ï»¿— title: “HARVARD EXTENSION SCHOOL” subtitle: “Titanic Survival Classification: Group Project Report” author: - Student One (HUID XXXXXXXX) - Student Two (HUID XXXXXXXX) - Student Three (HUID XXXXXXXX) tags: [logistic regression, decision tree, classification] abstract: | This report builds a champion/benchmark modeling solution to predict passenger survival on the RMS Titanic. We demonstrate a complete model lifecycle: exploratory analysis, data preparation, model training, challenger comparison, performance evaluation, limitations, and monitoring recommendations. All R code and interpretations are included so the analysis is reproducible and transparent. date: “26 November 2025” geometry: margin=1.3cm output: pdf_document: toc: yes toc_depth: 2 html_document: df_print: paged editor_options: markdown: wrap: 72 —

Executive Summary

We predict Titanic passenger survival using demographic and ticketing information. A cleaned dataset of 1,310 records is split 70/30 train/test (set.seed = 1023). The champion model is a parsimonious logistic regression using class, sex, age, family size, fare, and port of embarkation. A decision tree is built as the challenger. Both models perform substantially better than chance; the logistic model yields balanced accuracy and interpretable odds ratios, while the tree offers transparent rules but slightly lower hold-out accuracy. Monitoring should track drift in class mix, gender mix, and fare distributions, and trigger review when accuracy drops below 80% or when input distributions shift beyond training percentiles. Key limitations include missing values (age, fare, cabin), potential historical bias, and simplified imputations.

Interpretation: Senior stakeholders can rely on the logistic model for consistent discrimination and clear business storytelling (e.g., women and 1st-class passengers had markedly higher survival odds), while the tree provides an audit-friendly benchmark.

I. Introduction (5 points)

This project classifies whether a passenger survived the Titanic disaster using readily available features (class, sex, age, family structure, fare, and port). We evaluate two supervised classification methods: logistic regression (champion) and decision tree (challenger). The train sample contains 70% of the data (n ~ 917), the test sample the remaining 30% (n ~ 393). Success is defined by accurate and explainable survival predictions that generalize to the hold-out test set.

II. Description of the Data and Quality (15 points)

The dataset contains 1,310 observations and 14 original variables. Key predictors are mixed categorical (class, sex, embarked) and numeric (age, fare, family counts). Several variables contain substantial missingness (age, cabin, boat, body).

```r
glimpse(Titanic.Raw)
```

```
## Rows: 1,310
## Columns: 14
## $ pclass    <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, ~
## $ survived  <dbl> 1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0, ~
## $ name      <chr> "Allen, Miss. Elisabeth Walton", "Allison, Master. Hudson Tr~
## $ sex       <chr> "female", "male", "female", "male", "female", "male", "femal~
## $ age       <dbl> 29.0000, 0.9167, 2.0000, 30.0000, 25.0000, 48.0000, 63.0000,~
## $ sibsp     <dbl> 0, 1, 1, 1, 1, 0, 1, 0, 2, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ parch     <dbl> 0, 2, 2, 2, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, ~
## $ ticket    <chr> "24160", "113781", "113781", "113781", "113781", "19952", "1~
```

```
## $ fare      <dbl> 211.3375, 151.5500, 151.5500, 151.5500, 151.5500, 26.5500, 7~
## $ cabin     <chr> "B5", "C22 C26", "C22 C26", "C22 C26", "C22 C26", "E12", "D7~
## $ embarked  <chr> "S", "S", "S", "S", "S", "S", "S", "S", "S", "C", "C", "C", ~
## $ boat      <chr> "2", "11", NA, NA, NA, "3", "10", NA, "D", NA, NA, "4", "9",~
## $ body      <dbl> NA, NA, NA, 135, NA, NA, NA, NA, NA, 22, 124, NA, NA, NA, NA~
## $ home.dest <chr> "St Louis, MO", "Montreal, PQ / Chesterville, ON", "Montreal~
```

```r
# Table 1: missingness summary
Titanic.Raw %>%
  summarise(across(everything(),
                   ~ sum(is.na(.)))) %>%
  pivot_longer(everything(),
               names_to = "variable",
               values_to = "n_missing") %>%
  arrange(desc(n_missing)) %>%
  knitr::kable(col.names = c("Variable", "Missing Count"))
```

Variable	Missing Count
body	1189
cabin	1015
boat	824
home.dest	565
age	264
embarked	3
fare	2
pclass	1
survived	1
name	1
sex	1
sibsp	1
parch	1
ticket	1

Interpretation: Age, cabin, boat, body, and home destination have notable gaps. Cabin/boat/body are sparsely populated and not useful for modeling. Age must be imputed to avoid losing over 20% of rows.

