

# Project

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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

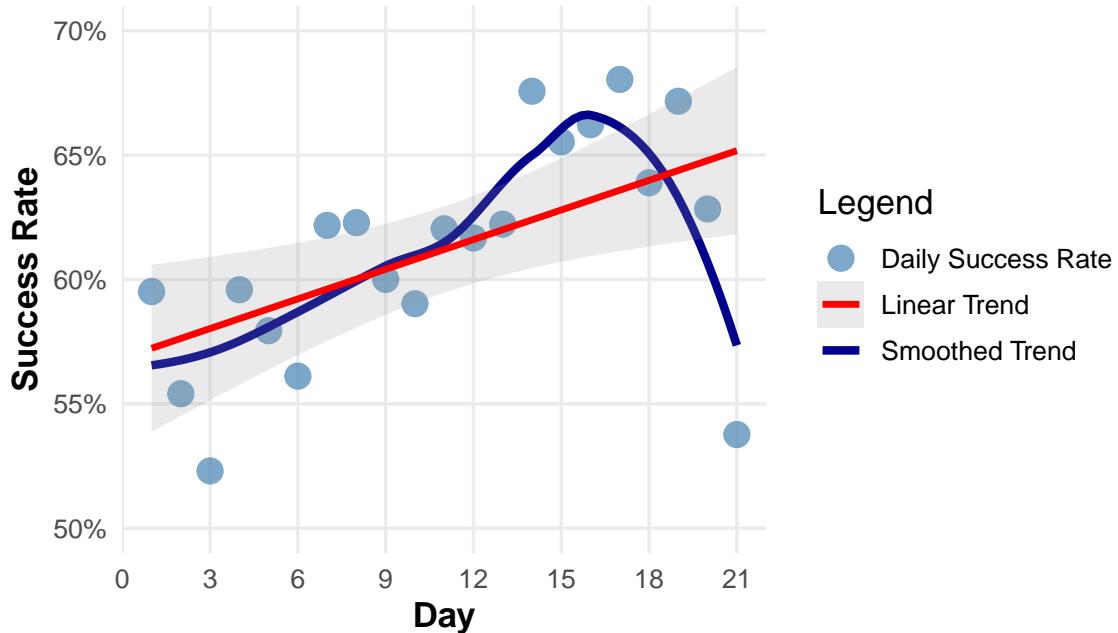
```

# 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(Interval):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

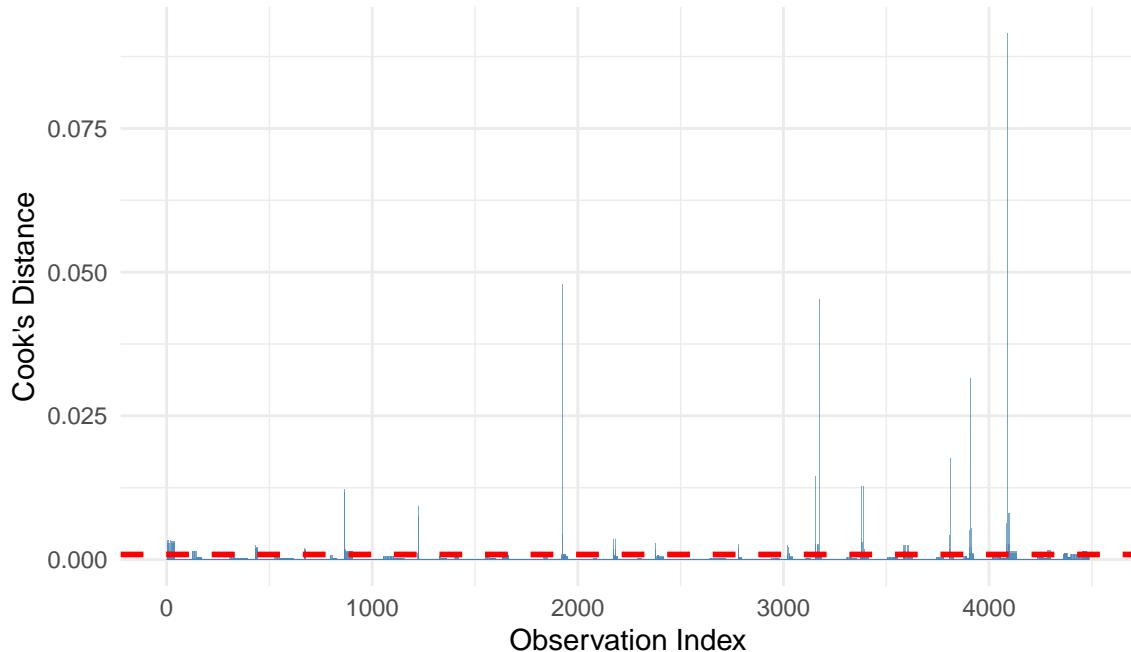
# 8. Influential Points
interval_data$cooks_d = cooks.distance(best_model)

# 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)], ")")

  # 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
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## 1000 0.8595456 0.007869814 0
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## 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
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## 1013 0.8595456 0.007869814 0
## 1014 0.8595456 0.007869814 0
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## 1017 0.8595456 0.007869814 0
## 1018 0.8595456 0.007869814 0

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## 1066 0.8595456 0.007869814 0

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## 1114 0.8595456 0.007869814 0

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## 1143 0.8717751 0.008900356 0
## 1144 0.8717751 0.008900356 0
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## 1146 0.8717751 0.008900356 0
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## 1156 0.8717751 0.008900356 0
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## 1158 0.8717751 0.008900356 0
## 1159 0.8717751 0.008900356 0
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## 1162 0.8717751 0.008900356 0

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## 1167 0.8717751 0.008900356 0
## 1168 0.8717751 0.008900356 0
## 1169 0.8717751 0.008900356 0
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## 1172 0.8717751 0.008900356 0
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## 1189 0.8717751 0.008900356 0
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## 1192 0.8717751 0.008900356 0
## 1193 0.8717751 0.008900356 0
## 1194 0.8717751 0.008900356 0
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## 1204 0.8717751 0.008900356 0
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## 1252 0.8834336 0.010039112 0
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## 1256 0.8834336 0.010039112 0
## 1257 0.8834336 0.010039112 0
## 1258 0.8834336 0.010039112 0

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## 1303 0.8944998 0.011292742 0
## 1304 0.8944998 0.011292742 0
## 1305 0.8944998 0.011292742 0
## 1306 0.8944998 0.011292742 0

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## 1307 0.8944998 0.011292742 0
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## 1348 0.8944998 0.011292742 0
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## 1352 0.8944998 0.011292742 0
## 1353 0.8944998 0.011292742 0
## 1354 0.9049565 0.012667503 1

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## 1355 0.9049565 0.012667503 1
## 1356 0.9049565 0.012667503 0
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## 1358 0.9049565 0.012667503 0
## 1359 0.9049565 0.012667503 0
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## 1368 0.9049565 0.012667503 0
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## 1388 0.9049565 0.012667503 0
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## 1401 0.9049565 0.012667503 0
## 1402 0.9049565 0.012667503 0

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## 1450 0.9147906 0.014169081 0

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## 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
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## 1523 0.9239933 0.015802404 0
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## 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
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## 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
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## 1586 0.9325609 0.017571453 0
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## 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
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## 1619 0.9404939 0.019479057 0
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## 1622 0.9404939 0.019479057 0
## 1623 0.9404939 0.019479057 0
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## 1625 0.9404939 0.019479057 0
## 1626 0.9404939 0.019479057 0
## 1627 0.9404939 0.019479057 0
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## 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
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## 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
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## 1687 0.9477977 0.021526693 0
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## 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
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## 1723 0.9544826 0.023714285 0
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## 1728 0.9544826 0.023714285 0
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## 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.

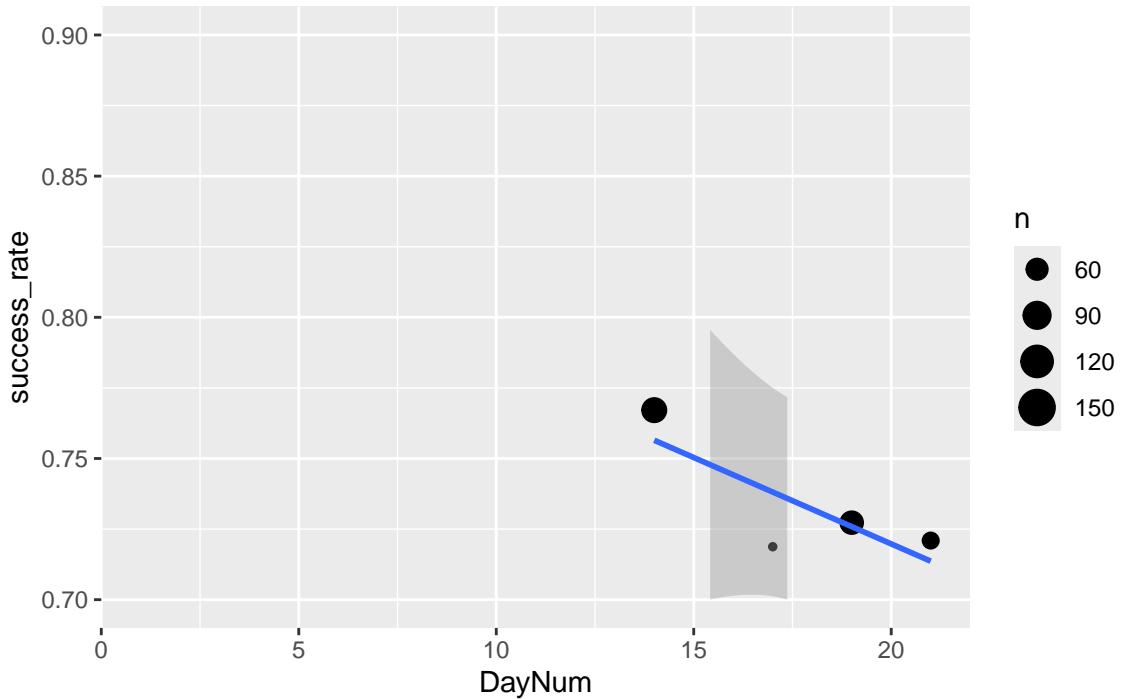
Priority 3: Visual Inspection

