The Wage Gap Persists: How pay imbalances unequally reward male professors at the University of Toronto*

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Abstract

In this work, exploratory data analysis alongside two Gaussian Bayesian models explores whether the persistence of wage gaps by gender exist for professors and staff at the University of Toronto. Using Ontario's Public Sector Salary Disclosure from 2012-2019 (colloquially known as "The Sunshine List"), University of Toronto staff populations earning greater than $100,000 per annum are compared by gender, title, and years of experience to examine whether or not wages are fairly distributed. Models find that female professors and staff are paid less than their male counterparts with similar titles, and this wage gap is increasingly worse year over year.

Introduction

Academia is increasingly female. Within Canadian institutions of higher education, gender parity was reached for students in 1989 (Council of Canadian Academies, 2012). Research in 2012 using Statistics Canada surveys found that women outnumbered men in both undergraduate and graduate programs and represented nearly 50% of all PhD students. As such, staff ratios at universities for both administrator and professor positions should begin to reach gender parity as qualified women graduates enter into the workforce. However, simply hiring more women does not address known wage gaps between genders. Momani et al. found, "men were paid on average 2.06%, 2.14%, and 5.26% more than their women colleagues for all employees, university teaching staff, and deans, respectively" within Ontario higher education from 1996-2016 (2019). Similarly, the CBC reported in 2020 that similar wage gaps existed in Alberta following preliminary data analysis from Statistics Canada salary data (Cummings, 2020). The University of Toronto Provost specifically addressed the gap in 2019, following the university's internal salary audits, noting that female faculty were at least 3.9% underpaid compared to men in similar positions (Benjamin et al. 2019).

This analysis highlights the inequality in both the number of female staff at the University of Toronto and their lower-than-male salaries through exploratory data analysis and two Gaussian Bayesian models using Ontario's Public Sector Salary Disclosure from 2012-2019 (also known as "The Sunshine List"). The Sunshine List is available for download through open data initiatives to disclose the salaries of all public employees earning more than $100,000 per annum in Ontario. The analysis examines the effects of gender, title, and years of experience (see §Dataset). Both exploratory data analysis and Bayesian models found that female professors and staff are paid less than their male counterparts with similar titles, and this wage gap is increasingly worse year over year.

Following context and exploratory data analysis, the first of two models will consider the entire University of Toronto staff from 2012-2019. High-level results reveal that women are indeed paid less than men, and despite increasing female employment each year, the wage gap is increasing. The second model focuses on the four most common professor titles in the most recent year (2019). High-level results reveal that female professors are paid less than male professors, and most full professor roles are still held by men rather than women.

*Code and data are available at: github.com/mrpotatocode/UniversitySunshine

Data Exploration

Ontario makes available public sector salary disclosures from 1996-2019 (or most current year) available through the Open Data Ontario portal, or for each year as a .csv file from ontario.ca/page/public-sector-salary-disclosure. Every file is limited to publicly held positions earning greater than $100,000 per annum.

Eight columns are present throughout: *Sector* and *Employer*, the *Last Name* and *First Name* of every employee, their corresponding *Salary Paid* and *Taxable Benefits* amounts, and their *Job Title*. *Calendar Year* is added as reference to differentiate years from one another.

Dataset

This analysis is limited from 2012-2019 calendar years to allow for local processing. The analysis should be reproducible for all years (1996-Present), though some additional flexibility may be required during file loading to handle column differences (however, several of these are already resolved).

Table 1 exemplifies typical formatting, in this case filtered to relevant University of Toronto staff (names have been generated for this purpose to preserve privacy using the `babynames` package (Hadley Wickham 2019), however job titles and salaries were randomly selected from all years). Salary Paid columns varied in formatting across years.

Table 1: Sample Dataset Rows

Last Name	First Name	Salary Paid	Job Title	Calendar Year
Smith	Evelyn	$ 117,710.04	Professor, Medicine	2018
Johnson	Doris	$ 106,736.83	Intermediate JAVA Developer	2018
Williams	George	131485.5	Director, Business Information Centre	2012
Brown	Madison	$ 106,921.02	Assistant Professor, Dalla Lana School of Public Health	2018
Jones	Judy	$144,758.04	Professor, Medicine	2017
Miller	Judith	$195,376.50	Professor of Cell and Systems Biology and Director of the Centre for Analysis of Genome Evolution and Function	2017

Table 1

It is worth noting that Ontario's public sector salary disclosure does not separate job titles into positions and corresponding departments/faculties. Future analysis should consider matching job titles to a supplementary dataset, rather than relying on text parsing. As such, this work limits job title to the broadest categories: properly parsed, Assistant Professor, Associate Professor, Professor, and Professor and Chair are the most frequently occurring job titles for each year. Inclusion of "lecturer" titles affects this frequency, where its prevalence is highly noted in earlier years (for example, it is more frequent than Assistant Professor in 2012-2014). Variance across years tends to emerge in less frequent titles, and small inconsistencies in Job Titles affect the overall precision of these groupings. **Table 2** represents the top three Job Titles after parsing for each year.

Table 2: Three Most Frequent Job Titles by Year

CalendarYear	JobTitle	count
2012	Professor	1608
2012	Associate Professor	130
2012	Assistant Professor	75
2013	Professor	1566
2013	Associate Professor	157
2013	Assistant Professor	98
2014	Professor	1562
2014	Associate Professor	172
2014	Assistant Professor	99
2015	Professor	1529
2015	Associate Professor	286
2015	Assistant Professor	131
2016	Professor	1578
2016	Associate Professor	477
2016	Assistant Professor	203
2017	Professor	1589
2017	Associate Professor	456
2017	Assistant Professor	247
2018	Professor	1630
2018	Associate Professor	451
2018	Assistant Professor	306
2019	Professor	1690
2019	Associate Professor	474
2019	Assistant Professor	337

Table 2

The variable 'years' was added alongside Job Titles to further separate employees with significant differences in salary but no other observable differences. Years represents an apparent level of experience by measuring the number of years a professor has been employed at the University of Toronto earning at least $100,000. The metric is limited to the total number of years run during data analysis: in this case, eight years. Including additional years to the dataset will further differentiate employees from one another. **Table 3**, limited to full professors, notes that while minimum values are generally low regardless of the number of years, median salaries increase as years increase, ranging from $100,899 to $556,898.

Table 3: Professor Salaries by Year, 2019

title	years	min	Q1	median	Q3	max
Professor	1	101296.0	105632.6	114178.8	139112.9	221683.5
Professor	2	103200.0	112238.5	121670.0	163855.5	350359.6
Professor	3	106342.0	118049.0	125206.5	166006.0	279921.5
Professor	4	104262.0	122577.2	129548.8	146503.3	335710.0
Professor	5	100899.0	133837.0	146798.3	191694.4	324202.6
Professor	6	113319.1	137398.5	161751.0	210611.2	286556.5
Professor	7	115447.0	142181.4	156236.5	192008.0	400431.0
Professor	8	101897.0	176188.4	196171.5	226845.2	556898.8

Table 3

Gender Encoding Process

Ontario's public sector salary disclosure does not specify "gender". As such, gender columns are calculated using the `gender` package (Mullen 2020) and its underlying dataset built from US Census and Social Security data. The package assigns a male/female label based on the frequency of male to female name occurrence (whichever is more frequent) within a specified time period (in this case, 1932-2012, the most recent period, as it can be safely assumed that nearly all working professionals will be born within this range). In cases where a name is not present, no gender is assigned.

There are 4215 distinct first names for University of Toronto staff between 2012 and 2019. At first pass, the package successfully assigned 2652 first names (63%). Among the unmatched, a highly frequent cause of non-matches was persons with two first names listed (e.g. Charles James). These were split, and 837 (53% of unmatched, 20% of total) were rematched successfully (bringing matched names to 83%). Priority was given to the first of these two names (i.e. Charles), but some were matched on the second of these names (i.e. James). The latter was especially useful for names which had been abbreviated (e.g. C. James). Similarly, some unmatched names were two hyphenated first names. An additional 90 were matched in the same manner. Of remaining unmatched names, a small number (15) were matched on alternative names listed in parentheses. **Table 4** shows each iteration's remaining unmatched assignment. In total, 3604 names were matched (86%). The remaining 14% are labeled as "unknown" throughout this analysis.

Table 4: Gender Encoding Iterations

iteration	unknown_names
Unique Names	4215
First Pass	1563
Two First Names	726
Names in Parentheses	701
Hyphenated First Names	611

Table 4

This process leaves much to be desired. See §Ethical Considerations for further discussion and the approach's ramifications.

Ethical Considerations

References to "gender" within this paper should be viewed with skepticism. These references are binary, presumptive, declarative without recourse, and are much closer in definition to "sex assigned at birth" than gender identity or expression. Current gender theory treats gender as a spectrum with nuance far beyond the capabilities of models presented here. Analytical and model-based research that uses gender as a primary motivator to answer research questions must acknowledge that conclusions drawn from binary categorization are prone to overgeneralization and reinforcement of stereotypes. This does not wholly invalidate results, but rather asks for them to grow with nuance and recognize limitations. The following concerns are thus expressed within this work.

The `gender` package (Mullen 2020) explicitly references several crucial ethical concerns with its use. Firstly, the use of this package should be used in aggregate. Secondly, the package's underlying dataset treats gender as a binary. Thirdly, the package is likely to misgender individuals, even those who conform to traditional gender binaries. Fourthly, the relationship between gender and names has not been and will not be static, creating ambiguity that is not resolvable without data outside of the package. Finally, the package should be implemented only when no other option is realizable. Each of these considerations is addressed below.

The University of Toronto ranges from 2854 (2012) to 4342 (2019) employees, which should sufficiently qualify as "in aggregate." *Table 5* shows employees by year with mean salaries as reference. No individuals are specifically examined within this dataset. Departments have been removed from job titles in an attempt to further obfuscate individuals and instead focus on larger populations and their trends.

Table 5: Employees by Year, with Mean Salaries

Calendar Year	Employees	mean_sal
2012	2854	152437.2
2013	3032	153316.0
2014	3195	153753.9
2015	3288	155419.3
2016	3551	160999.2
2017	3738	159903.0
2018	4037	160098.6
2019	4342	162007.1

Table 5

Models within this dataset leave Unknown gender as a possible outcome, rather than excluding these individuals entirely from analysis. With more robust data where gender may be knowable without an encoding process, models would remain reproducible while including an array of gender expressions (though the privacy of individuals should be considered if such an analysis would be done, especially as to whether or not collecting gender and making it available in openly accessible datasets is appropriate). Even without a more robust dataset, datasets that move beyond gender binaries are being incorporated into the `gender` package (Mullen 2020) to represent a wider spectrum of potential gender identities. Models would subsequently reflect those changes.

Reflecting on their own *gender encoding from first names* process three years prior, Mihaljević et al. detail the effects of misgendering in statistical studies (2019). Such reductive processes introduce both statistically significant and socially traditional biases, and as such "result[s] are seldom transparent, reproducible, or transferrable" (ibid). Gender-based outcome metrics should be viewed as unknowingly inaccurate unless gender has been volunteered by study subjects. Mihaljević et al. criticize the perpetuation of traditional binary approaches as likely to "objectify and justify already existing inequalities between groups" if "results [are not] within the right context" (ibid). Binary approaches also reject lived experiences of non-binary persons; Costanza-Chock's revealing depiction of #TravelingWhileTrans exemplifies the erasure of non-binary persons through statistical oversimplification (2020).

