

Project1-1

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0. Introduction

The first data was called US voter turnout, which includes number of age-eligible voters versus total votes counted by state and year. The second data was called US average tuition, which includes the average tuition by state and year. Both of these data were found on the github rfordatascience website, and they are interesting because I think there might be a potential correlation between the voter turnout and college tuition in some area of the US.

1. Tidying: Rearrange Wide/Long

The tuition data was first pivot longer to create new rows for each state with each year, and then the year was separated into two parts to make the year more tidy. Unnecessary columns are removed. For the turnout data, columns that contain unnecessary information were removed.

```
tuition_2 <- tuition%>%pivot_longer(c(2,3,4,5,6,7,8,9,10,11,12,13))%>%separate(name, into=c("year", "unknown"), convert=T)%>%rename(state = State)%>%select(-unknown)
glimpse(tuition_2)
```

```
## Observations: 600
## Variables: 3
## $ state <chr> "Alabama", "Alabama", "Alabama", "Alabama", "Alabama", "Al...
## $ year <int> 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013...
## $ value <dbl> 5682.838, 5840.550, 5753.496, 6008.169, 6475.092, 7188.954...
```

```
turnout_2 <- turnout%>%select(-X, -icpsr_state_code, -alphanumeric_state_code)
glimpse(turnout_2)
```

```
## Observations: 936
## Variables: 4
## $ year <int> 2014, 2014, 2014, 2014, 2014, 2014, 2014, 2014, ...
## $ state <fct> United States, Alabama, Alaska, Arizona, Arkansas...
## $ votes <int> 83262122, 1191274, 285431, 1537671, 852642, 7513...
## $ eligible_voters <int> 227157964, 3588783, 520562, 4510186, 2117881, 24...
```

2. Joining/Merging

Data `tuition_2` was joined with data `turnout_2` using `left_join`, and the joined data was piped into `na.omit` to remove any row with NA. These two data were joined by two columns, year and states, so there is no data being lost during the joining. Column value was renamed to `avg_tuition`.

```
temp <- tuition_2%>%left_join(turnout_2)%>%na.omit()%>%rename(tuition = value)
```

```
## Joining, by = c("state", "year")
```

```
## Warning: Column `state` joining character vector and factor, coercing into
## character vector
```

```
glimpse(temp)
```

```
## Observations: 273
## Variables: 5
## $ state      <chr> "Alabama", "Alabama", "Alabama", "Alabama", "Ala...
## $ year       <int> 2004, 2008, 2010, 2014, 2004, 2006, 2008, 2010, ...
## $ tuition    <dbl> 5682.838, 6475.092, 8071.134, 9496.084, 4328.281...
## $ votes      <int> 1890317, 2105622, 1503232, 1191274, 314502, 2383...
## $ eligible_voters <int> 3292608, 3454510, 3472582, 3588783, 452124, 4651...
```

3. Wrangling

A new column called rate was calculated with votes and eligible_voters, which represents the actual turnout rate for a given year and state. To understand the center and spread of the tuition, the mean and standard deviation of tuition was calculated, and we can see there is a great difference in tuition across states. In order to better understand the variance of tuition across the US, a robust statistic is required, since the range of variable tuition is large and may contain outliers. Thus, the median absolute deviation (MAD) of avg_tuition was calculated. This statistic measures the dispersion of the tuition across states, and a value of 1602.384 of MAD indicates a great variance in the tuition. Next, the data was arranged by rate to see which state has the highest voting turnout, and interestingly Minnesota has a relatively high voting turnout from 2004 to 2012. The min and max of number of eligible voters base on state were found, the min and max of number of votes base on year were found.

