TEAM INFORMATION (1 point)

Team #: 101 Team Members:

1. Daniel Avila; davila7. Graduated with bachelor's degree in electrical engineering; completed ISYE6501, CSE6040, and MGT8803; studying for OMSA.
2. Alain Daccache; adaccache3. Graduated with bachelor's degree in software engineering; worked as a data scientist for two years, on recommendation engines, marketing analytics, and truck fleet dispatching (operations research). Currently work as an ML Engineer to deploy and scale NLP and CV models in production.
3. Jeffrey Triemer; jtriemer3. Gratudated in 2020 with a Bachelors in Economics from Georgia State University. Worked over a year as a supply chain analyst and then a data engineer. Experienced with data vizualization and python and Alteryx ETL.
4. Bruce Dale Service; bservice3
5. Ethan Goldstein; egoldstein30. Completed a Honours Bachelor of Business Administration at Wilfrid Laurier University. Experienced developing data visualizations/analytics and pipelines/integrations for retailers and local governments, with a foucs on the SQL Server ecosystem.

OBJECTIVE/PROBLEM (5 points)

Project Title: Salary Prediction with Polling Data

Background Information

In 2022, it was estimated that over 158 million Americans were in some form of employment (reference). While the pandemic affected much of the nature of jobs as well as the supply-demand dynamics of the job market, many Americans spent their time reflecting on their career decisions. Was their choice of education appropriate, or does it matter at all when stacking against those with lower education-level? How about their occupation, distance from office, or age? Are there some statistically significant demographic biases that would prevent them from achieving their desired objectives?

Problem Statement

The primary objective of this project is to analyze and forecast job salaries in the context of the evolving employment landscape in the United States, while investigating the underlying drivers that influence salary level. This analysis aims to address the following key questions:

- How do factors such as occupation and age contribute to variations in job salaries, and is there some discernible demographic biases that affect those salaries?
- How can we predict an individual's salary based on such attributes so that they have more confidence in their current compensation, if applicable?

Through a thorough examination of these questions, this project aims to offer a deeper understanding of the intricate factors that influence job salaries, so that individuals can make more informed career choices. Businesses compensation packages are competitive; business owners would choose the employees that provide the highest value for the money.

Primary Research Question

How do factors such as occupation and years of experience contribute to variations in job salaries, and is there some discernible demographic bias that affects those salaries?

Supporting Research Questions

1. What are the key determinants of job salaries in the United States, and how do these determinants interact with each other?
2. Are there specific industries or occupations that consistently offer higher salaries?
3. To what extent does an individual's level of education impact their job salary? Are there significant differences in salary between those with varying educational backgrounds?
4. Is there any unjust bias in the given Salary based on protected classes?

Business Justification

From an employee perspective, this would allow them to make more informed career decisions, and in turn lead to job satisfaction, career progression, and ultimately a positive impact on the overall economy.

From a business's perspective, this would help them understand if their compensation packages are competitive and fair, so that they can better position themselves in their industry.

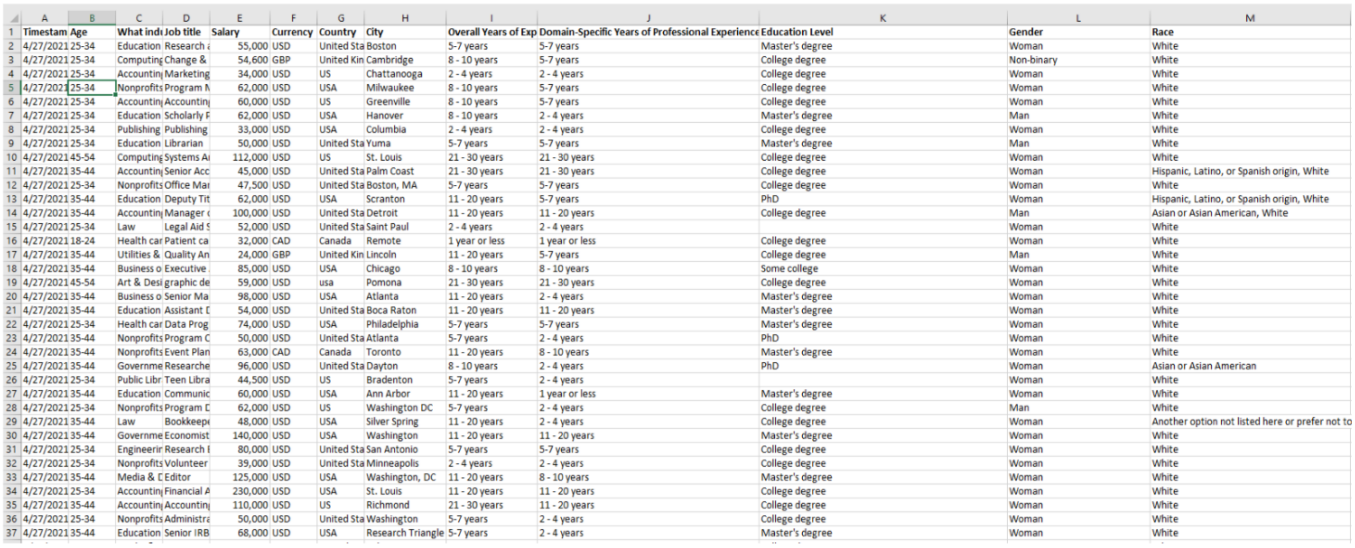
Governments could also use this analysis to inform labor policies i.e., minimum wage adjustments, so that the job market could be more equitable, reducing disparities in the economy. Illegal discrimination can be identified and rooted out, or discover any otherwise unjust DEI infractions to further inform and improve payroll and hiring decisions going forwards.

