Compare All

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3/29/2021

Loading Data From CSV and Update Header

```
my.data=read.csv("Online Recipe Sharing.csv", header=TRUE)
colnames(my.data)<-c("Timestamp", "Age", "Primary.Meal.Prepper", "Household.Dietary.Restriction",
"Home.Cooking.Rate",
"Primary.Recipe.Format",
"Primary.Search.Website",
"Enjoyed.Website.Searching", "Comments.Enjoyed.Website.Searching", "NOT.Enjoyed.Website.Searching", "Co
"Previous.Recipe.Search.Frequency",
"Browsing.While.Searching.Frequecny",
"Click.Rate",
"Search.Browse.Same.Websites",
"Primary.Browsing.Website",
"Enjoyed.Website.Browsing",
"Comments.Enjoyed.Website.Browsing", "NOT.Enjoyed.Website.Browsing", "Comments.NOT.Enjoyed.Website.Brows
"Source.of.Influential.Reviews", "Frequency.Reviews.Effect.Behavior",
"Frequency.Seek.Out.Review",
"Frequency.of.Review",
"Frequency.of.Recipe.Saving",
"Method.of.Recipe.Saving",
"Modification.Frequency",
"Modification.Influence.Factors",
"Modification.Record.Frequency",
"Modification.Record.Method",
"Satisfaction.with.Available.Record.Methods",
"Interest.in.Improved.Record.Method",
"Frequency.of.Recipe.Discussion", "Frequency.of.Reading.Discussion",
"Primary.Discussion.Medium", "Enjoyed.Features.of.Discussion.Mediums", "Ingredients.L.V.Above",
"Ingredients.L.Comments.Inline.V.Below", "Ingredients.Above.Comments.Below.V.Inline", "Ingredients.By.S
"Ingredients.By.Step.V.Scroll.L",
"Ingredients.Above.V.Scroll.L")
```

Re-Factor Data

If Respondent indicated that they search and browse on the same websites, populate the empty cells with the same data. This assumes that the user's searching behavior is exactly the same as the browsing behavior if the user selected yes for searching and browsing on the same websites.

```
for (i in 1:nrow(my.data)){
  if (my.data$Search.Browse.Same.Websites[i]=="No"){
    my.data$Primary.Browsing.Website[i]<-my.data$Primary.Search.Website[i]
    my.data$Enjoyed.Website.Browsing[i]<-my.data$Enjoyed.Website.Searching[i]
    my.data$NOT.Enjoyed.Website.Browsing[i]<-my.data$NOT.Enjoyed.Website.Searching[i]
  }
}
```

Since the data set is small, I am consolidating some of the categories.

- Primary Meal Prepper will be Respondent if the individual taking the survey indicated that they are the primary meal prepper in their household or if they cook for themselves, and other in all other cases.
- Dietary restriction will become a yes or no question
- Home Cooking Rate will become Daily if the respondents cooks at home most days, weekly if the respondent cooks several times a week, and monthly is the respondent cooks a couple times a month.

```
my.data.factored<-my.data
my.data.factored$Age<-as.factor(my.data$Age)

my.data.factored$Primary.Meal.Prepper<-as.factor(my.data.factored$Primary.Meal.Prepper)

my.data.factored$Household.Dietary.Restriction<-as.factor(my.data.factored$Household.Dietary.Restrictio

my.data.factored$Home.Cooking.Rate<-as.factor(my.data.factored$Home.Cooking.Rate)

my.data.factored$Ingredients.L.V.Above<-as.factor(my.data.factored$Ingredients.L.V.Above)
my.data.factored$Ingredients.By.Step.V.Above<-as.factor(my.data.factored$Ingredients.By.Step.V.Above)
my.data.factored$Ingredients.Above.V.Scroll.L<-as.factor(my.data.factored$Ingredients.Above.V.Scroll.L)
my.data.factored$Ingredients.L.Comments.Inline.V.Below<-as.factor(my.data.factored$Ingredients.L.Comment
my.data.factored$Ingredients.By.Step.V.Scroll.L<-
  as.factor(my.data.factored$Ingredients.By.Step.V.Scroll.L)
my.data.factored$Ingredients.Above.Comments.Below.V.Inline<-
  as.factor(my.data.factored$Ingredients.Above.Comments.Below.V.Inline)
my.data.factored<- mutate(my.data.factored,
                          Age = fct_collapse(Age,
                                             YA = c("18 - 24 years old","25 - 34 years old"),
                                             Adult = c("35 - 44 years old","45 - 54 years old","55 - 64
                          Primary.Meal.Prepper = fct_collapse(Primary.Meal.Prepper,
                                                              Respondent = c("You", "I cook for myself")
                                                              other_level = "Other"),
                  Household.Dietary.Restriction=fct_collapse(Household.Dietary.Restriction,
                                                             No="None",
                                                              other_level = "Yes"),
                  Home.Cooking.Rate=fct_collapse(Home.Cooking.Rate,
                                                 Daily=c("Almost every meal","Daily","Every meal"),
                                                 Weekly=c("Several times a week","Once or twice a week")
                                                 Monthly=c("Once or twice a month")),
                  Ingredients.L.V.Above=fct_collapse(Ingredients.L.V.Above,
                                                     Ing.L =c("A"),
                                                     Ing.Above=("B")),
                  Ingredients.By.Step.V.Above=fct_collapse(Ingredients.By.Step.V.Above,
                                                           Ing.By.Step=c("A"),
```

```
                                                        Ing.Abov=c("B")),
                         Ingredients.Above.V.Scroll.L=fct_collapse(Ingredients.Above.V.Scroll.L,
                                                         Ing.Above=c("A"),
                                                         Scroll.L=c("B")),
                         Ingredients.L.Comments.Inline.V.Below=fct_collapse(Ingredients.L.Comments.Inline.V.Bel
                                                                  Ing.L.Com.Inline=c("A"),
                                                                  Ing.L.Com.Below=c("B")),
                         Ingredients.By.Step.V.Scroll.L=fct_collapse(Ingredients.By.Step.V.Scroll.L,
                                                           Ing.By.Step=c("A"),
                                                           Ing.Scroll=("B")),
                         Ingredients.Above.Comments.Below.V.Inline=fct_collapse(Ingredients.Above.Comments.Bel
                                                                      Ing.Above.C.Below=c("A"),
                                                                      Ing.Above.C.Inline=c("B"))
                         )
```

Website Recoding:

For the sake of this analysis any website that has a test kitchen that creates editorial content or is able to curate content from professional sources is a magazine, a a website with one or two people testing recipes is a blog, and a website that allows users to contribute their own recipes is community based. The information for this classification is found on the website's about page. Additionally, media such as cookbooks and podcasts are classified under Influencers due to their personality driven nature.

Discussion Method Recoding:

Any type of online chatting be it texting, discord, etc. has been grouped together into Digital Chat. Any type of interpersonal communication where a chat method was not specified is grouped into verbal.

Note saving methods that mention remembering or memory are grouped into memory, while respondents that indicate that they do not take any type of notes and do not try to remember are group are grouped into None.

Modification Recoding:

Modification influence factors pertaining to diet, or nutrition are grouped together under the umbrella of "Diet".

Modification influence factors pertaining to personal preference for food, flavor, or preparation method are grouped together under the category of "Personal Preference.

Modification influence factors pertaining ingredients availability are grouped together under the category of "Ing. Availability"

```
unique(separate_rows(my.data.factored[32],1, sep = ";"))
```

```
## # A tibble: 18 x 1
##    Modification.Record.Method
##    <chr>
##  1 ""
##  2 "None"
##  3 "Mentally?"
##  4 "Digital notes"
```

```
##  5 "Physical notes"
##  6 "Mental note"
##  7 "I donâ€t :o"
##  8 "Comments section provided for recipe"
##  9 "Memory"
## 10 "N/A"
## 11 "I mostly just remember it for next time "
## 12 "brainpower"
## 13 "I dont"
## 14 "I don't"
## 15 "I store it in my noggin"
## 16 "I don't.."
## 17 "i dont"
## 18 "i don't"
```

```
my.data.selected<-my.data.factored[c(6,7,8,10,17,18,20,22,23,28,37,30,32,38)]
variables<-c()

##This creates a vector that will recode the variables with the proper names
 for (i in 1:ncol(my.data.selected)){
  temp<- my.data.selected[i]
  temp<-separate_rows(temp,1, sep = ";")
  variables<-append(variables,temp[[1]])
  variables<-unique(variables)
  data.frame(variables)
 }

cleaned.variables<-c(
  "Mobile",
  "Desktop",
  "Digital",
  "Physical Print",
  "Physical Print",
  "Digital",
  "Physical Family",
  "Physical Family",
  "Physical Family",
  "Physical Family",
  "Mags",
  "Blogs",
  "Google",
  "Video",
  "Community Based" ,
  "Mags",
  "Community Based" ,
  "Pinterest",
  "Blogs",
  "Video",
  "Mags",
  "Facebook",
  "Reddit",
  "Mags",
  "Mags",
  "Mags",
```

```
  "Mags",
  "Instagram",
  "Mags",
  "Friends/Family",
  "Blogs",
  "NA",
  "Blogs",
  "Mags",
  "Instagram",
  "Instagram",
  "None",
  "None",
  "Friends/Family",
  "Online Groups",
  "Other Users",
  "Influencers",
  "Influencers",
  "Facebook",
  "Browser Bookmarks",
  "Digital Filing",
  "Memory",
  "Search History",
  "Save Function",
  "Physical Filing",
  "None",
  "Memory",
  "Memory",
  "Memory",
  "Save Function",
  "Verbal",
  "Verbal",
  "Verbal",
  "Digital Chat",
  "Verbal",
  "Verbal",
  "Digital Chat",
  "Google Docs",
  "Digital Chat",
  "Verbal",
  "Verbal",
  "Verbal",
  "Verbal",
  "Verbal",
  "Verbal",
  "Verbal",
  "Verbal",
  "Digital Chat",
  "None",
  "Digital Chat",
  "Verbal",
  "Digital Chat",
  "Digital Chat",
  "None",
```

```
  "Diet",
  "Diet",
  "Preference",
  "Diet",
  "Ing. Availability",
  "Ing. Availability",
  "Recommendation",
  "Preference",
  "Memory",
  "Digital",
  "Physical",
  "Memory",
  "None",
  "Comments",
  "None",
  "Memory",
  "Memory",
  "None",
  "None",
  "Memory",
  "None",
  "None",
  "5 Star Review",
  "Groups",
  "Up/Down Vote Posts",
  "Up/Down Vote Com.",
  "Collapse Comment",
  "Comment Reply",
  "Comment Thread",
  "Inline Comment")

names(cleaned.variables)<-variables
```

Functions for Cleaning Data

The function dummies takes in a data frame and a vectorized column name.

1. separate entries delimited by ; in column into different rows
2. clean data using vector constructed above
3. replace empty responses with string "Empty"
4. create dummy variables and send duplicate rows to colums

```
dummies<-function(search.data, to.clean){
  col.names<-c(names(search.data))
  col.names<-col.names[col.names!=to.clean]
  search.data.clean<- search.data%>% separate_rows(all_of(to.clean), sep = ";")

  search.data.clean[to.clean]<-
    as.character(cleaned.variables[search.data.clean[[to.clean]]])
  search.data.clean[to.clean]<-lapply(search.data.clean[to.clean],function(x) replace(x,is.na(x),"Empty

  search.data.dummies<-search.data.clean%>%
```

```
    select((to.clean))%>%
    dummy()%>%
    bind_cols(search.data.clean)%>%
    select(-(to.clean))%>%
    pivot_longer(cols=-col.names, names_to = "key", values_to = "value")%>%
    filter(value!=0)

  search.data.dummies<-search.data.dummies%>%
    unique()

  search.data.dummies<-search.data.dummies%>%
    spread(key, value, fill = 0)

}
```

Load Factored Data

```
search.data<-my.data.factored[-c(1,9,11,19,21)]
search.data<-data.frame(search.data)
new.names=c("Age", "Meal.Prepper","Dietary.Restriction","Home.Cook.Rate","Primary.Format.C","Primary.S.(
            "Enjoyed.S.C","NOT.Enjoyed.S.C","Recipe.Search.F","Repeat.S.F","Browse.Search.F","Click.Rate
            "Search.Browse.Same","Primary.B.C","Enjoyed.B.C","NOT.Enjoyed.B.C", "Primary.R.C", "Influen
            "Use.R.F","Seek.R.F", "R.F","Save.F","Save.C","Mod.F","Why.Mod.C", "Mod.Note.F", "Mod.Note.(
            "Note.Method.S","Potential.Note.Taker","Disc.F","Read.Disc.F","Disc.C","Enjoy.Disc.C", "Ing
            "Ing.L.Com.Inline.V.Below","Ing.Above.Com.Below.V.Inline",  "Ing.By.Step.V.Above",  "Ing.By
            "Ing.Above.V.Scroll.L"
            )
colnames(search.data)<-new.names

## optional code below converts integers to proper likert scale.

# for (col in colnames(select(search.data,ends_with(".S")))){
#   search.data[[col]]<-factor(search.data[[col]], levels=c(NA,"1","2","3","4","5"))
#   levels(search.data[[col]])<- c("Dissatisfied","Somewhat Dissatisfied", "Neutral",
#            "Somewhat Satisfied","Satisfied")
# }
#
# for (col in colnames(select(search.data,ends_with(".F")))){
#   search.data[[col]]<-factor(search.data[[col]], levels=c(NA,"1","2","3","4","5"))
#   levels(search.data[[col]])<- c("Never","Rarely","Sometimes", "Often","Always")
# }
```

The categories that are farther from the origin explain more of the variance in the data set, and are well represented by the factor map. Furthermore, the categories that are closer together have similar profiles.

