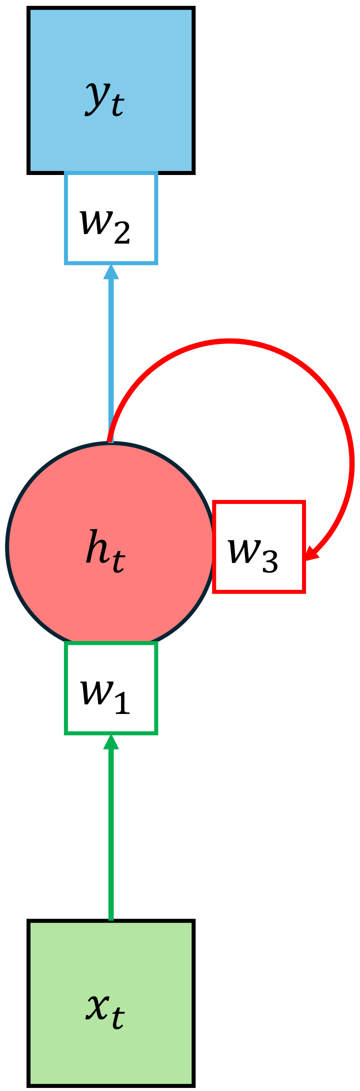
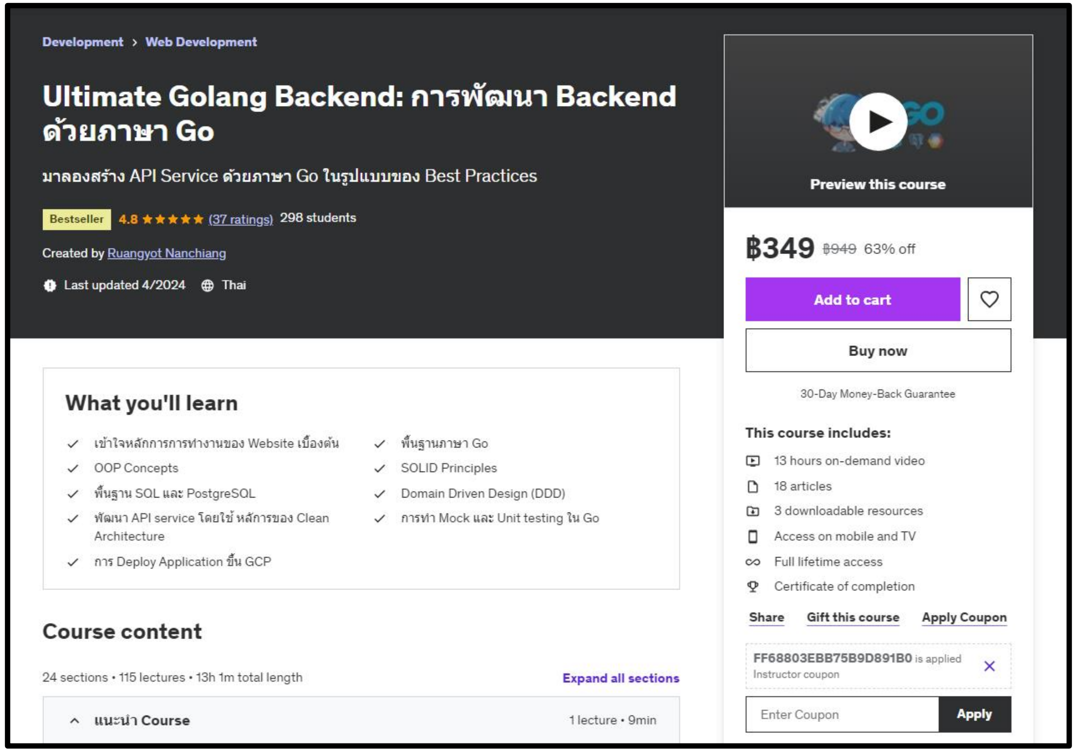
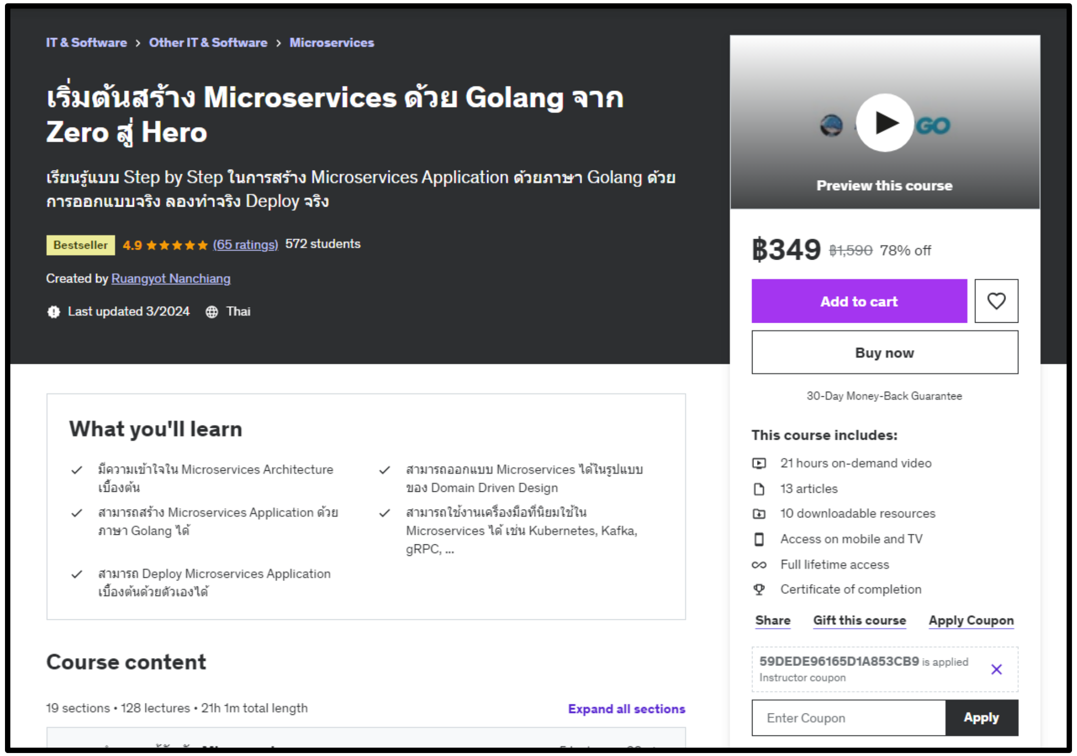
Recurrent Neural Network (RNN)





Development › Web Development
Ultimate Golang Backend: การพัฒนา Backend ด้วยภาษา Go
มาลองสร้าง API Service ด้วยภาษา Go ในรูปแบบของ Best Practices
Bestseller 4.8 (37 ratings) 298 students
Created by Ruangyot Nanchiang
Last updated 4/2024 Thai
Preview this course
฿349 ฿949 63% off
Add to cart
Buy now
30-Day Money-Back Guarantee
This course includes:
13 hours on-demand video
18 articles
3 downloadable resources
Access on mobile and TV
Full lifetime access
Certificate of completion
Share Gift this course Apply Coupon
FF68803EBB75B9D891B0 is applied
Instructor coupon
Enter Coupon Apply
What you'll learn
เข้าใจหลักการการทำงานของ Website เบื้องต้น
OOP Concepts
พื้นฐาน SQL และ PostgreSQL
พัฒนา API service โดยใช้ หลักการของ Clean Architecture
การ Deploy Application ขึ้น GCP
พื้นฐานภาษา Go
SOLID Principles
Domain Driven Design (DDD)
การทำ Mock และ Unit testing ใน Go
Course content
24 sections • 115 lectures • 13h 1m total length
Expand all sections
แนะนำ Course 1 lecture • 9min



IT & Software › Other IT & Software › Microservices
เริ่มต้นสร้าง Microservices ด้วย Golang จาก Zero สู่ Hero
เรียนรู้แบบ Step by Step ในการสร้าง Microservices Application ด้วยภาษา Golang ด้วยการออกแบบจริง ลองทำจริง Deploy จริง
Bestseller 4.9 (65 ratings) 572 students
Created by Ruangyot Nanchiang
Last updated 3/2024 Thai
Preview this course
฿349 ฿1,590 78% off
Add to cart
Buy now
30-Day Money-Back Guarantee
This course includes:
21 hours on-demand video
13 articles
10 downloadable resources
Access on mobile and TV
Full lifetime access
Certificate of completion
Share Gift this course Apply Coupon
59DEDE96165D1A853CB9 is applied
Instructor coupon
Enter Coupon Apply
What you'll learn
มีความเข้าใจใน Microservices Architecture เบื้องต้น
สามารถสร้าง Microservices Application ด้วยภาษา Golang ได้
สามารถ Deploy Microservices Application เบื้องต้นด้วยตัวเองได้
สามารถออกแบบ Microservices ได้ในรูปแบบของ Domain Driven Design
สามารถใช้งานเครื่องมือที่นิยมใช้ใน Microservices ได้ เช่น Kubernetes, Kafka, gRPC, ...
Course content
19 sections • 128 lectures • 21h 1m total length
Expand all sections

Let’s said you want to do **ANN**
to predict music notes scale.

For example, need to predict next note of input in **C major scale**.

