Seq2Seq in Action: Column Segmentation

Part 1

Bill Watson

S&P Global

January 16, 2020

What are Sequence to Sequence Models?

- Generally used to convert one set of tokens into another
  - Many - to - Many RNN
- Bleak view: map a sequence of indexes to another independent set of indexes

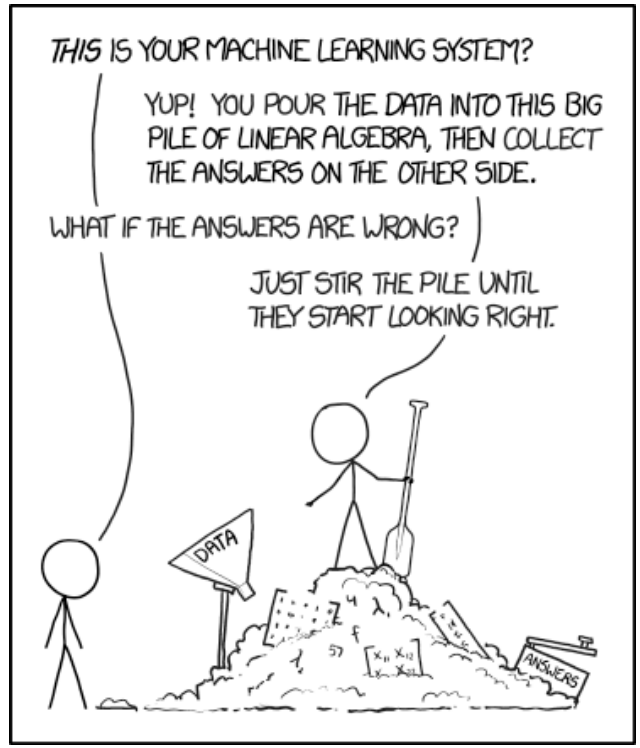

Figure: The pile gets soaked with data and starts to get mushy over time, so it's technically recurrent.

Use Case: Extracting Tables from Images

Primer: What are we trying to accomplish

- Tabular data is locked in PDFs
  - Either as a typeset document
  - Or as a scanned image
- Sometimes copy & paste won't suffice (or impossible with images)
- Let's take a quick look at the full pipeline to see where Seq2Seq models can fit in

What is our data?

Schedule 2
1 of 41

CITY OF COFFEYVILLE, KANSAS
GENERAL FUND
Schedule of Receipts and Expenditures - Actual and Budget
Regulatory Basis
For the Year Ended December 31, 2017
(With Comparative Actual Amounts for the Prior Year Ended December 31, 2016)

	Prior Year Actual	Current Year: Actual	Current Year: Budget	Current Year: Variance - Over (Under)
Receipts				
Taxes and Shared Receipts				
Ad Valorem Property Tax	$ 1,779,884.26	$ 1,872,543.39	$ 2,225,362.00	$ (352,818.61)
Delinquent Tax	107,335.16	83,439.02	60,000.00	23,439.02
Motor Vehicle Tax	185,104.64	198,703.03	206,631.00	(7,927.97)
Recreational Vehicle Tax	1,372.30	1,786.98	1,521.00	265.98
16/20 M Vehicle Tax	827.20	566.64	841.00	(274.36)
Vehicle Rental Excise Tax	95.10	51.82	177.00	(125.18)
Commercial Vehicle Tax	9,660.34	9,861.33	8,137.00	1,724.33
Watercraft Tax	657.49	532.70	517.00	15.70
Special Assessments	63,572.47	73,635.34	30,000.00	43,635.34
Franchise Tax	604,481.17	688,423.06	476,972.00	211,451.06
Sales Tax	5,137,239.57	4,852,214.72	5,145,516.00	(293,301.28)
Federal Grants	8,650.01	2,705.56	-	2,705.56
Local Alcohol Liquor Tax	18,091.55	28,878.71	16,327.00	12,551.71
Special Highway Tax	259,225.61	256,024.36	256,330.00	(305.64)
Highway Connecting Links	76,750.82	76,645.19	76,700.00	(54.81)
Highway County Aid	45,694.05	45,975.73	40,830.00	5,145.73
Licenses and Permits	94,108.50	92,606.00	-	92,606.00
Fines, Forfeitures and Penalties	183,460.84	207,414.75	308,445.00	(101,030.25)
Charges for Services	99,811.84	90,317.95	96,596.00	(6,278.05)
Use of Money and Property				
Interest Income	20,461.28	21,263.49	12,000.00	9,263.49
Rents	67,423.00	36,492.50	67,400.00	(30,907.50)
Sale of Equipment and Scrap	2,228.40	3,294.94	5,000.00	(1,705.06)
Other Receipts				
Donations	-	1,180.00	-	1,180.00
Reimbursed Expense	46,151.89	40,804.82	-	40,804.82
Insurance Proceeds	-	38,750.00	-	38,750.00
Miscellaneous	8,239.70	4,526.25	6,000.00	(1,473.75)
Operating Transfers from:				
Electric Utility Fund	2,327,045.74	2,408,082.70	2,583,695.00	(175,612.30)
Water and Sewer Utility Fund	694,334.64	777,054.10	723,775.00	53,279.10
Community Development Fund	218,655.33	-	-	-
Total Receipts	12,060,562.90	11,913,775.08	$ 12,348,772.00	$ (434,996.92)
Expenditures				
General Government				
Personal Services	838,080.11	782,088.99	$ 987,382.00	$ (205,293.01)
Contractual Services	259,202.84	269,145.94	313,797.00	(44,651.06)
Commodities	10,788.03	12,130.62	14,240.00	(2,109.38)
Capital Outlay	1,442.98	1,832.92	18,450.00	(16,617.08)

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5. CAPITAL LEASE OBLIGATIONS

The City has entered into a capital lease agreement in order to finance the purchase of a Blackstart Generator. Payments are made of $77,729.23 semi-annually, including interest at approximately 5.00%. Final maturity for the lease is in 2026. Future minimum lease payments are as follows:

Year Ended December 31	Totals
2018	$ 155,458.46
2019	155,458.46
2020	155,458.46
2021	155,458.46
2022	155,458.46
2023-2026	505,870.61
	1,283,162.91
Less imputed interest	(174,862.64)
Net Present Value of Minimum Lease Payments	1,108,300.27
Less: Current Maturities	(118,236.87)
Long-Term Capital Lease Obligations	$ 990,063.40

The City has entered into a capital lease agreement in order to finance the purchase of a Fire Truck. Payments are made of $30,023.18 semi-annually, including interest at approximately 3.27%. Final maturity for the lease is in 2027. Future minimum lease payments are as follows:

Year Ended December 31	Totals
2018	$ 60,046.36
2019	60,046.36
2020	60,046.36
2021	60,046.36
2022	60,046.36
2023-2027	300,110.21
	600,342.01
Less imputed interest	(91,679.72)
Net Present Value of Minimum Lease Payments	508,662.29
Less: Current Maturities	(43,858.90)
Long-Term Capital Lease Obligations	$ 464,803.39

6. OPERATING LEASES

As of December 31, 2017 the City has entered into an operating lease for office equipment. Rent expense for the year ended December 31, 2017, was $18,799.36. Under the current lease agreements, the future minimum rental payments are as follows:

2018	$ 4,216.68
2019	3,162.51

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Schedule 1

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Summary of Expenditures - Actual and Budget
(Budgeted Funds Only)
Regulatory Basis
For the Year Ended December 31, 2017

Funds	Total Certified Budget	Adjustments for Qualifying Budget Credits	Total Certified Budget for Comparison	Expenditures Charged to Current Year Budget	Variance - Over (Under)
General Fund	$ 12,922,113.00	$ 40,804.82	$ 12,962,917.82	$ 11,803,297.93	$ (1,159,619.89)
Special Purpose Funds:					
Library	390,713.00	-	390,713.00	365,952.13	(24,760.87)
Local Alcohol Liquor	130,578.00	-	130,578.00	40,451.25	(90,126.75)
Economic Development	212,738.00	-	212,738.00	138,956.05	(73,781.95)
Airport Holding	82,374.00	-	82,374.00	81,819.90	(554.10)
Golf Course	333,513.00	-	333,513.00	299,263.21	(34,249.79)
Youth Activities Center	34,158.00	-	34,158.00	27,626.54	(6,531.46)
Police VIN	47,434.00	-	47,434.00	1,609.00	(45,825.00)
Aquatic Center Operations	128,951.00	-	128,951.00	101,216.47	(27,734.53)
Business Development Training Center	155,919.00	-	155,919.00	155,918.90	(0.10)
Veterans Memorial Stadium	25,897.00	9,335.72	35,232.72	9,035.72	(26,197.00)
USD #445 Sales Tax	1,375,075.00	-	1,375,075.00	882,677.42	(492,397.58)
CRMC Sales Tax	857,586.00	-	857,586.00	598,715.38	(258,870.62)
1/2 Cent Sales Tax IRB Debt Service	518,265.00	-	518,265.00	518,265.00	-
Community Improvement District Sales Tax	-	-	-	-	-
Bond and Interest Funds:					
G.O. Bond and Interest	277,195.00	-	277,195.00	259,590.00	(17,605.00)
Business Funds:					
Electric Utility	60,092,640.00	-	60,092,640.00	58,101,092.67	(1,991,547.33)
Electric Debt Service	5,186,333.00	-	5,186,333.00	5,186,233.46	(99.54)
Water and Sewer Utility	6,572,728.00	3,122.42	6,575,850.42	6,354,174.48	(221,675.94)
Water and Sewer Debt Service	1,161,739.00	-	1,161,739.00	1,161,139.32	(599.68)
Stormwater Utility	481,991.00	-	481,991.00	463,849.33	(18,141.67)
Refuse/Trash Utility	606,036.00	-	606,036.00	536,368.81	(69,667.19)
Internet Utility	279,496.00	144.60	279,640.60	271,814.82	(7,825.78)

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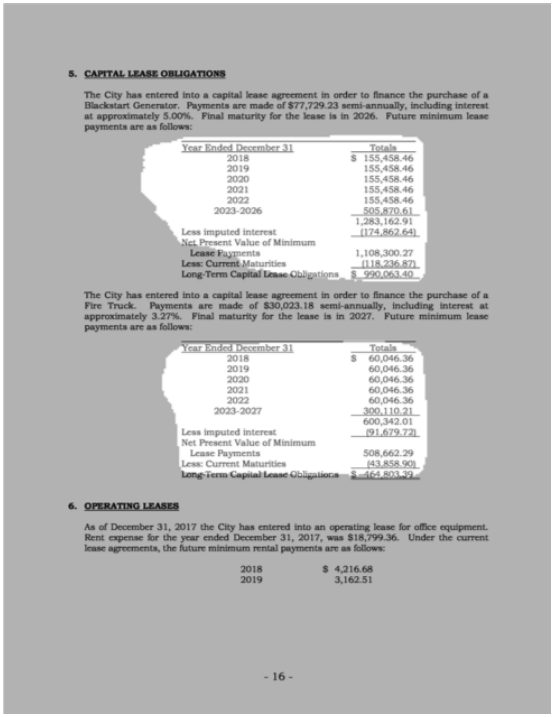
Current Pipeline for Table Extraction

- Convert to an Image
- Binary Page Classification: Is there a table on this page?
- Table Segmentation: U-Net Model
- Optical Character Recognition via Tesseract
- **Column Segmentation**
- Table Alignment
- Dump to CSV

Visual: Table Segmentation



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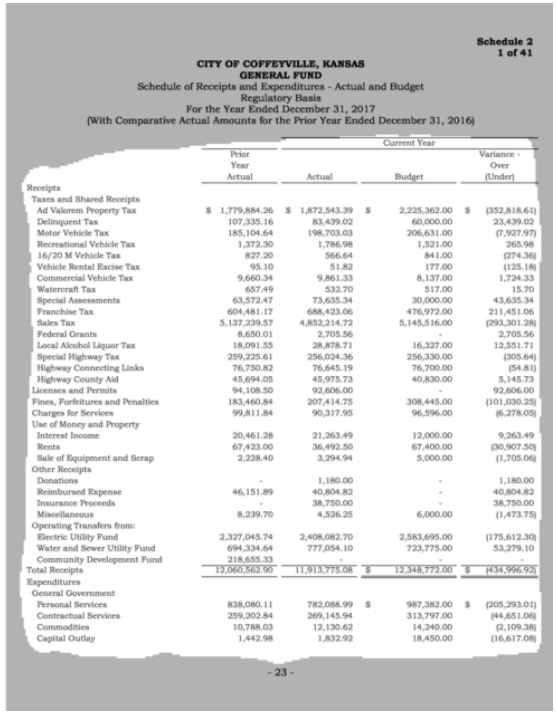

Schedule 2
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General Government				
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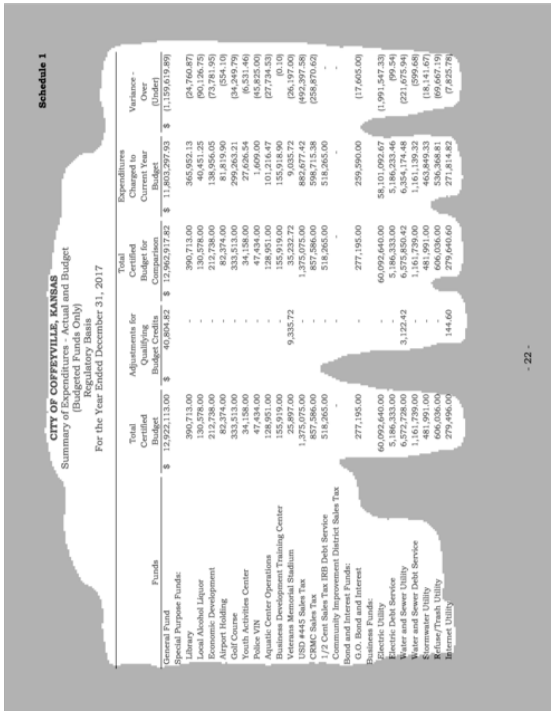

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Economic Development	212,738.00	-	212,738.00	138,956.05	(73,781.95)
Airport Holding	82,374.00	-	82,374.00	81,819.90	(554.10)
Golf Course	332,313.00	-	332,313.00	299,213.78	(33,099.22)
Youth Activities Center	34,158.00	-	34,158.00	27,626.54	(6,531.46)
Police VIN	47,434.00	-	47,434.00	1,609.00	(45,825.00)
Aquatic Center Operations	128,951.00	-	128,951.00	101,216.47	(27,734.53)
Business Development Training Center	155,919.00	-	155,919.00	155,918.90	(0.10)
Workforce Memorial Station	238,972.00	9,235.72	248,207.72	222,107.00	(26,100.72)
USD 445 Sales Tax	1,375,075.00	-	1,375,075.00	882,677.42	(492,397.58)
CRMC Sales Tax	857,586.00	-	857,586.00	598,715.38	(258,870.62)
1/2 Cent Sales Tax 1969 Debt Service	518,265.00	-	518,265.00	518,265.00	-
Community Improvement District Sales Tax	-	-	-	-	-
Bond and Interest Funds:					
G.O. Bond and Interest	277,195.00	-	277,195.00	259,590.00	(17,605.00)
Business Funds:					
Electric Utility	60,092,640.00	-	60,092,640.00	58,101,092.67	(1,991,547.33)
Electric Debt Service	5,186,333.00	-	5,186,333.00	5,186,233.46	(99.54)
Water and Sewer Utility	6,151,729.00	3,122.42	6,154,851.42	5,933,730.54	(221,120.88)
Water and Sewer Debt Service	1,161,729.00	-	1,161,729.00	1,161,139.33	(589.67)
Stormwater Utility	481,991.00	-	481,991.00	463,849.33	(18,141.67)
Refuse/Trash Utility	606,036.00	-	606,036.00	536,368.81	(69,667.19)
Internet Utility	279,496.00	144.60	279,640.60	271,814.82	(7,825.78)

Visual: Tesseract OCR Output

level	page_num	block_num	par_num	line_num	word_num	left	top	width	height	conf	text
5	1	1	1	1	1	1092	100	62	27	95	For
5	1	1	1	1	2	1165	100	55	26	95	the
5	1	1	1	1	3	1239	100	82	25	96	Year
5	1	1	1	1	4	1335	100	114	24	96	Ended
5	1	1	1	1	5	1463	100	82	24	93	June
5	1	1	1	1	7	1630	100	88	22	36	ZU18
5	1	1	1	2	1	1295	146	219	43	96	(Continued)
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5	1	1	1	3	2	605	263	16	31	90	1
5	1	1	1	3	3	637	280	13	5	87	-
5	1	1	1	3	4	665	260	245	34	96	SUMMARY
5	1	1	1	3	5	925	260	61	32	95	OF
5	1	1	1	3	6	1002	257	303	34	96	SIGNIFICANT
5	1	1	1	3	7	1319	254	318	34	95	ACCOUNTING
5	1	1	1	3	8	1651	252	220	34	95	POLICIES
5	1	1	1	3	9	1886	251	232	42	96	(Continued)
5	1	1	1	4	1	537	372	39	31	93	H.
5	1	1	1	4	2	612	369	206	34	96	Inventories
5	1	1	1	4	3	833	368	64	33	96	and
5	1	1	1	4	4	911	367	141	43	96	Prepaid
5	1	1	1	4	5	1066	368	98	31	96	Items
5	1	1	1	5	1	611	477	207	34	96	Inventories
5	1	1	1	5	2	831	487	54	22	96	are
5	1	1	1	5	3	896	476	123	32	96	valued
5	1	1	1	5	4	1031	480	32	27	96	at
5	1	1	1	5	5	1073	475	55	32	96	the
5	1	1	1	5	6	1141	474	101	33	96	lower
5	1	1	1	5	7	1253	473	41	33	96	of
5	1	1	1	5	8	1301	477	73	28	93	cost
5	1	1	1	5	9	1385	471	147	42	90	(first-in,
5	1	1	1	5	10	1545	470	163	41	96	first-out)

