E-RECRUITMENT – HOW IT CONTRIBUTES TO GENDER INEQUALITY

Presented by:

Yifan CAO and Toni LAW

Content

Introduction

Previous literature have focused on:

- Efficiency and accuracy of hiring process
- The perspective of recruiters

Our research aims to:

- To identify bias (gender bias)
- To improve in reliability

Theory & Hypothesis (Expectation of theory)

Theory:

Gender bias and gender inequality in the workplace is positively correlated

Hypothesis:

Gender inequality in job attainment is associated with gender bias during the E-recruitment process

Related work-Inequality in employment

Gender bias in employment:

Investigate 14 cities 316 law firm in America
To find out possibility of hiring in elite labor market:
higher class men > higher class women

Hierarchy bias in employment:

A qualitative case study of how elite reproduction occurs in hiring.

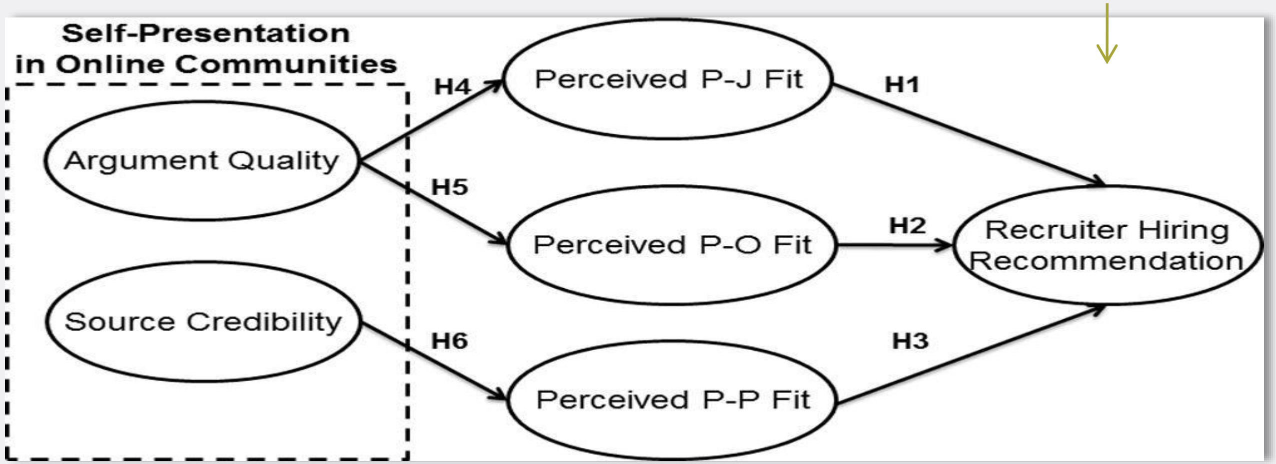
From 2006 to 2008, 120 semistructured interviews (40 interviews per firm type) with professionals involved in undergraduate and graduate hiring in
top-tier consulting, banking, and law firms.

"I originally intended to study gender in hiring. After the initial coding rounds, however, it
became clear that culture and socioeconomic status were highly salient bases of evaluation and stratification in these firms."

Lauren A. Rivera, & András *Tilcsik. (201*6). Class Advantage, Commitment Penalty: The Gendered Effect of Social *Class Signals in an Elite* Labor Market. American Sociological Review, 81(6), 1097-1131.
Rivera, L. A. (2015). Pedigree. Princeton: Princeton University Press.

Related work - Finding features of E-recruitment

Self-presentation → Matching mechanism → Hiring-recommendations



Methods:
focus group, interview, questionnaire, participant observation, statistical significance

Features & Hypothesis:
(1) portrait
(2) profile summary
(3) experience
(4) volunteer experience & causes
(5) projects
(6) languages
(7) certifications
(8) publications
(9) education
(10)discussion posts and comments
(11) recommendations
(12) endorsed skills and expertise
(13) interests
(14) honours and awards.

Table 1. Hypothesised path coefficients.