By grouping by state and year, we can measure the mean and see the 1 over rate. And then the quantile of tuition of each state was found, we can see a rough distribution of tuition can be observed. Next, a correlation was found between turnout rate and tuition of California, and there is no correlation between them.

```
# mutate()
temp <- temp%>%mutate(rate = votes/eligible_voters)
glimpse(temp)
```

```
## Observations: 273
## Variables: 6
## $ state      <chr> "Alabama", "Alabama", "Alabama", "Alabama", "Ala...
## $ year       <int> 2004, 2008, 2010, 2014, 2004, 2006, 2008, 2010, ...
## $ tuition    <dbl> 5682.838, 6475.092, 8071.134, 9496.084, 4328.281...
## $ votes      <int> 1890317, 2105622, 1503232, 1191274, 314502, 2383...
## $ eligible_voters <int> 3292608, 3454510, 3472582, 3588783, 452124, 4651...
## $ rate       <dbl> 0.5741093, 0.6095284, 0.4328860, 0.3319437, 0.69...
```

```
# group_by(), summarize(), select()
temp%>%group_by(state)%>%summarize(mean(tuition), sd(tuition))
```

```
## # A tibble: 49 x 3
##   state      `mean(tuition)` `sd(tuition)`
##   <chr>          <dbl>         <dbl>
## 1 Alabama        7431.         1697.
## 2 Alaska         5376.          716.
## 3 Arizona        7678.         2398.
## 4 Arkansas        6702.          688.
## 5 California      7210.         1920.
## 6 Colorado        7071.         1832.
## 7 Connecticut     9376.         1146.
## 8 Delaware        9616.         1351.
## 9 Florida         5039.         1231.
## 10 Georgia        6010.         1682.
## # ... with 39 more rows
```

```
temp%>%select(tuition)%>%
  mutate(median = median(tuition), dev = tuition-median, absdev = abs(dev), MAD=median(absdev))
```

```
## # A tibble: 273 x 5
##   tuition median    dev absdev  MAD
##   <dbl> <dbl> <dbl> <dbl> <dbl>
## 1  5683.  7476. -1793.  1793. 1602.
## 2  6475.  7476. -1001.  1001. 1602.
## 3  8071.  7476.   595.   595. 1602.
## 4  9496.  7476.  2020.  2020. 1602.
## 5  4328.  7476. -3148.  3148. 1602.
## 6  4919.  7476. -2557.  2557. 1602.
## 7  5075.  7476. -2400.  2400. 1602.
## 8  5759.  7476. -1717.  1717. 1602.
## 9  6026.  7476. -1450.  1450. 1602.
## 10 6149.  7476. -1327.  1327. 1602.
## # ... with 263 more rows
```

```
# arrange()
temp%>%arrange(desc(rate))
```

```
## # A tibble: 273 x 6
##   state      year tuition  votes eligible_voters rate
##   <chr>    <int>   <dbl>   <int>         <int> <dbl>
## 1 Minnesota  2004   8144. 2842912      3609185 0.788
## 2 Minnesota  2008   9024. 2921147      3740142 0.781
## 3 Minnesota  2012  10793. 2950780      3861598 0.764
## 4 Wisconsin  2004   6575. 3016288      4006948 0.753
## 5 Maine      2004   7058.  751519      1003792 0.749
## 6 Wisconsin  2008   7373. 2997086      4120694 0.727
## 7 Oregon     2004   6579. 1851671      2550887 0.726
## 8 New Hampshire 2008  11168.  719643        992226 0.725
## 9 Maine      2008   8764.  744456      1036242 0.718
## 10 Colorado   2008   6284. 2422236      3382959 0.716
## # ... with 263 more rows
```

