

Machine Learning with Python

Wenbin Guo Bioinformatics IDP, UCLA

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Notation of the slides

Code or Pseudo-Code chunk starts with ">", e.g.
 ▶ print("Hello world!")

Link is underlined

Important terminology is in **bold** font

Workshop goals

Understand the rationales behind machine learning algorithms

 Know the advantages/limitations of some machine learning algorithms

 Apply machine learning algorithms to solve problems, and make the models perform better

Workshop goals

Use online resources to transform your idea into a model!

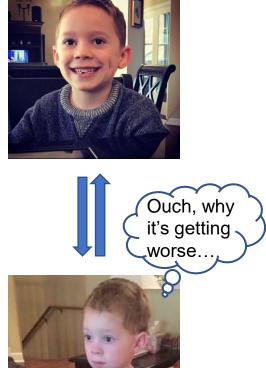


Workshop goals

• Use online resources to transform your idea into a model!



Tune parameters



It works better!

Agenda

- Day 1: Introduction to machine learning
 - Some key concepts in machine learning
 - Jupyter notebook and some packages usage
- Day 2: Supervised learning
 - Classification
 - Regression
 - Regularization
- Day 3: Unsupervised learning
 - Dimension reduction
 - Clustering





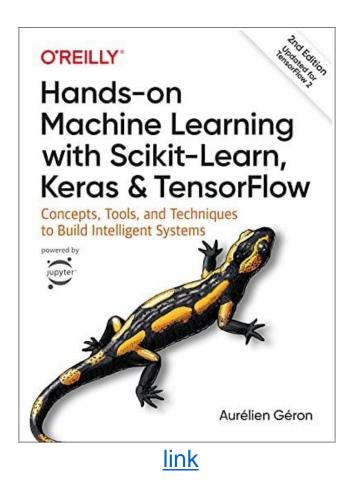








References



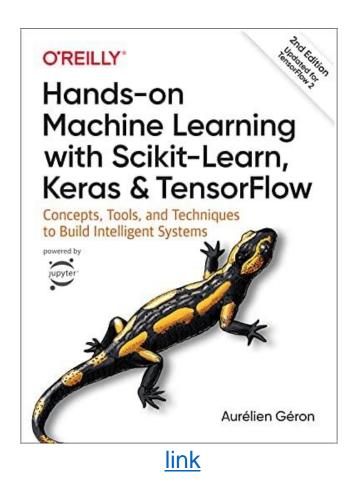
Other useful reference

When a beginner asks for recommendations for studying machine learning



Write down questions to this <u>Google doc</u>

References



Other useful reference

- An introduction to statistical learning
- Machine learning: a probabilistic perspective
- Deep learning



Write down questions to this <u>Google doc</u>



Day 1: Introduction to Machine Learning

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Overview

Time

3-hour workshop (45min + 45min + 30min + practice/Q&A)

Topics

- ☐ Introduction to machine learning
 - What's machine learning?
 - Types of machine learning
 - Machine learning applications
- ☐ Some key concepts in machine learning
- ☐ Recap of useful tools and packages
 - Jupyter notebook
 - NumPy, Matplotlib
- Examples and practices