Column Segmentation

- Naive approach is to merge words close together
  - But spacing is **variable** in tables
  - Text justification (left, center, right)
- **Union Find** to group columns by **Intersection Over Union (IOU)**

Column Segmentation

- Naive approach is to merge words close together
  - But spacing is **variable** in tables
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- **Idea:** Use a Seq2Seq to learn correct segmentation

Visual: Alignment

			——"——sSurrentYear t—(‘SOSCS~™S										
	Prior												Variance -
	Year												Over
	Actual				Actual				Budget				(Under)
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16/20 M Vehicle Tax	827.2				566.64				841				-274.36
Vehicle Rental Excise Tax	95.1				51.82				177				-125.18
Commercial Vehicle Tax	9,660.34				9,861.33				8,137				1,724.33
Watercraft Tax	657.49				532.7				517				15.7
Special Assessments	63,572.47				73,635.34				30,000				43,635.34
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Insurance Proceeds		-			38,750					-			38,750
Miscellaneous	8,239.7				4,526.25				6,000				-1,473.75
Operating Transfers from:													
Electric Utility Fund	2,327 ,045.74				2,408,082.7				2,583,695				-175,612.3
Water and Sewer Utility Fund	694,334.64				777,054.1				723,775				53,279.1
Community Development Fund	218,655.33					-				-			-
Total Receipts	12,060,562.9				11,913,775.08			§§	12,348,772		§§		-434,996.92
Expenditures							TT						
General Government													
Personal Services	838,080.11				782,088.99			$	987,382		§§		-205,293.01
Contractual Services	259,202.84				269,145.94				313,797				-44,651.06
Commodities	10,788.03				12,130.62				14,240				-2,109.38
Capital Outlay	1,442.98				1,832.92				18,450				-16,617.08
			-92-										

Problem Statement: Column Segmentation

Year Ended December 31	Totals
2018	$ 155,458.46
2019	155,458.46
2020	155,458.46
2021	155,458.46
2022	155,458.46
2023-2026	505,870.61
	1,283,162.91
Less imputed interest	(174,862.64)
Net Present Value of Minimum Lease Payments	1,108,300.27
Less: Current Maturities	(118,236.87)
Long-Term Capital Lease Obligations	$ 990,063.40

Year Ended December 31		Totals
	2018	$155,458.46
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	2020	155,458.46
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Less imputed interest		-174,862.64
Net Present Value of Minimum		
Lease Payments		1,108,300.27
Less: Current Maturities		-118,236.87
Long-Term Capital Lease Obligations		$990,063.40

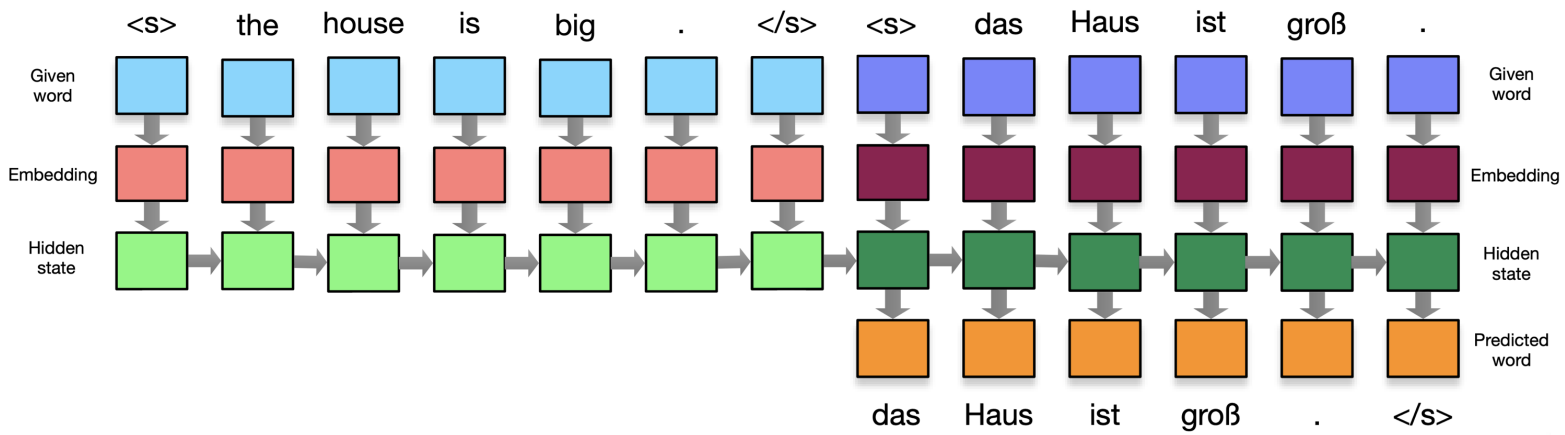
- Given a sequence of text, can we predict where to insert columns?

Revisiting Column Segmentation as a Seq2Seq Problem

- Translation Task
- Given a sequence of tokens
- Translate into the same set of tokens, but with a special ⟨SEG⟩ token

```
Less  imputed  interest        (  174,862.64  )
                          ⇓
Less  imputed  interest  ⟨SEG⟩  (  174,862.64  )
```

Seq2Seq Architecture



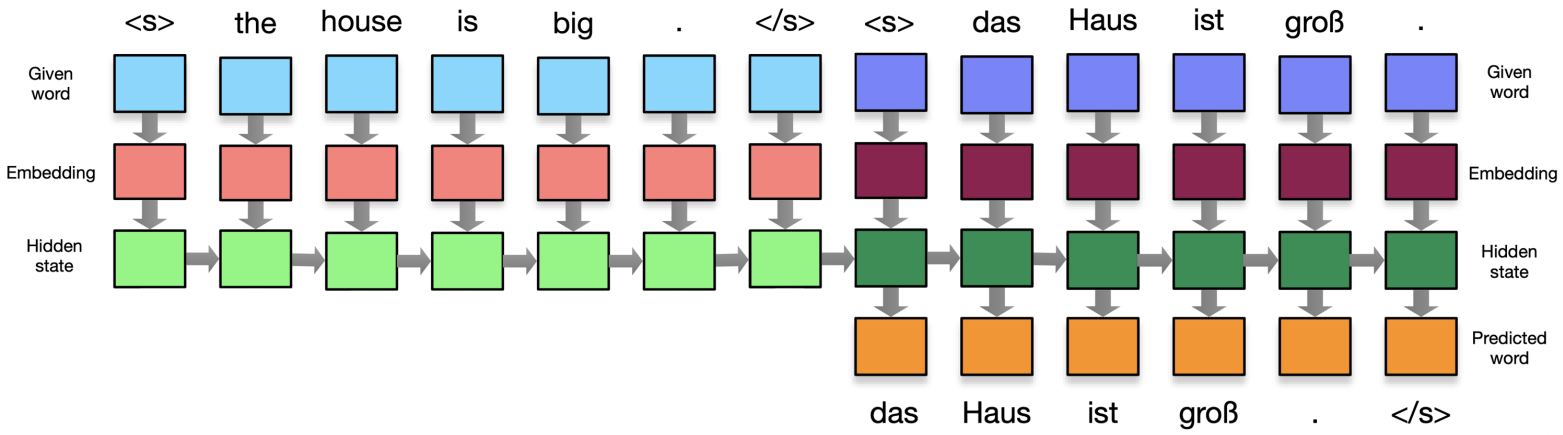
- We can use a **Encoder-Decoder** style model!

Encoder-Decoder Architecture

Overview: Encoders and Decoders

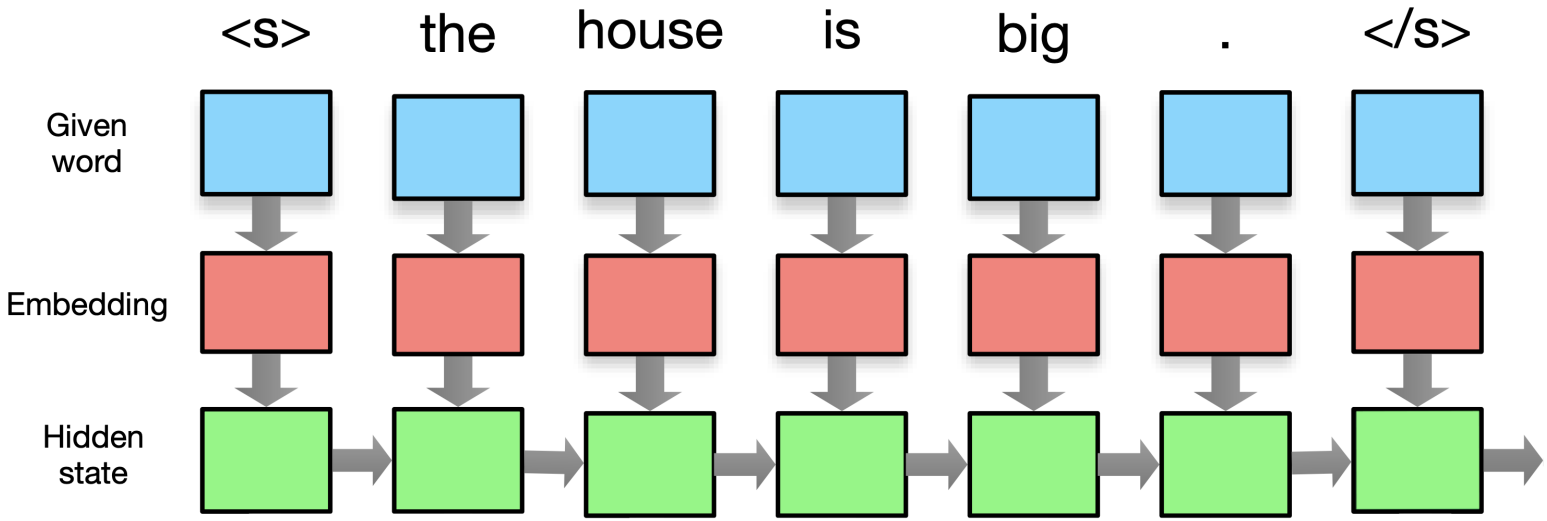
- We have 2 sub-networks: an **Encoder** and a **Decoder**
- Encoders
  - Give the source sentence meaning
- Decoders
  - Emit a variable-length sequence
- We will discuss how to connect the two for joint training

Overview: Encoders and Decoders



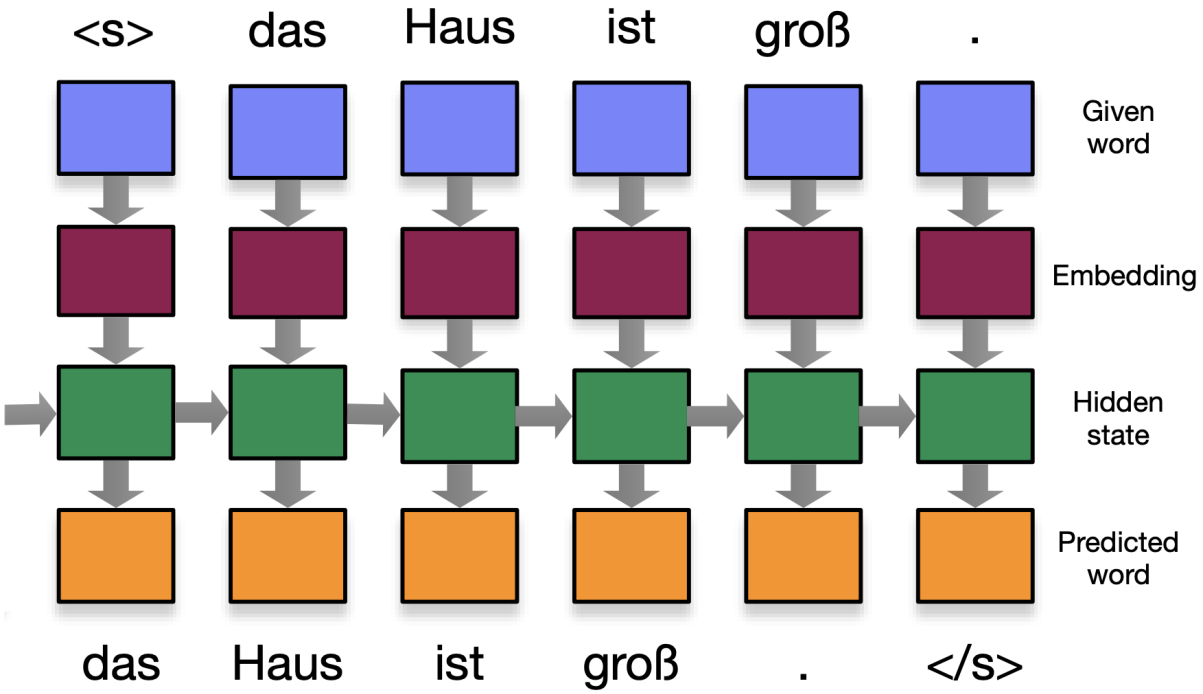
- Encapsulation allows for flexible design choices
- **Embeddings**
  - Pre-trained
  - DIY
- **Recurrent Layer**
  - Type
  - Depth
  - Directionality

What makes an Encoder?



- Recall: **Encoders** give the source sentence meaning
- Effectively a language model, without a layer to predict the next word
- Idea is to pass on the hidden state, and possibly use the encodings directly

What makes a Decoder?



- Recall: **Decoders** provide a new sequence conditioned on the Encoder's hidden state
- Starts with the Encoder's hidden state, and predicts one token at a time
- Re-feed the predicted token back into the decoder

Word Embeddings: Practical Considerations

Column Segmentation Issue: Vocabulary Size

- Is the text actually important?
- Over **10K unique tokens**, mostly numbers

Column Segmentation Issue: Vocabulary Size

- Is the text actually important?
- Over **10K unique tokens**, mostly numbers
- **Solutions:**
  - Token $\rightarrow$ Part-of-Speech
  - Numeric Value $\rightarrow \langle \text{NUM} \rangle$
- Reduces vocabulary size to **21 tokens**
- But lets take a look at alternative solutions to managing vocab size

Recap: Word Embeddings

$$
\begin{array}{rcl}
\texttt{the} & \rightarrow & \begin{bmatrix} 1.23 & -0.58 & 0.22 & -0.80 & 0.61 \end{bmatrix} \\
\texttt{cat} & \rightarrow & \begin{bmatrix} -1.10 & 1.23 & 0.17 & -0.21 & 1.43 \end{bmatrix} \\
\texttt{is} & \rightarrow & \begin{bmatrix} -0.26 & 0.70 & 0.27 & 0.59 & -1.04 \end{bmatrix} \\
\texttt{black} & \rightarrow & \begin{bmatrix} -1.13 & -0.81 & -0.53 & -0.59 & 0.26 \end{bmatrix}
\end{array}
$$

- A trick to map tokens to vector representations

Recap: Pretrained Word Embeddings

- Co-occurence Matrix
- Pointwise Mutual Information
- SVD Co-occurence
- Ngram
- CBOW, Skip Gram
- GloVe
- ELMo
- BERT

DIY Embeddings

- We can always train our own!

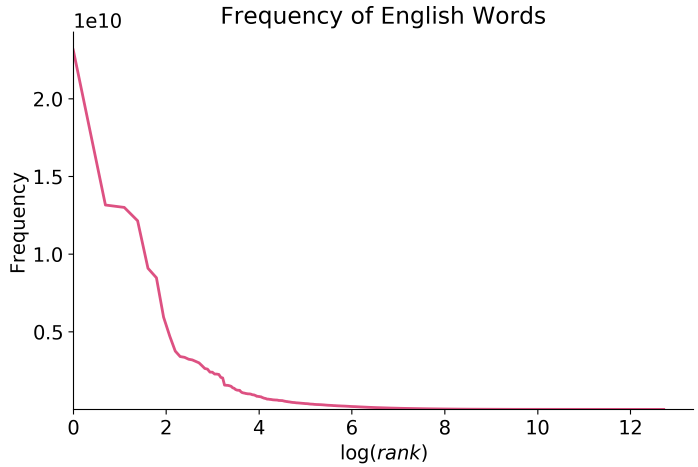
Special Tokens for Sequence Modeling

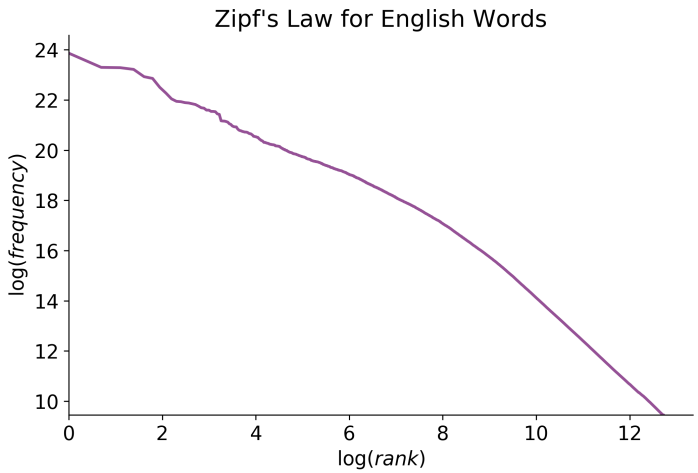
- ⟨PAD⟩ → Padding / Masking
- ⟨UNK⟩ → Unknown words
- ⟨SOS⟩ → Start of Sentence
- ⟨EOS⟩ → End of Sentence

⟨SOS⟩	Data	Science	is	the	⟨UNK⟩	!	⟨EOS⟩
⟨SOS⟩	I	⟨UNK⟩	for	S&P	.	⟨EOS⟩	⟨PAD⟩
⟨SOS⟩	Hello	World	!	⟨EOS⟩	⟨PAD⟩	⟨PAD⟩	⟨PAD⟩

Mangaging the Vocab Size

- Languages are unevenly distributed
- Many rare words, names $\rightarrow$ inflates the size of the vocabulary
- **Problem:**
  - Large embedding matrices for source, target language
  - Large output layers for prediction and softmax
- Naive Solution: Limit the vocab size to most frequent





Morphology, Compounding, and Transliteration

- Morphological Analysis

  tweet, *tweets*, *tweeted*, *tweeting*, *retweet*, ...

