Assessing important features in predicting U.S. income level

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01

Key results

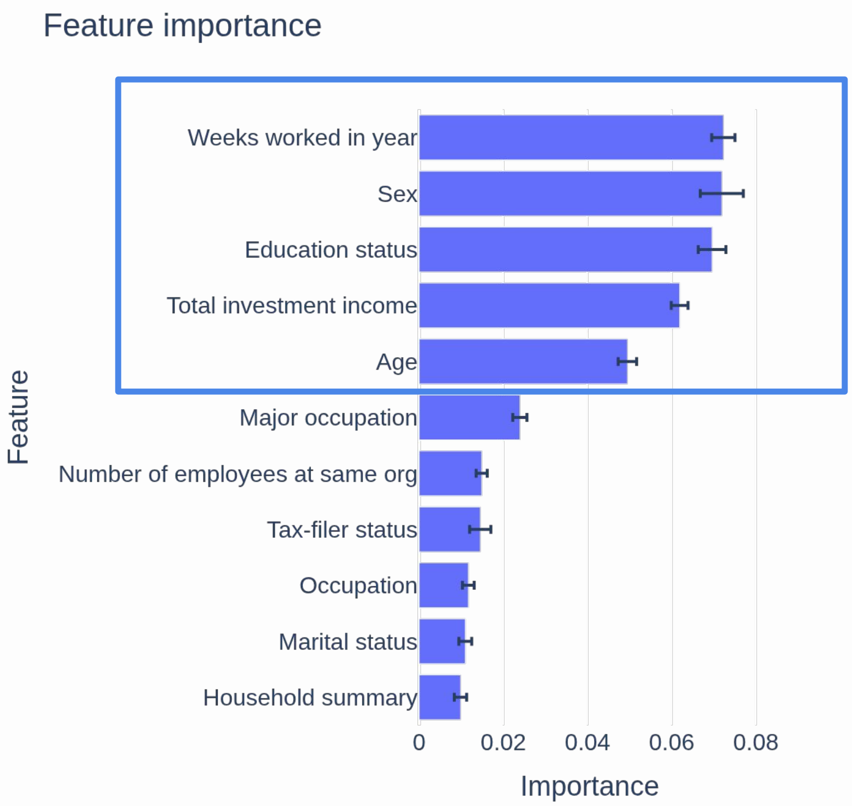
Important features and trends on income level

Top 5 important features

1. Weeks worked in year
2. Sex
3. Education status
4. Total investment income
5. Age

Positive effects predicting income level

Weeks worked in a year and education status have increasing, positive effects on predicting above 50K earners



02

Overview

Analysis goals and data overview

Overview

Goal

Identify important characteristics associated with a person making **more or less than $50,000 per year.**

01

Observations

Sampled 1994-1995 U.S. Census archive data with **~300K individuals**

02

Features

40 features (range of economic, demographic, employment, geographic)

03

Income Level

93.8% in Below $50K
6.2% in Above $50K

Full data

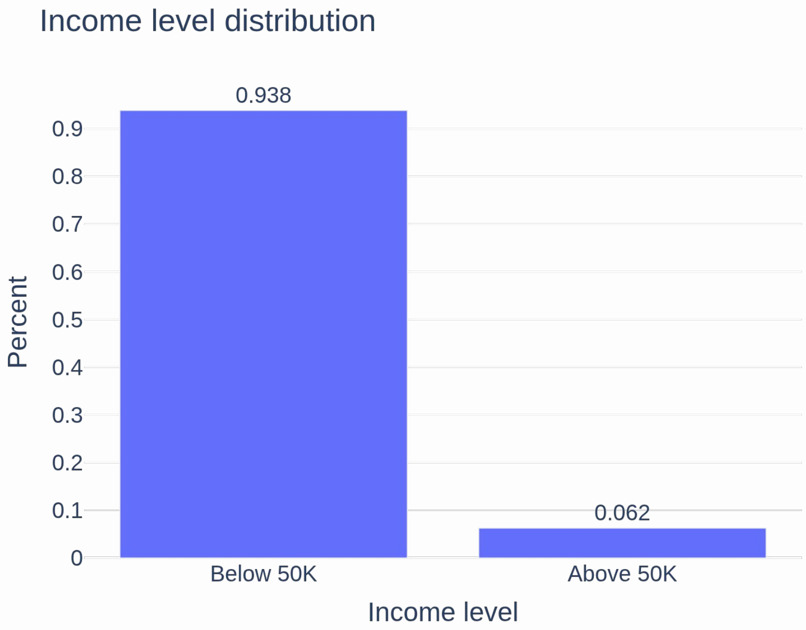
03

Data insights and methodology

Analytical trends, data preparation, and modeling strategy

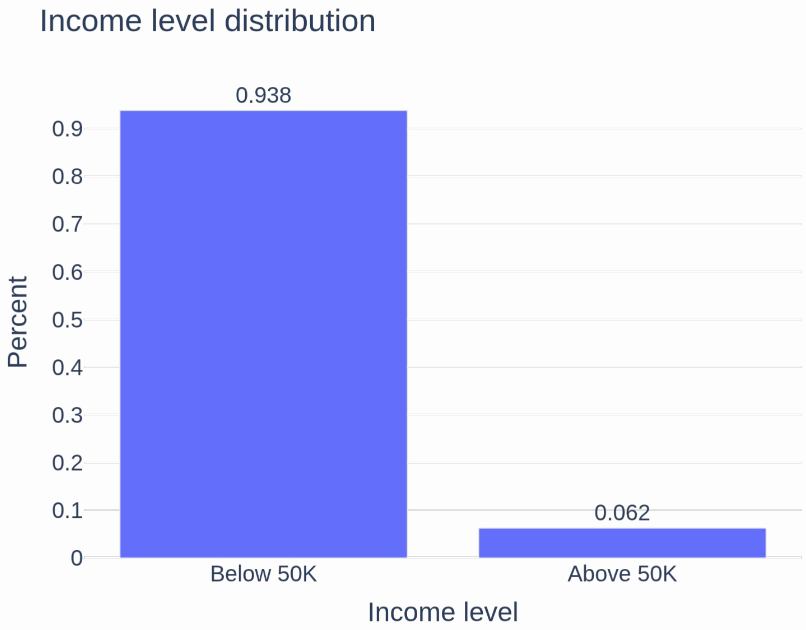
Insight - Income level

- Income split:
  - Below 50K earners represent large majority of the dataset, only 6% are Above 50K



