

社群網路行銷管理

Social Media Marketing Management



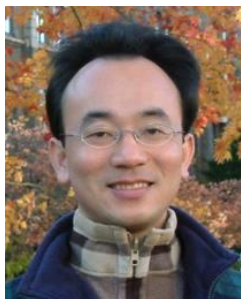
Tamkang
University
淡江大學

Sentiment Analysis on Social Media with Deep Learning (深度學習社群媒體情感分析)

1042SMMM10

MIS EMBA (M2200) (8615)

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2016-05-12



課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
1	2016/02/18	社群網路行銷管理課程介紹 (Course Orientation for Social Media Marketing Management)
2	2016/02/25	社群網路商業模式 (Business Models of Social Media)
3	2016/03/03	顧客價值與品牌 (Customer Value and Branding)
4	2016/03/10	社群網路消費者心理與行為 (Consumer Psychology and Behavior on Social Media)
5	2016/03/17	社群網路行銷蜻蜓效應 (The Dragonfly Effect of Social Media Marketing)

課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
6	2016/03/24	社群網路行銷管理個案研究 I (Case Study on Social Media Marketing Management I)
7	2016/03/31	行銷傳播研究 (Marketing Communications Research)
8	2016/04/07	教學行政觀摩日 (Off-campus study)
9	2016/04/14	社群網路行銷計劃 (Social Media Marketing Plan)
10	2016/04/21	期中報告 (Midterm Presentation)
11	2016/04/28	行動 APP 行銷 (Mobile Apps Marketing)

課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
12	2016/05/05	社群口碑與社群網路探勘 (Social Word-of-Mouth and Web Mining on Social Media)
13	2016/05/12	社群網路行銷管理個案研究 II (Case Study on Social Media Marketing Management II)
14	2016/05/19	深度學習社群網路情感分析 (Deep Learning for Sentiment Analysis on Social Media)
15	2016/05/26	Google TensorFlow 深度學習 (Deep Learning with Google TensorFlow)
16	2016/06/02	期末報告 I (Term Project Presentation I)
17	2016/06/09	端午節(放假一天)
18	2016/06/16	期末報告 II (Term Project Presentation II)

Sentiment Analysis on Social Media with Deep Learning



Example of Opinion: review segment on iPhone



“I bought an iPhone a few days ago.

It was such a nice phone.

The touch screen was really cool.

The voice quality was clear too.

However, my mother was mad with me as I did not tell her before I bought it.

She also thought the phone was too expensive, and wanted me to return it to the shop. ... ”

Example of Opinion: review segment on iPhone

“(1) I bought an iPhone a few days ago.

(2) It was such a **nice** phone.

(3) The touch screen was really **cool**.

(4) The voice quality was **clear** too.

(5) However, my mother was mad with me as I did not tell her before I bought it.

(6) She also thought the phone was too expensive, and wanted me to return it to the shop. ...”



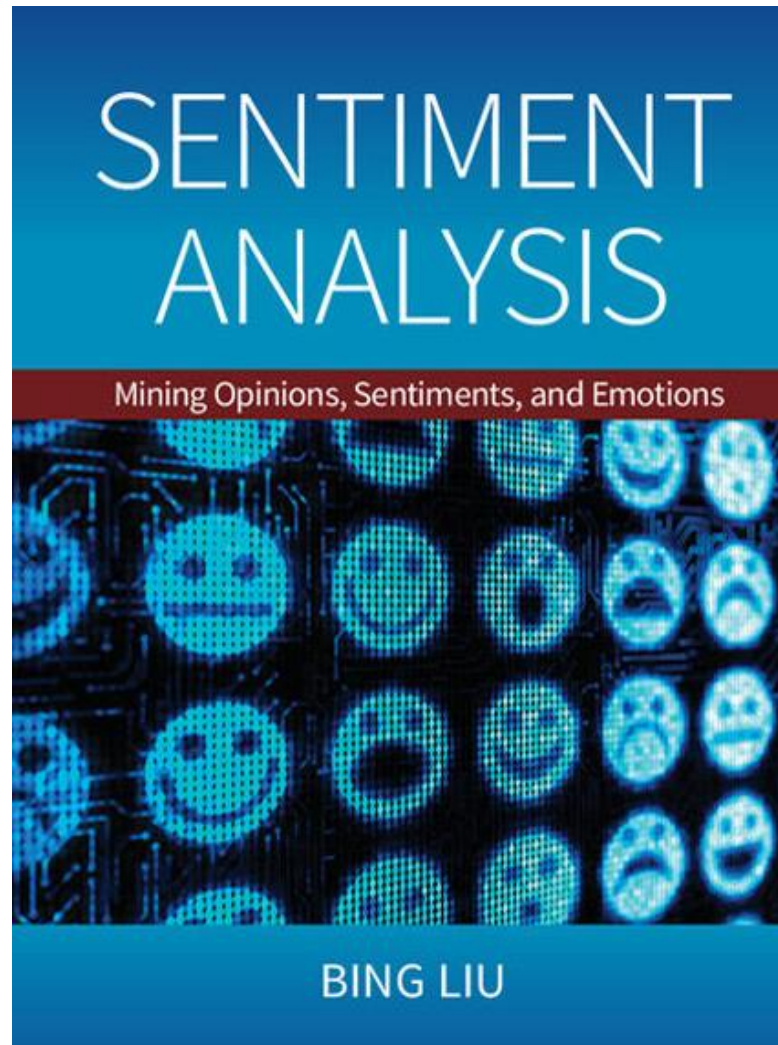
+Positive
Opinion



-Negative
Opinion

Architectures of Sentiment Analytics

**Bing Liu (2015),
Sentiment Analysis:
Mining Opinions, Sentiments, and Emotions,
Cambridge University Press**



Sentiment Analysis and Opinion Mining

- Computational study of opinions, sentiments, subjectivity, evaluations, attitudes, appraisal, affects, views, emotions, etc., expressed in text.
 - Reviews, blogs, discussions, news, comments, feedback, or any other documents

Research Area of Opinion Mining

- **Many names and tasks** with difference objective and models
 - **Sentiment analysis**
 - **Opinion mining**
 - Sentiment mining
 - Subjectivity analysis
 - Affect analysis
 - Emotion detection
 - Opinion spam detection

Sentiment Analysis

- Sentiment
 - A **thought**, **view**, or **attitude**, especially one based mainly on **emotion** instead of reason
- Sentiment Analysis
 - opinion mining
 - use of natural language processing (NLP) and computational techniques to automate the extraction or classification of sentiment from typically unstructured text

Applications of Sentiment Analysis

- Consumer information
 - Product reviews
- Marketing
 - Consumer attitudes
 - Trends
- Politics
 - Politicians want to know voters' views
 - Voters want to know politicians' stances and who else supports them
- Social
 - Find like-minded individuals or communities

Sentiment detection

- How to interpret features for sentiment detection?
 - Bag of words (IR)
 - Annotated lexicons (WordNet, SentiWordNet)
 - Syntactic patterns
- Which features to use?
 - Words (unigrams)
 - Phrases/n-grams
 - Sentences

Problem statement of Opinion Mining

- Two aspects of abstraction
 - Opinion definition
 - What is an opinion?
 - What is the structured definition of opinion?
 - Opinion summarization
 - Opinion are subjective
 - An opinion from a single person (unless a VIP) is often not sufficient for action
 - We need opinions from many people, and thus opinion summarization.

What is an opinion?

- Id: **Abc123** on **5-1-2008** *“I bought an iPhone a few days ago. It is such a nice phone. The touch screen is really cool. The voice quality is clear too. It is much better than my old BlackBerry, which was a terrible phone and so difficult to type with its tiny keys. However, my mother was mad with me as I did not tell her before I bought the phone. She also thought the phone was too expensive, ...”*
- One can look at this review/blog at the
 - Document level
 - Is this review + or -?
 - Sentence level
 - Is each sentence + or -?
 - Entity and feature/aspect level

Entity and aspect/feature level

- Id: **Abc123** on **5-1-2008** “*I bought an iPhone a few days ago. It is such a nice phone. The touch screen is really cool. The voice quality is clear too. It is much better than my old Blackberry, which was a terrible phone and so difficult to type with its tiny keys. However, my mother was mad with me as I did not tell her before I bought the phone. She also thought the phone was too expensive, ...*”
- **What do we see?**
 - Opinion targets: entities and their features/aspects
 - Sentiments: positive and negative
 - Opinion holders: persons who hold the opinions
 - Time: when opinion are expressed

Two main types of opinions

- **Regular opinions:** Sentiment/Opinion expressions on some target entities
 - **Direct opinions:** sentiment expressions on one object:
 - “The touch screen is really cool.”
 - “The picture quality of this camera is great”
 - **Indirect opinions:** comparisons, relations expressing similarities or differences (objective or subjective) of more than one object
 - “phone X is cheaper than phone Y.” (objective)
 - “phone X is better than phone Y.” (subjective)
- **Comparative opinions:** comparisons of more than one entity.
 - “iPhone is better than Blackberry.”

Subjective and Objective

- **Objective**

- An objective sentence expresses some **factual information** about the world.
- “I **returned** the phone yesterday.”
- Objective sentences can implicitly indicate opinions
 - “The **earphone** **broke** in two days.”

- **Subjective**

- A subjective sentence expresses some **personal feelings** or **beliefs**.
- “The voice on my phone was **not so clear**”
- Not every subjective sentence contains an opinion
 - “I wanted a phone with **good voice quality**”

- **➔ Subjective analysis**

Sentiment Analysis

vs.

Subjectivity Analysis

Sentiment Analysis	Subjectivity Analysis
Positive	Subjective
Negative	
Neutral	Objective

A (regular) opinion

- **Opinion** (a restricted definition)
 - An opinion (regular opinion) is simply a **positive or negative** sentiment, view, attitude, emotion, or appraisal about **an entity** or **an aspect of the entity** from an **opinion holder**.
- **Sentiment orientation of an opinion**
 - Positive, negative, or neutral (no opinion)
 - Also called:
 - **Opinion orientation**
 - **Semantic orientation**
 - **Sentiment polarity**

Entity and aspect

- Definition of **Entity**:
 - An *entity e* is a product, person, event, organization, or topic.
 - e is represented as
 - A hierarchy of components, sub-components.
 - Each node represents a components and is associated with a set of attributes of the components
- An opinion can be expressed on any node or attribute of the node
- **Aspects(features)**
 - represent both components and attribute

Opinion Definition

- An opinion is a quintuple

$(e_j, a_{jk}, so_{ijkl}, h_i, t_l)$

where

- e_j is a target entity.
 - a_{jk} is an aspect/feature of the entity e_j .
 - so_{ijkl} is the sentiment value of the opinion from the opinion holder on feature of entity at time.
 so_{ijkl} is +ve, -ve, or neu, or more granular ratings
 - h_i is an opinion holder.
 - t_l is the time when the opinion is expressed.
- (e_j, a_{jk}) is also called opinion target

Terminologies

- **Entity**: object
- **Aspect**: feature, attribute, facet
- **Opinion holder**: opinion source

- **Topic**: entity, aspect

- Product features, political issues

Subjectivity and Emotion

- **Sentence subjectivity**
 - An objective sentence presents some factual information, while a subjective sentence expresses some personal **feelings**, **views**, **emotions**, or **beliefs**.
- **Emotion**
 - Emotions are people's subjective **feelings** and **thoughts**.

Classification Based on Supervised Learning

- Sentiment classification
 - Supervised learning Problem
 - Three classes
 - *Positive*
 - *Negative*
 - *Neutral*

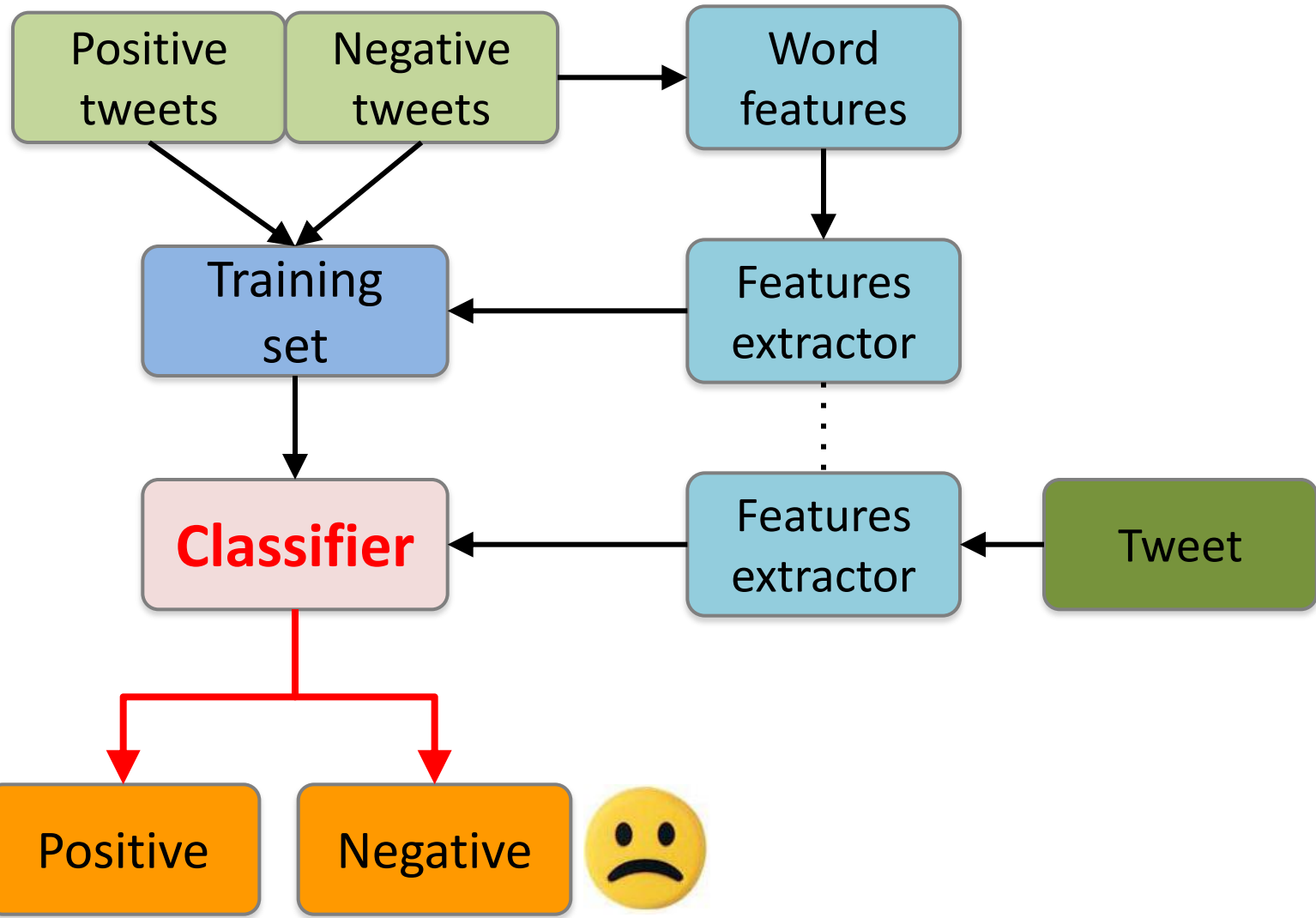
Opinion words in Sentiment classification

