# Machine Learning

Introduction by *Marina Barsky* 

- What is machine learning
- Why ML
- Types of ML tasks
- Course requirements

- Machine learning teaches machines to learn how to carry out tasks by themselves, without giving explicit instructions
- How can a machine learn something new, if all the instructions are given by a human programmer?
- This is possible only if the instructions are of a special type: they mimic the ways that humans learn

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What do we mean by learning?

- Based on the previous experiences assign a label to a new object
- Group similar things together into a single category
- Identify patterns

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What do we mean by learning?

- Based on the previous experiences assign a label to a new object
- Group similar things together into a single category
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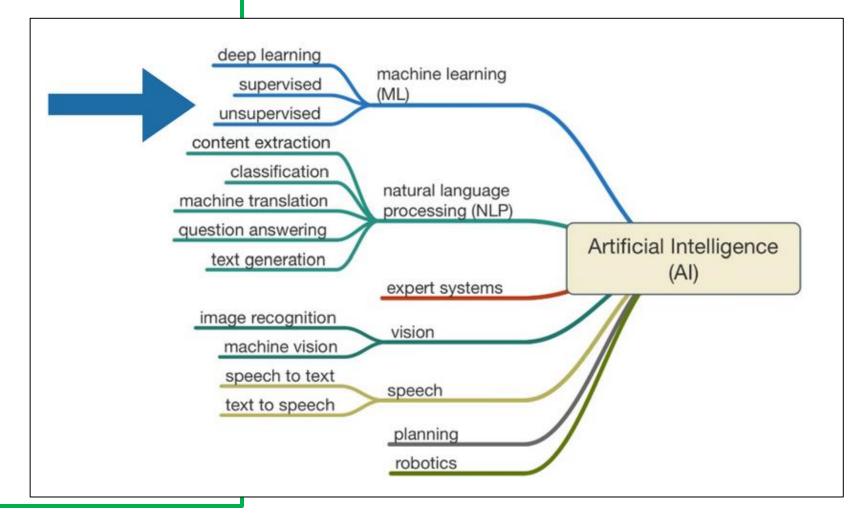
- What is machine learning
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# ML algorithms learn from previous experiences

- The previous experiences are encoded as a set of data points
- If data is non-random, it contains *patterns*
- Based on these patterns, ML algorithm discovers a *generalized model of data*
- That allows it to make *predictions* about other data that it might see in the future

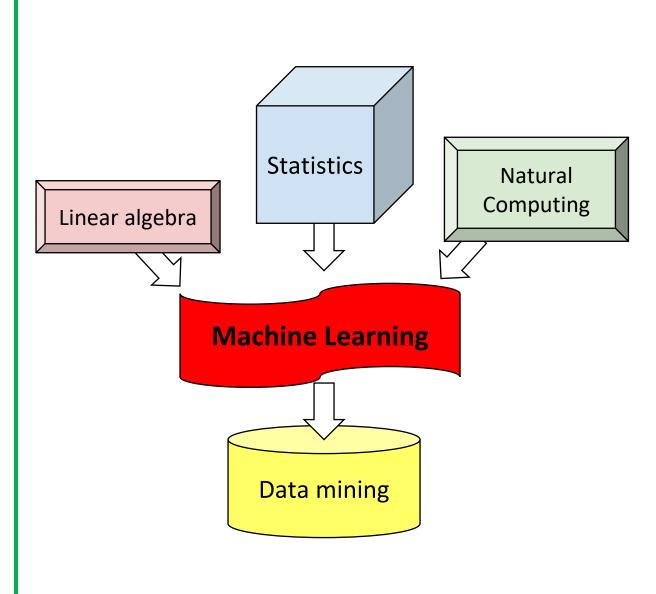
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# Machine Learning is a subfield of AI

