

Job Market Consulting



2024



Talent Optima



By Félix Veaux, Lincoln, Shuxi, Maralma



Felix Veaux

FelixVeaux



Shuxi Chen

shuxi-ch



Maral Batnasan

Maral-Batnasan



Xuanlong(Lincoln) Lyu

Lincolnlyu

D Our Team

LinkedInJobPosting

github.com/McGill-MMA-EnterpriseAnalytics/LinkedInJobPosting

Table of Contents

Business
Proposal

Machine
Learning
Lifecycle

TalentOptima HR Consulting

Optimizing Job Postings & Maximizing Career Value with Data-Driven Insights

The Problem

For Companies

- Companies have tasks that need to be done and need labour to do them.
- Nearly 70% of job seekers consider salary transparency critical (Glassdoor, 2022) yet only ~35% of job postings include salary data. [source](#)
- Average time-to-hire is around 42 days (SHRM), indicating inefficiencies in traditional hiring processes. [source](#)
- 87.6% of Human Resources (HR) managers report using salary benchmarks to set pay. [source](#)

For Job Seekers

- There is a Lack of transparent market data, leaving candidates vulnerable to undervalued compensation offers.
- Over 65% of candidates report difficulty in benchmarking salaries without reliable data. [source](#)



Our Solution

We offer comprehensive solutions for companies and individuals. Our solutions are at the core of our service and bring data-driven insights to customers.



ROBUST ML INSIGHTS



NLP TO EXTRACT
NUANCED INSIGHT



DATA-DRIVEN SALARY
RANGES



DATA INSIGHTS TO
REDUCE TIME-TO-HIRE

Business Model & Competitive Advantage

1



Revenue Streams

Consulting services, subscription-based SaaS platform, and premium analytics packages.

2



High Margins

SaaS models in HR tech typically enjoy recurring revenues and gross margins exceeding 70%. source

3



Competitive Edge

Our dual approach, targeting employers and job seekers and leveraging advanced ML (NLP, ensemble methods), differentiates us from traditional HR consultancies.

Software as a Service (SaaS)

Market Oportunity



TAM
(Total Addressable Market)

\$16.4 billion
global HR technology market



SAM
(Serviceable Addressable Market)

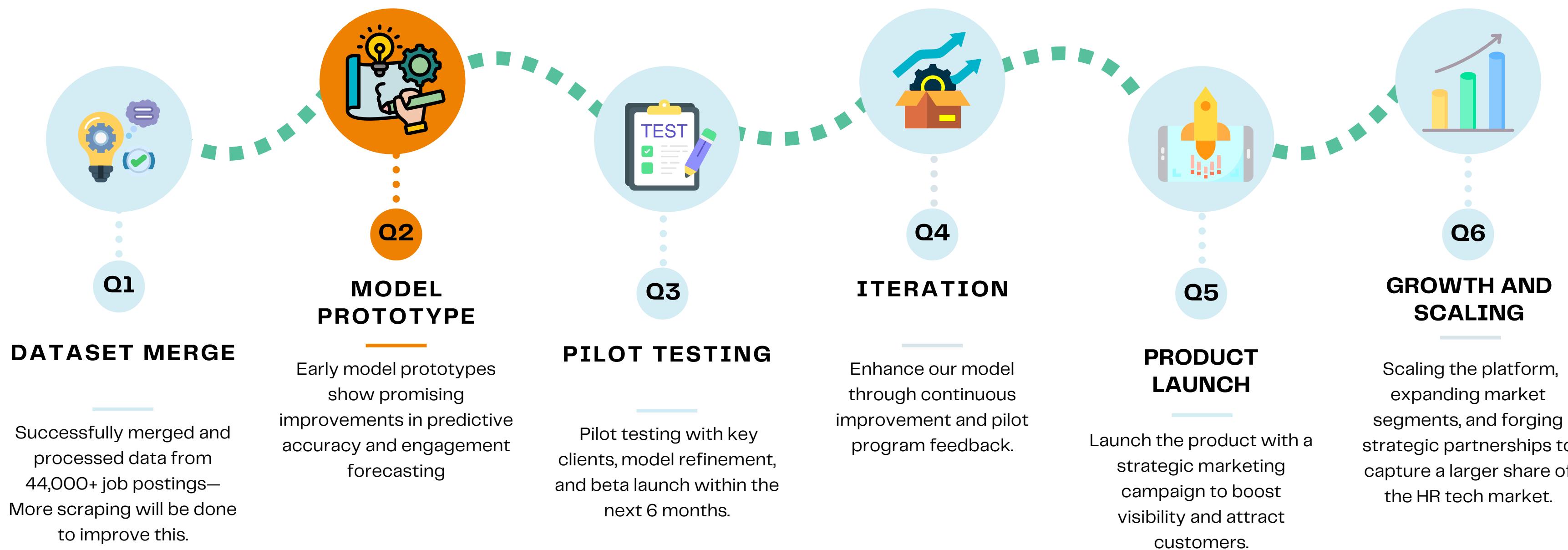
\$0.5 billion
recruitment analytics and job posting optimization



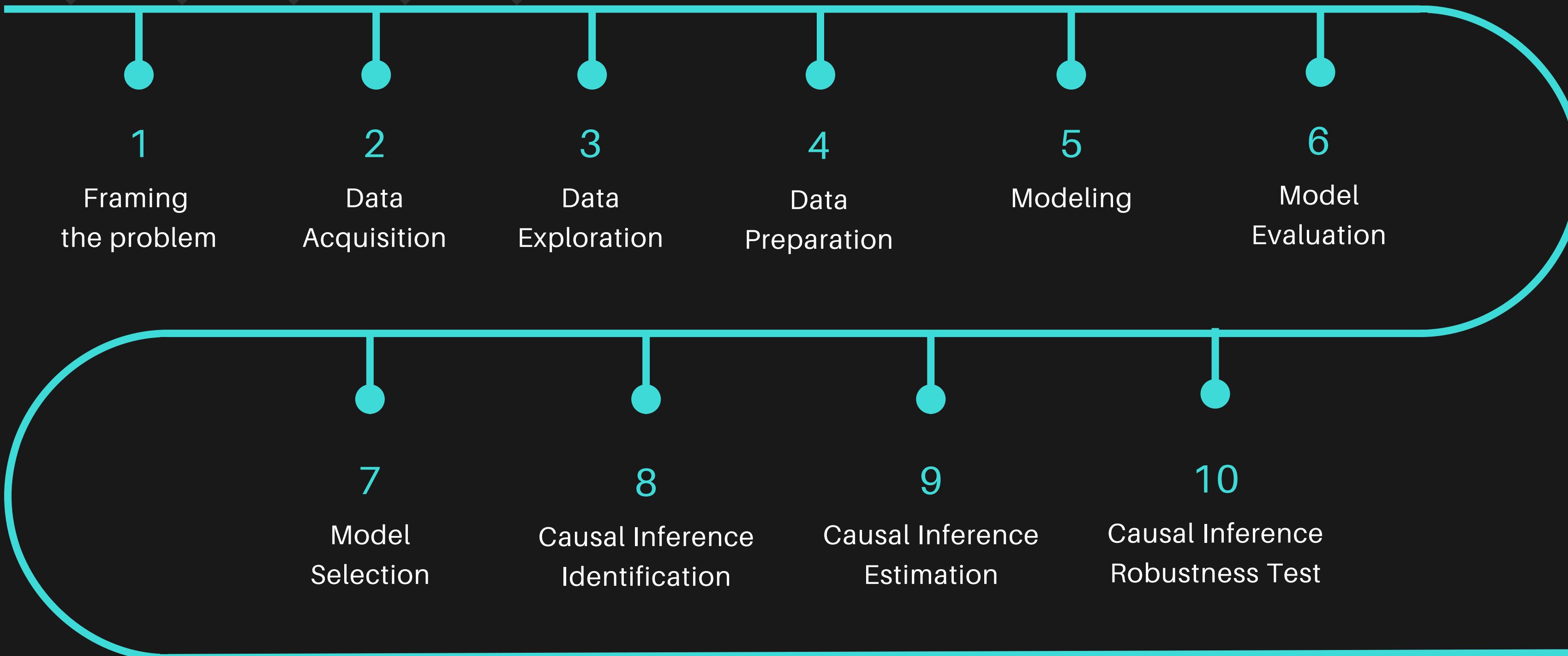
SOM
(Serviceable Obtainable Market)

