Machine Learning

Lecture 1: Introduction

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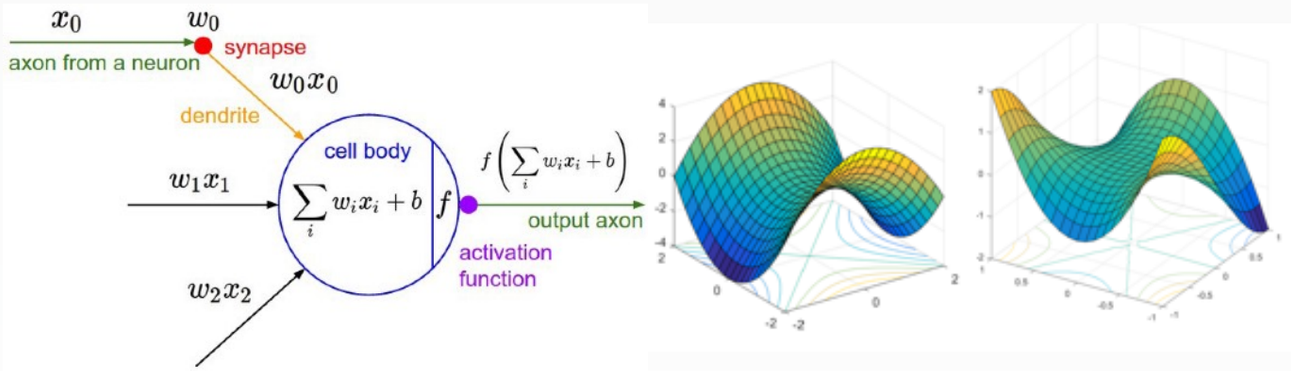
What do you learn from this course?

- Concepts, tools, and intuition you need to implement programs capable of **learning from data**
- From simple techniques such as linear regression to some of deep learning techniques
- A **hands-on approach** with just a little bit of theory to use production-ready Python frameworks

Public perception of ML

Reality




```
import tensorflow
```

```
---------------------------------------------------------------------------
ImportError                               Traceback (most recent call last)
<ipython-input-6-a649b509054f> in <module>()
----> 1 import tensorflow

ImportError: No module named tensorflow
```

Course prerequisites

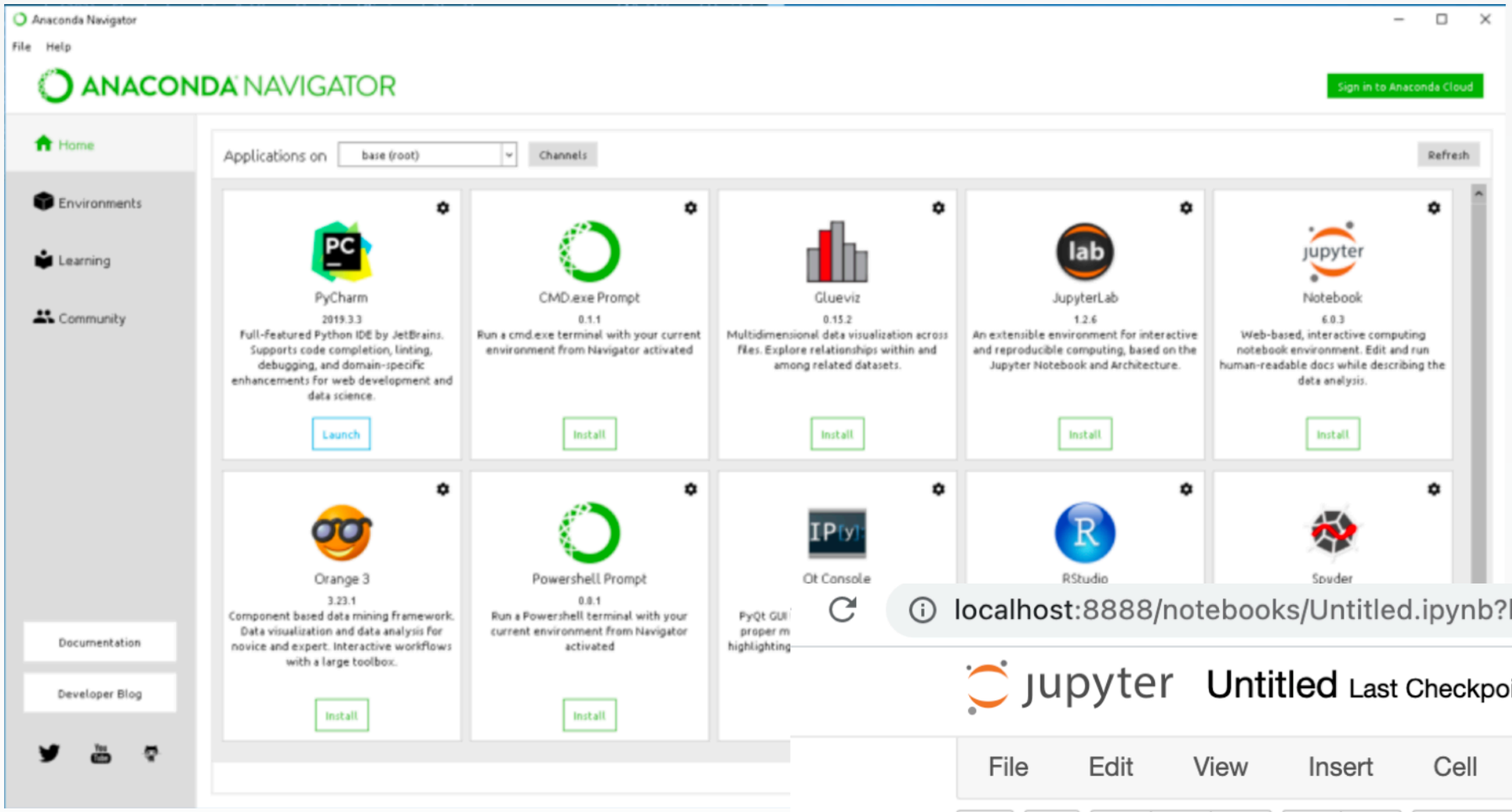
- We need some level of calculus and linear algebra
  - Vector, matrix, inner product, matrix-matrix multiplication
  - Derivatives of polynomials and exponential functions
  - Chain rule for finding the derivative of a composite function

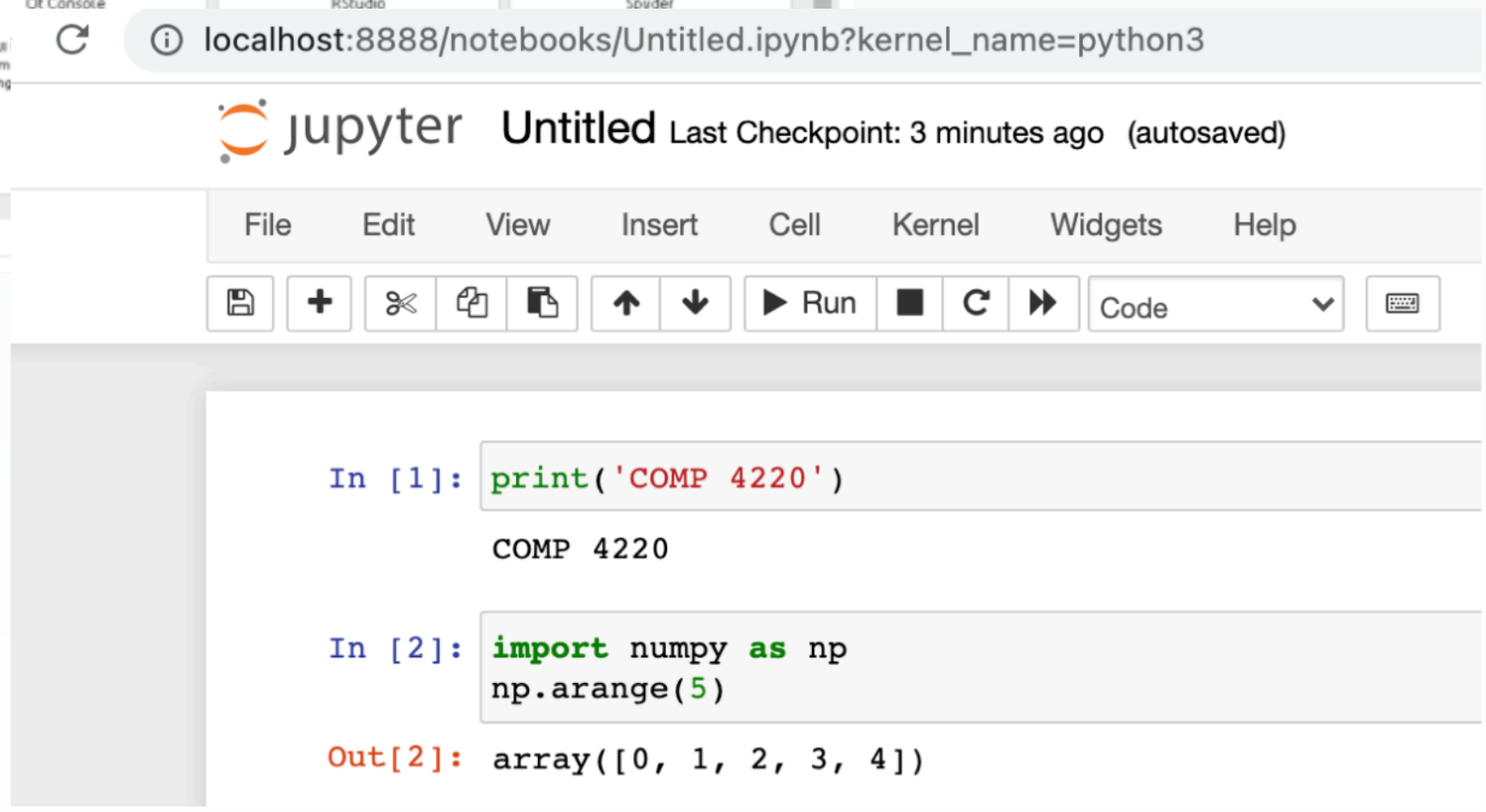
$$\begin{cases} y = f(t) \\ t = g(x) \end{cases} \rightarrow \frac{dy}{dx} = \frac{dy}{dt} \cdot \frac{dt}{dx}$$