	H1	H2	H3	H4	H5	H6
1. Portrait						
β	0.721**	0.164**	0.167	0.335**	0.158	0.634**
R^2		0.717		0.112	0.025	0.402
2. Profile summary						
β	0.722**	0.165**	0.164	0.603**	0.096	0.215
R^2		0.717		0.364	0.009	0.046
3. Experience						
β	0.720**	0.165**	0.166	0.448**	0.404**	0.283
R^2		0.714		0.200	0.163	0.008
4. Volunteer experience and causes						
β	0.719**	0.166**	0.166	−0.119	−0.224	0.674*
R^2		0.715		0.200	0.163	0.454
5. Projects						
β	0.722**	0.165**	0.168	0.377**	−0.091	0.19
R^2		0.715		0.142	0.008	0.036
6. Languages						
β	0.716**	0.167**	0.168	0.331**	−0.132	0.613*
R^2		0.710		0.109	0.017	0.375
7. Certifications						
β	0.714**	0.168**	0.168	0.723**	0.200	0.403
R^2		0.713		0.523	0.004	0.163
8. Publications						
β	0.719**	0.166**	0.166	0.151	−0.307	0.554*
R^2		0.712		0.023	0.094	0.307
9. Education						
β	0.718**	0.166**	0.168	0.268**	0.293**	0.11*
R^2		0.714		0.072	0.086	0.012
10. Discussion posts and comments						
β	0.720**	0.166*	0.163	0.474**	0.189	0.51*
R^2		0.714		0.225	0.036	0.260
11. Recommendations						
β	0.717**	0.167*	0.169	0.285*	−0.255	0.055
R^2		0.713		0.081	0.065	0.003
12. Endorsed skills and expertise						
β	0.722**	0.166*	0.162	0.322**	0.314	−0.289
R^2		0.713		0.104	0.171	0.083
13. Interests						
β	0.720**	0.166**	0.165	0.113	0.226	0.579**
R^2		0.715		0.013	0.051	0.335
14. Honours and awards						
β	0.715**	0.168*	0.169	0.432**	0–.173	0.711**
R^2		0.709		0.187	0.030	0.505

Note: $n = 100$.

* $p < 0.05$.

** $p < 0.01$.

Chiang, Johannes Kuo-Huie, & Suen, Hung-Yue. (2015). Self-presentation and hiring recommendations in online communities: Lessons from LinkedIn. *Computers in Human Behavior*, 48, 516-524.
Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR Analytics. *The International Journal of Human Resource Management*, 28(1), 3–26. doi:10.1080/09585192.2016.1244699
Jansen, Anne, König, Cornelius J, Stadelmann, Eveline H, & Kleinmann, Martin. (2012). Applicants' Self-Presentational Behavior: What Do Recruiters Expect and What Do They Get? Journal of Personnel Psychology, 11(2), 77-85.

Related works - Computational method

[Big data contributions to human resource management: a systematic review](https://doi.org/10.1080/09585192.2019.1674357)

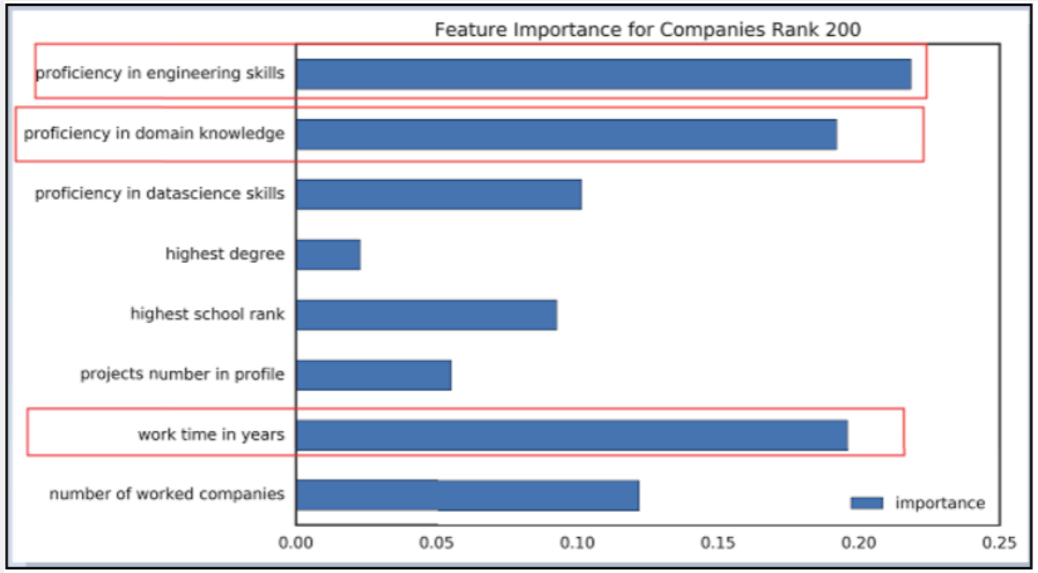
Table 2. Distribution of documents per year and cluster. (Table view)

