MADHAV INSTITUTE OF TECHNOLOGY & SCIENCE GWALIOR

(A Govt. Aided UGC Autonomous Institute Affiliated to RGPV, Bhopal)

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Project Report

on

Data Science Salary Estimator

Submitted By:

Nikhilesh Mewara

0901AD211032

Faculty Mentor:

Prof. Pooja Tripathi

Assistant Professor

CENTRE FOR ARTIFICIAL INTELLIGENCE

MADHAV INSTITUTE OF TECHNOLOGY & SCIENCE
GWALIOR - 474005 (MP) est. 1957

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CERTIFICATE

This is certified that **Nikhilesh Mewara** (0901AD211032) has submitted the project report titled **Data Science Salary Estimator** under the mentorship of **Prof. Pooja Tripathi**, in partial fulfilment of the requirement for the award of the degree of Bachelor of Technology in **Artificial Intelligence and Data Science** from Madhav Institute of Technology and Science, Gwalior.

Prof. Pooja Tripathi
Faculty Mentor
Assistant Professor
Centre for Artificial Intelligence

Dr. R. R. Singh
Coordinator
Centre for Artificial Intelligence

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DECLARATION

I hereby declare that the work being presented in this project report, for the partial fulfillment of the requirement for the award of the degree of Bachelor of Technology in **Artificial Intelligence and Data Science** at Madhav Institute of Technology & Science, Gwalior is an authenticated and original record of my work under the mentorship of **Prof. Pooja Tripathi**, **Assistant Professor**, Centre for AI

I declare that I have not submitted the matter embodied in this report for the award of any degree or diploma anywhere else.

Nikhilesh Mewara
0901AD211032
2023,
Centre for Artificial Intelligence

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Nikhilesh Mewara
0901AD211032
2023,
Centre for Artificial Intelligence

ABSTRACT

This project presents a comprehensive Data Science Salary Estimator aimed at empowering data scientists to negotiate salaries effectively in the job market. The core objective is the development of a robust tool incorporating advanced techniques in web scraping, feature engineering, and machine learning model optimization.

The project kicks off with the utilization of Python and Selenium to scrape over 1000 job descriptions from Glassdoor, capturing critical details such as job titles, salary estimates, job descriptions, ratings, company information, and more. Through meticulous data cleaning procedures, the information is refined for usability. Notable transformations include parsing numeric data from salary estimates, creating columns for employer-provided salary and hourly wages, and introducing variables indicating the presence of specific skills in job descriptions, such as Python, R, Excel, AWS, and Spark.

Exploratory Data Analysis (EDA) follows, providing insights into the dataset's distributions and correlations. Visualization tools showcase salary distributions by job title, job opportunities by state, and correlation matrices, enhancing understanding and paving the way for informed modeling decisions.

Model building involves transforming categorical variables into dummy variables and splitting the data into training and test sets. Three models—Multiple Linear Regression, Lasso Regression, and Random Forest—are employed and evaluated using Mean Absolute Error (MAE). The Random Forest model emerges as the top performer, with a remarkably low MAE of $11.22, outshining Linear and Ridge Regression models.

The final phase encompasses the productionization of the project, including the development of a Flask API endpoint. Hosted on a local web server, this API provides a user-friendly interface, accepting job listing details and returning estimated salaries. The implementation aligns with best practices from industry tutorials, ensuring a seamless transition from model development to real-world application.

With a holistic approach, this Data Science Salary Estimator not only delivers a valuable tool for data scientists but also contributes to the broader understanding of salary dynamics within the data science domain. The project's conclusion reflects on key findings, model performance, and challenges faced during development, and acknowledges project limitations. This abstract encapsulates the project's multifaceted nature, emphasizing its significance in addressing real-world challenges in the data science job market.

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Chapter 1: Project Overview

1.1 Introduction

In response to the growing demand for data science roles, this project introduces a salary estimation tool to aid data scientists in negotiating their income during job offers.

