Homework9

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Load packages

```
library(tidymodels)
library(tidyverse)
library(patchwork)
library(textrecipes)
library(stopwords)
```

Text Sentiment Analysis

Part 1

Setup parallel processing

We start a cluster for faster calculations.

```
library(doParallel)
cl <- makePSOCKcluster(parallel::detectCores(logical = FALSE))
registerDoParallel(cl)
```

1.1 Read in the data.

Here we use read_delim.

```
data <- as_tibble(read_delim('https://gedeck.github.io/DS-6030/datasets/homework/sentiment_labelled_sen
                   col_names = F,
                   show_col_types = FALSE))
```

And thn rename the columns as needed.

```
data <- data %>%
  rename( sentence = X1, sentiment = X2) %>%
  mutate(sentiment = as.factor(sentiment))
```

1.2 Split and cross validation

Now we partition the data into a training/test split and set up the 10 fold cross validation.

```
data_split <- initial_split(data, prop=0.8, strata = sentiment)
train <- training(data_split)
test <- testing(data_split)

resamples <- vfold_cv(train, strata = sentiment)
```

```
cv_control <- control_resamples(save_pred=TRUE)
cv_metrics <- metric_set(roc_auc, accuracy)
```

1.3 Create a recipe

```
formula <- sentiment~sentence

rec <- recipe(formula, data = train) %>%
