DATA 442: Neural Networks & Deep Learning

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Some Reminders

- Piazza
  - I - and the TAs - are checking Piazza regularly.

- Lab 1
  - Launches at midnight tonight! See Piazza for the deadline.
  - We'll be covering the content for lab 1 over the next couple of lectures.

Image Classification

We must pre-specify a set of labels that we want to choose between. For example:

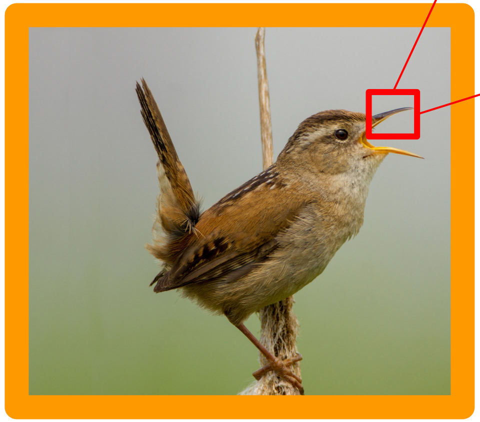
Car

Building

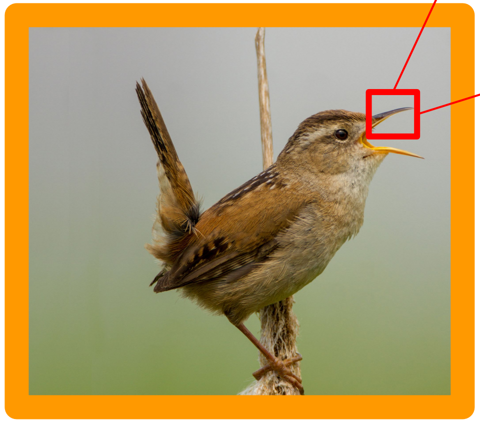
Person

Bird

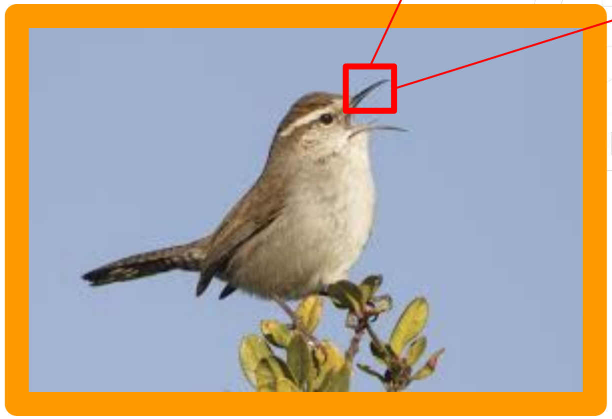
34	40	34	3	8	30	50	26	16	28	41	6	23	2	24	0
14	37	19	25	6	9	14	17	4	46	20	7	38	6	29	28
4	39	0	29	15	6	50	2	21	10	8	45	150	145	106	46
42	10	15	19	24	18	111	123	118	104	119	122	117	140	138	28
21	35	19	30	14	143	146	147	142	103	109	127	108	148	20	23
30	105	147	102	126	118	108	101	140	131	124	136	47	27	26	38
135	133	137	108	140	144	135	120	118	137	125	43	8	31	45	10
106	142	108	138	137	111	38	36	32	1	19	44	34	4	38	49
122	142	127	131	143	8	47	4	0	31	39	18	46	1	50	25
149	137	122	36	50	19	24	45	16	30	2	47	2	35	29	50
147	115	3	29	10	2	13	1	48	3	45	28	39	14	14	20



34	40	34	3	8	30	50	26	16	28	41	6	23	2	24	0
14	37	19	25	6	9	14	17	4	46	20	7	38	6	29	28
4	39	0	29	15	6	50	2	21	10	8	45	150	145	106	46
42	10	15	19	24	18	111	123	118	104	119	122	117	140	138	28
21	35	19	30	14	143	146	147	142	103	109	127	108	148	20	23
30	105	147	102	126	118	108	101	140	131	124	136	47	27	26	38
135	133	137	108	140	144	135	120	118	137	125	43	8	31	45	10
106	142	108	138	137	111	38	36	32	1	19	44	34	4	38	49
122	142	127	131	143	8	47	4	0	31	39	18	46	1	50	25
149	137	122	36	50	19	24	45	16	30	2	47	2	35	29	50
147	115	3	29	10	2	13	1	48	3	45	28	39	14	14	20



34	40	34	3	8	30	50	26	16	28	41	6	23	2	24	0
14	37	19	25	6	9	14	17	4	46	20	7	38	6	29	28
28	6	31	39	0	23	36	34	21	10	8	45	6	29	45	46
71	6	9	44	41	23	36	61	4	104	119	122	117	140	138	28
8	60	45	11	12	165	122	115	142	103	109	127	108	148	100	23
2	94	156	88	174	160	62	59	140	131	124	136	127	150	145	38
183	94	160	101	108	163	135	119	118	137	125	43	8	31	45	10
128	179	74	122	89	140	59	22	32	1	19	44	34	4	38	49
165	100	106	172	110	41	58	11	0	31	39	18	46	1	50	25
154	175	158	76	53	58	61	69	16	30	2	47	2	35	29	50
153	138	43	12	19	40	62	26	48	3	45	28	39	14	14	20



Viewpoint

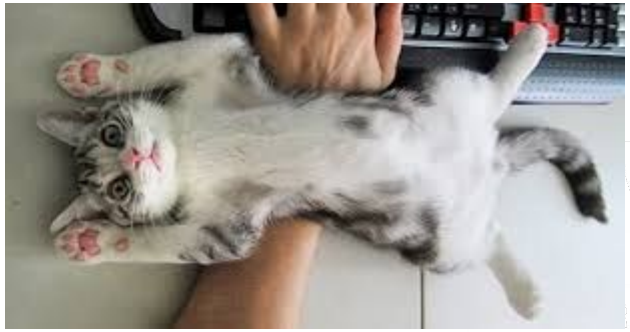
Lighting

Background

Background

Deformation

Deformation









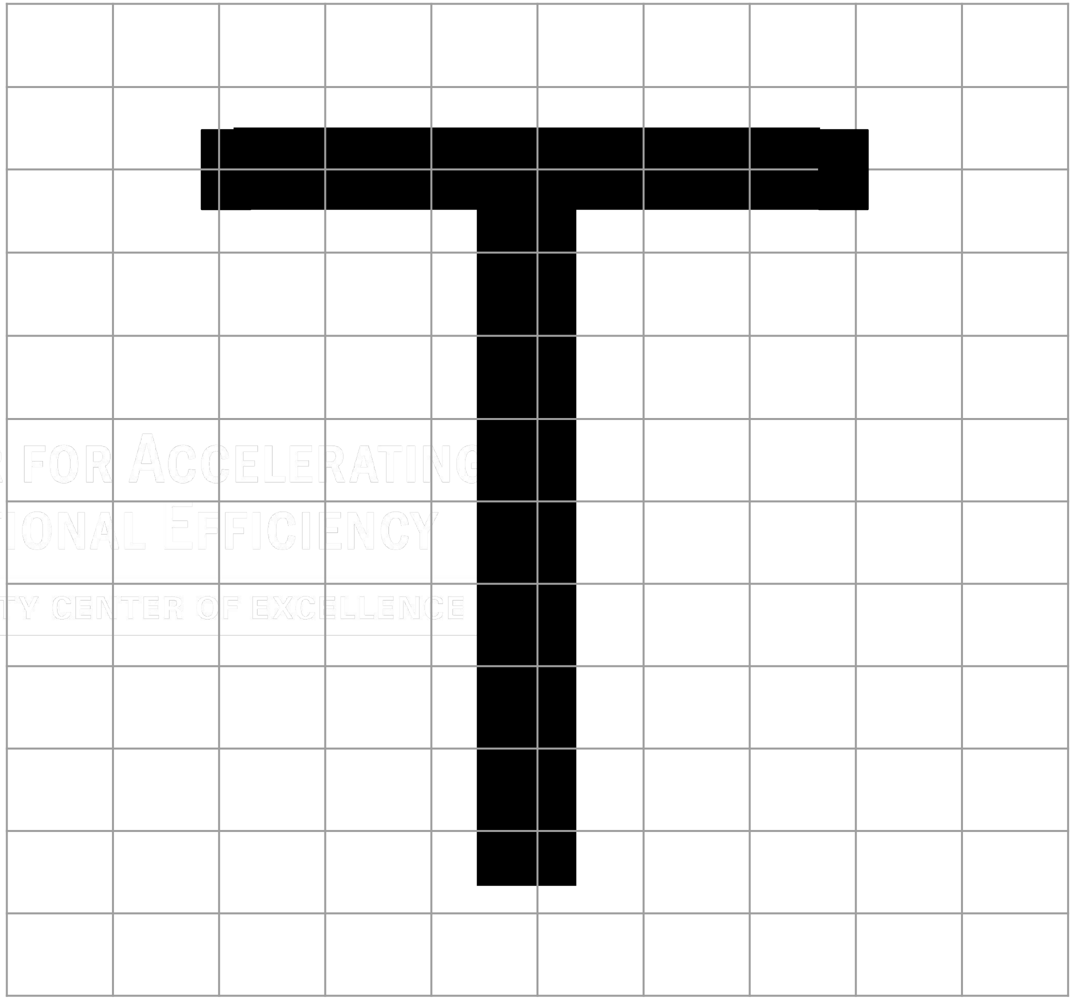
Occlusion






```
letterT = [0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
           0,  1,  1,  1,  1,  1,  1,  1,  1,  0,
           0,  1,  1,  1,  1,  1,  1,  1,  1,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  0,  0,  0,  0,  0,  0]
```

