CPSC429/529: Machine Learning

Lecture 1: Introduction

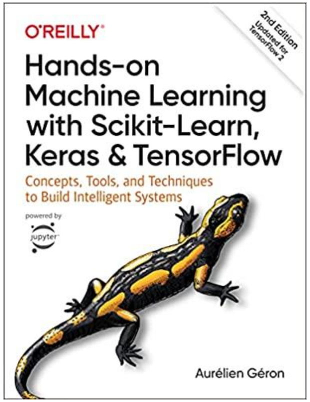
Dongsheng Che
Computer Science Department
East Stroudsburg University

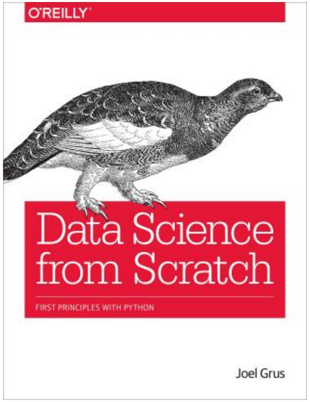
Acknowledgment:
Some slides adapted from Kevyn Collins-Thompson's Applied ML class on Coursera.

Course Syllabus

Course Information

- Textbooks:
  - Required: Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems by Aurélien Géron (AG book).
  - Optional: Data Science from Scratch: First Principles with Python, by Joel Grus



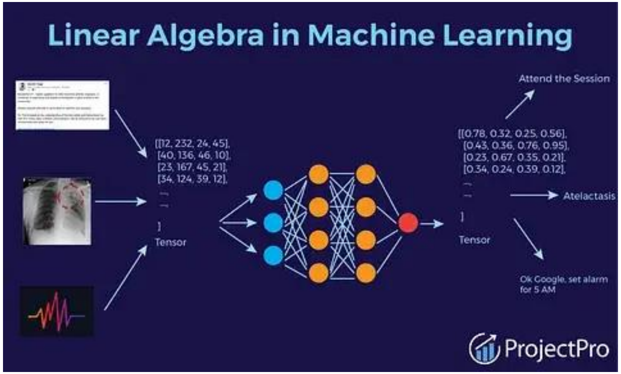


Course Prerequisites

- CPSC 380: Introduction to Data Science
    - Python language
    - Numpy: Scientific Computing Library
    - Pandas: Data Manipulation and Analysis
    - Matplotlib: Visualization library

Other skills you need

- Simple linear algebra (vectors, matrices): Math 320



- Basic probability theory: Math 311

Probability of B occurring given evidence A has already occurred

Probability of A occurring

$$P(\mathrm{A}|\mathrm{B}) = \frac{P(\mathrm{B}|A) \cdot P(A)}{P(B)}$$

Probability of A occurring given evidence B has already occurred

Probability of B occurring

What if I don't have these prerequisites?

Options:

- Take CPSC 380 (Introduction to Data Science)
- Stay in the class (If you are a faster learner and can teach numpy, pandas, matplotlib by yourself within a short period of time)

Class Topics

- Introduction to Machine Learning
- Scikit-learn: Machine Learning Framework
  - Predictive model pipeline
  - Select the best model
  - Hyperparameter tuning
  - Model evaluations
- Supervised learning:
  - Tree models and model ensembles
  - Linear models: Linear regression, logistic regression
- Neural networks and deep learning
  - Introduction to ANN with Keras
  - Training Deep NN
  - Custom Models and Training with TensorFlow
- Unsupervised learning:
  - Clustering, Dimensionality reduction

Grading Policy

CPSC429:

- Labs (25 pts)
- Programming assignments (20 pts)
- Term project (20 pts)
- Midterm exam (35pts)

CPSC529:

- Labs (20 pts)
- Programming assignments (20 pts)
- Term project (20 pts)
- Midterm exam (30pts)
- Literature Research Paper (10 pts)

Course Syllabus

Introduction to ML

What is Machine Learning?

ARTIFICIAL INTELLIGENCE VS MACHINE LEARNING VS DEEP LEARNING

1 Artificial Intelligence

Development of smart systems and machines that can carry out tasks that typically require human intelligence

2 Machine Learning

Creates algorithms that can learn from data and make decisions based on patterns observed

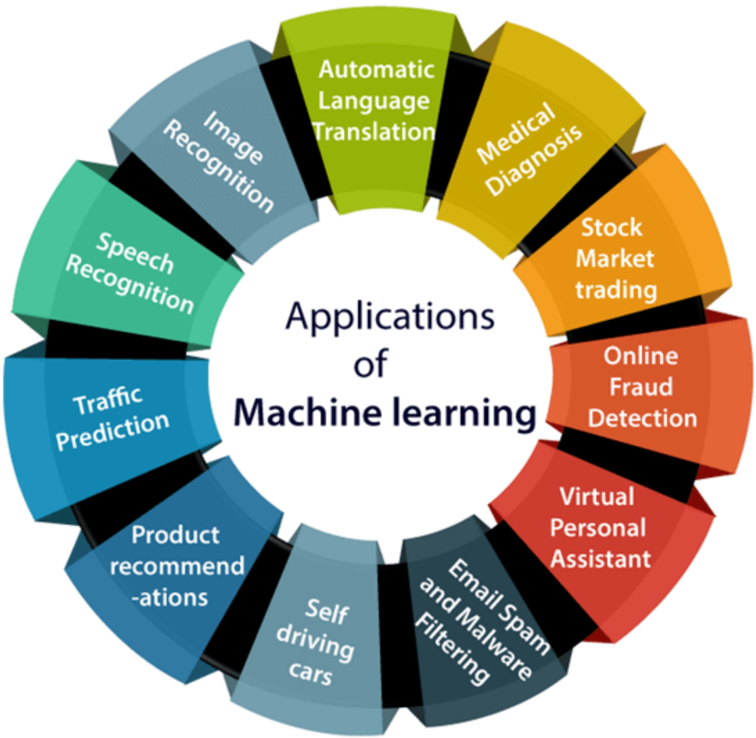
Require human intervention when decision is incorrect

3 Deep Learning

Uses an artificial neural network to reach accurate conclusions without human intervention

SINGAPORE COMPUTER SOCIETY

Applications of Machine learning



What is Machine Learning (ML)?

