



Unsupervised Learning: Word embedding(2)



Parcours Progis

Etudes, Medias, communication, Marketing

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Réduction dimensionnelle

La réduction de la dimension est un processus qui consiste à prendre des données dans un espace de grande dimension et à les remplacer par des données dans un espace de plus petite dimension

Dimension Reduction identifies the combination of attributes (principal components, or directions in the feature space) that account for the most variance in the data.

Réduction dimensionnelle

- We can say some of the features tell us the same information as other features.
- In this case we do not need all features. Maybe we need a little bit of one feature and a little bit of others.
- Or we can say that is a combination of these features that captures the information.
- Linear methods:
 - Principal Component Analysis (PCA)
 - Singular Value Decomposition (SVD)
- Non-Linear Methods
 - T-SNE

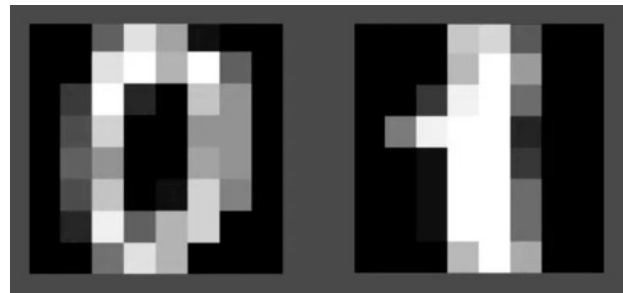
PCA (Principal Component Analysis)

- With PCA we figure out, if we have a bunch of features, how many component in the space do we need to explain the data.
- We are not deciding which feature to keep and drop, but we are **creating** new features that it is kind of a little bit of multiple features.
- Covariance matrix : when one variable changes how much does the other variable change
- Eigenvalue decomposition: what direction is the change
- The principal component are those with the largest eigenvalues

PCA is a process of figuring out the most important features, or principal components, that have the most impact on the target variable.

PCA

- Think that each pixel is one feature.
- Some of the pixels do not play any role at all in finding what digit it is.



- For example, these pixels, no matter what number we have, they are always black.



<https://www.youtube.com/watch?v=8klqIM9UvAc>

PCA

What if we eliminate features that aren't essential?

- Faster training and inference
- Data visualization gets simpler.

Visualization helps us. Regarding the final decision-making process.

PCA

Before using PCA, there are a few things to consider.

- Scale features before applying PCA.
- Accuracy might drop (imagine 100D to 2D; we lose lots of information).
- We should split our data if we have a label column.

PCA in Python

```
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA

pca = PCA(n_components=2)
X_pca = pca.fit_transform(sessions_embedding)

y=[0] * 61
# Plot the result
plt.figure(figsize=(8, 6))
scatter = plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y, cmap='viridis', edgecolor='k')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.title('PCA - 2D Projection')
plt.legend(*scatter.legend_elements(), title="Classes")
plt.grid(True)
plt.show()
```

Range() function

- The **range()** function returns a sequence of numbers, starting from 0 by default, and increments by 1 (by default), and ends at a specified number.

Loop

```
for i in range(6):  
    print(i)
```

→ {0,1,2,3,4,5}

0
1
2
3
4
5

Len() function

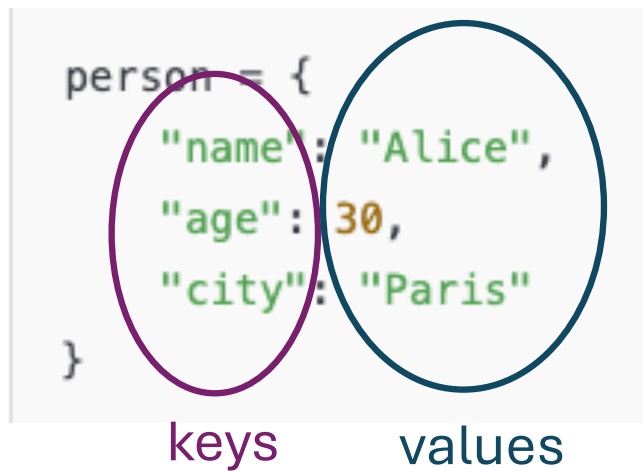
- The len() function in Python is used to **get the number of items:**

```
text = "hello"  
print(len(text)) # Output: 5
```

```
numbers = [1, 2, 3, 4]  
print(len(numbers)) # Output: 4
```

Dictionary

- is a built-in data structure that **stores data in key-value pairs**.



```
person = {  
    "name": "Alice",  
    "age": 30,  
    "city": "Paris"  
}
```

The diagram shows a Python dictionary definition. A purple oval highlights the keys: "name", "age", and "city". A blue oval highlights the values: "Alice", 30, and "Paris". Below the ovals, the word "keys" is written in purple and "values" is written in blue.

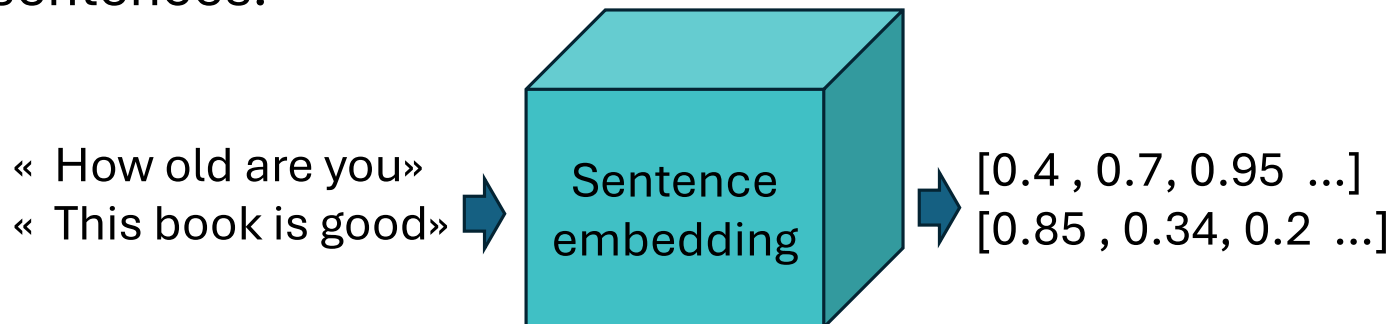
Here, "**person**" refers to the name of the dictionary.

Scanner



Sentence embeddings

- The idea behind sentence embeddings is to convert sentences into numerical vectors.
- These numerical vectors represent the sentences in a structured and machine-friendly format.
- The beauty of this vector representation lies in its ability to capture semantic relationships and contextual similarities between sentences.