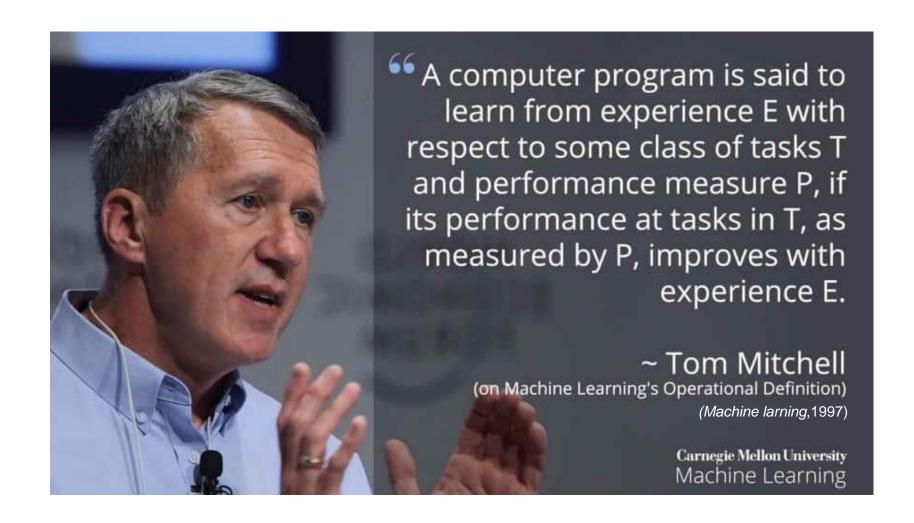
What is machine learning?



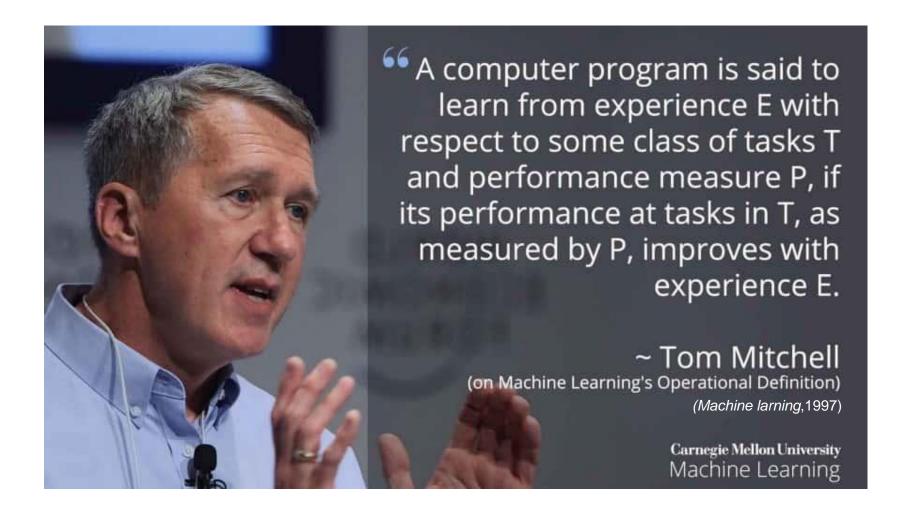
Arthur Lee Samuel (1959)

Machine Learning the "field of study that gives computers the ability to learn without being explicitly programmed".

What is machine learning?



What is machine learning?



Experience

o Data

Task

- Classification
- Regression
- Clustering
- Dimension reduction

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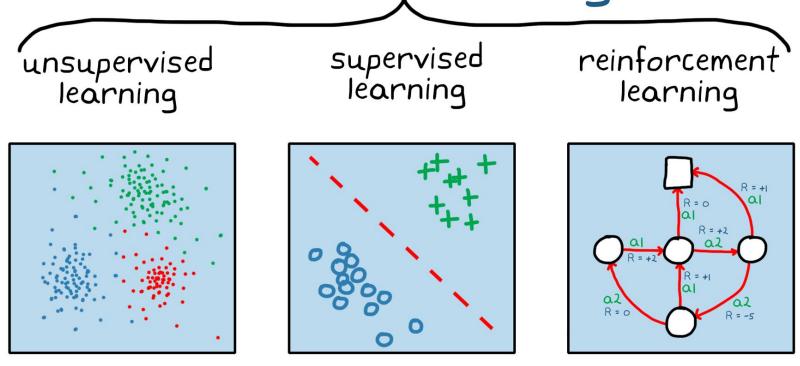
Performance

