LinkedIn Job Posting and Profiles Insights

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Abstract: This project analyzes job postings and LinkedIn profiles in the data field, focusing on insights into the job market and skill requirements. It employs web scraping to gather data, followed by thorough cleaning, exploratory data analysis, and visualization. Using Natural Language Processing, relevant skills are extracted from job descriptions to create a recommendation system for matching job postings with candidate profiles. Additionally, a Random Forest Classifier model predicts job prospects based on education, skills, and experience, evaluated through various metrics and feature importance analysis. The project aims to offer valuable insights for job seekers, employers, and educational institutions in data science and analytics.

1. Data Cleaning and EDA

Job Postings Dataset

	Industries	City	State	job_title_categorized	Job_title	Job_link	Company	Company_link	Post_time	Applicants_count	Job_description	Seniority_level	Employment_type	Job_function
1945	Government Administration	Boston	Massachusetts	data scientist	Life Scientist/E	https://www.linkedin.com/jobs/view/life-scient	US Environmental Protection Agency	https://www.linkedin.com/company/us-epa? trk=pu	2/6/24	Be among the f	Help Help Requirements Conditions of Employmen	Mid-Senior level	Full-time	Research, Analyst, and Information
833	Technology, Information and Internet	New York	United States	data engineer	Sr. DevOps Engin	https://www.linkedin.com/jobs/view/sr-devops-e	Experfy	https://www.linkedin.com/company/experfy?trk=p	4/3/23	Over 200 appli	We are looking for a Senior DevOps Engineer to	Mid-Senior level	Contract	Information Technology
869	Renewable Energy Semiconductor Manuf	Austin	Texas	data analyst	Data Analyst, Ne	https://www.linkedin.com/jobs/view/data-analys	Tesla	https://www.linkedin.com/company/tesla- motors?	2/7/24	Over 200 appli	What To ExpectThe Vehicle Operations team at T	Entry level	Full-time	Information Technology
285	IT Services and IT Consulting, Softw	Seattle	Washington	data analyst	Business Analyst	https://www.linkedin.com/jobs/view/business-an	Amazon	https://www.linkedin.com/company/amazon? trk=pu	2/1/24	Be among the f	DescriptionThe FBA Inventory and Capacity Mana	Not Applicable	Full-time	Strategy/Planning, Analyst, and In
3131	Appliances, Electrical, and Electron	Baltimore	Maryland	data engineer	Quality Engineer	https://www.linkedin.com/jobs/view/quality-eng	Tbest Services Inc	https://www.linkedin.com/company/tbestservices	2/6/24	Be among the f	TBest Services Inc. is currently seeking a hig	Mid-Senior level	Full-time	Quality Assurance

LinkedIn Profiles Dataset

	User Name	Headline	About	Job_title	Experience	Company	Company_size	University	Degree	Degree_type		R	Software_development	Git	HTML_CSS	AI	Has_certification	Follower_coun	t Connections	Uni_ranking	Has_job
11	Christophe H.	Data Scientist at Dropbox		data scientist	Data Scientist at Mount Sinai Health System	Dropbox	Big tech	Northern Arizona University	Bachelor of Science - BS, Business Administrat	Bachelor	•••	yes	no	no	no	yes	0	9632.0	9703.0	208.0	1
976	Nan Liu	Machine Learning Engineer	NaN	data engineer	Machine Learning Engineer at DoorDash	DoorDash	Big tech	Fordham University	Master's degree	Other	•••	yes	no	no	no	no	0	181.0	181.0	NaN	1
1398	Yiting L.	Data Scientist at Amrock	· Good interpersonal skills, strong work ethic	data scientist	Data Scientist at Amrockdata with NLP to	Amrock	Other	Beijing International Studies University	Bachelor's Degree, Journalism & English	Bachelor		yes	no	no	no	yes	1	341.0	341.0	NaN	1
1013	Niyal Thakkar	Actively seeking Data Analyst Internship Und	I am a highly driven undergraduate student at	other	Operations Manager at Rutgers University-New B	Rutgers University– New Brunswick	Grad school	Rutgers University-New Brunswick	Bachelor of Science - BS, Computer Science	Bachelor		yes	yes	no	no	no	0	798.0	800.0	NaN	0
707	Guru Prasad Kumar	Senior Data Analyst @ Capital One Data Analy	Enthusiastic data analyst with 5 years experie	data analyst	Senior Data Analyst at Capital One	Capital One	Big tech	SBOA School & Junior College	High School, Computer Science	High School		yes	yes	no	no	no	1	1930.0	1929.0	NaN	1