  step_tokenize(sentence) %>%
  step_tokenfilter(sentence, max_tokens = 1000) %>%
  step_tfidf(sentence) %>%
  step_normalize() %>%
  step_pca(num_comp = tune())
```

Part 2 Train Models

1.4 Workflow for L1 regularization

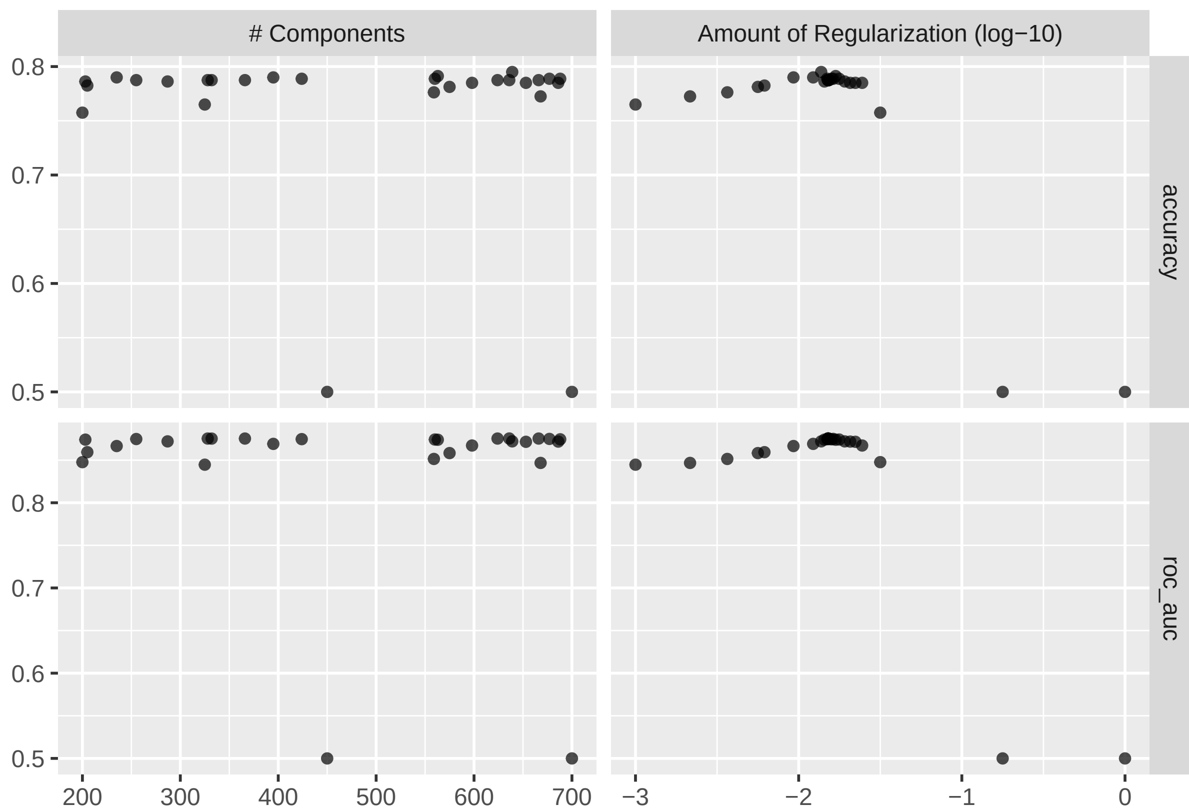
```
log_spec <- logistic_reg(mode="classification", penalty = tune()) %>%
    set_engine("glmnet")

log_wf <- workflow() %>%
  add_recipe(rec) %>%
  add_model(log_spec)
```

```
parameters <- extract_parameter_set_dials(log_wf)

parameters <- parameters %>%
  update(
    num_comp = num_comp(c(200, 700)),
    penalty = penalty(c(-3,0))
  )
```

```
tune_results_log  <- tune_bayes(log_wf,
                                resamples=resamples,
                                metrics = cv_metrics,
                                param_info=parameters,
                                iter=25)
```

```
## ! No improvement for 10 iterations; returning current results.
```

```
autoplot(tune_results_log)
```




```
best_params_log <- select_best(tune_results_log, metric = "roc_auc")
lb <- show_best(tune_results_log, metric = "roc_auc", n=1)
metric_pos <- which(names(lb) == ".metric")
lb<- lb %>%
  select(1:metric_pos,mean)
knitr::kable(lb,caption = "Hyperparameters for Logistic Regression",digits = 3)
```

