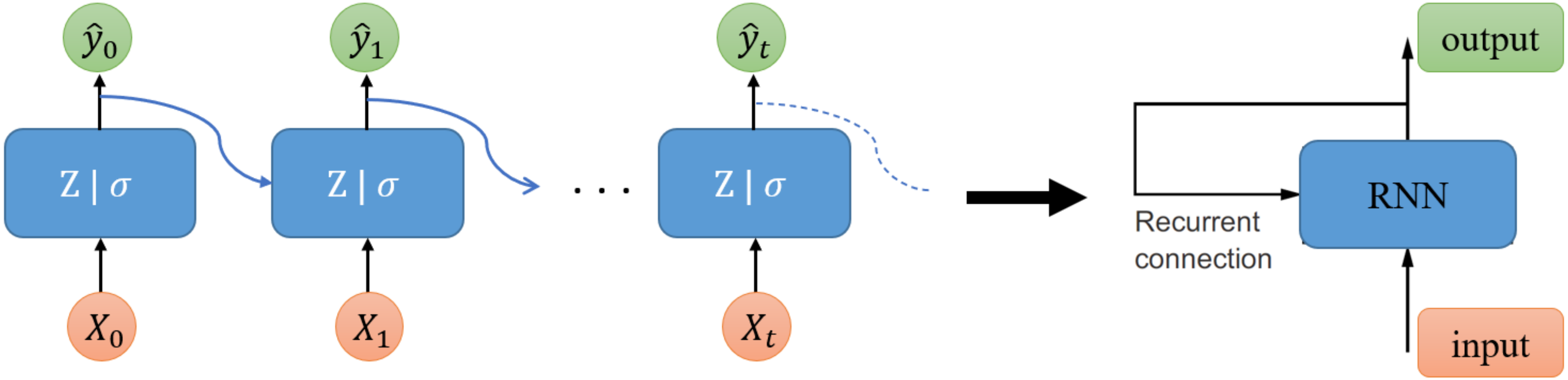
Module 7 – Part I

Deep Sequence Modeling

Recurrent Neural Networks (RNN)



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Road map!

- Module 1- Introduction to Deep Forecasting
- Module 2- Setting up Deep Forecasting Environment
- Module 3- Exponential Smoothing
- Module 4- ARIMA models
- Module 5- Machine Learning for Time series Forecasting
- Module 6- Deep Neural Networks
- **Module 7- Deep Sequence Modeling (RNN, LSTM)**
- Module 8- Transformers (Attention is all you need!)
- Module 9- Prophet and Neural Prophet

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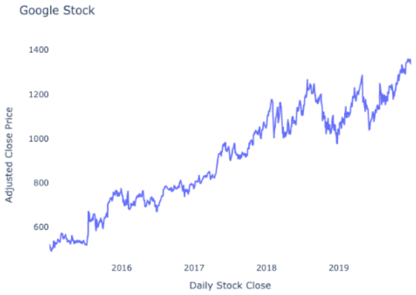
Different kinds of sequence data

Sequence data refers to any data that has a specific order or sequence to it!

- Time series data: sequence of data measured at regular intervals over time. (stock prices, weather patterns, medical records, …)
- Text data: sequence of data that is composed of words, sentences, or paragraphs. (tweets, news articles, product reviews, …)
- Audio data: sequence of data that is recorded or generated as sound waves. (speech recordings, music tracks, …)
- Video data: sequence of data that is represented as a sequence of images or frames. (movie clips, surveillance footage, …)



Different kinds of timeseries tasks

- Forecasting: Predicting what happens next

  Electricity consumption, temperature forecast, stock prediction, …

- Classification: Assign one or more labels to a time series

  Classify website visitors as human or bot based on their activity

- Event detection: Identify the occurrence of a specific expected event within a continuous data stream

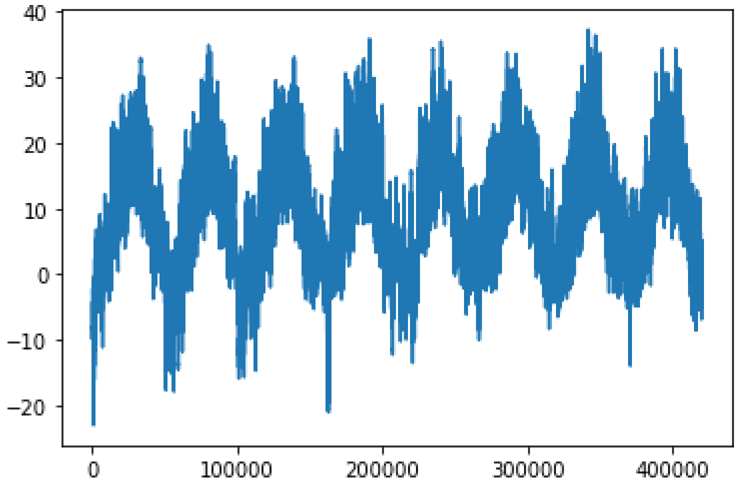
  Hotword detection: “Ok Google” or “Hey Siri”

- Anomaly Detection: Detect anything unusual happening within a continuous data stream

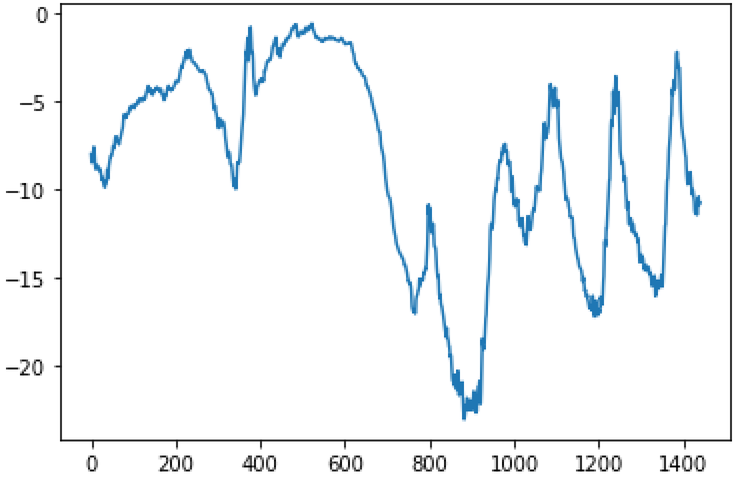
  Unusual activity on a network, …

A simple timeseries example

- A temperature forecasting example: deep-learning-with-python-notebooks
- Predicting the temperature 24 hours in the future
  - Target: temperature
  - Features: 14 different variables including pressure, humidity, wind direction and etc
  - Data recorded every 10 minutes from 2009-2016



Temperature between 2009-2016



Temperature in the first 10 days: 10*24*6 = 1440

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Preparing the data

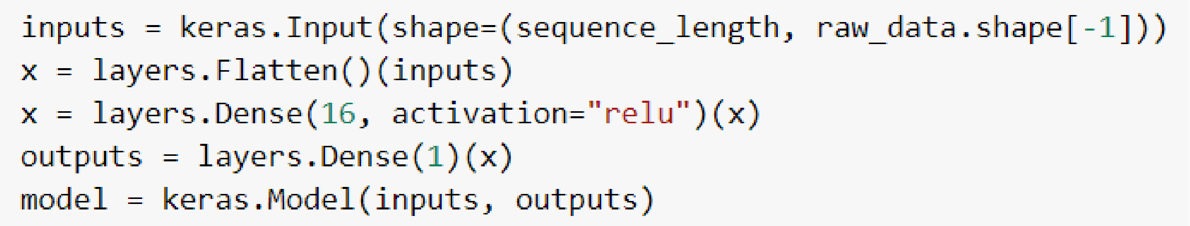
- Given the previous 5 days (120 hours) and samples once per hour, can we predict temperature in 24 hours (after the end of the sequence)?
- Data batches:
  - Sequence length = 120
  - [1,2,3,…,120][144]
  - [2,3,4,…,121][145]
  - [3,4,5,…,122][146]
  - Bath size: 256 of these samples are shuffled and batched
  - Sample shape: (256, 120, 14)
  - Target shape: (256,)

Naïve forecaster: common-sense baseline

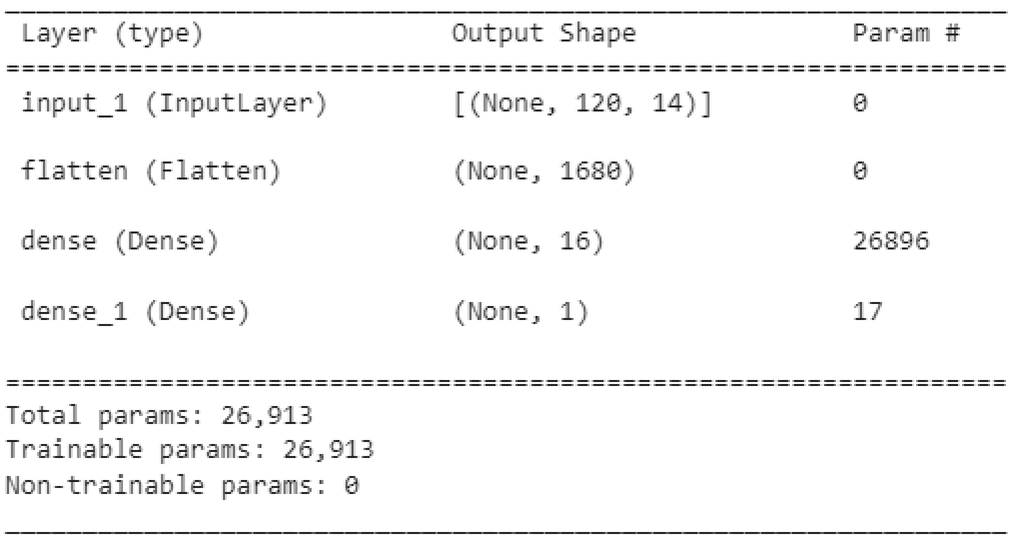
- Temperature 24 hours from now = Temperature right now
- This is our random walk with no drift forecaster.

- Performance:
  - Validation MAE = 2.44 degrees Celsius
  - Test MAE = 2.62 degrees Celsius
  - The baseline model is off by about 2.5 degrees on average. Not bad!!

Let’s try DNN (Deep Neural Networks)



```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.Flatten()(inputs)
x = layers.Dense(16, activation="relu")(x)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)
```



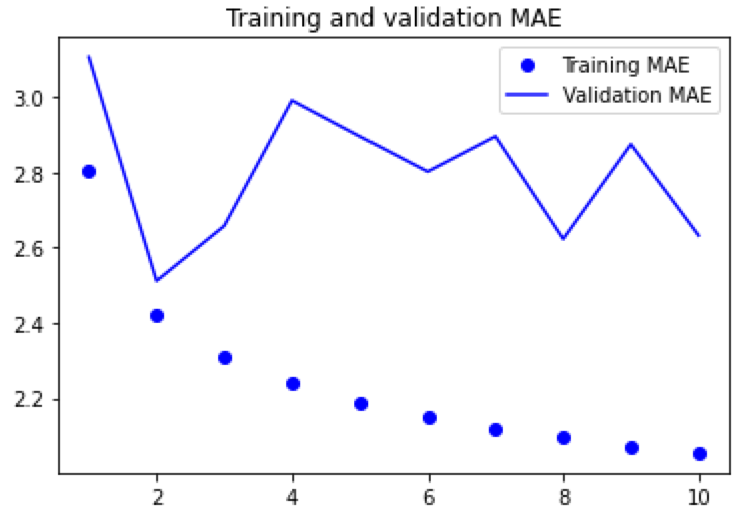
```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 120, 14)]         0

 flatten (Flatten)           (None, 1680)              0

 dense (Dense)               (None, 16)                26896

 dense_1 (Dense)             (None, 1)                 17

=================================================================
Total params: 26,913
Trainable params: 26,913
Non-trainable params: 0
_________________________________________________________________
```



- Test MAE = 2.62 degrees Celsius
- No improvement!!
- Flattening a timeseries data is not a good idea!

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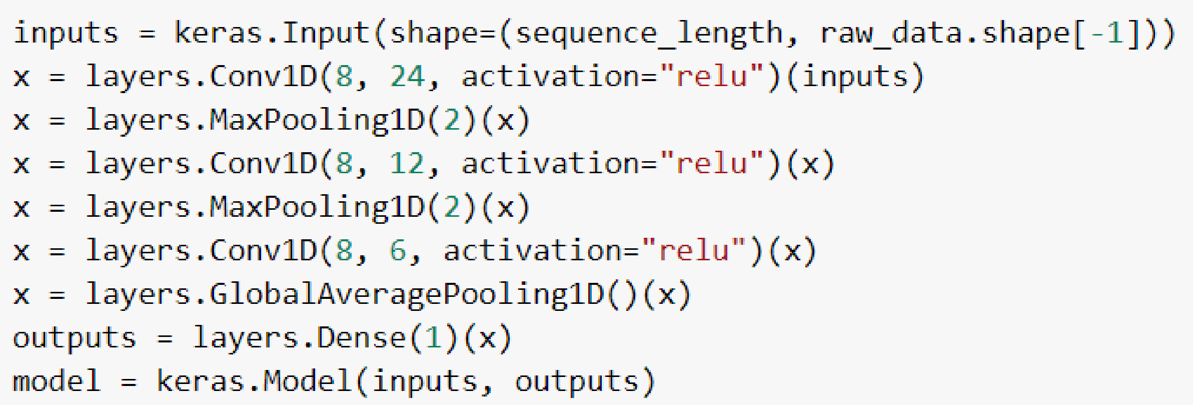
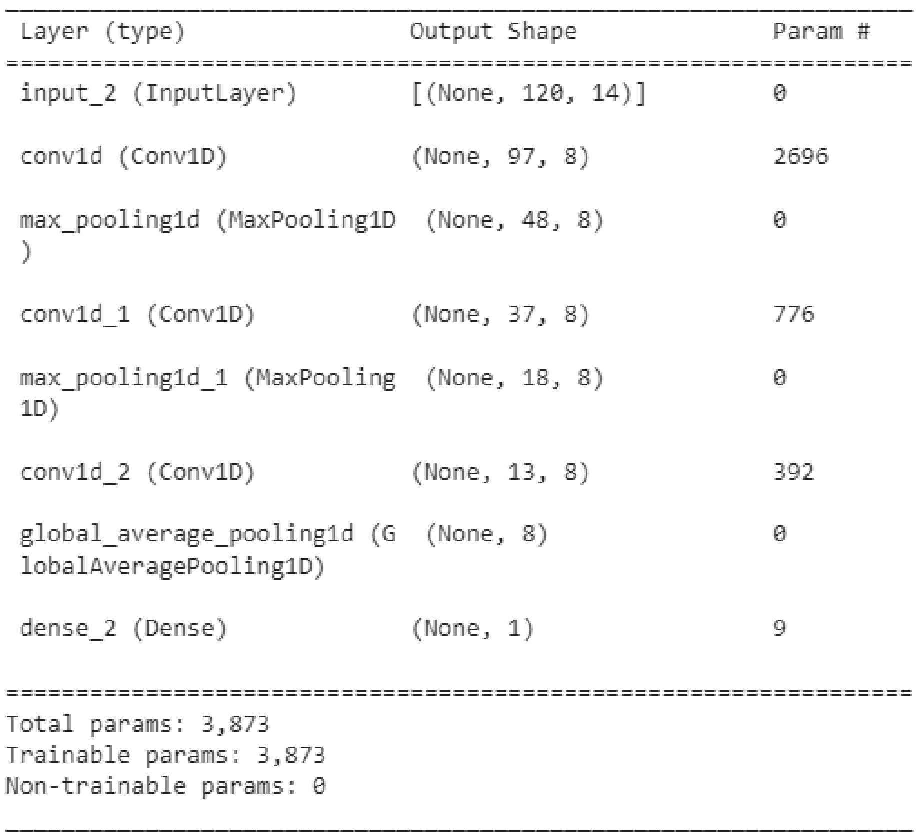
Let’s try CNN (Convolutional Neural Networks)

- Motivation: Maybe a temporal convnet could reuse the same representations across different days, much like a spatial convnet can reuse the same representations across different locations in an image!