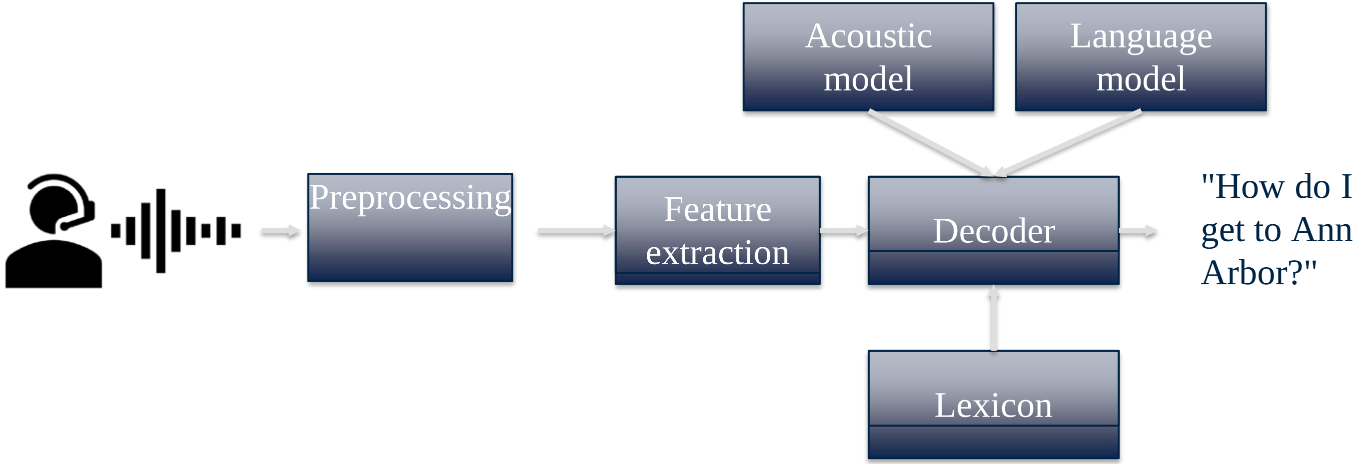
- **The study of computer programs (algorithms) that can learn by example**
- **ML algorithms can generalize from existing examples of a task**
  - *e.g. after seeing a training set of labeled images, an image classifier can figure out how to apply labels accurately to new, previously unseen images*

Machine Learning models can learn by example

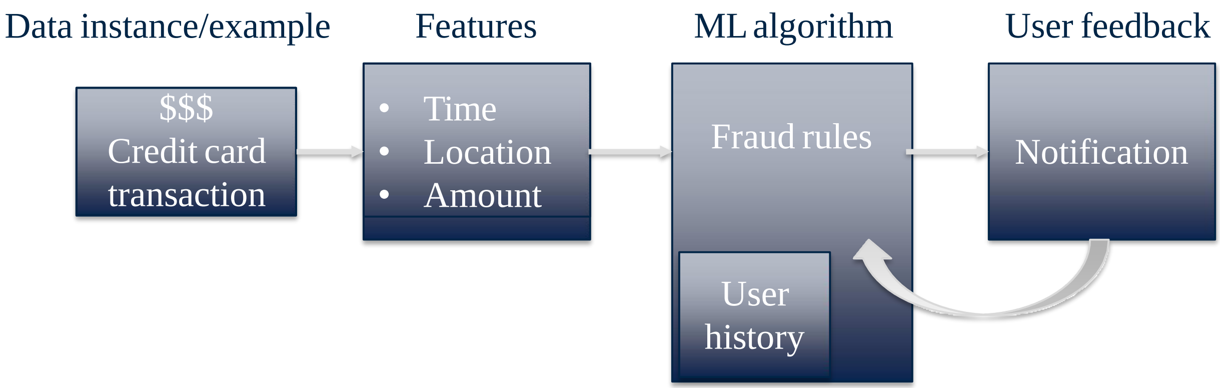
- **Algorithms learn rules from labelled examples**
- **A set of labelled examples used for learning is called training data.**
- **The learned rules should also be able to generalize to correctly recognize or predict new examples not in the training set.**

Audio signal	Output text
	How do I get to Ann Arbor?
	Hello!
	Please order me a pizza.

Machine Learning for Speech Recognition



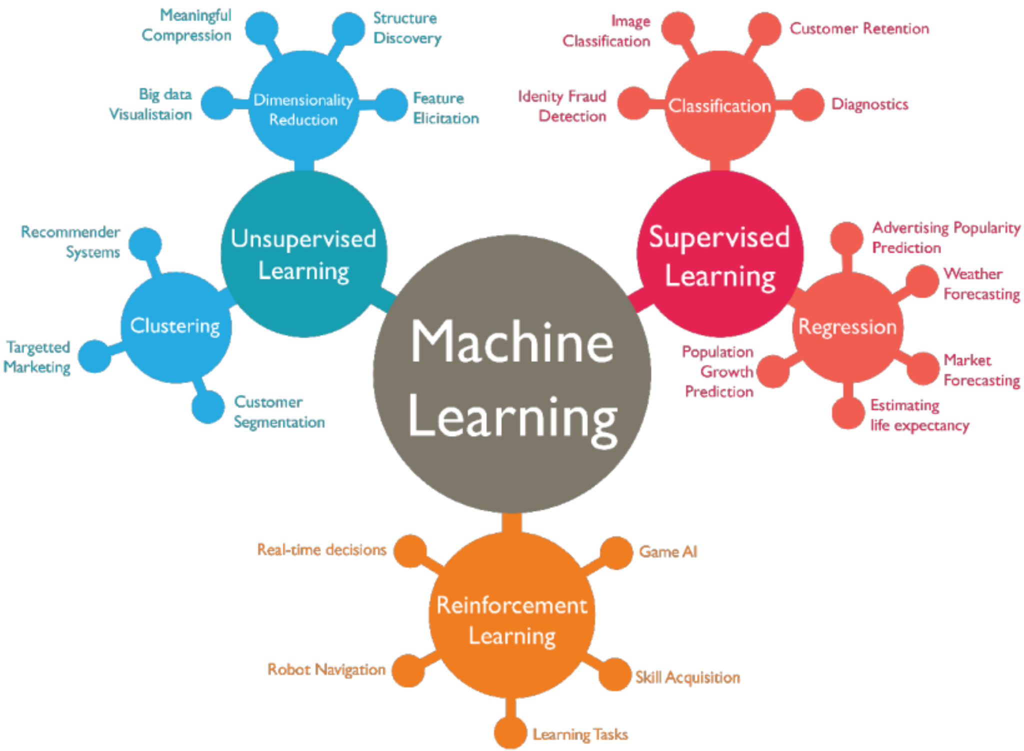
Machine Learning for fraud detection and credit scoring



Introduction to ML

Types of Machine Learning problems

Types of Machine Learning Models



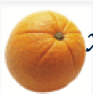
Key types of Machine Learning problems

<u>Supervised</u> machine learning: Learn to predict <u>target values</u> from labelled data.

