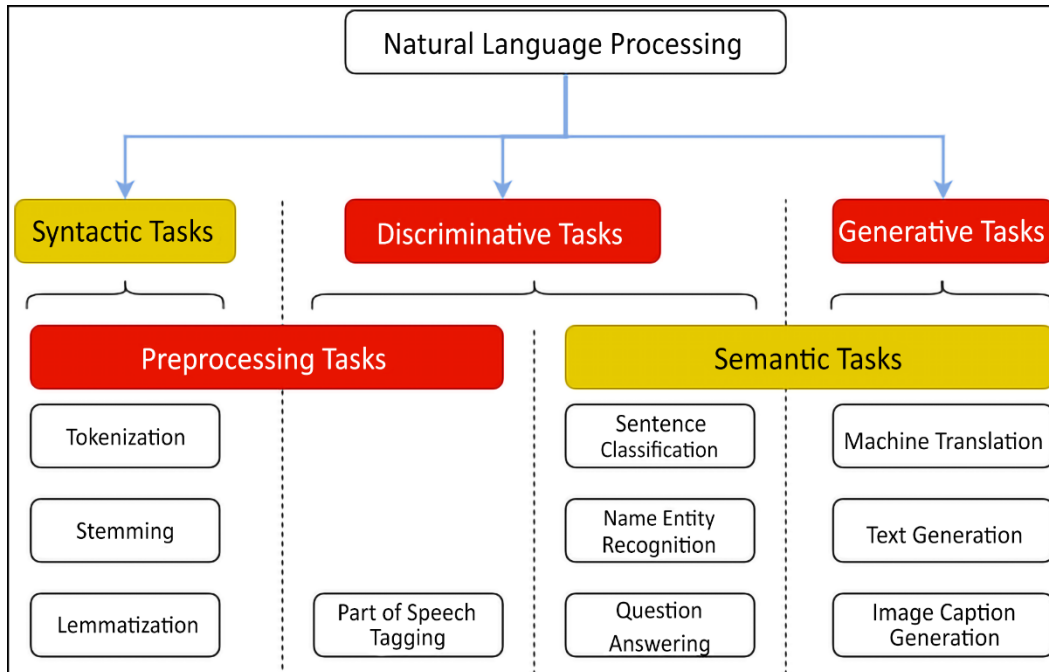
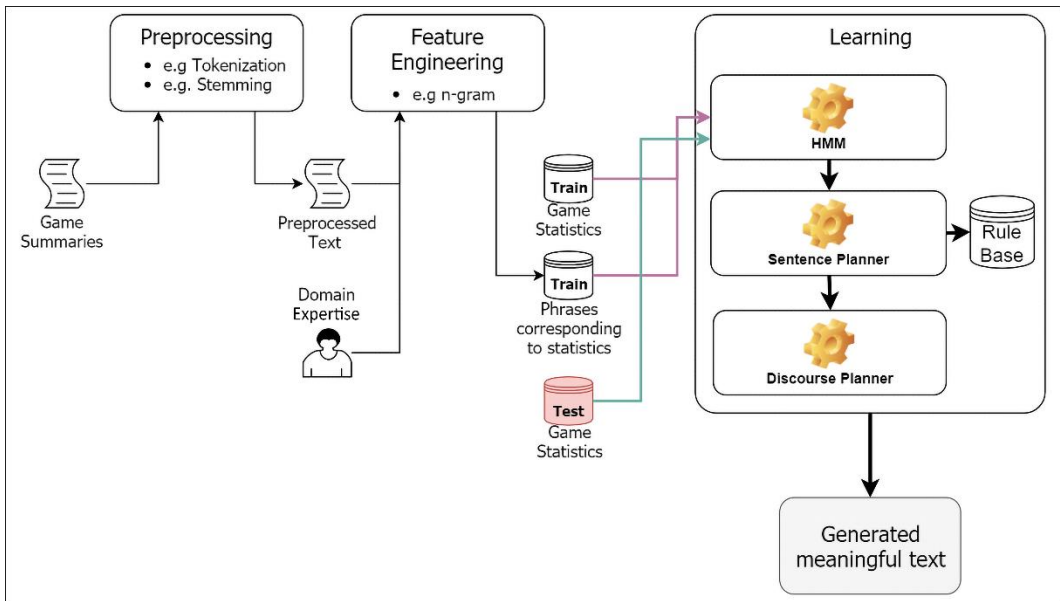
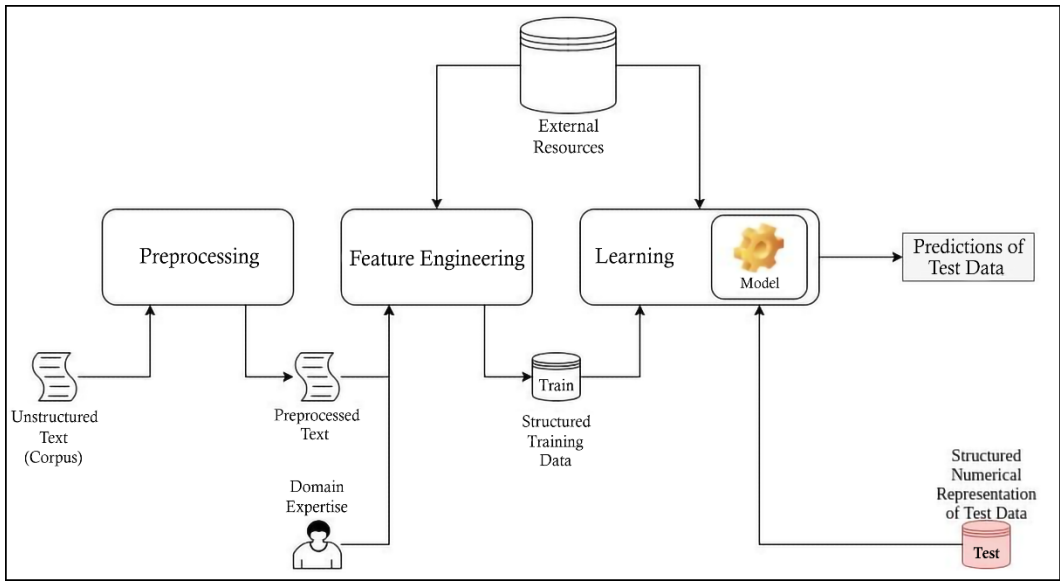
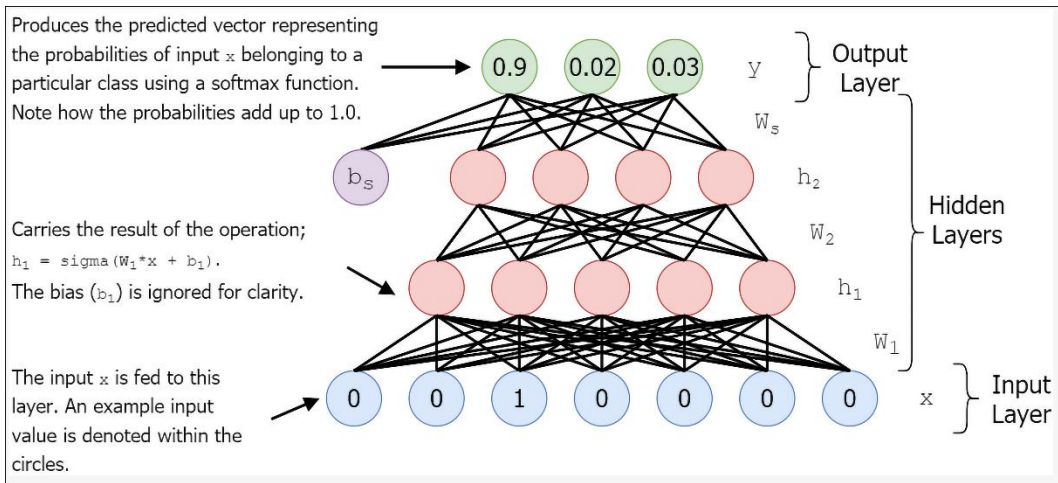
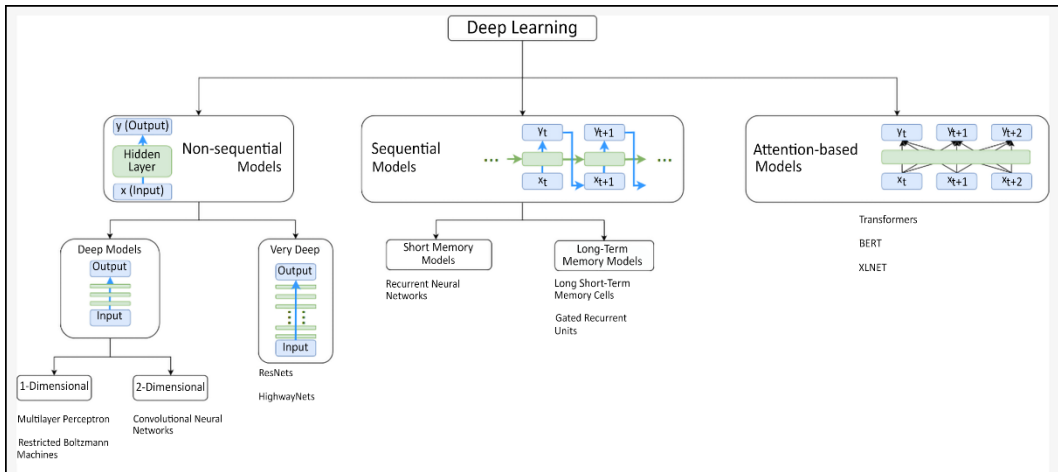


# Chapter 1: Introduction to Natural Language Processing







jupyter

Logout

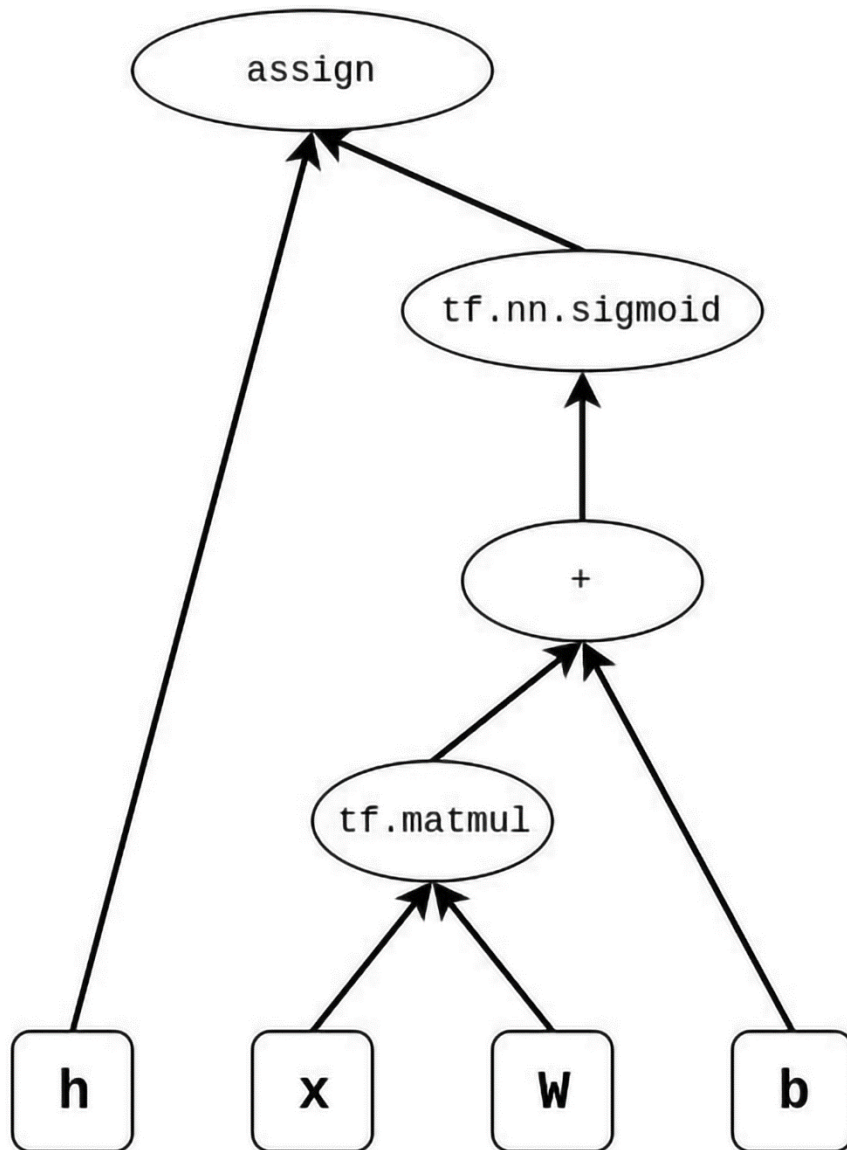
Files Running Clusters

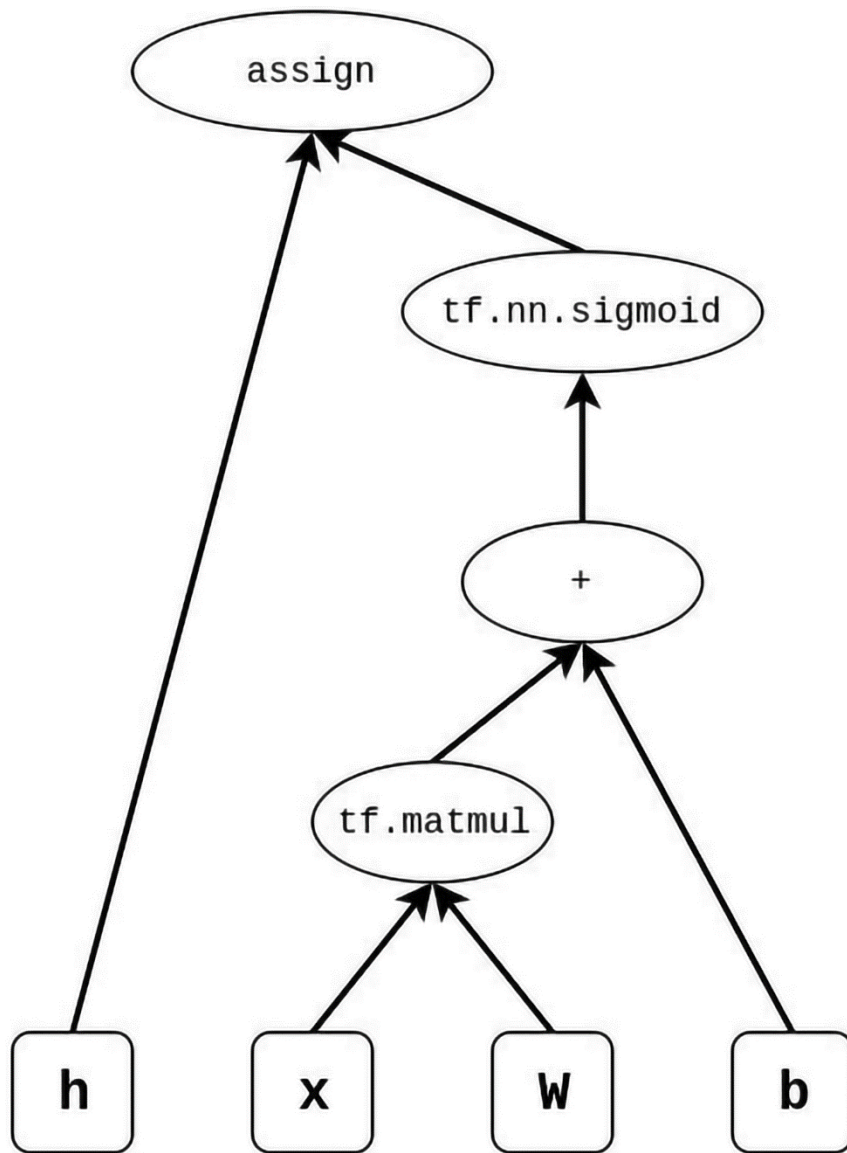
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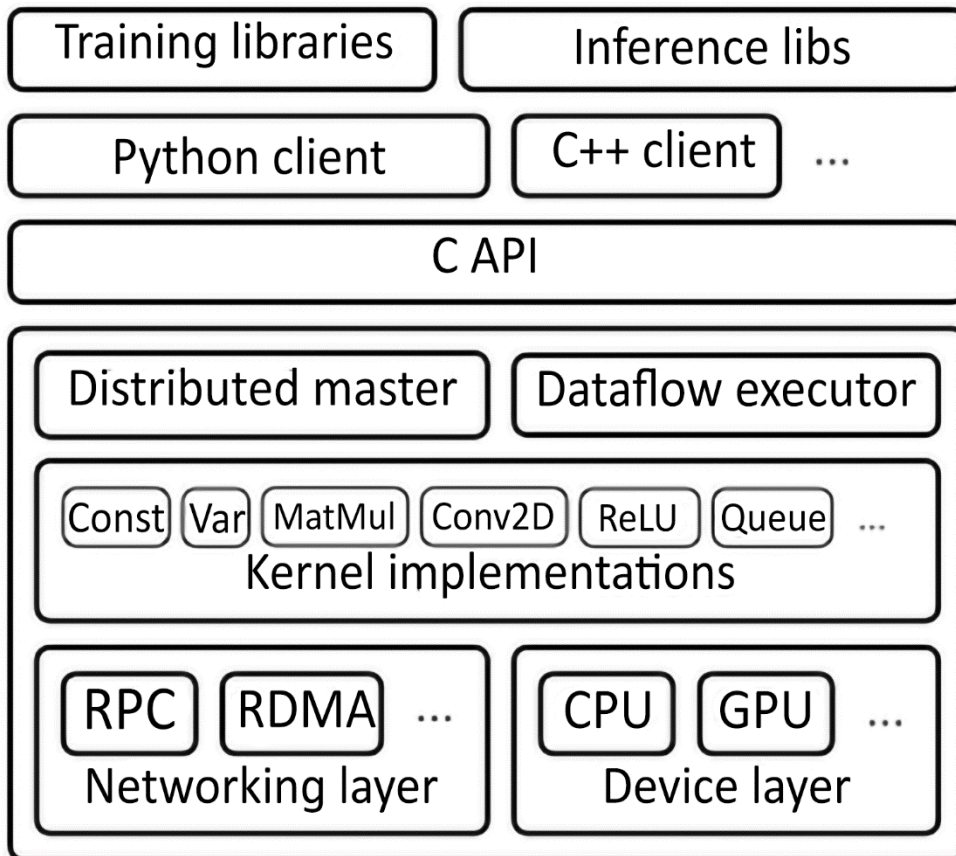
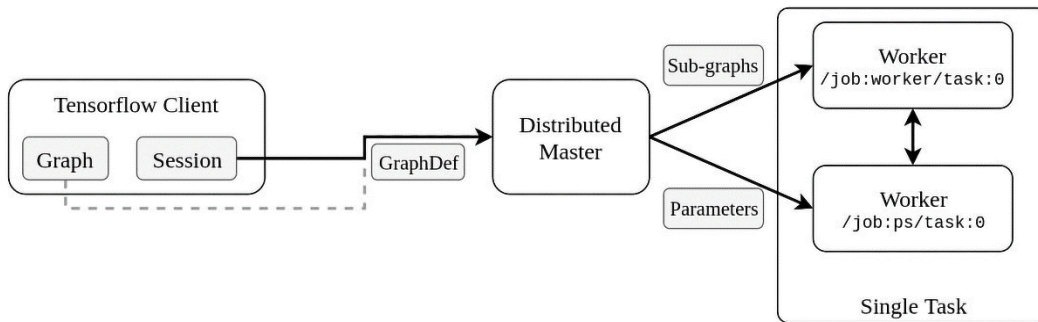
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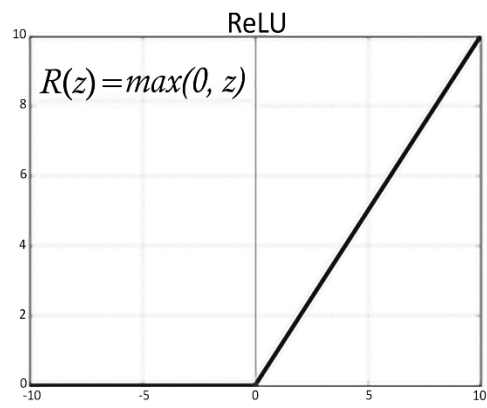
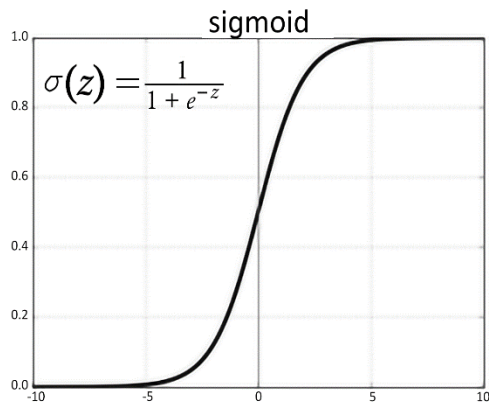
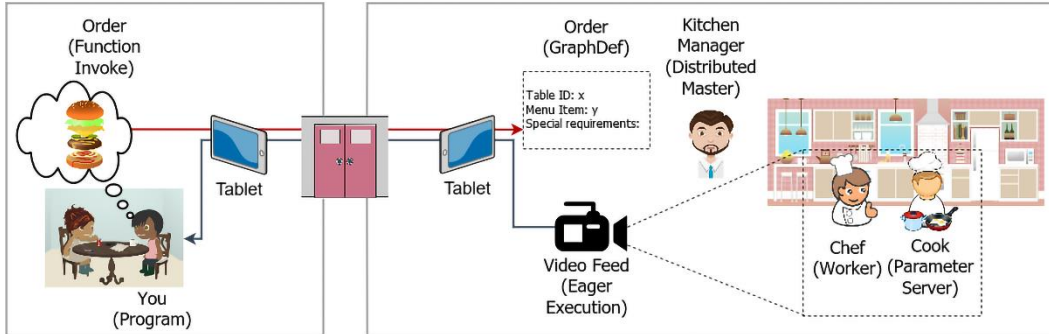
## Chapter 2: Understanding TensorFlow 2



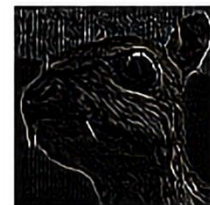


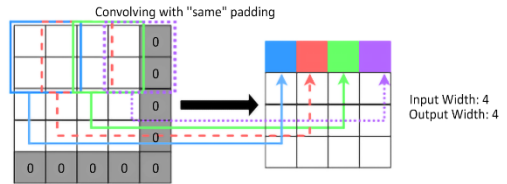
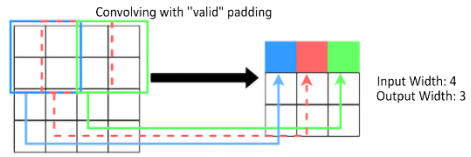
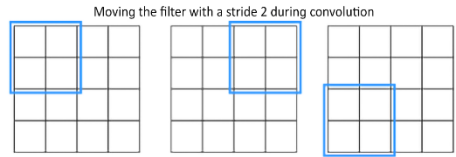
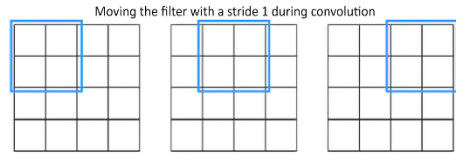
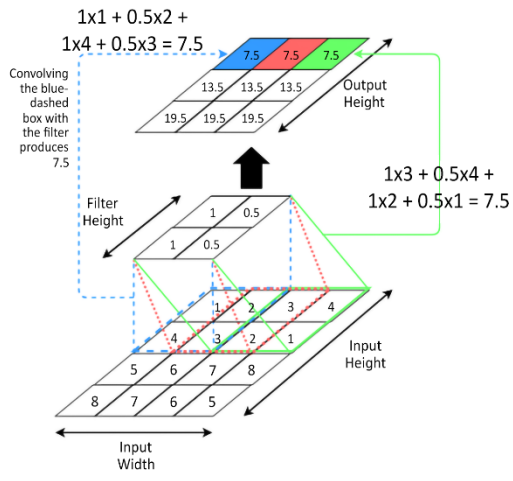


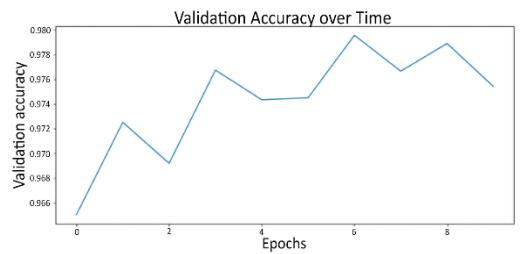
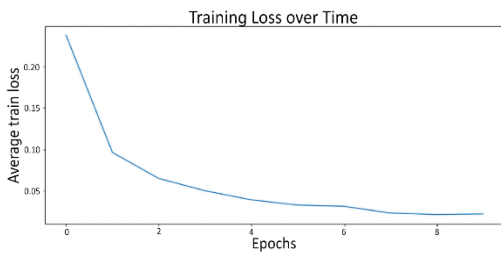
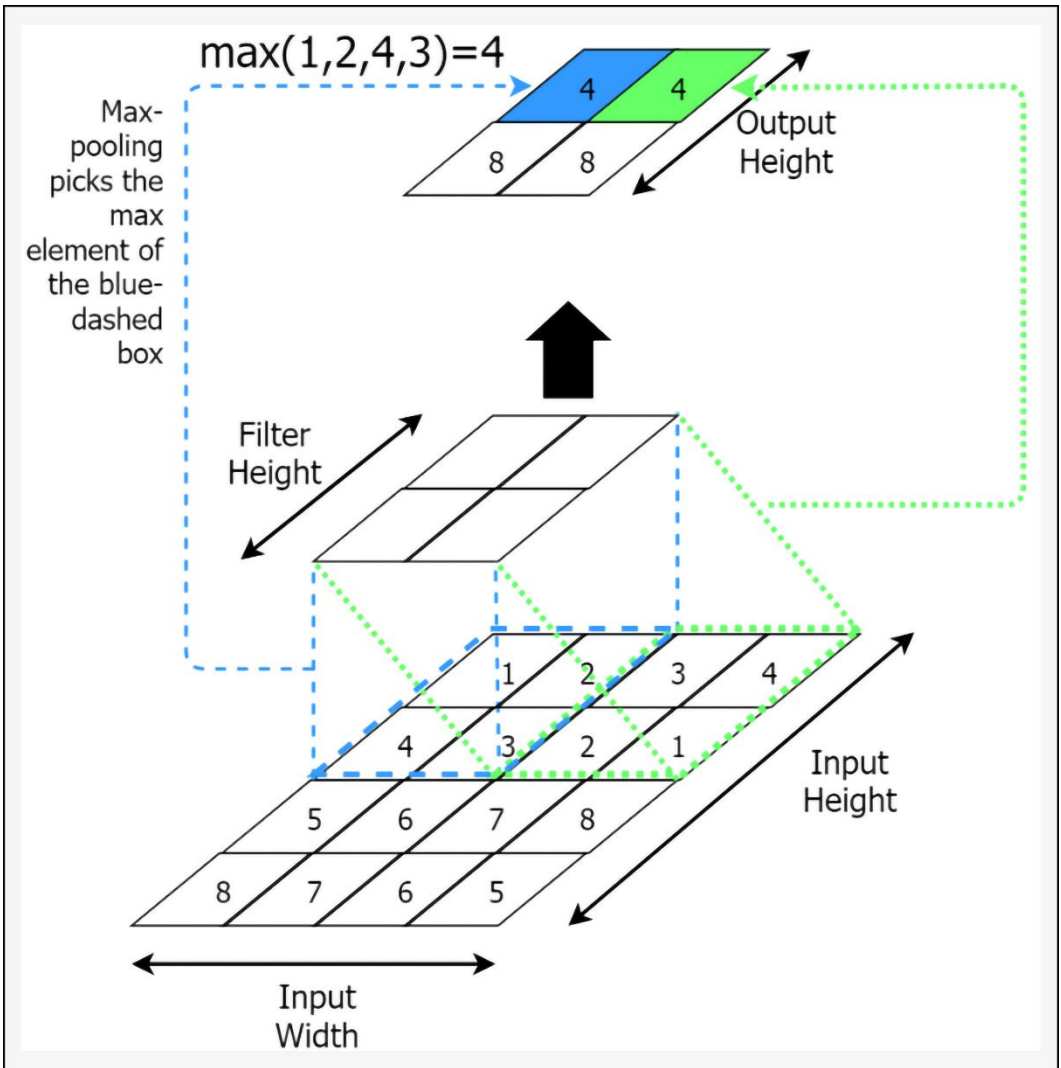
### Cafe Le TensorFlow 2



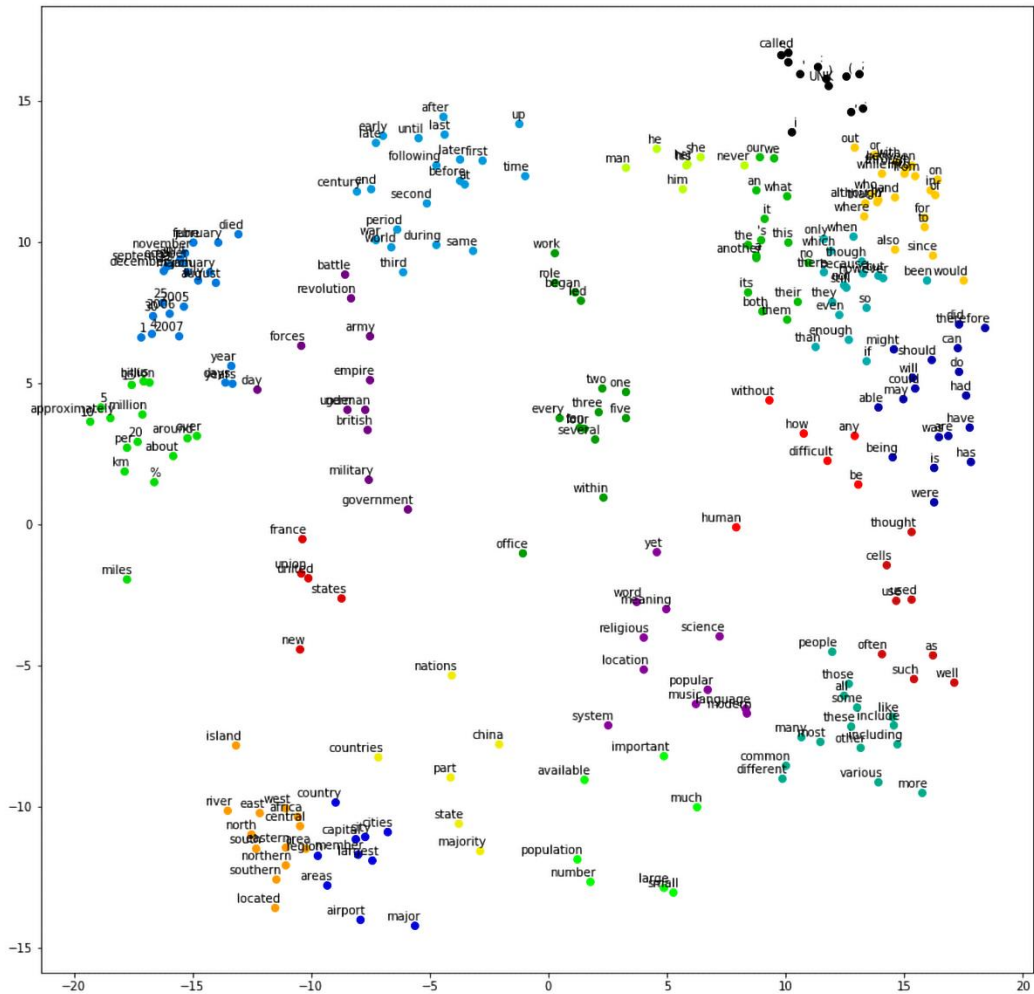
$$* \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix} =$$

