



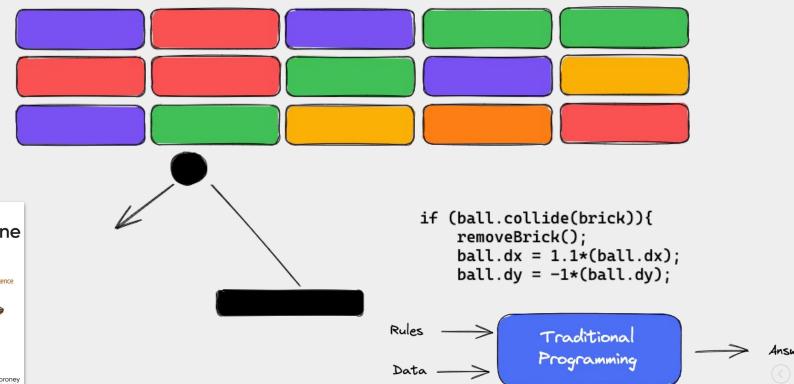
NE 4.0

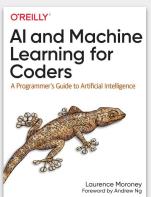
Aprendizado de Máquina

Fundamentos

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What is Machine Learning?





Limitations of traditional programming

<activity detection>









```
if (speed < 4){
    status = WALKING;
}</pre>
```

```
if (speed < 4){
    status = WALKING;
} else {
    status = RUNNING;
}</pre>
```

```
if (speed < 4){
    status = WALKING;
} else if (speed < 12) {
    status = RUNNING;
} else {
    status = BIKING;
}</pre>
```

// ????

```
Rules Traditional
Programming Answer
```



From coding to ML

<gathering and label data>











Label = WALKING

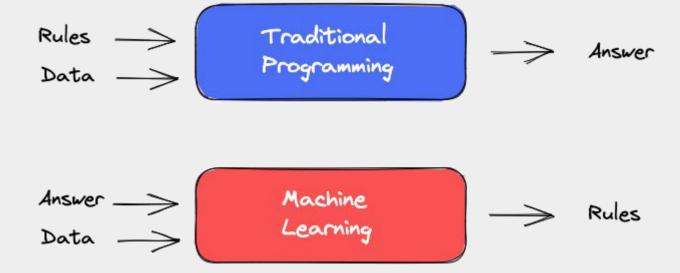
Label = RUNNING

Label = BIKING

Label = GOLFING



From programming to learning





What is Machine Learning?

Machine Learning (ML): a subset of AI that often uses statistical techniques to give machines the ability to "learn" from data without begging explicitly given the instructions for how to do so. This process is known as "training" a "model" using a learning "algorithm" that progressively improves models performance on a specific task.



