Supervised feature selection

DIMENSIONALITY REDUCTION IN R

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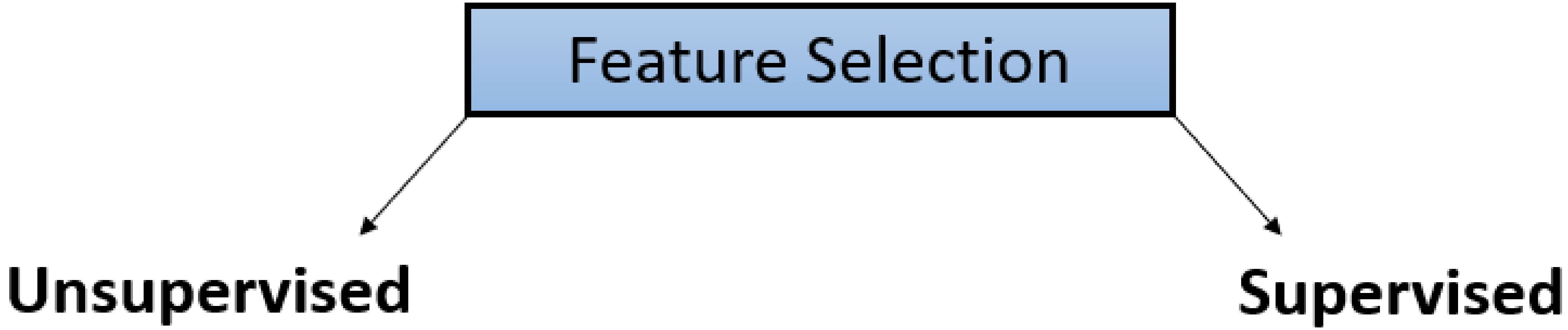
Unsupervised vs. supervised feature selection