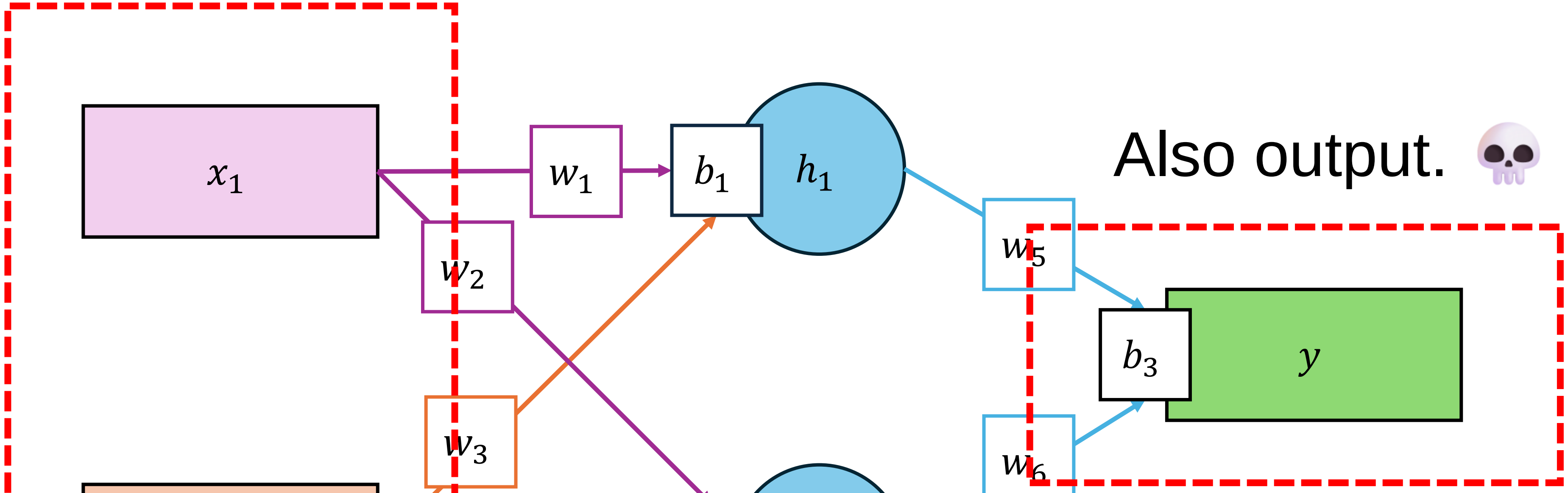
C Major Scale: C D E F G A B C …

Input: F → **Output:** G

Input: C D → **Output:** E

But, this is how **ANN** looks like.

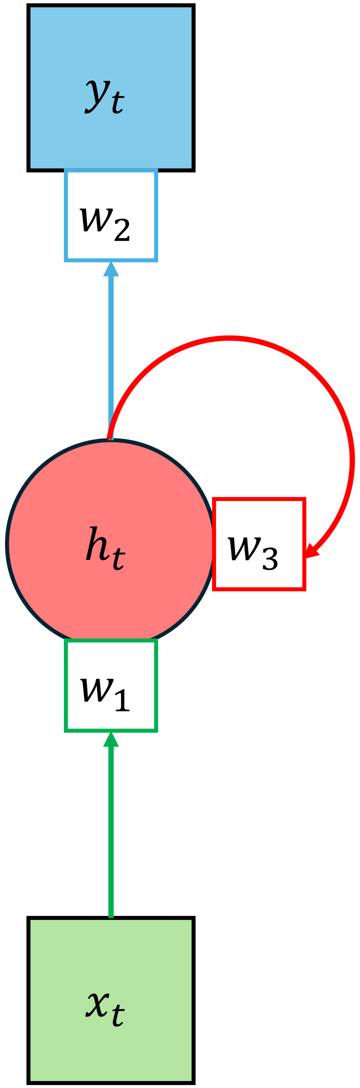
The input was **fixed**. 💀

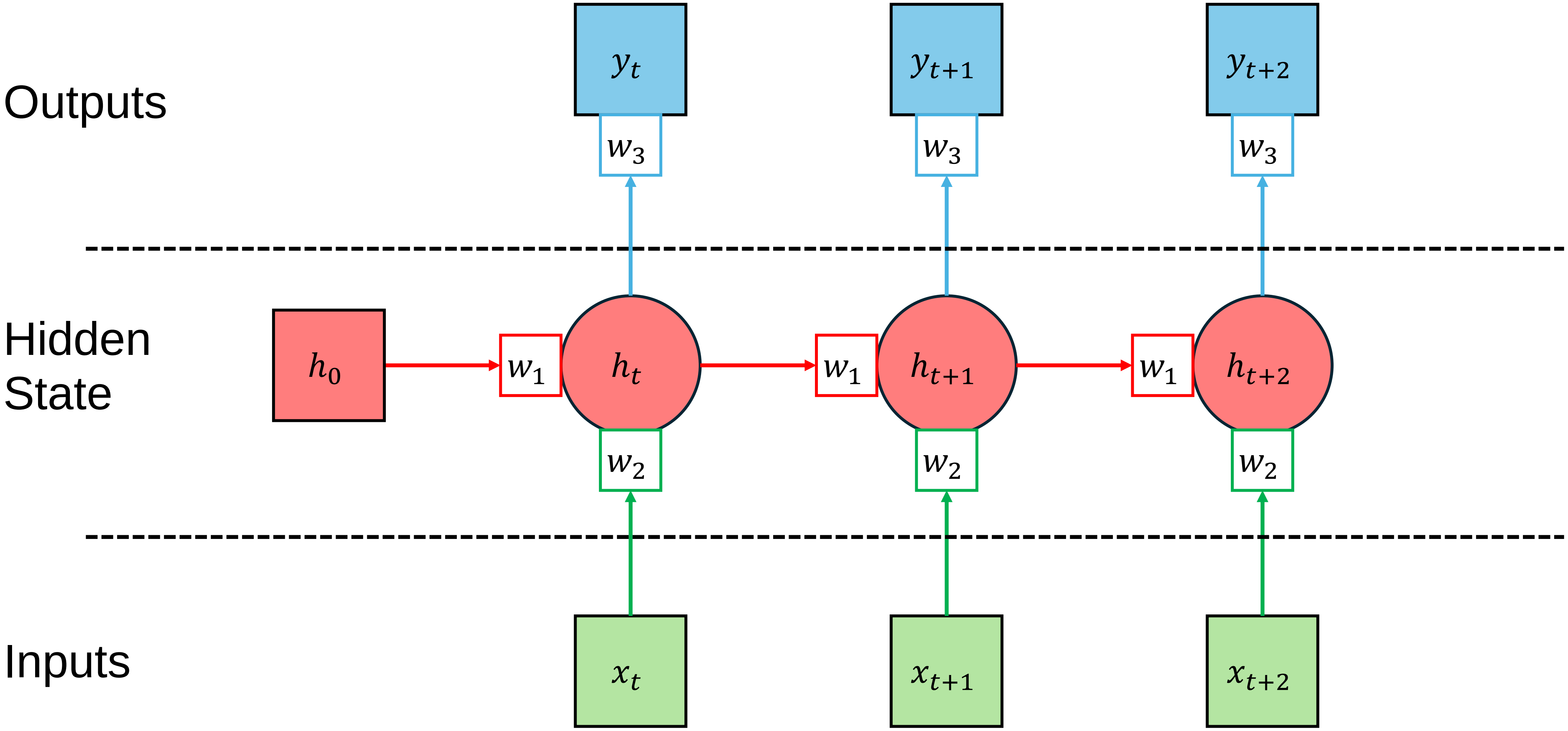


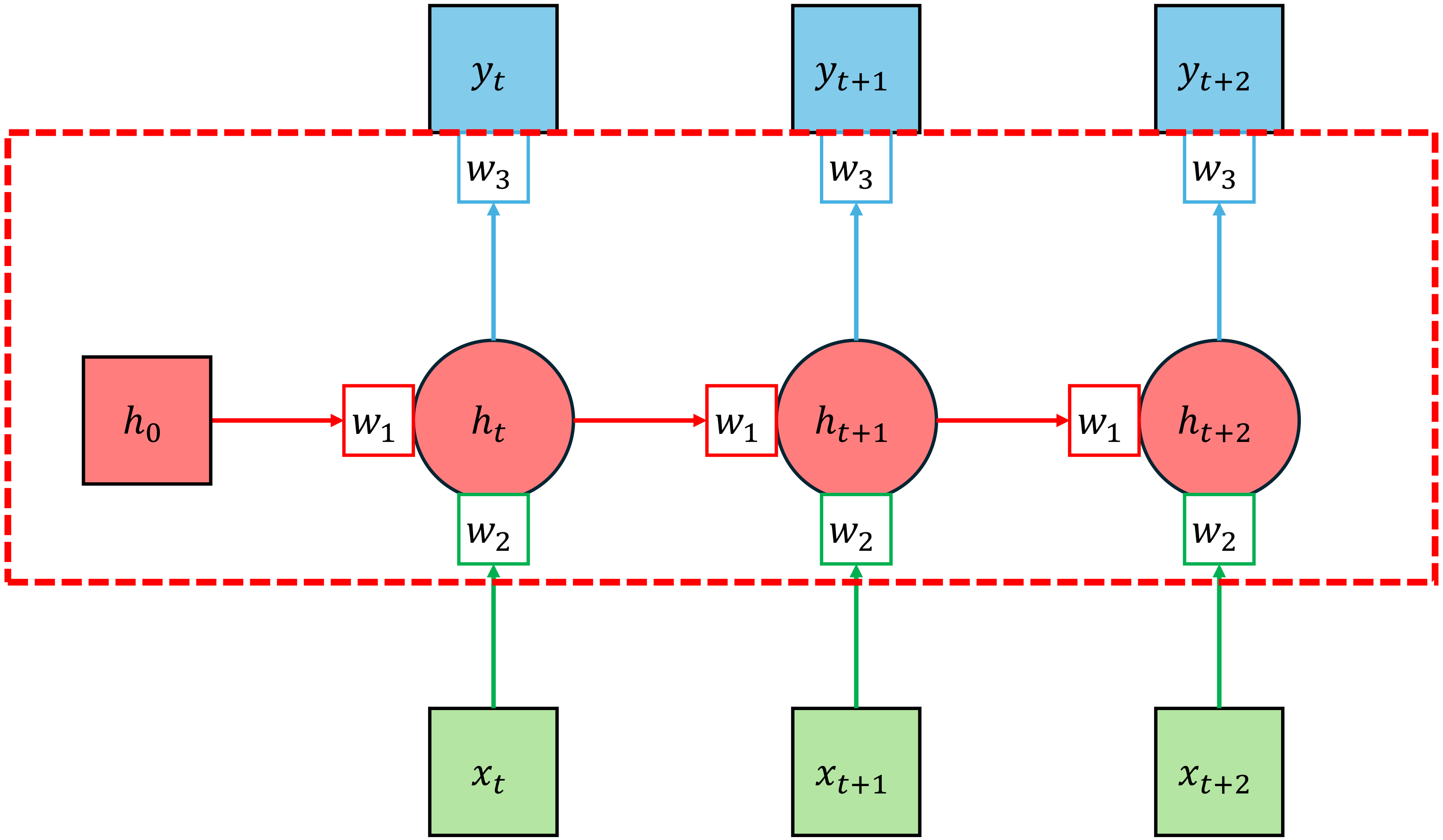
Also output. 💀

To solve this problem, we're going to use **RNN** model.

