Visual Analysis of Dota 2 Match Data

7CS519 Information Visualisation

Student ID: 100777241

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Contents

1 Introduction

This report presents a data-driven exploration of hero dynamics in *Dota 2*, using a dataset comprising approximately 100,000 public matches played on August 13, 2016 — the final day of *The International 2016* (TI6), one of the most prestigious tournaments in the game's competitive history [Wikipedia contributors, 2016]. As a multiplayer online battle arena (MOBA), *Dota 2* pits two teams of five players against one another, with each participant selecting a unique hero characterized by distinct abilities, roles, and synergies.

The aim of this analysis is to investigate how factors such as hero pick frequency, win rate, regional preferences, and five-hero team compositions influence match outcomes. In particular, the study examines whether frequently picked heroes are also the most effective, how performance differs by team alignment (Radiant vs. Dire), and whether professional meta trends are mirrored in public play. These questions are addressed through a combination of statistical aggregation and visual analysis.

The dataset's temporal alignment with TI6 enables a valuable comparison between community-level match behavior and professional hero usage. To assess its representativeness, findings are contextualized using hero statistics from Liquipedia [Liquipedia contributors, 2016] and Dotabuff's TI6 recap [Dotabuff, 2016]. Notably, heroes like **Mirana**, **Juggernaut**, and **Elder Titan** featured prominently in both professional and public matches, while tournament-dominant heroes such as **Shadow Demon** saw minimal public adoption — revealing gaps between strategic theory and practice.

A dual-tool approach was employed: R (with `ggplot2` and `dplyr`) for data wrangling and precise visualization, and Tableau for interactive dashboarding and exploratory storytelling. This combination allows for both reproducibility and user-friendly presentation. Informed by visualization theory [Cleveland and McGill, 1984, Kabacoff, 2018], this report emphasizes perceptual clarity and analytical rigor to draw insights relevant to both game strategy and data communication.

2 Dataset Justification and Research Questions

2.1 Dataset Selection

This dataset is ideal for visual analysis due to its sparsity and dimensionality. Each row represents a full match with binary indicators for 113 possible hero selections (values of `1` for Radiant, `-1` for Dire), as well as metadata including win outcome, region, gamemode, and gametype. This structure enables both individual-level and team-level analysis.

Key advantages include:

- **Structural sparsity**: Only 10 of 113 heroes are active per match
- **Temporal specificity**: Matches align with the final date of TI6
- **Rich metadata**: Allows regional and contextual segmentation
- **Public reproducibility**: Based on open, anonymized game data

Comparisons to TI6 professional match data (Liquipedia, 2016; Dotabuff, 2016) confirm that many of the same heroes were prevalent. However, some highly successful professional picks (e.g. Shadow Demon, Oracle) were underrepresented in public games, underscoring the value of examining both datasets side-by-side.

2.2 Research Questions

Each of the following questions is addressed through visual analysis, with corresponding evidence labeled in **Appendix A (R)** and **Appendix B (Tableau)**:

1. **Are popular heroes also the most successful?**
   → See **Figure A1 (R)** & **Figure B1 (Tableau)** (Top Picks) vs **Figure A2 (R)** & **Figure B2 (Tableau)** (Top Win Rates)
2. **Does team alignment affect win probability (Radiant vs Dire)?**
   → See **Figure A3 (R)** and **Figure B3 (Tableau)**
3. **Do hero picks and win rates vary by region?**
   → See **Figure A4 (R)** vs **Figure B5 (Tableau)**
4. **Which team compositions yield the highest win rates?**
   →**Figure A6 (R)** and **Figure B6 (Tableau)** presents the top 10 five-hero combinations based on win performance.
5. **Do public match trends reflect professional tournament strategies?**
   → Findings are contextualized through comparison with TI6 hero data

3 Tool Comparison: R vs Tableau

3.1 R (tidyverse + ggplot2)

R was employed for the core data wrangling, metric development, and analytical visualizations. Leveraging the `tidyverse` ecosystem — including `dplyr`, `tidyr`, and `ggplot2` [Wickham, 2024, Posit, PBC, 2024] — we transformed a sparse, high-dimensional dataset into structured insights. Specific tasks included:

- Multi-condition aggregations for computing hero win rates and team outcomes
- Win probability segmentation by region and game type
- Generation of 5-hero synergy combinations
- Export of preprocessed data to Tableau-ready CSVs

The high degree of control in R allowed us to fine-tune both the data logic and the visual grammar of plots, particularly for Figures A1–A6. In addition, reproducibility through scripting ensured transparent analysis pipelines.

While R offers unparalleled versatility, it comes with a steep learning curve. Users without a programming background may find it less accessible for rapid, low-barrier exploration or presentation.

3.2 Tableau

Tableau was used to build the interactive dashboard presented in Appendix B (Figure B7), synthesizing the results into a visually navigable story. Its strength lies in enabling non-programmers to build, explore, and communicate insights through simple drag-and-drop mechanics [Tableau Software, 2024].

Using the preprocessed datasets exported from R, Tableau offered:

- **Interactive filters** for regions and heroes, allowing users to isolate and explore specific match characteristics (e.g., filtering by *Southeast Asia* reveals that *Mirana* is popular but not among top win-rate heroes).

- **Visual juxtaposition** of metrics, such as comparing pick frequency (Figure B1) with win rate (Figure B2).
- **Hover and drill-down functionality**, enhancing engagement and understanding.
- **Cross-linked dashboards**, where selecting a region dynamically updates all charts.

Although Tableau lacks support for complex metric creation (e.g., hero synergy logic), its user-centric design and interactivity make it ideal for stakeholder-facing reports. The visual design was harmonized with R (e.g., consistent color palette for heroes) to reduce cognitive friction when comparing across tools.

3.3 Chart Design Rationale

Visualization choices followed best-practice guidelines from Cleveland and McGill [Cleveland and McGill, 1984], who demonstrated that aligned axis-based encodings (e.g., bar length) are cognitively superior to angles or areas for quantitative comparison.

- **Horizontal bar charts** were used to represent ranked hero pick counts and win rates (Figures B1–B2).
- **Dot plots** were applied for region-based categorical comparisons (Figures B4–B5), minimizing clutter in dense layouts.
- **Gradient-filled bars** visually reinforced win rate strength in the synergy chart (Figure B6).

Advanced chart types such as Sankey flows, violin plots, and diverging bars were evaluated but excluded to avoid unnecessary complexity and reader confusion [Kabacoff, 2018].

3.4 Summary of Tool Suitability

Task	Recommended Tool
Statistical summarization & transformation	R
Interactive filtering & user navigation	Tableau
Reproducible scripting & auditability	R
Storytelling dashboards for non-technical users	Tableau
Highly customized visual aesthetics	R
Rapid prototyping of analytical views	Tableau

By integrating both platforms, we achieved **analytical depth with R** and **accessible narrative delivery with Tableau**. This combination ensured rigorous backend logic with visually communicative front-end dashboards — a best-of-both-worlds approach suited for both technical and non-technical audiences.

