Bonus Lab 2: Introduction to Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) Implementatoin in R and Python

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Table of contents

1 Lab Overview

1.1 Learning Objectives

1. Understand CNN and LSTM Architecture.
2. Understand the potential of CNN and LSTM for predictive analytics.
3. Understand the limitations of CNN and LSTM.
4. Understand the potential of CNN and LSTM for text analysis.
5. Compare implementation of CNN and LSTM in R and Python.

2 Assignment Overview

In this bonus lab we introduce the concept of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models. We will explore the architecture of these models and their potential for predictive analytics. We will also discuss the limitations of these models and their potential for text analysis. Finally, we will compare the implementation of CNN and LSTM in R and Python.

2.1 There are three main parts to the lab:

Exercise 1: Introduction to Convolutional Neural Networks (CNN) in R and Python

Exercise 2: Introduction to Long Short-Term Memory (LSTM) in R and Python

Exercise 3: Comparing CNN and LSTM in R and Python

3 Lab Instructions

Make sure you have the following packages installed in R and Python: keras, tensorflow, tidyverse, and nltk.

3.1 Exercise 1: Building a CNN Image Classier with Fashion MNIST Data

```r
library(keras)
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   3.5.1     v tibble    3.2.1
v lubridate 1.9.3     v tidyr     1.3.1
v purrr     1.0.2
-- Conflicts ------------------------------------------ tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag()    masks stats::lag()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becor
```

```r
library(gridExtra)
```

```
Attaching package: 'gridExtra'

The following object is masked from 'package:dplyr':

    combine
```

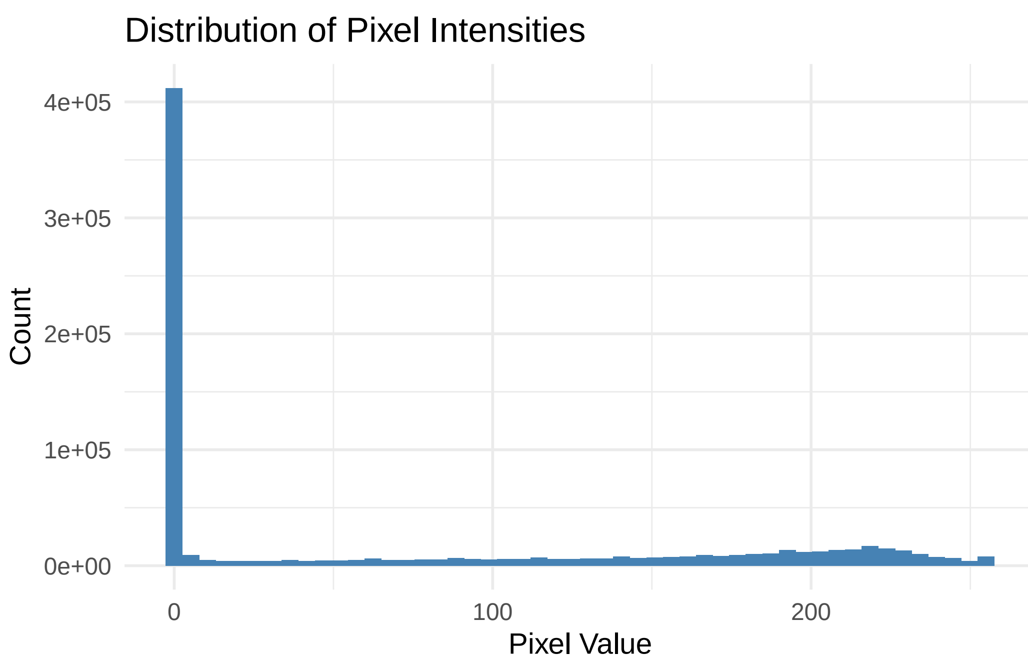
```r
library(reshape2)
```

```
Attaching package: 'reshape2'

The following object is masked from 'package:tidyr':

    smiths
```

```r
# Load Fashion MNIST dataset
fashion_mnist <- dataset_fashion_mnist()
x_train <- fashion_mnist$train$x
y_train <- fashion_mnist$train$y
x_test <- fashion_mnist$test$x
y_test <- fashion_mnist$test$y

# Define class labels
fashion_labels <- c(
  "T-shirt/top", "Trouser", "Pullover", "Dress", "Coat",
  "Sandal", "Shirt", "Sneaker", "Bag", "Ankle boot"
)

# Explore data distribution
plot_fashion_distribution <- function(y_train, labels) {
  tibble(
    class = factor(y_train, labels = labels),
    count = 1
  ) %>%
    count(class) %>%
    ggplot(aes(x = reorder(class, n), y = n)) +
    geom_bar(stat = "identity", fill = "steelblue") +
```

```r
    coord_flip() +
    theme_minimal() +
    labs(title = "Distribution of Fashion MNIST Classes",
         x = "Class",
         y = "Count")
}

# Visualize sample images with labels
plot_fashion_samples <- function(x_train, y_train, labels, samples_per_class = 5) {
  par(mfrow = c(length(unique(y_train)), samples_per_class),
      mar = c(0.5, 0.5, 1.5, 0.5))

  for(class in 0:9) {
    class_indices <- which(y_train == class)[1:samples_per_class]
    for(idx in class_indices) {
      image(t(x_train[idx,,]),
            col = gray.colors(256),
            axes = FALSE,
            main = labels[class + 1])
    }
  }
}

plot_pixel_distribution <- function(x_train) {
  # Check dimensions
  dims <- dim(x_train)

  if(length(dims) == 4) {
    # If 4D array, remove the channel dimension
    sample_images <- x_train[1:1000,,,1]
  } else if(length(dims) == 3) {
    # If 3D array, take as is
    sample_images <- x_train[1:1000,,]
  } else {
    stop("Input must be 3D or 4D array")
  }

  # Convert to vector
  pixel_values <- as.vector(sample_images)

  # Create plot
  ggplot(data.frame(pixel = pixel_values), aes(x = pixel)) +
```

```
    geom_histogram(bins = 50, fill = "steelblue") +
    theme_minimal() +
    labs(title = "Distribution of Pixel Intensities",
         x = "Pixel Value",
         y = "Count")
}

# Now you can use it with either format:
plot_pixel_distribution(x_train)  # Will work with either 3D or 4D array
```



