Uncovering Hiring Inequities:

A Machine Learning Study of Fair Employment Factors Across the U.S.

Machine Learning

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INTRODUCTION

Unfair recruitment practices are a real phenomenon today. This is not only a case of individuals, but also of communities, companies deny opportunities to communities and perpetuate disparity. This led us to study in-depth the factors leading to such employment deficits.

We utilized machine learning platforms for this research to study employment trends in data. We collected data from the Data Commons platform and the census.gov API, which gave us large datasets on demographics, education, and economic status.

Our main goal was to utilize clustering and classification methods to identify patterns that are not necessarily obvious. By doing so, we aimed to better see how certain groups might be disproportionately impacted throughout the hiring process.

This was not just about examining the past, but also of contributing to the conversation about how we might design less biased, more equitable hiring processes in the future. In this study, we sought to center on the unseeable difficulties of workplace discrimination and observe how data science and machine learning might be utilized to effect change.

METHODOLOGY

We combined data science and machine learning in our research, using classification and clustering to study recruitment policies. We used large datasets from Data Commons and the U.S. Census API, selecting variables like age, gender, ethnicity, socioeconomic measures like education and occupation and health-related factors, including healthcare spending, that are related to demographics, education, work, and healthcare.

Clustering allowed us to see patterns and group together areas with similar characteristics, and classification allowed us to analyze and predict how such variables are connected to income inequality. By looking at a wide range of variables we were able to better understand what causes unequal fluctuations in hiring.

REGIONAL CATEGORIZATION

One key part of our research was using clustering to group U.S. regions with similar income trends. This helped us spot geographic patterns and better understand how hiring practices vary across the country.

By combining data analytics with machine learning, we aimed to uncover the deeper causes of unfair hiring and offer a more structured way to study complex social and economic issues. Our goal was to support more informed conversations and policies around employment inequality using real data and advanced methods.

DESIGN

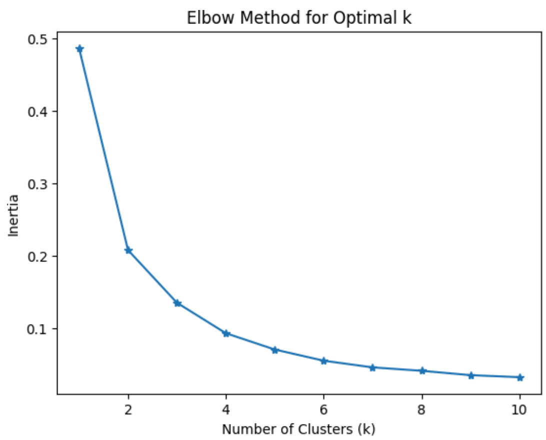
In designing this project, we took a strategic approach to gather and analyze data from **Data Commons** and the **census.gov API** to better understand unfair hiring practices. We focused on key variables like employment by race and gender, education levels, disability status, and worker population.

We first pulled data from the Census API, which required converting string values to numbers so we could run our analysis. To make the data more representative across states, we used additional info from Data Commons, like employment by age, education, race, and gender, focusing on **percentages instead of raw numbers** to account for population differences.

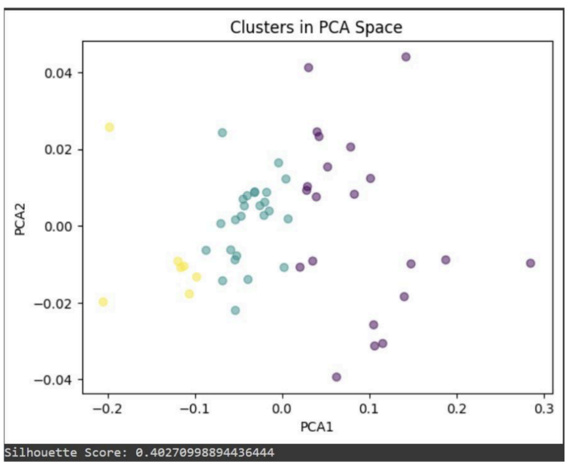
Next, we normalized the data by converting everything into percentages and calculating the mean for each variable to use as a baseline for our analysis. Next, we used **KMeans clustering** to find patterns in the data. We applied the **elbow method** to choose the best number of clusters and used **silhouette scores** to check the quality of the groupings. To make the results easier to understand, we labeled each cluster based on its characteristics.

After clustering, we used the **K-Nearest Neighbors (KNN)** algorithm to test the accuracy of our model. We analyzed results with a **confusion matrix** and **ROC curves** to understand how well the model predicted outcomes. To make sure our results were reliable, we also used **cross-validation** to test the model on different parts of the data.