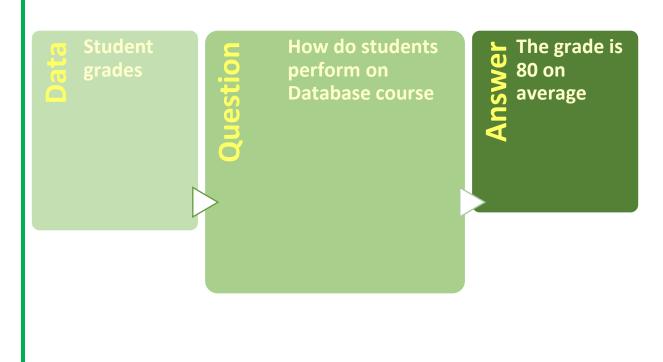


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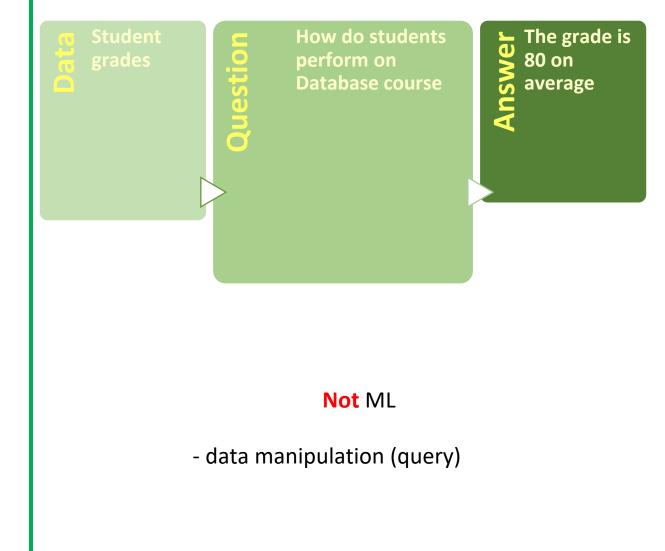
#### Machine Learning overlaps



- What is machine learning
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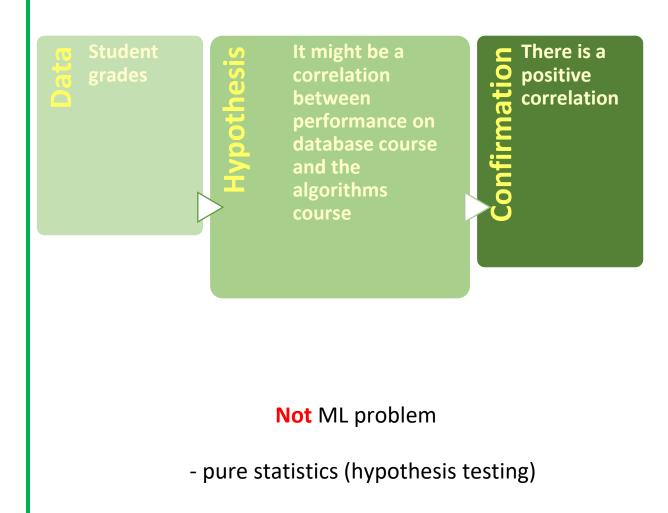
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It might be a There is a ဟ e S positive correlation correlation between Hypoth performance on onfirm database course and the algorithms course

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If good at Is there any S algorithms correlation in then good at performance on att **Databases** computer science courses? 🛕 If good at Hardware Given courses, then performance in not good at some courses Java can we predict performance in the others?

#### Machine learning!

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## Why study Machine Learning? 1/3

#### Get competitive advantage in business

- Google uses web links to rank pages, it gathers your every click and learns to adapt its search to your preferences
- Amazon and Netflix use information about the things people buy or watch to learn which people or items are similar to one another, and then make recommendations
- Pandora and Last.fm use your ratings of songs to create custom radio stations with music they think you will enjoy
- The predictions made by the Hollywood Stock Exchange are routinely better than those made by individual experts
- eHarmony uses information collected from participants to determine who would be a good match

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## Why study Machine Learning? 2/3

#### In science:

...

