final

2025-12-06

Setup

```
# Load packages
library(dplyr)
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(ggplot2)
```

Data loading

```
# read math dataset (395 students, 33 vars)
dat <- read.csv("student-mat.csv", sep = ";")
str(dat) # inspect structure and variable types
```

```
## 'data.frame':    395 obs. of  33 variables:
##  $ school    : chr  "GP" "GP" "GP" "GP" ...
##  $ sex       : chr  "F" "F" "F" "F" ...
##  $ age       : int  18 17 15 15 16 16 16 17 15 15 ...
##  $ address   : chr  "U" "U" "U" "U" ...
##  $ famsize   : chr  "GT3" "GT3" "LE3" "GT3" ...
##  $ Pstatus   : chr  "A" "T" "T" "T" ...
##  $ Medu      : int  4 1 1 4 3 4 2 4 3 3 ...
##  $ Fedu      : int  4 1 1 2 3 3 2 4 2 4 ...
##  $ Mjob      : chr  "at_home" "at_home" "at_home" "health" ...
##  $ Fjob      : chr  "teacher" "other" "other" "services" ...
##  $ reason    : chr  "course" "course" "other" "home" ...
##  $ guardian  : chr  "mother" "father" "mother" "mother" ...
##  $ traveltime: int  2 1 1 1 1 1 1 2 1 1 ...
##  $ studytime : int  2 2 2 3 2 2 2 2 2 2 ...
##  $ failures  : int  0 0 3 0 0 0 0 0 0 0 ...
##  $ schoolsup : chr  "yes" "no" "yes" "no" ...
##  $ famsup    : chr  "no" "yes" "no" "yes" ...
##  $ paid      : chr  "no" "no" "yes" "yes" ...
##  $ activities: chr  "no" "no" "no" "yes" ...
##  $ nursery   : chr  "yes" "no" "yes" "yes" ...
```

```
##  $ higher    : chr  "yes" "yes" "yes" "yes" ...
##  $ internet  : chr  "no" "yes" "yes" "yes" ...
##  $ romantic  : chr  "no" "no" "no" "yes" ...
##  $ famrel    : int  4 5 4 3 4 5 4 4 4 5 ...
##  $ freetime  : int  3 3 3 2 3 4 4 1 2 5 ...
##  $ goout     : int  4 3 2 2 2 2 4 4 2 1 ...
##  $ Dalc      : int  1 1 2 1 1 1 1 1 1 1 ...
##  $ Walc      : int  1 1 3 1 2 2 1 1 1 1 ...
##  $ health    : int  3 3 3 5 5 5 3 1 1 5 ...
##  $ absences  : int  6 4 10 2 4 10 0 6 0 0 ...
##  $ G1        : int  5 5 7 15 6 15 12 6 16 14 ...
##  $ G2        : int  6 5 8 14 10 15 12 5 18 15 ...
##  $ G3        : int  6 6 10 15 10 15 11 6 19 15 ...
```

Data preprocessing

The data is pretty clean actually from visual inspection, we just need to cast certain variables into categorical with factor().

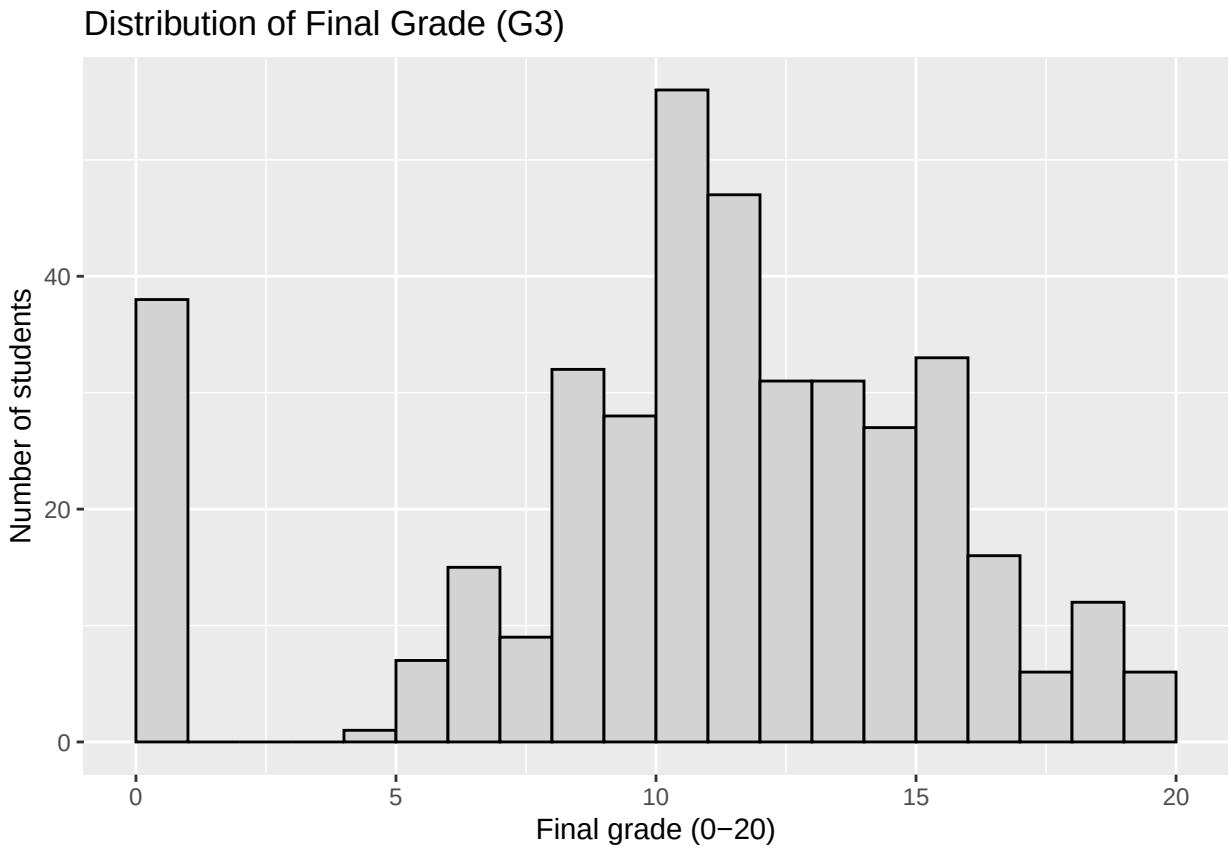
```r
# Convert character/binary variables to factors and recode studytime as an ordered factor
dat <- dat %>%
  mutate(
    # Core categorical variables
    school    = factor(school),
    sex       = factor(sex),
    address   = factor(address),
    famsize   = factor(famsize),
    Pstatus   = factor(Pstatus),

    # Jobs & reasons
    Mjob      = factor(Mjob),
    Fjob      = factor(Fjob),
    reason    = factor(reason),
    guardian  = factor(guardian),

    # Supports and activities
    schoolsup = factor(schoolsup),
    famsup    = factor(famsup),
    paid      = factor(paid),
    activities= factor(activities),
    nursery   = factor(nursery),
    higher    = factor(higher),
    internet  = factor(internet),
    romantic  = factor(romantic),

    # Study time as ordered-ish factor
    studytime = factor(
      studytime,
      levels = 1:4,
      labels = c("low", "moderate", "high", "very high")
    )
  )

str(dat)
```

```
## 'data.frame':    395 obs. of  33 variables:
##  $ school    : Factor w/ 2 levels "GP","MS": 1 1 1 1 1 1 1 1 1 1 ...
##  $ sex       : Factor w/ 2 levels "F","M": 1 1 1 1 1 2 2 1 2 2 ...
##  $ age       : int  18 17 15 15 16 16 16 17 15 15 ...
##  $ address   : Factor w/ 2 levels "R","U": 2 2 2 2 2 2 2 2 2 2 ...
##  $ famsize   : Factor w/ 2 levels "GT3","LE3": 1 1 2 1 1 2 2 1 2 1 ...
##  $ Pstatus   : Factor w/ 2 levels "A","T": 1 2 2 2 2 2 2 1 1 2 ...
##  $ Medu      : int  4 1 1 4 3 4 2 4 3 3 ...
##  $ Fedu      : int  4 1 1 2 3 3 2 4 2 4 ...
##  $ Mjob      : Factor w/ 5 levels "at_home","health",..: 1 1 1 2 3 4 3 3 4 3 ...
##  $ Fjob      : Factor w/ 5 levels "at_home","health",..: 5 3 3 4 3 3 3 5 3 3 ...
##  $ reason    : Factor w/ 4 levels "course","home",..: 1 1 3 2 2 4 2 2 2 2 ...
##  $ guardian  : Factor w/ 3 levels "father","mother",..: 2 1 2 2 1 2 2 2 2 2 ...
##  $ traveltime: int  2 1 1 1 1 1 1 2 1 1 ...
##  $ studytime : Factor w/ 4 levels "low","moderate",..: 2 2 2 3 2 2 2 2 2 2 ...
##  $ failures  : int  0 0 3 0 0 0 0 0 0 0 ...
##  $ schoolsup : Factor w/ 2 levels "no","yes": 2 1 2 1 1 1 1 2 1 1 ...
##  $ famsup    : Factor w/ 2 levels "no","yes": 1 2 1 2 2 2 1 2 2 2 ...
##  $ paid      : Factor w/ 2 levels "no","yes": 1 1 2 2 2 2 1 1 2 2 ...
##  $ activities: Factor w/ 2 levels "no","yes": 1 1 1 2 1 2 1 1 1 2 ...
##  $ nursery   : Factor w/ 2 levels "no","yes": 2 1 2 2 2 2 2 2 2 2 ...
##  $ higher    : Factor w/ 2 levels "no","yes": 2 2 2 2 2 2 2 2 2 2 ...
##  $ internet  : Factor w/ 2 levels "no","yes": 1 2 2 2 1 2 2 1 2 2 ...
##  $ romantic  : Factor w/ 2 levels "no","yes": 1 1 1 2 1 1 1 1 1 1 ...
##  $ famrel    : int  4 5 4 3 4 5 4 4 4 5 ...
##  $ freetime  : int  3 3 3 2 3 4 4 1 2 5 ...
##  $ goout     : int  4 3 2 2 2 2 4 4 2 1 ...
##  $ Dalc      : int  1 1 2 1 1 1 1 1 1 1 ...
##  $ Walc      : int  1 1 3 1 2 2 1 1 1 1 ...
##  $ health    : int  3 3 3 5 5 5 3 1 1 5 ...
##  $ absences  : int  6 4 10 2 4 10 0 6 0 0 ...
##  $ G1        : int  5 5 7 15 6 15 12 6 16 14 ...
##  $ G2        : int  6 5 8 14 10 15 12 5 18 15 ...
##  $ G3        : int  6 6 10 15 10 15 11 6 19 15 ...
```

