# IDS 702: MODULE 1.1

#### MOTIVATING EXAMPLE

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#### INTRODUCTION

- By now, you should already be familiar with t-tests and simple linear regression (SLR).
- At the very least, you should know the basics.
- Specifically, you should know how to fit a SLR model and assess whether or not the model assumptions are violated.
- We will use those ideas as building blocks for the models we will explore throughout this course.

#### MOTIVATING EXAMPLE

- In the 1970's, Harris Trust and Savings Bank was sued for discrimination on the basis of sex.
- As evidence, the defense presented analysis of salaries of employees of one type (skilled, entry level clerical).
- The data is in the file wagediscrim.txt on Sakai.
- We are interested in answering the question: did female employees tend to receive lower base/starting salaries than similarly qualified and experienced male employees?

Which statistical tests can we use to probe the question above?

#### Data

93 employees on data file (61 female, 32 male).

Variable	Description		
bsal	Annual salary at time of hire		
sal77	Annual salary in 1977.		
educ	years of education.		
exper	months previous work prior to hire at bank.		
fsex	1 if female, 0 if male		
senior	months worked at bank since hired		
age	months		

Since we care about inference on bsal, as our response variable, we will exclude sal77 for all analysis.

Is this reasonable? Why or why not?



#### Data

How many rows? How many columns?

```
wages <- read.csv("data/wagediscrim.txt", header= T)
dim(wages)</pre>
```

## [1] 93 8

Take a look at the first few rows of the data.

head(wages)

##		bsal	sal77	sex	senior	age	educ	exper	fsex
##	1	5040	12420	Male	96	329	15	14.0	Θ
##	2	6300	12060	Male	82	357	15	72.0	Θ
##	3	6000	15120	Male	67	315	15	35.5	Θ
##	4	6000	16320	Male	97	354	12	24.0	Θ
##	5	6000	12300	Male	66	351	12	56.0	Θ
##	6	6840	10380	Male	92	374	15	41.5	Θ

#### Data

Check variable types.

```
wages$sex <- factor(wages$sex,levels=c("Male","Female"))
wages$fsex <- factor(wages$fsex)
str(wages)</pre>
```

## 'data.frame': 93 obs. of 8 variables: ## \$ bsal : int 5040 6300 6000 6000 6000 6840 8100 6000 6000 6900 ... ## \$ sal77 : int 12420 12060 15120 16320 12300 10380 13980 10140 12360 10920 ... ## \$ sex : Factor w/ 2 levels "Male", "Female": 1 1 1 1 1 1 1 1 1 1 1 ... ## \$ senior: int 96 82 67 97 66 92 66 82 88 75 ... ## \$ age : int 329 357 315 354 351 374 369 363 555 416 ... ## \$ educ : int 15 15 15 12 12 15 16 12 12 15 ... ## \$ exper : num 14 72 35.5 24 56 41.5 54.5 32 252 132 ... ## \$ fsex : Factor w/ 2 levels "0", "1": 1 1 1 1 1 1 1 1 1...

## EXPLORATORY DATA ANALYSIS (EDA)

Next, quick summaries of each variable.

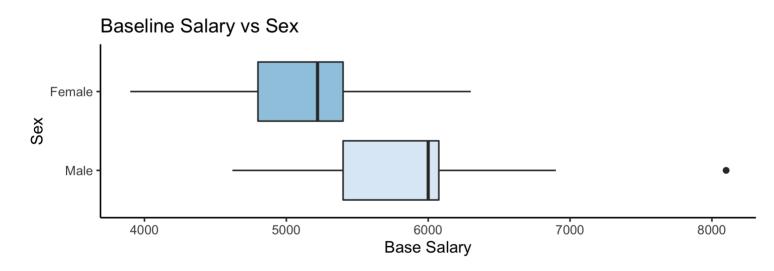
#### summary(wages)