- Compound Splitting
  - homework $\rightarrow$ home·work
  - website $\rightarrow$ web·site
- Names, Places, Proper Nouns
  - Hoboken, Baltimore, Obama, Michelle
  - Can do Transliteration

Handling Numbers

- Do we really need to encode every number? **NO!**

`I pay 950.00 in May 2007` $>$ `I pay 2007 in May 950.00`

Handling Numbers

- Do we really need to encode every number? **NO!**

  `I pay` 950.00 `in May` 2007 $>$ `I pay` 2007 `in May` 950.00

- **Solution 1:** Replace with a ⟨NUM⟩ token, but

  `I pay` ⟨NUM⟩ `in May` ⟨NUM⟩ $=$ `I pay` ⟨NUM⟩ `in May` ⟨NUM⟩

Handling Numbers

- Do we really need to encode every number? **NO!**

  I pay 950.00 in May 2007 > I pay 2007 in May 950.00

- **Solution 1:** Replace with a ⟨NUM⟩ token, but

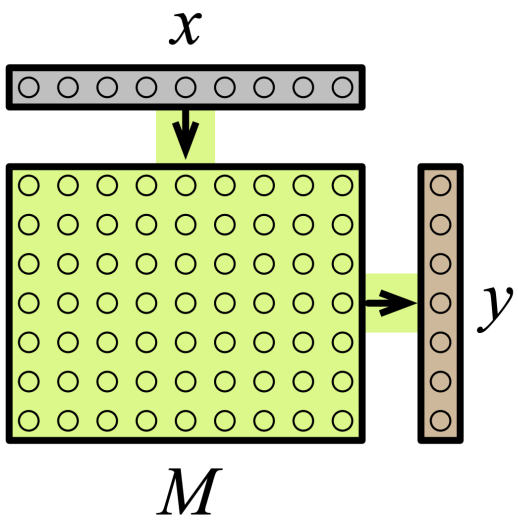
  I pay ⟨NUM⟩ in May ⟨NUM⟩ = I pay ⟨NUM⟩ in May ⟨NUM⟩

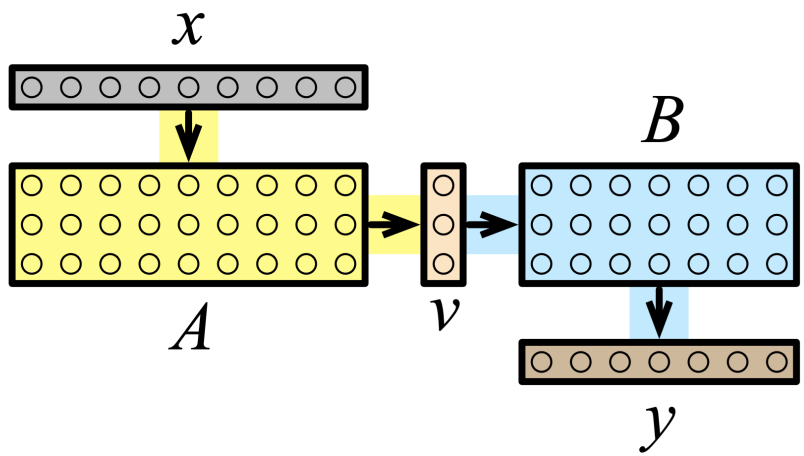
- **Solution 2:** Replace each digit with a unique symbol, e.g. 5

I pay 555.55 in May 5555 > I pay 5555 in May 555.55

- This reduces the need for embeddings, when we can simply do transliteration

Factored Decomposition





- **Problem:** Large input and output vectors
  - $|x| = 20,000$, $|y| = 50,000 \rightarrow |M| = 1,000,000,000$
- **Solution:** Use a bottleneck with smaller matrices A, B
  - $|v| = 100 \rightarrow |A| = 2,000,000$, $|B| = 5,000,000$
  - Total Parameters: $7,000,000$

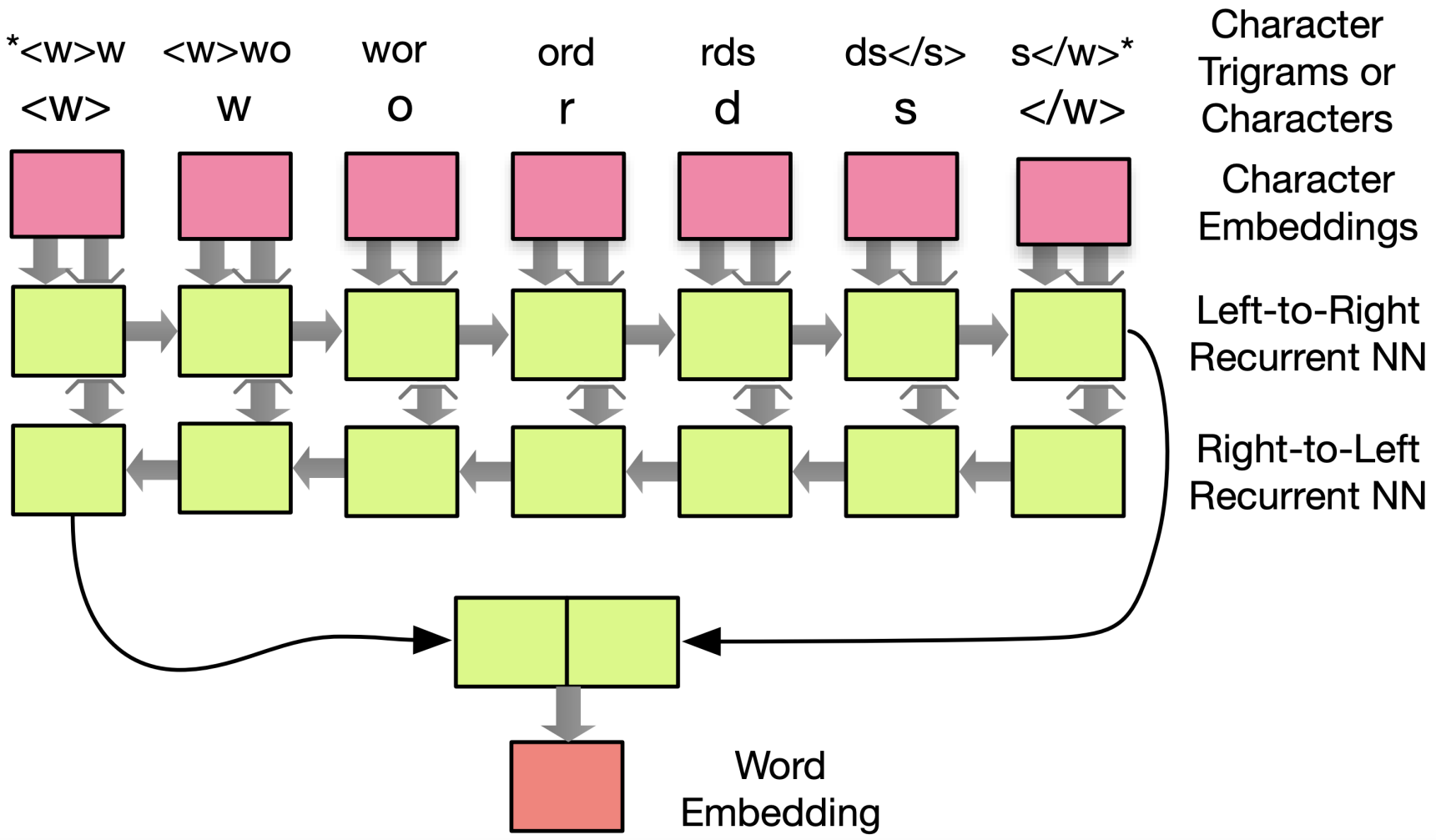
Character-Based Models

- Instead use embeddings for character string
  `b e a u t i f u l`
- Idea is to induce embeddings for unseen morphological variants:
  `beautiful`
- Tokens are single characters, symbols, whitespace

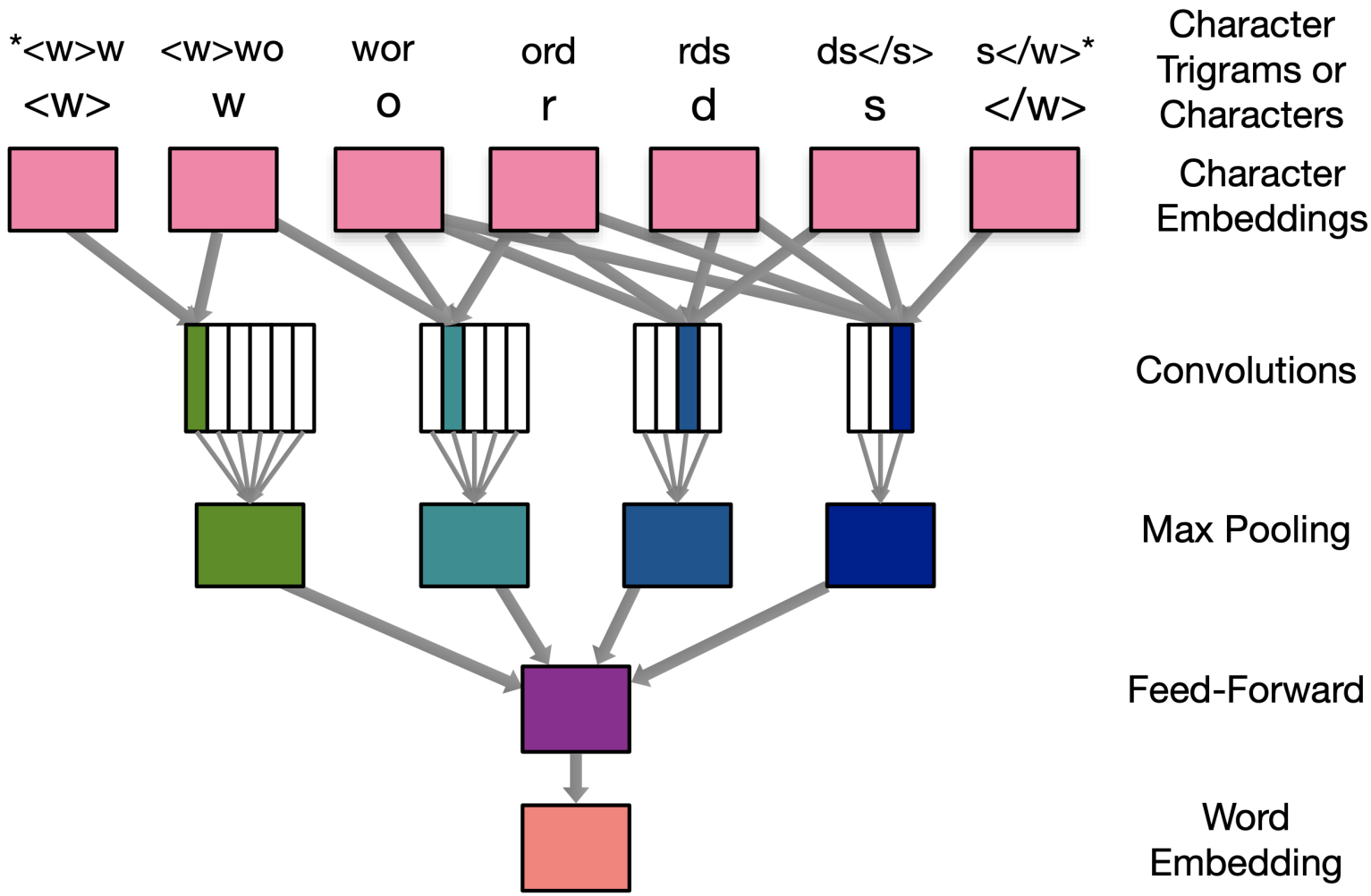
Character-Based Models

- Instead use embeddings for character string
  `b e a u t i f u l`
- Idea is to induce embeddings for unseen morphological variants:
  `beautiful`
- Tokens are single characters, symbols, whitespace
- Generally poor performance

Character-Based Models



Character-Based Models



BPE Subwords

t h e · f a t · c a t · i s · i n · t h e · t h i n · b a g

t h → th	th e · f a t · c a t · i s · i n · th e · th i n · b a g
a t → at	th e · f at · c at · i s · i n · th e · th i n · b a g
i n → in	th e · f at · c at · i s · in · th e · th in · b a g
th e → the	the · f at · c at · i s · in · the · th in · b a g

- Breaks words into subwords
  - Starts with the character set
  - Merges the most frequent pairs, one per iteration
- Unsupervised (accidental) morphology (frequency suffixes)

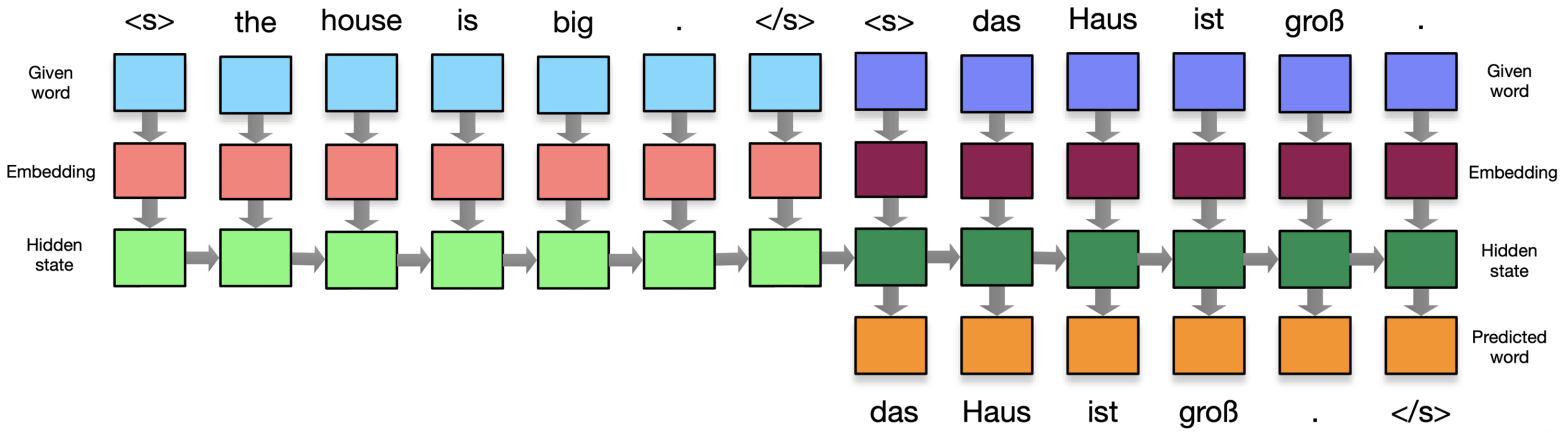
BPE Tokenization on HHGTTG

- Unique Characters: 101
- Unique BPE Tokens (1K iterations): 1,093
- Unique BPE Tokens (5K iterations): 4,817
- Unique Tokens: 9,541

```
there is a the@@ ory which st@@ at@@ es that if ever any@@ one
di@@ sc@@ o@@ ver@@ s ex@@ ac@@ tly what the universe is for
and why it is here , it will in@@ stan@@ tly di@@ s@@ ap@@ pe@@ ar
and be re@@ pl@@ ac@@ ed by something even more bi@@ zar@@ re
and in@@ ex@@ p@@ li@@ c@@ able .
there is another the@@ ory which st@@ at@@ es that
this has al@@ re@@ ad@@ y happ@@ ened .
in the beg@@ in@@ ning the universe was cre@@ ated .
this has made a lot of people very an@@ gr@@ y and
been wi@@ de@@ ly re@@ gar@@ ded as a b@@ ad mo@@ ve .
```

Column Segmentation Architecture

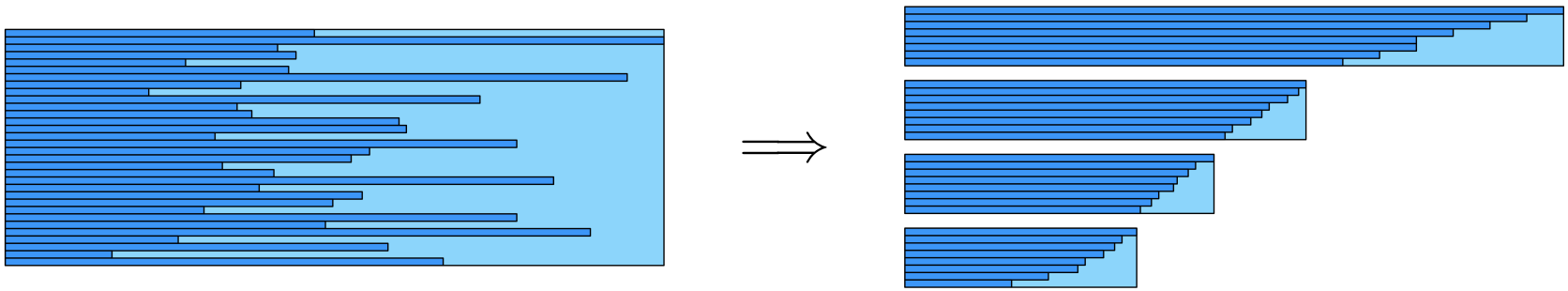
Seq2Seq Architecture




```
Seq2Seq(
  (encoder): Encoder(
    (embedding): Embedding(21, 256)
    (gru): GRU(256, 128, num_layers=2, batch_first=True)
  )
  (decoder): Decoder(
    (embedding): Embedding(22, 256)
    (gru): GRU(256, 128, num_layers=2, batch_first=True)
    (fc): Linear(in_features=128, out_features=22, bias=True)
  )
)
The model has 508,438 trainable parameters
```

