

NBA_Win_Percentage

2025-11-13

```
# Install Once in Console
# install.packages(c("tidyverse", "janitor", "lubridate", "tidymodels", "vip", "finetune"))
# install.packages("hoopR")

library(tidyverse)

## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr     1.1.4      v readr     2.1.5
## vforcats   1.0.0      v stringr   1.5.1
## v ggplot2   4.0.0      v tibble    3.3.0
## v lubridate 1.9.4      v tidyr    1.3.1
## v purrr    1.1.0

## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()   masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
library(janitor)

##
## Attaching package: 'janitor'
##
## The following objects are masked from 'package:stats':
##
##     chisq.test, fisher.test

library(lubridate)
library(tidymodels)

## -- Attaching packages ----- tidymodels 1.4.1 --
## v broom      1.0.10     v rsample    1.3.1
## v dials      1.4.2       v tailor    0.1.0
## v infer      1.0.9       v tune      2.0.1
## v modeldata   1.5.1       v workflows 1.3.0
## v parsnip     1.3.3       v workflowsets 1.1.1
## v recipes     1.3.1       v yardstick 1.3.2
## -- Conflicts ----- tidymodels_conflicts() --
## x scales::discard() masks purrr::discard()
## x dplyr::filter()   masks stats::filter()
## x recipes::fixed() masks stringr::fixed()
## x dplyr::lag()     masks stats::lag()
## x yardstick::spec() masks readr::spec()
## x recipes::step()  masks stats::step()

library(hoopR)
library(vip)
```

```

## 
## Attaching package: 'vip'
## 
## The following object is masked from 'package:utils':
## 
##     vi
set.seed(123)

df_raw <- load_nba_team_box(seasons = 2015:2024)

# Check
df_raw %>% count(season) %>% arrange(season)

## -- ESPN NBA Team Boxscores from hoopR data repository ----- hoopR 2.1.0 --
## i Data updated: 2025-04-18 17:42:31 MDT

## # A tibble: 10 x 2
##   season      n
##   <int> <int>
## 1 2015    2624
## 2 2016    2634
## 3 2017    2618
## 4 2018    2626
## 5 2019    2628
## 6 2020    2290
## 7 2021    2242
## 8 2022    2648
## 9 2023    2642
## 10 2024   2640

unique(df_raw$season)

## [1] 2015 2016 2017 2018 2019 2020 2021 2022 2023 2024

df_team_season <- df_raw %>%
  filter(season_type == 2) %>%           # 2 = Regular season
  group_by(season, team_id, team_abbreviation, team_name) %>%
  summarise(
    games = n(),
    wins = sum(team_winner, na.rm = TRUE),    # TRUE = win
    win_pct = wins / games,

    # per-game averages of all numeric stats (box score + scores)
    across(where(is.numeric), mean, na.rm = TRUE),
    .groups = "drop"
  )

## Warning: There was 1 warning in `summarise()` .
## i In argument: `across(where(is.numeric), mean, na.rm = TRUE)` .
## i In group 1: `season = 2015` , `team_id = 1` , `team_abbreviation = "ATL"` ,
##   `team_name = "Hawks"` .
## Caused by warning:
## ! The `...` argument of `across()` is deprecated as of dplyr 1.1.0.
## Supply arguments directly to `.fns` through an anonymous function instead.
## 
```

```

##    # Previously
##    across(a:b, mean, na.rm = TRUE)
##
##    # Now
##    across(a:b, \((x) mean(x, na.rm = TRUE))
```

df_team_season %>%
 summarise(
 n_teams = n(),
 min_win = min(win_pct),
 max_win = max(win_pct),
 mean_win = mean(win_pct),
 sd_win = sd(win_pct)
)

```

## # A tibble: 1 x 5
##   n_teams min_win max_win mean_win sd_win
##       <int>     <dbl>     <dbl>      <dbl>    <dbl>
## 1       326        0         1      0.499    0.200
```