```
temp%>%group_by(state)%>%summarize(min(eligible_voters), max(eligible_voters))
```

```
## # A tibble: 49 x 3
##   state `min(eligible_voters)` `max(eligible_voters)`
##   <chr>      <int>      <int>
## 1 Alabama      3292608      3588783
## 2 Alaska        452124      520562
## 3 Arizona      3717055      4510186
## 4 Arkansas      1969208      2117881
## 5 California   21132533     24440416
## 6 Colorado      3192647      3800664
## 7 Connecticut   2429634      2577311
## 8 Delaware       584817       681526
## 9 Florida      11811921     13914216
## 10 Georgia       5878186       6725041
## # ... with 39 more rows
```

```
temp%>%group_by(year)%>%summarize(min(votes), max(votes))
```

```
## # A tibble: 6 x 3
##   year `min(votes)` `max(votes)`
##   <int>      <int>      <int>
## 1  2004      245789     12589367
## 2  2006      196217      8899059
## 3  2008      256035     13743177
## 4  2010      190822     10529134
## 5  2012      250701     13202158
## 6  2014      171153      7513972
```

```
temp%>%group_by(state, year)%>%summarize(1/rate)
```

```
## # A tibble: 273 x 3
## # Groups:   state [49]
##   state year `1/rate`
##   <chr> <int>   <dbl>
## 1 Alabama 2004     1.74
## 2 Alabama 2008     1.64
## 3 Alabama 2010     2.31
## 4 Alabama 2014     3.01
## 5 Alaska  2004     1.44
## 6 Alaska  2006     1.95
## 7 Alaska  2008     1.46
## 8 Alaska  2010     1.89
## 9 Alaska  2012     1.70
## 10 Alaska 2014     1.82
## # ... with 263 more rows
```

```
temp%>%group_by(state)%>%do(data.frame(t(quantile(. $tuition))))
```

```
## # A tibble: 49 x 6
## # Groups:   state [49]
##   state      X0.   X25.   X50.   X75.  X100.
##   <chr>    <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 Alabama  5683.  6277.  7273.  8427.  9496.
## 2 Alaska   4328.  4958.  5417.  5959.  6149.
## 3 Arizona  5138.  5626.  7449.  9810. 10414.
## 4 Arkansas 5772.  6278.  6659.  7190.  7606.
## 5 California 5286.  5476.  7046.  8939.  9361.
## 6 Colorado 4704.  5768.  7016.  8532.  9299.
## 7 Connecticut 7984.  8368.  9827. 10037. 10664.
## 8 Delaware 8353.  8682.  8995. 10534. 11515.
## 9 Florida  3848.  3953.  4830.  6136.  6495.
## 10 Georgia 4298.  4646.  5630.  7497.  8063.
## # ... with 39 more rows
```

```
# filter()
temp%>%filter(state=="California")%>%select(rate, tuition)%>%cor()
```