	2013	2014	2015	2016	2017	2018	Total
HR research and practice				3	1	1	5
Selecting, hiring			3	1			4
Assessment, development				1	2	1	4
Information, learning, knowledge	2	2	5	2	5	3	19
Strategic, efficiency, performance	1	1	2	2	2	1	9
Total	4	3	10	9	10	6	41

e.g. 1）Predicting the Probability and Salary to Get Data Science Job in Top Companies by Gradient Boosting Decision Tree (GBDT algorithm)

Data features from the LinkedIn profile of candidate (above 18 features):

- Username: name of the candidate which will not use in this study
- Summary: self-written personal summary
- Education: University name, degree, and campus performance summary
- Skillsets: names of skills with endorsement value from first-degree connections
- Organizations: professional and academic organizations
- Publications and patents: intellectual property record
- Recommendations: comments on historical performance from very close first degree connections
- Certification and courses: record of training and coursework history
- Current job: company name, job title, responsibility, location, occupation time
- Past jobs: company name, job title, responsibility, location, occupation time



Marivate, V., & Moorosi, N. (2017). Employment relations: A data driven analysis of job markets using online job boards and online professional networks. *Proceedings of the International Conference on Web Intelligence*. doi:10.1145/3106426.3115589

Garcia-Arroyo, J., & Osca, A. (2019). Big data contributions to human resource management: a systematic review. *The International Journal of Human Resource Management*, 1–26. https://doi.org/10.1080/09585192.2019.1674357

Hazra, S., & Sanyal, S. (2016). Recruitment Prediction Using Id3 Decision Tree. *International Journal of Advance Engineering and Research Development*, 3(10). doi:10.21090/ijaerd.031010

Situ, W., Zheng, L., Yu, X., & Daneshmand, M. (2017). Predicting the Probability and Salary to Get Data Science Job in Top Companies. *Industrial and Systems Engineering Research Conference*.

