Visualizations LDA coefficients

```
library(ggplot2)
## Warning: package 'ggplot2' was built under R version 4.0.5
library(dplyr)
## Warning: package 'dplyr' was built under R version 4.0.5
##
## Attaching package: 'dplyr'
## The following objects are masked from 'package:stats':
##
##
       filter, lag
## The following objects are masked from 'package:base':
##
       intersect, setdiff, setequal, union
library(tidyr)
## Warning: package 'tidyr' was built under R version 4.0.5
library("ggpubr")
## Warning: package 'ggpubr' was built under R version 4.0.5
library(LDATS)
## Warning: package 'LDATS' was built under R version 4.0.5
library(ggVennDiagram)
## Warning: package 'ggVennDiagram' was built under R version 4.0.5
library(stringr)
library(abind)
## Warning: package 'abind' was built under R version 4.0.3
```

```
library(patchwork)
## Warning: package 'patchwork' was built under R version 4.0.3
source("utils.R")
## Warning: package 'hash' was built under R version 4.0.5
## hash-2.2.6.1 provided by Decision Patterns
## Warning: package 'reticulate' was built under R version 4.0.5
## Warning: package 'berryFunctions' was built under R version 4.0.5
##
## Attaching package: 'berryFunctions'
## The following object is masked from 'package:ggVennDiagram':
##
##
       circle
## The following object is masked from 'package:dplyr':
##
##
       between
## Warning: package 'purrr' was built under R version 4.0.3
## Warning: package 'reshape2' was built under R version 4.0.3
## Attaching package: 'reshape2'
## The following object is masked from 'package:tidyr':
##
```

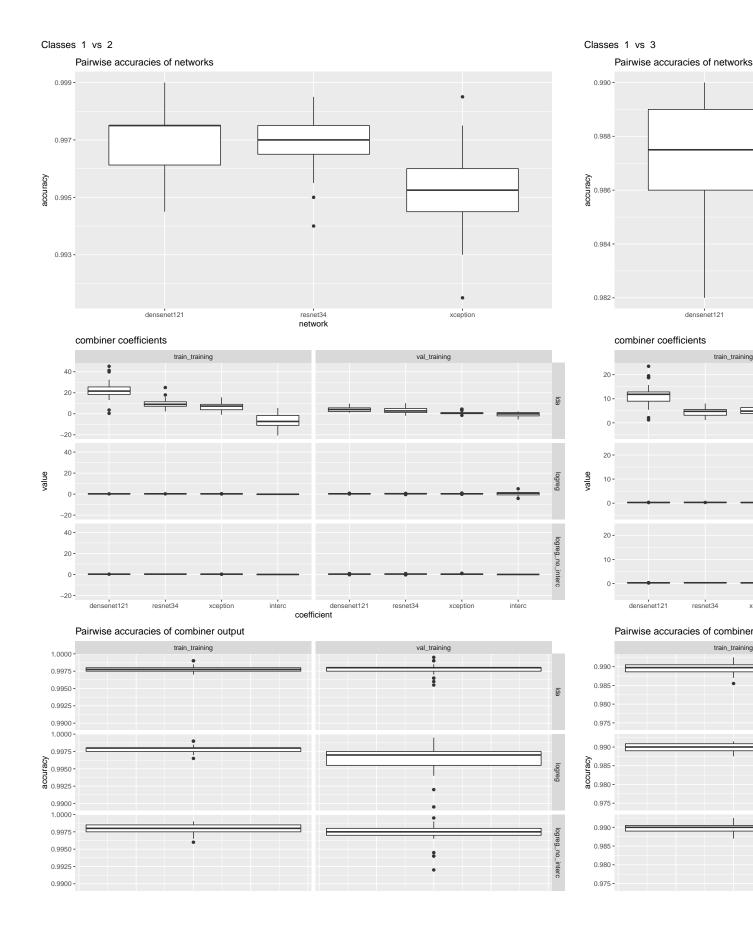
Visualizations on three sets of networks. First set consists of networks trained in 30 replications on CIFAR 10 training set with 500 sample validation set extracted randomly in each replication. Second set consists of networks trained in a single replication on half of CIFAR 10 training set. Third set are networks trained in 10 replications on half of CIFAR 100 training set.

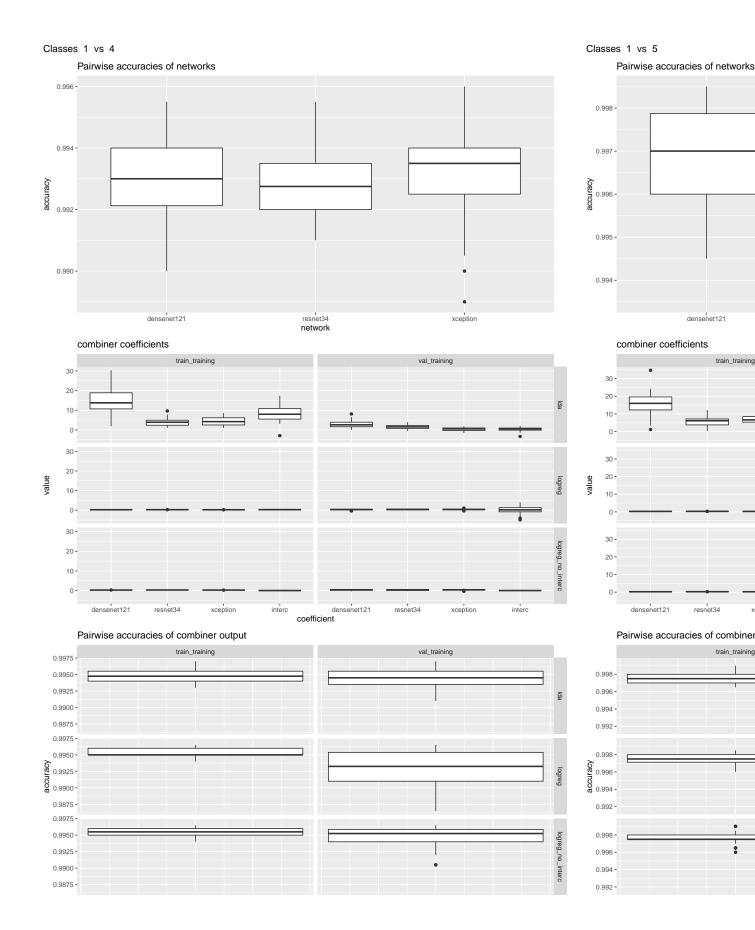
CIFAR 10

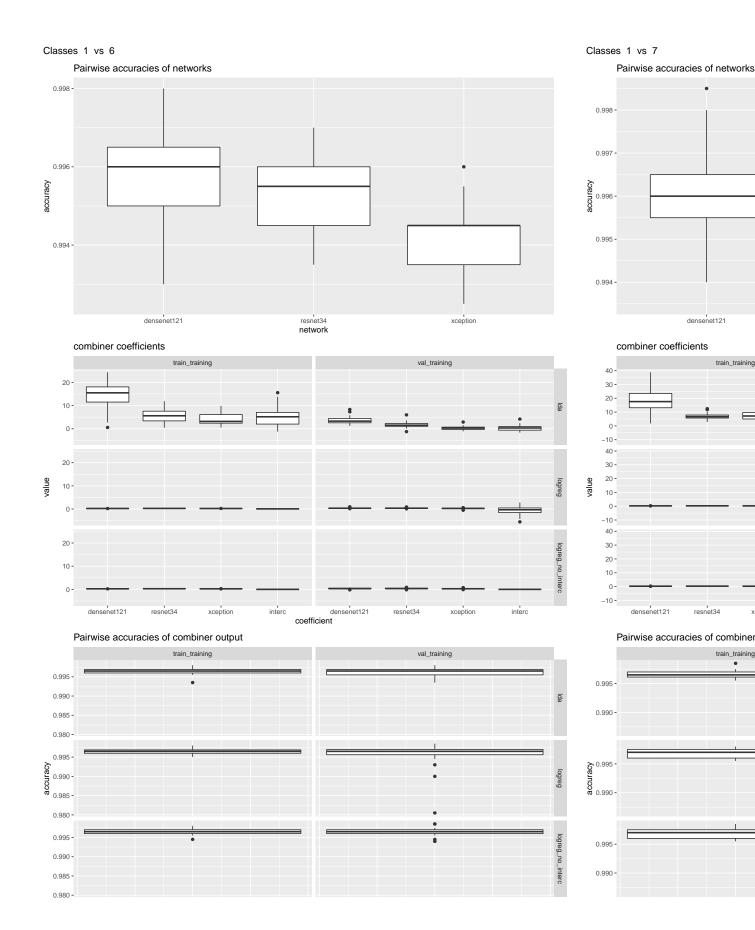
smiths

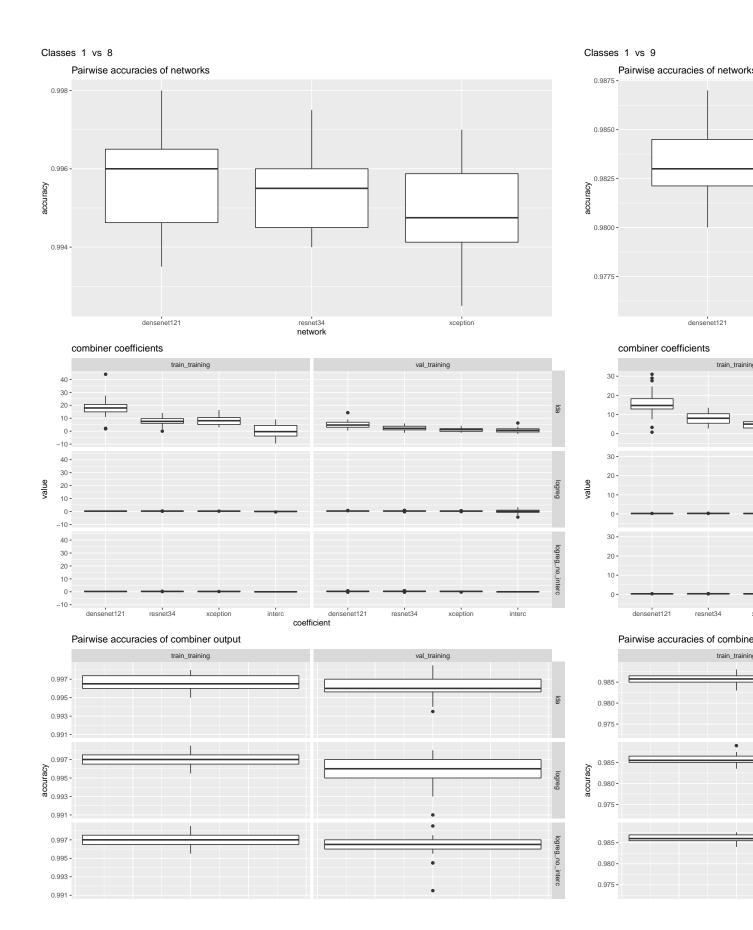
##

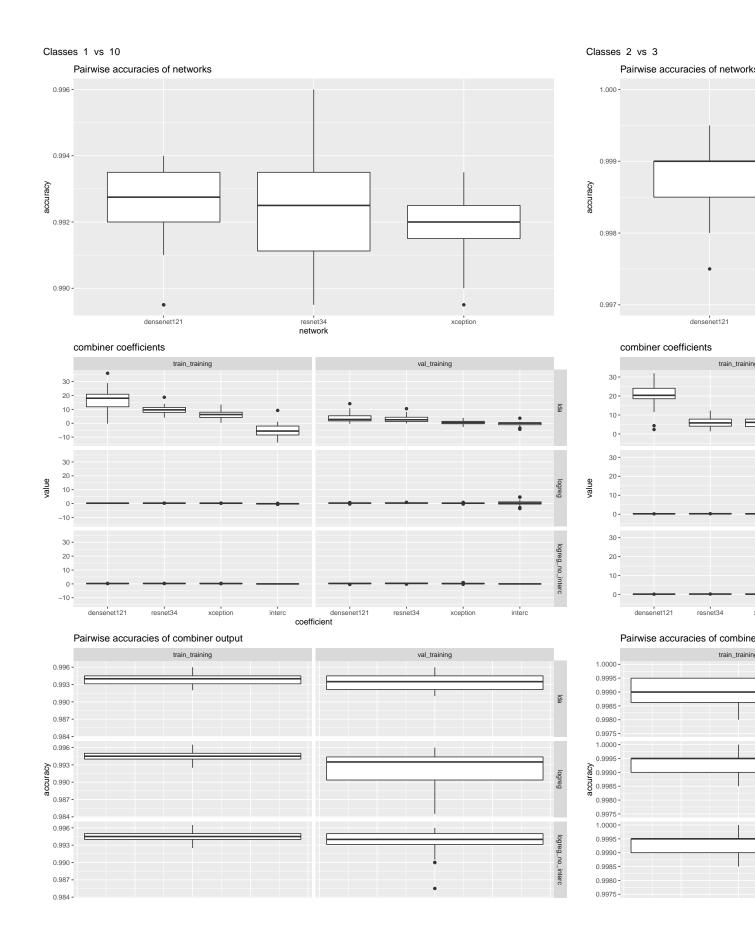
```
base_dir <- "../data/data_train_val_c10"</pre>
repls <- 0:29
classes <- 10
combiner_coefs <- load_combiner_coefs(base_dir, repls)</pre>
net_pw_results <- read.csv(file.path(base_dir, "net_pw_accuracies.csv"))</pre>
ens_pw_results <- read.csv(file.path(base_dir, "ensemble_pw_accuracies.csv"))</pre>
ens_pw_cal <- read.csv(file.path(base_dir, "ensemble_pw_calibration.csv"))</pre>
ens pw irrel <- read.csv(file.path(base dir, "ensemble pw irrelevant.csv"))</pre>
net_pw_results[, c("class1", "class2")] <- lapply(net_pw_results[, c("class1", "class2")], as.factor)</pre>
ens_pw_results[, c("class1", "class2", "combining_method")] <- lapply(ens_pw_results[, c("class1", "cla
ens_pw_cal$bin_c <- (ens_pw_cal$conf_min + ens_pw_cal$conf_max) / 2</pre>
ens_pw_cal[, c("class1", "class2", "bin_c", "combining_method")] <- lapply(ens_pw_cal[, c("class1", "cl
ens_pw_irrel[, c("class1", "class2", "combining_method")] <- lapply(ens_pw_irrel[, c("class1", "class2"</pre>
for (cl1 in 1:(classes - 1))
 for (cl2 in (cl1 + 1):classes)
    combiner_plt <- combiner_coefs %>% filter(class1 == cl1 & class2 == cl2) %>% ggplot() + geom_boxplo
      facet_grid(cols=vars(train_type), rows=vars(combining_method)) + ggtitle("combiner coefficients")
    acc_plt_net <- net_pw_results %% filter(class1 == (cl1 - 1) & class2 == (cl2 - 1)) %>% ggplot(mapp
      geom_boxplot() + ggtitle("Pairwise accuracies of networks")
    acc_plt_ens <- ens_pw_results %>% filter(class1 == (cl1 - 1) & class2 == (cl2 - 1)) %>% ggplot(mapp
      geom_boxplot() + facet_grid(cols=vars(train_set), rows=vars(combining_method)) + ggtitle("Pairwis
      theme(axis.ticks.x=element_blank(), axis.text.x=element_blank())
    print((acc_plt_net/combiner_plt/acc_plt_ens) + plot_annotation(title=paste("Classes ", cl1, " vs ",
 }
```