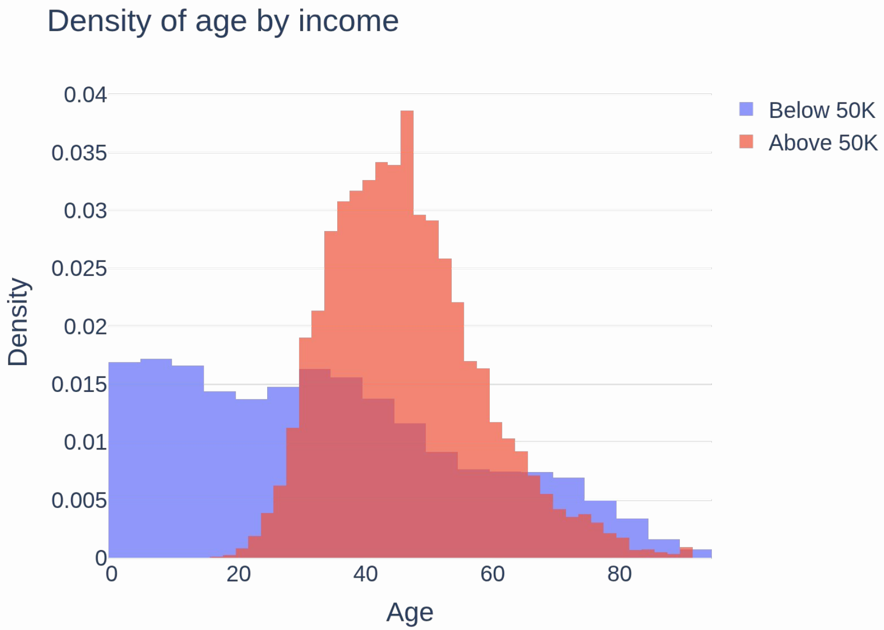
Insight - Income level

- Income split:
  - Below 50K earners represent large majority of the dataset, only 6% are Above 50K
- Technical consideration:
  - Balance training data to improve model predictions on both groups



Insight - Age and income level

- Above 50K:
  - Predominantly middle-age (35-50)



Insight - Age and income level

- Above 50K:
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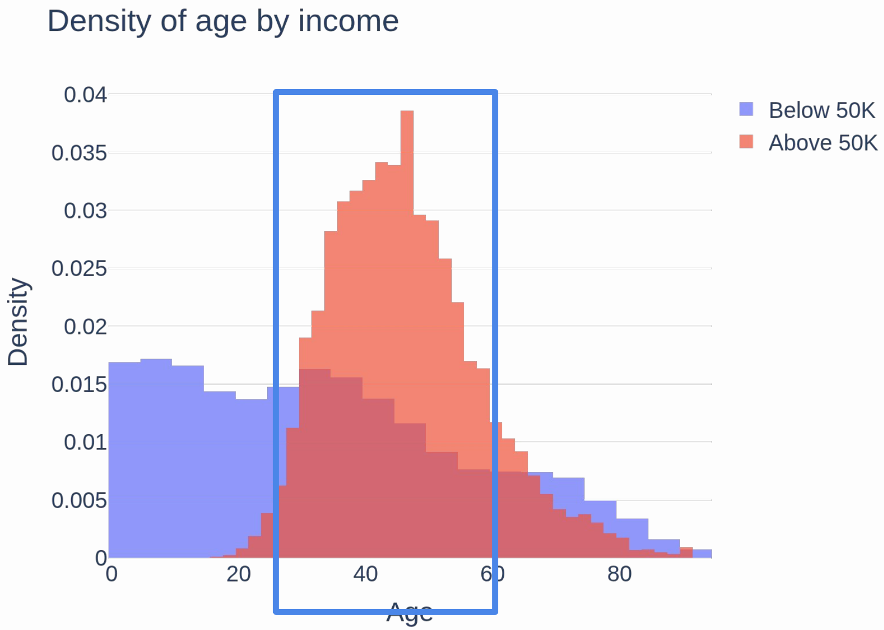
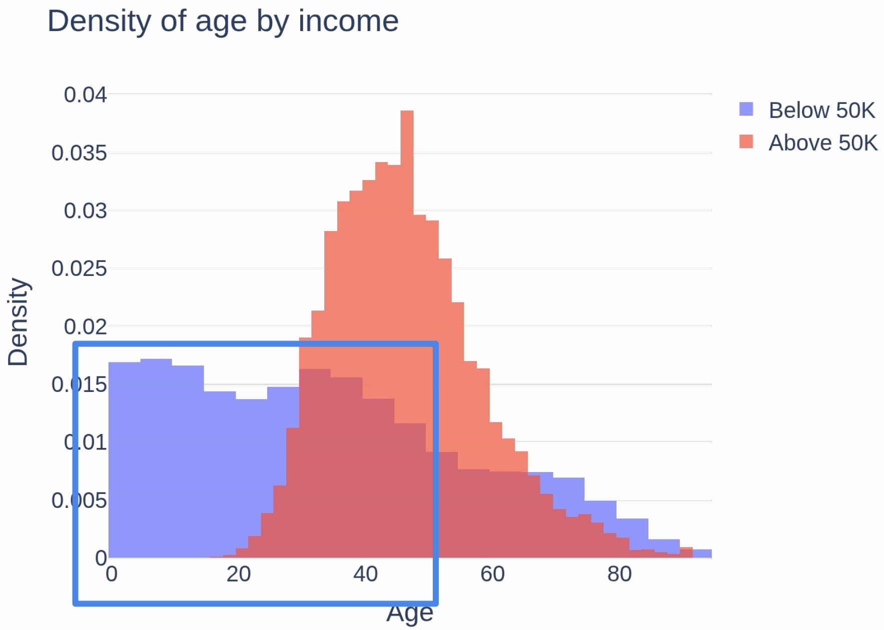
  - Significant overlap, but higher earners more common



