Introduction to Modern AI
Week 7: Natural Language Processing

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Overview

Motivation

- There is a wide range of useful applications for computer systems that can process and to some extent understand natural language
  - search
  - translation
  - spam filters
  - text completion suggestions
  - AI assistants and chatbots
  - automatic captioning, transcription
  - information extraction
  - and so on
- Natural language is fundamental to how we (humans) think, reason, and communicate with one another
- Therefore, NLP could be an important area for developing "true" artificial intelligence

Working with Text Data

Numerical Representation of Textual Data

- How should we represent textual data?

  The quick brown fox jumps over the lazy dog
- Word level:

  [The, quick, brown, fox, jumps, over, the, lazy, dog]
- Character level:

  [t, h, e, , q, u, i, c, k, , b, r, ...]
- Quick observations:
  - The data is a sequence of symbols. Order matters!
  - There are upper, lower-case letters, punctuation, special characters, etc

ASCII

- The precise way we will numerically represent the data will depend on our application, choice of methodology
- Typically this represent differs from how the computer stores the data
- The American Standard Code for Information Interchange (ASCII) developed for telegraph communication
- Assigns a number 0-127 (7 bit $= 2^7 = 128$ options) to each character
- Tailored to Latin alphabet, English in particular
- Includes some non-printing control codes that are no obsolete

ASCII Table

ASCII TABLE

Decimal	Hex	Char	Decimal	Hex	Char	Decimal	Hex	Char	Decimal	Hex	Char
0	0	[NULL]	32	20	[SPACE]	64	40	@	96	60	`
1	1	[START OF HEADING]	33	21	!	65	41	A	97	61	a
2	2	[START OF TEXT]	34	22	"	66	42	B	98	62	b
3	3	[END OF TEXT]	35	23	#	67	43	C	99	63	c
4	4	[END OF TRANSMISSION]	36	24	$	68	44	D	100	64	d
5	5	[ENQUIRY]	37	25	%	69	45	E	101	65	e
6	6	[ACKNOWLEDGE]	38	26	&	70	46	F	102	66	f
7	7	[BELL]	39	27	'	71	47	G	103	67	g
8	8	[BACKSPACE]	40	28	(	72	48	H	104	68	h
9	9	[HORIZONTAL TAB]	41	29	)	73	49	I	105	69	i
10	A	[LINE FEED]	42	2A	*	74	4A	J	106	6A	j
11	B	[VERTICAL TAB]	43	2B	+	75	4B	K	107	6B	k
12	C	[FORM FEED]	44	2C	,	76	4C	L	108	6C	l
13	D	[CARRIAGE RETURN]	45	2D	-	77	4D	M	109	6D	m
14	E	[SHIFT OUT]	46	2E	.	78	4E	N	110	6E	n
15	F	[SHIFT IN]	47	2F	/	79	4F	O	111	6F	o
16	10	[DATA LINK ESCAPE]	48	30	0	80	50	P	112	70	p
17	11	[DEVICE CONTROL 1]	49	31	1	81	51	Q	113	71	q
18	12	[DEVICE CONTROL 2]	50	32	2	82	52	R	114	72	r
19	13	[DEVICE CONTROL 3]	51	33	3	83	53	S	115	73	s
20	14	[DEVICE CONTROL 4]	52	34	4	84	54	T	116	74	t
21	15	[NEGATIVE ACKNOWLEDGE]	53	35	5	85	55	U	117	75	u
22	16	[SYNCHRONOUS IDLE]	54	36	6	86	56	V	118	76	v
23	17	[ENG OF TRANS. BLOCK]	55	37	7	87	57	W	119	77	w
24	18	[CANCEL]	56	38	8	88	58	X	120	78	x
25	19	[END OF MEDIUM]	57	39	9	89	59	Y	121	79	y
26	1A	[SUBSTITUTE]	58	3A	:	90	5A	Z	122	7A	z
27	1B	[ESCAPE]	59	3B	;	91	5B	[	123	7B	{
28	1C	[FILE SEPARATOR]	60	3C	<	92	5C	\	124	7C	|
29	1D	[GROUP SEPARATOR]	61	3D	=	93	5D	]	125	7D	}
30	1E	[RECORD SEPARATOR]	62	3E	>	94	5E	^	126	7E	~
31	1F	[UNIT SEPARATOR]	63	3F	?	95	5F	_	127	7F	[DEL]