Because, RNN can solve a **time series problem**.




Outputs
Hidden State
Inputs
y_t
y_{t+1}
y_{t+2}
w_3
w_3
w_3
h_0
w_1
h_t
w_1
h_{t+1}
w_1
h_{t+2}
w_2
w_2
w_2
x_t
x_{t+1}
x_{t+2}

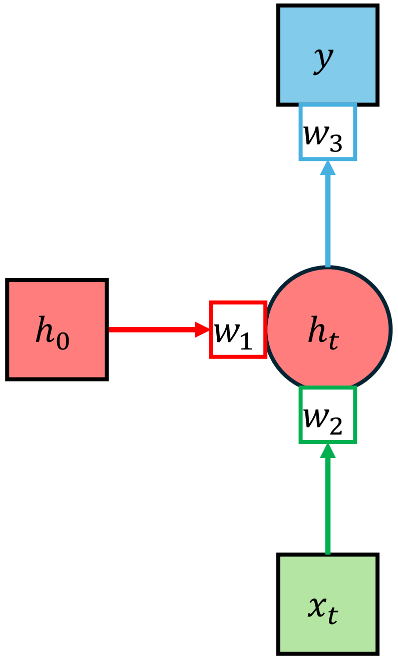


Note:

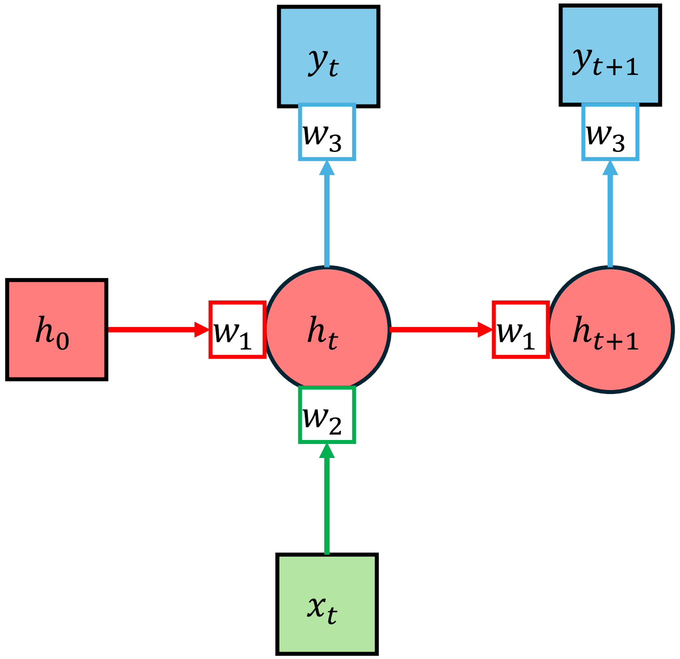
RNN always use the **same weights** and bias for every hidden states.

