convnn_r_plots

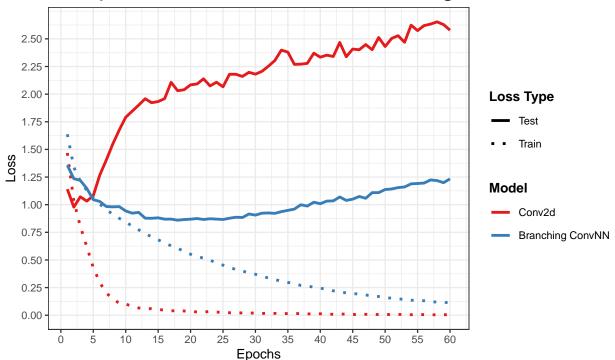
2025-09-27

```
## Loss Plot
\# \ "Convolutional-Nearest-Neighbor/Output/Sep\_24\_Branching\_NoSplit/vgg\_1e-5\_cos/CIFAR10/Col\_Col\_Branch/"
setwd("/Users/mingikang/Developer/Convolutional-Nearest-Neighbor/plots")
data = read.csv("csv/Loss_Comparison.csv")
library(tidyverse)
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr 1.1.4
                       v readr
                                   2.1.5
## v forcats 1.0.0 v stringr 1.5.1
## v ggplot2 3.5.2 v tibble 3.2.1
## v lubridate 1.9.4
                                    1.3.1
                        v tidyr
## v purrr
              1.0.4
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag() masks stats::lag()
## i Use the conflicted package (<a href="http://conflicted.r-lib.org/">http://conflicted.r-lib.org/</a>) to force all conflicts to become error
# Assuming 'data' is loaded correctly, we create the long format data frame
df_long <- data %>%
 pivot_longer(
   cols = -epoch,
   names_to = c("Model", "Type", ".value"),
   names sep = " "
# Create a single combined plot
combined_plot <- df_long %>%
 ggplot(aes(x = epoch, y = Loss, color = Model, linetype = Type)) +
 geom_line(linewidth = 1.0) +
 # --- Manual Scales for Aesthetics ---
 scale_color_brewer(
   palette = "Set1",
   labels = c("ConvNN" = "Branching ConvNN")
   ) +
 scale_linetype_manual(
   name = "Loss Type", # Legend title for linetype
   values = c("Train" = "dotted", "Test" = "solid") # Assign specific linetypes
 ) +
 scale x continuous(
```

```
breaks = seq(0, 60, by=5)
  ) +
  scale_y_continuous(
  breaks = seq(0, 2.5, by=0.25)
  ) +
  # --- Labels and Titles ---
   title = "Training and Test Loss",
   subtitle = "Comparison of Conv2d and Branching ConvNN",
   x = "Epochs",
   y = "Loss",
   color = "Model" # Legend title for color
  # --- Theme and Styling ---
  theme_bw(base_size = 10) +
  theme(
   legend.position = "right",
   plot.title = element_text(face = "bold", size = 23),
   plot.subtitle = element_text(size = 18),
   legend.title = element_text(face = "bold") # Make legend titles bold
  )
# Display the combined plot
print(combined_plot)
```

Training and Test Loss

Comparison of Conv2d and Branching ConvNN



```
# Save the combined plot to a file
ggsave(
   "csv/loss_comparison_plot.png",
   plot = combined_plot,
   width = 8,
   height = 5,
   units = "in",
   dpi = 300,
   bg = "white"
)
```

```
## Ks Plot # Load the necessary libraries
# "Output/Sep_25_Branching_NoSplit_KTest/vgg_1e-5_cos/CIFAR10/LocCol_LocCol_Branch"

library(tidyverse)
# The stringr package (part of tidyverse) is used for str_detect()
library(stringr)

# --- Data Reading ---
# Set your working directory and read the data using the robust read_csv()
setwd("/Users/mingikang/Developer/Convolutional-Nearest-Neighbor/plots")
df <- read_csv("csv/Ks_Comparison.csv")</pre>
```

