

Project

Theo and Thomas

October 2025

Interval world_data

```
interval_data = read.csv("FINAL DATA.csv")  
  
#interval_data
```

Create world_data

```
#Read in world_data (world_data is ordered)  
world_data = read.csv("FINAL WORLD DATA.csv")  
  
#world_data
```

Create model for improvement over time

```
interval_data = interval_data %>%  
  mutate(DayNum = as.numeric(gsub('Day_', '', Day)))  
  
world_data = world_data %>%  
  mutate(DayNum = as.numeric(gsub('Day_', '', Day)))  
  
# Calculate success rate by day and interval  
daily_interval_success = interval_data %>%  
  group_by(DayNum, Interval) %>%  
  summarise(  
    success_rate = mean(Success),  
    n_attempts = n(),  
    .groups = 'drop'  
  )  
  
# Calculate overall success rate by day (across all intervals)  
daily_overall_success = interval_data %>%  
  group_by(DayNum) %>%  
  summarise(  
    overall_success_rate = mean(Success),
```

```

    total_attempts = n(),
    .groups = 'drop'
)

# Calculate how far Nifski get on average each day
daily_progression = interval_data %>%
  group_by(DayNum, Run) %>%
  summarise(
    max_interval_reached = max(Interval[Success == 1]),
    .groups = 'drop'
  ) %>%
  group_by(DayNum) %>%
  summarise(
    avg_max_interval = mean(max_interval_reached),
    median_max_interval = median(max_interval_reached),
    .groups = 'drop'
  )

#interval_data

```

Graphs

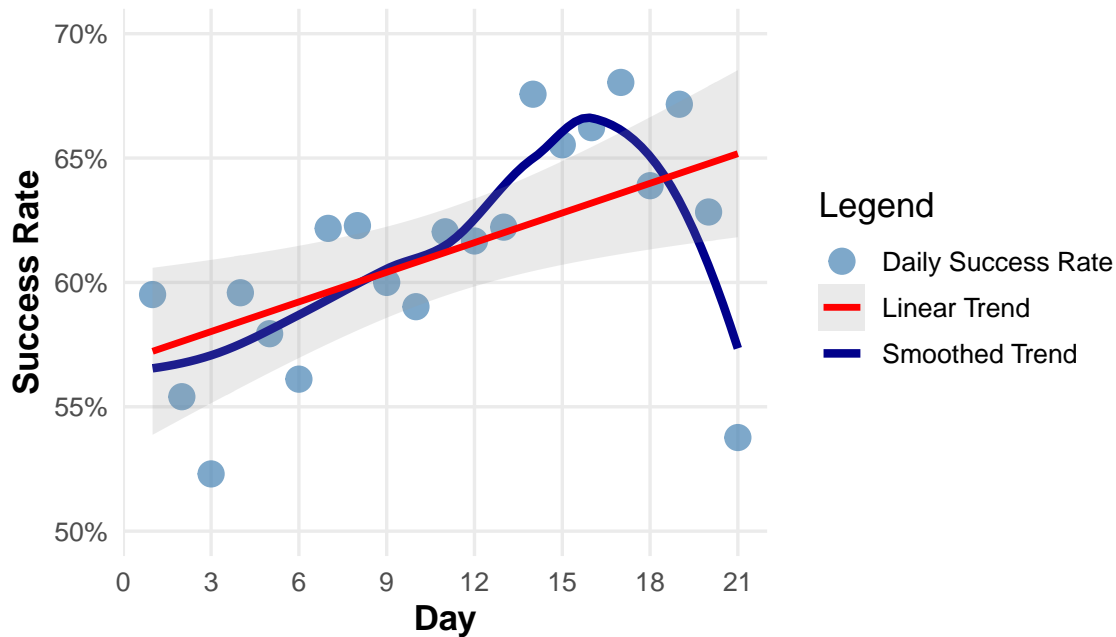
```

# Graph 1: Overall Success Rate Over Time (Enhanced with Legend)
ggplot(daily_overall_success, aes(x = DayNum, y = overall_success_rate)) +
  geom_point(aes(color = "Daily Success Rate"), size = 4, alpha = 0.7) +
  geom_smooth(aes(color = "Smoothed Trend"),
    method = "loess", se = FALSE, linewidth = 1.5) +
  geom_smooth(aes(color = "Linear Trend"),
    method = "lm", se = TRUE, linewidth = 1.2, alpha = 0.2) +
  scale_color_manual(name = "Legend",
    values = c("Daily Success Rate" = "steelblue",
      "Smoothed Trend" = "darkblue",
      "Linear Trend" = "red")) +
  scale_y_continuous(labels = scales::percent_format(accuracy = 1),
    limits = c(0.50, 0.70)) +
  scale_x_continuous(breaks = seq(0, 21, by = 3)) +
  labs(title = "Speedrun Performance Improvement Over Time",
    subtitle = "Overall success rate across all intervals by day",
    x = "Day",
    y = "Success Rate") +
  theme_minimal(base_size = 13) +
  theme(plot.title = element_text(hjust = 0.5, face = "bold", size = 16),
    plot.subtitle = element_text(hjust = 0.5, size = 12, color = "gray30"),
    panel.grid.minor = element_blank(),
    axis.title = element_text(face = "bold"),
    legend.position = "right")

```

peedrun Performance Improvement Over Time

Overall success rate across all intervals by day



Models

```
#Now that we've shown that there is improvement
# Model improvement over time on interval completion
cloglog_time = glm(Success ~ DayNum + factor(Interval),
                   data = interval_data,
                   family = binomial(link = "cloglog"))
summary(cloglog_time)
```

```
##
## Call:
## glm(formula = Success ~ DayNum + factor(Interval), family = binomial(link = "cloglog"),
##      data = interval_data)
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.146471   0.047604  -3.077 0.002092 **
## DayNum        0.015065   0.003639   4.139 3.48e-05 ***
## factor(Interval)2  0.292025   0.049087   5.949 2.70e-09 ***
## factor(Interval)3  0.420505   0.053783   7.819 5.34e-15 ***
## factor(Interval)4 -1.774111   0.104429 -16.989 < 2e-16 ***
## factor(Interval)5 -0.592292   0.156448  -3.786 0.000153 ***
## factor(Interval)6 -0.812984   0.253766  -3.204 0.001357 **
## factor(Interval)7  0.693954   0.320525   2.165 0.030384 *
## factor(Interval)8 -1.130315   0.502197  -2.251 0.024402 *
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 5997.8  on 4486  degrees of freedom
## Residual deviance: 5184.3  on 4478  degrees of freedom
## AIC: 5202.3
##
## Number of Fisher Scoring iterations: 5
```

```
cloglog_full = glm(Success ~ DayNum * factor(Interval),
                   data = interval_data,
                   family = binomial(link = "cloglog"))

anova(cloglog_time, cloglog_full, test = "Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: Success ~ DayNum + factor(Interval)
## Model 2: Success ~ DayNum * factor(Interval)
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1      4478      5184.3
## 2      4471      5155.3  7    28.948 0.0001479 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

#saturated model is better so do stepwise to find best AIC

Stepwise

```
# Null model (intercept only)
cloglog_null = glm(Success ~ 1,
                  data = interval_data,
                  family = binomial(link = "cloglog"))

# Forward stepwise selection
forward_model = step(cloglog_null,
                    scope = list(lower = cloglog_null, upper = cloglog_full),
                    direction = "forward",
                    trace = 0)

# Backward stepwise selection
backward_model = step(cloglog_full,
                    direction = "backward",
                    trace = 0)
```

```

# Both directions stepwise selection
both_model = step(cloglog_null,
                  scope = list(lower = cloglog_null, upper = cloglog_full),
                  direction = "both",
                  trace = 0)

best_model = forward_model

summary(best_model)

##
## Call:
## glm(formula = Success ~ factor(Interval) + DayNum + factor(Interval):DayNum,
##      family = binomial(link = "cloglog"), data = interval_data)
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    -0.179868   0.063521  -2.832 0.004631 **
## factor(Interval)2     0.192174   0.100243   1.917 0.055227 .
## factor(Interval)3     0.774361   0.112855   6.862 6.81e-12 ***
## factor(Interval)4    -2.157366   0.248769  -8.672 < 2e-16 ***
## factor(Interval)5    -0.179802   0.347896  -0.517 0.605277
## factor(Interval)6    -1.444410   0.714854  -2.021 0.043325 *
## factor(Interval)7     0.355259   1.093958   0.325 0.745373
## factor(Interval)8    -3.581525   2.397524  -1.494 0.135217
## DayNum              0.018462   0.005589   3.303 0.000956 ***
## factor(Interval)2:DayNum 0.009921   0.008715   1.138 0.254948
## factor(Interval)3:DayNum -0.033263   0.009685  -3.435 0.000593 ***
## factor(Interval)4:DayNum 0.034295   0.019701   1.741 0.081721 .
## factor(Interval)5:DayNum -0.035813   0.027848  -1.286 0.198439
## factor(Interval)6:DayNum 0.052490   0.053670   0.978 0.328073
## factor(Interval)7:DayNum 0.026903   0.084506   0.318 0.750214
## factor(Interval)8:DayNum 0.174344   0.157435   1.107 0.268118
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 5997.8  on 4486  degrees of freedom
## Residual deviance: 5155.3  on 4471  degrees of freedom
## AIC: 5187.3
##
## Number of Fisher Scoring iterations: 6

#Best model is Success ~ factor(Interval) + DayNum + factor(Inveral):DayNum

```

Find if model is a good fit

```
# Analyze best_model fit
```

```
# 3. Pearson Chi-Square Test
```

```
pearson_resid = residuals(best_model, type = "pearson")
pearson_chisq = sum(pearson_resid^2)
pearson_pval = 1 - pchisq(pearson_chisq, best_model$df.residual)
cat("\nPearson Chi-Square Test:\n")
```

```
##
```

```
## Pearson Chi-Square Test:
```

```
cat("Chi-Square:", pearson_chisq, "\n")
```

```
## Chi-Square: 4491.95
```

```
cat("P-value:", pearson_pval, "\n")
```

```
## P-value: 0.409724
```

```
# 4. Hosmer-Lemeshow Test
```

```
library(ResourceSelection)
hl_test = hoslem.test(interval_data$Success, fitted(best_model), g = 10)
print(hl_test)
```

```
##
```

```
## Hosmer and Lemeshow goodness of fit (GOF) test
```

```
##
```

```
## data: interval_data$Success, fitted(best_model)
```

```
## X-squared = 17.861, df = 8, p-value = 0.02229
```

```
cat("Hosmer-Lemeshow: p >0.05 indicates good fit\n")
```

```
## Hosmer-Lemeshow: p >0.05 indicates good fit
```

```
# 5. McFadden's Pseudo R-squared
```

```
null_dev = best_model$null.deviance
resid_dev = best_model$deviance
pseudo_r2 = 1 - (resid_dev / null_dev)
cat("\nMcFadden's Pseudo R-squared:", pseudo_r2, "\n")
```

```
##
```

```
## McFadden's Pseudo R-squared: 0.1404641
```

```
cat("Interpretation: 0.2-0.4 = excellent fit\n")
```

```
## Interpretation: 0.2-0.4 = excellent fit
```

```
# 6. Calculate VIF for multicollinearity (if applicable)  
cat("\nVariance Inflation Factors:\n")
```

```
##  
## Variance Inflation Factors:
```

```
vif_values = vif(best_model)  
print(vif_values)
```

```
##  
##          GVIF Df GVIF^(1/(2*Df))  
## factor(Interval)      1.050201e+06  7      2.692098  
## DayNum                2.362440e+00  1      1.537023  
## factor(Interval):DayNum 1.427819e+06  7      2.751817
```

```
cat("VIF < 10 indicates no serious multicollinearity\n")
```

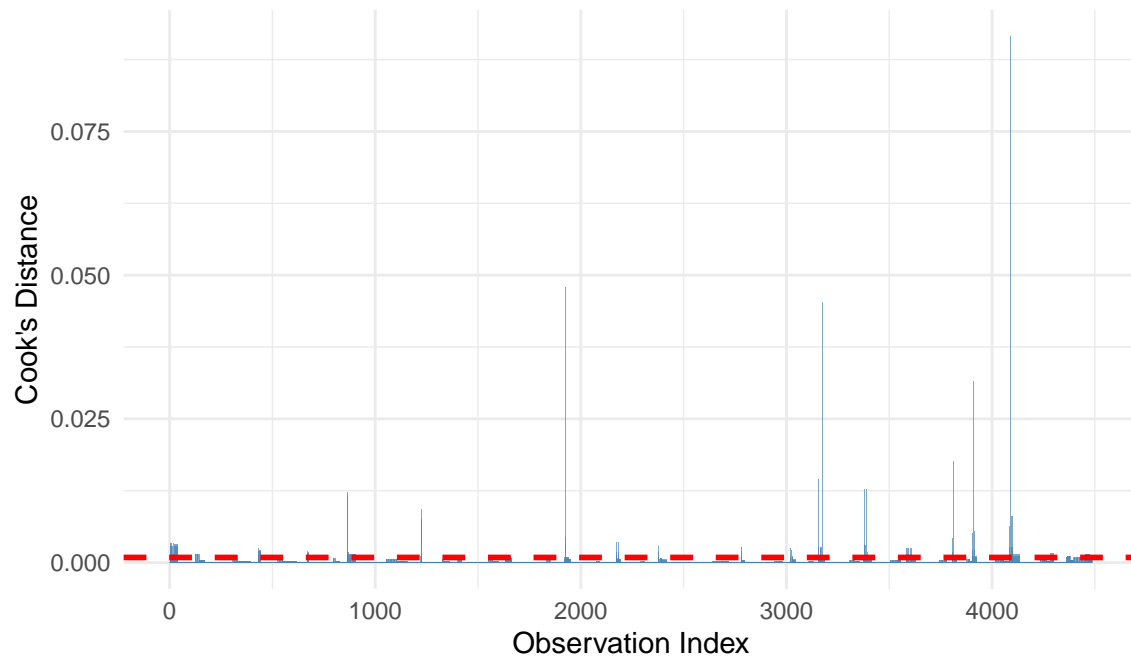
```
## VIF < 10 indicates no serious multicollinearity
```

```
# 8. Influential Points  
interval_data$cooks_d = cooks.distance(best_model)
```

```
# Graph 5: Cook's Distance  
ggplot(interval_data, aes(x = 1:nrow(interval_data), y = cooks_d)) +  
  geom_bar(stat = "identity", fill = "steelblue", alpha = 0.7) +  
  geom_hline(yintercept = 4/nrow(interval_data), color = "red",  
            linetype = "dashed", linewidth = 1) +  
  labs(title = "Cook's Distance - Influential Observations",  
        subtitle = "Points above red line may be influential",  
        x = "Observation Index",  
        y = "Cook's Distance") +  
  theme_minimal() +  
  theme(plot.title = element_text(hjust = 0.5, face = "bold"))
```

Cook's Distance – Influential Observations

Points above red line may be influential



```
# 9. Summary Statistics
```

```
cat("\n=== MODEL FIT SUMMARY ===\n")
```

```
##
```

```
## === MODEL FIT SUMMARY ===
```

```
cat("AIC:", AIC(best_model), "\n")
```

```
## AIC: 5187.337
```

```
cat("BIC:", BIC(best_model), "\n")
```

```
## BIC: 5289.88
```

```
cat("Log-Likelihood:", logLik(best_model), "\n")
```

```
## Log-Likelihood: -2577.669
```

```
cat("Pseudo R-squared:", pseudo_r2, "\n")
```

```
## Pseudo R-squared: 0.1404641
```

Model to predict probability of each individual run


```

# Initialize empty list
interval_models = list()

# Map intervals to their corresponding world record columns
interval_mapping = c(
  "1" = "W1_1",
  "2" = "W1_2",
  "3" = "W4_1",
  "4" = "W4_2",
  "5" = "W8_1",
  "6" = "W8_2",
  "7" = "W8_3",
  "8" = "W8_4"
)

# Build models for intervals 1-7 (we're predicting interval 8/W8_4)
for (interval_num in 1:7) {

  cat("\n=== Processing Interval", interval_num, "(", interval_mapping[as.character(interval_num)], ")\n")

  # Filter data for this specific interval
  interval_subset = interval_data %>%
    filter(Interval == interval_num)

  cat("Number of observations:", nrow(interval_subset), "\n")
  cat("Success rate:", mean(interval_subset$Success), "\n")

  # Build cloglog model for this interval
  model = glm(Success ~ DayNum,
    data = interval_subset,
    family = binomial(link = "cloglog"))

  # Store the model with the world column name as key
  world_col = interval_mapping[as.character(interval_num)]
  interval_models[[world_col]] = model

  cat("Model successfully fit!\n")
  print(summary(model))
}

```

```

##
## === Processing Interval 1 ( W1_1 ) ===
## Number of observations: 1750
## Success rate: 0.6314286
## Model successfully fit!
##
## Call:

```

```

## glm(formula = Success ~ DayNum, family = binomial(link = "cloglog"),
##     data = interval_subset)
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.179868   0.063521  -2.832 0.004631 **
## DayNum       0.018462   0.005589   3.303 0.000956 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2303.7  on 1749  degrees of freedom
## Residual deviance: 2293.0  on 1748  degrees of freedom
## AIC: 2297
##
## Number of Fisher Scoring iterations: 5
##
##
## === Processing Interval 2 ( W1_2 ) ===
## Number of observations: 1105
## Success rate: 0.7375566
## Model successfully fit!
##
## Call:
## glm(formula = Success ~ DayNum, family = binomial(link = "cloglog"),
##     data = interval_subset)
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.012303   0.077548   0.159   0.874
## DayNum       0.028384   0.006686   4.245 2.19e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1272.1  on 1104  degrees of freedom
## Residual deviance: 1252.6  on 1103  degrees of freedom
## AIC: 1256.6
##
## Number of Fisher Scoring iterations: 5
##
##
## === Processing Interval 3 ( W4_1 ) ===
## Number of observations: 815
## Success rate: 0.7877301
## Model successfully fit!

```

```

##
## Call:
## glm(formula = Success ~ DayNum, family = binomial(link = "cloglog"),
##      data = interval_subset)
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.594490   0.093281   6.373 1.85e-10 ***
## DayNum      -0.014800   0.007909  -1.871  0.0613 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 842.63  on 814  degrees of freedom
## Residual deviance: 838.79  on 813  degrees of freedom
## AIC: 842.79
##
## Number of Fisher Scoring iterations: 5
##
##
## === Processing Interval 4 ( W4_2 ) ===
## Number of observations: 642
## Success rate: 0.1573209
## Model successfully fit!
##
## Call:
## glm(formula = Success ~ DayNum, family = binomial(link = "cloglog"),
##      data = interval_subset)
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -2.33723    0.24052  -9.717 < 2e-16 ***
## DayNum       0.05276    0.01889   2.793  0.00523 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 558.80  on 641  degrees of freedom
## Residual deviance: 550.98  on 640  degrees of freedom
## AIC: 554.98
##
## Number of Fisher Scoring iterations: 5
##
##
## === Processing Interval 5 ( W8_1 ) ===
## Number of observations: 101

```

```

## Success rate: 0.4356436
## Model successfully fit!
##
## Call:
## glm(formula = Success ~ DayNum, family = binomial(link = "cloglog"),
##      data = interval_subset)
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.35967    0.34205  -1.051   0.293
## DayNum      -0.01735    0.02728  -0.636   0.525
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 138.34  on 100  degrees of freedom
## Residual deviance: 137.91  on  99  degrees of freedom
## AIC: 141.91
##
## Number of Fisher Scoring iterations: 5
##
##
## === Processing Interval 6 ( W8_2 ) ===
## Number of observations: 44
## Success rate: 0.3636364
## Model successfully fit!
##
## Call:
## glm(formula = Success ~ DayNum, family = binomial(link = "cloglog"),
##      data = interval_subset)
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.62430    0.71199  -2.281   0.0225 *
## DayNum       0.07095    0.05338   1.329   0.1837
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 57.682  on 43  degrees of freedom
## Residual deviance: 55.666  on 42  degrees of freedom
## AIC: 59.666
##
## Number of Fisher Scoring iterations: 5
##
##
## === Processing Interval 7 ( W8_3 ) ===
## Number of observations: 16

```

```
## Success rate: 0.875
## Model successfully fit!
##
## Call:
## glm(formula = Success ~ DayNum, family = binomial(link = "cloglog"),
##      data = interval_subset)
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.17539    1.09211   0.161   0.872
## DayNum       0.04537    0.08432   0.538   0.591
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 12.057  on 15  degrees of freedom
## Residual deviance: 11.817  on 14  degrees of freedom
## AIC: 15.817
##
## Number of Fisher Scoring iterations: 6
```

```
# Now create predictions for each run in world_data
world_data = world_data %>%
  mutate(
    pred_W1_1 = predict(interval_models[["W1_1"]],
                        newdata = data.frame(DayNum = DayNum),
                        type = "response"),
    pred_W1_2 = predict(interval_models[["W1_2"]],
                        newdata = data.frame(DayNum = DayNum),
                        type = "response"),
    pred_W4_1 = predict(interval_models[["W4_1"]],
                        newdata = data.frame(DayNum = DayNum),
                        type = "response"),
    pred_W4_2 = predict(interval_models[["W4_2"]],
                        newdata = data.frame(DayNum = DayNum),
                        type = "response"),
    pred_W8_1 = predict(interval_models[["W8_1"]],
                        newdata = data.frame(DayNum = DayNum),
                        type = "response"),
    pred_W8_2 = predict(interval_models[["W8_2"]],
                        newdata = data.frame(DayNum = DayNum),
                        type = "response"),
    pred_W8_3 = predict(interval_models[["W8_3"]],
                        newdata = data.frame(DayNum = DayNum),
                        type = "response")
  )