Exploratory Data Analysis

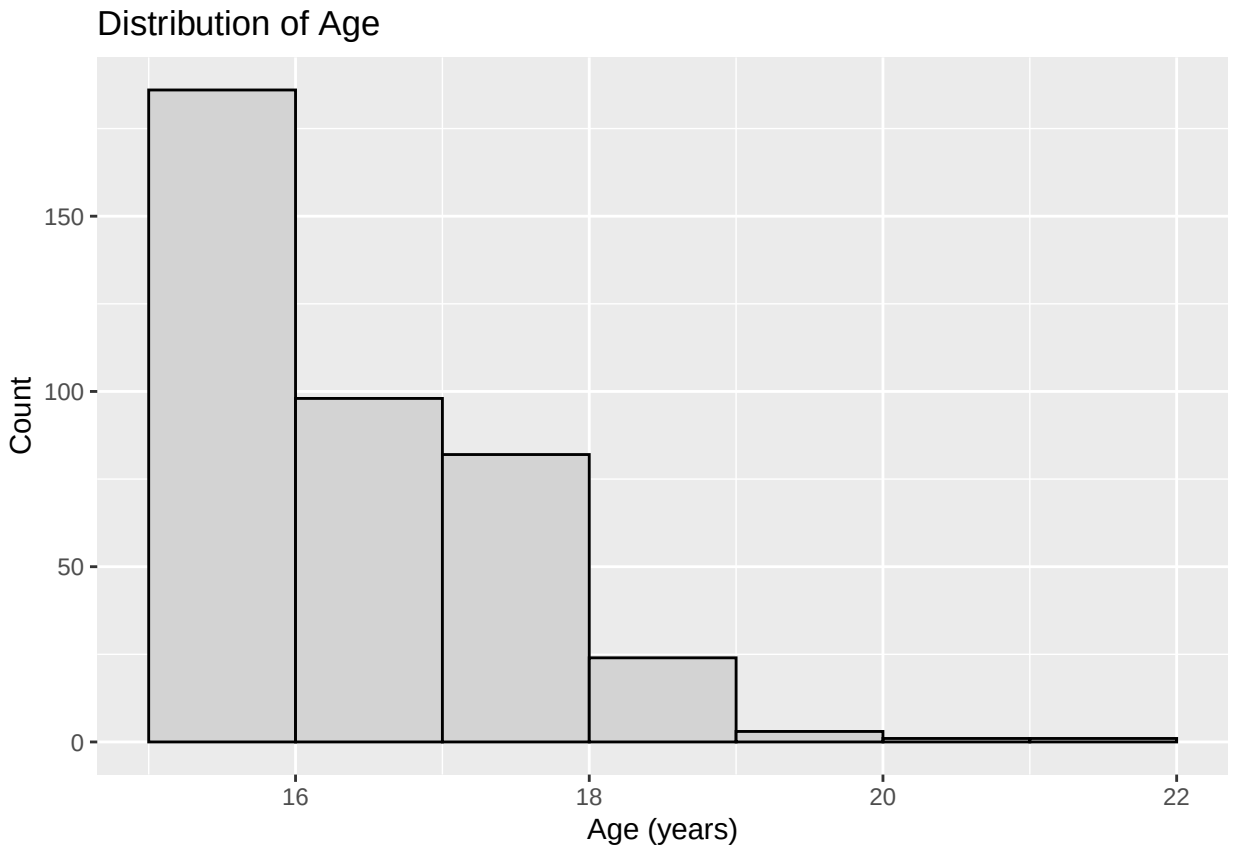
Now we move onto inspecting the data and seeing how different variables look. Firstly, let's look at the grade distribution for the final math grade:

```
ggplot(dat, aes(x = G3)) +
  geom_histogram(binwidth = 1, boundary = 0, closed = "left", color = "black", fill = "lightgray") +
  labs(
    title = "Distribution of Final Grade (G3)",
    x = "Final grade (0-20)",
    y = "Number of students"
  )
```

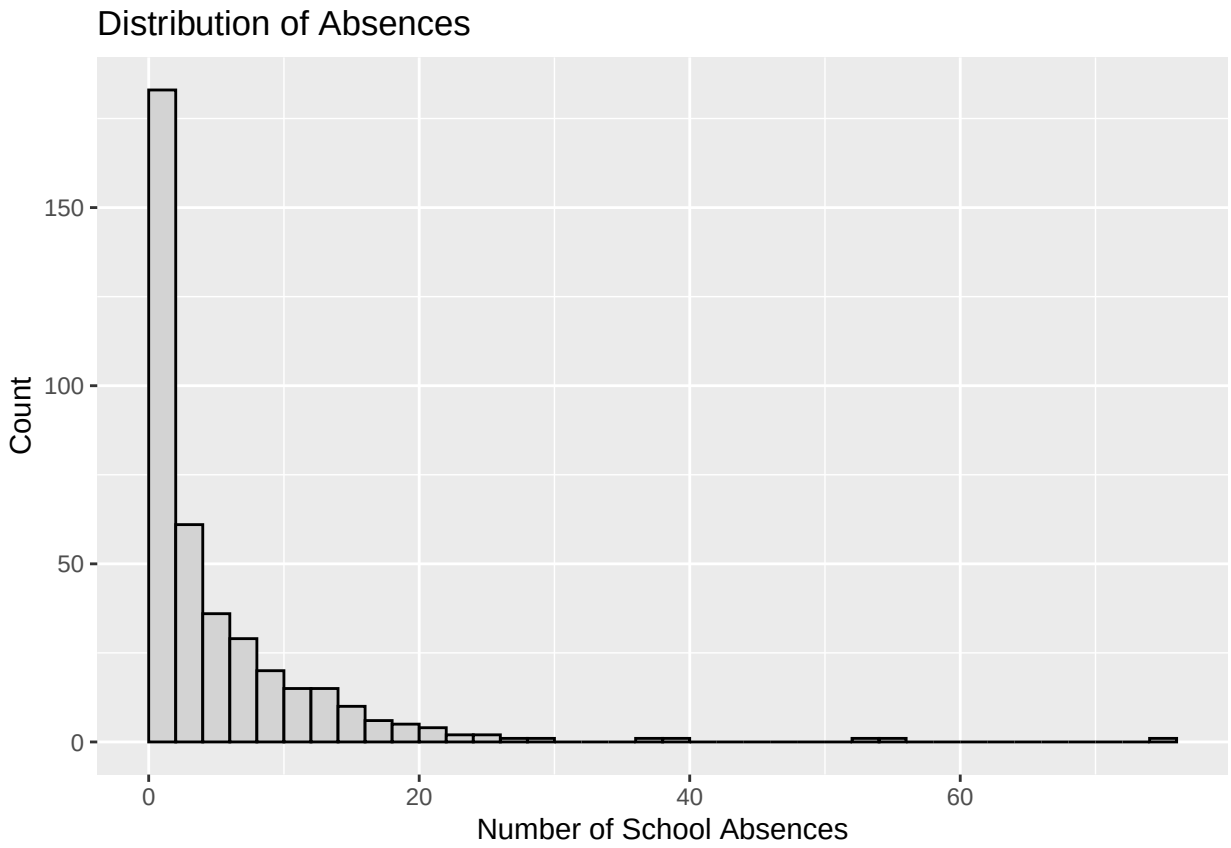


Observing distributions of some numeric variables like age, absences, failures.