\$25 Million
5% SAM within 5 years

Traction & Roadmap



Data Science Lifecycle



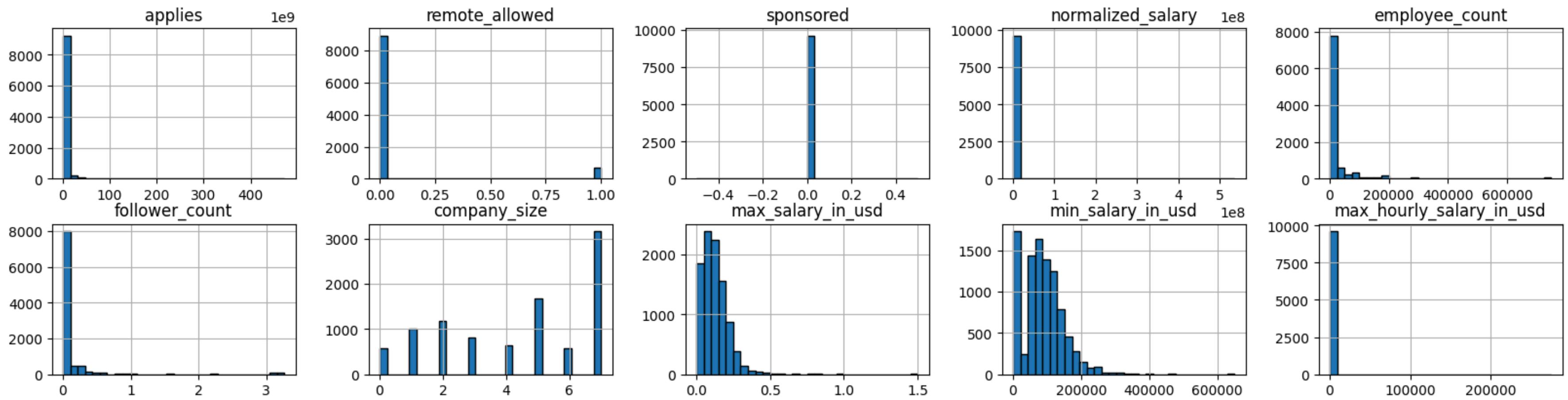
DATA ACQUISITION



NUMERICAL PREDICTORS	CATEGORICAL PREDICTORS	BINARY PREDICTORS
<ul style="list-style-type: none">• Maximum salary• Minimum salary• Normalized salary• Number of times the job posting has been viewed• Number of applications that have been submitted• Number of employees at company• Number of company followers on LinkedIn	<ul style="list-style-type: none">• Job experience level<ul style="list-style-type: none">◦ (entry, associate, executive)• Job Title<ul style="list-style-type: none">◦ (Extracted from Job Description using TF-IDF)• Job Location• Application Type (onsite, offsite)	<ul style="list-style-type: none">• Remote allowed• Child care support• Commuter benefits• Dental insurance• Disability insurance• Medical insurance• Paid maternity leave• Paid paternity leave• Pension plan• Student loan assistance• Tuition assistance• Vision insurance

3

DATA EXPLORATION



DATA PREPARATION

NEW FEATURES CREATED

- **Salary difference percentage** (between Min and Max salary)
- **Views and Applies per day**

NUMERICAL PREDICTORS

- Log transformation, outlier detection applied on employee count, follower count, normalized salary (for classification model)

CATEGORICAL PREDICTORS

- Job Title (NLP and TF-IDF)
- Skills (NLP and TF-IDF)
- State/City (One Hot Encode)

SMOTE

SMOTEEN

SMOTETOMEK

5

MODELING

A. Classification Model - Engagement Level Prediction

**Random Forest
Classification**

SVM

6

MODEL EVALUATION

Metric	High Engagement	Low Engagement
Precision	0.71	0.74
Recall	0.60	0.82
F1-score	0.65	0.78

RF ACCURACY: 0.73

Metric	High Engagement	Low Engagement
Precision	0.58	0.71
Recall	0.65	0.65
F1-score	0.61	0.68

SVM ACCURACY: 0.65

7

MODEL SELECTION

**Random Forest
Classification**

8

MODEL FINE-TUNING

RANDOM FOREST – GRID SEARCH

Metric	High Engagement	Low Engagement
Precision	0.76	0.76
Recall	0.64	0.85
F1-score	0.70	0.81

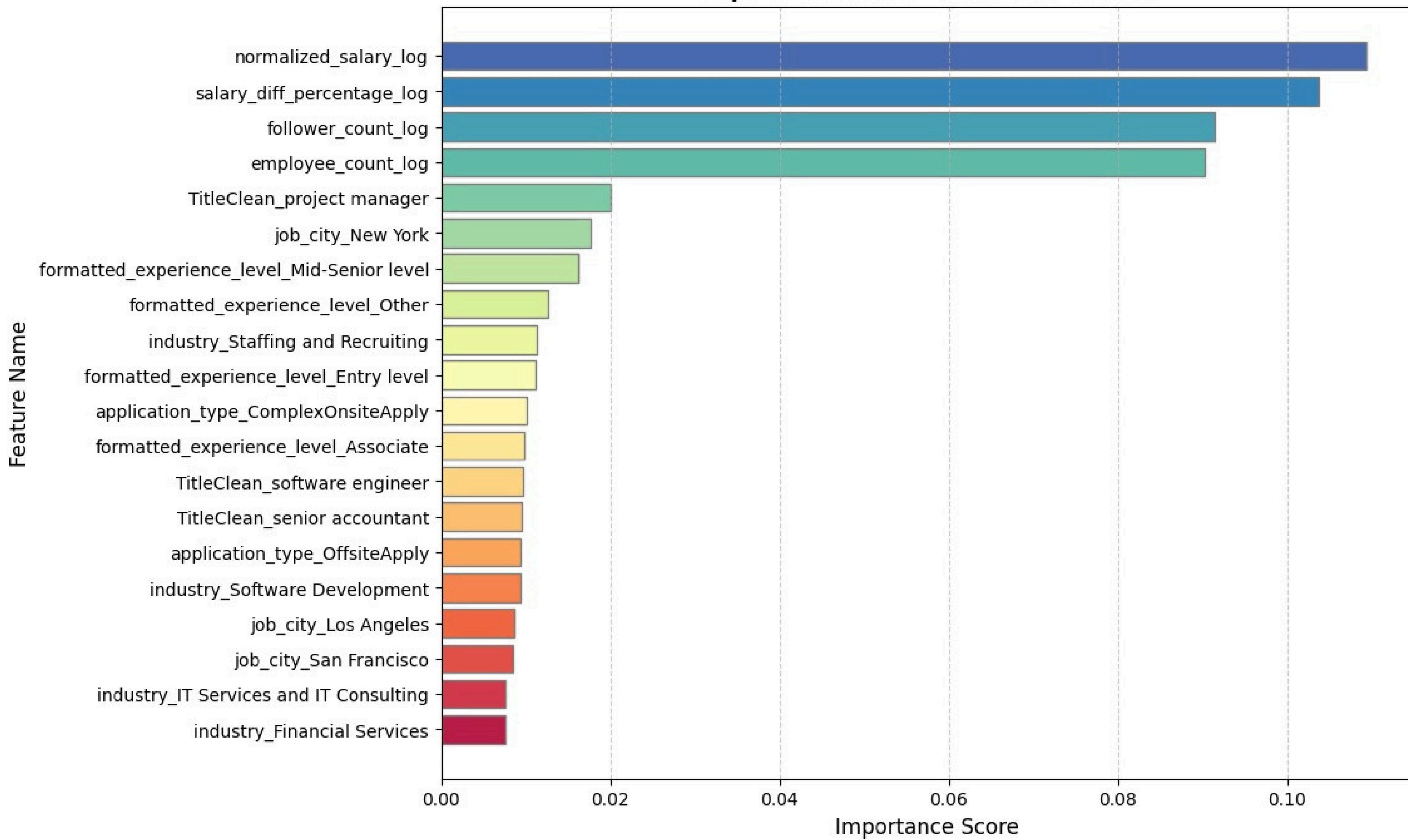
RF ACCURACY: 0.76

VOTING CLASSIFIER: RANDOM FOREST AND SVM

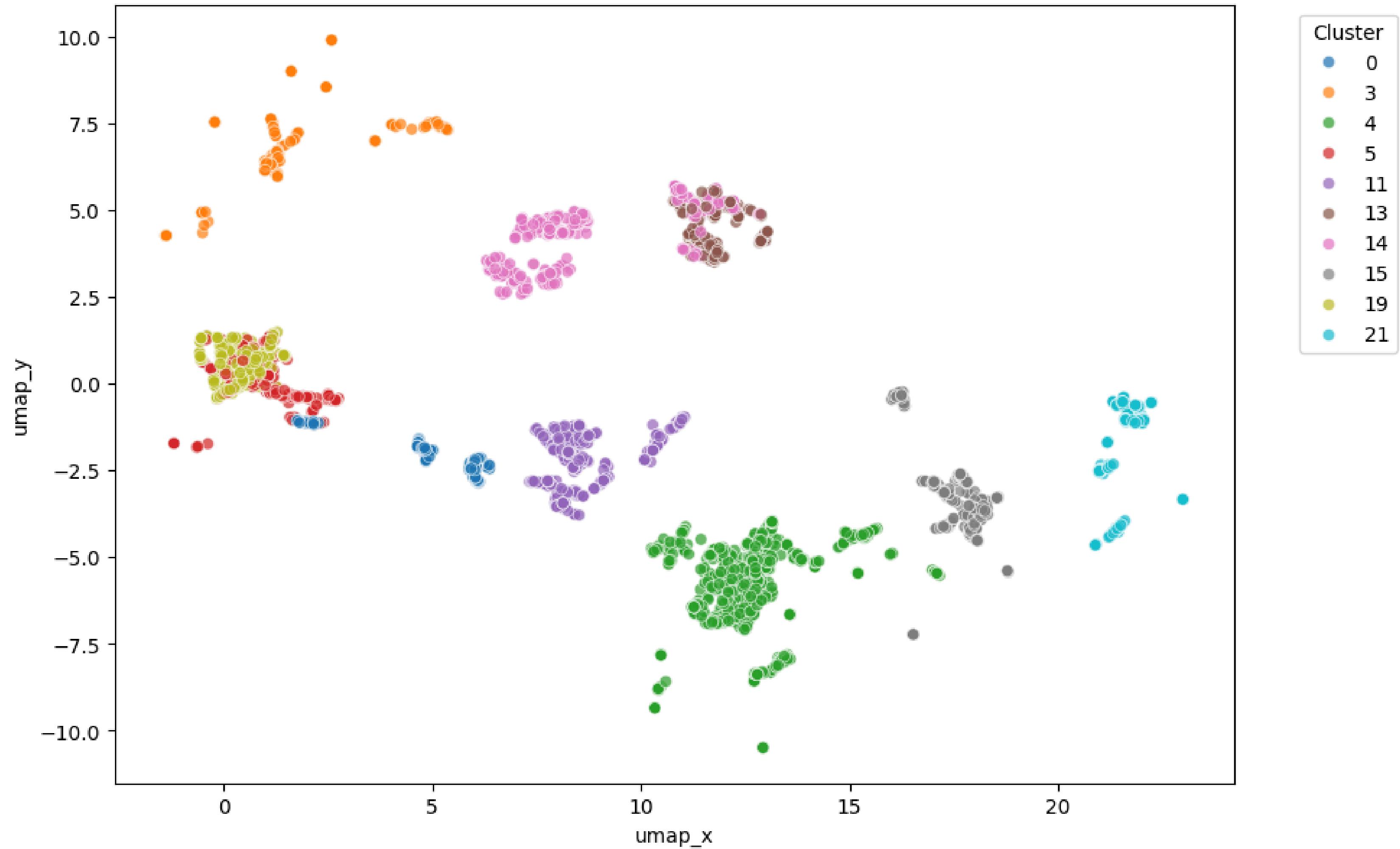
Metric	High Engagement	Low Engagement
Precision	0.60	0.78
Recall	0.76	0.62
F1-score	0.67	0.69