DATASET/PLAN FOR DATA (4 points)

Data Sources and Description

The data sets below show this forecasting as both a classification and regression task. We will be evaluating different models (e.g. logistic regression, linear regression) and identify whether different datasets could lead us to similar conclusions. Since one dataset is more recent than the other, we could also see if some factor importance or interactions changed over time.

Ask a Manager Salary Survey: In 2021, ALISON GREEN conducted a survey on AskAManager.org, which primarily focuses on the United States but also considers responses from various countries. The survey was created to investigate compensation differences across industries, taking into account factors such as years of experience, field-specific experience, as well as demographic variables like gender, race, and educational background.



	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Timestam	Age	What ind	Job title	Salary	Currency	Country	City	Overall Years of Exp	Domain-Specific Years of Professional Experience	Education Level	Gender	Race
2	4/27/2021	25-34	Education	Research a	55,000	USD	United Sta	Boston	5-7 years	5-7 years	Master's degree	Woman	White
3	4/27/2021	25-34	Computing	Change &	54,600	GBP	United Kin	Cambridge	8 - 10 years	5-7 years	College degree	Non-binary	White
4	4/27/2021	25-34	Accountin	Marketing	34,000	USD	US	Chattanooga	2 - 4 years	2 - 4 years	College degree	Woman	White
5	4/27/2021	25-34	Nonprofits	Program M	62,000	USD	USA	Milwaukee	8 - 10 years	5-7 years	College degree	Woman	White
6	4/27/2021	25-34	Accountin	Accountin	60,000	USD	US	Greenville	8 - 10 years	5-7 years	College degree	Woman	White
7	4/27/2021	25-34	Education	Scholarly F	62,000	USD	USA	Hanover	8 - 10 years	2 - 4 years	Master's degree	Man	White
8	4/27/2021	25-34	Publishing	Publishing	33,000	USD	USA	Columbia	2 - 4 years	2 - 4 years	College degree	Woman	White
9	4/27/2021	25-34	Education	Librarian	50,000	USD	United Sta	Yuma	5-7 years	5-7 years	Master's degree	Man	White
10	4/27/2021	45-54	Computing	Systems Ai	112,000	USD	US	St. Louis	21 - 30 years	21 - 30 years	College degree	Woman	White
11	4/27/2021	35-44	Accountin	Senior Acc	45,000	USD	United Sta	Palm Coast	21 - 30 years	21 - 30 years	College degree	Woman	Hispanic, Latino, or Spanish origin, White
12	4/27/2021	25-34	Nonprofits	Office Mar	47,500	USD	United Sta	Boston, MA	5-7 years	5-7 years	College degree	Woman	White
13	4/27/2021	35-44	Education	Deputy Tit	62,000	USD	USA	Scranton	11 - 20 years	5-7 years	PhD	Woman	Hispanic, Latino, or Spanish origin, White
14	4/27/2021	35-44	Accountin	Manager (	100,000	USD	United Sta	Detroit	11 - 20 years	11 - 20 years	College degree	Man	Asian or Asian American, White
15	4/27/2021	25-34	Law	Legal Aid S	52,000	USD	United Sta	Saint Paul	2 - 4 years	2 - 4 years		Woman	White
16	4/27/2021	18-24	Health car	Patient ca	32,000	CAD	Canada	Remote	1 year or less	1 year or less	College degree	Woman	White
17	4/27/2021	35-44	Utilities &	Quality An	24,000	GBP	United Kin	Lincoln	11 - 20 years	5-7 years	College degree	Man	White
18	4/27/2021	35-44	Business o	Executive	85,000	USD	USA	Chicago	8 - 10 years	8 - 10 years	Some college	Woman	White
19	4/27/2021	45-54	Art & Desi	graphic de	59,000	USD	usa	Pomona	21 - 30 years	21 - 30 years	College degree	Woman	White
20	4/27/2021	35-44	Business o	Senior Ma	98,000	USD	USA	Atlanta	11 - 20 years	2 - 4 years	Master's degree	Woman	White
21	4/27/2021	35-44	Education	Assistant D	54,000	USD	United Sta	Boca Raton	11 - 20 years	11 - 20 years	Master's degree	Woman	White