- topic-based classification
 - topic-related words are important
 - e.g., *politics, sciences, sports*
- Sentiment classification
 - topic-related words are unimportant
 - **opinion words** (also called **sentiment words**)
 - that indicate **positive** or **negative** opinions are important,
e.g., *great, excellent, amazing, horrible, bad, worst*

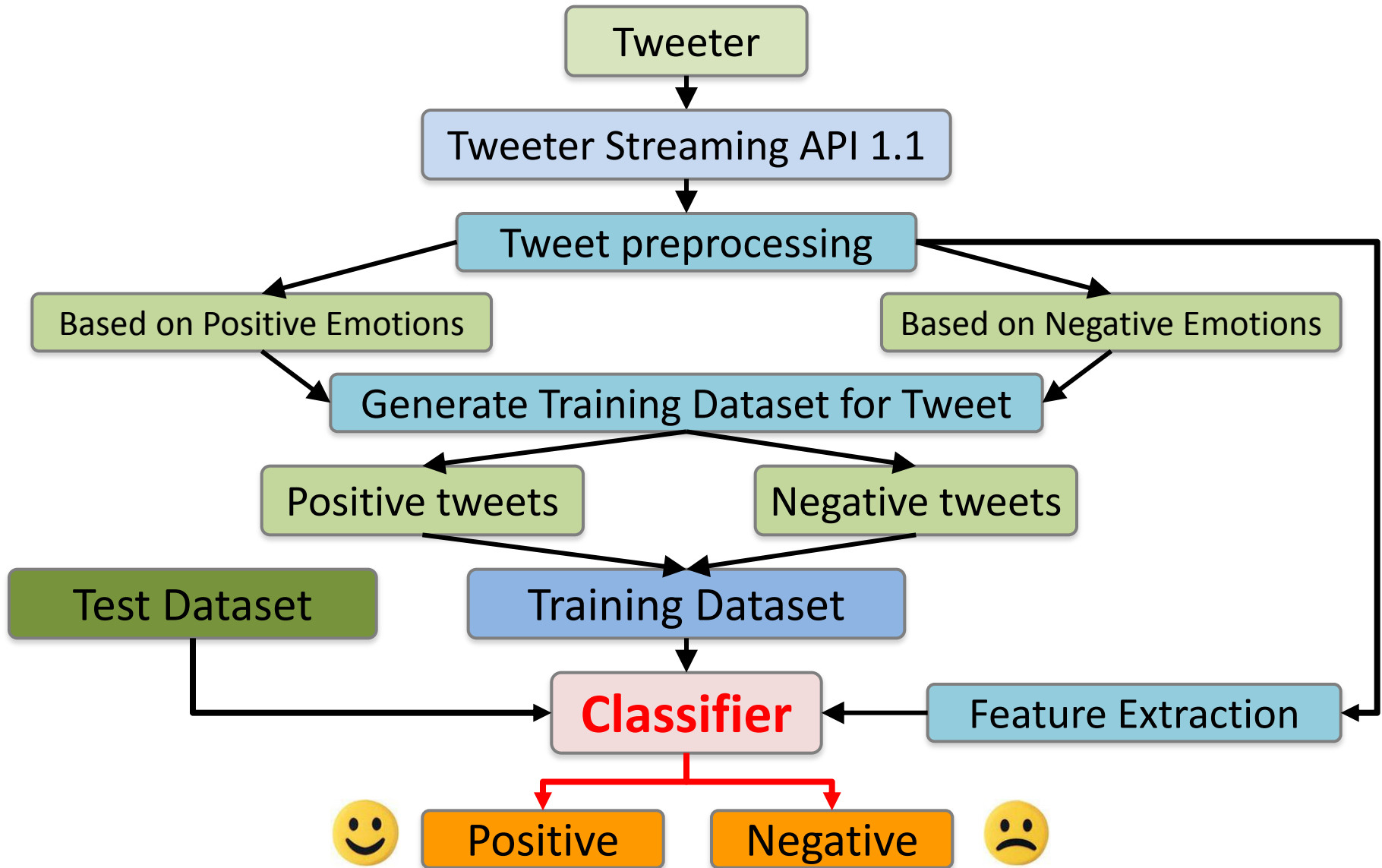
Features in Opinion Mining

- *Terms and their frequency*
 - TF-IDF
- *Part of speech (POS)*
 - Adjectives
- *Opinion words and phrases*
 - *beautiful, wonderful, good, and amazing are positive opinion words*
 - *bad, poor, and terrible are negative opinion words.*
 - opinion phrases and idioms,
e.g., *cost someone an arm and a leg*
- *Rules of opinions*
- *Negations*
- *Syntactic dependency*

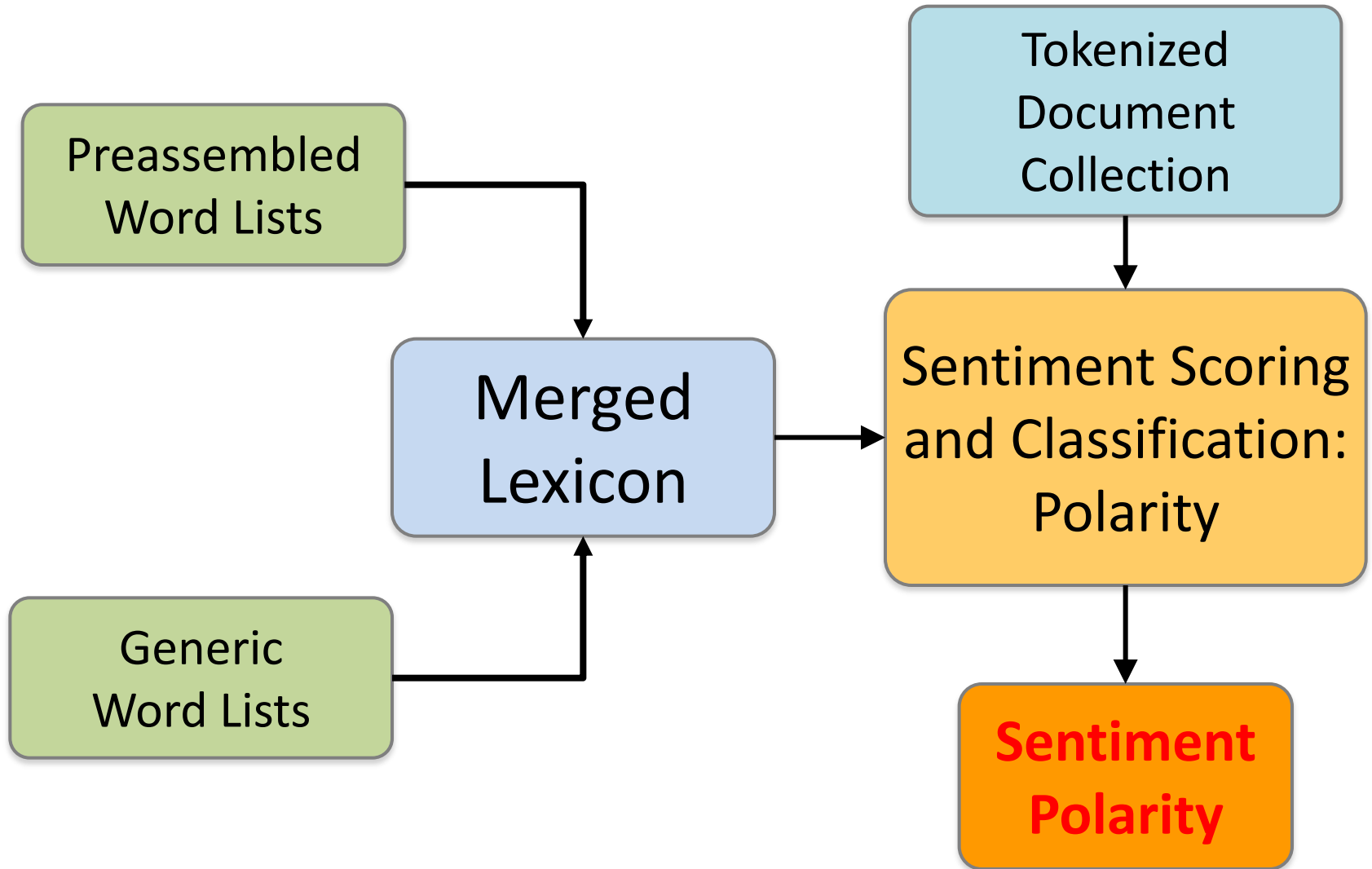
Sentiment Analysis Architecture



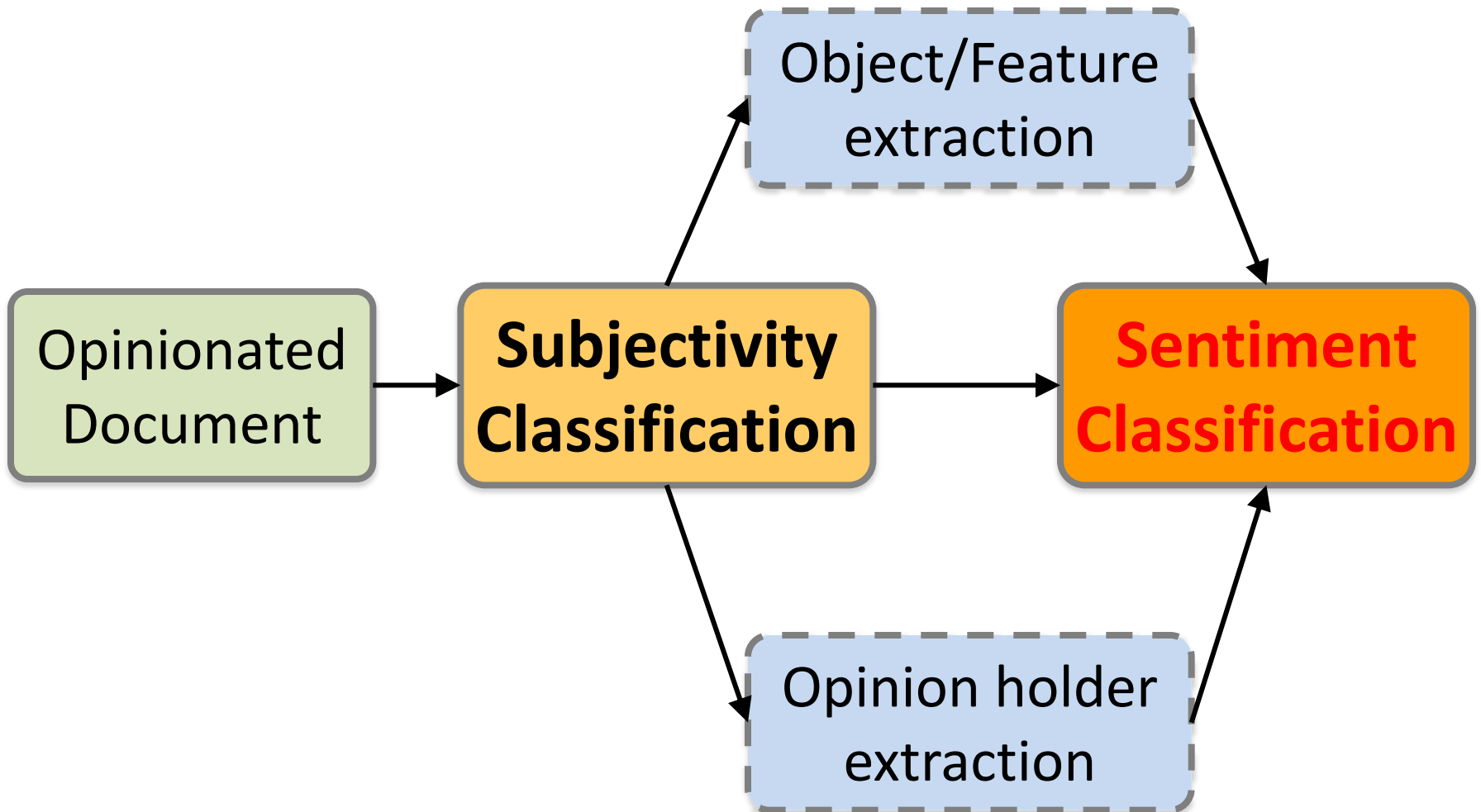
Sentiment Classification Based on Emoticons