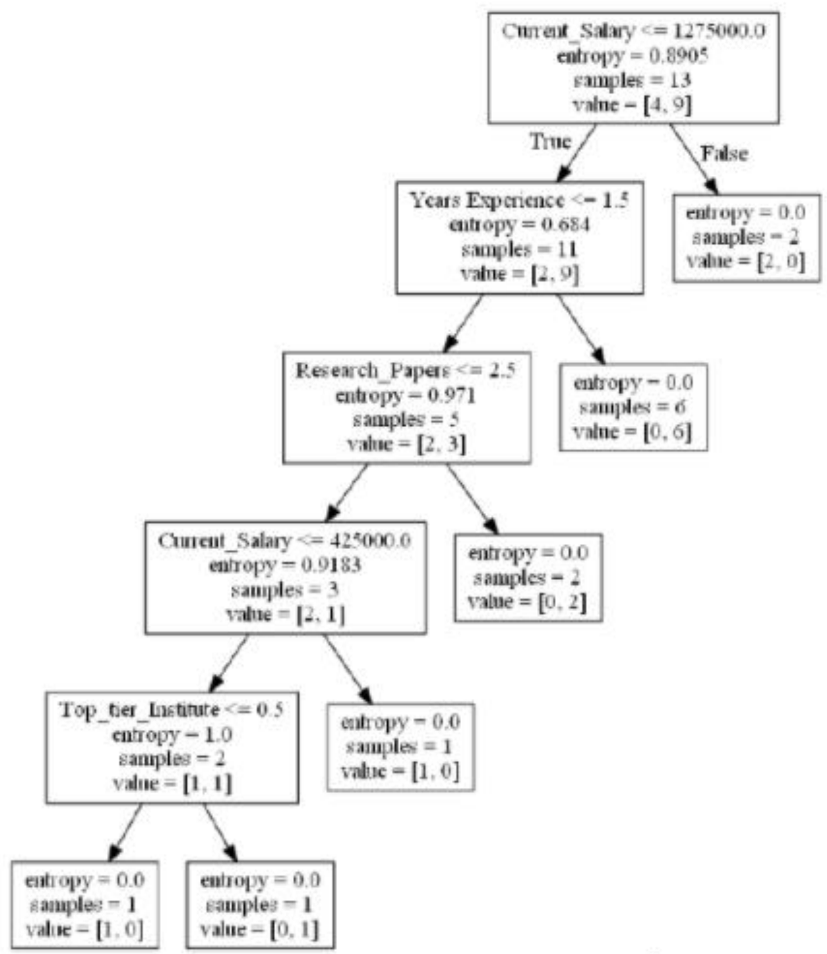
Related works - Computational method

e.g. 2）Recruitment Prediction Using ID3 Decision Tree

TABLE 1

Attributes and their possible values

PARAMETERS	DESCRIPTION	POSSIBLE VALUES
Years of experience	Shows the number of years of experience of the candidate.	Numeric (≥ 0)
Employed	Checks if the candidate is currently employed.	{ Y (Yes), N (No) }
Previous employers	Lists the number of previous employers.	Numeric (≥ 0)
Level of education	Shows the highest level of degree pursued by the candidate.	{ BS (Bachelors), MS (Masters), PhD (Post graduate) }