Training Considerations

Increasing Throughput through Batching



- We can pad sentences of different lengths to increase batch size
- While also minimizing the use of padding
- Matrix Operations are faster
- **Warning!** Make sure padding is not influencing the hidden state

Teacher Forcing

- Instead of refeeding the predicted token, replace it with the true token randomly
- This is only done during training, not inference

$$y_{i+1} = \begin{cases} \text{argmax}_j \, \theta_i & \mathcal{U}(0,1) < \text{TF} \\ t_{i+1} & \textit{else} \end{cases}$$

- t_{i+1} is the true token
- TF is the teacher forcing ratio

Cross Entropy and Label Smoothing

$$\ell(\mathbf{x}, y_i) = -\log\left(\frac{\exp x_{y_i}}{\sum_j \exp x_j}\right)$$
$$= -\underbrace{x_{y_i}}_{max} + \underbrace{\log \sum_j \exp x_j}_{min}$$

- Softmax and Cross-Entropy loss assign all the probability mass to a single word
  - LogSumExp is minimized on confident predictions
- Solution: **smooth** the distribution

Cross Entropy and Label Smoothing

- Softmax

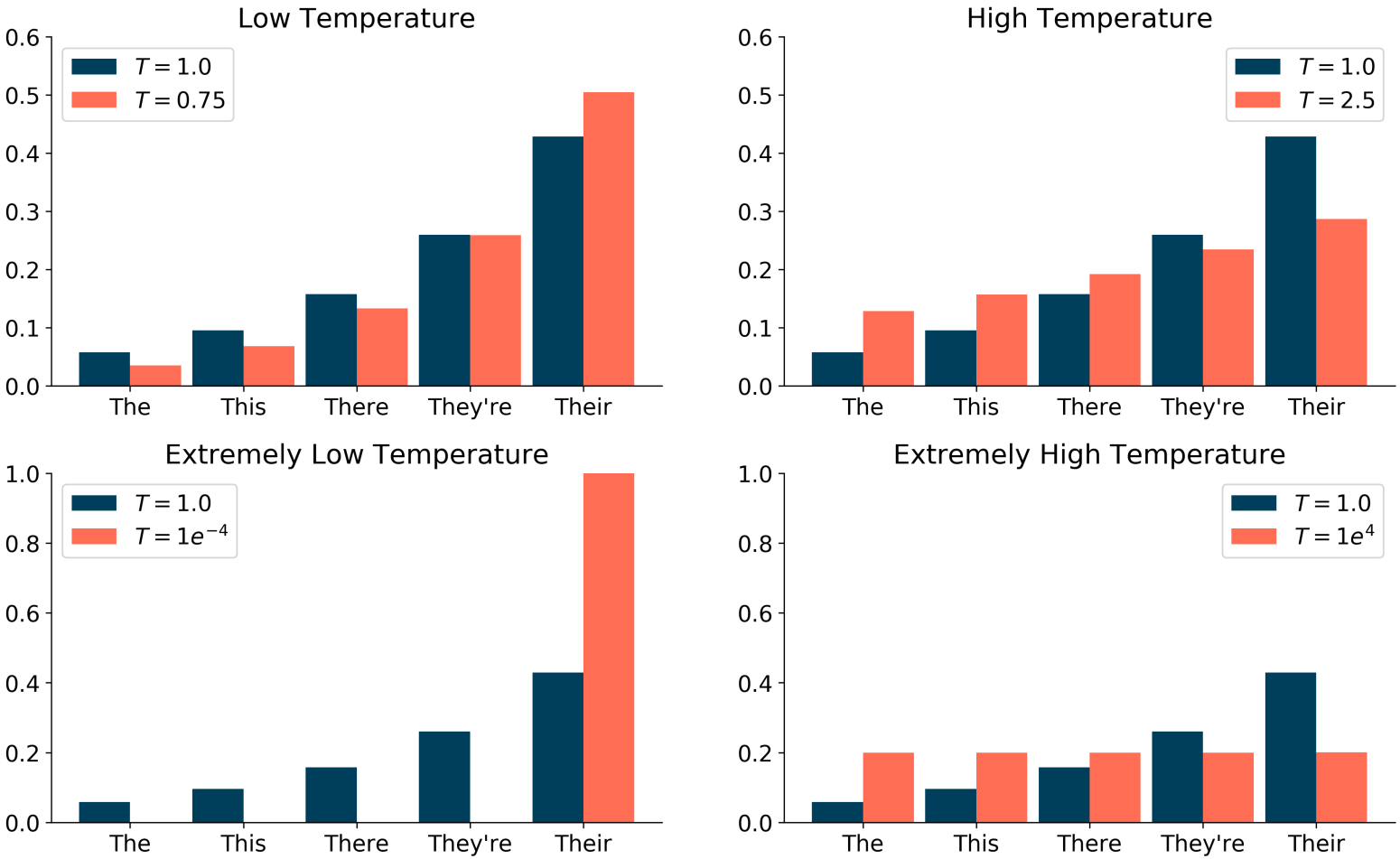
$$p(y_i) = \frac{\exp x_{y_i}}{\sum_j \exp x_j}$$

- Smoothed Softmax with Temperature T

$$p(y_i) = \frac{\exp\left(x_{y_i}/T\right)}{\sum_j \exp\left(x_j/T\right)}$$

- As $T \to \infty$, the distribution is smoother, uniform
- AS $T \to 0$, the distribution approaches a kronecker delta centered on the class with the most mass
- **Question:** Why do we divide instead of adding/subtracting?

Visualizing Temperature



Monte Carlo Decoding

- Recall how we select the next token:
  - **Greedy:** Top token weight
  - **Teacher Forcing:** Randomly select the true token
- Note that the outputs are a distribution over the target vocabulary
- **Use these weights in a multinomial to randomly select a continuation**

$$y_{i+1} \sim \text{Multinomial}\left(\theta_i\right)$$

Different Token Decoding Schemes

- **Greedy:**

$$y_{i+1} = \underset{j}{\text{argmax}}\, \theta_i$$

- **Teacher Forcing:**

$$y_{i+1} = \begin{cases} \text{argmax}_j\, \theta_i & \mathcal{U}(0,1) < \text{TF} \\ t_{i+1} & \textit{else} \end{cases}$$

- **Monte Carlo:**

$$y_{i+1} \sim \text{Multinomial}\,(\theta_i)$$

- θ_i are the output weights from the Decoder
- t_{i+1} is the true token at position $i+1$
- TF is the teacher forcing ratio

Masked Loss

- Remember, we don't care what gets predicted after seeing a ⟨EOS⟩
- Hence, we need to mask out the loss for predicted tokens associated with ⟨PAD⟩

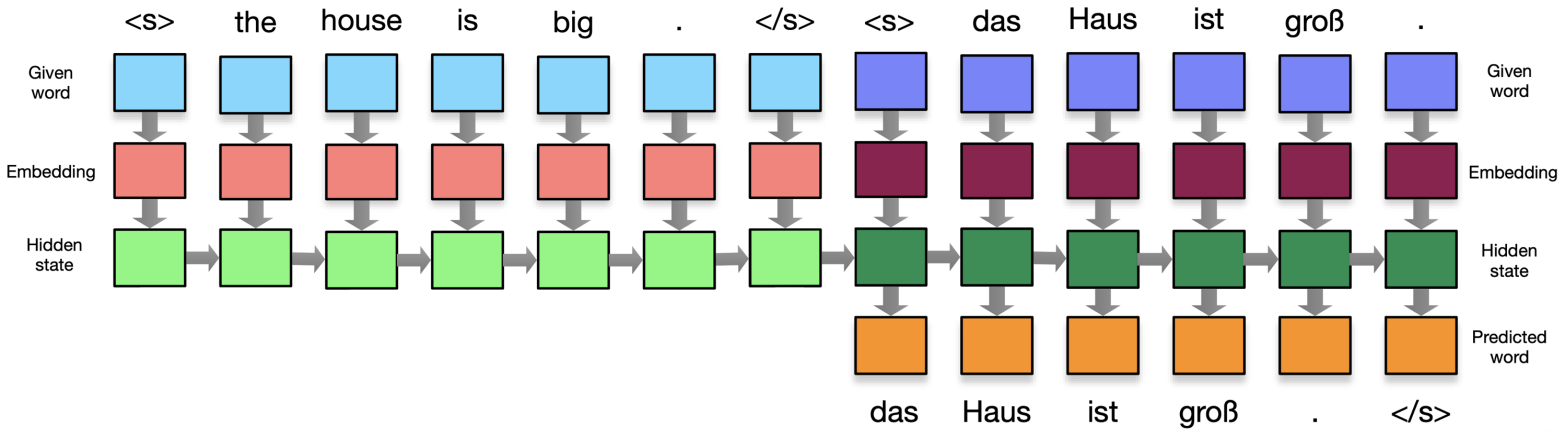
pred	→	*le*	*le*	*chat*	*chat*	*chat*	*chat*
		↓	↓	↓	↓	↓	↓
		ℓ	ℓ	ℓ	ℓ	ℓ	0
		↑	↑	↑	↑	↑	↑
true	→	*le*	*chat*	*est*	*noir*	⟨EOS⟩	⟨PAD⟩

- **Solution:** Zero out elements by either:
  - Multiply pad outputs by 0
  - Specify the label to ignore in Cross Entropy call

$$\ell(\mathbf{x}, y_i) = \mathbb{1}_{\{y_i \neq \langle \text{PAD} \rangle\}} \cdot \left(-x_{y_i} + \log \sum_j \exp x_j \right)$$

Initial Training Results

Recall: Seq2Seq Architecture

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  )
)
The model has 508,438 trainable parameters
```

Seq2Seq: Sample Results

```
>  num num num punct
=  num ⟨SEG⟩ num ⟨SEG⟩ num ⟨SEG⟩ punct
<  num ⟨SEG⟩ num ⟨SEG⟩ num ⟨SEG⟩ punct

>  adj num num num
=  adj ⟨SEG⟩ num ⟨SEG⟩ num ⟨SEG⟩ num
<  adj ⟨SEG⟩ num ⟨SEG⟩ num ⟨SEG⟩ num num num num num