Lexicon-Based Model



Sentiment Analysis Tasks



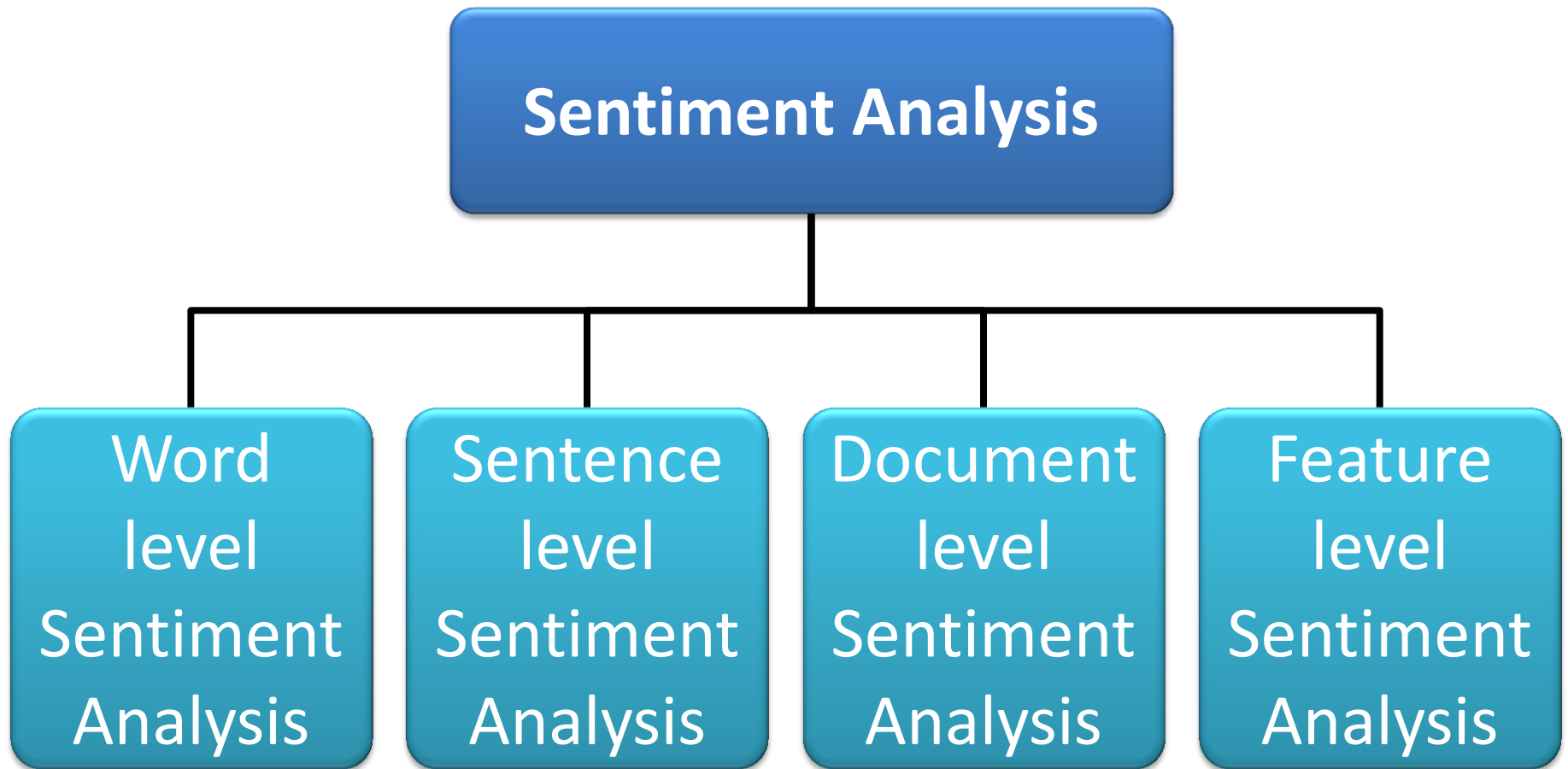
Sentiment Analysis

vs.

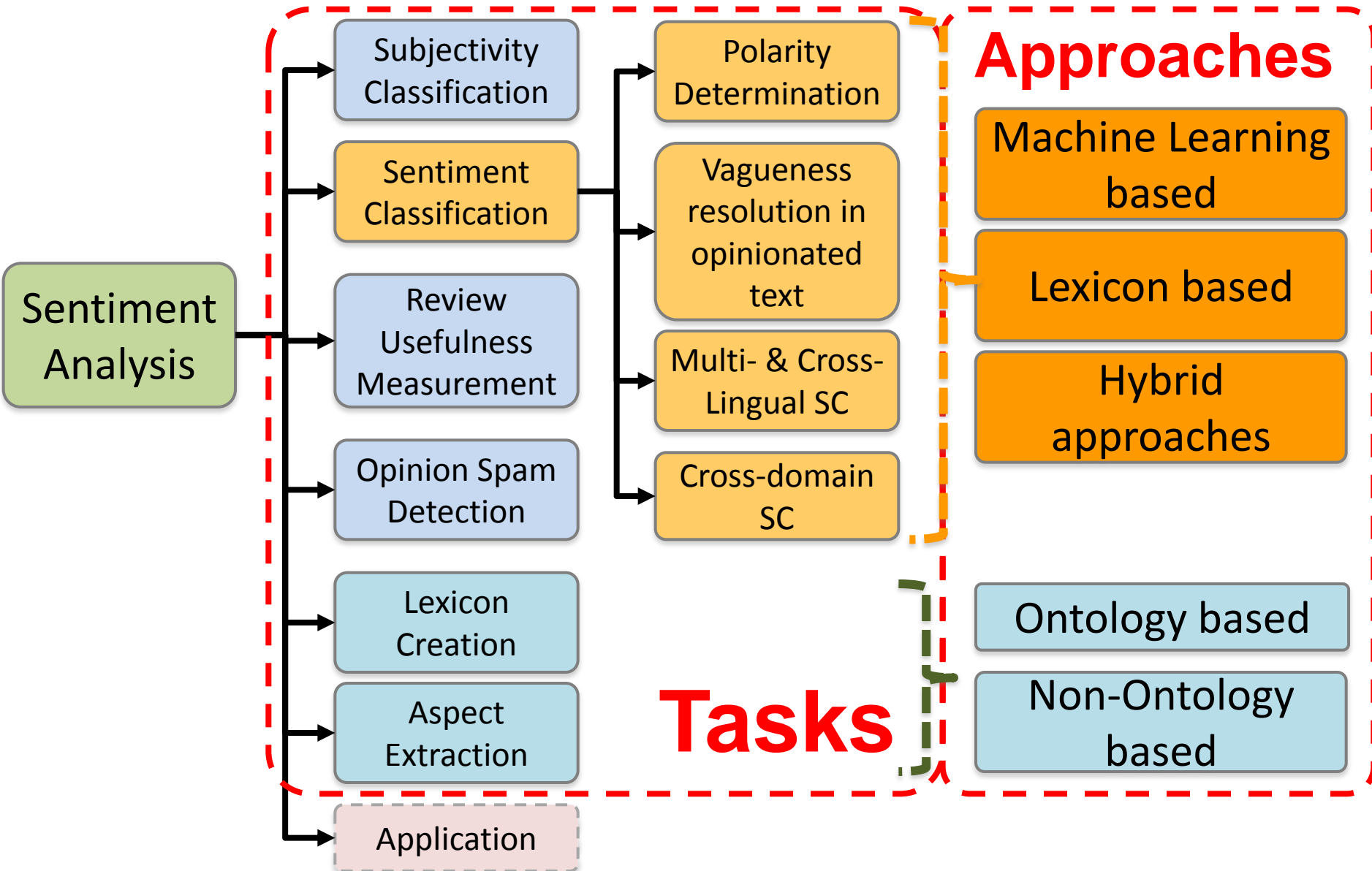
Subjectivity Analysis

Sentiment Analysis	Subjectivity Analysis
Positive	Subjective
Negative	
Neutral	Objective

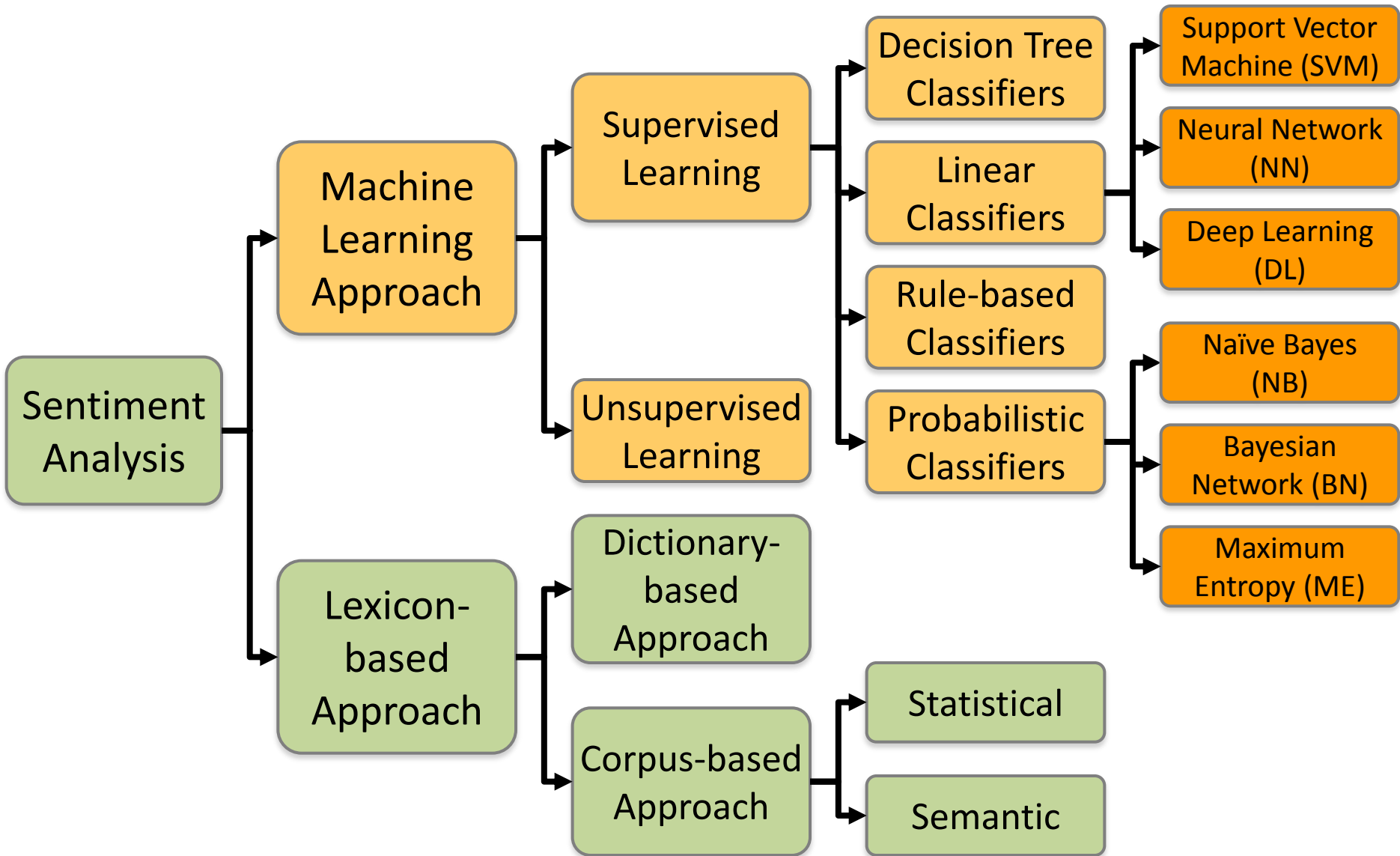
Levels of Sentiment Analysis



Sentiment Analysis



Sentiment Classification Techniques



A Brief Summary of Sentiment Analysis Methods

Study	Analysis Task	Sentiment Identification		Sentiment Aggregation		Nature of Measure
		Method	Level	Method	Level	
Hu and Li, 2011	Polarity	ML (Probabilistic model)	Snippet			Valence
Li and Wu, 2010	Polarity	Lexicon/Rule	Phrase	Sum	Snippet	Valence
Thelwall et al., 2010	Polarity	Lexicon/Rule	Sentence	Max & Min	Snippet	Range
Boiy and Moens, 2009	Both	ML (Cascade ensemble)	Sentence			Valence
Chung 2009	Polarity	Lexicon	Phrase	Average	Sentence	Valence
Wilson, Wiebe, and Hoffmann, 2009	Both	ML (SVM, AdaBoost, Rule, etc.)	Phrase			Valence
Zhang et al., 2009	Polarity	Lexicon/Rule	Sentence	Weighted average	Snippet	Valence
Abbasi, Chen, and Salem, 2008	Polarity	ML (GA + feature selection)	Snippet			Valence
Subrahmanian and Reforgiato, 2008	Polarity	Lexicon/Rule	Phrase	Rule	Snippet	Valence
Tan and Zhang 2008	Polarity	ML (SVM, Winnow, NB, etc.)	Snippet			Valence
Airoldi, Bai, and Padman, 2007	Polarity	ML (Markov Blanket)	Snippet			Valence
Das and Chen, 2007	Polarity	ML (Bayesian, Discriminate, etc.)	Snippet	Average	Daily	Valence
Liu et al., 2007	Polarity	ML (PLSA)	Snippet			Valence
Kennedy and Inkpen, 2006	Polarity	Lexicon/Rule, ML (SVM)	Phrase	Count	Snippet	Valence
Mishne 2006	Polarity	Lexicon	Phrase	Average	Snippet	Valence
Liu et al., 2005	Polarity	Lexicon/Rule	Phrase	Distribution	Object	Range
Mishne 2005	Polarity	ML (SVM)	Snippet			Valence
Popescu and Etzioni 2005	Polarity	Lexicon/Rule	Phrase			Valence
Efron 2004	Polarity	ML (SVN, NB)	Snippet			Valence
Wilson, Wiebe, and Hwa, 2004	Both	ML (SVM, AdaBoost, Rule, etc.)	Sentence			Valence
Nigam and Hurst 2004	Polarity	Lexicon/Rule	Chunk	Rule	Sentence	Valence
Dave, Lawrence, and Pennock, 2003	Polarity	ML (SVM, Rainbow, etc.)	Snippet			Valence
Nasukawa and Yi 2003	Polarity	Lexicon/Rule	Phrase	Rule	Sentence	Valence
Yi et al., 2003	Polarity	Lexicon/Rule	Phrase	Rule	Sentence	Valence
Yu and Hatzivassiloglou 2003	Both	ML (NB) + Lexicon/Rule	Phrase	Average	Sentence	Valence
Pang, Lee, and Vaithyanathan 2002	Polarity	ML (SVM, MaxEnt, NB)	Snippet			Valence
Subasic and Huettner 2001	Polarity	Lexicon/Fuzzy logic	Phrase	Average	Snippet	Valence
Turney 2001	Polarity	Lexicon/Rule	Phrase	Average	Snippet	Valence