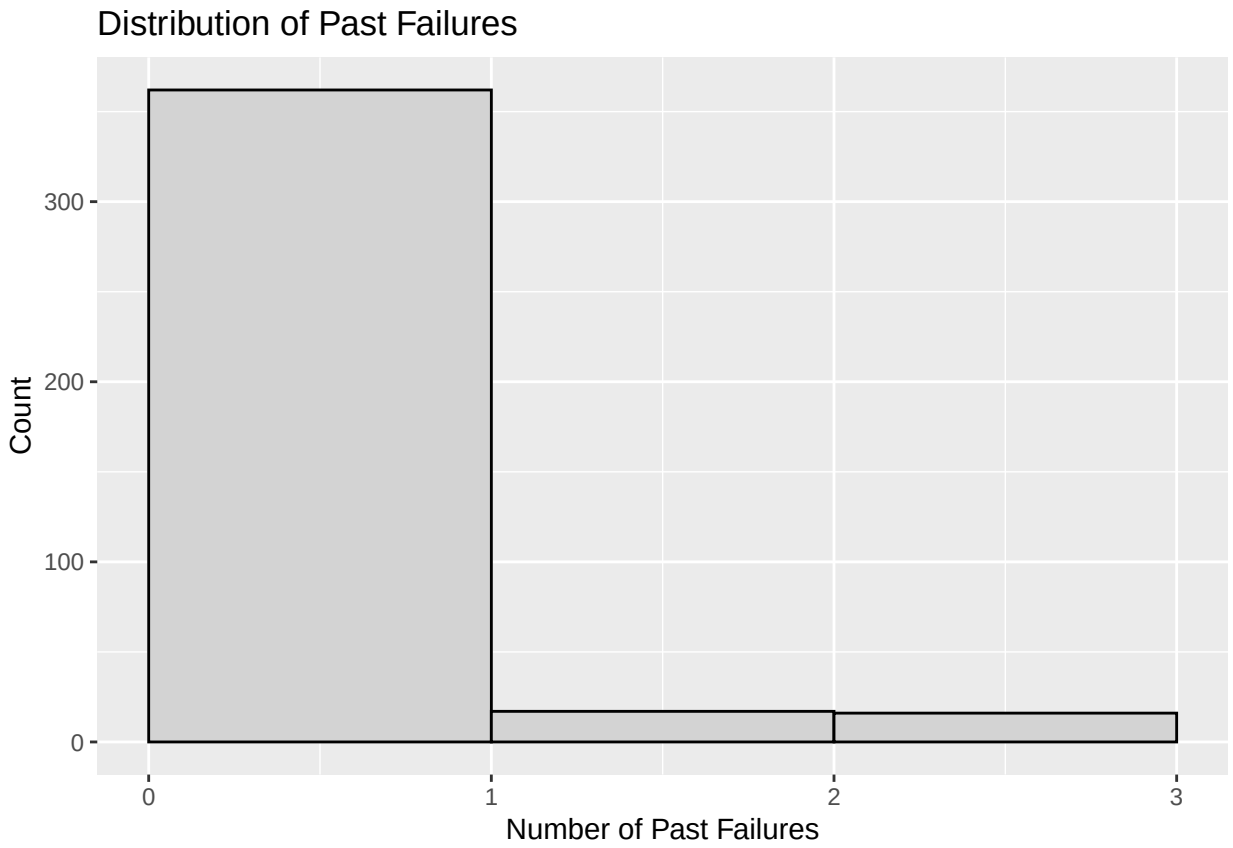
```
ggplot(dat, aes(x = age)) +
  geom_histogram(
    binwidth = 1,
    boundary = 0,
    color = "black",
    fill = "lightgray"
  ) +
  labs(
    title = "Distribution of Age",
    x = "Age (years)",
    y = "Count"
  )
```




```
ggplot(dat, aes(x = absences)) +
  geom_histogram(
    binwidth = 2,
    boundary = 0,
    color = "black",
    fill = "lightgray"
  ) +
  labs(
    title = "Distribution of Absences",
    x = "Number of School Absences",
    y = "Count"
  )
```



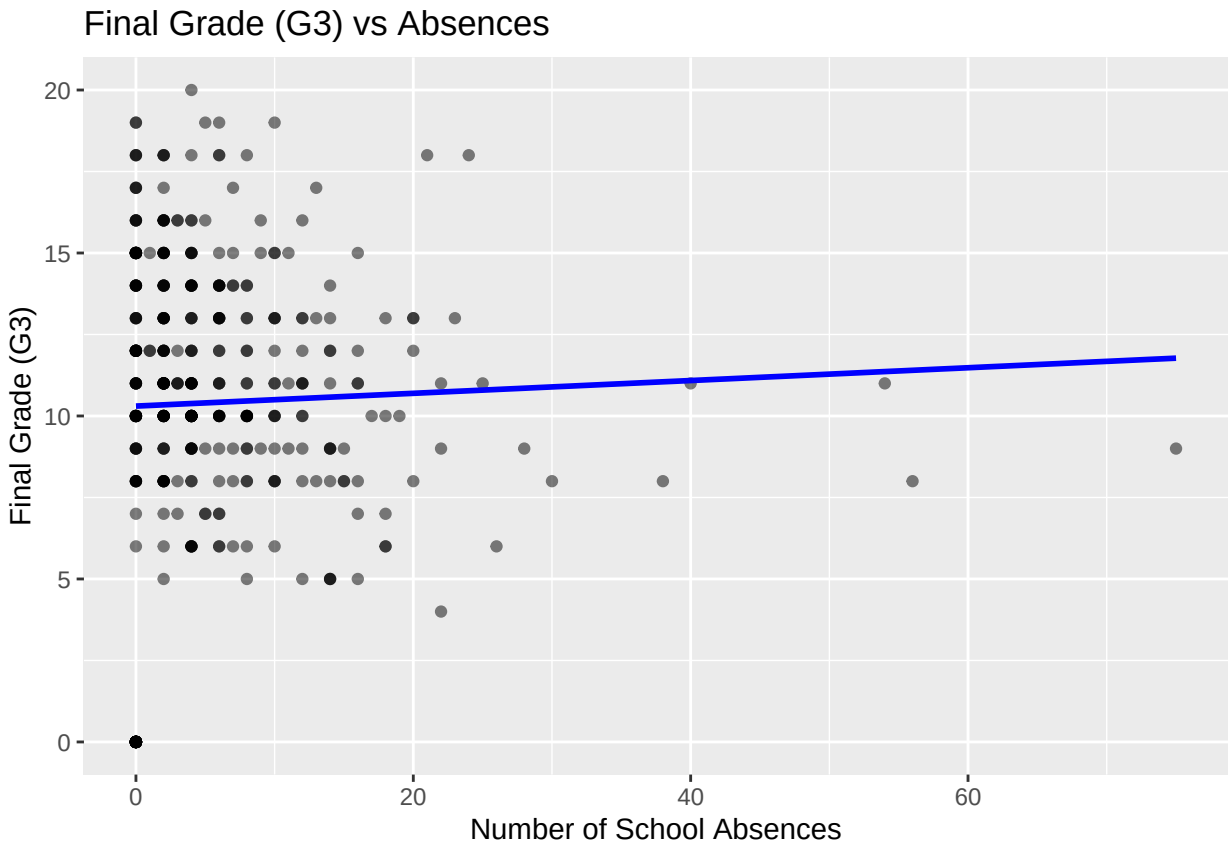

```
ggplot(dat, aes(x = failures)) +
  geom_histogram(
    binwidth = 1,
    boundary = 0,
    color = "black",
    fill = "lightgray"
  ) +
  labs(
    title = "Distribution of Past Failures",
    x = "Number of Past Failures",
    y = "Count"
  )
```



Now to contrast the final grade with some of the variables of interest.

```
ggplot(dat, aes(x = absences, y = G3)) +
  geom_point(alpha = 0.5) +
  geom_smooth(method = "lm", se = FALSE, color = "blue") +
  labs(
    title = "Final Grade (G3) vs Absences",
    x = "Number of School Absences",
    y = "Final Grade (G3)"
  )
```

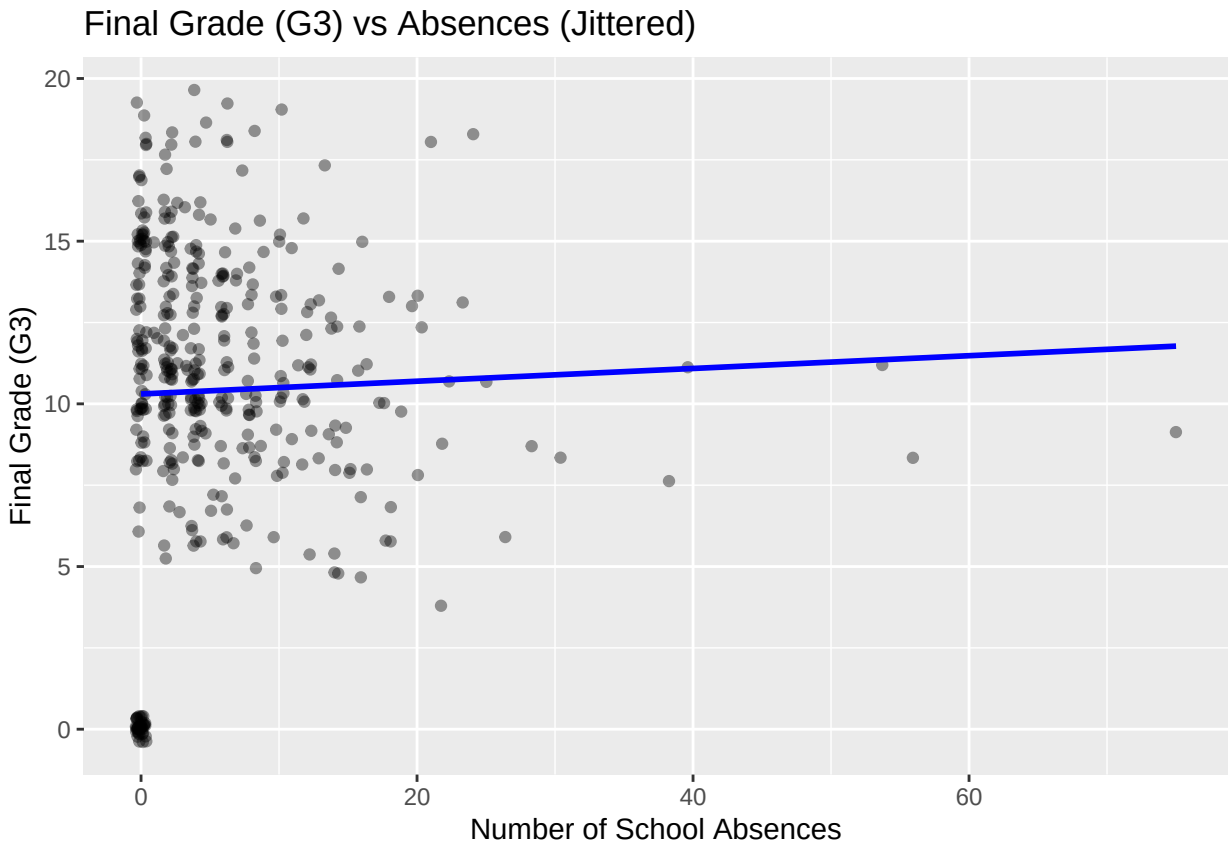
```
## `geom_smooth()` using formula = 'y ~ x'
```



Adding some jitter for a better visual understanding of the quantity of different data points.

