INTRO TO DATA SCIENCE USING AZURE ML STUDIO

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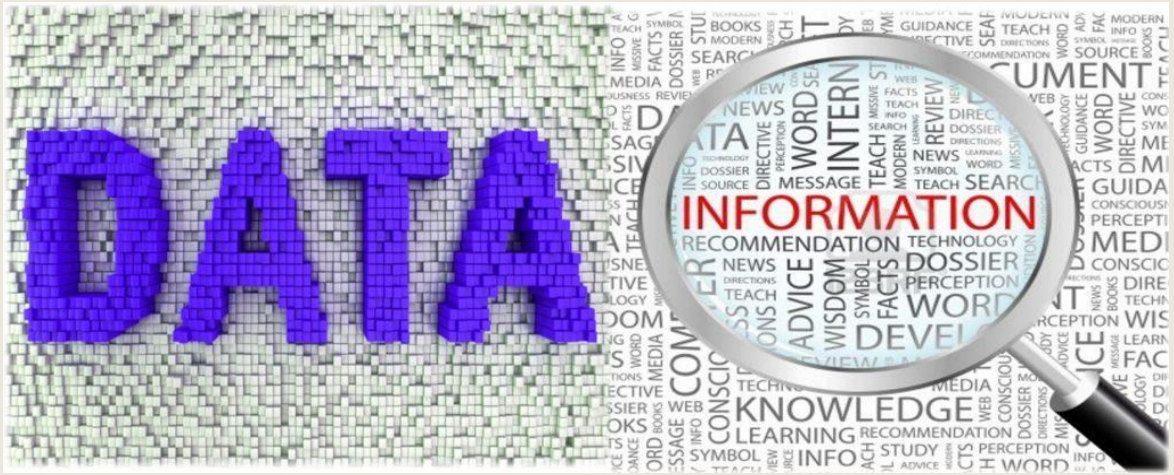
Topics for today:

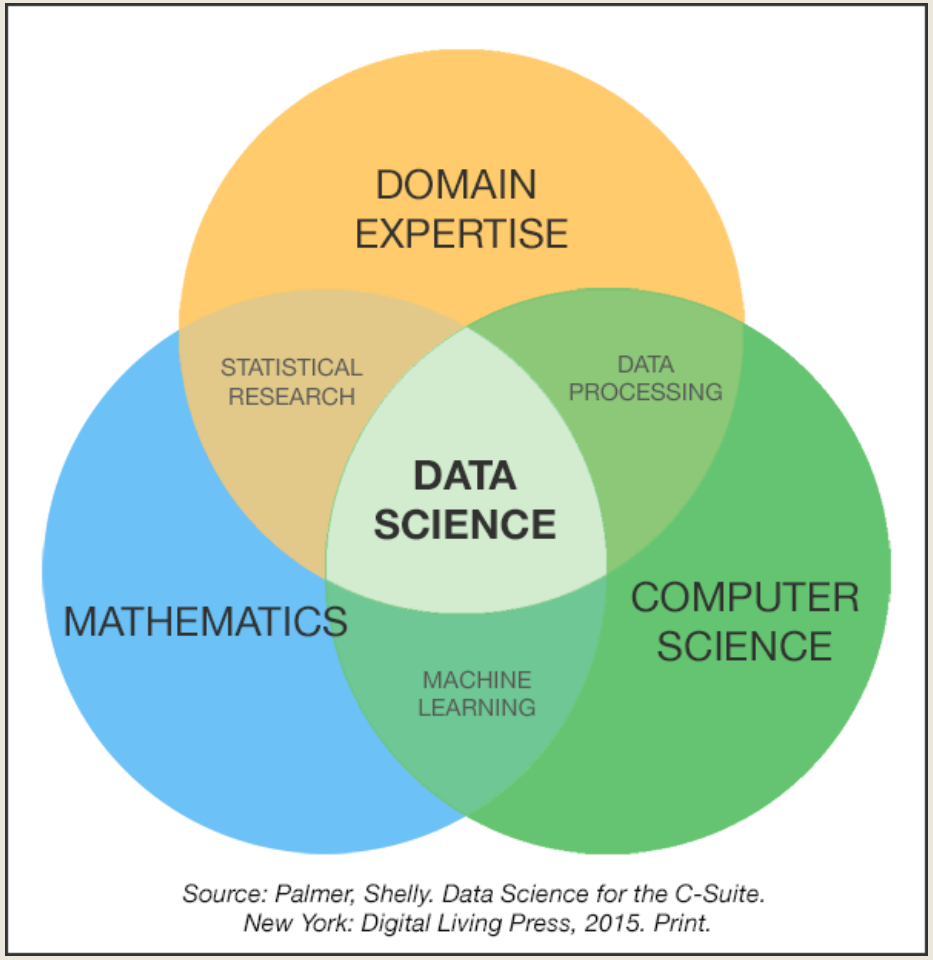
- Intro to data science
- Data science applications
- Intro to machine learning
- Data science life cycle
- Getting started with Azure ML Studio