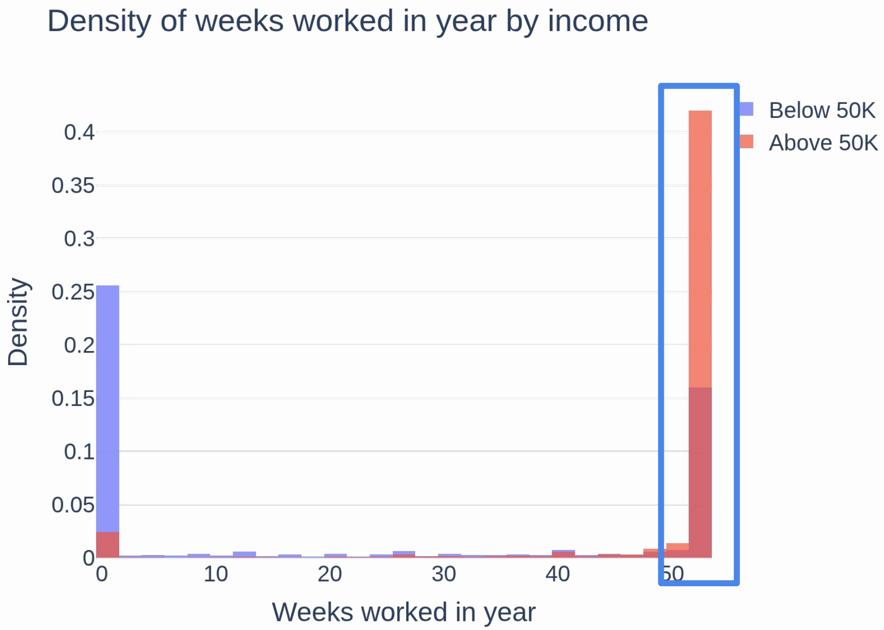
Insight - Age and income level

- Above 50K:
  - Predominantly middle-age (35-50)
  - Significant overlap, but higher earners more common
- Below 50K:
  - Predominantly <40
  - Flatter distribution across younger ages



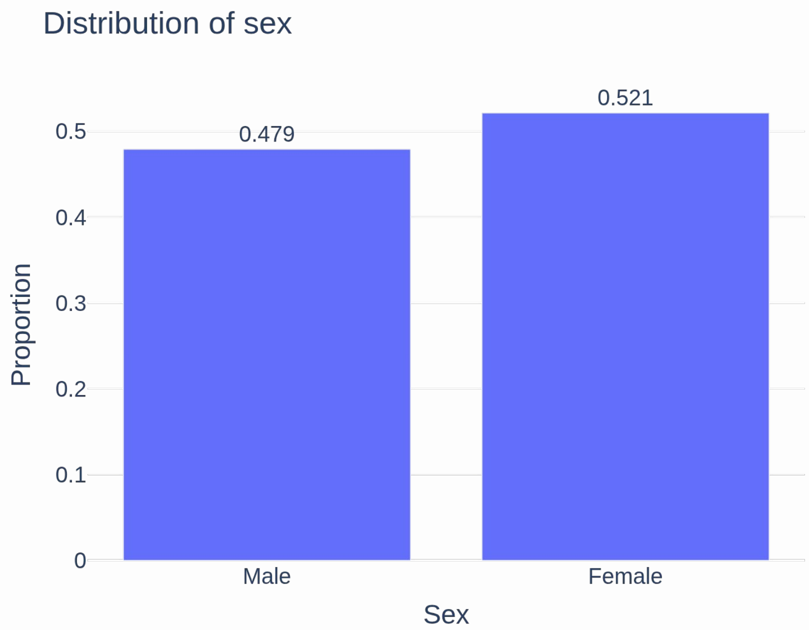
Insight - Weeks worked in year and income level

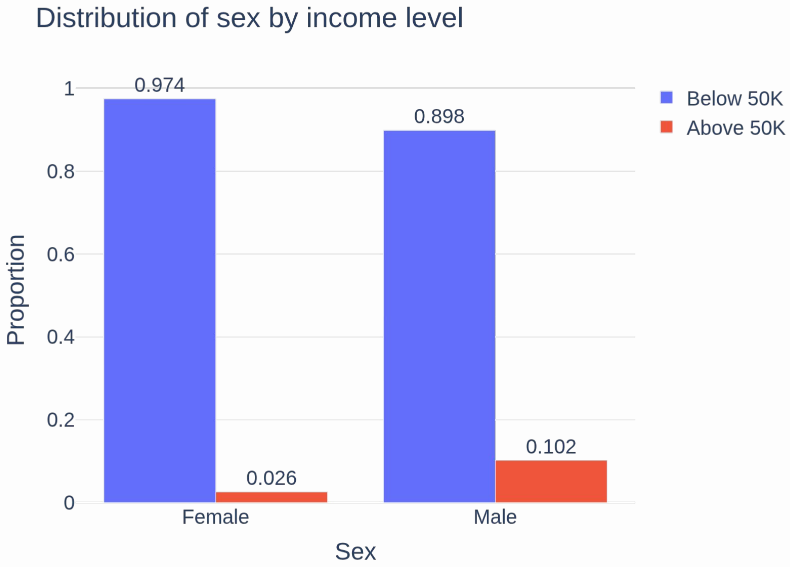
- Above 50K:
  - Concentrated in **full-time work** 52 weeks worked in a year



Insight - Gender and income level

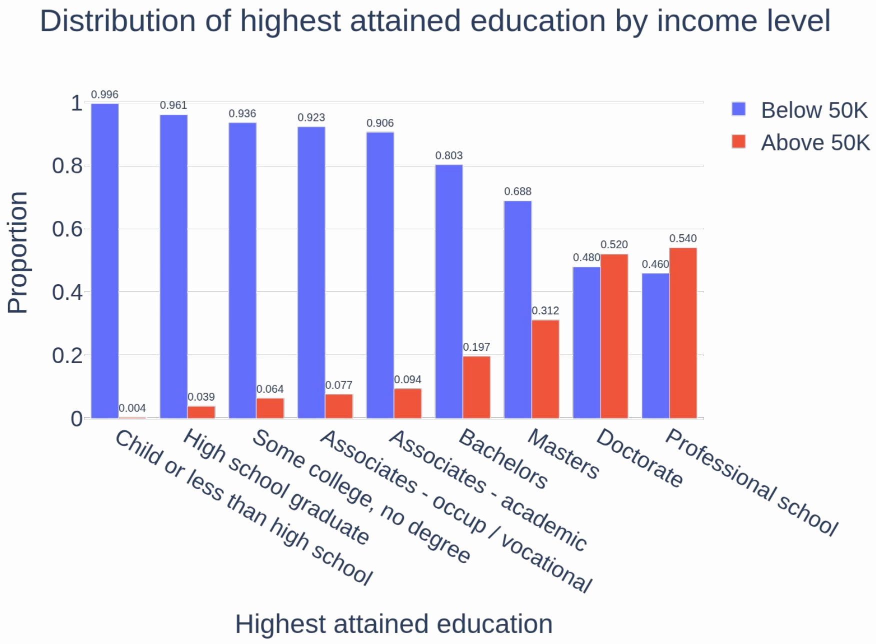
Despite similar overall male-female proportions in the dataset, males earning above $50K are significantly more represented at nearly **5 times** the rate of females in the same income level