- Basics of probability and statistics
  - Probability distributions (normal distribution, Bernoulli distribution, etc.)
  - Mean, standard deviation, …

Anaconda

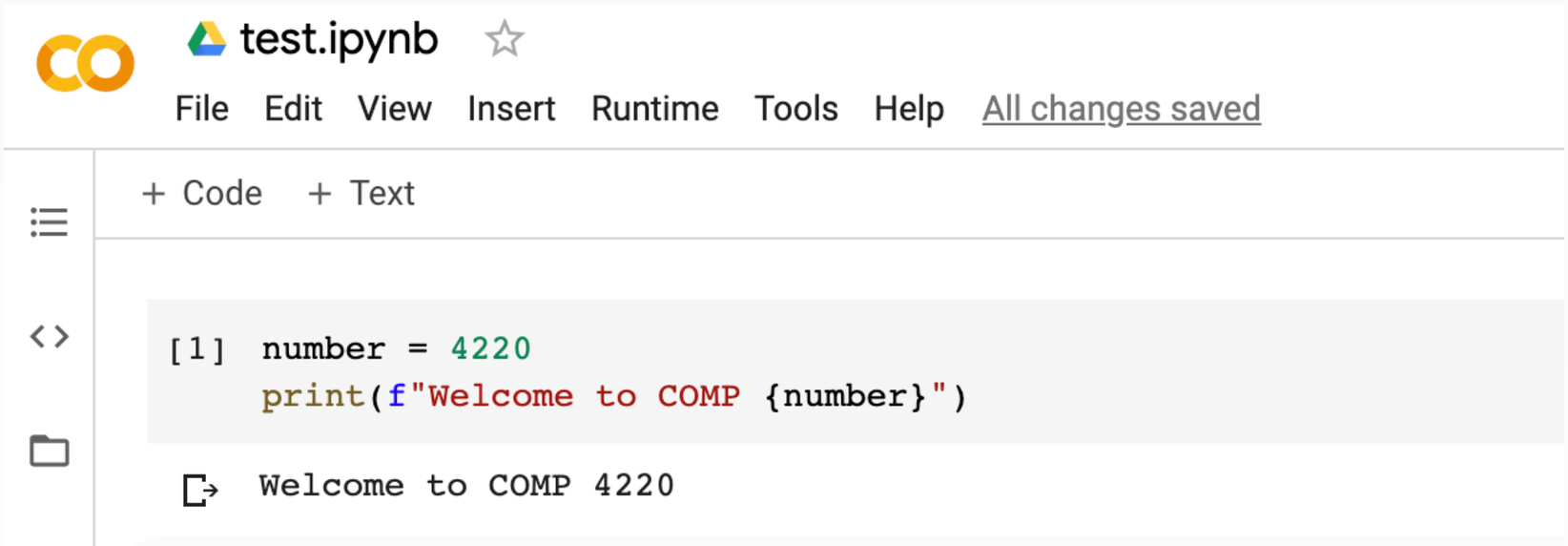
- https://www.anaconda.com/





Google Colab

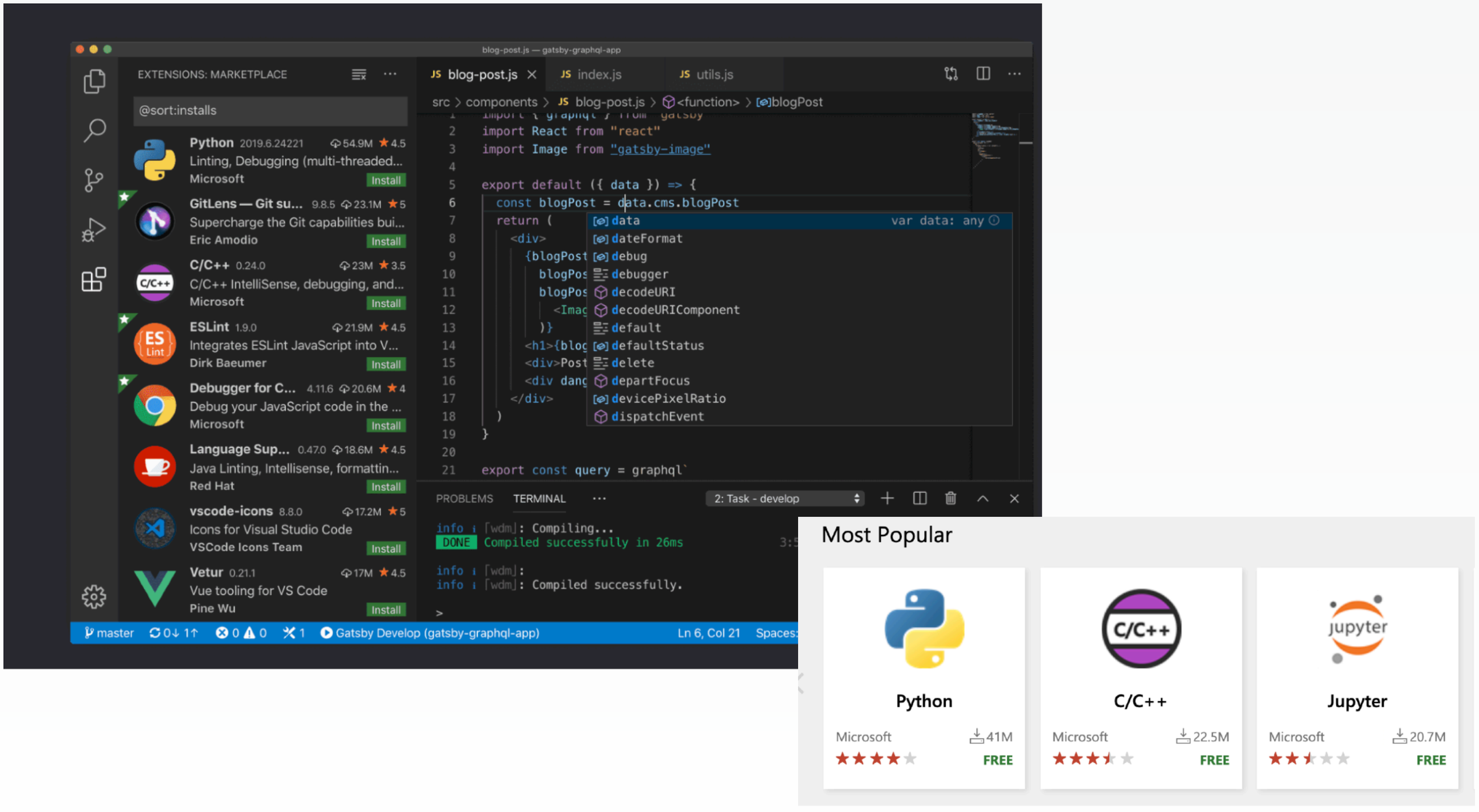
- Google Colaboratory, or “Colab” for short, allows you to write and execute Python in your browser
  - Zero configuration required
  - Free access to GPUs and other computing resources
  - Use terminal commands on Google Colab



- https://drive.google.com (for the first time, select “Connect more apps”)

Visual Studi Code

- Better alternative for “real” machine learning projects
  - https://code.visualstudio.com/



Course structure

- Part 1: Fundamentals of Machine Learning (Scikit-Learn)
  - Review of Python's main scientific libraries: NumPy, pandas, and Matplotlib
  - Steps in a typical machine learning project
  - Learning by fitting a model to data and optimizing a cost function
  - Challenges of using machine learning systems

- Part 2: Neural Networks and Deep Learning (TensorFlow 2.0, Keras, and PyTorch)
  - What neural nets are and what they are good for
  - Building and training feedforward neural nets (basics and implementation)
  - Convolutional nets for deep computer vision and recurrent neural nets (mainly fundamental concepts)

A little bit history

- Alan Turing gave quite possibly the earliest public lecture on this topic in 1947:

"What we want is a machine that can learn from experience"

1950s–1970s

Neural Networks

Early work with neural networks stirs excitement for "thinking machines."

1980s–2010s

Machine Learning

Machine learning becomes popular.

