STAT527 Term Project

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Part 1: Define Helper Functions

(a) These functions are used for tables. useful_columns() checks each column and keeps only the ones that don't have too many missing values, based on a threshold. df_stats() then uses that result to report simple summary info about the data, like how many rows it has and how many "useful" columns remain after filtering out columns with lots of NAs.

```
useful_columns <- function(df, na_threshold = 0.85) {
  na_fraction <- sapply(df, function(col) mean(is.na(col)))
  names(na_fraction[na_fraction <= na_threshold])
}

df_stats <- function(df, na_threshold=0.85) {
  cols <- useful_columns(df, na_threshold)
  list(rows = nrow(df), useful_cols = length(cols))
}
```

(b) These functions are used for plotting. int_plot() automatically turns ggplot figures into interactive Plotly plots when the output is HTML, but keeps them static for PDFs. plot_time_series() cleans out missing values, makes a simple time-series plot with points and a smooth trend line so we don't have to repeat the same code.

```
# make sure plots are interactive in the R when compiled but static when in PDF
int_plot <- function(p) {
  if (knitr::is_html_output()) {
    plotly::ggplotly(p)
  } else {
    p
  }
}

plot_time_series <- function(data, y, title, ylab, color_point, color_line) {
  clean_data <- data |> filter(!is.na(testDate), !is.na(.data[[y]]))
  p <- ggplot(clean_data, aes(x = testDate, y = .data[[y]])) +
    geom_point(alpha = 0.4, color = color_point) +
    geom_smooth(method = "loess", se = FALSE, color = color_line) +
    theme_minimal() +
    scale_x_continuous(breaks = seq(min(clean_data$testDate),
                                    max(clean_data$testDate), by = 1)) +
    labs(title = title, x = "Year", y = ylab)
  int_plot(p)
}
```

Part 2: Loading in Datasets

(a) Load in Geekbench

```
recent_cpu <- read.csv(here("Datasets", "Geekbench", "recent-cpu-v6.csv"))
recent_gpu <- read.csv(here("Datasets", "Geekbench", "recent-gpu-v6.csv"))
single_core <- read.csv(here("Datasets", "Geekbench", "single-core-v4.csv"))
top_multi <- read.csv(here("Datasets", "Geekbench", "top-multi-core-v6.csv"))
top_single <- read.csv(here("Datasets", "Geekbench", "top-single-core-v6.csv"))
```

(b) Load in Kaggle

```
gpu_benchmarks <- read.csv(here("Datasets", "Kaggle", "GPU_benchmarks_v7.csv"))
gpu_scores <- read.csv(here("Datasets", "Kaggle", "GPU_scores_graphicsAPIs.csv"))
```

Part 3: Preprocessing and Merging Datasets

(a) Make GPU names consistent across datasets (lowercase and trimmed). Merge the PassMark and Geekbench data based on the GPU name. After merging, removes duplicate name columns, prints out how many rows are in each dataset (before and after the merge), and shows a quick preview of the merged result.

```
gpu_benchmarks$gpu_name <- tolower(trimws(gpu_benchmarks$gpuName))
gpu_scores$gpu_name <- tolower(trimws(gpu_scores$Device))
merged_gpu <- merge(gpu_benchmarks, gpu_scores, by="gpu_name")
merged_gpu <- merged_gpu |> select(-gpuName, -Device)

cat("Rows in PassMark dataset:", nrow(gpu_benchmarks), "\n")
```

```
## Rows in PassMark dataset: 2317
```

```
cat("Rows in Geekbench dataset:", nrow(gpu_scores), "\n")
```

```
## Rows in Geekbench dataset: 1213
```

```
cat("Rows in merged dataset:", nrow(merged_gpu), "\n\n")
```

```
## Rows in merged dataset: 647
```

```
head(merged_gpu, 50)
```

```
##          gpu_name G3Dmark G2Dmark   price gpuValue TDP powerPerformance
## 1         a40-12q    5573     198      NA       NA  NA               NA
## 2   firepro m4000    1597     410   72.83    21.92  NA               NA
## 3   firepro m4100    1059     623      NA       NA  NA               NA
## 4   firepro m4150     999     207      NA       NA  NA               NA
## 5   firepro m4170    1067     290      NA       NA  NA               NA
## 6   firepro m5100    2103     800      NA       NA  NA               NA
## 7   firepro m5950    1314     574      NA       NA  NA               NA
## 8   firepro m6000    1820     776  325.99     5.58  NA               NA
## 9   firepro m6100    1945     338      NA       NA  NA               NA
## 10 firepro s10000    5315     493      NA       NA  NA               NA
## 11  firepro s7150    6276     866 1697.99     3.70  NA               NA
## 12  firepro v3900     662     242  238.44     2.78  50            13.24
## 13  firepro v4900     974     318  149.99     6.50  75            12.99
## 14  firepro v5800    1186     339   53.00    22.37  NA               NA
## 15  firepro v5900    1271     352   86.00    14.78  75            16.94
```

```
## 16  firepro v7800    2034     290  190.00    10.70  NA              NA
## 17  firepro w2100     890     327   59.00    15.09  26           34.24
## 18  firepro w4100    1541     535  184.00     8.38  50           30.82
## 19 firepro w4170m     953     223      NA       NA  NA              NA
## 20 firepro w4190m    1086     194      NA       NA  NA              NA
## 21  firepro w5000    3056     587  184.00    16.61  75           40.74
## 22  firepro w5100    2957     541  125.99    23.47  75           39.43
## 23 firepro w5130m    1341     307      NA       NA  NA              NA
## 24 firepro w5170m    1555     399      NA       NA  NA              NA
## 25  firepro w7000    4276     551  278.05    15.38 150           28.51
## 26  firepro w7100    5175     667  389.30    13.29 150           34.50
## 27  firepro w8100    7327     759  704.00    10.41 220           33.30
## 28  firepro w9000    6138     720  845.00     7.26 274           22.40
## 29  firepro w9100    7719     790 1729.99     4.46 275           28.07
## 30   geforce 410m     250     129      NA       NA  12           20.80
## 31    geforce 510     257     199   69.99     3.67  25           10.27
## 32    geforce 605     305     179  136.83     2.23  NA              NA
## 33   geforce 610m     292     103      NA       NA  NA              NA
## 34    geforce 615     552     412      NA       NA  NA              NA
## 35   geforce 710a     451     258      NA       NA  33           13.67
## 36   geforce 710m     450     116      NA       NA  12           37.48
## 37   geforce 730a     769     205      NA       NA  NA              NA
## 38   geforce 800m     468     388      NA       NA  NA              NA
## 39   geforce 810a     622     319      NA       NA  NA              NA
## 40   geforce 810m     402      71      NA       NA  NA              NA
## 41   geforce 820a     568     162      NA       NA  NA              NA
## 42   geforce 820m     511     111      NA       NA  15           34.04
## 43   geforce 830a    1005     736      NA       NA  NA              NA
## 44   geforce 830m     976     136      NA       NA  25           39.06
## 45   geforce 840a    1180     266      NA       NA  NA              NA
## 46   geforce 840m    1067     147      NA       NA  30           35.56
## 47   geforce 845m    1430     233      NA       NA  NA              NA
## 48   geforce 910m     578     150      NA       NA  NA              NA
## 49   geforce 920m     723     119      NA       NA  NA              NA
## 50  geforce 920mx    1088     149      NA       NA  NA              NA
##    testDate           category Manufacturer  CUDA Metal OpenCL Vulkan
## 1      2022            Unknown       Nvidia 95329    NA 156643     NA
## 2      2012        Workstation          AMD    NA    NA   6494     NA
## 3      2015        Workstation          AMD    NA    NA   5067     NA
## 4      2015            Unknown          AMD    NA    NA   5063   6685
## 5      2015            Unknown          AMD    NA    NA   6347     NA
## 6      2014        Workstation          AMD    NA    NA   9305  10692
## 7      2011        Workstation          AMD    NA    NA   1505     NA
## 8      2012        Workstation          AMD    NA    NA   9420     NA
## 9      2013        Workstation          AMD    NA    NA  15612  16951
## 10     2015            Unknown          AMD    NA    NA  30631  34145
## 11     2016            Unknown          AMD    NA    NA  29623  33575
## 12     2012        Workstation          AMD    NA    NA   1395     NA
## 13     2012        Workstation          AMD    NA    NA   1666     NA
## 14     2016            Unknown          AMD    NA    NA   2740     NA
## 15     2011        Workstation          AMD    NA    NA   2880     NA
## 16     2018            Unknown          AMD    NA    NA   4894     NA
## 17     2014        Workstation          AMD    NA    NA   4425     NA
## 18     2014        Workstation          AMD    NA    NA   6575   7852
```

```
## 19      2015              Unknown          AMD    NA    NA   5507      NA
## 20      2016              Unknown          AMD    NA    NA   5705      NA
## 21      2012          Workstation          AMD    NA    NA  12387   16955
## 22      2014          Workstation          AMD    NA    NA  13903   16106
## 23      2016              Unknown          AMD    NA    NA   7779    8337
## 24      2015 Mobile, Workstation          AMD    NA    NA   8775      NA
## 25      2012          Workstation          AMD    NA    NA  21082      NA
## 26      2015          Workstation          AMD    NA    NA  26357   25403
## 27      2014          Workstation          AMD    NA    NA  34705      NA
## 28      2012          Workstation          AMD    NA    NA  31775      NA
## 29      2014          Workstation          AMD    NA    NA  43046      NA
## 30      2011               Mobile       Nvidia    NA    NA    872      NA
## 31      2011              Desktop       Nvidia    NA    NA    758      NA
## 32      2012              Unknown       Nvidia    NA    NA    764      NA
## 33      2012              Unknown       Nvidia    NA    NA   1086      NA
## 34      2013              Unknown       Nvidia    NA    NA   1162      NA
## 35      2014              Desktop       Nvidia    NA    NA   2638      NA
## 36      2013               Mobile       Nvidia    NA    NA   1976      NA
## 37      2015              Unknown       Nvidia    NA    NA   3088      NA
## 38      2014              Unknown       Nvidia    NA    NA   1303      NA
## 39      2014              Unknown       Nvidia    NA    NA   1828      NA
## 40      2014              Unknown       Nvidia    NA    NA   1644      NA
## 41      2015              Unknown       Nvidia    NA    NA   2708      NA
## 42      2014               Mobile       Nvidia    NA    NA   2347      NA
## 43      2014              Unknown       Nvidia    NA    NA   4315      NA
## 44      2014               Mobile       Nvidia  4342    NA   4422    4078
## 45      2014              Unknown       Nvidia    NA    NA   5596      NA
## 46      2014               Mobile       Nvidia  5629    NA   5938    5207
## 47      2015               Mobile       Nvidia    NA    NA   6112      NA
## 48      2015              Unknown       Nvidia    NA    NA   2629      NA
## 49      2015              Unknown       Nvidia  2766    NA   3462    3215
## 50      2016              Unknown       Nvidia  4274    NA   4210    3723
```