Rows: 12 Columns: 7

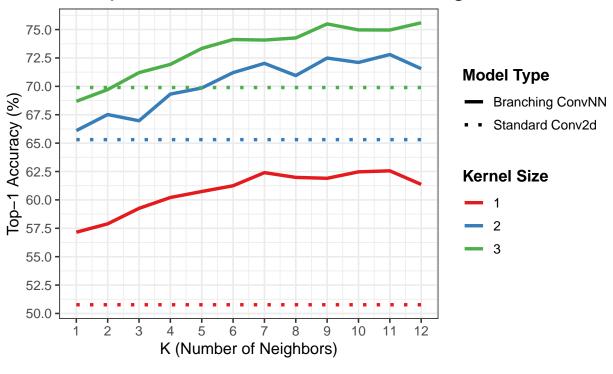
```
## -- Column specification -----
## Delimiter: ","
## dbl (7): K, Ks1_K, Ks2_K, Ks3_K, Ks1, Ks2, Ks3
## i Use 'spec()' to retrieve the full column specification for this data.
## i Specify the column types or set 'show_col_types = FALSE' to quiet this message.
# --- Step 1: Reshape and Process Data ---
# Reshape the data and create new columns for Kernel Size and Model Type
df_processed <- df %>%
 pivot_longer(
   cols = -K
   names_to = "Metric",
   values to = "Value"
  ) %>%
  mutate(
    # Create a 'Kernel Size' column by extracting the number from the 'Metric' string
   Kernel Size = case when(
     str_detect(Metric, "Ks1") ~ "1",
     str_detect(Metric, "Ks2") ~ "2",
     str_detect(Metric, "Ks3") ~ "3"
   ),
   # Create a 'Model Type' column based on whether ' K' is in the 'Metric' string
   Model_Type = case_when(
     str_detect(Metric, "_K") ~ "Branching ConvNN",
     TRUE
                              ~ "Standard Conv2d" # 'TRUE' acts as an else condition
   )
  )
# --- Step 2: Create the Plot with New Aesthetics ---
# Map 'color' to Kernel_Size and 'linetype' to Model_Type
k_plot <- ggplot(df_processed, aes(x = K, y = Value, color = Kernel_Size, linetype = Model_Type)) +
 geom_line(linewidth = 1.2) + # Draw the lines
  # --- Customize Scales and Legends ---
  scale_color_brewer(
   palette = "Set1",
   name = "Kernel Size" # Sets the title for the color legend
  ) +
  scale_linetype_manual(
   name = "Model Type", # Sets the title for the linetype legend
   values = c("Standard Conv2d" = "dotted", "Branching ConvNN" = "solid")
  ) +
  # --- Customize Axes and Labels ---
  scale_x_continuous(breaks = 1:12) + # Ensure integer ticks for K
  scale_y_continuous(breaks = seq(50, 77.25, 2.5)) + # Ensure integer ticks for K
 labs(
   title = "Model Accuracy by Kernel Size and Type",
   subtitle = "Comparison of Conv2d and Branching ConvNN",
   x = "K (Number of Neighbors)",
   y = "Top-1 Accuracy (%)"
 ) +
```

```
# --- Apply a Theme ---
theme_bw(base_size = 12) +
theme(
   legend.position = "right",
   plot.title = element_text(face = "bold", size = 23),
   plot.subtitle = element_text(size=18),
   legend.title = element_text(face = "bold") # Make legend titles bold
)

# Step 3: Display the plot
print(k_plot)
```

