EDAN95
Applied Machine Learning
Lecture 6: Recurrent Neural Networks

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Natural Language Processing

High-level applications:

- Spoken interaction: Apple Siri, Google Assistant, Amazon Echo
- Speech dictation of letters or reports: *Windows 10*, *macOS*
- Question answering: *IBM Watson* and *Jeopardy!*

The inner engines of these applications tend to be powered by neural networks.

Big change from the

- 1980's (rules),
- 1990's (Bayes), and
- 2000's (SVM and logistic regression, still usable for most tasks).

Neural net expansion started in 2010. What in 2030?

Scope of this Course

Applications we will consider:

1. Text categorization
2. Word or segment categorization
3. Translation: *Google Translate*, *DeepL*, *Bing translator*, etc.

Preprocessing Text

Before we can apply machine learning algorithm, we need to preprocess the texts: Format it so that it can use it as input to our programs
It includes (but it is not limited to):

1. Format parsing (HTML, XML, etc.) and text extraction
2. Tokenization
3. Sentence segmentation
4. Encoding
5. Cleaning.

Encoding Words

Neural networks can only handle numbers
We need then to encode the words or the characters with numbers.
Using ordinal numbers (a:1, b:2, c:3, d:4, etc) is impossible.
Is *a* closer to *b*, than *c*?
The most simple encoding is the one-hot encoding (or contrast encoding), that we have seen in the 3rd lecture.

Matrix Notation

- A feature vector (predictors): $\mathbf{x}$, and feature matrix: $\mathbf{X}$;
- The class: y and the class vector: $\mathbf{y}$;
- The predicted class (response): $\hat{y}$, and predicted class vector: $\hat{\mathbf{y}}$

$$\mathbf{X} = \begin{bmatrix} Sunny & Hot & High & False \\ Sunny & Hot & High & True \\ Overcast & Hot & High & False \\ Rain & Mild & High & False \\ Rain & Cool & Normal & False \\ Rain & Cool & Normal & True \\ Overcast & Cool & Normal & True \\ Sunny & Mild & High & False \\ Sunny & Cool & Normal & False \\ Rain & Mild & Normal & False \\ Sunny & Mild & Normal & True \\ Overcast & Mild & High & True \\ Overcast & Hot & Normal & False \\ Rain & Mild & High & True \end{bmatrix} ; \mathbf{y} = \begin{bmatrix} \mathrm{N} \\ \mathrm{N} \\ \mathrm{P} \\ \mathrm{P} \\ \mathrm{P} \\ \mathrm{N} \\ \mathrm{P} \\ \mathrm{N} \\ \mathrm{P} \\ \mathrm{P} \\ \mathrm{P} \\ \mathrm{P} \\ \mathrm{P} \\ \mathrm{N} \end{bmatrix}$$

Converting Symbolic Attributes into Numerical Vectors

Linear classifiers are numerical systems.

Symbolic – nominal – attributes are mapped onto vectors of binary values.

This is called a one-hot encoding
A conversion of the weather data set.

Object	Attributes										Class
	Outlook			Temperature			Humidity		Windy		
	Sunny	Overcast	Rain	Hot	Mild	Cool	High	Normal	True	False	
1	1	0	0	1	0	0	1	0	0	1	*N*
2	1	0	0	1	0	0	1	0	1	0	*N*
3	0	1	0	1	0	0	1	0	0	1	*P*
4	0	0	1	0	1	0	1	0	0	1	*P*
5	0	0	1	0	0	1	0	1	0	1	*P*
6	0	0	1	0	0	1	0	1	1	0	*N*
7	0	1	0	0	0	1	0	1	1	0	*P*
8	1	0	0	0	1	0	1	0	0	1	*N*
9	1	0	0	0	0	1	0	1	0	1	*P*
10	0	0	1	0	1	0	0	1	0	1	*P*
11	1	0	0	0	1	0	0	1	1	0	*P*
12	0	1	0	0	1	0	1	0	1	0	*P*
13	0	1	0	1	0	0	0	1	0	1	*P*
14	0	0	1	0	1	0	1	0	1	0	*N*

Code Example

Jupyter Notebook: Chollet 6.1 https://github.com/fchollet/deep-learning-with-python-notebooks 6.1-one-hot-encoding-of-words-or-characters.ipynb

Text Categorization

1. spam/not spam
2. Language identification, French, English, or Spanish? (https://github.com/google/cld3)
3. Sentiment analysis: Is this comment on my favorite tooth paste positive, neutral, or negative?
4. Newswire categorization.