5 rows × 27 columns

<class 'pandas.core.frame.DataFrame'> RangeIndex: 3440 entries, 0 to 3439

Data	columns (total 14 colum			
#	Column	Non-Nu	ull Count	Dtype
0	Industries	3389 r	non-null	object
1	City	3440 r	non-null	object
2	State	3440 r	non-null	object
3	job_title_categorized	3440 r	non-null	object
4	Job_title	3426 r	non-null	object
5	Job_link	3440 r	non-null	object
6	Company	3426 r	non-null	object
7	Company_link	3426 r	non-null	object
8	Post_time	3440 r	non-null	object
9	Applicants_count	3439 r	non-null	object
10	Job_description	3439 r	non-null	object
11	Seniority_level	3439 r	non-null	object
12	Employment_type	3389 r	non-null	object
13	Job_function	3389 r	non-null	object

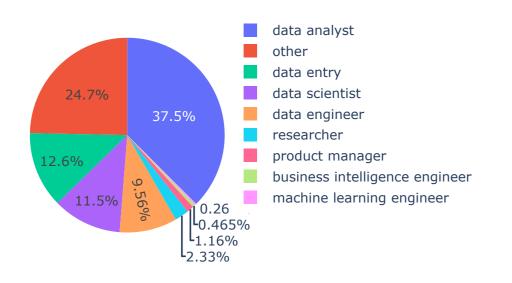
dtypes: object(14) memory usage: 376.4+ KB

<class 'pandas.core.frame.DataFrame'> RangeIndex: 1514 entries, 0 to 1513 Data columns (total 27 columns):

Data	Cocomins (cocac 27 coc	UIII 13 / •	
#	Column	Non-Null Count	Dtype
0	User Name	1514 non-null	object
1	Headline	1511 non-null	object
2	About	1093 non-null	object
3	Job_title	1514 non-null	object
4	Experience	1494 non-null	object
5	Company	1369 non-null	object
6	Company_size	1514 non-null	object
7	University	1383 non-null	object
8	Degree	1257 non-null	object
9	Degree_type	1514 non-null	object
10	Major	1514 non-null	object
11	Python	1514 non-null	object
12	Java	1514 non-null	object
13	SQL	1514 non-null	object
14	Machine_learning	1514 non-null	object
15	Statistical_analysis	1514 non-null	object
16	Visualization	1514 non-null	object
17	R	1514 non-null	object
18	Software_development	1514 non-null	object
19	Git	1514 non-null	object
20	HTML_CSS	1514 non-null	object
21	AI	1514 non-null	object
22	Has_certification	1514 non-null	int64
23	Follower_count	1398 non-null	float64
24		1398 non-null	float64
25	Uni_ranking	498 non-null	float64
26	Has_job	1514 non-null	int64
dtyp	es: float64(3), int64(2), object(22)	