Types of **RNN**

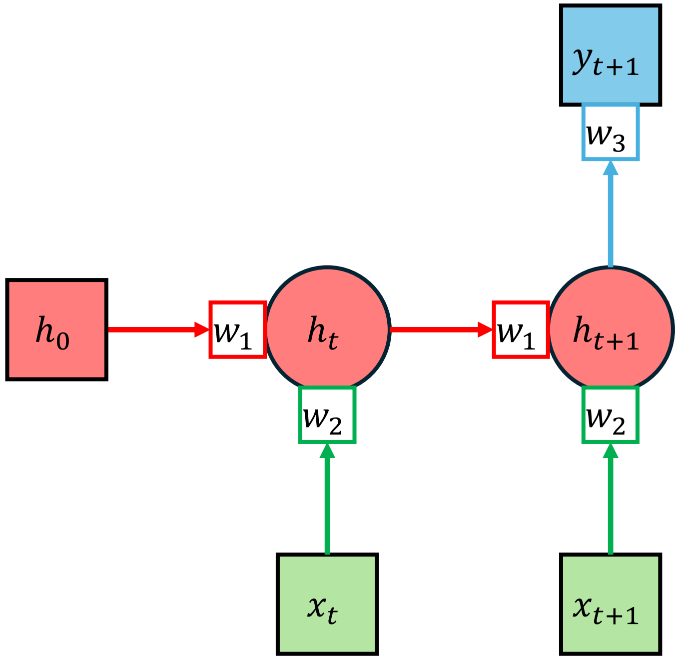
One to One



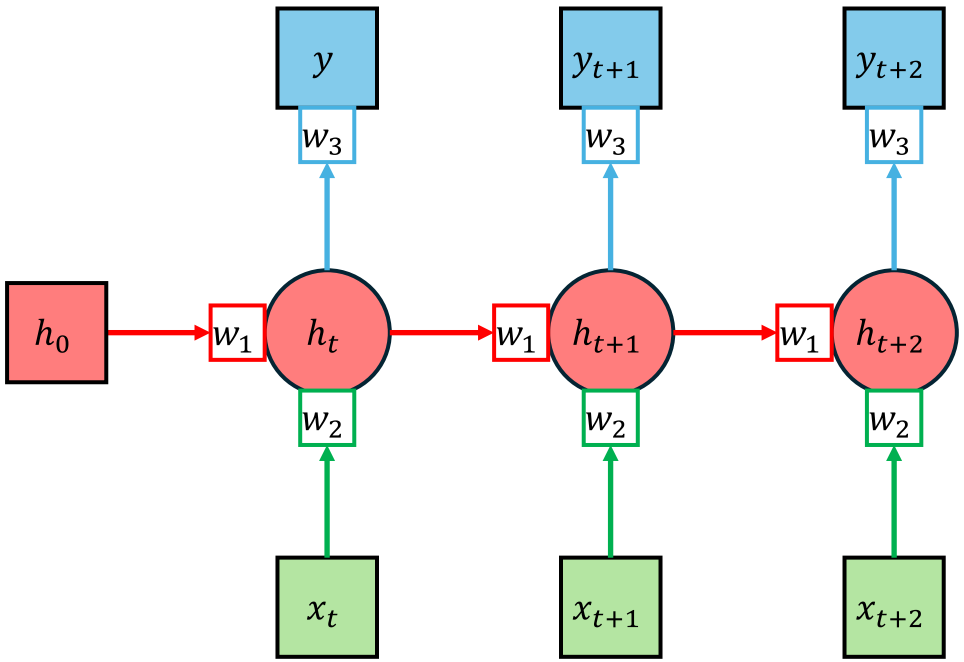
One to Many



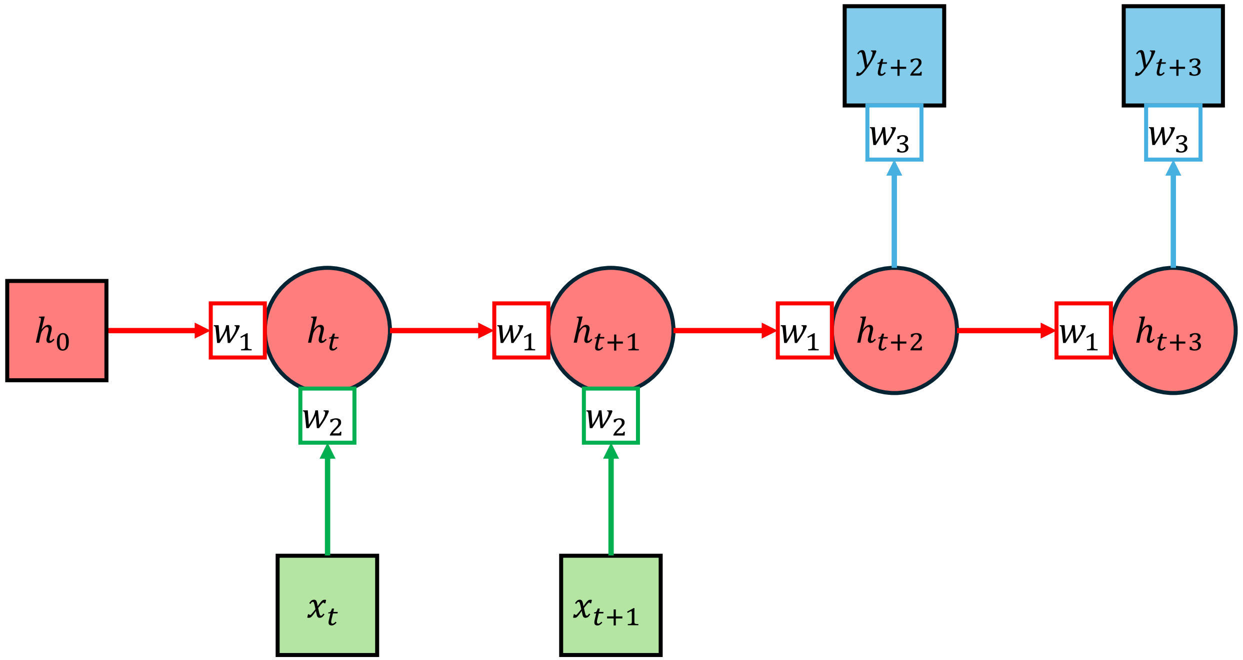
Many to One



Many to **Many**



Many to **Many**



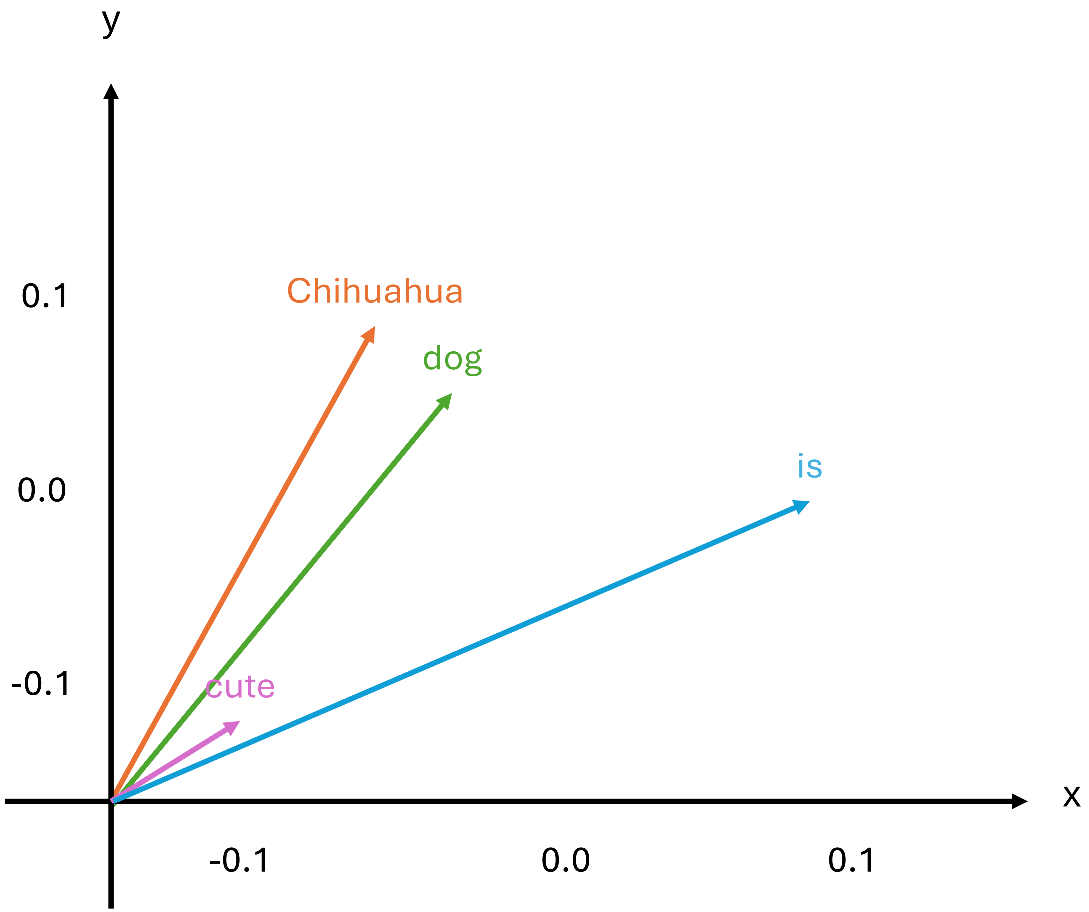
For example, need to predict next note of input in **C major scale**.

C Major Scale: C D E F G A B C …

Input: F → **Output:** G

Input: C D → **Output:** E

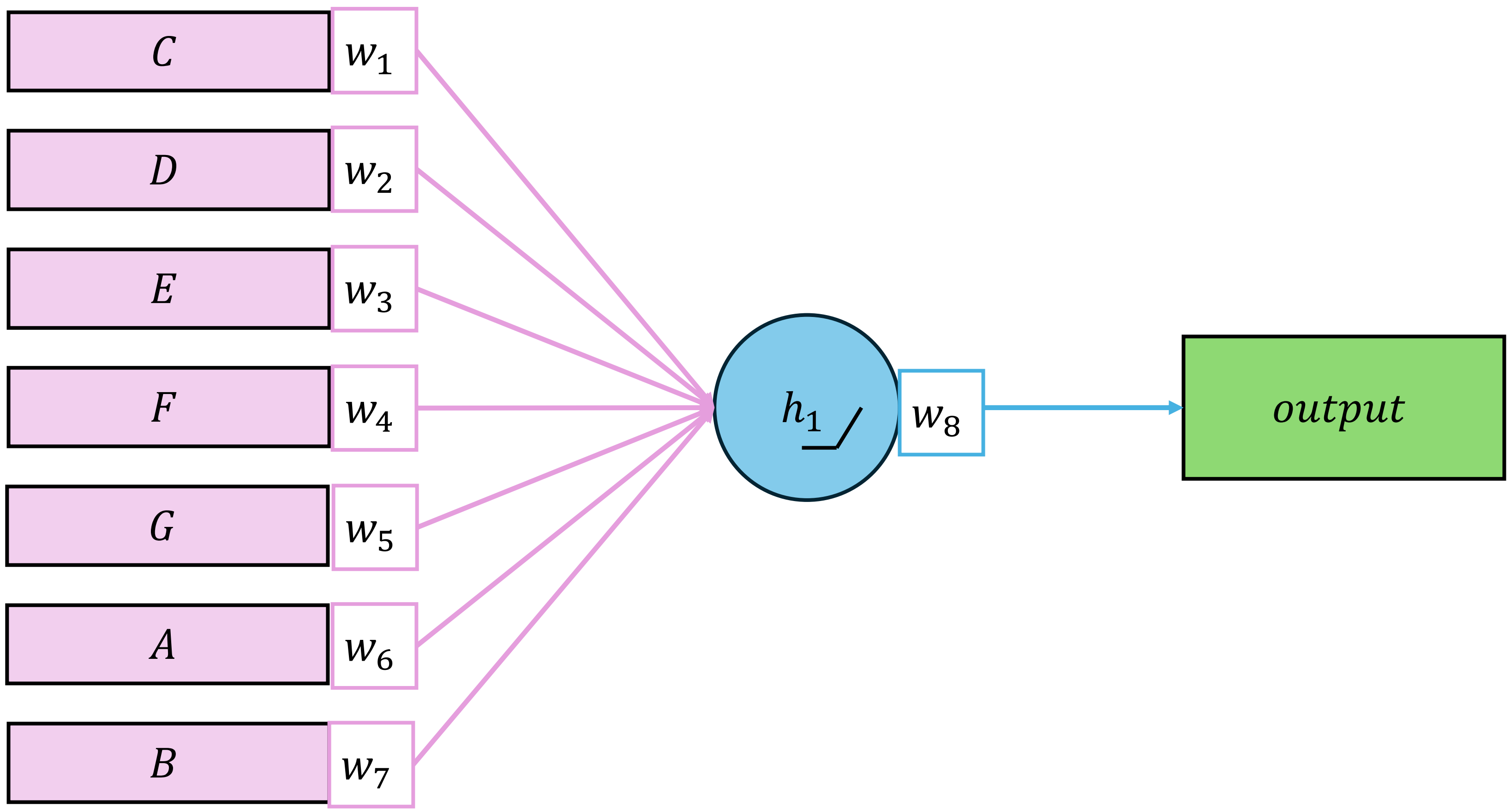
Word Embedding + Word2Vec



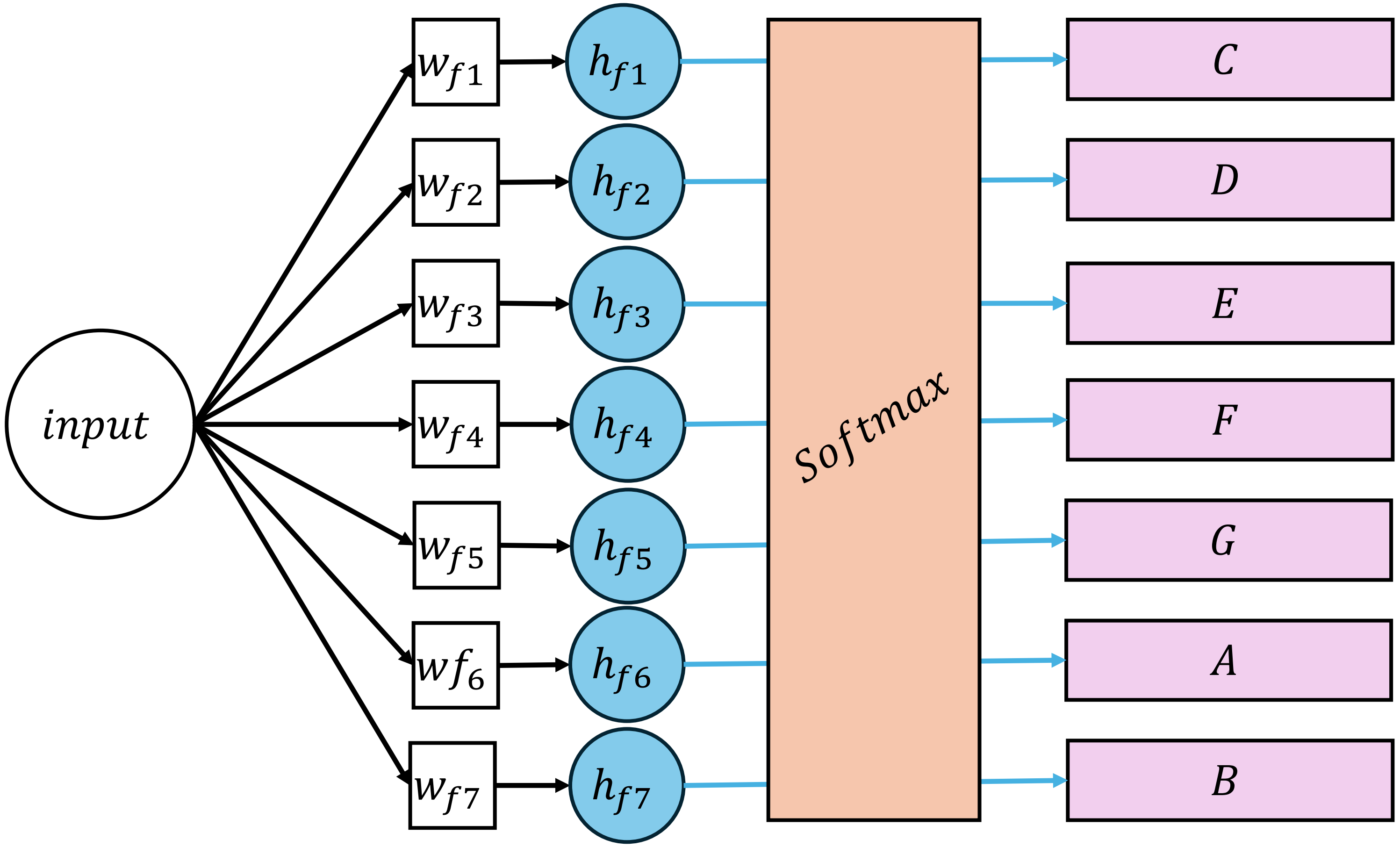
One Hot Encode to All Notes

	C	D	E	F	G	A	B
C	1	0	0	0	0	0	0
D	0	1	0	0	0	0	0
E	0	0	1	0	0	0	0
F	0	0	0	1	0	0	0
G	0	0	0	0	1	0	0
A	0	0	0	0	0	1	0
B	0	0	0	0	0	0	1