Text Categorization: The Reuters Corpus


```
<title>USA: Tylan stock jumps; weighs sale of company.</title>
<headline>Tylan stock jumps; weighs sale of company.</headline>
<dateline>SAN DIEGO</dateline>
<text>
<p>The stock of Tylan General Inc. jumped Tuesday after the maker of
process-management equipment said it is exploring the sale of the company and
added that it has already received some  inquiries from potential buyers.</p>
<p>Tylan was up $2.50 to $12.75 in early trading on the Nasdaq market.</p>
<p>The company said it has set up a committee of directors to oversee the sale and
that Goldman, Sachs &amp; Co. has been retained as its financial adviser.</p>
</text>
<metadata>
<codes class="bip:topics:1.0">
<code code="C15"/>
<code code="C152"/>
<code code="C18"/>
<code code="C181"/>
<code code="CCAT"/>
</codes>
```

Text Categorization: The Categories

In total 103 topic categories:

C11	STRATEGY/PLANS	C15	PERFORMANCE
C12	LEGAL/JUDICIAL	C151	ACCOUNTS/EARNINGS
C13	REGULATION/POLICY	C1511	ANNUAL RESULTS
C14	SHARE LISTINGS	C152	COMMENT/FORECASTS
C15	PERFORMANCE	C16	INSOLVENCY/LIQUIDITY
C151	ACCOUNTS/EARNINGS	C17	FUNDING/CAPITAL
C1511	ANNUAL RESULTS	C171	SHARE CAPITAL
C152	COMMENT/FORECASTS	C172	BONDS/DEBT ISSUES
C16	INSOLVENCY/LIQUIDITY	C173	LOANS/CREDITS
C17	FUNDING/CAPITAL	C174	CREDIT RATINGS
C171	SHARE CAPITAL	C18	OWNERSHIP CHANGES
C172	BONDS/DEBT ISSUES	C181	MERGERS/ACQUISITIONS
C173	LOANS/CREDITS	C182	ASSET TRANSFERS
C174	CREDIT RATINGS	C183	PRIVATISATIONS
C11	STRATEGY/PLANS	C21	PRODUCTION/SERVICES
C12	LEGAL/JUDICIAL	C22	NEW PRODUCTS/SERVICES
C13	REGULATION/POLICY	C23	RESEARCH/DEVELOPMENT
C14	SHARE LISTINGS	...	

Text Categorization Using Bags of Words

A first technique to carry out categorization is to represent documents as vectors in a space of words.

The word order plays no role and it is often called a *bag-of-word model*.

To represent the two documents:

D1: Chrysler plans new investments in Latin America.

D2: Chrysler plans major investments in Mexico.

We would have:

D#\ Words	america	chrysler	in	investments	latin	major	mexico	new	plans	Category
1	1	1	1	1	1	0	0	1	1	spam
2	0	1	1	1	0	1	1	0	1	nospam

Text Categorization Using TFIDF

For a collection of documents, we would have a word by document matrix. As parameter, (w_i, D_j) could contain the frequency of w_i in document D_j

D#\Words	w_1	w_2	w_3	...	w_m	Category
D_1	$C(w_1, D_1)$	$C(w_2, D_1)$	$C(w_3, D_1)$	...	$C(w_m, D_1)$	spam
D_2	$C(w_1, D_2)$	$C(w_2, D_2)$	$C(w_3, D_2)$	...	$C(w_m, D_2)$	nospam
...						
D_n	$C(w_1, D_1 n)$	$C(w_2, D_n)$	$C(w_3, D_n)$	...	$C(w_m, D_n)$	spam

Most of the time, the counts are replaced by the term frequency times the inverse document frequency: $tf \times idf$.

The term frequencies $tf_{i,j}$ are normalized by the sum of the frequencies of all the terms in the document:

$$tf_{i,j} = \frac{t_{i,j}}{\sum_i t_{i,j}},$$

The inverse document frequency is defined as:

$$idf_i = \log(\frac{N}{n_i}),$$

where N is the total number of documents in the collection.