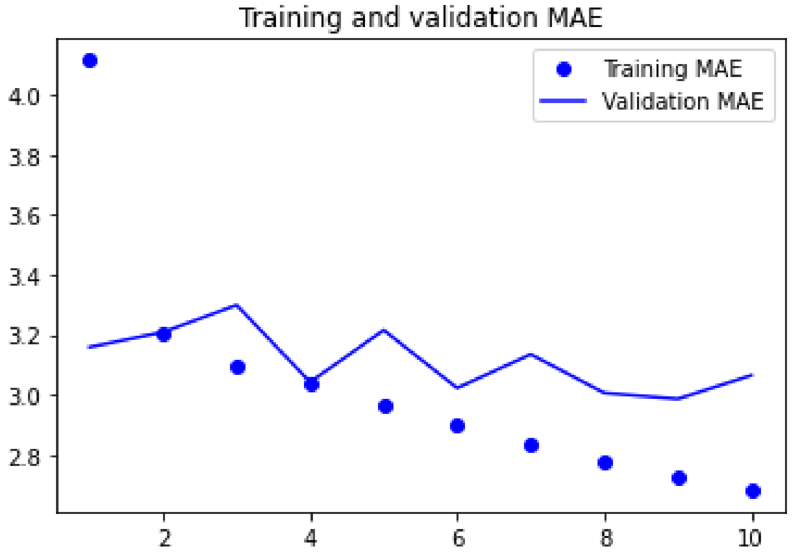
```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.Conv1D(8, 24, activation="relu")(inputs)
x = layers.MaxPooling1D(2)(x)
x = layers.Conv1D(8, 12, activation="relu")(x)
x = layers.MaxPooling1D(2)(x)
x = layers.Conv1D(8, 6, activation="relu")(x)
x = layers.GlobalAveragePooling1D()(x)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)
```



```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_2 (InputLayer)        [(None, 120, 14)]         0

 conv1d (Conv1D)             (None, 97, 8)             2696

 max_pooling1d (MaxPooling1D  (None, 48, 8)            0
 )

 conv1d_1 (Conv1D)           (None, 37, 8)             776

 max_pooling1d_1 (MaxPooling  (None, 18, 8)            0
 1D)

 conv1d_2 (Conv1D)           (None, 13, 8)             392

 global_average_pooling1d (G  (None, 8)                0
 lobalAveragePooling1D)

 dense_2 (Dense)             (None, 1)                 9

=================================================================
Total params: 3,873
Trainable params: 3,873
Non-trainable params: 0
_________________________________________________________________
```

CNN performance

- Test MAE = 3.10 degrees Celsius
- Even worse than the densely connected model!! !
  - CNN treats every segment of the data the same way!
  - Pooling layers are destroying order information.



Sequence Modeling

To model sequence data efficiently, we need a new architecture that:

- Preserve the order
- Account for long-term dependencies
- Handle input-length
- Share parameters across the sequence

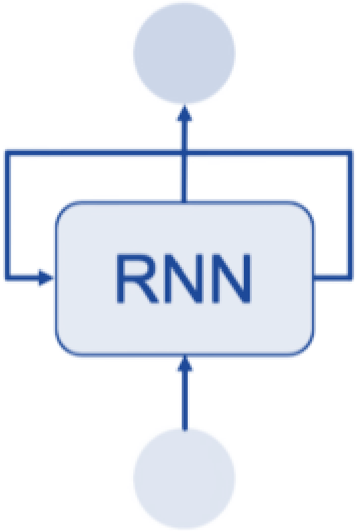
What is RNN (Recurrent Neural Network)?

- The architecture of RNNs is inspired by the way biological intelligence processes information incrementally while maintaining an internal model of what it is processing.

- This ability to remember previous inputs and incorporate them into the current output allows RNNs to model sequential data.

- RNN maintains a state that contains information relative to what it has seen so far

- RNNs can be thought of as neural networks with an internal loop, which allows them to process sequences of varying lengths and learn from temporal dependencies.



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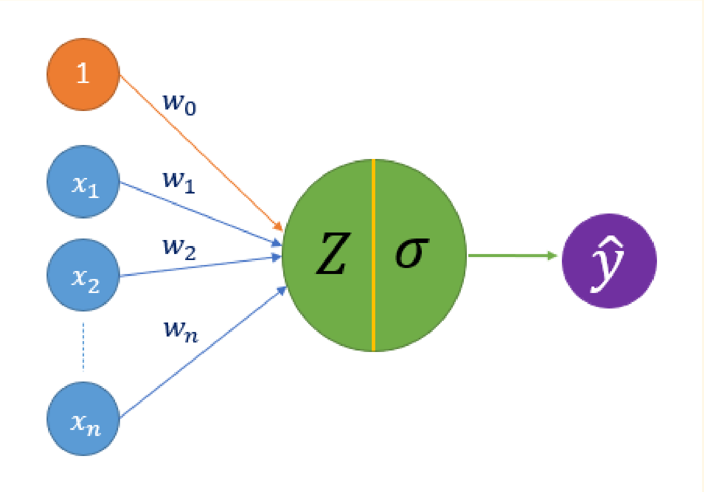
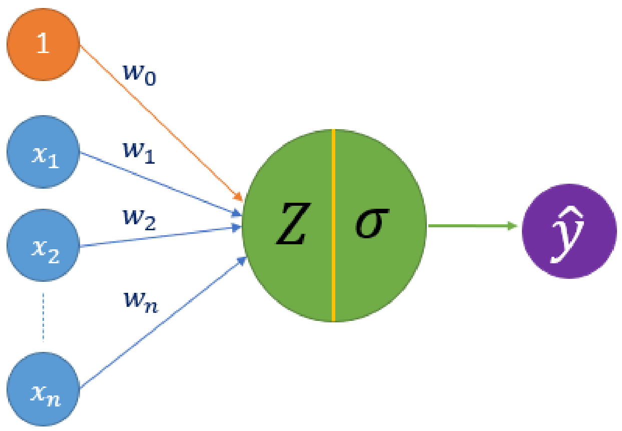
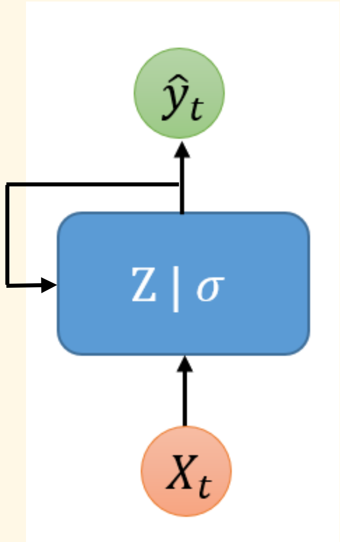
Perceptron vs Recurrent Cell



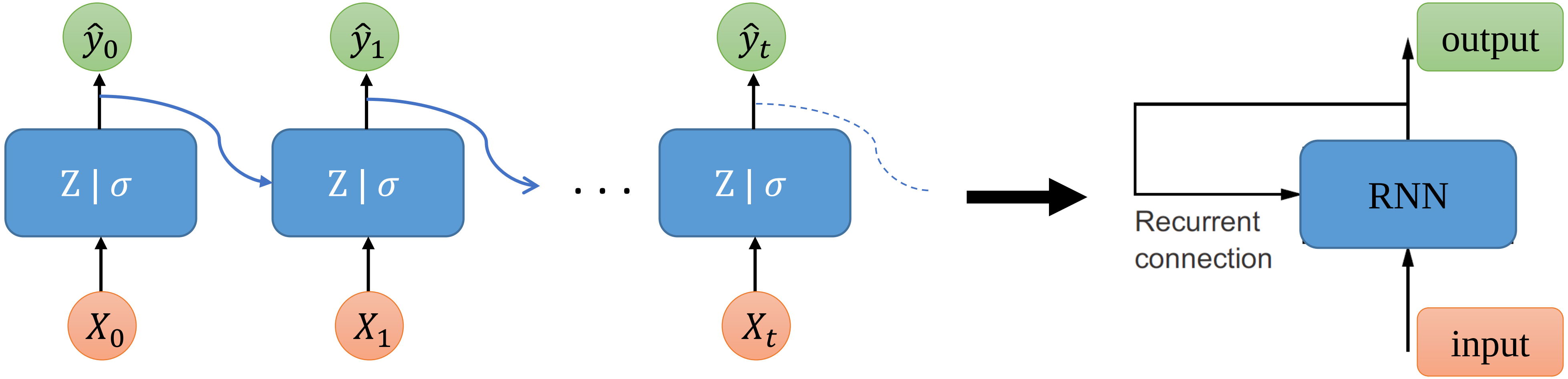
Perceptron



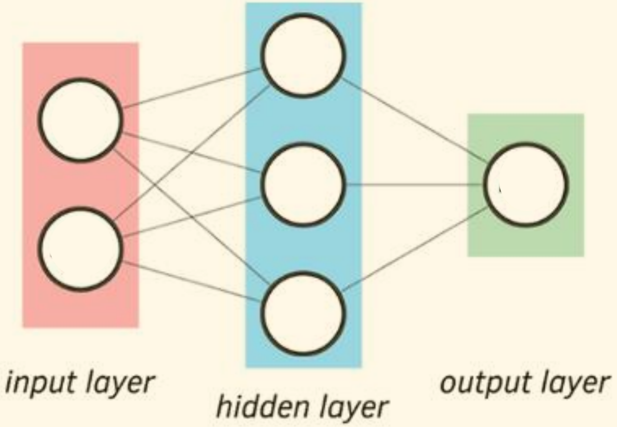


Recurrent Cell

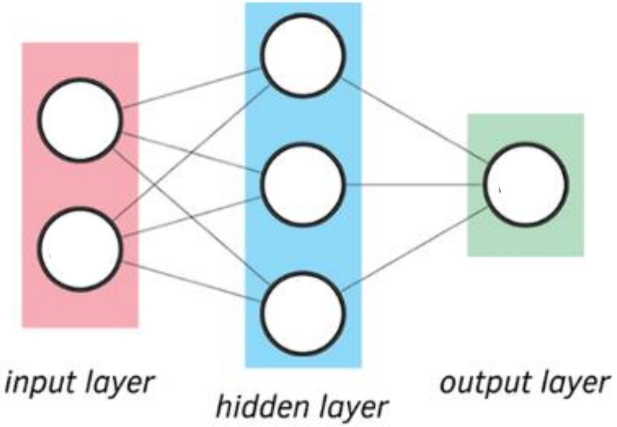
Unrolling the Recurrent Cell

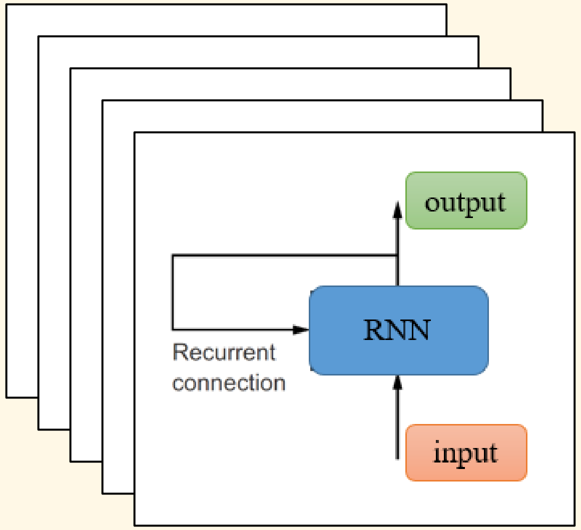


Dense Layer vs Recurrent Layer



Dense Layer

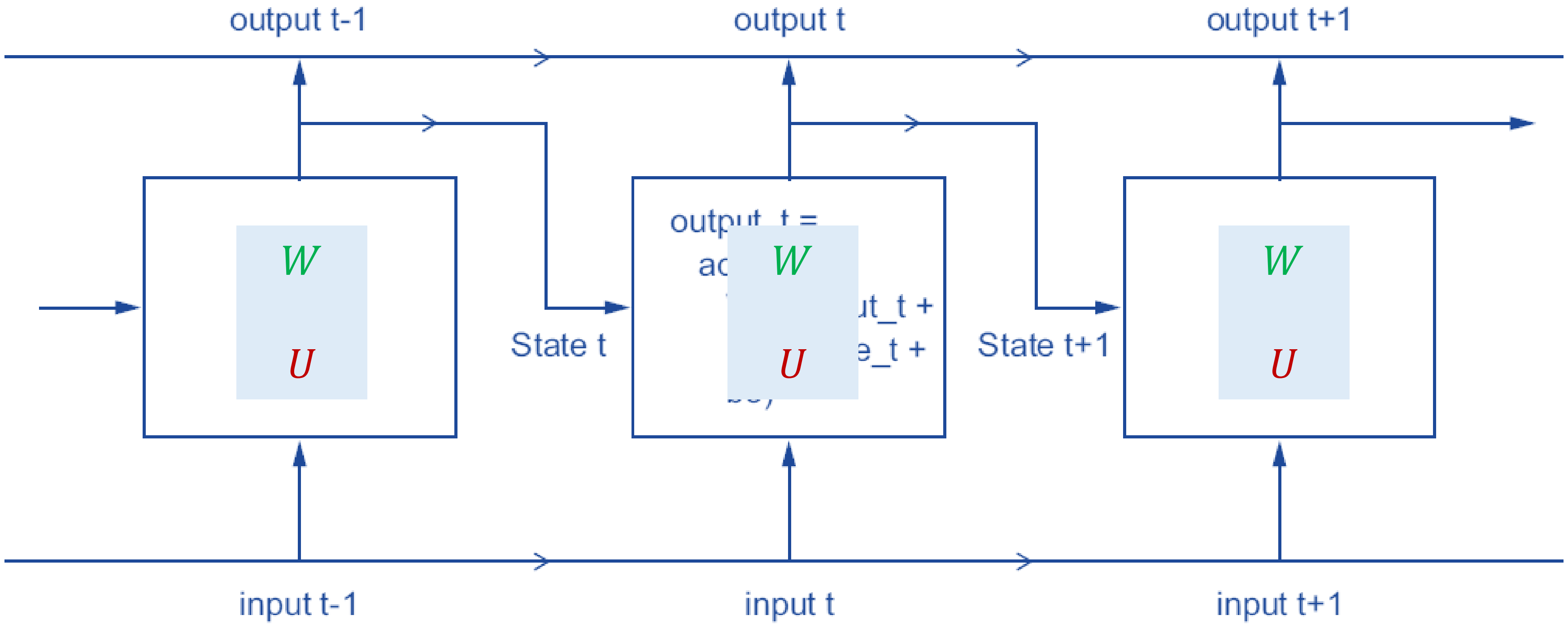




Recurrent Layer

Inside the Recurrent Cell

$$output_t = f(input_t, State_t)$$



$$s_{t+1} = activation(WX_t + Us_t + b)$$

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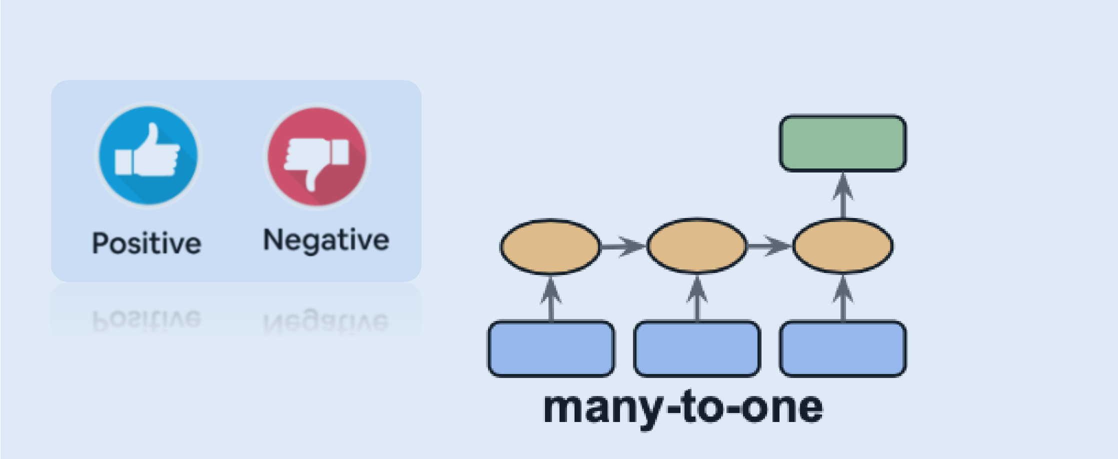
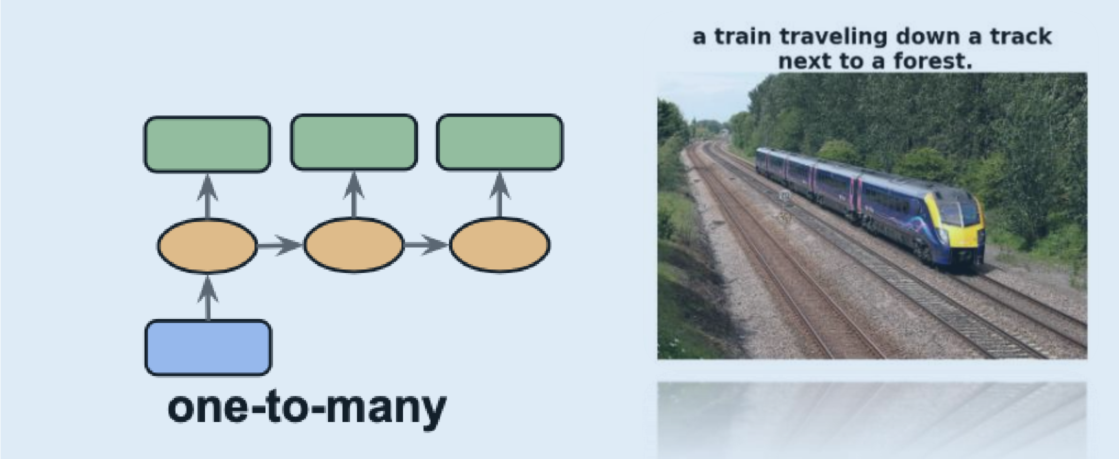
Deep learning with Python, Francois Chollet