Part 4: Filtering the Datasets

(a) Split the GPU data by manufacturer and generate a small summary showing how many rows and usable columns each manufacturer has.

```r
manufacturers <- unique(gpu_scores$Manufacturer)
gpu_split <- split(gpu_scores, factor(gpu_scores$Manufacturer, levels = manufacturers))

for (m in manufacturers) {
  assign(sprintf("%s_gpu_scores", tolower(m)), subset(gpu_scores, Manufacturer == m))
}

manufacturers <- unique(gpu_scores$Manufacturer)
manufacturer_summary <- map_df(manufacturers, function(m) {
  df <- gpu_scores |> filter(Manufacturer == m)
  s <- df_stats(df)
  tibble(Manufacturer = m, Rows = s$rows, UsefulCols = s$useful_cols)
})

manufacturer_summary
```

```
## # A tibble: 9 x 3
##   Manufacturer  Rows UsefulCols
##   <chr>        <int>      <int>
## 1 Nvidia         404          7
## 2 AMD            546          6
## 3 Apple           21          5
## 4 Qualcomm        22          4
## 5 Intel          144          6
## 6 Other            7          4
## 7 ARM             58          5
## 8 PowerVR         10          4
## 9 Samsung          1          5
```

(b) This splits the GPU benchmark data by supported API (CUDA, Metal, OpenCL, Vulkan) and summarizes each subset. For every test type, it keeps only GPUs with valid scores and reports how many useful rows and columns.

```
cuda_tests <- subset(gpu_scores, !is.na(CUDA))
metal_tests <- subset(gpu_scores, !is.na(Metal))
opencl_tests <- subset(gpu_scores, !is.na(OpenCL))
vulkan_tests <- subset(gpu_scores, !is.na(Vulkan))

test_types <- c("CUDA", "Metal", "OpenCL", "Vulkan")
test_summary <- map_df(test_types, function(t) {
  df <- gpu_scores |> filter(!is.na(.data[[t]]))
  if (nrow(df) == 0) return(NULL)
  s <- df_stats(df)
  tibble(Test = t, Rows = s$rows, UsefulCols = s$useful_cols)
})

test_summary
```

```
## # A tibble: 4 x 3
##   Test    Rows UsefulCols
##   <chr>  <int>      <int>
## 1 CUDA     266          7
## 2 Metal    241          7
## 3 OpenCL   976          7
## 4 Vulkan   629          7
```

(c) This builds a summary table by manufacturer and benchmark type (CUDA, Metal, OpenCL, Vulkan). For each valid combo, reports how many rows exist and how many columns useful.

```
summary_table <- map_df(manufacturers, function(m) {
  map_df(test_types, function(t) {
    df <- gpu_scores |> filter(Manufacturer == m, !is.na(.data[[t]]))
    if (nrow(df) == 0) return(NULL)
      s <- df_stats(df)
      tibble(Manufacturer = m, Test = t, Rows = s$rows, UsefulCols = s$useful_cols)
  })
})

summary_table
```