- Classify faint galaxies
- Find similar gene expressions for different drug treatments
- Predict the structure of a chemical from magnetic resonance data

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Facial recognition? http://www.pictriev.com/

## Why study Machine Learning? 3/3

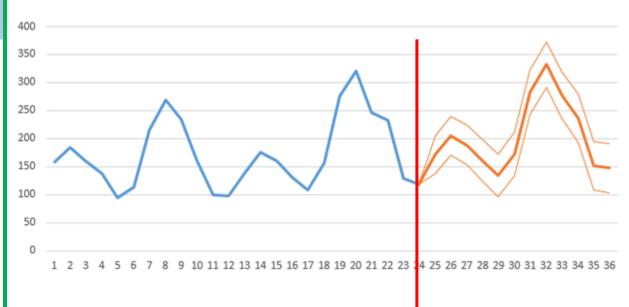
#### Automate everyday tasks

- Show to the algorithm which messages you consider a spam, and the task of separating spam can be carried out automatically
- Collect only positive or only negative news articles

Once you learn about a few machine-learning algorithms, you'll start seeing places to apply them just about everywhere

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# ML predicts the future

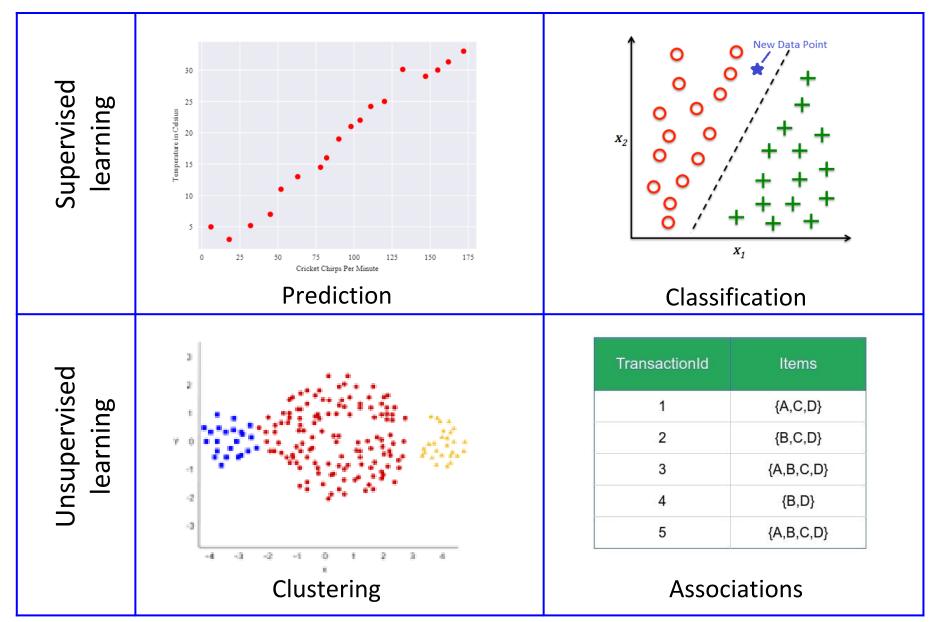


Data analytics Business analytics Reports

Predictive analytics Machine Learning Data mining

now

## Types of learning tasks



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Supervised learning: Classification

- Given a collection of records (*training set*)
  - Each record contains a set of *attributes*, one of the attributes is the *class*.
- Find ("learn") a *model* for the class attribute as a function of the values of the other attributes.
- Objective: new previously unseen records should be assigned a class as accurately as possible.

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### Classification example

Tid	Refund	Marital Status	Taxable Income	Cheat	No Yes	Single Married
1	Yes	Single	125K	No	No	Married
2	No	Married	100K	No	Yes	Divorce
3	No	Single	70K	No	No	Single
4	Yes	Married	120K	No	No	Married
5	No	Divorced	95K	Yes		
6	No	Married	60K	No		
7	Yes	Divorced	220K	No		
3	No	Single	85K	Yes		
)	No	Married	75K	No		
10	No	Single	90K	Yes		
		Training Set			earn ssifie	

Refund	Marital Status	Taxable Income	Cheat
No	Single	75K	?
Yes	Married	50K	?
No	Married	150K	?
Yes	Divorced	90K	?
No	Single	40K	?
No	Married	80K	?