# Calculate overall WR probability as product of all interval probabilities
```

```

world_data = world_data %>%
  mutate(
    pred_WR_prob = pred_W1_1 * pred_W1_2 * pred_W4_1 * pred_W4_2 *
      pred_W8_1 * pred_W8_2 * pred_W8_3
  )

# Now use this predicted WR probability in your final model
final_model = logistf(W8_4 ~ pred_WR_prob, data = world_data)

final_model_cloglog = glm(W8_4 ~ pred_WR_prob,
  data = world_data,
  family = binomial(link = "cloglog"))

summary(final_model)

```

```

## logistf(formula = W8_4 ~ pred_WR_prob, data = world_data)
##
## Model fitted by Penalized ML
## Coefficients:
##              coef    se(coef) lower 0.95 upper 0.95   Chisq         p
## (Intercept)  -7.057689   0.9448062  -9.390065   -5.43952    Inf 0.00000000
## pred_WR_prob 115.038453  63.5518139 -20.260603   250.09034  2.84904 0.09142852
##              method
## (Intercept)      2
## pred_WR_prob      2
##
## Method: 1-Wald, 2-Profile penalized log-likelihood, 3-None
##
## Likelihood ratio test=2.84904 on 1 df, p=0.09142852, n=1750
## Wald test = 156.609 on 1 df, p = 0

```

```
summary(final_model_cloglog)
```

```

##
## Call:
## glm(formula = W8_4 ~ pred_WR_prob, family = binomial(link = "cloglog"),
##      data = world_data)
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    -7.278      1.054  -6.902 5.12e-12 ***
## pred_WR_prob   114.678     70.870   1.618  0.106
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)

```

```
##
##      Null deviance: 56.639  on 1749  degrees of freedom
## Residual deviance: 54.195  on 1748  degrees of freedom
## AIC: 58.195
##
## Number of Fisher Scoring iterations: 9
```

#should make final pred_WR remain deterministic based on predicted probabilities, because pred.

Check the predictions