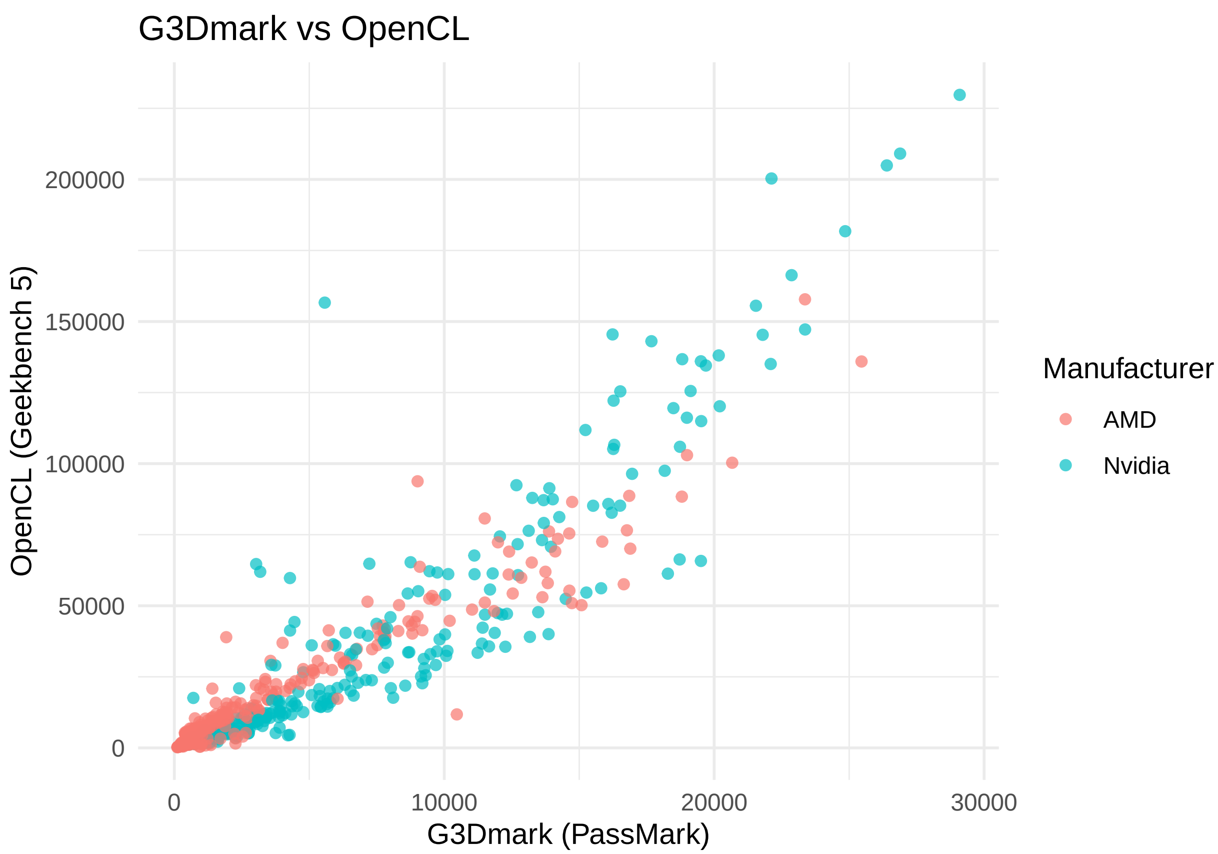
```
## # A tibble: 21 x 4
##    Manufacturer Test    Rows UsefulCols
```

```
##    <chr>         <chr>  <int>      <int>
##  1 Nvidia        CUDA     266          7
##  2 Nvidia        Metal     73          7
##  3 Nvidia        OpenCL   381          7
##  4 Nvidia        Vulkan   225          7
##  5 AMD           Metal    123          6
##  6 AMD           OpenCL   452          6
##  7 AMD           Vulkan   251          6
##  8 Apple         Metal     20          5
##  9 Apple         OpenCL     5          5
## 10 Qualcomm      OpenCL     1          4
## # i 11 more rows
```

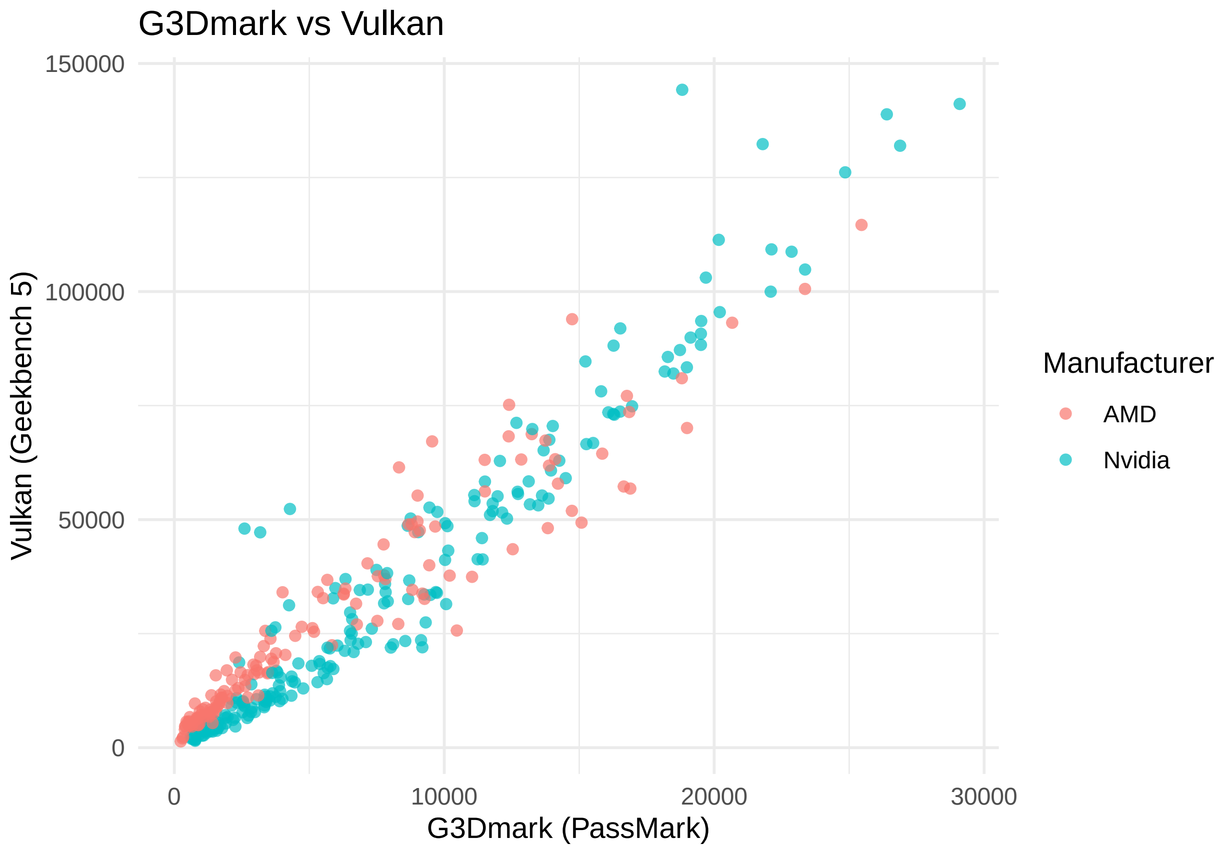
Part 5: Exploring Data Through ggplot() and plotly()