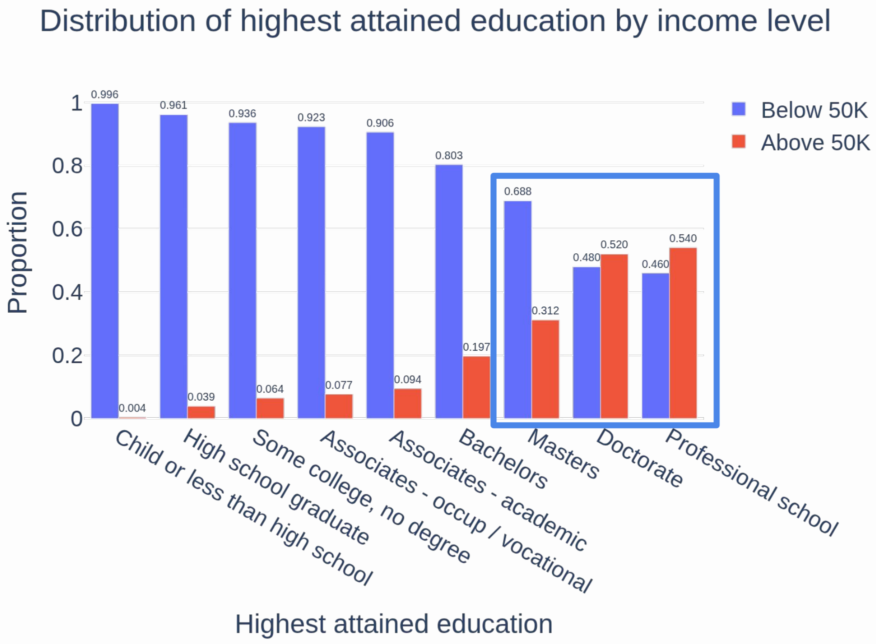
Insight - Education and income level

- Higher education levels show increased representation in Above 50K



Insight - Education and income level

- Higher education levels show increased representation in Above 50K
- Advanced degrees (Masters, Doctorate, Professional) have significantly* higher proportions than prior levels



*: Evaluated using pairwise chi-square tests at 0.01 significance level with multiple test correction

Methodology

Preprocessing	**Model selection**	**Model evaluation**	**Feature importance**

- Migration feature missing values
- Univariate feature selection (correlations, chi-square)
- Separation concerns for baseline modeling
- Feature engineering

Missing values in migration features

- **Data quality issue:** Migration features had missing values for observations where:
  - “Lived in this house 1 year ago” = “Not in universe under 1 year old”
  - Age > 0 for these observations (qualifies for migration questions)

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- **Bias validation:**
    - Compared income level patterns and feature distributions between:
        - Observations with complete migration data
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- **Bias validation:**
  - Compared income level patterns and feature distributions between:
    - Observations with complete migration data
    - Observations with missing migration data
- **Result:**
  - Excluding migration features won't bias our predictions and make feature importance unreliable for recommendations

Missing values in migration features

49.3%

Observations impacted

7

Migration features with all missing values or NIU

Features

40

33

Feature engineering and selection

1

Feature created: total investment income
Collapsed categories in employment stat, country to reduce dimensions

4

Features removed: capital gains, capital losses, stock dividends, household stat

Features

33

30

Methodology

Preprocessing	Model selection	Model evaluation	Feature importance

- Models tested:
    - Logistic regression with regularization (mitigate multicollinearity)
    - Random forest (handle non-linear patterns)

Methodology

Preprocessing	**Model selection**	Model evaluation	Feature importance

- Models tested:
  - Logistic regression with regularization (mitigate multicollinearity)
  - Random forest (handle non-linear patterns)
- Cross validation (CV) assessment
  - Hyperparameter tuning and selecting final model
  - Oversampling during CV to address income level imbalance

Methodology

Preprocessing	Model selection	**Model evaluation**	Feature importance

- Evaluation metrics:
    - **Precision**:
        - Of all the times the model predicted Above 50K, how often was it correct?

Methodology

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    - Of all the actual Above 50K observations, what percentage did the model catch?

Methodology

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- Evaluation metrics:
  - **Precision**:
    - Of all the times the model predicted Above 50K, how often was it correct?
  - **Recall**:
    - Of all the actual Above 50K observations, what percentage did the model catch?
  - **F1**:
    - How good is the model at catching Above 50K and be accurate when making predictions?

Methodology

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- Feature importance ranking:
  - **Permutation feature importance**
    - How important is a feature based on the model error when we break its relationship?

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  - **Random variable ranking**
    - How important is a feature compared to randomly guessing?

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- Important feature influence:
  - **Partial dependence plots**
    - What is the isolated effect of this feature on our income level predictions?