Furthermore, misgendering occurs even for persons who identify as either male or female. Blevins & Mullen (2015) exemplify this as the "Leslie Problem" (see **Figure 1**). Historically, Leslie was predominately a male name in the United States until reaching parity in 1950 and becoming nearly entirely female by the year 2000. The `gender` package (Mullen 2020) attempts to counteract this effect by including a date range; studying historical datasets from the 1800s will as such classify Leslie as male, rather than female. The Leslie Problem highlights the likelihood of classifying all instances of a name as the same gender based on perceived frequency. For names that are near parity, the `gender` package (ibid) will misgender people half of the time on average. Conclusions drawn from such inaccuracy are dangerous.

Within this dataset, an examination of a highly ambiguous name J**** demonstrates the issue; for example, three professors teaching in 2012-2019 are gendered as "female" but manual review of faculty profiles suggests two of these three are much more likely to be "male". Even if provided with birth years, this misgendering is unlikely to be resolved (the example name becomes equally male:female between 1975 and 1980, before becoming considerably more male by 2000). The rate at which this occurs across the entire dataset is unknown. The example name J**** varies greatly in gender frequency by cultural origin. In the Netherlands, Catalonia, and Norway the name has been one of the most popular (if not the most popular) "male" first names. The `gender` package (Mullen 2020) by contrast, is based solely on US data, where J**** popularity and gender frequency have varied. As such, the encoding process erases any cultural nuance, even when it might be otherwise interpretable by last names.

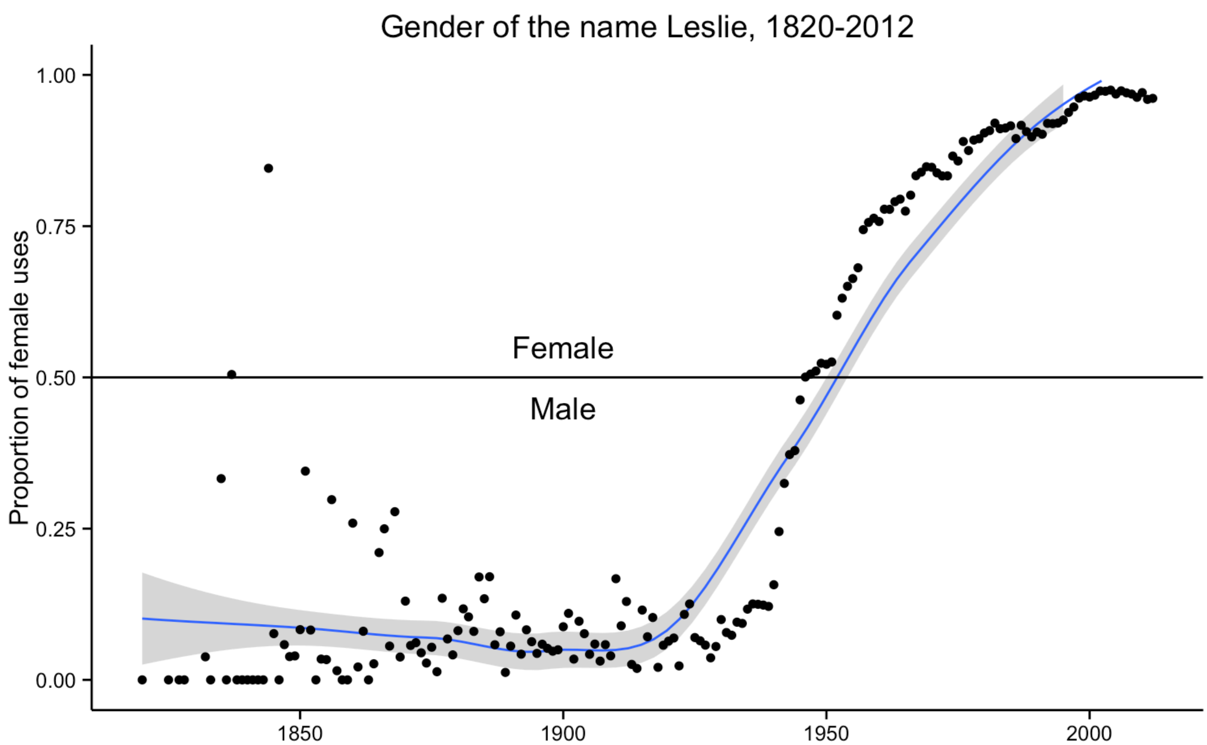


Figure 1: Leslie "Gender", Image from Blevins & Mullen (2015)

Logically, it should be realized that using a predominately US data source will outright exclude many common names found in other countries and languages, especially those of non-European origin. Any effort made by the university to hire from a diverse set of professors and applicants, especially within the context of the city of Toronto's highly diverse demographics, is immediately erased by statistical analyses here. This gender encoding process punishes diversity, pushing all unmatched names into an "unknown" categorization from which coefficients are drawn. The unknown category is assumed to be both male and female—as such, high-paying salaries for female staff who are unmatched by the gender encoding process are not adequately captured in exploratory data analysis or modelling. Efforts to become more inclusive in hiring are thus hampered by such crude gender proxies.

Furthermore, it is unknown how Ontario (or the University of Toronto) handles further nuance in names. Conforming to a "First Name Last Name" Western standard may already reduce the complexity in naming that is found throughout the world. The effect of this cultural bias on the data is noticeable for first names that have an added name in parentheses. Though these instances were not highly frequent, names within parentheses were nearly always Anglo-Saxon in origin. Whether these parentheticals were voluntarily provided to the public salary disclosure or not is unknown.

A logical question drawn from these ethical concerns is whether or not this analysis should be done at all. While the complexity of this problem is by no means fully captured, subset populations examined manually where gender was known (either through personal interaction with these professors or through their work, faculty pages, video introductions, and/or pronoun usage) showed similar male:female inequality in salaries at the University of Toronto. The university's status as a "leading institution" in Canada and its highly regarded reputation elsewhere in the world warrants a critical eye. With consideration of the Provost's announcement that female faculty would be equally compensated (Benjamin, et al. 2019), it is paramount to design a statistical study that can externally validate these results and be reproducible in order to encourage conversations as to whether or not the university is addressing these inequities in a fair and timely manner.

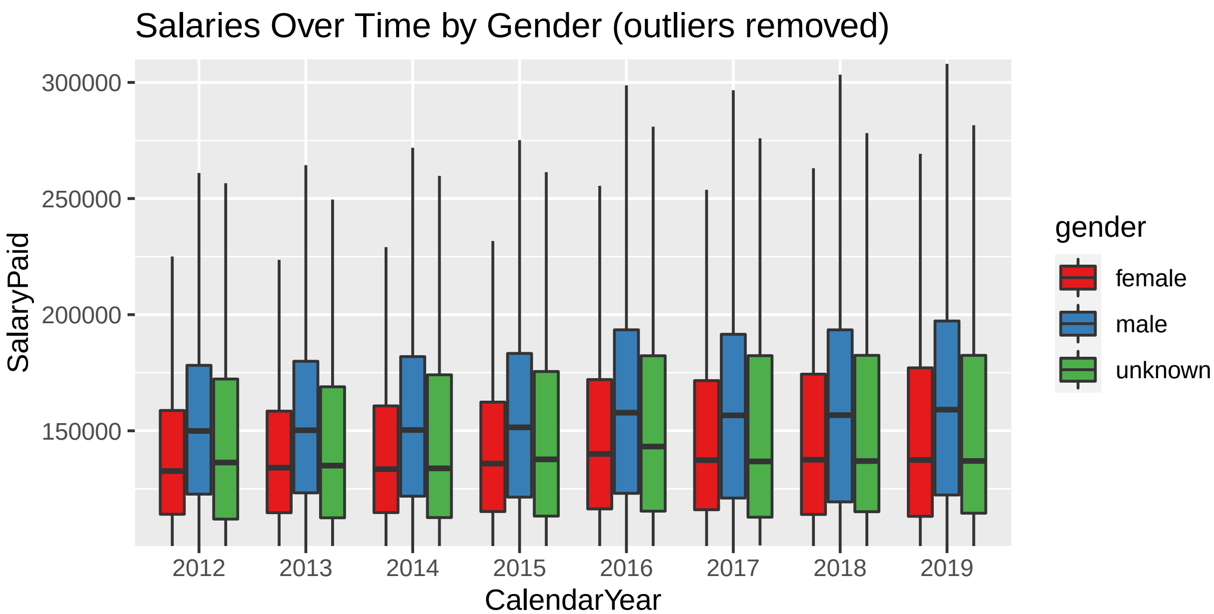
Exploratory Results

Following the gender encoding process, summarized counts and corresponding salary data is presented in **Table 6**. With significant outliers removed, **Plot 1** shows the general upward increase over time for male salaries but may also be misleading, as the number of female employees has been increasing at a faster rate, as shown in **Table 7**. Combined with lower mean salaries and a much lower upper quartile, increases in female salaries for existing versus new employees are harder to estimate.

Table 6: Salaries by Gender (all years, all positions)

gender	count	mean	max
female	11003	147492.2	499678.8
male	15156	165157.9	1473446.0
unknown	1878	157274.3	498730.0

