# Stats 101C Regression Final

Group 13

2025-12-09

## Table of contents

**Introduction** 1

**Preprocessing** 2

**Exploratory Data Analysis** 7
- Response (HH Size) Distribution . . . 8
- Numeric Variable Correlation . . . 9
  - Category purchase frequency correlation . . . 9
  - Category spending correlation . . . 10
  - Misc. leftover numeric variables . . . 11
- Location . . . 13
- Product Categories . . . 15
- Gender . . . 17

**Model Evaluation and Tuning** 18
- XGBoost Model 1 . . . 19
- Random Forest Model 1 . . . 24
- NEW DATA VARIABLES . . . 28
- Final Model: XGBoost Model 2 . . . 28
- comparing models w/ xgb1 . . . 33

## Introduction

Research shows that factors such as income, age, gender, and household composition often influence spending behavior and product choice (U.S. Bureau of Labor Statistics). This background makes us interested to see if online spending is associated with variables such as income, education, age, and household sizes. The household size could be associated with how often and how many products are typically purchased but the different demographics of the customer or household could be associated with the purchase category. Personal habits and factors related to personal health could also place an influential role in purchasing behavior. These variables are all plausible predictors of online spending behavior.

## Preprocessing

```r
# Load datasets
purchases <- read_csv("data/amazon-purchases.csv")
survey <- read_csv("data/survey_train_test.csv")

purchases <- purchases |> clean_names(sep_out = ".")
survey <- survey |> clean_names(sep_out = ".")
```

```r
## Umbrella grouping for categories

# regex keywords -> umbrella

# 1. Baby & Kids
pat_baby <- "BABY|INFANT|DIAPER|NURSERY|STROLLER|CRIB|PACIFIER|WIPE|CAR_SEAT|HIGH_CHAIR|SAFET

# 2. Video Games
pat_video_games <- "VIDEO_GAME|CONSOLE|CONTROLLER|NINTENDO|XBOX|PLAYSTATION|GAMING|GAME_BOY|

# 3. Electronics
pat_electronics <- "COMPUTER|LAPTOP|TABLET|PHONE|MOBILE|WIRELESS|HEADPHONE|SPEAKER|CAMERA|AU

# 4. Grocery & Food
pat_grocery <- "FOOD|GROCERY|SNACK|CANDY|CHOCOLATE|BEVERAGE|COFFEE|TEA|JUICE|WATER|MEAT|DAIR

# 5. Apparel
pat_apparel <- "CLOTH|SHIRT|PANT|DRESS|COAT|JACKET|SWEATER|UNDERWEAR|SOCK|SHOE|BOOT|SNEAKER|

# 6. Health & Medical
pat_health <- "HEALTH|MEDIC|VITAMIN|SUPPLEMENT|FIRST_AID|BRACE|THERMOMETER|MASK|OPTICAL|LENS

# 7. Beauty & Personal Care
pat_beauty <- "MAKE_UP|BEAUTY|MAKEUP|SKIN|HAIR|COSMETIC|PERFUME|FRAGRAN|SHAMPOO|LOTION|NAIL|

# 8. Household Essentials
```

```
pat_household <- "PAPER_TOWEL|TOILET_PAPER|CLEAN|DETERGENT|TRASH|LAUNDRY|SOAP|TISSUE|FOIL|WRA

# 9. Home Decor & Furniture
pat_home <- "SHADE|FURNITURE|BED|MATTRESS|RUG|CURTAIN|DECOR|FRAME|SHEET|PILLOW|STORAGE|MIRRO

# 10. Kitchen & Dining
pat_kitchen <- "CHOPSTICK|KITCHEN|COOK|BAKE|DISH|KNIFE|PAN|POT|BLENDER|MIXER|TOASTER|MICROWA

# 11. Pets
pat_pets <- "PET|DOG|CAT|ANIMAL|FISH|AQUARIUM|LITTER|HAMSTER|BIRD|REPTILE|VETERINARY|LEASH|F

# 12. Sports & Outdoors
pat_sports <- "SPORT|EXERCISE|GYM|FITNESS|CAMPING|HIKING|TENT|FISHING|BIKE|BICYCLE|GOLF|BALL

# 13. Garden & Outdoor Living
pat_garden <- "GARDEN|LAWN|PLANT|PATIO|POOL|FERTILIZER|WEED|MOSS|INSECT|REPELLENT|HOSE|SPRIN

# 14. DIY, Auto & Tools
pat_diy_auto <- "LIGHT|TOOL|HARDWARE|DRILL|SAW|HAMMER|SCREW|WRENCH|PLUMBING|FIXTURE|PAINT|LA

# 15. Office & School
pat_office <- "OFFICE|PAPER|PEN|PENCIL|NOTEBOOK|BINDER|STAPLER|ENVELOPE|LABEL|DESK_ACCESSORY

# 16. Arts & Crafts
pat_arts <- "ART|CRAFT|SEWING|KNITTING|YARN|FABRIC|BEAD|CANVAS|PAINT_BRUSH|EASEL|SCRAPBOOK|T

# 17. Toys & Hobbies
pat_toys <- "TOY|PUZZLE|DOLL|FIGURE|LEGO|HOBBY|COLLECTIBLE|MODEL|DRONE|ROBOT|PLAYSET|FIDGE|P

# 18. Books & Media
pat_media <- "BOOK|DVD|MOVIE|MUSIC|CD|VINYL|MAGAZINE|MEDIA"

# 19. Party & Occasion
pat_party <- "PARTY|GIFT|WRAP|DECORATION|BALLOON|FAVOR|CANDLE|RIBBON|BOW|CONFETTI"

# Note: order here implies priority in the case_when below i.e. if a keyphrase is in multipl
category_lookup <- purchases |>
    distinct(category) |> # speed up process by shrinking dataset to unique categories = nro
    mutate(
        umbrella_category = case_when(
            # 0. Missing Data
            is.na(category) ~ "Unknown",
            # 1. High Priority / Specific
            str_detect(category, regex(pat_baby, ignore_case = TRUE)) ~ "Baby_Product",
            str_detect(category, regex(pat_video_games, ignore_case = TRUE)) ~ "Video_Games"
            str_detect(category, regex(pat_electronics, ignore_case = TRUE)) ~ "Electronics_a
            # 2. Food & Consumables
            str_detect(category, regex(pat_grocery, ignore_case = TRUE)) ~ "Grocery_and_Food'
            # 3. Personal Items
            str_detect(category, regex(pat_apparel, ignore_case = TRUE)) ~ "Apparel_and_Acces
            str_detect(category, regex(pat_health, ignore_case = TRUE)) ~ "Health_and_Medical
            str_detect(category, regex(pat_beauty, ignore_case = TRUE)) ~ "Beauty_and_Persona
            # 4. Home & Living (Order matters: Essentials -> Kitchen -> Decor -> General)
            str_detect(category, regex(pat_household, ignore_case = TRUE)) ~ "Household_Essen
            str_detect(category, regex(pat_kitchen, ignore_case = TRUE)) ~ "Kitchen_and_Dinin
            str_detect(category, regex(pat_home, ignore_case = TRUE)) ~ "Home_Decor_and_Furni
            # 5. Specialized
            str_detect(category, regex(pat_pets, ignore_case = TRUE)) ~ "Pet_Supplies",
            str_detect(category, regex(pat_sports, ignore_case = TRUE)) ~ "Sports_and_Outdoor
            str_detect(category, regex(pat_garden, ignore_case = TRUE)) ~ "Garden_and_Outdoor
            str_detect(category, regex(pat_diy_auto, ignore_case = TRUE)) ~ "DIY_Auto_and_Lig
            str_detect(category, regex(pat_arts, ignore_case = TRUE)) ~ "Arts_and_Crafts",
            str_detect(category, regex(pat_toys, ignore_case = TRUE)) ~ "Toys_and_Hobbies",
            # 6. General / Low Priority
            str_detect(category, regex(pat_office, ignore_case = TRUE)) ~ "Office_and_School'
            str_detect(category, regex(pat_media, ignore_case = TRUE)) ~ "Books_and_Media",
            str_detect(category, regex(pat_party, ignore_case = TRUE)) ~ "Party_and_Occasion'

            TRUE ~ "Other"
        )
    )

# join category -> umbrella category maps back to purchases

purchases <- purchases |>
    left_join(category_lookup, by = "category")

# check umbrella sizes

purchases |>
    select(umbrella_category) |>
    count(umbrella_category, sort = TRUE) |>
    print(n = 30)
```

```
# A tibble: 21 x 2
   umbrella_category              n
   <chr>                      <int>
 1 Grocery_and_Food          359319
 2 Apparel_and_Accessories   247471
 3 Electronics_and_Computers 238030
 4 Beauty_and_Personal_Care  142515
 5 Home_Decor_and_Furniture  132921
 6 Books_and_Media           108126
 7 Unknown                    89458
 8 Health_and_Medical         84155
 9 DIY_Auto_and_Lighting      81768
10 Office_and_School          76897
11 Household_Essentials       60271
12 Kitchen_and_Dining         46644
13 Pet_Supplies               40273
14 Toys_and_Hobbies           39811
15 Other                      23749
16 Sports_and_Outdoors        22028
17 Video_Games                19815
18 Baby_Product               18587
19 Garden_and_Outdoor          9860
20 Arts_and_Crafts             5895
21 Party_and_Occasion          3124
```

```
# check leftover "Other" categories

# purchases |>
#   filter(umbrella_category == "Other") |>
#   count(category, sort = TRUE) |> filter(n>=100) |> print(n=100)
```

```
purchases <- purchases |> select(!c(title, asin.isbn.product.code, category)) |> relocate(su
```

```
## create category freq per id
# n.distinct.categories

cat_freq_by_id <- purchases |>
    group_by(survey.response.id) |>
    mutate(total_user_purchases = n()) |> # total purchases made per-user
    group_by(survey.response.id, umbrella_category, total_user_purchases) |>
    summarise(n = n(), .groups = "drop") |> # purchases per-user, per-category
    mutate(share = n / total_user_purchases) |> # category share per-user
    pivot_wider(
        id_cols = "survey.response.id",
        names_from = "umbrella_category",
        values_from = "share",
        names_prefix = "freq_",
        values_fill = 0 # default behavior would fill unpurchased-from categories with NA
    ) |>
    rowwise() |>
    mutate(n.distinct.categories = sum(c_across(starts_with("freq_")) > 0), .after = "survey

## top shipping address state for each ID

top_destination_state_by_id <- purchases |>
    group_by(survey.response.id, shipping.address.state) |>
    summarise(n = n(), .groups = 'drop_last') |>
    arrange(desc(n), .by_group = TRUE) |>
    mutate(shipping.address.state = replace_na(shipping.address.state, replace = "digital/lo
    # some users' top state is NA ("Shipping Address State is often missing when the purchas
    slice_head(n = 1) |>
    select(survey.response.id, shipping.address.state) |>
    ungroup()


## summarize spending data

# summarize total.spent by the user
# and the average amount spent per order for the user
# and total.order.count
purchases <- purchases |>
    group_by(survey.response.id, order.date) |>
    summarize(order.price = sum(purchase.price.per.unit * quantity), n.orders = n()) |> # su
    group_by(survey.response.id) |>
    summarize(
        total.spent = sum(order.price),
        total.orders = sum(n.orders),
        avg.order.price = mean(order.price),
        .groups = 'drop'
    )

## merge category and address data into spending

purchases <- purchases |>
```

```r
    left_join(top_destination_state_by_id, by = "survey.response.id") |>
    left_join(cat_freq_by_id, by = "survey.response.id")

## add cols for total spend per category

purchases <- purchases %>%
    mutate(across(
        starts_with("freq_"),
        ~ .x * total.spent,
        .names = "{str_replace(.col, 'freq_', 'spend_')}"
    ))
```