(a) Comparing AMD vs Nvidia (CUDA/OpenCL/Vulkan/G3dmark)

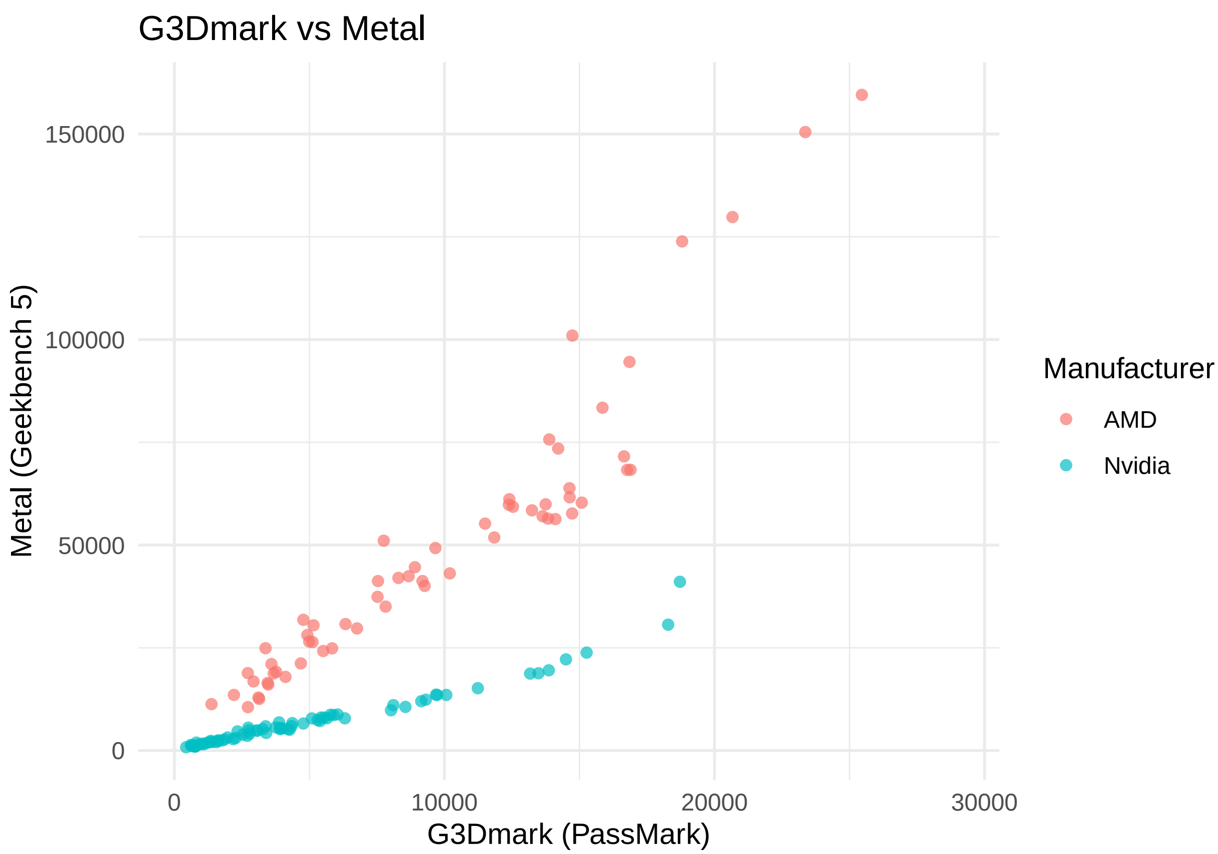
```r
plot_scatter <- function(x_col, y_col, data) {
  p <- ggplot(data, aes_string(x = x_col, y = y_col, color = "Manufacturer")) +
    geom_point(alpha = 0.7) +
    theme_minimal() +
    labs(title = paste(x_col, "vs", y_col), x = paste(x_col, "(PassMark)"),
         y = paste(y_col, "(Geekbench 5)"))
  int_plot(p)
}

print(plot_scatter("G3Dmark", "OpenCL", merged_gpu))
```




```r
print(plot_scatter("G3Dmark", "Vulkan", merged_gpu))
```



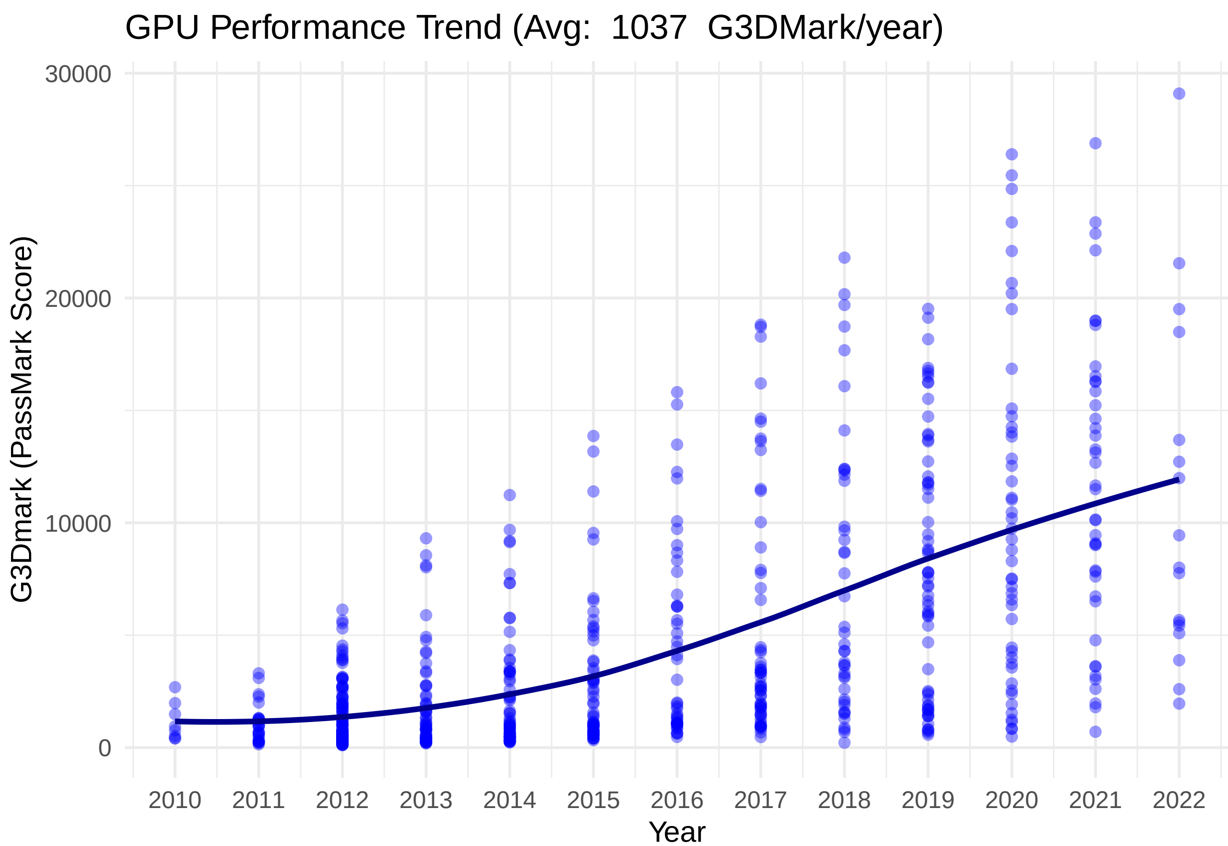

```
if (!is.null(merged_gpu$Metal)) {
  print(plot_scatter("G3Dmark", "Metal", merged_gpu))
}
```