>  verb noun noun noun noun noun verb
=  verb ⟨SEG⟩ noun noun ⟨SEG⟩ noun noun noun ⟨SEG⟩ verb
<  verb noun ⟨SEG⟩ ⟨SEG⟩ noun noun noun noun ⟨SEG⟩ noun ···
```

Translation Results: TL;DR

- Reasonably for small sequences
- Struggles to terminate properly
  - Maybe more training?
- Long Sequences are a mess

Translation Results: TL;DR

- Reasonably for small sequences
- Struggles to terminate properly
  - Maybe more training?
- Long Sequences are a mess
- **However** this indicates that enough noise can be transfered via the hidden state

Review

- We have covered:
  - What are Seq2Seq Models?
  - How can I reduce my vocabulary size?
  - How do I train a Seq2Seq model?
- Part 2 will explore more advanced concepts such as:
  - Decoding with Beam Search
  - Modeling Recurrent Relations
  - Other applications of Sequence Modeling

Thank You!

Seq2Seq in Action: Column Segmentation

Part 2

Bill Watson

S&P Global

January 23, 2020

Review

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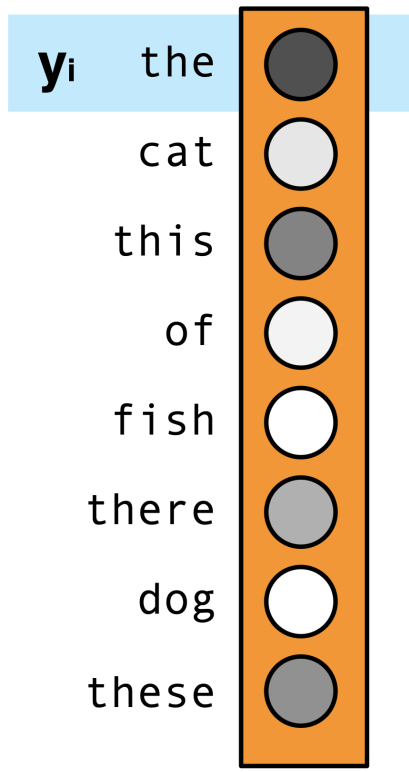
  - What are Seq2Seq Models?
  - How can I reduce my vocabulary size?
  - How do I train a Seq2Seq model?
- Part 2 will explore more advanced concepts such as:
  - Decoding with Beam Search
  - Modeling Recurrent Relations
  - Other applications of Sequence Modeling

Decoding: Making better Translations

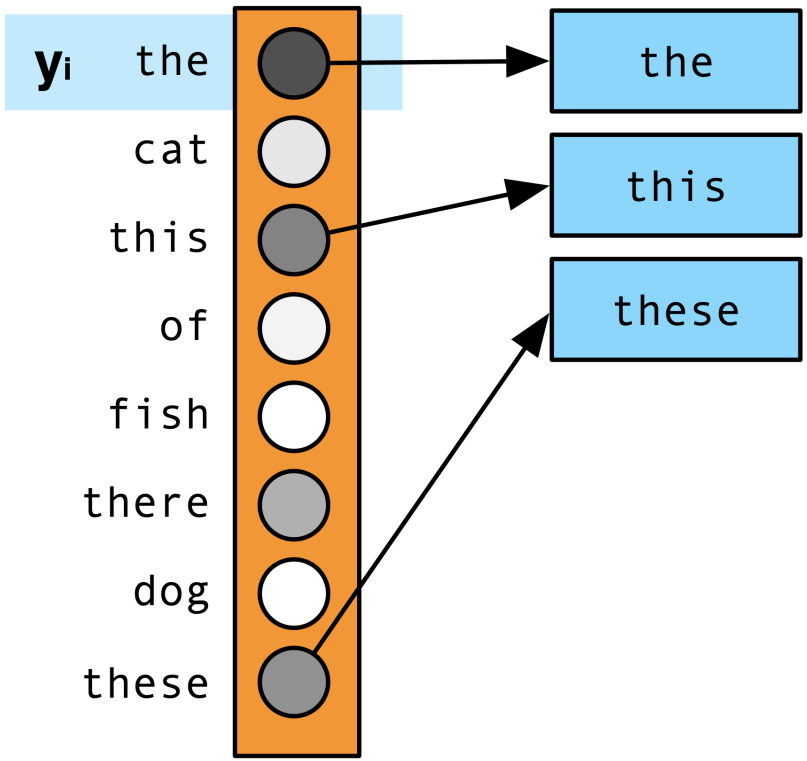
Beam Search

- Beam Search is a technique to explore different translation paths
- Based on the idea that you **shouldn't take the greedy path**
- And that the best path may be sub-optimal during early iterations

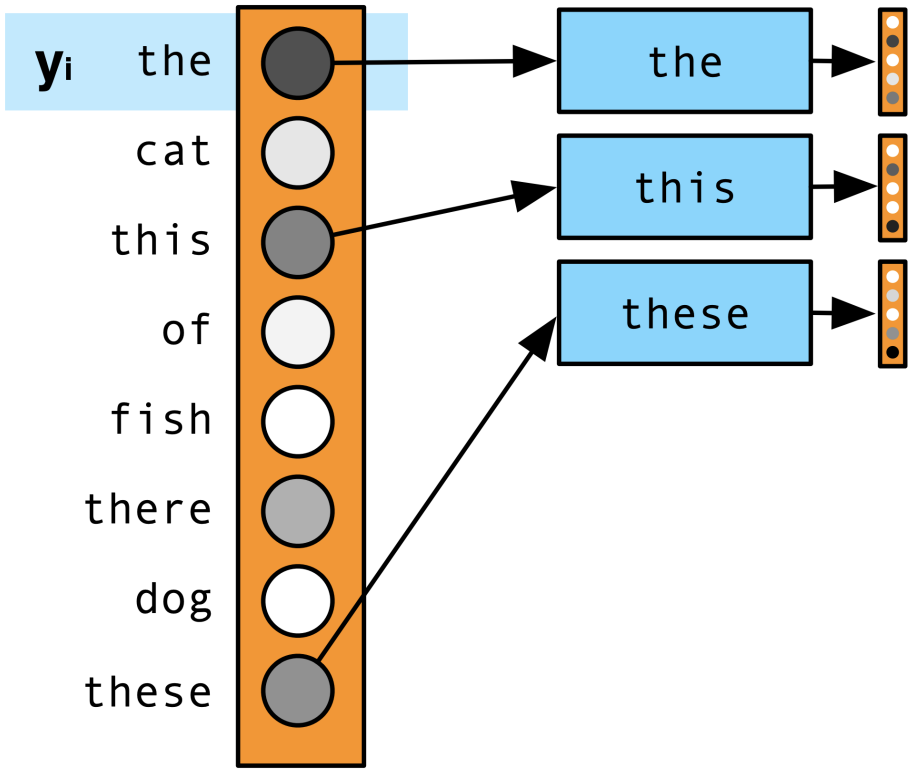
Beam Search



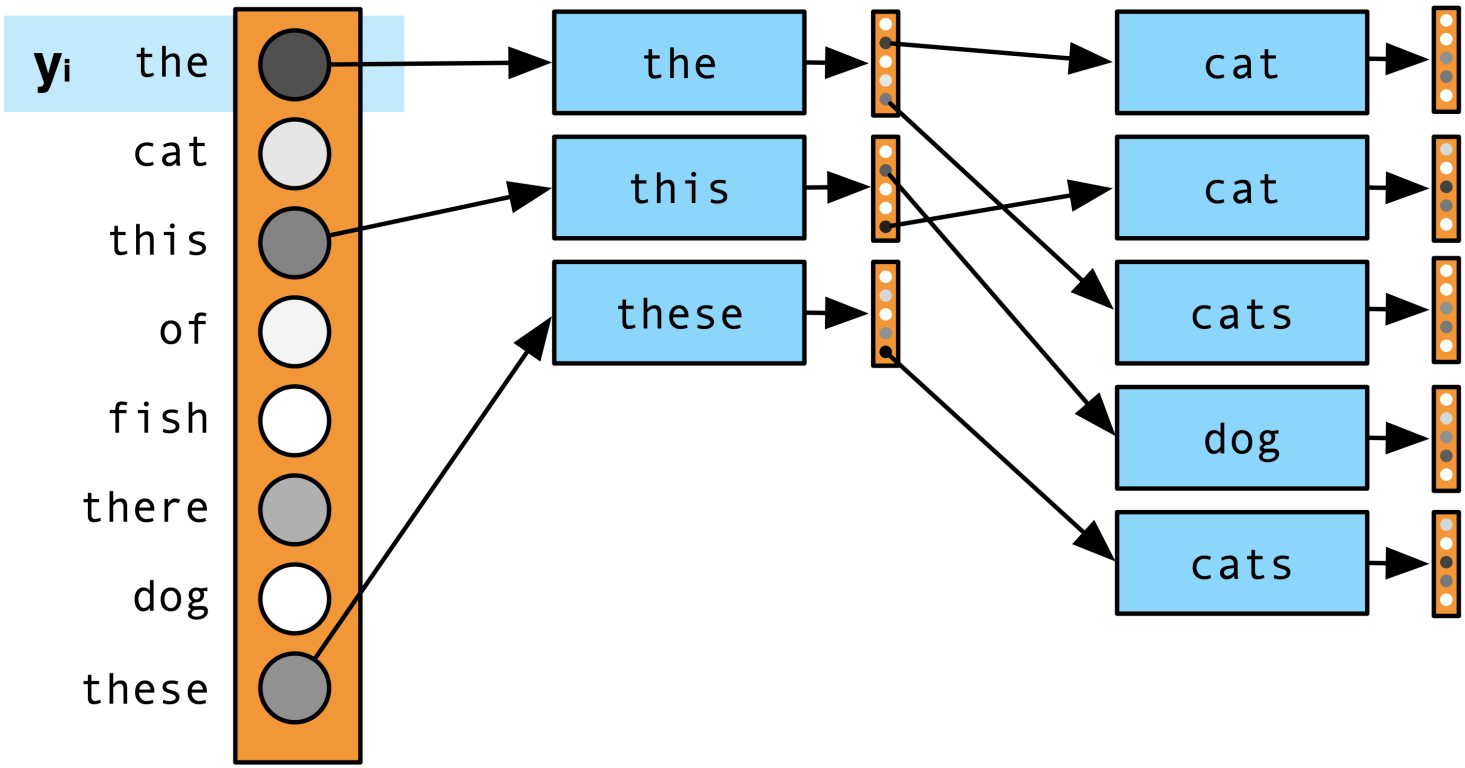
Beam Search



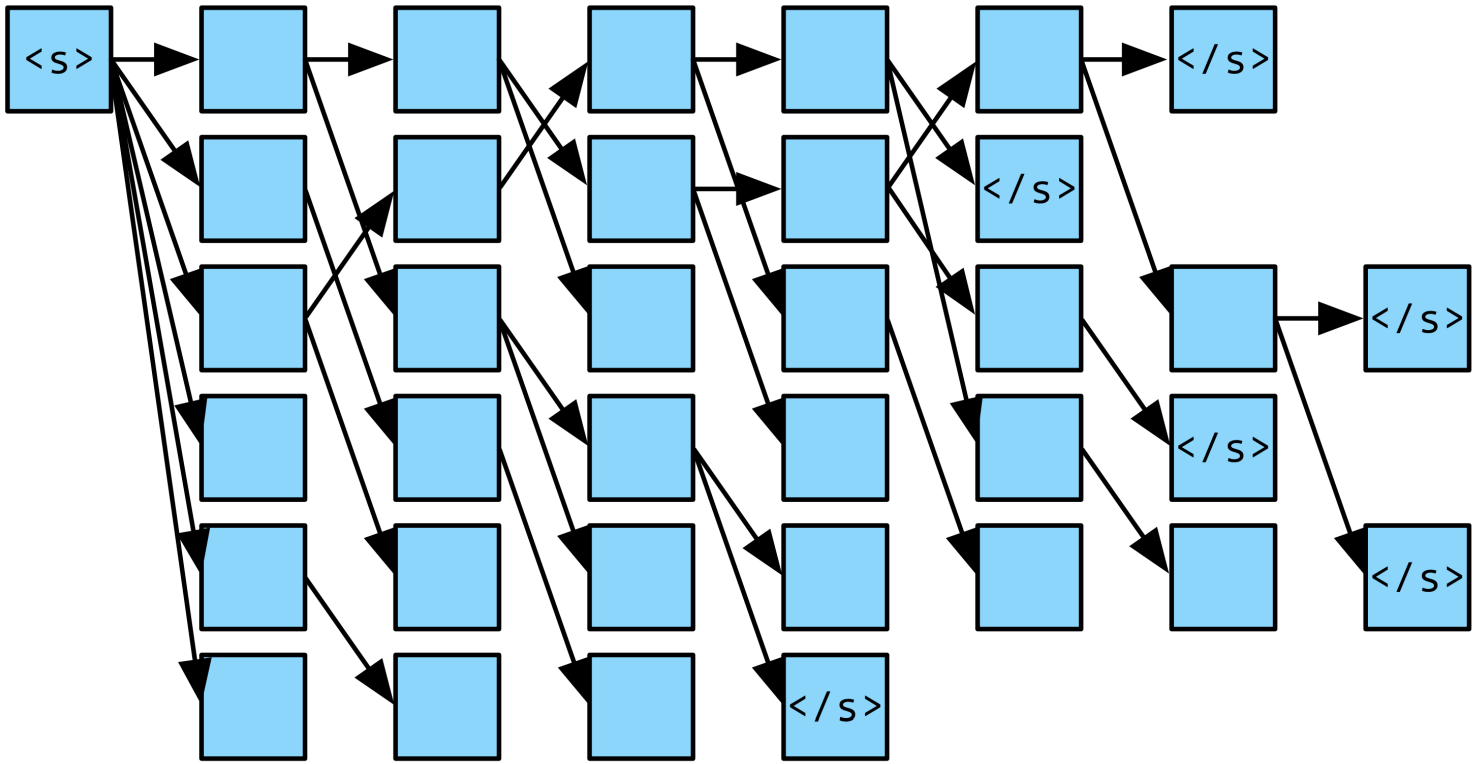
Beam Search



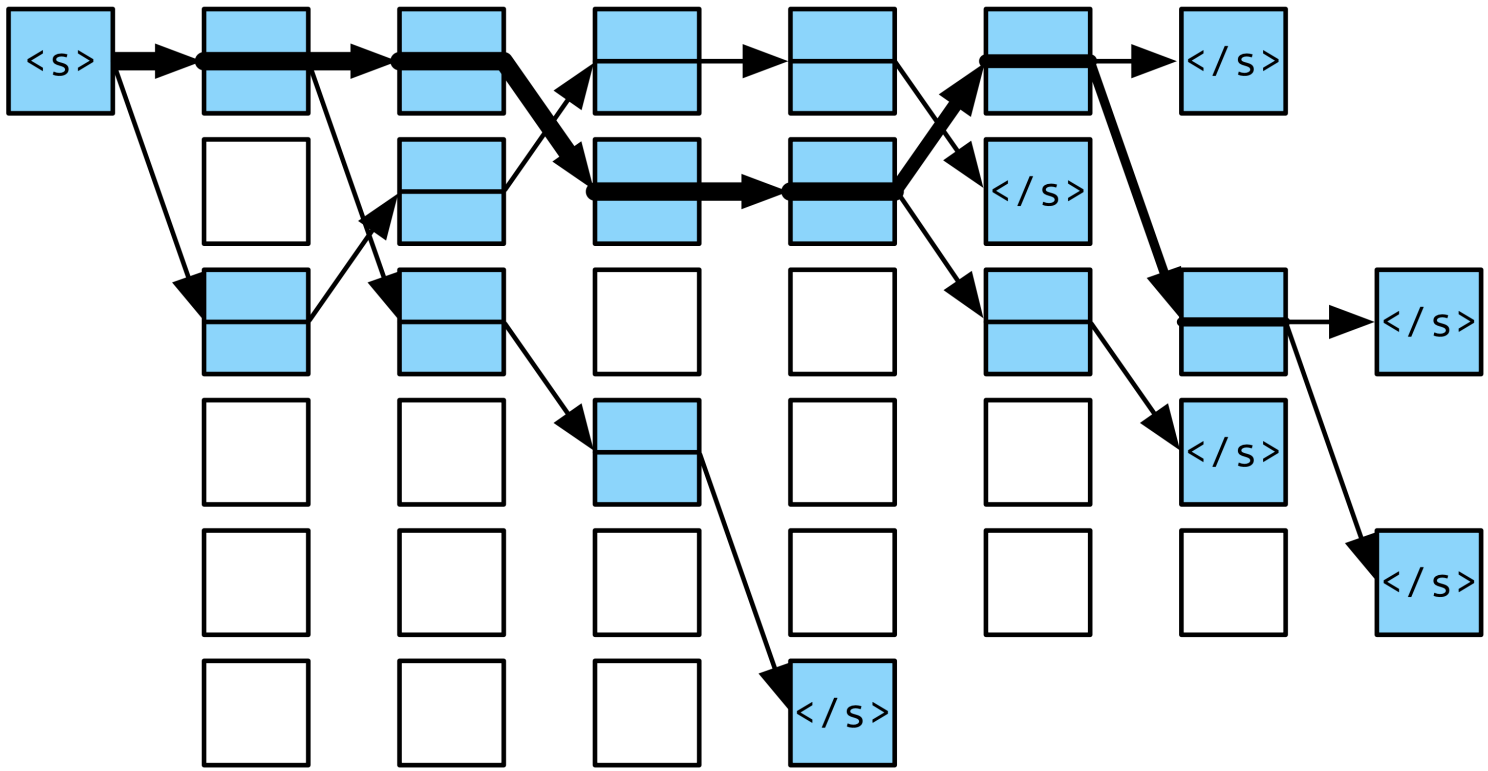
Beam Search


y_i
the
cat
this
of
fish
there
dog
these
the
this
these
cat
cat
cats
dog
cats

Beam Search

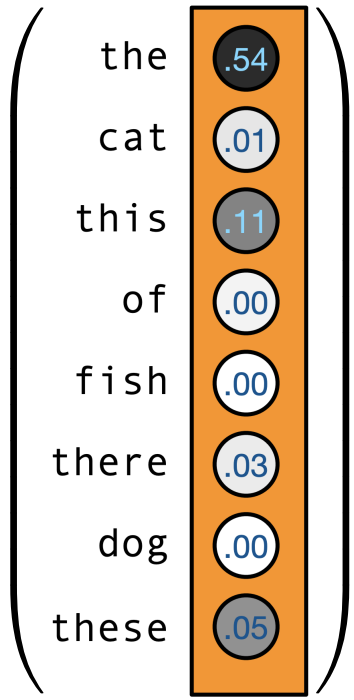


Beam Search



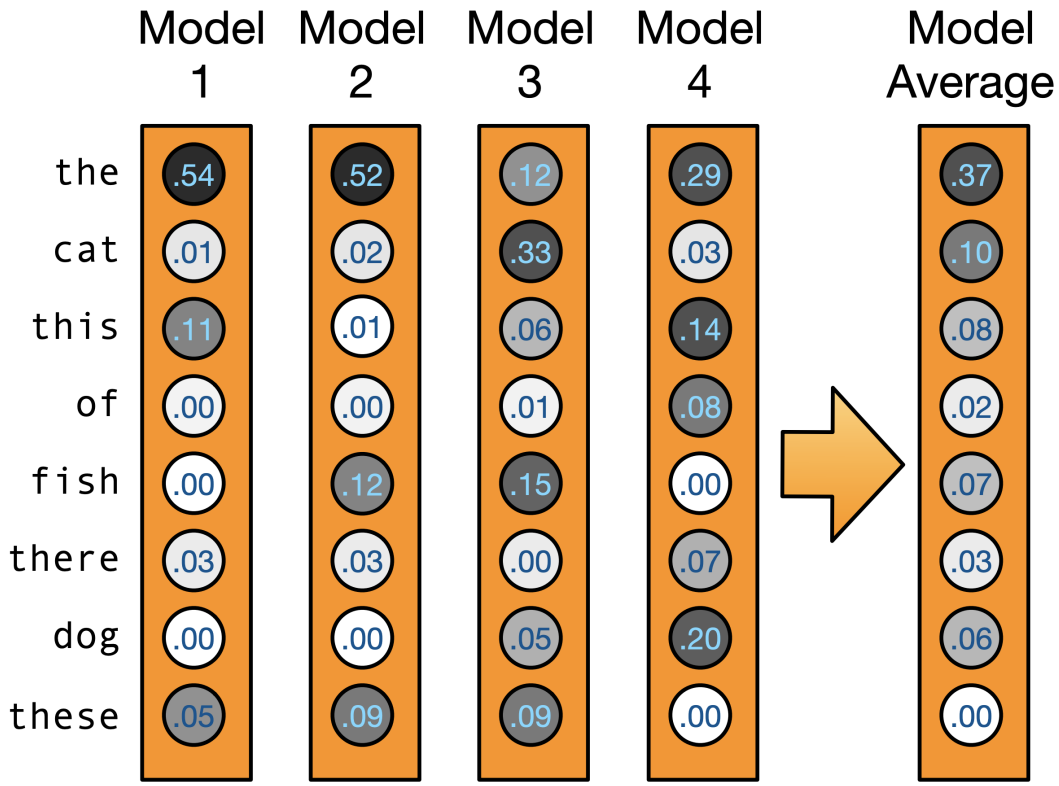
Monte Carlo Beam Search

$$y_{i+1} \sim \text{Multinomial}$$



- Why not sample n words based on their probabilities?
- Adds more diversity to beam search results

Ensembling



- Why not average different models?
- Random initialization leads to different local solutions
- Could also use model dumps from different iterations

Modeling Recurrent Relations

Vanilla RNNs

$$h_t = \tanh\left(\overbrace{W_{ih}x_t + b_{ih}}^{input} + \underbrace{W_{hh}h_{t-1} + b_{hh}}_{hidden}\right)$$

- h_t is the hidden state at time t
- x_t is the input at time t
- h_{t-1} is the previous hidden state
- h_0 is initialized to $\mathbf{0}$

Long Short Term Memory (LSTM)

$$
\begin{aligned}
\text{Gates} \rightarrow & \begin{cases}
i_t = \sigma(W_{ii} x_t + b_{ii} + W_{hi} h_{t-1} + b_{hi}) \\
f_t = \sigma(W_{if} x_t + b_{if} + W_{hf} h_{t-1} + b_{hf}) \\
o_t = \sigma(W_{io} x_t + b_{io} + W_{ho} h_{t-1} + b_{ho}) \\
g_t = \tanh(W_{ig} x_t + b_{ig} + W_{hg} h_{t-1} + b_{hg})
\end{cases} \\
\text{Outputs} \rightarrow & \begin{cases}
c_t = f_t \odot c_{t-1} + i_t \odot g_t \\
h_t = o_t \odot \tanh(c_t)
\end{cases}
\end{aligned}
$$

- h_t is the hidden state at time t
- c_t is the cell state at time t
- x_t is the input at time t

Gated Recurrent Units (GRU)

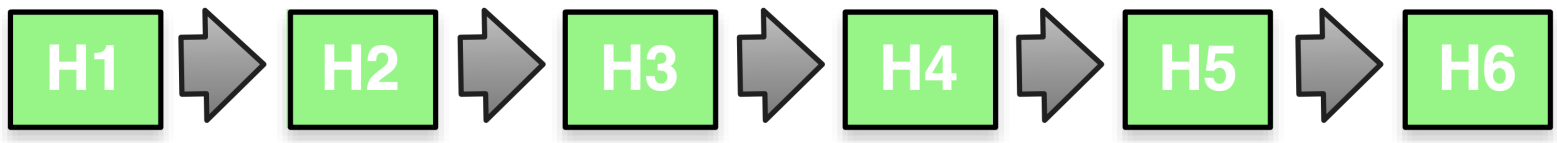
$$\text{Gates} \rightarrow \begin{cases} r_t = \sigma(W_{ir} x_t + b_{ir} + W_{hr} h_{(t-1)} + b_{hr}) \\ z_t = \sigma(W_{iz} x_t + b_{iz} + W_{hz} h_{(t-1)} + b_{hz}) \\ n_t = \tanh(W_{in} x_t + b_{in} + r_t \odot (W_{hn} h_{(t-1)} + b_{hn})) \end{cases}$$

$$\text{Outputs} \rightarrow \begin{cases} h_t = (1 - z_t) \odot n_t + z_t \odot h_{(t-1)} \end{cases}$$

- h_t is the hidden state at time t
- x_t is the input at time t

Aside: Different Perspectives on Deep Recurrent Models

- So far we've only seen Left to Right Sequencing



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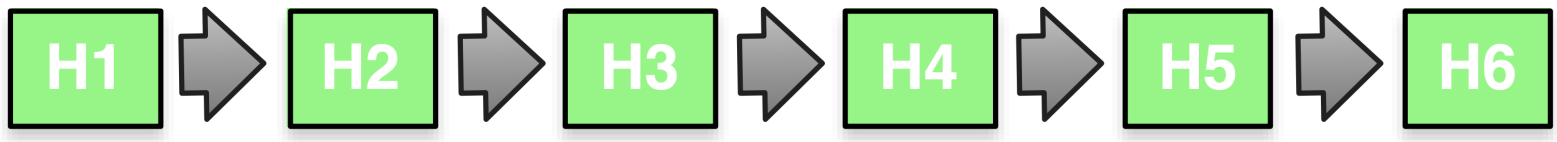
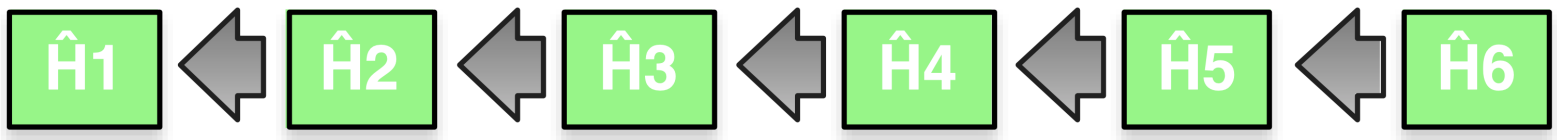
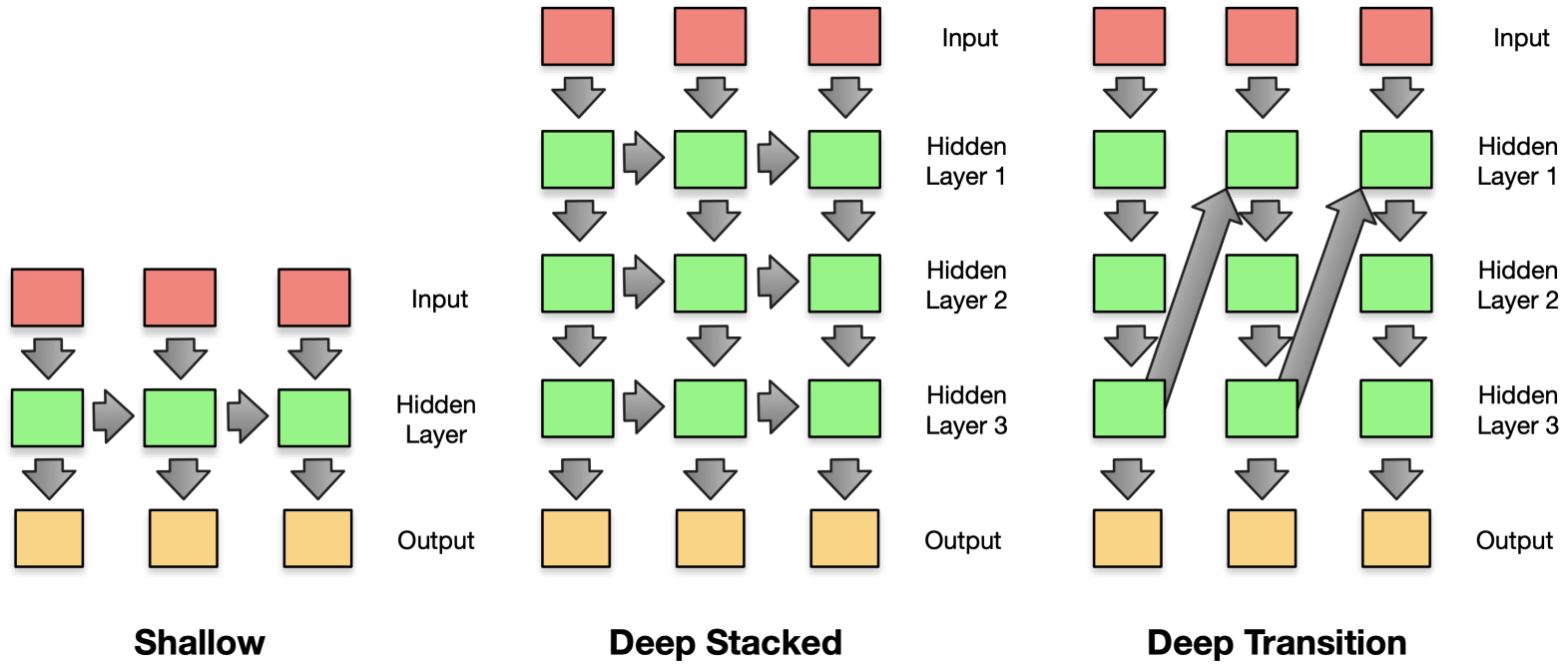


- Why not Right to Left?

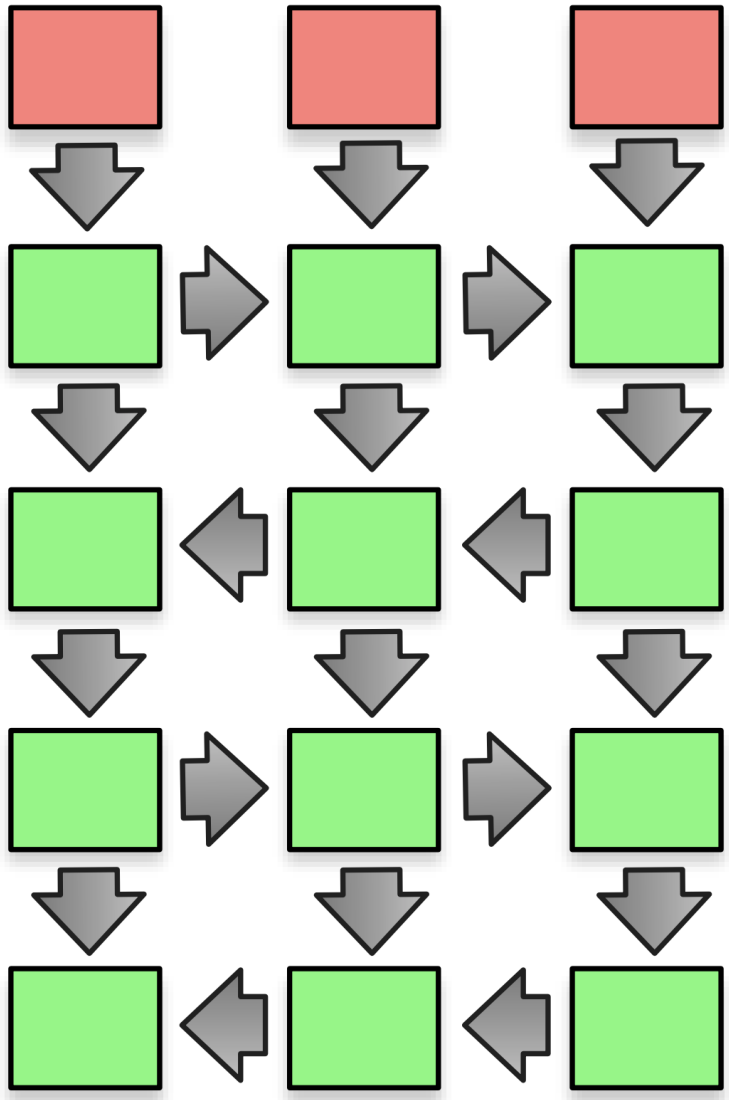


Aside: Different Perspectives on Deep Recurrent Models

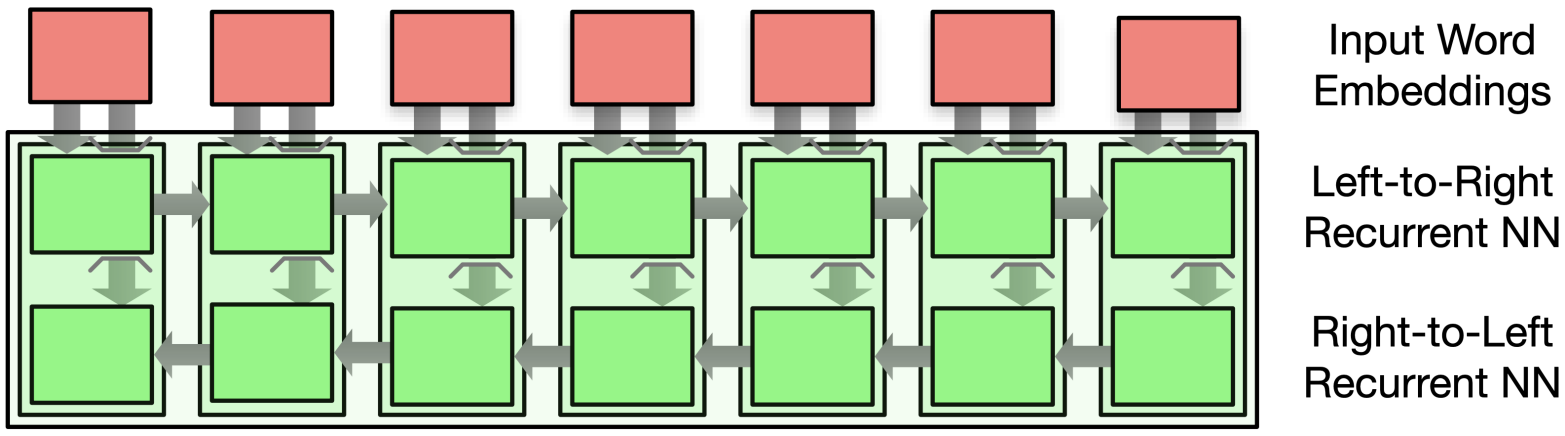


- Experiment with different stacking techniques

Alternating Recurrent Directions



Bidirectional Sequence Modeling



- Can capture both left and right context
- Implementation usually concatenates RNN states

Aside: Dimensionality of Inputs and Outputs (Batch First)

Type	RNN	LSTM	GRU
In	B, L, H_{in}	B, L, H_{in}	B, L, H_{in}
h_{t-1}	$N_L \cdot N_D, B, H_{out}$	$N_L \cdot N_D, B, H_{out}$	$N_L \cdot N_D, B, H_{out}$
c_{t-1}	-	$N_L \cdot N_D, B, H_{out}$	-
h_t	$N_L \cdot N_D, B, H_{out}$	$N_L \cdot N_D, B, H_{out}$	$N_L \cdot N_D, B, H_{out}$
c_t	-	$N_L \cdot N_D, B, H_{out}$	-
Out	$B, L, N_D \cdot H_{out}$	$B, L, N_D \cdot H_{out}$	$B, L, N_D \cdot H_{out}$

- B is the batch size
- L is the sequence length
- N_D is the number of directions
- N_L is the number of layers
- H_{in}, H_{out} are the input and hidden size

Aside: The Influence of Padding in RNNs

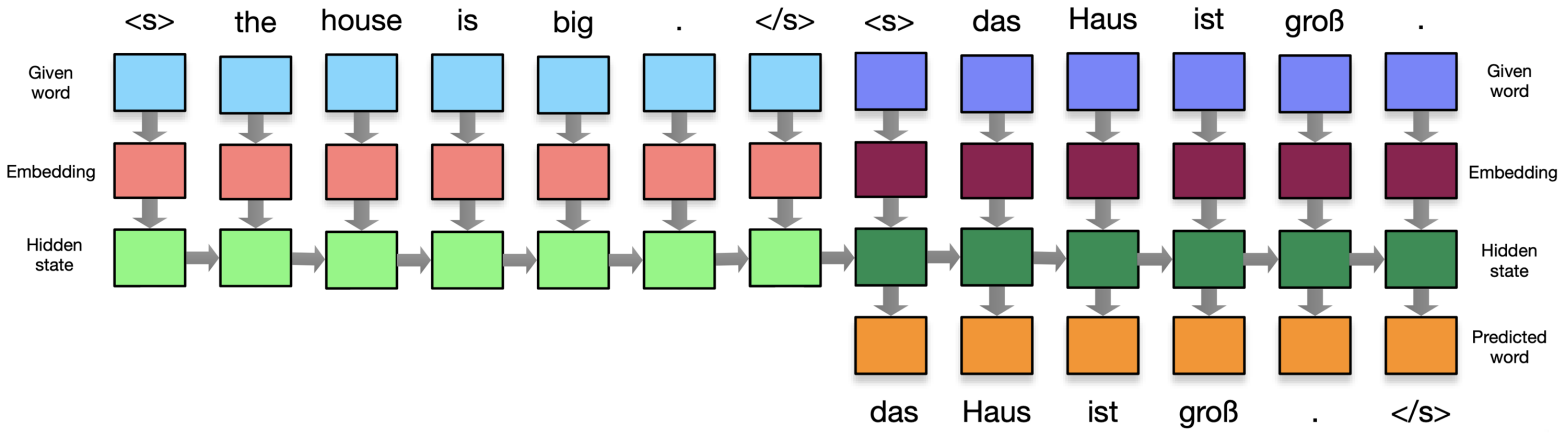
- Assume the embedding $E[\langle \text{PAD} \rangle] = \mathbf{0}$
- Are we safe?

Aside: The Influence of Padding in RNNs

- Assume the embedding $E[\langle \text{PAD} \rangle] = \mathbf{0}$
- Are we safe? **NO!**
- Because of the bias term, zero input does not result in a zero output
  - This alters the hidden state being passed onto the next iteration
- Don't even think about the mess bidirectionals become...
- **Question:** Does this mean we learn the amount of padding for a given sequence?

Applications to Column Segmentation

Applications to Column Segmentation