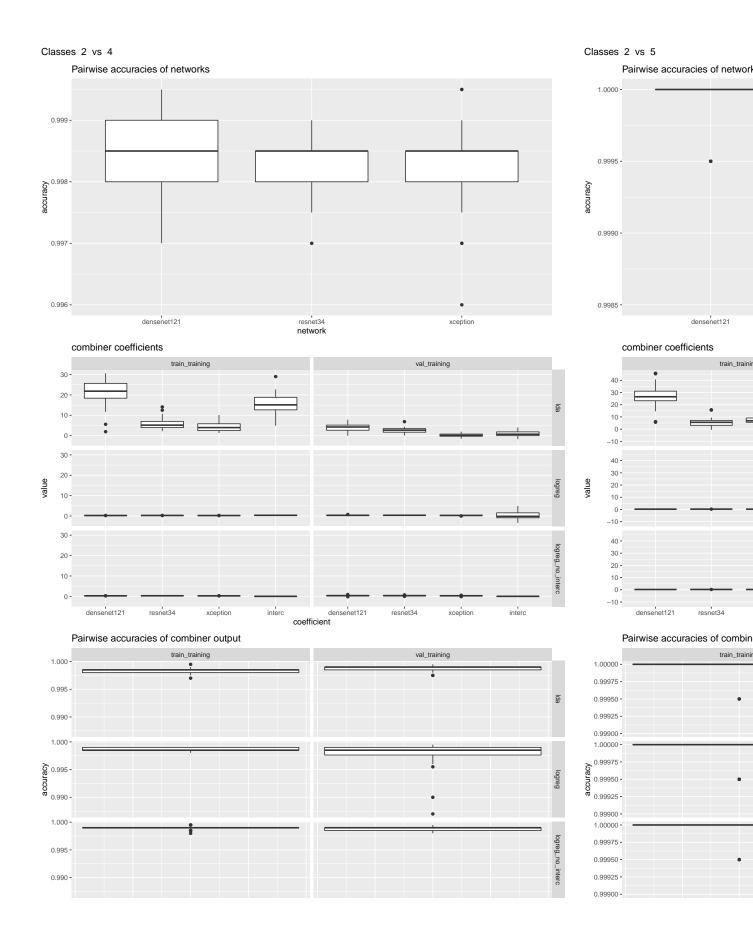


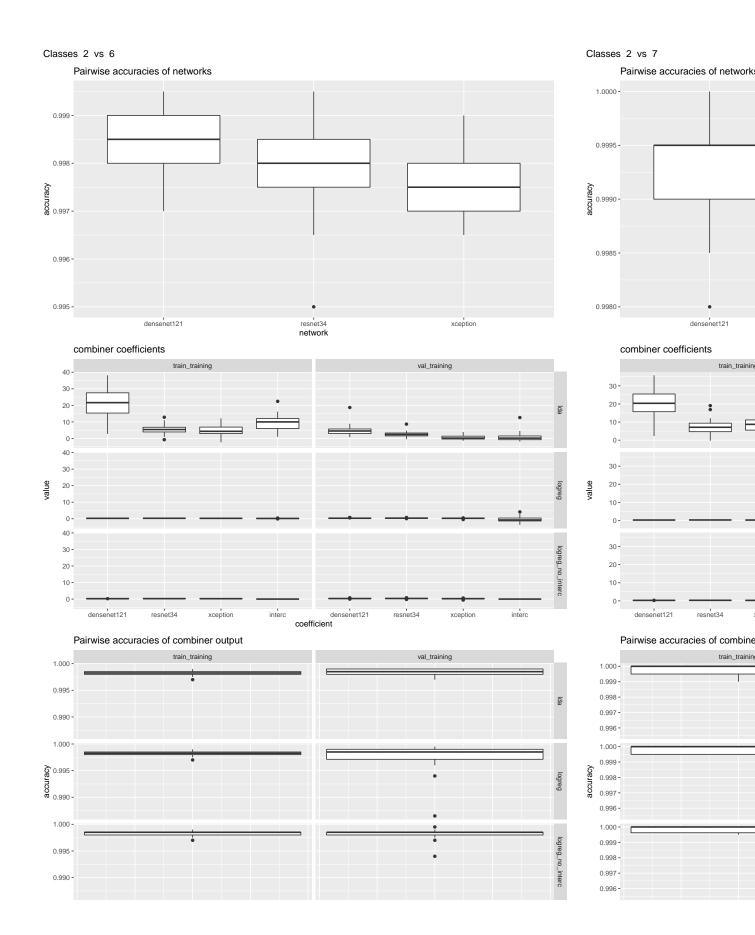


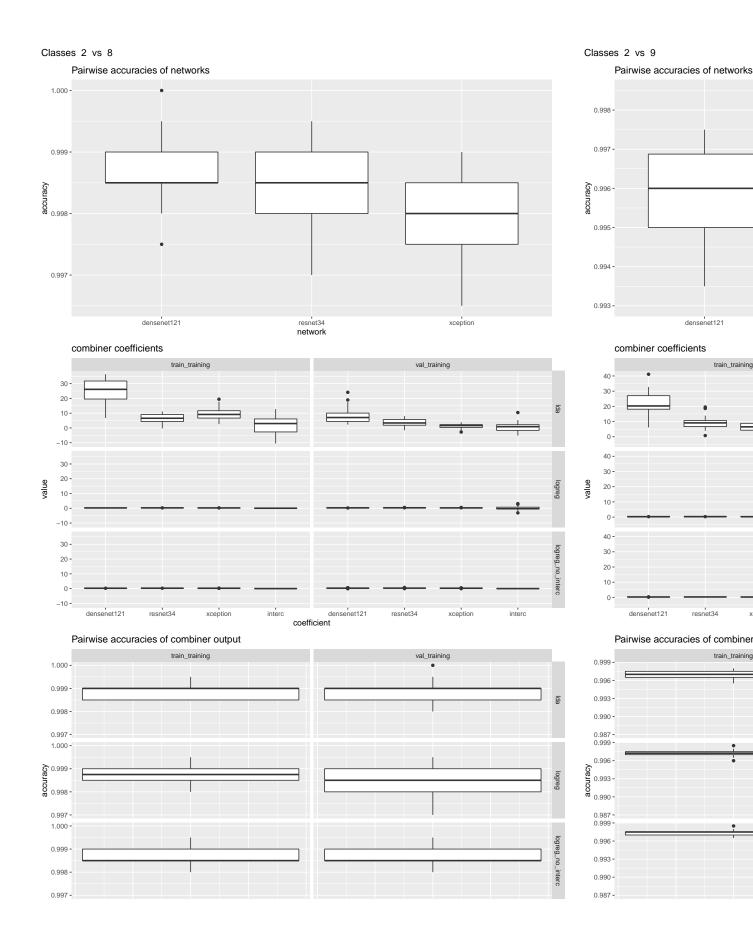


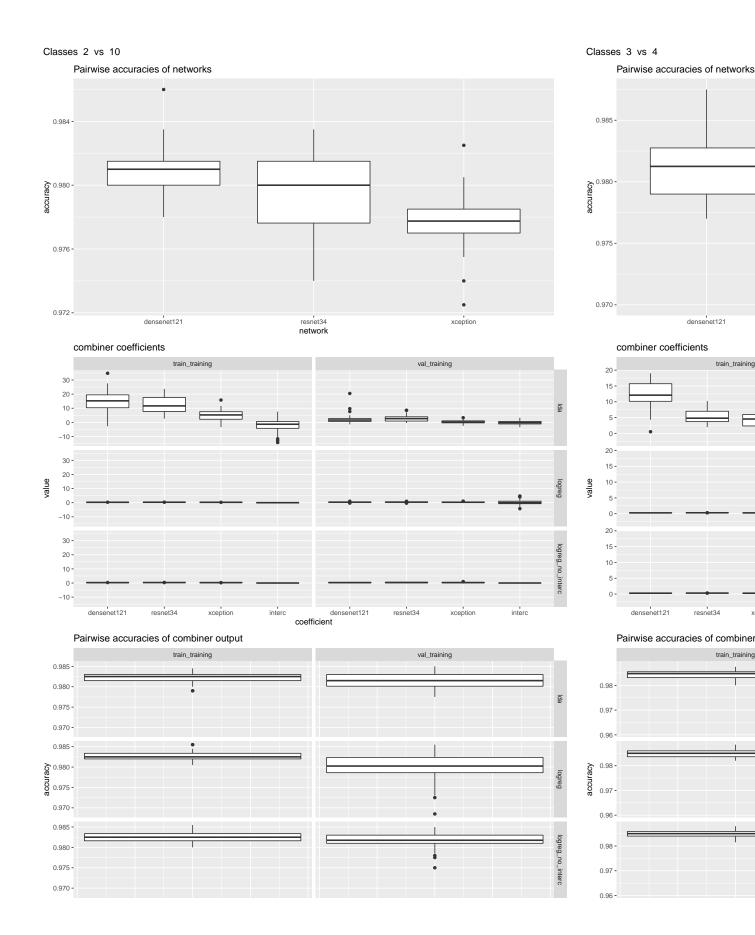


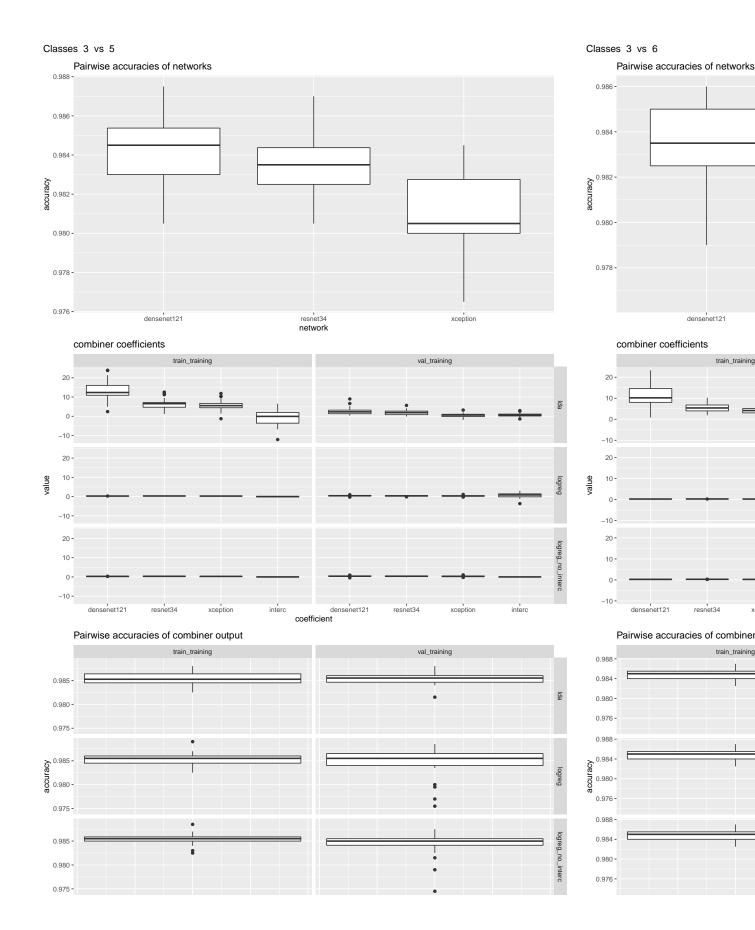


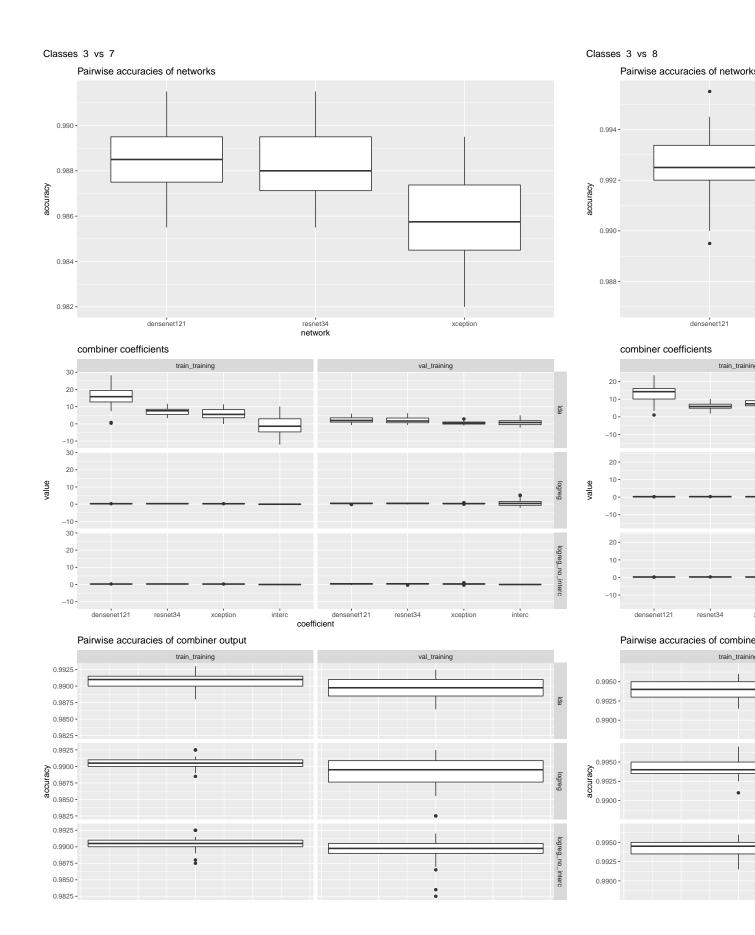


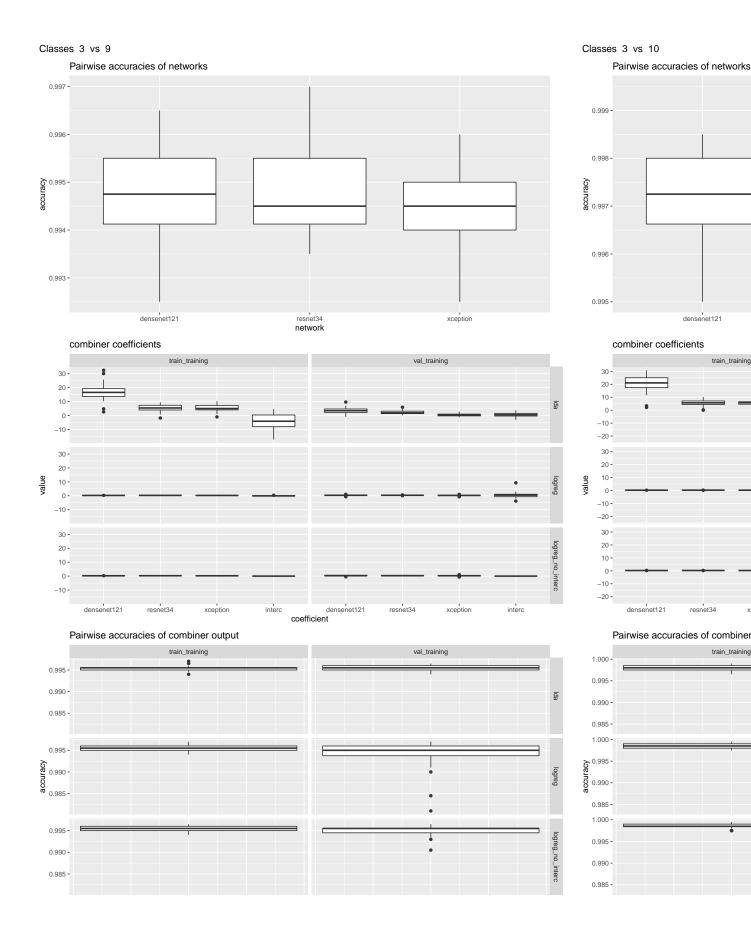


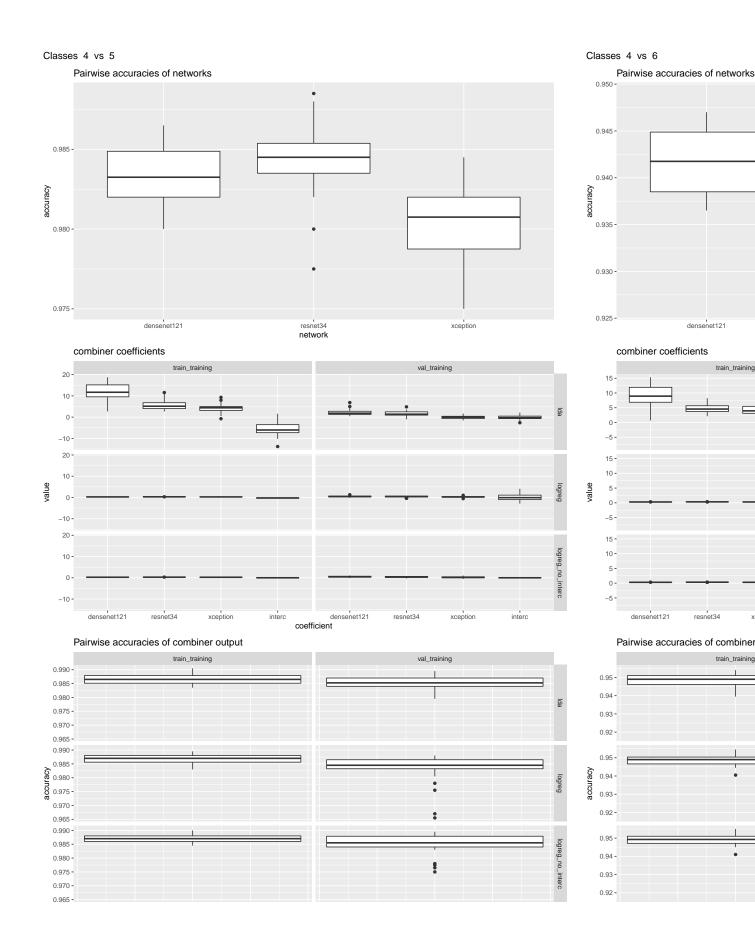


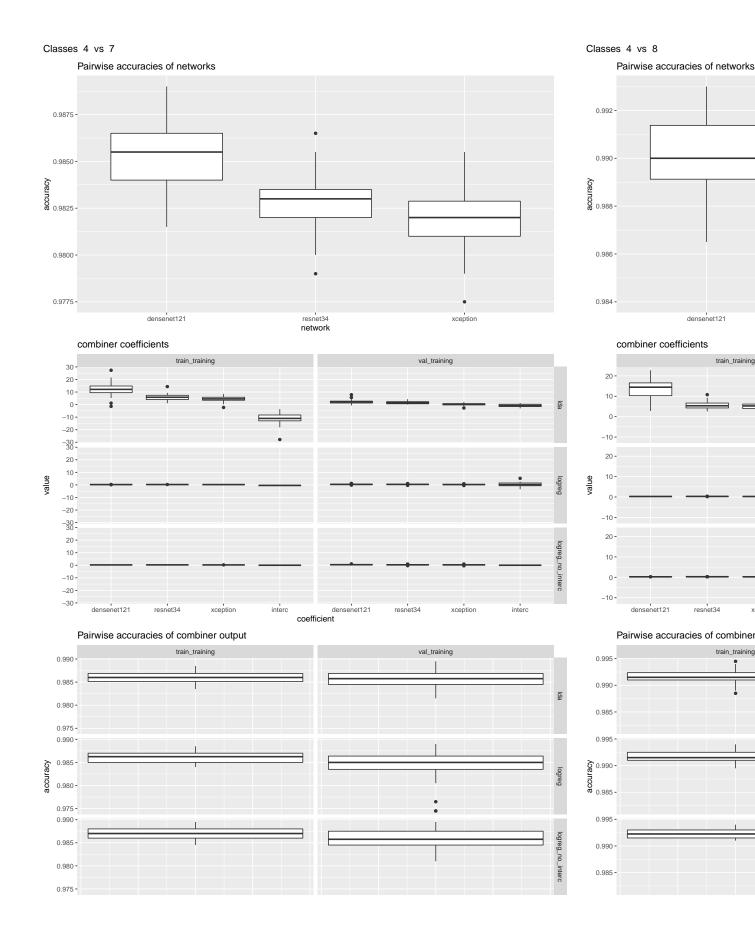


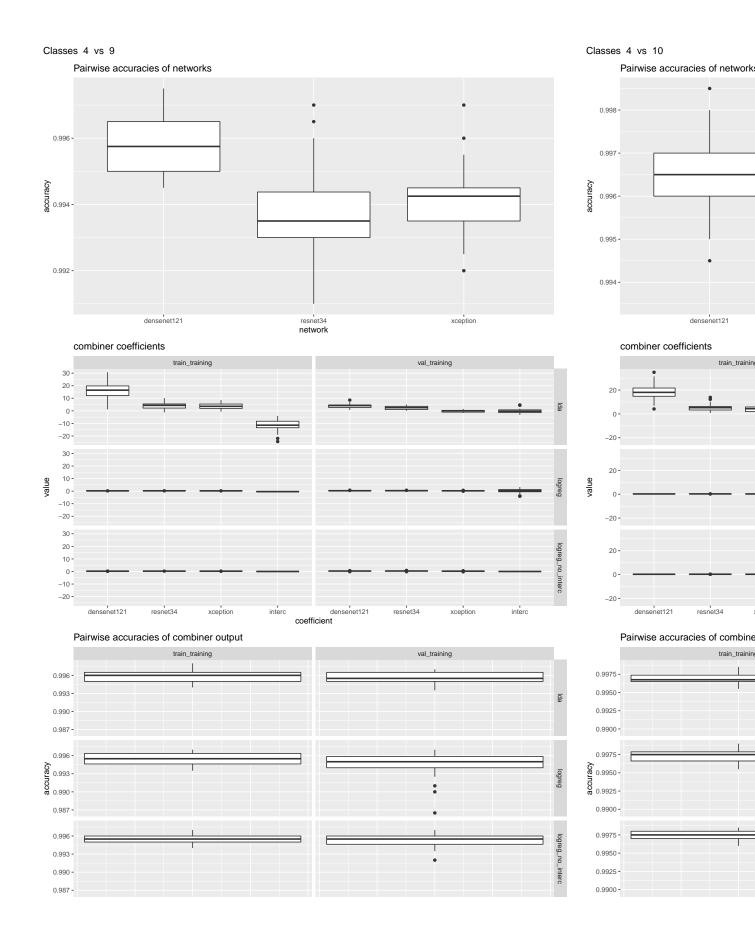


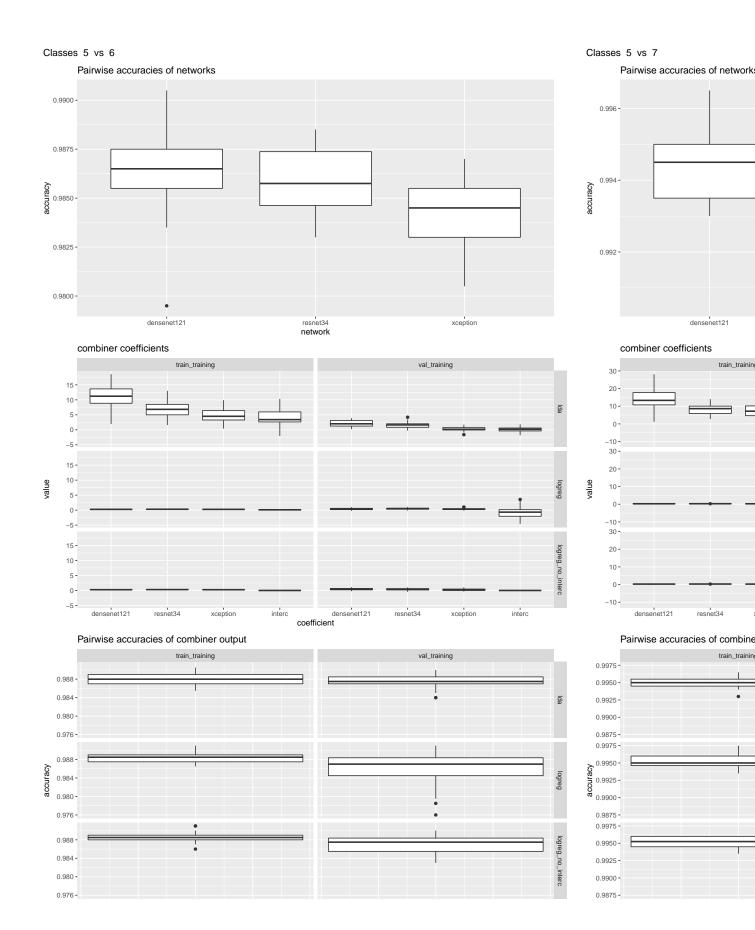


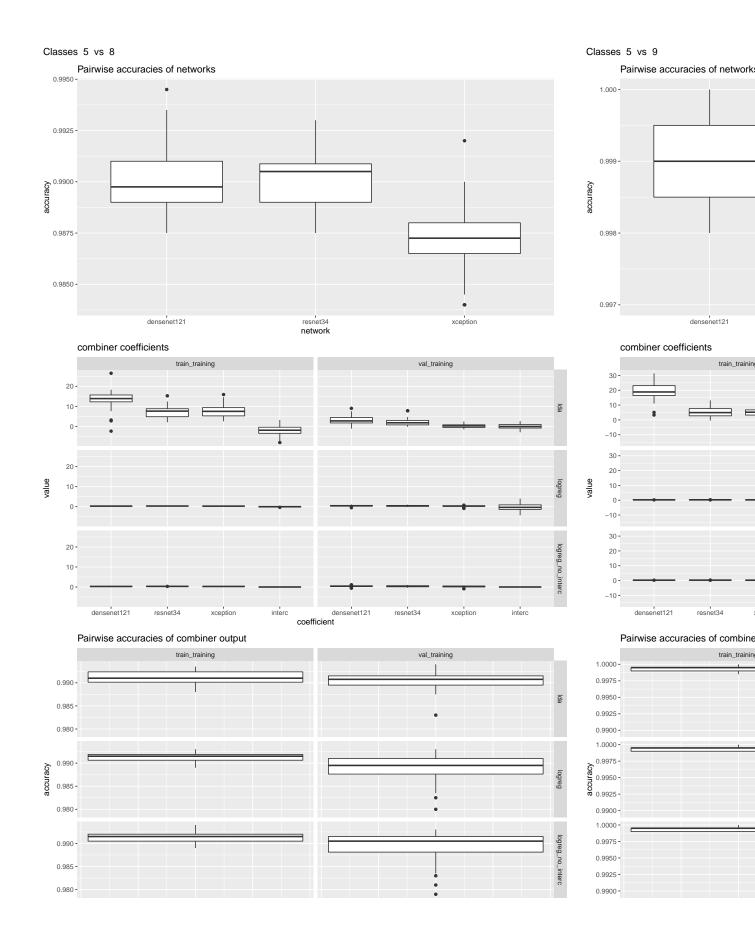


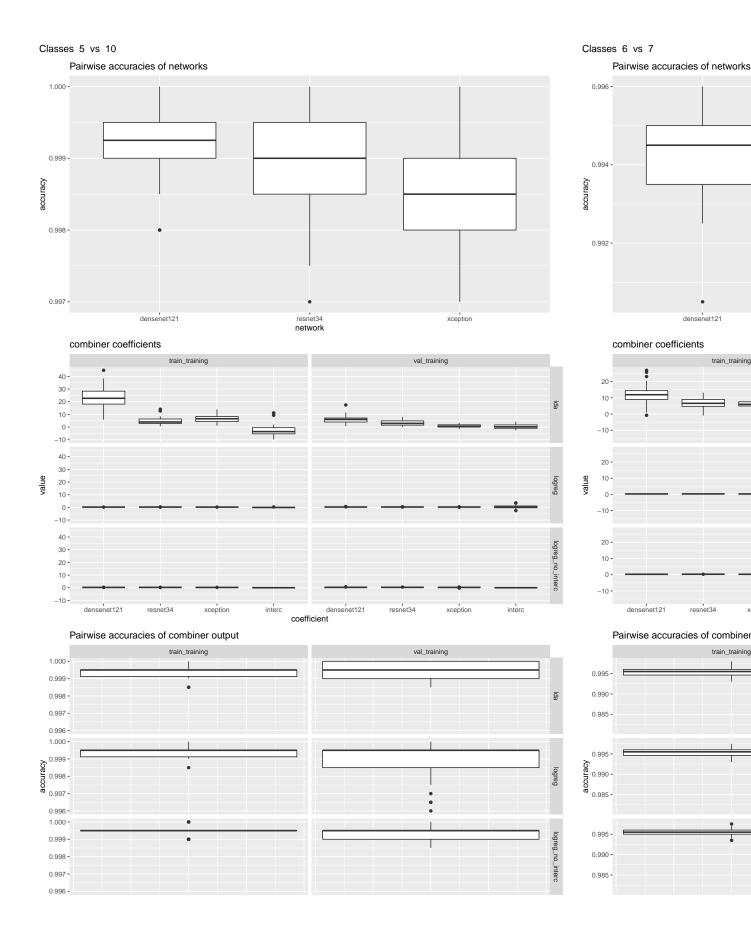


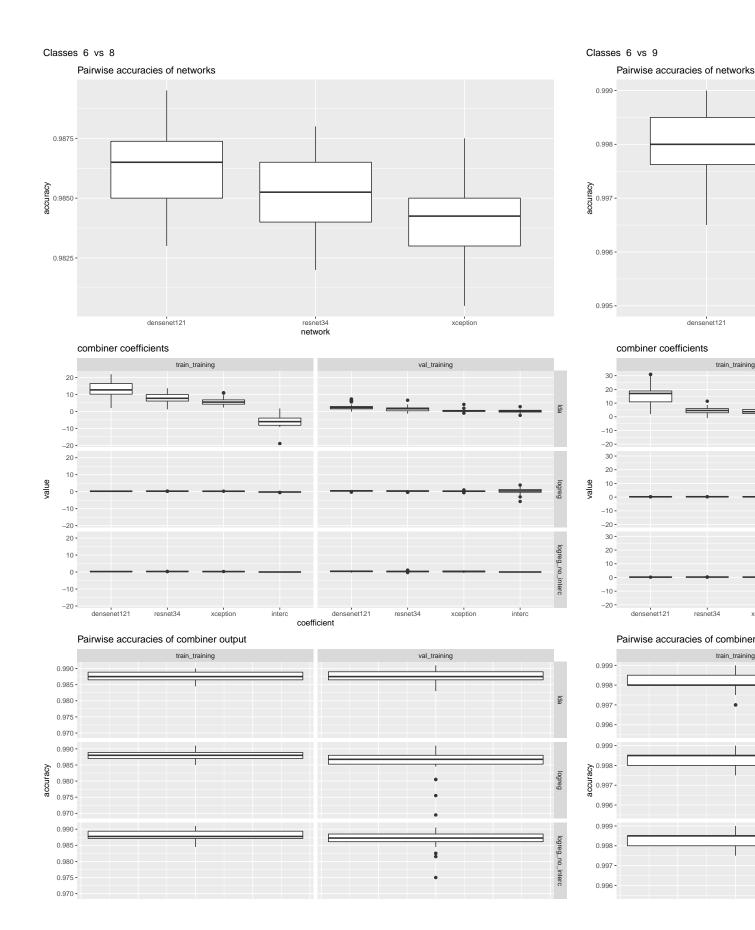


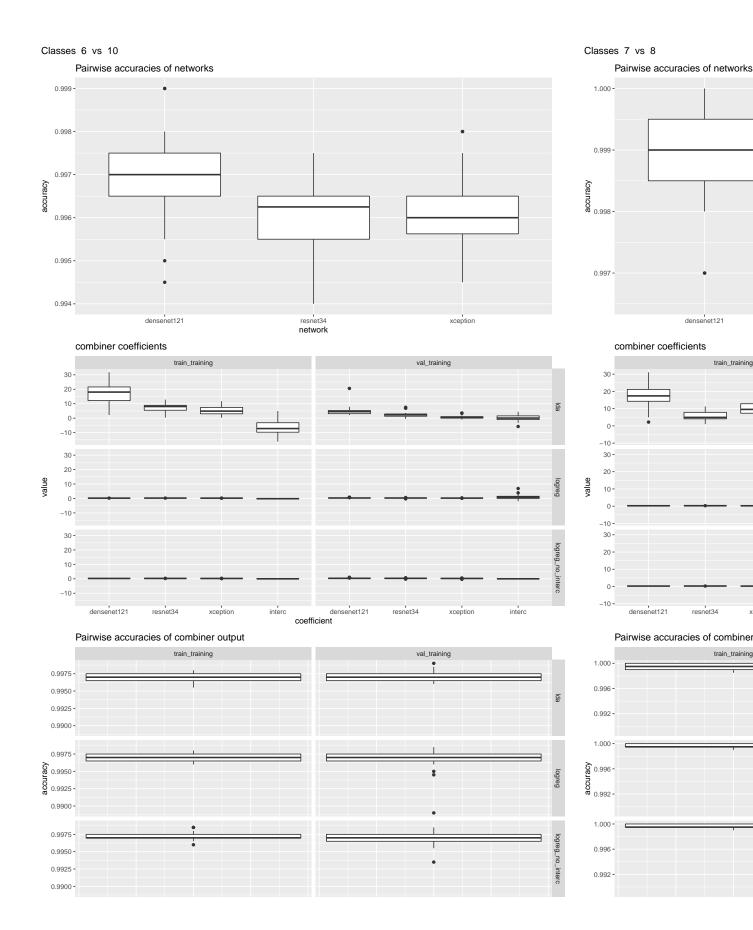


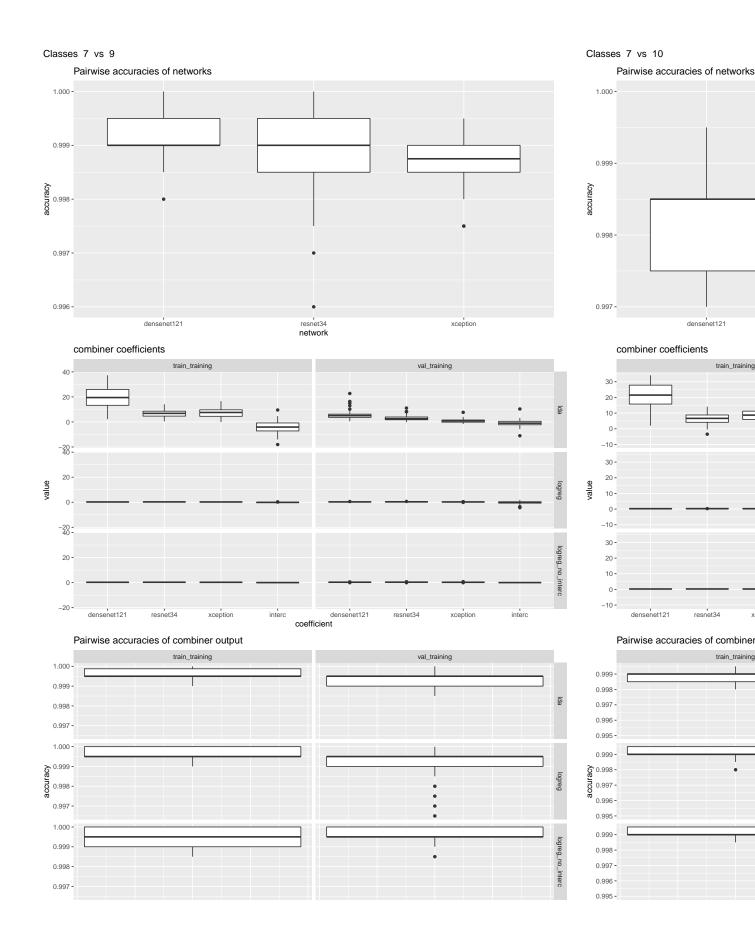


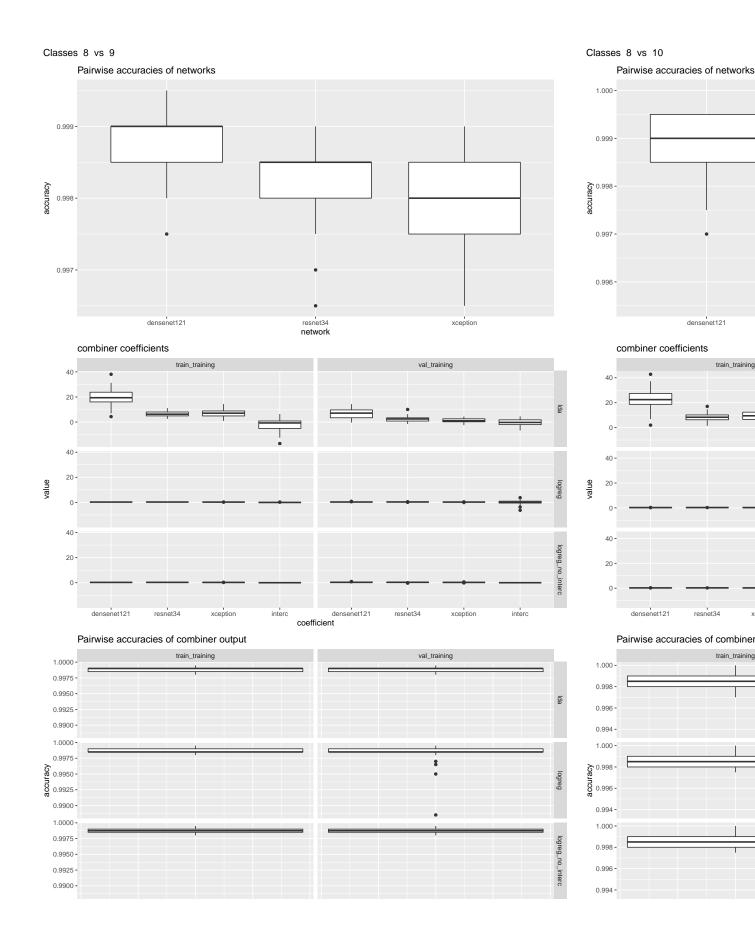




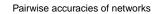


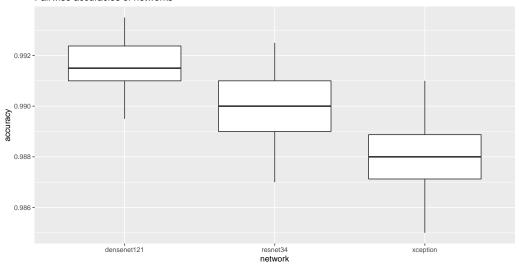




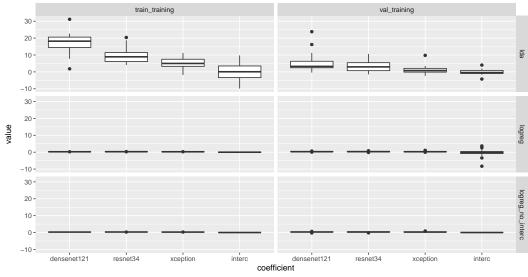


Classes 9 vs 10

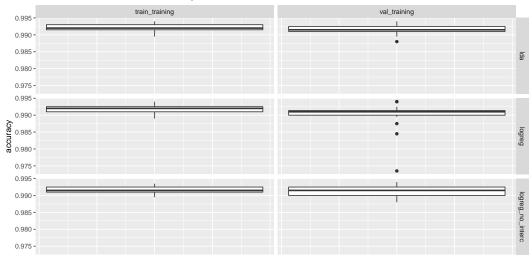




combiner coefficients



Pairwise accuracies of combiner output

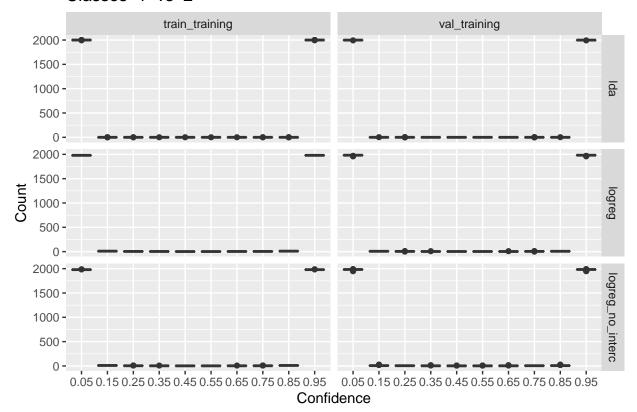


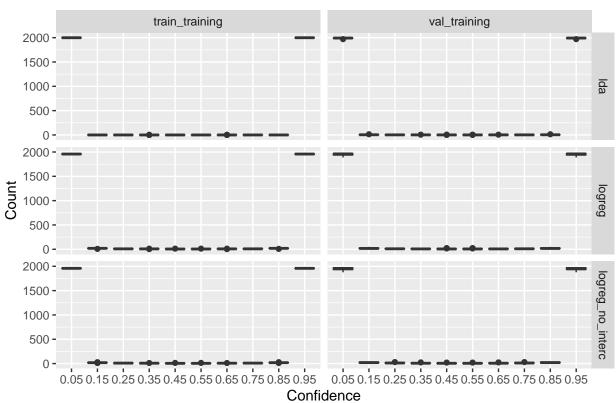
Val training

accuracies have higher variance.

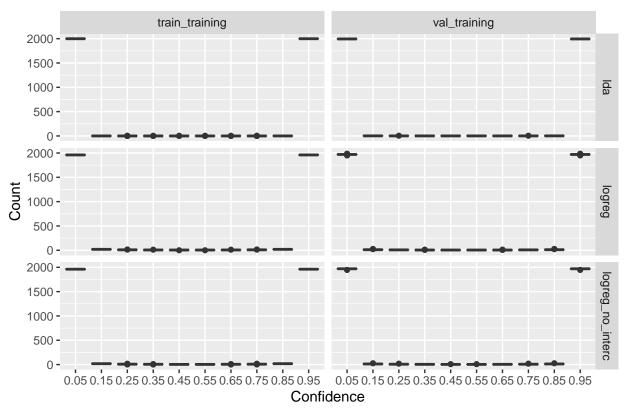
An attempt to visualize calibration of LDAs. Almost all elements are present near the zero and one probabilities, therefore the visualization is not very informative.

```
for (cl1 in 1:(classes - 1))
{
   for (cl2 in (cl1 + 1):classes)
   {
      cal_count_plt <- ens_pw_cal %>% filter(class1 == (cl1 - 1) & class2 == (cl2 - 1)) %>% ggplot() +
            geom_boxplot(mapping=aes(x=bin_c, y=bin_count)) + facet_grid(cols=vars(train_set), rows=vars(comb
            ggtitle(paste("Classes ", cl1, " vs ", cl2)) + xlab("Confidence") + ylab("Count")
      print(cal_count_plt)
   }
}
```