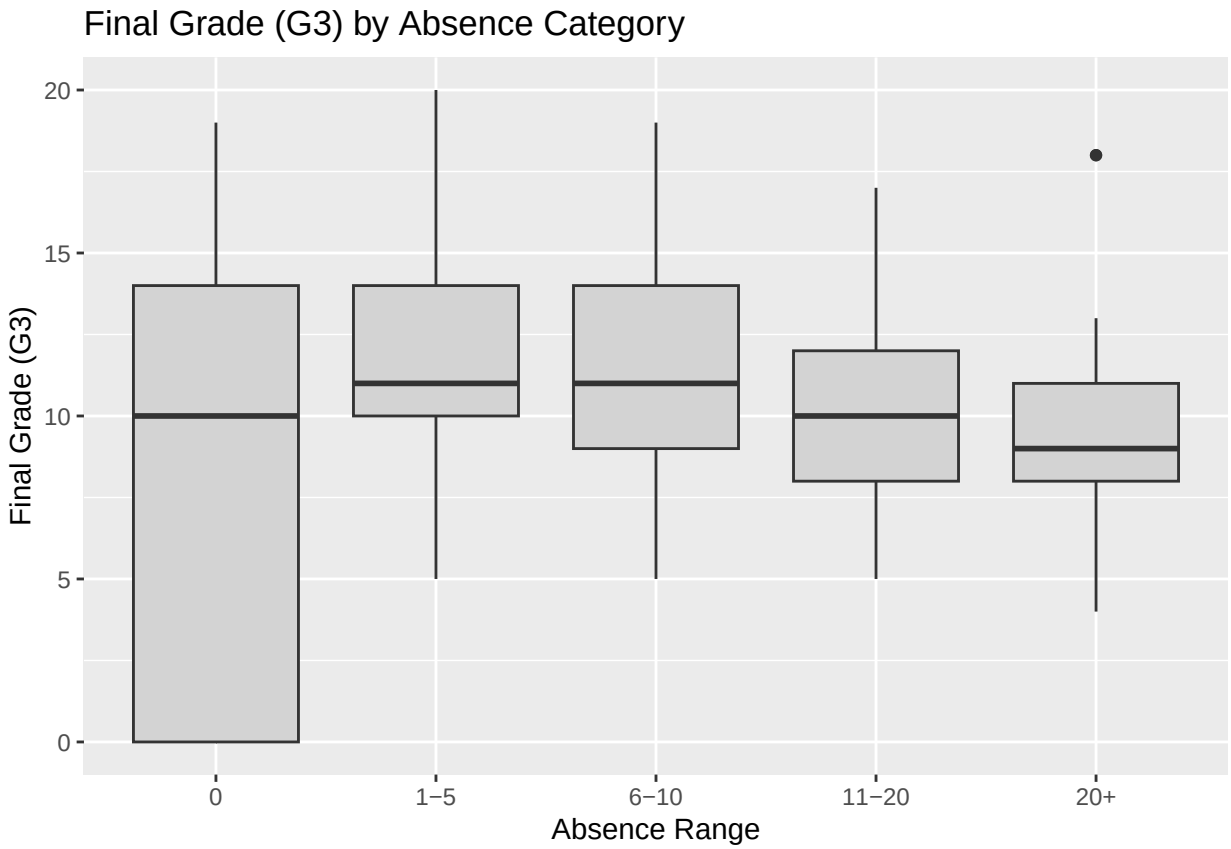
```
ggplot(dat, aes(x = absences, y = G3)) +
  geom_jitter(width = 0.4, alpha = 0.4) +
  geom_smooth(method = "lm", se = FALSE, color = "blue") +
  labs(
    title = "Final Grade (G3) vs Absences (Jittered)",
    x = "Number of School Absences",
    y = "Final Grade (G3)"
  )
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



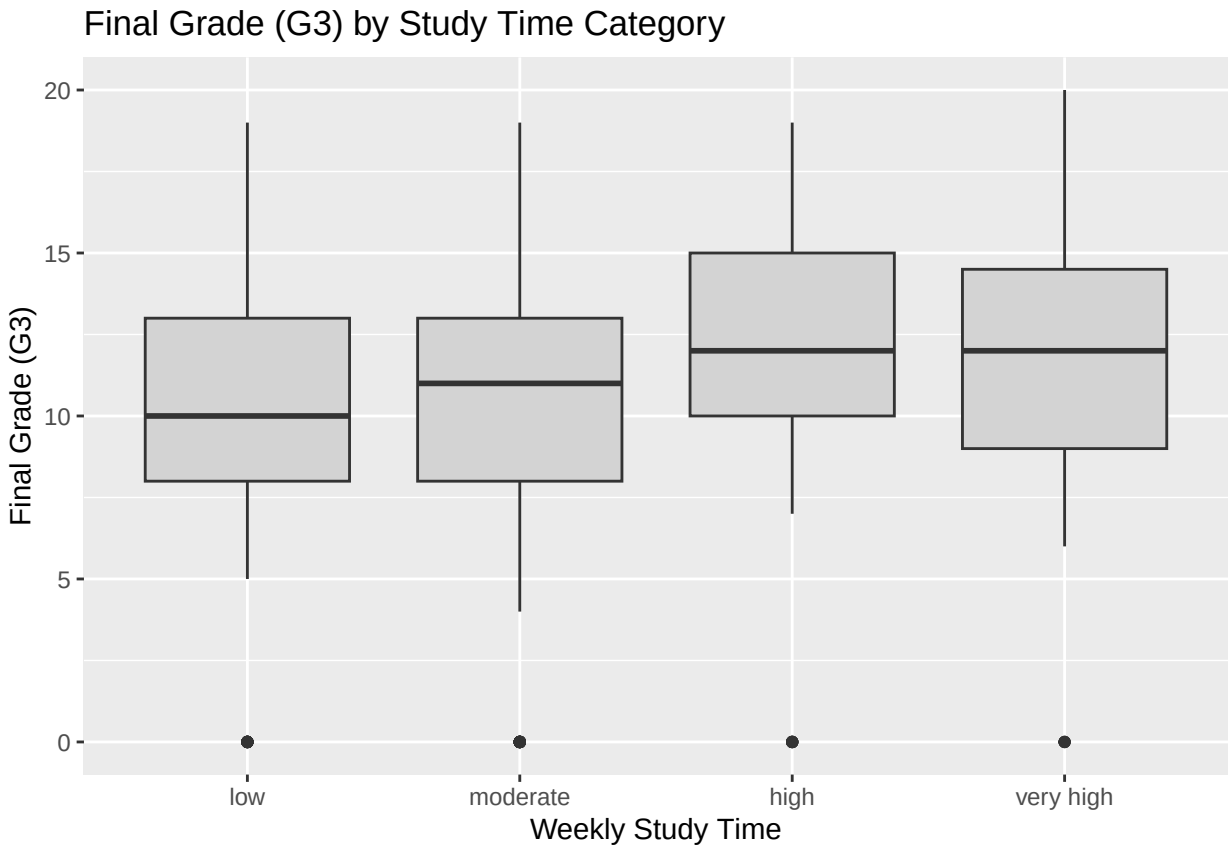
We can also visually show the disparities between different categorical groups with a box plot.

```
# create categorical absence bins for boxplot comparison
dat <- dat %>%
  mutate(abs_bin = cut(
    absences,
    breaks = c(-1, 0, 5, 10, 20, 100),
    labels = c("0", "1-5", "6-10", "11-20", "20+")
  ))

ggplot(dat, aes(x = abs_bin, y = G3)) +
  geom_boxplot(fill = "lightgray") +
  labs(
    title = "Final Grade (G3) by Absence Category",
    x = "Absence Range",
    y = "Final Grade (G3)"
  )
```

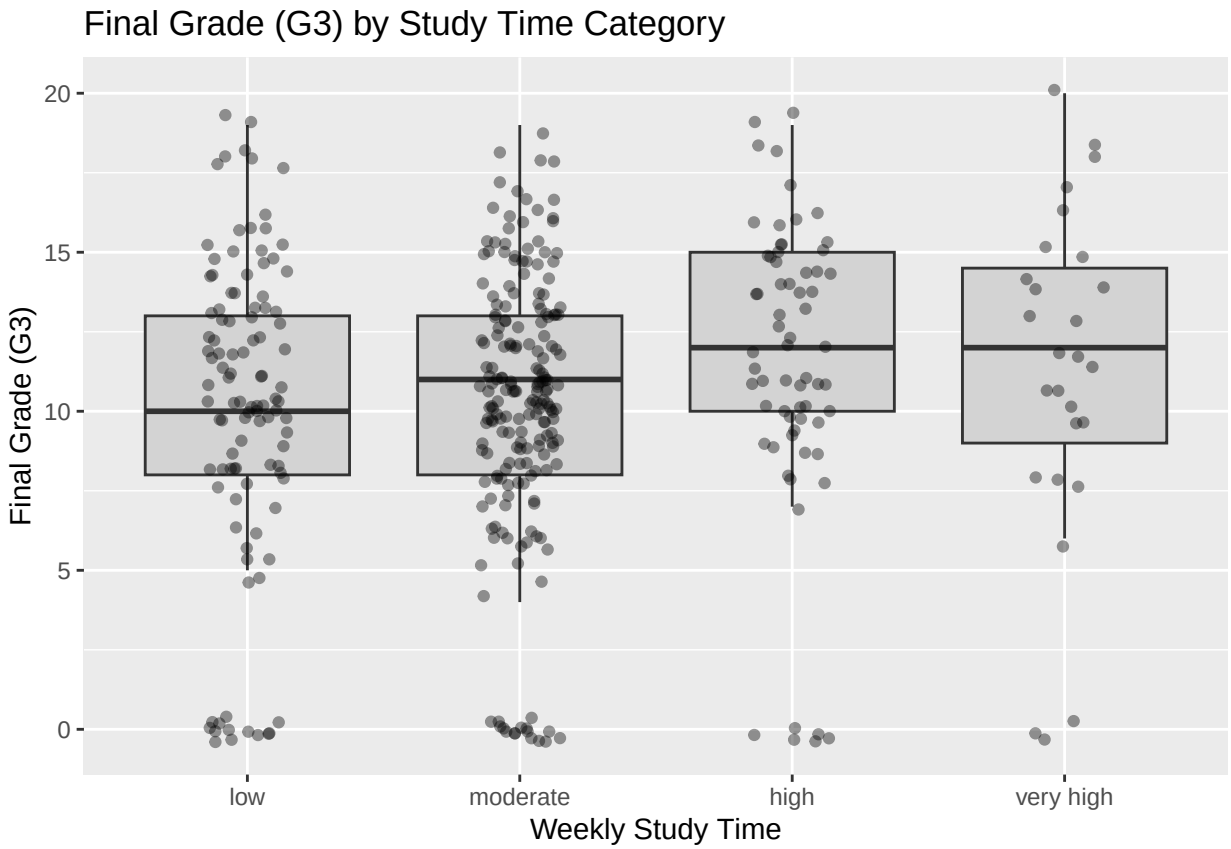


Let's look at other variables like study time:

```
# Normal box plot
ggplot(dat, aes(x = studytime, y = G3)) +
  geom_boxplot(fill = "lightgray") +
  labs(
    title = "Final Grade (G3) by Study Time Category",
    x = "Weekly Study Time",
    y = "Final Grade (G3)"
  )
```

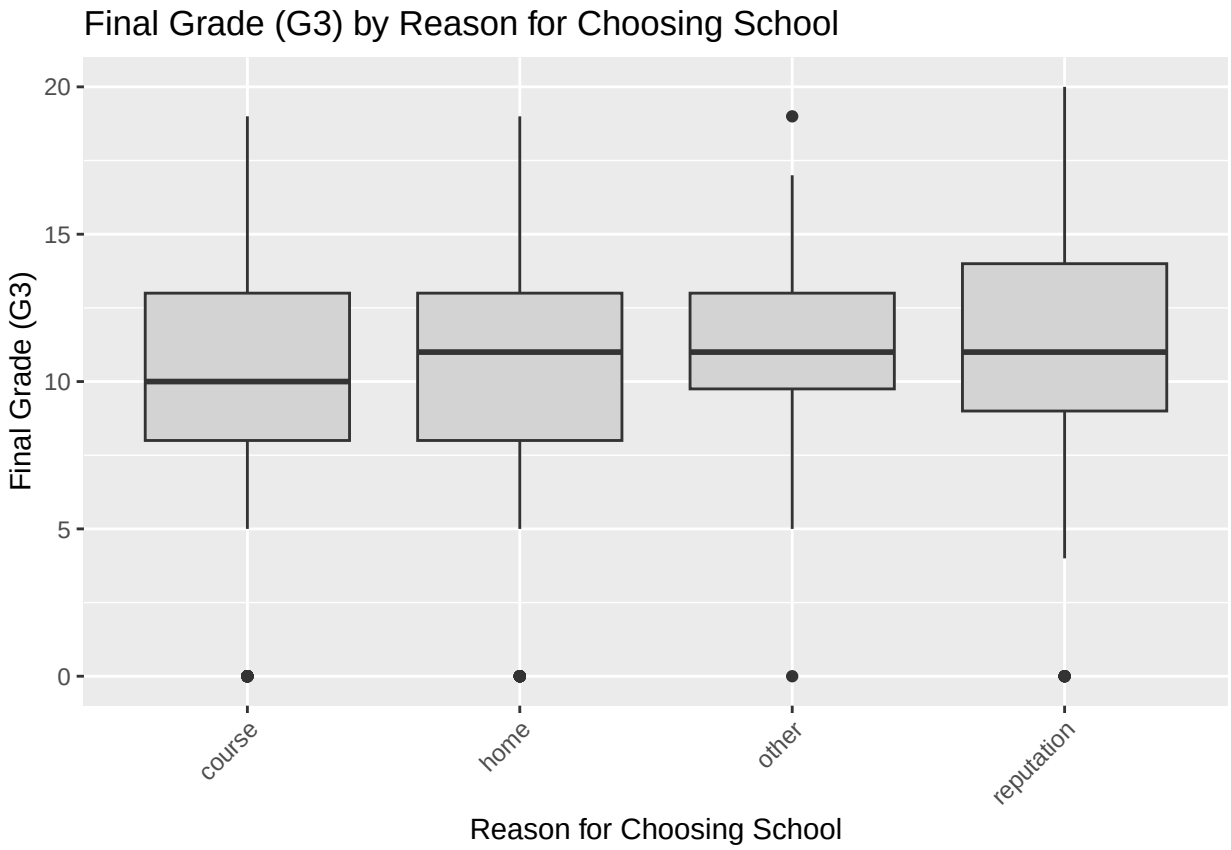



```
# Box plot including the jittered data points overlaid
ggplot(dat, aes(x = studytime, y = G3)) +
  geom_boxplot(fill = "lightgray", outlier.shape = NA) +
  geom_jitter(width = 0.15, alpha = 0.4) +
  labs(
    title = "Final Grade (G3) by Study Time Category",
    x = "Weekly Study Time",
    y = "Final Grade (G3)"
  )
```



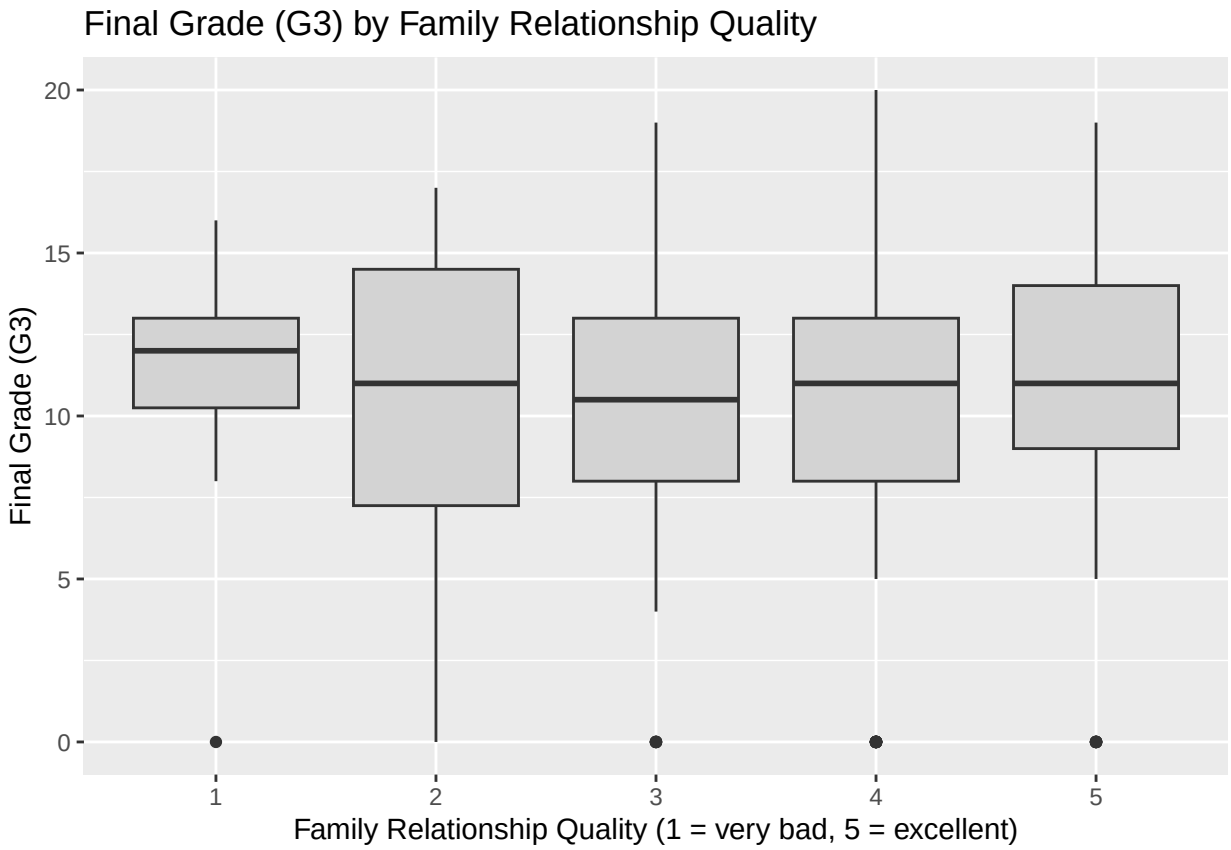
And also variables like reason for doing school:

```
ggplot(dat, aes(x = reason, y = G3)) +
  geom_boxplot(fill = "lightgray") +
  labs(
    title = "Final Grade (G3) by Reason for Choosing School",
    x = "Reason for Choosing School",
    y = "Final Grade (G3)"
  ) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