```

# 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?")

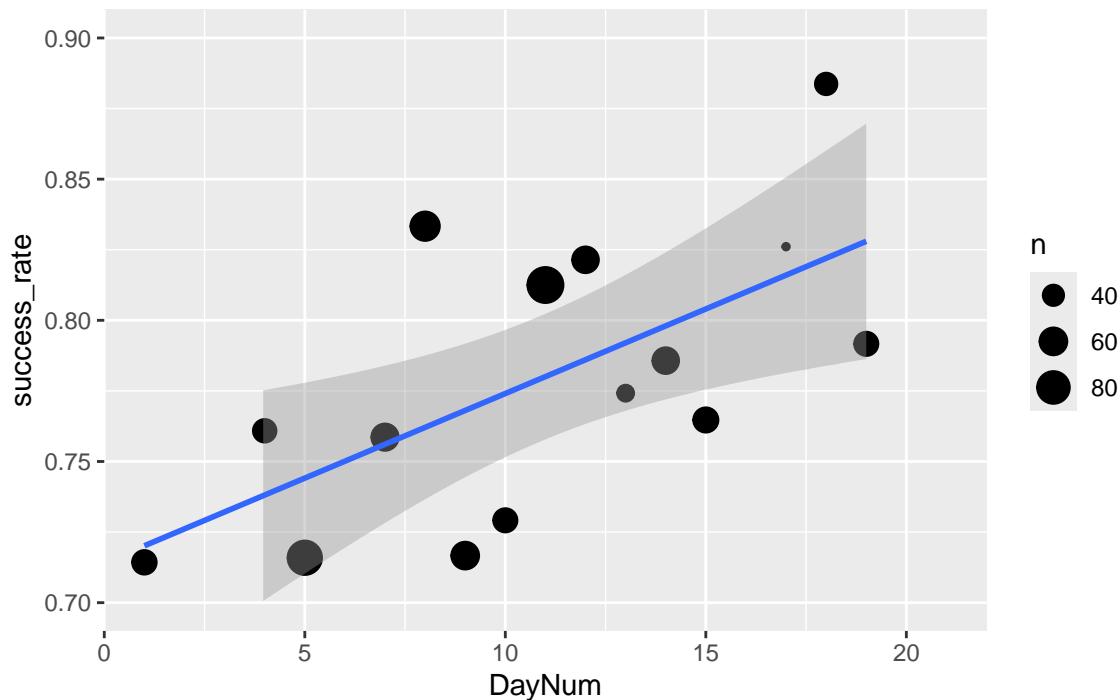
```

## W1\_1 Success Rate Over Time – Does This Look Real?



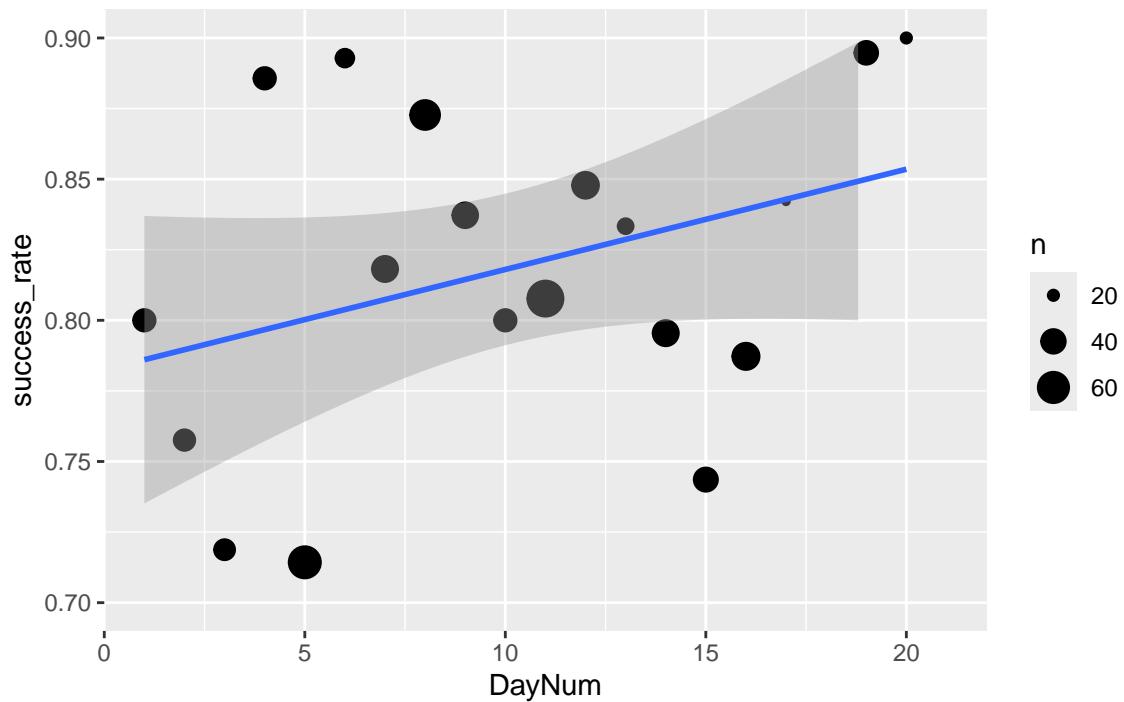
```
# Plot W1_2 success rate over time
interval_data %>%
  filter(Interval == 2) %>%
  group_by(DayNum) %>%
  summarize(success_rate = mean(Success), n = n()) %>%
  ggplot(aes(x = DayNum, y = success_rate)) +
  geom_point(aes(size = n)) +
  geom_smooth(method = "lm", se = TRUE) +
  scale_y_continuous(limits = 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?



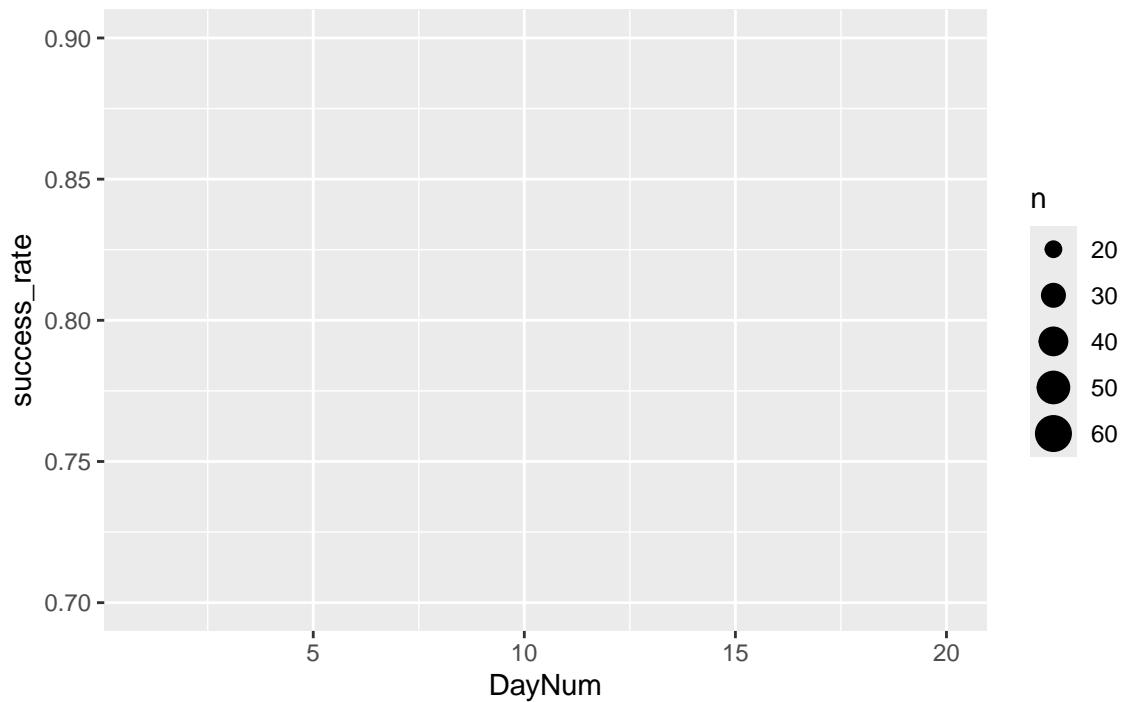
```
# Plot W4_1 success rate over time
interval_data %>%
  filter(Interval == 3) %>%