Now, we will look at CNN Architecture and Feature Maps

```
# Create CNN model with visualization capabilities
create_cnn_model <- function(input_shape = c(28, 28, 1)) {
  model <- keras_model_sequential()

  model %>%
    # First convolution block
    layer_conv_2d(filters = 32, kernel_size = c(3,3), activation = "relu",
                  input_shape = input_shape, name = "conv1") %>%
    layer_max_pooling_2d(pool_size = c(2,2), name = "pool1") %>%

    # Second convolution block
```

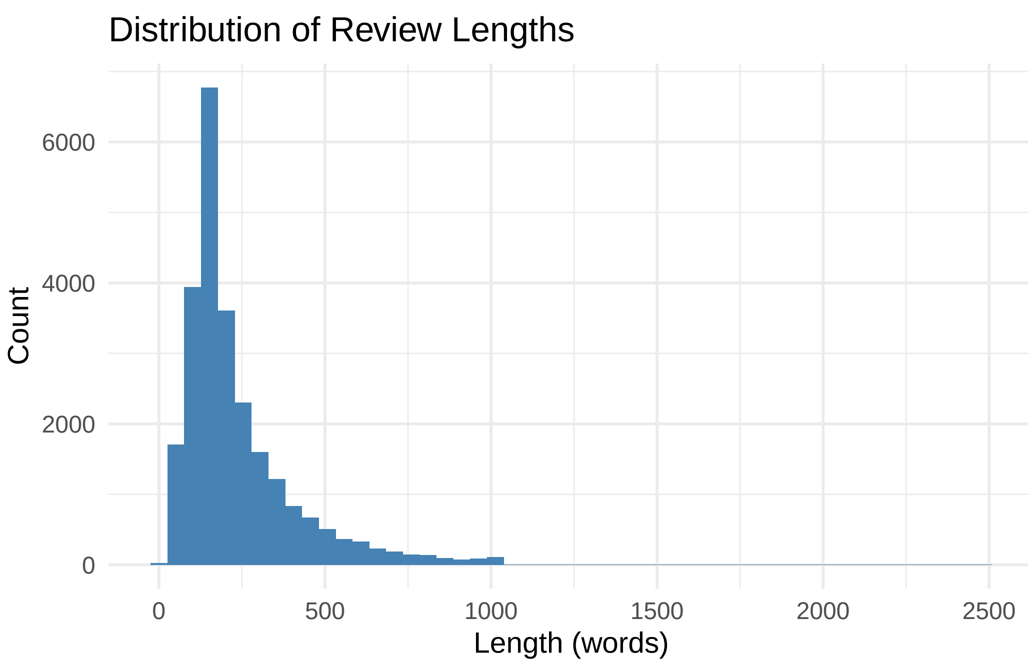
```r
    layer_conv_2d(filters = 64, kernel_size = c(3,3), activation = "relu",
                  name = "conv2") %>%
    layer_max_pooling_2d(pool_size = c(2,2), name = "pool2") %>%

    # Dense layers
    layer_flatten(name = "flatten") %>%
    layer_dense(units = 128, activation = "relu", name = "dense1") %>%
    layer_dropout(0.5, name = "dropout") %>%
    layer_dense(units = 10, activation = "softmax", name = "output")

  return(model)
}

# Function to visualize feature maps
visualize_feature_maps <- function(model, image) {
  # Create model that outputs feature maps
  layer_outputs <- lapply(1:length(model$layers),
                          function(i) model$layers[[i]]$output)
  activation_model <- keras_model(inputs = model$input,
                                  outputs = layer_outputs)

  # Get activations
  activations <- activation_model %>% predict(image)

  # Plot feature maps for convolutional layers
  conv_layers <- which(sapply(model$layers, function(x)
    inherits(x, "keras.layers.convolutional.Conv2D")))

  for(i in seq_along(conv_layers)) {
    layer_name <- model$layers[[conv_layers[i]]]$name
    n_features <- dim(activations[[conv_layers[i]]])[4]

    # Plot first 16 feature maps (or all if less than 16)
    n_cols <- min(4, n_features)
    n_rows <- min(4, ceiling(n_features/4))

    par(mfrow = c(n_rows, n_cols), mar = c(0.5, 0.5, 2, 0.5))

    for(j in 1:min(16, n_features)) {
      feature_map <- activations[[conv_layers[i]]][1,,,j]
      image(t(feature_map), main = paste(layer_name, "- Filter", j),
            col = viridis::viridis(100))
```

```
    }
  }
}
```