Image source: https://commons.wikimedia.org/wiki/File:ASCII-Table-wide.svg

Unicode

- ASCII falls short in many ways
  - What about other languages (e.g., Mandarin)?
  - What about Emojis?
  - Unicode is another approach
  - Currently captures 144,697 characters, easy to add new ones
- Unicode has multiple implementations (UTF-8, UTF-16, etc)
- UTF-8 is most dominant worldwide
- For the most part in doing NLP you won't need to worry about ASCII, Unicode, but occasionally it will be important
- Mainly becomes an issue during the initial preprocessing/downloading of textual data

Vectorization and N-Gram Representations

- Goal: convert text sequence into a *sparse* numerical vector
- sparse means that most entries will be zero
- General Strategy:
  - Introduce vocabulary $\mathcal{V}$ containing $N = |\mathcal{V}|$ distinct tokens
  - 1-gram: vocabulary consists of distinct words
  - 2-gram: vocabulary consists of distinct pairs of words
  - N-gram: vocabulary consists of distinct sequences of N words

Example: 1-Gram

$$\mathcal{V} = \{\text{The, quick, brown, fox, jumps, over, lazy, dog}\}$$

word	The	quick	brown	fox	jumps	over	lazy	dog
	vector							
The	1	0	0	0	0	0	0	0
quick	0	1	0	0	0	0	0	0
brown	0	0	1	0	0	0	0	0
fox	0	0	0	1	0	0	0	0
jumps	0	0	0	0	1	0	0	0
over	0	0	0	0	0	1	0	0
The	1	0	0	0	0	0	0	0
lazy	0	0	0	0	0	0	1	0
dog	0	0	0	0	0	0	0	1

Example: 2-Gram

- *The quick brown fox jumps over the lazy dog*
- Vocabulary is:

$$\mathcal{V}_2 = \{\text{the quick}, \text{the brown}, ..., \text{quick brown}, \text{quick fox}, ..., \text{lazy dog}\}$$

- If there are n words, 2-gram vocab has size $N = n(n-1)/2$
- Retains a bit more of the structure than 1-gram (e.g., 'lazy dog' is a distinct term, not just 'lazy' and 'dog' separately
- Vocab size grows exponentially with number of graphs, quickly becomes impractical

$$N_p = |\mathcal{V}_p| = \binom{N}{p}$$

- Typically incorporate lower-grams, i.e. use 1-gram plus 2-gram
- higher-grams might be only partially added (i.e., include a few common 3-grams)

Tokenization

- Tokenization is the process of breaking up text into constituent parts (tokens)
- We've already seen an example of this:

  The quick brown fox jumps over the lazy dog

  [The, quick, brown, fox, jumps, over, the, lazy, dog]
- There are multiple ways to perform the tokenization, and the way this is done can have important implications
- For example: how should punctuation be handled? What about white-spaces?
- Modern NLP approaches actually learn a tokenizer

Stemming and Lemmatization

- Stemming and Lemmatization are similar, and can help improve performance by reducing the number of distinct words in the vocabulary
- E.g., sit, sitting, sat are all distinct words but they share a common meaning called the *lexeme*
- One word is chosen as the *lemma*, or representative of the lexeme
- Stemming and Lematization both reduce words down to lemma form
- Stemming acts only on individual words (1-grams), and is quick
- Lemmatization can handle words whose meaning is ambiguous without context, such as ‘meeting’ (noun or verb?)