- **Classification (target values are discrete classes)**
- **Regression (target values are continuous values)**

Supervised Learning (classification example)

Training set

X Sample	Y Target Value (Label)	
 x_1	Apple	y_1
 x_2	Lemon	y_2
 x_3	Apple	y_3
 x_4	Orange	y_4

Classifier
$f : X \rightarrow Y$

At training time, the classifier uses labelled examples to learn rules for recognizing each fruit type.

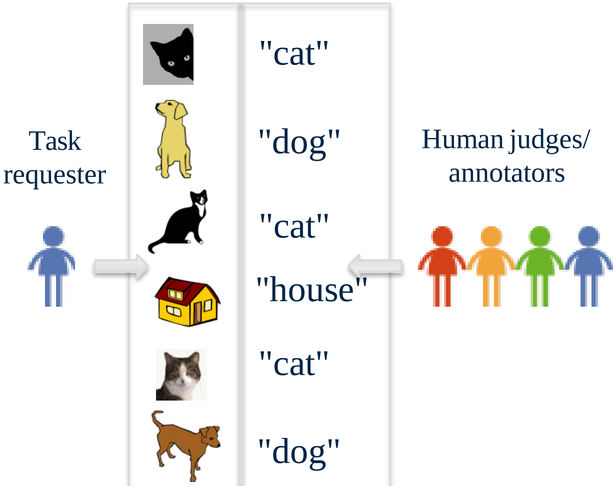
Future sample

Label: Orange

After training, at prediction time, the trained model is used to predict the fruit type for new instances using the learned rules.

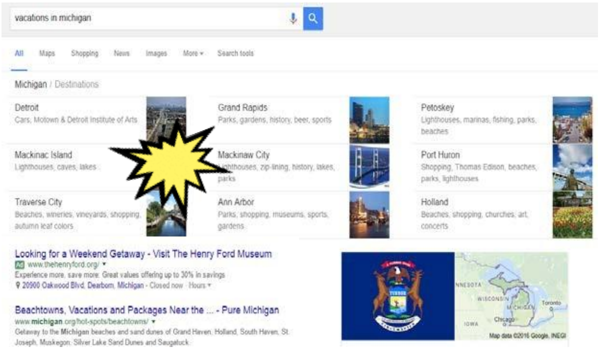
Examples of explicit and implicit label sources

Explicit labels



Crowdsourcing platform

Implicit labels



Clicking and reading the "Mackinac Island" result can be an implicit label for the search engine to learn that "Mackinac Island" is especially relevant for the query `[vacations in michigan]` for that specific user.

Key types of Machine Learning problems

Supervised machine learning: Learn to predict target values from labelled data.

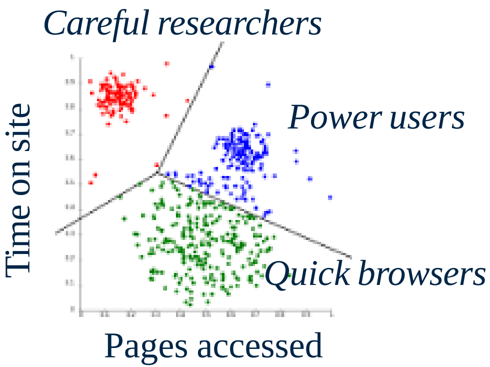
- **Classification (target values are discrete classes)**
- **Regression (target values are continuous values)**

Unsupervised machine learning: Find structure in *unlabeled data*

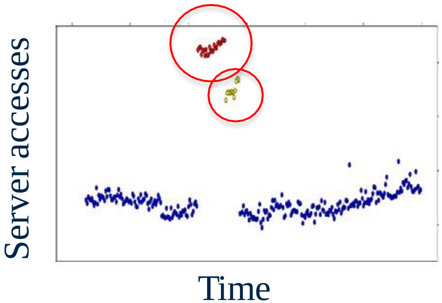
- **Find groups of similar instances in the data (clustering)**
- **Finding unusual patterns (outlier detection)**

Unsupervised learning: finding useful structure or knowledge in data when no labels are available

- **Finding clusters of similar users (clustering)**



- **Detecting abnormal server access patterns (unsupervised outlier detection)**



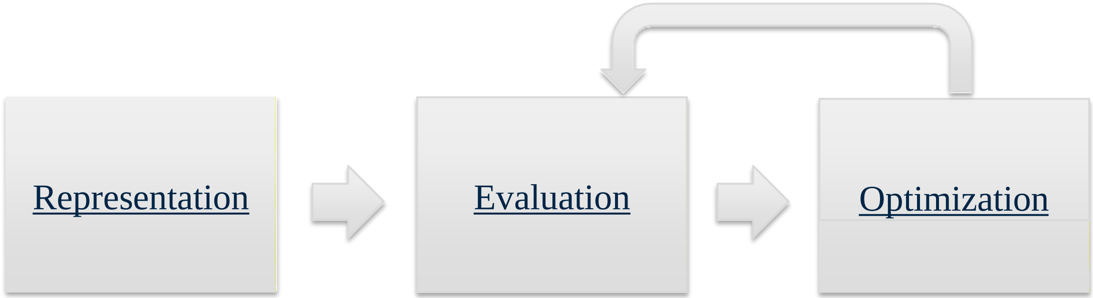
Introduction to ML

Types of Machine Learning problems

Introduction to ML

Machine Learning Workflow

A Basic Machine Learning Workflow



Choose:
- A feature representation
- Type of classifier to use

e.g. image pixels, with
k-nearest neighbor classifier

Choose:
- What criterion distinguishes good vs. bad classifiers?

e.g. % correct predictions on test set

Choose:
- How to search for the settings/parameters that give the best classifier for this evaluation criterion

e.g. try a range of values for "k" parameter in k-nearest neighbor classifier

Feature Representations

Feature representation

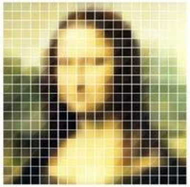
Email

```
To: Chris Brooks
From: Daniel Romero
Subject: Next course offering
Hi Daniel,
Could you please send the outline for the
next course offering? Thanks! -- Chris
```

Feature	Count
to	1
chris	2
brooks	1
from	1
daniel	2
romero	1
the	2
...	