INTRO TO DATA SCIENCE

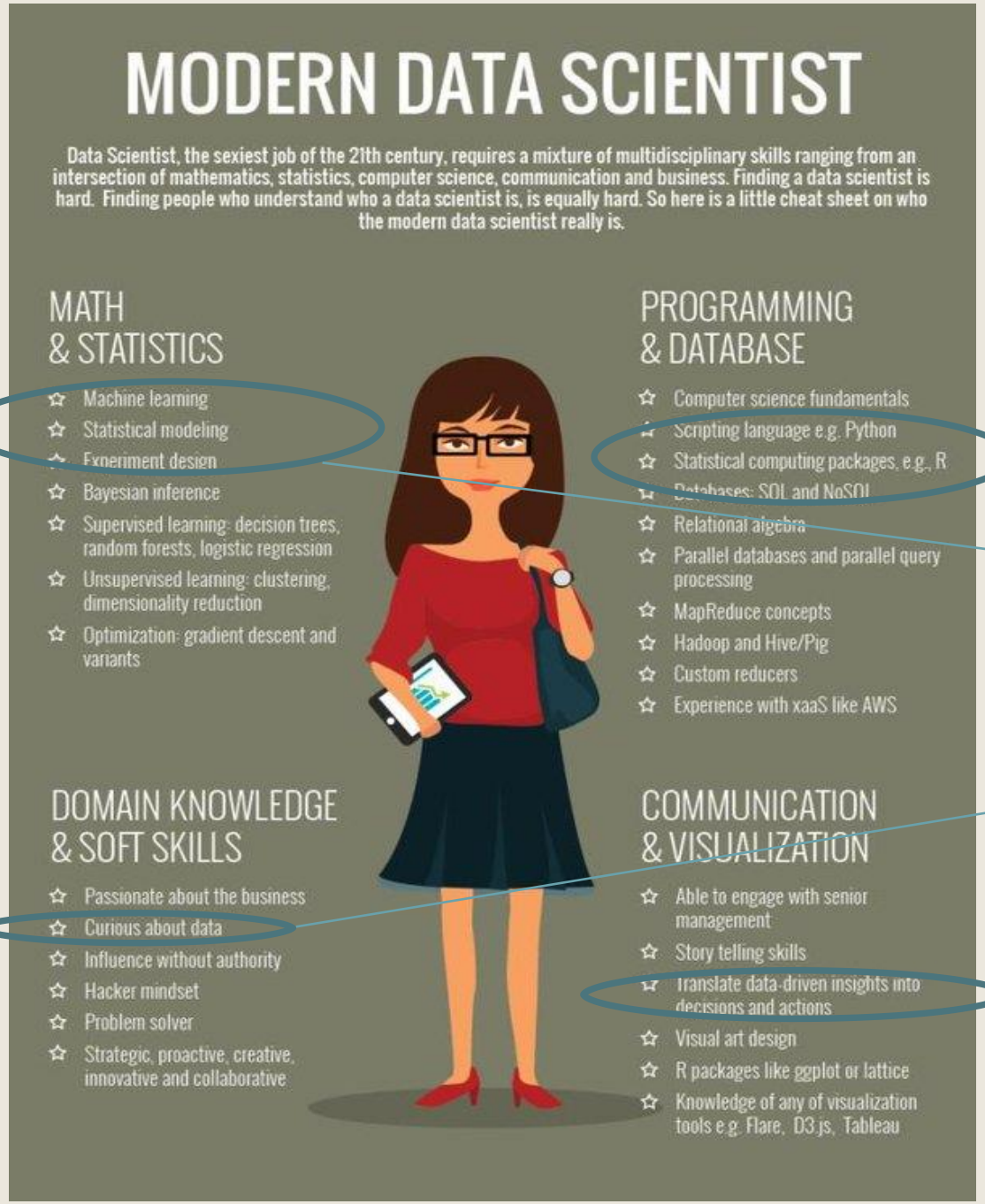
What is Data Science?



What to learn to become a Data Scientist?



Source: Palmer, Shelly. Data Science for the C-Suite. New York: Digital Living Press, 2015. Print.



What skills are expected from a Data Scientist?

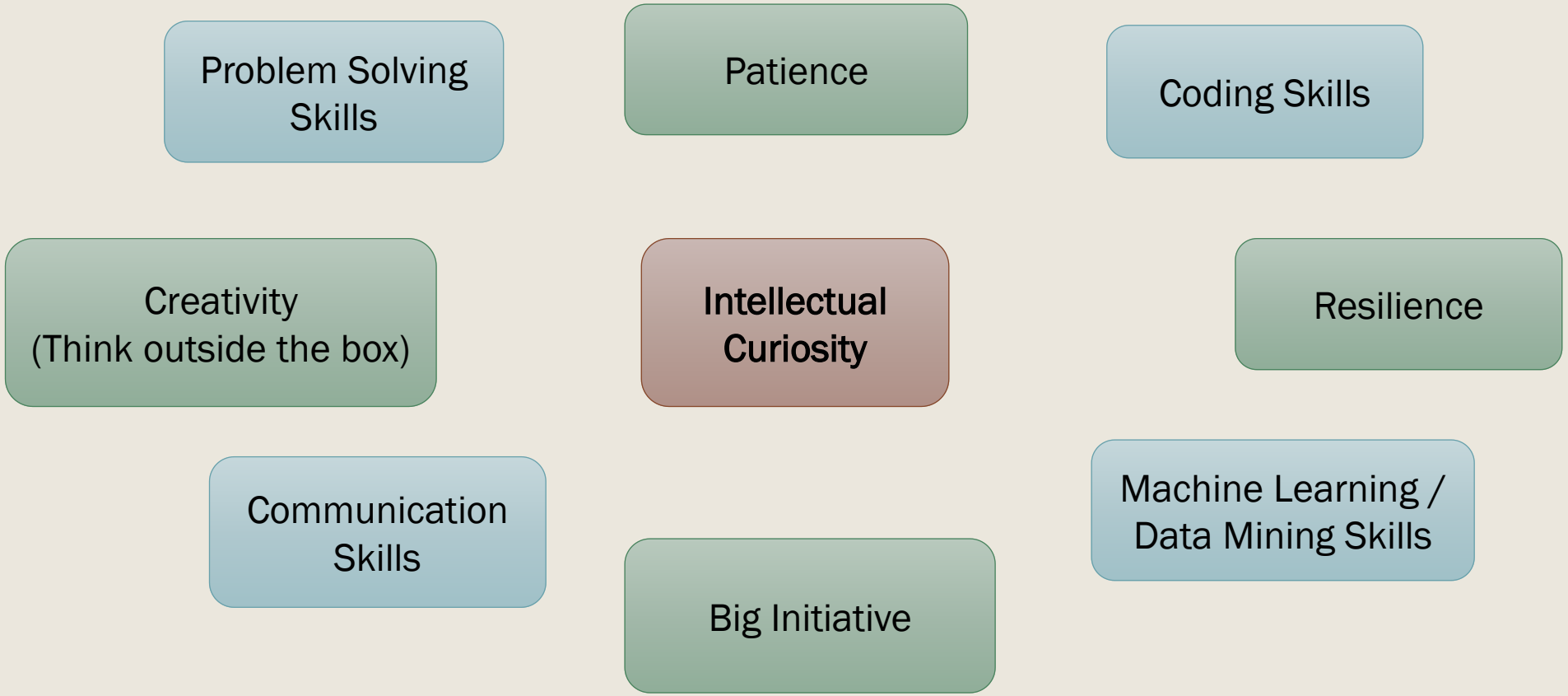
Experience coding (SQL, R, Python)