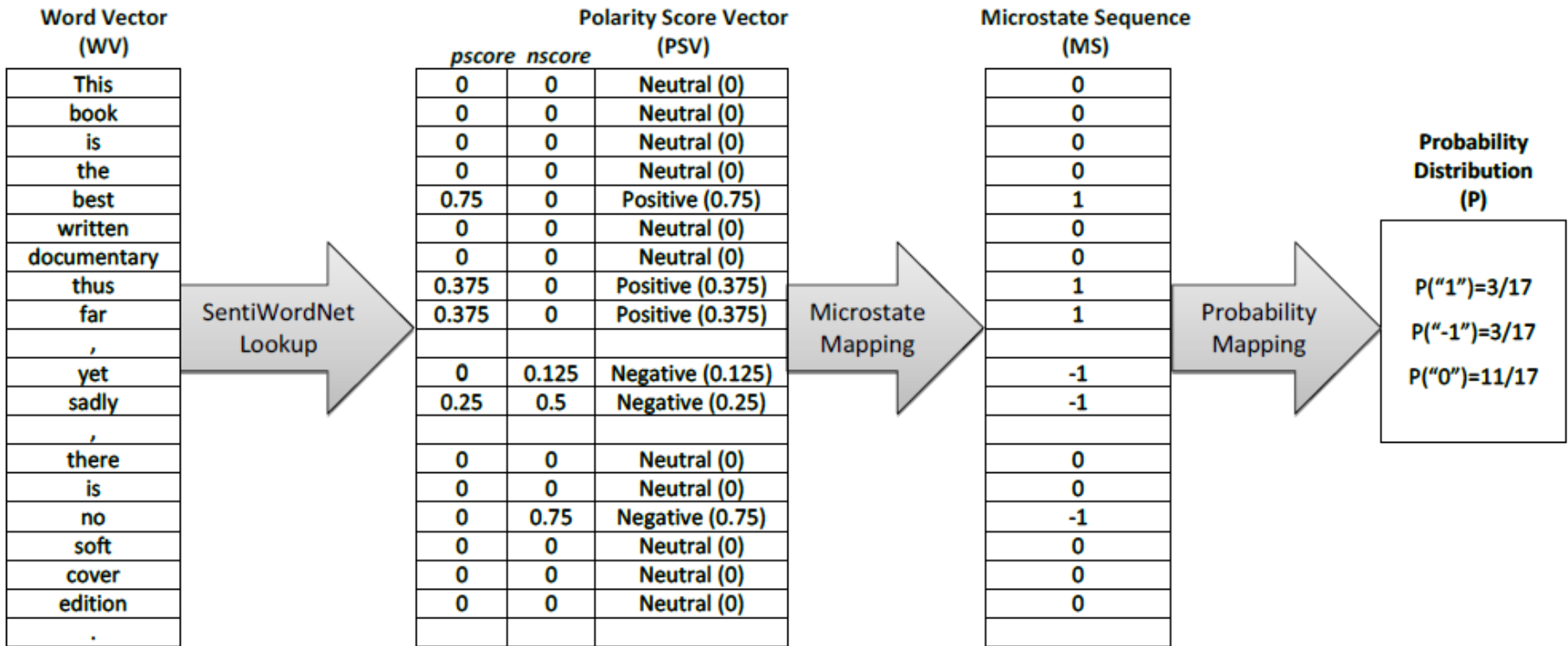
(Both = Subjectivity and Polarity; ML= Machine Learning; Lexicon/Rule= Lexicon enhanced by linguistic rules)

Word-of-Mouth (WOM)

- “This book is the best written documentary thus far, yet sadly, there is no soft cover edition.”
- “This book is the **best** written documentary **thus far**, **yet** **sadly**, there is **no** soft cover edition.”

	Word	POS
This	This	DT
book	book	NN
is	is	VBZ
the	the	DT
best	best	JJS
written	written	VCN
documentary	documentary	NN
thus	thus	RB
far	far	RB
,	,	,
yet	yet	RB
sadly	sadly	RB
,	,	,
there	there	EX
is	is	VBZ
no	no	DT
soft	soft	JJ
cover	cover	NN
edition	edition	NN
.	.	.

Conversion of text representation



Example of SentiWordNet

POS	ID	PosScore	NegScore	SynsetTerms	Gloss
a	00217728	0.75	0	beautiful#1	delighting the senses or exciting intellectual or emotional admiration; "a beautiful child"; "beautiful country"; "a beautiful painting"; "a beautiful theory"; "a beautiful party"
a	00227507	0.75	0	best#1	(superlative of `good') having the most positive qualities; "the best film of the year"; "the best solution"; "the best time for planting"; "wore his best suit"
r	00042614	0	0.625	unhappily#2 sadly#1	in an unfortunate way; "sadly he died before he could see his grandchild"
r	00093270	0	0.875	woefully#1 sadly#3 lamentably#1 deplorably#1	in an unfortunate or deplorable manner; "he was sadly neglected"; "it was woefully inadequate"
r	00404501	0	0.25	sadly#2	with sadness; in a sad manner; "'She died last night,' he said sadly"

Evaluation of Text Mining and Sentiment Analysis

- Evaluation of Information Retrieval
- Evaluation of Classification Model (Prediction)
 - Accuracy
 - Precision
 - Recall
 - F-score

**LeCun, Yann,
Yoshua Bengio,
and Geoffrey Hinton.**

"Deep learning."

**Nature 521, no. 7553 (2015): 436-
444.**

Deep learning

Yann LeCun^{1,2}, Yoshua Bengio³ & Geoffrey Hinton^{4,5}

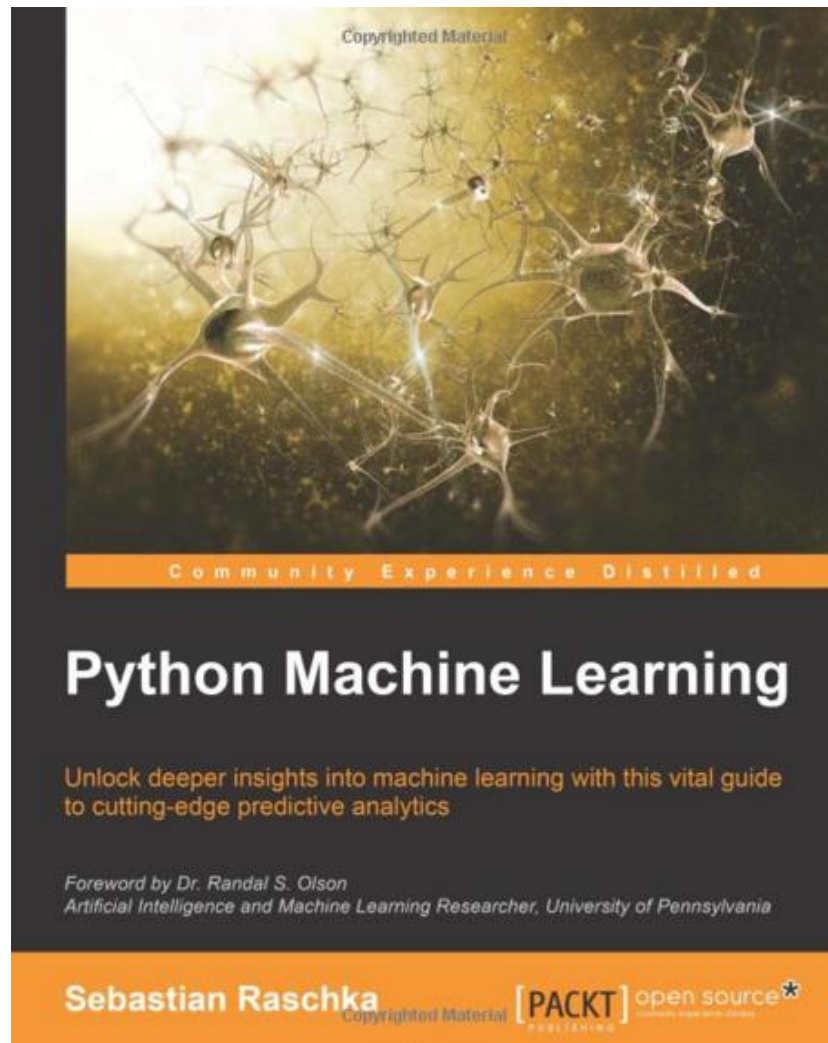
Deep learning allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction. These methods have dramatically improved the state-of-the-art in speech recognition, visual object recognition, object detection and many other domains such as drug discovery and genomics. Deep learning discovers intricate structure in large data sets by using the backpropagation algorithm to indicate how a machine should change its internal parameters that are used to compute the representation in each layer from the representation in the previous layer. Deep convolutional nets have brought about breakthroughs in processing images, video, speech and audio, whereas recurrent nets have shone light on sequential data such as text and speech.

Machine-learning technology powers many aspects of modern society: from web searches to content filtering on social networks to recommendations on e-commerce websites, and it is increasingly present in consumer products such as cameras and smartphones. Machine-learning systems are used to identify objects in images, transcribe speech into text, match news items, posts or products with users' interests, and select relevant results of search. Increasingly, these applications make use of a class of techniques called deep learning.

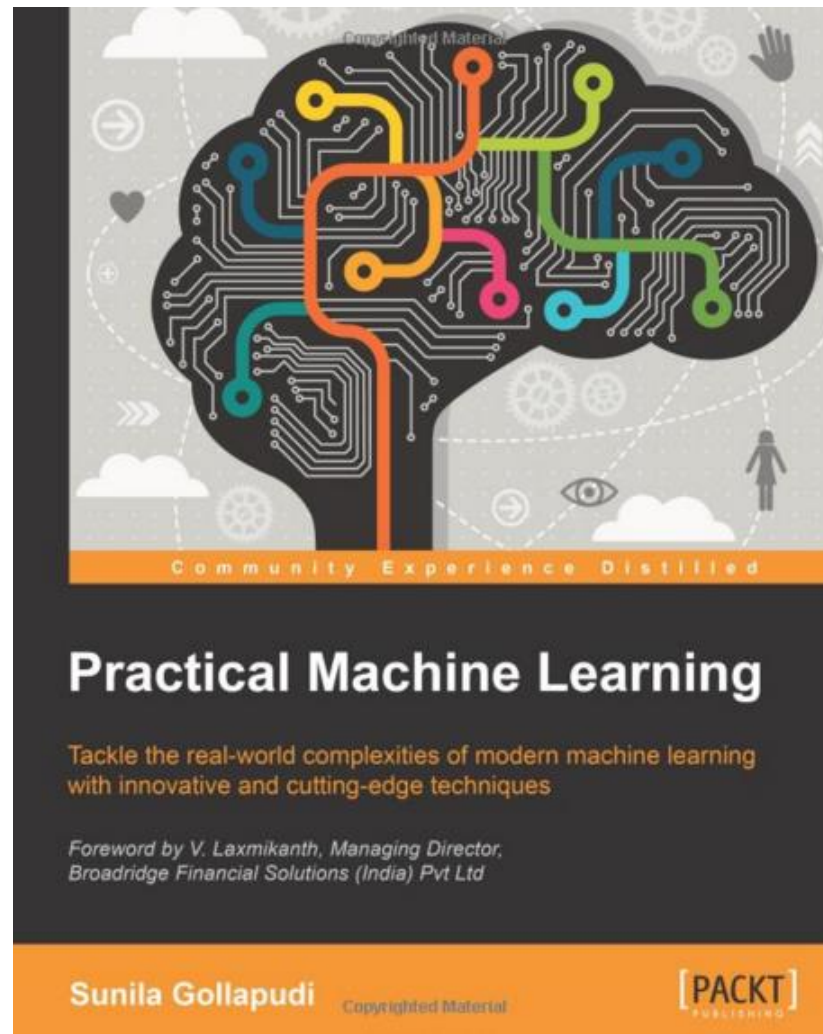
Conventional machine-learning techniques were limited in their ability to process natural data in their raw form. For decades, con-

intricate structures in high-dimensional data and is therefore applicable to many domains of science, business and government. In addition to beating records in image recognition¹⁻⁴ and speech recognition⁵⁻⁷, it has beaten other machine-learning techniques at predicting the activity of potential drug molecules⁸, analysing particle accelerator data^{9,10}, reconstructing brain circuits¹¹, and predicting the effects of mutations in non-coding DNA on gene expression and disease^{12,13}. Perhaps more surprisingly, deep learning has produced extremely promising results for various tasks in natural language understanding¹⁴, particularly topic classification, sentiment analysis, question answering¹⁵ and language translation^{16,17}.

Sebastian Raschka (2015),
Python Machine Learning,
Packt Publishing



Sunila Gollapudi (2016),
Practical Machine Learning,
Packt Publishing



Machine Learning Models

Deep Learning

Association rules

Decision tree

Clustering

Bayesian

Kernel

Ensemble

Dimensionality reduction

Regression Analysis

Instance based

Neural networks (NN) 1960

Multilayer Perceptrons (MLP) 1985

Restricted Boltzmann Machine (RBM) 1986

Support Vector Machine (SVM) 1995



Hinton presents the

Deep Belief Network (DBN)

**New interests in deep learning
and RBM**

State of the art MNIST

2005

Deep Recurrent Neural Network (RNN) 2009

Convolutional DBN 2010

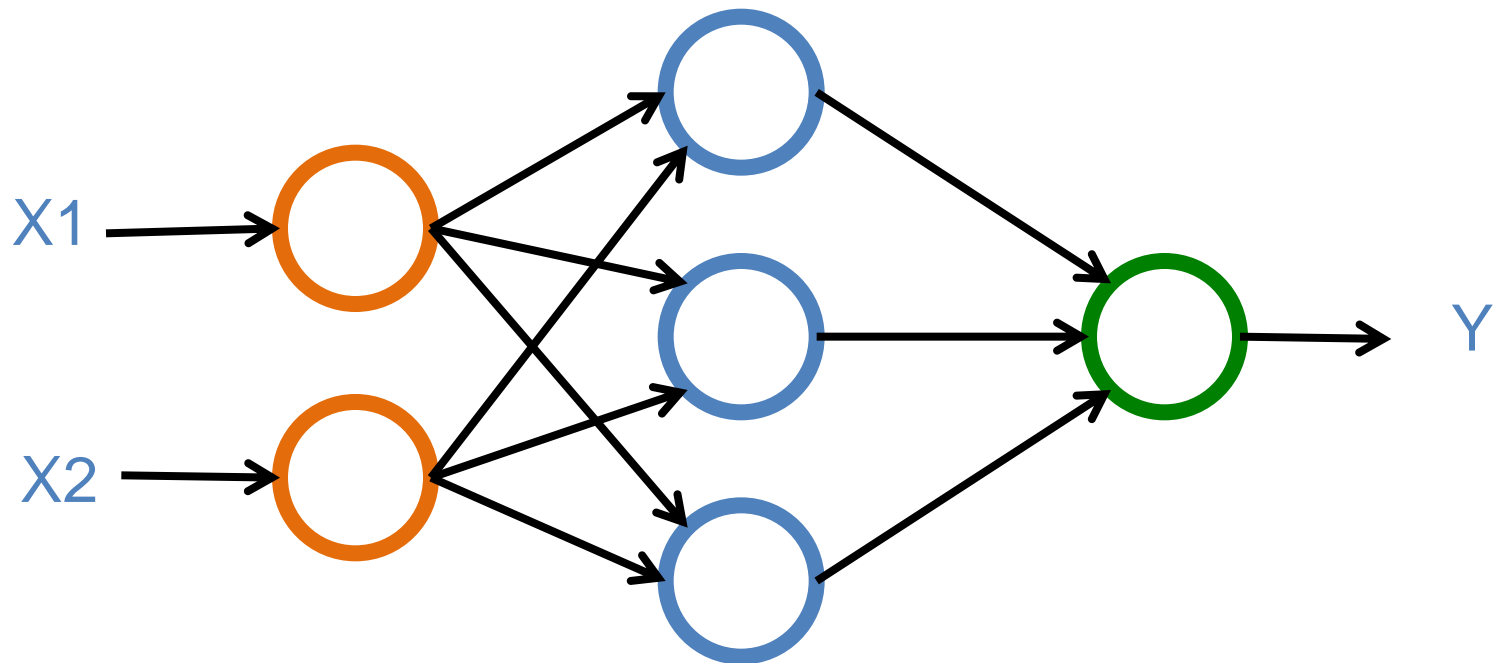
Max-Pooling CDBN 2011

Neural Networks

Input Layer
(X)