Feature Selection

Unsupervised vs. supervised feature selection



Unsupervised vs. supervised feature selection

Feature Selection

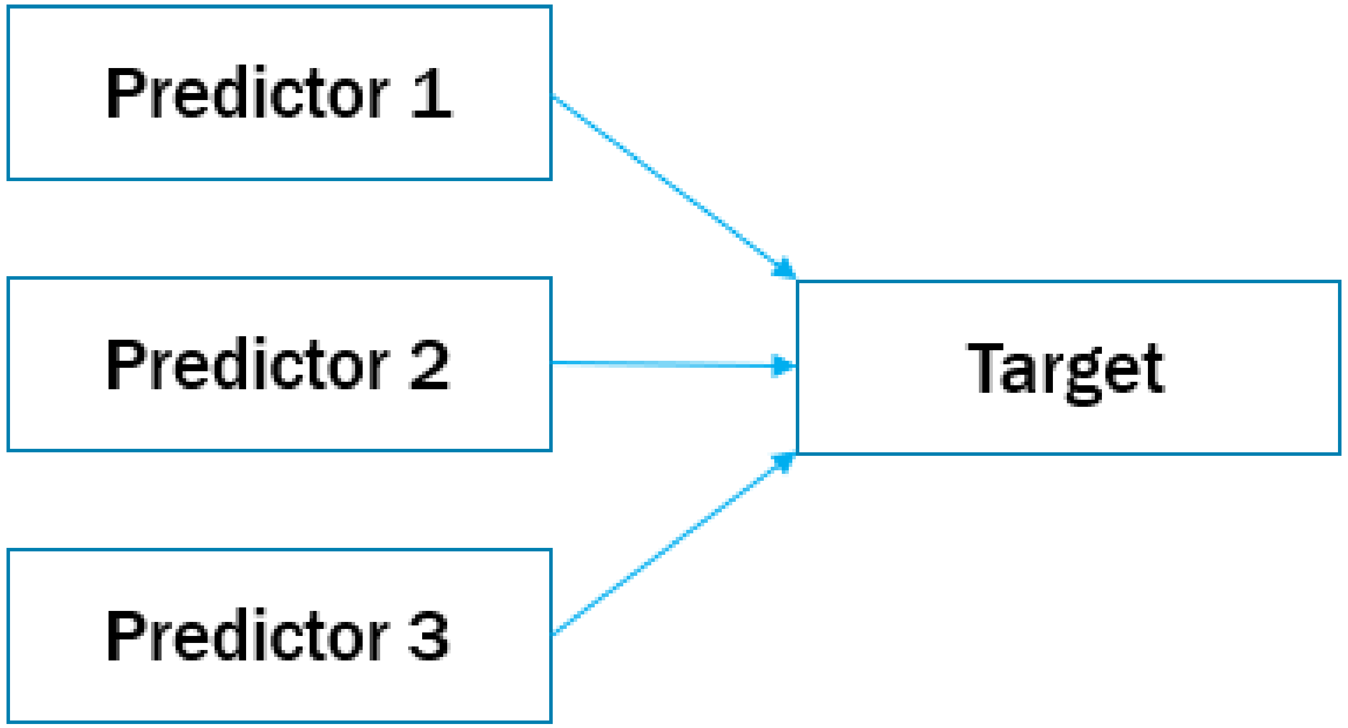
Unsupervised

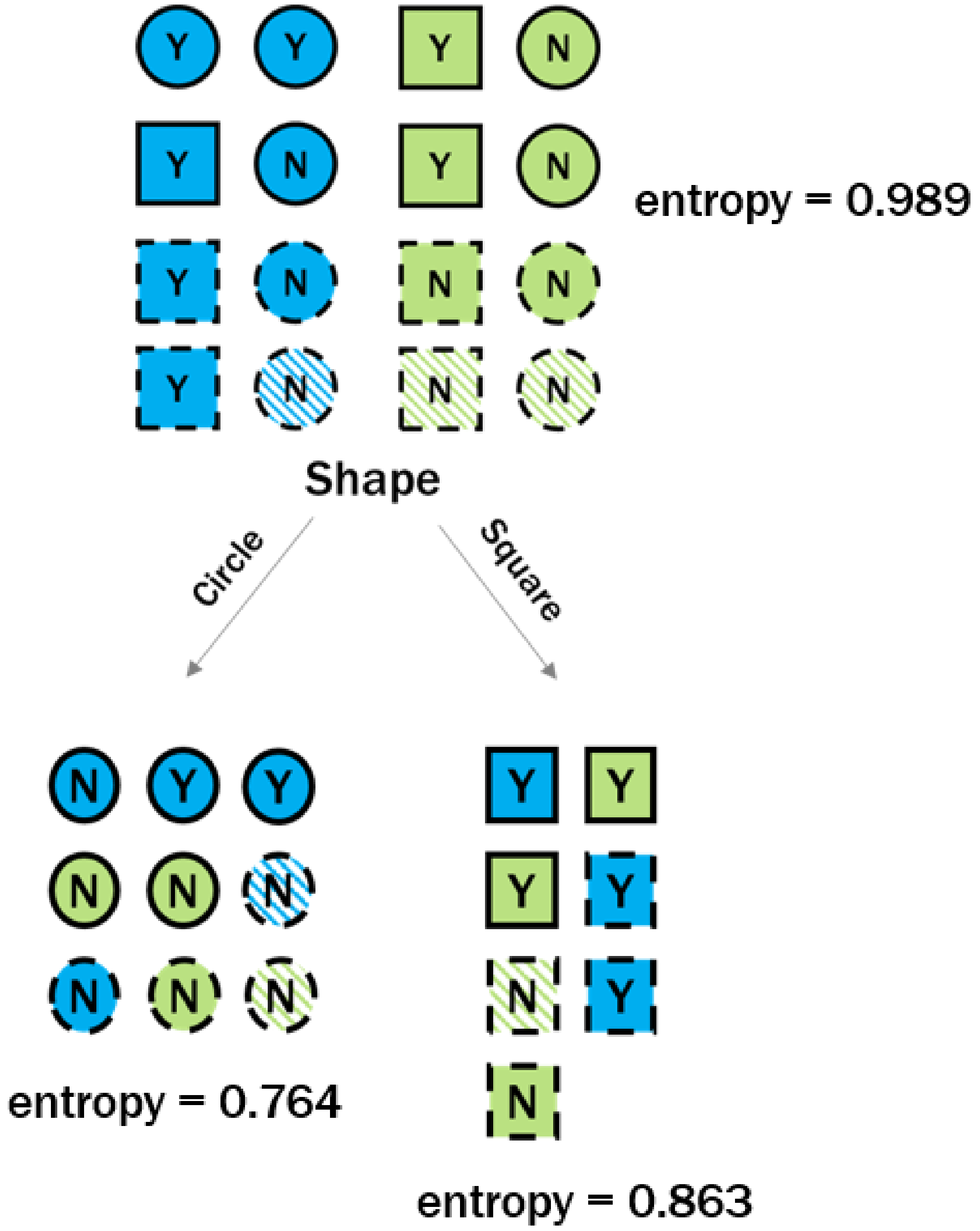
- Drop missing-value features
- Drop low-variance features
- Drop correlated features

Supervised

Supervised feature selection explained

Selection based on information the predictor provides about the target variable





Unsupervised vs. supervised feature selection

Feature Selection

Unsupervised

- Drop missing-value features
- Drop low-variance features
- Drop correlated features

Supervised

- Recursive feature elimination

Unsupervised vs. supervised feature selection

Feature Selection

- **Unsupervised**
  - Drop missing-value features
  - Drop low-variance features
  - Drop correlated features
- **Supervised**
  - Recursive feature elimination
  - Lasso regression

Unsupervised vs. supervised feature selection

Feature Selection

Unsupervised

- Drop missing-value features
- Drop low-variance features
- Drop correlated features

Supervised

- Recursive feature elimination
- Lasso regression
- Random forest

Let's practice!