Model

- What is machine learning
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## Toy classification problem

#### My neighbour dataset

	My	y neighbo	our datas	set	c18551200
Temp	Precip	Day	Shop	Clothes	
25	None	Sat	No	Casual	Walk
-5	Snow	Mon	Yes	Casual	Drive
15	Snow	Mon	Yes	Casual	Walk

(Adopted from Leslie Kaelbling's example in the MIT courseware)

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### Classify:



Temp	Precip	Day	Shop	Clothes	
25	None	Sat	No	Casual	Walk
-5	Snow	Mon	Yes	Casual	Drive
15	Snow	Mon	Yes	Casual	Walk
-5	Snow	Mon	Yes	Casual	?

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### Classify: memory



Temp	Precip	Day	Shop	Clothes	
25	None	Sat	No	Casual	Walk
-5	Snow	Mon	Yes	Casual	Drive
15	Snow	Mon	Yes	Casual	Walk
-5	Snow	Mon	Yes	Casual	Drive

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## Classification problem: noise

Temp	Precip	Day	Clothes	
25	None	Sat	Casual	Walk
25	None	Sat	Casual	Walk
25	None	Sat	Casual	Drive
25	None	Sat	Casual	Drive
25	None	Sat	Casual	Walk
25	None	Sat	Casual	Walk
25	None	Sat	Casual	Walk
25	None	Sat	Casual	?

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#### Classification: averaging

Temp	Precip	Day	Clothes	
25	None	Sat	Casual	Walk
25	None	Sat	Casual	Walk
25	None	Sat	Casual	Drive
25	None	Sat	Casual	Drive
25	None	Sat	Casual	Walk
25	None	Sat	Casual	Walk
25	None	Sat	Casual	Walk
25	None	Sat	Casual	Walk

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#### Classification: generalization

Temp	Precip	Day	Clothes	
22	None	Fri	Casual	Walk
3	None	Sun	Casual	Walk
10	Rain	Wed	Casual	Walk
30	None	Mon	Casual	Drive
20	None	Sat	Formal	Drive
25	None	Sat	Casual	Drive
-5	Snow	Mon	Casual	Drive
27	None	Tue	Casual	Drive
24	Rain	Mon	Casual	?

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Three main ideas used for classification:

- memory
- averaging
- generalization

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Unsupervised learning. Associations

#### The Market-Basket Model

- A large set of *items*, e.g., things sold in a supermarket.
- A large set of *baskets*, each of which is a small set of the items, e.g., the things one customer buys in one transaction.

#### **Fundamental question**

• What sets of items are often bought together?

#### Motivation

• If a large number of baskets contain both hot dogs and mustard, we can use this information. How?

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# Solving association problem: market basket

	Transactions
1	{bread, milk, peanut butter}
2	{bread, milk}
3	{beer, potato chips}
4	{beer, diapers}
5	{beer, milk, diapers}
6	{bread, milk, yogurt}
7	{beer, bread, diapers}
8	{bread, milk, jelly}
9	{beer, cigarettes, diapers}
10	{bread, milk}

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# Solving association problem: market basket

	Transactions
1	{ <b>bread</b> , milk, peanut butter}
2	{bread, milk}
3	{beer, potato chips}
4	{beer, diapers}
5	{beer, milk, diapers}
6	{ <b>bread</b> , milk, yogurt}
7	{beer, bread, diapers}
8	{ <b>bread</b> , <b>milk</b> , jelly}
9	{beer, cigarettes, diapers}
10	{bread, milk}

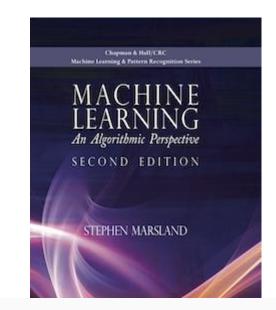
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## Beer and diapers?

