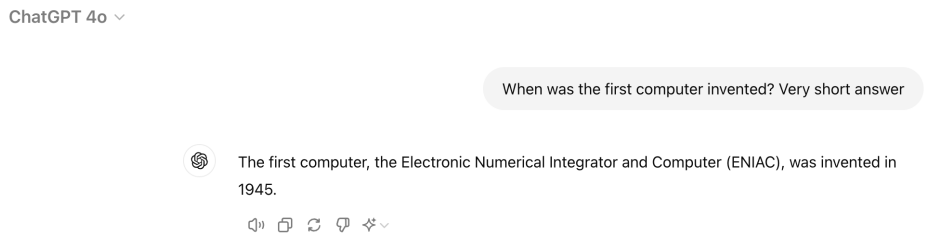
Introduction

Since the invention of the computer in 1945, we have needed to translate our thoughts into machine instructions. To solve a problem requiring a computer, we must first find the solution and then translate this solution into "machine language." In order to overcome this difficulty, a wide range of programming languages have been developed in the last decade. Below, you can find a table with the different categories of programming languages along with some examples, classified subjectively into different levels of proximity to human language (Very Low, Low, Moderate, Moderate to High, High, Very High).

Category	**Example**	**Proximity to Human Language**
Machine Languages	Binary code	Very Low
Assembly Languages	x86 Assembly	Low
Low-Level Programming Languages	C, C++	Moderate
High-Level Programming Languages	Python, Java	High
Very High-Level Programming Languages	SQL, MATLAB	Very High
Scripting Languages	JavaScript, PHP	High
Markup Languages	HTML, XML	Moderate to High
Natural Language Programming	Inform 7	Very High



So, could a machine understand natural language? This is the purpose of a branch of Machine Learning known as Natural Language Processing (NLP). NLP aims to

minimize, even eliminate, the friction between humans and computers. In words of the current Nvidia CEO Jensen Huang: "It is our job to create computing technology such that nobody has to program, and that the programming language is human. Everybody in the world is now a programmer. This is the miracle of Artificial Intelligence." This is a strong and groundbreaking statement with which I partially agree. Although I personally think that the role of Natural Language in this context might be overestimated. The programmer's purpose nowadays is not only to translate algorithms to machine language but also to actually come up with these algorithms and sometimes, natural language is not sufficient to express very complex ideas, which is why mathematics has its own language.

Data Extraction

One of the common tasks that it has gained relevance in the last decade is data extraction. In the time of Big Data, Data Analysis and Data Science extracting data from literally anywhere is crucial. NLP provides a new tool to extract data which requires some understanding of Human Language.

In this bachelor's thesis, we will use NLP to extract data from the Boletín Oficial del Estado, which is the official gazette of Spain. The number of pdfs published per month make incredibly difficult for an only person to keep up with all the information (see graph below). LLMs combined with a RAG system can very useful to retrieve information so it can enhance transparency and accessibility to information. What is more, it is already being used in law firms

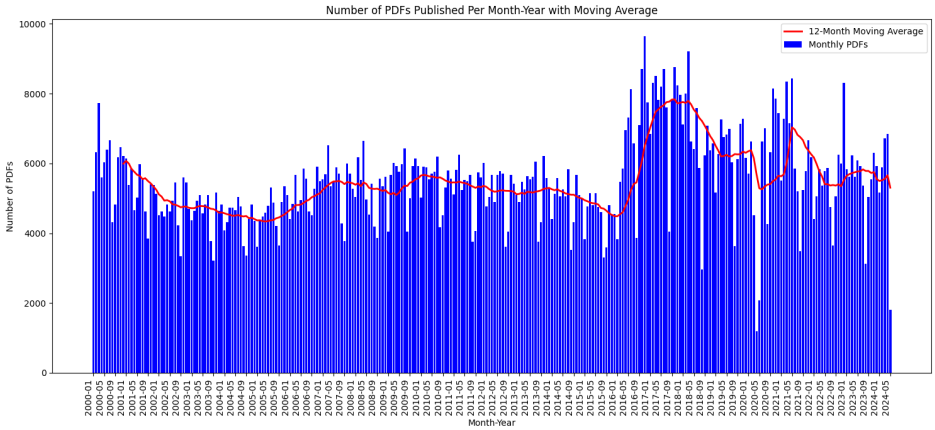


Image in https://github.com/danmorper/NLP/blob/main/boe/xml.ipynb

What is the Boletín Oficial del Estado (BOE)?