- Entropy loss
- Mean squared error
- Reconstruction error

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Types of machine learning

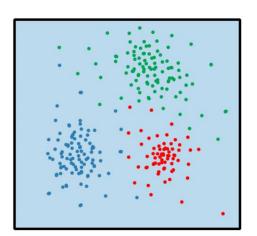
machine learning



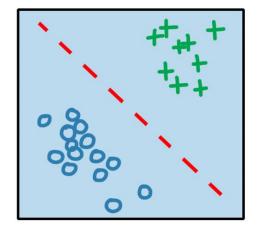
Types of machine learning

machine learning

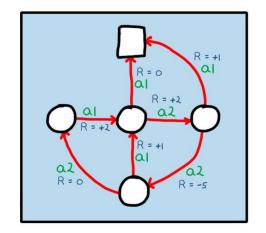
unsupervised learning

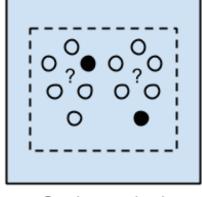


supervised learning



reinforcement learning





Semi-supervised Learning Algorithms

Self-supervised Learning



Other category types

- Batch learning vs Online-learning
 - Batch learning: system is trained using all available data
 - Online learning: system is trained incrementally by feeding data sequentially, data can be on the fly

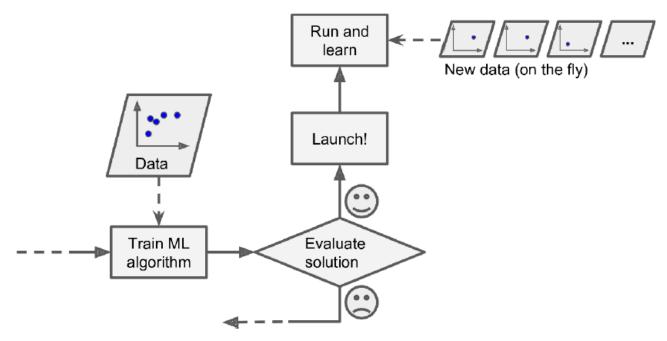
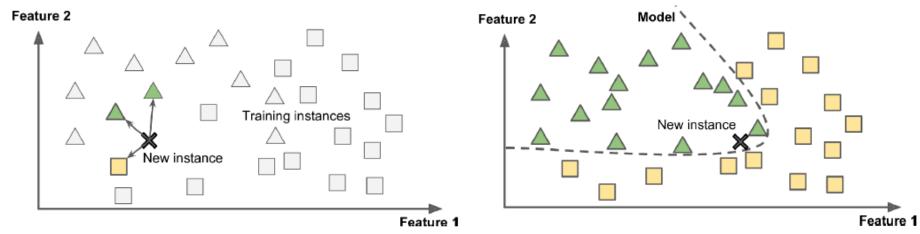


Figure 1-13. In online learning, a model is trained and launched into production, and then it keeps learning as new data comes in

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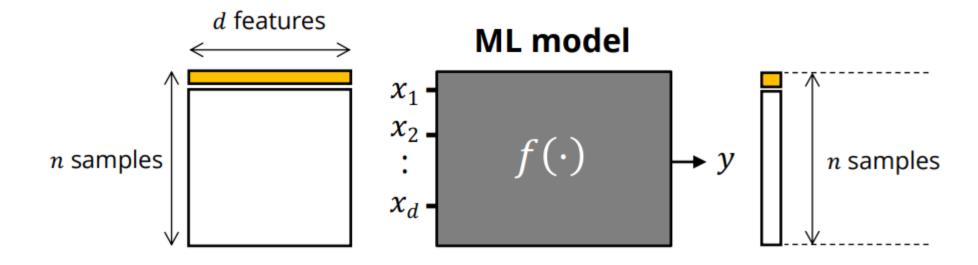
- Instance-based learning vs model-based learning
 - Instance-based learning: the system learns the example by heart, then generalizes to new cases by using a similarity measure
 - Model-based learning: build a model from existing examples, and use the model to make predictions