Code Example

Jupyter Notebooks: Chollet 3.5 and 3.6 `https://github.com/fchollet/deep-learning-with-python-notebooks`

`3.5-classifying-movie-reviews.ipynb`

`3.6-classifying-newswires.ipynb`

Dimension Reduction

One-hot encoding of TFIDF encoding can produce very long vectors:

Imagine a vocabulary of one million words per language with 100 languages.

A solution is to produce dense vectors also called word embeddings using a dimension reduction

This reduction is very close to principal component analysis or singular value decomposition

It can be automatically obtained through training or initialized with pretrained vectors

Principal Component Analysis

We will use a small dataset to explain principal component analysis: The characters in *Salammbô*

Ch.	'a'	'b'	'c'	'd'	'e'	'f'	'g'	'h'	'i'	'j'	'k'	'l'	'm'	'n'	'o'	'p'	'q'	'r'	's'	't'	'u'	'v'
01_fr	2503	365	857	1151	4312	264	349	295	1945	65	4	1946	726	1896	1372	789	248	1948	2996	1938	1792	414
02_fr	2992	391	1006	1388	4993	319	360	350	2345	81	6	2128	823	2308	1560	977	281	2376	3454	2411	2069	499
03_fr	1042	152	326	489	1785	136	122	126	784	41	7	816	397	778	612	315	102	792	1174	856	707	147
04_fr	2487	303	864	1137	4158	314	331	287	2028	57	3	1796	722	1958	1318	773	274	2000	2792	2031	1734	422
05_fr	2014	268	645	949	3394	223	215	242	1617	67	3	1513	651	1547	1053	672	166	1601	2192	1736	1396	315
06_fr	2805	368	910	1266	4535	332	384	378	2219	97	3	1900	841	2179	1569	868	285	2205	3065	2293	1895	453
07_fr	5062	706	1770	2398	8512	623	622	620	4018	126	19	3726	1596	3851	2823	1532	468	4015	5634	4116	3518	844
08_fr	2643	325	869	1085	4229	307	317	359	2102	85	4	1857	811	2041	1367	833	239	2132	2814	2134	1788	437
09_fr	2126	289	771	920	3599	278	289	279	1805	52	6	1499	619	1711	1130	651	187	1719	2404	1763	1448	348
10_fr	1784	249	546	805	3002	179	202	215	1319	60	5	1462	598	1246	922	557	172	1242	1769	1423	1191	270
11_fr	2641	381	817	1078	4306	263	277	330	1985	114	0	1886	900	1966	1356	763	230	1912	2564	2218	1737	425
12_fr	2766	373	935	1237	4618	329	350	349	2273	65	2	1955	812	2285	1419	865	272	2276	3131	2274	1923	455
13_fr	5047	725	1730	2273	8678	648	566	642	3940	140	22	3746	1597	3984	2736	1550	425	4081	5599	4387	3480	767
14_fr	5312	689	1754	2149	8870	628	630	673	4278	143	2	3780	1610	4255	2713	1599	512	4271	5770	4467	3697	914
15_fr	1215	173	402	582	2195	150	134	148	969	27	6	950	387	906	697	417	103	985	1395	1037	893	206
01_en	2217	451	729	1316	3967	596	662	2060	1823	22	200	1204	656	1851	1897	525	19	1764	1942	2547	704	258
02_en	2761	551	777	1548	4543	685	769	2530	2163	13	284	1319	829	2218	2237	606	21	2019	2411	3083	861	295
03_en	990	183	271	557	1570	279	253	875	783	4	82	520	333	816	828	194	13	711	864	1048	298	94
04_en	2274	454	736	1315	3814	595	559	1978	1835	22	198	1073	690	1771	1865	514	33	1726	1918	2704	745	245
05_en	1865	400	553	1135	3210	515	525	1693	1482	7	153	949	571	1468	1586	517	17	1357	1646	2178	663	194
06_en	2606	518	797	1509	4237	687	669	2254	2097	26	216	1239	763	2174	2231	613	25	1931	2192	2955	899	277
07_en	4805	913	1521	2681	7834	1366	1163	4379	3838	42	416	2434	1461	3816	4091	1040	39	3674	4060	5369	1552	465
08_en	2396	431	702	1416	4014	621	624	2171	2011	24	216	1152	748	2085	1947	527	33	1915	1966	2765	789	266
09_en	1993	408	653	1096	3373	575	517	1766	1648	16	146	861	629	1728	1698	442	20	1561	1626	2442	683	208
10_en	1627	359	451	933	2690	477	409	1475	1196	7	131	789	506	1266	1369	325	23	1211	1344	1759	502	181
11_en	2375	437	643	1364	3790	610	644	2217	1830	16	217	1122	799	1833	1948	486	23	1720	1945	2424	767	246
12_en	2560	489	757	1566	4331	677	650	2348	2033	28	234	1102	746	2125	2105	581	32	1939	2152	3046	750	278
13_en	4597	987	1462	2689	7963	1254	1201	4278	3634	39	432	2281	1493	3774	3911	1099	49	3577	3894	5540	1379	437
14_en	4871	948	1439	2799	8179	1335	1140	4534	3829	36	427	2218	1534	4053	3989	1019	36	3689	3946	5858	1490	539
15_en	1119	229	335	683	1994	323	281	1108	912	9	112	579	351	924	1004	305	9	863	997	1330	310	108