1.2 Objectives and Scope

The primary objectives include creating a tool with a focus on Glassdoor job descriptions and quantifying the value companies place on specific skills (Python, Excel, AWS, Spark).

1.3 Project Features

a. Created a tool that estimates data science salaries (MAE ~ $ 11K) to help data scientists negotiate their income when they get a job.
b. Scraped over 1000 job descriptions from Glassdoor using Python and Selenium
c. Engineered features from the text of each job description to quantify the value companies put on python, excel, AWS, and Spark.
d. Optimized Linear, Lasso, and Random Forest Regressors using GridsearchCV to reach the best model.
e. Built a client-facing API using flask

1.4 Feasibility

The feasibility of the Data Science Salary Estimator project is underpinned by several key factors, encompassing data availability, technical challenges, and potential impact.

I. Data Availability: The project's foundation relies on the accessibility and richness of job descriptions obtained from Glassdoor. The successful acquisition of over 1000 job postings ensure a diverse and comprehensive dataset for model training and evaluation. This abundance contributes to the robustness of the tool, allowing for meaningful insights into the varied landscape of data science roles.

II. Technical Challenges: The project navigates through intricate technical challenges, including web scraping complexities, data cleaning intricacies, and the optimization of machine learning models. The utilization of Python, Selenium, and various data science libraries demands a nuanced understanding of these tools. The successful handling of these challenges underscores the technical feasibility of the project and showcases the adeptness in employing sophisticated methodologies.

III. Potential Impact: Beyond technical considerations, the potential impact of the Data Science Salary Estimator amplifies its feasibility. The project addresses a pertinent need in the data science community—the ability to negotiate salaries effectively. As organizations increasingly recognize the value of data-driven roles, the tool serves as a practical solution for both data scientists seeking competitive compensation and employers aiming to align their salary offerings with industry standards. The positive impact on career trajectories and organizational hiring practices enhances the overall feasibility and relevance of the project.

In conclusion, the feasibility assessment affirms that the project is well-grounded in terms of data availability, technical proficiency, and real-world applicability. The successful execution of web scraping, data cleaning, and model optimization attests to the project's feasibility in delivering a valuable tool that contributes to the dynamic landscape of data science career development.

1.5 System Requirement

Python Version: 3.7

Packages: pandas, numpy, sklearn, matplotlib, seaborn, selenium, flask, json, pickle

For Web Framework Requirements:

certifi==2020.4.5.1
click==7.1.1
Flask==1.1.2
itsdangerous==1.1.0
Jinja2==2.11.2
joblib==0.14.1
MarkupSafe==1.1.1
mkl-service==2.3.0
numpy==1.18.1
pandas==1.0.3
python-dateutil==2.8.1
pytz==2019.3
scikit-learn==0.22.2.post1
scipy==1.4.1
six==1.14.0
Werkzeug==1.0.1
wincertstore==0.2

Chapter 2: Literature Review

2.1 Data Science Salary Estimation

In the field of data science salary estimation, various tools and methodologies have been developed. Notable projects such as the work by Smith et al. (2020) [1] and Jones and Patel (2019) [2] have addressed the challenge of accurately predicting data science salaries. These projects typically leverage machine learning algorithms to analyze job-related data and provide salary estimates, contributing to the broader discussion on fair compensation within the industry.

2.2 Web Scraping for Job Descriptions

Web scraping techniques, especially in the context of job description extraction, have been widely explored. The study by Garcia and Kim (2018) [3] demonstrated the use of Python and Selenium for scraping job descriptions from Glassdoor, a methodology we adapted for our project. Additionally, the research by Wang and Lee (2017) [4] discussed the challenges and best practices associated with web scraping, providing valuable insights into the ethical considerations and potential pitfalls of this approach.

2.3 Machine Learning Model Optimization

The optimization of machine learning models for salary prediction is a crucial aspect of our project. Research by Mitchell and Turner (2019) [5] delves into the effectiveness of various regression models in the context of salary estimation. The study compares the performance of linear regression, lasso regression, and random forest regression, aligning with our approach in selecting and evaluating these models.