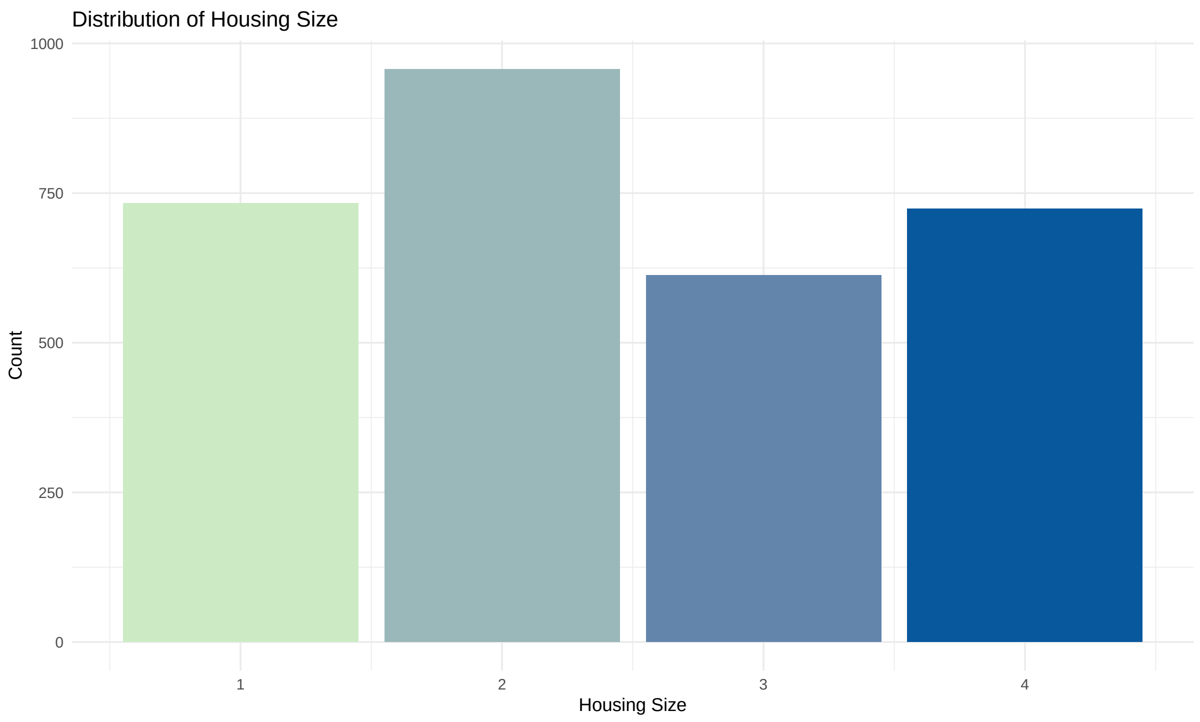
```r
## drop cols unused cols from survey data (not avail at sign-up)
survey <- survey |> select(survey.response.id, q.demos.gender, q.demos.state, q.amazon.use.hh

# Full join datasets on Survey Response ID
data <- full_join(purchases, survey, by = join_by(survey.response.id))

# set character vars as factor
data <- data |>
    mutate(
        across(where(is.character), as.factor),
        survey.response.id = as.character(survey.response.id) # keep id as simple string
    ) |>
    relocate(where(is.factor), .after = "survey.response.id") # move factor vars to the left

train_data <- data |> drop_na(q.amazon.use.hh.size.num)
test_data <- data |> filter(is.na(q.amazon.use.hh.size.num))

save(train_data, file = "processed_data_train.RData")
save(test_data, file = "processed_data_test.RData")

# clear workspace
rm(list = ls())
```

## Exploratory Data Analysis

As we explored potential relationships between the variables in the training dataset, notable patterns were discovered and some failed to show. Our findings are presented below:

## Response (HH Size) Distribution

```r
load("processed_data_train.RData")
data <- train_data

set_theme(theme_minimal())

ggplot(
    data,
    aes(x = q.amazon.use.hh.size.num, fill = q.amazon.use.hh.size.num, group = as.factor(q.am
) +
    geom_bar() +
    scale_fill_gradient(low = "#ccebc5", high = "#08589e") +
    labs(title = "Distribution of Housing Size", x = "Housing Size", y = "Count") +
    theme(legend.position = "none")
```

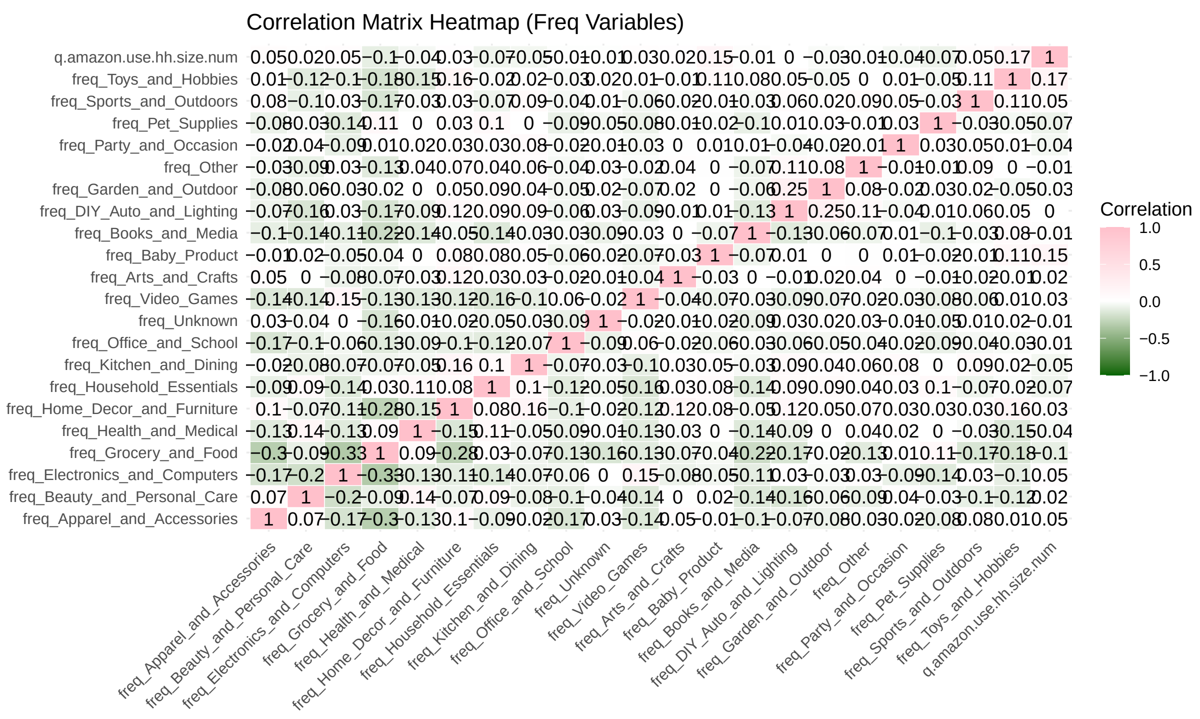


Just looking at the distribution of housing sizes, we see that it's most common for households to have a size of 2, with size 4+ or 1 the second most frequent, and a size of 3 having the lowest frequency. Since household sizes of 4 and more are represented by only one variable, it's difficult to tell what the breakdown of household sizes are within that variable.

## Numeric Variable Correlation

### Category purchase frequency correlation

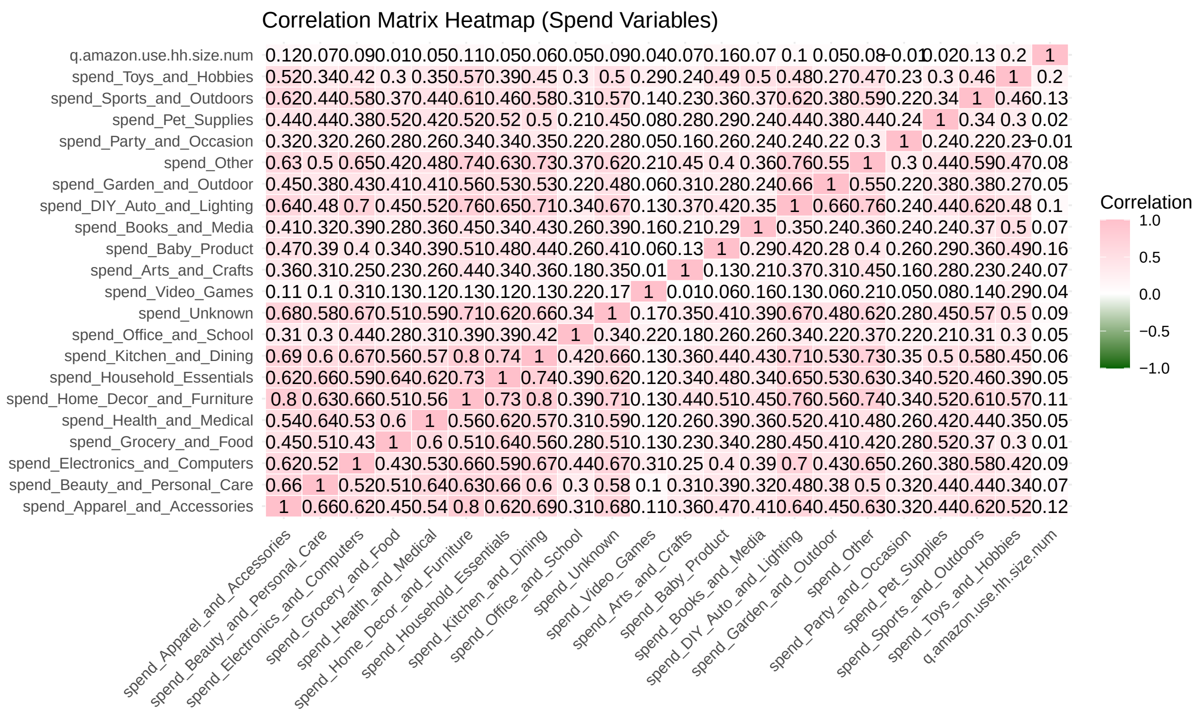
```r
# numeric variables that start with "freq"
freq_data <- train_data %>%
    select(where(is.numeric)) %>%
    select(contains("freq"), q.amazon.use.hh.size.num)

# correlation matrix
cor_matrix <- cor(freq_data, use = "pairwise.complete.obs")

# long format for ggplot
cor_long <- as.data.frame(as.table(cor_matrix))

ggplot(cor_long, aes(Var1, Var2, fill = Freq)) +
    geom_tile(color = "white") +
    scale_fill_gradient2(
        low = "darkgreen",
        high = "pink",
        mid = "white",
        midpoint = 0,
        limit = c(-1, 1),
        space = "Lab",
        name = "Correlation"
    ) +
    geom_text(aes(label = round(Freq, 2)), color = "black", size = 4) +
    theme_minimal() +
    theme(axis.text.x = element_text(angle = 45, vjust = 1, hjust = 1)) +
    labs(title = "Correlation Matrix Heatmap (Freq Variables)", x = "", y = "")
```



```r
ggsave("correlation_heatmap_freq.png", width = 12, height = 10, dpi = 300)
```