	Transactions
1	{bread, milk, peanut butter}
2	{bread, milk}
3	{beer, potato chips}
4	{beer, diapers}
5	{ <b>beer</b> , milk, <b>diapers</b> }
6	{bread, milk, yogurt}
7	{ <b>beer</b> , bread, <b>diapers</b> }
8	{bread, milk, jelly}
9	{beer, cigarettes, diapers}
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#### Amazon example

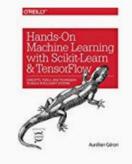


Customers who viewed Machine Learning: An Algorithmic Perspective (Chapman & Hall/Crc Machine... also viewed



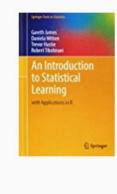
Machine Learning: An Algorithmic Perspective, Second Edition ★★★★☆ 46 \$69.29 ✓prime 48 used and new from

\$59.61



Hands-On Machine Learning with Scikit-Learn and TensorFlow: 251 \$29.35

✓prime
85 used and
new from
\$22.86



An Introduction to Statistical Learning: with Applications in R (Springer Texts ★★★☆ 200 \$49.60

✓prime
20 used and
new from
\$39.95

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#### **Customers Who Bought This Item Also Bought**



Revere Polished Aluminum 8-Inch Nonstick Skillet by Revere (16) \$14.99



Pyrex Smart Essentials 8-Piece Mixing Bowl Set by Pyrex

\$26.82



Kodak Portra 400 Professional ISO 400, 35mm, 36 Exposures, Color...

\$29.88

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#### This course: Computer Science part of Machine Learning

- We focus on *algorithms*
- By the end you understand ideas behind ML algorithms
- You will experiment with code based on these algorithms and see by yourselves whether machines can or cannot learn

#### **Far-reaching Course Objectives**

- Develop interest in math as a tool for learning about the world
- Learn how to handle ambiguity
- Formalize mental models of learning
- Make your future programs smart by incorporating ML algorithms
- Invent new ML approaches and new algorithms

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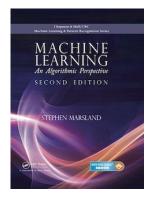
#### Books, blogs, videos

Programming Collective Intelligence by Toby Segaran

Building Machine Learning Systems with Python by Willi Richert and Luis Pedro Coelho



Machine Learning: An Algorithmic Perspective by Stephen Marsland



Web sites:

- Analytics Vidhya
- <u>Kaggle</u>
- <u>Datacamp</u>
- <u>KDNuggets</u>

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### Types of assignments

- Problem solving quizzes and short labs every week: 35%
- Mini-projects real coding, real problems: 35%
- Final project: large, professional, open-ended: 30%

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## Learning by doing

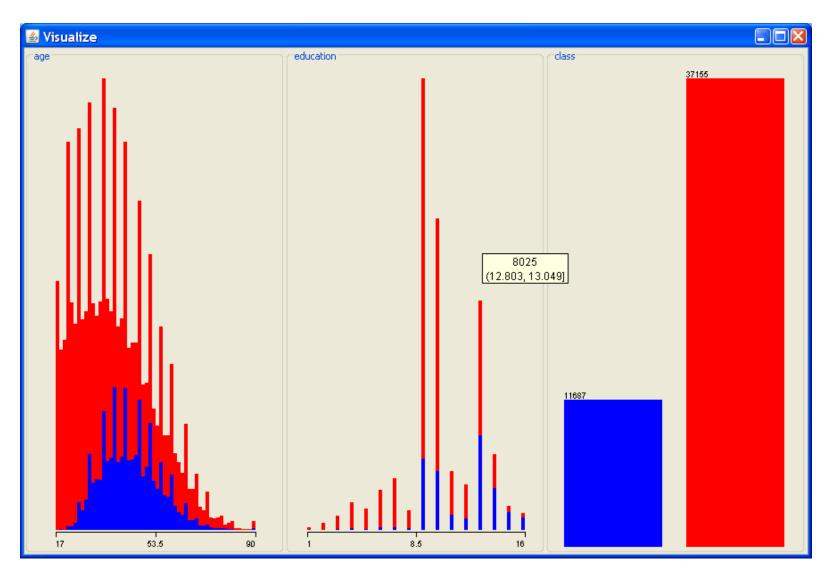
- Learning by example: on toy datasets which exhibit features of real-life datasets
- Implementation of some algorithms in Python
- Python library of ML algorithms: *sklearn*
- Analysis of real-life datasets

