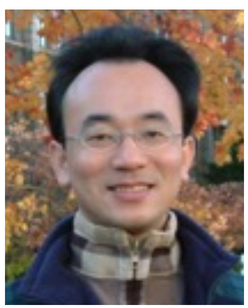
資料探勘
(Data Mining)

遞歸神經網絡
(Recurrent Neural Networks)

1092DM10
MBA, IM, NTPU (M5026) (Spring 2021)
Tue 2, 3, 4 (9:10-12:00) (B8F40)



Min-Yuh Day
戴敏育
Associate Professor
副教授
Institute of Information Management, National Taipei University
國立臺北大學 資訊管理研究所
https://web.ntpu.edu.tw/~myday

2021-05-25

課程大綱 (Syllabus)

週次 (Week) 日期 (Date) 內容 (Subject/Topics)

1 2021/02/23 資料探勘介紹 (Introduction to data mining)

2 2021/03/02 ABC：人工智慧，大數據，雲端運算
(ABC: AI, Big Data, Cloud Computing)

3 2021/03/09 Python資料探勘的基礎
(Foundations of Data Mining in Python)

4 2021/03/16 資料科學與資料探勘：發現，分析，可視化和呈現數據
(Data Science and Data Mining:
Discovering, Analyzing, Visualizing and Presenting Data)

5 2021/03/23 非監督學習：關聯分析，購物籃分析
(Unsupervised Learning: Association Analysis,
Market Basket Analysis)

6 2021/03/30 資料探勘個案研究 I
(Case Study on Data Mining I)

課程大綱 (Syllabus)

週次 (Week) 日期 (Date) 內容 (Subject/Topics)

7 2021/04/06 放假一天 (Day off)

8 2021/04/13 非監督學習：集群分析，行銷市場區隔
(Unsupervised Learning: Cluster Analysis, Market Segmentation)

9 2021/04/20 期中報告 (Midterm Project Report)

10 2021/04/27 監督學習：分類和預測
(Supervised Learning: Classification and Prediction)

11 2021/05/04 機器學習和深度學習
(Machine Learning and Deep Learning)

12 2021/05/11 卷積神經網絡
(Convolutional Neural Networks)

課程大綱 (Syllabus)

週次 (Week) 日期 (Date) 內容 (Subject/Topics)

13 2021/05/18 資料探勘個案研究 II
(Case Study on Data Mining II)

14 2021/05/25 遞歸神經網絡
(Recurrent Neural Networks)

15 2021/06/01 強化學習
(Reinforcement Learning)

16 2021/06/08 社交網絡分析
(Social Network Analysis)

17 2021/06/15 期末報告 I (Final Project Report I)

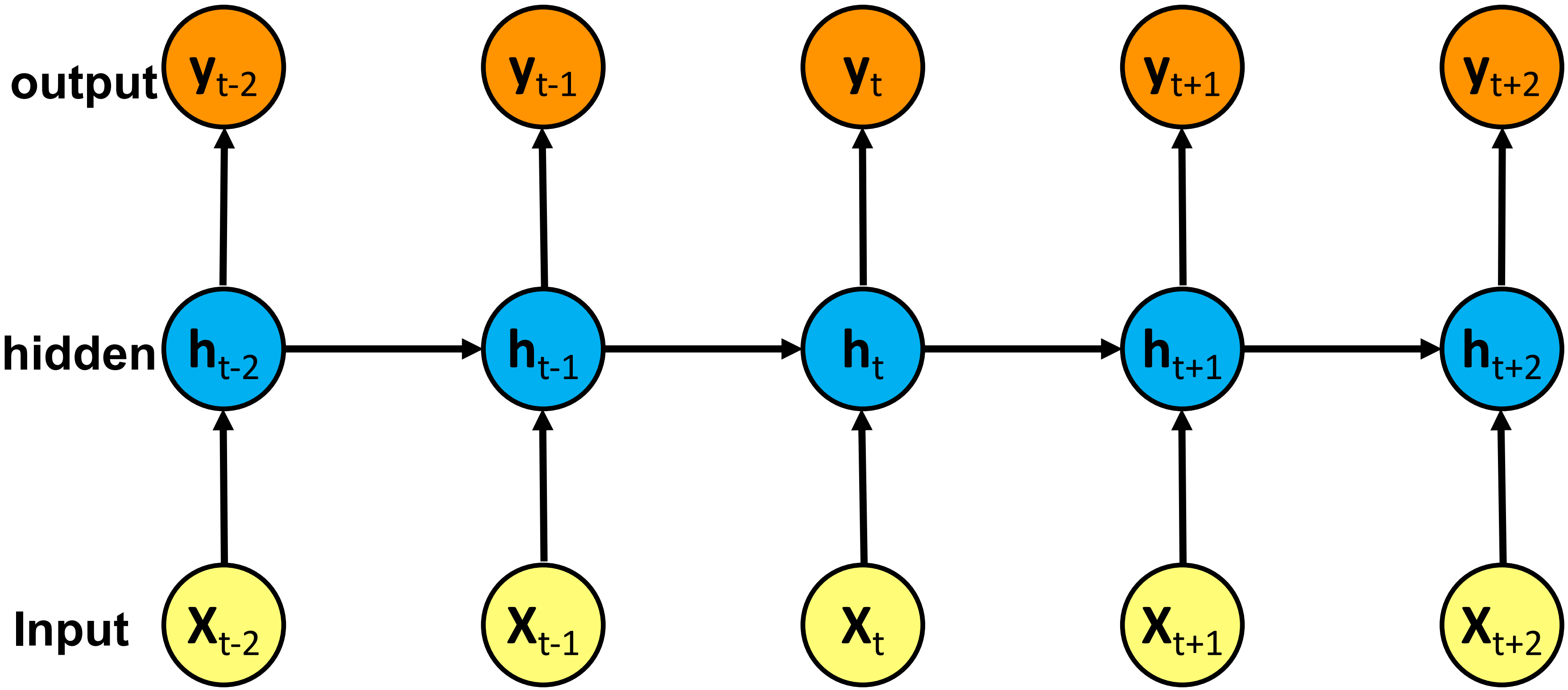
18 2021/06/22 期末報告 II (Final Project Report II)

Recurrent Neural Networks (RNN)

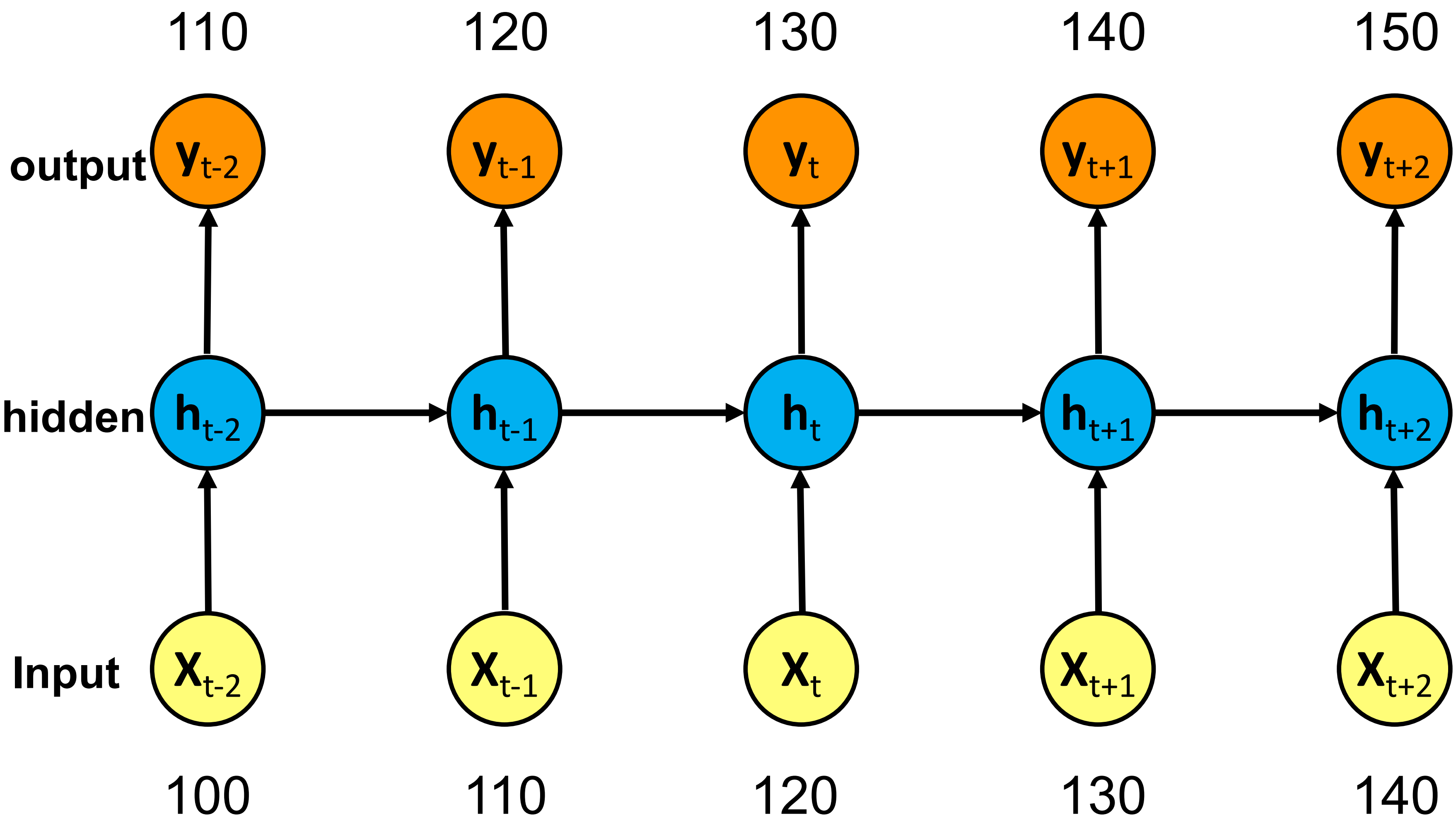
Outline

- Recurrent Neural Networks (RNN)
  - Long Short Term Memory (LSTM)
  - Gated Recurrent Unit (GRU)
- Deep Learning (RNN) for Time Series Prediction
- Deep Learning (RNN) for Text Analytics (NLP)

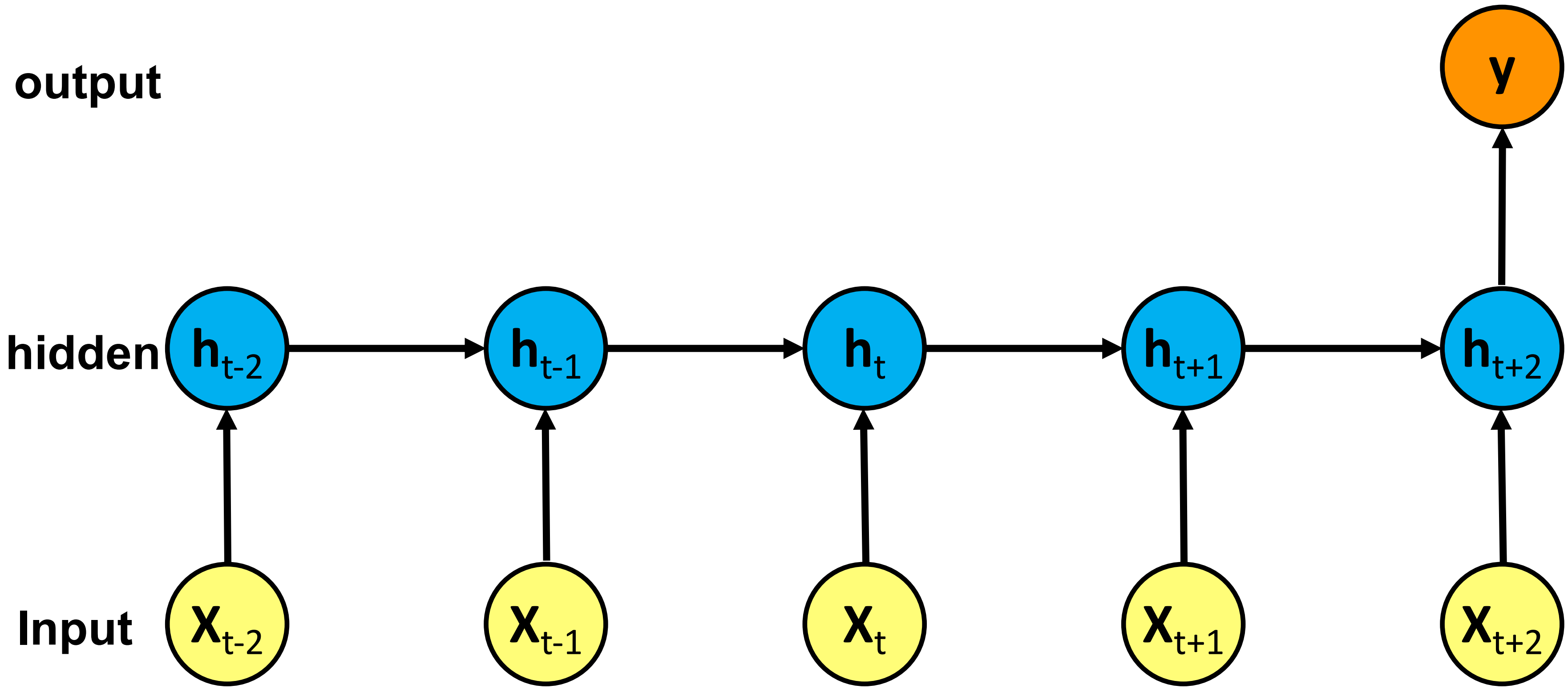
Recurrent Neural Networks (RNN)



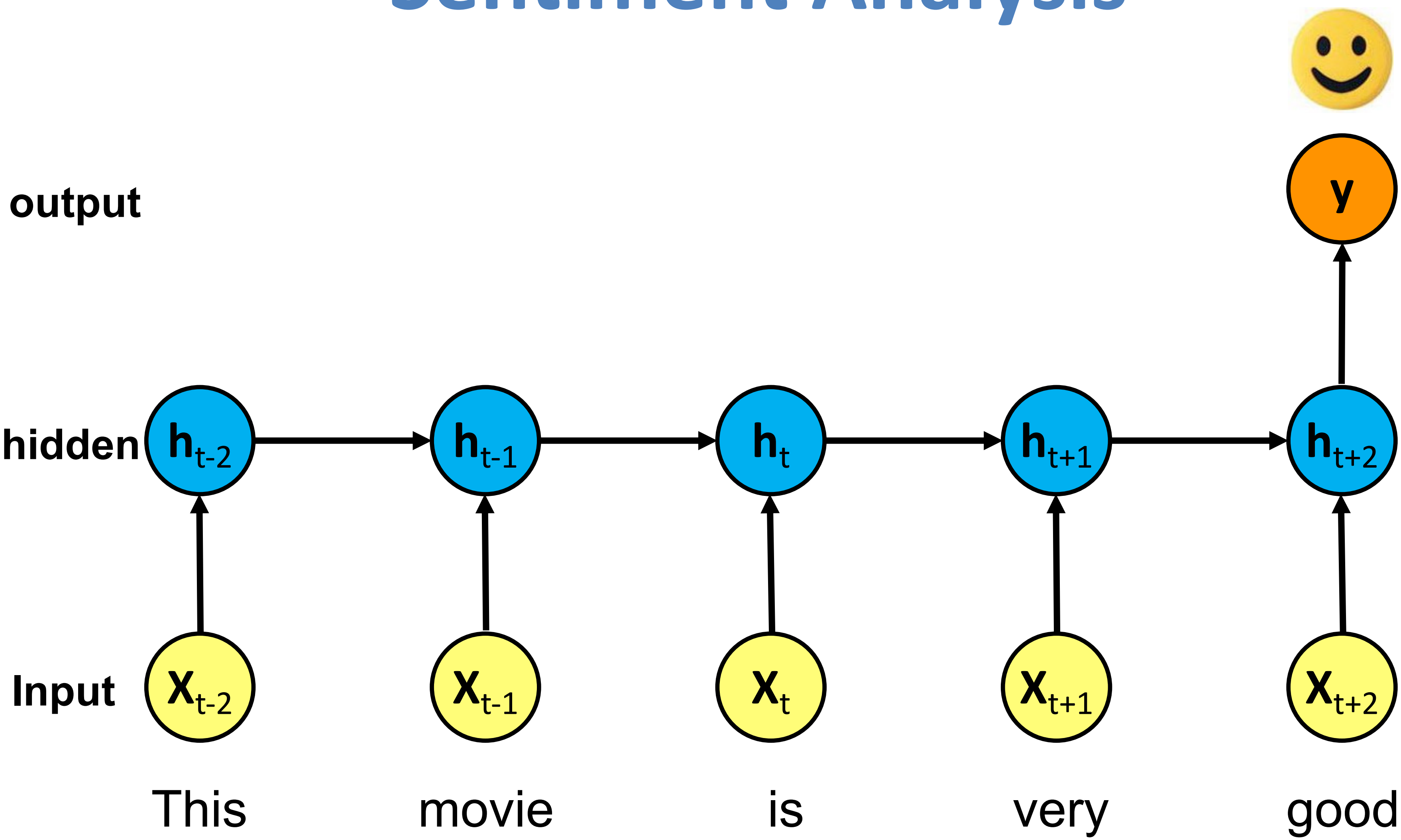
Recurrent Neural Networks (RNN)
Time Series Forecasting



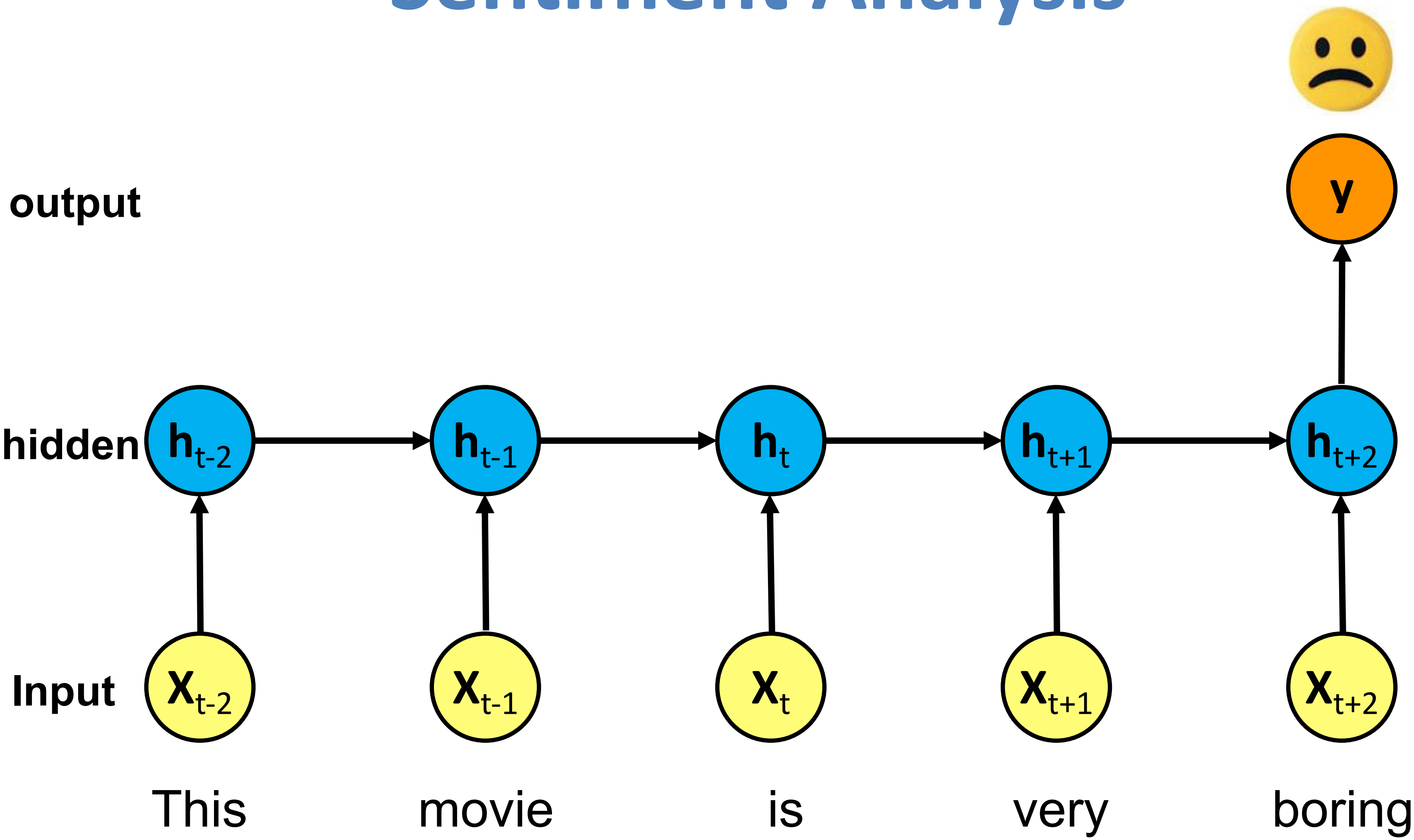
Recurrent Neural Networks (RNN)



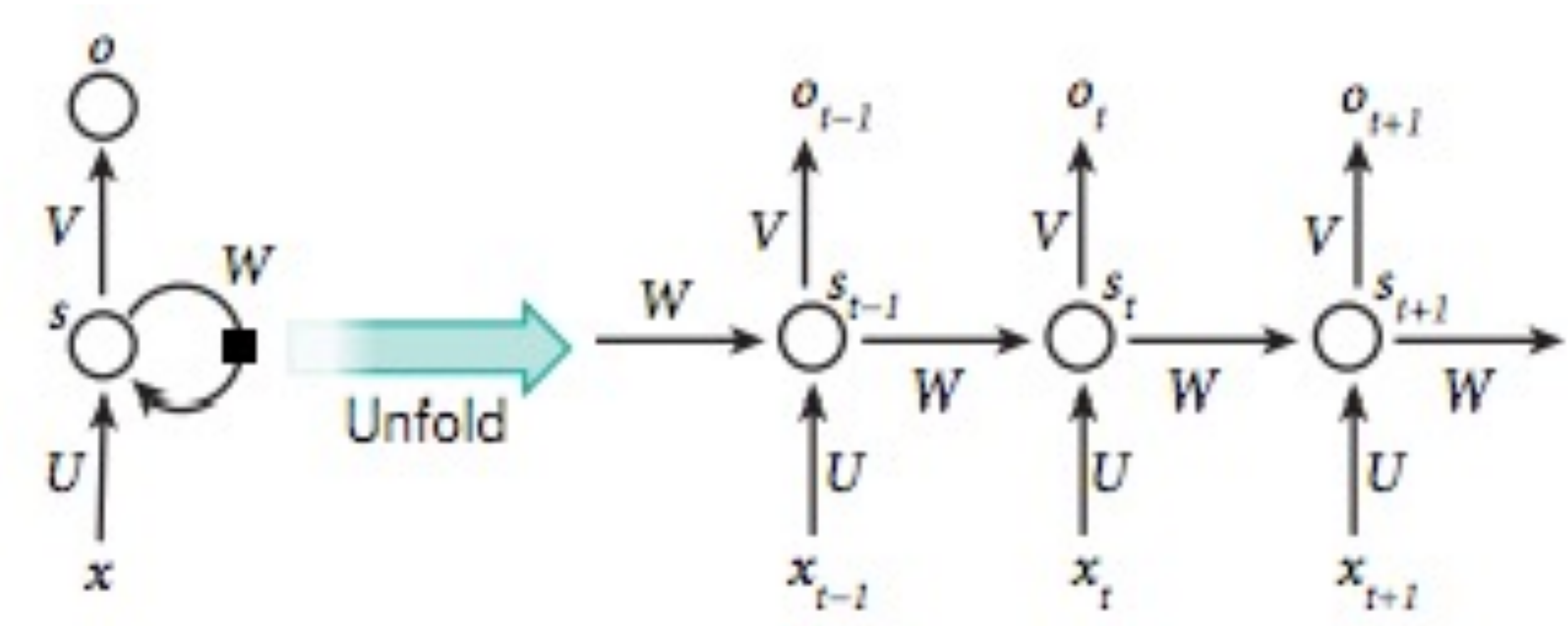
Recurrent Neural Networks (RNN) Sentiment Analysis