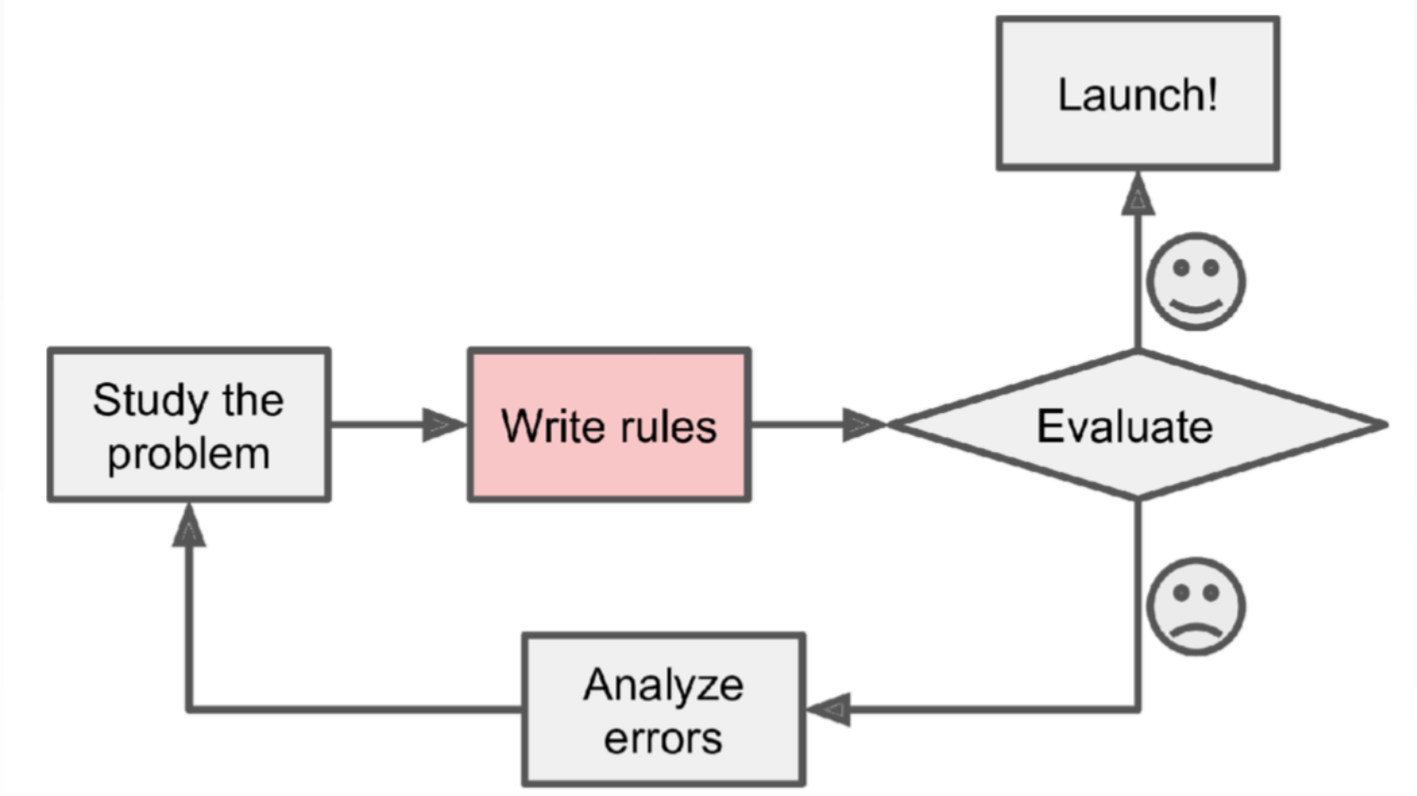
Present Day

Deep Learning

Deep learning breakthroughs drive AI boom.

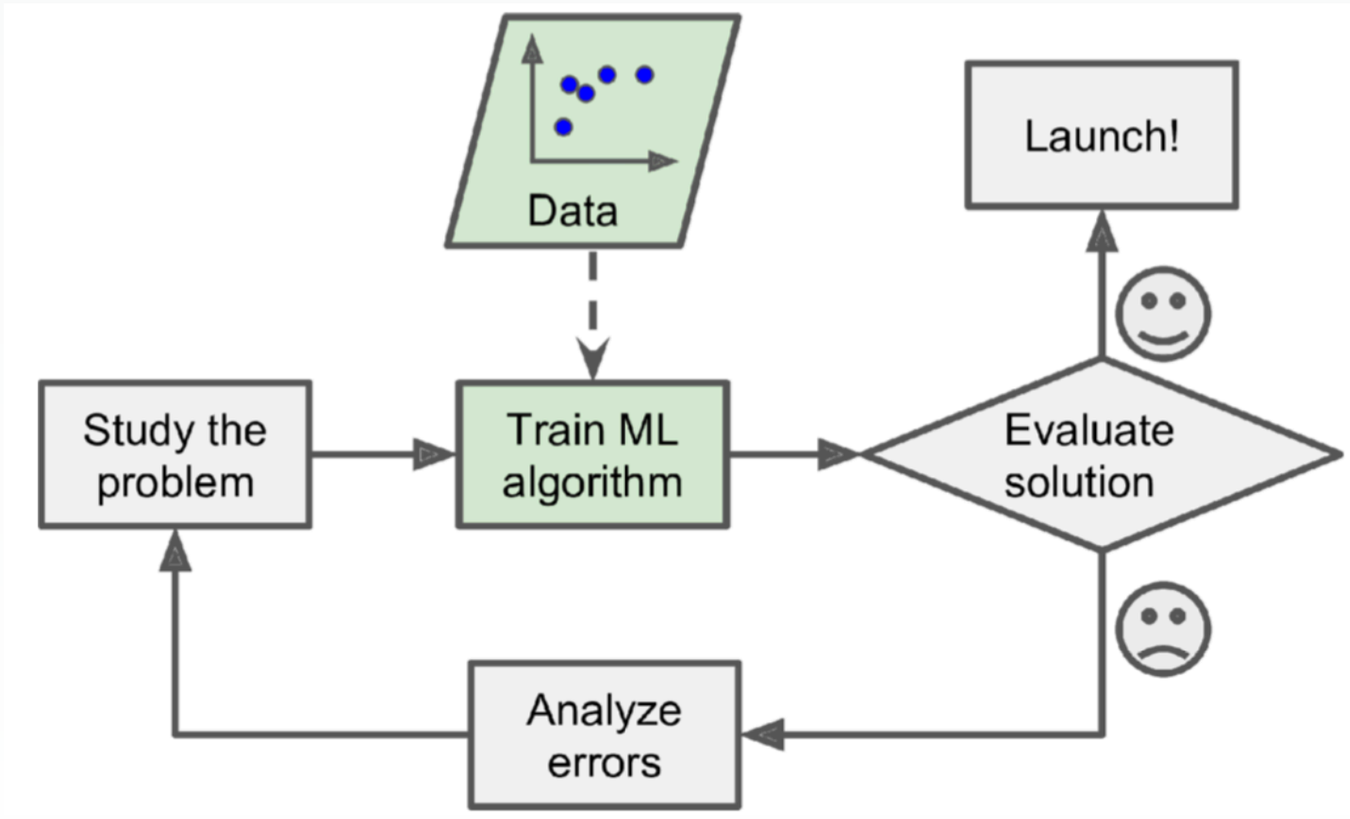
Why should we use machine learning?

- Let's say we want to design a spam filtering system
- One approach is to use traditional programming techniques
  - Look for words or phrases such as: credit card, free, bank information, "C U"
  - Write a detection algorithm for each of the patterns
  - Test your program and improve it



Why use machine learning?