22	4/27/2021	25-34	Health car	Data Progr	74,000	USD	USA	Philadelphia	5-7 years	5-7 years	Master's degree	Woman	White
23	4/27/2021	35-44	Nonprofits	Program C	50,000	USD	United Sta	Atlanta	5-7 years	2 - 4 years	PhD	Woman	White
24	4/27/2021	35-44	Nonprofits	Event Plan	63,000	CAD	Canada	Toronto	11 - 20 years	8 - 10 years	Master's degree	Woman	White
25	4/27/2021	35-44	Governme	Researche	96,000	USD	United Sta	Dayton	8 - 10 years	2 - 4 years	PhD	Woman	Asian or Asian American
26	4/27/2021	25-34	Public Libr	Teen Libra	44,500	USD	US	Bradenton	5-7 years	2 - 4 years		Woman	White
27	4/27/2021	35-44	Education	Communic	60,000	USD	USA	Ann Arbor	11 - 20 years	1 year or less	Master's degree	Woman	White
28	4/27/2021	25-34	Nonprofits	Program D	62,000	USD	US	Washington DC	5-7 years	2 - 4 years	College degree	Man	White
29	4/27/2021	35-44	Law	Bookkeepe	48,000	USD	USA	Silver Spring	11 - 20 years	2 - 4 years	College degree	Woman	Another option not listed here or prefer not to
30	4/27/2021	35-44	Governme	Economist	140,000	USD	USA	Washington	11 - 20 years	11 - 20 years	Master's degree	Woman	White
31	4/27/2021	25-34	Engineerir	Research I	80,000	USD	United Sta	San Antonio	5-7 years	5-7 years	College degree	Woman	White
32	4/27/2021	25-34	Nonprofits	Volunteer	39,000	USD	United Sta	Minneapolis	2 - 4 years	2 - 4 years	College degree	Woman	White
33	4/27/2021	35-44	Media & C	Editor	125,000	USD	USA	Washington, DC	11 - 20 years	8 - 10 years	Master's degree	Woman	White
34	4/27/2021	25-34	Accountin	Financial A	230,000	USD	USA	St. Louis	11 - 20 years	11 - 20 years	College degree	Woman	White
35	4/27/2021	35-44	Accountin	Accountin	110,000	USD	US	Richmond	21 - 30 years	11 - 20 years	College degree	Woman	White
36	4/27/2021	25-34	Nonprofits	Administra	50,000	USD	United Sta	Washington	5-7 years	2 - 4 years	College degree	Woman	White
37	4/27/2021	35-44	Education	Senior IRB	68,000	USD	USA	Research Triangle	5-7 years	2 - 4 years	Master's degree	Woman	White

Census Income Dataset (https://archive.ics.uci.edu/dataset/20/census+income) The "Census Income" dataset, extracted by Barry Becker on April 30, 1996 from the 1994 Census database, is used for predicting whether a person's income exceeds $50,000 per year based on census data. It is also known as the "Adult dataset.

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=50K
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=50K
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<=50K
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<=50K
5	37	Private	284582	Masters	14	Married-civ-spouse	Exec-managerial	Wife	White	Female	0	0	40	United-States	<=50K
6	49	Private	160187	9th	5	Married-spouse-absent	Other-service	Not-in-family	Black	Female	0	0	16	Jamaica	<=50K
7	52	Self-emp-not-inc	209642	HS-grad	9	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	45	United-States	>50K
8	31	Private	45781	Masters	14	Never-married	Prof-specialty	Not-in-family	White	Female	14084	0	50	United-States	>50K
9	42	Private	159449	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	5178	0	40	United-States	>50K

Key Variables

Independent variables:

- Demographic Related: Age Range, Gender, Marital Status, Race, Native Country
- Professional Related: Work Class (private, self-employed, government), Education level (Bachelors, Masters, PhD), Occupation (Farming, Transport, Protective Services, Tech Support, Sales...), Overall Years of Experience, Years of Experience in the Current Domain

Dependent variables:

- Salary: could be binary (i.e. above or below 50k) or continuous.