Hidden Layer
(H)

Output Layer
(Y)



Deep Learning

Geoffrey Hinton

Yann LeCun

Yoshua Bengio

Andrew Y. Ng



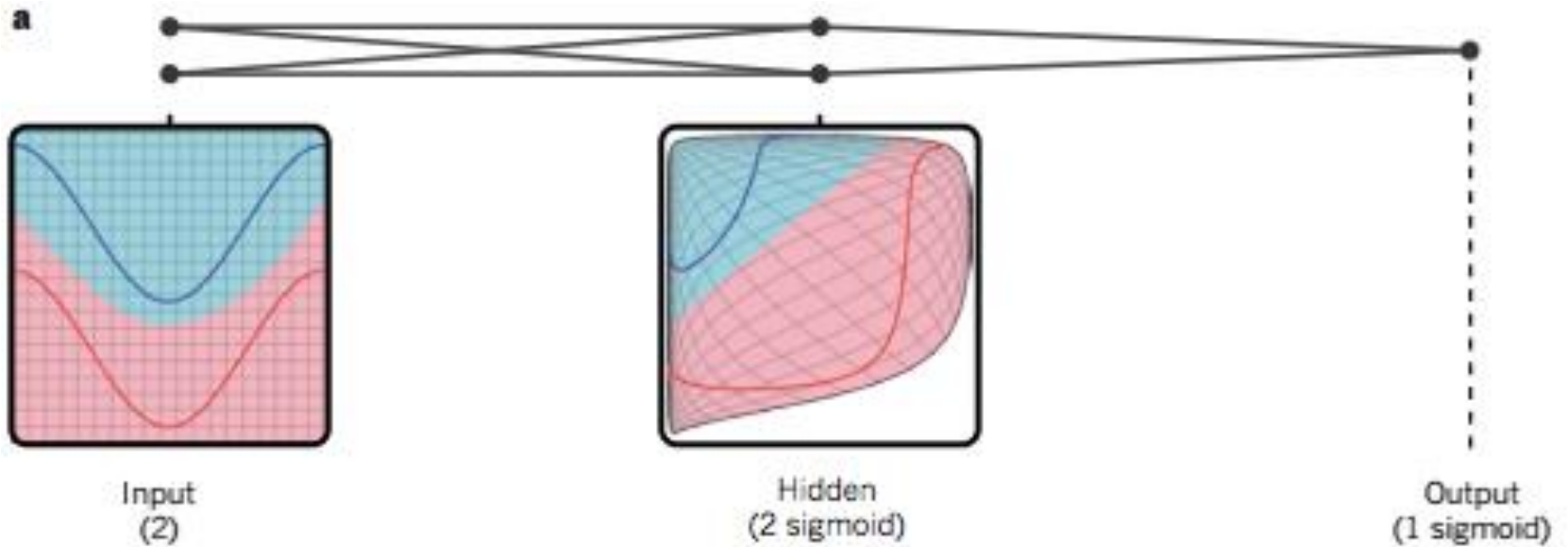
Geoffrey Hinton
Google
University of Toronto

LeCun, Yann,
Yoshua Bengio,
and Geoffrey Hinton.

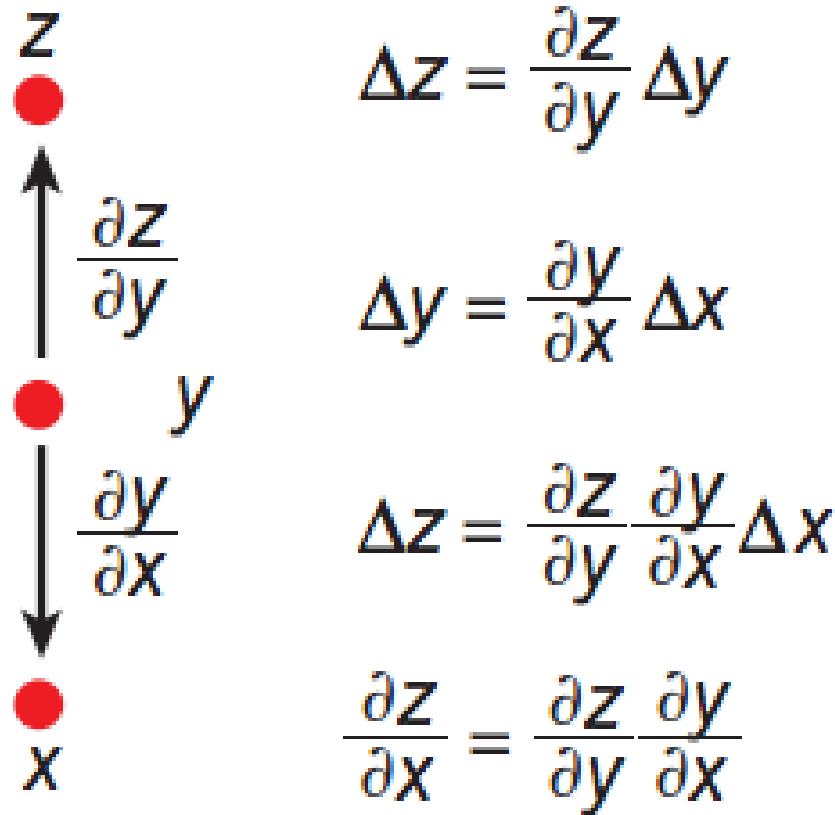
"Deep learning."

Nature 521, no. 7553 (2015): 436-
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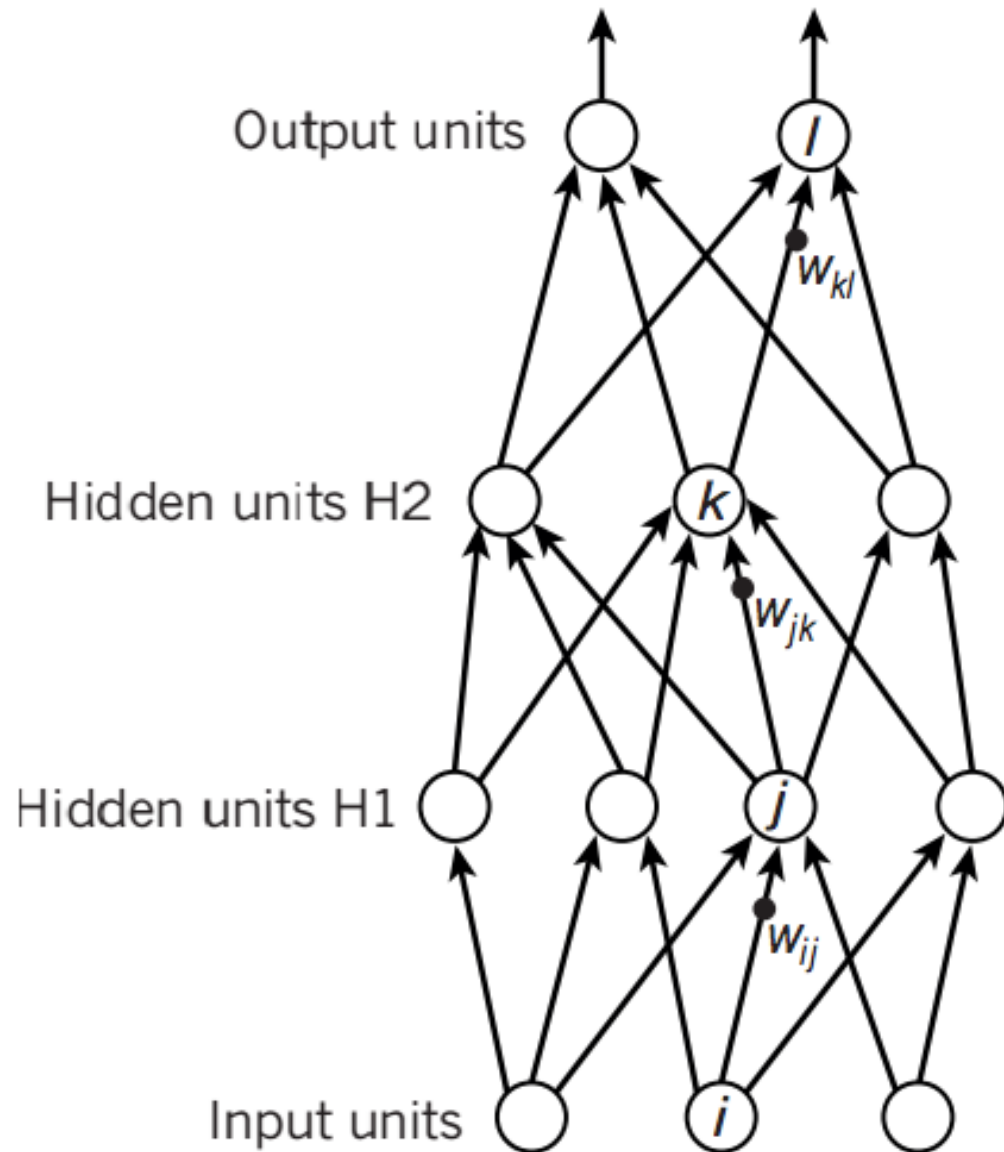
Deep Learning