Scanner case study

- Logs
 - Are records of events that occurred during the running of a software system.
 - Are generated by log statements in software source code.
 - Logs are a primary source for problem diagnosis.
 - **Event** : Units of information in a log are often called events.

Index	Time	Session ID	Object	Action	Input	Output	
51,	1585070116817,	client6,	scan12,	unlock,	[],	0	event
52,	1585070116819,	client0,	scan0,	scan,	[3270190022534],	0	
53,	1585070116820,	client1,	cashier1,	CloseSession,	[],	0	
54,	1585070116820,	client2,	cashier2,	add,	[3570590109324],	0	
55,	1585070116824,	client5,	scan5,	scan,	[8718309259938],	0	
56,	1585070116825,	client6,	scan12,	scan,	[3560070139675],	0	
57,	1585070116837,	client0,	scan0,	scan,	[3560070048786],	0	
58,	1585070117030,	client6,	scan12,	scan,	[7640164630021],	-2	
59,	1585070117073,	client6,	scan12,	delete,	[7640164630021],	-2	
60,	1585070116838,	client1,	cashier1,	pay,	[353.06],	0	

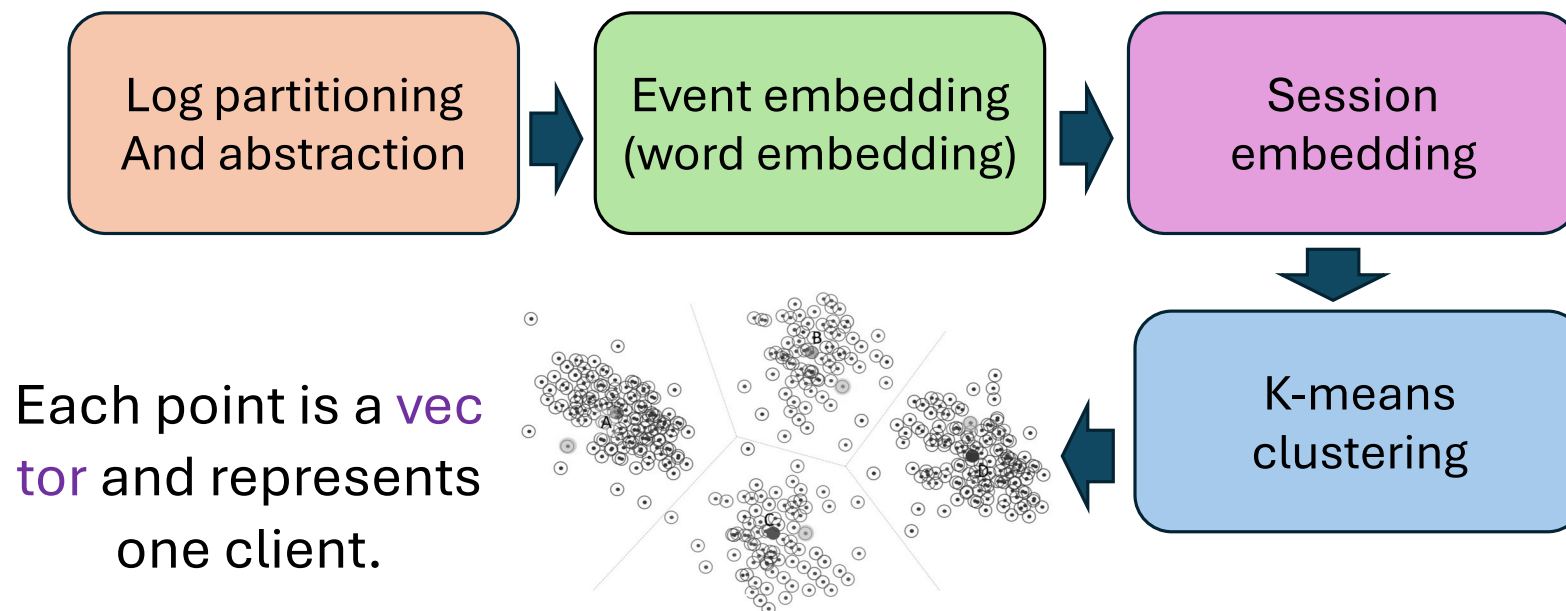
Scanner case study

Client6 **session** from Unlock to Pay

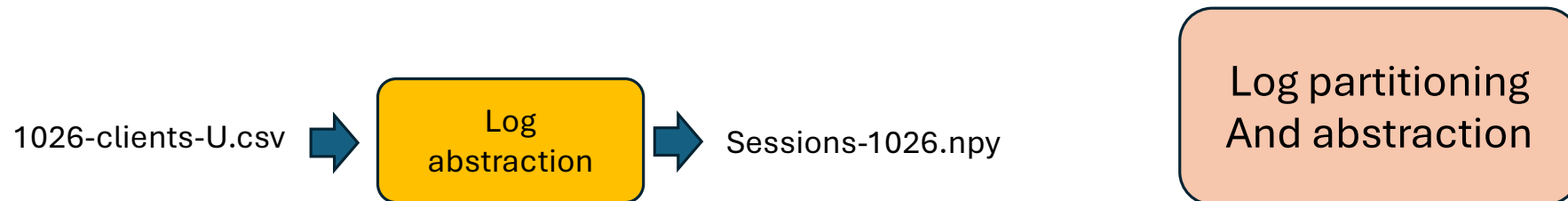
Index	Time	Session ID	Object	Action	Input	Output
51,	1585070116817,	client6,	scan12,	unlock,	[],	0
52,	1585070116819,	client0,	scan0,	scan,	[3270190022534],	0
53,	1585070116820,	client1,	cashier1,	CloseSession,	[],	0
54,	1585070116820,	client2,	cashier2,	add,	[3570590109324],	0
55,	1585070116824,	client5,	scan5,	scan,	[8718309259938],	0
56,	1585070116825,	client6,	scan12,	scan,	[3560070139675],	0
57,	1585070116837,	client0,	scan0,	scan,	[3560070048786],	0
58,	1585070117030,	client6,	scan12,	scan,	[7640164630021],	-2
59,	1585070117073,	client6,	scan12,	delete,	[7640164630021],	-2
60,	1585070116838,	client1,	cashier1,	pay,	[353.06],	0
61,	1585070116839,	client2,	cashier2,	CloseSession,	[],	0
62,	1585070116840,	client3,	cashier3,	add,	[3570590109324],	0
64,	1585070117687,	client6,	scan12,	transmission,	[caisse6],	0
65,	1585070117687,	client6,	scan12,	abandon,	[],	?
66,	1585070117701,	client6,	cashier4,	OpenSession,	[],	0
67,	1585070116855,	client0,	scan0,	transmission,	[cashier0],	0
68,	1585070116855,	client0,	scan0,	abandon,	[],	?
69,	1585070117716,	client6,	cashier4,	add,	[7640164630021],	0
70,	1585070117731,	client6,	cashier4,	CloseSession,	[],	0
71,	1585070117747,	client6,	cashier4,	Pay,	[260],	9.11