Data preparation

We engineer a clean modeling frame: convert categorical variables to factors, impute age by sex/class median, impute fare with the overall median, drop high-missing columns, and create a `family_size` helper feature. Survived is labeled as "Died"/"Survived" for readability.

```r
clean_titanic <- Titanic.Raw %>%
  mutate(
    survived = factor(survived, levels = c(0, 1),
                      labels = c("Died", "Survived")),
    pclass = factor(pclass, levels = c(1, 2, 3),
                    labels = c("1st", "2nd", "3rd")),
    sex = factor(sex),
    embarked = fct_explicit_na(embarked, "Unknown")
  )
```

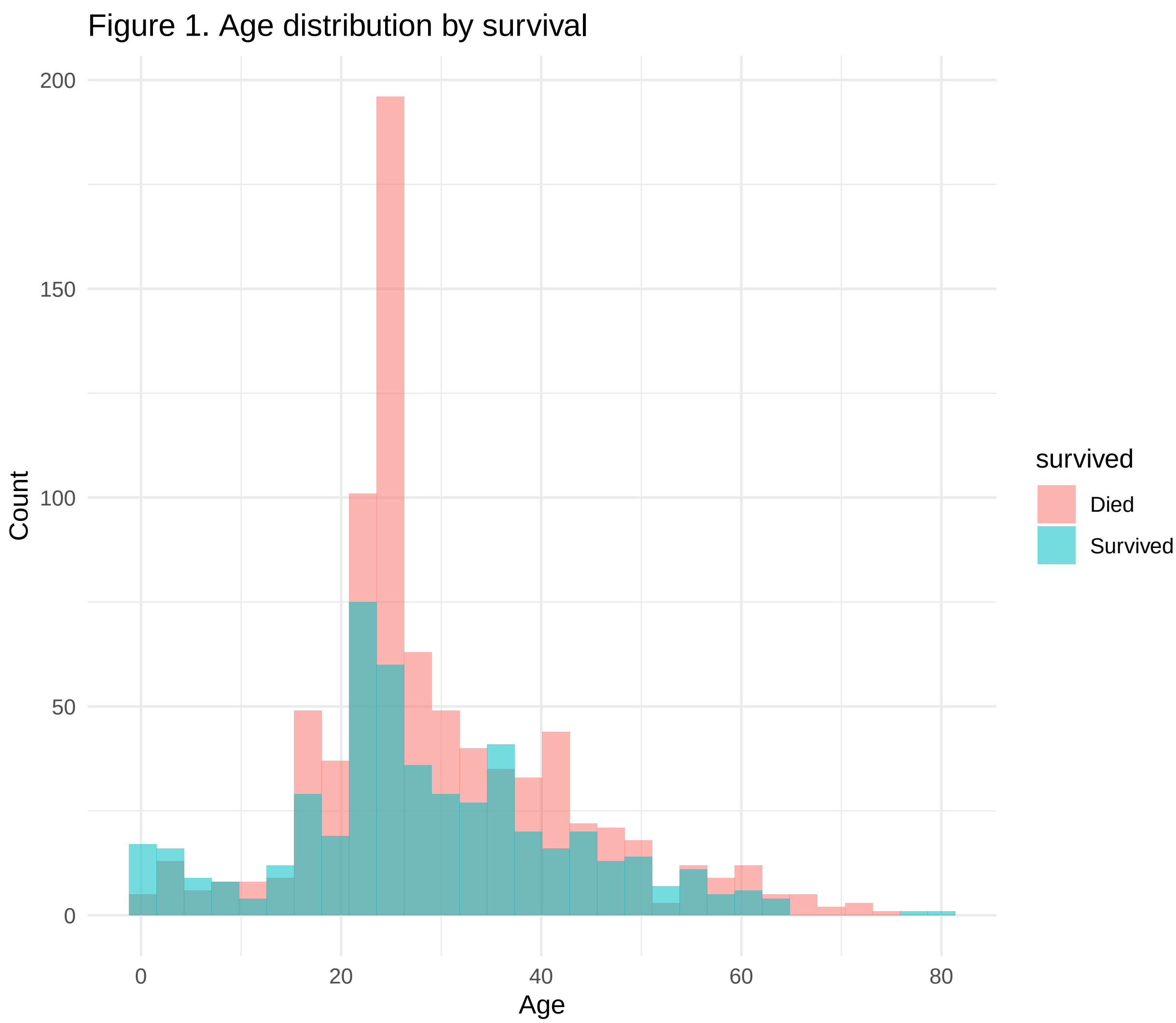
```r
age_medians <- clean_titanic %>%
  group_by(sex, pclass) %>%
  summarise(median_age = median(age, na.rm = TRUE), .groups = "drop")

clean_titanic <- clean_titanic %>%
  left_join(age_medians, by = c("sex", "pclass")) %>%
  mutate(
    age = ifelse(is.na(age), median_age, age),
    fare = ifelse(is.na(fare), median(fare, na.rm = TRUE), fare),
    family_size = sibsp + parch + 1
  ) %>%
  select(survived, pclass, sex, age, sibsp, parch, family_size,