Improved MCA

```
cleaned<-search.data
to.dummy<-select(cleaned, ends_with(".C"))
```

```r
to.dummy.cols<-c(colnames(to.dummy))

for (col in to.dummy.cols){
   cleaned<-dummies(cleaned,c(col))

}
```

```
## Note: Using an external vector in selections is ambiguous.
## i Use ‘all_of(to.clean)‘ instead of ‘to.clean‘ to silence this message.
## i See <https://tidyselect.r-lib.org/reference/faq-external-vector.html>.
## This message is displayed once per session.
```

```
## Note: Using an external vector in selections is ambiguous.
## i Use ‘all_of(col.names)‘ instead of ‘col.names‘ to silence this message.
## i See <https://tidyselect.r-lib.org/reference/faq-external-vector.html>.
## This message is displayed once per session.
```

```r
cols<-names(cleaned)
cleaned.factored<-lapply(cleaned[cols], as.factor)
```

cleaner function selects and cleans columns.

```r
cleaner.S<-function(df){
  to.dummy<-select(df, ends_with(".C"))
  to.dummy.cols<-c(colnames(to.dummy))

  for (col in to.dummy.cols){
    df<-dummies(df,c(col))
  }

  cols<-names(df)
  cleaned.factored<-lapply(df[cols], as.factor)
  cleaned.table<-data.frame(cleaned.factored[-c(1)])
}
```

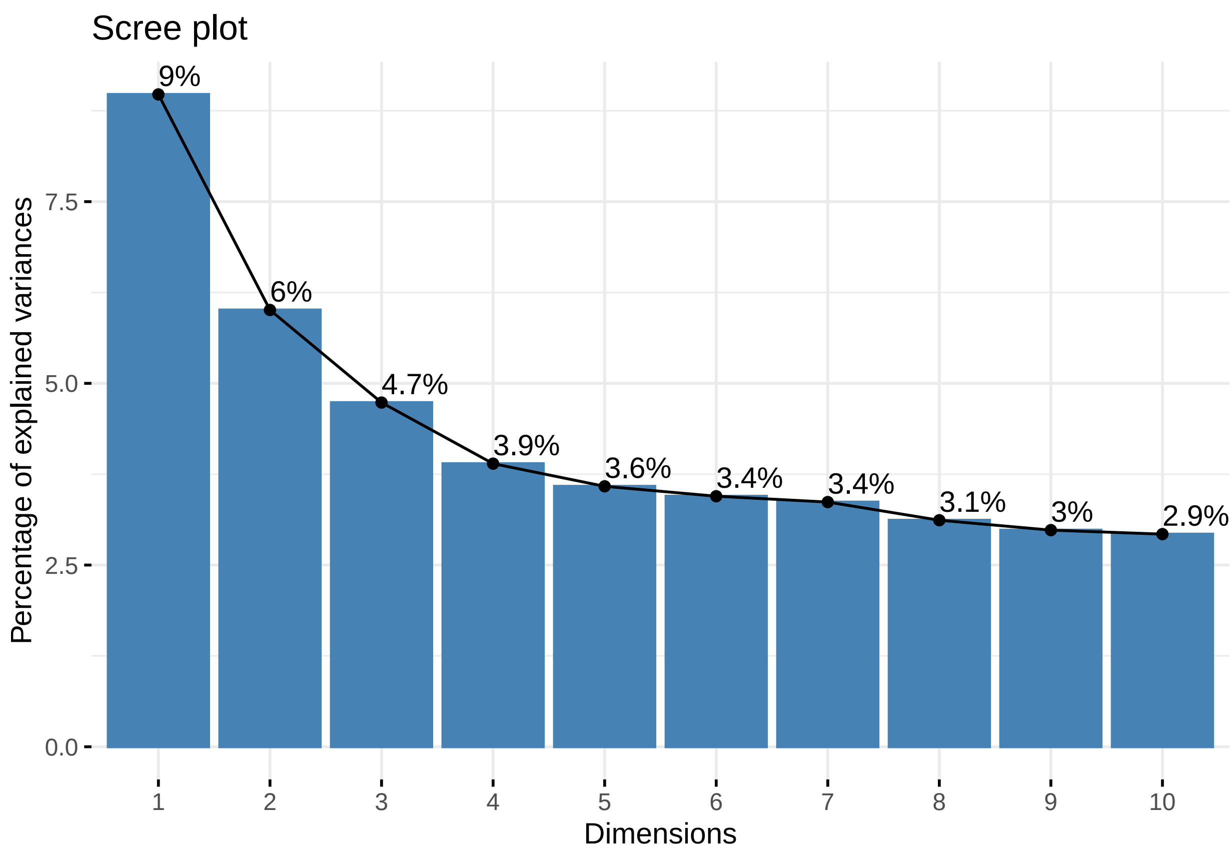
About the Graphs

Skree Plot Displays the components in order of importance i.e. in order of variance explained. This plot is used to understand how many components to keep in the analysis. I will be using the elbow rule to decide which components to include. This rule cuts off components at the inflection point (or elbow) of the explained variance. One can chose to cut off at or before the elbow. For the sake of simplicity, I will make the choice that results in keeping the closest to two components in the analysis.

Variable Biplot This plot shows the association of variables and the association between the variables and the dimensions Variables that are close together have similar profiles. Variables that are far from the origin are better represented in the components.

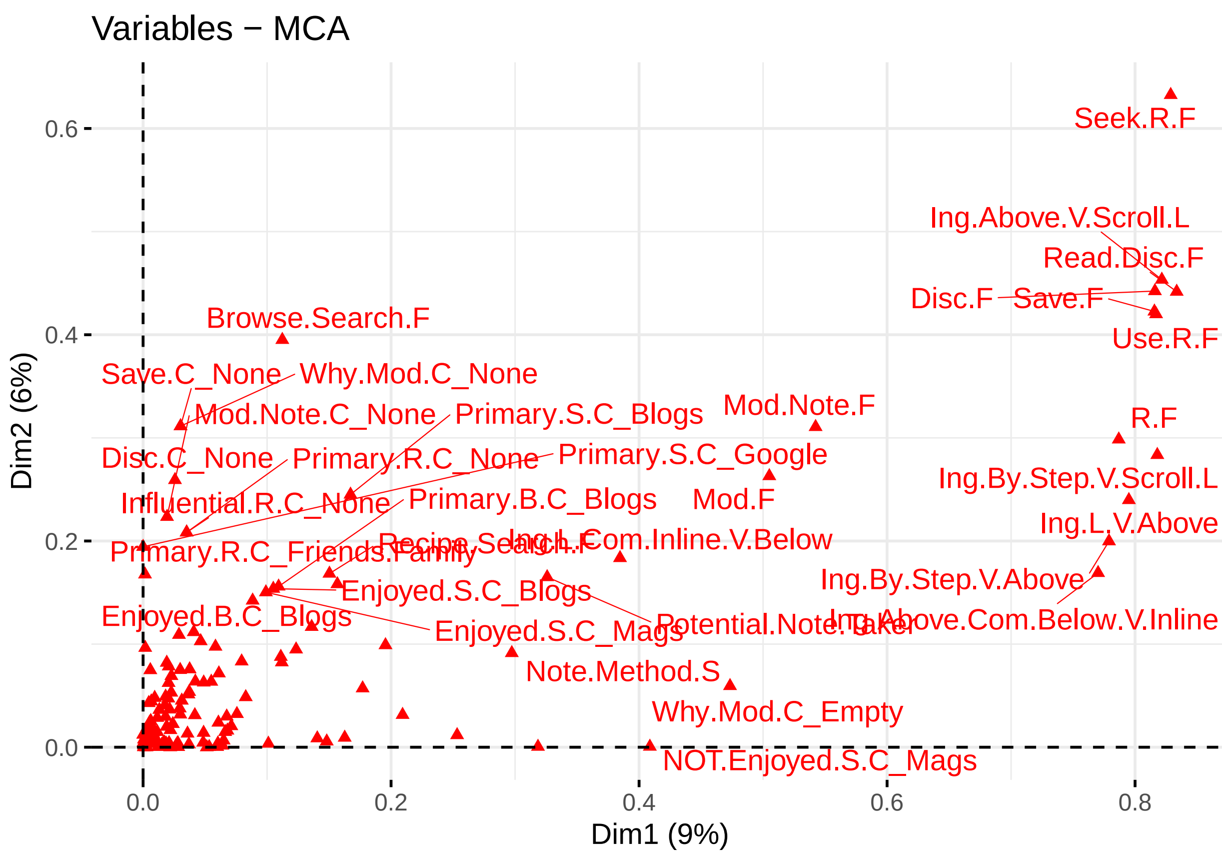
Variable Category Biplot This plot shows patterns in the data. Variables that are close together have similar profiles.Categories with negative associations to the dimension are contrasted with categories with positive associations.The larger the distance between the variable category and the origin, the better he quality of its representation.The categories are colored based on their cos2 value which measures the quality of their representation. A high cos2 value means the the quality of representation is good. A low cos2 value means that any interpretation made based on that category should be taken with caution. When there are many categories with high inertia i.e. high contribution I will focus on categories with high quality representation i.e. a high cos2 value.

```
cleaned.search.data<-data.frame(cleaned.factored[-c(1)])
search.MCA=MCA(cleaned.search.data,graph=FALSE)
fviz_screeplot(search.MCA,addlabels=T)
```



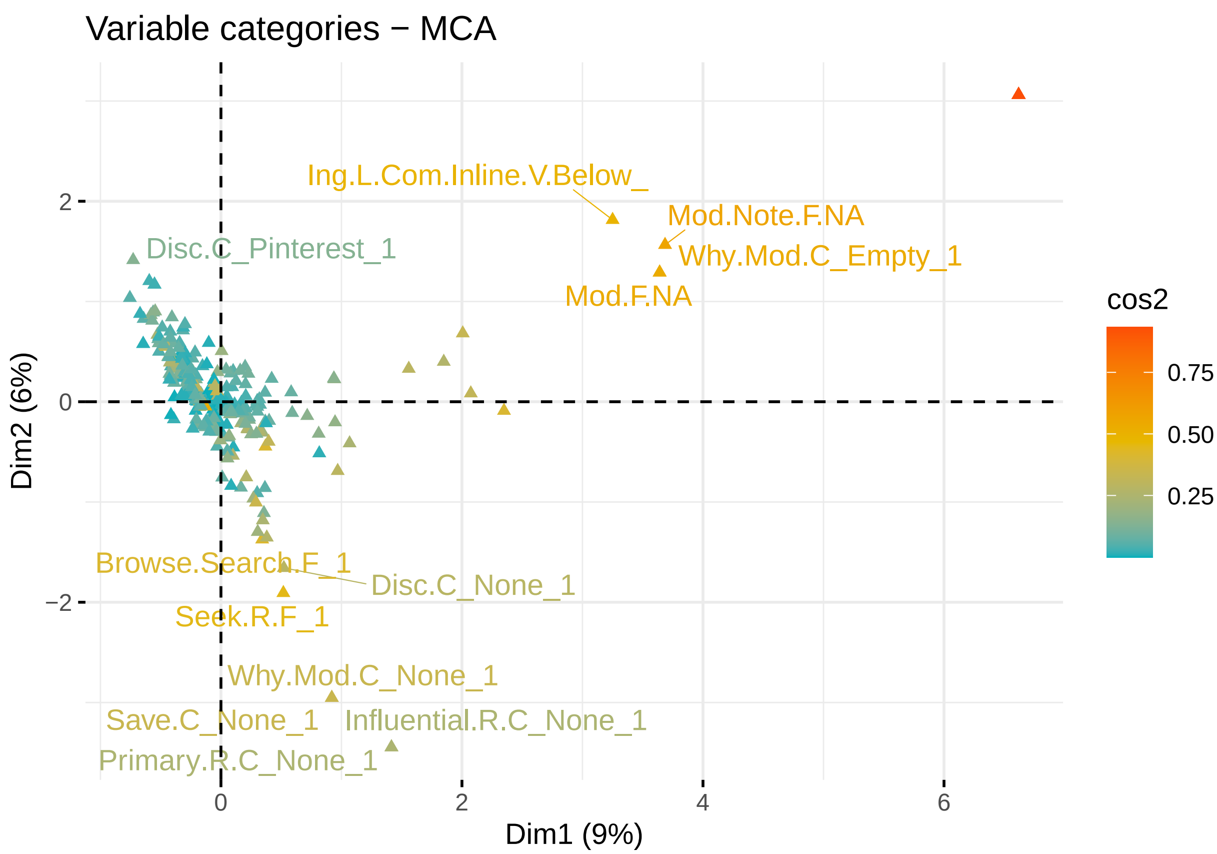

```
fviz_mca_var(search.MCA, choice = "mca.cor", repel = TRUE,
             ggtheme = theme_minimal())
```

```
## Warning: ggrepel: 108 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps
```




```r
fviz_mca_var(search.MCA, col.var = "cos2",
             gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"),
             repel = TRUE, ggtheme = theme_minimal())
```

```
## Warning: ggrepel: 326 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps
```



Scree Plot Using the elbow rule, I will be looking at the first two components of this MCA analysis. Therefore this plot will only capture 15% of the variability in the data.

Variables Seeking Reviews is well represented and correlated with both dimensions.

Ingredients above vs ingredients pinned left while scrolling, reading discussion frequency, discussion frequency, save frequency, and useing review frequency have similar profiles and are well represented in both dimensions.

No saving method, no modification note method, no discussion platform, and no primary recipe website are associated with dimension two and have similar profiles.

Ingredients listed step by step vs. ingredients listed above, review frequency, given ingredients above comment location below vs inline, and Ingredient listed step by step vs. ingredients pinned left when scrolling have similar profiles and are associated with dimension one.

From this data we can see that frequency of discussion, seeking reviews, reading discussion, reviewing, and saving recipes have similar profiles. Additionally, neither the first nor the second component have negatively correlated variable categories.

Variable Categories Users that did not answer questions are associated in this analysis.

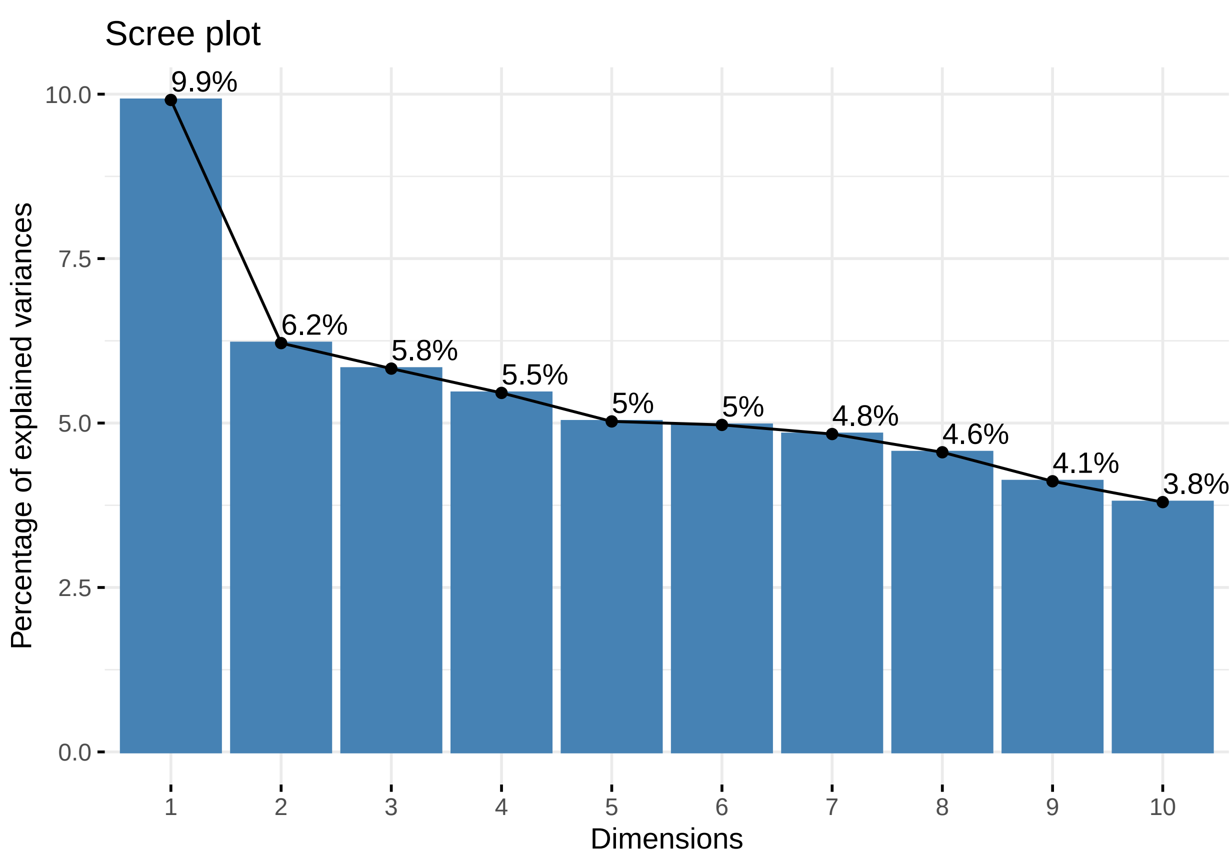
Users that had no primary website for discussion, saving, saving modification notes, seeking reviews, discussing and browsing are associated.

