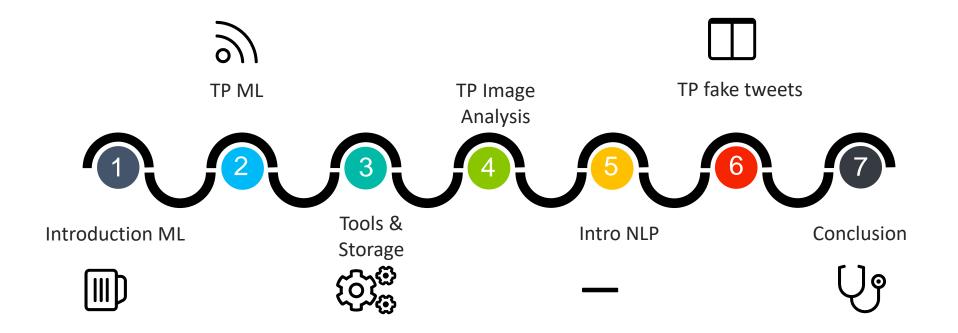
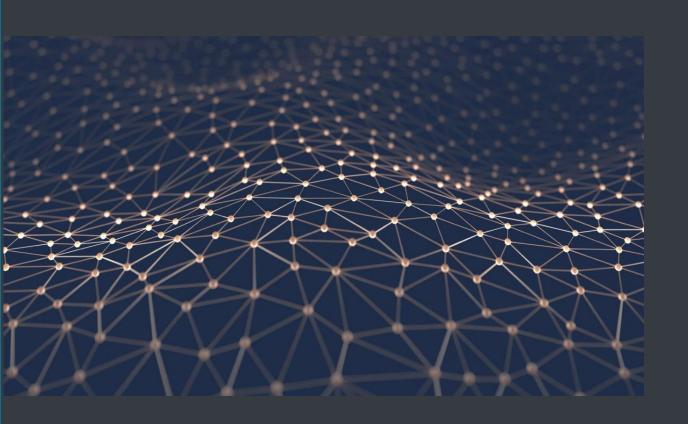
Introduction to IA With Python Mickael BOLNET – Python Instructor

Introduction to IA

Table of contents





Intro to Machine Learning

50s - Walter Pitts & Warren McCulloch

60s – Bayesian Methods

1969 - Marvin Minsky: non linearity &

conexity issue for perceptrons

80s – Multilayer perceptron (still not enough

power)

90s – SVM

2000s – Kernel Methods: SVC

2009 – ImageNet : The importance of DBs

2014 XGBoost

2017 Transformer Nets: « All you need is

Attention »

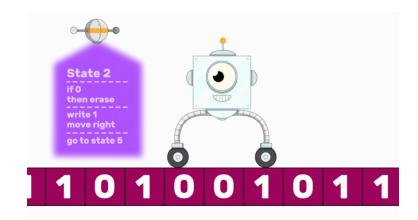
Introduction to Machine Learning



Introduction to Machine Learning



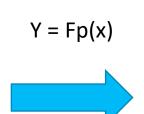


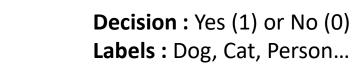


Algorithm

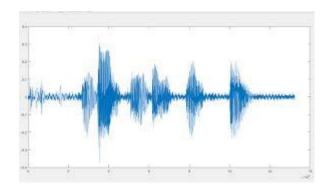








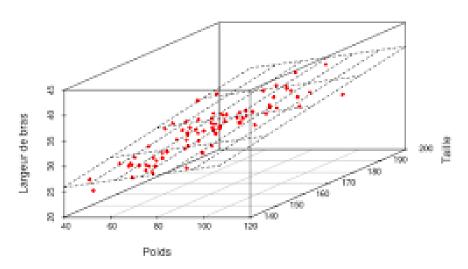
Product : Another Image



$$Y = F_{a,b}(X) = a * x_1 + b * x_2$$

$$avec X = \frac{x_1}{x_2}$$

Nuage de points en 3D



$$Y = F_{a,b}(X) = a * x_1 + b * x_2$$

$$avec X = \frac{x_1}{x_2}$$

Suite d'exemples :

$$(Y_1^*, X_1^*), (Y_2^*, X_2^*), (Y_3^*, X_3^*), (Y_4^*, X_4^*), (Y_5^*, X_5^*) \dots$$

$$Y = F_{a,b}(X) = a * x_1 + b * x_2$$
$$avec X = \frac{x_1}{x_2}$$

Suite d'exemples :

$$(Y_1^*, X_1^*), (Y_2^*, X_2^*), (Y_3^*, X_3^*), (Y_4^*, X_4^*), (Y_5^*, X_5^*) \dots$$

Erreurs:

$$Y_1^* - F_{a,b}(X_1)$$

 $Y_2^* - F_{a,b}(X_2)$

• • •

$$Y = F_{a,b}(X) = a * x_1 + b * x_2$$
$$avec X = \frac{x1}{x2}$$

Suite d'exemples :

$$(Y_1^*, X_1^*), (Y_2^*, X_2^*), (Y_3^*, X_3^*), (Y_4^*, X_4^*), (Y_5^*, X_5^*) \dots$$

Erreurs:

$$Y_1^* - F_{a,b}(X_1)$$

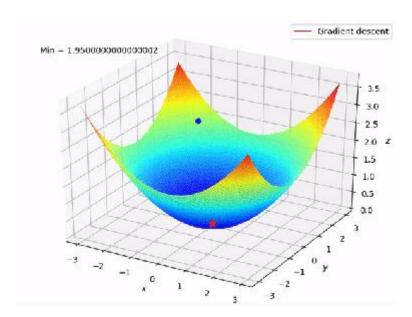
 $Y_2^* - F_{a,b}(X_2)$

Minimiser:

$$J(a,b) = \sum_{i} (E_i(a,b))^2$$

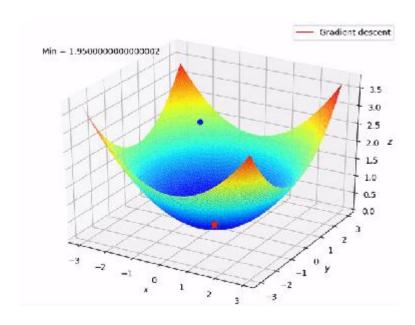
Fonction modèle simple -> Solution algébrique

