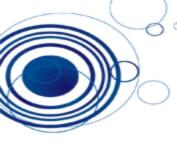


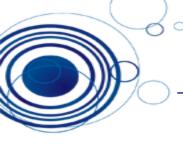
#### We covered...

- Data management by python
  - Numpy, pandas, data acquisition
- Machine learning workflow with data



## **Today's Subjects**

- EDA (Exploratory Data Analysis)
- Supervised learning
  - Examples k-NN classifier
  - Regression : linear regression
  - Classification : logistic regression based binary classification



# Represent / Train / Evaluate / Refine Cycle



Extract and select object features



#### <u>Train models</u>:

Fit the estimator to the data



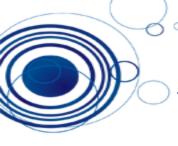


Feature and model refinement



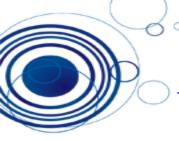
Evaluation





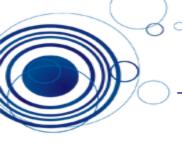
# Before feature representation.....

- EDA (Exploratory Data Analysis)
  - Understanding your variables
  - Cleaning your dataset
  - Analyzing relationship between variables
- Read: <a href="https://towardsdatascience.com/an-extensive-guide-to-exploratory-data-analysis-ddd99a03199e">https://towardsdatascience.com/an-extensive-guide-to-exploratory-data-analysis-ddd99a03199e</a>

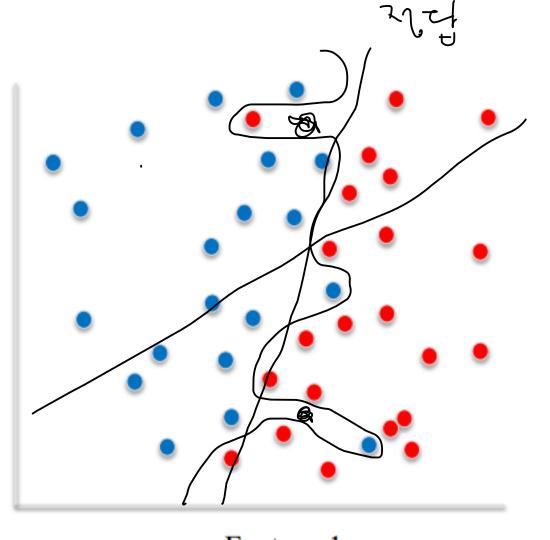


# Generalization, overfitting, and underfitting

- <u>Generalization</u> ability refers to an algorithm's ability to give accurate predictions for new, previously unseen data.
- Assumptions:
  - Future unseen data (test set) will have the same properties as the current training sets.
  - Thus, models that are accurate on the training set are expected to be accurate on the test set.
  - But that may not happen if the trained model is tuned too specifically to the training set.
- Models that are too complex for the amount of training data available are said to <u>overfit</u> and are not likely to generalize well to new examples.
- Models that are too simple, that don't even do well on the training data, are said to <u>underfit</u> and also not likely to generalize well.