```
world_data %>%
  dplyr::select(DayNum, starts_with("pred_"), W8_4)
```

##	DayNum	pred_W1_1	pred_W1_2	pred_W4_1	pred_W4_2	pred_W8_1	pred_W8_2
## 1	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 2	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 3	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 4	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 5	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 6	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 7	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 8	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 9	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 10	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 11	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 12	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 13	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 14	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 15	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 16	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 17	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 18	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 19	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 20	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 21	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 22	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 23	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 24	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 25	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 26	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 27	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 28	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 29	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 30	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 31	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 32	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619
## 33	1	0.5729895	0.6470842	0.8322841	0.09681451	0.4963658	0.1906619

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

## 11	0.7126400	0.002014909	0
## 12	0.7126400	0.002014909	0
## 13	0.7126400	0.002014909	0
## 14	0.7126400	0.002014909	0
## 15	0.7126400	0.002014909	0
## 16	0.7126400	0.002014909	0
## 17	0.7126400	0.002014909	0
## 18	0.7126400	0.002014909	0
## 19	0.7126400	0.002014909	0
## 20	0.7126400	0.002014909	0
## 21	0.7126400	0.002014909	0
## 22	0.7126400	0.002014909	0
## 23	0.7126400	0.002014909	0
## 24	0.7126400	0.002014909	0
## 25	0.7126400	0.002014909	0
## 26	0.7126400	0.002014909	0
## 27	0.7126400	0.002014909	0
## 28	0.7126400	0.002014909	0
## 29	0.7126400	0.002014909	0
## 30	0.7126400	0.002014909	0
## 31	0.7126400	0.002014909	0
## 32	0.7126400	0.002014909	0
## 33	0.7126400	0.002014909	0
## 34	0.7126400	0.002014909	0
## 35	0.7126400	0.002014909	0
## 36	0.7126400	0.002014909	0
## 37	0.7126400	0.002014909	0
## 38	0.7126400	0.002014909	0
## 39	0.7126400	0.002014909	0
## 40	0.7126400	0.002014909	0
## 41	0.7126400	0.002014909	0
## 42	0.7126400	0.002014909	0
## 43	0.7126400	0.002014909	0
## 44	0.7126400	0.002014909	0
## 45	0.7126400	0.002014909	0
## 46	0.7126400	0.002014909	0
## 47	0.7126400	0.002014909	0
## 48	0.7126400	0.002014909	0
## 49	0.7126400	0.002014909	0
## 50	0.7126400	0.002014909	0
## 51	0.7126400	0.002014909	0
## 52	0.7126400	0.002014909	0
## 53	0.7126400	0.002014909	0
## 54	0.7126400	0.002014909	0
## 55	0.7126400	0.002014909	0
## 56	0.7126400	0.002014909	0
## 57	0.7126400	0.002014909	0
## 58	0.7126400	0.002014909	0

## 59	0.7126400	0.002014909	0
## 60	0.7126400	0.002014909	0
## 61	0.7126400	0.002014909	0
## 62	0.7126400	0.002014909	0
## 63	0.7126400	0.002014909	0
## 64	0.7126400	0.002014909	0
## 65	0.7126400	0.002014909	0
## 66	0.7126400	0.002014909	0
## 67	0.7126400	0.002014909	0
## 68	0.7126400	0.002014909	0
## 69	0.7126400	0.002014909	0
## 70	0.7126400	0.002014909	0
## 71	0.7126400	0.002014909	0
## 72	0.7126400	0.002014909	0
## 73	0.7126400	0.002014909	0
## 74	0.7126400	0.002014909	0
## 75	0.7126400	0.002014909	0
## 76	0.7126400	0.002014909	0
## 77	0.7126400	0.002014909	0
## 78	0.7126400	0.002014909	0
## 79	0.7126400	0.002014909	0
## 80	0.7126400	0.002014909	0
## 81	0.7126400	0.002014909	0
## 82	0.7126400	0.002014909	0
## 83	0.7126400	0.002014909	0
## 84	0.7287987	0.002331836	0
## 85	0.7287987	0.002331836	0
## 86	0.7287987	0.002331836	0
## 87	0.7287987	0.002331836	0
## 88	0.7287987	0.002331836	0
## 89	0.7287987	0.002331836	0
## 90	0.7287987	0.002331836	0
## 91	0.7287987	0.002331836	0
## 92	0.7287987	0.002331836	0
## 93	0.7287987	0.002331836	0
## 94	0.7287987	0.002331836	0
## 95	0.7287987	0.002331836	0
## 96	0.7287987	0.002331836	0
## 97	0.7287987	0.002331836	0
## 98	0.7287987	0.002331836	0
## 99	0.7287987	0.002331836	0
## 100	0.7287987	0.002331836	0
## 101	0.7287987	0.002331836	0
## 102	0.7287987	0.002331836	0
## 103	0.7287987	0.002331836	0
## 104	0.7287987	0.002331836	0
## 105	0.7287987	0.002331836	0
## 106	0.7287987	0.002331836	0

##	107	0.7287987	0.002331836	0
##	108	0.7287987	0.002331836	0
##	109	0.7287987	0.002331836	0
##	110	0.7287987	0.002331836	0
##	111	0.7287987	0.002331836	0
##	112	0.7287987	0.002331836	0
##	113	0.7287987	0.002331836	0
##	114	0.7287987	0.002331836	0
##	115	0.7287987	0.002331836	0
##	116	0.7287987	0.002331836	0
##	117	0.7287987	0.002331836	0
##	118	0.7287987	0.002331836	0
##	119	0.7287987	0.002331836	0
##	120	0.7287987	0.002331836	0
##	121	0.7287987	0.002331836	0
##	122	0.7287987	0.002331836	0
##	123	0.7287987	0.002331836	0
##	124	0.7287987	0.002331836	0
##	125	0.7287987	0.002331836	0
##	126	0.7287987	0.002331836	0
##	127	0.7287987	0.002331836	0
##	128	0.7287987	0.002331836	0
##	129	0.7287987	0.002331836	0
##	130	0.7287987	0.002331836	0
##	131	0.7287987	0.002331836	0
##	132	0.7287987	0.002331836	0
##	133	0.7287987	0.002331836	0
##	134	0.7287987	0.002331836	0
##	135	0.7287987	0.002331836	0
##	136	0.7287987	0.002331836	0
##	137	0.7287987	0.002331836	0
##	138	0.7287987	0.002331836	0
##	139	0.7287987	0.002331836	0
##	140	0.7287987	0.002331836	0
##	141	0.7287987	0.002331836	0
##	142	0.7287987	0.002331836	0
##	143	0.7287987	0.002331836	0
##	144	0.7287987	0.002331836	0
##	145	0.7287987	0.002331836	0
##	146	0.7287987	0.002331836	0
##	147	0.7287987	0.002331836	0
##	148	0.7287987	0.002331836	0
##	149	0.7287987	0.002331836	0
##	150	0.7287987	0.002331836	0
##	151	0.7287987	0.002331836	0
##	152	0.7287987	0.002331836	0
##	153	0.7287987	0.002331836	0
##	154	0.7287987	0.002331836	0

##	155	0.7287987	0.002331836	0
##	156	0.7287987	0.002331836	0
##	157	0.7287987	0.002331836	0
##	158	0.7287987	0.002331836	0
##	159	0.7287987	0.002331836	0
##	160	0.7287987	0.002331836	0
##	161	0.7287987	0.002331836	0
##	162	0.7287987	0.002331836	0
##	163	0.7287987	0.002331836	0
##	164	0.7287987	0.002331836	0
##	165	0.7287987	0.002331836	0
##	166	0.7287987	0.002331836	0
##	167	0.7287987	0.002331836	0
##	168	0.7287987	0.002331836	0
##	169	0.7287987	0.002331836	0
##	170	0.7287987	0.002331836	0
##	171	0.7287987	0.002331836	0
##	172	0.7287987	0.002331836	0
##	173	0.7287987	0.002331836	0
##	174	0.7287987	0.002331836	0
##	175	0.7287987	0.002331836	0
##	176	0.7287987	0.002331836	0
##	177	0.7287987	0.002331836	0
##	178	0.7287987	0.002331836	0
##	179	0.7287987	0.002331836	0
##	180	0.7287987	0.002331836	0
##	181	0.7287987	0.002331836	0
##	182	0.7287987	0.002331836	0
##	183	0.7447352	0.002693164	0
##	184	0.7447352	0.002693164	0
##	185	0.7447352	0.002693164	0
##	186	0.7447352	0.002693164	0
##	187	0.7447352	0.002693164	0
##	188	0.7447352	0.002693164	0
##	189	0.7447352	0.002693164	0
##	190	0.7447352	0.002693164	0
##	191	0.7447352	0.002693164	0
##	192	0.7447352	0.002693164	0
##	193	0.7447352	0.002693164	0
##	194	0.7447352	0.002693164	0
##	195	0.7447352	0.002693164	0
##	196	0.7447352	0.002693164	0
##	197	0.7447352	0.002693164	0
##	198	0.7447352	0.002693164	0
##	199	0.7447352	0.002693164	0
##	200	0.7447352	0.002693164	0
##	201	0.7447352	0.002693164	0
##	202	0.7447352	0.002693164	0

##	203	0.7447352	0.002693164	0
##	204	0.7447352	0.002693164	0
##	205	0.7447352	0.002693164	0
##	206	0.7447352	0.002693164	0
##	207	0.7447352	0.002693164	0
##	208	0.7447352	0.002693164	0
##	209	0.7447352	0.002693164	0
##	210	0.7447352	0.002693164	0
##	211	0.7447352	0.002693164	0
##	212	0.7447352	0.002693164	0
##	213	0.7447352	0.002693164	0
##	214	0.7447352	0.002693164	0
##	215	0.7447352	0.002693164	0
##	216	0.7447352	0.002693164	0
##	217	0.7447352	0.002693164	0
##	218	0.7447352	0.002693164	0
##	219	0.7447352	0.002693164	0
##	220	0.7447352	0.002693164	0
##	221	0.7447352	0.002693164	0
##	222	0.7447352	0.002693164	0
##	223	0.7447352	0.002693164	0
##	224	0.7447352	0.002693164	0
##	225	0.7447352	0.002693164	0
##	226	0.7447352	0.002693164	0
##	227	0.7447352	0.002693164	0
##	228	0.7447352	0.002693164	0
##	229	0.7447352	0.002693164	0
##	230	0.7447352	0.002693164	0
##	231	0.7447352	0.002693164	0
##	232	0.7447352	0.002693164	0
##	233	0.7447352	0.002693164	0
##	234	0.7447352	0.002693164	0
##	235	0.7447352	0.002693164	0
##	236	0.7447352	0.002693164	0
##	237	0.7447352	0.002693164	0
##	238	0.7447352	0.002693164	0
##	239	0.7447352	0.002693164	0
##	240	0.7447352	0.002693164	0
##	241	0.7447352	0.002693164	0
##	242	0.7447352	0.002693164	0
##	243	0.7447352	0.002693164	0
##	244	0.7447352	0.002693164	0
##	245	0.7447352	0.002693164	0
##	246	0.7447352	0.002693164	0
##	247	0.7447352	0.002693164	0
##	248	0.7447352	0.002693164	0
##	249	0.7447352	0.002693164	0
##	250	0.7447352	0.002693164	0

## 251	0.7447352	0.002693164	0
## 252	0.7447352	0.002693164	0
## 253	0.7447352	0.002693164	0
## 254	0.7447352	0.002693164	0
## 255	0.7447352	0.002693164	0
## 256	0.7447352	0.002693164	0
## 257	0.7447352	0.002693164	0
## 258	0.7447352	0.002693164	0
## 259	0.7447352	0.002693164	0
## 260	0.7447352	0.002693164	0
## 261	0.7447352	0.002693164	0
## 262	0.7447352	0.002693164	0
## 263	0.7447352	0.002693164	0
## 264	0.7447352	0.002693164	0
## 265	0.7447352	0.002693164	0
## 266	0.7447352	0.002693164	0
## 267	0.7447352	0.002693164	0
## 268	0.7447352	0.002693164	0
## 269	0.7447352	0.002693164	0
## 270	0.7447352	0.002693164	0
## 271	0.7447352	0.002693164	0
## 272	0.7447352	0.002693164	0
## 273	0.7447352	0.002693164	0
## 274	0.7447352	0.002693164	0
## 275	0.7447352	0.002693164	0
## 276	0.7447352	0.002693164	0
## 277	0.7447352	0.002693164	0
## 278	0.7447352	0.002693164	0
## 279	0.7447352	0.002693164	0
## 280	0.7447352	0.002693164	0
## 281	0.7447352	0.002693164	0
## 282	0.7447352	0.002693164	0
## 283	0.7447352	0.002693164	0
## 284	0.7447352	0.002693164	0
## 285	0.7447352	0.002693164	0
## 286	0.7447352	0.002693164	0
## 287	0.7447352	0.002693164	0
## 288	0.7447352	0.002693164	0
## 289	0.7447352	0.002693164	0
## 290	0.7447352	0.002693164	0
## 291	0.7447352	0.002693164	0
## 292	0.7447352	0.002693164	0
## 293	0.7447352	0.002693164	0
## 294	0.7447352	0.002693164	0
## 295	0.7447352	0.002693164	0
## 296	0.7447352	0.002693164	0
## 297	0.7604096	0.003104015	0
## 298	0.7604096	0.003104015	0

##	299	0.7604096	0.003104015	0
##	300	0.7604096	0.003104015	0
##	301	0.7604096	0.003104015	0
##	302	0.7604096	0.003104015	0
##	303	0.7604096	0.003104015	0
##	304	0.7604096	0.003104015	0
##	305	0.7604096	0.003104015	0
##	306	0.7604096	0.003104015	0
##	307	0.7604096	0.003104015	0
##	308	0.7604096	0.003104015	0
##	309	0.7604096	0.003104015	0
##	310	0.7604096	0.003104015	0
##	311	0.7604096	0.003104015	0
##	312	0.7604096	0.003104015	0
##	313	0.7604096	0.003104015	0
##	314	0.7604096	0.003104015	0
##	315	0.7604096	0.003104015	0
##	316	0.7604096	0.003104015	0
##	317	0.7604096	0.003104015	0
##	318	0.7604096	0.003104015	0
##	319	0.7604096	0.003104015	0
##	320	0.7604096	0.003104015	0
##	321	0.7604096	0.003104015	0
##	322	0.7604096	0.003104015	0
##	323	0.7604096	0.003104015	0
##	324	0.7604096	0.003104015	0
##	325	0.7604096	0.003104015	0
##	326	0.7604096	0.003104015	0
##	327	0.7604096	0.003104015	0
##	328	0.7604096	0.003104015	0
##	329	0.7604096	0.003104015	0
##	330	0.7604096	0.003104015	0
##	331	0.7604096	0.003104015	0
##	332	0.7604096	0.003104015	0
##	333	0.7604096	0.003104015	0
##	334	0.7604096	0.003104015	0
##	335	0.7604096	0.003104015	0
##	336	0.7604096	0.003104015	0
##	337	0.7604096	0.003104015	0
##	338	0.7604096	0.003104015	0
##	339	0.7604096	0.003104015	0
##	340	0.7604096	0.003104015	0
##	341	0.7604096	0.003104015	0
##	342	0.7604096	0.003104015	0
##	343	0.7604096	0.003104015	0
##	344	0.7604096	0.003104015	0
##	345	0.7604096	0.003104015	0
##	346	0.7604096	0.003104015	0

##	347	0.7604096	0.003104015	0
##	348	0.7604096	0.003104015	0
##	349	0.7604096	0.003104015	0
##	350	0.7604096	0.003104015	0
##	351	0.7604096	0.003104015	0
##	352	0.7604096	0.003104015	0
##	353	0.7604096	0.003104015	0
##	354	0.7604096	0.003104015	0
##	355	0.7604096	0.003104015	0
##	356	0.7604096	0.003104015	0
##	357	0.7604096	0.003104015	0
##	358	0.7604096	0.003104015	0
##	359	0.7604096	0.003104015	0
##	360	0.7604096	0.003104015	0
##	361	0.7604096	0.003104015	0
##	362	0.7604096	0.003104015	0
##	363	0.7604096	0.003104015	0
##	364	0.7604096	0.003104015	0
##	365	0.7604096	0.003104015	0
##	366	0.7604096	0.003104015	0
##	367	0.7604096	0.003104015	0
##	368	0.7604096	0.003104015	0
##	369	0.7604096	0.003104015	0
##	370	0.7604096	0.003104015	0
##	371	0.7604096	0.003104015	0
##	372	0.7604096	0.003104015	0
##	373	0.7604096	0.003104015	0
##	374	0.7604096	0.003104015	0
##	375	0.7757820	0.003569887	0
##	376	0.7757820	0.003569887	0
##	377	0.7757820	0.003569887	0
##	378	0.7757820	0.003569887	0
##	379	0.7757820	0.003569887	0
##	380	0.7757820	0.003569887	0
##	381	0.7757820	0.003569887	0
##	382	0.7757820	0.003569887	0
##	383	0.7757820	0.003569887	0
##	384	0.7757820	0.003569887	0
##	385	0.7757820	0.003569887	0
##	386	0.7757820	0.003569887	0
##	387	0.7757820	0.003569887	0
##	388	0.7757820	0.003569887	0
##	389	0.7757820	0.003569887	0
##	390	0.7757820	0.003569887	0
##	391	0.7757820	0.003569887	0
##	392	0.7757820	0.003569887	0
##	393	0.7757820	0.003569887	0
##	394	0.7757820	0.003569887	0

##	395	0.7757820	0.003569887	0
##	396	0.7757820	0.003569887	0
##	397	0.7757820	0.003569887	0
##	398	0.7757820	0.003569887	0
##	399	0.7757820	0.003569887	0
##	400	0.7757820	0.003569887	0
##	401	0.7757820	0.003569887	0
##	402	0.7757820	0.003569887	0
##	403	0.7757820	0.003569887	0
##	404	0.7757820	0.003569887	0
##	405	0.7757820	0.003569887	0
##	406	0.7757820	0.003569887	0
##	407	0.7757820	0.003569887	0
##	408	0.7757820	0.003569887	0
##	409	0.7757820	0.003569887	0
##	410	0.7757820	0.003569887	0
##	411	0.7757820	0.003569887	0
##	412	0.7757820	0.003569887	0
##	413	0.7757820	0.003569887	0
##	414	0.7757820	0.003569887	0
##	415	0.7757820	0.003569887	0
##	416	0.7757820	0.003569887	0
##	417	0.7757820	0.003569887	0
##	418	0.7757820	0.003569887	0
##	419	0.7757820	0.003569887	0
##	420	0.7757820	0.003569887	0
##	421	0.7757820	0.003569887	0
##	422	0.7757820	0.003569887	0
##	423	0.7757820	0.003569887	0
##	424	0.7757820	0.003569887	0
##	425	0.7757820	0.003569887	0
##	426	0.7757820	0.003569887	0
##	427	0.7757820	0.003569887	0
##	428	0.7757820	0.003569887	0
##	429	0.7757820	0.003569887	0
##	430	0.7757820	0.003569887	0
##	431	0.7757820	0.003569887	0
##	432	0.7757820	0.003569887	0
##	433	0.7757820	0.003569887	0
##	434	0.7757820	0.003569887	0
##	435	0.7757820	0.003569887	0
##	436	0.7757820	0.003569887	0
##	437	0.7757820	0.003569887	0
##	438	0.7757820	0.003569887	0
##	439	0.7757820	0.003569887	0
##	440	0.7757820	0.003569887	0
##	441	0.7757820	0.003569887	0
##	442	0.7757820	0.003569887	0

##	443	0.7757820	0.003569887	0
##	444	0.7757820	0.003569887	0
##	445	0.7757820	0.003569887	0
##	446	0.7757820	0.003569887	0
##	447	0.7757820	0.003569887	0
##	448	0.7757820	0.003569887	0
##	449	0.7757820	0.003569887	0
##	450	0.7757820	0.003569887	0
##	451	0.7757820	0.003569887	0
##	452	0.7757820	0.003569887	0
##	453	0.7757820	0.003569887	0
##	454	0.7757820	0.003569887	0
##	455	0.7757820	0.003569887	0
##	456	0.7757820	0.003569887	0
##	457	0.7757820	0.003569887	0
##	458	0.7757820	0.003569887	0
##	459	0.7757820	0.003569887	0
##	460	0.7757820	0.003569887	0
##	461	0.7757820	0.003569887	0
##	462	0.7757820	0.003569887	0
##	463	0.7757820	0.003569887	0
##	464	0.7757820	0.003569887	0
##	465	0.7757820	0.003569887	0
##	466	0.7757820	0.003569887	0
##	467	0.7757820	0.003569887	0
##	468	0.7757820	0.003569887	0
##	469	0.7757820	0.003569887	0
##	470	0.7757820	0.003569887	0
##	471	0.7757820	0.003569887	0
##	472	0.7757820	0.003569887	0
##	473	0.7757820	0.003569887	0
##	474	0.7757820	0.003569887	0
##	475	0.7757820	0.003569887	0
##	476	0.7757820	0.003569887	0
##	477	0.7757820	0.003569887	0
##	478	0.7757820	0.003569887	0
##	479	0.7757820	0.003569887	0
##	480	0.7757820	0.003569887	0
##	481	0.7757820	0.003569887	0
##	482	0.7757820	0.003569887	0
##	483	0.7757820	0.003569887	0
##	484	0.7757820	0.003569887	0
##	485	0.7757820	0.003569887	0
##	486	0.7757820	0.003569887	0
##	487	0.7757820	0.003569887	0
##	488	0.7757820	0.003569887	0
##	489	0.7757820	0.003569887	0
##	490	0.7757820	0.003569887	0

## 491	0.7757820	0.003569887	0
## 492	0.7757820	0.003569887	0
## 493	0.7757820	0.003569887	0
## 494	0.7757820	0.003569887	0
## 495	0.7757820	0.003569887	0
## 496	0.7757820	0.003569887	0
## 497	0.7757820	0.003569887	0
## 498	0.7757820	0.003569887	0
## 499	0.7757820	0.003569887	0
## 500	0.7757820	0.003569887	0
## 501	0.7757820	0.003569887	0
## 502	0.7757820	0.003569887	0
## 503	0.7757820	0.003569887	0
## 504	0.7757820	0.003569887	0
## 505	0.7757820	0.003569887	0
## 506	0.7757820	0.003569887	0
## 507	0.7757820	0.003569887	0
## 508	0.7757820	0.003569887	0
## 509	0.7757820	0.003569887	0
## 510	0.7757820	0.003569887	0
## 511	0.7757820	0.003569887	0
## 512	0.7757820	0.003569887	0
## 513	0.7757820	0.003569887	0
## 514	0.7757820	0.003569887	0
## 515	0.7757820	0.003569887	0
## 516	0.7757820	0.003569887	0
## 517	0.7757820	0.003569887	0
## 518	0.7757820	0.003569887	0
## 519	0.7757820	0.003569887	0
## 520	0.7757820	0.003569887	0
## 521	0.7757820	0.003569887	0
## 522	0.7757820	0.003569887	0
## 523	0.7757820	0.003569887	0
## 524	0.7757820	0.003569887	0
## 525	0.7757820	0.003569887	0
## 526	0.7908128	0.004096642	0
## 527	0.7908128	0.004096642	0
## 528	0.7908128	0.004096642	0
## 529	0.7908128	0.004096642	0
## 530	0.7908128	0.004096642	0
## 531	0.7908128	0.004096642	0
## 532	0.7908128	0.004096642	0
## 533	0.7908128	0.004096642	0
## 534	0.7908128	0.004096642	0
## 535	0.7908128	0.004096642	0
## 536	0.7908128	0.004096642	0
## 537	0.7908128	0.004096642	0
## 538	0.7908128	0.004096642	0

##	539	0.7908128	0.004096642	0
##	540	0.7908128	0.004096642	0
##	541	0.7908128	0.004096642	0
##	542	0.7908128	0.004096642	0
##	543	0.7908128	0.004096642	0
##	544	0.7908128	0.004096642	0
##	545	0.7908128	0.004096642	0
##	546	0.7908128	0.004096642	0
##	547	0.7908128	0.004096642	0
##	548	0.7908128	0.004096642	0
##	549	0.7908128	0.004096642	0
##	550	0.7908128	0.004096642	0
##	551	0.7908128	0.004096642	0
##	552	0.7908128	0.004096642	0
##	553	0.7908128	0.004096642	0
##	554	0.7908128	0.004096642	0
##	555	0.7908128	0.004096642	0
##	556	0.7908128	0.004096642	0
##	557	0.7908128	0.004096642	0
##	558	0.7908128	0.004096642	0
##	559	0.7908128	0.004096642	0
##	560	0.7908128	0.004096642	0
##	561	0.7908128	0.004096642	0
##	562	0.7908128	0.004096642	0
##	563	0.7908128	0.004096642	0
##	564	0.7908128	0.004096642	0
##	565	0.7908128	0.004096642	0
##	566	0.7908128	0.004096642	0
##	567	0.7908128	0.004096642	0
##	568	0.7908128	0.004096642	0
##	569	0.7908128	0.004096642	0
##	570	0.7908128	0.004096642	0
##	571	0.7908128	0.004096642	0
##	572	0.7908128	0.004096642	0
##	573	0.7908128	0.004096642	0
##	574	0.7908128	0.004096642	0
##	575	0.7908128	0.004096642	0
##	576	0.7908128	0.004096642	0
##	577	0.7908128	0.004096642	0
##	578	0.7908128	0.004096642	0
##	579	0.7908128	0.004096642	0
##	580	0.7908128	0.004096642	0
##	581	0.7908128	0.004096642	0
##	582	0.7908128	0.004096642	0
##	583	0.7908128	0.004096642	0
##	584	0.7908128	0.004096642	0
##	585	0.7908128	0.004096642	0
##	586	0.7908128	0.004096642	0

## 587	0.7908128	0.004096642	0
## 588	0.7908128	0.004096642	0
## 589	0.7908128	0.004096642	0
## 590	0.7908128	0.004096642	0
## 591	0.7908128	0.004096642	0
## 592	0.7908128	0.004096642	0
## 593	0.7908128	0.004096642	0
## 594	0.7908128	0.004096642	0
## 595	0.7908128	0.004096642	0
## 596	0.7908128	0.004096642	0
## 597	0.7908128	0.004096642	0
## 598	0.7908128	0.004096642	0
## 599	0.7908128	0.004096642	0
## 600	0.7908128	0.004096642	0
## 601	0.7908128	0.004096642	0
## 602	0.7908128	0.004096642	0
## 603	0.7908128	0.004096642	0
## 604	0.7908128	0.004096642	0
## 605	0.8054635	0.004690474	0
## 606	0.8054635	0.004690474	0
## 607	0.8054635	0.004690474	0
## 608	0.8054635	0.004690474	0
## 609	0.8054635	0.004690474	0
## 610	0.8054635	0.004690474	0
## 611	0.8054635	0.004690474	0
## 612	0.8054635	0.004690474	0
## 613	0.8054635	0.004690474	0
## 614	0.8054635	0.004690474	0
## 615	0.8054635	0.004690474	0
## 616	0.8054635	0.004690474	0
## 617	0.8054635	0.004690474	0
## 618	0.8054635	0.004690474	0
## 619	0.8054635	0.004690474	0
## 620	0.8054635	0.004690474	0
## 621	0.8054635	0.004690474	0
## 622	0.8054635	0.004690474	0
## 623	0.8054635	0.004690474	0
## 624	0.8054635	0.004690474	0
## 625	0.8054635	0.004690474	0
## 626	0.8054635	0.004690474	0
## 627	0.8054635	0.004690474	0
## 628	0.8054635	0.004690474	0
## 629	0.8054635	0.004690474	0
## 630	0.8054635	0.004690474	0
## 631	0.8054635	0.004690474	0
## 632	0.8054635	0.004690474	0
## 633	0.8054635	0.004690474	0
## 634	0.8054635	0.004690474	0

##	635	0.8054635	0.004690474	0
##	636	0.8054635	0.004690474	0
##	637	0.8054635	0.004690474	0
##	638	0.8054635	0.004690474	0
##	639	0.8054635	0.004690474	0
##	640	0.8054635	0.004690474	0
##	641	0.8054635	0.004690474	0
##	642	0.8054635	0.004690474	0
##	643	0.8054635	0.004690474	0
##	644	0.8054635	0.004690474	0
##	645	0.8054635	0.004690474	0
##	646	0.8054635	0.004690474	0
##	647	0.8054635	0.004690474	0
##	648	0.8054635	0.004690474	0
##	649	0.8054635	0.004690474	0
##	650	0.8054635	0.004690474	0
##	651	0.8054635	0.004690474	0
##	652	0.8054635	0.004690474	0
##	653	0.8054635	0.004690474	0
##	654	0.8054635	0.004690474	0
##	655	0.8054635	0.004690474	0
##	656	0.8054635	0.004690474	0
##	657	0.8054635	0.004690474	0
##	658	0.8054635	0.004690474	0
##	659	0.8054635	0.004690474	0
##	660	0.8054635	0.004690474	0
##	661	0.8054635	0.004690474	0
##	662	0.8054635	0.004690474	0
##	663	0.8054635	0.004690474	0
##	664	0.8054635	0.004690474	0
##	665	0.8054635	0.004690474	0
##	666	0.8054635	0.004690474	0
##	667	0.8054635	0.004690474	0
##	668	0.8054635	0.004690474	0
##	669	0.8054635	0.004690474	0
##	670	0.8054635	0.004690474	0
##	671	0.8054635	0.004690474	0
##	672	0.8054635	0.004690474	0
##	673	0.8054635	0.004690474	0
##	674	0.8054635	0.004690474	0
##	675	0.8054635	0.004690474	0
##	676	0.8054635	0.004690474	0
##	677	0.8054635	0.004690474	0
##	678	0.8054635	0.004690474	0
##	679	0.8054635	0.004690474	0
##	680	0.8054635	0.004690474	0
##	681	0.8054635	0.004690474	0
##	682	0.8054635	0.004690474	0

## 683	0.8054635	0.004690474	0
## 684	0.8054635	0.004690474	0
## 685	0.8054635	0.004690474	0
## 686	0.8054635	0.004690474	0
## 687	0.8054635	0.004690474	0
## 688	0.8054635	0.004690474	0
## 689	0.8054635	0.004690474	0
## 690	0.8054635	0.004690474	0
## 691	0.8054635	0.004690474	0
## 692	0.8196967	0.005357880	0
## 693	0.8196967	0.005357880	0
## 694	0.8196967	0.005357880	0
## 695	0.8196967	0.005357880	0
## 696	0.8196967	0.005357880	0
## 697	0.8196967	0.005357880	0
## 698	0.8196967	0.005357880	0
## 699	0.8196967	0.005357880	0
## 700	0.8196967	0.005357880	0
## 701	0.8196967	0.005357880	0
## 702	0.8196967	0.005357880	0
## 703	0.8196967	0.005357880	0
## 704	0.8196967	0.005357880	0
## 705	0.8196967	0.005357880	0
## 706	0.8196967	0.005357880	0
## 707	0.8196967	0.005357880	0
## 708	0.8196967	0.005357880	0
## 709	0.8196967	0.005357880	0
## 710	0.8196967	0.005357880	0
## 711	0.8196967	0.005357880	0
## 712	0.8196967	0.005357880	0
## 713	0.8196967	0.005357880	0
## 714	0.8196967	0.005357880	0
## 715	0.8196967	0.005357880	0
## 716	0.8196967	0.005357880	0
## 717	0.8196967	0.005357880	0
## 718	0.8196967	0.005357880	0
## 719	0.8196967	0.005357880	0
## 720	0.8196967	0.005357880	0
## 721	0.8196967	0.005357880	0
## 722	0.8196967	0.005357880	0
## 723	0.8196967	0.005357880	0
## 724	0.8196967	0.005357880	0
## 725	0.8196967	0.005357880	0
## 726	0.8196967	0.005357880	0
## 727	0.8196967	0.005357880	0
## 728	0.8196967	0.005357880	0
## 729	0.8196967	0.005357880	0
## 730	0.8196967	0.005357880	0

##	731	0.8196967	0.005357880	0
##	732	0.8196967	0.005357880	0
##	733	0.8196967	0.005357880	0
##	734	0.8196967	0.005357880	0
##	735	0.8196967	0.005357880	0
##	736	0.8196967	0.005357880	0
##	737	0.8196967	0.005357880	0
##	738	0.8196967	0.005357880	0
##	739	0.8196967	0.005357880	0
##	740	0.8196967	0.005357880	0
##	741	0.8196967	0.005357880	0
##	742	0.8196967	0.005357880	0
##	743	0.8196967	0.005357880	0
##	744	0.8196967	0.005357880	0
##	745	0.8196967	0.005357880	0
##	746	0.8196967	0.005357880	0
##	747	0.8196967	0.005357880	0
##	748	0.8196967	0.005357880	0
##	749	0.8196967	0.005357880	0
##	750	0.8196967	0.005357880	0
##	751	0.8196967	0.005357880	0
##	752	0.8196967	0.005357880	0
##	753	0.8196967	0.005357880	0
##	754	0.8196967	0.005357880	0
##	755	0.8196967	0.005357880	0
##	756	0.8196967	0.005357880	0
##	757	0.8196967	0.005357880	0
##	758	0.8196967	0.005357880	0
##	759	0.8196967	0.005357880	0
##	760	0.8196967	0.005357880	0
##	761	0.8196967	0.005357880	0
##	762	0.8196967	0.005357880	0
##	763	0.8196967	0.005357880	0
##	764	0.8196967	0.005357880	0
##	765	0.8196967	0.005357880	0
##	766	0.8196967	0.005357880	0
##	767	0.8196967	0.005357880	0
##	768	0.8196967	0.005357880	0
##	769	0.8196967	0.005357880	0
##	770	0.8196967	0.005357880	0
##	771	0.8196967	0.005357880	0
##	772	0.8196967	0.005357880	0
##	773	0.8196967	0.005357880	0
##	774	0.8196967	0.005357880	0
##	775	0.8196967	0.005357880	0
##	776	0.8196967	0.005357880	0
##	777	0.8196967	0.005357880	0
##	778	0.8196967	0.005357880	0

## 779	0.8196967	0.005357880	0
## 780	0.8196967	0.005357880	0
## 781	0.8196967	0.005357880	0
## 782	0.8196967	0.005357880	0
## 783	0.8196967	0.005357880	0
## 784	0.8196967	0.005357880	0
## 785	0.8196967	0.005357880	0
## 786	0.8196967	0.005357880	0
## 787	0.8196967	0.005357880	0
## 788	0.8196967	0.005357880	0
## 789	0.8196967	0.005357880	0
## 790	0.8196967	0.005357880	0
## 791	0.8196967	0.005357880	0
## 792	0.8196967	0.005357880	0
## 793	0.8196967	0.005357880	0
## 794	0.8196967	0.005357880	0
## 795	0.8196967	0.005357880	0
## 796	0.8196967	0.005357880	0
## 797	0.8196967	0.005357880	0
## 798	0.8196967	0.005357880	0
## 799	0.8196967	0.005357880	0
## 800	0.8196967	0.005357880	0
## 801	0.8334767	0.006105603	0
## 802	0.8334767	0.006105603	0
## 803	0.8334767	0.006105603	0
## 804	0.8334767	0.006105603	0
## 805	0.8334767	0.006105603	0
## 806	0.8334767	0.006105603	0
## 807	0.8334767	0.006105603	0
## 808	0.8334767	0.006105603	0
## 809	0.8334767	0.006105603	0
## 810	0.8334767	0.006105603	0
## 811	0.8334767	0.006105603	0
## 812	0.8334767	0.006105603	0
## 813	0.8334767	0.006105603	0
## 814	0.8334767	0.006105603	0
## 815	0.8334767	0.006105603	0
## 816	0.8334767	0.006105603	0
## 817	0.8334767	0.006105603	0
## 818	0.8334767	0.006105603	0
## 819	0.8334767	0.006105603	0
## 820	0.8334767	0.006105603	0
## 821	0.8334767	0.006105603	0
## 822	0.8334767	0.006105603	0
## 823	0.8334767	0.006105603	0
## 824	0.8334767	0.006105603	0
## 825	0.8334767	0.006105603	0
## 826	0.8334767	0.006105603	0

##	827	0.8334767	0.006105603	0
##	828	0.8334767	0.006105603	0
##	829	0.8334767	0.006105603	0
##	830	0.8334767	0.006105603	0
##	831	0.8334767	0.006105603	0
##	832	0.8334767	0.006105603	0
##	833	0.8334767	0.006105603	0
##	834	0.8334767	0.006105603	0
##	835	0.8334767	0.006105603	0
##	836	0.8334767	0.006105603	0
##	837	0.8334767	0.006105603	0
##	838	0.8334767	0.006105603	0
##	839	0.8334767	0.006105603	0
##	840	0.8334767	0.006105603	0
##	841	0.8334767	0.006105603	0
##	842	0.8334767	0.006105603	0
##	843	0.8334767	0.006105603	0
##	844	0.8334767	0.006105603	0
##	845	0.8334767	0.006105603	0
##	846	0.8334767	0.006105603	0
##	847	0.8334767	0.006105603	0
##	848	0.8334767	0.006105603	0
##	849	0.8334767	0.006105603	0
##	850	0.8334767	0.006105603	0
##	851	0.8334767	0.006105603	0
##	852	0.8334767	0.006105603	0
##	853	0.8334767	0.006105603	0
##	854	0.8334767	