## Category spending correlation

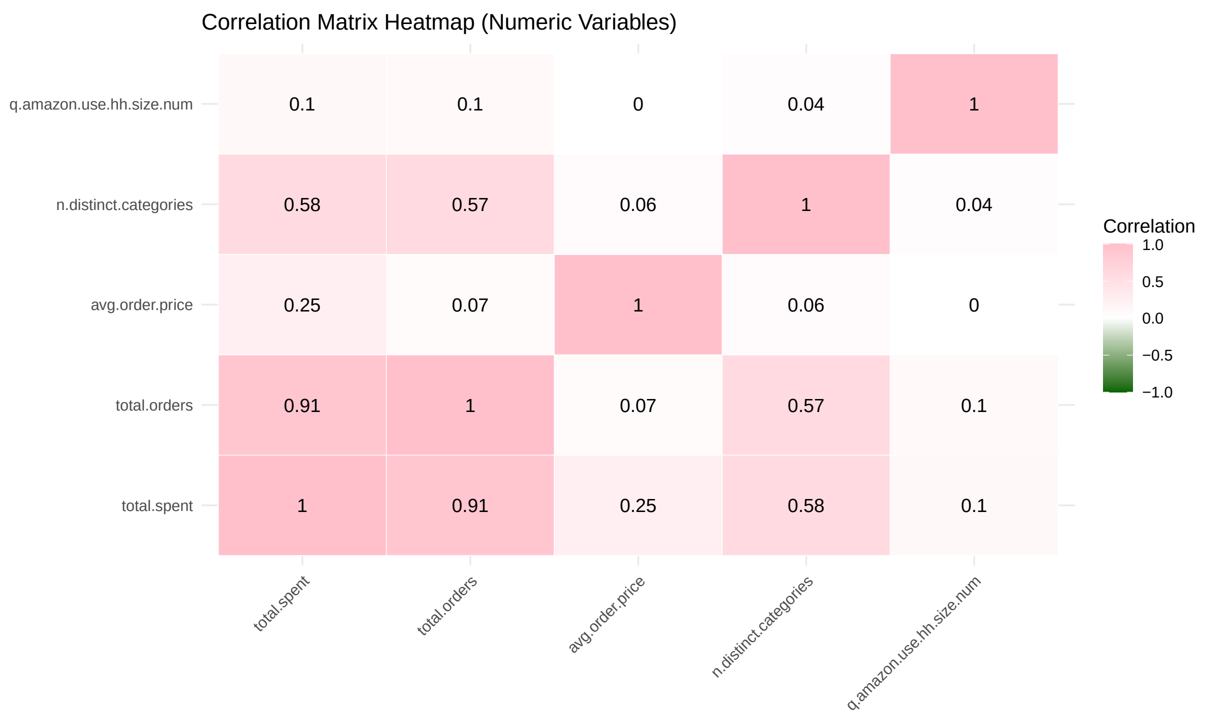
```r
# numeric variables that start with "spend"
spend_data <- train_data %>%
    select(where(is.numeric)) %>%
    select(contains("spend"), q.amazon.use.hh.size.num)

# correlation matrix
cor_matrix <- cor(spend_data, use = "pairwise.complete.obs")

# long format for ggplot
cor_long <- as.data.frame(as.table(cor_matrix))

ggplot(cor_long, aes(Var1, Var2, fill = Freq)) +
    geom_tile(color = "white") +
    scale_fill_gradient2(
        low = "darkgreen",
        high = "pink",
        mid = "white",
        midpoint = 0,
        limit = c(-1, 1),
        space = "Lab",
        name = "Correlation"
    ) +
    geom_text(aes(label = round(Freq, 2)), color = "black", size = 4) +
    theme_minimal() +
    theme(axis.text.x = element_text(angle = 45, vjust = 1, hjust = 1)) +
    labs(title = "Correlation Matrix Heatmap (Spend Variables)", x = "", y = "")
```



```r
ggsave("correlation_heatmap_spend.png", width = 13, height = 10, dpi = 300)
```

### Misc. leftover numeric variables

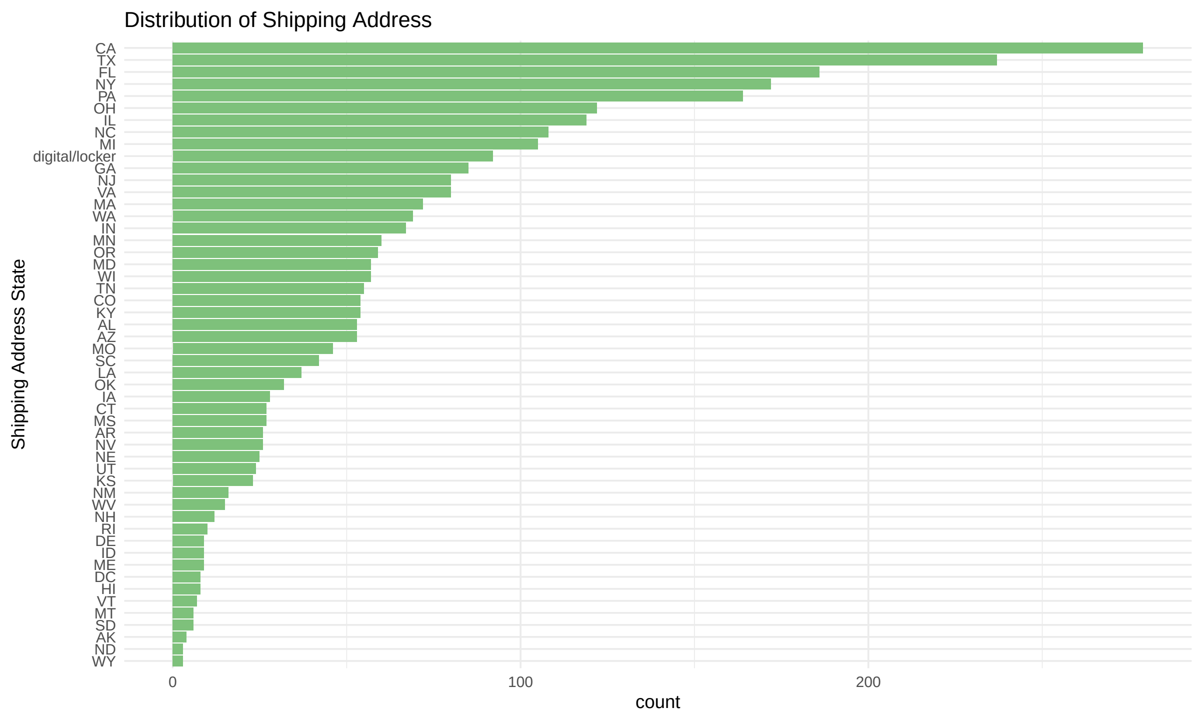
```r
numeric_data <- train_data %>%
    select(where(is.numeric)) %>%
    select(
        -contains("freq"),
        -contains("spend"),
        q.amazon.use.hh.size.num
    )

# correlation matrix
cor_matrix <- cor(numeric_data, use = "pairwise.complete.obs")

# long format for ggplot
cor_long <- as.data.frame(as.table(cor_matrix))

ggplot(cor_long, aes(Var1, Var2, fill = Freq)) +
    geom_tile(color = "white") +
    scale_fill_gradient2(
        low = "darkgreen",
        high = "pink",
        mid = "white",
        midpoint = 0,
        limit = c(-1, 1),
        space = "Lab",
        name = "Correlation"
    ) +
    geom_text(aes(label = round(Freq, 2)), color = "black", size = 4) +
    theme_minimal() +
    theme(axis.text.x = element_text(angle = 45, vjust = 1, hjust = 1)) +
    labs(title = "Correlation Matrix Heatmap (Numeric Variables)", x = "", y = "")
```



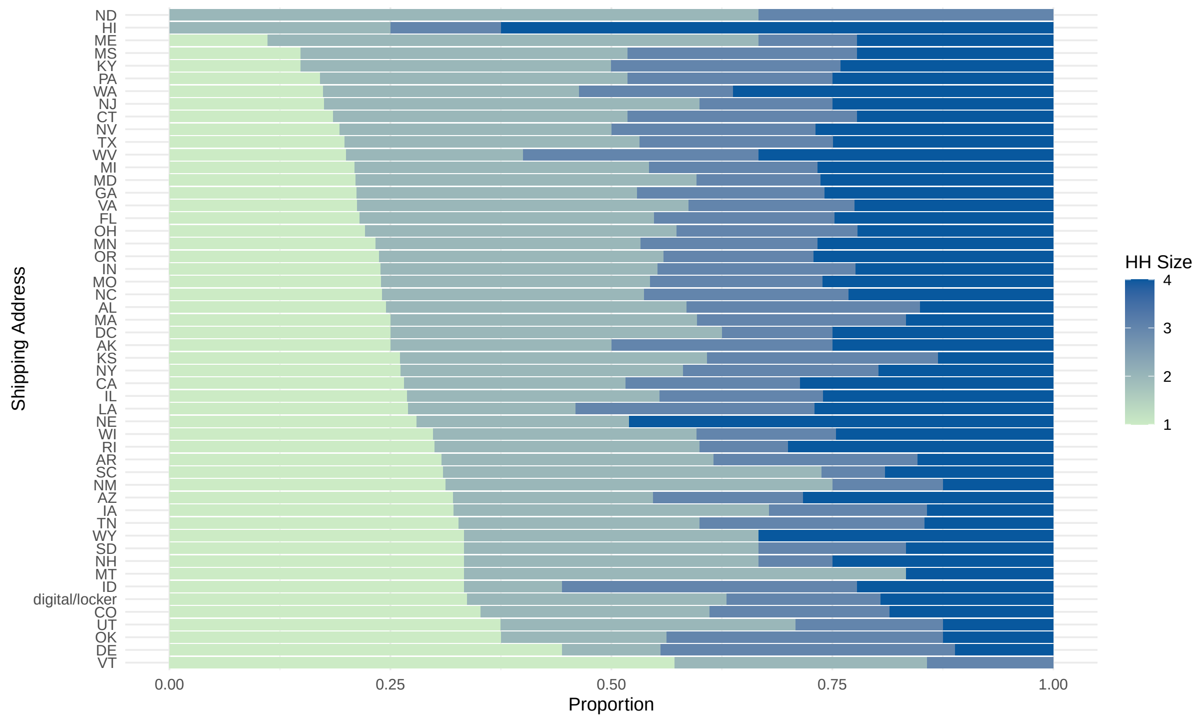
```r
ggsave("correlation_heatmap_orders.png", width = 12, height = 10, dpi = 300)
```

### Location

```r
ggplot(train_data, aes(y = fct_rev(fct_infreq(shipping.address.state)))) +
    geom_bar(fill = "#7ec17bff") +
    labs(
        title = "Distribution of Shipping Address",
        y = "Shipping Address State"
    )
```