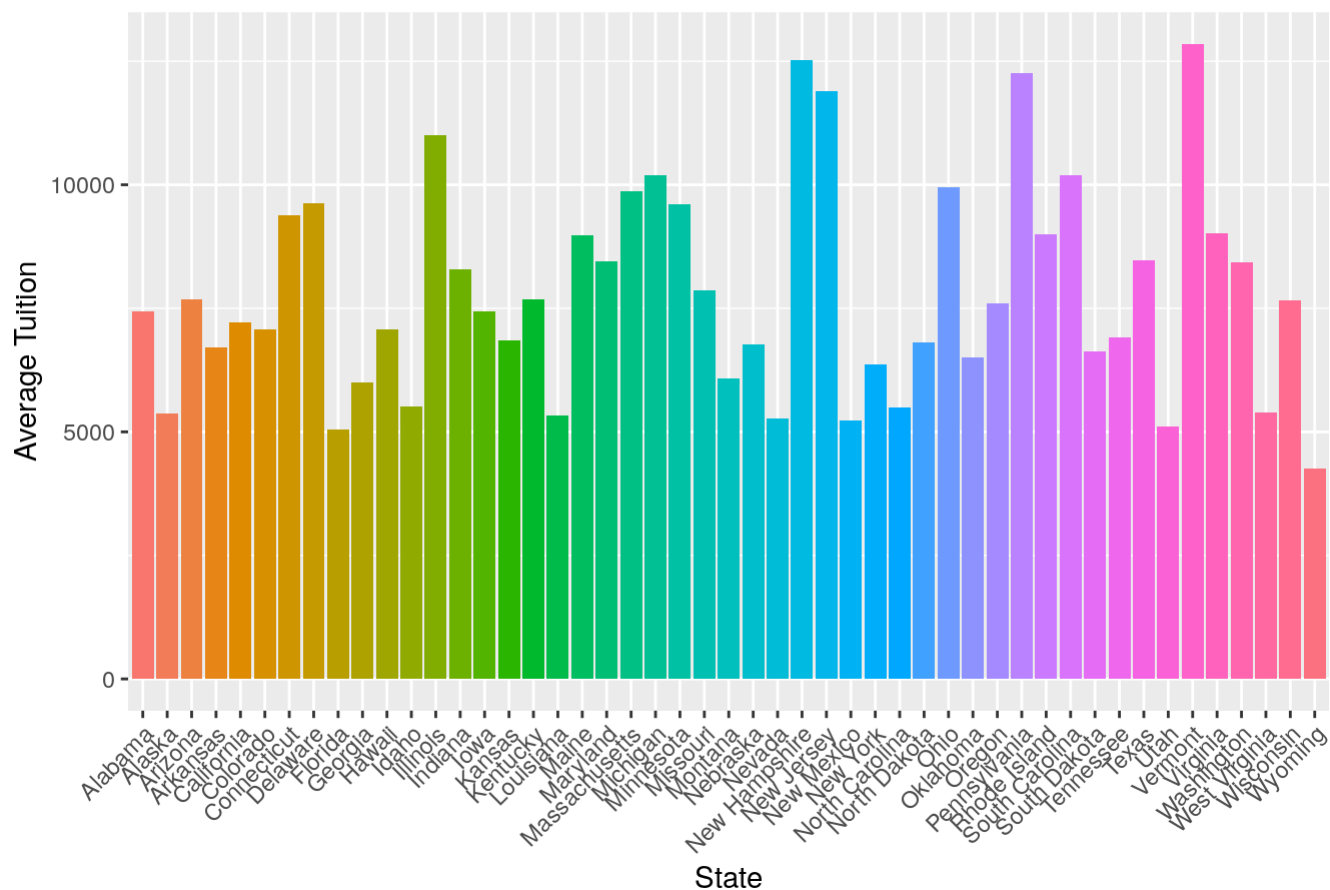
```
##           rate    tuition
## rate      1.0000000 -0.4082598
## tuition -0.4082598  1.0000000
```