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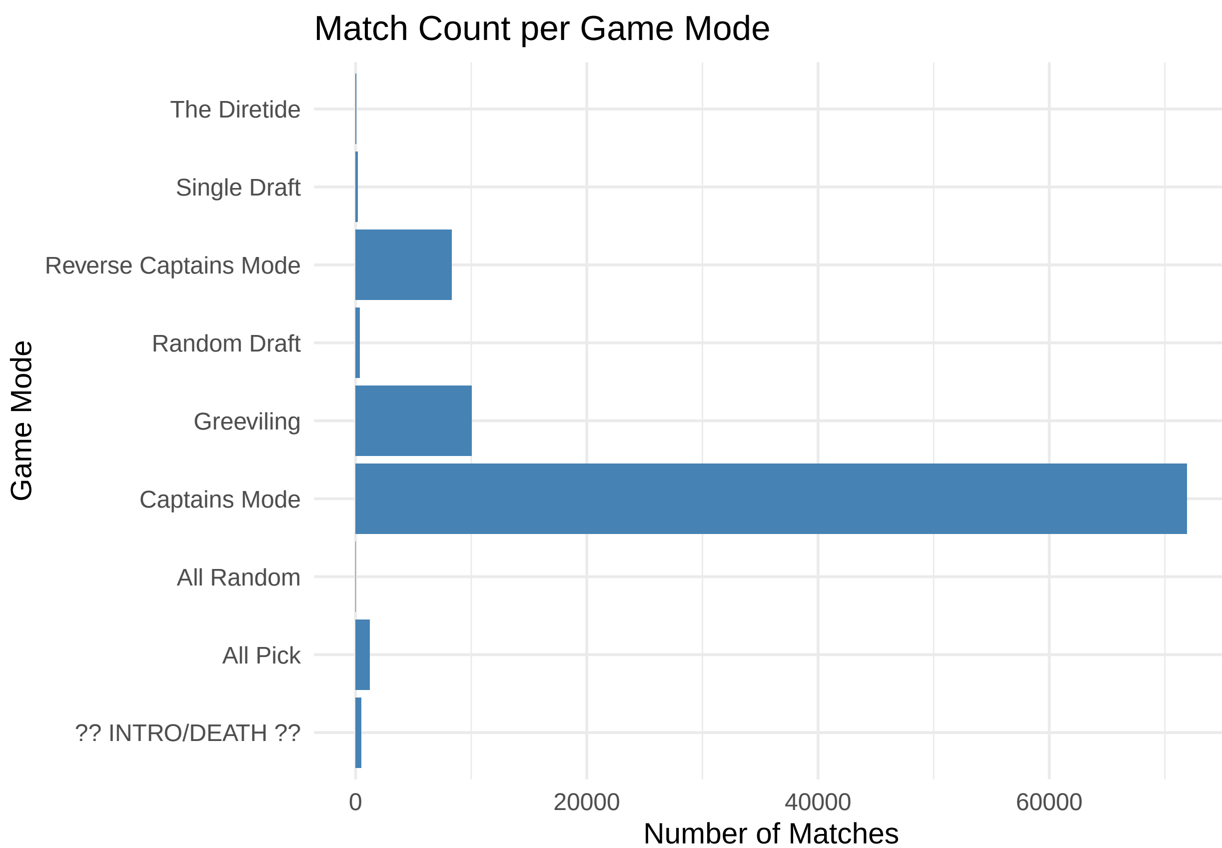
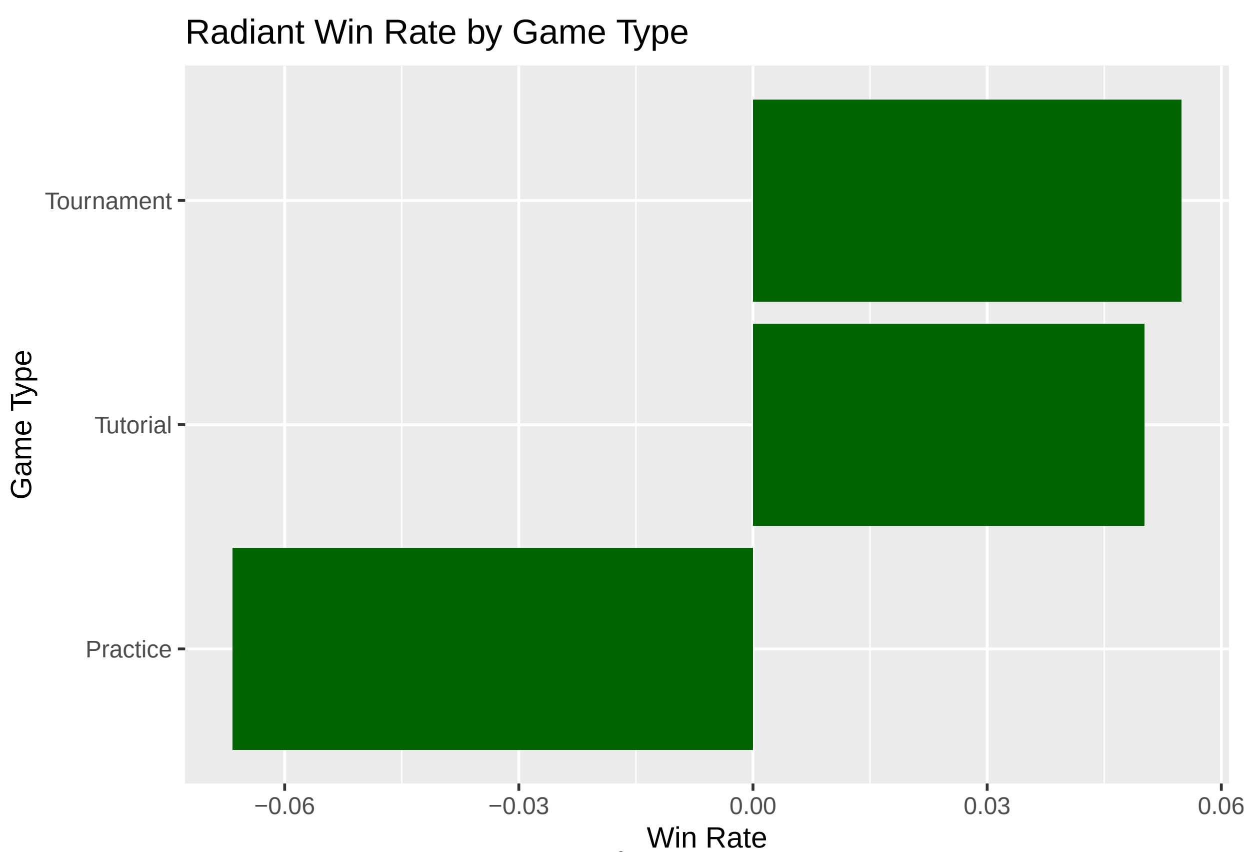
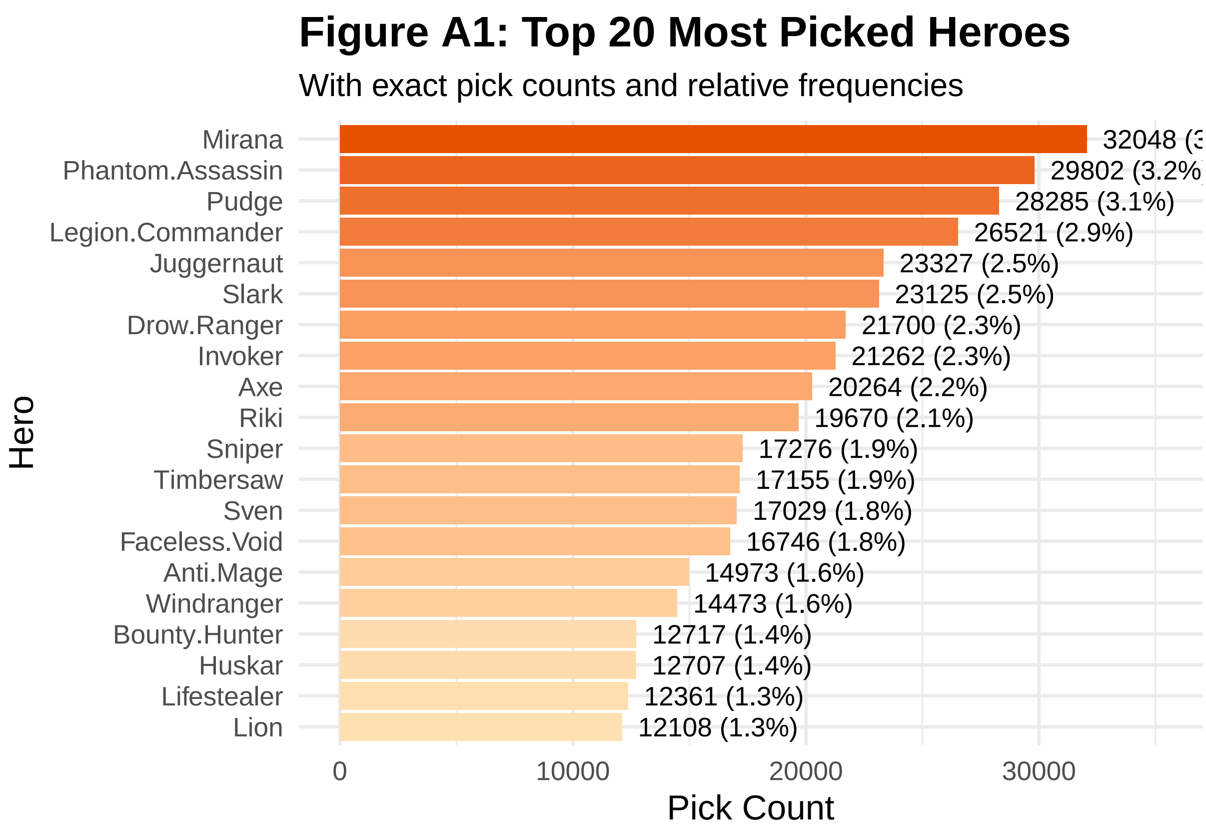
4 Appendix A