  group_by(DayNum) %>%
  summarize(success_rate = mean(Success), n = n()) %>%
  ggplot(aes(x = DayNum, y = success_rate)) +
  geom_point(aes(size = n)) +
  geom_smooth(method = "lm", se = TRUE) +
  scale_y_continuous(limits = 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?



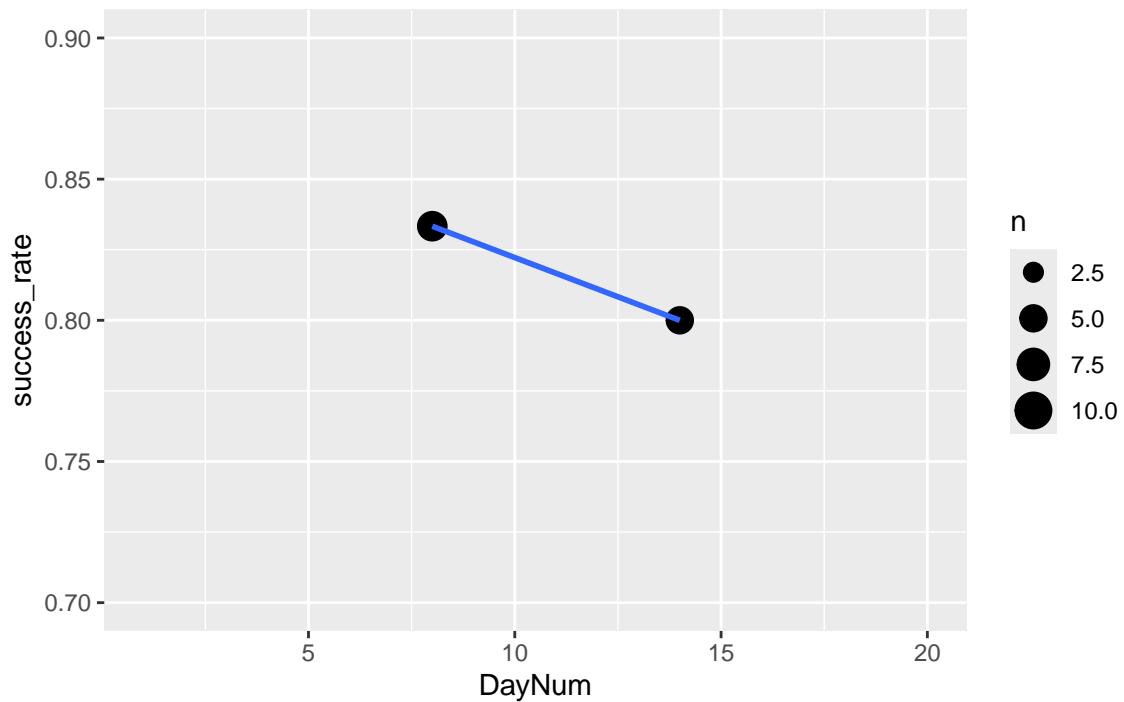
```
# Plot W4_2 success rate over time
interval_data %>%
  filter(Interval == 4) %>%
  group_by(DayNum) %>%
  summarize(success_rate = mean(Success), n = n()) %>%
  ggplot(aes(x = DayNum, y = success_rate)) +
  geom_point(aes(size = n)) +
  geom_smooth(method = "lm", se = TRUE) +
  scale_y_continuous(limits = 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?



