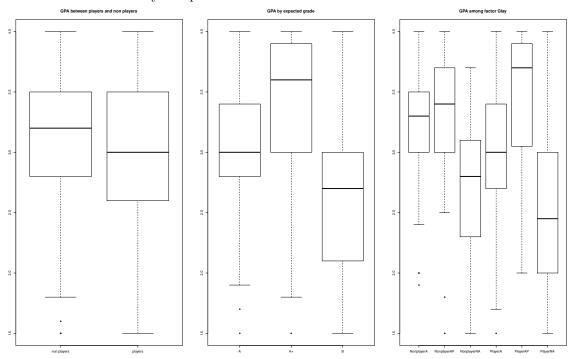
GPA and grade expectation & game playing analysis

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1. Construct the three side by side plot as shown below:



The three plot appear to be different due to the size of levels of factors.

In the first plot, Player is a factor with 2 levels: 0 - non player and 1 - player;

In the second plot, Grade is a factor with 3 levels: A, A+, B;

In the third plot, Glay is a factor with 6 levels: NonplayerA, NonplayerAP, NonplayerNA, PlayerA, PlayerAP, PlayerNA.

2. With the **two sample t-test** procedure, the hypothesis is:

$$H_0: \mu_{\texttt{player_gpa}} - \mu_{\texttt{non_player_gpa}} = 0, H_A: \mu_{\texttt{player_gpa}} - \mu_{\texttt{non_player_gpa}} \neq 0$$

t.test gives an output with p-value = 0.2383, as shown in the Appendix. The p-value does not give evidence to reject the null hypothesis, which implies that there is not a significant difference in the mean of GPA between the player and non player of video and/or computer games.

3. From **one-way analysis of variance** with

$$H_0: \mu_{\mathtt{A_gpa}} = \mu_{\mathtt{A+_gpa}} = \mu_{\mathtt{B_gpa}}, \ H_A: \exists \ i \neq j \ \text{ s.t. } \mu_i \neq \mu_j$$

the summary of the one way anova function: summary(aov()) gives an output with p-value <2e-16 as shown in the **Appendix**, which provides significant evidence to reject the null hypothesis of equal means.

In order to find which levels grades differ, perform **pair-wise t test** with Bonferroni's correction method, with **pairwise.t.test(gpa, grade, p.adj = "bonf")**, we get a table of statistical significance between each pairs:

$$\begin{array}{cccc} & A & A+ \\ A+ & 1.8\text{e-}07 & \text{-} \\ B & 2.6\text{e-}11 & <2\text{e-}16 \end{array}$$

Which suggests that the difference of means of gpa between group with expected grade of A and A+, A and B, A+ and B are all significantly difference from each other, with p-value of 1.8e-07, 2.6e-11, 2e-16 respectively.

4. Let μ_i denote the mean of gpa of *i*th category in the six category of of students classified by the combination of their player status and expected grade. Then the null hypothesis is:

$$H_0: \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5 = \mu_6, \ H_A: \exists \ i \neq j \ \text{s.t.} \ \mu_i \neq \mu_j$$

As shown in **Appendix** section, the p-value from the output is less than 2e-16, which provides strong evidence to reject the null hypothesis of equal means.

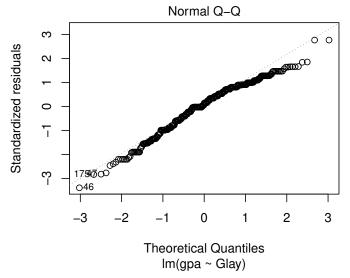
With the **Tukey's Honest Significance Test**, we can also compare the statistical significance between each pair in the group. The following table provides a detailed look for pairs with significant difference, which can also be find in the **Appendix**:

	p adj
NonplayerNA-NonplayerA	0.0092179
PlayerAP-NonplayerA	0.0477882
PlayerNA-NonplayerA	0.0000000
NonplayerNA-NonplayerAP	0.0005766
PlayerNA-NonplayerAP	0.0000000
PlayerAP-NonplayerNA	0.0000000
PlayerAP-PlayerA	0.0000002
PlayerNA-PlayerA	0.0000000
PlayerNA-PlayerAP	0.0000000

5. (a) In order to ensure the results from above tests are valid, several assumptions about the model need to be checked: One is **Homoscedasticity**, Second is **Normality**.