### Mini-project example: what determines high salary

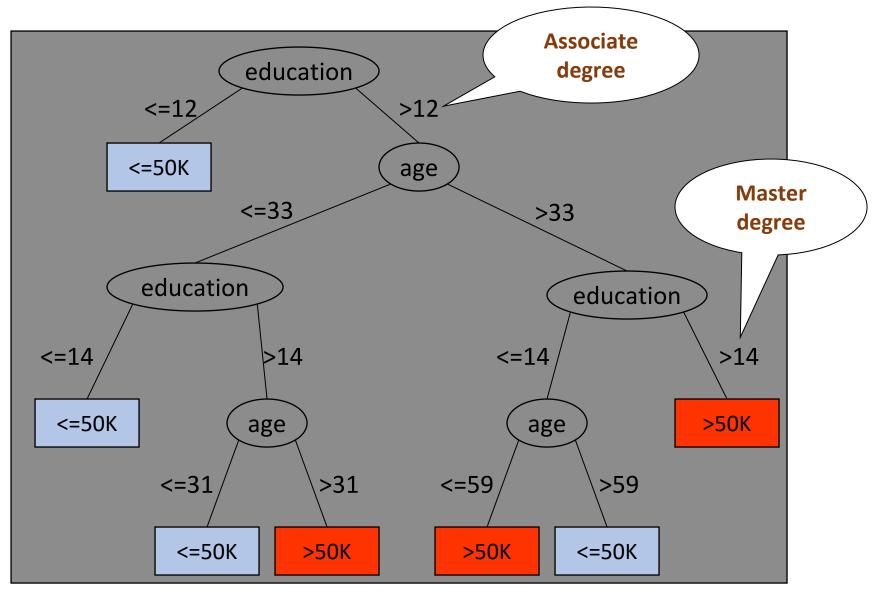
Adult income dataset (US census 1994)

Age	Education	Mar. status	Occupation	Race	Sex	Born in	Yearly income
39	Bachelors	Never-married	Adm-clerical	White	М	US	<=50 K
50	Bachelors	Married-civ-spouse	Exec-managerial	White	М	US	<=50 K
54	7th-8th	Married-civ-spouse	Machine-op-inspct	White	М	US	>50K
37	Bachelors	Never-married	Exec-managerial	Black	М	US	>50K
28	Bachelors	Married-civ-spouse	Prof-specialty	Black	F	Cuba	<=50 K
37	Masters	Married-civ-spouse	Exec-managerial	White	F	US	<=50 K

### Visualization of attributes: age and education



# The result of learning: decision tree on age and education attributes

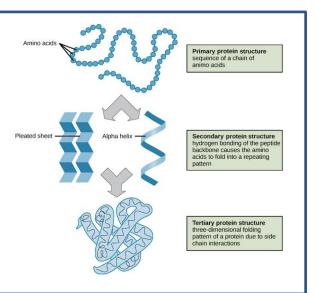


### Sample Past Final Projects: 1/2

• Predicting protein secondary structure using Recurrent Neural Networks by Joyee Wang

Sample input sequence: Human Hemoglobin

MVLSPADKTNVKAAWGKVGAHAGEYGAEALERMFLSFPTTKTYFPHFDLSHGSA QVKGHGKKVADALTNAVAHVDDMPNALSALSDLHAHKLRVDPVNFKLLSHCLLVT LAAHLPAEFTPAVHASLDKFLASVSTVLTSKYR