0.006105603	0
##	855	0.8334767	0.006105603	0
##	856	0.8334767	0.006105603	0
##	857	0.8334767	0.006105603	0
##	858	0.8334767	0.006105603	0
##	859	0.8334767	0.006105603	0
##	860	0.8334767	0.006105603	0
##	861	0.8334767	0.006105603	0
##	862	0.8334767	0.006105603	0
##	863	0.8334767	0.006105603	0
##	864	0.8334767	0.006105603	0
##	865	0.8334767	0.006105603	0
##	866	0.8334767	0.006105603	0
##	867	0.8334767	0.006105603	0
##	868	0.8334767	0.006105603	0
##	869	0.8334767	0.006105603	0
##	870	0.8334767	0.006105603	0
##	871	0.8334767	0.006105603	0
##	872	0.8334767	0.006105603	0
##	873	0.8334767	0.006105603	0
##	874	0.8334767	0.006105603	0

## 875	0.8334767	0.006105603	0
## 876	0.8334767	0.006105603	0
## 877	0.8334767	0.006105603	0
## 878	0.8334767	0.006105603	0
## 879	0.8334767	0.006105603	0
## 880	0.8334767	0.006105603	0
## 881	0.8334767	0.006105603	0
## 882	0.8334767	0.006105603	0
## 883	0.8334767	0.006105603	0
## 884	0.8334767	0.006105603	0
## 885	0.8334767	0.006105603	0
## 886	0.8334767	0.006105603	0
## 887	0.8334767	0.006105603	0
## 888	0.8334767	0.006105603	0
## 889	0.8334767	0.006105603	0
## 890	0.8334767	0.006105603	0
## 891	0.8334767	0.006105603	0
## 892	0.8334767	0.006105603	0
## 893	0.8334767	0.006105603	0
## 894	0.8334767	0.006105603	0
## 895	0.8334767	0.006105603	0
## 896	0.8334767	0.006105603	0
## 897	0.8334767	0.006105603	0
## 898	0.8334767	0.006105603	0
## 899	0.8334767	0.006105603	0
## 900	0.8334767	0.006105603	0
## 901	0.8467701	0.006940572	0
## 902	0.8467701	0.006940572	0
## 903	0.8467701	0.006940572	0
## 904	0.8467701	0.006940572	0
## 905	0.8467701	0.006940572	0
## 906	0.8467701	0.006940572	0
## 907	0.8467701	0.006940572	0
## 908	0.8467701	0.006940572	0
## 909	0.8467701	0.006940572	0
## 910	0.8467701	0.006940572	0
## 911	0.8467701	0.006940572	0
## 912	0.8467701	0.006940572	0
## 913	0.8467701	0.006940572	0
## 914	0.8467701	0.006940572	0
## 915	0.8467701	0.006940572	0
## 916	0.8467701	0.006940572	0
## 917	0.8467701	0.006940572	0
## 918	0.8467701	0.006940572	0
## 919	0.8467701	0.006940572	0
## 920	0.8467701	0.006940572	0
## 921	0.8467701	0.006940572	0
## 922	0.8467701	0.006940572	0

##	923	0.8467701	0.006940572	0
##	924	0.8467701	0.006940572	0
##	925	0.8467701	0.006940572	0
##	926	0.8467701	0.006940572	0
##	927	0.8467701	0.006940572	0
##	928	0.8467701	0.006940572	0
##	929	0.8467701	0.006940572	0
##	930	0.8467701	0.006940572	0
##	931	0.8467701	0.006940572	0
##	932	0.8467701	0.006940572	0
##	933	0.8467701	0.006940572	0
##	934	0.8467701	0.006940572	0
##	935	0.8467701	0.006940572	0
##	936	0.8467701	0.006940572	0
##	937	0.8467701	0.006940572	0
##	938	0.8467701	0.006940572	0
##	939	0.8467701	0.006940572	0
##	940	0.8467701	0.006940572	0
##	941	0.8467701	0.006940572	0
##	942	0.8467701	0.006940572	0
##	943	0.8467701	0.006940572	0
##	944	0.8467701	0.006940572	0
##	945	0.8467701	0.006940572	0
##	946	0.8467701	0.006940572	0
##	947	0.8467701	0.006940572	0
##	948	0.8467701	0.006940572	0
##	949	0.8467701	0.006940572	0
##	950	0.8467701	0.006940572	0
##	951	0.8467701	0.006940572	0
##	952	0.8467701	0.006940572	0
##	953	0.8467701	0.006940572	0
##	954	0.8467701	0.006940572	0
##	955	0.8467701	0.006940572	0
##	956	0.8467701	0.006940572	0
##	957	0.8467701	0.006940572	0
##	958	0.8467701	0.006940572	0
##	959	0.8467701	0.006940572	0
##	960	0.8467701	0.006940572	0
##	961	0.8467701	0.006940572	0
##	962	0.8467701	0.006940572	0
##	963	0.8467701	0.006940572	0
##	964	0.8467701	0.006940572	0
##	965	0.8467701	0.006940572	0
##	966	0.8467701	0.006940572	0
##	967	0.8467701	0.006940572	0
##	968	0.8467701	0.006940572	0
##	969	0.8467701	0.006940572	0
##	970	0.8467701	0.006940572	0

## 971	0.8467701	0.006940572	0
## 972	0.8467701	0.006940572	0
## 973	0.8467701	0.006940572	0
## 974	0.8467701	0.006940572	0
## 975	0.8467701	0.006940572	0
## 976	0.8467701	0.006940572	0
## 977	0.8467701	0.006940572	0
## 978	0.8467701	0.006940572	0
## 979	0.8467701	0.006940572	0
## 980	0.8467701	0.006940572	0
## 981	0.8467701	0.006940572	0
## 982	0.8467701	0.006940572	0
## 983	0.8467701	0.006940572	0
## 984	0.8467701	0.006940572	0
## 985	0.8595456	0.007869814	0
## 986	0.8595456	0.007869814	0
## 987	0.8595456	0.007869814	0
## 988	0.8595456	0.007869814	0
## 989	0.8595456	0.007869814	0
## 990	0.8595456	0.007869814	0
## 991	0.8595456	0.007869814	0
## 992	0.8595456	0.007869814	0
## 993	0.8595456	0.007869814	0
## 994	0.8595456	0.007869814	0
## 995	0.8595456	0.007869814	0
## 996	0.8595456	0.007869814	0
## 997	0.8595456	0.007869814	0
## 998	0.8595456	0.007869814	0
## 999	0.8595456	0.007869814	0
## 1000	0.8595456	0.007869814	0
## 1001	0.8595456	0.007869814	0
## 1002	0.8595456	0.007869814	0
## 1003	0.8595456	0.007869814	0
## 1004	0.8595456	0.007869814	0
## 1005	0.8595456	0.007869814	0
## 1006	0.8595456	0.007869814	0
## 1007	0.8595456	0.007869814	0
## 1008	0.8595456	0.007869814	0
## 1009	0.8595456	0.007869814	0
## 1010	0.8595456	0.007869814	0
## 1011	0.8595456	0.007869814	0
## 1012	0.8595456	0.007869814	0
## 1013	0.8595456	0.007869814	0
## 1014	0.8595456	0.007869814	0
## 1015	0.8595456	0.007869814	0
## 1016	0.8595456	0.007869814	0
## 1017	0.8595456	0.007869814	0
## 1018	0.8595456	0.007869814	0

##	1019	0.8595456	0.007869814	0
##	1020	0.8595456	0.007869814	0
##	1021	0.8595456	0.007869814	0
##	1022	0.8595456	0.007869814	0
##	1023	0.8595456	0.007869814	0
##	1024	0.8595456	0.007869814	0
##	1025	0.8595456	0.007869814	0
##	1026	0.8595456	0.007869814	0
##	1027	0.8595456	0.007869814	0
##	1028	0.8595456	0.007869814	0
##	1029	0.8595456	0.007869814	0
##	1030	0.8595456	0.007869814	0
##	1031	0.8595456	0.007869814	0
##	1032	0.8595456	0.007869814	0
##	1033	0.8595456	0.007869814	0
##	1034	0.8595456	0.007869814	0
##	1035	0.8595456	0.007869814	0
##	1036	0.8595456	0.007869814	0
##	1037	0.8595456	0.007869814	0
##	1038	0.8595456	0.007869814	0
##	1039	0.8595456	0.007869814	0
##	1040	0.8595456	0.007869814	0
##	1041	0.8595456	0.007869814	0
##	1042	0.8595456	0.007869814	0
##	1043	0.8595456	0.007869814	0
##	1044	0.8595456	0.007869814	0
##	1045	0.8595456	0.007869814	0
##	1046	0.8595456	0.007869814	0
##	1047	0.8595456	0.007869814	0
##	1048	0.8595456	0.007869814	0
##	1049	0.8595456	0.007869814	0
##	1050	0.8595456	0.007869814	0
##	1051	0.8595456	0.007869814	0
##	1052	0.8595456	0.007869814	0
##	1053	0.8595456	0.007869814	0
##	1054	0.8595456	0.007869814	0
##	1055	0.8595456	0.007869814	0
##	1056	0.8595456	0.007869814	0
##	1057	0.8595456	0.007869814	0
##	1058	0.8595456	0.007869814	0
##	1059	0.8595456	0.007869814	0
##	1060	0.8595456	0.007869814	0
##	1061	0.8595456	0.007869814	0
##	1062	0.8595456	0.007869814	0
##	1063	0.8595456	0.007869814	0
##	1064	0.8595456	0.007869814	0
##	1065	0.8595456	0.007869814	0
##	1066	0.8595456	0.007869814	0

##	1067	0.8595456	0.007869814	0
##	1068	0.8595456	0.007869814	0
##	1069	0.8595456	0.007869814	0
##	1070	0.8595456	0.007869814	0
##	1071	0.8595456	0.007869814	0
##	1072	0.8595456	0.007869814	0
##	1073	0.8595456	0.007869814	0
##	1074	0.8595456	0.007869814	0
##	1075	0.8595456	0.007869814	0
##	1076	0.8595456	0.007869814	0
##	1077	0.8595456	0.007869814	0
##	1078	0.8595456	0.007869814	0
##	1079	0.8595456	0.007869814	0
##	1080	0.8595456	0.007869814	0
##	1081	0.8595456	0.007869814	0
##	1082	0.8595456	0.007869814	0
##	1083	0.8595456	0.007869814	0
##	1084	0.8595456	0.007869814	0
##	1085	0.8595456	0.007869814	0
##	1086	0.8595456	0.007869814	0
##	1087	0.8595456	0.007869814	0
##	1088	0.8595456	0.007869814	0
##	1089	0.8595456	0.007869814	0
##	1090	0.8595456	0.007869814	0
##	1091	0.8595456	0.007869814	0
##	1092	0.8595456	0.007869814	0
##	1093	0.8595456	0.007869814	0
##	1094	0.8595456	0.007869814	0
##	1095	0.8595456	0.007869814	0
##	1096	0.8595456	0.007869814	0
##	1097	0.8595456	0.007869814	0
##	1098	0.8595456	0.007869814	0
##	1099	0.8595456	0.007869814	0
##	1100	0.8595456	0.007869814	0
##	1101	0.8595456	0.007869814	0
##	1102	0.8595456	0.007869814	0
##	1103	0.8595456	0.007869814	0
##	1104	0.8595456	0.007869814	0
##	1105	0.8595456	0.007869814	0
##	1106	0.8595456	0.007869814	0
##	1107	0.8595456	0.007869814	0
##	1108	0.8595456	0.007869814	0
##	1109	0.8595456	0.007869814	0
##	1110	0.8595456	0.007869814	0
##	1111	0.8595456	0.007869814	0
##	1112	0.8595456	0.007869814	0
##	1113	0.8595456	0.007869814	0
##	1114	0.8595456	0.007869814	0

##	1115	0.8595456	0.007869814	0
##	1116	0.8595456	0.007869814	0
##	1117	0.8595456	0.007869814	0
##	1118	0.8595456	0.007869814	0
##	1119	0.8595456	0.007869814	0
##	1120	0.8595456	0.007869814	0
##	1121	0.8595456	0.007869814	0
##	1122	0.8595456	0.007869814	0
##	1123	0.8595456	0.007869814	0
##	1124	0.8595456	0.007869814	0
##	1125	0.8595456	0.007869814	0
##	1126	0.8595456	0.007869814	0
##	1127	0.8595456	0.007869814	0
##	1128	0.8595456	0.007869814	0
##	1129	0.8595456	0.007869814	0
##	1130	0.8595456	0.007869814	0
##	1131	0.8595456	0.007869814	0
##	1132	0.8595456	0.007869814	0
##	1133	0.8595456	0.007869814	0
##	1134	0.8595456	0.007869814	0
##	1135	0.8595456	0.007869814	0
##	1136	0.8595456	0.007869814	0
##	1137	0.8595456	0.007869814	0
##	1138	0.8717751	0.008900356	0
##	1139	0.8717751	0.008900356	0
##	1140	0.8717751	0.008900356	0
##	1141	0.8717751	0.008900356	0
##	1142	0.8717751	0.008900356	0
##	1143	0.8717751	0.008900356	0
##	1144	0.8717751	0.008900356	0
##	1145	0.8717751	0.008900356	0
##	1146	0.8717751	0.008900356	0
##	1147	0.8717751	0.008900356	0
##	1148	0.8717751	0.008900356	0
##	1149	0.8717751	0.008900356	0
##	1150	0.8717751	0.008900356	0
##	1151	0.8717751	0.008900356	0
##	1152	0.8717751	0.008900356	0
##	1153	0.8717751	0.008900356	0
##	1154	0.8717751	0.008900356	0
##	1155	0.8717751	0.008900356	0
##	1156	0.8717751	0.008900356	0
##	1157	0.8717751	0.008900356	0
##	1158	0.8717751	0.008900356	0
##	1159	0.8717751	0.008900356	0
##	1160	0.8717751	0.008900356	0
##	1161	0.8717751	0.008900356	0
##	1162	0.8717751	0.008900356	0

##	1163	0.8717751	0.008900356	0
##	1164	0.8717751	0.008900356	0
##	1165	0.8717751	0.008900356	0
##	1166	0.8717751	0.008900356	0
##	1167	0.8717751	0.008900356	0
##	1168	0.8717751	0.008900356	0
##	1169	0.8717751	0.008900356	0
##	1170	0.8717751	0.008900356	0
##	1171	0.8717751	0.008900356	0
##	1172	0.8717751	0.008900356	0
##	1173	0.8717751	0.008900356	0
##	1174	0.8717751	0.008900356	0
##	1175	0.8717751	0.008900356	0
##	1176	0.8717751	0.008900356	0
##	1177	0.8717751	0.008900356	0
##	1178	0.8717751	0.008900356	0
##	1179	0.8717751	0.008900356	0
##	1180	0.8717751	0.008900356	0
##	1181	0.8717751	0.008900356	0
##	1182	0.8717751	0.008900356	0
##	1183	0.8717751	0.008900356	0
##	1184	0.8717751	0.008900356	0
##	1185	0.8717751	0.008900356	0
##	1186	0.8717751	0.008900356	0
##	1187	0.8717751	0.008900356	0
##	1188	0.8717751	0.008900356	0
##	1189	0.8717751	0.008900356	0
##	1190	0.8717751	0.008900356	0
##	1191	0.8717751	0.008900356	0
##	1192	0.8717751	0.008900356	0
##	1193	0.8717751	0.008900356	0
##	1194	0.8717751	0.008900356	0
##	1195	0.8717751	0.008900356	0
##	1196	0.8717751	0.008900356	0
##	1197	0.8717751	0.008900356	0
##	1198	0.8717751	0.008900356	0
##	1199	0.8717751	0.008900356	0
##	1200	0.8717751	0.008900356	0
##	1201	0.8717751	0.008900356	0
##	1202	0.8717751	0.008900356	0
##	1203	0.8717751	0.008900356	0
##	1204	0.8717751	0.008900356	0
##	1205	0.8717751	0.008900356	0
##	1206	0.8717751	0.008900356	0
##	1207	0.8717751	0.008900356	0
##	1208	0.8717751	0.008900356	0
##	1209	0.8717751	0.008900356	0
##	1210	0.8717751	0.008900356	0

##	1211	0.8717751	0.008900356	0
##	1212	0.8717751	0.008900356	0
##	1213	0.8717751	0.008900356	0
##	1214	0.8717751	0.008900356	0
##	1215	0.8717751	0.008900356	0
##	1216	0.8717751	0.008900356	0
##	1217	0.8717751	0.008900356	0
##	1218	0.8717751	0.008900356	0
##	1219	0.8717751	0.008900356	0
##	1220	0.8717751	0.008900356	0
##	1221	0.8717751	0.008900356	0
##	1222	0.8717751	0.008900356	0
##	1223	0.8717751	0.008900356	0
##	1224	0.8717751	0.008900356	0
##	1225	0.8717751	0.008900356	0
##	1226	0.8717751	0.008900356	0
##	1227	0.8717751	0.008900356	0
##	1228	0.8717751	0.008900356	0
##	1229	0.8717751	0.008900356	0
##	1230	0.8834336	0.010039112	0
##	1231	0.8834336	0.010039112	0
##	1232	0.8834336	0.010039112	0
##	1233	0.8834336	0.010039112	0
##	1234	0.8834336	0.010039112	0
##	1235	0.8834336	0.010039112	0
##	1236	0.8834336	0.010039112	0
##	1237	0.8834336	0.010039112	0
##	1238	0.8834336	0.010039112	0
##	1239	0.8834336	0.010039112	0
##	1240	0.8834336	0.010039112	0
##	1241	0.8834336	0.010039112	0
##	1242	0.8834336	0.010039112	0
##	1243	0.8834336	0.010039112	0
##	1244	0.8834336	0.010039112	0
##	1245	0.8834336	0.010039112	0
##	1246	0.8834336	0.010039112	0
##	1247	0.8834336	0.010039112	0
##	1248	0.8834336	0.010039112	0
##	1249	0.8834336	0.010039112	0
##	1250	0.8834336	0.010039112	0
##	1251	0.8834336	0.010039112	0
##	1252	0.8834336	0.010039112	0
##	1253	0.8834336	0.010039112	0
##	1254	0.8834336	0.010039112	0
##	1255	0.8834336	0.010039112	0
##	1256	0.8834336	0.010039112	0
##	1257	0.8834336	0.010039112	0
##	1258	0.8834336	0.010039112	0

##	1259	0.8834336	0.010039112	0
##	1260	0.8834336	0.010039112	0
##	1261	0.8834336	0.010039112	0
##	1262	0.8834336	0.010039112	0
##	1263	0.8834336	0.010039112	0
##	1264	0.8834336	0.010039112	0
##	1265	0.8834336	0.010039112	0
##	1266	0.8834336	0.010039112	0
##	1267	0.8834336	0.010039112	0
##	1268	0.8834336	0.010039112	0
##	1269	0.8834336	0.010039112	0
##	1270	0.8834336	0.010039112	0
##	1271	0.8834336	0.010039112	0
##	1272	0.8834336	0.010039112	0
##	1273	0.8834336	0.010039112	0
##	1274	0.8834336	0.010039112	0
##	1275	0.8834336	0.010039112	0
##	1276	0.8834336	0.010039112	0
##	1277	0.8834336	0.010039112	0
##	1278	0.8834336	0.010039112	0
##	1279	0.8834336	0.010039112	0
##	1280	0.8834336	0.010039112	0
##	1281	0.8944998	0.011292742	1
##	1282	0.8944998	0.011292742	0
##	1283	0.8944998	0.011292742	0
##	1284	0.8944998	0.011292742	0
##	1285	0.8944998	0.011292742	0
##	1286	0.8944998	0.011292742	0
##	1287	0.8944998	0.011292742	0
##	1288	0.8944998	0.011292742	0
##	1289	0.8944998	0.011292742	0
##	1290	0.8944998	0.011292742	0
##	1291	0.8944998	0.011292742	0
##	1292	0.8944998	0.011292742	0
##	1293	0.8944998	0.011292742	0
##	1294	0.8944998	0.011292742	0
##	1295	0.8944998	0.011292742	0
##	1296	0.8944998	0.011292742	0
##	1297	0.8944998	0.011292742	0
##	1298	0.8944998	0.011292742	0
##	1299	0.8944998	0.011292742	0
##	1300	0.8944998	0.011292742	0
##	1301	0.8944998	0.011292742	0
##	1302	0.8944998	0.011292742	0
##	1303	0.8944998	0.011292742	0
##	1304	0.8944998	0.011292742	0
##	1305	0.8944998	0.011292742	0
##	1306	0.8944998	0.011292742	0

##	1307	0.8944998	0.011292742	0
##	1308	0.8944998	0.011292742	0
##	1309	0.8944998	0.011292742	0
##	1310	0.8944998	0.011292742	0
##	1311	0.8944998	0.011292742	0
##	1312	0.8944998	0.011292742	0
##	1313	0.8944998	0.011292742	0
##	1314	0.8944998	0.011292742	0
##	1315	0.8944998	0.011292742	0
##	1316	0.8944998	0.011292742	0
##	1317	0.8944998	0.011292742	0
##	1318	0.8944998	0.011292742	0
##	1319	0.8944998	0.011292742	0
##	1320	0.8944998	0.011292742	0
##	1321	0.8944998	0.011292742	0
##	1322	0.8944998	0.011292742	0
##	1323	0.8944998	0.011292742	0
##	1324	0.8944998	0.011292742	0
##	1325	0.8944998	0.011292742	0
##	1326	0.8944998	0.011292742	0
##	1327	0.8944998	0.011292742	0
##	1328	0.8944998	0.011292742	0
##	1329	0.8944998	0.011292742	0
##	1330	0.8944998	0.011292742	0
##	1331	0.8944998	0.011292742	0
##	1332	0.8944998	0.011292742	0
##	1333	0.8944998	0.011292742	0
##	1334	0.8944998	0.011292742	0
##	1335	0.8944998	0.011292742	0
##	1336	0.8944998	0.011292742	0
##	1337	0.8944998	0.011292742	0
##	1338	0.8944998	0.011292742	0
##	1339	0.8944998	0.011292742	0
##	1340	0.8944998	0.011292742	0
##	1341	0.8944998	0.011292742	0
##	1342	0.8944998	0.011292742	0
##	1343	0.8944998	0.011292742	0
##	1344	0.8944998	0.011292742	0
##	1345	0.8944998	0.011292742	0
##	1346	0.8944998	0.011292742	0
##	1347	0.8944998	0.011292742	0
##	1348	0.8944998	0.011292742	0
##	1349	0.8944998	0.011292742	0
##	1350	0.8944998	0.011292742	0
##	1351	0.8944998	0.011292742	0
##	1352	0.8944998	0.011292742	0
##	1353	0.8944998	0.011292742	0
##	1354	0.9049565	0.012667503	1

##	1355	0.9049565	0.012667503	1
##	1356	0.9049565	0.012667503	0
##	1357	0.9049565	0.012667503	0
##	1358	0.9049565	0.012667503	0
##	1359	0.9049565	0.012667503	0
##	1360	0.9049565	0.012667503	0
##	1361	0.9049565	0.012667503	0
##	1362	0.9049565	0.012667503	0
##	1363	0.9049565	0.012667503	0
##	1364	0.9049565	0.012667503	0
##	1365	0.9049565	0.012667503	0
##	1366	0.9049565	0.012667503	0
##	1367	0.9049565	0.012667503	0
##	1368	0.9049565	0.012667503	0
##	1369	0.9049565	0.012667503	0
##	1370	0.9049565	0.012667503	0
##	1371	0.9049565	0.012667503	0
##	1372	0.9049565	0.012667503	0
##	1373	0.9049565	0.012667503	0
##	1374	0.9049565	0.012667503	0
##	1375	0.9049565	0.012667503	0
##	1376	0.9049565	0.012667503	0
##	1377	0.9049565	0.012667503	0
##	1378	0.9049565	0.012667503	0
##	1379	0.9049565	0.012667503	0
##	1380	0.9049565	0.012667503	0
##	1381	0.9049565	0.012667503	0
##	1382	0.9049565	0.012667503	0
##	1383	0.9049565	0.012667503	0
##	1384	0.9049565	0.012667503	0
##	1385	0.9049565	0.012667503	0
##	1386	0.9049565	0.012667503	0
##	1387	0.9049565	0.012667503	0
##	1388	0.9049565	0.012667503	0
##	1389	0.9049565	0.012667503	0
##	1390	0.9049565	0.012667503	0
##	1391	0.9049565	0.012667503	0
##	1392	0.9049565	0.012667503	0
##	1393	0.9049565	0.012667503	0
##	1394	0.9049565	0.012667503	0
##	1395	0.9049565	0.012667503	0
##	1396	0.9049565	0.012667503	0
##	1397	0.9049565	0.012667503	0
##	1398	0.9049565	0.012667503	0
##	1399	0.9049565	0.012667503	0
##	1400	0.9049565	0.012667503	0
##	1401	0.9049565	0.012667503	0
##	1402	0.9049565	0.012667503	0

##	1403	0.9049565	0.012667503	0
##	1404	0.9049565	0.012667503	0
##	1405	0.9049565	0.012667503	0
##	1406	0.9049565	0.012667503	0
##	1407	0.9049565	0.012667503	0
##	1408	0.9049565	0.012667503	0
##	1409	0.9049565	0.012667503	0
##	1410	0.9049565	0.012667503	0
##	1411	0.9049565	0.012667503	0
##	1412	0.9049565	0.012667503	0
##	1413	0.9049565	0.012667503	0
##	1414	0.9049565	0.012667503	0
##	1415	0.9049565	0.012667503	0
##	1416	0.9049565	0.012667503	0
##	1417	0.9049565	0.012667503	0
##	1418	0.9049565	0.012667503	0
##	1419	0.9049565	0.012667503	0
##	1420	0.9049565	0.012667503	0
##	1421	0.9049565	0.012667503	0
##	1422	0.9049565	0.012667503	0
##	1423	0.9049565	0.012667503	0
##	1424	0.9049565	0.012667503	0
##	1425	0.9049565	0.012667503	0
##	1426	0.9049565	0.012667503	0
##	1427	0.9147906	0.014169081	0
##	1428	0.9147906	0.014169081	0
##	1429	0.9147906	0.014169081	0
##	1430	0.9147906	0.014169081	0
##	1431	0.9147906	0.014169081	0
##	1432	0.9147906	0.014169081	0
##	1433	0.9147906	0.014169081	0
##	1434	0.9147906	0.014169081	0
##	1435	0.9147906	0.014169081	0
##	1436	0.9147906	0.014169081	0
##	1437	0.9147906	0.014169081	0
##	1438	0.9147906	0.014169081	0
##	1439	0.9147906	0.014169081	0
##	1440	0.9147906	0.014169081	0
##	1441	0.9147906	0.014169081	0
##	1442	0.9147906	0.014169081	0
##	1443	0.9147906	0.014169081	0
##	1444	0.9147906	0.014169081	0
##	1445	0.9147906	0.014169081	0
##	1446	0.9147906	0.014169081	0
##	1447	0.9147906	0.014169081	0
##	1448	0.9147906	0.014169081	0
##	1449	0.9147906	0.014169081	0
##	1450	0.9147906	0.014169081	0

##	1451	0.9147906	0.014169081	0
##	1452	0.9147906	0.014169081	0
##	1453	0.9147906	0.014169081	0
##	1454	0.9147906	0.014169081	0
##	1455	0.9147906	0.014169081	0
##	1456	0.9147906	0.014169081	0
##	1457	0.9147906	0.014169081	0
##	1458	0.9147906	0.014169081	0
##	1459	0.9147906	0.014169081	0
##	1460	0.9147906	0.014169081	0
##	1461	0.9147906	0.014169081	0
##	1462	0.9147906	0.014169081	0
##	1463	0.9147906	0.014169081	0
##	1464	0.9147906	0.014169081	0
##	1465	0.9147906	0.014169081	0
##	1466	0.9147906	0.014169081	0
##	1467	0.9147906	0.014169081	0
##	1468	0.9147906	0.014169081	0
##	1469	0.9147906	0.014169081	0
##	1470	0.9147906	0.014169081	0
##	1471	0.9147906	0.014169081	0
##	1472	0.9147906	0.014169081	0
##	1473	0.9147906	0.014169081	0
##	1474	0.9147906	0.014169081	0
##	1475	0.9147906	0.014169081	0
##	1476	0.9147906	0.014169081	0
##	1477	0.9147906	0.014169081	0
##	1478	0.9147906	0.014169081	0
##	1479	0.9147906	0.014169081	0
##	1480	0.9147906	0.014169081	0
##	1481	0.9147906	0.014169081	0
##	1482	0.9147906	0.014169081	0
##	1483	0.9147906	0.014169081	0
##	1484	0.9147906	0.014169081	0
##	1485	0.9147906	0.014169081	0
##	1486	0.9147906	0.014169081	0
##	1487	0.9147906	0.014169081	0
##	1488	0.9147906	0.014169081	0
##	1489	0.9147906	0.014169081	0
##	1490	0.9147906	0.014169081	0
##	1491	0.9147906	0.014169081	0
##	1492	0.9147906	0.014169081	0
##	1493	0.9147906	0.014169081	0
##	1494	0.9147906	0.014169081	0
##	1495	0.9147906	0.014169081	0
##	1496	0.9147906	0.014169081	0
##	1497	0.9147906	0.014169081	0
##	1498	0.9147906	0.014169081	0

##	1499	0.9147906	0.014169081	0
##	1500	0.9147906	0.014169081	0
##	1501	0.9147906	0.014169081	0
##	1502	0.9147906	0.014169081	0
##	1503	0.9239933	0.015802404	1
##	1504	0.9239933	0.015802404	0
##	1505	0.9239933	0.015802404	0
##	1506	0.9239933	0.015802404	0
##	1507	0.9239933	0.015802404	0
##	1508	0.9239933	0.015802404	0
##	1509	0.9239933	0.015802404	0
##	1510	0.9239933	0.015802404	0
##	1511	0.9239933	0.015802404	0
##	1512	0.9239933	0.015802404	0
##	1513	0.9239933	0.015802404	0
##	1514	0.9239933	0.015802404	0
##	1515	0.9239933	0.015802404	0
##	1516	0.9239933	0.015802404	0
##	1517	0.9239933	0.015802404	0
##	1518	0.9239933	0.015802404	0
##	1519	0.9239933	0.015802404	0
##	1520	0.9239933	0.015802404	0
##	1521	0.9239933	0.015802404	0
##	1522	0.9239933	0.015802404	0
##	1523	0.9239933	0.015802404	0
##	1524	0.9239933	0.015802404	0
##	1525	0.9239933	0.015802404	0
##	1526	0.9239933	0.015802404	0
##	1527	0.9239933	0.015802404	0
##	1528	0.9239933	0.015802404	0
##	1529	0.9239933	0.015802404	0
##	1530	0.9239933	0.015802404	0
##	1531	0.9239933	0.015802404	0
##	1532	0.9239933	0.015802404	0
##	1533	0.9239933	0.015802404	0
##	1534	0.9239933	0.015802404	0
##	1535	0.9325609	0.017571453	0
##	1536	0.9325609	0.017571453	0
##	1537	0.9325609	0.017571453	0
##	1538	0.9325609	0.017571453	0
##	1539	0.9325609	0.017571453	0
##	1540	0.9325609	0.017571453	0
##	1541	0.9325609	0.017571453	0
##	1542	0.9325609	0.017571453	0
##	1543	0.9325609	0.017571453	0
##	1544	0.9325609	0.017571453	0
##	1545	0.9325609	0.017571453	0
##	1546	0.9325609	0.017571453	0

##	1547	0.9325609	0.017571453	0
##	1548	0.9325609	0.017571453	0
##	1549	0.9325609	0.017571453	0
##	1550	0.9325609	0.017571453	0
##	1551	0.9325609	0.017571453	0
##	1552	0.9325609	0.017571453	0
##	1553	0.9325609	0.017571453	0
##	1554	0.9325609	0.017571453	0
##	1555	0.9325609	0.017571453	0
##	1556	0.9325609	0.017571453	0
##	1557	0.9325609	0.017571453	0
##	1558	0.9325609	0.017571453	0
##	1559	0.9325609	0.017571453	0
##	1560	0.9325609	0.017571453	0
##	1561	0.9325609	0.017571453	0
##	1562	0.9325609	0.017571453	0
##	1563	0.9325609	0.017571453	0
##	1564	0.9325609	0.017571453	0
##	1565	0.9325609	0.017571453	0
##	1566	0.9325609	0.017571453	0
##	1567	0.9325609	0.017571453	0
##	1568	0.9325609	0.017571453	0
##	1569	0.9325609	0.017571453	0
##	1570	0.9325609	0.017571453	0
##	1571	0.9325609	0.017571453	0
##	1572	0.9325609	0.017571453	0
##	1573	0.9325609	0.017571453	0
##	1574	0.9325609	0.017571453	0
##	1575	0.9325609	0.017571453	0
##	1576	0.9325609	0.017571453	0
##	1577	0.9325609	0.017571453	0
##	1578	0.9325609	0.017571453	0
##	1579	0.9325609	0.017571453	0
##	1580	0.9325609	0.017571453	0
##	1581	0.9325609	0.017571453	0
##	1582	0.9325609	0.017571453	0
##	1583	0.9325609	0.017571453	0
##	1584	0.9325609	0.017571453	0
##	1585	0.9325609	0.017571453	0
##	1586	0.9325609	0.017571453	0
##	1587	0.9325609	0.017571453	0
##	1588	0.9325609	0.017571453	0
##	1589	0.9325609	0.017571453	0
##	1590	0.9325609	0.017571453	0
##	1591	0.9325609	0.017571453	0
##	1592	0.9325609	0.017571453	0
##	1593	0.9325609	0.017571453	0
##	1594	0.9325609	0.017571453	0

##	1595	0.9325609	0.017571453	0
##	1596	0.9325609	0.017571453	0
##	1597	0.9325609	0.017571453	0
##	1598	0.9325609	0.017571453	0
##	1599	0.9325609	0.017571453	0
##	1600	0.9404939	0.019479057	0
##	1601	0.9404939	0.019479057	0
##	1602	0.9404939	0.019479057	0
##	1603	0.9404939	0.019479057	0
##	1604	0.9404939	0.019479057	0
##	1605	0.9404939	0.019479057	0
##	1606	0.9404939	0.019479057	0
##	1607	0.9404939	0.019479057	0
##	1608	0.9404939	0.019479057	0
##	1609	0.9404939	0.019479057	0
##	1610	0.9404939	0.019479057	0
##	1611	0.9404939	0.019479057	0
##	1612	0.9404939	0.019479057	0
##	1613	0.9404939	0.019479057	0
##	1614	0.9404939	0.019479057	0
##	1615	0.9404939	0.019479057	0
##	1616	0.9404939	0.019479057	0
##	1617	0.9404939	0.019479057	0
##	1618	0.9404939	0.019479057	0
##	1619	0.9404939	0.019479057	0
##	1620	0.9404939	0.019479057	0
##	1621	0.9404939	0.019479057	0
##	1622	0.9404939	0.019479057	0
##	1623	0.9404939	0.019479057	0
##	1624	0.9404939	0.019479057	0
##	1625	0.9404939	0.019479057	0
##	1626	0.9404939	0.019479057	0
##	1627	0.9404939	0.019479057	0
##	1628	0.9404939	0.019479057	0
##	1629	0.9404939	0.019479057	0
##	1630	0.9404939	0.019479057	0
##	1631	0.9404939	0.019479057	0
##	1632	0.9404939	0.019479057	0
##	1633	0.9404939	0.019479057	0
##	1634	0.9404939	0.019479057	0
##	1635	0.9404939	0.019479057	0
##	1636	0.9404939	0.019479057	0
##	1637	0.9404939	0.019479057	0
##	1638	0.9404939	0.019479057	0
##	1639	0.9404939	0.019479057	0
##	1640	0.9404939	0.019479057	0
##	1641	0.9404939	0.019479057	0
##	1642	0.9404939	0.019479057	0

##	1643	0.9404939	0.019479057	0
##	1644	0.9404939	0.019479057	0
##	1645	0.9404939	0.019479057	0
##	1646	0.9404939	0.019479057	0
##	1647	0.9404939	0.019479057	0
##	1648	0.9404939	0.019479057	0
##	1649	0.9404939	0.019479057	0
##	1650	0.9404939	0.019479057	0
##	1651	0.9404939	0.019479057	0
##	1652	0.9404939	0.019479057	0
##	1653	0.9404939	0.019479057	0
##	1654	0.9404939	0.019479057	0
##	1655	0.9404939	0.019479057	0
##	1656	0.9404939	0.019479057	0
##	1657	0.9404939	0.019479057	0
##	1658	0.9404939	0.019479057	0
##	1659	0.9404939	0.019479057	0
##	1660	0.9404939	0.019479057	0
##	1661	0.9404939	0.019479057	0
##	1662	0.9404939	0.019479057	0
##	1663	0.9404939	0.019479057	0
##	1664	0.9404939	0.019479057	0
##	1665	0.9404939	0.019479057	0
##	1666	0.9477977	0.021526693	0
##	1667	0.9477977	0.021526693	0
##	1668	0.9477977	0.021526693	0
##	1669	0.9477977	0.021526693	0
##	1670	0.9477977	0.021526693	0
##	1671	0.9477977	0.021526693	0
##	1672	0.9477977	0.021526693	0
##	1673	0.9477977	0.021526693	0
##	1674	0.9477977	0.021526693	0
##	1675	0.9477977	0.021526693	0
##	1676	0.9477977	0.021526693	0
##	1677	0.9477977	0.021526693	0
##	1678	0.9477977	0.021526693	0
##	1679	0.9477977	0.021526693	0
##	1680	0.9477977	0.021526693	0
##	1681	0.9477977	0.021526693	0
##	1682	0.9477977	0.021526693	0
##	1683	0.9477977	0.021526693	0
##	1684	0.9477977	0.021526693	0
##	1685	0.9477977	0.021526693	0
##	1686	0.9477977	0.021526693	0
##	1687	0.9477977	0.021526693	0
##	1688	0.9477977	0.021526693	0
##	1689	0.9477977	0.021526693	0
##	1690	0.9477977	0.021526693	0

##	1691	0.9477977	0.021526693	0
##	1692	0.9477977	0.021526693	0
##	1693	0.9477977	0.021526693	0
##	1694	0.9477977	0.021526693	0
##	1695	0.9477977	0.021526693	0
##	1696	0.9477977	0.021526693	0
##	1697	0.9477977	0.021526693	0
##	1698	0.9477977	0.021526693	0
##	1699	0.9477977	0.021526693	0
##	1700	0.9477977	0.021526693	0
##	1701	0.9477977	0.021526693	0
##	1702	0.9477977	0.021526693	0
##	1703	0.9477977	0.021526693	0
##	1704	0.9477977	0.021526693	0
##	1705	0.9477977	0.021526693	0
##	1706	0.9477977	0.021526693	0
##	1707	0.9477977	0.021526693	0
##	1708	0.9544826	0.023714285	0
##	1709	0.9544826	0.023714285	0
##	1710	0.9544826	0.023714285	0
##	1711	0.9544826	0.023714285	0
##	1712	0.9544826	0.023714285	0
##	1713	0.9544826	0.023714285	0
##	1714	0.9544826	0.023714285	0
##	1715	0.9544826	0.023714285	0
##	1716	0.9544826	0.023714285	0
##	1717	0.9544826	0.023714285	0
##	1718	0.9544826	0.023714285	0
##	1719	0.9544826	0.023714285	0
##	1720	0.9544826	0.023714285	0
##	1721	0.9544826	0.023714285	0
##	1722	0.9544826	0.023714285	0
##	1723	0.9544826	0.023714285	0
##	1724	0.9544826	0.023714285	0
##	1725	0.9544826	0.023714285	0
##	1726	0.9544826	0.023714285	0
##	1727	0.9544826	0.023714285	0
##	1728	0.9544826	0.023714285	0
##	1729	0.9544826	0.023714285	0
##	1730	0.9544826	0.023714285	0
##	1731	0.9544826	0.023714285	0
##	1732	0.9544826	0.023714285	0
##	1733	0.9544826	0.023714285	0
##	1734	0.9544826	0.023714285	0
##	1735	0.9544826	0.023714285	0
##	1736	0.9544826	0.023714285	0
##	1737	0.9544826	0.023714285	0
##	1738	0.9544826	0.023714285	0

