

# Phonetic Normalization using Recurrent Neural Networks

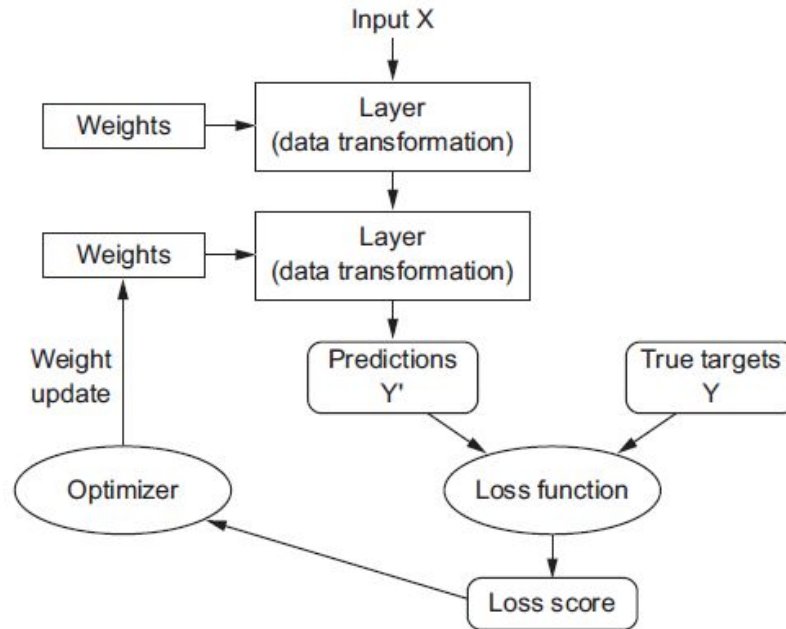
*Jasper Ginn*

# Overview

- Neural Network Refresher
- Problem context
- Data collection
- Evaluation
- Modeling