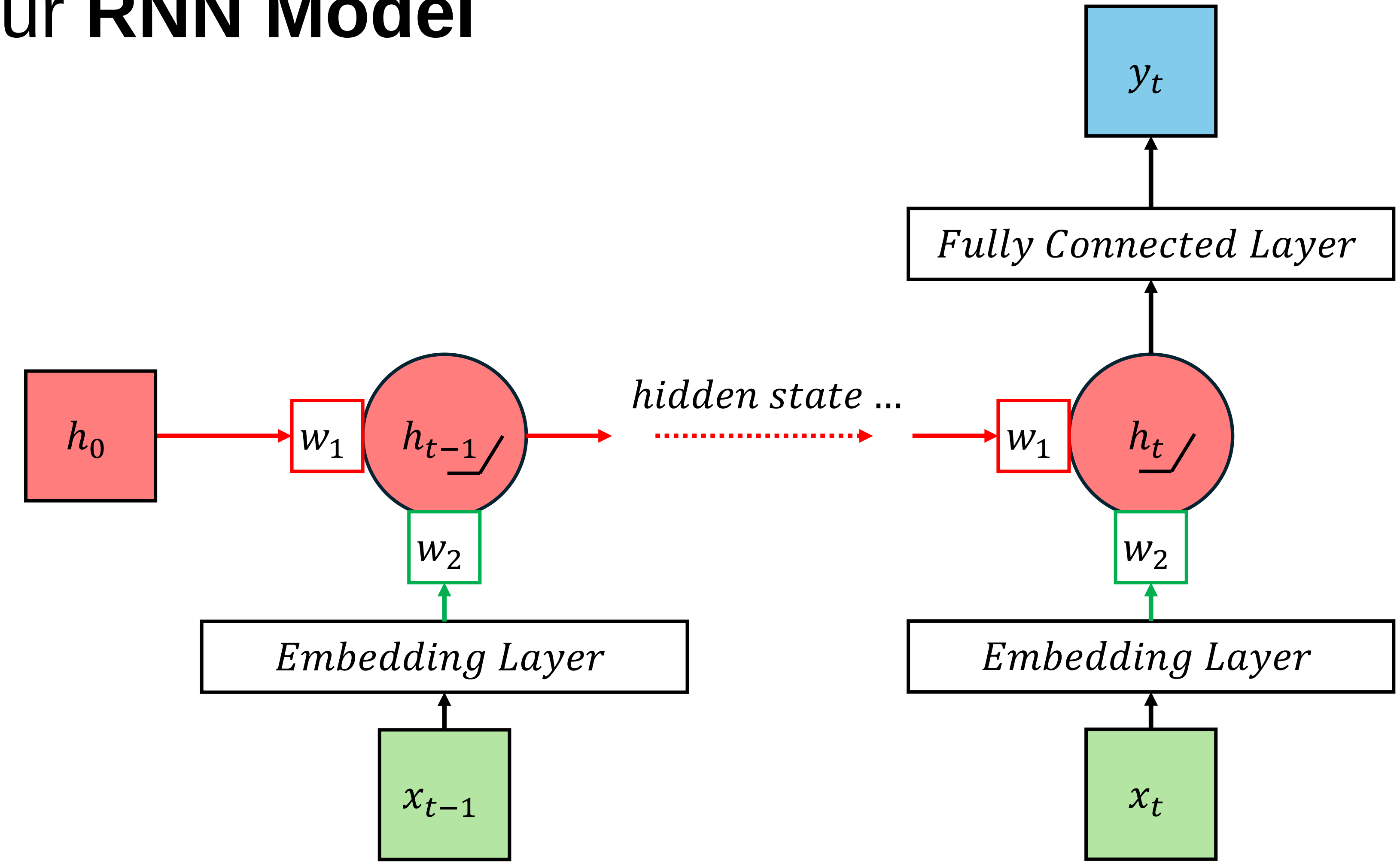
Embedding Layer



Fully Connected Layer



This is our **RNN Model**



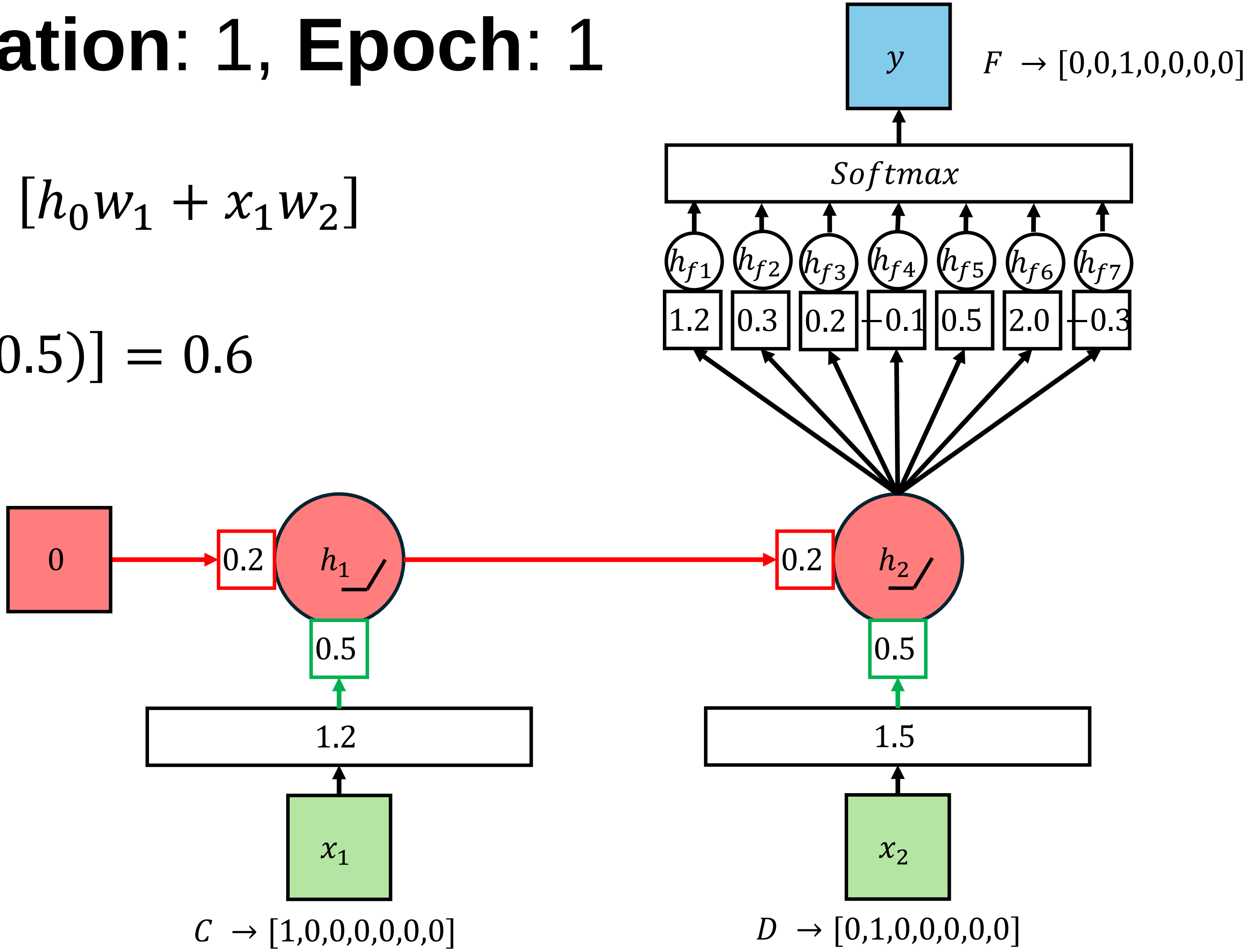
Let's **forward propagation**

Hidden State	Input	Output
1	[1,0,0,0,0,0,0]	None
2	[0,1,0,0,0,0,0]	[0,0,1,0,0,0,0]

Iteration: 1, **Epoch**: 1

$$[sum_1] = [h_0 \quad x_1] \times \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} = [h_0 w_1 + x_1 w_2]$$

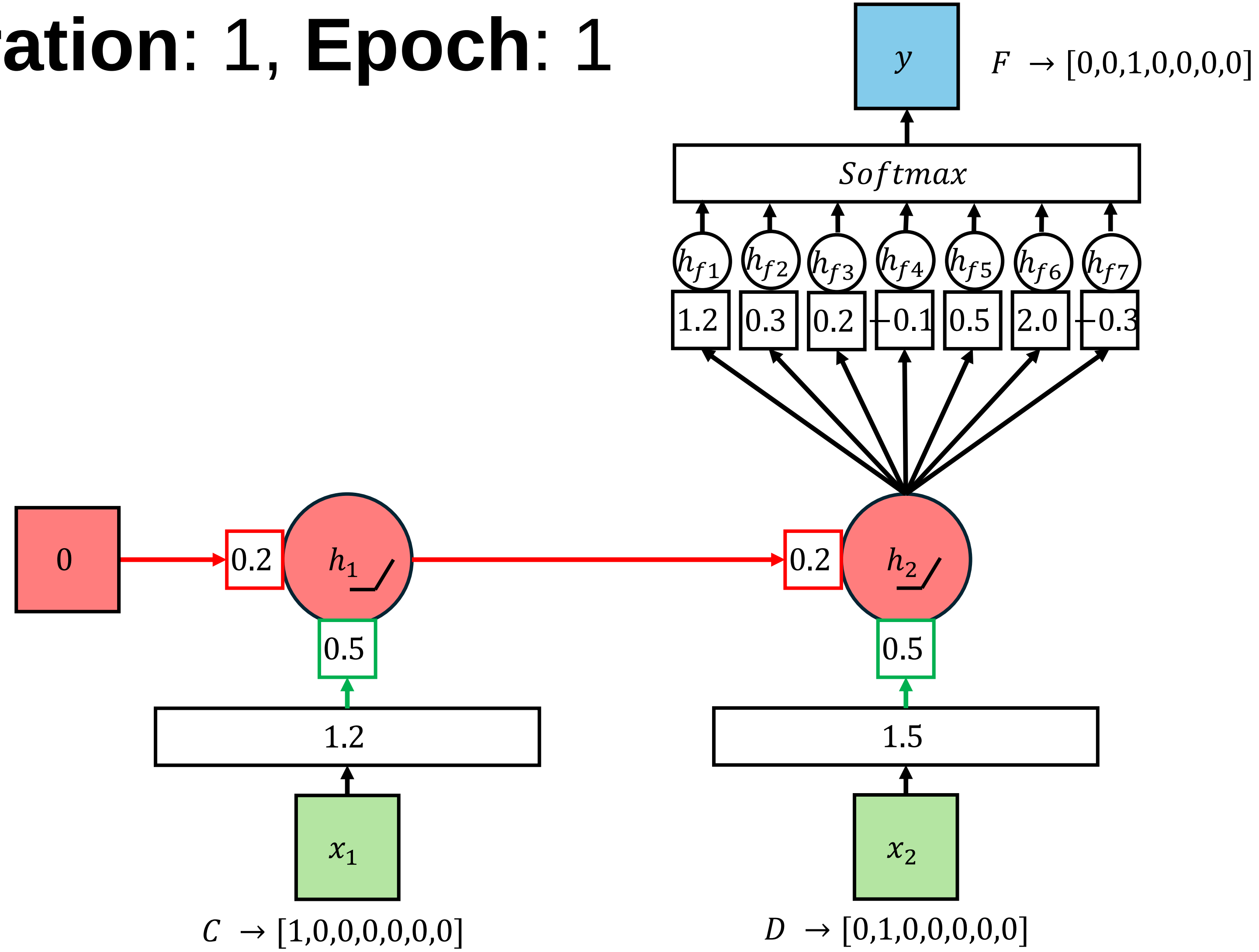
$$[sum_1] = [(0)(0.2) + (1.2)(0.5)] = 0.6$$