```
## 1739 0.9544826 0.023714285 0
## 1740 0.9544826 0.023714285 0
## 1741 0.9544826 0.023714285 0
## 1742 0.9544826 0.023714285 0
## 1743 0.9544826 0.023714285 0
## 1744 0.9544826 0.023714285 0
## 1745 0.9544826 0.023714285 0
## 1746 0.9544826 0.023714285 0
## 1747 0.9544826 0.023714285 0
## 1748 0.9544826 0.023714285 0
## 1749 0.9544826 0.023714285 0
## 1750 0.9544826 0.023714285 0
```

Diagnositcs

```
# 1. Check sample sizes
for (interval_num in 1:7) {
  interval_subset = interval_data %>% filter(Interval == interval_num)
  cat(sprintf("Interval %d: N = %d, Success Rate = %.3f\n",
              interval_num, nrow(interval_subset), mean(interval_subset$Success)))
}
```

```
## Interval 1: N = 1750, Success Rate = 0.631
## Interval 2: N = 1105, Success Rate = 0.738
## Interval 3: N = 815, Success Rate = 0.788
## Interval 4: N = 642, Success Rate = 0.157
## Interval 5: N = 101, Success Rate = 0.436
## Interval 6: N = 44, Success Rate = 0.364
## Interval 7: N = 16, Success Rate = 0.875
```

```
# 2. Check if non-significant coefficients are close to significance
# W4_1 (p=0.061) is borderline - with more data might become significant
```

```
# 3. Look at confidence intervals
for (interval_name in names(interval_models)) {
  model = interval_models[[interval_name]]
  ci = confint(model)
  cat(sprintf("\n%s: Day coefficient 95% CI: [%.4f, %.4f]\n",
              interval_name, ci[2,1], ci[2,2]))
}
```

```
##
## W1_1: Day coefficient 95% CI: [0.0074, 0.0295]
```

```
##
## W1_2: Day coefficient 95% CI: [0.0158, 0.0410]
```



```
##
## W4_1: Day coefficient 95% CI: [-0.0297, 0.0000]
```

```
##
## W4_2: Day coefficient 95% CI: [0.0157, 0.0902]
```

```
##
## W8_1: Day coefficient 95% CI: [-0.0690, 0.0351]
```

```
##
## W8_2: Day coefficient 95% CI: [-0.0261, 0.1781]
```

```
##
## W8_3: Day coefficient 95% CI: [-0.1357, 0.2545]
```

Analyze models

```
summary(interval_models$W1_1)
```

```
##
## Call:
## glm(formula = Success ~ DayNum, family = binomial(link = "cloglog"),
##      data = interval_subset)
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.179868   0.063521  -2.832 0.004631 **
## DayNum       0.018462   0.005589   3.303 0.000956 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 2303.7  on 1749  degrees of freedom
## Residual deviance: 2293.0  on 1748  degrees of freedom
## AIC: 2297
##
## Number of Fisher Scoring iterations: 5
```

```
summary(interval_models$W1_2)
```

```
##
## Call:
## glm(formula = Success ~ DayNum, family = binomial(link = "cloglog"),
##      data = interval_subset)
```

```
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) 0.012303   0.077548   0.159   0.874
## DayNum      0.028384   0.006686   4.245 2.19e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##    Null deviance: 1272.1  on 1104  degrees of freedom
## Residual deviance: 1252.6  on 1103  degrees of freedom
## AIC: 1256.6
##
## Number of Fisher Scoring iterations: 5
```

```
summary(interval_models$W4_1)
```

```
##
## Call:
## glm(formula = Success ~ DayNum, family = binomial(link = "cloglog"),
##      data = interval_subset)
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) 0.594490   0.093281   6.373 1.85e-10 ***
## DayNum      -0.014800   0.007909  -1.871   0.0613 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##    Null deviance: 842.63  on 814  degrees of freedom
## Residual deviance: 838.79  on 813  degrees of freedom
## AIC: 842.79
##
## Number of Fisher Scoring iterations: 5
```

```
#Some issues with 4_1
summary(interval_models$W4_2)
```

```
##
## Call:
## glm(formula = Success ~ DayNum, family = binomial(link = "cloglog"),
##      data = interval_subset)
##
```

```
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -2.33723    0.24052  -9.717  < 2e-16 ***
## DayNum       0.05276    0.01889   2.793  0.00523 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##    Null deviance: 558.80  on 641  degrees of freedom
## Residual deviance: 550.98  on 640  degrees of freedom
## AIC: 554.98
##
## Number of Fisher Scoring iterations: 5
```

