

# Helping Users with Text Generation



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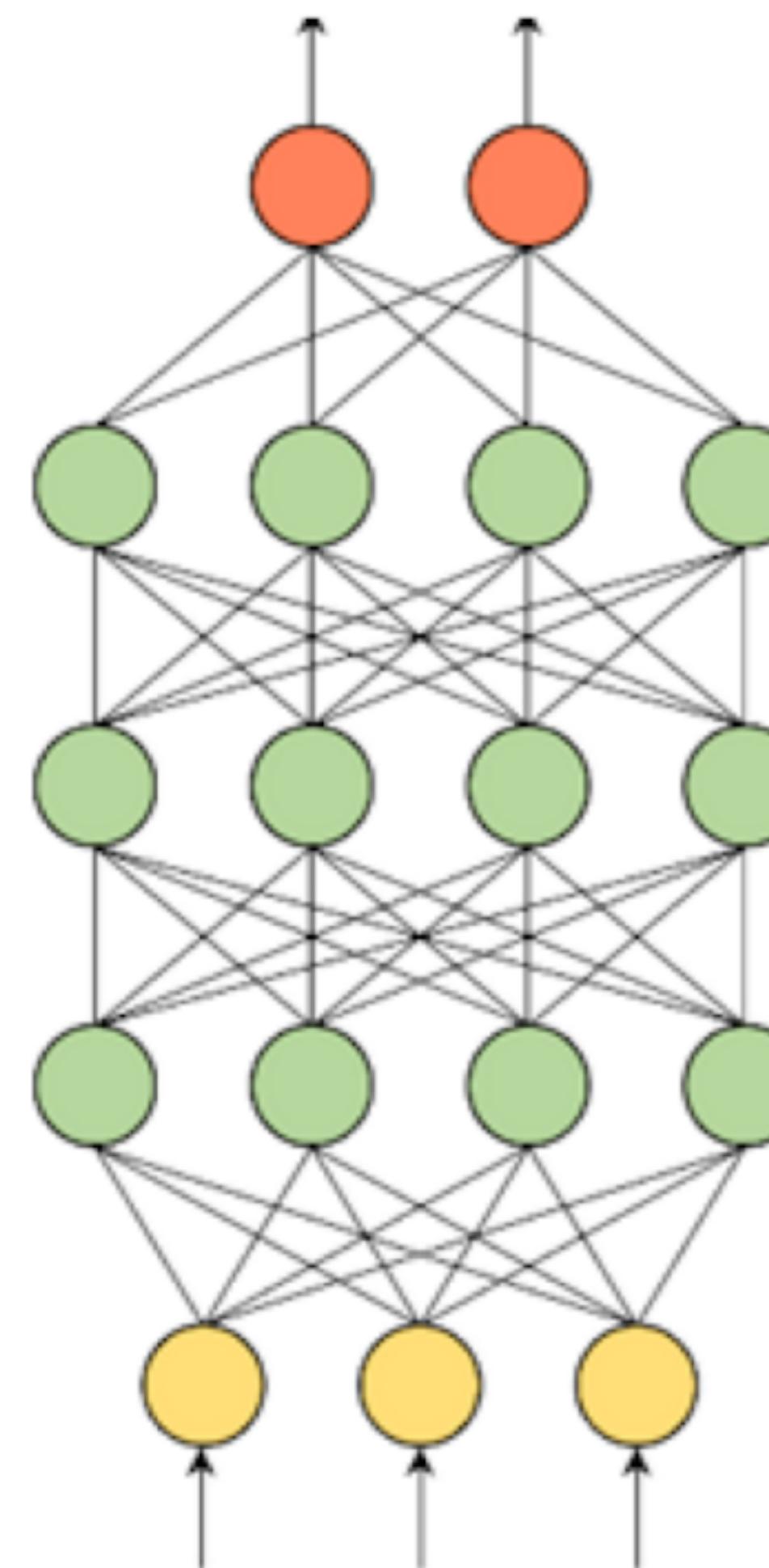
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## Probabilities over char set