##	bsal	sal77	sex	senior	age
##	Min. :3900	Min. : 7860	Male :32	Min. :65.00	Min. :280.0
##	1st Qu.:4980	1st Qu.: 9000	Female:61	1st Qu.:74.00	1st Qu.:349.0
##	Median :5400	Median :10020		Median :84.00	Median :468.0
##	Mean :5420	Mean :10393		Mean :82.28	Mean :474.4
##	3rd Qu.:6000	3rd Qu.:11220		3rd Qu.:90.00	3rd Qu.:590.0
##	Max. :8100	Max. :16320		Max. :98.00	Max. :774.0
##	educ	exper	fsex		
##	Min. : 8.00	Min. : 0.0	0:32		
##	1st Qu.:12.00	1st Qu.: 35.5	1:61		
##	Median :12.00	Median : 70.0			
##	Mean :12.51	Mean :100.9			
##	3rd Qu.:15.00	3rd Qu.:144.0			
##	Max. :16.00	Max. :381.0			



Since we only care about comparing starting salaries for male and female employees for now, let's look at boxplots of bsal by sex.

```
ggplot(wages,aes(x=sex, y=bsal, fill=sex)) +
geom_boxplot() + coord_flip() +
scale_fill_brewer(palette="Blues") +
labs(title="Baseline Salary vs Sex",y="Base Salary",x="Sex") +
theme_classic() + theme(legend.position="none")
```



What do you think? What can you infer from this plot?

#### **T-**TEST?

We could go further and try a t-test for the hypotheses.

```
H_0: \mu_{	ext{male}} - \mu_{	ext{female}} \leq 0 ~ 	ext{vs.} ~ H_A: \mu_{	ext{male}} - \mu_{	ext{female}} > 0
```

t.test(bsal~sex,data=wages,alternative="greater")

```
##
##
       Welch Two Sample t-test
##
## data: bsal by sex
## t = 5.83, df = 51.329, p-value = 1.855e-07
## alternative hypothesis: true difference in means is greater than 0
## 95 percent confidence interval:
   582.9857
##
                  Tnf
## sample estimates:
     mean in group Male mean in group Female
##
##
               5956.875
                                    5138.852
```

Is a t-test sufficient here? Any concerns?



#### SLR?

How about fitting a SLR model to the two variables.

```
	ext{bsal}_i = eta_0 + eta_1 	ext{sex}_i + \epsilon_i; \ \ \epsilon_i \stackrel{iid}{\sim} \mathcal{N}(0,\sigma^2), \ \ i=1,\dots,n.
```

```
model1 <- lm(bsal~sex,data=wages); summary(model1)</pre>
```

```
##
## Call:
## lm(formula = bsal ~ sex, data = wages)
##
## Residuals:
       Min 10 Median
##
                                 30
                                        Max
## -1336.88 -338.85 43.12 261.15 2143.12
##
## Coefficients:
##
             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 5956.9 105.3 56.580 < 2e-16
## sexFemale -818.0 130.0 -6.293 1.08e-08
##
## Residual standard error: 595.6 on 91 degrees of freedom
## Multiple R-squared: 0.3032, Adjusted R-squared: 0.2955
## F-statistic: 39.6 on 1 and 91 DF, p-value: 1.076e-08
```

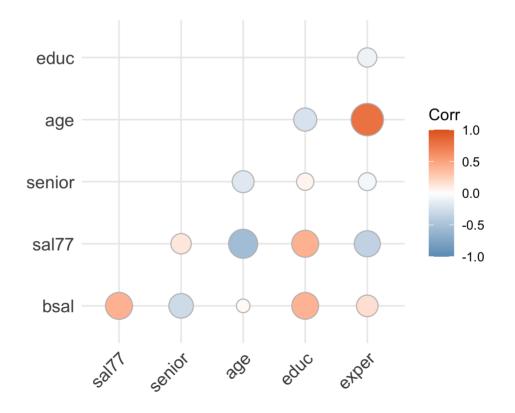
#### What can we infer from these results?