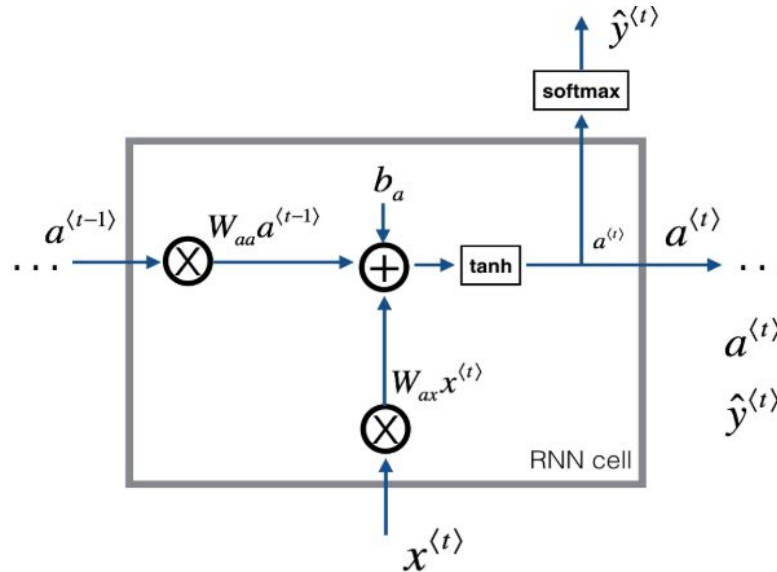
# Neural Network Refresher

# Vanilla Neural Network



From: Cholet, F. "Deep Learning with Python" (Manning), p.11

# Recurrent Neural Network



$$a^{(t)} = \tanh(W_{ax}x^{(t)} + W_{aa}a^{(t-1)} + b_a)$$

$$\hat{y}^{(t)} = \text{softmax}(W_{ya}a^{(t)} + b_y)$$

Andrew Ng, "Sequence Models" (week 1) on Coursera

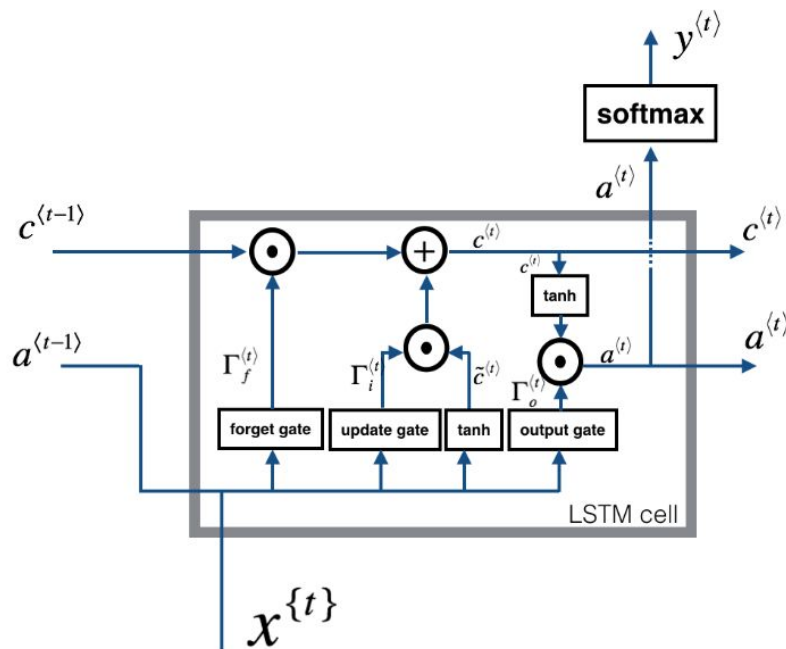
# Looooooooong-term dependencies

- RNN bad at capturing long-term dependencies

“Boaz, who was, . . . . . , went to work”

- Who does the verb refer to?
- ‘Vanishing gradients’
- Introduce memory cell

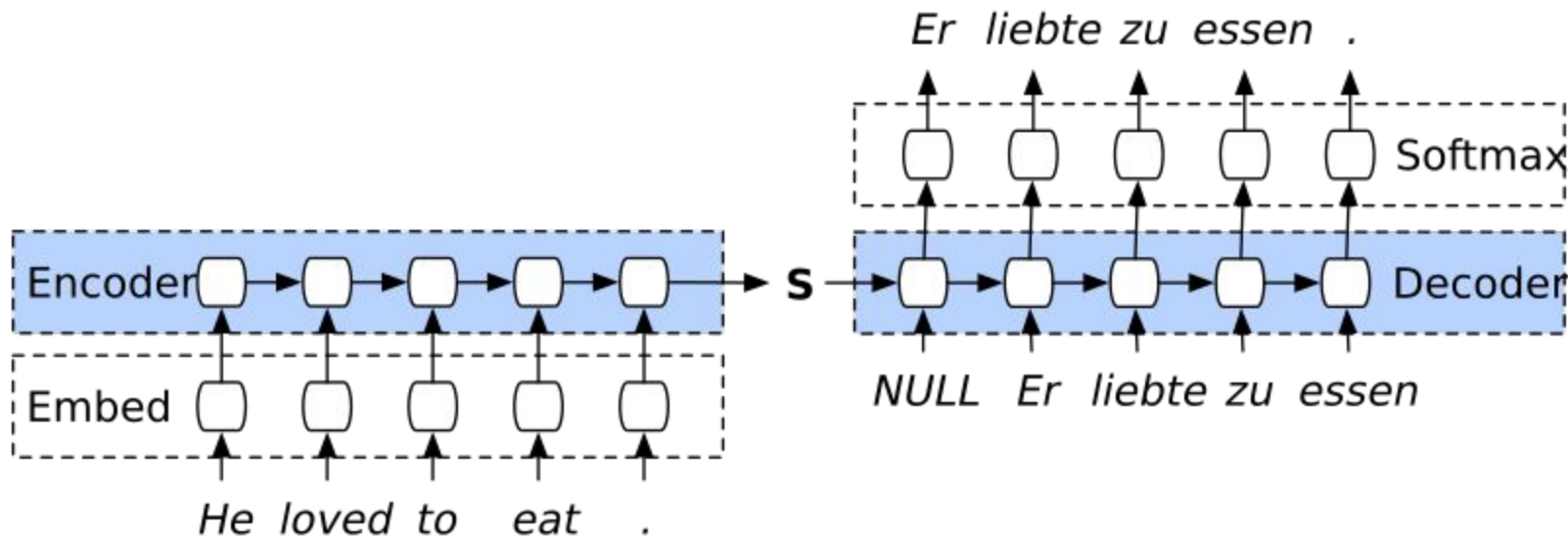
# Long Short-Term Memory (LSTM)