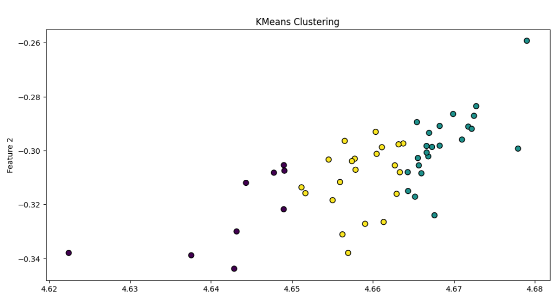
Overall, this step-by-step process, from collecting data to running and evaluating models, helped us build a solid framework for exploring unfair hiring and supporting more equitable employment solutions.



Graph of our elbow method, showing our optimal k = 3.



A figure showing clusters in PCA space and our silhouette score of 0.4.



A figure showing our kMeans clusters.

```
accuracy: 0.75
              precision    recall  f1-score   support

        Fair       0.60      1.00      0.75         6
        Good       1.00      0.20      0.33         5
        Poor       1.00      1.00      1.00         5

    accuracy                           0.75        16
   macro avg       0.87      0.73      0.69        16
ghted avg       0.85      0.75      0.70        16
```

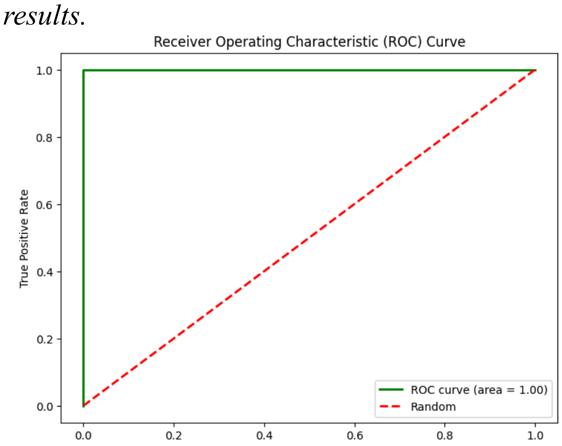
A figure showing the model's kNN accuracy score of 0.75.

	Poor	Fair	Good
Poor	6	0	0
Fair	4	1	0
Good	0	0	5

A figure showing the outcome of our confusion matrix.

```
The cross validation accuracy scores are: 1.0 1.0 0.91 1.0 1.0
The cross validation precision scores are: 1.0 1.0 0.8 1.0 1.0
The cross validation recall scores are: 1.0 1.0 1.0 1.0 1.0
The cross validation f1 scores are: 1.0 1.0 0.89 1.0 1.0
```

A figure showing the cross-validation results.

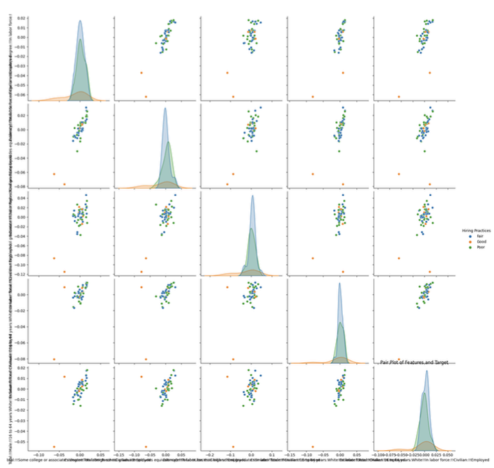


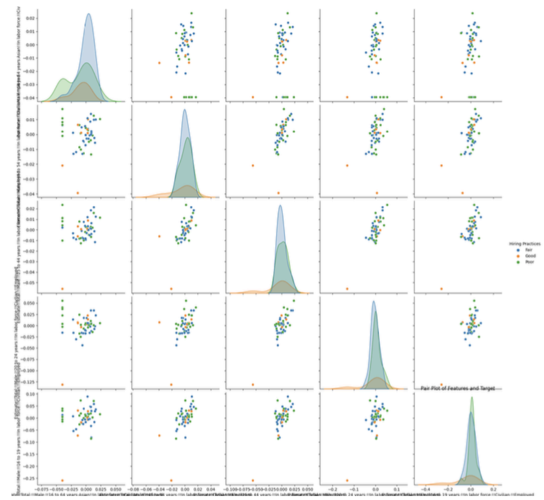
A figure showing the ROC curve visualization.

