Using Machine Learning to Predict Executive Gender Pay Gaps

Tess Cotter, Claudia Durkin, Jess Matthews

W207 - 18 April 2023

Introduction: Problem motivation

"Women are underrepresented in the corporate business world and the top of the income distribution more generally, where relatively large gender wage gaps remain."
(Blau and Kahn, 2017; Goldin 2014, Guvene et al., 2020).

Focus: The World Economic Forum projected that it will take at *least 151 years* to close the gender pay gap.

Utilizing a public SEC dataset focused on executive compensation, we sought to analyze total compensation variation by gender.

Introduction: Problem motivation

“One of the major problems with surfacing pay disparities and pay discrimination in lack of transparency. People often do not know how much they make in comparison to the person next to them.” – Jocelyn Frye, president of National Partnership for Women and Families

Employers:

- 74% of executives consider pay equity to be a priority.
- 46% percent of employers admit they’ve not been transparent with employees on the subject.
- 49% of companies in the survey say they don’t have a well-established pay equity plan.
- Inconsistent opinions on who should be responsible, with the most common opinion being CHROs, followed by CEOs.
- 34% of organizations say that absence of executive-level commitment is standing in the way of improving pay equity.

Employees:

- 71% of employees consider pay equity to be a priority.
- Only 41% of employees say they believe their employers have successfully done something about it.
- Tend to believe the CEO, followed by the senior executive team, and a compensation committee should take ownership.
- 34% of organizations say that absence of executive-level commitment is standing in the way of improving pay equity.

HBR, UKG: *Making Pay Equity Work for All*

Berkeley
UNIVERSITY OF CALIFORNIA

Building the Dataset

1

Get all public company tickers

- Wrote code to pull this list from public filings from YFinance API

11,470 number of public companies included

2

Call SEC API ExecComp

- Queries DEF 14A filing
- Response is a list of dictionaries with each entry representing an executive's compensation data for a specific year

Created a dataset of nearly 300,000 rows

3

Call genderize API

- Split the name column into two columns to isolate the first name
- Write python code to call Genderize API
- Response is the assumed gender, male or female, with a 99% probability

650 executives were excluded due to inconclusive results, mostly those using a first initial

4

Call YFinance API

- Query Market Capitalization, Industry type, sector information from Yahoo Finance API
- Pruned, replicated and merged this information

Multiple industries are included in the dataset

5

Classify titles to roles

- Write python code to identify the most common c-suite roles based on their individual titles
- Some iteration was needed to find the bulk of executives

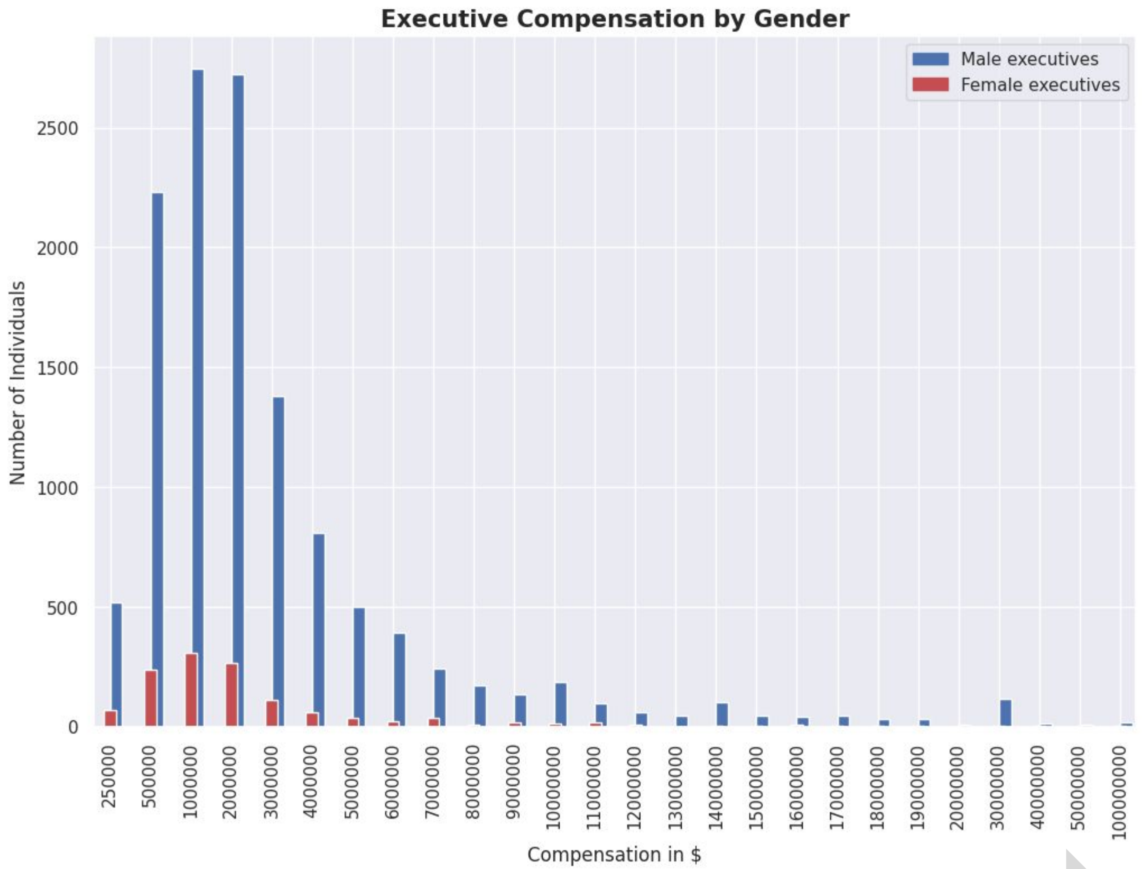
The role 'president' was excluded from the analysis due to a wide variety of role scopes and false positives from other roles

We focus our analysis on 2021 compensation that is the most recent full year of filings.