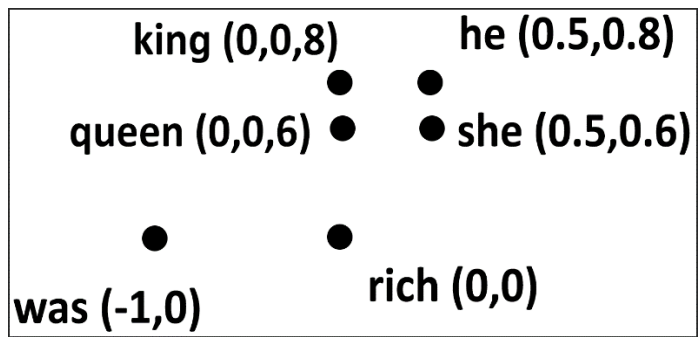
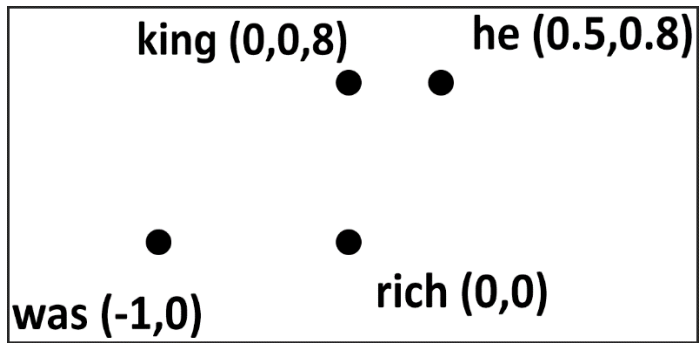
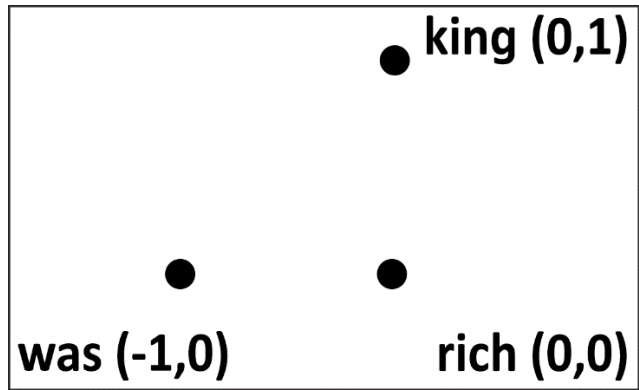


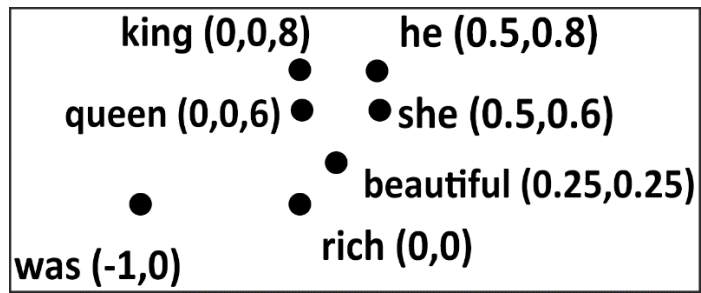


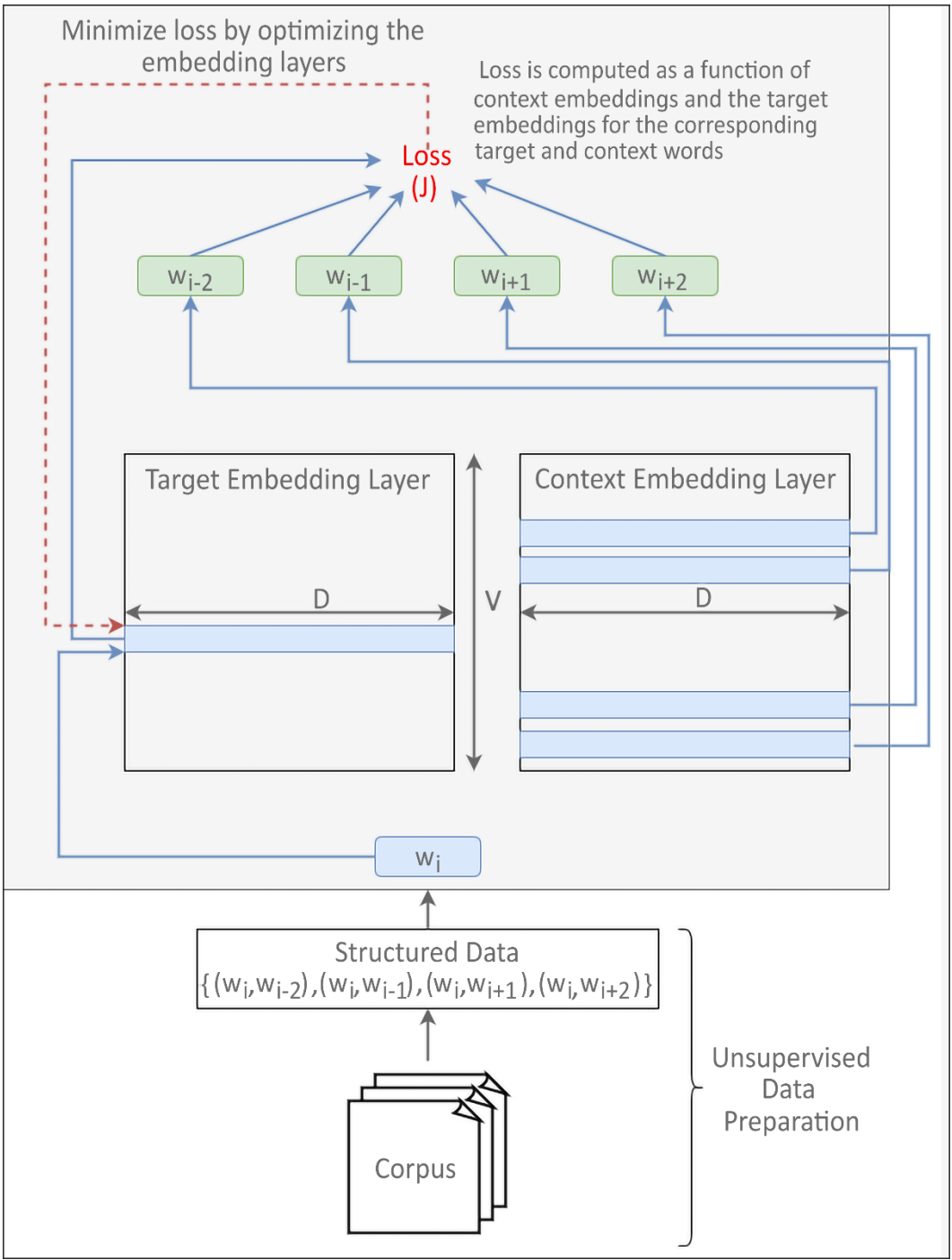


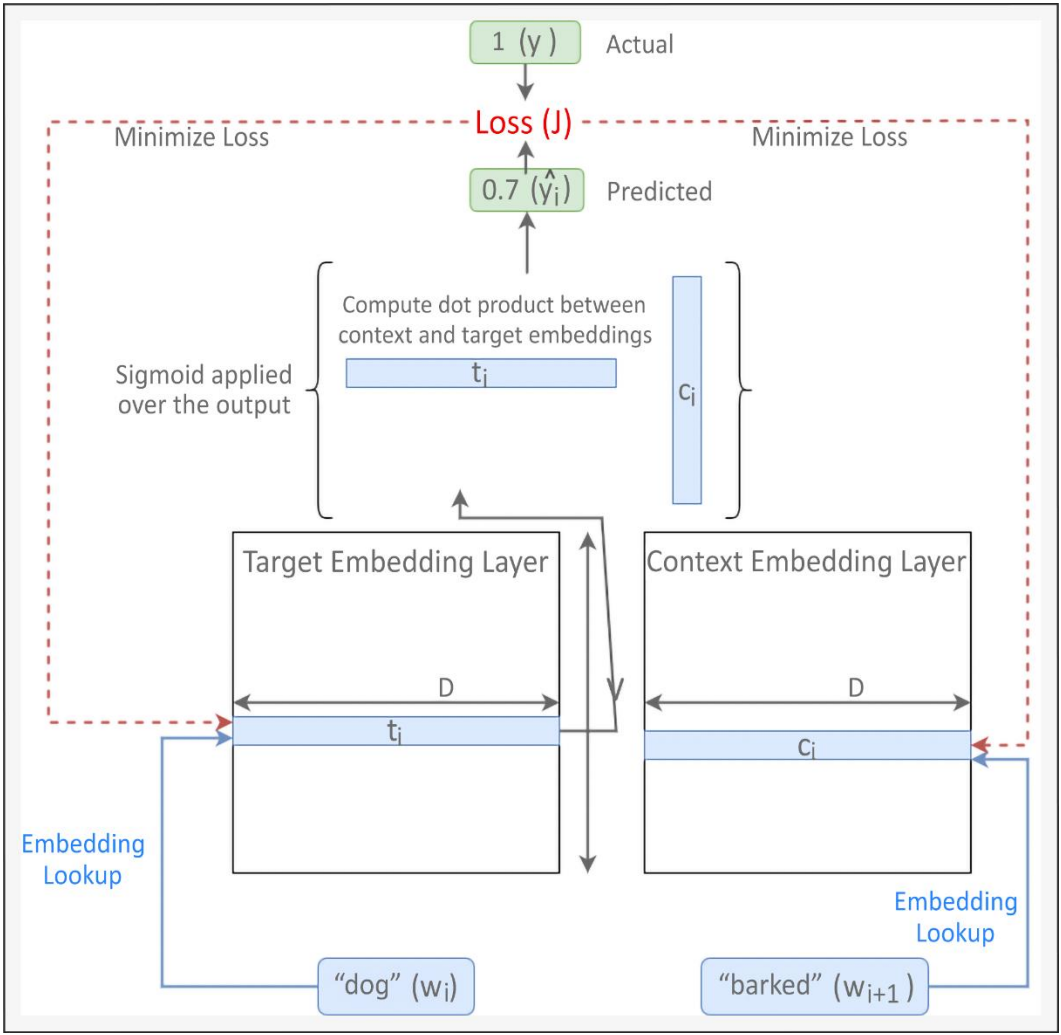
# Chapter 3: Word2vec - Learning Word Embeddings







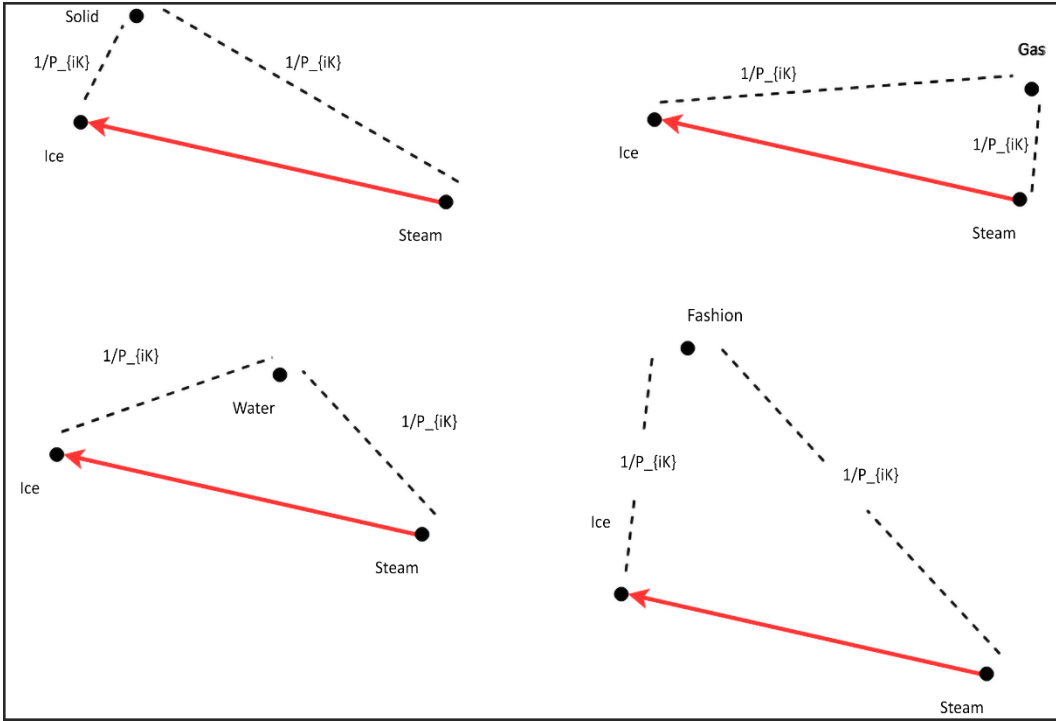




Minimize loss by optimizing softmax weights and the embedding layer



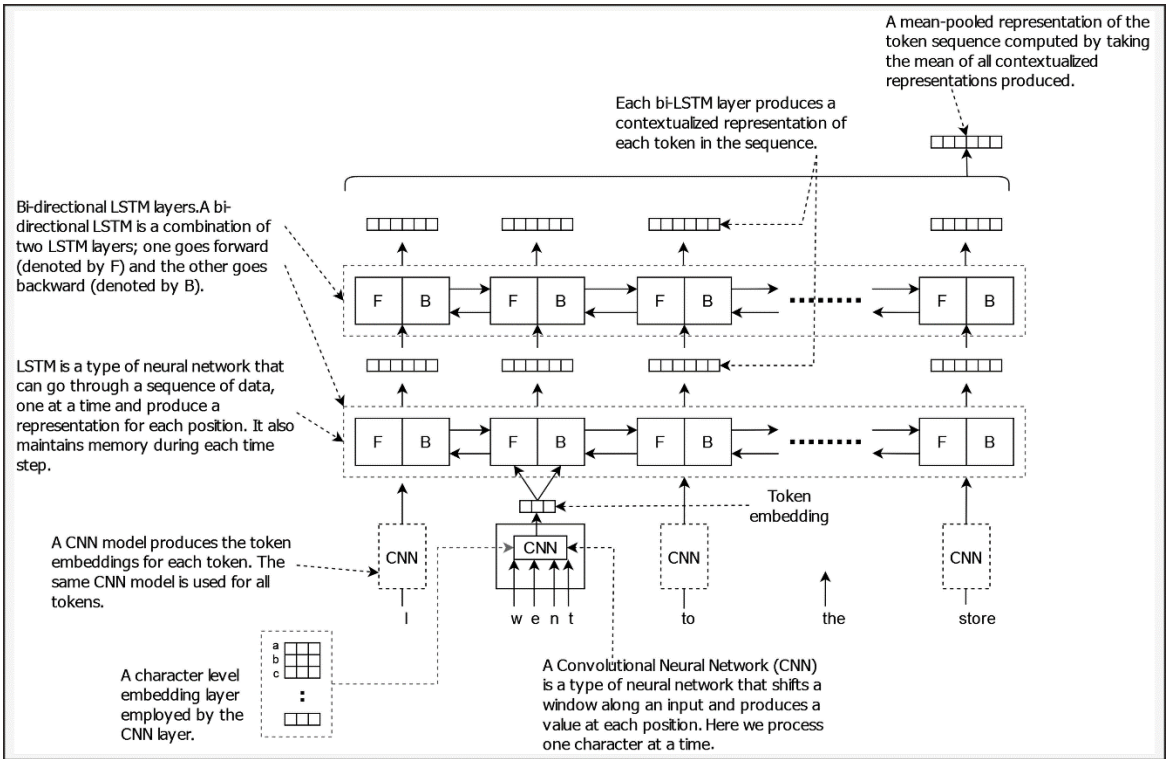
# Chapter 4: Advanced Word Vector Algorithms



$$J = \sum_{i,j=1}^V f(X_{ij}) (w_i^T w_j + b_i + b_j - \log(X_{ij}))^2$$

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Sample Weights
Prediction
Target

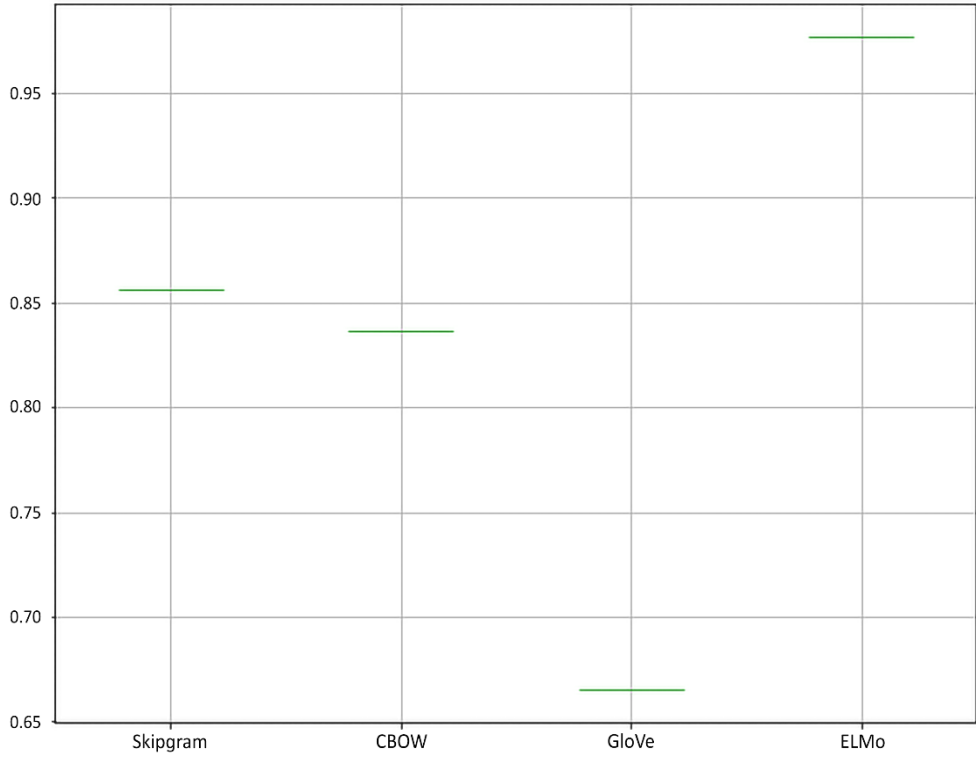
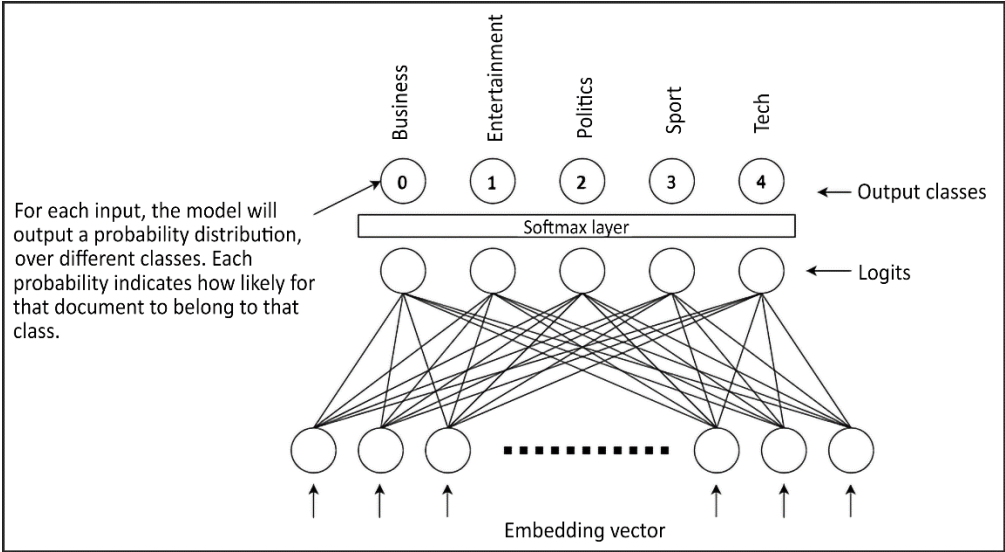


	0	1	2	3	4	5	6	7	8	9 ...	118	119	120	
<b>NaN</b>	-1.440415	1.375493	-1.205786	-1.326926	-1.336768	-1.205858	-1.366250	-1.036717	-1.365316	-0.775372 ...	1.205486	1.138118	-1.385370	-1.264
	-0.290653	0.574326	0.026581	-0.329045	-0.171542	0.224572	0.071370	0.146927	-0.041791	0.086741 ...	0.259992	0.278289	-0.879627	-0.351
<b>the</b>	-0.058531	0.310743	0.232947	-0.338871	-0.334953	0.003350	-0.061267	0.257632	0.031830	-0.587573 ...	0.484254	-0.228630	-0.044630	-0.305
<b>to</b>	-0.276640	0.025122	-0.024782	-0.624656	-0.016077	0.046590	-1.094414	-0.848296	-0.327094	-1.684406 ...	-0.261233	-0.106222	-0.139904	-0.411
<b>of</b>	-0.281321	-0.034827	-0.068643	-0.210236	0.122180	0.021023	-0.258712	0.238127	-0.408491	-1.221611 ...	0.083432	0.030410	-0.390671	-0.030
<b>and</b>	-0.207726	0.023091	0.186237	-0.209033	-0.121335	0.271208	-0.033538	0.390482	0.217749	-1.416989 ...	-0.351555	0.300373	-0.019044	-0.298
<b>a</b>	-0.452312	0.305802	-0.962776	-0.884619	0.180468	-0.150204	-0.387859	0.362963	-0.194890	0.303527 ...	-0.297423	0.582571	-0.498461	-0.074
<b>in</b>	0.264359	0.130696	0.374273	0.023650	-0.385127	0.085398	0.314853	-1.038579	-0.981065	0.308113 ...	-0.258953	0.010786	-0.503573	0.038
<b>for</b>	-0.866129	0.162434	-0.183391	0.079462	-0.439157	-0.600472	-0.600996	-1.004945	-0.321327	-1.096564 ...	0.153067	0.338188	-0.180635	0.506
<b>is</b>	-0.004946	0.531260	-0.119664	-0.702005	-0.368837	-0.918419	0.164347	-0.694515	-0.470691	0.242414 ...	0.780400	-0.017688	-0.529367	0.020

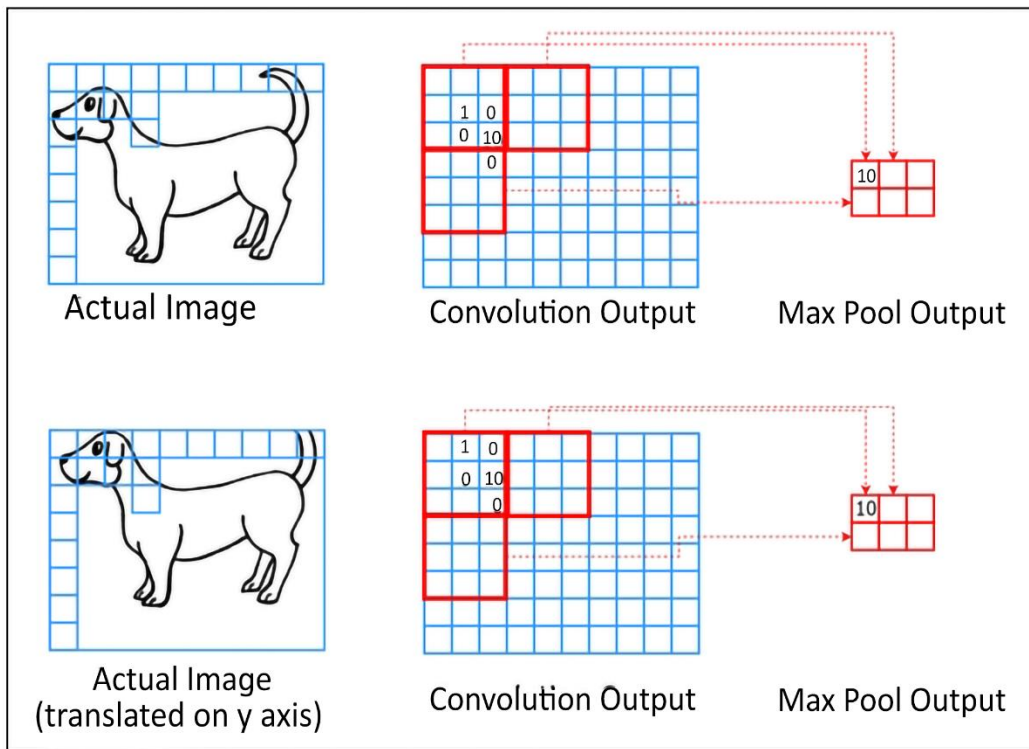
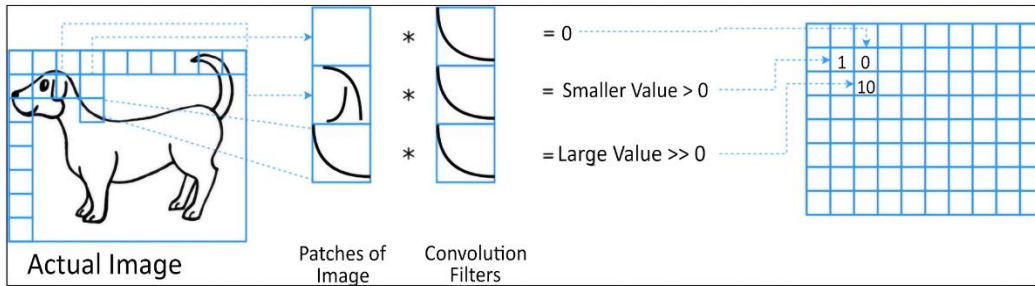
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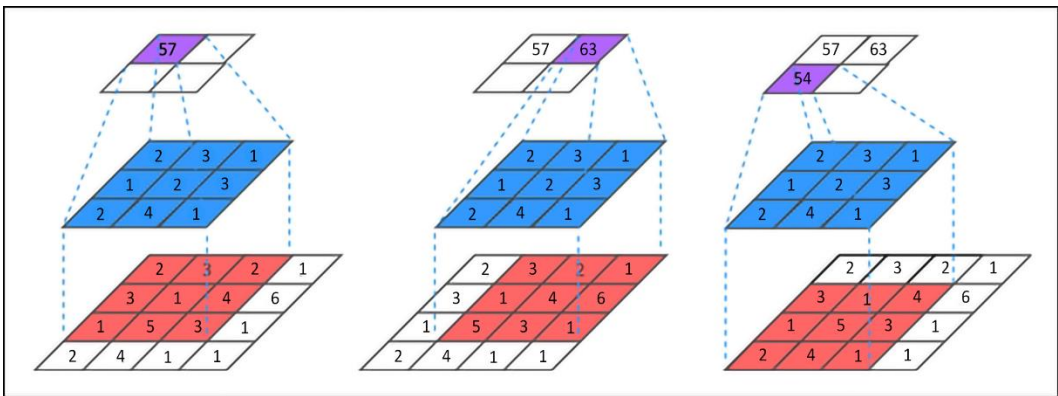
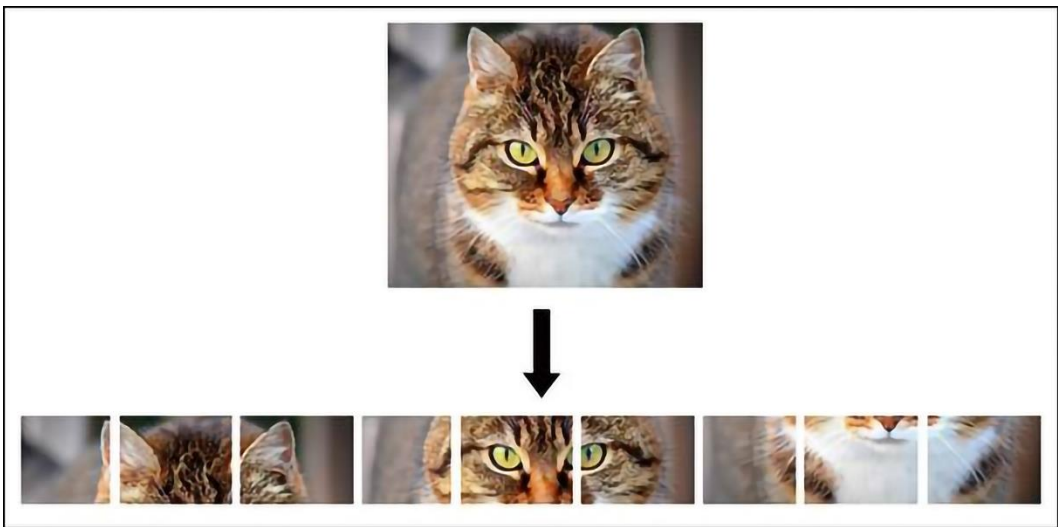
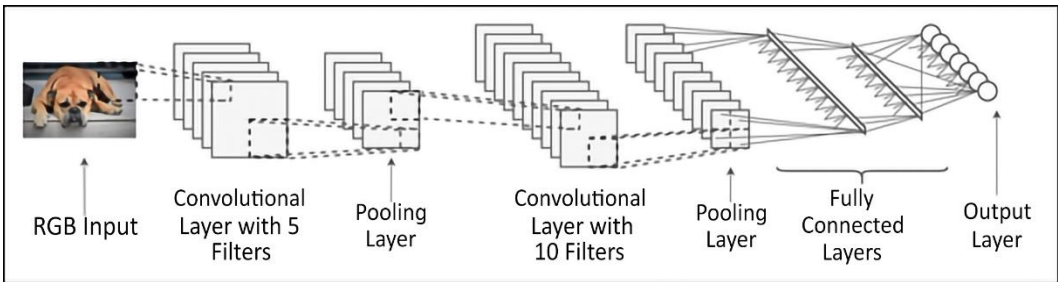
	0	1	2	3	4	5	6	7	8	9 ...	1014	1015	
<b>data/bbc/tech/272.txt</b>	0.144291	0.015962	-0.151633	0.096555	-0.015913	0.075896	-0.033353	-0.118644	-0.192030	-0.124919 ...	-0.418126	0.204618	0.
<b>data/bbc/tech/127.txt</b>	0.022870	-0.142899	-0.017096	-0.084165	0.320108	0.424914	-0.043930	0.257134	-0.215543	-0.046845 ...	-0.219130	0.264653	0.
<b>data/bbc/tech/370.txt</b>	0.207623	0.058697	-0.008874	-0.088409	0.193419	0.046109	-0.107221	0.199647	-0.167632	0.003790 ...	-0.054829	0.225892	0.
<b>data/bbc/tech/329.txt</b>	0.022106	0.060943	-0.127390	-0.100214	0.184243	-0.077529	-0.157470	-0.042993	-0.204254	-0.021419 ...	-0.337353	0.153419	0.
<b>data/bbc/tech/240.txt</b>	0.259128	-0.108082	0.076262	-0.080416	0.183988	0.329807	0.156697	0.495652	-0.104913	-0.120077 ...	-0.218093	0.236378	0.
<b>data/bbc/tech/379.txt</b>	0.071111	-0.112660	0.038746	-0.084503	0.207438	0.231360	-0.015819	0.235174	-0.238940	0.030840 ...	-0.330608	0.267756	0.
<b>data/bbc/tech/339.txt</b>	0.080515	0.216040	-0.090722	0.118778	0.336153	0.223334	0.075926	0.472938	-0.046222	0.124439 ...	-0.240382	0.015074	-0.
<b>data/bbc/tech/046.txt</b>	0.019151	-0.029814	-0.046270	-0.139506	0.255929	0.230742	-0.011093	0.426066	0.112122	-0.130358 ...	-0.285940	0.280919	-0.
<b>data/bbc/tech/140.txt</b>	0.379357	-0.174718	-0.062910	-0.017047	-0.034842	0.260822	0.129207	0.358961	-0.040298	-0.027103 ...	-0.144901	0.096271	0.
<b>data/bbc/tech/349.txt</b>	0.241237	-0.013553	0.033077	-0.159186	0.367290	0.414783	0.176808	0.556002	-0.273304	0.108183 ...	-0.235471	0.265600	-0.