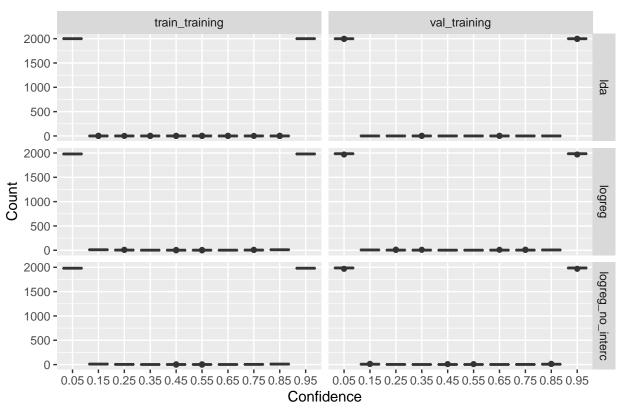




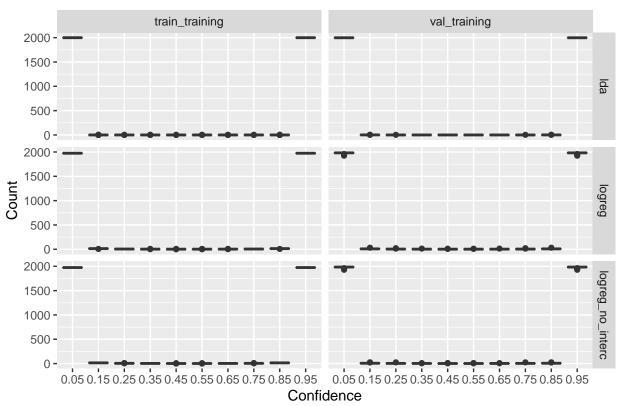
Classes 1 vs 4



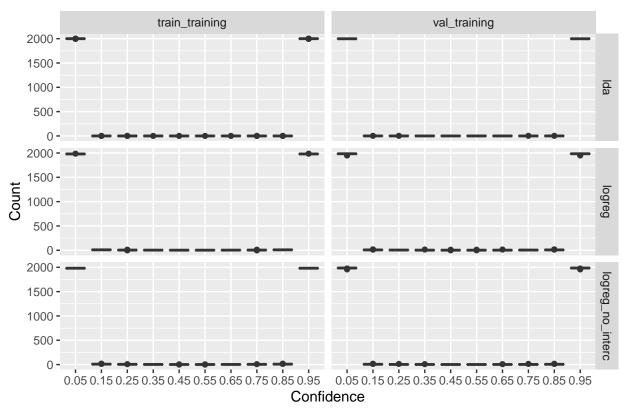
Classes 1 vs 5



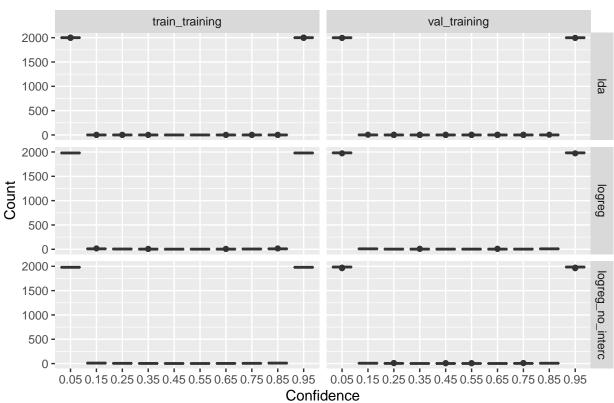
Classes 1 vs 6

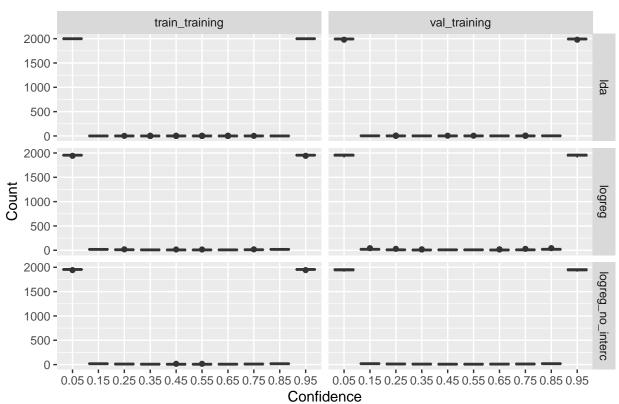


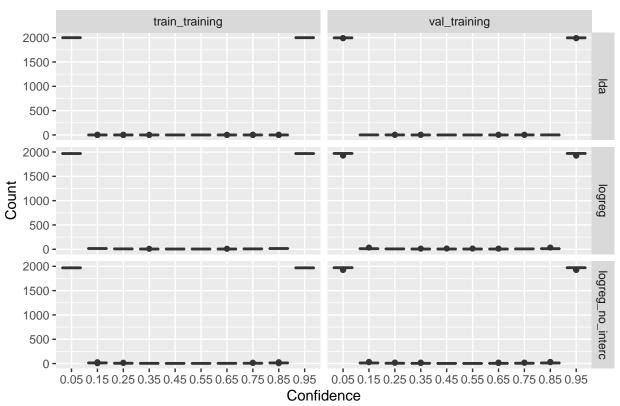
Classes 1 vs 7

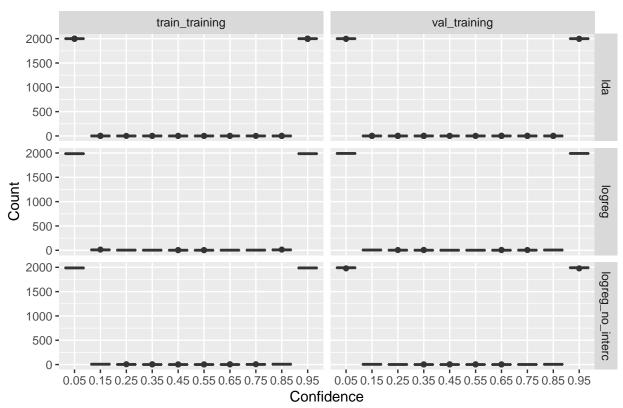


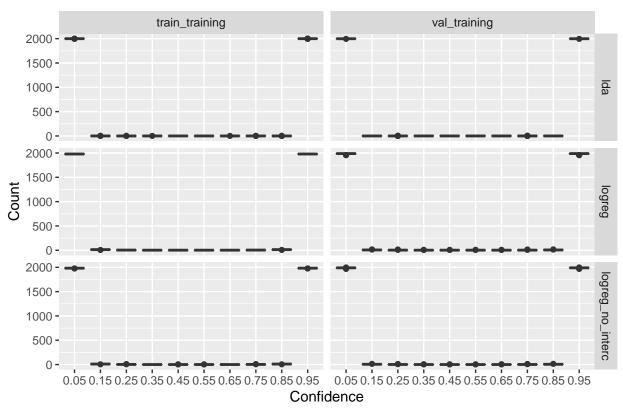
Classes 1 vs 8

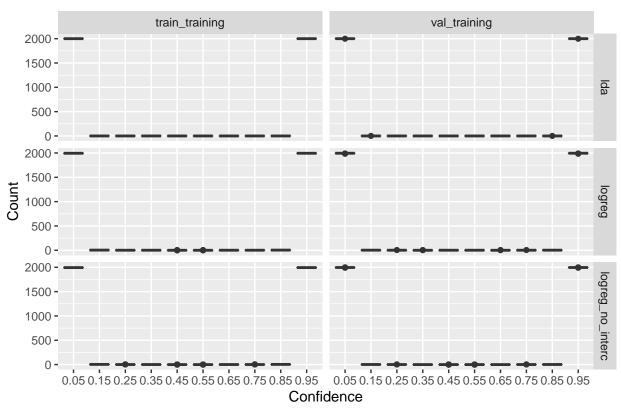


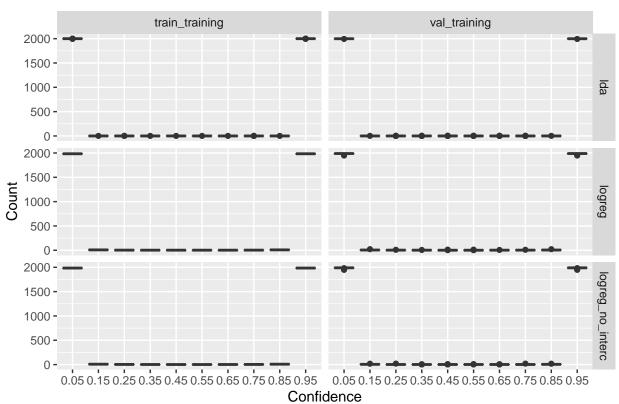


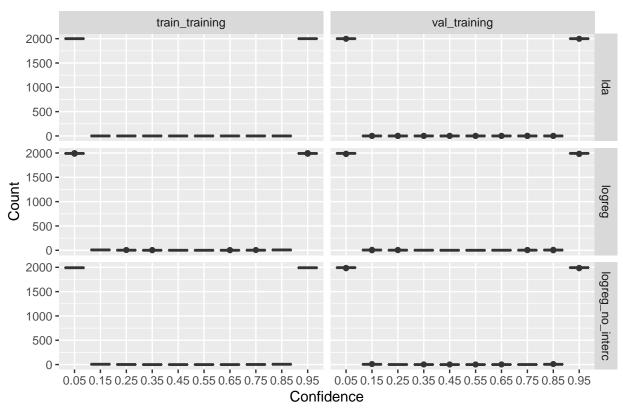


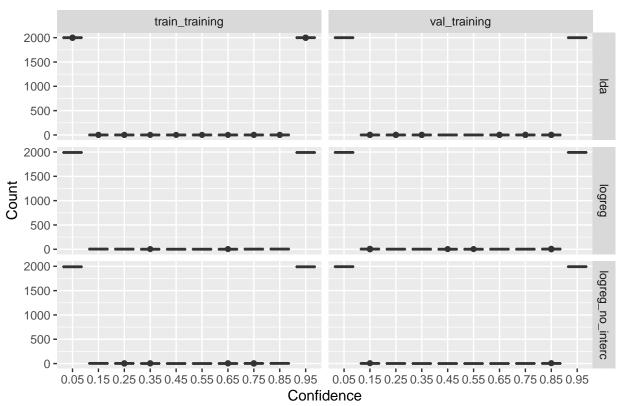


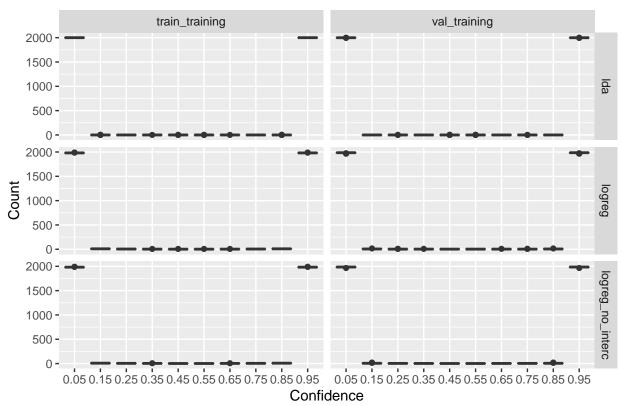


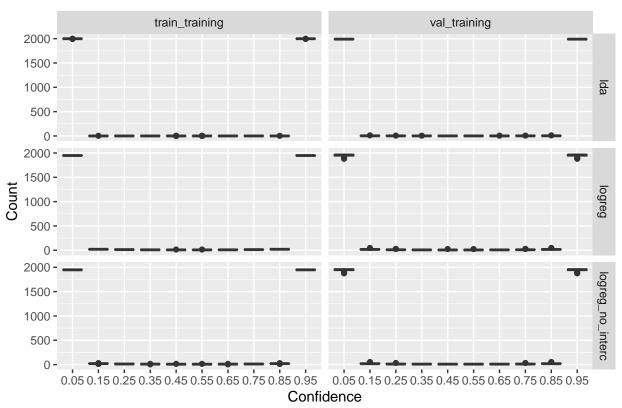




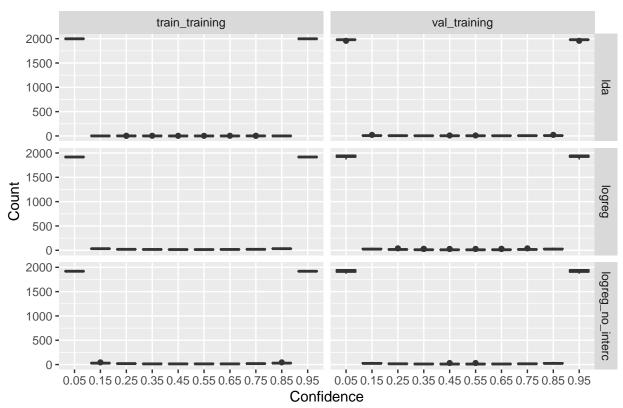


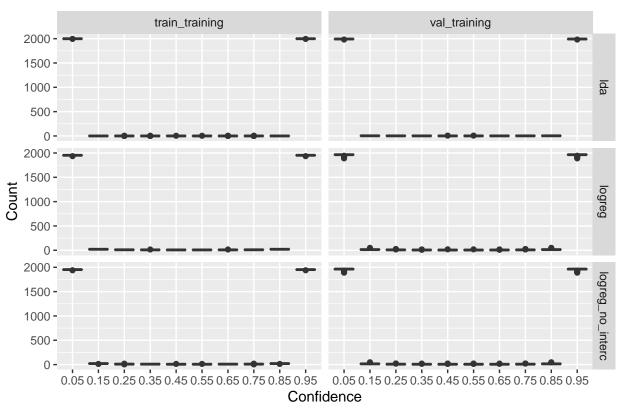


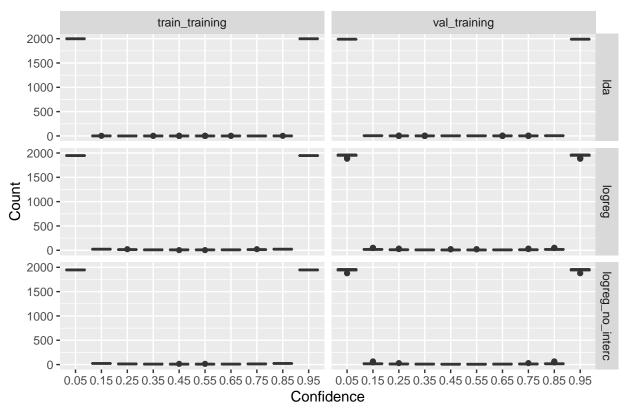




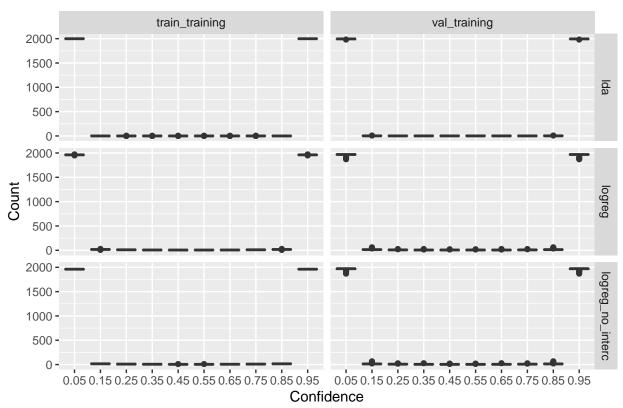
Classes 3 vs 4

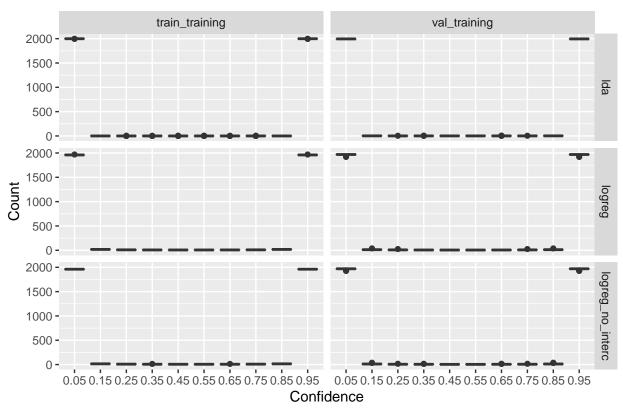


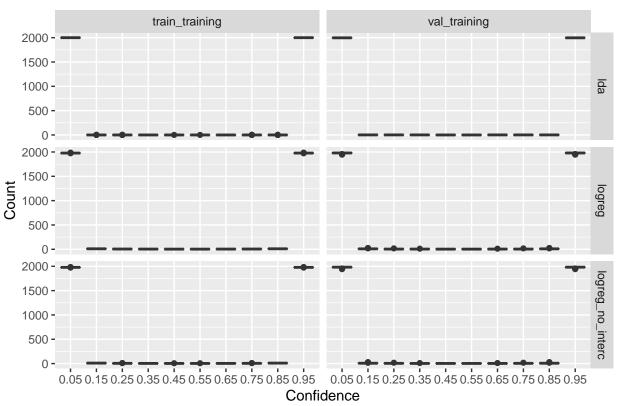




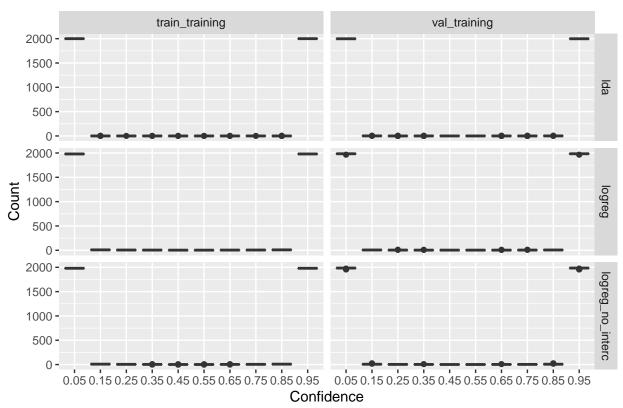
Classes 3 vs 7



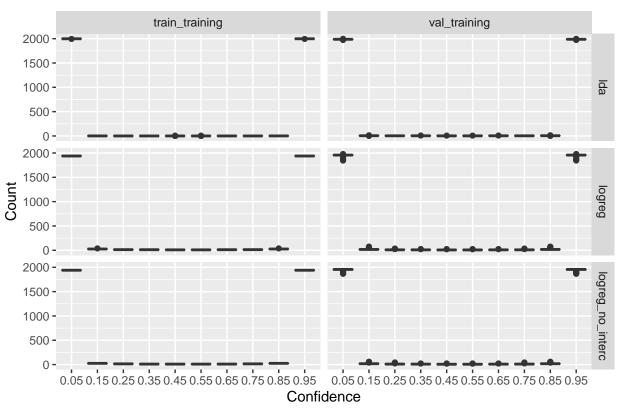




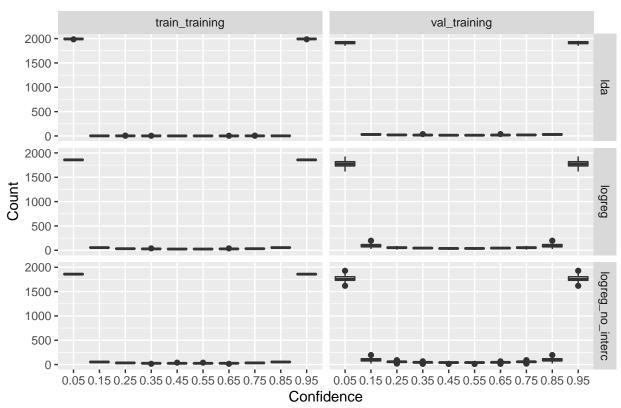
Classes 3 vs 10



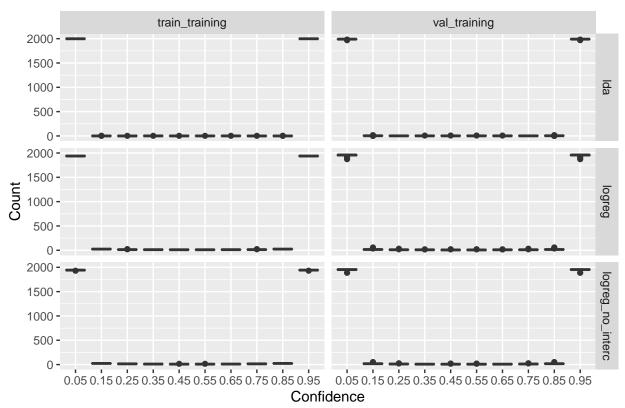
Classes 4 vs 5

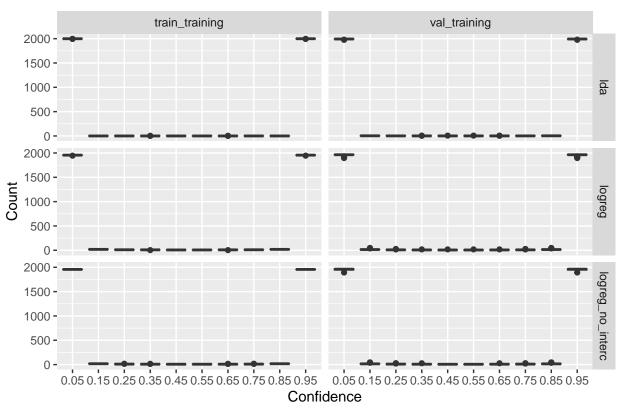


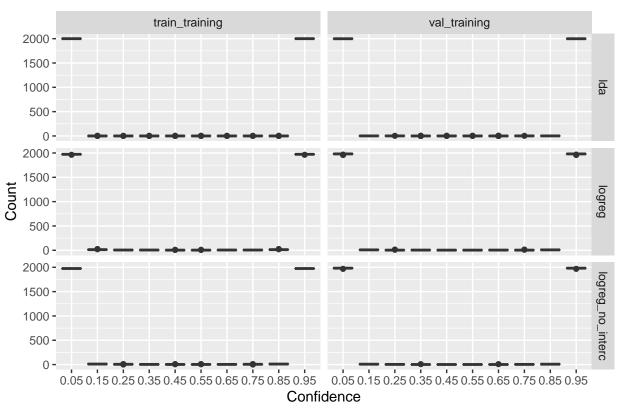
Classes 4 vs 6

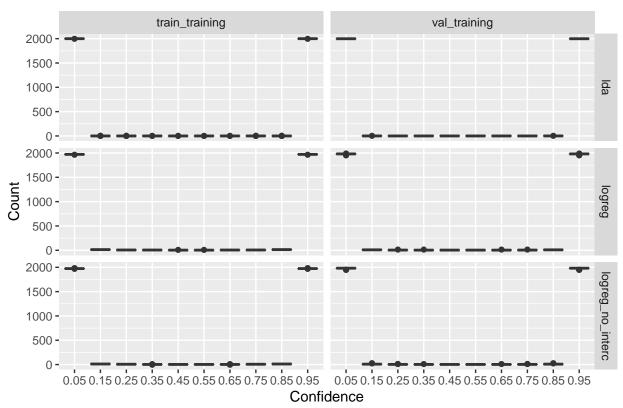


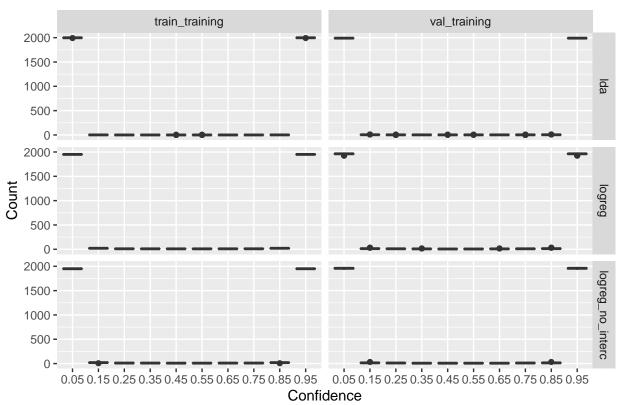
Classes 4 vs 7



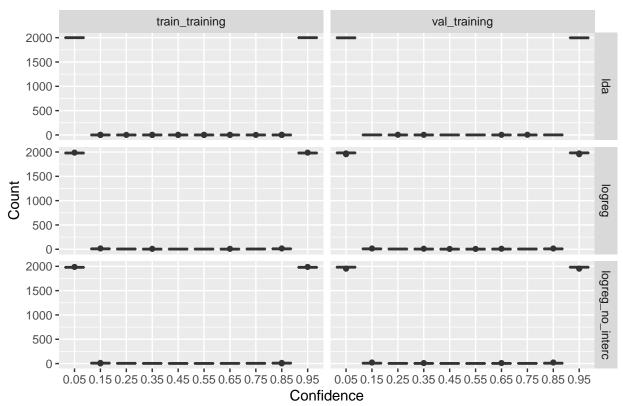


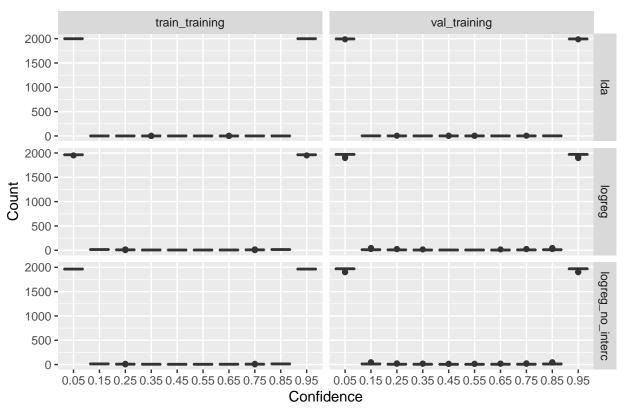




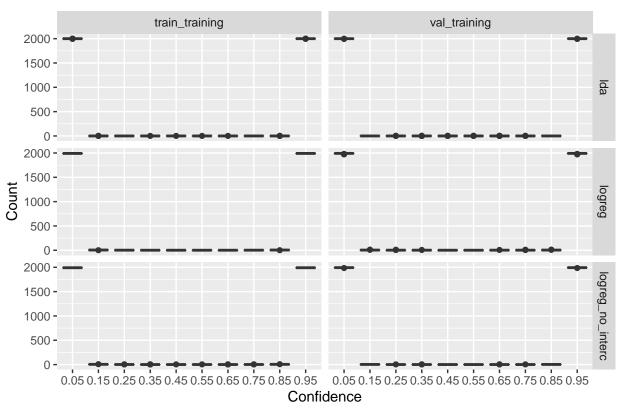


Classes 5 vs 7

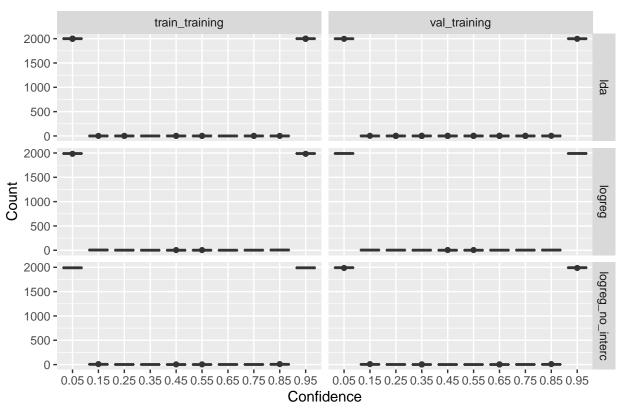




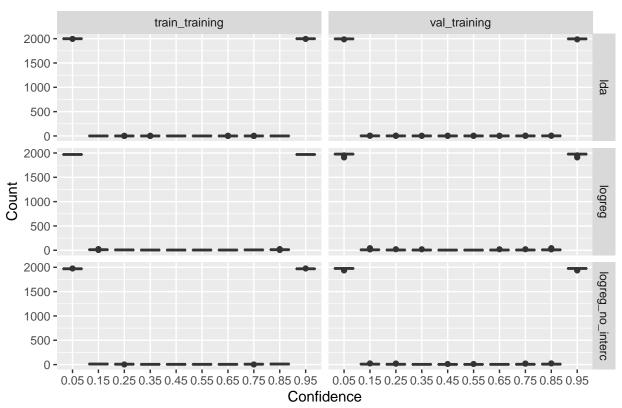
Classes 5 vs 9



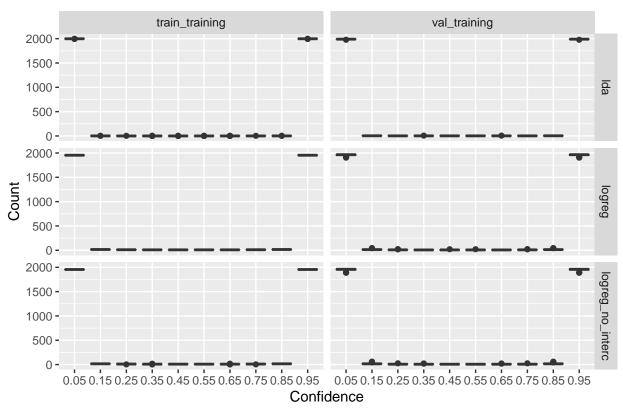
Classes 5 vs 10

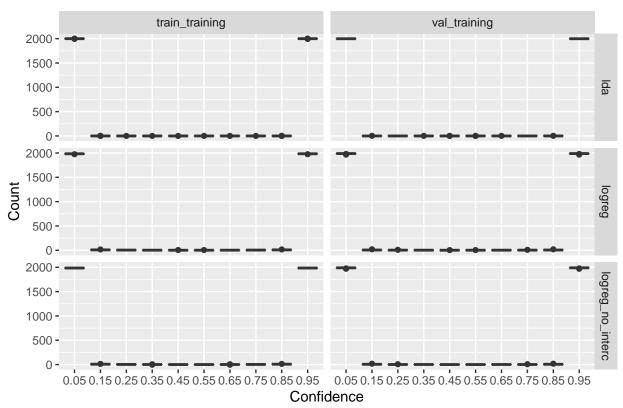


Classes 6 vs 7

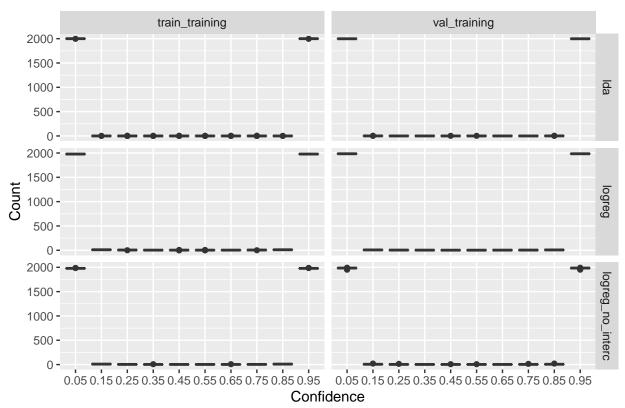


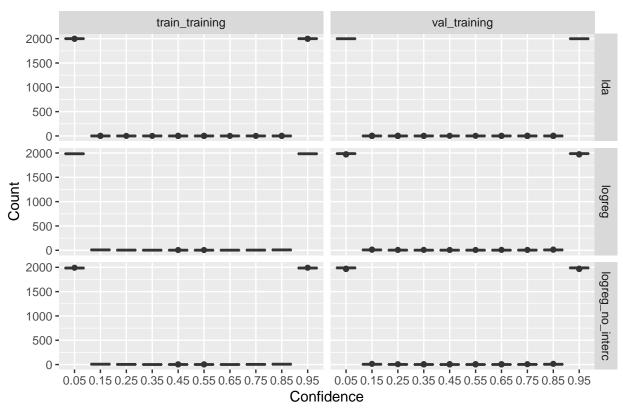
Classes 6 vs 8

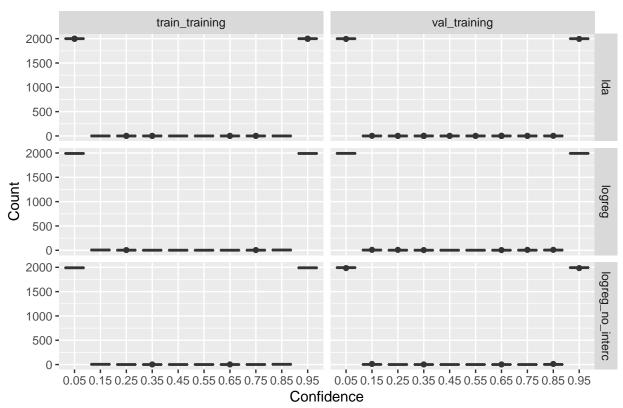


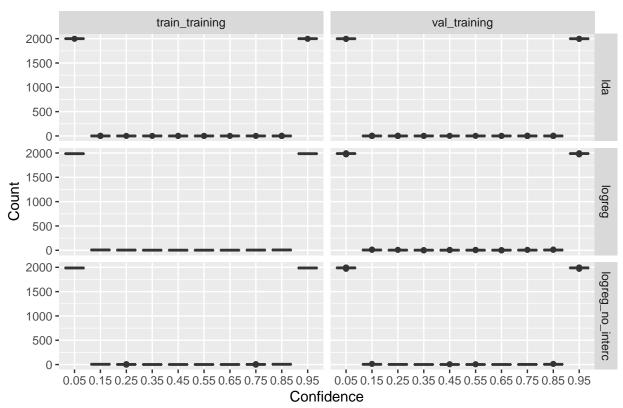


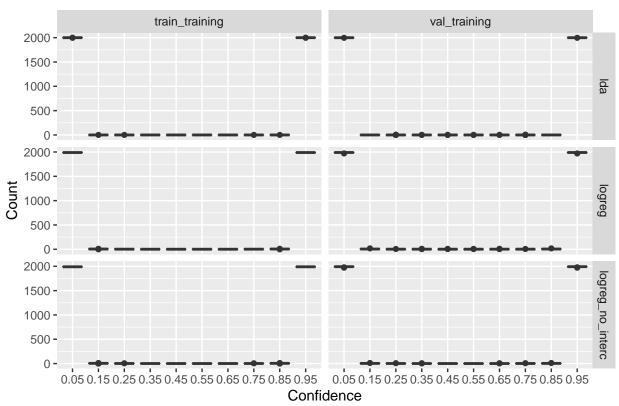
Classes 6 vs 10



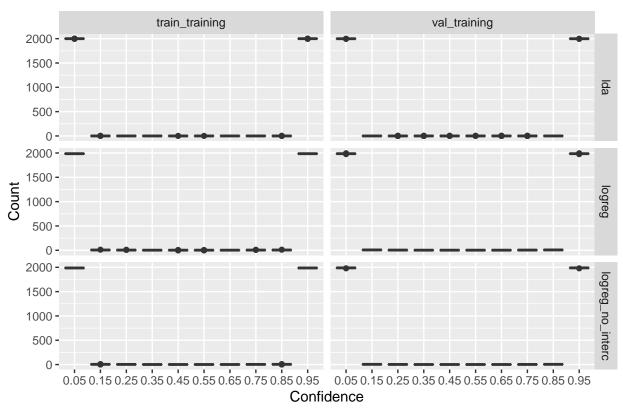


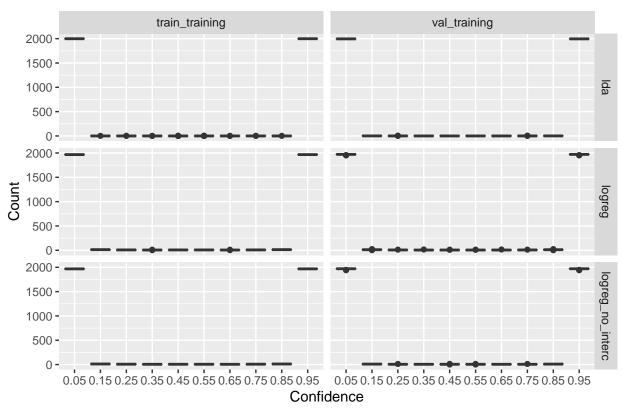






Classes 8 vs 10

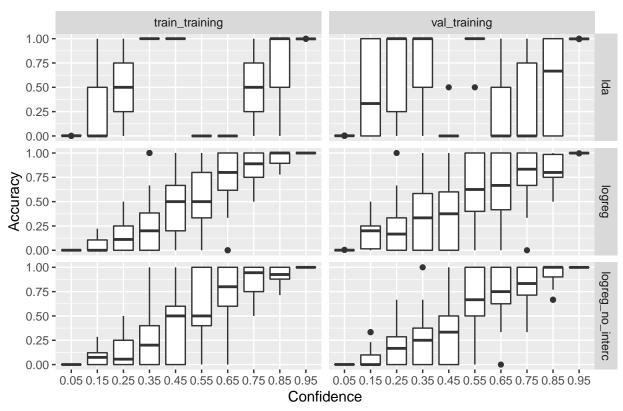




```
for (cl1 in 1:(classes - 1))
{
  for (cl2 in (cl1 + 1):classes)
  {
    cal_plt <- ens_pw_cal %>% filter(class1 == (cl1 - 1) & class2 == (cl2 - 1)) %>% ggplot() +
        geom_boxplot(mapping=aes(x=bin_c, y=bin_accuracy)) + facet_grid(cols=vars(train_set), rows=vars(c
        ggtitle(paste("Classes ", cl1, " vs ", cl2)) + xlab("Confidence") + ylab("Accuracy")
    print(cal_plt)
  }
}
```

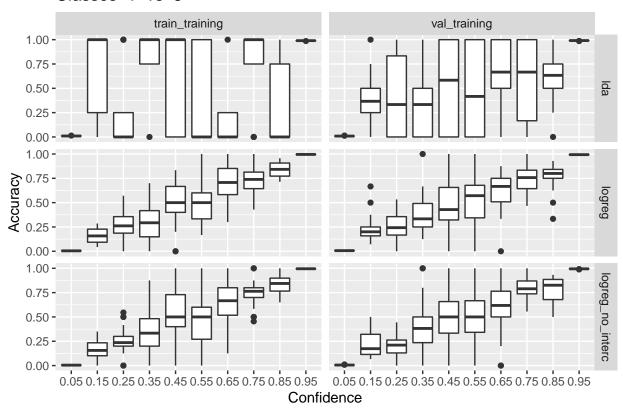
Warning: Removed 438 rows containing non-finite values (stat_boxplot).

Classes 1 vs 2



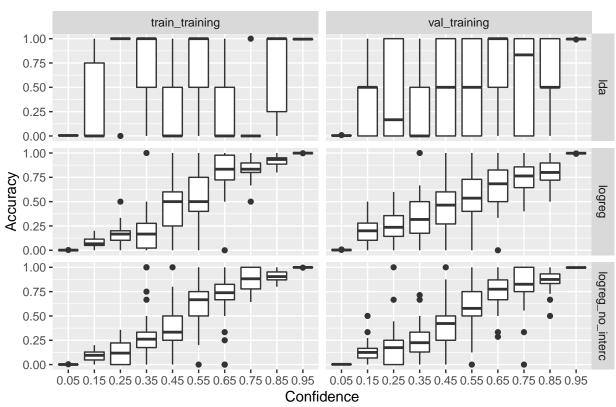
Warning: Removed 216 rows containing non-finite values (stat_boxplot).

Classes 1 vs 3



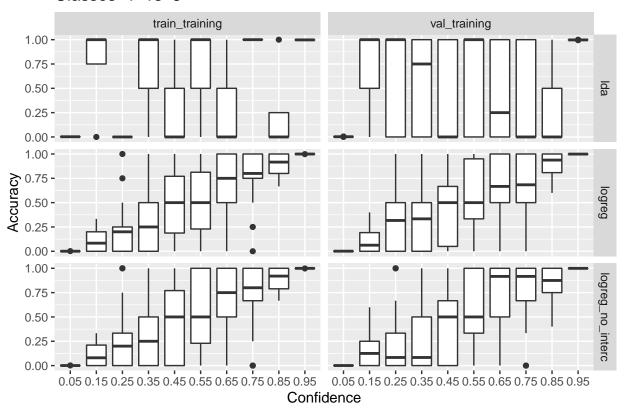
Warning: Removed 262 rows containing non-finite values (stat_boxplot).

Classes 1 vs 4



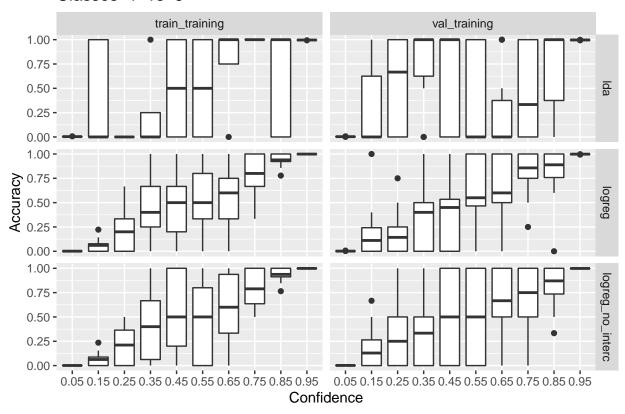
Warning: Removed 428 rows containing non-finite values (stat_boxplot).

Classes 1 vs 5



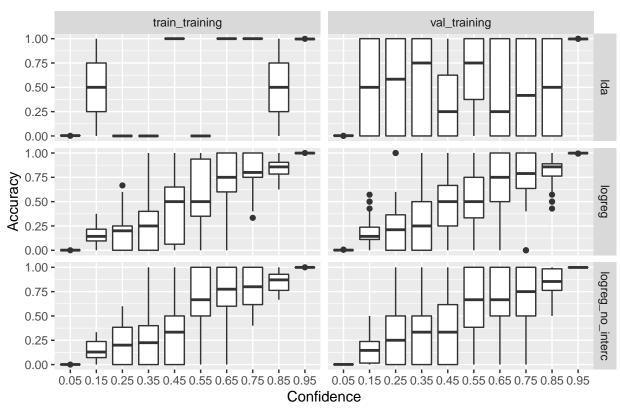
Warning: Removed 380 rows containing non-finite values (stat_boxplot).

Classes 1 vs 6



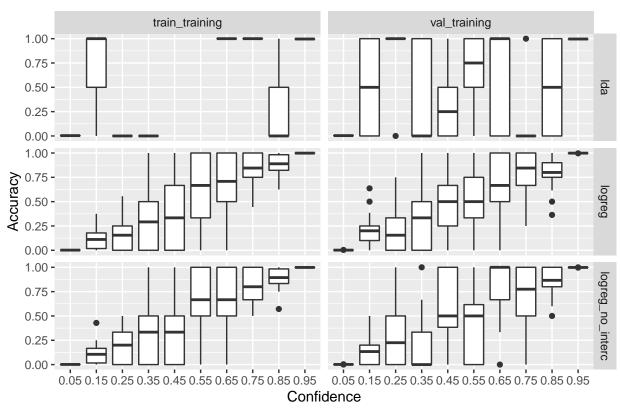
Warning: Removed 388 rows containing non-finite values (stat_boxplot).

Classes 1 vs 7



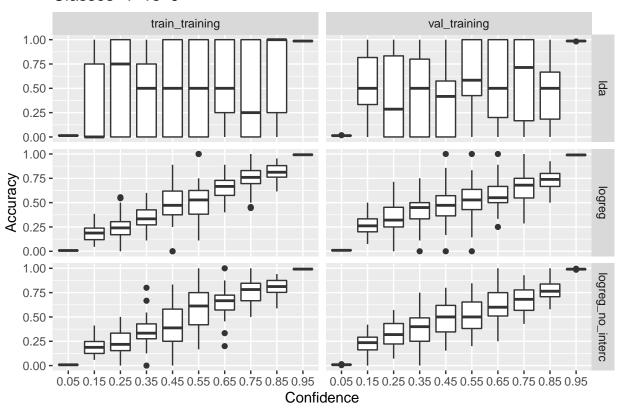
Warning: Removed 420 rows containing non-finite values (stat_boxplot).

Classes 1 vs 8



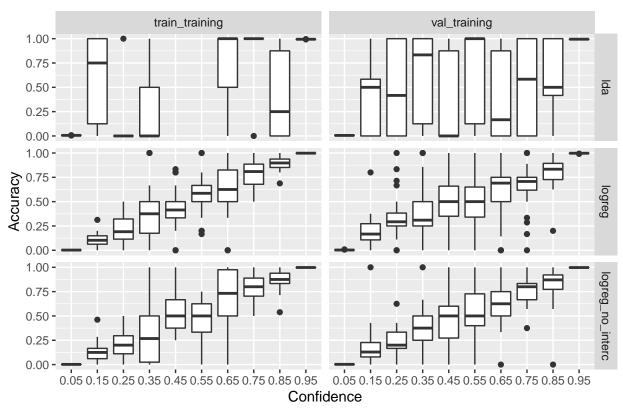
Warning: Removed 230 rows containing non-finite values (stat_boxplot).

Classes 1 vs 9



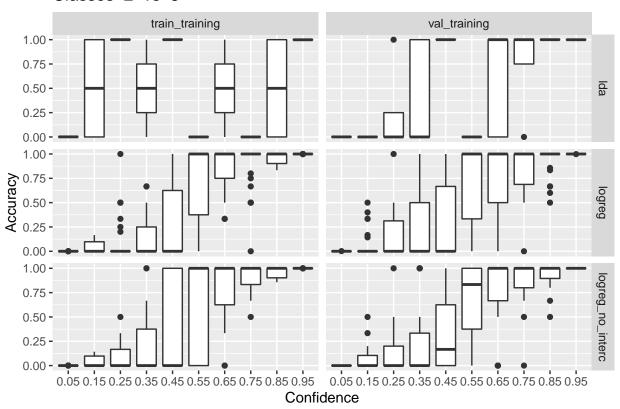
Warning: Removed 344 rows containing non-finite values (stat_boxplot).

Classes 1 vs 10



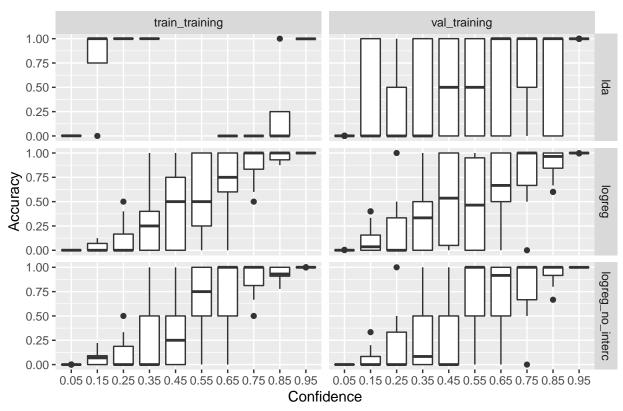
Warning: Removed 598 rows containing non-finite values (stat_boxplot).

