

DATA MINING 2

Time Series - Classification

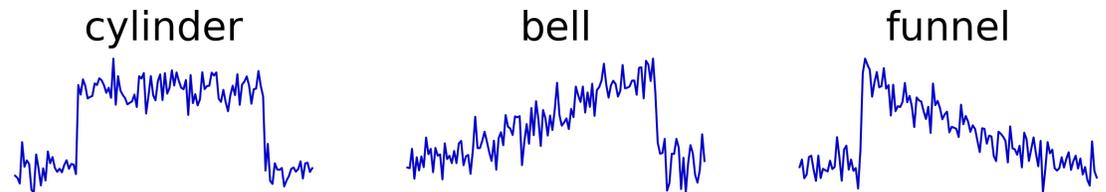
Riccardo Guidotti

a.a. 2019/2020



Time Series Classification

- Main difference between classification and forecasting: forecasting is about predicting a future state/value, classification is about predicting the current label/class.
- Applications:
 - Automated detection of heart diseases
 - Discovery of presence in a room from temperature, humidity, light
 - Identification of the activity performed from smart devices (walking, sitting, laying)
 - Identification of stock market anomalies in pricing, sales volumes, stocks
 - Warning of Natural Disasters (flooding, hurricane, snowstorm),
- Techniques:
 - Motif Discovery
 - Machine Learning Classifiers
 - Deep Neural Networks



Problem Formulation

- Given a set X of n time series, $X = \{x_1, x_2, \dots, x_n\}$, each time series has m ordered values $x_i = \langle x_{t1}, x_{t2}, \dots, x_{tm} \rangle$ and a class value c_i .
- The objective is to find a function f that maps from the space of possible time series to the space of possible class values.
- Generally, it is assumed that all the TS have the same length m .

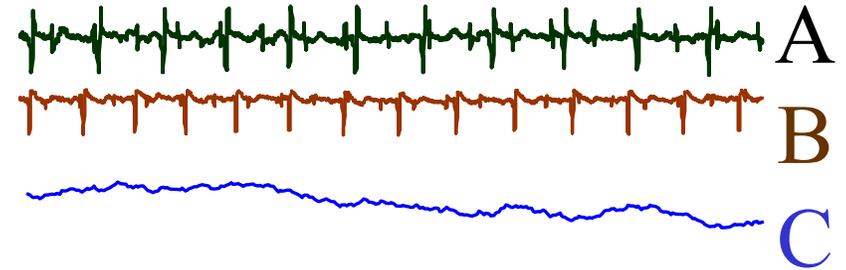
Time Series Classification and Similarities

- To some extent, TS classification rely on a measure of similarity between data.
- What makes time series classification an interesting area of investigation is that similarity between series is often embedded within the autocorrelation structure of the data.
- General approaches to measuring similarity between time series:
 - similarity in time (i.e. correlation-based)
 - similarity in change (autocorrelation-based)
 - **similarity in shape** (shape-based)
 - **similarity in structure** (features-based)
 - **similarity in representation** (NN-based)

Structural-based Classification

Structural-based Classification

- The basic idea is to:
 1. Extract *global* features from the time series,
 2. Create a feature vector, and
 3. Use it to as input for machine learning classifiers
- Example of features:
 - mean, variance, skewness, kurtosis,
 - 1st derivative mean, 1st derivative variance, ...
 - parameters of regression, forecasting, Markov model

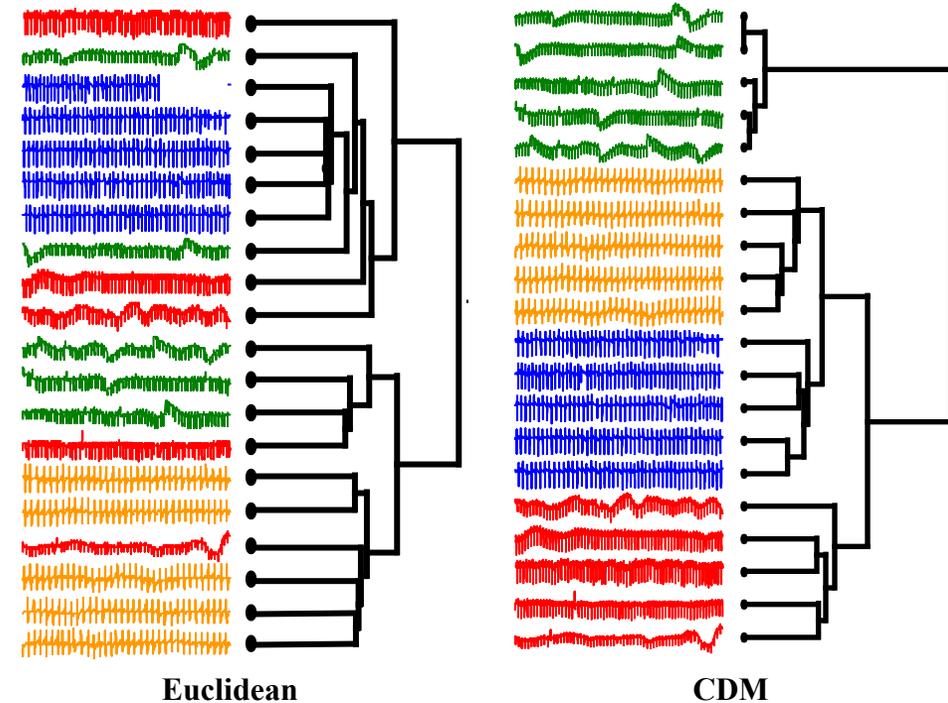


Feature\Time Series	A	B	C
Max Value	11	12	19
Mean	5.3	6.4	4.8
Min Value	3	2	5
Autocorrelation	0.2	0.3	0.5
...

Shape-based Classification

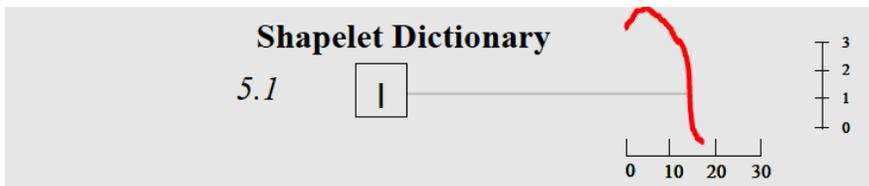
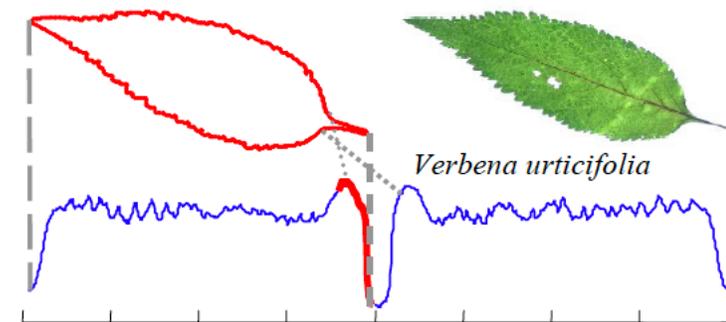
Shape-based Classification

- Calculate the distance between TS using an appropriate distance function:
 - Euclidean/Manhattan
 - Dynamic Time Warping
 - Compression Based Dissimilarity
- Use an instance-based classifier (k-NN) to make the classification.

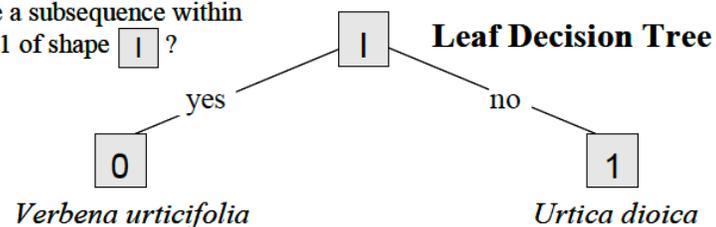


Shape-based Classification

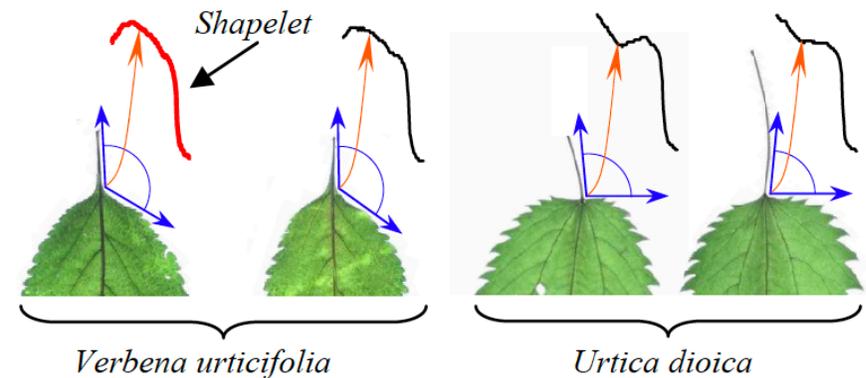
1. Represent a TS as a vector of distances with representative subsequences, namely shapelets.
2. Use it to as input for machine learning classifiers.



Does Q have a subsequence within a distance 5.1 of shape I ?

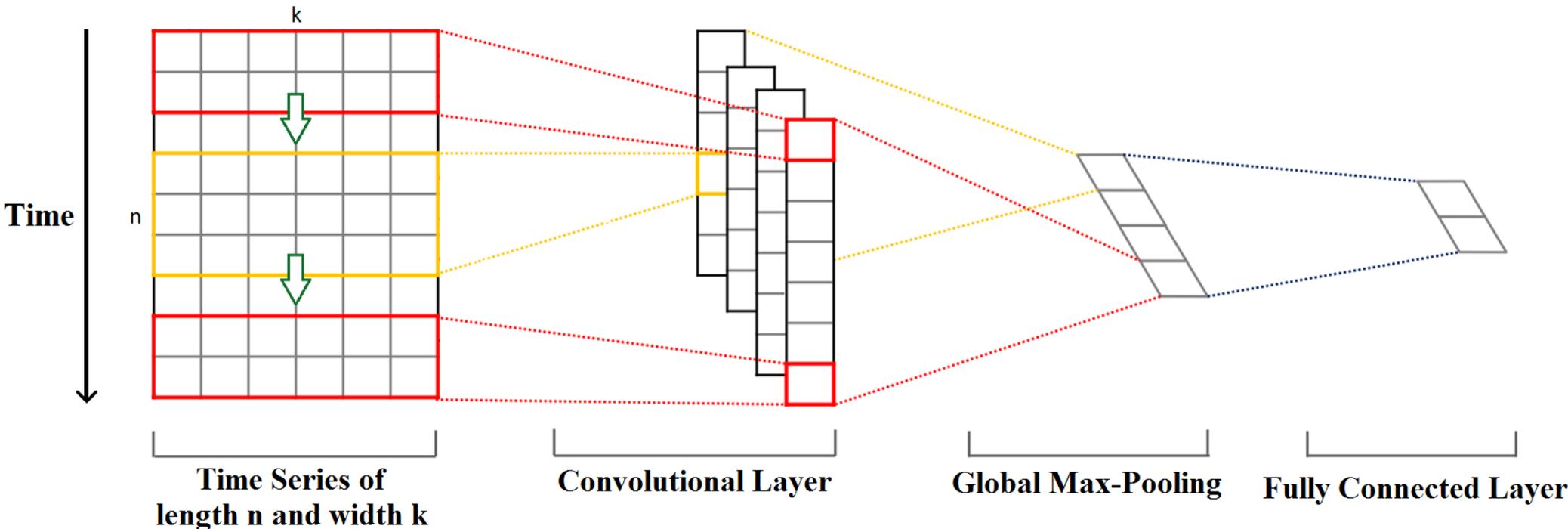


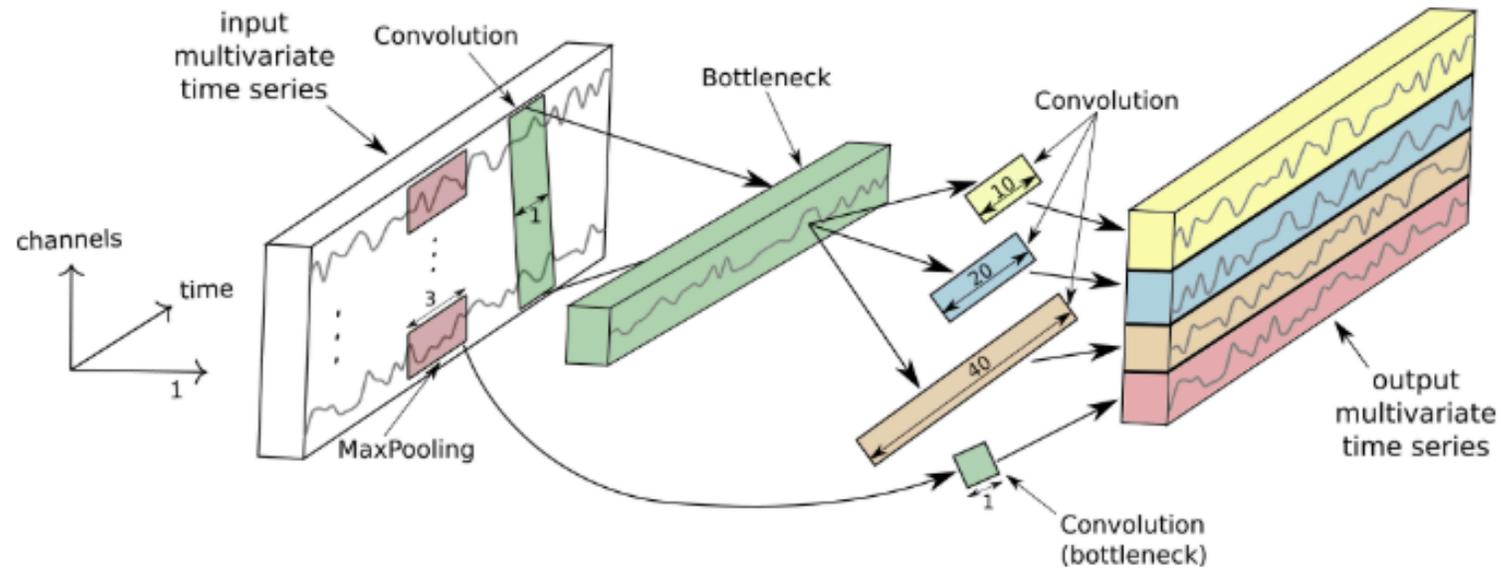
3.2	8.7
1.4	7.9
6.7	4.2
9.2	3.4



Time Series Classification with DNN

Time Series Classification with DNN





Convolutional Neural Network

Slides edited from Stanford

http://cs231n.stanford.edu/slides/2019/cs231n_2019_lecture09.pdf

Convolutional Neural Network

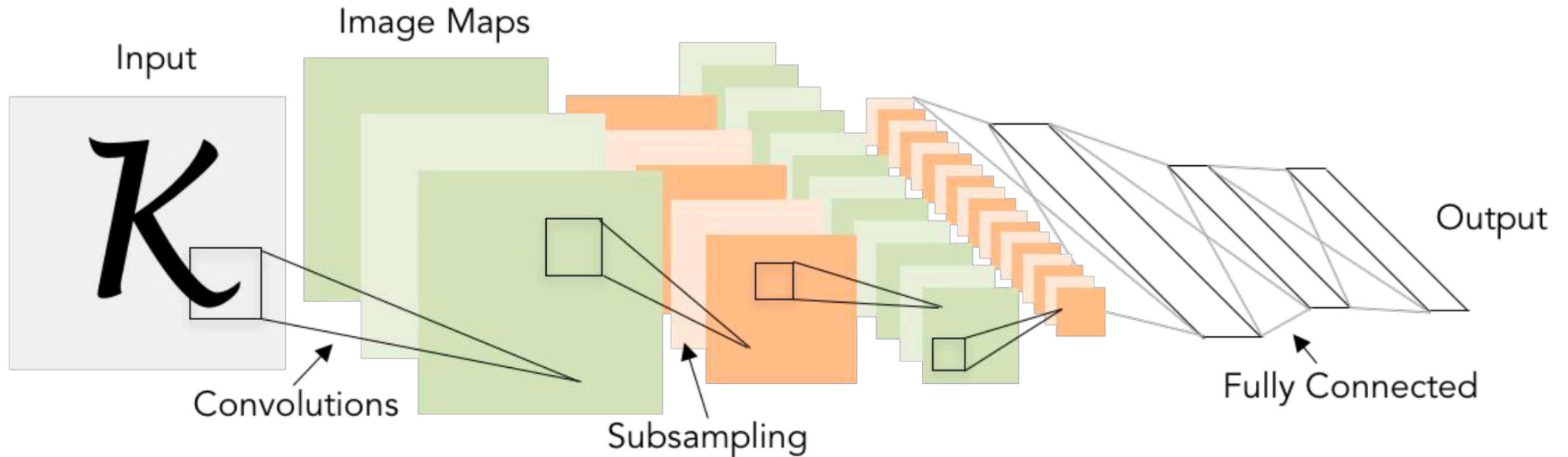
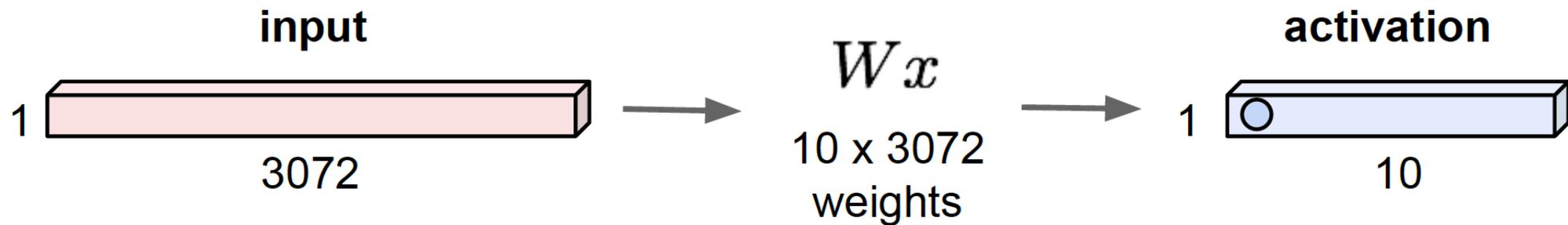