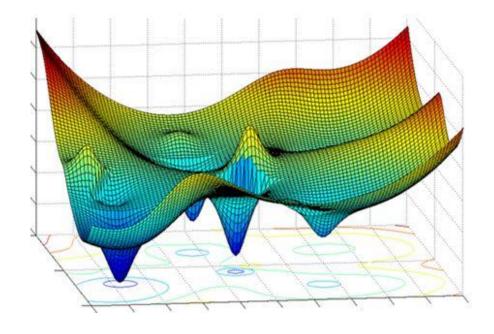
Fonction modèle complexe et prise en compte du bruit -> Autres algos : i.e. Descente de Gradient



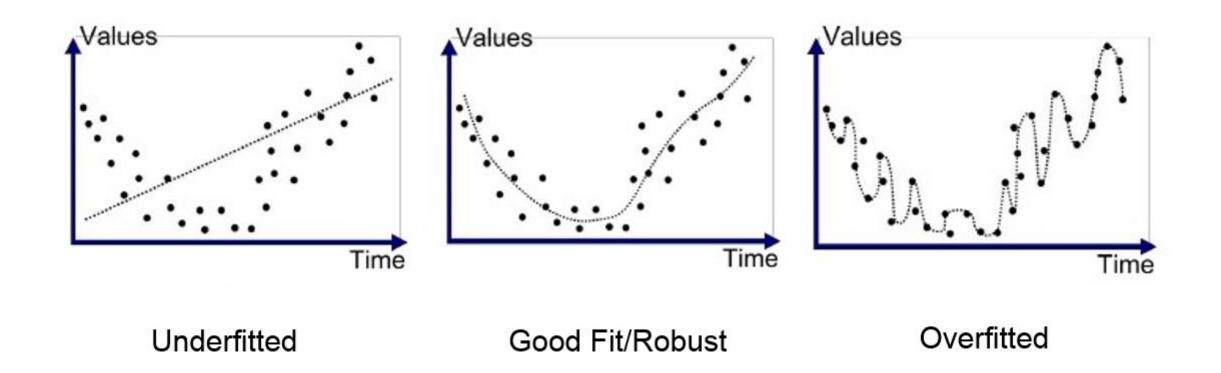
Fonction modèle simple -> Solution algébrique

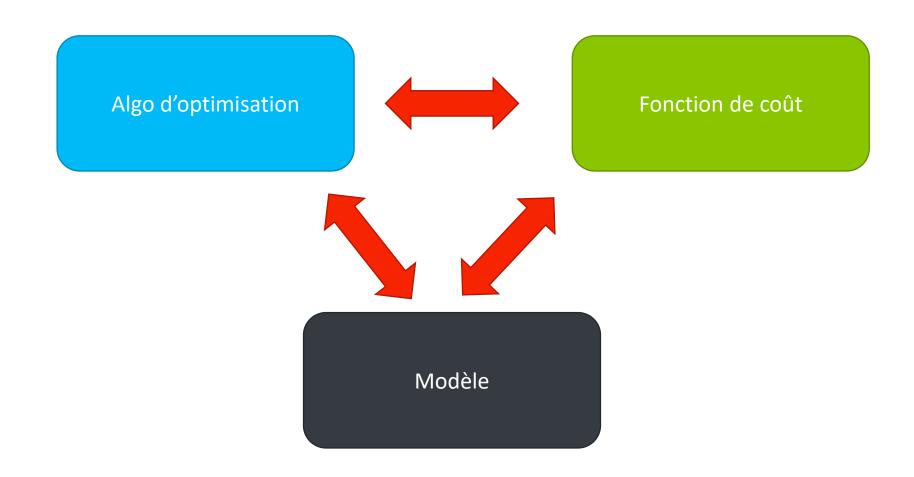
Fonction modèle complexe et prise en compte du bruit -> Autres algos : i.e. Descente de Gradient

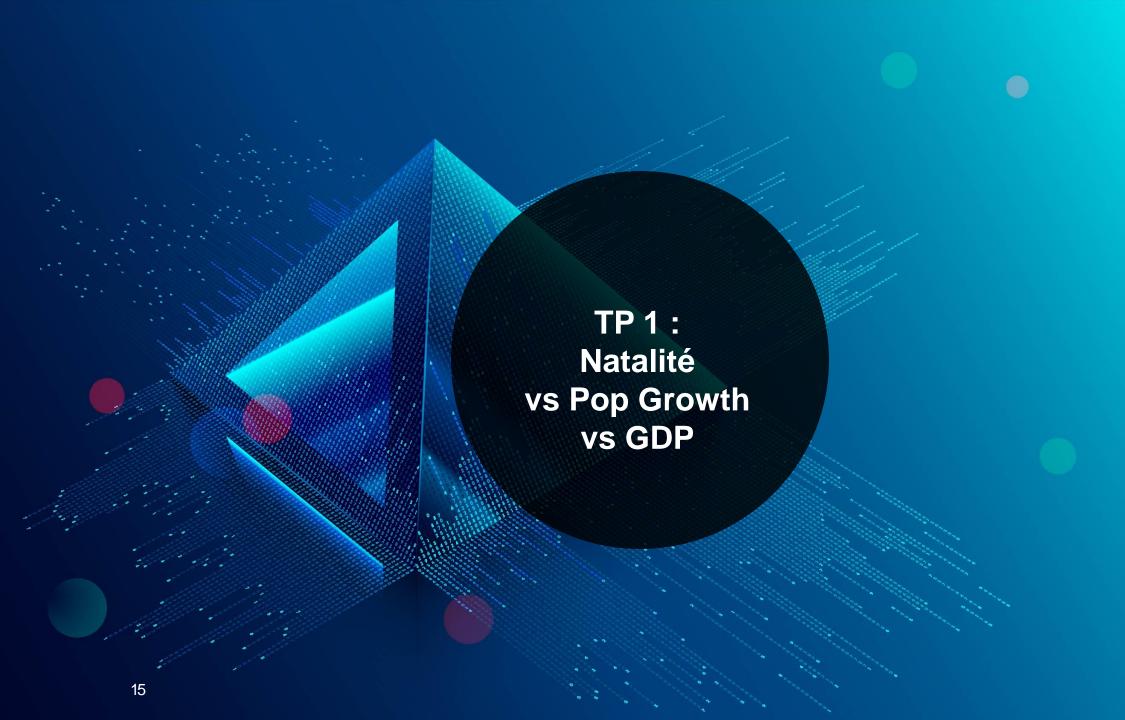




Problème du coût



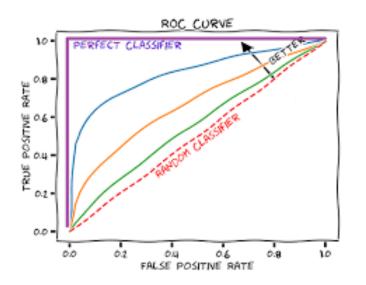


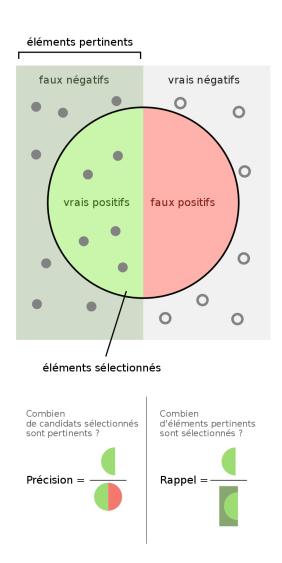


Basic Error measurement

(for classification)