Machine Learning (Maths & Statistics)

Curious about data

Good communicator: Translate data-driven insights into decisions and actions

General skills for becoming a Data Scientist



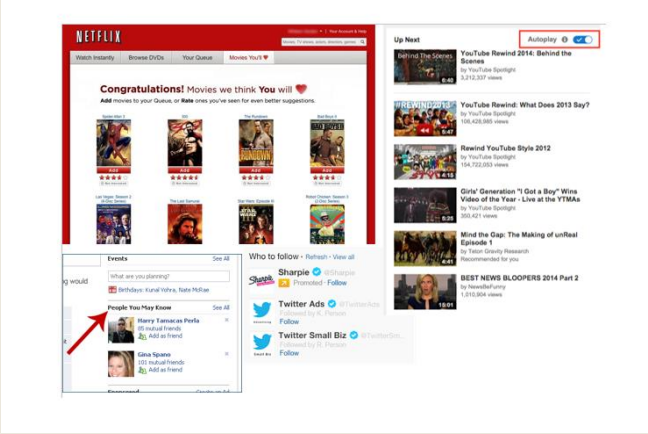
Because in your every day you will be …

- *Solving problems* for getting the best solution for your client/company
- *Understanding data* and business objectives
- *Transforming data* to give it a coherent and useful form
- Implementing new *algorithms* to make predictions on data
- Studying and using *models* to understand specific data
- Using feedback to learn how to improve your solution or make better predictions

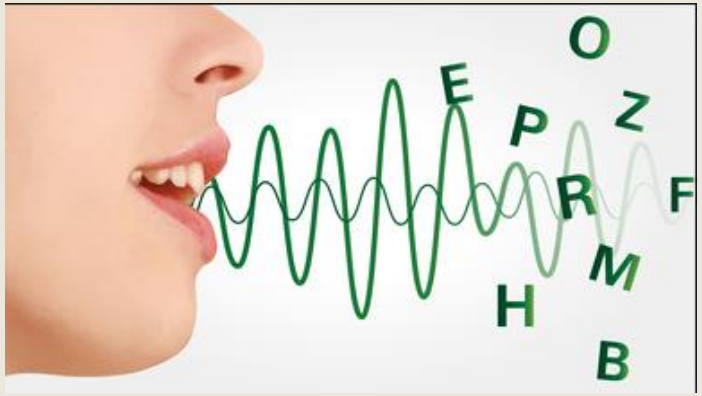
DATA SCIENCE APPLICATIONS

Data Science Applications

Current Trends

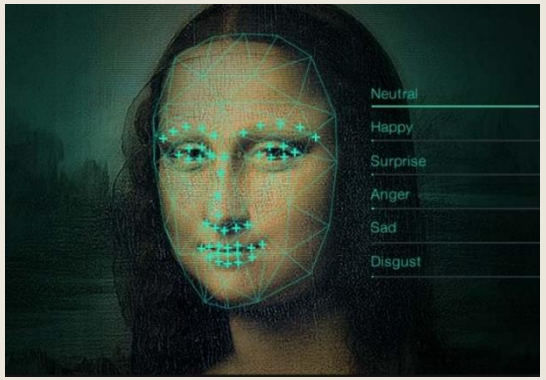


Recommender Systems

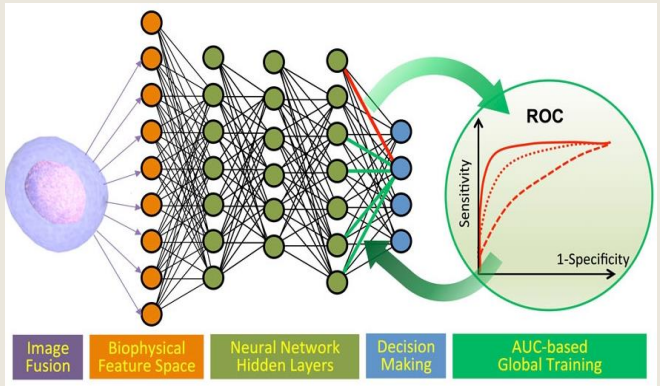


Speech recognition

Fraud detection



Facial identification/recognition



Health (detection of cancer)