12 Row * 10 Column Resolution Data

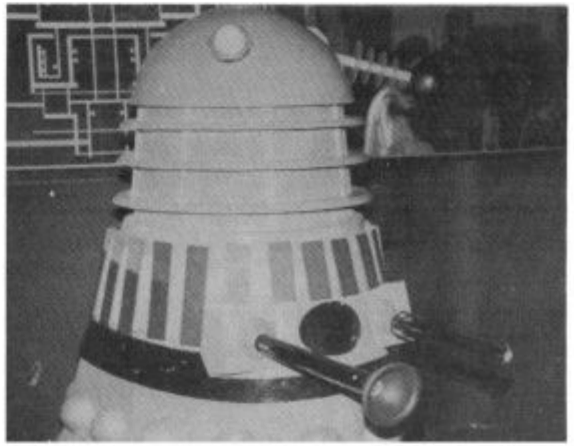


```python
def imageClassifier(letter):

    # Pick a label based on the data input
    predictedLabel = "Some Letter"

    return(predictedLabel)

print(imageClassifier(letterT))
```

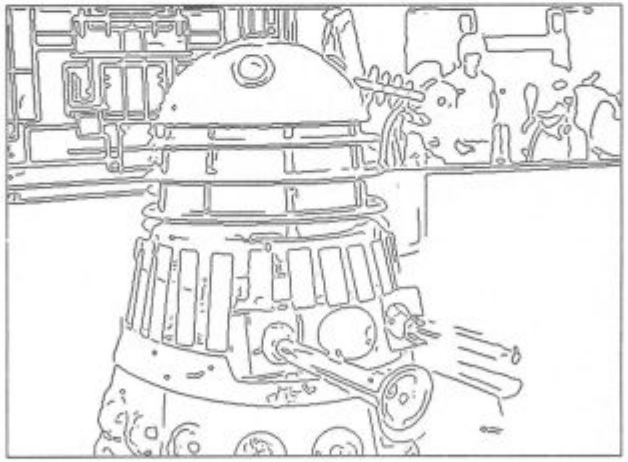
32 “1” Values

```
letterT = [0  0  0  0  0  0  0  0  0  0
           0  1  1  1  1  1  1  1  1  0
           0  1  1  1  1  1  1  1  1  0
           0  0  0  0  1  1  0  0  0  0
           0  0  0  0  1  1  0  0  0  0
           0  0  0  0  1  1  0  0  0  0
           0  0  0  0  1  1  0  0  0  0
           0  0  0  0  1  1  0  0  0  0
           0  0  0  0  1  1  0  0  0  0
           0  0  0  0  1  1  0  0  0  0
           0  0  0  0  1  1  0  0  0  0
           0  0  0  0  0  0  0  0  0  0 ]
```

```python
def imageClassifier(letter):
    if(sum(letter) == 32):
        predictedLabel = "T"

    # Pick a label based on the data input

    return(predictedLabel)


print(imageClassifier(letterT))
```



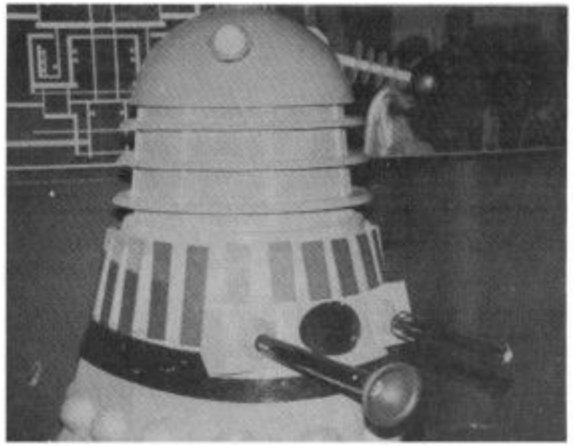
(a)



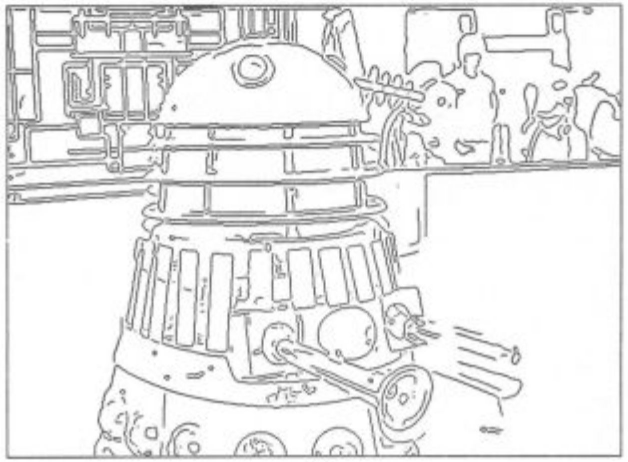
(b)

```python
def imageClassifier(letter):
    #Detect number of line intersections
    #(For the case of "T", this would be 1 intersection)
    intersections = 1

    if(intersections == 1):
        predictedLabel = "T"
    # Pick a label based on the data input

    return(predictedLabel)

print(imageClassifier(letterT))
```

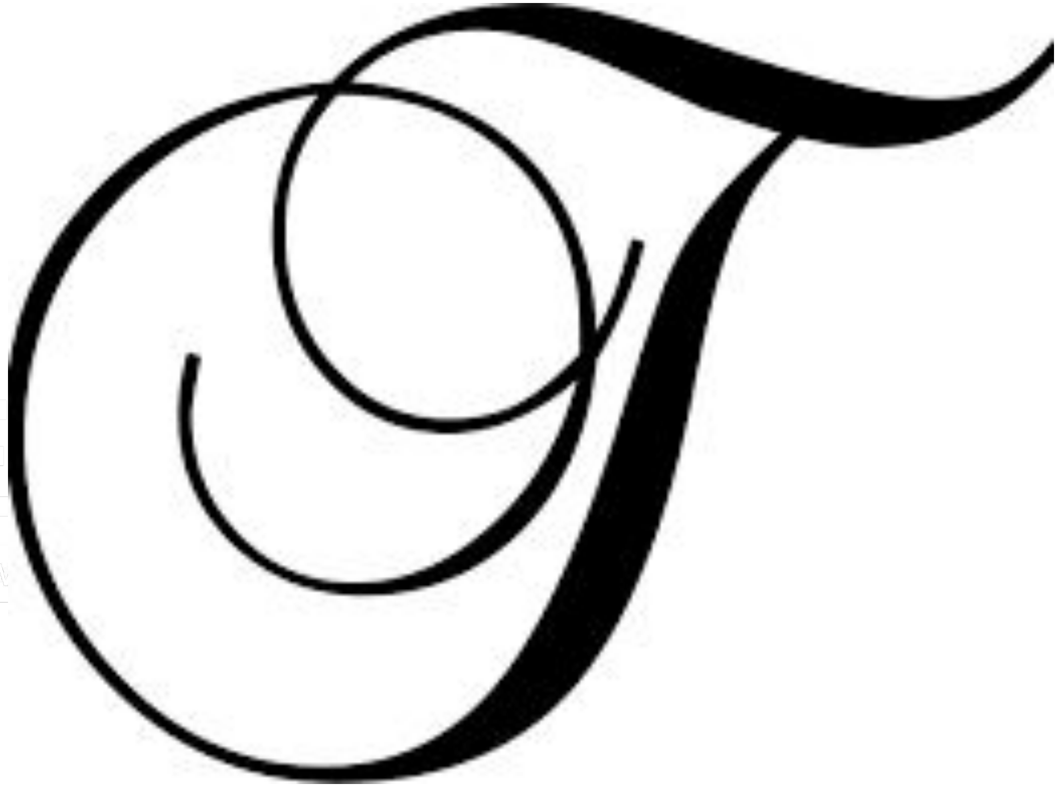
J. Canny, "A Computational Approach to Edge Detection," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. PAMI-8, no. 6, pp. 679-698, Nov. 1986, doi: 10.1109/TPAMI.1986.4767851.