# Overfitting in classification



Feature 1

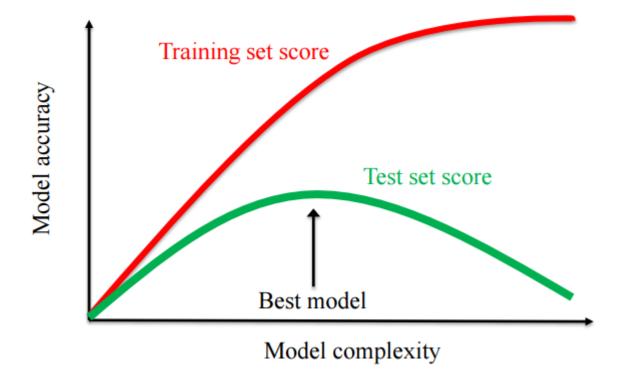
UnderEit

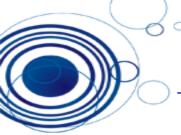
Feature 2



## **Overfitting**

• The relationship between model complexity and training/test performance



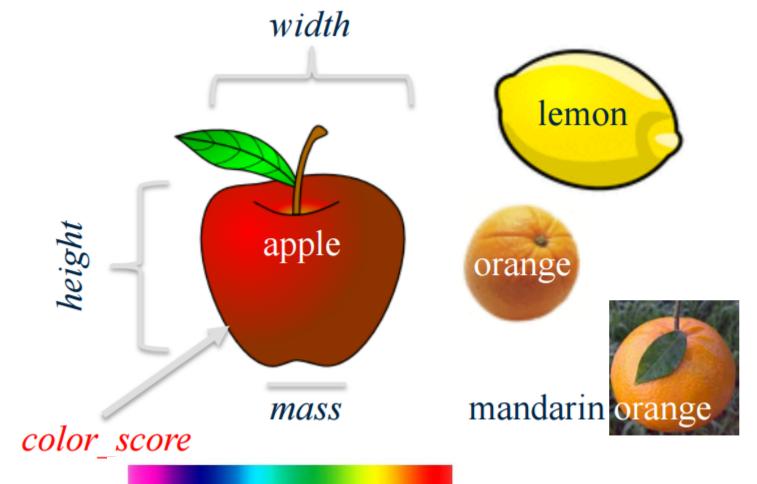


0.00

0.25

0.50

#### **Fruit Dataset**



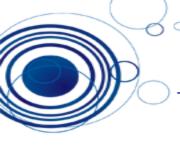
0.75

1.00

	fruit_label	fruit_name	fruit_subtype	mass	width	height	color_score
0	1	apple	granny_smith	192	8.4	7.3	0.55
1	1	apple	granny_smith	180	8.0	6.8	0.59
2	1	apple	granny_smith	176	7.4	7.2	0.60
3	2	mandarin	mandarin	86	6.2	4.7	0.80
4	2	mandarin	mandarin	84	6.0	4.6	0.79
5	2	mandarin	mandarin	80	5.8	4.3	0.77
6	2	mandarin	mandarin	80	5.9	4.3	0.81
7	2	mandarin	mandarin	76	5.8	4.0	0.81
8	1	apple	braeburn	178	7.1	7.8	0.92
9	1	apple	braeburn	172	7.4	7.0	0.89
10	1	apple	braeburn	166	6.9	7.3	0.93
11	1	apple	braeburn	172	7.1	7.6	0.92
12	1	apple	braeburn	154	7.0	7.1	0.88
13	1	apple	golden_delicious	164	7.3	7.7	0.70
14	1	apple	golden_delicious	152	7.6	7.3	0.69
15	1	apple	golden_delicious	156	7.7	7.1	0.69
16	1	apple	aolden delicious	156	7.6	7.5	0.67