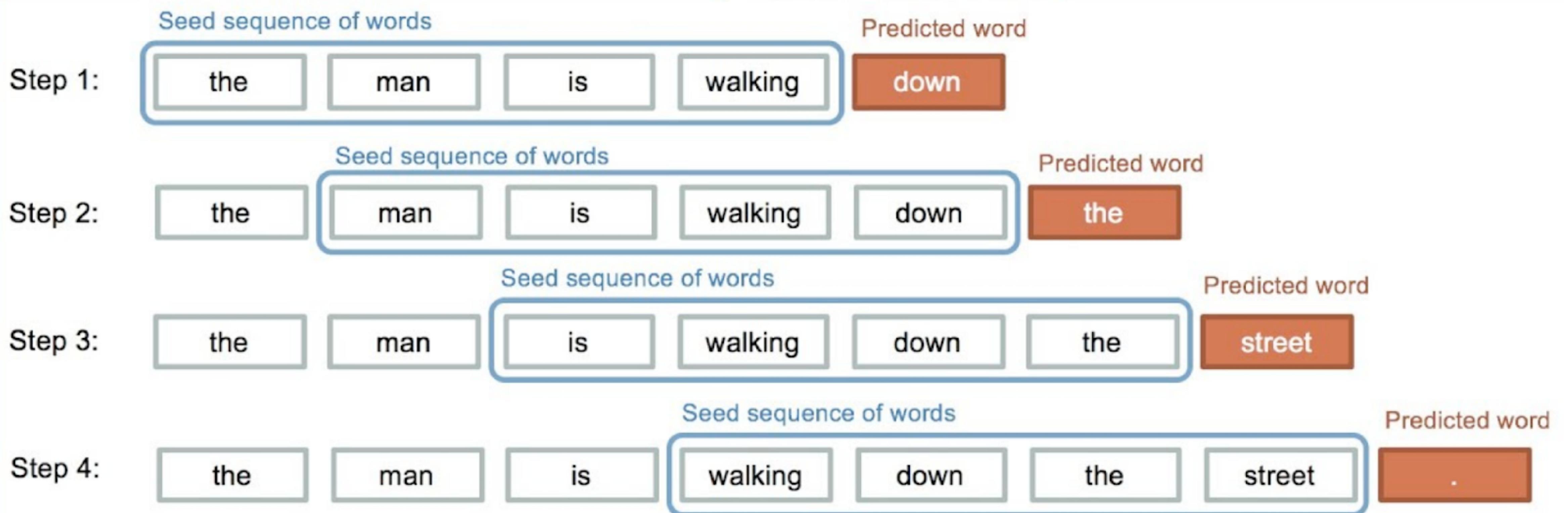
	a	b	c	d	e	f	g	...	z	
	0.01	0.02	0.36	0.25	0.02	0.001	0.22	0.001	...	0.06