#Quick Correlation for WIN PCT

```

num_vars <- df_team_season %>%
  select(where(is.numeric))

cor_with_win <- num_vars %>%
  summarise(across(everything(), ~ cor(.x, win_pct, use = "complete.obs")))) %>%
  pivot_longer(everything(), names_to = "variable", values_to = "cor_win_pct") %>%
  arrange(desc(abs(cor_win_pct)))
```

Warning: There was 1 warning in `summarise()`.
 ## i In argument: `across(everything(), ~cor(.x, win_pct, use = "complete.obs"))`.
 ## Caused by warning in `cor()`:
 ## ! the standard deviation is zero

```

head(cor_with_win, 20)
```

```

## # A tibble: 20 x 2
##   variable           cor_win_pct
##   <chr>                 <dbl>
## 1 win_pct                  1
## 2 three_point_field_goal_pct 0.644
## 3 wins                     0.515
## 4 defensive_rebounds       0.276
## 5 three_point_field_goals_made 0.265
## 6 team_score                0.178
## 7 opponent_team_score      -0.167
## 8 total_rebounds             0.116
## 9 three_point_field_goals_attempted 0.114
## 10 field_goals_made          0.112
## 11 field_goal_pct            0.0773
## 12 technical_fouls           0.0754
## 13 total_technical_fouls      0.0754
## 14 turnovers                 -0.0683
## 15 total_turnovers            -0.0682
## 16 blocks                    0.0634
## 17 free_throw_pct              0.0568
```

```

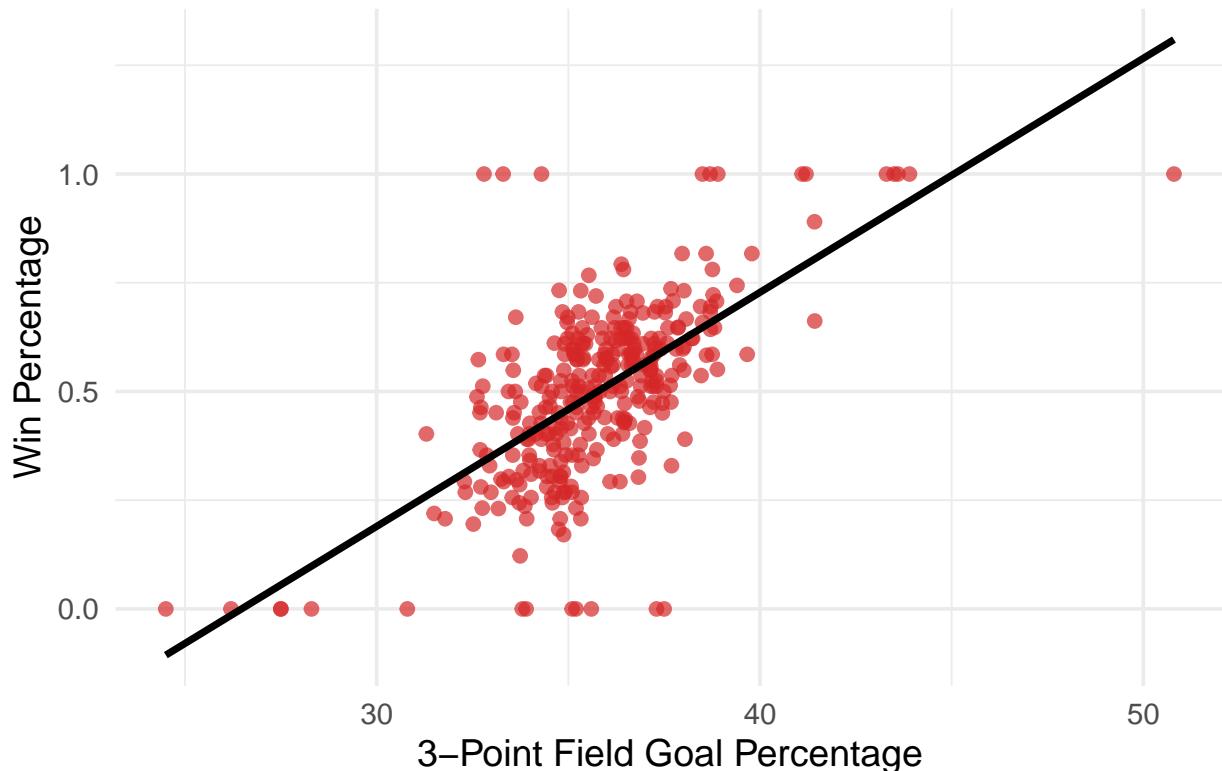
## 18 assists                         0.0550
## 19 offensive_rebounds              -0.0496
## 20 steals                           0.0351

df_team_season %>%
  ggplot(aes(x = three_point_field_goal_pct, y = win_pct)) +
  geom_point(alpha = 0.7, color = "#d62728") +
  geom_smooth(method = "lm", se = FALSE, color = "black") +
  labs(
    title = "Relationship Between 3-Point Percentage and Win Percentage",
    x = "3-Point Field Goal Percentage",
    y = "Win Percentage"
  ) +
  theme_minimal(base_size = 14)

## `geom_smooth()` using formula = 'y ~ x'