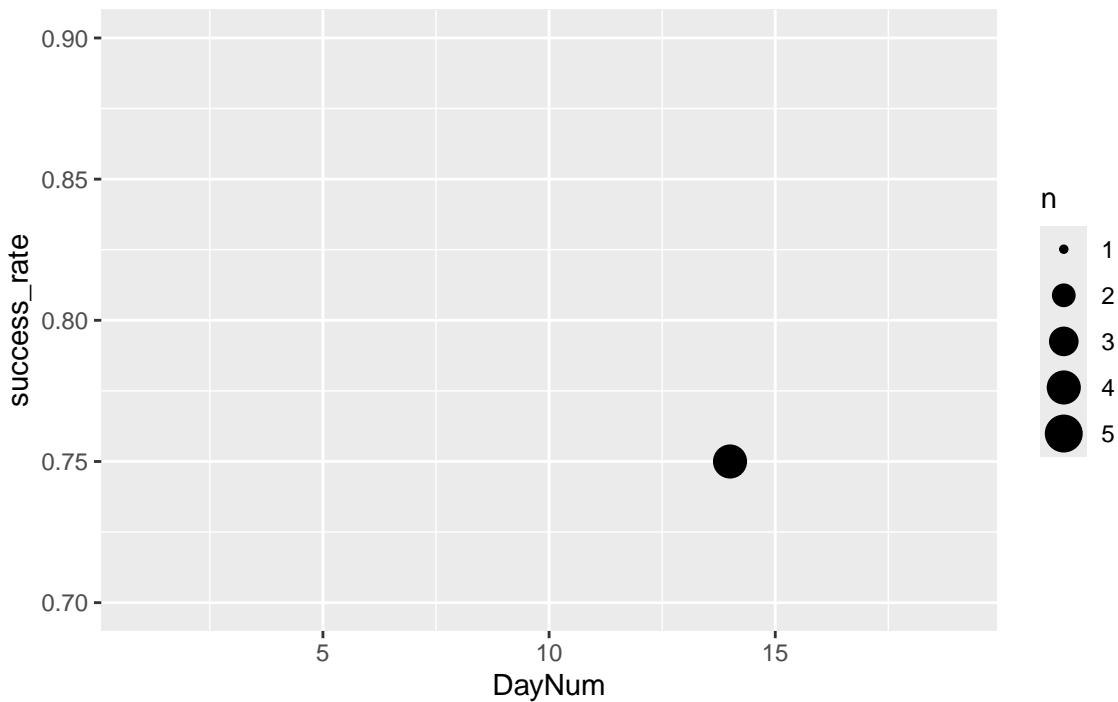
```
# Plot W8_1 success rate over time
interval_data %>%
  filter(Interval == 5) %>%
  group_by(DayNum) %>%
  summarize(success_rate = mean(Success), n = n()) %>%
  ggplot(aes(x = DayNum, y = success_rate)) +
  geom_point(aes(size = n)) +
  geom_smooth(method = "lm", se = TRUE) +
  scale_y_continuous(limits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

## W8\_1 Success Rate Over Time – Does This Look Real?



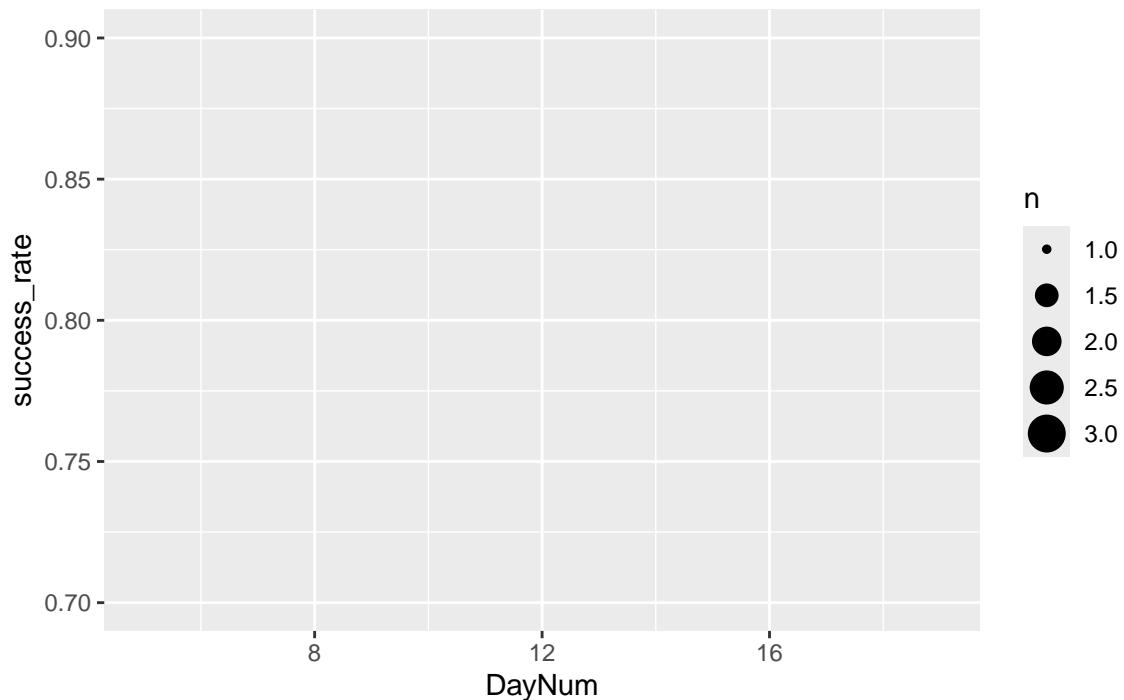
```
# Plot W8_2 success rate over time
interval_data %>%
  filter(Interval == 6) %>%
  group_by(DayNum) %>%
  summarize(success_rate = mean(Success), n = n()) %>%
  ggplot(aes(x = DayNum, y = success_rate)) +
  geom_point(aes(size = n)) +
  geom_smooth(method = "lm", se = TRUE) +
  scale_y_continuous(limits = 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?