RF ACCURACY: 0.68

Top 20 Features - Random Forest

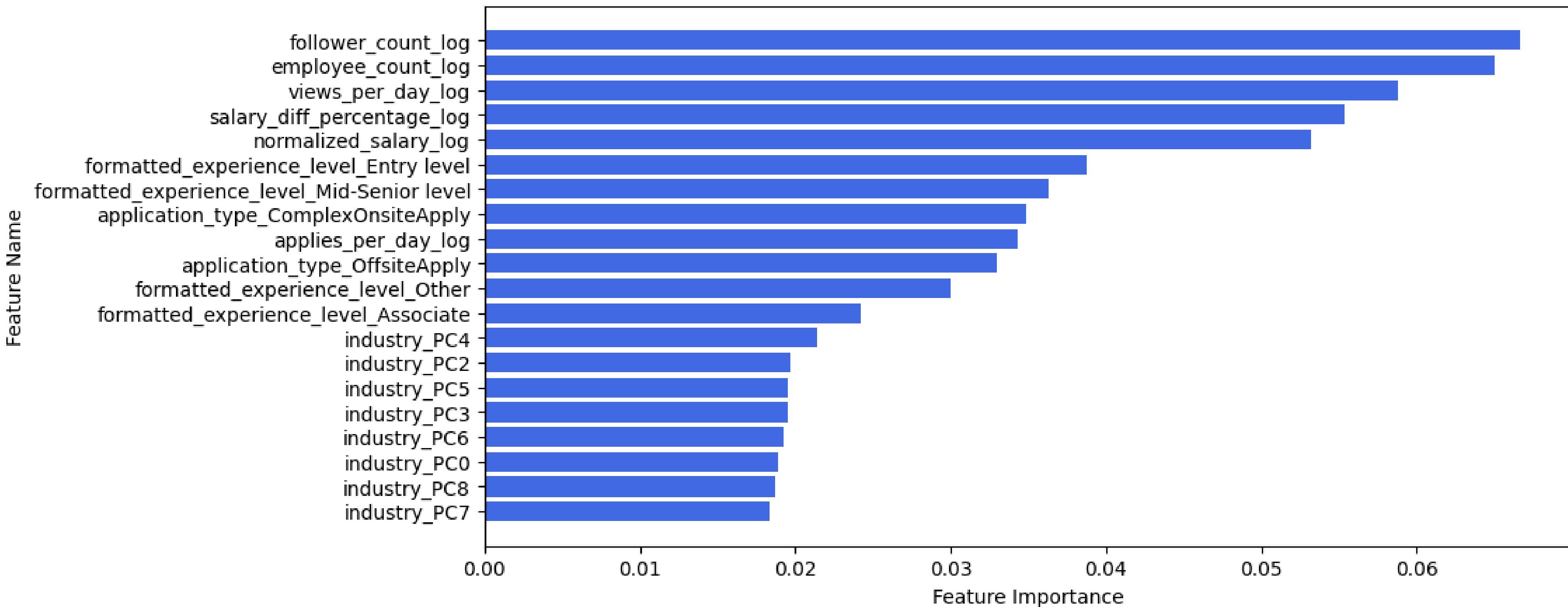


UMAP Visualization of Top Clusters



EXPLORING CLUSTER FORMATION

Top 10 Features driving cluster formation



5

MODELING

Drop High Correlated Features



Feature Selection



Fine Tuning

Deep Feed-Forward Neural Network

Decision Tree

Gradient Boosting

MODEL EVALUATION

	Model	Test RMSE	Test R Square
Max Salary	Deep Feed-Forward Neural Network	72394.874515	0.487176
	Decision Tree	77848.260640	0.407006
	Gradient Boosting	0.507990	0.103441

MODEL EVALUATION

	Model	Test RMSE	Test R Square
Min Salary	Deep Feed-Forward Neural Network	45535.034424	0.500267
	Decision Tree	46888.618490	0.470115
	Gradient Boosting	59888.620254	0.135559

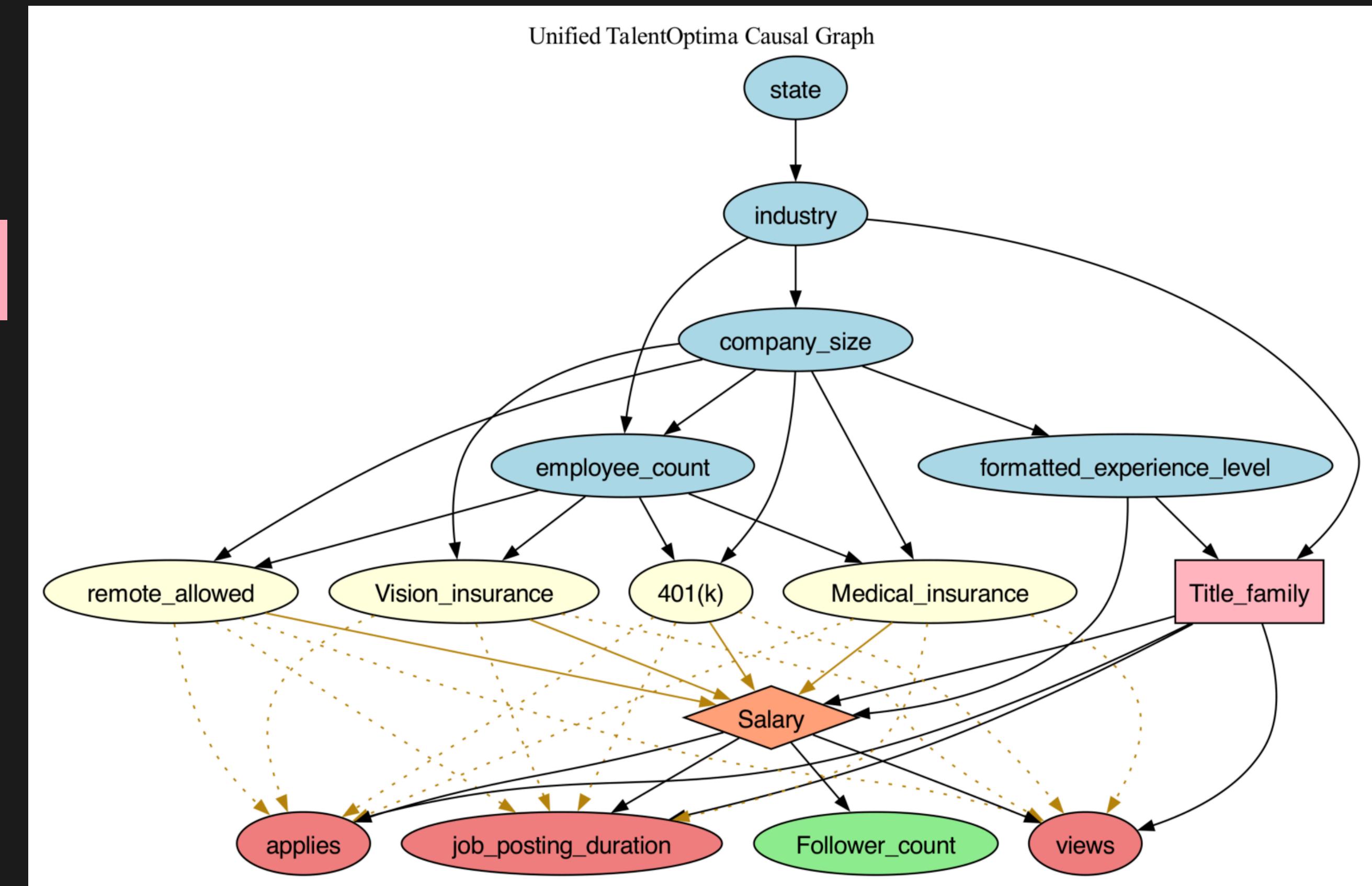
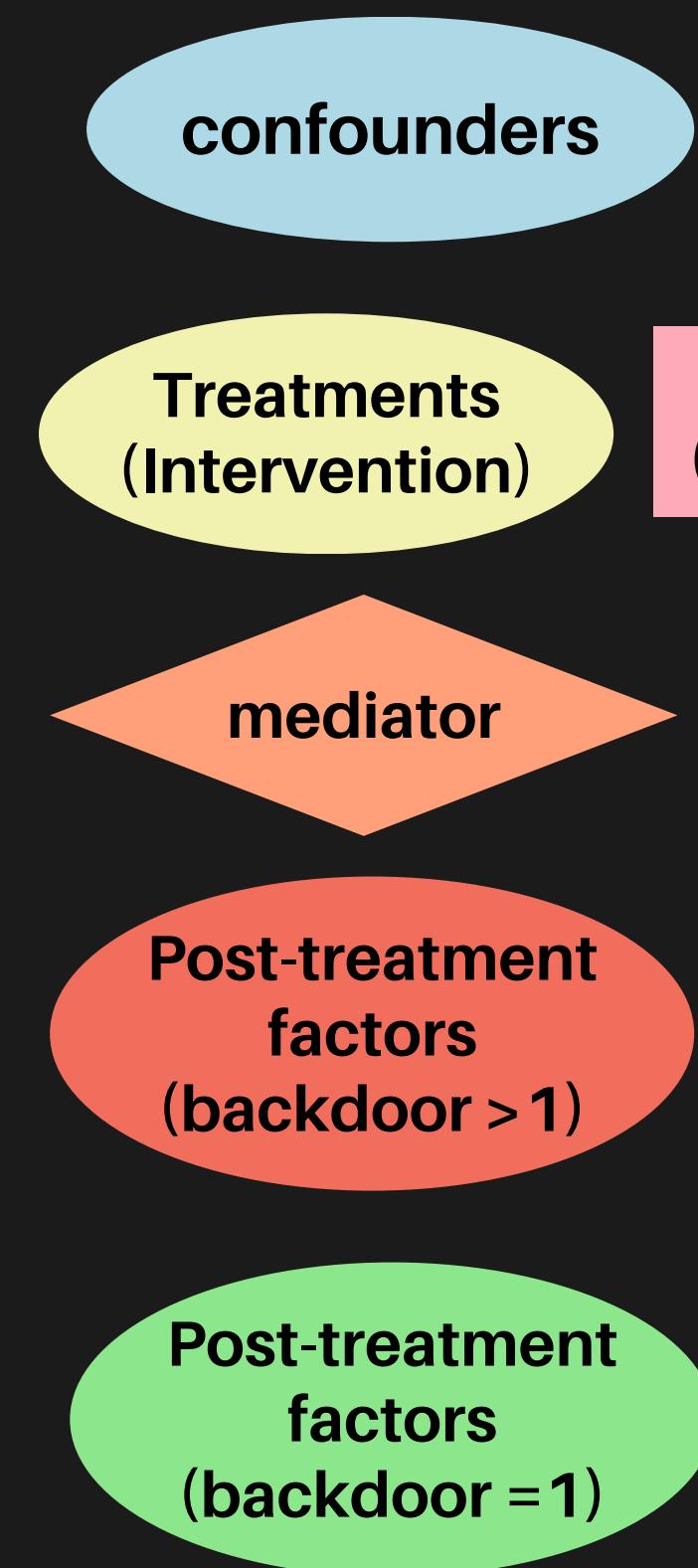
MODEL EVALUATION