Top tier institute	Checks if the candidate pursued his/her education from a reputed institution.	{ Y (Yes), N (No) }
Research papers	Lists the number of research papers published by the candidate.	Numeric (≥ 0)
Internships	Shows the number of internships done by the candidate.	Numeric (≥ 0)
Current salary	The salary which the candidate has been receiving on his/her current job.	Numeric (≥ 0)



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Gap and framework

Current computational method of E-recruitment study always:

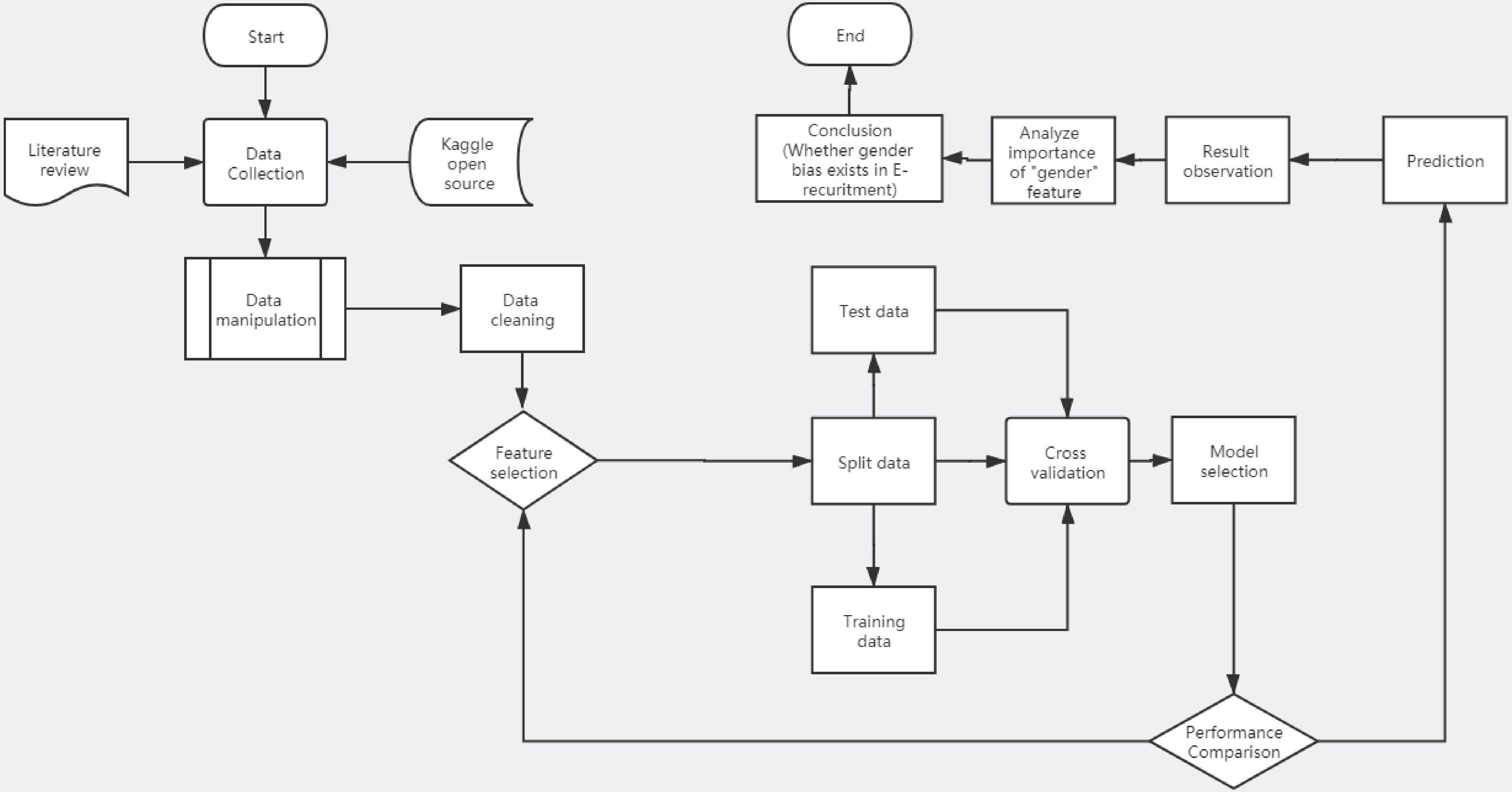
- focusing on features
- solve the problems of enterprises
- fulfill automatic match systems
- emphasize efficiency