We treat each client as a sentence (session)

The propose model



Log partitioning based on ClientID



	1	1584454655792	client0	scan0_0	debloquer		0
0	2	1584454655801	client0	scan0_0	scanner	[8718309259938]	0
1	3	1584454656089	client1	scan1_1	debloquer		0
2	4	1584454656095	client0	scan0_0	scanner	[3560070976478]	0
3	5	1584454656105	client1	scan1_1	scanner	[3560070048786]	0
4	6	1584454656127	client2	scan2_2	debloquer		0

```

client0: [['debloquer', 'Nothing', '0'], ['scanner', 'Barcode', '0'], ['scanner',
'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner',
'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner',
'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner',
'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['transmission',
'CaisseNumber', '0'], ['abandon', 'Nothing', 'Error'], ['payer', 'Price-float', '0']],
client1: [['debloquer', 'Nothing', '0'], ['scanner', 'Barcode', '0'], ['scanner',
'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner',
'Barcode', '0'], ['transmission', 'CaisseNumber', '0'], ['abandon', 'Nothing', 'Error'],
['payer', 'Price-integer', 'Float Number']],
client2: [['debloquer', 'Nothing', '0'], ['scanner', 'Barcode', '0'], ['scanner',
'Barcode', '0'], ['scanner', 'Barcode', '-2'], ['transmission', 'CaisseNumber', '0'],
['abandon', 'Nothing', 'Error'], ['ouvrirSession', 'Nothing', '0'], ['ajouter', 'Barcode',
'0'], ['fermerSession', 'Nothing', '0'], ['payer', 'Price-float', '0']],

```

Word2Vec on all the Sessions

Event embedding
(word embedding)

The Word2Vec package from the Gensim library

The dimension of the W2V vectors are equal to the number of vocabs

word

[illegible]

session

Averaging Word Embeddings (Averaging a session)

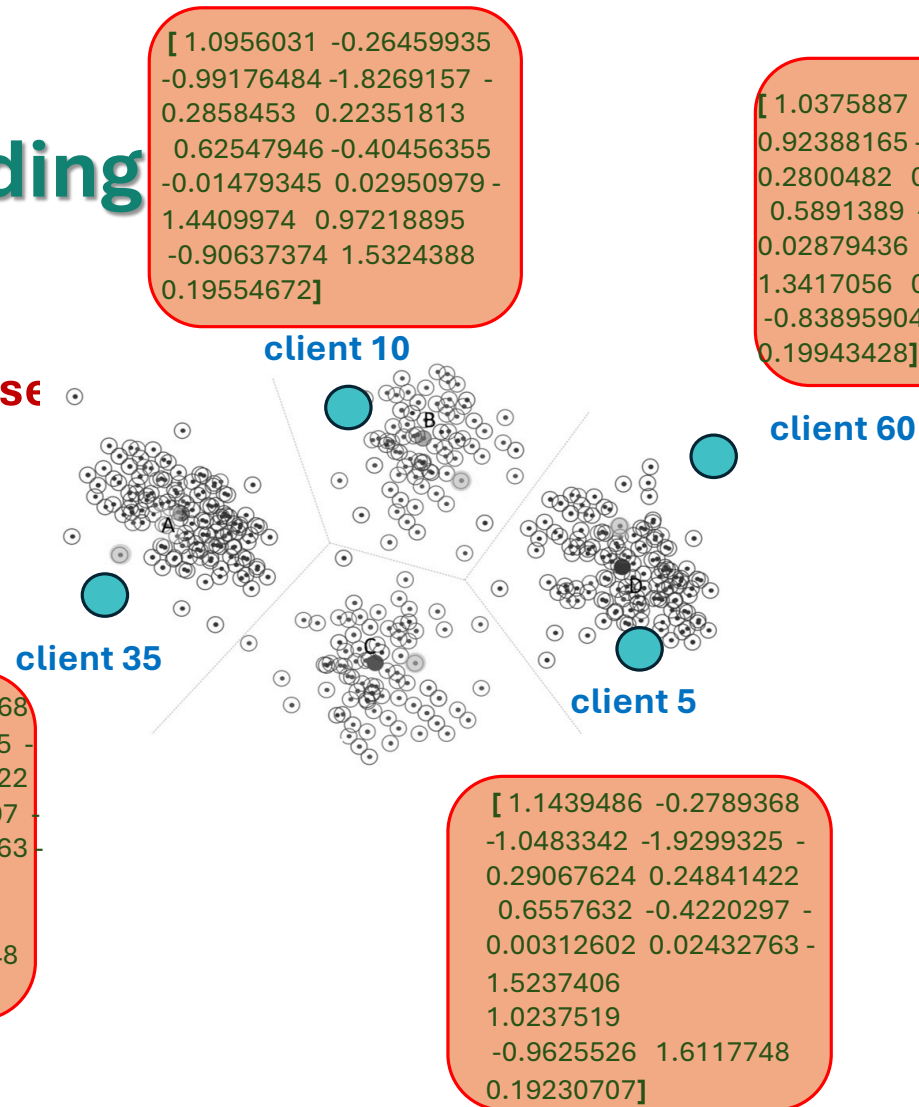
- client60:**

['debloquer', 'Nothing', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['abandon', 'Nothing', 'Error'], ['payer', 'Price-float', '0']