04

Results

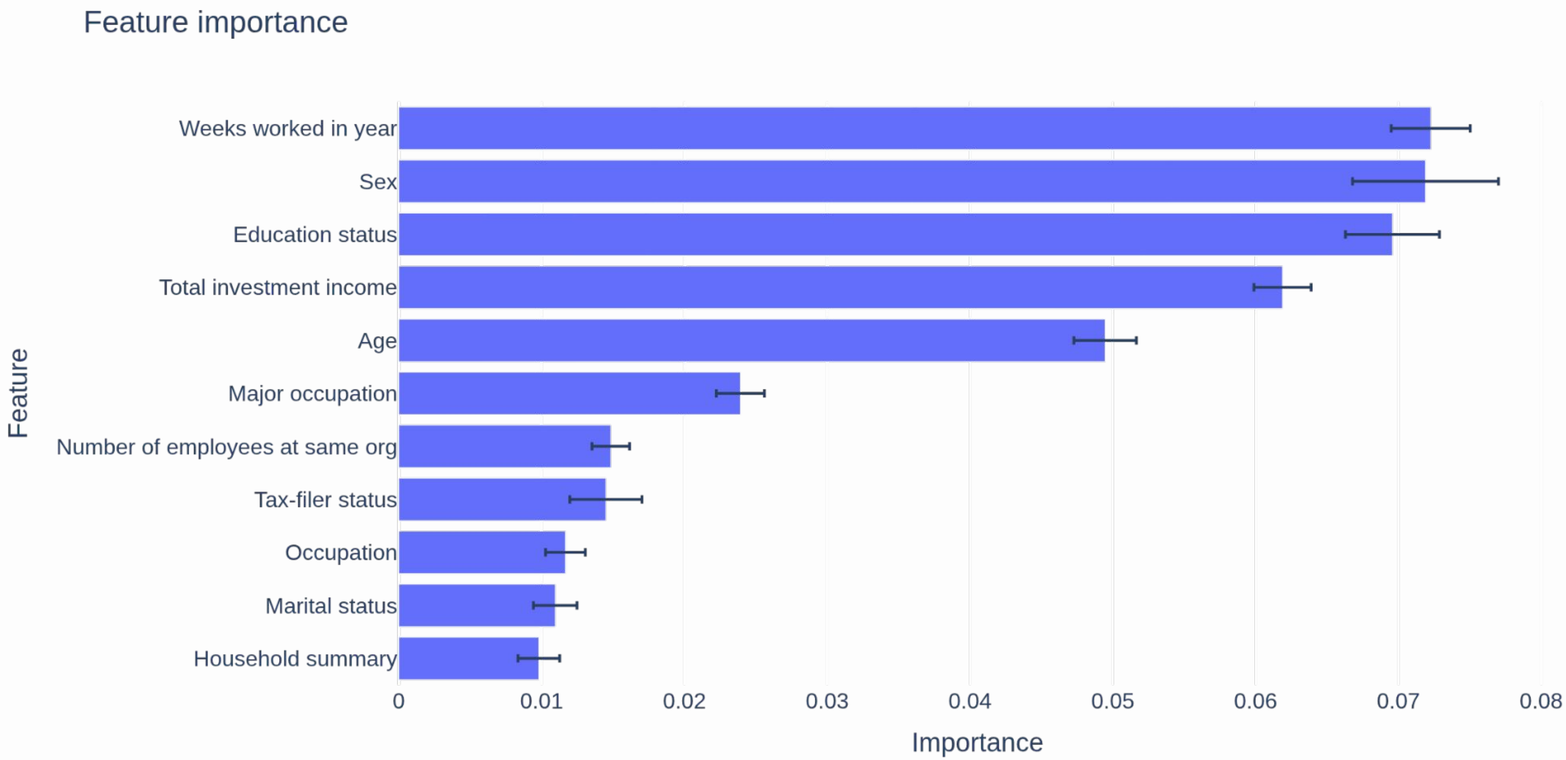
Model results and important features

Results - Performance

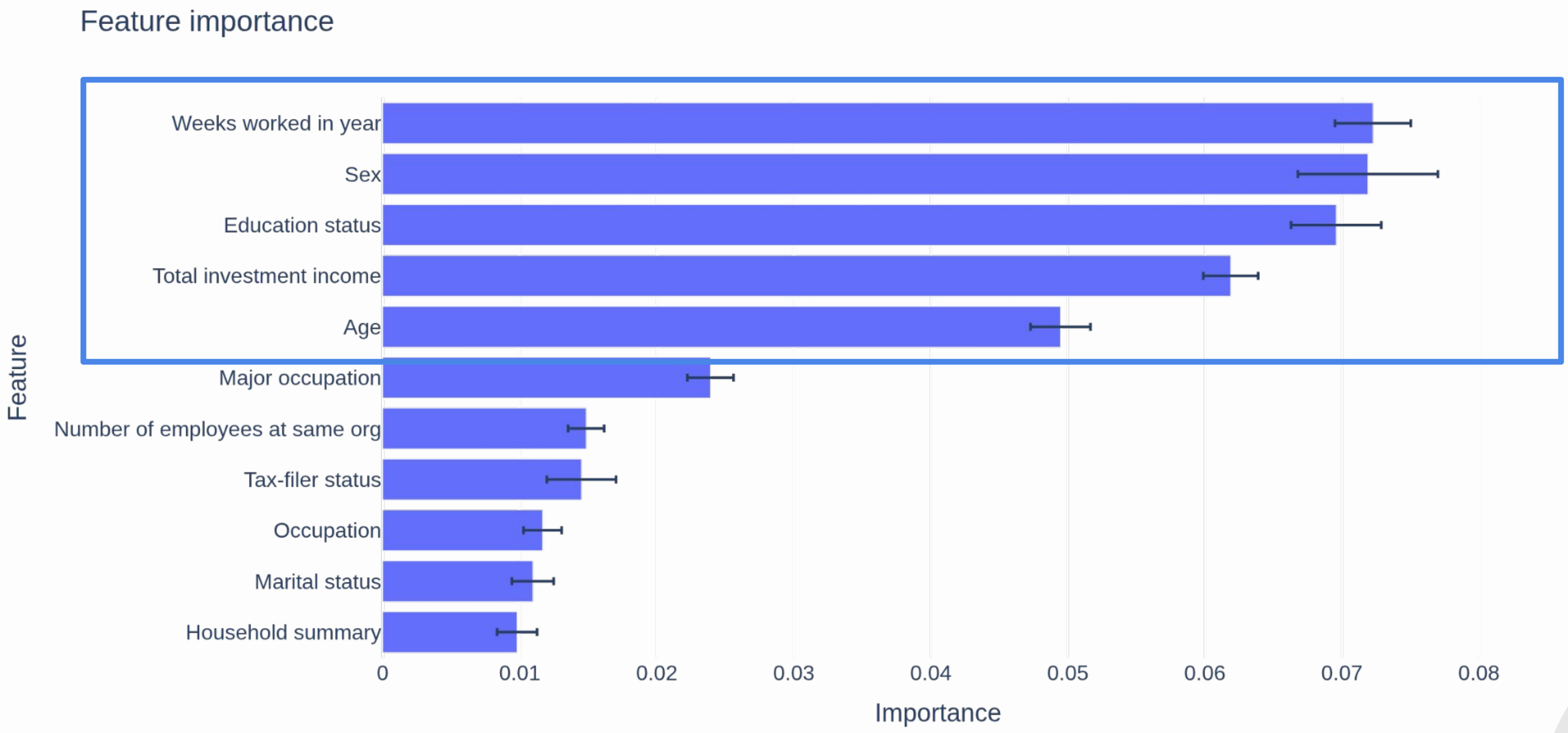
Random forest was selected as the final model and evaluated on the test set.