Model	Test RMSE	Test R Square
Deep Feed-Forward Neural Network	1551.718080	0.111550
Hourly Salary	2320.786726	0.013887
Gradient Boosting	1710.365083	0.079407

8

CAUSAL INFERENCE

Identification



8

CAUSAL INFERENCE

Identification

confounders

Treatments
(Intervention)Treatments
(Intervention)

mediator

Post-treatment factors
(backdoor = 1)Post-treatment factors
(backdoor > 1)

$$Applies_i = \alpha_0 + \alpha_1 \cdot Benefit_i + \alpha_2 \cdot Confounders_i + \epsilon_i$$

$$Salary_i = \beta_0 + \beta_1 \cdot Benefit_i + \beta_2 \cdot Confounders_i + \epsilon_i$$

$$Applies_i = \gamma_0 + \gamma_1 \cdot Salary_i + \gamma_2 \cdot Benefit_i + \gamma_3 \cdot Confounders_i + \epsilon_i$$

Total Effect of Benefits (α_1)

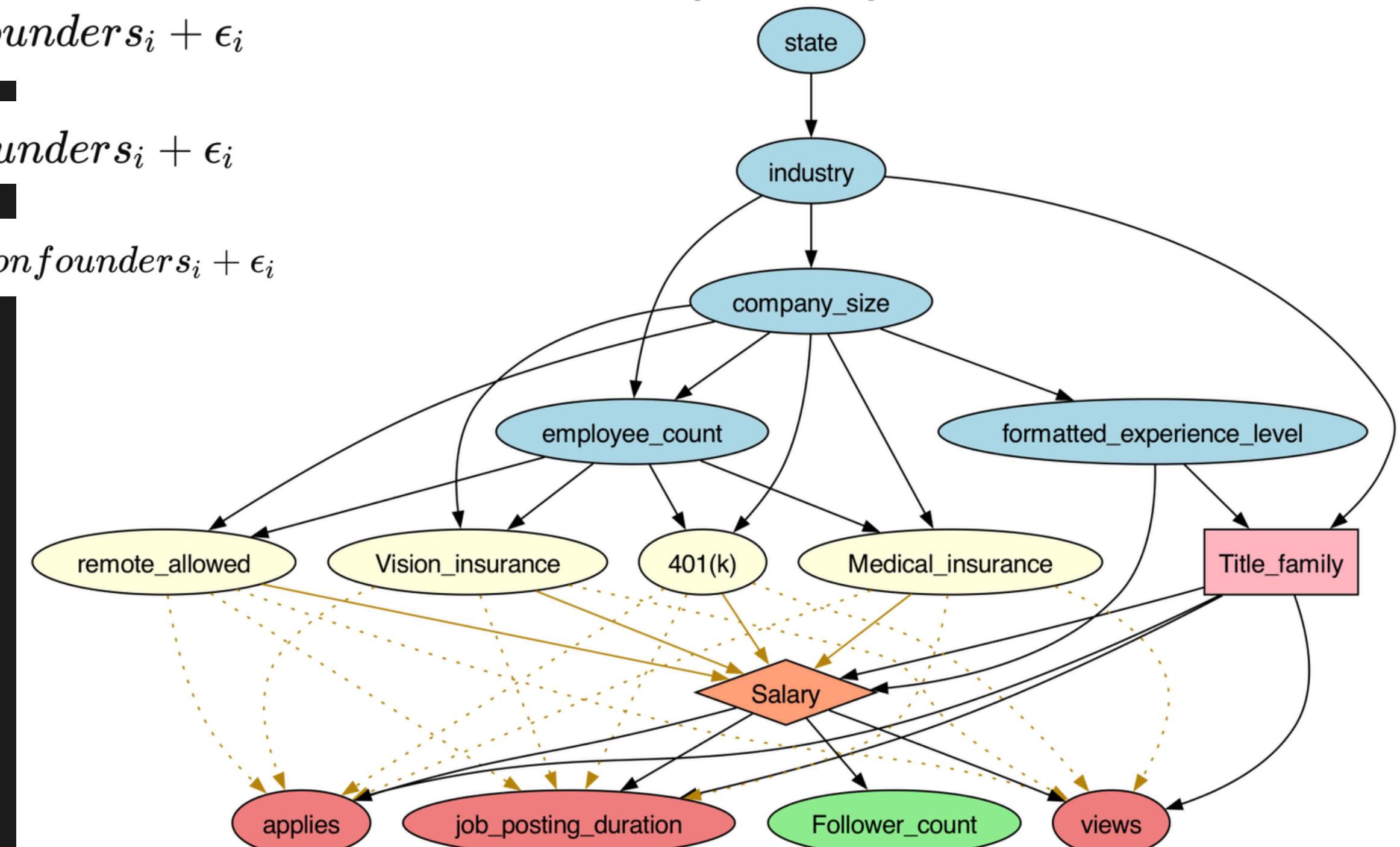
$$= (\text{benefits} \rightarrow \text{Salary} \rightarrow \text{applies}) + (\text{benefits} \rightarrow \text{applies})$$

$$= (\text{Solid brown arrows}) + (\text{dotted brown arrows})$$

$$= (\text{Indirect effect}) + (\text{Direct Effect})$$

$$= (\beta_1 * \gamma_1) + \gamma_2$$

Unified TalentOptima Causal Graph



CAUSAL INFERENCE

Estimation

Standardized Mean Difference (SMD)

&

Propensity Score Matching (PSM)

```
Analyzing benefit: remote_allowed
```

```
SMD Before Matching Summary:  
Extreme imbalance (SMD > 1): 0  
Some imbalance (SMD > 0.1): 23  
Large imbalance (SMD > 0.25): 2
```

```
SMD After Matching Summary:  
Extreme imbalance (SMD > 1): 0  
Some imbalance (SMD > 0.1): 0  
Large imbalance (SMD > 0.25): 0
```

```
Matched Sample: 3995 treated, 3995 control
```

```
Analyzing benefit: Medical insurance
```

```
SMD Before Matching Summary:  
Extreme imbalance (SMD > 1): 0  
Some imbalance (SMD > 0.1): 15  
Large imbalance (SMD > 0.25): 4
```

```
SMD After Matching Summary:  
Extreme imbalance (SMD > 1): 0  
Some imbalance (SMD > 0.1): 0  
Large imbalance (SMD > 0.25): 0
```

```
Matched Sample: 4111 treated, 4111 control
```

```
Analyzing benefit: 401(k)
```

```
SMD Before Matching Summary:  
Extreme imbalance (SMD > 1): 0  
Some imbalance (SMD > 0.1): 7  
Large imbalance (SMD > 0.25): 0
```

```
SMD After Matching Summary:  
Extreme imbalance (SMD > 1): 0  
Some imbalance (SMD > 0.1): 0  
Large imbalance (SMD > 0.25): 0
```

```
Matched Sample: 7577 treated, 7577 control
```

```
Analyzing benefit: Vision insurance
```

```
SMD Before Matching Summary:  
Extreme imbalance (SMD > 1): 0  
Some imbalance (SMD > 0.1): 16  
Large imbalance (SMD > 0.25): 2
```