Illustration of LeCun et al. 1998 from CS231n 2017 Lecture 1

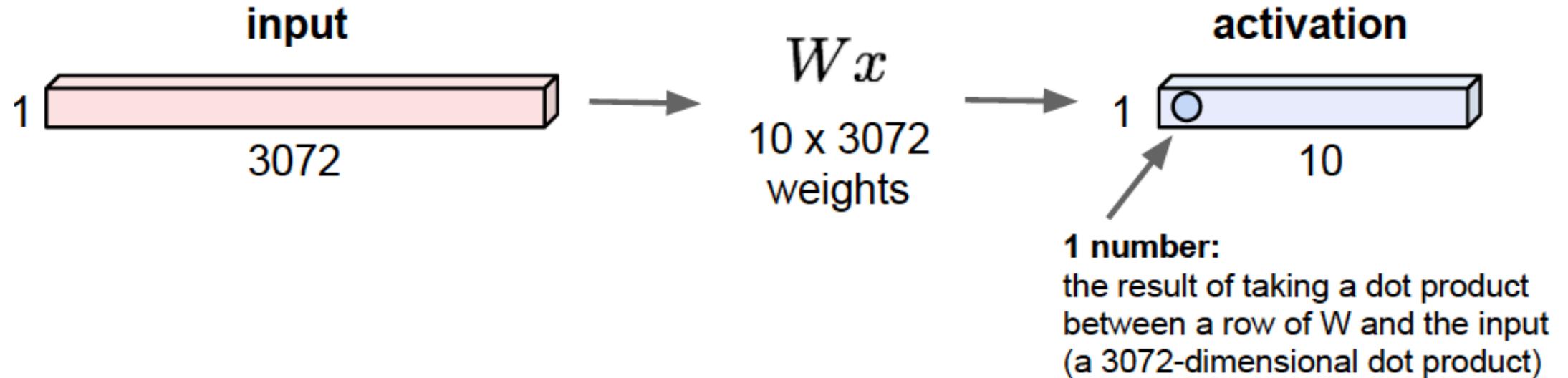
Fully Connected Layer

32x32x3 image -> stretch to 3072 x 1



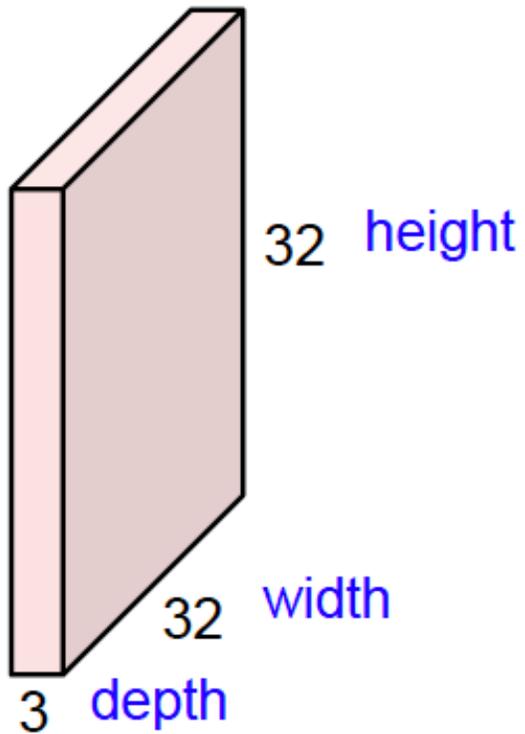
Fully Connected Layer

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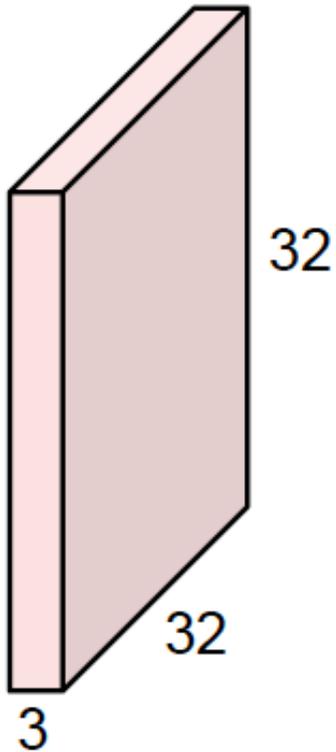
Convolution Layer

32x32x3 image -> preserve spatial structure



Convolution Layer

32x32x3 image



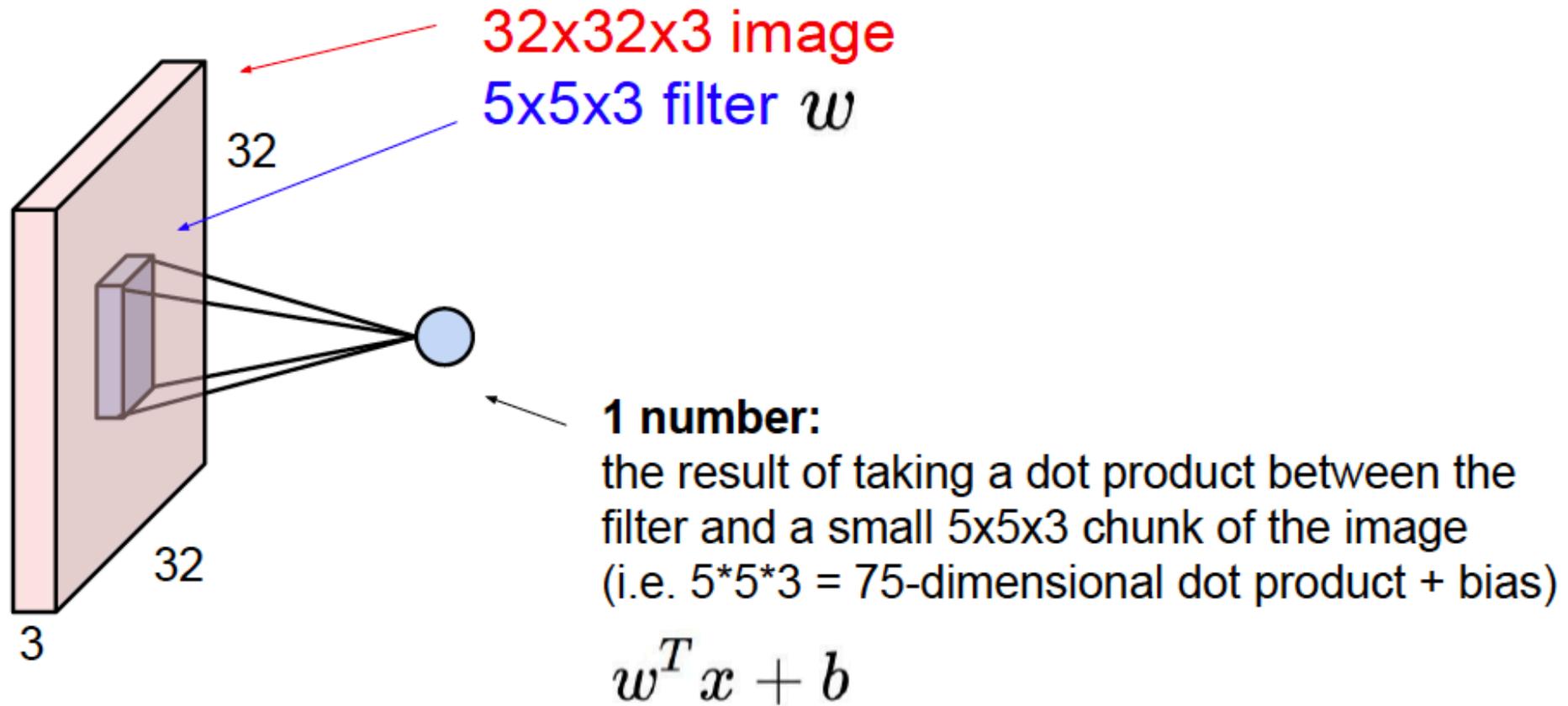
Filters always extend the full depth of the input volume

5x5x3 filter

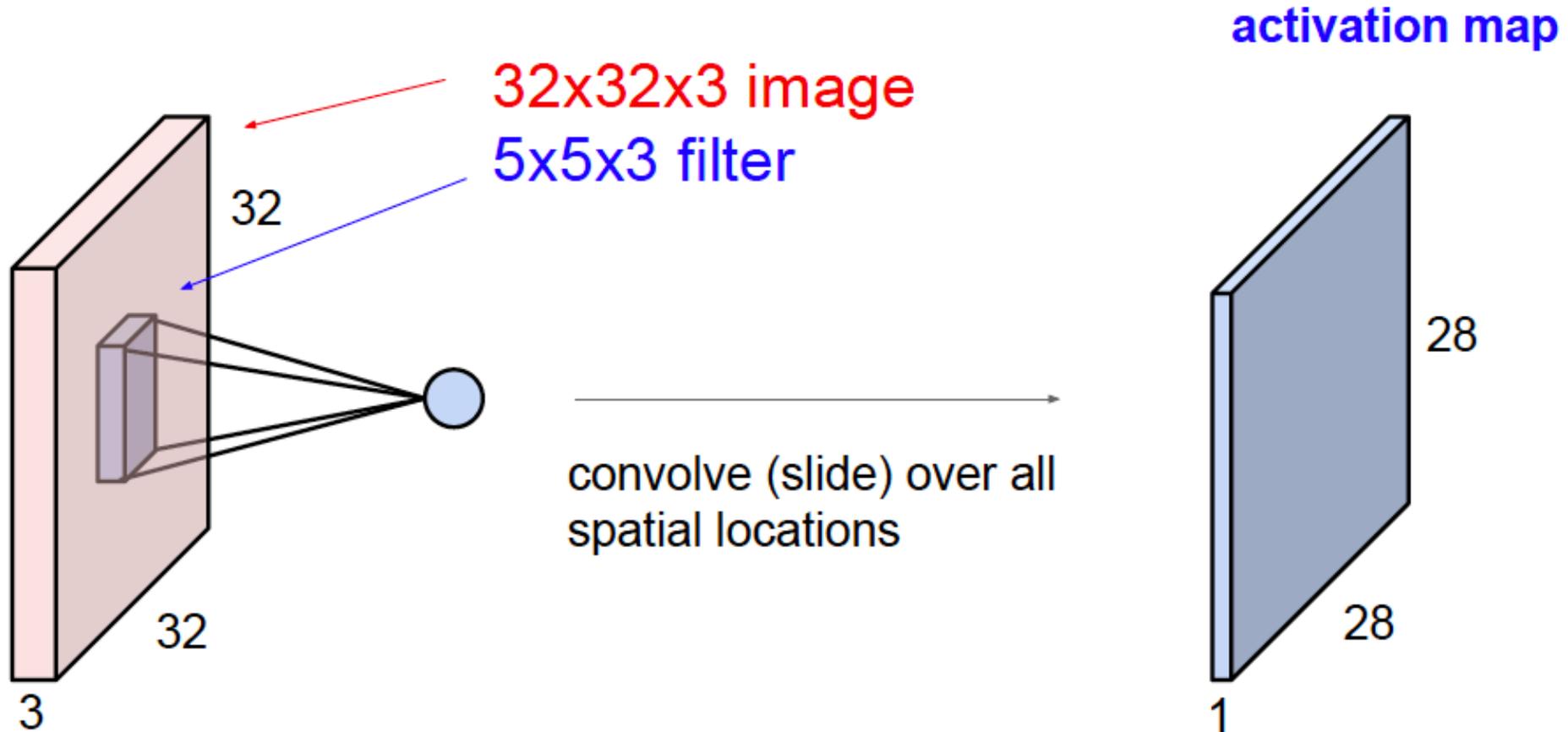


Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”

Convolution Layer



Convolution Layer



Convolution Layer

1 _{x1}	1 _{x0}	1 _{x1}	0	0
0 _{x0}	1 _{x1}	1 _{x0}	1	0
0 _{x1}	0 _{x0}	1 _{x1}	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

Convolved
Feature

1	0	1
0	1	0
1	0	1

Convolution
Kernel

Convolution Layer

0	0	0	0	0	0	...
0	156	155	156	158	158	...
0	153	154	157	159	159	...
0	149	151	155	158	159	...
0	146	146	149	153	158	...
0	145	143	143	148	158	...
...

Input Channel #1 (Red)

0	0	0	0	0	0	...
0	167	166	167	169	169	...
0	164	165	168	170	170	...
0	160	162	166	169	170	...
0	156	156	159	163	168	...
0	155	153	153	158	168	...
...

Input Channel #2 (Green)

0	0	0	0	0	0	...
0	163	162	163	165	165	...
0	160	161	164	166	166	...
0	156	158	162	165	166	...
0	155	155	158	162	167	...
0	154	152	152	157	167	...
...

Input Channel #3 (Blue)

-1	-1	1
0	1	-1
0	1	1

Kernel Channel #1



308

+

1	0	0
1	-1	-1
1	0	-1

Kernel Channel #2



-498

+

0	1	1
0	1	0
1	-1	1

Kernel Channel #3



164

+ 1 = -25

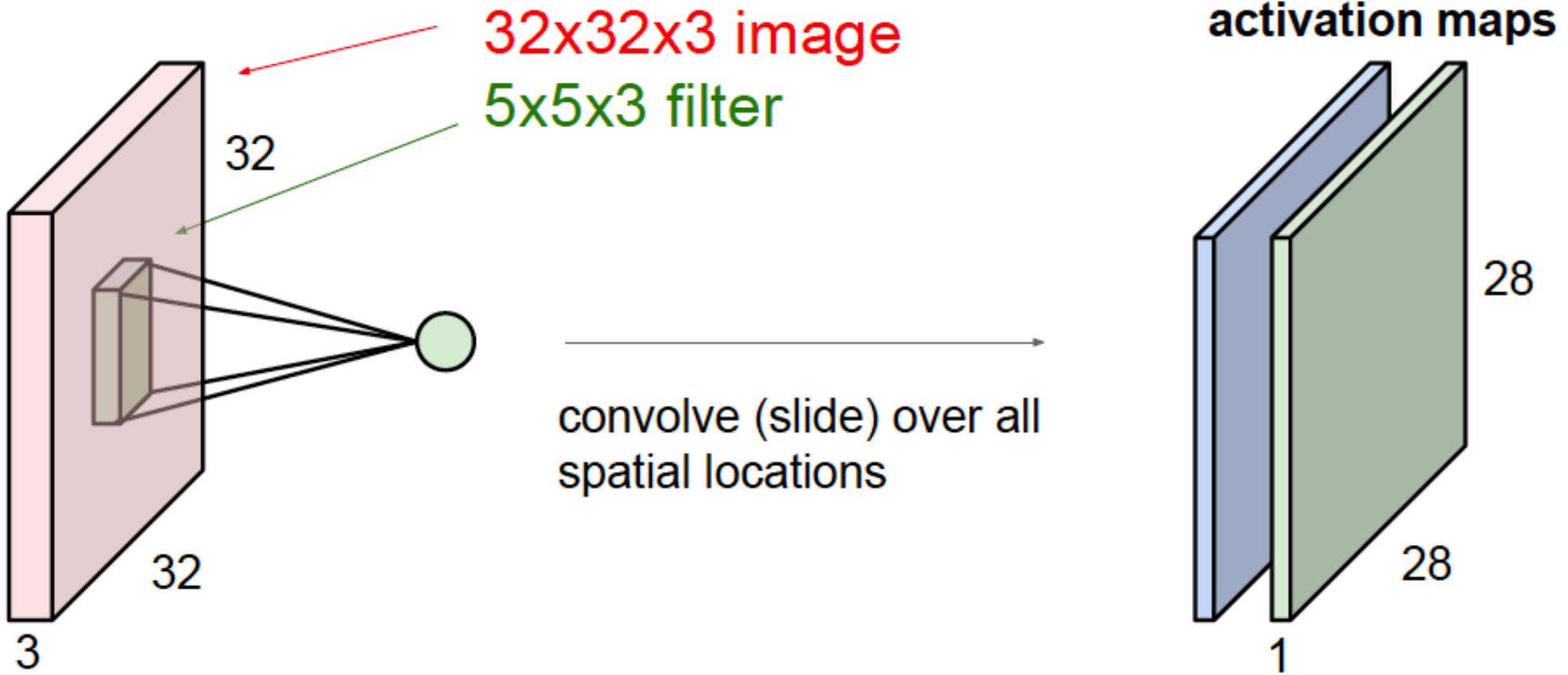


Bias = 1

Output

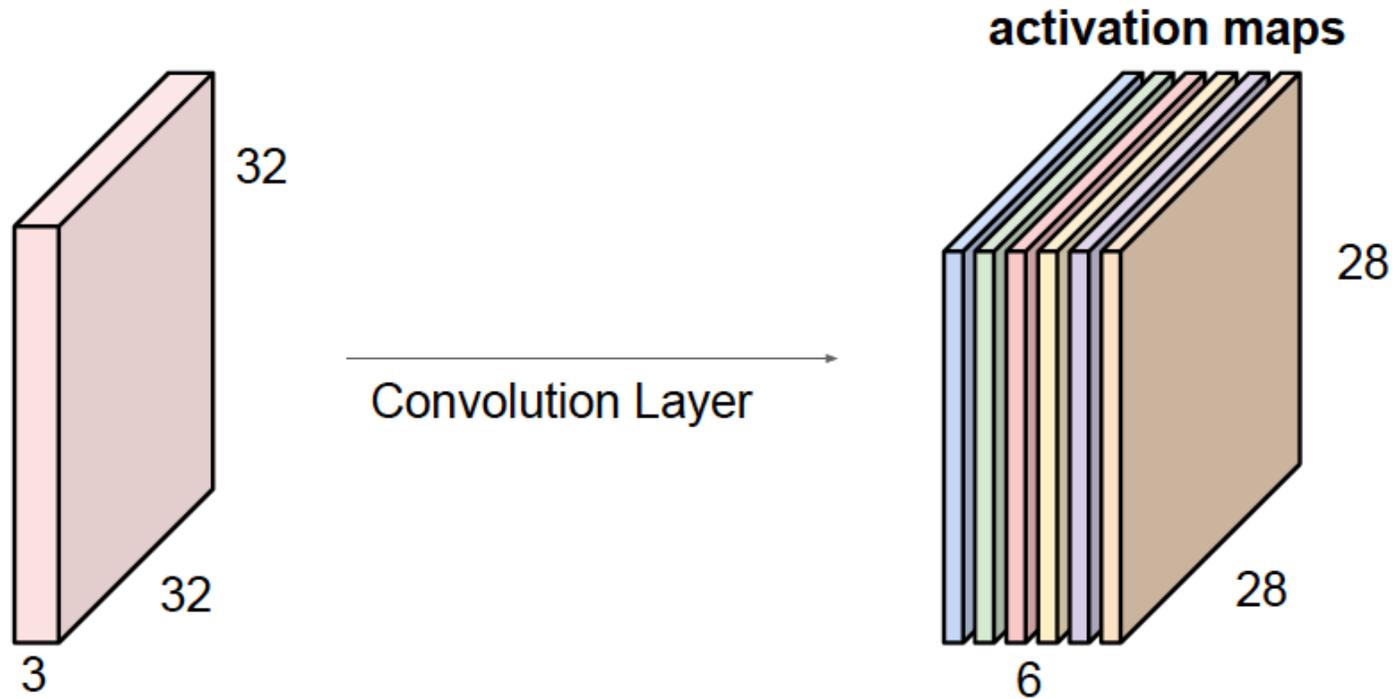
-25				...
				...
				...
				...
...