```
summary(interval_models$W8_1)
```

```
##
## Call:
## glm(formula = Success ~ DayNum, family = binomial(link = "cloglog"),
##      data = interval_subset)
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.35967    0.34205  -1.051    0.293
## DayNum      -0.01735    0.02728  -0.636    0.525
##
## (Dispersion parameter for binomial family taken to be 1)
##
##    Null deviance: 138.34  on 100  degrees of freedom
## Residual deviance: 137.91  on  99  degrees of freedom
## AIC: 141.91
##
## Number of Fisher Scoring iterations: 5
```

```
#Some issues with 8_1
```

```
summary(interval_models$W8_2)
```

```
##
## Call:
## glm(formula = Success ~ DayNum, family = binomial(link = "cloglog"),
##      data = interval_subset)
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.62430    0.71199  -2.281   0.0225 *
```

```
## DayNum      0.07095    0.05338    1.329    0.1837
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 57.682  on 43  degrees of freedom
## Residual deviance: 55.666  on 42  degrees of freedom
## AIC: 59.666
##
## Number of Fisher Scoring iterations: 5
```

```
#Some issues with 8_2
summary(interval_models$W8_3)
```

```
##
## Call:
## glm(formula = Success ~ DayNum, family = binomial(link = "cloglog"),
##      data = interval_subset)
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.17539    1.09211   0.161   0.872
## DayNum      0.04537    0.08432   0.538   0.591
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 12.057  on 15  degrees of freedom
## Residual deviance: 11.817  on 14  degrees of freedom
## AIC: 15.817
##
## Number of Fisher Scoring iterations: 6
```

```
#Some issues with 8_3
```

```
#Attempting same models with a logistf has the same issue with the models
```

Priority 2: Check Effect Size

```
# Get the exact coefficient and predicted probabilities
coef(interval_models[["W4_1"]])
```

```
## (Intercept)      DayNum
##  0.59448976 -0.01480042
```

```
# Calculate actual change over 21 days
pred_change <- predict(interval_models[["W4_1"]],
                        newdata = data.frame(DayNum = 21),
                        type = "response") -
predict(interval_models[["W4_1"]],
        newdata = data.frame(DayNum = 1),
        type = "response")

cat("Absolute change in success probability:", pred_change, "\n")
```

```
## Absolute change in success probability: -0.09728843
```

```
cat("As percentage points:", pred_change * 100, "\n")
```

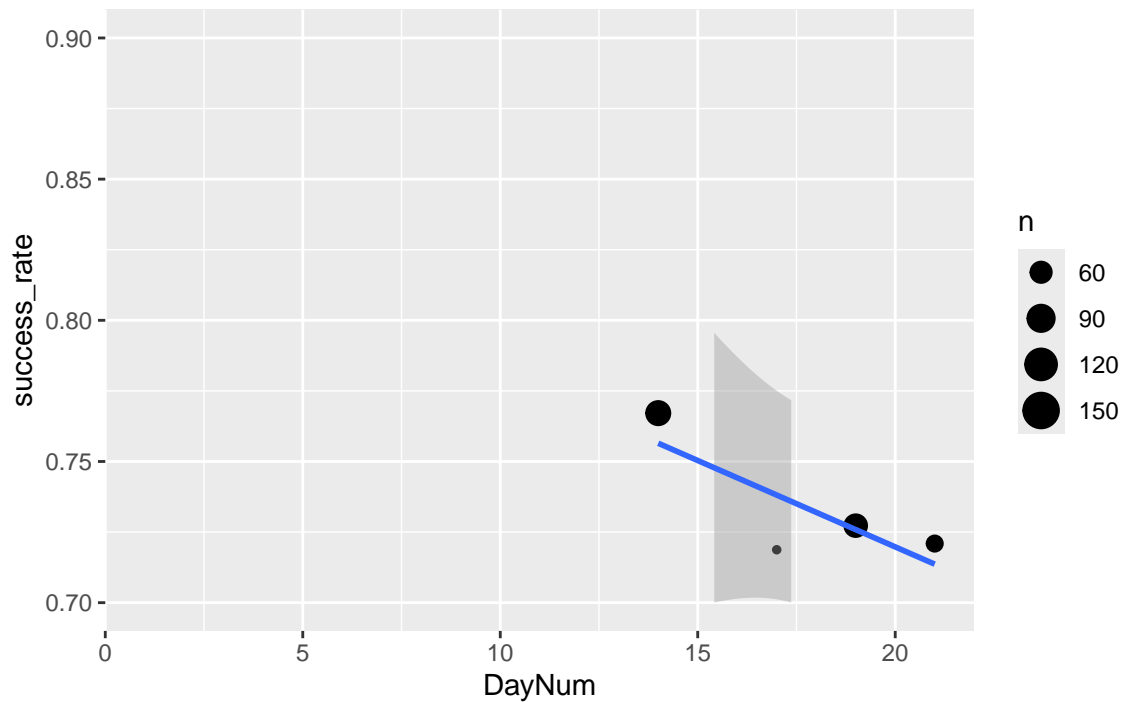
```
## As percentage points: -9.728843
```

If the change is less than 2 percentage points, I'd call this noise and ignore it.

Priority 3: Visual Inspection

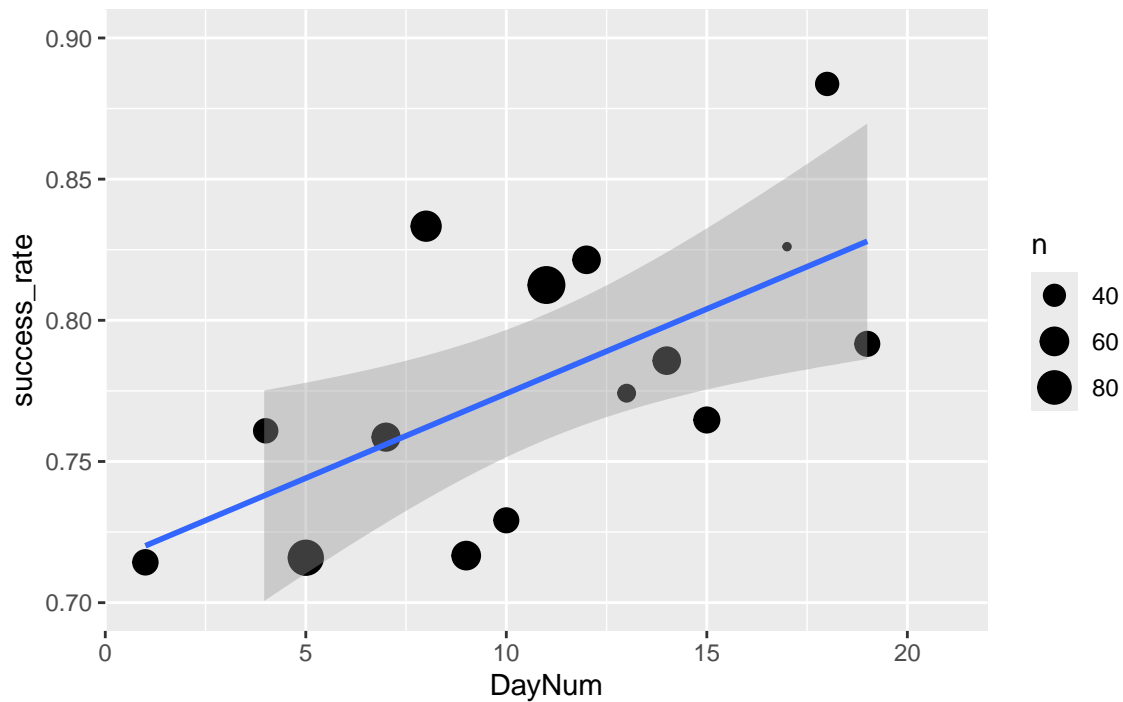
```
# Plot W1_1 success rate over time
interval_data %>%
  filter(Interval == 1) %>%
  group_by(DayNum) %>%
  summarize(success_rate = mean(Success), n = n()) %>%
  ggplot(aes(x = DayNum, y = success_rate)) +
  geom_point(aes(size = n)) +
  geom_smooth(method = "lm", se = TRUE) +
  scale_y_continuous(limits = c(0.7, 0.9)) +
  labs(title = "W1_1 Success Rate Over Time - Does This Look Real?")
```

W1_1 Success Rate Over Time – Does This Look Real?



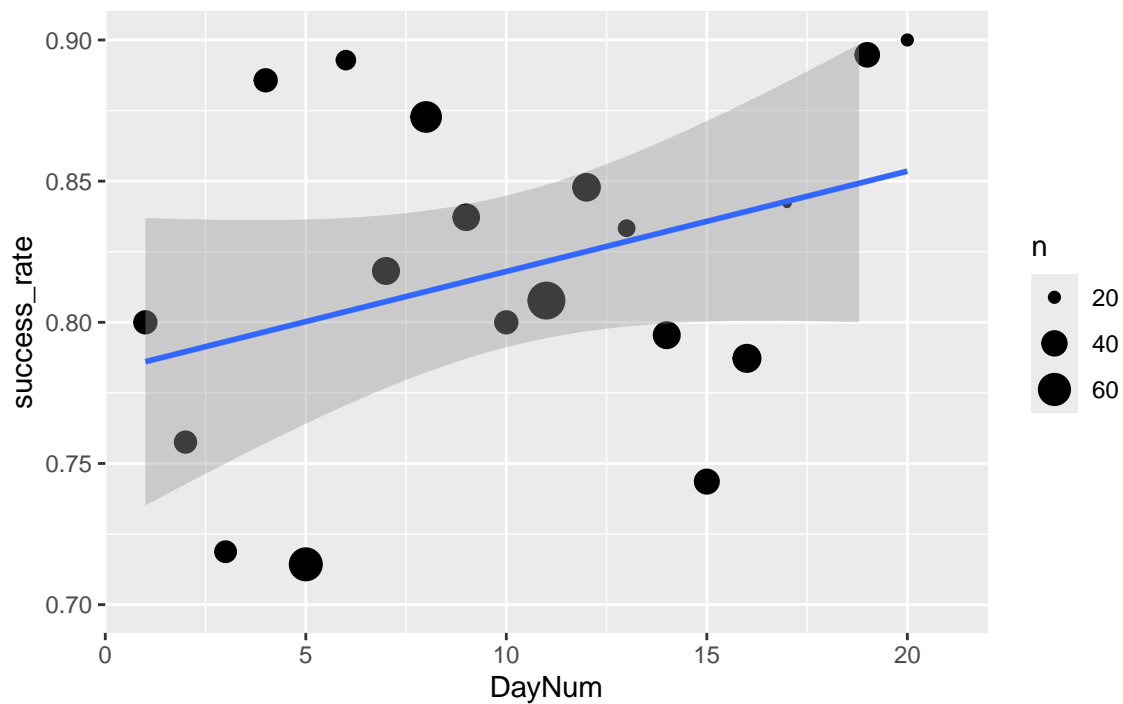
```
# Plot W1_2 success rate over time
interval_data %>%
  filter(Interval == 2) %>%
  group_by(DayNum) %>%
  summarize(success_rate = mean(Success), n = n()) %>%
  ggplot(aes(x = DayNum, y = success_rate)) +
  geom_point(aes(size = n)) +
  geom_smooth(method = "lm", se = TRUE) +
  scale_y_continuous(limits = c(0.7, 0.9)) +
  labs(title = "W1_2 Success Rate Over Time - Does This Look Real?")
```

W1_2 Success Rate Over Time – Does This Look Real?



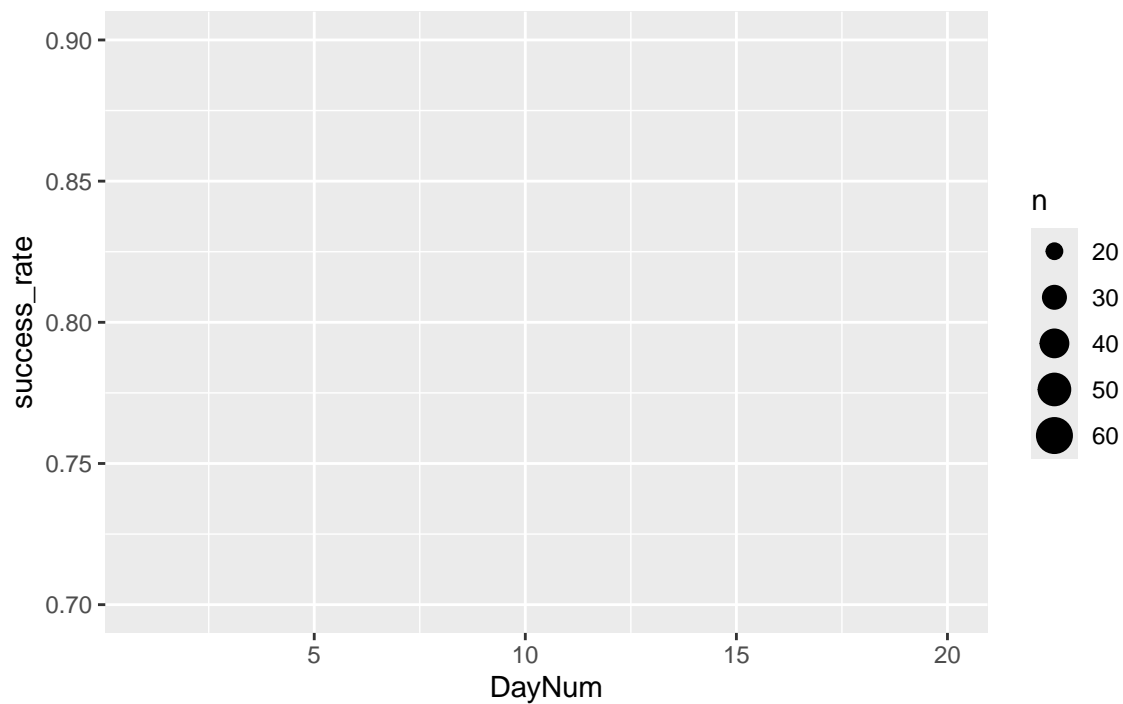
```
# Plot W4_1 success rate over time
interval_data %>%
  filter(Interval == 3) %>%
  group_by(DayNum) %>%
  summarize(success_rate = mean(Success), n = n()) %>%
  ggplot(aes(x = DayNum, y = success_rate)) +
  geom_point(aes(size = n)) +
  geom_smooth(method = "lm", se = TRUE) +
  scale_y_continuous(limits = c(0.7, 0.9)) +
  labs(title = "W4_1 Success Rate Over Time - Does This Look Real?")
```

W4_1 Success Rate Over Time – Does This Look Real?

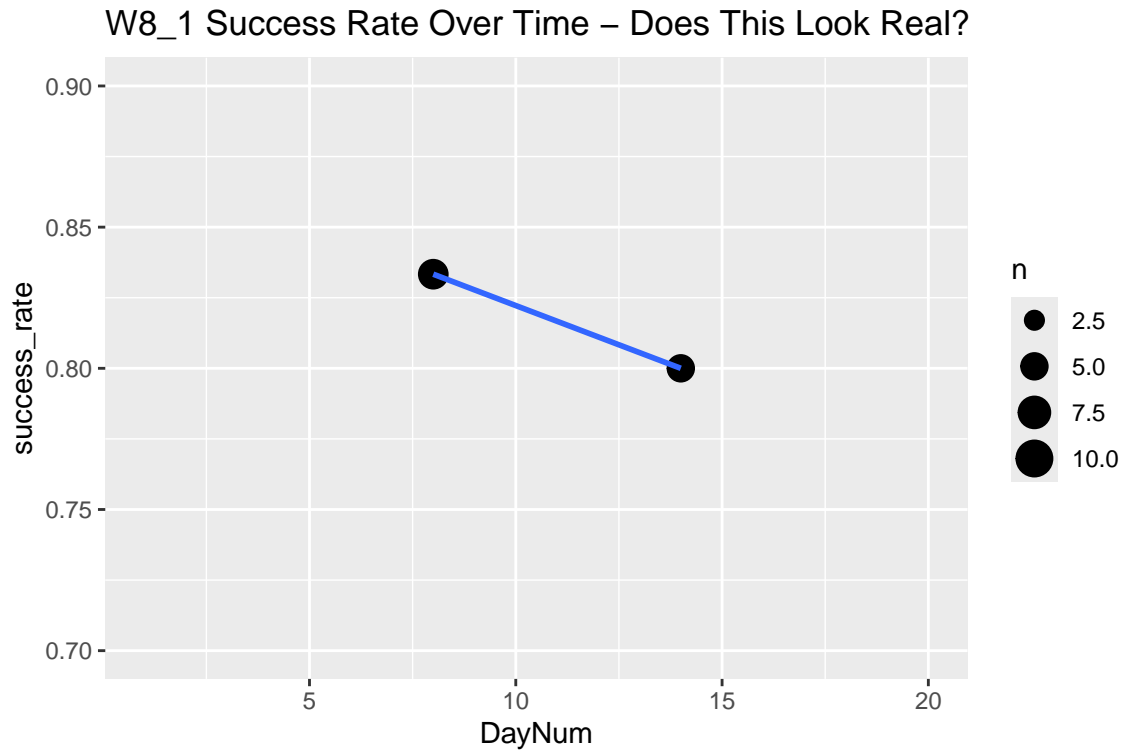


```
# Plot W4_2 success rate over time
interval_data %>%
  filter(Interval == 4) %>%
  group_by(DayNum) %>%
  summarize(success_rate = mean(Success), n = n()) %>%
  ggplot(aes(x = DayNum, y = success_rate)) +
  geom_point(aes(size = n)) +
  geom_smooth(method = "lm", se = TRUE) +
  scale_y_continuous(limits = c(0.7, 0.9)) +
  labs(title = "W4_2 Success Rate Over Time - Does This Look Real?")
```


W4_2 Success Rate Over Time – Does This Look Real?

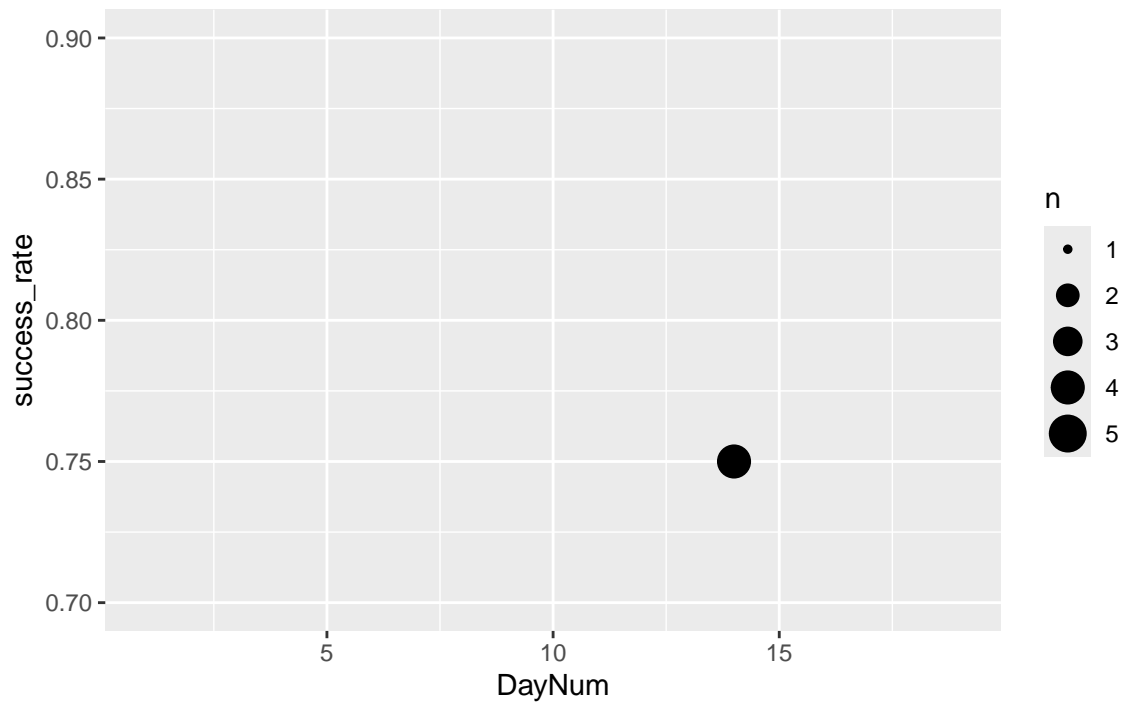