(a)



(b)



J. Canny, "A Computational Approach to Edge Detection," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. PAMI-8, no. 6, pp. 679-698, Nov. 1986, doi: 10.1109/TPAMI.1986.4767851.

Machine Learning & AI


```python
def train(observedImages, humanLabels):
    #Teach the model all of the exceptions and rules
    return imageClassifier
```

```python
def predict(imageClassifier, myNewImage):
    #Use the classifier
    return predictedLabel
```

1) Curate / Label a Huge Dataset of Images

2) Train a Classifier

3) Test How Well It Does on Data It's Never Seen

Nearest Neighbor & Imagery

```
def train(observedImages, humanLabels):
    #Teach the model all of the exceptions and rules
    return imageClassifier
```

1) Saves All Observations into Memory

```
def predict(imageClassifier, myNewImage):
    #Use the classifier
    return predictedLabel
```

2) Compares and Contrasts Input to all Observations to Select Most Similar

Example Training Data

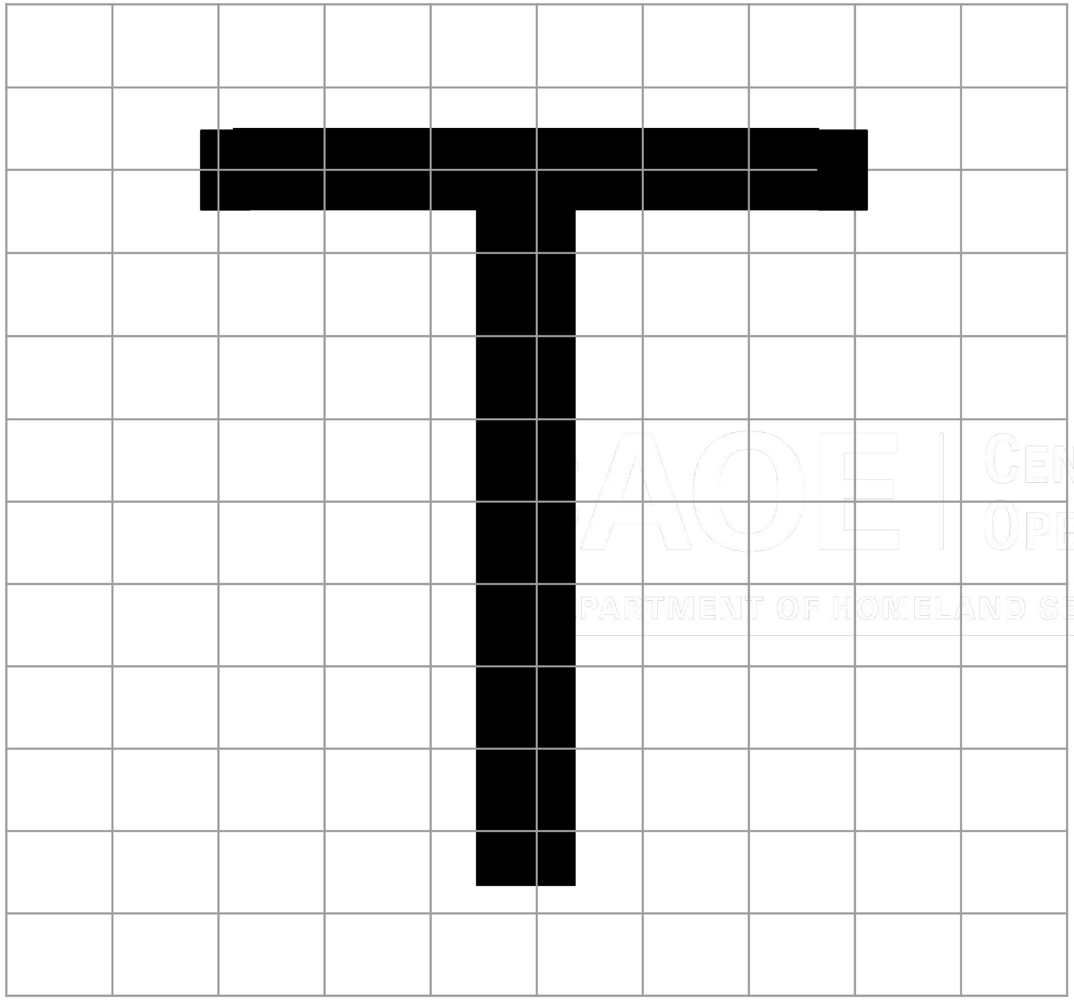
```python
letterT = [0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
           0,  1,  1,  1,  1,  1,  1,  1,  1,  0,
           0,  1,  1,  1,  1,  1,  1,  1,  1,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  0,  0,  0,  0,  0,  0]
```

```python
letterl = [0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  0,  0,  0,  0,  0,  0]
```

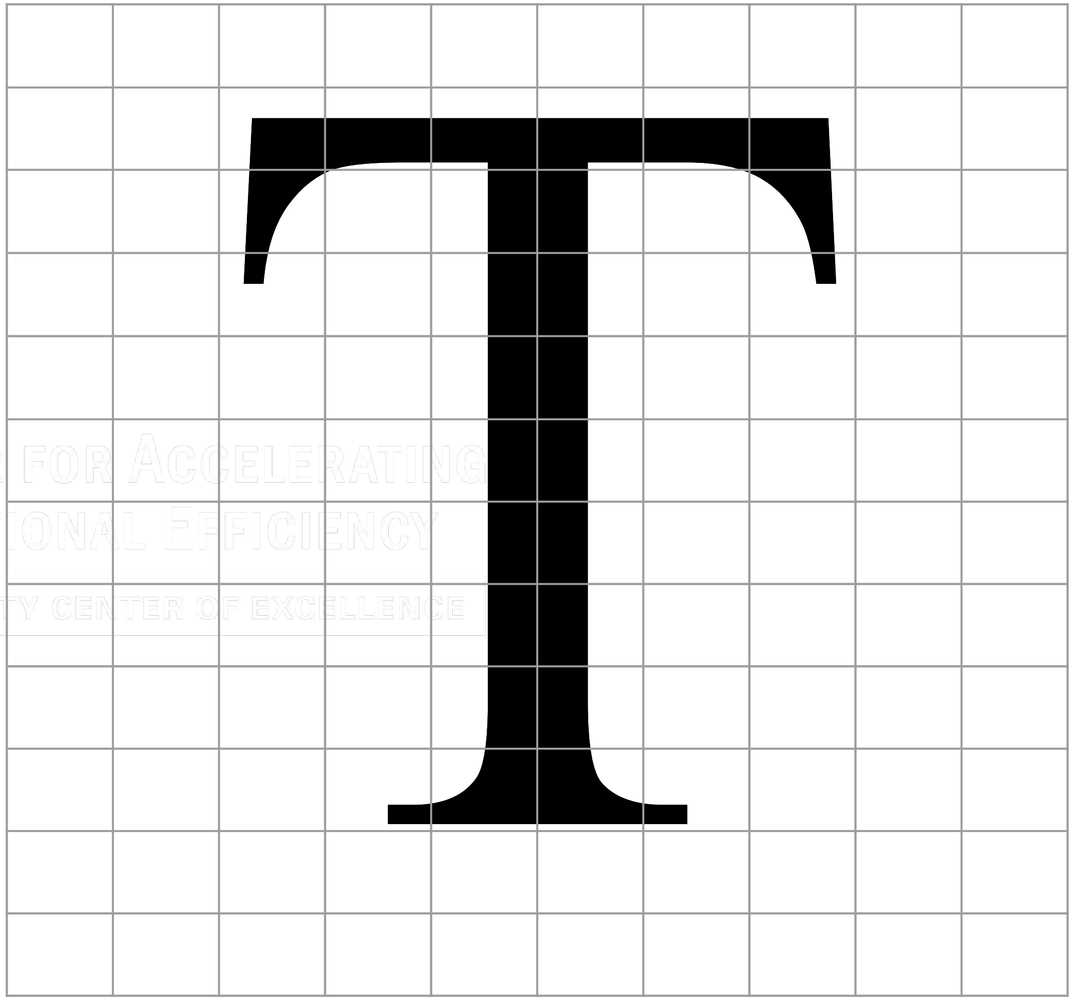


```python
letterI = [0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
           0,  1,  1,  1,  1,  1,  1,  1,  1,  0,
           0,  1,  1,  1,  1,  1,  1,  1,  1,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  1,  1,  1,  1,  1,  1,  1,  1,  0,
           0,  1,  1,  1,  1,  1,  1,  1,  1,  0,
           0,  0,  0,  0,  0,  0,  0,  0,  0,  0]
```