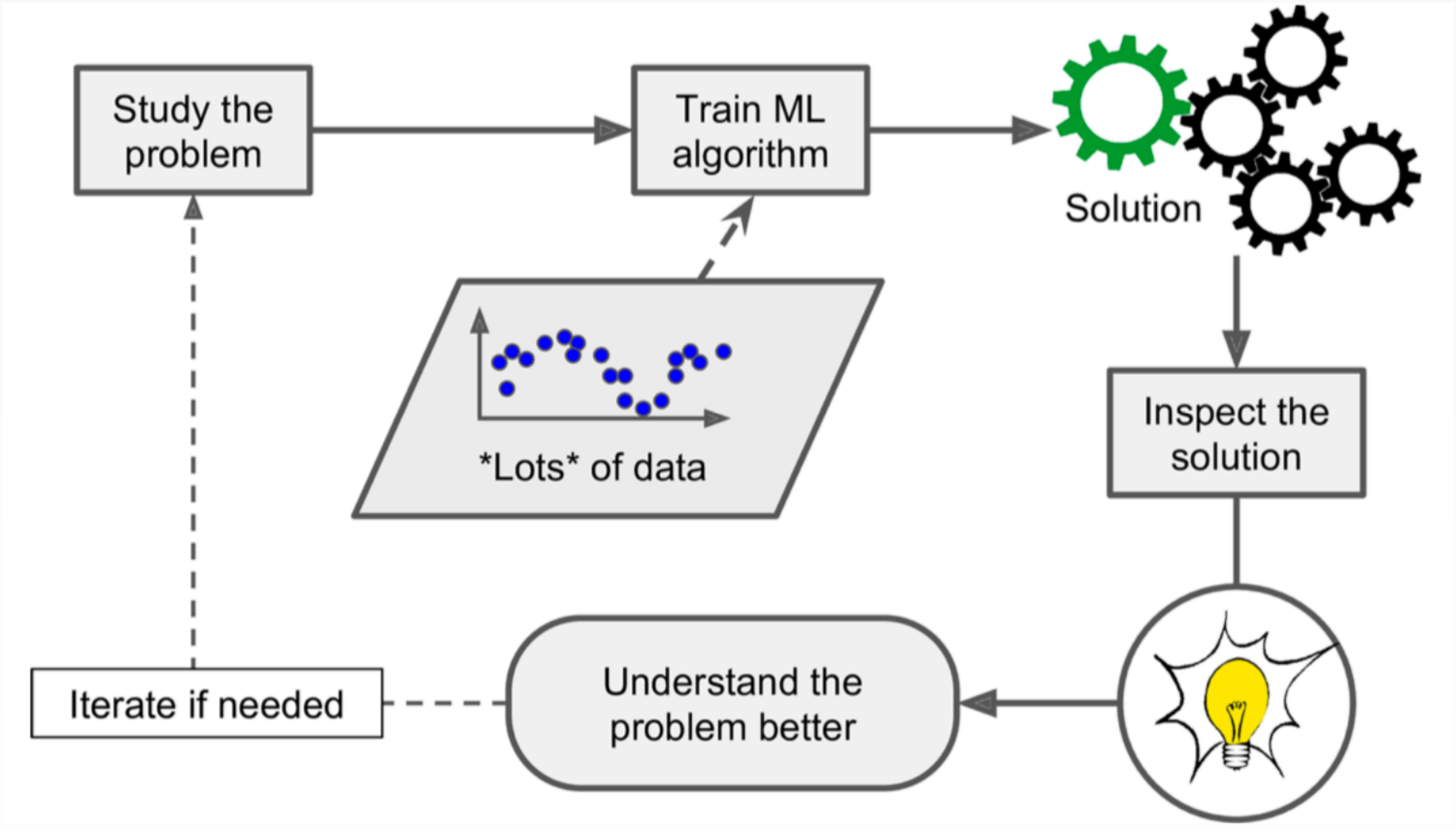
- A spam filter based on machine learning automatically learns which words and phrases are good predictors
- Possible benefits: simpler, easier to maintain, and more accurate
- The examples that the system uses are called the training set
- We should also think of a performance measure



Beyond prediction

- Machine learning can help human learn and discover patterns from large amounts of data that are not immediately apparent

- This is usually called data mining



A few applications of machine learning

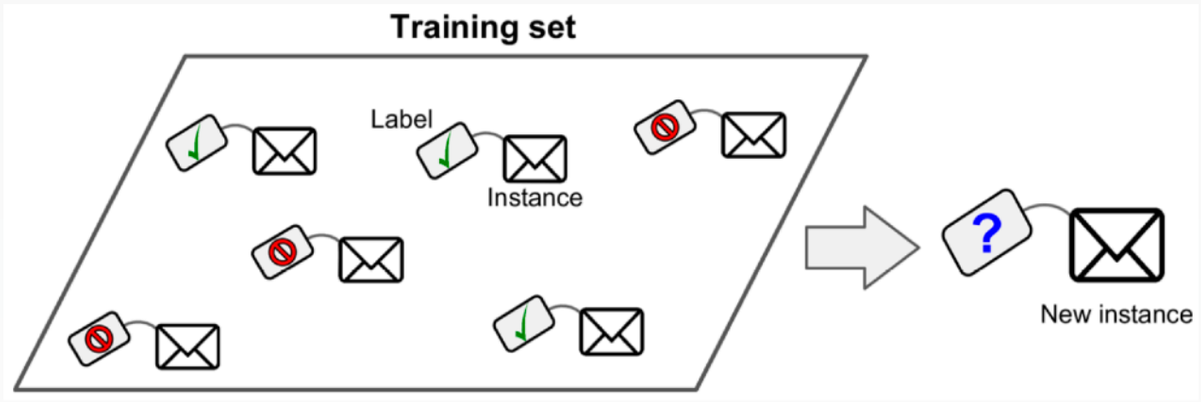
- Autonomous navigation systems
- Analyzing images of items on a product line
- Analyzing medical images
- Automatically flagging offensive comments on social media platforms
- Forecasting revenue
- Creating a recommendation engine
- Speech recognition (like Siri and Alexa)
- And many more!

Types of machine learning

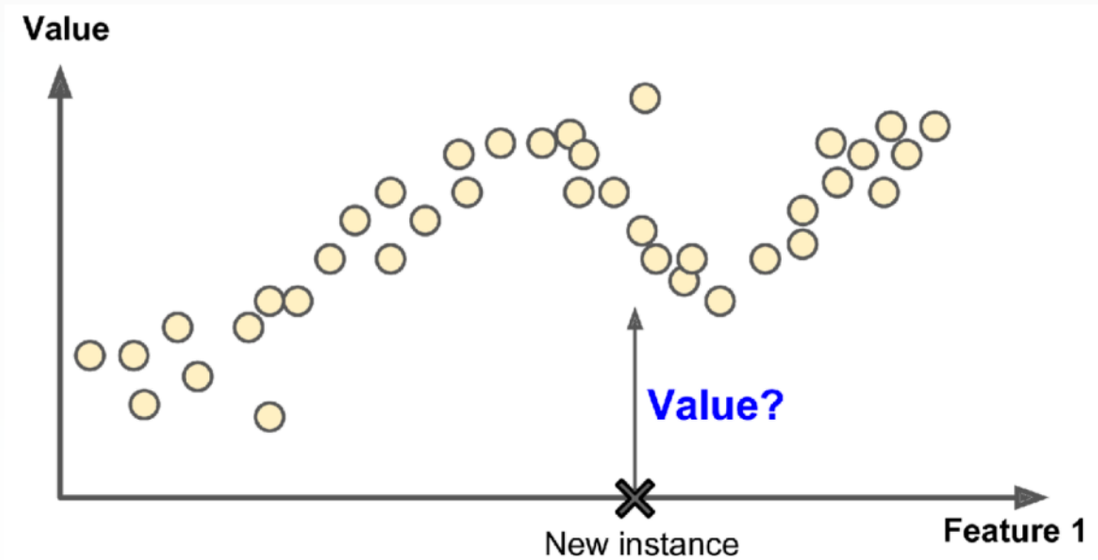
- ML systems can be classified according to the amount and type of supervision

1. Supervised learning: training set includes the desired solutions or labels

   - Classification: labels are classes (e.g., spam or ham)



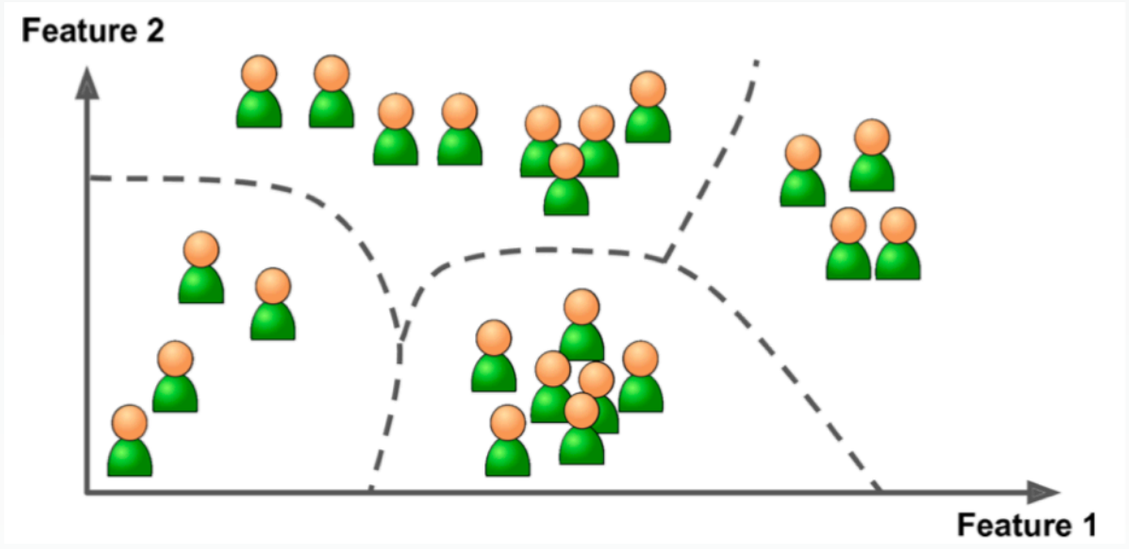
   - Regression: labels are numeric values (e.g., price of car)