Table: Character counts per chapter, where the fr and en suffixes designate the language, either French or English

Each chapter is modeled by a vector of characters.

Character Counts

French	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15
a	2503	2992	1042	2487	2014	2805	5062	2643	2126	1784	2641	2766	5047	5312	1215
b	365	391	152	303	268	368	706	325	289	249	381	373	725	689	173
c	857	1006	326	864	645	910	1770	869	771	546	817	935	1730	1754	402
d	1151	1388	489	1137	949	1266	2398	1085	920	805	1078	1237	2273	2149	582
e	4312	4993	1785	4158	3394	4535	8512	4229	3599	3002	4306	4618	8678	8870	2195
f	264	319	136	314	223	332	623	307	278	179	263	329	648	628	150
g	349	360	122	331	215	384	622	317	289	202	277	350	566	630	134
h	295	350	126	287	242	378	620	359	279	215	330	349	642	673	148
i	1945	2345	784	2028	1617	2219	4018	2102	1805	1319	1985	2273	3940	4278	969
j	65	81	41	57	67	97	126	85	52	60	114	65	140	143	27
k	4	6	7	3	3	3	19	4	6	5	0	2	22	2	6
l	1946	2128	816	1796	1513	1900	3726	1857	1499	1462	1886	1955	3746	3780	950
m	726	823	397	722	651	841	1596	811	619	598	900	812	1597	1610	387
n	1896	2308	778	1958	1547	2179	3851	2041	1711	1246	1966	2285	3984	4255	906
o	1372	1560	612	1318	1053	1569	2823	1367	1130	922	1356	1419	2736	2713	697
p	789	977	315	773	672	868	1532	833	651	557	763	865	1550	1599	417
q	248	281	102	274	166	285	468	239	187	172	230	272	425	512	103
r	1948	2376	792	2000	1601	2205	4015	2132	1719	1242	1912	2276	4081	4271	985
s	2996	3454	1174	2792	2192	3065	5634	2814	2404	1769	2564	3131	5599	5770	1395
t	1938	2411	856	2031	1736	2293	4116	2134	1763	1423	2218	2274	4387	4467	1037
u	1792	2069	707	1734	1396	1895	3518	1788	1448	1191	1737	1923	3480	3697	893
v	414	499	147	422	315	453	844	437	348	270	425	455	767	914	206
w	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
x	129	175	42	138	83	151	272	135	119	65	114	149	288	283	63
y	94	89	31	81	67	80	148	64	58	61	61	98	119	145	36
z	20	23	7	27	18	39	71	30	20	11	25	37	41	41	3
à	128	136	39	110	90	131	246	130	90	73	101	129	209	224	48
â	36	50	9	43	67	42	50	43	24	18	40	33	55	75	20
æ	0	1	0	0	0	0	1	0	2	0	0	0	3	0	2
ç	35	28	10	22	24	30	46	34	16	16	34	23	61	56	17
è	102	147	49	138	112	122	232	119	99	68	108	151	237	260	58
é	423	513	194	424	367	548	966	502	370	304	438	480	940	1019	221
ê	43	68	24	36	44	57	96	54	43	53	68	60	126	94	32
ë	1	0	0	0	1	0	2	0	1	0	1	0	0	0	0
î	17	20	12	15	11	15	42	11	8	15	26	13	32	28	12
ï	2	0	0	2	8	12	9	1	2	5	15	3	5	2	0
ô	20	20	27	15	23	15	41	14	13	38	50	15	37	45	24
ù	14	9	4	6	18	14	30	6	5	3	7	11	24	21	7
û	7	9	7	4	15	15	38	8	15	10	9	14	30	21	11
œ	5	5	2	8	7	9	9	5	3	5	7	0	13	12	6