Convolution Layer



Convolution Layer

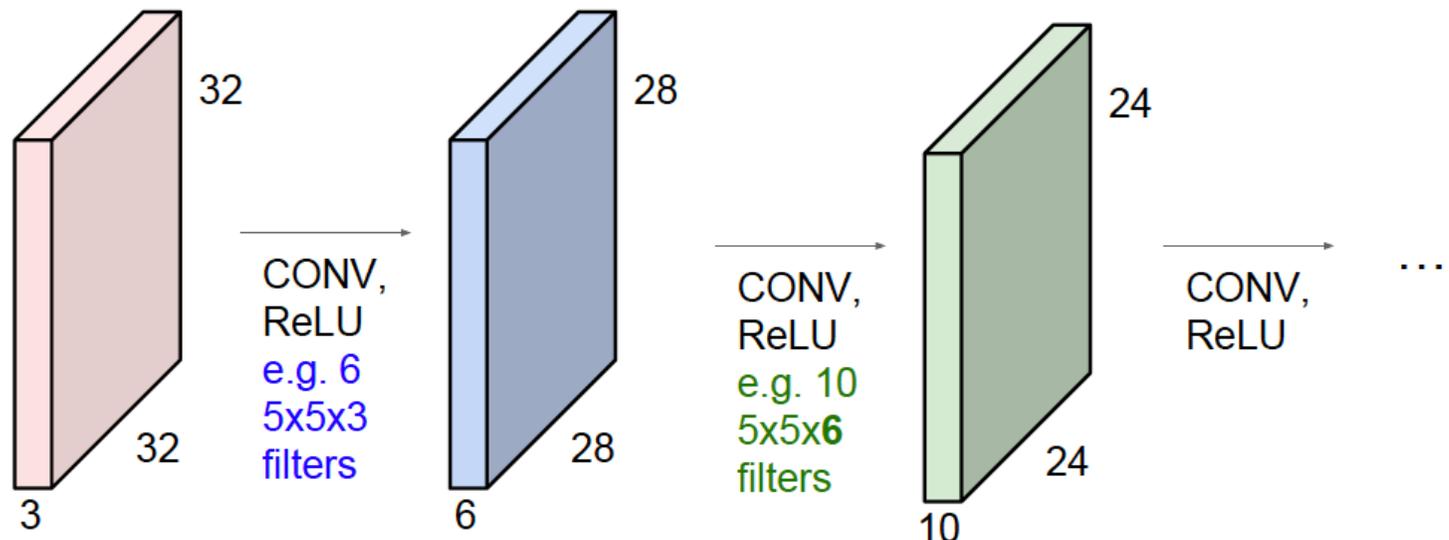
For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



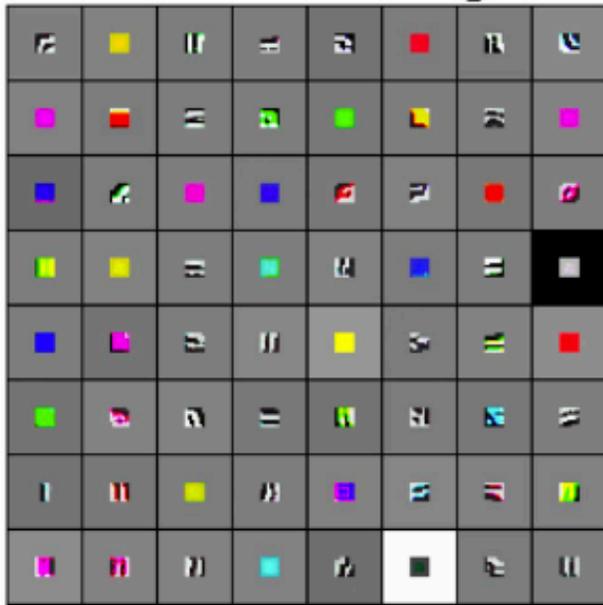
We stack these up to get a “new image” of size 28x28x6!

Convolutional Neural Network

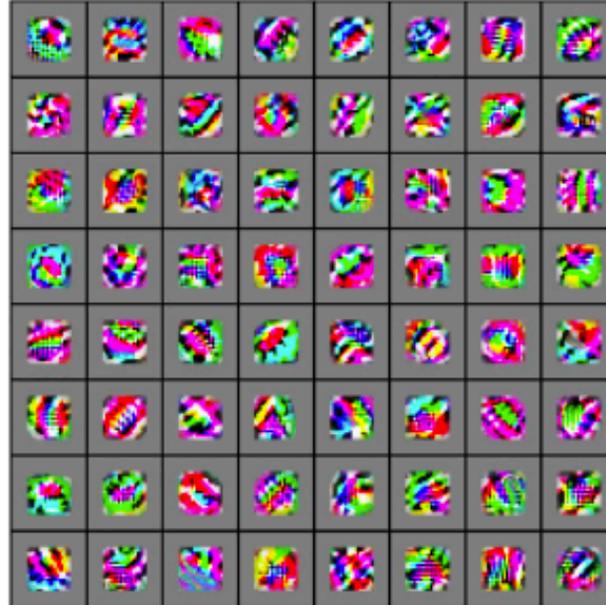
- CNN is a sequence of Conv Layers, interspersed with activation functions.
- CNN shrinks volumes spatially.
- E.g. 32x32 input convolved repeatedly with 5x5 filters! (32 -> 28 -> 24 ...).
- Shrinking too fast is not good, doesn't work well.



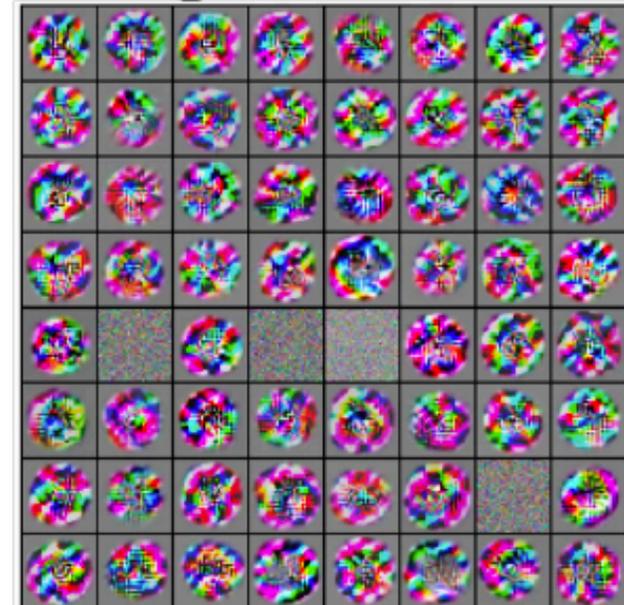
CNN for Image Classification



VGG-16 Conv1_1



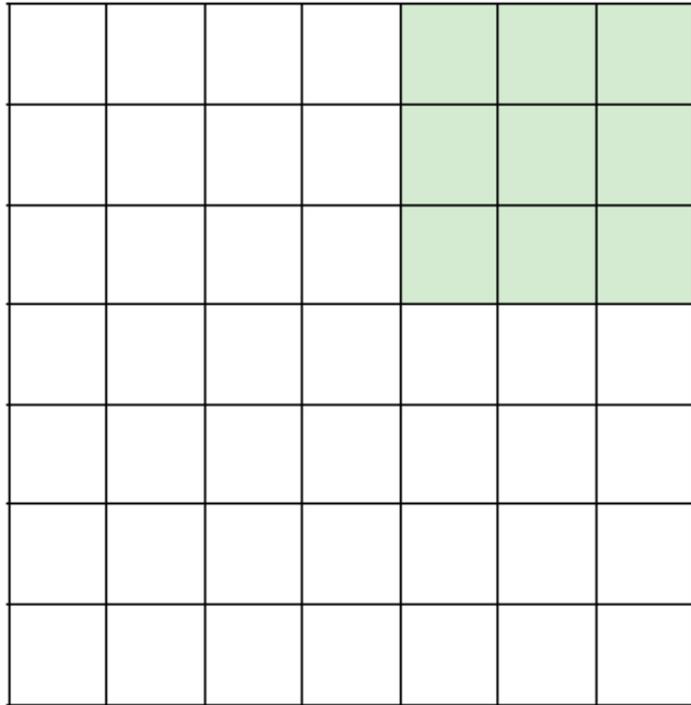
VGG-16 Conv3_2



VGG-16 Conv5_3

Stride

7

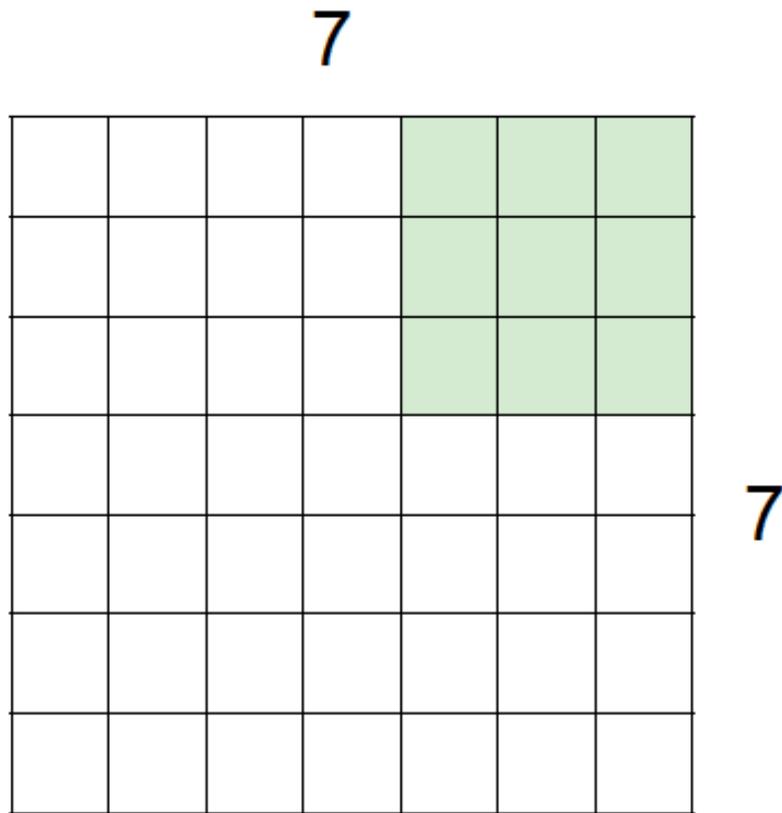


7x7 input (spatially)
assume 3x3 filter

=> 5x5 output

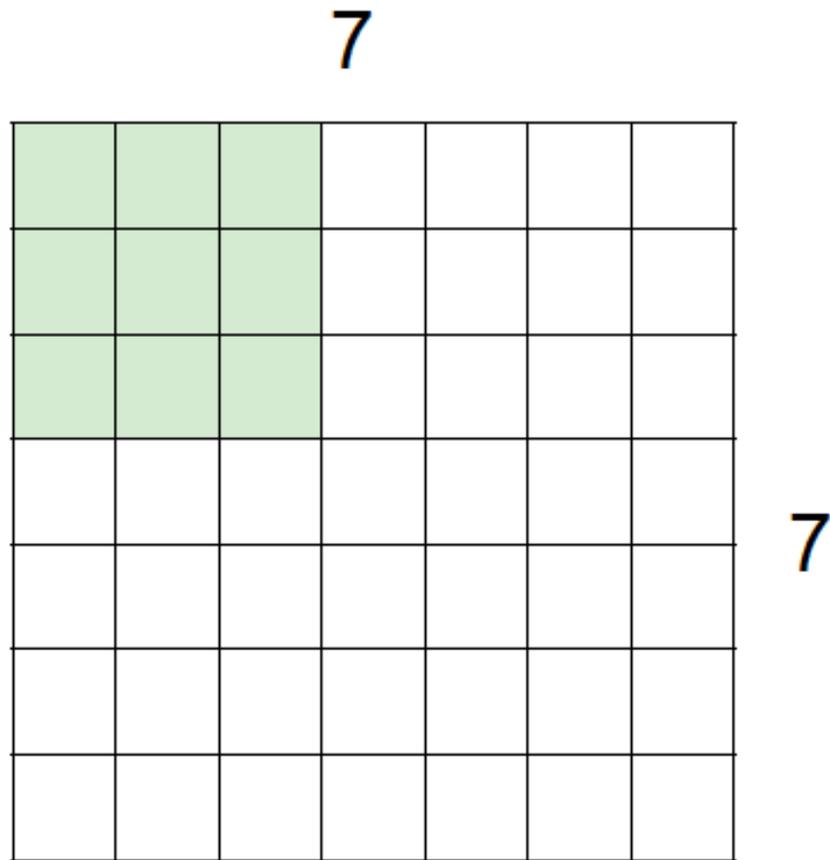
7

Stride



7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**
=> 3x3 output!

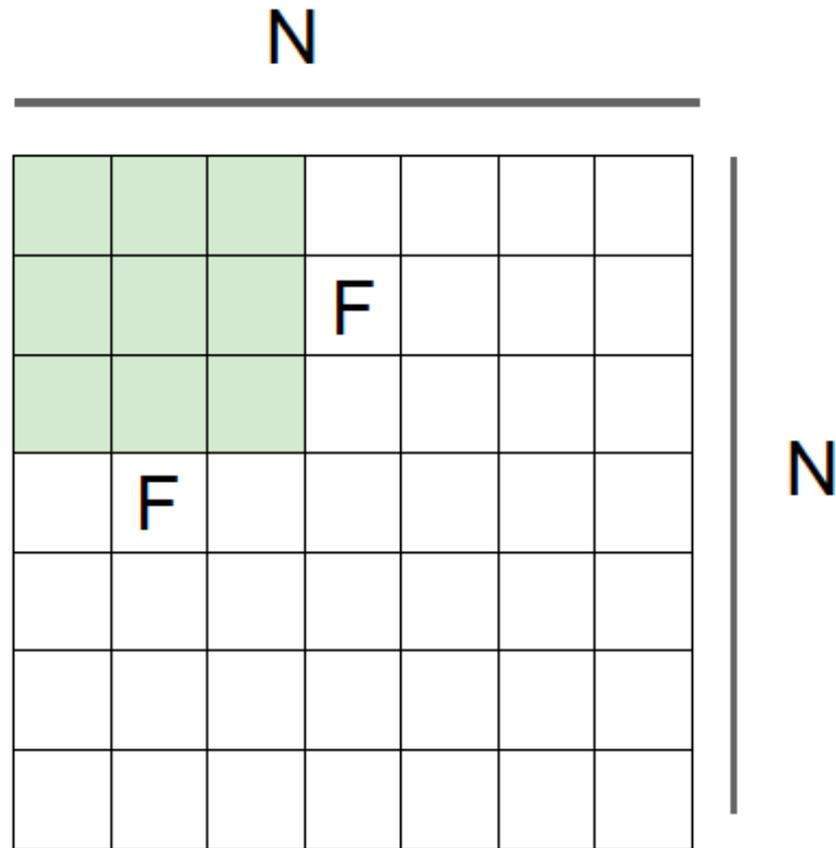
Stride



7x7 input (spatially)
assume 3x3 filter
applied **with stride 3?**

doesn't fit!
cannot apply 3x3 filter on
7x7 input with stride 3.

Stride



Output size:

$$(N - F) / \text{stride} + 1$$

e.g. $N = 7, F = 3$:

$$\text{stride } 1 \Rightarrow (7 - 3) / 1 + 1 = 5$$

$$\text{stride } 2 \Rightarrow (7 - 3) / 2 + 1 = 3$$

$$\text{stride } 3 \Rightarrow (7 - 3) / 3 + 1 = 2.33 \text{ :}\backslash$$

Padding

0	0	0	0	0	0			
0								
0								
0								
0								

e.g. input 7x7

3x3 filter, applied with **stride 1**

pad with 1 pixel border => what is the output?

7x7 output!