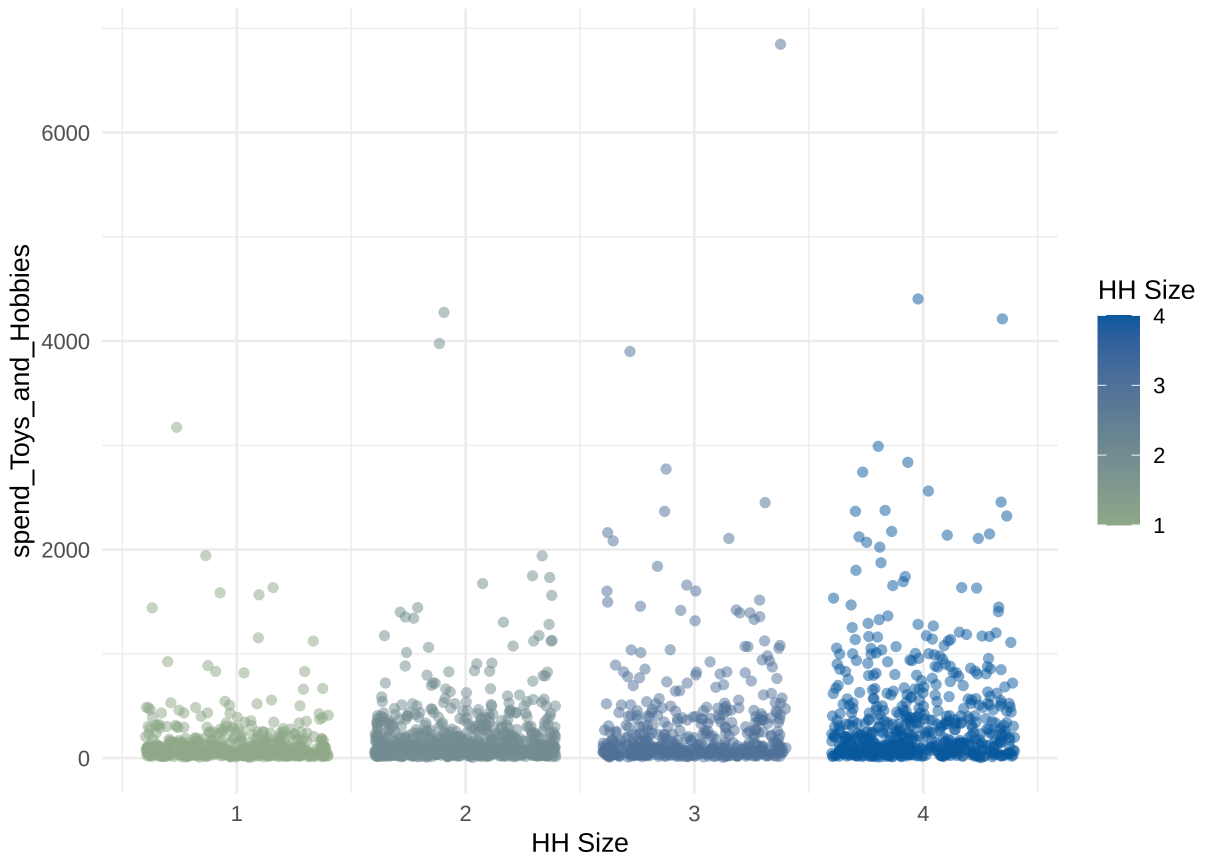
```
ggsave("distr_shipping_address.png", width = 12, height = 10, dpi = 300)

# diff attempt at plotting per-state distr of hhsize
state_order <- train_data %>%
    group_by(shipping.address.state) %>%
    summarize(prop_size_1 = mean(q.amazon.use.hh.size.num == 1)) %>%
    arrange(desc(prop_size_1)) %>% # Use desc(prop_size_2) if you want top-to-bottom
    pull(shipping.address.state)

train_data |>
    mutate(shipping.address.state = factor(shipping.address.state, levels = state_order)) |>
    ggplot(aes(
        x = shipping.address.state,
        fill = q.amazon.use.hh.size.num,
        group = as.factor(q.amazon.use.hh.size.num)
    )) +
    geom_bar(position = position_fill(reverse = TRUE)) +
    scale_fill_gradient(low = "#ccebc5", high = "#08589e") +
    coord_flip() +
    labs(y = "Proportion", x = "Shipping Address", fill = "HH Size")
```



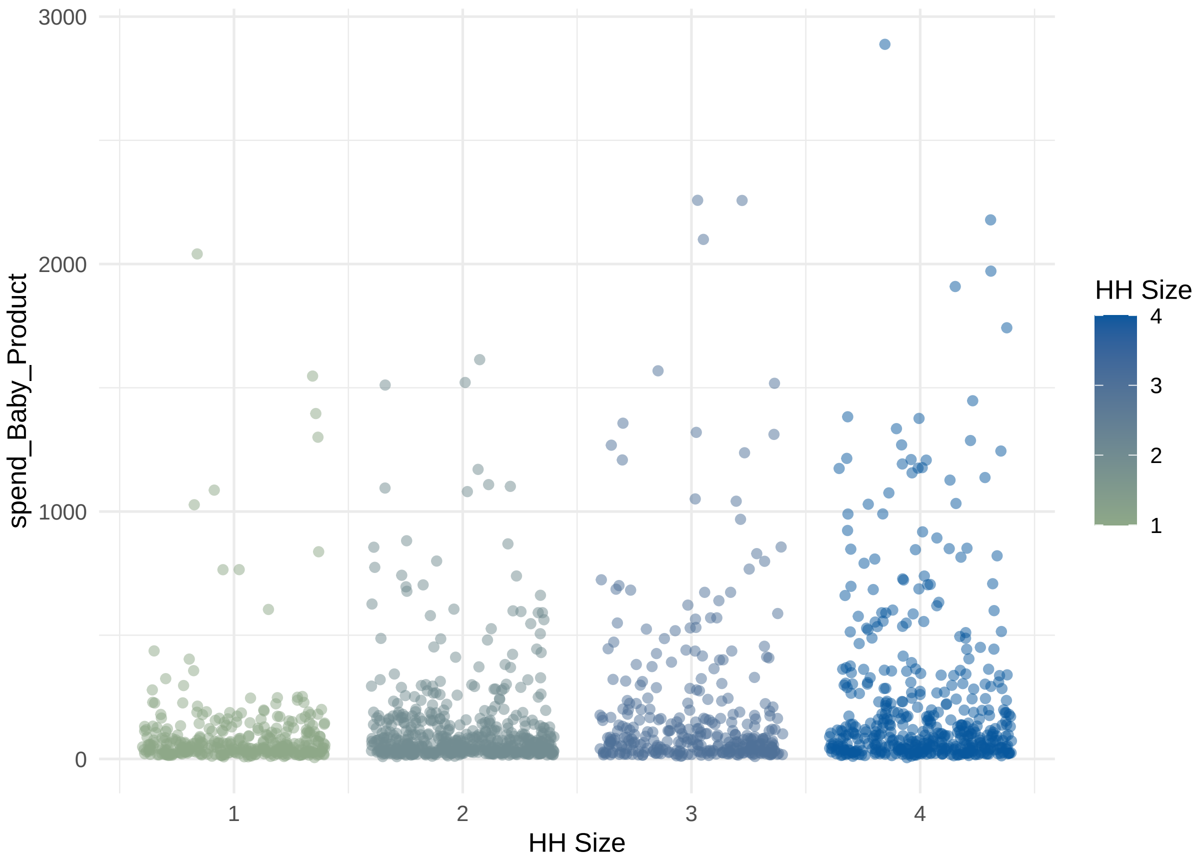
```
ggsave("hhsize_by_state_address.png", width = 12, height = 10, dpi = 300)
```

## Product Categories

```
# plot high correlated cat frequencies against hhsize
ggplot(
    train_data |> filter(freq_Toys_and_Hobbies > 0),
    aes(
        x = q.amazon.use.hh.size.num,
        y = spend_Toys_and_Hobbies,
        color = q.amazon.use.hh.size.num,
        group = as.factor(q.amazon.use.hh.size.num)
    )
) +
    geom_jitter(alpha = 0.5) +
    scale_color_gradient(low = "#8ea888ff", high = "#08589e") +
    labs(
        color = "HH Size",
        x = "HH Size"
    )
```



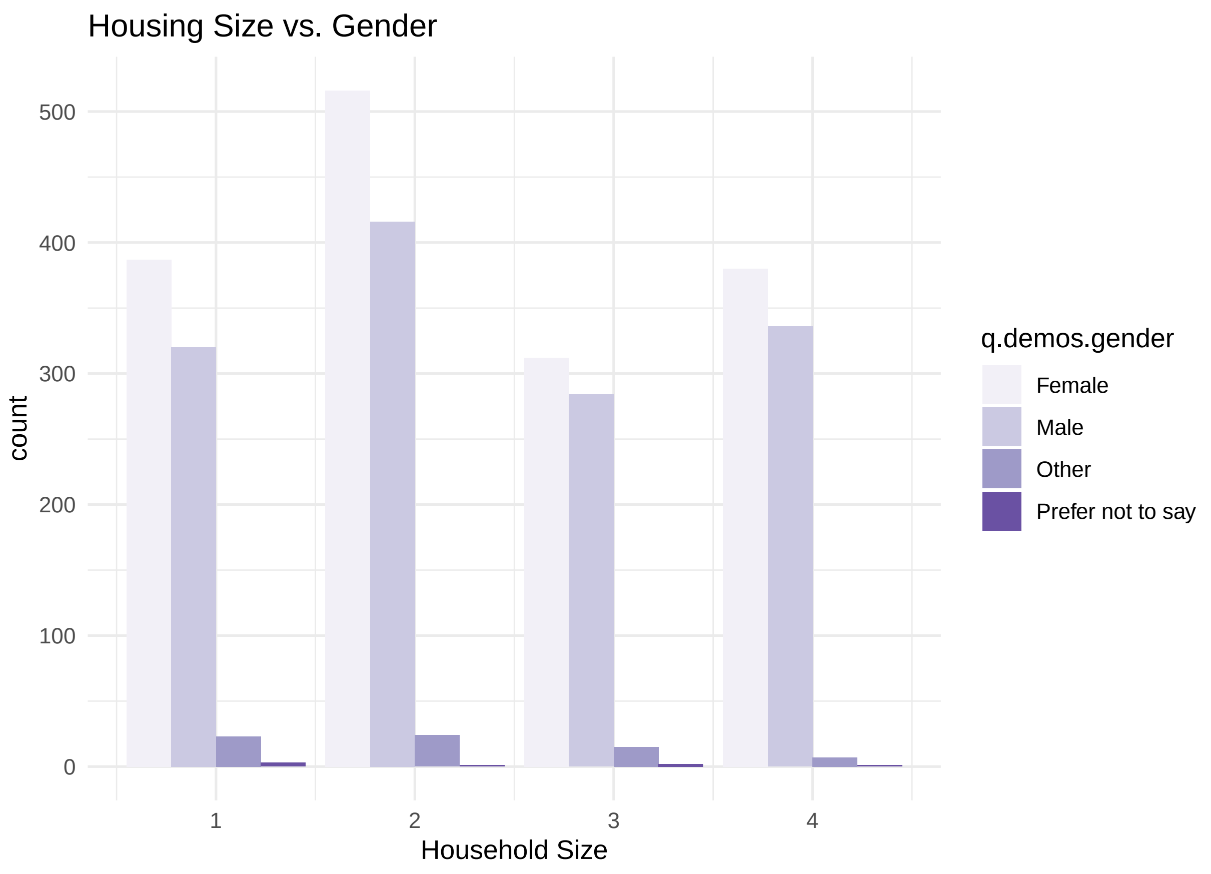
```r
ggsave("hhsize_by_spend_toys.png", width = 12, height = 10, dpi = 300)

ggplot(
    data |> filter(freq_Baby_Product > 0),
    aes(
        x = q.amazon.use.hh.size.num,
        y = spend_Baby_Product,
        color = q.amazon.use.hh.size.num,
        group = as.factor(q.amazon.use.hh.size.num)
    )
) +
    geom_jitter(alpha = 0.5) +
    scale_color_gradient(low = "#8ea888ff", high = "#08589e") +
    labs(
        color = "HH Size",
        x = "HH Size"
    )
```



```
ggsave("hhsize_by_spend_baby.png", width = 12, height = 10, dpi = 300)
```

### Gender

```
ggplot(data, aes(fill = q.demos.gender, x = q.amazon.use.hh.size.num, group = as.factor(q.den
    geom_bar(position = "dodge") +
    scale_fill_brewer(palette = "Purples") +
    labs(title = "Housing Size vs. Gender ", x = "Household Size")
```



```r
ggsave("hhsize_by_gender.png", width = 12, height = 10, dpi = 300)
```

## Model Evaluation and Tuning

```r
load("processed_data_train.RData")
train_data <- train_data |> select(!c(survey.response.id, starts_with("spend_")))

# defining the task
housing_tsk <- as_task_regr(train_data, target = "q.amazon.use.hh.size.num")

## spliting training and test data
set.seed(101)
split <- partition(housing_tsk, ratio = 0.8)
train_idx <- split$train
test_idx <- split$test
```