Exploratory data analysis

Some findings:

- US executives of large publicly-traded companies have **very high total compensation**, and the deviations are **extremely large.**
- Very few women executives earning at the top compensation levels.
- Female **CEOs** out earn males on average but no female CEOs earning top compensation.



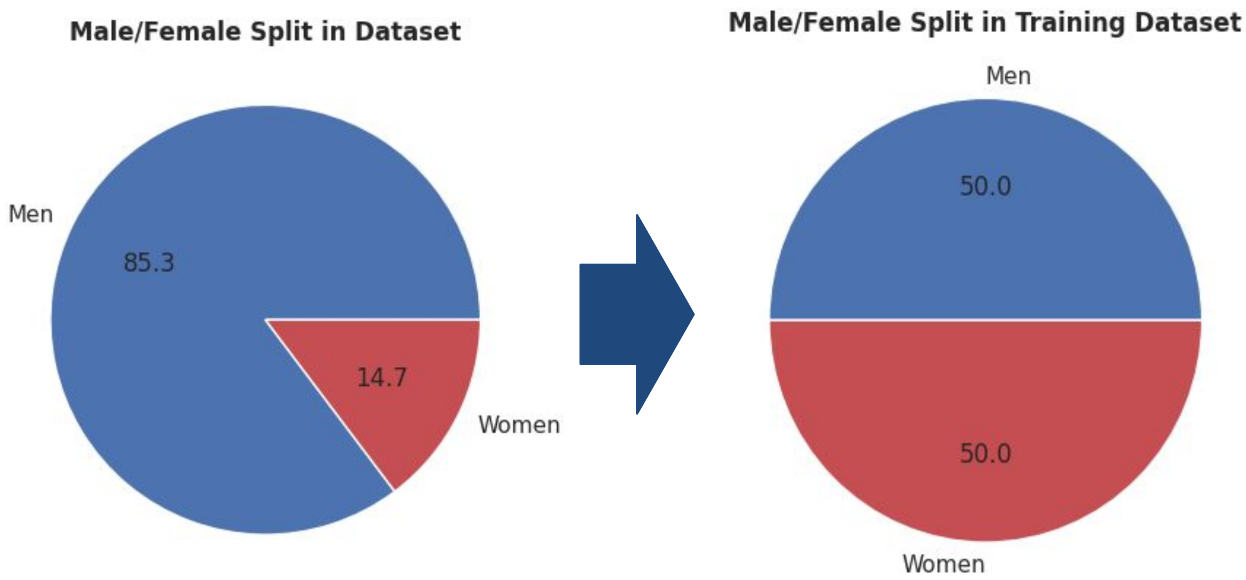
$250,000 $11 mln $100 mln

Berkeley UNIVERSITY OF CALIFORNIA

Data rebalance and transformations

The raw data are unbalanced with male executives accounting for over 85%. We rebalanced to a 50/50 split in the training dataset.

- Due to a massive range, total compensation was normalized between 0 and 1 after taking the log.
- The string-based gender variable was transformed to 0 or 1.