memory usage: 319.5+ KB

Distribution of job titles

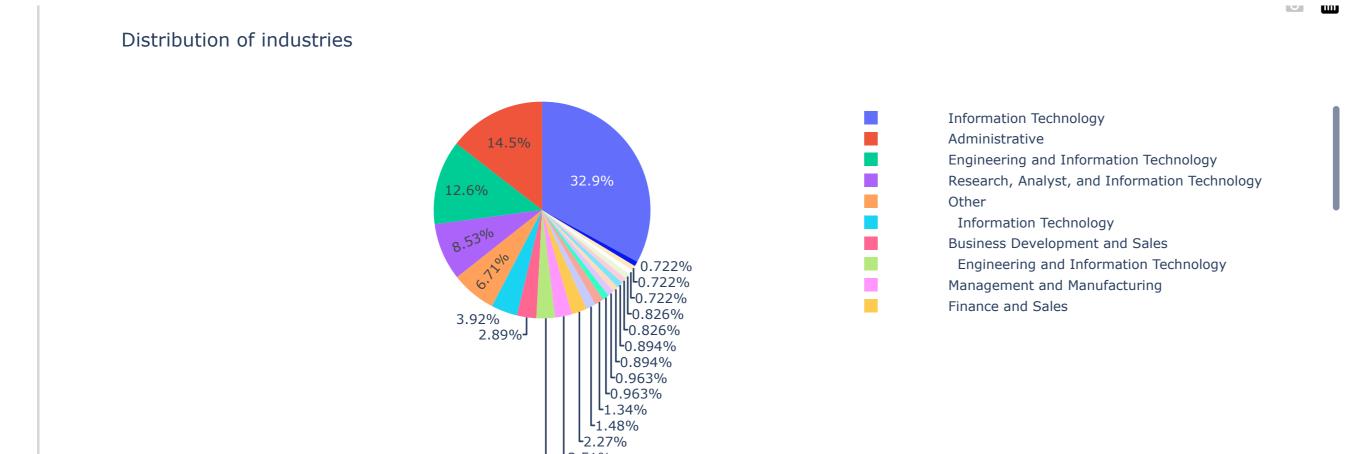


3440

Job postings

Cities

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2. Text analysis of job descriptions

- Text Preprocessing: The job descriptions are preprocessed by converting the text to lowercase, removing punctuation, and other cleaning operations.
- **Tokenization:** The preprocessed job descriptions are tokenized into individual words or terms using NLTK's word_tokenize function.
- Stop Word Removal: Common stop words (e.g., 'the', 'and', 'is') that do not contribute significantly to the meaning of the text are removed from the tokenized job descriptions using NLTK's stopwords.
- Skill Filtering: A list of relevant skills is defined, and the tokenized job descriptions are filtered to keep only the relevant skills.

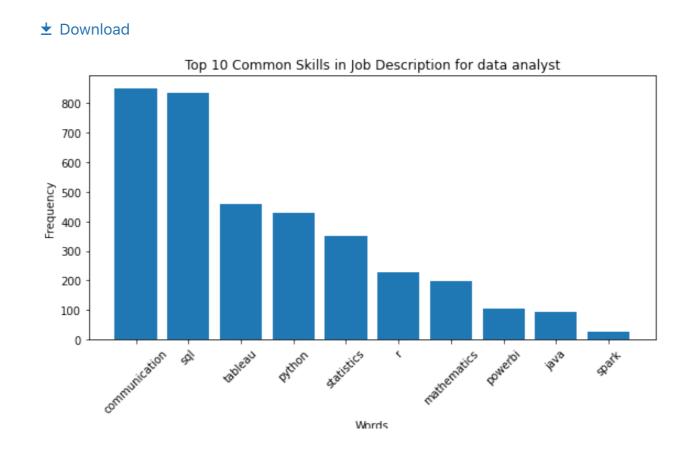
Choose your job title data analyst

Job Description Word Cloud

★ Download



Skill sets required for each data job



Recommendation system to match jobs with candidate's profile

- Create a TF-IDF (Term Frequency-Inverse Document Frequency) matrix from the job descriptions. This matrix represents how important each word or term is in each job description and gives higher scores to words that are more relevant and unique to a particular
- job description. • Then, we also convert the user's profile text into a TF-IDF vector.
- Next, the cosine similarity between the user's TF-IDF vector and each job description. Cosine similarity is a measure of how similar two vectors are, in this case, the user's profile and each job description.
- The cosine similarity scores range from 0 to 1, where 1 means the vectors are identical, and 0 means they are completely different. So, job descriptions with higher cosine similarity scores to the user's profile are considered more relevant or similar to the user's interests and skills.

user_profile = """I am a data scientist with experience in machine learning, Python, and SQL. I am interested in roles related to predictive modeling, and developing AI solutions."""