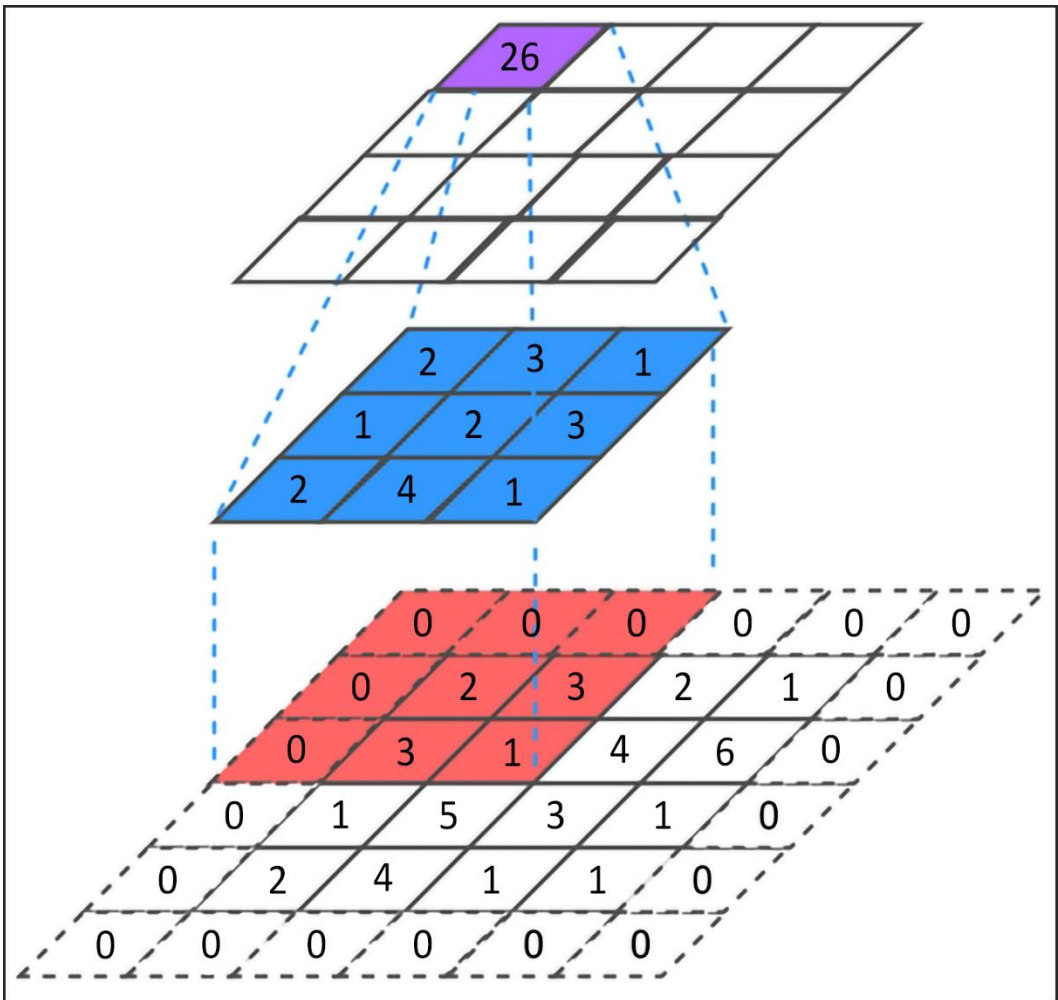
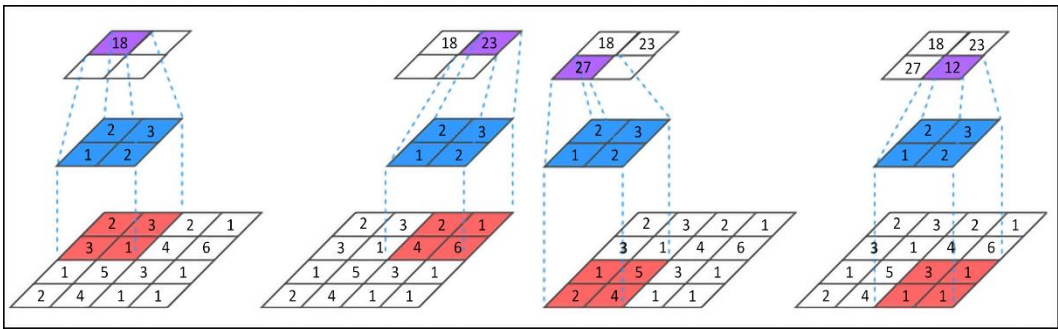
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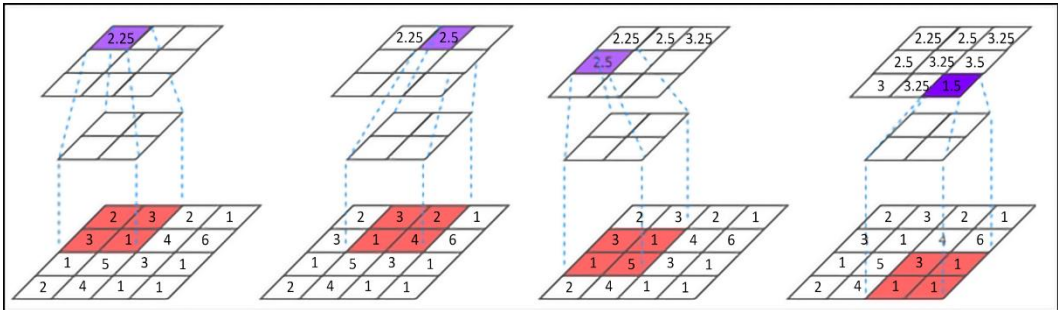
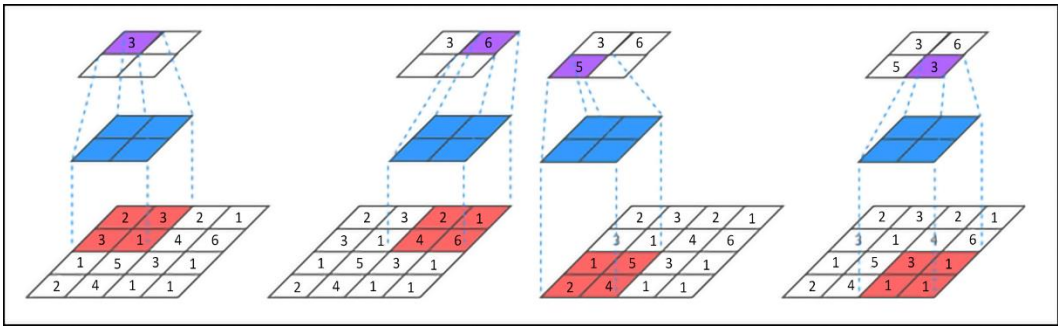
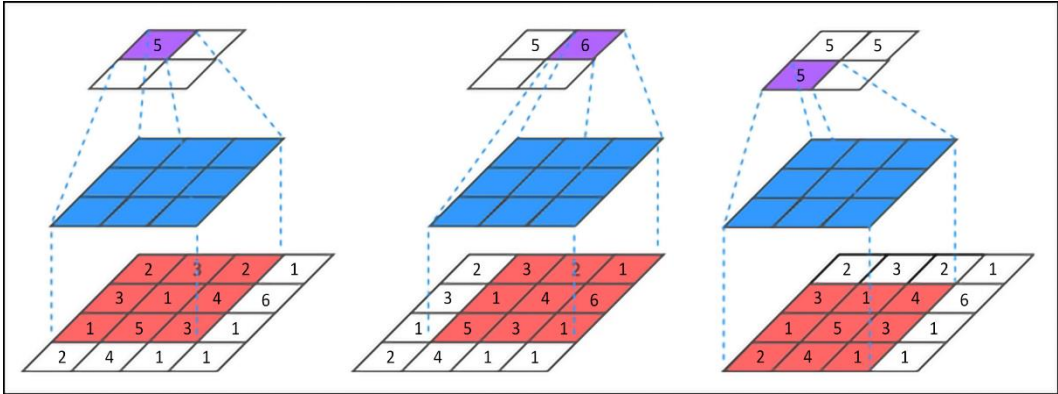


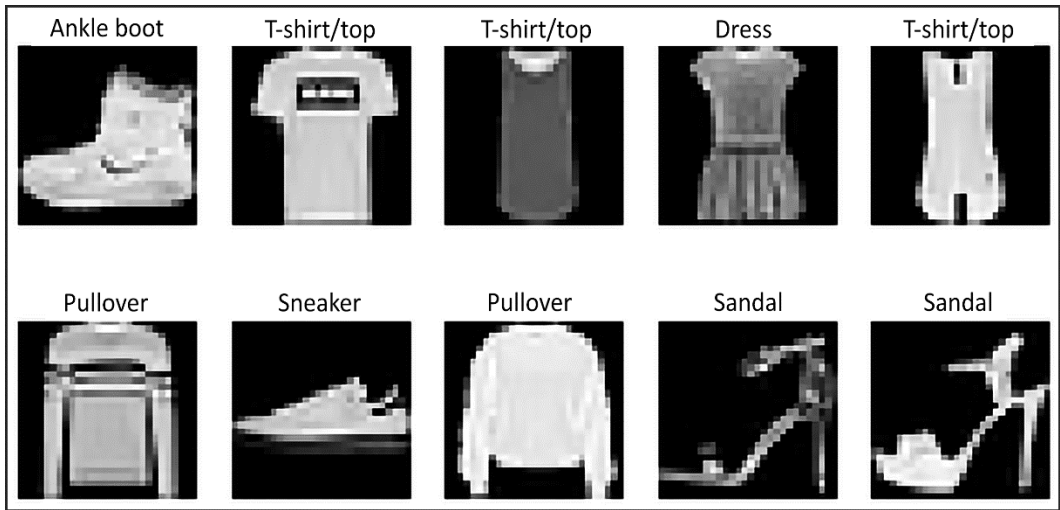
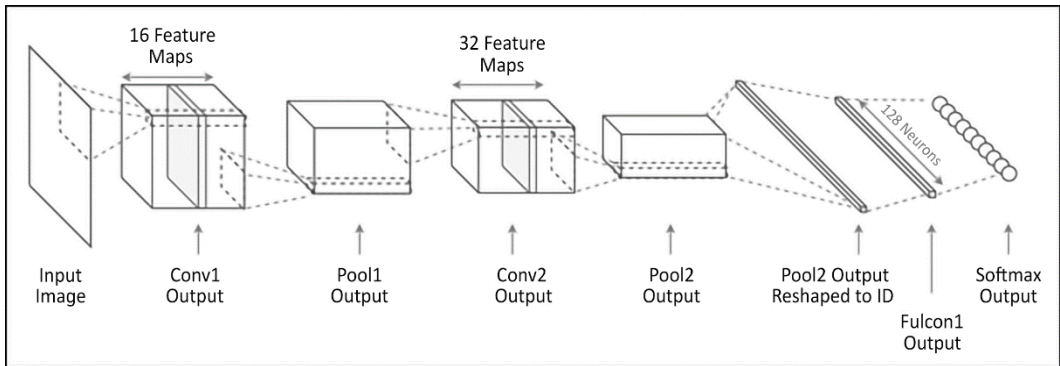
# Chapter 5: Sentence Classification with Convolutional Neural Networks

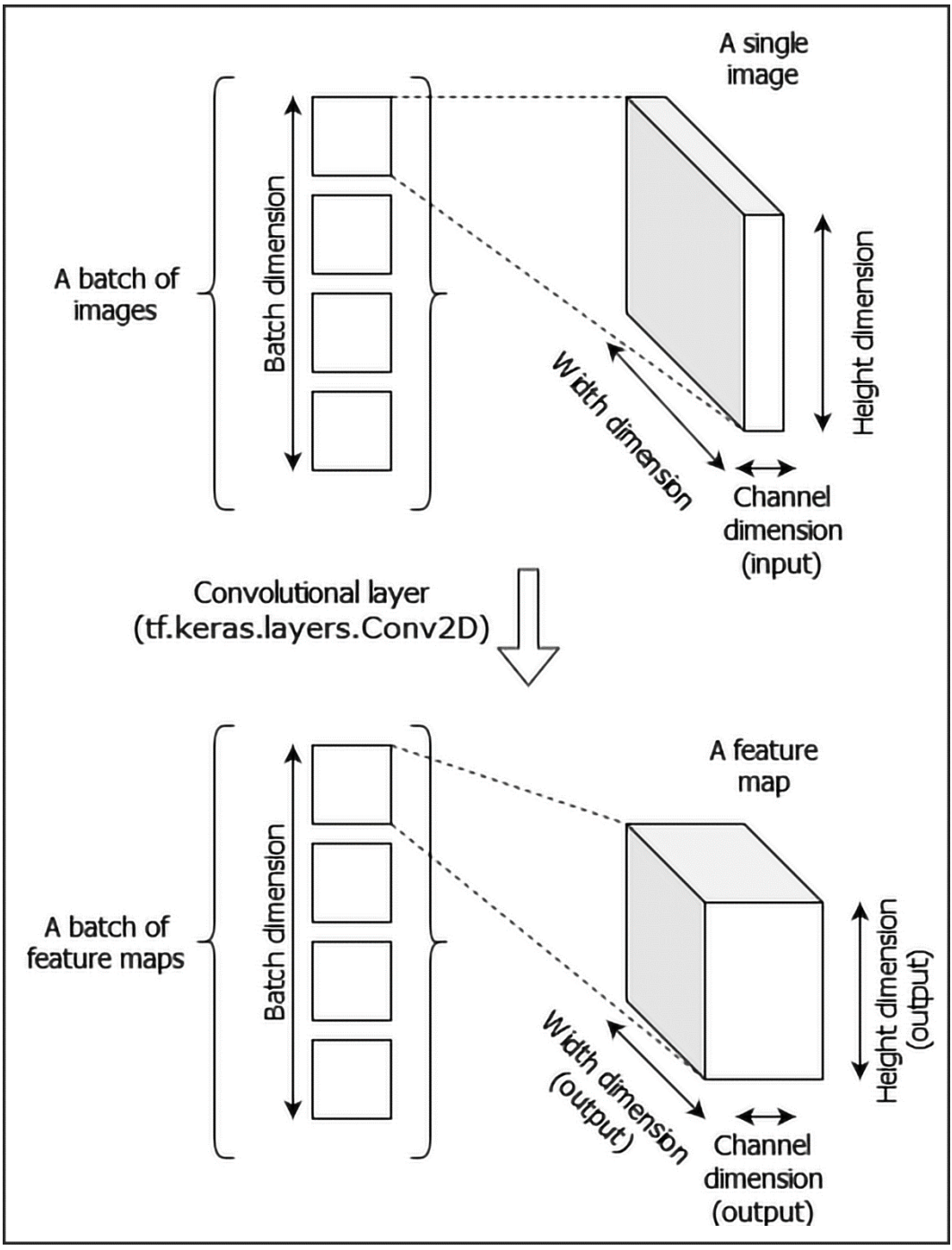










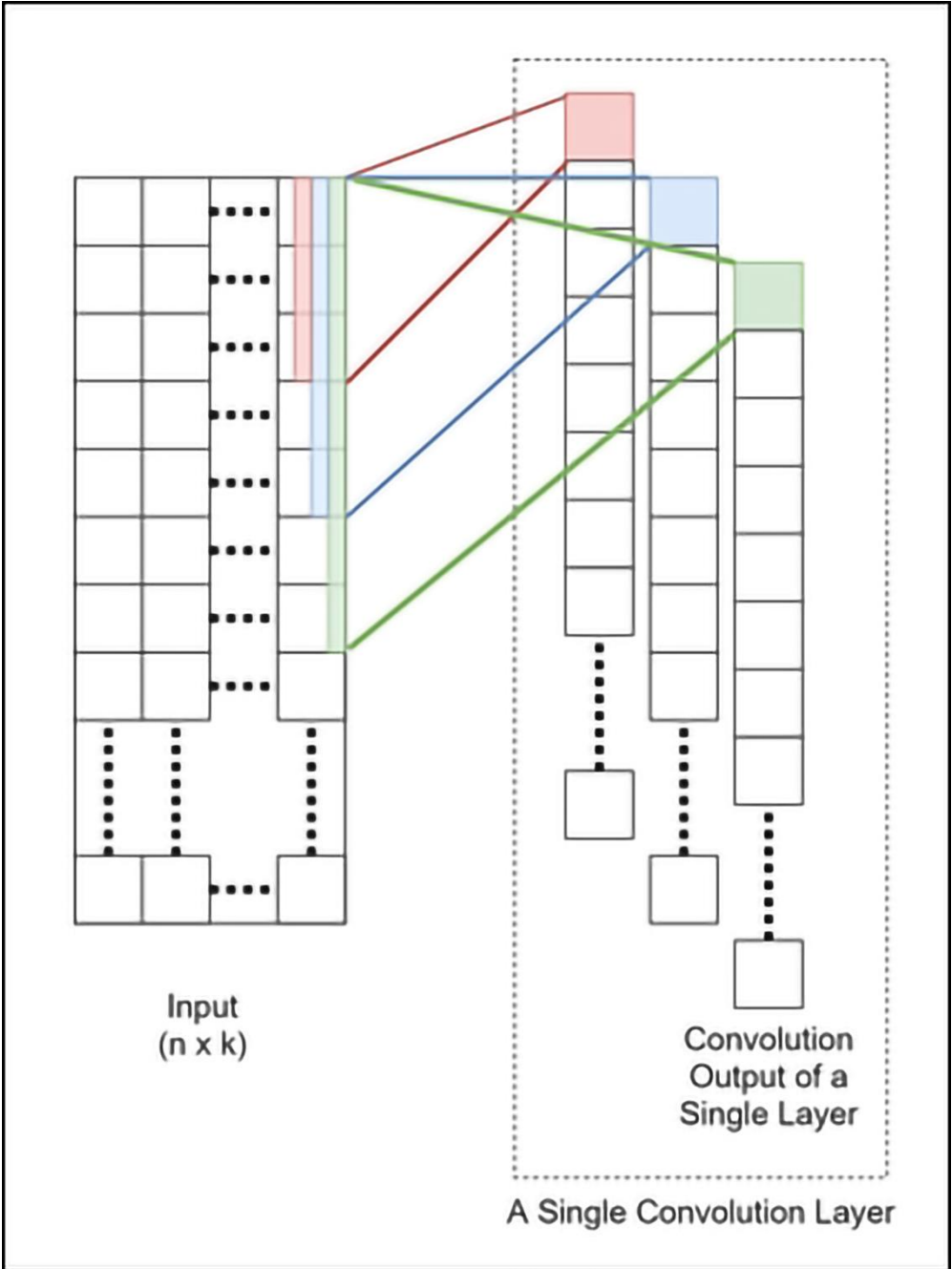


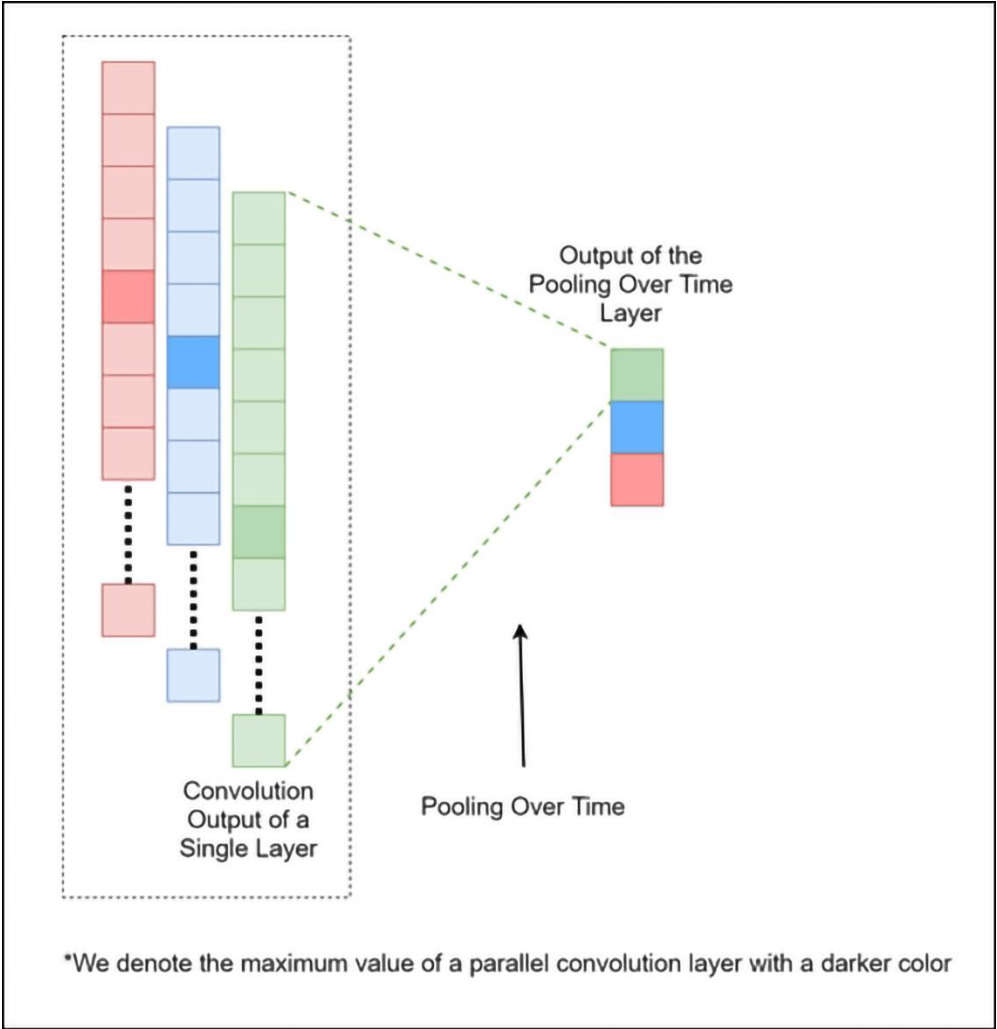


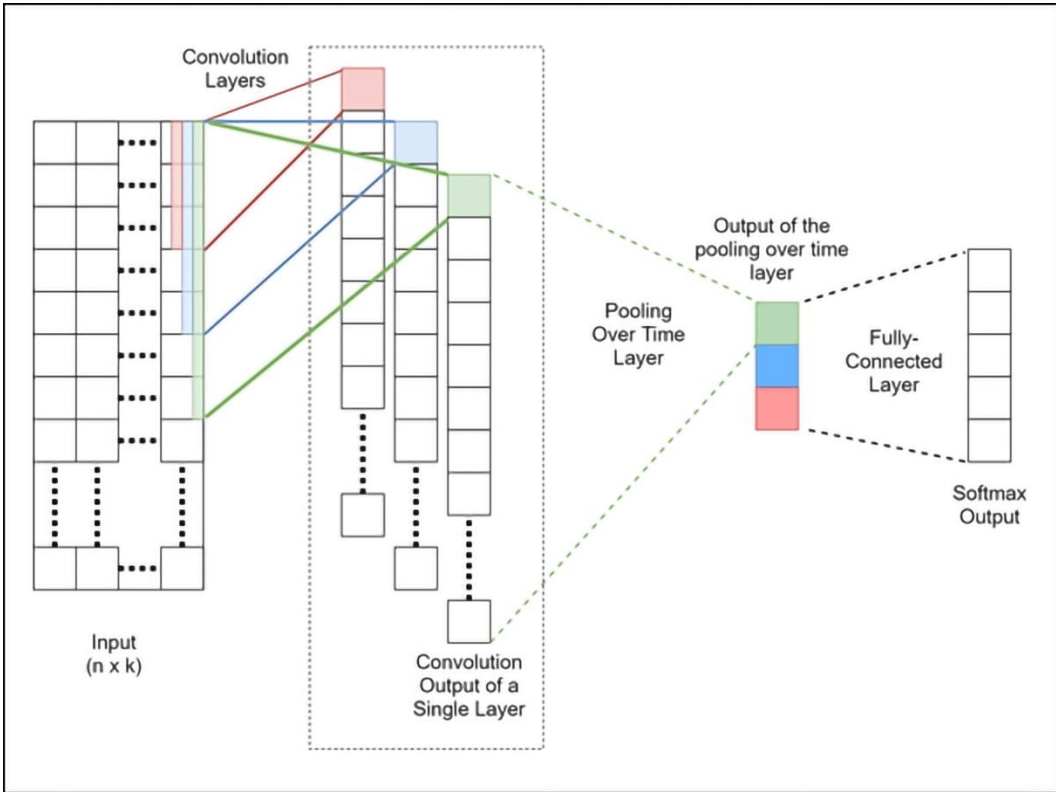


	question	category	sub_category
0	how did serfdom develop in and then leave russ...	DESC	manner
1	what films featured the character popeye doyle ?	ENTY	cremat
2	how can i find a list of celebrities ' real na...	DESC	manner
3	what fowl grabs the spotlight after the chines...	ENTY	animal
4	what is the full form of .com ?	ABBR	exp
5	what contemptible scoundrel stole the cork fro...	HUM	ind
6	what team did baseball 's st. louis browns bec...	HUM	gr
7	what is the oldest profession ?	HUM	title
8	what are liver enzymes ?	DESC	def
9	name the scar-faced bounty hunter of the old w...	HUM	ind

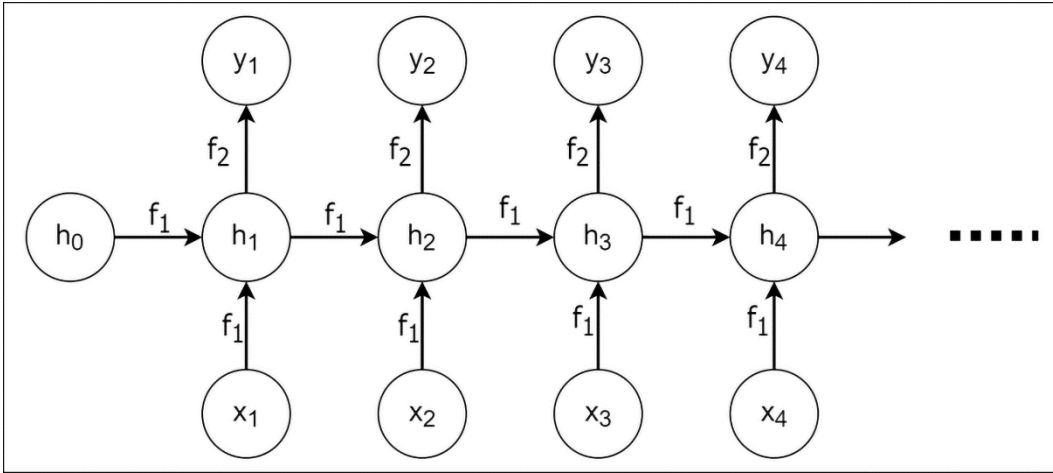
	question	category	sub_category
4343	how can i get started in writing for television ?	0	manner
2318	what were the achievements of richard nixon ?	1	other
2808	what was the alternate to vhs ?	1	other
3217	what country would you visit to ski in the dol...	2	country
3966	what country imposed the berlin blockade in 19...	2	country
5189	where on the web is adventours tours from sydn...	2	other
1675	what u.s. state ends with a g ?	2	state
1408	what country was sir edmund hillary born in ?	2	country
4916	what was the name of the u.s. navy gunboat in ...	1	veh
730	what 19th-century writer had a country estate ...	3	ind