In general, common to see CONV layers with stride 1, filters of size $F \times F$, and zero-padding with $(F-1)/2$.
(will preserve size spatially)

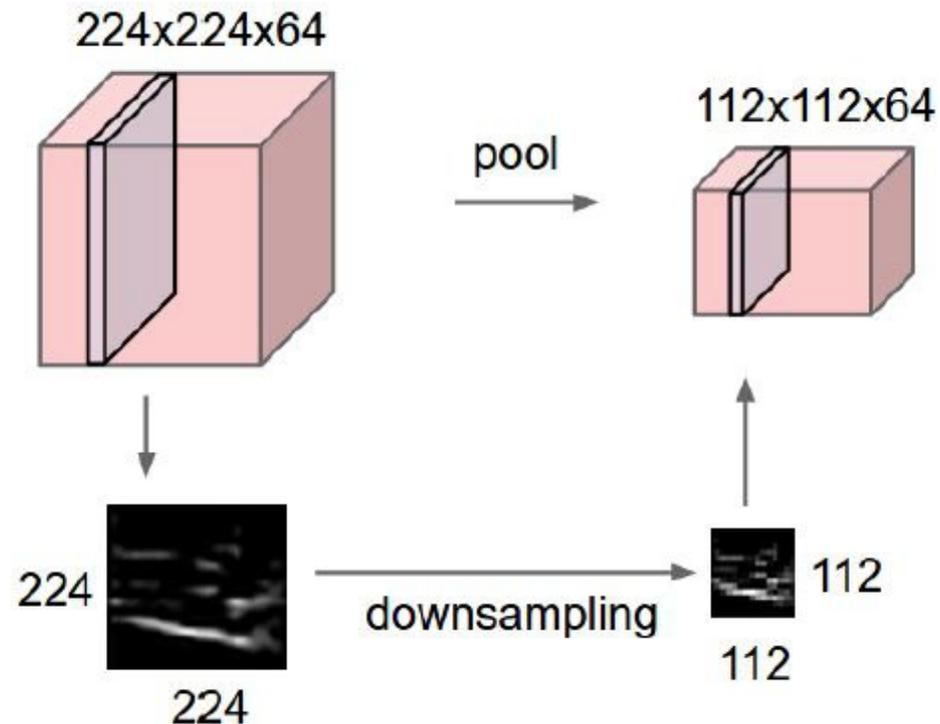
- $F = 3 \Rightarrow$ zero pad with 1 pixel
- $F = 5 \Rightarrow$ zero pad with 2 pixel
- $F = 7 \Rightarrow$ zero pad with 3 pixel

Summary

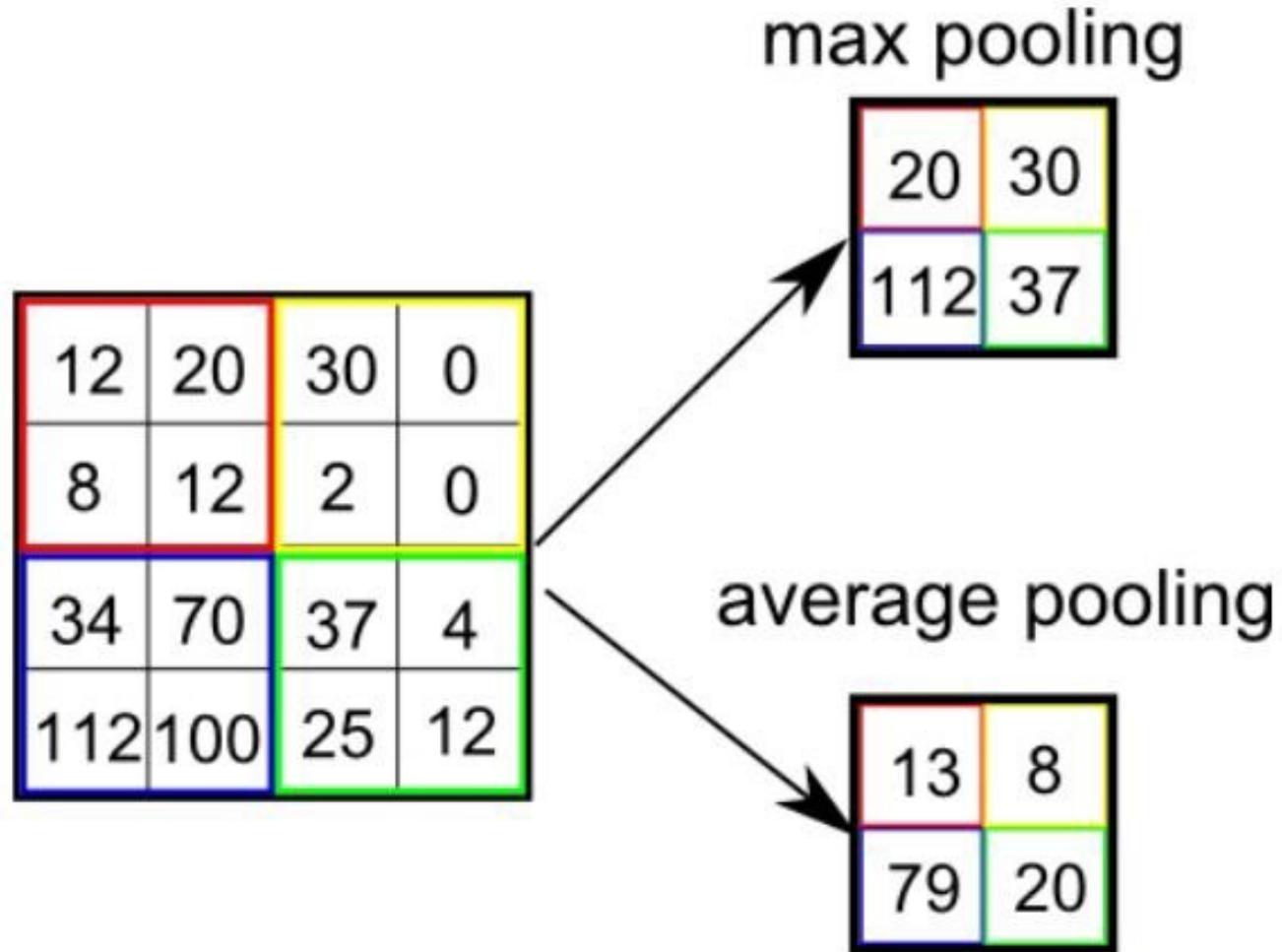
- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires four hyperparameters:
 - Number of filters K ,
 - their spatial extent F ,
 - the stride S ,
 - the amount of zero padding P .
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
 - $W_2 = (W_1 - F + 2P)/S + 1$
 - $H_2 = (H_1 - F + 2P)/S + 1$ (i.e. width and height are computed equally by symmetry)
 - $D_2 = K$
- With parameter sharing, it introduces $F \cdot F \cdot D_1$ weights per filter, for a total of $(F \cdot F \cdot D_1) \cdot K$ weights and K biases.
- In the output volume, the d -th depth slice (of size $W_2 \times H_2$) is the result of performing a valid convolution of the d -th filter over the input volume with a stride of S , and then offset by d -th bias.

Pooling Layer

- Makes the representations smaller and more manageable
- Operates over each activation map independently



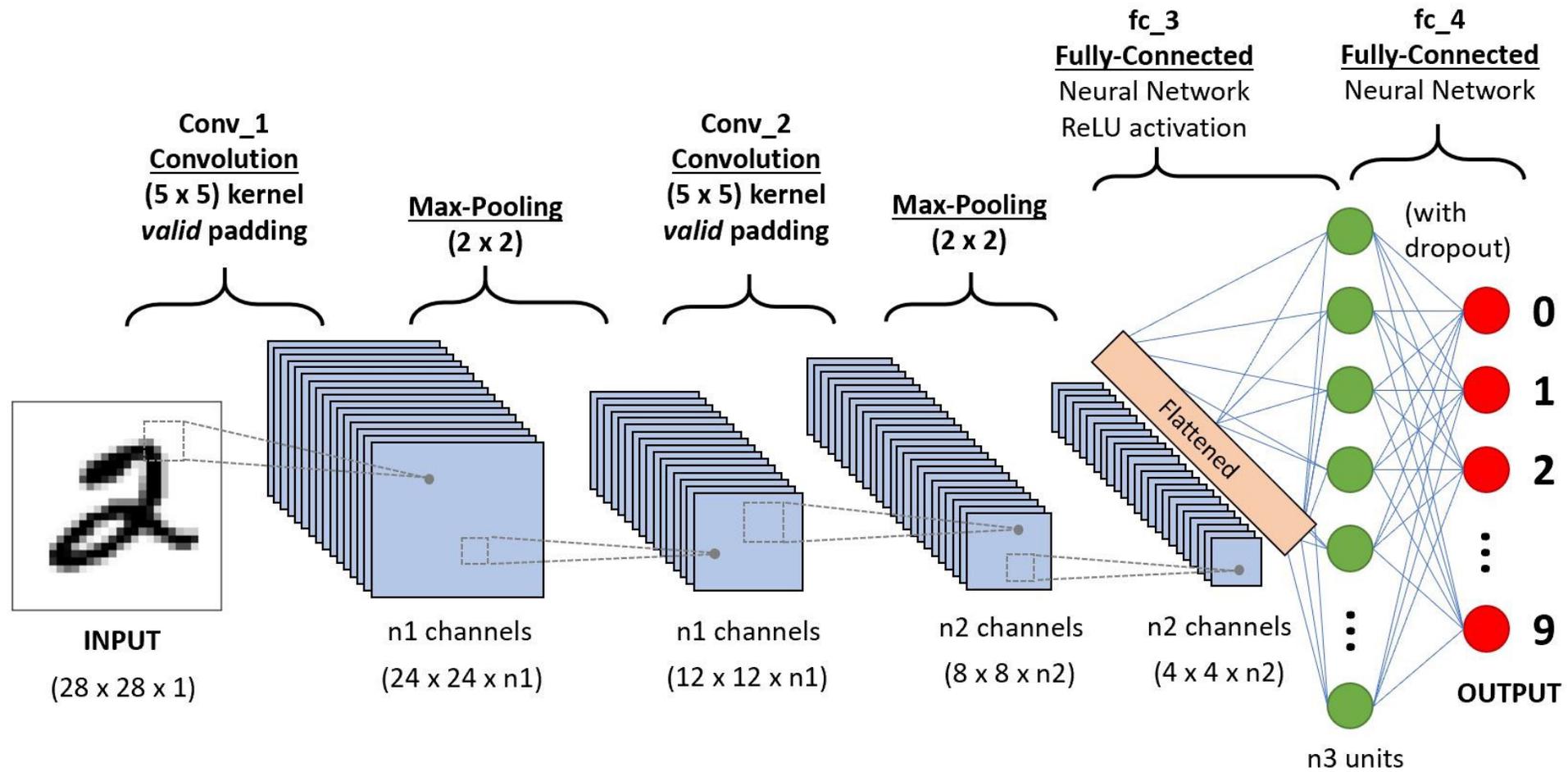
MaxPooling and AvgPoling



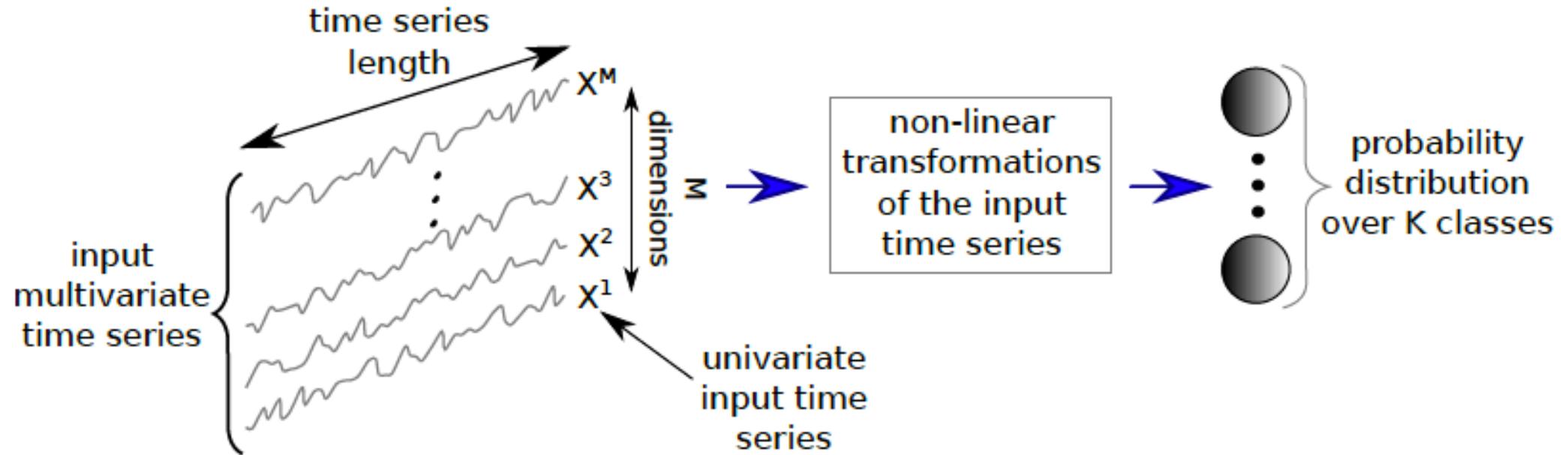
Pooling

- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires three hyperparameters:
 - their spatial extent F ,
 - the stride S ,
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
 - $W_2 = (W_1 - F) / S + 1$
 - $H_2 = (H_1 - F) / S + 1$
 - $D_2 = D_1$
- Introduces zero parameters since it computes a fixed function of the input
- Note that it is not common to use zero-padding for Pooling layers

Example of CNN

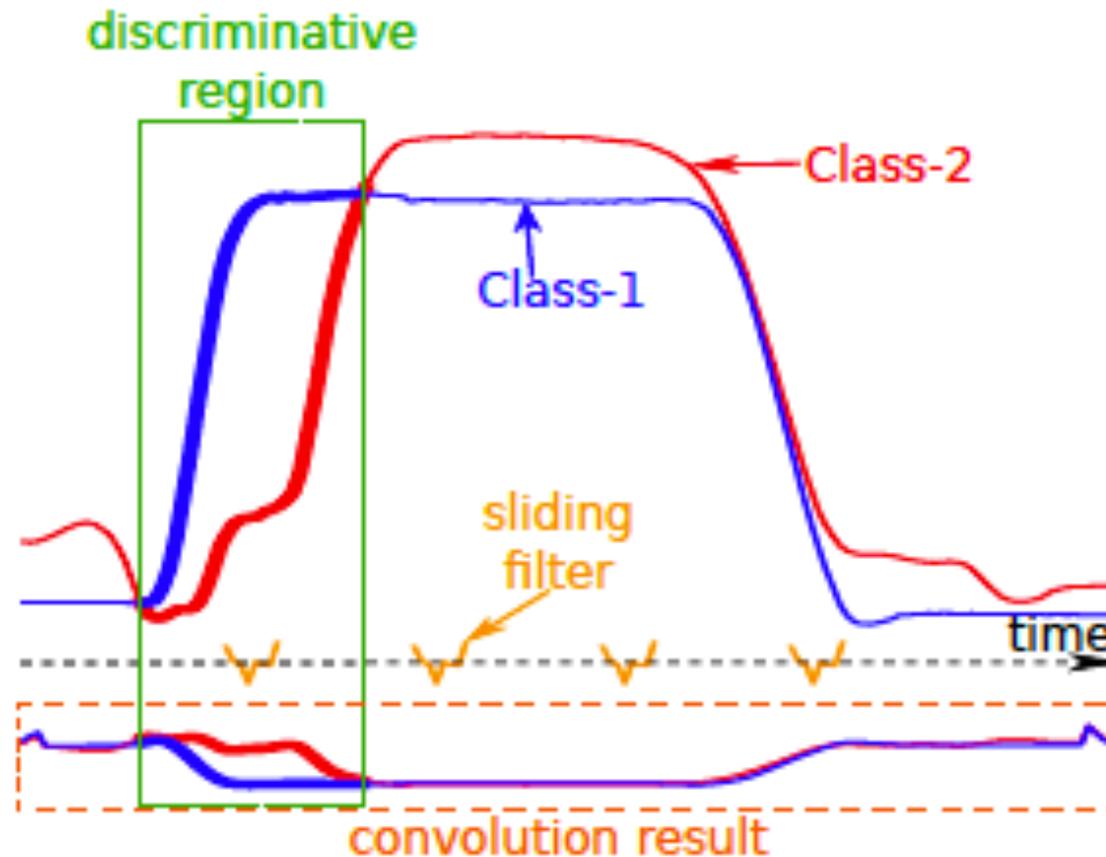


CNN for Time Series Classification

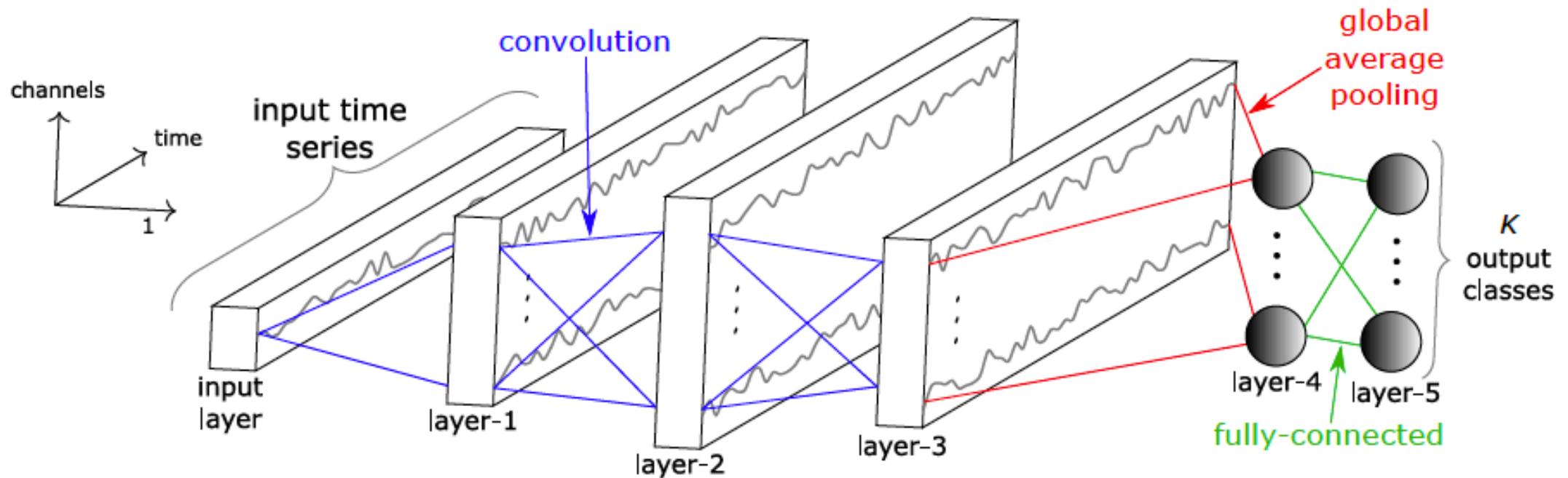


CNN for Time Series Classification

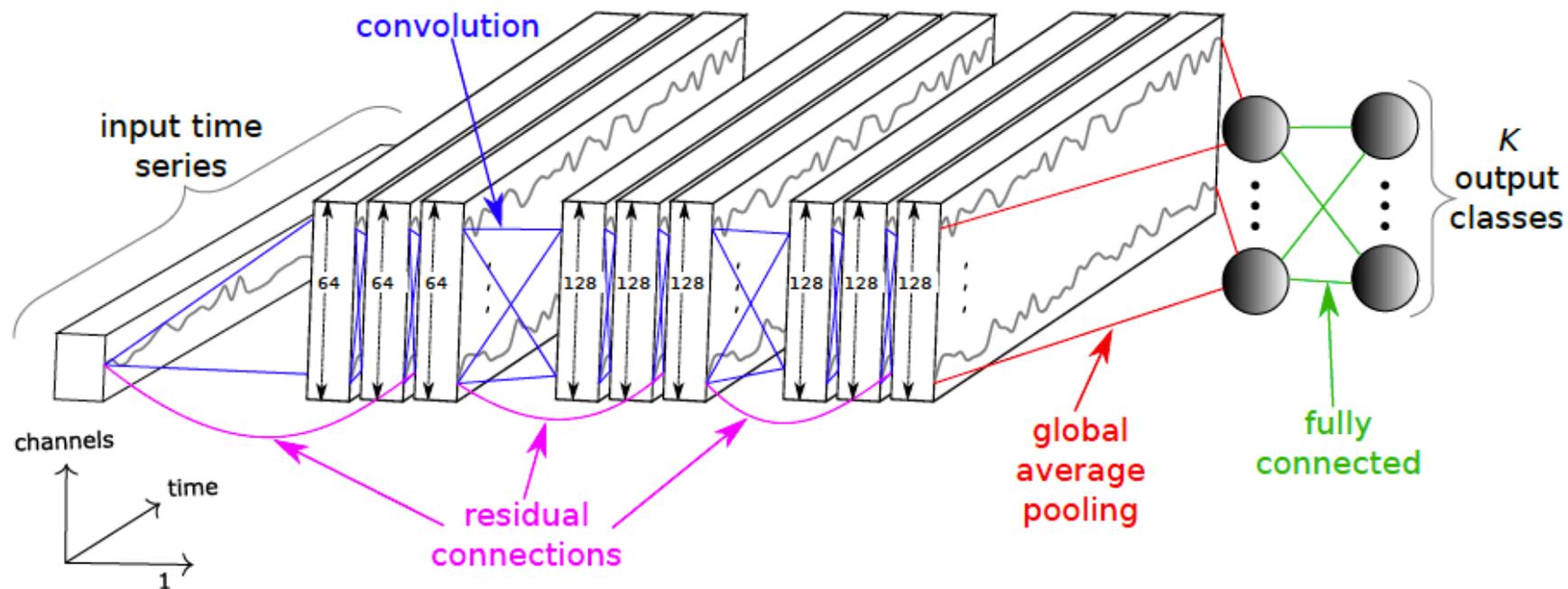
- Result of applying a learned discriminative convolution.