T from Training Data



T to Recognize



T from Training Data

	1	1	1	1	1	1	1	1	
	1	1	1	1	1	1	1	1	
				1	1				
				1	1				
				1	1				
				1	1				
				1	1				
				1	1				
				1	1				
				1	1				

T to Recognize

		1	1	1	1	1	1		
		1	1	1	1	1	1		
		1		1	1		1		
				1	1				
				1	1				
				1	1				
				1	1				
				1	1				
			1	1	1	1			

Nearest Neighbor - L1 Distance

$$L_1(I_1, I_2) = \sum_p |I_{1,p} - I_{2,p}|$$

L_1 = L1 Distance
I_i = Image i
p = Index for a given pixel in image
$I_{i,p}$ = Value for a given pixel p in image I

Sum of Absolute Difference: 10

	1	1	1	1	1	1	1	1	
	1	1	1	1	1	1	1	1	
				1	1				
				1	1				
				1	1				
				1	1				
				1	1				
				1	1				
				1	1				
				1	1				

T from Training Data

−

		1	1	1	1	1	1		
		1	1	1	1	1	1		
		1		1	1		1		
				1	1				
				1	1				
				1	1				
				1	1				
				1	1				
			1	1	1	1			

T we want to Recognize

=

	1							1	
	1							1	
		1					1		
			1			1			
				1	1				

$$L_1(I_1, I_2) = \sum_p |I_{1,p} - I_{2,p}|$$

$$L_1 = \text{L1 Distance}$$

$$I_i = \text{Image } i$$

$$p = \text{Index for a given pixel in image}$$

$$I_{i,p} = \text{Value for a given pixel } p \text{ in image } I$$

```python
import numpy as np
def L1Norm(imageA, imageB):
    print("Total number of black pixels in Image A: " +
          str(np.sum(imageA)))

    print("Total number of black pixels in Image B: " +
          str(np.sum(imageB)))

    pixelWiseDiff = str(np.sum(np.abs(np.asarray(imageA) - np.asarray(imageB))))
    print("Absolute pixelwise difference: " +
          pixelWiseDiff)

    return(pixelWiseDiff)

L1Norm(letterT, testedT)
```

```
Total number of black pixels in Image A: 32
Total number of black pixels in Image B: 30
Absolute pixelwise difference: 10
```

Training Data

```python
letterT = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
           0, 1, 1, 1, 1, 1, 1, 1, 1, 0,
           0, 1, 1, 1, 1, 1, 1, 1, 1, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
```

```python
letterl = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
```

```python
letterI = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
           0, 1, 1, 1, 1, 1, 1, 1, 1, 0,
           0, 1, 1, 1, 1, 1, 1, 1, 1, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 1, 1, 1, 1, 1, 1, 1, 1, 0,
           0, 1, 1, 1, 1, 1, 1, 1, 1, 0,
           0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
```

```python
testedT = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
           0, 0, 1, 1, 1, 1, 1, 1, 0, 0,
           0, 0, 1, 1, 1, 1, 1, 1, 0, 0,
           0, 0, 1, 0, 1, 1, 0, 1, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
           0, 0, 0, 1, 1, 1, 1, 0, 0, 0,
           0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
           0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
```

```python
training = {}
training["T"] = letterT
training["l"] = letterl
training["I"] = letterI

predictLetter = testedT
estimates = {}
for l in training:
    distance = L1Norm(training[l], predictLetter)
    estimates[l] = distance

print(estimates)
```

```
{'T': '10', 'l': '14', 'I': '18'}
```

Interlude - Numpy

```python
letterT = [0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
           0,  1,  1,  1,  1,  1,  1,  1,  1,  0,
           0,  1,  1,  1,  1,  1,  1,  1,  1,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  0,  0,  0,  0,  0,  0]
```



```python
letterT = np.asarray(letterT)
print(letterT)
```

```
[0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 0 0 1 1 1 1 1 1 1 1 0 0 0 0 0 1 1 0
 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0
 1 1 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0
 0 0 0 0 0 0 0 0 0]
```

A toy nearest neighbor classifier

```python
class NearestNeighborSinglePrediction:
    def __init__(self):
        pass

    def train(self, X, y):
        #For nearest neighbor, we just copy the data for later use.
        self.Xtr = X
        self.ytr = y

    def predict(self, X):
        l1Distances = np.sum(np.abs(self.Xtr - X[0]), axis=1)
        minimumDistance = np.argmin(l1Distances)
        Ypred = self.ytr[minimumDistance]

        return Ypred
```

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```
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```

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        l1Distances = np.sum(np.abs(self.Xtr - X[0]), axis=1)
        minimumDistance = np.argmin(l1Distances)
        Ypred = self.ytr[minimumDistance]

        return Ypred
```

```python
trainingX = [letterT, letterI, letterl]
trainingy = np.array(["T", "I", "l"])

nn = NearestNeighborSinglePrediction()
nn.train(X=trainingX, y=trainingy)
estimates = nn.predict(X=[testLetter])

print(estimates)
```

T

A toy nearest neighbor classifier

```python
class NearestNeighborSinglePrediction:
    def __init__(self):
        pass

    def train(self, X, y):
        #For nearest neighbor, we just copy the data for later use.
        self.Xtr = X
        self.ytr = y

    def predict(self, X):
        l1Distances = np.sum(np.abs(self.Xtr - X[0]), axis=1)
        minimumDistance = np.argmin(l1Distances)
        Ypred = self.ytr[minimumDistance]

        return Ypred
```

```python
for l in training:
    distance = L1Norm(training[l], predictLetter)
    estimates[l] = distance
```

A toy nearest neighbor classifier

l =

```
testedL = [0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  1,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  1,  1,  0,  0,
           0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
           0,  0,  0,  0,  0,  0,  0,  0,  0,  0]
```

T =

```
testedT = [0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
           0,  0,  1,  1,  1,  1,  1,  1,  0,  0,
           0,  0,  1,  1,  1,  1,  1,  1,  0,  0,
           0,  0,  1,  0,  1,  1,  0,  1,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  0,  1,  1,  0,  0,  0,  0,
           0,  0,  0,  1,  1,  1,  1,  0,  0,  0,
           0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
           0,  0,  0,  0,  0,  0,  0,  0,  0,  0]
```

A toy nearest neighbor classifier

```python
class NearestNeighbor:
    def __init__(self):
        pass

    def train(self, X, y):
        #For nearest neighbor, we just copy the data for later use.
        self.Xtr = X
        self.ytr = y

    def predict(self, X):
        #We'll be doing our test for every input X this time,
        #just in case we want to test multiple
        #cases (As we'll be doing later!)