```
Seq2Seq(
  (encoder): Encoder(
    (embedding): Embedding(21, 256)
    (gru): GRU(256, 128, num_layers=2, batch_first=True)
  )
  (decoder): Decoder(
    (embedding): Embedding(22, 256)
    (gru): GRU(256, 128, num_layers=2, batch_first=True)
    (fc): Linear(in_features=128, out_features=22, bias=True)
  )
)
The model has 508,438 trainable parameters
```

Column Segmentation: Throw away the decoder

- Just use an encoder, with an output layer
- For every token, predict if we should insert a ⟨SEG⟩
- No longer have to learn the actual sequence

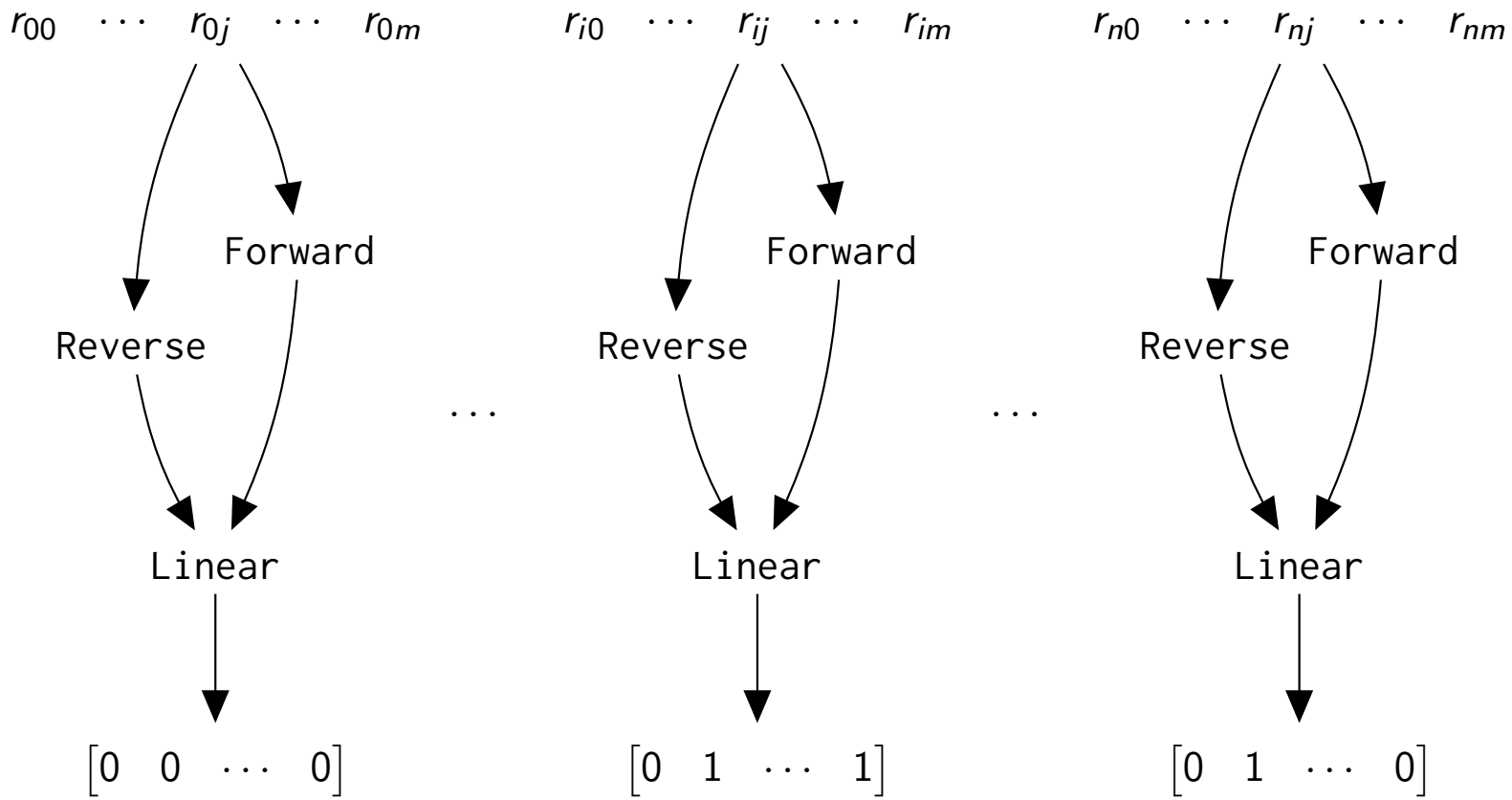
```
Classifier(
  (encoder): Encoder(
    (embedding): Embedding(21, 128)
    (gru): GRU(128, 128, batch_first=True, bidirectional=True)
  )
  (linear): Linear(in_features=256, out_features=1, bias=True)
)
The model has 201,089 trainable parameters
```

Independent Row: Training Labels

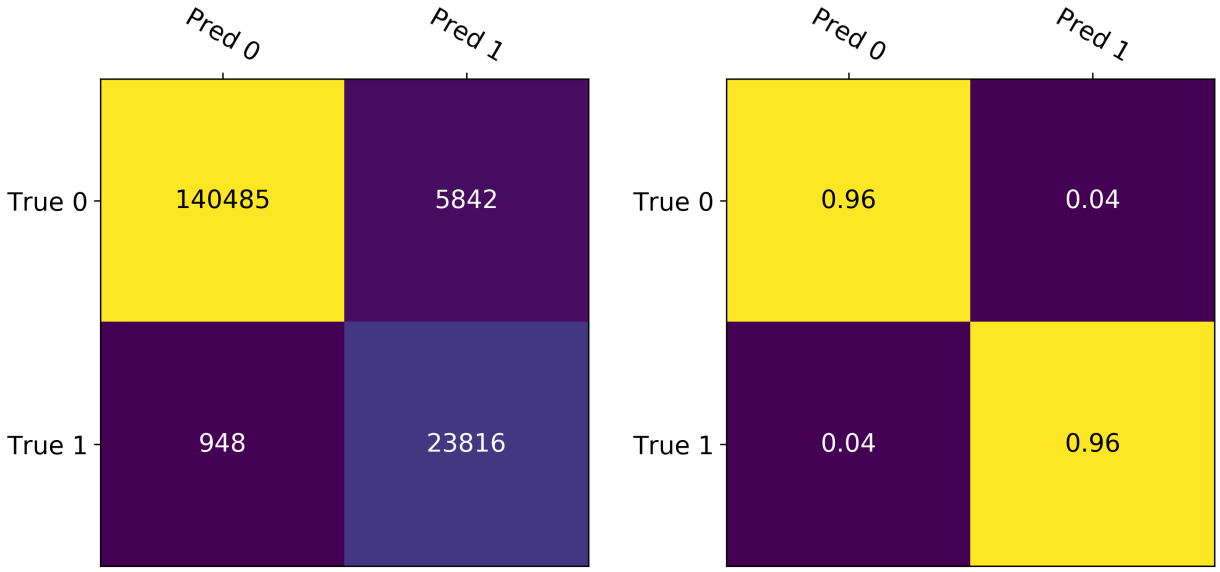
- Labels are now binary vectors, where $x_i = 1$ implies that there is a ⟨SEG⟩ between x_i and x_{i+1}

Less	imputed	interest		(	174,862.64	)
0	0	**1**		0	0	0
Less	imputed	interest	⟨SEG⟩	(	174,862.64	)

Independent Row Training Visual

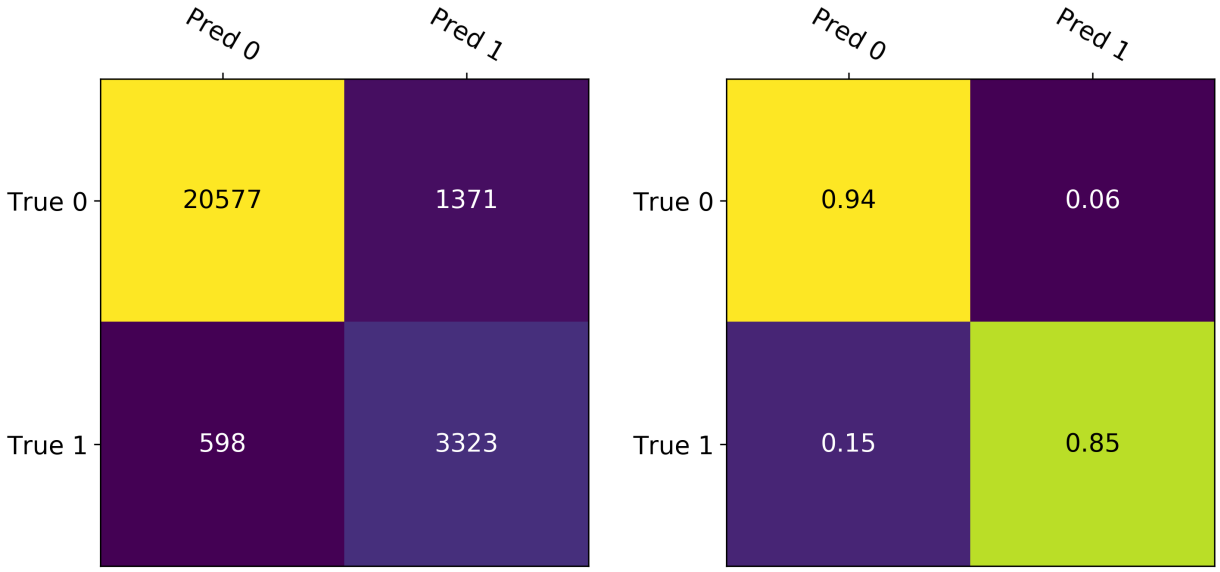


Independent Row: Sample Results (Training)



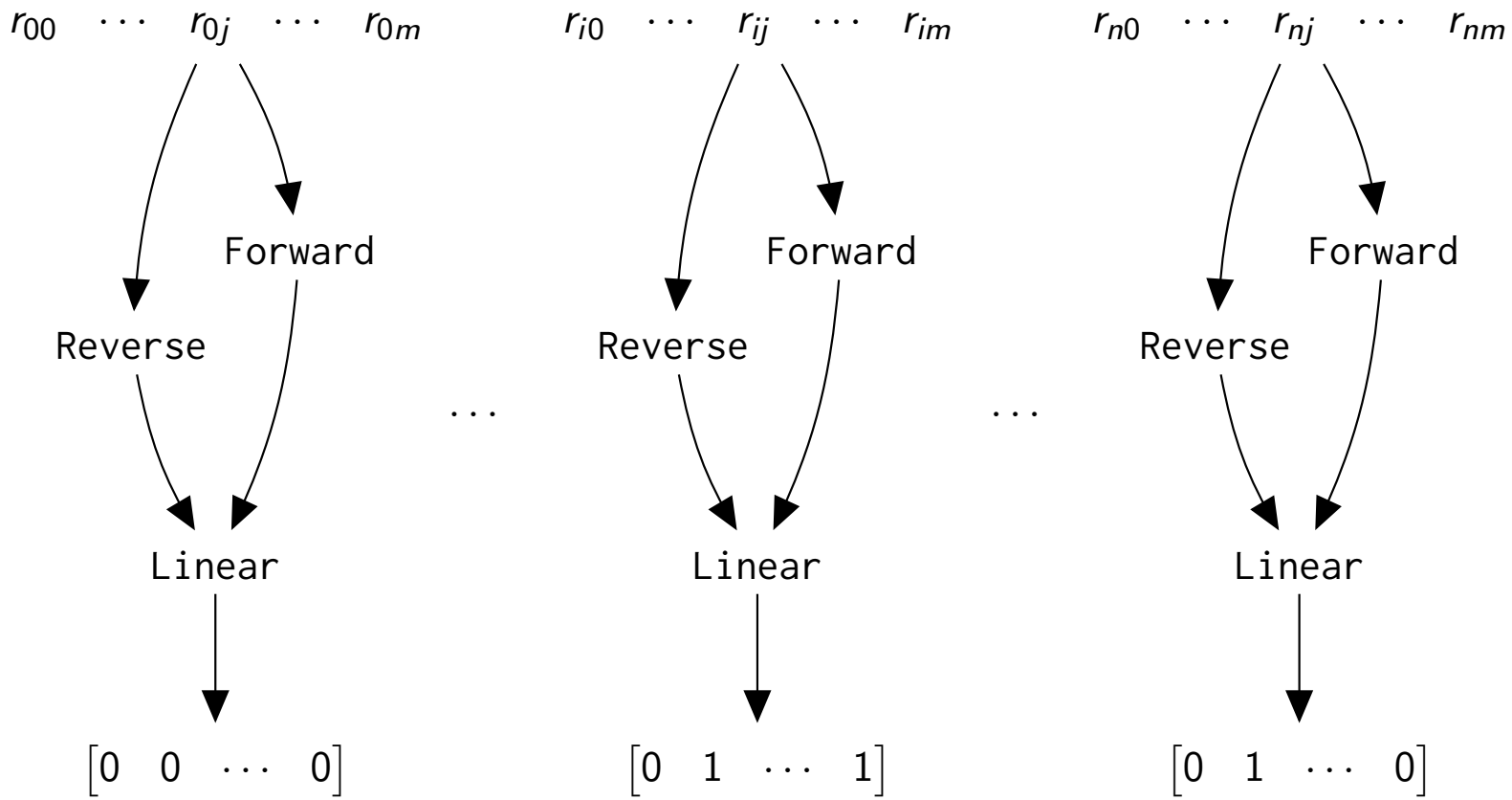
	Precision	Recall	F1-Score	Support
Label: 0	0.99	0.96	0.98	146,327
Label: 1	0.80	0.96	0.88	24,764
accuracy			0.96	171,091
macro avg	0.90	0.96	0.93	171,091
weighted avg	0.97	0.96	0.96	171,091

Independent Row: Sample Results (Validation)



	Precision	Recall	F1-Score	Support
Label: 0	0.97	0.94	0.95	21,948
Label: 1	0.71	0.85	0.77	3,921
accuracy			0.92	25,869
macro avg	0.84	0.89	0.86	25,869
weighted avg	0.93	0.92	0.93	25,869

How can we improve on this?

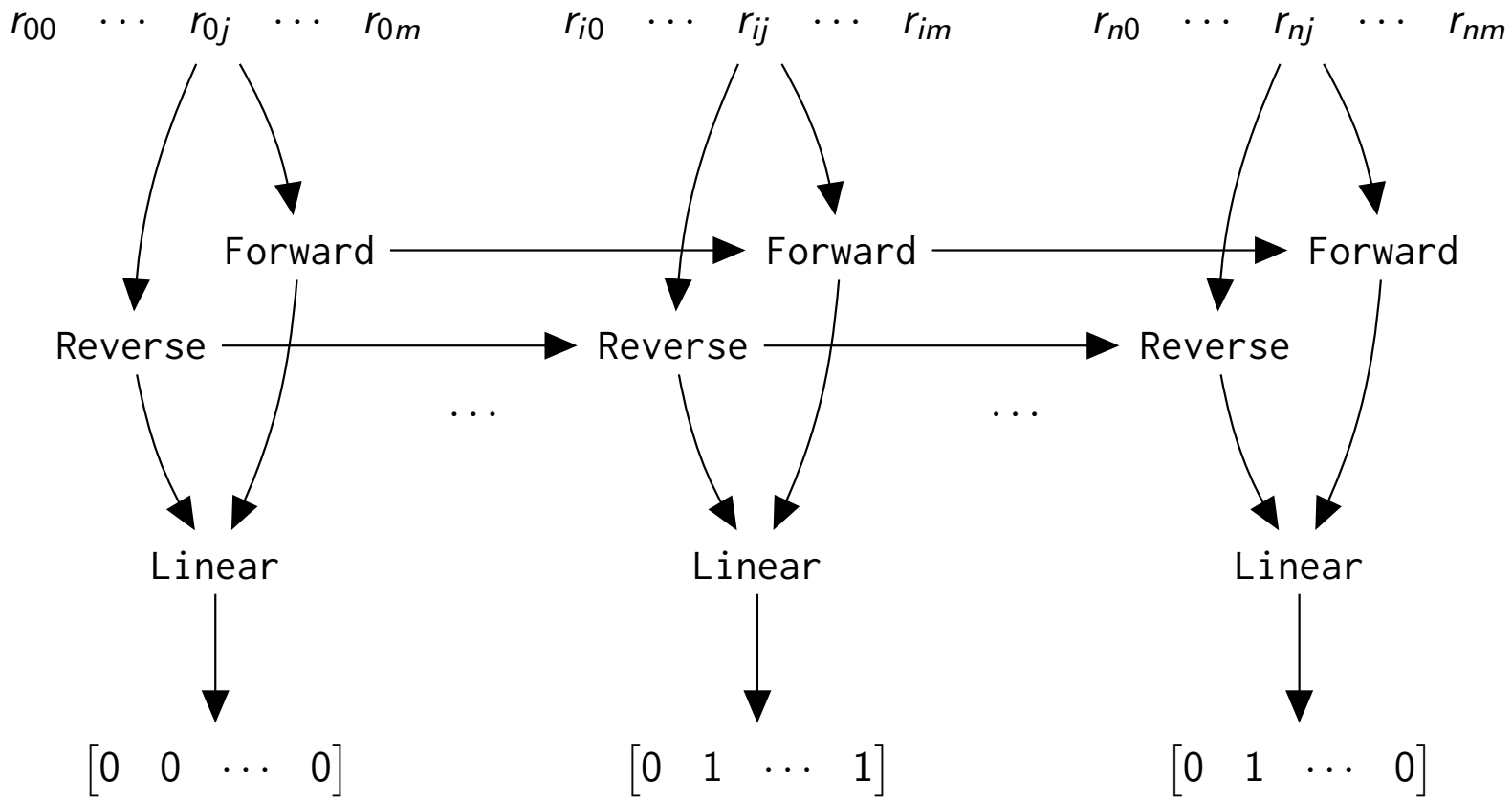


Joint Training on a Table

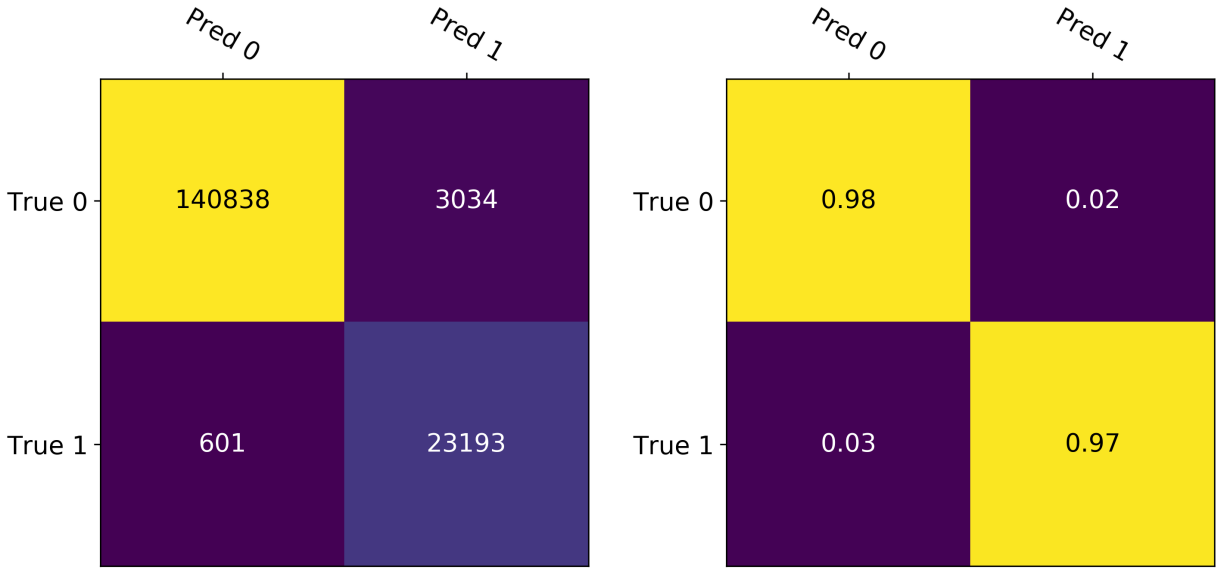
- We saw that we could regenerate a sequence from its hidden state alone.
- Why not use this information to link rows within the same table?
  - Bidirectional for each row
  - Propagate hidden state to next row
  - Linear layers for prediction