4. Visualizing

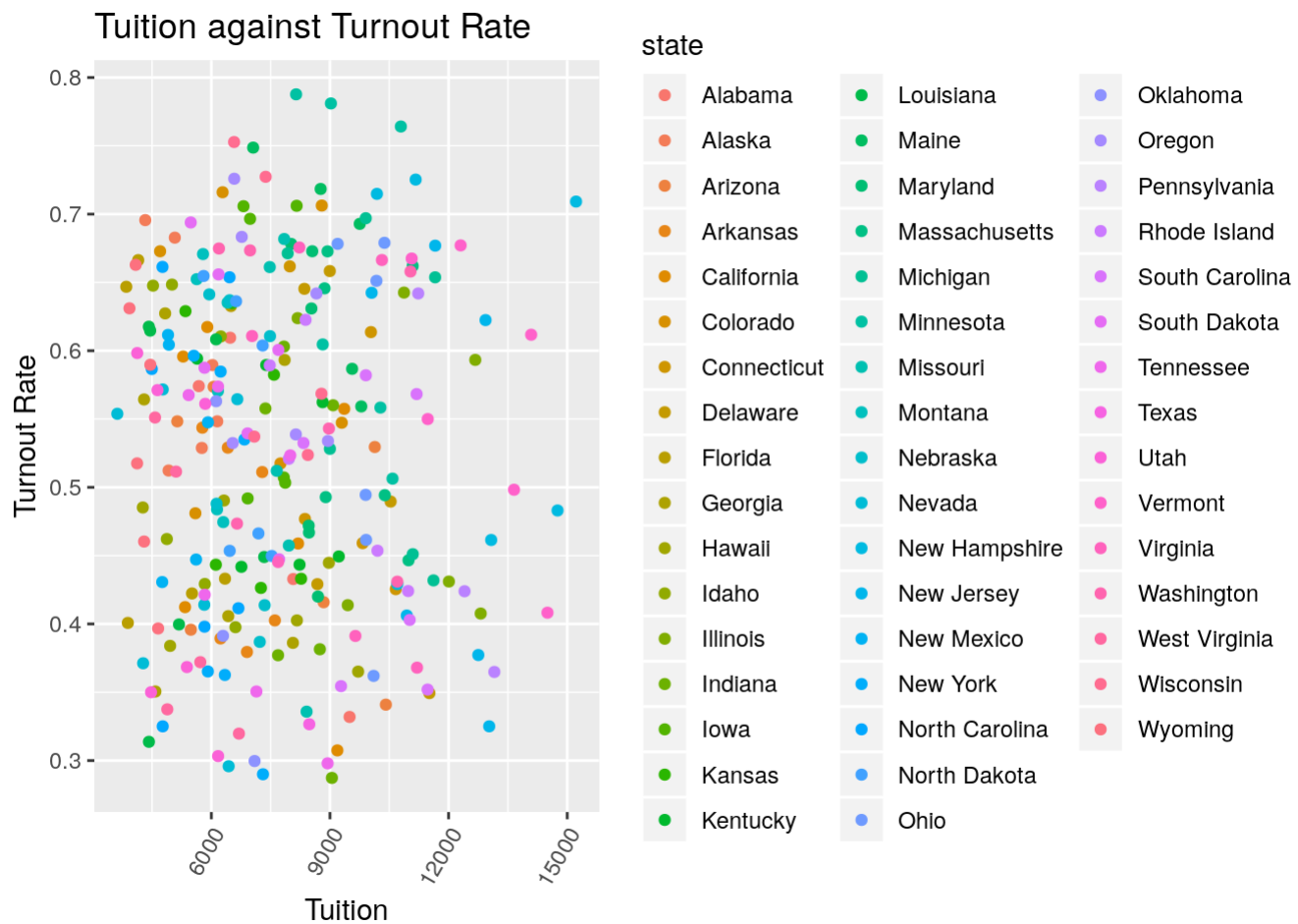
The first plot demonstrates the average tuition across different states, and the mean of tuition from different year was calculated within the `fun.y` function. The second plot demonstrates the relationship between tuition and turnout rate across different states, but there is no clear linear correlation among them. The potential effect was measured during the dimensionality reduction section.

```
ggplot(temp, aes(state))+
  geom_bar(aes(y=tuition, fill=state), stat="summary", fun.y="mean")+
  theme(axis.text.x = element_text(angle=45, hjust=1), legend.position="none")+
  labs(title = "Average Tuition across States", x = "State", y = "Average Tuition")
```