DIMENSIONALITY REDUCTION IN R

Model Building and Evaluation with tidymodels

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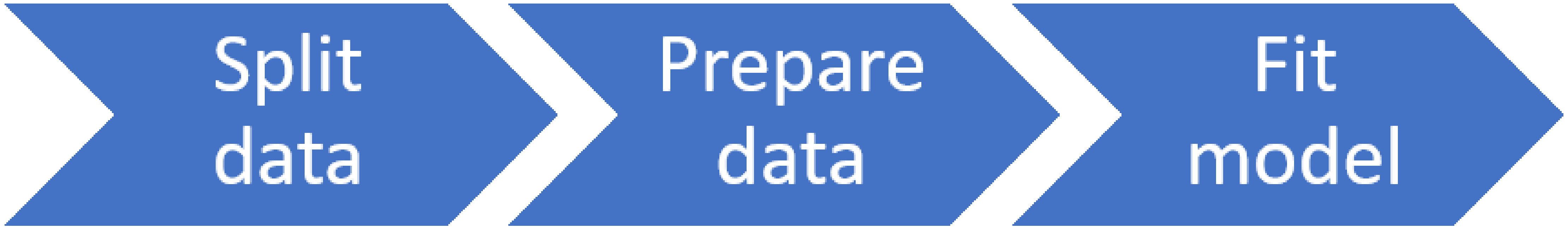
Model fitting process