CNN for Time Series Classification



Residual Neural Network (ResNet/ResNet)



The main characteristic of ResNets is the shortcut residual connection between consecutive CONV layers. The difference with the usual CNN is that a linear shortcut is added to link the output of a residual block to its input thus enabling the flow of the gradient directly through these connections, which makes training a DNN much easier by reducing the vanishing gradient effect.

CNN Summary

- ConvNets stack Convolutional, Pooling, Fully Connected Layers
- Trend towards smaller filters and deeper architectures
- Trend towards getting rid of POOL/FC layers (just CONV)
- Historically CNN looked like
 - $[(\text{CONV-RELU})^*N\text{-POOL?}]^*M\text{-(FC-RELU)}^*K, \text{SOFTMAX}$
 - where N is usually up to ~ 5 , M is large, $0 \leq K \leq 2$.
- Recent advances such as ResNet/GoogLeNet have challenged this paradigm

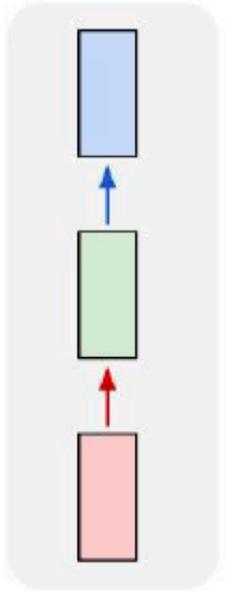
Recurrent Neural Network

Slides edited from Stanford

http://cs231n.stanford.edu/slides/2019/cs231n_2019_lecture10.pdf

Types of Recurrent Neural Networks

one to one



Vanilla NN

one to many

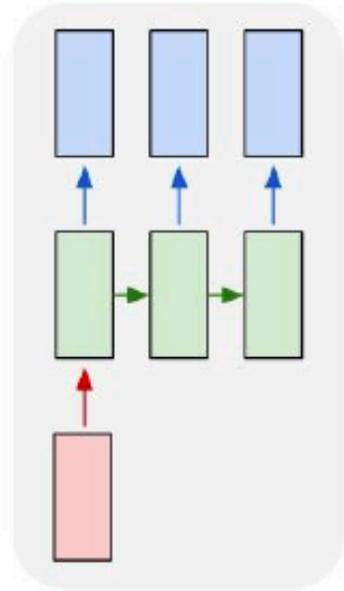
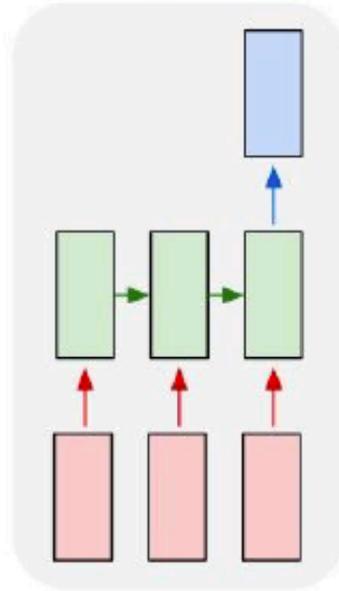


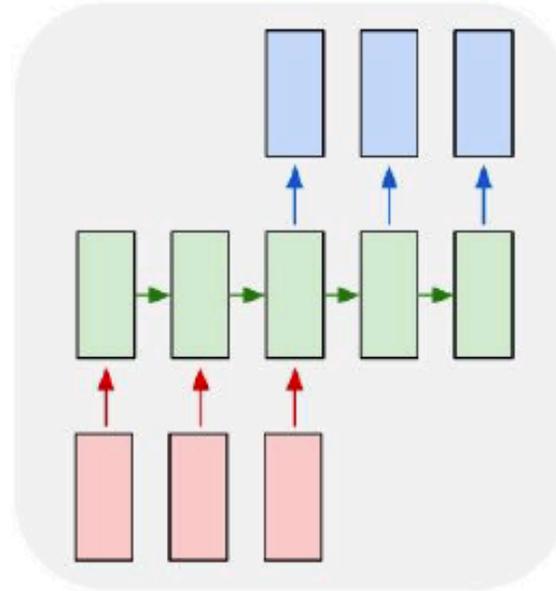
Image -->
Sequence of Words
Image Captioning

many to one



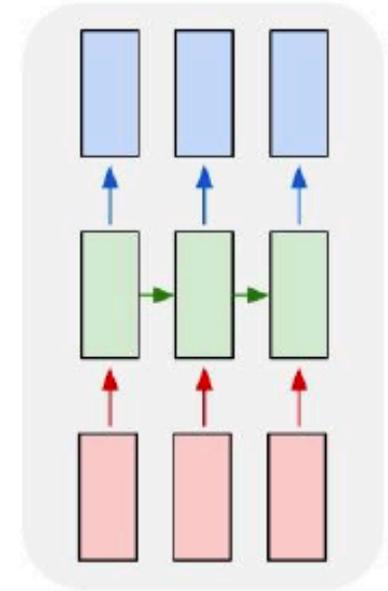
Sequence of Words -->
Sentiment
Sentiment Classification
TS Classification

many to many



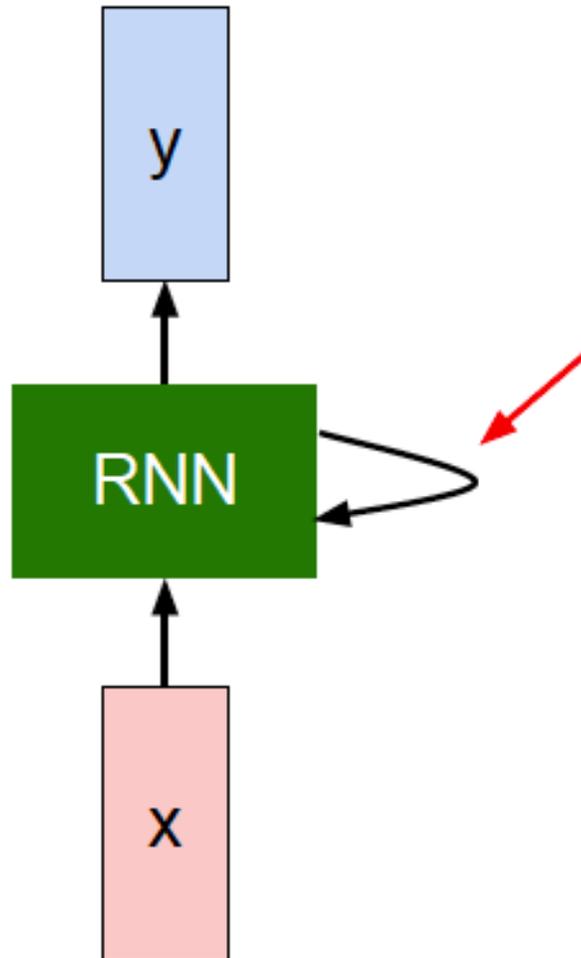
Sequence of Words -->
Sequence of Words
Machine Translation

many to many



Video Classification

Recurrent Neural Network - RNN



Key idea: RNNs have an “internal state” that is updated as a sequence is processed

Recurrent Neural Network - RNN

- We can process a sequence of vectors \mathbf{x} by applying a *recurrence formula* at every time step:

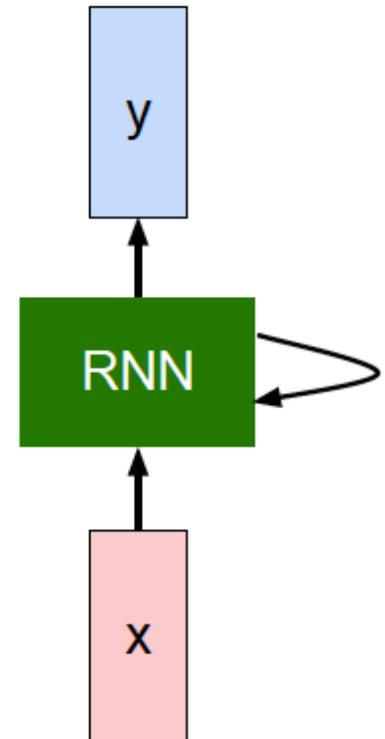
$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

new state

some function
with parameters W

old state

input vector at
some time step



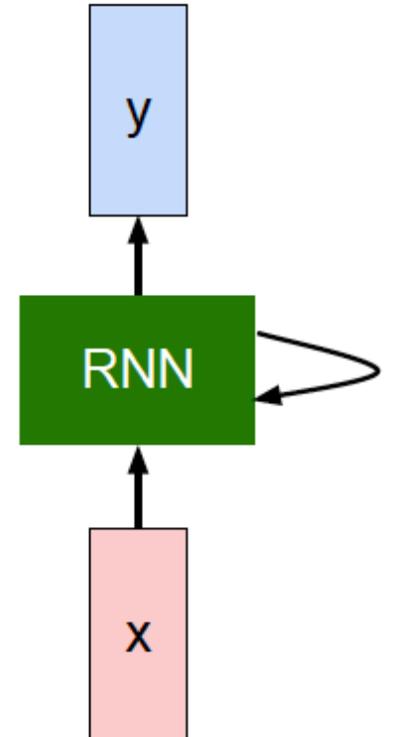
(Simple) Recurrent Neural Network

$$h_t = f_W(h_{t-1}, x_t)$$



$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

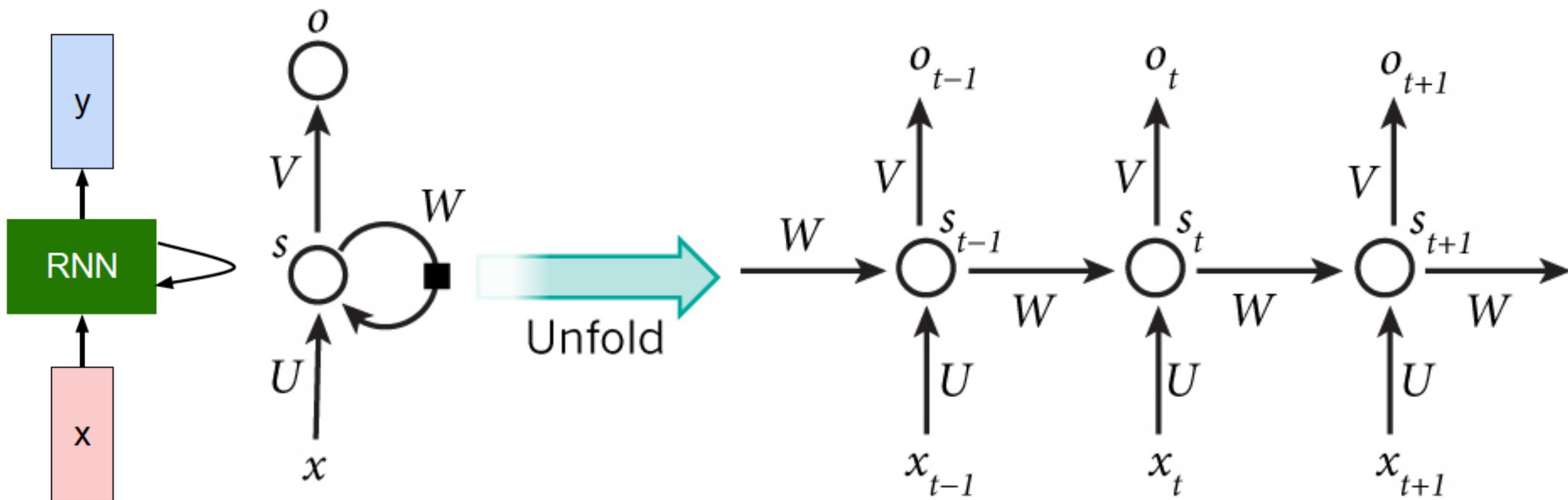
$$y_t = W_{hy}h_t$$



RNN Idea

- The idea behind RNNs is to make use of sequential information.
- In a traditional NN we assume that all inputs (and outputs) are independent of each other.
- But for sequence dependent task this is a bad idea: if you want to predict the next word in a sentence you better know which words came before it.
- RNNs are called *recurrent* because they perform the same task for every element of a sequence, with the output being depended on the previous computations.
- Another way to think about RNNs is that they have a “memory” which captures information about what has been calculated so far.
- In theory RNNs can make use of information in arbitrarily long sequences, but in practice they are limited to looking back only a few steps

Unfolded RNN



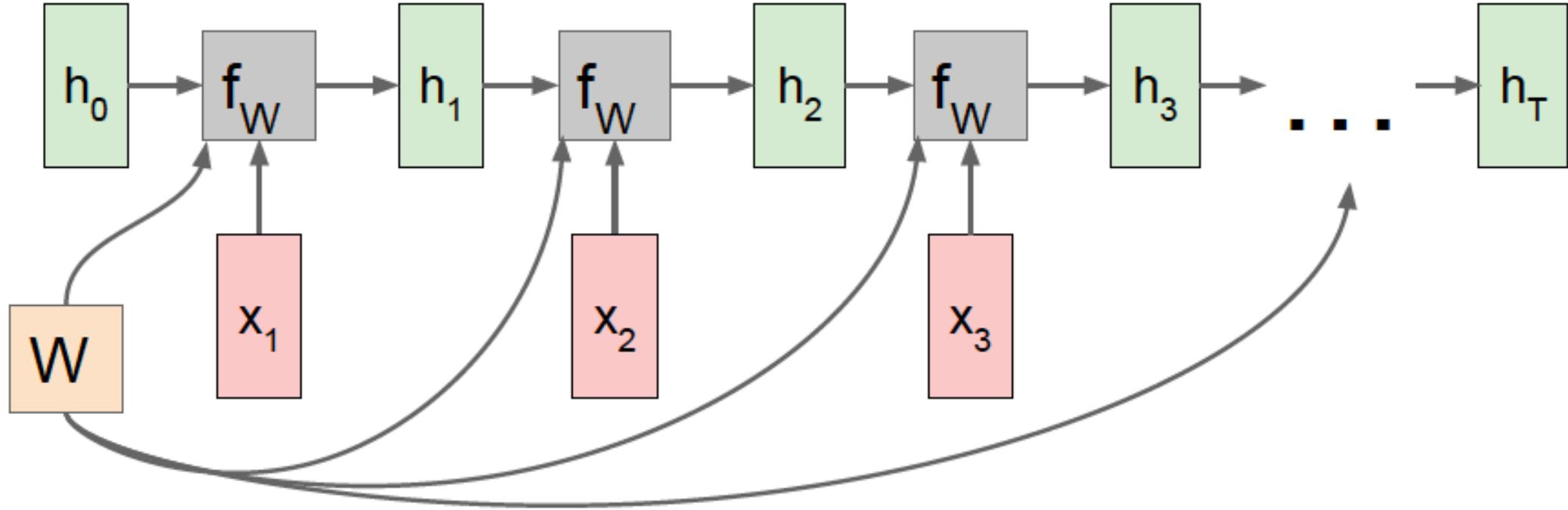
Unfolded RNN

- x_t is the input at time t . For example, x_1 could be a one-hot vector corresponding to the second word of a sentence.
- s_t is the hidden state at time t . It is the “memory” of the network. s_t is calculated based on the previous hidden state and the input at the current step: $s_t = f(U x_t + W s_{t-1})$.
- The function f is usually *tanh* or *ReLU*. s_{-1} , which is required to calculate the first hidden state, is typically initialized to all zeroes.
- o_t is the output at time t . For example, if we wanted to predict the next word in a sentence it would be a vector of probabilities across our vocabulary. $o_t = \text{softmax}(V s_t)$.