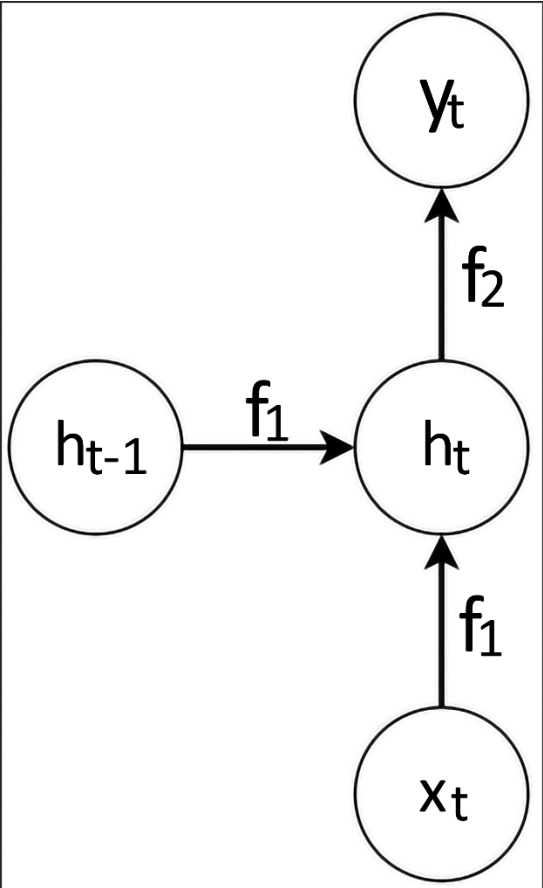


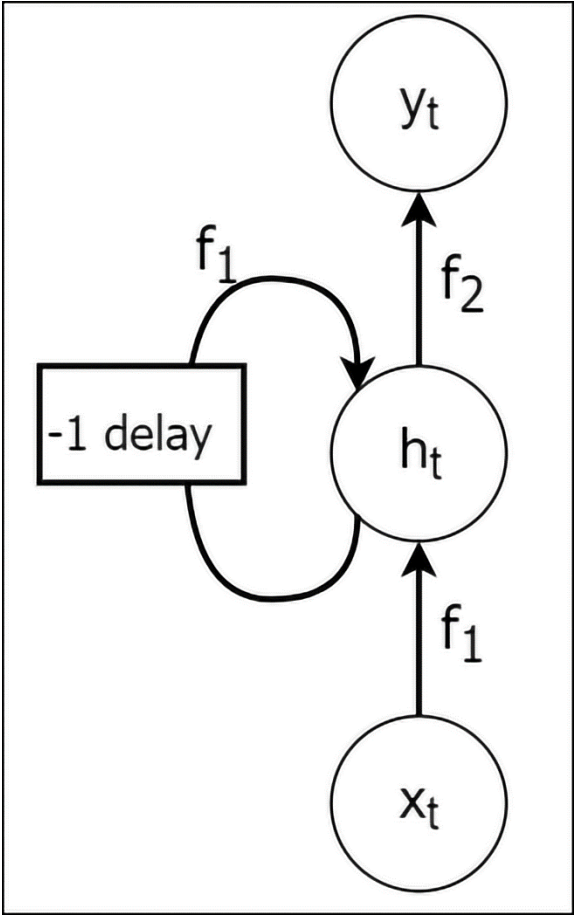


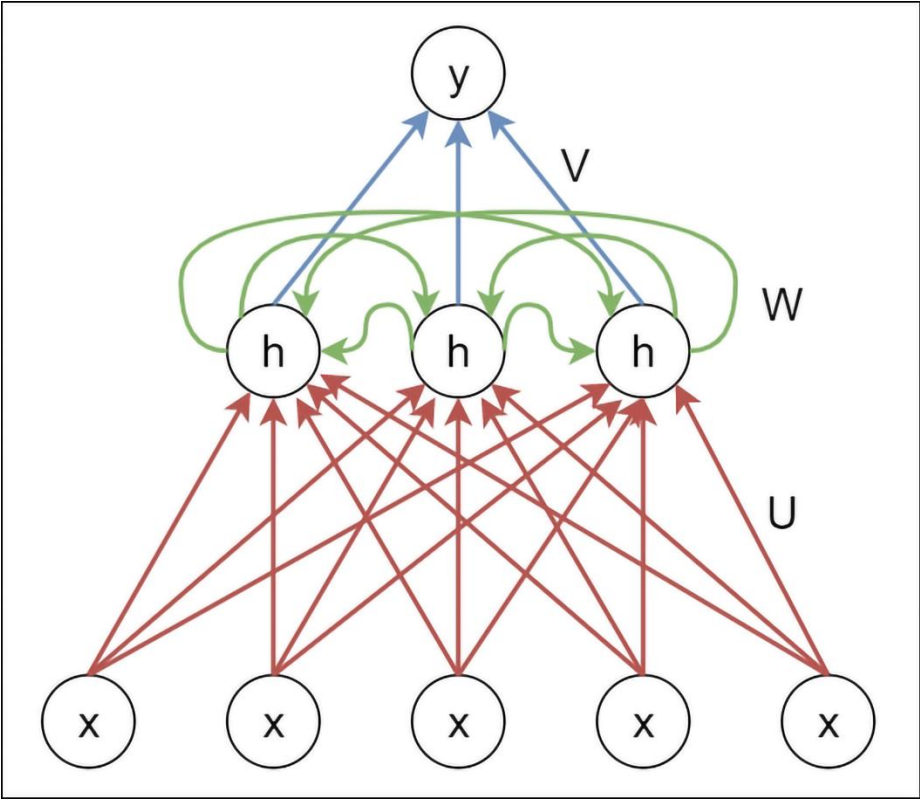


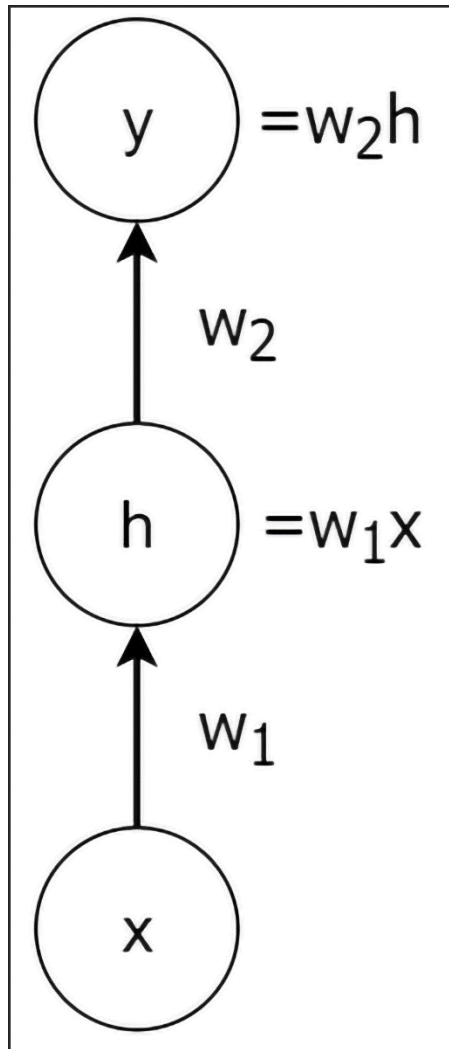
## Chapter 6: Recurrent Neural Networks

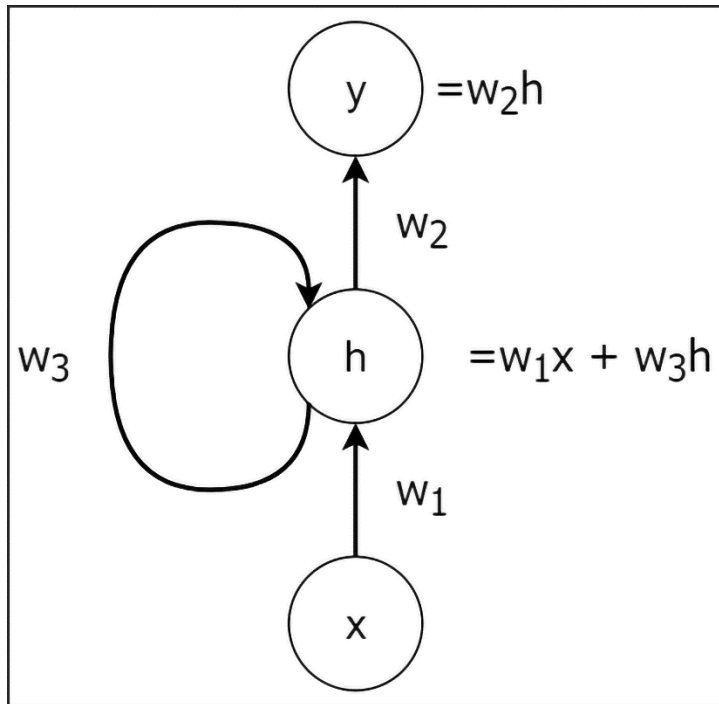


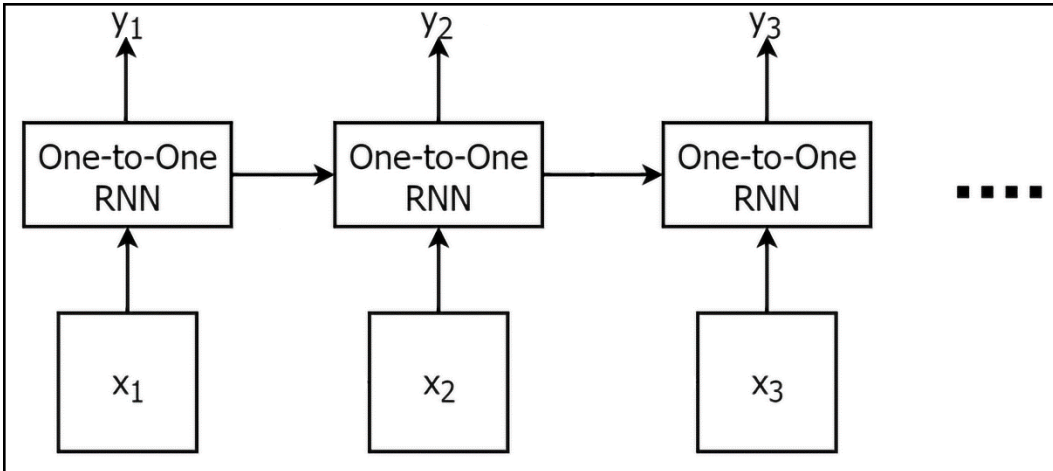
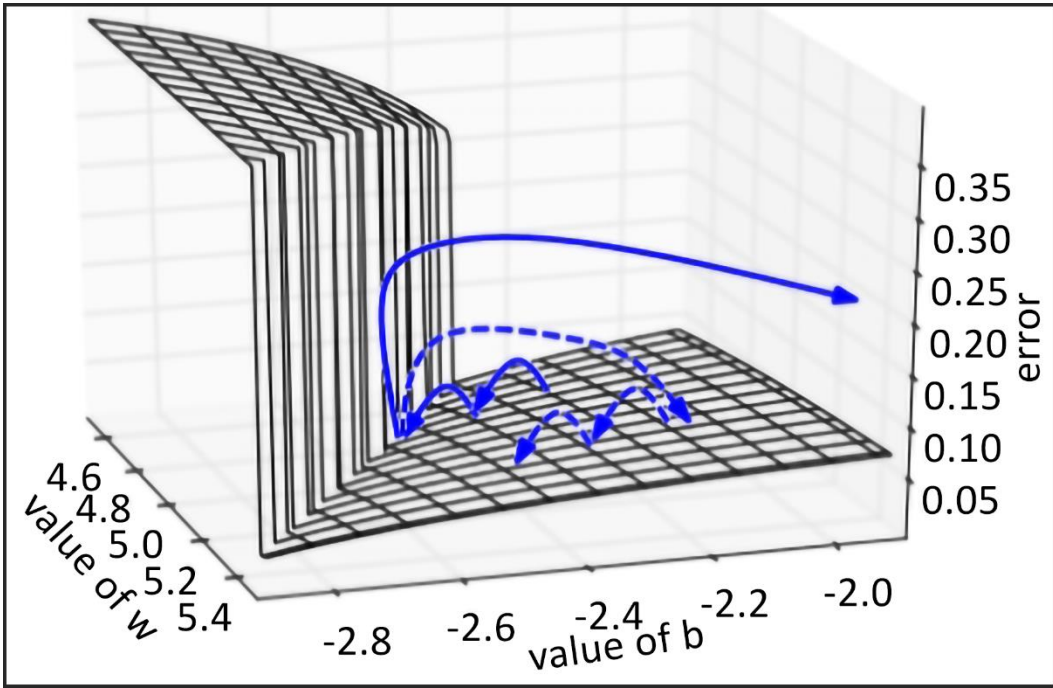


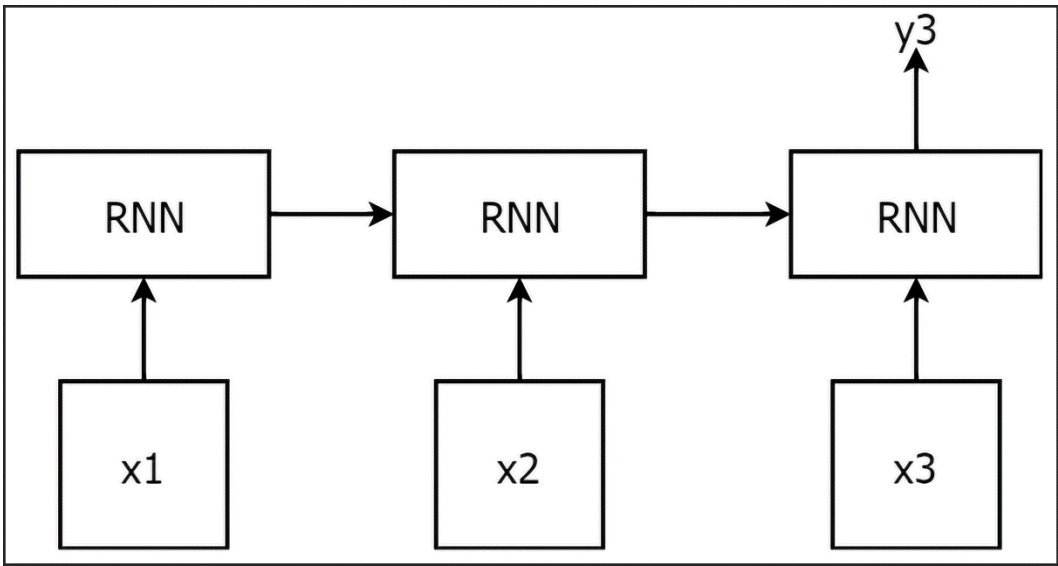
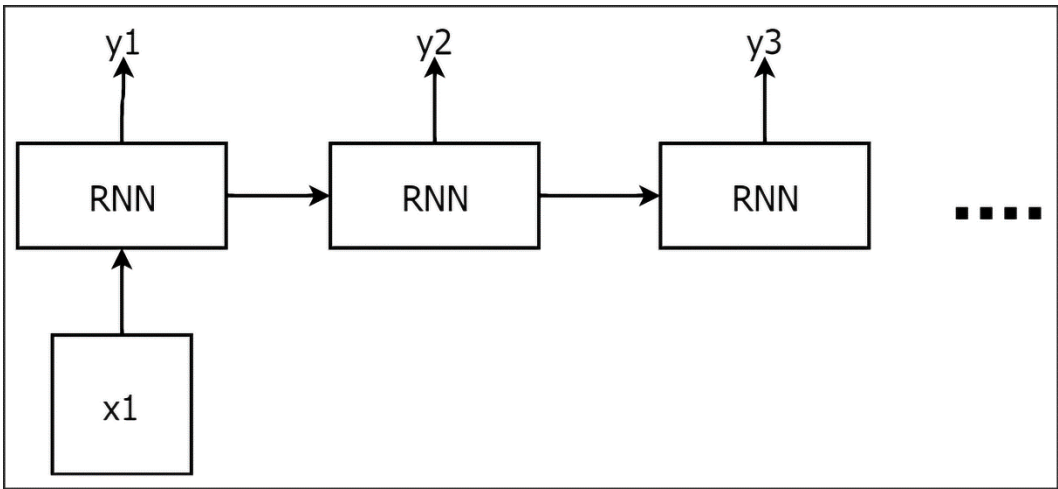


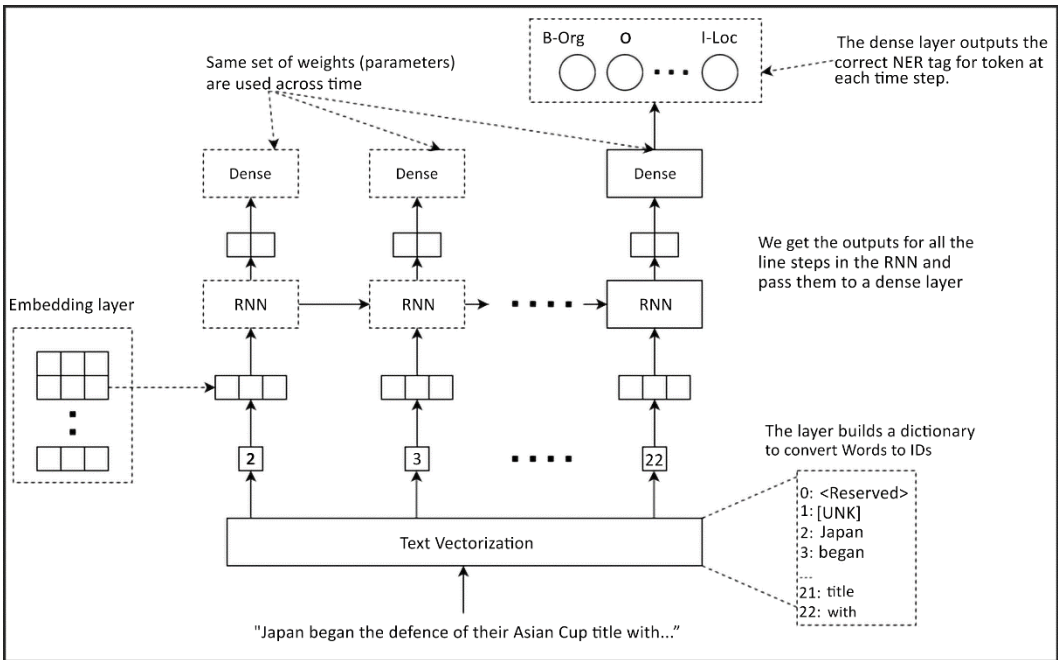
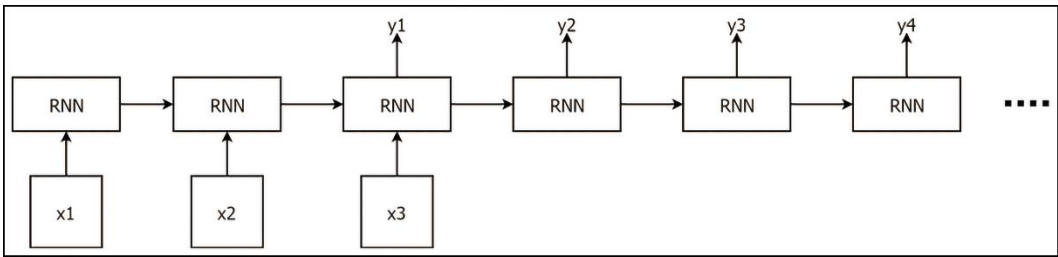




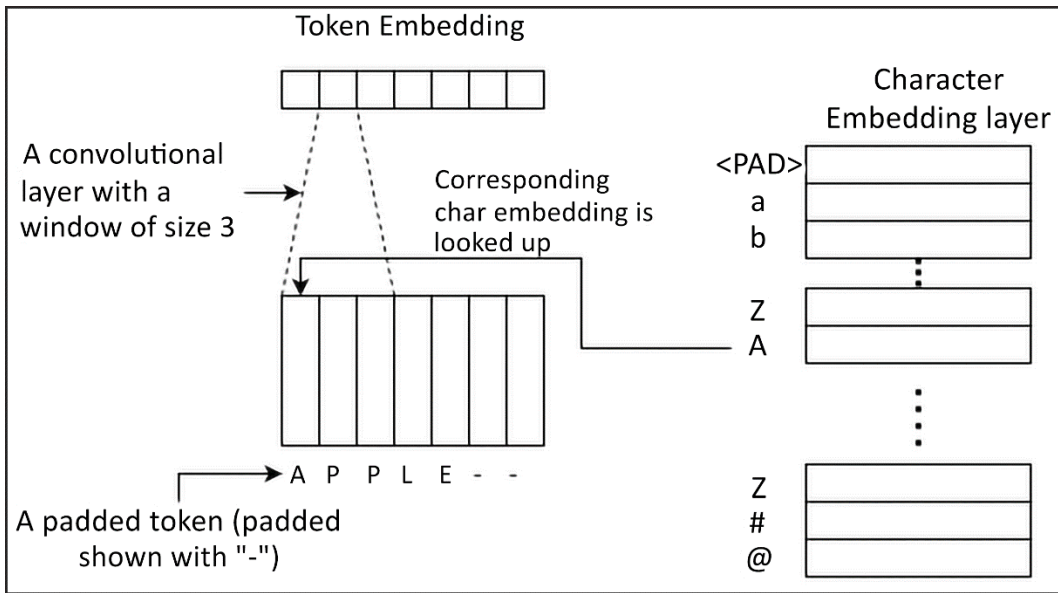




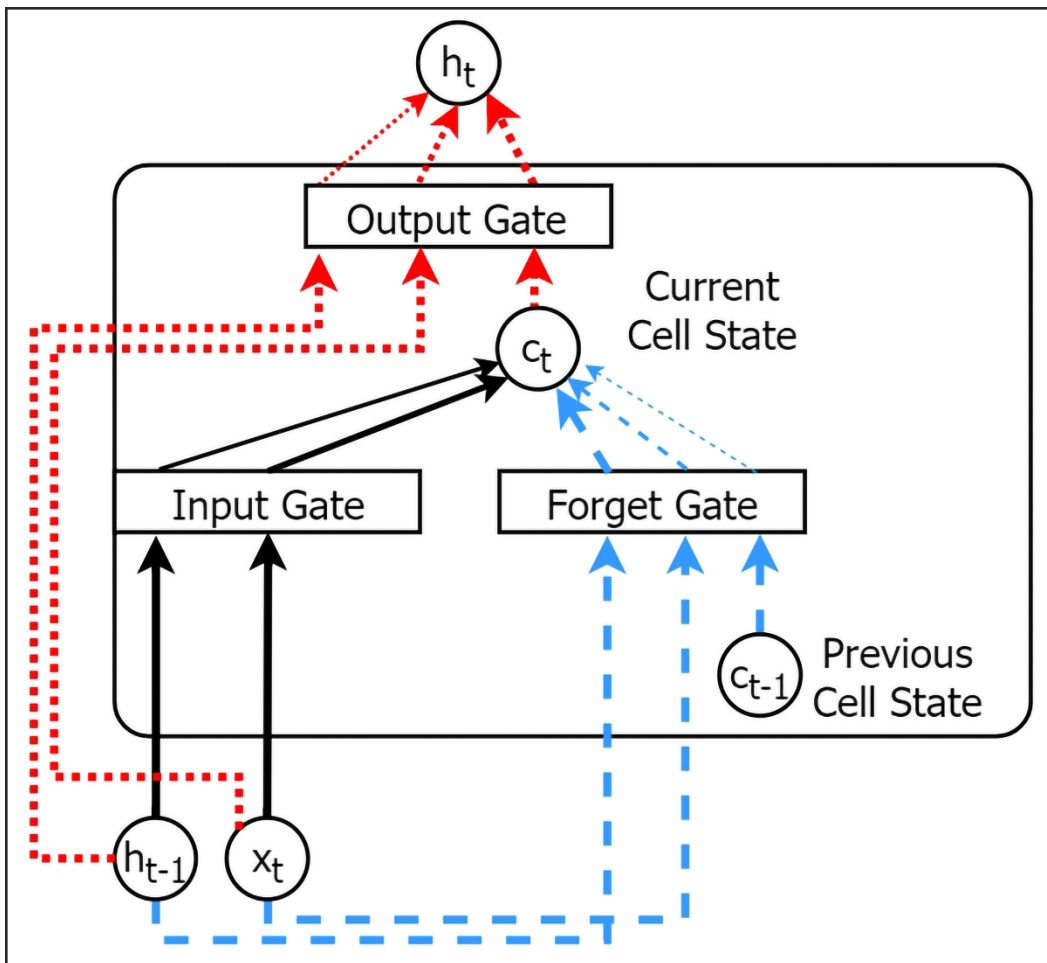


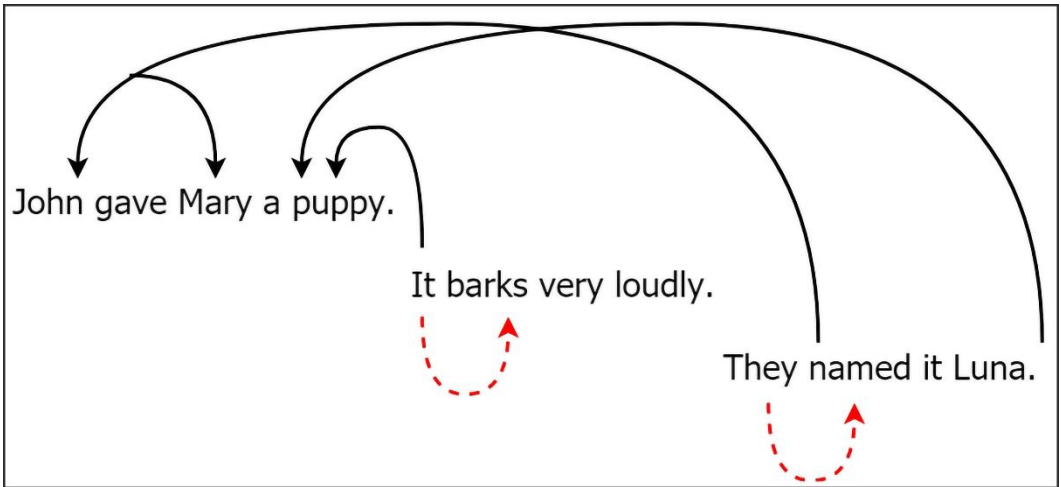
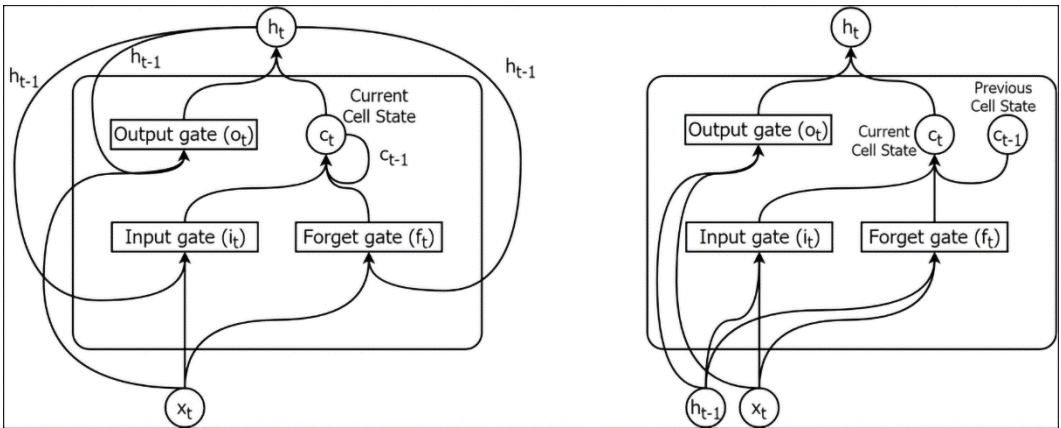


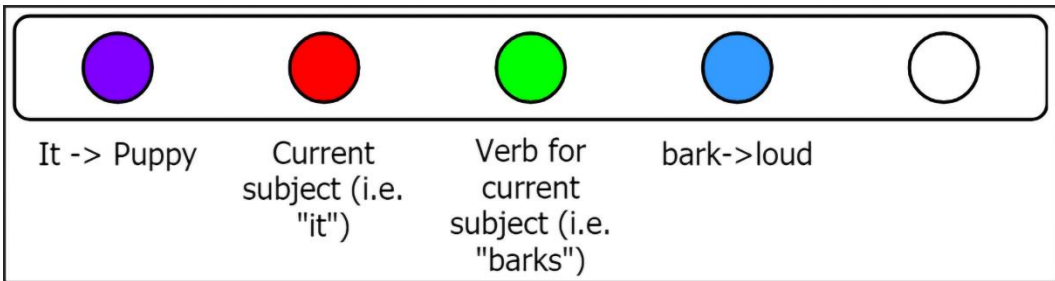
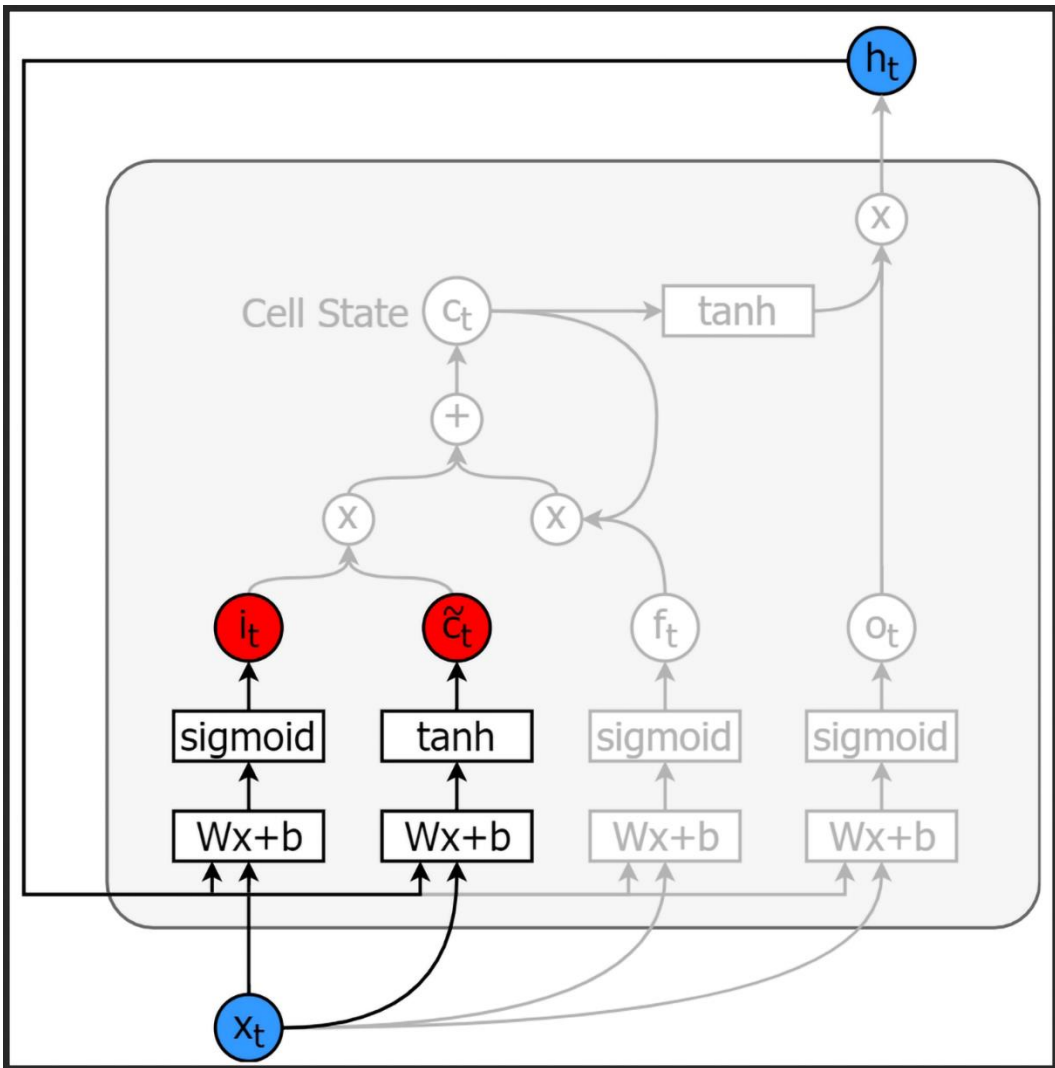
		Predicted		Support
		0	1	
True	0	35	5	40
	1	25	0	25

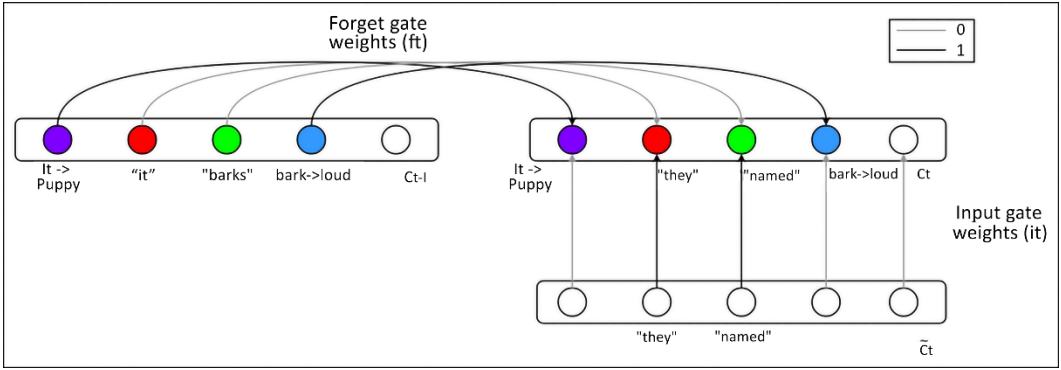
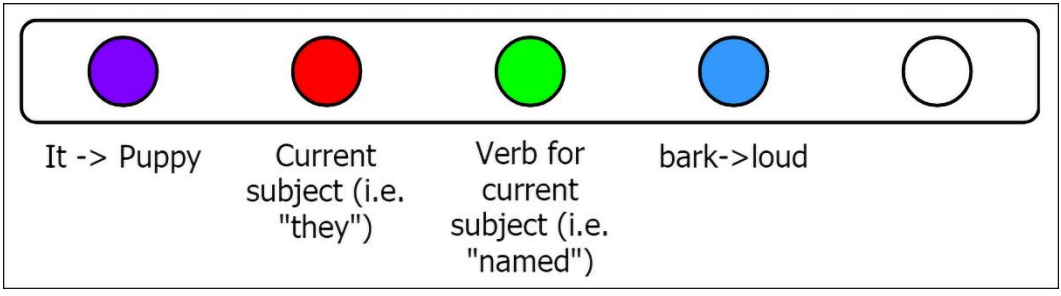


