CS 360: Machine Learning

Prof. Sara Mathieson

Fall 2019

HAVERFORD
COLLEGE

Admin

- **Roster** is semi-finalized

- **First lab today**, may need to bring a computer if you’re on the waitlist and have never taken a CS course at Haverford

- **Lab 1** due Tues night (next office hours Friday 3-5pm) if you did NOT get a Piazza notification about Lab 1, email me ASAP

Outline for Sept 5

- Reading quiz 1
- Introductions
- Style guidelines for Python
- Continue K-nearest neighbors
- Featurization (intro)
- If time: begin entropy and decision trees

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Reading Quiz 1

1) *Generalization*: ability to answer new questions related to the topic studied

2) No! If we look at the test data (either the *features* or the *labels*), then any measurement of the performance of our algorithm becomes inaccurate

3) *Multiclass classification*

4) *Regression*

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Python style

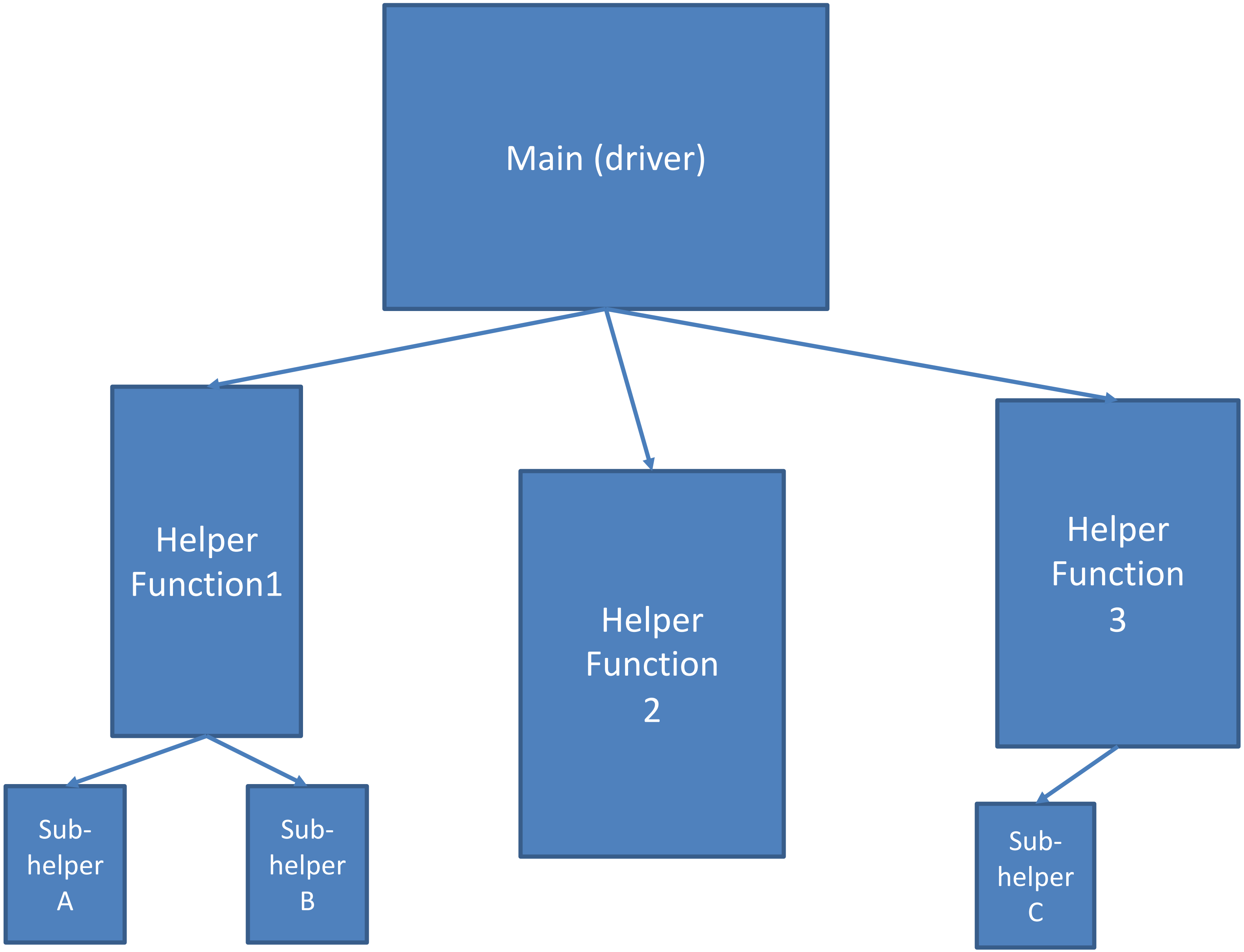
- Decompose code into natural functions
- Avoid global variables (sometimes useful)
- Include a file header with purpose, author, and date
- Include headers for each function
- No lines over 80 chars
- Variable names implicitly show type
- Include line breaks and comments!