#### <u>LINK</u>



• Solving Captcha Challenge with Convolutional Neural Networks by Aung Wai Yan Hein

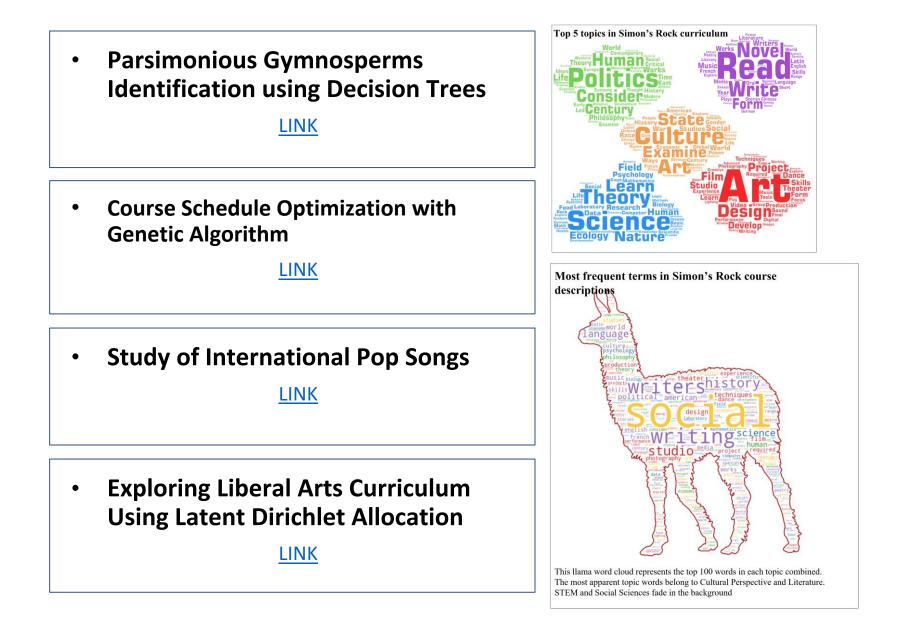
Can machines emulate humans and pretend that they are not robots?

<u>LINK</u>

• Creating a Pokémon Battle AI with Decision Trees by Kai Dai

LINK

### Sample Past Final Projects: 2/2



### Course syllabus (minimalistic version)

#### Part I. Basic algorithms

#### Learning to optimize

1. Hill climbing, Simulated annealing, Genetic algorithm

#### **Supervised learning**

2. Decision trees and classification rules

- 3. Regression vs Logistic regression
- 4. Nearest neighbors

#### **Unsupervised learning**

- 5. Clustering
- 6. Associations and correlations

#### Part II. Advanced topics Probabilistic classifiers

7. Naive Bayes.Bayesian Belief Networks8. Evaluating and comparing classifiers

#### **Artificial Neural networks**

9. Classification with ANNs10. Bias-variance trade-off.Regularization

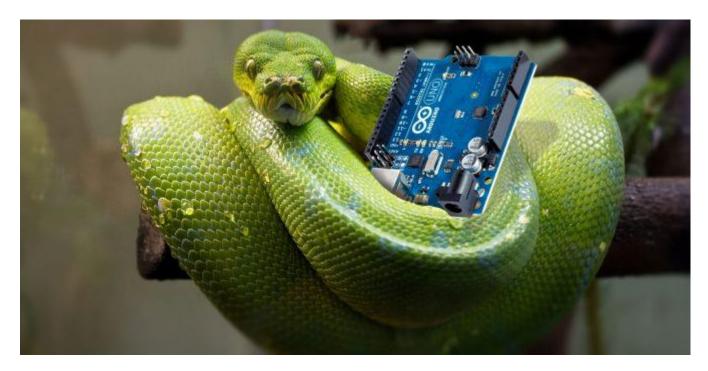
Project ideas live web page: LINK

### We all are familiar with Python



#### It's time to get a faster cleaner Anaconda

https://docs.anaconda.com/anaconda/install/



It comes with all the libraries plus Jupyter notebooks

Launch Anaconda Navigator → Jupyter notebooks

#### Directories

Check what local directories you can access from Jupyter tree. Create a lab folder inside one of these directories. Create a separate folder where you are going to store all the datasets.