With **Bartlett's test**, one can access assumption of equal variance. From the function **bartlett.test()**, p-value = 0.8644 is obtained as shown in **Appendix**, which provides a conclusion that there is no evidence to reject the hypothesis of equal variance.

The following qq-plot suffice to access the assumption of normality:



As shown above, the assumption of normality roughly holds, thus one can conclude the previous tests are valid.

- (b) We should concern the issue, since unequal sample sizes can affect the homogeneity of variance assumption, especially for small sample sizes. Since homogeneity is already checked, then there is no need to concern for the results above. The larger and closer sample size for each group, the better for analysis.
- 6. (a) Let the Y_i denotes the GPA on the *i*-th row, $\mathbb{1}_{\text{play},i}$ indicator variable denoting whether play games or not. $\mathbb{1}_{A,i}\&\mathbb{1}_{A+,i}\&\mathbb{1}_{B,i}$ denoting the expected grade, then:

$$Y_i = \beta_0 + \beta_1 \mathbbm{1}_{\text{play},i} + \beta_2 \mathbbm{1}_{A,i} + \beta_3 \mathbbm{1}_{A+,i} + \beta_4 \mathbbm{1}_{B,i} + \beta_5 \mathbbm{1}_{\text{play},i} \times \mathbbm{1}_{A,i} + \beta_6 \mathbbm{1}_{\text{play},i} \times \mathbbm{1}_{A+,i} + \beta_7 \mathbbm{1}_{\text{play},i} \times \mathbbm{1}_{B,i} + \epsilon_i \mathbbm{1}_{A+,i} + \beta_6 \mathbbm{1}_{\text{play},i} \times \mathbbm{1}_{A+,i} + \beta_7 \mathbbm{1}_{\text{play},i} \times \mathbbm{1}_{A+,i} \times \mathbbm1}_{A+,i} \times \mathbbm1_{A+,$$

- (b) The total number of predictors increases since two-way anova also includes the independent factor as predictors along with interaction term.
- (c) The null hypothesis for F-test is

$$H_0: \beta_1 = \beta_2 = ... = \beta_{\text{df model}}$$

which implies non of the factors contribute to the response variable in the general linear model.

Since results from question 4 implies that there is significant difference of mean between a subset of groups, this implies that some predictor variable in question 4 does affect GPA in a statistical significant way, which implies that the for sure a subset of β 's will differ from each other, thus the F-test will be statistically significant to reject the null hypothesis.

7. When using **Play** as a quantitative explanatory variable, one wants to find if the change of play time affect GPA; That is, if y is the GPA and x as a quantitative explanatory variable that denotes play time, one can check the statistical significance of β 's in a linear model:

$$y_i = \beta_1 + \beta_2 x_i + \beta_3 z_i + \dots + \epsilon_i$$

When as a factor in an additive model, play is treated as categorical factor that one only whether play games or not have an effect on GPA is investigated.

That is, **Play** is used as an indicator variable $\mathbb{1}_{\text{play}}$, with a hypothesis that the coefficient of this indicator variable $\beta_i = 0$, and thus will only have a treatment effect of the value β_i , which can possiblly shift response variable vertically.

8. The following indicator variable can potentially influence GPA: Let $\mathbbm{1}_g$ denote whether a student wear a glasses or not, with two levels: 0 - do not wear, 1 - wear. $\mathbbm{1}_f$ denote if a student is in a relationship, also with two levels: 0 - no, and 1 - yes.