A list of words with their frequency counts

Picture



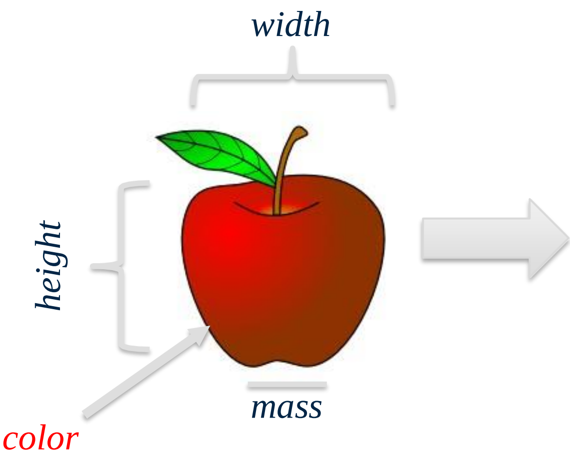
A matrix of color values (pixels)

Sea Creatures

Feature	Value
DorsalFin	Yes
MainColor	Orange
Stripes	Yes
StripeColor1	White
StripeColor2	Black
Length	4.3 cm

A set of attribute values

Representing a piece of fruit as an array of features (plus label information)



1. Feature representation

Label information (available in training data only)

Feature representation

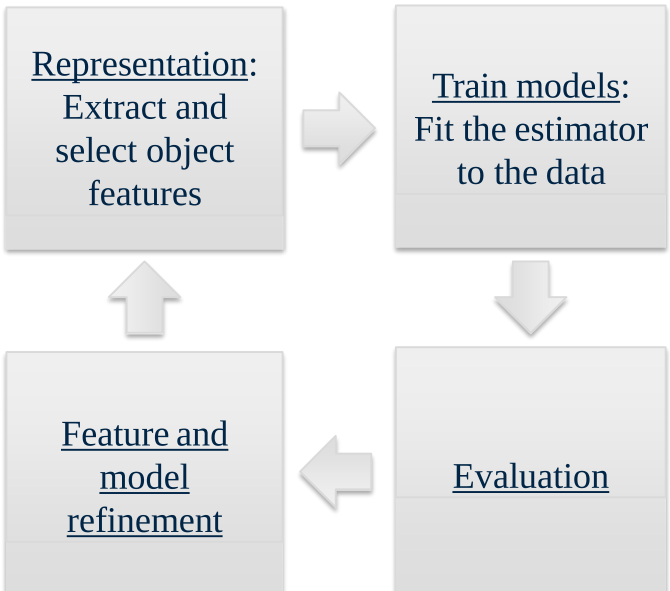
	fruit_label	fruit_name	fruit_subtype	mass	width	height	color_score
18	1	apple	cripps_pink	162	7.5	7.1	0.83

2. Learning model

Classifier

Predicted class (apple)

Represent / Train / Evaluate / Refine Cycle



Introduction to ML

Machine Learning Workflow

Introduction to ML

Python Tools for Machine Learning

NumPy: Scientific Computing Library

http://www.numpy.org/

- **Provides fundamental data structures used by scikit-learn, particularly multi-dimensional arrays.**
- **Typically, data that is input to scikit-learn will be in the form of a NumPy array.**
- **Example import:** `import numpy as np`

Pandas: Data Manipulation and Analysis

http://pandas.pydata.org/

- **Provides key data structures like `DataFrame`**

- **Also, support for reading/writing data in different formats**

- **Example import: `import pandas as pd`**

matplotlib and other plotting libraries

matplotlib http://matplotlib.org/

- We typically use matplotlib's **pyplot** module:

```
import matplotlib.pyplot as plt
```

- We also sometimes use the **seaborn** visualization library (http://seaborn.pydata.org/)

```
import seaborn as sn
```

- And sometimes the **graphviz** plotting library:

```
import graphviz
```

SciPy Library: Scientific Computing Tools

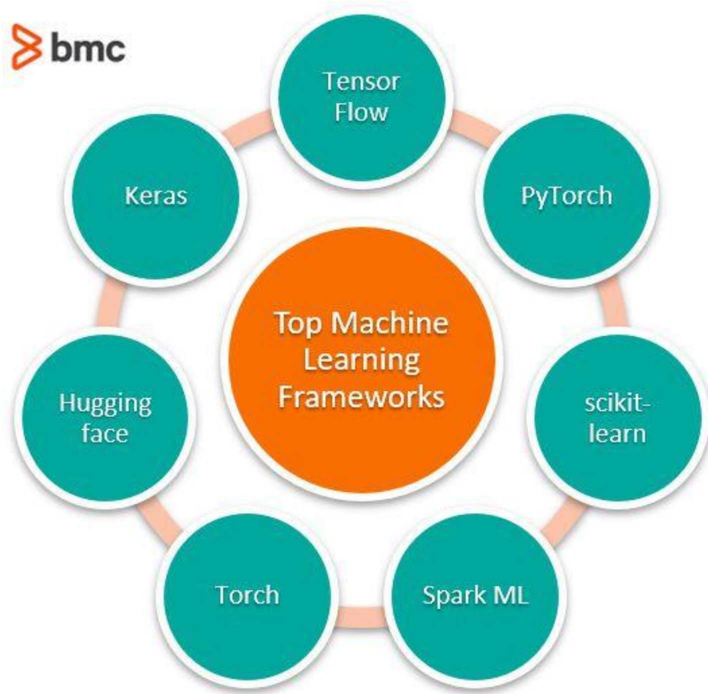
http://www.scipy.org/

- **Provides a variety of useful scientific computing tools, including statistical distributions, optimization of functions, linear algebra, and a variety of specialized mathematical functions.**

- **With scikit-learn, it provides support for *sparse matrices*, a way to store large tables that consist mostly of zeros.**