Python style examples

```python
"""
Ask the user for their name and welcome them to CS21.
Author: Sara Mathieson
Date: 9/7/18
"""

def main():

    # ask user for their name and print greeting
    name = input("Enter your name: ")
    print("Hello", name, "!")

main()
```

```python
def factorial(n):
    """
    Given a non-negative integer n, return n! = n*(n-1)*(n-2)....3*2*1.
    """
    fact = 1 # set up an accumulator variable
    for i in range(n):
        fact = fact * (i+1) # accumulator pattern
    return fact
```

Structure of main and "helper" functions



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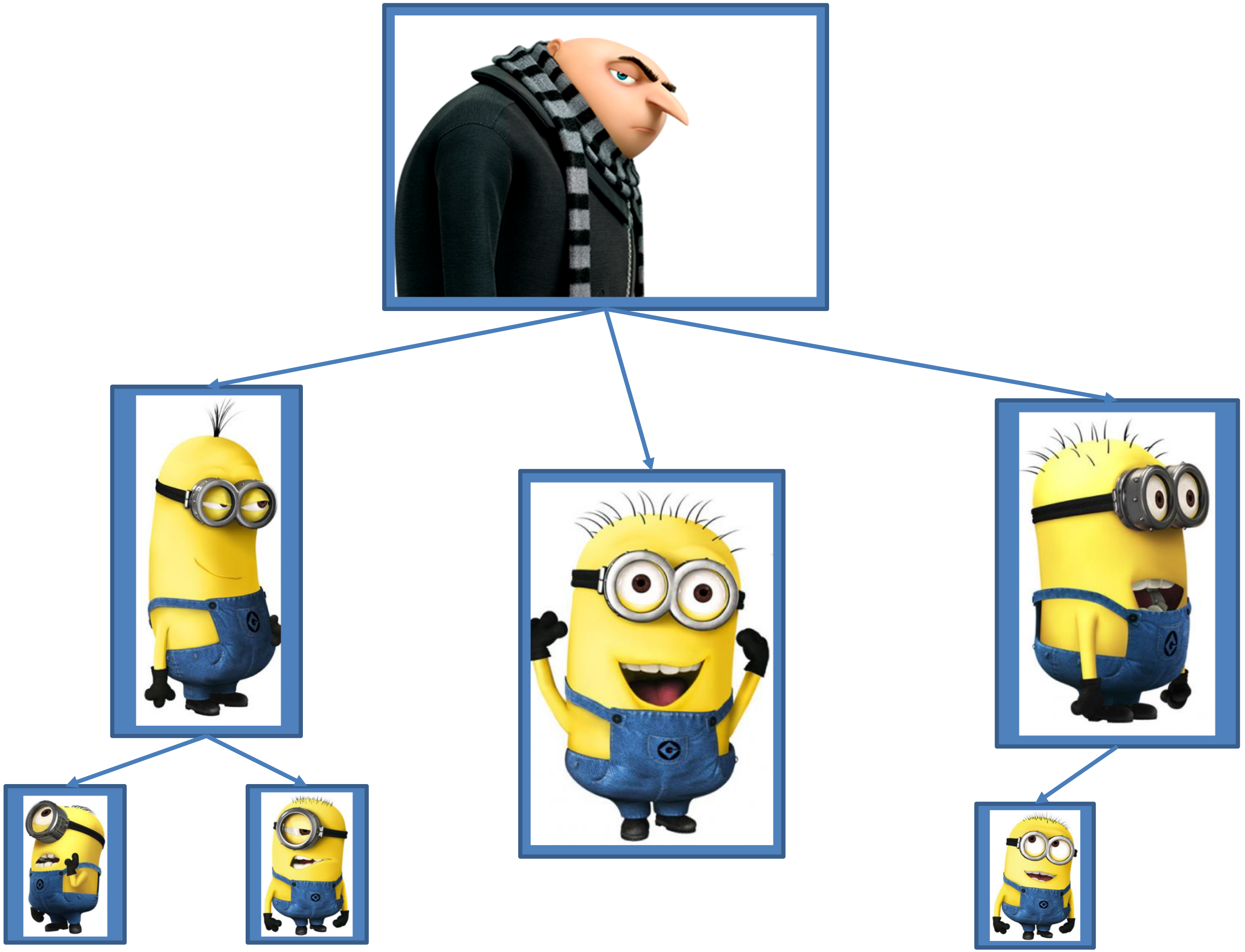

Reminder: steps of top-down-design (TDD)

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3) "Stub" out the functions. This means that they should work and return the correct type so that your code runs, but they don't do the correct task yet. For example, if a function should return a list, you can return []. Or if it returns a boolean, you can return False.

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4) Iterate on your design until you have a working main and stubbed out functions. Then start implementing the functions, starting from the "bottom up".

