# 11-785: Lab 7 (Spring 24) **RNN Basics**

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#### **Sequential Data**

- Data from which various inputs are dependent
- Examples:
  - Text: "Hi. How are you doing today?"
  - Audio/speech
  - Video
  - Any other time series data like stock price, daily temperature, etc.







SONNET 116

Let me not to the marriage of true minds Admit impediments. Love is not love Which alters when it alteration finds, Or bends with the remover to remove: O, nol it is an ever-fixed mark, That looks on tempests and is never shaken; It is the star to every wandering bark, Whose worth's unknown, although his height be taken. Love 's not Time's fool, though rosy lips and cheeks Within his bending sickle's compass come; Love alters not with his brief hours and weeks, But bears it out even to the edge of doom. If this be error, and upon me prov'd, I never writ, nor no man ever lov'd.

William Shakespeare

Reference: Audio, Stock, Text, Video

## **Data Modeling**

#### one to one



one to many



"man in black shirt is playing guitar."



Image Captioning (ref)

(https://i.stack.imgur.com/b4sus.jpg)

## **Data Modeling**

many to one



Sentiment Analysis (Movie Review)

The Batman (2022) is everything a superhero movie should be. (Positive)

many to many



many to many



Machine Translation "How are you?" -> "எப்படி இருக்கிறீர்கள்?" Object Tracking in videos Video

#### **Recurrent Neural Networks**

- Looping network
- Parameter sharing across timesteps
- Derivatives aggregated across all time steps
- "Backpropagation through time (BPTT)"



(http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

#### **RNN Unrolled**



#### An unrolled recurrent neural network.

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- One hot encoding
  - "Never gonna give you up" {N=5}
    One Hot Encoding: Never = [1, 0, 0, 0, 0]



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https://nlp.stanford.edu/projects/glove/

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     P(w)=[0.01, 0.03, 0.04, 0.05, 0.87]



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"Never gonna give you up. Never gonna let you <u>down</u>" {N=8} [Never, gonna, give, you, up, let, down] P(w)=[0.01, 0.01, 0.01, 0.03, 0.44, 0.03, 0.03, 0.44]



https://nlp.stanford.edu/projects/glove/

0.4

0.3

0.2

01

-0.1

-0.2

-0.3

-0.5

#### **RNN** examples



For the next images: **x0** → **h0: transcription** x0 → h1: prediction/generation

#### **RNN** examples













Never gonna give you up





Never gonna give you up



Never gonna give you up



Never gonna \_\_\_\_\_ \_\_\_ Never gonna give you up



Never gonna \_\_\_\_\_ \_\_\_ Never gonna give you up



Never gonna \_\_\_\_\_ \_\_\_ Never gonna give you up



Never gonna give you up







Never gonna give you up



Never gonna give you up



#### RNN backprop







#### RNN Problems — Architectural Solutions



- After many iterations
  - Short Term Memory
  - Vanishing Gradients

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  - LSTMs and GRUs combat these issues

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#### RNN Dependency Issues → Attention



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  - Short Term Memory
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  - LSTMs and GRUs combat these issues
- Early training for tasks like generation
  - Lack of exploration noise
  - Cold start teacher forcing
- Long-term dependencies may be reduced or lost
  - Attention (later lectures)

#### **Dropout in sequence models**

- 1. Different mask on each timestep (naive, available in PyTorch LSTM)
- 2. Same mask on each timestep for input/output connections (locked dropout)
- 3. Variational dropout same mask on each time step for input/output and recurrent connections



Gal, Yarin, and Zoubin Ghahramani. "A theoretically grounded application of dropout in recurrent neural networks." Advances in neural information processing systems 29 (2016).