Classes 2 vs 3



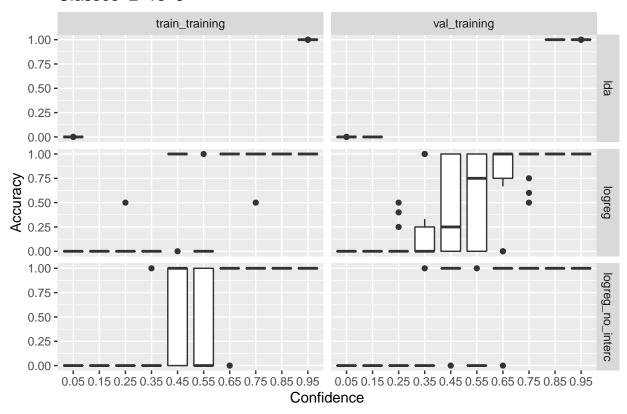
Warning: Removed 486 rows containing non-finite values (stat_boxplot).

Classes 2 vs 4



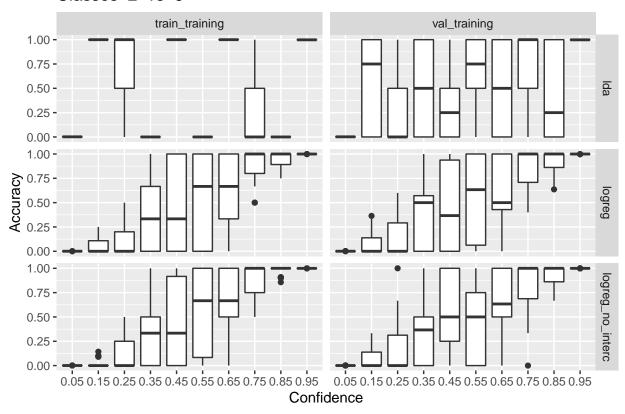
Warning: Removed 828 rows containing non-finite values (stat_boxplot).

Classes 2 vs 5



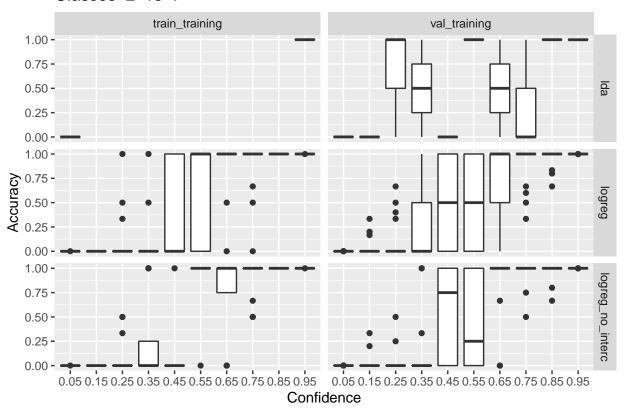
Warning: Removed 472 rows containing non-finite values (stat_boxplot).

Classes 2 vs 6



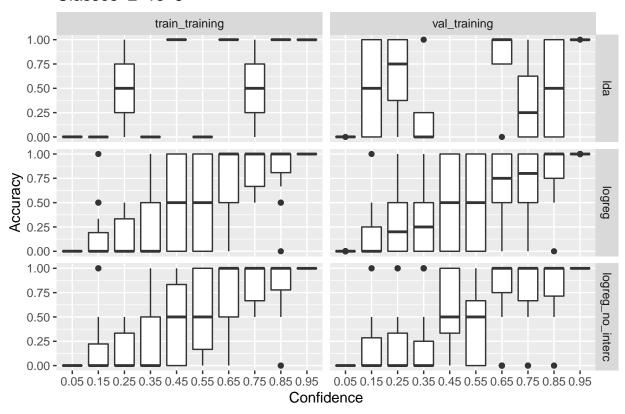
Warning: Removed 772 rows containing non-finite values (stat_boxplot).

Classes 2 vs 7



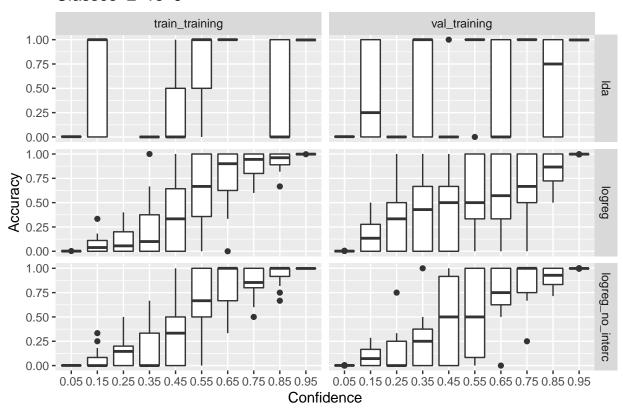
Warning: Removed 542 rows containing non-finite values (stat_boxplot).

Classes 2 vs 8



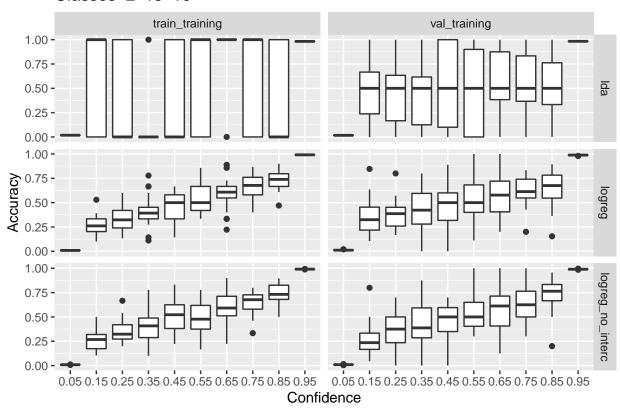
Warning: Removed 448 rows containing non-finite values (stat_boxplot).

Classes 2 vs 9



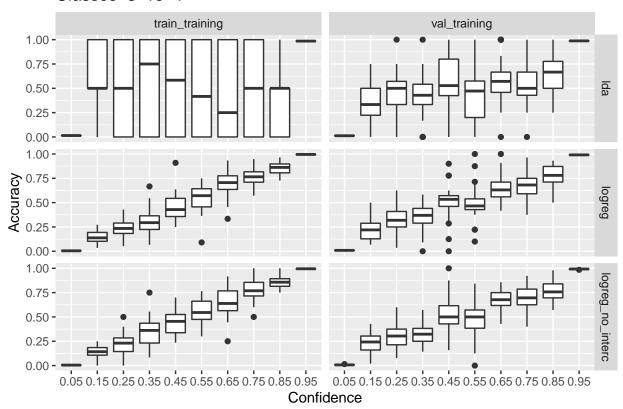
Warning: Removed 220 rows containing non-finite values (stat_boxplot).

Classes 2 vs 10



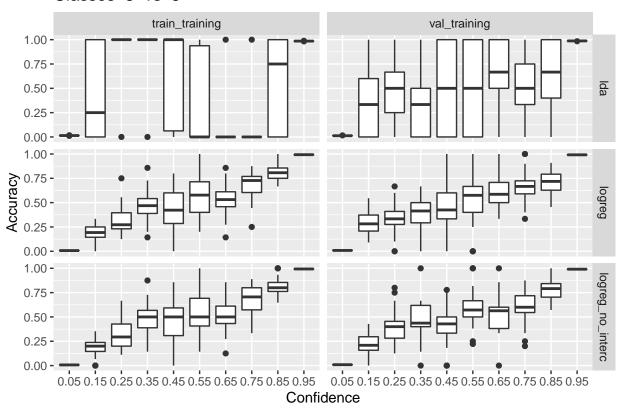
Warning: Removed 124 rows containing non-finite values (stat_boxplot).

Classes 3 vs 4



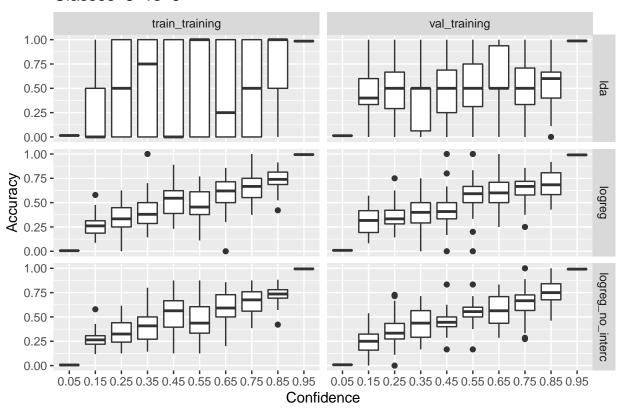
Warning: Removed 226 rows containing non-finite values (stat_boxplot).

Classes 3 vs 5



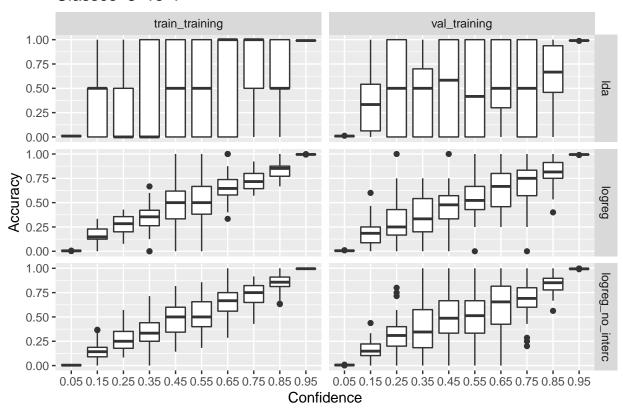
Warning: Removed 170 rows containing non-finite values (stat_boxplot).

Classes 3 vs 6



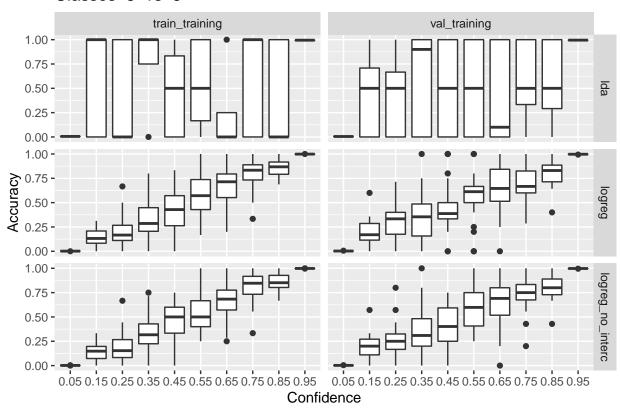
Warning: Removed 260 rows containing non-finite values (stat_boxplot).

Classes 3 vs 7



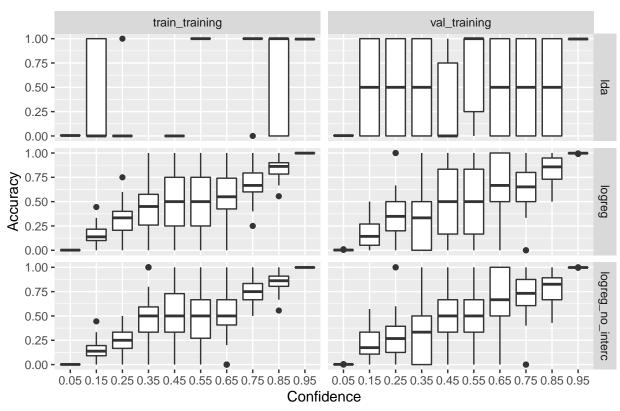
Warning: Removed 258 rows containing non-finite values (stat_boxplot).

Classes 3 vs 8



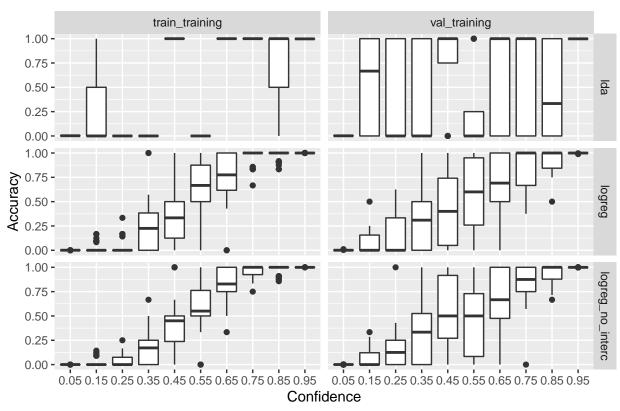
Warning: Removed 332 rows containing non-finite values (stat_boxplot).

Classes 3 vs 9



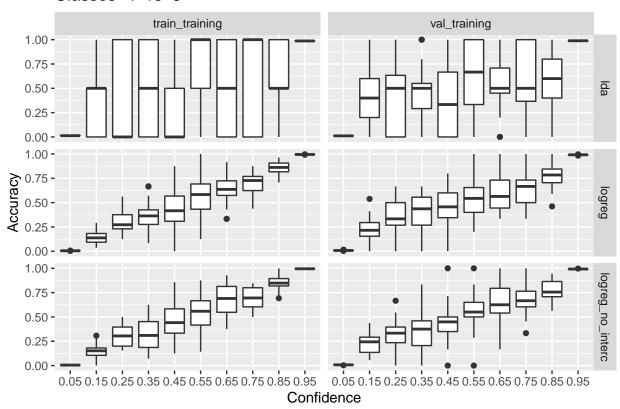
Warning: Removed 404 rows containing non-finite values (stat_boxplot).

Classes 3 vs 10



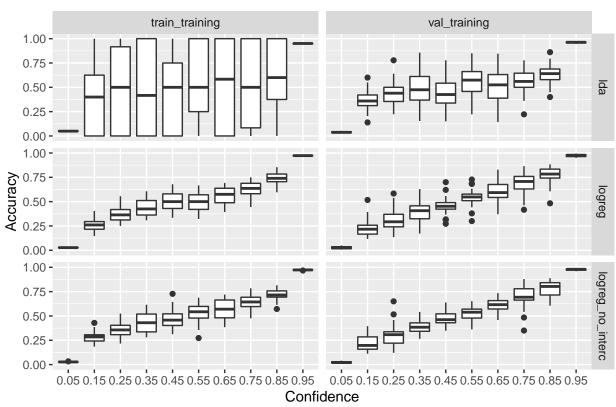
Warning: Removed 172 rows containing non-finite values (stat_boxplot).

Classes 4 vs 5



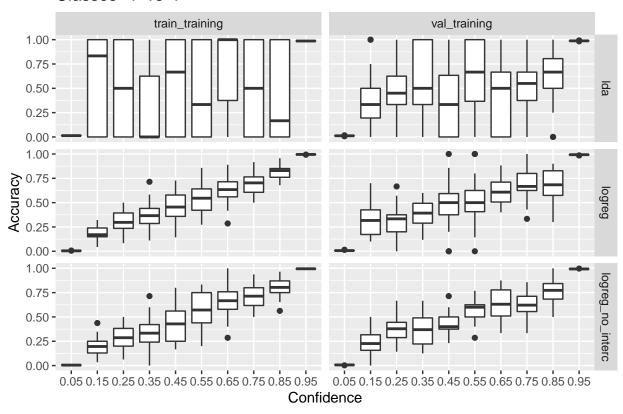
Warning: Removed 42 rows containing non-finite values (stat_boxplot).

Classes 4 vs 6



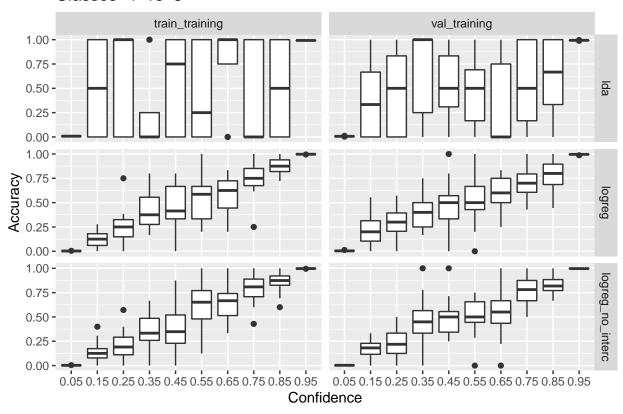
Warning: Removed 152 rows containing non-finite values (stat_boxplot).

Classes 4 vs 7



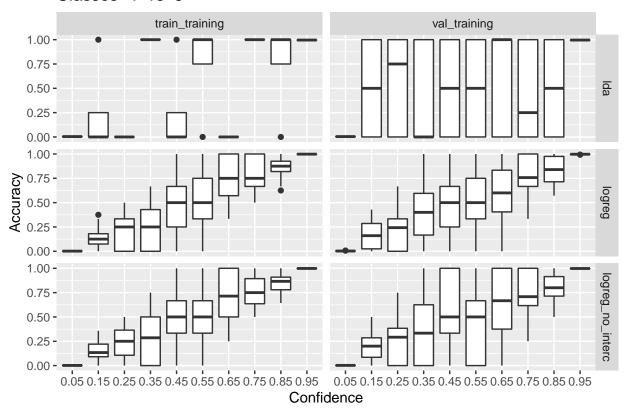
Warning: Removed 220 rows containing non-finite values (stat_boxplot).

Classes 4 vs 8



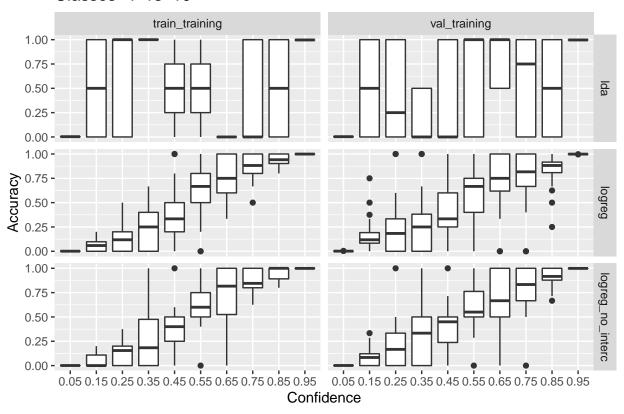
Warning: Removed 386 rows containing non-finite values (stat_boxplot).

Classes 4 vs 9



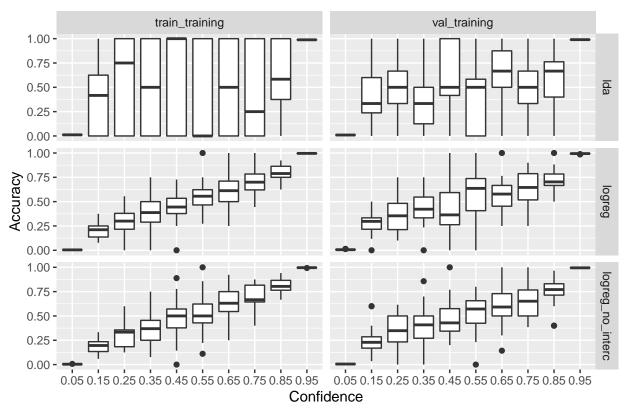
Warning: Removed 380 rows containing non-finite values (stat_boxplot).

Classes 4 vs 10



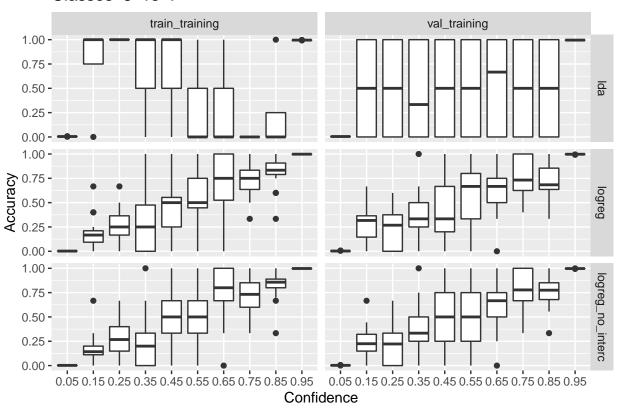
Warning: Removed 174 rows containing non-finite values (stat_boxplot).

Classes 5 vs 6



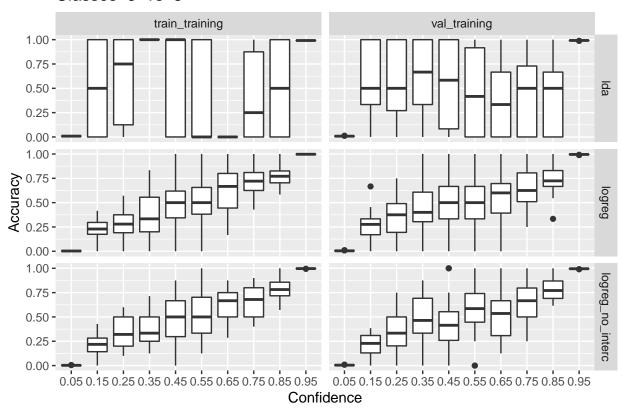
Warning: Removed 360 rows containing non-finite values (stat_boxplot).

Classes 5 vs 7



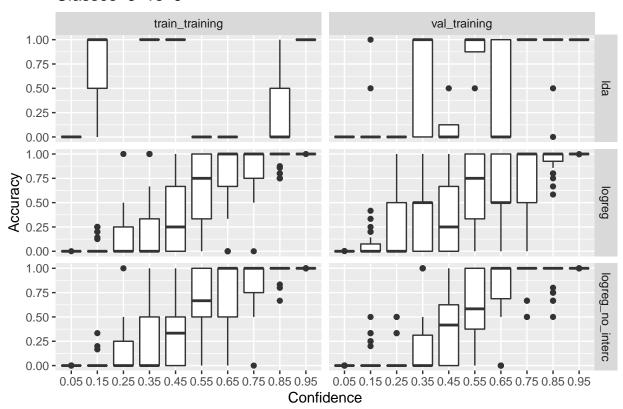
Warning: Removed 236 rows containing non-finite values (stat_boxplot).

Classes 5 vs 8



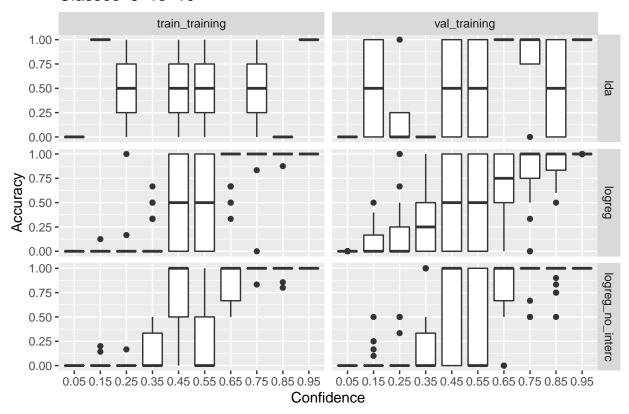
Warning: Removed 544 rows containing non-finite values (stat_boxplot).

Classes 5 vs 9



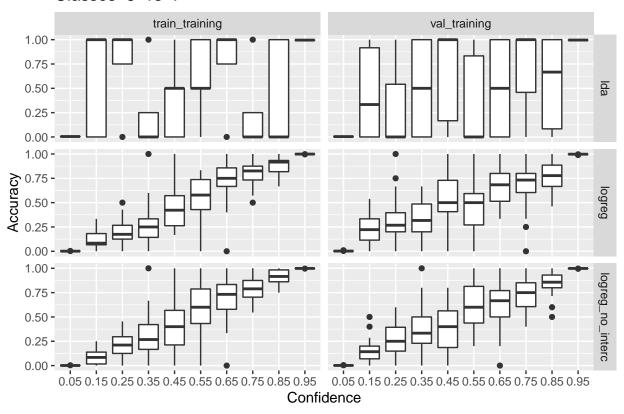
Warning: Removed 516 rows containing non-finite values (stat_boxplot).

Classes 5 vs 10



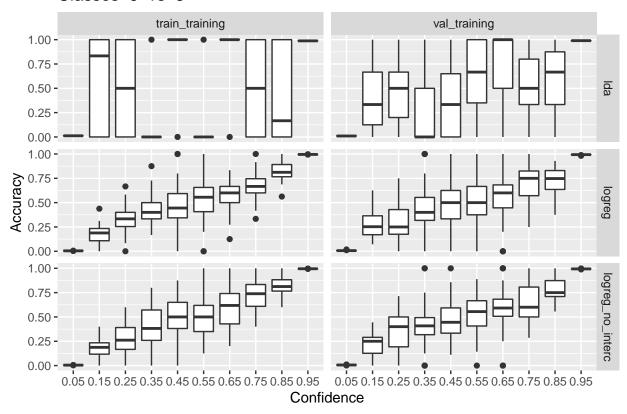
Warning: Removed 284 rows containing non-finite values (stat_boxplot).

Classes 6 vs 7



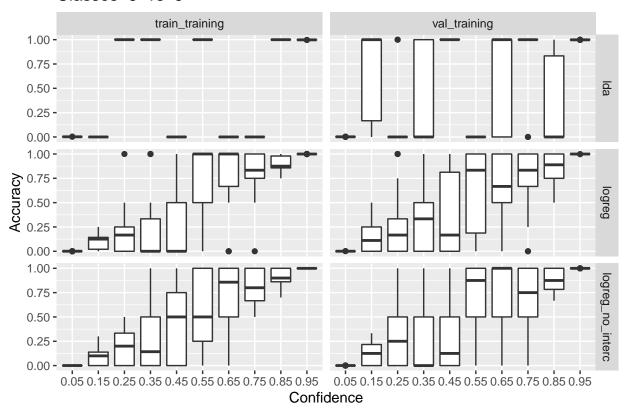
Warning: Removed 190 rows containing non-finite values (stat_boxplot).

Classes 6 vs 8



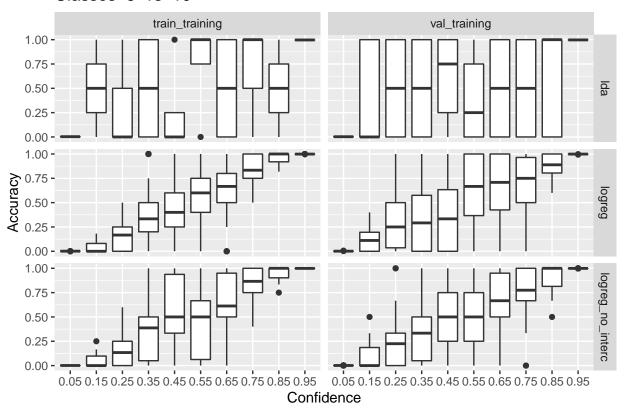
Warning: Removed 498 rows containing non-finite values (stat_boxplot).

Classes 6 vs 9



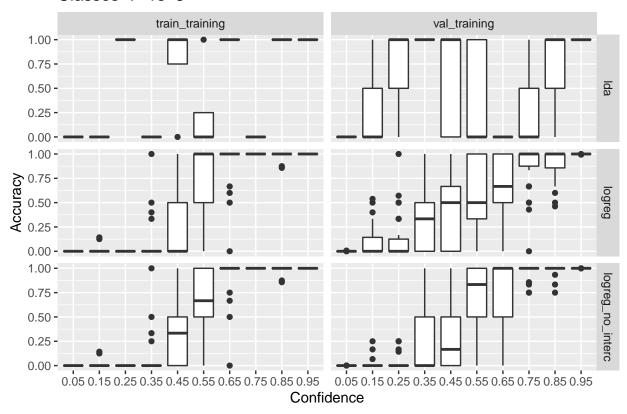
Warning: Removed 362 rows containing non-finite values (stat_boxplot).

Classes 6 vs 10



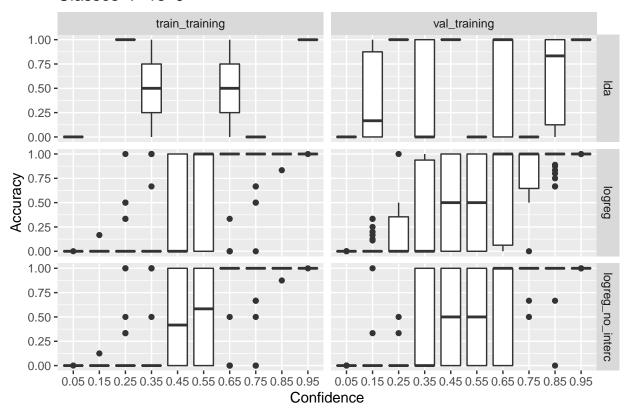
Warning: Removed 502 rows containing non-finite values (stat_boxplot).

Classes 7 vs 8



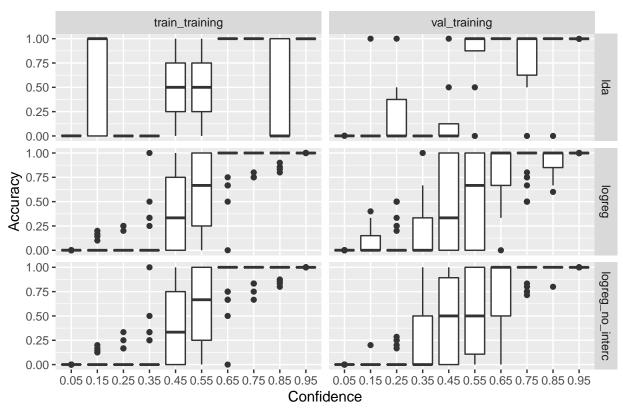
Warning: Removed 610 rows containing non-finite values (stat_boxplot).

Classes 7 vs 9



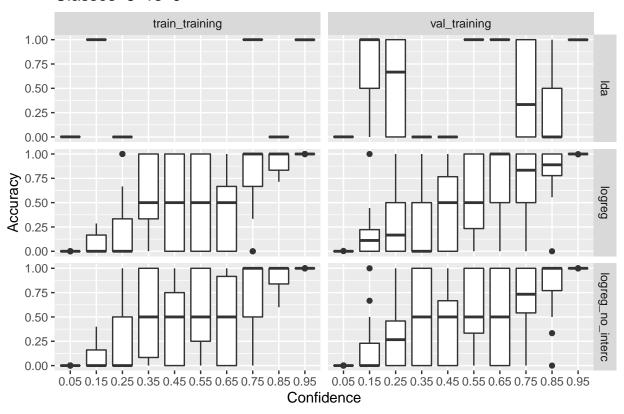
Warning: Removed 458 rows containing non-finite values (stat_boxplot).

Classes 7 vs 10



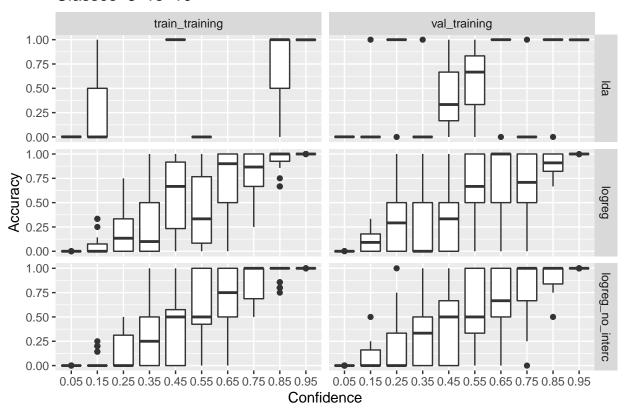
Warning: Removed 562 rows containing non-finite values (stat_boxplot).

Classes 8 vs 9



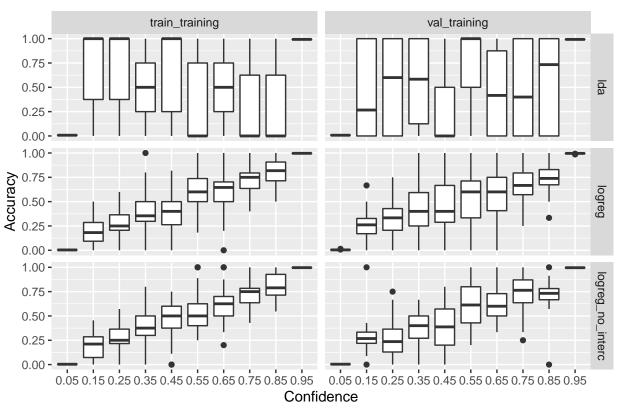
Warning: Removed 482 rows containing non-finite values (stat_boxplot).

Classes 8 vs 10



Warning: Removed 308 rows containing non-finite values (stat_boxplot).

