TFT_Revised_241108

Hana Kwon, WB Macleod

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Introduction

This document details the approach used to identify player strategies *(Tit-for-Tat, Grim, Always Cooperate, and Always Defect)* and calculate payoffs in an experimental dataset.

Definitions and Assumptions

- **Payoff Values**
  - `r`: *(Reward)* Payoff for mutual cooperation
  - `s`: *(Sucker)* Payoff when one cooperates and the other defects
  - `t`: *(Temptation)* Payoff for defection when the other cooperates
  - `p`: *(Punishment)* Payoff for mutual defection
- **Strategies**
  1. **Always Cooperate**: Player cooperates in all rounds.
  2. **Always Defect**: Player defects in all rounds.
  3. **Grim**: Player starts by cooperating and defects permanently if the opponent defects.
  4. **Tit-for-Tat**: Player mirrors the opponent's previous move.
- **Dataset Information**
  - `session`: Experiment session number.
  - `id`: Participant ID.
  - `oid`: Partner's ID.
  - `supergame`: Match number.
  - `round`: Round number within a supergame.
  - `horizon`: Length of supergame.
  - `coop`: Cooperation indicator (1 if cooperated, 0 otherwise).
  - `r`, `s`, `t`, `p`: Payoff values based on cooperation and defection as described above.

Analysis Overview

- **Core Analysis**
  1. Data Loading and Initial Exploration
  2. Data Preparation and Preprocessing

Core Analysis

Step 1: Data Loading, Initial Exploration, and Preparation

- **Objective:** Load the dataset and examine its structure to ensure successful data import and check for any missing values.

```r
### 1.1 Load Necessary Libraries and Dataset
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```r
library(readr)
library(ggplot2)

file_data <- "/Users/hanakwon/Desktop/0_RA_McLeod_TFT/Embrey_2018a_new_data.txt"
data <- read.table(file_data, header = TRUE, sep = "\t", stringsAsFactors = FALSE)

### 1.2 Initial Data Exploration
str(data)      # Check the structure of the data
```

```
## 'data.frame':    33360 obs. of  14 variables:
##  $ id       : int  73 73 73 73 73 73 73 73 73 73 ...
##  $ oid      : int  77 80 75 78 81 86 83 85 74 82 ...
##  $ supergame: int  1 2 3 4 5 6 7 8 9 10 ...
##  $ round    : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ horizon  : int  8 8 8 8 8 8 8 8 8 8 ...
##  $ r        : int  51 51 51 51 51 51 51 51 51 51 ...
##  $ s        : int  22 22 22 22 22 22 22 22 22 22 ...
##  $ t        : int  63 63 63 63 63 63 63 63 63 63 ...
##  $ p        : int  39 39 39 39 39 39 39 39 39 39 ...
##  $ g        : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ l        : num  1.42 1.42 1.42 1.42 1.42 ...
##  $ sizebad  : num  0.191 0.191 0.191 0.191 0.191 ...
##  $ session  : int  4 4 4 4 4 4 4 4 4 4 ...
##  $ coop     : int  0 0 0 0 1 1 0 0 1 1 ...
```

```
summary(data)  # Summary of data to examine distributions and any NA values
```

```
##        id             oid          supergame         round      
##  Min.   :  1.0   Min.   :  1.0   Min.   : 1.00   Min.   :1.000  
##  1st Qu.: 98.0   1st Qu.: 98.0   1st Qu.: 7.00   1st Qu.:2.000  
##  Median :150.0   Median :150.0   Median :14.00   Median :3.000  
##  Mean   :152.3   Mean   :152.3   Mean   :14.28   Mean   :3.785  
##  3rd Qu.:212.0   3rd Qu.:212.0   3rd Qu.:21.00   3rd Qu.:5.000  
##  Max.   :284.0   Max.   :284.0   Max.   :30.00   Max.   :8.000  
##                                                                 
##     horizon            r            s              t               p     
##  Min.   :4.000   Min.   :51   Min.   : 5.0   Min.   :63.00   Min.   :39  
##  1st Qu.:4.000   1st Qu.:51   1st Qu.: 5.0   1st Qu.:63.00   1st Qu.:39  
##  Median :8.000   Median :51   Median : 5.0   Median :87.00   Median :39  
##  Mean   :6.571   Mean   :51   Mean   :13.4   Mean   :75.14   Mean   :39  
##  3rd Qu.:8.000   3rd Qu.:51   3rd Qu.:22.0   3rd Qu.:87.00   3rd Qu.:39  
##  Max.   :8.000   Max.   :51   Max.   :22.0   Max.   :87.00   Max.   :39  
##                                                                          
##        g               l            sizebad         session      
##  Min.   :1.000   Min.   :1.417   Min.   :0.191   Min.   : 1.000  
##  1st Qu.:1.000   1st Qu.:1.417   1st Qu.:0.415   1st Qu.: 5.000  
##  Median :3.000   Median :2.833   Median :0.415   Median : 7.000  
##  Mean   :2.012   Mean   :2.133   Mean   :0.504   Mean   : 6.954  
##  3rd Qu.:3.000   3rd Qu.:2.833   3rd Qu.:0.415   3rd Qu.: 9.000  
##  Max.   :3.000   Max.   :2.833   Max.   :1.000   Max.   :12.000  
##                                  NA's   :27700                   
##       coop       
##  Min.   :0.0000  
##  1st Qu.:0.0000  
##  Median :0.0000  
##  Mean   :0.3589  
##  3rd Qu.:1.0000  
##  Max.   :1.0000  
## 
```

Step 2: Data Preparation, Preprocessing, and PD Difficulty Setting

- **Objective:** Prepare player and opponent data frames to align cooperation values and payoff values for each round. Classify games by PD difficulty (EasyPD or HardPD) based on payoff values.
- **Code Updates (Nov 1, 2024) => 2x2 Design**

```r
###Updated
# Set normalized payoff values
data <- data %>%
  mutate(
    r = 1.0,               # Reward for mutual cooperation
    s = -l,                # Sucker's payoff
    t = 1.0 + g,           # Temptation payoff
    p = 0.0                # Punishment for mutual defection
  )

# Create player and opponent data frames
df_self <- data %>%
  select(id, oid, supergame, round, horizon, coop, r, s, t, p) %>%
  rename(player_id = id, opponent_id = oid, player_coop = coop)

df_opp <- data %>%
  select(id, oid, supergame, round, horizon, coop) %>%
  rename(opponent_id = id, player_id = oid, opponent_coop = coop)

# Merge player and opponent data
df_merged <- df_self %>%
  left_join(df_opp, by = c("player_id", "opponent_id", "supergame", "round", "horizon"))


# Add PD difficulty column
df_merged <- df_merged %>%
  mutate(pd_difficulty = case_when(
    abs(t - 2) < 0.1 & abs(s + 1.41) < 0.1 ~ "EasyPD",
    abs(t - 4) < 0.1 & abs(s + 2.8) < 0.1 ~ "HardPD",
    TRUE ~ NA_character_
  ))
```

Step 3: Descriptive Payoff Analysis

3.1 Payoff Calculation Based on Actions

- **Objective:** Calculate the payoff based on cooperation and defection combinations for each round and assign values to the `payoff` column.

```r
#Updated

# Calculate the Payoff Column Based on Actions
df_merged <- df_merged %>%
  mutate(payoff = case_when(
    player_coop == 1 & opponent_coop == 1 ~ r,  # Both Cooperate
    player_coop == 1 & opponent_coop == 0 ~ s,  # Only Player Cooperates
    player_coop == 0 & opponent_coop == 1 ~ t,  # Only Player Defects
    player_coop == 0 & opponent_coop == 0 ~ p,  # Both Defect
    TRUE ~ NA_real_                             # Default value for any unspecified cases
  ))

# Calculate payoffs
df_merged <- df_merged %>%
  mutate(payoff = case_when(
    player_coop == 1 & opponent_coop == 1 ~ r,
    player_coop == 1 & opponent_coop == 0 ~ s,
    player_coop == 0 & opponent_coop == 1 ~ t,
    player_coop == 0 & opponent_coop == 0 ~ p,
    TRUE ~ NA_real_
  ))

# Verify that the 'payoff' column exists
if (!"payoff" %in% colnames(df_merged)) {
  stop("Error: 'payoff' column was not created.")
} else {
  print("Payoff column created successfully.")
}
```

```
## [1] "Payoff column created successfully."
```

3.2 Round-by-Round Average Payoff Calculation

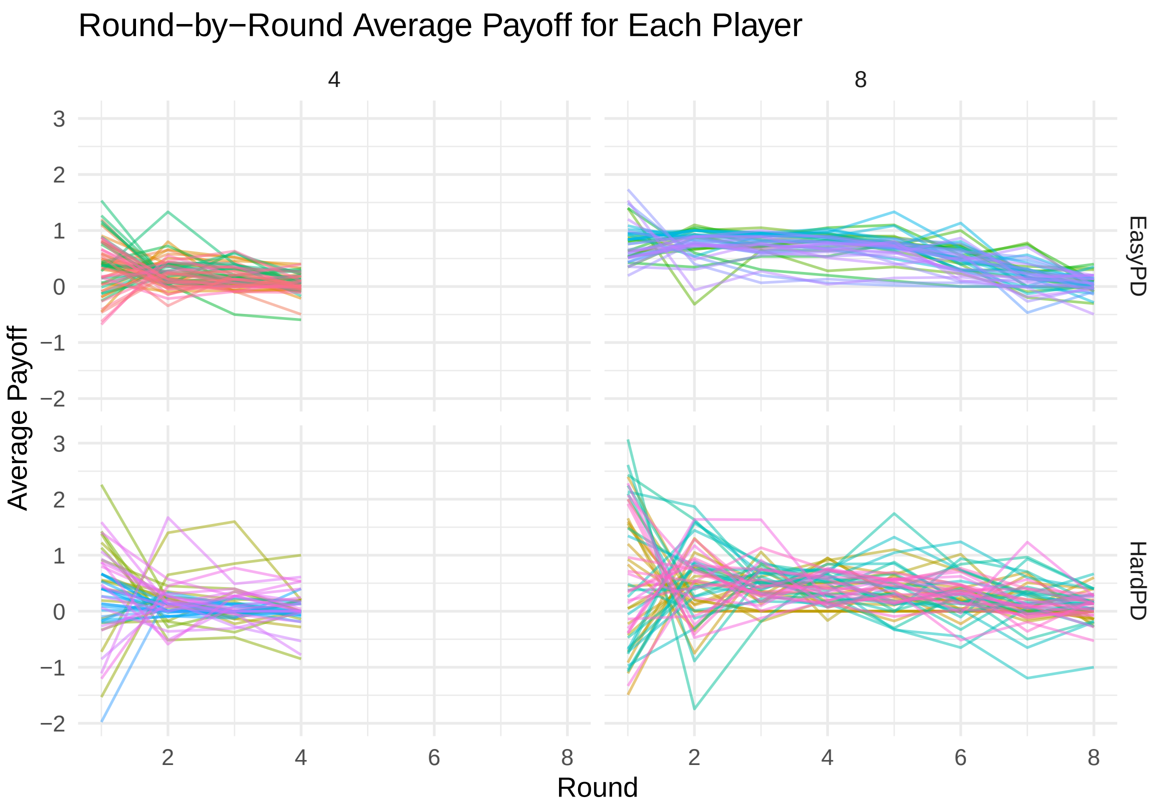
- **Objective:** Calculate the round-by-round average payoff for each player and visualize changes in performance over each round.
- **Code Updates (Nov 1, 2024) => 2x2 Design**

  ```
  # 3.2 Round-by-Round Average Payoff Calculation with 2x2 Design

  round_avg_payoff <- df_merged %>%
    group_by(player_id, round, horizon, pd_difficulty) %>%
    summarize(avg_round_payoff = mean(payoff, na.rm = TRUE), .groups = "drop")

  print(round_avg_payoff)
  ```

  ```
  ## # A tibble: 1,248 x 5
  ##    player_id round horizon pd_difficulty avg_round_payoff
  ##        <int> <int>   <int> <chr>                    <dbl>
  ##  1         1     1       4 EasyPD                  0.829
  ##  2         1     2       4 EasyPD                  0.0875
  ##  3         1     3       4 EasyPD                 -0.0708
  ##  4         1     4       4 EasyPD                 -0.0708
  ##  5         2     1       4 EasyPD                  0.446
  ##  6         2     2       4 EasyPD                  0.387
  ##  7         2     3       4 EasyPD                  0.437
  ##  8         2     4       4 EasyPD                 -0.0417
  ```

```
##  9          3     1       4 EasyPD                      0.408
## 10          3     2       4 EasyPD                      0.129
## # i 1,238 more rows
```

```
# Visualization: Round-by-Round Payoff Distribution for Each Player in 2x2 Design
ggplot(round_avg_payoff, aes(x = round, y = avg_round_payoff, color = factor(player_id), group = pl
  geom_line(alpha = 0.5) +
  labs(title = "Round-by-Round Average Payoff for Each Player", x = "Round", y = "Average Payoff")
  facet_grid(pd_difficulty ~ horizon) +  # 2x2 design: Difficulty by Game Length
  theme_minimal() +
  theme(legend.position = "none")
```