## Language Model



Train Input  
from Corpus

I | w a n t | t o b a k e

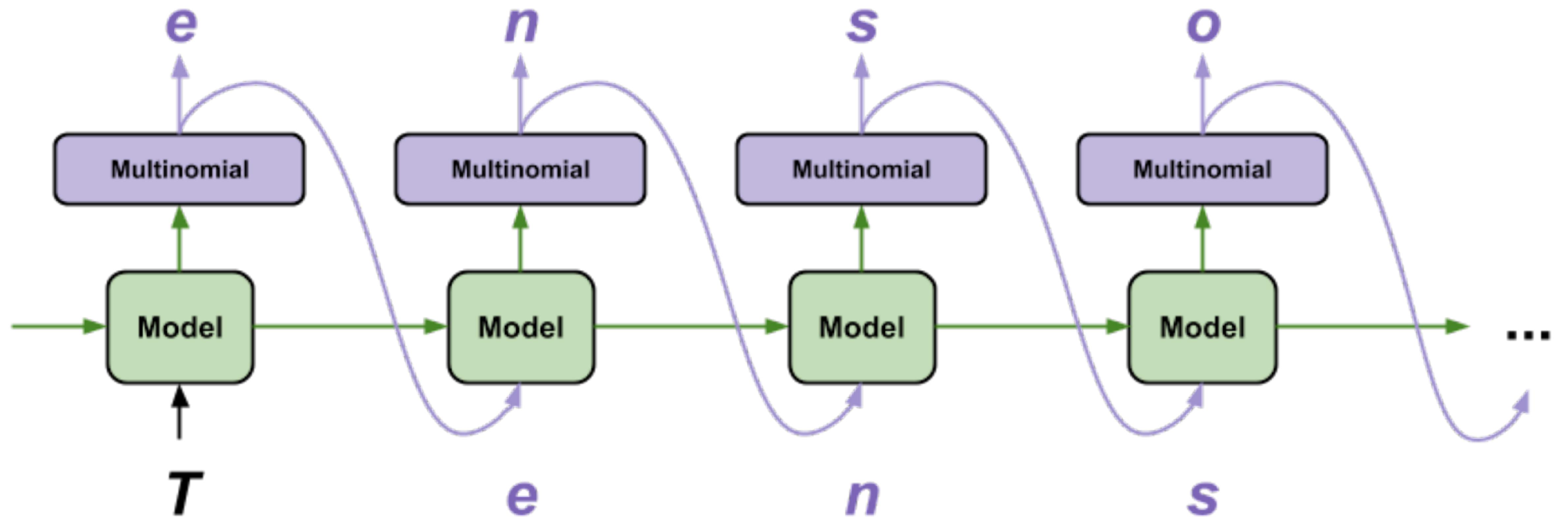


# Problems??

Predicting words needs many parameters

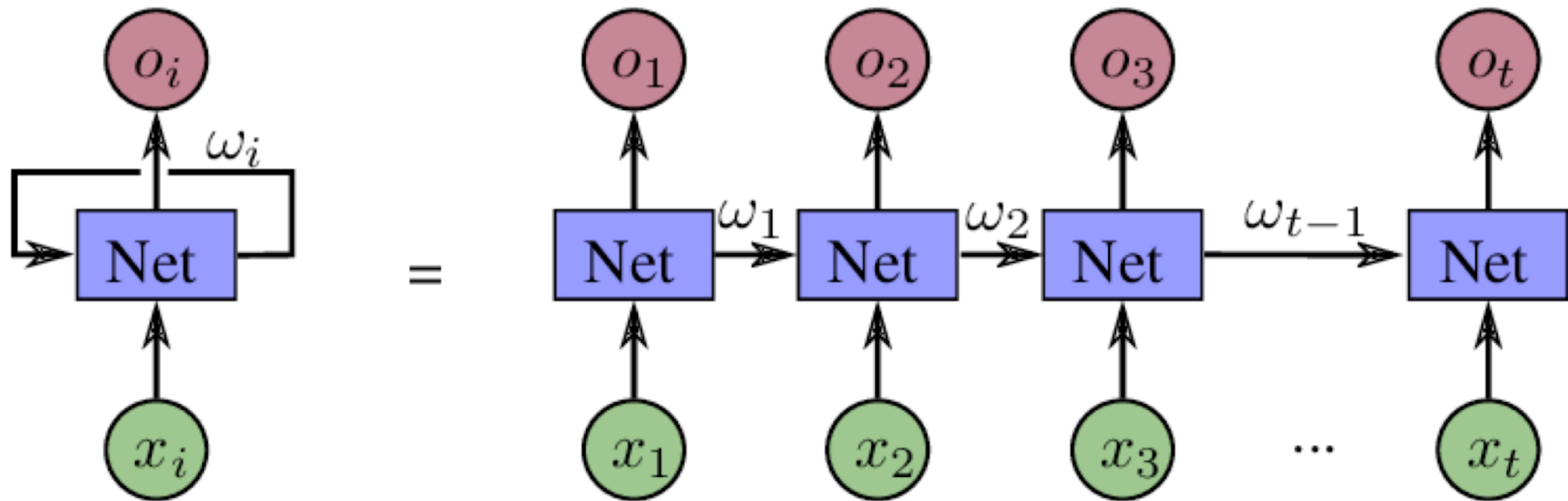
To lose the long-term relationships:

- Local high school dropouts cut in half
  - 7-foot doctors sue hospitals
  - I am a big metal fan



