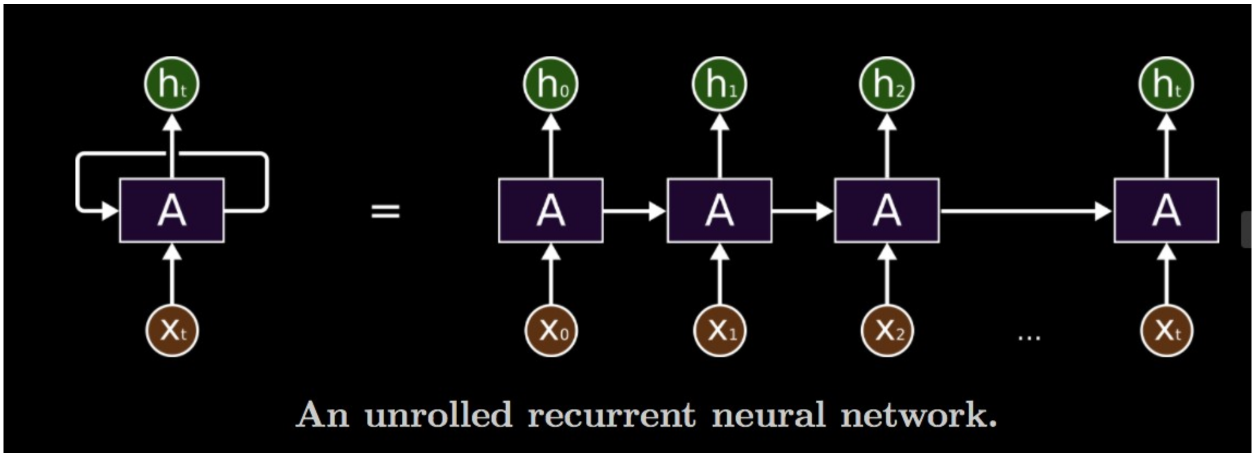
Recurrent Neural Network using Numpy (Practice and for base concept Only)



***Definition**: A recurrent neural network (RNN) is a type of artificial neural network that processes sequential data. RNNs are used to model data like speech, text, and time series.*

- vocab = ["I", "eat", "Cake"] # Example input sentence
- convert into a vector representation
- Vectors stored into **x1,x2,x3**
- Initiate weights "Manually"

- input to hidden *wxh*
- hidden to hidden *whh*
- hidden to output *why*
- hidden and output biases *bh* and *by*

```
import numpy as np # Numpy
vocab = ["I", "eat", "Cake"] # Example input sentence

# convert into a vector representation
vocab[0] = [1, 0, 0]
vocab[1] = [0, 1, 0]
vocab[2] = [0, 0, 1]

# Vectors stored into x1,x2,x3 array
x1 = np.array(vocab[0])
x2 = np.array(vocab[1])
x3 = np.array(vocab[2])

# Initiate weights "Manually"
```

```python
wxh = np.array([[1., 0.1, -0.3],    # input to hidden
                [-0.2, 1., 1.]])


whh = np.array([[0.6, 0.2],          # hidden to hidden
                [0.1, 0.7]])


why = np.array([[0.3, 0.5],          # hidden to output
                [-0.1, 0.2],
                [0.4, 0.7]])


bh = np.array([0.1, 0.2])            # hidden bias

by = np.array([0.1, 0.2, 0.3])       # output bias

print(f"The shape of input  to hidden  (wxh): {wxh.shape} Matrix")
print(f"The shape of hidden to hidden (whh): {whh.shape} Matrix")
print(f"The shape of hidden to Output (why): {why.shape} Matrix")
print(f"The shape of hidden bias (bh):       {bh.shape} Matrix")
print(f"The shape of Output bias (by):       {wxh.shape} Matrix")
```

```
The shape of input  to hidden  (wxh): (2, 3) Matrix
The shape of hidden to hidden (whh): (2, 2) Matrix
The shape of hidden to Output (why): (3, 2) Matrix
The shape of hidden bias (bh):       (2,) Matrix
The shape of Output bias (by):       (2, 3) Matrix
```

Step by Step Guide of calculation

- step 1: Initialize hidden state

- step 2: Proceed for input -> x1 [1 0 0]

- step 3: Preceed for input -> x2 [0 1 0]

- step 4: Output Prediction Yout

Steps to print the vectors (optional):

- Convert to NumPy arrays if they are lists.
- Iterate over h1
- Iterate over h2
- Iterate over Yout