Match Count per Game Mode
Game Mode
The Diretide
Single Draft
Reverse Captains Mode
Random Draft
Greeviling
Captains Mode
All Random
All Pick
?? INTRO/DEATH ??
0
20000
40000
60000
Number of Matches


Radiant Win Rate by Game Type
Game Type
Tournament
Tutorial
Practice
−0.06
−0.03
0.00
0.03
0.06
Win Rate

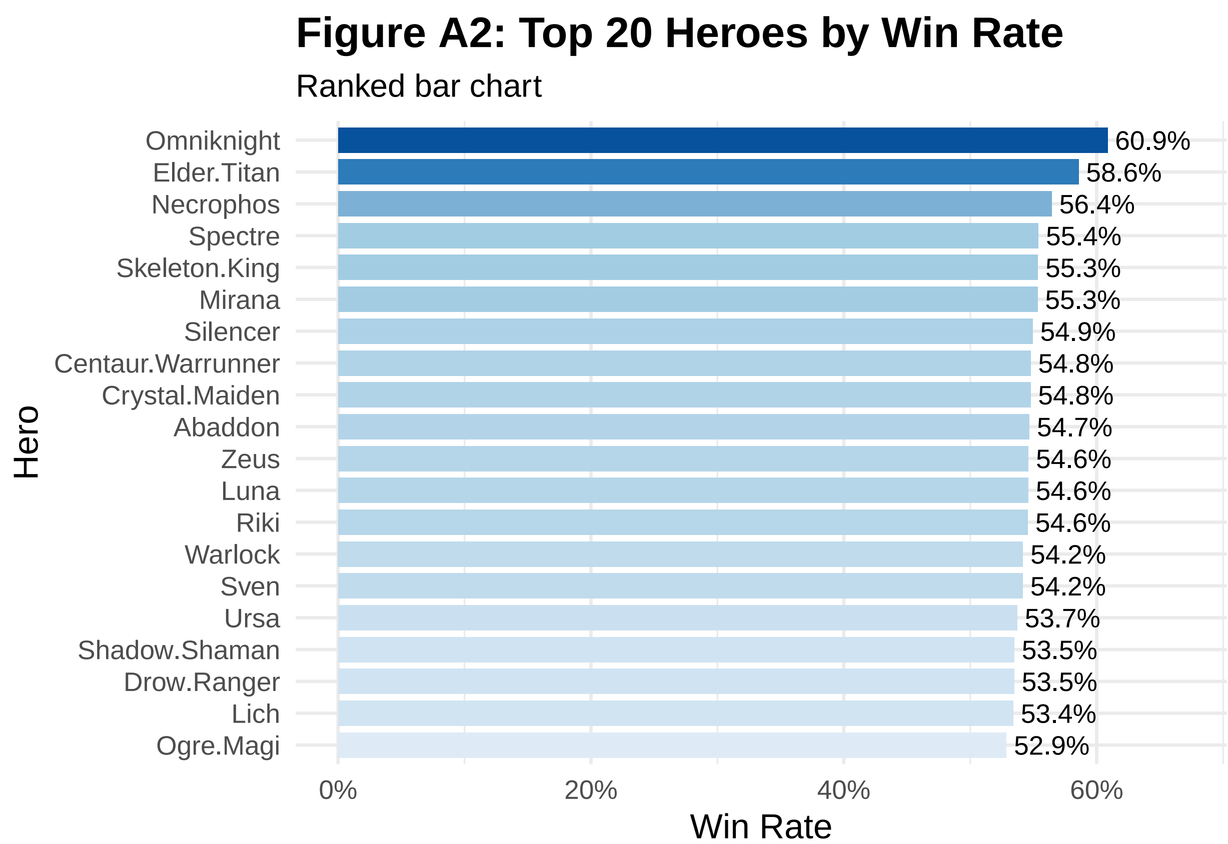
4.1 Hero Frequency Analysis