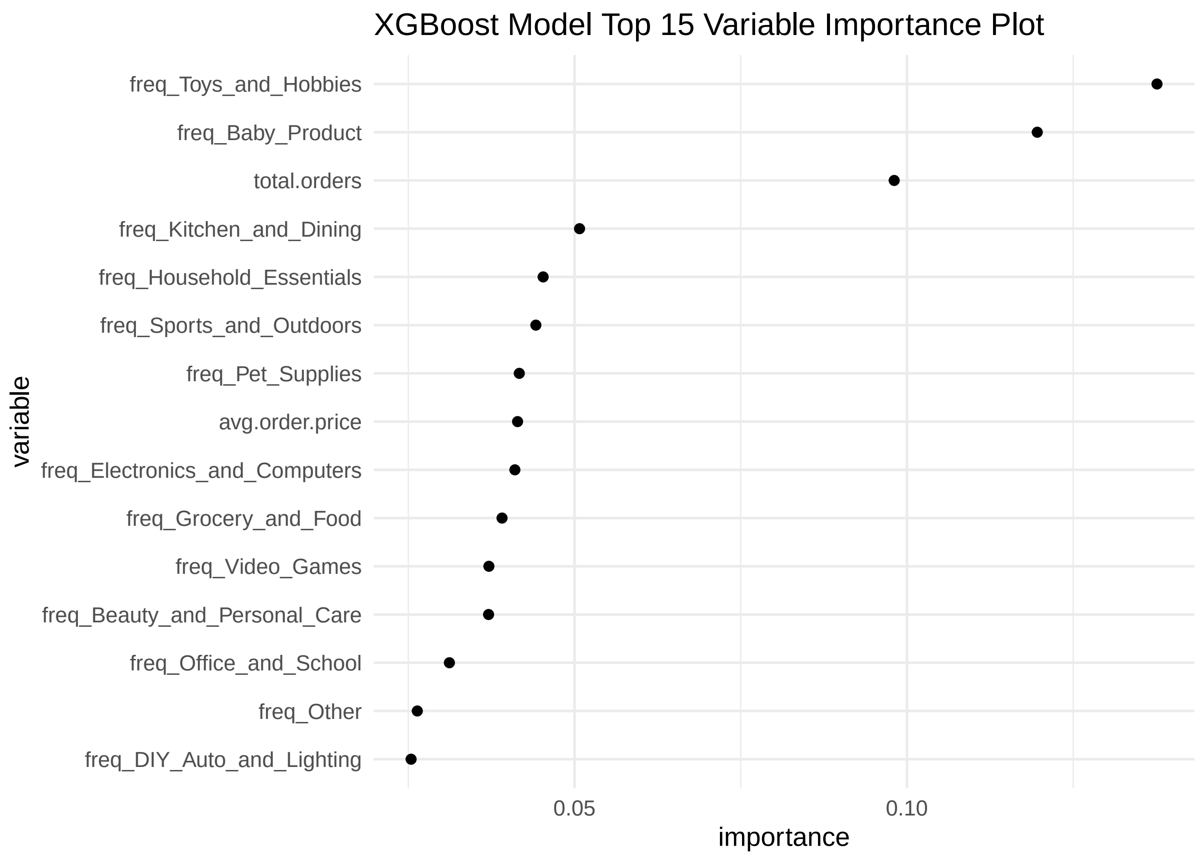
```r
# measures
measures <- list(msr("regr.rmse"), msr("regr.mse"))
```

### XGBoost Model 1

```r
# learner
lrn_xgboost1 <- as_learner(
    po("encode", method = "one-hot") %>>%
        lrn(
            "regr.xgboost",
            eta = to_tune(1e-4, 1, logscale = TRUE),
            max_depth = to_tune(1, 10),
            colsample_bytree = to_tune(1e-1, 1),
            colsample_bylevel = to_tune(1e-1, 1),
            lambda = to_tune(1e-3, 1e3, logscale = TRUE),
            alpha = to_tune(1e-3, 1e3, logscale = TRUE),
            subsample = to_tune(1e-1, 1)
        )
)

# 5-fold cv
resampling1 <- rsmp("cv", folds = 5)
# terminate at 5 evals
terminator1 <- trm("evals", n_evals = 5)
# grid search tuner
tuner_gs = tnr("grid_search")

#auto tuner
at_xgboost1 <- auto_tuner(
    learner = lrn_xgboost1,
    resampling = resampling1,
    measure = msr("regr.rmse"), # evaluate by the rmse value
    terminator = terminator1,
    tuner = tuner_gs
)

# train the model
# commented out the below lines to prevent knitting from taking too long
# we extracted the best parameters and made a duplicate model with the best paramters set
# at_xgboost1$train(housing_tsk, row_ids = train_idx)
# store the best parameters
# best_param1 <- at_xgboost1$tuning_result

tuned_lrn_xgboost1 <- as_learner(
    po("encode", method = "one-hot") %>>%
        lrn(
            "regr.xgboost",
            eta = exp(-5.116856),
            max_depth = 3,
            colsample_bytree = 0.8,
            colsample_bylevel = 0.6,
            lambda = exp(3.837642),
            alpha = exp(-0.7675284),
            subsample = 1
        )
)

# train the model
set.seed(101)
tuned_lrn_xgboost1$train(housing_tsk, row_ids = train_idx)
# predict on train indecies
preds1 <- tuned_lrn_xgboost1$predict(housing_tsk, row_ids = test_idx)
# obtain score
preds1$score(measures)
```

```
regr.rmse  regr.mse
 1.081812  1.170318
```

```
# regr.rmse  regr.mse
#  1.081812  1.170318

## code to create predictions on the 2000 observations of test data
# test_predict <- tuned_lrn_xgboost1$predict_newdata(test_data)
# testing <- test_predict$response

# submit <- data.frame(ids, testing)
# str(submit)
# colnames(submit) <- c("Survey.ResponseID", "Q.amazon.use.hh.size.num")

# library(data.table)
# write_csv(submit, "submit.csv")
# extract variable importance
importance_scores <- tuned_lrn_xgboost1$importance()
# variable importance plot
ggplot(
    data = data.frame(var = names(importance_scores), value = importance_scores) |>
        dplyr::arrange(desc(value)) |>
        dplyr::slice(1:15)
) +
    ggtitle("XGBoost Model Top 15 Variable Importance Plot") +
    geom_point(aes(x = value, y = reorder(var, value))) +
    ylab("variable") +
    xlab("importance")
```

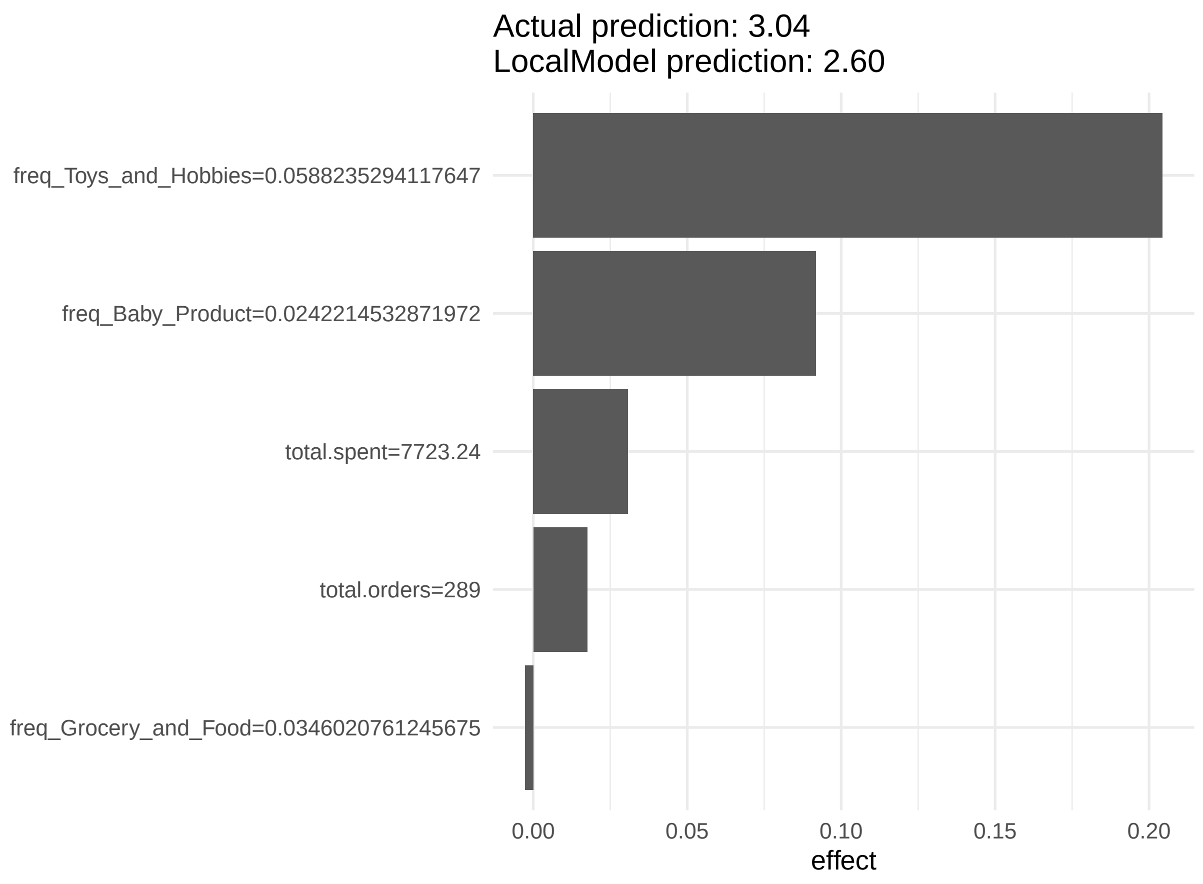


```
# lime visual
X_test <- housing_tsk$data(
    rows = test_idx,
    cols = housing_tsk$feature_names
```

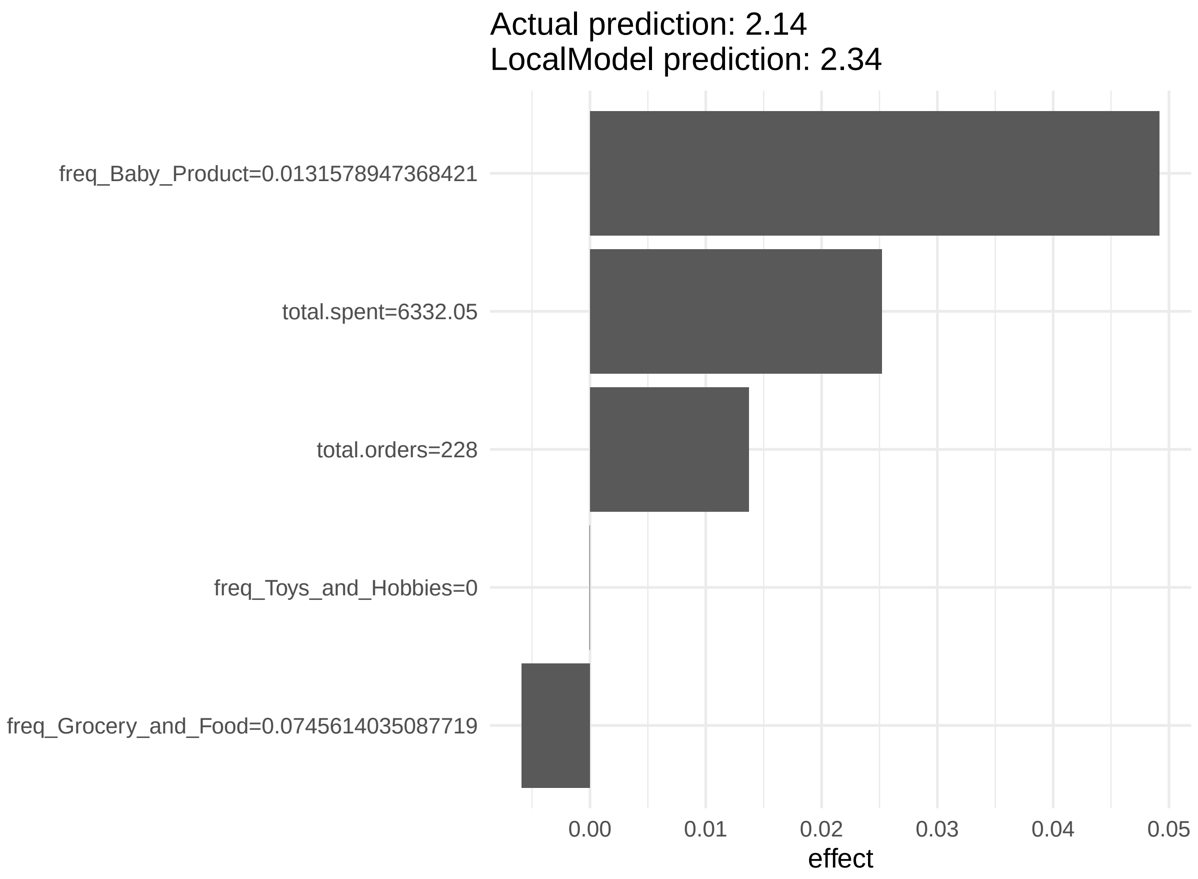
```r
)

y_test <- housing_tsk$data(
    rows = test_idx,
    cols = housing_tsk$target_names
)[[1]]

pred_fun <- function(model, newdata) {
    model$predict_newdata(newdata)$response
}

predictor <- Predictor$new(
    model = tuned_lrn_xgboost1,
    data = X_test,
    y = y_test,
    predict.function = pred_fun
)

# pick some interesting test points (rows within X_test)
example_ids <- c(1, 20)

set.seed(101)
# see their predictions for context
tuned_lrn_xgboost1$predict_newdata(X_test[example_ids, ])
```

```
-- <PredictionRegr> for 2 observations: ----------------------------------------
 row_ids truth response
       1    NA 3.035510
       2    NA 2.135257
```

```r
set.seed(101)
# LocalModel = LIME-style local surrogate
loc_1 <- LocalModel$new(predictor, x.interest = X_test[example_ids[1], ], k = 5)
loc_2 <- LocalModel$new(predictor, x.interest = X_test[example_ids[2], ], k = 5)

# plots: contribution of top features for each case
plot(loc_1)
```