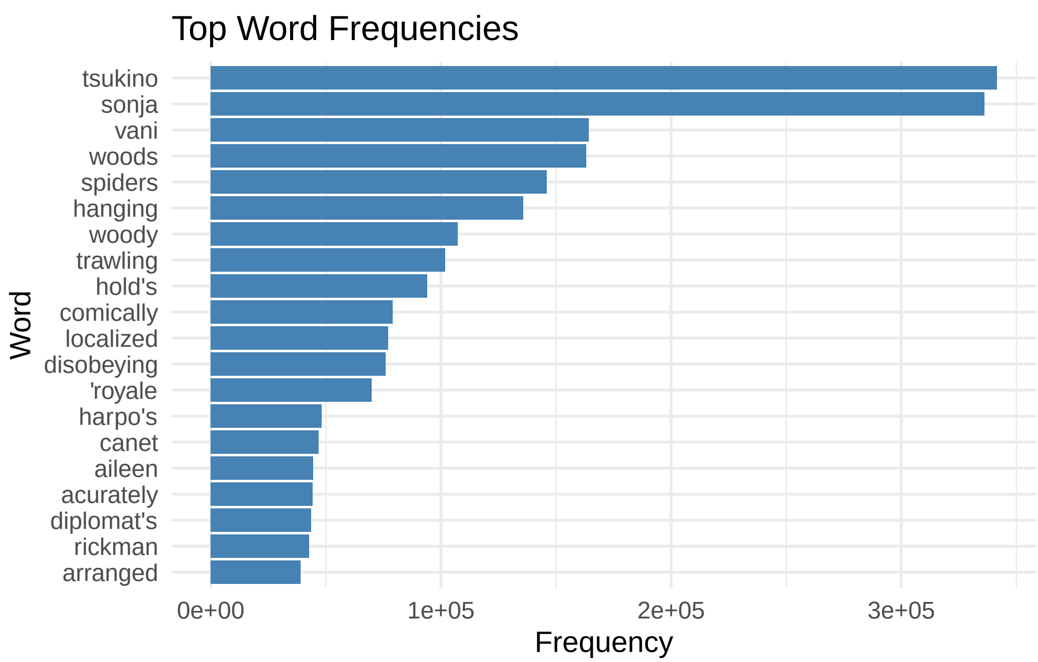
Now, we will look at LSTM for Text Classification

```
# Load IMDB dataset with preprocessing
max_features <- 10000
max_len <- 500

imdb <- dataset_imdb(num_words = max_features)

# Explore text data
analyze_text_lengths <- function(sequences) {
  lengths <- sapply(sequences, length)

  ggplot(data.frame(length = lengths), aes(x = length)) +
    geom_histogram(bins = 50, fill = "steelblue") +
    theme_minimal() +
    labs(title = "Distribution of Review Lengths",
         x = "Length (words)",
         y = "Count")
}

# Visualize word frequency
plot_word_frequency <- function(sequences, word_index, top_n = 20) {
  # Count word frequencies
  word_counts <- table(unlist(sequences))

  # Get word labels
  reverse_word_index <- names(word_index)[1:length(word_index)]

  # Create frequency dataframe
  freq_df <- data.frame(
    word = reverse_word_index[as.numeric(names(word_counts))],
    count = as.numeric(word_counts)
  ) %>%
    arrange(desc(count)) %>%
    head(top_n)

  ggplot(freq_df, aes(x = reorder(word, count), y = count)) +
    geom_bar(stat = "identity", fill = "steelblue") +
```

```
    coord_flip() +
    theme_minimal() +
    labs(title = "Top Word Frequencies",
         x = "Word",
         y = "Frequency")
}

# Show text length distribution
analyze_text_lengths(imdb$train$x)
```




```
# Show word frequencies
plot_word_frequency(imdb$train$x, dataset_imdb_word_index())
```




```r
# Create and visualize LSTM model
create_lstm_model <- function(max_features, max_len) {
  model <- keras_model_sequential()

  model %>%
    layer_embedding(input_dim = max_features,
                    output_dim = 128,
                    input_length = max_len,
                    name = "embedding") %>%
    layer_lstm(units = 64,
               return_sequences = TRUE,
               name = "lstm1") %>%
    layer_lstm(units = 32,
               name = "lstm2") %>%
    layer_dense(units = 1,
                activation = "sigmoid",
                name = "output")

  return(model)
}
```