Deep Learning



Deep Learning



$$y_l = f(z_l)$$

$$z_l = \sum_{k \in H2} w_{kl} y_k$$

$$y_k = f(z_k)$$

$$z_k = \sum_{j \in H1} w_{jk} y_j$$

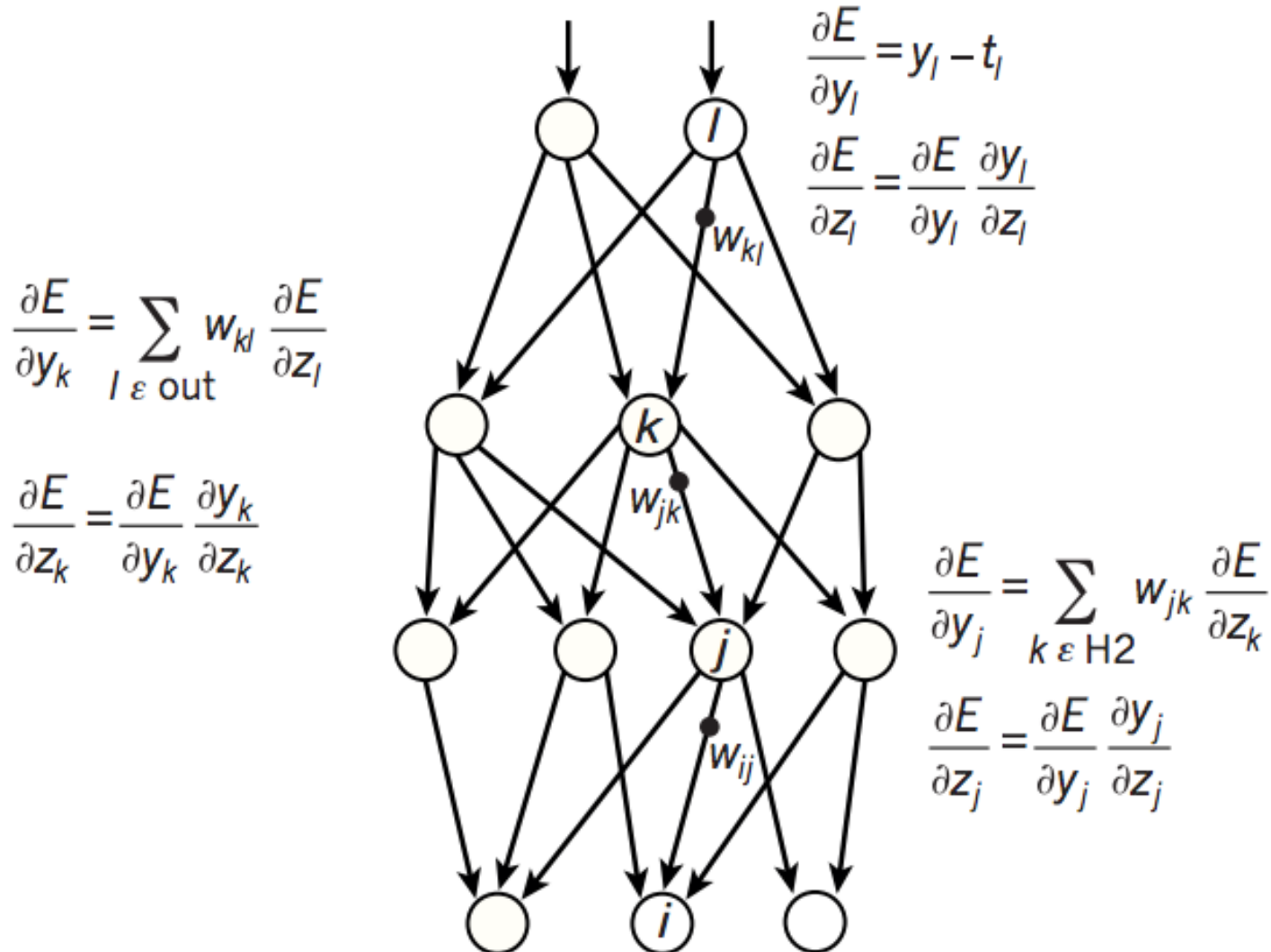
$$y_j = f(z_j)$$

$$z_j = \sum_{i \in \text{Input}} w_{ij} x_i$$

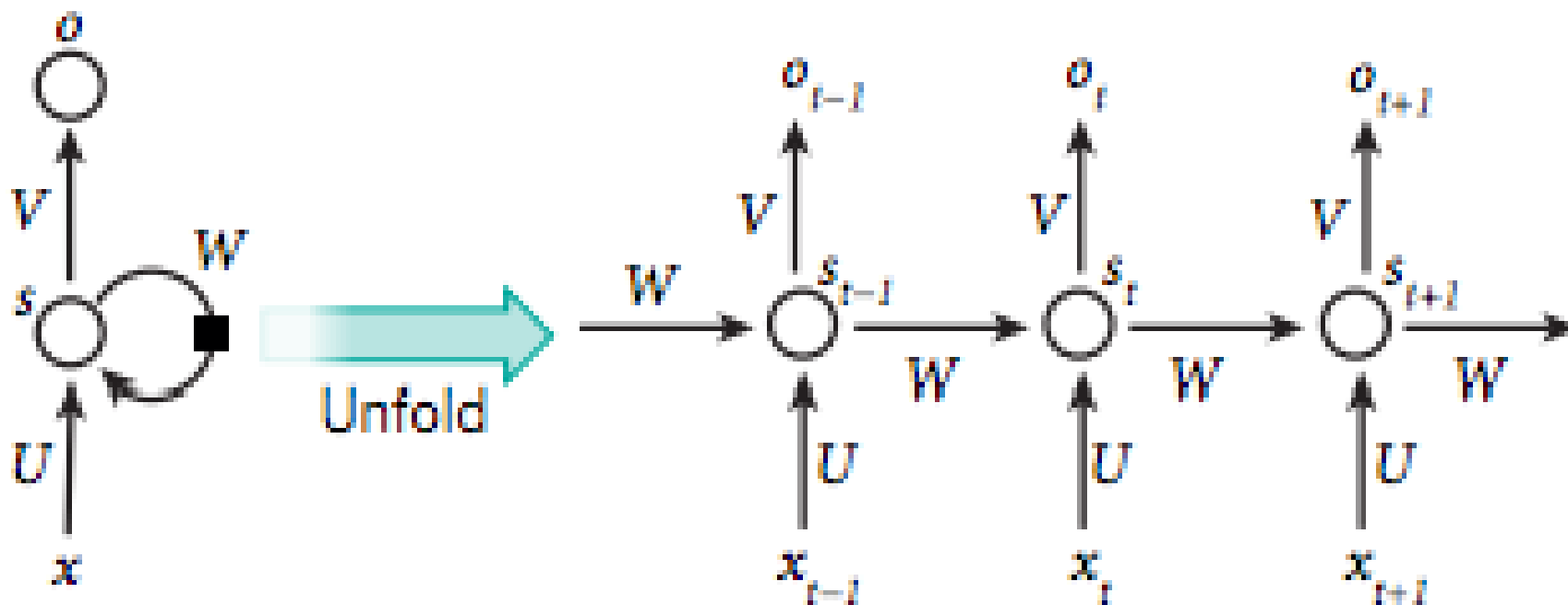
Deep Learning

d

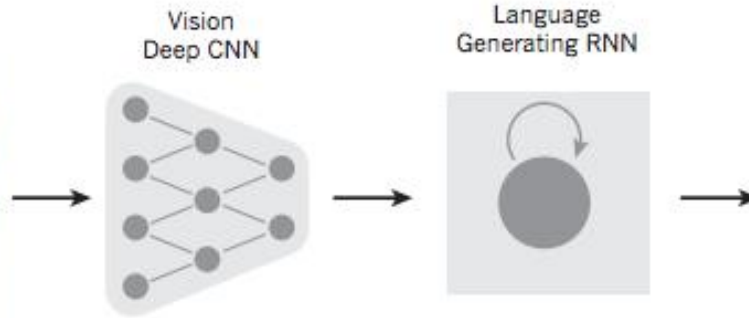
Compare outputs with correct answer to get error derivatives



Recurrent Neural Network (RNN)



From image to text



A woman is throwing a **frisbee** in a park.



A **dog** is standing on a hardwood floor.



A **stop** sign is on a road with a mountain in the background



A little **girl** sitting on a bed with a teddy bear.



A group of **people** sitting on a boat in the water.



A giraffe standing in a forest with **trees** in the background.

From image to text

Image: deep convolution neural network (CNN)

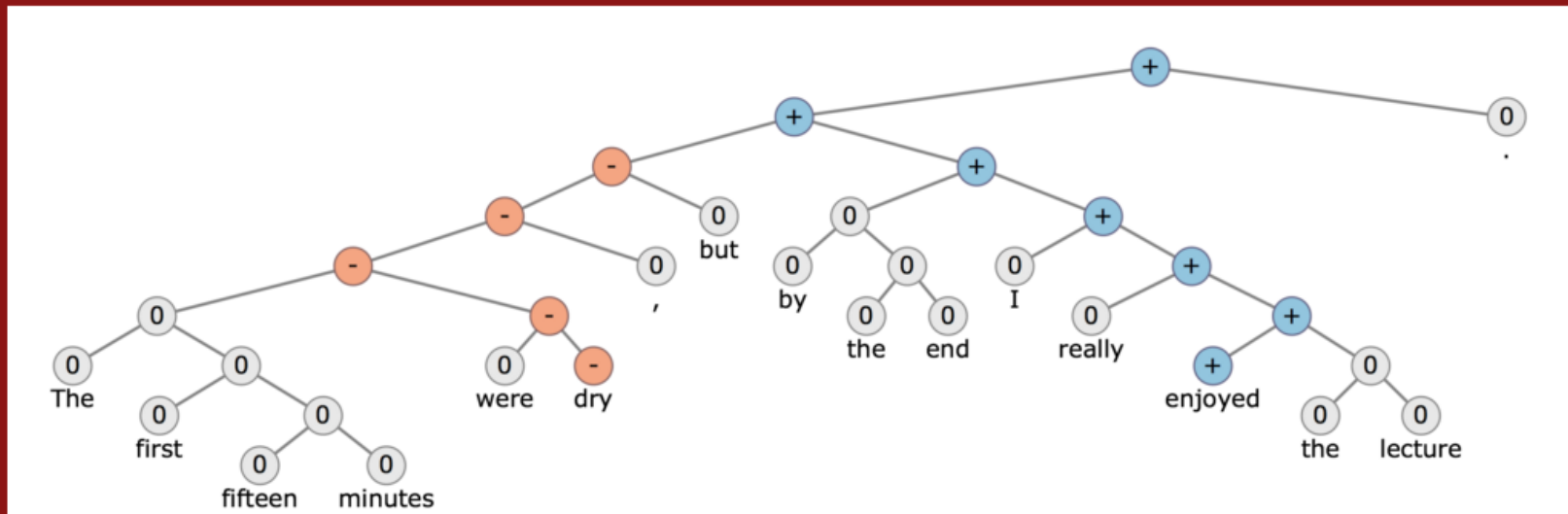
Text: recurrent neural network (RNN)



A group of **people** sitting on a boat in the water.

CS224d: Deep Learning for Natural Language Processing

CS224d: Deep Learning for Natural Language Processing

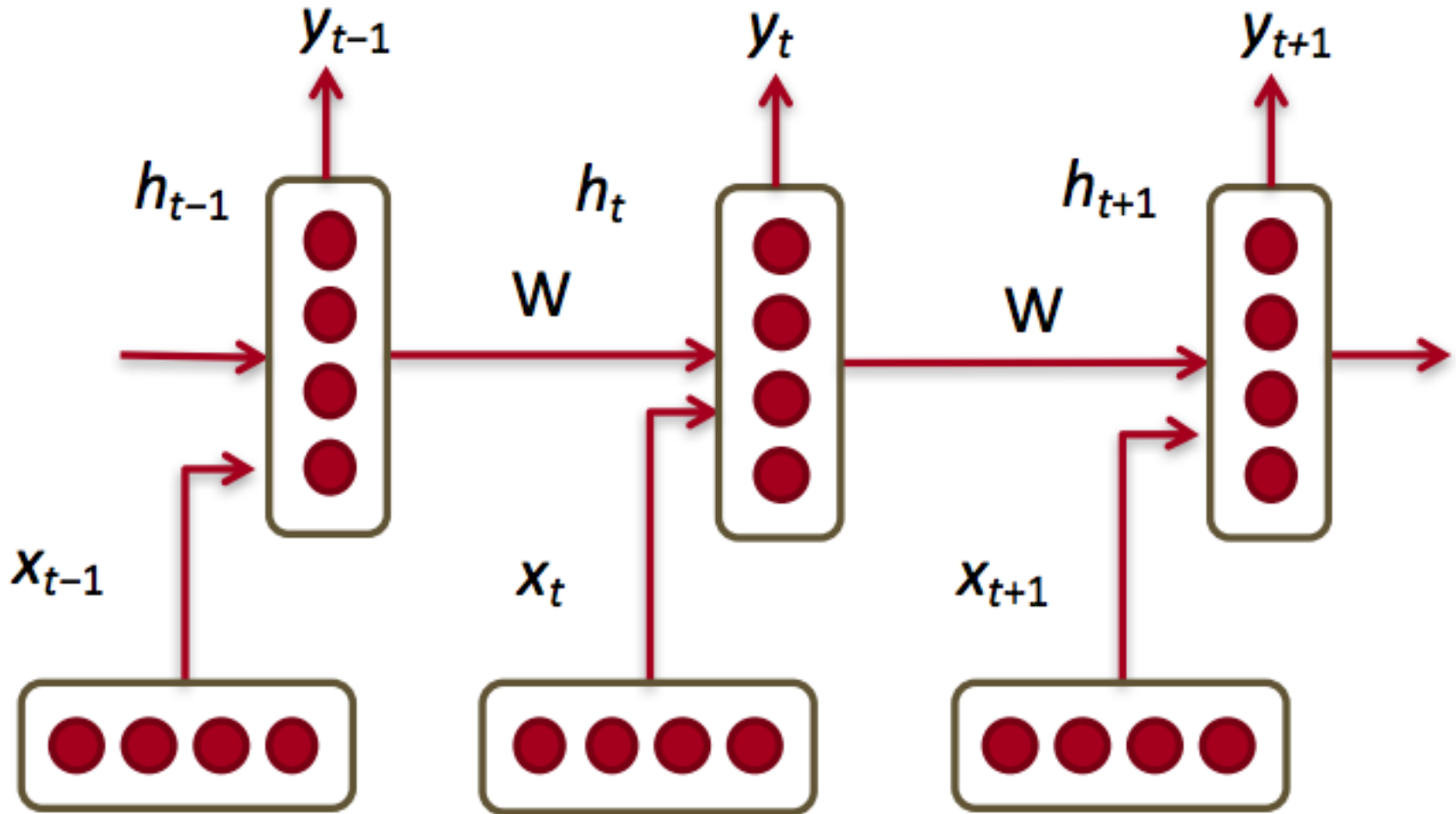


Course Description

Natural language processing (NLP) is one of the most important technologies of the information age. Understanding complex language utterances is also a crucial part of artificial intelligence. Applications of NLP are everywhere because people communicate most everything in language: web search, advertisement, emails, customer service, language translation, radiology reports, etc. There are a large variety of underlying tasks and machine learning models powering NLP applications. Recently, deep learning approaches have obtained very high performance across many different NLP tasks. These models can often be trained with a single end-to-end model and do not require traditional, task-specific feature engineering. In this spring quarter course students will learn to implement, train, debug, visualize and invent their own neural network models. The course provides a deep excursion into cutting-edge research in deep learning applied to NLP. The final project will involve training a complex recurrent neural network and applying it to a large scale NLP problem. On the model side we will cover word vector representations,

<http://cs224d.stanford.edu/>

Recurrent Neural Networks (RNNs)

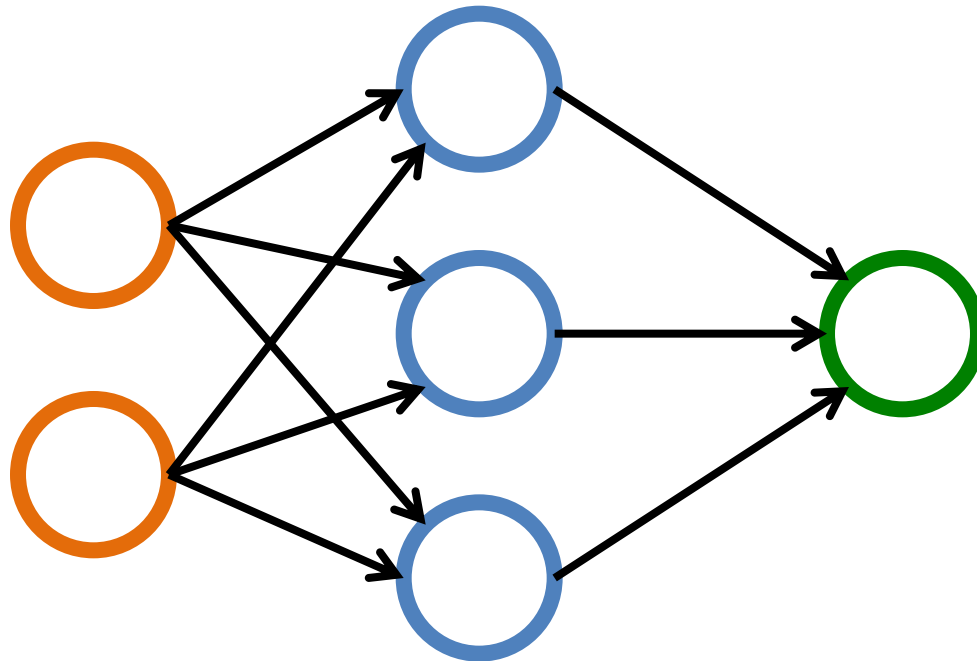


X		Y
Hours Sleep	Hours Study	Score
3	5	75
5	1	82
10	2	93
8	3	?

	X		Y
	Hours Sleep	Hours Study	Score
Training	3	5	75
	5	1	82
	10	2	93
Testing	8	3	?