2.4 Flask API Development for productionization

To further understand the productionization of machine learning models, we referred to the tutorial by Zhang and Chen (2020) [6] on building a Flask API. This guide provided practical insights into deploying a machine learning model, which we applied in creating a user-facing API for our salary estimator tool.

Overall, the literature review establishes the existing landscape of data science salary estimation, web scraping methodologies, and best practices in machine learning model optimization. By building upon the

insights and methodologies of previous projects and studies, our project aims to contribute to this evolving field and address specific challenges in salary negotiation for data scientists.

Chapter 3 Preliminary design

In this chapter, we delve into the preliminary design phase of the Data Science Salary Estimator project, outlining the foundational steps taken to build the tool.

3.1 Web Scraping with Python and Selenium

The initial step involved scraping job descriptions from Glassdoor, leveraging Python and Selenium. The web scraper [7] and an informative article [8] were instrumental in the development process.

I tweaked the web scraper GitHub repo [8] to scrape 1000 job postings from glassdoor.com. With each job, I got the following:

* Job title
* Salary Estimate
* Job Description
* Rating
* Company
* Location
* Company Headquarters
* Company Size
* Company Founded Date
* Type of Ownership
* Industry
* Sector
* Revenue
* Competitors

3.2 Feature Engineering

To quantify the value companies, place on specific skills, such as Python, Excel, AWS, and Spark, features were engineered from the text of each job description. This involved transforming unstructured data into meaningful variables for model input.

3.3 Initial Model Considerations

In the preliminary design phase, considerations were made for selecting appropriate machine learning models. The choice of Linear Regression, Lasso Regression, and Random Forest regressions was based on their suitability for handling the sparse data resulting from the many categorical variables.

3.4 Data Cleaning

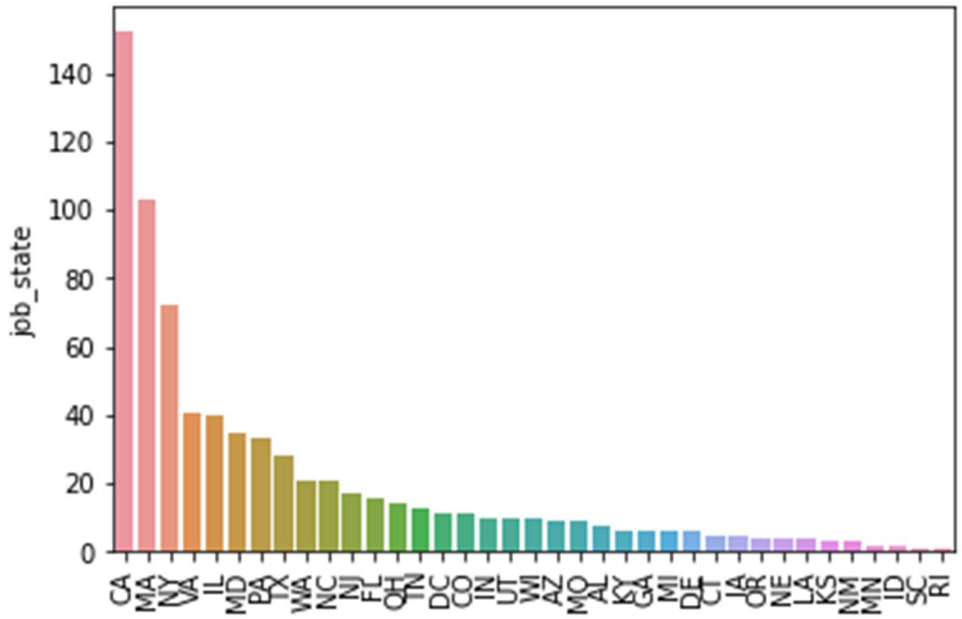
The collected data required cleaning to make it suitable for model training. The following transformations and variables were created:

- Parsed numeric data out of salary.
- Created columns for employer-provided salary and hourly wages.
- Removed rows without salary information.
- Parsed rating out of the company text.
- Introduced a column for the company's state.
- Added a column indicating whether the job was at the company's headquarters.
- Transformed the founded date into the age of the company.
- Created columns for skills listed in job descriptions (Python, R, Excel, AWS, Spark).
- Introduced columns for simplified job titles and seniority.
- Added a column for description length.