previous computaional studies on E-recruitment tend to be utilitarian, besides help job-hunters to find a suitable job, there are more information we can study from data.

While traditional method of E-recruritment study highlight:

- social fairness
- opportunity equality
- bias in algorithm
- the situation of disadvantaged groups

Frame work


Start
Literature review
Data Collection
Kaggle open source
Data manipulation
Data cleaning
Feature selection
Split data
Test data
Training data
Cross validation
Model selection
Performance Comparison
Prediction
Result observation
Analyze importance of "gender" feature
Conclusion (Whether gender bias exists in E-recuritment)
End

Input-Data describe

Anonymized data from profiles scraped on LinkedIn. Contains data from about 60000 profiles with 52 features. Includes all their work history,gender, ethnicity, number of followers as well as analysis of their photo and name.

In original Data files each row contains:

- Profile data
- Job data
- Name analysis (Race, Gender)
- Profile picture analysis (Age, Race, Gender, Attractiveness, Health, Emotionality)

However the dataset was unequal especially in ethnicity & gender:

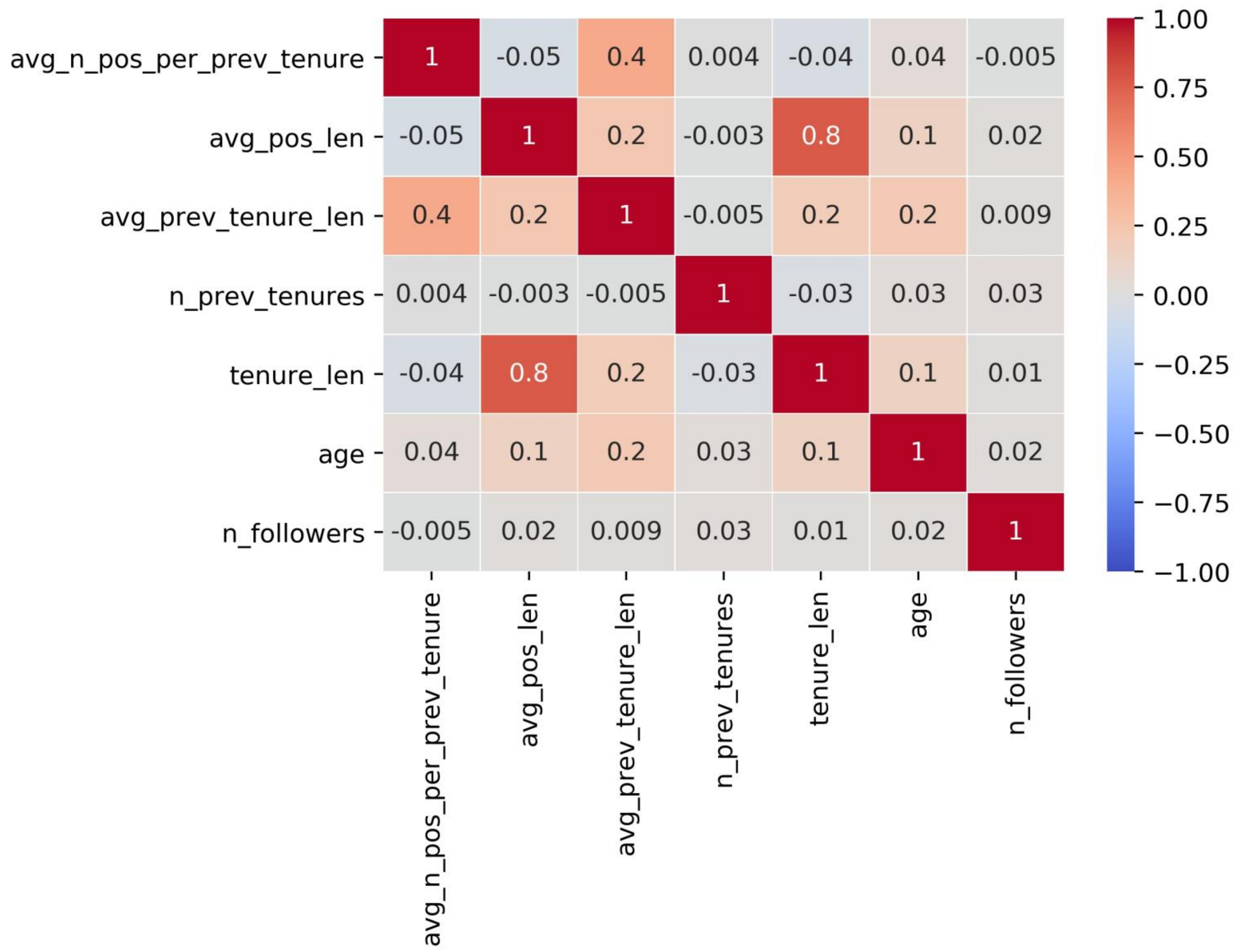
White	76%	Asian	16%
Male	76%	Female	24%

Feature selection

	avg_n_pos_per_prev_tenure	avg_pos_len	avg_prev_tenure_len	n_prev_tenures	tenure_len	age	n_followers
unt	62674.000000	62674.000000	62674.000000	62674.000000	62674.000000	62674.000000	62612.000000
ean	1.194420	765.494312	1100.858561	4.302119	961.743434	44.071074	1226.329713
std	0.506835	750.559928	985.960617	38.679425	1088.256794	11.108183	6411.388029
nin	1.000000	-120.000000	0.000000	0.000000	-120.000000	1.000000	0.000000
5%	1.000000	274.000000	537.000000	2.000000	304.000000	37.000000	405.000000
0%	1.000000	578.000000	882.800000	3.000000	640.000000	44.000000	725.000000
5%	1.200000	1035.000000	1400.000000	4.000000	1217.000000	51.000000	1244.000000
ax	15.000000	21884.000000	39781.000000	4930.000000	21884.000000	791.000000	530566.000000

```
RangeIndex: 62674 entries, 0 to 62673
Data columns (total 11 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   avg_n_pos_per_prev_tenure  62674 non-null  float64
 1   avg_pos_len                62674 non-null  float64
 2   avg_prev_tenure_len        62674 non-null  float64
 3   n_pos                      62674 non-null  object
 4   n_prev_tenures             62674 non-null  int64
 5   tenure_len                 62674 non-null  int64
 6   age                        62674 non-null  float64
 7   ethnicity                  62674 non-null  object
 8   gender                     62674 non-null  object
 9   n_followers                62612 non-null  float64
 10  c_name                     62668 non-null  object
dtypes: float64(5), int64(2), object(4)
memory usage: 5.3+ MB
```