Reasons to use TDD

- Creates code that is easier to implement, debug, modify, and extend

- Avoids going off in the wrong direction (i.e. implementing functions that are not useful or don't serve the program)

- Creates code that is easier for you or someone else to read and understand later on

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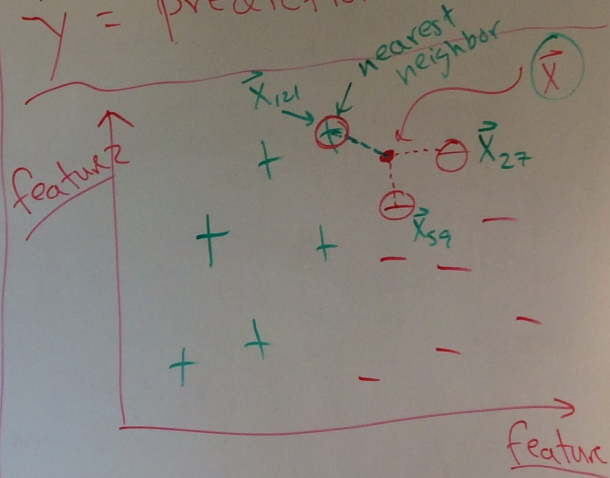
X = $\underbrace{n \times p}_{\text{row} \times \text{col}}$ matrix of features → "rom-com"

X_{train} = training data (80%)

X_{test} = test data (20%)

y = label / output (vector)

$\hat{y}$ = prediction.



$K=1 \Rightarrow$ nearest neighbor

$\hat{y} = \text{sign}(+1) = +1$

$K=2 \Rightarrow \hat{y} = \underbrace{\text{sign}(+1-1)}_{\text{sign}(0) \Rightarrow -1} = -1$

$K=3 \Rightarrow$ 3 nearest neighbors

$\hat{y} = \text{sign}(+1-1-1) = -1$

$$\text{sign}(z) = \begin{cases} +1 & \text{if } z > 0 \\ -1 & \text{if } z \le 0 \end{cases}$$

conservative

Algorithm input: $\vec{x}$ (test), K, X_{train}
(binary) $y \in \{-1, +1\}$ y_{train}

$\vec{S}$ = vector of len n

for $i = 1 \ldots n$:
 $S_i = [d(\vec{x}, \vec{x}_i), i]$

test, train, index

$\boxed{\text{or}}$ y_i

sort $\vec{S}$ by dist.

votes = 0
for $k = 1 \ldots K$:
 [dist, i] = S_k
 votes += y_i
return sign(votes)

Multiclass

$N_K(\vec{x})$ = set of nearest neighbors for $\vec{x}$

$$N_3(\vec{x}) = \{\vec{x}_{121}, \vec{x}_{27}, \vec{x}_{59}\}$$

$$p(y = c \mid \vec{x}) = \frac{1}{K} \sum_{\vec{x}_i \in N_K(\vec{x})} \mathbb{1}(y_i = c)$$