- **Example import:** `import scipy as sp`

Top Machine Learning Frameworks



scikit-learn: Python Machine Learning Library

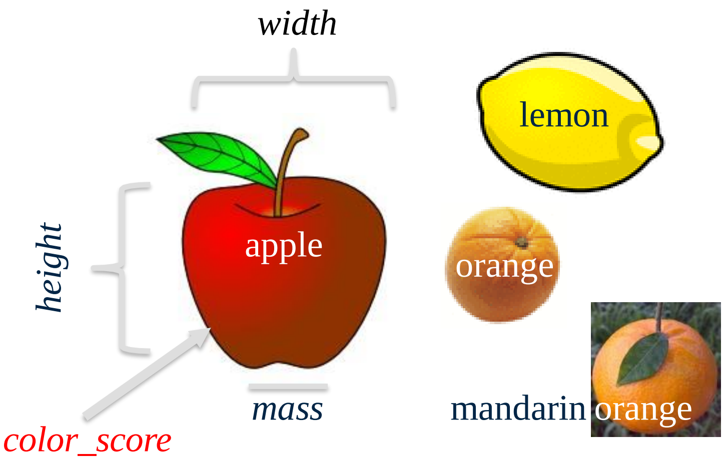
- **scikit-learn Homepage**
  http://scikit-learn.org/
- **scikit-learn User Guide**
  http://scikit-learn.org/stable/user_guide.html
- **scikit-learn API reference**
  http://scikit-learn.org/stable/modules/classes.html
- **In Python, we typically import classes and functions we need like this:**

```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
```

Introduction to ML

An Example Machine Learning Problem

The Fruit Dataset



	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	golden_delicious	156	7.6	7.5	0.67

`fruit_data_with_colors.txt`

Credit: Original version of the fruit dataset created by Dr. Iain Murray, Univ. of Edinburgh

The input data as a table

Each row corresponds to a single data instance (sample)

	fruit_label	uit_name	fruit_subtype	mass	width	height	color_score
0	1	pple	granny_smith	192	8.4	7.3	0.55
1	1	pple	granny_smith	180	8.0	6.8	0.59
2	1	pple	granny_smith	176	7.4	7.2	0.60
3	2	handarin	mandarin	86	6.2	4.7	0.80
4	2	handarin	mandarin	84	6.0	4.6	0.79
5	2	handarin	mandarin	80	5.8	4.3	0.77
6	2	handarin	mandarin	80	5.9	4.3	0.81
7	2	handarin	mandarin	76	5.8	4.0	0.81
8	1	pple	braeburn	178	7.1	7.8	0.92
9	1	pple	braeburn	172	7.4	7.0	0.89
1	1	pple	braeburn	166	6.9	7.3	0.93
1	1	pple	braeburn	172	7.1	7.6	0.92
1	1	pple	braeburn	154	7.0	7.1	0.88
1	1	pple	golden_delicious	164	7.3	7.7	0.70
1	1	pple	golden_delicious	152	7.6	7.3	0.69
1	1	pple	golden_delicious	156	7.7	7.1	0.69
1	1	pple	golden_delicious	156	7.6	7.5	0.67
1	1	pple	golden_delicious	168	7.5	7.6	0.73
1	1	pple	cripps_pink	162	7.5	7.1	0.83
1	1	pple	cripps_pink	162	7.4	7.2	0.85
2	1	pple	cripps_pink	160	7.5	7.5	0.86

These four columns contain the features of each data instance (sample)

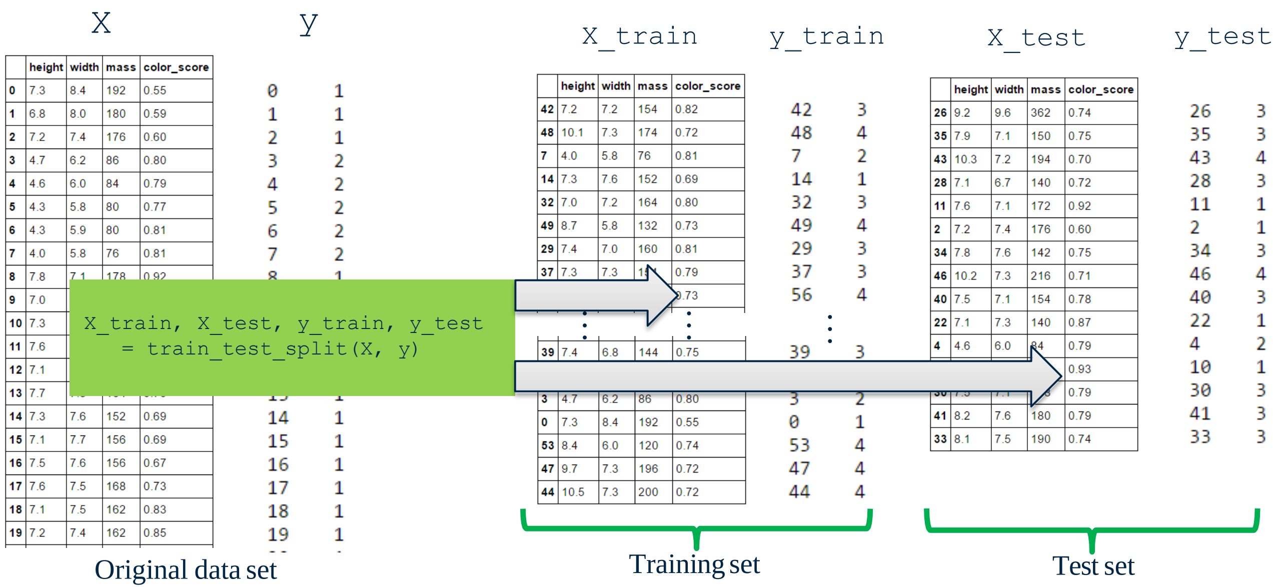
The `fruit_label` column contains the label for each data instance (sample)

The scale for the (simplistic) `color_score` feature used in the fruit dataset

0.00 0.25 0.50 0.75 1.00

Color category	`color_score`
Red	0.85 - 1.00
Orange	0.75 - 0.85
Yellow	0.65 - 0.75
Green	0.45 - 0.65

Creating Training and Testing Sets



Some reasons why looking at the data initially is important

- Inspecting feature values may help identify what cleaning or preprocessing still needs to be done once you can see the range or distribution of values that is typical for each attribute.

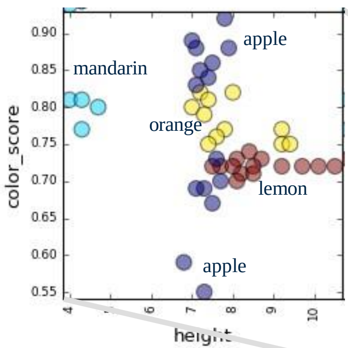
- You might notice missing or noisy data, or inconsistencies such as the wrong data type being used for a column, incorrect units of measurements for a particular column, or that there aren't enough examples of a particular class.