4.1.1 Figure A1: Top 20 Most Picked Heroes



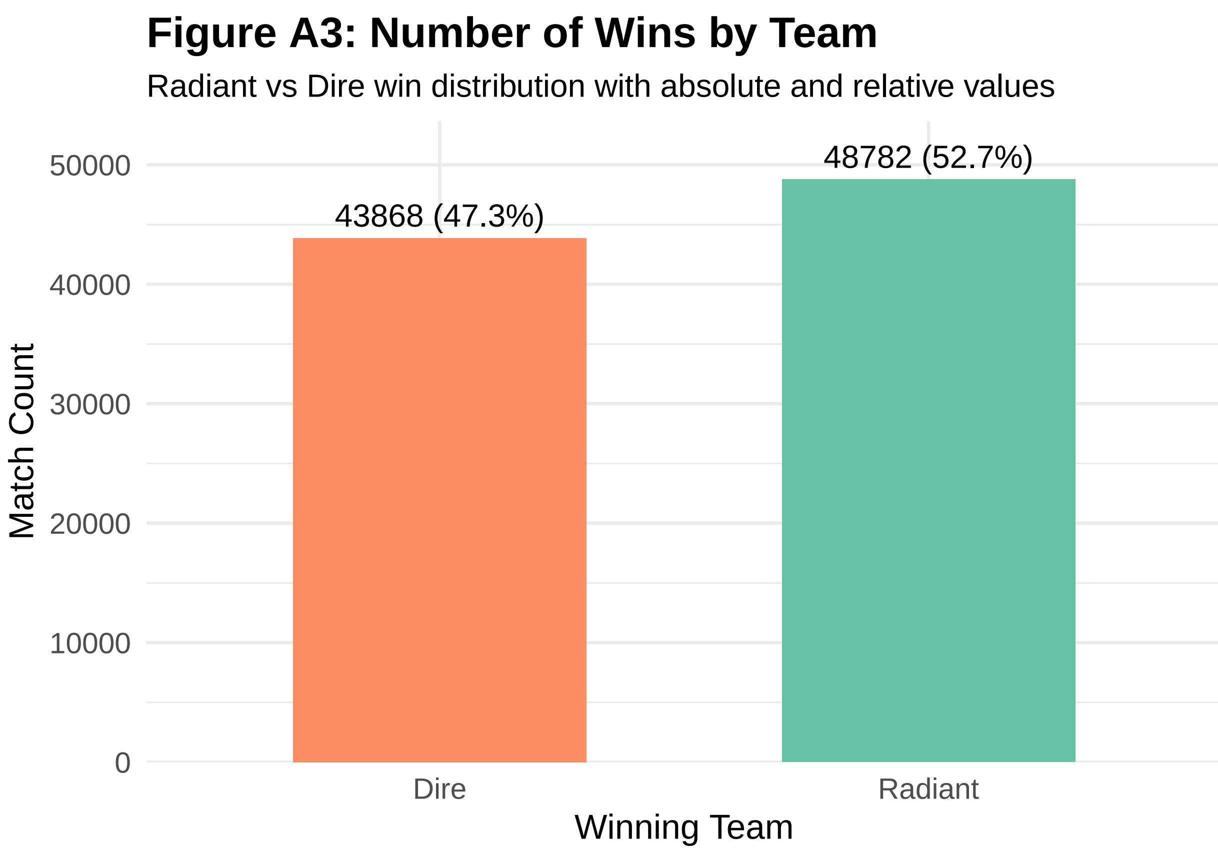
4.2 Win Rate per Hero

4.2.1 Figure A2: Top 20 Heroes by Win Rate



4.3 Radiant vs Dire Win Count

4.3.1 Figure A3: Number of Wins by Team



4.4 Top 3 Most Picked Heroes Per Region

4.4.1 Figure A4: Top 3 Most Picked Heroes per Region

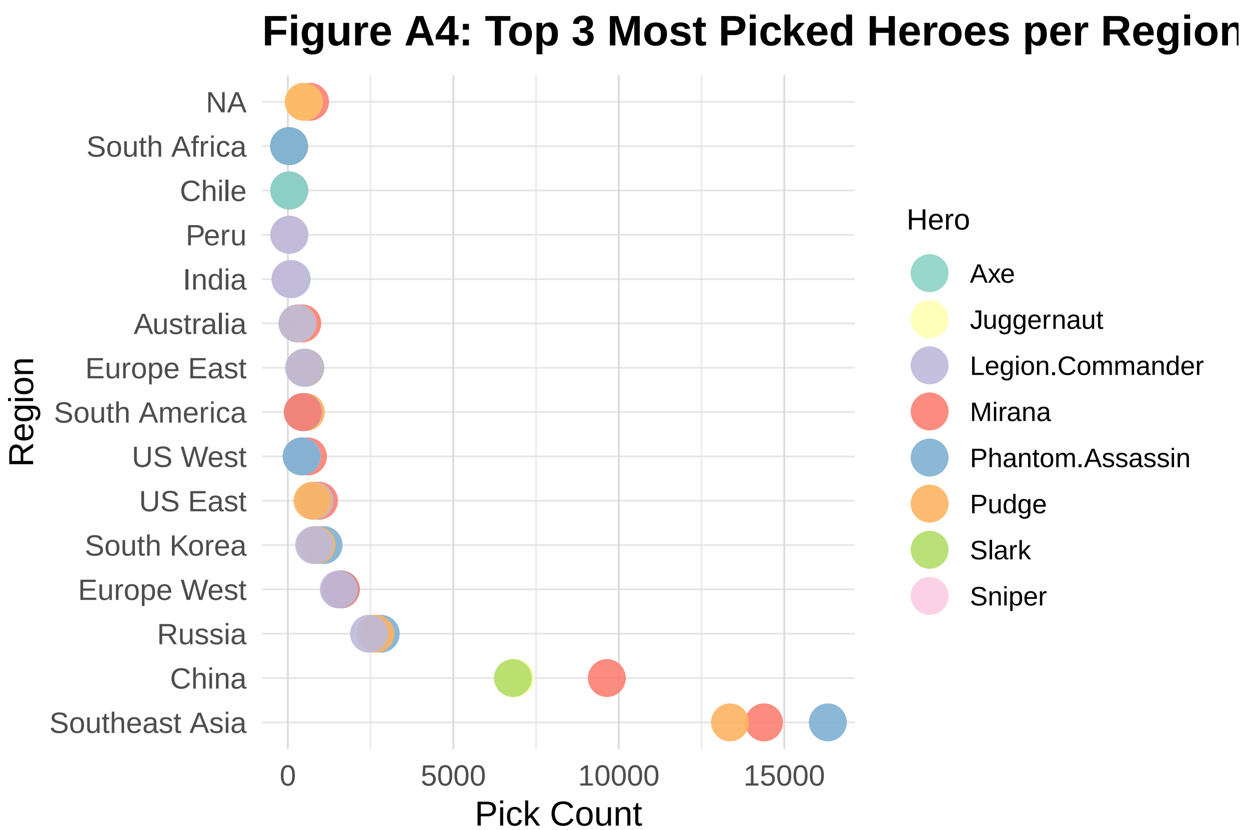
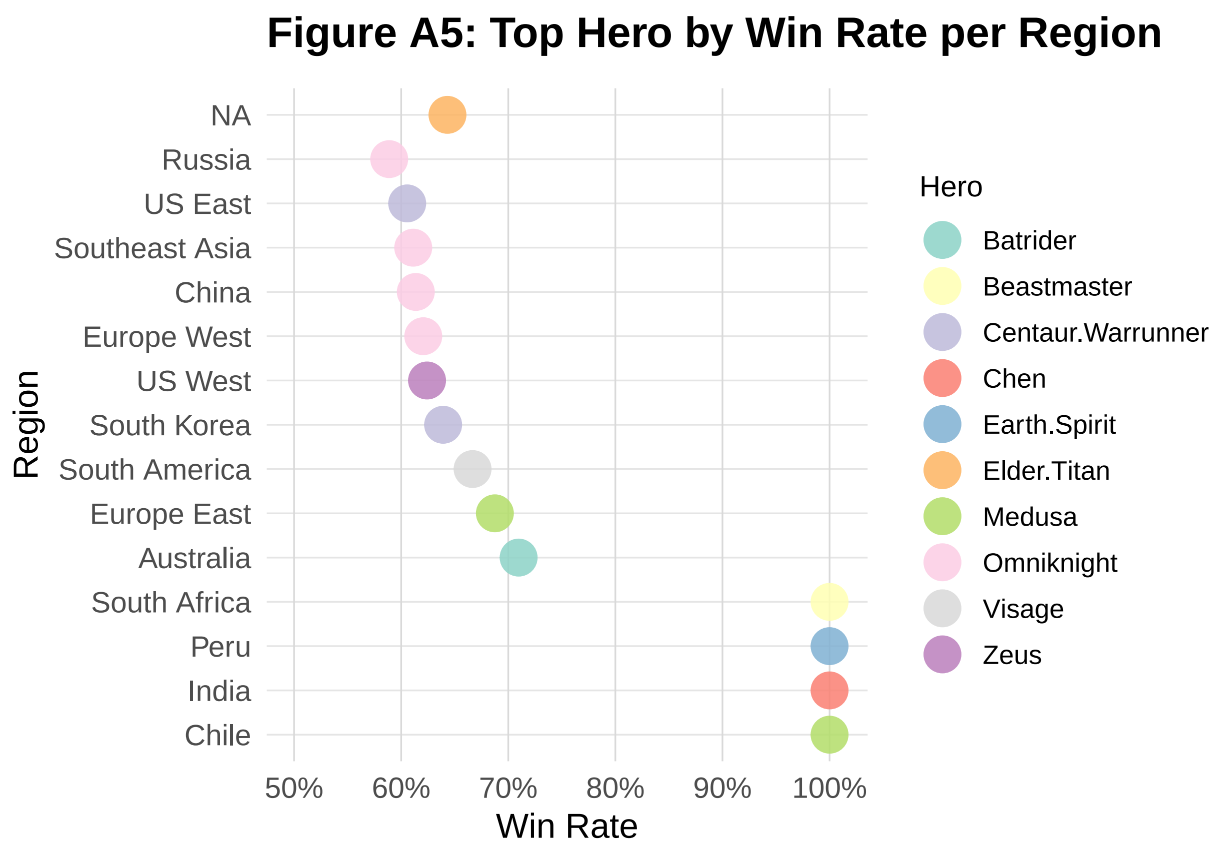