English	01	02	03	04	05	06	07	08	09	10	11
a	2217	2761	990	2274	1865	2606	4805	2396	1993	1627	2375
b	451	551	183	454	400	518	913	431	408	359	437
c	729	777	271	736	553	797	1521	702	653	451	643
d	1316	1548	557	1315	1135	1509	2681	1416	1096	933	1364
e	3967	4543	1570	3814	3210	4237	7834	4014	3373	2690	3790
f	596	685	279	595	515	687	1366	621	575	477	610
g	662	769	253	559	525	669	1163	624	517	409	644
h	2060	2530	875	1978	1693	2254	4379	2171	1766	1475	2217
i	1823	2163	783	1835	1482	2097	3838	2011	1648	1196	1830
j	22	13	4	22	7	26	42	24	16	7	16
k	200	284	82	198	153	216	416	216	146	131	217
l	1204	1319	520	1073	949	1239	2434	1152	861	789	1122
m	656	829	333	690	571	763	1461	748	629	506	799
n	1851	2218	816	1771	1468	2174	3816	2085	1728	1266	1833
o	1897	2237	828	1865	1586	2231	4091	1947	1698	1369	1948
p	525	606	194	514	517	613	1040	527	442	325	486
q	19	21	13	33	17	25	39	33	20	23	23
r	1764	2019	711	1726	1357	1931	3674	1915	1561	1211	1720
s	1942	2411	864	1918	1646	2192	4060	1966	1626	1344	1945
t	2547	3083	1048	2704	2178	2955	5369	2765	2442	1759	2424
u	704	861	298	745	663	899	1552	789	683	502	767
v	258	295	94	245	194	277	465	266	208	181	246
w	653	769	254	663	568	733	1332	695	560	410	632
x	29	37	8	60	26	49	74	65	25	31	20
y	401	475	145	467	330	464	843	379	328	255	457
z	18	31	15	19	33	37	52	24	18	20	39
à	0	0	0	0	0	0	0	0	0	0	0
â	0	0	0	0	0	0	0	0	0	0	0
æ	0	0	0	0	0	0	0	0	0	0	0
ç	0	0	0	0	0	0	0	0	0	0	0
è	0	0	0	0	0	0	0	0	0	0	0
é	0	0	0	0	0	0	0	0	0	0	0
ê	0	0	0	0	0	0	0	0	0	0	0
ë	0	0	0	0	0	0	0	0	0	0	0
î	0	0	0	0	0	0	0	0	0	0	0
ï	0	0	0	0	0	0	0	0	0	0	0
ô	0	0	0	0	0	0	0	0	0	0	0
ù	0	0	0	0	0	0	0	0	0	0	0
û	0	0	0	0	0	0	0	0	0	0	0
œ	0	0	0	0	0	0	0	0	0	0	0

Table: Character counts per chapter in French, left part, and English, right part

Each characters is modeled by a vector of chapters.

Singular Value Decomposition

There are as many as 40 characters: the 26 unaccented letters from *a* to *z* and the 14 French accented letters

Singular value decomposition (SVD) reduces these dimensions, while keeping the resulting vectors semantically close

X is the $m \times n$ matrix of the letter counts per chapter, in our case, $m = 30$ and $n = 40$.

We can rewrite X as:

$$\mathrm{X} = \mathrm{U}\Sigma\mathrm{V}^{\intercal},$$

where U is a matrix of dimensions $m \times m$, Σ, a diagonal matrix of dimensions $m \times n$, and V, a matrix of dimensions $n \times n$.