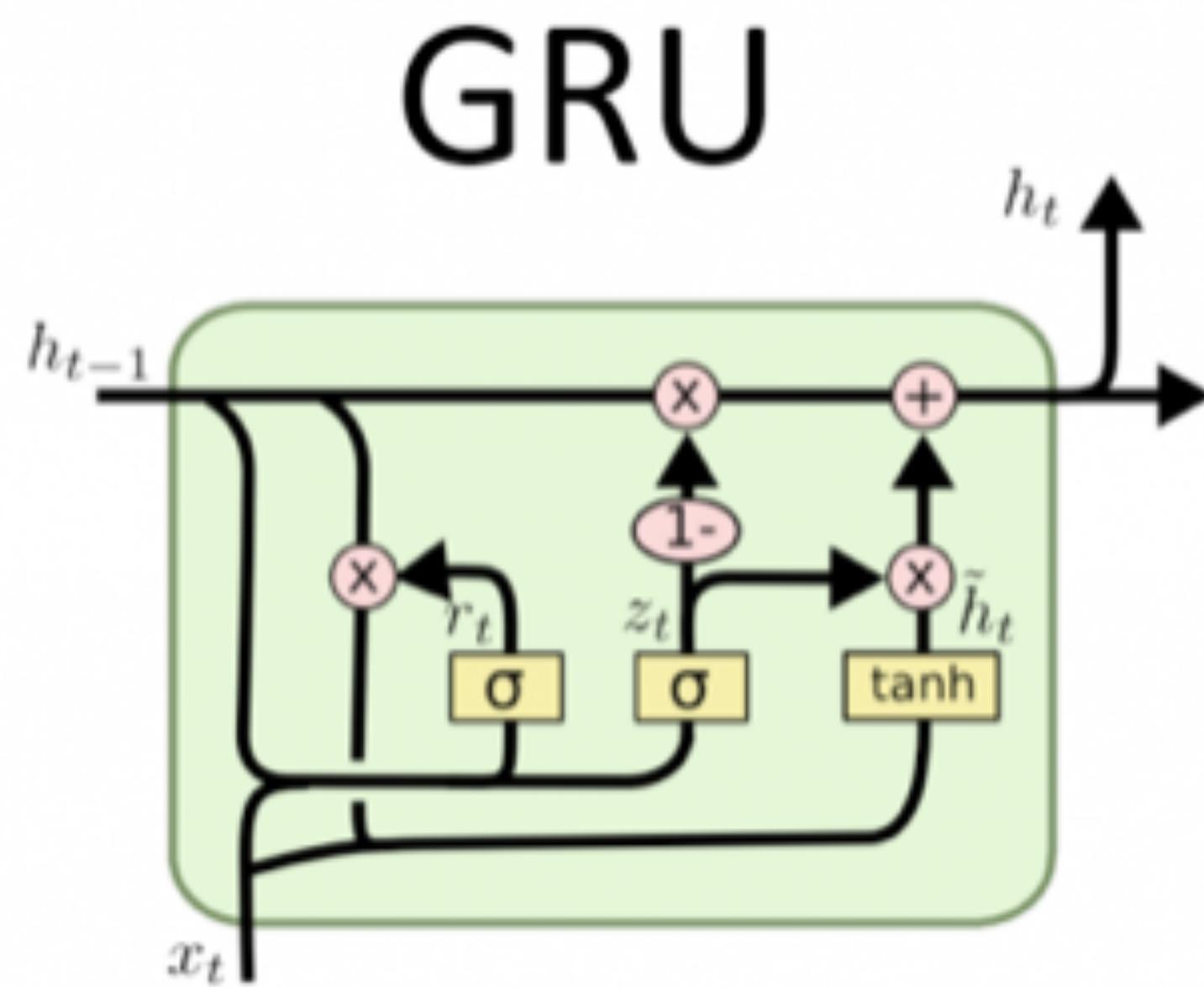


# **Introducing RNN and LSTM**



**As the network grows, the gradient of the first steps are closer to zero, which makes the whole gradient of the network closer to zero due to the chain rule**