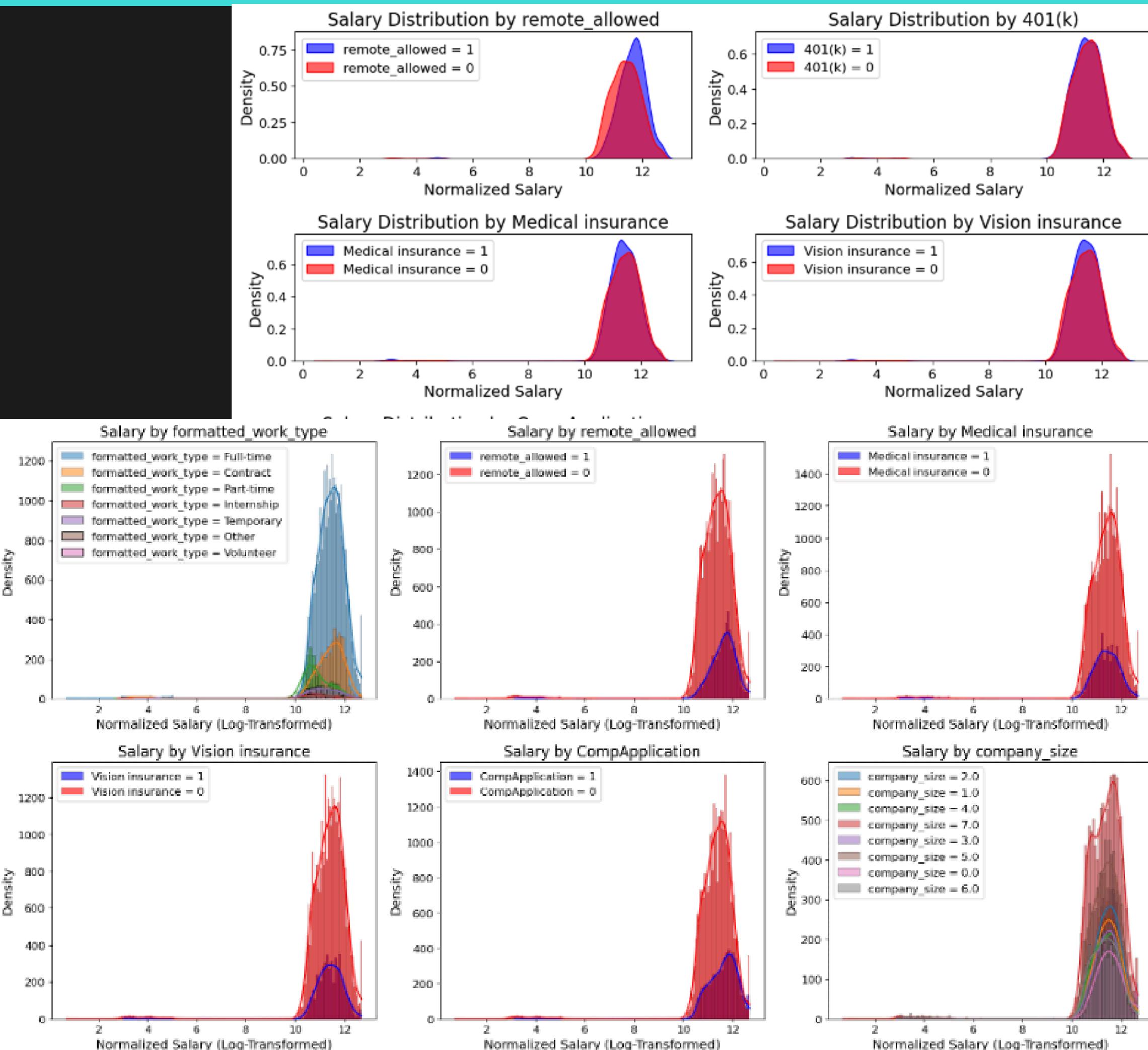
```
SMD After Matching Summary:  
Extreme imbalance (SMD > 1): 0  
Some imbalance (SMD > 0.1): 0  
Large imbalance (SMD > 0.25): 0
```

```
Matched Sample: 4014 treated, 4014 control
```

CAUSAL INFERENCE

Estimation

Standardized Mean Difference
(SMD)
&
Propensity Score Matching
(PSM)



CAUSAL INFERENCE

Estimation

OLS - ATE

Summary of All Benefits Analysis:

Benefit	Direct Effect	Indirect Effect	Total Effect
remote_allowed	0.5776249367842361	-0.0023801389926877176	0.5752447977915565
401(k)	0.01811189355879506	0.0031359116185031835	0.021247805177299572
Medical insurance	0.042192981626901056	0.0065570627642114665	0.04875004439111449
Vision insurance	0.055923020913214085	0.00016062615305846738	0.056083647066268616

Remote >

Vision insurance >

Medical insurance >

remote_allowed

CAUSAL INFERENCE

Estimation

OLS - ATE

Summary of All Benefits Analysis:				
Benefit	Direct Effect	Indirect Effect	Total Effect	
remote_allowed	0.5776249367842361	-0.0023801389926877176	0.5752447977915565	0.5975475767900111
401(k)	0.01811189355879506	0.0031359116185031835	0.021247805177299572	0.02775046644542822
Medical insurance	0.042192981626901056	0.0065570627642114665	0.04875004439111449	0.06406321586353232
Vision insurance	0.055923020913214085	0.00016062615305846738	0.056083647066268616	0.061334590274938275

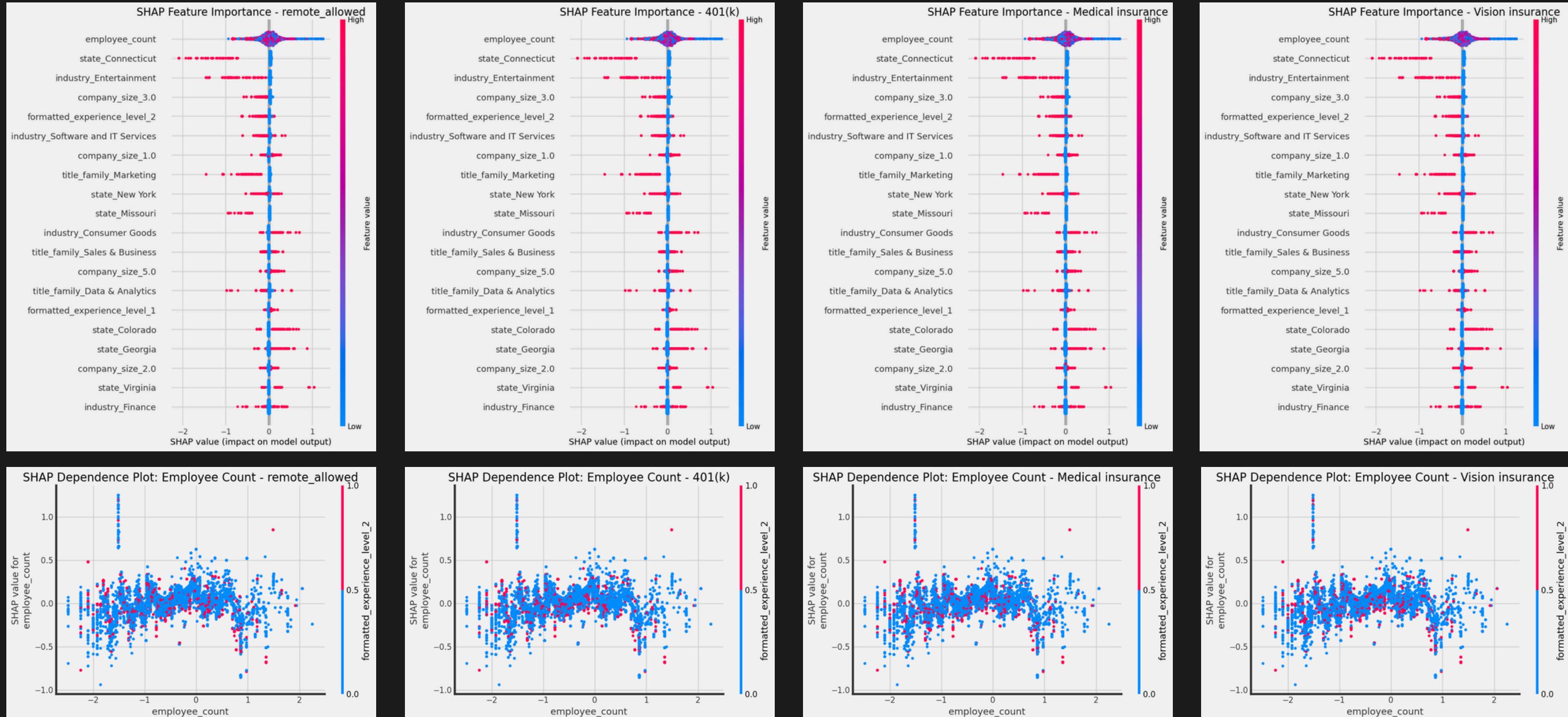
TLearner + XGBoost - CATE

	Mean CATE	Sample Size (T/C)	Imbalanced Covariates (Before→After)
remote_allowed	0.5975475767900111	3995 ↘ 3995	23 → 0
401(k)	0.02775046644542822	7577 ↘ 7577	7 → 0
Medical insurance	0.06406321586353232	4111 ↘ 4111	15 → 0
Vision insurance	0.061334590274938275	4014 ↘ 4014	16 → 0