Berkeley
UNIVERSITY OF CALIFORNIA

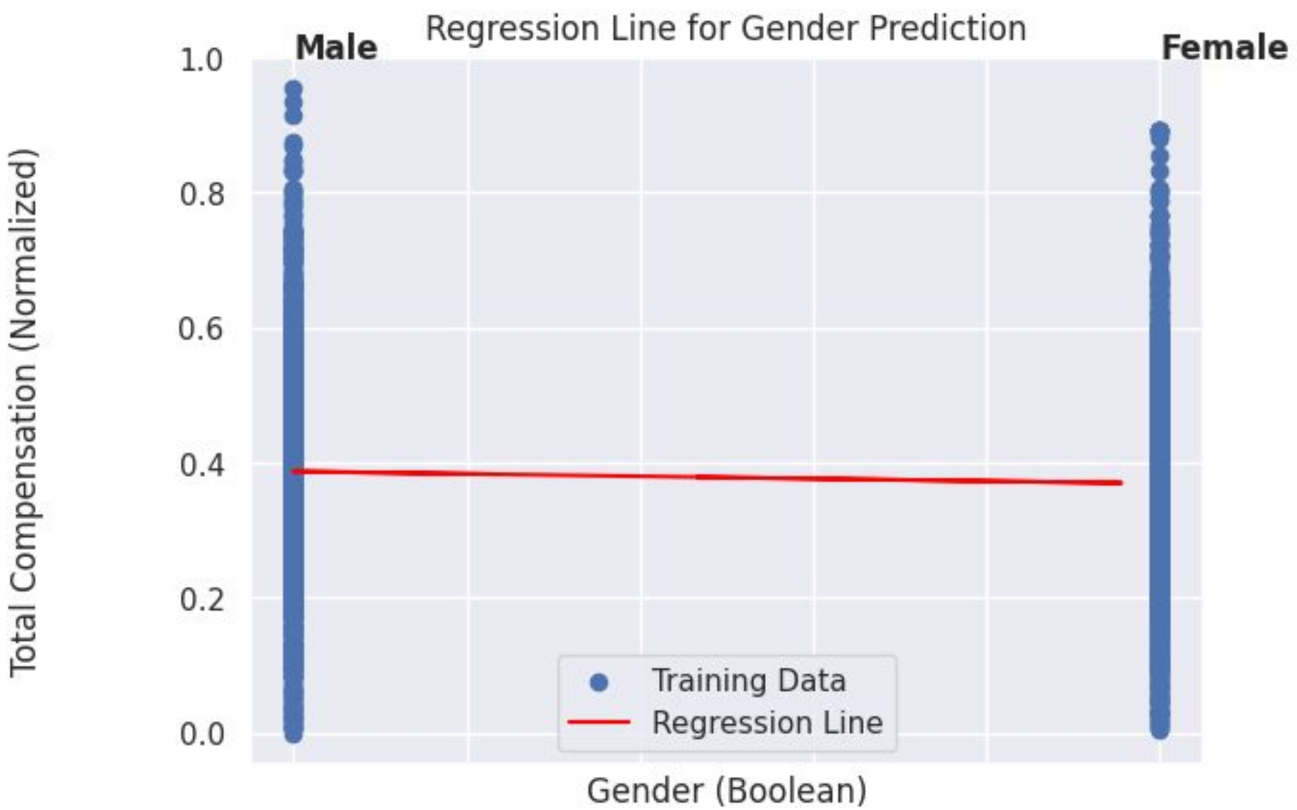
Model Experimentation

Berkeley
UNIVERSITY OF CALIFORNIA

Regression finds slightly downward slope

We started with a simple OLS regression to build up complexity slowly.

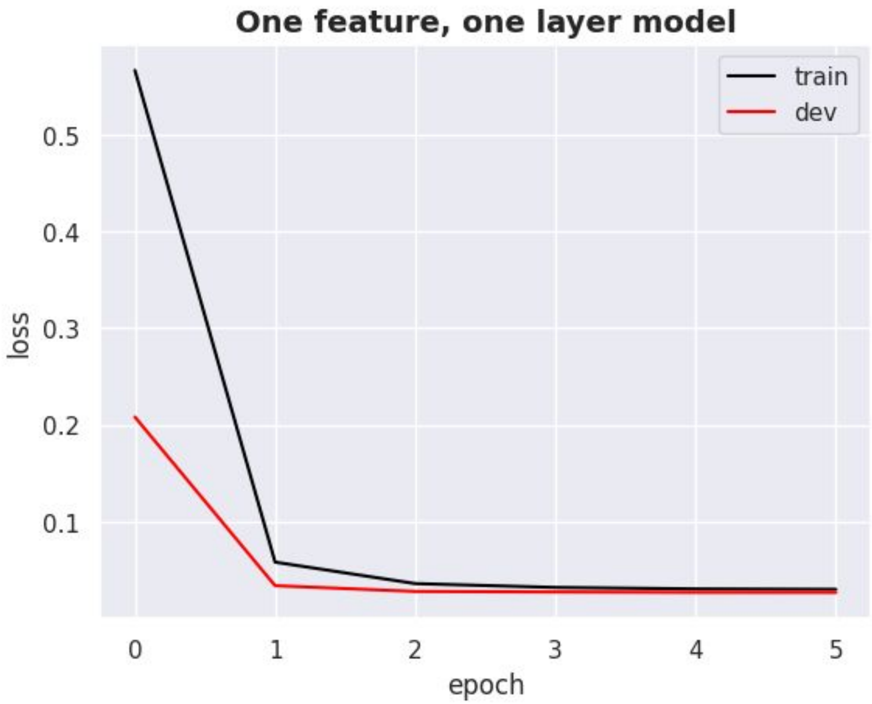
- Correlation coefficient between gender and normalized total compensation is slightly negative at -0.08.
- You can see in the plot of dots for each gender that there are more male data points at the top of total compensation.



Berkeley
UNIVERSITY OF CALIFORNIA

Simple model: one feature, single layer

Next, we build a simple model, using one feature, gender, and one layer.
Our simple model predicts that using gender alone, male executive compensation is \$1.6 million and female executive compensation is \$1.4 million.