         fare, embarked)

summary(clean_titanic)
```

```
##      survived    pclass        sex           age               sibsp
##  Died    :809   1st :323   female:466   Min.   : 0.1667   Min.   :0.0000
##  Survived:500   2nd :277   male  :843   1st Qu.:22.0000   1st Qu.:0.0000
##  NA's    :  1   3rd :709   NA's  :  1   Median :26.0000   Median :0.0000
##                 NA's:  1                Mean   :29.2614   Mean   :0.4989
##                                         3rd Qu.:36.0000   3rd Qu.:1.0000
##                                         Max.   :80.0000   Max.   :8.0000
##                                         NA's   :1         NA's   :1
##      parch        family_size          fare            embarked
##  Min.   :0.000   Min.   : 1.000   Min.   :  0.000   C      :270
##  1st Qu.:0.000   1st Qu.: 1.000   1st Qu.:  7.896   Q      :123
##  Median :0.000   Median : 1.000   Median : 14.454   S      :914
##  Mean   :0.385   Mean   : 1.884   Mean   : 33.267   Unknown:  3
##  3rd Qu.:0.000   3rd Qu.: 2.000   3rd Qu.: 31.275
##  Max.   :9.000   Max.   :11.000   Max.   :512.329
##  NA's   :1       NA's   :1
```