We can now compare

```r
# Function to compare model architectures visually
compare_architectures <- function(cnn_model, lstm_model) {
  # Extract layer information
  get_layer_info <- function(model) {
    tibble(
      layer = sapply(model$layers, function(x) x$name),
      type = sapply(model$layers, function(x) class(x)[1]),
      parameters = sapply(model$layers, function(x) x$count_params())
    )
  }

  cnn_info <- get_layer_info(cnn_model)
  lstm_info <- get_layer_info(lstm_model)

  # Plot comparisons
  p1 <- ggplot(cnn_info, aes(x = layer, y = parameters)) +
    geom_bar(stat = "identity", fill = "steelblue") +
    theme_minimal() +
    theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
    labs(title = "CNN Architecture",
         x = "Layer",
         y = "Parameters")

  p2 <- ggplot(lstm_info, aes(x = layer, y = parameters)) +
    geom_bar(stat = "identity", fill = "coral") +
    theme_minimal() +
    theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
    labs(title = "LSTM Architecture",
         x = "Layer",
         y = "Parameters")

  grid.arrange(p1, p2, ncol = 2)
}

# Compare training metrics
compare_training_histories <- function(cnn_history, lstm_history) {
  # Combine histories
  cnn_df <- data.frame(
    epoch = 1:length(cnn_history$metrics$accuracy),
    accuracy = cnn_history$metrics$accuracy,
    model = "CNN"
  )
```

```r
  lstm_df <- data.frame(
    epoch = 1:length(lstm_history$metrics$accuracy),
    accuracy = lstm_history$metrics$accuracy,
    model = "LSTM"
  )

  combined_df <- rbind(cnn_df, lstm_df)

  ggplot(combined_df, aes(x = epoch, y = accuracy, color = model)) +
    geom_line() +
    theme_minimal() +
    labs(title = "Training Progress Comparison",
         x = "Epoch",
         y = "Accuracy")
}
```

