Evaluation of Artificial Neural Networks

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I. Introduction

Recurrent ANN aree architectures focused in the processing of sequential data such as time series, speech, and natural language processing. This ANN keeps information thanks to its structure.

In contrast with MLP, RNN or Recurrent Neural Network are used with sequential data, similar to a modified Markov chain, using past information to predict future values, this approach starts getting the concept of context.

II. Core Concepts and Methods

A. Historical Context and Development

The concept of recurrent connections in neural networks dates back to 1960s. Frank Rosenblatt introduced "close-loop cross-coupled perceptrons" in, which included recurrent connections in a three-layered perceptron network. These connections allowed the network to keep a kind of memory, updating weights based on a Hebbian learning rule Wikipedia [6]. Further developments were made by Kaoru Nakano in 1971 and ShunIchi Amari in 1972, who explored similar architectures with recurrent connections Wikipedia [6].

B. Architecture and Working Principles

RNNs are characterized by their ability to maintain a hidden state that gets updated as the network processes each element in a sequence. This hidden state acts as some sort of memory, influencing future outputs. The basic structure of an RNN can be visualized as a "rolled" network, where the same set of weights is used across different time steps, creating a loop that allows information to flow back through the network Singh [5].

C. Applications

RNNs have found applications in a wide range of fields, including:

- Natural Language Processing (NLP): RNNs are used for tasks such as language modeling, machine translation, and sentiment analysis. They can capture the context and dependencies between words in a sentence, which is crucial for understanding language IBM [4].
- Speech Recognition: RNNs are employed to convert spoken language into text by processing audio signals sequentially and recognizing patterns in the sound waves IBM [4].
- Time Series Prediction: In finance and economics, RNNs are used to predict future values based on historical data, such as stock prices or economic indicators Encyclopedia [2].
- Healthcare: RNNs have been applied to analyze medical time series data, such as ECG signals or patient vital signs, to detect anomalies or predict health outcomes "A Comprehensive Review of Deep Learning: Architectures, Recent Advances, and Applications" [1].
- Music Generation: RNNs can generate musical sequences by learning patterns in existing music, allowing for the creation of new compositions that follow similar structures Encyclopedia [2].

III. Challenges and Advances

Despite their effectiveness, RNNs face several challenges, particularly with long-term dependencies. Traditional RNNs can struggle to maintain relevant information over long sequences due to issues like vanishing and exploding gradients during training. To address these issues, variants such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) have been developed. These architectures include gating mechanisms that allow the network to selectively remember or forget information, improving performance on long sequences GeeksforGeeks [3].

IV. RNN Implementation

Here, a simple RNN implementation in Python is made using tensorflow.

```
!pip install tensorflow
!pip install seaborn
!pip install matplotlib
!pip install numpy
!pip install pandas
!pip install scikit-learn
!pip install nltk
!pip install plotly
```

Importing Modules ans Libraries

```
import warnings
from tensorflow.keras.utils import pad_sequences
from tensorflow.keras.preprocessing.text import Tokenizer
from sklearn.model_selection import train_test_split
import tensorflow as tf
from tensorflow import keras
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import numpy as np
```

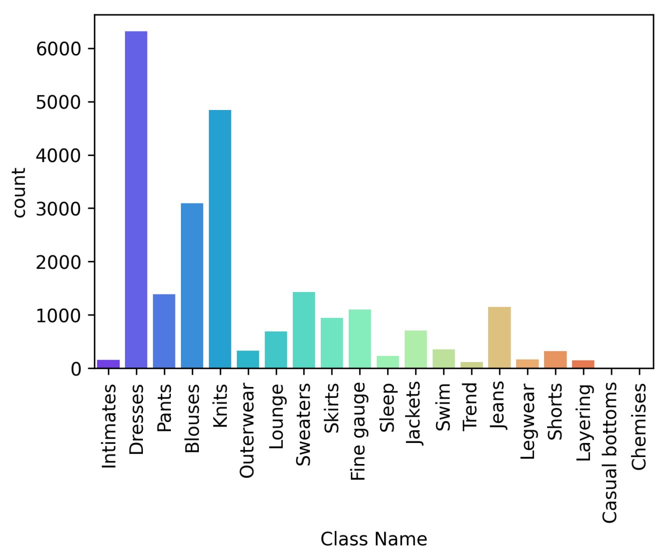
```
import re
import nltk
nltk.download('all')
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer
lemm = WordNetLemmatizer()

warnings.filterwarnings("ignore")
```