- You may realize that your problem is actually solvable without machine learning.

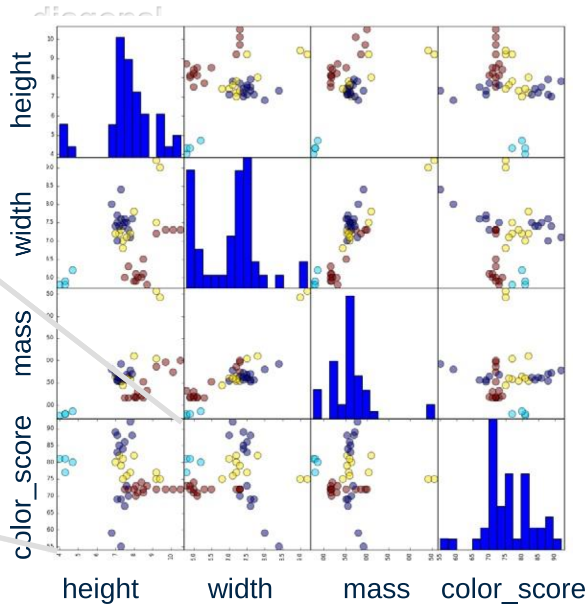
Examples of incorrect or missing feature values

	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	192
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	apple	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		7.4	7.0	0.89
10	1	apple	braeburn		6.9	7.3	0.93
11	1	apple	braeburn		7.1	7.6	0.92
12	1	apple	braeburn		7.0	7.1	0.88
13	1	apple	golden_delicious	[illegible]	7.3	7.7	0.70
14	1	apple	golden_delicious	152	7.6	7.3	0.69

A pairwise feature scatterplot visualizes the data using all possible pairs of features, with one scatterplot per feature pair, and histograms for each feature along the diagonal



Individual scatterplot plotting all fruits by their **height** and **color_score**.
Colors represent different fruit classes.



```
In [27]: fruits
```

Out[27]:

	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	golden_delicious	156	7.6	7.5	0.67

```
In [88]: fruits.shape
Out[88]: (59, 7)
```

In [88]:
```
fruits.shape
```
Out[88]: (59, 7)

In [92]:
```
X_train.shape
```
Out[92]: (44, 4)

In [93]:
```
X_test.shape
```
Out[93]: (15, 4)

In [94]:
```
y_train.shape
```
Out[94]: (44,)

In [95]:
```
y_test.shape
```
Out[95]: (15,)

In [96]:
```
X_train
```
Out[96]:

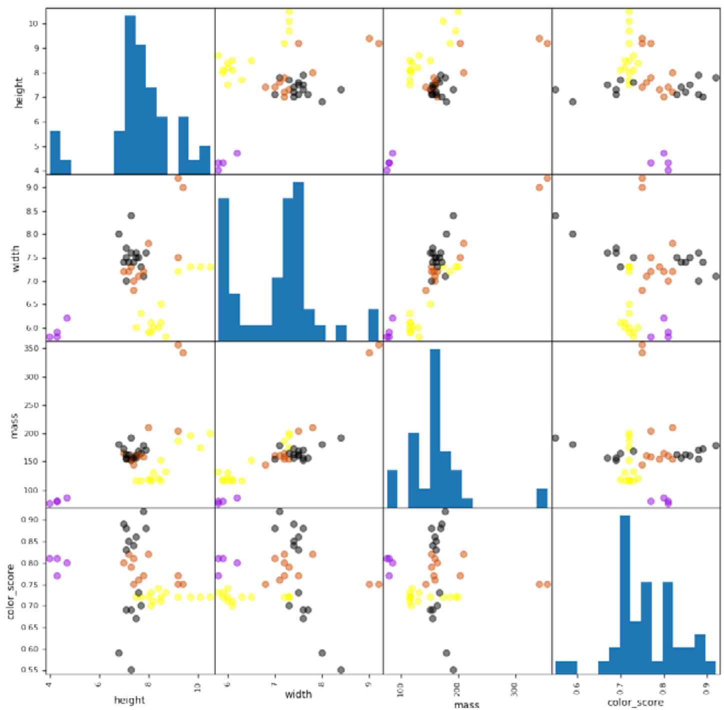
	height	width	mass	color_score
42	7.2	7.2	154	0.82
48	10.1	7.3	174	0.72
7	4.0	5.8	76	0.81
14	7.3	7.6	152	0.69
32	7.0	7.2	164	0.80
49	8.7	5.8	132	0.73
29	7.4	7.0	160	0.81
37	7.3	7.3	154	0.79
56	8.1	5.9	116	0.73
18	7.1	7.5	162	0.83
55	7.7	6.3	116	0.72
27	9.2	7.5	204	0.77
15	7.1	7.7	156	0.69
5	4.3	5.8	80	0.77
31	8.0	7.8	210	0.82
16	7.5	7.6	156	0.67

In [98]:
```
y_train
```
Out[98]:
```
42    3
48    4
7     2
14    1
32    3
49    4
29    3
37    3
56    4
18    1
55    4
27    3
15    1
5     2
31    3
16    1
50    4
20    1
51    4
8     1
13    1
25    3
17    1
58    4
57    4
52    4
38    3
1     1
12    1
45    4
24    3
6     2
```

In [97]:
```
X_test
```
Out[97]:

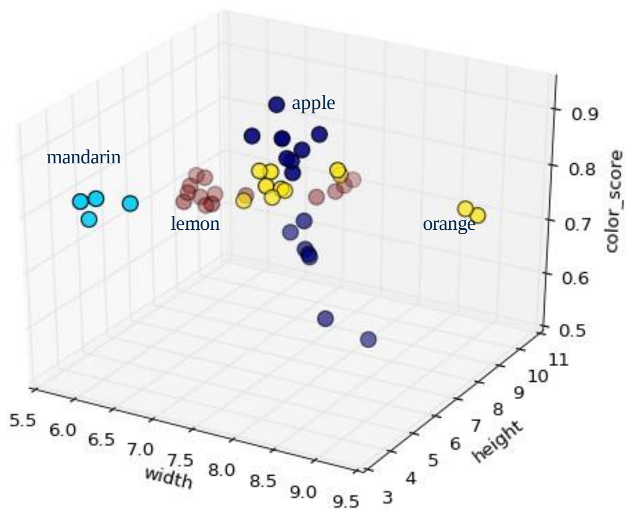
	height	width	mass	color_score
26	9.2	9.6	362	0.74
35	7.9	7.1	150	0.75
43	10.3	7.2	194	0.70
28	7.1	6.7	140	0.72
11	7.6	7.1	172	0.92
2	7.2	7.4	176	0.60
34	7.8	7.6	142	0.75
46	10.2	7.3	216	0.71
40	7.5	7.1	154	0.78
22	7.1	7.3	140	0.87
4	4.6	6.0	84	0.79
10	7.3	6.9	166	0.93
30	7.5	7.1	158	0.79
41	8.2	7.6	180	0.79
33	8.1	7.5	190	0.74

In [99]:
```
y_test
```
Out[99]:
```
26    3
35    3
43    4
28    3
11    1
2     1
34    3
46    4
40    3
22    1
4     2
10    1
30    3
41    3
33    3
```




```
from matplotlib import cm
cmap = cm.get_cmap('gnuplot')
scatter = pd.scatter_matrix(X_train, c= y_train, marker = 'o', s=40, hist_kwds={'bins':15}, figsize=(12,12), cmap=cmap)
```

A three-dimensional feature scatterplot




```
from mpl_toolkits.mplot3d import Axes3D
fig = plt.figure()
ax = fig.add_subplot(111, projection = '3d')
ax.scatter(X_train['width'], X_train['height'], X_train['color_score'], c = y_train, marker = 'o', s=100)
ax.set_xlabel('width')
ax.set_ylabel('height')
ax.set_zlabel('color_score')
plt.show()
```

Introduction to ML

An Example Machine Learning Problem

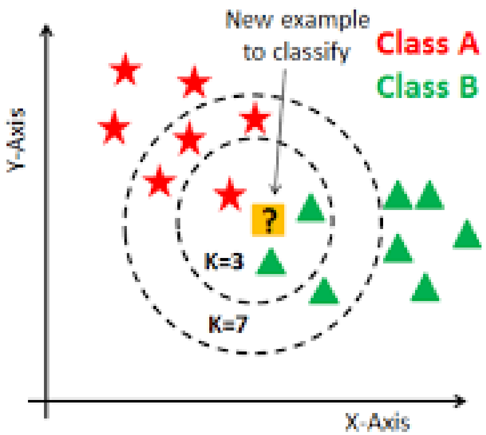
Introduction to ML

K-Nearest Neighbors
Classification

The k-Nearest Neighbor (k-NN) Algorithm

Given a training set X_train with labels y_train, and given a new instance x_test to be classified:

1. **Find the most similar instances (let's call them X_NN) to x_test that are in X_train.**
2. **Get the labels y_NN for the instances in X_NN**
3. **Predict the label for x_test by combining the labels y_NN. e.g. simple majority vote**



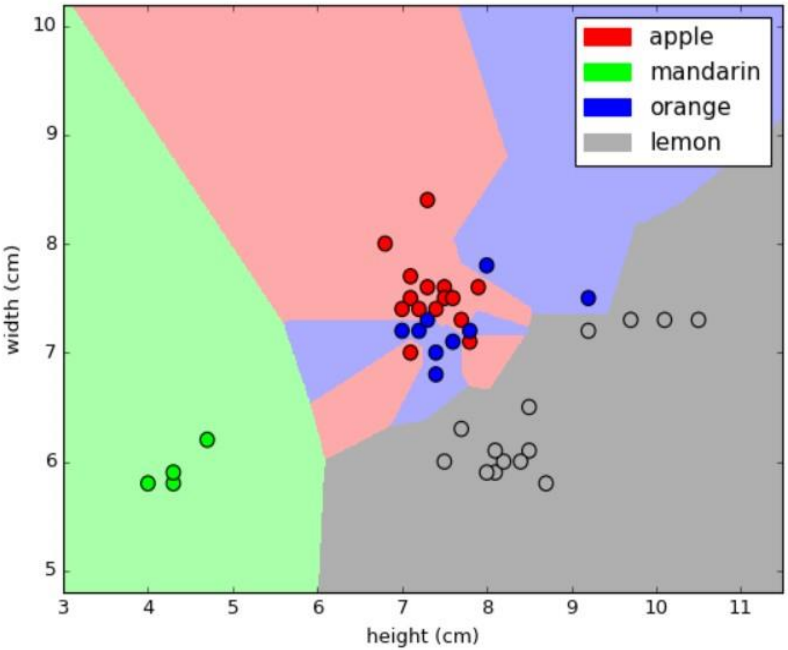
A nearest neighbor algorithm needs four things specified

1. A distance metric
2. How many 'nearest' neighbors to look at?
3. Optional weighting function on the neighbor points
4. Method for aggregating the classes of neighbor points

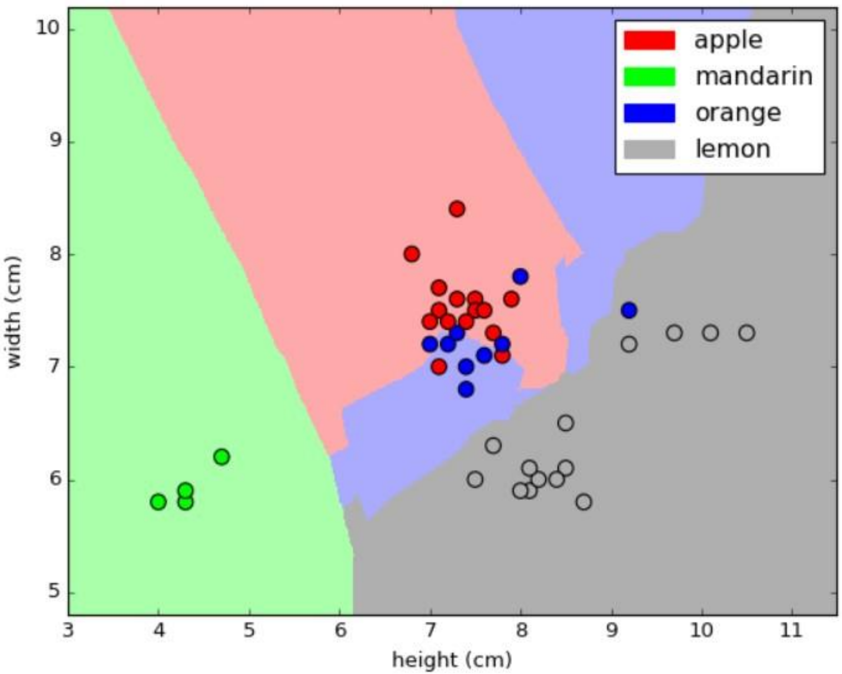
A nearest neighbor algorithm needs four things specified