- T-test shows men started at higher salaries than women (t = 5.83, p < .0001); same conclusion from the regression.
- But one could argue this is so because both methods do not control for other characteristics. Indeed, we have ignored the other variables.
- There are other variables that are correlated with bsal. Here's the correlation matrix of all numerical variables using the corr function in R.

	bsal	sal77	senior	age	educ	exper
bsal	1.00	0.42	-0.29	0.03	0.41	0.17
sal77	0.42	1.00	0.13	-0.55	0.42	-0.37
senior	-0.29	0.13	1.00	-0.18	0.06	-0.07
age	0.03	-0.55	-0.18	1.00	-0.23	0.80
educ	0.41	0.42	0.06	-0.23	1.00	-0.10
exper	0.17	-0.37	-0.07	0.80	-0.10	1.00



Or visually (using the ggcorrplot package),

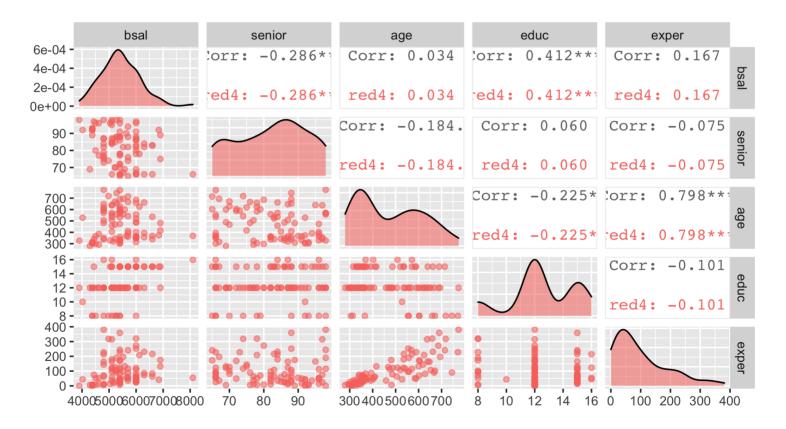


- So, let's take a look at scatter plots of all variables
- First, recall the description of all the variables.

Variable	Description		
bsal	Annual salary at time of hire		
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fsex	1 if female, 0 if male		
senior	months worked at bank since hired		
age	months		



#### ggpairs(wages[,!is.element(colnames(wages),c("sal77","sex","fsex"))], mapping=ggplot2::aes(colour = "red4",alpha=0.6)) #GGally package

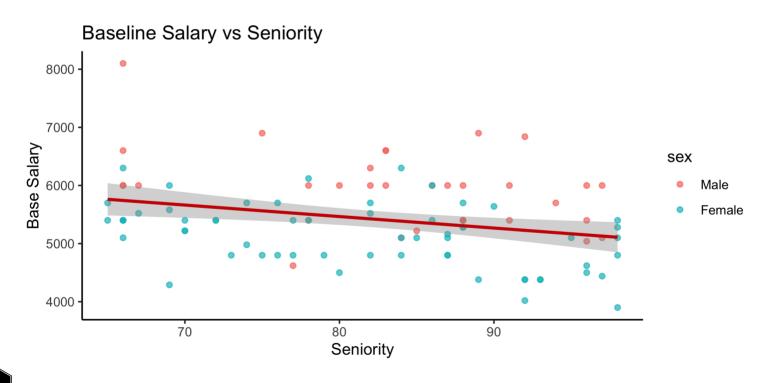


This plot looks very busy!

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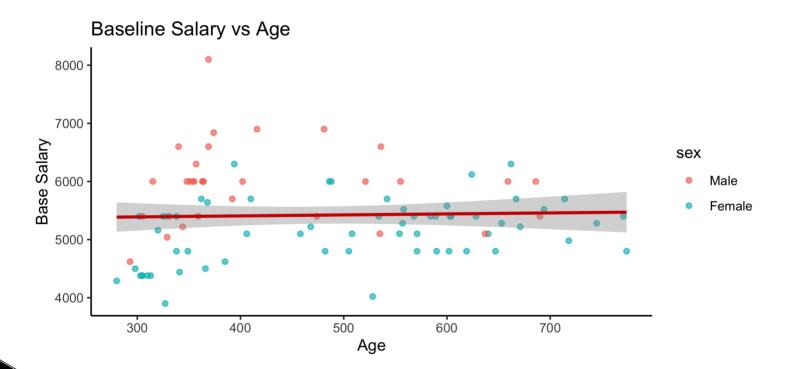
Let's take a closer look one variable at a time. First, bsal vs. senior.

```
ggplot(wages,aes(x=senior, y=bsal)) +
geom_point(alpha = .7,aes(color=sex)) +
geom_smooth(method="lm",col="red3") + theme_classic() +
labs(title="Baseline Salary vs Seniority",x="Seniority",y="Base Salary")
```