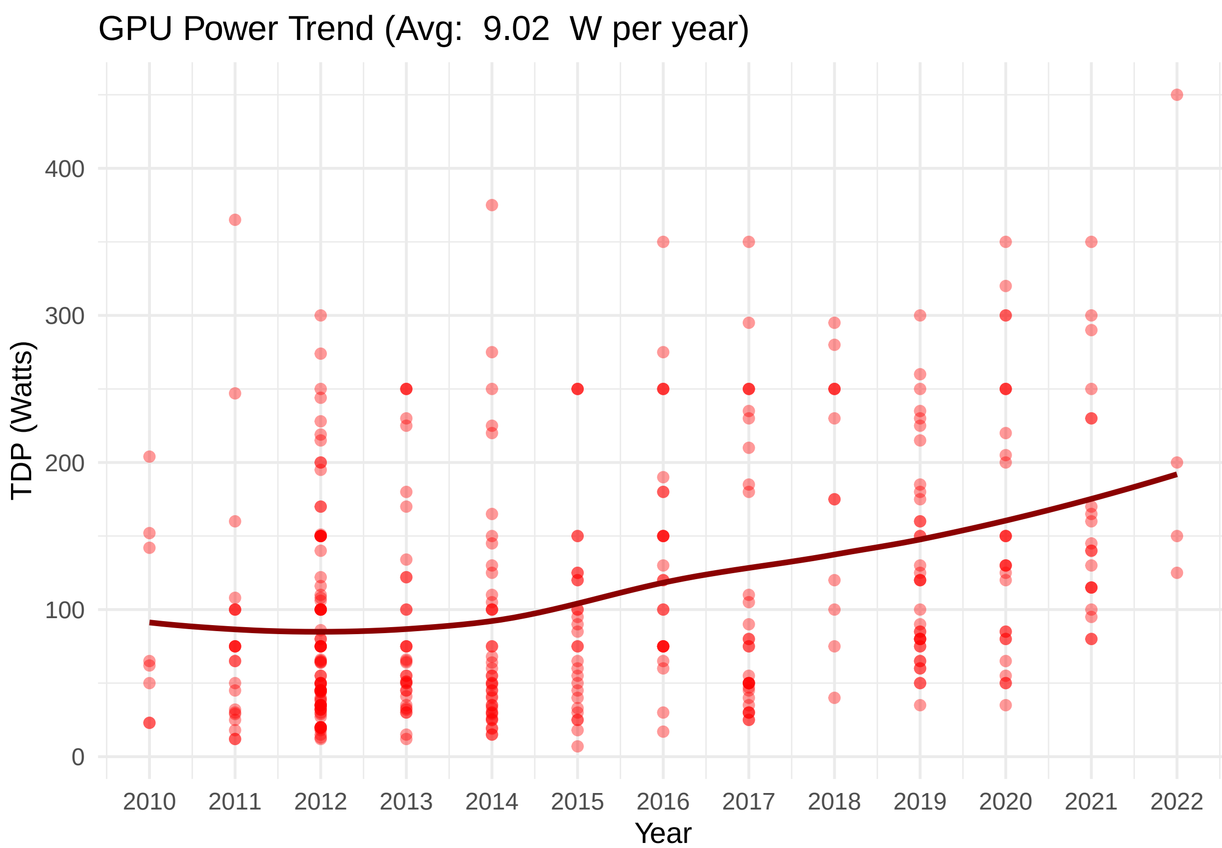
(b) Plotting different trends over time

```
# add PerfPerWatt column once
merged_gpu <- merged_gpu |> mutate(PerfPerWatt = G3Dmark / TDP)

get_slope <- function(data, y, manufacturer = NULL, digits = 0) {
  d <- data |> filter(!is.na(testDate), !is.na(.data[[y]]))

  if (!is.null(manufacturer)) {
    d <- d |> filter(Manufacturer == manufacturer)
  }

  fit <- lm(reformulate("testDate", response = y), data = d)
  round(coef(fit)["testDate"], digits)
}

slope_g3d <- get_slope(merged_gpu, "G3Dmark")
slope_tdp <- get_slope(merged_gpu, "TDP", digits = 2)
slope_eff <- get_slope(merged_gpu, "PerfPerWatt", digits = 2)
slope_amd <- get_slope(merged_gpu, "G3Dmark", manufacturer = "AMD")
slope_nv  <- get_slope(merged_gpu, "G3Dmark", manufacturer = "Nvidia")

# plots
plot_time_series(
  merged_gpu, "G3Dmark",
  paste("GPU Performance Trend (Avg: ", slope_g3d, " G3DMark/year)"),
  "G3Dmark (PassMark Score)", "blue", "darkblue"
```