```

Relationship Between 3-Point Percentage and Win Perc



Add All Plots or Correlations here, leave RF Model at end

```

df_model <- df_team_season %>%
  # drop obvious leaks / not useful predictors
  select(
    -wins,
    -games,
  )

set.seed(123)

```

```

nba_split <- initial_split(df_model, prop = 0.8, strata = win_pct)
nba_train <- training(nba_split)
nba_test <- testing(nba_split)

nba_recipe <- recipe(win_pct ~ ., data = nba_train) %>%
  # Mark ID columns so they're not used as predictors
  update_role(season, team_id, team_abbreviation, team_name, new_role = "ID") %>%

  step_zv(all_predictors()) %>%
  step_impute_median(all_numeric_predictors()) %>%
  step_normalize(all_numeric_predictors())

rf_spec <- rand_forest(
  mtry   = tune(),
  min_n  = tune(),
  trees  = 1000
) %>%
  set_mode("regression") %>%
  set_engine("ranger", importance = "impurity")

#Cross Validation
set.seed(123)
nba_folds <- vfold_cv(nba_train, v = 5, strata = win_pct)

# Workflow
rf_workflow <- workflow() %>%
  add_model(rf_spec) %>%
  add_recipe(nba_recipe)

#Small Tuning Grid
rf_grid <- grid_regular(
  mtry(range = c(5, 30)),
  min_n(range = c(2, 15)),
  levels = 5
)

#Tune
rf_tuned <- tune_grid(
  rf_workflow,
  resamples = nba_folds,
  grid = rf_grid,
  metrics = metric_set(rmse, rsq)
)

## > A | warning: ! 30 columns were requested but there were 26 predictors in the data.
##           i 26 predictors will be used.

## There were issues with some computations    A: x1There were issues with some computations    A: x3There
collect_metrics(rf_tuned) %>%
  arrange(mean)

## # A tibble: 50 x 8
##       mtry min_n .metric .estimator  mean     n std_err .config