Recurrent Neural Networks (RNN) Sentiment Analysis

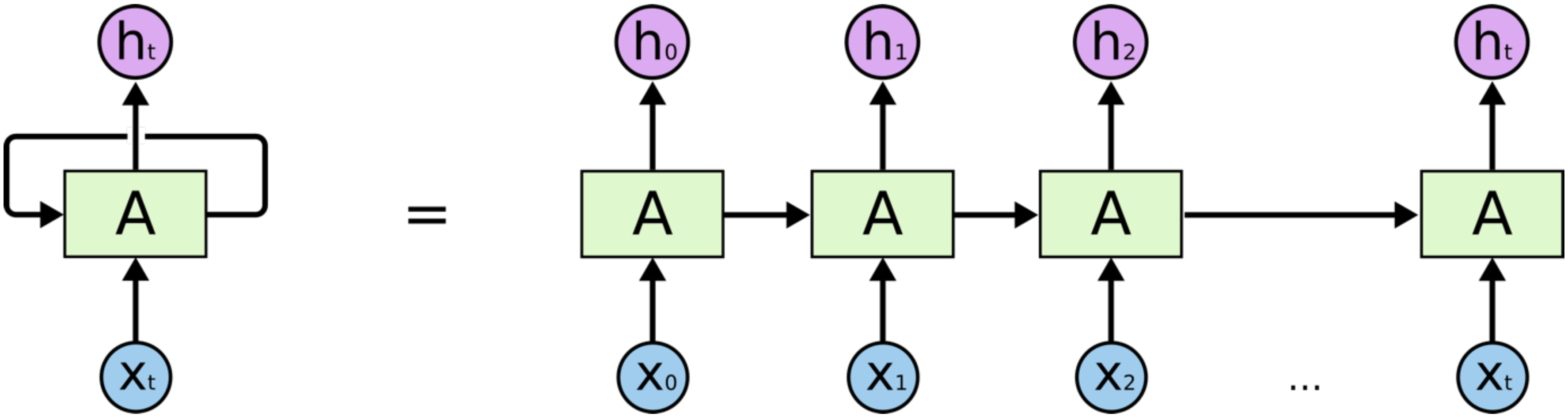


Recurrent Neural Network (RNN)



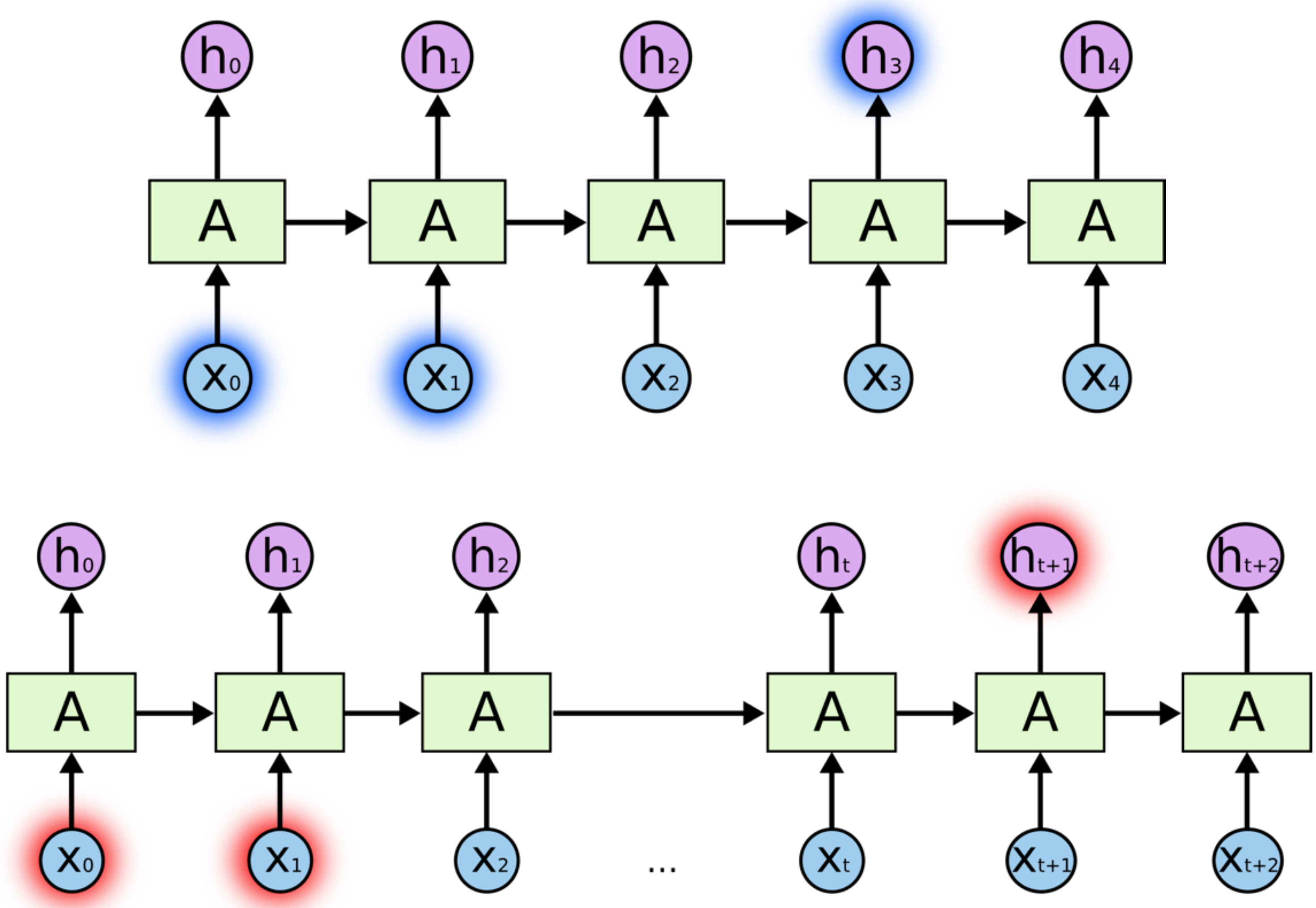
Source: LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. "Deep learning." Nature 521, no. 7553 (2015): 436-444.

RNN



Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

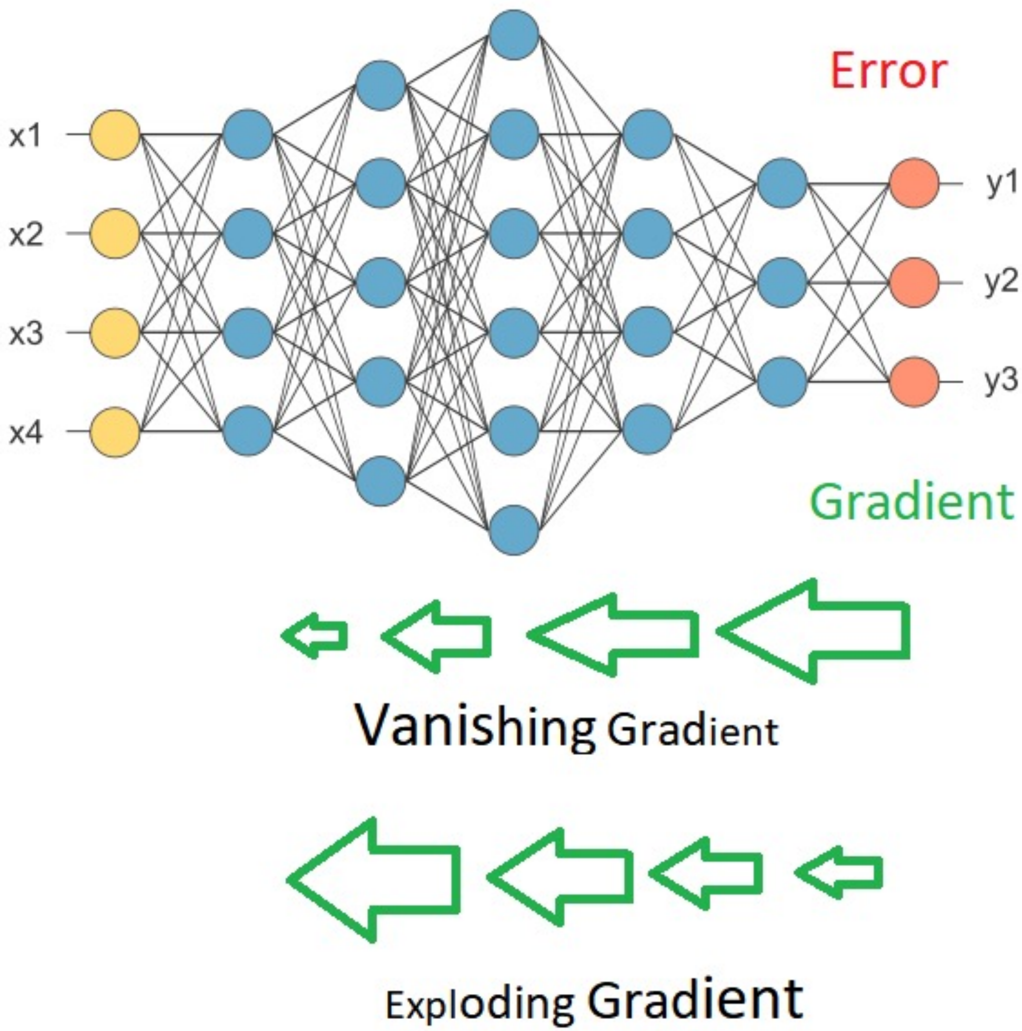
RNN long-term dependencies



I grew up in France… I speak fluent French.

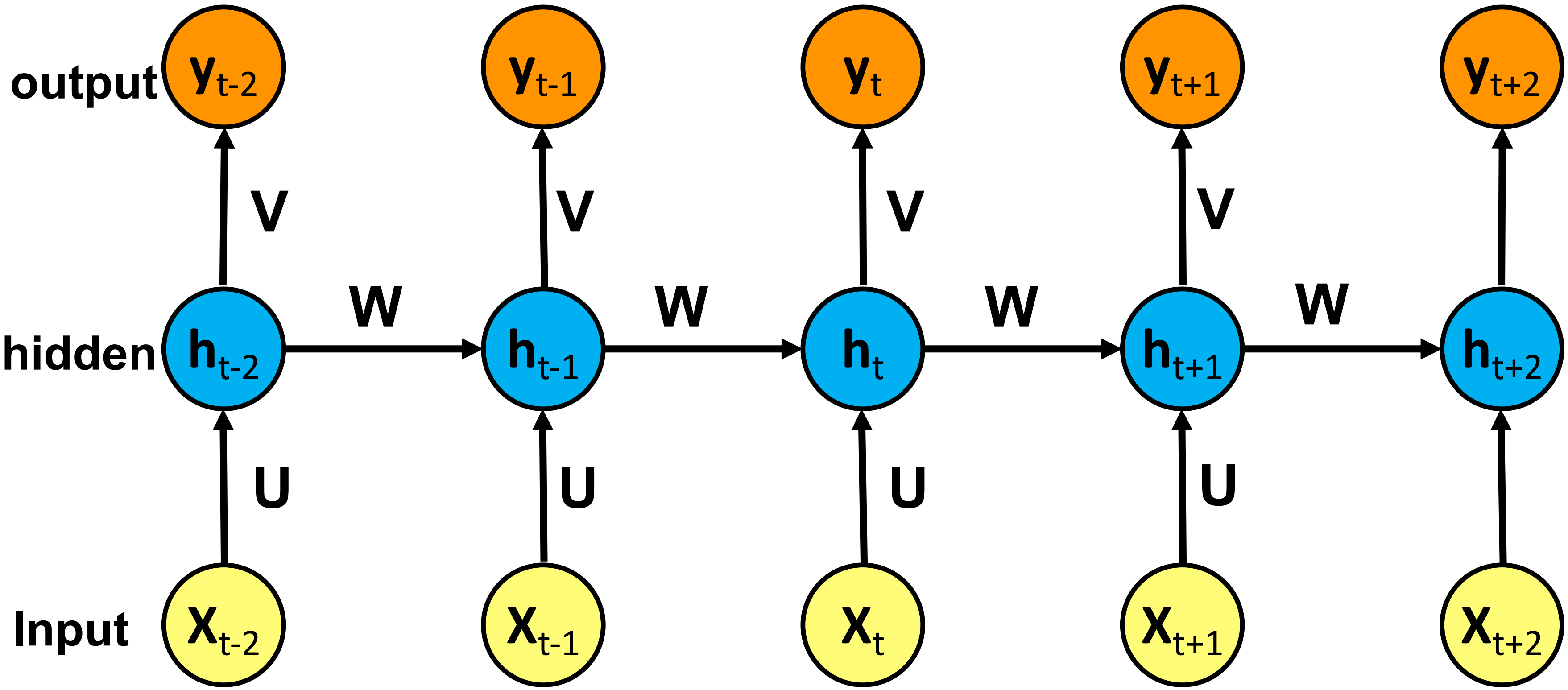
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Vanishing Gradient
Exploding Gradient

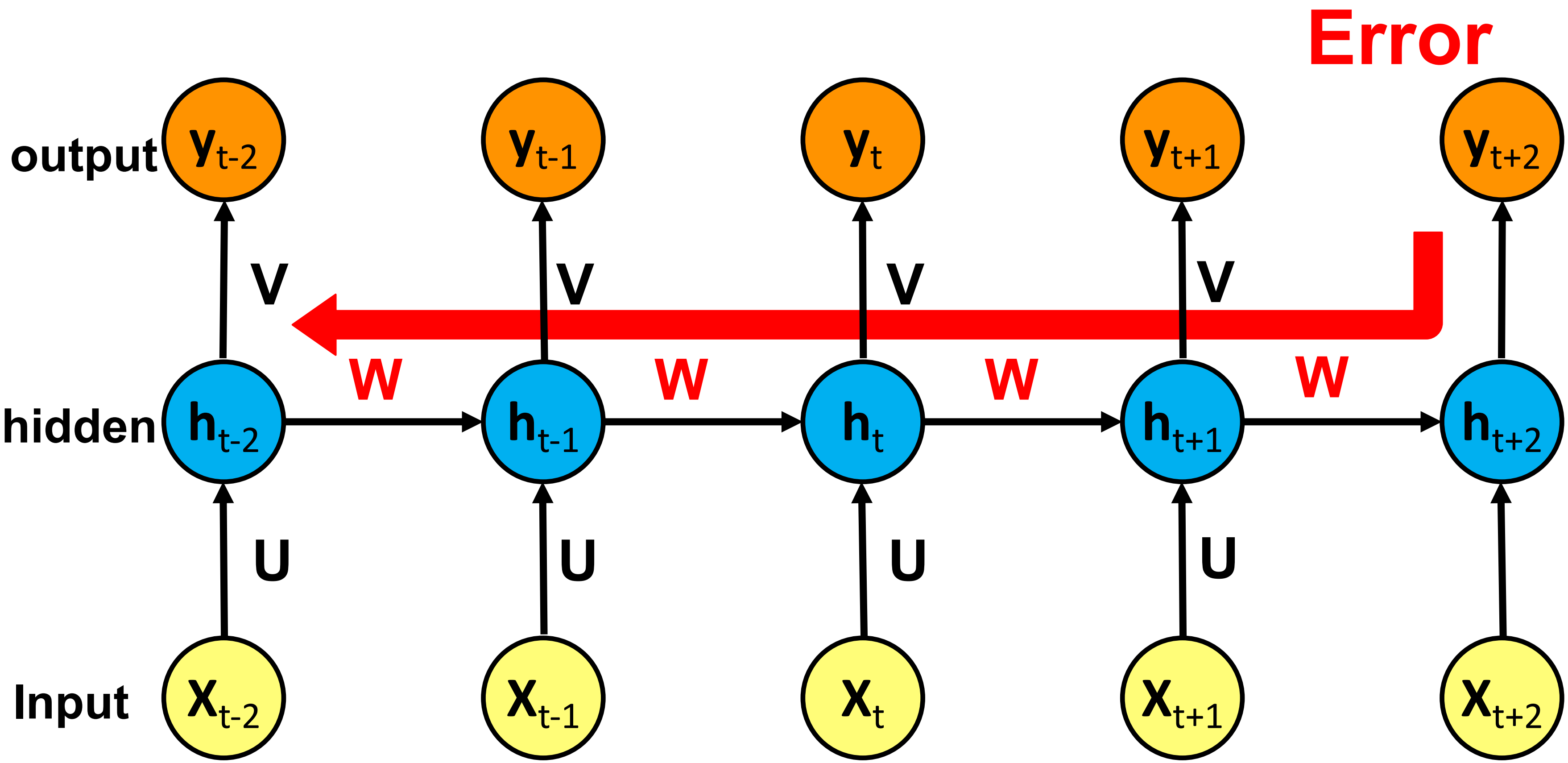


Source: https://medium.com/deep-math-machine-learning-ai/chapter-10-1-deepnlp-lstm-long-short-term-memory-networks-with-math-21477f8e4235

Recurrent Neural Networks (RNN)



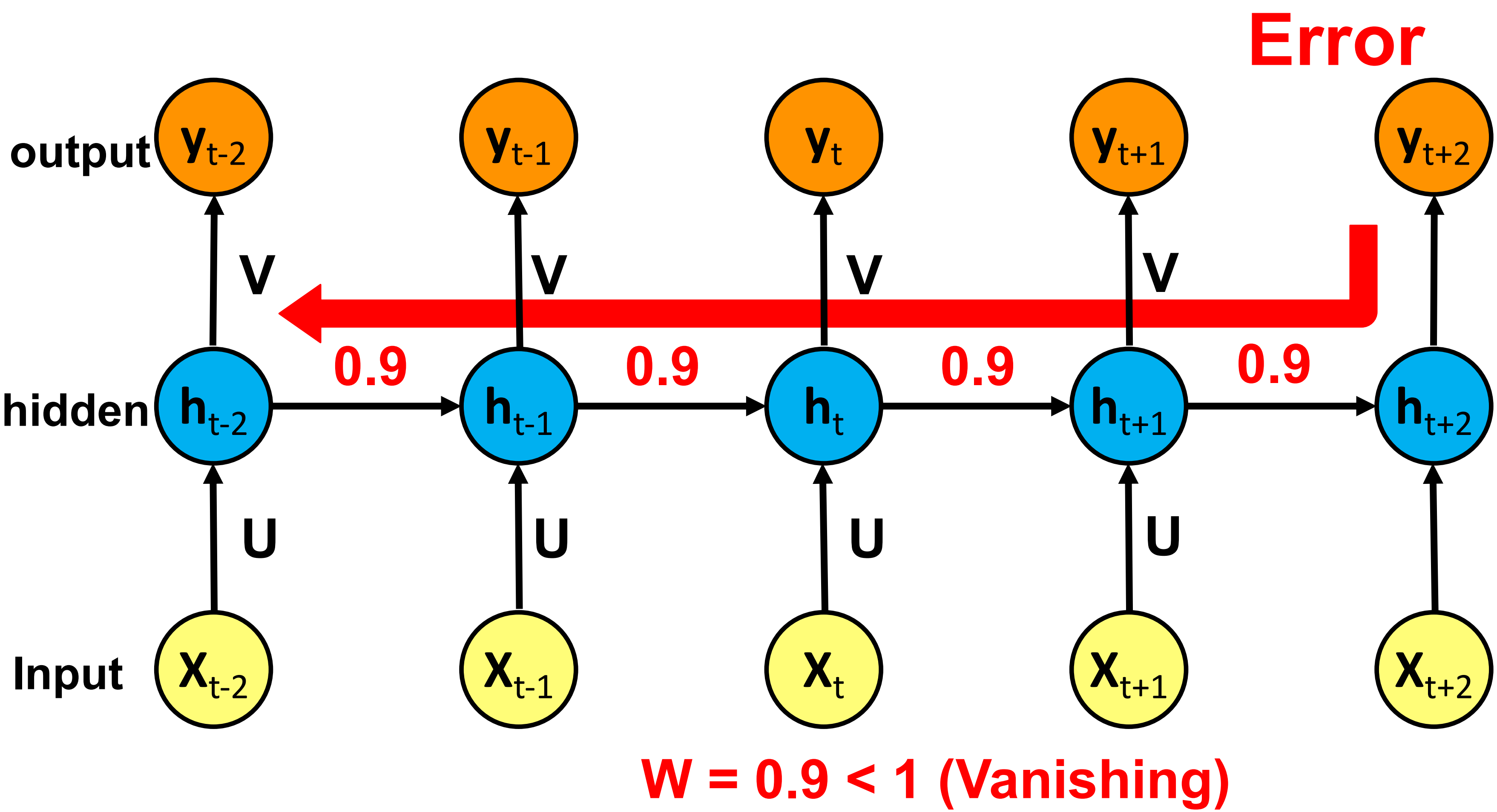
RNN
Vanishing Gradient problem
Exploding Gradient problem



if $|W| < 1$ (Vanishing)
if $|W| > 1$ (Exploding)

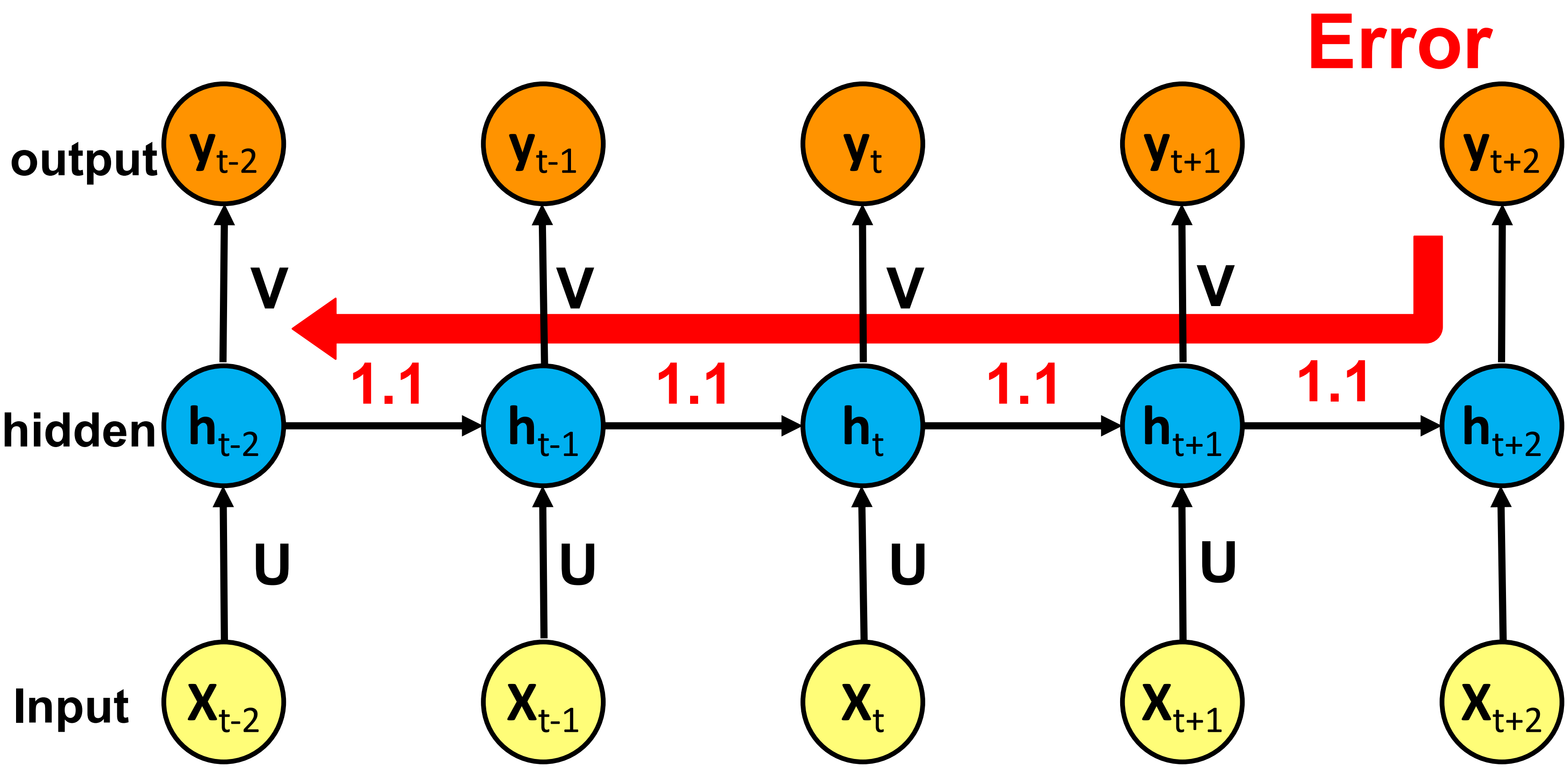
Source: https://medium.com/deep-math-machine-learning-ai/chapter-10-1-deepnlp-lstm-long-short-term-memory-networks-with-math-21477f8e4235

RNN
Vanishing Gradient problem



Source: https://medium.com/deep-math-machine-learning-ai/chapter-10-1-deepnlp-lstm-long-short-term-memory-networks-with-math-21477f8e4235