Self Driving cars

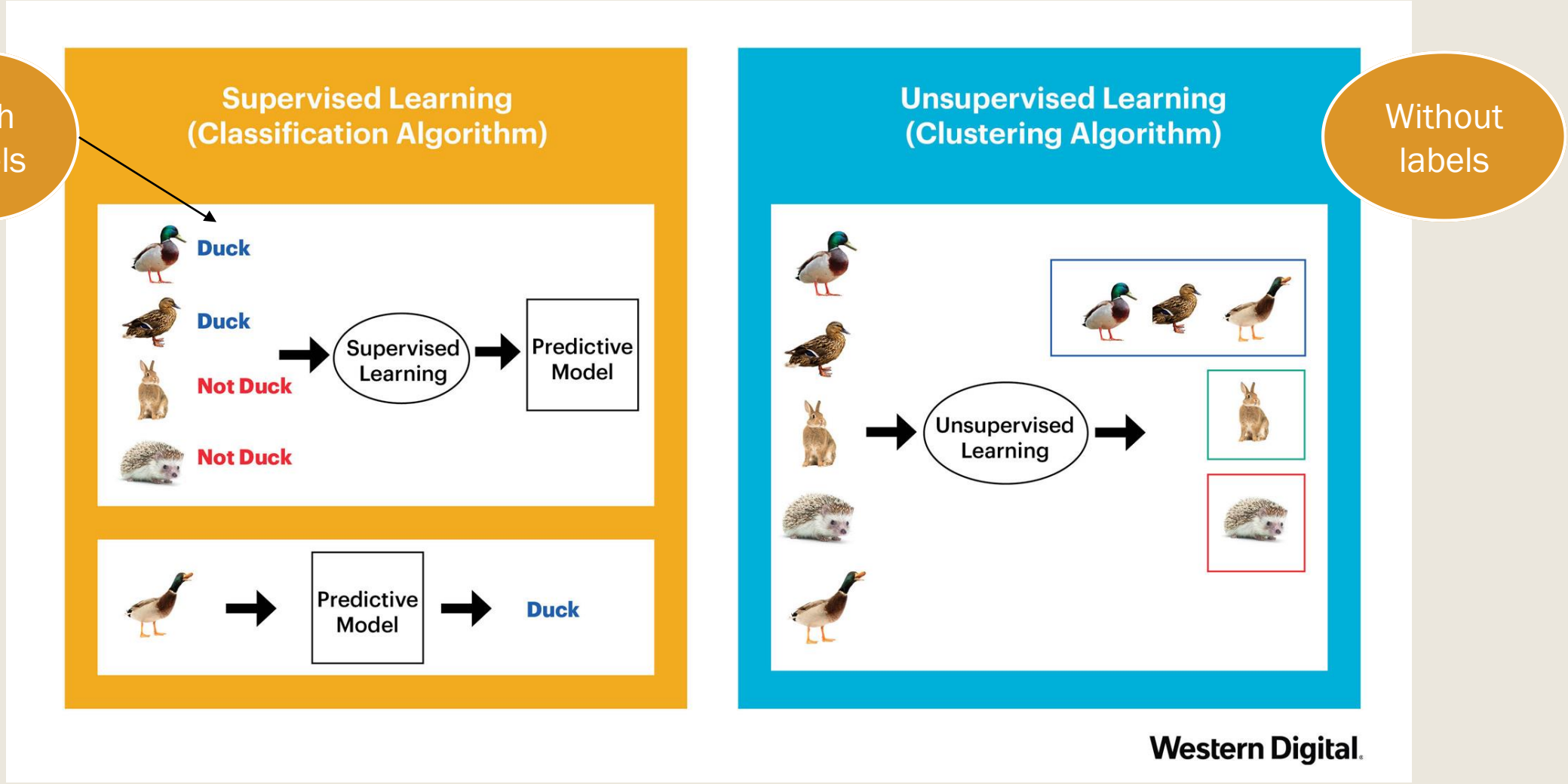
Smart houses

Data Science Applications

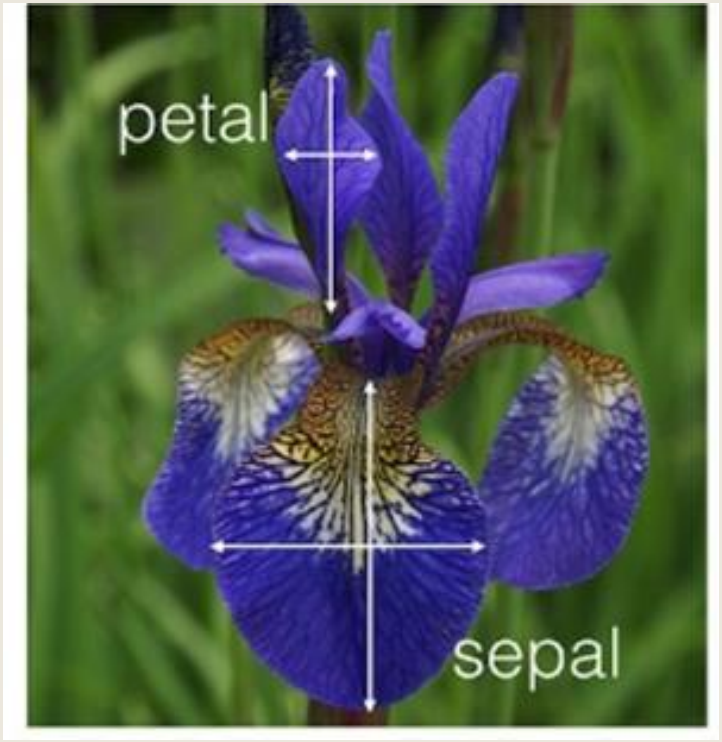
https://youtu.be/hRUvWdUZyF0

INTRO TO MACHINE LEARNING

Intro to Machine learning



Example: Iris flower



Features				Labels
Sepal length	Sepal width	Petal length	Petal width	Species
5.1	3.5	1.4	0.2	Iris setosa
4.9	3.0	1.4	0.2	Iris setosa
7.0	3.2	4.7	1.4	Iris versicolor
6.4	3.2	4.5	1.5	Iris versicolor
6.3	3.3	6.0	2.5	Iris virginica
5.8	3.3	6.0	2.5	Iris virginica

Unsupervised Learning

Definition
- You give the input data (X) and no corresponding output variables (labels).
Techniques
- Clustering: you want to discover the inherent groupings in the data. - Association: you want to discover rules that describe large portions of your data.

Features				Labels
Sepal length	Sepal width	Petal length	Petal width	Species
5.1	3.5	1.4	0.2	Iris setosa
4.9	3.0	1.4	0.2	Iris setosa
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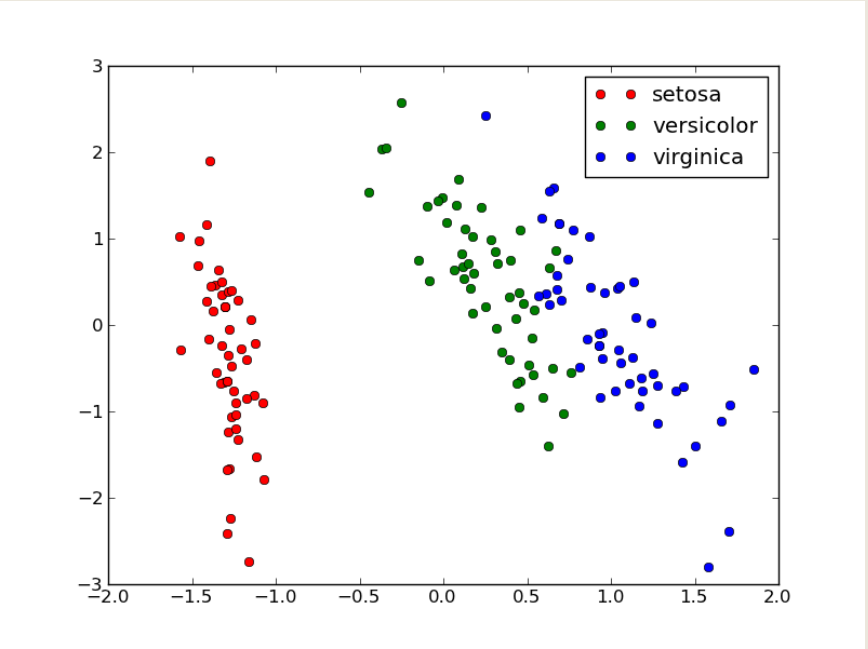

Supervised Learning

Definition
- You give the input data (X) and an output variable (Y) (labels), and you use an algorithm to learn the mapping function from the input to the output. Y = f(X)
Techniques
- Classification: you want to classify a new input value. - Regression: you want to get a function that fit really well the data so you can predict the future.