Table 1: Hyperparameters for Logistic Regression

penalty	num_comp	.metric	mean
0.015	636	roc_auc	0.875

1.5 Tune a linear SVM

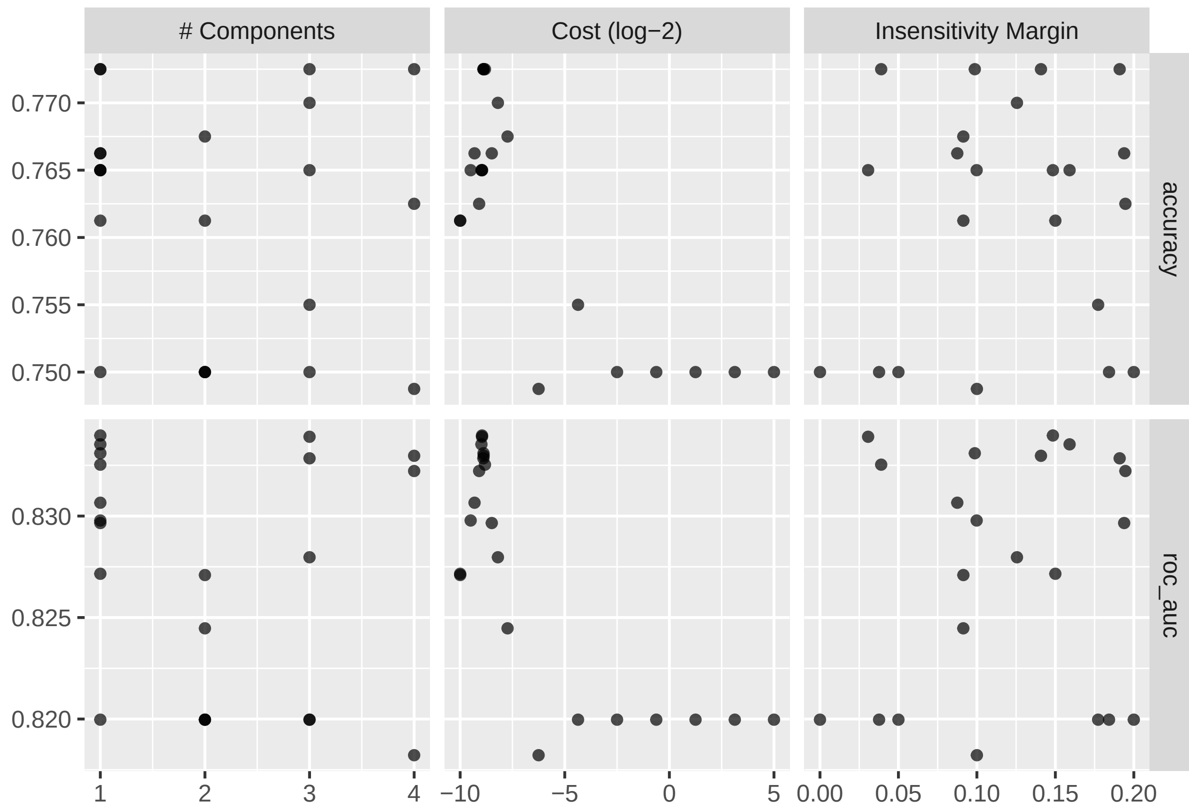
```
linear_svm_spec <- svm_linear(mode="classification",
                              cost = tune(),
                              margin = tune()) %>%
    set_engine("kernlab")

linear_wf <- workflow() %>%
  add_recipe(rec) %>%
  add_model(linear_svm_spec)
```

```
parameters <- extract_parameter_set_dials(linear_wf)
```

```
tune_results_linear_svm <- tune_bayes(linear_wf,
                                      resamples=resamples,
                                      metrics = cv_metrics,
                                      param_info=parameters,
                                      iter=25)
```

```
## ! No improvement for 10 iterations; returning current results.
```

```
autoplot(tune_results_linear_svm)
```




```
best_params_linear <- select_best(tune_results_linear_svm, metric = "roc_auc")
sb <- show_best(tune_results_linear_svm, metric = "roc_auc", n=1)
metric_pos <- which(names(sb) == ".metric")
sb<- sb %>%
  select(1:metric_pos,mean)
knitr::kable(sb,caption = "Hyperparameters for Linear SVM",digits = 3)
```