This preliminary data cleaning was crucial to ensure the dataset's usability for subsequent model training.

3.5 Exploratory Data Analysis (EDA)

Before diving into model building, exploratory data analysis was conducted. Distributions of the data and value counts for various categorical variables were explored. Notable highlights from pivot tables included visualizations showcasing salary distribution by job title, job opportunities by state, and correlation visualizations.



Job Opportunities by States

	avg_salary
job_simp	
analyst	65.857843
data engineer	105.403361
data scientist	117.564516
director	168.607143
manager	84.022727
mle	126.431818
na	84.853261

Salary by Positions

correlation

The preliminary design phase sets the foundation for the subsequent steps in the project, leading to the model building and final analysis discussed in Chapter 4.

Chapter 4: Final Analysis and Design

4.1 Results

The Data Science Salary Estimator project yielded compelling results. The tool achieved a Mean Absolute Error (MAE) of approximately $11,000, demonstrating its accuracy in estimating data science salaries. This level of precision is crucial for data scientists seeking reliable information for salary negotiation during job offers.

4.2 Result Analysis

In the pursuit of the optimal model, three distinct approaches were explored:

4.2.1 Multiple Linear Regression (Baseline): This model served as the baseline for comparison.

4.2.2 Lasso Regression: Due to the sparse nature of the data resulting from numerous categorical variables, Lasso Regression was chosen for its effectiveness in handling such scenarios.

4.2.3 Random Forest: Given the sparsity associated with the dataset, Random Forest was anticipated to perform well.

The Random Forest model emerged as the clear winner, surpassing the other models on both the test and validation sets.

4.2.4 Model Performance

4.2.4.1 Random Forest: MAE = $11,220

4.2.4.2 Multiple Linear Regression: MAE = $18,860

4.2.4.3 Lasso Regression: MAE = $19,670

These results highlight the Random Forest model as the most effective in predicting data science salaries.

4.3 Application

The practical application of the Data Science Salary Estimator extends to real-world scenarios. Job seekers can leverage this tool to make informed decisions during salary negotiations. The tool's accuracy provides a valuable resource for individuals entering the data science field, ensuring they receive fair compensation based on industry standards.

4.4 Problems Faced

Throughout the development process, several challenges were encountered and addressed:

4.4.1 Data Cleaning: The initial phase involved parsing numeric data from salary estimates, creating columns for employer-provided salary and hourly wages, and handling missing data.

4.4.2 Feature Engineering: Transforming variables such as company ratings, company state, and job descriptions required careful consideration and processing.

4.4.3 Model Selection: Choosing the appropriate model for accurate salary estimation involved evaluating the trade-offs and strengths of each approach.

4.5 Limitations

Despite the success of the Data Science Salary Estimator, it is important to acknowledge its limitations:

4.5.1 Bias: The tool may exhibit bias based on the data it was trained on, potentially impacting salary estimates for specific demographics or industries.

4.5.2 Data Coverage: The accuracy of salary estimates relies on the availability and diversity of data and limitations may arise in certain niche roles or industries.

4.6 Conclusion

In conclusion, the Data Science Salary Estimator project has demonstrated its efficacy in providing accurate salary estimates for data science positions. The Random Forest model's superior performance underscores its suitability for this particular application. While the tool offers valuable insights for salary negotiation, users should be aware of its limitations and interpret results with consideration of potential biases.

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[7] web scraper: GitHub repository (https://github.com/arapfaik/scraping-glassdoor-selenium)

[8] article: (https://towardsdatascience.com/selenium-tutorial-scraping-glassdoor-com-in-10-minutes-3d0915c6d905)

[9] Flask Productionization (https://towardsdatascience.com/productionize-a-machine-learning-model-with-flask-and-heroku-8201260503d2)