- 1. Precision & Recall
- 2. ROC & AUC
- 3. Log loss





Basic Error measurement

(for regressions)

MAE =
$$\frac{1}{n} \sum_{j=1}^{n} |y_j - \hat{y}_j|$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{j=1}^{n} (y_j - \hat{y}_j)^2}$$

$$\hat{R}^2 = 1 - \frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2} = 1 - \frac{\frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{\frac{1}{n} \sum_{i=1}^n (Y_i - \bar{Y})^2}$$

$$R_{adj}^2 = 1 - \left[\frac{(1-R^2)(n-1)}{n-k-1} \right]$$

CASE 1: Evenly distributed errors

ID	Error	Error	Error^2
1	2	2	4
2	2	2	4
3	2	2	4
4	2	2	4
5	2	2	4
6	2	2	4
7	2	2	4
8	2	2	4
9	2	2	4
10	2	2	4

CASE 2: Small variance in errors

ID Error | Error | Error

ID	Error	Error	Error^2
1	1	1	1
2	1	1	1
3	1	1	1
4	1	1	1
5	1	1	1
6	3	3	9
7	3	3	9
8	3	3	9
9	3	3	9
10	3	3	9 ,

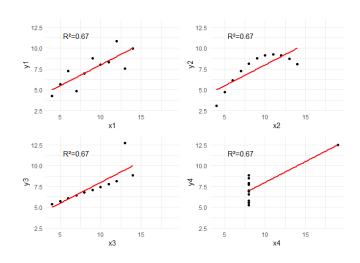
CASE 3	: Large	error	outlier
--------	---------	-------	---------

ID	Error	Error	Error^2
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
5	0	0	0
6	0	0	0
7	0	0	0
8	0	0	0
9	0	0	0
10	20	20	400

MAE	RMSE
2.000	2.000

MAE	RMSE
2.000	2.236

MAE	RMSE
2.000	6.325



BLEU (Bilingual Evaluation Understudy) (for NLP)

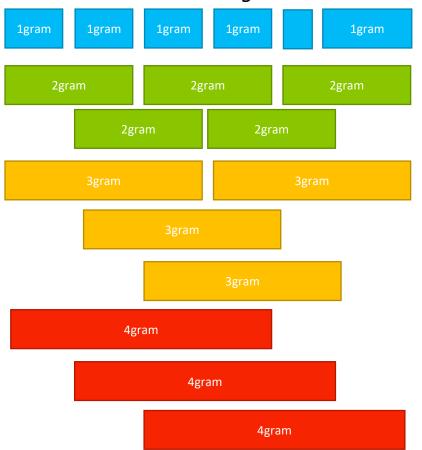
$$BLEU = BP * \exp\left(\sum w_n \log\left(P_n\right)\right)$$

$$BP = \begin{cases} 1 & c \ge r \\ \exp\left(1 - \frac{r}{c}\right) & c < r \end{cases}$$

Etapes:

1. Couper la phrase en n-grams de 1 à 4

Demain nous allons manger au restaurant



BLEU (Bilingual Evaluation Understudy)

(for NLP)

$$BLEU = BP * \exp\left(\sum w_n \log\left(P_n\right)\right)$$

$$BP = \begin{cases} 1 & c \ge r \\ \exp\left(1 - \frac{r}{c}\right) & c < r \end{cases}$$

Etapes:

- 1. Couper la phrase en n-grams de 1 à 4
- 2. Calculer la précision des n-grams (Pn)

Résultat attendu : *Demain nous allons manger au restaurant*

Résultat 1: Demain manger au aller restaurant nous. P1 = 1

Résultat 2: Nous allons diner au restaurant demain. P1 = 0.83

Résultat 1: P1 = 100%

Demain	Manger	au	Aller	Restaurant	nous
1	1	1	1	1	1

Résultat 2: P1 = 83%

Nous	allons	diner	au	Restaurant	demain
1	1	0	1	1	1

BLEU (Bilingual Evaluation Understudy)

(for NLP)

$$BLEU = BP * \exp\left(\sum w_n \log\left(P_n\right)\right)$$

$$BP = \begin{cases} 1 & c \ge r \\ \exp\left(1 - \frac{r}{c}\right) & c < r \end{cases}$$

Etapes:

- 1. Couper la phrase en n-grams
- 2. Calculer la précision des n-grams (Pn)

Résultat attendu : *Demain nous allons manger*

au restaurant

Résultat 1: *Demain manger au aller restaurant*

nous. P1 = 1; P2 = 0,20

Résultat 2: Nous allons diner au restaurant

demain. P1 = 0,83; P2=0,40

Résu	ltat	1:	P1	=	20%
11634	Itat				20/0

Demain manger	Manger au	Au aller	Aller restaurant	Restaurant nous
0	1	0	0	0

Résultat 2: P1 = 40%

Nous allons	Allons diner	Diner au	Au restaurant	Restaurant demain
1	0	0	1	0

BLEU (Bilingual Evaluation Understudy)

(for NLP)

$$BLEU = BP * \exp\left(\sum w_n \log\left(P_n\right)\right)$$

$$BP = \begin{cases} 1 & c \ge r \\ \exp\left(1 - \frac{r}{c}\right) & c < r \end{cases}$$

Etapes:

- 1. Couper la phrase en n-grams de 1 à 4
- 2. Calculer la précision des n-grams (Pn)
- 3. Calculer la moyenne pondérée des logPn
- 4. Exp. et Multiplier par la Brevity Penality

Résultat attendu : *Demain nous allons manger au restaurant*

Résultat 1: Demain manger au aller restaurant nous. P1 = 1; P2 = 0,20; BLEU = 0,84