# GRU Diagram

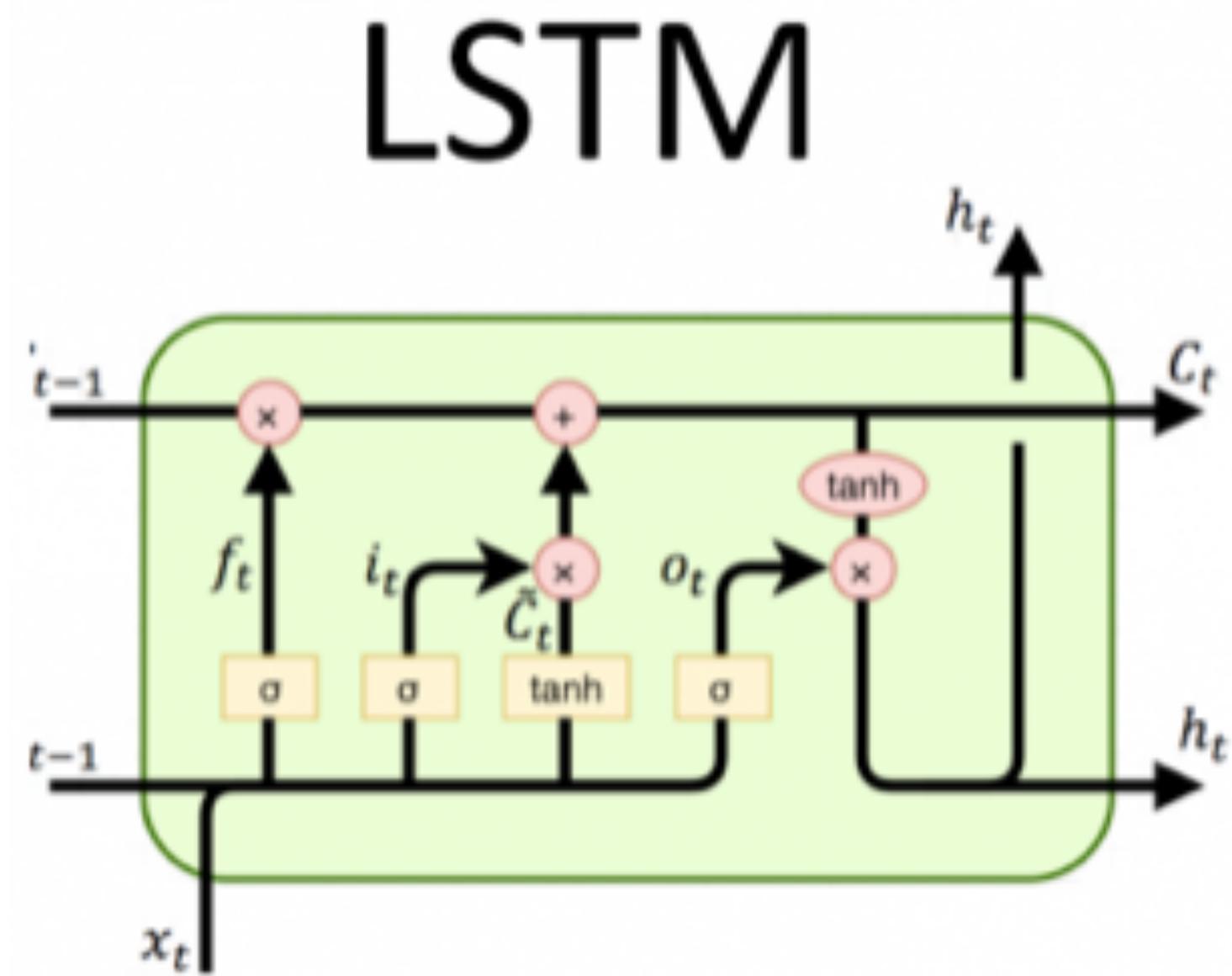


$h_{t-1}$  represents memory in the previous cell

$x_t$  represents input at time t

$h_t$  represents memory in time t

# LSTM Diagram



This hidden vector  $h$  from always  
The output vector as always  
New memory vector  $C$  to capture long-term  
relationships

## **Training a character-based text generation model**

# Takeaways



**Recurrent networks solve the issue of fixed size window sizes for variable length text**



**The two most common ones are GRUs and LSTMs**



**Both pass a hidden state vector weighting the input vs previous outputs; but LSTMs also have a proper memory state.**

# Keys



Ensure to understand how the secret vector and memory passes through the units in each scenario



Check the OneStep model and make sure you understand each step



Do the homework with LSTMs

# Where to Go Next?

**Google: Sequence Models for Time Series and Natural Language Processing on Google Cloud**

**“AI and Machine Learning for Coders: A Programmer's Guide to Artificial Intelligence” by Laurence Moroney**

**“Deep Learning”, by Ian Goodfellow, Yoshua Bengio and Aaron Courville**