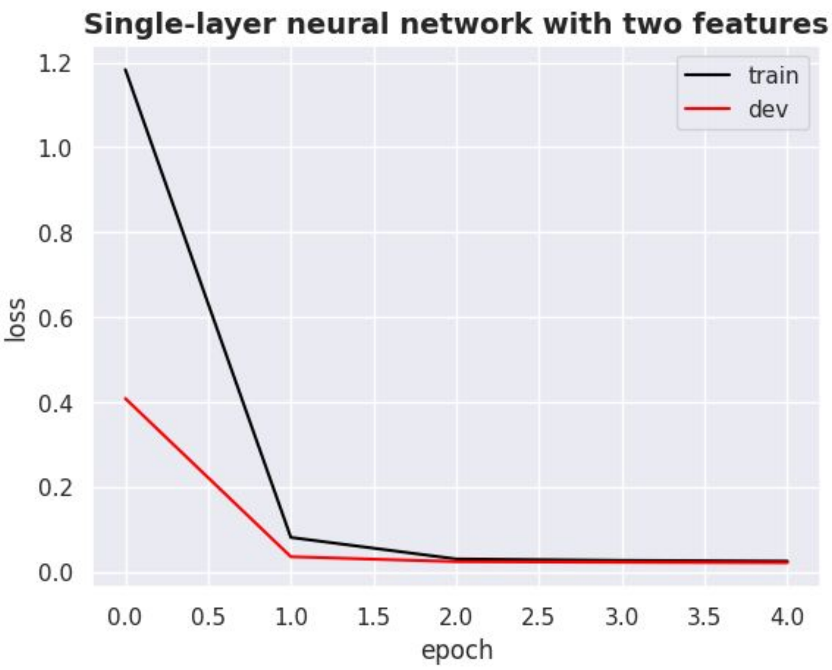


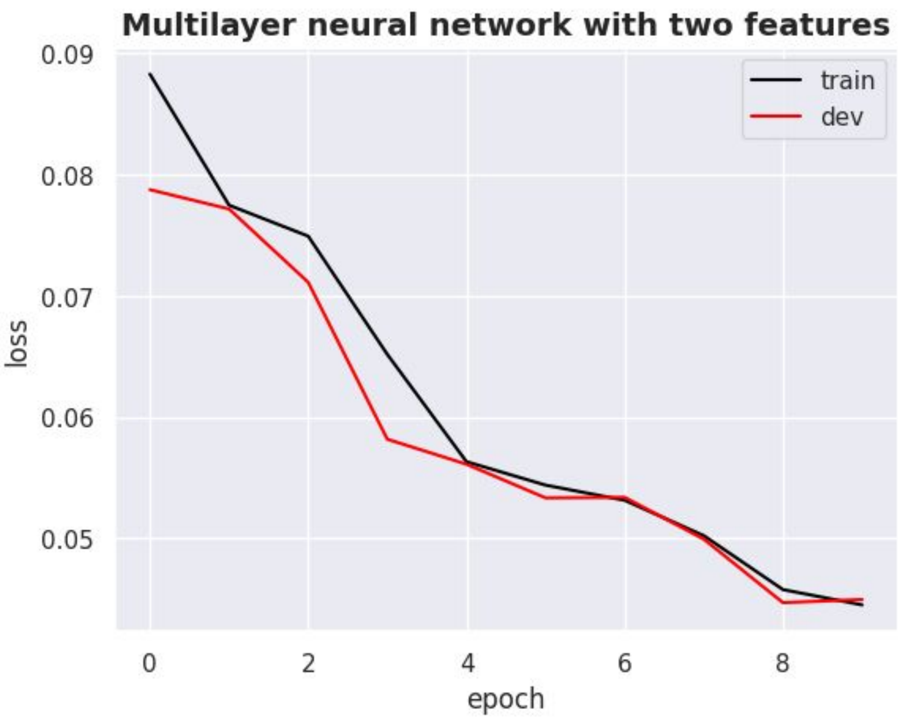
Model	Optimizer	Learning rate	Loss	Val Loss
Model 1: Gender	SGD	0.01	0.046	0.049
Model 1: Gender	SGD	0.001	0.700	1.344
Model 1: Gender	SGD	0.0001	1.476	2.801
Model 1: Gender	Adam	0.01	0.0359	0.0362
Model 1: Gender	Adam	0.001	1.038	1.934

Berkeley
UNIVERSITY OF CALIFORNIA

Single and multilayer neural networks

We added an additional feature, market cap (a proxy for market size) to gender. We run single and multi-layer neural networks. The single -layer seems to have faster convergence of training and validation losses.