```
TableClassifier(
  (embedding): Embedding(21, 128)
  (rnn): GRU(128, 128, batch_first=True, bidirectional=True)
  (ff): Linear(in_features=256, out_features=1, bias=True)
)
The model has 201,089 trainable parameters
```

Joint Table Training Visual

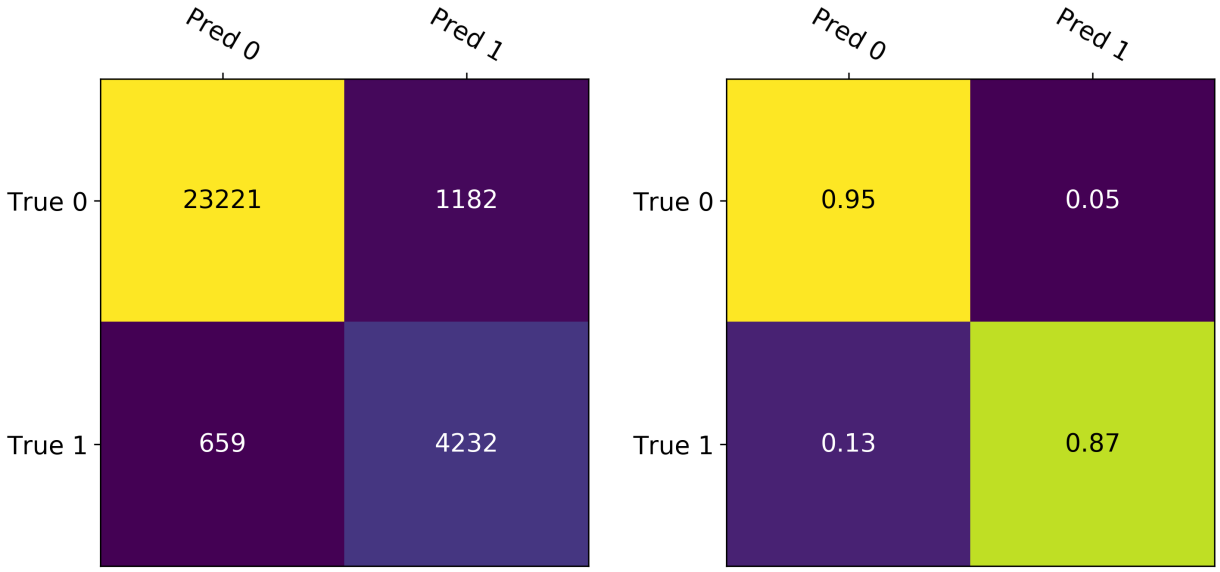


Joint Table Training: Sample Results (Training)



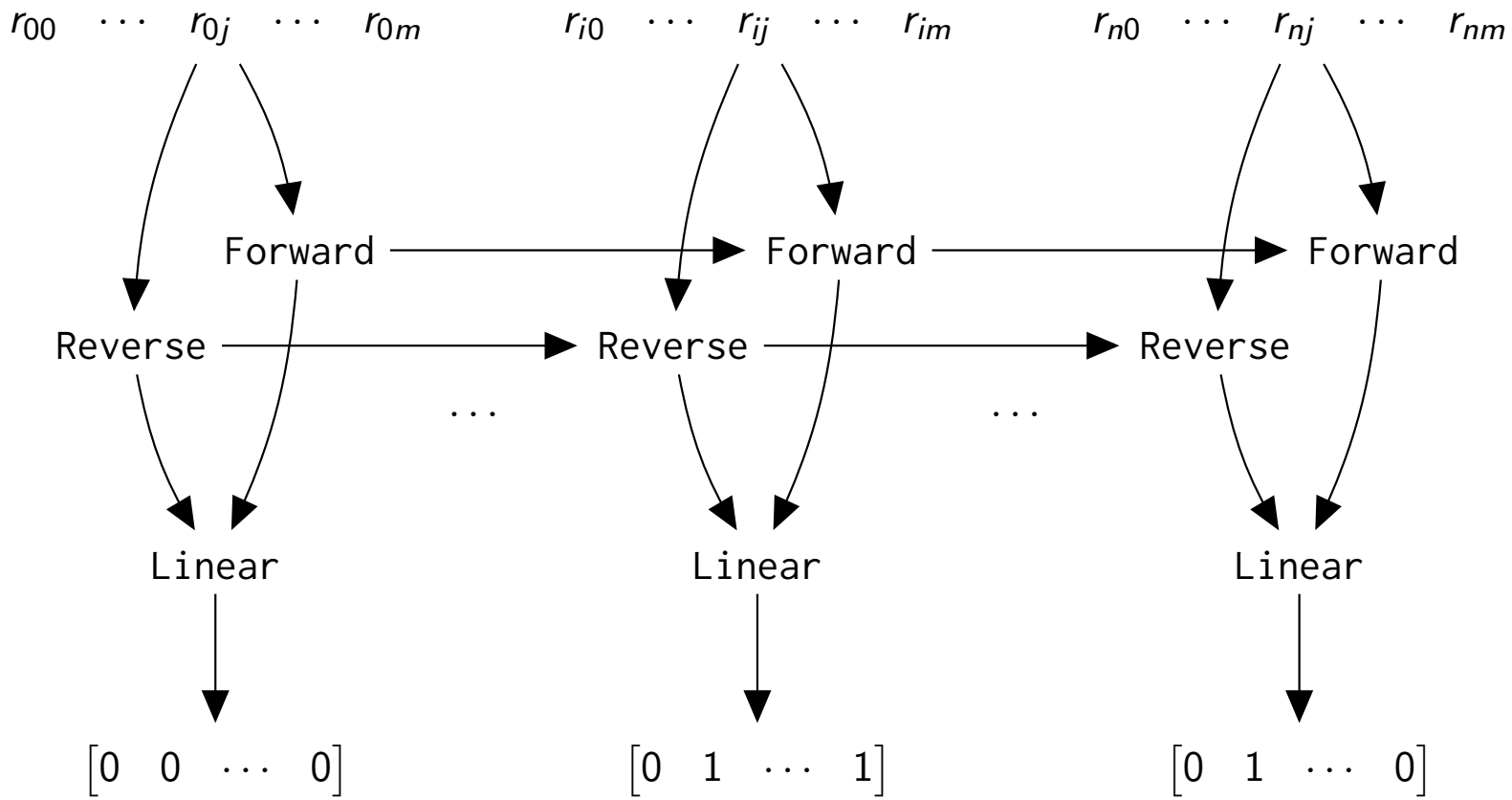
	Precision	Recall	F1-Score	Support
Label: 0	1.00	0.98	0.99	143,872
Label: 1	0.88	0.97	0.93	23,794
accuracy			0.98	167,666
macro avg	0.94	0.98	0.96	167,666
weighted avg	0.98	0.98	0.98	167,666

Joint Table Training: Sample Results (Validation)

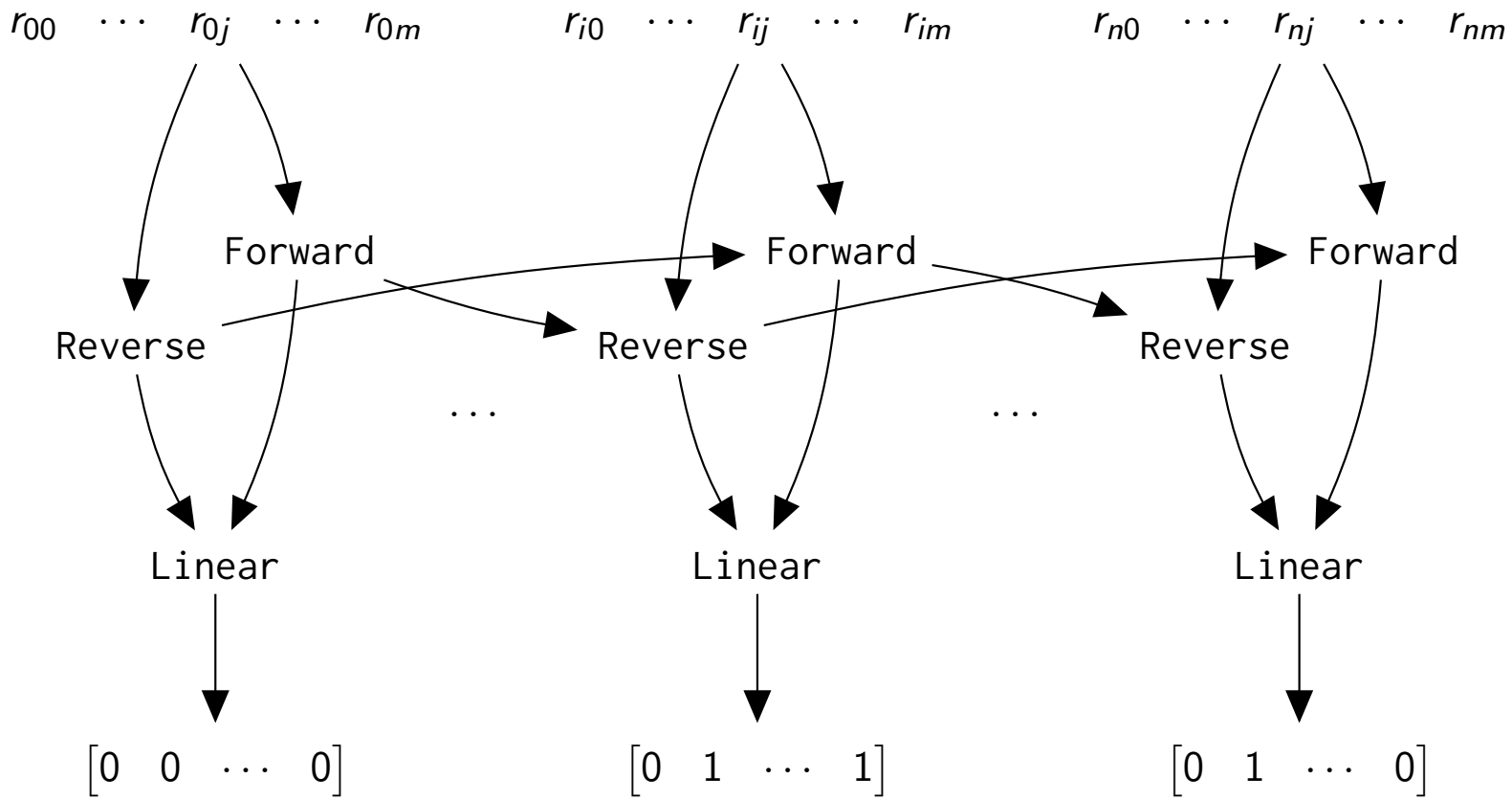


	Precision	Recall	F1-Score	Support
Label: 0	0.97	0.95	0.96	24,403
Label: 1	0.78	0.87	0.82	4,891
accuracy			0.94	29,294
macro avg	0.88	0.91	0.89	29,294
weighted avg	0.94	0.94	0.94	29,294

Is this a correct way to link rows?



Joint Table Training with Swapping Visual



Trick for Swapping in Joint Table Training

- Note that the hidden state is biased towards the items closest to it
- So the beginning of a new row has context from the end of the last row
  - Is this a good choice?
  - What if we flip the bidirectional hidden states every iteration
  - AKA the beginning of a new row has the hidden state info from the beginning of the last row
  - And vice-versa