We will likely be creating new variables, including interaction terms in order to capture the relationships between some of our predictors. For instance, age and occupation would give us insights on whether some occupations value or have biases towards age. We will also be creating some dummy variables for our categorical variables i.e. education and age range, effectively creating m – 1 variables for predictors that could take m values.

Finally, we hypothesize that the most important predictors of our dependent variable, salary, would be certain occupation fields and years of experience.

APPROACH/METHODOLOGY (8 points)

Planned Approach

Data Preprocessing: this will involve cleaning the dataset; this might involve specifying the types of the variables (i.e., factor in R for categorical), and cleaning rows that have missing data. For example, factors may be developed for categorical variables and data may be cleaned through an evaluating tradeoff of imputation process.

Exploratory Data Analysis: Involves exploring univariate and bivariate distributions, identifying linear and nonlinear relationships / correlations, and identifying and treating outliers (e.g. evaluating tradeoff imputing, deleting). We will verify assumptions of linear regressions by testing the linearity and homoscedasticity of the data.

Feature Engineering: In this step, we will apply some data transformations to account for non-linear relationships, such as heteroscedasticity if identified above; this will be done via Box-Cox transformations including natural log and square root transforms of predictor and/or response variables as we see fit. This will also involve adding some features as mentioned previously, specifically indicator (dummy) variables (for encoding categorical variables) and then interaction terms (i.e. age * occupation).

Feature Selection: Based on correlations found above, we can preliminarily reduce the dimensionality of the dataset. We will likely run a regression model first and let metrics such as the VIF help us determine which features could be removed, and whether it makes sense from a business perspective. This could also involve techniques such as Principal Component Analysis (or PCA).

Model Building: This will involve performing linear regression (e.g. linear, log-linear, linear-log, log-log) as well as logistic regression. Then, we will evaluate the quality of the factors (p-value, confidence interval, t-stat), and overall model; this will involve choosing metrics such R-squared, adjusted R-squared, RMSE, F-score for linear regression, as well as metrics like Precision, Recall, AUC-ROC for our logistic regression. Based on some diagnostic plots, we could identify whether we meet the assumptions of the model, and otherwise proceed with treatment and reiterate on our data preprocessing, feature engineering and feature selection steps above.

- Further investigating our non-linear transformations if non-normality of residuals (QQ Plot, Jacque-Berra), heteroscedasticity (found in residuals vs. Fitted), or autocorrelation (found via Durbin-Watson) is found.

- Further performing feature selection based on VIFs when testing for multicollinearity.

- Treating high-leverage points if found via Cook's distances plot.

Model Selection: We will test different linear regression models e.g. linear-log, as well as regularized linear regression models that handle overfitting e.g. Ridge, Lasso, ElasticNet. We will select the best models by performing methods such as cross-validation, which will optimize our hyper-parameters (I.e. alpha, the penalty term for amount of shrinkage, and the classification threshold) w.r.t. to the quality metrics we mentioned previously. Cross-validation will help us prevent overfitting and provide unbiased performance assessments.

Interpret the Results: We will quantify the impact of variables while keeping others constant, and examine the significance of coefficients i.e. keeping all else constant, and on average, one unit or % increase of one variable could result in how much of an increase / decrease of the response variable (salary). Interpreting indicator variables w.r.t. base case, and same with the interaction terms.

Anticipated Conclusions/Hypothesis

Our null hypothesis will be that any protected class information we have in the model, such as age, race, sex, or gender will all have statistically insignificant coefficients. If we find that any such independent variable can be declared as statistically significant for a model built to predict Salary, then we must reject the null hypothesis and we can assert that the data reflects there is a bias is the payroll based on those protected classes.

Rejecting the null hypothesis would reflect that there are major DEI concerns to address within the given dataset.

What business decisions will be impacted by the results of your analysis? What could be some benefits?

Hiring and payroll packages can be reassesed to reflect DEI values in a more just way. A linear regression model can not only reflect that some parameter is statistically significant, but give a sense of magnitude and direction. We can use those coefficients to estimate in what ways payroll can be changed to reflect what an individual's Salary would have been had they been another classification of protected class.

PROJECT TIMELINE/PLANNING (2 points)

Project Timeline/Mention key dates you hope to achieve certain milestones by:

10/30 Project Progress Report Deliverables:

- ☐ **Data Preprocessing**
- ☐ **Exploratory Data Analysis**

11/13 Monday before November Break Deliverables:

- ☐ **Feature Engineering**
- ☐ **Feature Selection**
- ☐ **Model Building**
- ☐ **Model Selection**

11/17 Day before November Break Deliverables:

- [ ] Final Paper First Draft Complete Followed by a week of revisions

11/27 Final Paper Due