1. A distance metric
   Typically Euclidean (Minkowski with p = 2)
2. How many 'nearest' neighbors to look at?
   e.g. five
3. Optional weighting function on the neighbor points
   Ignored
4. How to aggregate the classes of neighbor points
   Simple **majority vote**
   (Class with the most representatives among nearest neighbors)

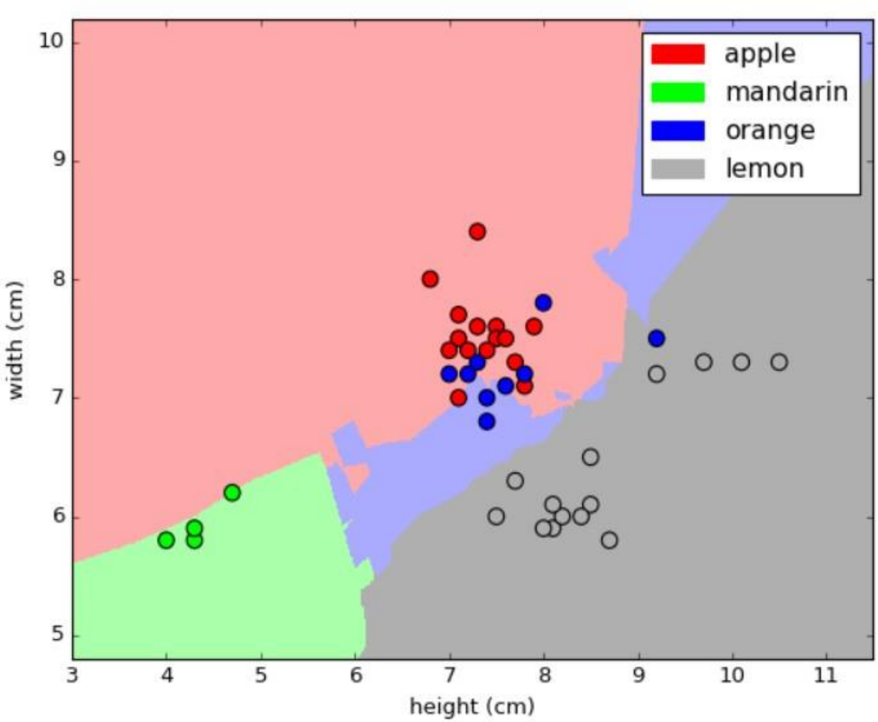
K-nearest neighbors (k=1) for fruit dataset

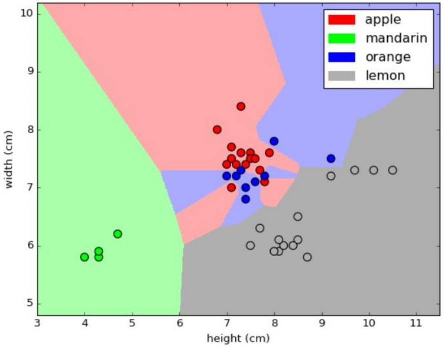


K-nearest neighbors (k=5) for fruit dataset

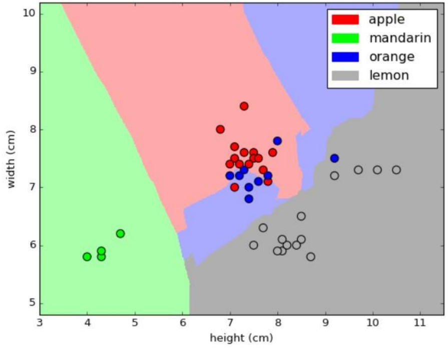


K-nearest neighbors (k=10) for fruit dataset

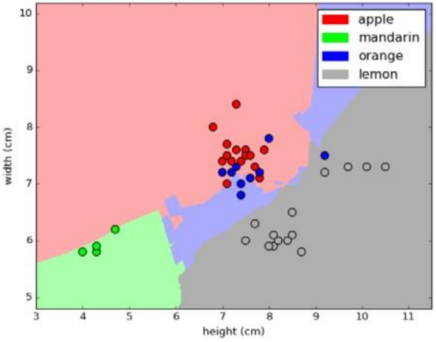



apple
mandarin
orange
lemon
width (cm)
height (cm)

K=1

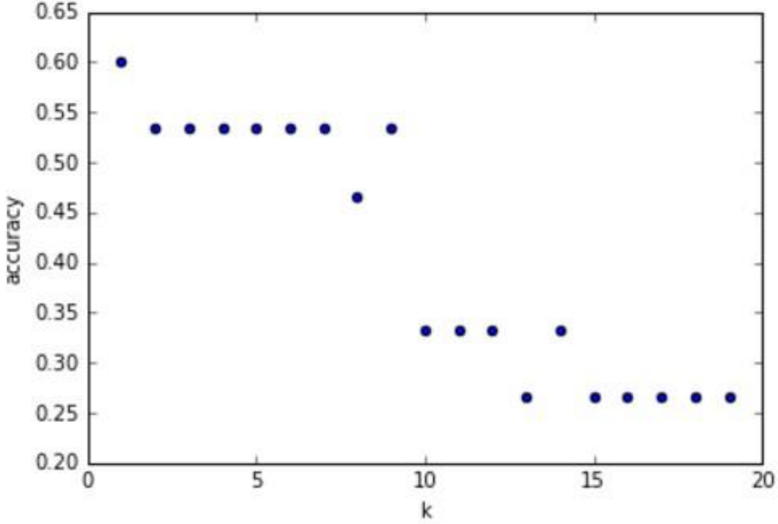

apple
mandarin
orange
lemon
width (cm)
height (cm)

K=5


apple
mandarin
orange
lemon
width (cm)
height (cm)

K=10

How sensitive is k-NN classifier accuracy to the choice of 'k' parameter?



Fruit dataset with 75%/25% train-test split

Introduction to ML

K-Nearest Neighbors
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