```
TableClassifierSwap(
  (embedding): Embedding(21, 128)
  (rnn): GRU(128, 128, batch_first=True, bidirectional=True)
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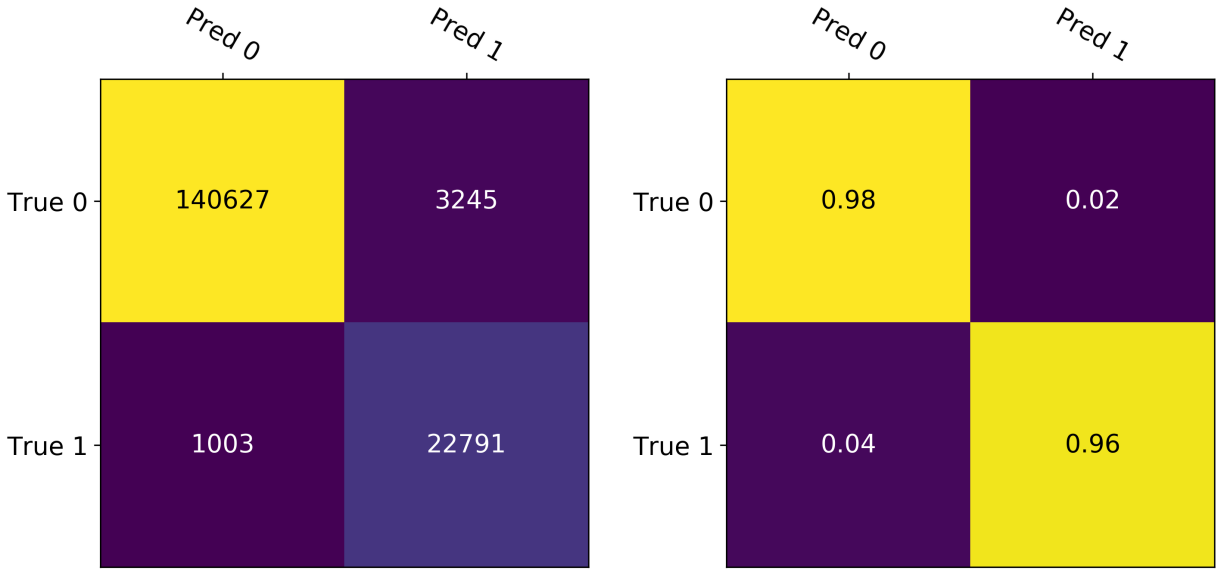
Joint Table Training with Swapping: Sample Results (Training)



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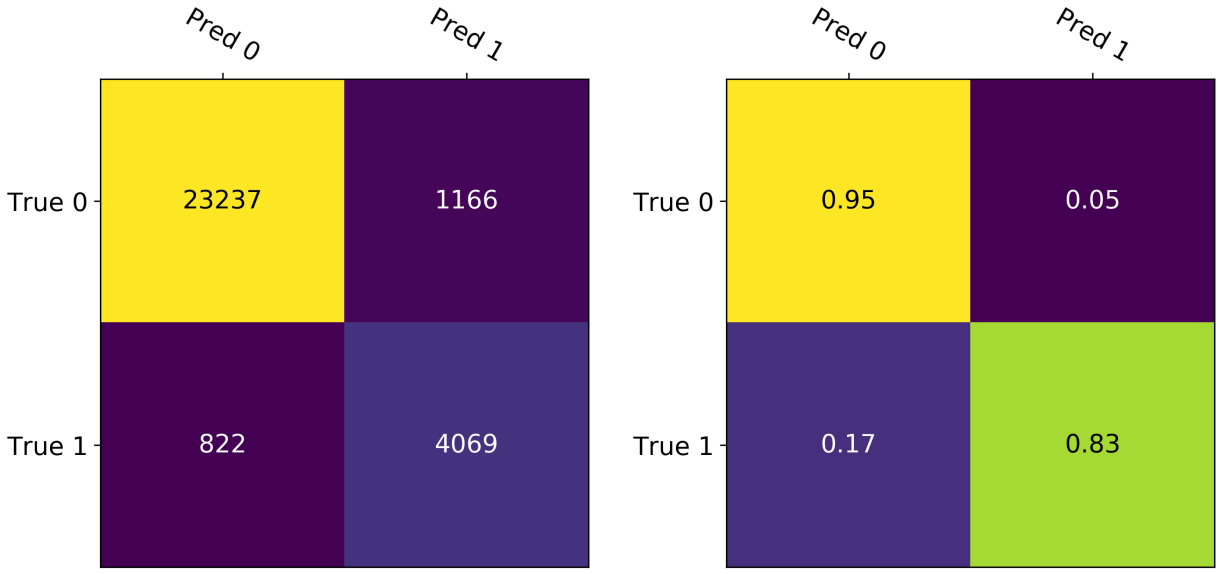
weighted avg	0.98	0.97	0.98	167,666

Joint Table Training with Swapping: Sample Results (Validation)



	Precision	Recall	F1-Score	Support
Label: 0	0.97	0.95	0.96	24,403
Label: 1	0.78	0.83	0.80	4,891
accuracy			0.93	29,294
macro avg	0.87	0.89	0.88	29,294
weighted avg	0.93	0.93	0.93	29,294

Summary of Methods (Validation)

		Independent	Joint	Joint Swapped
Label: 0	Precision	**0.97**	**0.97**	**0.97**
	Recall	0.94	**0.95**	**0.95**
	F1-Score	0.95	**0.96**	**0.96**
Label: 1	Precision	0.71	**0.78**	**0.78**
	Recall	0.85	**0.87**	0.83
	F1-Score	0.77	**0.82**	0.80
	Accuracy	0.92	**0.94**	0.93

What have we learned?

- We can learn text segments purely from the sequence of Part-of-Speech tags
- It is useful to jointly train/predict on the table instead of assuming independence
- Is there any benefit to swapping hidden states during propagation?
- **Note:**
  - We use the concept of *deep transition* in Seq2Seq for joint training
  - Where our training is dependent on the hidden state encoding useful information

Future Plans

- Features
  - Use word location information
  - Tesseract gives bounding boxes
- Encoder Structure
  - Convolution
  - Transformer

Other Applications For Sequence Modeling

Recall: Encoders, Decoders, and Seq2Seq Models

- **Encoders** given a sequence meaning
- **Decoders** generate a new sequence
- **Seq2Seq** generate sequences conditioned on another sequence

What to use for which application?

- **Encoders**
  - POS Tagging
  - Sentence Embeddings
  - Anything where you are given the sentence at test time
- **Decoders**
  - Text Generation
  - Language Modeling
  - Anything where you need to create a sequence at test time
- **Seq2Seq**
  - Translation
  - Speech Recognition
  - Summarization
  - Question/Answering
  - Anything where you convert a sequence into another sequence

Tools, References, and Further Reading

Papers

- Sutskever et al., Sequence to Sequence Learning with Neural Networks
- Cho et al., Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation
- Sennrich et al., Neural Machine Translation of Rare Words with Subword Units
- Koehn, Neural Machine Translation
- Koehn, Six Challenges for Neural Machine Translation

Tutorials

- Pytorch
  - Official PyTorch Seq2Seq Tutorial
  - PyTorch Seq2Seq with Torchtext
  - Ben Trevett Seq2Seq Tutorial
- Tensorflow
  - NMT with Attention

Libraries

- Facebook: fairseq (PyTorch)
- Open NMT (PyTorch)
- Open NMT (Tensorflow)

Thank You!