Recommended postings

	Job_title	Company	Job_link	Job_description
801	Senior Linux Sys	Canonical	https://www.linkedin.com/jobs/view/senior-linu	Job DescriptionPosition Description:
800	Business Analyst	Jobs for Humanity	https://www.linkedin.com/jobs/view/business-an	Job DescriptionPosition Description:
876	Machine Learning	LeanDNA	https://www.linkedin.com/jobs/view/machine-lea	Company OverviewLeanDNA is a dynamic software
868	Entry-Level AI/M	Austin Fraser	https://www.linkedin.com/jobs/view/entry-level	Austin Fraser is supporting a client in the Al
2152	Junior Data Scie	Flexon Technologies Inc.	https://www.linkedin.com/jobs/view/junior-data	Job DescriptionJob Summary:We are se
1839	Data Scientist I	CodaMetrix	https://www.linkedin.com/jobs/view/data-scient	CodaMetrix is revolutionizing Revenue Cycle Ma
1907	Transmission Dat	New Leaf Energy, Inc.	https://www.linkedin.com/jobs/view/transmissio	Job Summary: As an Al Business Analy
1906	AI Business Anal	Futurism Technologies, INC.	https://www.linkedin.com/jobs/view/ai-business	Job Summary: As an Al Business Analyst within o
3085	Junior Software	GliaCell Technologies	https://www.linkedin.com/jobs/view/junior-soft	We are looking for Machine Learning

3. Predictive Modeling using Random Forest

Research Question: What contributes to landing a data job?

Data Preprocessing: The LinkedIn profile data is loaded and preprocessed, including feature engineering, encoding of categorical variables, and imputation of missing values.

Data Splitting:

- The preprocessed data is split into features (X) and labels (y), where y represents the target variable ('Has_job' or 'No job').
- The data is further split into training and testing sets using techniques like train_test_split from scikit-learn.

Model Training:

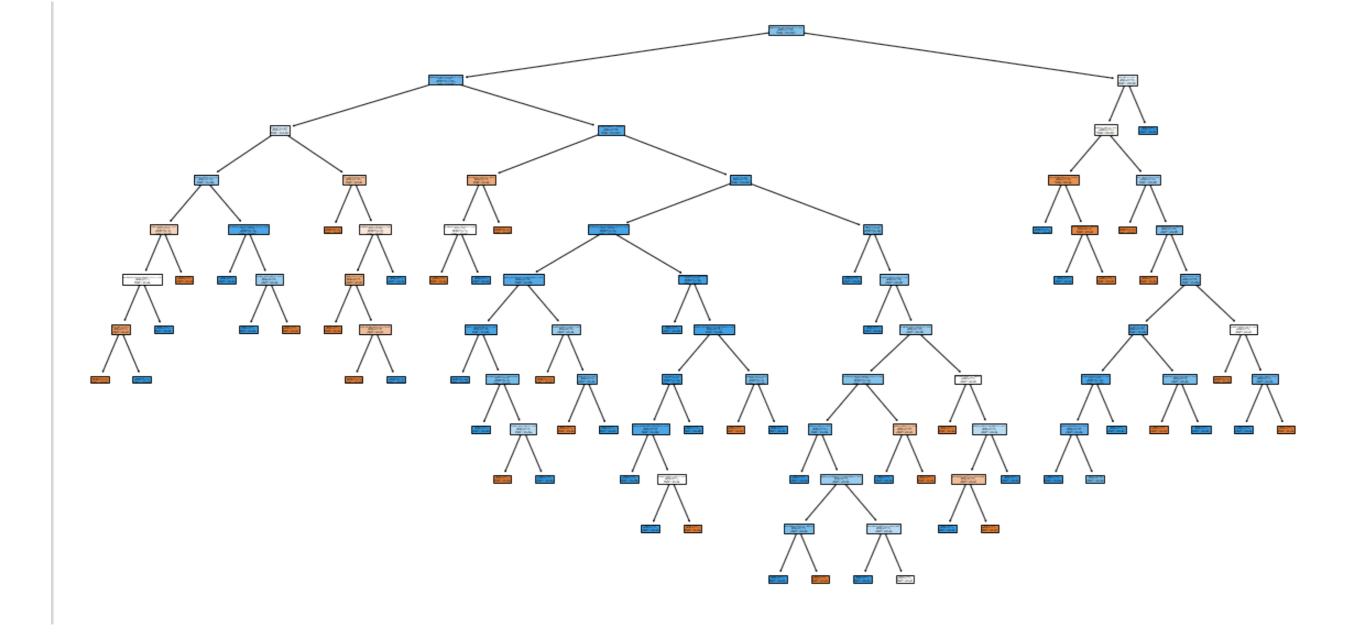
- A Random Forest Classifier is instantiated with appropriate hyperparameters, such as the number of trees (n_estimators) and random state for reproducibility.
- The model is trained on the training data (X_train, y_train) using the fit method.