	Features			Labels
Sepal length	Sepal width	Petal length	Petal width	Species
5.1	3.5	1.4	0.2	Iris setosa
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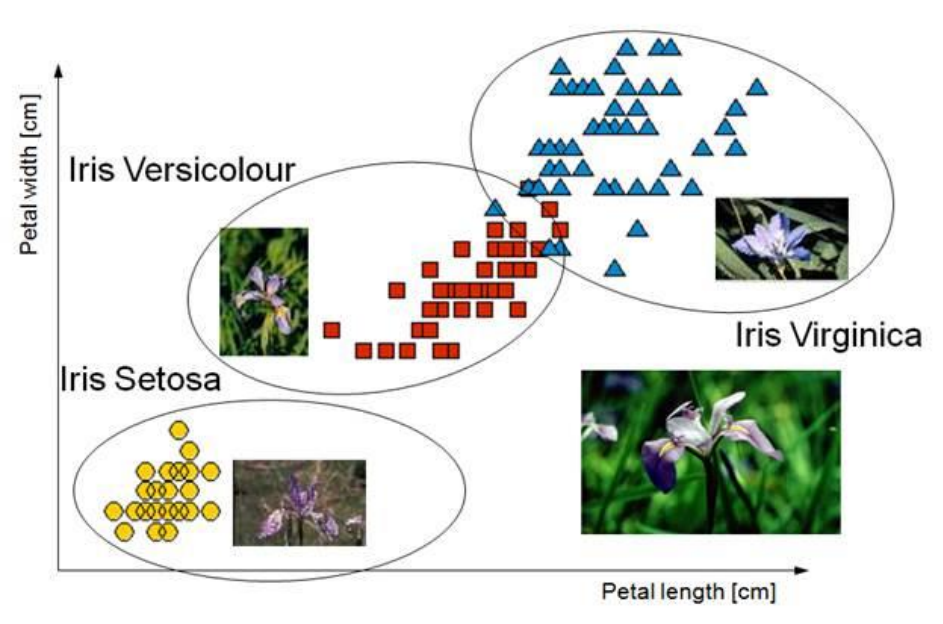


DATA SCIENCE LIFE CYCLE

Supervised learning example: Titanic survivor predictor

The titanic survivor predictor example will predict the probability of surviving in the Titanic based on data about passengers on the Titanic.

1. Let's explore the dataset

2. Let's follow the instructions together to get our predictions

Data Science cycle

Titanic Survivor Predictor

Data format

Delete empty and weird values

Deploy a web service that other people can use

Binary classifier (1: survived, 0: not survived)

How well is the ML model predicting? Confusion matrix

The ORIGINAL Dataset

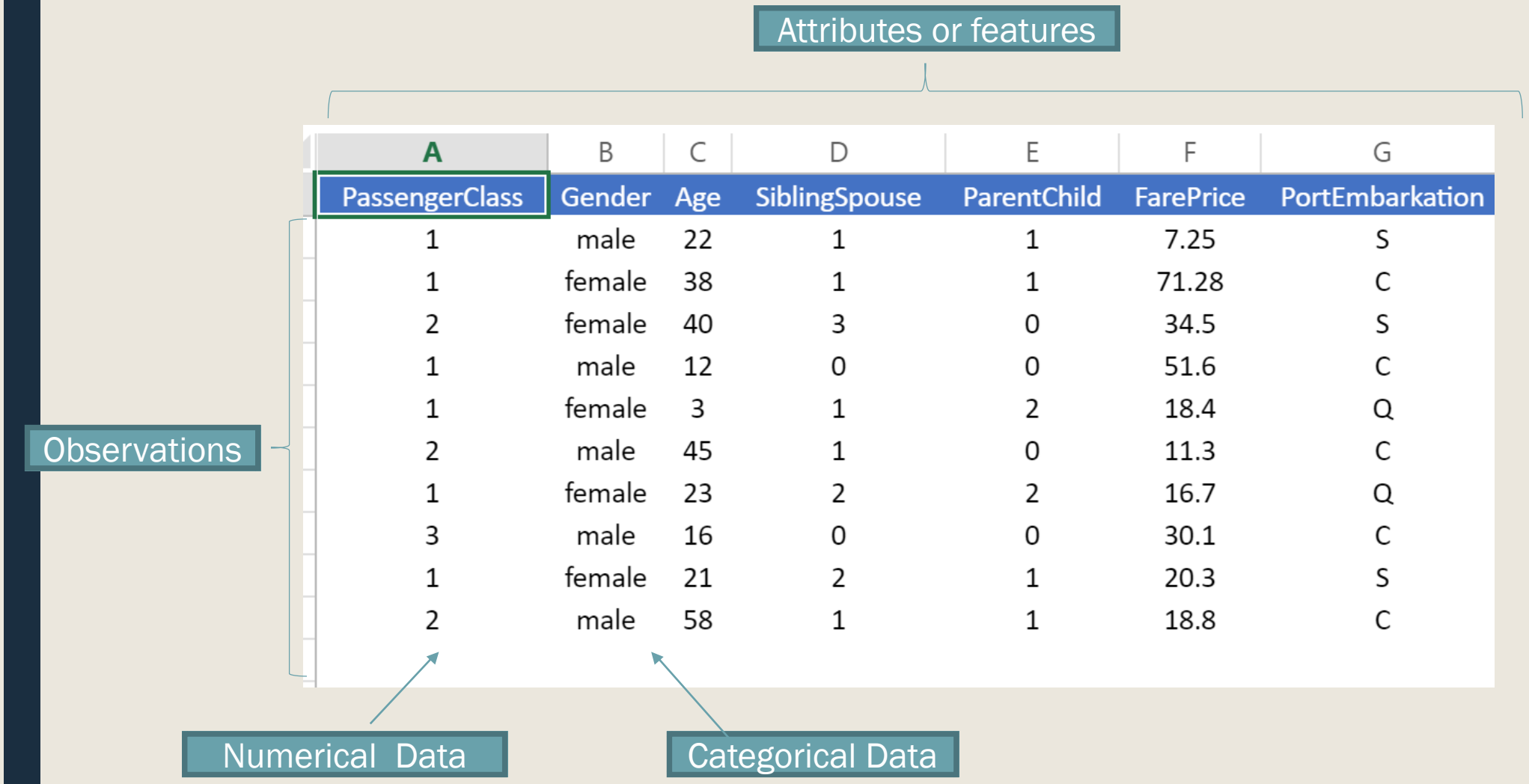
The original dataset usually has to be transformed in order to be used