RNN
Exploding Gradient problem

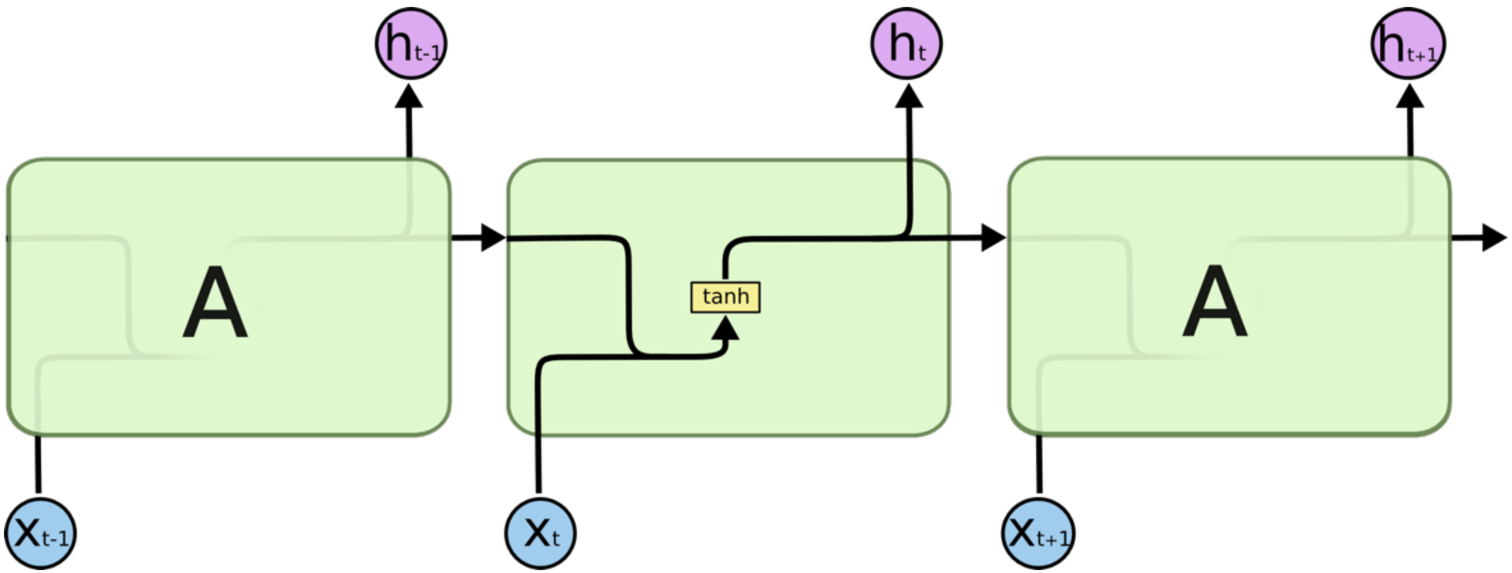


W = 1.1 > 1 (Exploding)

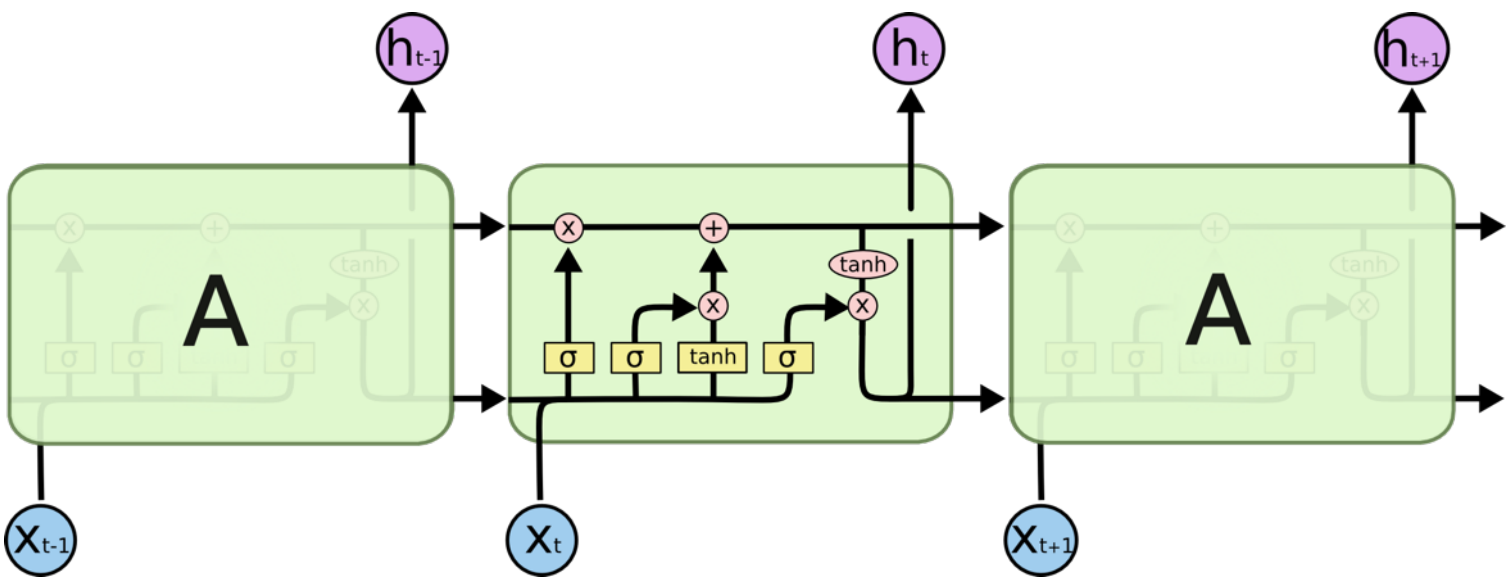
Source: https://medium.com/deep-math-machine-learning-ai/chapter-10-1-deepnlp-lstm-long-short-term-memory-networks-with-math-21477f8e4235

RNN LSTM

RNN

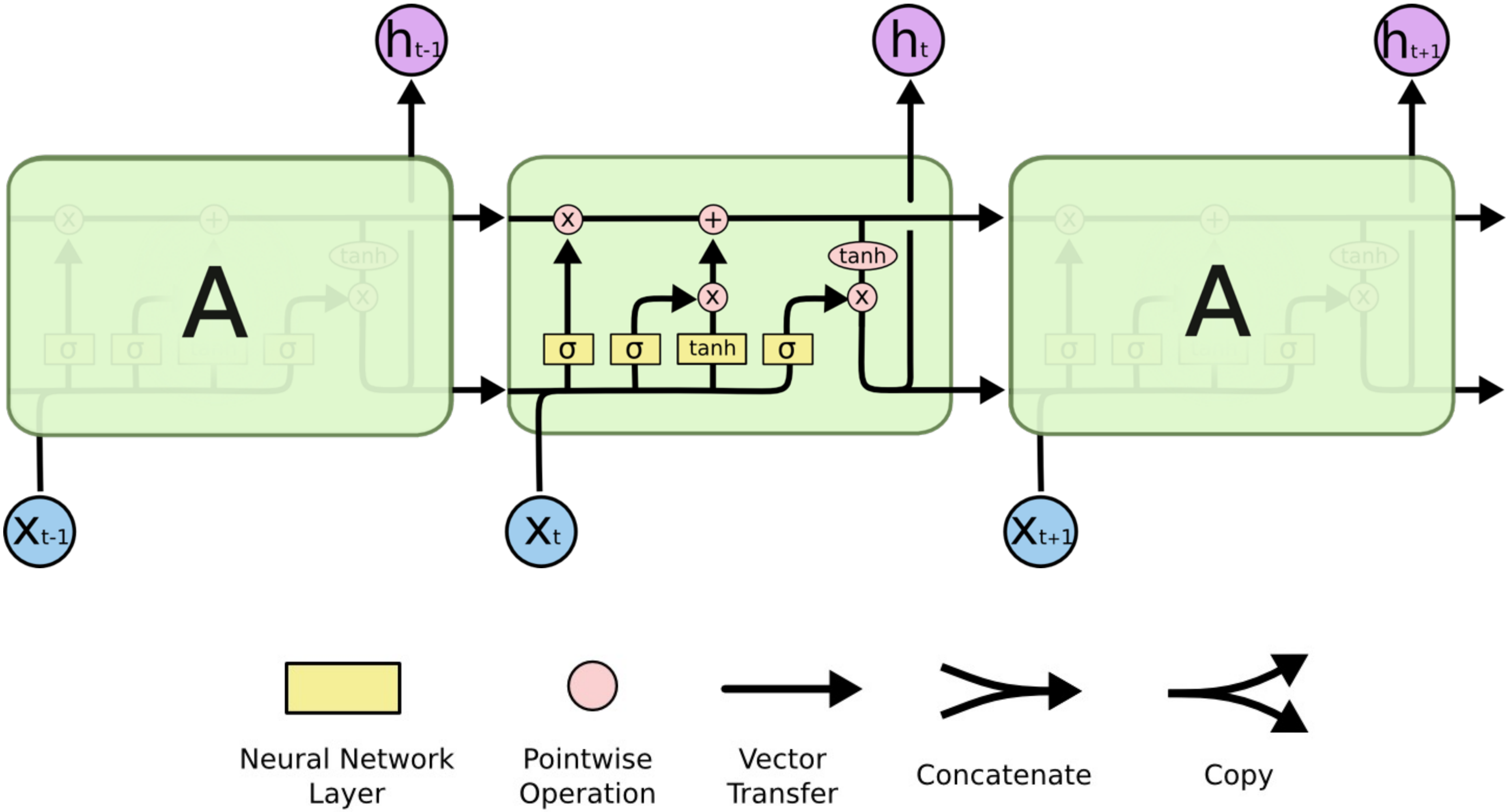


LSTM



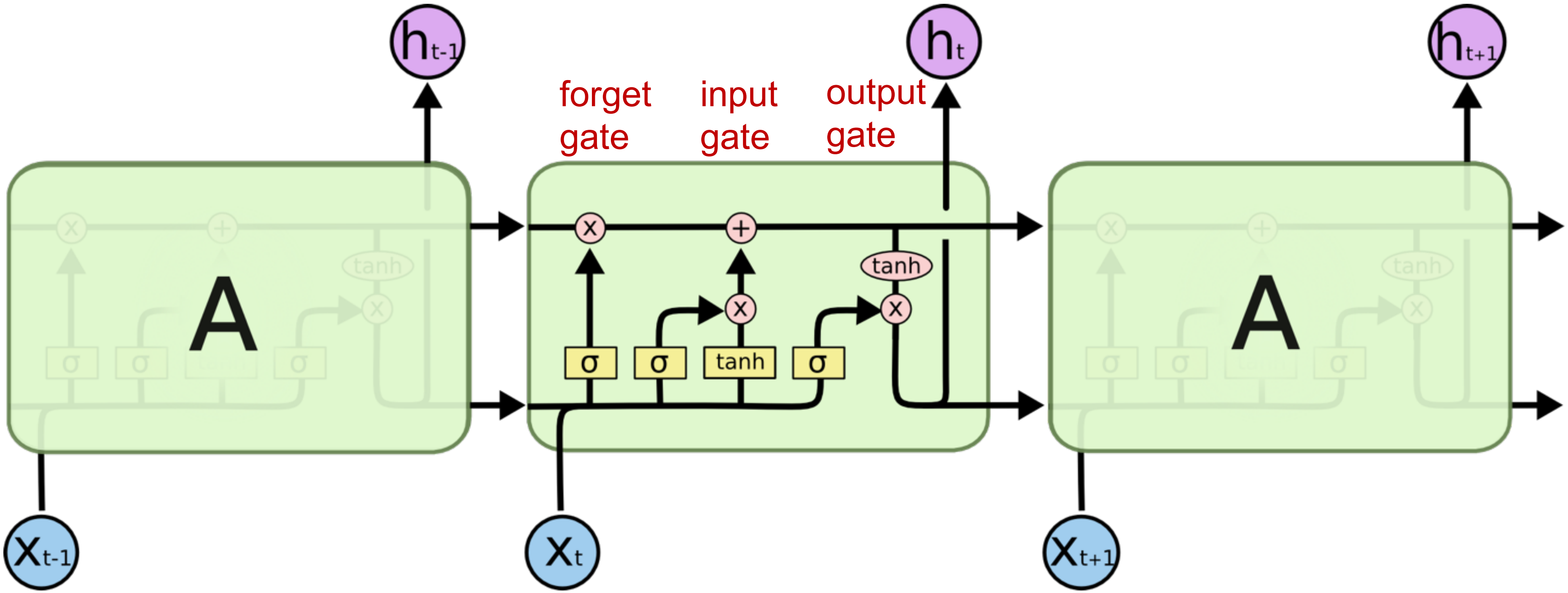
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Long Short Term Memory (LSTM)



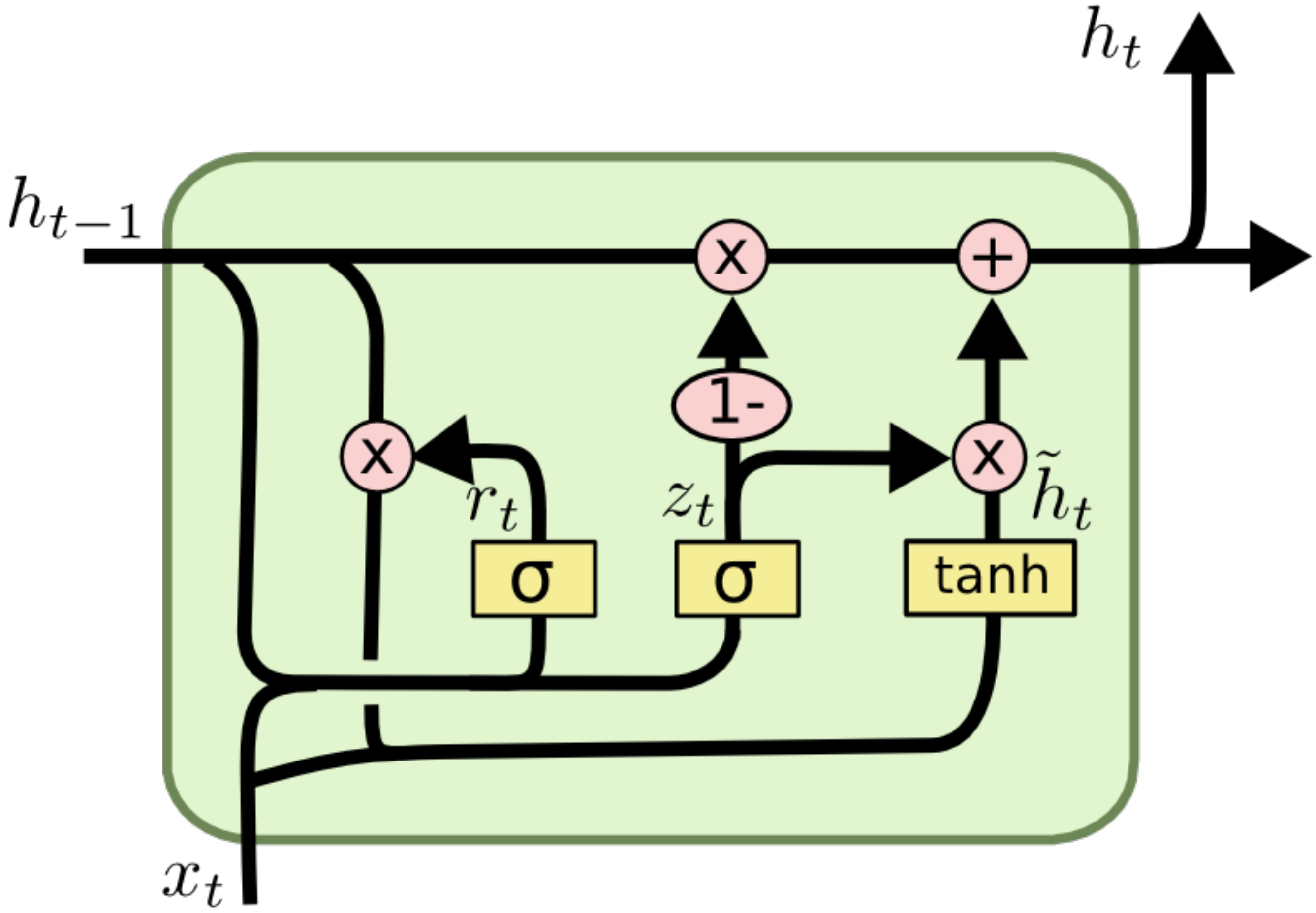
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Long Short Term Memory (LSTM)



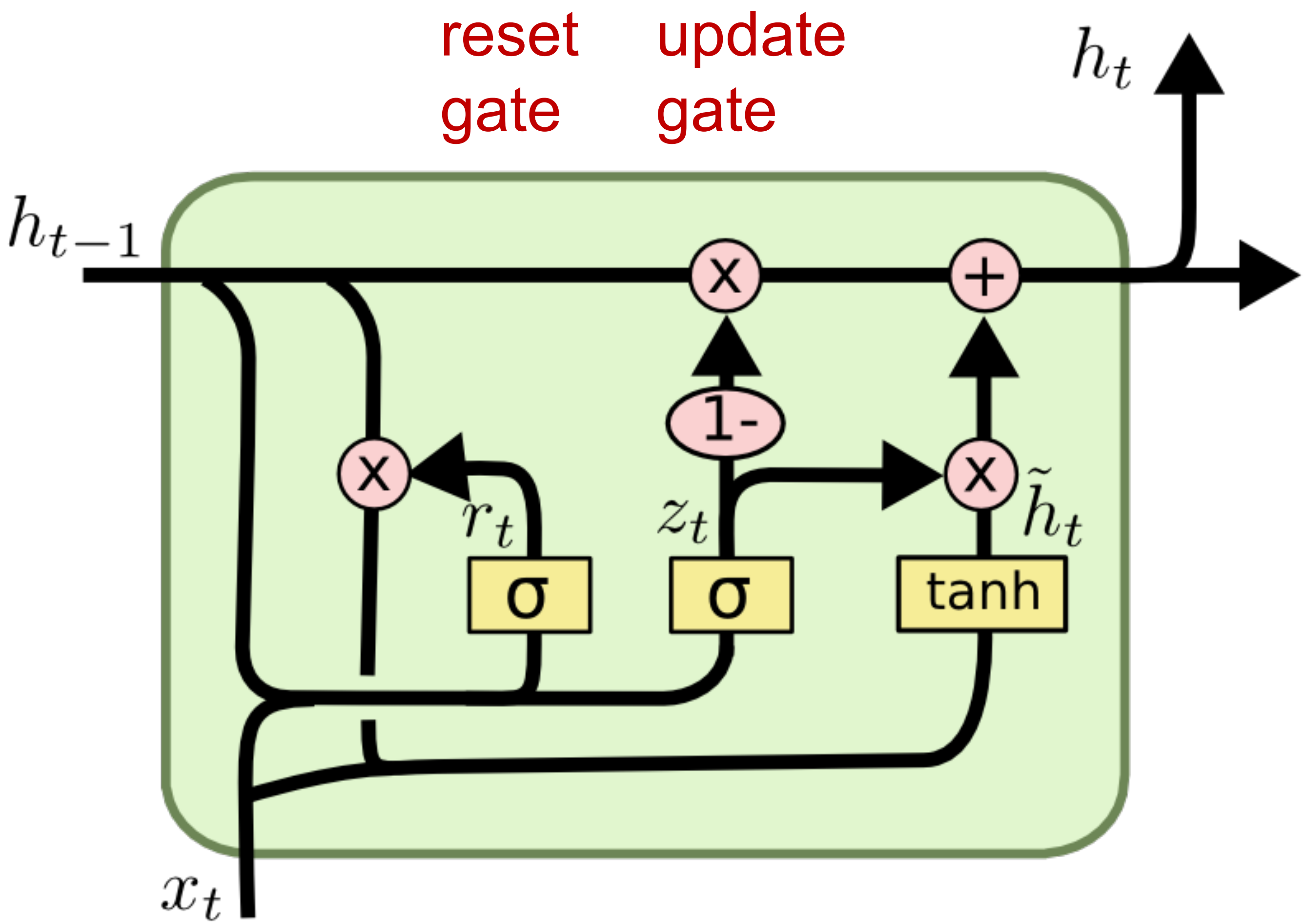
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Gated Recurrent Unit (GRU)



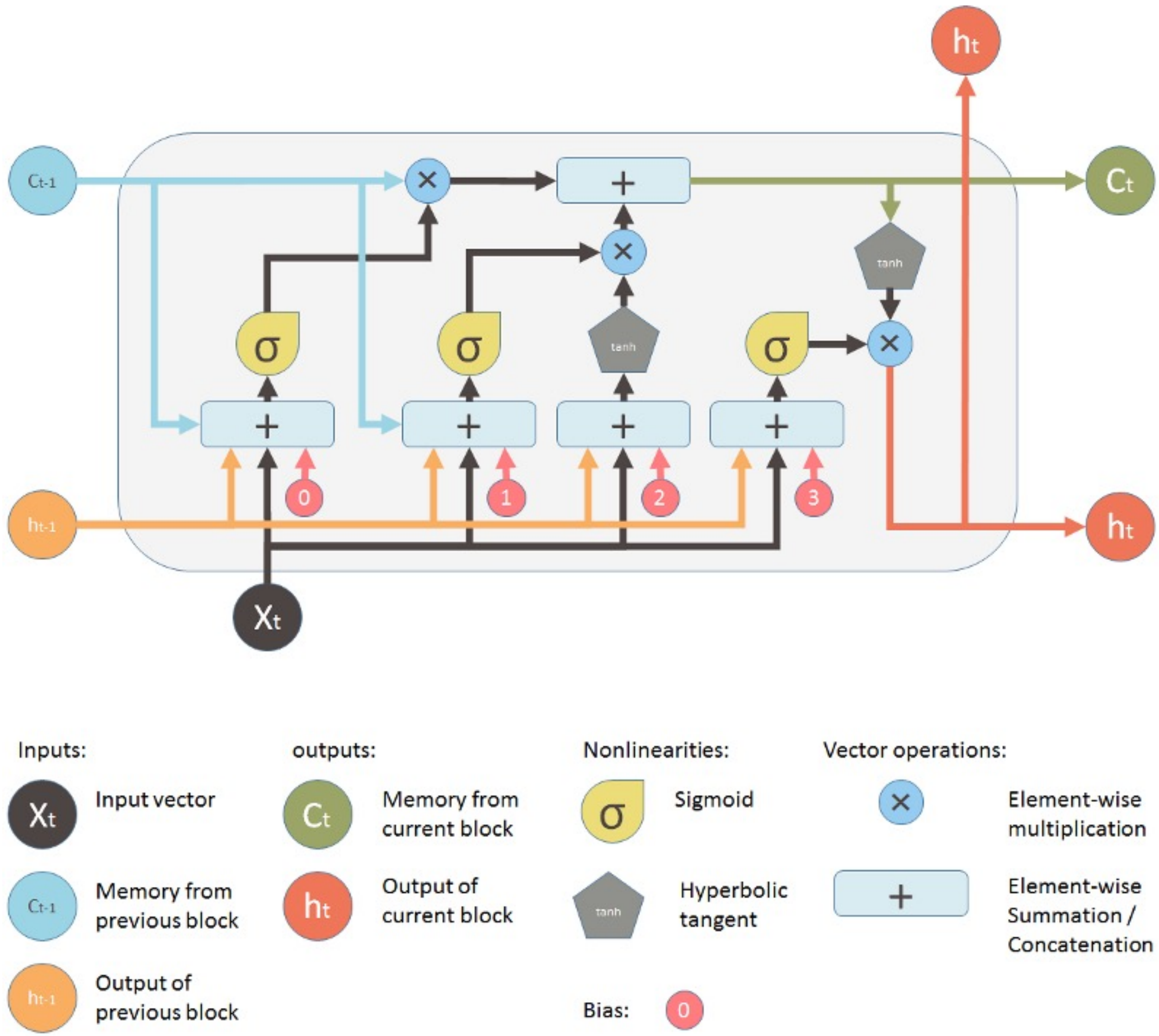
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Gated Recurrent Unit (GRU)



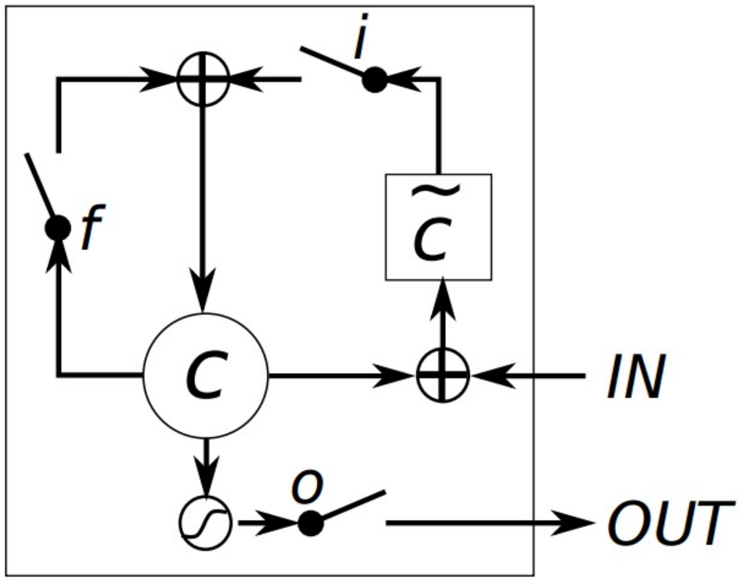
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

