select regression predictors

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First, let's read in data.frames for annual area burned and climate. Also import the 'car' library for regression diagnostic calculations

```
suppressPackageStartupMessages(library(car))
suppressPackageStartupMessages(library(data.table))

aab <- read.csv("../data/dataframes/annual_area_burned.csv")
cffdrs_vars <- read.csv("../data/dataframes/cffdrs-stats_era5_1979-2020.csv")</pre>
```

Now let's just check a quick summary for some of the variables in each of these datasets for the Alaskan ecoregion (50607).

```
summary(aab$annual_area_burned_km2[aab$ecos == 50607.0])
##
      Min. 1st Qu. Median
                              Mean 3rd Qu.
##
             341.5
                    1319.0
                            3133.4 3469.5 18315.0
summary(cffdrs_vars$bui_95d[aab$ecos == 50607.0])
      Min. 1st Qu.
##
                    Median
                              Mean 3rd Qu.
                                               Max.
             9.526 16.242 18.160 24.557 52.906
summary(cffdrs_vars$isi_max[aab$ecos == 50607.0])
       Min. 1st Qu.
                       Median
                                  Mean
                                        3rd Qu.
                                                     Max.
## -3.68080 -1.22300 0.02629 0.16767
                                        1.49174 5.69301
# Merge datasets together using data.table
data_table <- data.table::merge.data.table(cffdrs_vars, aab,</pre>
                                            by = c("year", "ecos"))
# Rename "annual area burned km2" -> "aab
colnames(data table)[15] <- "aab"</pre>
```

Now, we want to create a list of model formulas that will be used for modeling aab in each ecoregion. This list of formulas will combine all possible bui and isi predictors so we can identify which specific combinations of explanatory variables should be used in a given ecoregion.

```
# Before we do this make sure to set any aab values < 4 km2 to a random uniform
# variable to help remove zeros.
id <- data_table$aab < 4
data_table$aab[id] <- runif(sum(id), 0, 4)

# Unique ecoregions
ecos = unique(data_table$ecos)

# Variables for CFFDDRS summaries:
# 1. max: Annual maximum anomaly relative 1980-2009
# 2. 95d: Number of days in a given year that exceed historical (1980-2009)</pre>
```

```
## [1] "aab ~ isi_max + bui_max" "aab ~ isi_max + bui_95d"
## [3] "aab ~ isi_max + bui_fs" "aab ~ isi_max + bui_fwsl"
```

The next step is to calculate a set of diagnostics for each set of explanatory variables, this includes AIC, BIC, Deviance, R-squared, and Variance Inflation Factor

In a nested for loop, go through and calculate each of the above diagnostics

```
for (i in seq_along(ecos)){
  eco_id <- data_table$ecos == ecos[i]</pre>
  for (j in seq_along(mdl_forms)){
    glm_ij <- glm(mdl_forms[j],</pre>
                    family = Gamma(link = "log"),
                    data = data_table,
                    subset = eco_id)
    aic <- AIC(glm_ij)</pre>
    bic <- BIC(glm_ij)</pre>
    dev <- glm_ij$deviance</pre>
    dev.null <- glm_ij$null.deviance</pre>
    R2 \leftarrow 1 - dev / dev.null
    VIF <- car::vif(glm_ij)[1]</pre>
    df_ij <- data.frame(ecos = ecos[i],</pre>
                           mdl = mdl_forms[j],
                           AIC = aic,
```

```
BIC = bic,
Dev = dev,
R2 = R2,
vif = VIF)

diagnostics <- rbind(diagnostics, df_ij, make.row.names = FALSE)
}</pre>
```

Before we identify best models based on BIC and R2, remove models with high covariance among the predictors using VIF < 3 as a cutoff.

```
vif.id <- diagnostics$vif < 3
diagnostics <- diagnostics[vif.id, ]</pre>
```

In the following code, we fill in two empty vectors to hold the index of which models produced the lowest BIC and max R2 for each ecoregion.

```
min_bic_id <- numeric(length = length(ecos))

for (i in seq_along(ecos)){
    ecos.id <- which(diagnostics$ecos == ecos[i])
    bic.id <- which(diagnostics$BIC[ecos.id] == min(diagnostics$BIC[ecos.id]))
    min_bic_id[i] <- ecos.id[bic.id]
}

print(diagnostics[min_bic_id, ])</pre>
```

```
##
       ecos
                                  mdl
                                           AIC
                                                    BIC
                                                             Dev
       50602 aab ~ isi 95d + bui fwsl 682.1707 689.1214 64.36877 0.2453642
## 8
      50605 aab ~ isi max + bui max 566.8772 573.8278 84.83704 0.4668267
## 17
## 47
      50606 aab ~ isi_fwsl + bui_fs 650.6431 657.5937 74.92835 0.3850060
## 51
      50607
              aab ~ isi_max + bui_fs 727.5290 734.4797 24.15015 0.6451976
## 65
      50608 aab ~ isi_max + bui_max 713.2214 720.1721 53.27285 0.4215299
## 81 50609
              aab ~ isi_max + bui_max 771.1774 778.1281 16.36043 0.6589442
## 107 50610
                aab ~ isi_fs + bui_fs 628.7879 635.7386 83.97130 0.4891310
## 114 50612 aab ~ isi_max + bui_95d 731.9129 738.8636 36.78712 0.5587972
## 131 50613
              aab ~ isi_max + bui_fs 595.7497 602.7004 76.34447 0.4111273
## 150 50614
              aab ~ isi_95d + bui_95d 693.3521 700.3028 46.72102 0.4083286
## 165 50616
              aab ~ isi_95d + bui_max 591.5839 598.5345 71.87658 0.4180263
## 179 51111
              aab ~ isi_max + bui_fs 646.8580 653.8087 50.27782 0.4838409
##
## 8
      2.410950
## 17 1.797443
## 47 2.062715
      1.768871
## 51
## 65 1.657674
## 81 2.096363
## 107 2.941773
## 114 1.555721
```

```
## 131 1.954968
## 150 1.945852
## 165 2.417577
## 179 1.596996
```

We now have an estimate of the best predictors to use for each ecoregion. We now want to export these results for use in the models