Remote > Vision insurance > Medical insurance > remote_allowed

CAUSAL INFERENCE

Estimation



remote_allowed

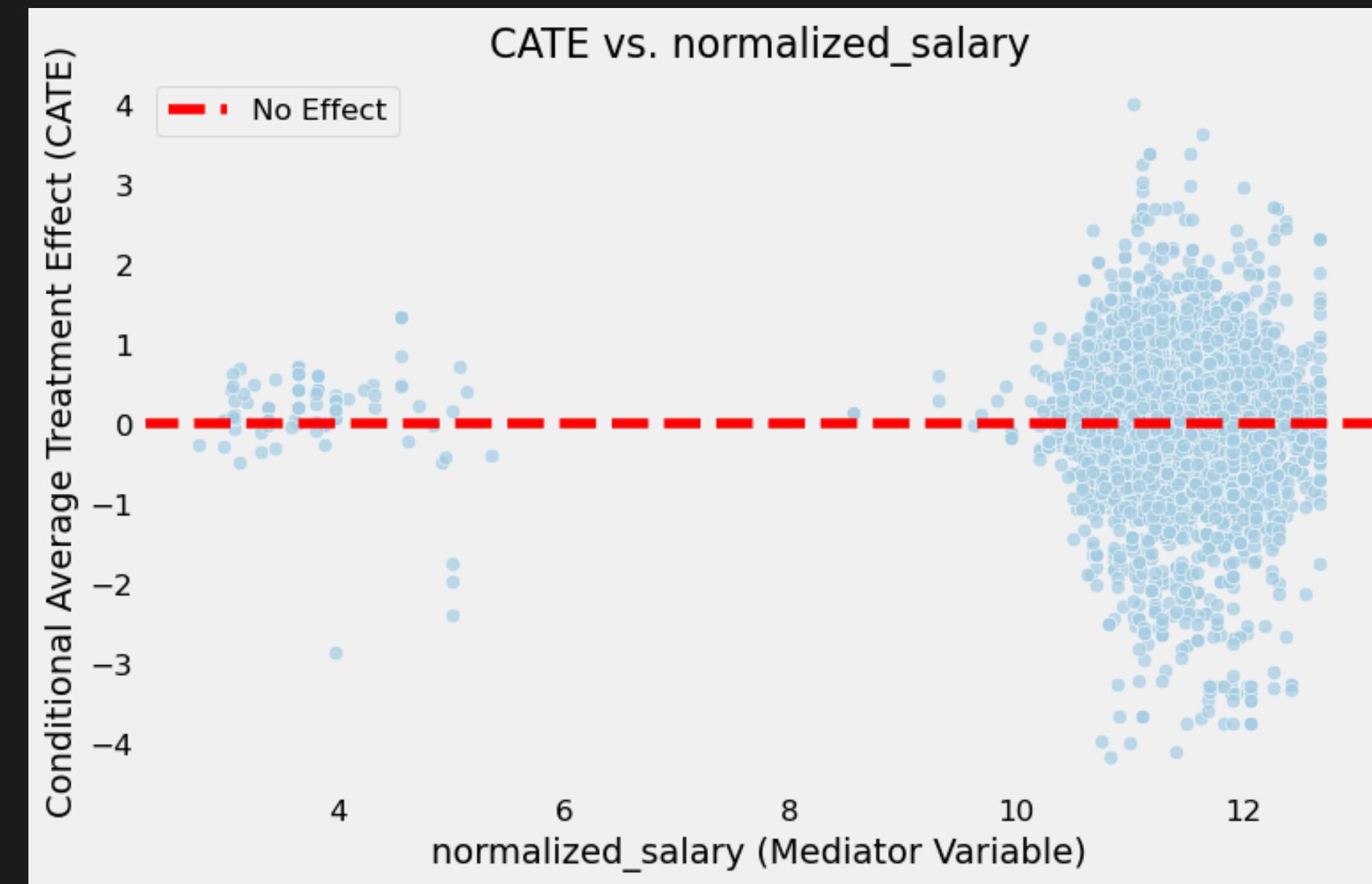
401 K

Medical indurance

Vision indurance

CAUSAL INFERENCE

Estimation



For lower salaries (~3-6)

CATE varies more, with some negative effects --> offering benefits alone may not always compensate for lower salaries

For higher salaries (~10-12)

Data points cluster around CATE = 0 --> benefits have limited additional impact on engagement at high salary levels

CAUSAL INFERENCE

9

Estimation

Titles

Data & Analytics

"data scientist": "Data & Analytics",
 "data analyst": "Data & Analytics",
 "data engineer": "Data & Analytics",
 "business analyst": "Data & Analytics",
 "financial analyst": "Data & Analytics",
 "senior data": "Data & Analytics",

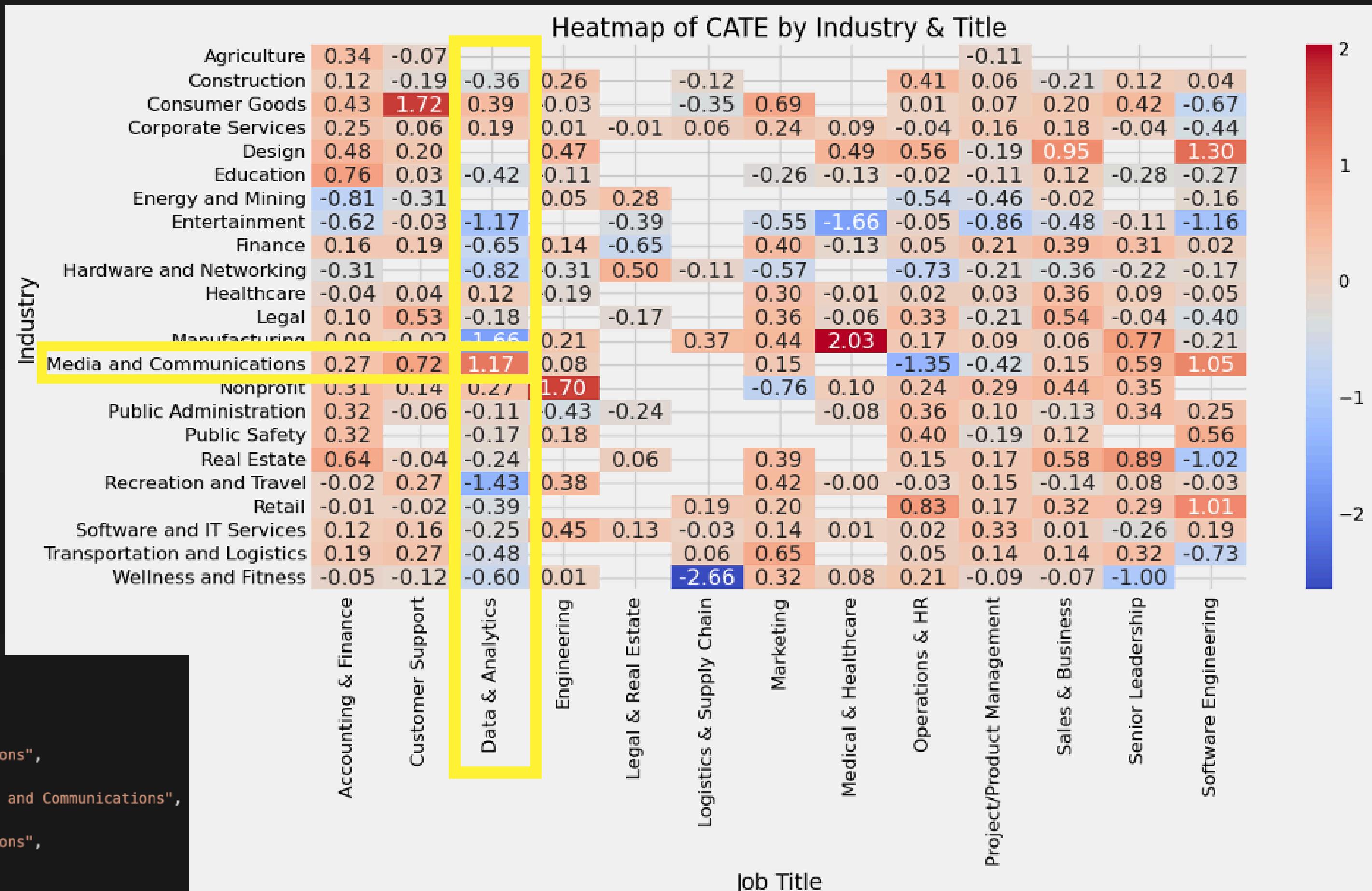
Industries

Retail

"Retail": "Retail",
 "Retail Groceries": "Retail",
 "Wholesale": "Retail",
 "Retail Apparel and Fashion": "Retail",

Media and Communications

"Market Research": "Media and Communications",
 "Marketing & Advertising": "Media and Communications",
 "Newspaper Publishing": "Media and Communications",
 "Online Audio and Video Media": "Media and Communications",
 "Printing Services": "Media and Communications",
 "Public Relations and Communications Services": "Media and Communications",
 "Publishing": "Media and Communications",
 "Translation and Localization": "Media and Communications",
 "Writing and Editing": "Media and Communications",
 "Advertising Services": "Media and Communications",