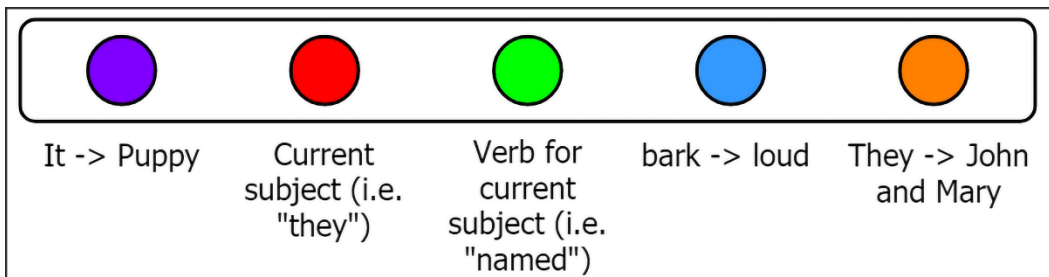
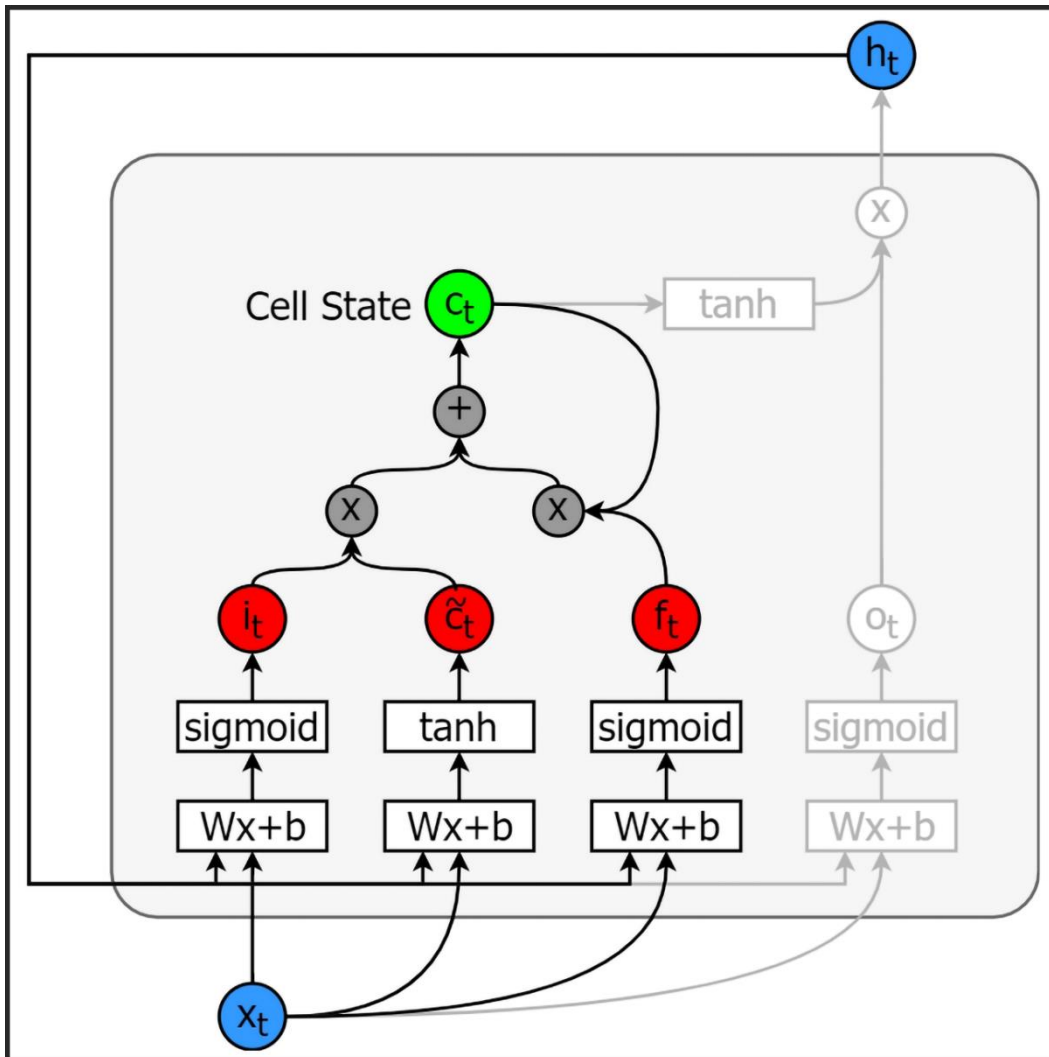
## Chapter 7: Understanding Long Short-Term Memory Networks

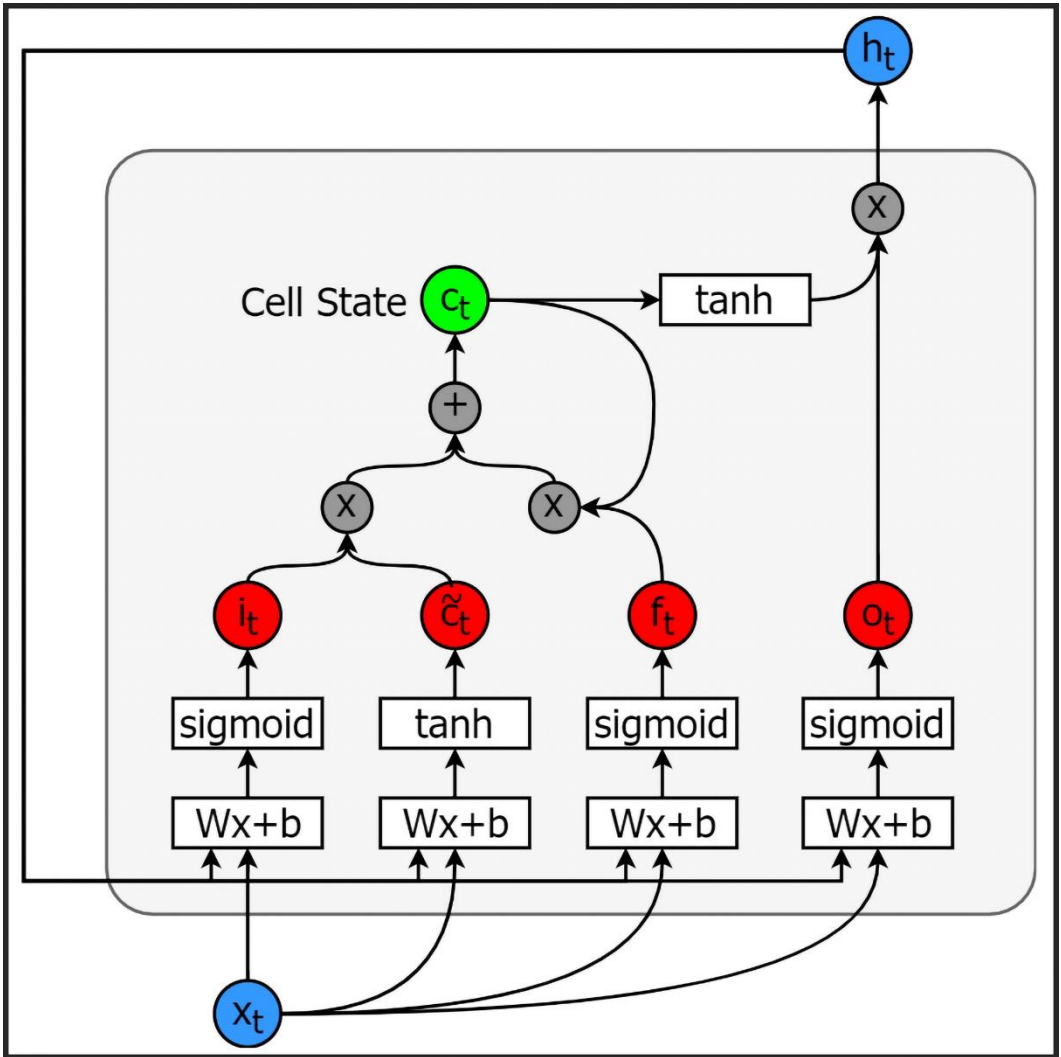


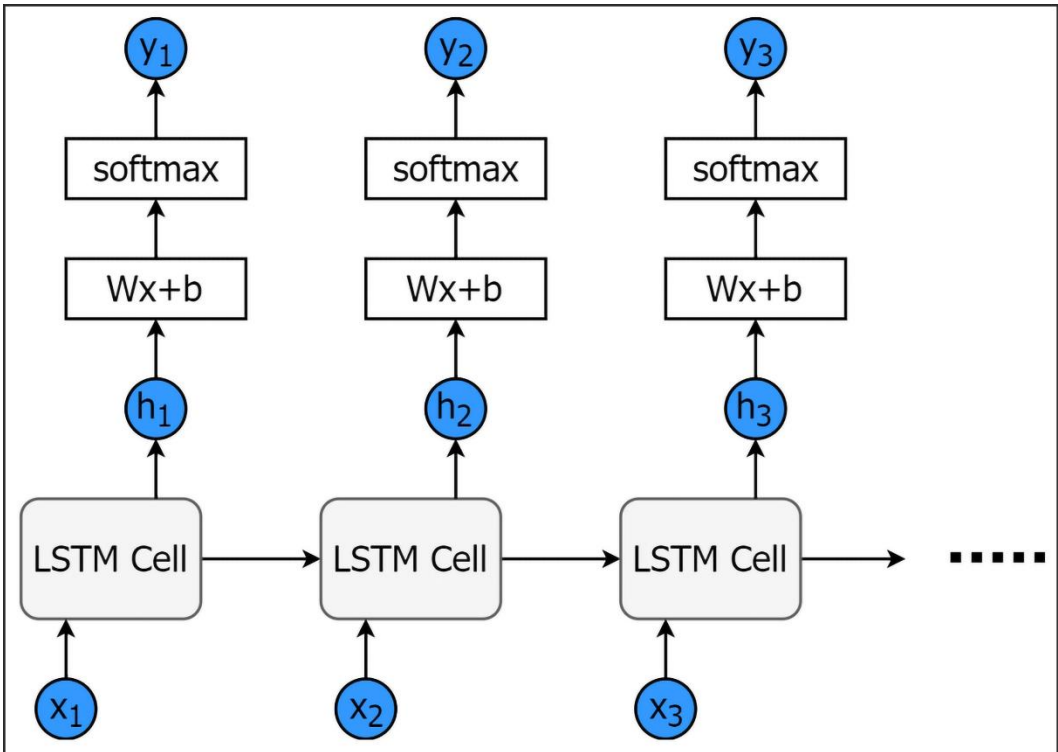
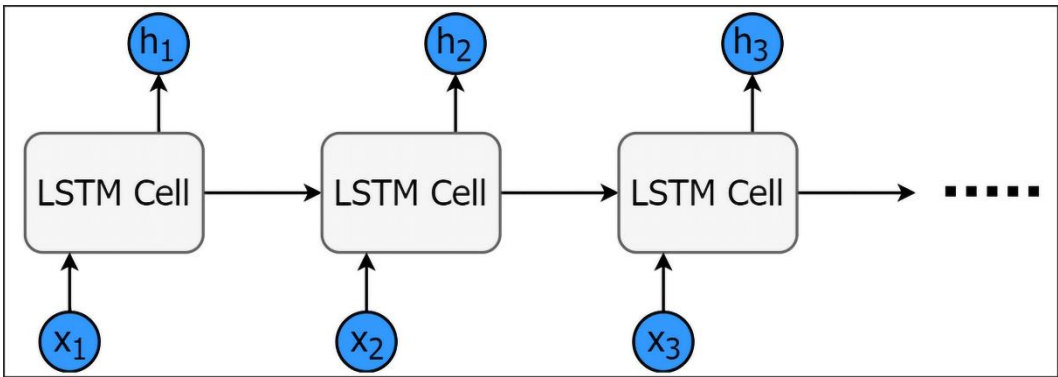


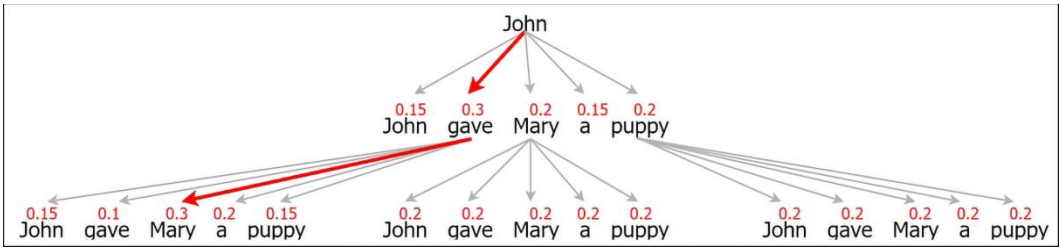
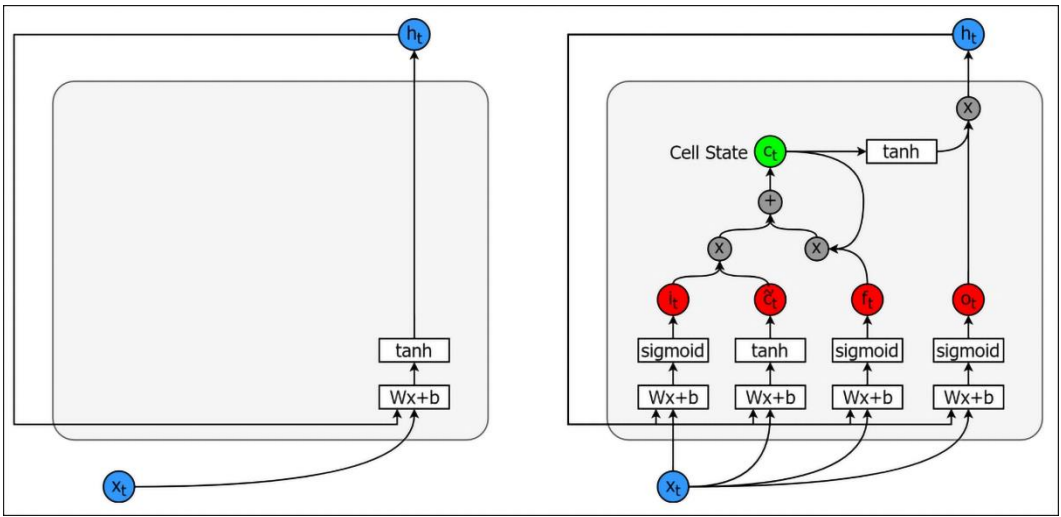


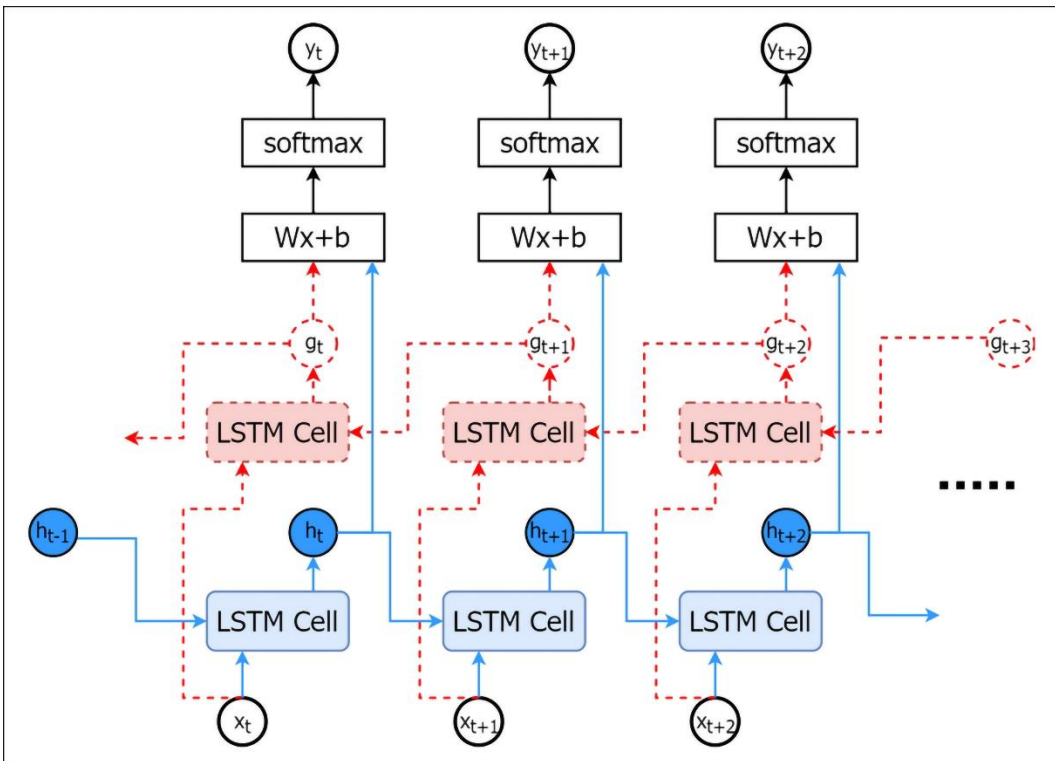
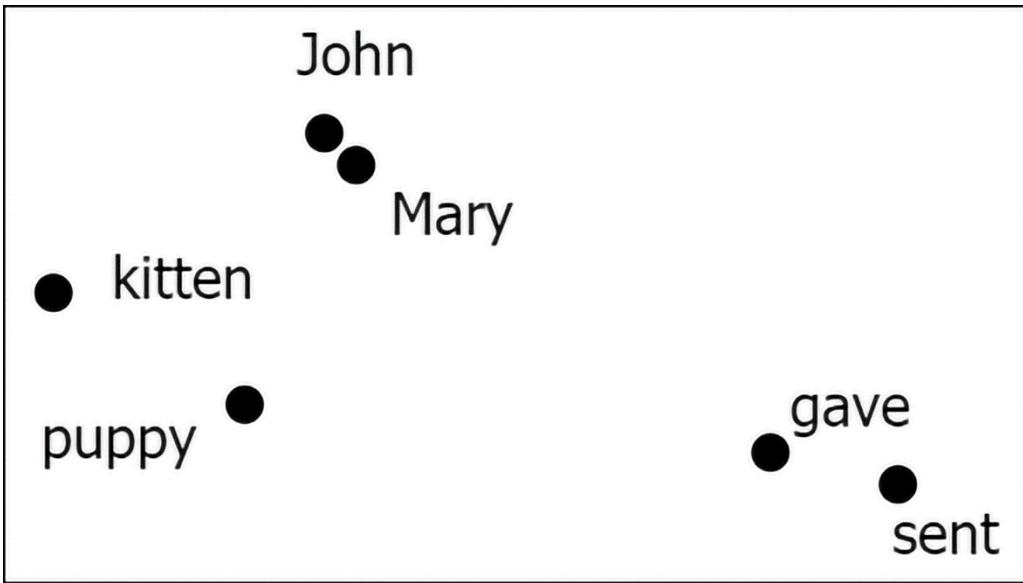


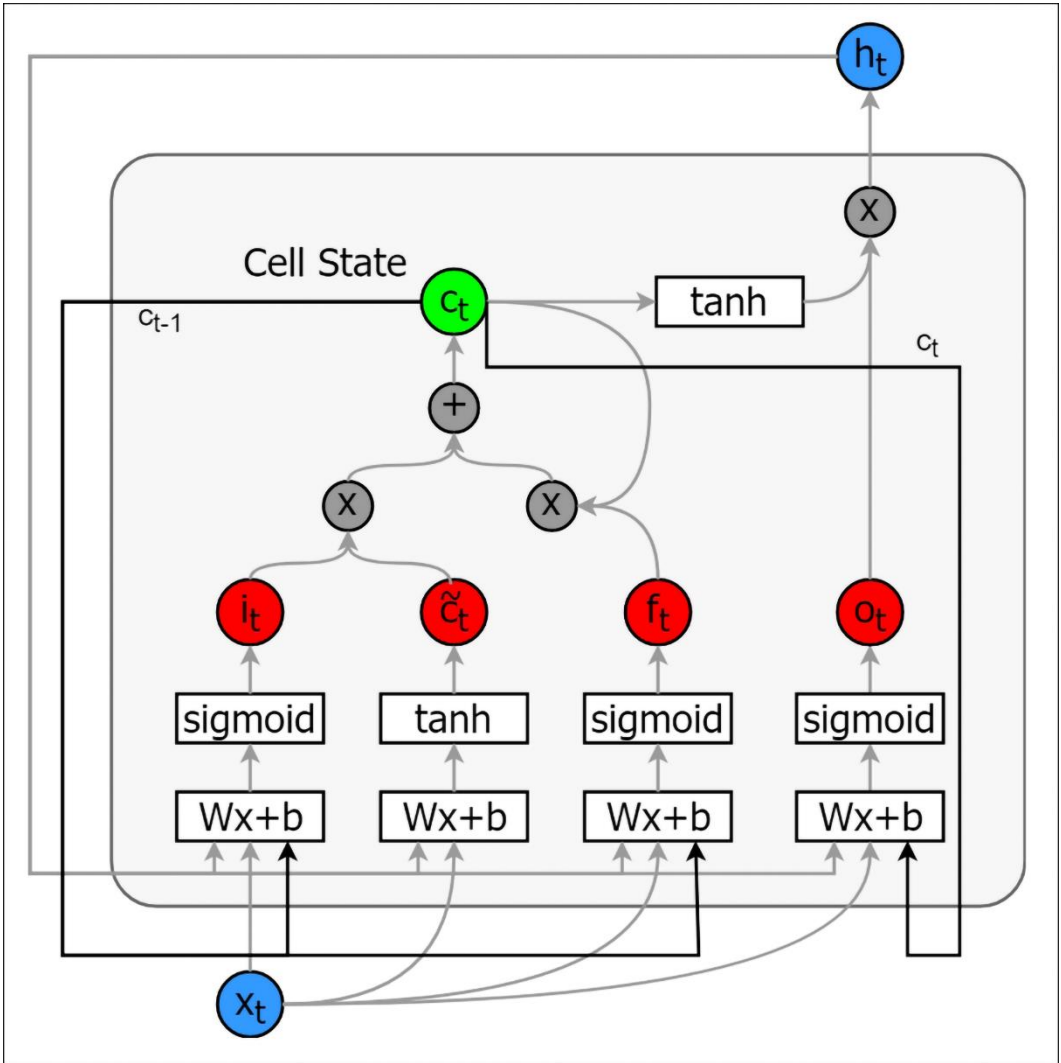


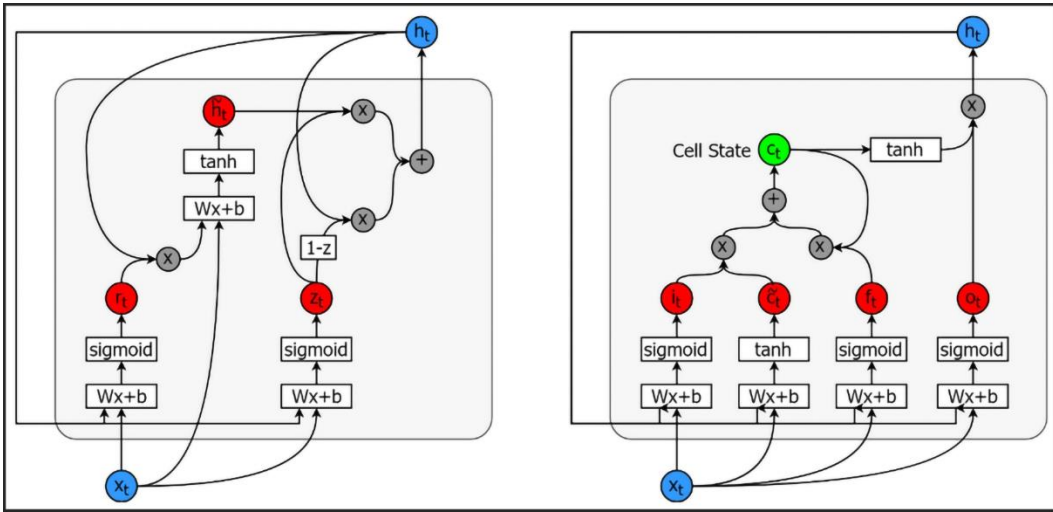




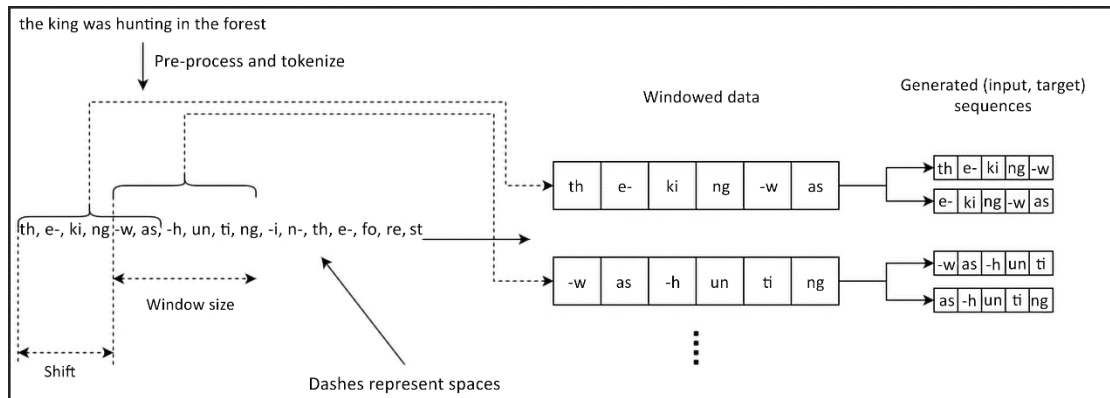


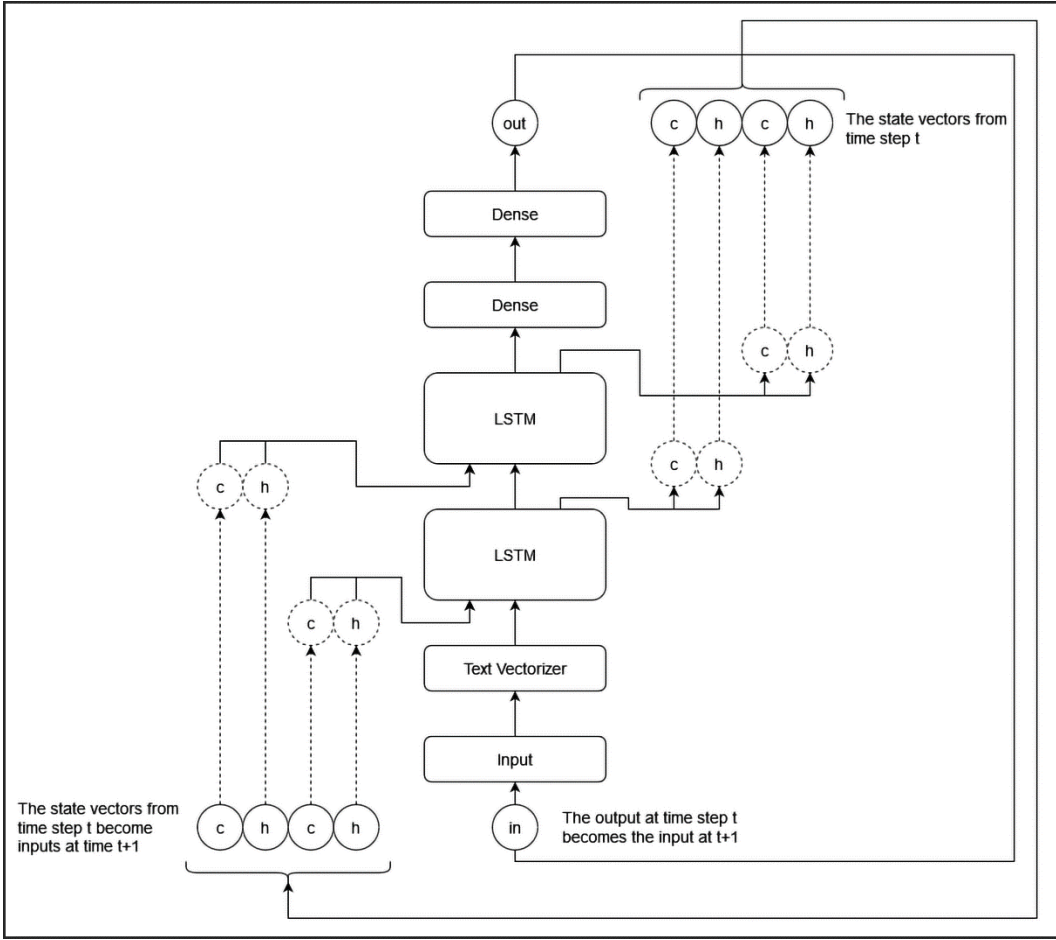


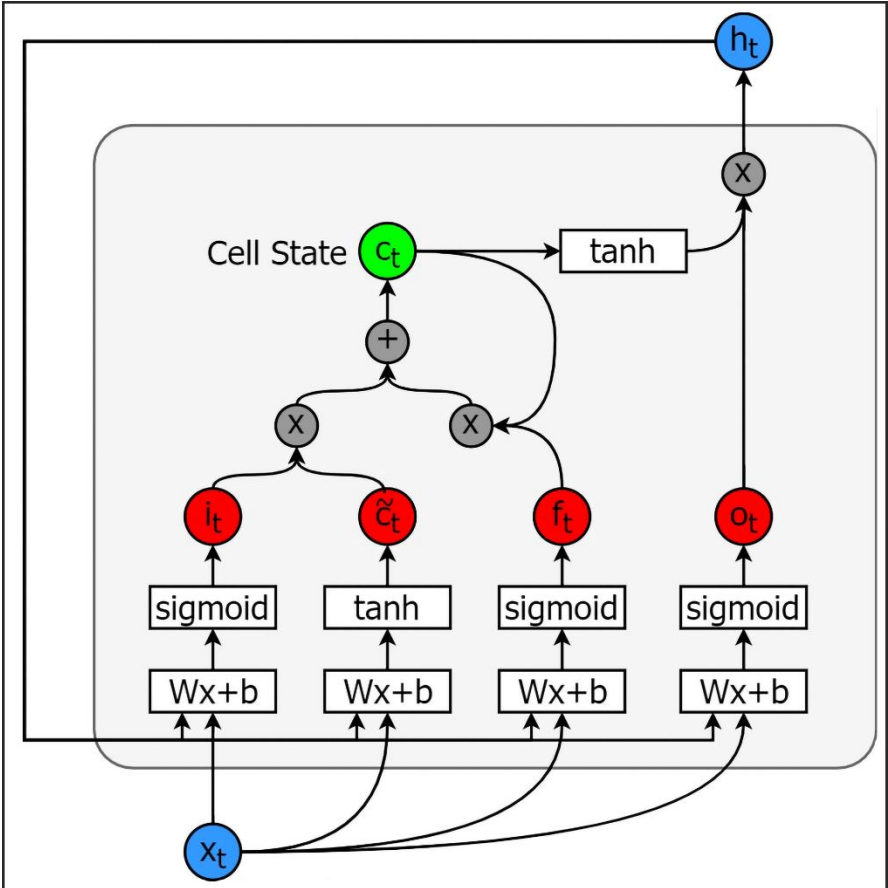


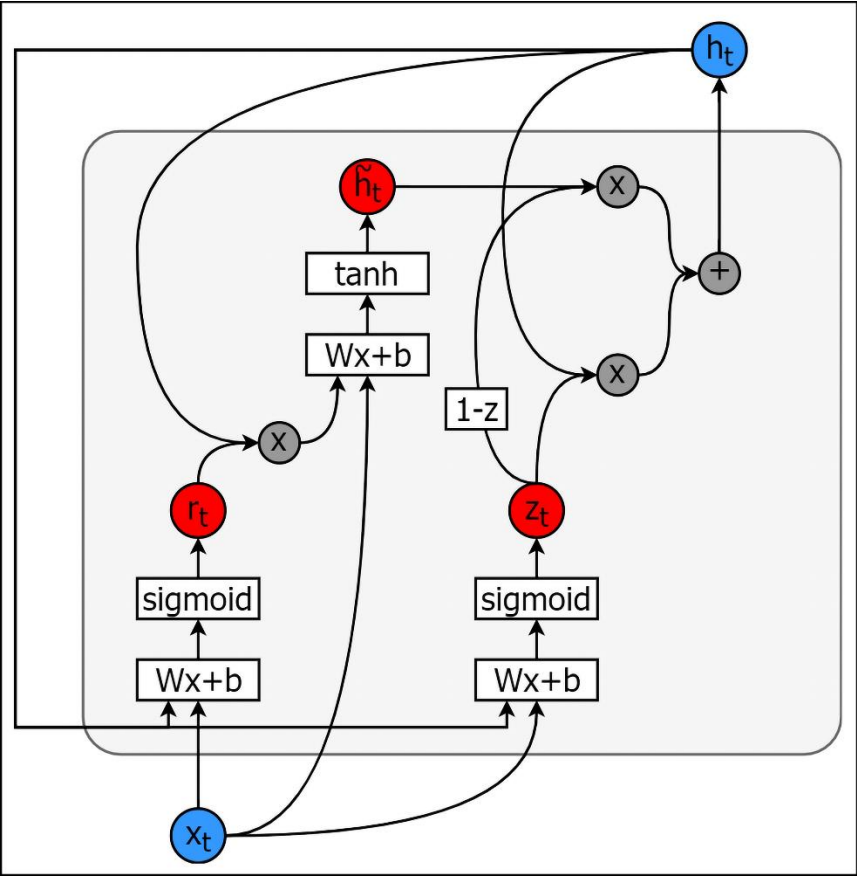


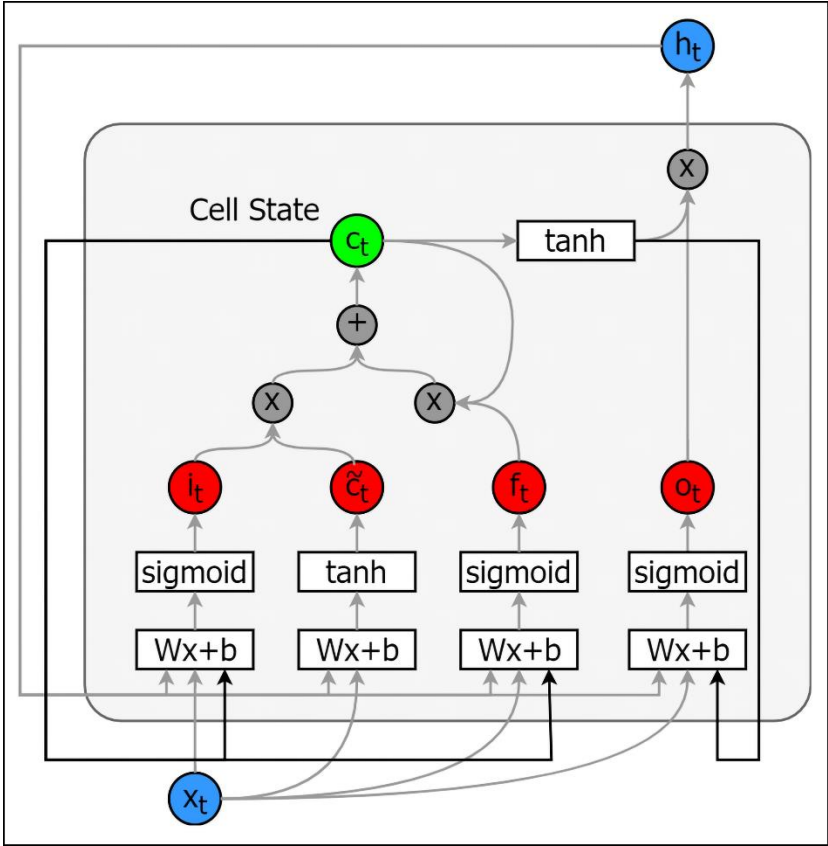
## Chapter 8: Applications of LSTM - Generating Text