$\{+1, -1\}$

$\{1, 2, 3, 4, 5\}$

$K = 5$

$$p(y = \bullet \mid \vec{x}) = \frac{1}{5}$$

$$p(y = \square \mid \vec{x}) = \frac{2}{5}$$

$$p(y = \Delta \mid \vec{x}) = \frac{2}{5}$$

K-nearest neighbors creates implicit decision boundaries

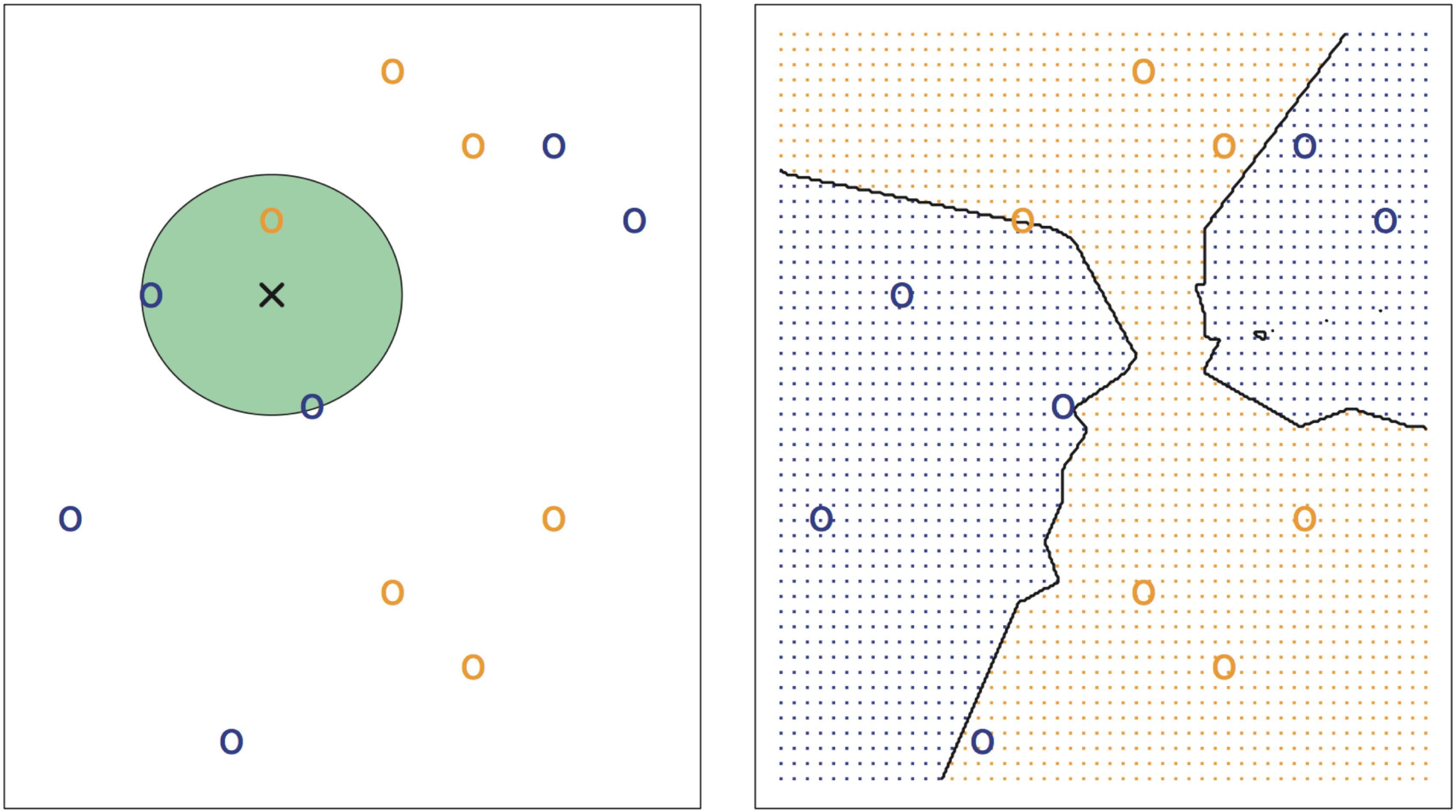


Figure 2.14 from ISL book, KNN with two classes (C=2), and K=3

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Terminology

- *Features:* feature names
  - i.e. shape
- *Feature values:* what values are possible
  - i.e. {circle, square, triangle}
- *Feature vector:* values for a particular example
  - i.e. $\boldsymbol{x} = [x_1, x_2, x_3, \ldots, x_p]$

Terminology

- *Decision boundary*: separates regions of the feature space that would be classified as positive or negative (or multiclass)
- *Underfitting*: “had the opportunity to learn something but didn’t” (Duame)
- *Overfitting*: memorized individual training examples (fit to noise) and can’t generalize

Handout 2
(find and work with a partner)

