

- Inputs: array of numbers
e.g.: `poorhousing`
(1000 houses)
- challenges:
 - class point
 - dimension
 - deformation
 - rotation
 - background changes
 - irrelevant variation
- algorithm:


```
def desc(image):
    # magic
    return classifier
```
- solution proposed:
 - edge?
 - convex?
- data-driven


```
def extract(img, labels):
    # magic
    return model
```
- def predict(image):


```
return class
```
- **first classification: Nearest Neighbors**
 - pixels are points
 - same labels
 - predict the label of the most similar neighboring image
 - e.g.: CIFAR10

10 classes
50,000 training images
10,000 testing images
- L1 distance
 $| \frac{1}{2} \frac{2}{3} - 1 \frac{1}{2} | = | \frac{1}{2} \frac{1}{3} | = 15$

```
class NearestNeighbor:
    def train(self, X, y):
        pass

    def predict(self, X, k=1):
        """X is N x D where each row is an example. Y is 1-dimension of size N
        i.e. labels for training data. Nearest neighbor classifier simply remembers all the training data
        self.Xtr = X
        self.ytr = y

        def predict(self, X, k=1):
            """X is N x D where each row is an example we wish to predict label for"""
            num_test = X.shape[0]
            # init distances
            dists = np.zeros((num_test, k))
            # loop over all test rows
            for i in range(num_test):
                # loop over all training rows
                for j in range(Xtr.shape[0]):
                    # calculate L1 distance (sum of absolute value differences)
                    dists[i, j] = np.sum(np.abs(Xtr[j] - Xtr[i]), axis=0)
            Ypred = self.ytr[np.argsort(dists)[:, :k]] # predict the label of the nearest neighbor
            Ypred = y[np.argmin(dists, axis=1)] # predict the label of the nearest neighbor
            return Ypred
```

• **@ k NN**
K-Nearest Neighbors



- K-NN

K-Nearest Neighbors

Instead of copying label from nearest neighbor,
take majority vote from K closest points



• hyperparameter

- the parameters are static training
- split data into $\begin{cases} \text{train} \\ \text{val} \\ \text{test} \end{cases}$ choose hyperparameters on val \forall $\begin{cases} \text{train} \\ \text{val} \\ \text{test} \end{cases}$
- cross-validation

Setting Hyperparameters

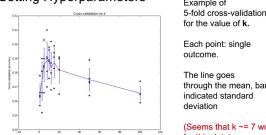
Your Dataset

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

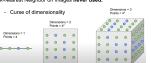
fold 1	fold 2	fold 3	fold 4	fold 5	test
fold 1	fold 2	fold 3	fold 4	fold 5	test
fold 1	fold 2	fold 3	fold 4	fold 5	test

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

Setting Hyperparameters



- curse of dimensionality



• Linear classifiers

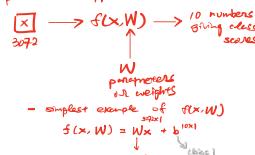
- Neural Network



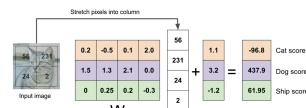
- CIFAR10

50,000 train (32x32x3)
10,000 test 3072

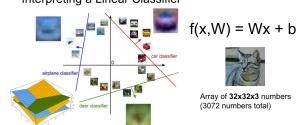
- parametric approach



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



Interpreting a Linear Classifier



Hard cases for a linear classifier

Class 1:
number of pixels > 0 odd

Class 1:
number of pixels > 0 even

Class 1:
Everything else

Class 1:
Everything else</