Processing-Why use nonlinear model

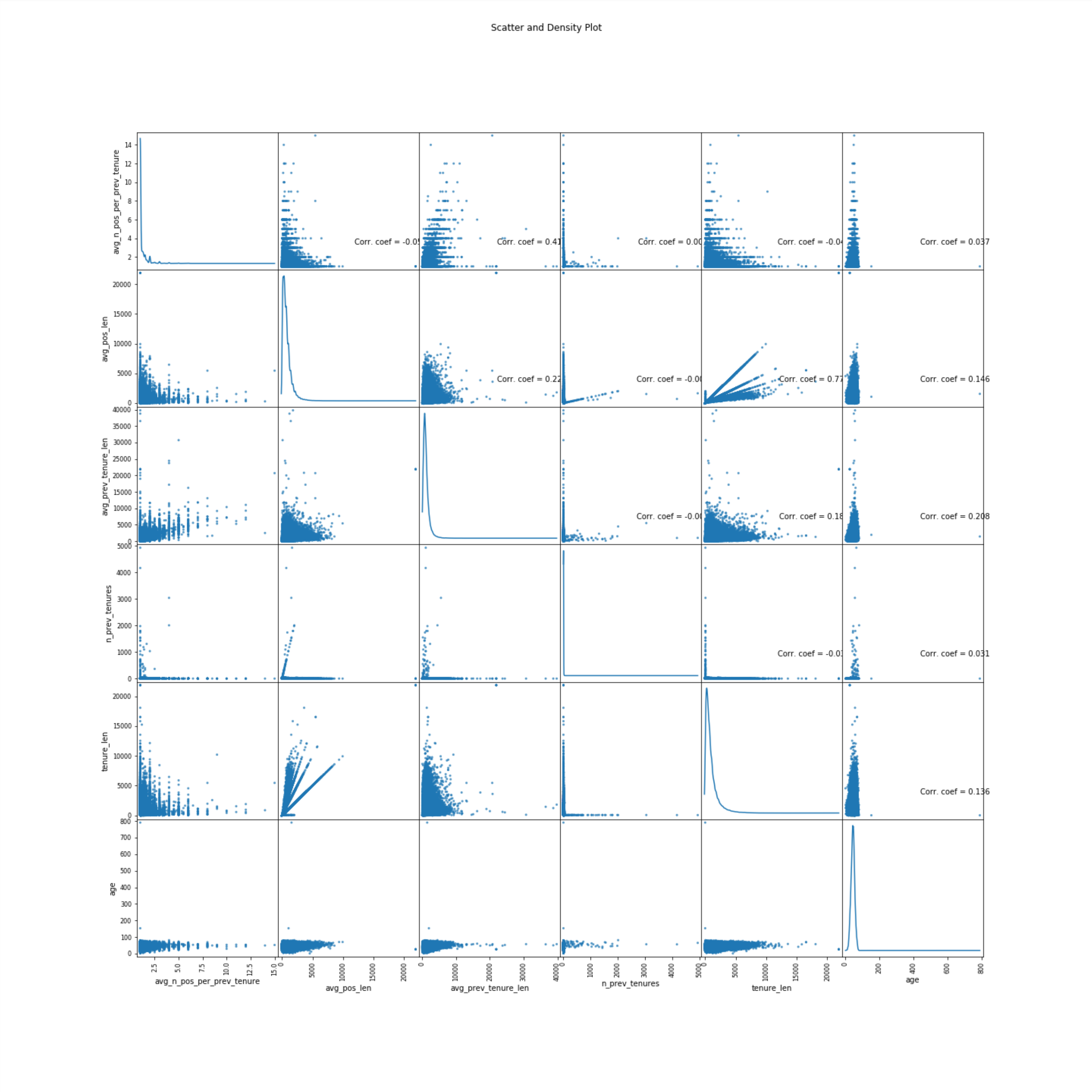


$$r_{xy} = \frac{Cov\ xy}{\sigma\ x\ \sigma y}$$

Pearson's correlation

Processing- Poisson Distribution

$$P(X = x) = e^{-u\frac{\mu^x}{x!}} \qquad x \in R$$



Future work- Data cleaning

To observe whether gender inequality exists in top high-tech industry E-recruitment, we revised the data in 3 dimensions:

1) Reduce male profiles until the proportion of male and female approaches the same.

2) Select target top high-tech corporations, which are Microsoft, IBM, Google, Adobe and some other similar companies.

3) One-hot encoding

- Binary Classification

1) Try to use Decision Tree and Random Forest as model to predict the Probability of getting Job in Top high-tech Companies.

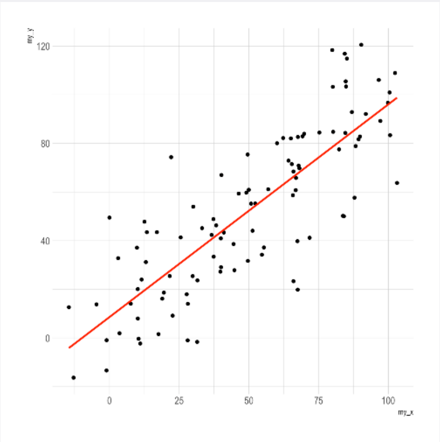
2) Analyze the significance of variables and find out which variable affect probability most, especially the gender feature.