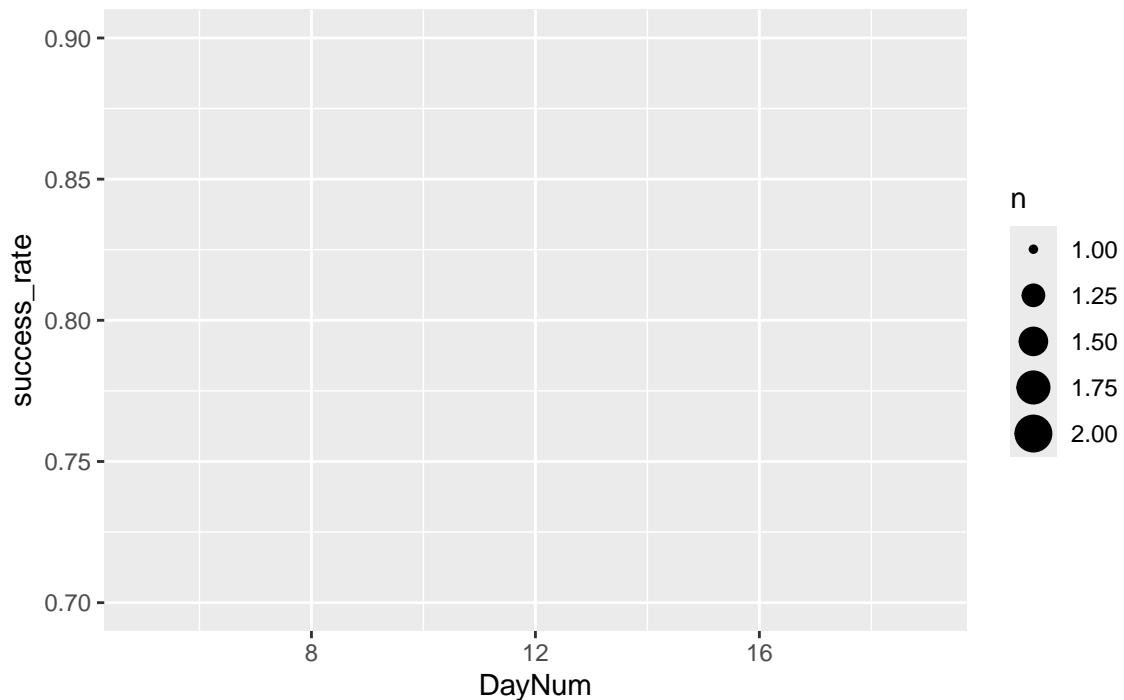
```
# Plot W8_3 success rate over time
interval_data %>%
  filter(Interval == 7) %>%
  group_by(DayNum) %>%
  summarize(success_rate = mean(Success), n = n()) %>%
  ggplot(aes(x = DayNum, y = success_rate)) +
  geom_point(aes(size = n)) +
  geom_smooth(method = "lm", se = TRUE) +
  scale_y_continuous(limits = 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?")
```