Actual prediction: 3.04
LocalModel prediction: 2.60
freq_Toys_and_Hobbies=0.0588235294117647
freq_Baby_Product=0.0242214532871972
total.spent=7723.24
total.orders=289
freq_Grocery_and_Food=0.0346020761245675
0.00
0.05
0.10
0.15
0.20
effect

```r
plot(loc_2)
```



### Random Forest Model 1

```r
## manually changed the parameters to reduce time waiting to tune the model
lrn_rf1 <- lrn(
    "regr.ranger",
    num.trees = 618,
    mtry = 4,
    min.node.size = 11,
    sample.fraction = 0.8449092,
    importance = "impurity"
)

## train the model
set.seed(101)
lrn_rf1$train(housing_tsk, row_ids = train_idx)
## predict on test indicies
```

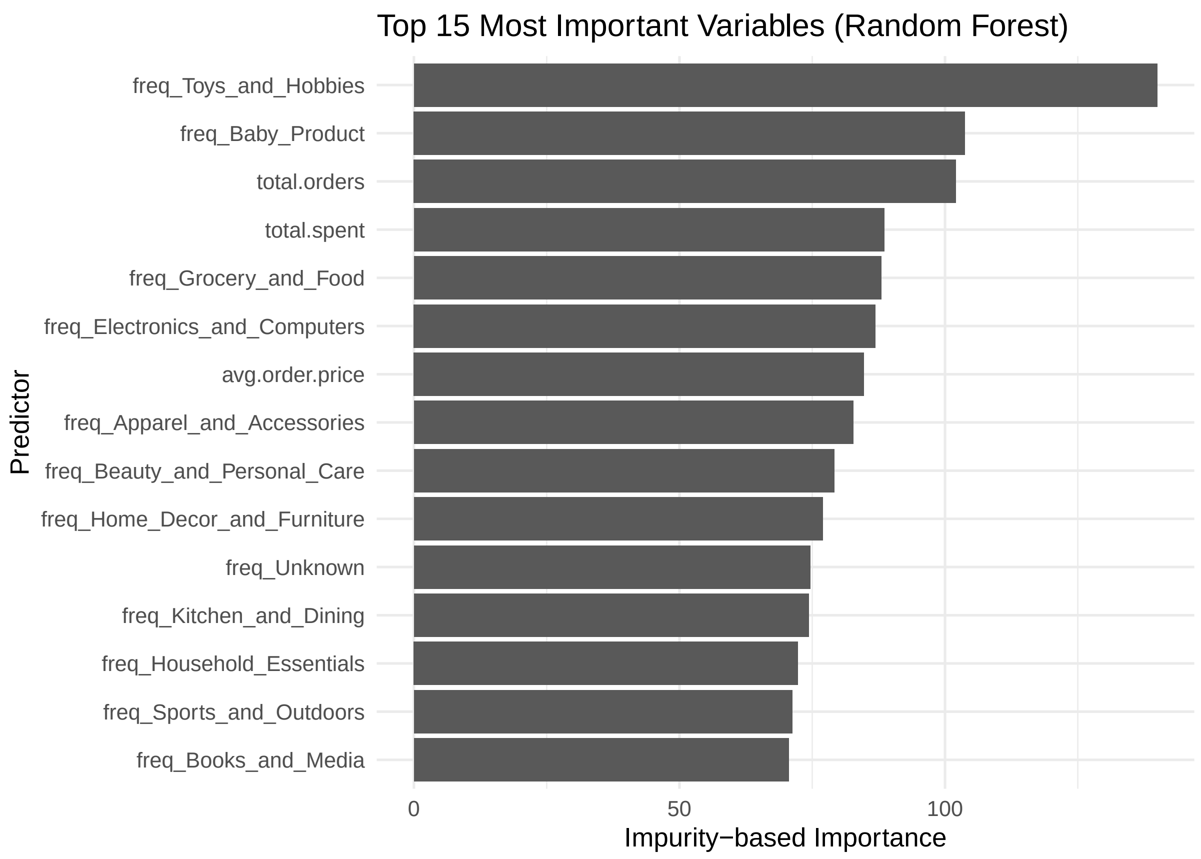
```r
preds2 <- lrn_rf1$predict(housing_tsk, row_ids = test_idx)
preds2$score(measures)
```

```
regr.rmse  regr.mse
 1.076661  1.159199
```

```r
# regr.rmse  regr.mse
#  1.076661  1.159199

# getting importance values
importance <- lrn_rf1$importance()
class(importance) # should be "numeric"
```

```
[1] "numeric"
```

```r
# str(importance)

# importance values as a dataframe for plotting
vip_df <- data.frame(
    variable = names(importance),
    importance = as.numeric(importance)
)

# sort by importance, descending
vip_df <- vip_df[order(-vip_df$importance), ]
# plot
ggplot(vip_df[1:15, ], aes(x = reorder(variable, importance), y = importance)) +
    geom_bar(stat = "identity") +
    coord_flip() +
    labs(
        title = "Top 15 Most Important Variables (Random Forest)",
        x = "Predictor",
        y = "Impurity-based Importance"
    ) +
    theme_minimal()
```

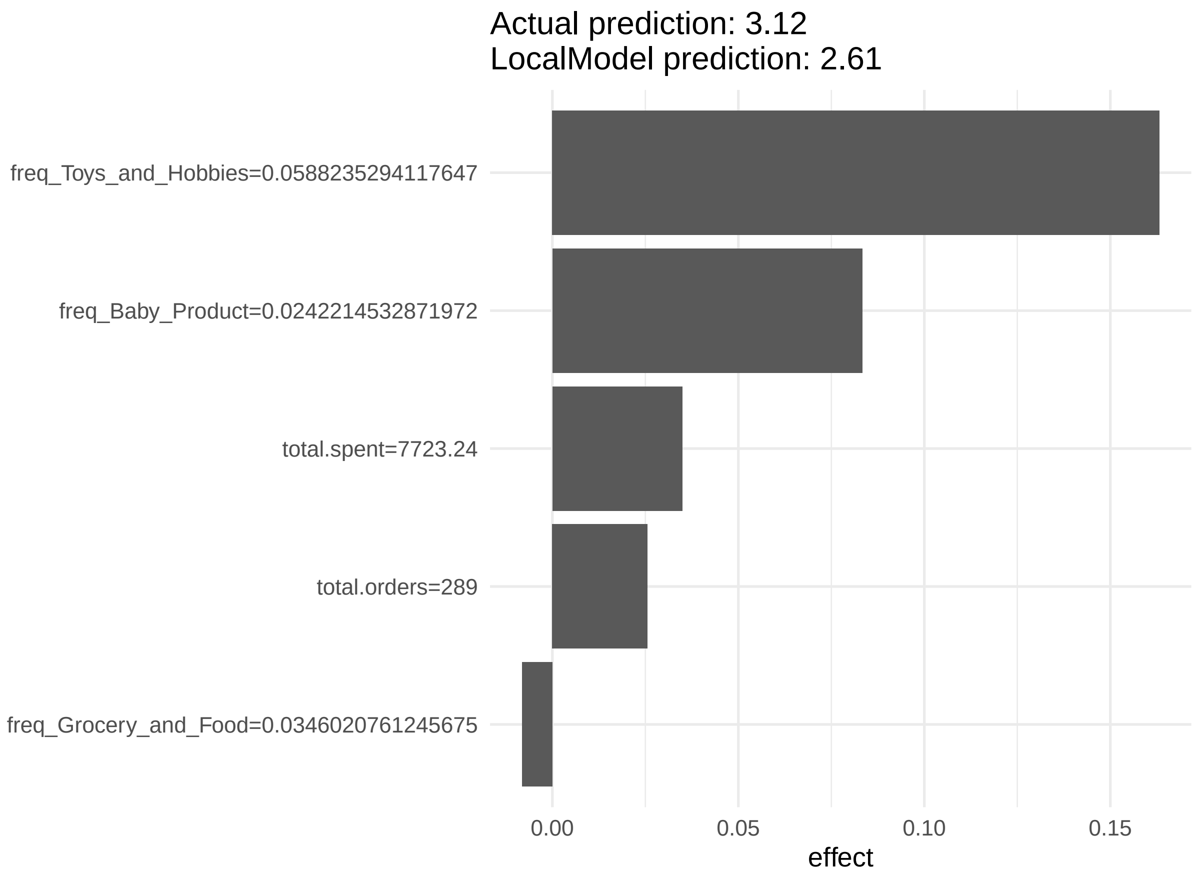


```r
# lime visuals
predictor <- Predictor$new(
    model = lrn_rf1,
    data = X_test,
    y = y_test,
    predict.function = pred_fun
)

# pick some interesting test points (rows within X_test)
example_ids <- c(1, 20)

# see their predictions for context
set.seed(101)
lrn_rf1$predict_newdata(X_test[example_ids, ])
```