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
37	37	1	3	Mamee, Mr. Hanna	male	NA	0	0	2677	7.2292		C
38	38	0	3	Cann, Mr. Ernest Charles	male	21.00	0	0	A./5. 2152	8.0500		S
39	39	0	3	Vander Planke, Miss. Augusta Maria	female	18.00	2	0	345764	18.0000		S
40	40	1	3	Nicola-Yarred, Miss. Jamila	female	14.00	1	0	2651	11.2417		C
41	41	0	3	Ahlin, Mrs. Johan (Johanna Persdotter Larsson)	female	40.00	1	0	7546	9.4750		S
42	42	0	2	Turpin, Mrs. William John Robert (Dorothy Ann Wonna...	female	27.00	1	0	11668	21.0000		S
43	43	0	3	Kraeff, Mr. Theodor	male	NA	0	0	349253	7.8958		C
44	44	1	2	Laroche, Miss. Simonne Marie Anne Andree	female	3.00	1	2	SC/Paris 2123	41.5792		C
45	45	1	3	Devaney, Miss. Margaret Delia	female	19.00	0	0	330958	7.8792		Q
46	46	0	3	Rogers, Mr. William John	male	NA	0	0	S.C./A.4. 23567	8.0500		S
47	47	0	3	Lennon, Mr. Denis	male	NA	1	0	370371	15.5000		Q
48	48	1	3	O'Driscoll, Miss. Bridget	female	NA	0	0	14311	7.7500		Q
49	49	0	3	Samaan, Mr. Youssef	male	NA	2	0	2662	21.6792		C
50	50	0	3	Arnold-Franchi, Mrs. Josef (Josefine Franchi)	female	18.00	1	0	349237	17.8000		S
51	51	0	3	Panula, Master. Juha Niilo	male	7.00	4	1	3101295	39.6875		S
52	52	0	3	Nosworthy, Mr. Richard Cater	male	21.00	0	0	A/4. 39886	7.8000		S
53	53	1	1	Harper, Mrs. Henry Sleeper (Myna Haxtun)	female	49.00	1	0	PC 17572	76.7292	D33	C

Data Dictionary

Variable Name	Description
Survived	Survived (1) or died (0)
Pclass	Passenger's class
Name	Passenger's name
Sex	Passenger's sex
Age	Passenger's age
SibSp	Number of siblings/spouses aboard
Parch	Number of parents/children aboard
Ticket	Ticket number
Fare	Fare
Cabin	Cabin
Embarked	Port of embarkation

Final dataset



A	B	C	D	E	F	G
PassengerClass	Gender	Age	SiblingSpouse	ParentChild	FarePrice	PortEmbarkation
1	male	22	1	1	7.25	S
1	female	38	1	1	71.28	C
2	female	40	3	0	34.5	S
1	male	12	0	0	51.6	C
1	female	3	1	2	18.4	Q
2	male	45	1	0	11.3	C
1	female	23	2	2	16.7	Q
3	male	16	0	0	30.1	C
1	female	21	2	1	20.3	S
2	male	58	1	1	18.8	C