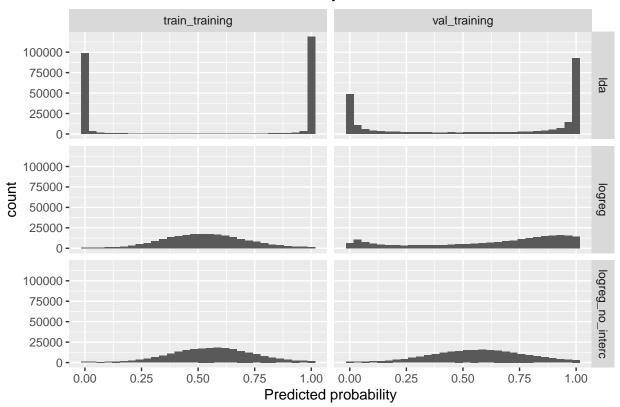
Classes 9 vs 10



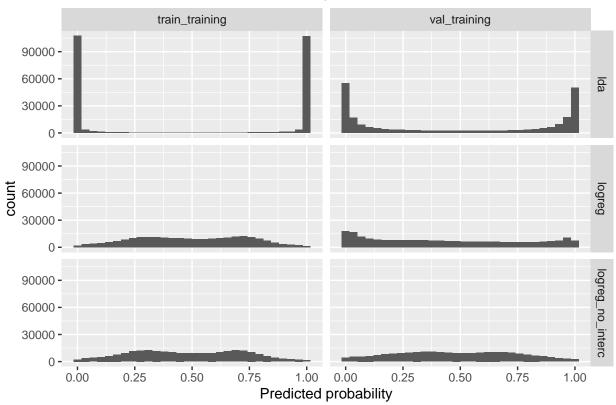
Even with low bin counts, better calibration can be observed for logreg than for lda.

```
for (cl1 in 1:(classes - 1))
{
   for (cl2 in (cl1 + 1):classes)
   {
     irrel_plt <- ens_pw_irrel %>% filter(class1 == (cl1 - 1) & class2 == (cl2 - 1)) %>% ggplot() +
        geom_histogram(mapping=aes(x=pred1), bins=30) + facet_grid(cols=vars(train_set), rows=vars(combin
        ggtitle(paste("Predictions for irrelevant classes by combiner method ", cl1, " vs ", cl2)) +
        xlab("Predicted probability")
        print(irrel_plt)
    }
}
```

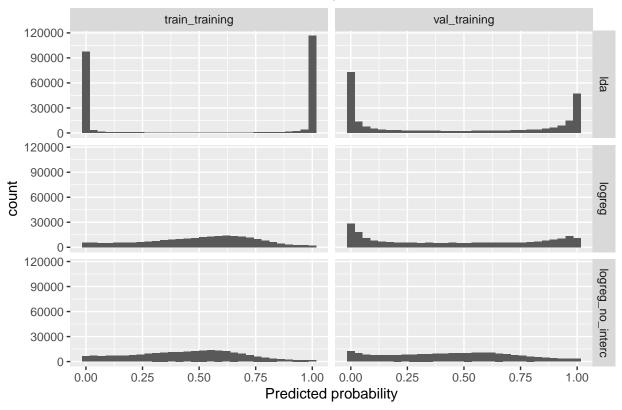
Predictions for irrelevant classes by combiner method 1 vs 2



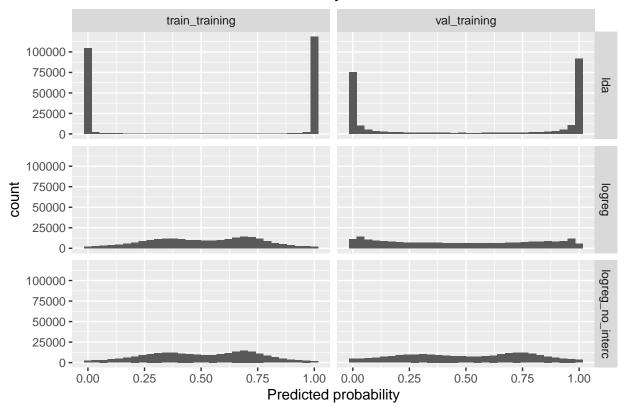
Predictions for irrelevant classes by combiner method 1 vs 3



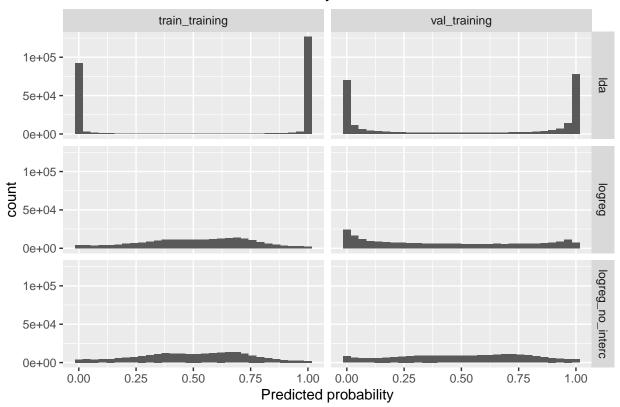
Predictions for irrelevant classes by combiner method 1 vs 4



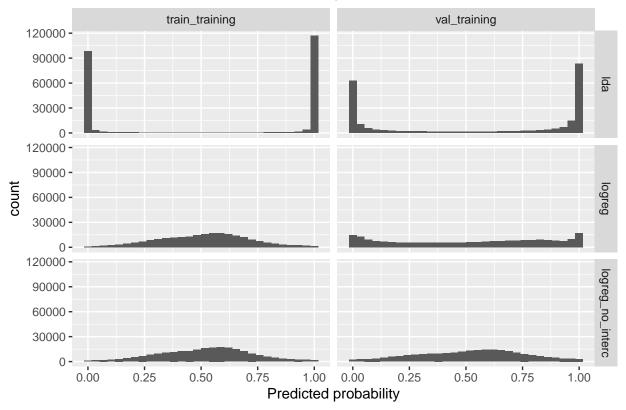
Predictions for irrelevant classes by combiner method 1 vs 5



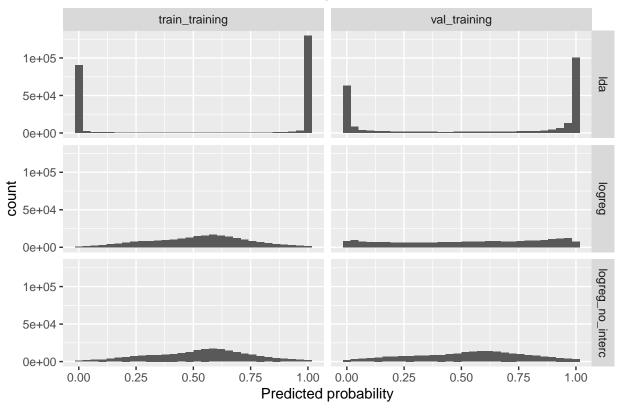
Predictions for irrelevant classes by combiner method 1 vs 6



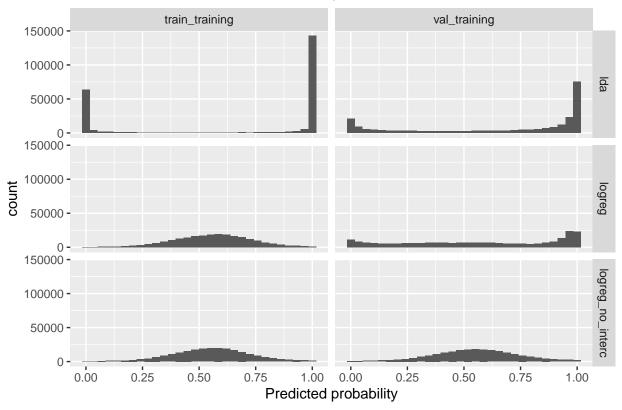
Predictions for irrelevant classes by combiner method 1 vs 7



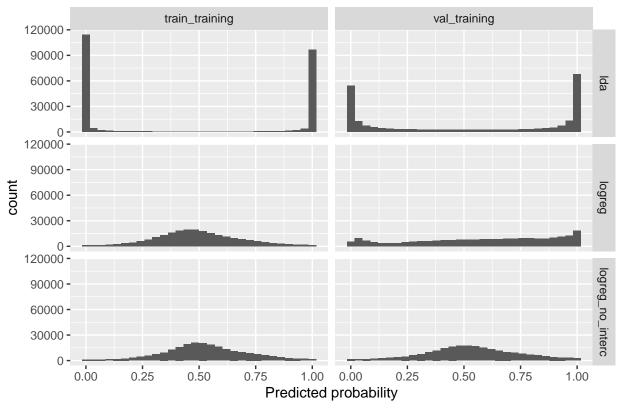
Predictions for irrelevant classes by combiner method 1 vs 8

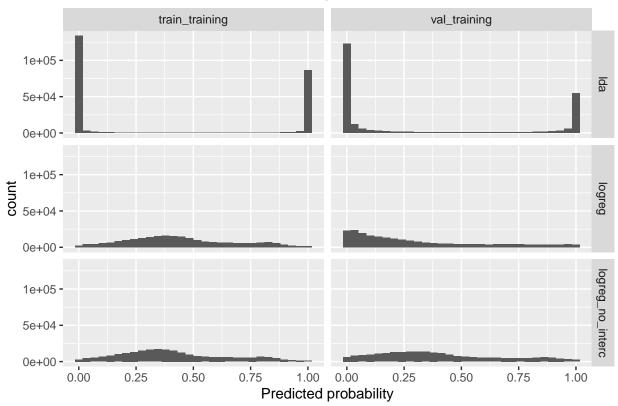


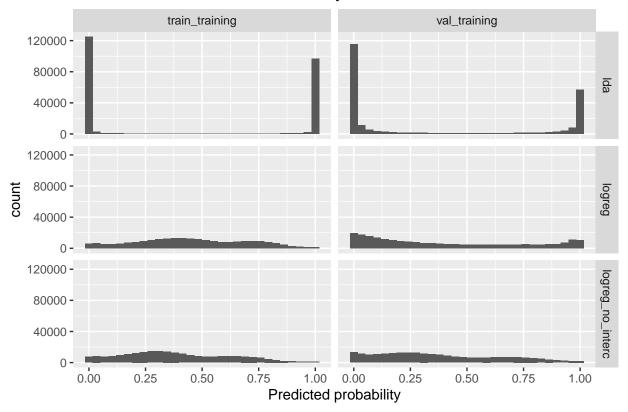
Predictions for irrelevant classes by combiner method 1 vs 9

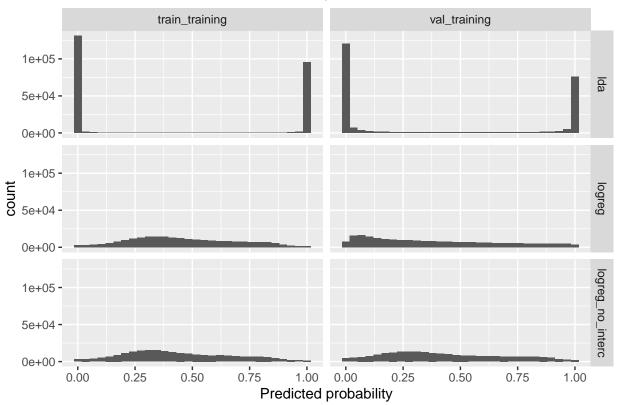


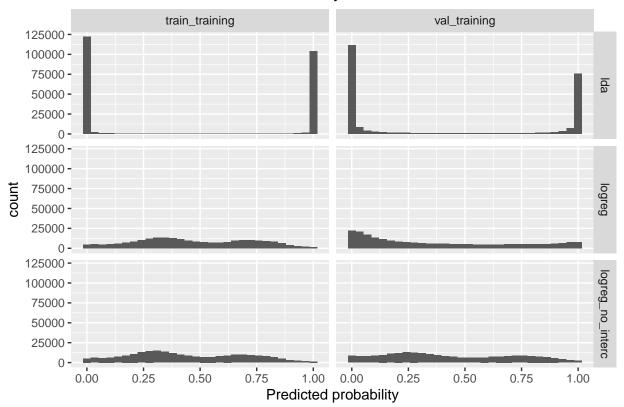
Predictions for irrelevant classes by combiner method 1 vs 10

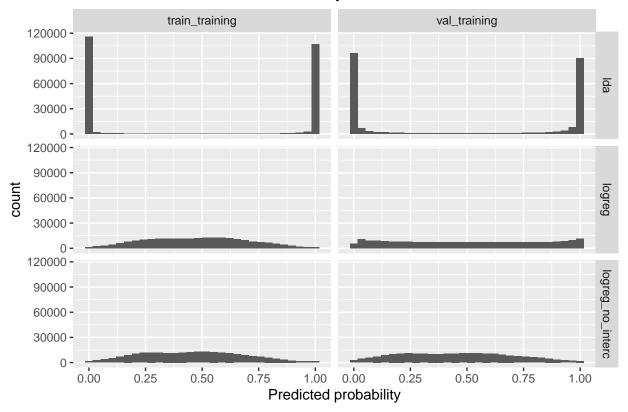


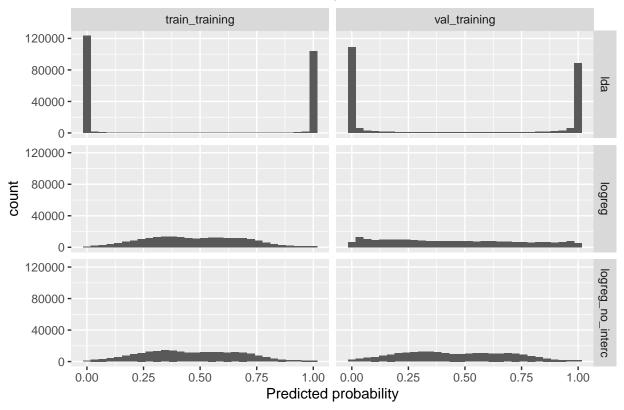


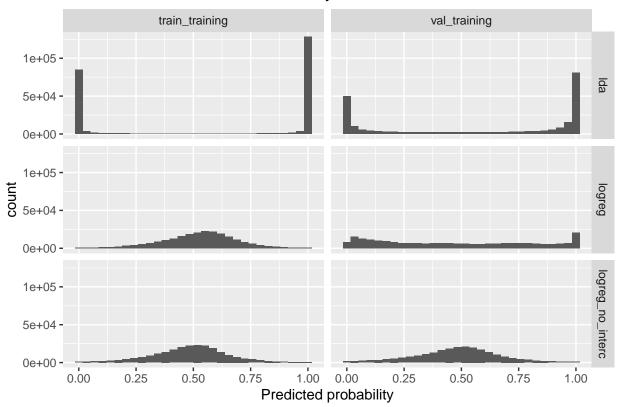


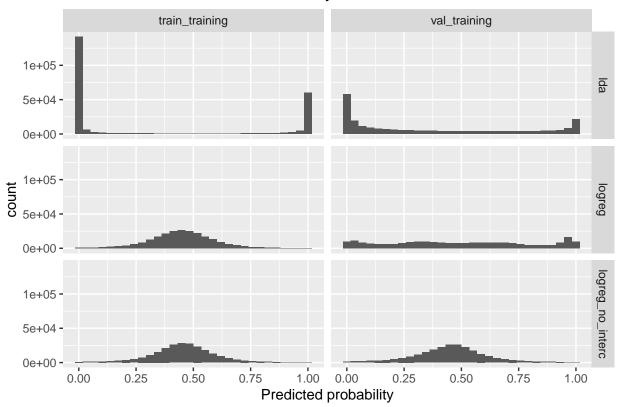


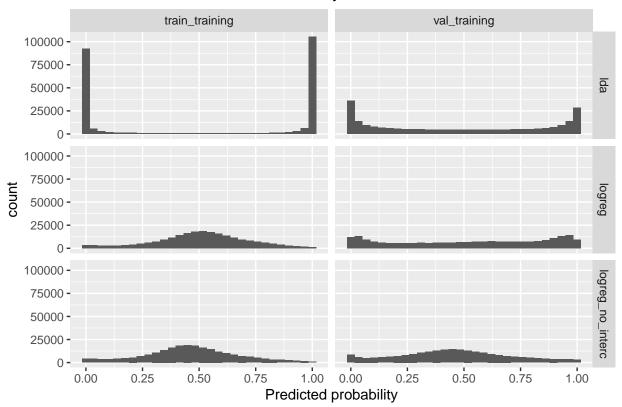




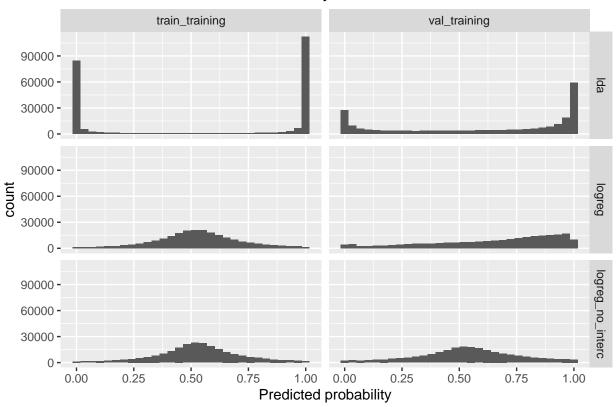


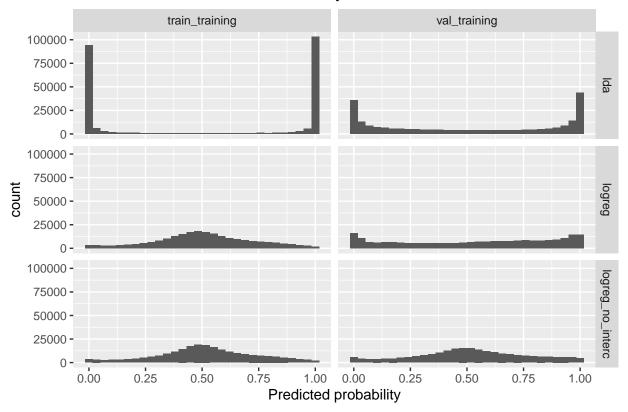


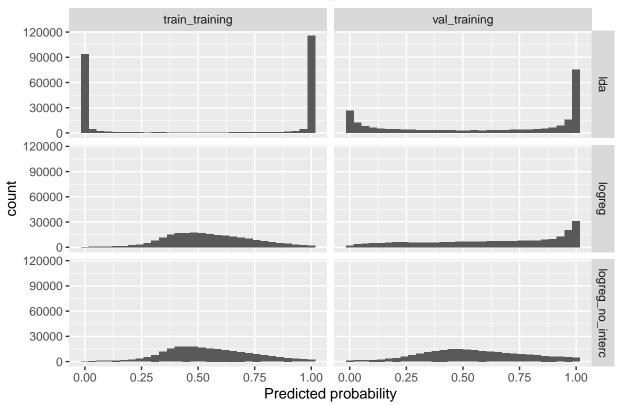




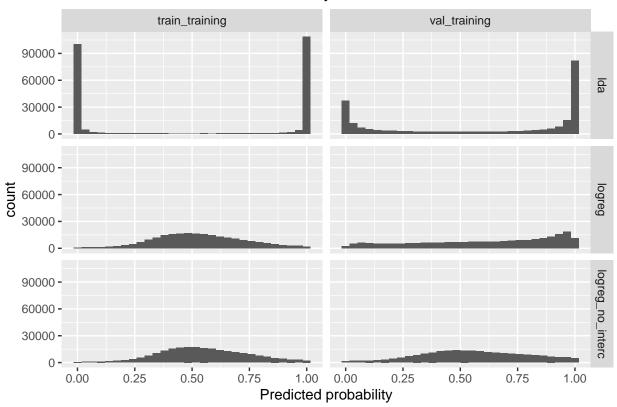
Predictions for irrelevant classes by combiner method 3 vs 5

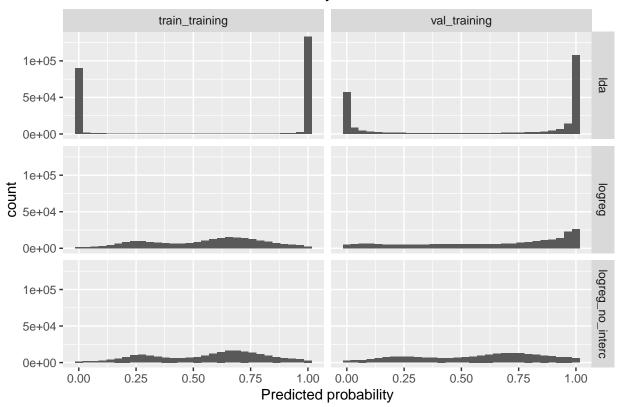


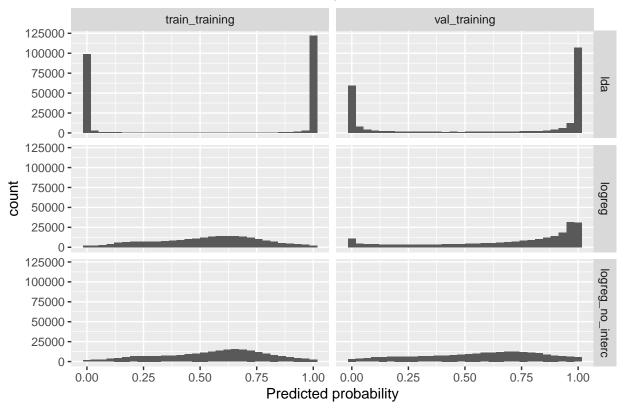




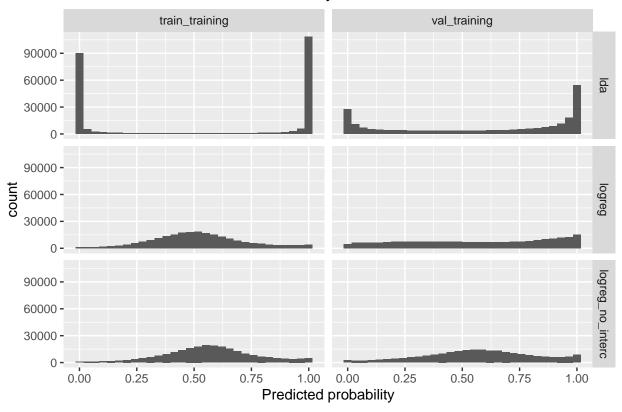
Predictions for irrelevant classes by combiner method 3 vs 8

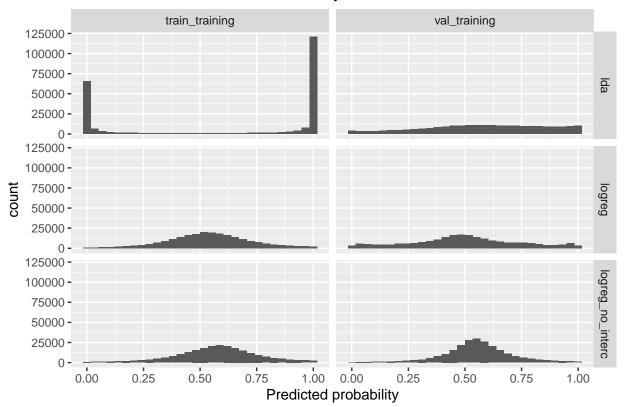




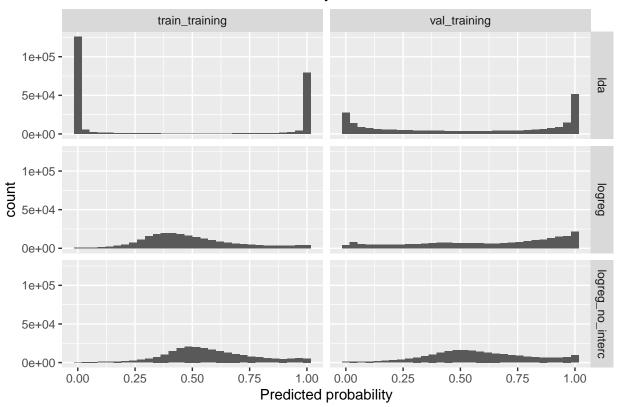


Predictions for irrelevant classes by combiner method 4 vs 5

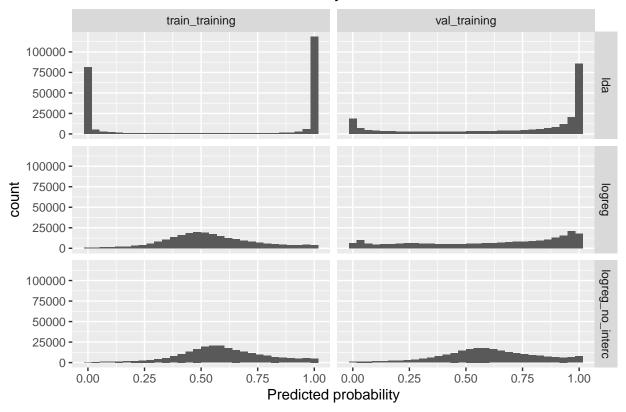


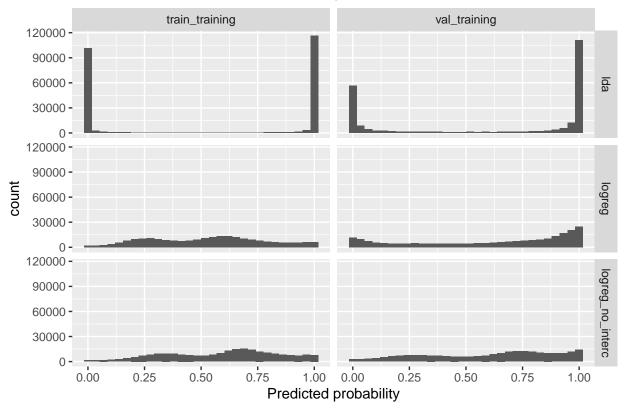


Predictions for irrelevant classes by combiner method 4 vs 7

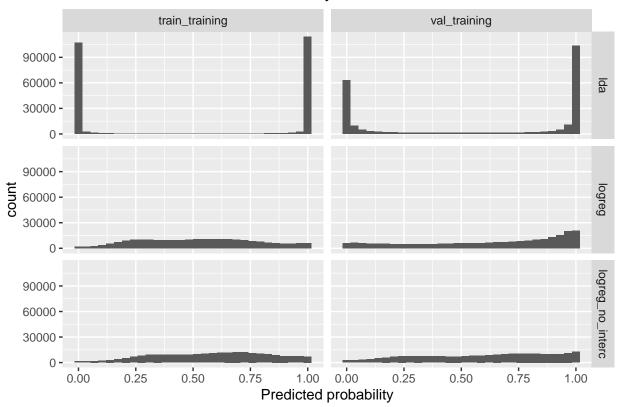


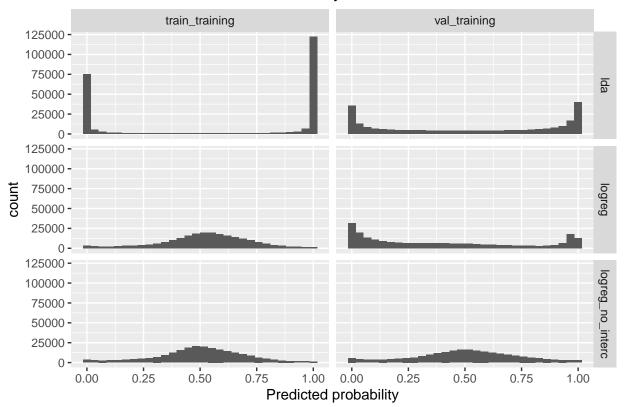
Predictions for irrelevant classes by combiner method 4 vs 8



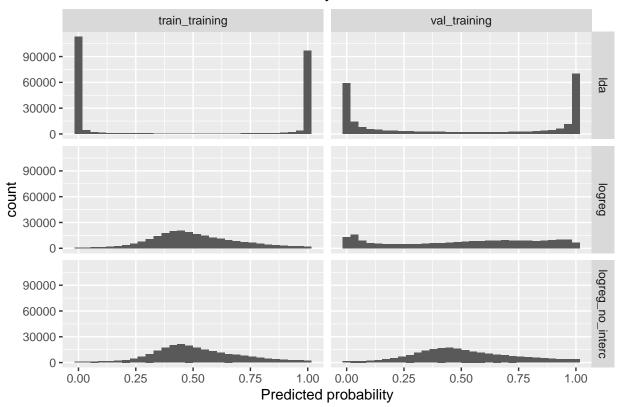


Predictions for irrelevant classes by combiner method 4 vs 10

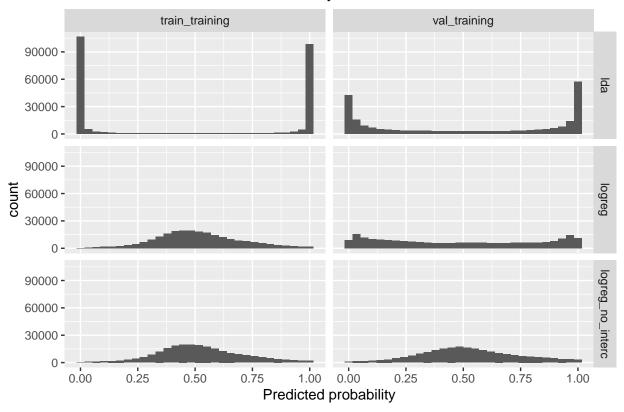


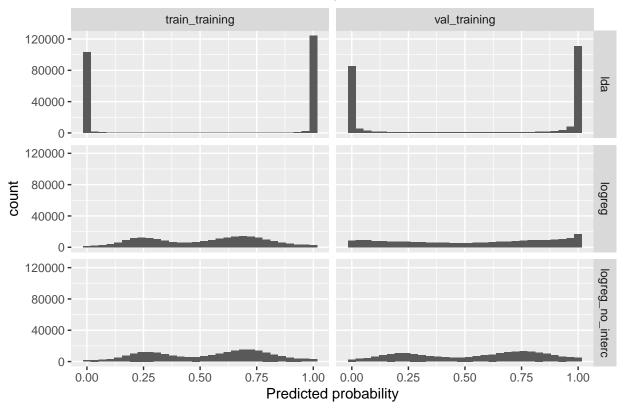


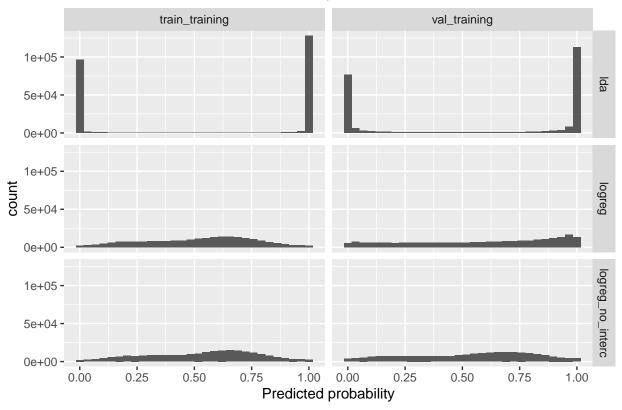
Predictions for irrelevant classes by combiner method 5 vs 7

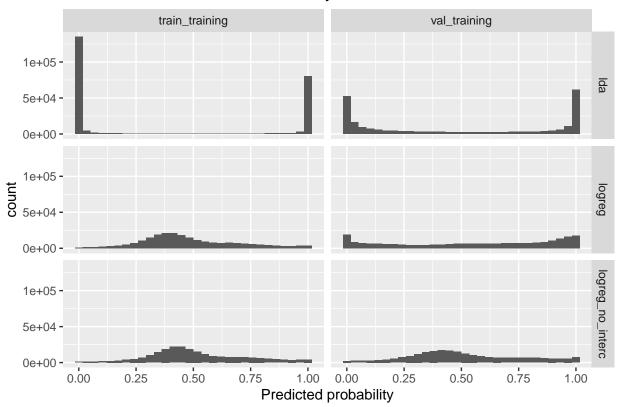


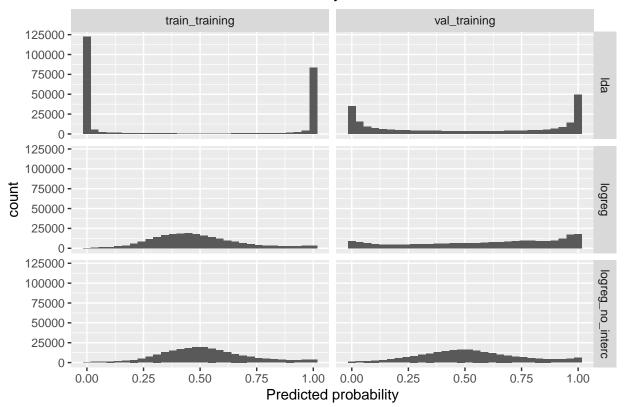
Predictions for irrelevant classes by combiner method 5 vs 8

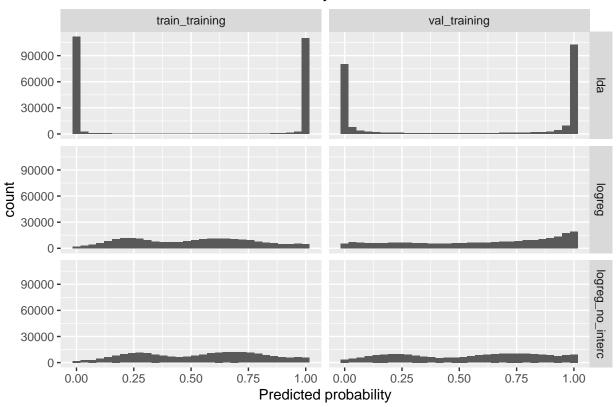


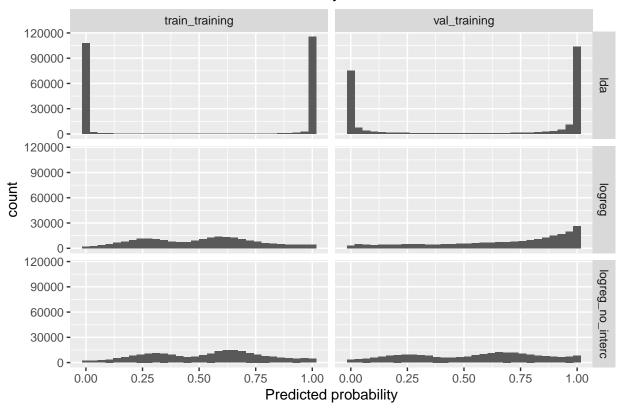


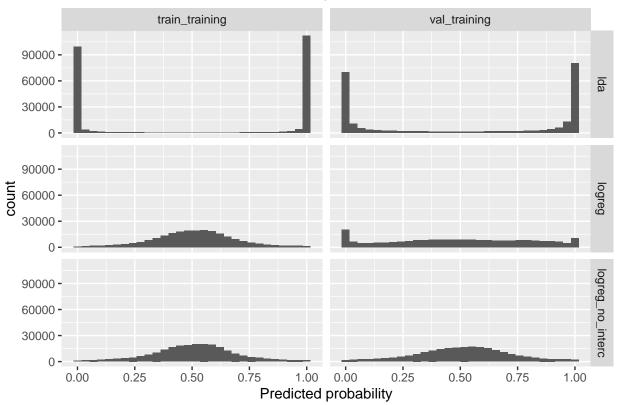


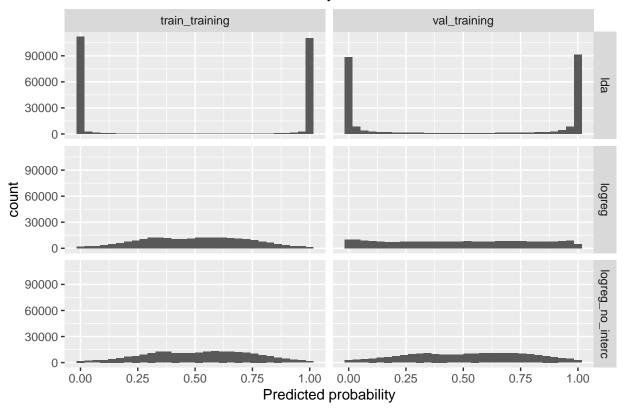


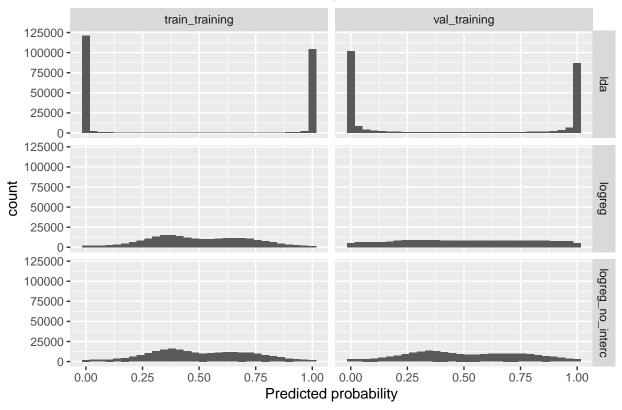


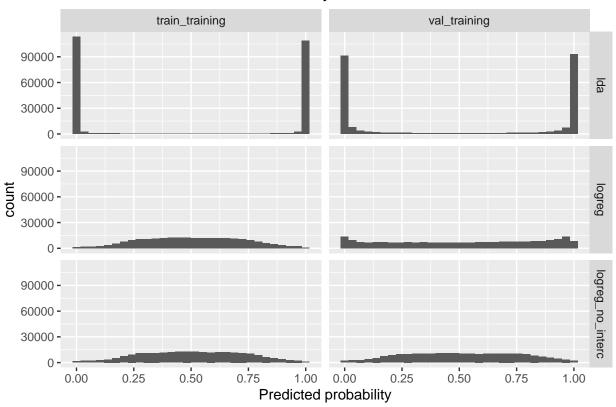


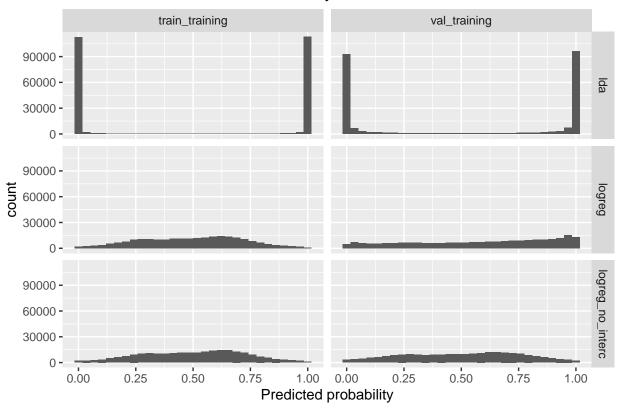


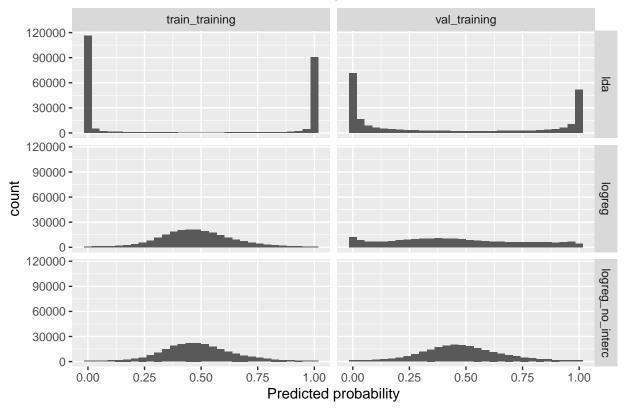












These histograms show, that even for unknown classes, LDA most often produces probabilities close to one and zero. One exception is val_train LDA for class pair 4 and 6, where probabilities are divided evenly. Also the confidence plot for this LDA looks sensibly. Histograms for method logreg, on the other hand produce more evenly distributed probabilities.