$$\begin{aligned}
 & \left(\begin{array}{l} [0.15698704 - \\ 0.79322034 -0.3945347 \\ -0.82248145 \ 0.21587323 \\ -0.4298337 \\ 0.11635129 \\ 0.06533043 -0.01920184 \\ 0.09027459 -0.78751177 \\ -0.46802115 \\ -0.5892027 \ -0.9514586 \\ -0.21800822] \end{array} \right. + \begin{array}{l} [1.13778 \ -2.4118261 \\ -1.158108 \ -2.5120077 \\ 0.8757284 \ -0.8175933 \\ 0.31543404 \\ 0.43288264 \\ 0.16992638 - \\ 0.16874686 -2.5441096 \\ -1.5867229 \\ -2.180273 \ -1.9017196 \\ -0.28566715] \end{array} + \dots \left. \right) = \begin{array}{l} [7.398182 - \\ 13.992377 - \\ 6.3737016 - \\ 14.275244 \\ 5.5125384 - \\ 3.9403927 \\ 1.6540279 \ 2.750914 \\ 1.7304657 \ -1.40134 \\ -14.432299 - \\ 9.090877 \\ -12.594746 - \\ 9.036384 \ -1.28486] \end{array} / 7 = \begin{array}{l} [0.7877907 - \\ 0.47995558 - \\ 0.06433037 \ -1.0645988 \\ -0.9146954 \\ 0.08257212 \\ -0.16243137 \\ 0.6493701 \ -1.9037664 \\ 0.31899315 \ 1.2860477 \\ 1.3689787 \\ 0.51519257 - \\ 0.04324638 - \\ 0.37049222] \end{array}
 \end{aligned}$$

Session embedding

We are going to cluster these
61 clients



What is the dimension of our vectors?

```
print(len(sessions_embedding[0])) #client0
```

15

--

```
print(len(sessions_embedding[1])) #client1
```

15

All vectors have dimension 15. Since the dimension is equal to the dimension of each word(W2V vector).

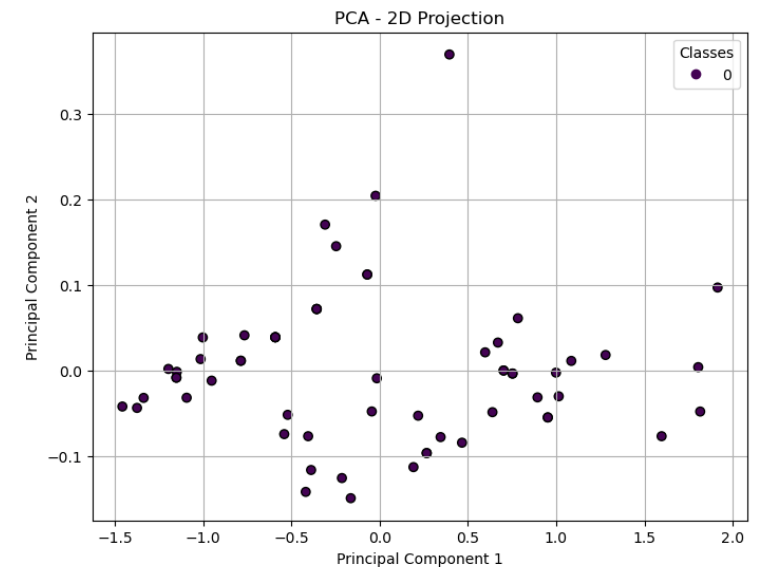
Visualisation de l'espace vectoriel (PCA)

15D → 2D

```
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA

pca = PCA(n_components=2)
X_pca = pca.fit_transform(sessions_embedding)

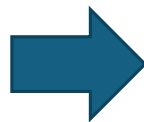
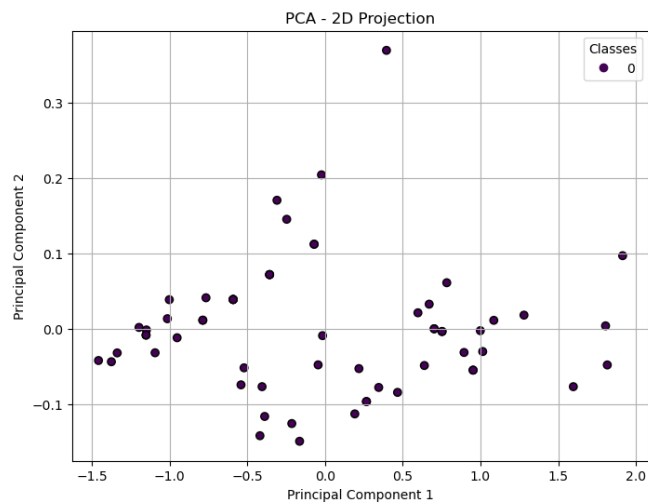
y=[0] * 61
# Plot the result
plt.figure(figsize=(8, 6))
scatter = plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y, cmap='viridis', edgecolor='k')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.title('PCA - 2D Projection')
plt.legend(*scatter.legend_elements(), title="Classes")
plt.grid(True)
plt.show()
```