Model fitting process

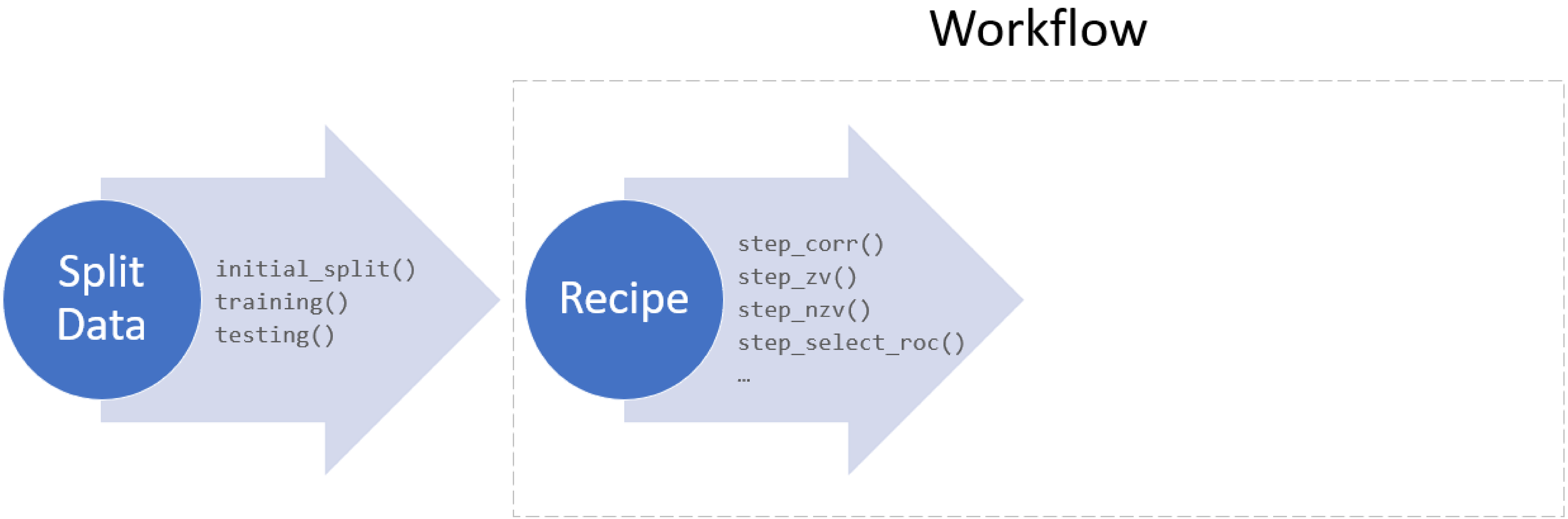
Model fitting process



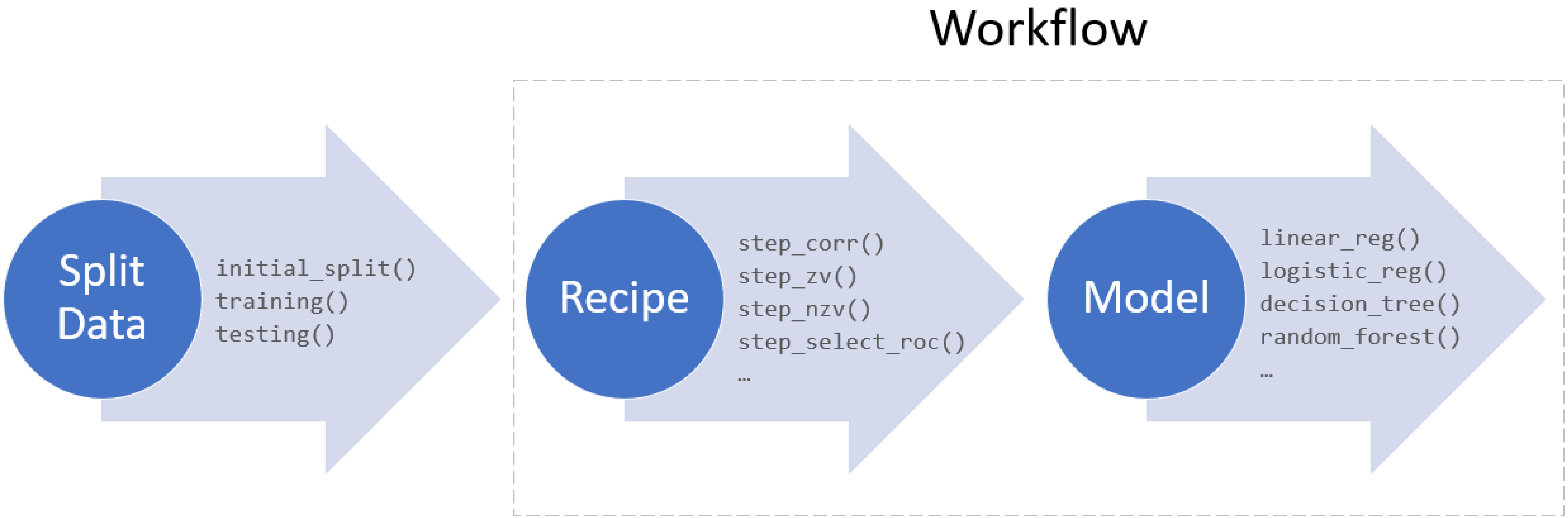
Model fitting process

Model fitting with tidymodels

Model fitting with tidymodels



Model fitting with tidymodels



Splitting out train and test sets

```
split <- initial_split(credit_df, prop = 0.8, strata = credit_score)

train <- split %>% training()

test <-  split %>% testing()
```

Creating a recipe and a model

```
feature_selection_recipe <-
  recipe(credit_score ~ ., data = train) %>%
  step_filter_missing(all_predictors(), threshold = 0.5) %>%
  step_scale(all_numeric_predictors()) %>%
  step_nzv(all_predictors()) %>%
  prep()
```

```
lr_model <- logistic_reg() %>%
  set_engine("glm")
```

Create and fit the workflow

```
credit_wflow <- workflow() %>%
  add_recipe(feature_selection_recipe) %>%
  add_model(lr_model)

credit_fit <-
  credit_wflow %>% fit(data = train)
```

Evaluate the model

```
# Predict test data
credit_pred_df <- predict(credit_fit, test) %>%
  bind_cols(test %>% select(credit_score))

# Evaluate F score
f_meas(credit_pred_df, credit_score, .pred_class)
```

```
# A tibble: 1 × 3
  .metric .estimator .estimate
  <chr>   <chr>          <dbl>
1 f_meas  macro          0.519
```

Explore the recipe with tidy()

```
tidy(feature_selection_recipe, number = 1)
```

```
# A tibble: 2 × 2
  terms            id
  <chr>            <chr>
1 age              filter_missing_gVVfc
2 outstanding_debt filter_missing_gVVfc
```

Explore the model with tidy()

```r
# Display model estimates
tidy(credit_fit)
```

```
# A tibble: 44 × 5
   term                    estimate std.error statistic p.value
   <chr>                      <dbl>     <dbl>     <dbl>   <dbl>
 1 (Intercept)               2.88       0.918    3.13   0.00173
 2 monthAugust              -0.449      0.236   -1.91   0.0565
 3 monthFebruary            17.7      677.        0.0262 0.979
 4 monthJanuary             17.7      661.        0.0268 0.979
 ...                        ...       ...         ...     ...
```

Let's practice!