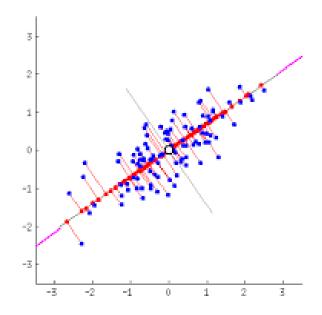
Résultat 2: Nous allons diner au restaurant demain. P1 = 0,83; P2=0,40; BLEU = 1,46



Dimensionality Reduction: PCA

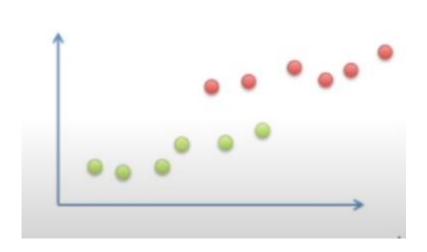
Diagonaliser la matrice de covariance pour sortir les directions principales

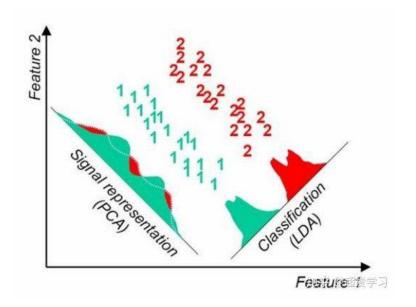
$$D = P^{-1}AP = \frac{1}{2} \begin{pmatrix} -1 & 1 & 0 \\ 1 & 1 & 2 \\ 1 & 1 & 0 \end{pmatrix} \begin{pmatrix} 0 & -1 & 0 \\ -1 & 0 & 0 \\ 1 & 1 & 1 \end{pmatrix} \begin{pmatrix} -1 & 0 & 1 \\ 1 & 0 & 1 \\ 0 & 1 & -1 \end{pmatrix}$$
$$= \frac{1}{2} \begin{pmatrix} -1 & 1 & 0 \\ 1 & 1 & 2 \\ 1 & 1 & 0 \end{pmatrix} \begin{pmatrix} -1 & 0 & 1 \\ 1 & 0 & 1 \\ 0 & 1 & -1 \end{pmatrix}$$
$$= \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & -1 \end{pmatrix}$$