Table 6



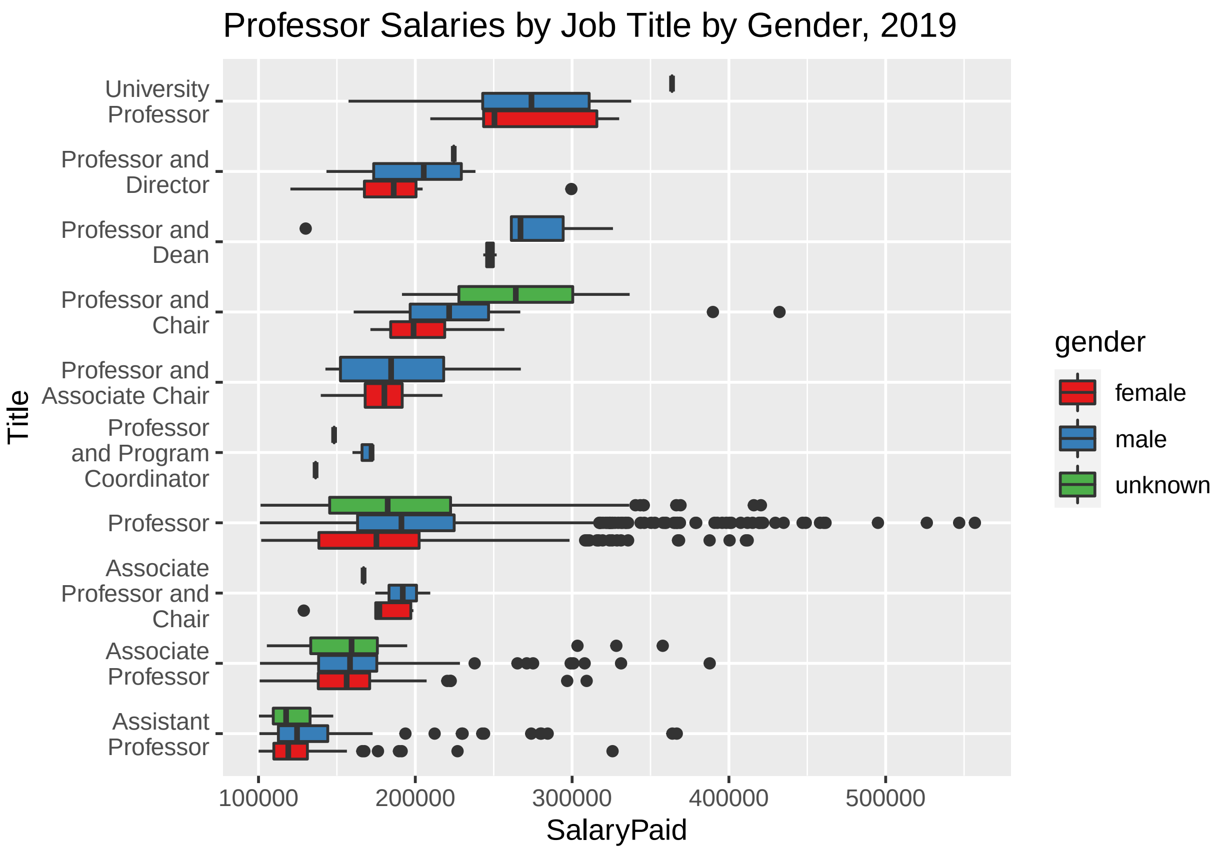
Plot 1

Table 7: YoY pct change by Gender 2012-2019

gender	CalendarYear	count	pct_change
female	2012	1048	NA
female	2013	1153	10.0190840
female	2014	1225	6.2445794
female	2015	1255	2.4489796
female	2016	1388	10.5976096
female	2017	1492	7.4927954
female	2018	1635	9.5844504
female	2019	1807	10.5198777
male	2012	1602	NA
male	2013	1698	5.9925094
male	2014	1773	4.4169611
male	2015	1835	3.4968979
male	2016	1933	5.3405995
male	2017	1996	3.2591826
male	2018	2113	5.8617234
male	2019	2206	4.4013251
unknown	2012	204	NA
unknown	2013	181	-11.2745098
unknown	2014	197	8.8397790
unknown	2015	198	0.5076142
unknown	2016	230	16.1616162
unknown	2017	250	8.6956522
unknown	2018	289	15.6000000
unknown	2019	329	13.8408304

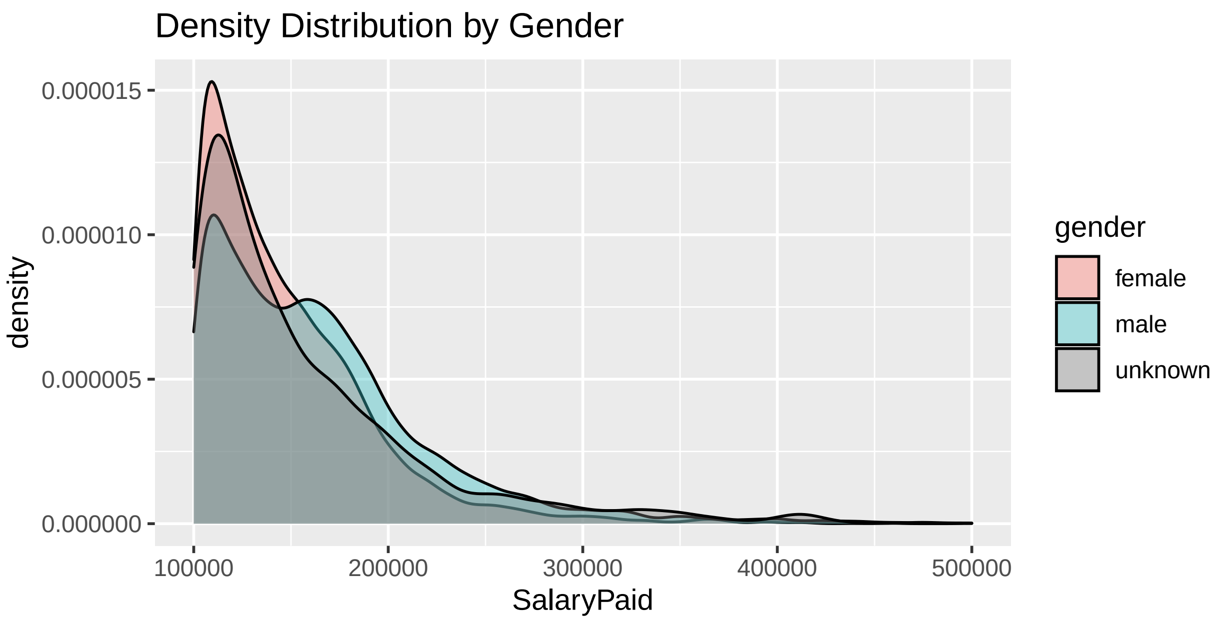
Table 7

When limited strictly to Job Titles matching “Professor”, male boxplots are nearly always higher (**Plot 2**). Of the three most common titles, (Assistant Professor, Associate Professor, and Professor) male professors earn more at median levels, more at lower quartile levels, and more at upper quartile levels. While the minimum for all titles within the dataset is $100,000, it is not known how many professors are under this threshold, or their gender breakdowns. Less frequent titles rarely result in higher salaries for females over their male counterparts, and the frequency of females in these roles is considerably less. Significant outliers are noticeable for male professors. Maximum salaries for males are significantly higher.



Plot 2

Within the context of this exploratory analysis, it is important to emphasize that the bulk of salaries for all genders occur between $100,000 and $200,000. **Plot 3** demonstrates the overlapping densities of all genders. Female employees make the minimum $100,00 more than any other gender and peak near $110,000 before sharply declining. Compared to male employees, female employees rarely make more than $200,000. Male employees also peak near $110,000 but also experience a secondary peak above $150,000. Additionally, very few females make $300,000 or above; male employees by contrast continue to see salaries up to $400,000 before becoming significant outliers. Absolute maximum salaries for employees as referenced in **Table 6** show that males continue to earn well beyond $500,000, even if extremely rarely. No female or unknown gender employee makes more than $500,000 for any year or any position in this dataset.



Plot 3

Models

A Bayesian approach allows us to make inferences about the values of our parameters (such as gender and salary values). Following Gabry & Goodrich's (2020) processes outlined for Bayesian analysis using the `rstanarm` package (Brilleman et al., n.d.), two Gaussian models were built to examine relationships between Salary Paid and explanatory variables including gender, calendar year, job title, and years of experience. The first model focuses on all University of Toronto employees, whereas the latter is limited to the four most common job titles containing "Professor" and is limited to 2019. Both models are compared across their iterations with leave-one-out (LOO) cross-validation. For both models, default priors were used. For both models, attempts to predict from the posterior distribution were unsuccessful. Lack of informative prior selection and predictions made are a significant limitation of this work, which is otherwise explanatory.

Model 1

Model 1 begins with salary paid (in 100s of dollars) as a function of gender:

$$y_i \sim N(\beta_0 + \beta_1 x_i, \sigma^2)$$

Model 1 is then updated to include calendar year:

$$y_i \sim N(\beta_0 + \beta_1 x_i, +\beta_2 z_i, \sigma^2)$$

Final updates to Model 1 add years of experience:

$$y_i \sim N(\beta_0 + \beta_1 x_i, +\beta_2 z_i + \beta_3 a_i, \sigma^2)$$

- y_i is salary paid (in 100s of dollars)
- x_i is gender (as female, male, unknown)
- z_i is calendar year (2012-2019)
- a_i is years of experience (1-8)

Model 2

Model 2 begins with salary paid (in 100s of dollars) as a function of gender:

$$y_i \sim N(\beta_0 + \beta_1 x_i, \sigma^2)$$

where $\mathcal{D}_{t=\tau} \subset \mathcal{D} = \{\mathbf{x}_{i,t} \mid t = \tau\}$ denotes the subset of all rows taken at time τ.

Model 2 is then updated to include job title:

$$y_i \sim N(\beta_0 + \beta_1 x_i, +\beta_2 z_i, \sigma^2)$$

Final updates to Model 2 add years of experience:

$$y_i \sim N(\beta_0 + \beta_1 x_i, +\beta_2 z_i + \beta_3 a_i, \sigma^2)$$

- y_i is salary paid (in 100s of dollars)
- x_i is gender (as female, male, unknown)
- z_i is job title (as Assistant Professor, Associate Professor, Professor, Professor and Chair)
- a_i is years of experience (1-8)
- $\tau = 2019$

Results

Model 1

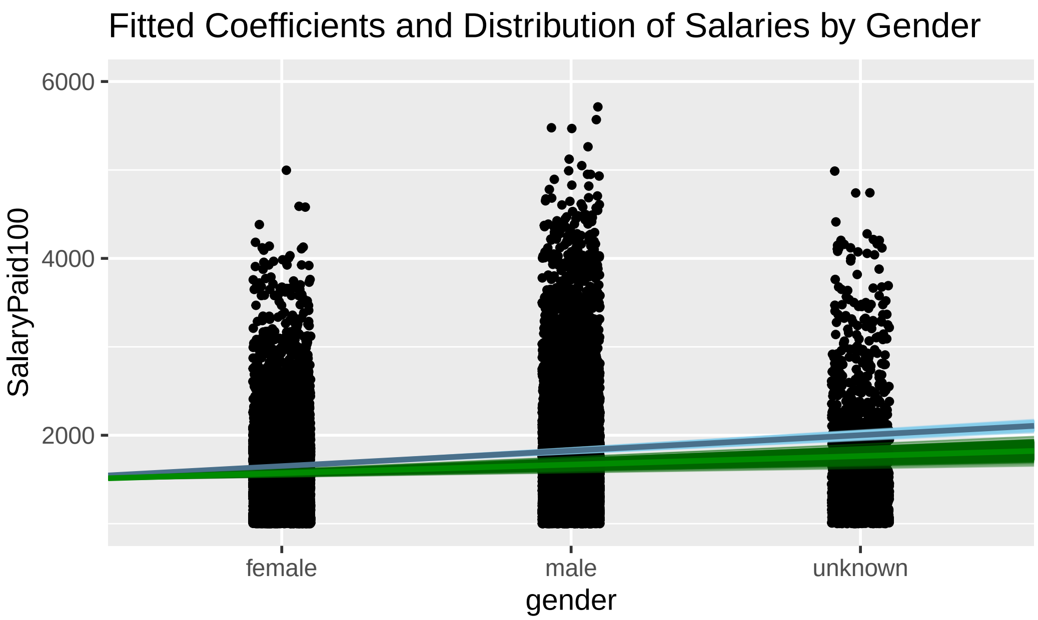
At its simplest, Model 1 considers gender's effect on salary paid (in 100s of dollars) for the entire University of Toronto dataset. Exploratory data analysis (**Table 6**) shows that average salaries are higher for males than females at the same rate as the model (**Table 8**). Mean Post Posterior Distribution is within 100 of the intercept mean. Rhat scores of 1.0 indicate that convergence from chains was successful. This is a stable first model to iterate on.