Other Preprocessing Issues

- Punctuation should be handled. One idea is to convert all to lower-case.
- Special characters, url links, email address, hashtags, etc must be handled.
- Stop words (e.g., is, the, like, ...) might be removed
- Useful Python libraries exist for these preprocessing steps:
  - Natural Language ToolKit (NLTK)
  - HuggingFace

Naive Bayes and the Bag of Words Assumption

Text Classification: Naive Bayes

- Let's now consider how we might go about classifying text documents
- Each data point/observation is a document
- document consists of tokens (words)
- We'll represent this as a series words/tokens:

$$d = \{w_1, w_2, ..., w_n\}$$

- We want to model $P(c|d)$
- Model $P(d|c)$ directly and use Bayes theorem

$$P(c|d) = \frac{P(d|c)P(c)}{P(d)}$$

- Example of generative (vs discriminative) approach

Text Classification: Naive Bayes

- Goal: model for $P(c|d)$
- Use Bayes theorem and model $P(d|c)$ directly:

$$P(c|d) = \frac{P(d|c)P(c)}{P(d)}$$

- Iteratively apply $P(x, y|c) = P(x|y, c)P(y|c)$ rule:

$$\begin{aligned}
P(d|c) &= P(w_1, w_2, w_3, ..., w_n|c) \\
&= P(w_1|w_2, w_3, ..., w_n, c)P(w_2, w_3, ..., w_n|c) \\
&= P(w_1|w_2, w_3, ..., w_n, c)P(w_2|w_3..., w_n, c)P(w_3..., w_n|c) \\
&= ...
\end{aligned}$$

- assume conditional independence (bag of words):

$$P(w_i|w_{i+1}, ..., w_n, c) = P(w_i|c)$$

- Then

$$P(d|c) = \prod_{i=1}^{n} P(w_i|c)$$

Text Classification: Naive Bayes

- Main challenge of NLP is how to capture/handle the temporal correlations in the sequence
- Naive Bayes/Bag of Words is the simplest way to represent text once it has been tokenized - ignore the time ordering completely

$$P(d|c) = \prod_{i=1}^{n} P(w_i|c)$$

- How to model/estimate $P(w_i|c)$?

$$\hat{P}(w_i|c) = \frac{\text{count}(w_i, c)}{\sum_{w \in \mathcal{V}} \text{count}(w_i, c)}$$

- Here $\text{count}(w, c)$ just counts the number of times word w appears in documents of class c

TF-IDF

Information Retrieval and TF-IDF

- Naive Bayes utilizes raw counts/frequencies
- For many applications, raw counts/frequencies are too naive
- Information Retrieval
  - Example: return all documents most relevant to the phrase "machine learning is hard"
  - "is" is a very common word, many documents will have high occurrences
- TF: term frequency

$$\mathrm{tf}(t, d) = \frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}}$$

- IDF: inverse document frequency

$$\mathrm{idf}(t, \mathcal{D}) = \log\left(\frac{|\mathcal{D}|}{|d \in \mathcal{D} : t \in d|}\right)$$

- TF-IDF

$$\text{tf-idf}(t, d, \mathcal{D}) = \mathrm{tf}(t, d) \times \mathrm{idf}(t, \mathcal{D})$$

Information Retrieval and TF-IDF

- TF-IDF

$$\text{tf-idf}(t, d, \mathcal{D}) = \text{tf}(t, d) \times \text{idf}(t, \mathcal{D})$$

- TF: how frequent is a term in a given document
- IDF: small for terms that show up in many documents
- TF-IDF values are often used as useful features to work with
- Can consider TF-IDF to be a dense vector feature for each *document*:

$$\boldsymbol{v}(d) = \{\text{idf}(t_1, \mathcal{D}), \text{idf}(t_2, \mathcal{D}), ..., \text{idf}(t_n, \mathcal{D})\}$$

- Can now introduce a concept of distance/similarity between documents

Vector Embeddings and Representation Learning

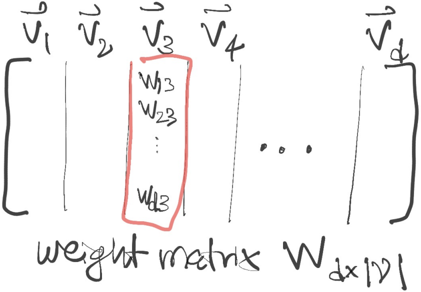
Vector Embeddings and Representation Learning