Table 2: Hyperparameters for Linear SVM

cost	margin	num_comp	.metric	mean
0.002	0.148	1	roc_auc	0.834

1.6 Tune a polynomial kernel

```
poly_svm_spec <- svm_poly(mode="classification",
                          cost = tune(),
```

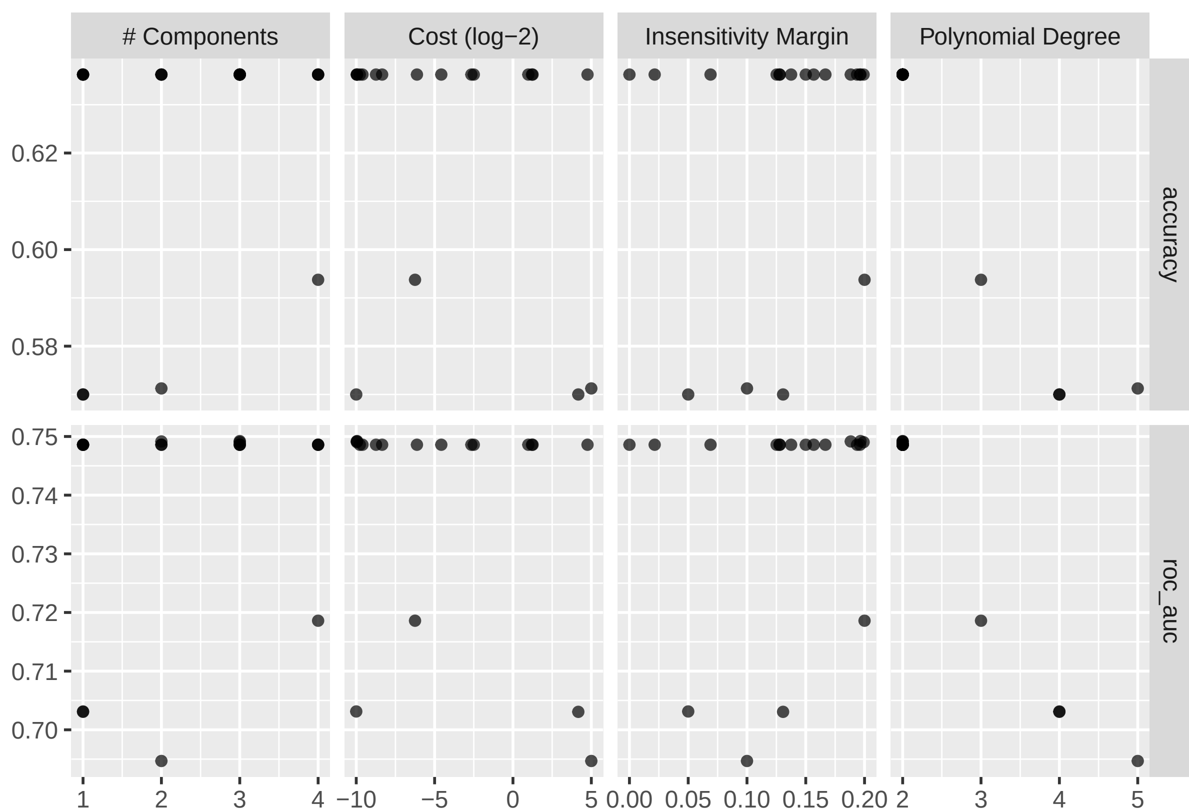
```r
                              margin = tune(),
                              degree = tune()) %>%
    set_engine("kernlab")

poly_wf <- workflow() %>%
  add_recipe(rec) %>%
  add_model(poly_svm_spec)
```

```r
parameters <- extract_parameter_set_dials(poly_wf)

parameters <- parameters %>%
  update(
    degree = degree_int(range = c(2,5))
  )
```

```r
tune_results_poly_svm <- tune_bayes(poly_wf,
                                    resamples=resamples,
                                    metrics = cv_metrics,
                                    param_info=parameters,
                                    iter=25)
```

```
## ! The Gaussian process model is being fit using 4 features but only has 5
##   data points to do so. This may cause errors or a poor model fit.

## ! No improvement for 10 iterations; returning current results.
```

```r
autoplot(tune_results_poly_svm)
```



```r
best_params_poly <- select_best(tune_results_poly_svm, metric = "roc_auc")
pb <- show_best(tune_results_poly_svm, metric = "roc_auc", n=1)
metric_pos <- which(names(pb) == ".metric")
pb<- pb %>%
  select(1:metric_pos,mean)
knitr::kable(pb,caption = "Hyperparameters for Polynomial SVM",digits = 3)
```