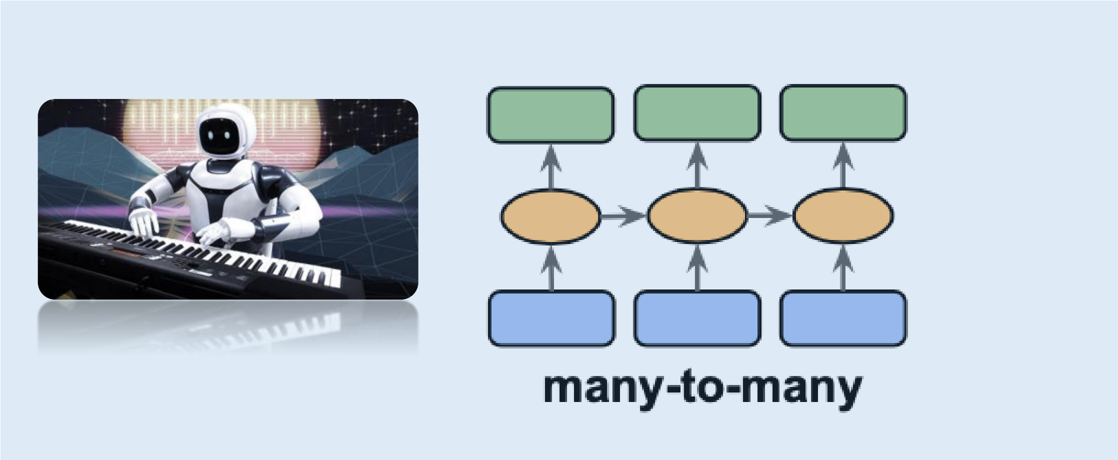
RNN architectures



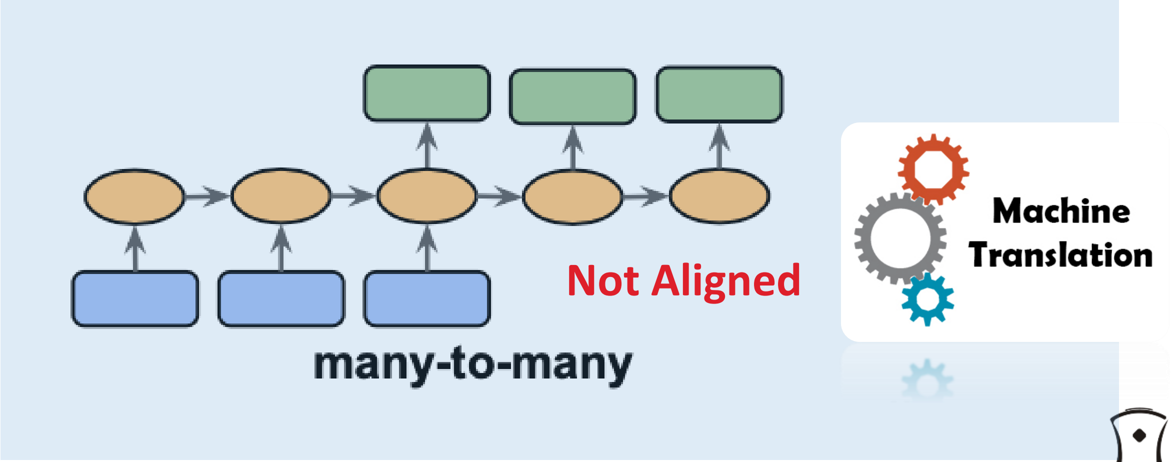
many-to-one



one-to-many



many-to-many

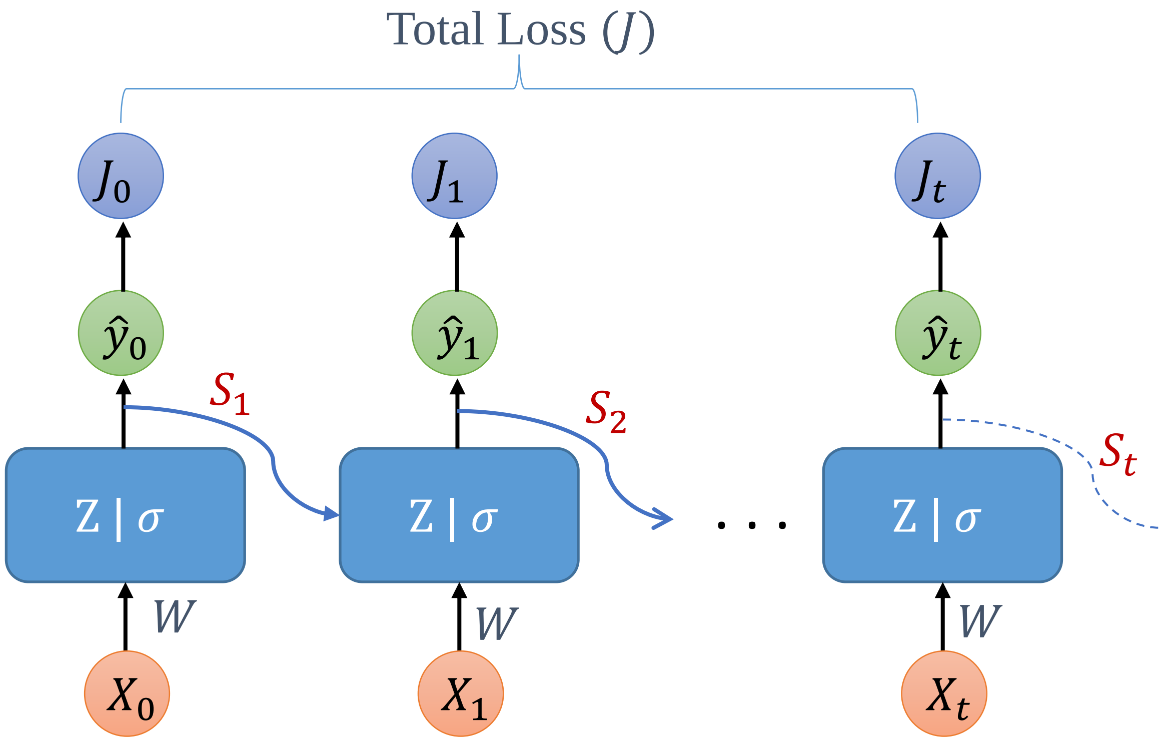


Not Aligned

many-to-many

How does RNN learn representations?

- Backpropagation Through Time (BPTT)
- $\frac{\partial J}{\partial P}$ P are the parameters
- $\frac{\partial J}{\partial W} = \frac{\partial J_0}{\partial W} + \frac{\partial J_1}{\partial W} + ..$
- $\frac{\partial J_0}{\partial W} = \frac{\partial J_0}{\partial y_0}\frac{\partial y_0}{\partial S_0}\frac{\partial S_0}{\partial W}$
- $\frac{\partial J_1}{\partial W} = \frac{\partial J_1}{\partial y_1}\frac{\partial y_1}{\partial S_1}\frac{\partial S_1}{\partial W}$, $\frac{\partial S_1}{\partial W} = \frac{\partial S_1}{\partial S_0}\frac{\partial S_0}{\partial W}$
- …
- $\frac{\partial J_t}{\partial W} = \sum_{k=0}^{t} \frac{\partial J_t}{\partial y_t}\frac{\partial y_t}{\partial S_t}\frac{\partial S_t}{\partial S_k}\frac{\partial S_k}{\partial W}$

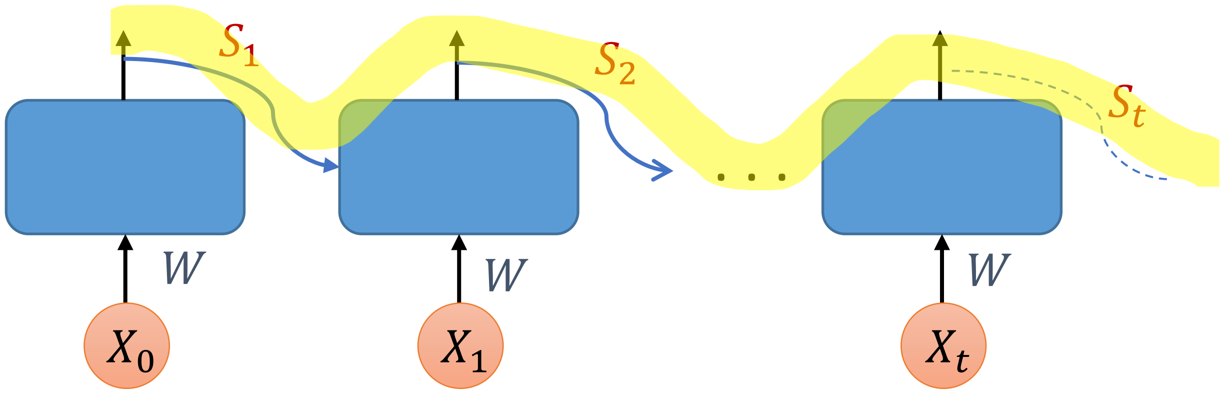


Vanishing Gradient Problem

- As the time horizon gets bigger, this product gets longer and longer.
- We are multiplying a lot of small numbers → smaller gradients → biased parameters unable to capture long term dependencies.

- $\frac{\partial J_t}{\partial W} = \sum_{k=0}^{t} \frac{\partial J_t}{\partial y_t} \frac{\partial y_t}{\partial S_t} \frac{\partial S_t}{\partial S_k} \frac{\partial S_k}{\partial W}$
- $\frac{\partial S_{10}}{\partial S_0} = \frac{\partial S_{10}}{\partial S_9} \frac{\partial S_9}{\partial S_8} \frac{\partial S_8}{\partial S_7} \frac{\partial S_7}{\partial S_6} \cdots \frac{\partial S_1}{\partial S_0}$

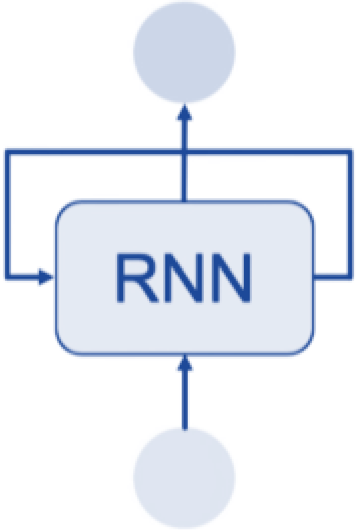
$$S_t = activation\left(W X_{t\_1} + U s_{t-1}\right)$$



Beyond RNN

RNN can handle the following sequence modeling criteria:

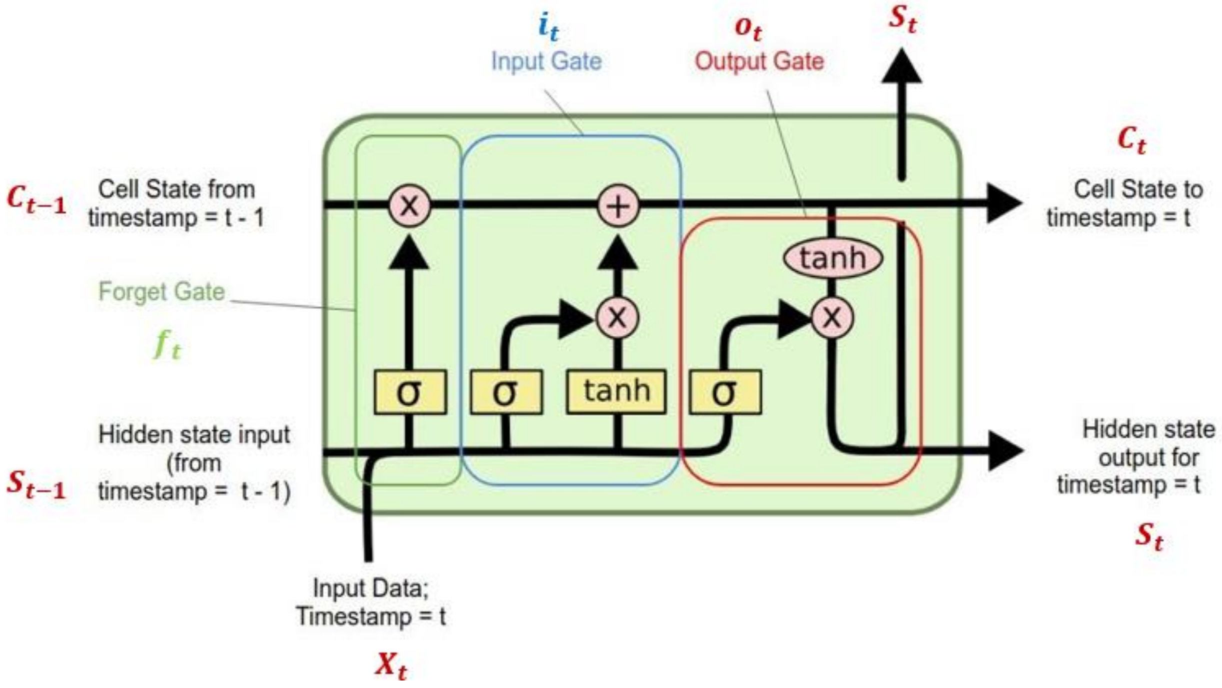
- Preserve the order
- Handle input-length
- Share parameters across the sequence



RNN limitations:

- Does not account for long-term dependencies (only remember short term history)
- Vanishing Gradient Problem

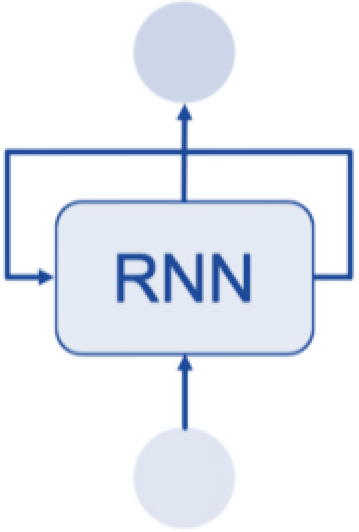
Module 7 – Part II
Deep Sequence Modeling
(Gated cells, LSTM)


i_t
Input Gate
o_t
Output Gate
S_t
C_t
Cell State to timestamp = t
C_{t-1}
Cell State from timestamp = t - 1
Forget Gate
f_t
x
+
tanh
x
x
σ
σ
tanh
σ
Hidden state input (from timestamp = t - 1)
S_{t-1}
Hidden state output for timestamp = t
S_t
Input Data; Timestamp = t
X_t

Beyond RNN

RNN can handle the following sequence modeling criteria:

- Preserve the order
- Handle input-length
- Share parameters across the sequence