Figure A4: Top 3 Most Picked Heroes per Region
Region
NA
South Africa
Chile
Peru
India
Australia
Europe East
South America
US West
US East
South Korea
Europe West
Russia
China
Southeast Asia
0
5000
10000
15000
Pick Count
Hero
Axe
Juggernaut
Legion.Commander
Mirana
Phantom.Assassin
Pudge
Slark
Sniper

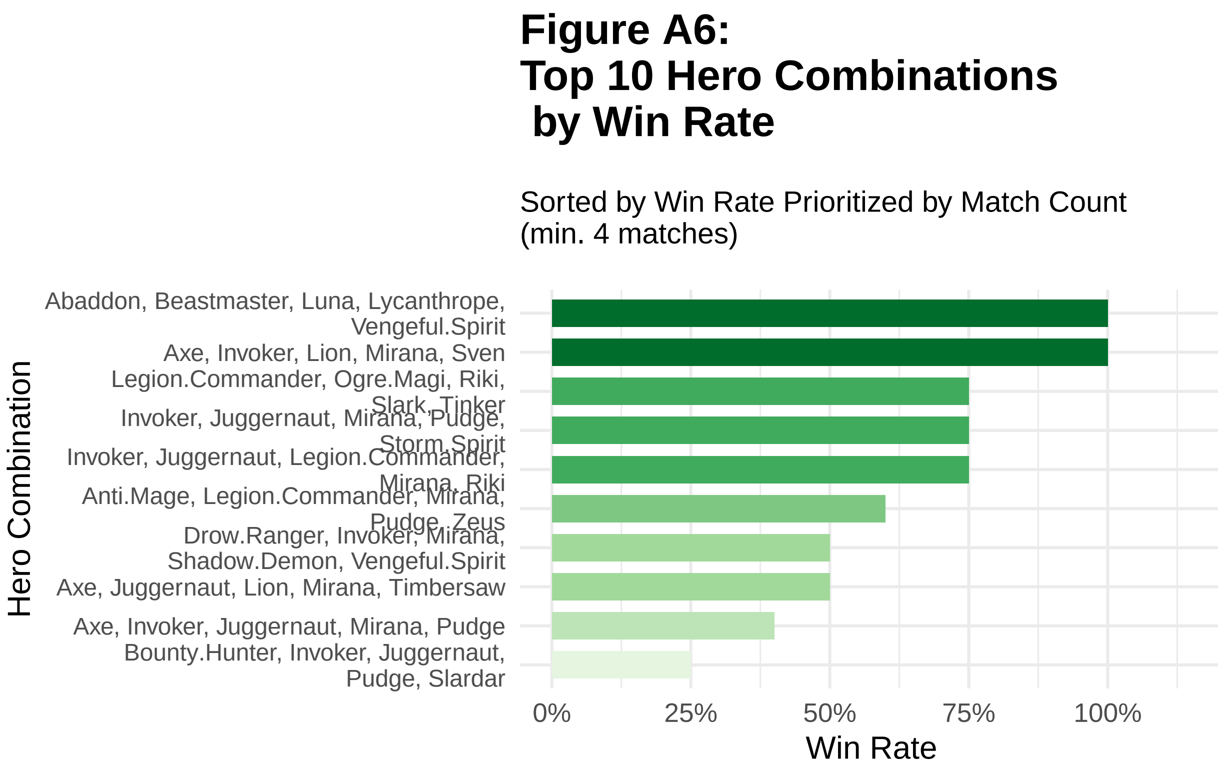
4.5 Hero Win Rate by Region

4.5.1 Figure A5: Top Hero by Win Rate per Region



4.6 Top Winning Combos

4.6.1 Figure A6: Top 10 Hero Combinations by Win Rate



5 Appendix B: Tableau Summary Dashboard

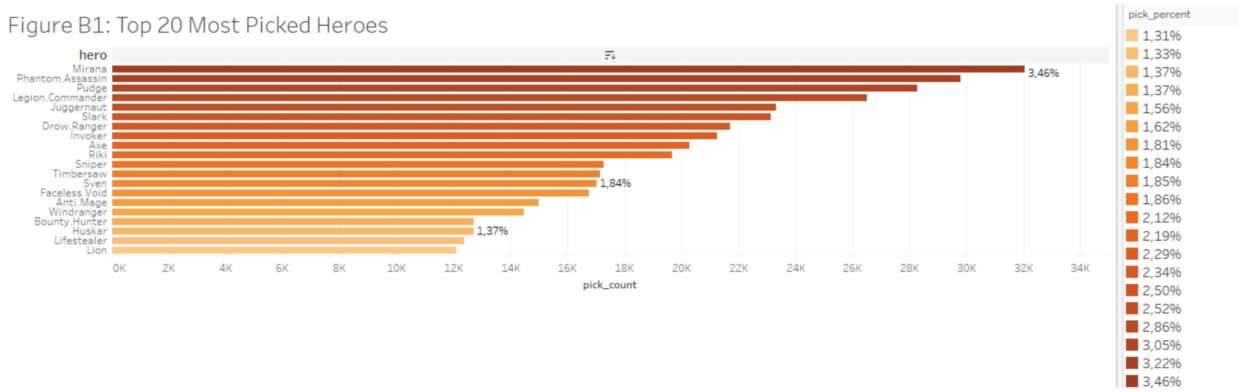


Figure 1: Figure B1: Top 20 Most Picked Heroes

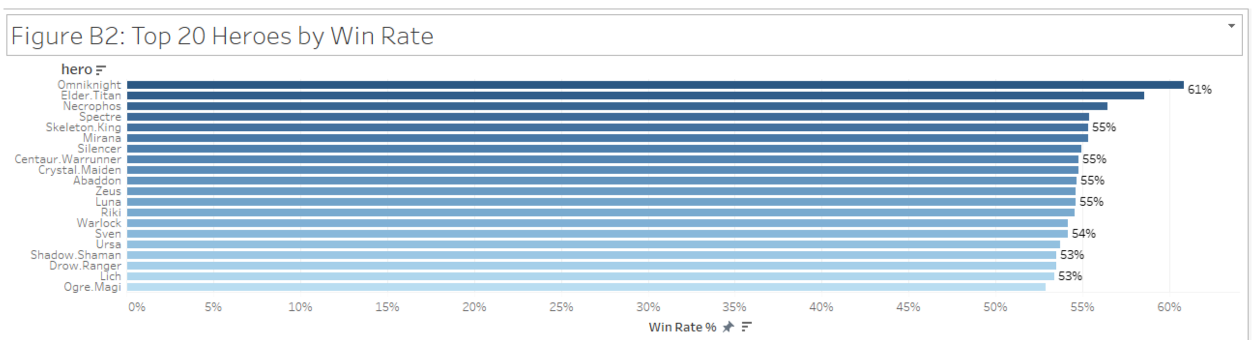


Figure 2: Figure B2: Top 20 Heroes by Win Rate

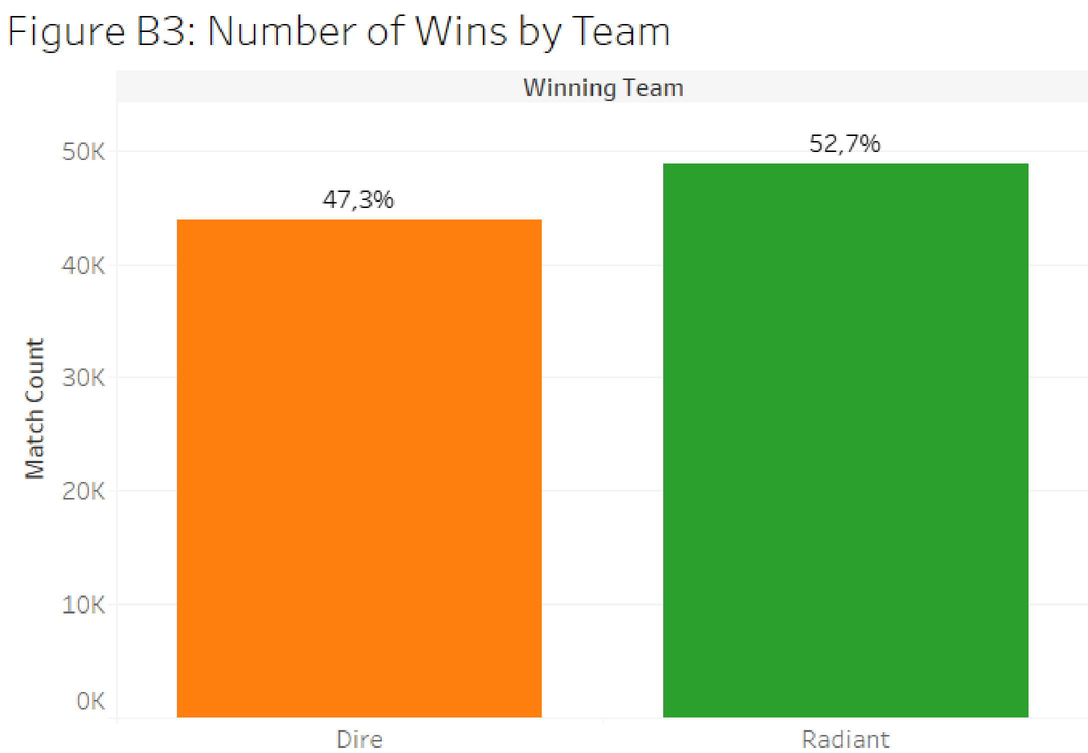


Figure 3: Figure B3: Win Distribution by Team (Radiant vs Dire)