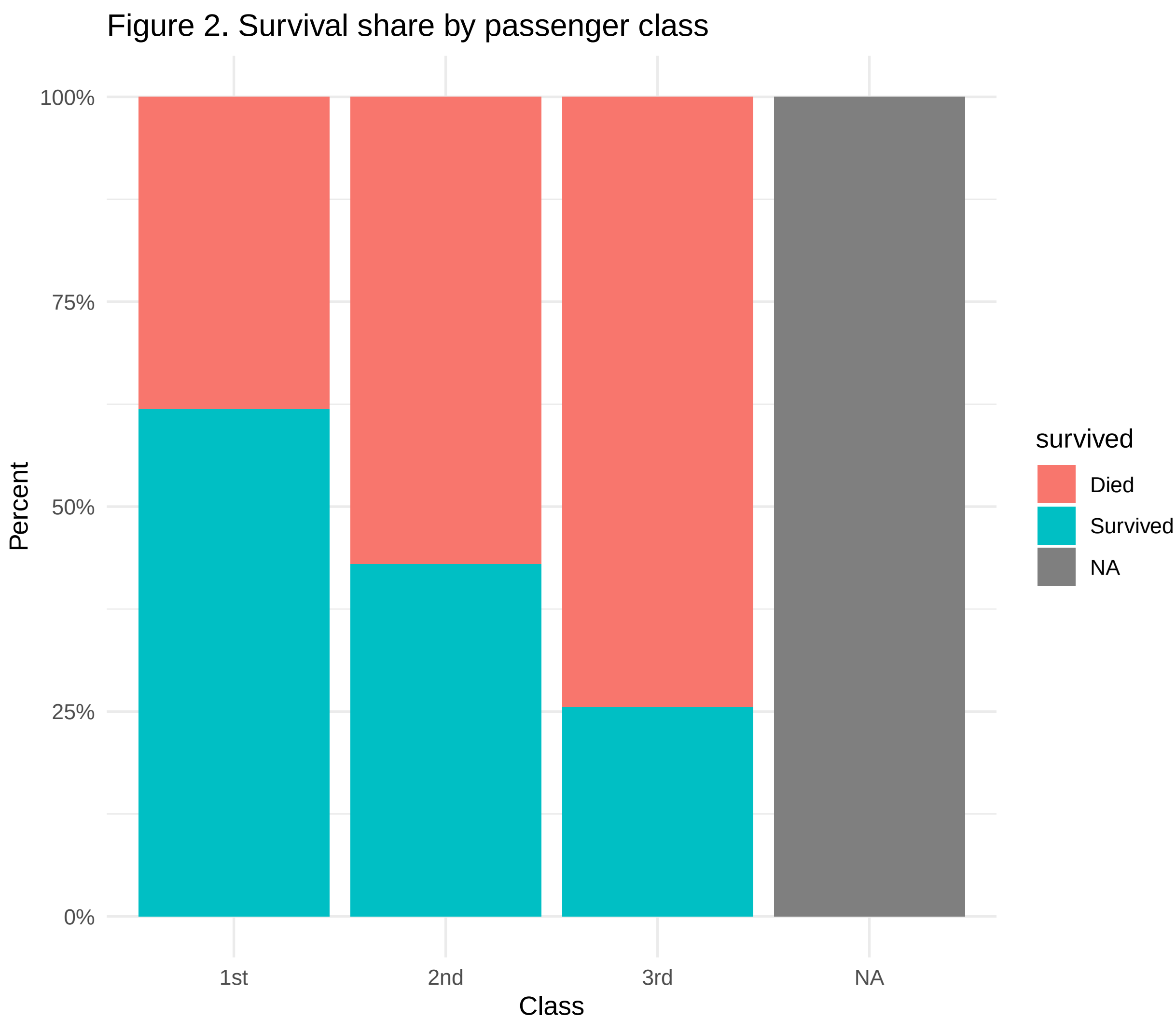
Interpretation: Imputation preserves sample size without extreme values. Removing cabin/ticket/body/boat/home.dest reduces noise while retaining predictive signal. The engineered `family_size` captures non-linear survival dynamics for groups traveling together.