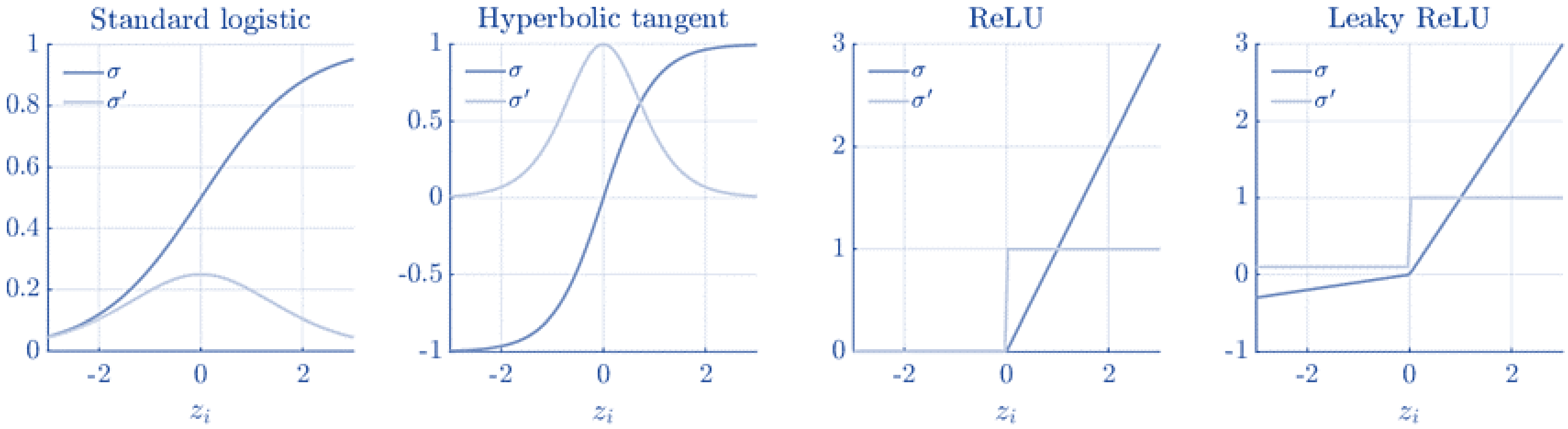


RNN limitations:

- Does not account for long-term dependencies (only remember short term history)
- Vanishing Gradient Problem

How to solve vanishing gradient problem

1. Use Activation Function that prevents fast shrinkage of gradient



$$S_t = activation(WX_{t-1} + Us_{t-1})$$

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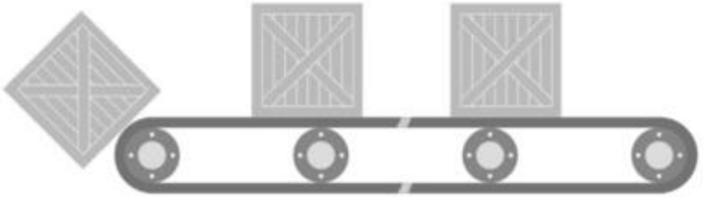
How to solve vanishing gradient problem

1. Use Activation Function that prevents fast shrinkage of gradient
2. Use weight initialization techniques that ensure that the initial weights are not too small
3. Use gradient clipping which limits the magnitude of the gradients from becoming too small (vanishing gradient) or too large (exploding gradient)
4. Use batch normalization, which normalizes the input to each layer and helps to reduce the range of activation values and thus the likelihood of vanishing gradients.
5. Use a different optimization algorithm that is more resilient to vanishing gradients, such as Adam or RMSprop.
6. **Gated cells:** Use some sort of **skip connections**, which allow gradients to bypass some of the layers in the network and thus prevent them from becoming too small.

Gated cells

- Instead of using a simple RNN cell, let’s use a more complex cell with gates which control the flow of information.
- Think of a conveyer belt running parallel to the sequence being processed:
  - Information can jump on → transported to a later timestep → jump off when needed.
  - This is what a gated cell does! Analogous to residual connections we saw before.

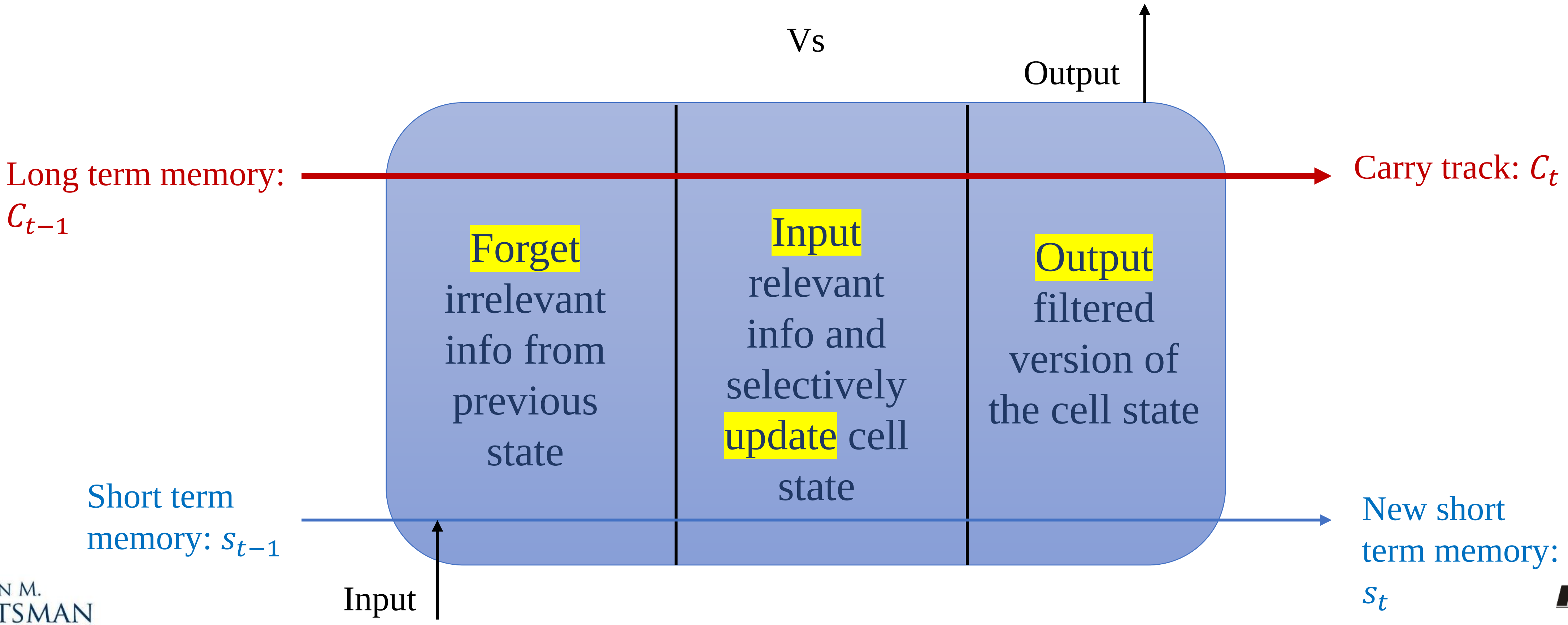


- Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are two examples of gated cells that can keep track of information throughout many timesteps.

Inside the LSTM cell

Simple RNN

Vs



Output

Long term memory: C_{t-1}

Carry track: C_t

Forget irrelevant info from previous state

Input relevant info and selectively **update** cell state

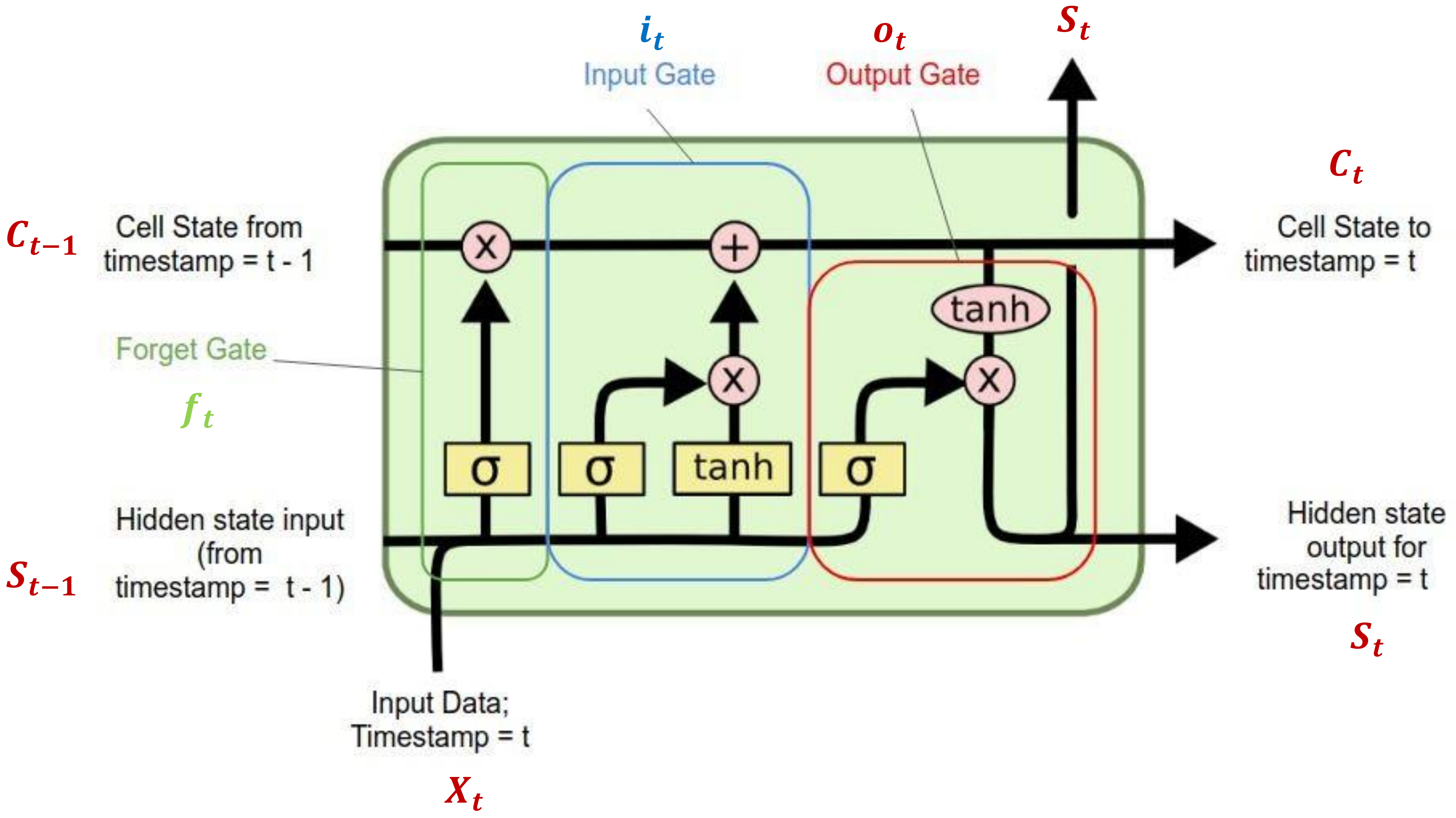
Output filtered version of the cell state

Short term memory: s_{t-1}

New short term memory: s_t

Input

LSTM details


i_t
Input Gate
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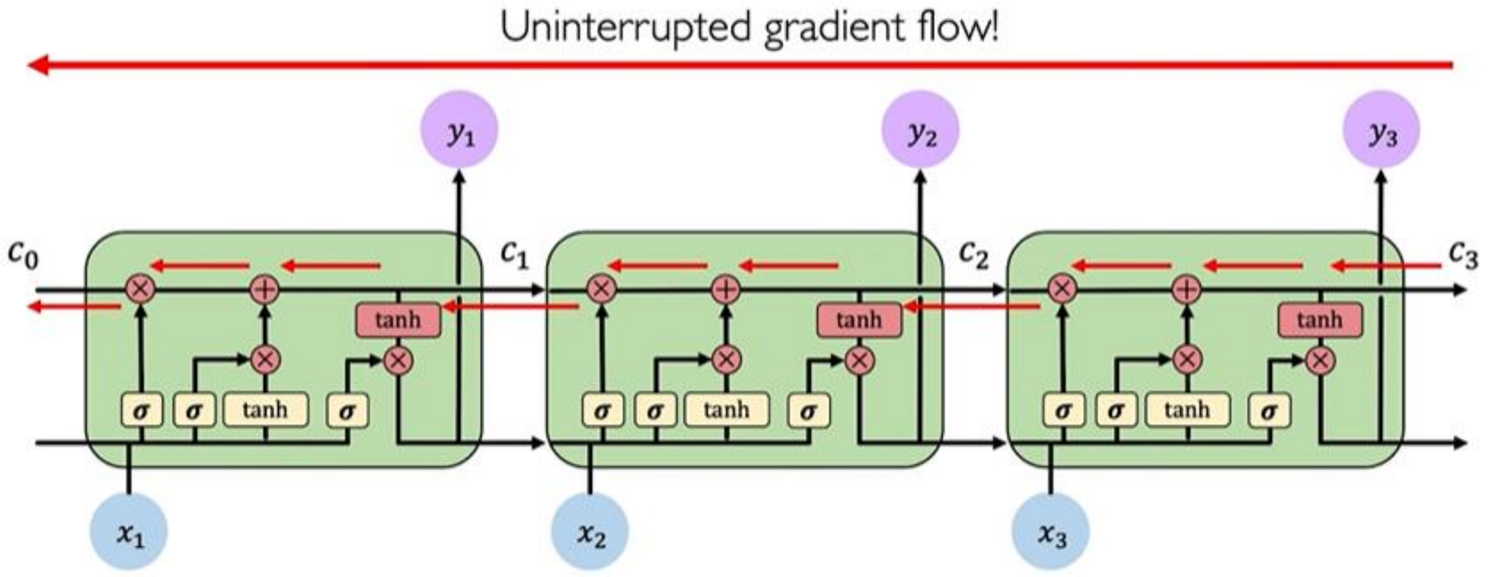
Output Gate
S_t
C_t
C_{t-1}
Cell State from timestamp = t - 1
Cell State to timestamp = t
Forget Gate
f_t
σ
σ
tanh
σ
tanh
Hidden state input (from timestamp = t - 1)
S_{t-1}
Hidden state output for timestamp = t
S_t
Input Data; Timestamp = t
X_t

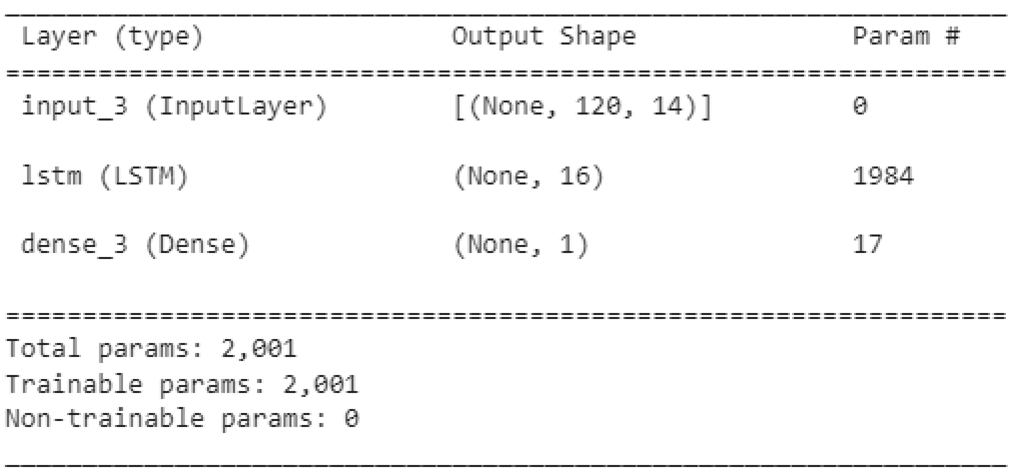
LSTM takeaway

- LSTM uses gates to regulate the information flow (allows past information to be reinjected later)
- This new cell state (carry) can better capture longer term dependencies
- LSTM fights the vanishing gradient problem



Let’s try LSTM on the temperature example

```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.LSTM(16)(inputs)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)
```