These two groups of users are contrasted in this analysis.

```
mca.plot<-function(selected.data){
    selected.data.cleaned<-cleaner.S(selected.data)
    search.MCA=MCA(selected.data.cleaned,graph=FALSE)
    scree<-fviz_screeplot(search.MCA,addlabels=T)
    contrib<-fviz_mca_var(search.MCA,
                          choice = "mca.cor", repel = TRUE,ggtheme = theme_minimal())

    biplot<-fviz_mca_var(search.MCA, col.var = "cos2",
                 gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"),
                 repel = TRUE, ggtheme = theme_minimal())
    print(scree)
    print(contrib)
    print(biplot)
    return(search.MCA)
}
```

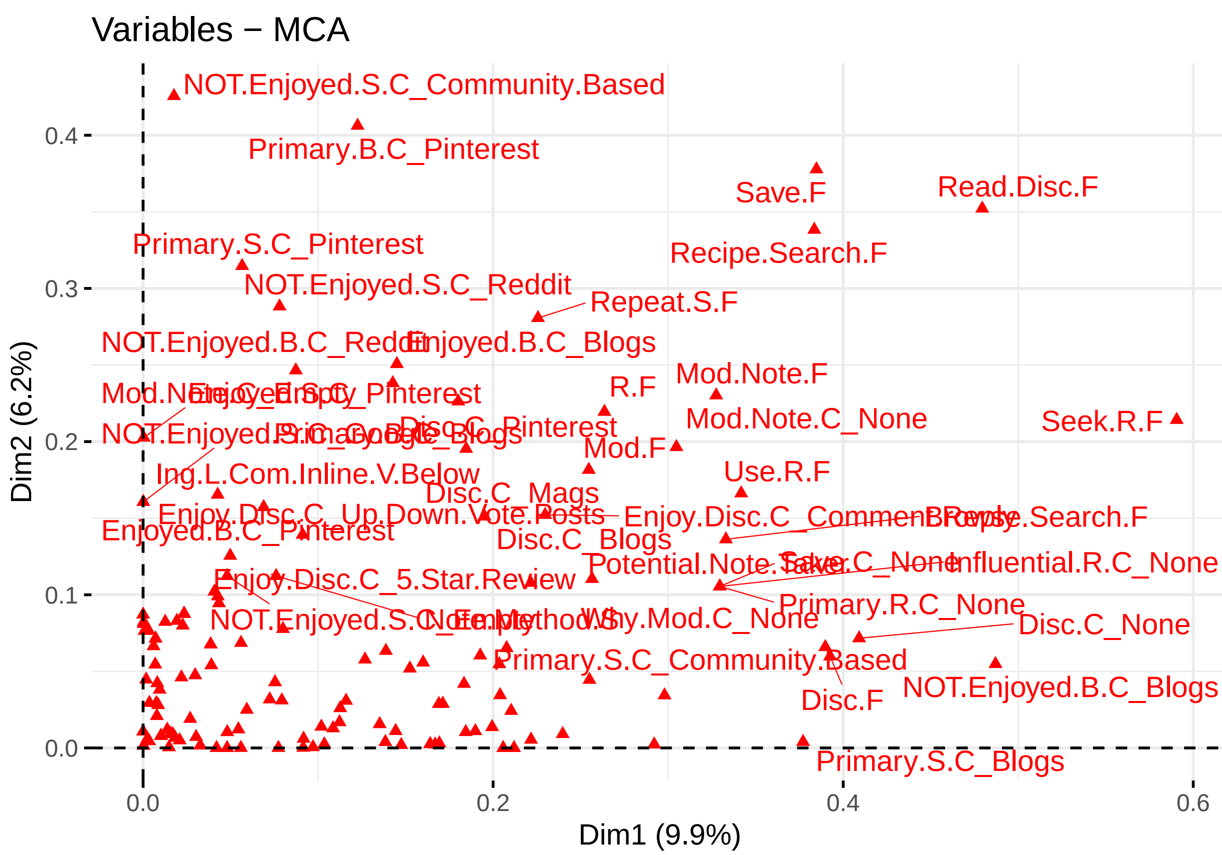
Stratify By Diet

```
cleaned.Diet.Yes<-filter(search.data, Dietary.Restriction == "Yes")
cleaned.Diet.Yes<-cleaned.Diet.Yes%>%select(-c(Dietary.Restriction))
cleaned.data<-mca.plot(cleaned.Diet.Yes)
```

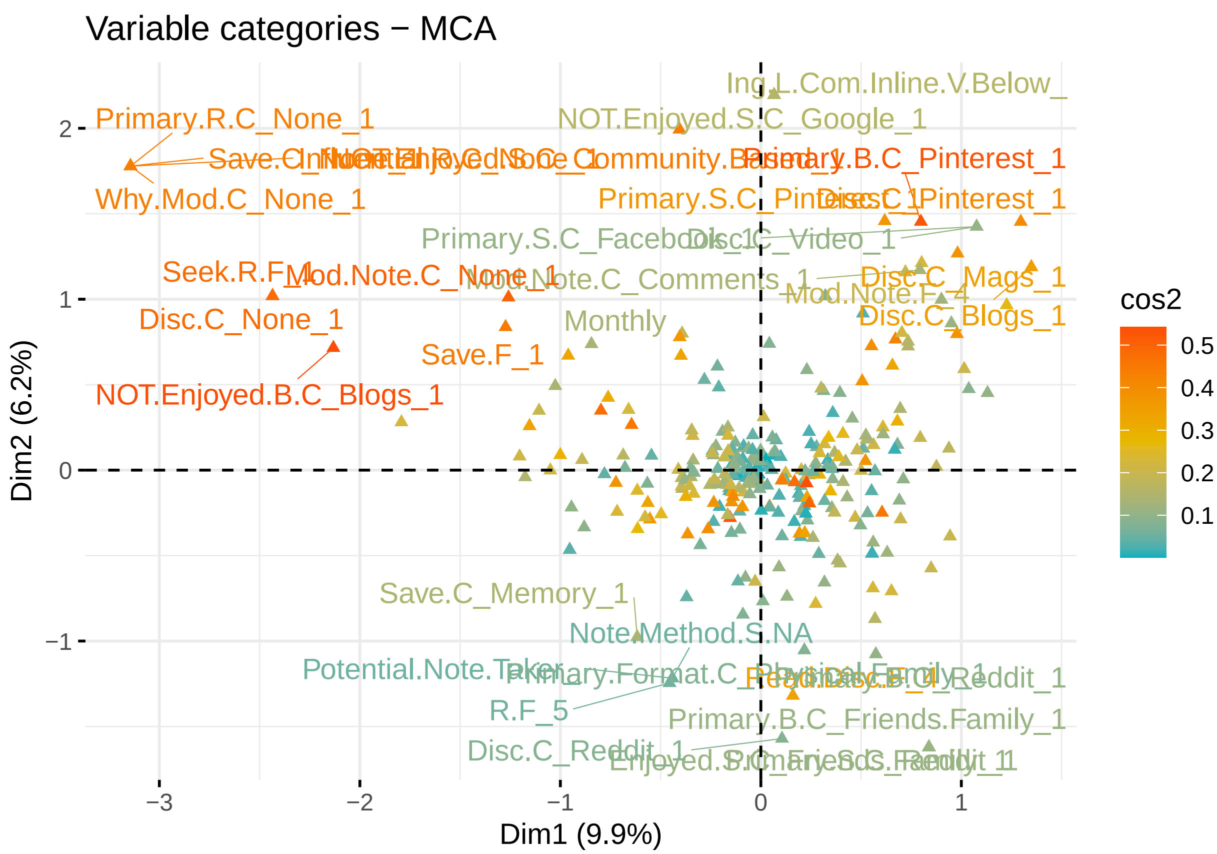



```
## Warning: ggrepel: 97 unlabeled data points (too many overlaps). Consider
```

```
## increasing max.overlaps
```




```
## Warning: ggrepel: 283 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps
```



Scree Plot Using the elbow rule, I will be looking at the first two components of this MCA analysis. Therefore this plot will only capture 16.1% of the variability in the data. Slightly More variance is captured in the components when we stratify by diet.

Variables Save frequency, Recipe search frequency, and Reading the recipe discussion frequency have similar profiles in individuals who do follow a diet. These three columns are well represented by both dimensions.

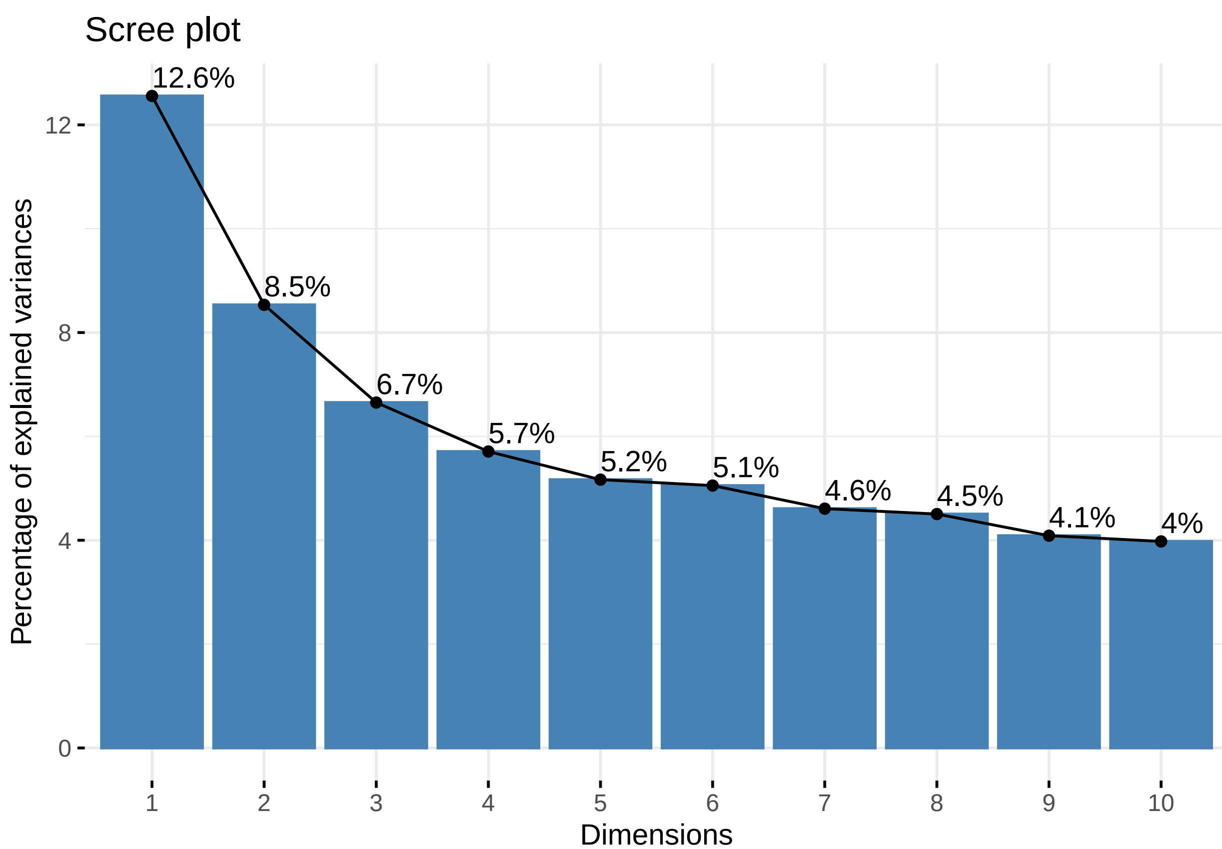
Not enjoying community based websites for searching and using pinterest as the primary browsing website have similar profiles and are well represented in dimension two. The similarity in column profiles implies that users who's primary browsing website is pinterest also do not enjoy searching community based recipe websites.

Not enjoying blog browsing, primarily searching community based websites, no primary review site, primarily searching blogs, and no discussion websites are associated with dimension one.