Unfolded RNN

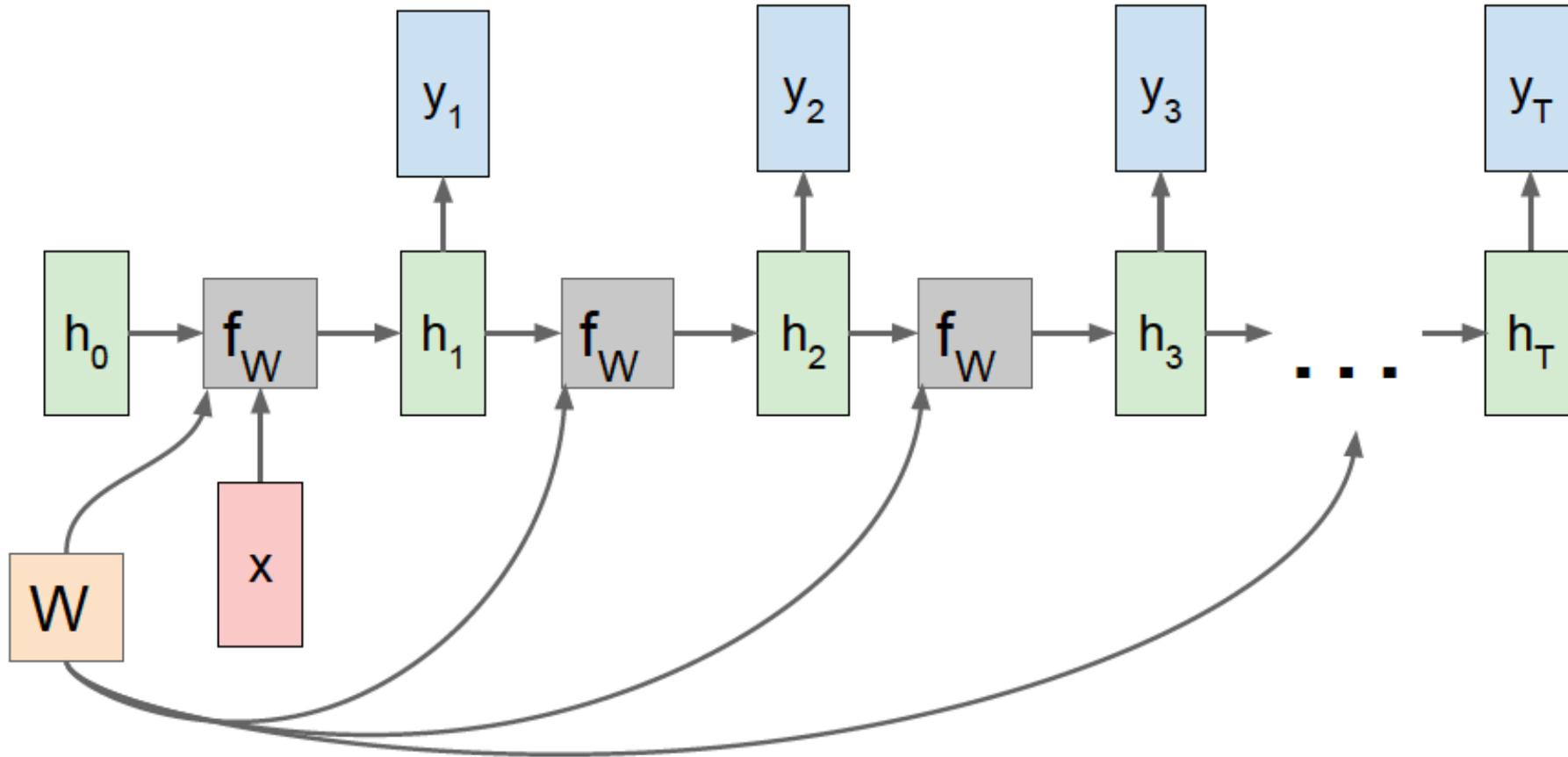
- The hidden state s_t is the memory of the network. s_t captures information about what happened in all the previous time steps.
- The output at step o_t is calculated solely based on the memory at time t .
- s_t typically can not capture information from too many time steps ago.
- Unlike a DNN, which uses different parameters at each layer, a RNN shares the same parameters (U, V, W) across all steps. This reflects the fact that we are performing the same task at each step, just with different inputs.
- The previous diagram has outputs at each time step, but depending on the task this may not be necessary.

RNN: Computational Graph

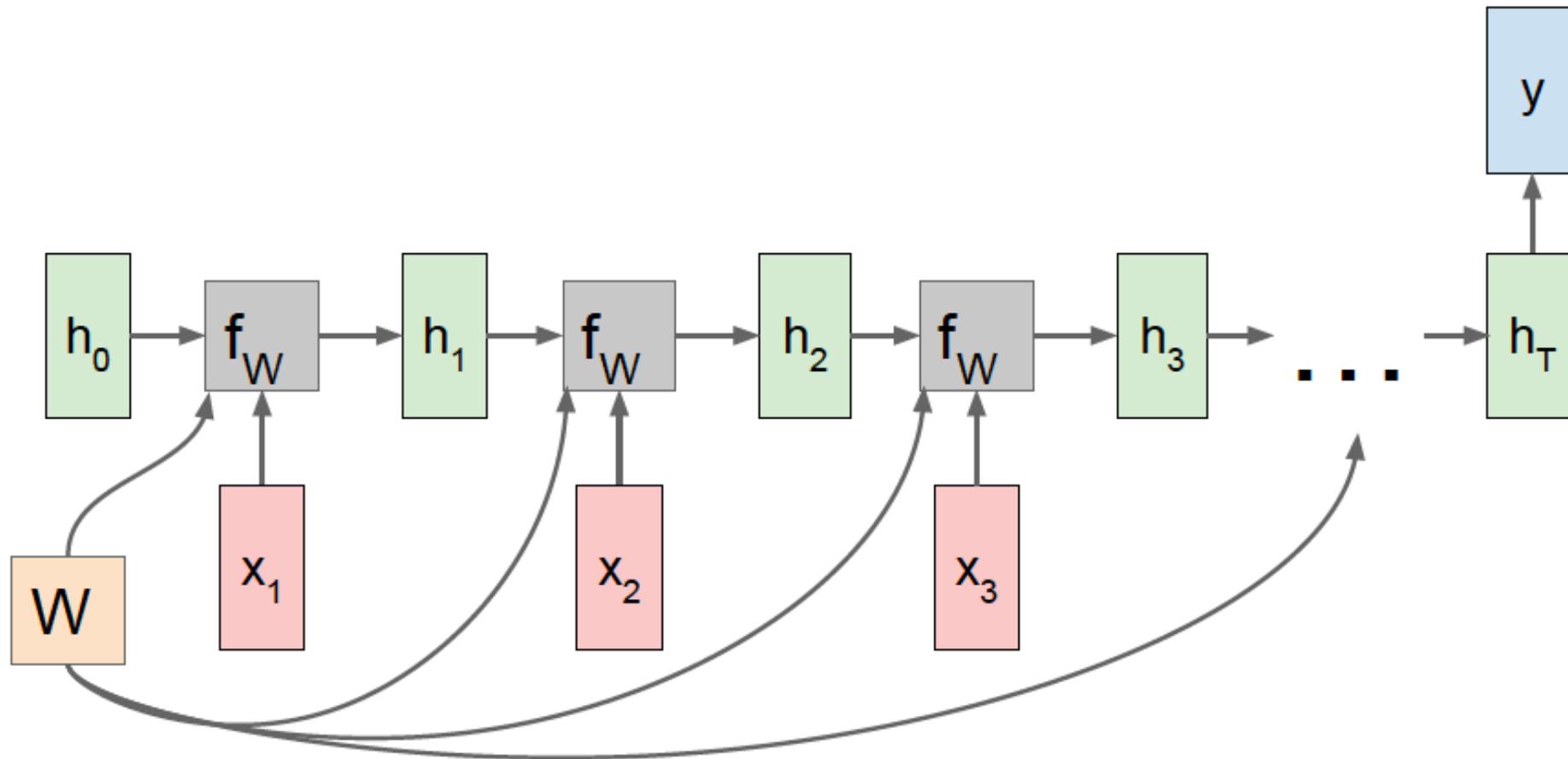


Reminder: Re-use the same weight matrix at every time-step

RNN: Computational Graph: Many to Many



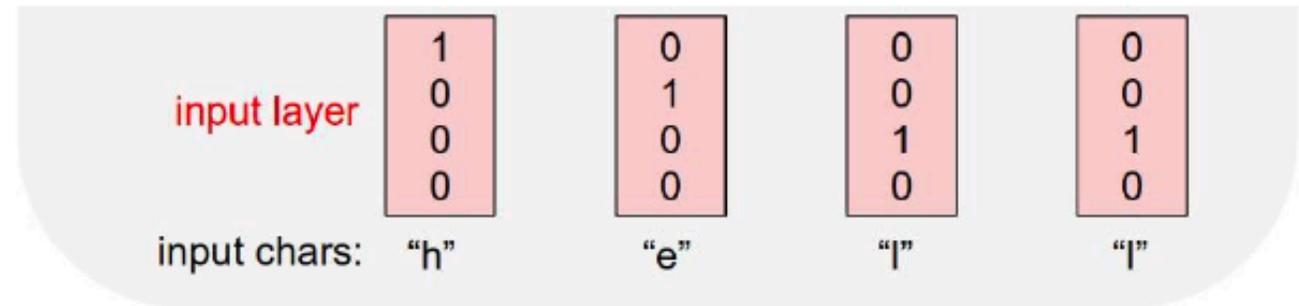
RNN: Computational Graph: Many to One



RNN: Example Training

Vocabulary:
[h,e,l,o]

Example training
sequence:
“hello”



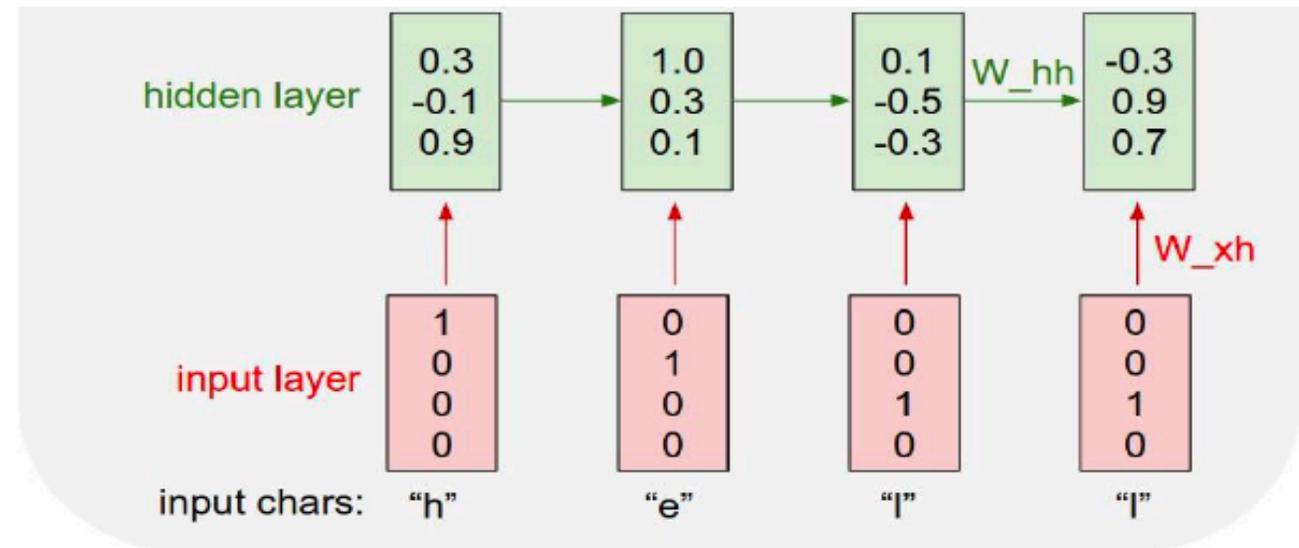
RNN: Example Training

Example: Character-level Language Model

Vocabulary:
[h,e,l,o]

Example training
sequence:
“hello”

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

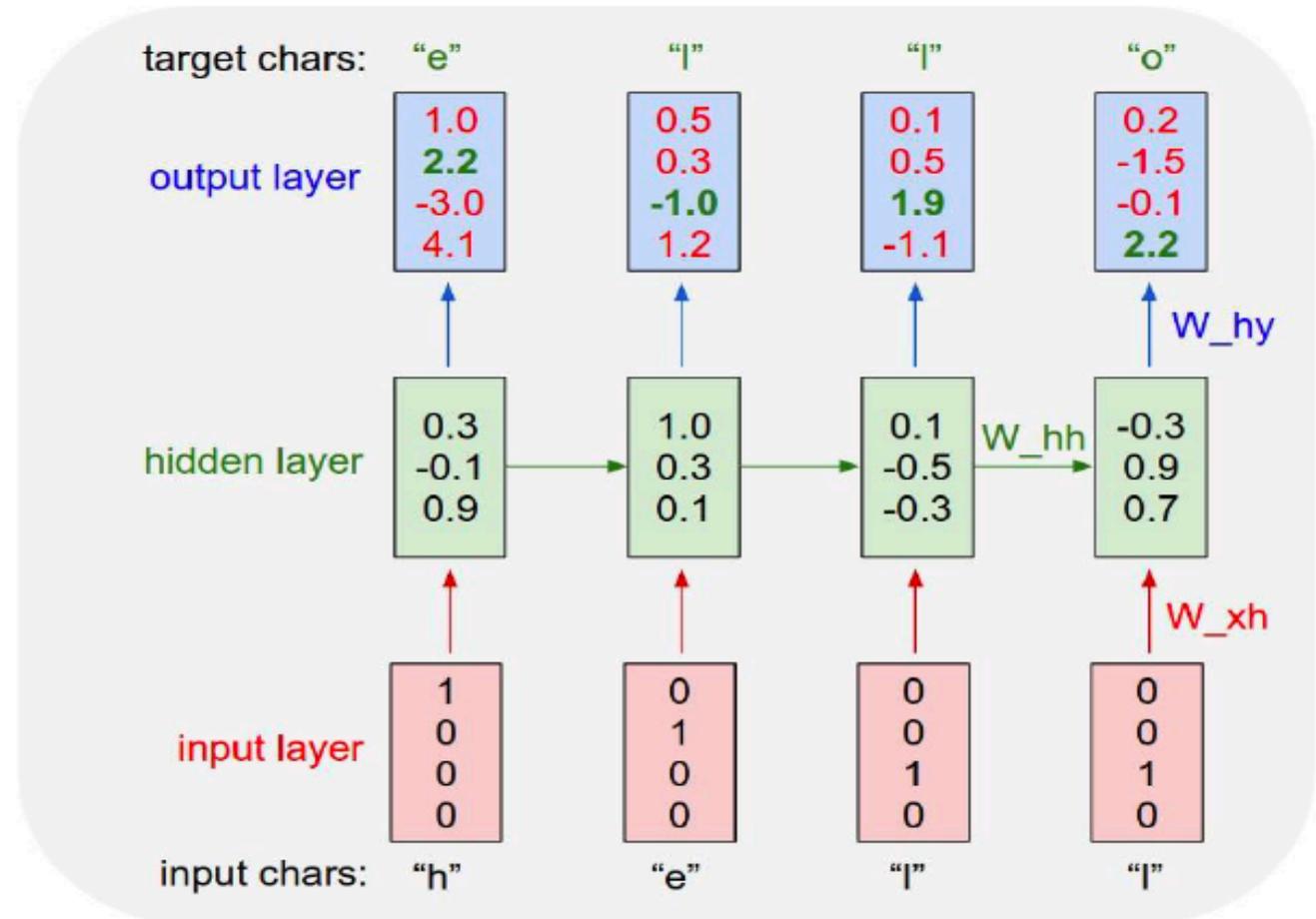


RNN: Example Training

Example: Character-level Language Model

Vocabulary:
[h,e,l,o]

Example training
sequence:
“hello”

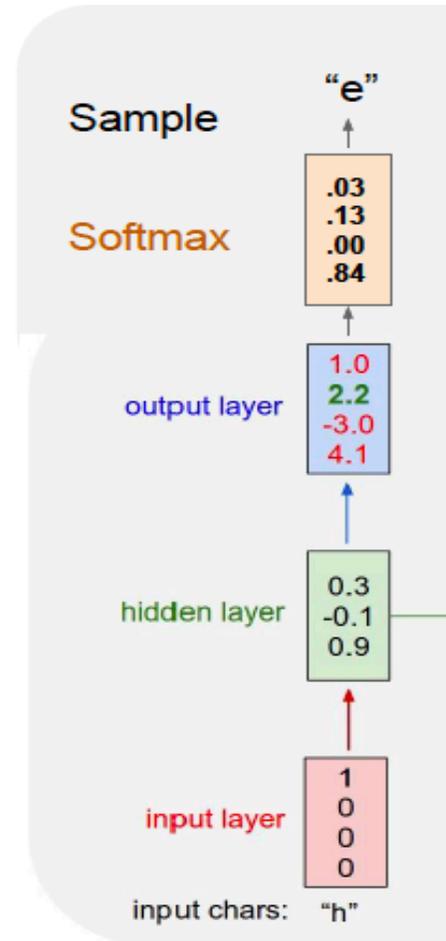


RNN: Example Test

Example: Character-level Language Model Sampling

Vocabulary:
[h,e,l,o]

At test-time sample
characters one at a time,
feed back to model

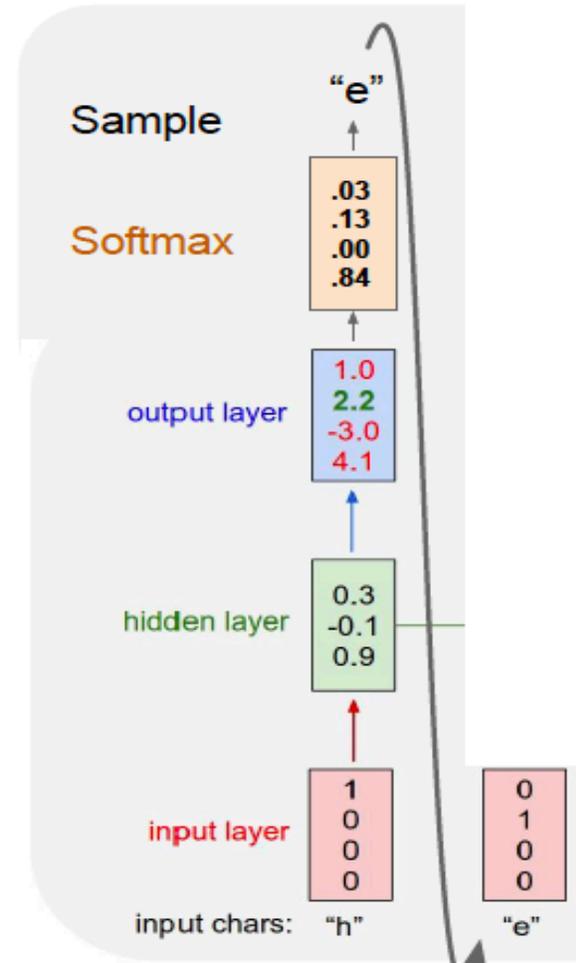


RNN: Example Test

Example: Character-level Language Model Sampling

Vocabulary:
[h,e,l,o]

