

**LinkedIn**

JOP Analysis



focuses on analyzing the global job market using LinkedIn job postings. We wanted to turn raw job listing data into useful insights for understanding hiring trends, in-demand skills, and market patterns. We combined Python for data cleaning, feature engineering, and machine learning with Power BI for an interactive dashboard.

[let's Start](#)

Problem Statement

Job markets change rapidly and are highly competitive

1



huge amounts of job data, but it's messy and unstructured

2



Difficult for job seekers to know which skills to focus on

3



Companies struggle to quickly identify hiring trends

4



Goal of the Project

Turn messy LinkedIn job data into clean, structured insights

1



Identify hiring trends, top skills, and in demand industries

2



Understand job market patterns across locations and time

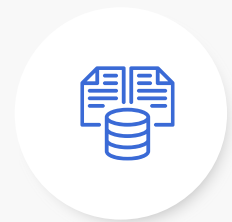
3



Present insights in an interactive dashboard for easy exploration

4





Dataset

31,475

LinkedIn job postings



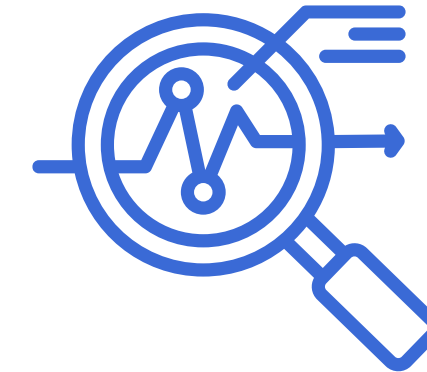
Columns

- job title – Title of the posted job
- company name – Company offering the job
- location – City, region, and country
- hiring status – Posting status (early applicant, etc.)
- date – Posting date



Columns

- seniority level – Required experience level
- job function – Main role function (IT, Sales, etc.)
- employment type – Full-time, part-time, contract, etc.
- industry – Industry category of the job
- city – Extracted city name
- country – Extracted country name



Data Overview

Data Cleaning Problem

Web scraped data had unusual issues

1



Emojis, random spaces, and formatting errors

2



**Solved using NLP text
cleaning techniques**



Feature Engineering



Columns Created

- City & Country: Extracted from location text to enable geographic analysis.
- Job Title Category: Grouped similar job titles into broader categories for trend detection.



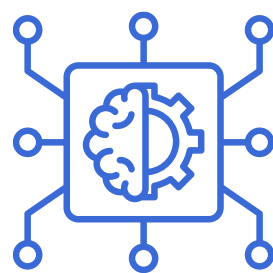
Columns Created

- Posting Weekday: Day of the week each job was posted, to identify posting patterns.
- Country Job Density: Number of postings per country to measure hiring concentration.



Columns Created

- Seniority Code: Numeric code representing seniority levels, useful for modeling.
- Month & Day of Year: Extracted from posting date for seasonal and time-based analysis.



Machine Learning Models

● 60.69% MeanShift

● 60.43% Kmean

● 59.84% AgglomerativeC
lustering

● -1.00 DBSCAN

Model Comparison

Before PCA

```
KMeans Silhouette Score: 0.4196
=====
AgglomerativeClustering Silhouette Score: 0.3237
=====
DBSCAN: Only one cluster found. Silhouette Score skipped.
=====
MeanShift: Only one cluster found. Silhouette Score skipped.
=====
GaussianMixture Silhouette Score: 0.4013
=====
```


Model Comparison

After PCA

```
KMeans Silhouette Score: 0.4310
=====
AgglomerativeClustering Silhouette Score: 0.3843
=====
DBSCAN: Only one cluster found.
=====
MeanShift Silhouette Score: 0.6069
=====
GaussianMixture Silhouette Score: 0.2700
=====
```

Model Comparison

After Hyber Parameter Tuning

```
=== KMeans ===
Best Params: {'n_init': 10, 'n_clusters': 2, 'max_iter': 200, 'init': 'random'}
Best Silhouette Score: 0.6043

=== AgglomerativeClustering ===
Best Params: {'n_clusters': 2, 'linkage': 'ward'}
Best Silhouette Score: 0.5984

=== DBSCAN ===
Best Params: None
Best Silhouette Score: -1.0000

=== MeanShift ===
Best Params: {'bandwidth': None}
Best Silhouette Score: 0.6069

=== GaussianMixture ===
Best Params: {'n_components': 2, 'covariance_type': 'spherical'}
Best Silhouette Score: 0.5644

=== Final Best Results ===
KMeans: Score=0.6043, Params={'n_init': 10, 'n_clusters': 2, 'max_iter': 200, 'init': 'random'}
AgglomerativeClustering: Score=0.5984, Params={'n_clusters': 2, 'linkage': 'ward'}
DBSCAN: Score=-1.0000, Params=None
MeanShift: Score=0.6069, Params={'bandwidth': None}
GaussianMixture: Score=0.5644, Params={'n_components': 2, 'covariance_type': 'spherical'}
```

Explore Our Dashboard





Thank You

