

# STA 325 Case Study

## Load libraries and data

```
## # A tibble: 89 x 7
##       St      Re      Fr R_moment_1 R_moment_2 R_moment_3 R_moment_4
##   <dbl> <dbl> <dbl>    <dbl>    <dbl>    <dbl>    <dbl>
## 1 0.1    224 0.052  0.00216  0.130    14.4    1586.
## 2 3      224 0.052  0.00379  0.470    69.9   10404
## 3 0.7    224 Inf    0.00291  0.0435   0.822    15.6
## 4 0.05   90 Inf    0.0635   0.0907   0.467     3.27
## 5 0.7    398 Inf    0.000369 0.00622  0.126     2.57
## 6 2      90 0.3    0.148    2.01    36.2    672.
## 7 0.2    90 Inf    0.0813   0.324    3.04    33.0
## 8 3      224 Inf    0.00575  0.120    2.75    63.2
## 9 0.9    224 Inf    0.00302  0.0452   0.845    15.8
## 10 0.6   398 0.052  0.000314 0.00447  0.0821   1.51
## # ... with 79 more rows

##           St      Re      Fr R_moment_1 R_moment_2 R_moment_3
## St      1.00000000 -0.03169871 NaN  0.2147681  0.1479257  0.1647465
## Re      -0.03169871  1.00000000 NaN -0.7747206 -0.3932344 -0.3844289
## Fr           NaN           NaN  1          NaN          NaN          NaN
## R_moment_1 0.21476813 -0.77472058 NaN  1.0000000  0.6298829  0.6217326
## R_moment_2 0.14792571 -0.39323445 NaN  0.6298829  1.0000000  0.9984335
## R_moment_3 0.16474648 -0.38442895 NaN  0.6217326  0.9984335  1.0000000
## R_moment_4 0.18004537 -0.37741773 NaN  0.6150484  0.9946671  0.9988414
##           R_moment_4
## St      0.1800454
## Re      -0.3774177
## Fr           NaN
## R_moment_1 0.6150484
## R_moment_2 0.9946671
## R_moment_3 0.9988414
## R_moment_4 1.0000000

## # A tibble: 23 x 3
##       St      Re      Fr
##   <dbl> <dbl> <dbl>
## 1 0.05   398 0.052
## 2 0.2    398 0.052
## 3 0.7    398 0.052
## 4 1      398 0.052
## 5 0.1    398 Inf
## 6 0.6    398 Inf
## 7 1      398 Inf
## 8 1.5    398 Inf
```

```
## 9 3      398 Inf
## 10 3      224 0.3
## # ... with 13 more rows
```

## Exploratory Data Analysis

*# We transform the 'Fr' variable using the sigmoid function so that this variable  
# will be within a finite range.*

```
train1 <- train %>%
  mutate(Fr_sigmoid = 1 / ( 1 + exp(-Fr))) %>%
  subset(select = c(1:3, 8, 4:7))
```

```
train1
```

```
## # A tibble: 89 x 8
##       St      Re      Fr Fr_sigmoid R_moment_1 R_moment_2 R_moment_3 R_moment_4
##   <dbl> <dbl> <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
## 1 0.1    224 0.052   0.513   0.00216   0.130   14.4    1586.
## 2 3      224 0.052   0.513   0.00379   0.470   69.9    10404
## 3 0.7    224 Inf      1      0.00291   0.0435   0.822    15.6
## 4 0.05   90 Inf      1      0.0635   0.0907   0.467     3.27
## 5 0.7    398 Inf      1      0.000369 0.00622   0.126     2.57
## 6 2      90 0.3     0.574   0.148    2.01    36.2    672.
## 7 0.2    90 Inf      1      0.0813   0.324    3.04    33.0
## 8 3      224 Inf      1      0.00575   0.120    2.75    63.2
## 9 0.9    224 Inf      1      0.00302   0.0452   0.845    15.8
## 10 0.6   398 0.052   0.513   0.000314 0.00447   0.0821    1.51
## # ... with 79 more rows
```

```
cor(train1)
```

```
##              St      Re      Fr      Fr_sigmoid R_moment_1 R_moment_2
## St          1.00000000 -0.03169871 NaN -0.04734175 0.2147681 0.1479257
## Re          -0.03169871 1.00000000 NaN 0.11152749 -0.7747206 -0.3932344
## Fr           NaN      NaN      1      NaN      NaN      NaN
## Fr_sigmoid -0.04734175 0.11152749 NaN 1.00000000 -0.1364384 -0.2896720
## R_moment_1 0.21476813 -0.77472058 NaN -0.13643841 1.0000000 0.6298829
## R_moment_2 0.14792571 -0.39323445 NaN -0.28967203 0.6298829 1.0000000
## R_moment_3 0.16474648 -0.38442895 NaN -0.28369640 0.6217326 0.9984335
## R_moment_4 0.18004537 -0.37741773 NaN -0.27852083 0.6150484 0.9946671
##              R_moment_3 R_moment_4
## St          0.1647465 0.1800454
## Re          -0.3844289 -0.3774177
## Fr           NaN      NaN
## Fr_sigmoid -0.2836964 -0.2785208
## R_moment_1 0.6217326 0.6150484
## R_moment_2 0.9984335 0.9946671
## R_moment_3 1.0000000 0.9988414
## R_moment_4 0.9988414 1.0000000
```

```
test1 <- test %>%
  mutate(Fr_sigmoid = 1 / ( 1 + exp(-Fr)))

test1
```

```
## # A tibble: 23 x 4
##       St     Re     Fr Fr_sigmoid
##   <dbl> <dbl> <dbl>   <dbl>
## 1  0.05   398  0.052   0.513
## 2  0.2    398  0.052   0.513
## 3  0.7    398  0.052   0.513
## 4  1      398  0.052   0.513
## 5  0.1    398 Inf      1
## 6  0.6    398 Inf      1
## 7  1      398 Inf      1
## 8  1.5    398 Inf      1
## 9  3      398 Inf      1
## 10 3      224  0.3     0.574
## # ... with 13 more rows
```

*# R\_moment\_2 is almost perfectly correlated with R\_moment\_3 and R\_moment 4.*

We will try to create these 4 models:

- **Response:** R\_moment\_1 & **Predictors (Main Effects):** St, Re, Fr\_sigmoid

We will attempt to use a combination of subset selection, polynomial, transformation, and interaction variables.

- **Response:** R\_moment\_2 & **Predictors (Main Effects):** St, Re, Fr\_sigmoid, R\_moment\_1

We will attempt to use a combination of subset selection, polynomial, transformation, and interaction variables. We will also include R\_moment\_1 since it has significant positive relationship with R\_moment\_2 (~0.63).

- **Response:** R\_moment\_3 & **Predictors (Main Effects):** R\_moment\_2

We know that R\_moment\_2 is almost perfectly correlated (>0.99) with R\_moment\_3, so only using one predictor variable is enough. We try to avoid overfitting by using only R\_moment\_2 as our only predictor to predict R\_moment\_3. We will attempt to use polynomial and transformation variables.

- **Response:** R\_moment\_4 & **Predictors (Main Effects):** R\_moment\_2, R\_moment\_3

Same reasoning - R\_moment\_2 and R\_moment\_3 are almost perfectly correlated with R\_moment\_4. We will only use these 2 predictors and will attempt to use both transformation and interaction variables (since R\_moment\_2 and R\_moment\_3 are also highly correlated to each other).

## Predictive models

### Apply to test data