Table 8: Model 1, Iteration 1

	mean	mcse	sd	10%	50%	90%	n_eff	Rhat
(Intercept)	1475.28514	0.0856294	5.255904	1468.66330	1475.24093	1481.9380	3767	1.0000872
gendermale	175.23454	0.1035258	6.970298	166.30404	175.27301	184.2323	4533	0.9995185
genderunknown	96.54992	0.2108575	13.579665	79.08309	96.45908	114.0169	4148	1.0000211
sigma	549.17926	0.0331052	2.374545	546.11694	549.20357	552.2032	5145	0.9995601
mean_PPD	1576.18917	0.0752473	4.602901	1570.28463	1576.15354	1582.1269	3742	0.9996821
log-posterior	-212488.96493	0.0338005	1.417476	-212490.86645	-212488.64969	-212487.4985	1759	1.0012838

Table 8

As such, relative to female salaries, **Plot 4** AB lines show coefficients with greater intercepts for male and unknown gender employees. Standard deviation is higher for unknown than male genders.



Plot 4

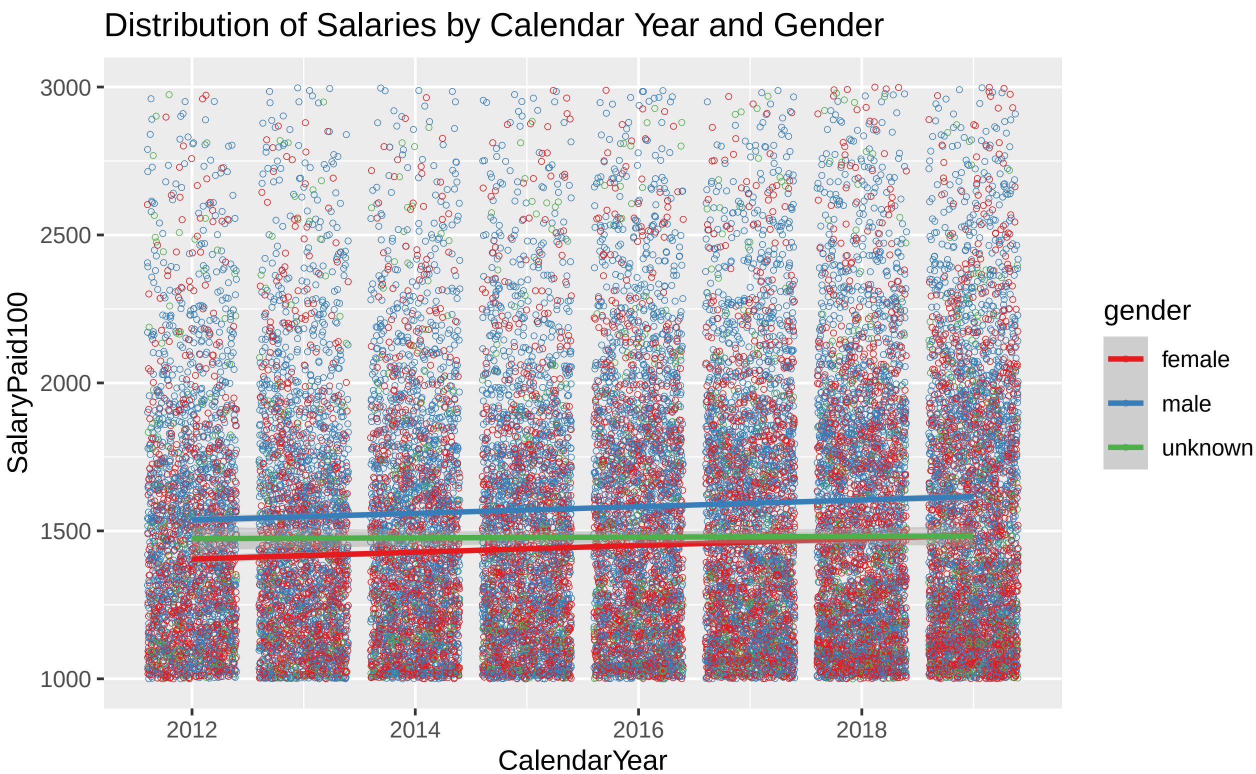
At second iteration, the addition of calendar year is more revealing (**Table 9**). While male and unknown salaries are higher to nearly the same degree as the previous model, salaries as a whole have increased substantially in recent years. Estimates for earlier years show that salaries were increasing at much slower rates. Mean Post Posterior Distribution is again near to the intercept mean, and Rhat scores of 1.0 indicate that convergence from chains was successful. Monte Carlo standard errors are higher than the previous iteration.

Table 9: Model 1, Iteration 2

	mean	mcse	sd	10%	50%	90%	n_eff	Rhat
(Intercept)	1416.503669	0.3122675	10.705459	1402.581989	1416.666888	1430.13995	1175	1.0005621
gendermale	177.765268	0.1122323	6.904364	168.974665	177.753249	186.70093	3785	0.9996791
genderunknown	95.480924	0.2450486	13.574825	78.281753	95.613012	112.66700	3069	0.9999721
CalendarYear2013	9.963412	0.3570598	13.933475	-7.968252	9.886253	28.10716	1523	0.9997908
CalendarYear2014	14.894387	0.3559565	13.802155	-2.881960	14.982724	32.76914	1503	1.0003544
CalendarYear2015	31.304623	0.3385334	13.612404	14.050544	31.178339	48.69293	1617	1.0003173
CalendarYear2016	89.503235	0.3593502	13.289309	72.813192	89.505294	106.73753	1368	1.0003853
CalendarYear2017	82.364485	0.3453372	13.291794	65.391981	82.335728	99.40592	1481	1.0004040
CalendarYear2018	83.935744	0.3408902	12.948969	67.444044	83.857761	100.46264	1443	1.0004421
CalendarYear2019	105.589367	0.3238448	12.904214	89.257047	105.331844	122.15940	1588	1.0004603
sigma	547.767424	0.0355160	2.339049	544.788398	547.747286	550.80975	4337	0.9995529
mean_PPD	1576.145750	0.0792738	4.679392	1570.161485	1576.229695	1582.13064	3484	0.9995196
log-posterior	-212428.267408	0.0529393	2.249289	-212431.150226	-212427.947795	-212425.68249	1805	1.0021615

Table 9

Plot 5 shows far fewer female employees making more than $200,000 in a year. Additionally, the number of female employees hired in recent years has increased, but they appear to be clustered towards the minimum $100,000 threshold (the degree at which this is occurring is presented in **Table 7**). The concentration of higher-paid males is obvious for all years; significantly more males make more than AB line coefficients than females. Male salaries have accelerated slightly faster from 2012-2019 than female and unknown gender salaries. Note the reduced y-axis to better show AB lines, which are otherwise highly overlapped and difficult to differentiate.



Plot 5

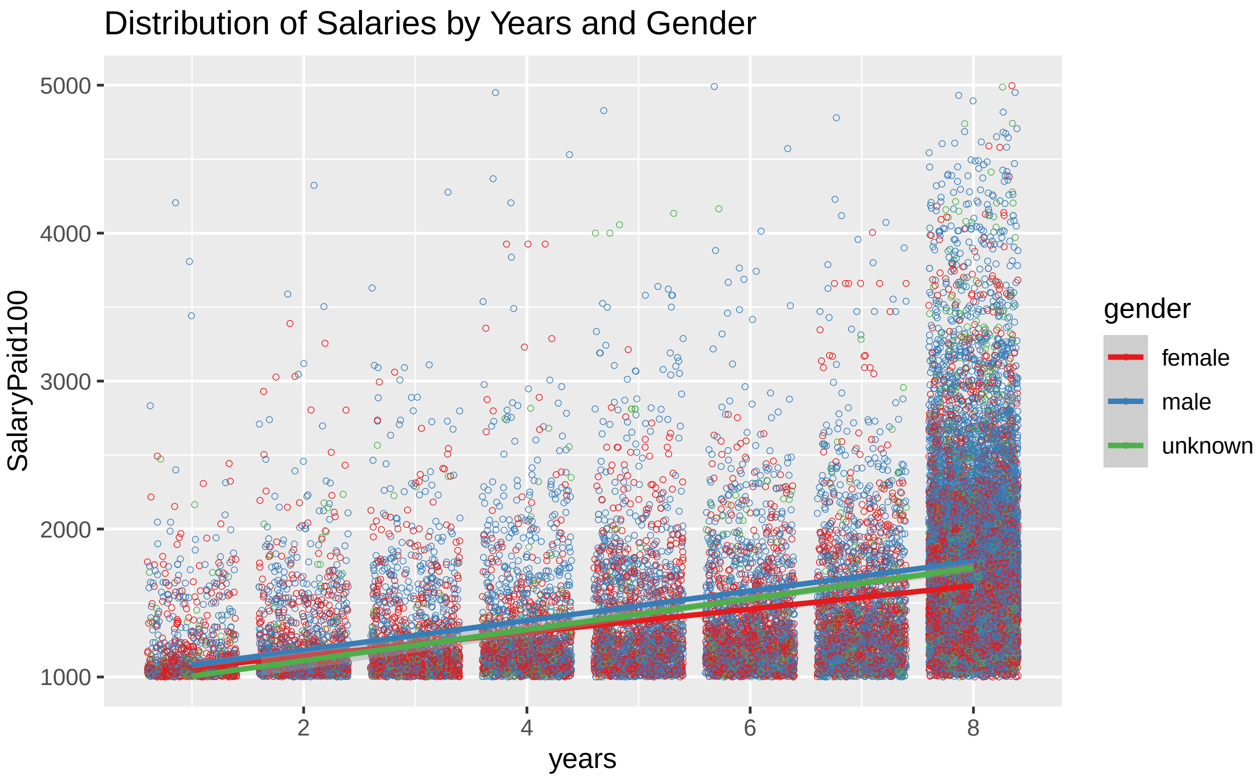
In its final iteration, the addition of years of experience is both useful and slightly confounding. A clear connection to salary and years exists, but calendar year coefficients are drastically changed from the previous model (**Table 10**). This is certainly due to the lack of variety in year values in earlier calendar years (in 2012, the maximum year value would be one, because no other data to measure from was present in the analysis). As the relationship between years and salary is evident, it is apparent that the inclusion of further years would prove useful. Mean Post Posterior Distribution is much further from the intercept mean (nearly double), as the intercept mean has decreased significantly (and is now below the $100,000 threshold). Rhat scores of 1.0 indicate that convergence from chains was successful. Monte Carlo standard errors are lower than the previous iteration, but still high for calendar year variables.