- Display vectors after training

```
# step 1: Initialize hidden state
h0 = np.array([0,0])

# step 2: Proceed for input -> x1 [1 0 0]
wxh_x1 = np.dot(wxh,x1)
whh_h0 = np.dot(whh,h0)
h1 = np.tanh(wxh_x1 + whh_h0 + bh)
print("The Prediction of h1 is: ",h1)

# step 3: Preceed for input -> x2 [0 1 0]
wxh_x2 = np.dot(wxh,x2)
whh_h1 = np.dot(whh,h1)
h2 = np.tanh(wxh_x2 + whh_h1 + bh)
print("The Prediction of h2 is: ",h2)

# step 4: Output Prediction
Yout = np.dot(why,h2) + by
print("The Prediction of Yout is: ",Yout)

# Convert to NumPy arrays if they are lists
h1 = np.array(h1)
h2 = np.array(h2)
Yout = np.array(Yout)



# Steps to print Vectors
Vector1, Vector2, Vector3 = [], [], []
# Iterate over h1
for i in range(len(h1)):
    if h1[i] == np.max(h1):  # Use np.max() for getting the maximum 
value
        Vector1.append(1)
    else:
        Vector1.append(0)

# Iterate over h2
for i in range(len(h2)):
    if h2[i] == np.max(h2):  # Use np.max() for getting the maximum 
value
        Vector2.append(1)
    else:
        Vector2.append(0)

# Iterate over Yout
for i in range(len(Yout)):
    if Yout[i] == np.max(Yout):  # Use np.max() for getting the 
maximum value
        Vector3.append(1)
    else:
```

```
        Vector3.append(0)



# Display vectors after training
print()
print("The vectors after training")
print(Vector1)
print(Vector2)
print(Vector3)
```

```
The Prediction of h1 is:  [0.80049902 0.        ]
The Prediction of h2 is:  [0.59171401 0.85649821]
The Prediction of Yout is:  [0.70576331 0.31212824 1.13623435]
[1, 0]
[0, 1]
[0, 0, 1]
```

Final Output: apply softmax on the Output vector Yout

$$\text{Softmax}(y_2) = \frac{e^{y_2}}{\sum e^{y_2}}$$

Steps:

- finding ey2
- Applying softmax on Yout
- Probabilities of prediction
- logic to convert prediction into vector representation
- Print the whole prediction with predictive vector

```
# finding ey2
Exponencial_Yout = []
for i in range(len(Yout)):
   e = np.exp(Yout[i])
   Exponencial_Yout.append(e)


# Applying softmax on Yout
predictions = []
for i in range(len(Exponencial_Yout)):
    softmax = Exponencial_Yout[i] / np.sum(Exponencial_Yout)
    predictions.append(softmax)
```

```python
# Probabilities of predictions
predictions = np.array(predictions)
print("The final predictions after SOFTMAX is")
print(predictions)


# logic to convert prediction to vector representation
predicted_vector = []
for i in range(len(predictions)):
    if predictions[i] == max(predictions):
        predicted_vector.append(1)
    else:
        predicted_vector.append(0)


# Print the whole predcition with predictive vector
print()
print("When the input is  (I Eat) ....")
print("The predicted Vector is: ", predicted_vector,"--> Cake")
print("The resultant prediction I eat -->[Cake: [0 0 1]]")
```

```
The final predictions after SOFTMAX is
[0.3112761  0.20998692 0.47873698]

When the input is  (I Eat) ....
The predicted Vector is:  [0, 0, 1] --> Cake
The resultant prediction I eat -->[Cake: [0 0 1]]
```

Detailed overview:

The input data and vector representations

The input sentence: "I eat Cake". Three words, three timestamps The model trained on three vectors started from timestamps (t = 0, t = 1, t = 2).

- **x1: [1 0 0]** *vector representation of -> **["I"]** ---> t = 0*
- **x2: [0 1 0]** *vector representation of -> **["eat"]** ---> t = 1*
- **x3: [0 0 1]** *vector representation of -> **["Cake"]** --->t = 2*

Understanding the Logic

The logic and rule behind vectors:

- 1 for high *Probability*.
- 0 for low *Probability*.

Example-1.1: Example probabilities.

by using 1 and 0 logic

- [0.31] --->low means 0
- [0.20] --->low means 0
- [0.47] --->high means 1

Conclusion:

Resultant vector or predicted_vector will become: [0 0 1]. At the end, training from ***(t=0, t=1, and*** *UPTO* ***t=3).***
*Which Means****: According to the predicted_vector if the input is ("I" "eat")*** THEN*** the predicted word should be a "cake". We already proved that the vector representation of the ["cake": [0 0 1]]. *As already discuss in **Example-1.1** the logic and representation of the data.