Types of machine learning

2. Unsupervised learning: ML system tries to learn without a teacher

- For example, based on the shopping history, detect groups of similar visitors

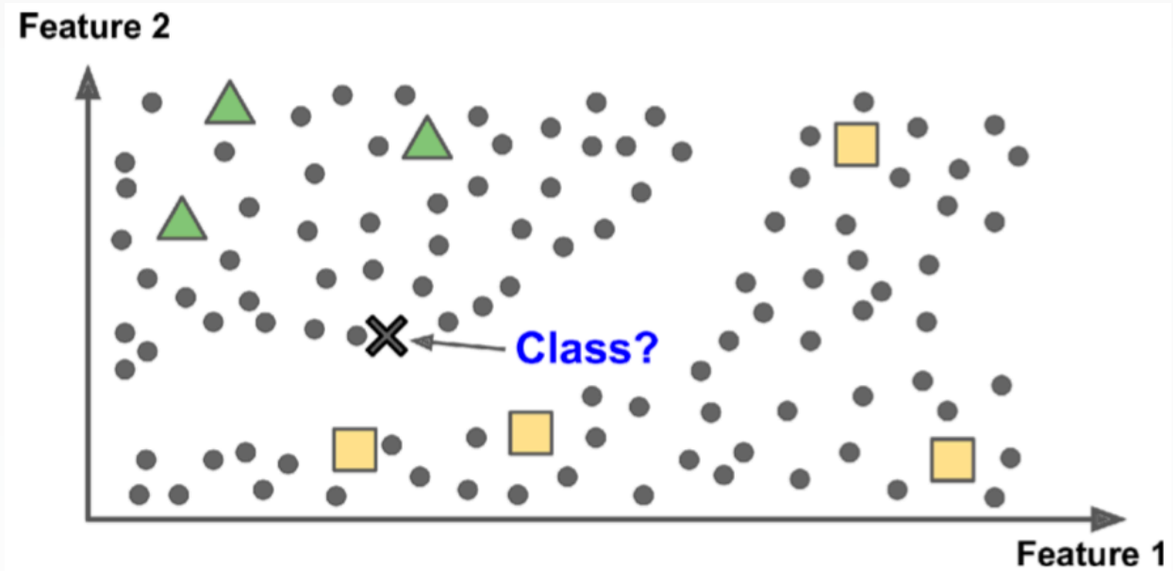


- Another example is novelty detection: find new instances that look different

Types of machine learning

3. Semisupervised learning: plenty of unlabeled instances and few labeled

   - Why? Labeling data is costly and time-consuming
   - Application: Google Photo
   - Tools: Amazon SageMaker Ground Truth



4. Reinforcement learning: select and perform actions, and get rewards or penalties in return

   - Find the best strategy known as policy to get the most reward

Another categorization

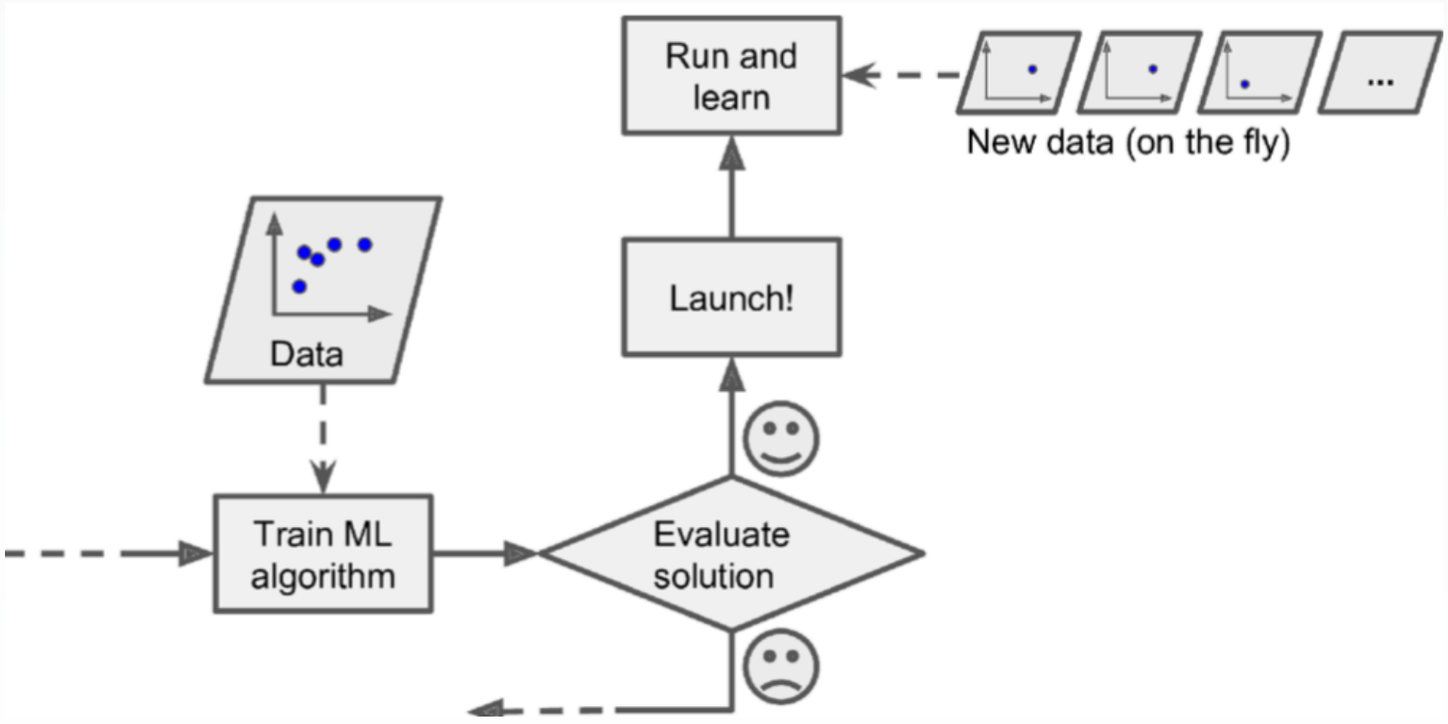
1. Batch learning or offline learning: the system must be trained using all the available data

    - Drawbacks:

        - Take a lot of time, computing resources, and storage space

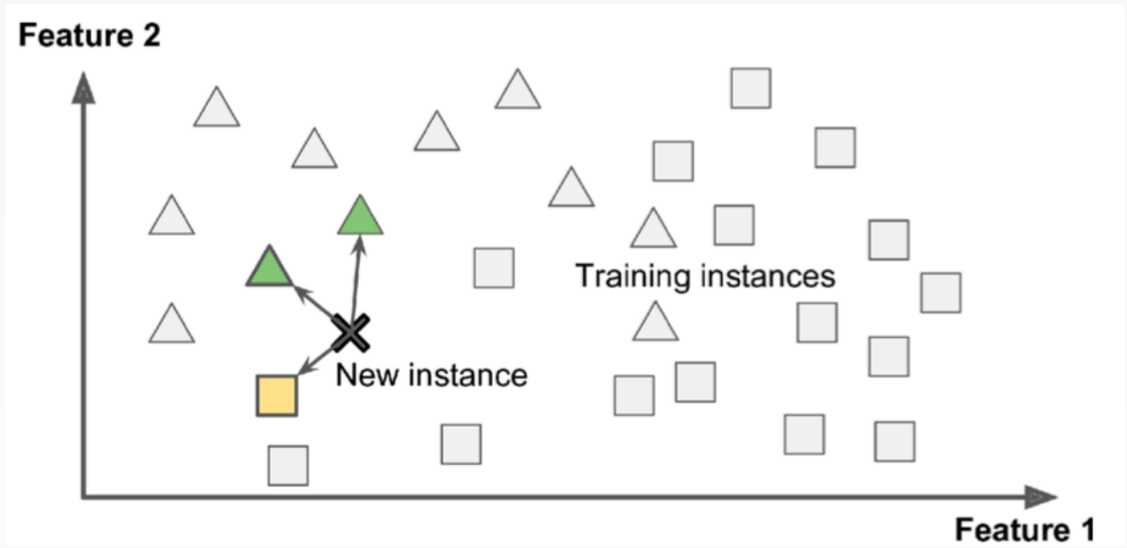
        - Not suitable for rapidly changing data