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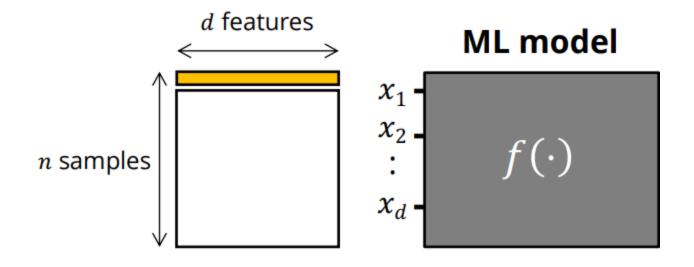
Supervised learning

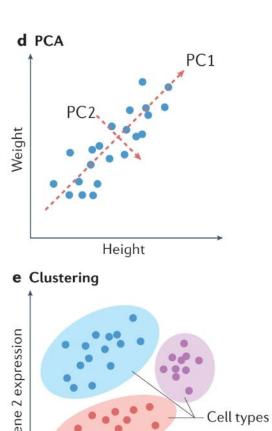
- Training data with n samples of features x and labels y
- Learn a function class f(x) to describe y based on x



Unsupervised learning

- Training data with n samples of features x, no label
- Identify underlying patterns in unlabeled data

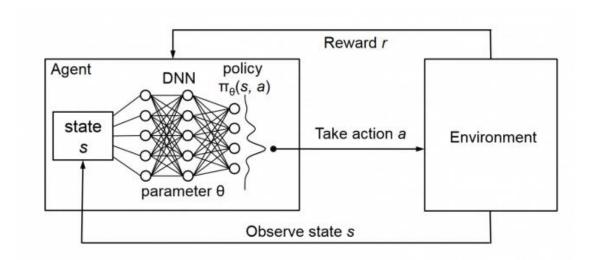


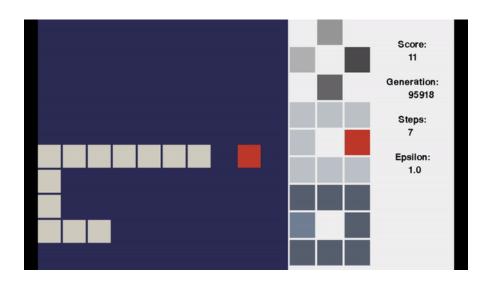


Gene 1 expression

Reinforcement learning

- Learning system (agent) observe the environment, select and perform actions, and get rewards in return
- Learn by itself what is the best strategy (policy), to get the most reward over time





What can machine learning do?

- Face/Speech recognition
- Recommendation system
- Machine translation
- Self-driving system
- Stock market prediction
- Create images/songs/paintings/stories

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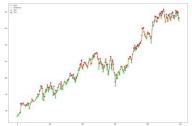