        #Create an empty list to hold our results
        #Note the dtype tells Numpy if the output (y) estimates
        #should be a float, integer, or string based on the training y.
        Ypred = np.zeros(len(X), dtype=np.dtype(self.ytr.dtype))

        for i in range(0, len(X)):
            l1Distances = np.sum(np.abs(self.Xtr - X[i]), axis=1)
            minimumDistance = np.argmin(l1Distances)
            Ypred[i] = self.ytr[minimumDistance]

        return Ypred
```

```python
nn = NearestNeighbor()
nn.train(X=trainingX, y=trainingy)
estimates = nn.predict(X=[testLetter, testLetter2])

print(estimates)
```

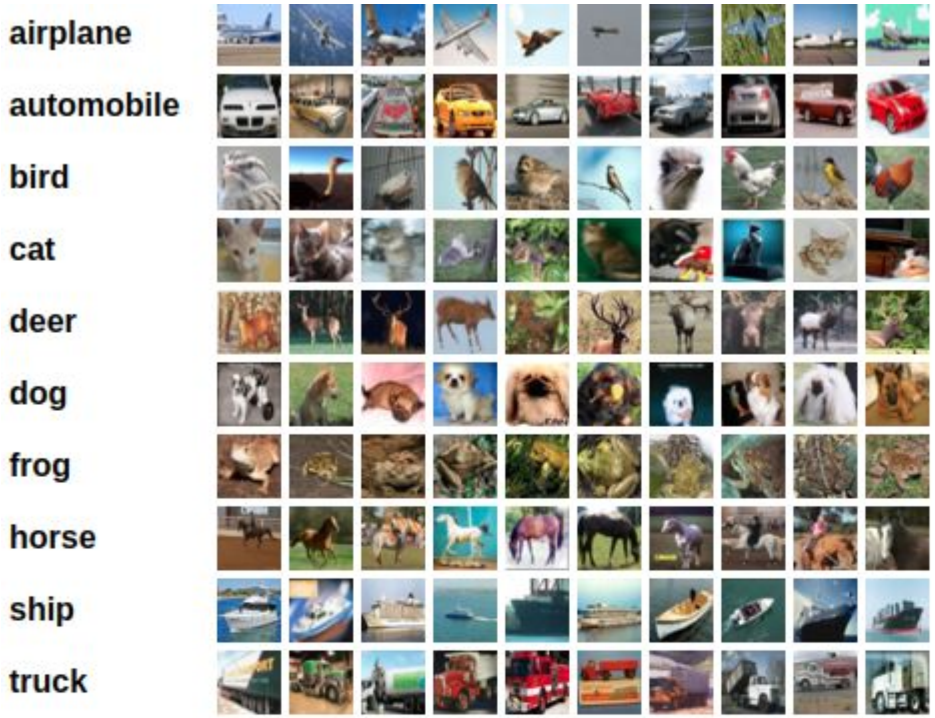
['T', '1']

A toy nearest neighbor classifier

```python
class NearestNeighbor:
    def __init__(self):
        pass

    def train(self, X, y):
        #For nearest neighbor, we just copy the data for later use.
        self.Xtr = X
        self.ytr = y

    def predict(self, X):
        #We'll be doing our test for every input X this time,
        #just in case we want to test multiple
        #cases (As we'll be doing later!)

        #Create an empty list to hold our results
        #Note the dtype tells Numpy if the output (y) estimates
        #should be a float, integer, or string based on the training y.
        Ypred = np.zeros(len(X), dtype=np.dtype(self.ytr.dtype))

        for i in range(0, len(X)):
            l1Distances = np.sum(np.abs(self.Xtr - X[i]), axis=1)
            minimumDistance = np.argmin(l1Distances)
            Ypred[i] = self.ytr[minimumDistance]