The Boletín Oficial del Estado (BOE) is the official gazette of Spain, functioning as a daily publication that serves as the official channel for disseminating legal norms, regulations, and other important official announcements from the

government and other public bodies. The BOE is published every day and made available in both PDF and XML formats. This allows for easy access and verification of legal documents by citizens, organizations, and legal entities.

Here is a general schema of how BOE XML files are structured:

Structure of BOE XML Files

```
Sumario
|
|-- Meta
|   |-- pub
|   |-- ano
|   |-- fecha
|   |-- fechaInv
|   |-- fechaAnt
|   |-- fechaAntAnt
|   |-- fechaSig
|   |-- fechaPub
|   |-- pubDate
|
|-- diario (nbo)
|   |-- sumario_nbo (id)
|   |   |-- urlPdf (szBytes, szKBytes)
|   |
|   |-- seccion (num, nombre)
|       |-- departamento (nombre, etq)
|           |-- item (id)
|               |-- urlPdf
|               |-- urlHtm
|               |-- urlXml
```

- **sumario**
  - **meta**
  - **pub**: Publication identifier (e.g., "BOE")
  - **anno**: Year of publication
  - **fecha**: Publication date in DD/MM/YYYY format
  - **fechaInv**: Inverted publication date in YYYY/MM/DD format
  - **fechaAnt**: Previous publication date
  - **fechaAntAnt**: Date before the previous publication
  - **fechaSig**: Next publication date
  - **fechaPub**: Human-readable publication date
  - **pubDate**: RFC 822 formatted publication date

- **diario** (with attribute `nbo` for the issue number)
  - **sumario_nbo** (with attribute `id` for summary identifier)
    - **urlPdf**: URL to the PDF file
  - **seccion** (with attributes `num` for section number and `nombre` for section name)
    - **departamento** (with attributes `nombre` for department name and `etq` for department code)
      - **item** (with attribute `id` for item identifier)
        - **titulo**: Title of the item
        - **urlPdf**: URL to the item's PDF file (with attributes `szBytes`, `szKBytes`, and `numPag` for number of pages)
        - **urlHtm**: URL to the item's HTML version
        - **urlXml**: URL to the item's XML version

Principal Component Analysis (PCA)

[X = \begin{pmatrix} x_{1.} \ \vdots \ x_{n.} \end{pmatrix} \quad \implies \quad X \in \mathbb{R}^{n \times p}]

Only assumption on X is that its mean vector and covariance matrix exist.

Let $\delta = (\delta_1, \ldots, \delta_p)'$ be called the weighting vector. Then the weighted average is: [\delta' X = \sum_{j=1}^{p} \delta_j X_j \quad \text{such that} \quad \sum_{j=1}^{p} \delta_j = 1]

In order to properly choose δ, we will maximize the variance: [\max_{\delta \in M} \text{Var}(\delta' X) = \max_{\delta \in M} \delta' \text{Var}(X) \delta] [M = {\delta : |\delta| = 1}]

We call $\Sigma = \text{Var}(X)$.

[\max_{\delta \in M} \delta' \Sigma \delta]

This is a quadratic convex maximization problem with nonlinear constraints.

[\mathcal{L} (\delta, \lambda) = \delta' \Sigma \delta - \lambda (\delta' \delta - 1)]

- $\nabla_{\delta} \mathcal{L} = 0 : \Sigma \delta = \lambda \delta$
- λ: eigenvalue
- δ: eigenvector of λ
- $\delta' \Sigma \delta = \lambda \delta' \delta = \lambda$

Thus, [\max_{\delta} \lambda \quad \text{subject to} \quad \Sigma \delta = \lambda \delta, |\delta| = 1] So we call δ the first principal component.