Splitting the data for training and testing

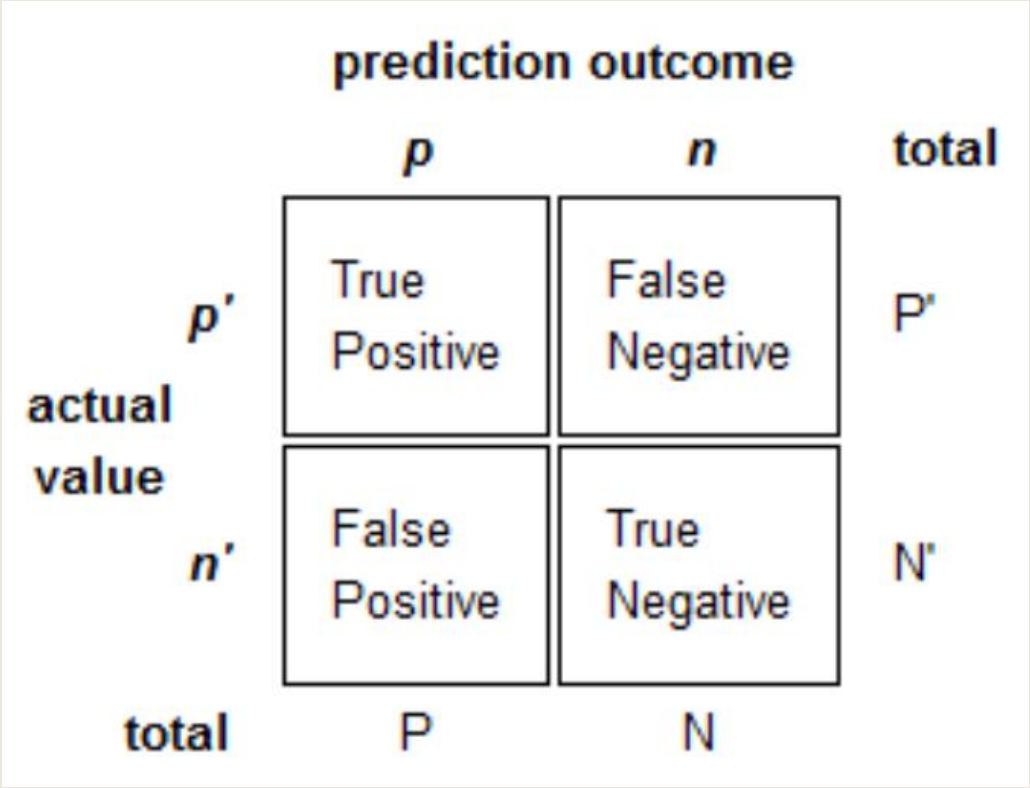
70%

Class	Sex	Age	SibSp	Parch	Fare	Embarked	FamilySize	Survived

30%

Class	Sex	Age	SibSp	Parch	Fare	Embarked	FamilySize

Model evaluation: the confusion matrix



n=165	Predicted: NO	Predicted: YES
Actual: NO	50	10
Actual: YES	5	100

AZURE ML STUDIO

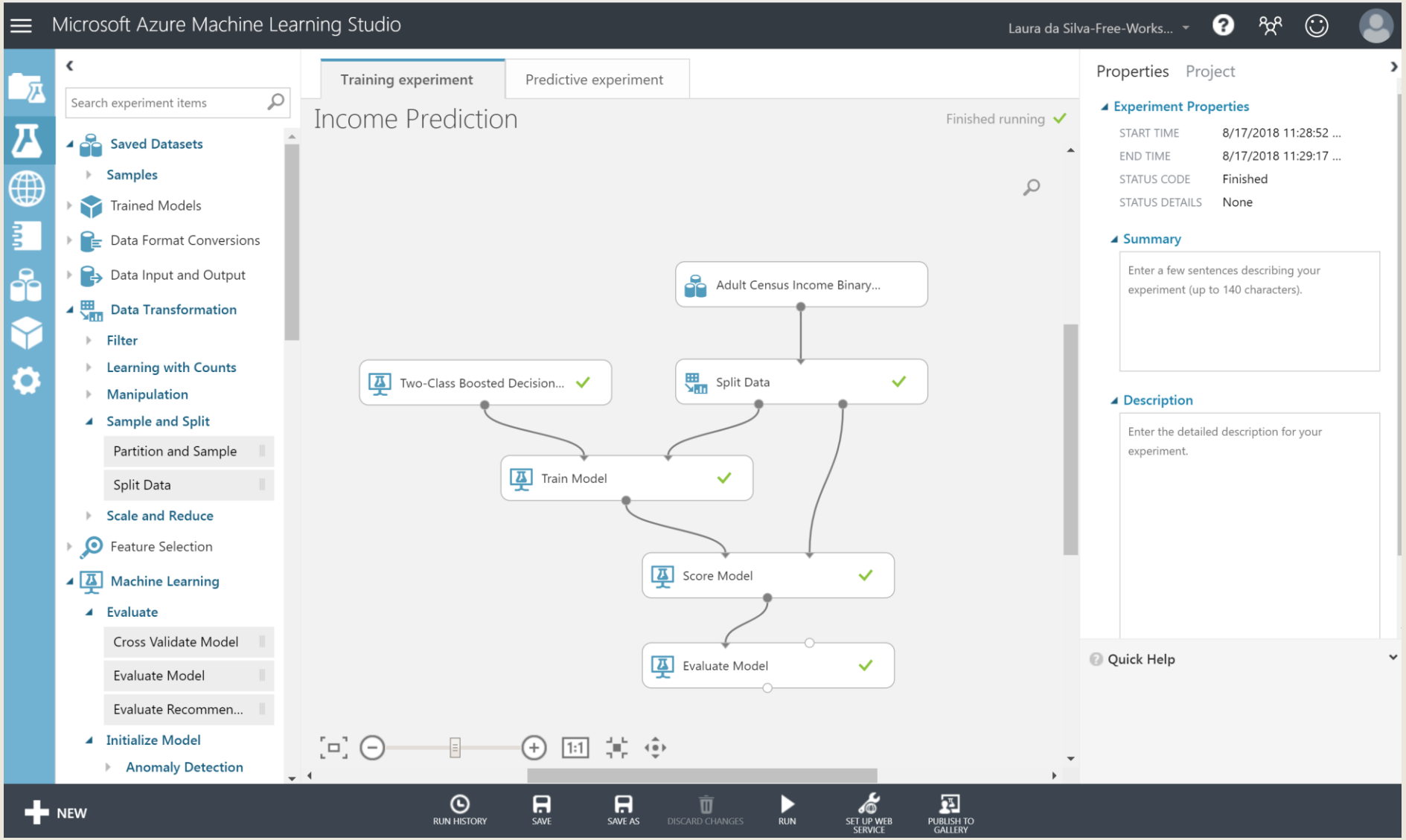
Create your first experiment in Azure Machine Learning Studio