DIMENSIONALITY REDUCTION IN R

Lasso Regression

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Lasso regression overview

- Supervised feature selection
- L1 regularization
- Penalizes the regression coefficients
- Shrinks coefficients
- Less important coefficients shrink to zero
- Naturally performs feature selection

```
linear_reg(engine = "glmnet", penalty = 0.001 , mixture = 1)
```

Standardize data

- Standardize data first, so penalty applies equally across features
- Use `scale()` for target variable
  - returns matrix, so convert to vector with `as.vector()`
- Use `step_normalize()` for predictor variables

Example

```
# Scale target variable
df <- df %>% mutate(target = as.vector(scale(target)))
...
# Scale predictor variables
recipe() %>% step_normalize(all_numeric_predictors())
```

Choosing a penalty value

- Penalty is a hyperparameter to optimize
- Search for the best penalty value
- Use `tune()` in `tidymodels`

```
linear_reg(engine = "glmnet", penalty = tune() , mixture = 1)
```

Preparing the data

Scale the target variable

```
house_sales_subset_df <- house_sales_subset_df %>%
  mutate(price = as.vector(scale(price)))
```

Create the training and testing sets

```
split <- initial_split(house_sales_subset_df, prop = 0.8)
train <- split %>% training()
test <-  split %>% testing()
```

Create a recipe

Create a recipe

```
lasso_recipe <-
  recipe(price ~ ., data = train) %>%
  step_normalize(all_numeric_predictors())
```

Create the workflow

Create the model spec

```
lasso_model <- linear_reg(penalty = 0.01, mixture = 1, engine = "glmnet")
```

Create the workflow

```
lasso_workflow <- workflow(preprocessor = lasso_recipe, spec =  lasso_model)
```

Fit the workflow

```
tidy(lasso_workflow %>% fit(train)) %>% filter(estimate > 0)
```

```
# A tibble: 9 × 3
  term           estimate penalty
  <chr>             <dbl>   <dbl>
1 bathrooms       0.0477     0.01
2 sqft_living     0.434      0.01
3 floors          0.0262     0.01
4 waterfront      0.133      0.01
5 view            0.0510     0.01
6 condition       0.0319     0.01
...               ...        ...
```

Create a tunable model workflow

Create a tunable model spec

```
lasso_model <- linear_reg(penalty = tune(), mixture = 1, engine = "glmnet")
lasso_workflow <- workflow(preprocessor = lasso_recipe, spec =  lasso_model)
```

Create cross validation training sample

```
train_cv <- vfold_cv(train, v = 5)
```

Create grid of penalty values

```
penalty_grid <- grid_regular(penalty(range = c(-3, -1)), levels = 20)
```

- A penalty range of 0.001 to 0.1 is specified as `range = c(-3, -1)`

Fit a grid of models

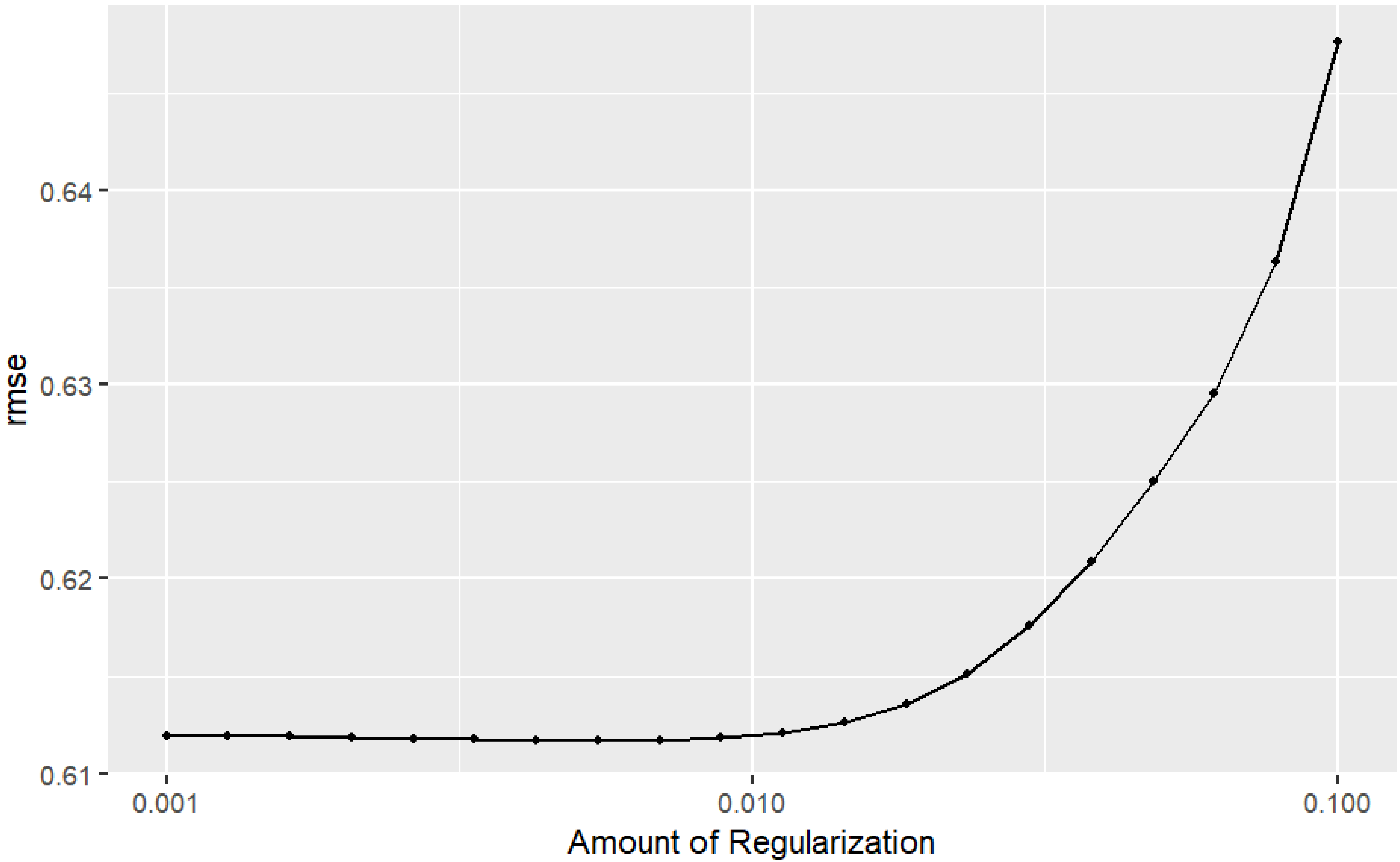
Create grid of fitted models

```
lasso_grid <- tune_grid(
  lasso_workflow,
  resamples = train_cv,
  grid = penalty_grid)
```