        return Ypred
```

Slow! We have to compare every single case in our training data to every input.

Example: Nearest Neighbor & CIFAR 10



60,000 Images
50,000 Training
10,000 Testing

32 x 32 Pixels

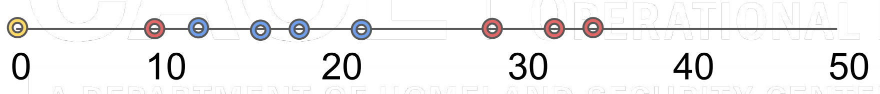
10 Classes (shown to left)

https://www.cs.toronto.edu/~kriz/cifar.html
Learning Multiple Layers of Features from Tiny Images, Alex Krizhevsky, 2009.

K Nearest Neighbors

In this example, we have multiple examples of letters we're using for training. Every red dot is an "A", and every blue dot is a "T". The yellow dot is representative of a hand-written T, that we're trying to identify the letter of.

Red = Examples of Letter A
Blue = Examples of Letter T

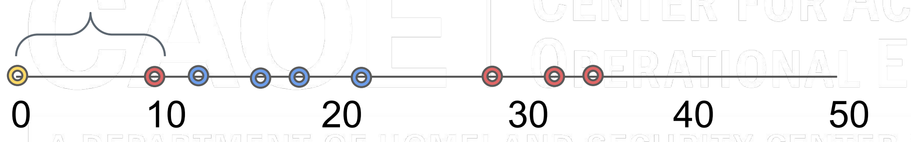


Pixelwise Difference Between Test Image and Observed Image

K Nearest Neighbors

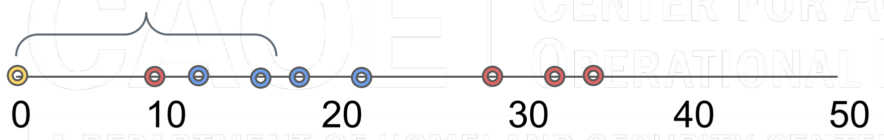
Most similar letter with a L1 Distance of ~10.

Red = Examples of Letter A
Blue = Examples of Letter T



Pixelwise Difference Between Test Image and Observed Image

K=3 Nearest Neighbors



Red = Examples of Letter A
Blue = Examples of Letter T

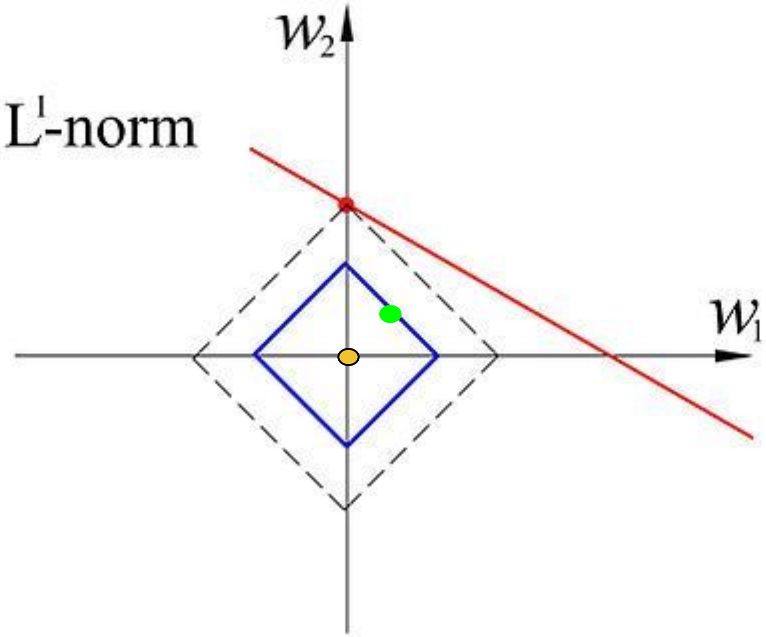
Pixelwise Difference Between Test Image and Observed Image

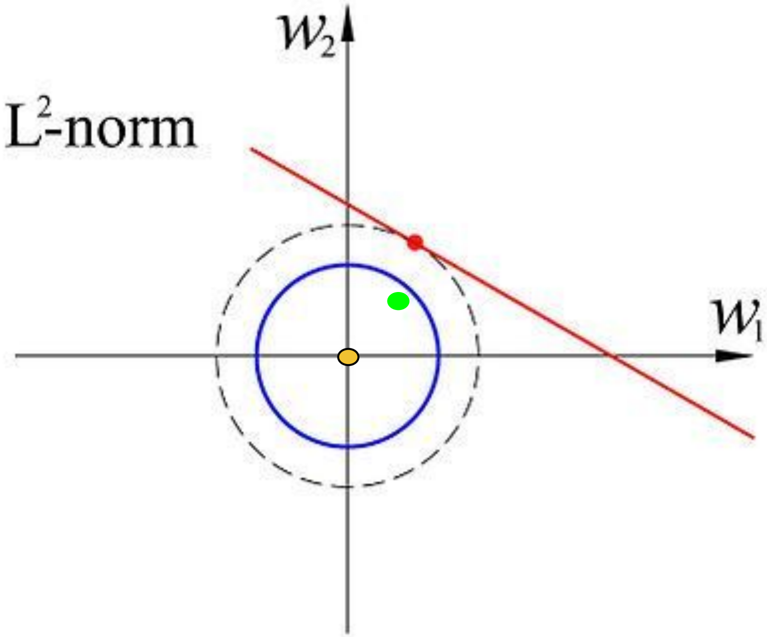
	N=1	N=2	N=3	N=4	N=5	N=6	N=7	N=8	N=9	N=10
Airplane	0	0	0	0	20%	16%	14%	13%	22%	20%
Car	0	0	0	0	0	0	0	13%	11%	10%
Bird	0	0	0	0	0	0	0	0	0	0
Cat	100%	50%	66%	50%	40%	50%	43%	37%	33%	30%
Deer	0	0	0	0	0	0	0	0	0	0
Dog	0	0	0	0	0	0	0	0	0	0
Frog	0	50%	33%	50%	40%	34%	43%	37%	33%	30%
Horse	0	0	0	0	0	0	0	0	0	0
Ship	0	0	0	0	0	0	0	0	0	10%
Truck	0	0	0	0	0	0	0	0	0	0

KNN - Distance Metric pt 2.

$$L_1(I_1, I_2) = \sum_p |I_{1,p} - I_{2,p}|$$

$$L2(I_1, I_2) = \sqrt{\sum_p (I_{1,p} - I_{2,p})^2}$$

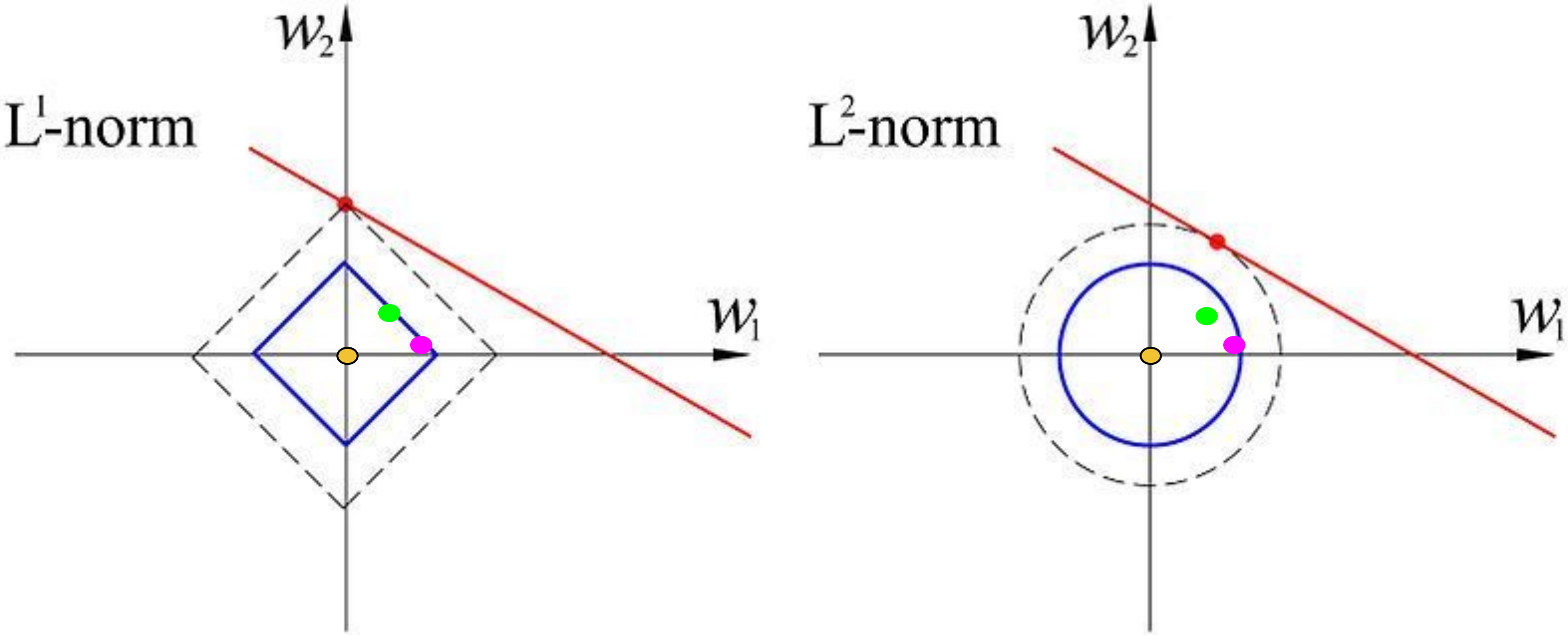