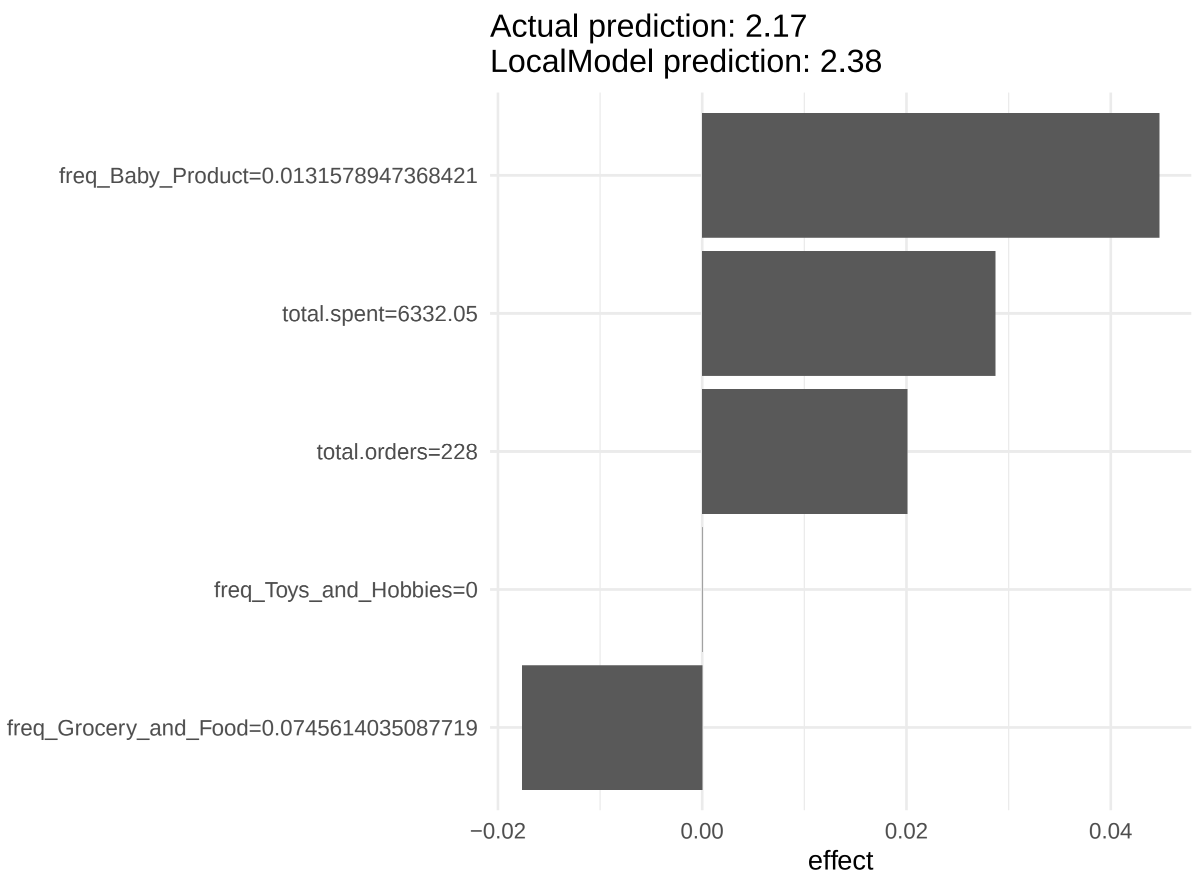
```
-- <PredictionRegr> for 2 observations: ----------------------------------------
 row_ids truth response
```

```
1    NA 3.117842
2    NA 2.166861
```

```
set.seed(101)
# LocalModel = LIME-style local surrogate
loc_1 <- LocalModel$new(predictor, x.interest = X_test[example_ids[1], ], k = 5)
loc_2 <- LocalModel$new(predictor, x.interest = X_test[example_ids[2], ], k = 5)

# plots: contribution of top features for each case
plot(loc_1)
```



```
plot(loc_2)
```



## NEW DATA VARIABLES

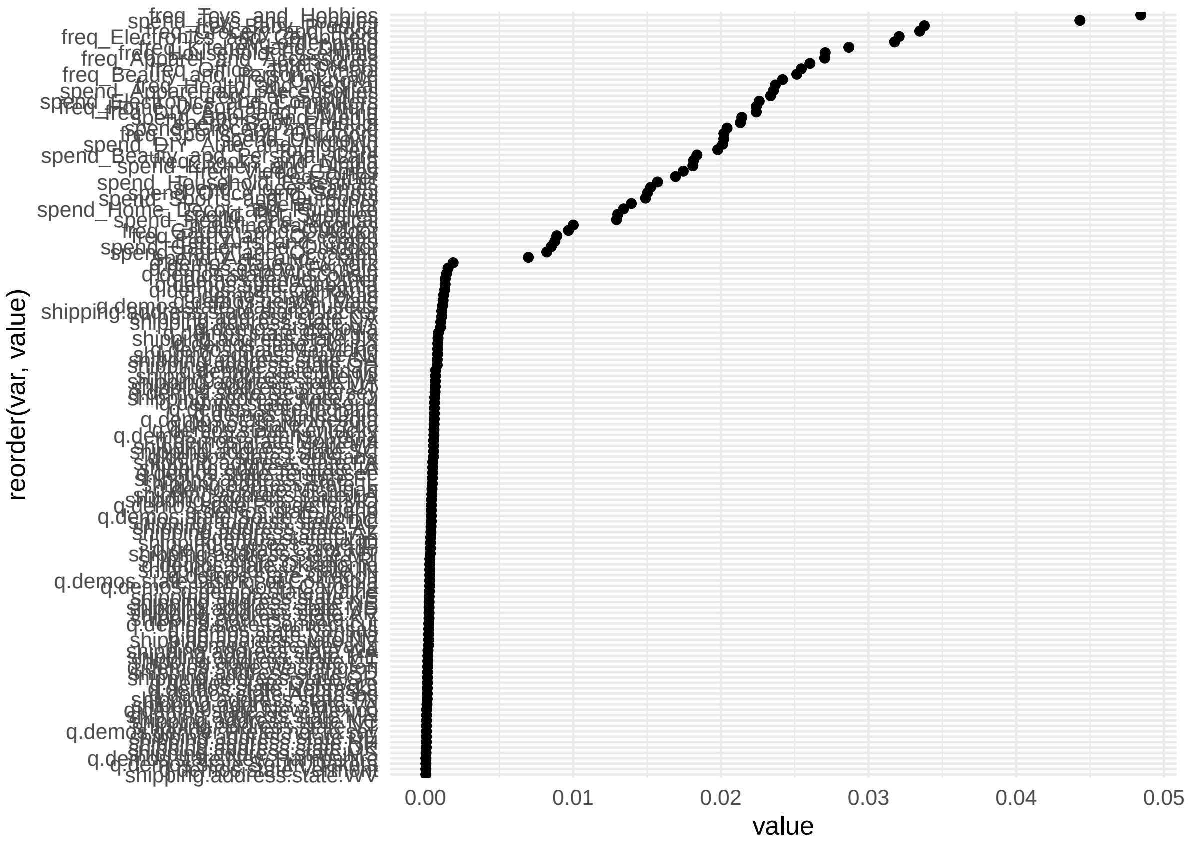
```
load("processed_data_train.RData")
data <- train_data |> select(-survey.response.id)
# defining the task
tsk_hhsize <- as_task_regr(data, target = "q.amazon.use.hh.size.num", id = "amazon_hh_size")
```

## Final Model: XGBoost Model 2

```
lrn_xgb <- as_learner(
    po("encode", method = "one-hot") %>>%
        lrn(
            "regr.xgboost",
            eta = to_tune(1e-4, 1, logscale = TRUE),
```

```r
            max_depth = to_tune(1, 15),
            colsample_bytree = to_tune(0.1, 1),
            subsample = to_tune(0.1, 1),
            lambda = to_tune(1e-3, 1e3, logscale = TRUE),
            alpha = to_tune(1e-3, 1e3, logscale = TRUE)
        )
)

set.seed(13)
plan(list(
    tweak("multisession", workers = 3),
    tweak("multisession", workers = 3)
))

instance = ti(
    task = tsk_hhsize,
    learner = lrn_xgb,
    resampling = rsmp("cv", folds = 5),
    measure = msr("regr.rmse"),
    terminator = trm("evals", n_evals = 60)
)

## commenting the below code out to save time for knitting
# tuner_rs$optimize(instance)
## extract best params, fit and train final model
# best_params <- instance$result_learner_param_vals
xgb_tune4 <- as_learner(
    po("encode", method = "one-hot") %>>%
        lrn(
            "regr.xgboost",
            eta = 0.007055363,
            max_depth = 4,
            colsample_bytree = 0.319908,
            subsample = 0.369098,
            lambda = exp(-1.05846993385),
            alpha = exp(0.73788139955)
        )
)

set.seed(13)
hhsize_split <- partition(tsk_hhsize, ratio = 0.7)
train_idx2 <- hhsize_split$train
```

```r
test_id2 <- hhsize_split$test
xgb_tune4$train(tsk_hhsize, row_ids = hhsize_split$train)

# var importance plot sanity check
as_tibble(xgb_tune4$importance(), rownames = "var") |> ggplot() + geom_point(aes(y = reorder
```



```r
# evaluate on test set
preds <- xgb_tune4$predict(tsk_hhsize, row_ids = hhsize_split$test)
preds$score(c(msr("regr.rmse"), msr("regr.mae"), msr("regr.mse")))
```

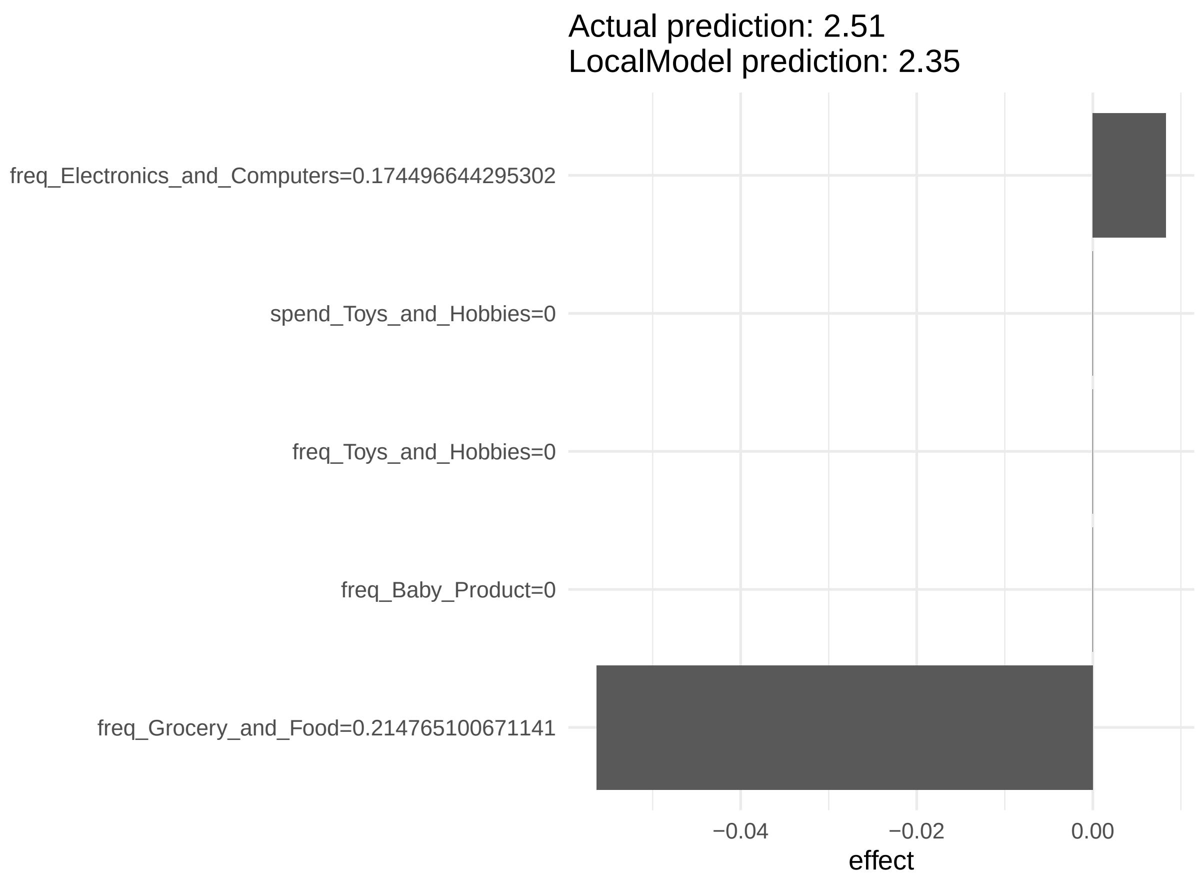
```
regr.rmse  regr.mae  regr.mse
1.0487332 0.8917467 1.0998414
```

```r
# regr.rmse  regr.mae  regr.mse
# 1.0438824 0.8887537 1.0896904

# lime visuals
```