2. Incremental learning: train the system incrementally by feeding data instances sequentially

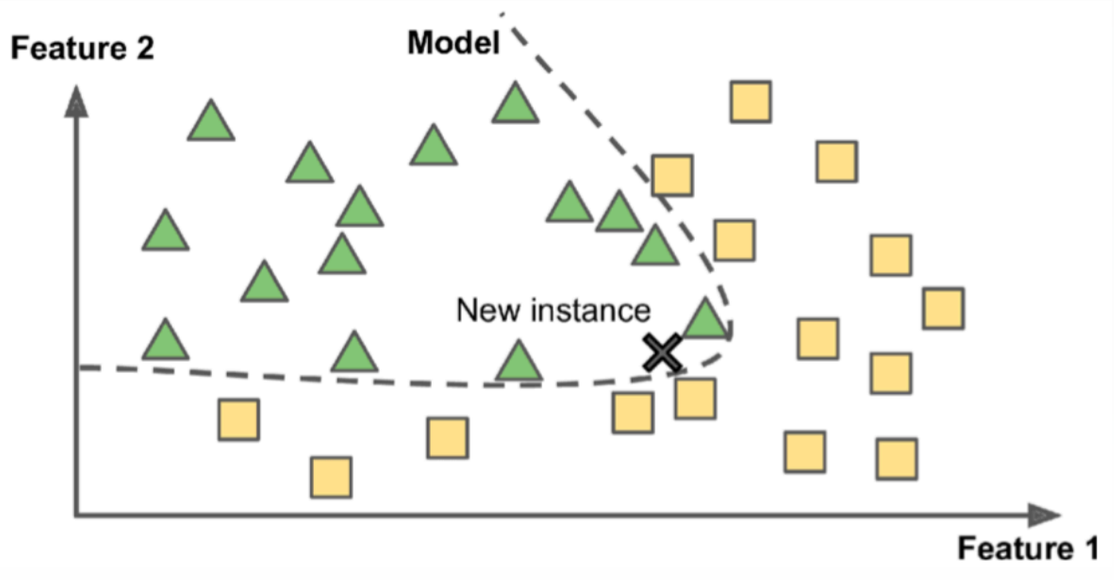


Another categorization

1. Instance-based learning: the system uses a similarity measure to compare new cases to the learned examples



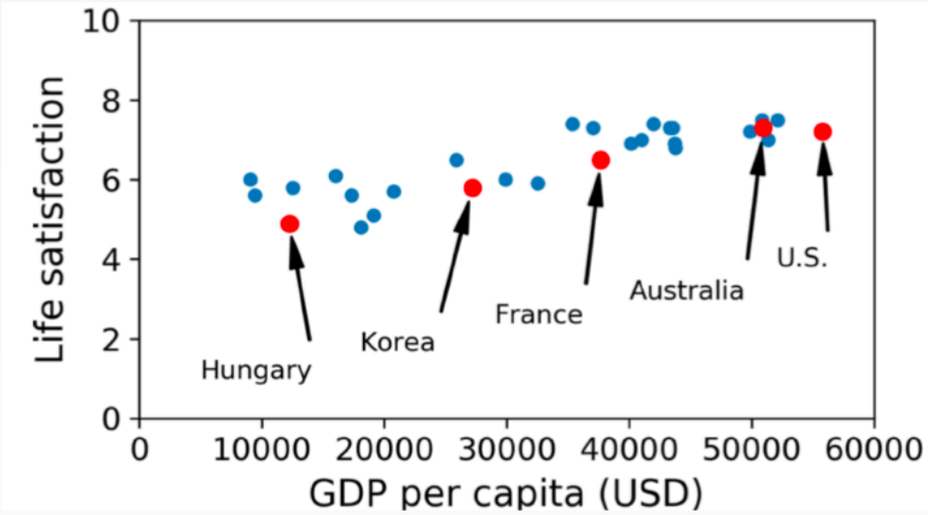
6. Model-based learning: build a model of the learned examples and then use that model to make predictions



Model-based learning

- Does money make people happier?

Country	GDP per capita (USD)	Life satisfaction
Hungary	12,240	4.9
Korea	27,195	5.8
France	37,675	6.5
Australia	50,962	7.3
United States	55,805	7.2

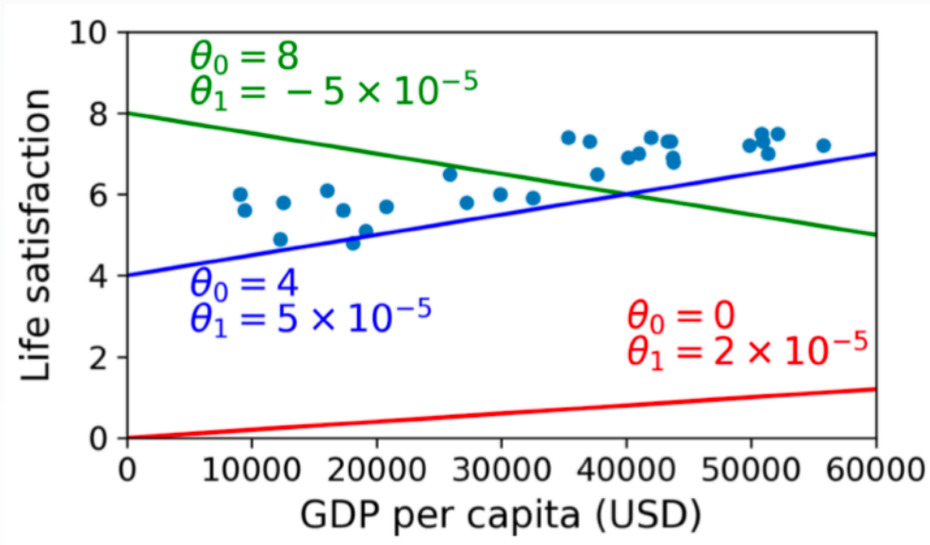


- Let us model life satisfaction as a linear function of GDP

- A simple linear model

$$\text{life\_satisfaction} = \theta_0 + \theta_1 \times \text{GDP\_per\_capita}$$

- Examples



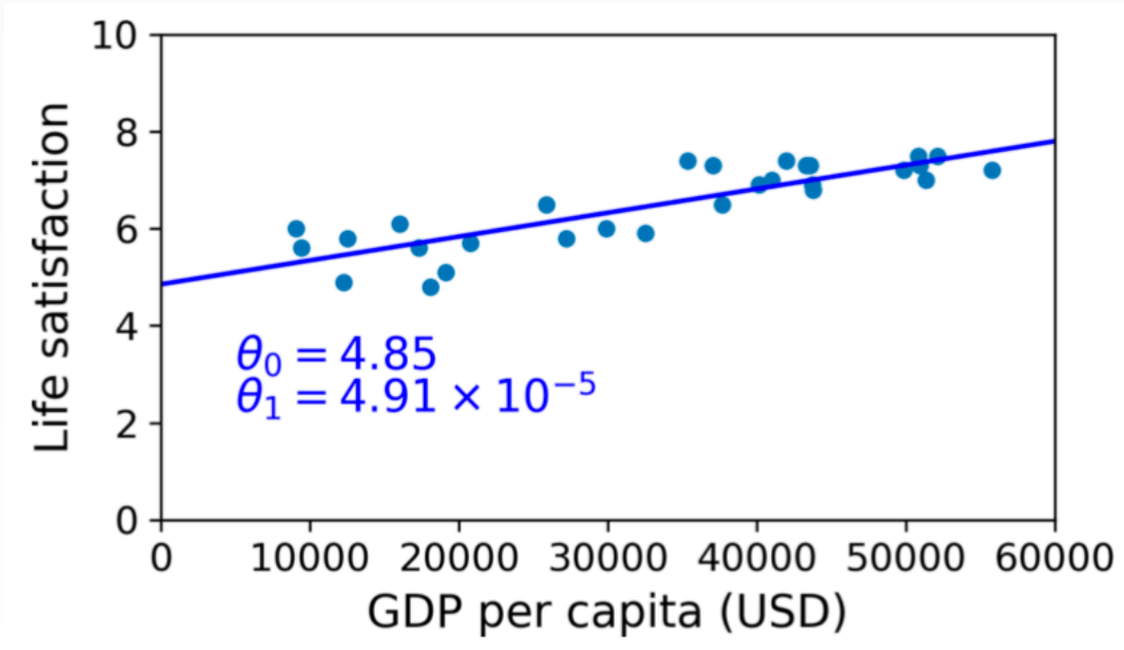
Training a linear model using Scikit-Learn

- A few lines of code

```
# Select a linear model
model = sklearn.linear_model.LinearRegression()

# Train the model
model.fit(X, y)

# Make a prediction for Cyprus
X_new = [[22587]]  # Cyprus's GDP per capita
print(model.predict(X_new)) # outputs [[ 5.96242338]]
```

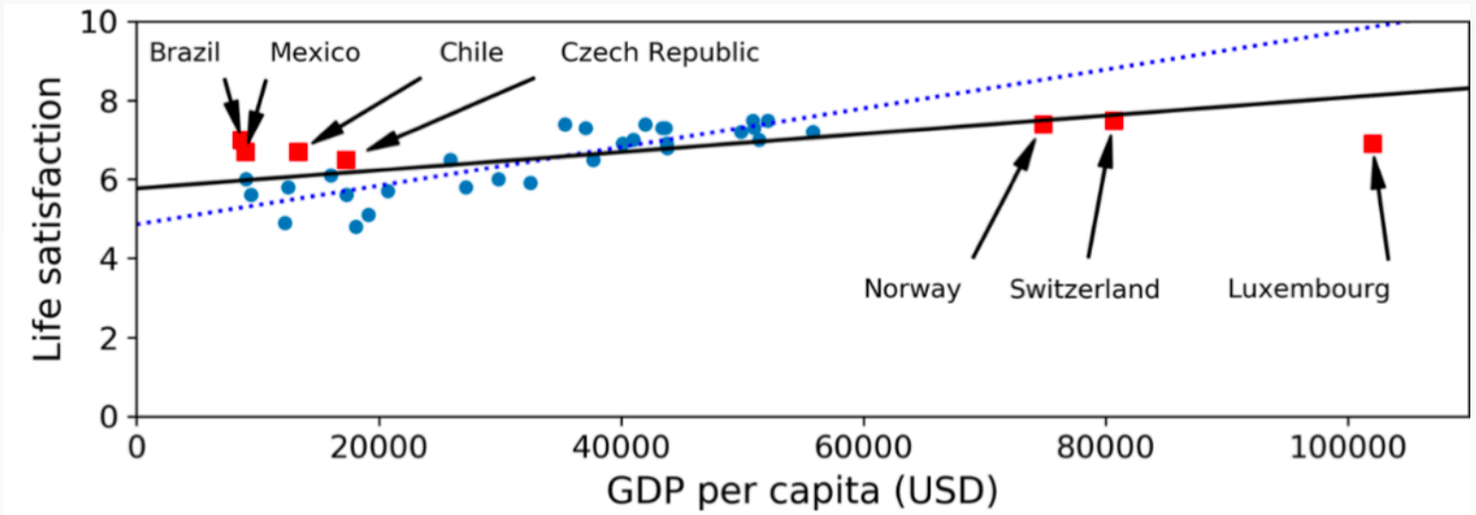


Summary of steps

- Study the data (data preparation)
- Select a model or learning algorithm
- Train on the available data and assess performance
- Apply the model to make predictions on new cases