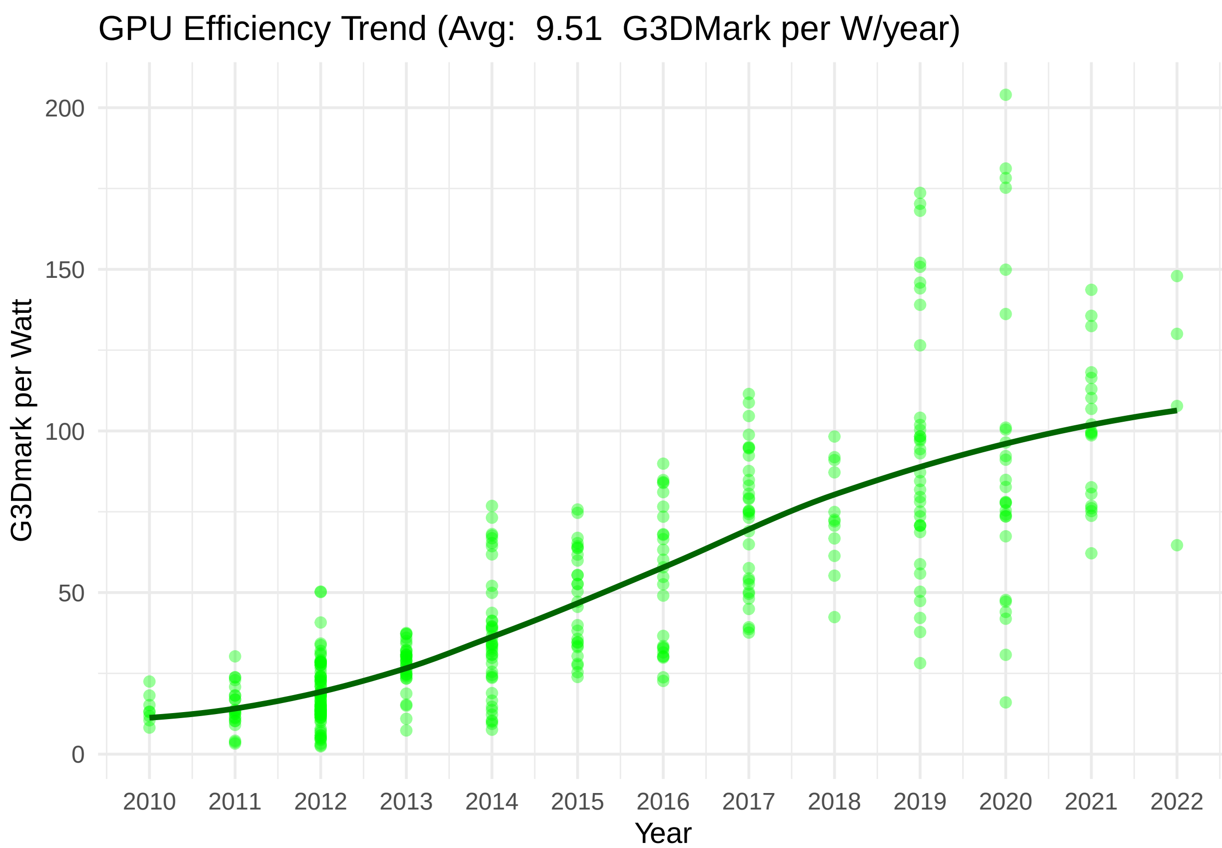
```
)
```



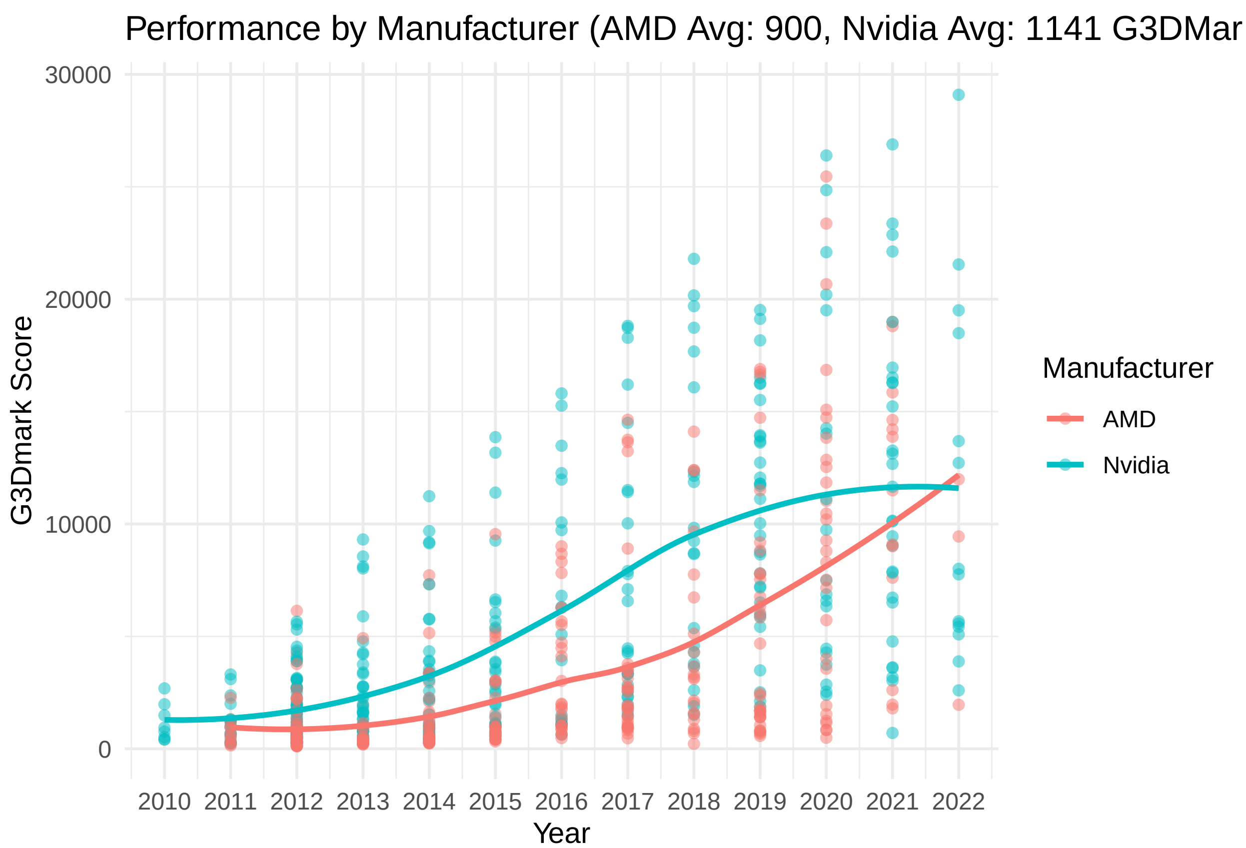

```
plot_time_series(
  merged_gpu, "TDP",
  paste("GPU Power Trend (Avg: ", slope_tdp, " W per year)"),
  "TDP (Watts)", "red", "darkred"
)
```




```r
plot_time_series(
  merged_gpu, "PerfPerWatt",
  paste("GPU Efficiency Trend (Avg: ", slope_eff, " G3DMark per W/year)"),
  "G3Dmark per Watt", "green", "darkgreen"
)
```