- The TF-IDF vectors are dense, compared to the sparse vectors we encountered before
- E.g., *The quick brown fox jumps over the lazy dog*
  word-level: $v(\text{quick}) = \{0, 1, 0, 0, 0, 0, 0, 0, ...\}$
  Bag of Words doc-level: $v(d) = \{1, 2, 1, 1, 1, 1, 1, 1, ...\}$
- The TF-IDF vectors contain less info than original data which makes them easier to work with
- Can act as useful features for down-stream tasks such as classification
- Big idea: *learn* the dense vector representations (embeddings)
- These vectors will not be useful in and of themselves, they will be useful for downstream tasks
- General approach is called *representation learning* or *feature learning*

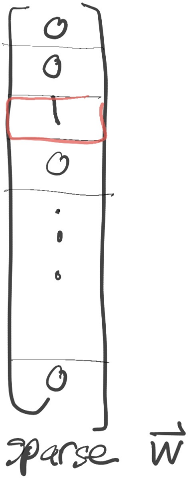
Word2Vec

- Word2Vec is a very well-known approach for learning useful vector embeddings at the word level
- Most popular implementation is in the Gensim library
- The basic idea is the important first step in more sophisticated and modern language models

Word2Vec



W is essentially a lookup table



Word2Vec

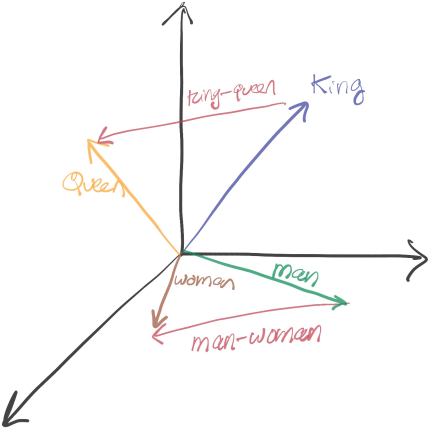
- There are two versions of Word2Vec (Skip-gram, Continuous Bag of Words)
- Embeddings are trained differently in the two versions, but both are based on utilizing *context*
- Both effectively use a 2-layer NN
- Both learn vector representations that are useful for predicting other words in a sentence
- If you are curious, here are some useful references for further reading:
  - Original paper 1
  - Original paper 2
  - Lillian Weng's blog
- There is also a document-level version called doc2vec

Word2Vec

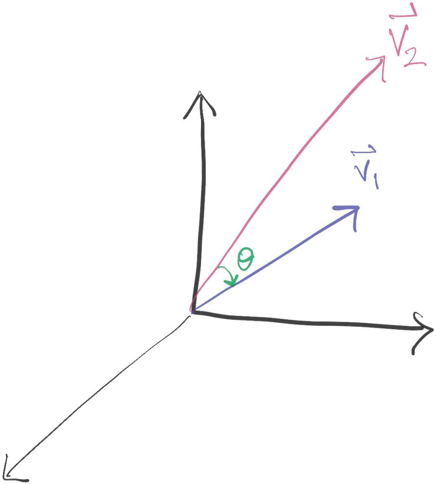
- The learned vector embeddings can be shown to encode some interesting relationships
- Having mapped words to vectors, we can now perform algebraic operations on words!
- E.g., can subtract word vectors:

$$\boldsymbol{v}' = \boldsymbol{v}(\text{king}) - \boldsymbol{v}(\text{queen}) + \boldsymbol{v}(\text{woman})$$

- Can then search through vocabulary to find closest word vector to $\boldsymbol{v}'$
- Often the result makes sense: in this case it will be $\boldsymbol{v}(\text{man})$



Cosine Similarity



$$S_C(v_1, v_2) = \cos\theta$$

$$= \frac{v_1 \cdot v_2}{\|v_1\| \, \|v_2\|}$$

$S_C = 1$: parallel (similar)

$= 0$: orthogonal (unrelated)

$= -1$: anti-parallel (opposite)

Cosine Similarity

- Cosine similarity

$$S_C(\boldsymbol{v}_1, \boldsymbol{v}_2) = \frac{\boldsymbol{v}_1 \cdot \boldsymbol{v}_2}{||\boldsymbol{v}_1||||\boldsymbol{v}_2||}$$

- Can be used to assess how closely related two documents are
  - nearly parallel ($S_C \approx 1$): closely related
  - nearly orthogonal ($S_C \approx 0$): unrelated
  - nearly anti-parallel ($S_C \approx -1$): closely related as opposites
- Note: that the vector lengths do not matter, just relative positioning
- S_C is *not* a distance measure, but it can be used to define one