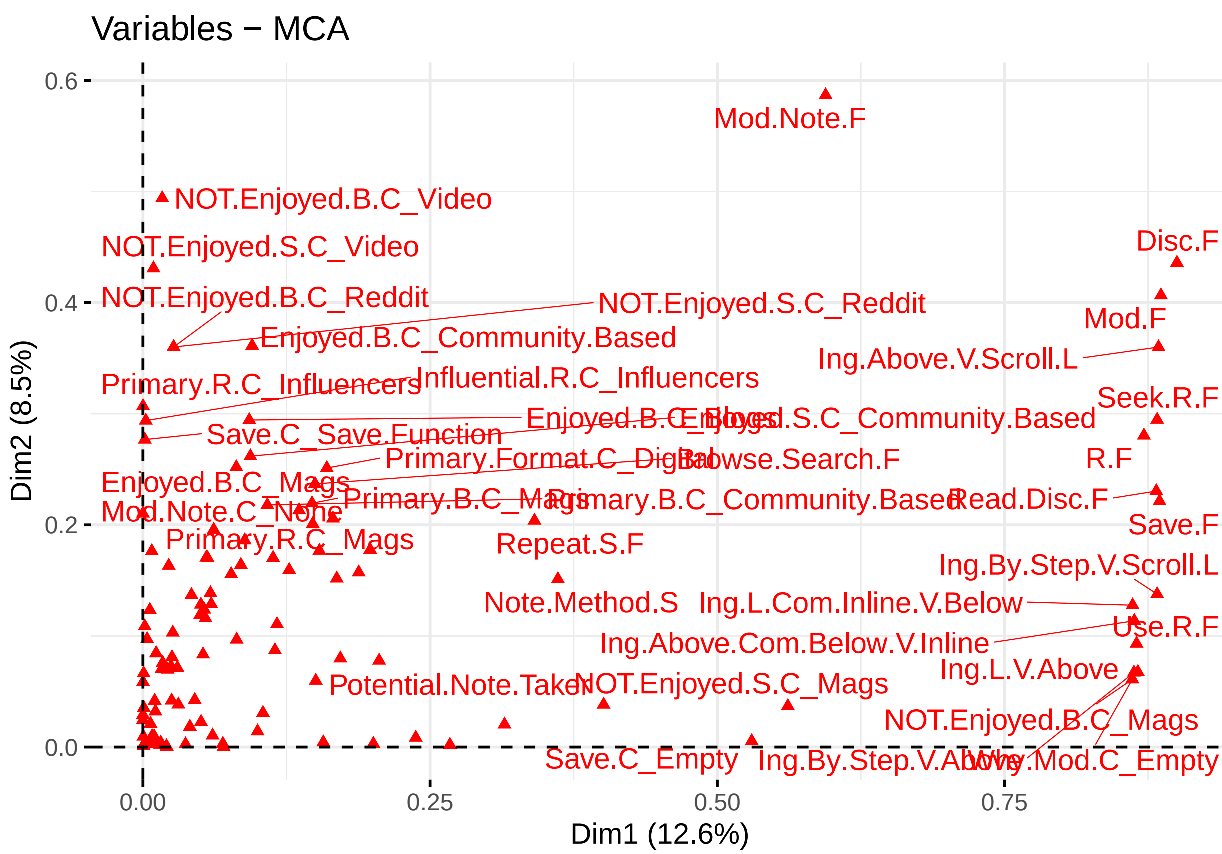
Variable Categories Dimension 1 contrasts users who do not save recipes, do not have a primary recipe website, do not modify recipes, etc. with users who use various platforms like Pinterest, blogs, videos, and online magazines to browse and discuss recipes. Basically users who do not often interact with online recipe content are negatively weighted and users who do frequently interact with recipes on various platforms are positively weighted.

Dimension 2 contrasts users who use Reddit to discuss and search recipes, often discuss recipes, and speak to their family and friends when browsing with users who use various platforms like Pinterest, blogs, videos, and online magazines to browse and discuss recipes, and who do not modify recipes. In other words, users who enjoy a more personal community/discussion based experience are negatively weighted, and users who prefer to use professionally developed recipes as written.

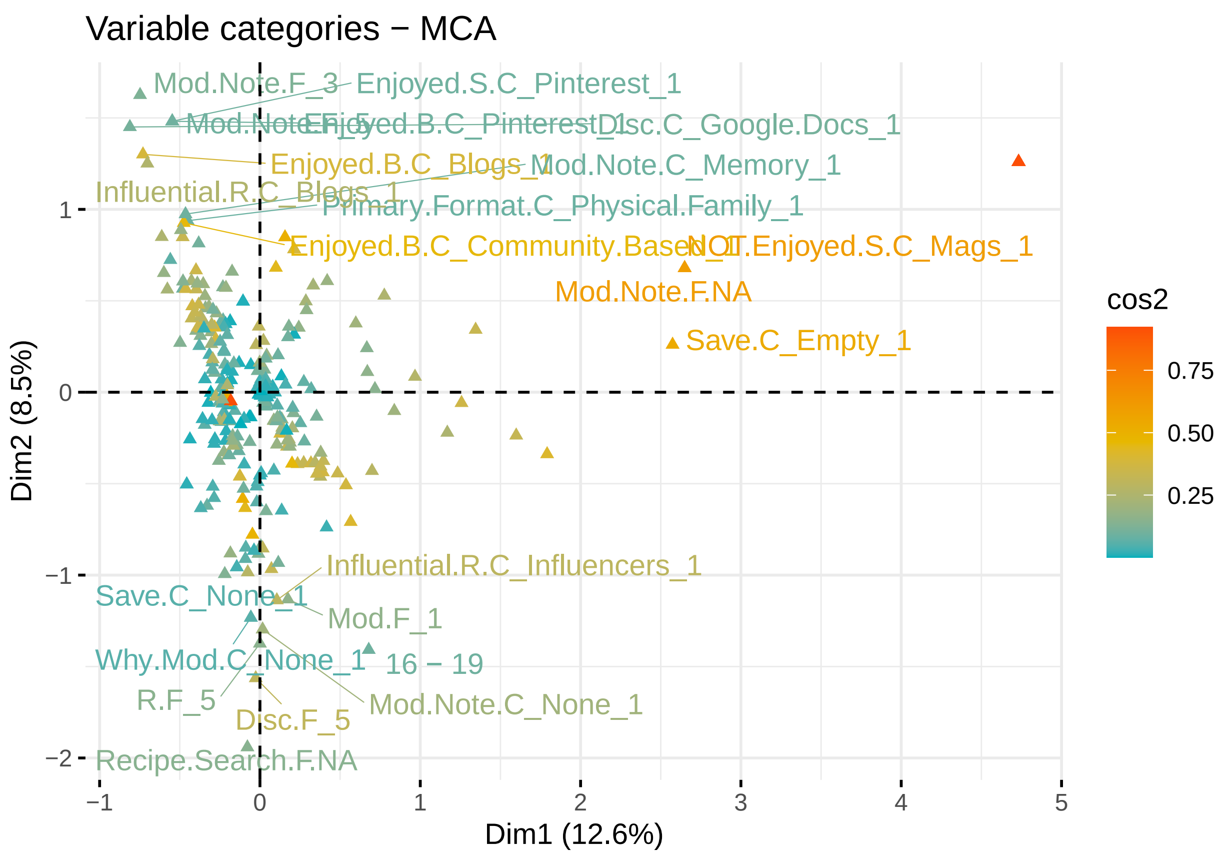
```
cleaned.Diet.No<-filter(search.data, Dietary.Restriction == "No")
cleaned.Diet.No<-cleaned.Diet.No%>%select(-c(Dietary.Restriction))
options(ggrepel.max.overlaps = 20)

cleaned.data<-mca.plot(cleaned.Diet.No)
```




```
## Warning: ggrepel: 86 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps
```




```
## Warning: ggrepel: 279 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps
```



Scree Plot

Using the elbow rule, I will be looking at the first two components of this MCA analysis. Therefore this plot will only capture 21.1% of the variability in the data. Slightly More variance is captured in the components when we stratify by diet.

Variables Recipe discussion frequency, modification frequency, ingredients listed above vs. ingredients pinned left while scrolling, review frequency, save frequency, and seeking review frequency are all well represented in both dimensions.

Save frequency, ingredients step by step vs pinned left while scrolling, useing reviews frequency, ingredients listed left vs. listed above, and ingredients step by step vs. listed above are associated with dimension 1.

Not enjoying video for searching or browsing and not enjoying Reddit for browsing are well represented in dimension 2.

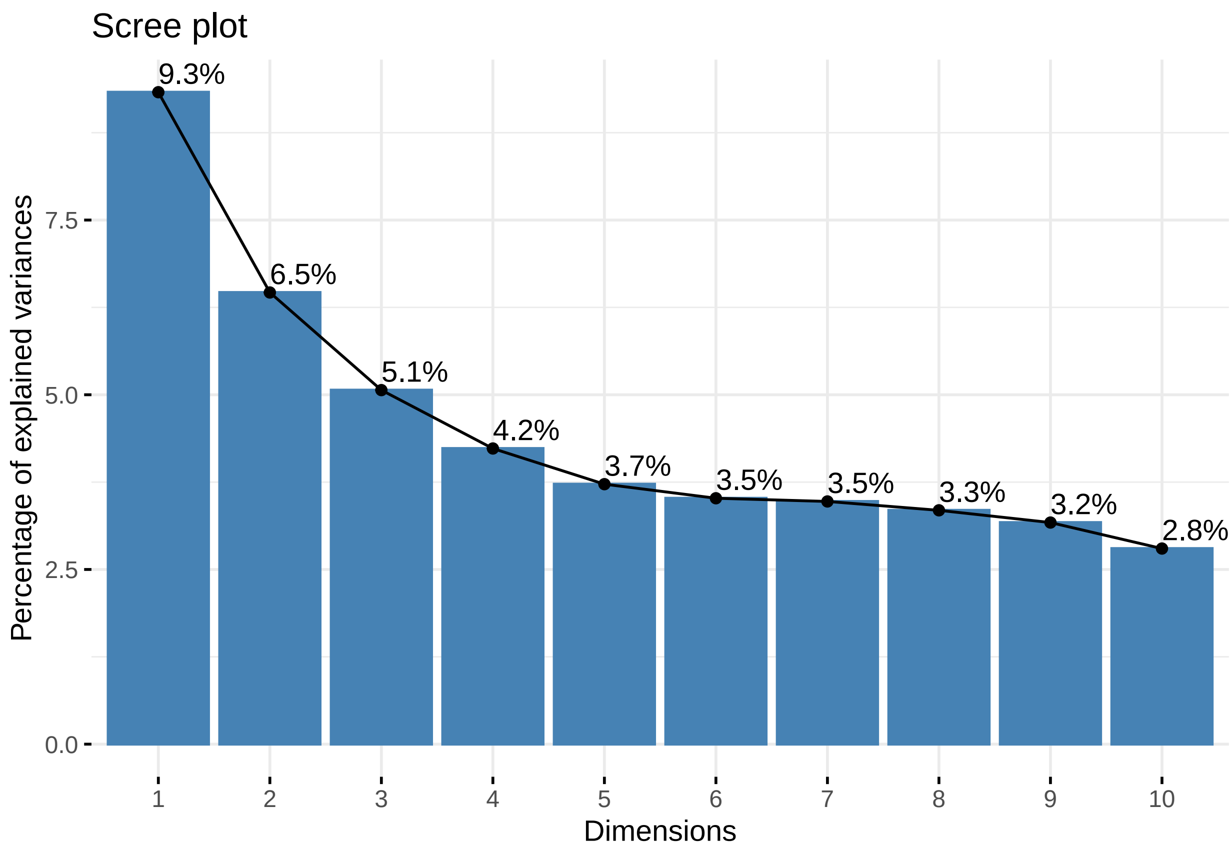
Variable Categories The red point in the top left is all the questions answered with NA.

Dimension 1 contrasts users who left questions blank with users who answered survey questions.

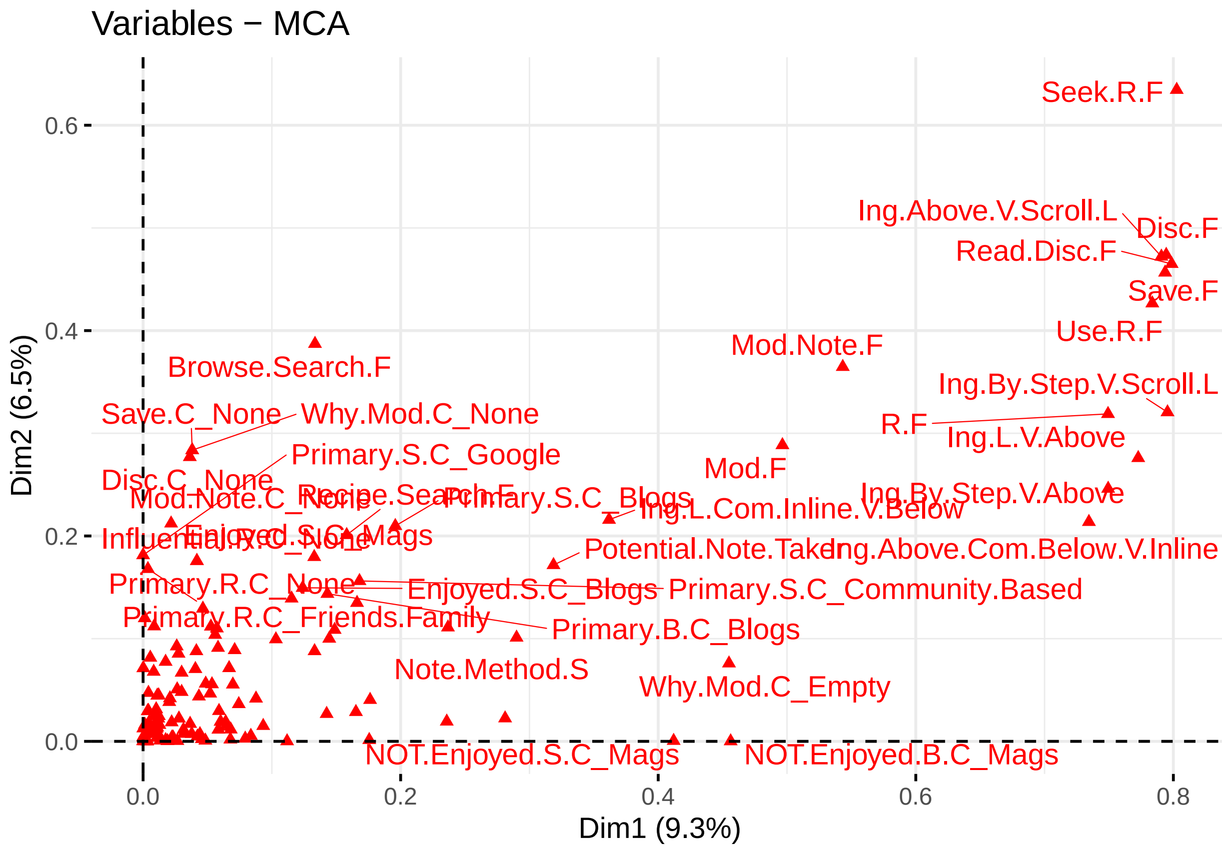
Dimension 2 contrasts users who frequently review and discuss recipes, don't have a save method, don't have a modification motivation, do not frequently modify recipes, click on many recipes before cooking, and follow influencers recommendations with users who frequently take note of their modification, save recipes, and enjoy blogs, magazines and family/friends for browsing, searching, and receiving recommendations. In other words, adults users are positively weighted and associated with physical filing, frequent note taking, and using well recognized sources for recipes and reviews, while Users who do not modify recipes often, organize their recipe saves, consult influencers recommendations, and click through/browse many recipes are negatively weighted.