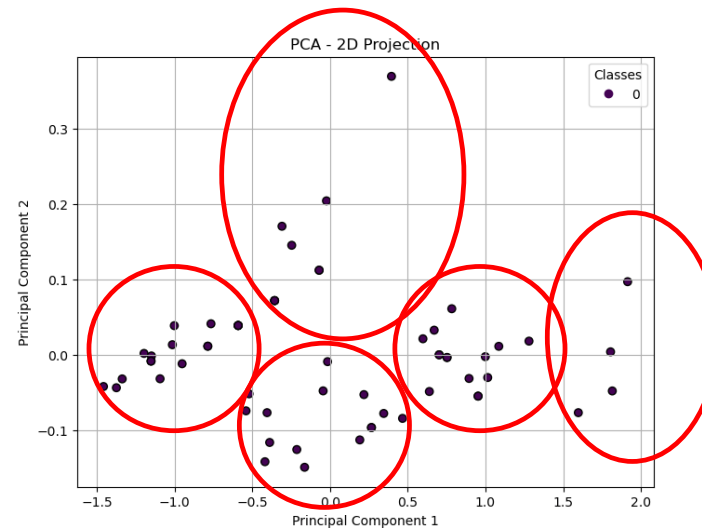
Clustering

K-means
clustering

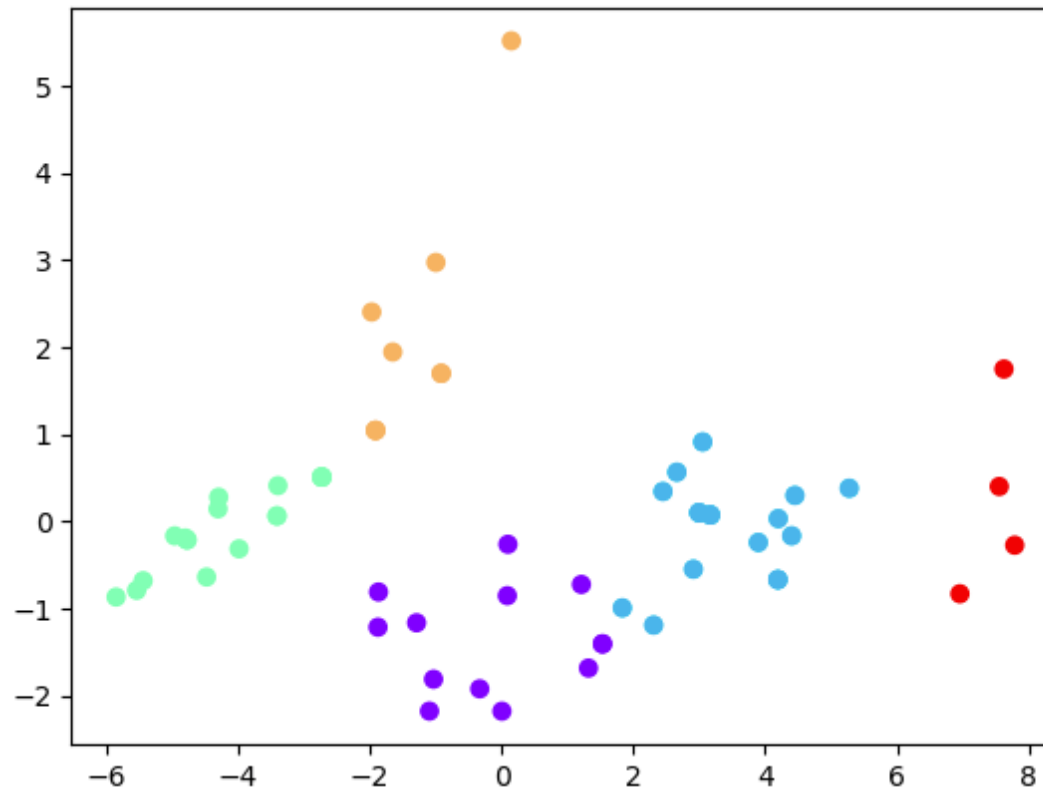
- K-Means & Elbow method
 - K-means needs to know number of cluster K
 - Elbow method finds the optimal K



K=5

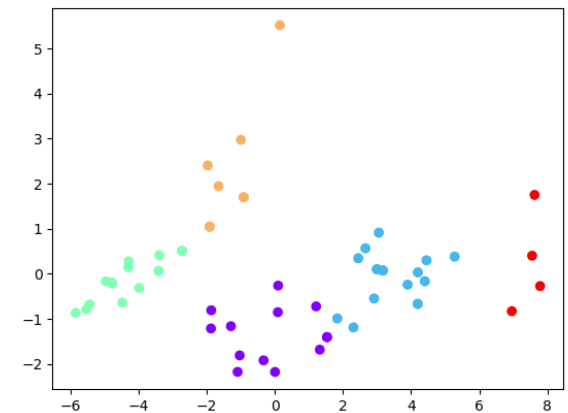


Clustering



Clustering

```
from sklearn.cluster import KMeans  
kmeans = KMeans(n_clusters=5)  
kmeans.fit(X_pca)  
plt.scatter(X_pca[:,0],X_pca[:,1], c=kmeans.labels_, cmap='rainbow')  
plt.show()
```



TP

TP

```
import pandas as pd
data='./1026-clients-U.csv'
df=pd.read_csv(data)
df.head()
```

	1	1584454655792	client0	scan0_0	debloquer	[]	0
0	2	1584454655801	client0	scan0_0	scanner	[8718309259938]	0
1	3	1584454656089	client1	scan1_1	debloquer	[]	0
2	4	1584454656095	client0	scan0_0	scanner	[3560070976478]	0
3	5	1584454656105	client1	scan1_1	scanner	[3560070048786]	0
4	6	1584454656127	client2	scan2_2	debloquer	[]	0

```
import numpy as np
Sessions = np.load('Sessions-1026.npy', allow_pickle='TRUE').item()
print(Sessions)
```

```
{ 'client0': [['debloquer', 'Nothing', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'ErrorBarcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['transmission', 'CaisseNumber', '0']], 'client1': [['debloquer', 'Nothing', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['transmission', 'CaisseNumber', '0'], ['abandon', 'Nothing', 'Error'], ['payer', 'Price-integer', 'Float Number', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '-2'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['abandon', 'Nothing', 'Error'], ['ouvrirSession', 'Nothing', '0'], ['ajouter', 'Barcode', '0'], ['fermerSession', 'Nothing', '0']], 'client3': [['debloquer', 'Nothing', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['transmission', 'CaisseNumber', '0'], ['abandon', 'Nothing', 'Error'], ['payer', 'Price-integer', 'Float Number', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '-2'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['supprimer', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['transmission', 'CaisseNumber', '0'], ['abandon', 'Nothing', 'Error'], ['ajouter', 'Barcode', '0'], ['fermerSession', 'Nothing', '0'], ['payer', 'Price-float', '0']], 'client5': [['debloquer', 'Nothing', '0'], ['scanner', 'Barcode', '0'], ['scanner', 'ErrorBarcode', '0'], ['scanner', 'Barcode', '-2'], ['scanner', 'Barcode', '0']]
```

Here, Sessions is a dictionary.

Iterate over dictionary keys: keys()

```
for sent in Sessions:  
    print(sent)
```

```
client0  
client1  
client2  
client3  
client4  
client5  
client6  
client7  
client8  
client9  
client10  
client11  
client12  
client13  
client14  
client15  
client16  
client17  
client18  
client19
```

Iterate over dictionary values: values()

```
for sent in Sessions.values():  
    print(sent)
```

```
[['debloquer', 'Nothing', '0'], ['scanner', 'Barcode', '0'],  
['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0'], ['s  
'0'], ['scanner', 'Barcode', '0'], ['scanner', 'Barcode', '0']  
[['debloquer', 'Nothing', '0'], ['scanner', 'Barcode', '0'],  
['transmission', 'CaisseNumber', '0'], ['abandon', 'Nothing',  
[['debloquer', 'Nothing', '0'], ['scanner', 'Barcode', '0'],  
'0'], ['transmission', 'CaisseNumber', '0'], ['abandon', 'Not  
['payer', 'Price-float', '0']]
```