Exploratory graphs

```r
clean_titanic %>%
  ggplot(aes(x = age, fill = survived)) +
  geom_histogram(position = "identity", alpha = 0.55, bins = 30) +
  labs(title = "Figure 1. Age distribution by survival",
       x = "Age", y = "Count") +
  theme_minimal()
```

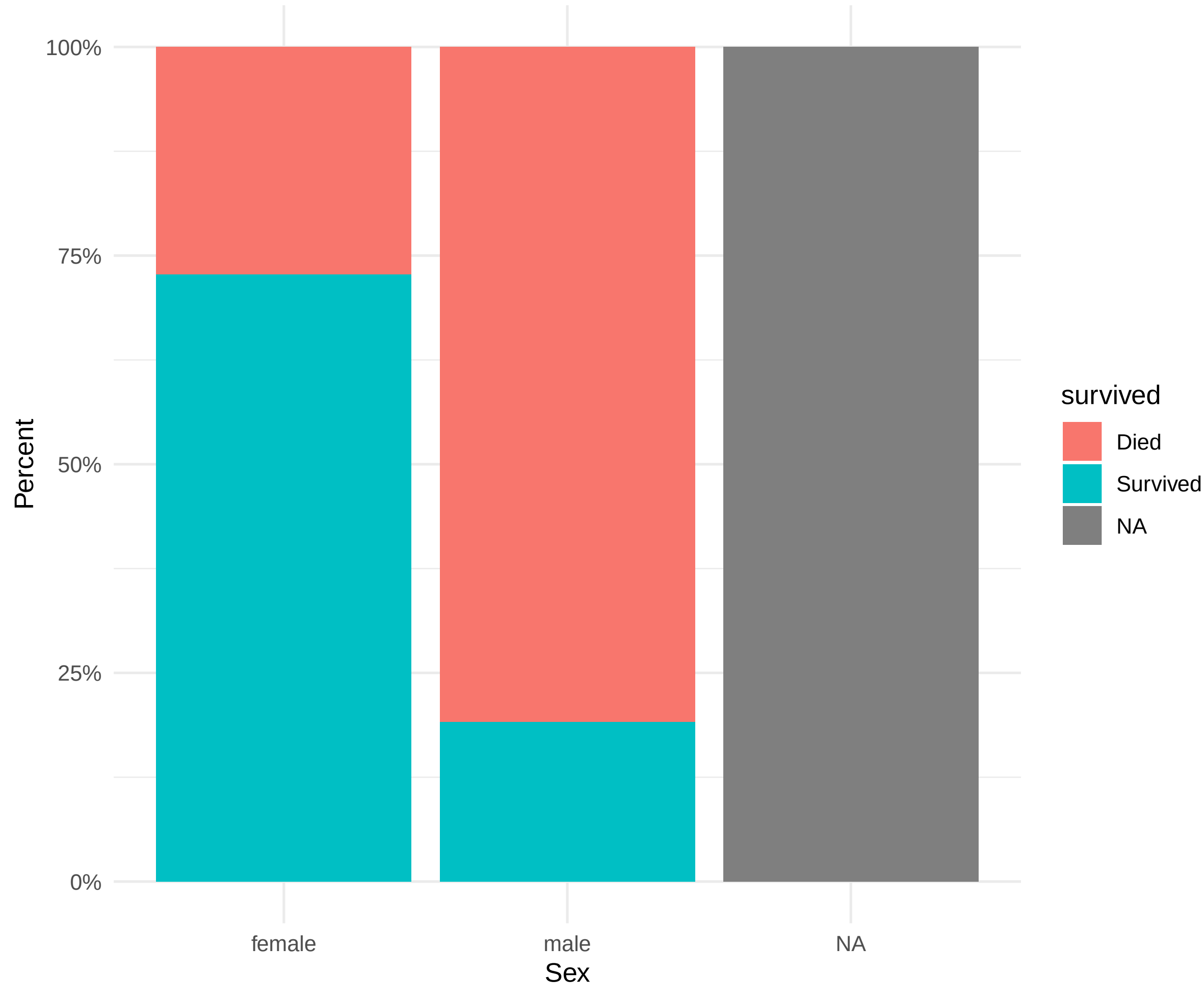



```
clean_titanic %>%
  ggplot(aes(x = pclass, fill = survived)) +
  geom_bar(position = "fill") +
  scale_y_continuous(labels = scales::percent_format()) +
  labs(title = "Figure 2. Survival share by passenger class",
       x = "Class", y = "Percent") +
  theme_minimal()
```




```r
clean_titanic %>%
  ggplot(aes(x = sex, fill = survived)) +
  geom_bar(position = "fill") +
  scale_y_continuous(labels = scales::percent_format()) +
  labs(title = "Figure 3. Survival share by sex",
       x = "Sex", y = "Percent") +
  theme_minimal()
```

Figure 3. Survival share by sex



Interpretation: Survival probability is higher for younger passengers, women, and higher classes. These patterns justify including class, sex, and age in the model and suggest potential interactions between class and sex.

III. Model Development Process (15 points)

Train/test split

```
set.seed(1023)
train_index <- sample(seq_len(nrow(clean_titanic)),
                      size = floor(0.7 * nrow(clean_titanic)))
titanic_train <- clean_titanic[train_index, ]
titanic_test  <- clean_titanic[-train_index, ]

table(titanic_train$survived)
```

```
##
```

```
##     Died Survived
##      548      367
```

```
table(titanic_test$survived)
```

```
##
##     Died Survived
##      261      133
```

Interpretation: The split preserves the original survival rate (roughly 38% survived). Using a fixed seed allows full reproducibility.