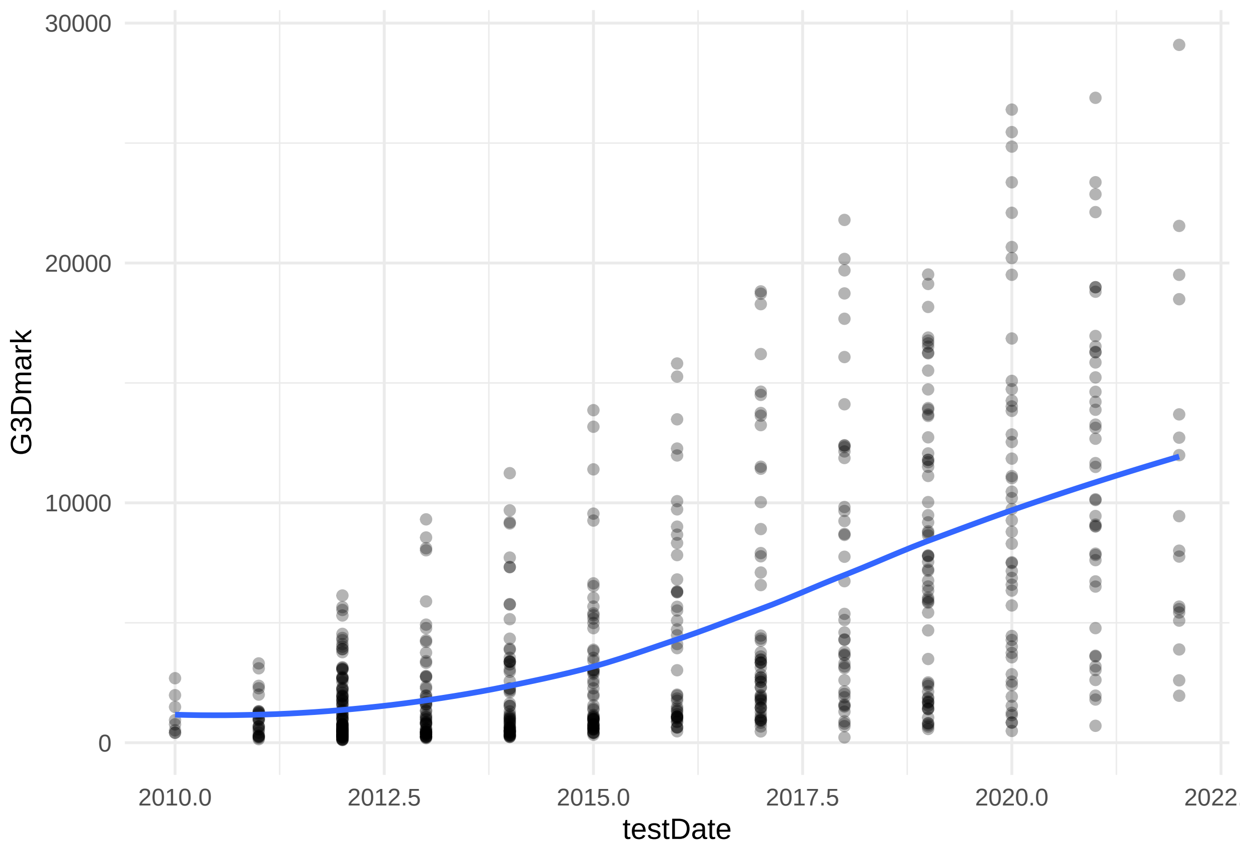



```r
int_plot(
  ggplot(merged_gpu, aes(testDate, G3Dmark, color = Manufacturer)) +
    geom_point(alpha = 0.5) +
    geom_smooth(method = "loess", se = FALSE) +
    theme_minimal() +
    scale_x_continuous(breaks = seq(min(merged_gpu$testDate),
                                    max(merged_gpu$testDate), by = 1)) +
    labs(
      title = paste0(
        "Performance by Manufacturer (AMD Avg: ",
        slope_amd, ", Nvidia Avg: ", slope_nv, " G3DMark/year)"
      ),
      x = "Year", y = "G3Dmark Score"
    )
)
```



(c) Plotting ALL GPU Trend Line

```
merged_gpu <- merged_gpu |> mutate(PerfPerWatt = G3Dmark / TDP)

int_plot(
  ggplot(merged_gpu, aes(testDate, G3Dmark)) +
    geom_point(alpha=0.3) +
    geom_smooth(se=FALSE) +
    theme_minimal()
)
```



Part 6: Exploring the data with TidyModels

(a) Split/train/test on the merged dataset for our tidymodels. We clean up the merged dataset, keep only the variables we care about, drop missing values, and split the data into training and testing sets so we can fairly evaluate our models. Also, create a common recipe to use for all models (except Random Forest). Dummy variables are needed for linear models, but random forests already know how to work with categories.

```
set.seed(123)
model_data <- merged_gpu |>
  select(G3Dmark, testDate, TDP, price, Manufacturer, category) |> drop_na()
split <- initial_split(model_data, prop = 0.8)
train <- training(split)
test <- testing(split)

common_recipe <- recipe(G3Dmark ~ ., data = train) |>
  step_dummy(all_nominal_predictors()) |> step_normalize(all_numeric_predictors())
```

Model 1: Linear Regression

(b) We start with a simple linear regression as a baseline model, using dummy variables for categorical features and checking how well it predicts GPU performance on the test set.

```
lin_spec <- linear_reg() |> set_engine("lm")
lin_wf <- workflow() |> add_recipe(common_recipe) |> add_model(lin_spec)
lin_fit <- lin_wf |> fit(data = train)
```

```
lin_preds <- predict(lin_fit, new_data = test) |> bind_cols(test)
metrics(lin_preds, truth = G3Dmark, estimate = .pred)
```

```
## # A tibble: 3 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard    2530.
## 2 rsq     standard       0.851
## 3 mae     standard    1927.
```

Model 3, 4: LASSO/Ridge Regression

(d) We try Ridge and LASSO regression, tuning the regularization strength with cross-validation to control overfitting and compare their predictive performance.

```
folds <- vfold_cv(train, v=10)
lambda_grid <- grid_regular(penalty(), levels= 30)

ridge_spec <-linear_reg(mixture=0, penalty =tune()) |> set_engine("glmnet")
lasso_spec <- linear_reg(mixture=1, penalty= tune()) |> set_engine("glmnet")

ridge_wf <- workflow() |> add_recipe(common_recipe) |> add_model(ridge_spec)
lasso_wf <- workflow() |> add_recipe(common_recipe) |> add_model(lasso_spec)

ridge_t <- tune_grid(ridge_wf, resamples=folds, grid=lambda_grid)
lasso_t <- tune_grid(lasso_wf, resamples=folds, grid=lambda_grid)

best_ridge <- select_best(ridge_t, metric="rmse")
best_lasso <- select_best(lasso_t, metric="rmse")

ridge_final_fit <- ridge_wf |> finalize_workflow(best_ridge) |> fit(data=train)
lasso_final_fit <- lasso_wf |> finalize_workflow(best_lasso) |> fit(data=train)

ridge_preds <- predict(ridge_final_fit, new_data=test) |> bind_cols(test)
lasso_preds <- predict(lasso_final_fit, new_data=test) |> bind_cols(test)

ridge_metrics <- ridge_preds |> metrics(truth=G3Dmark, estimate=.pred)
lasso_metrics <- lasso_preds |> metrics(truth=G3Dmark, estimate=.pred)

best_ridge
```

```
## # A tibble: 1 x 2
##        penalty .config
##          <dbl> <chr>
## 1 0.0000000001 pre0_mod01_post0
```

```
best_lasso
```

```
## # A tibble: 1 x 2
##        penalty .config
##          <dbl> <chr>
## 1 0.0000000001 pre0_mod01_post0
```

```
ridge_metrics
```

```
## # A tibble: 3 x 3
```

```
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard    2360.
## 2 rsq     standard       0.858
## 3 mae     standard    1751.
```

```r
lasso_metrics
```

```
## # A tibble: 3 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard    2522.
## 2 rsq     standard       0.850
## 3 mae     standard    1922.
```