Iterate over dictionary key-value pairs: items()

```
for c,sent in Sessions.items():  
    print(c,sent)
```

```
client0 [['debloquer', 'Nothing', '0'], ['scanner',  
e', '0'], ['scanner', 'Barcode', '0'], ['scanner',  
ode', '0'], ['scanner', 'Barcode', '0'], ['scanner',  
client1 [['debloquer', 'Nothing', '0'], ['scanner',  
e', '0'], ['transmission', 'CaisseNumber', '0'], ['a  
client2 [['debloquer', 'Nothing', '0'], ['scanner',  
arcode', '0'], ['transmission', 'CaisseNumber', '0'],  
g', '0'], ['payer', 'Price-float', '0']]  
client3 [['debloquer', 'Nothing', '0'], ['scanner',  
e', '0'], ['scanner', 'Barcode', '0'], ['scanner',  
ber']]
```

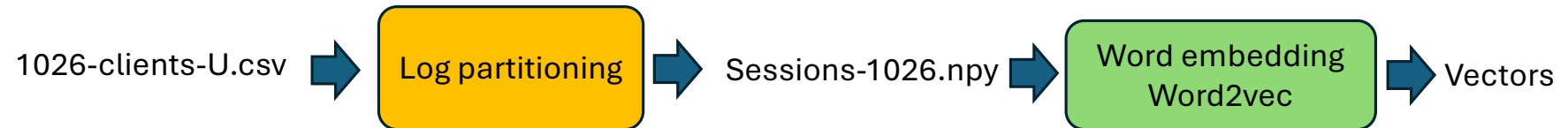
Change event to string

```
: Sentences=[]  
all_clients_string=[]  
for c,sent in Sessions.items():  
    Sentences.append(sent)  
    SentencesString=[]  
    for i in sent:  
        SentencesString.append(str(i))  
    all_clients_string.append(SentencesString)  
print(all_clients_string)
```

[['debloquer', 'Nothing', '0'], ['scanner', 'Barcode', '0']]

["['debloquer', 'Nothing', '0']", "['scanner', 'Barcode', '0']"]

Log partitioning based on ClientID



Word2Vec

```
import multiprocessing
from gensim.models import Word2Vec
cores = multiprocessing.cpu_count()
w2v_model = Word2Vec(min_count=1, window=3, vector_size=15, sample=0, alpha=0.03, min_alpha=0.0007, negative=2, workers=cores-1)
w2v_model.build_vocab(all_clients_string)
w2v_model.train(all_clients_string, total_examples=w2v_model.corpus_count, epochs=10, report_delay=1)
```

```
index2word_set = set(w2v_model.wv.index_to_key) # Our Vocab
print("the word that we have are: ", index2word_set)
```

The word that we have are:

15

```
{['supprimer', 'Barcode', '0'], ['payer', 'Price-float', '0'], ['ajouter', 'Barcode', '0'], ['payer', 'Price-integer', 'Float Number'], ['scanner', 'ErrorBarcode', '0'], ['scanner', 'Barcode', '-2'], ['fermerSession', 'Nothing', '0'], ['abandon', 'Nothing', 'Error'], ['debloquer', 'Nothing', '0'], ['scanner', 'Barcode', '0'], ['ouvrirSession', 'Nothing', '0'], ['transmission', 'CaisseNumber', '0'], ['transmission', 'CaisseNumber', 'Integer Number'], ['supprimer', 'ErrorBarcode', '0'], ['supprimer', 'Barcode', '-2']}
```

Each word is represented as a vector

```
w2v_model.wv["['payer', 'Price-float', '0']"]
```

```
array([-0.208438 , -0.17140363,  0.58019   , -0.8334066 , -0.4235734 ,  
       0.43202496,  0.16815467,  0.51377785, -0.1497903 ,  0.54200566,  
       0.1650343 ,  0.39274028,  0.00320614, -0.7347753 ,  0.13456789],  
      dtype=float32)
```

All words and their associated vectors

```

##### Create a dictionary of words and associated vectors. #####
word_vector=dict()
for w in index2word_set:
    if w in w2v_model.wv:
        print("word is ",w)
        print("w2v_vector is",w2v_model.wv[w])
        word_vector[w]=w2v_model.wv[w]
    print("^^^^^^^^^^^^^^^^^^^^")
#####

```

Dictionary (word_vector)

Word 1..... vector

Word 2..... vector

Word 15..... vector



word1

['ouvrirSession', 'Nothing', '0']

vector

w2v_vector is [-0.43123573 -0.24409345 1.1653835 -1.482715 -0.5842829 0.602372
0.2035547 0.751147 -0.2633315 0.82852894 0.3240775 0.5277217
-0.04162983 -1.1414808 0.19814692]

A session concerning the client0

```
print(all_clients_string[0])
```

[illegible]

Sessions

client0	[scan, scan, ...]
client1	[scan, delete,...]
client2	[scan, delete,...]
⋮	⋮

All_client_string

0 ["scan", "scan", ...]

1

2

A vector concerning the client0

```

print(all_clients_string[0]) ← List of Actions of client0=session of client0

feature_vec = np.zeros((15, ), dtype='float32')
number_words = 0
for word in all_clients_string[0]:
    number_words = number_words+1 ← Counting the number of actions that client0 did
    feature_vec = np.add(feature_vec, w2v_model.wv[word])

feature_vec = np.divide(feature_vec, number_words)
print(feature_vec)

[["['debloquer', 'Nothing', '0']", "['scanner', 'Barcode', '0']", "['scanner', 'Barcode', '0']", "['scanner', 'Barcode', '0']", "['scanner', 'Barcode', '0']", "['scanner', 'Barcode', '0']", "['scanner', 'Barcode', '0']", "['scanner', 'Barcode', '0']", "['scanner', 'Barcode', '0']", "['scanner', 'Barcode', '0']", "['scanner', 'Barcode', '0']", "['scanner', 'Barcode', '0']", "['scanner', 'Barcode', '0']", "['scanner', 'Barcode', '0']", "['payer', 'Price-float', '0']"]]
[ 0.20394726  0.1303705   0.4773702   2.5052588  -0.05649199 -1.7890764
  0.95154786  0.04148404 -0.29469082 -1.2973394   0.07733324 -0.4541708
 -1.4051955   1.7533631  -0.36733612]

```

Range() function

- The **range()** function returns a sequence of numbers, starting from 0 by default, and increments by 1 (by default), and ends at a specified number.