Appendix:

```
1. > par(mfrow=c(1,3))
  > boxplot(gpa~Player, main = 'GPA between players and non players',
  names=c("non players","players"))
  > boxplot(gpa~Grade, main = 'GPA by expected grade')
  > boxplot(gpa~Glay, main = 'GPA among factor Glay')
2. > np = data[which(Play == 0),]
  > p = data[which(Play > 0),]
  > t.test(p$GPA, np$GPA)
          Welch Two Sample t-test
  data: p$GPA and np$GPA
  t = -1.1831, df = 187.34, p-value = 0.2383
  alternative hypothesis: true difference in means is not equal to 0
  95 percent confidence interval:
   -0.21561458 0.05394441
  sample estimates:
  mean of x mean of y
   3.001689 3.082524
3. > aov(gpa~Grade)
  Call:
     aov(formula = gpa ~ Grade)
  Terms:
                      Grade Residuals
  Sum of Squares
                   34.86739 115.36960
  Deg. of Freedom
                                  396
  Residual standard error: 0.5397568
  Estimated effects may be unbalanced
  > result = aov(gpa~Grade)
  > summary(result)
               Df Sum Sq Mean Sq F value Pr(>F)
  Grade
                2 34.87 17.434
                                  59.84 <2e-16 ***
  Residuals 396 115.37 0.291
  Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '. 0.1 ' 1
```

```
> pairwise.t.test(gpa, grade, p.adj = "bonf")
          Pairwise comparisons using t tests with pooled SD
  data: gpa and grade
     Α
             A+
  A+ 1.8e-07 -
  B 2.6e-11 < 2e-16
  P value adjustment method: bonferroni
4. > rGlay = aov(gpa~Glay)
  > summary(rGlay)
              Df Sum Sq Mean Sq F value Pr(>F)
               5 37.15
                          7.431
  Glay
                                  25.82 <2e-16 ***
             393 113.08
                          0.288
  Residuals
  Signif. codes: 0 '***, 0.001 '**, 0.01 '*, 0.05 '., 0.1 ', 1
  > TukeyHSD(rGlay, conf.level = 0.95)
    Tukey multiple comparisons of means
      95% family-wise confidence level
  Fit: aov(formula = gpa ~ Glay)
  $Glay
                               diff
                                             lwr
                                                        upr
                                                                p adj
  NonplayerAP-NonplayerA
                          NonplayerNA-NonplayerA -0.4441548 -0.816898923 -0.07141058 0.0092179
  PlayerA-NonplayerA
                         -0.1510952 -0.420523778 0.11833332 0.5950421
  PlayerAP-NonplayerA
                          0.3063342 0.001730383 0.61093798 0.0477882
  PlayerNA-NonplayerA
                         -0.6405149 -0.941076726 -0.33995308 0.0000000
  NonplayerNA-NonplayerAP -0.5667712 -0.957785463 -0.17575686 0.0005766
  PlayerA-NonplayerAP
                         -0.2737116 -0.567898161 0.02047488 0.0848409
                          0.1837178 -0.142989193 0.51042474 0.5921294
  PlayerAP-NonplayerAP
                         -0.7631313 -1.086073067 -0.44018956 0.0000000
  PlayerNA-NonplayerAP
                         0.2930595 -0.017439629 0.60355867 0.0768963
  PlayerA-NonplayerNA
  PlayerAP-NonplayerNA
                         0.7504889 0.409019383 1.09195849 0.0000000
  PlayerNA-NonplayerNA
                         -0.1963602 -0.534229046 0.14150874 0.5562541
  PlayerAP-PlayerA
                         0.4574294 0.233253189 0.68160564 0.0000002
                         -0.4894197 -0.708072168 -0.27076718 0.0000000
  PlayerNA-PlayerA
  PlayerNA-PlayerAP
                         -0.9468491 -1.207618423 -0.68607975 0.0000000
5. > bartlett.test(gpa~Glay)
          Bartlett test of homogeneity of variances
  data: gpa by Glay
  Bartlett's K-squared = 1.8885, df = 5, p-value = 0.8644
  # for the qq-plot:
  > plot(lm(gpa~Glay), which = 2)
```