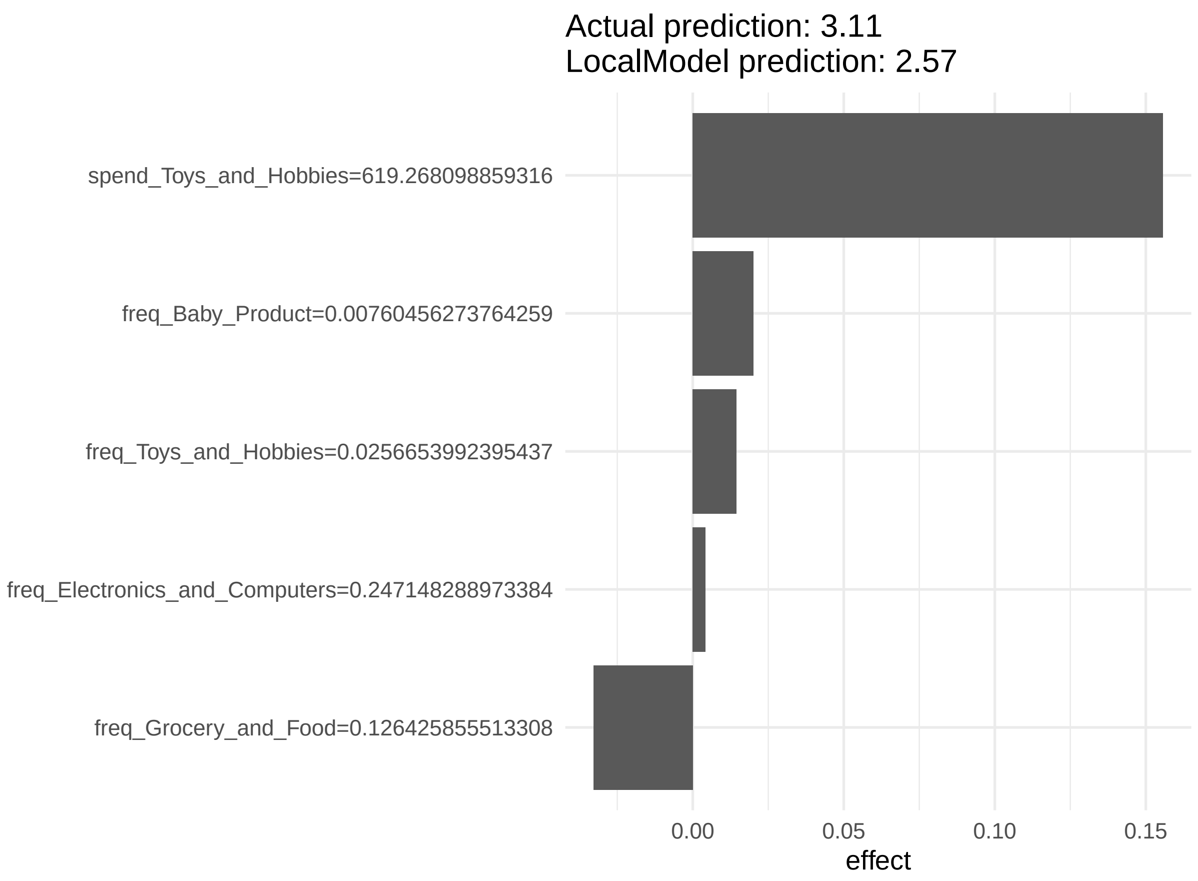
```r
X_test <- tsk_hhsize$data(
    rows = test_id2,
    cols = tsk_hhsize$feature_names
)

y_test <- tsk_hhsize$data(
    rows = test_id2,
    cols = tsk_hhsize$target_names
)[[1]]

predictor <- Predictor$new(
    model = xgb_tune4,
    data = X_test,
    y = y_test,
    predict.function = pred_fun
)

# pick some interesting test points (rows within X_test)
example_ids <- c(1, 20)

# see their predictions for context
set.seed(101)
xgb_tune4$predict_newdata(X_test[example_ids, ])
```

```
-- <PredictionRegr> for 2 observations: ----------------------------------------
 row_ids truth response
       1    NA 2.512735
       2    NA 3.108597
```

```r
set.seed(101)
# LocalModel = LIME-style local surrogate
loc_1 <- LocalModel$new(predictor, x.interest = X_test[example_ids[1], ], k = 5)
loc_2 <- LocalModel$new(predictor, x.interest = X_test[example_ids[2], ], k = 5)

# plots: contribution of top features for each case
plot(loc_1)
```


Actual prediction: 2.51
LocalModel prediction: 2.35
freq_Electronics_and_Computers=0.174496644295302
spend_Toys_and_Hobbies=0
freq_Toys_and_Hobbies=0
freq_Baby_Product=0
freq_Grocery_and_Food=0.214765100671141
−0.04
−0.02
0.00
effect

```
plot(loc_2)
```



### comparing models w/ xgb1

```r
tuned_lrn_xgboost1$id <- "tuned_lrn_xgboost1"
lrn_rf1$id <- "lrn_rf1"
xgb_tune4$id <- "xgb_tune4"
learners_to_compare <- list(tuned_lrn_xgboost1, lrn_rf1, lrn("regr.featureless"), xgb_tune4)

rsmp_cv5 <- rsmp("cv", folds = 5)

bmr_design <- benchmark_grid(
    tasks = housing_tsk,
    learners = learners_to_compare,
    resamplings = rsmp_cv5
)

# running the actual benchmark experiment
```

```r
set.seed(101)
bmr <- benchmark(design = bmr_design)
```

```
INFO  [23:56:45.488] [mlr3] Applying learner 'tuned_lrn_xgboost1' on task 'train_data' (iter
INFO  [23:56:45.765] [mlr3] Applying learner 'tuned_lrn_xgboost1' on task 'train_data' (iter
INFO  [23:56:46.054] [mlr3] Applying learner 'tuned_lrn_xgboost1' on task 'train_data' (iter
INFO  [23:56:49.479] [mlr3] Applying learner 'tuned_lrn_xgboost1' on task 'train_data' (iter
INFO  [23:56:49.759] [mlr3] Applying learner 'tuned_lrn_xgboost1' on task 'train_data' (iter
INFO  [23:56:50.002] [mlr3] Applying learner 'lrn_rf1' on task 'train_data' (iter 1/5)
INFO  [23:56:51.735] [mlr3] Applying learner 'lrn_rf1' on task 'train_data' (iter 2/5)
INFO  [23:56:53.089] [mlr3] Applying learner 'lrn_rf1' on task 'train_data' (iter 3/5)
INFO  [23:56:53.180] [mlr3] Applying learner 'lrn_rf1' on task 'train_data' (iter 4/5)
INFO  [23:56:53.261] [mlr3] Applying learner 'lrn_rf1' on task 'train_data' (iter 5/5)
INFO  [23:56:54.620] [mlr3] Applying learner 'regr.featureless' on task 'train_data' (iter 1/
INFO  [23:56:54.710] [mlr3] Applying learner 'regr.featureless' on task 'train_data' (iter 2/
INFO  [23:56:54.817] [mlr3] Applying learner 'regr.featureless' on task 'train_data' (iter 3/
INFO  [23:56:54.911] [mlr3] Applying learner 'regr.featureless' on task 'train_data' (iter 4/
INFO  [23:56:55.008] [mlr3] Applying learner 'regr.featureless' on task 'train_data' (iter 5/
INFO  [23:56:55.096] [mlr3] Applying learner 'xgb_tune4' on task 'train_data' (iter 1/5)
INFO  [23:56:55.173] [mlr3] Applying learner 'xgb_tune4' on task 'train_data' (iter 2/5)
INFO  [23:56:55.253] [mlr3] Applying learner 'xgb_tune4' on task 'train_data' (iter 3/5)
INFO  [23:56:58.080] [mlr3] Applying learner 'xgb_tune4' on task 'train_data' (iter 4/5)
INFO  [23:56:58.167] [mlr3] Applying learner 'xgb_tune4' on task 'train_data' (iter 5/5)
```

```r
bmr_rmse <- bmr$aggregate(measures = msr("regr.rmse"))[, c("learner_id", "regr.rmse")]
bmr_rmse[, c("learner_id", "regr.rmse")]
```

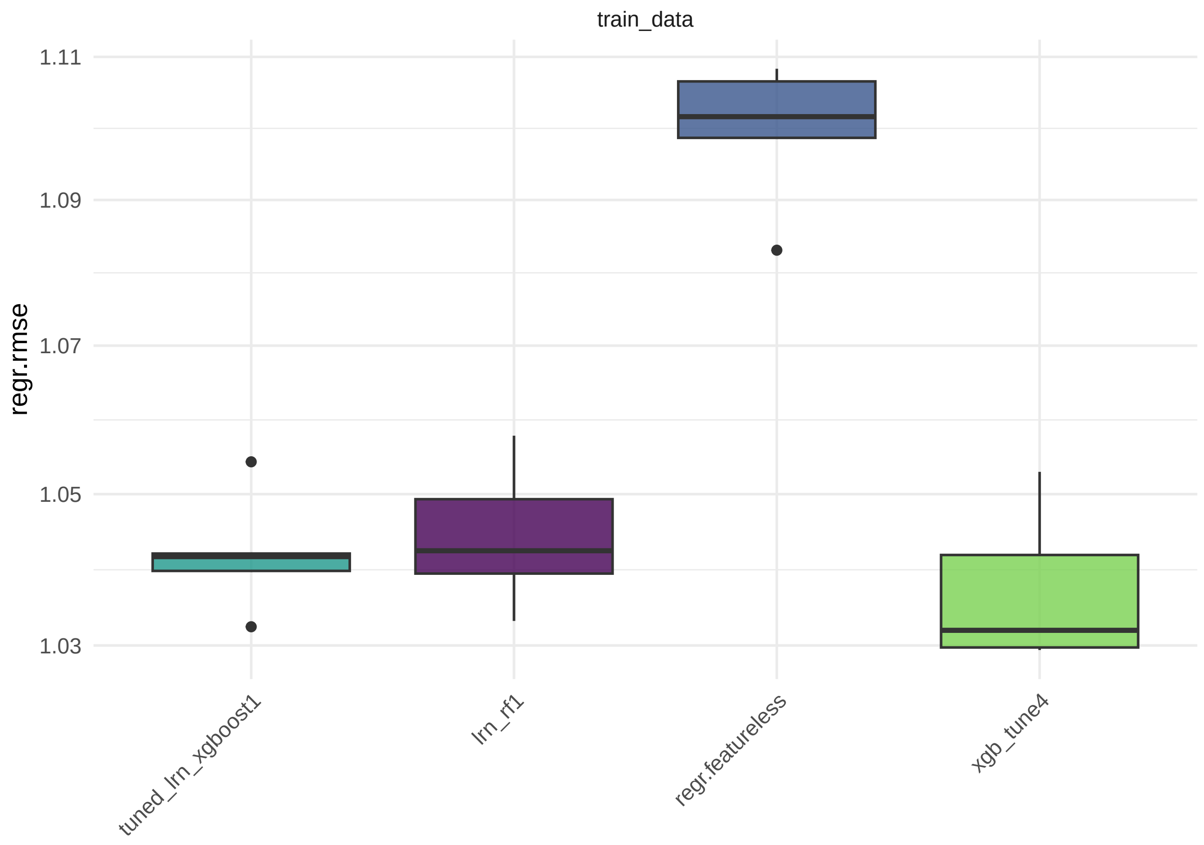
```
           learner_id regr.rmse
               <char>     <num>
1: tuned_lrn_xgboost1  1.042073
2:            lrn_rf1  1.044457
3:   regr.featureless  1.099632
4:          xgb_tune4  1.037201
```

```r
bmr_rmse
```

```
           learner_id regr.rmse
               <char>     <num>
1: tuned_lrn_xgboost1  1.042073
2:            lrn_rf1  1.044457
```

```
3:   regr.featureless  1.099632
4:          xgb_tune4  1.037201
```

```r
# visualizing benchmark results
autoplot(bmr, measure = msr("regr.rmse")) + scale_y_log10()
```


train_data
regr.rmse
tuned_lrn_xgboost1
lrn_rf1
regr.featureless
xgb_tune4