Comparison of decision boundaries

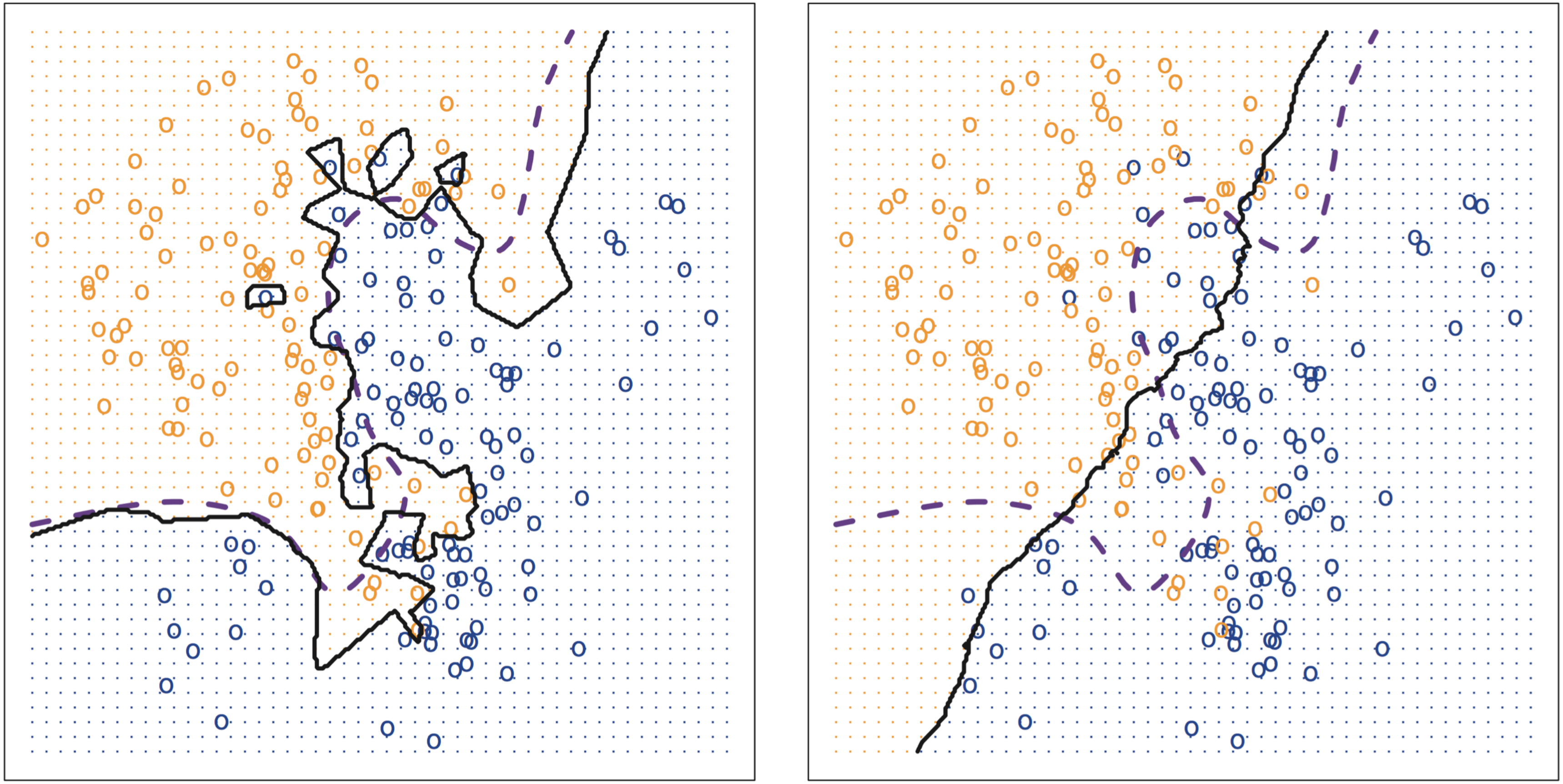
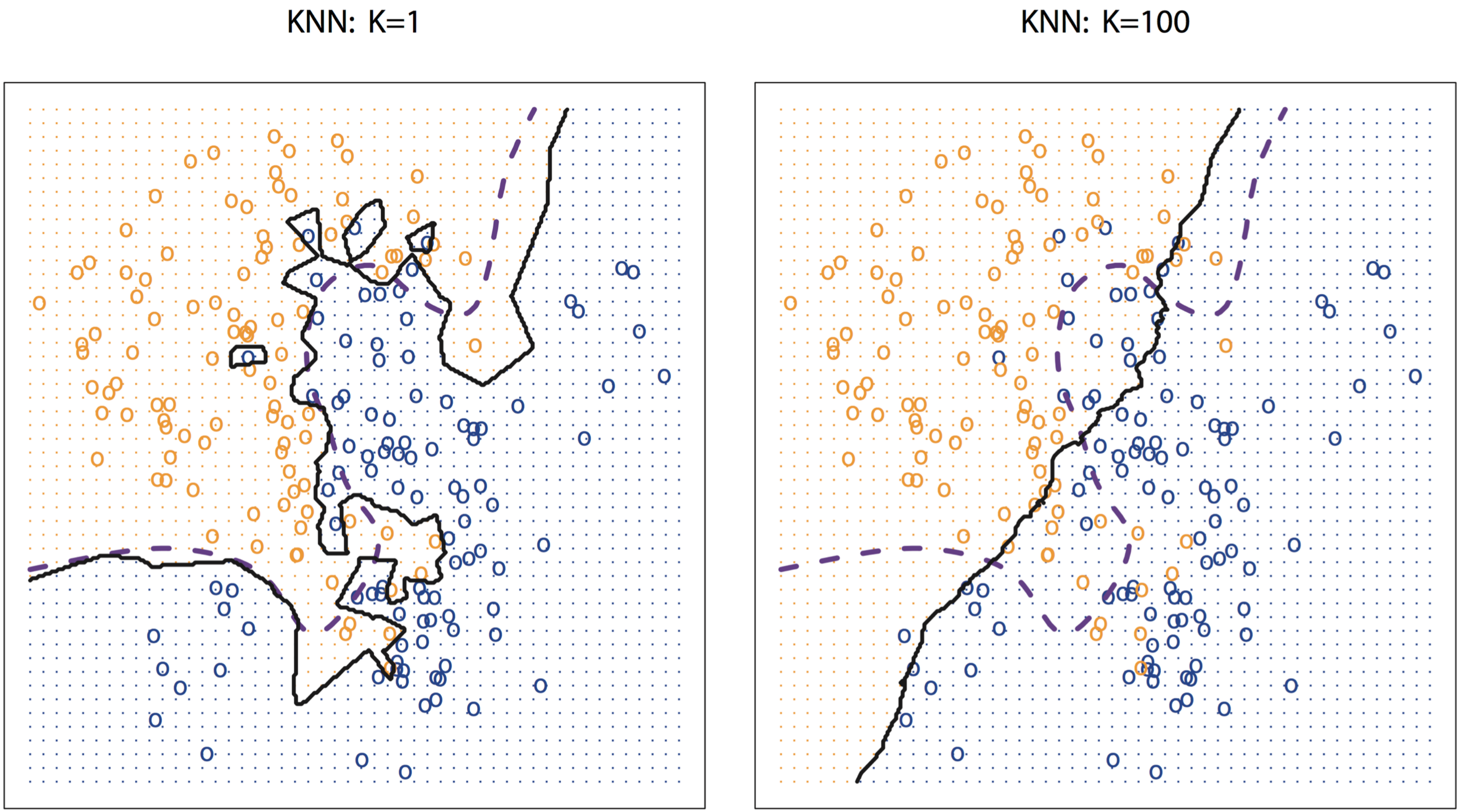