At test-time sample
characters one at a time,
feed back to model

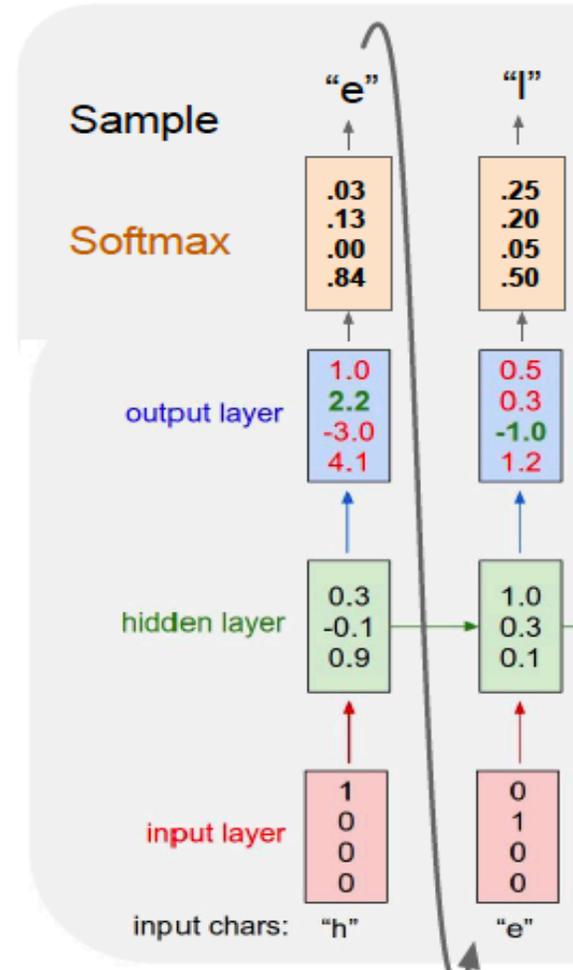


RNN: Example Test

Example: Character-level Language Model Sampling

Vocabulary:
[h,e,l,o]

At test-time sample
characters one at a time,
feed back to model

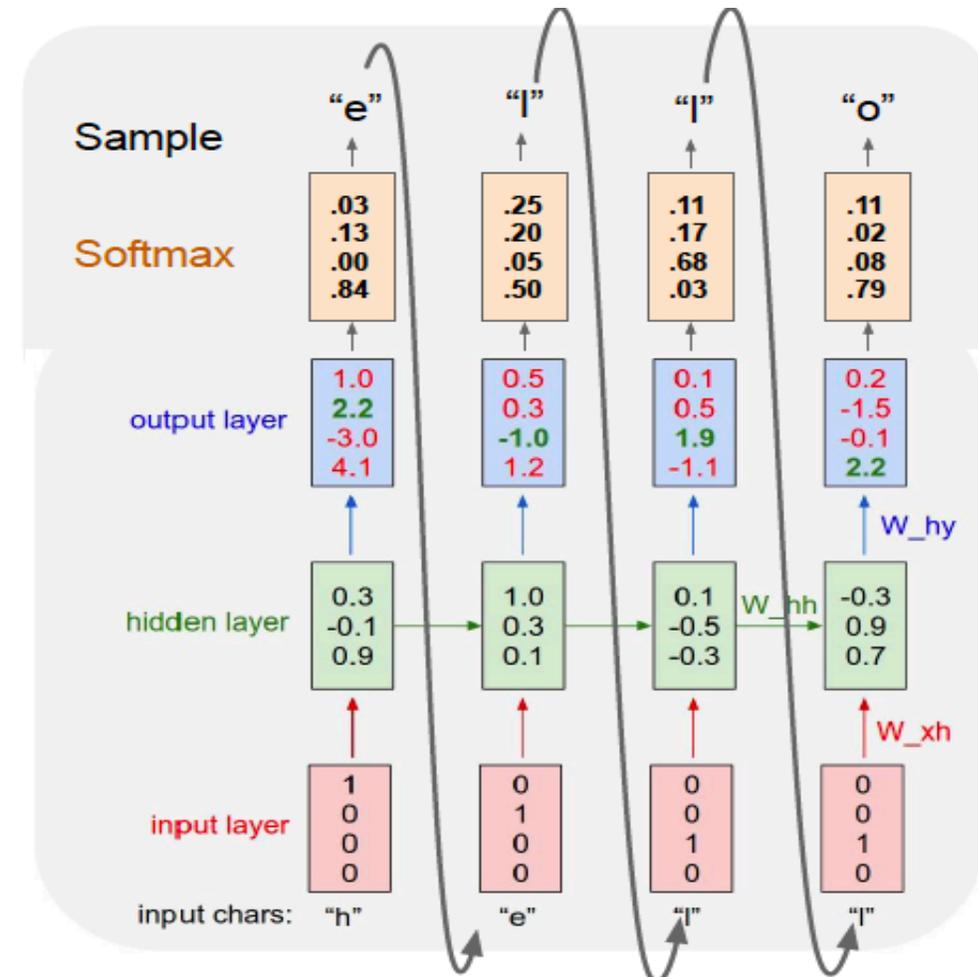


RNN: Example Test

**Example:
Character-level
Language Model
Sampling**

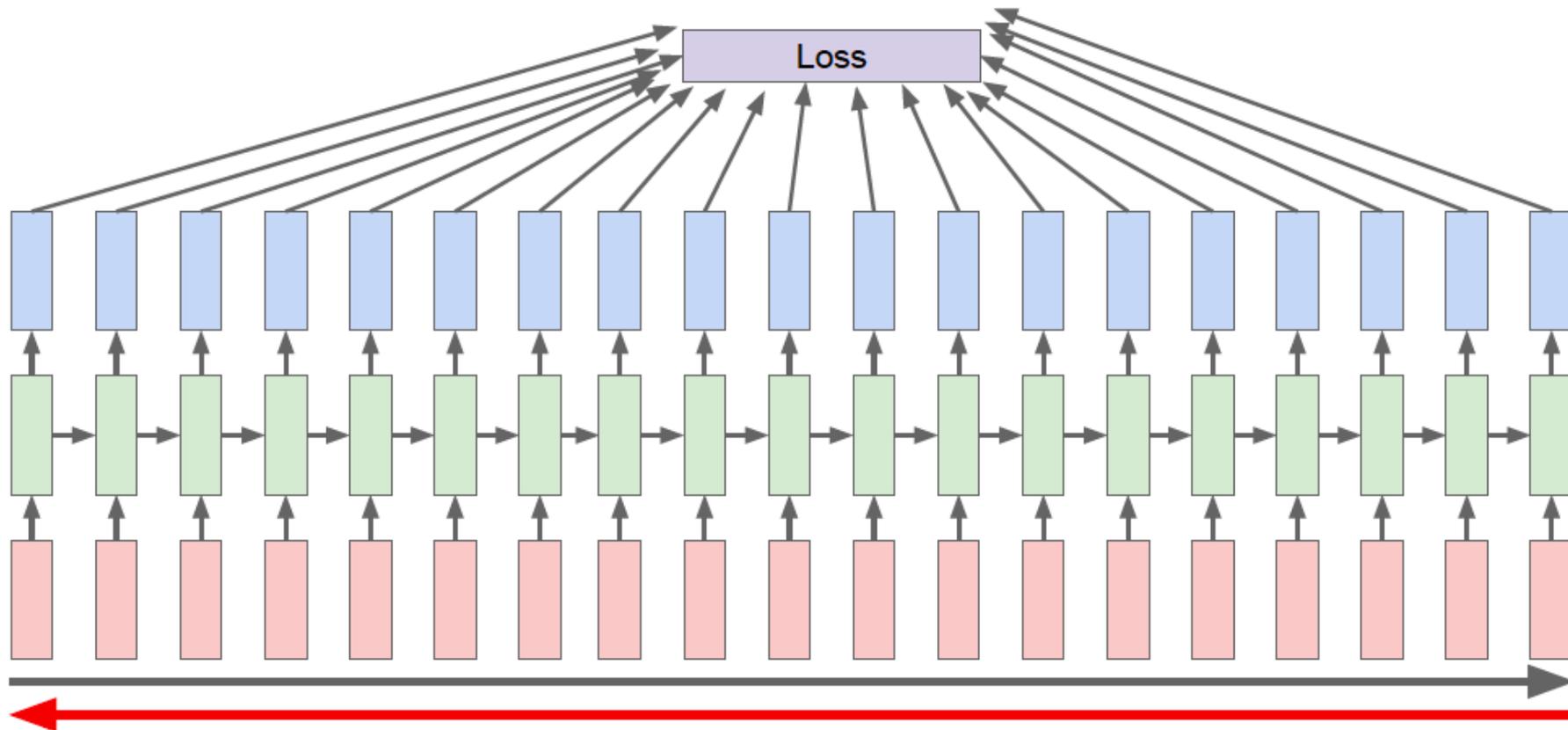
Vocabulary:
[h,e,l,o]

At test-time sample
characters one at a time,
feed back to model



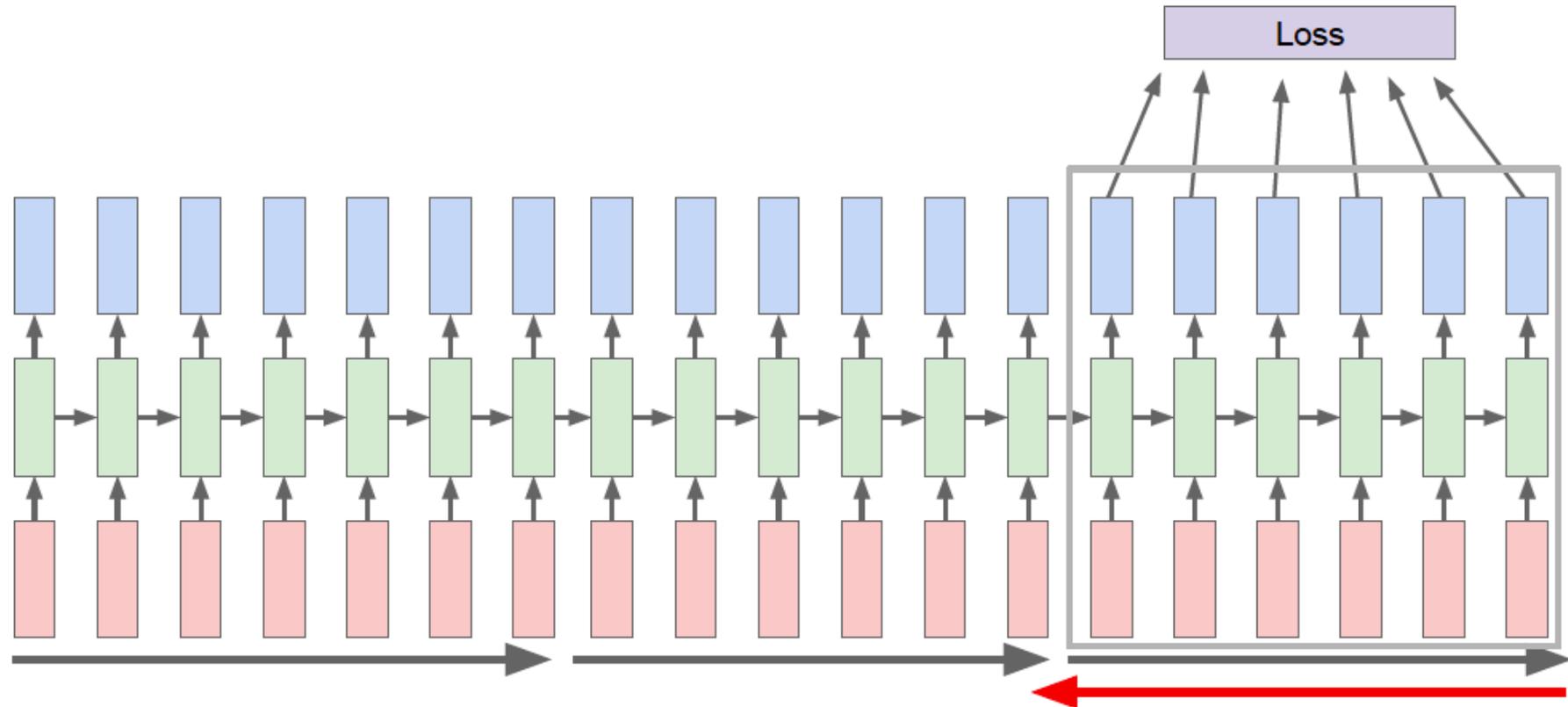
Backpropagation Through Time

- Forward through entire sequence to compute loss
- Then backward through entire sequence to compute gradient



Truncated BPTT

- It is an approximation of full BPTT that is preferred for long sequences since full BPTT's forward/backward cost per parameter update becomes very high over many time steps.
- The downside is that the gradient can only flow back so far due to that truncation, so the network can not learn dependencies that are as long as in full BPTT.

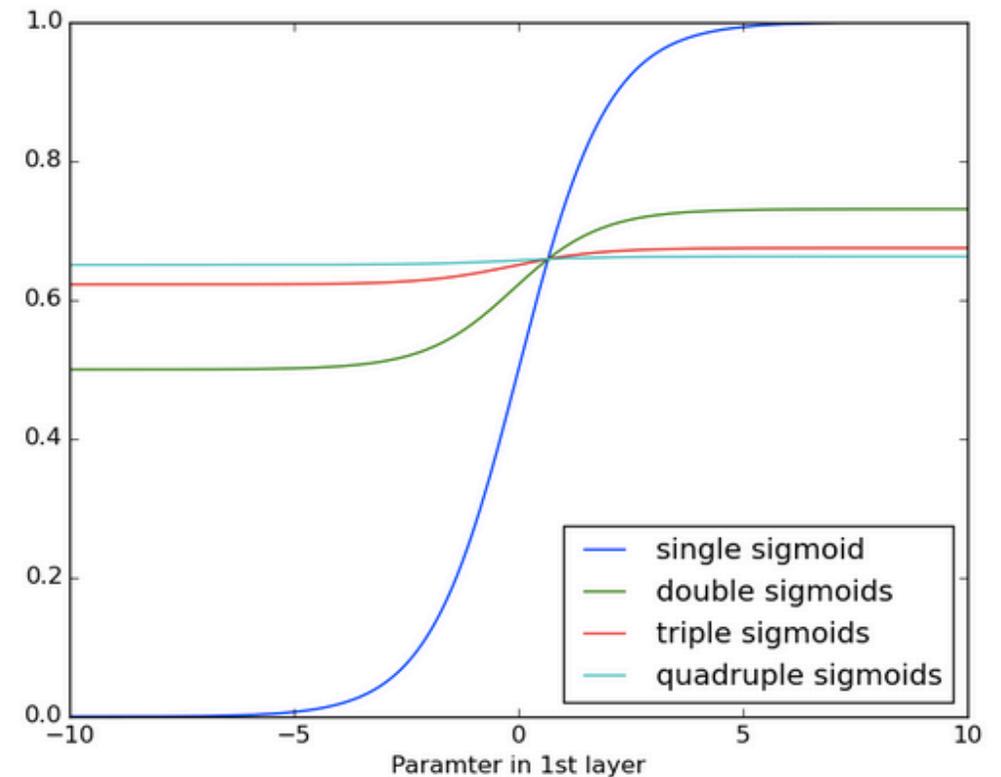


Limitations of RNNs

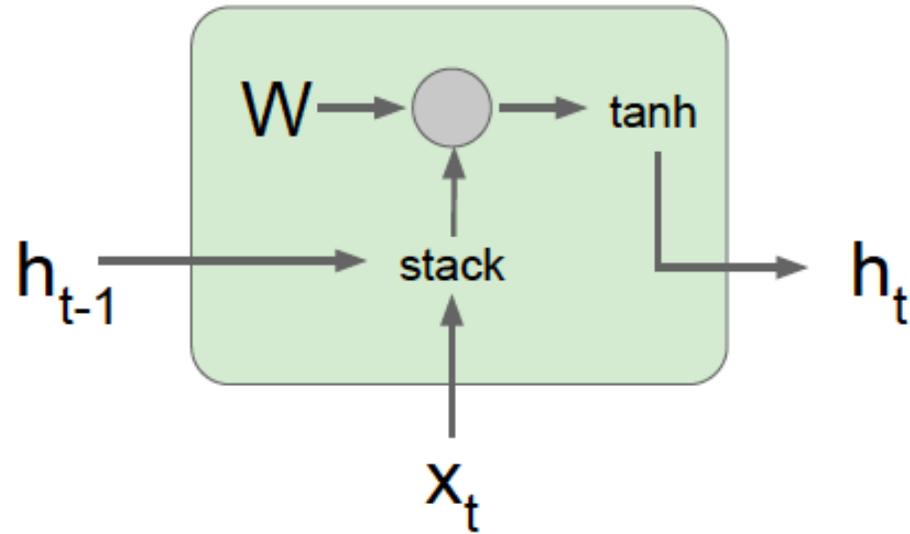
- RNN work fine when we are dealing with *short-term* dependencies.
- However, RNNs fail to understand the context behind an input.
- For instance, something that was said long before, cannot be recalled when making predictions in the present.
- The reason behind this is the problem of *Vanishing Gradient*.
- For a DNN, the weight updating that is applied on a particular layer is a multiple of the learning rate, the error term from the previous layer and the input to that layer. The error for a particular layer is a product of all previous layers' errors.
- When dealing with functions like *sigmoid/tanh*, the small values of its derivatives (occurring in the error function) gets multiplied multiple times as we move towards the starting layers. As a result of this, the gradient almost vanishes as we move towards the starting layers, and it becomes difficult to train these layers.

Vanishing (and Exploding) Gradients

- The gradient expresses the change in all weights with regard to the change in error.
- If we can not know the gradient, we can not adjust the weights in a direction that will decrease error, and our network ceases to learn.
- Effects of applying a sigmoid function over and over again.