Plot model performances

```
autoplot(lasso_grid, metric = "rmse")
```

Penalty performance plot



Finalize the model

Retrieve the penalty value for the best model

```
best_rmse <- lasso_grid %>% select_best("rmse")
```

Refit the best model

```
final_lasso <-
  finalize_workflow(lasso_workflow, best_rmse) %>%
  fit(train)
```

Display the best model's coefficients

```
tidy(final_lasso) %>% filter(estimate > 0)
```

Let's practice!

DIMENSIONALITY REDUCTION IN R

Random forest models

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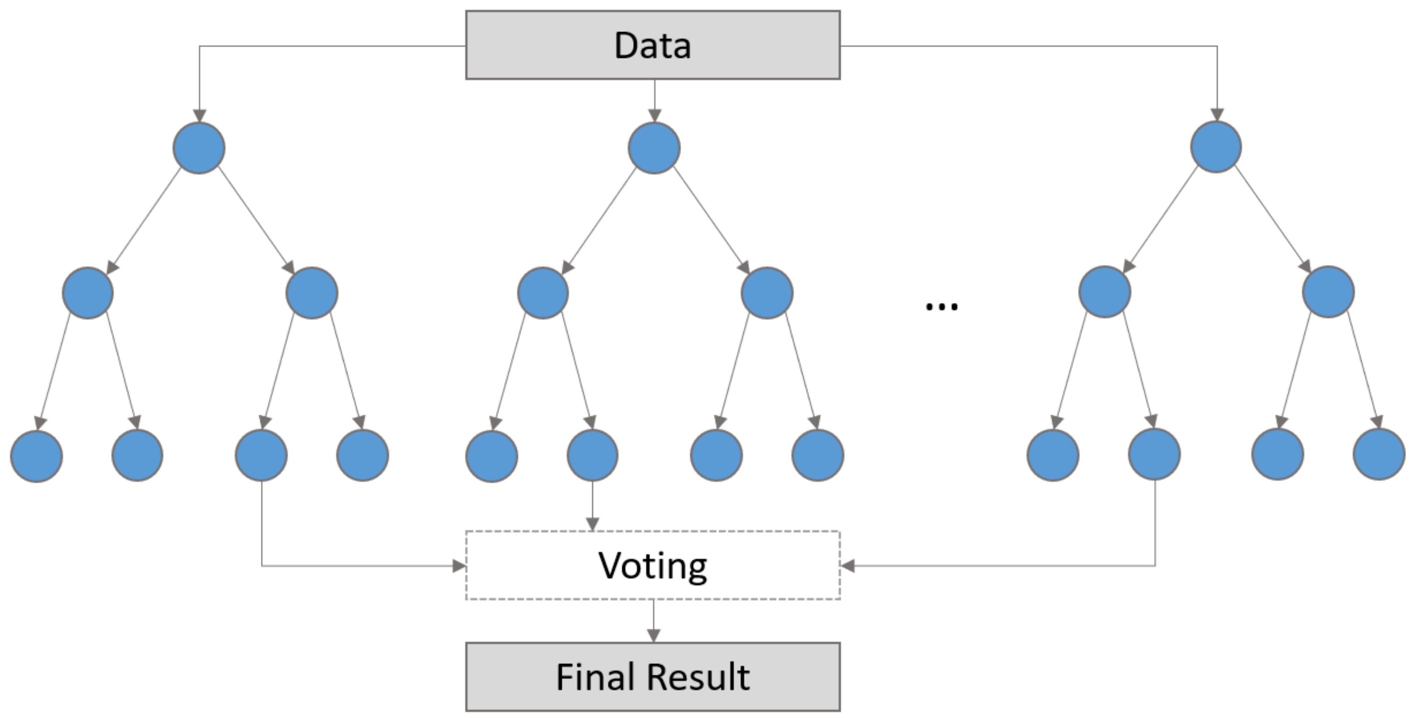