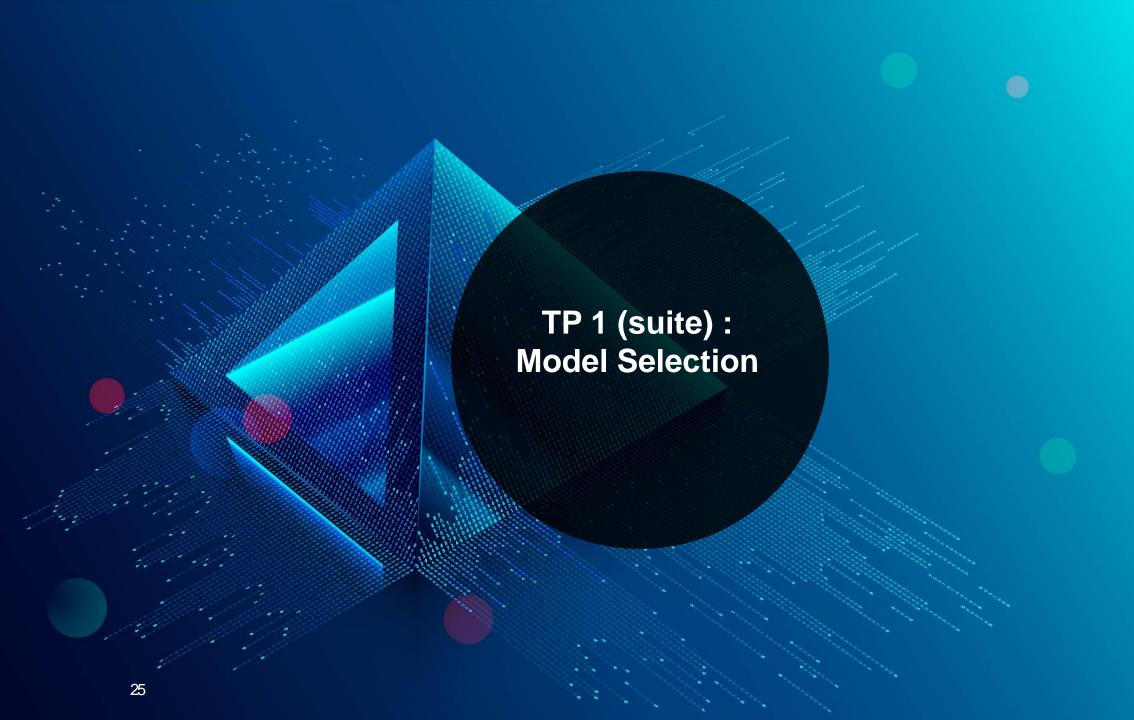


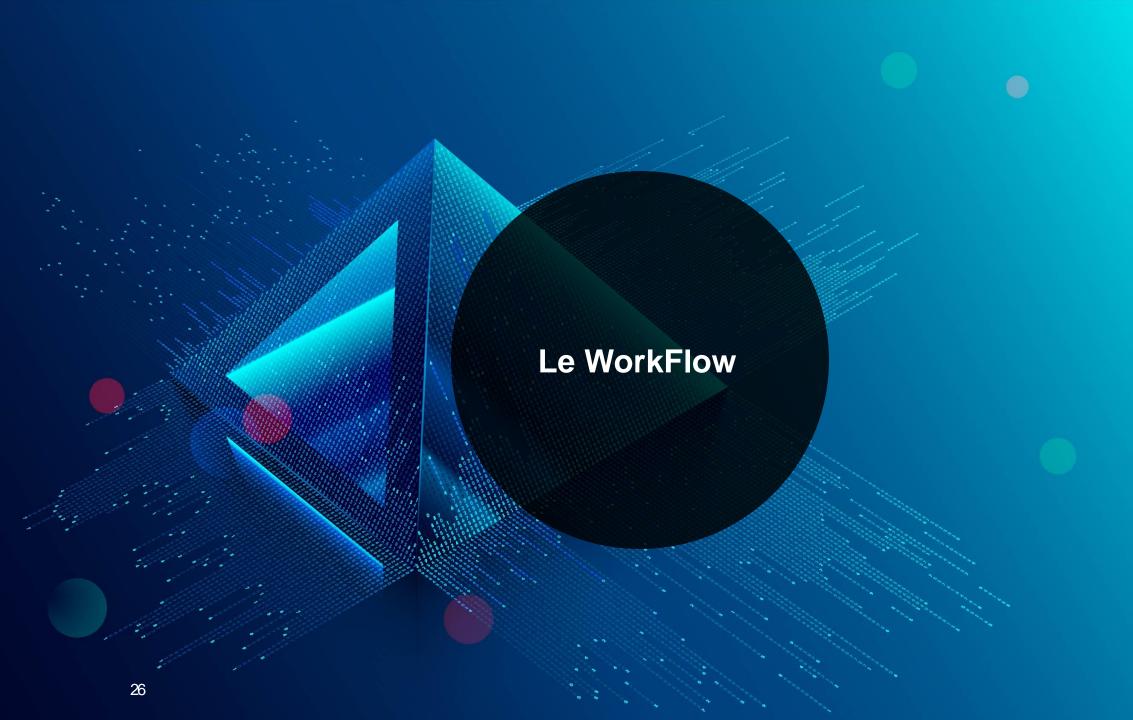
Dimensionality Reduction: LDA

Maximiser la distance entre les classes Minimiser la variance intra classe

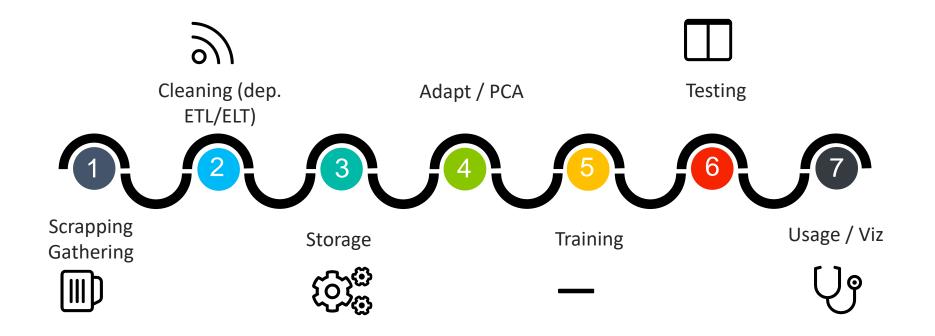








Workflow data



Famous Dataset

MNIST: dataset digit numbers

MS-COCO: object detection and segmentation

ImageNet : object classification

Open Image Dataset

IMDB
Sentiment140
WordNet

FreeSpoken Digit dataset LibriSpeech VoxCeleb

Kaggle Data.gouv

Cleaning / Feature Enginering

Cleaning avec Pandas

- Dropna
- Fillna
- Interpolate
- Custom map

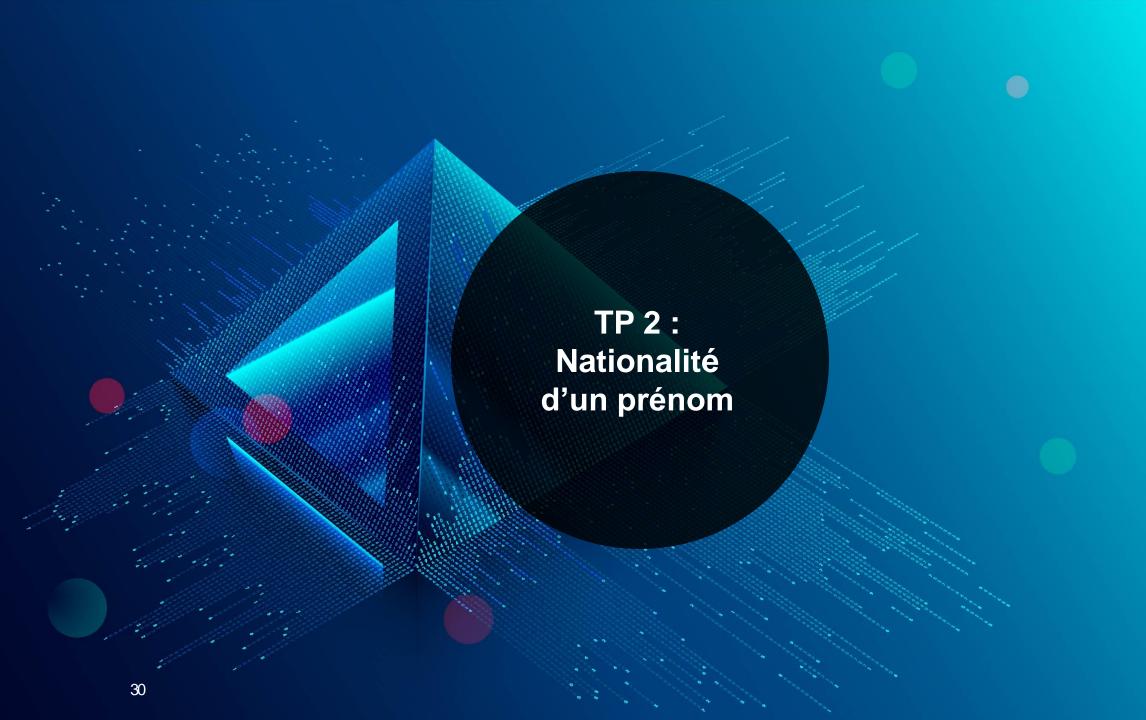
Labeliser avec Sklearn

LabelEncoders:

- OneHotEncoder (dummy spread)
- OrdinalEncoder (use order 1 dim)
- LabelEncoder (use for target)
- FeatureHasher
- Cyclic encoding
- KFold

Pre traitement

- Normalization: MinMaxScaler (and other Scalers)
- Outlier: **Seaborn boxplot**
- OpenCV equalization
- Signal : Noise Removal