The diagonal terms of Σ are called the **singular values** and are traditionally arranged by decreasing value.

We keep the highest values and set the rest to zero.

Code Example

Jupyter Notebook 3.1-SVD

Word Embeddings

We can extend singular value decomposition from characters to words.
The rows will represent the words in the corpus, and the columns, documents,
We can replace documents by a context of a few words to the left and to the right of the focus word: w_i.
A context C_j is then defined by a window of $2K$ words centered on the word:

$$w_{i-K}, w_{i-K+1}, ..., w_{i-1}, w_{i+1}, ..., w_{i+K-1}, w_{i+K},$$

where the context representation uses a bag of words.
We can even reduce the context to a single word to the left or to the right of w_i and use bigrams.

Word Embeddings

We store the word-context pairs (w_i, C_j) in a matrix.
Each matrix element measures the association strength between word w_i and context C_j, for instance mutual information.
Mutual information, often called pointwise mutual information (the strength of an association) is defined as:

$$I(w_i, w_j) = \log_2 \frac{P(w_i, w_j)}{P(w_i)P(w_j)} \approx \log_2 \frac{N \cdot C(w_i, w_j)}{C(w_i)C(w_j)}.$$

D#\Words	C_1	C_2	C_3	...	C_n
w_1	$MI(w_1, C_1)$	$MI(w_1, C_2)$	$MI(w_1, C_3)$	...	$MI(w_1, C_n)$
w_2	$MI(w_2, C_1)$	$MI(w_2, C_2)$	$MI(w_2, C_3)$	...	$MI(w_2, C_n)$
w_3	$MI(w_3, C_1)$	$MI(w_3, C_2)$	$MI(w_3, C_3)$	...	$MI(w_3, C_n)$
...	...	...	...	...	...
w_m	$MI(w_m, C_1)$	$MI(w_m, C_2)$	$MI(w_m, C_3)$	...	$MI(w_m, C_n)$

Word Embeddings

We compute the word embeddings with a singular value decomposition, where we truncate the $U\Sigma$ matrix to 50, 100, 300, or 500 dimensions.
The word embeddings are the rows of this matrix.
We usually measure the similarity between two embeddings $\vec{u}$ and $\vec{v}$ with the cosine similarity, the normalized dot product of the vectors:

$$\cos(\vec{u}, \vec{v}) = \frac{\vec{u} \cdot \vec{v}}{||\vec{u}|| \cdot ||\vec{v}||},$$

ranging from -1 (most dissimilar) to 1 (most similar) or with the cosine distance ranging from 0 (closest) to 2 (most distant):

$$1 - \cos(\vec{u}, \vec{v}) = 1 - \frac{\vec{u} \cdot \vec{v}}{||\vec{u}|| \cdot ||\vec{v}||}.$$

Popular Word Embeddings

Embeddings from large corpora are obtained with iterative techniques
Some popular embedding algorithms with open source programs:

- word2vec: `https://github.com/tmikolov/word2vec`
- GloVe: Global Vectors for Word Representation `https://nlp.stanford.edu/projects/glove/`
- ELMo: `https://allennlp.org/elmo`
- fastText: `https://fasttext.cc/`

To derive word embeddings, you will have to apply these programs on a very large corpus
Embeddings for many languages are also publicly available. You just download them
gensim is a Python library to create word embeddings from a corpus.
`https://radimrehurek.com/gensim/index.html`

Semantic Similarity

Word embeddings mitigate the dimension problem relatively to one-hot encoding

In addition, similar words will have similar vectors

Demo: `http://bionlp-www.utu.fi/wv_demo/`

This enables to cope with words unseen in a training set

Text Categorization

Following Chollet, we will now train a network to categorize movie reviews.
We will use embeddings and a feedforward network first
We will then use recurrent networks.