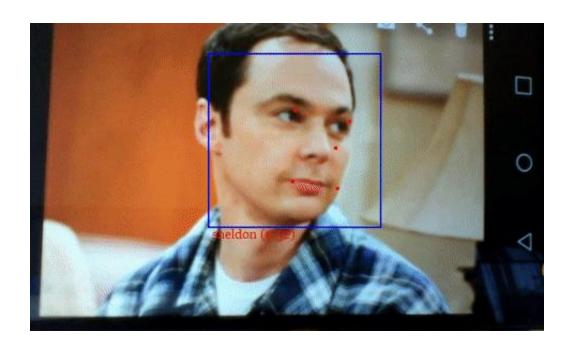


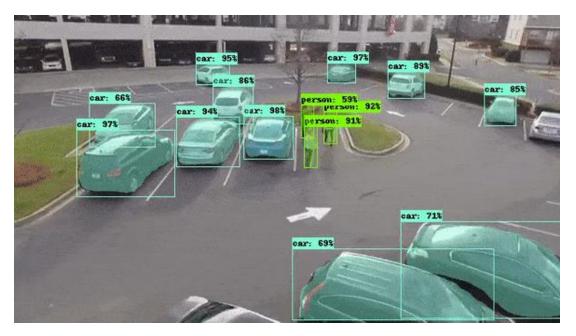




More examples

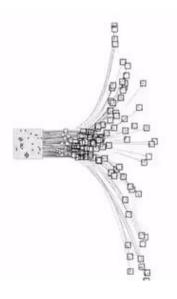
Object segmentation and recognition





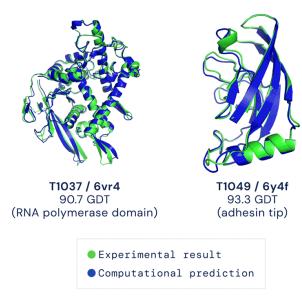
More examples

AlphaGo (2016)



Monte Carlo tree search

AlphaFold (2021)



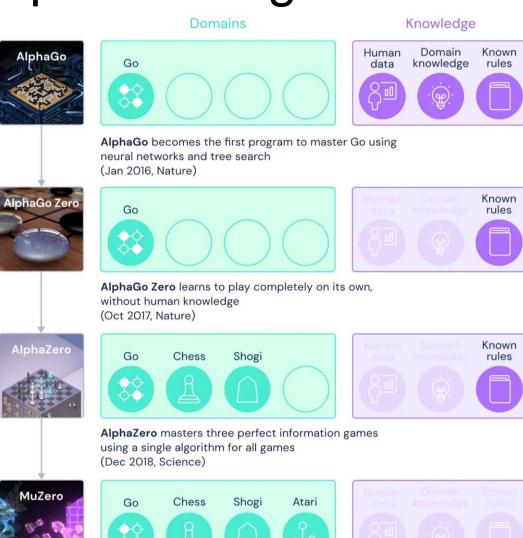
Transformer (self-attention)

AlphaTensor (2022)



Reinforcement learning

AlphaGo keeps evolving



MuZero learns the rules of the game, allowing it to also master environments with unknown dynamics. (Dec 2020, Nature)

Machine learning in biomedical research

- Imaging/sequencing processing
- Protein 3D structure prediction
- Genetic risk assessment
- Disease diagnosis
- Drug design

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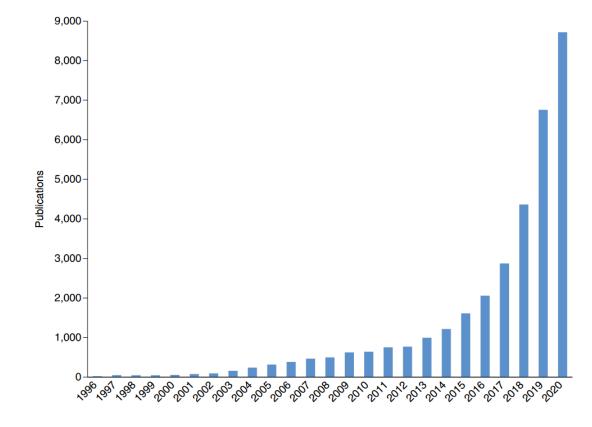


Fig. 1 | Exponential increase of ML publications in biology. The number of ML publications per year is based on Web of Science from 1996 onwards using the topic category for "machine learning" in combination with each of the following terms: "biolog*", "medicine", "genom*", "prote*", "cell*", "post translational", "metabolic" and "clinical".





- Frame the problem
 - Supervised or unsupervised?
 - Classification or regression?