Computer Vision



Semantic Segmentation

≥ 203 benchmarks 2300 papers with code



≥ 279 benchmarks

1989 papers with code

Image Classification

Detection ≥ 264 benchmarks

1737 papers with code

Object

Image Generation

№ 169 benchmarks

771 papers with code

Denoising

≥ 100 benchmarks 739 papers with code **Time Series**

∠ 2 benchmarks

1127 papers with code



Time Series



EEG

 8 benchmarks 177 papers with code

Imputation

10 benchmarks

10 benchmarks

11 benchmarks

12 benchmarks

13 benchmarks

14 benchmarks

15 benchmarks

16 benchmarks

16 benchmarks

17 benchmarks

18 benchmarks 160 papers with code

Natural Language Processing



27 benchmarks

1513 papers with code



₩ 73 benchmarks

1366 papers with code

Machine Translation

№ 103 benchmarks 1307 papers with code



 69 benchmarks 836 papers with code



Text Generation

№ 84 benchmarks 649 papers with code

Speech



Speech Recognition

121 benchmarks

121 benc 575 papers with code



Synthesis

 3 benchmarks 142 papers with code

Dialogue Generation

10 benchmarks

10 benchmarks

11 benchmarks

12 benchmarks

13 benchmarks

14 benchmarks

15 benchmarks

16 benchmarks

16 benchmarks

17 benchmarks

18 benchmarks 108 papers with code

Medical



Medical Image Segmentation

№ 86 benchmarks 244 papers with code



Drug Discovery

14 benchmarks

 6 benchmarks 104 papers with code

Lesion

Brain Tumor

10 benchmarks

69 papers with code

COVID-19 Diagnosis

4 benchmarks

4 benchmar 59 papers with code

Playing Games



Continuous Control

₩ 76 benchmarks 242 papers with code

60 papers with code



Atari Games

 65 benchmarks 213 papers with code OpenAl Gym

112 papers with code

9 benchmarks

Graphs



Link Prediction

 69 benchmarks 463 papers with code



370 papers with code

151 papers with code



Embedding

∠ 2 benchmarks 252 papers with code



Classification

 54 benchmarks 209 papers with code



Community Detection

11 benchmarks 156 papers with code

Music



Music Generation



55 papers with code

Music Information Retrieval



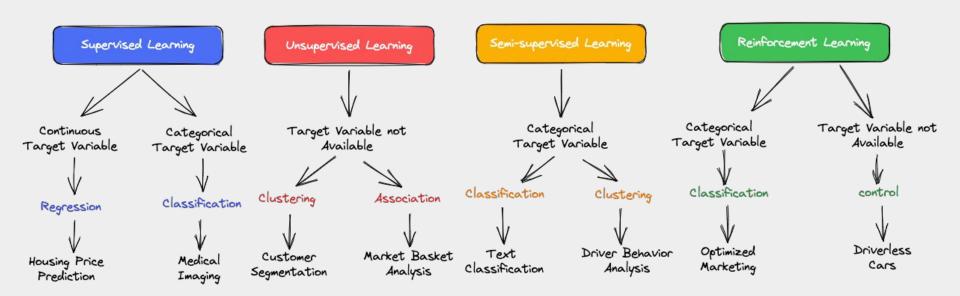
Music Source Separation

3 benchmarks

31 papers with code



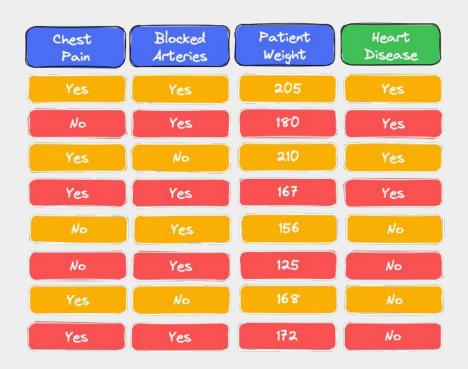
Machine Learning Types





Supervised Learning

Classification Problem







Supervised Learning

Regression Problem





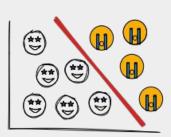




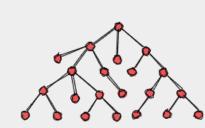




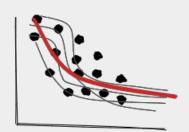
Support Vector Machines (SVM)