Vanilla RNN Gradient Flow

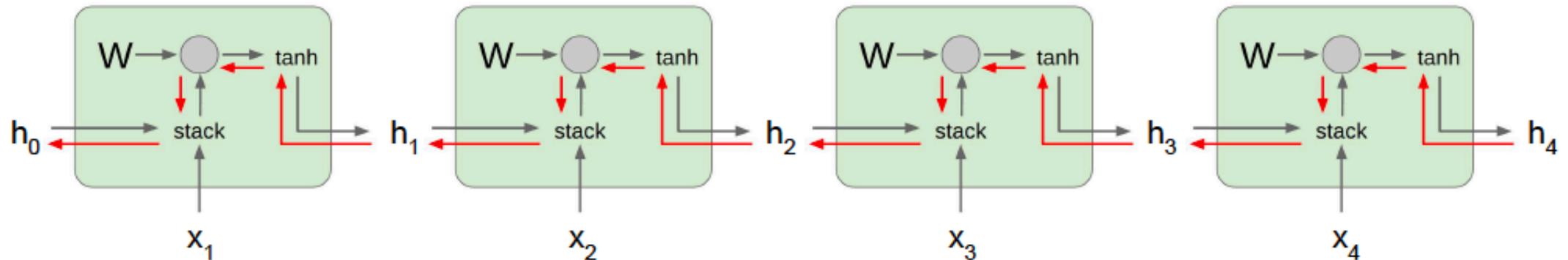


$$\begin{aligned}h_t &= \tanh(W_{hh}h_{t-1} + W_{hx}x_t) \\ &= \tanh\left(\begin{pmatrix} W_{hh} & W_{hx} \end{pmatrix} \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right) \\ &= \tanh\left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)\end{aligned}$$

Backpropagation from h_t
to h_{t-1} multiplies by W

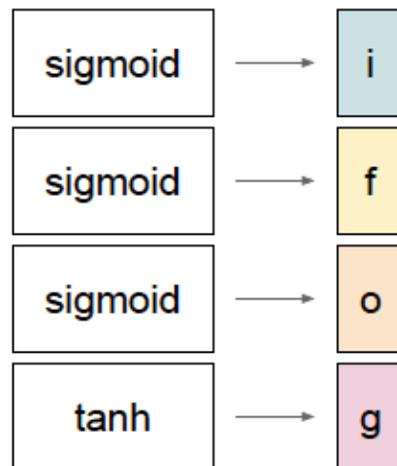
Vanilla RNN Gradient Flow

- Computing gradient of h_0 involves many factors of W (and repeated \tanh)
- Largest singular value $> 1 \rightarrow$ **Exploding Gradients**
 - Gradient clipping: Scale Computing gradient if its norm is too big
- Largest singular value $< 1 \rightarrow$ **Vanishing Gradients**
 - Change RNN architecture



Long Short Term Memory (LSTM)

- LSTM contains in a gated cell information outside the normal flow of the recurrent network.
- Information can be stored in, written to, or read from a cell.



Vanilla RNN

$$h_t = \tanh \left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix} \right)$$

LSTM

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

$$c_t = f \odot c_{t-1} + i \odot g$$

$$h_t = o \odot \tanh(c_t)$$

Long Short Term Memory (LSTM)

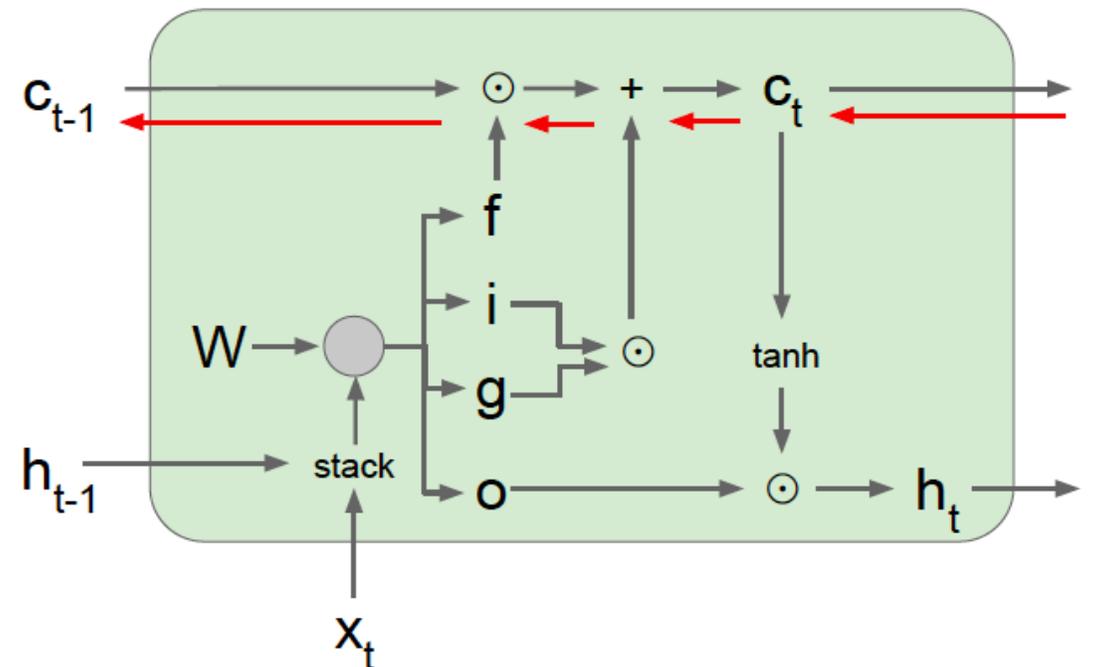
- The cell makes decisions about what to store, and when to allow reads, writes and erasures, via gates that open and close.
- These gates are implemented with element-wise multiplication by sigmoids, which are all in the range of 0-1, thus are differentiable and suitable for backpropagation

Backpropagation from c_t to c_{t-1} only elementwise multiplication by f , no matrix multiply by W

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

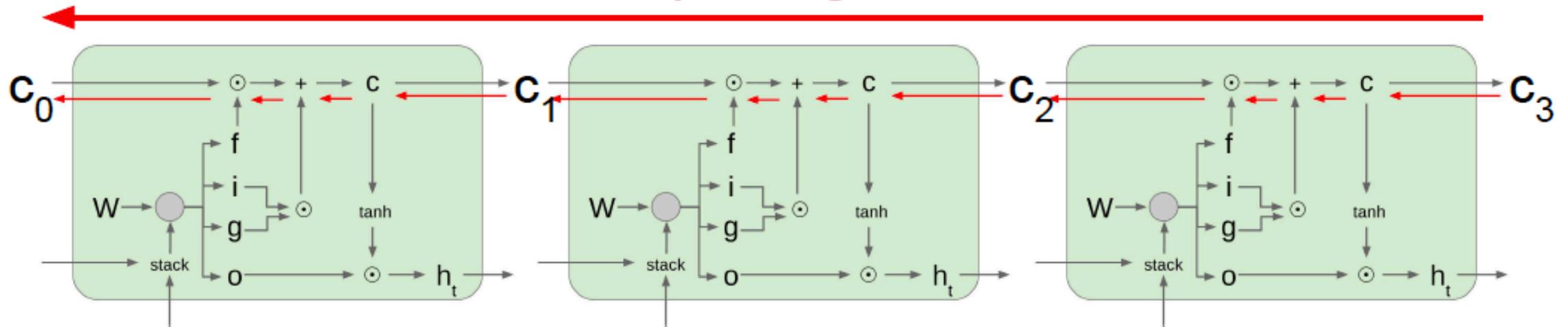
$$c_t = f \odot c_{t-1} + i \odot g$$

$$h_t = o \odot \tanh(c_t)$$

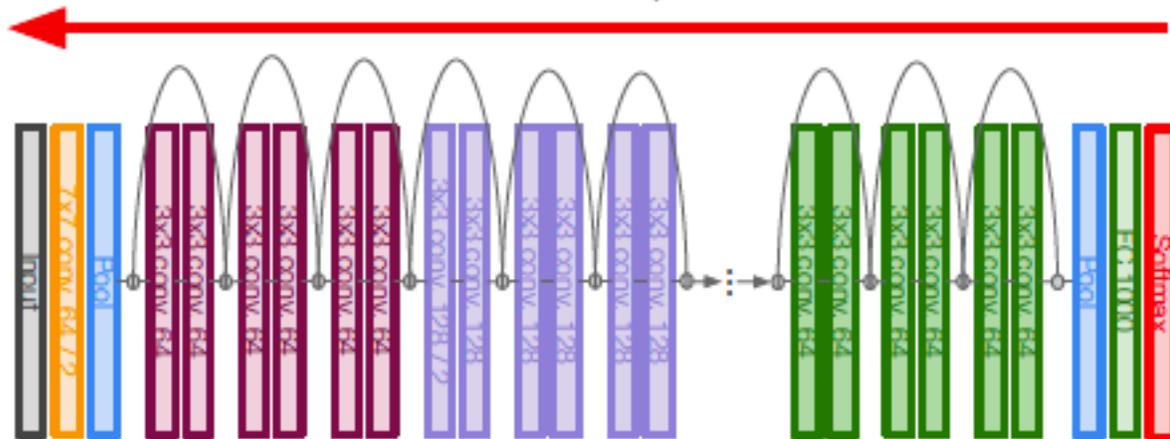


Long Short Term Memory (LSTM): Gradient Flow

Uninterrupted gradient flow!



Similar to ResNet!



RNN Summary

- RNNs allow a lot of flexibility in architecture design
- Vanilla RNNs are simple but don't work very well
- Common to use LSTM or GRU: their additive interactions improve gradient flow
- Backward flow of gradients in RNN can explode or vanish. Exploding is controlled with gradient clipping. Vanishing is controlled with additive interactions (LSTM)
- Better/simpler architectures are a hot topic of current research, as well as new paradigms for reasoning over sequences
- Better understanding (both theoretical and empirical) is needed.

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arXiv:1809.04356v4 [cs.LG] 14 May 2019

Matrix Profile I: All Pairs Similarity Joins for Time Series: A Unifying View that Includes Motifs, Discords and Shapelets

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Abstract—The all-pairs-similarity-search (or similarity join) problem has been extensively studied for text and a handful of other domains. However, surprisingly little progress has been made on similarity joins for time series subsequences. The lack of progress probably stems from the daunting nature of the problem. For even modest sized datasets the obvious nested-loop algorithm can take months, and typical speed-up techniques in this domain (e.g., indexing, lower-bounding, irregularly-inequality pruning and early-abandonment) at best produce one or two orders of magnitude speeding. In this work we introduce a novel scalable algorithm for time series subsequence all-pairs-similarity-search. For exceptionally large datasets, the algorithm can be trivially cast as an anytime algorithm and produce high-quality approximate solutions in reasonable time. The exact similarity join algorithm computes the answer to the time series motif and time series discord problem as a side-effect, and our algorithm incidentally provides the fastest known algorithm for both these extensively-studied problems. We demonstrate the utility of our ideas for many time series data mining problems, including motif discovery, anomaly discovery, shapelet discovery, semantic segmentation, density estimation, and contrast set mining.

Keywords—Time Series; Similarity Joins; Motif Discovery

INTRODUCTION
The all-pairs-similarity-search (also known as similarity join) problem comes in several variants. The basic task is: Given a collection of data objects, retrieve the nearest neighbor for each object in the text domain. The algorithm has applications in a host of problems, including community discovery, duplicate detection, collaborative filtering, clustering, and query refinement [1]. While virtually all text processing algorithms have autotuned to time series data mining, there has been surprisingly little progress on Time Series subsequence All-Pairs-Similarity-Search (TSAPSS).

We believe that this lack of progress stems not from a lack of interest in this useful primitive, but from the daunting nature of the problem. Consider the following example that reflects the needs of an industrial collaborator. A boiler at a chemical refinery reports pressure once a minute. After a year, we have a time series of length 524,608. A plant manager may wish to do a similarity self-join on this data with week-long subsequences (10,800) to discover any operating regimes (summer vs. winter or light distillate vs. heavy distillate, etc). The obvious nested loop algorithm requires 112,800,602,560 Euclidean distance computations. If we assume each one takes 0.0001 seconds, then the join will take 11.8 days. The core combination of this work is to show that we can reduce this time to 4-5 hours, using an off-the-shelf desktop computer. Moreover, we show that this join can be computed and/or updated incrementally. This we could maintain this join execution forever on a standard

desktop, even if the data arrival frequency was much faster than one a minute.
Our algorithm uses an ultra-fast similarity-search algorithm under a novel notion of Euclidean distance as a subroutine, exploiting the overlap between subsequences using the classic Fast Fourier Transform (FFT) algorithm.
Our method has the following advantages/features:
• It is exact, providing no false positives or false dismissals.
• It is simple and parameter-free. In contrast, the more general metric space APSS algorithms require building and tuning spatial access methods and/or hash functions.
• Our algorithm requires an inconsequential space overhead, just $O(n)$ with a small constant factor.
• While our exact algorithm is extremely scalable, for extremely large datasets we can compute the results in an anytime fashion, allowing ultra-fast approximate solutions.
• Having computed the similarity join for a dataset, we can incrementally update it very efficiently. In many domains this means we can effectively maintain exact joins on streaming data forever.
• Our method provides full joins, eliminating the need to specify a similarity threshold, which as we will show, is a near impossible task in this domain.
• Our algorithm is embarrassingly parallelizable, both on multicore processors and on distributed systems.

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Deep learning for time series classification

Hassan Ismail Fawaz¹ · Germain Forestier^{1,2} · Jonathan W. Ross¹ · Pierre-Alain Muller¹

Abstract Time Series Classification (TSC) is an important and challenging task. With the increase of time series data availability, hundreds of TSC algorithms have been proposed since 2015 (Bagnall et al., 2017). Due to their natural temporal ordering, time series data are present in almost every task that requires some sort of human cognitive process (Langkvist et al., 2014). In fact, any classification problem, using data that is registered taking into account some notion of ordering, can be cast as a TSC problem (Christian Borges Gombos, 2017). Time series are encountered in many real-world applications ranging from electronic health records (Rajkumar et al., 2018) and human activity recognition (Nweke et al., 2018; Wang et al., 2018) to acoustic scene classification (Nwe et al., 2017) and cyber-security (Susto et al., 2018). In addition, the diversity of the datasets' types in the UCR/UEA archive (Chen et al., 2015b; Bagnall et al., 2017) (the largest repository of time series datasets) shows the different applications of the TSC problem.

Keywords Deep learning · Time series · Classification · Review

1 Introduction

During the last two decades, Time Series Classification (TSC) has been considered as one of the most challenging problems in data mining (Yang and Wu, 2006; Ealing and Agon, 2012). With the increase of temporal data availability (Silva et al., 2018), hundreds of TSC algorithms have been proposed since 2015 (Bagnall et al., 2017). Due to their natural temporal ordering, time series data are present in almost every task that requires some sort of human cognitive process (Langkvist et al., 2014). In fact, any classification problem, using data that is registered taking into account some notion of ordering, can be cast as a TSC problem (Christian Borges Gombos, 2017). Time series are encountered in many real-world applications ranging from electronic health records (Rajkumar et al., 2018) and human activity recognition (Nweke et al., 2018; Wang et al., 2018) to acoustic scene classification (Nwe et al., 2017) and cyber-security (Susto et al., 2018). In addition, the diversity of the datasets' types in the UCR/UEA archive (Chen et al., 2015b; Bagnall et al., 2017) (the largest repository of time series datasets) shows the different applications of the TSC problem.

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Time Series Shapelets: A New Primitive for Data Mining

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ABSTRACT
Classification of time series has been attracting great interest over the past decade. Recent empirical evidence has strongly suggested that the simple nearest neighbor algorithm is very difficult to beat for most time series problems. While this may be considered good news, given the simplicity of implementing the nearest neighbor algorithm, there are some negative consequences of this. First, the nearest neighbor algorithm requires storing and searching the entire dataset, resulting in a time and space complexity that limits its applicability to especially large datasets. Second, beyond near classification accuracy, we often wish to gain some insight into the data.
In this work we introduce a new time series primitive, time series shapelets, which addresses these limitations. Informally, shapelets are time series subsequences which are in some sense maximally representative of a class. As we shall show with extensive empirical evaluation on diverse datasets, algorithms based on the time series shapelet primitives can be interpreted, more accurate and significantly faster than state-of-the-art classifiers.

Categories and Subject Descriptors H.2.8 (Database Management): Database Applications · Data Mining

General Terms Algorithms; Experimentation

1. INTRODUCTION

While the last decade has seen a huge interest in time series classification, to date the most accurate and robust method is the simple nearest neighbor algorithm [4][12][14]. While the nearest neighbor algorithm has the advantages of simplicity and not requiring extensive parameter tuning, it does have several important disadvantages. Chief among these are its space and time requirements, and the fact that it does not tell us anything about why a particular object was assigned to a particular class.

In this work we present a novel time series data mining primitive called time series shapelets. Informally, shapelets are time series subsequences which are in some sense maximally representative of a class. While we believe there can be many uses for this primitive, one obvious implication of them is to mitigate the two weaknesses of the nearest neighbor algorithm: its space and time requirements. In some applications, it is not possible to store all of a part of the data for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear the notice and full citation on the first page. To copy otherwise, to republish, to post in servers or to redistribute to lists, requires prior specific permission and/or a fee. Copyright 2009 ACM 978-1-60558-493-9/09/06...\$5.00



Figure 1: Sample of leaves from two species. Note that several leaves have the insect-bite damage.

Suppose we wish to build a classifier to distinguish these two plants, what features should we use? Since the main variability of color and size within each class completely dwarfs the inter-variability between classes, our best hope is based on the shapes of the leaves. However, as we can see in Figure 1, the difference in the global shape are very subtle. Furthermore, it is very common for leaves to have distinctive or "irregular" due to insect damage, and these are likely to confuse any global measures of shape. Instead we attempt the following. We first convert each leaf into a one-dimensional representation as shown in Figure 2.

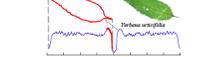


Figure 2: A shape can be converted into a one-dimensional "time series" representation. The reason for the highlighted section of the time series will be made apparent shortly.

Such representations have been successfully used for the classification, clustering and outlier detection of shapes in recent years [8]. However, here we find that using a nearest neighbor classifier with either the (position-normalized) Euclidean distance or Dynamic Time Warping (DTW) distance does not significantly outperform random guessing. The reason for this poor performance of these otherwise very competitive classifiers seems to be due to the fact that the data is somewhat noisy (i.e. insect holes, and different insect lengths), and this noise is enough to swamp the subtle differences in the shapes.