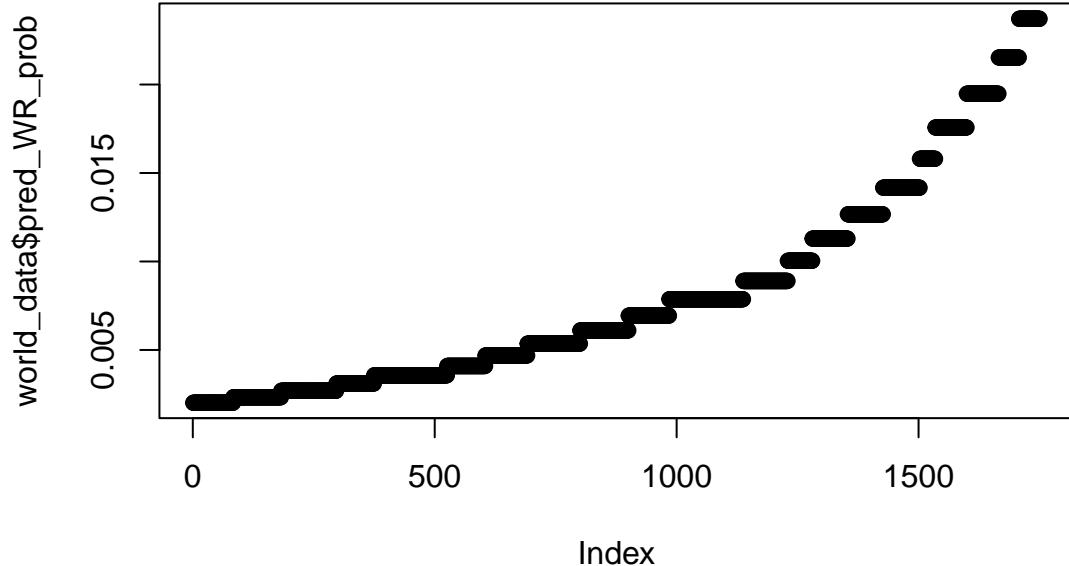
## W8\_4 Success Rate Over Time – Does This Look Real?



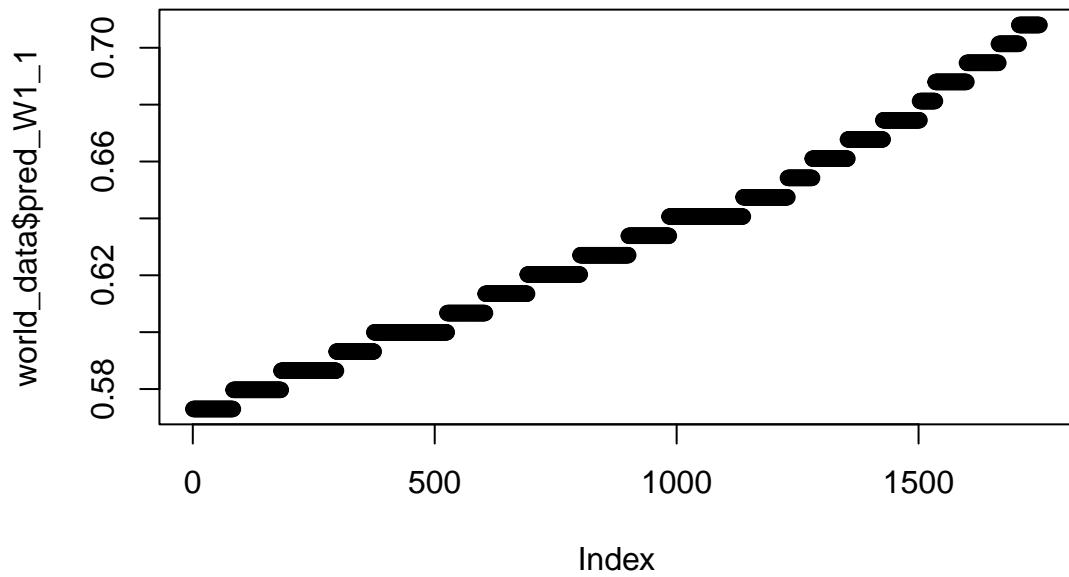
```
# interval_data %>%
#   filter(Interval == 5)
```