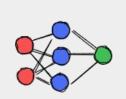
Decision Trees



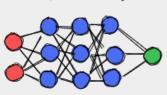
Ensemble



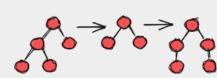
Neural Networks



Deep Learning



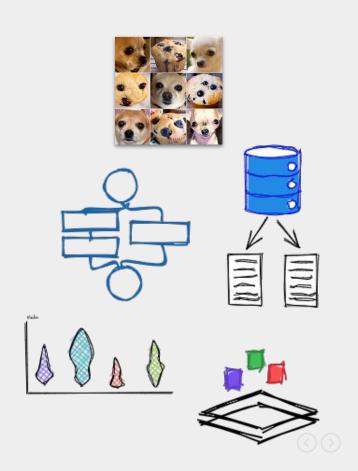
Bosting







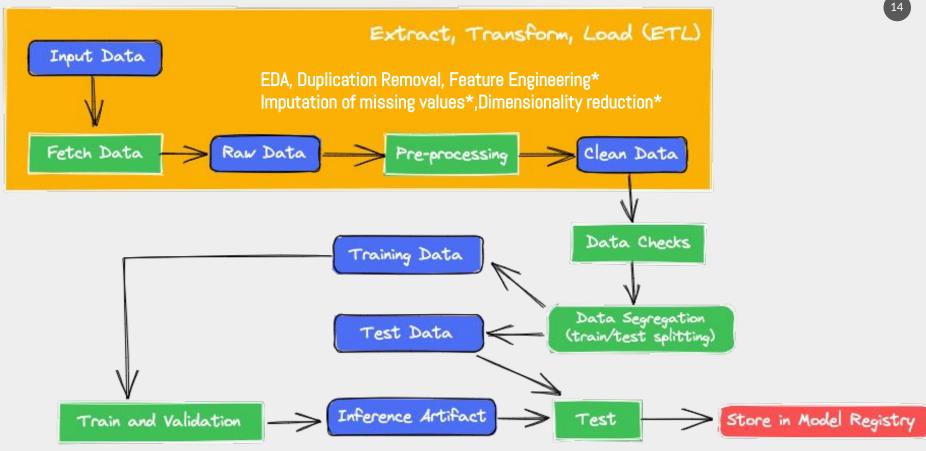
Main Challenges
Of Machine
Learning



Titanic: Machine Learning from Disaster

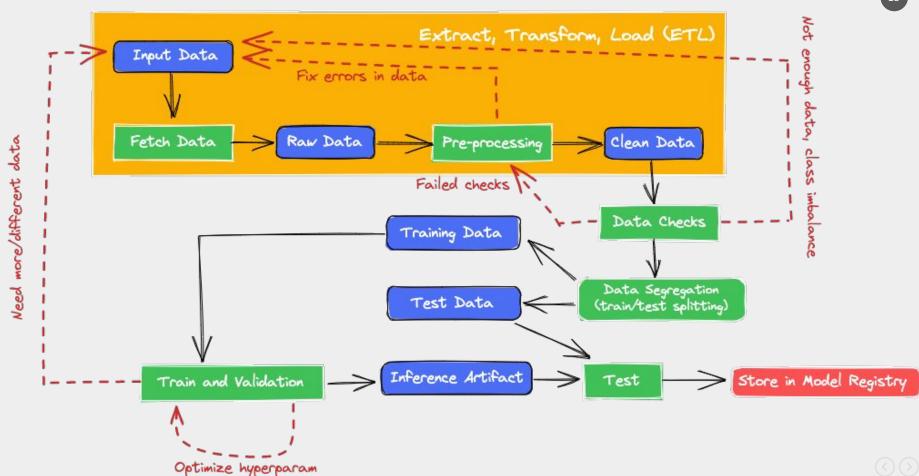
Survived	Pclass	Name	Sex	Age	Ticket	Cabin	Embarked
0	3	Braund, Mr. Owen	Male	22	A/5 21171	NaN	S
1	1	Cummings, Mrs John	Female	38	PC 17599	C85	С
1	3	Heikkinen, Ms Laina	Female	26	STON/02	NaN	S
1	1	Futrelle, Mrs Jacques	Female	35	113803	C123	S
0	3	Allen, Mr. William	Male	35	373450	NaN	S

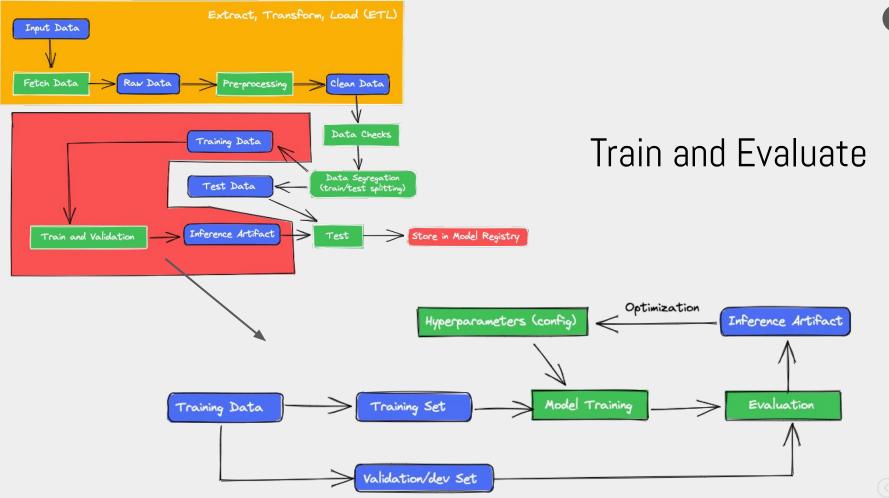




Feature Store, Categorical encoding missing values imputation, Dimensionality Reduction







Controlled Chaos



Assume you are going to iterate A LOT



Nothing is lost You learn something with every experiment



Give yourself time within the project deadlines





Perfection is the enemy of good

Be clear on your objective and stop once you reach it



Be systematic Normaly, change one thing at the time



Nothing is fixed data, code and hyperparameters





Train - Dev - Test Sets

Making good choices in how you set up your training, development, and test sets can make a huge difference in helping you quickly find a good high performance neural network.