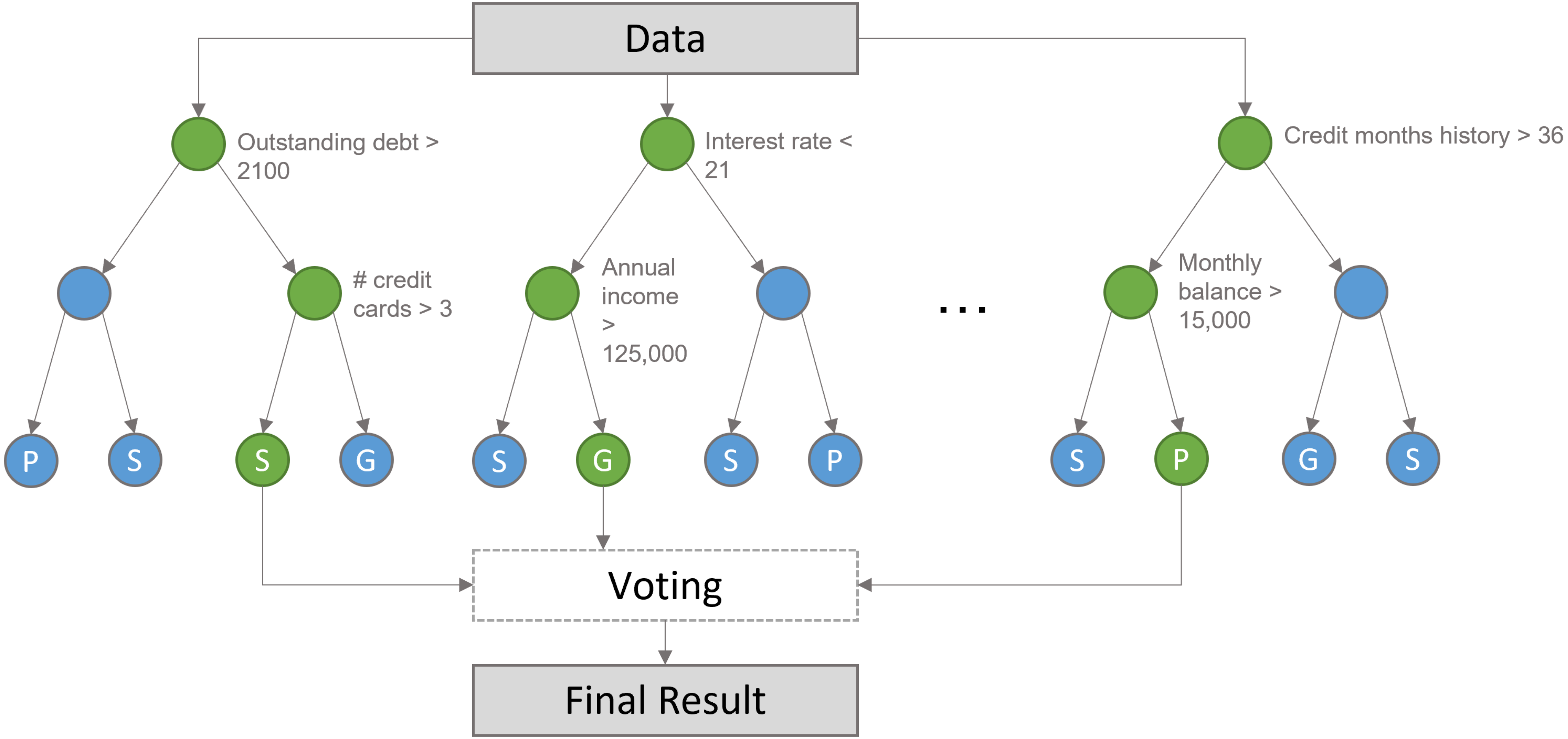
Random Forest

- An ensemble model
  - a "wisdom of the crowds" approach
- Aggregates predictions of many random trees
- Random uncorrelated trees mitigate error
- Avoids overfitting
- Accurate
- Performs feature selection



Random Forest



Train a Random Forest

```r
library(tidymodels)

rf <- rand_forest(mode = "classification",  trees = 200) %>%
  set_engine("ranger", importance = "impurity")

rf_fit <- rf %>%
  fit(credit_score ~ ., data = train)

predict_df <- test %>%
  bind_cols(predict = predict(rf_fit, test))
```