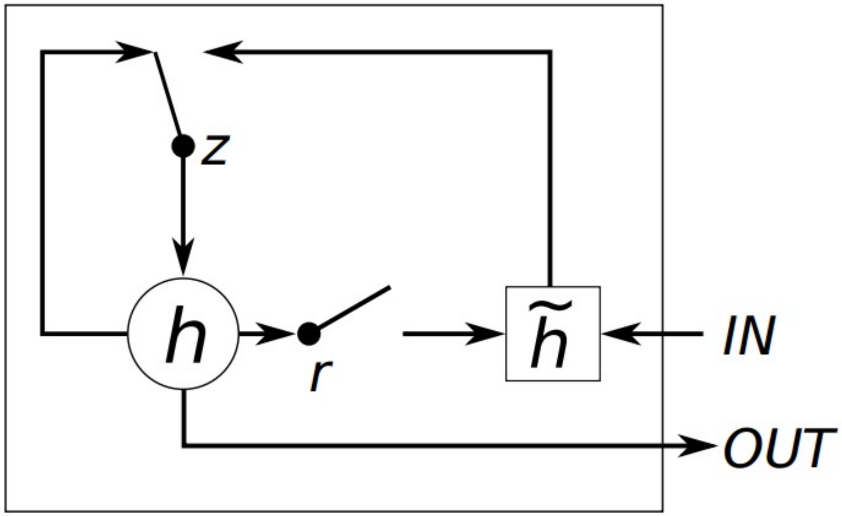
LSTM



Source: Shi Yan (2016), Understanding LSTM and its diagrams, https://medium.com/mlreview/understanding-lstm-and-its-diagrams-37e2f46f1714

LSTM vs GRU





LSTM

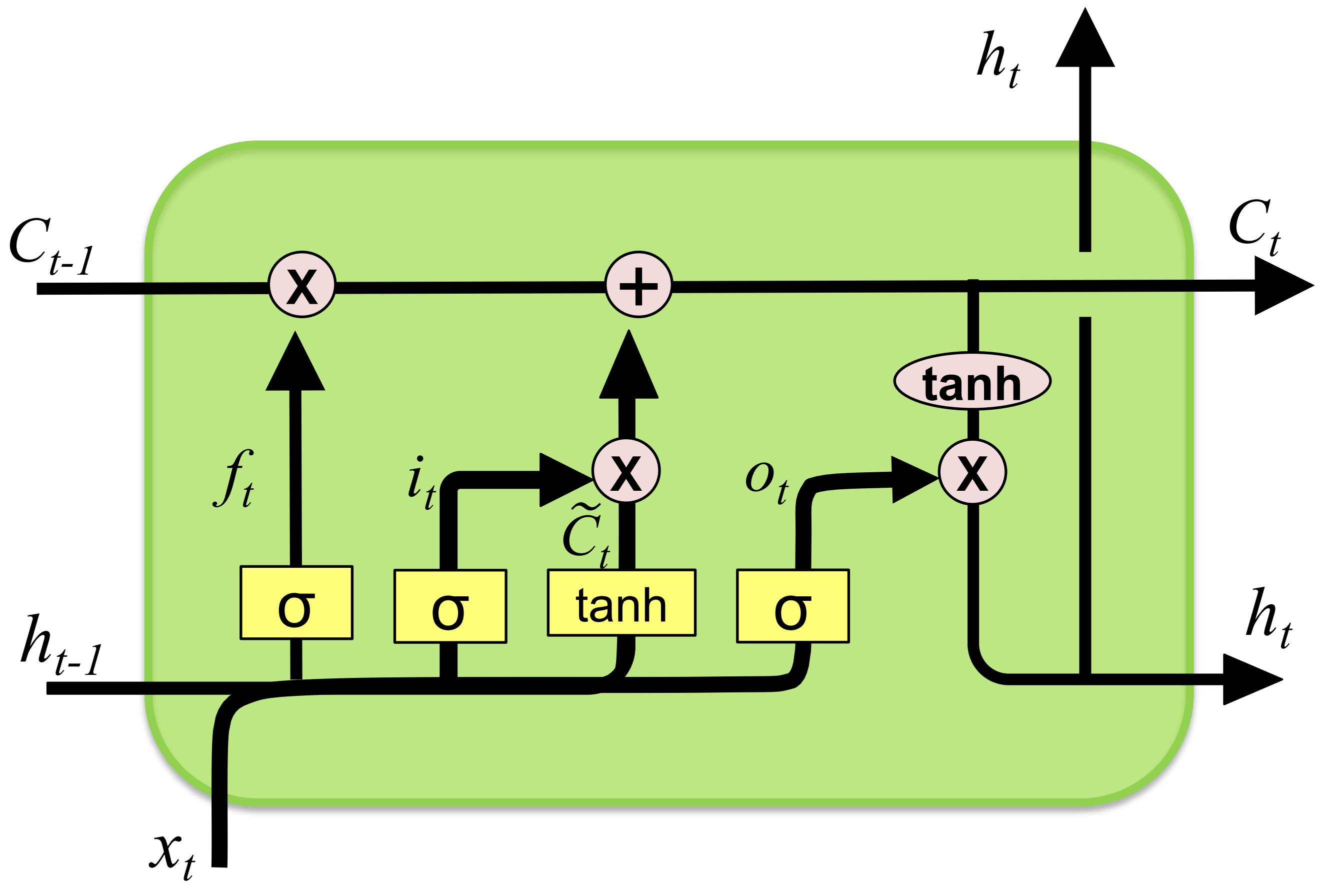
i, f and o are the input, forget and output gates, respectively.
c and c˜ denote the memory cell and the new memory cell content.

GRU

r and z are the reset and update gates, and h and h˜ are the activation and the candidate activation.

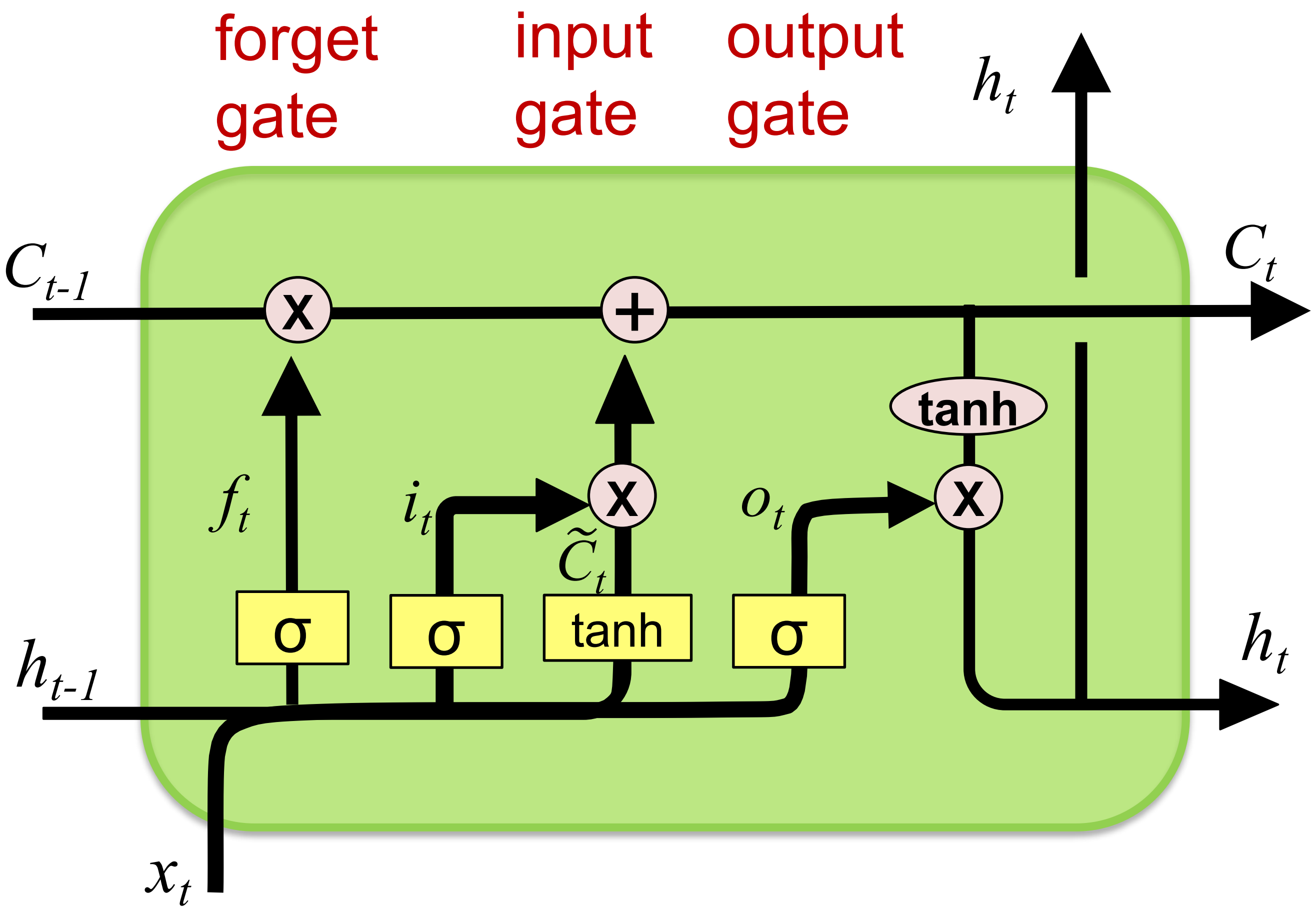
Source: Chung, Junyoung, Caglar Gulcehre, KyungHyun Cho, and Yoshua Bengio. "Empirical evaluation of gated recurrent neural networks on sequence modeling." *arXiv preprint arXiv:1412.3555* (2014).

Long Short Term Memory (LSTM)



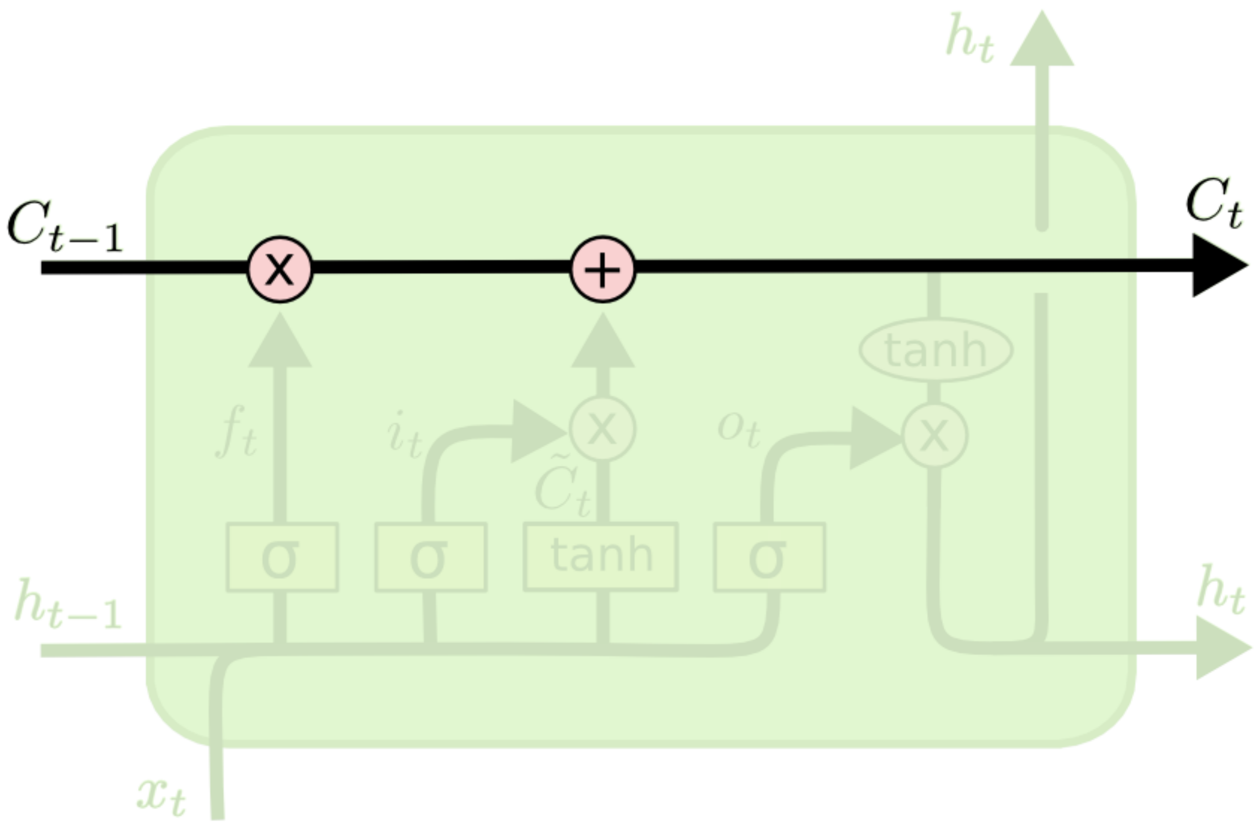
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Long Short Term Memory (LSTM)



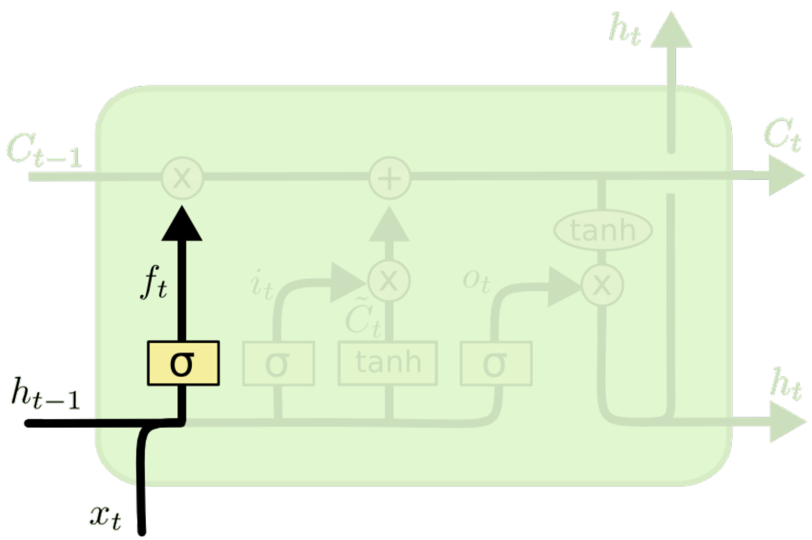
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM
Memory state (C)



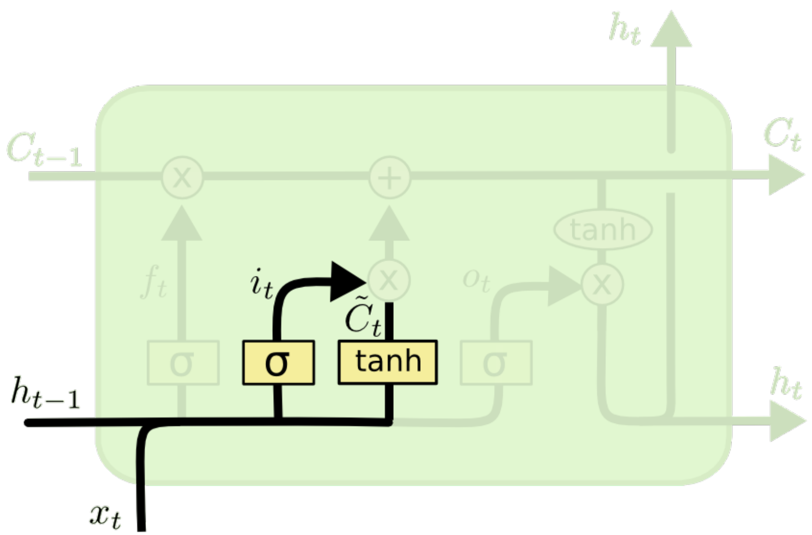
Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM
forget gate (f)



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

LSTM
input gate (i)

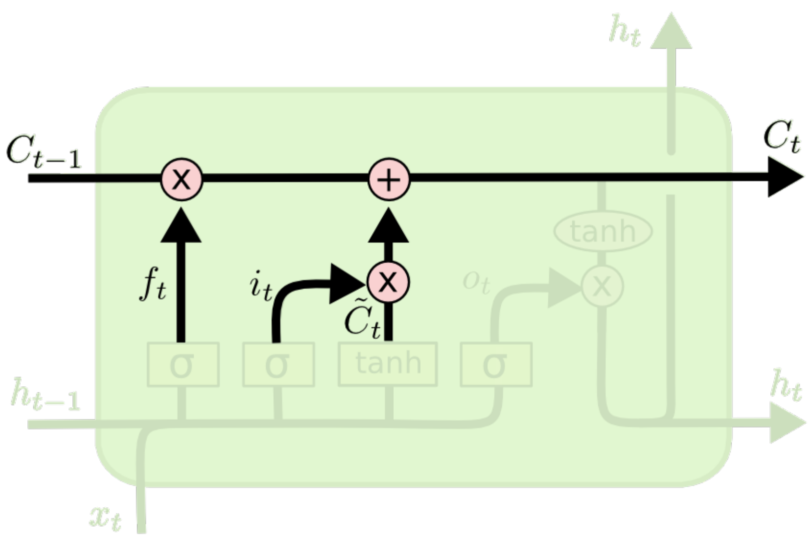


$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

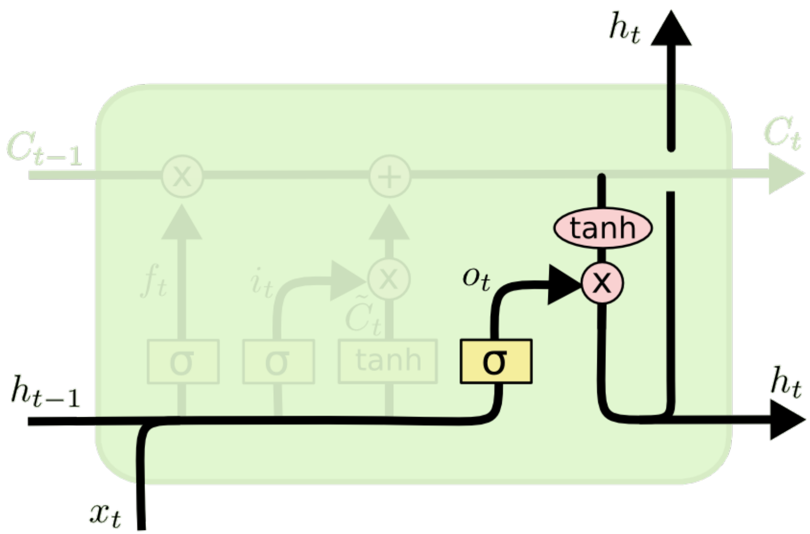
LSTM
Memory state (C)



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM
output gate (o)

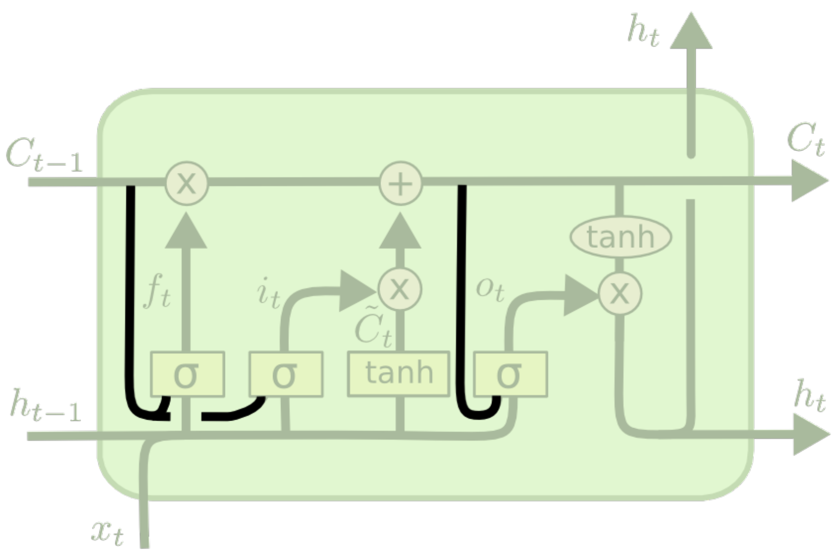


$$o_t = \sigma\left(W_o \ [h_{t-1}, x_t] \ + \ b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM
forget (f), input (i), output (o) gates



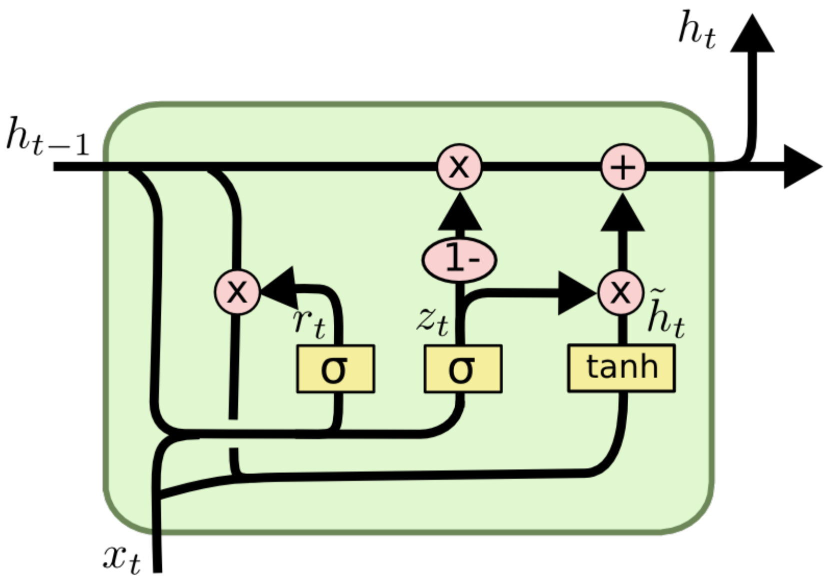
$$f_t = \sigma\left(W_f \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \; + \; b_f\right)$$

$$i_t = \sigma\left(W_i \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \; + \; b_i\right)$$

$$o_t = \sigma\left(W_o \cdot [\boldsymbol{C_t}, h_{t-1}, x_t] \; + \; b_o\right)$$

Gated Recurrent Unit (GRU)

update (z), reset (r) gates



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

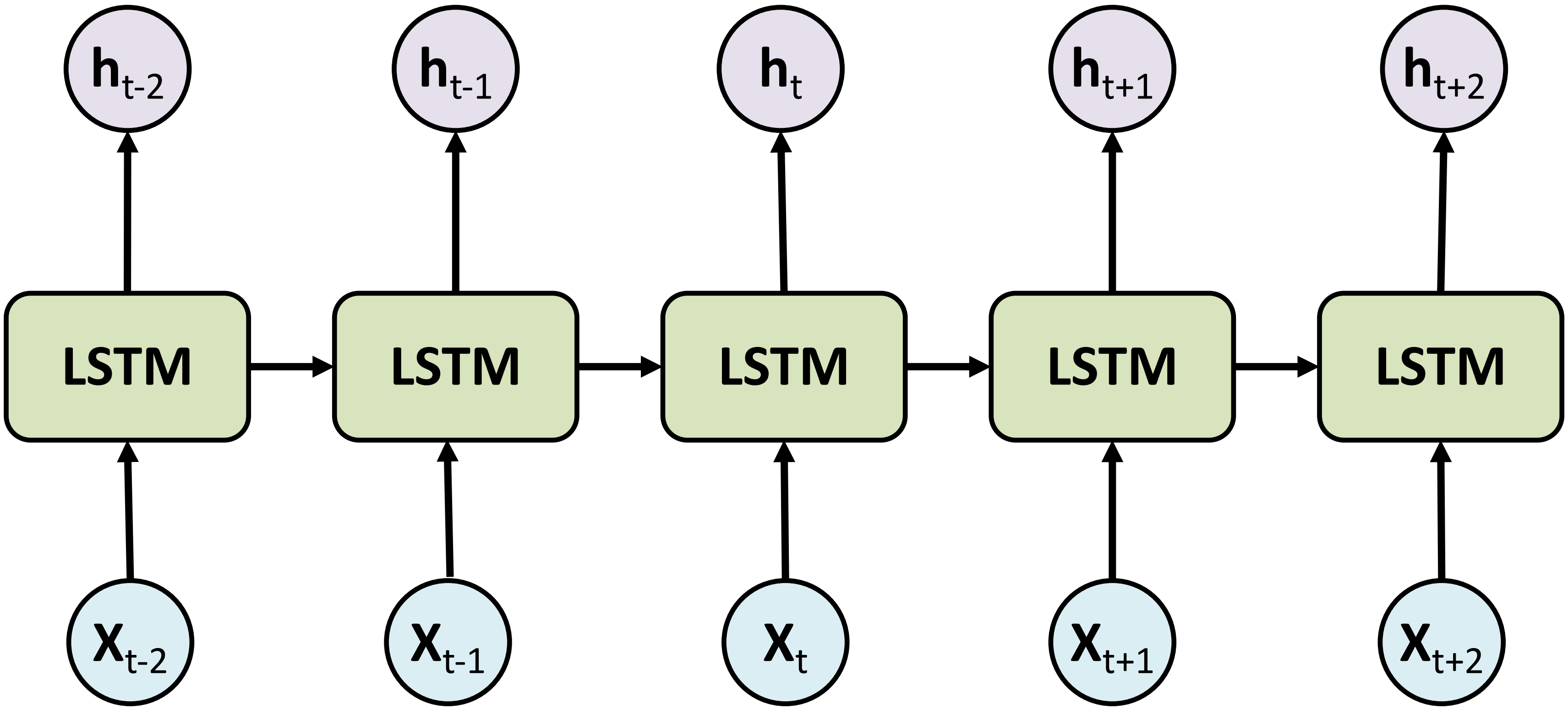
$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Source: Christopher Olah, (2015) Understanding LSTM Networks, http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Long Short Term Memory (LSTM) for Time Series Forecasting