TP : Storage

Amazon S3

PostGreSQL

Cassandra

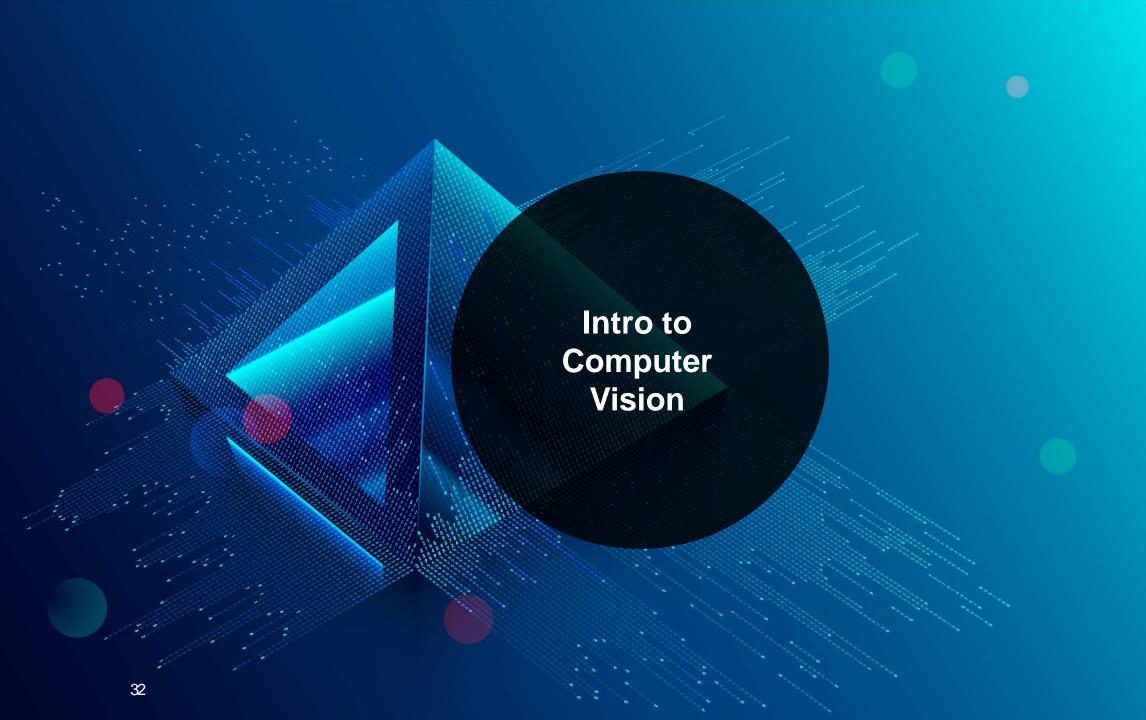


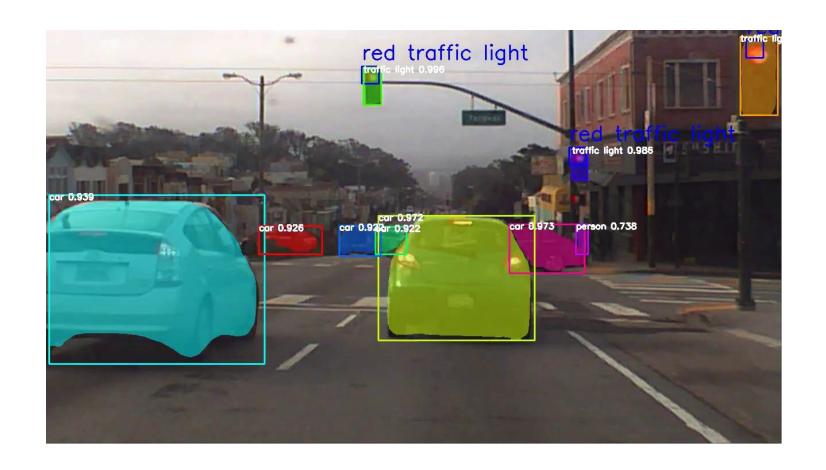
Image processing: OpenCV

Cleaning

Histogram equalization
Image linear filtering
Morphology (non linear filtering)
Calibration
Color quantization (kmean)

Feature extraction

Spectral Analysis
Edge detection
Segmentation
SIFT, ORB, KAZE, SURF
Optical flow
Object detection/tracking



Keras: Intro to deeplearning

Keras: Intro to deeplearning

Loading data with Keras

```
import numpy as np
import tensorflow as tf
from tensorflow import keras

# Create a dataset.
dataset = keras.preprocessing.image_dataset_from_directory(
    'path/to/main_directory', batch_size=64, image_size=(200, 200))
```

Keras: Intro to deeplearning

Preprocessing with Keras

```
from tensorflow.keras.layers.experimental.preprocessing import CenterCrop
from tensorflow.keras.layers.experimental.preprocessing import Rescaling

# Example image data, with values in the [0, 255] range
training_data = np.random.randint(0, 256, size=(64, 200, 200, 3)).astype("float32")

cropper = CenterCrop(height=150, width=150)
scaler = Rescaling(scale=1.0 / 255)

output_data = scaler(cropper(training_data))
print("shape:", output_data.shape)
print("min:", np.min(output_data))
print("max:", np.max(output_data))
```

Keras: Intro to deeplearning

A Keras Model is made of Layers packed together

```
from keras.models import Sequential

model = Sequential()
input_layer = Dense(32, input_shape=(8,)) model.add(input_layer)
hidden_layer = Dense(64, activation='relu'); model.add(hidden_layer)
output_layer = Dense(8)
model.add(output_layer)
```

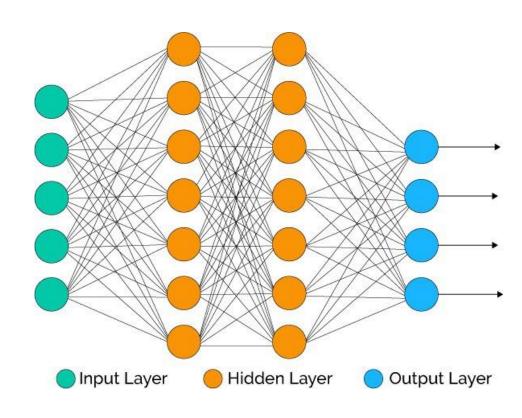
Connected sequencially

```
from keras.layers import Input
from keras.layers import Dense
from keras.models import Model

data = Input(shape=(2,3))
layer = Dense(2)(data)
model = Model(inputs = data, outputs = layer)

8
```

Connected with functionnal API



Keras: Intro to deeplearning

Chaque neuronne combine ses entrées pour fournir une sortie par sa fonction d'activation

Activation Functions

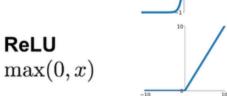
Sigmoid

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

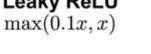
tanh

ReLU

tanh(x)