Training a Network
=
Minimize the Cost Function

Neural Networks

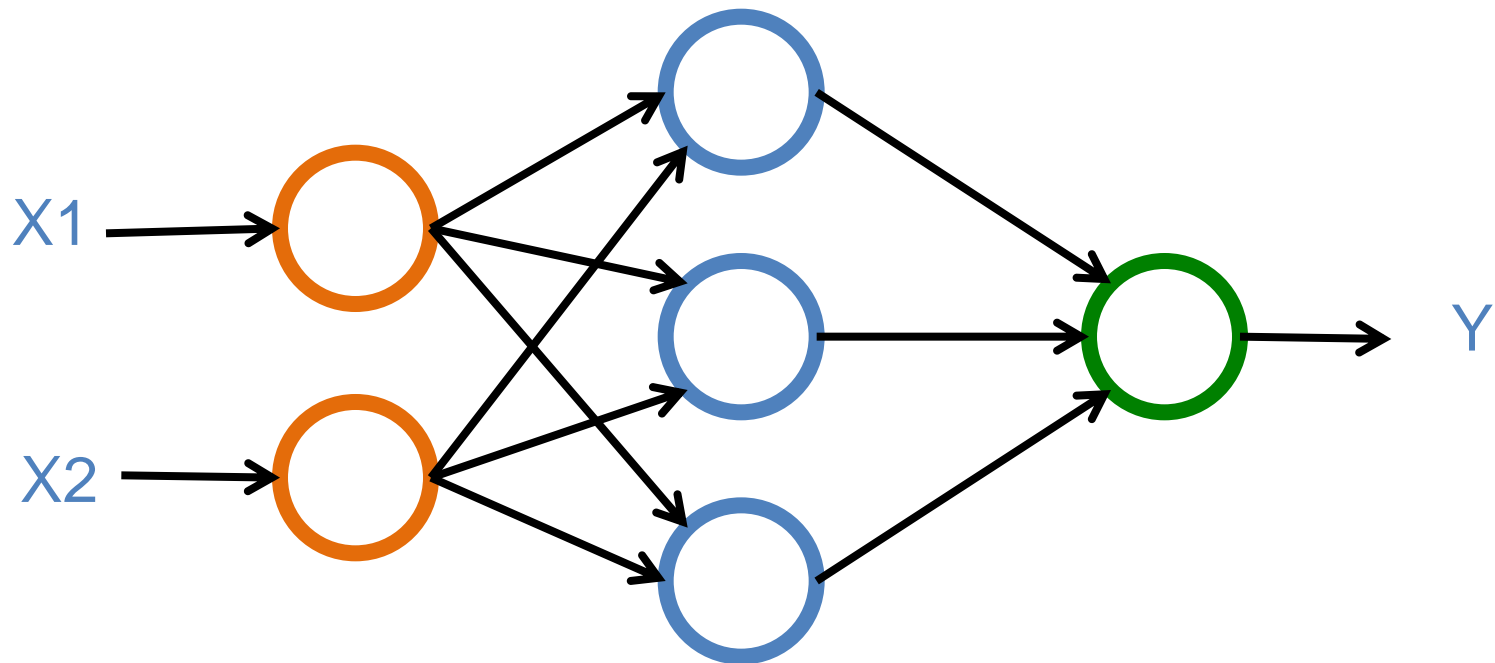


Neural Networks

Input Layer
(X)

Hidden Layer
(H)

Output Layer
(Y)



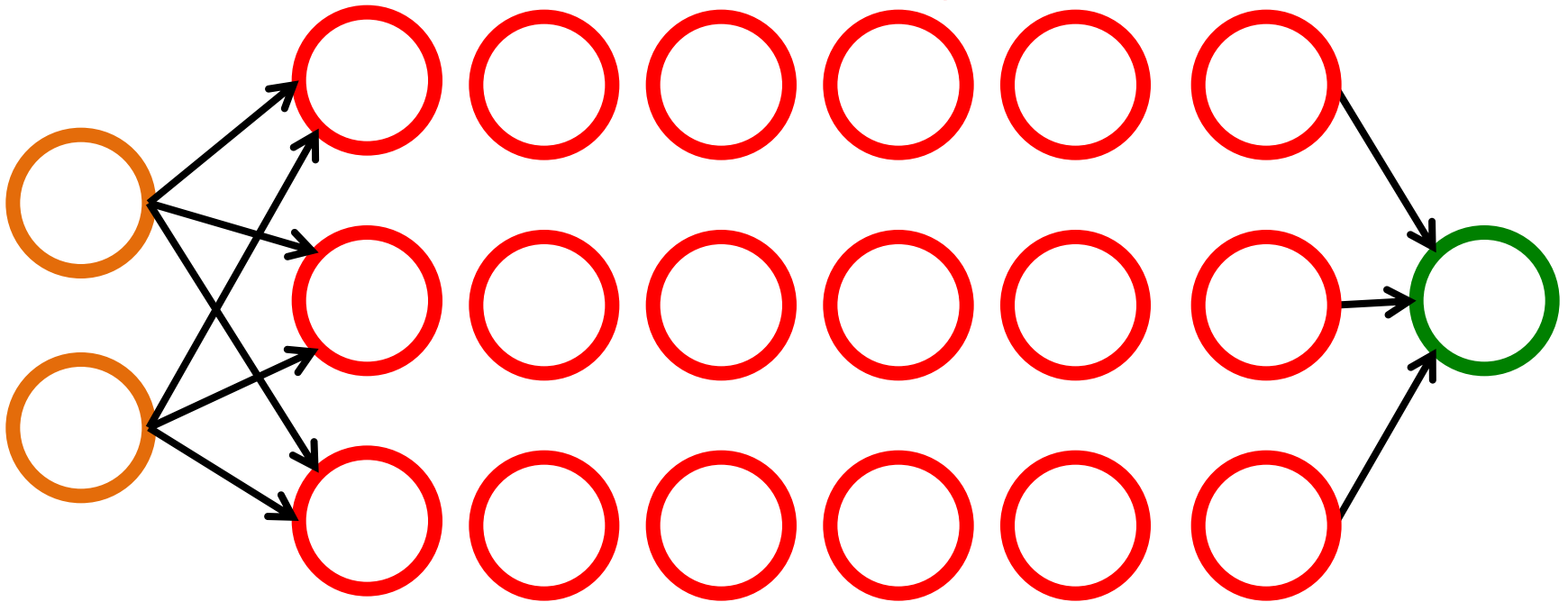
Neural Networks

Input Layer
(X)

Hidden Layers
(H)

Output Layer
(Y)

Deep Neural Networks
Deep Learning

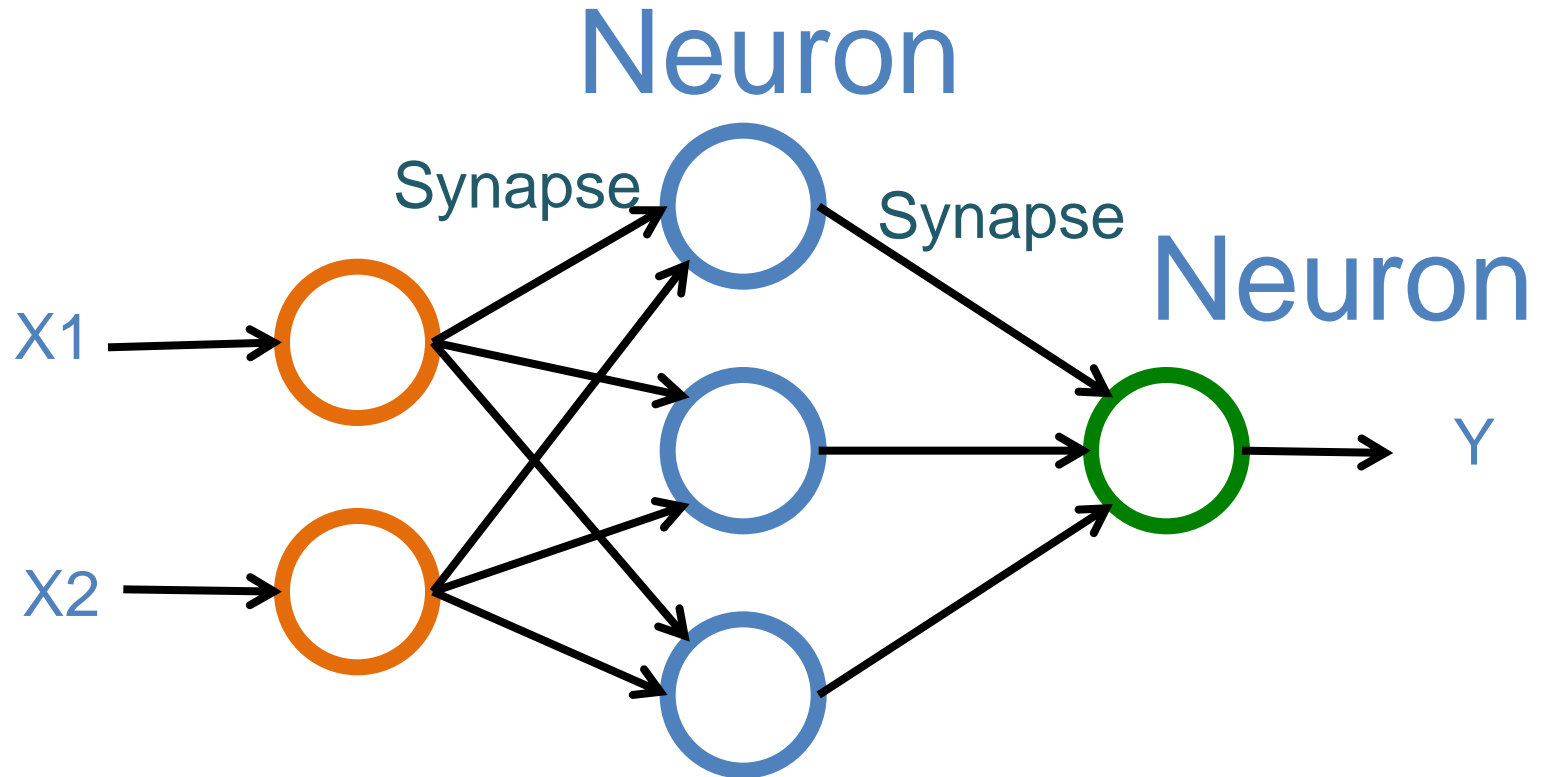


Neural Networks

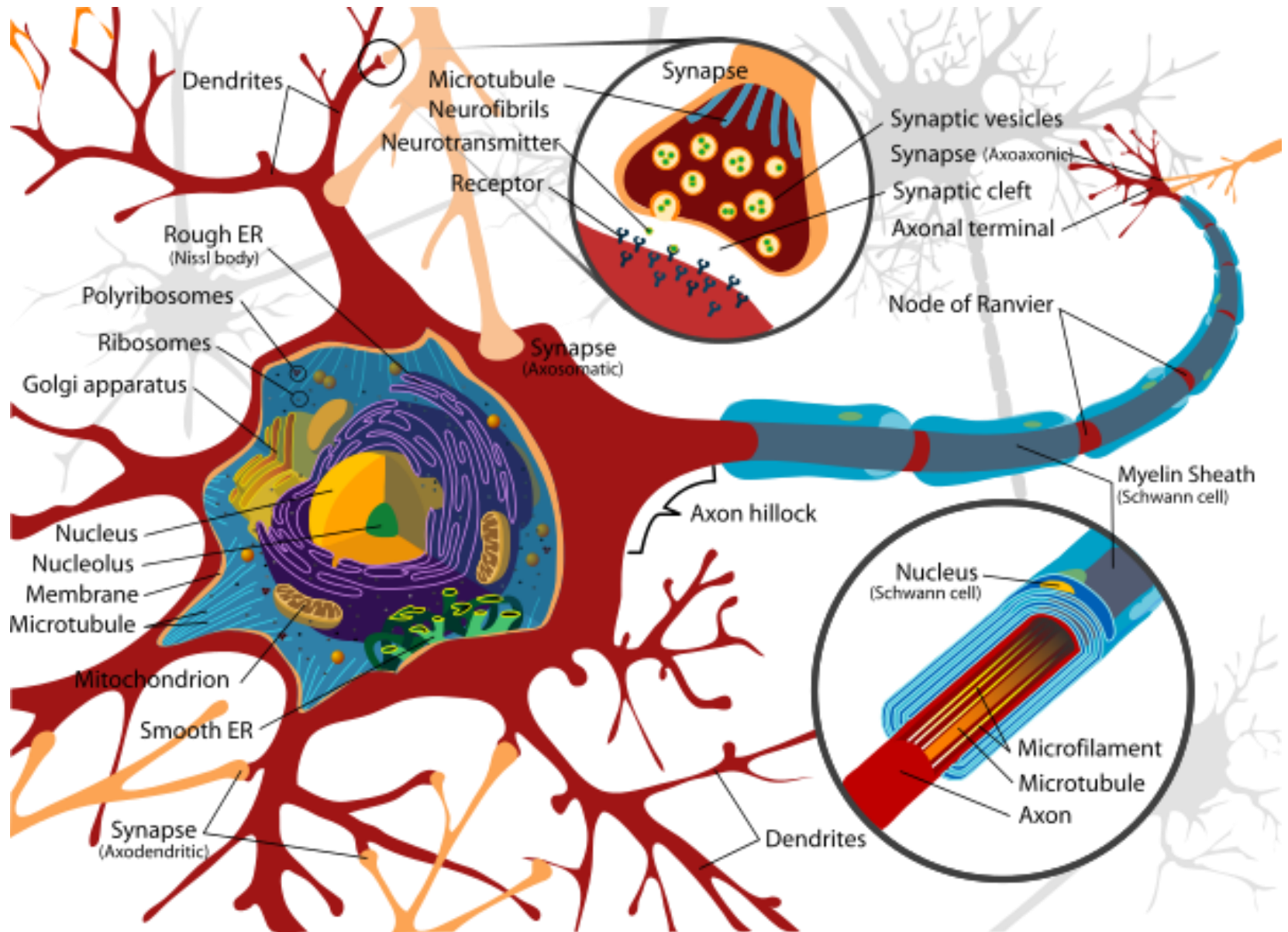
Input Layer
(X)

Hidden Layer
(H)

Output Layer
(Y)