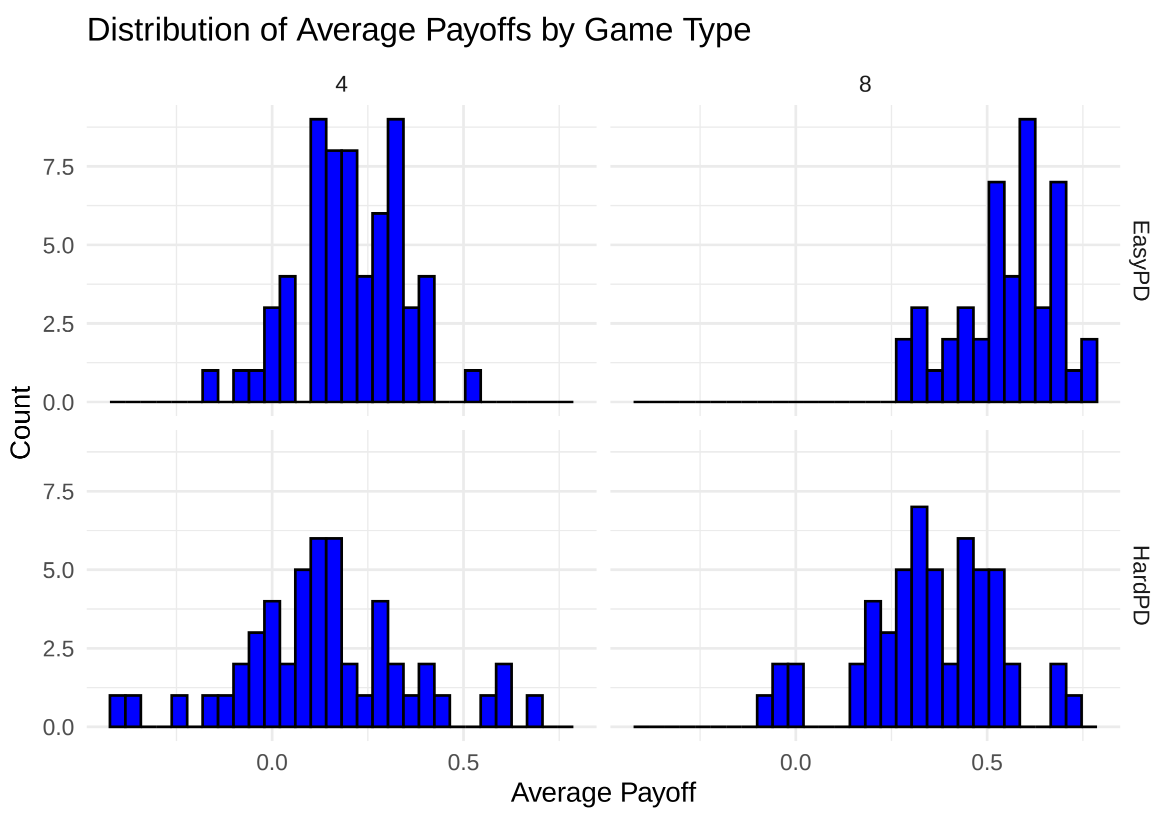


3.3 Average Payoff and Variance Calculation per Player

- **Objective:** Calculate the overall average payoff and payoff variance for each player to understand the distribution of player performance.
- **Code Updates (Nov 1, 2024) => 2x2 Design**

```
avg_payoff_variance <- df_merged %>%
  group_by(player_id, horizon, pd_difficulty) %>%
  summarize(
    avg_payoff = mean(payoff, na.rm = TRUE),
    payoff_variance = var(payoff, na.rm = TRUE),
    .groups = "drop"
  )
```

```r
# Visualization with 2x2 Design
ggplot(avg_payoff_variance, aes(x = avg_payoff)) +
  geom_histogram(bins = 30, fill = "blue", color = "black") +
  facet_grid(pd_difficulty ~ horizon) +
  labs(title = "Distribution of Average Payoffs by Game Type", x = "Average Payoff", y = "Count") +
  theme_minimal()
```



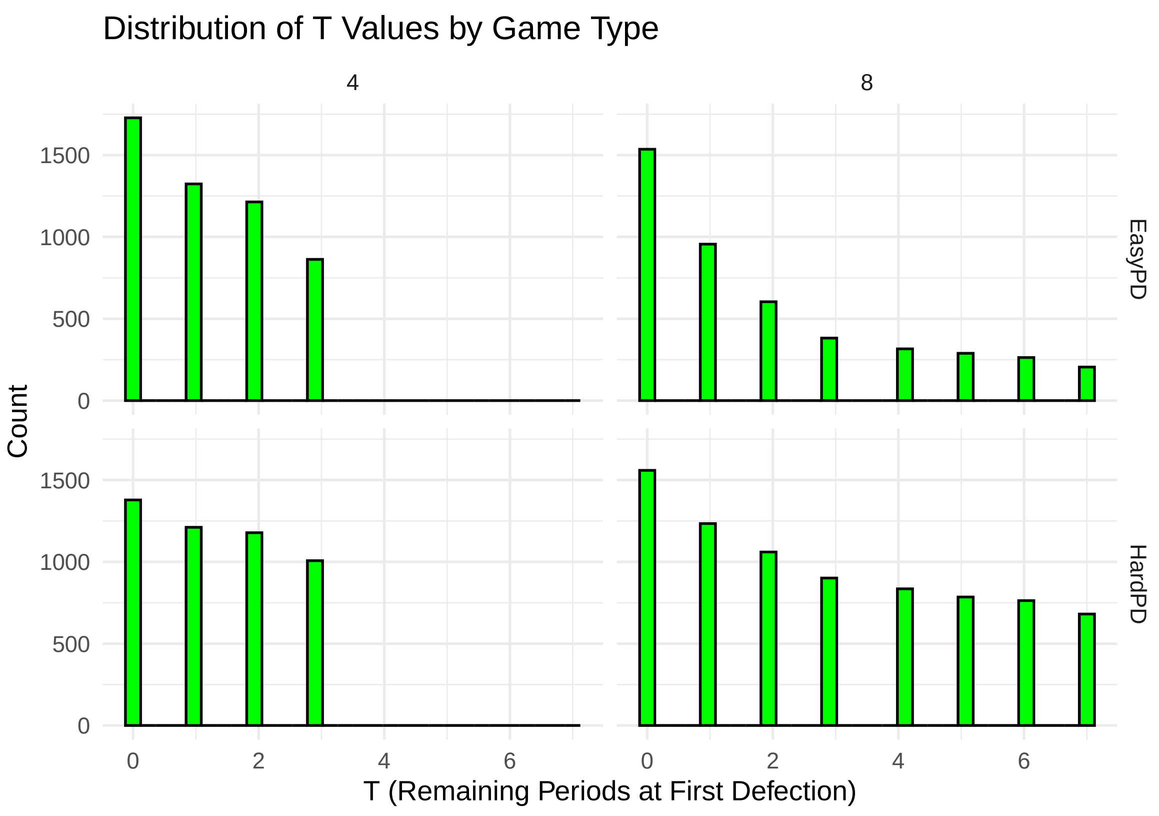
3.4 'T' Value Calculation and Distribution Visualization

- **Objective:** Calculate T value (the number of remaining rounds when a player first defects) and visualize the distribution of T values.
- **Code Updates (Nov 1, 2024) => 2x2 Design**

```r
df_merged <- df_merged %>%
  group_by(player_id, supergame) %>%
  mutate(
    first_defect_round = ifelse(player_coop == 0 & !is.na(player_coop), round, NA),
    T = ifelse(!is.na(first_defect_round), horizon - first_defect_round, ifelse(all(player_coop ==
  ) %>%
  ungroup()

print(df_merged %>% select(player_id, supergame, round, player_coop, horizon, T))
```

```
## # A tibble: 33,360 x 6
##    player_id supergame round player_coop horizon     T
##        <int>     <int> <int>       <int>   <int> <dbl>
##  1        73         1     1           0       8     7
##  2        73         2     1           0       8     7
##  3        73         3     1           0       8     7
##  4        73         4     1           0       8     7
##  5        73         5     1           1       8     0
##  6        73         6     1           1       8    NA
##  7        73         7     1           0       8     7
##  8        73         8     1           0       8     7
##  9        73         9     1           1       8    NA
## 10        73        10     1           1       8    NA
## # i 33,350 more rows
```

```
# Visualization: Distribution of T Values with 2x2 Design
ggplot(df_merged %>% filter(!is.na(T)), aes(x = T)) +
  geom_histogram(bins = 30, fill = "green", color = "black") +
  facet_grid(pd_difficulty ~ horizon) +
  labs(title = "Distribution of T Values by Game Type", x = "T (Remaining Periods at First Defectio
  theme_minimal()
```



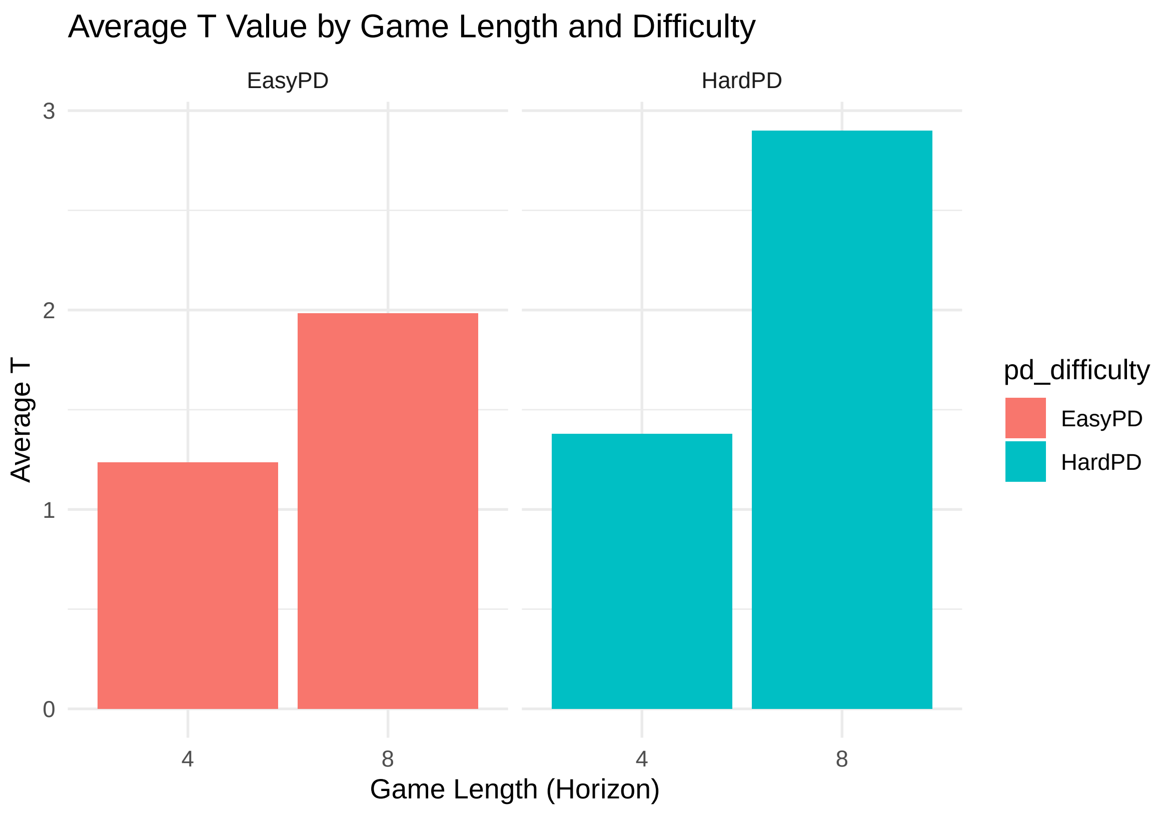
3.5 Cross-Tabulation of T Values by Game Length