CAUSAL INFERENCE

9

Estimation

Titles

Data & Analytics

"data scientist": "Data & Analytics",
 "data analyst": "Data & Analytics",
 "data engineer": "Data & Analytics",
 "business analyst": "Data & Analytics",
 "financial analyst": "Data & Analytics",
 "senior data": "Data & Analytics",

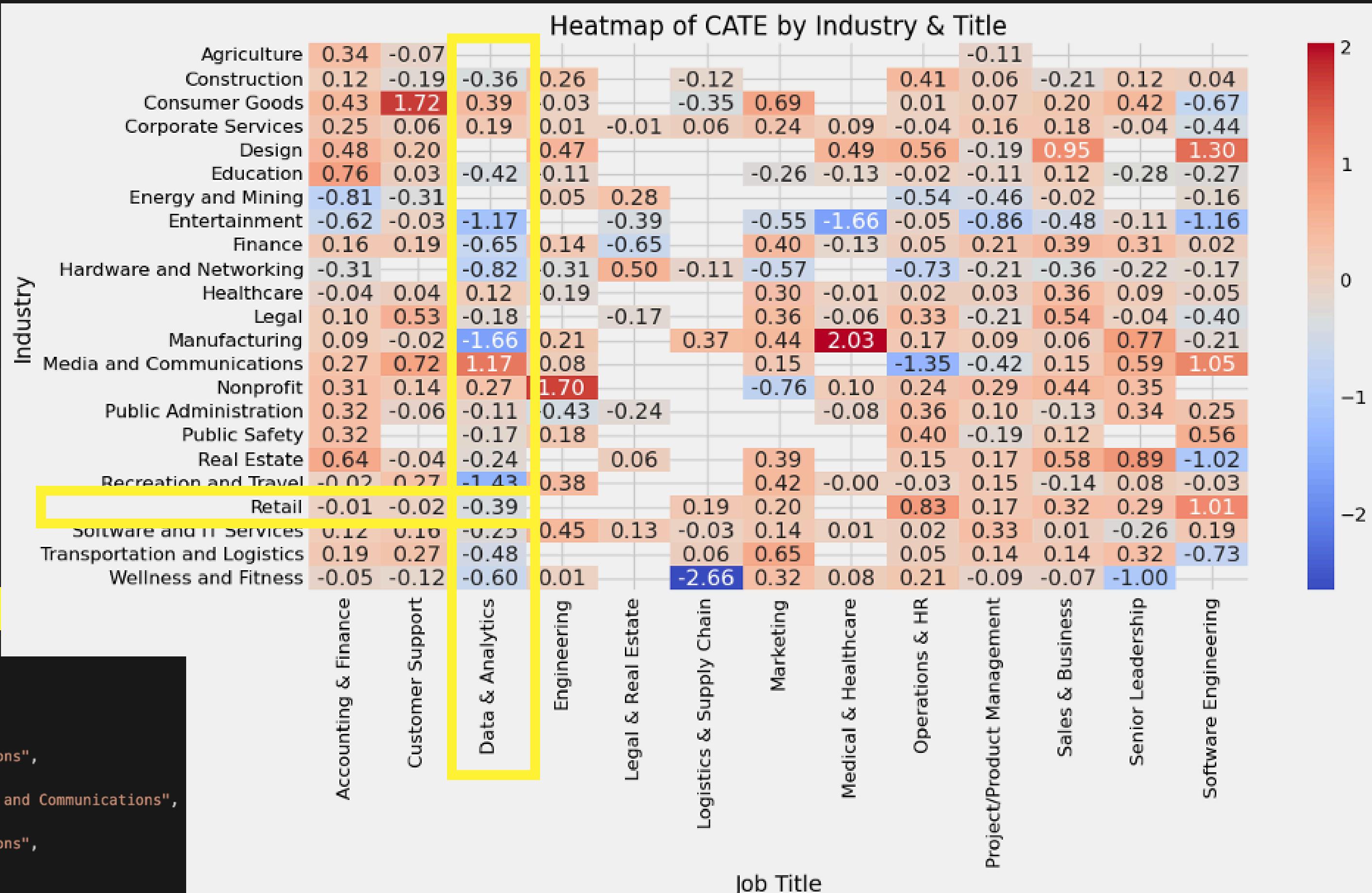
Industries

Retail

"Retail": "Retail",
 "Retail Groceries": "Retail",
 "Wholesale": "Retail".

"Retail Apparel and Fashion": "Retail",

Media and Communications
 "Market Research": "Media and Communications",
 "Marketing & Advertising": "Media and Communications",
 "Newspaper Publishing": "Media and Communications",
 "Online Audio and Video Media": "Media and Communications",
 "Printing Services": "Media and Communications",
 "Public Relations and Communications Services": "Media and Communications",
 "Publishing": "Media and Communications",
 "Translation and Localization": "Media and Communications",
 "Writing and Editing": "Media and Communications",
 "Advertising Services": "Media and Communications",

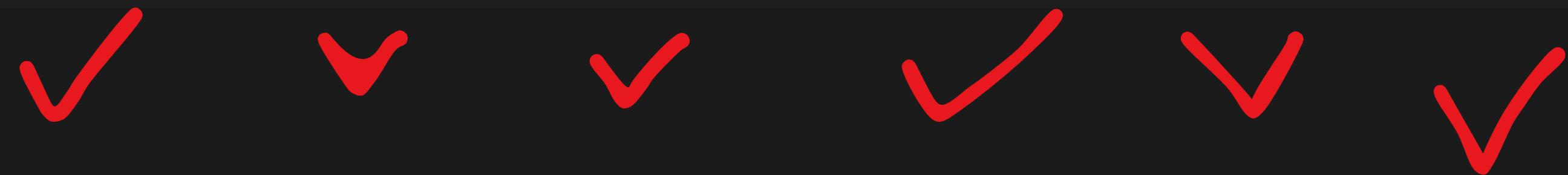


CAUSAL INFERENCE

Refutation Tests

Refutation Summary Across Benefits:

Benefit	Original Effect	Random Common Cause	Placebo Effect	Subset Effect	Random Change (%)	Placebo Change (%)	Subset Change (%)
remote_allowed	0.6908030920549518	0.6907947013641201	0.002062953517294121	0.6915748722884923	0.0012146284416206627	99.70136880668015	0.11172217415018845
401(k)	0.027687242295725906	0.02767092087464515	0.0010187562073829517	0.027892284390984505	0.05894924783923428	96.32048509381444	0.7405652504809087
Medical insurance	0.11216525674546696	0.11215481802973785	0.0016424242181714735	0.11351699369977795	0.009306550024479268	98.53571037429302	1.2051298178530017
Vision insurance	0.12462325054081744	0.12462576441594309	0.0017549306864286121	0.12537411264767337	0.0020171798719251	98.59181117583366	0.6025056348614535



CAUSAL INFERENCE

(Experience Level Model - Multi-level treatment) Failed Experiment

?

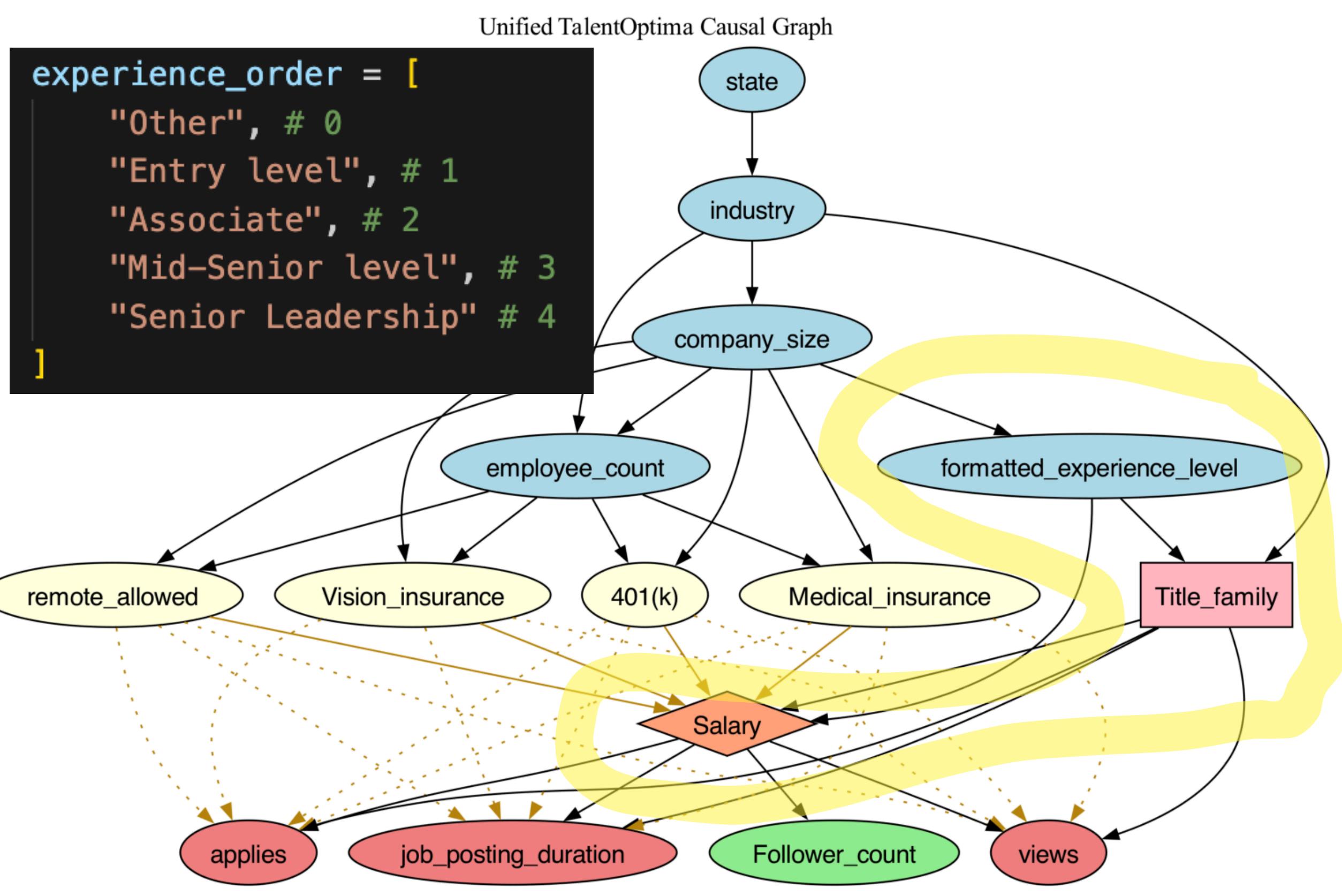
confounders

Treatments
(Intervention)

mediator

Post-treatment
factors
(backdoor > 1)