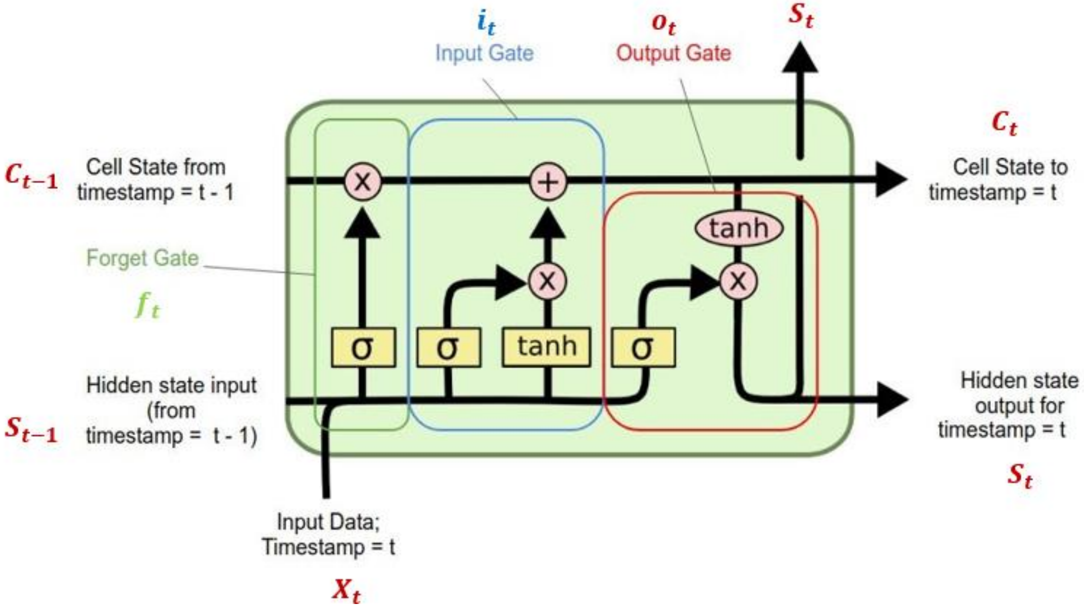


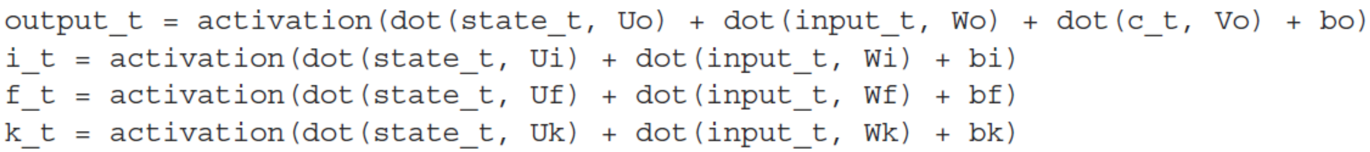
```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_3 (InputLayer)        [(None, 120, 14)]         0

 lstm (LSTM)                 (None, 16)                1984

 dense_3 (Dense)             (None, 1)                 17

=================================================================
Total params: 2,001
Trainable params: 2,001
Non-trainable params: 0
_________________________________________________________________
```

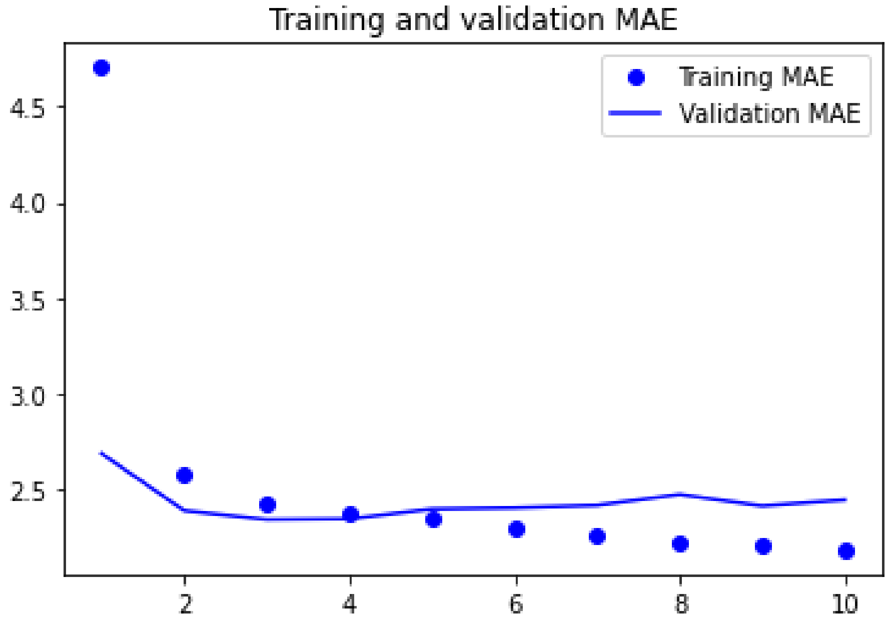

i_t
Input Gate
o_t
Output Gate
S_t
C_t
Cell State to timestamp = t
C_{t-1}
Cell State from timestamp = t - 1
Forget Gate
f_t
X
+
tanh
X
X
σ
σ
tanh
σ
Hidden state input (from timestamp = t - 1)
S_{t-1}
Hidden state output for timestamp = t
S_t
Input Data; Timestamp = t
X_t



```
output_t = activation(dot(state_t, Uo) + dot(input_t, Wo) + dot(c_t, Vo) + bo)
i_t = activation(dot(state_t, Ui) + dot(input_t, Wi) + bi)
f_t = activation(dot(state_t, Uf) + dot(input_t, Wf) + bf)
k_t = activation(dot(state_t, Uk) + dot(input_t, Wk) + bk)
```

LSTM performance

- Baseline Test MAE = 2.62
- Simple LSTM Test MAE = 2.53
- Finally beat the naïve forecaster.
- Overfitting?



Deep learning with Python, Francois Chollet

Can we do better?

Improving the simple LSTM model

- We can improve the performance of the simple LSTM model by:

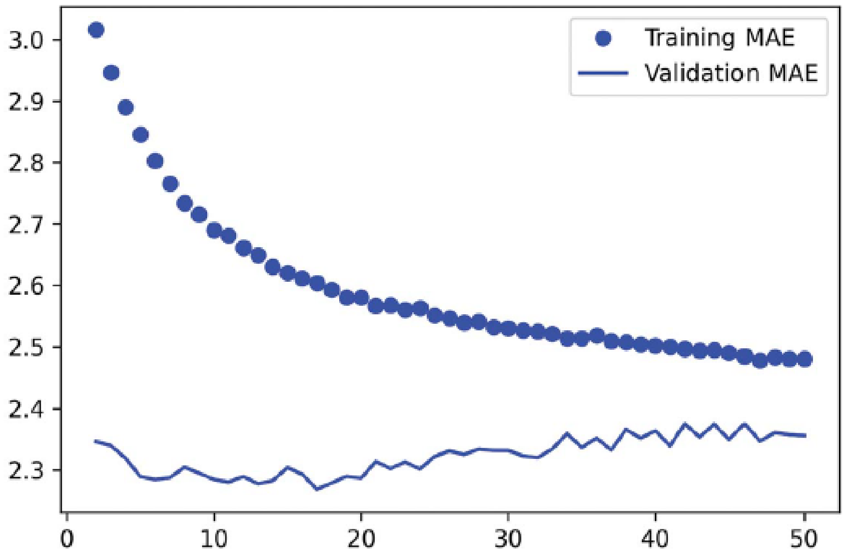
1. Recurrent Dropout : use drop out to fight overfitting in the recurrent layers (in addition to drop out for the dense layers)
2. Stacking recurrent layers: increase model complexity to boost representation power
3. Using bidirectional RNN: processing the same information differently! Mostly used in NLP.

Recurrent Drop out

- The same dropout pattern should be applied at every timestep

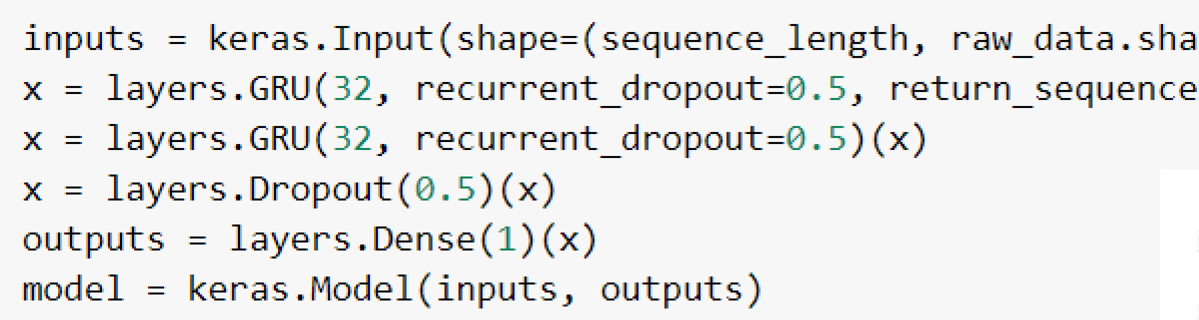
```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.LSTM(32, recurrent_dropout=0.25)(inputs)
x = layers.Dropout(0.5)(x)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)
```

- Baseline Test MAE = 2.62
- Simple LSTM, Test MAE = 2.53
- LSTM with dropout, Test MAE = 2.45

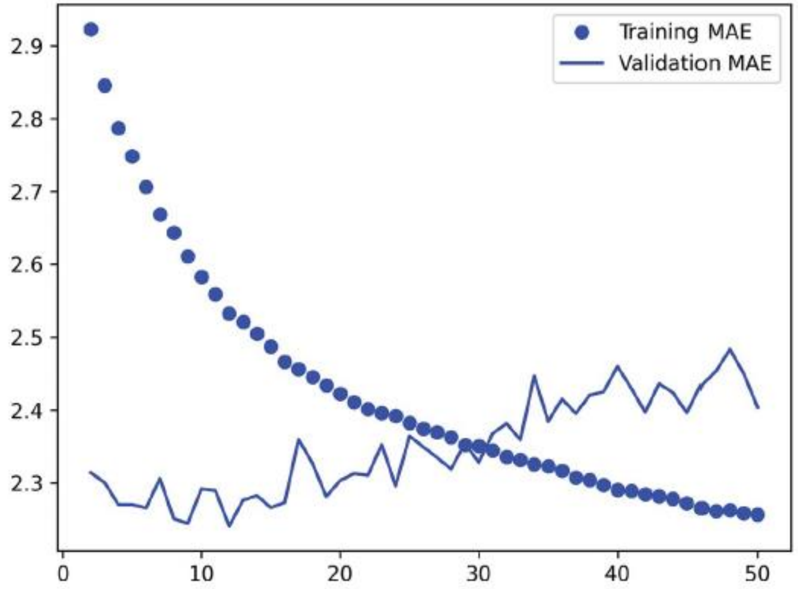


Stacking Recurrent Layers

- Let’s train a dropout-regulated, stacked GRU model.
- GRU is a slightly simpler version (hence, faster) of LSTM architecture



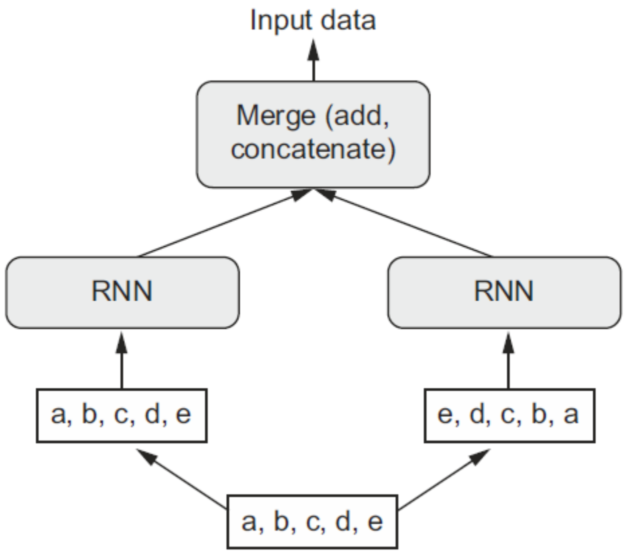
```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.GRU(32, recurrent_dropout=0.5, return_sequences=True)(inputs)
x = layers.GRU(32, recurrent_dropout=0.5)(x)
x = layers.Dropout(0.5)(x)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)
```



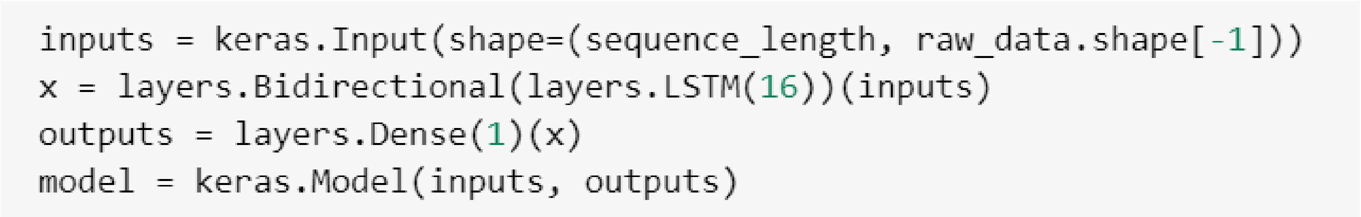
- Baseline Test MAE = 2.62
- Simple LSTM, Test MAE = 2.53
- Stacking GRU, Test MAE = 2.39

Bidirectional RNN

- Bidirectional RNN process the input sequence both chronologically and antichronologically.
- Idea: capturing patterns (representations) that might be overlooked by a unidirectional RNN.



- For the temperature example, the bidirectional LSTM strongly underperforms even the common-sense baseline.



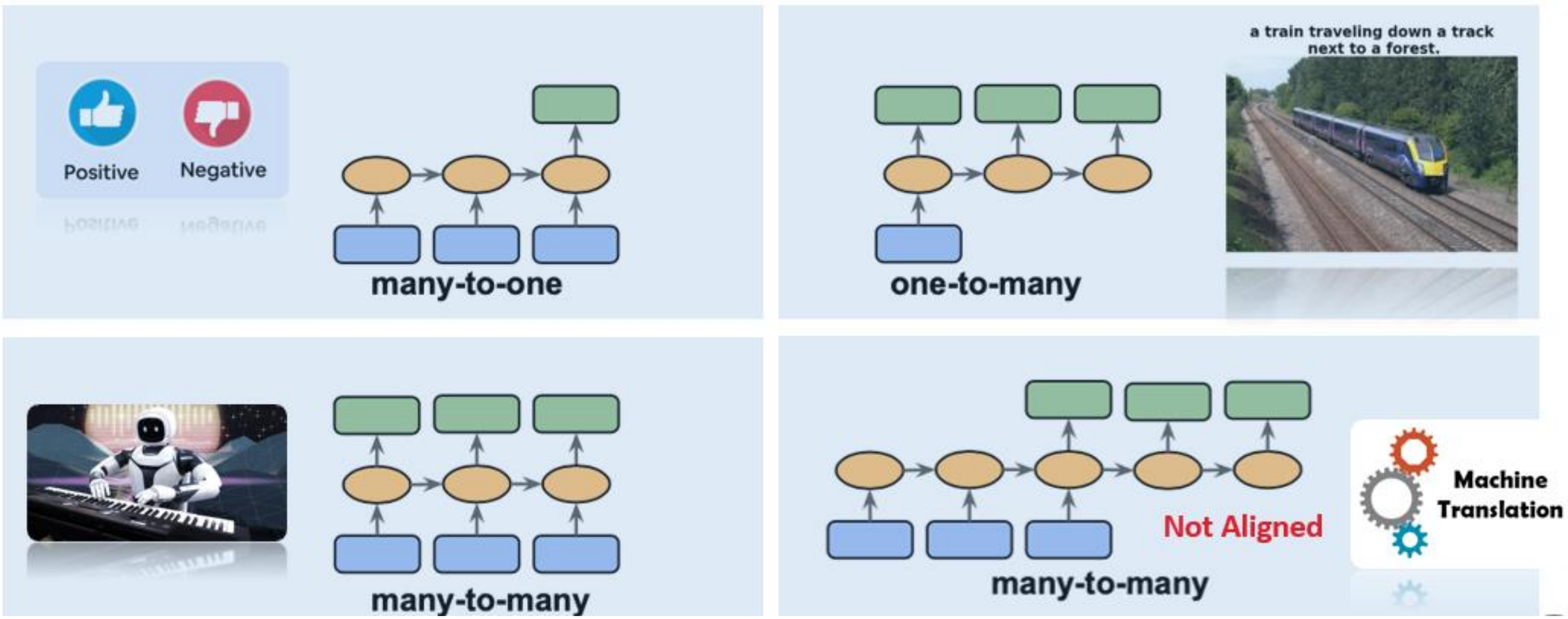
```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.Bidirectional(layers.LSTM(16))(inputs)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)
```

Deep learning with Python, Francois Chollet

Final message

- Deep learning is more an art than science! Too many moving part!
  - Number of units in each recurrent layer
  - Number of stacked layers
  - Amount of dropout and recurrent dropout
  - Number of dense layers
  - Sequence horizon!
  - Optimizers, learning rates and etc
  - ….
- Apply RNN to datasets that past is a good predictor of the future! Not the stock market!