```

```

##      <int> <int> <chr>    <chr>      <dbl> <int>    <dbl> <chr>
## 1    30     2 rmse standard  0.145     5 0.0121 pre0_mod21_post0
## 2    30     8 rmse standard  0.146     5 0.0124 pre0_mod23_post0
## 3    23     2 rmse standard  0.146     5 0.0119 pre0_mod16_post0
## 4    30     5 rmse standard  0.146     5 0.0124 pre0_mod22_post0
## 5    23     5 rmse standard  0.146     5 0.0122 pre0_mod17_post0
## 6    23     8 rmse standard  0.147     5 0.0121 pre0_mod18_post0
## 7    23    11 rmse standard  0.147     5 0.0116 pre0_mod19_post0
## 8    30    11 rmse standard  0.147     5 0.0120 pre0_mod24_post0
## 9    17     5 rmse standard  0.148     5 0.0106 pre0_mod12_post0
## 10   30    15 rmse standard  0.148     5 0.0118 pre0_mod25_post0
## # i 40 more rows

#Pick Best and Refit
best_rf <- select_best(rf_tuned, metric = "rmse")

rf_final_wf <- finalize_workflow(rf_workflow, best_rf)

rf_fit <- fit(rf_final_wf, data = nba_train)

## Warning: ! 30 columns were requested but there were 26 predictors in the data.
## i 26 predictors will be used.

rf_test_preds <- predict(rf_fit, new_data = nba_test) %>%
  bind_cols(nba_test %>% select(win_pct))

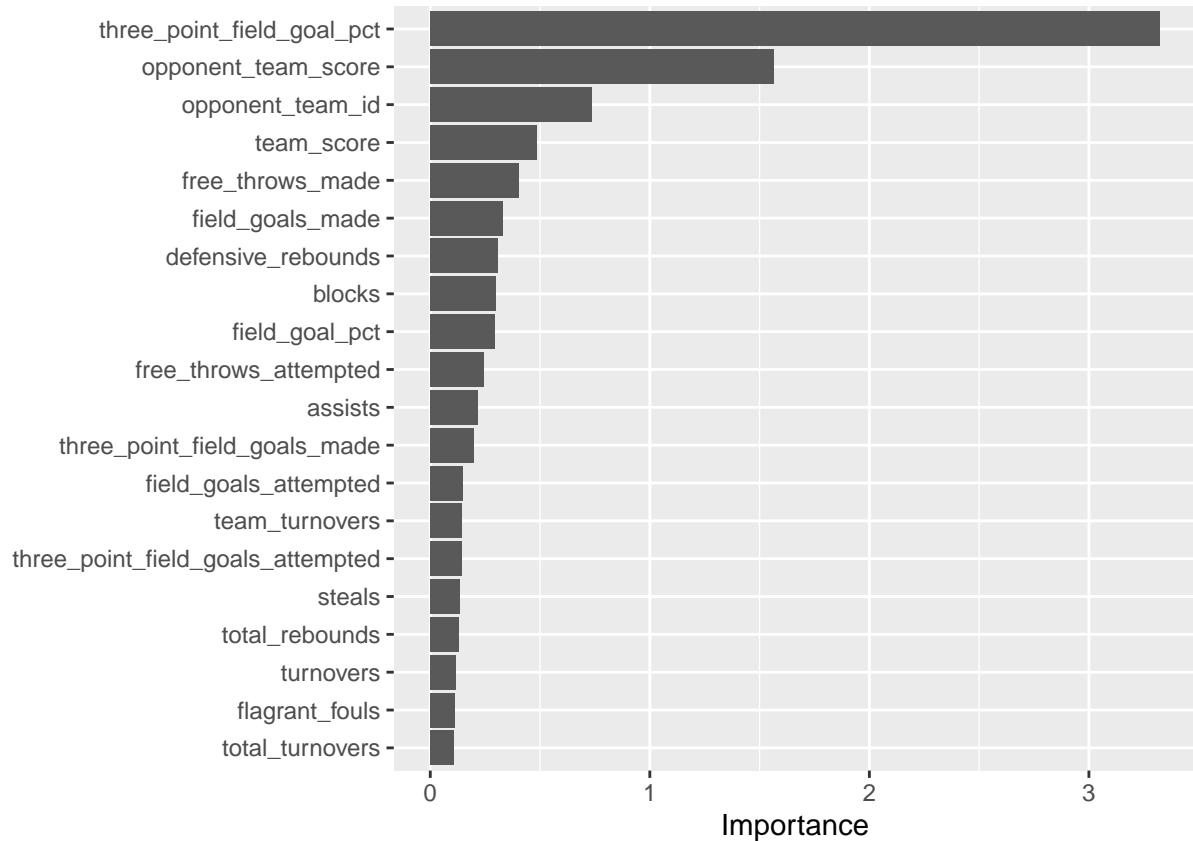
rf_test_preds %>%
  metrics(truth = win_pct, estimate = .pred)

## # A tibble: 3 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>       <dbl>
## 1 rmse    standard    0.178
## 2 rsq     standard    0.322
## 3 mae     standard    0.102

rf_fit_ranger <- rf_fit %>%
  extract_fit_parsnip() %>%
  pluck("fit")

vip(rf_fit_ranger, num_features = 20)