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- Select the performance measure (loss function):
 - Regression: RMSE, MAE
 - Classification: cross entropy
 - Dimension reduction: reconstruction error

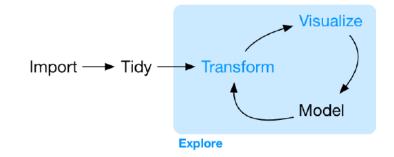
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Cost / loss function measures how bad your model fits the data



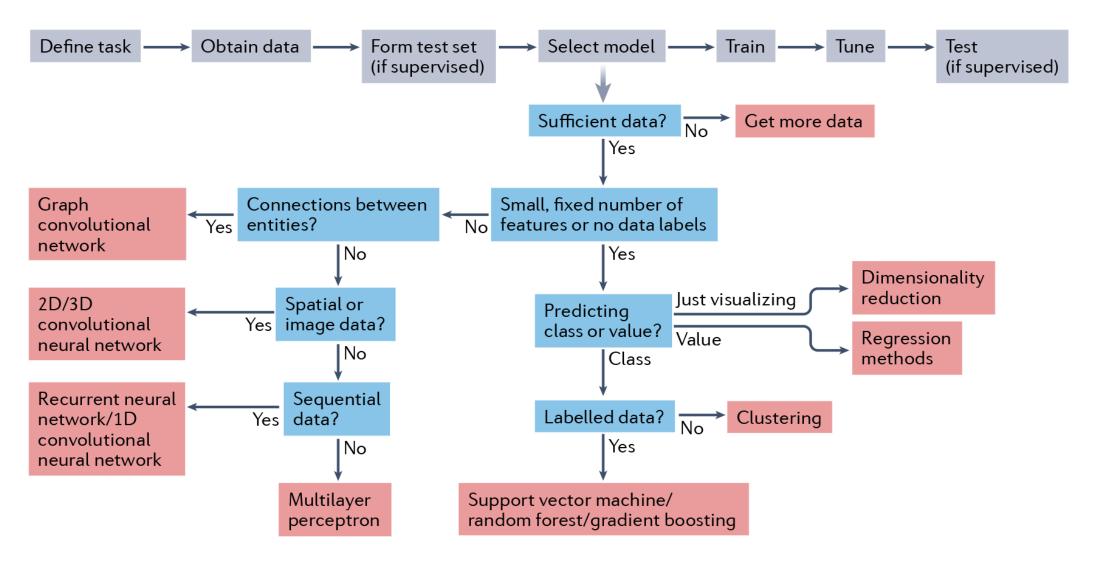
Prepare the data

- Download / gather data
- Explore the data structure (descriptive analysis)
- Perform data cleansing, processing, feature engineering



Create a test set (for supervised learning)

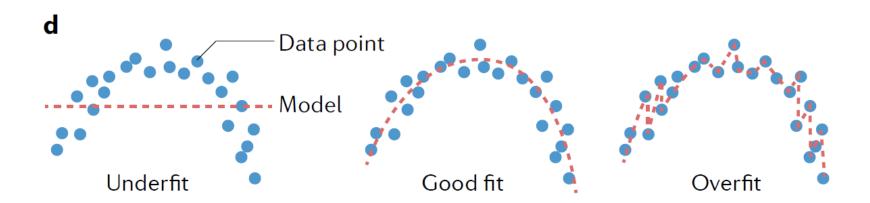
- The only way to know how well a model will generalize to new cases is to actually try
 it out on new cases
- Split the data into training and test set
 - Training set: train your models
 - Test set: evaluate the model (estimate the generalization error)
 - usually use 80% samples for training, holdout 20% samples for test





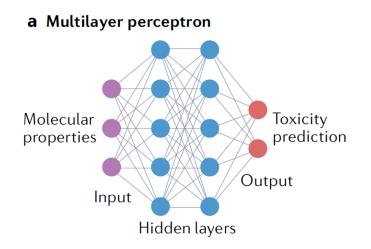
Train a model:

 Run an algorithm to find the model parameters that fits the training data the best (and hopefully make good predictions on new data)





- Tune hyperparameters:
 - Hyperparameters are parameters of a learning algorithm (not of the model)
 - Unlike model parameters, hyperparameters are not updated during training (although they are adjustable)



Example of hyperparameters:

- Number of neurons per layer
- Number of hidden layers

. . .



- Consider you have a set of hyperparameters/models to try
 - For each of them, you trained the model on training dataset, and then evaluate it on the test dataset, then you pick out the model with the best performance
 - Any problem?