Loading the dataset

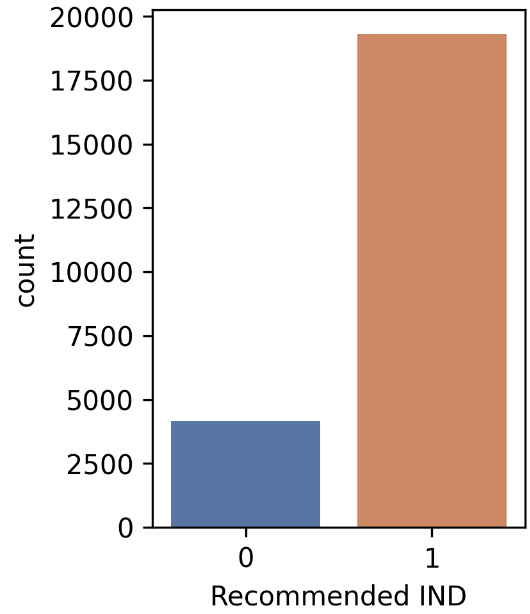
```
data = pd.read_csv("Clothing-Review.csv")
data.head(7)

data = data[data['Class Name'].isnull() == False]
plt.subplots(figsize=(12, 5))
plt.subplot(1, 2, 1)
sns.countplot(data=data, x='Rating',palette="deep")
```

Exploratory Data Analysis

```
sns.countplot(data=data, x='Class Name', palette='rainbow')
plt.xticks(rotation=90)
plt.show()
```




```
plt.subplot(1, 2, 2)
sns.countplot(data=data, x="Recommended IND", palette="deep")
plt.show()
fig = px.histogram(data, marginal='box',
                   x="Age", title="Age Group",
                   color="Recommended IND",
                   nbins=65-18,
                   color_discrete_sequence=['green', 'red'])
fig.update_layout(bargap=0.2)
```




```
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Unable to display output for mime type(s): text/html
```

```
fig = px.histogram(data,
                   x="Age",
                   marginal='box',
                   title="Age Group",
                   color="Rating",
                   nbins=65-18,
                   color_discrete_sequence
                   =['black', 'green', 'blue', 'red', 'yellow'])
fig.update_layout(bargap=0.2)
```

```
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```

Preparing the data to build the model

```
def filter_score(rating):
    return int(rating > 3)

features = ['Class Name', 'Title', 'Review Text']

X = data[features]
y = data['Rating']
y = y.apply(filter_score)


def toLower(data):
    if isinstance(data, float):
        return '<UNK>'
    else:
        return data.lower()

stop_words = stopwords.words("english")

def remove_stopwords(text):
    no_stop = []
    for word in text.split(' '):
        if word not in stop_words:
```

```
            no_stop.append(word)
    return " ".join(no_stop)

def remove_punctuation_func(text):
    return re.sub(r'[^a-zA-Z0-9]', ' ', text)

X['Title'] = X['Title'].apply(toLower)
X['Review Text'] = X['Review Text'].apply(toLower)

X['Title'] = X['Title'].apply(remove_stopwords)
X['Review Text'] = X['Review Text'].apply(remove_stopwords)

X['Title'] = X['Title'].apply(
   lambda x: lemm.lemmatize(x))
X['Review Text'] = X['Review Text'].apply(
   lambda x: lemm.lemmatize(x))

X['Title'] = X['Title'].apply(
   remove_punctuation_func)
X['Review Text'] = X['Review Text'].apply(
   remove_punctuation_func)

X['Text'] = list(X['Title']+\
         X['Review Text']+X['Class Name'])


X_train, X_test, y_train, y_test = train_test_split(
    X['Text'], y, test_size=0.25, random_state=42)
```

Tokenize the text