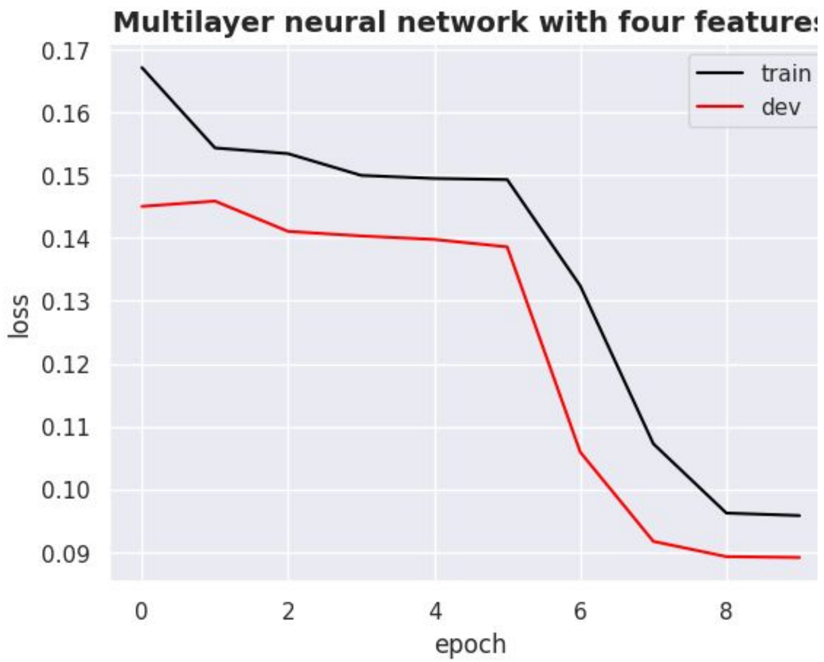


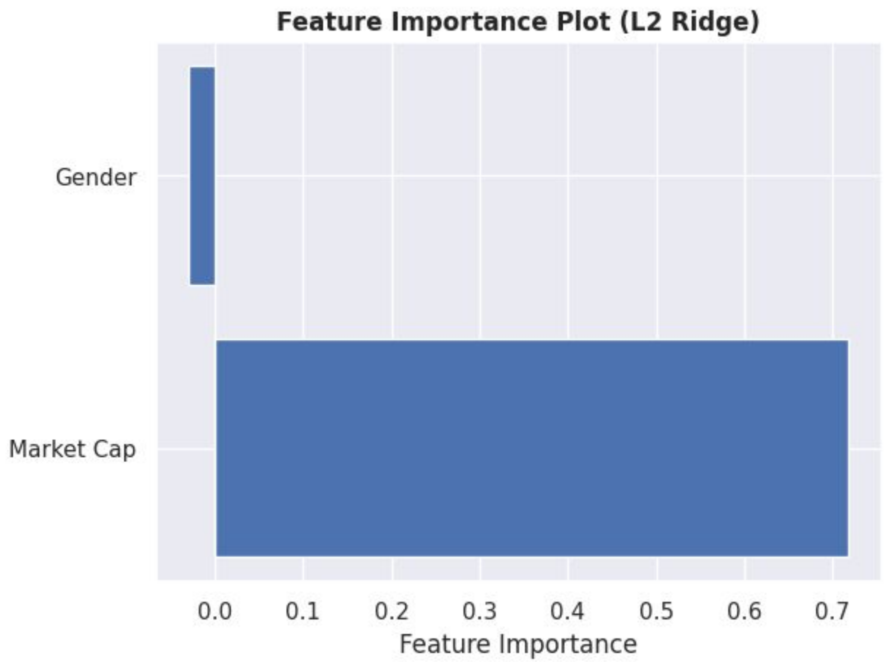


Berkeley
UNIVERSITY OF CALIFORNIA

Market capitalization has the biggest impact on compensation

A neural network assessing executive role, sector, gender and market cap was less accurate than simpler models. An L2 Ridge Model shows the outsized impact of market capitalization, a proxy for company size.





Integer encoding was required for sector and executive role.

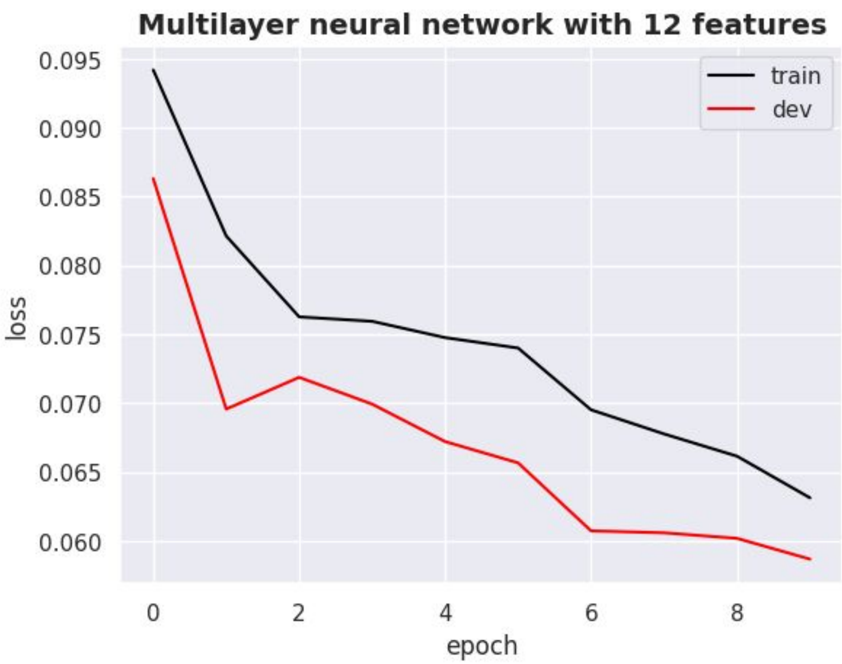
Berkeley
UNIVERSITY OF CALIFORNIA

Adding in sectors, using one-hot encoding

We added sectors (eg, tech, finance), categorical features, transforming to one-hot numeric array

Basic Materials
Communication Services
Consumer Discretionary
Energy
Financial Services
Technology
Utilities
Industrials
Health Care
Real Estate
Communication Services