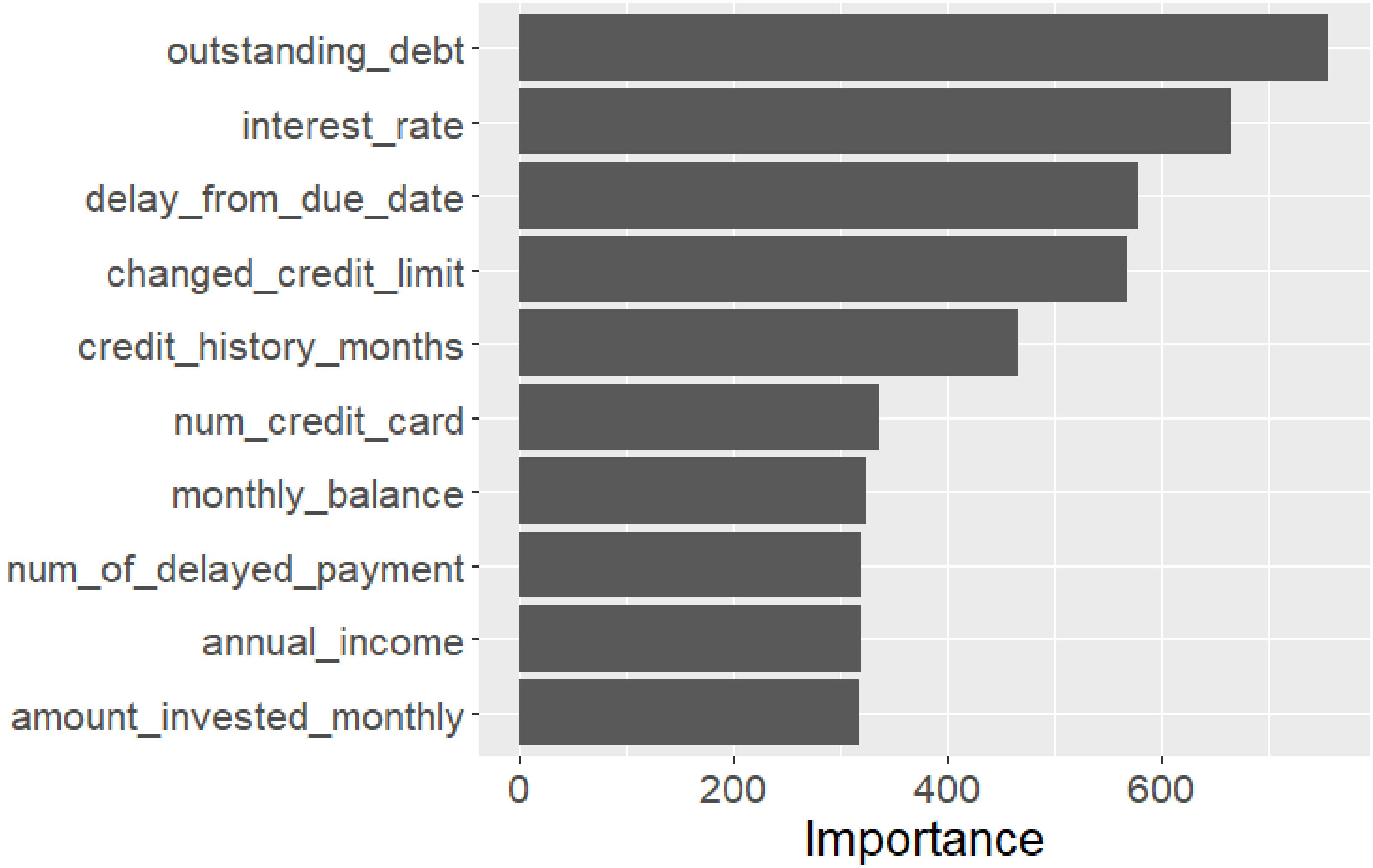
Evaluate the Model

```
f_meas(predict_df, credit_score, .pred_class)
```

```
0.6895
```

Variable Importance

```
library(vip)
rf_fit %>% vip()
```



Feature Mask

```
top_features <- rf_fit %>%
  vi(rank = TRUE) %>%
  filter(Importance <= 10) %>%
  pull(Variable)
top_features
```

```
 [1] "outstanding_debt"         "interest_rate"
 [3] "delay_from_due_date"      "changed_credit_limit"
 [5] "credit_history_months"    "num_credit_card"
 [7] "monthly_balance"          "num_of_delayed_payment"
 [9] "annual_income"            "amount_invested_monthly"
```

Reduce the data

```
train_reduced <- train[top_features]
test_reduced <- test[top_features]
```

Performance

```
rf_fit <- rf %>%
  fit(credit_score ~ ., data = train_reduced)
predict_reduced_df <- test_reduced %>%
  bind_cols(predict = predict(rf_fit, test_reduced))
f_meas(predict_reduced_df, credit_score, .pred_class)
```

```
0.6738
```

F-score of the unreduced model:

```
0.6895
```

Let's practice!

DIMENSIONALITY REDUCTION IN R