```
tokenizer = Tokenizer(num_words=10000, oov_token='<OOV>')
tokenizer.fit_on_texts(X_train)

train_seq = tokenizer.texts_to_sequences(X_train)
test_seq = tokenizer.texts_to_sequences(X_test)

train_pad = pad_sequences(train_seq,
                          maxlen=40,
                          truncating="post",
                          padding="post")
test_pad = pad_sequences(test_seq,
                         maxlen=40,
                         truncating="post",
                         padding="post")
```

Creating the RNN Model

```
from tensorflow import keras

model = keras.models.Sequential()
model.add(keras.layers.Embedding(
   input_dim=10000, output_dim=128, input_length=40))
model.add(keras.layers.SimpleRNN(64, return_sequences=True))
model.add(keras.layers.SimpleRNN(64))
model.add(keras.layers.Dense(128, activation="relu"))
model.add(keras.layers.Dropout(0.4))
model.add(keras.layers.Dense(1, activation="sigmoid"))
```

```
model.build(input_shape=(None, 40))
```

MODEL SUMMARY:

- Layers
  - Embedding (Embedding)
    - Output Shape: (None, 40, 128)
    - Parameters: 1,280,000
  - Simple_rnn (SimpleRNN)
    - Output Shape: (None, 40, 64)
    - Parameters: 12,352
  - Simple_rnn_1 (SimpleRNN)
    - Output Shape: (None, 64)
    - Parameters: 8,256
  - Dense (Dense)
    - Output Shape: (None, 128)
    - Parameters: 8,320
  - Dropout (Dropout)
    - Output Shape: (None, 128)
    - Parameters: 0
  - Dense_1 (Dense)
    - Output Shape: (None, 1)
    - Parameters: 129
- Total params: 1,309,057 (4.99 MB)
- Trainable params: 1,309,057 (4.99 MB)
- Non-trainable params: 0 (0.00 B)

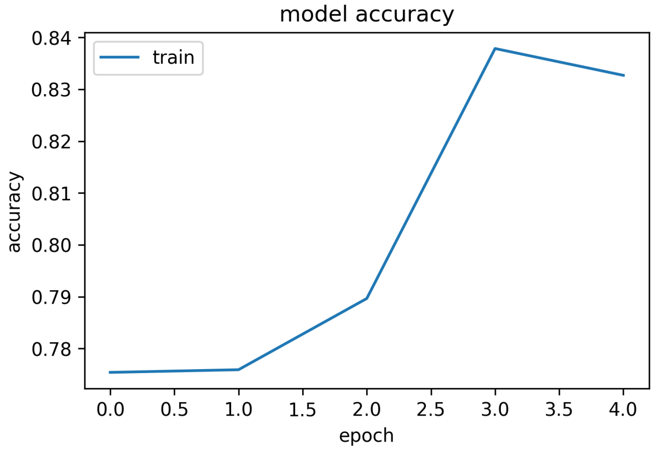
```
model.compile(loss="binary_crossentropy",
              optimizer="adam",
              metrics=["accuracy"])


history = model.fit(train_pad,
                    y_train,
                    epochs=5)

results = model.evaluate(test_pad, y_test)
```

```
plt.plot(history.history['accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()

print(results)
```




```
[0.5045214891433716, 0.7597137093544006]
```

V. Conclusion

RNN are actually usefuill for a majority of applications that nowadays are based on context needed events. Despite it's advantages, some new insights were needed letting more complex tasks to be done and aiming to achieve better results increasing it's application areas.

References

[1] "A Comprehensive Review of Deep Learning: Architectures, Recent Advances, and Applications". In: *Sensors* 15.12 (2025). Available at: https://www.mdpi.com/2078-2489/15/12/755, p. 755.

[2] Network Encyclopedia. *Recurrent Neural Networks and the Secrets of Sequence Learning*. Available at: https://networkencyclopedia.com/recurrent-neural-networks/. 2025.

[3] GeeksforGeeks. *Gated Recurrent Unit Networks*. Available at: https://www.geeksforgeeks.org/machine-learning/gated-recurrent-unit-networks/. 2025.

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[6] Wikipedia. *Recurrent neural network*. Available at: https://en.wikipedia.org/wiki/Recurrent_neural_network. 2025.