11 sectors
one-hot encoded



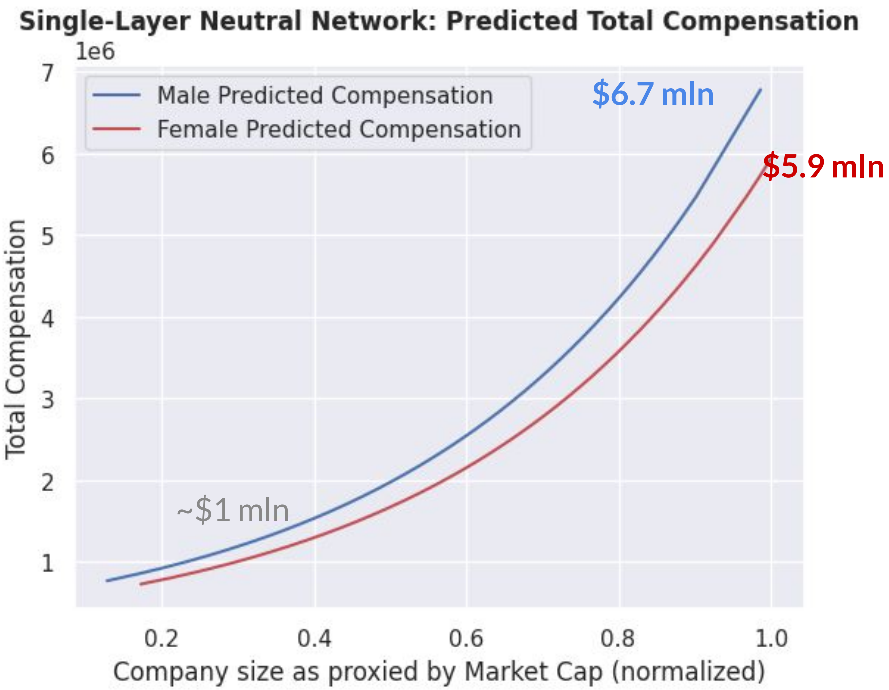
Berkeley
UNIVERSITY OF CALIFORNIA

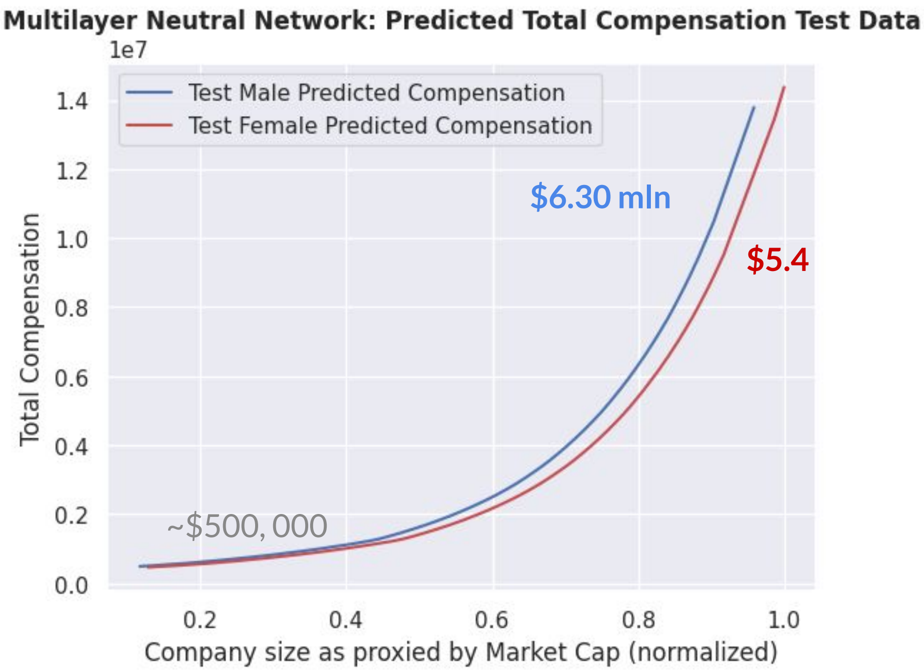
Results

Predictions from two-feature models

Both models predict that as company size increases, executive compensation increases. The models predict that gap between male earnings and female earnings *diverge* as company value increases.

Predictions using test dataset





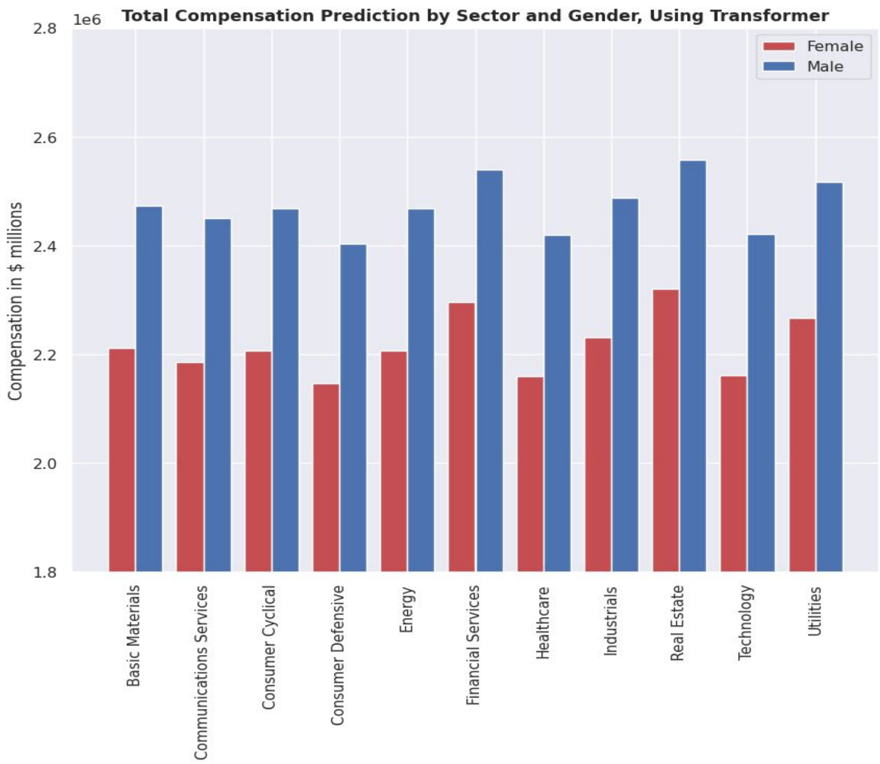
Berkeley
UNIVERSITY OF CALIFORNIA

Predictions from multi-feature, multilayer model using one-hot encoding

Male executives are predicted to outearn women, *irrespective* of the sector.

The largest wage gap is predicted to be 88 cents to the dollar for Finance, Consumer Defensive, Real Estate, and Health Care sectors.