	Precision	Recall	F1
Below 50K	0.97	0.96	**0.97**
Above 50K	0.53	0.62	**0.57**
Macro Avg.	0.75	0.79	**0.77**

Results - 11 important features



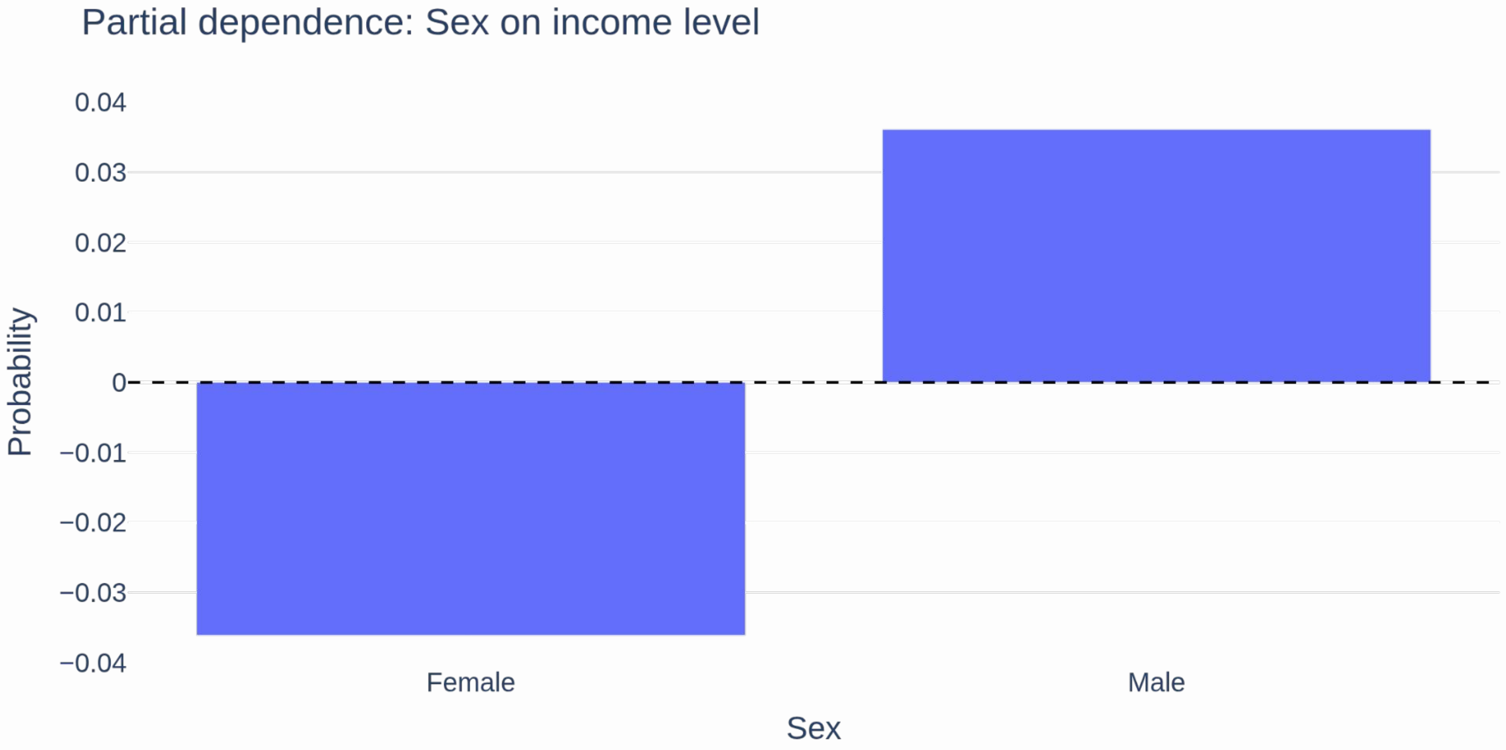
Results - Top 5 important features



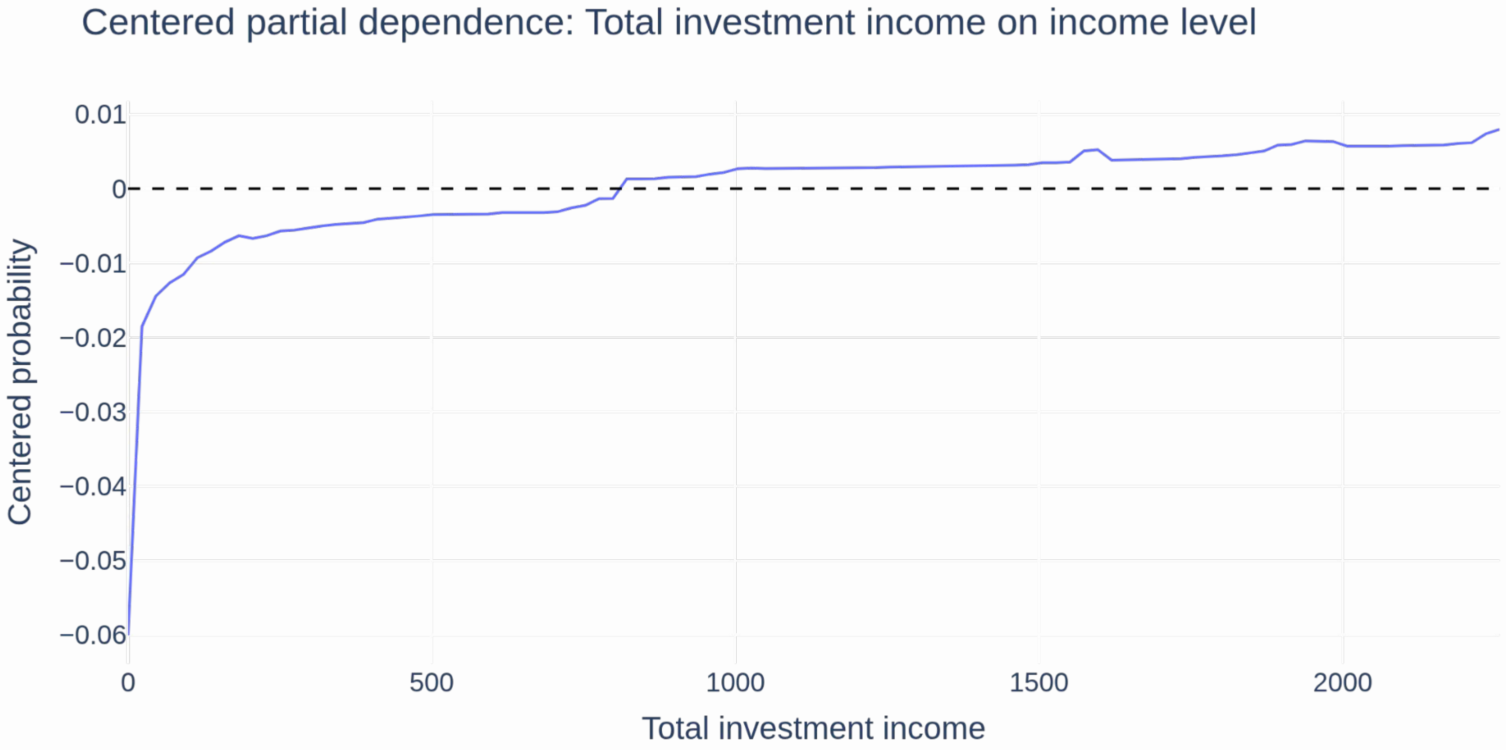
Results - Weeks worked in year effect

Results - Weeks worked in year effect

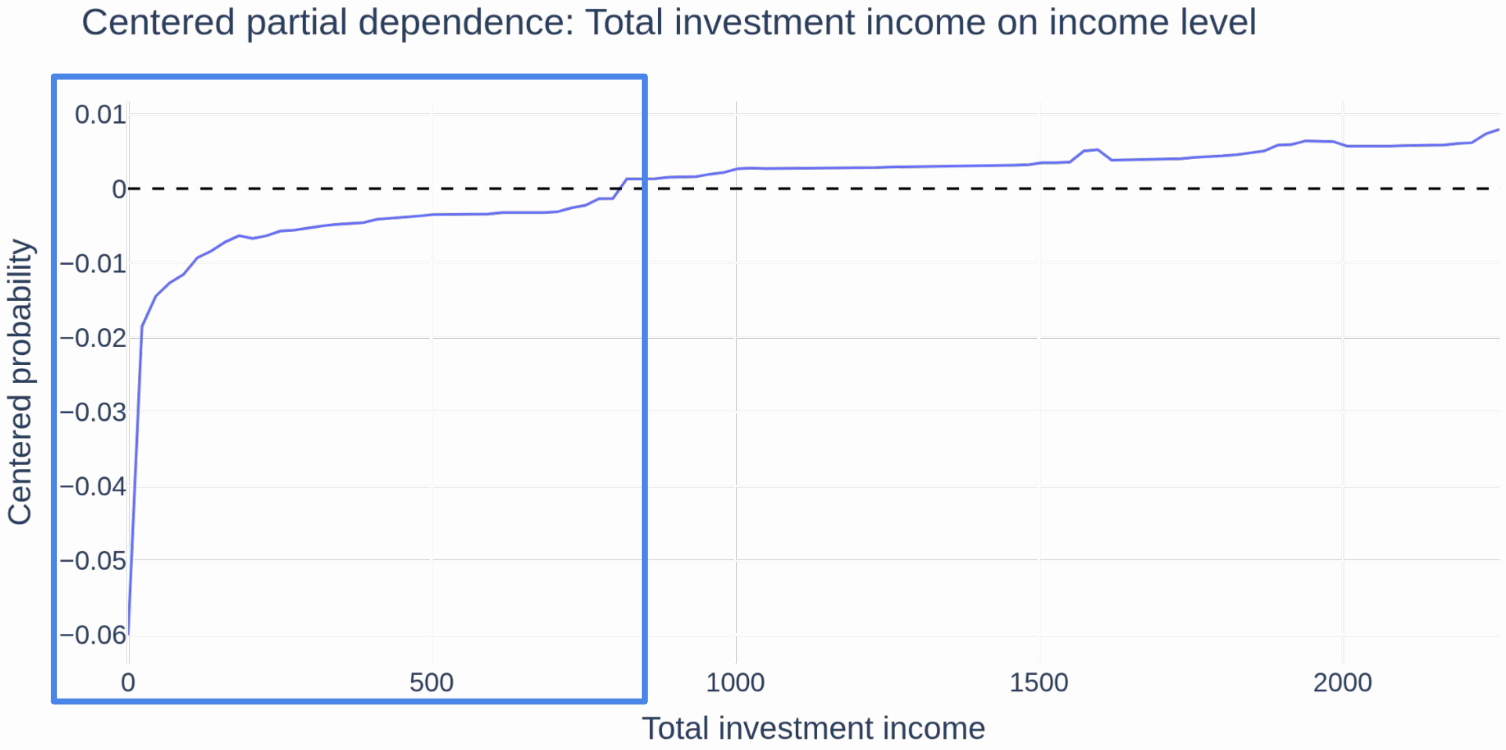