Post-treatment
factors
(backdoor = 1)



CAUSAL INFERENCE

(Experience Level Model - Multi-level treatment) Failed Experiment

SMD + GPS

SMD Before Matching Summary:
 Extreme imbalance (SMD > 1): 0
 Some imbalance (SMD > 0.1): 215
 Large imbalance (SMD > 0.25): 41

SMD After Matching Summary:
 Extreme imbalance (SMD > 1): 0
 Some imbalance (SMD > 0.1): 20
 Large imbalance (SMD > 0.25): 4

Matched Sample Sizes per Treatment Level:
 Treatment Level 0: 6045 samples
 Treatment Level 1: 6045 samples
 Treatment Level 2: 0 samples
 Treatment Level 3: 0 samples
 Treatment Level 4: 0 samples

OLS (ATE)

Mediation Analysis Results:

Total Effect of Experience on Salary:

const -0.232030
 formatted_experience_level_1 -0.196768

dtype: float64

Indirect Effect via Title: -0.0029463682201514682

Direct Effect of Experience on Salary:

formatted_experience_level_1 -0.052137

dtype: float64

Total Effect (Direct + Indirect):

formatted_experience_level_1 -0.055084

dtype: float64

RLearner + XGBoost (CATE)

Estimated Heterogeneous Treatment Effects (HTE) per Treatment Level:

formatted_experience_level

0 -0.022112

1 -0.125633

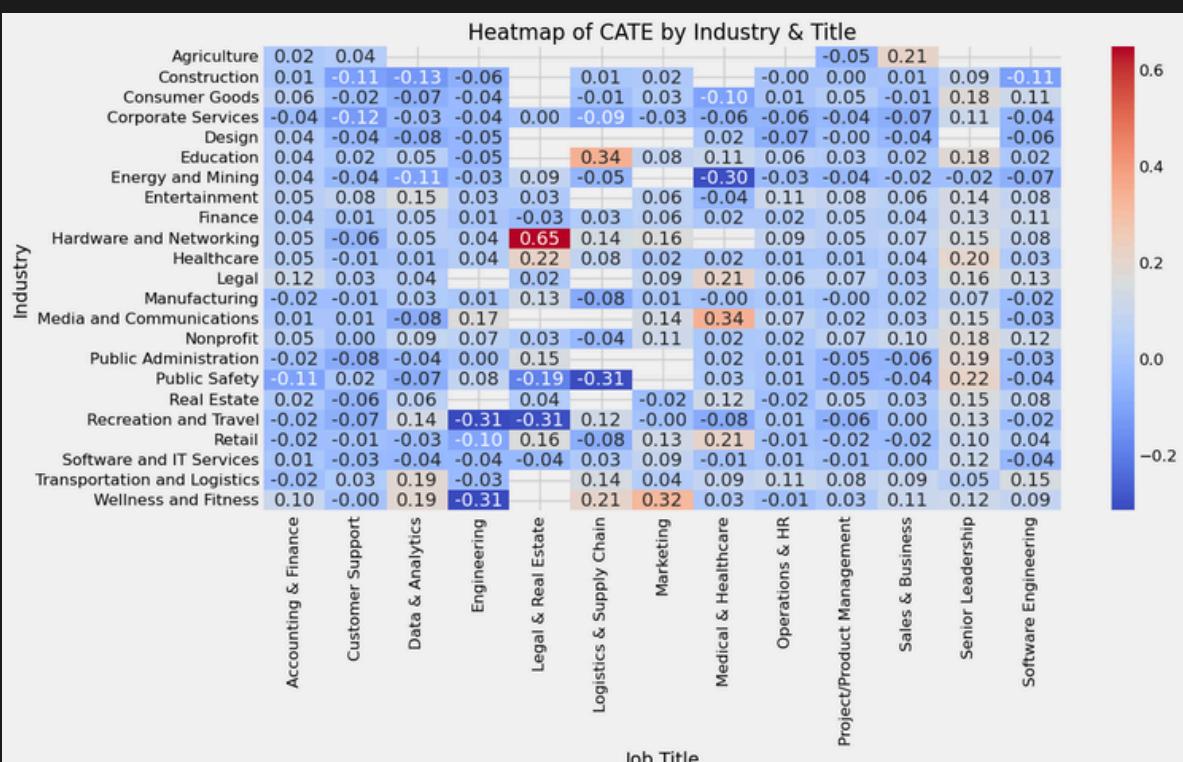
2 -0.104301

3 0.064679

4 0.291328

Name: tau_hat, dtype: float64

Robustness Tests



Refutation using Random Common Cause:

Refute: Add a random common cause

Estimated effect: 0.07315654101107721

New effect: 0.07315635756224806

p value: 0.98

Refutation using Data Subset:

Refute: Use a subset of data

Estimated effect: 0.07315654101107721

New effect: 0.07318060120476405

p value: 1.0

Refutation using Placebo Treatment:

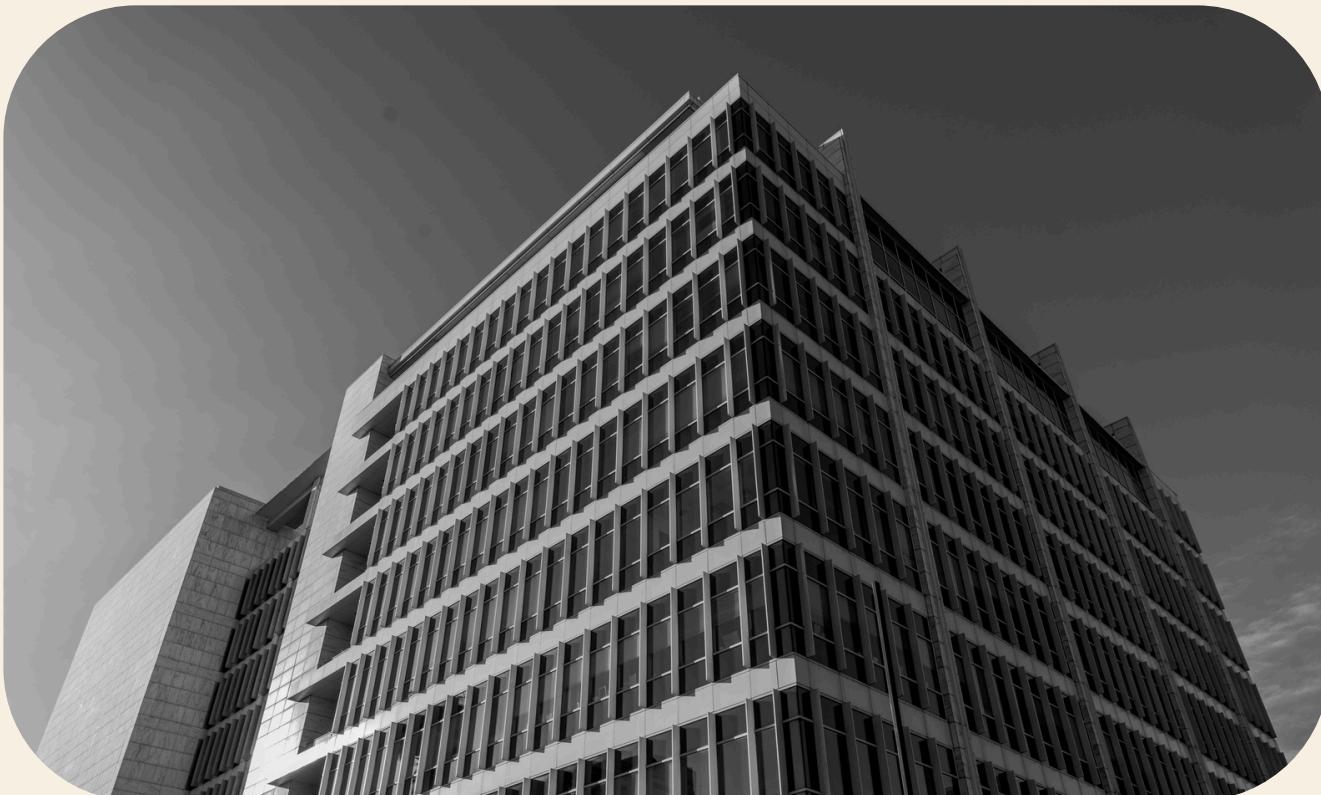
Refute: Use a Placebo Treatment

Estimated effect: 0.07315654101107721

New effect: 3.1402564460144155e-05

p value: 0.98

Thank You



Website

www.TalentOptima.com



E-mail

Invest@TalentOptima.com



Phone

+123-456-7890/+123-456-7890



HQ address

123 Sherbrook St., Montreal, QC 12345