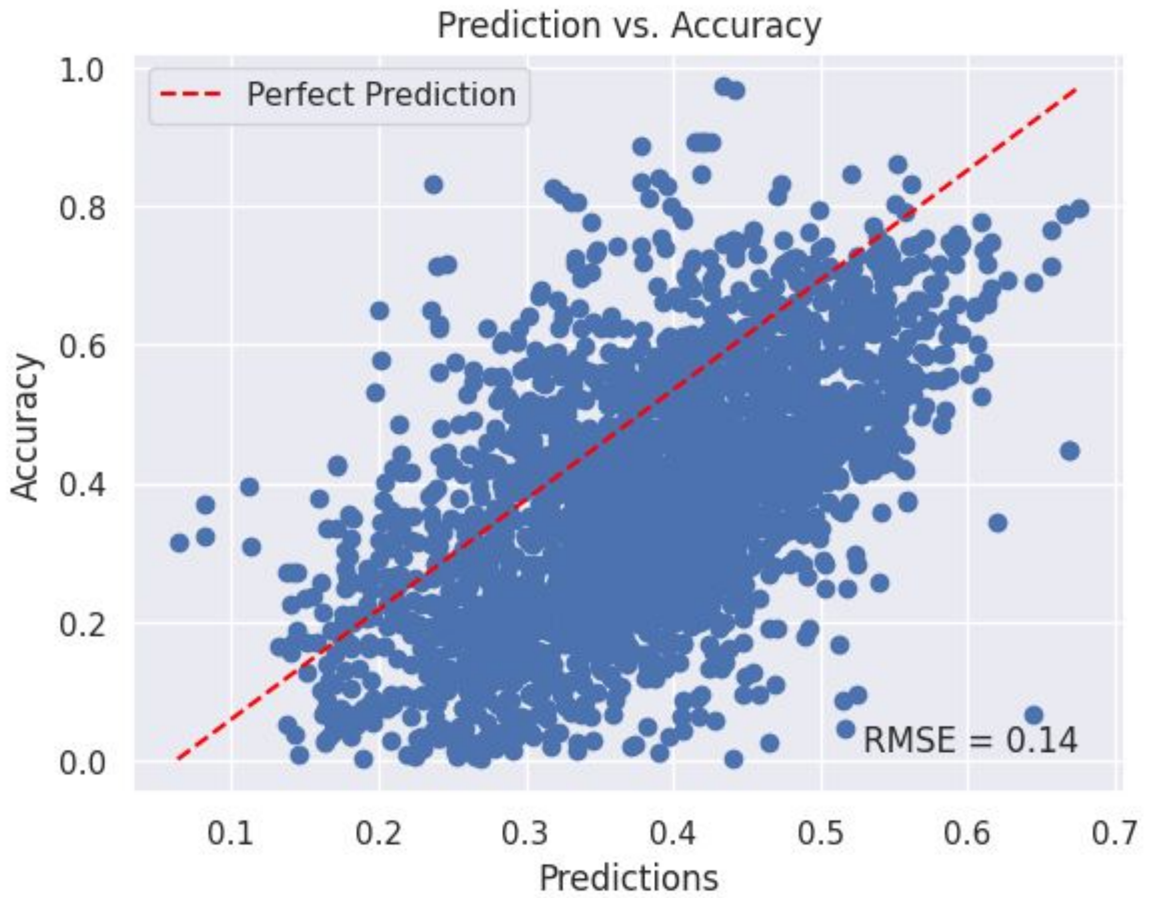
The smallest gap is 93 cents, for the Utility sector.