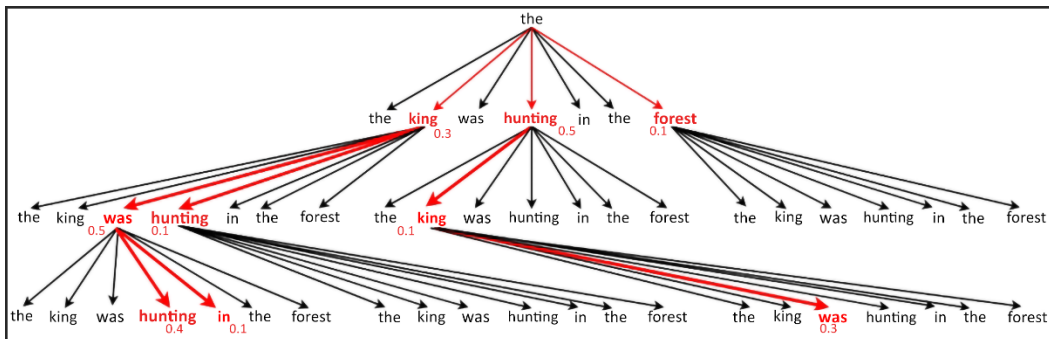
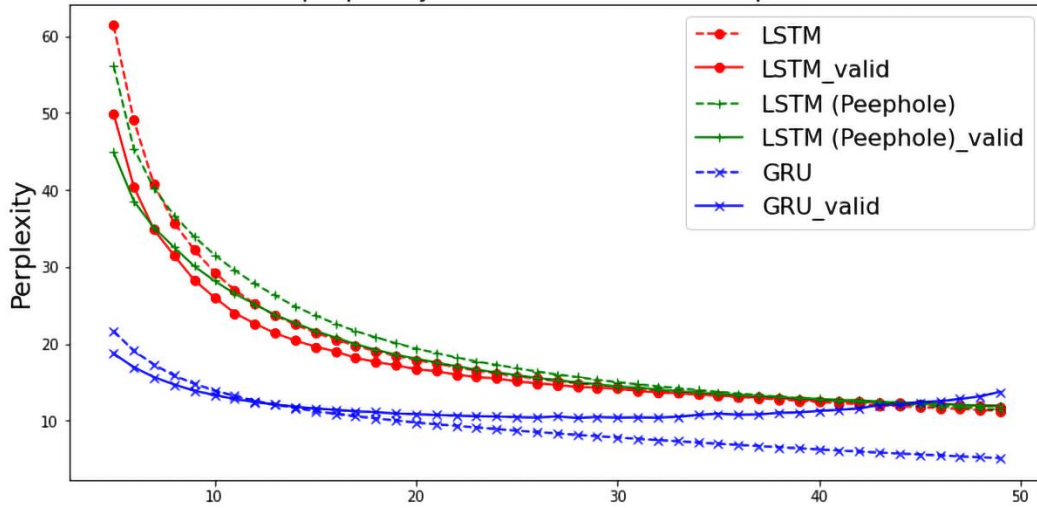


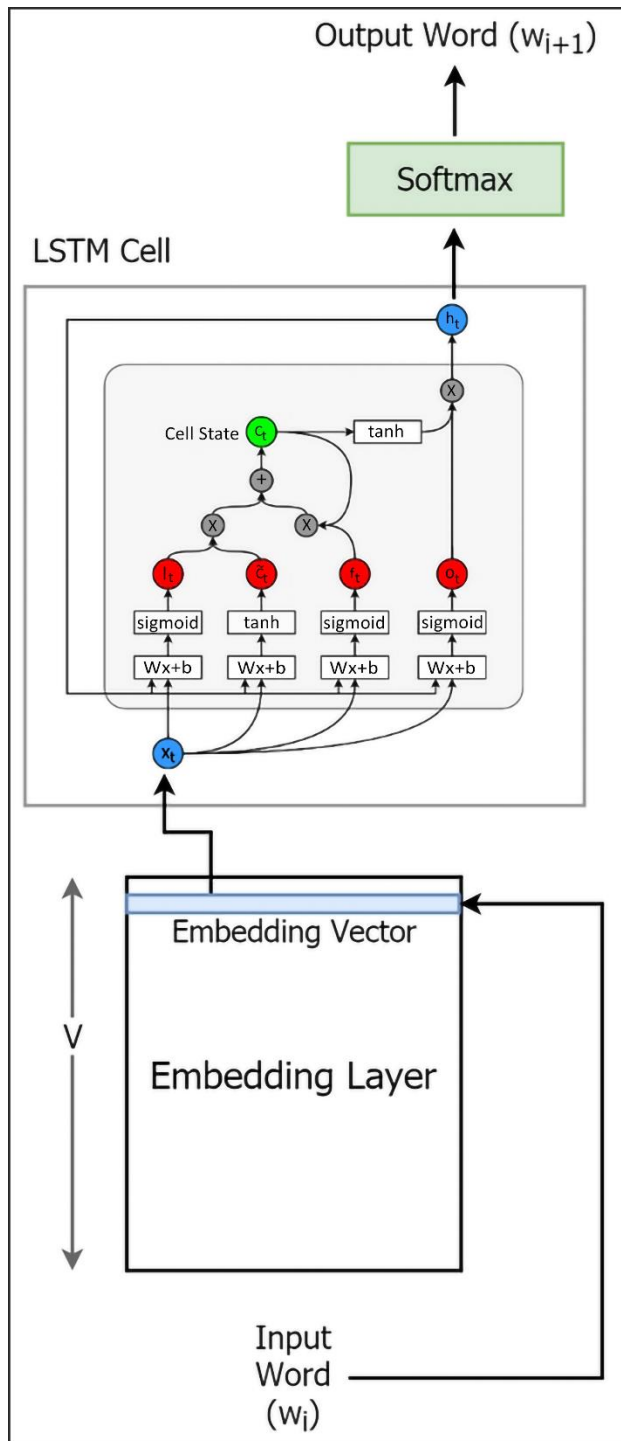




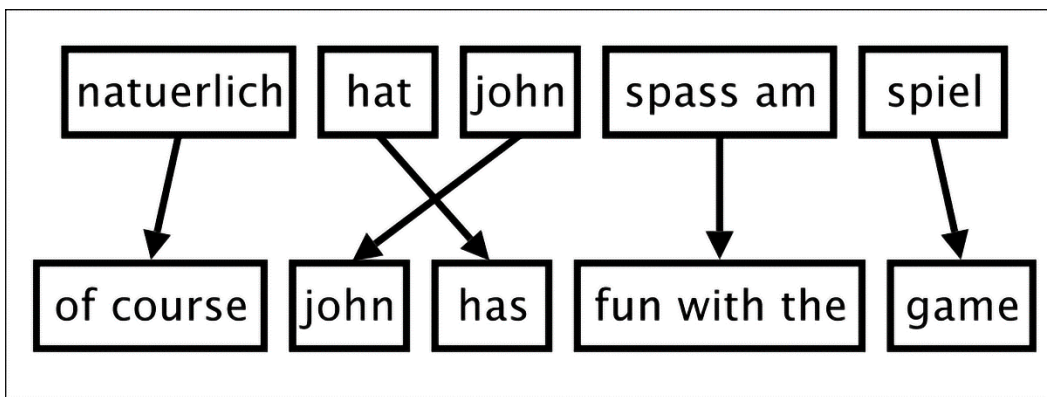
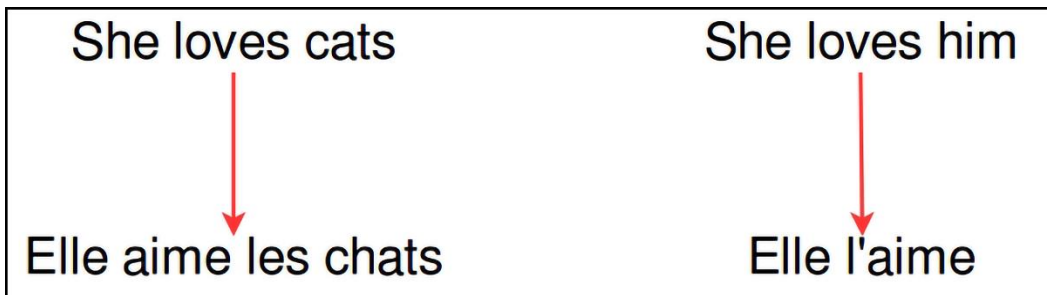


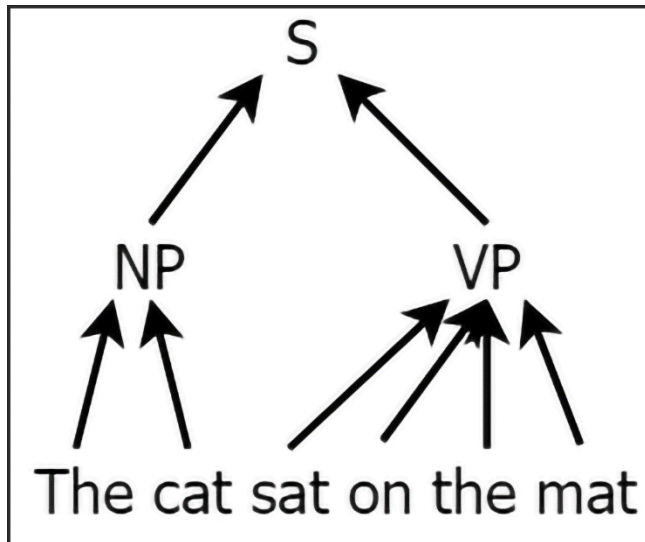
Train/Valid perplexity behavior for various sequential models

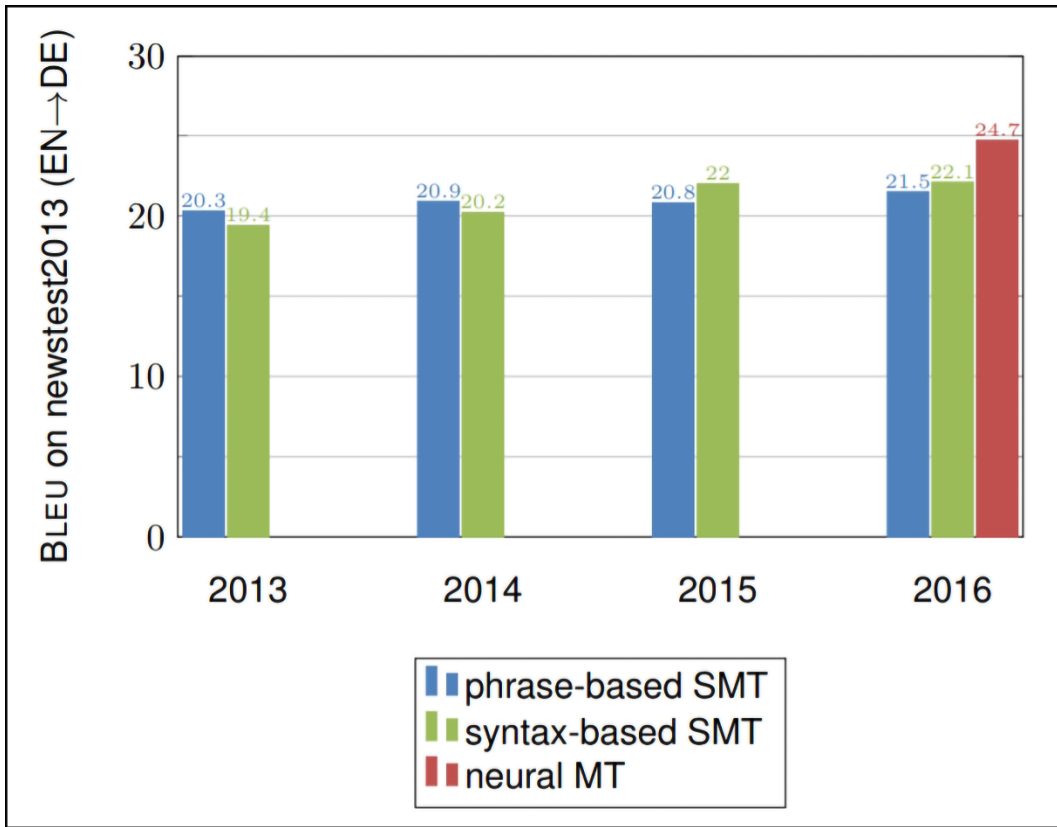




## Chapter 9: Sequence-to-Sequence Learning - Neural Machine Translation

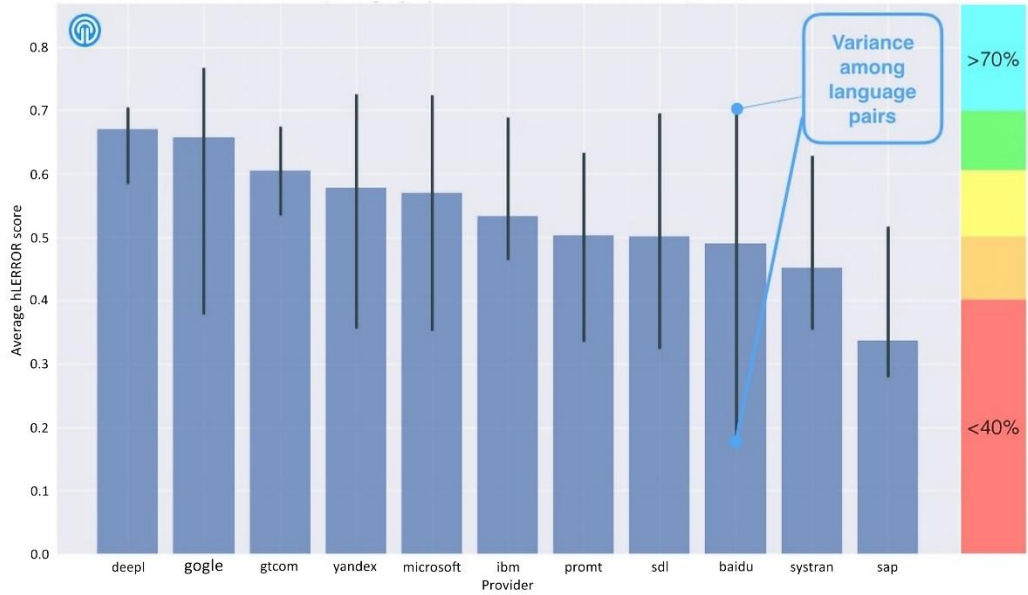




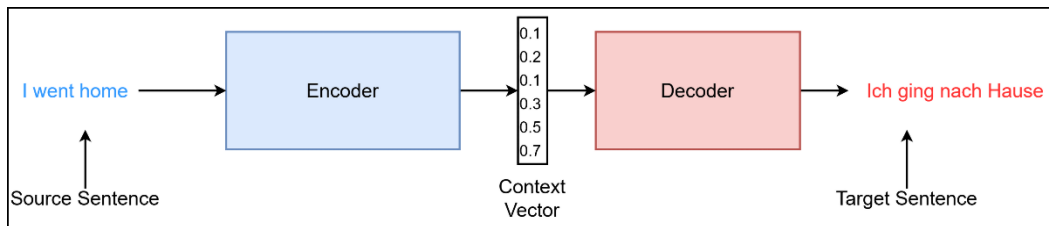


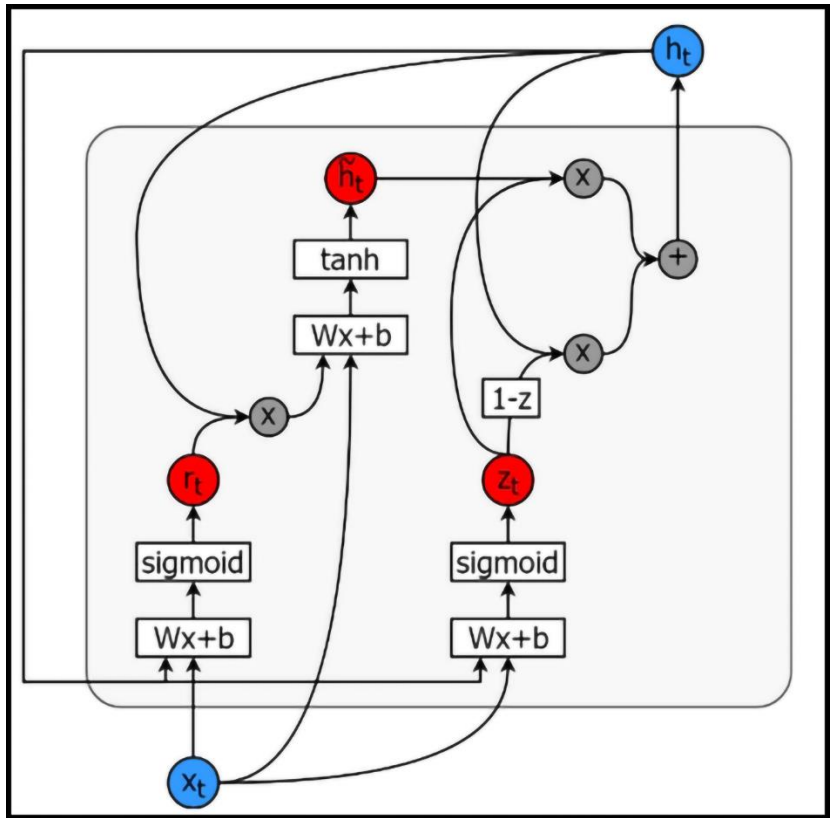
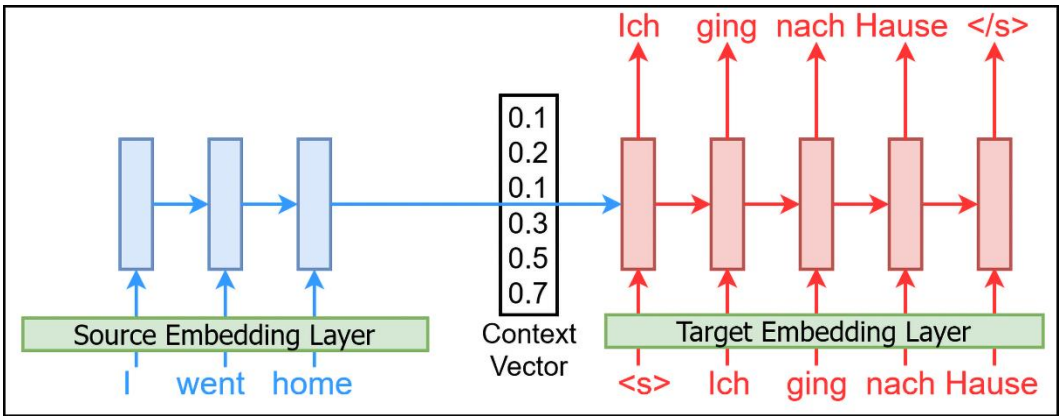
# Overall Performance

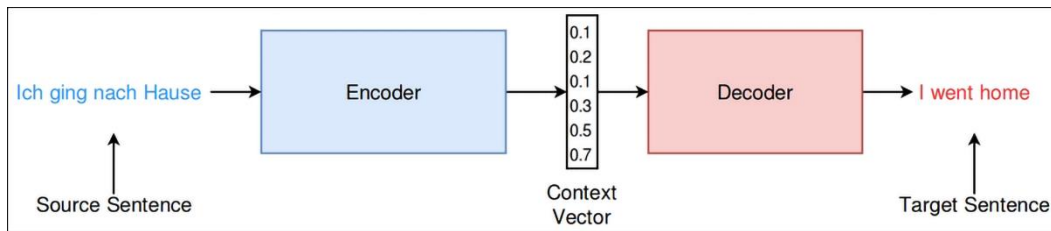
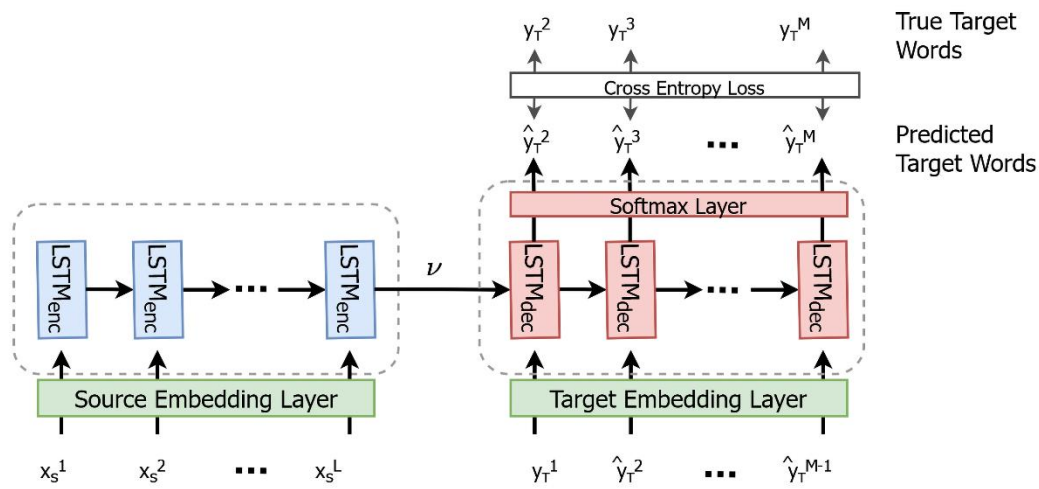
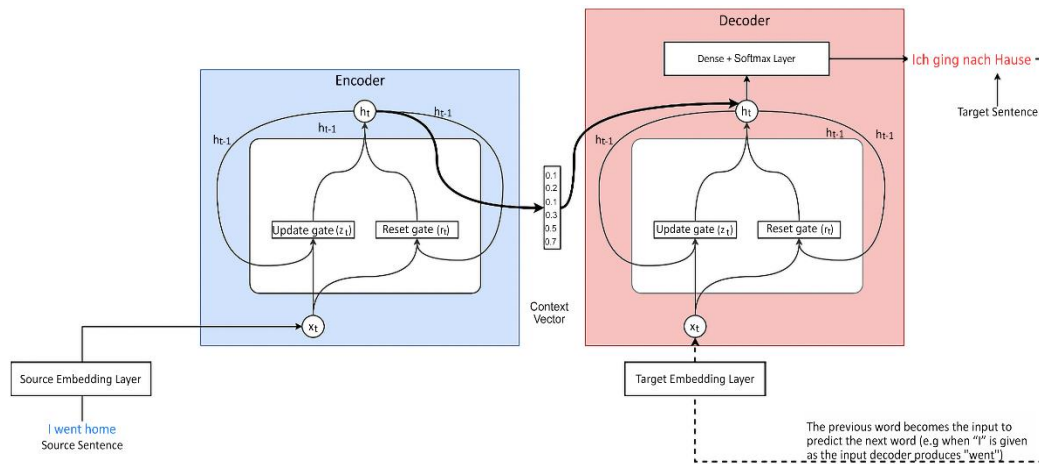
35 language pairs, 1440-3000 sentences per pair

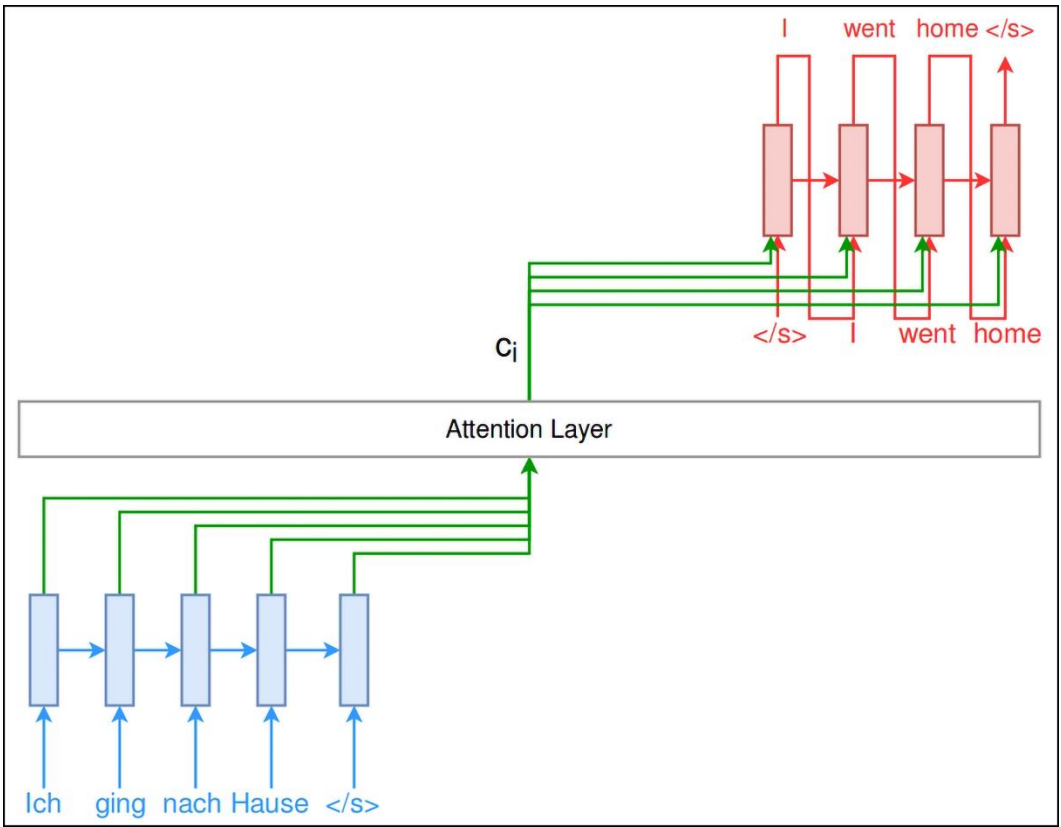


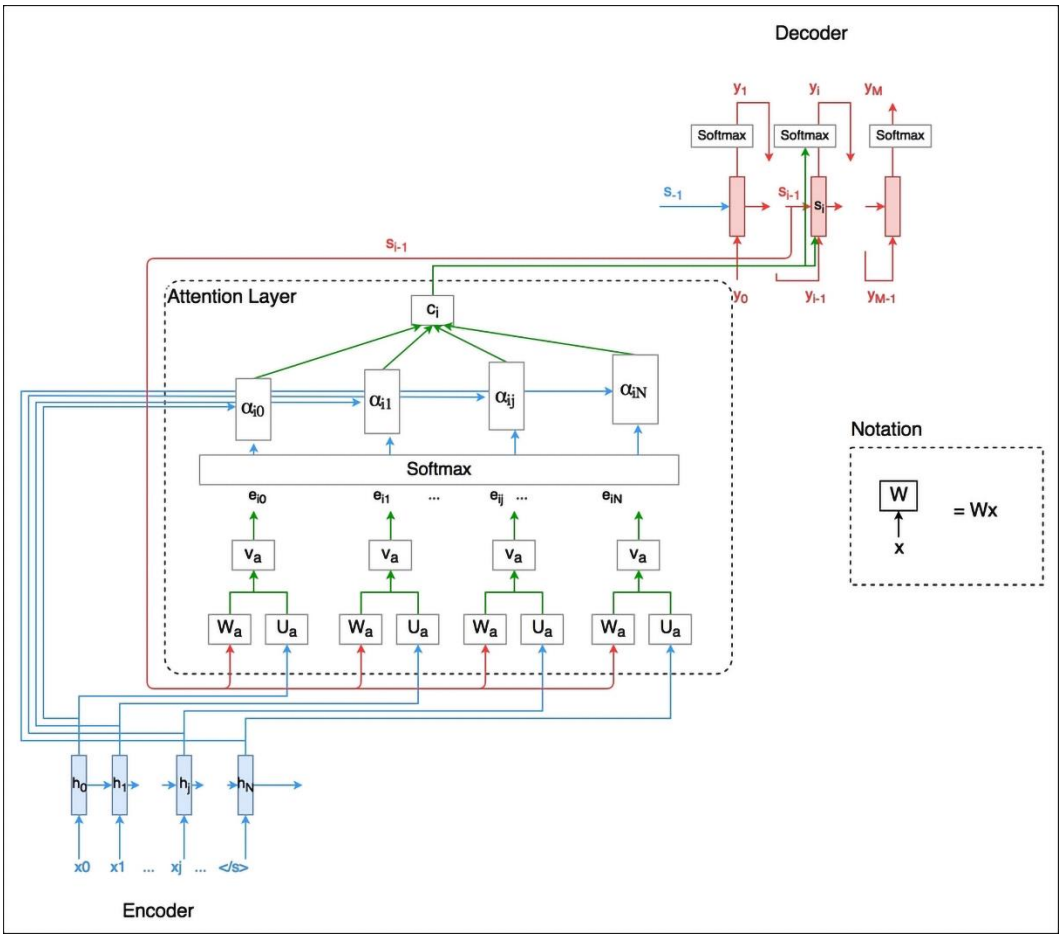
Detailed data on each language pair provided in the full report