Model Evaluation:

- The trained Random Forest model is evaluated on the test data (X_test, y_test) by making predictions using the predict method.
- Evaluation metrics such as accuracy, precision, recall, and F1-score are calculated to assess the model's performance.
- The project calculates and visualizes the feature importance scores to identify the most relevant features for predicting the target variable.

RandomForestClassifier RandomForestClassifier(random_state=0)

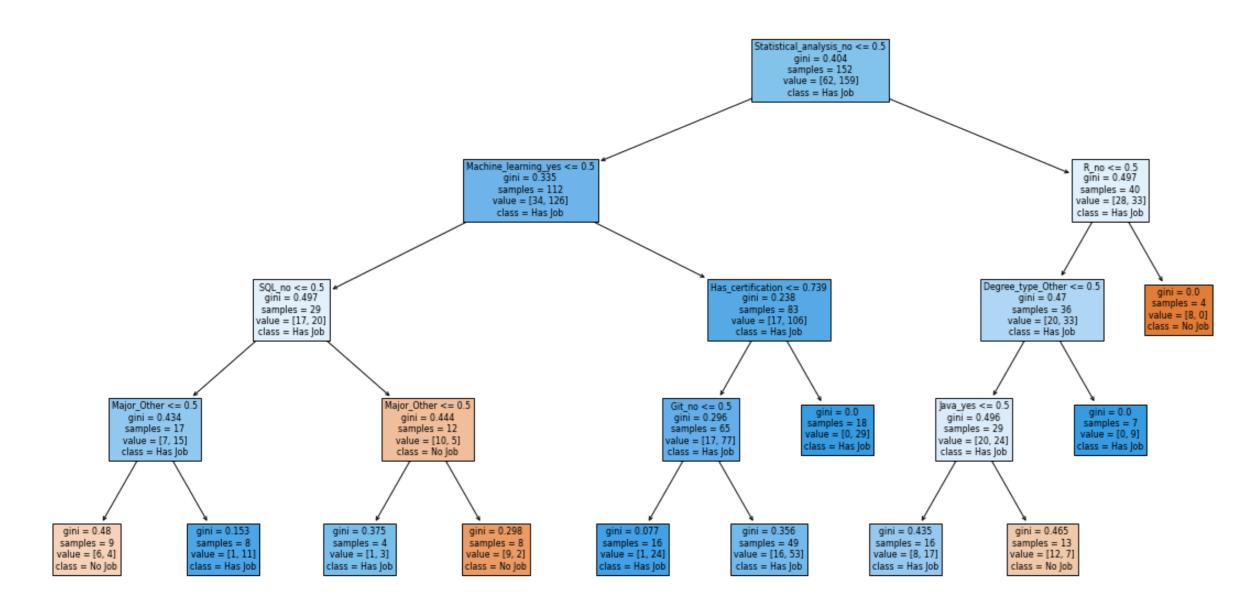




That looks like quite an expansive tree! Let's limit the depth of trees in the forest to produce an understandable image.