Figure 2.16 from ISL book (dashed line is “ideal” boundary)

Comparison of decision boundaries



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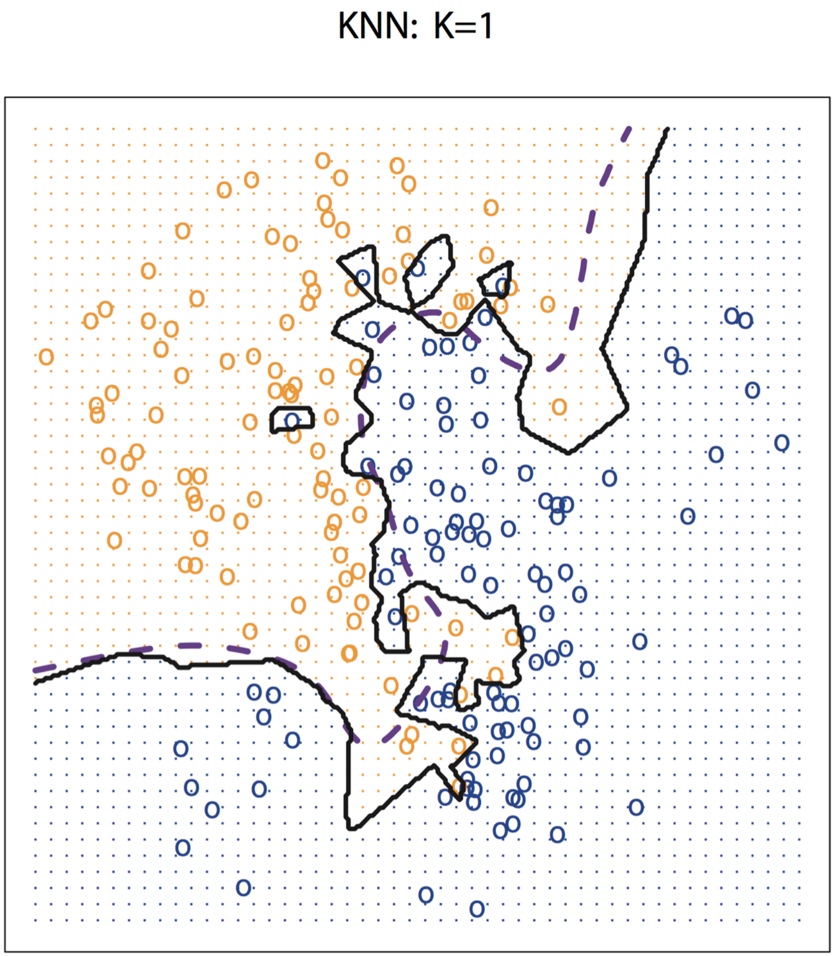
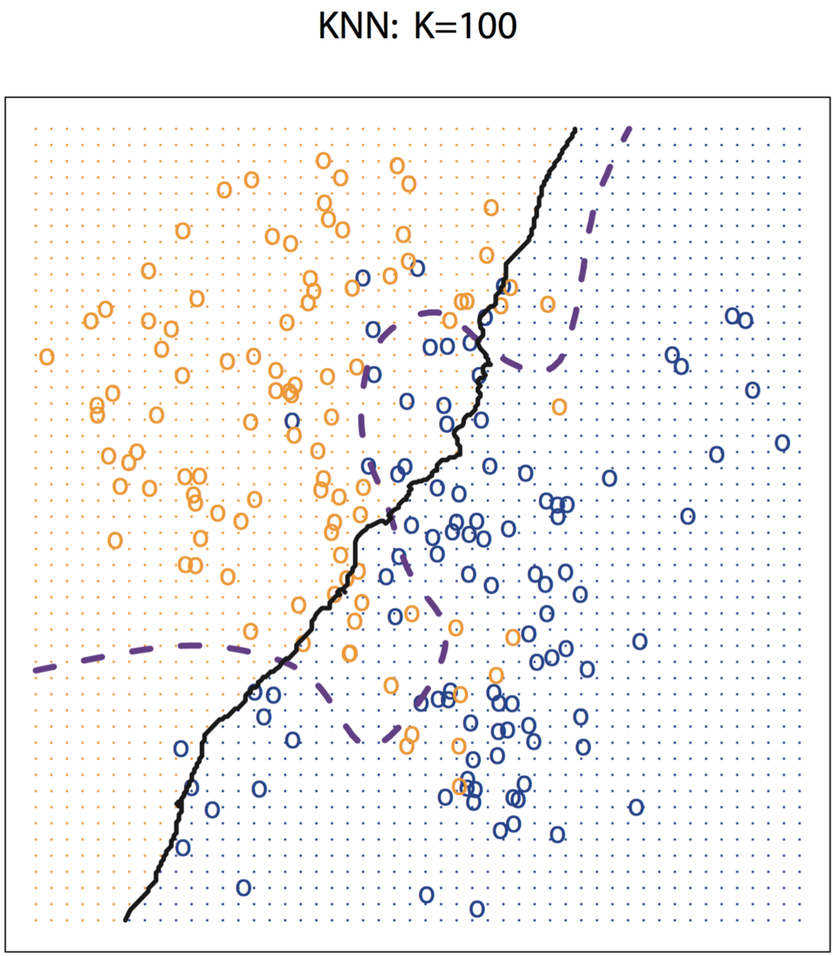