Sign in Azure Machine Learning Studio: https://studio.azureml.net/

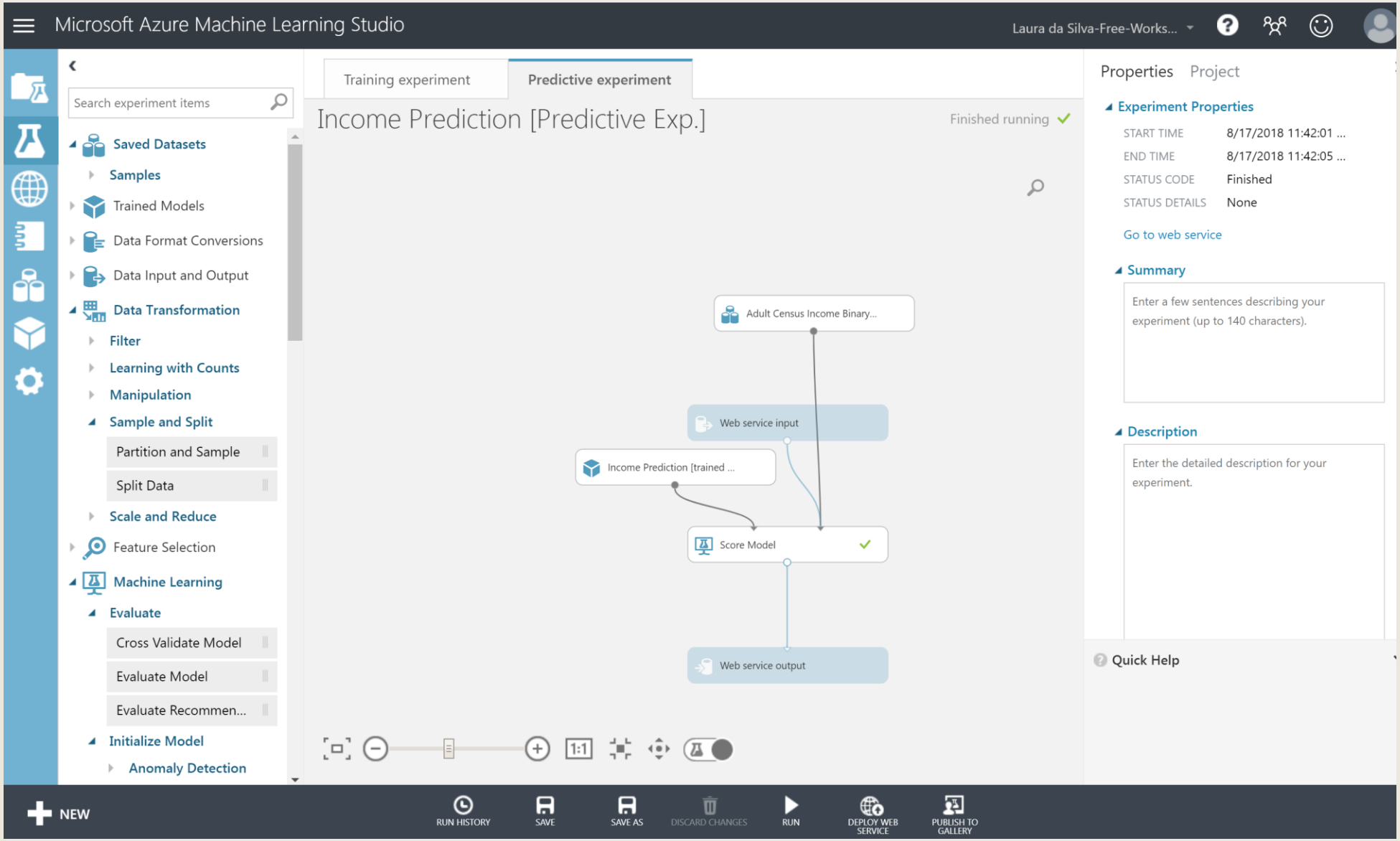
Let’s follow the tutorial of creating an experiment in Azure ML for Income prediction.

Details about the dataset can be found at:
https://archive.ics.uci.edu/ml/datasets/adult

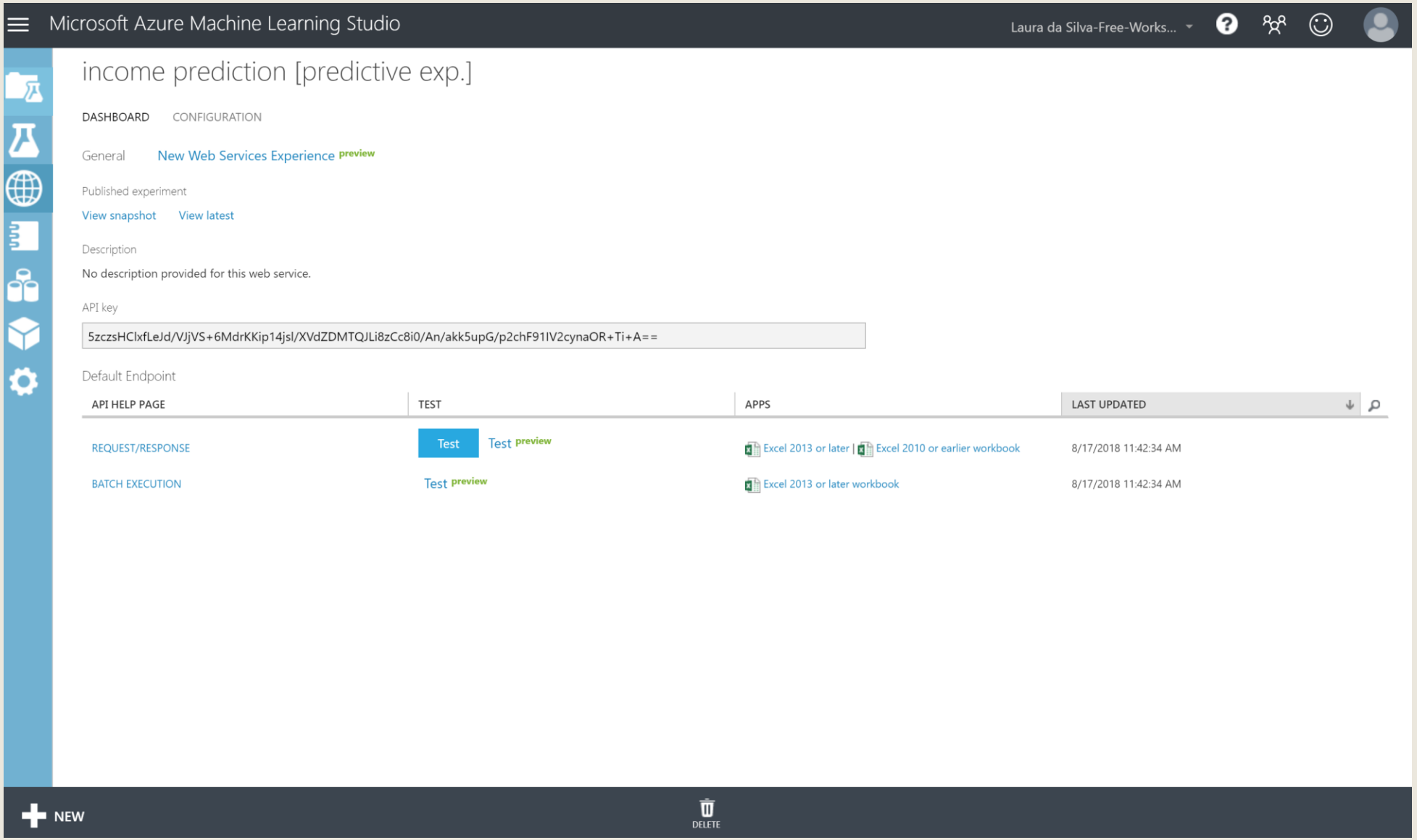
The training experiment



The predictive experiment



The web service details



Challenges

Looking at examples you will find in the Gallery (https://gallery.azure.ai/):

- Create the experiment for the Titanic survivor predictor.
- Create the experiment for Sentiment analysis using messages from Twitter.
- Create an experiment for movie recommendation.