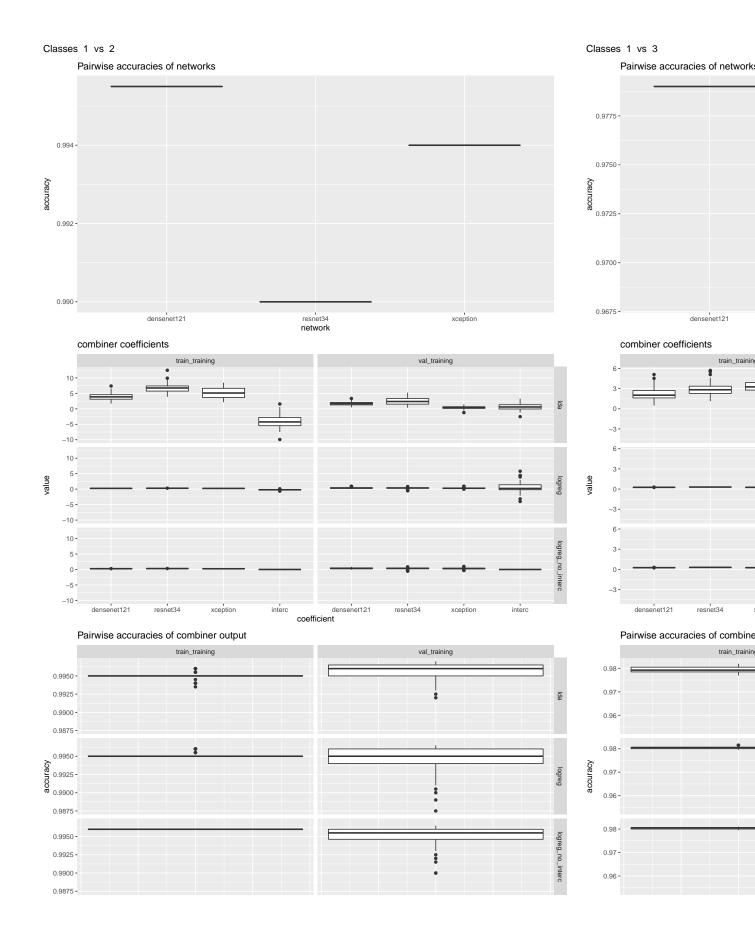
CIFAR 10 half

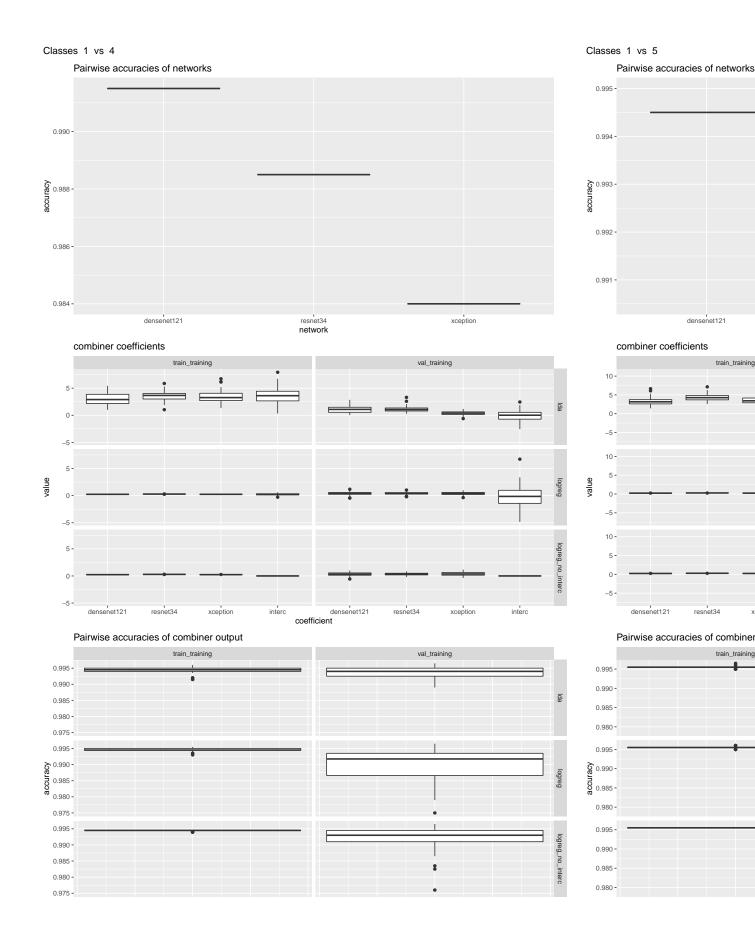
```
base_dir <- "../data/data_train_val_half_c10"
repls <- 0:0
folds <- 0:49
classes <- 10
combiner_coefs <- load_combiner_coefs(base_dir, repls, folds)
net_pw_results <- read.csv(file.path(base_dir, "net_pw_accuracies.csv"))
ens_pw_results (- read.csv(file.path(base_dir, "ensemble_pw_accuracies.csv"))
net_pw_results[, c("class1", "class2")] <- lapply(net_pw_results[, c("class1", "class2")], as.factor)
ens_pw_results[, c("class1", "class2", "combining_method")] <- lapply(ens_pw_results[, c("class1", "class2", "class2")]
for (cl1 in 1:(classes - 1))
{
    combiner_plt <- combiner_coefs %>% filter(class1 == cl1 & class2 == cl2) %>% ggplot() +
        geom_boxplot(aes(x=coefficient, y=value)) +
        facet_grid(cols=vars(train_type), rows=vars(combining_method)) + ggtitle("combiner_coefficients")
```

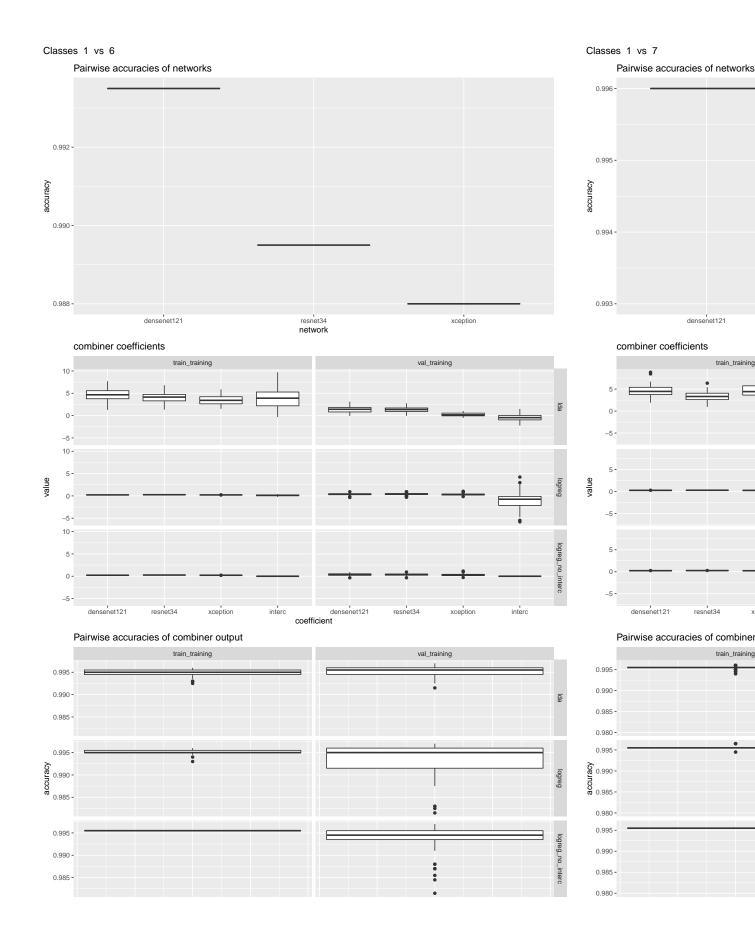
```
acc_plt_net <- net_pw_results %>% filter(class1 == (cl1 - 1) & class2 == (cl2 - 1)) %>% ggplot(mapp
geom_boxplot() + ggtitle("Pairwise accuracies of networks")

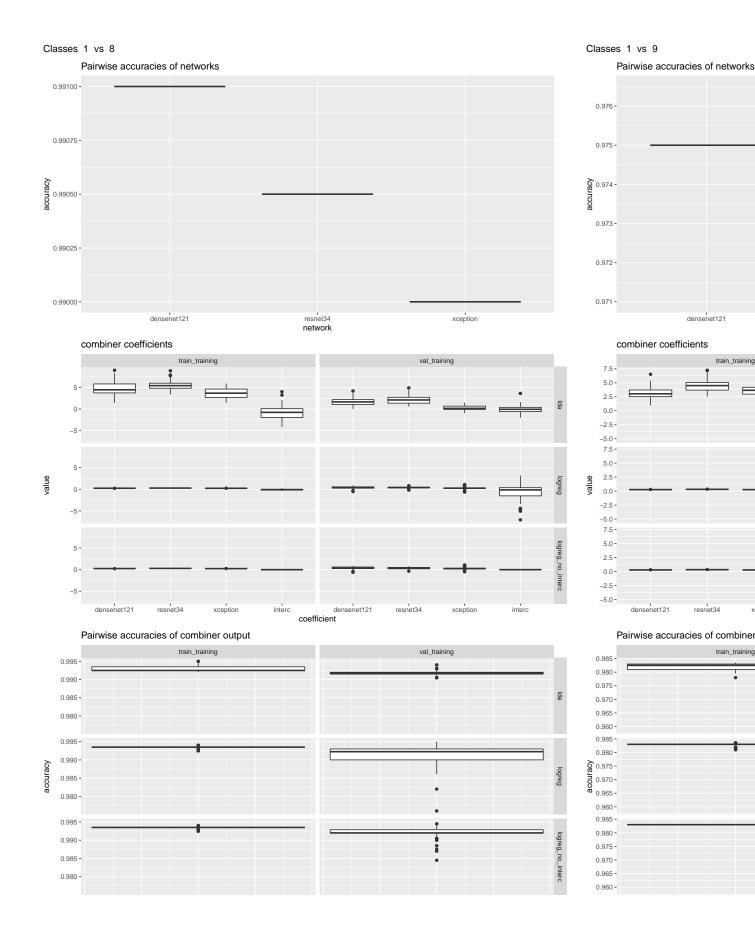
acc_plt_ens <- ens_pw_results %>% filter(class1 == (cl1 - 1) & class2 == (cl2 - 1)) %>% ggplot(mapp
geom_boxplot() + facet_grid(cols=vars(train_set), rows=vars(combining_method)) + ggtitle("Pairwis
theme(axis.ticks.x=element_blank(), axis.text.x=element_blank())

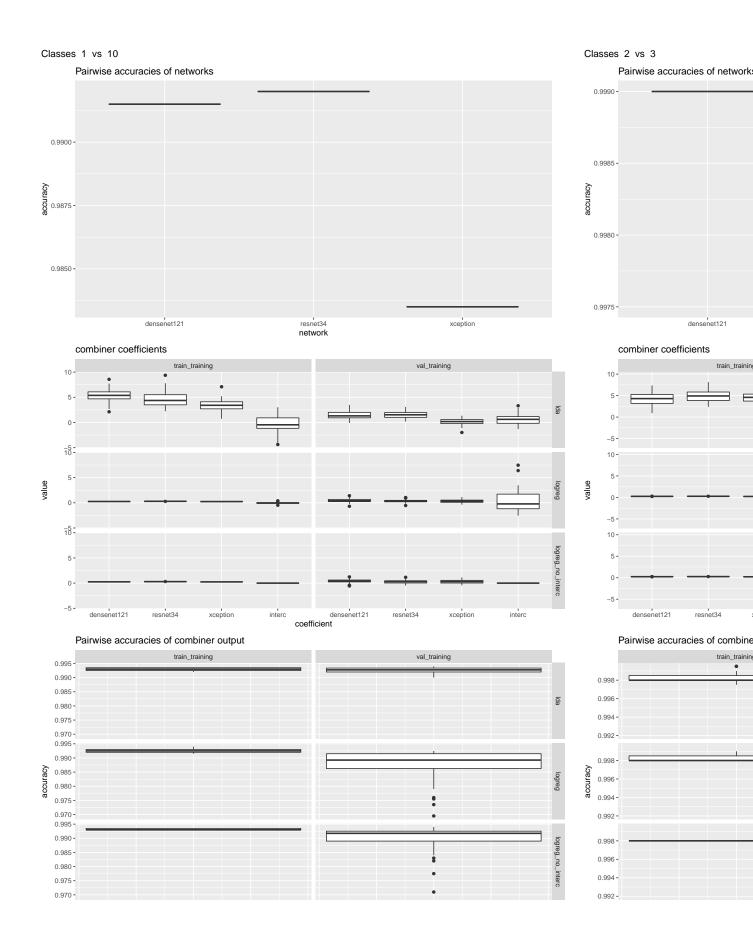
print((acc_plt_net/combiner_plt/acc_plt_ens) + plot_annotation(title=paste("Classes ", cl1, " vs ",
}
}
```