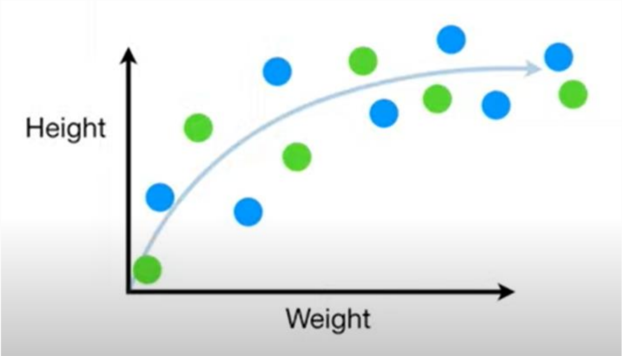
- Evaluation

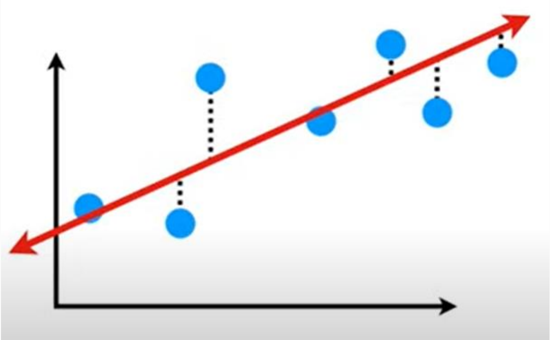
Suggestion - Machine Learning Design and Algorithm (Recruiter's perspective)

- **Design puzzle or riddle to test candidates aptitude and problems solving skills**
- **Interview candidate with machine learning algorithm (*HireVue, Inc.*)**
- assess their responses by using Natural Language Processing(NLP)
- assess body language by machine vision
- **Assess candidates' soft skills using dictionary method**

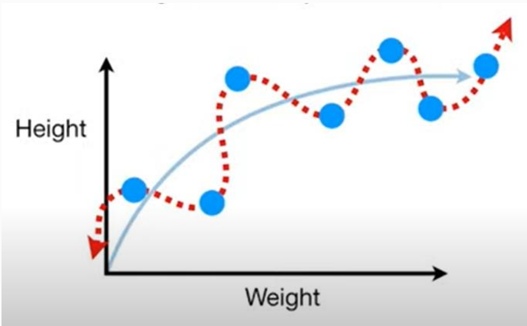
Machine learning limitations



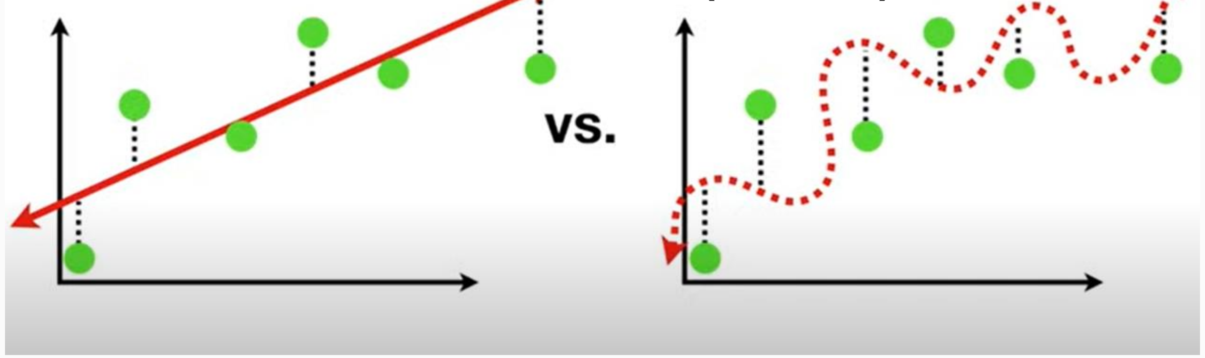




Linear: High bias, low variance



Wave line: Low bias, high variance (Overfit)



3 methods to find better fit: Regularization, Boosting and Bagging(random forest).

Big data – limitation

- E-recruitment is 85% of all recruitment
- Data of what platform candidate obtained job offer is missing

Thank you for listening!

Q&A