Table 10: Model 1, Iteration 3

	mean	mcse	sd	10%	50%	90%	n_eff	Rhat
(Intercept)	766.539109	0.3410937	13.725332	749.04916	766.533780	784.311633	1619	1.0032201
gendermale	139.655327	0.1037140	6.373447	131.40976	139.753164	147.858419	3776	0.9994107
genderunknown	73.674828	0.2340936	12.885118	57.10076	73.433869	90.350705	3030	1.0000252
CalendarYear2013	-6.593044	0.3441610	13.229322	-23.27363	-6.667608	10.742451	1478	1.0044959
CalendarYear2014	-10.019600	0.3483016	12.725414	-26.86191	-9.632510	5.934064	1335	1.0035427
CalendarYear2015	4.303011	0.3652166	12.962085	-12.01563	4.146288	20.880721	1260	1.0061485
CalendarYear2016	85.423800	0.3411489	12.604776	69.09214	85.344806	101.880741	1365	1.0049854
CalendarYear2017	103.807019	0.3418299	12.524109	88.27369	103.985504	119.530880	1342	1.0056861
CalendarYear2018	153.238373	0.3430763	12.455855	137.15100	153.453777	168.798698	1318	1.0043880
CalendarYear2019	229.734083	0.3421855	12.281805	214.06397	230.002244	245.503511	1288	1.0049228
years	100.549452	0.0172517	1.455156	98.69641	100.542792	102.399461	7115	0.9994719
sigma	506.647209	0.0334121	2.132375	503.90264	506.621524	509.385705	4073	0.9997613
mean_PPD	1576.154758	0.0743786	4.330971	1570.59813	1576.184663	1581.798857	3391	1.0009972
log-posterior	-210282.751328	0.0613233	2.529883	-210286.01539	-210282.362793	-210279.891426	1702	1.0001921

Table 10

Reducing the artificially overweight "eighth" year will likely affect coefficients and AB lines (**Plot 6**). As such, while increases in male salaries appear to be accelerating at a rate faster than female and unknown gender salaries, it's visibly noticeable that considerably more males at "eight" years are paid above $200,000 than females. Whether the bulk of males have simply been in positions for longer (far beyond eight years presented), or benefitted significantly from faster pay increases (a compounding effect), is unclear. Female AB lines are both lower and growing at a slower rate than male AB lines as years increase.



Plot 6

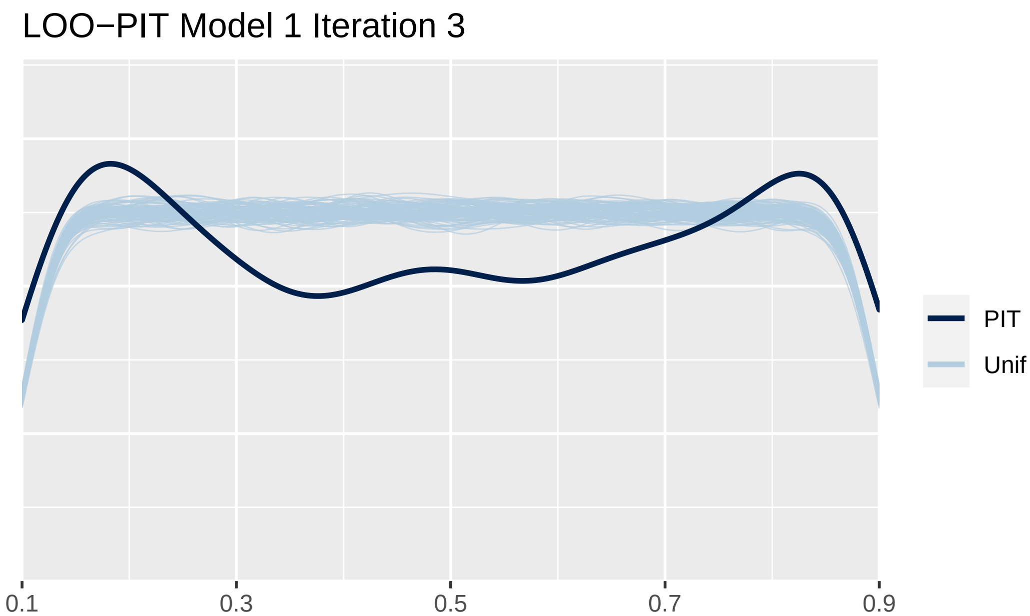
Following modelling, LOO analysis (**Table 11**) allows a comparison of model iterations. Differences in the expected log predictive densities (elpd_diff) show that the third iteration (fit3) is preferred over previous iterations. Standard error for this fit is considerably less than expected log predictive densities of other models. As such, this iteration is the most representative of the three.

Table 11: Model 1, LOO analysis of all three iterations

	elpd_diff	se_diff	elpd_loo	se_elpd_loo	p_loo	se_p_loo	looic	se_looic
fit3	0.000	0.00000	-210278.0	514.7903	29.42693	9.086150	420555.9	1029.5805
fit2	-2143.213	95.63991	-212421.2	438.4778	23.49342	6.231303	424842.4	876.9556
fit1	-2207.182	99.02312	-212485.1	436.5559	16.89826	6.193654	424970.3	873.1117

Table 11

The LOO probability integral transform (PIT) shows a comparison for each point as it falls in its predictive distribution (**Plot 7**). The model is underperforming; this diagnostic metric shows that the PIT line, when compared to 4000 simulated uniform distribution (Unif) lines, is fairly far off in shape. Further model diagnostic tests are performed within the Appendix.



Plot 7

Model 2

Like Model 1, Model 2 in its simplest form examines gender's effect on salary paid (in 100s of dollars), but is limited to 2019 (the most recent year) and the four most common job titles containing "professor". As a point of clarity, throughout this analysis, the "Professor" job title (in title case) refers to what is commonly called "Full Professor". By contrast, "professor" (in lower case) refers to the collection of all professor job titles.

As *Table 2* and its discussion indicated during exploratory data analysis, these job titles are relatively stable in frequency. "University Professor" and "Professor" were merged into a single title throughout this model. Like Model 1, average salaries for males are higher than females, but in Model 2, mean values are larger for all genders, as are the differences between them (**Table 12**). Mean Post Posterior Distribution is slightly higher than the previous but is relatively the same degree larger (about 8%). Rhat scores of 1.0 indicate that convergence from chains was successful. Monte Carlo standard errors are particularly high for unknown gender professors as there are far fewer of them. This is a stable second model to iterate on.

Table 12: Model 2, Iteration 1

	mean	mcse	sd	10%	50%	90%	n_eff	Rhat
(Intercept)	1662.1365	0.2970145	19.278706	1637.1794	1662.2593	1686.3371	4213	0.9999693
gendermale	221.0712	0.3797577	24.905278	189.3050	221.4215	253.0332	4301	0.9997095
genderunknown	148.9464	0.7017531	46.980354	89.2368	149.4444	209.9223	4482	1.0001451
sigma	589.2079	0.1155348	8.011870	579.1430	589.1435	599.3674	4809	0.9999944
mean_PPD	1795.4510	0.2498820	16.293597	1774.5283	1795.2061	1815.9605	4252	0.9997382
log-posterior	-20013.3025	0.0316670	1.414619	-20015.1331	-20012.9877	-20011.8574	1996	1.0021312

Table 12

Relative to female salaries, male and unknown gender professors earn more (**Plot 9**). It is clear there are far more male professors earning $200,000 than female or unknown gender professors. Standard deviations are larger for both male and unknown gender AB lines.

Plot 9

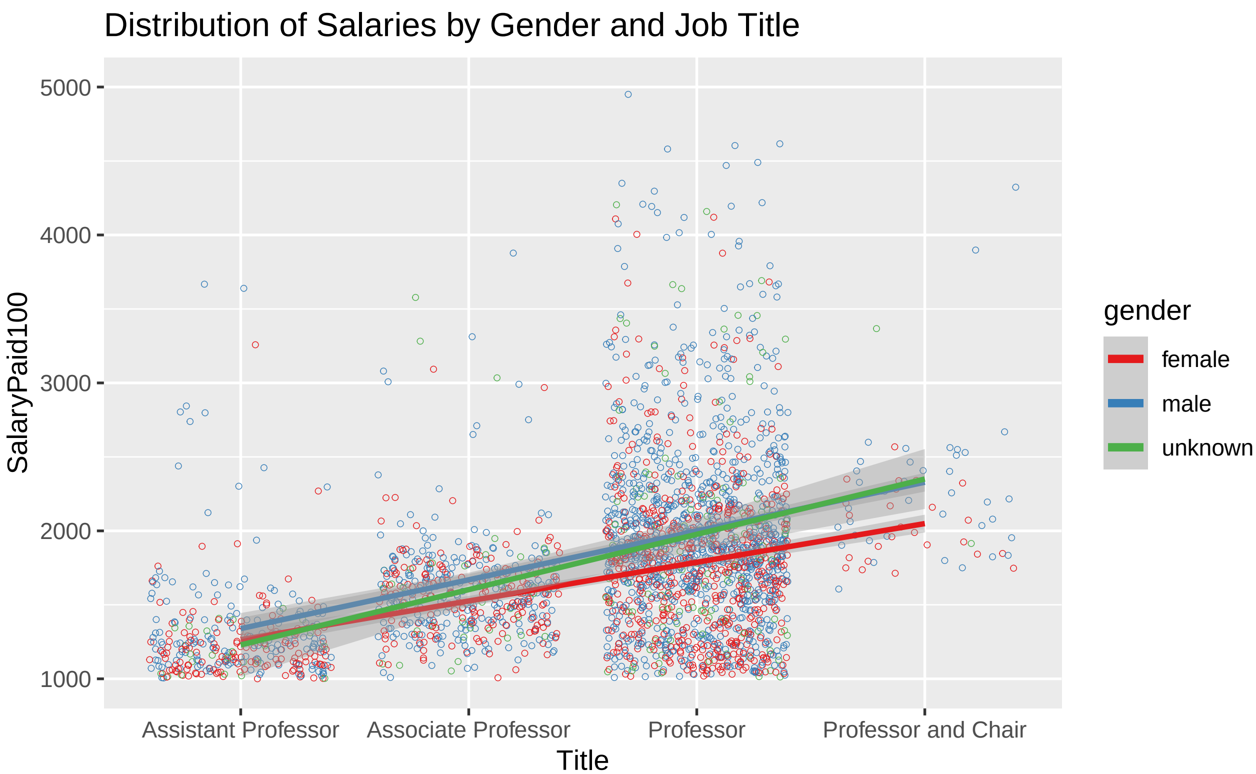
At second iteration (**Table 13**), the addition of Job Title (Assistant Professor, Associate Professor, Professor, or Professor and Chair) further separates the professors into smaller segments earning significantly different salaries from one another. Intercept means (female Assistant Professors) are much lower than the previous iteration. Becoming Professor or Professor and Chair has a large effect on salary: on average increasing by $61,000 and $88,200 per year respectively for each position. Mean Post Posterior Distribution is again further from the intercept mean as there are a larger number of Professors than any other title. Rhat scores of 1.0 indicate that convergence from chains was successful. Monte Carlo standard errors are higher than the previous model and previous iterations. High MCSEs are likely due to the relative infrequency of the job titles.