Analyze Results

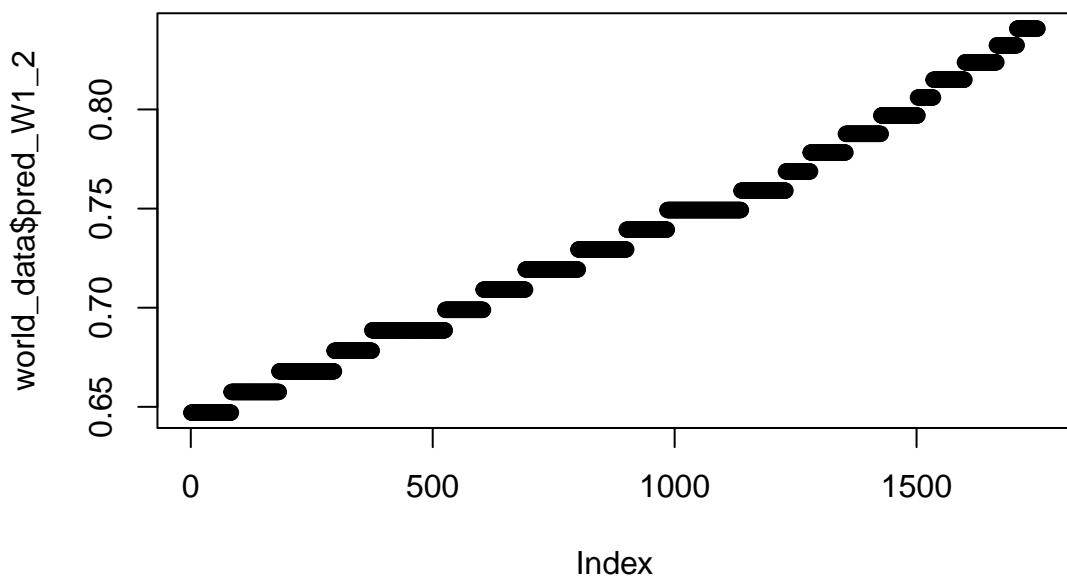
```
plot(world_data$pred_WR_prob)
```



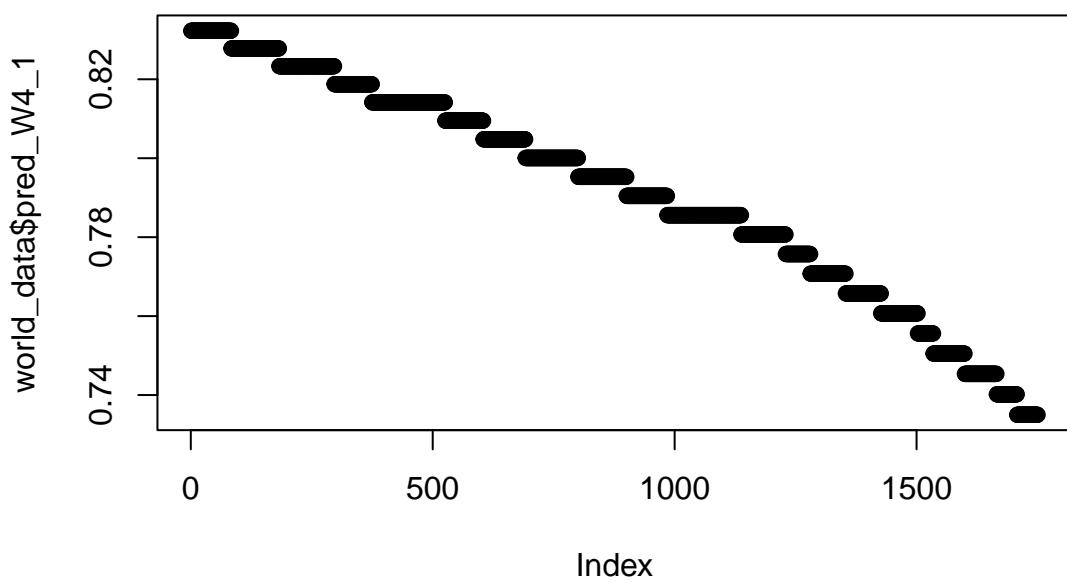
```
plot(world_data$pred_W1_1)
```



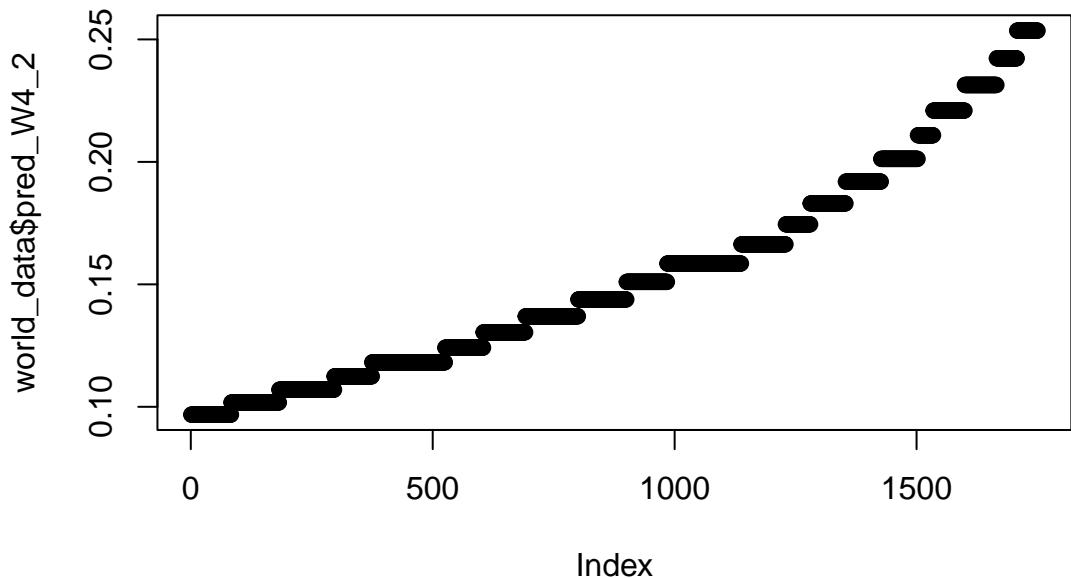
```
plot(world_data$pred_W1_2)
```



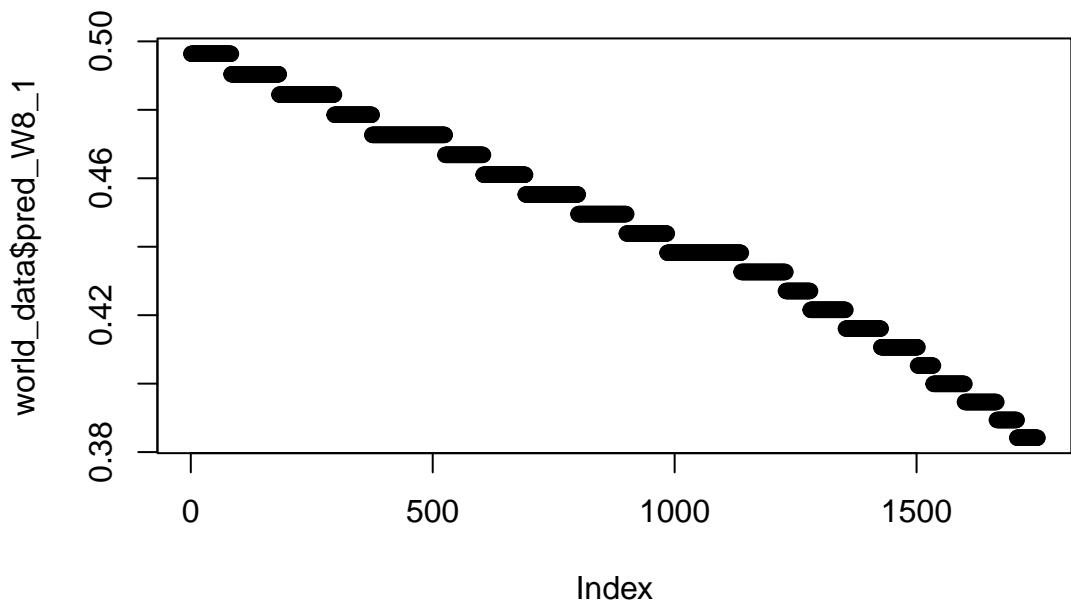
```
plot(world_data$pred_W4_1)
```



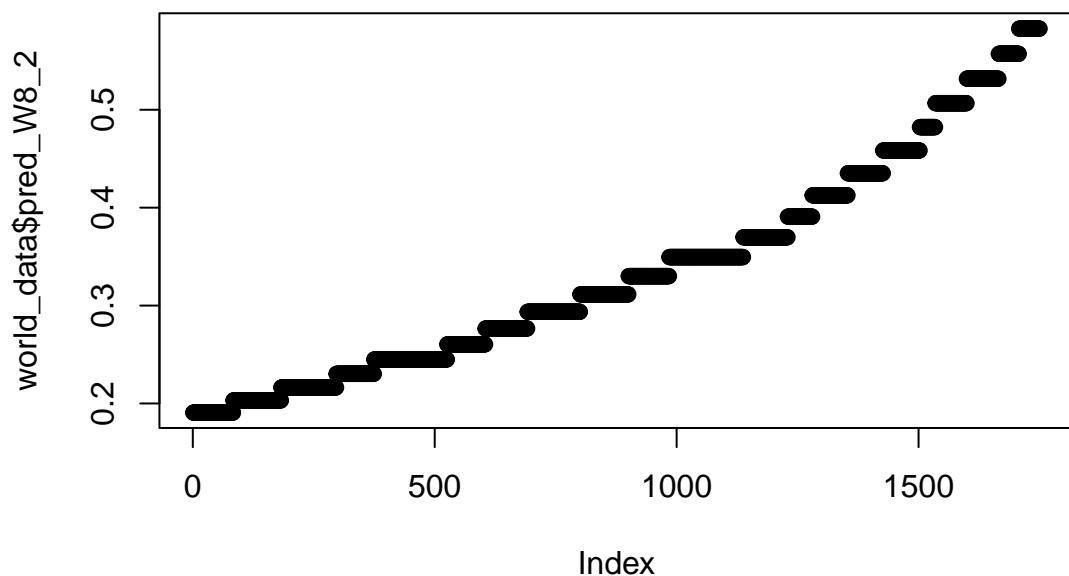
```
plot(world_data$pred_W4_2)
```



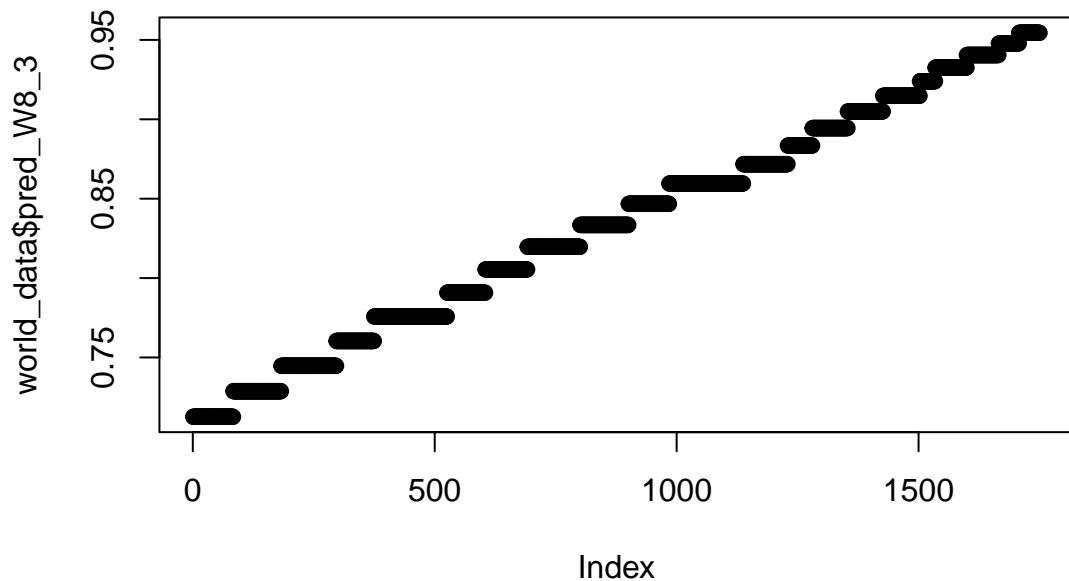
```
plot(world_data$pred_W8_1)
```



```
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"))