Stratify by Age

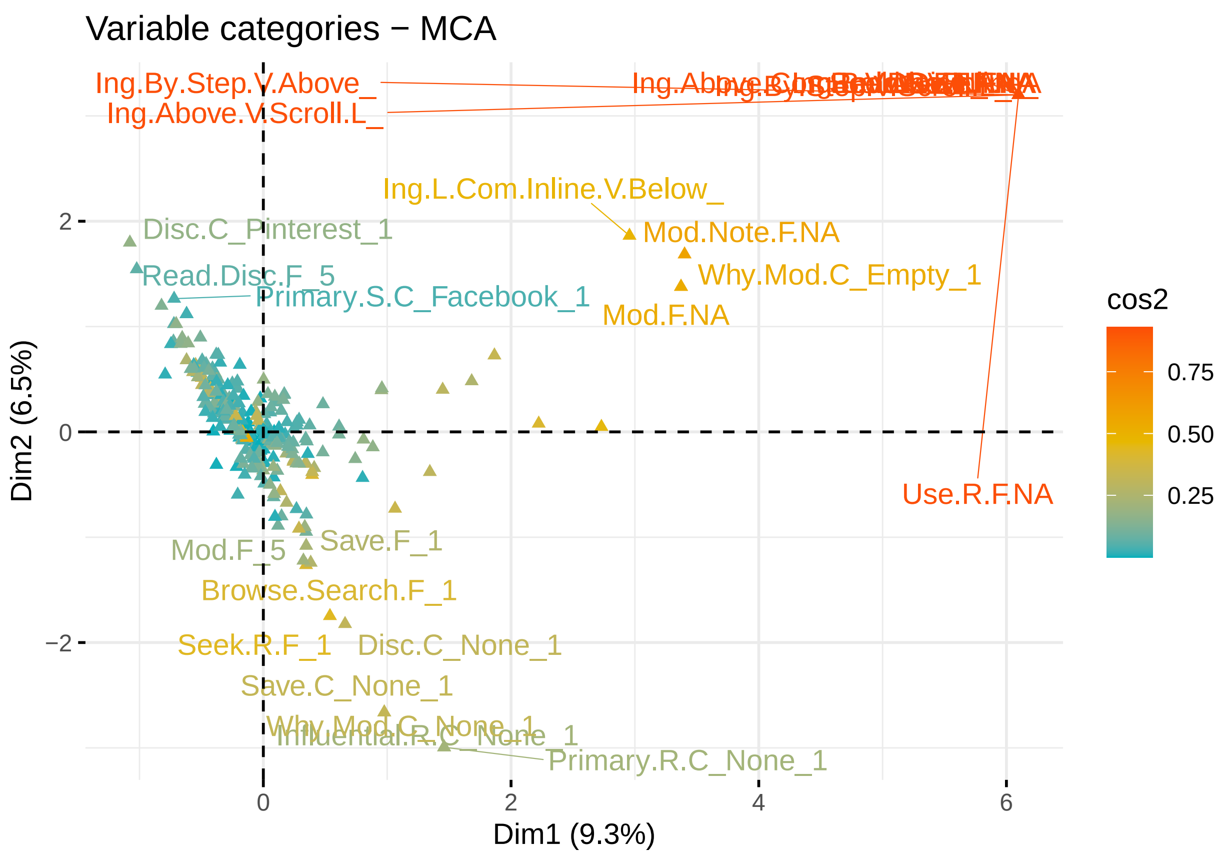
```
cleaned.YA<-filter(search.data, Age == "YA")
cleaned.YA<-cleaned.YA%>%select(-c(Age))
options(ggrepel.max.overlaps = 22)

cleaned.data<-mca.plot(cleaned.YA)
```




```
## Warning: ggrepel: 104 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps
```




```
## Warning: ggrepel: 305 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps
```



Scree Plot Using the elbow rule, I will be looking at the first two components of this MCA analysis. Therefore this plot will only capture 15.8% of the variability in the data. Slightly More variance is captured in the components when we stratify by age.

Variables Recipe discussion frequency, using review frequency, ingredients listed above vs. ingredients pinned left while scrolling, ingredients listed left vs above, review frequency, save frequency, and reading discussion frequency are all well represented in dimension 1.

Seeking review review frequency is well represented in both dimension.

Variable Categories The red point in the top left is all the questions answered with NA.

Dimension 1 contrasts users who left questions blank with users who answered survey questions.

Dimension 2 contrasts users who frequently discuss recipes and read recipe discussions, use Facebook to search, and use pinterest to browse with users who do not regularly interact with recipes online or do not have a primary website for the different types of recipe interaction discussed in the survey.

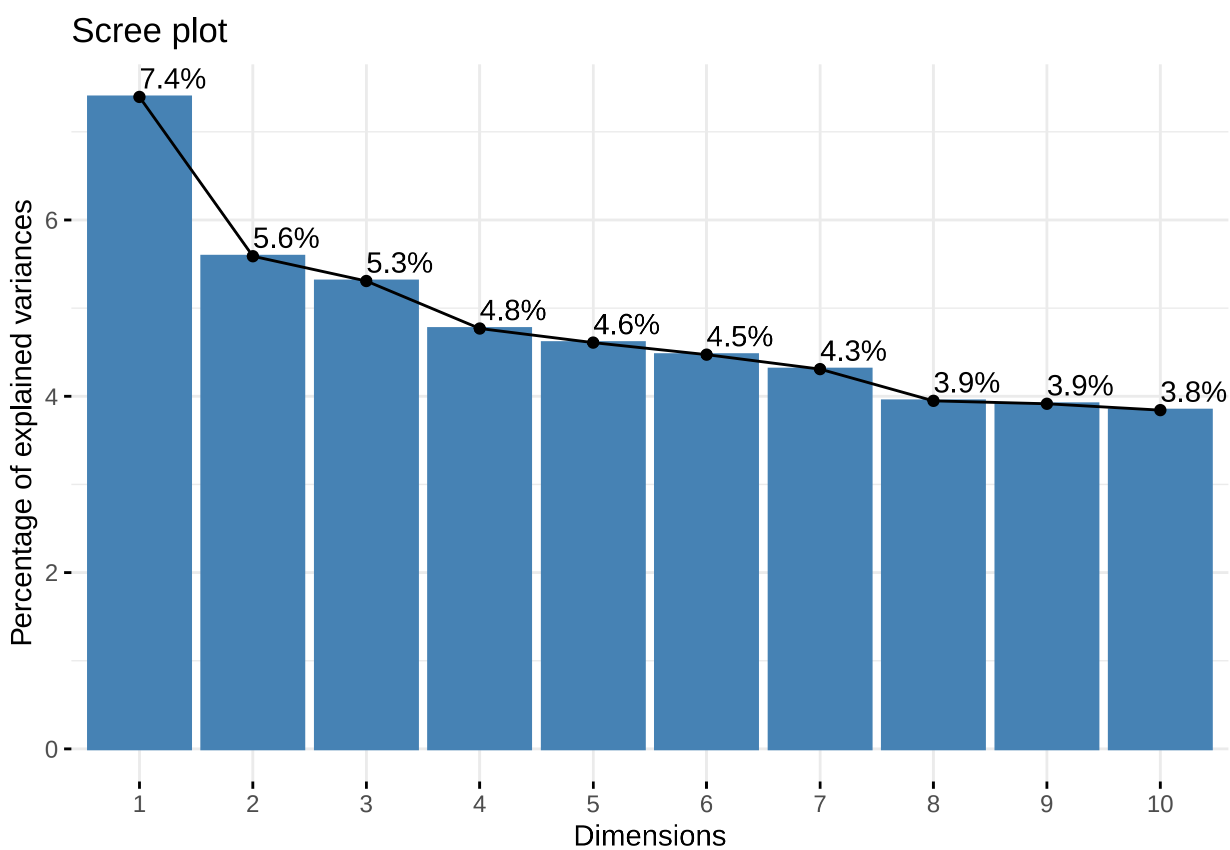
```
options(ggrepel.max.overlaps = 15)
cleaned.adult<-filter(search.data, Age == "Adult")
cleaned.adult<-cleaned.adult%>%select(-c(Age))
nrow(cleaned.adult)
```

```
## [1] 6
```

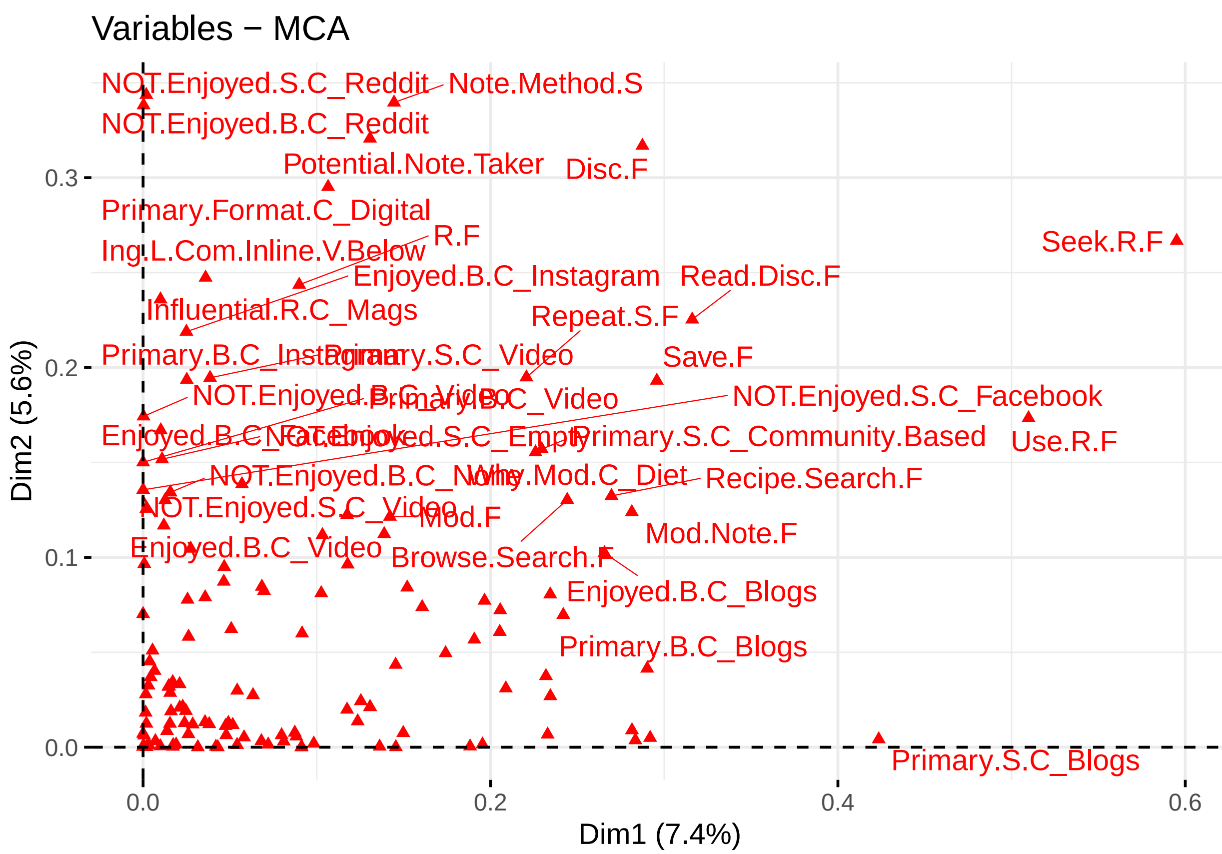
This strata only has 6 sample units, so I will skip it in my further analysis. This strata has an artificially low variance due to its low membership.

Stratify by Who Cooks

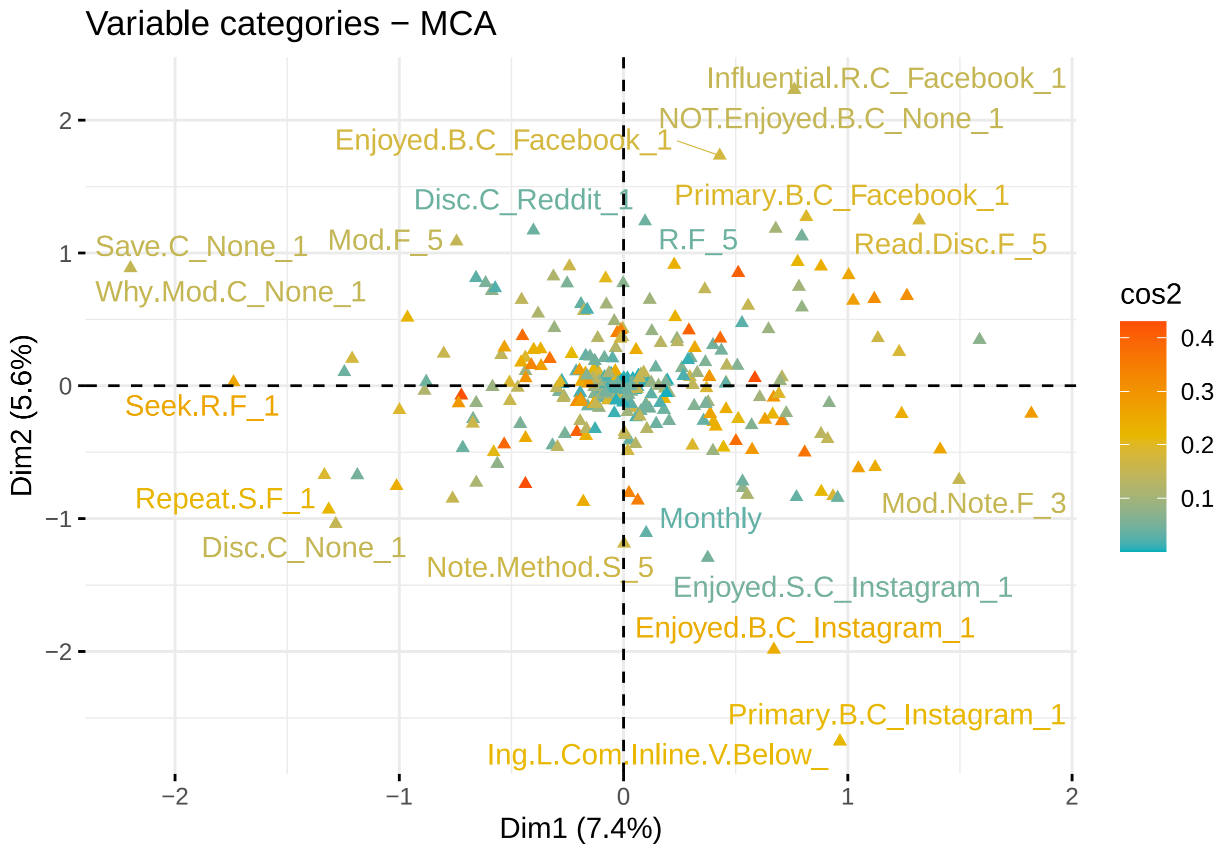
```
primary.cook<-filter(search.data, Meal.Prepper == "Respondent")
primary.cook<-primary.cook%>%select(-c(Meal.Prepper))
cleaned.data<-mca.plot(primary.cook)
```




```
## Warning: ggrepel: 104 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps
```




```
## Warning: ggrepel: 298 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps
```



Scree Plot Using the elbow rule, I will be looking at the first two components of this MCA analysis. Therefore this plot will only capture 13% of the variability in the data. Slightly less variance is captured in the components when we stratify by who cooks.