Berkeley
UNIVERSITY OF CALIFORNIA

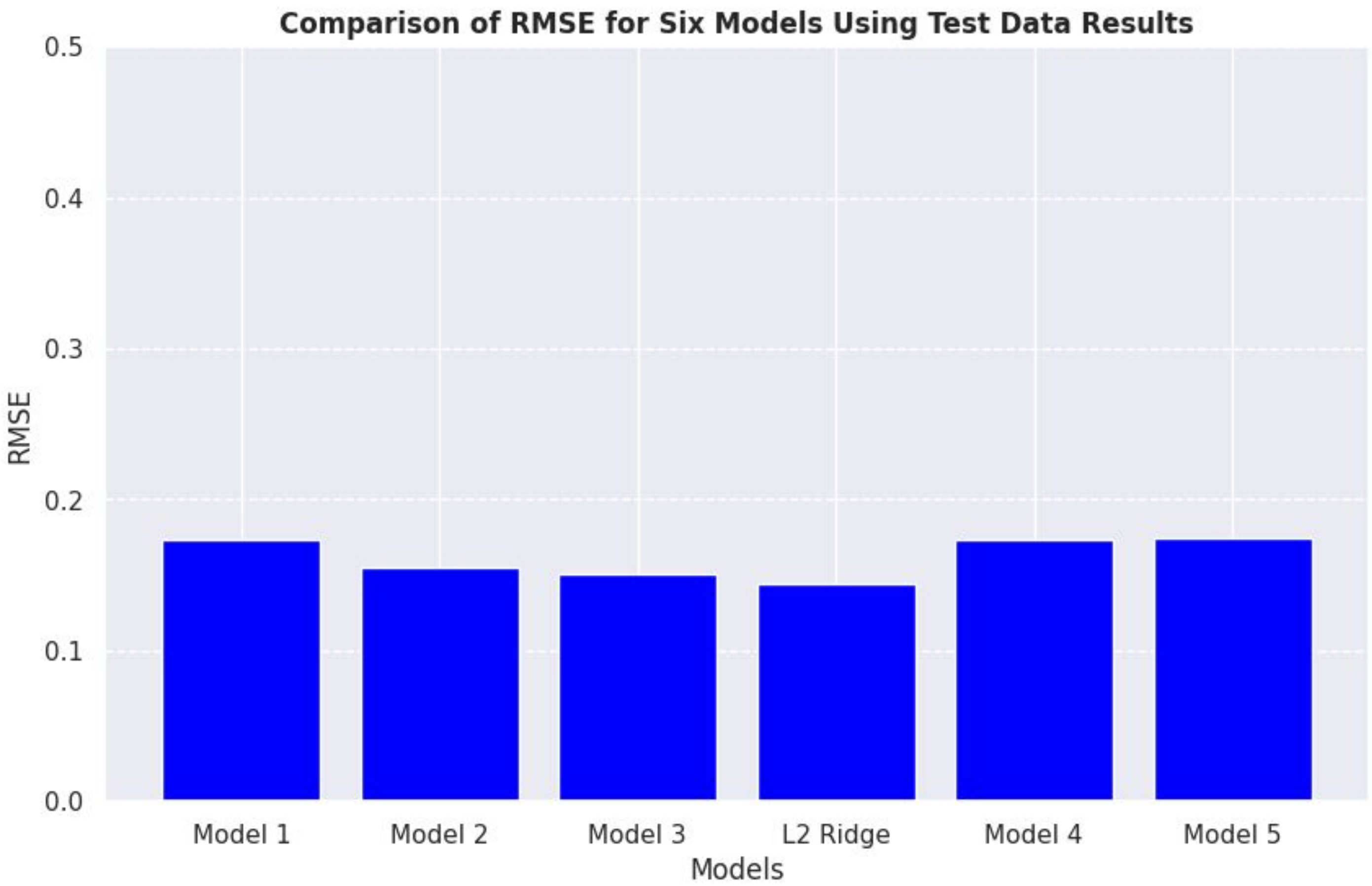
Predictions from two-feature L2 Ridge

- The correlation coefficients indicate that market capitalization has the biggest impact of role, sector, or gender.



L2 Ridge Model is the most accurate

Normalization yielded greater accuracy than additional layers or features.



Berkeley
UNIVERSITY OF CALIFORNIA

Conclusions & Considerations

Ethical Considerations

Using machine learning to predict executive gender pay gaps raises several ethical considerations, including:

Fairness and Bias: The Genderize API

- NIH found a significant number of misclassifications (16.4%), particularly when testing in more multicultural contexts
- In our usage, the approach was to drop names where Genderize is inconclusive, raising concerns of removing data from the sample in a biased way
- Using Genderize.io risks marginalizing some individuals who do not recognize themselves in binary differentiation

Unintended Consequences and Privacy: important to consider the potential unintended consequences of using machine learning to predict executive gender pay gaps.

- Need thorough checks to avoid encoding or potentially exacerbating bias against people of certain gender identities and consider tradeoffs between model performance and explainability
- Outside of certain contexts where salary transparency and total pay disclosure is established, it is vital to adhere to requirements around consent and PII protections, which change frequently due to increased ability to identify someone based on limited information

Berkeley
UNIVERSITY OF CALIFORNIA

Ethical considerations

Dataset:

- **Fairness and bias:**
  - **Limited Sample Size of Female Executives:** The SEC data has a limited sample size of female executives relative to male executives, particularly in certain sectors or companies where women are especially underrepresented in leadership positions. This can make it difficult to draw meaningful conclusions about gender pay disparities at the executive level and may lead to underestimating the extent of the problem.
  - **Biases in Compensation:** The SEC data may not account for biases in executive compensation, such as differences in pay variability, promotion, performance evaluation, and experience. This can result in inaccurate or incomplete assessments of pay equity at the executive level and may reinforce or perpetuate gender pay disparities in the company.
  - **Choice to focus on executives:** The SEC data focuses primarily on executive compensation, which is plausibly not reflective the compensation differences amongst employee groups at different levels of seniority, particularly those in lower-level positions who may be more vulnerable to pay disparities. This will of course result in an incomplete or skewed understanding of pay equity if used to understand pay equity across the company. The models are not well-suited to deployment in contexts related to non-executive compensation.
- **Accountability & transparency:**
  - Concerns surrounding data quality for the SEC training data
  - Lack of information on factors such as length of tenure, family situation, or previous experience

Berkeley
UNIVERSITY OF CALIFORNIA

Conclusions and further research

Conclusions

- Using publically available data on executive compensation, our models, which range from a simple regression to multi-featured, multilayer neural networks, consistently predict that male executives outearn female executives
- There have some observational studies that show that in some positions and sectors, there are some women that outearn but our machine learning models do not support this.

Limitations:

- Data quality is an issue, pulling raw data from SEC filings
- We noted several discrepancies and issues in our data cleaning
- Not a complete picture: lack of information on length of tenure, family situation, etc.

Further research:

- Understand and predict success of different pay equity initiatives (e.g state pay transparency requirements)
- Compensation by gender at different seniority levels
- Within different organizations, industries, and sectors, predict ascent to C-suite

References

1. https://initiatives.weforum.org/accelerators-network/gender-parity
2. https://www.ukg.com/resources/analyst-report/new-study-shows-importance-making-pay-equity-work-all
3. https://neurips.cc/Conferences/2021/PaperInformation/PaperChecklist
4. https://blog.neurips.cc/2021/08/23/neurips-2021-ethics-guidelines/
5. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8608220/