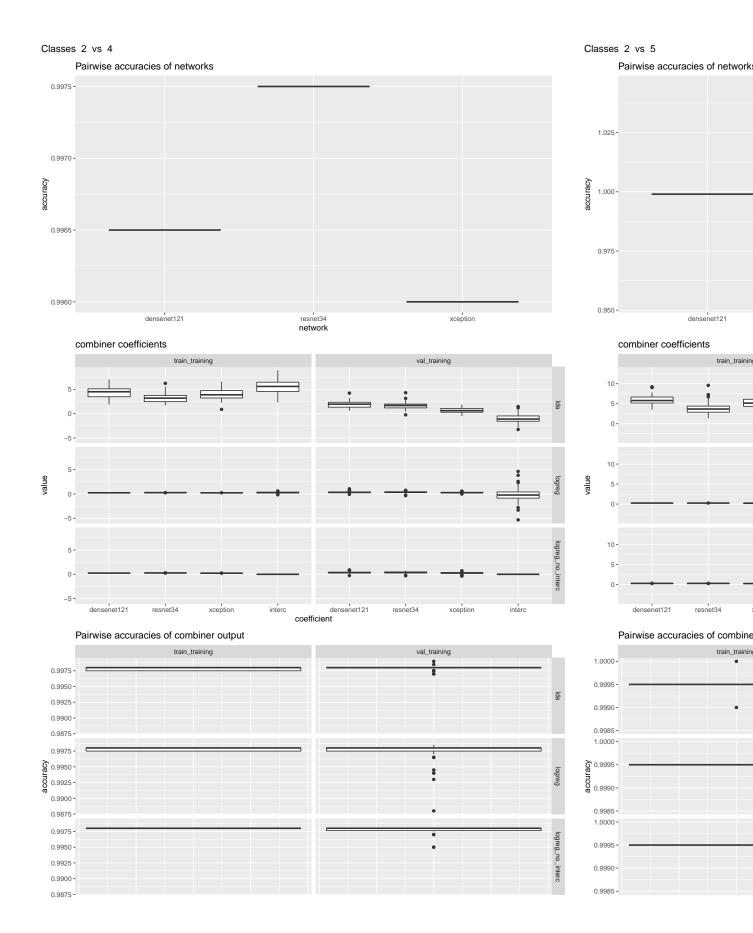




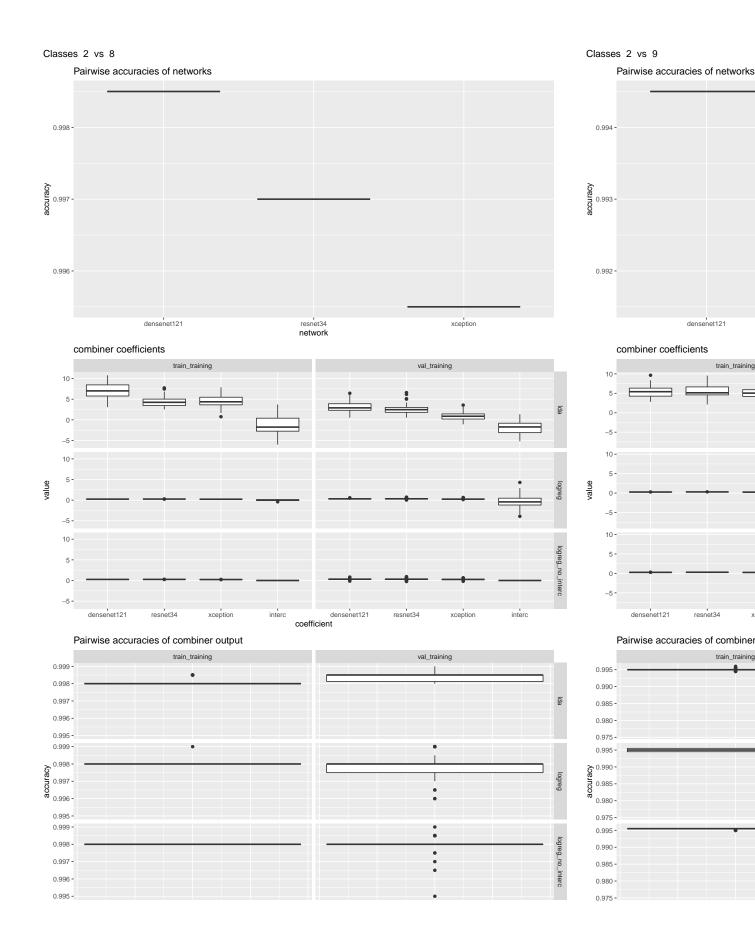


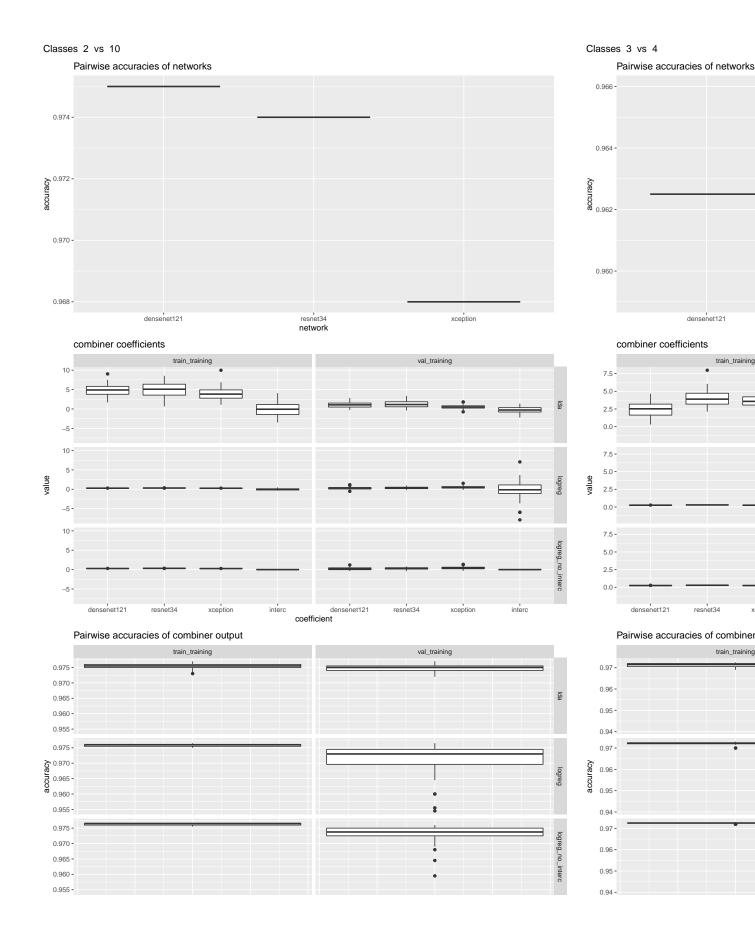


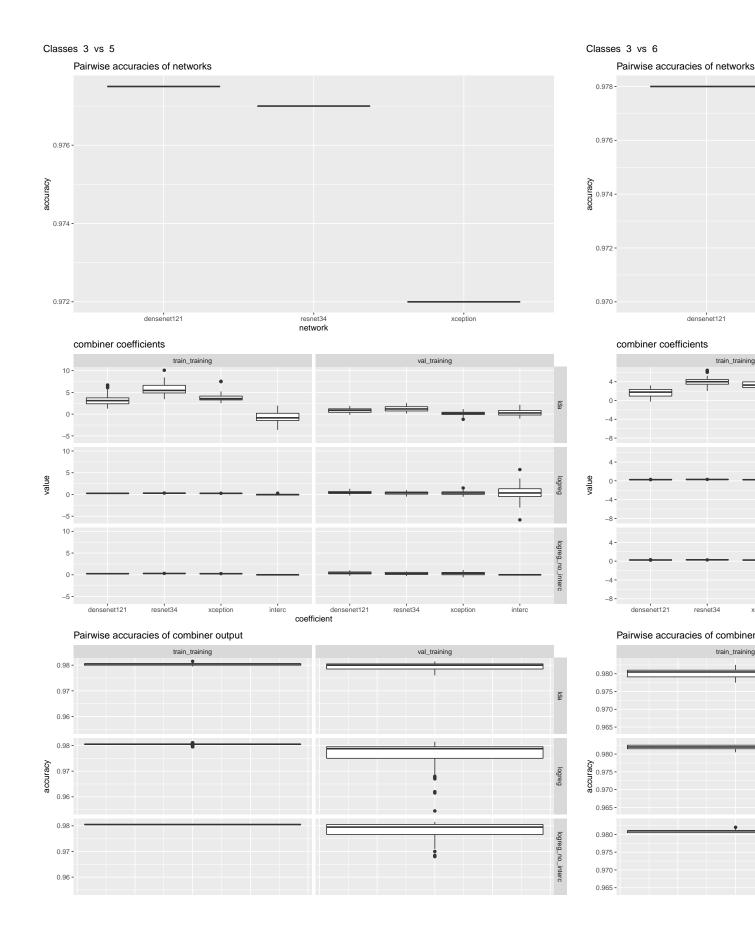


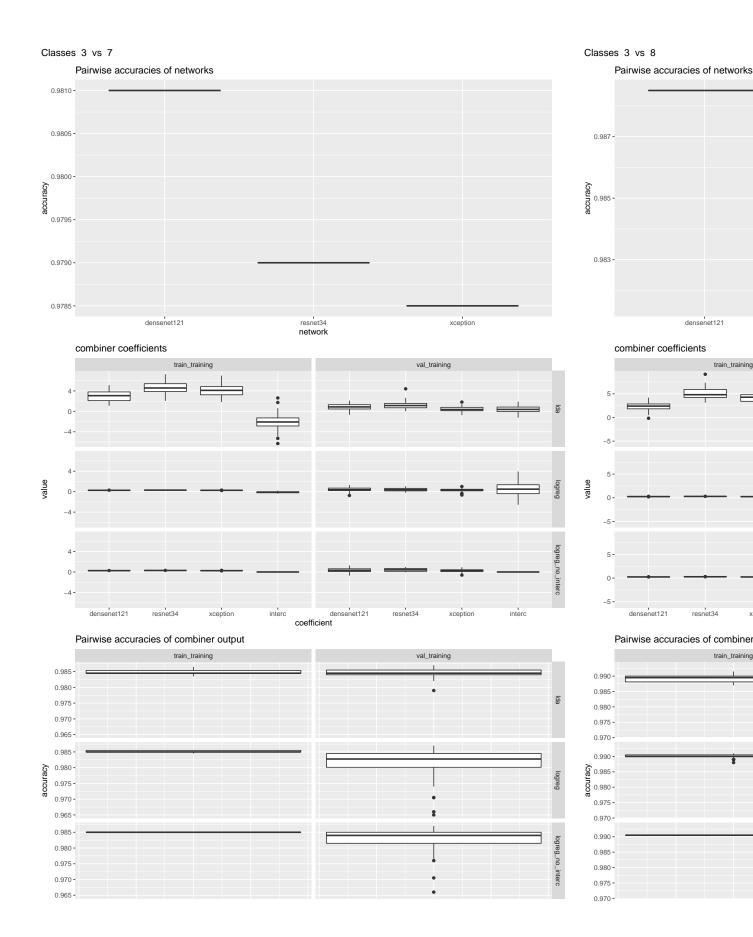


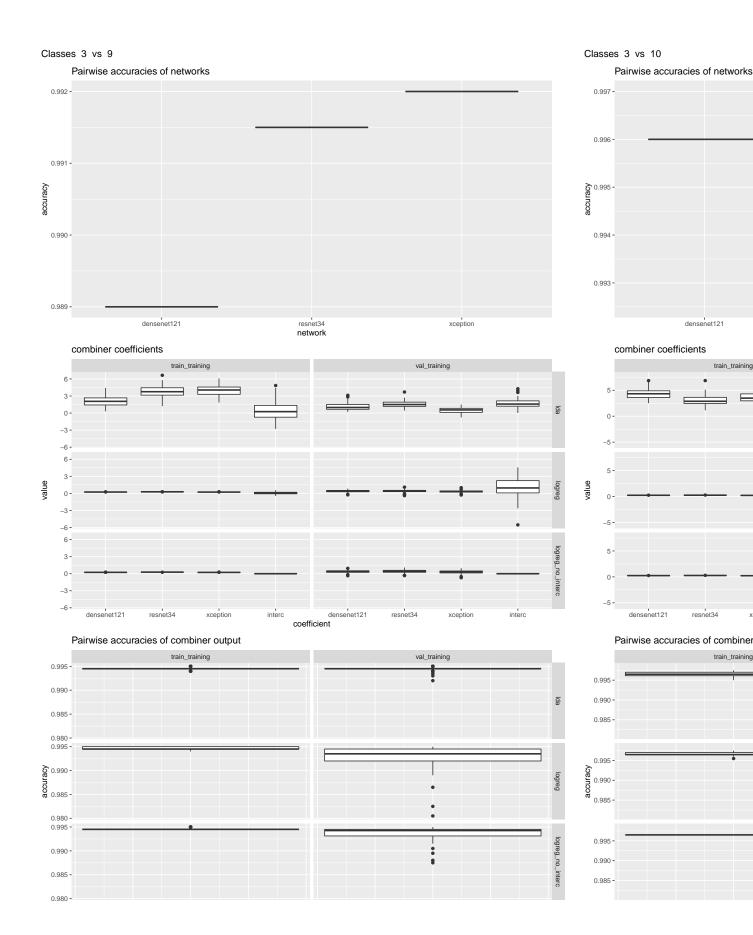


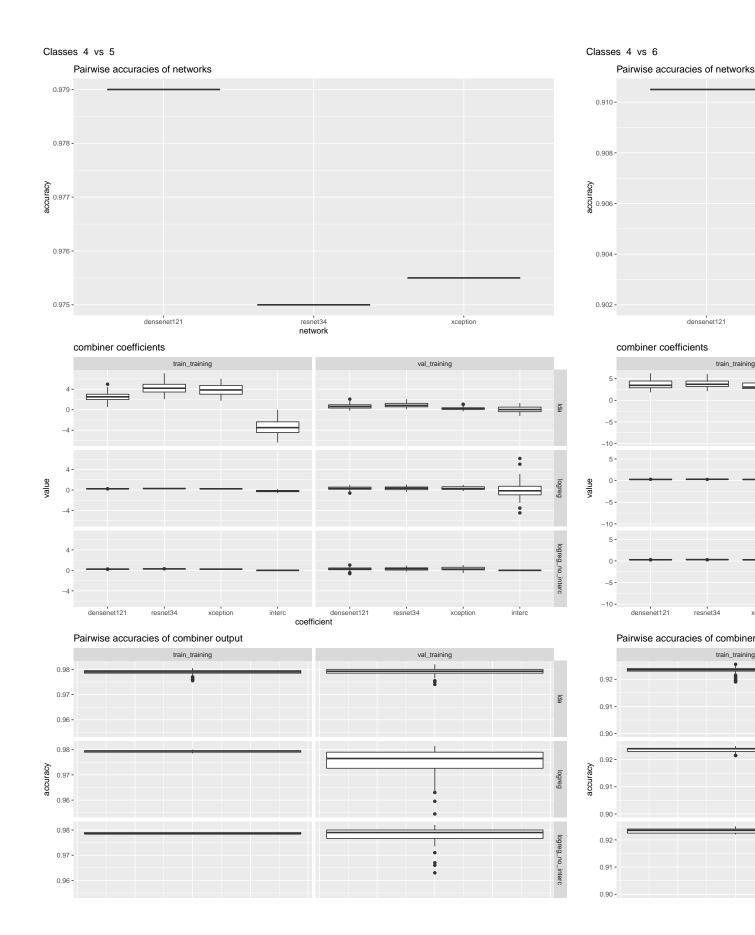


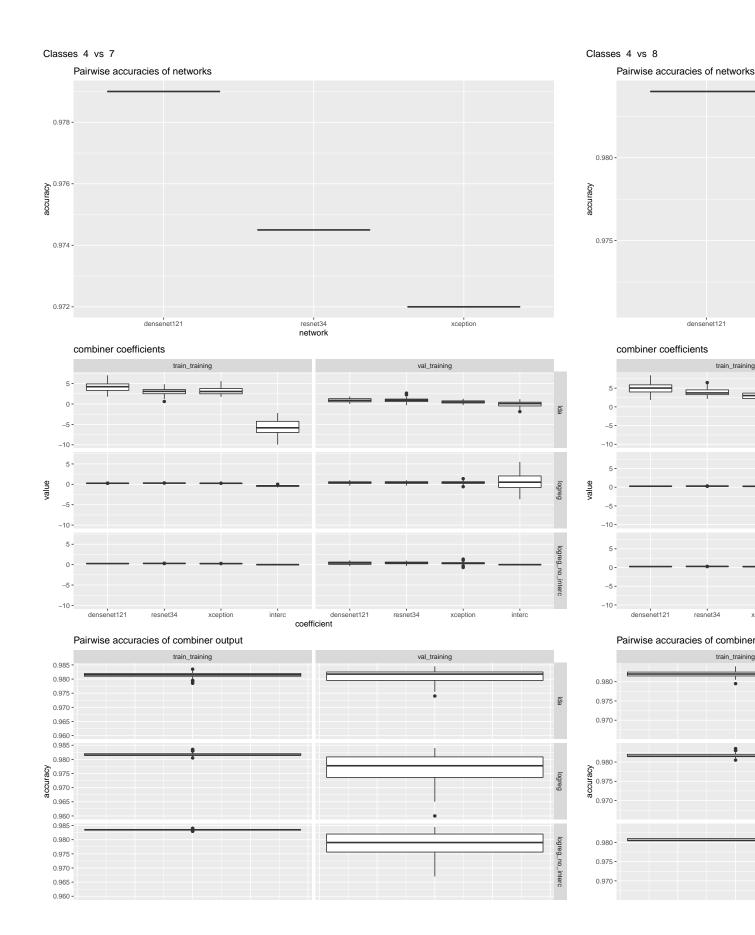


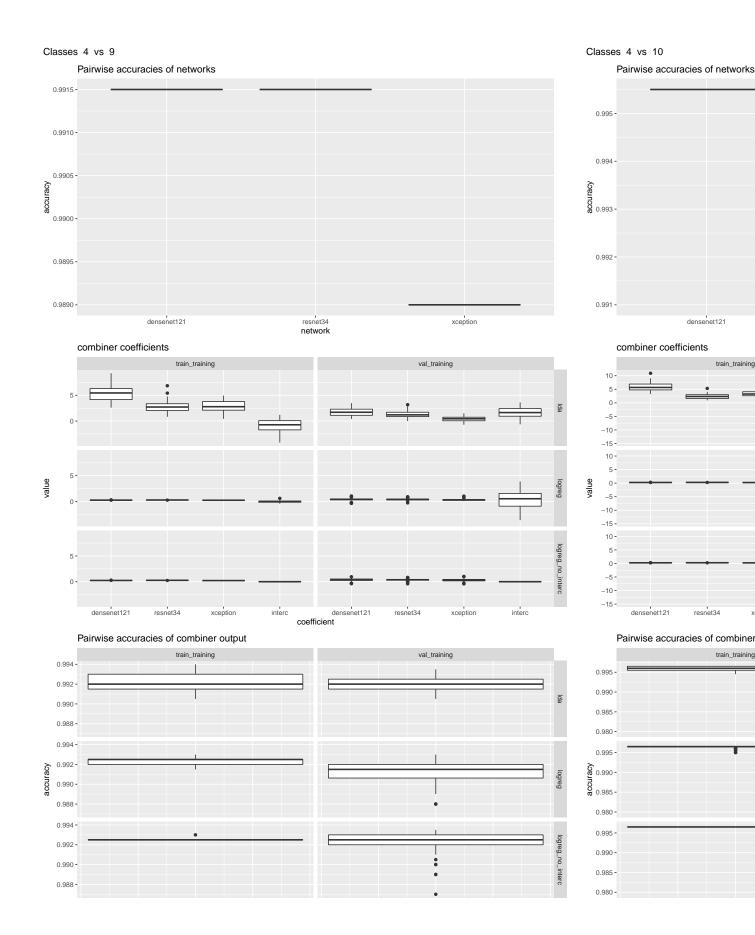


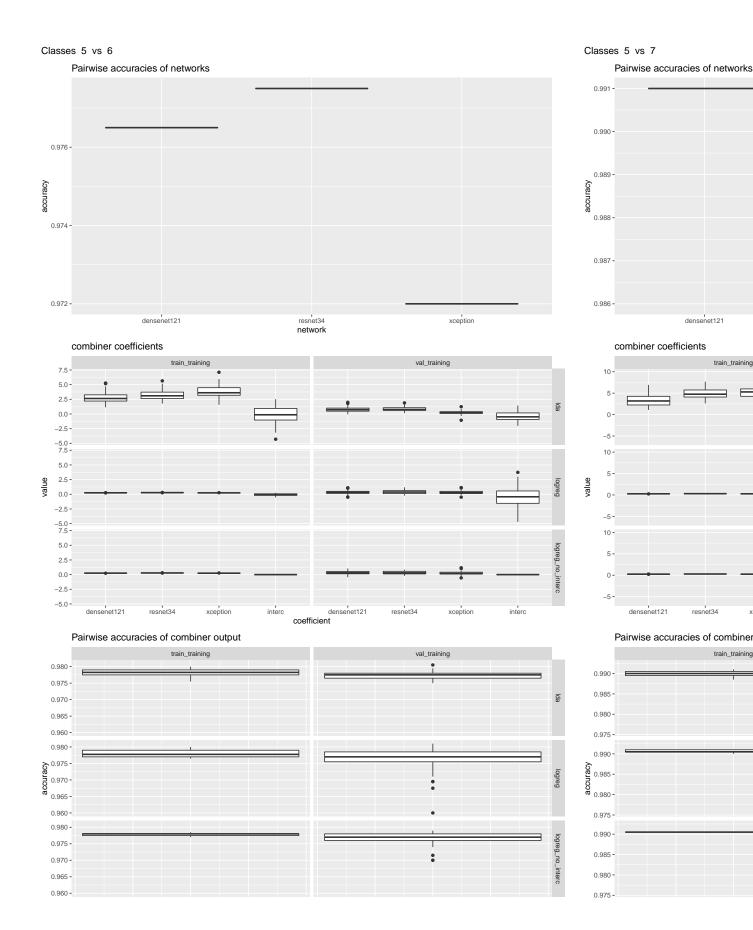


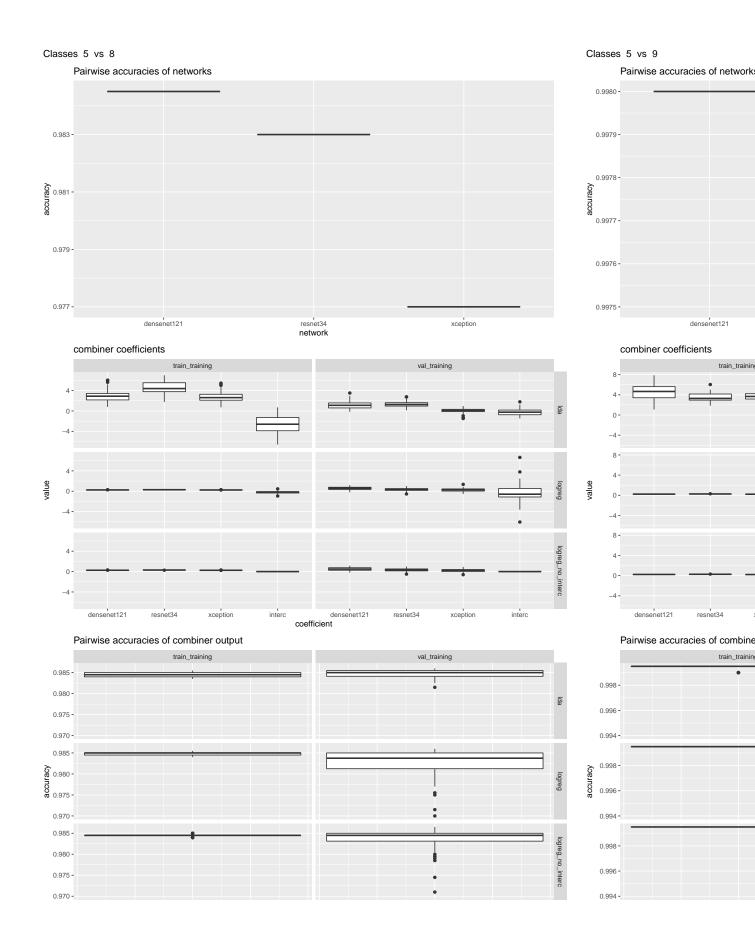


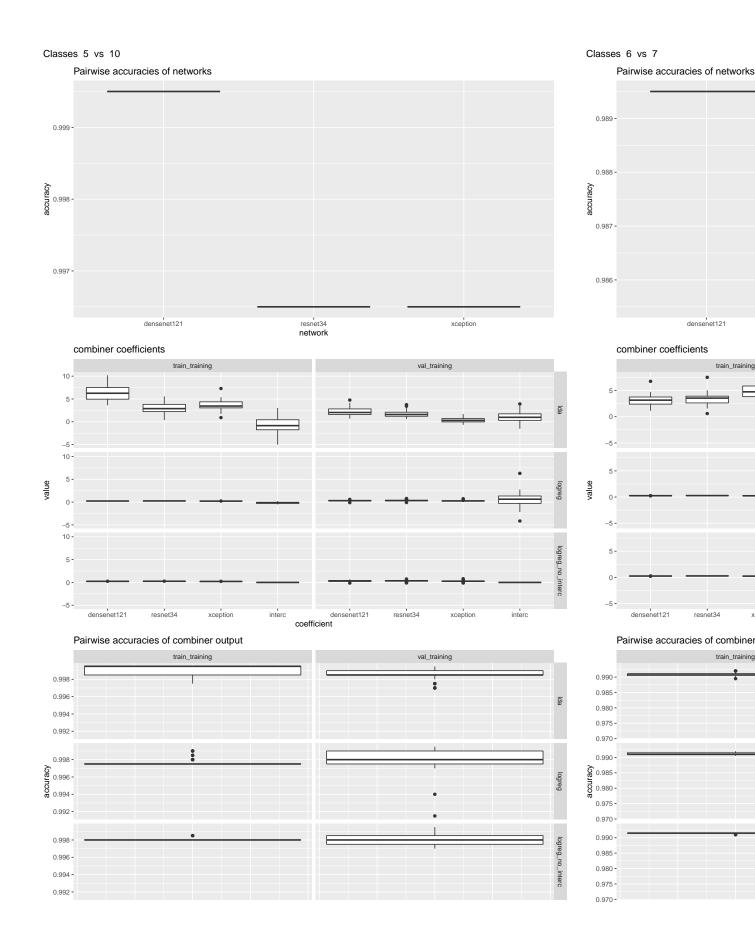


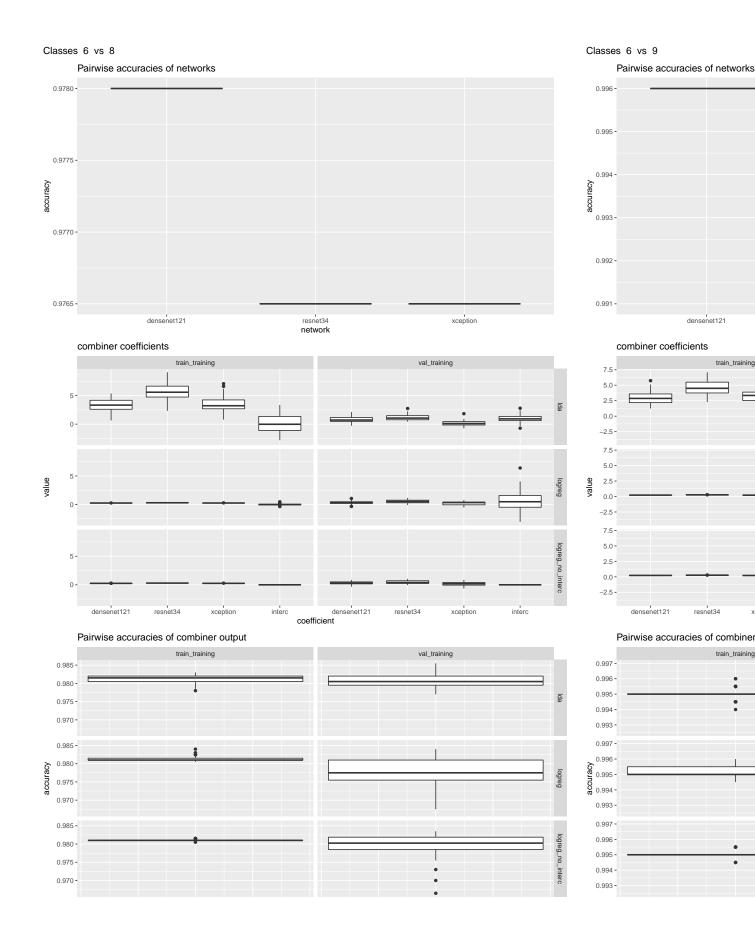


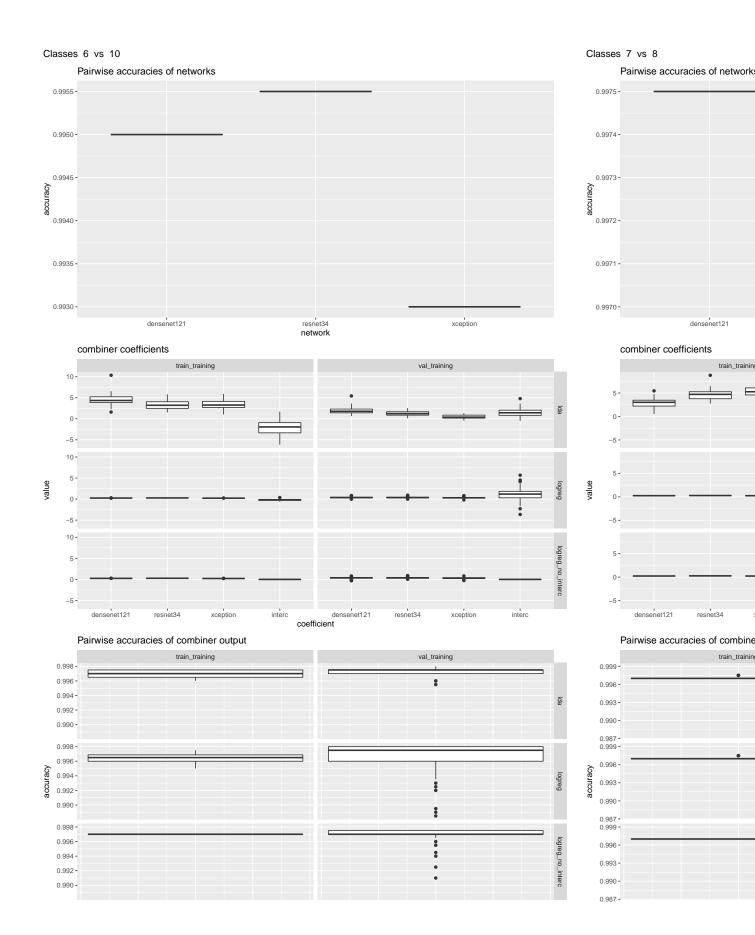


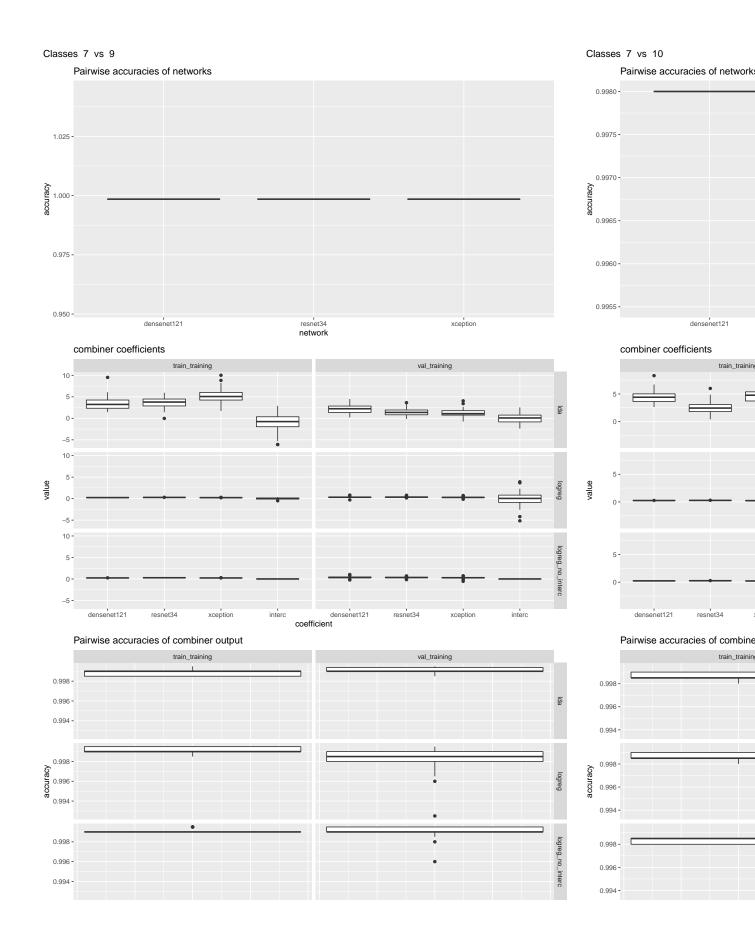


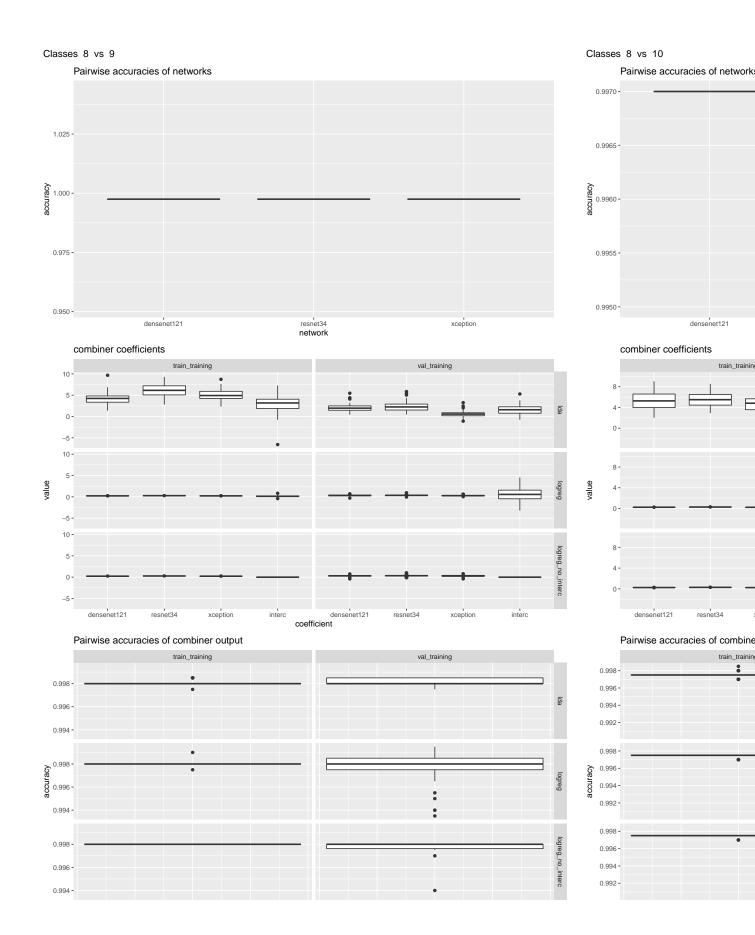




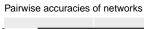


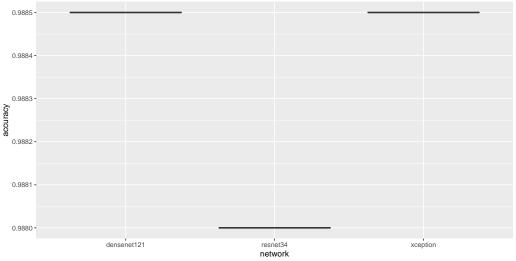




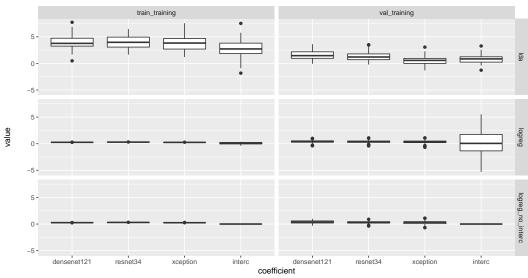


Classes 9 vs 10

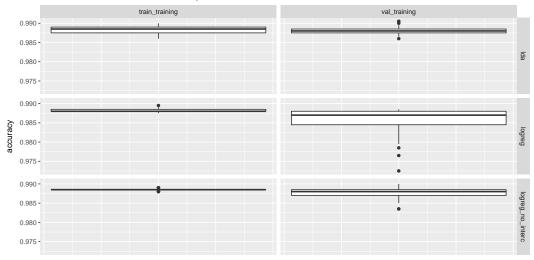




combiner coefficients



Pairwise accuracies of combiner output

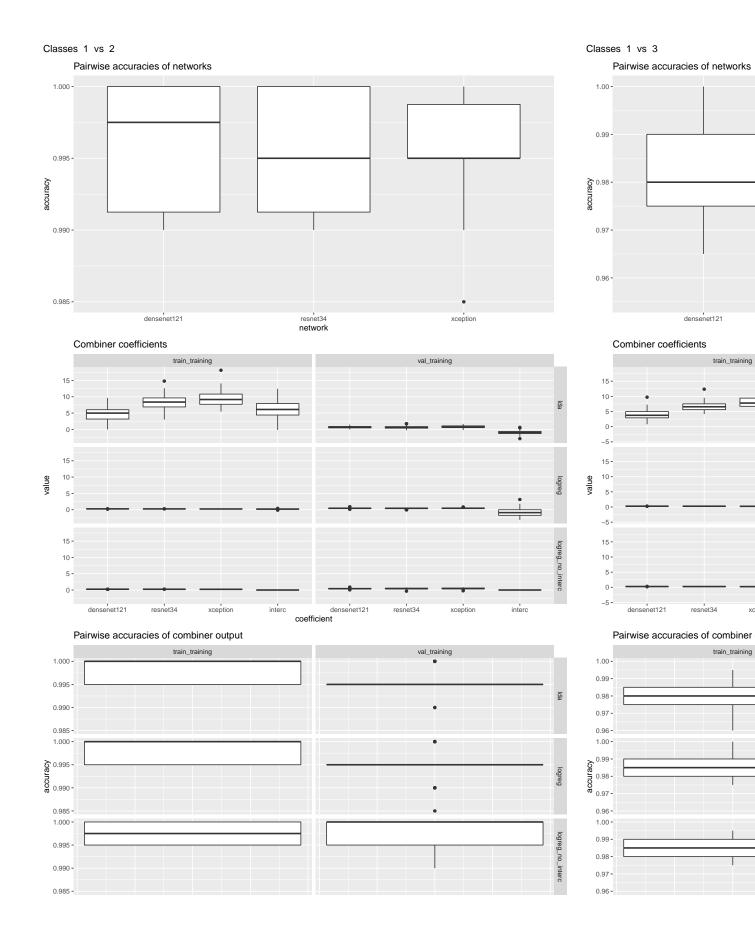


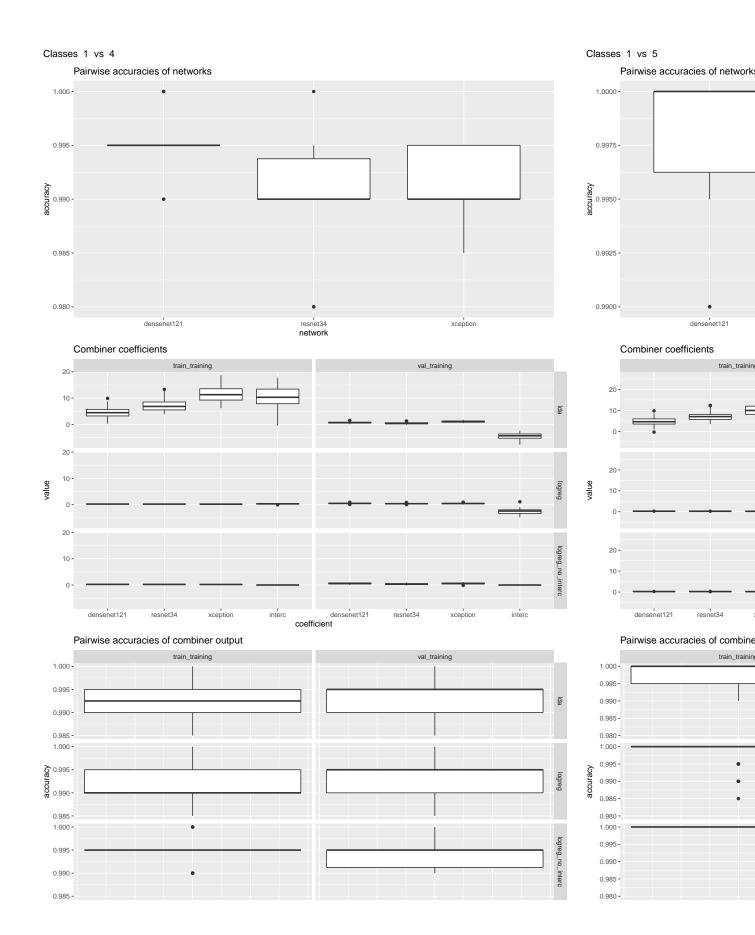
Val training

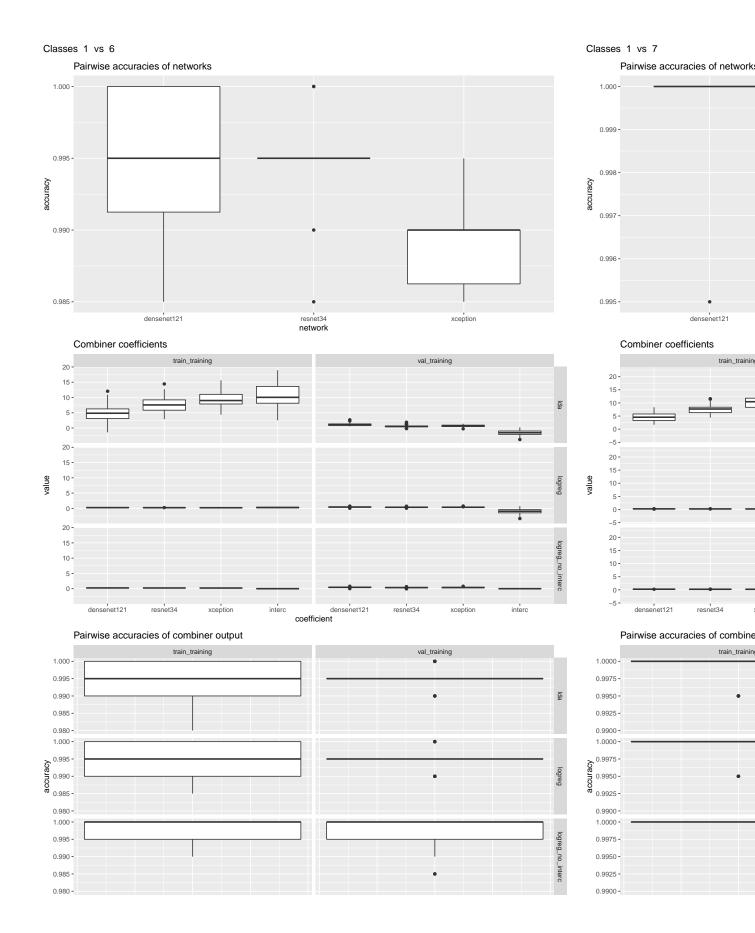
accuracies have higher variance.

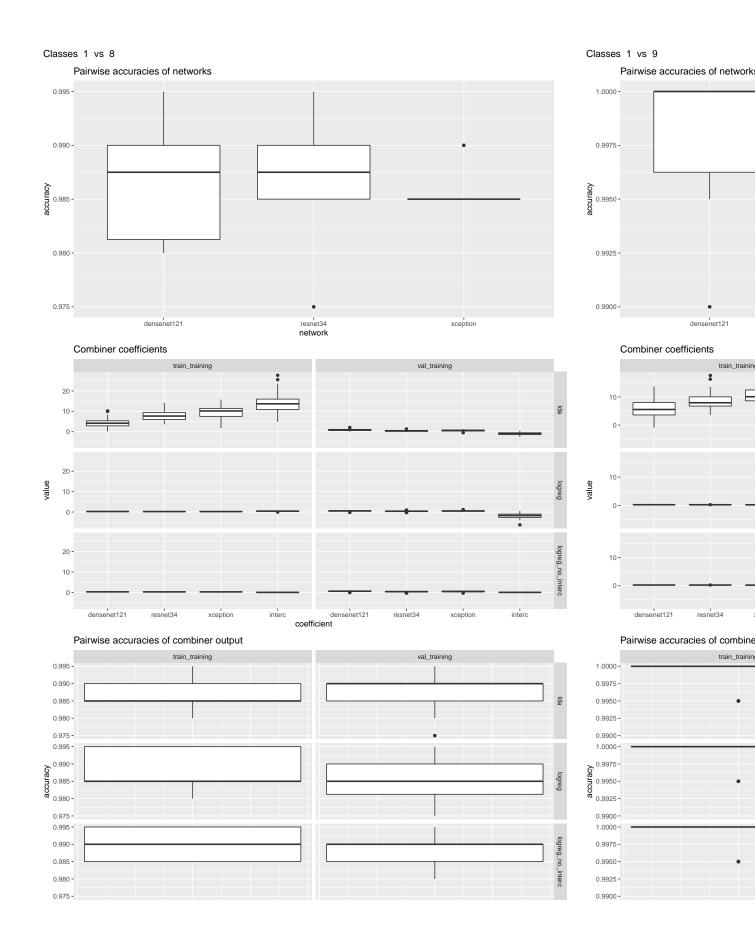
CIFAR 100 half

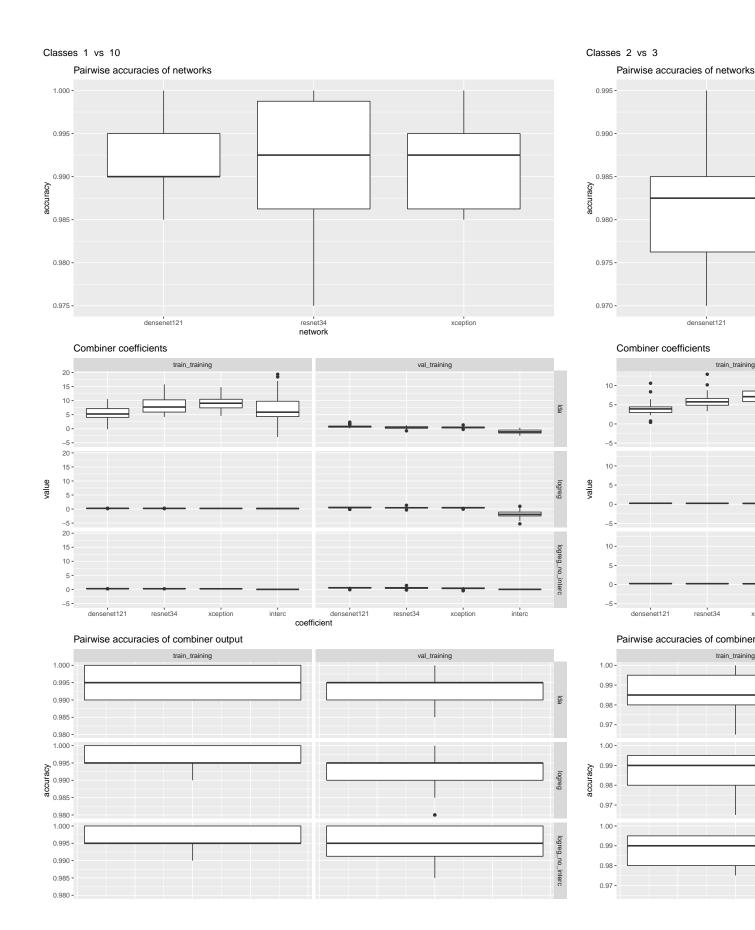
```
base_dir <- "../data/data_train_val_half_c100"</pre>
repls <- 0:9
folds <- 0:4
disp_classes <- 10
combiner_coefs <- load_combiner_coefs(base_dir, repls, folds)</pre>
net_pw_results <- read.csv(file.path(base_dir, "net_pw_accuracies.csv"))</pre>
ens_pw_results <- read.csv(file.path(base_dir, "ensemble_pw_accuracies.csv"))</pre>
net_pw_results[, c("class1", "class2")] <- lapply(net_pw_results[, c("class1", "class2")], as.factor)</pre>
ens_pw_results[, c("class1", "class2", "combining_method")] <- lapply(ens_pw_results[, c("class1", "cla
for (cl1 in 1:(disp_classes - 1))
  for (cl2 in (cl1 + 1):disp_classes)
    combiner plt <- combiner coefs %>% filter(class1 == cl1 & class2 == cl2) %>% ggplot() + geom boxplo
      facet_grid(cols=vars(train_type), rows=vars(combining_method)) + ggtitle("Combiner coefficients")
    acc_plt_net <- net_pw_results %% filter(class1 == (cl1 - 1) & class2 == (cl2 - 1)) %>% ggplot(mapp
      geom_boxplot() + ggtitle("Pairwise accuracies of networks")
    acc_plt_ens <- ens_pw_results %>% filter(class1 == (cl1 - 1) & class2 == (cl2 - 1)) %>% ggplot(mapp
      geom_boxplot() + facet_grid(cols=vars(train_set), rows=vars(combining_method)) +
      ggtitle("Pairwise accuracies of combiner output") +
      theme(axis.ticks.x=element_blank(), axis.text.x=element_blank())
    print((acc_plt_net/combiner_plt/acc_plt_ens) + plot_annotation(title=paste("Classes ", cl1, " vs ",
  }
}
```