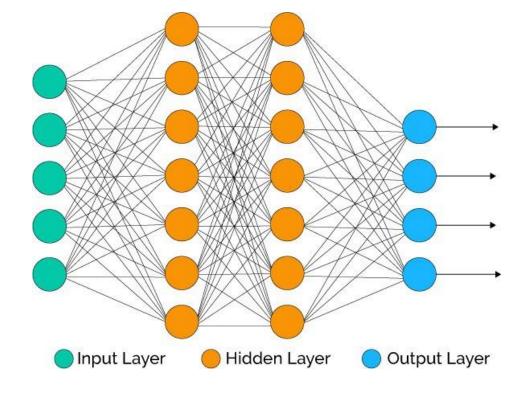


Leaky ReLU



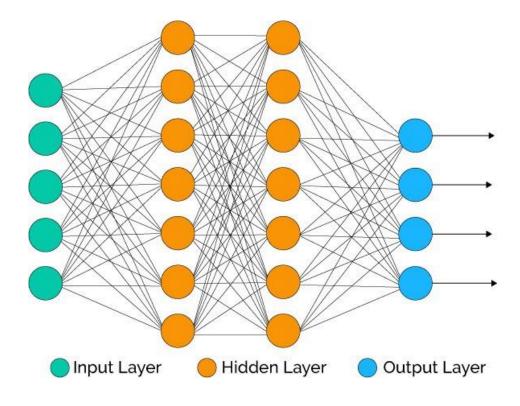
$$\begin{aligned} & \textbf{Maxout} \\ & \max(w_1^T x + b_1, w_2^T x + b_2) \end{aligned}$$

$$\begin{cases} x & x \ge 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



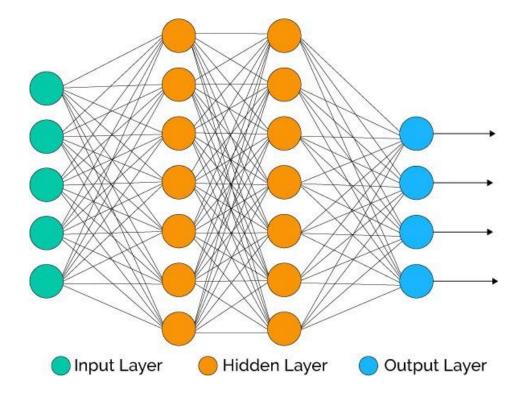
Input Layer

```
tf.keras.Input(
    shape=None,
    batch_size=None,
    name=None,
    dtype=None,
    sparse=False,
    tensor=None,
    ragged=False,
    **kwargs
)
```



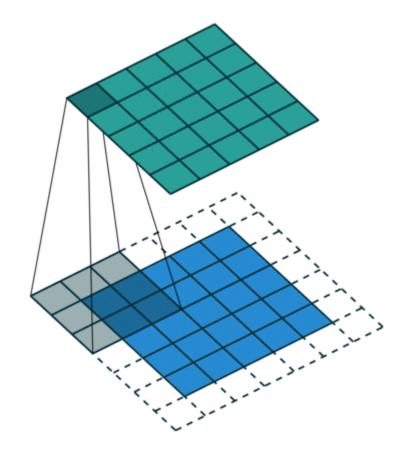
Dense Layer

```
tf.keras.layers.Dense(
    units,
    activation=None,
    use_bias=True,
    kernel_initializer="glorot_uniform",
    bias_initializer="zeros",
    kernel_regularizer=None,
    bias_regularizer=None,
    activity_regularizer=None,
    kernel_constraint=None,
    bias_constraint=None,
    **kwargs
)
```



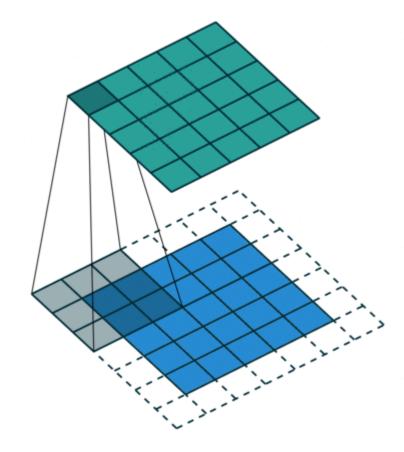
Conv2D Layer

```
tf keras layers Conv2D(
    filters,
    kernel_size,
   strides=(1, 1),
   padding="valid",
   data_format=None,
    dilation_rate=(1, 1),
    activation=None,
   use_bias=True,
    kernel_initializer="glorot_uniform",
   bias_initializer="zeros",
    kernel_regularizer=None,
   bias_regularizer=None,
    activity_regularizer=None,
    kernel_constraint=None,
    bias_constraint=None,
    **kwargs
```



MaxPooling Layer

```
tf.keras.layers.MaxPooling2D(
    pool_size=(2, 2), strides=None, padding="valid", data_format=None, **kwargs
)
```



Loss functions

Regression:

Mean_squared_error
MSLE
MAE

Binary classification:

Cross_entropy

Hinge loss

Squared hinge loss

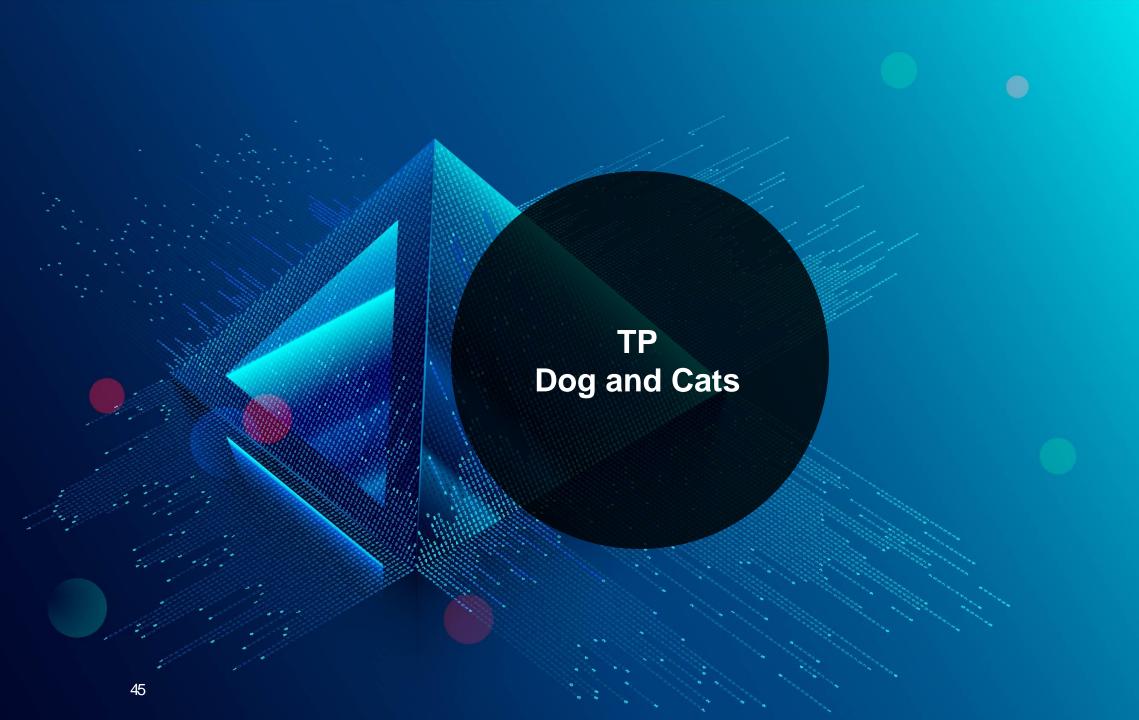
multi classification:
Cross_entropy
Sparse cross entropy
KL Divergence