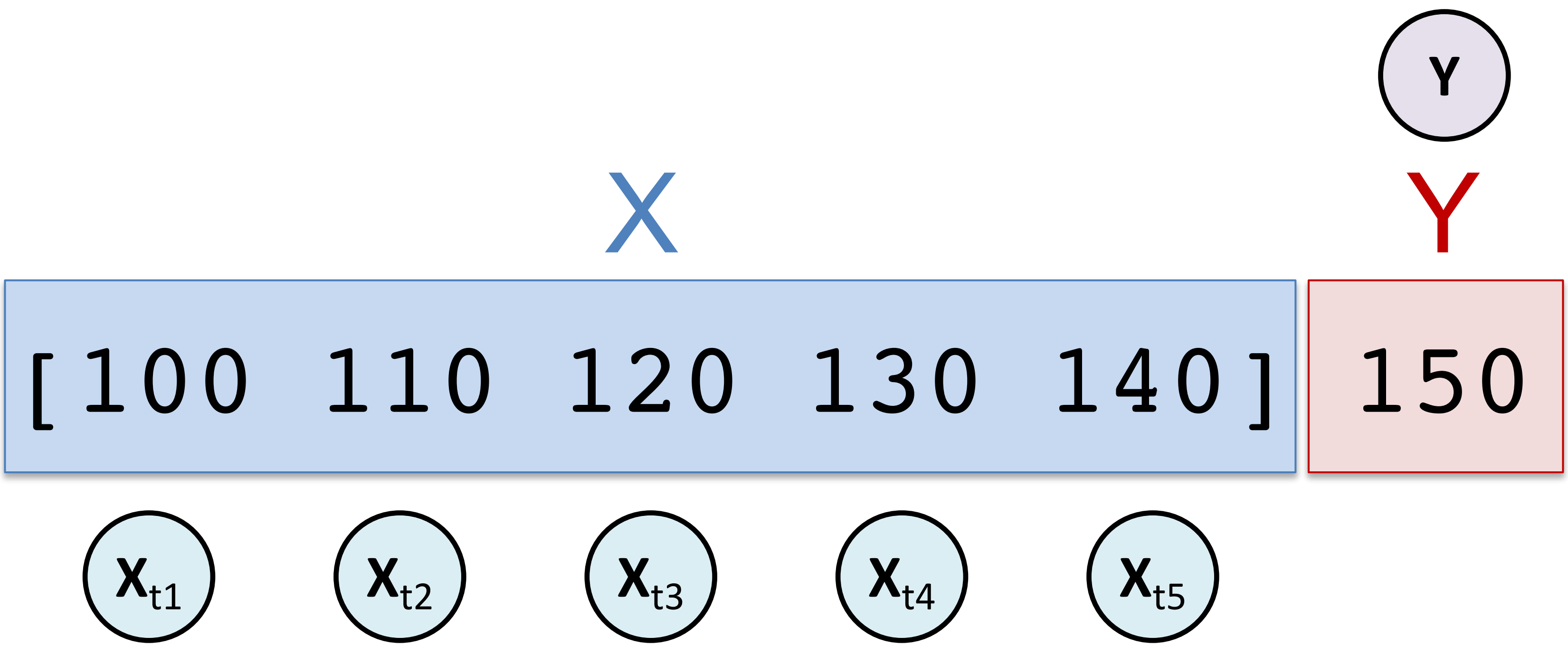


Deep Learning for Time Series Prediction

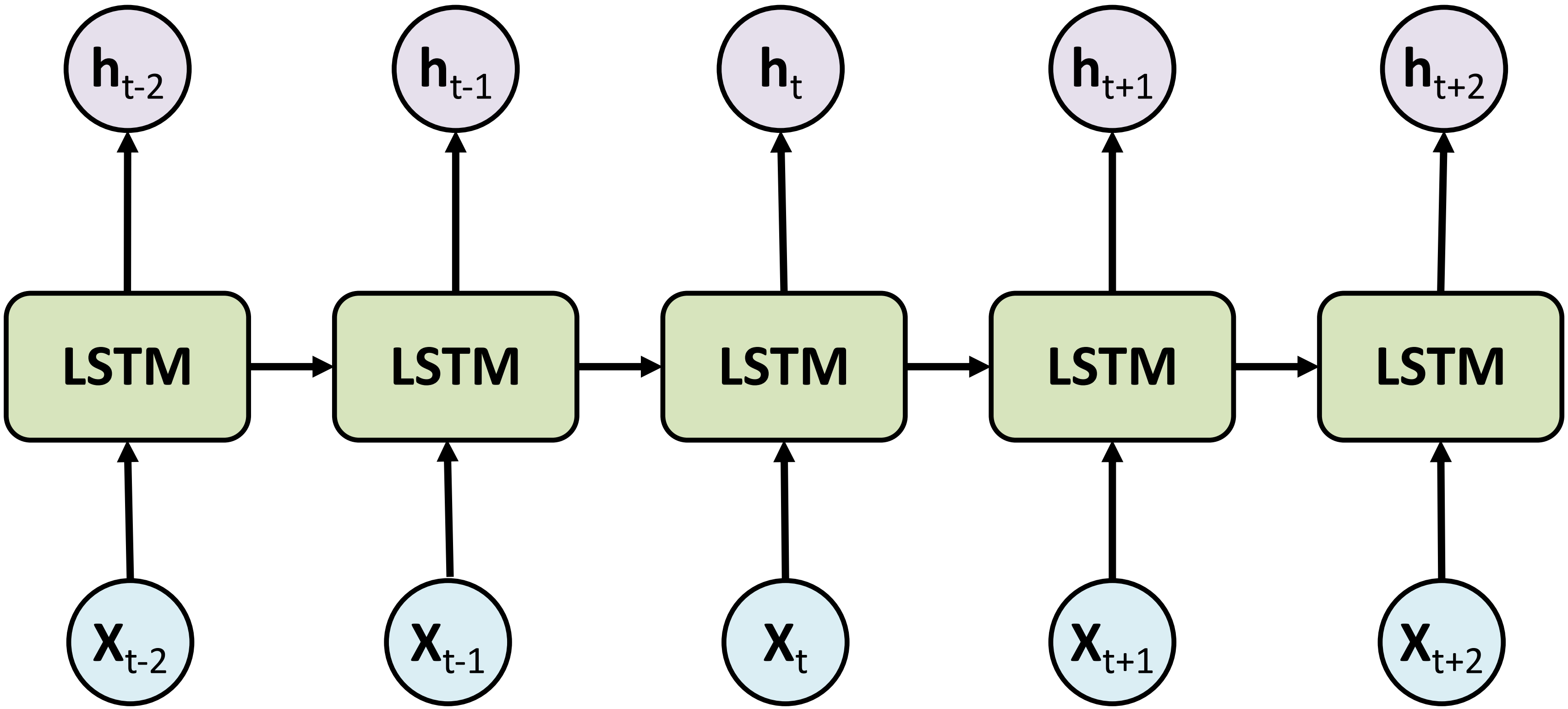
Deep Learning
for
Time Series Prediction
Financial Market Prediction
Stock Market Prediction
Stock Price Prediction

Time Series Data

[100, 110, 120, 130, 140, 150]



Long Short Term Memory (LSTM) for Time Series Forecasting



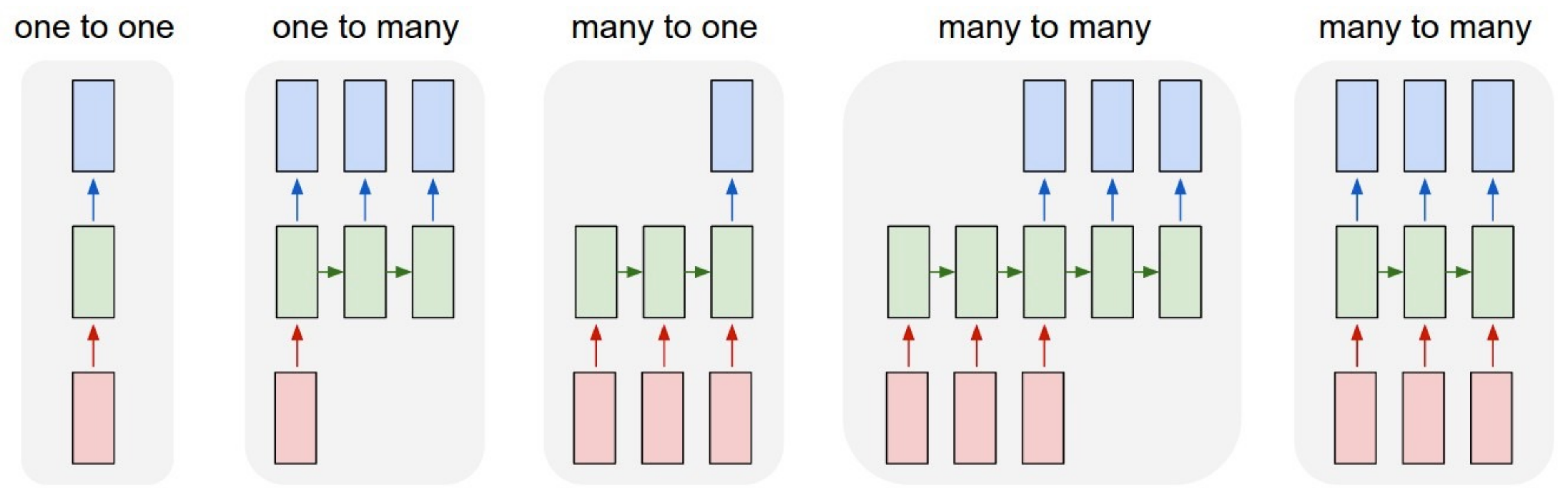
Time Series Data

[10, 20, 30, 40, 50, 60, 70, 80, 90]

X	Y
[10 20 30]	40
[20 30 40]	50
[30 40 50]	60
[40 50 60]	70
[50 60 70]	80
[60 70 80]	90

Deep Learning
for
Text Analytics
(NLP)

LSTM Recurrent Neural Network



Traditional Neural Network

Music Generation

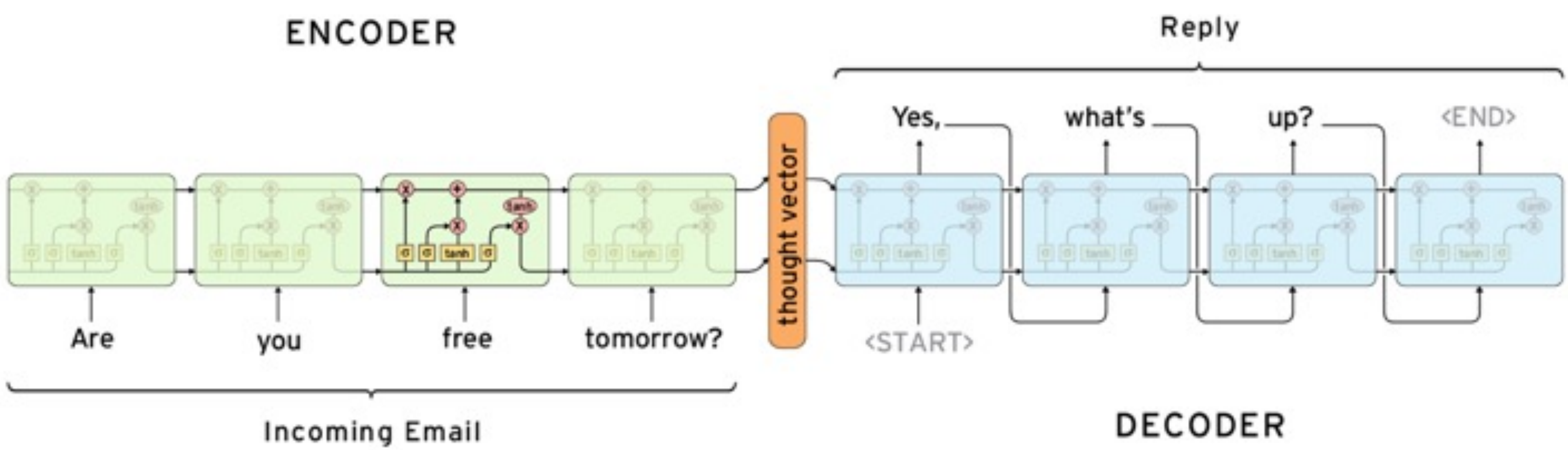
Sentiment Classification

Name Entity Recognition

Machine Translation

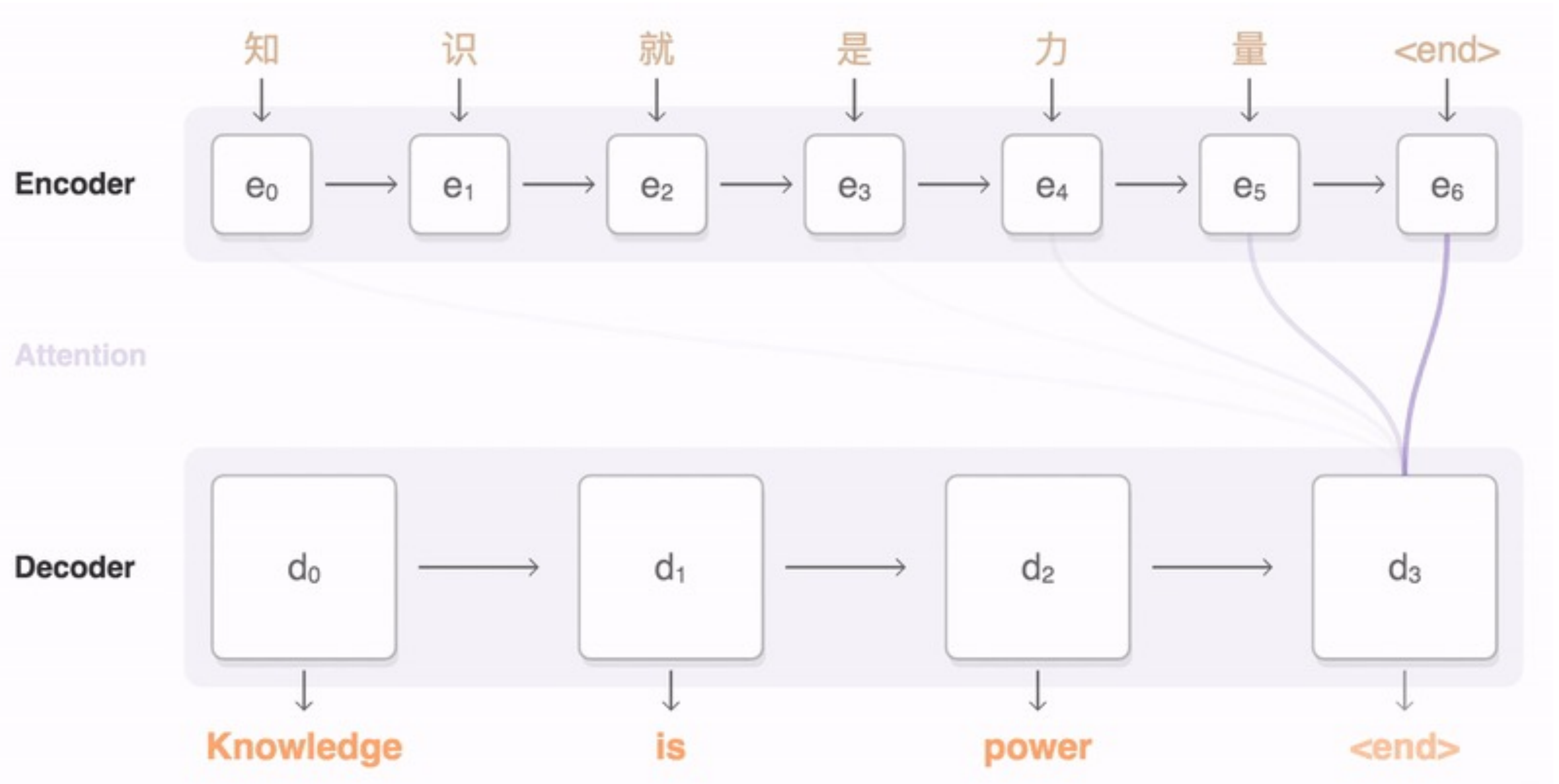
Source: https://github.com/Vict0rSch/deep_learning/tree/master/keras/recurrent

The Sequence to Sequence model (seq2seq)



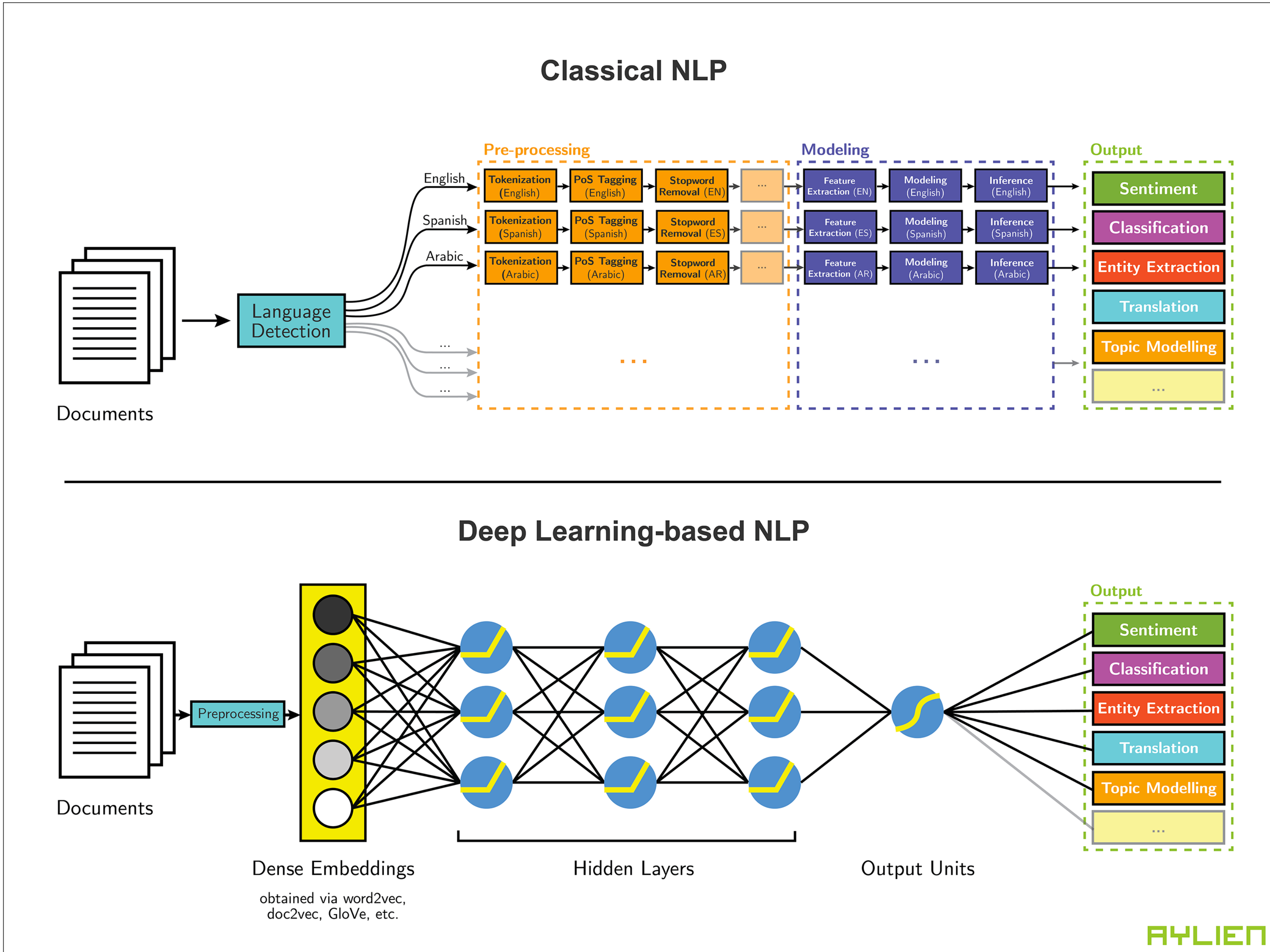
Source: http://suriyadeepan.github.io/2016-12-31-practical-seq2seq/

Sequence to Sequence (Seq2Seq)



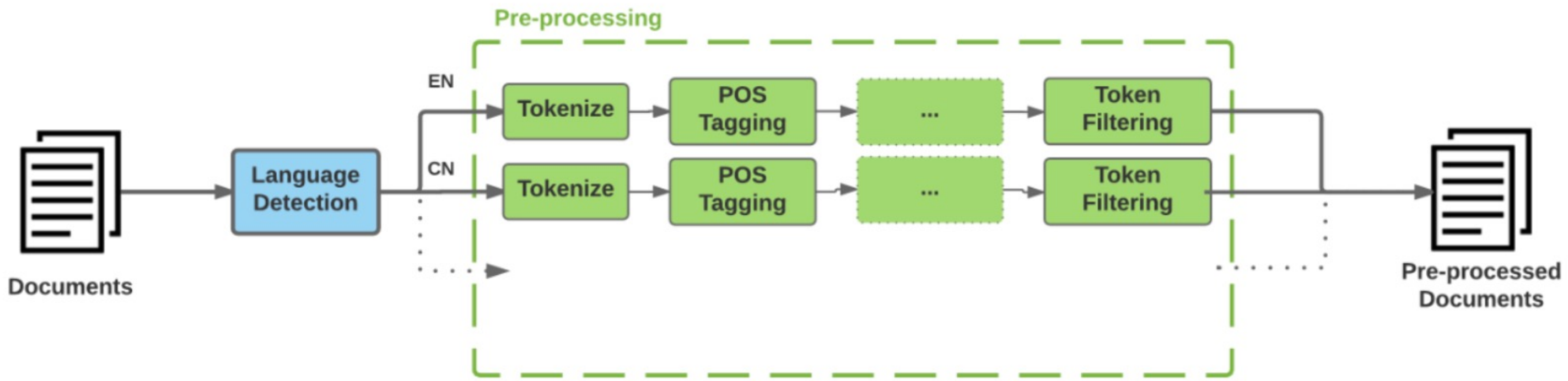
Source: https://google.github.io/seq2seq/