KNN - Distance Metric pt 2.

$$L_1(I_1, I_2) = \sum_p |I_{1,p} - I_{2,p}|$$

$$L2(I_1, I_2) = \sqrt{\sum_p (I_{1,p} - I_{2,p})^2}$$



Hyperparameters

How do we choose the right K?

How do we choose between L1 and L2?

Both of these are **hyperparameters** - settings we choose about the algorithm that are not learned from the data.

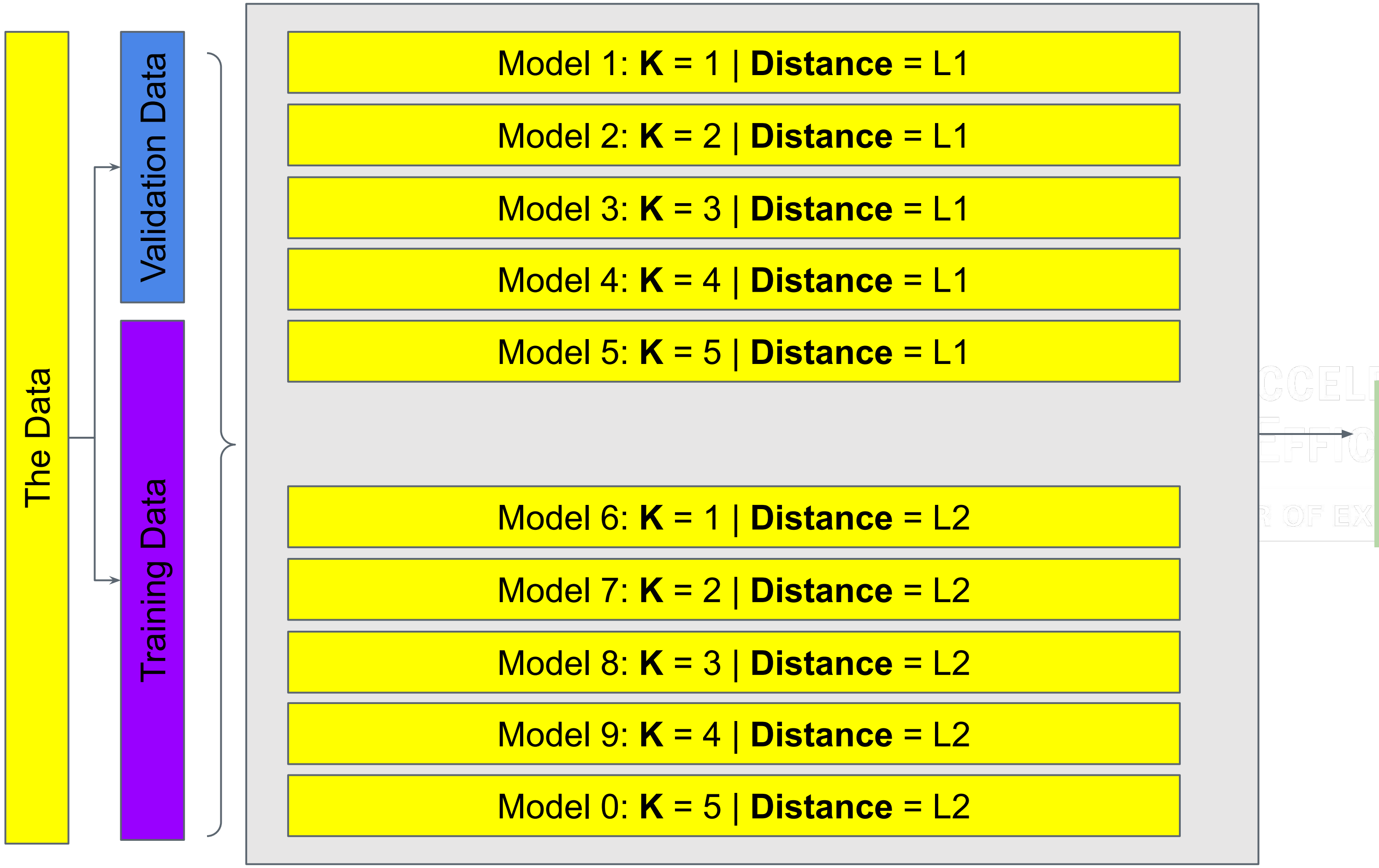
Choosing Hyperparameters

The Data

- Model 1: **K** = 1 | **Distance** = L1
- Model 2: **K** = 2 | **Distance** = L1
- Model 3: **K** = 3 | **Distance** = L1
- Model 4: **K** = 4 | **Distance** = L1
- Model 5: **K** = 5 | **Distance** = L1
- Model 6: **K** = 1 | **Distance** = L2
- Model 7: **K** = 2 | **Distance** = L2
- Model 8: **K** = 3 | **Distance** = L2
- Model 9: **K** = 4 | **Distance** = L2
- Model 0: **K** = 5 | **Distance** = L2

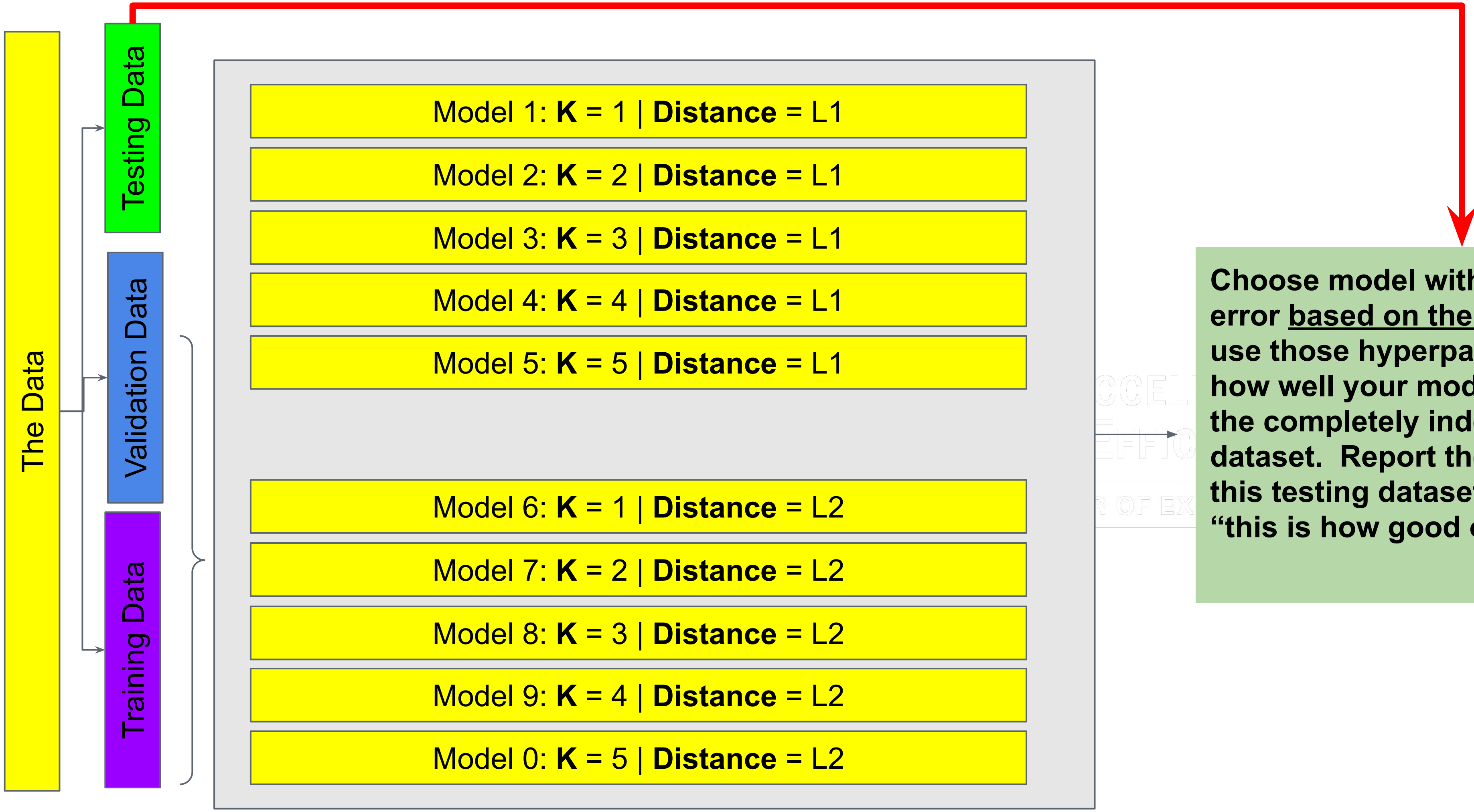
Choose model with lowest overall error, use those hyperparameters. All data is used for fitting and accuracy calculation.

Choosing Hyperparameters



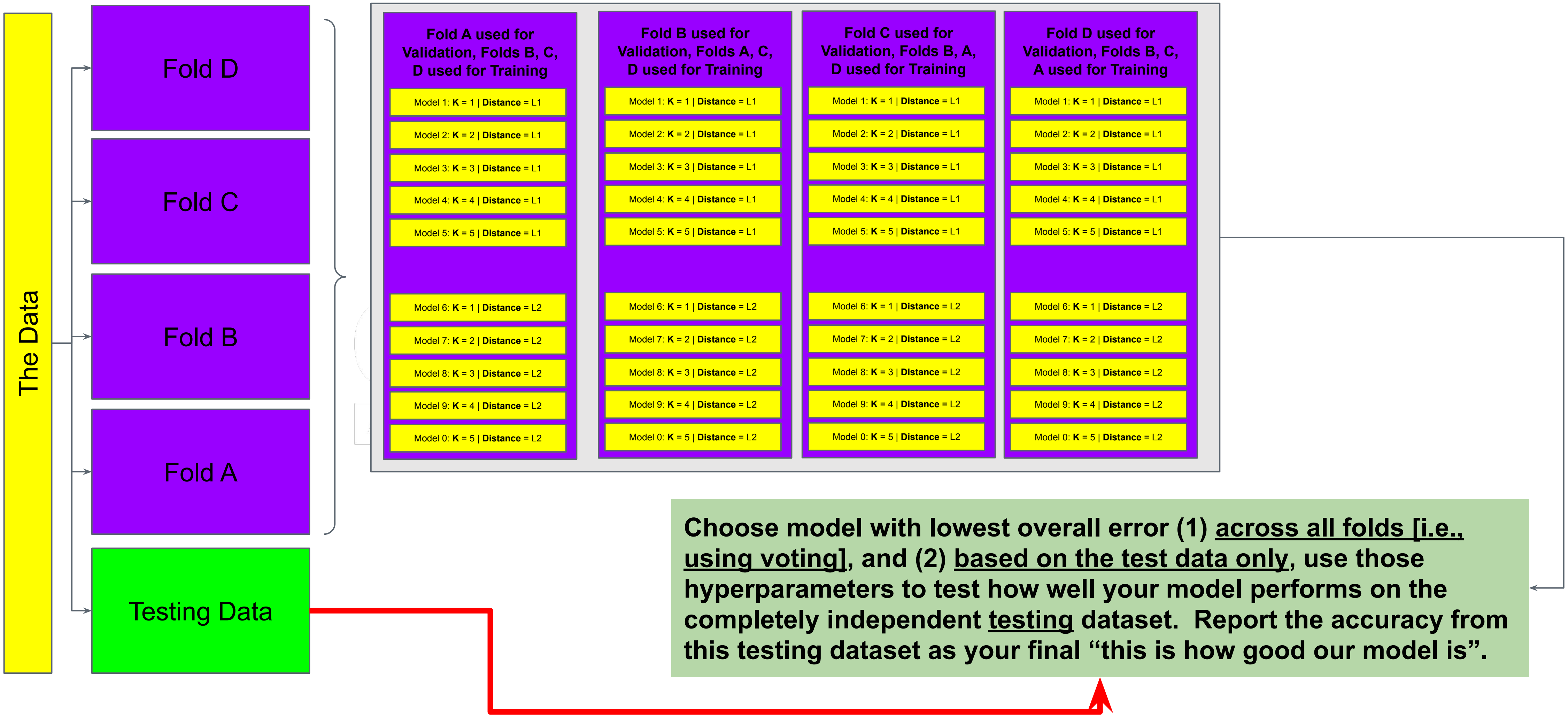
Choose model with lowest overall error <u>based on the test data</u>, use those hyperparameters.

Choosing Hyperparameters



Choose model with lowest overall error based on the test data only, use those hyperparameters to test how well your model performs on the completely independent testing dataset. Report the accuracy from this testing dataset as your final "this is how good our model is".

Cross Validation



Choose model with lowest overall error (1) <u>across all folds [i.e., using voting]</u>, and (2) <u>based on the test data only</u>, use those hyperparameters to test how well your model performs on the completely independent <u>testing</u> dataset. Report the accuracy from this testing dataset as your final "this is how good our model is".