★ Download

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The root node gives us several information:

- There are 152 profiles (samples = 152).
- value = [62,159] describes the repartition of these profiles among the tree possible classes (i.e. 62 for the 'No Job', 159 for 'Has Job').
- class = job . This is the job prospect predicted by the Decision Tree at the root node.
- Gini impurity is a metric that measures the probability from a randomly chosen element (here a profile) to be incorrectly classified.

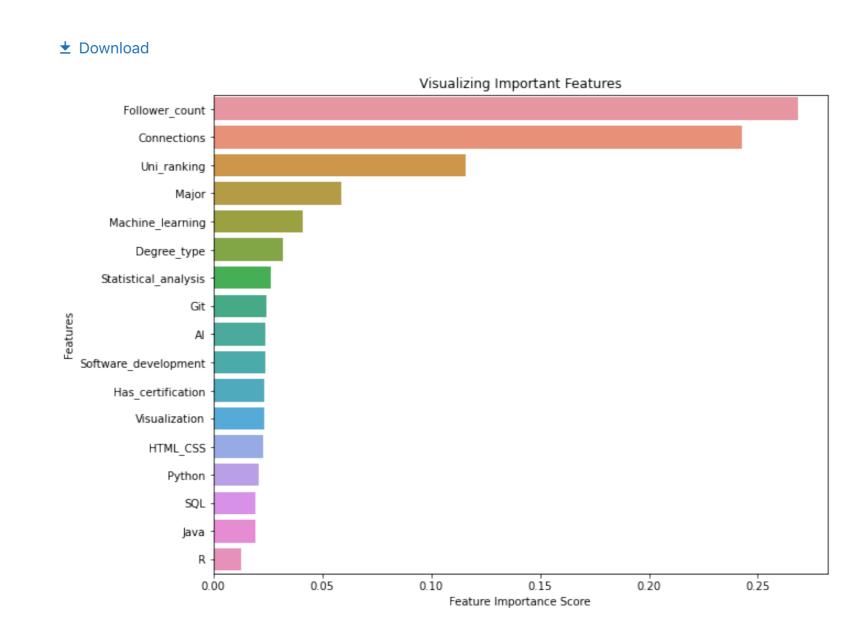
Model Evaluation

Accuracy: 0.92 Precision: 0.97 Recall: 0.91 F1-score: 0.94

Feature Importance

0.268526 Follower_count Connections 0.242866 Uni_ranking 0.115728 Major 0.059006 0.041271 Machine_learning 0.032234 Degree_type Statistical_analysis 0.026456 Git 0.024332 ΑI 0.023935 Software_development 0.023730 Has_certification 0.023527 Visualization 0.023445 HTML_CSS 0.022668 Python 0.020746 SQL 0.019325 0.019177 Java 0.013026 dtype: float64

Visualize feature scores



The feature importance scores emphasize that follower count and connections are the most influential factors, closely followed by university ranking. While skills like machine learning and statistical analysis contribute significantly, proficiency in programming languages such as Python and SQL, though important, holds slightly less weight in predicting job possibilities. Additionally, certifications and expertise in areas like artificial intelligence (AI) remain impactful in enhancing job probability.

4. Implications

4.1. Implications for Stakeholders:

- Job Seekers: The project provides valuable insights into job requirements, skill sets, and the probability of landing a data job based on a candidate's profile. This information can help job seekers tailor their resumes, acquire relevant skills, and apply to suitable job opportunities.
- Employers: The project's analysis of job descriptions and requirements can assist employers in crafting more effective job postings and aligning their expectations with industry standards.
- Educational Institutions: The identification of in-demand skills can help educational institutions update their curricula and prepare students for the job market. • Career Counselors: The project's findings can aid career counselors in providing better guidance to individuals interested in data-related fields.

4.2. Ethical, Legal, and Societal Implications:

- Ethical Considerations: The project scrapes public LinkedIn profiles, the project does not violate any terms of service or privacy policies.
- Legal Implications: The project's findings can contribute to the development of unbiased hiring policies, promoting equal employment opportunities and preventing discrimination. • Societal Impact: The project empowers job seekers by providing valuable insights into the skills and qualifications required in the data science and analytics fields, potentially leading to better career opportunities.