Overfitting



Underfitting

Figure 2.16 from ISL book (dashed line is “ideal” boundary)

Featurization (rule of thumb)

Duame, Chap 3

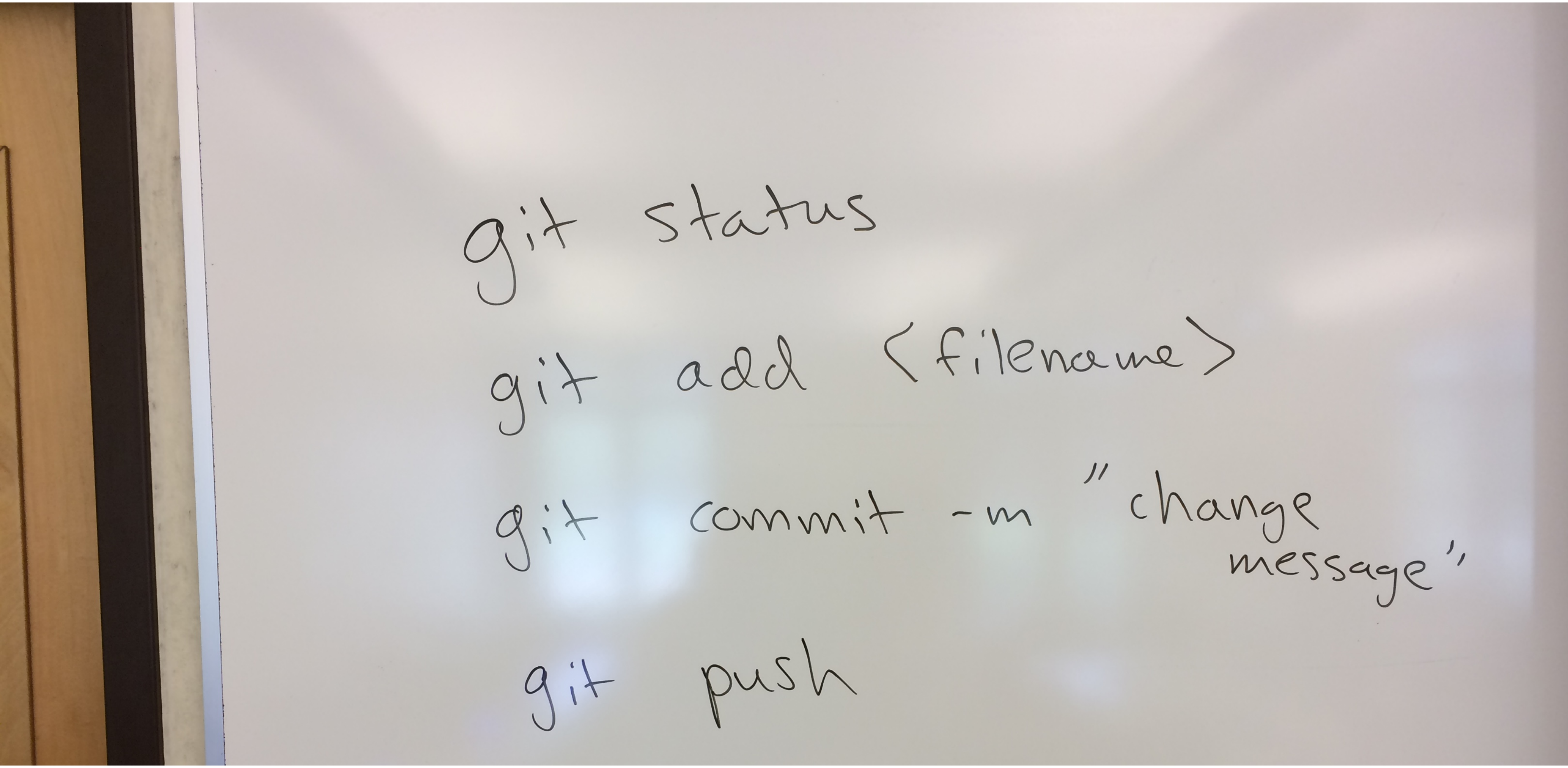
- Real-valued features get copied directly.
- Binary features become 0 (for false) or 1 (for true).
- Categorical features with V possible values get mapped to V-many binary indicator features.