KNN

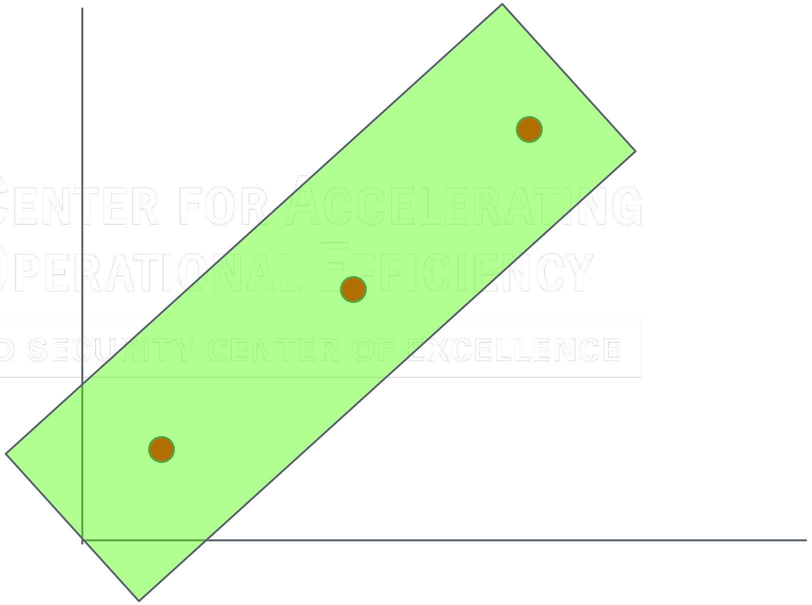
- Great as an example for some basic machine learning terminology.
- Not great for actual use.
  - Operational use very slow (training is fast, prediction is slow).
  - Simple distance metrics can't capture perceptual differences that matter.
  - "Curse of Dimensionality"

Dimensionality of Images

<u>"Normal Data"</u>

Dimensions: 2

Observation	Height	Weight
A	3ft	10lb
B	4ft	20lb
C	5ft	30lb

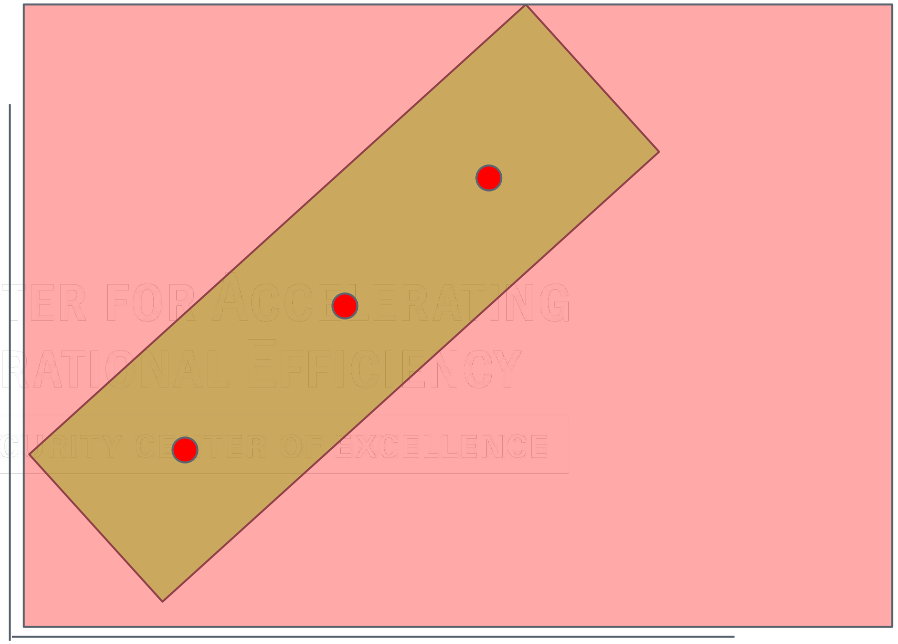


Dimensionality of Images

“Normal Data”

Dimensions: 2

Observation	**Height**	**Weight**
A	3ft	10lb
B	4ft	20lb
C	5ft	30lb

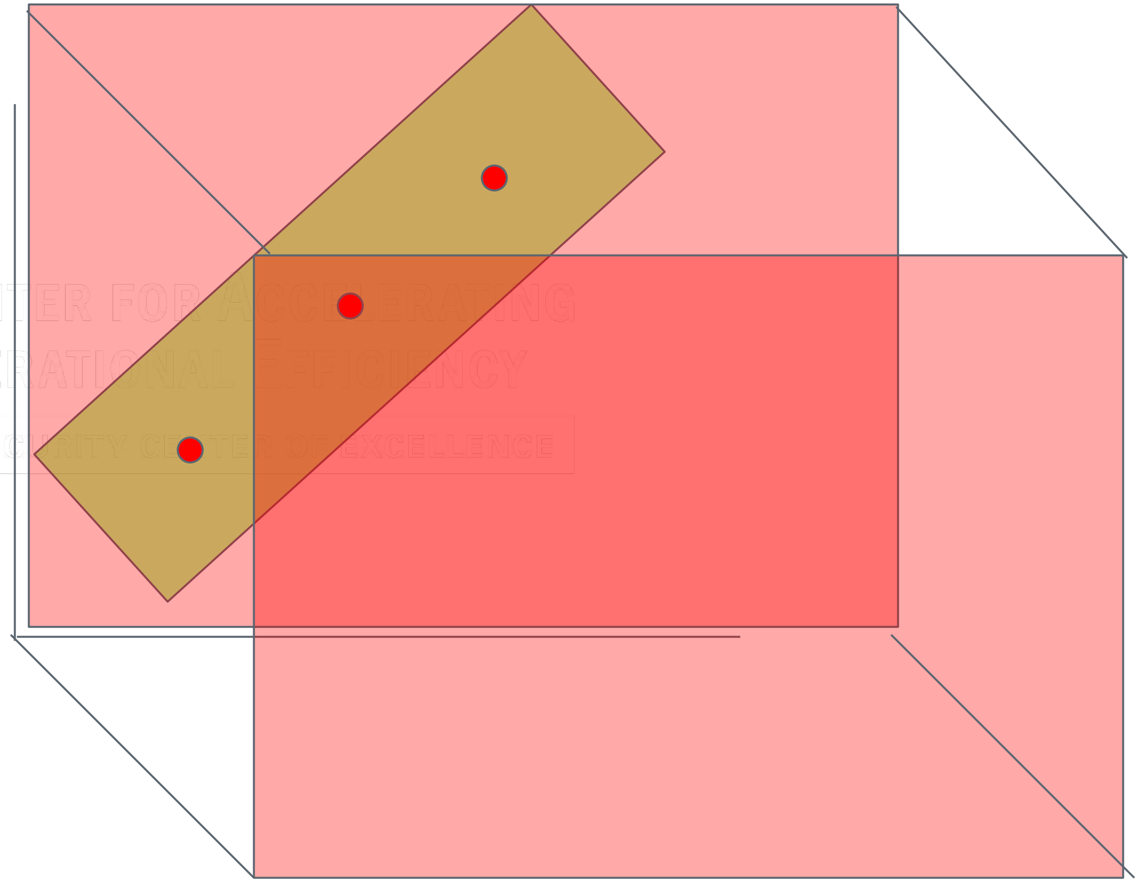


Dimensionality of Images

“Normal Data”

Dimensions: 2

Observation	Height	Weight	Age
A	3ft	10lb	5
B	4ft	20lb	5
C	5ft	30lb	5



Dimensionality of Images

Image Data

Dimensions: Thousands

Observations: 3

Observation	Pixel 1	Pixel 2	...	Pixel 12000	Pixel 12001
A	10	10		25	85
B	20	20		35	75
C	30	30		65	95

Recap

- We are exploring the topic of image classification, in which we are using a large training set of images that have human-created labels, and we are using this to predict the correct labels for a test set of data.

- KNN is an example of how you can do this, though not a good one. It predicts based on the nearest training example.

- In the case of KNN, the distance metric (L1 vs. L2) and K are the hyperparameters you must choose.

- A validation set and test set allow you to choose appropriate hyperparameters.

- For small datasets, cross-fold validation can improve the robustness of your results.

Reminders

- Remember to check in on Piazza with any questions!
- Piazza will also have information on the first lab.
- Group study is encouraged, but your submissions should be your own!