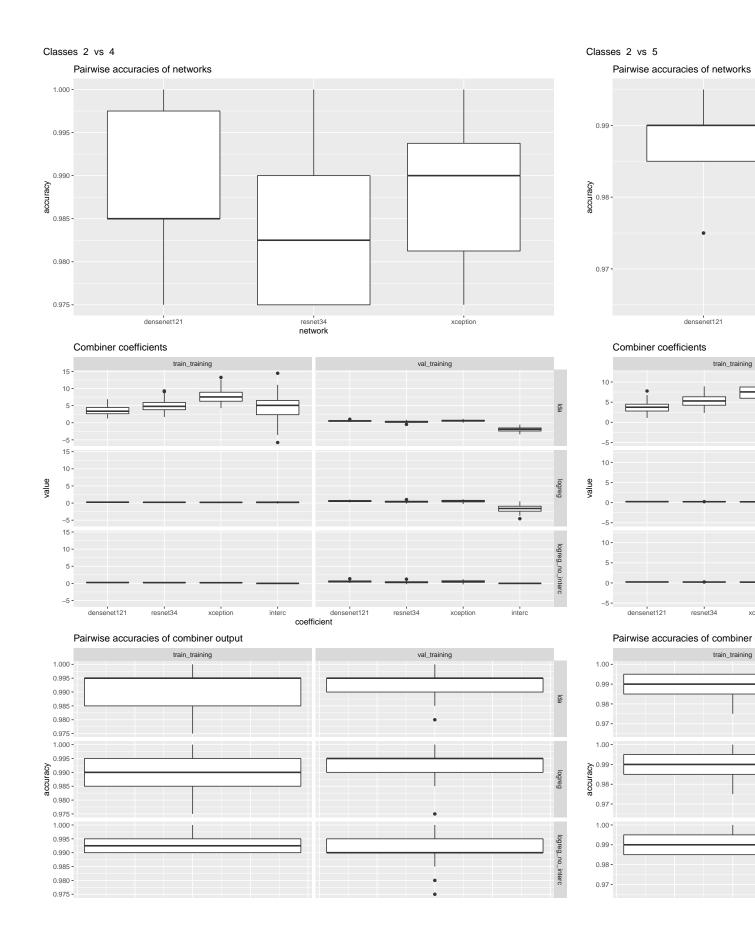


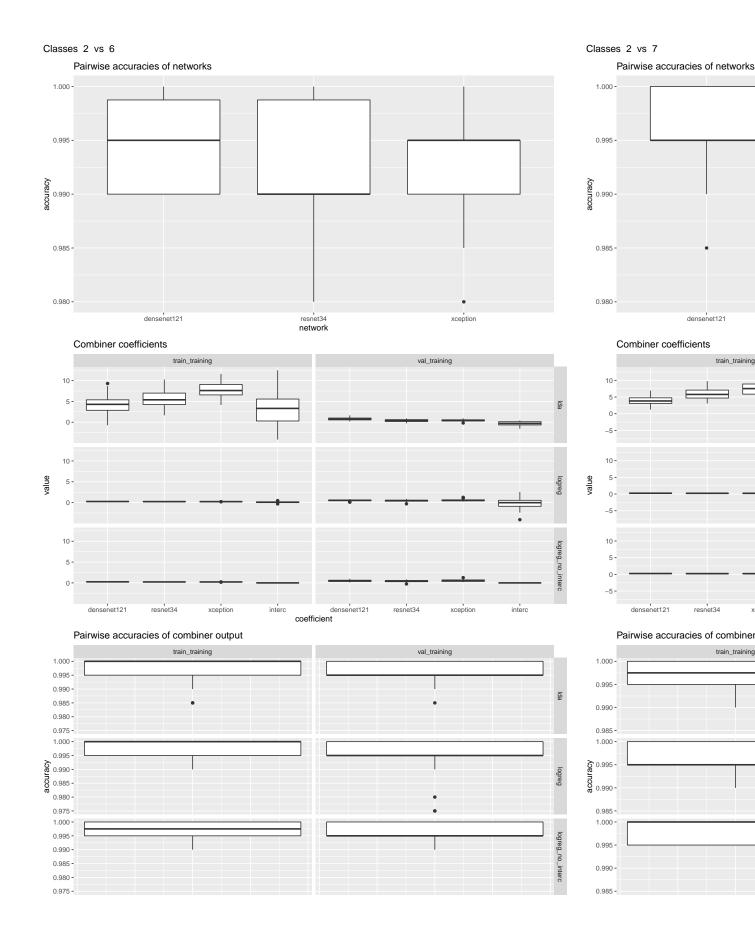


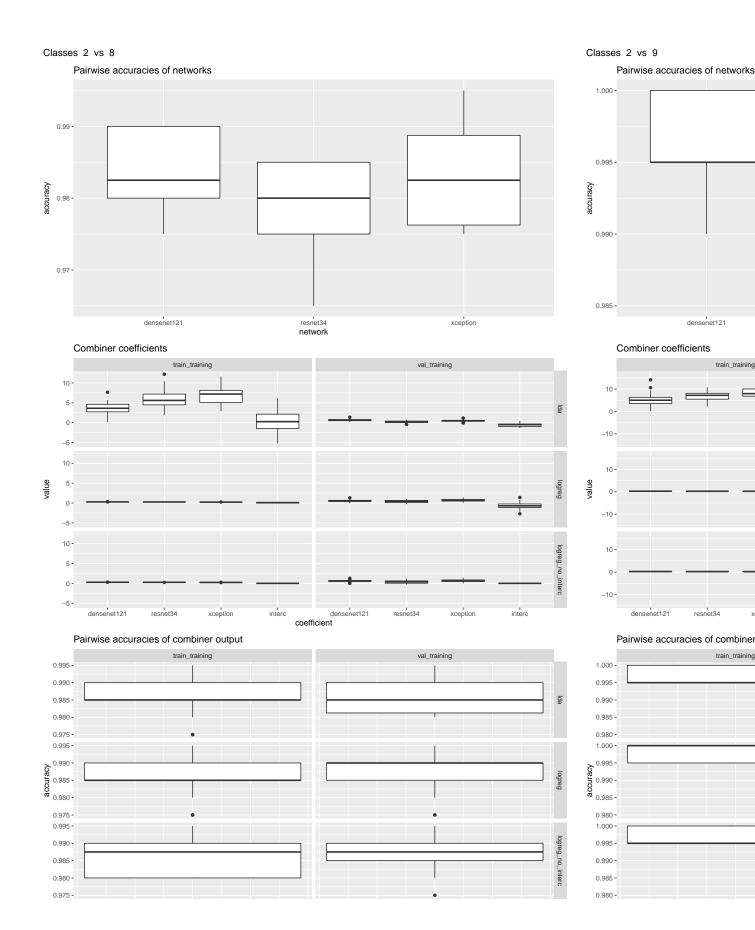


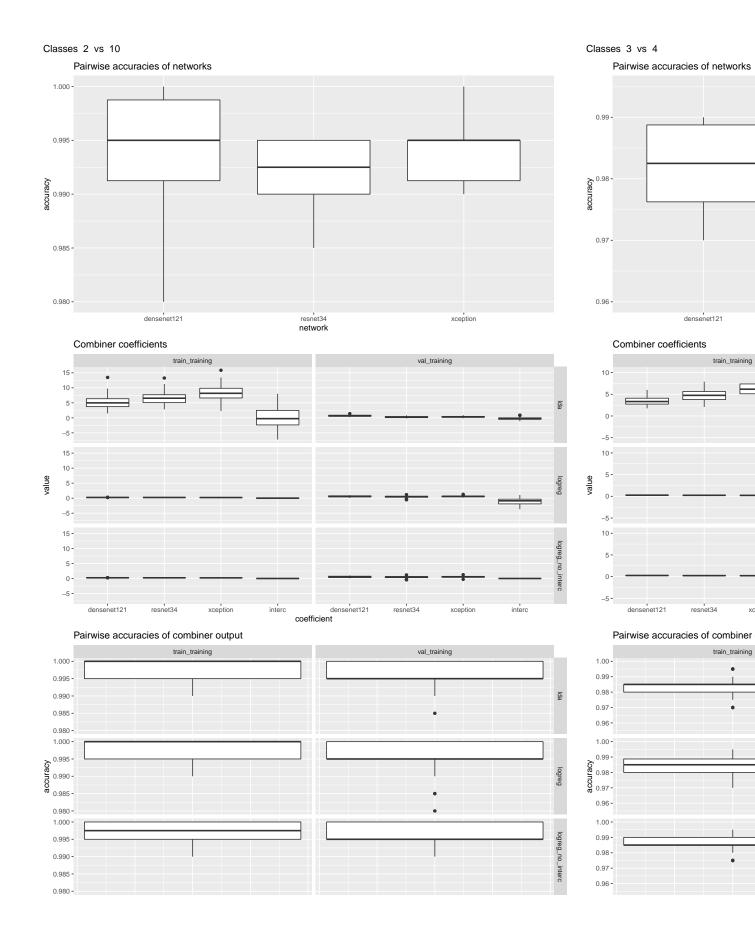


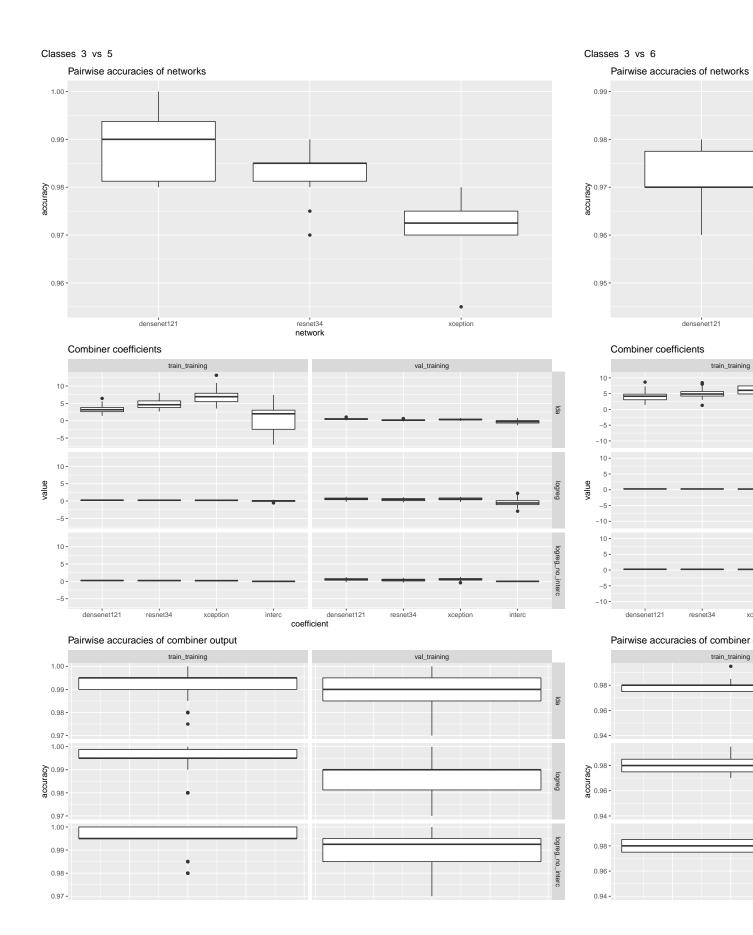


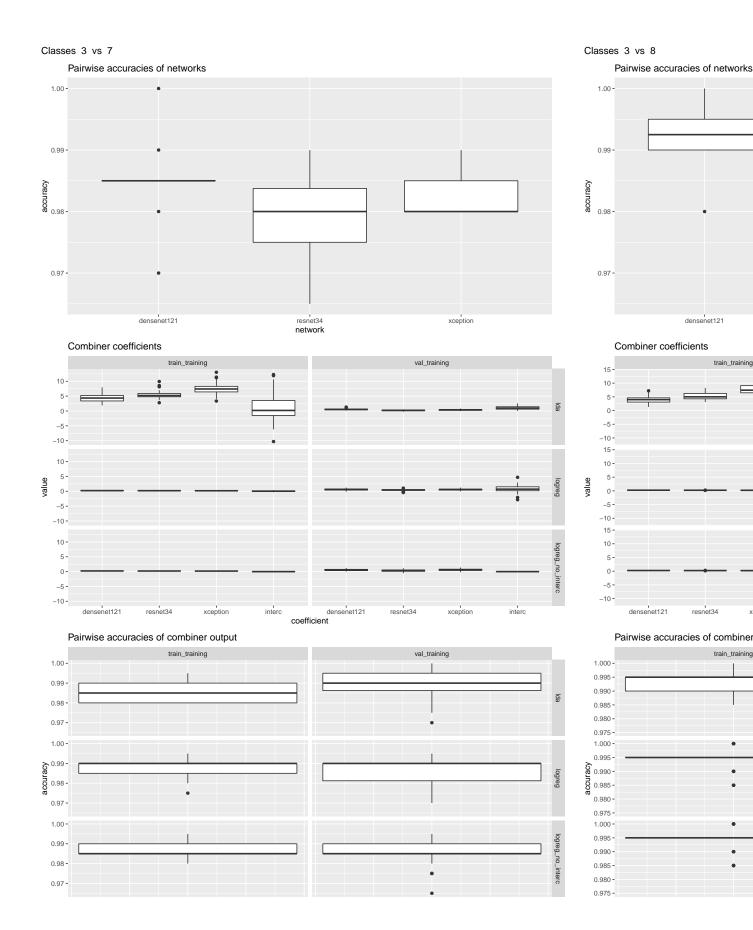


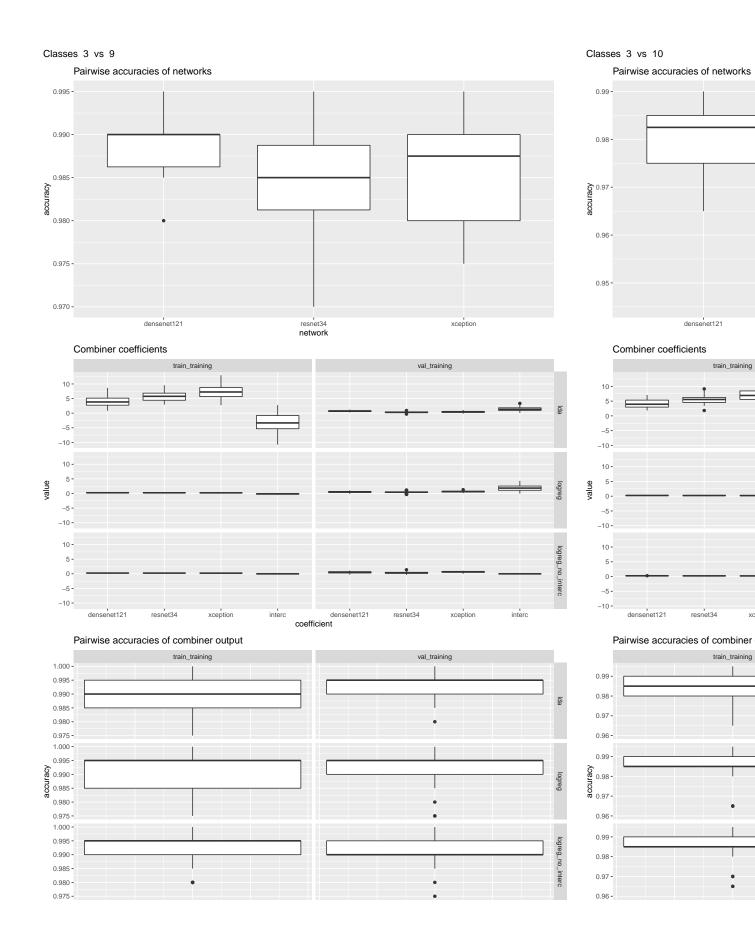


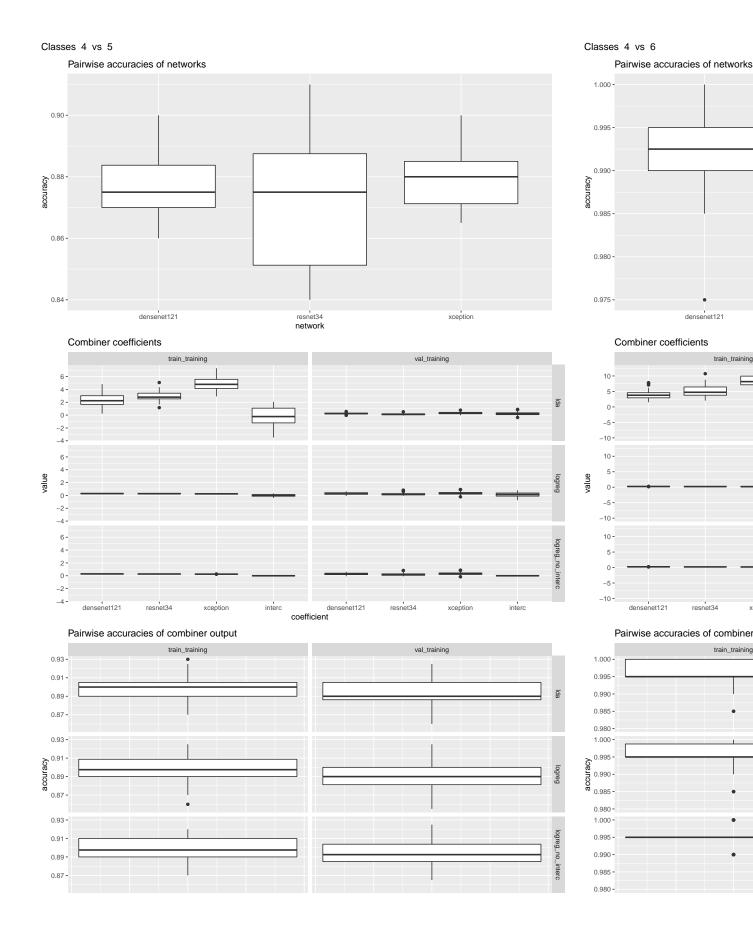


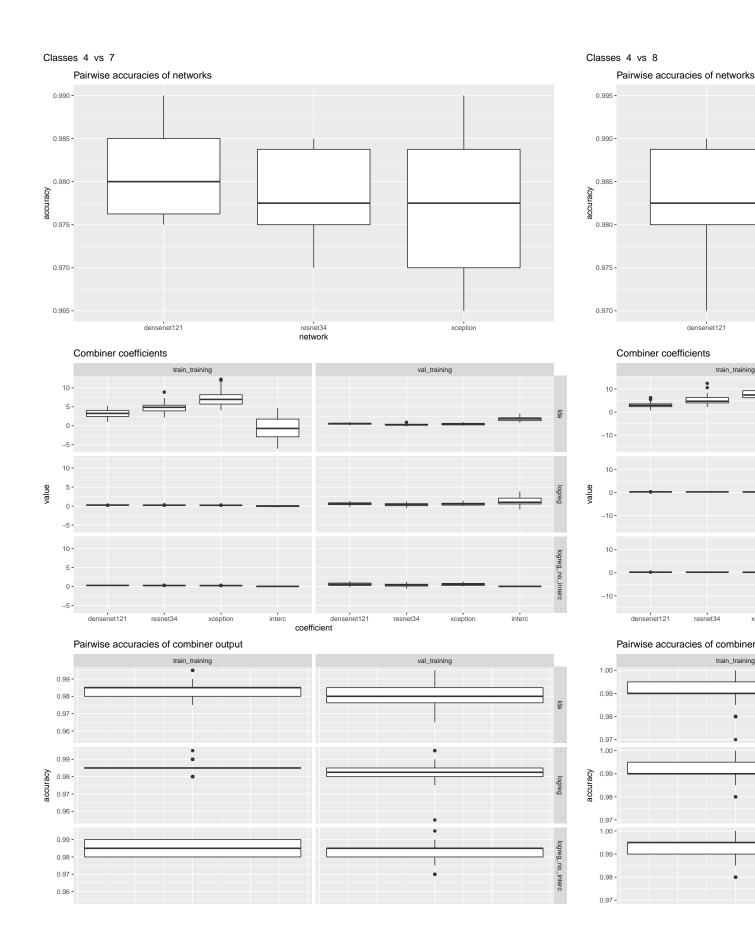


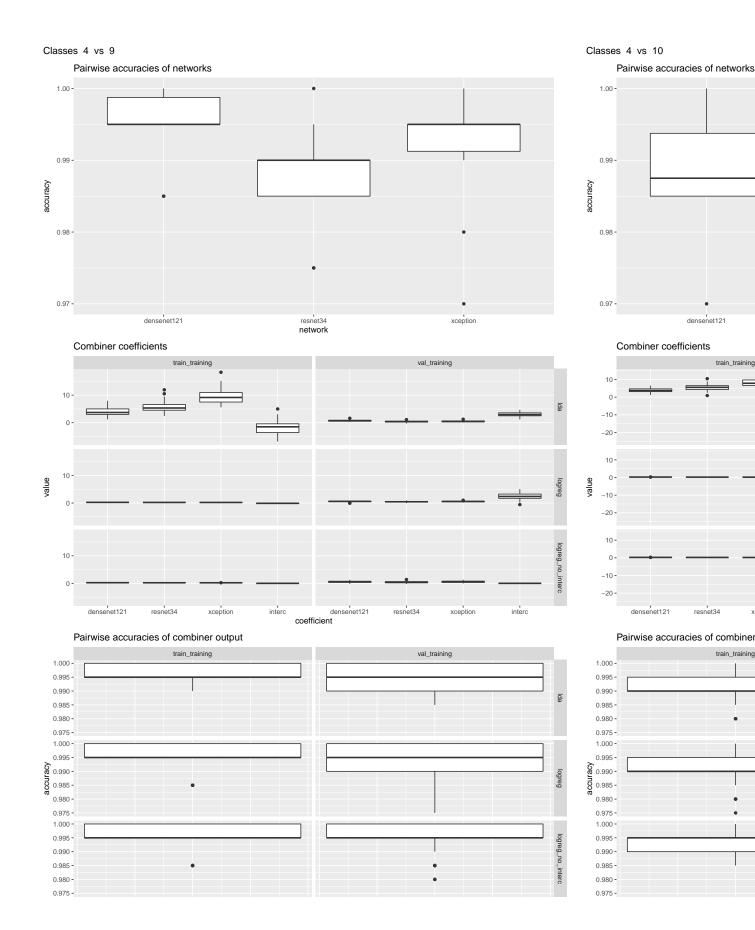


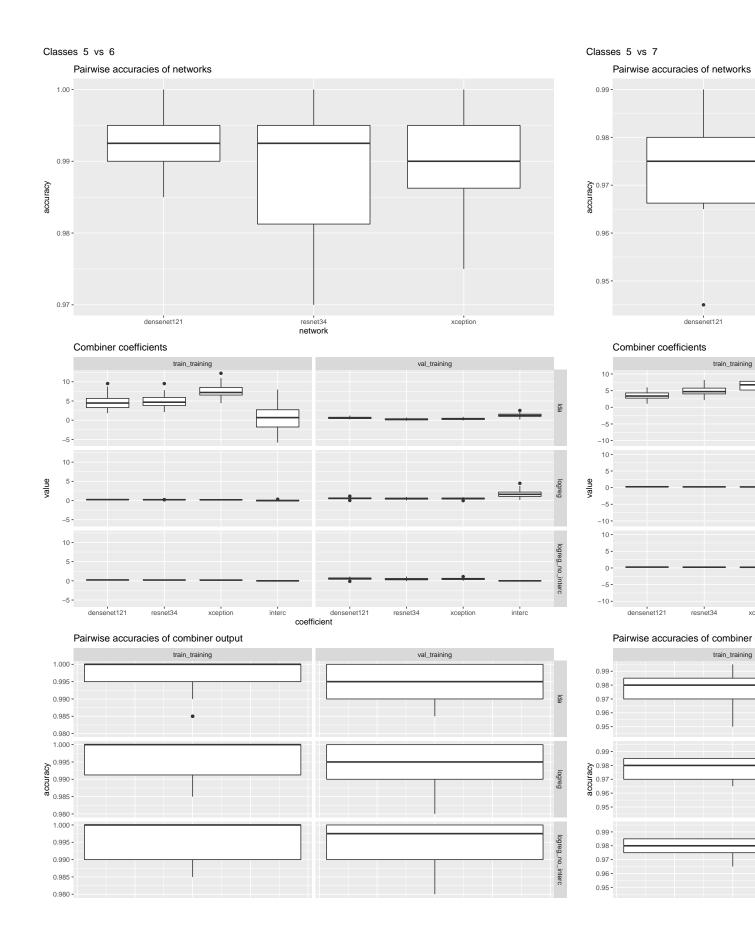


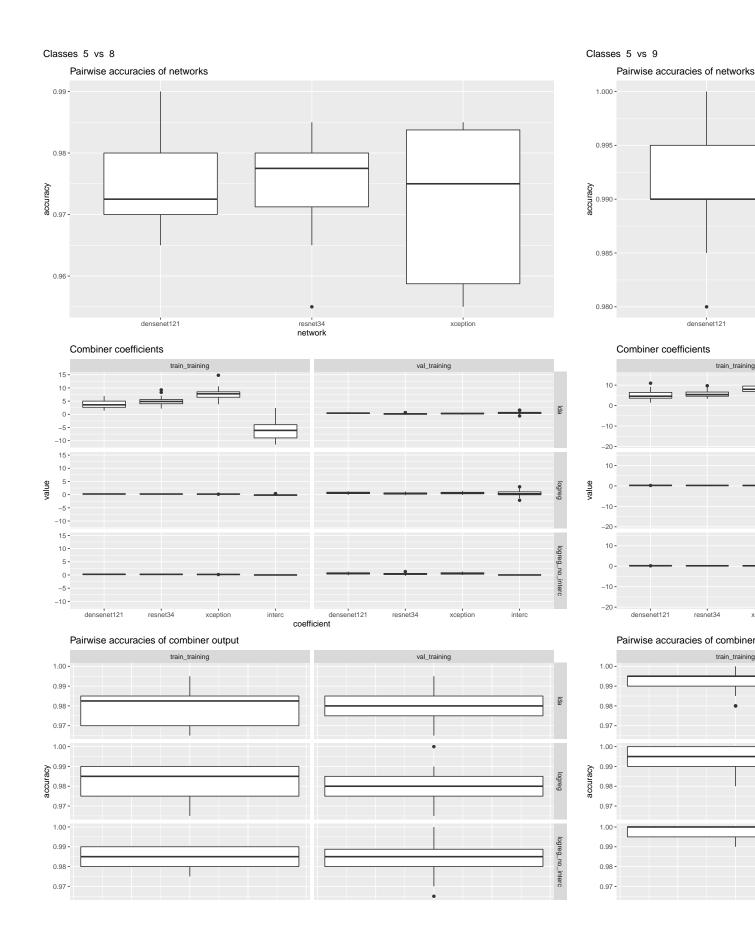


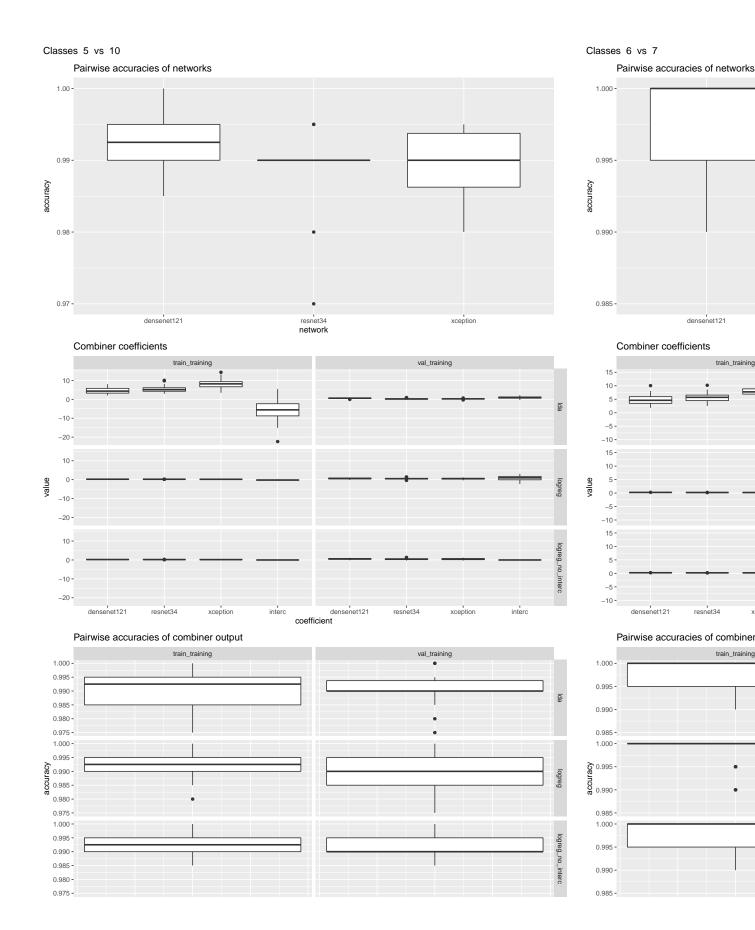


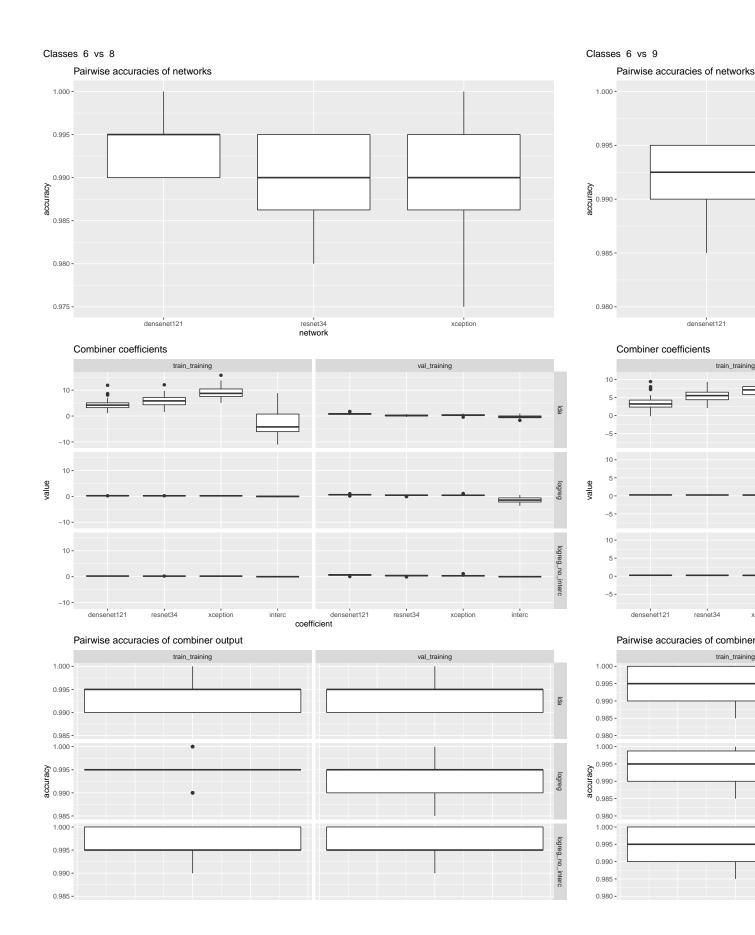


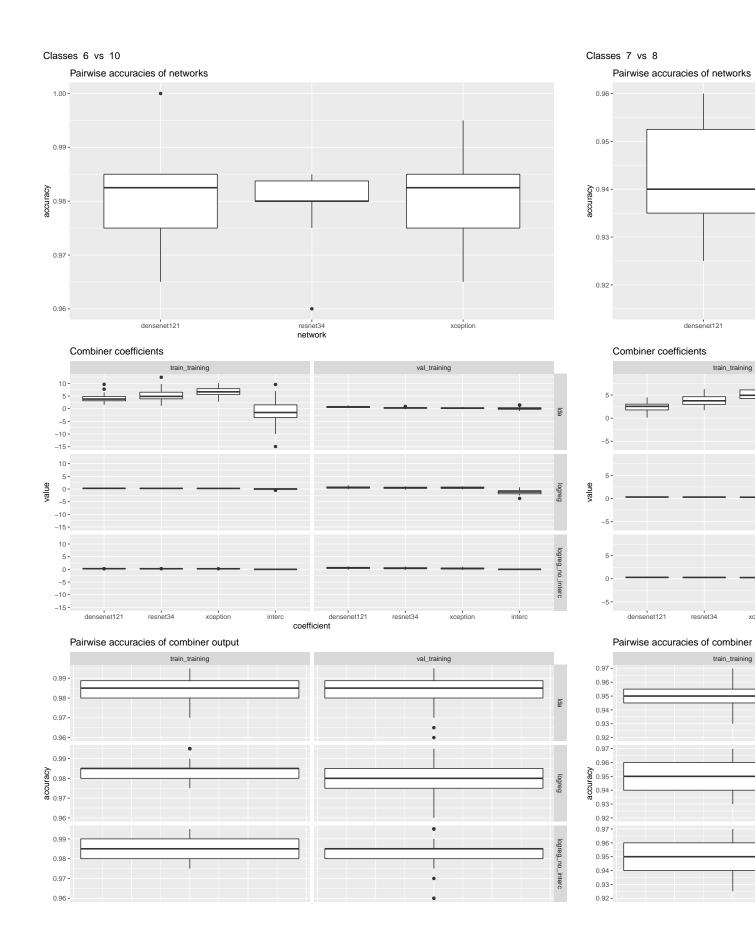


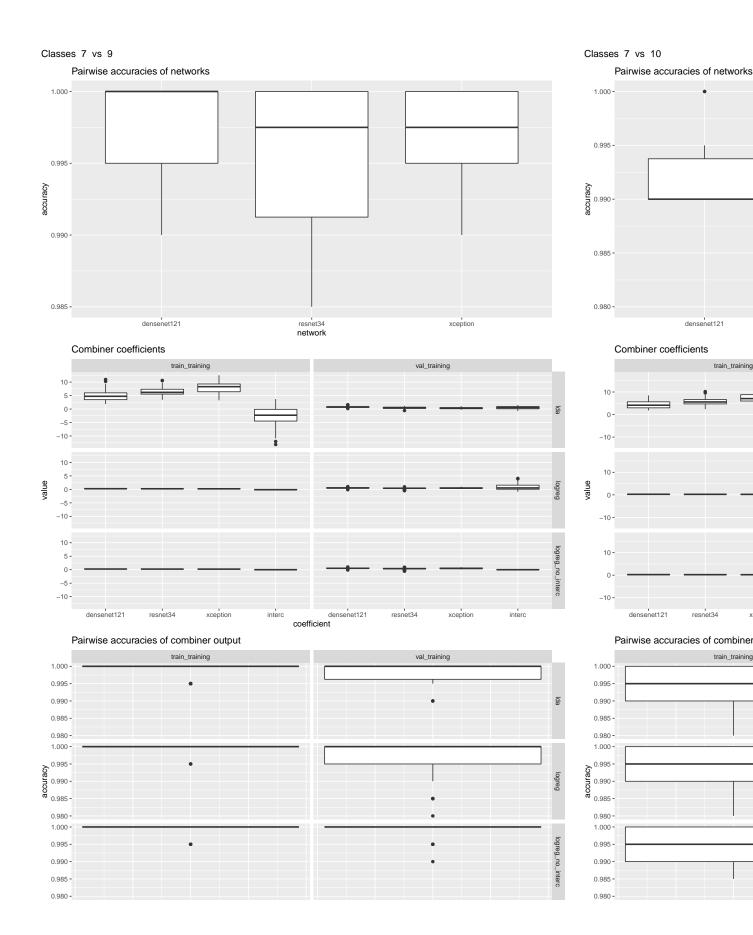


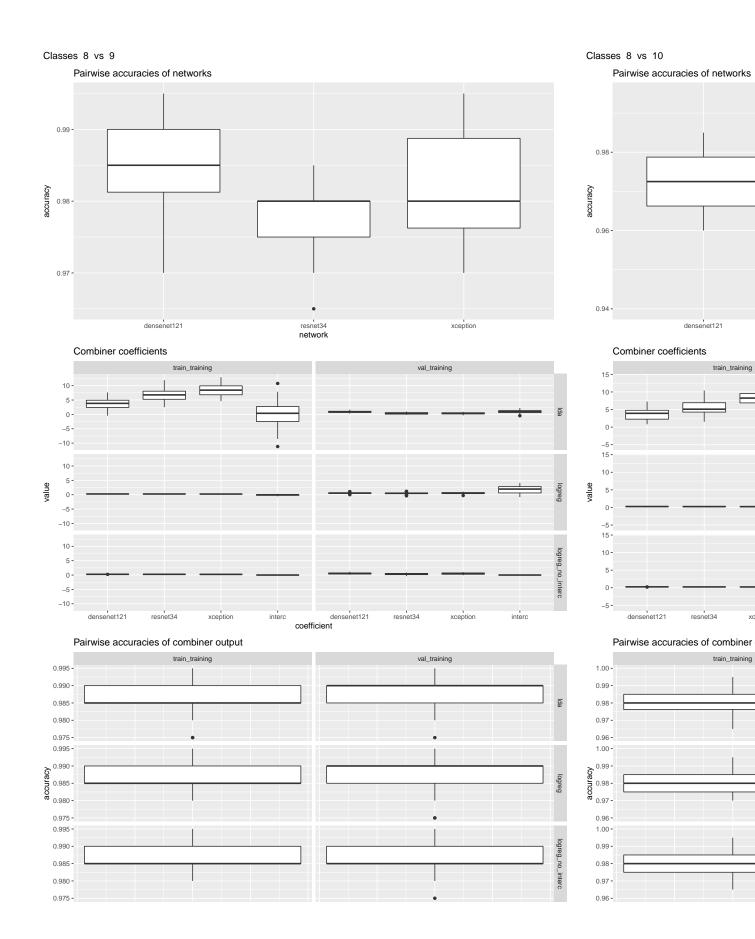




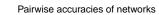


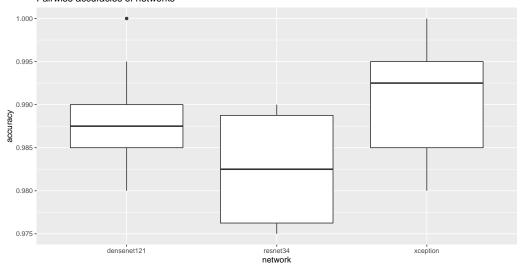




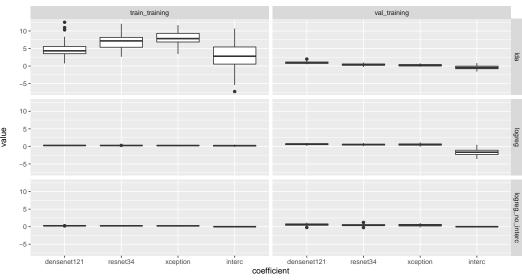


Classes 9 vs 10

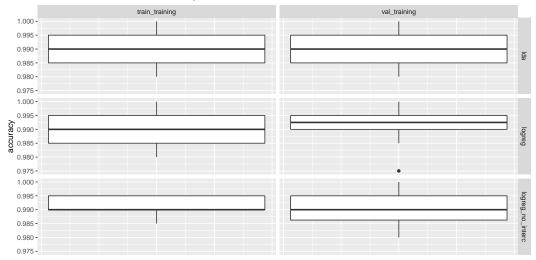




Combiner coefficients



Pairwise accuracies of combiner output



Here are too many class pair combinations to draw them all. ones.	TODO: think of some criteria to draw interesting