Let $\delta^1, \ldots, \delta^j$ fit j principal components. The $j+1$ principal component is the result of: [\max \delta' \Sigma \delta] subject to [\delta' \delta^i = 0 \quad \forall i \in {1, \ldots, j}] [\delta' \delta = 1]

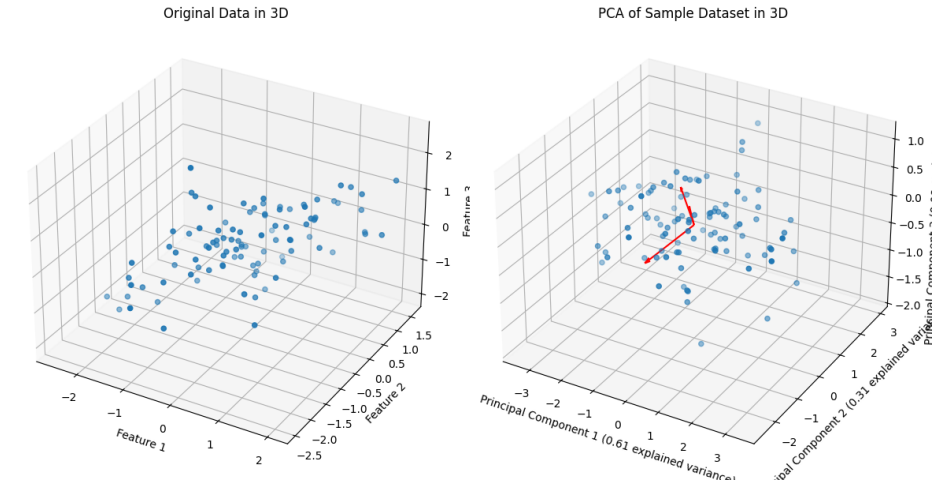
The j-th principal component is an eigenvector associated to the j-th eigenvalue of Σ.

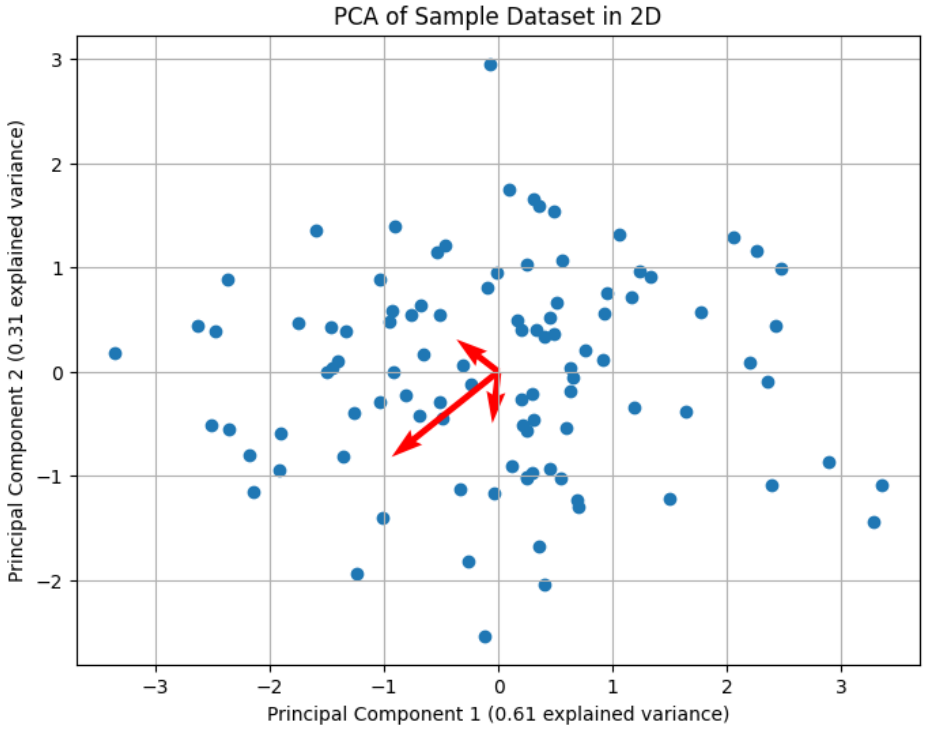
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
from sklearn.preprocessing import StandardScaler

# Create a sample dataset in 3 dimensions
np.random.seed(42)
mean = [0, 0, 0]
cov = [[1, 0.8, 0.5], [0.8, 1, 0.3], [0.5, 0.3,
1]]  # covariance matrix
data = np.random.multivariate_normal(mean, cov,
100)
df = pd.DataFrame(data, columns=['Feature_1',
'Feature_2', 'Feature_3'])