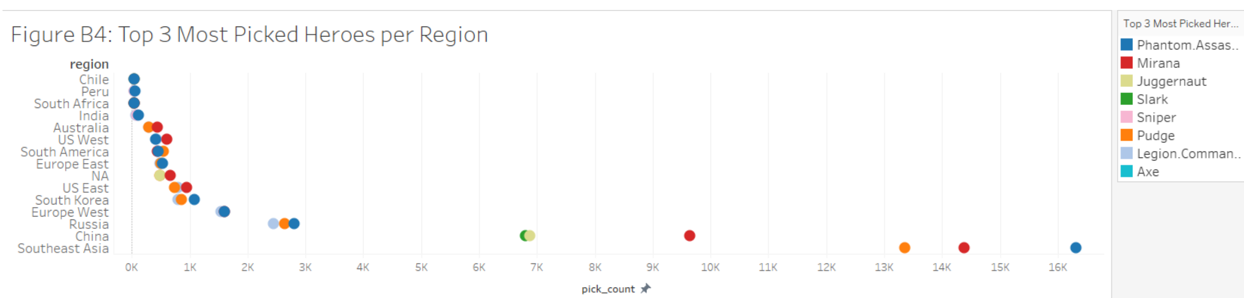


Figure 4: Figure B4: Top 3 Most Picked Heroes per Region

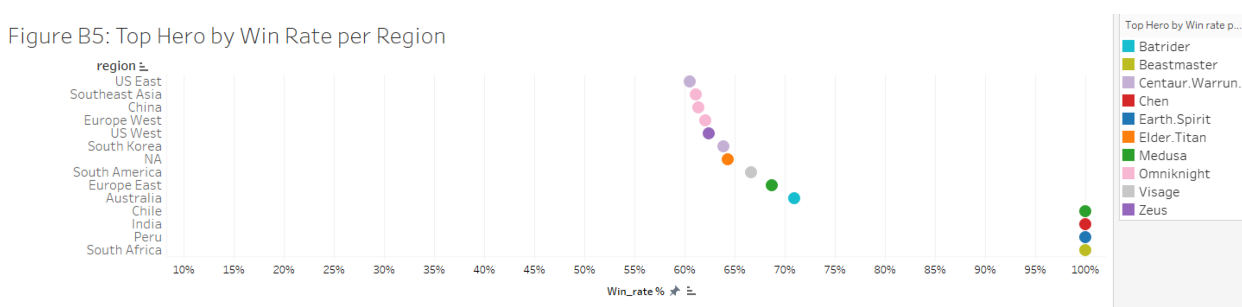


Figure 5: Figure B5: Top Hero by Win Rate per Region

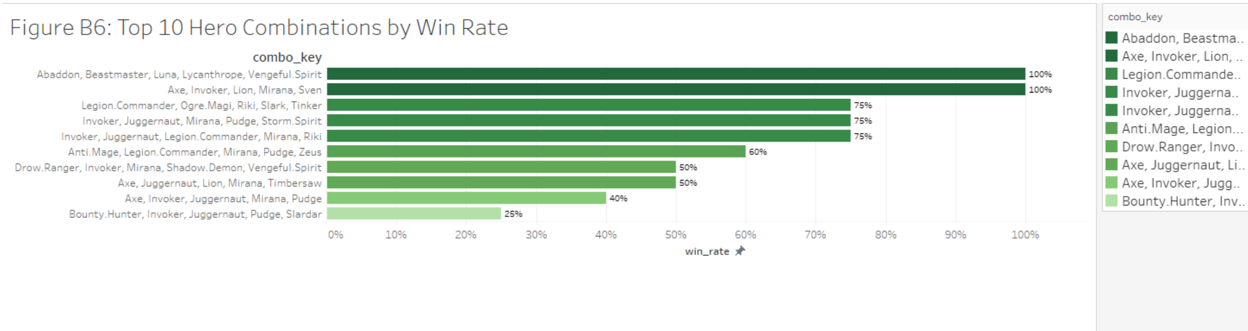


Figure 6: Figure B6: Top 10 Hero Combinations by Win Rate

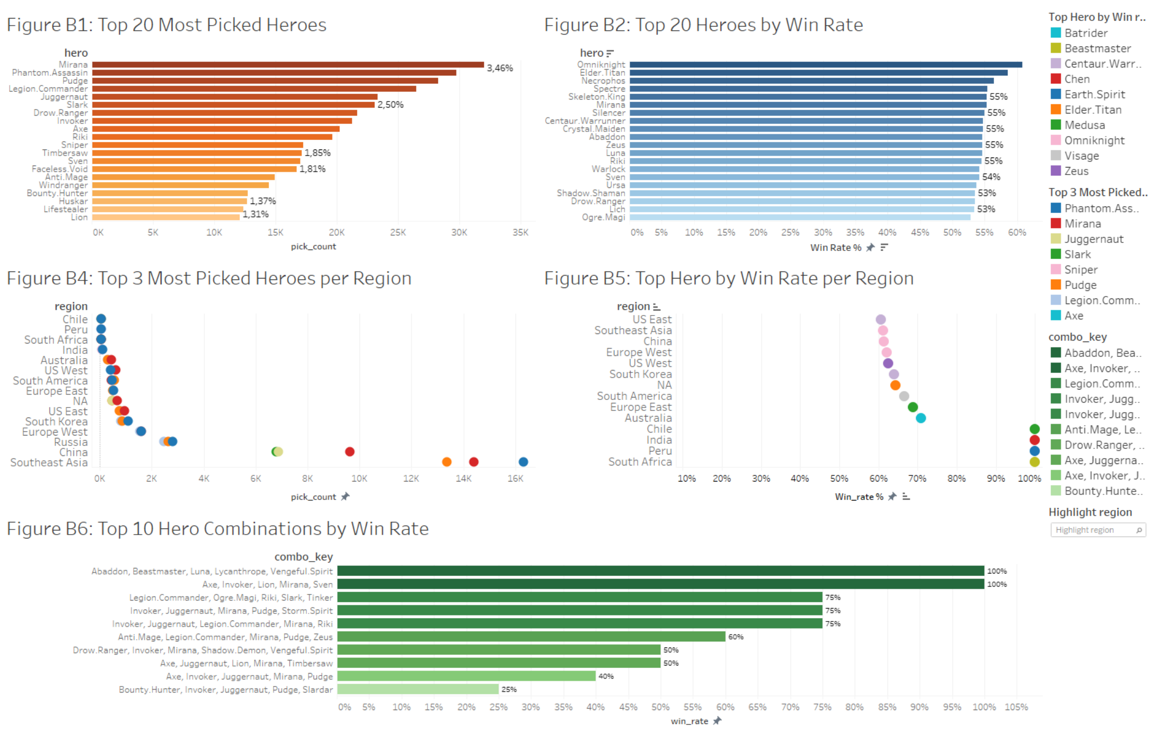


Figure 7: Figure B7: Tableau Summary Dashboard

6 The code

```r
# Load the dataset (no headers)
df <- read.csv("dota2Train.csv", header = FALSE)

# Manually assign proper column names
colnames(df)[1:4] <- c("win", "clusterid", "gamemode", "gametype")
colnames(df)[5:117] <- paste0("hero", 1:113)  # 113 hero features

# Read JSONs
heroes <- fromJSON("heroes.json")$heroes
mods <- fromJSON("mods.json")$mods
lobbies <- fromJSON("lobbies.json")$lobbies
regions <- fromJSON("regions.json")$regions

# Create mapping vectors
gamemode_map <- setNames(mods$name, mods$id)
gametype_map <- setNames(lobbies$name, lobbies$id)
region_map <- setNames(regions$name, regions$id)
hero_map <- setNames(heroes$localized_name, heroes$id)

# Map gamemode, gametype, clusterid to names
df$gamemode <- gamemode_map[as.character(df$gamemode)]
df$gametype <- gametype_map[as.character(df$gametype)]
df$region <- region_map[as.character(df$clusterid)]

# Replace heroX with real hero names, skipping missing IDs
hero_colnames <- paste0("hero", 1:113)
real_names <- hero_map[as.character(1:113)]
real_names[is.na(real_names)] <- paste0("Hero_", which(is.na(real_names)))
names(df)[5:117] <- real_names


unique(df$gametype)
table(df$gamemode)

# Export the mapped dataset
write.csv(df, here("dota2_cleaned.csv"), row.names = FALSE)
```

EDA Analysis

```r
# Read the cleaned dataset
dota <- read.csv("dota2_cleaned.csv", header = TRUE)
```

Basic Descriptive Stats & Distributions

```r
#  Count matches by region:
dota %>%
  count(region, sort = TRUE)

#  Distribution of gamemodes:
ggplot(dota, aes(x = gamemode)) +
```

```r
  geom_bar(fill = "steelblue") +
  theme_minimal() +
  coord_flip() +
  labs(title = "Match Count per Game Mode", x = "Game Mode", y = "Number of Matches")

# Win rate by gametype:
dota %>%
  group_by(gametype) %>%
  summarise(win_rate = mean(win)) %>%
  ggplot(aes(x = reorder(gametype, win_rate), y = win_rate)) +
  geom_col(fill = "darkgreen") +
  coord_flip() +
  labs(title = "Radiant Win Rate by Game Type", x = "Game Type", y = "Win Rate")
```

Hero Frequency Analysis

```r
# Most frequently picked heroes:

hero_cols <- names(dota)[grepl("^[A-Z]", names(dota))]

hero_counts <- dota %>%
  pivot_longer(cols = all_of(hero_cols), names_to = "hero", values_to = "picked") %>%
  filter(picked != 0) %>%
  group_by(hero) %>%
  summarise(pick_count = n(), .groups = "drop") %>%
  arrange(desc(pick_count)) %>%
  mutate(
    pick_percent = (pick_count / sum(pick_count)) * 100,
    label_text = paste0(pick_count, " (", round(pick_percent, 1), "%)")
  )

hero_counts$highlight <- ifelse(row_number(hero_counts$pick_count) <= 5, "top", "rest")
```

```r
# Plot
ggplot(hero_counts[1:20,], aes(x = reorder(hero, pick_count), y = pick_count,
                               fill = pick_count)) +
  geom_col(show.legend = FALSE) +