- **Objective:** Summarize T values by game length (horizon) to show mean and standard deviation of T for each horizon and visualize these statistics.
- **Code Updates (Nov 1, 2024) => 2x2 Design**

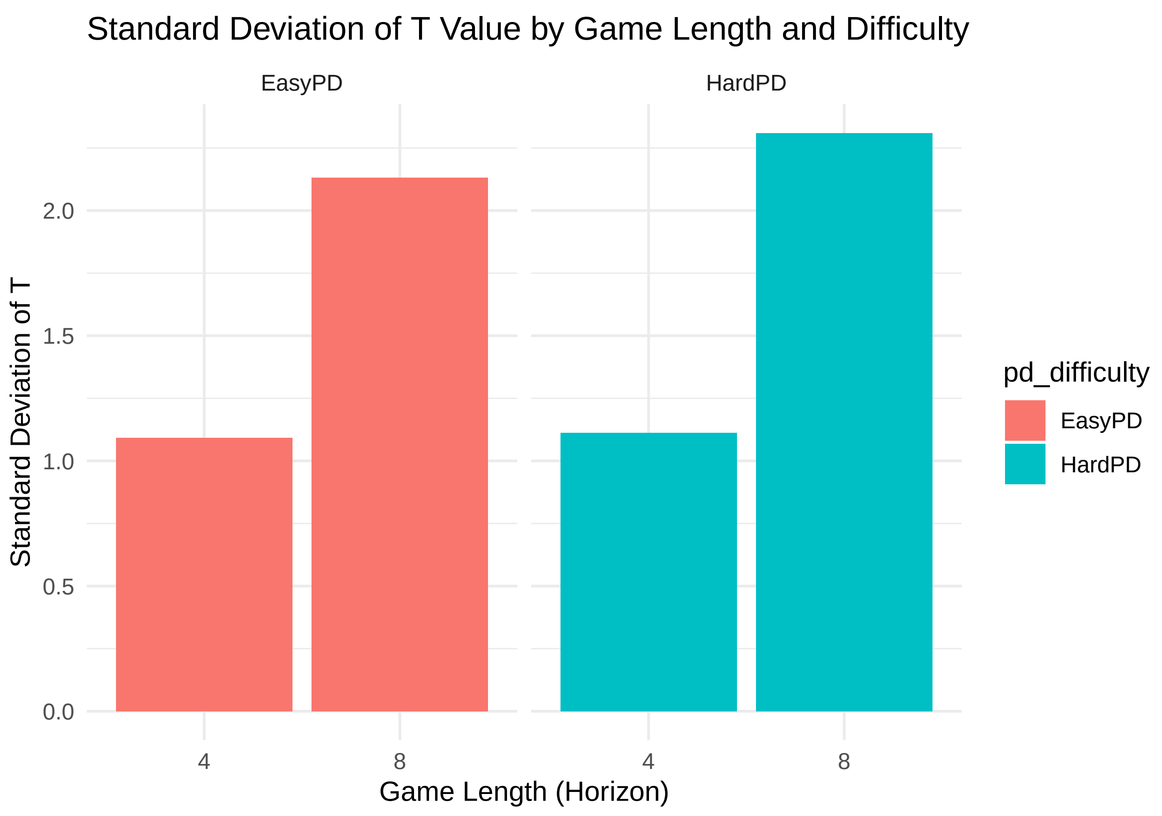
```r
# Update T_summary to group by both horizon and pd_difficulty
T_summary <- df_merged %>%
  group_by(horizon, pd_difficulty) %>%
  summarise(
    mean_T = mean(T, na.rm = TRUE),
    sd_T = sd(T, na.rm = TRUE),
    count = n(),
    .groups = "drop"
  )

print(T_summary)
```

```
## # A tibble: 4 x 5
##   horizon pd_difficulty mean_T  sd_T count
##     <int> <chr>          <dbl> <dbl> <int>
## 1       4 EasyPD          1.24  1.09  6560
## 2       4 HardPD          1.38  1.11  5360
## 3       8 EasyPD          1.98  2.13  9920
## 4       8 HardPD          2.90  2.31 11520
```

```r
# Visualization: Average T Value by Game Length and Difficulty
ggplot(T_summary, aes(x = factor(horizon), y = mean_T, fill = pd_difficulty)) +
  geom_bar(stat = "identity", position = "dodge") +
  facet_wrap(~ pd_difficulty) +
  labs(title = "Average T Value by Game Length and Difficulty", x = "Game Length (Horizon)", y = "A
  theme_minimal()
```



```r
# Visualization: Standard Deviation of T Value by Game Length and Difficulty
ggplot(T_summary, aes(x = factor(horizon), y = sd_T, fill = pd_difficulty)) +
  geom_bar(stat = "identity", position = "dodge") +
  facet_wrap(~ pd_difficulty) +
  labs(title = "Standard Deviation of T Value by Game Length and Difficulty", x = "Game Length (Ho
  theme_minimal()
```



Step 4: Strategy Identification

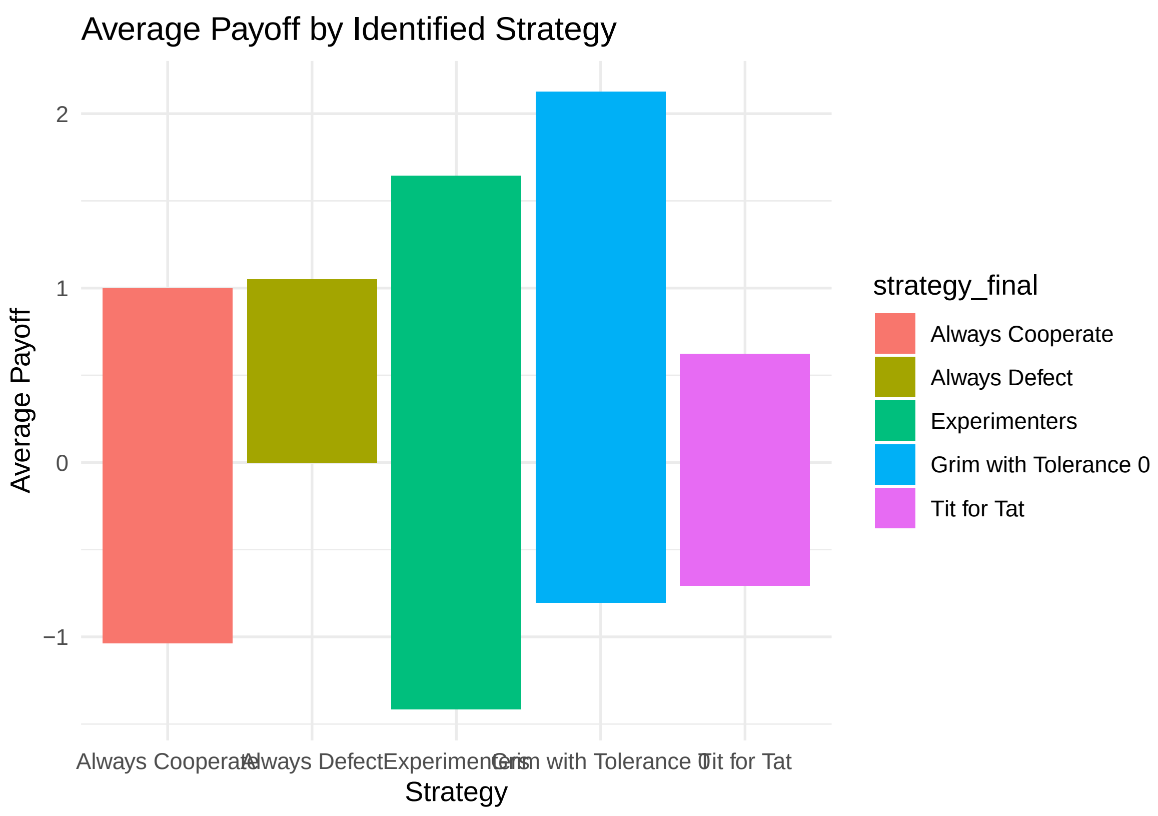
- **Objective:** Define a function to classify player strategies (Always Cooperate, Always Defect, Grim, Tit-for-Tat, and Experimenter) and merge the identified strategies with the main dataset.
- **Code Updates (Nov 1, 2024) => 2x2 Design**
- **Code Updates (Nov 5, 2024) => Added Grim strategy refinement with tolerance levels (G_0, G_1, G_2) and implemented interaction-based strategy classification.**

```r
# 4.1: Apply Grim strategy tolerance refinement (G_0, G_1, G_2)
df_merged <- df_merged %>%
  mutate(
    G_0 = if_else(player_coop == 1 & lag(opponent_coop, default = 1) == 0, 1, 0),
    G_1 = if_else(lag(player_coop, 1, default = 1) == 1 & lag(opponent_coop, 1, default = 1) == 0,
    G_2 = if_else(lag(player_coop, 2, default = 1) == 1 & lag(opponent_coop, 2, default = 1) == 0,
  )
```

```r
# 4.2: Define function for interaction-based strategy classification
identify_strategy <- function(player_coop, opponent_coop, tolerance) {

  # Check for Always Cooperate (AC)
  if (all(player_coop == 1, na.rm = TRUE)) {
    return("Always Cooperate")
  }

  # Check for Always Defect (AD)
  if (all(player_coop == 0, na.rm = TRUE)) {
    return("Always Defect")
  }

  # Check for Grim strategy with varying levels of tolerance
  if (all((player_coop == 1) | (cumsum(opponent_coop == 0) <= tolerance), na.rm = TRUE)) {
    return(paste("Grim with Tolerance", tolerance))
  }

  # Check for Tit-for-Tat (TFT) - mirrors opponent's previous action
  if (length(player_coop) > 1 && all(player_coop[-1] == lag(opponent_coop)[-1], na.rm = TRUE)) {
    return("Tit for Tat")
  }

  # Default to Experimenters if no match
  return("Experimenters")
}

# 4.3: Apply the classification across interactions
df_merged <- df_merged %>%
  group_by(player_id, opponent_id, supergame) %>%
  mutate(
    strategy_label = identify_strategy(player_coop, opponent_coop, tolerance = 0), # Strict Grim
    strategy_label_tolerance_1 = identify_strategy(player_coop, opponent_coop, tolerance = 1), # Gr
    strategy_label_tolerance_2 = identify_strategy(player_coop, opponent_coop, tolerance = 2) # Gr
  ) %>%
  ungroup()

# 4.4: Check the consistency of strategy labels across different Grim tolerance levels
df_merged <- df_merged %>%
  mutate(
    strategy_final = case_when(
      strategy_label == "Always Cooperate" ~ "Always Cooperate",
      strategy_label == "Always Defect" ~ "Always Defect",
      strategy_label == "Tit for Tat" ~ "Tit for Tat",
      strategy_label == "Experimenters" ~ "Experimenters",
      TRUE ~ strategy_label # Defaulting to the primary Grim strategy identified
    )
  )

# 4.5: Print a summary of strategies by game for inspection
strategy_summary <- df_merged %>%
  group_by(player_id, strategy_final) %>%
  summarise(
    avg_payoff = mean(payoff, na.rm = TRUE),
    payoff_variance = var(payoff, na.rm = TRUE),
    count = n(),
    .groups = "drop"
  )

# Display strategy summary
print(strategy_summary)
```

```
## # A tibble: 665 x 5
##    player_id strategy_final        avg_payoff payoff_variance count
##        <int> <chr>                      <dbl>           <dbl> <int>
##  1         1 Always Defect             0.281           0.491    64
##  2         1 Grim with Tolerance 0    -0.563           2.92      4
##  3         1 Tit for Tat              -0.0208          1.27     12
##  4         2 Always Cooperate          0.396           1.46      4
##  5         2 Always Defect             0               0         8
##  6         2 Experimenters             0.474           1.14     52
##  7         2 Tit for Tat              -0.104           0.790    16
##  8         3 Always Defect             0.233           0.419    60
##  9         3 Experimenters            -0.0250          1.37     20
## 10         4 Always Defect             0.278           0.492    36
## # i 655 more rows
```