```
# Plot W8_1 success rate over time
interval_data %>%
  filter(Interval == 5) %>%
  group_by(DayNum) %>%
  summarize(success_rate = mean(Success), n = n()) %>%
  ggplot(aes(x = DayNum, y = success_rate)) +
  geom_point(aes(size = n)) +
  geom_smooth(method = "lm", se = TRUE) +
  scale_y_continuous(limits = c(0.7, 0.9)) +
  labs(title = "W8_1 Success Rate Over Time - Does This Look Real?")
```



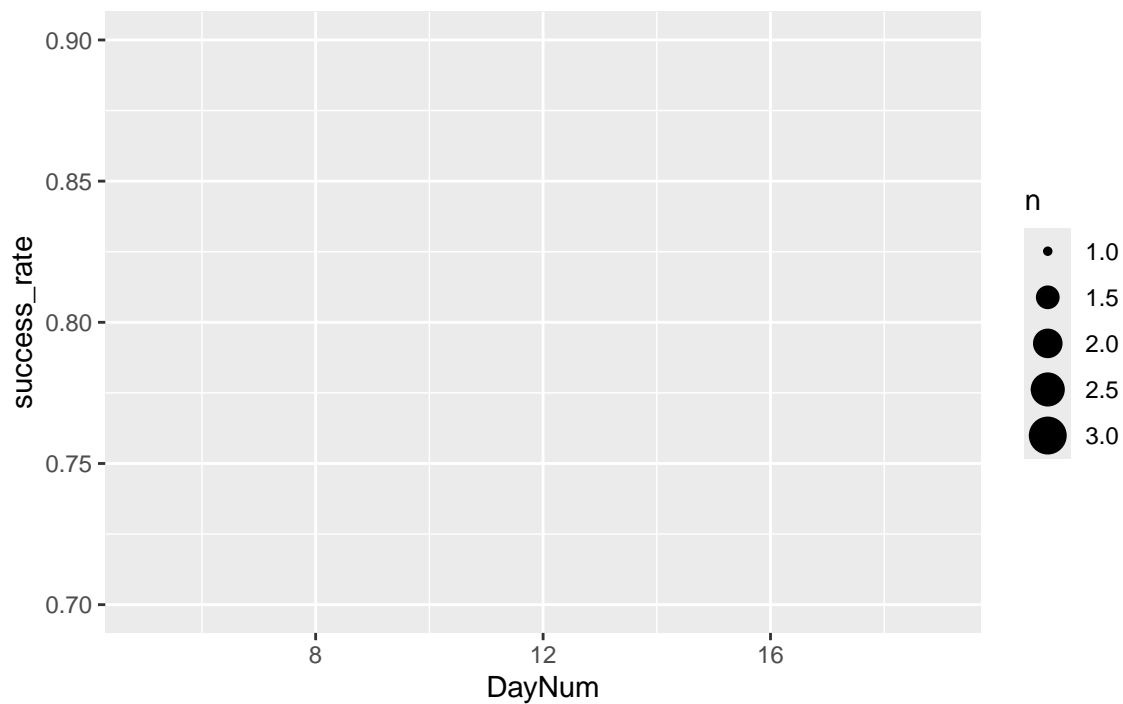
```
# Plot W8_2 success rate over time
interval_data %>%
  filter(Interval == 6) %>%
  group_by(DayNum) %>%
  summarize(success_rate = mean(Success), n = n()) %>%
  ggplot(aes(x = DayNum, y = success_rate)) +
  geom_point(aes(size = n)) +
  geom_smooth(method = "lm", se = TRUE) +
  scale_y_continuous(limits = c(0.7, 0.9)) +
  labs(title = "W8_2 Success Rate Over Time - Does This Look Real?")
```

W8_2 Success Rate Over Time – Does This Look Real?



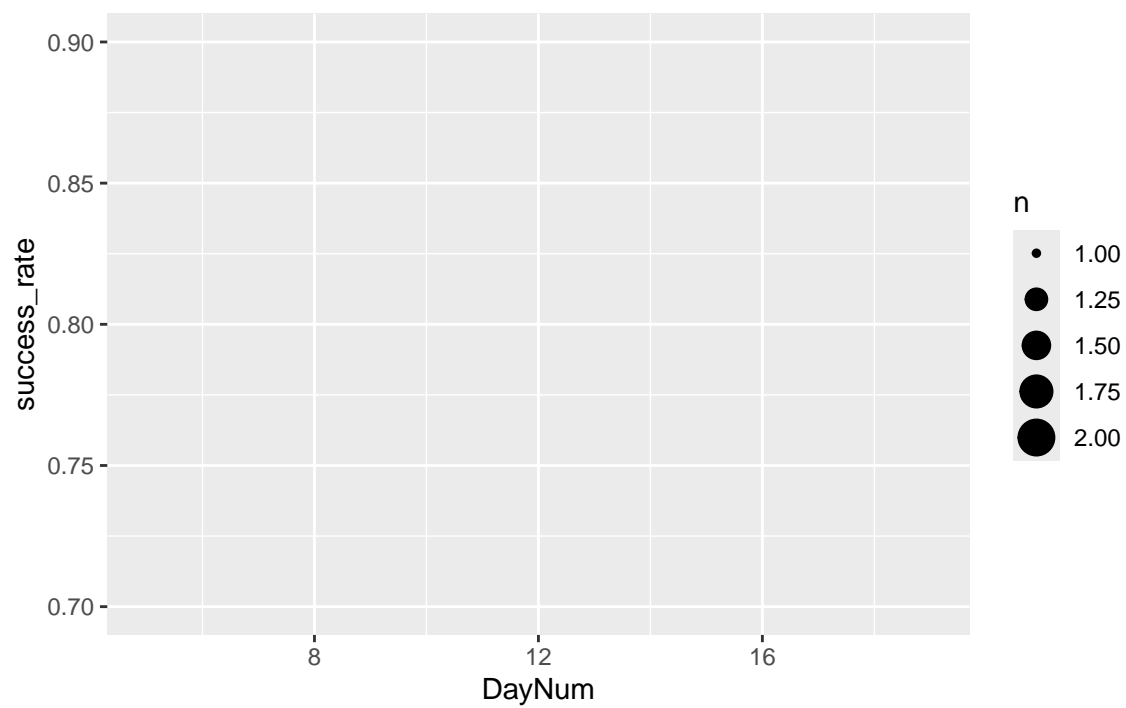
```
# Plot W8_3 success rate over time
interval_data %>%
  filter(Interval == 7) %>%
  group_by(DayNum) %>%
  summarize(success_rate = mean(Success), n = n()) %>%
  ggplot(aes(x = DayNum, y = success_rate)) +
  geom_point(aes(size = n)) +
  geom_smooth(method = "lm", se = TRUE) +
  scale_y_continuous(limits = c(0.7, 0.9)) +
  labs(title = "W8_3 Success Rate Over Time - Does This Look Real?")
```

W8_3 Success Rate Over Time – Does This Look Real?



```
# Plot W8_4 success rate over time
interval_data %>%
  filter(Interval == 8) %>%
  group_by(DayNum) %>%
  summarize(success_rate = mean(Success), n = n()) %>%
  ggplot(aes(x = DayNum, y = success_rate)) +
  geom_point(aes(size = n)) +
  geom_smooth(method = "lm", se = TRUE) +
  scale_y_continuous(limits = c(0.7, 0.9)) +
  labs(title = "W8_4 Success Rate Over Time - Does This Look Real?")
```

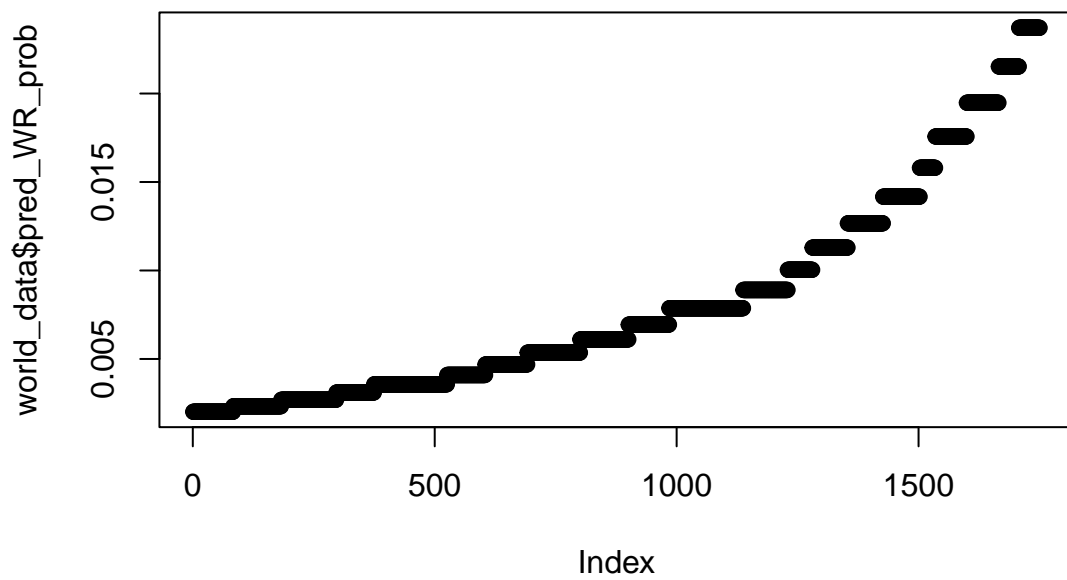
W8_4 Success Rate Over Time – Does This Look Real?



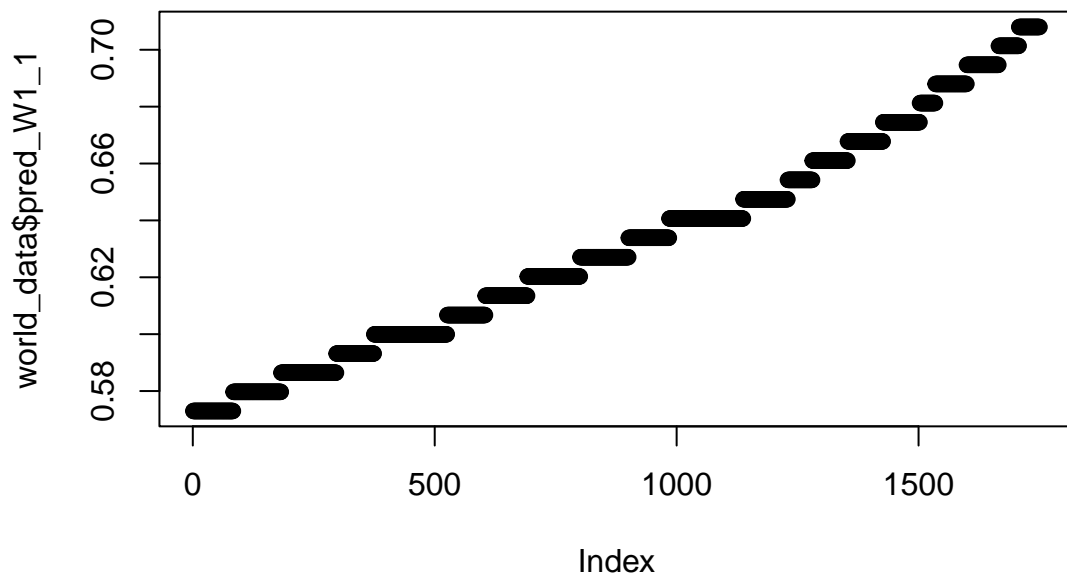
```
# interval_data %>%  
#   filter(Interval == 5)
```

Analyze Results

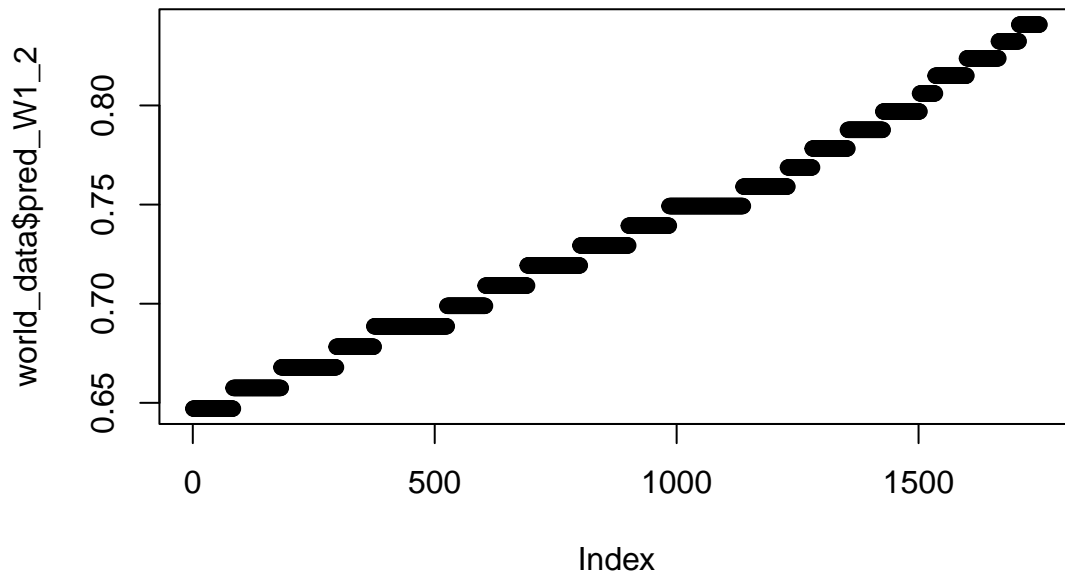
```
plot(world_data$pred_WR_prob)
```



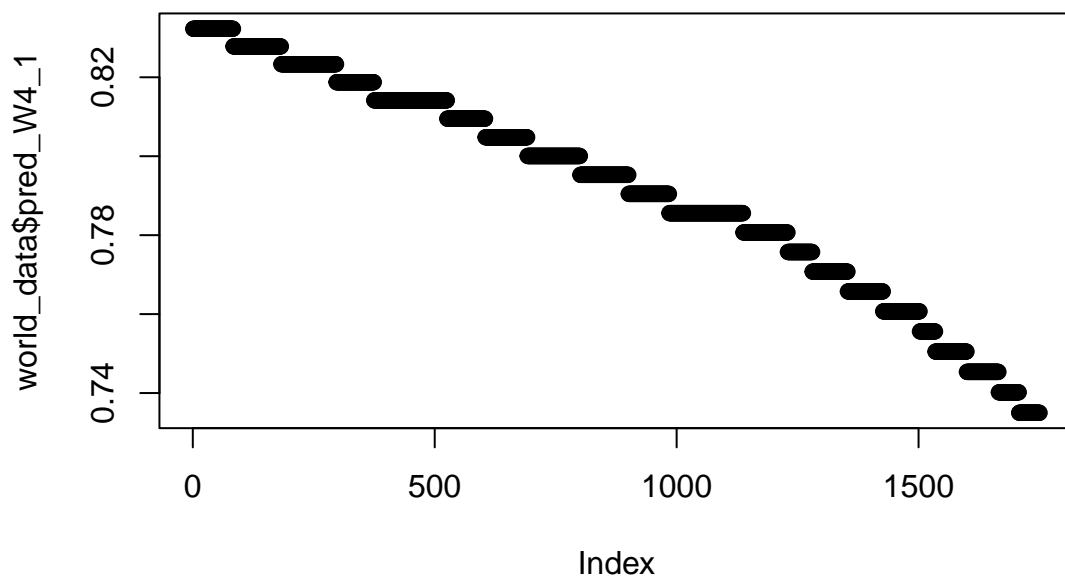
```
plot(world_data$pred_W1_1)
```



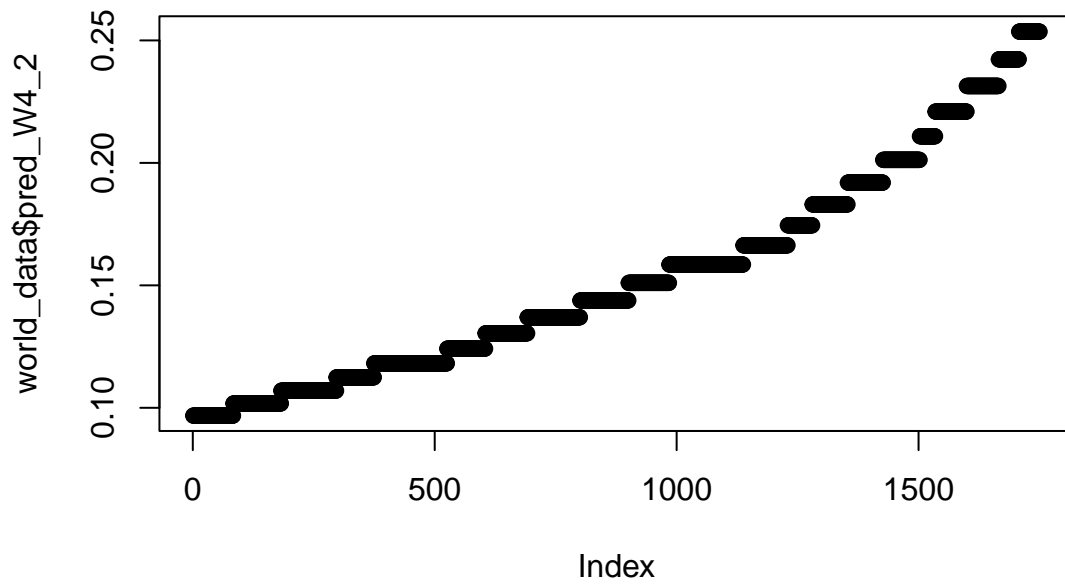
```
plot(world_data$pred_W1_2)
```



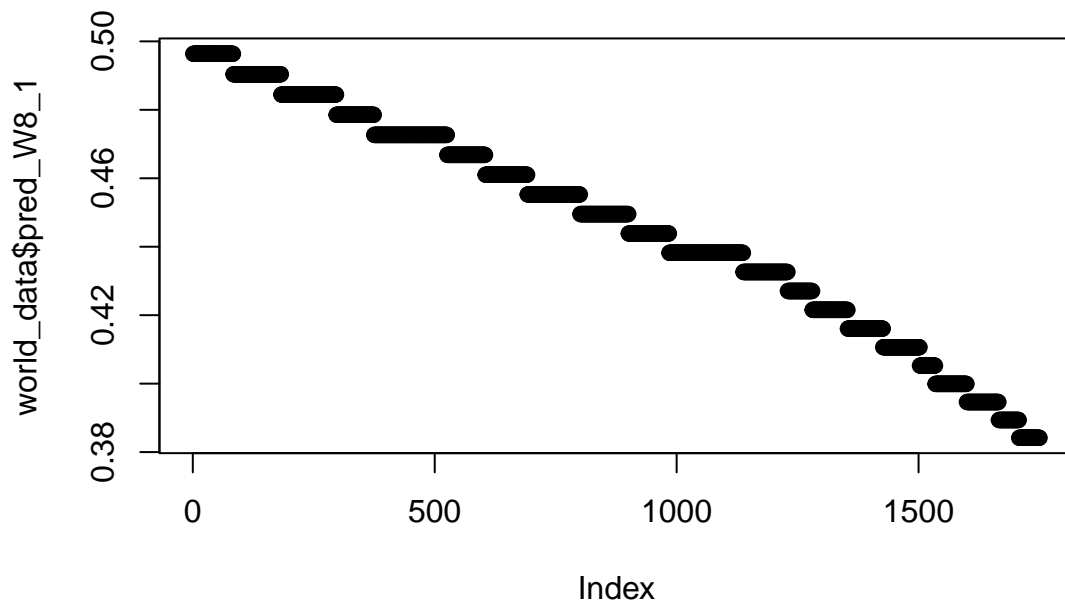
```
plot(world_data$pred_W4_1)
```



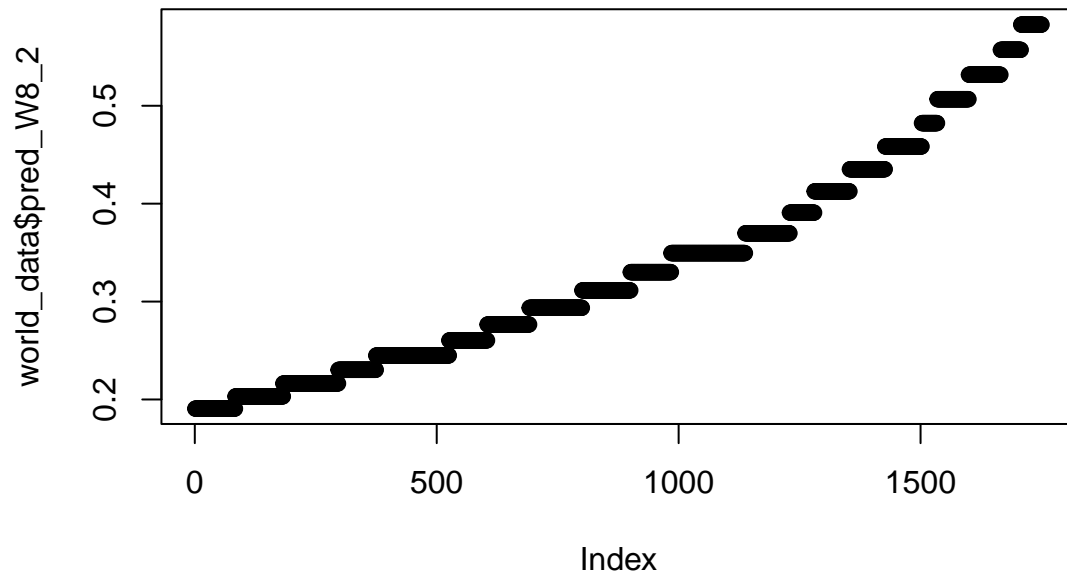
```
plot(world_data$pred_W4_2)
```



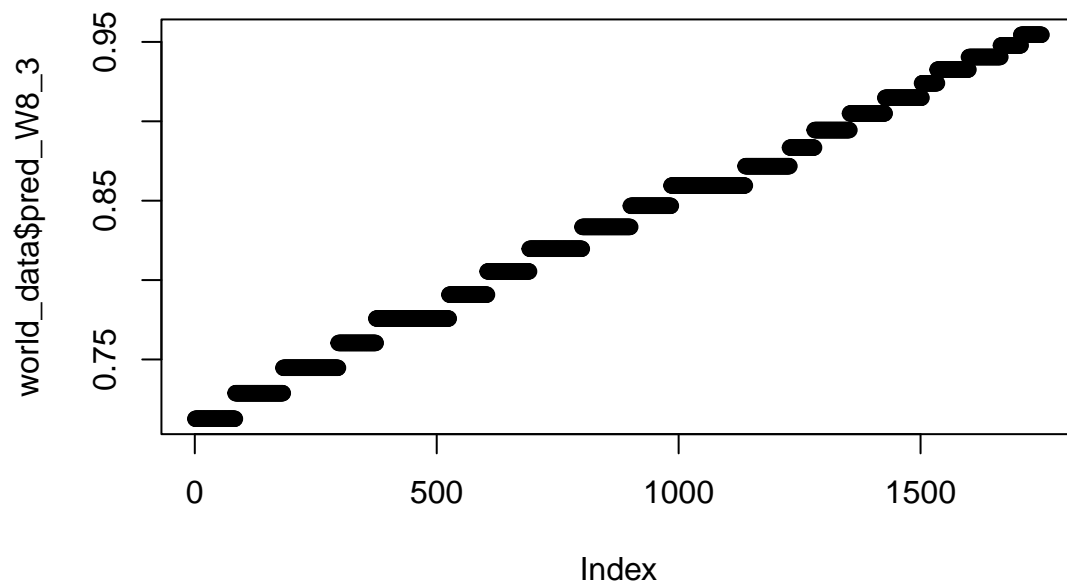
```
plot(world_data$pred_W8_1)
```