Iteration: 1, **Epoch**: 1

$$[h_1] = [ReLU(sum_1)]$$

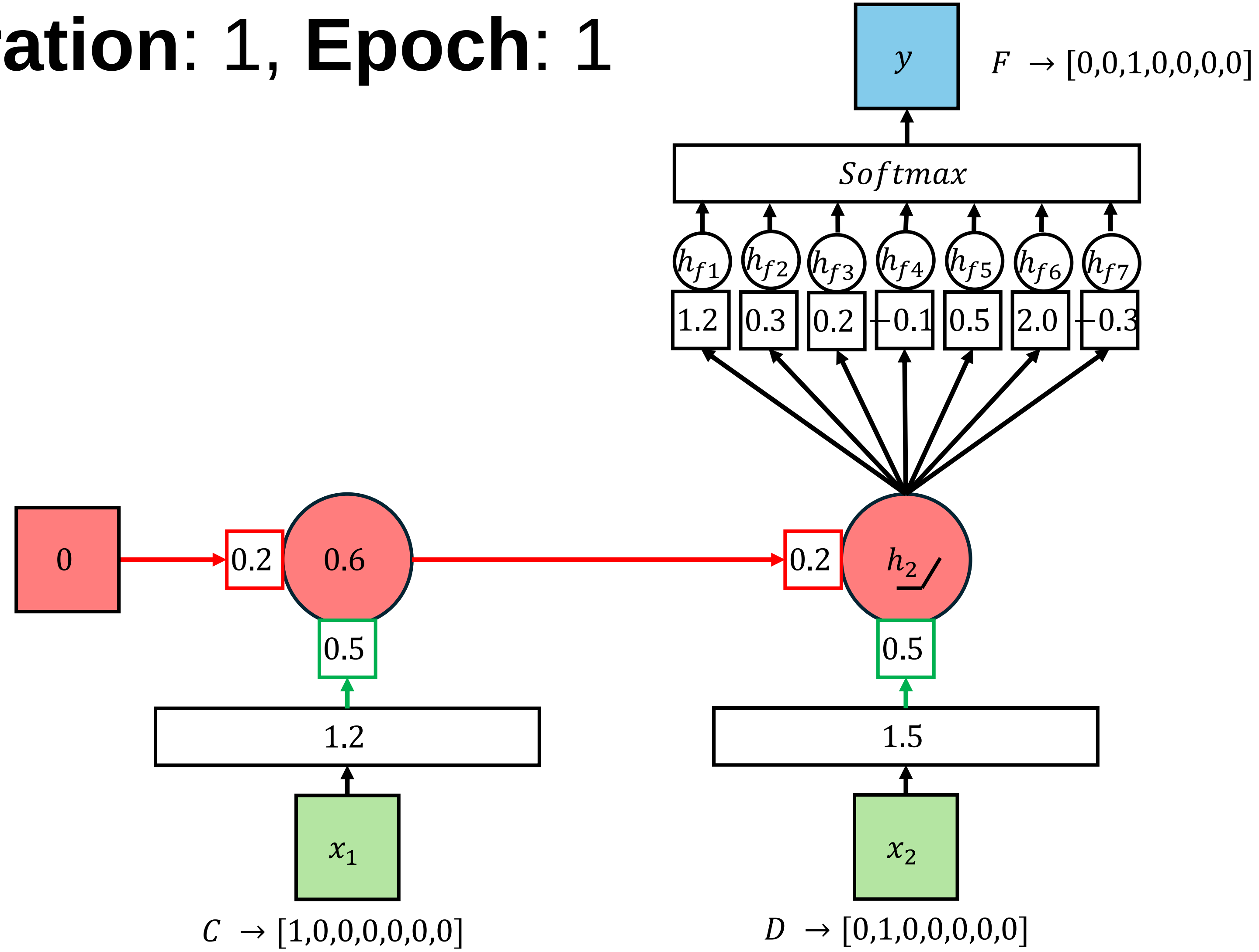
$$[h_1] = [ReLU(0.6)] = 0.6$$



Iteration: 1, **Epoch**: 1

$$[h_1] = [ReLU(sum_1)]$$

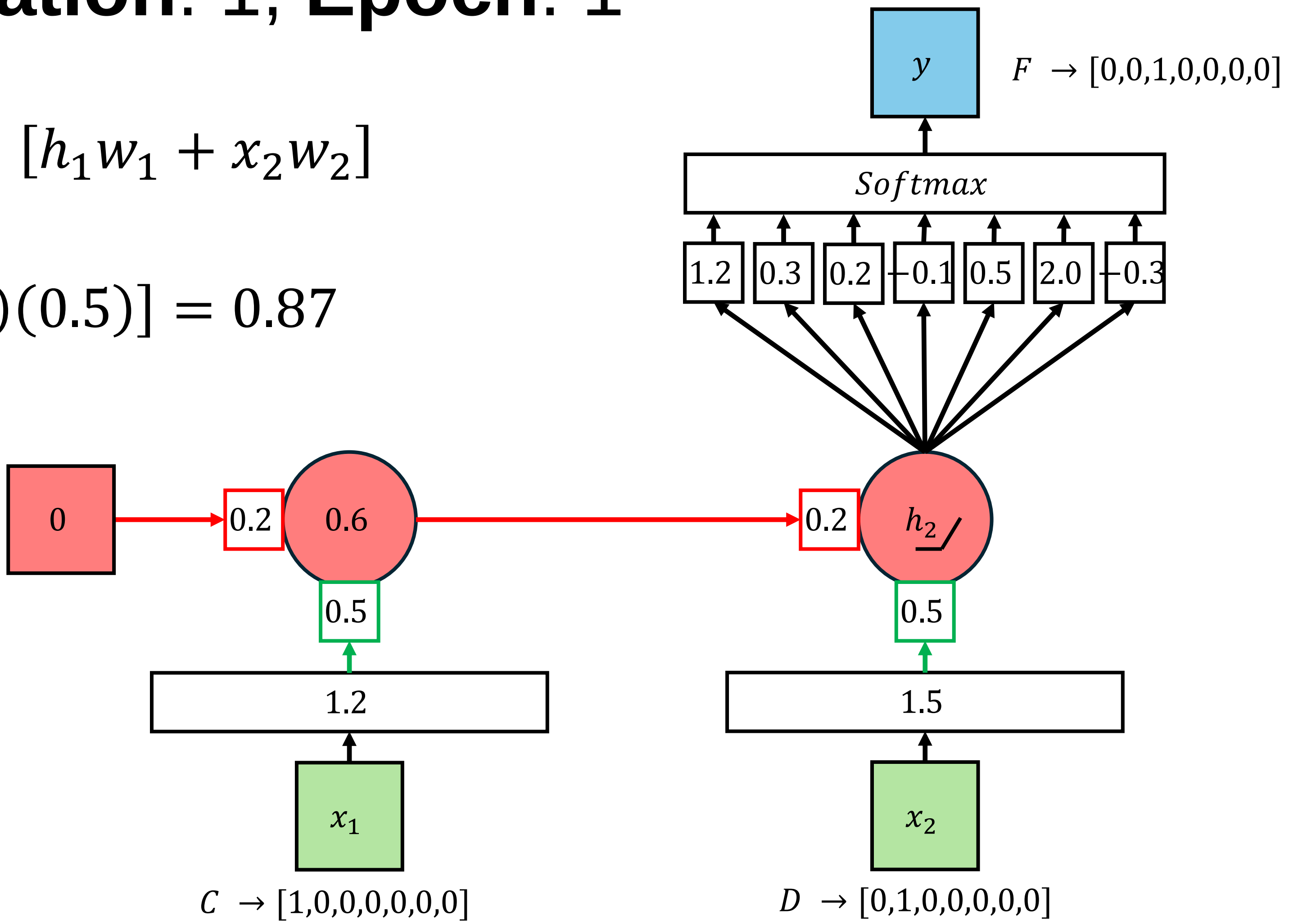
$$[h_1] = [ReLU(0.6)] = 0.6$$



Iteration: 1, **Epoch**: 1

$$[sum_2] = [h_1 \quad x_2] \times \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} = [h_1 w_1 + x_2 w_2]$$