Variables Using review frequency are very well represented in dimension 1.

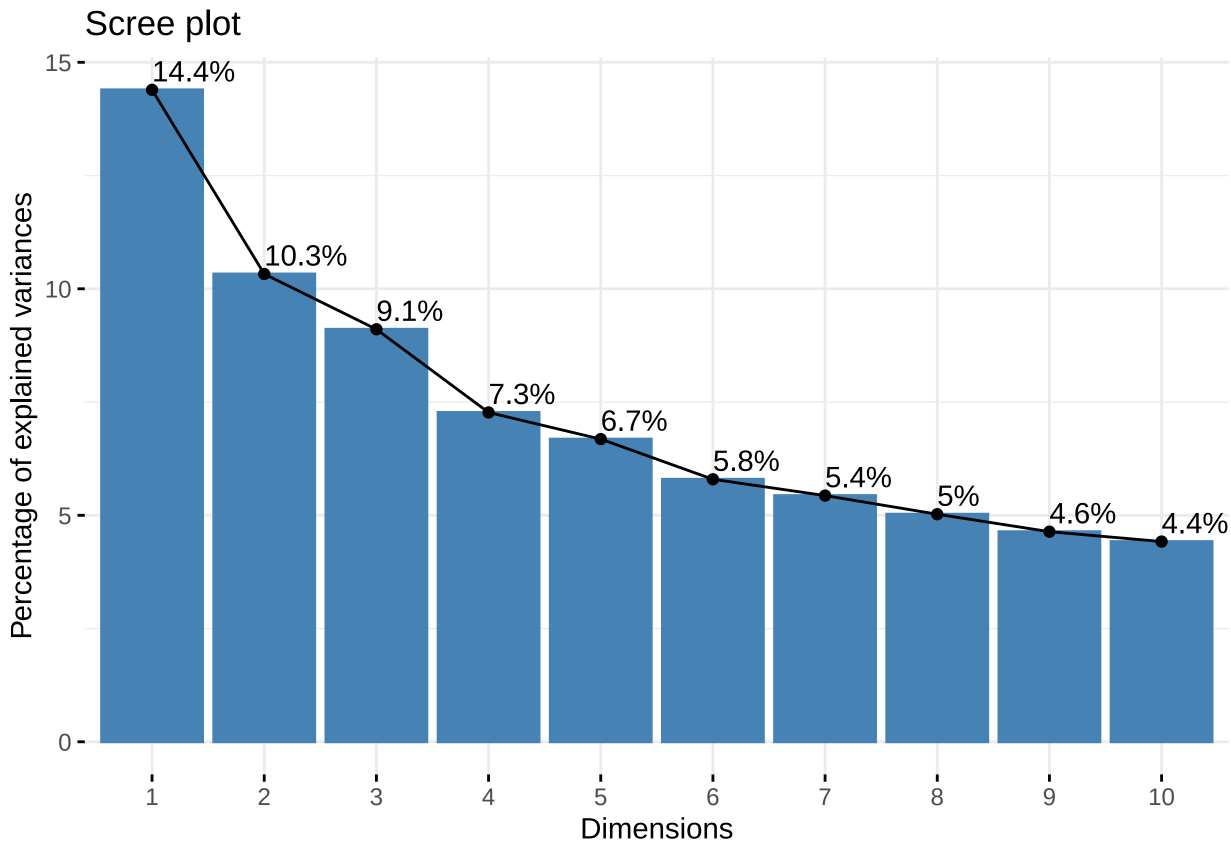
Not enjoying Reddit for searching or browsing, discussion frequency, note taking potential, and note method satisfaction, and using digital recipes are well represented in dimension 2.

Seeking review review frequency is well represented in both dimension.

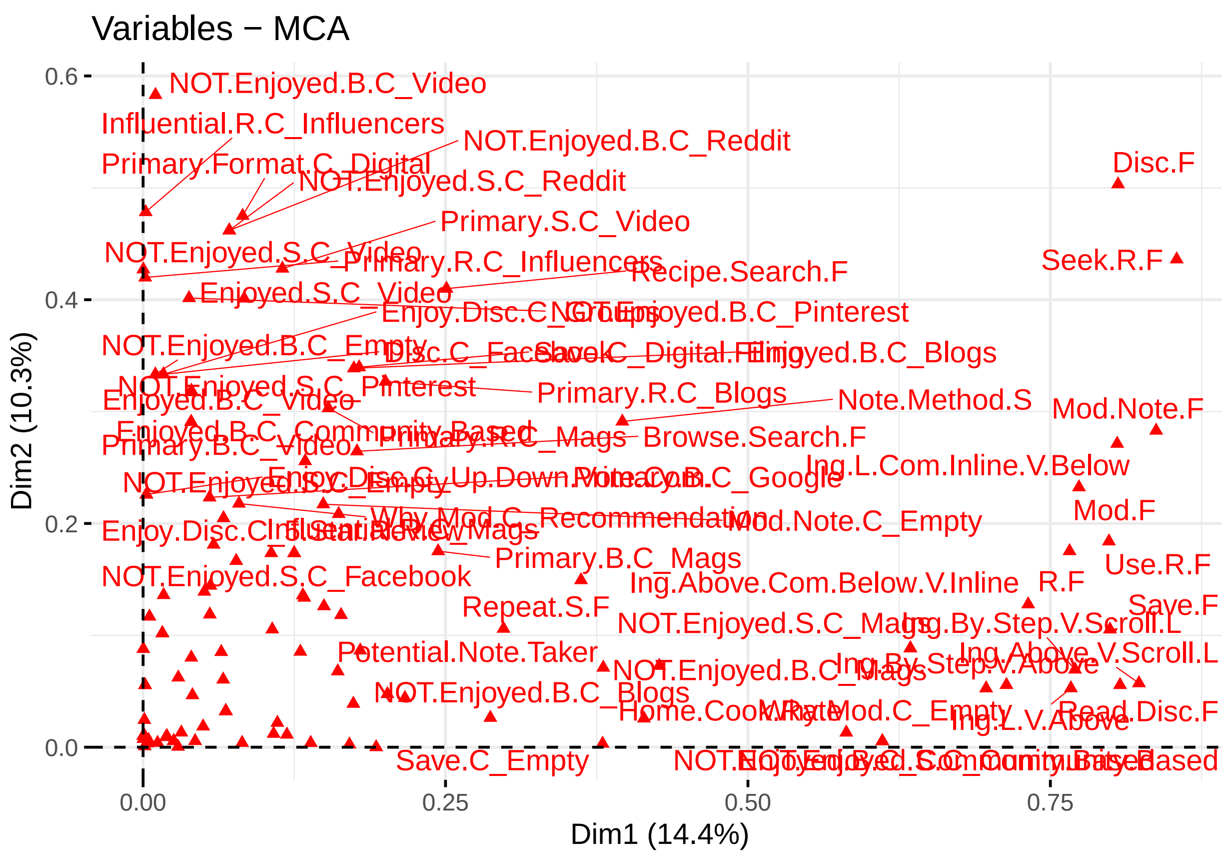
Variable Categories Dimension 1 contrasts users who do not frequently interact with recipes with users who frequently discuss recipes, take notes and use pinterest to discuss recipes.

Dimension 2 contrasts users that enjoy Instagram for browsing and searching, with users who enjoy Facebook and Reddit.

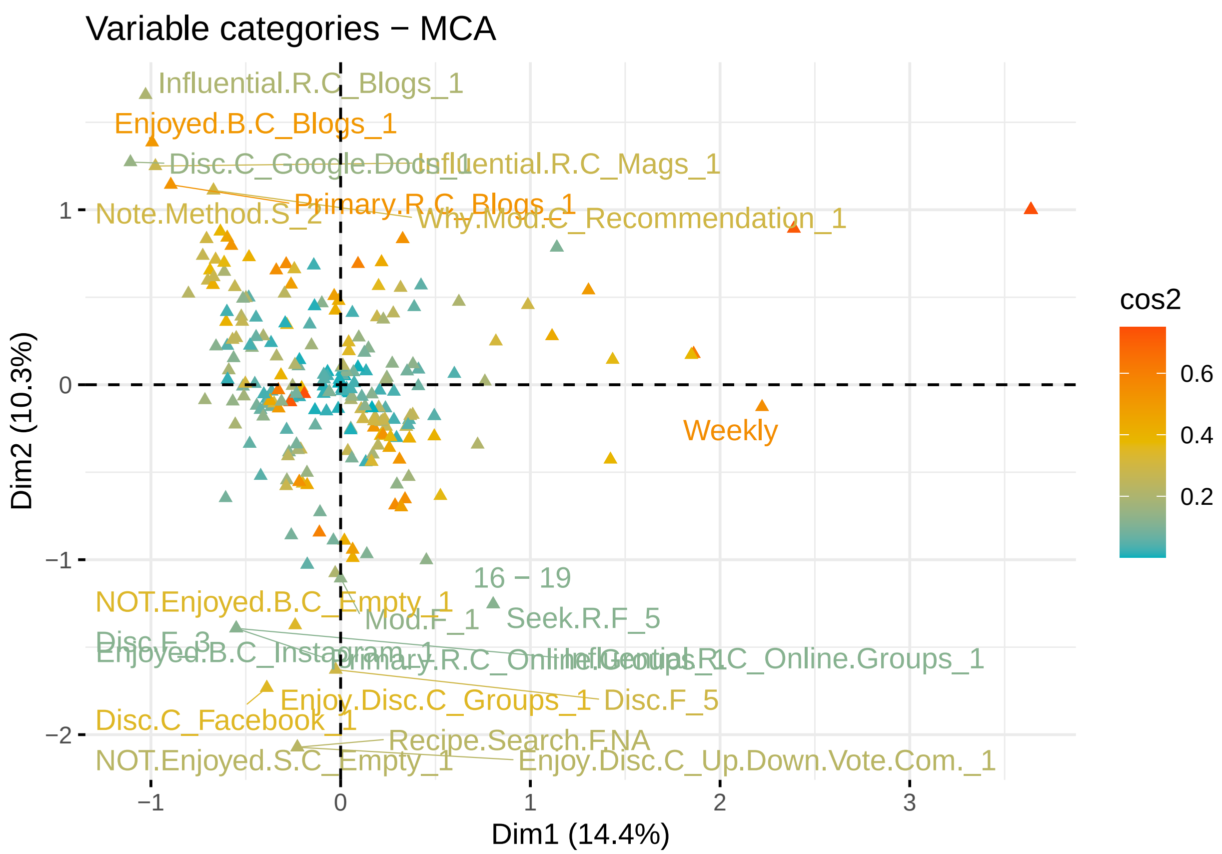
```
options(ggrepel.max.overlaps = 15)

primary.cook.o<-filter(search.data, Meal.Prepper == "Other")
primary.cook.o<-primary.cook.o%>%select(-c(Meal.Prepper))
cleaned.data<-mca.plot(primary.cook.o)
```




```
## Warning: ggrepel: 61 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps
```




```
## Warning: ggrepel: 267 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps
```



Scree Plot

Using the elbow rule, I will be looking at the first two components of this MCA analysis. Therefore this plot will only capture 24.7% of the variability in the data. Slightly less variance is captured in the components when we stratify by who cooks.

Variables Using review frequency, save frequency, modification note frequency, ingredients above vs. pinned left while scrolling, and ingredients listed step by step vs. ingredients pinned left while scrolling are very well represented in dimension 1.

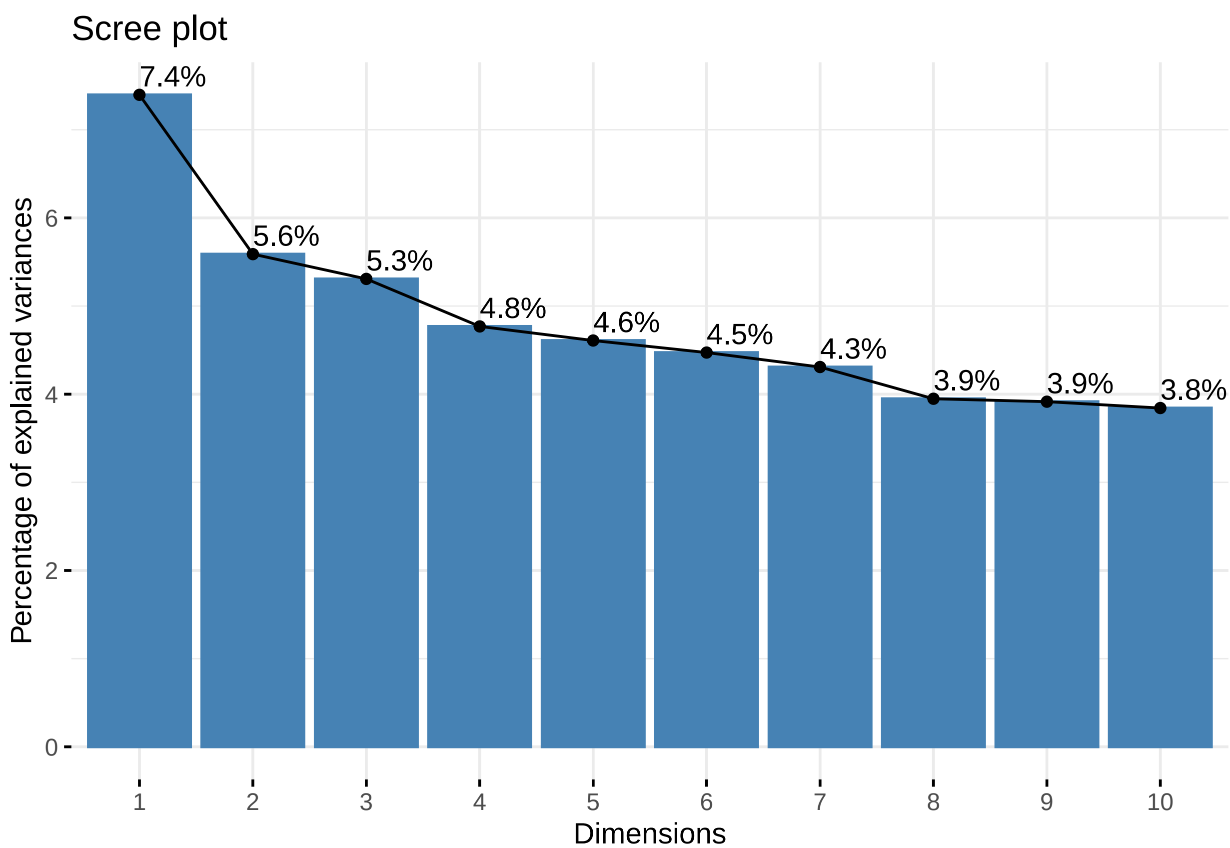
Not enjoying Reddit and video for searching or browsing, and trusting influencers' reviews are well represented in dimension 2.

