



**EC3305 Programming Tools for Economics**  
**SEMESTER II 2020-2021**

**Group Project Report**

Group: W01-03

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## Project Report

Objective: To assign brand names to a list of automobile names.

Before we started on the project, we first had to perform exploratory data analysis on both of *model\_and\_brand.csv* and *autoswithout.csv*. Exploratory data analysis is important in providing a gauge of how the datasets look like and check for any abnormalities, guiding our steps ahead.

### Exploratory Data Analysis

- **model\_and\_brand.csv**
  - *brands*
    - 39 unique brands excluding NA, 2 observations of NA
    - All lower case with no special characters
  - *models*
    - 203 unique models excluding NA, 31 observations of NA
    - All lower case with ' \_ ' being the separator, absence of brand in model
- **autos\_without.csv**
  - *name*
    - 4759 observations of names to be tagged to a brand, 0 observation of NA
    - Mixed case with special characters, lack of special characters as affixes

### Problems and solutions

#### Problem 1: Similarity between merce and mercedes benz

In this particular case, “merce” only has one model, NA. In addition, there is an absence of brands in model names. Hence, when we iterate through *autoswithout\$name*, if “merce” is present, we can safely assign “mercedes\_benz” instead.

#### Problem 2: Models belonging to more than one brand (1 reihe, 3 reihe, 5 reihe, andere)

Instead of randomly assigning brands to duplicate models, our group would like to eliminate such “wrongly-tagged” possibility. As there is no way for us to differentiate between such models, we assigned ‘NA’ to allow for manual processing by the informed to ensure accuracy.

Hence, we created a data frame called *unique\_models\_df* counting the number of occurrences of a particular model name in *model\_brand*. This allowed us to identify problematic models.

#### Problem 3: Common abbreviations of brands present in *autowithout\$name* (“Mercedes”, “VW”)

For abbreviations that we are able to identify, we assigned appropriate matches from brand to abbreviation.

## **Methodology Overview**

Step 1: Creating *unique\_models\_df* from the list of *unique\_models* excluding NA and a list of 0s (Line 33 to 37)

Step 2: Iterate through *model\_brand* counting the number of occurrences of a model name and updating *unique\_models\_df* accordingly (Line 45 to 47)

Step 3: Removing rows of problematic models from *model\_brand* and naming it *unique\_models\_df\_final* (Line 50 to 55)

Step 4: Iterate through *autoswithout\$name*, logging names with assigned brands in *assigned\_brand* and unassigned ones to *unassigned\_name* (Line 67 to 114)

1. Check if *name* matches any *brand* in *unique\_brands*
  - a. If *name* matches “merce”, log “mercedes\_benz”
  - b. If else, *name* matches *brand*, log matching *brand*
2. Check if *name* matches “Mercedes”, the short form of “mercedes\_benz”
  - a. If *name* matches, log “mercedes\_benz”
3. Check if *name* matches “Vw”, the short form for “volkswagen”
  - a. If *name* matches, log “volkswagen”
4. Check if *name* matches any *model* in *unique\_models\_df\_final*
  - a. If *name* matches, log *brand* of *model*
  - b. Else, log NA and log *name* into *unassigned\_name* (All models identified to be problematic in *unique\_models\_df* are in this category)

Step 5: *returnNA* data frame is created by converting *unassigned\_name* into a dataframe, *innerjoin()* with *autoswithout* to get the whole data frame (Line 120 to 123)

## **Method Evaluation**

- In reality, datasets will be way larger and it will become significantly harder to expect manual tagging for such “special” cases identified in Problem 2 by informed personnel. In such cases, regular expressions can be utilised with a more extensive *model\_and\_brand.csv* to conduct unigrams, bigrams and even trigrams on *autoswithout\$name* after tokenizing by ‘\_’, to produce only one outcome for brands.
- For shorter model names, there is a tendency of brand mistag. However, we cannot limit model names to (*\_model | model\_*) as models may not exist as a token on it’s own. Hence, with extensive information, a better method can be conceived.
- In cases whereby the special characters in *autoswithout\$name* breaks up the string of the brand or name itself (affixes), more preprocessing will be required such as substituting whole tags, <br> with “”
- Language proficiency in German may be helpful for the dataset as we realised later on that the “special” cases such as *andere* and *reihe* refers to “other” and “line” respectively.

# EC3305 Project Flowchart



# EC3305 Project Flowchart

## Creating "returnNA" dataframe

```
## This will be our predictions column
assigned_brand = c()
## To track unassigned names
unassigned_name =c()
Here we create the returnNA using inner_join by joining unassigned to autoswithout since unassigned
contains observations which we fail to find a brand for.
```

## For loop to assign brand for name column from autoswithout

```
for( names in autoswithout$name ) {
  check_brand = FALSE #boolean check for brand
  check_model = FALSE #boolean check for model
Here we create two boolean variables to indicate a match in different part of the for loop.
```

## Assignment of brand by unique\_brands

```
for( brands in unique_brands ) {
  if (grepl( brands, names, ignore.case = TRUE )) {
    check_brand = TRUE
    if( brands == "merce" ) {
      assigned_brand = c( assigned_brand, "mercedes_benz" )
      break
    } else {
      assigned_brand = c( assigned_brand, brands )
      break
    }
  }
}
This nested for loop searches for unique brand names inside autoswithout$name. If there is a match, the
unique brand name is assigned to the corresponding names and the boolean variable is assigned TRUE.
```

## Assignment for "mercedes" and "vw"

```
if( check_brand == FALSE) {
  if( grepl( "Mercedes", names, ignore.case = TRUE)) {
    assigned_brand = c( assigned_brand, "mercedes_benz" )
    check_brand = TRUE
  } else if( grepl( "VW", names, ignore.case = TRUE)) {
    assigned_brand = c( assigned_brand, "volkswagen" )
    check_brand = TRUE
  }
}
Here we manually search for "mercedes" manually since some of the cars are named "mercedes"
instead of "mercedes_benz". We also manually search for vw since some of the cars are named "vw"
instead of "volkswagen".
```

## Assignment of brand by unique\_model

```
if( check_brand == FALSE) {
  for( i in 1 : length( unique_models_df_final$model)) {
    if( grepl( unique_models_df_final$model[i], names, ignore.case = TRUE)) {
      assigned_brand = c( assigned_brand, unique_models_df_final$brand[i] )
      check_model = TRUE
      break
    }
  }
}
The datapoints that have arrived at this condition have not had their brand assigned by unique_brand.
Hence, we assign brand by unique_model instead by searching whether the unique_model is in names
using grepl. If grepl returns TRUE, we assign the corresponding brand of the matching unique_model to
the brand of the name. We also assign TRUE to the boolean variable check_model.
```

## Assignment of NA

```
if( check_brand == FALSE && check_model == FALSE){
  assigned_brand = c( assigned_brand, NA )
  unassigned_name = c( unassigned_name, names ) ## keeping to create unassigned dataframe
}
The datapoints that have arrived at this condition have not had their brand assigned by unique_brand or
unique_model. Hence, we assign NA. We also included the names of these datapoints into the
unassigned_name variable to keep track of them.
```

## Creating "returnNA" dataframe

```
unassigned = data.frame( unassigned_name )
colnames( unassigned ) = c( "name" )
unassigned$name = as.character(unassigned$name )
returnNA = inner_join( unassigned, autoswithout, by = "name" )
Here we create the returnNA using inner_join by joining unassigned to autoswithout since unassigned
contains observations which we fail to find a brand for.
```