Model Accuracy by Kernel Size and Type

Comparison of Conv2d and Branching ConvNN



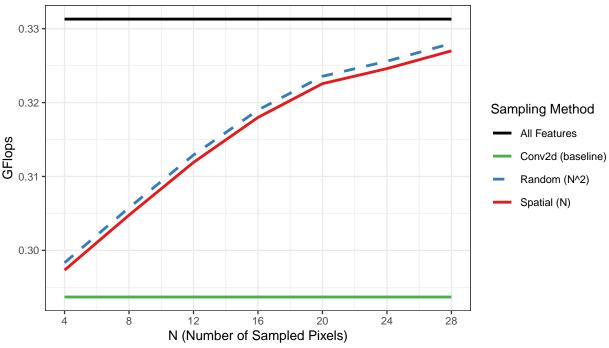
```
# Step 4: Save the plot to a file
ggsave(
   "csv/ks_comparison_plot.png",
   plot = k_plot,
   width = 10,
   height = 6,
   units = "in",
   dpi = 300,
   bg = "white"
)
```

```
## Random + Spatial Sampling Plot
{\tt\#"Convolutional-Nearest-Neighbor/Output/Sep\_27\_Branching\_NTest/vgg\_1e-5\_cos/CIFAR10/LocCol\_LocCol\_Branching\_NTest/vgg\_1e-5\_cos/CIFAR10/LocCol\_LocCol\_Branching\_NTest/vgg\_1e-5\_cos/CIFAR10/LocCol\_LocCol\_Branching\_NTest/vgg\_1e-5\_cos/CIFAR10/LocCol\_LocCol\_Branching\_NTest/vgg\_1e-5\_cos/CIFAR10/LocCol\_LocCol\_Branching\_NTest/vgg\_1e-5\_cos/CIFAR10/LocCol\_LocCol\_Branching\_NTest/vgg\_1e-5\_cos/CIFAR10/LocCol\_LocCol\_Branching\_NTest/vgg\_1e-5\_cos/CIFAR10/LocCol\_LocCol\_Branching\_NTest/vgg\_1e-5\_cos/CIFAR10/LocCol\_LocCol\_Branching\_NTest/vgg\_1e-5\_cos/CIFAR10/LocCol\_LocCol\_Branching\_NTest/vgg\_1e-5\_cos/CIFAR10/LocCol\_LocCol\_Branching\_NTest/vgg\_1e-5\_cos/CIFAR10/LocCol\_LocCol\_Branching\_NTest/vgg\_1e-5\_cos/CIFAR10/LocCol\_LocCol\_Branching\_NTest/vgg\_1e-5\_cos/CIFAR10/LocCol\_LocCol\_Branching\_NTest/vgg\_1e-5\_cos/CIFAR10/LocCol\_LocCol\_Branching\_NTest/vgg\_1e-5\_cos/CIFAR10/LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_LocCol\_Loc
# Make sure the necessary library is loaded
library(tidyverse)
# --- Step 1: Load Data (Your code) ---
setwd("/Users/mingikang/Developer/Convolutional-Nearest-Neighbor/plots")
df = read.csv("csv/N_Samples_Comparison-oct6.csv")
# --- Step 2: Reshape the Data for Plotting (Your code) ---
df_long <- df %>%
    select(N, Rand_GFlops, Rand_Top1, Spat_GFlops, Spat_Top1, All_GFlops, All_Top1, Conv_GFlops, Conv_Top
   pivot_longer(
       cols = -N,
       names_to = c("Type", ".value"),
      names_sep = "_"
   )
# --- NEW: Define an offset value and apply it to the data ---
# This creates a new data frame with a new column for the offset GFlops values.
offset value <- 0.001
df long offset <- df long %>%
    mutate(GFlops_offset = GFlops + if_else(Type == "Rand", offset_value, 0.0))
# --- Step 3: Create the GFlops Plot with the offset data ---
gflops_plot <- ggplot(df_long_offset, aes(x = N, y = GFlops_offset, color = Type, linetype = Type)) + #
    geom_line(linewidth = 1) +
    # --- Color scale (Your code) ---
    scale_color_manual(
      name = "Sampling Method",
       labels = c(Rand = "Random (N^2)", Spat = "Spatial (N)", All = "All Features", Conv = "Conv2d (basel
       values = c(Rand = "#377EB8", Spat = "#E41A1C", All = "black", Conv = "#4DAF4A")
    ) +
    # --- NEW: Add a manual linetype scale to make the "Random" line dashed ---
    scale_linetype_manual(
       name = "Sampling Method",
       labels = c(Rand = "Random (N^2)", Spat = "Spatial (N)", All = "All Features", Conv = "Conv2d (basel
       values = c(Rand = "dashed", Spat = "solid", All = "solid", Conv = "solid")
    # --- Customize Axes and Labels ---
    scale_x_continuous(breaks = seq(4, 28, 4)) +
    scale_y_continuous(breaks = seq(0.27, 0.34, 0.01)) +
    # --- NEW: Update labs to remove the redundant color title and add a caption ---
    labs(
       title = "Computational Cost (GFlops) vs. N",
       subtitle = "Comparison of Random and Spatial Sampling Methods",
       x = "N (Number of Sampled Pixels)",
       y = "GFlops",
       caption = "Note: The Random (blue dashed) line is slightly offset vertically for visibility."
```

```
theme_bw(base_size = 10) +
  theme(
   legend.position = "right",
   plot.title = element_text(face = "bold", size = 23),
   plot.subtitle = element_text(size = 18)
  )
# --- Display the final plot ---
# --- Step 4: Create the Top-1 Accuracy Plot ---
top1_plot <- ggplot(df_long, aes(x = N, y = Top1, color = Type)) +</pre>
  geom line(linewidth = 1) +
    # --- NEW: Use the same manual color scale ---
  scale_color_manual(
   name = "Sampling Method", # Legend title
   labels = c(
     Rand = "Random (N^2)",
     Spat = "Spatial (N)",
     All = "All Samples",
     Conv = "Conv2d (baseline)"
   ),
   values = c(
     Rand = "#377EB8", # Blue
     Spat = "#E41A1C", # Red
     All = "black",
                       # Black
     Conv = "#4DAF4A" # Green
  ) +
  # --- Customize Axes and Labels ---
  scale_x_continuous(breaks = seq(4, 28, 4)) + # Ensure integer ticks for N
  scale_y_continuous(breaks = seq(67, 76, 1)) + # Ensure integer ticks for K
   title = "Model Performance vs. N",
   subtitle = "Top-1 Accuracy for Random and Spatial Sampling Methods",
   x = "N (Number of Sampled Pixels)",
   y = "Top-1 Accuracy (%)",
   color = "Sampling Method"
  ) +
  theme_bw(base_size = 10) +
  theme(legend.position = "right",
       plot.title = element_text(face = "bold", size = 23),
       plot.subtitle = element_text(size = 18)
        )
# --- Step 5: Display the Plots ---
print(gflops_plot)
```