Structure of a Network

First, a network, where we train the embeddings (Chollet, Listing 6.7):

```
model = Sequential()
model.add(Embedding(10000, 8, input_length=maxlen))
model.add(Flatten())
model.add(Dense(1, activation='sigmoid'))
model.compile(optimizer='rmsprop',
  loss='binary_crossentropy',
  metrics=['acc'])
model.summary()
history = model.fit(x_train, y_train,
  epochs=10,
  batch_size=32,
  validation_split=0.2)
```

Using GloVe Embeddings

We create a dictionary, where the keys are the words and the value, the embedding vector

```
glove_dir = '/Users/pierre/Documents/Cours/EDAN20/programs/ch08
embeddings_index = {}
f = open(os.path.join(glove_dir, 'glove.6B.100d.txt'))

for line in f:
    values = line.strip().split()
    word = values[0]
    vector = np.array(values[1:], dtype='float32')
    embeddings_index[word] = vector
f.close()
print('Found %s word vectors.' % len(embeddings_index))
```

Initializing the Matrix

We create the embeddings matrix by using the GloVe embedding or the 0, if not in GloVe

```
embedding_dim = 100
embedding_matrix = np.zeros((max_words, embedding_dim))
for word, i in word_index.items():
    if i < max_words:
        embedding_vector = embeddings_index.get(word)
        if embedding_vector is not None:
            embedding_matrix[i] = embedding_vector
```

Building the Network

The embedding layer is set to the GloVe parameters.

```
model = Sequential()
model.add(Embedding(max_words, embedding_dim,
  input_length=maxlen))
model.add(Flatten())
model.add(Dense(32, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
model.summary()

model.layers[0].set_weights([embedding_matrix])
model.layers[0].trainable = False
```

Complete Code Example

Jupyter Notebook: Chollet 6.1 https://github.com/fchollet/deep-learning-with-python-notebooks 6.1-using-word-embeddings.ipynb

Recurrent Neural Networks

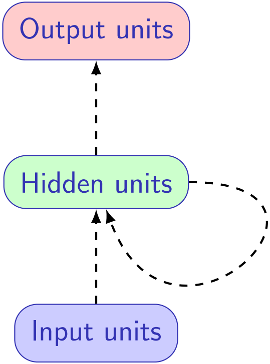
In feed-forward networks, predictions in a sequence of classifications are independent.

In many cases, given an input, the prediction also depends on the previous decision.

For instance, in weather forecast, if the input is the temperature and the output is rain/not rain, for a same temperature, it the previous output was rain, the next one is likely to be rain.

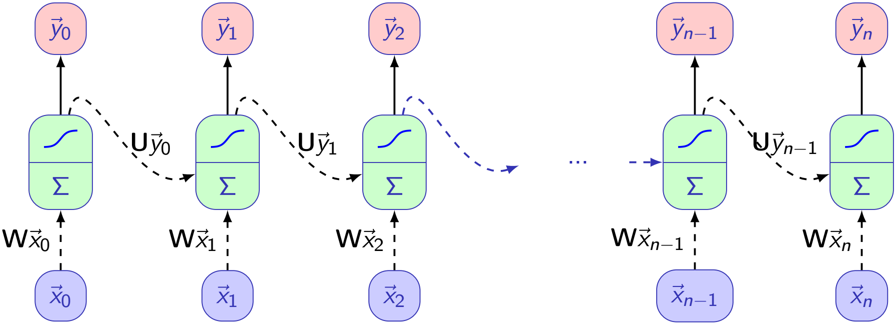
This is modeled by recurrent neural networks (RNN)

The RNN Architecture



A simple recurrent neural network; the dashed lines represent trainable connections.

The Unfolded RNN Architecture



The network unfolded in time. Equation used by implementations[1].

$$\mathrm{y}_{(t)} = \tanh(\mathrm{W} \cdot \mathrm{x}_{(t)} + \mathrm{U} \cdot \mathrm{y}_{(t-1)} + \mathrm{b})$$

[1] See: https://pytorch.org/docs/stable/nn.html#torch.nn.RNN

Building a Simple RNN with Keras

```
model = Sequential()
model.add(Embedding(max_features, 32))
model.add(SimpleRNN(32))
model.add(Dense(1, activation='sigmoid'))
model.summary()
```

We can run them in both directions: Left to right and right to left

Complete Code Example

Jupyter Notebook: Chollet 6.2 https://github.com/fchollet/deep-learning-with-python-notebooks 6.2-understanding-recurrent-neural-networks.ipynb

LSTMs

Simple RNNs use the previous output as input. They have then a very limited feature context.