$$\begin{aligned}\Gamma_f^{(t)} &= \sigma(W_f[a^{(t-1)}, x^{(t)}] + b_f) \\ \Gamma_u^{(t)} &= \sigma(W_u[a^{(t-1)}, x^{(t)}] + b_u) \\ \tilde{c}^{(t)} &= \tanh(W_c[a^{(t-1)}, x^{(t)}] + b_c) \\ c^{(t)} &= \Gamma_f^{(t)} \circ c^{(t-1)} + \Gamma_u^{(t)} \circ \tilde{c}^{(t)} \\ \Gamma_o^{(t)} &= \sigma(W_o[a^{(t-1)}, x^{(t)}] + b_o) \\ a^{(t)} &= \Gamma_o^{(t)} \circ \tanh(c^{(t)})\end{aligned}$$

Andrew Ng, "Sequence Models" (week 1) on Coursera

# Encoder / Decoder Architecture



Source: <https://tinyurl.com/ydcdblun>



# Teacher Forcing



# Problem Context

# Goal

- Normalize written text on the ChitChat chatbot
- A lot of this text is ‘ritten’ like it is ‘spoken’
- Solution: find a way to map text to ‘spoken’ words (phonetics)

# Spoken versus written words

- {‘owpen’ = ‘open’} → [OW P AH N]
- {‘bard’ = ‘barred’} → [B AA R D]
- {‘aksiom’ = ‘axiom’} → [AE K S IY AH M]
- {‘effekt’ = ‘effect’} → [IH F EH K T]
- {‘prophet’ = ‘profit’} → [P R AA F AH T]
- {‘raise’ = ‘raze’} → [R EY Z]
- ...

# Model Requirements

- Normalize written text on the ChitChat chatbot
- A lot of this text is ‘ritten’ like it is ‘spoken’
- Solution: find a way to map text to ‘spoken’ words (phonetics)

# Goal

- Similar-sounding words should map to the same output
- Non similar-sounding words should not map to the same output

# Data Collection, Models & Evaluation

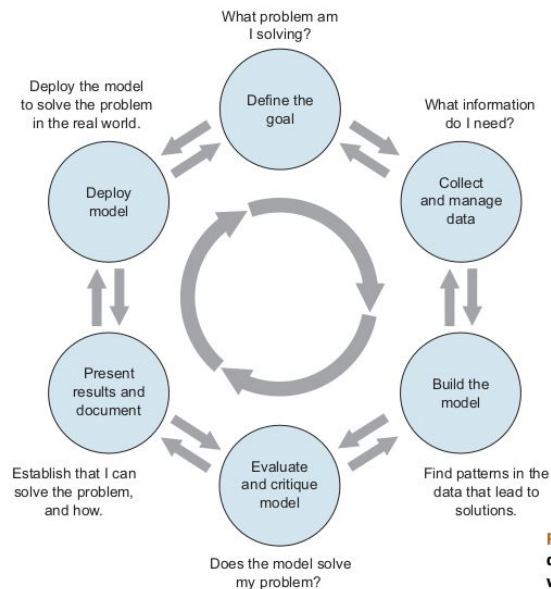
# Data Sources

- **Wikipedia**
  - Extracted using the wikt2pron module
  - Unreliable (many pronunciations, we don't know which belong to which dialect)
- **Carnegie Mellon CMUDict**
  - ARPAbet phonemes (see slide 14)



# Measuring Performance

- BLEU / model accuracy
- **Do models map homophones and non-homophones?**
- Misspelled words from wikipedia