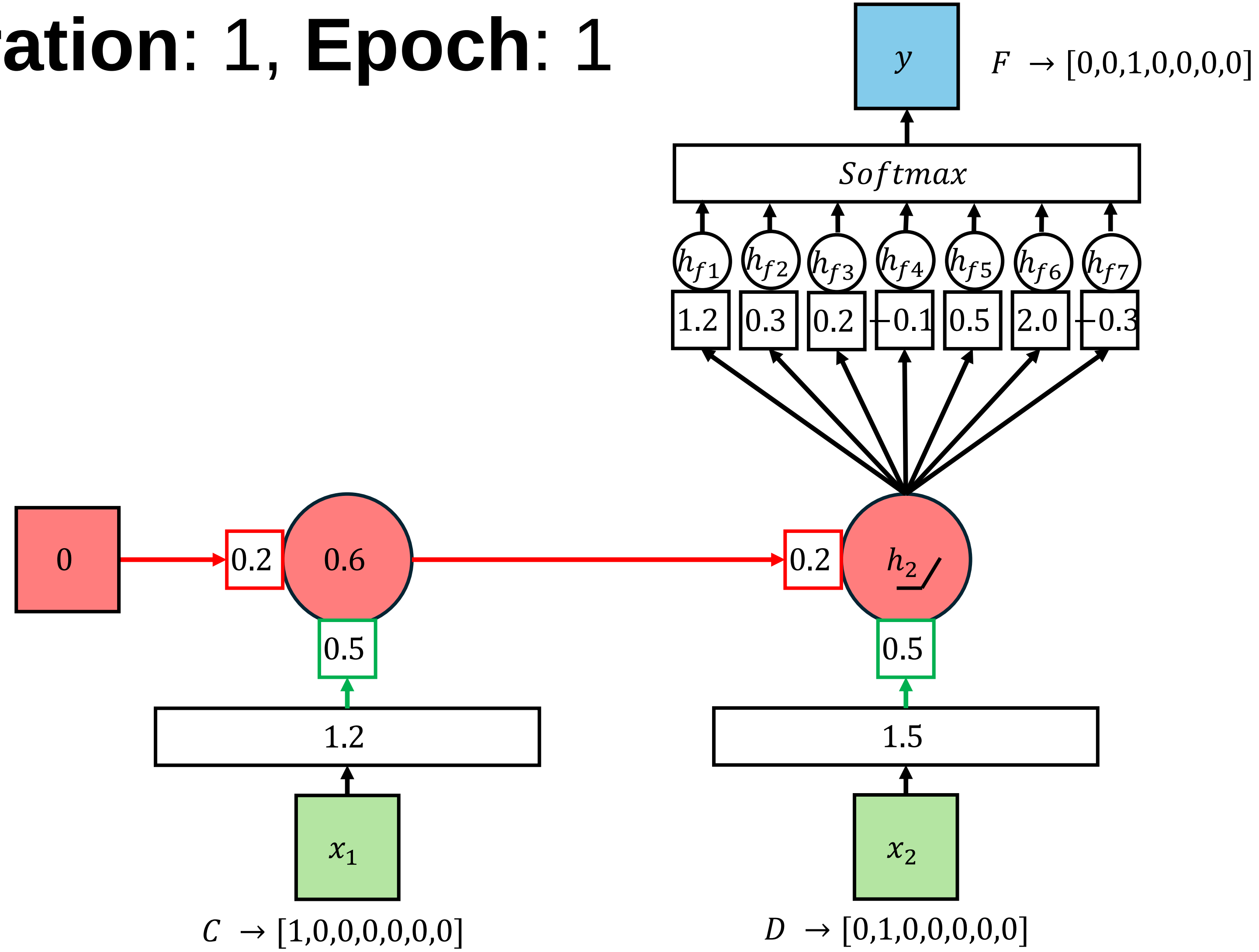
$$[sum_2] = [(0.6)(0.2) + (1.5)(0.5)] = 0.87$$



Iteration: 1, **Epoch**: 1

$$[h_2] = [ReLU(sum_2)]$$

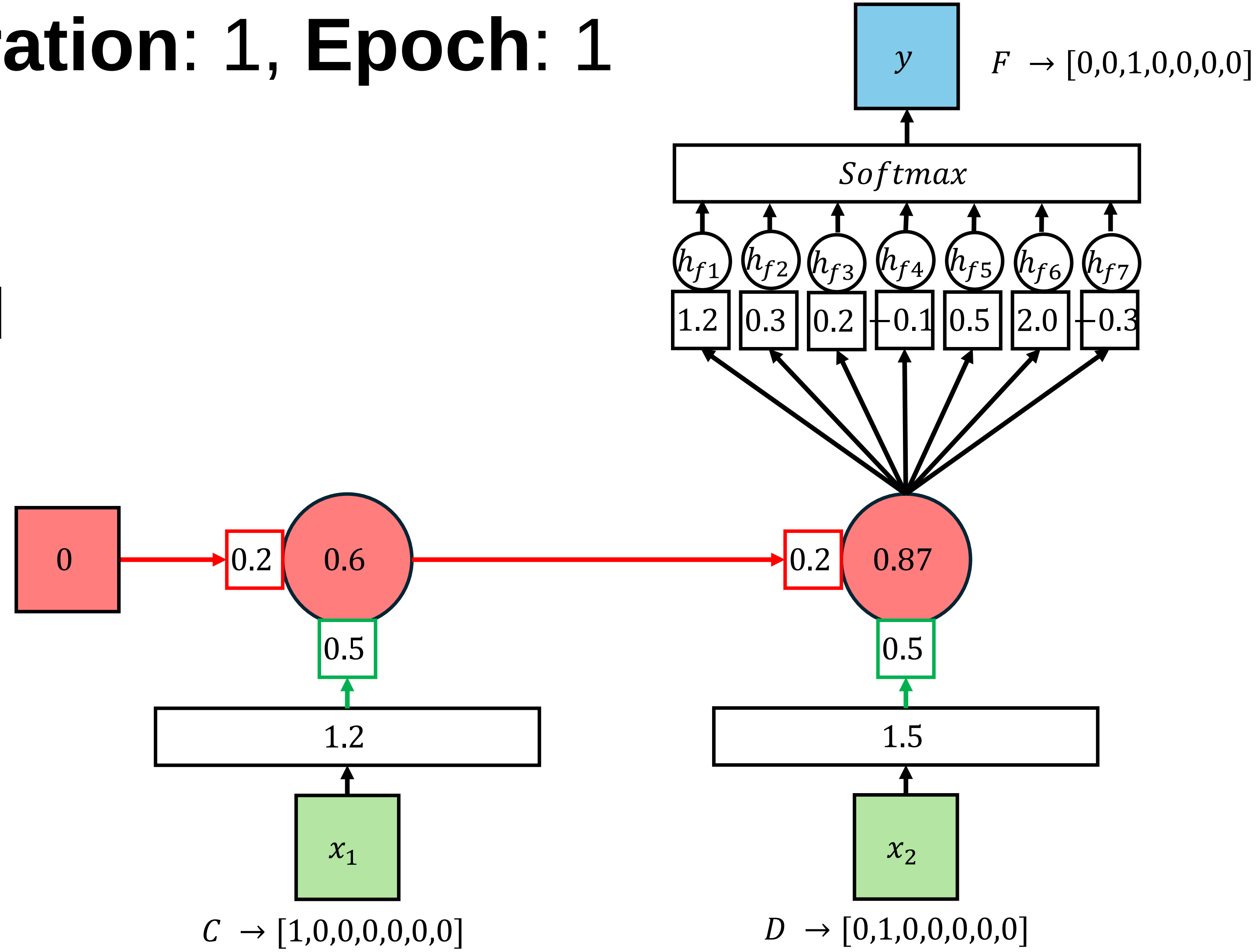
$$[h_2] = [ReLU(0.87)] = 0.87$$



Iteration: 1, **Epoch**: 1

$$[h_2] = [ReLU(sum_2)]$$

$$[h_2] = [ReLU(0.87)] = [0.87]$$



$$[h_{f1} \quad h_{f2} \quad h_{f3} \quad h_{f4} \quad h_{f5} \quad h_{f6} \quad h_{f7}] = [h_2] \times [w_{f1} \quad w_{f2} \quad w_{f3} \quad w_{f4} \quad w_{f5} \quad w_{f6} \quad w_{f7}]$$

$$[h_{f1} \quad h_{f2} \quad h_{f3} \quad h_{f4} \quad h_{f5} \quad h_{f6} \quad h_{f7}] = [0.87] \times [1.2 \quad 0.3 \quad 0.2 \quad -0.1 \quad 0.5 \quad 2.0 \quad -0.3]$$

$$[S_1 \quad S_2 \quad S_3 \quad S_4 \quad S_5 \quad S_6 \quad S_7] = Softmax([1.04 \quad 2.06 \quad 0.17 \quad -0.08 \quad 0.44 \quad 1.74 \quad -0.26])$$

$$[S_1 \quad S_2 \quad S_3 \quad S_4 \quad S_5 \quad S_6 \quad S_7] = [0.2 \quad 0.09 \quad 0.08 \quad 0.06 \quad 0.11 \quad 0.4 \quad 0.05]$$

$$[C \quad D \quad E \quad F \quad G \quad A \quad B] = [1 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0]$$