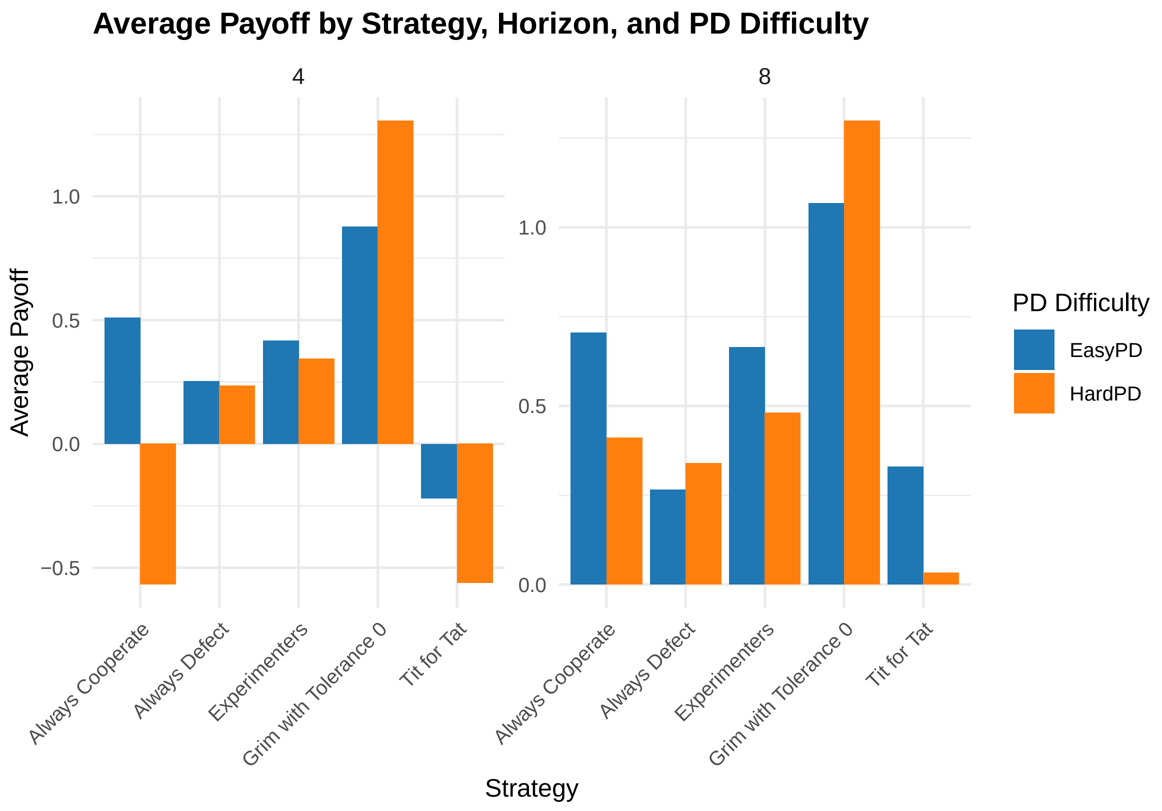
```r
# Visualization for average payoff by strategy
ggplot(strategy_summary, aes(x = strategy_final, y = avg_payoff, fill = strategy_final)) +
  geom_bar(stat = "identity", position = position_dodge()) +
  labs(title = "Average Payoff by Identified Strategy", x = "Strategy", y = "Average Payoff") +
  theme_minimal()
```



```r
# Calculate average payoff by strategy, horizon, and PD difficulty
strategy_payoff_difficulty <- df_merged %>%
  group_by(strategy_label, horizon, pd_difficulty) %>%
  summarise(
    avg_payoff = mean(payoff, na.rm = TRUE),
    payoff_variance = var(payoff, na.rm = TRUE),
    count = n(),
    .groups = "drop"
  )
# Print summary table
print(strategy_payoff_difficulty)
```

```
## # A tibble: 20 x 6
##    strategy_label        horizon pd_difficulty avg_payoff payoff_variance count
##    <chr>                   <int> <chr>              <dbl>           <dbl> <int>
##  1 Always Cooperate            4 EasyPD             0.510           0.949   212
##  2 Always Cooperate            4 HardPD            -0.568           3.59     88
##  3 Always Cooperate            8 EasyPD             0.704           0.629   376
##  4 Always Cooperate            8 HardPD             0.410           1.92    208
##  5 Always Defect               4 EasyPD             0.253           0.442  3076
##  6 Always Defect               4 HardPD             0.235           0.884  3768
##  7 Always Defect               8 EasyPD             0.266           0.461  1032
##  8 Always Defect               8 HardPD             0.340           1.24   3344
##  9 Experimenters               4 EasyPD             0.418           1.19   1336
## 10 Experimenters               4 HardPD             0.344           5.46    608
## 11 Experimenters                 8 EasyPD           0.664            0.610  5432
## 12 Experimenters                 8 HardPD           0.480            3.62   5328
## 13 Grim with Tolerance 0         4 EasyPD           0.878            1.19    288
## 14 Grim with Tolerance 0         4 HardPD           1.31             5.24    108
## 15 Grim with Tolerance 0         8 EasyPD           1.07             0.350   376
## 16 Grim with Tolerance 0         8 HardPD           1.30             2.73    192
## 17 Tit for Tat                   4 EasyPD          -0.220            0.656  1648
## 18 Tit for Tat                   4 HardPD          -0.562            2.19    788
## 19 Tit for Tat                   8 EasyPD           0.330            0.692  2704
## 20 Tit for Tat                   8 HardPD           0.0326           2.11   2448
```

```
#####========Updated_241101====================================================#####

# Visualization: Average Payoff by Strategy, Horizon, and PD Difficulty with adjusted text size
ggplot(strategy_payoff_difficulty, aes(x = strategy_label, y = avg_payoff, fill = pd_difficulty)) +
  geom_bar(stat = "identity", position = position_dodge()) +
  facet_wrap(~ horizon, scales = "free") +
  scale_fill_manual(values = c("EasyPD" = "#1f77b4", "HardPD" = "#ff7f0e", "NA" = "grey70")) +
  labs(title = "Average Payoff by Strategy, Horizon, and PD Difficulty",
       x = "Strategy",
       y = "Average Payoff",
       fill = "PD Difficulty") +
  theme_minimal() +
  theme(
    text = element_text(size = 10),  # Decrease overall text size
    axis.text.x = element_text(angle = 45, hjust = 1, size = 8),  # Rotate and reduce x-axis label
    strip.text = element_text(size = 9),  # Decrease size of facet labels
    plot.title = element_text(size = 12, face = "bold")  # Title size adjustment
  )
```

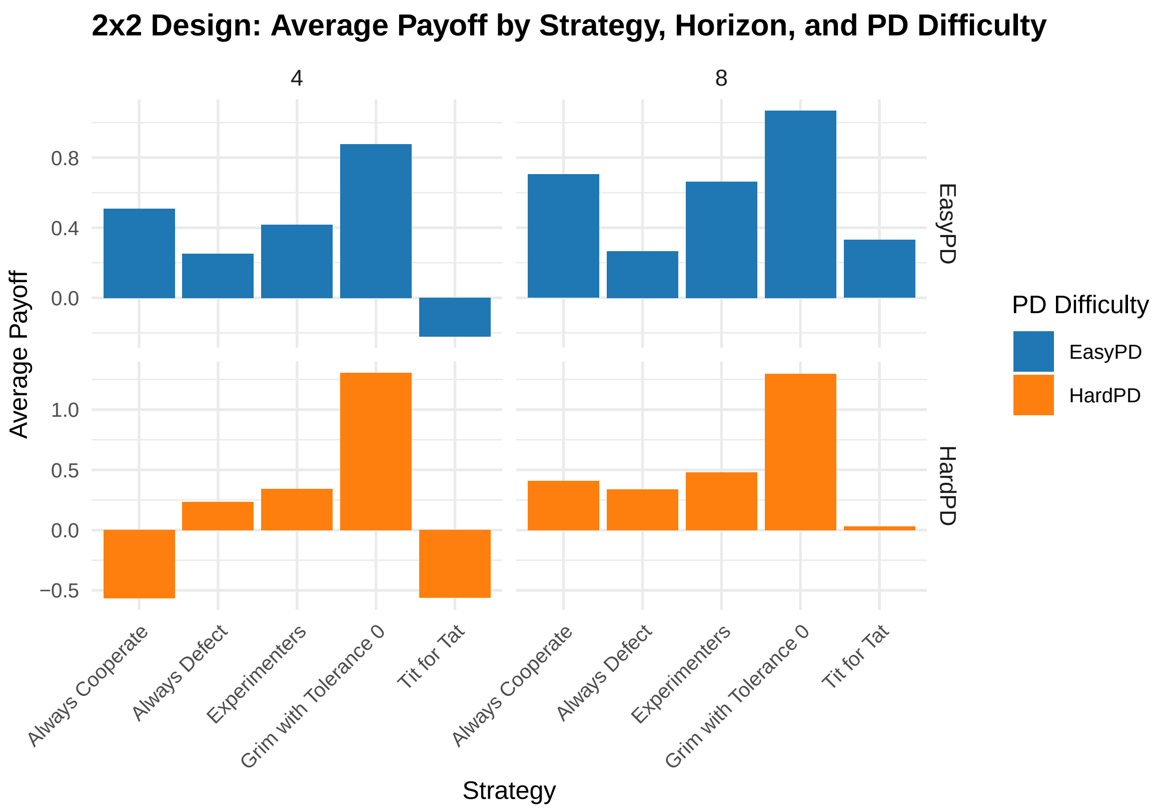


```
#==========================================================================#
```