Module 7 – Part III
Deep Sequence Modeling for Text
Natural Language Processing (NLP)

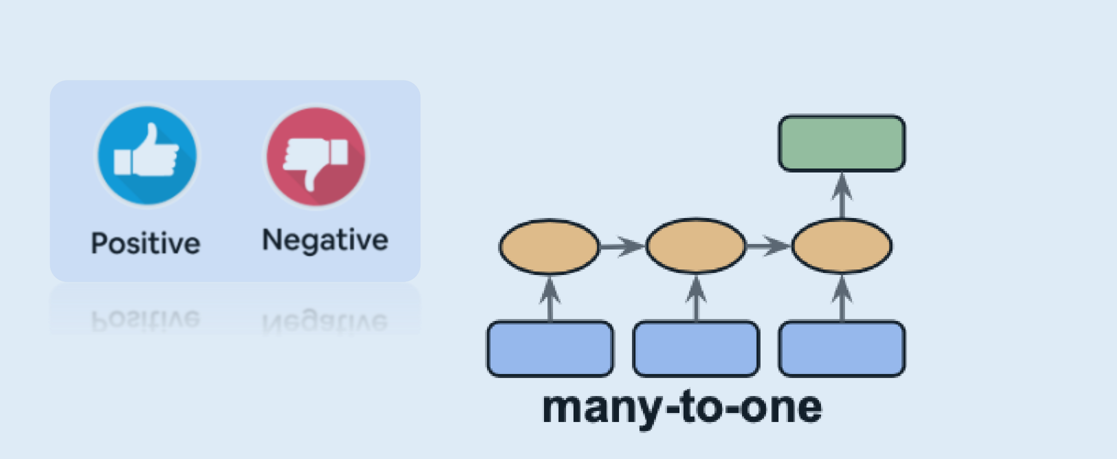


Different kinds of sequence data

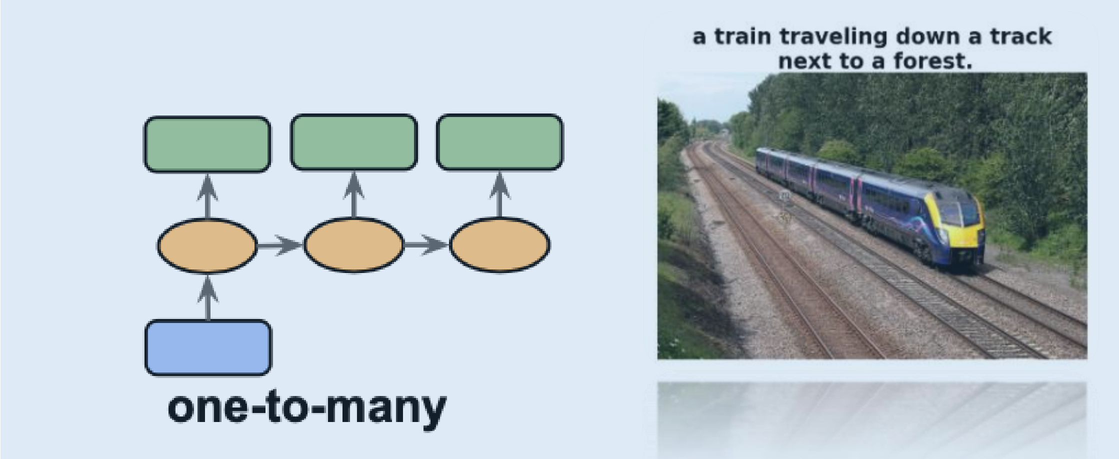
Sequence data refers to any data that has a specific order or sequence to it!

- Time series data: Time series data is a sequence of data points that are measured at regular intervals over time. (stock prices, weather patterns, medical records, …)
- Text data: Text data refers to any type of data that is composed of words, sentences, or paragraphs. (tweets, news articles, product reviews, …)
- Audio data: Audio data refers to any type of data that is recorded or generated as sound waves. (speech recordings, music tracks, …)
- Video data: Video data refers to any type of data that is represented as a sequence of images or frames. (movie clips, surveillance footage, …)

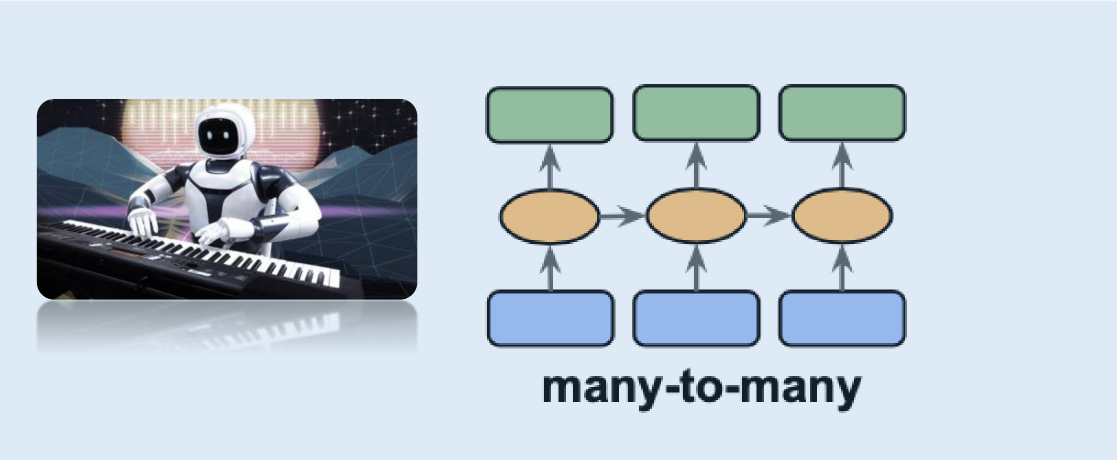
RNN architectures

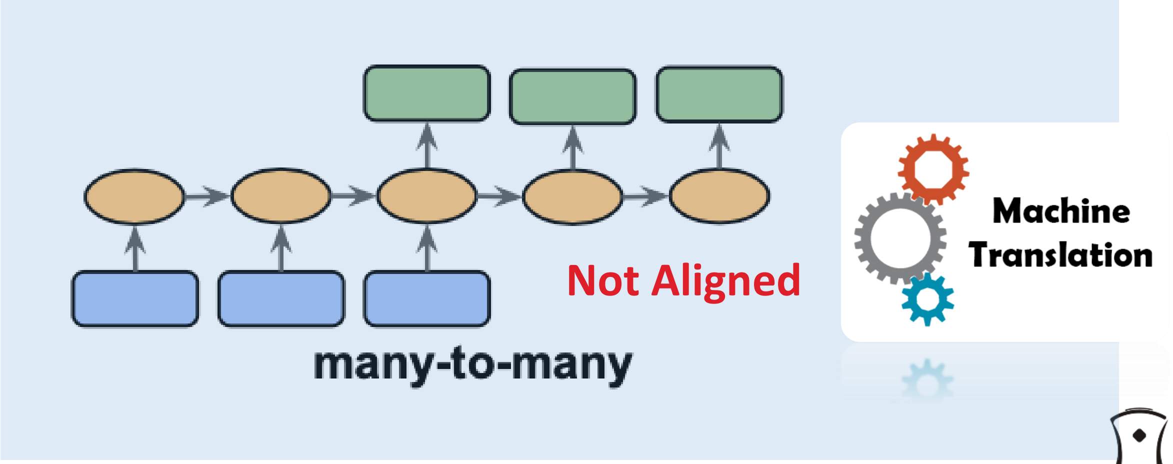


many-to-one


a train traveling down a track next to a forest.

one-to-many


many-to-many


Not Aligned

Machine Translation

many-to-many

Human language vs machine language

- In compute science: Human language → Natural language (shaped by an evolution process)
- Machine language designed for machines (XML, Assembly, …)

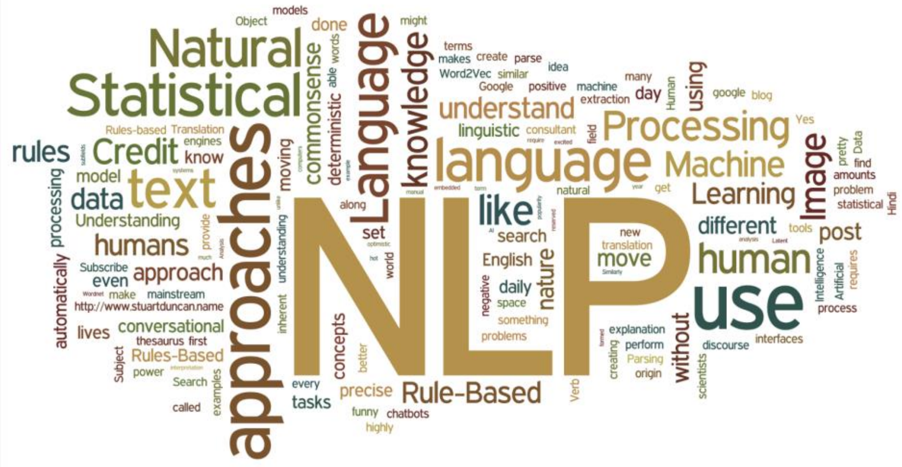
Factors	Human Language	Machine Language
Complexity	Highly complex	Structured and logical
Creativity	Can be highly creative	Limited creativity
Ambiguity	High levels of ambiguity	Little to no ambiguity
Learning	Acquired naturally	Taught through programming
Adaptability	Highly adaptable	Fixed and rigid

Natural Language Processing

- Making sense of human language through algorithms is a big deal!
- NLP is a subfield of computer science and AI that deals with the interaction between computers and human language
- Traditional NLP started with finding handcrafted rules to understand human language (1960-1990)
- Modern NLP is all about using machine learning to automate the search for these rules and enabling computers to do the followings:
  - Sentiment analysis
  - Machine translation
  - Content filtering
  - Text classification and …

NLP, the goal and toolset

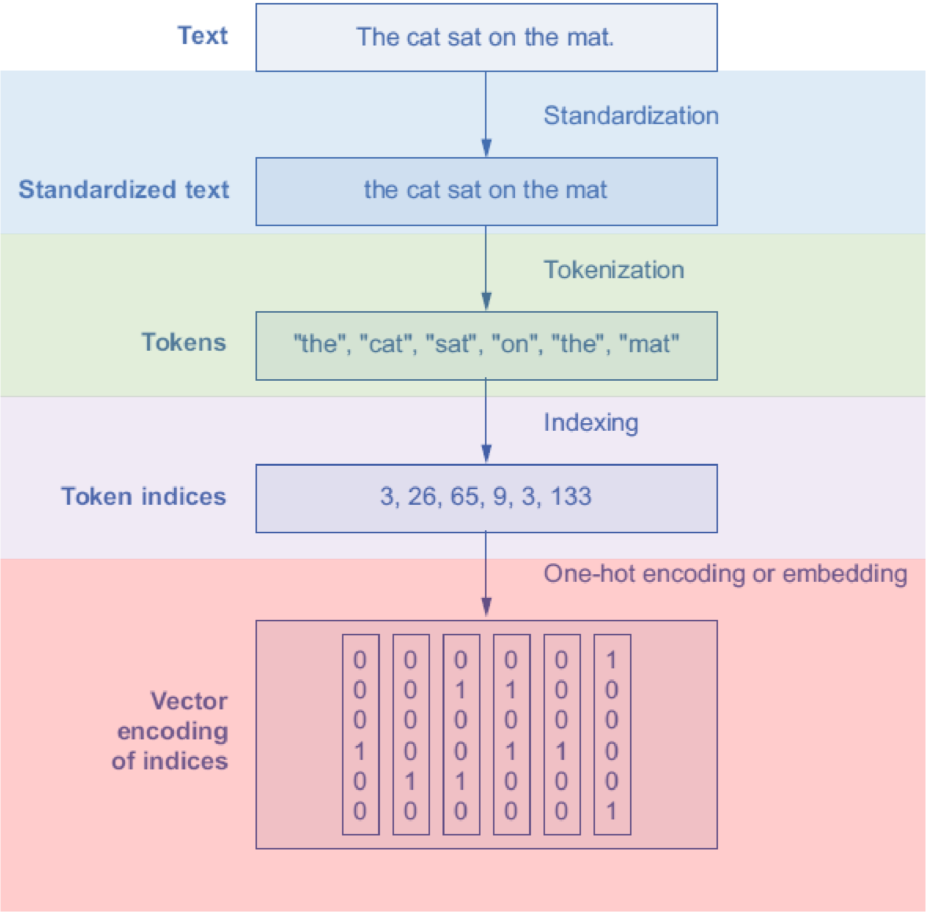
- Goal: automated Pattern recognition → statistical regularities
- Computer vision is pattern recognition applied to pixels,
- NLP is pattern recognition applied to text (words, sentences, and paragraphs)
- NLP toolset:
  - 1990-2010: ML models like decision trees and logistic regression
  - 2010-2017: DL models like RNN and LSTM
  - 2018-present: Transformers



Preparing text data

- TextVectorization: the process of transforming text into numeric values.

1. Standardization
2. Tokenization
3. Indexing
4. Encoding

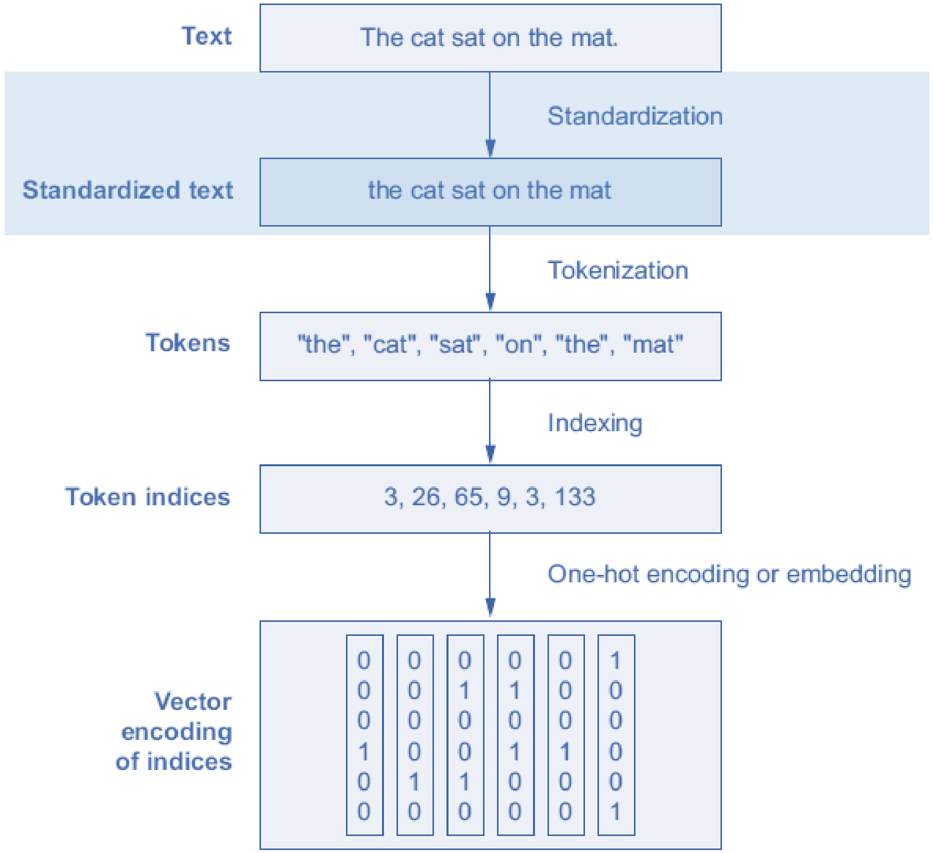


Deep learning with Python, Francois Chollet

TextVectorization: standardization, tokenization, indexing, encoding

- Standardization:
  - Converting to ***lowercase***,
  - Removing ***punctuations***,
  - Converting ***special characters***,
  - ***Stemming*** (converting variations of a term into a single shared representation)

- Standardization is a basic form of feature engineering
- With standardization, your model requires less training data and generalize better.



Text: The cat sat on the mat.