Seeking review review frequency and discussion frequency is well represented in both dimension.

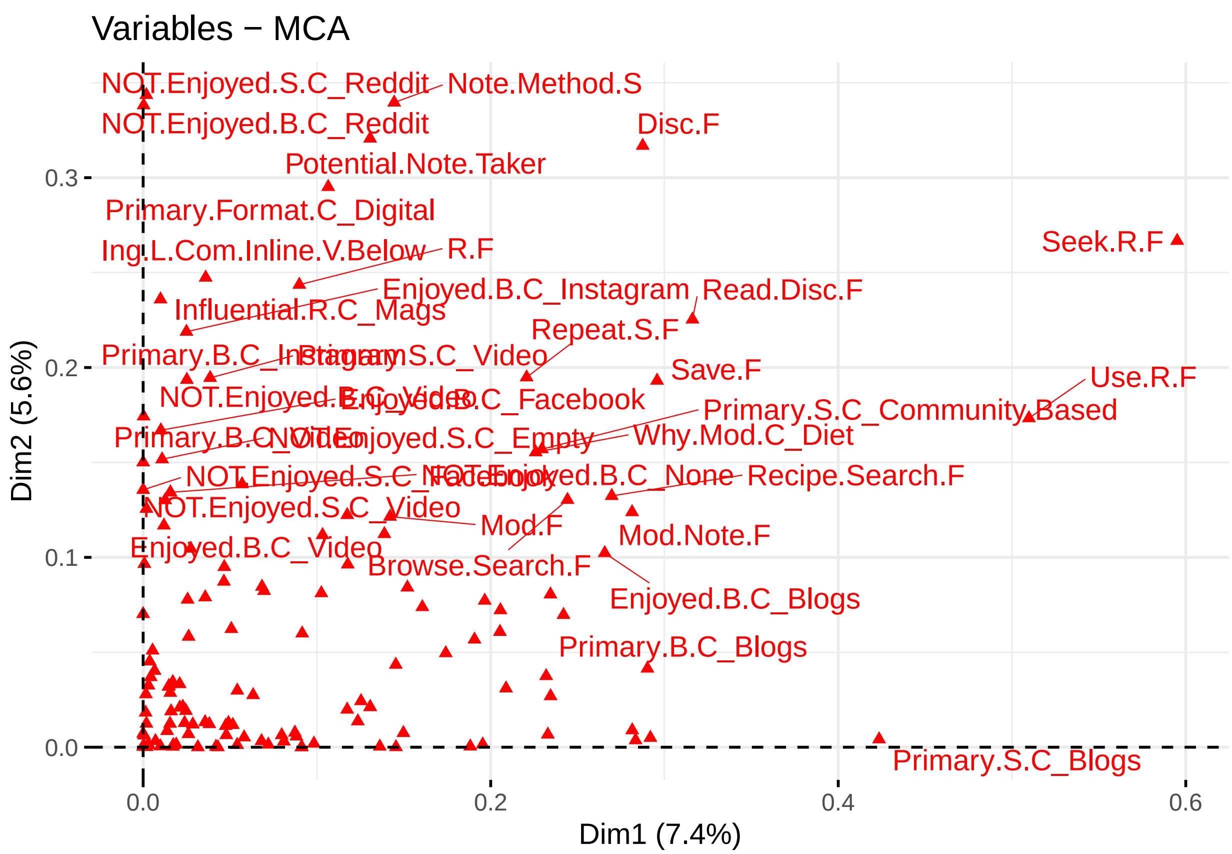
Variable Categories Dimension 1 contrasts users cook weekly and do not enjoy online magazines for searching and browsing with users who enjoy blogs for searching and browsing.

Dimension 2 contrasts users enjoy blogs for searching and browsing, discuss recipes on Google, and have a low level of satisfaction with available note taking methods with users who enjoy discussion groups for recipes and enjoy discussing on Facebook.

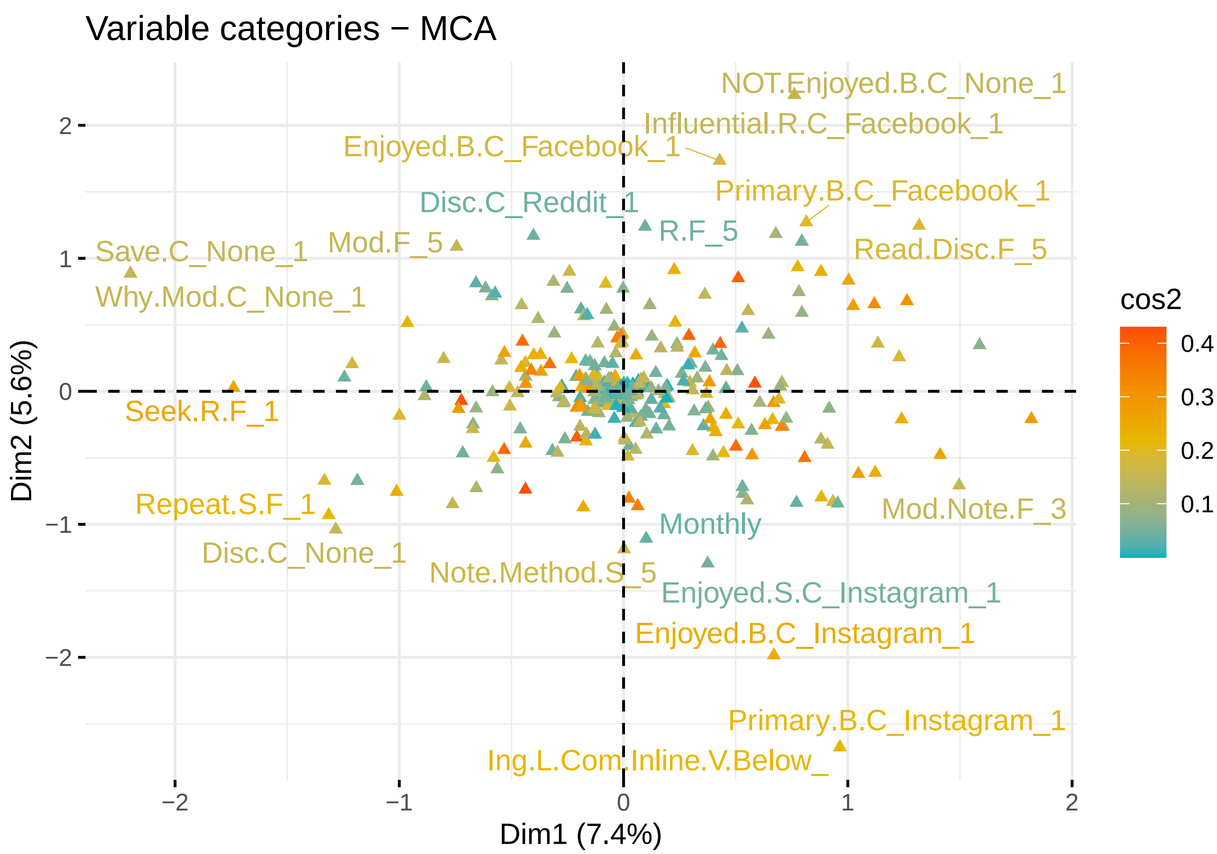
```
primary.cook.o<-filter(search.data, Meal.Prepper == "Respondent")
primary.cook.o<-primary.cook.o%>%select(-c(Meal.Prepper))
cleaned.data<-mca.plot(primary.cook.o)
```




```
## Warning: ggrepel: 104 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps
```




```
## Warning: ggrepel: 298 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps
```



Scree Plot Using the elbow rule, I will be looking at the first two components of this MCA analysis. Therefore this plot will only capture 13% of the variability in the data. Slightly less variance is captured in the components when we stratify by who cooks.

Variables Using review frequencyand primary use of blogs are well represented in dimension one.

Not enjoying Reddit, video, and Instagam for searching or browsing, discussion frequency, and trusting influencer reviews are well represented in dimension 2.

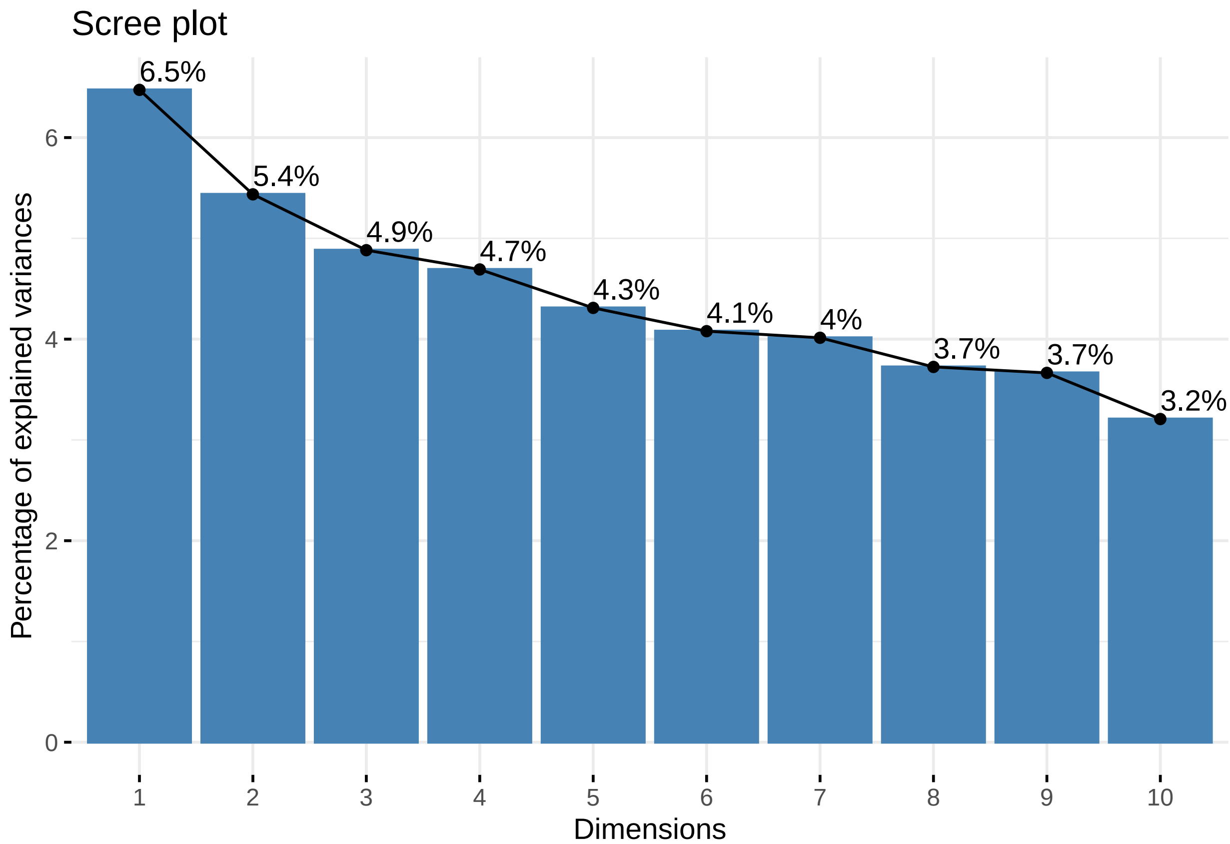
Seeking review review frequency and discussion frequency is well represented in both dimension.