Long short-term memory units (LSTM) are an extension to RNNs that can remember, possibly forget, information from longer or more distant sequences.

Given an input at index t, x_t, a LSTM unit produces:

- A short term state, called h_t and
- A long-term state, called c_t or memory cell.

The short-term state, h_t, is the unit output, i.e. y_t; but both the long-term and short-term states are reused as inputs to the next unit.

LSTM Equations

A LSTM unit starts from a core equation that is identical to that of a RNN:

$$\mathrm{g}_t = \tanh(\mathrm{W}_g \mathrm{x}_t + \mathrm{U}_g \mathrm{h}_{t-1} + \mathrm{b}_g).$$

From the previous output and current input, we compute three kinds of filters, or gates, that will control how much information is passed through the LSTM cell

The two first gates, i and f, defined as:

$$\begin{aligned} \mathrm{i}_t &= \mathrm{activation}(\mathrm{W}_i \mathrm{x}_t + \mathrm{U}_i \mathrm{h}_{t-1} + \mathrm{b}_i), \\ \mathrm{f}_t &= \mathrm{activation}(\mathrm{W}_f \mathrm{x}_t + \mathrm{U}_f \mathrm{h}_{t-1} + \mathrm{b}_f), \end{aligned}$$

model respectively how much we will keep from the base equation and how much we will forget from the long-term state.

LSTM Equations (II)

To implement this selective memory, we apply the two gates to the base equation and to the previous long-term state with the element-wise product (Hadamard product), denoted $\circ$, and we sum the resulting terms to get the current long-term state:

$$\mathrm{c}_t = \mathrm{i}_t \circ \mathrm{g}_t + \mathrm{f}_t \circ \mathrm{c}_{t-1}.$$

The third gate:

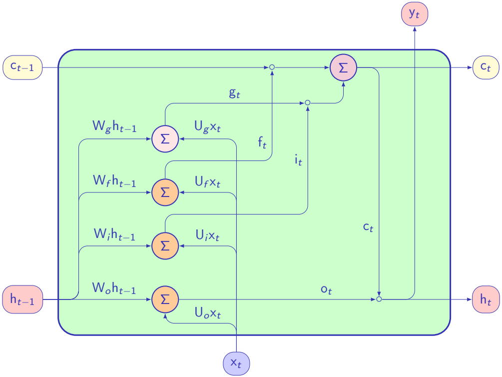
$$\mathrm{o}_t = \mathrm{activation}(\mathrm{W}_o \mathrm{x}_t + \mathrm{U}_o \mathrm{h}_{t-1} + \mathrm{b}_o)$$

modulates the current long-term state to produce the output:

$$\mathrm{h}_t = \mathrm{o}_t \circ \tanh(\mathrm{c}_t).$$

The LSTM parameters are determined by a gradient descent.
See also:
`https://pytorch.org/docs/stable/nn.html#torch.nn.LSTM`

The LSTM Architecture



An LSTM unit showing the data flow, where g_t is the unit input, i_t, the input gate, f_t, the forget gate, and o_t, the output gate. The activation functions have been omitted

Building a LSTM with Keras

```
model = Sequential()
model.add(Embedding(max_features, 32))
model.add(LSTM(32))
model.add(Dense(1, activation='sigmoid'))
model.summary()
```

CNN for Sequences

RNN and LSTM are expensive for long sequences
CNN are much faster and you can downsample the results
We can apply one-dimensional convolutions to time or word sequences
If the input consists of embedding vectors, the embedding directions correspond to the feature maps.

Building a One Dimensional Convolution with Keras

```
model = Sequential()
model.add(layers.Embedding(max_features, 128,
    input_length=max_len))
model.add(layers.Conv1D(32, 7, activation='relu'))
model.add(layers.MaxPooling1D(5))
model.add(layers.Conv1D(32, 7, activation='relu'))
model.add(layers.GlobalMaxPooling1D())
model.add(layers.Dense(1, activation='sigmoid'))
model.summary()
```

Complete Code Example

Jupyter Notebook: Chollet 6.4 https://github.com/fchollet/deep-learning-with-python-notebooks 6.4-sequence-processing-with-convnets.ipynb