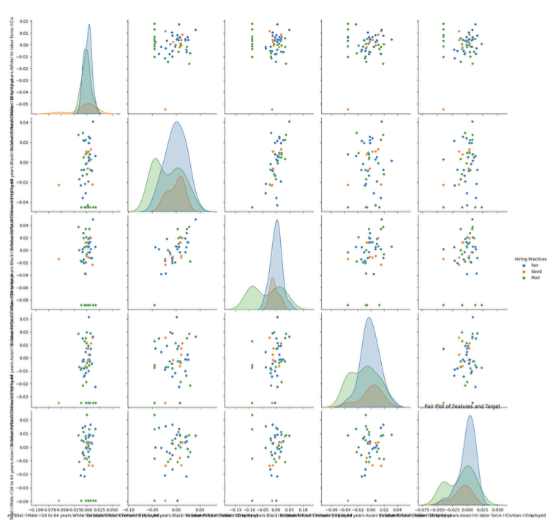
RESULTS

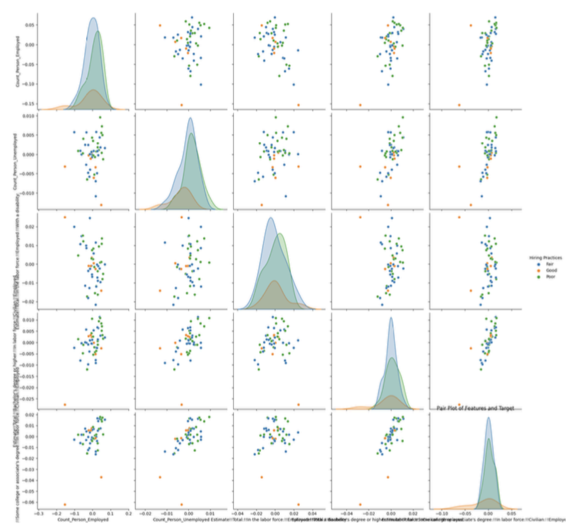
Pair Plot Visualizations

We used pair plots to help visualize how different variables interact and influence hiring practices. Color coding made the charts easier to understand—orange showed good hiring practices, green and blue represented fair hiring practices. These visuals helped us better grasp how complex factors like race, education, and employment status affect outcomes across states.









KMeans Clustering

Using KMeans and the elbow method, we found the best number of clusters for the data. We evaluated the clusters using silhouette scores to measure how well the groups were formed. This step helped us group states with similar hiring conditions.

KNN Classification & Confusion Matrix

Our K-Nearest Neighbors model had an accuracy of **75%** overall. The confusion matrix showed strong results for states with **poor hiring practices**, with perfect precision and recall. For **fair practices**, the model performed well across all metrics. For **good practices**, it had high precision but lower recall, meaning it identified them accurately but missed some.

ROC Curves & Cross-Validation

ROC curves showed that the model had a perfect AUC score of **1**, meaning it did a great job at telling the difference between the categories. Cross-validation confirmed that the model was reliable, with accuracy scores between **0.80 and 1.00**.

State-Level Predictions

We categorized states into three groups:

- **Good Hiring Practices**: Arizona, Texas, Ohio, etc.
- **Fair Hiring Practices**: Georgia, Illinois, New York, etc.
- **Poor Hiring Practices**: California, Florida, Massachusetts, etc.

This breakdown helps identify where improvements are most needed and where strong practices already exist.

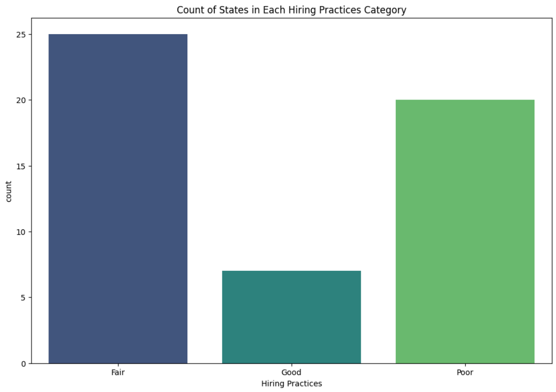
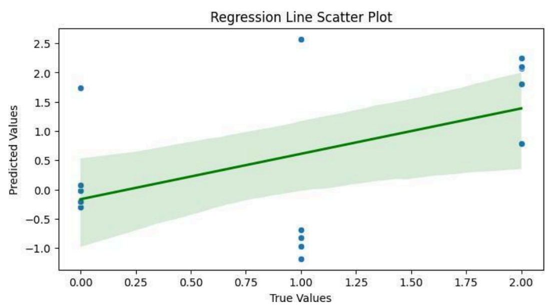


Figure showing count of states in each hiring practices category.

Regression Line Plots

We also used regression plots to show how certain variables (like education and race) impact hiring fairness. These visuals made the relationships in the data easier to understand and explain.



Regression Line Plot

CONCLUSION

This project used machine learning to explore how hiring practices vary across the U.S. It combined clustering, classification, and visualization tools to analyze patterns in employment inequality. The results gave insight into where fair hiring is happening—and where it's not. This work aims to support more informed conversations and decisions around building a fairer job market.

FUTURE WORK

In the future, this project can be improved by:

- Using **more complete datasets**, including legal and policy-related data
- Handling **missing values (NaNs)** with better techniques
- Setting up **regular monitoring** to track fairness and real-world impact
- Improving **documentation** to ensure transparency and reproducibility

These steps will help create even stronger, more ethical, and more accurate models for analyzing and promoting fair hiring.

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