Step 5: Strategy Payoff Analysis

- **Objective:** Analyze the average payoff and payoff variance for each identified strategy, segmented by game length (horizon) and PD difficulty level (EasyPD or HardPD). This step provides insights into the effectiveness of each strategy in different game conditions and helps identify which strategies yield higher payoffs across varying difficulty levels and game lengths.
- **Code Updates (Nov 1, 2024) => 2x2 Design**

```
# Calculate average payoff by strategy, horizon, and PD difficulty
strategy_payoff_summary <- df_merged %>%
  group_by(strategy_label, horizon, pd_difficulty) %>%
  summarise(
    avg_strategy_payoff = mean(payoff, na.rm = TRUE),
    payoff_variance = var(payoff, na.rm = TRUE),
    count = n(),
    .groups = "drop"
  )

# 2x2 Design Visualization with adjusted text size
ggplot(strategy_payoff_summary, aes(x = strategy_label, y = avg_strategy_payoff, fill = pd_difficul
  geom_bar(stat = "identity", position = position_dodge()) +
  facet_grid(pd_difficulty ~ horizon, scales = "free") +
  scale_fill_manual(values = c("EasyPD" = "#1f77b4", "HardPD" = "#ff7f0e", "NA" = "grey70")) +
  labs(title = "2x2 Design: Average Payoff by Strategy, Horizon, and PD Difficulty",
       x = "Strategy",
       y = "Average Payoff",
       fill = "PD Difficulty") +
  theme_minimal() +
  theme(
    text = element_text(size = 10),  # Adjust overall text size
    axis.text.x = element_text(angle = 45, hjust = 1, size = 8),  # Rotate and resize x-axis label
    strip.text = element_text(size = 9),  # Decrease facet label size
    plot.title = element_text(size = 12, face = "bold")  # Adjust title size and make bold
  )
```

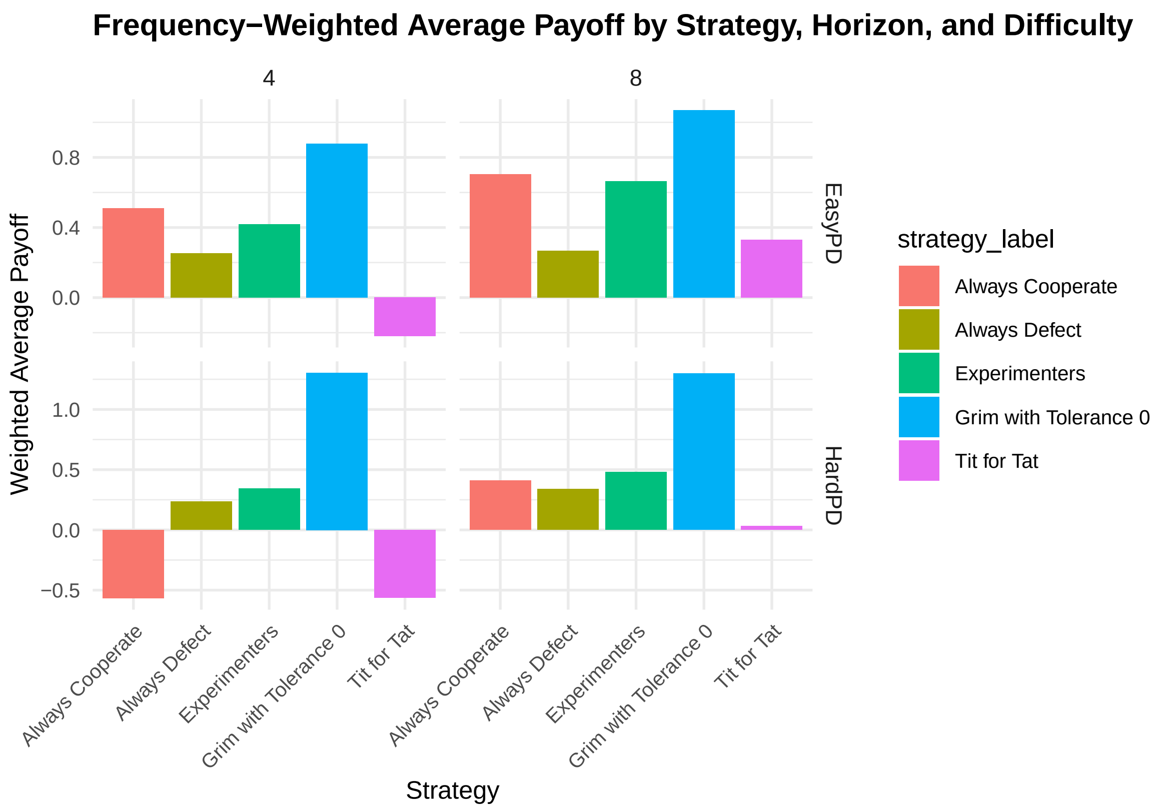


Extended Analysis

Step 6: Frequency-Weighted Payoff Calculation

- **Objective:** This calculation weights each strategy's average payoff by its frequency, providing a clearer view of strategy effectiveness.
- **Code Updates (Nov 1, 2024) => 2x2 Design**

```r
# Calculate Frequency-Weighted Payoff
weighted_payoff_summary <- strategy_payoff_summary %>%
  group_by(strategy_label, horizon, pd_difficulty) %>%
  mutate(weighted_avg_payoff = avg_strategy_payoff * (count / sum(count)))

# Visualization with 2x2 Design and adjusted text size
ggplot(weighted_payoff_summary, aes(x = strategy_label, y = weighted_avg_payoff, fill = strategy_la
  geom_bar(stat = "identity", position = "dodge") +
  facet_grid(pd_difficulty ~ horizon, scales = "free") +
  labs(title = "Frequency-Weighted Average Payoff by Strategy, Horizon, and Difficulty",
       x = "Strategy", y = "Weighted Average Payoff") +
  theme_minimal() +
  theme(
    text = element_text(size = 10),  # Set overall text size
    axis.text.x = element_text(angle = 45, hjust = 1, size = 8),  # Rotate and resize x-axis label
    strip.text = element_text(size = 9),  # Decrease facet label size
    plot.title = element_text(size = 12, face = "bold")  # Bold and adjust title size
  )
```



Step 7: Performance Against Non-Fixed Strategies

- **Objective:** This analysis compares each fixed strategy's performance when interacting with non-fixed strategies, highlighting adaptability.

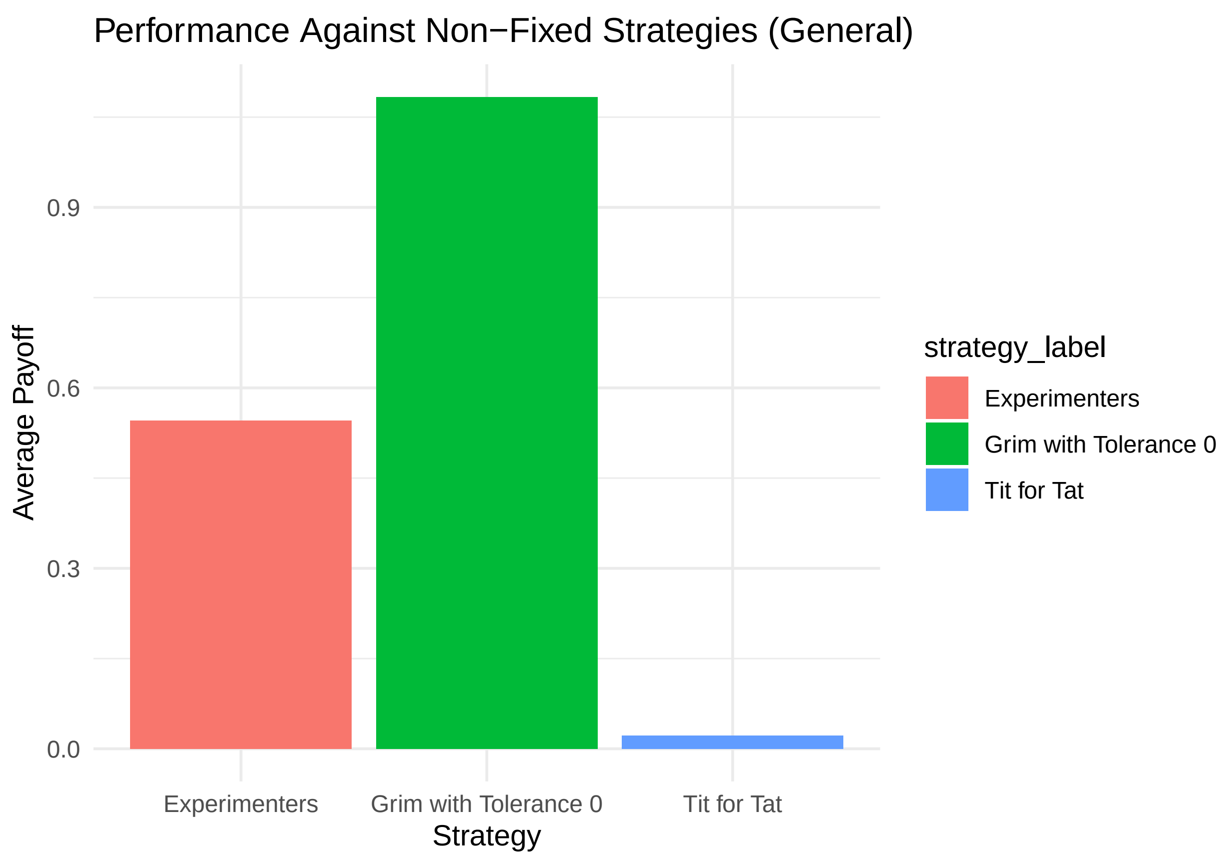
- **Code Updates (Nov 8, 2024)**

7.1. Approach 1. General Comparison Against Non-Fixed Strategies In this first approach, we calculate the average payoff of each strategy when competing against any non-fixed strategy. This provides an overall measure of performance without distinguishing specific opponent strategies.

```
### Approach 1: Overall Performance Against Non-Fixed Strategies

non_fixed_performance_general <- df_merged %>%
  filter(strategy_label != "Always Cooperate" & strategy_label != "Always Defect") %>%
  group_by(strategy_label) %>%
  summarise(
    avg_payoff_against_non_fixed = mean(payoff, na.rm = TRUE),
    variance_against_non_fixed = var(payoff, na.rm = TRUE)
  )

# Print General Non-Fixed Performance Results
print(non_fixed_performance_general)
```

```
## # A tibble: 3 x 3
##   strategy_label        avg_payoff_against_non_fixed variance_against_non_fixed
##   <chr>                                        <dbl>                      <dbl>
## 1 Experimenters                               0.546                        2.18
## 2 Grim with Tolerance 0                       1.08                         1.64
## 3 Tit for Tat                                 0.0221                       1.38
```

```
# Visualization for General Non-Fixed Strategy Performance
ggplot(non_fixed_performance_general, aes(x = strategy_label, y = avg_payoff_against_non_fixed, fill = s
  geom_bar(stat = "identity") +
  labs(title = "Performance Against Non-Fixed Strategies (General)", x = "Strategy", y = "Average Payof
  theme_minimal()
```