Standardization

Standardized text: the cat sat on the mat

Tokenization

Tokens: "the", "cat", "sat", "on", "the", "mat"

Indexing

Token indices: 3, 26, 65, 9, 3, 133

One-hot encoding or embedding

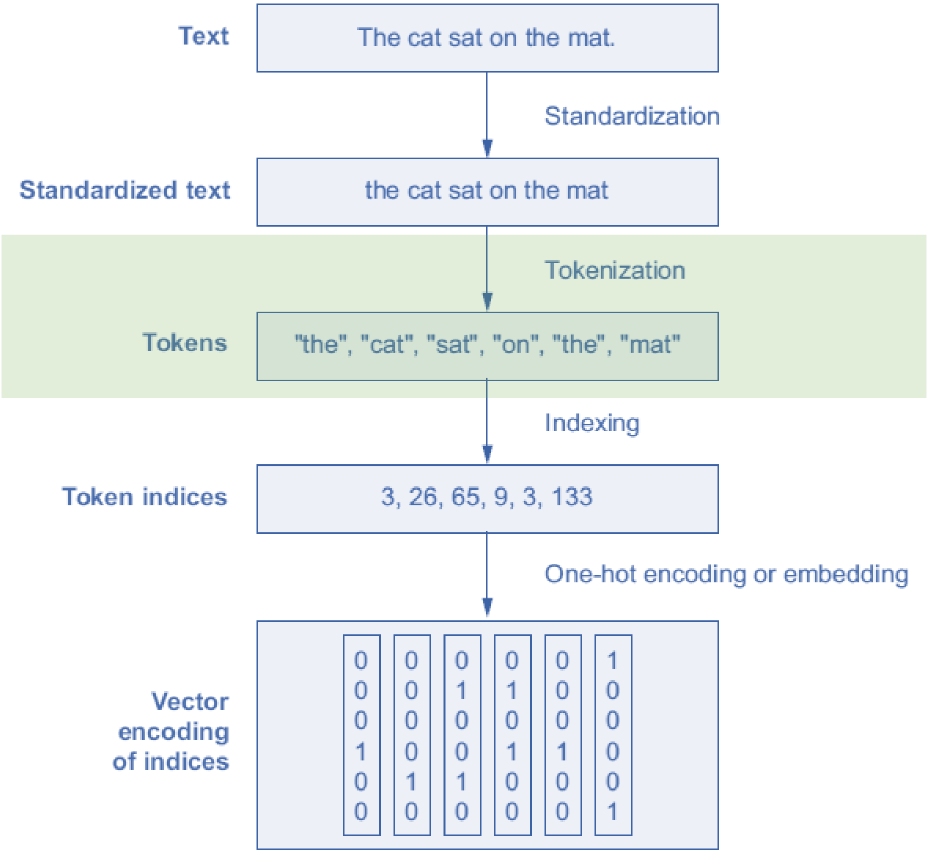
Vector encoding of indices

0	0	0	0	0	1
0	0	1	1	0	0
0	0	0	0	0	0
1	0	0	1	1	0
0	1	1	0	0	0
0	0	0	0	0	1

TextVectorization: standardization, tokenization, indexing, encoding

- Tokenization: Splitting text into units/token
  - ***Word-level*** tokenization: space-separated tokens
  - ***N-gram*** tokenization: groups of **N (or fewer)** consecutive words
  - ***Character-level*** tokenization: each character is a token

- Two kinds of text processing models:
  - Bag-of-words models (discarding original order) → N-gram tokenization
  - Sequence models (word order matters) → word-level tokenization



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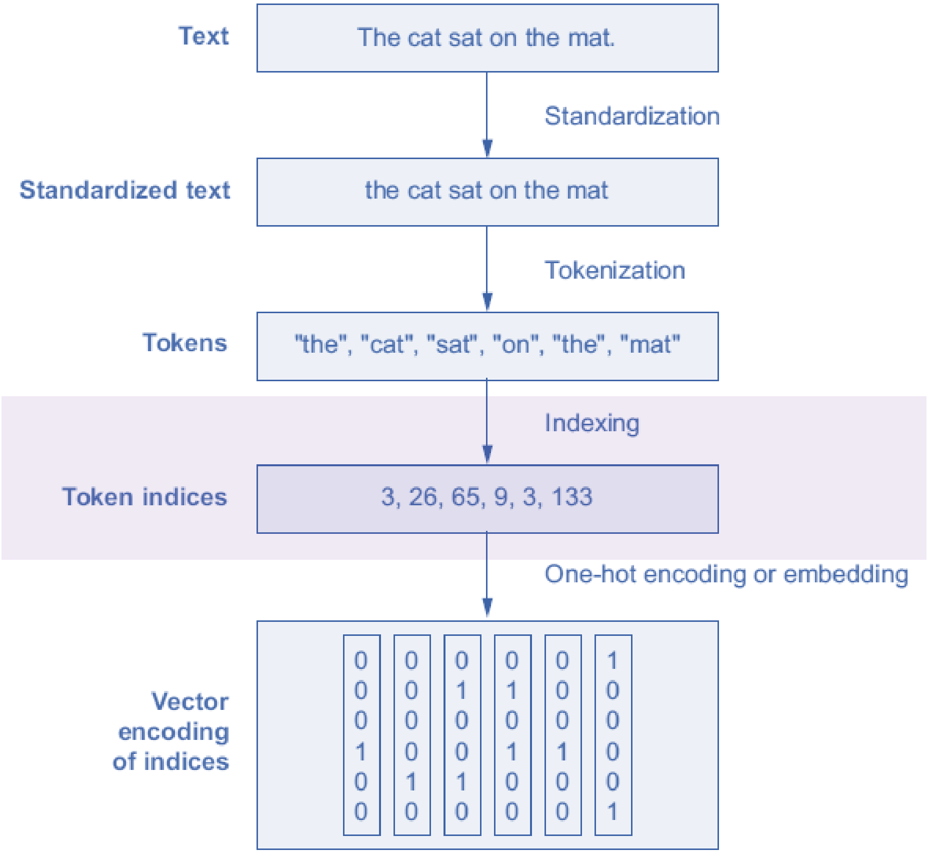
One-hot encoding or embedding

Vector encoding of indices:

0	0	0	0	0	1
0	0	1	1	0	0
0	0	0	0	0	0
1	0	0	1	1	0
0	1	1	0	0	0
0	0	0	0	0	1

TextVectorization: standardization, tokenization, indexing, encoding

- Indexing:
  - ***Integer***: return sequences of words encoded as integer indices
  - Restrict to top 20k or 30k most common words
  - OOV token (out of vocabulary) index 1
  - Mask token index 0 (ignore it, used for padding)



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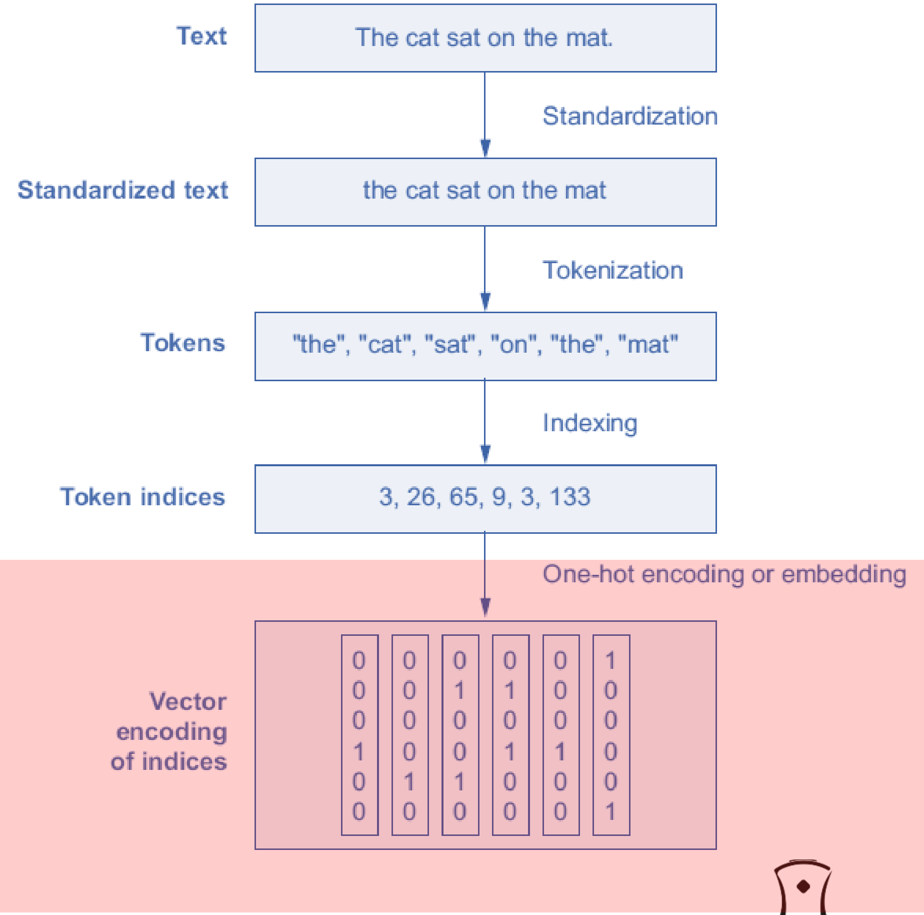
Vector encoding of indices

0	0	0	0	0	1
0	0	1	1	0	0
0	0	0	0	0	0
1	0	0	1	1	0
0	1	1	0	0	0
0	0	0	0	0	1

Pedram Jahangiry

TextVectorization: standardization, tokenization, indexing, encoding

- Encoding:
  - ***Multi-hot (binary)***: Encode the tokens as a multi-hot binary vector
  - ***One-hot:*** Encode the tokens as one-hot binary vectors
  - ***TF-IDF***: term frequency, inverse document frequency



Text: The cat sat on the mat.

Standardization

Standardized text: the cat sat on the mat

Tokenization

Tokens: "the", "cat", "sat", "on", "the", "mat"

Indexing

Token indices: 3, 26, 65, 9, 3, 133

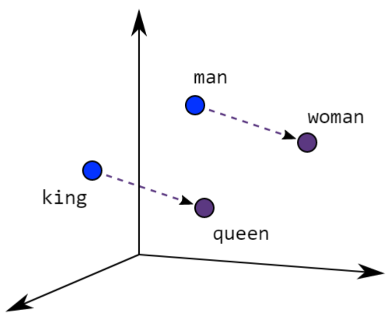
One-hot encoding or embedding

Vector encoding of indices:

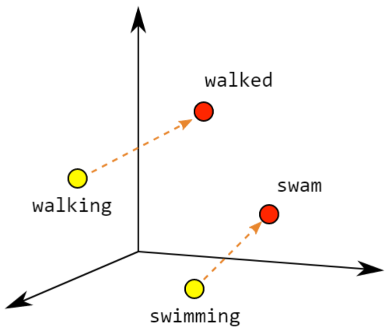
0 0 0 0 0 1
0 0 1 1 0 0
0 0 0 0 0 0
1 0 0 1 1 0
0 1 1 0 0 0
0 0 0 0 0 1

Word Embedding

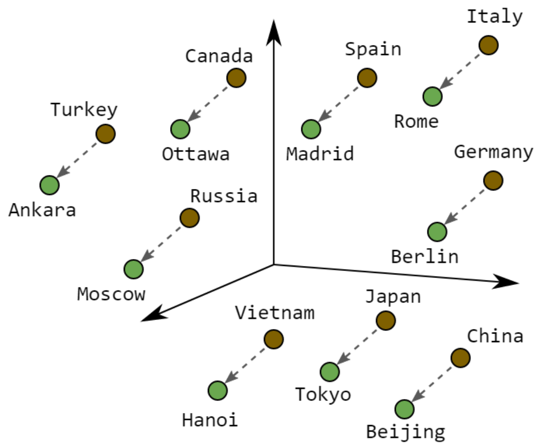
- Word embedding are dense, structured representations learned from data.



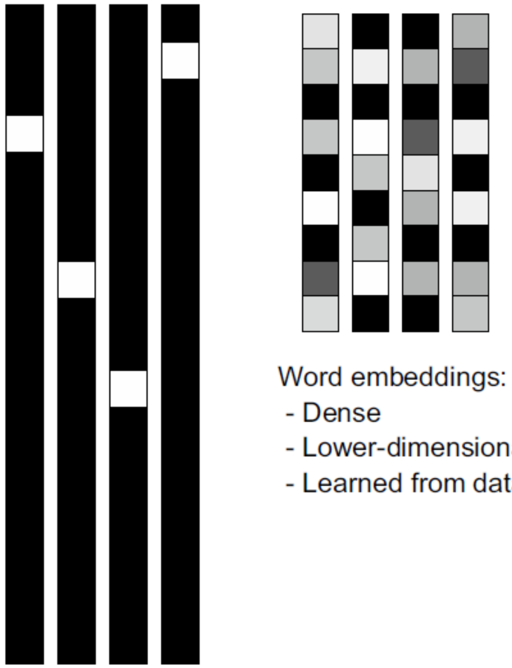
Male-Female



Verb Tense



Country-Capital



Word embeddings:
- Dense
- Lower-dimensional
- Learned from data

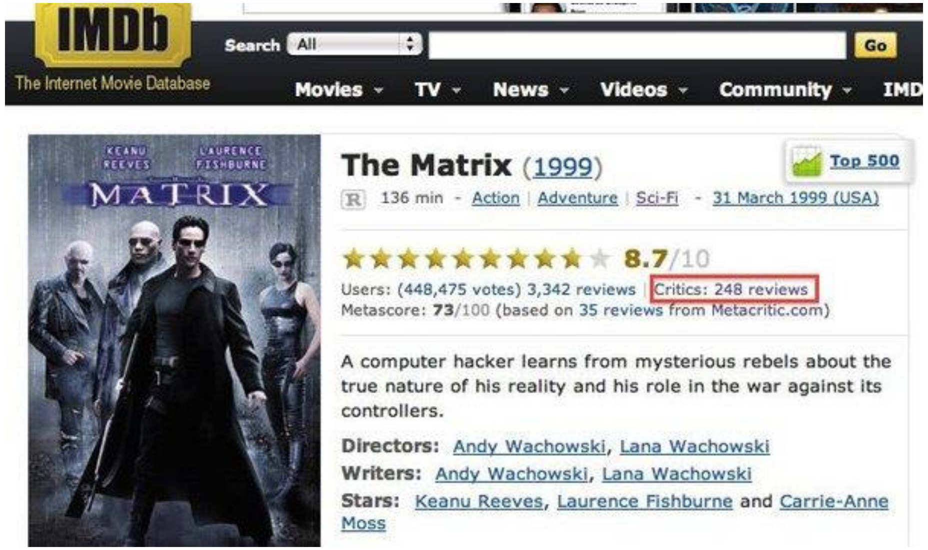
One-hot word vectors:
- Sparse
- High-dimensional
- Hardcoded

Representing groups of words

	Bag-of-Words Approach	Sequential Modeling Approach
Input	Collection of text documents	Sequence of words
Output	Vector representation of each document	Sequential output, e.g. text classification, machine translation
Order	Ignores the order of words	Captures the order of words
Context	Ignores the context of words	Captures the context of words
Features	Each word is a feature	Features depend on the model architecture
Dimensionality	High dimensionality	Lower dimensionality
Sparsity	High sparsity	Lower sparsity
Performance	Faster training and inference	Slower training and inference
Suitability	Good for simple tasks like document classification	Good for complex tasks like language modeling and machine translation

A simple example

- Historically, most early applications of machine learning to NLP involved bag-of-words models.
- Interest in sequence models started rising in 2015, with the rebirth of RNN
- Today, both approaches remain relevant. Let's look at a simple example: [IMDB movie review]
- Task: sentiment-classification of IMDB movie reviews (positive-negative)



The Matrix (1999)

R 136 min - Action | Adventure | Sci-Fi - 31 March 1999 (USA)

★★★★★★★★★☆ 8.7/10

Users: (448,475 votes) 3,342 reviews | Critics: 248 reviews

Metascore: 73/100 (based on 35 reviews from Metacritic.com)

A computer hacker learns from mysterious rebels about the true nature of his reality and his role in the war against its controllers.