Table 3: Hyperparameters for Polynomial SVM

cost	degree	margin	num_comp	.metric	mean
0.001	2	0.197	3	roc_auc	0.749

1.7 Tune a Radial Kernel

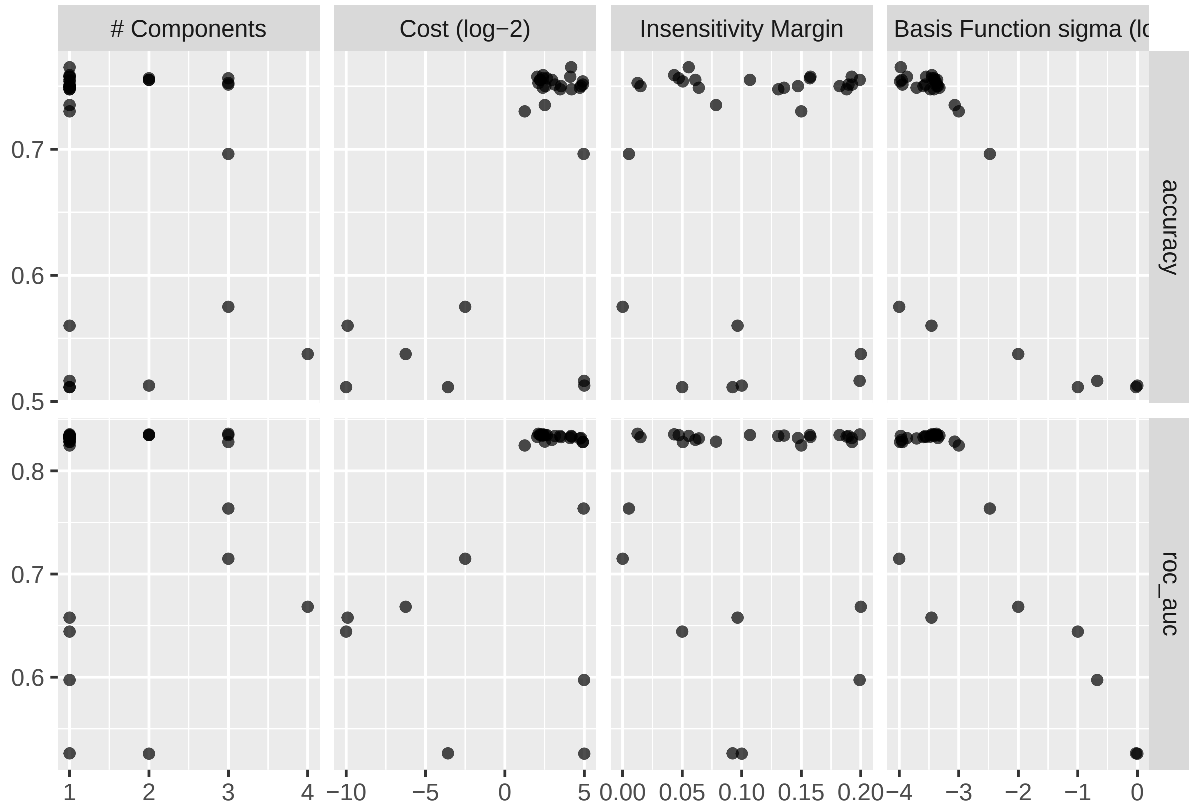
```r
radial_svm_spec <- svm_rbf(mode="classification",
                            cost = tune(),
                            margin = tune(),
                            rbf_sigma = tune()) %>%
    set_engine("kernlab")

radial_wf <- workflow() %>%
  add_recipe(rec) %>%
  add_model(radial_svm_spec)
```

```r
parameters <- extract_parameter_set_dials(radial_wf)

parameters <- parameters %>%
  update(
    rbf_sigma = rbf_sigma(range = c(-4,0),trans = log10_trans())
  )
```

```r
tune_results_radial_svm <- tune_bayes(radial_wf,
                                resamples=resamples,
                                metrics = cv_metrics,
                                param_info=parameters,
                                iter=25)
```

```
## ! The Gaussian process model is being fit using 4 features but only has 5
##   data points to do so. This may cause errors or a poor model fit.
```

```r
autoplot(tune_results_radial_svm)
```




```r
best_params_radial <- select_best(tune_results_radial_svm, metric = "roc_auc")
rb <- show_best(tune_results_radial_svm, metric = "roc_auc", n=1)
metric_pos <- which(names(rb) == ".metric")
rb<- rb %>%
  select(1:metric_pos,mean)
knitr::kable(rb,caption = "Hyperparameters for Radial SVM",digits = 3)
```

Table 4: Hyperparameters for Radial SVM

cost	rbf_sigma	margin	num_comp	.metric	mean
4.329	0	0.013	3	roc_auc	0.836

Part C Model Peformance

1.8 Compare performances

```r
final_wf_log <- finalize_workflow(log_wf, best_params_log)
final_fit_log <- fit_resamples(final_wf_log, resamples = resamples,
                               metrics = cv_metrics, data = train,
                               control = cv_control)
```

```r
fit_log_metric <- collect_metrics(final_fit_log)
```

```r
final_wf_linear <- finalize_workflow(linear_wf, best_params_linear)
final_fit_linear <- fit_resamples(final_wf_linear, resamples = resamples,
```

```r
                              metrics = cv_metrics, data = train,
                              control = cv_control)
```

```r
fit_linear_metric <- collect_metrics(final_fit_linear)
```

```r
final_wf_poly <- finalize_workflow(poly_wf, best_params_poly)
final_fit_poly <- fit_resamples(final_wf_poly, resamples = resamples,
                              metrics = cv_metrics, data = train,
                              control = cv_control)
```