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 - Any problem?
 - You measured the generalization error multiple times on the test set, and you adapted the model and hyperparameters to produce the best model for that particular set

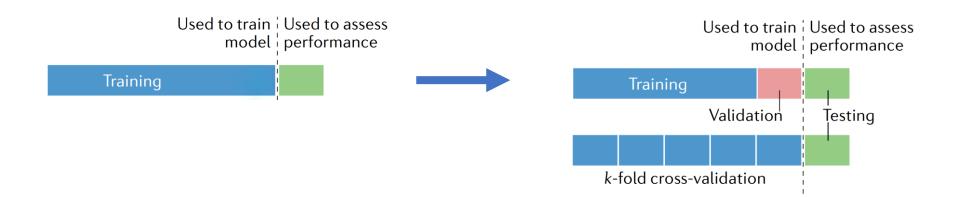


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 - Solution: holdout validation





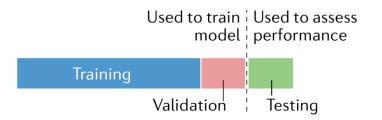
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 - Any problem?
 - You measured the generalization error multiple times on the test set, and you adapted the model and hyperparameters to produce the best model for that particular set
 - Solution: holdout validation, typically use cross validation when validation set is small





Tune hyperparameters

- > Train multiple models with various hyperparameters on the reduced training set
- > Select the model that performs best on the validation set (or repeated cross validation)
- ➤ Train the best model on the full training set (including the validation set), this gives you the final model
- Lastly, evaluate this final model on the test set to get an estimate of the generalization error



Main challenges for machine learning

The system will not perform well if your training set is too small, or if the data is not representative, is noisy, or is polluted with irrelevant features

- Insufficient data
 - It takes a lot of data for many Machine Learning algorithms to work properly
 - but small- and medium-sized datasets are still very common in biological research
- Nonrepresentative data
 - Use a training set that is representative of the cases you want to generalize to

Main challenges for machine learning

The system will not perform well if your training set is too small, or if the data is not representative, is noisy, or is polluted with irrelevant features

Insufficient data

- It takes a lot of data for many Machine Learning algorithms to work properly
- but small- and medium-sized datasets are still very common in biological research

Nonrepresentative data

- Use a training set that is representative of the cases you want to generalize to
- Poor quality data (garbage in, garbage out)
 - Spend time cleaning up your training data
 - · Remove clear outliers

Irrelevant features

- Feature selection: selecting the most useful features
- Feature extraction: combing existing features to produce a more useful one
- Creating new features

Summary: what we have learned so far

Key concepts in machine learning:

- ☐ Definition of machine learning
- ☐ 3 types of machine learning
- ☐ The big picture of training a machine learning model

More details about:

- ☐ Training/test set
- ☐ Loss function
- □ Overfitting/underfitting
- ☐ Hyperparameters tunning (model selection)
- ☐ Cross validation
- ☐ Challenges in machine learning

Enough theory, let's play!

- Jupyter notebook
- Usage of some popular packages
- A toy example in machine learning

Jupyter notebook

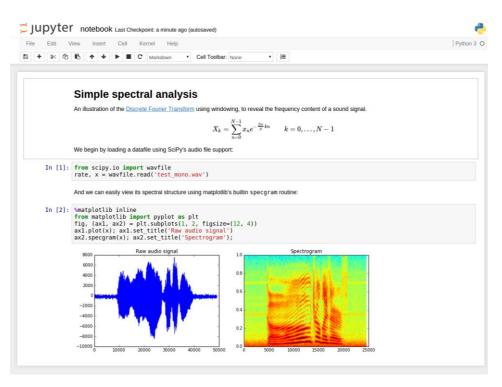


- An open-source, web-based interactive computing platform
 - Suitable for exploration, and prototyping
 - Convenient in sharing, documentation and making plots, powerful for data analysis

Similar applications:

- JupyterLab (an extension of Jupyter notebook)
- R markdown Notebook (R)
- Matlab Live Script (Matlab)

Fun fact: Jupyter stands for **Julia**, **Python**, **R**.