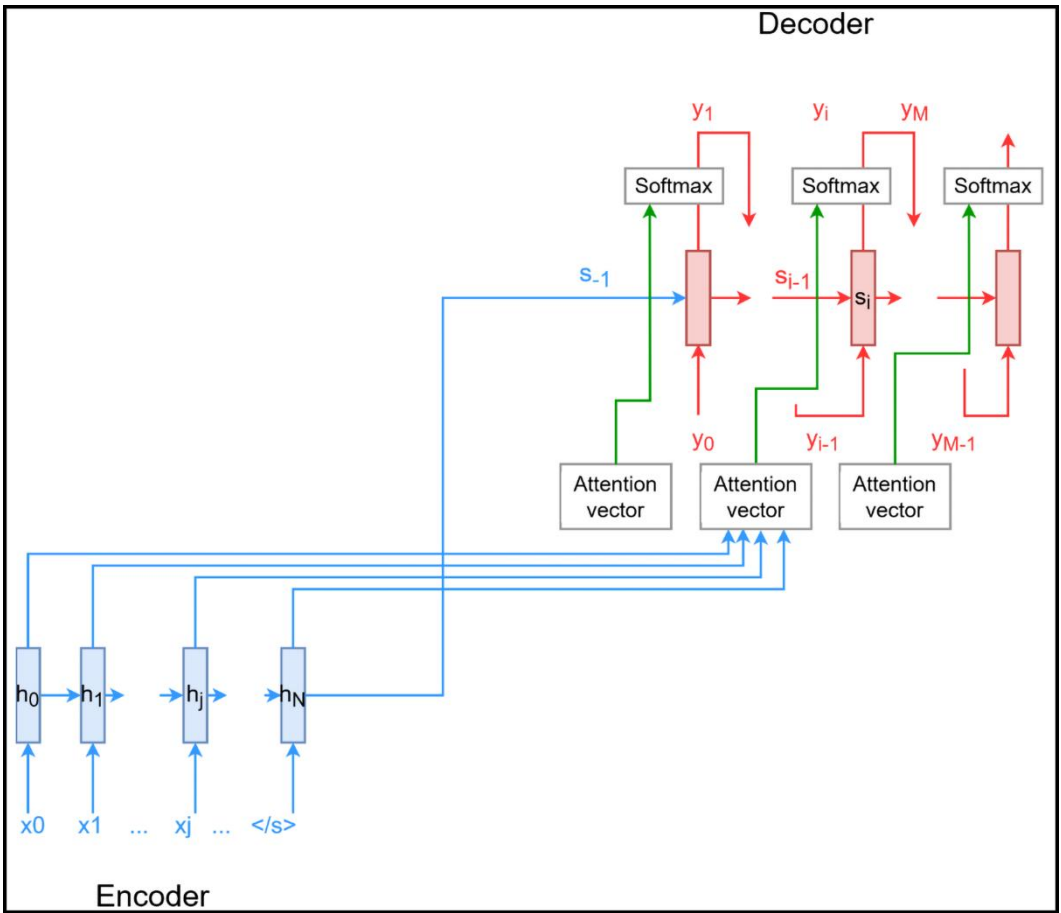


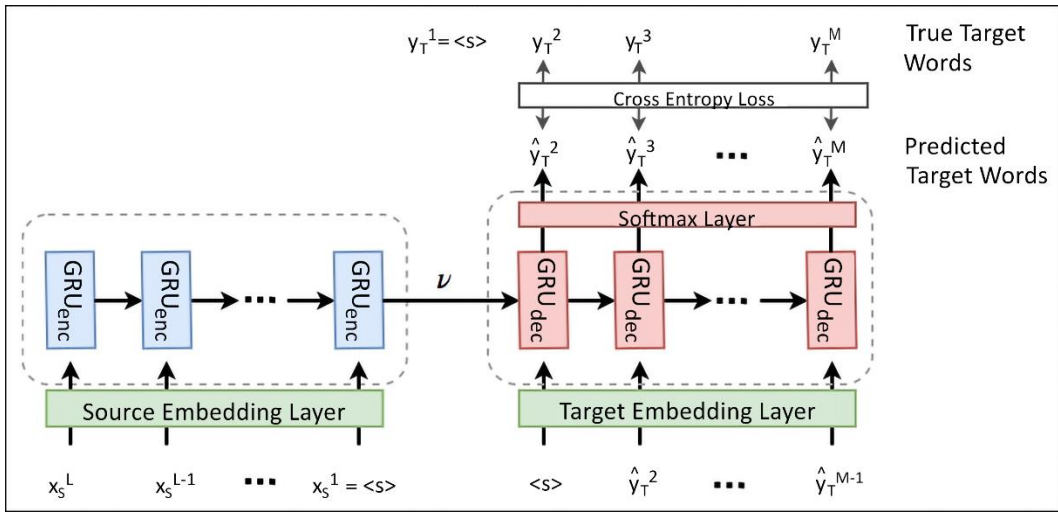




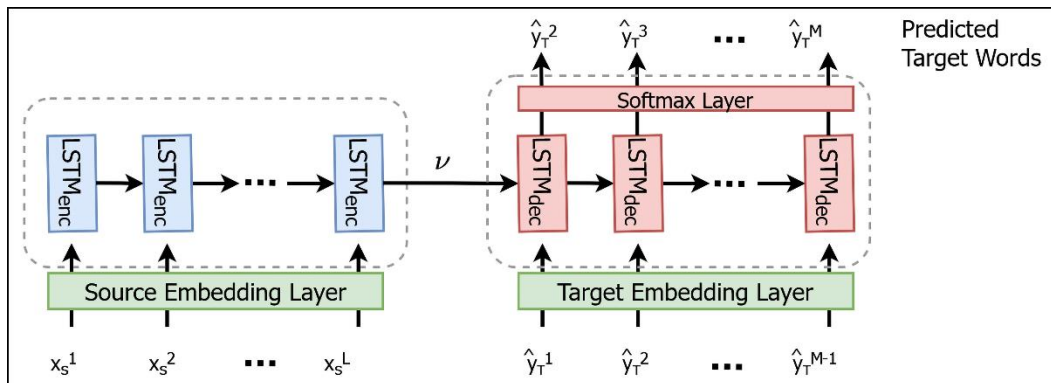
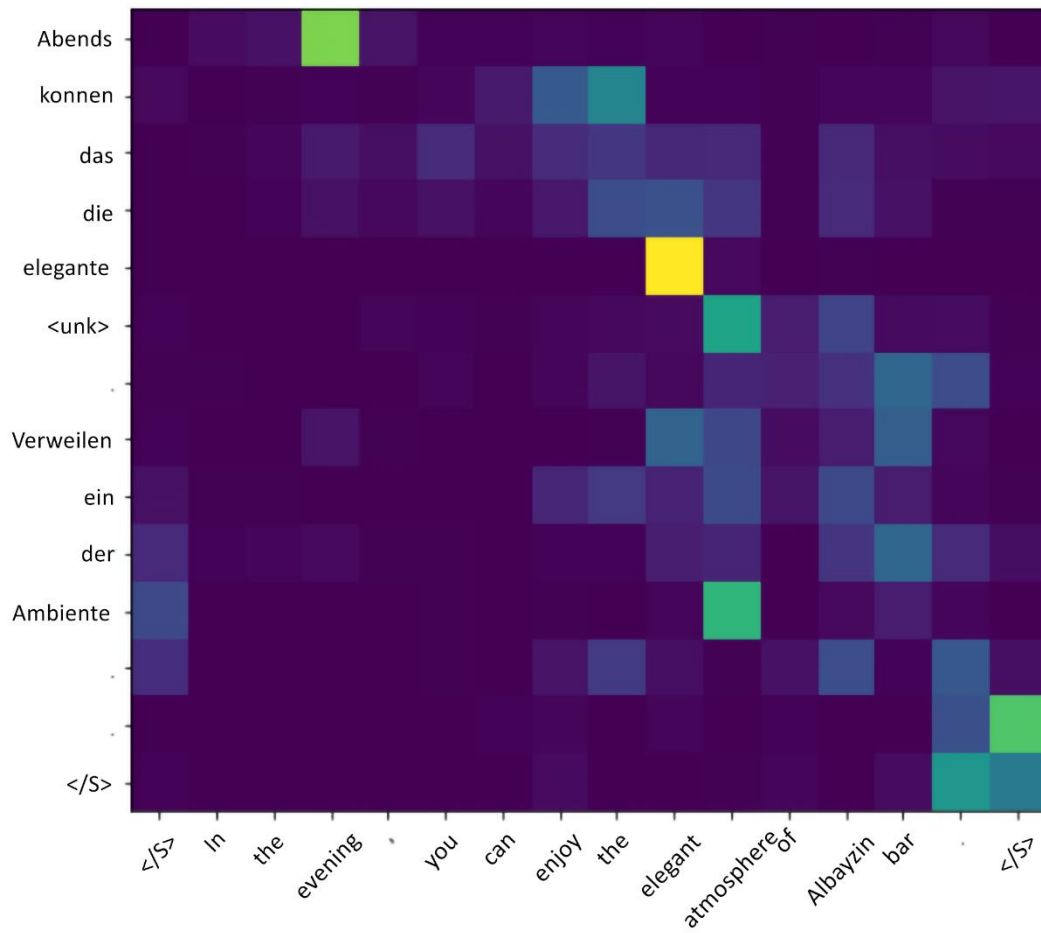


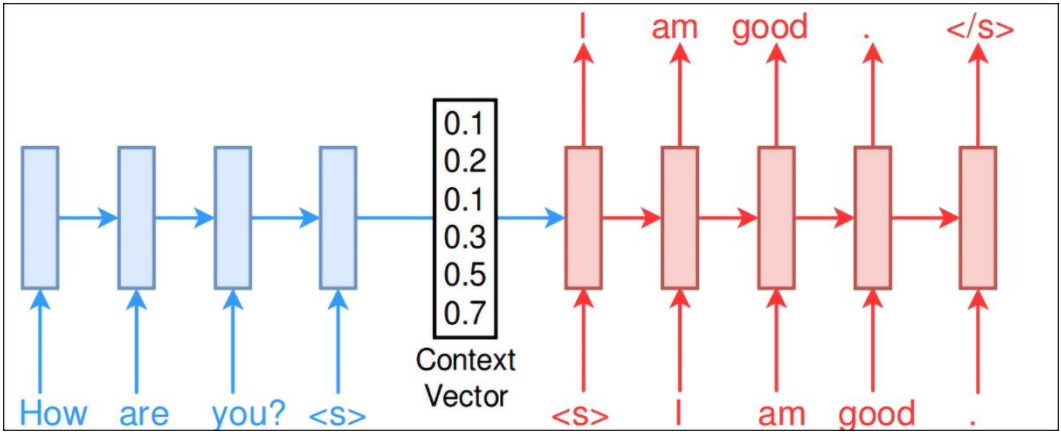


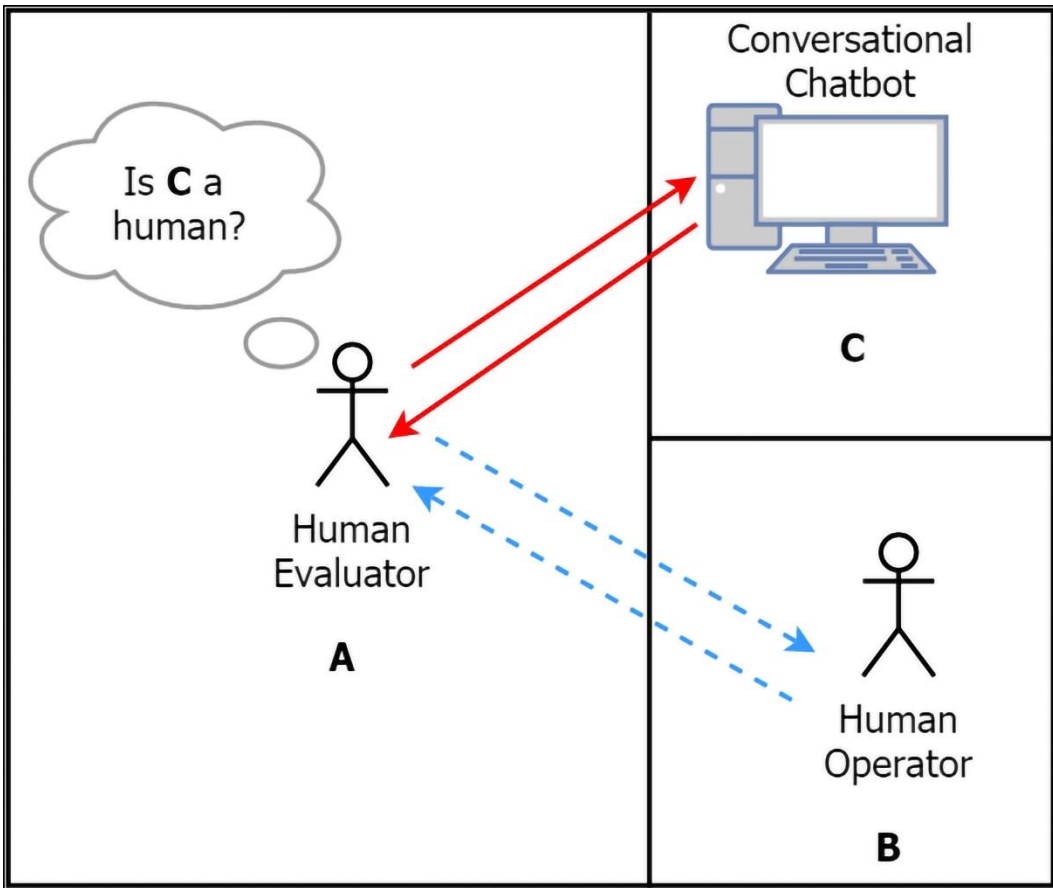




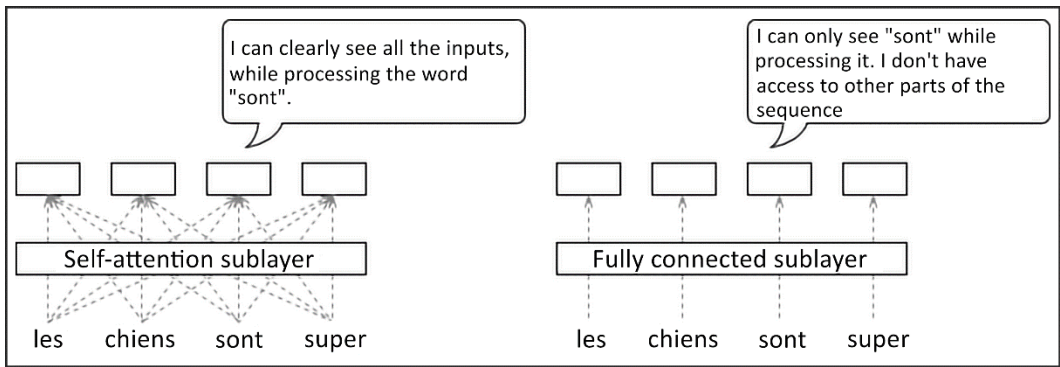
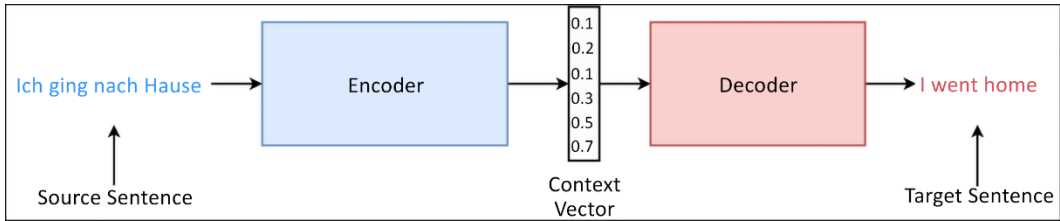


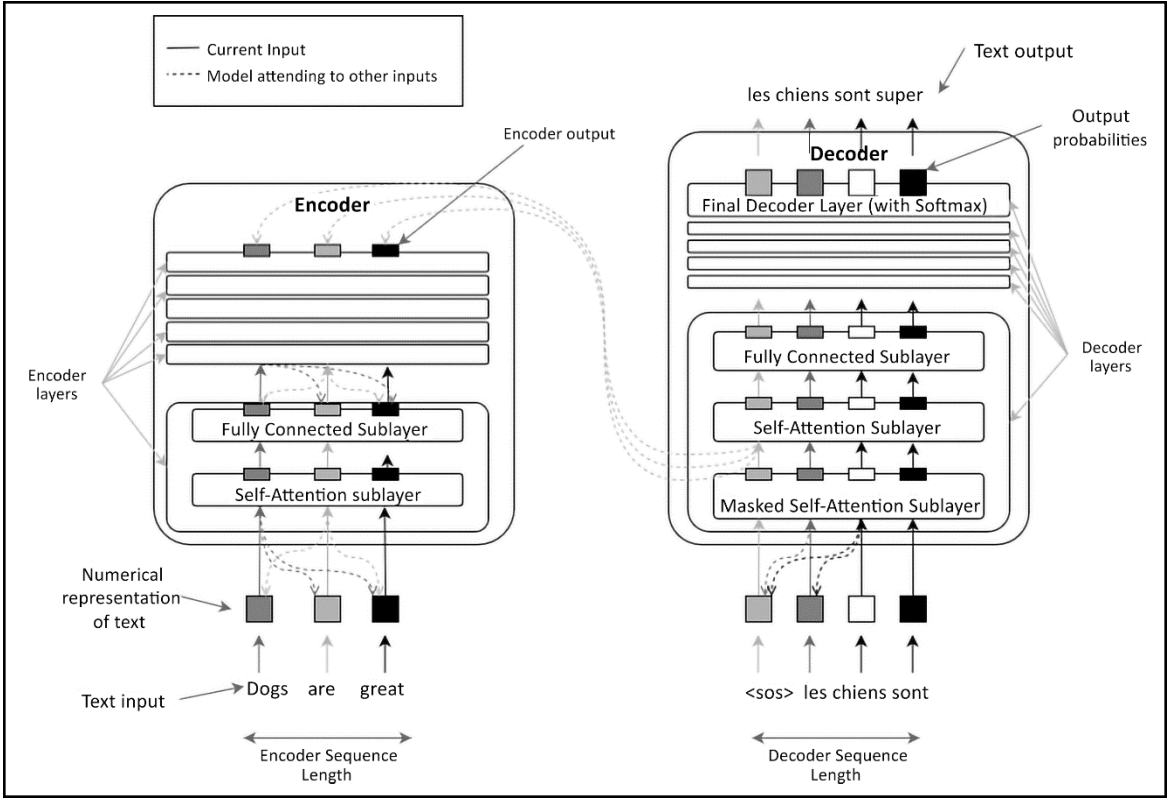


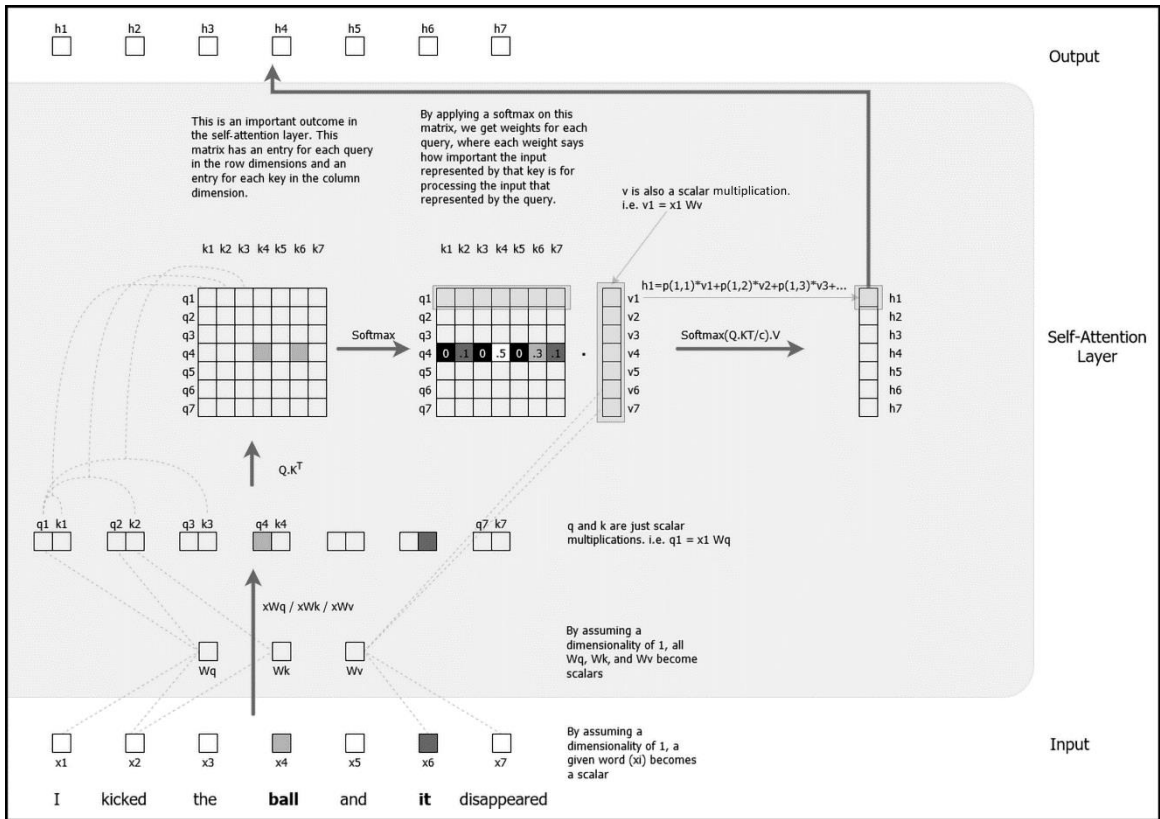


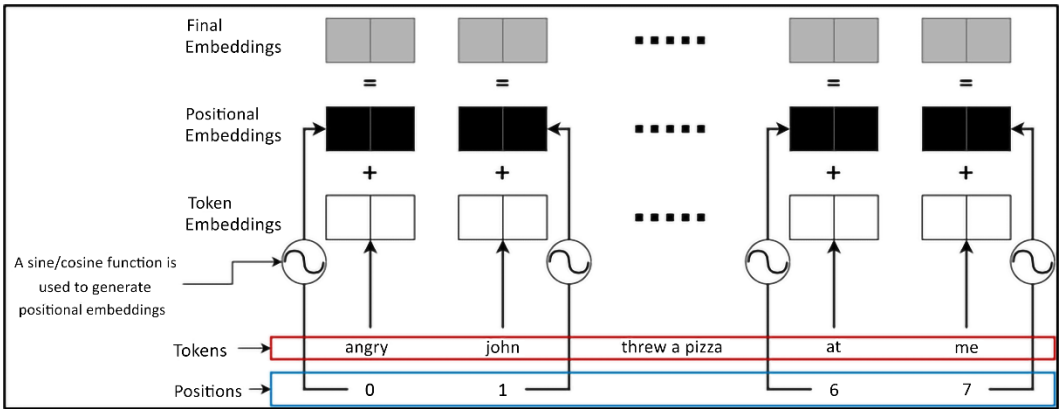
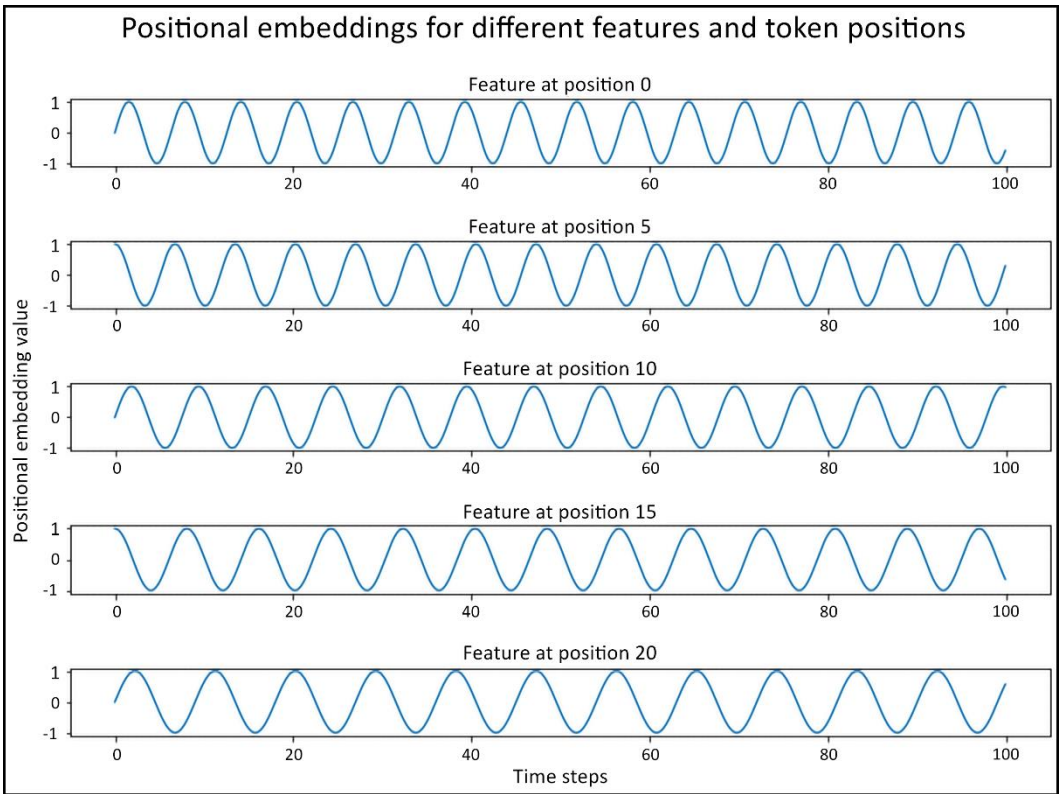


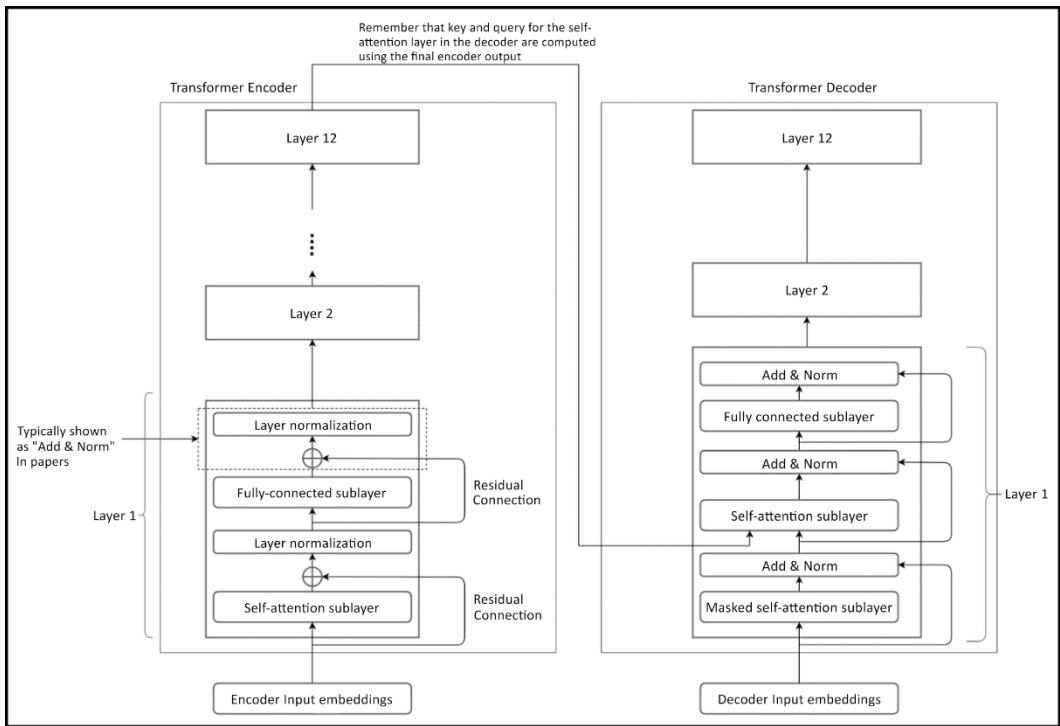
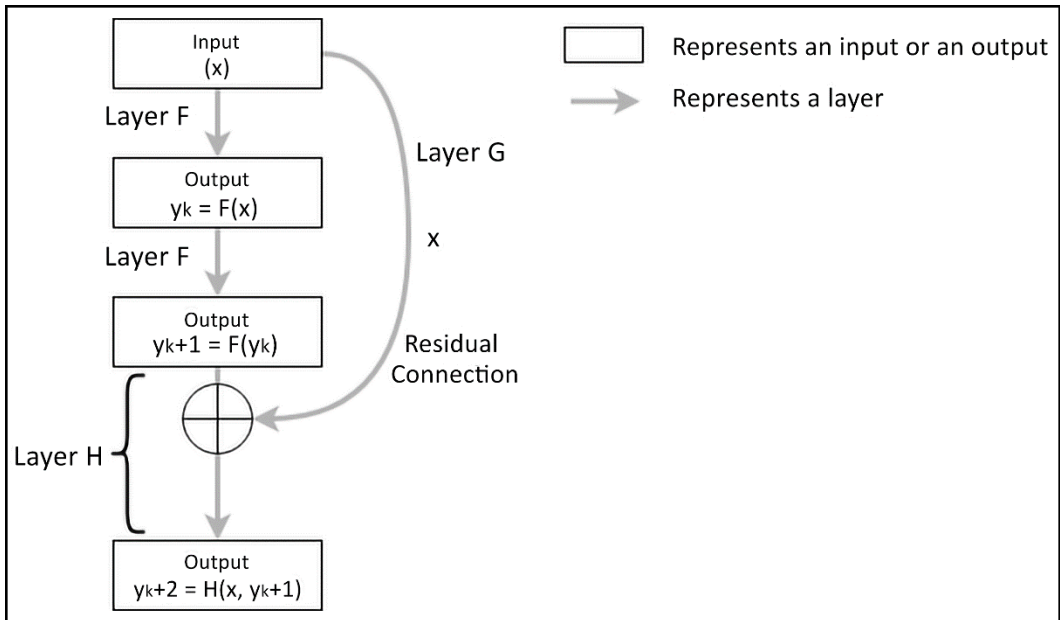
# Chapter 10: Transformers