Vector Embeddings and Representation Learning

- Vector embeddings aim to geometrically encode semantic meaning of words and sentences
- Original text is high dimensional, sparse, embeddings are much lower dimensional, typically dense
- Embeddings can be immediately useful for certain tasks, such as information retrieval
- They can also be used as inputs to downstream applications, such as classification
- discuss pre-training, transfer learning

Modern NLP

Deep Learning for NLP

- In this class we are just giving a short intro to NLP
- "Deep NLP" will be covered in more detail in the advanced class
- These next few slides will just set the stage and give a very general overview of the field

Neural Architectures for NLP

- There are several neural network architectures tailored for processing sequence/text data
- Recurrent Neural Networks (RNNs) can process sequences of arbitrary length
- In principle, they can capture long-term dependencies, but in practice this is difficult
- There are many variants aimed to address this and improve performance
- Basic "Vanilla" RNN: for $t = 0, 1, \ldots$, compute

$$\boldsymbol{a}^{(t)} = \boldsymbol{b} + \boldsymbol{W}\boldsymbol{h}^{(t-1)} + \boldsymbol{U}\boldsymbol{x}^{(t)}$$
$$\boldsymbol{h}^{(t)} = \tanh(\boldsymbol{a}^{(t)})$$
$$\boldsymbol{o}^{(t)} = \boldsymbol{c} + \boldsymbol{V}\boldsymbol{h}^{(t)}$$

- seq2seq: maps input $\{\boldsymbol{x}^{(0)}, \boldsymbol{x}^{(1)}, \ldots\}$ to output $\{\boldsymbol{o}^{(0)}, \boldsymbol{o}^{(1)}, \ldots\}$

Neural Architectures for NLP

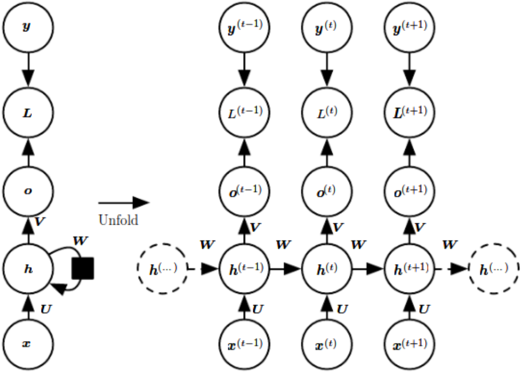


Figure 10.3: The computational graph to compute the training loss of a recurrent network that maps an input sequence of $\boldsymbol{x}$ values to a corresponding sequence of output $\boldsymbol{o}$ values. A loss L measures how far each $\boldsymbol{o}$ is from the corresponding training target $\boldsymbol{y}$. When using softmax outputs, we assume $\boldsymbol{o}$ is the unnormalized log probabilities. The loss L internally computes $\hat{\boldsymbol{y}} = \text{softmax}(\boldsymbol{o})$ and compares this to the target $\boldsymbol{y}$. The RNN has input to hidden connections parametrized by a weight matrix $\boldsymbol{U}$, hidden-to-hidden recurrent connections parametrized by a weight matrix $\boldsymbol{W}$, and hidden-to-output connections parametrized by a weight matrix $\boldsymbol{V}$. Equation 10.8 defines forward propagation in this model. *(Left)* The RNN and its loss drawn with recurrent connections. *(Right)* The same seen as a time-unfolded computational graph, where each node is now associated with one particular time instance.

Attention Is All You Need

- RNNs and variants have fallen out of favor relative to so-called transformer models
- Transformer models employ an operation called *attention* which allows the model to learn which parts of the sequence to focus on (context)
- This allows them to be more efficient compared to RNNs which process data in serial
- This in turns allows transformers to scale up to incredibly large model sizes
- Results in super large, expensive models called by many names
  - Sesame Street Models
  - Large Language Models
  - Foundation Models

Attention Is All You Need

- Discussion about GPT

Things I would have liked to cover if we had more time

- Zipf's law
- Topic modeling and LDA
- More applications of Word2Vec, Doc2Vec