Average Tuition across States



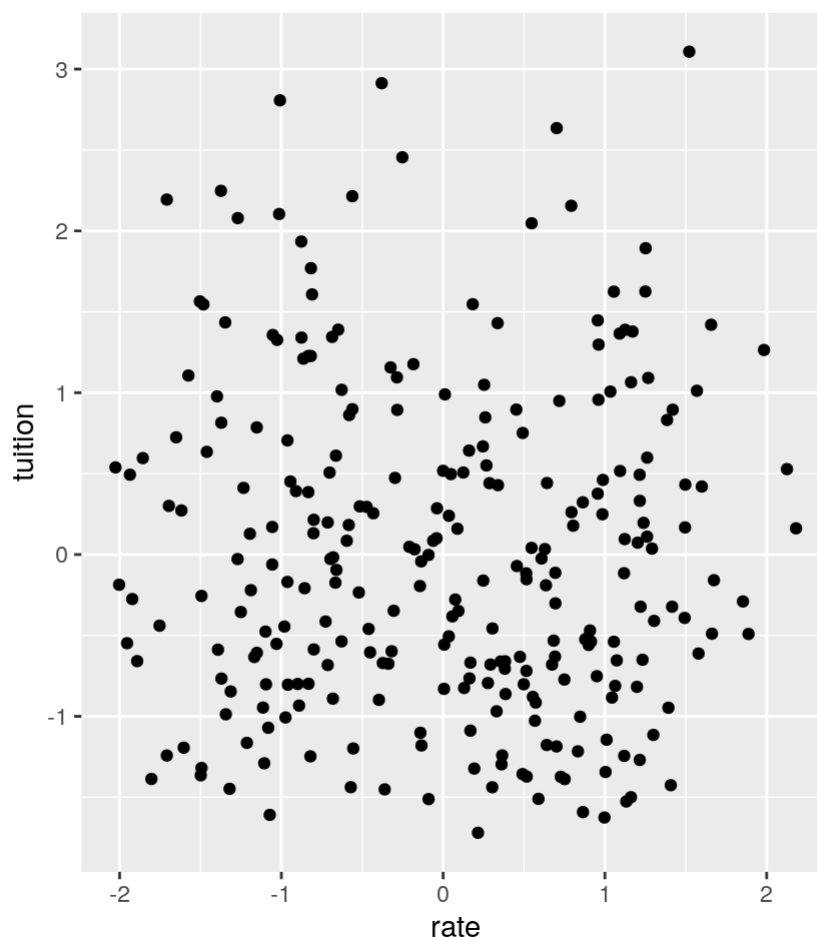
```
ggplot(temp, aes(tuition, rate, color=state))+
  geom_point()+
  theme(axis.text.x=element_text(angle=60, hjust=1))+
  labs(title = "Tuition against Turnout Rate", x = "Tuition", y = "Turnout Rate")
```



5. Dimensionality Reduction

From the result of PCA and corresponding plot, we can see that the votes variable and the eligible voters variable are strongly correlated, but the other two variables do not address much variation on other variables.

```
temp2 <- temp%>%select(-year, -state)
temp2_scaled = data.frame(scale(temp2))
ggplot(temp2_scaled, aes(x = rate, y = tuition))+geom_point()+coord_fixed()
```



```
temp_pca<-princomp(temp2_scaled)
summary(temp_pca, loadings = T)
```

```
## Importance of components:
```

	Comp.1	Comp.2	Comp.3	Comp.4
## Standard deviation	1.3954926	1.0267524	0.9786094	0.161405002
## Proportion of Variance	0.4886398	0.2645241	0.2402993	0.006536838
## Cumulative Proportion	0.4886398	0.7531639	0.9934632	1.000000000