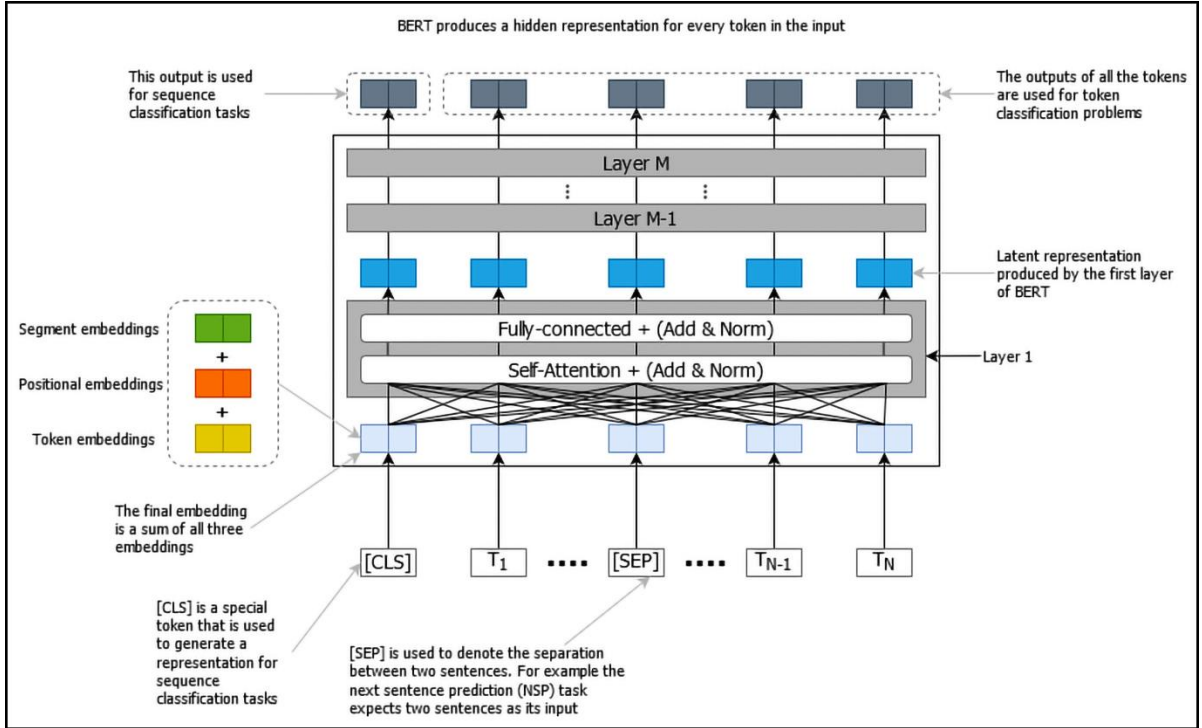


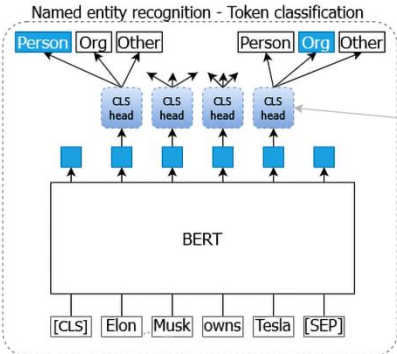
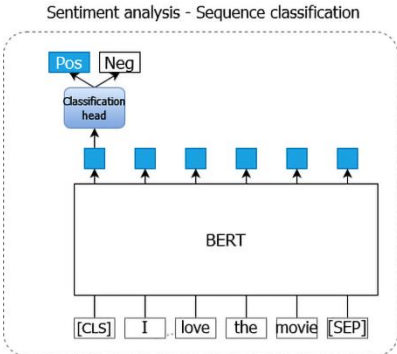




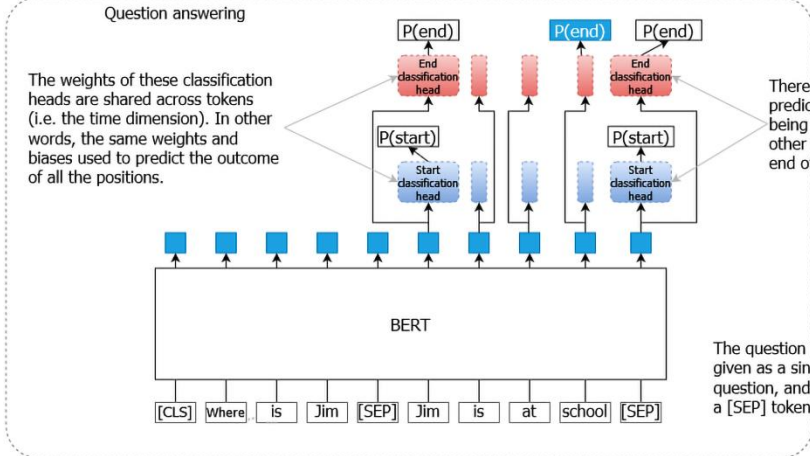








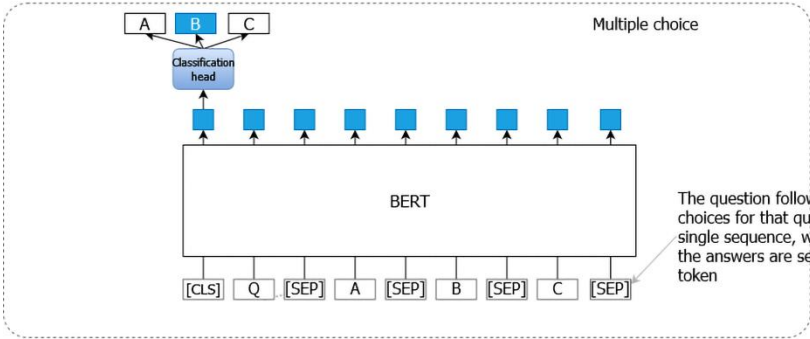
The weights of the classification head are shared across tokens (i.e. the time dimension). In other words, the same weights and biases are used to predict the outcome of all the positions.



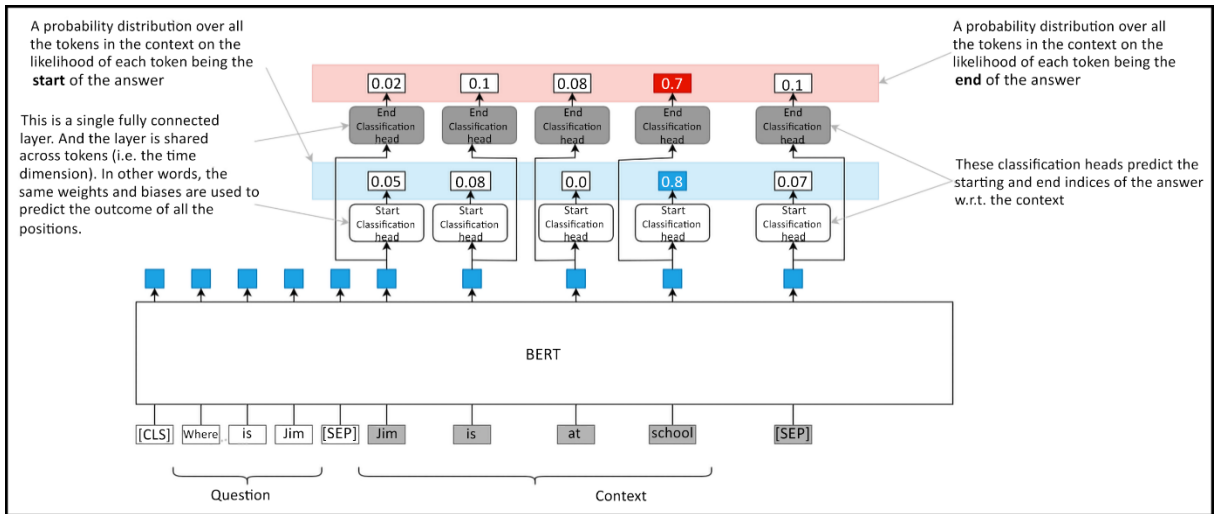
The weights of these classification heads are shared across tokens (i.e. the time dimension). In other words, the same weights and biases used to predict the outcome of all the positions.

There are two classification heads. One predicts the probability of a given token being the start of the answer, where the other head predicts if a token marks the end of an answer.

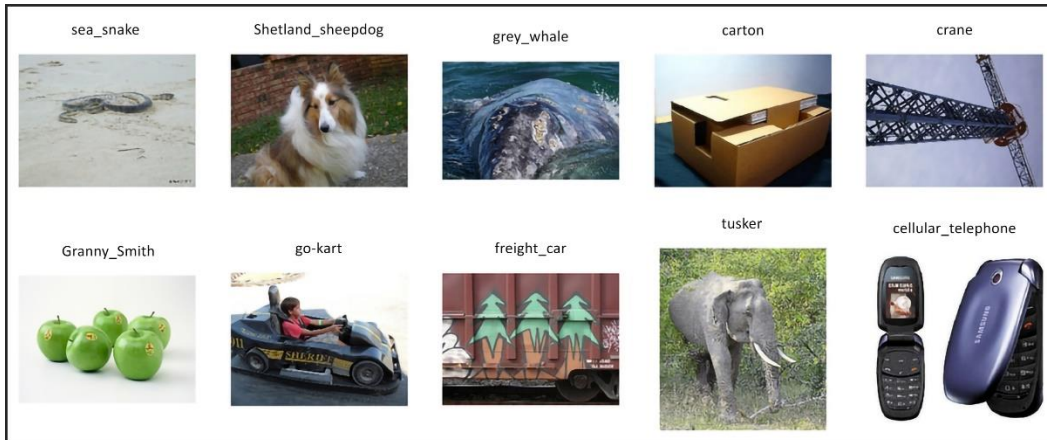
The question followed by the context are given as a single sequence, where the question, and the context are separated by a [SEP] token.



The question followed by the multiple choices for that question are given as a single sequence, where the question, and the answers are separated by a [SEP] token



# Chapter 11: Image Captioning with Transformers





A woman stands in the dining area at the table.  
A room with chairs, a table, and a woman in it.  
A woman standing in a kitchen by a window  
A person standing at a table in a room.  
A living area with a television and a table



A big burly grizzly bear is shown with grass in the background.  
The large brown bear has a black nose.  
Closeup of a brown bear sitting in a grassy area.  
A large bear that is sitting on grass.  
A close up picture of a brown bear's face.



Bedroom scene with a bookcase, blue comforter and window.  
A bedroom with a bookshelf full of books.  
This room has a bed with blue sheets and a large bookcase  
A bed and a mirror in a small room.  
a bed room with a neatly made bed a window and a book shelf



A stop sign is mounted upside-down on its post.  
A stop sign that is hanging upside down.  
An upside down stop sign by the road.  
a stop sign put upside down on a metal pole  
A stop sign installed upside down on a street corner

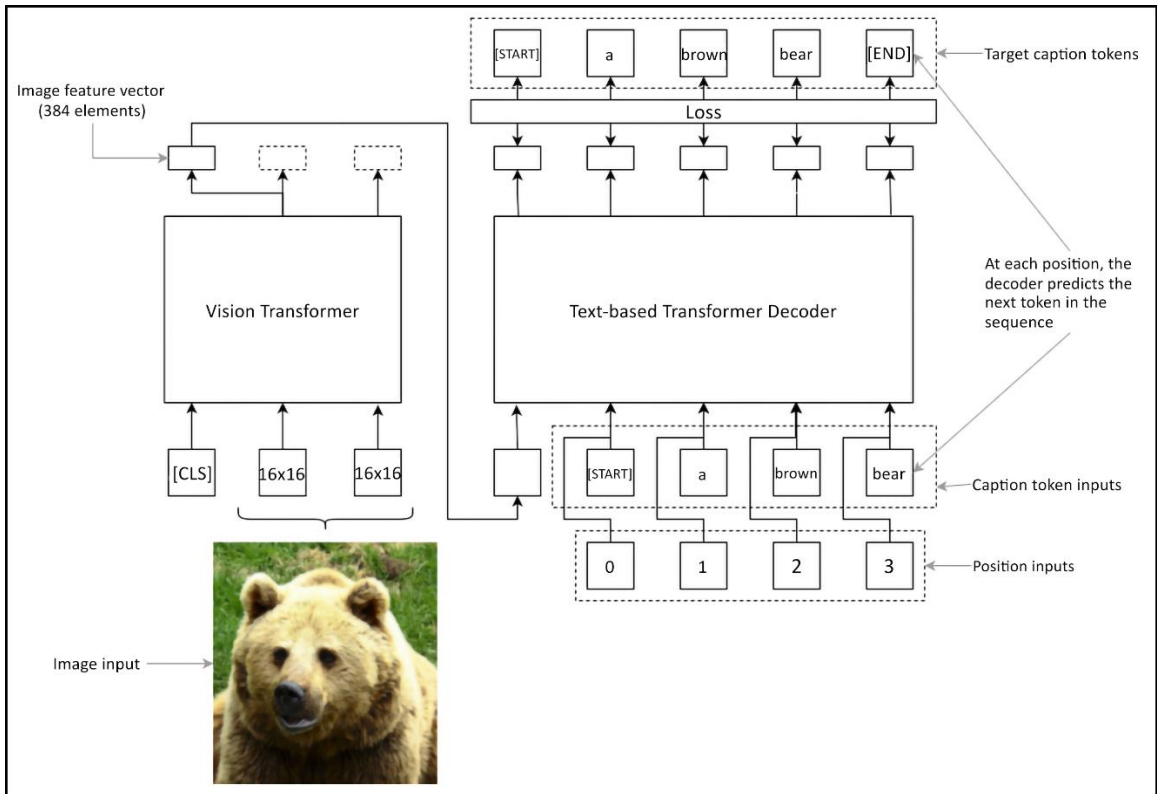


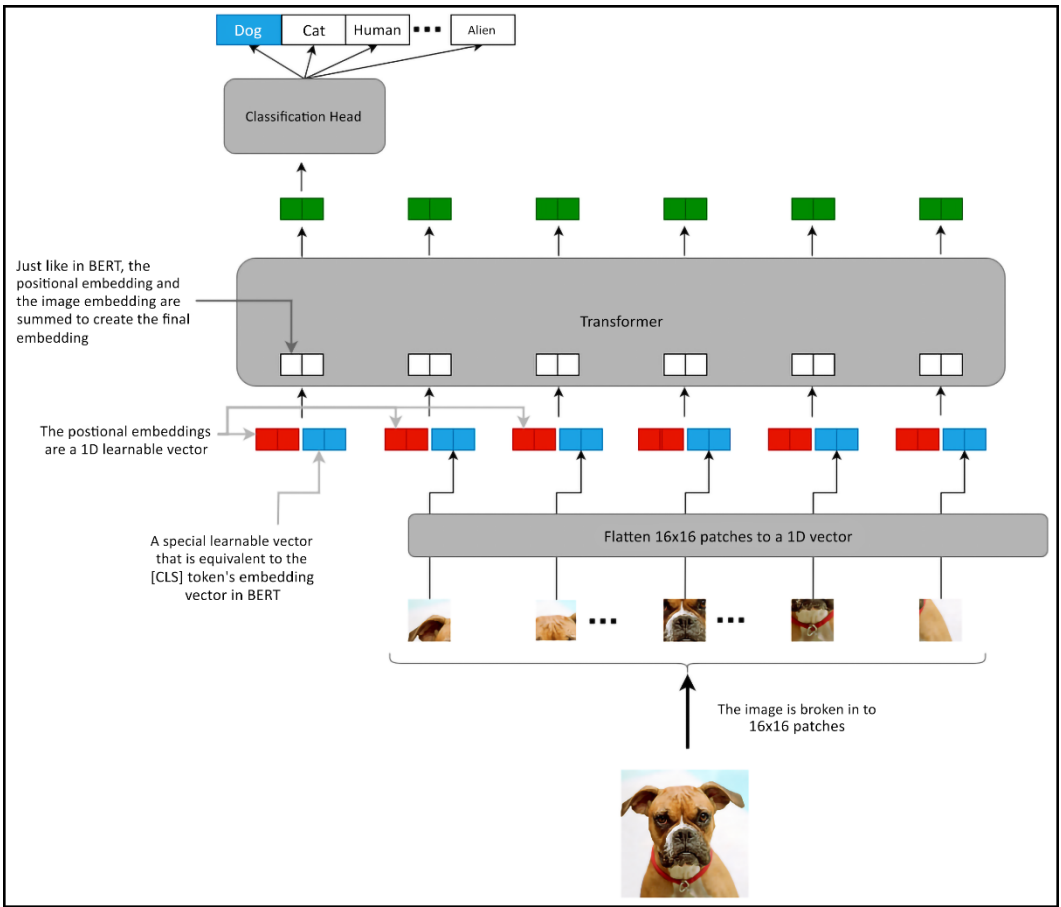
Three teddy bears, each a different color, snuggling together.  
Three stuffed animals are sitting on a bed.  
three teddy bears giving each other a hug  
A group of three stuffed animal teddy bears.  
Three stuffed bears hugging and sitting on a blue pillow

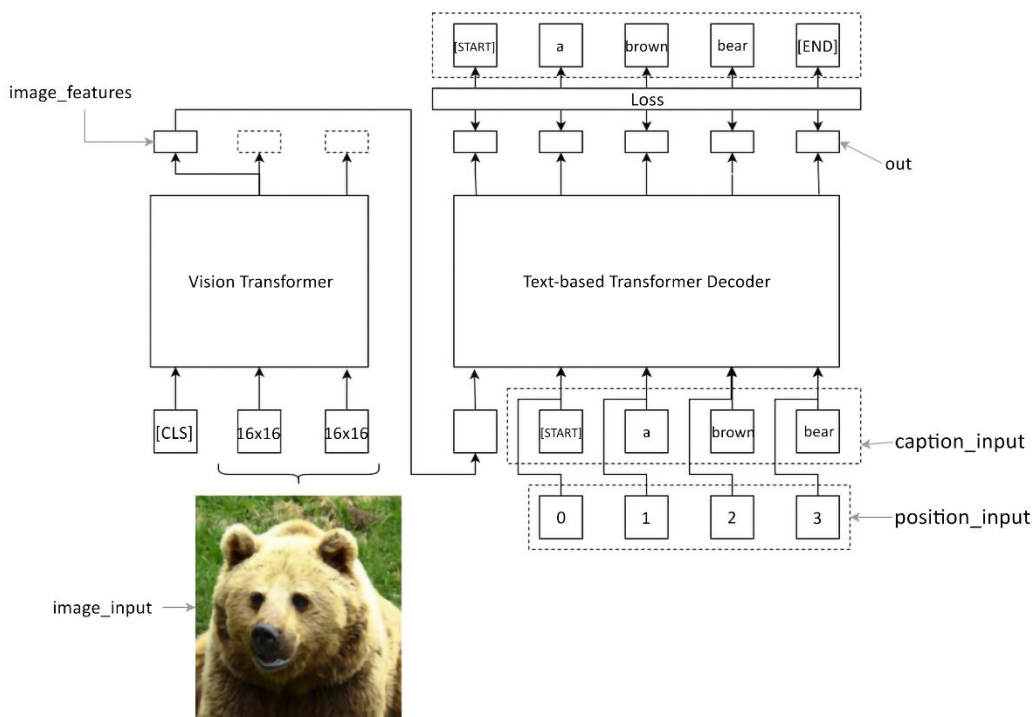


image_id	id	caption	image_filepath	preprocessed_caption
0	318556 48	A very clean and well decorated empty bathroom	data\train2014\train2014\COCO_train2014_000000...	[START] a very clean and well decorated empty ...
1	116100 67	A panoramic view of a kitchen and all of its a...	data\train2014\train2014\COCO_train2014_000000...	[START] a panoramic view of a kitchen and all ...
2	318556 126	A blue and white bathroom with butterfly theme...	data\train2014\train2014\COCO_train2014_000000...	[START] a blue and white bathroom with butterf...
3	116100 148	A panoramic photo of a kitchen and dining room	data\train2014\train2014\COCO_train2014_000000...	[START] a panoramic photo of a kitchen and din...
4	379340 173	A graffiti-ed stop sign across the street from...	data\train2014\train2014\COCO_train2014_000000...	[START] a graffitied stop sign across the stre...

	<b>0</b>	<b>1</b>
<b>count</b>	808.000000	808.000000
<b>mean</b>	571.698020	499.007426
<b>std</b>	95.377281	100.333224
<b>min</b>	332.000000	182.000000
<b>25%</b>	480.000000	427.000000
<b>50%</b>	640.000000	480.000000
<b>75%</b>	640.000000	640.000000
<b>max</b>	640.000000	640.000000

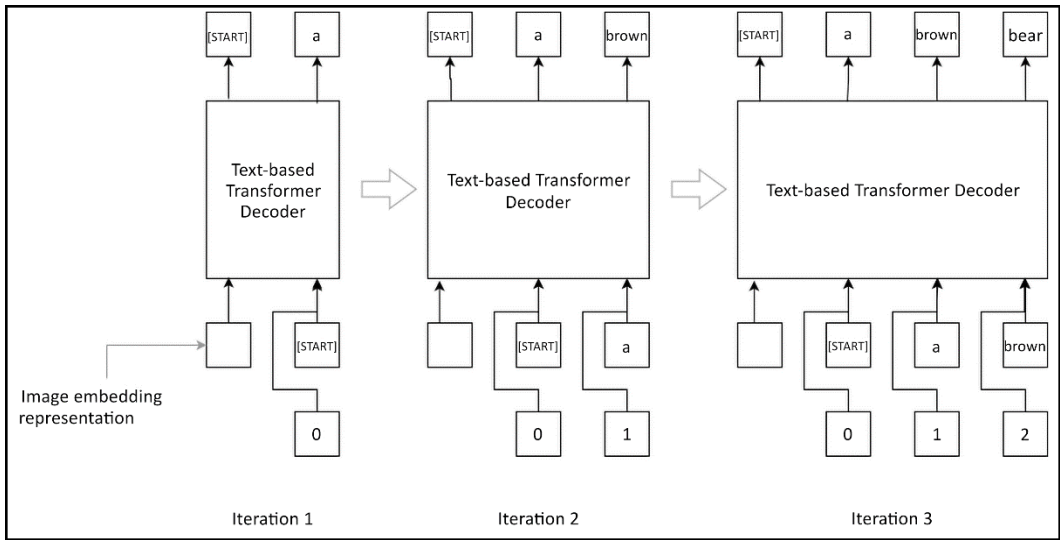






<p>the cat sat on the mat</p> <p><del>the cat sat on the mat</del></p> <p>on the mat sat the cat</p>	<p>the cat sat on the mat</p> <p><del>the cat sat on the mat</del></p> <p>on the mat sat the cat</p>
--	--







TRUE: [START] cars parked along a street with a street light that is green [END]

PRED: [START] a car stopped on a city street with cars [END]



TRUE: [START] several containers of food and beverages on a wooden table outdoors [END]

PRED: [START] a table and a plates on a table [END]



TRUE: [START] a few street lights on the side of the road [END]

PRED: [START] a traffic light on a pole in the middle of a city [END]



TRUE: [START] a person riding the horse jumping over a wooden obstacle [END]

PRED: [START] a person on a horse in a field [END]



TRUE: [START] a blue cake features a small island on top and sharks swimming on the bottom of the cake [END]

PRED: [START] a cake with a blue and white frosting on it [END]



TRUE: [START] a plastic dish with the food sectioned off [END]

PRED: [START] a tray of food and vegetables and a sandwich [END]



TRUE: [START] three images of the same man hitting a tennis ball [END]

PRED: [START] a man standing on a tennis court holding a racquet [END]



TRUE: [START] two people who are swimming in the water on surfboards [END]

PRED: [START] a dog in a body of water in the water [END]



TRUE: [START] a person on a surf board riding a wave [END]

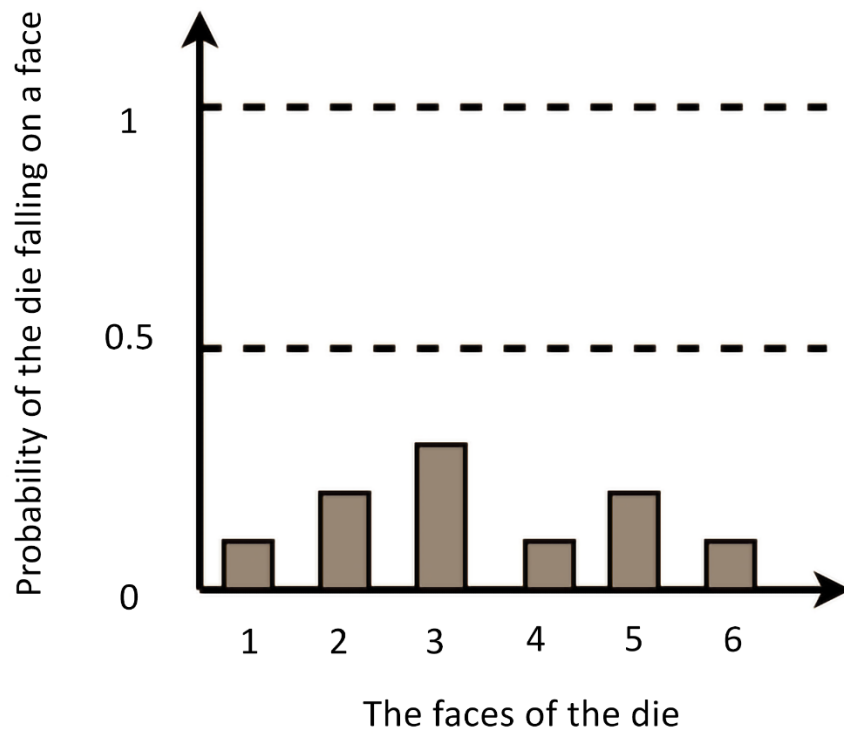
PRED: [START] a man on a surfboard in the ocean [END]

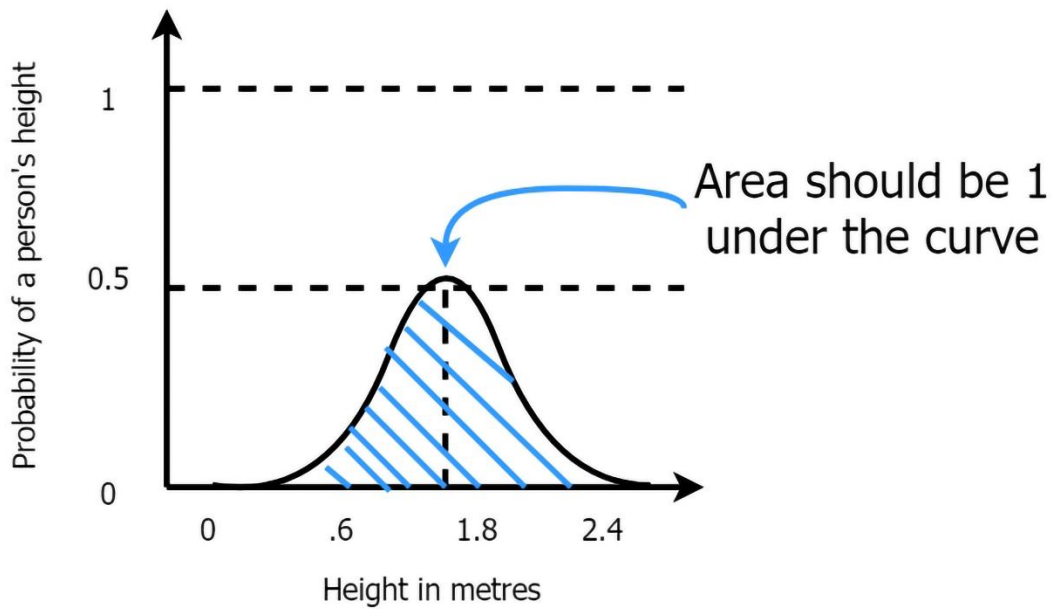


TRUE: [START] an individual is taken in this very picture [END]

PRED: [START] a group of people standing in a terminal [END]

## Appendix A: Mathematical Foundations and Advanced TensorFlow





	0	1	2	3	4	5	6	7	8	9	...	40	41	42	43	44
<b>the</b>	0.418000	0.249680	-0.41242	0.121700	0.345270	-0.044457	-0.49688	-0.178620	-0.000680	-0.656600	...	-0.298710	-0.157490	-0.347580	-0.045637	-0.442510
<b>,</b>	0.013441	0.236820	-0.16899	0.409510	0.638120	0.477090	-0.42852	-0.556410	-0.364000	-0.239380	...	-0.080262	0.630030	0.321110	-0.467650	0.227860
<b>.</b>	-0.151640	0.301770	-0.16763	0.176840	0.317190	0.339730	-0.43478	-0.310860	-0.449990	-0.294860	...	-0.000064	0.068987	0.087939	-0.102850	-0.139310
<b>of</b>	0.708530	0.570880	-0.47160	0.180480	0.544490	0.726030	0.18157	-0.523930	0.103810	-0.175660	...	-0.347270	0.284830	0.075693	-0.062178	-0.389880
<b>to</b>	0.680470	-0.039263	0.30186	-0.177920	0.429620	0.032246	-0.41376	0.132280	-0.298470	-0.085253	...	-0.094375	0.018324	0.210480	-0.030880	-0.197220
<b>and</b>	0.268180	0.143460	-0.27877	0.016257	0.113840	0.699230	-0.51332	-0.473680	-0.330750	-0.138340	...	-0.069043	0.368850	0.251680	-0.245170	0.253810
<b>in</b>	0.330420	0.249950	-0.60874	0.109230	0.036372	0.151000	-0.55083	-0.074239	-0.092307	-0.328210	...	-0.486090	-0.008027	0.031184	-0.365760	-0.426990
<b>a</b>	0.217050	0.465150	-0.46757	0.100820	1.013500	0.748450	-0.53104	-0.262560	0.168120	0.131820	...	0.138130	0.369730	-0.642890	0.024142	-0.039315
<b>"</b>	0.257690	0.456290	-0.76974	-0.376790	0.592720	-0.063527	0.20545	-0.573850	-0.290090	-0.136620	...	0.030498	-0.395430	-0.385150	-1.000200	0.087599
<b>'s</b>	0.237270	0.404780	-0.20547	0.588050	0.655330	0.328670	-0.81964	-0.232360	0.274280	0.242650	...	-0.123420	0.659610	-0.518020	-0.829950	-0.082739

10 rows x 50 columns

TensorBoard PROJECTOR UPLOAD Settings Refresh Help

DATA Points: 50001 | Dimension: 50

1 tensor found  
embedding/ATTRIBUTES/VARIABLE\_

Sort by label Tag selection as

Load Download Label

Spherize data

Checkpoint: embeddings\embeddingckpt-1  
Metadata: metadata.tsv

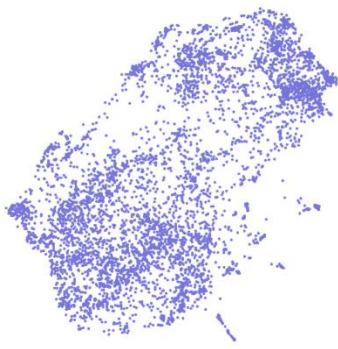
**UMAP** T-SNE PCA CUSTOM

Dimension 2D  3D

Neighbors  15

Run

For faster results, the data will be sampled down to 5,000 points.  
[Learn more about UMAP.](#)



2

3

Show All Data Isolate selection Clear selection

Search by label

BOOKMARKS (0)

TensorBoard PROJECTOR UPLOAD Settings Refresh Help

DATA Points: 50001 | Dimension: 50 | Selected: 108 points

1 tensor found  
embedding/ATTRIBUTES/VARIABLE\_

Sort by label Tag selection as

Load Download Label

Spherize data

Checkpoint: embeddings\embeddingckpt-1  
Metadata: metadata.tsv


**UMAP** T-SNE PCA CUSTOM

Dimension 2D  3D

Neighbors  15

Run

For faster results, the data will be sampled down to 5,000 points.  
[Learn more about UMAP.](#)



fruit  
syndrome

Show All Data Isolate selection Clear selection

Search by label

- fruit
- strain
- syndrome
- drinks
- anthrax
- scars
- dried
- recipes
- medication
- chopped
- cherry
- sodium
- poisoning
- resistant
- baking
- strains

BOOKMARKS (0)

TensorBoard PROJECTOR UPLOAD 108 points Clear selection

DATA Points: 50001 | Dimension: 50 | chiseled

1 tensor board embedding: ATTRIBUTES/VARIABLE\_ 1

Sort by label Tag selection as

Load Download Label

Spherelize data

Checkpoint: embeddings/embedding\_ckpt-1  
Metadata: metadata.tsv

UMAP T-SNE PCA CUSTOM

Dimension 2D  3D

Neighbors  15

Run

For faster results, the data will be sampled down to 5,000 points.  
[Learn more about UMAP.](#)

Search by label

BOOKMARKS (0)