Challenges of machine learning

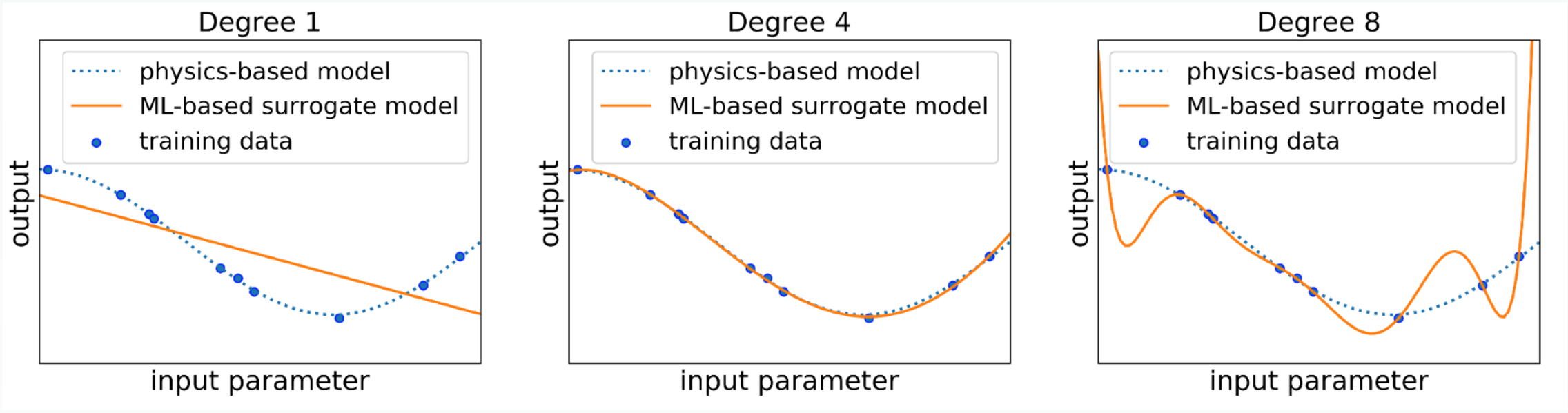
- Insufficient quantity of training data
- Non-representative and poor-quality training data



- Irrelevant features: coming up with a good set of features

Challenges of machine learning

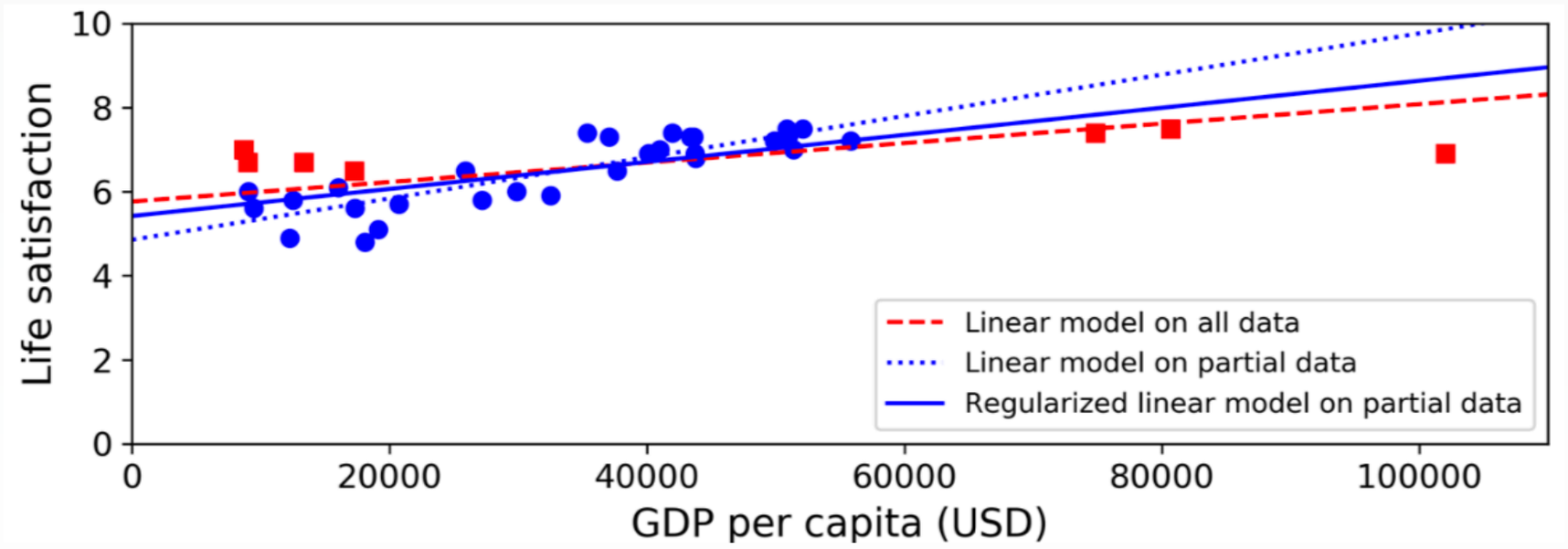
- Overfitting the training data
  - When the model is too complex relative to the amount and noisiness of data



- How to alleviate this problem?
  - Simplify the model
  - Gather more training data
  - Reduce noise and outliers (i.e., data preparation)

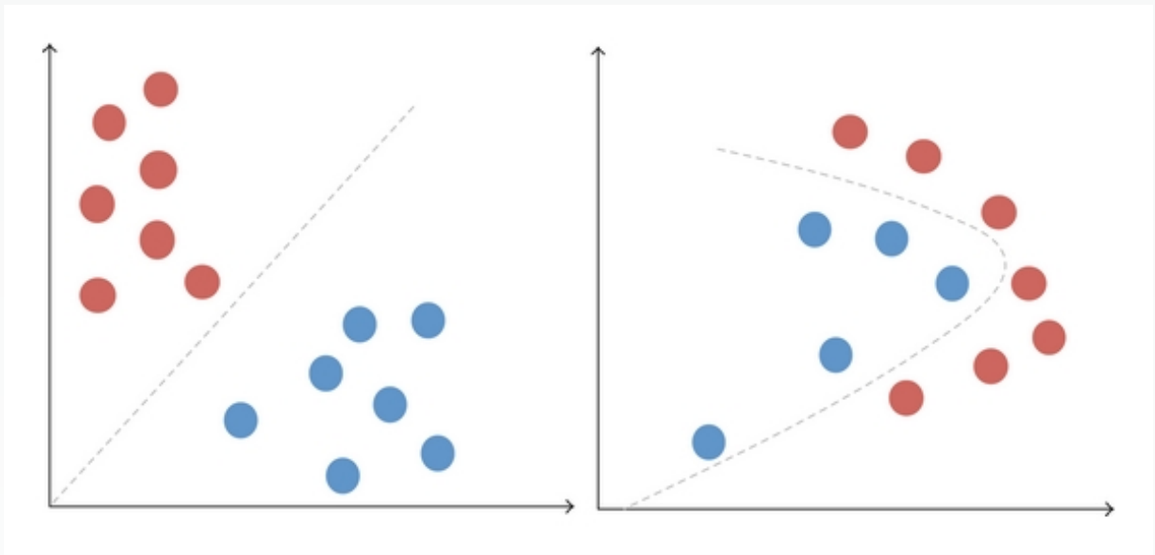
Example of reducing overfitting

- Use a subset of data and regularization
  - Regularization: balance between fitting the data perfectly and keeping the model simple enough
  - Amount of regularization is controlled by a hyperparameter (must be set prior to learning and remains constant during training)
  - Tuning hyperparameters is extremely important



Challenges of machine learning

- Underfitting the training data
  - When the model is too simple



- How to solve this problem?
  - Select a more powerful model
  - Reduce constraints on the model such as regularization

Testing and validation

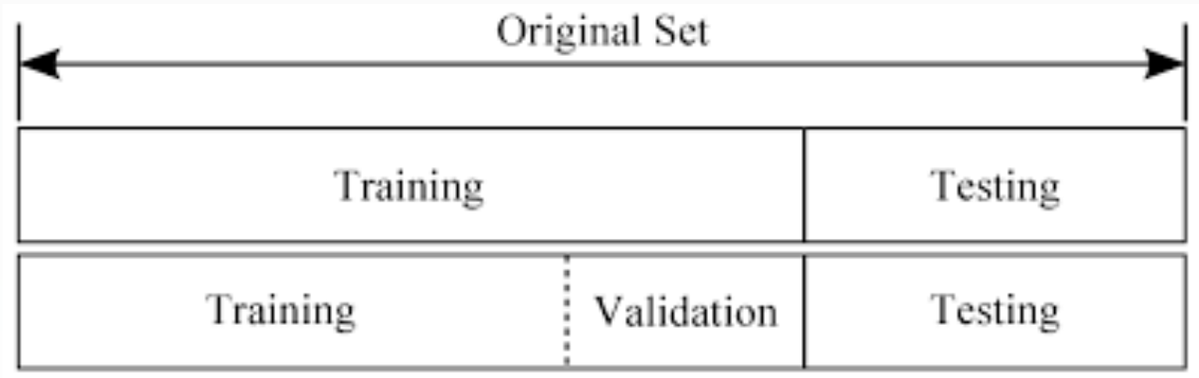
- The only way to know how a model will generalize to new cases is to actually try it out on new cases

- Split the available data into two sets: training set and testing set

  - The error on the test set is called the generalization error or out-of-sample error

  - If training error is low and generalization error is high, then overfitting occurs

- How to choose suitable models and their hyperparameters?