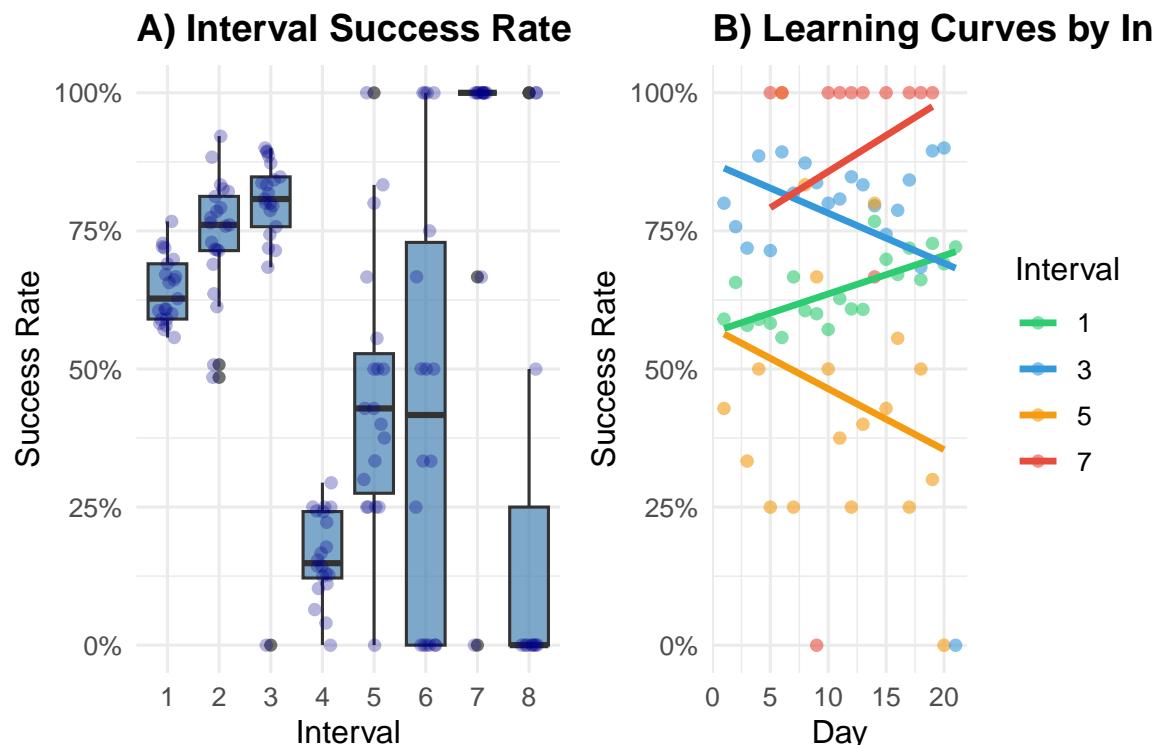
# Panel B: Improvement over time by interval
panel_b <- ggplot(interval_success_by_day %>% filter(Interval %in% c(1, 3, 5, 7)),
  aes(x = DayNum, y = success_rate, color = factor(Interval))) +
  geom_point(alpha = 0.6) +
```

```

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=====\\n")

```

```

## =====
## =====

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

```

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

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