Table 13: Model 2, Iteration 2

	mean	mcse	sd	10%	50%	90%	n_eff	Rhat
(Intercept)	1203.1320	0.6158485	32.361252	1160.5974	1203.8046	1244.9585	2761	0.9995587
gendermale	187.5336	0.3627648	22.363968	158.6576	187.2379	216.5266	3801	1.0011465
genderunknown	136.7547	0.6774024	42.377405	83.2324	136.8076	190.3354	3914	0.9991726
JobTitleSimpleAssociate Professor	285.9145	0.7507813	38.108724	235.3967	285.8673	335.0629	2576	1.0001123
JobTitleSimpleProfessor	610.7264	0.6217590	32.509026	568.5329	611.3171	651.1954	2734	0.9998759
JobTitleSimpleProfessor and Chair	882.4052	1.3217740	74.406390	788.1662	881.6869	978.3781	3169	0.9996275
sigma	543.0634	0.1237308	7.652206	533.3143	543.0597	552.9429	3825	0.9995993
mean_PPD	1795.3452	0.2364079	15.060967	1775.8965	1795.2819	1815.1689	4059	0.9999792
log-posterior	-19807.4042	0.0408905	1.823696	-19809.8853	-19807.0893	-19805.3594	1989	1.0023131

Table 13

While gender does not appear within the model to be as influential as job title, both the number of male Professors and their salaries are higher than female counterparts (**Plot 10**). There are significantly more male Professors who make more than $250,000 than female Professors. Male Assistant Professors also appear to make more, despite there being fewer of them. Both Associate Professor and Professor and Chair titles on the whole have higher minimum salaries (greater than $100,000), not wholly unsurprising, but this trend is not kept for Professors. This may be indicative that Professor is a more flexible title across different disciplines or that ranks are less formal. Considering that this is 2019 data, where female professors are more frequent than other years, this inequality is likely to be far worse in previous years.



Plot 10

In its final iteration, the addition of years of experience is highly valuable in differentiating the professor dataset further. Like the previous model, the eighth year is overweighted, with more professors being at (and presumably above) eight years of experience than the other years combined (1489 vs 1076). **Table 14** shows intercept means (female Assistant Professors) are again much lower than the previous iteration. Male coefficients are for the first time slightly lower than unknown gender coefficients. Becoming Professor or (less frequently) Professor and Chair has a large effect on salary again, but year coefficents result in considerably higher salaries: an increase of $10,000 per year of experience. Combined with the relative frequency of professors with at least eight years of experience, salaries will be closer to $180,000 than $100,000, and then even higher for a Professor or Professor and Chair. Mean Post Posterior Distribution is half of the intercept mean as most Assistant Professors have the least experience (shown in **Plot 12**). Rhat scores of 1.0 indicate that convergence from chains was successful. Monte Carlo standard errors are at their absolute highest.

Table 14: Model 2, Iteration 3

	mean	mcse	sd	10%	50%	90%	n_eff	Rhat
(Intercept)	899.82274	0.4637595	31.386368	858.90383	900.11413	939.40259	4580	0.9991163
gendermale	134.83044	0.3613661	21.391574	107.80328	134.58173	162.34018	3504	1.0009762
genderunknown	142.18715	0.6402987	39.598108	91.72452	142.29089	192.75877	3825	1.0004831
JobTitleSimpleAssociate Professor	-93.96933	0.8032322	38.893924	-143.34427	-93.35127	-43.10477	2345	1.0005233
JobTitleSimpleProfessor	232.67422	0.7218843	33.921170	189.31773	232.41540	275.71698	2208	1.0000862
JobTitleSimpleProfessor and Chair	408.88124	1.1991779	67.628235	323.51002	407.66021	496.84548	3180	1.0002854
years	106.72814	0.0859591	4.543945	100.92822	106.74600	112.58961	2794	1.0004425
sigma	493.15414	0.1055792	6.749534	484.48152	493.08757	501.85009	4087	1.0000214
mean_PPD	1795.33632	0.2151867	13.881867	1777.87455	1795.53926	1812.97739	4162	0.9993625
log-posterior	-19560.51393	0.0456990	2.000246	-19563.21421	-19560.15568	-19558.27269	1916	1.0016053

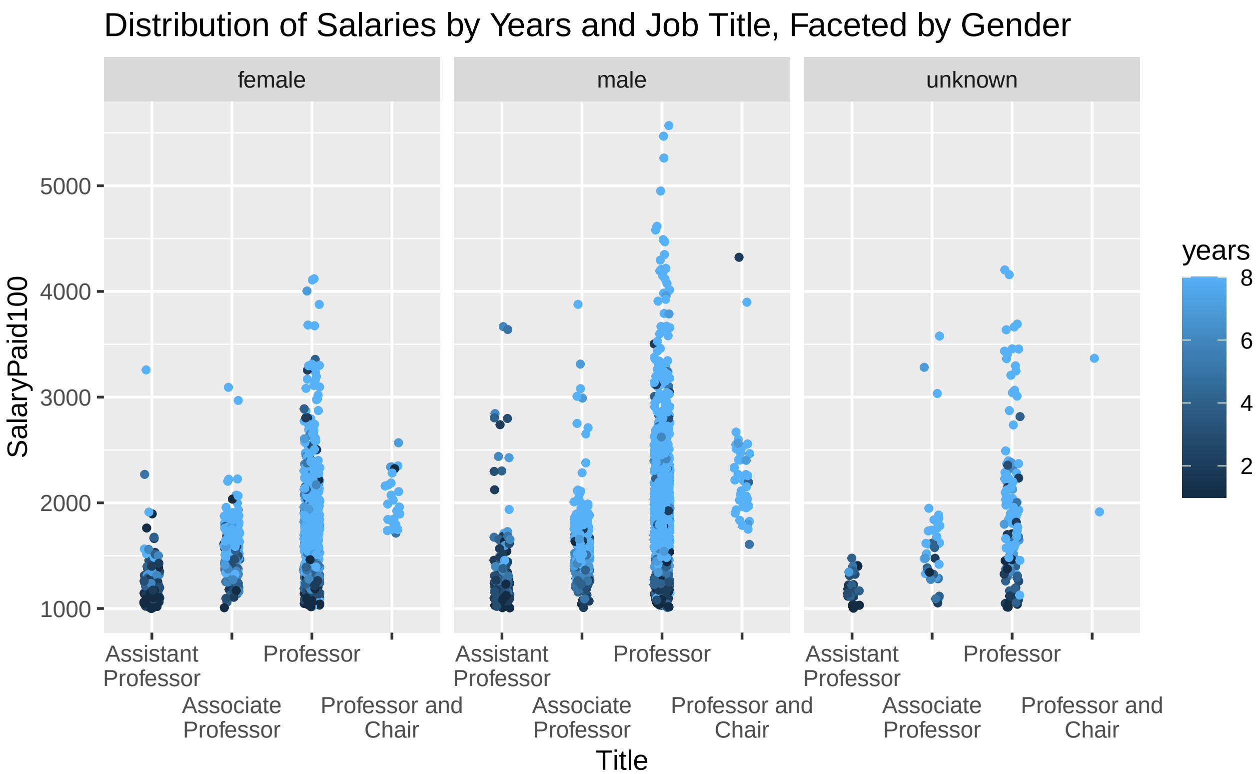
Table 14

The complexity of visualizing three separate explanatory variables requires a myriad of different views into the resulting data. **Plot 11** combines AB lines for all genders with years of experience. **Plot 12** clusters years of experience and job titles within a facet for each gender. **Plot 13** clusters job titles for each gender within a facet for each year of experience.

As mentioned previously, more than half of staff with professor titles are captured within the artificially overweight "eighth" year (**Plot 11**). AB lines for each gender show that years of experience result in significantly larger salaries. Male salaries again increase more than female salaries, even when AB lines are very close together at `years=1`. Salaries are lifted off the $100,000 x-axis minimum for each year quite significantly (though the eighth is an odd exception to this trend). Male professors dominate the eighth year at a frequency of 896:492 compared to female professors. By contrast, the remaining year categories are relatively equal for both male and female professors.

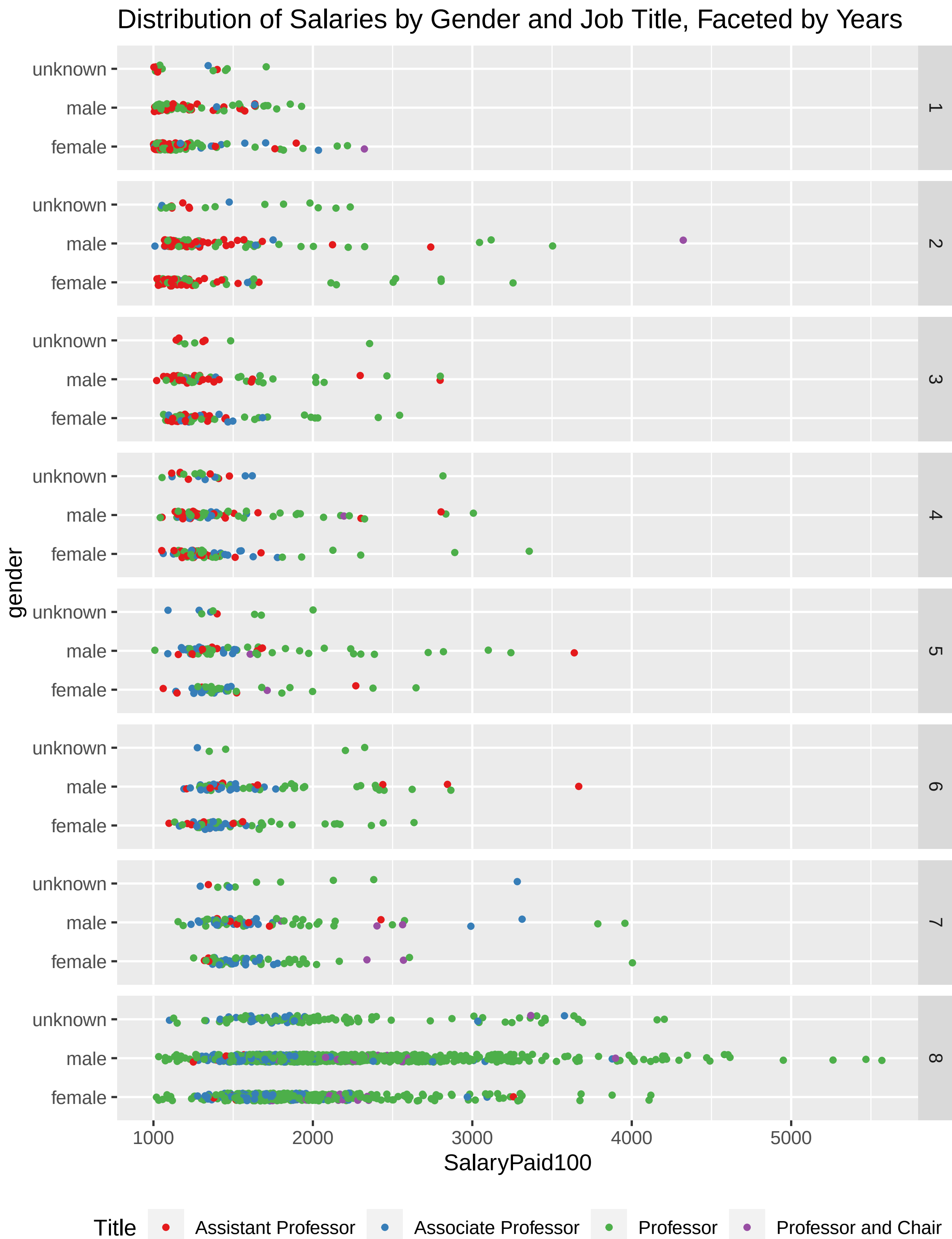
Plot 11

Plot 12 shows that the relative composition of years of experience and job titles is fairly conserved between male and female professor titles. Both female and male Assistant Professors have fewer years of experience. However, several male Assistant Professors make more than $200,000—more than nearly all female *Associate* Professors. Similarly, many male Associate Professors make more than $200,000, a salary more consistent with Professor and Professor and Chair job titles. Professor salaries near $100,000 appear to be associated with lower years of experience. This might mean that these Professors are new to the University of Toronto, but not new to academia, and thus can join faculties as Full Professors. This highlights another limitation to the "years of experience" metric. Male Professors, as noted elsewhere, are far more likely to make more than $300,000 compared to female Professors. Without further differentiation, it is difficult to identify a discernable reason for this trend.