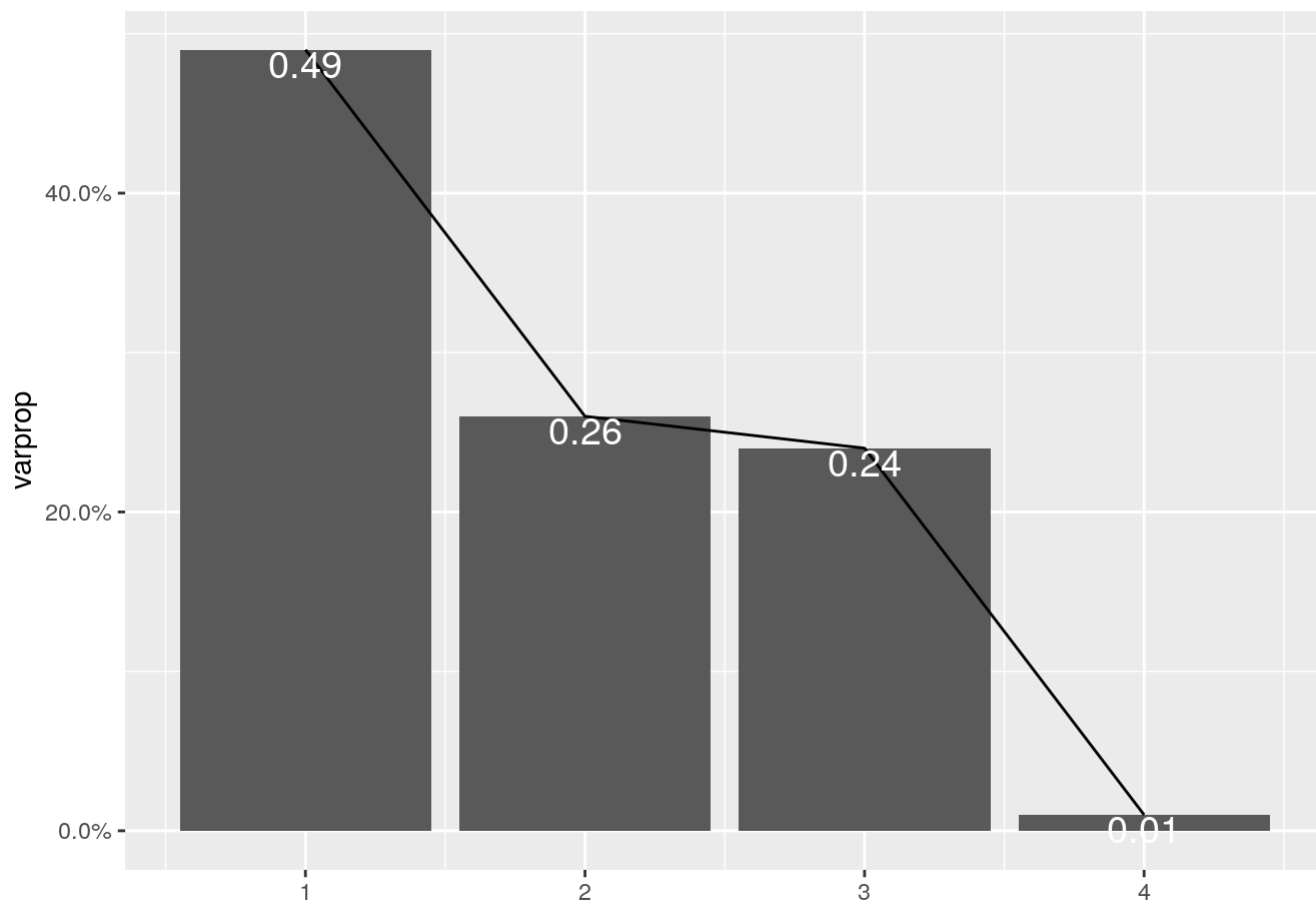
```
## Loadings:
```

	Comp.1	Comp.2	Comp.3	Comp.4
## tuition	-0.106	-0.535	0.838	
## votes	-0.703	0.141		-0.697
## eligible_voters	-0.703		-0.129	0.696
## rate		0.830	0.530	0.173

```
eigval<-temp_pca$sdev^2
```

```
varprop=round(eigval/sum(eigval),2)
```

```
ggplot()+geom_bar(aes(y=varprop,x=1:4),stat="identity")+xlab("")+geom_path(aes(y=varprop,x=1:4))
+
  geom_text(aes(x=1:4,y=varprop,label=round(varprop,2)),vjust=1,col="white",size=5)+
  scale_y_continuous(breaks=seq(0,.6,.2),labels = scales::percent)+
  scale_x_continuous(breaks=1:10)
```