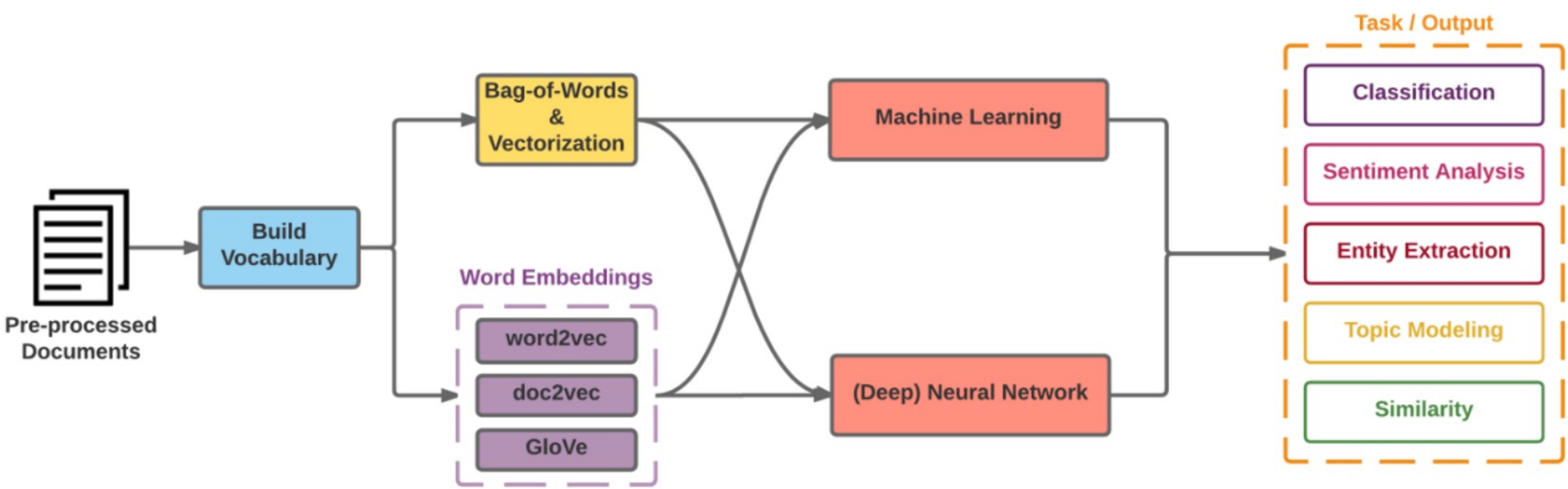
NLP



Source: http://blog.aylien.com/leveraging-deep-learning-for-multilingual/

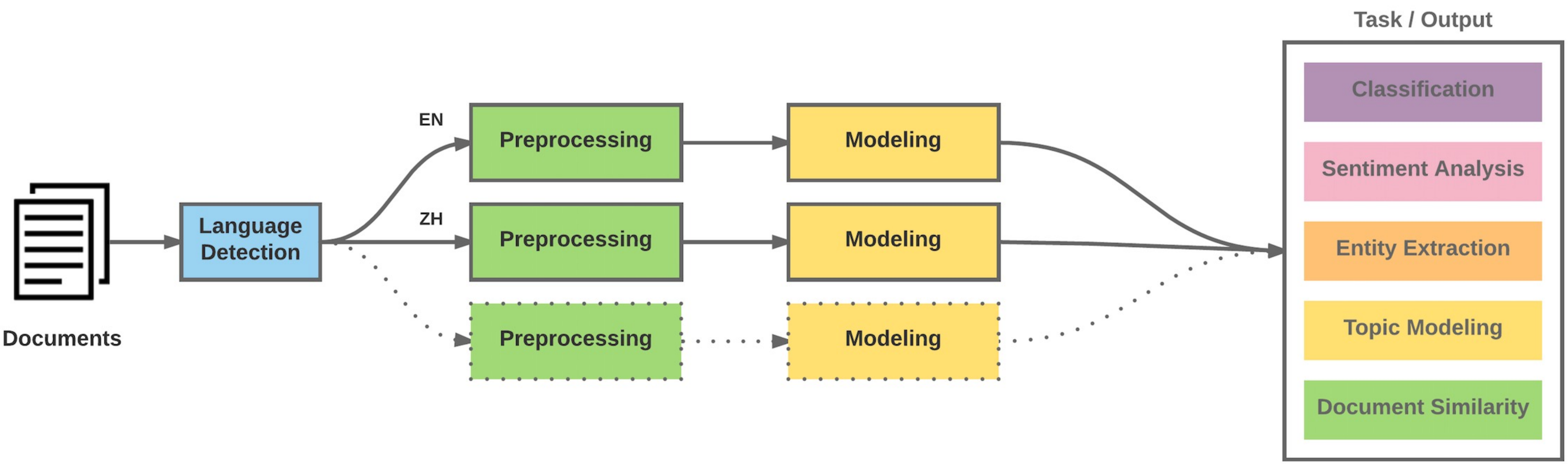
Modern NLP Pipeline





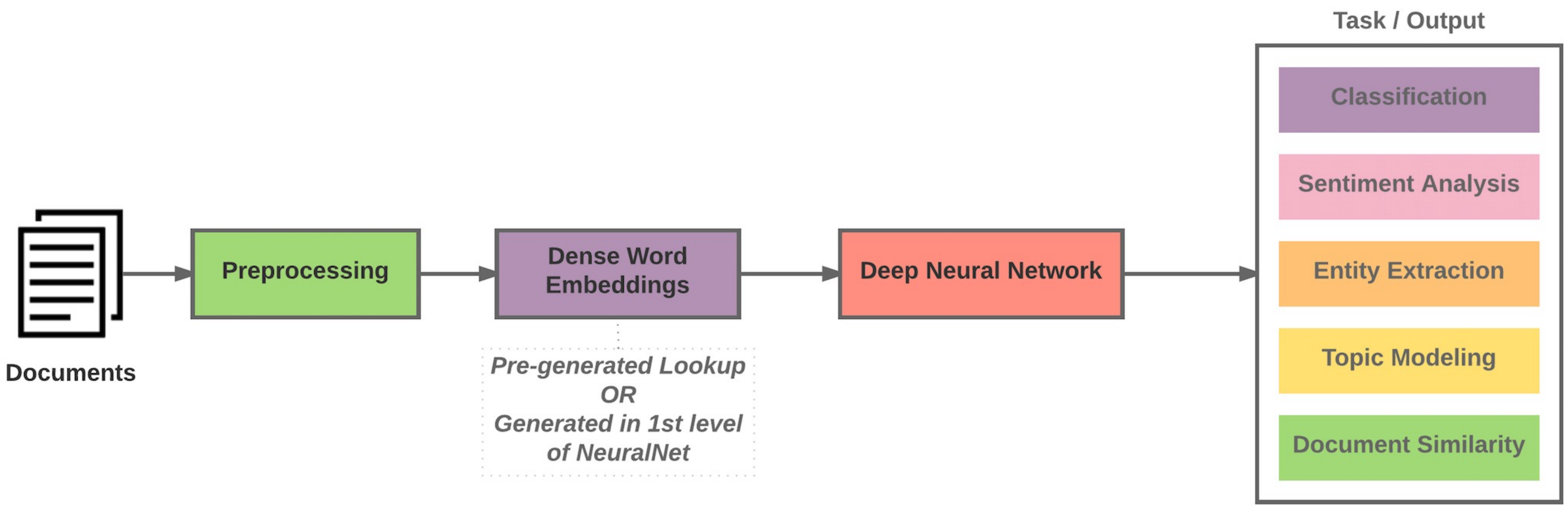
Source: https://github.com/fortiema/talks/blob/master/opendata2016sh/pragmatic-nlp-opendata2016sh.pdf

Modern NLP Pipeline



Source: http://mattfortier.me/2017/01/31/nlp-intro-pt-1-overview/

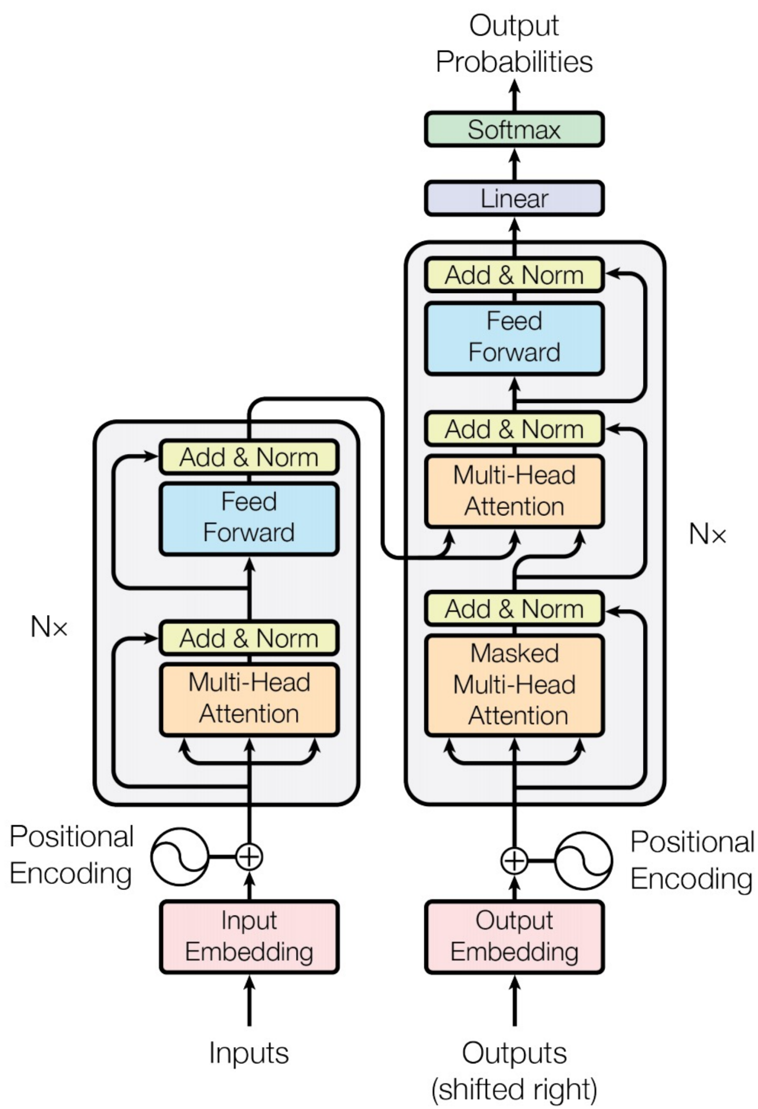
Deep Learning NLP



Source: http://mattfortier.me/2017/01/31/nlp-intro-pt-1-overview/

Transformer (Attention is All You Need)

(Vaswani et al., 2017)



Source: Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. "Attention is all you need." In *Advances in neural information processing systems*, pp. 5998-6008. 2017.

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

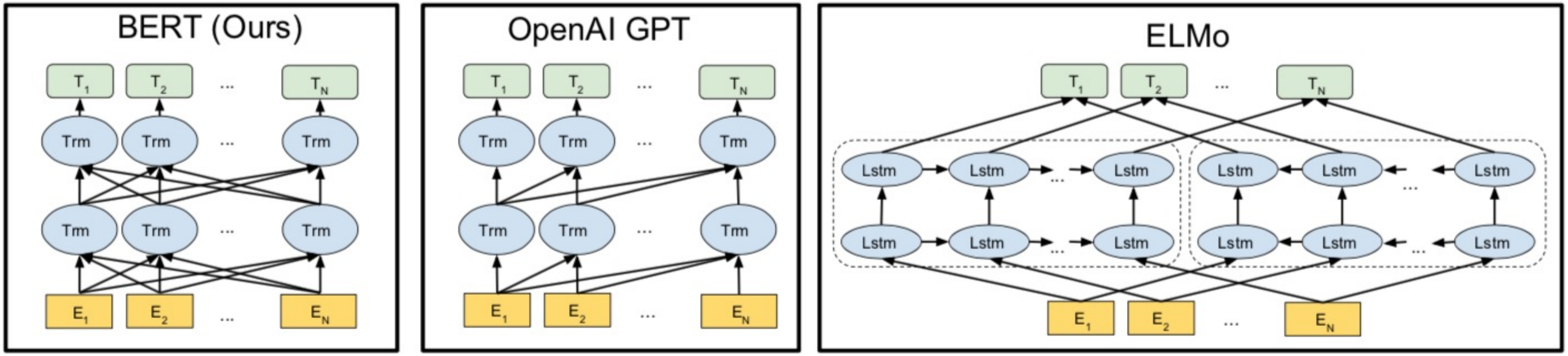
BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Jacob Devlin   Ming-Wei Chang   Kenton Lee   Kristina Toutanova
Google AI Language
{jacobdevlin,mingweichang,kentonl,kristout}@google.com

Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018).
"BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." arXiv preprint arXiv:1810.04805

BERT

Bidirectional Encoder Representations from Transformers



Pre-training model architectures

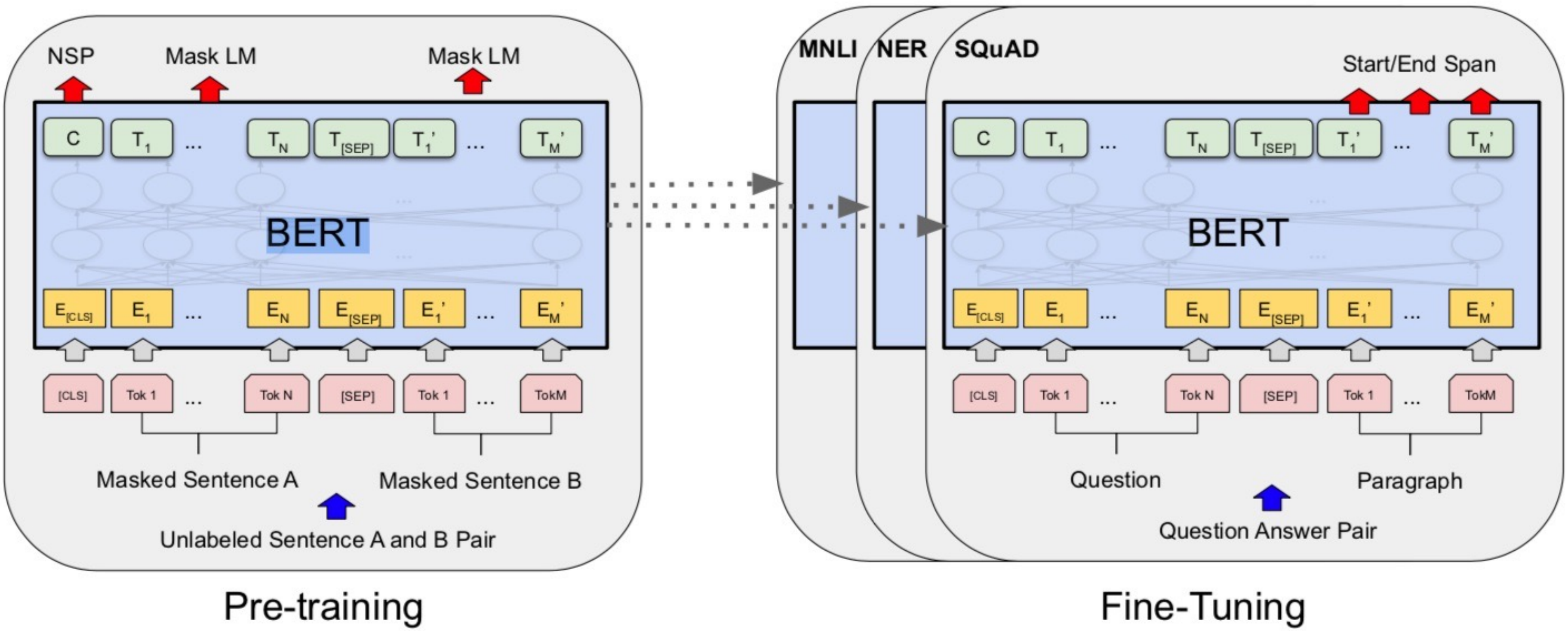
BERT uses a bidirectional Transformer.
OpenAI GPT uses a left-to-right Transformer.
ELMo uses the concatenation of independently trained left-to-right and right- to-left LSTM to generate features for downstream tasks.
Among three, only BERT representations are jointly conditioned on both left and right context in all layers.

Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018). "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." arXiv preprint arXiv:1810.04805

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

BERT (Bidirectional Encoder Representations from Transformers)

Overall pre-training and fine-tuning procedures for BERT

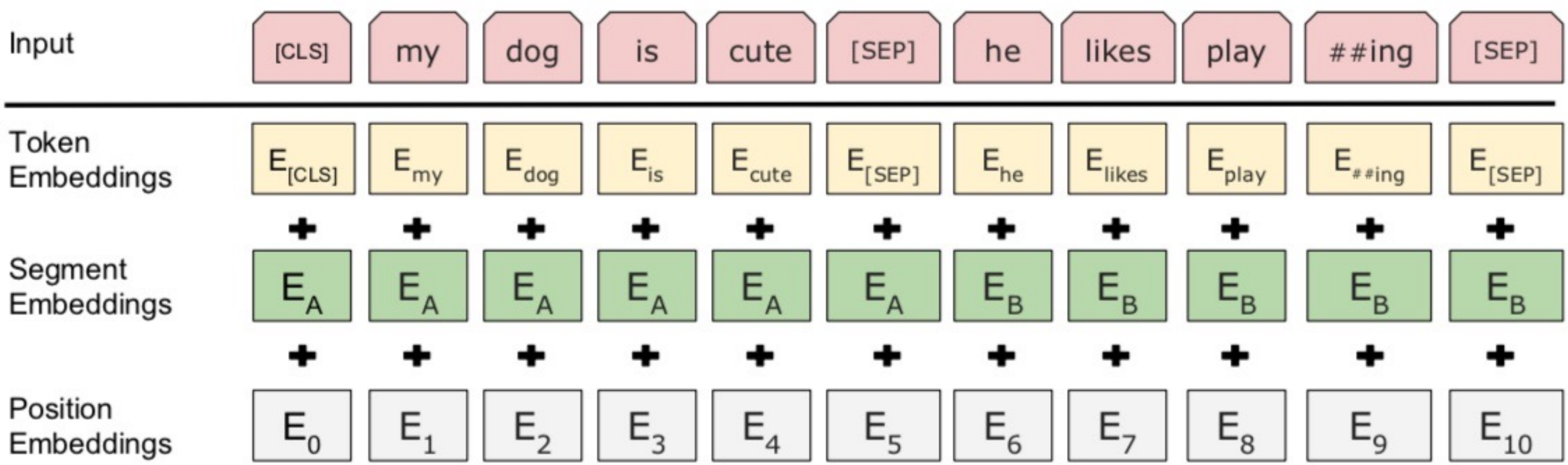


Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018).
"Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

BERT (Bidirectional Encoder Representations from Transformers)

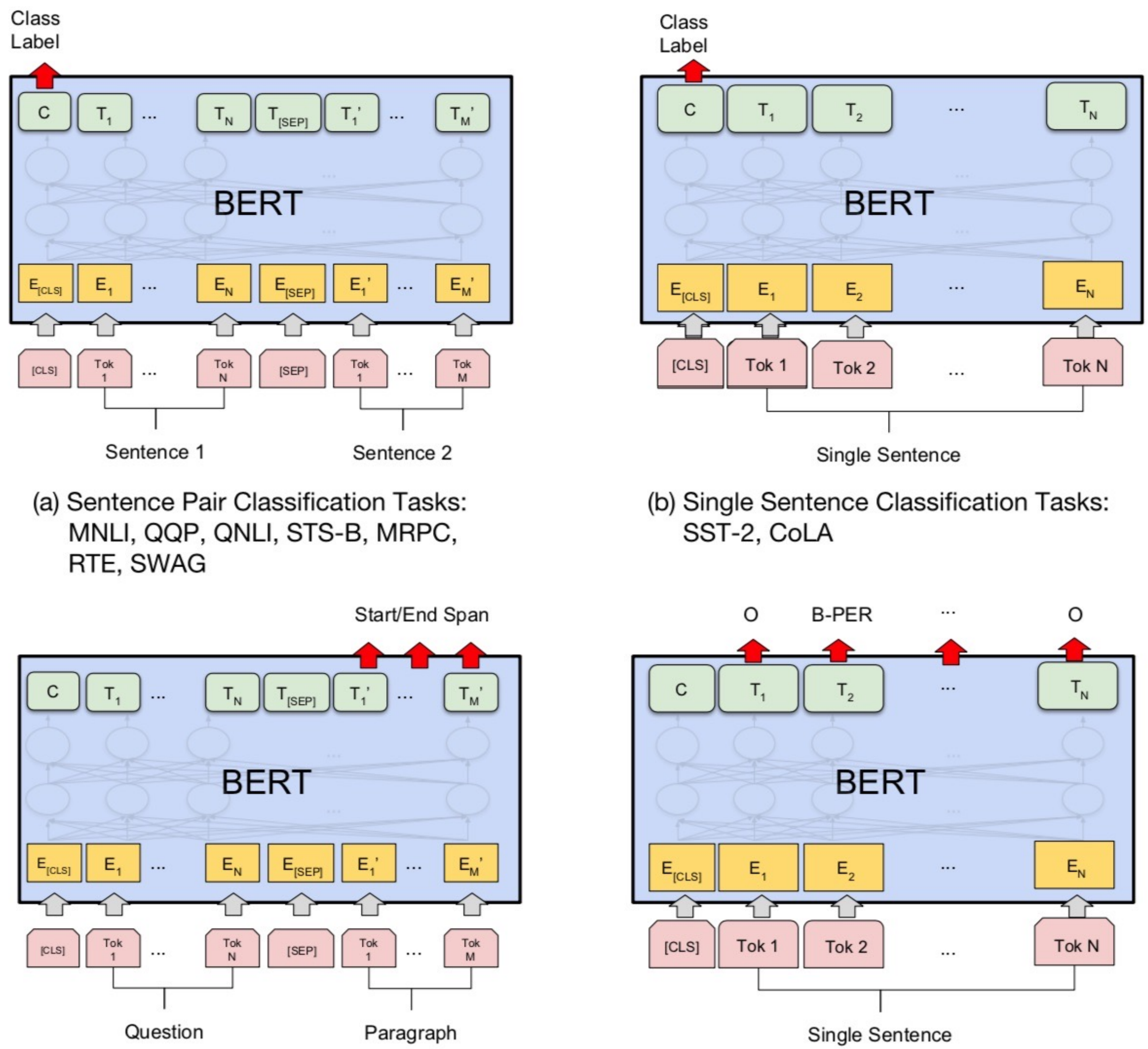
BERT input representation



The input embeddings is the sum of the token embeddings, the segmentation embeddings and the position embeddings.

Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018). "Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

Fine-tuning BERT on Different Tasks



(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

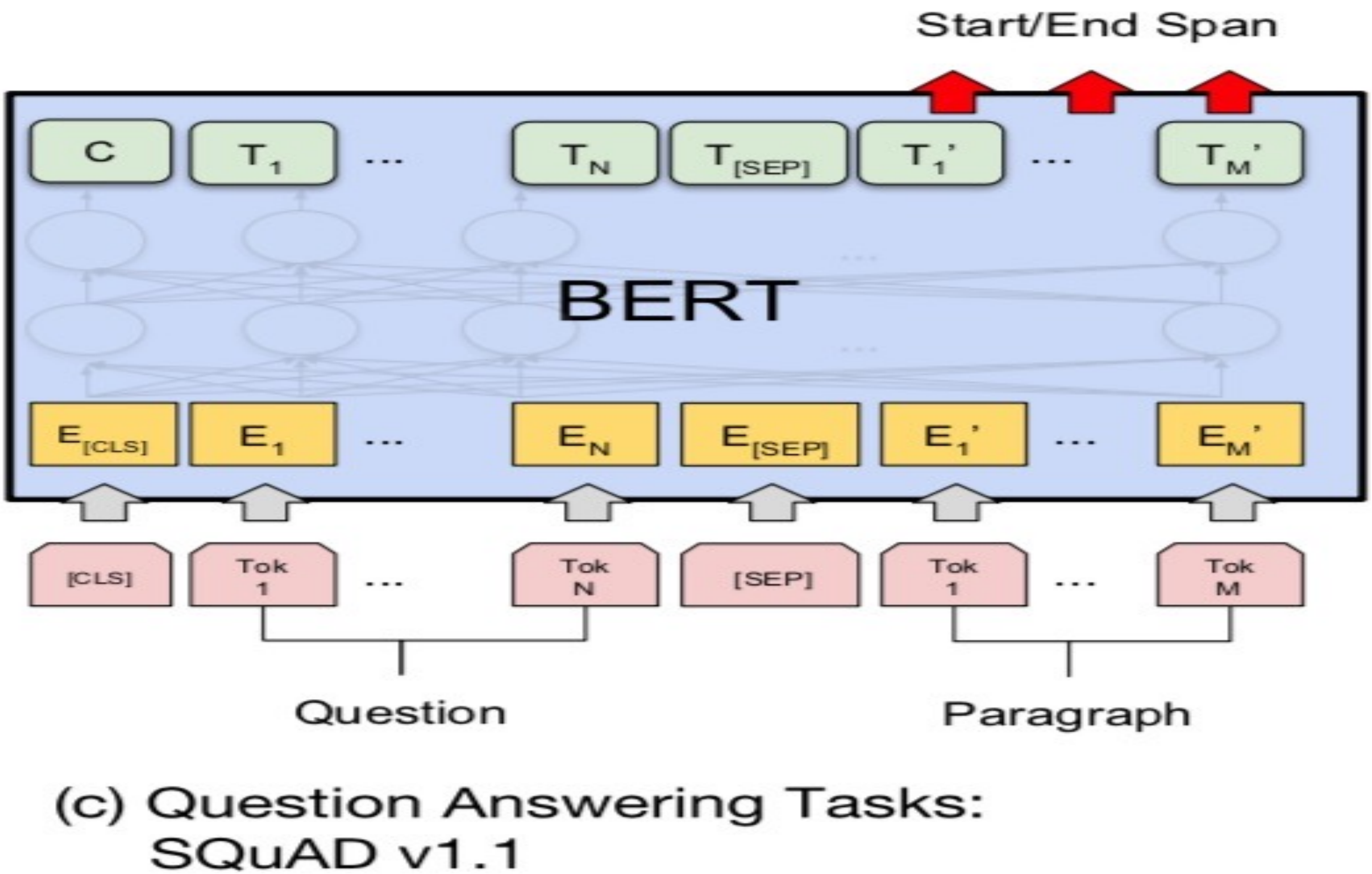
(b) Single Sentence Classification Tasks: SST-2, CoLA

(c) Question Answering Tasks: SQuAD v1.1

(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018). "Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