  geom_text(aes(label = label_text), hjust = -0.1, size = 3.5, color = "black") +
  scale_fill_gradient(low = "#FFE0B2", high = "#E65100") +
  coord_flip() +
  labs(
    title = "Figure A1: Top 20 Most Picked Heroes",
    subtitle = "With exact pick counts and relative frequencies",
    x = "Hero",
    y = "Pick Count"
  ) +
  theme_minimal(base_size = 13) +
  theme(
    plot.title = element_text(size = 16, face = "bold"),
    plot.subtitle = element_text(size = 12),
    axis.text.x = element_text(angle = 0),
    plot.margin = margin(10, 10, 10, 10)
  ) +
```

```
  ylim(0, max(hero_counts$pick_count[1:20]) * 1.1)
```

Win Rate per Hero

```
# Create win rate per hero
win_by_hero <- dota %>%
  select(win, all_of(hero_cols)) %>%
  pivot_longer(-win, names_to = "hero", values_to = "picked") %>%
  filter(picked != 0) %>%
  group_by(hero) %>%
  summarise(
    matches = n(),
    wins = sum((win == 1 & picked == 1) | (win == -1 & picked == -1)),
    win_rate = wins / matches,
    .groups = "drop"
  ) %>%
  arrange(desc(win_rate))


# Calculate average win rate
avg_win_rate <- mean(win_by_hero$win_rate)

# Use only top 20 heroes by win rate
top20_win <- win_by_hero[1:20, ]
```

```
# Plot
ggplot(top20_win, aes(x = reorder(hero, win_rate), y = win_rate, fill = win_rate)) +
  geom_col(width = 0.8) +
  scale_fill_gradientn(colors = c("#deebf7", "#9ecae1", "#3182bd", "#08519c")) +
  geom_text(aes(label = paste0(round(win_rate * 100, 1), "%")),
            hjust = -0.1, size = 3.5, color = "black") +
  coord_flip() +
  labs(
    title = "Figure A2: Top 20 Heroes by Win Rate",
    subtitle = "Ranked bar chart",
    x = "Hero",
    y = "Win Rate"
  ) +
  scale_y_continuous(
    labels = percent_format(accuracy = 1),
    limits = c(0, max(top20_win$win_rate) * 1.1)
  ) +
  theme_minimal(base_size = 13) +
  theme(
    plot.title = element_text(size = 16, face = "bold"),
    plot.subtitle = element_text(size = 12),
    axis.text.x = element_text(angle = 0),
    legend.position = "none"
  )
```

Radiant vs Dire Win Count

```r
# Count wins by team
team_wins <- dota %>%
  mutate(winning_team = ifelse(win == 1, "Radiant", "Dire")) %>%
  count(winning_team)


# Calculate percentages
team_wins <- team_wins %>%
  mutate(percent = n / sum(n),
         label = paste0(n, " (", percent(percent, accuracy = 0.1), ")"))

# Set colors from ColorBrewer Set2
colors <- c("Radiant" = "#66c2a5", "Dire" = "#fc8d62")
```

```r
# Plot
ggplot(team_wins, aes(x = winning_team, y = n, fill = winning_team)) +
  geom_col(width = 0.6, show.legend = FALSE) +
  geom_text(aes(label = label), vjust = -0.5, size = 4.2, color = "black") +
  scale_fill_manual(values = colors) +
  labs(
    title = "Figure A3: Number of Wins by Team",
    subtitle = "Radiant vs Dire win distribution with absolute and relative values",
    x = "Winning Team",
    y = "Match Count"
  ) +
  scale_y_continuous(
    expand = expansion(mult = c(0, 0.1))
  ) +
  theme_minimal(base_size = 13) +
  theme(
    plot.title = element_text(size = 16, face = "bold"),
    plot.subtitle = element_text(size = 12),
    axis.text.x = element_text(size = 11),
    axis.text.y = element_text(size = 11)
  )
```