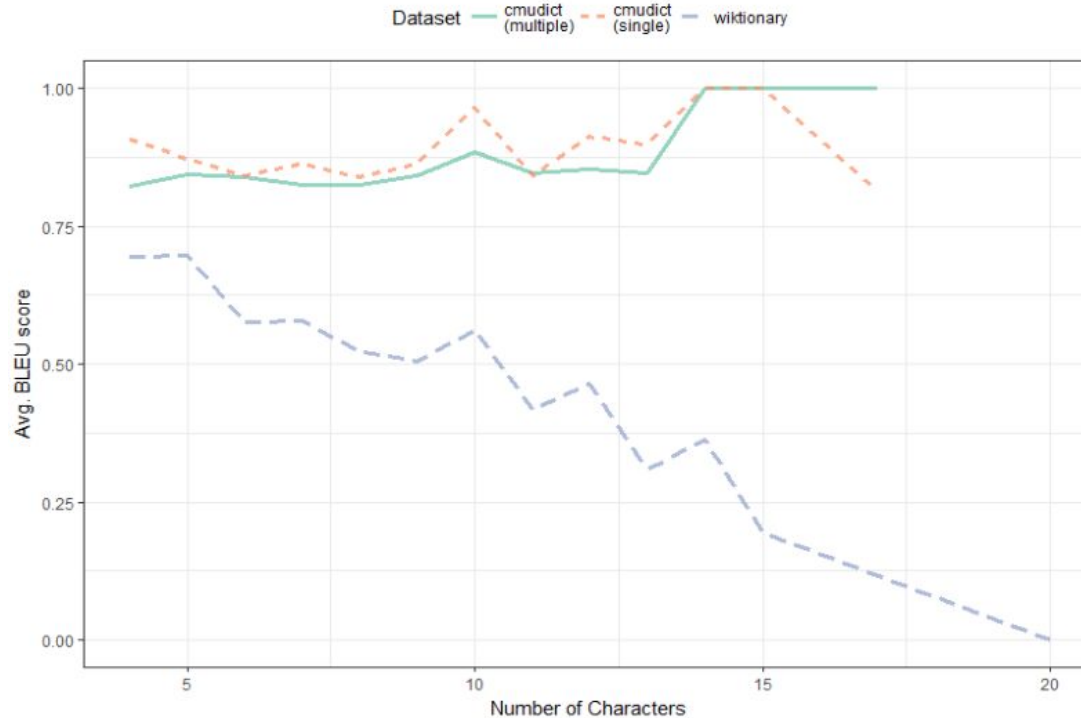
**Figure 1.1** The lifecycle of a data science project: loops within loops

Zumel, N. and Mount, J.  
“Practical Data Science with R”,  
p.6

# Three models, two datasets

- Models
  - cmudict (single)
    - Disregard phonemes
    - [OW P AH N]  $\Rightarrow$  {O, W, P, A, H, N}
  - cmudict (multiple)
    - Phonemes as characters
    - [OW P AH N]  $\Rightarrow$  {OW, P, AH, N}
  - Wiktionary
    - Use XSAMPA-style phonetics

# Model performance



	All equal	Largest subgroup	Equal to reference
cmudict (single)	77.33%	91.15%	86.94%
cmudict (multiple)	63.56%	86.58%	76.87%
wiktionary	42.11%	80.2%	51.02%

	cmudict (single)	cmudict (multiple)	wiktionary
Accuracy	0.94	0.83	0.76
Sensitivity	0.87	0.77	0.69
Specificity	0.92	0.89	0.87
F1	0.90	0.83	0.77

# Model Performance (2)

- On all metrics, cmudict (single) performs best
  - Bleu, homophones, misspelled words

# Takeaways

# Which framework to use?

- **Keras:**
  - Abundance of documentation
  - Can be used in R/Python
- **PyTorch:**
  - Flexible + Pythonic



# The fall of RNN / LSTM



Eugenio Culurciello

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We fell for Recurrent neural networks (RNN), Long-short term memory (LSTM), and all their variants. **Now it is time to drop them!**