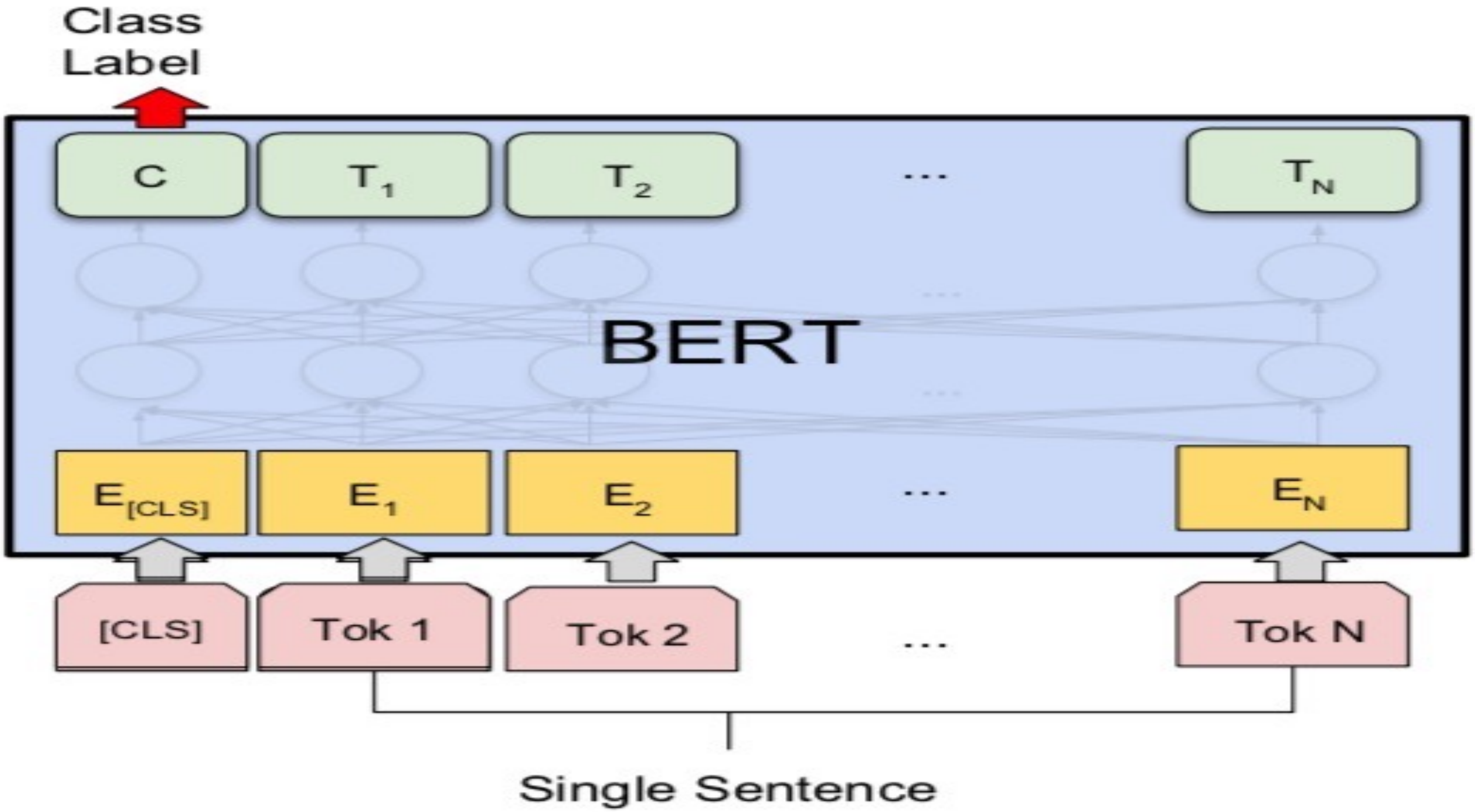
Fine-tuning BERT on Question Answering (QA)



Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018). "Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

Fine-tuning BERT on Dialogue

Intent Detection (ID; Classification)

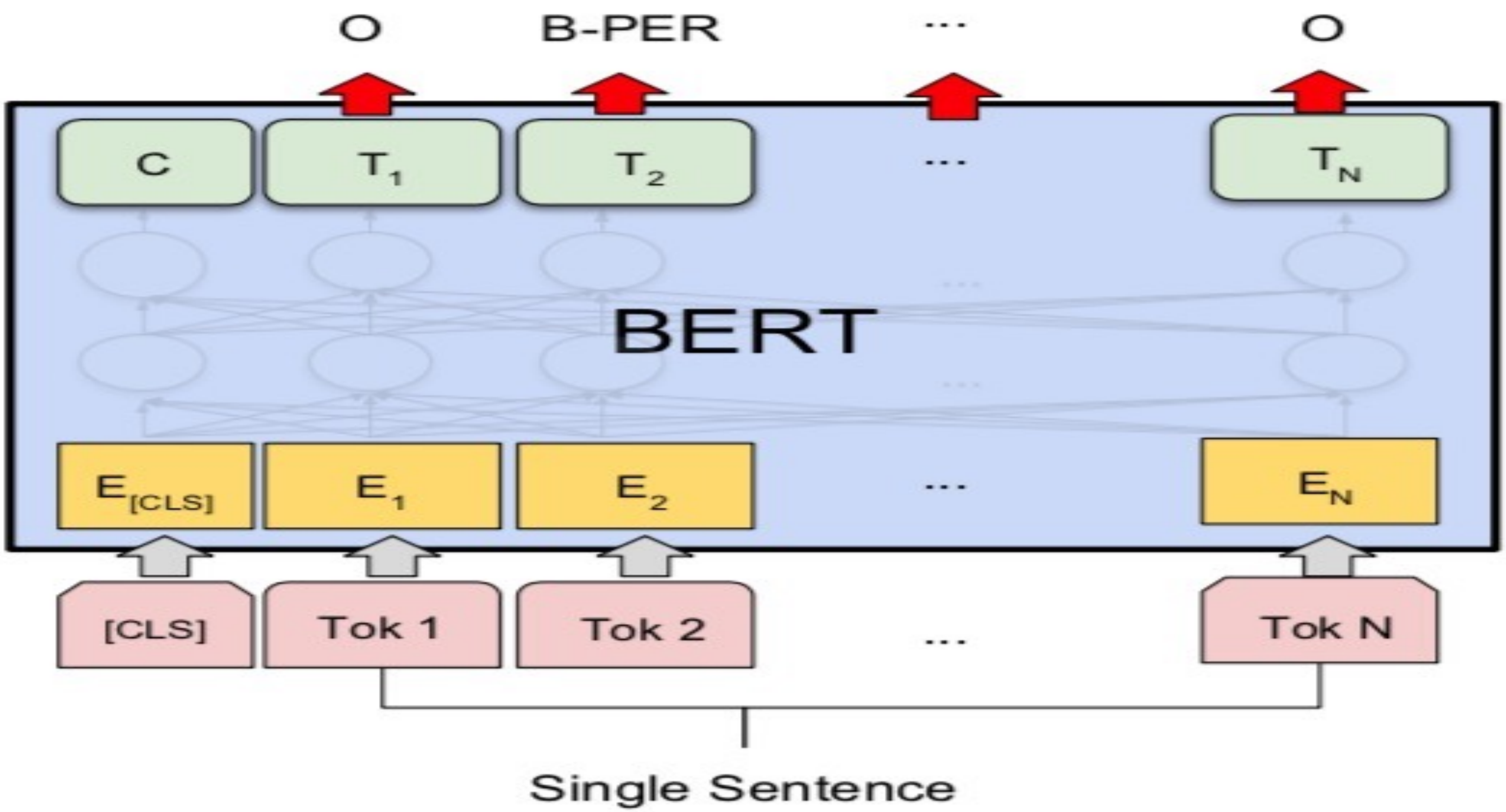


(b) Single Sentence Classification Tasks: SST-2, CoLA

Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018). "Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

Fine-tuning BERT on Dialogue

Slot Filling (SF)



(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018). "Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

General Language Understanding Evaluation (GLUE) benchmark

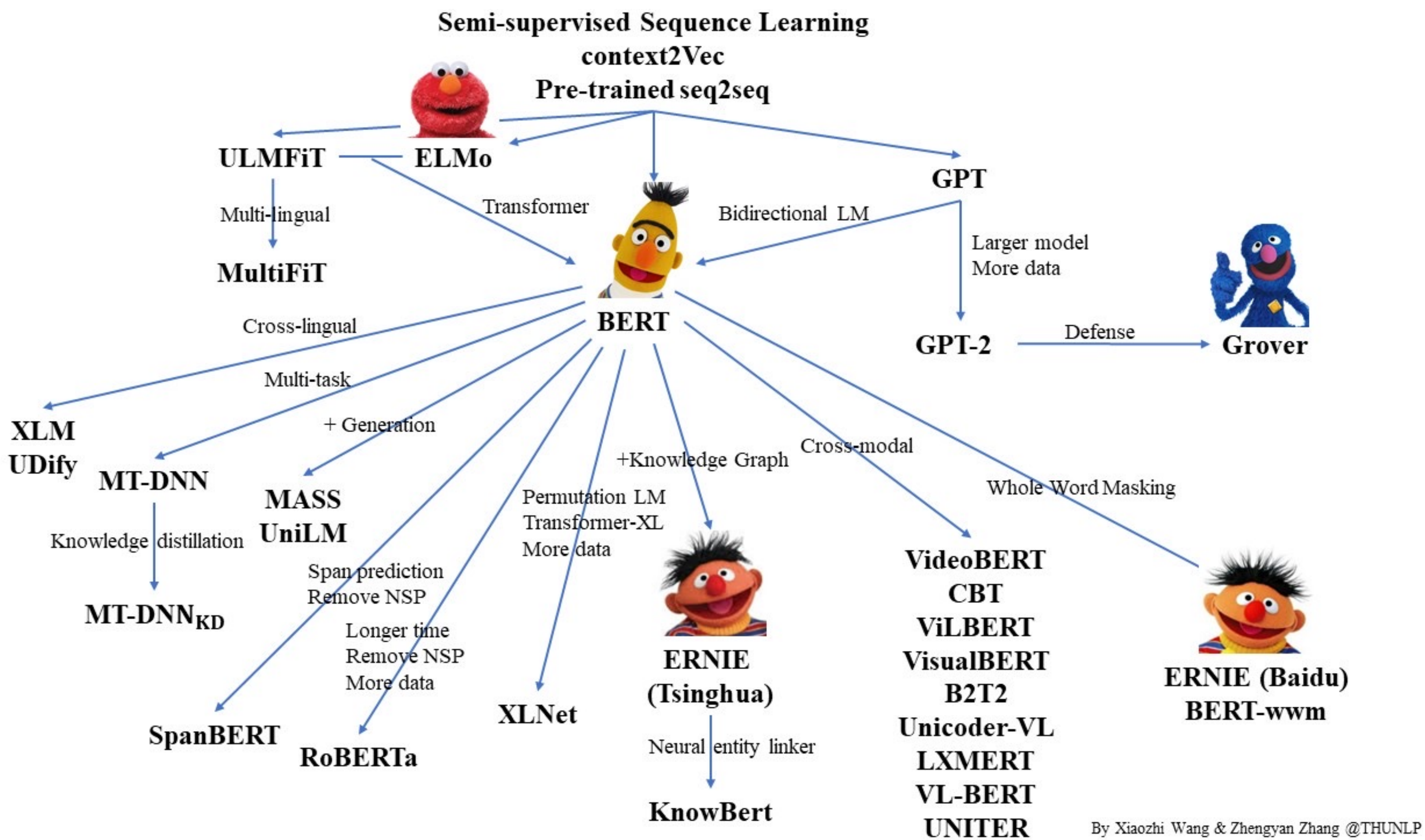
GLUE Test results

System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	**Average**
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.9	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	88.1	91.3	45.4	80.0	82.3	56.0	75.2
$BERT_{BASE}$	84.6/83.4	71.2	90.1	93.5	52.1	85.8	88.9	66.4	79.6
$BERT_{LARGE}$	**86.7/85.9**	**72.1**	**91.1**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**81.9**

MNLI: Multi-Genre Natural Language Inference
QQP: Quora Question Pairs
QNLI: Question Natural Language Inference
SST-2: The Stanford Sentiment Treebank
CoLA: The Corpus of Linguistic Acceptability
STS-B:The Semantic Textual Similarity Benchmark
MRPC: Microsoft Research Paraphrase Corpus
RTE: Recognizing Textual Entailment

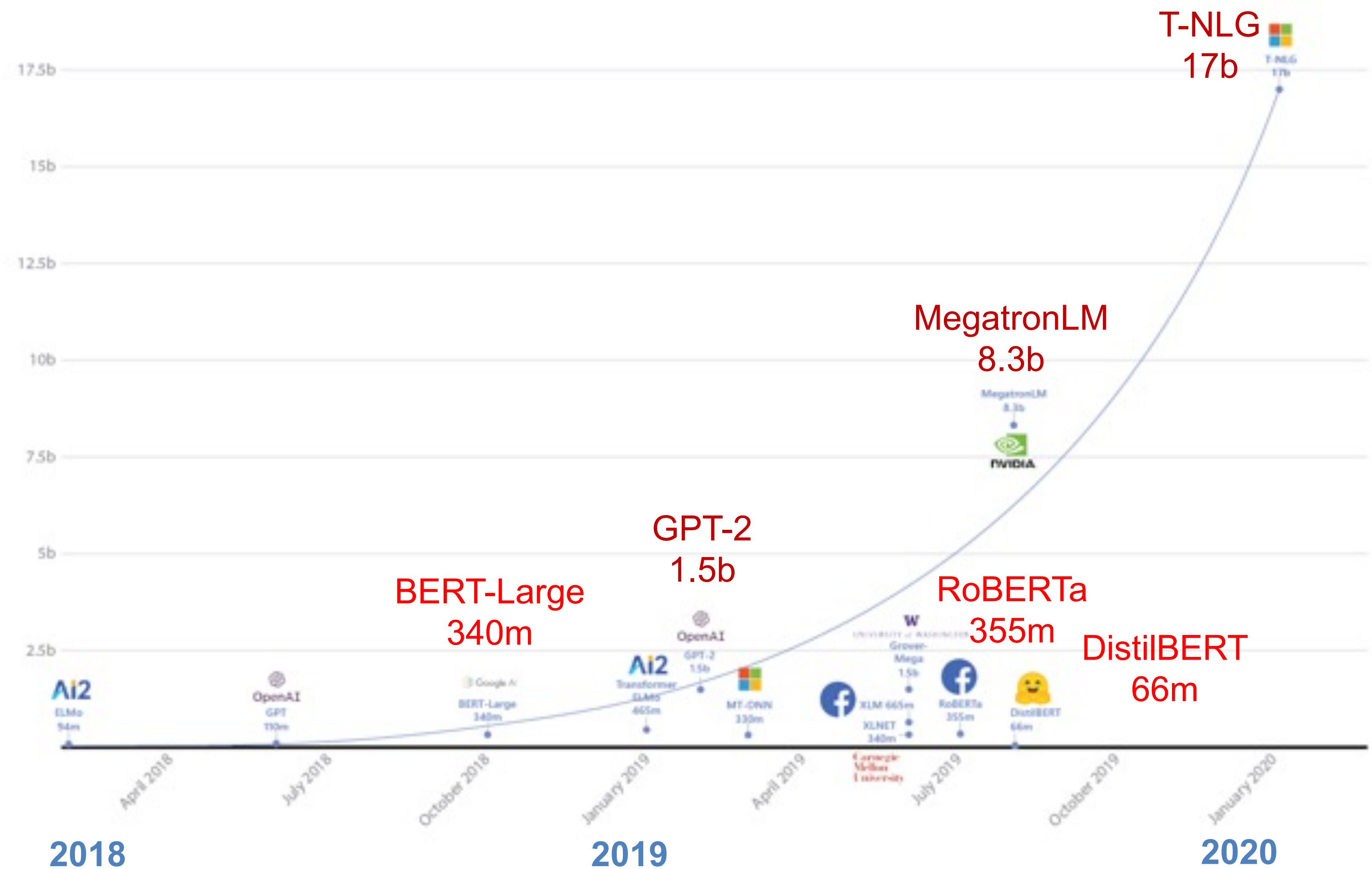
Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018).
"BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." arXiv preprint arXiv:1810.04805

Pre-trained Language Model (PLM)



Source: https://github.com/thunlp/PLMpapers

Turing Natural Language Generation (T-NLG)



Source: https://www.microsoft.com/en-us/research/blog/turing-nlg-a-17-billion-parameter-language-model-by-microsoft/

Transformers

Transformers

State-of-the-art Natural Language Processing for TensorFlow 2.0 and PyTorch

- Transformers
  - pytorch-transformers
  - pytorch-pretrained-bert
- provides state-of-the-art general-purpose architectures
  - (BERT, GPT-2, RoBERTa, XLM, DistilBert, XLNet, CTRL...)
  - for Natural Language Understanding (NLU) and Natural Language Generation (NLG) with over 32+ pretrained models in 100+ languages and deep interoperability between TensorFlow 2.0 and PyTorch.

Source: https://github.com/huggingface/transformers

Question Answering (QA)

SQuAD

Stanford **Qu**estion **A**nswering **D**ataset

SQuAD

SQuAD | Home | Explore 2.0 | Explore 1.1

SQuAD2.0

The Stanford Question Answering Dataset

What is SQuAD?

Stanford **Q**uestion **A**nswering **D**ataset (SQuAD) is a reading comprehension dataset, consisting of questions posed by crowdworkers on a set of Wikipedia articles, where the answer to every question is a segment of text, or *span*, from the corresponding reading passage, or the question might be unanswerable.

SQuAD2.0 combines the 100,000 questions in SQuAD1.1 with over 50,000 unanswerable questions written adversarially by crowdworkers to look similar to answerable ones. To do well on SQuAD2.0, systems must not only answer questions when possible, but also determine when no answer is supported by the paragraph and abstain from answering.

Leaderboard

SQuAD2.0 tests the ability of a system to not only answer reading comprehension questions, but also abstain when presented with a question that cannot be answered based on the provided paragraph.

Rank	Model	EM	F1
	Human Performance *Stanford University* (Rajpurkar & Jia et al. '18)	86.831	89.452
1 Apr 06, 2020	SA-Net on Albert (ensemble) *QIANXIN*	**90.724**	**93.011**
2 May 05, 2020	SA-Net-V2 (ensemble) *QIANXIN*	90.679	92.948
2	Retro-Reader (ensemble)	90.578	92.978

https://rajpurkar.github.io/SQuAD-explorer/

SQuAD

SQuAD: 100,000+ Questions for Machine Comprehension of Text

Pranav Rajpurkar and **Jian Zhang** and **Konstantin Lopyrev** and **Percy Liang**
{pranavsr,zjian,klopyrev,pliang}@cs.stanford.edu
Computer Science Department
Stanford University

Abstract

We present the Stanford Question Answering Dataset (SQuAD), a new reading comprehension dataset consisting of 100,000+ questions posed by crowdworkers on a set of Wikipedia articles, where the answer to each question is a segment of text from the corresponding reading passage. We analyze the dataset to understand the types of reasoning required to answer the questions, leaning heavily on dependency and constituency trees. We build a strong logistic regression model, which achieves an F1 score of 51.0%, a significant improvement over a simple baseline (20%). However, human performance (86.8%) is much higher, indicating that the dataset presents a good challenge problem for future research. The dataset is freely available at https://stanford-qa.com.

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under **gravity**. The main forms of precipitation include drizzle, rain, sleet, snow, **graupel** and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals **within a cloud**. Short, intense periods of rain in scattered locations are called "showers".

What causes precipitation to fall?
gravity

What is another main form of precipitation besides drizzle, rain, snow, sleet and hail?
graupel

Where do water droplets collide with ice crystals to form precipitation?
within a cloud

Figure 1: Question-answer pairs for a sample passage in the

Source: Rajpurkar, Pranav, Jian Zhang, Konstantin Lopyrev, and Percy Liang. "Squad: 100,000+ questions for machine comprehension of text." arXiv preprint arXiv:1606.05250 (2016).

SQuAD (Question Answering)

Q: What causes precipitation to fall?

Precipitation

From Wikipedia, the free encyclopedia

For other uses, see Precipitation (disambiguation).

In meteorology, **precipitation** is any product of the condensation of atmospheric water vapor that falls under gravity from clouds.[2] The main forms of precipitation include drizzle, rain, sleet, snow, ice pellets, graupel and hail. Precipitation occurs when a portion of the atmosphere becomes saturated with water vapor (reaching 100% relative humidity), so that the water condenses and "precipitates". Thus, fog and mist are not precipitation but suspensions, because the water vapor does not condense sufficiently to precipitate. Two processes, possibly acting together, can lead to air becoming saturated: cooling the air or adding water vapor to the air. Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals within a cloud. Short, intense periods of rain in scattered locations are called "showers."[3]

https://en.wikipedia.org/wiki/Precipitation

SQuAD (Question Answering)

Paragraph

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under gravity. The main forms of precipitation include drizzle, rain, sleet, snow, graupel and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals within a cloud. Short, intense periods of rain in scattered locations are called “showers”.

Q: What causes precipitation to fall?

SQuAD (Question Answering)

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under gravity. The main forms of precipitation include drizzle, rain, sleet, snow, graupel and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals within a cloud. Short, intense periods of rain in scattered locations are called “showers”.

Q: What causes precipitation to fall?

A: gravity

SQuAD (Question Answering)

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under gravity. The main forms of precipitation include drizzle, rain, sleet, snow, graupel and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals within a cloud. Short, intense periods of rain in scattered locations are called “showers”.

Q: What is another main form of precipitation besides drizzle, rain, snow, sleet and hail?

A: graupel

SQuAD (Question Answering)

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under gravity. The main forms of precipitation include drizzle, rain, sleet, snow, graupel and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals within a cloud. Short, intense periods of rain in scattered locations are called “showers”.

Q: Where do water droplets collide with ice crystals to form precipitation?

A: within a cloud

SQuAD (Question Answering)

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under gravity. The main forms of precipitation include drizzle, rain, sleet, snow, graupel and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals within a cloud. Short, intense periods of rain in scattered locations are called “showers”.

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A: gravity

Q: What is another main form of precipitation besides drizzle, rain, snow, sleet and hail?

A: graupel

Q: Where do water droplets collide with ice crystals to form precipitation?

A: within a cloud

Natural Language Processing with Python
– Analyzing Text with the Natural Language Toolkit

www.nltk.org/book/

Natural Language Processing with Python

NLTK

– Analyzing Text with the Natural Language Toolkit

Steven Bird, Ewan Klein, and Edward Loper

This version of the NLTK book is updated for Python 3 and NLTK 3. The first edition of the book, published by O'Reilly, is available at http://nltk.org/book_1ed/. (There are currently no plans for a second edition of the book.)

Please post any questions about the materials to the nltk-users mailing list. Please report any errors on the issue tracker.

http://www.nltk.org/book/

spaCy

https://spacy.io/

gensim

https://radimrehurek.com/gensim/

TextBlob

TextBlob

Star 3,777

TextBlob is a Python (2 and 3) library for processing textual data. It provides a consistent API for diving into common natural language processing (NLP) tasks such as part-of-speech tagging, noun phrase extraction, sentiment analysis, and more.

Useful Links

TextBlob @ PyPI
TextBlob @ GitHub
Issue Tracker

Stay Informed

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If you find TextBlob useful,

TextBlob: Simplified Text Processing

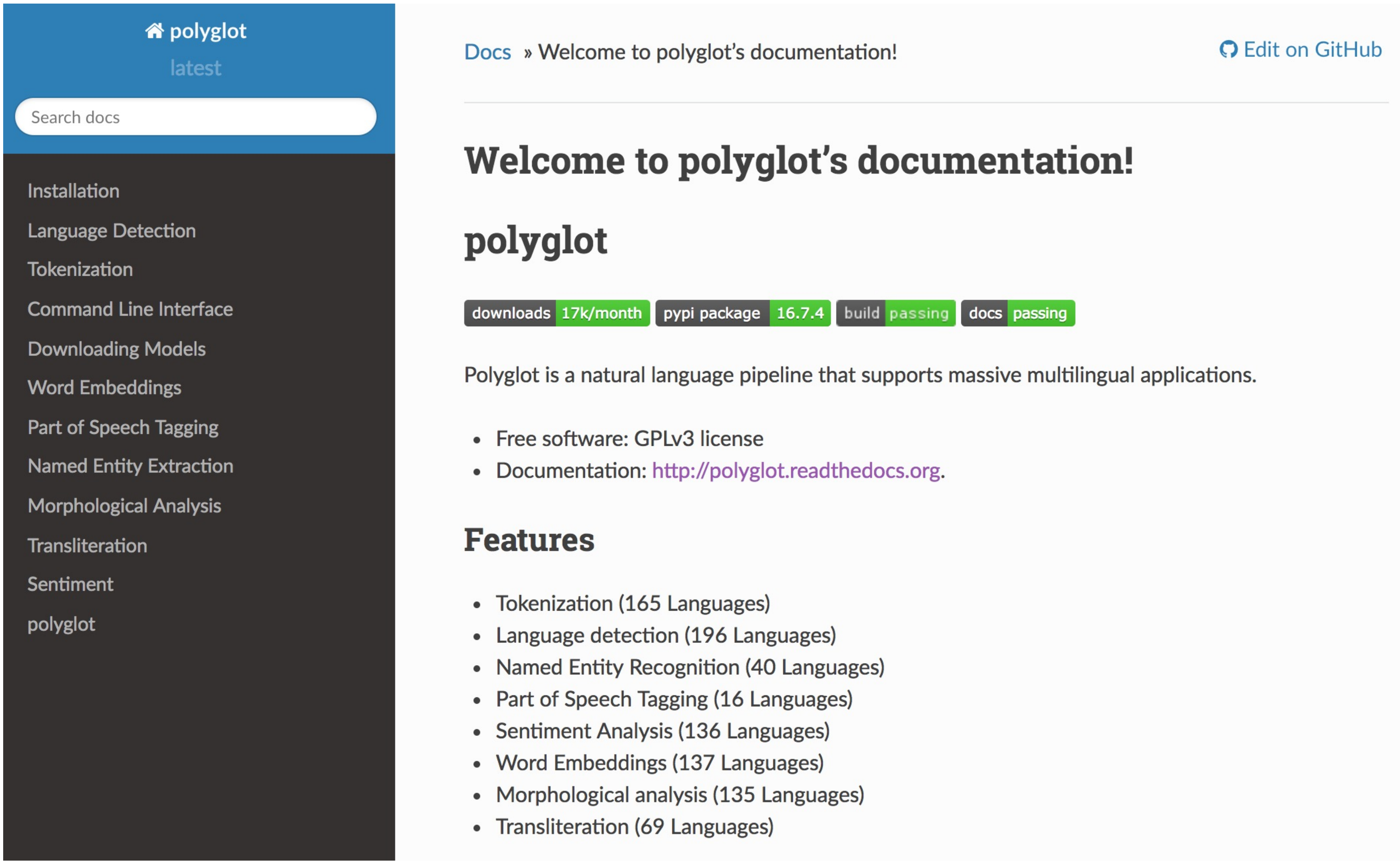
Release v0.12.0. (Changelog)

TextBlob is a Python (2 and 3) library for processing textual data. It provides a simple API for diving into common natural language processing (NLP) tasks such as part-of-speech tagging, noun phrase extraction, sentiment analysis, classification, translation, and more.

```
from textblob import TextBlob

text = '''
The titular threat of The Blob has always struck me as the ultimate movie
monster: an insatiably hungry, amoeba-like mass able to penetrate
virtually any safeguard, capable of--as a doomed doctor chillingly
describes it--"assimilating flesh on contact.
Snide comparisons to gelatin be damned, it's a concept with the most
devastating of potential consequences, not unlike the grey goo scenario
proposed by technological theorists fearful of
artificial intelligence run rampant.
'''

blob = TextBlob(text)
blob.tags           # [('The', 'DT'), ('titular', 'JJ'),
                    #  ('threat', 'NN'), ('of', 'IN'), ...]

blob.noun_phrases   # WordList(['titular threat', 'blob',
                    #             'ultimate movie monster',
                    #             'amoeba-like mass', ...])

for sentence in blob.sentences:
    print(sentence.sentiment.polarity)
# 0.060
```

https://textblob.readthedocs.io

Polyglot



polyglot
latest
Search docs

- Installation
- Language Detection
- Tokenization
- Command Line Interface
- Downloading Models
- Word Embeddings
- Part of Speech Tagging
- Named Entity Extraction
- Morphological Analysis
- Transliteration
- Sentiment
- polyglot

Docs » Welcome to polyglot's documentation!