Loop

```
for i in range(6):  
    print(i)
```

→ {0,1,2,3,4,5}

0
1
2
3
4
5

61 vectors concerning all clients

```
sessions_embedding=[]
for i in range(61):
    feature_vec = np.zeros((15, ), dtype='float32')
    number_words = 0
    for word in all_clients_string[i]:
        number_words = number_words+1
        feature_vec = np.add(feature_vec, w2v_model.wv[word])

    feature_vec = np.divide(feature_vec, number_words) #vector for one client
    print(i,":",feature_vec)
    sessions_embedding.append(feature_vec)
print(sessions_embedding)
```

61 vectors concerning all clients

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sessions_embedding=[]
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    feature_vec = np.divide(feature_vec, number_words) #vector for one client
    print(i,":",feature_vec)
    sessions_embedding.append(feature_vec)
print(sessions_embedding)
```

By using a loop (for), we can calculate the average for all 61 clients

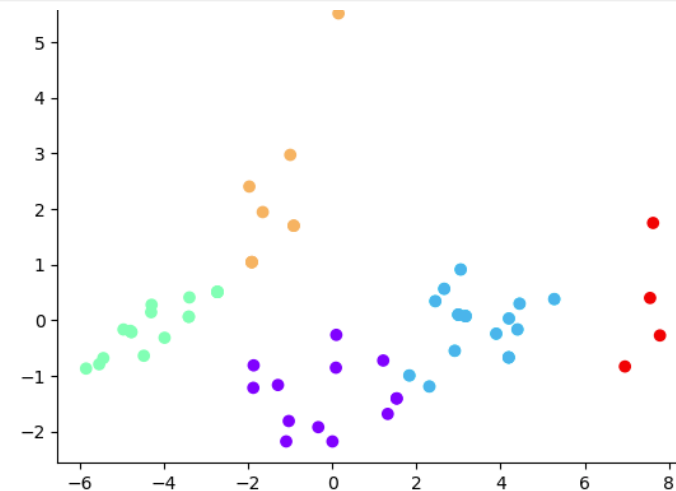
61 vectors concerning all clients

```
sessions_embedding=[] To keep all the vectors
for i in range(61):
    feature_vec = np.zeros((15, ), dtype='float32')
    number_words = 0
    for word in all_clients_string[i]:
        number_words = number_words+1
        feature_vec = np.add(feature_vec, w2v_model.wv[word])

    feature_vec = np.divide(feature_vec, number_words) #vector for one client
    print(i, ":", feature_vec)
    sessions_embedding.append(feature_vec) .append can add new vector
print(sessions_embedding)
```

Clustering

```
from sklearn.cluster import KMeans  
kmeans = KMeans(n_clusters=5)  
kmeans.fit(X_pca)  
plt.scatter(X_pca[:,0],X_pca[:,1], c=kmeans.labels_, cmap='rainbow')  
plt.show()
```



Clustering