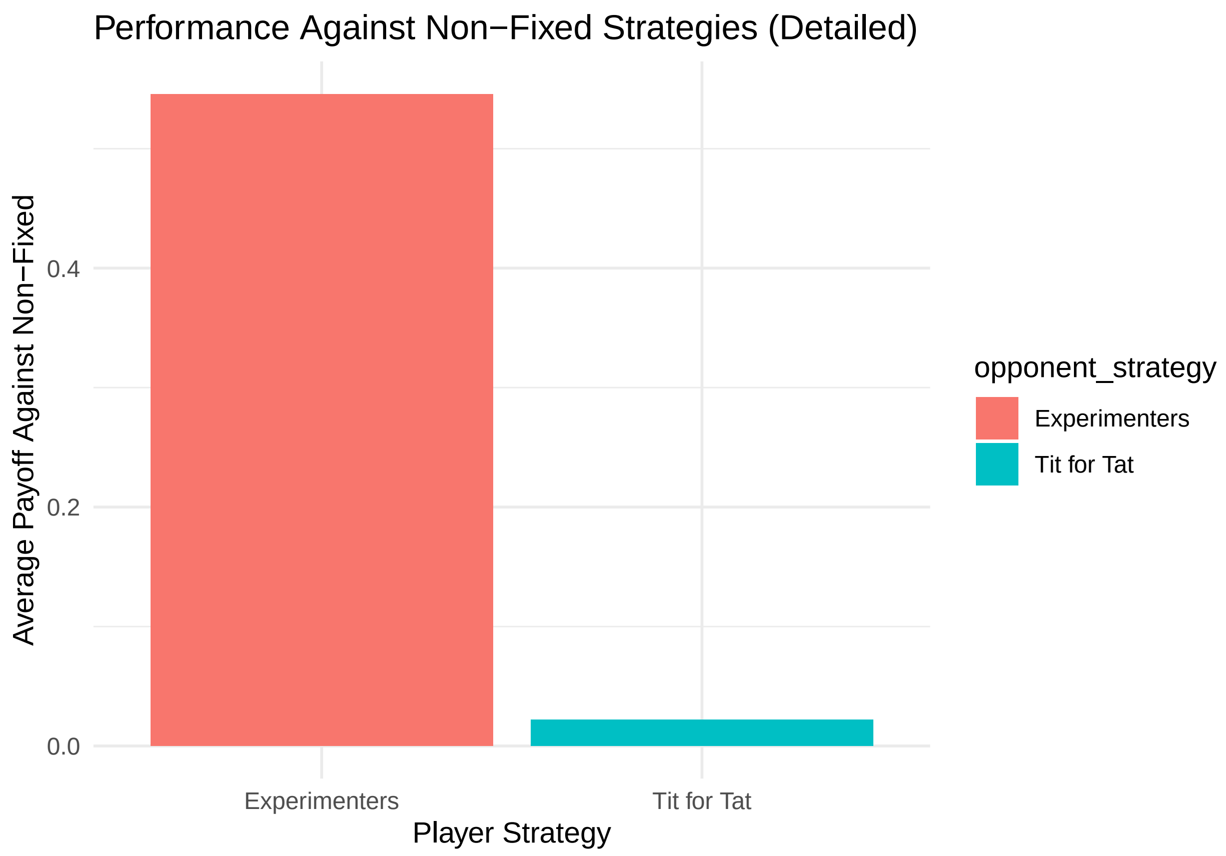


7.2. Approach 2: Specific Comparison Against Each Non-Fixed Strategy In this second approach, we expand the analysis by considering each non-fixed strategy (e.g., Tit-for-Tat, Experimenters) separately. This allows us to see how each strategy performs against specific non-fixed strategies, offering a more granular view of strategy adaptability.

```r
non_fixed_performance_detailed <- df_merged %>%
  filter(strategy_label %in% c("Tit for Tat", "Experimenters")) %>%
  group_by(player_strategy = strategy_label, opponent_strategy = strategy_label) %>%
  summarise(
    avg_payoff_against_non_fixed = mean(payoff, na.rm = TRUE),
    variance_against_non_fixed = var(payoff, na.rm = TRUE),
    count = n(),
    .groups = "drop"
  )

# Print Detailed Non-Fixed Performance Results
print(non_fixed_performance_detailed)
```

```
## # A tibble: 2 x 5
##   player_strategy opponent_strategy avg_payoff_against_non_fixed
##   <chr>           <chr>                                    <dbl>
## 1 Experimenters   Experimenters                           0.546
## 2 Tit for Tat     Tit for Tat                             0.0221
## # i 2 more variables: variance_against_non_fixed <dbl>, count <int>
```

```r
# Visualization for Detailed Non-Fixed Strategy Performance
ggplot(non_fixed_performance_detailed, aes(x = player_strategy, y = avg_payoff_against_non_fixed, fill =
  geom_bar(stat = "identity", position = position_dodge()) +
  labs(title = "Performance Against Non-Fixed Strategies (Detailed)", x = "Player Strategy", y = "Averag
  theme_minimal()
```

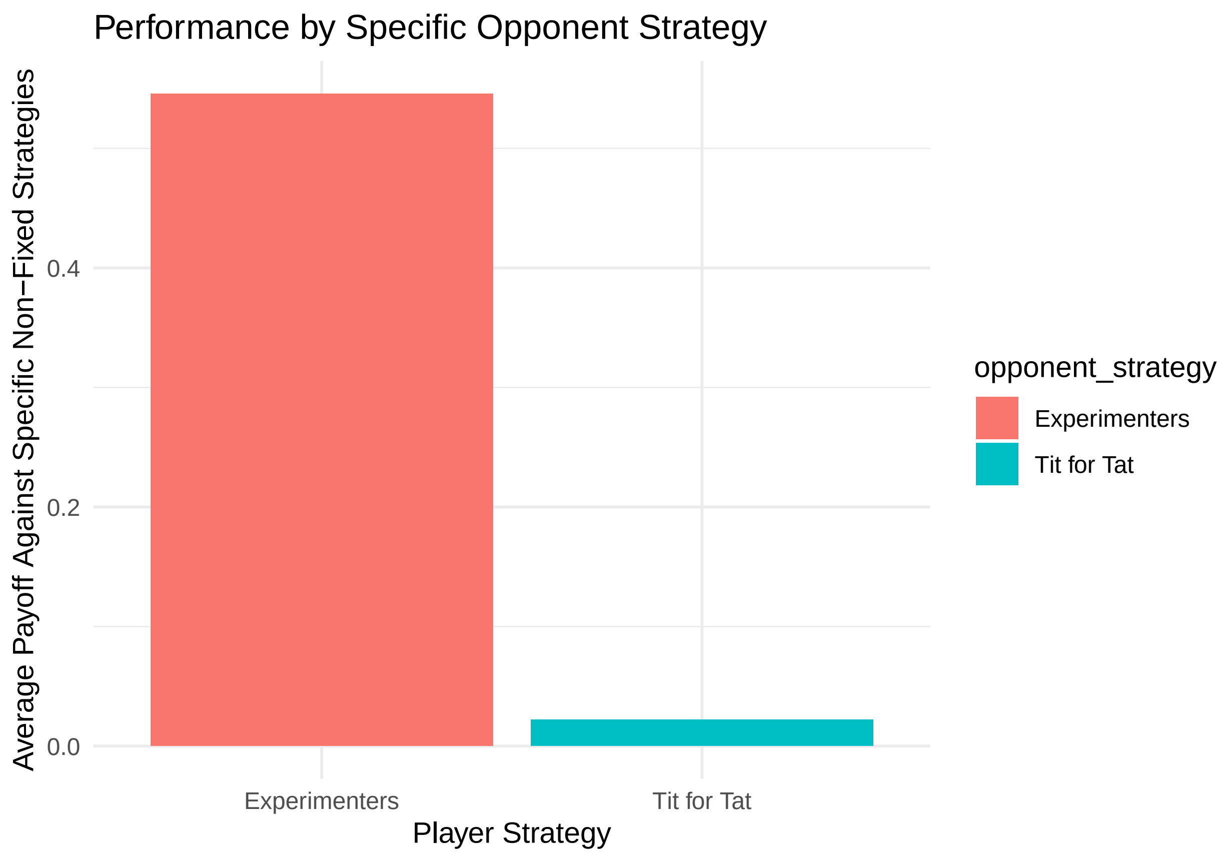


7.3. Additional Analysis: Performance by Specific Opponent Strategy This final analysis adds one more layer of specificity by grouping by both the player's and opponent's strategy. This allows us to see exactly how each non-fixed strategy (like Tit-for-Tat or Experimenters) performs against specific opponent strategies, rather than treating all non-fixed strategies as a single group.

```r
# Step 1: Add Opponent Strategy
df_merged <- df_merged %>%
  group_by(opponent_id, supergame) %>%
  mutate(opponent_strategy = first(strategy_label)) %>%
  ungroup()

# Step 2: Performance Analysis by Specific Opponent Strategy
non_fixed_performance_by_opponent <- df_merged %>%
  filter(strategy_label %in% c("Tit for Tat", "Experimenters")) %>%
  group_by(player_strategy = strategy_label, opponent_strategy) %>%
  summarise(
    avg_payoff_against_non_fixed = mean(payoff, na.rm = TRUE),
    variance_against_non_fixed = var(payoff, na.rm = TRUE),
    count = n(),
    .groups = "drop"
  )

# Print Non-Fixed Performance by Specific Opponent Strategy
print(non_fixed_performance_by_opponent)
```

```
## # A tibble: 2 x 5
##   player_strategy opponent_strategy avg_payoff_against_non_fixed
##   <chr>           <chr>                                    <dbl>
## 1 Experimenters   Experimenters                           0.546
## 2 Tit for Tat     Tit for Tat                             0.0221
## # i 2 more variables: variance_against_non_fixed <dbl>, count <int>
```

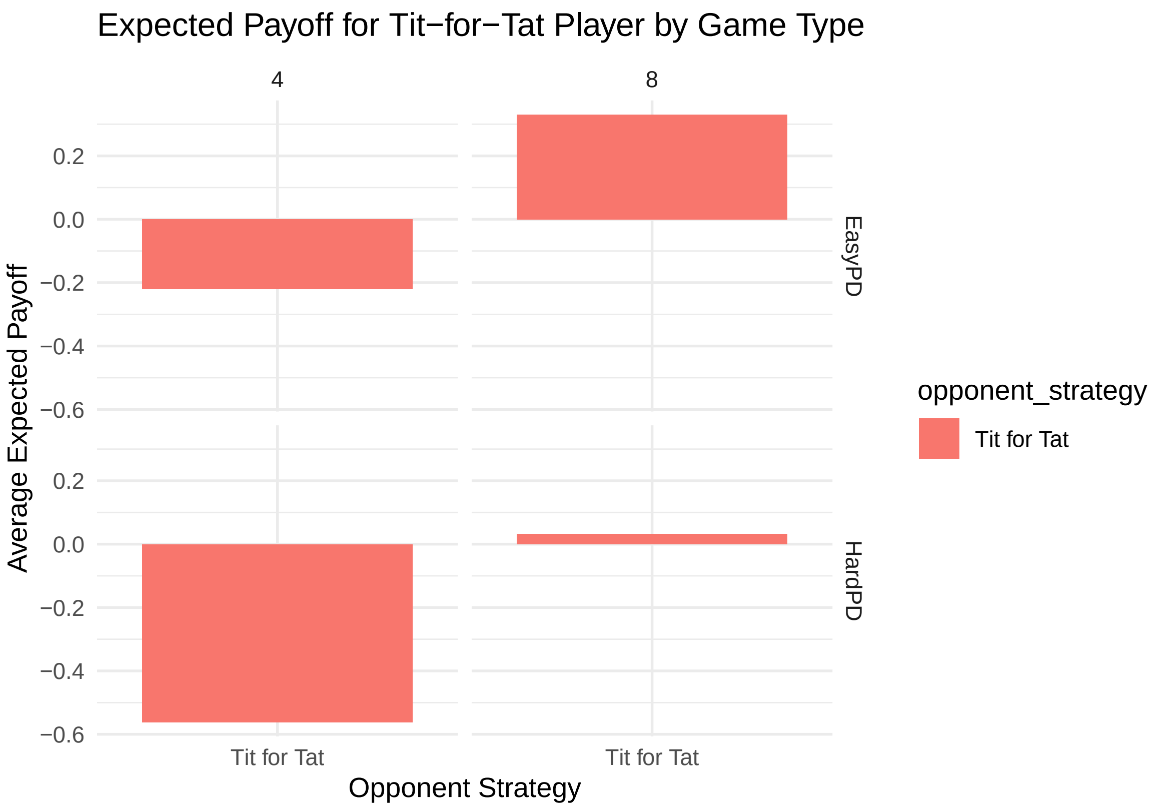
```
# Visualization for Performance by Specific Opponent Strategy
ggplot(non_fixed_performance_by_opponent, aes(x = player_strategy, y = avg_payoff_against_non_fixed, fi
  geom_bar(stat = "identity", position = position_dodge()) +
  labs(title = "Performance by Specific Opponent Strategy", x = "Player Strategy", y = "Average Payoff A
  theme_minimal()
```



Step 8: Expected Payoff Simulation for Hypothetical Tit-for-Tat Player

- **Objective:** In this step, we estimate the expected payoff for a hypothetical Tit-for-Tat player when competing against various other strategies. This analysis provides insights into how a Tit-for-Tat strategy might perform on average against other identified strategies.
- **Code Updates (Nov 1, 2024) => 2x2 Design**