$\boldsymbol{Input}$: $C, D \rightarrow \boldsymbol{Answer}$: C

$\boldsymbol{But\ True\ Answer}$: E

Loss Calculation

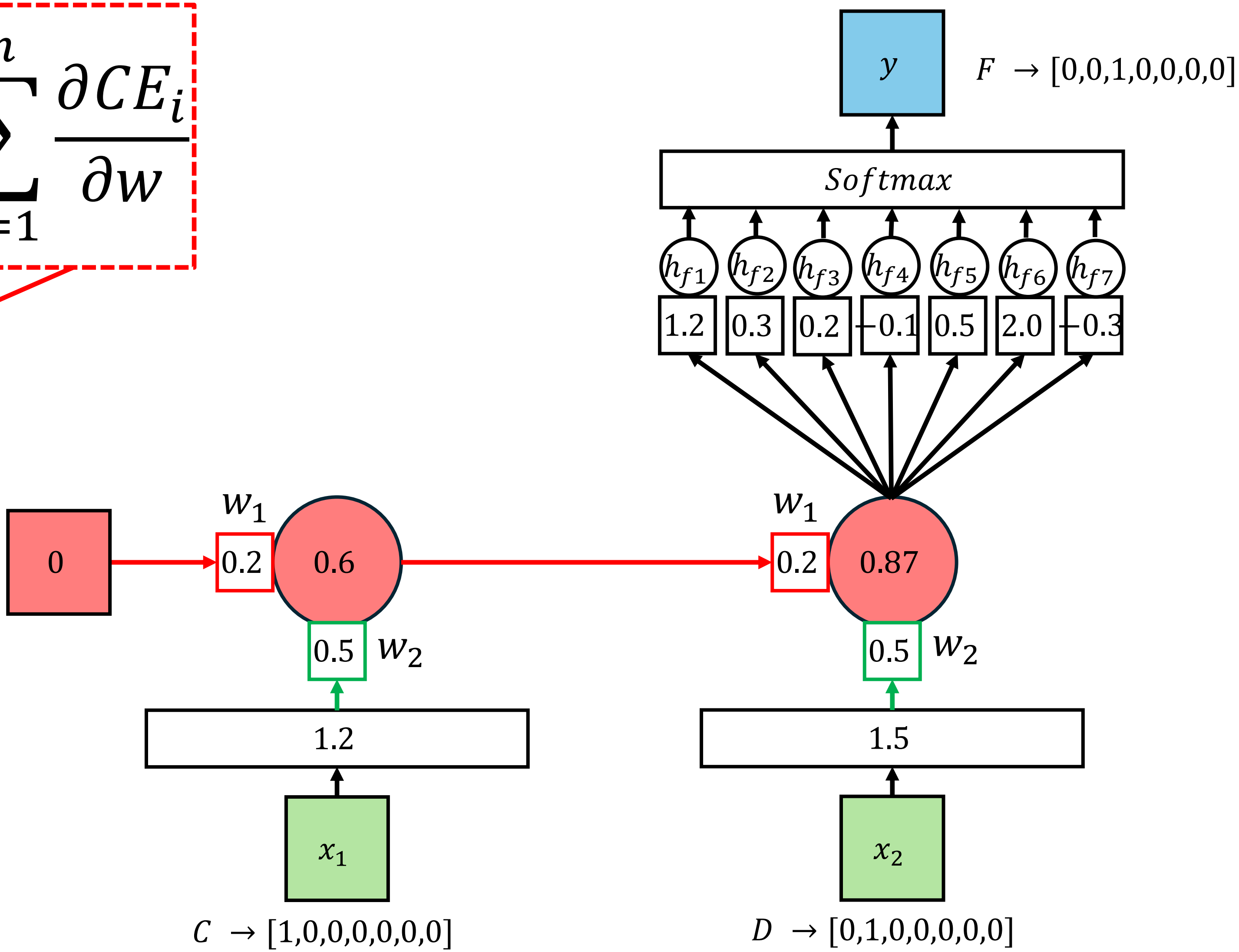
$$CE = -\sum_{i=1}^{n} Observed \cdot \log(Softmax_i)$$

$$CE = -\log(0.08) = 1.04$$

Let’s **backpropagation**

$$w_{new} = w_{current} - \alpha \boxed{\sum_{i=1}^{n} \frac{\partial CE_i}{\partial w}}$$

$$\sum_{i=1}^{n} \frac{\partial CE_i}{\partial w} = \begin{bmatrix} \sum_{i=1}^{n} \frac{\partial CE_i}{\partial w_1} \\ \sum_{i=1}^{n} \frac{\partial CE_i}{\partial w_2} \end{bmatrix}$$



Shared Weights

$$\sum_{i=1}^{n}\frac{\partial CE_i}{\partial w_2}=\sum_{i=1}^{n}\frac{\partial CE_i}{\partial S_{fi}}\cdot\frac{\partial S_{fi}}{\partial h_{fi}}\cdot\frac{\partial h_{fi}}{\partial h_2}\cdot\frac{\partial}{\partial w_2}(x_2w_2+h_1w_1)$$

Beware this little sh*t

$$\boldsymbol{Where}:\ \frac{\partial}{\partial w_2}(x_2w_2+h_1w_1)=\frac{\partial h_2}{\partial w_2}+\frac{\partial h_2}{\partial h_1}\cdot\frac{\partial h_1}{\partial w_2}$$

$$\sum_{i=1}^{n}\frac{\partial CE_i}{\partial w_2}=\sum_{i=1}^{n}\frac{\partial CE_i}{\partial S_{fi}}\cdot\frac{\partial S_{fi}}{\partial h_{fi}}\cdot\frac{\partial h_{fi}}{\partial h_2}\cdot\left(\frac{\partial h_2}{\partial w_2}+\frac{\partial h_2}{\partial h_1}\cdot\frac{\partial h_1}{\partial w_2}\right)$$

$$\boldsymbol{Therefore}:\ \sum_{i=1}^{n}\frac{\partial CE_i}{\partial w_2}=\sum_{i=1}^{n}\frac{\partial CE_i}{\partial S_{fi}}\cdot\frac{\partial S_{fi}}{\partial h_{fi}}\cdot\frac{\partial h_{fi}}{\partial h_2}\cdot\frac{\partial h_2}{\partial w_2}+\sum_{i=1}^{n}\frac{\partial CE_i}{\partial S_{fi}}\cdot\frac{\partial S_{fi}}{\partial h_{fi}}\cdot\frac{\partial h_{fi}}{\partial h_2}\cdot\frac{\partial h_2}{\partial h_1}\cdot\frac{\partial h_1}{\partial w_2}$$

Shared Weights

$$\sum_{i=1}^{n}\frac{\partial CE_i}{\partial w_1}=\sum_{i=1}^{n}\frac{\partial CE_i}{\partial S_{fi}}\cdot\frac{\partial S_{fi}}{\partial h_{fi}}\cdot\frac{\partial h_{fi}}{\partial h_2}\cdot\boxed{\frac{\partial h_2}{\partial w_1}}+\sum_{i=1}^{n}\frac{\partial CE_i}{\partial S_{fi}}\cdot\frac{\partial S_{fi}}{\partial h_{fi}}\cdot\frac{\partial h_{fi}}{\partial h_2}\cdot\boxed{\frac{\partial h_2}{\partial h_1}\cdot\frac{\partial h_1}{\partial w_1}}$$

What if our chain is too huge.

$$\sum_{i=1}^{n}\frac{\partial CE_i}{\partial w_n}=\sum_{i=1}^{n}\frac{\partial CE_i}{\partial S_{fi}}\cdot\frac{\partial S_{fi}}{\partial h_{fi}}\cdot\frac{\partial h_{fi}}{\partial h_n}\cdot\frac{\partial h_n}{\partial w_n}+\sum_{i=1}^{n}\frac{\partial CE_i}{\partial S_{fi}}\cdot\frac{\partial S_{fi}}{\partial h_{fi}}\cdot\frac{\partial h_{fi}}{\partial h_2}\cdot\frac{\partial h_n}{\partial h_{n-1}}\cdot\frac{\partial h_{n-1}}{\partial w_n}$$
$$+\sum_{i=1}^{n}\frac{\partial CE_i}{\partial S_{fi}}\cdot\frac{\partial S_{fi}}{\partial h_{fi}}\cdot\frac{\partial h_{fi}}{\partial h_n}\cdot\frac{\partial h_n}{\partial h_{n-1}}\cdot\frac{\partial h_{n-1}}{\partial h_{n-2}}\cdot\frac{\partial h_{n-2}}{\partial w_n}+$$
$$+\sum_{i=1}^{n}\frac{\partial CE_i}{\partial S_{fi}}\cdot\frac{\partial S_{fi}}{\partial h_{fi}}\cdot\frac{\partial h_{fi}}{\partial h_n}\cdot\frac{\partial h_n}{\partial h_{n-1}}\cdot\frac{\partial h_{n-1}}{\partial h_{n-2}}\cdot\frac{\partial h_{n-2}}{\partial h_{n-3}}\cdot\frac{\partial h_{n-3}}{\partial w_n}$$
$$+\cdots$$

Vanishing Gradient Problem

Shared Weights

$$\sum_{i=1}^{n}\frac{\partial CE_i}{\partial w_1}=\sum_{i=1}^{n}\frac{\partial CE_i}{\partial S_{fi}}\cdot\frac{\partial S_{fi}}{\partial h_{fi}}\cdot\frac{\partial h_{fi}}{\partial h_2}\cdot\boxed{\frac{\partial h_2}{\partial w_1}}+\sum_{i=1}^{n}\frac{\partial CE_i}{\partial S_{fi}}\cdot\frac{\partial S_{fi}}{\partial h_{fi}}\cdot\frac{\partial h_{fi}}{\partial h_2}\cdot\boxed{\frac{\partial h_2}{\partial h_1}\cdot\frac{\partial h_1}{\partial w_1}}$$

What if our chain is too huge.

$$\sum_{i=1}^{n}\frac{\partial CE_i}{\partial w_n}=\sum_{i=1}^{n}\frac{\partial CE_i}{\partial S_{fi}}\cdot\frac{\partial S_{fi}}{\partial h_{fi}}\cdot\frac{\partial h_{fi}}{\partial h_n}\cdot\frac{\partial h_n}{\partial w_n}+\sum_{i=1}^{n}\frac{\partial CE_i}{\partial S_{fi}}\cdot\frac{\partial S_{fi}}{\partial h_{fi}}\cdot\frac{\partial h_{fi}}{\partial h_2}\cdot\frac{\partial h_n}{\partial h_{n-1}}\cdot\frac{\partial h_{n-1}}{\partial w_n}$$
$$+\sum_{i=1}^{n}\frac{\partial CE_i}{\partial S_{fi}}\cdot\frac{\partial S_{fi}}{\partial h_{fi}}\cdot\frac{\partial h_{fi}}{\partial h_n}\cdot\frac{\partial h_n}{\partial h_{n-1}}\cdot\frac{\partial h_{n-1}}{\partial h_{n-2}}\cdot\frac{\partial h_{n-2}}{\partial w_n}+$$
$$+\sum_{i=1}^{n}\frac{\partial CE_i}{\partial S_{fi}}\cdot\frac{\partial S_{fi}}{\partial h_{fi}}\cdot\frac{\partial h_{fi}}{\partial h_n}\cdot\frac{\partial h_n}{\partial h_{n-1}}\cdot\frac{\partial h_{n-1}}{\partial h_{n-2}}\cdot\frac{\partial h_{n-2}}{\partial h_{n-3}}\cdot\frac{\partial h_{n-3}}{\partial w_n}$$
$$+\cdots$$

Exploding Problem

RNN is a lot of problems then, we’re going to move to **LSTM** next time.

See ya!!!