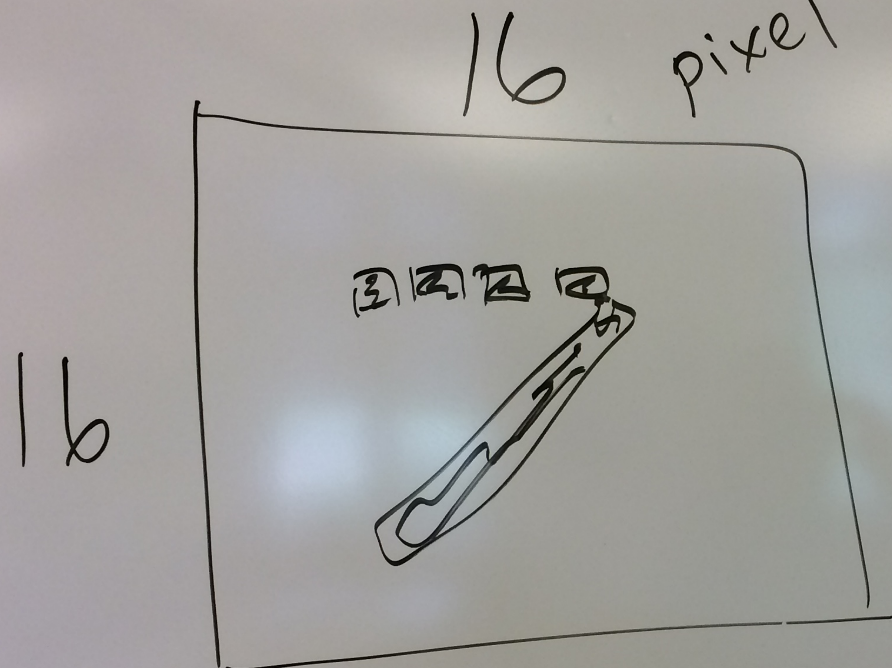
Haven't discussed:

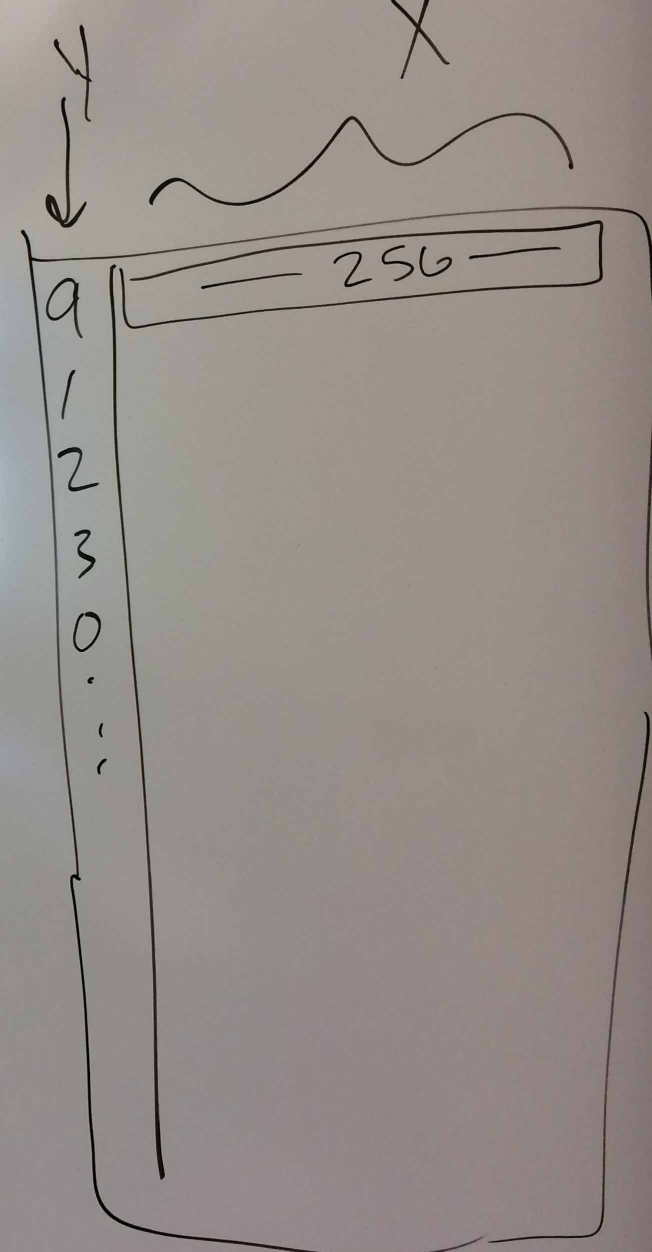
-normalization

-categorical variables on a spectrum

Lab 1 Notes


git status
git add <filename>
git commit -m "change message"
git push


16 pixel
16


y
X
256
9
1
2
3
0