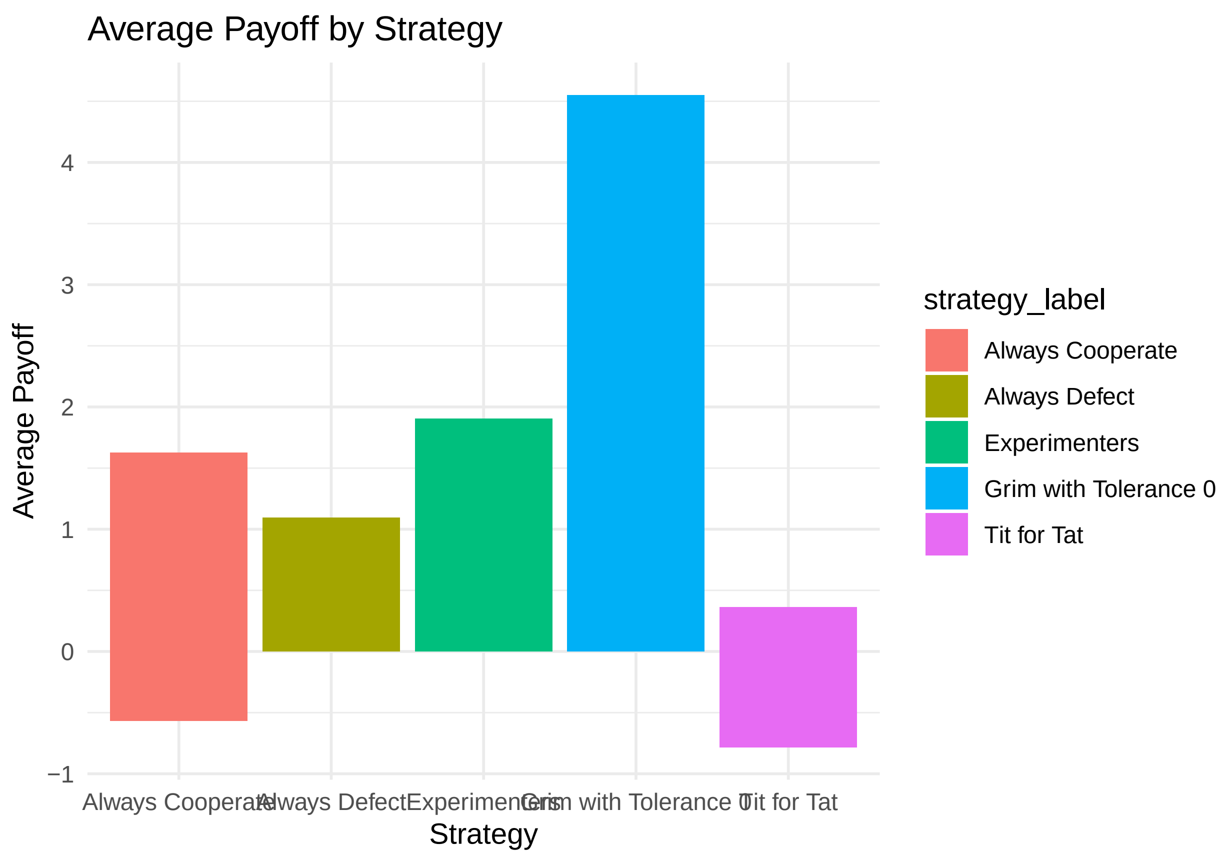
```r
### 8 Simulating Tit-for-Tat Performance

# Calculating Expected Payoff for Tit-for-Tat vs Opponent Strategies
hypothetical_tft_performance <- df_merged %>%
  filter(strategy_label == "Tit for Tat") %>%
  group_by(opponent_strategy = strategy_label, horizon, pd_difficulty) %>%
  summarise(
    avg_expected_payoff = mean(payoff, na.rm = TRUE),
    variance_expected_payoff = var(payoff, na.rm = TRUE),
    count = n(),
    .groups = "drop"
  )

# Visualization with 2x2 Design
ggplot(hypothetical_tft_performance, aes(x = opponent_strategy, y = avg_expected_payoff, fill = opp
  geom_bar(stat = "identity", position = "dodge") +
  facet_grid(pd_difficulty ~ horizon) +
  labs(title = "Expected Payoff for Tit-for-Tat Player by Game Type",
       x = "Opponent Strategy", y = "Average Expected Payoff") +
  theme_minimal()
```



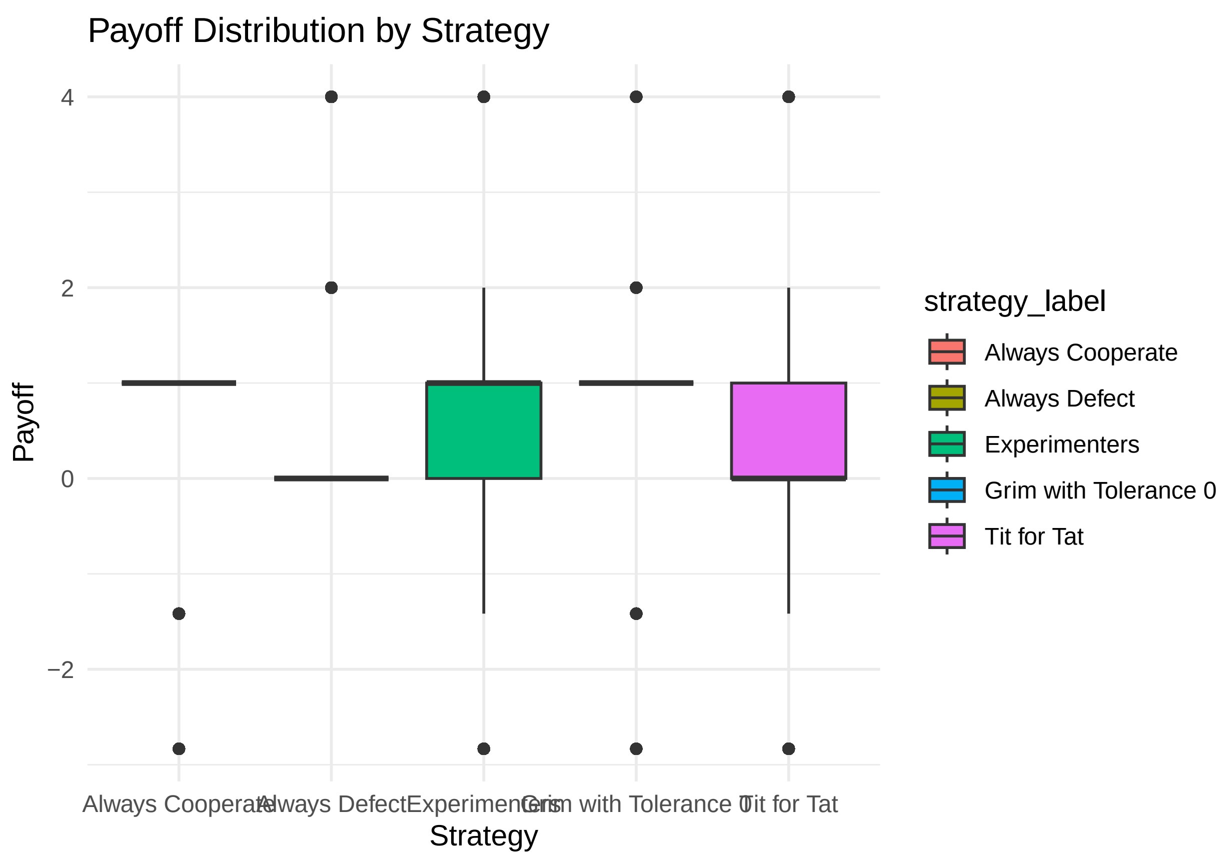
Step 9: Visualizations and Graphical Analysis

- **Objective:** Provides a visualization of strategy payoff distributions and strategy counts, offering a visual comparison of each strategy's performance and popularity.
- **Code Updates (Nov 1, 2024)**

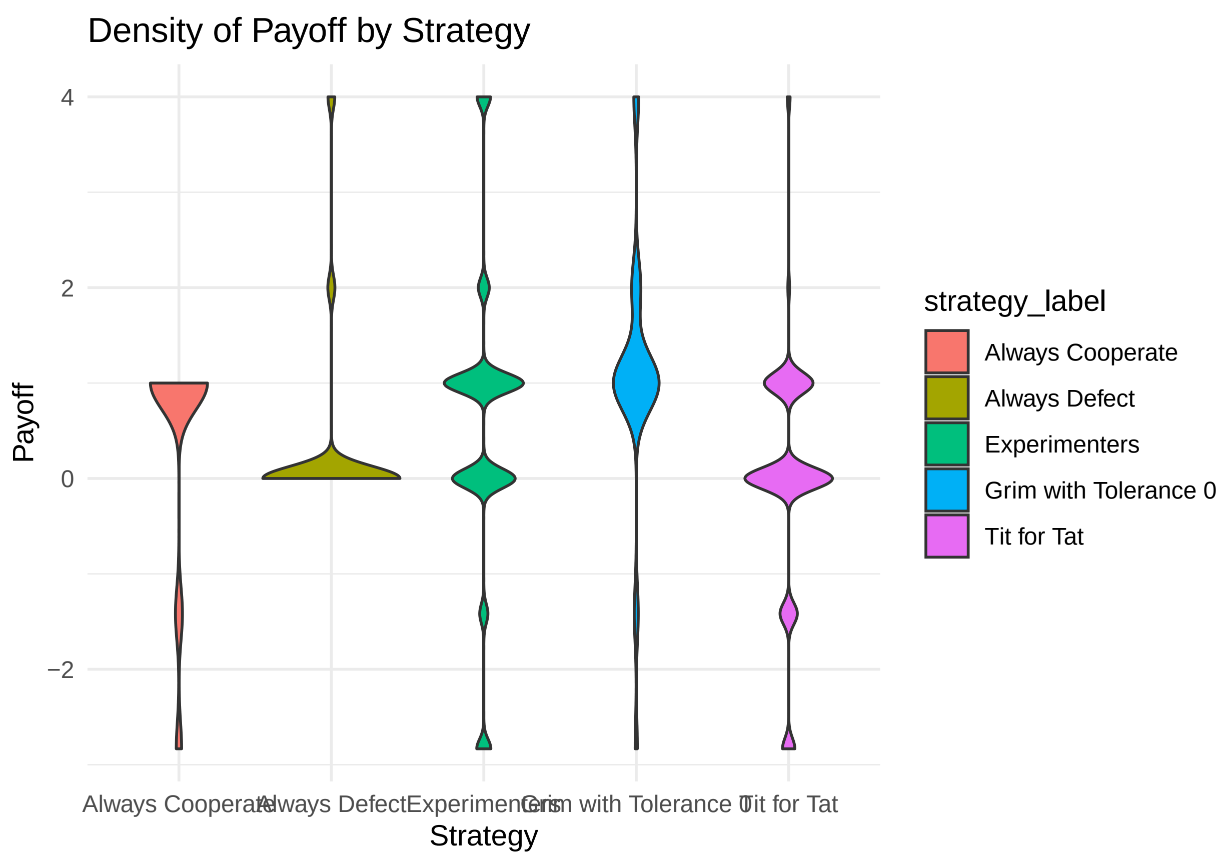
```r
### 9 Visualizations

library(ggplot2)
library(ggridges)

# 1. Bar Plot: Average Payoff by Strategy
ggplot(strategy_payoff_summary, aes(x = strategy_label, y = avg_strategy_payoff, fill = strategy_label)
  geom_bar(stat = "identity") +
  labs(title = "Average Payoff by Strategy", x = "Strategy", y = "Average Payoff") +
  theme_minimal()
```