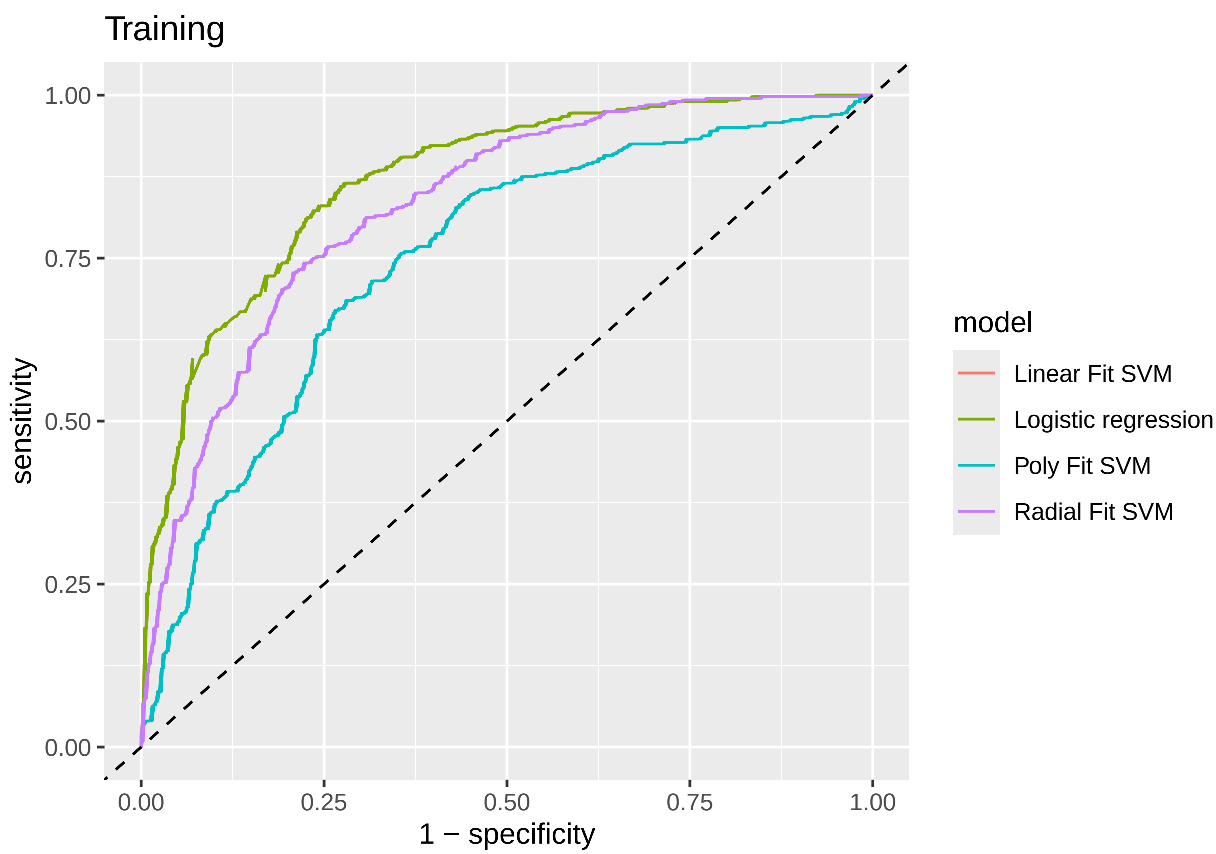
```r
fit_poly_metric <- collect_metrics(final_fit_poly)
```

```r
final_wf_radial <- finalize_workflow(radial_wf, best_params_radial)
final_fit_radial <- fit_resamples(final_wf_radial, resamples = resamples,
                              metrics = cv_metrics, data = train,
                              control = cv_control)
```

```r
fit_radial_metric <- collect_metrics(final_fit_radial)
```

```r
roc_cv_data <- function(model_cv) {
    cv_predictions <- collect_predictions(model_cv)
    cv_predictions %>%
        roc_curve(truth=sentiment, .pred_0, event_level="first")
}
roctrain <- bind_rows(
    roc_cv_data(final_fit_log) %>% mutate(model="Logistic regression"),
    roc_cv_data(final_fit_log) %>% mutate(model="Linear Fit SVM"),
    roc_cv_data(final_fit_poly) %>% mutate(model="Poly Fit SVM"),
    roc_cv_data(final_fit_radial) %>% mutate(model='Radial Fit SVM')
) %>%
ggplot(aes(x=1 - specificity, y=sensitivity, color=model)) +
    geom_line(show.legend = T)+
    geom_abline(linetype = 'dashed')+
  labs(title='Training')
```

```r
roctrain
```




```
fit_log_metric <- fit_log_metric %>% mutate(Model = "Logistic Regression")
fit_linear_metric <- fit_linear_metric %>% mutate(Model = "Linear Fit SVM")
fit_poly_metric <- fit_poly_metric %>% mutate(Model = "Polynomial Fit SVM")
fit_radial_metric <-  fit_radial_metric %>% mutate(Model = "Radial Fit SVM")

test_results <- bind_rows(fit_log_metric,fit_linear_metric,
                          fit_poly_metric,fit_radial_metric) %>%
  select(Model, .metric, mean)
 knitr::kable(test_results, caption =
              "Comparison of Different Models on Training Data",
            digits = 3)
```