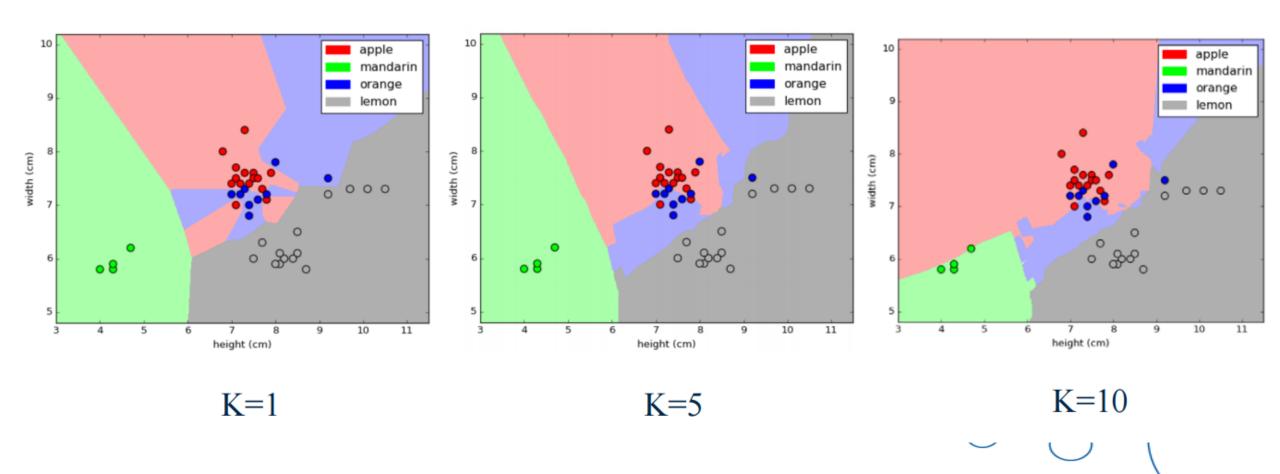
fruit\_data\_with\_colors.txt

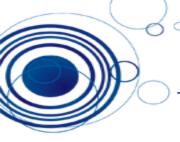




# The k-Nearest Neighbor(k-NN) Algorithm

Find k nearest neighbor data to classification





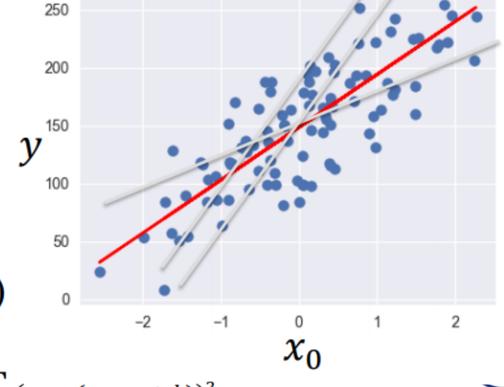
# Linear regression

• Example: linear regression model with one variable

Input instance: 
$$x = (x_0)$$

Predicted 
$$\hat{y} = \widehat{w_0} x_0 + \hat{b}$$
 output:

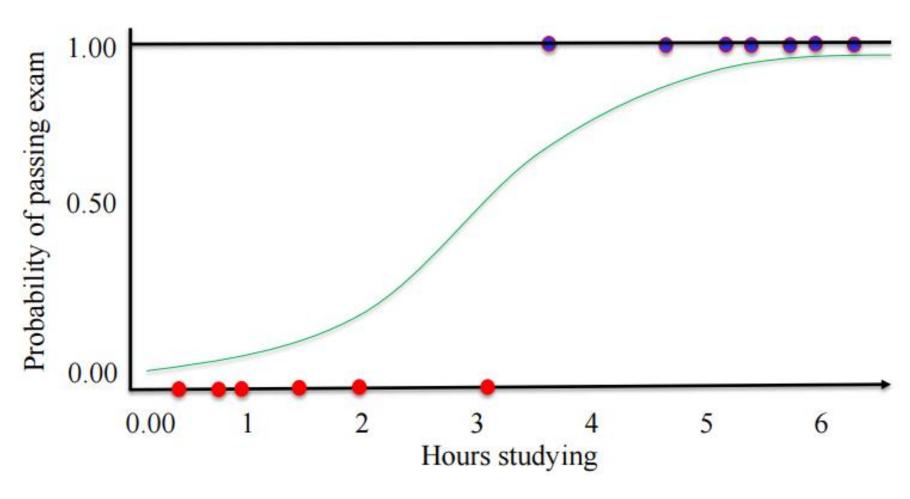
Parameters  $\widehat{w_0}$  (slope) to estimate:  $\widehat{b}$  (y-intercept)



• Objective: minimize  $RSS(w,b) = \sum_{i=1}^{N} (y_i - (w \cdot x_i + b))^2$ 



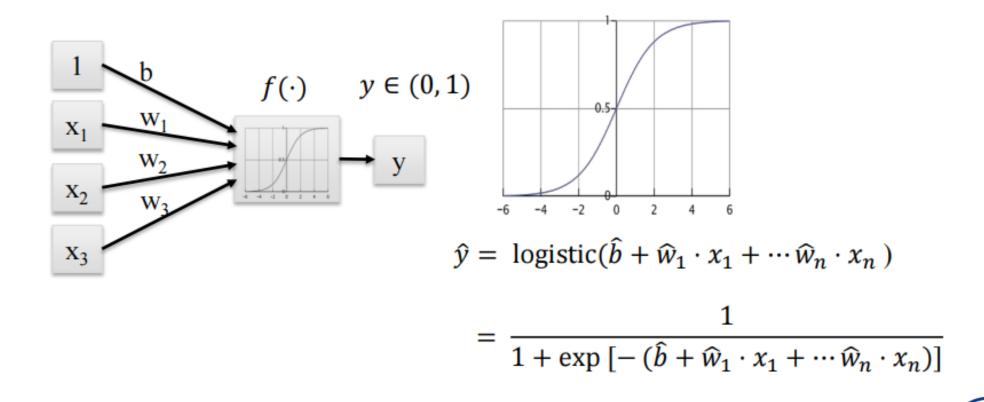
## Linear Regression to Logistic Regression

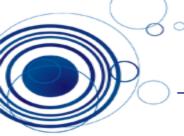




# Linear models for classification:

# Logistic Regression





# Multi-class classification with linear models

```
clf = LinearSVC(C=5, random_state = 67)
clf.fit(X_train, y_train)

print(clf.coef_)

[[-0.23401135     0.72246132]
  [-1.63231901     1.15222281]
  [ 0.0849835     0.31186707]
  [ 1.26189663 -1.68097   ]]

print(clf.intercept_)
[-3.31753728     1.19645936 -2.7468353     1.16107418]
```