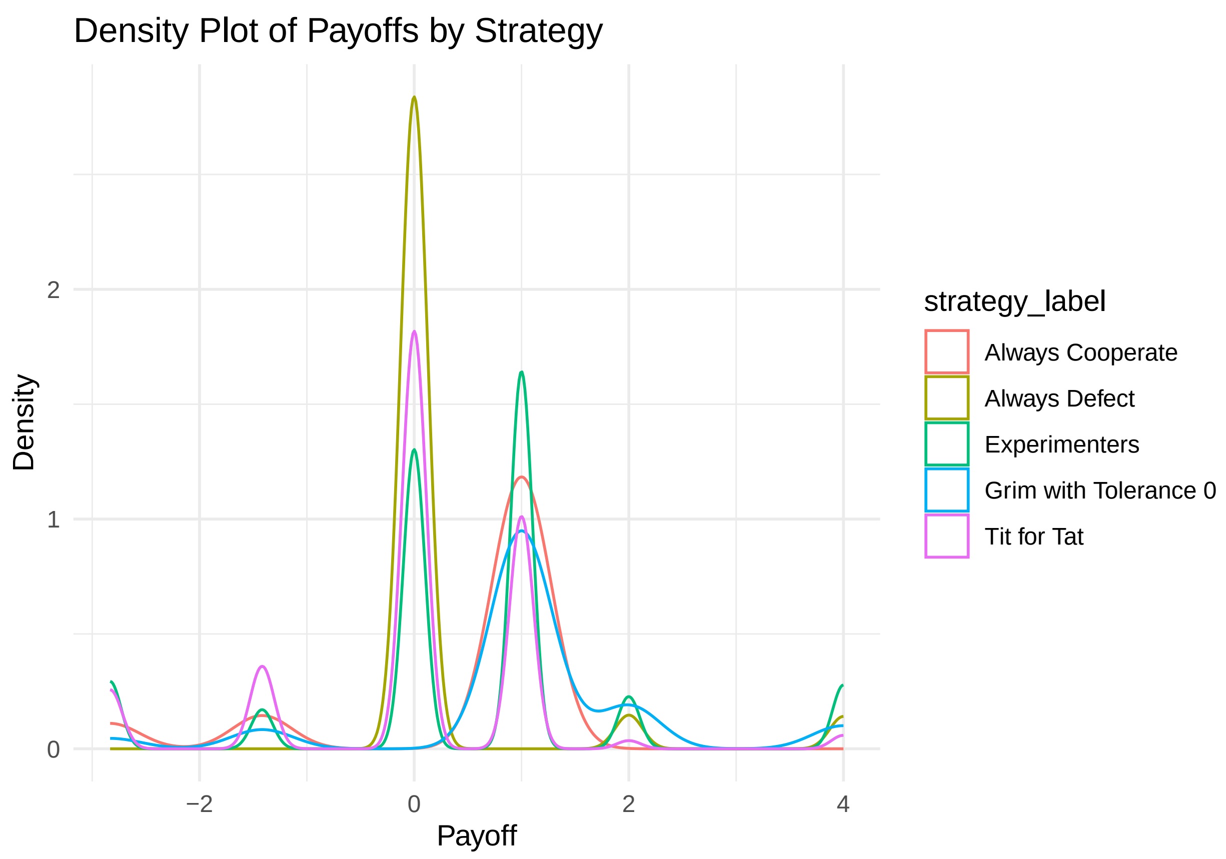
```r
# 2. Box Plot: Payoff Distribution by Strategy
ggplot(df_merged, aes(x = strategy_label, y = payoff, fill = strategy_label)) +
  geom_boxplot() +
  labs(title = "Payoff Distribution by Strategy", x = "Strategy", y = "Payoff") +
  theme_minimal()
```



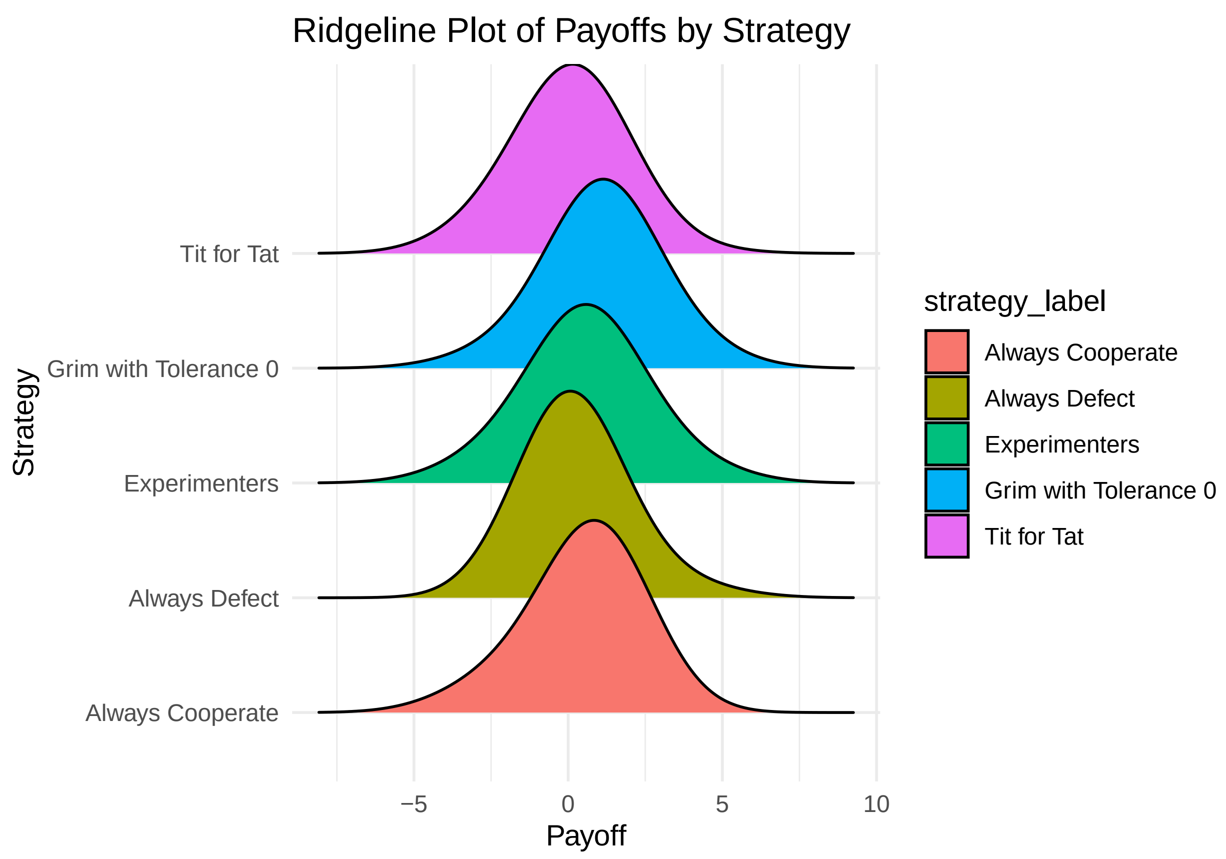
```r
# 3. Violin Plot: Density of Payoff by Strategy
ggplot(df_merged, aes(x = strategy_label, y = payoff, fill = strategy_label)) +
  geom_violin() +
  labs(title = "Density of Payoff by Strategy", x = "Strategy", y = "Payoff") +
  theme_minimal()
```



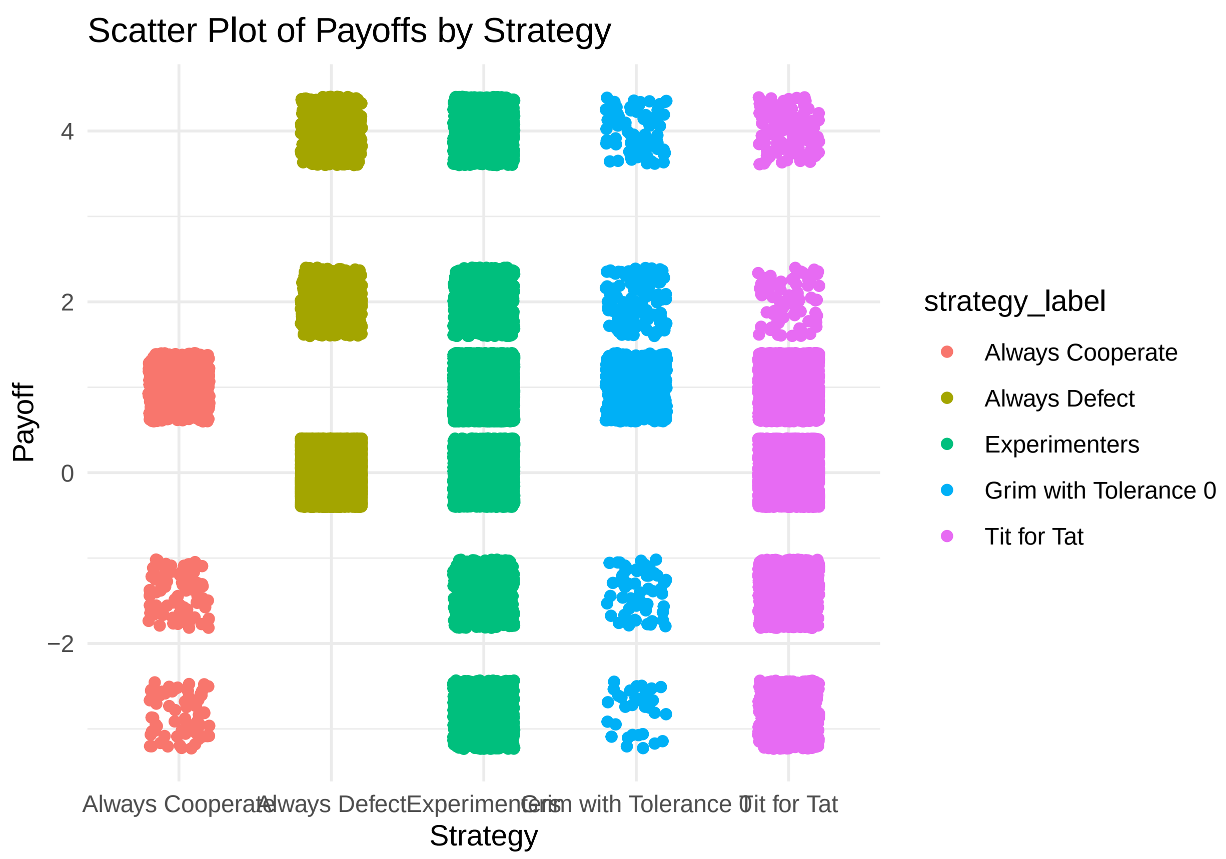
```r
# 4. Density Plot: Density of Payoffs by Strategy
ggplot(df_merged, aes(x = payoff, color = strategy_label)) +
  geom_density() +
  labs(title = "Density Plot of Payoffs by Strategy", x = "Payoff", y = "Density") +
  theme_minimal()
```



```r
# 5. Ridgeline Plot: Payoffs by Strategy
ggplot(df_merged, aes(x = payoff, y = strategy_label, fill = strategy_label)) +
  geom_density_ridges(bandwidth = 1.75) +
  labs(title = "Ridgeline Plot of Payoffs by Strategy", x = "Payoff", y = "Strategy") +
  theme_minimal()
```



```r
# 6. Scatter Plot: Payoffs by Strategy
ggplot(df_merged, aes(x = strategy_label, y = payoff, color = strategy_label)) +
  geom_jitter(width = 0.2) +
  labs(title = "Scatter Plot of Payoffs by Strategy", x = "Strategy", y = "Payoff") +
  theme_minimal()
```



Scatter Plot of Payoffs by Strategy
Payoff
4
2
0
−2
Always Cooperate
Always Defect
Experimenters
Grim with Tolerance 0
Tit for Tat
Strategy
strategy_label
Always Cooperate
Always Defect
Experimenters
Grim with Tolerance 0
Tit for Tat