```
clusters=dict()
for l in range(5):
    vocab_elem=[]
    OneCluster = np.where(kmeans.labels_ == l)
    print("Cluster ",l,":")
    for j in OneCluster[0]:
        print("client",j,":")
        print(all_clients_string[j])
        vocab_elem.append(j)
    clusters[l]=vocab_elem
    print("*****")
```

Cluster 0 :

client 4 :

["['debloquer', 'Nothing', '0']", "['scanner', 'Barcode', 'Barcode', '0']", "['scanner', 'Barcode', '0']", "['de', '0']", "['scanner', 'Barcode', '0']", "['scanner', 'Barcode', 'Barcode', '0']", "['scanner', 'Barcode', '0']", "['scanner', 'Barcode', '0', 'abandon', 'Nothing', 'Error']", "['ouvrirSession', 'No', '0']"]

client 5 :

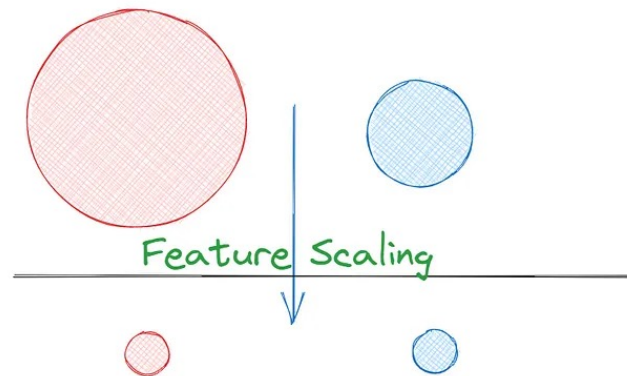
["['debloquer', 'Nothing', '0']", "['scanner', 'Barcode', 'Barcode', 'Barcode', '0']", "['scanner', 'Barcode', '0']", "['arc', '0']", "['scanner', 'Barcode', '-2']", "['scann', '0']", "['scanner', 'Barcode', '0']", "['transmission', 'code', '0']", "['ajouter', 'Barcode', '0']", "['fermerSe", '0']"]

client 11 :

["['debloquer', 'Nothing', '0']", "['scanner', 'Barcode', 'Barcode', 'Barcode', '0']", "['scanner', 'Barcode', '0']", "['", 'Barcode', '0']"]

Feature Scaling

- Imagine you're comparing apples and oranges; it's nonsensical.
- Features measured in vastly different units (like income and age) can skew machine learning algorithms if not addressed.
- Feature scaling addresses this by transforming data into a standard scale, enabling fair comparison between different features.



Feature Scaling

- Feature scaling is a fundamental preprocessing step in machine learning aimed at ensuring that numerical features have a **similar scale**.
- Apply feature scaling before feeding the data into the machine learning model (K-NN), **except** for algorithms that are scale-invariant, such as **decision trees**.

Common Techniques for Feature Scaling

- **Normalization :**

- This method scales each feature so that all values are within the range of 0 and 1.
- x is the value you want to normalize
- $\min(X)$ is the minimum value in your data set
- $\max(X)$ is the maximum value in your data set

$$(x - \min(X)) / (\max(X) - \min(X))$$

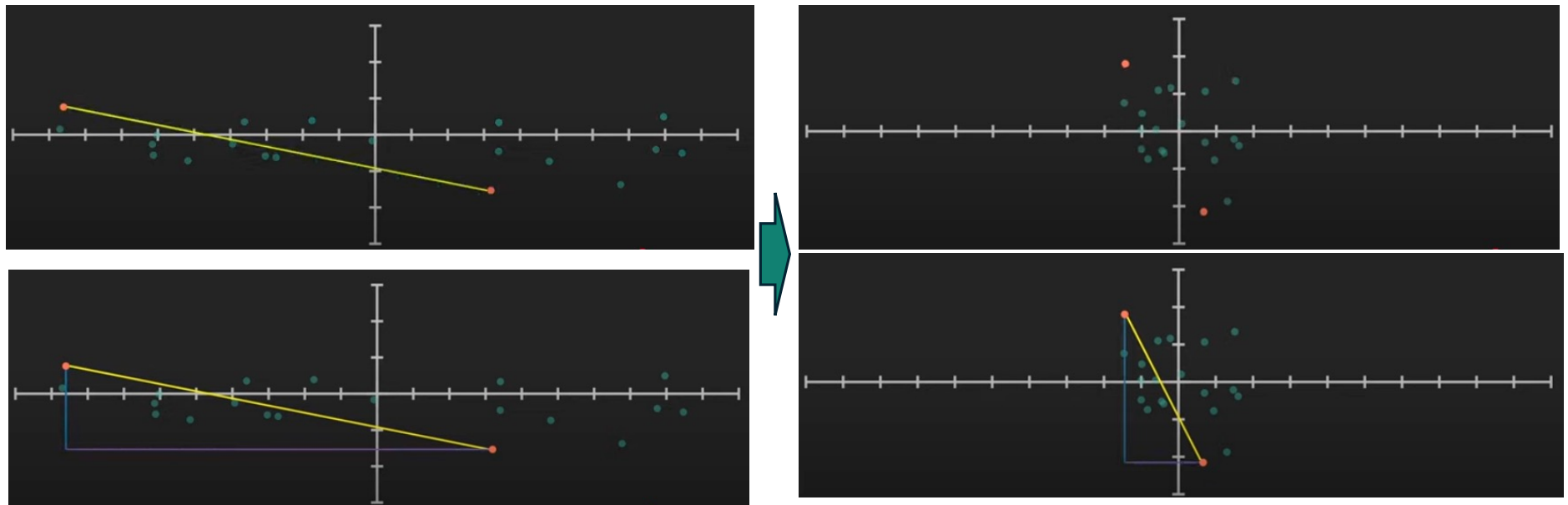
- **Standardization (Z-score Scaling):**

- Here, each feature is transformed to have a mean of 0 and a standard deviation of 1.
- This is achieved by subtracting the mean value and dividing by the standard deviation of the feature.
- x is the original value you want to standardize, μ (mu) is the mean of the data set, σ (sigma) is the standard deviation of the data set

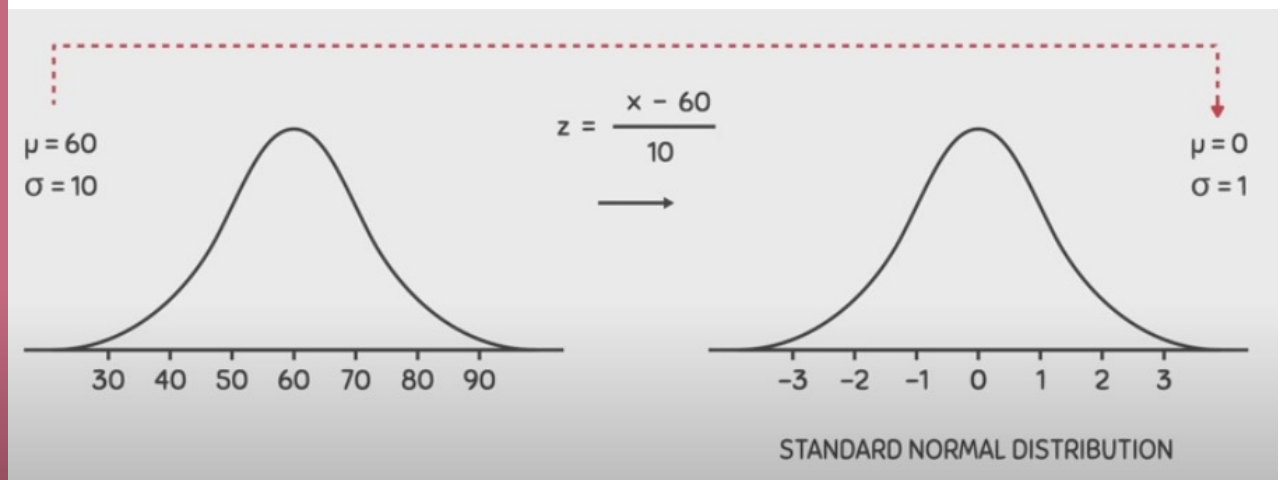
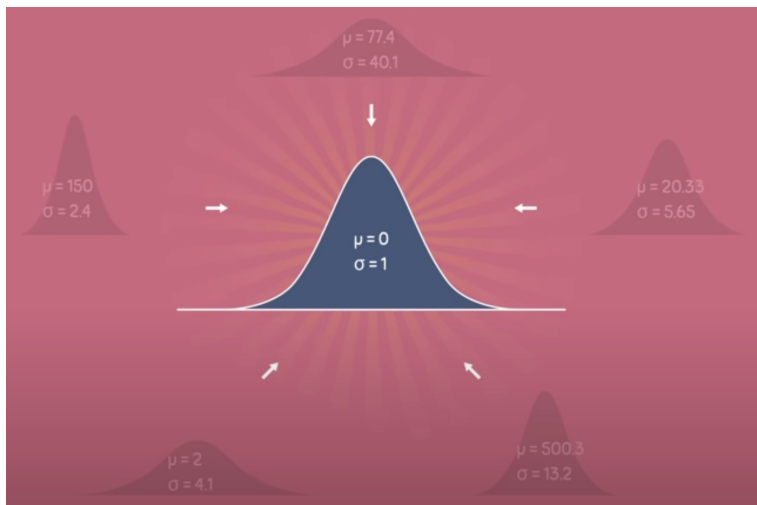
$$Z = (x - \mu) / \sigma$$

Feature Scaling

- In the last figure, both feature contribute equally to the distance
- After that, your algorithm won't be affected by the feature with a higher scale.



```
from sklearn.preprocessing import StandardScaler
stdsc=StandardScaler()
X_std=pd.DataFrame(stdsc.fit_transform(X_all), index=X_all.index, columns=X_all.columns)
```



Any normal distribution with any value of mean and standard deviation(sigma) can be transformed into the standard normal distribution where we have a mean of zero and a standard deviation of one.

End

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