Now, let's take a look at buiding an image classifer in Python using the Fashion MNIST dataset.

```python
import tensorflow as tf
from tensorflow import keras
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# Load Fashion MNIST dataset
(x_train, y_train), (x_test, y_test) = keras.datasets.fashion_mnist.load_data()

# Class labels
fashion_labels = ['T-shirt/top', 'Trouser', 'Pullover', 'Dress', 'Coat',
                 'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boot']

# Data visualization functions
def plot_fashion_distribution(y_train, labels):
    plt.figure(figsize=(10, 6))
    sns.countplot(y=pd.Series(y_train).map(lambda x: labels[x]))
    plt.title('Distribution of Fashion MNIST Classes')
    plt.xlabel('Count')
    plt.tight_layout()
    plt.show()
```

```python
def plot_fashion_samples(x_train, y_train, labels, samples_per_class=5):
    fig, axes = plt.subplots(len(labels), samples_per_class,
                             figsize=(samples_per_class*2, len(labels)*2))
    for i, label in enumerate(range(len(labels))):
        indices = np.where(y_train == label)[0][:samples_per_class]
        for j, idx in enumerate(indices):
            axes[i, j].imshow(x_train[idx], cmap='gray')
            axes[i, j].axis('off')
            if j == 0:
                axes[i, j].set_ylabel(labels[label])
    plt.tight_layout()
    plt.show()

# Create CNN model
def create_cnn_model(input_shape=(28, 28, 1)):
    model = keras.Sequential([
        keras.layers.Conv2D(32, (3, 3), activation='relu',
                           input_shape=input_shape, name='conv1'),
        keras.layers.MaxPooling2D((2, 2), name='pool1'),
        keras.layers.Conv2D(64, (3, 3), activation='relu', name='conv2'),
        keras.layers.MaxPooling2D((2, 2), name='pool2'),
        keras.layers.Flatten(name='flatten'),
        keras.layers.Dense(128, activation='relu', name='dense1'),
        keras.layers.Dropout(0.5, name='dropout'),
        keras.layers.Dense(10, activation='softmax', name='output')
    ])
    return model

# Visualize feature maps
def visualize_feature_maps(model, image):
    # Create a model that will output feature maps
    layer_outputs = [layer.output for layer in model.layers
                     if isinstance(layer, keras.layers.Conv2D)]
    activation_model = keras.Model(inputs=model.input, outputs=layer_outputs)

    # Get feature maps
    activations = activation_model.predict(np.expand_dims(image, 0))

    # Plot feature maps
    for i, activation in enumerate(activations):
        n_features = activation.shape[-1]
        size = activation.shape[1]
```

```
        n_cols = min(n_features, 8)
        n_rows = n_features // n_cols
        fig, axes = plt.subplots(n_rows, n_cols, figsize=(n_cols*2, n_rows*2))
        for j in range(n_features):
            row, col = j // n_cols, j % n_cols
            axes[row, col].imshow(activation[0, :, :, j], cmap='viridis')
            axes[row, col].axis('off')
        plt.suptitle(f'Feature maps for layer {model.layers[i*2].name}')
        plt.show()
```

Now, we will use LSTM for Text Classification in Python

```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences

# Load IMDB dataset
max_features = 10000
max_len = 500
(x_train, y_train), (x_test, y_test) = keras.datasets.imdb.load_data(
    num_words=max_features)

# Text analysis functions
def analyze_text_lengths(sequences):
    lengths = [len(seq) for seq in sequences]
    plt.figure(figsize=(10, 6))
    plt.hist(lengths, bins=50)
    plt.title('Distribution of Review Lengths')
    plt.xlabel('Length (words)')
    plt.ylabel('Count')
    plt.show()

def plot_word_frequency(sequences, word_index, top_n=20):
    # Count word frequencies
    word_freq = {}
    for seq in sequences:
        for word_id in seq:
            if word_id not in word_freq:
                word_freq[word_id] = 0
            word_freq[word_id] += 1
```

```python
    # Sort and plot
    word_freq_sorted = sorted(word_freq.items(), key=lambda x: x[1], reverse=True)
    words = [list(word_index.keys())[list(word_index.values()).index(id)]
             for id, _ in word_freq_sorted[:top_n]]
    freqs = [freq for _, freq in word_freq_sorted[:top_n]]

    plt.figure(figsize=(12, 6))
    sns.barplot(x=freqs, y=words)
    plt.title('Top Word Frequencies')
    plt.xlabel('Frequency')
    plt.show()

# Create LSTM model
def create_lstm_model(max_features, max_len):
    model = keras.Sequential([
        keras.layers.Embedding(max_features, 128, input_length=max_len,
                               name='embedding'),
        keras.layers.LSTM(64, return_sequences=True, name='lstm1'),
        keras.layers.LSTM(32, name='lstm2'),
        keras.layers.Dense(1, activation='sigmoid', name='output')
    ])
    return model

# Architecture comparison visualization
def compare_architectures(cnn_model, lstm_model):
    def get_model_info(model):
        return pd.DataFrame({
            'layer': [layer.name for layer in model.layers],
            'parameters': [layer.count_params() for layer in model.layers]
        })

    cnn_info = get_model_info(cnn_model)
    lstm_info = get_model_info(lstm_model)

    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15, 6))

    sns.barplot(data=cnn_info, x='layer', y='parameters', ax=ax1)
    ax1.set_title('CNN Architecture')
    ax1.tick_params(axis='x', rotation=45)

    sns.barplot(data=lstm_info, x='layer', y='parameters', ax=ax2)
    ax2.set_title('LSTM Architecture')
```

```python
    ax2.tick_params(axis='x', rotation=45)

    plt.tight_layout()
    plt.show()
```