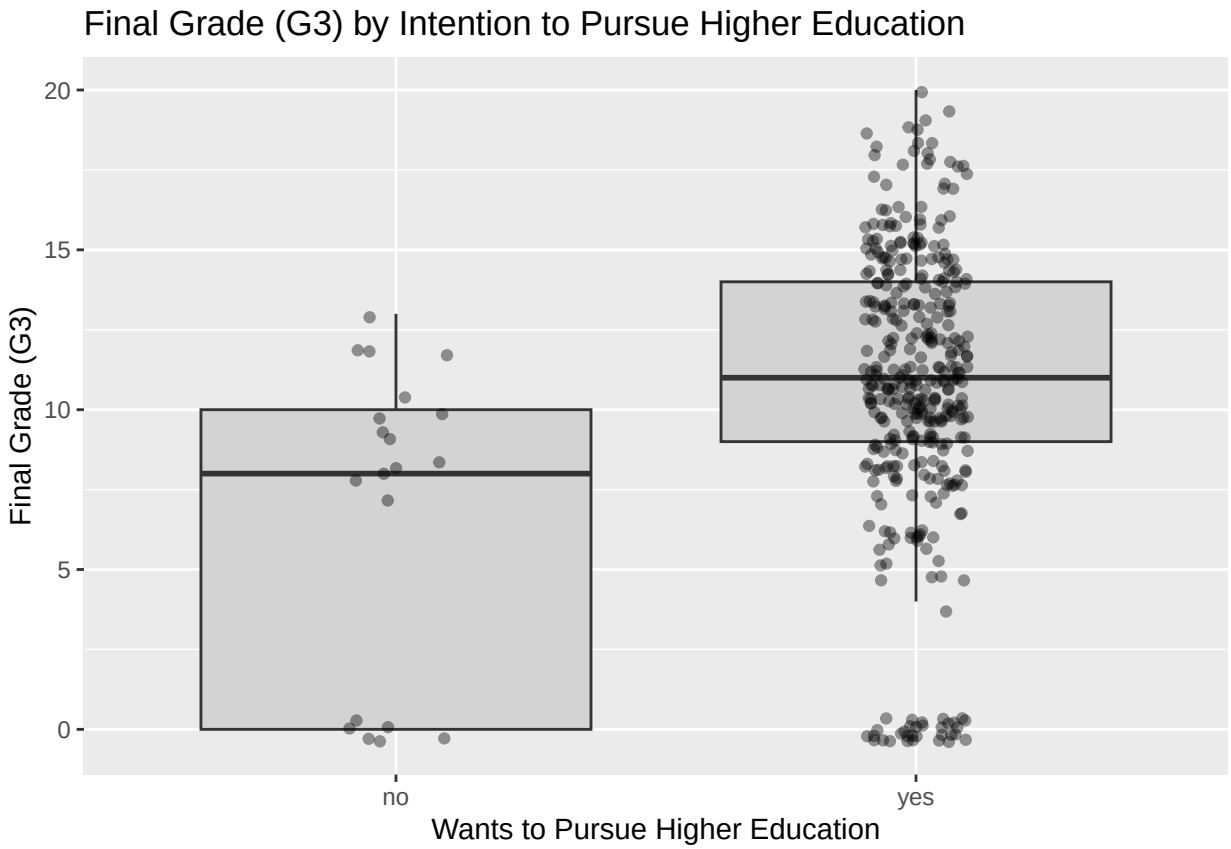
Family relations, rated from 0 (very bad) to 5 (excellent):

```
ggplot(dat, aes(x = factor(famrel), y = G3)) +
  geom_boxplot(fill = "lightgray") +
  labs(
    title = "Final Grade (G3) by Family Relationship Quality",
    x = "Family Relationship Quality (1 = very bad, 5 = excellent)",
    y = "Final Grade (G3)"
  )
```

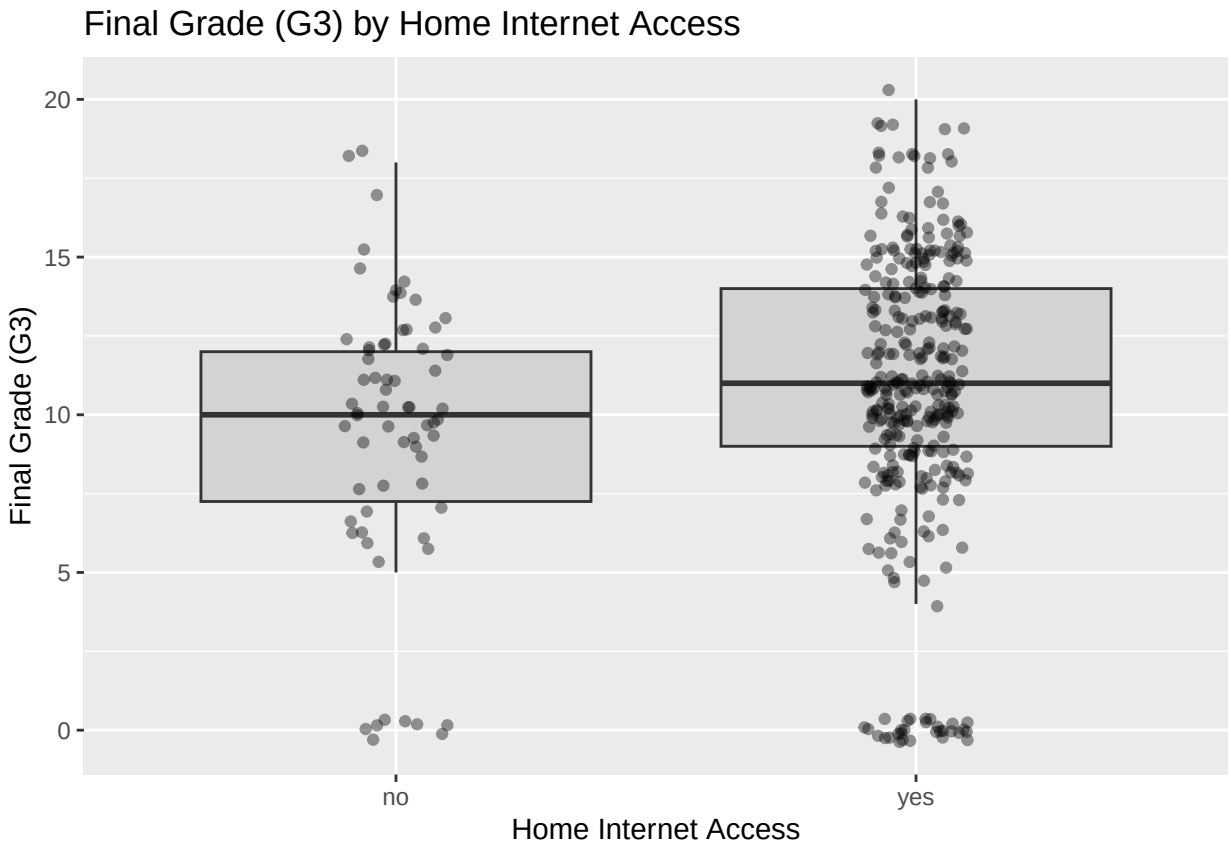


A few more binary variables of interest like whether they want to pursue higher education, Internet access, rural/urban, and whether they have a romantic relationship.

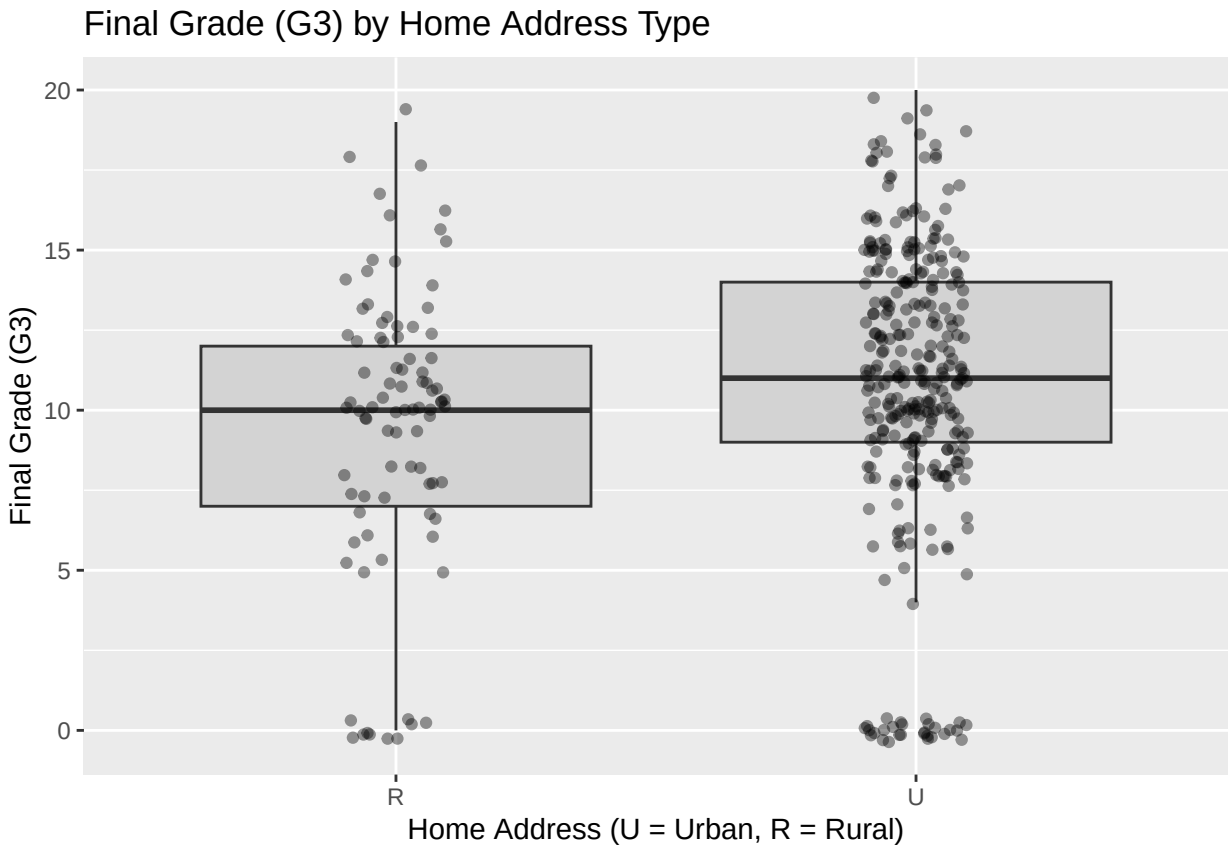
```
ggplot(dat, aes(x = higher, y = G3)) +
  geom_boxplot(fill = "lightgray", outlier.shape = NA) +
  geom_jitter(width = 0.1, alpha = 0.4) +
  labs(
    title = "Final Grade (G3) by Intention to Pursue Higher Education",
    x = "Wants to Pursue Higher Education",
    y = "Final Grade (G3)"
  )
```