# Standardize the data
scaler = StandardScaler()
scaled_data = scaler.fit_transform(df)

# Calculate the covariance matrix manually
cov_matrix = np.cov(scaled_data, rowvar=False)
print("Covariance Matrix:")
print(cov_matrix)

# Perform eigenvalue and eigenvector decomposition
eigenvalues, eigenvectors =
np.linalg.eigh(cov_matrix)
print("Eigenvalues:")
print(eigenvalues)
print("Eigenvectors:")
print(eigenvectors)

# Sort the eigenvalues and eigenvectors in
descending order
idx = np.argsort(eigenvalues)[::-1]
eigenvalues = eigenvalues[idx]
eigenvectors = eigenvectors[:, idx]
```

```
# Transform the data to the principal components
pca_result = np.dot(scaled_data, eigenvectors)
pca_df = pd.DataFrame(pca_result, columns=['PC1',
'PC2', 'PC3'])

# Plot the original data in 3D
fig = plt.figure(figsize=(12, 6))
ax = fig.add_subplot(121, projection='3d')
ax.scatter(df['Feature_1'], df['Feature_2'],
df['Feature_3'])
ax.set_xlabel('Feature 1')
ax.set_ylabel('Feature 2')
ax.set_zlabel('Feature 3')
ax.set_title('Original Data in 3D')

# Plot the principal components in 3D
ax = fig.add_subplot(122, projection='3d')
ax.scatter(pca_df['PC1'], pca_df['PC2'],
pca_df['PC3'])
for i in range(len(eigenvectors)):
    vector = eigenvectors[:, i] *
np.sqrt(eigenvalues[i])
    ax.quiver(0, 0, 0, vector[0], vector[1],
vector[2], color='r', arrow_length_ratio=0.1)
ax.set_xlabel(f'Principal Component 1
({eigenvalues[0]/np.sum(eigenvalues):.2f}
explained variance)')
ax.set_ylabel(f'Principal Component 2
({eigenvalues[1]/np.sum(eigenvalues):.2f}
explained variance)')
ax.set_zlabel(f'Principal Component 3
({eigenvalues[2]/np.sum(eigenvalues):.2f}
explained variance)')
ax.set_title('PCA of Sample Dataset in 3D')
plt.tight_layout()
plt.show()

# Plot the PCA result in 2D
plt.figure(figsize=(8, 6))
plt.scatter(pca_df['PC1'], pca_df['PC2'])
for i in range(len(eigenvectors)):
    plt.quiver(0, 0, eigenvectors[0, i] *
np.sqrt(eigenvalues[i]), eigenvectors[1, i] *
np.sqrt(eigenvalues[i]),
               angles='xy', scale_units='xy',
scale=1, color='r')
plt.xlabel(f'Principal Component 1
({eigenvalues[0]/np.sum(eigenvalues):.2f}
explained variance)')
plt.ylabel(f'Principal Component 2
```

```
({eigenvalues[1]/np.sum(eigenvalues):.2f}
explained variance)')
plt.title('PCA of Sample Dataset in 2D')
plt.grid(True)
plt.show()

# Show the explained variance
explained_variance = eigenvalues /
np.sum(eigenvalues)
print('Proportion of explained variance:',
explained_variance)
```

```
Covariance Matrix:
[[1.01010101 0.67589685 0.41006669]
 [0.67589685 1.01010101 0.08990523]
 [0.41006669 0.08990523 1.01010101]]
Eigenvalues:
[0.257185   0.93058501 1.84253303]
Eigenvectors:
[[-0.72348439 -0.05353698 -0.68826167]
 [ 0.61113817 -0.51334632 -0.60248294]
 [ 0.32106148  0.85650998 -0.40411654]]
```





The red arrows in the plot represent the eigenvectors scaled by the square roots of their respective eigenvalues. These vectors indicate the directions of maximum variability in the data, which are the principal axes determined by Principal Component Analysis (PCA). **Sources:**

- 2015_Book_AppliedMultivariateStatistical.pdf
- ADM_PCA.pdf