Install on your local computer: <u>link</u>

Install the classic Jupyter Notebook with:

pip install notebook

To run the notebook:

jupyter notebook

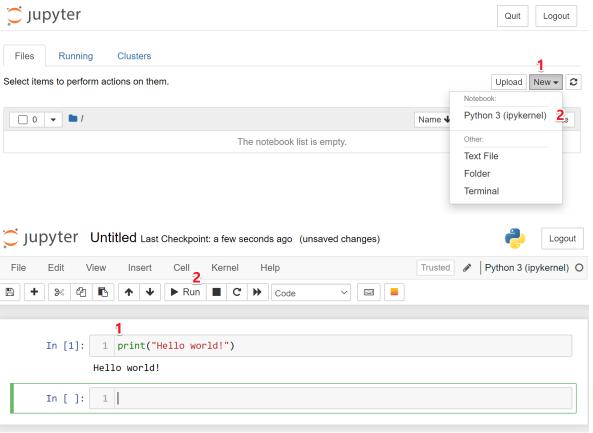
- If you are on Hoffman2: <u>link</u>
 - ▶ wget https://raw.githubusercontent.com/rdauria/jupyter-notebook/main/h2jupynb
 - ➤ chmod u+x h2jupynb
 - ➤ ./h2jupynb --help
 - ➤ ./h2jupynb -u your_username -t 4 -m 8 -v 3.9.6
- Alternatively, you can use <u>Google colab</u>

Preparation: Create a new notebook

Jupyter

Create a new notebook

Say "Hello world!"



- Now let's move to the Jupyter notebook tutorial
 - git clone https://github.com/wbvguo/qcbio-ML_w_Python.git

Where to get help?

https://www.google.com

https://stackoverflow.com

https://stats.stackexchange.com/

https://towardsdatascience.com/

https://openai.com/blog/chatgpt/



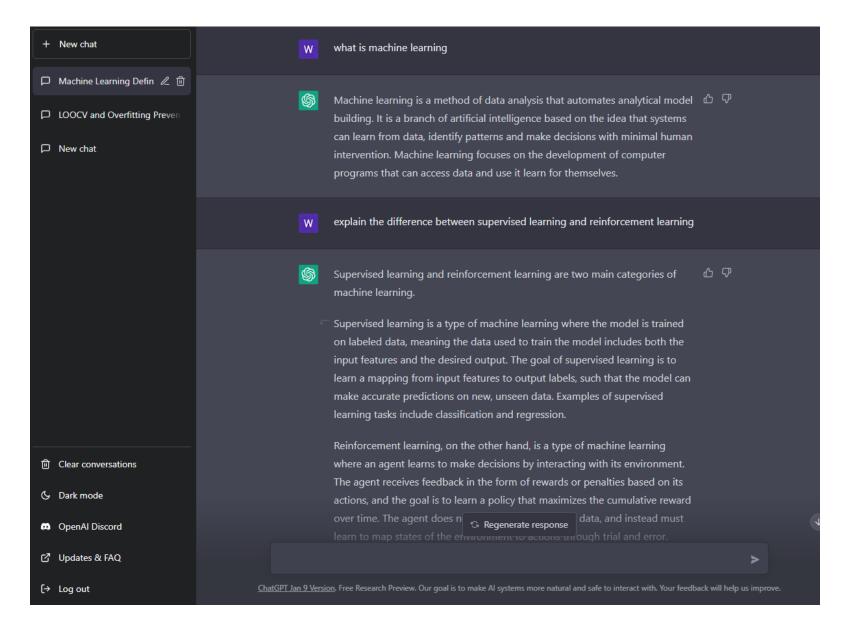




towards data science



ChatGPT



Q&A

Google docs