Table 5: Comparison of Different Models on Training Data

Model	.metric	mean
Logistic Regression	accuracy	0.787
Logistic Regression	roc_auc	0.875
Linear Fit SVM	accuracy	0.765
Linear Fit SVM	roc_auc	0.834
Polynomial Fit SVM	accuracy	0.636
Polynomial Fit SVM	roc_auc	0.749
Radial Fit SVM	accuracy	0.752
Radial Fit SVM	roc_auc	0.836

In this case we surprisingly see that the best metric on Training data is the Logistic Regression, then followed by the Radial Fit.

1.9 Compare Finalized Models on Test Data

```
final_fit_log_model <- fit(final_wf_log, data = train)
final_fit_linear_model <- fit(final_wf_linear, data = train)
```

```
##  Setting default kernel parameters
```

```
final_fit_poly_model <- fit(final_wf_poly, data = train)
final_fit_radial_model <- fit(final_wf_radial, data = train)

holdout_log <- augment(final_fit_log_model, new_data = test,)
holdout_linear <- augment(final_fit_linear_model, new_data = test)
holdout_poly <- augment(final_fit_poly_model, new_data = test)
holdout_radial <- augment(final_fit_radial_model, new_data = test)
```

```
bind_rows(
  cv_metrics(holdout_log, truth = sentiment, estimate = .pred_class, .pred_0)
  %>% mutate(model = "Logistic"),
  cv_metrics(holdout_linear, truth = sentiment, estimate = .pred_class, .pred_0)
  %>% mutate(model = "Linear SVM"),
  cv_metrics(holdout_poly, truth = sentiment, estimate = .pred_class, .pred_0)
  %>% mutate(model = "Poly SVM"),
  cv_metrics(holdout_radial, truth = sentiment, estimate = .pred_class, .pred_0)
  %>% mutate(model = "Radial SVM")
) %>%
  select(model, .metric, .estimate) %>%
  knitr::kable(caption = "Test Set Performance Across Models", digits = 3)
```

Table 6: Test Set Performance Across Models

model	.metric	.estimate
Logistic	accuracy	0.830
Logistic	roc_auc	0.899
Linear SVM	accuracy	0.750
Linear SVM	roc_auc	0.832
Poly SVM	accuracy	0.650
Poly SVM	roc_auc	0.759
Radial SVM	accuracy	0.745
Radial SVM	roc_auc	0.836

Here we see the similar results from the holdout, The best is Logistic, followed by radial and Poly.

```
stopCluster(cl)
registerDoSEQ()
```