Model 5: KNN

(e) We use KNN model, tuning the number of neighbors with cross-validation to see how a distance-based approach performs on this dataset.

```r
knn_folds <- vfold_cv(train, v = 10)
knn_model <- nearest_neighbor(neighbors = tune()) |>
  set_engine("kknn") |> set_mode("regression")
knn_wf <- workflow() |> add_recipe(common_recipe) |> add_model(knn_model)

knn_tuned <- tune_grid(knn_wf, resamples = knn_folds,
                       grid = tibble(neighbors = c(1, 3, 5, 10, 20, 50)),
                       metrics = metric_set(rmse, rsq, mae))

show_best(knn_tuned, metric = "rmse")
```

```
## # A tibble: 5 x 7
##   neighbors .metric .estimator  mean     n std_err .config
##       <dbl> <chr>   <chr>      <dbl> <int>   <dbl> <chr>
## 1         5 rmse    standard   2160.    10    270. pre0_mod3_post0
## 2         3 rmse    standard   2219.    10    254. pre0_mod2_post0
## 3        10 rmse    standard   2266.    10    262. pre0_mod4_post0
## 4        20 rmse    standard   2463.    10    252. pre0_mod5_post0
## 5         1 rmse    standard   2629.    10    223. pre0_mod1_post0
```

```r
best_k <- select_best(knn_tuned, metric = "rmse")

knn_final <- finalize_workflow(knn_wf, best_k) |> fit(data = train)
knn_preds <- predict(knn_final, new_data = test) |> bind_cols(test)
metrics(knn_preds, truth = G3Dmark, estimate = .pred)
```

```
## # A tibble: 3 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard    1709.
## 2 rsq     standard       0.918
## 3 mae     standard    1172.
```

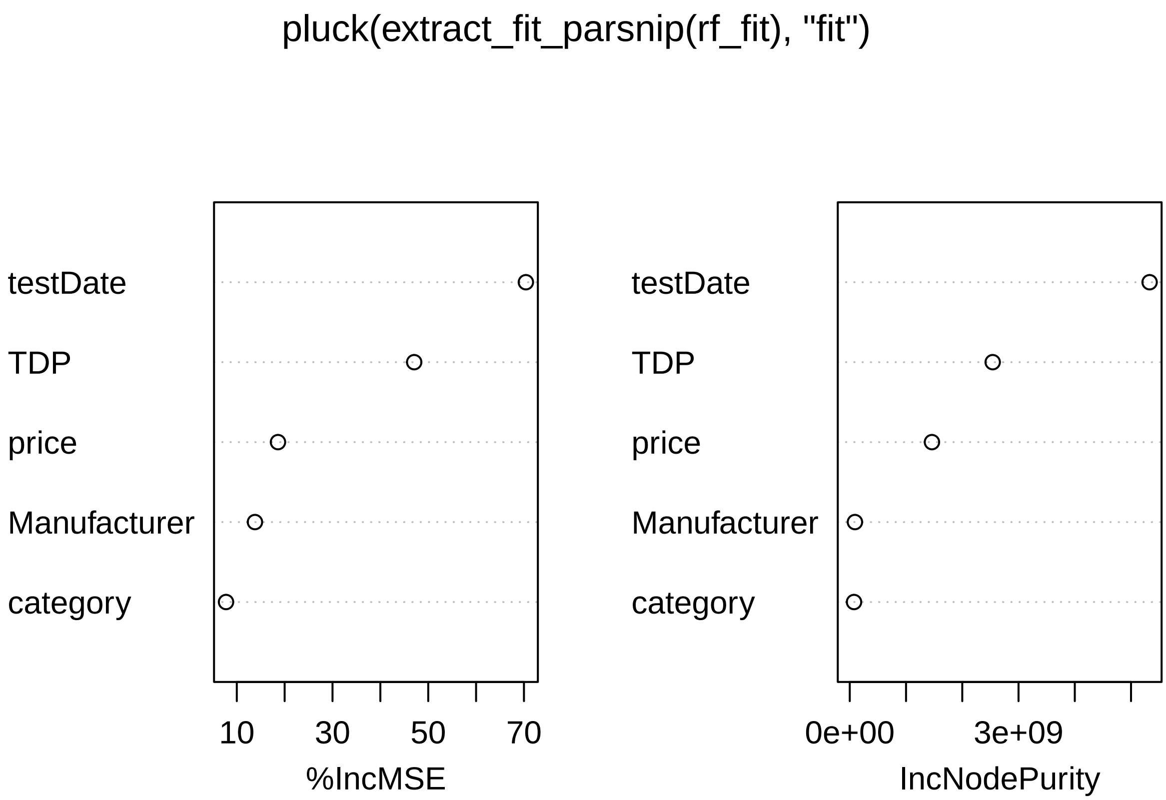
Model 2: Random Forest

(c) Finally, we fit a random forest model to see which features matter most.

```r
rf_recipe <- recipe(G3Dmark ~ ., data = train) |>
  step_normalize(all_numeric_predictors()) # we do not want dummy for rf.

rf_spec <- rand_forest(mtry = tune(), trees = tune(), min_n = tune()) |>
  set_engine("randomForest", importance = TRUE) |>
  set_mode("regression")

rf_wf <- workflow() |> add_recipe(rf_recipe) |> add_model(rf_spec)
folds <- vfold_cv(train, v = 10)

rf_params <- parameters(finalize(mtry(), train), trees(range = c(200, 600)),
  min_n(range = c(2, 25)))

rf_grid <- grid_regular(rf_params, levels = 4)

rf_tune <- tune_grid(rf_wf, resamples = folds, grid = rf_grid,
  metrics = metric_set(rmse, rsq, mae))

best_rf <- select_best(rf_tune, metric = "rmse")
final_rf <- finalize_workflow(rf_wf, best_rf)
rf_fit <- final_rf |> fit(data = train)
rf_preds <- predict(rf_fit, test) |> bind_cols(test)
rf_metrics <- metrics(rf_preds, truth = G3Dmark, estimate = .pred)
rf_metrics
```

```
## # A tibble: 3 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 rmse    standard    1466.
## 2 rsq     standard       0.946
## 3 mae     standard     998.
```

```r
rf_fit |> extract_fit_parsnip() |> pluck("fit") |> varImpPlot()
```



pluck(extract_fit_parsnip(rf_fit), "fit")
testDate
TDP
price
Manufacturer
category
10
30
50
70
%IncMSE
testDate
TDP
price
Manufacturer
category
0e+00
3e+09
IncNodePurity