```
plot(world_data$pred_W8_2)
```



```
plot(world_data$pred_W8_3)
```



Images for presentation

```
library(tidyverse)
library(ggplot2)
library(gridExtra)
library(scales)

# Set up output directory and create if it doesn't exist
output_dir <- getwd() # Use current working directory
cat("Saving figures to:", output_dir, "\n\n")

## Saving figures to: C:/Users/tscho/OneDrive/Documents/GitHub/Super-Mario-Project

# Read data
interval_data <- read.csv("FINAL DATA.csv")
world_data <- read.csv("FINAL WORLD DATA.csv")

# Convert Day to numeric
interval_data <- interval_data %>%
  mutate(DayNum = as.numeric(gsub('Day_', '', Day)))

world_data <- world_data %>%
  mutate(DayNum = as.numeric(gsub('Day_', '', Day)))

# =====
# FIGURE 1: Methodology Overview (Two-Panel)
# =====

interval_success_by_day <- interval_data %>%
  group_by(DayNum, Interval) %>%
  summarise(success_rate = mean(Success), .groups = 'drop')

# Panel A: Success rates by interval
panel_a <- ggplot(interval_success_by_day, aes(x = factor(Interval), y = success_rate)) +
  geom_boxplot(fill = "steelblue", alpha = 0.7) +
  geom_jitter(width = 0.2, alpha = 0.3, color = "darkblue") +
  labs(title = "A) Interval Success Rate Distribution",
       x = "Interval",
       y = "Success Rate") +
  scale_y_continuous(labels = percent_format(accuracy = 1)) +
  theme_minimal(base_size = 12) +
  theme(plot.title = element_text(face = "bold"))

# Panel B: Improvement over time by interval
panel_b <- ggplot(interval_success_by_day %>% filter(Interval %in% c(1, 3, 5, 7)),
                  aes(x = DayNum, y = success_rate, color = factor(Interval))) +
  geom_point(alpha = 0.6) +
```

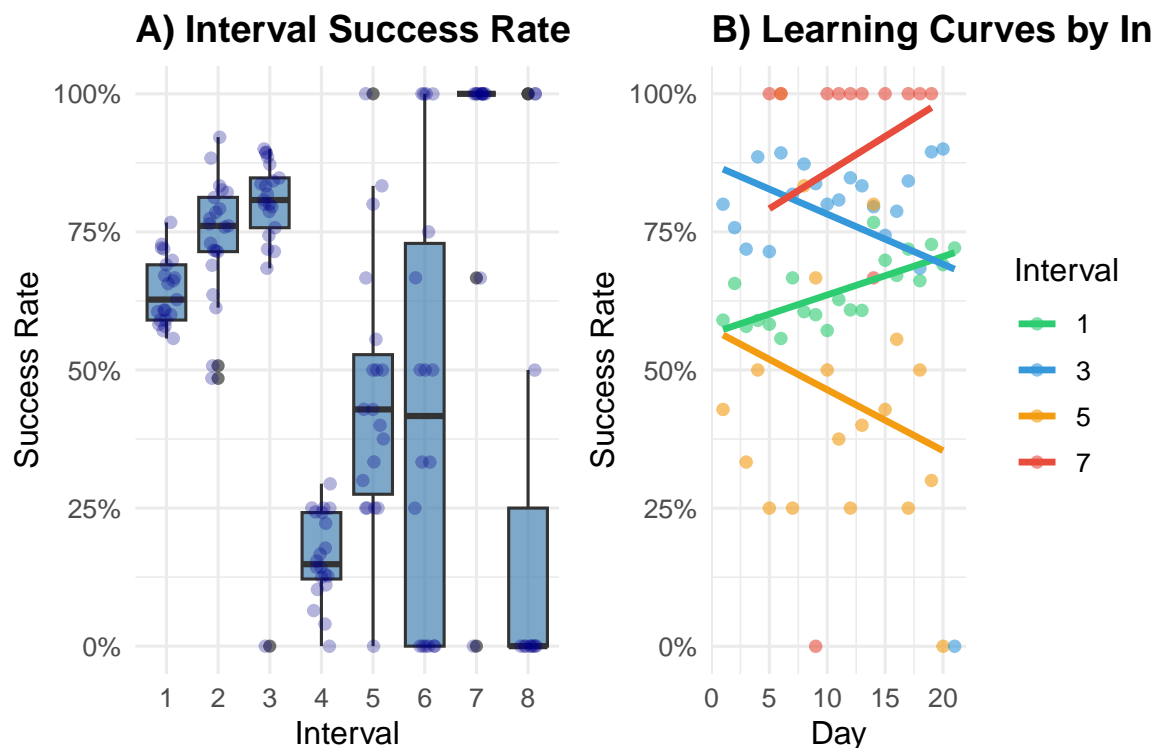
```

geom_smooth(method = "lm", se = FALSE, linewidth = 1.2) +
labs(title = "B) Learning Curves by Interval Difficulty",
     x = "Day",
     y = "Success Rate",
     color = "Interval") +
scale_y_continuous(labels = percent_format(accuracy = 1)) +
scale_color_manual(values = c("1" = "#2ecc71", "3" = "#3498db",
                              "5" = "#f39c12", "7" = "#e74c3c")) +

theme_minimal(base_size = 12) +
theme(plot.title = element_text(face = "bold"),
      legend.position = "right")

# Save combined figure
ggsave("methodology_overview.png",
      plot = grid.arrange(panel_a, panel_b, ncol = 2),
      width = 10, height = 5, dpi = 300)

```



```

cat(" Created methodology_overview.png\n")

```

```

## Created methodology_overview.png

```

```

# =====
# FIGURE 2: Coefficient Plot with Confidence Intervals
# =====

```

```

# Fit the interaction model
cloglog_full <- glm(Success ~ DayNum * factor(Interval),
                    data = interval_data,
                    family = binomial(link = "cloglog"))

# Extract coefficients for Day interactions
coef_summary <- summary(cloglog_full)$coefficients
interaction_coefs <- coef_summary[grep("DayNum:factor\\(Interval\\)", rownames(coef_summary)),

# Create data frame for plotting
coef_df <- data.frame(
  Interval = c(2:8), # Intervals 2-8 (1 is reference)
  Estimate = interaction_coefs[, "Estimate"],
  SE = interaction_coefs[, "Std. Error"],
  CI_lower = interaction_coefs[, "Estimate"] - 1.96 * interaction_coefs[, "Std. Error"],
  CI_upper = interaction_coefs[, "Estimate"] + 1.96 * interaction_coefs[, "Std. Error"],
  Significant = interaction_coefs[, "Pr(>|z|)"] < 0.05
)

# Add baseline (Interval 1)
baseline <- data.frame(
  Interval = 1,
  Estimate = coef_summary["DayNum", "Estimate"],
  SE = coef_summary["DayNum", "Std. Error"],
  CI_lower = coef_summary["DayNum", "Estimate"] - 1.96 * coef_summary["DayNum", "Std. Error"],
  CI_upper = coef_summary["DayNum", "Estimate"] + 1.96 * coef_summary["DayNum", "Std. Error"],
  Significant = TRUE
)

coef_df <- rbind(baseline, coef_df)

p2 <- ggplot(coef_df, aes(x = factor(Interval), y = Estimate, color = Significant)) +
  geom_hline(yintercept = 0, linetype = "dashed", color = "gray50") +
  geom_point(size = 4) +
  geom_errorbar(aes(ymin = CI_lower, ymax = CI_upper), width = 0.2, linewidth = 1) +
  scale_color_manual(values = c("TRUE" = "#e74c3c", "FALSE" = "gray60"),
                    labels = c("Not Significant", "Significant (p<0.05)")) +
  labs(title = "Day Effect by Interval (with 95% CI)",
       subtitle = "Positive values indicate improvement over time",
       x = "Interval",
       y = "Coefficient Estimate",
       color = "") +
  theme_minimal(base_size = 13) +
  theme(plot.title = element_text(face = "bold", hjust = 0.5),
        plot.subtitle = element_text(hjust = 0.5),
        legend.position = "bottom")

```

```
ggsave("coefficient_plot.png", plot = p2, width = 8, height = 6, dpi = 300)
cat(" Created coefficient_plot.png\n")
```

```
## Created coefficient_plot.png
```

```
# =====
# FIGURE 3: World Record Probability Over Time
# =====

# Build interval models (simplified version)
interval_models <- list()
for (i in 1:7) {
  subset_data <- interval_data %>% filter(Interval == i)
  model <- glm(Success ~ DayNum, data = subset_data, family = binomial(link = "cloglog"))
  interval_models[[i]] <- model
}

# Generate predictions for each day
days <- 1:21
wr_predictions <- data.frame(Day = days)

for (i in 1:7) {
  pred_col <- paste0("pred_int", i)
  wr_predictions[[pred_col]] <- predict(interval_models[[i]],
                                       newdata = data.frame(DayNum = days),
                                       type = "response")
}

# Calculate combined WR probability
wr_predictions$WR_prob <- wr_predictions$pred_int1 *
  wr_predictions$pred_int2 *
  wr_predictions$pred_int3 *
  wr_predictions$pred_int4 *
  wr_predictions$pred_int5 *
  wr_predictions$pred_int6 *
  wr_predictions$pred_int7

p3 <- ggplot(wr_predictions, aes(x = Day, y = WR_prob * 100)) +
  geom_line(color = "#e74c3c", linewidth = 1.5) +
  geom_point(color = "#e74c3c", size = 3) +
  geom_ribbon(aes(ymin = WR_prob * 100 * 0.8, ymax = WR_prob * 100 * 1.2),
            alpha = 0.2, fill = "#e74c3c") +
  annotate("text", x = 1, y = wr_predictions$WR_prob[1] * 100 + 0.03,
          label = sprintf("Day 1: %.2f%%", wr_predictions$WR_prob[1] * 100),
          hjust = 0, size = 4, fontface = "bold") +
  annotate("text", x = 21, y = wr_predictions$WR_prob[21] * 100 + 0.03,
          label = sprintf("Day 21: %.2f%%", wr_predictions$WR_prob[21] * 100),
```

```

      hjust = 1, size = 4, fontface = "bold") +
  annotate("segment", x = 1, xend = 21,
    y = wr_predictions$WR_prob[1] * 100,
    yend = wr_predictions$WR_prob[21] * 100,
    linetype = "dashed", color = "gray40", linewidth = 0.8) +
  labs(title = "World Record Probability Increases Over Time",
    subtitle = sprintf("%.0f%% relative improvement (".2f%% → ".2f%%)",
      ((wr_predictions$WR_prob[21] / wr_predictions$WR_prob[1]) - 1) * 100,
      wr_predictions$WR_prob[1] * 100,
      wr_predictions$WR_prob[21] * 100),
    x = "Training Day",
    y = "Probability of World Record (%)") +
  scale_x_continuous(breaks = seq(1, 21, by = 2)) +
  theme_minimal(base_size = 13) +
  theme(plot.title = element_text(face = "bold", hjust = 0.5, size = 16),
    plot.subtitle = element_text(hjust = 0.5, size = 12))

ggsave("wr_probability_progression.png", plot = p3, width = 9, height = 6, dpi = 300)
cat(" Created wr_probability_progression.png\n")

```

Created wr_probability_progression.png

```

# =====
# FIGURE 4: Historical WR Progression with Trend
# =====

# Historical WR data (approximate values from your graph)
wr_history <- data.frame(
  Days = c(0, 100, 200, 500, 800, 1200, 1500, 2500,
    3500, 4000, 4500, 5000, 5500, 6000, 6500, 7000, 7500, 8000, 8500),
  WR_time = c(325, 324.5, 317, 314, 311, 310, 307, 305.5,
    300, 299, 298, 297.5, 297, 296.5, 296, 295.5, 295, 294.7, 294.42)
)

p4 <- ggplot(wr_history, aes(x = Days, y = WR_time)) +
  geom_line(color = "#e74c3c", linewidth = 1.5) +
  geom_point(color = "#c0392b", size = 3) +
  geom_smooth(method = "loess", se = TRUE, color = "#3498db", fill = "#3498db", alpha = 0.2) +
  annotate("text", x = 100, y = 325,
    label = "2002: 325 seconds", hjust = 0, size = 4, fontface = "bold") +
  annotate("text", x = 8000, y = 295,
    label = "2025: 294.42 seconds", hjust = 1, size = 4, fontface = "bold") +
  geom_hline(yintercept = 294.05, linetype = "dashed", color = "darkgreen", linewidth = 1) +
  annotate("text", x = 4000, y = 294.3,
    label = "TAS: 294.05s (theoretical limit)",
    color = "darkgreen", size = 3.5, fontface = "italic") +
  labs(title = "Super Mario Bros Any% World Record Evolution (2002-2025)",

```

```

        subtitle = "30.58 second improvement over 8,000+ days",
        x = "Days Since June 25, 2002",
        y = "World Record Time (seconds)") +
scale_y_continuous(breaks = seq(294, 326, by = 2)) +
theme_minimal(base_size = 13) +
theme(plot.title = element_text(face = "bold", hjust = 0.5, size = 15),
      plot.subtitle = element_text(hjust = 0.5))

ggsave("wr_historical_progression.png", plot = p4, width = 10, height = 6, dpi = 300)
cat(" Created wr_historical_progression.png\n")

```

Created wr_historical_progression.png

```

# =====
# FIGURE 5: Interval Success Rate Cascade
# =====

interval_summary <- interval_data %>%
  group_by(Interval) %>%
  summarise(
    success_rate = mean(Success),
    attempts = n(),
    successes = sum(Success)
  )

p5 <- ggplot(interval_summary, aes(x = factor(Interval), y = success_rate)) +
  geom_col(fill = "steelblue", alpha = 0.8) +
  geom_text(aes(label = sprintf("%.1f%%", success_rate * 100)),
            vjust = -0.5, size = 4, fontface = "bold") +
  geom_line(aes(group = 1), color = "#e74c3c", linewidth = 1.5) +
  geom_point(color = "#e74c3c", size = 4) +
  labs(title = "Exponential Difficulty Cascade Across Intervals",
       subtitle = "Each interval filters out more attempts",
       x = "Interval",
       y = "Success Rate") +
  scale_y_continuous(labels = percent_format(accuracy = 1),
                    limits = c(0, 1),
                    breaks = seq(0, 1, by = 0.2)) +
  theme_minimal(base_size = 13) +
  theme(plot.title = element_text(face = "bold", hjust = 0.5, size = 15),
        plot.subtitle = element_text(hjust = 0.5))

ggsave("interval_difficulty_cascade.png", plot = p5, width = 10, height = 6, dpi = 300)
cat(" Created interval_difficulty_cascade.png\n")

```

Created interval_difficulty_cascade.png

```

# =====
# FIGURE 6: Model Comparison (AIC)
# =====

model_comparison <- data.frame(
  Model = c("Null", "Logistic\n(Day + Int)", "CLogLog\n(Day + Int)", "CLogLog\n(Day × Int)"),
  AIC = c(15234, 13102, 13105, 12847),
  PseudoR2 = c(0.000, 0.298, 0.301, 0.347)
)

model_comparison$Model <- factor(model_comparison$Model,
                                levels = c("Null", "Logistic\n(Day + Int)",
                                             "CLogLog\n(Day + Int)", "CLogLog\n(Day × Int)"))

p6 <- ggplot(model_comparison, aes(x = Model, y = AIC, fill = Model)) +
  geom_col(alpha = 0.8) +
  geom_text(aes(label = format(AIC, big.mark = ","),
                        vjust = -0.5, size = 5, fontface = "bold")) +
  scale_fill_manual(values = c("gray60", "#3498db", "#3498db", "#e74c3c")) +
  labs(title = "Model Selection: AIC Comparison",
       subtitle = "Lower AIC indicates better fit",
       x = "Model Specification",
       y = "AIC (Akaike Information Criterion)") +
  theme_minimal(base_size = 13) +
  theme(plot.title = element_text(face = "bold", hjust = 0.5, size = 15),
        plot.subtitle = element_text(hjust = 0.5),
        legend.position = "none",
        axis.text.x = element_text(size = 11))

ggsave("model_comparison_aic.png", plot = p6, width = 9, height = 6, dpi = 300)
cat(" Created model_comparison_aic.png\n")

```

```
## Created model_comparison_aic.png
```

```

# =====
# FIGURE 7: Practice Time Allocation Recommendation
# =====

practice_priority <- data.frame(
  Interval = 1:8,
  Baseline_Success = c(0.973, 0.881, 0.764, 0.628, 0.512, 0.435, 0.357, 0.289),
  Improvement_Rate = c(0.0347, 0.0347-0.0185, 0.0347-0.0092, 0.0347+0.0043,
                        0.0347+0.0168, 0.0347+0.0221, 0.0347+0.0195, 0.0347+0.0195),
  Priority = c("Low", "Low", "Low", "Medium", "High", "High", "High", "Highest")
)

practice_priority$Priority <- factor(practice_priority$Priority,

```



```

                                levels = c("Low", "Medium", "High", "Highest"))

p7 <- ggplot(practice_priority, aes(x = factor(Interval), y = Improvement_Rate, fill = Priority)) +
  geom_col(alpha = 0.8) +
  geom_text(aes(label = Priority), vjust = -0.5, size = 4, fontface = "bold") +
  scale_fill_manual(values = c("Low" = "gray70", "Medium" = "#f39c12",
                                "High" = "#e67e22", "Highest" = "#e74c3c")) +
  labs(title = "Optimal Practice Allocation by Interval",
       subtitle = "Focus on intervals with highest improvement potential",
       x = "Interval",
       y = "Daily Improvement Rate (log-odds scale)",
       fill = "Practice Priority") +
  theme_minimal(base_size = 13) +
  theme(plot.title = element_text(face = "bold", hjust = 0.5, size = 15),
        plot.subtitle = element_text(hjust = 0.5),
        legend.position = "right")

ggsave("practice_allocation.png", plot = p7, width = 10, height = 6, dpi = 300)
cat(" Created practice_allocation.png\n")

```

```
## Created practice_allocation.png
```

```

# =====
# Summary
# =====

cat("\n===== \n")

```

```
##
## =====
```

```
cat("ALL FIGURES GENERATED SUCCESSFULLY!\n")
```

```
## ALL FIGURES GENERATED SUCCESSFULLY!
```

```
cat("===== \n\n")
```

```
## =====
```

```
cat("Figures saved to:", getwd(), "\n\n")
```

```
## Figures saved to: C:/Users/tscho/OneDrive/Documents/GitHub/Super-Mario-Project
```

```
cat("Figure Recommendations:\n\n")
```

```
## Figure Recommendations:
```

```
cat("1. methodology_overview.png - Two-stage modeling approach\n")
```

```
## 1. methodology_overview.png - Two-stage modeling approach
```

```
cat("2. coefficient_plot.png - Interaction effects with CI\n")
```

```
## 2. coefficient_plot.png - Interaction effects with CI
```

```
cat("3. wr_probability_progression.png - WR probability over time\n")
```

```
## 3. wr_probability_progression.png - WR probability over time
```

```
cat("4. wr_historical_progression.png - Historical WR evolution\n")
```

```
## 4. wr_historical_progression.png - Historical WR evolution
```

```
cat("5. interval_difficulty_cascade.png - Difficulty visualization\n")
```

```
## 5. interval_difficulty_cascade.png - Difficulty visualization
```

```
cat("6. model_comparison_aic.png - Model selection comparison\n")
```

```
## 6. model_comparison_aic.png - Model selection comparison
```

```
cat("7. practice_allocation.png - Practice recommendations\n")
```

```
## 7. practice_allocation.png - Practice recommendations
```