Mismatched train/test distribution

Scenario: say you are building a cat-image classifier application that determines if an image is of a cat or not. The application is intended for users in rural areas who can take pictures of animals by their mobile devices for the application to classify the animals for them.



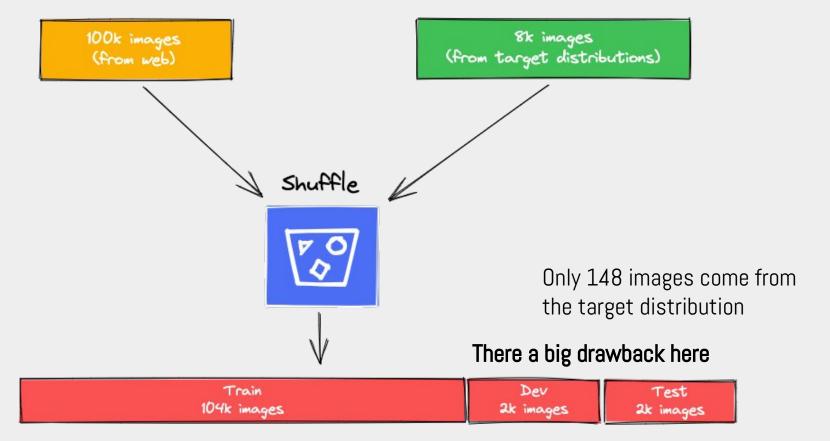
Scraped from Web Pages 100k images



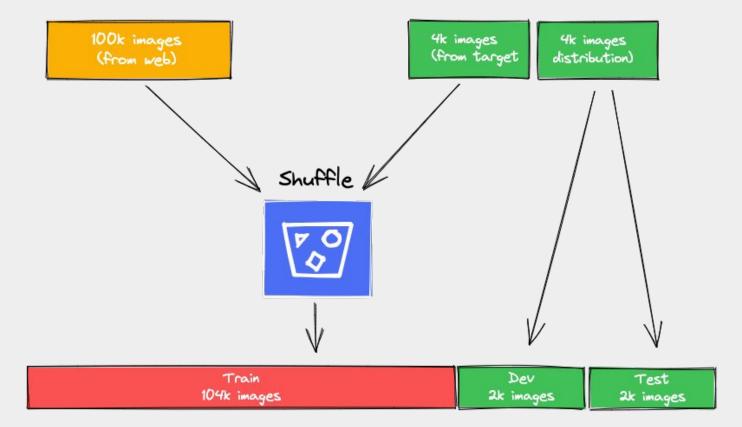
Collected from Mobile Devices <<target distribution>> 8k images



A possible option: shuffling the data



A better option





Rule of the thumb

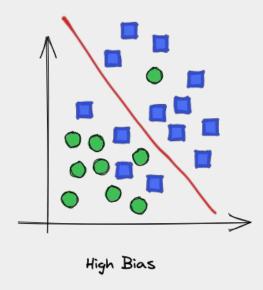
>> make sure that the dev and test sets come from the same distribution

Not having a test set might be okay. (Only dev set)

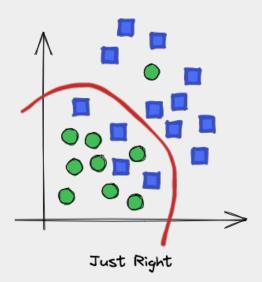




Bias vs Variance



Underfitting



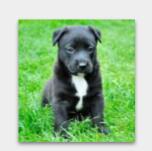
High Variance

Overfitting

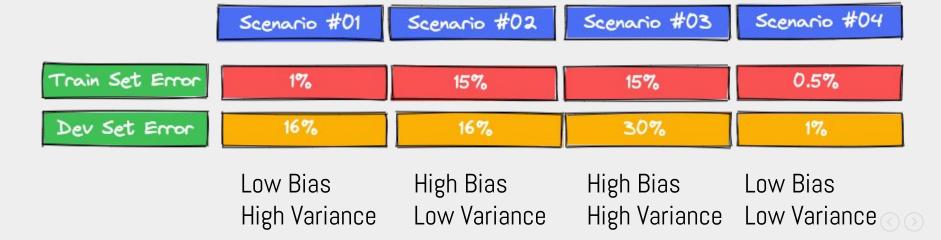


Bias vs Variance





Cat Classification



Basic Recipe for Machine Learning