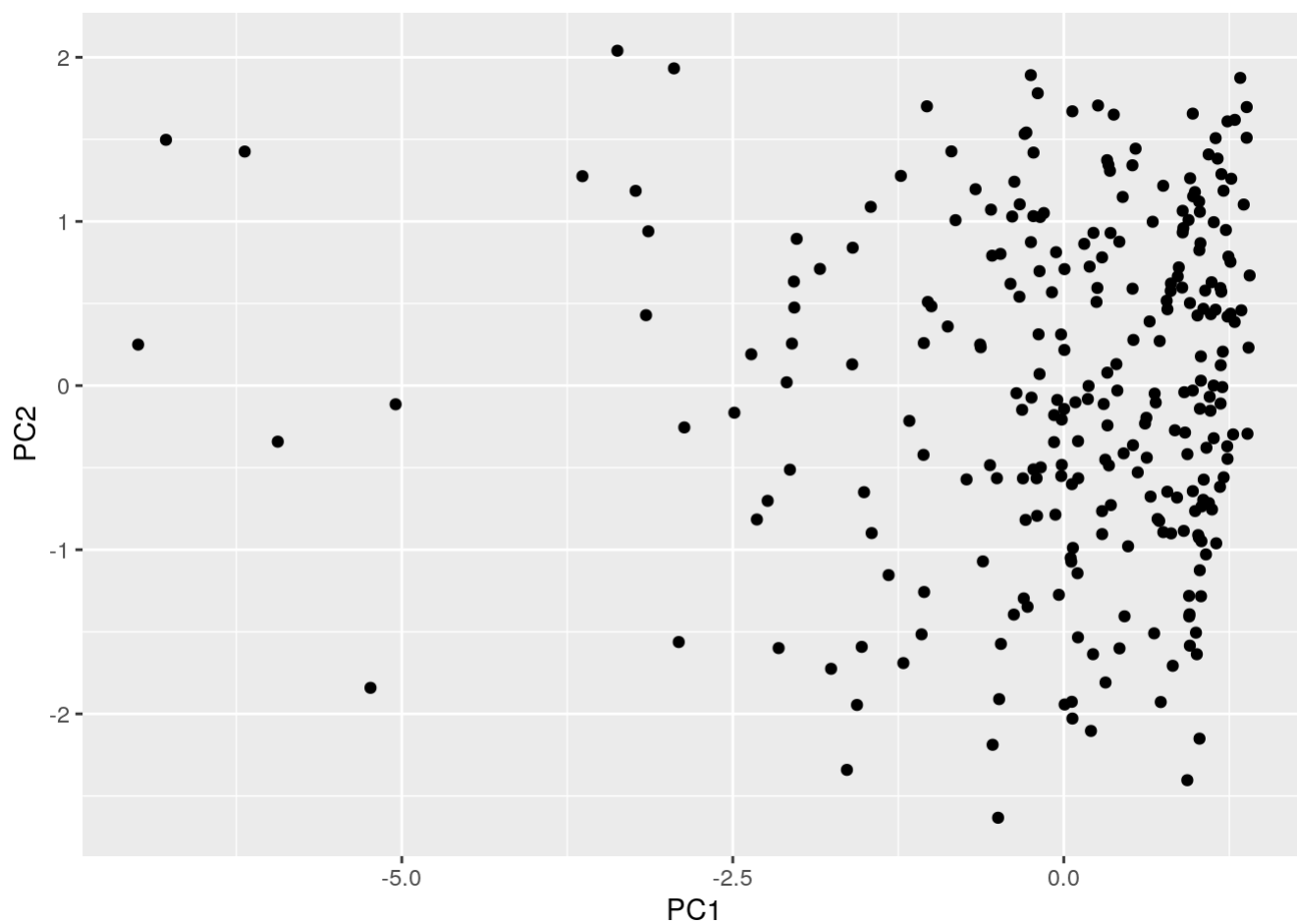
```
round(cumsum(eigval)/sum(eigval),2)
```

```
## Comp.1 Comp.2 Comp.3 Comp.4
## 0.49 0.75 0.99 1.00
```

```
eigval
```

```
## Comp.1 Comp.2 Comp.3 Comp.4
## 1.94739969 1.05422040 0.95767633 0.02605157
```

```
ggplot()+geom_point(aes(temp_pca$scores[,1], temp_pca$scores[,2]))+xlab("PC1")+ylab("PC2")
```



```
temp_pca$loadings[1:4,1:2]%>%as.data.frame%>%rownames_to_column%>%
ggplot()+geom_hline(aes(yintercept=0),lty=2)+
  geom_vline(aes(xintercept=0),lty=2)+ylab("PC2")+xlab("PC1")+
  geom_segment(aes(x=0,y=0,xend=Comp.1,yend=Comp.2),arrow=arrow(),col="red")+
  geom_label(aes(x=Comp.1*1.1,y=Comp.2*1.1,label=rowname))
```