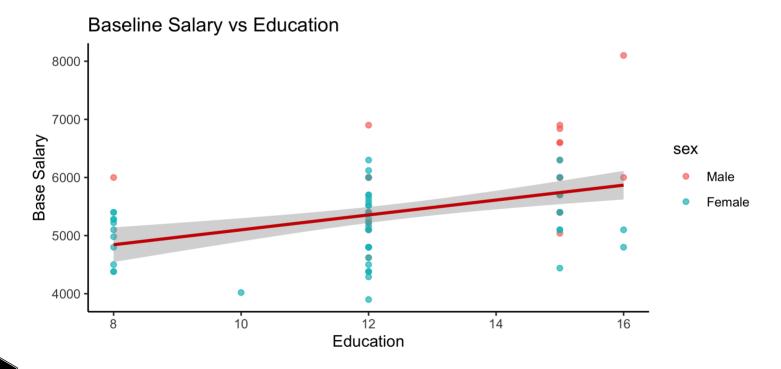
#### Next, bsal vs. age

```
ggplot(wages,aes(x=age, y=bsal)) +
geom_point(alpha = .7,aes(color=sex)) +
geom_smooth(method="lm",col="red3") + theme_classic() +
labs(title="Baseline Salary vs Age",x="Age",y="Base Salary")
```



#### bsal vs. educ

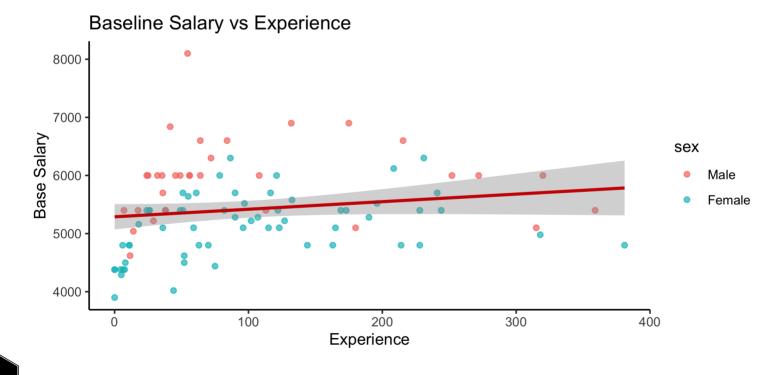
```
ggplot(wages,aes(x=educ, y=bsal)) +
geom_point(alpha = .7,aes(color=sex)) +
geom_smooth(method="lm",col="red3") + theme_classic() +
labs(title="Baseline Salary vs Education",x="Education",y="Base Salary")
```



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#### Finally, bsal vs. exper

```
ggplot(wages,aes(x=exper, y=bsal)) +
geom_point(alpha = .7,aes(color=sex)) +
geom_smooth(method="lm",col="red3") + theme_classic() +
labs(title="Baseline Salary vs Experience",x="Experience",y="Base Salary")
```



#### TAKEAWAYS

- Clearly, they are other variables that may be relevant in explaining baseline salary.
- We need to explore other statistical methods than the t-test and simple linear regression.
- We need methods that can explore the relationship between baseline salary and sex while also controlling for the other variables that clearly may be relevant.
- This brings us to multiple linear regression (MLR).
- Something to keep in mind, the overall conclusions may not change after using a better model for this data.

In general, this should never stop you from exploring and reporting the results from better models; you should always be rigorous when doing analyses and be honest when reporting the results!



# WHAT'S NEXT?

Move on to the readings for the next module!