Plot 12

Lastly, **Plot 13** further helps to emphasize the relationship between years of experience and job title. While gender is somewhat lost in the scale of the visualization, it becomes clear that there are very few Assistant Professors (red) for either gender when `years>4`. Associate Professors (blue) are not easily distinguished from Professors (green) except by salary. There appear to be far more male Professors by the fifth year than females. It is unknown whether this is caused by changing universities, or if other social barriers limit female Associate Professors from becoming Full Professors.



Plot 13

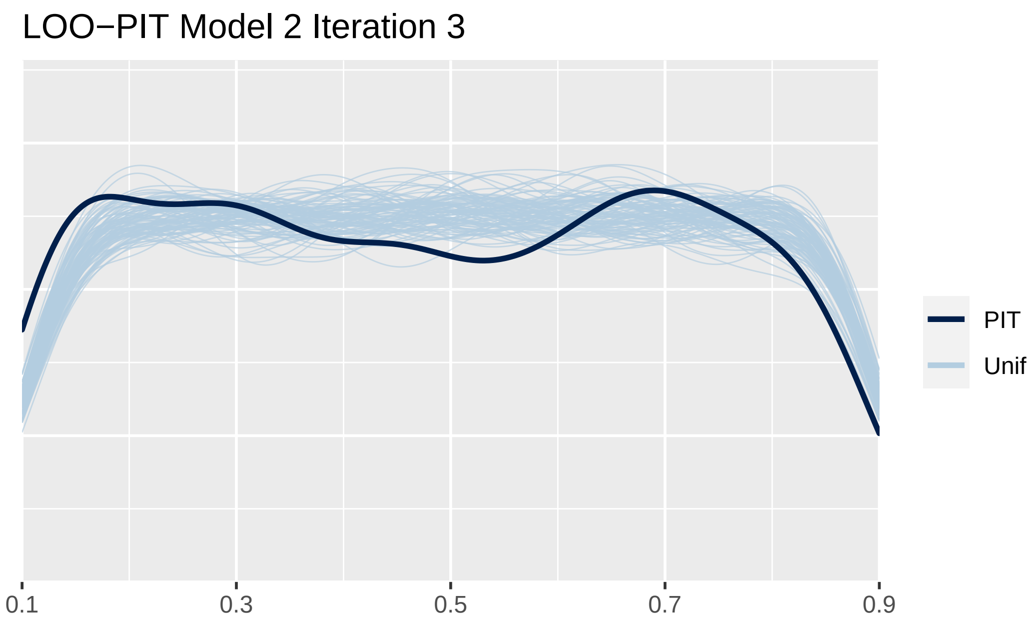
LOO analysis (**Table 15**) again shows preference to the third and final iteration (fit6). Differences in the expected log predictive densities (elpd_diff) are less drastic, showing that while the inclusion of additional explanatory variables makes for a better model, filtering the overall dataset to the four most common professor titles for the calendar year 2019 results in a better uniform distribution. Standard error for this fit is also less than the expected log predictive densities of other models.

Table 15: Model 2, LOO analysis of all three iterations

	elpd_diff	se_diff	elpd_loo	se_elpd_loo	p_loo	se_p_loo	looic	se_looic
fit6	0.0000	0.00000	-19549.59	76.04399	10.590831	1.1730731	39099.18	152.0880
fit5	-246.5938	21.80091	-19796.19	68.35855	8.596233	0.8733031	39592.37	136.7171
fit4	-454.2491	25.91388	-20003.84	62.55362	6.062164	0.6172564	40007.68	125.1072

Table 15

The LOO PIT (**Plot 14**) diagnostic metric is significantly better than the previous model. Nearly all points fall within its predictive distribution. The model performs better because there no pareto outliers of concern (which were present in Model 1, as discussed within the Appendix). The model is not bad, although limitations have been discussed throughout this section. Further model diagnostic tests are also performed within the Appendix.



Plot 14

Discussion

Model 1 evaluation generally shows a strong trend of males being paid more than females throughout the University of Toronto. As model complexity increases, explanatory variables show that despite claims of narrowing pay inequality made by the University Provost in 2019, the wage gap between female and male staff exists and is increasingly worse year over year. The model would perform better with additional years of data and should be run again with 2020 data to see if the mean differences between genders decrease. The university appears, on the whole, to be hiring more female staff, and perhaps a more diverse set of staff (as noted by the increasing frequency of encoding staff as unknown gender caused by names less likely to be referenced in the underlying datasets of the `gender` package (Mullen 2020)). It is unclear whether these newer hires are always brought into lower level positions; for example, we see an increase in Assistant Professors across years but the number of employees also increases every year. To see better equality in pay across gender, the university needs to also balance promotions equally across gender. Simply put, the vast majority of the highest paying jobs are held by males. Model 1 diagnostics (§Appendix 1) show sensitivity to some of these extreme outliers. A logical next step might be to simulate high salary female outliers.

Even if the university is in fact hiring more female staff, Model 2 shows that female professors are paid less than males, regardless of job title and years of experience. It is apparent that many factors contribute to the wage gap and the model does not sufficiently explain these with the explanatory variables developed within this dataset. The model should be run again on previous calendar years. The overweight "eighth" year again limits more complex conclusions from being drawn from the model. Patterns may emerge that suggest some of the highest paid male Professors have remained at the University of Toronto for many, many years. It would be useful to explore whether male and female professors successfully progress to each year of experience at the same rate (in other words, is a male professor more likely to reach major milestones than a female professor). This might help to determine if social barriers result in higher salaries for males, rather than strictly differences in salaries paid to each gender. The analysis should be rerun with 2020 data as soon as it is available.

Next steps for both models should, first and foremost, incorporate more years into the dataset. The addition of years of experience begins to differentiate staff quite significantly (as both **Plot 12** and **Plot 13** do well to articulate for professors). However, there is so much grouping at the eighth year that it becomes extremely difficult to draw any real conclusions on models that use gender and years of experience together to explain variances in salary paid. Greater differentiation amongst staff, by either years of experience or a supplemental dataset for titles and departments, using variants of these models to generate future salary predictions should be possible. Predictions made without this differentiation were largely unsuccessful because they relied too heavily on only a few discrete bins (three "genders", four job titles, and 1-8 years of experience: a total of 72 different combinations from which to classify ~2000 professors, all of which seem to have relatively similar salaries). Connections between these variables emerge even within this limited set of explanatory variable levels.

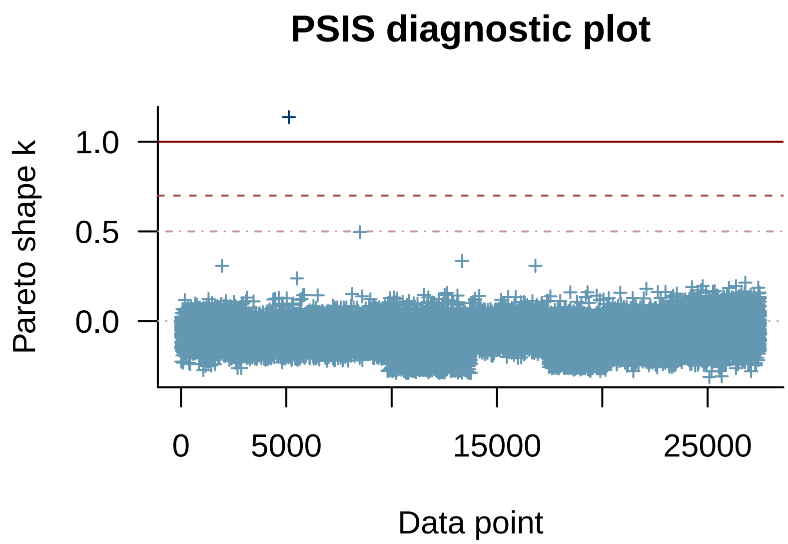
From both of these models, it remains apparent that female staff and professors are paid less than their male counterparts. This is consistent with studies conducted previously. Due to the limitations of the dataset ($100,000 minimum salary, difficulty in parsing job titles and faculties, and no explicitly stated gender), the University of Toronto should consider providing an internally generated dataset (albeit, anonymity issues may arise, so access to this dataset should be restricted). Research conducted appropriately might help address the wage gap with greater clarity.

Appendix

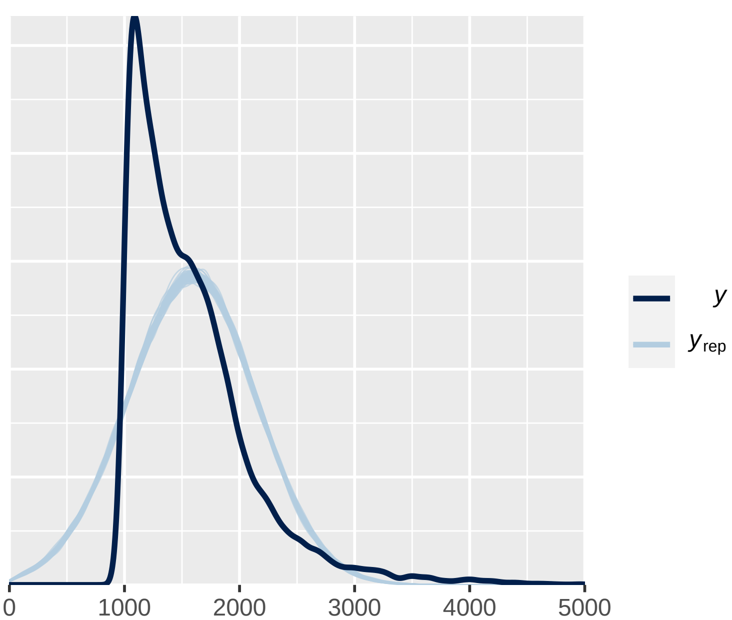
Model 1 evaluation metrics

The following metrics were performed on the final iteration of the model:

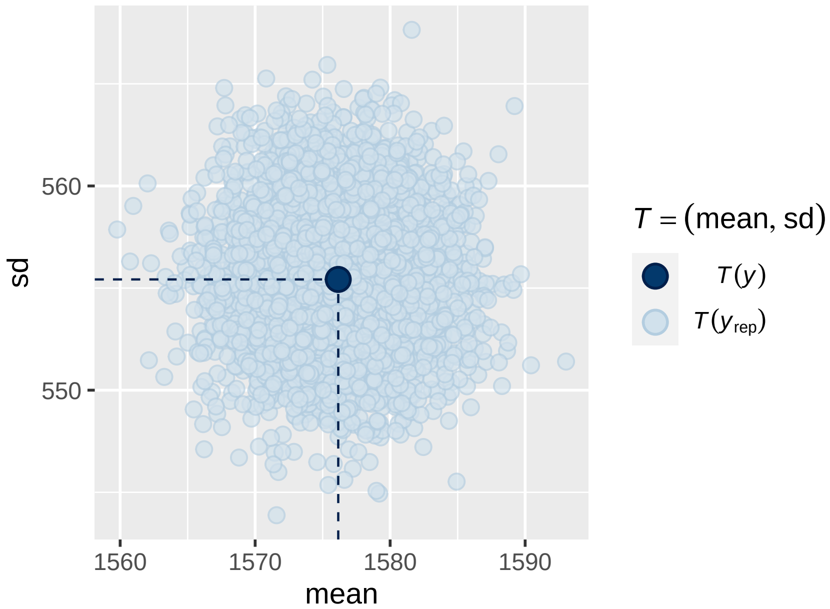
- A PSIS diagnostic plot checking for pareto values above 0.6. One point was present above this value (*Plot A1.1*).
- A density plot, comparing the distribution of `y` and `y_rep` predicted values. Model shapes are not as similar as we would expect, especially as `y_rep` values overly represent values below the $100,000 cut-off imposed by the dataset (*Plot A1.2*).
- A scatterplot of means and standard deviations for `y` and `y_rep`. Clustering is heavily focused near to the mean and standard deviation is reasonable (*Plot A1.3*).
- A scatterplot comparing `y` to average `y_rep`. The average line is extremely low, showing that the model cannot predict salaries significantly above the average `y` mean as seen in the previous plot (*Plot A1.4*).



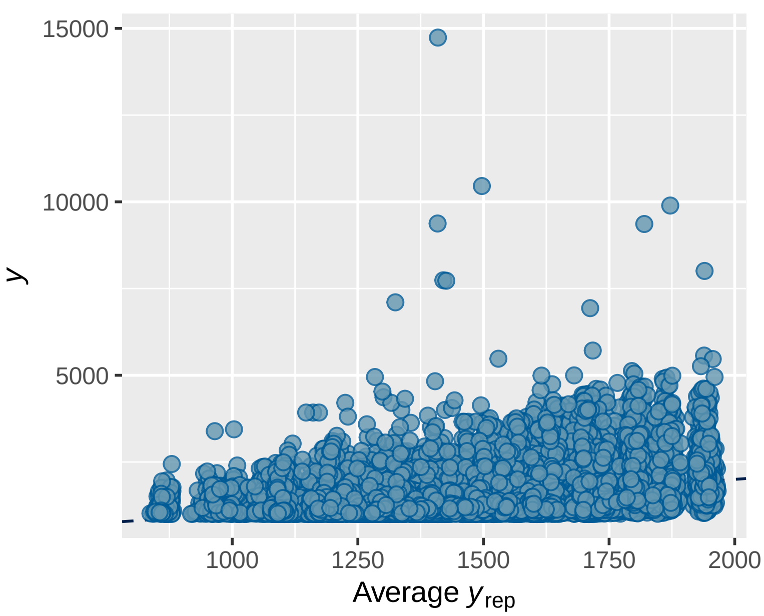
Plot A1.1



Plot A2.1



Plot A3.1



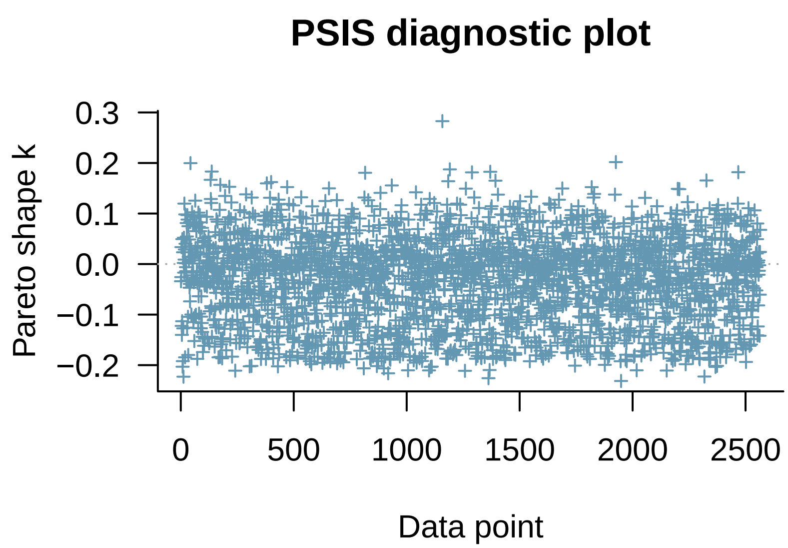
Plot A4.1

Evaluation metrics show that Model 1's final iteration performs slightly below necessary requirements. Additional data points would likely improve this model significantly. The inability for the model to differentiate supporting staff from professors, as well as outlier staff members who make significantly larger salaries, have a demonstrated effect on the model.

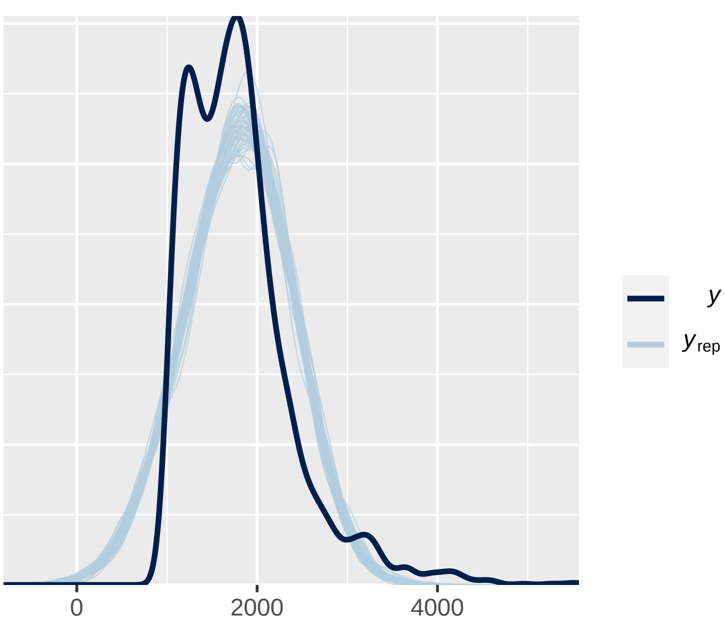
Model 2 evaluation metrics

Like Model 1, the following metrics were performed on the final iteration of the model:

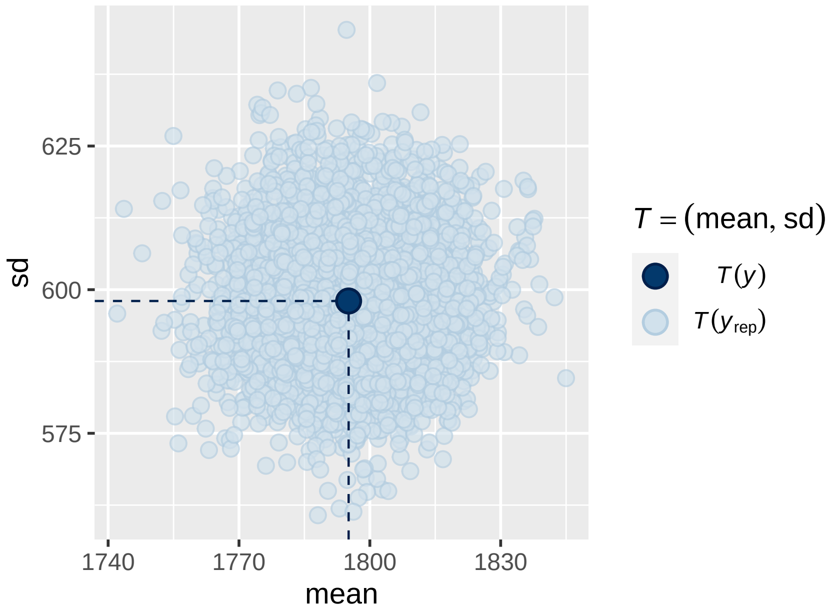
- A PSIS diagnostic plot checking for pareto values above 0.6. No points were above this value (*Plot A2.1*).
- A density plot, comparing the distribution of `y` and `y_rep` predicted values. Model shapes are better than Model 1, though fail to account for the steep drop-off in salaries just above $200,000. Like Model 1, `y_rep` values overly represent values below the $100,000 cut-off imposed by the dataset (*Plot A2.1*).
- A scatterplot of means and standard deviations for `y` and `y_rep`. Standard deviations are much higher and means span a significantly larger range than Model 1. (*Plot A2.3*)
- A scatterplot comparing `y` to average `y_rep`. The average line is significantly better at predicting higher salaries (those above $250,000) than Model 1, but shows significant vertical grouping at various `y_rep` intervals. (*Plot A2.4*)



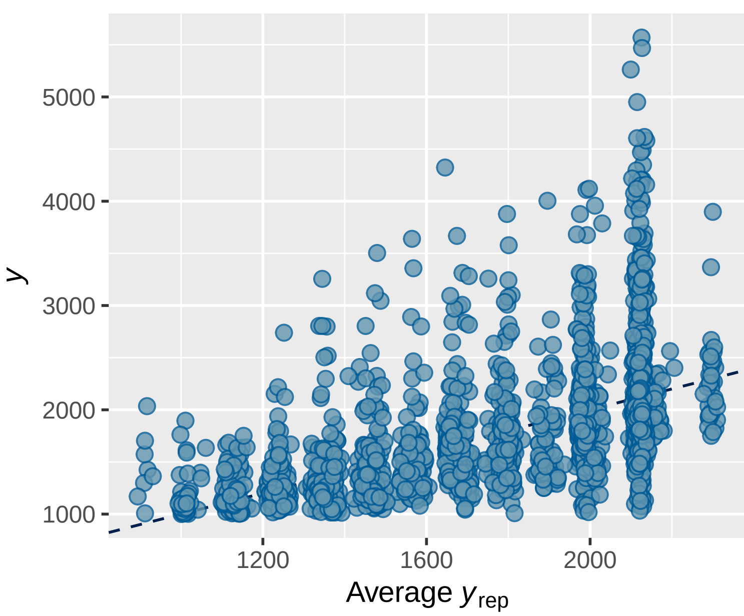
Plot A1.2



Plot A2.2



Plot A3.2



Plot A4.2

Evaluation metrics show that while Model 2 performs much better than Model 1, it too lacks the necessary variables to accurate predict differences in professor salaries. As mentioned in §Results, Model 2 was disproportionately shaped by "eighth" year professors, where insufficient history created an artificially large grouping for professors who appeared on the sunshine list for all years of data.

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