Variable Categories

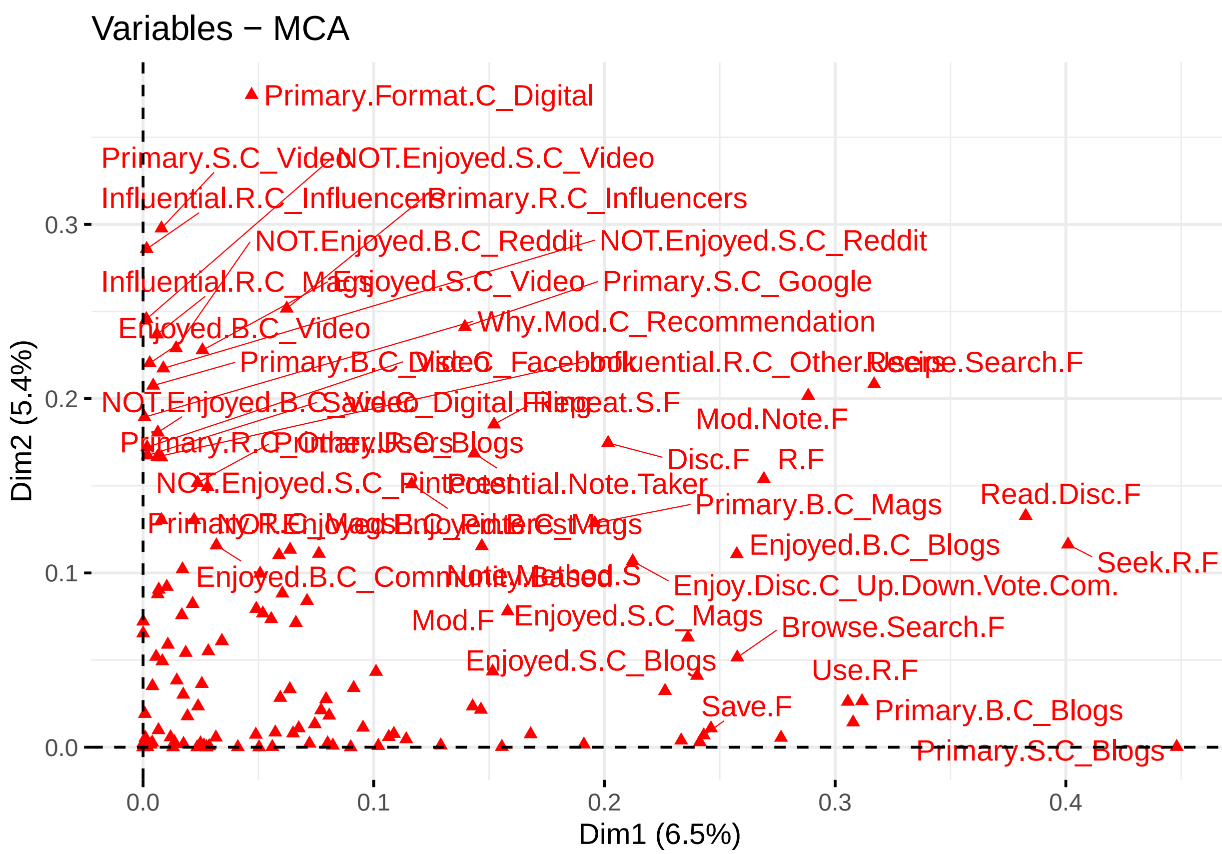
Stratify By Cooking Frequency

Overview

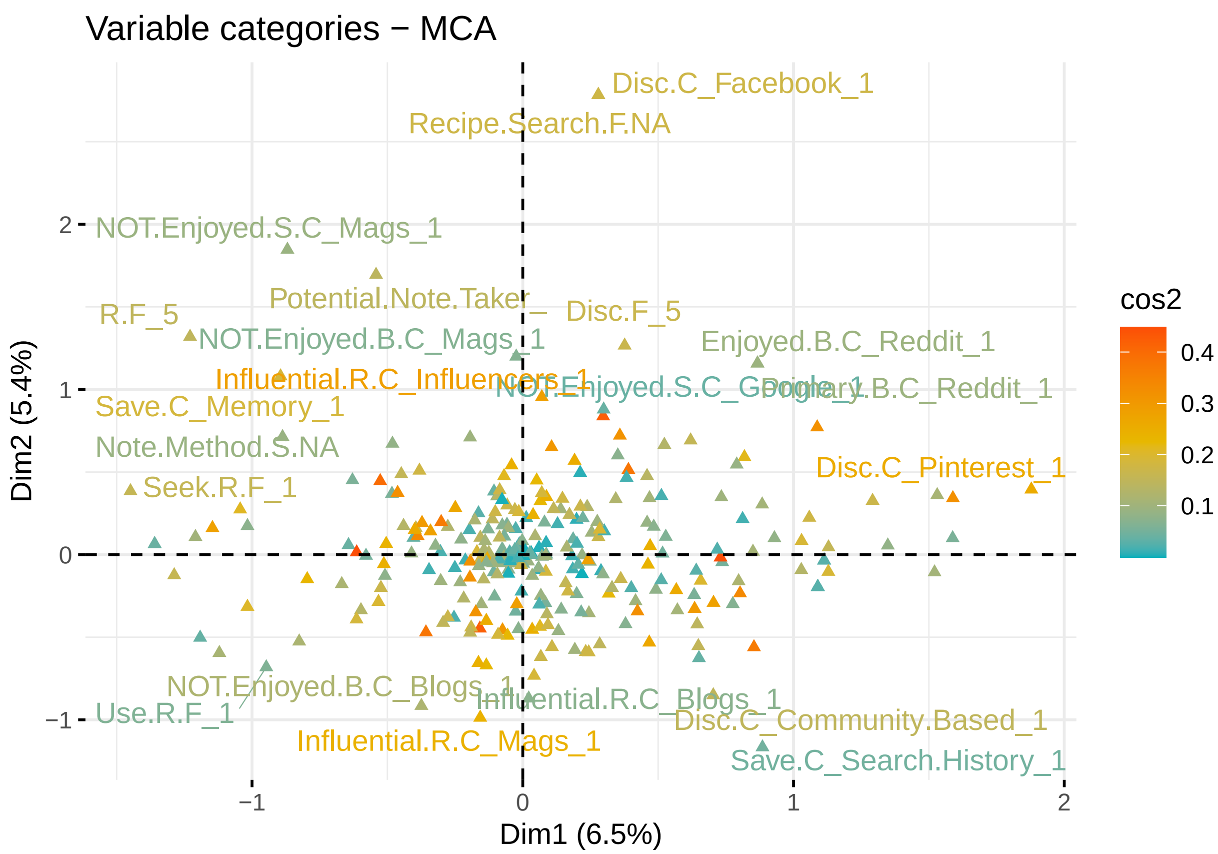
```
daily.cooks<-filter(search.data, Home.Cook.Rate == "Daily")
daily.cooks<-daily.cooks%>%select(-c(Home.Cook.Rate))
cleaned.data<-mca.plot(daily.cooks)
```




```
## Warning: ggrepel: 92 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps
```

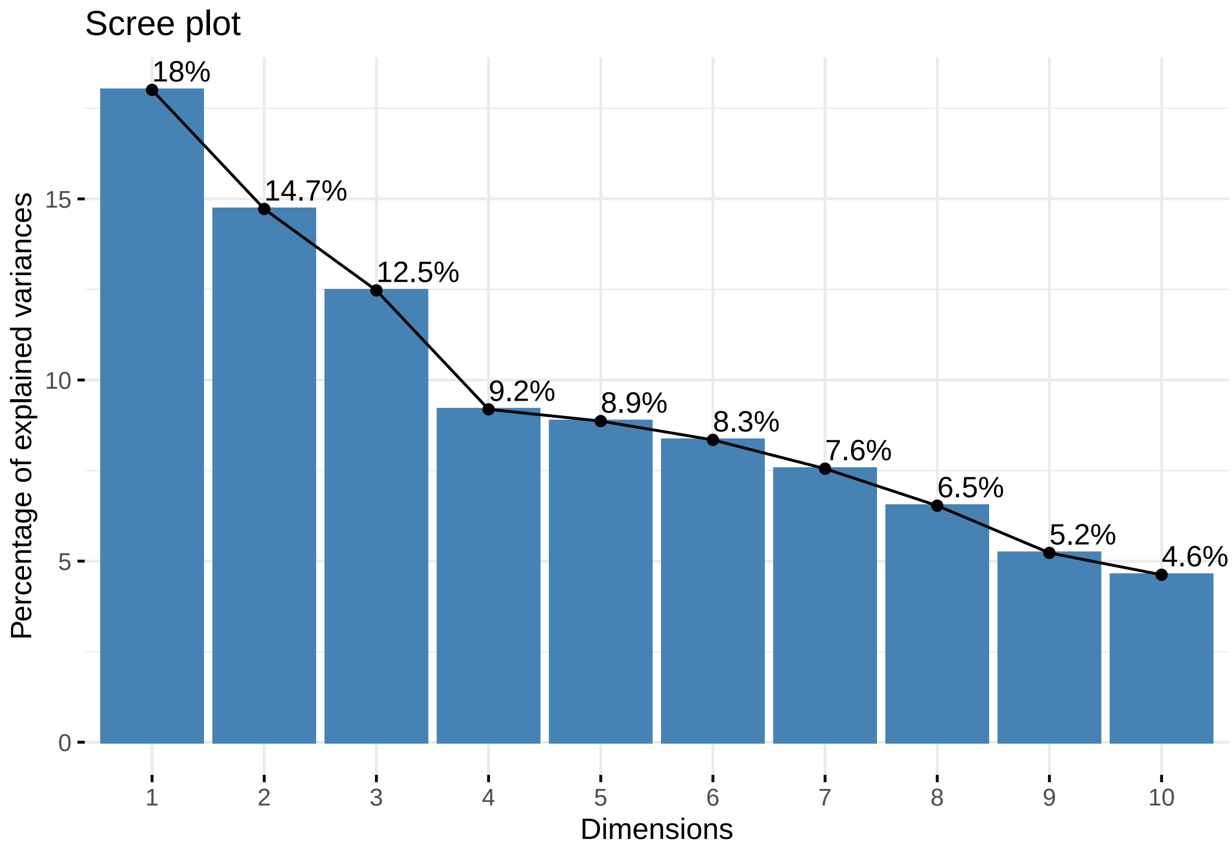



```
## Warning: ggrepel: 293 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps
```

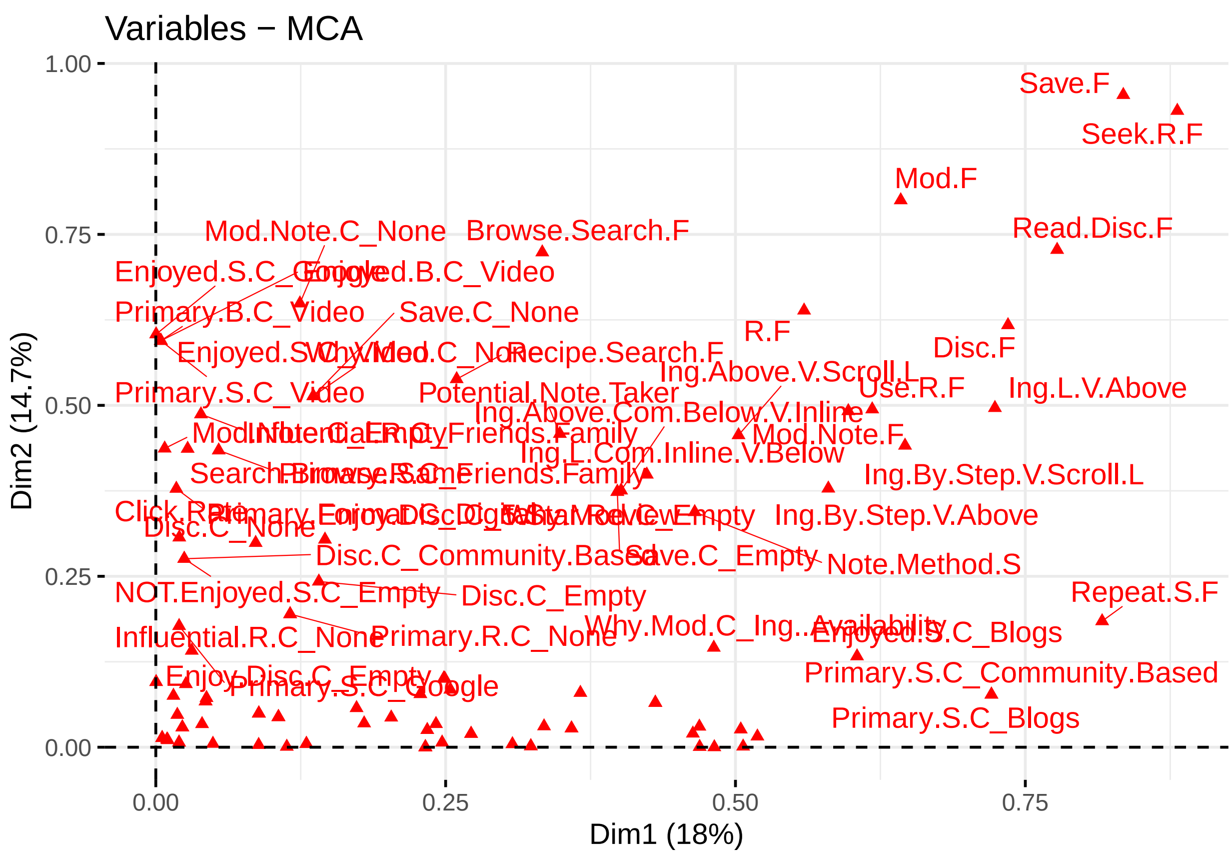


Only 11.8% of the variance is explained by the components using the elbow rule, therefore this analysis is not as significant as the others I am considering.

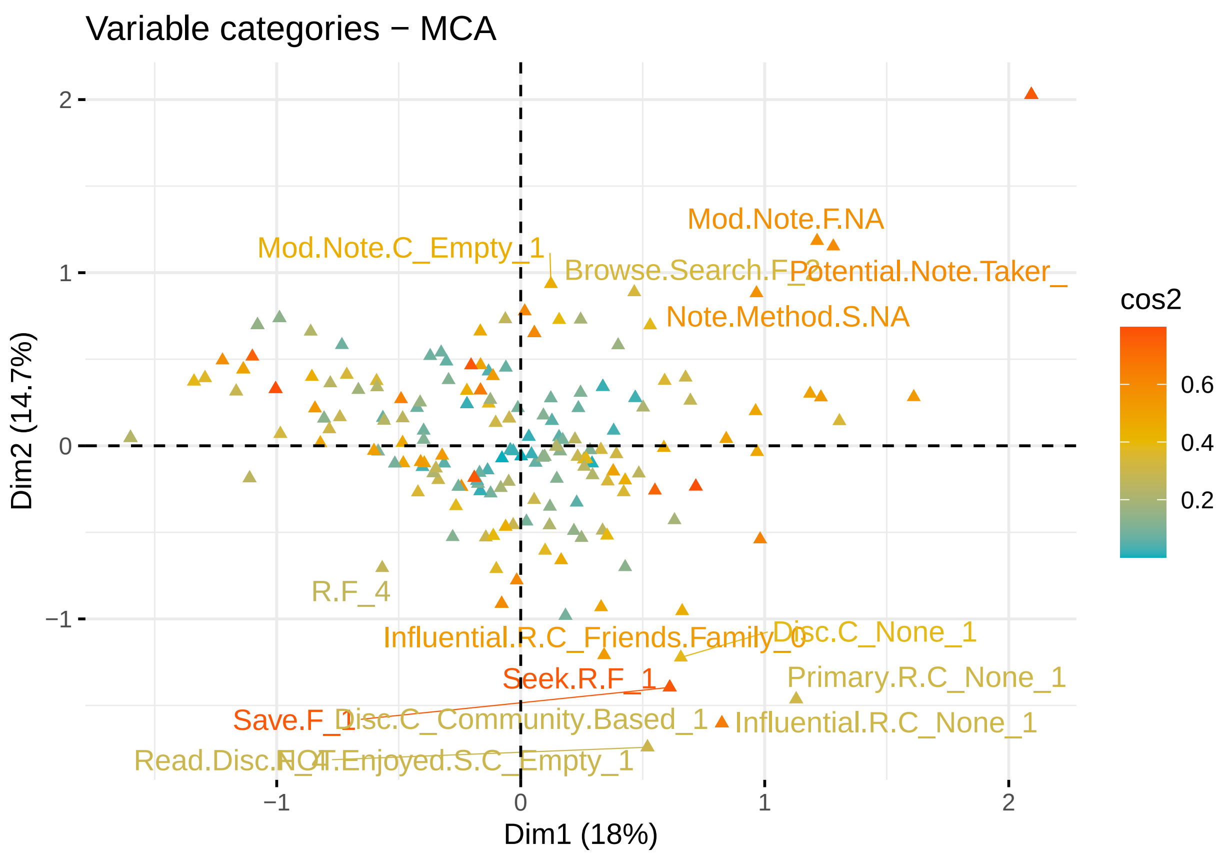
```
weekly.cooks<-filter(search.data, !(Home.Cook.Rate == "Daily") )
weekly.cooks<-weekly.cooks%>%select(-c(Home.Cook.Rate))
cleaned.data<-mca.plot(weekly.cooks)
```




```
## Warning: ggrepel: 61 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps
```




```
## Warning: ggrepel: 250 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps
```



Looking at the Biplot, none of the variable categories have a high cos2 value, so they are not well represented by the components. Therefore, further analysis will not be significant and should be interpreted with caution.