Review of linear algebra and NumPy

Introduction

- Please review: https://github.com/ageron/handson-ml2/blob/master/tools_numpy.ipynb

- NumPy offers mathematical functions, random number generators, linear algebra routines, and more

  - ‘’de-facto” standards of array computing

- 1D (vector) and 2D arrays (matrix)

$$\mathbf{a} = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} \in \mathbb{R}^n \qquad \mathbf{A} = \begin{bmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & & \vdots \\ a_{n1} & & a_{nm} \end{bmatrix} \in \mathbb{R}^{n \times m}$$

Creating arrays

```
[1] import numpy as np
    print(np.__version__)
```

```
1.18.5
```

```
[2] np.zeros(3)
```

```
array([0., 0., 0.])
```

```
[3] np.zeros((4,5))
```

```
array([[0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 0.]])
```

```
[4] print(np.zeros(3).shape, np.zeros((4,5)).shape)
```

```
(3,) (4, 5)
```

```
[5] np.zeros((4,5)).ndim # number of array dimensions (each dimension is called axis)
```

```
2
```

- Notice the difference between 1D and 2D arrays

Creating arrays

```
[6] np.ones((3,4))
```

```
array([[1., 1., 1., 1.],
       [1., 1., 1., 1.],
       [1., 1., 1., 1.]])
```

```
[7] np.array([[1,2,3,4], [10, 20, 30, 40]]) # convert regular python array
```

```
array([[ 1,  2,  3,  4],
       [10, 20, 30, 40]])
```

```
[8] type(np.array([[1,2,3,4], [10, 20, 30, 40]]))
```

```
numpy.ndarray
```

```
[9] np.arange(1,5)
```

```
array([1, 2, 3, 4])
```

```
[10] np.arange(1, 5, 0.5) # step parameter
```

```
array([1. , 1.5, 2. , 2.5, 3. , 3.5, 4. , 4.5])
```

```
[11] print(np.linspace(0, 4, 8))
```

```
[0.         0.57142857 1.14285714 1.71428571 2.28571429 2.85714286
 3.42857143 4.        ]
```

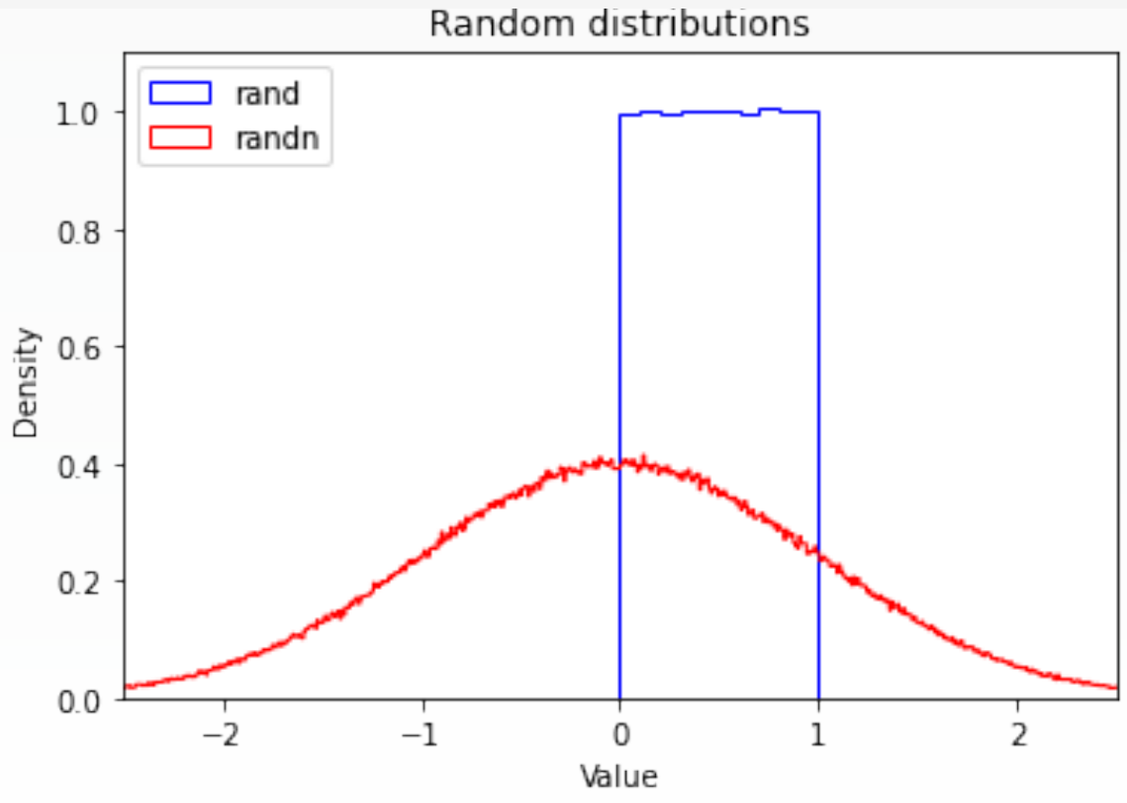
```
[12] 4/7
```

```
0.5714285714285714
```

Creating random numbers

- Two popular choices are uniform distribution between 0 and 1, and a univariate normal distribution

```
%matplotlib inline
import matplotlib.pyplot as plt
plt.hist(np.random.rand(1000000), density=True, bins=10, histtype="step", color="blue", label="rand")
plt.hist(np.random.randn(1000000), density=True, bins=1000, histtype="step", color="red", label="randn")
plt.axis([-2.5, 2.5, 0, 1.1])
plt.legend(loc = "upper left")
plt.title("Random distributions")
plt.xlabel("Value")
plt.ylabel("Density")
plt.show()
```



Array data

- NumPy's ndarrays are efficient because their elements must have the same type
  - Data types: https://numpy.org/doc/stable/user/basics.types.html

```
c = np.arange(1, 5)
print(c.dtype, c)
```

```
int64 [1 2 3 4]
```

```
c = np.arange(1.0, 5.0)
print(c.dtype, c)
```

```
float64 [1. 2. 3. 4.]
```

```
z = np.arange(3, dtype=np.uint8)
print(z.dtype)
```

```
uint8
```

Array data

- NumPy's ndarrays are efficient because their elements must have the same type

```
import numpy as np
import time

class Timer:
    """Record multiple running times."""
    def __init__(self):
        self.times = []
        self.start()

    def start(self):
        """Start the timer."""
        self.tik = time.time()

    def stop(self):
        """Stop the timer and record the time in a list."""
        self.times.append(time.time() - self.tik)
        return self.times[-1]
```

```
n = 10000
a = np.ones(n)
b = np.ones(n)
```

```
c = np.zeros(n)
timer = Timer()
for i in range(n):
    c[i] = a[i] + b[i]
f'{timer.stop():.5f} sec'
```

```
'0.01340 sec'
```

```
timer.start()
d = a + b
f'{timer.stop():.5f} sec'
```

```
'0.00019 sec'
```

Reshaping an array

```
g = np.arange(18)
```

```
g.shape = (6, 3)
print(g)
print("Rank:", g.ndim)
```

```
[[ 0  1  2]
 [ 3  4  5]
 [ 6  7  8]
 [ 9 10 11]
 [12 13 14]
 [15 16 17]]
Rank: 2
```

```
g2 = g.reshape(3,6)
print(g2)
print("Rank:", g2.ndim)
```

```
[[ 0  1  2  3  4  5]
 [ 6  7  8  9 10 11]
 [12 13 14 15 16 17]]
Rank: 2
```

```
g2[1, 2] = 1000
g2
```

```
array([[   0,    1,    2,    3,    4,    5],
       [   6,    7, 1000,    9,   10,   11],
       [  12,   13,   14,   15,   16,   17]])
```

Reshaping an array

- The reshape function returns a new array object pointing at the same data.

```
g2 = g.reshape(3,6)
print(g2)
print("Rank:", g2.ndim)
```

```
[[ 0  1  2  3  4  5]
 [ 6  7  8  9 10 11]
 [12 13 14 15 16 17]]
Rank: 2
```

```
g2[1, 2] = 1000
g2
```

```
array([[   0,    1,    2,    3,    4,    5],
       [   6,    7, 1000,    9,   10,   11],
       [  12,   13,   14,   15,   16,   17]])
```

```
g # pointing at the same data
```

```
array([[   0,    1,    2],
       [   3,    4,    5],
       [   6,    7, 1000],
       [   9,   10,   11],
       [  12,   13,   14],
       [  15,   16,   17]])
```

Conditional operators

```
m = np.array([20, -5, 30, 40])
```

```
m<25
```

```
array([ True,  True, False, False])
```

```
m[m<25]
```

```
array([20, -5])
```

Conditional operators

```
def f(a):
    if a.sum() < 0:
        c = -a
    if a.sum() > 0:
        c = a
    return c
```

```
x = np.array([1,2])
f(x)
```

```
array([1, 2])
```

```
x = np.array([-1,-2])
f(x)
```

```
array([1, 2])
```