On github:

First, fork the repository, and then clone it into the lab directory.

#### Publishing notebooks

You can publish your notebooks using your google account in Google colab:

https://colab.research.google.com/notebooks/intro.ipynb

If you have a nice notebook for one of kaggle datasets, you can also publish it on kaggle:

https://www.kaggle.com/notebooks

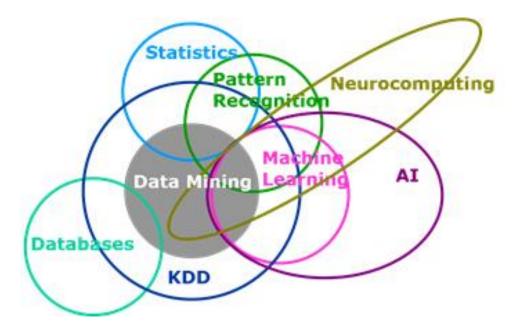
To avoid any problems with sharing and security, we are going to use local notebooks.

You can publish the notebook with your final project.

### To do (a lot):

- Take Quiz 0: what is ML? We will discuss the answers in the next meeting
- Research and answer the writing prompt in Assignment 0.
- Install Anaconda
- Get familiar with Jupyter notebooks: follow this tutorial
- Create a github account

## What is the difference?



# Some discussions

- <u>https://discuss.analyticsvidhya.com/t/what-is-the-difference-between-</u> machine-learning-data-analysis-data-mining-data-science-and-ai/572
- <u>https://bernardmarr.com/what-is-the-difference-between-data-mining-and-machine-learning/#:~:text=Data%20mining%20is%20used%20on,predictions%20about%20new%20data%20sets.</u>
- <u>https://www.simplilearn.com/data-mining-vs-machine-learning-article</u>
- <u>https://www.quora.com/Whats-the-relationship-between-machine-learning-and-data-mining</u>
- <u>https://www.kdnuggets.com/2021/11/3-differences-coding-data-science-machine-learning.html</u>
- <u>https://www.researchgate.net/post/What is the difference between mac hine learning and data mining2</u>
- <u>https://www.kdnuggets.com/2016/11/machine-learning-vs-statistics.html</u>

# Practitioner Observations

- Statistics: applies statistically sound sampling techniques to make the input small. Many famous algorithms used in ML and DM are invented by statisticians and are a part of Statistics
- Machine Learning: encompasses all the techniques and algorithms which allow machines extract new insights from data
- Data Mining: adopts all of the Machine Learning algorithms plus their efficient implementation for very large datasets (Big Data, parallel processing)
- Data Science: a new way of learning about the world from data

# **Evolution of Science**

- Empirical Science collect and systematize facts
- Theoretical Science formulate theories and empirically test them
- Computational Science run automatic proofs, simulations
- e-Science (Data Science)

   collect data without clear goal - and test theories, find patterns in the data itself





# Science is about asking questions

**Traditionally: "Query the world" Data acquisition for a specific hypotheses** 

Data science: "Download the world" Data acquired en masse in support of future hypotheses

# Computational challenge

The cost of data acquisition has dropped The cost of **processing**, **integrating** and **analyzing** data is the new <u>bottleneck</u>

"...the necessity of grappling with Big Data, and the desirability of unlocking the information hidden within it, is now a key theme in all the sciences – arguably the key scientific theme of our times"

F. Diebold

# Efficient data manipulation

Poll: How much time modern scientists spend "handling data" as opposed to "doing science"? Mode answer: 90%

"the Next Wave of InfraSress" (J. Mashey)