```



```
var_imp <- rf_fit_ranger$variable.importance %>%
```

```
  sort(decreasing = TRUE)
```

```
head(var_imp, 30)
```

##	three_point_field_goal_pct	opponent_team_score
##	3.32338798	1.56244976
##	opponent_team_id	team_score
##	0.73395888	0.48652163
##	free_throws_made	field_goals_made
##	0.40520673	0.33047505
##	defensive_rebounds	blocks
##	0.30785477	0.29801706
##	field_goal_pct	free_throws_attempted
##	0.29243095	0.24257150
##	assists	three_point_field_goals_made
##	0.21606435	0.19691119
##	field_goals_attempted	team_turnovers
##	0.14814133	0.14494877
##	three_point_field_goals_attempted	steals
##	0.14156217	0.13268603
##	total_rebounds	turnovers
##	0.12953774	0.11662880
##	flagrant_fouls	total_turnovers
##	0.11358668	0.10675867
##	free_throw_pct	offensive_rebounds
##	0.10507568	0.08991222

```

##          fouls      total_technical_fouls
##          0.08511494      0.07220005
##      technical_fouls      game_id
##          0.06590008      0.05713184

lm_spec <- linear_reg() %>%
  set_engine("lm")

lm_wf <- workflow() %>%
  add_model(lm_spec) %>%
  add_recipe(nba_recipe)

lm_fit <- fit(lm_wf, data = nba_train)

tidy(lm_fit) %>%
  arrange(desc(abs(estimate))) %>%
  head(20)

## # A tibble: 20 x 5
##   term            estimate std.error statistic p.value
##   <chr>           <dbl>     <dbl>     <dbl>    <dbl>
## 1 field_goals_made     1.33      9.57     0.139  8.90e- 1
## 2 team_score        -0.977     9.92    -0.0985 9.22e- 1
## 3 (Intercept)       0.496     0.00445   111.   1.94e-205
## 4 opponent_team_score -0.423     0.0304    -13.9   1.57e- 32
## 5 three_point_field_goals_made 0.395     2.61     0.151  8.80e- 1
## 6 free_throws_made    0.206     2.30     0.0893 9.29e- 1
## 7 fouls              0.105     0.0235     4.47   1.23e- 5
## 8 field_goal_pct      0.0957    0.0315     3.04   2.67e- 3
## 9 free_throws_attempted 0.0929    0.0377     2.46   1.45e- 2
## 10 free_throw_pct     0.0712    0.0160     4.44   1.37e- 5
## 11 flagrant_fouls     0.0697    0.0270     2.58   1.05e- 2
## 12 blocks             0.0648    0.0186     3.48   6.06e- 4
## 13 assists            0.0537    0.0177     3.03   2.74e- 3
## 14 steals             -0.0468   0.0120    -3.90   1.28e- 4
## 15 field_goals_attempted 0.0368   0.0576     0.638  5.24e- 1
## 16 three_point_field_goals_attempted -0.0303   0.0525    -0.577  5.65e- 1
## 17 game_id            -0.0225   0.0107    -2.09   3.73e- 2
## 18 offensive_rebounds -0.0158   0.0116    -1.36   1.74e- 1
## 19 total_turnovers    -0.0143   0.0232    -0.617  5.38e- 1
## 20 total_rebounds      -0.0111   0.0127    -0.872  3.84e- 1

```

Summary

Interpretation of Variable Importance for Predicting Win Percentage

The random forest model identifies which team statistics are most strongly associated with overall winning percentage across all NBA seasons from 2015–2024. The most important predictor by far is three-point field goal percentage, followed by several offensive and defensive efficiency indicators such as scoring, opponent scoring, free throws made, and defensive rebounding.

Overall, the model suggests that efficient shooting—especially from three, limiting opponent scoring, and winning key possession battles (rebounds, blocks, turnovers) are the strongest predictors of a successful season.