Optimizer

SGD

RMSProp

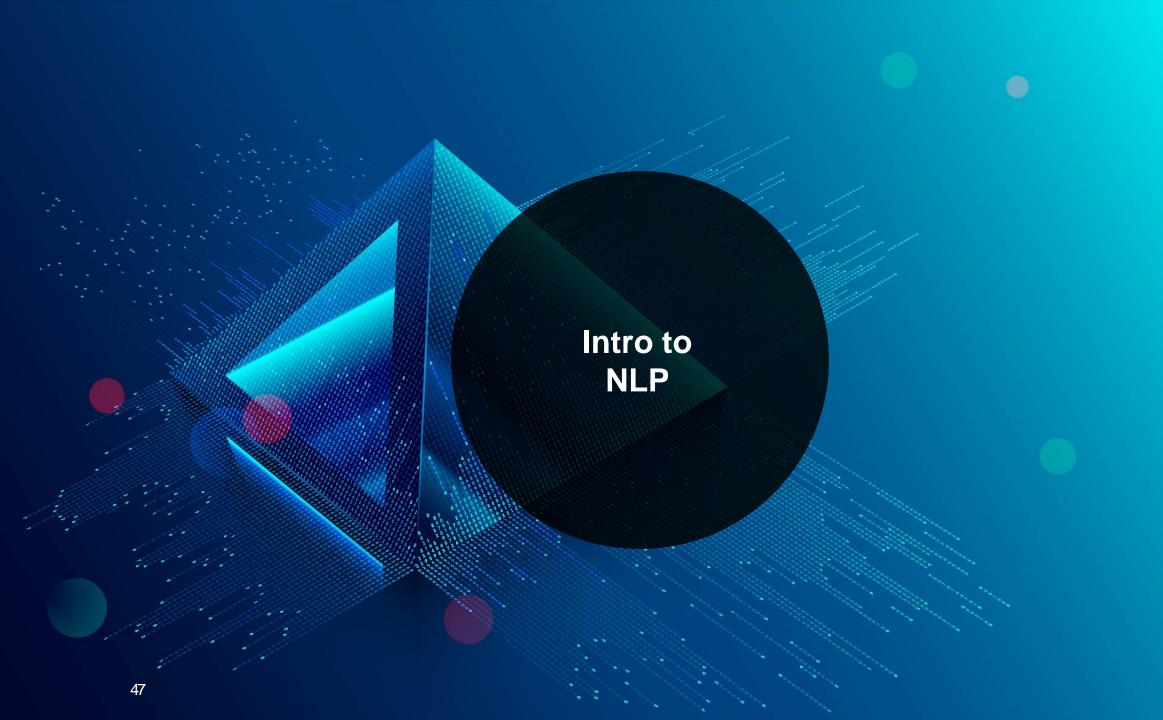
ADAM



Create your service

AWS Lambda

FLask



Intro to NLP

Pre processing classique:

Lemnatisation

Stemming

Stopwords

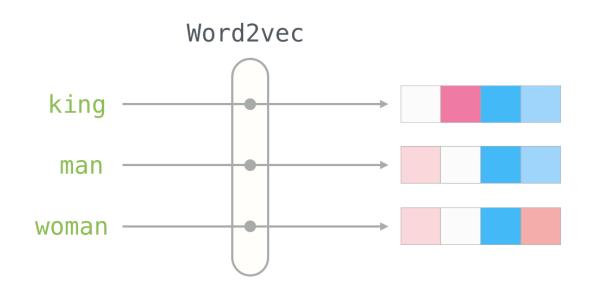
Vectorization

Pre processing NN:

GloVe

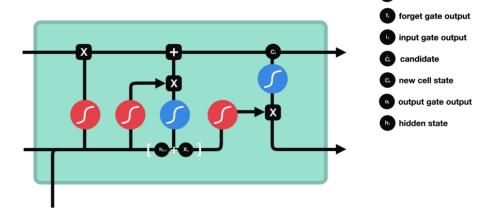
BERT

GPT-2



LSTM Layer

```
tf keras layers LSTM(
   units,
   activation="tanh",
   recurrent_activation="sigmoid",
    use_bias=True,
   kernel_initializer="glorot_uniform",
   recurrent_initializer="orthogonal",
   bias_initializer="zeros",
    unit_forget_bias=True,
   kernel_regularizer=None,
   recurrent_regularizer=None,
    bias_regularizer=None,
    activity_regularizer=None,
    kernel constraint=None,
    recurrent_constraint=None,
    bias_constraint=None,
    dropout=0.0,
    recurrent_dropout=0.0,
    implementation=2,
    return_sequences=False,
    return state=False,
    go_backwards=False,
    stateful=False,
   time_major=False,
   unroll=False,
    **kwargs
```



Cы previous cell state

Transformer Networks

Attention is all you need

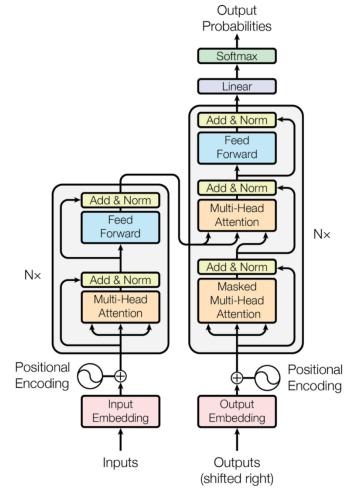


Figure 1: The Transformer - model architecture.