Edit on GitHub

Welcome to polyglot's documentation!

polyglot

downloads 17k/month | pypi package 16.7.4 | build passing | docs passing

Polyglot is a natural language pipeline that supports massive multilingual applications.

- Free software: GPLv3 license
- Documentation: http://polyglot.readthedocs.org.

Features

- Tokenization (165 Languages)
- Language detection (196 Languages)
- Named Entity Recognition (40 Languages)
- Part of Speech Tagging (16 Languages)
- Sentiment Analysis (136 Languages)
- Word Embeddings (137 Languages)
- Morphological analysis (135 Languages)
- Transliteration (69 Languages)

https://polyglot.readthedocs.io/

TensorFlow

Text Classification with TF Hub

TensorFlow | Install | Learn | API | Resources | More | Search | Language | GitHub | Sign in

Overview | Tutorials | Guide | TF 1

TensorFlow > Learn > TensorFlow Core > Tutorials

Text classification with TensorFlow Hub: Movie reviews

Run in Google Colab | View source on GitHub | Download notebook

Contents

This notebook classifies movie reviews as *positive* or *negative* using the text of the review. This is an example of *binary*—or two-class—classification, an important and widely applicable kind of machine learning problem.

The tutorial demonstrates the basic application of transfer learning with TensorFlow Hub and Keras.

We'll use the IMDB dataset that contains the text of 50,000 movie reviews from the Internet Movie Database. These are split into 25,000 reviews for training and 25,000 reviews for testing. The training and testing sets are *balanced*, meaning they contain an equal number of positive and negative reviews.

This notebook uses tf.keras, a high-level API to build and train models in TensorFlow, and TensorFlow Hub, a library and platform for transfer learning. For a more advanced text classification tutorial using `tf.keras`, see the MLCC Text Classification Guide.

```
from __future__ import absolute_import, division, print_function, unicode_literals
```

https://www.tensorflow.org/tutorials/keras/text_classification_with_hub

TensorFlow

Text Classification with Pre Text

TensorFlow | Install | Learn | API | Resources | More | Search | Language | GitHub | Sign in

TensorFlow tutorials
Quickstart for beginners
Quickstart for experts

BEGINNER

ML basics with Keras
- Basic image classification
- Text classification with TF Hub
- Text classification with preprocessed text
- Regression
- Overfit and underfit
- Save and load

Load and preprocess data
- CSV
- NumPy
- pandas.DataFrame
- Images
- Text
- Unicode
- TF.Text
- TFRecord and tf.Example
- Additional formats with tf.io

Estimator

TensorFlow > Learn > TensorFlow Core > Tutorials

Text classification with preprocessed text: Movie reviews

Run in Google Colab | View source on GitHub | Download notebook

This notebook classifies movie reviews as *positive* or *negative* using the text of the review. This is an example of *binary*—or two-class—classification, an important and widely applicable kind of machine learning problem.

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Setup

```
from __future__ import absolute_import, division, print_function, unicode_literals
```

Contents
- Setup
- Download the IMDB dataset
- Try the encoder
- Explore the data
- Prepare the data for training
- Build the model
  - Hidden units
  - Loss function and optimizer
- Train the model
- Evaluate the model
- Create a graph of accuracy and loss over time

https://www.tensorflow.org/tutorials/keras/text_classification

Text Classification
IMDB Movie Reviews

https://colab.research.google.com/drive/1x16h1GhHsLIrLYtPCvCHaoO1W-i_gror

tf02_basic-text-classification.ipynb

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↳ *2 cells hidden*

Text classification with movie reviews

View on TensorFlow.org | Run in Google Colab | View source on GitHub

This notebook classifies movie reviews as *positive* or *negative* using the text of the review. This is an example of *binary*—or two-class—classification, an important and widely applicable kind of machine learning problem.

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This notebook uses tf.keras, a high-level API to build and train models in TensorFlow. For a more advanced text classification tutorial using `tf.keras`, see the MLCC Text Classification Guide.

```
# memory footprint support libraries/code
!ln -sf /opt/bin/nvidia-smi /usr/bin/nvidia-smi
!pip install gputil
!pip install psutil
!pip install humanize
import psutil
import humanize
import os
import GPUtil as GPU
GPUs = GPU.getGPUs()
gpu = GPUs[0]
def printm():
```

Source: https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/keras/basic_text_classification.ipynb

Basic Regression
Predict House Prices

https://colab.research.google.com/drive/1v4c8ZHTnRtgd2_25K_AURjR6SCVBRdlj

CO tf03_basic-regression.ipynb ☆

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Predict house prices: regression

The Boston Housing Prices dataset

Examples and features

Labels

Normalize features

Create the model

Train the model

Predict

Conclusion

SECTION

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↳ *2 cells hidden*

Predict house prices: regression

View on TensorFlow.org Run in Google Colab View source on GitHub

In a *regression* problem, we aim to predict the output of a continuous value, like a price or a probability. Contrast this with a *classification* problem, where we aim to predict a discrete label (for example, where a picture contains an apple or an orange).

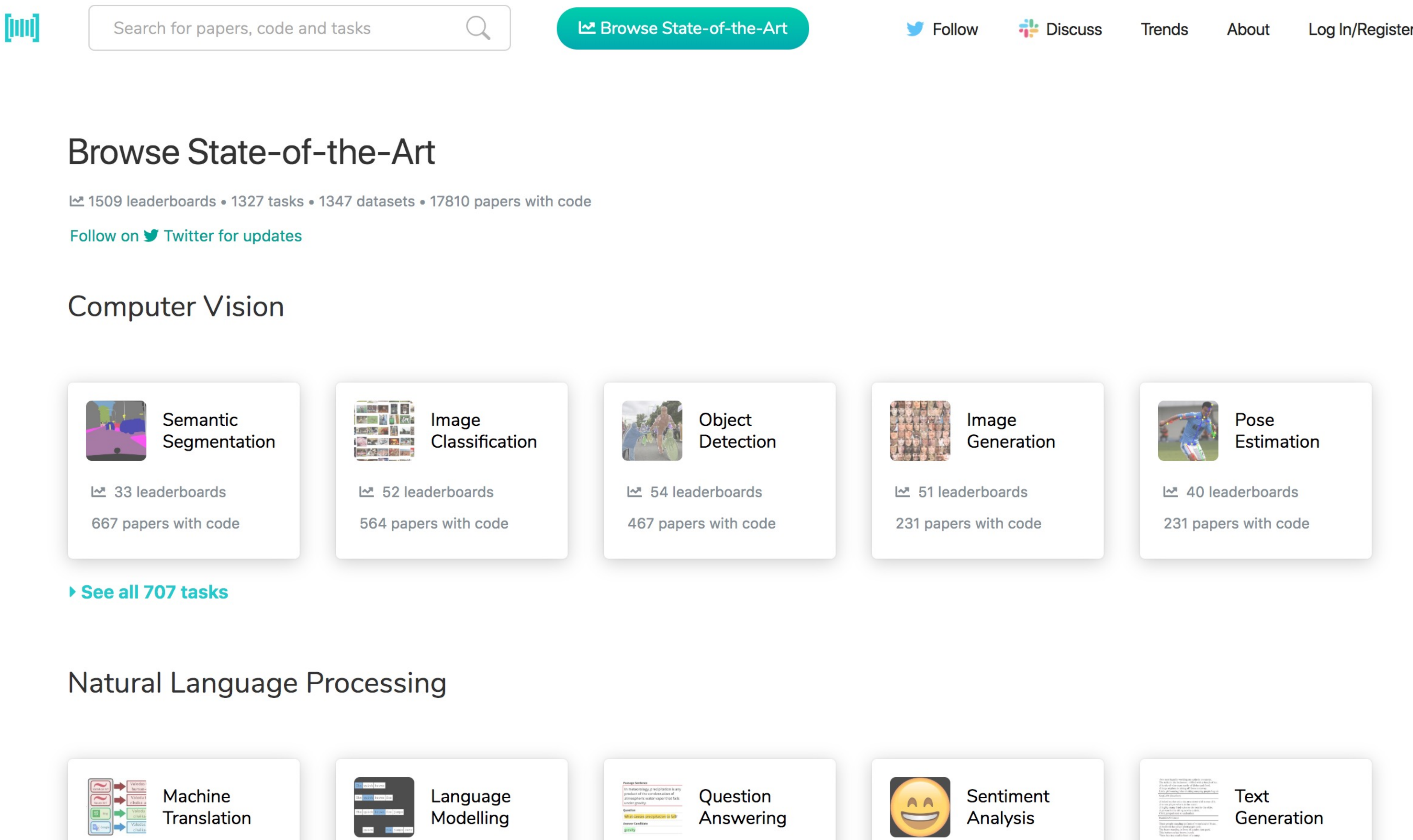
This notebook builds a model to predict the median price of homes in a Boston suburb during the mid-1970s. To do this, we'll provide the model with some data points about the suburb, such as the crime rate and the local property tax rate.

This example uses the `tf.keras` API, see this guide for details.

```
# memory footprint support libraries/code
!ln -sf /opt/bin/nvidia-smi /usr/bin/nvidia-smi
!pip install gputil
!pip install psutil
!pip install humanize
import psutil
import humanize
import os
import GPUtil as GPU
GPUs = GPU.getGPUs()
gpu = GPUs[0]
def printm():
    process = psutil.Process(os.getpid())
    print("Gen RAM Free: " + humanize.naturalsize( psutil.virtual_memory().available ), " | Proc size: "
    print("GPU RAM Free: {0:.0f}MB | Used: {1:.0f}MB | Util {2:3.0f}% | Total {3:.0f}MB".format(gpu.memo
```

Source: https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/keras/basic_regression.ipynb

Papers with Code
State-of-the-Art (SOTA)

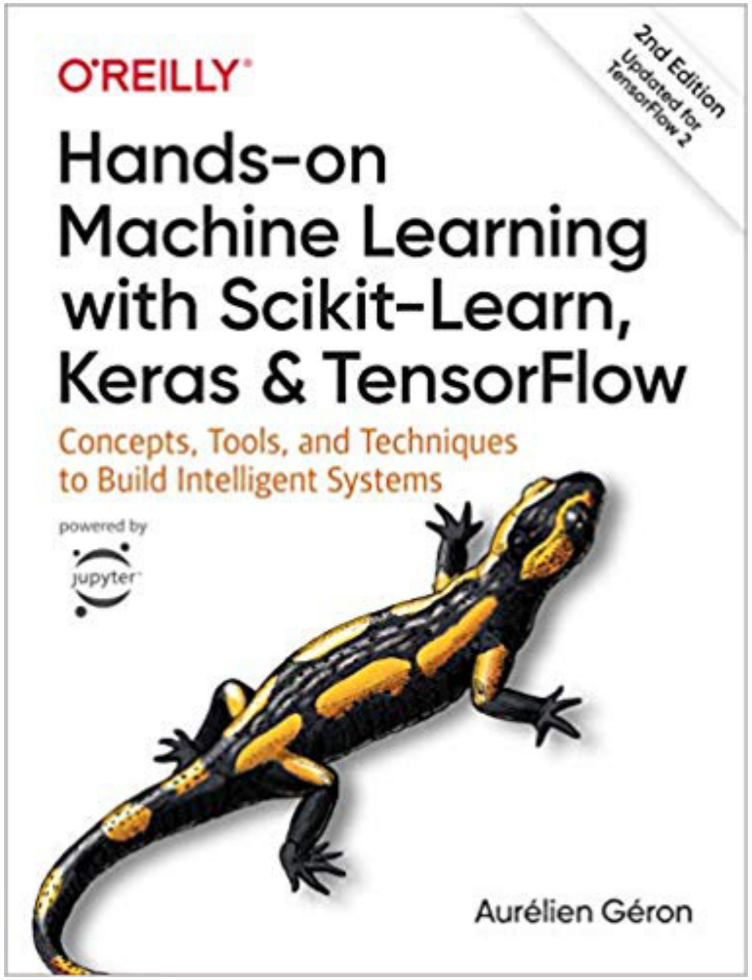


https://paperswithcode.com/sota

Aurélien Géron (2019),

Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems, 2nd Edition

O'Reilly Media, 2019



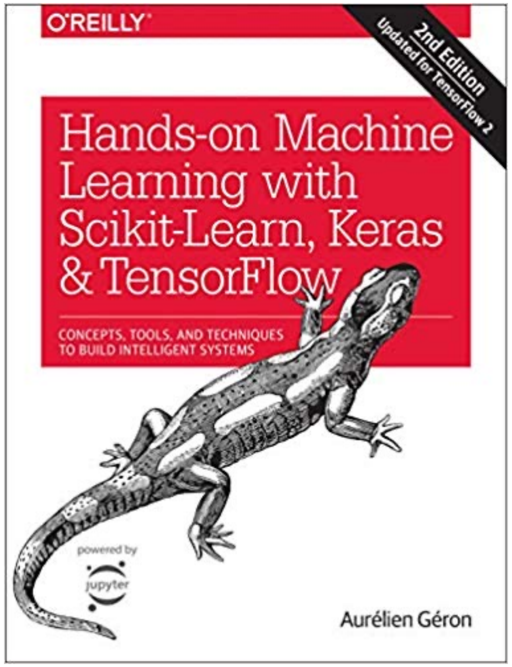
https://github.com/ageron/handson-ml2

Source: https://www.amazon.com/Hands-Machine-Learning-Scikit-Learn-TensorFlow/dp/1492032646/

Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow

Notebooks

1. The Machine Learning landscape
2. End-to-end Machine Learning project
3. Classification
4. Training Models
5. Support Vector Machines
6. Decision Trees
7. Ensemble Learning and Random Forests
8. Dimensionality Reduction
9. Unsupervised Learning Techniques
10. Artificial Neural Nets with Keras
11. Training Deep Neural Networks
12. Custom Models and Training with TensorFlow
13. Loading and Preprocessing Data
14. Deep Computer Vision Using Convolutional Neural Networks
15. Processing Sequences Using RNNs and CNNs
16. Natural Language Processing with RNNs and Attention
17. Representation Learning Using Autoencoders
18. Reinforcement Learning
19. Training and Deploying TensorFlow Models at Scale



https://github.com/ageron/handson-ml2

Python in Google Colab (Python101)

https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT

python101.ipynb

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Table of contents

Text Classification: IMDB Movie Review

- Source: https://www.tensorflow.org/tutorials/keras/text_classification_with_hub

[1]
```
!pip install -q tensorflow-hub
!pip install -q tensorflow-datasets
```

[2]
```
import os
import numpy as np

import tensorflow as tf
import tensorflow_hub as hub
import tensorflow_datasets as tfds

print("Version: ", tf.__version__)
print("Eager mode: ", tf.executing_eagerly())
print("Hub version: ", hub.__version__)
print("GPU is", "available" if tf.config.list_physical_devices("GPU") else "NOT AVAILABLE")
```

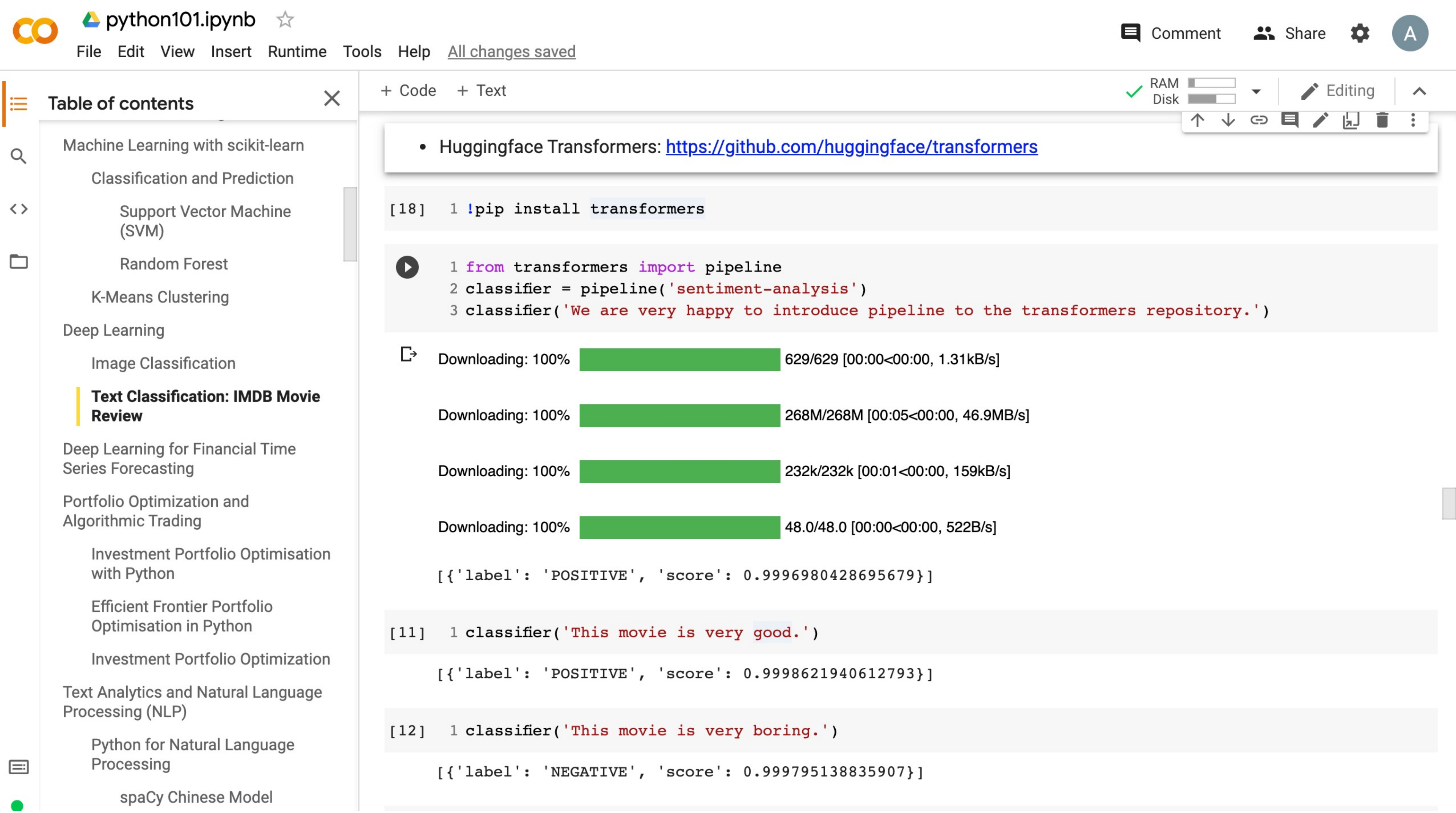
```
Version:  2.4.1
Eager mode:  True
Hub version:  0.12.0
GPU is available
```

[3]
```
# Split the training set into 60% and 40% to end up with 15,000 examples
# for training, 10,000 examples for validation and 25,000 examples for testing.
train_data, validation_data, test_data = tfds.load(
    name="imdb_reviews",
```

https://tinyurl.com/aintpupython101

Python in Google Colab (Python101)

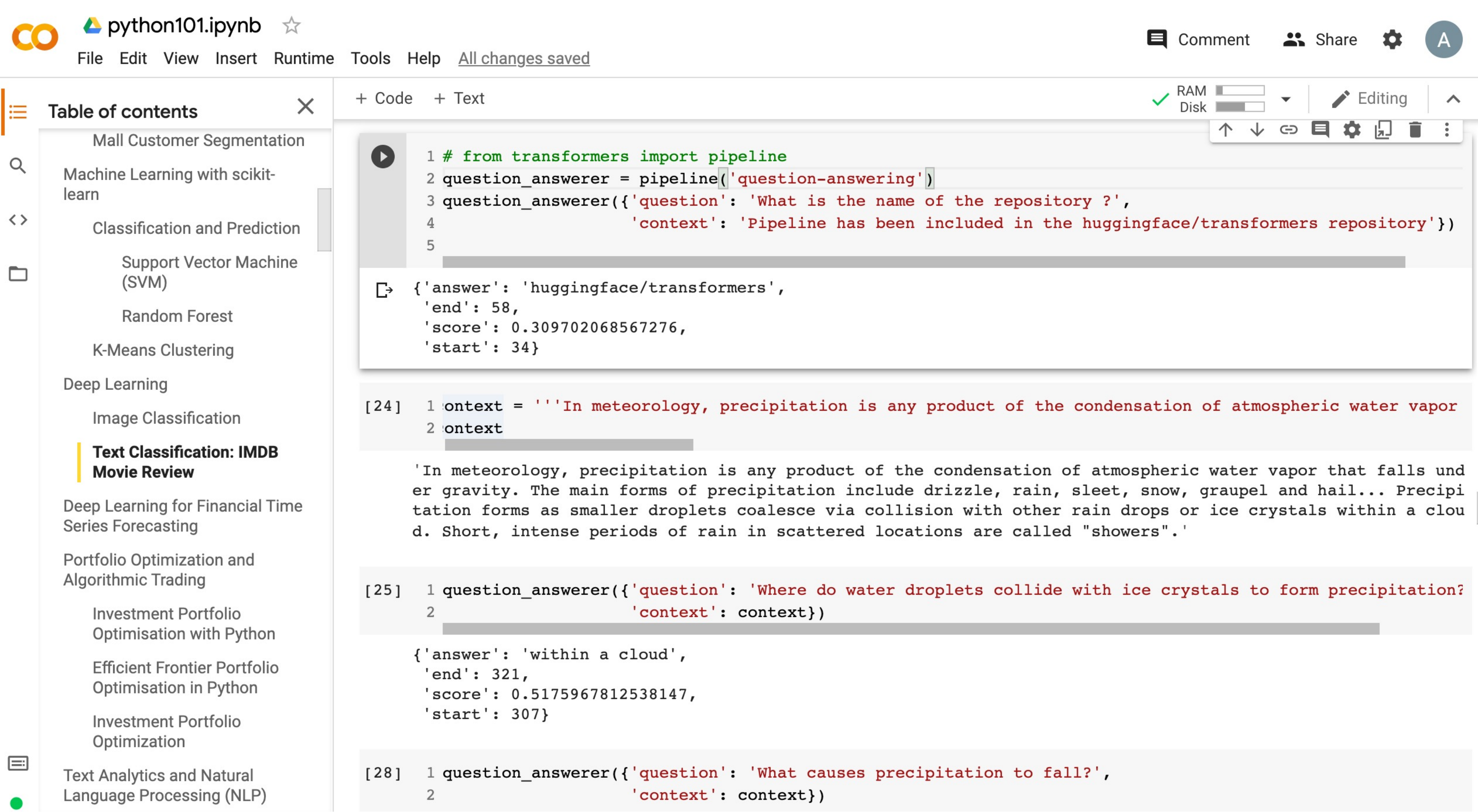
https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT



https://tinyurl.com/aintpupython101

Python in Google Colab (Python101)

https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT



https://tinyurl.com/aintpupython101

Summary

- Recurrent Neural Networks (RNN)
  - Long Short Term Memory (LSTM)
  - Gated Recurrent Unit (GRU)
- Deep Learning (RNN) for Time Series Prediction
- Deep Learning (RNN) for Text Analytics (NLP)

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