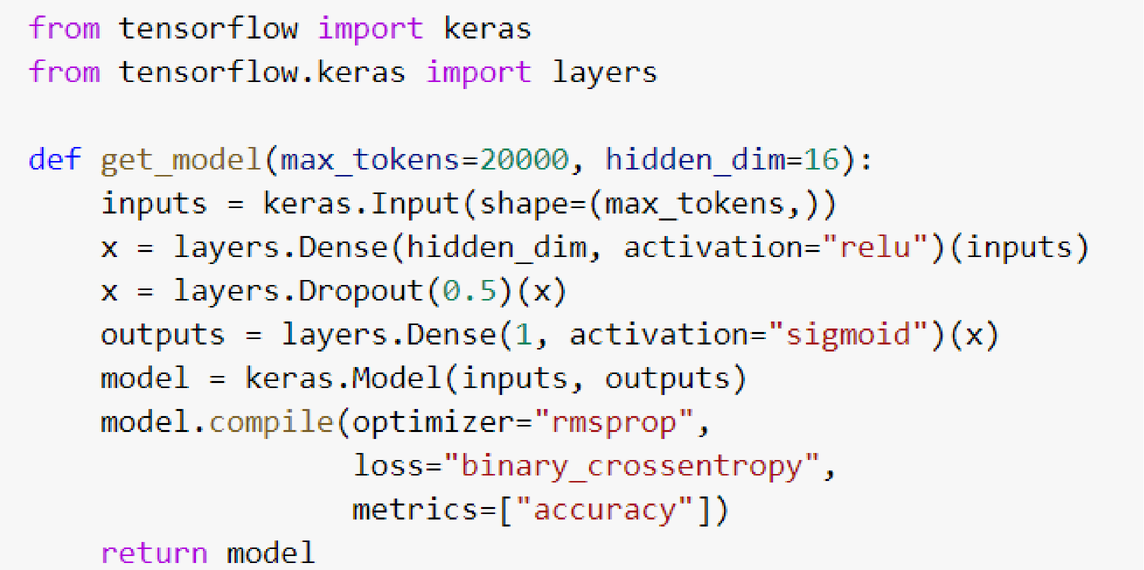
Directors: Andy Wachowski, Lana Wachowski

Writers: Andy Wachowski, Lana Wachowski

Stars: Keanu Reeves, Laurence Fishburne and Carrie-Anne Moss

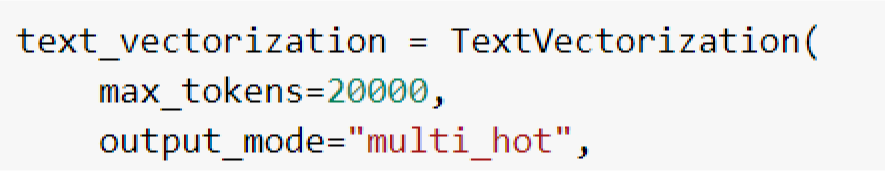
IMDB review example (bag-of-word approach)

- Single words (Unigram) with binary encoding (multi-hot)
- You can represent the entire text as a single vector!
- The cat sat on the mat → {“cat”, “mat”, “sat”, “on”, “the”} → (0,0,1,..,1,0,…,1,0,..,1,..1)
- Bag-of-words model is mainly made of dense layers (No recurrent layers)



```python
from tensorflow import keras
from tensorflow.keras import layers

def get_model(max_tokens=20000, hidden_dim=16):
    inputs = keras.Input(shape=(max_tokens,))
    x = layers.Dense(hidden_dim, activation="relu")(inputs)
    x = layers.Dropout(0.5)(x)
    outputs = layers.Dense(1, activation="sigmoid")(x)
    model = keras.Model(inputs, outputs)
    model.compile(optimizer="rmsprop",
                  loss="binary_crossentropy",
                  metrics=["accuracy"])
    return model
```



```python
text_vectorization = TextVectorization(
    max_tokens=20000,
    output_mode="multi_hot",
```

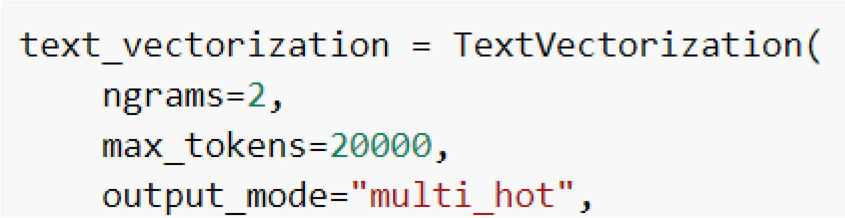
- Naïve baseline = 50% (balance data)
- Test accuracy = 89.2%

IMDB review example (improving bag-of-word approach)

- We started with Single words (Unigram) with binary encoding (multi-hot)
- Two words (Bigrams) with binary encoding (multi-hot): adding local order information
- The cat sat on the mat → {“the”, “the cat”, “cat”, “cat sat”, “sat”, “sat on”, “on”, “on the”, “the mat”, “mat”}

Test accuracy

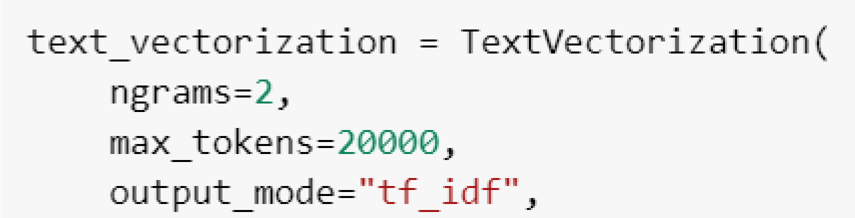
- Naïve baseline = 50% (balance data)
- Unigram binary = 89.2%
- Bigram binary = 90.4%



```
text_vectorization = TextVectorization(
    ngrams=2,
    max_tokens=20000,
    output_mode="multi_hot",
```

IMDB review example (improving bag-of-word approach)

- Bigrams with TF-IDF encoding



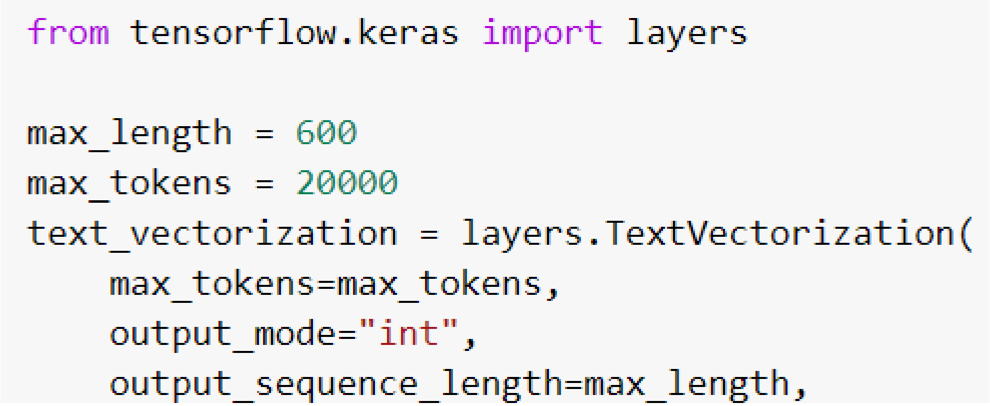
```
text_vectorization = TextVectorization(
    ngrams=2,
    max_tokens=20000,
    output_mode="tf_idf",
```

Test accuracy

- Naïve baseline = 50% (balance data)
- Unigram binary = 89.2%
- Bigram binary = 90.4%
- Bigram TF-IDF = 89.8%
- Typically, TF-IDF increases the model performance by 1%. It wasn’t the case for the IMDB dataset.

IMDB review example (sequence modeling approach)

1. Starting by representing the input as sequences of integer indices (one integer for one word)
2. Map each integer to a vector to get sequences of vectors (one-hot or word embedding)
3. Finally, feed these vectors into a stack of layers such as 1D Convnet, RNN or a Transformer.



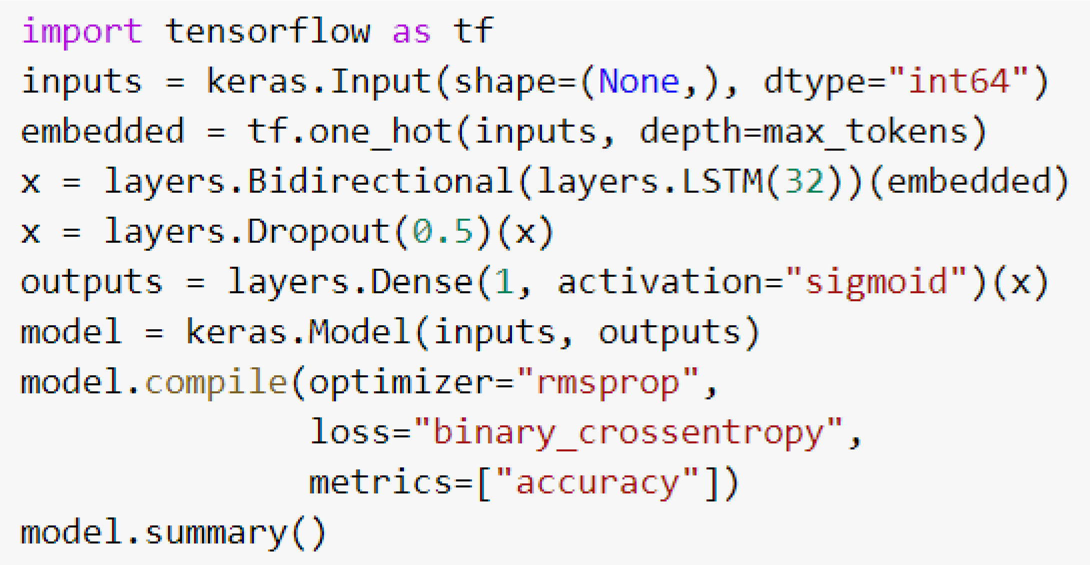
```
from tensorflow.keras import layers

max_length = 600
max_tokens = 20000
text_vectorization = layers.TextVectorization(
    max_tokens=max_tokens,
    output_mode="int",
    output_sequence_length=max_length,
```

Deep learning with Python, Francois Chollet

IMDB review example (sequence modeling approach)

- One-hot encoding approach: Encode the integers into binary 20,000-dimensional vectors.



```
import tensorflow as tf
inputs = keras.Input(shape=(None,), dtype="int64")
embedded = tf.one_hot(inputs, depth=max_tokens)
x = layers.Bidirectional(layers.LSTM(32))(embedded)
x = layers.Dropout(0.5)(x)
outputs = layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs, outputs)
model.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
model.summary()
```

Test accuracy

- Naïve baseline = 50% (balance data)
- Unigram binary = 89.2%
- Bigram binary = 90.4%
- Bigram TF-IDF = 89.8%
- Sequence one-hot encode = 87%

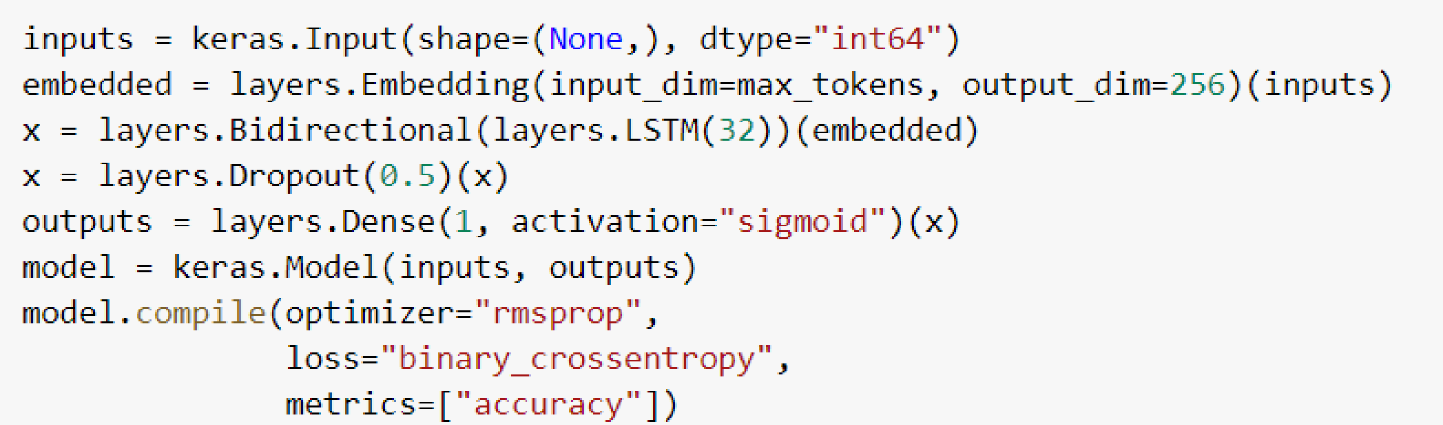
- This model trains very slowly. 600*20,000 = 12 million floats for a single movie review!
- There must be a better way than one-hot encoding!

IMDB review example (improving sequence modeling approach)

- Word-embedding approach:

1. Simultaneously trained word embedding (trained jointly with the weights of a NN)
2. Pretrained word embedding

- Sometimes it is reasonable to learn a new embedding space for different tasks (for example movie-review is different from legal-document classification)
- Word index → word embedding layer → corresponding word vector



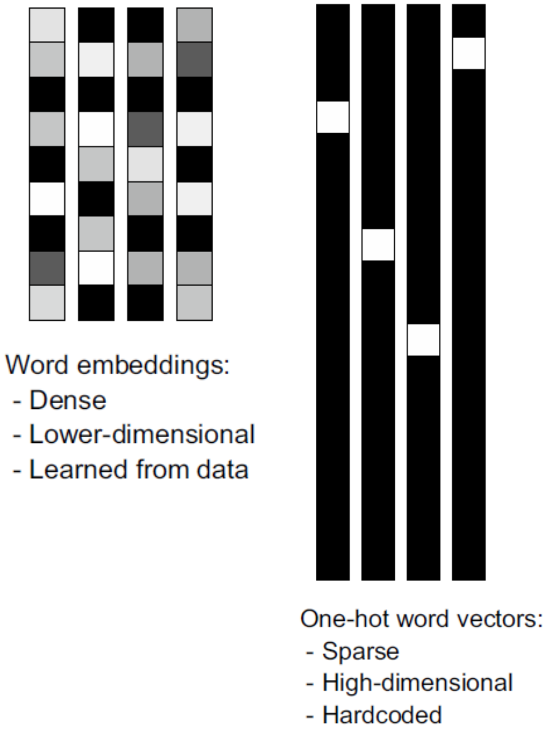
```
inputs = keras.Input(shape=(None,), dtype="int64")
embedded = layers.Embedding(input_dim=max_tokens, output_dim=256)(inputs)
x = layers.Bidirectional(layers.LSTM(32))(embedded)
x = layers.Dropout(0.5)(x)
outputs = layers.Dense(1, activation="sigmoid")(x)
model = keras.Model(inputs, outputs)
model.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
```

IMDB review example (improving sequence modeling approach)

- Word-embedding approach performance:
- It trains much faster than the one-hot encoding (256 vs 20k dim)

Test accuracy

- Naïve baseline = 50% (balance data)
- Unigram binary = 89.2%
- Bigram binary = 90.4%
- Bigram TF-IDF = 89.8%
- Sequence one-hot encode = 87%
- Sequence word embedding simultaneously trained = 87%
- Sequence word embedding simultaneously trained with masks = 88%



Word embeddings:
- Dense
- Lower-dimensional
- Learned from data

One-hot word vectors:
- Sparse
- High-dimensional
- Hardcoded

Pretrained word embedding

- Motivation: little training data! The network cannot learn an appropriate embedding.
- Analogous to using pretrained convnets in image classification
- Useful when expecting generic features.
- Schemes:
  - The Word2Vec algorithm (Tomas MiKolov at Google 2013): a predictive model that uses a neural network to predict the probability of a word given its context
  - GloVe (Stanford researchers 2014): a count-based model that computes the co-occurrence probabilities between words in a corpus
- Word2Vec is faster to train than GloVe, especially for large corpora

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Pedram Jahangiry

Road map!

- ✓ Module 1- Introduction to Deep Forecasting
- ✓ Module 2- Setting up Deep Forecasting Environment
- ✓ Module 3- Exponential Smoothing
- ✓ Module 4- ARIMA models
- ✓ Module 5- Machine Learning for Time series Forecasting
- ✓ Module 6- Deep Neural Networks
- Module 7- Deep Sequence Modeling (RNN, LSTM)
- Module 8- Transformers (Attention is all you need!)
- Module 9- Prophet and Neural Prophet