Computational Cost (GFlops) vs. N

Comparison of Random and Spatial Sampling Method

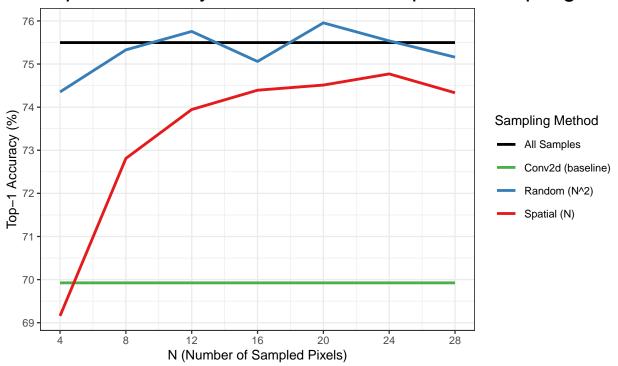


Note: The Random (blue dashed) line is slightly offset vertically for visibility.

print(top1_plot)

Model Performance vs. N

Top-1 Accuracy for Random and Spatial Sampling Met



```
# --- Step 6: (Optional) Save the Plots to Files ---
ggsave("csv/N_Gflops_New.png", plot = gflops_plot, width = 8, height = 5, dpi = 300, bg = "white")
ggsave("csv/N_Accuracy_New.png", plot = top1_plot, width = 8, height = 5, dpi = 300, bg = "white")
```