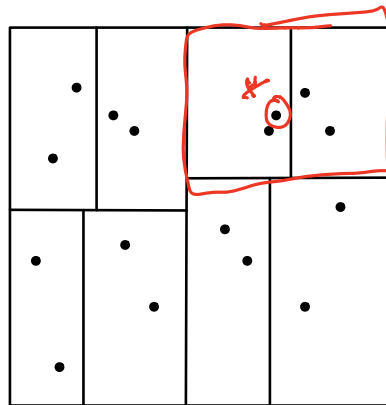
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Two types of search, given a query $q \in \mathbb{R}^d$:

- **Defeatist search:** Route q to a leaf cell and return the NN in that cell. This might not be the true NN.
- **Comprehensive search:** Grow the search region to other cells that cannot be ruled out using the triangle inequality.