Top 3 Most Picked Heroes Per Region

```r
library(tidyverse)


# Select top 3 most picked heroes per region
top3_picked_per_region <- dota %>%
  select(region, all_of(hero_cols)) %>%
  pivot_longer(-region, names_to = "hero", values_to = "pick") %>%
  filter(pick != 0) %>%
  group_by(region, hero) %>%
  summarise(pick_count = n(), .groups = "drop") %>%
  group_by(region) %>%
  slice_max(pick_count, n = 3) %>%
  ungroup()

# Sort regions by max pick count for better y-axis readability
```

```r
region_order_top3 <- top3_picked_per_region %>%
  group_by(region) %>%
  summarise(max_pick = max(pick_count)) %>%
  arrange(desc(max_pick)) %>%
  pull(region)

top3_picked_per_region$region <- factor(top3_picked_per_region$region,
                                        levels = region_order_top3)

# Use consistent color palette (Set3 reused and repeated if needed)
unique_heroes_top3 <- sort(unique(top3_picked_per_region$hero))
n_top3 <- length(unique_heroes_top3)
hero_colors_top3 <- setNames(
  rep(brewer.pal(12, "Set3"), length.out = n_top3),
  unique_heroes_top3
)
```

```r
# Plot
ggplot(top3_picked_per_region, aes(x = pick_count, y = region, color = hero)) +
  geom_point(size = 6, alpha = 0.9) +
  scale_color_manual(values = hero_colors_top3) +
  labs(
    title = "Figure A4: Top 3 Most Picked Heroes per Region",
    x = "Pick Count",
    y = "Region",
    color = "Hero"
  ) +
  theme_minimal(base_size = 13) +
  theme(
    panel.grid.major.y = element_line(color = "gray90", size = 0.3),
    panel.grid.major.x = element_line(color = "gray85", size = 0.3),
    plot.title = element_text(size = 16, face = "bold", margin = margin(b = 12)),
    axis.text.y = element_text(size = 11),
    axis.text.x = element_text(size = 11),
    legend.position = "right",
    legend.title = element_text(size = 11),
    legend.text = element_text(size = 10)
  )
```

Hero Win Rate by Region

```r
# Create hero_region_winrate
hero_region_winrate <- dota %>%
  select(win, region, all_of(hero_cols)) %>%
  pivot_longer(cols = all_of(hero_cols), names_to = "hero",
               values_to = "picked") %>%
  filter(picked != 0) %>%
  group_by(region, hero) %>%
  summarise(
    matches = n(),
    wins = sum((win == 1 & picked == 1) | (win == -1 & picked == -1)),
    win_rate = wins / matches,
    .groups = "drop"
```

```r
  )


# Select only the top 1 hero by win rate per region
top1_winrate_per_region <- hero_region_winrate %>%
  filter(!is.na(win_rate) & win_rate > 0) %>%
  group_by(region) %>%
  slice_max(order_by = win_rate, n = 1, with_ties = FALSE) %>%
  ungroup()

# Prepare hero color palette again (now fewer colors needed)
unique_heroes_top1 <- sort(unique(top1_winrate_per_region$hero))
n_top1 <- length(unique_heroes_top1)
hero_colors_top1 <- setNames(
  rep(brewer.pal(12, "Set3"), length.out = n_top1),
  unique_heroes_top1
)

# Sort regions by top hero win rate
region_order_top1 <- top1_winrate_per_region %>%
  arrange(desc(win_rate)) %>%
  pull(region)

top1_winrate_per_region$region <- factor(top1_winrate_per_region$region,
                                         levels = region_order_top1)
```

```r
# Final Plot
ggplot(top1_winrate_per_region, aes(x = win_rate, y = region, color = hero)) +
  geom_point(size = 6, alpha = 0.85) +
  scale_color_manual(values = hero_colors_top1) +
  scale_x_continuous(labels = percent_format(accuracy = 1),
                     limits = c(0.5, 1.01)) +
  labs(
    title = "Figure A5: Top Hero by Win Rate per Region",
    x = "Win Rate",
    y = "Region",
    color = "Hero"
  ) +
  theme_minimal(base_size = 13) +
  theme(
    panel.grid.major.y = element_line(color = "gray90", size = 0.3),
    panel.grid.major.x = element_line(color = "gray85", size = 0.3),
    panel.grid.minor = element_blank(),
    plot.title = element_text(size = 16, face = "bold", margin = margin(b = 12)),
    axis.text.y = element_text(size = 11),
    axis.text.x = element_text(size = 11),
    legend.position = "right",
    legend.title = element_text(size = 11),
    legend.text = element_text(size = 10)
  )
```

Top Winning Combos

```r
# Step 1: Subset hero columns
hero_matrix <- dota %>%
  select(all_of(hero_cols))

# Step 2: Extract Radiant and Dire heroes
get_team_combos <- function(team_val = 1) {
  hero_matrix %>%
    mutate(row = row_number()) %>%
    pivot_longer(-row, names_to = "hero", values_to = "value") %>%
    filter(value == team_val) %>%
    group_by(row) %>%
    summarise(team_heroes = list(sort(hero))) %>%
    mutate(team = ifelse(team_val == 1, "Radiant", "Dire"))
}

radiant_teams <- get_team_combos(1) %>% mutate(win = dota$win)
dire_teams    <- get_team_combos(-1) %>% mutate(win = -dota$win)

# Step 3: Combine both teams
team_data <- bind_rows(radiant_teams, dire_teams)

# Step 4: Create a combo key
team_data <- team_data %>%
  mutate(combo_key = map_chr(team_heroes, ~ paste(sort(.x), collapse = ", ")))


# Aggregate and calculate win rates
combo_stats <- team_data %>%
  group_by(combo_key) %>%
  summarise(
    matches = n(),
    wins = sum(win == 1),
    win_rate = wins / matches,
    .groups = "drop"
  ) %>%
  filter(matches >= 4) %>%  # ignore very rare combos
  arrange(desc(win_rate))

# Sort by win_rate, then by match count (both descending)
top_combos <- combo_stats %>%
  filter(matches >= 4) %>%
  arrange(desc(win_rate), desc(matches)) %>%
  slice_head(n = 10)


# Wrap combo labels at 40 characters (optional: adjust if needed)
top_combos$combo_key_wrapped <- str_wrap(top_combos$combo_key, width = 40)
```

```r
# Plot
ggplot(top_combos, aes(x = reorder(combo_key_wrapped, win_rate + matches / 1000),
                       y = win_rate, fill = win_rate)) +
  geom_col(width = 0.7) +
  scale_fill_gradientn(colors = c("#e5f5e0", "#a1d99b", "#41ab5d", "#006d2c")) +
```

```r
  coord_flip() +
  labs(
    title = "Figure A6: \nTop 10 Hero Combinations\n by Win Rate",
    subtitle = "Sorted by Win Rate Prioritized by Match Count \n(min. 4 matches)",
    x = "Hero Combination",
    y = "Win Rate"
  ) +
  scale_y_continuous(
    labels = scales::label_percent(accuracy = 1),
    breaks = seq(0, 1, 0.25),
    limits = c(0, 1.15)
  ) +
  theme_minimal(base_size = 12) +
  theme(
    plot.background = element_rect(fill = "white", color = NA),
    panel.background = element_rect(fill = "white", color = NA),
    plot.title = element_text(size = 16, face = "bold", margin = margin(t = 30,
                                                                         b = 12)),
    plot.subtitle = element_text(size = 11, margin = margin(t = 5, b = 15)),
    axis.text.y = element_text(size = 9),
    legend.position = "none"
  )
```

---

7 References

Dataset: **Dota2 Games Results https://archive.ics.uci.edu/dataset/367/dota2+games+results**

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