Results - Sex effect



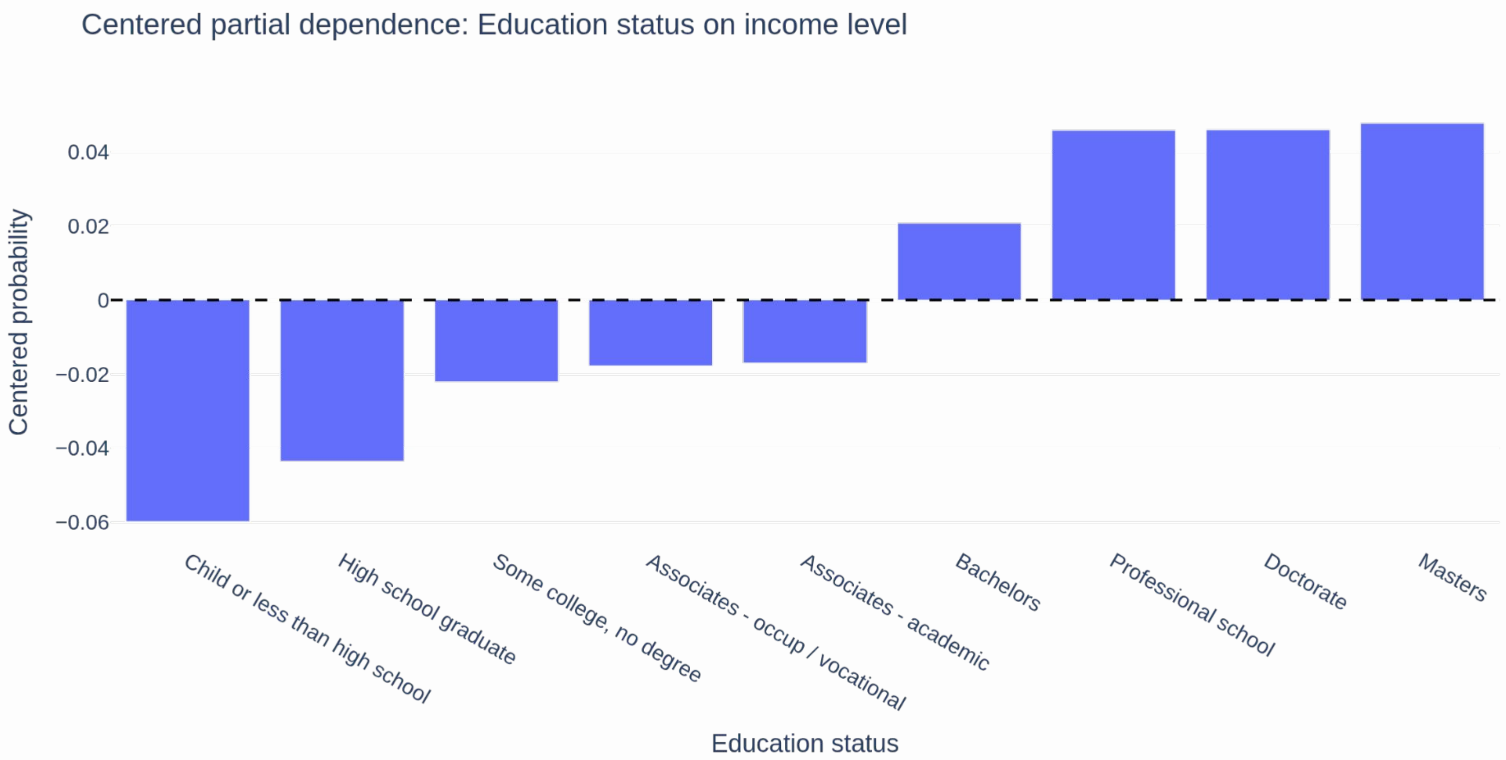
Results - Investment income effect



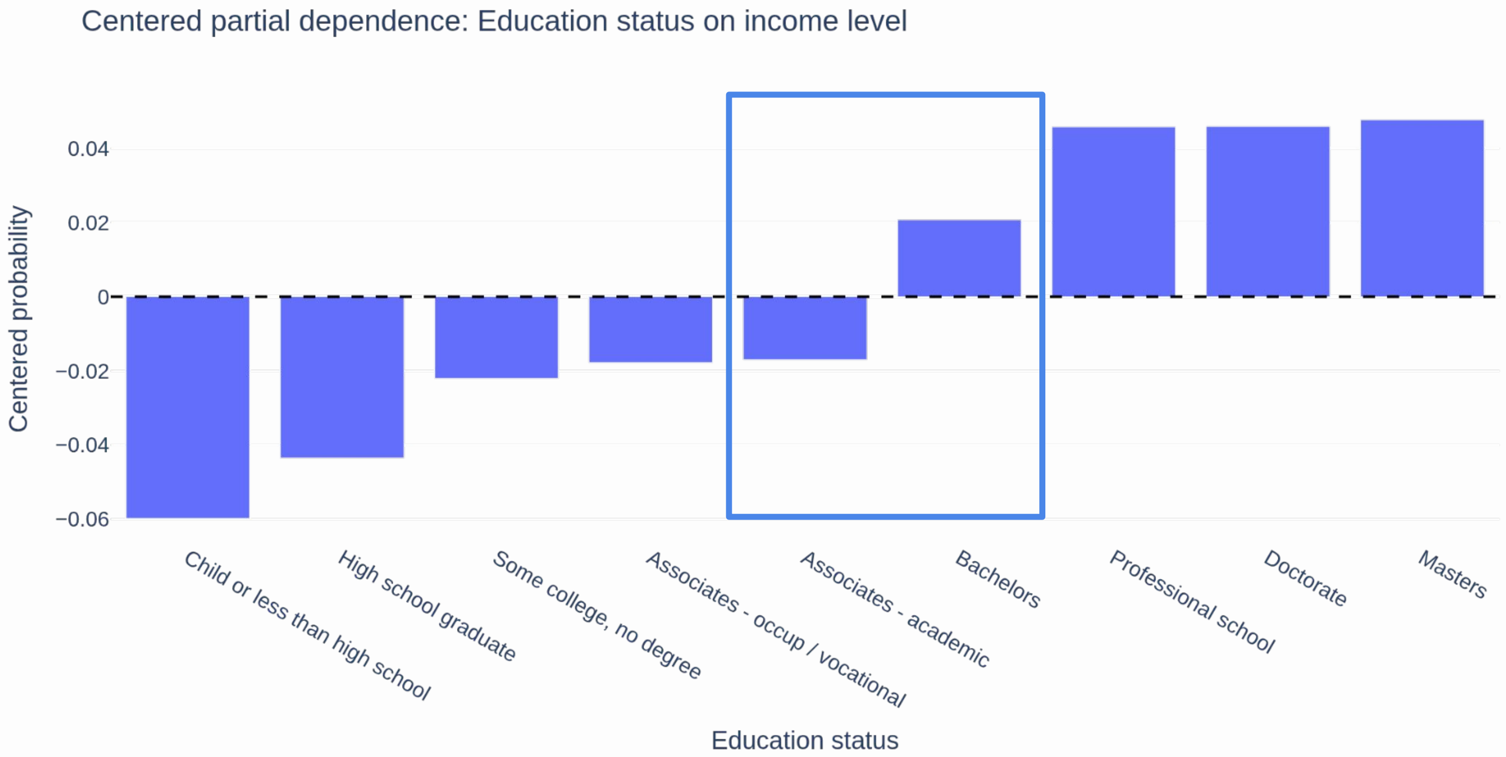
Results - Investment income effect



Results - Education effect



Results - Education effect



05

Recommendations

Recommendations

- Compare with more recent time frame
- Focus investigative efforts in important features
- Investigate potential gender bias
- Leverage education to income connection

06

Future Improvements

Future improvements

- Determine missing value pattern for migration features using other demographic information
- Develop more interactions between features
- Create additional features on business context
- Implement additional feature selection methods
- Evaluate model ensembles

Thank you!
Questions?