Champion: Logistic regression

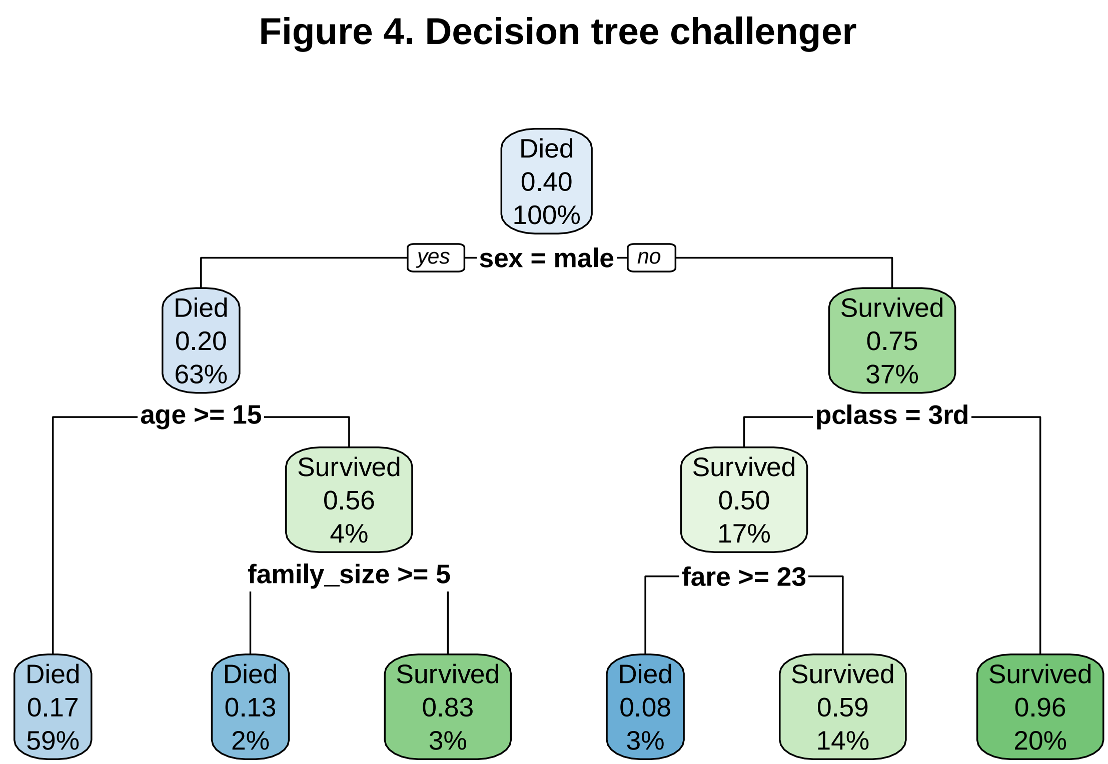
```
logit_model <- glm(
  survived ~ pclass + sex + age + family_size + fare + embarked,
  data = titanic_train,
  family = binomial
)

logit_summary <- tidy(logit_model, exponentiate = TRUE, conf.int = TRUE)
logit_summary %>%
  knitr::kable(
    digits = 3,
    col.names = c("Term", "Odds Ratio", "Std. Error", "z", "p-value",
                  "CI Lower", "CI Upper")
  )
```

Term	Odds Ratio	Std. Error	z	p-value	CI Lower	CI Upper
(Intercept)	96.868	0.510	8.963	0.000	36.475	270.272
pclass2nd	0.391	0.294	-3.193	0.001	0.219	0.695
pclass3rd	0.117	0.307	-7.007	0.000	0.064	0.212
sexmale	0.059	0.204	-13.897	0.000	0.039	0.087
age	0.964	0.008	-4.703	0.000	0.949	0.978
family_size	0.802	0.068	-3.243	0.001	0.698	0.912
fare	1.002	0.002	0.787	0.432	0.998	1.007
embarkedQ	0.394	0.369	-2.523	0.012	0.190	0.808
embarkedS	0.534	0.230	-2.734	0.006	0.340	0.838
embarkedUnknown	35725.759	535.411	0.020	0.984	0.000	NA

Interpretation: Odds ratios show strong positive lift for females and 1st-class passengers; higher fares also increase survival odds. Increasing age slightly decreases survival odds. Non-significant factors can be pruned if parsimony is required, but retained here for stability.

Challenger: Decision tree

```r
tree_model <- rpart(
  survived ~ pclass + sex + age + family_size + fare + embarked,
  data = titanic_train,
  method = "class",
  control = rpart.control(cp = 0.01, minsplit = 20)
)

rpart.plot(tree_model, main = "Figure 4. Decision tree challenger")
```



Interpretation: The tree yields intuitive rules (e.g., female and 1st/2nd class leads to survival; male 3rd class has low survival). It is less smooth than logistic regression but offers auditability.