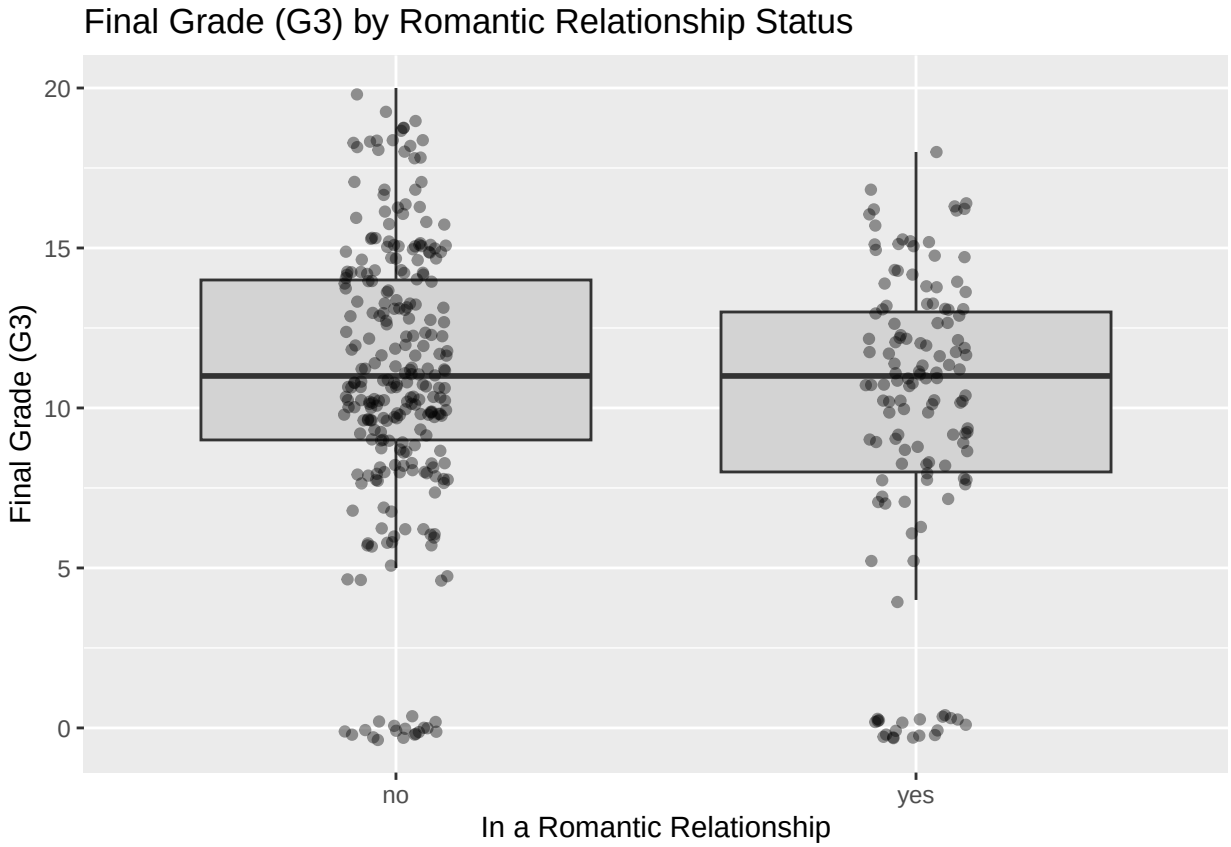

```
ggplot(dat, aes(x = internet, y = G3)) +
  geom_boxplot(fill = "lightgray", outlier.shape = NA) +
  geom_jitter(width = 0.1, alpha = 0.4) +
  labs(
    title = "Final Grade (G3) by Home Internet Access",
    x = "Home Internet Access",
    y = "Final Grade (G3)"
  )
```




```r
ggplot(dat, aes(x = address, y = G3)) +
  geom_boxplot(fill = "lightgray", outlier.shape = NA) +
  geom_jitter(width = 0.1, alpha = 0.4) +
  labs(
    title = "Final Grade (G3) by Home Address Type",
    x = "Home Address (U = Urban, R = Rural)",
    y = "Final Grade (G3)"
  )
```



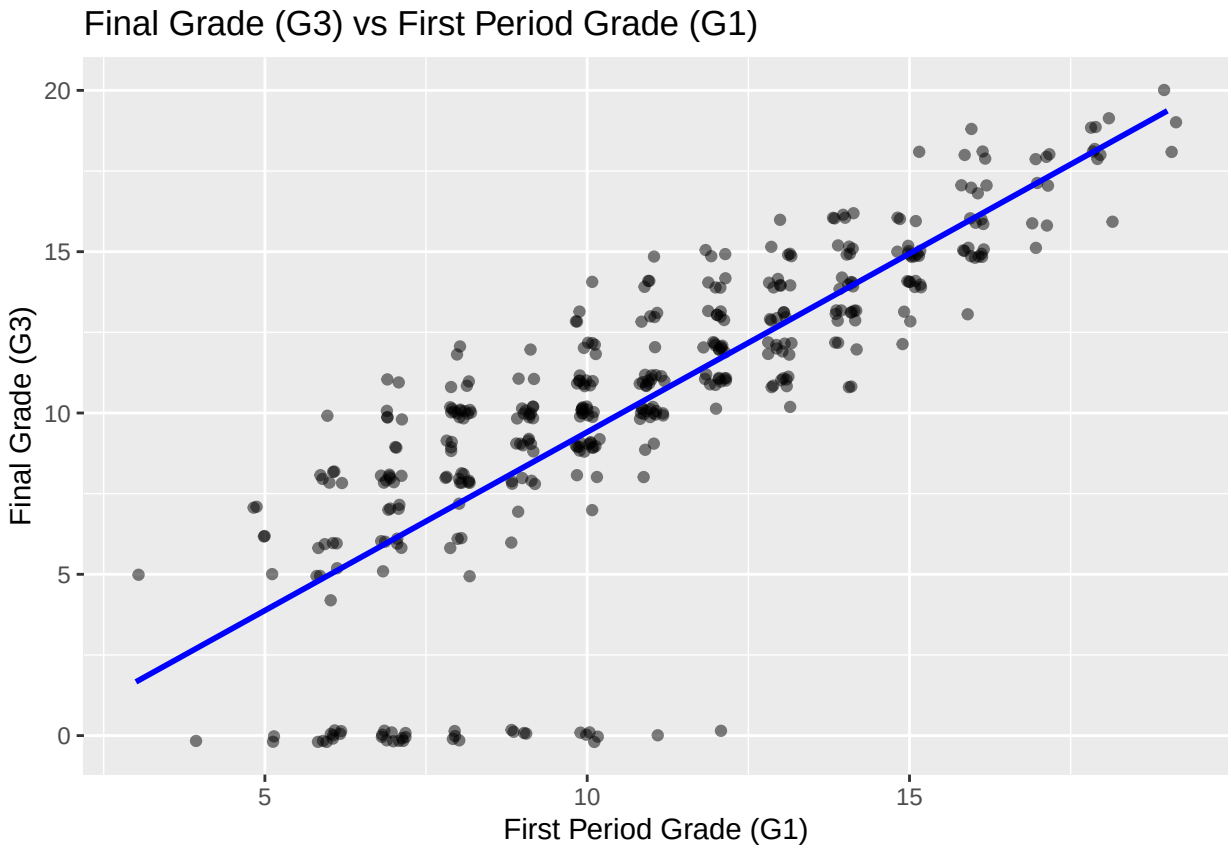

```
ggplot(dat, aes(x = romantic, y = G3)) +
  geom_boxplot(fill = "lightgray", outlier.shape = NA) +
  geom_jitter(width = 0.1, alpha = 0.4) +
  labs(
    title = "Final Grade (G3) by Romantic Relationship Status",
    x = "In a Romantic Relationship",
    y = "Final Grade (G3)"
  )
```



Also let's do a scatter plot analysis between G1/G2 and G3, because this is the few strictly numeric vs numeric comparisons we have:

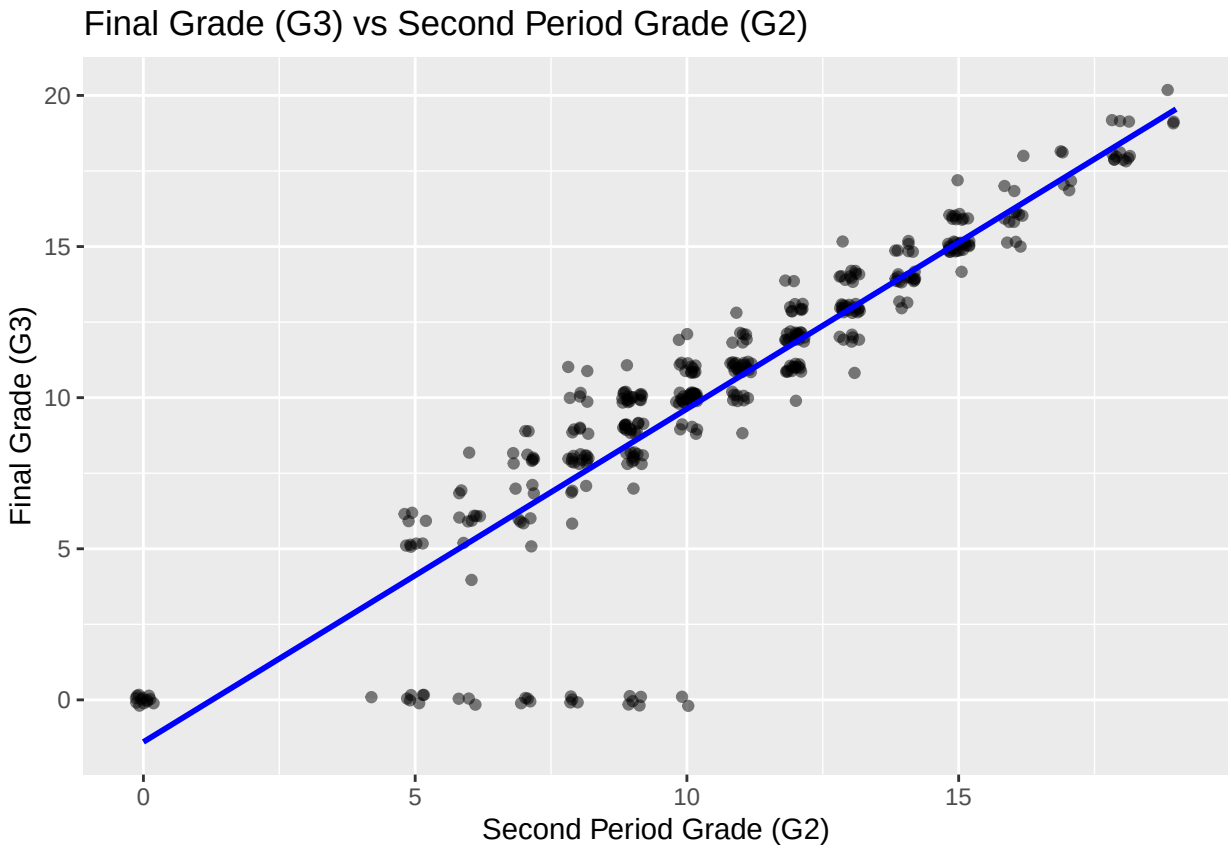
```
# Relationship between G3 and earlier period grades G1 and G2

ggplot(dat, aes(x = G1, y = G3)) +
  geom_jitter(width = 0.2, height = 0.2, alpha = 0.5) +
  geom_smooth(method = "lm", se = FALSE, color = "blue") +
  labs(
    title = "Final Grade (G3) vs First Period Grade (G1)",
    x = "First Period Grade (G1)",
    y = "Final Grade (G3)"
  )
```

```
## `geom_smooth()` using formula = 'y ~ x'
```




```
ggplot(dat, aes(x = G2, y = G3)) +
  geom_jitter(width = 0.2, height = 0.2, alpha = 0.5) +
  geom_smooth(method = "lm", se = FALSE, color = "blue") +
  labs(
    title = "Final Grade (G3) vs Second Period Grade (G2)",
    x = "Second Period Grade (G2)",
    y = "Final Grade (G3)"
  )
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



So it looks like we have many variables that do show pretty big gaps in performance between different categorical groups. Now let's turn to exploring some regressions to see if we can quantify these relationships with the final math grade.

Regressions

We'll reuse `dat` from above and fit several linear regression models

Model 1: Background and behavior only (no prior grades)

Here we first focus on non-grade predictors to see how demographics, family background, and behaviors relate to the final grade, without using G1 or G2.

```
# Model 1: background and behavior only (no prior grades)
# Goal: see how non-grade factors relate to G3 on their own

model1 <- lm(
  G3 ~ sex + age + Medu + Fedu +
    studytime + failures + absences +
    higher + goout + Walc + internet,
  data = dat
)

summary(model1)
```

```
##
## Call:
```

```
## lm(formula = G3 ~ sex + age + Medu + Fedu + studytime + failures +
##     absences + higher + goout + Walc + internet, data = dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -13.2241  -2.0116   0.4896   2.8137   8.7655
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         11.56584    3.42278   3.379 0.000802 ***
## sexM                 1.37284    0.47235   2.906 0.003870 **
## age                 -0.21051    0.18045  -1.167 0.244091
## Medu                 0.49122    0.25664   1.914 0.056365 .
## Fedu                -0.11465    0.25433  -0.451 0.652406
## studytimemoderate    0.07606    0.53510   0.142 0.887040
## studytimehigh        1.30893    0.73093   1.791 0.074124 .
## studytimevery high   0.55157    0.94906   0.581 0.561468
## failures            -1.78689    0.31490  -5.674 2.76e-08 ***
## absences             0.04123    0.02779   1.484 0.138686
## higheryes            1.64756    1.04281   1.580 0.114955
## goout               -0.45638    0.21340  -2.139 0.033104 *
## Walc                 0.09027    0.19390   0.466 0.641807
## internetyes          0.44558    0.58660   0.760 0.447962
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.178 on 381 degrees of freedom
## Multiple R-squared:  0.1959, Adjusted R-squared:  0.1685
## F-statistic: 7.141 on 13 and 381 DF,  p-value: 1.74e-12
```

Model 1 shows that background and behavioral variables explain only a modest amount of variation in final grades (adjusted R^2 ~~ 0.17). The strongest predictors are the number of past failures (negative effect), gender (males scoring slightly higher), and going out with friends (slightly negative effect). Most other variables, including parental education and study time, show weak or non-significant associations.

Model 2: Prior grades only (G1 and G2)

```r
# Model 2: prior grades only
# Goal: quantify how well G1 and G2 alone predict the final grade

model2 <- lm(G3 ~ G1 + G2, data = dat)
summary(model2)
```

```
##
## Call:
## lm(formula = G3 ~ G1 + G2, data = dat)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -9.5713 -0.3888  0.2885  0.9725  3.7089
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.83001    0.33531  -5.458 8.57e-08 ***
```

```
## G1           0.15327    0.05618   2.728  0.00665 **
## G2           0.98687    0.04957  19.909  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.937 on 392 degrees of freedom
## Multiple R-squared:  0.8222, Adjusted R-squared:  0.8213
## F-statistic: 906.1 on 2 and 392 DF,  p-value: < 2.2e-16
```

Model 2 demonstrates that prior grades (G1 and G2) are extremely strong predictors of final grade, explaining over 80% of the variation in G3. Both earlier grades are significant, with G2 having the largest effect. This indicates that most of a student's final performance is already reflected in their prior achievement.

Model 3: Combined model (prior grades + background and behavior)

```r
# Model 3: full model combining prior grades + background/behavior variables

model3_full <- lm(
  G3 ~ G1 + G2 +
    sex + age + Medu + Fedu +
    studytime + failures + absences +
    higher + goout + Walc + internet,
  data = dat
)

summary(model3_full)
```

```
##
## Call:
## lm(formula = G3 ~ G1 + G2 + sex + age + Medu + Fedu + studytime +
##     failures + absences + higher + goout + Walc + internet, data = dat)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -9.0225 -0.4694  0.2749  0.9955  3.6924
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)          1.25742    1.58303   0.794 0.427511
## G1                   0.16100    0.05741   2.804 0.005302 **
## G2                   0.96538    0.05040  19.153  < 2e-16 ***
## sexM                 0.19145    0.21834   0.877 0.381128
## age                 -0.19603    0.08299  -2.362 0.018681 *
## Medu                 0.09254    0.11745   0.788 0.431278
## Fedu                -0.16847    0.11634  -1.448 0.148402
## studytimemoderate   -0.11125    0.24381  -0.456 0.648438
## studytimehigh        0.13159    0.33603   0.392 0.695578
## studytimevery high  -0.78727    0.43380  -1.815 0.070342 .
## failures            -0.25375    0.14943  -1.698 0.090297 .
## absences             0.04264    0.01266   3.368 0.000834 ***
## higheryes            0.24349    0.47667   0.511 0.609776
## goout                0.06398    0.09822   0.651 0.515153
## Walc                 0.06668    0.08887   0.750 0.453523
## internetyes         -0.29108    0.26863  -1.084 0.279252
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.903 on 379 degrees of freedom
## Multiple R-squared:  0.834,  Adjusted R-squared:  0.8274
## F-statistic:   127 on 15 and 379 DF,  p-value: < 2.2e-16
```

Model 3 combines prior grades with background and behavioral factors. The adjusted R^2 rises only slightly compared to Model 2, meaning the additional predictors add little explanatory value once G1 and G2 are included. G1 and G2 remain dominant predictors, while nearly all other variables become non-significant.

Stepwise model

```
# Stepwise model: use AIC-based selection to find a simpler subset of predictors

model_step <- step(model3_full, direction = "both", trace = FALSE)
summary(model_step)
```

```
##
## Call:
## lm(formula = G3 ~ G1 + G2 + age + failures + absences + Walc,
##     data = dat)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -8.9517 -0.4347  0.2737  0.9542  3.7652
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.80205    1.35383   0.592  0.55390
## G1           0.16845    0.05628   2.993  0.00294 **
## G2           0.95808    0.04962  19.309  < 2e-16 ***
## age         -0.17375    0.07963  -2.182  0.02971 *
## failures    -0.21104    0.14266  -1.479  0.13987
## absences     0.03974    0.01224   3.247  0.00127 **
## Walc         0.11149    0.07635   1.460  0.14504
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.901 on 388 degrees of freedom
## Multiple R-squared:  0.8305, Adjusted R-squared:  0.8279
## F-statistic: 316.9 on 6 and 388 DF,  p-value: < 2.2e-16
```

The stepwise model retains a small subset of predictors—primarily G1, G2, and a few minor variables, while achieving nearly the same fit as the full model. This confirms that most predictors contribute very little beyond prior grades and that a simpler model performs equally well.

Comparing the models

To summarize how much each model explains, we can extract the R^2 and adjusted R^2 values:

```
# Compare model fits (how much variation each model explains)

get_fit <- function(mod) {
  s <- summary(mod)
```

```
  data.frame(
    R2 = s$r.squared,
    Adj_R2 = s$adj.r.squared
  )
}

model_fits <- rbind(
  Model1_no_grades   = get_fit(model1),
  Model2_grades_only = get_fit(model2),
  Model3_full        = get_fit(model3_full),
  Model_stepwise     = get_fit(model_step)
)

model_fits
```

```
##                           R2    Adj_R2
## Model1_no_grades   0.1959106 0.1684745
## Model2_grades_only 0.8221632 0.8212559
## Model3_full        0.8340173 0.8274481
## Model_stepwise     0.8305031 0.8278820
```

Comparing all models, non-grade factors alone explain little, prior grades explain most of the variation, and adding extra variables yields minimal improvement. This highlights that previous academic performance is by far the strongest indicator of final math achievement.