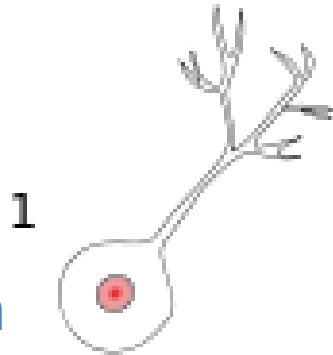


Neuron and Synapse

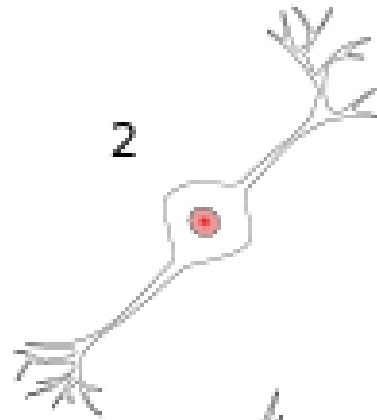


Neurons

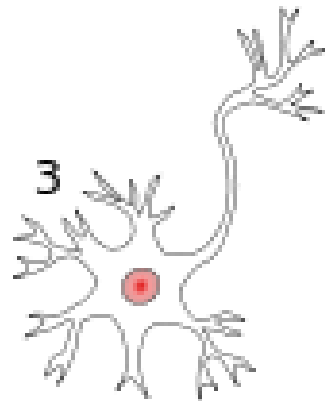
1 Unipolar neuron



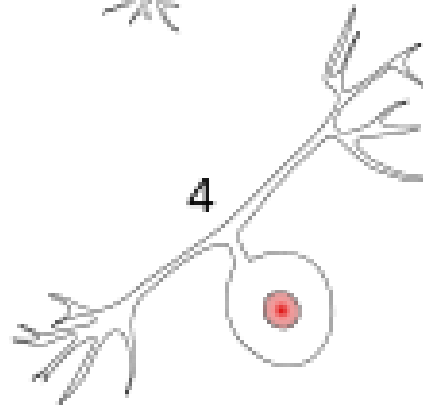
2 Bipolar neuron



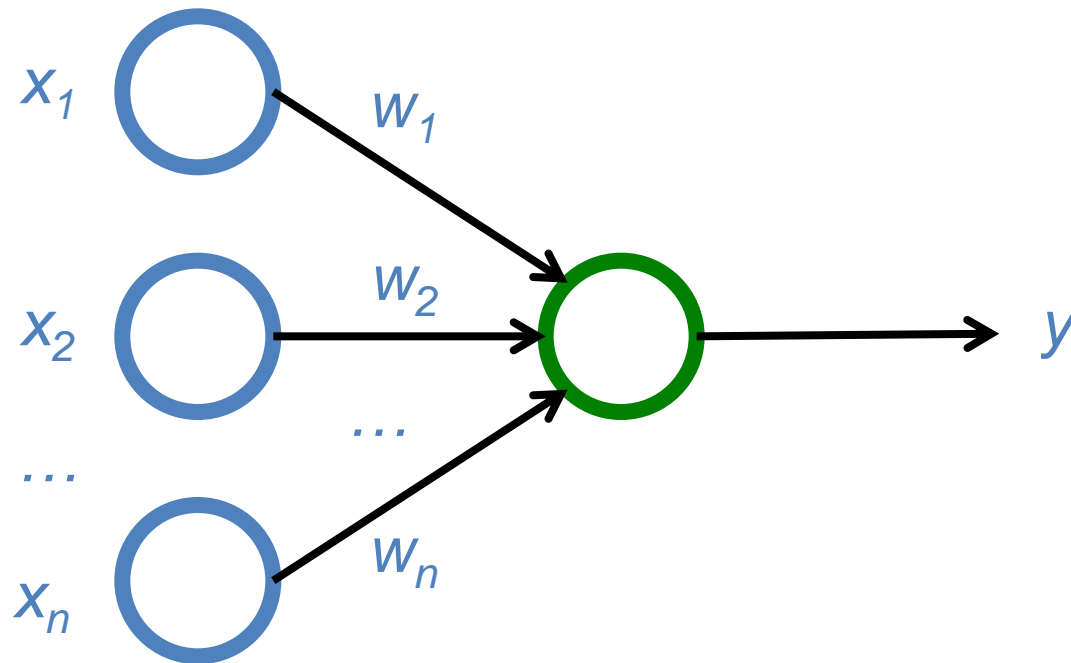
3 Multipolar neuron



4 Pseudounipolar neuron

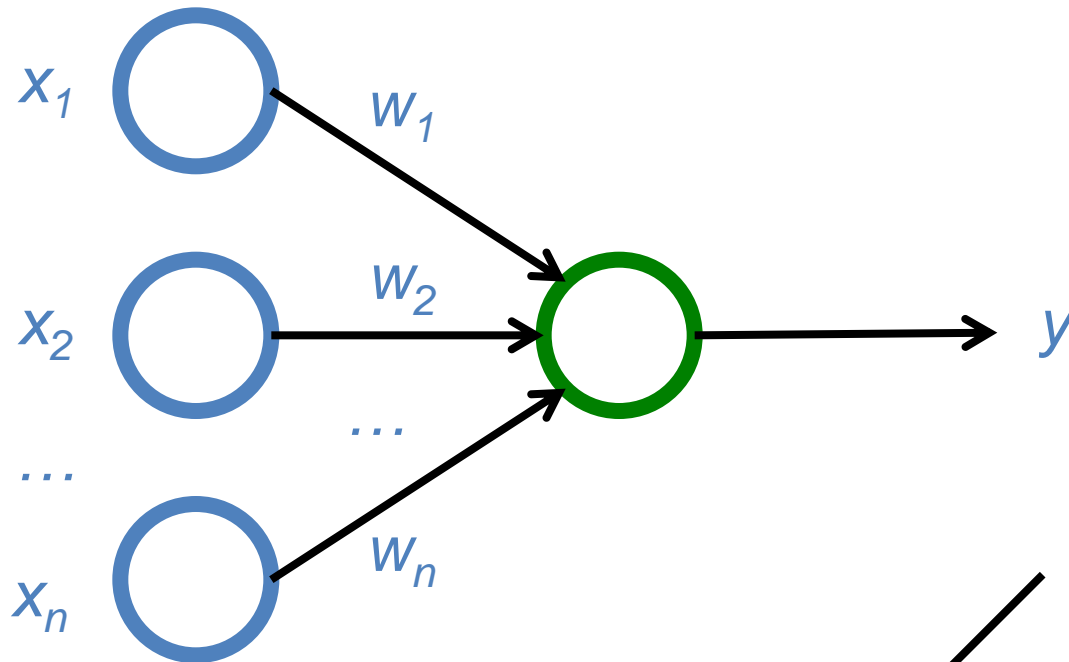


The Neuron



The Neuron

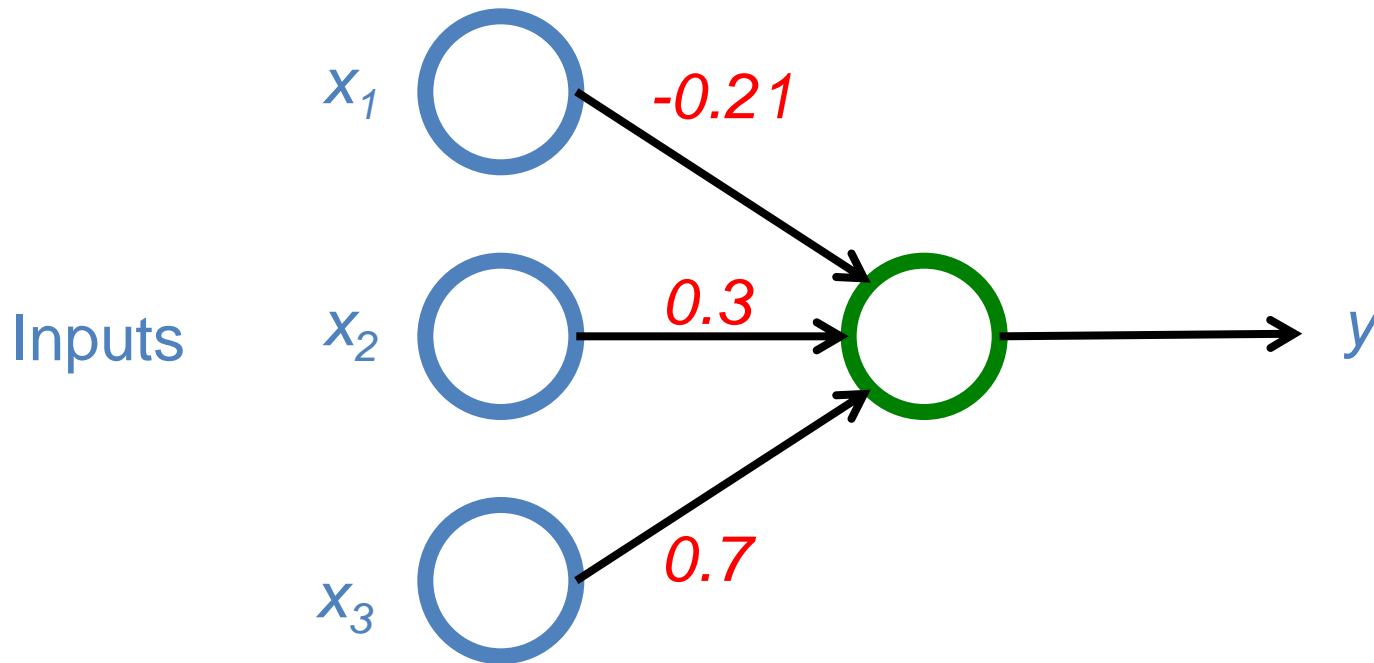
$$y = F\left(\sum_i w_i x_i\right)$$



$$F(x) = \max(0, x)$$

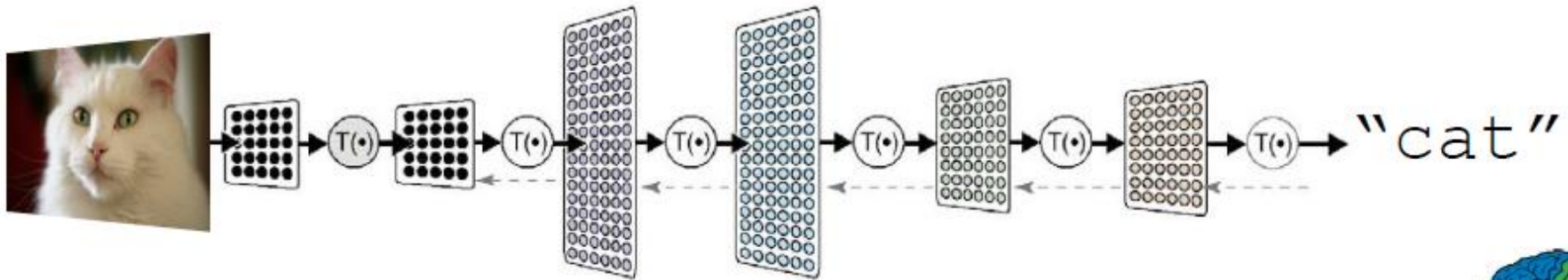
$$y = \max (0, -0.21 * x_1 + 0.3 * x_2 + 0.7 * x_3)$$

Weights



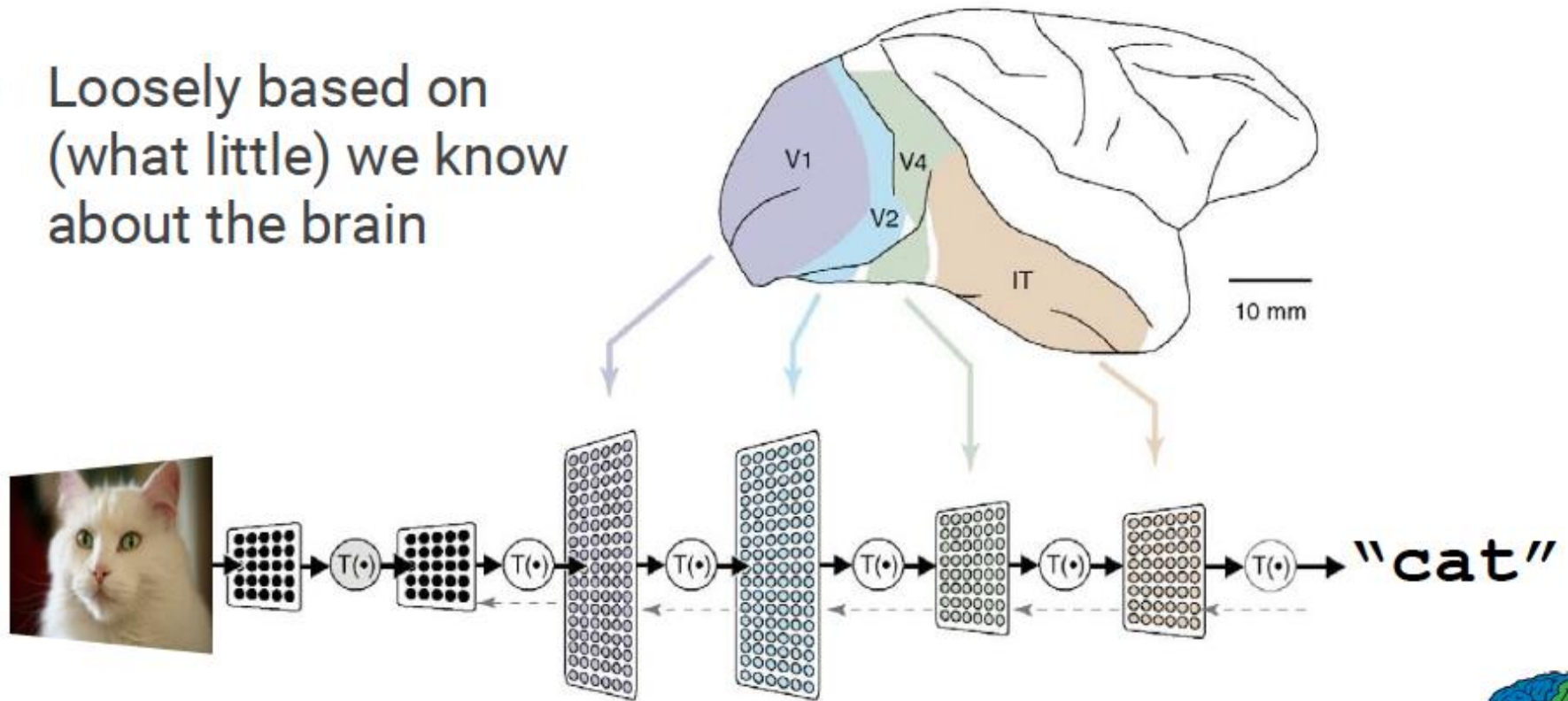
Deep Learning

- A powerful class of **machine learning** model
- **Modern reincarnation** of **artificial neural networks**
- Collection of simple, trainable mathematical functions
- Compatible with many variants of machine learning



What is Deep Learning?

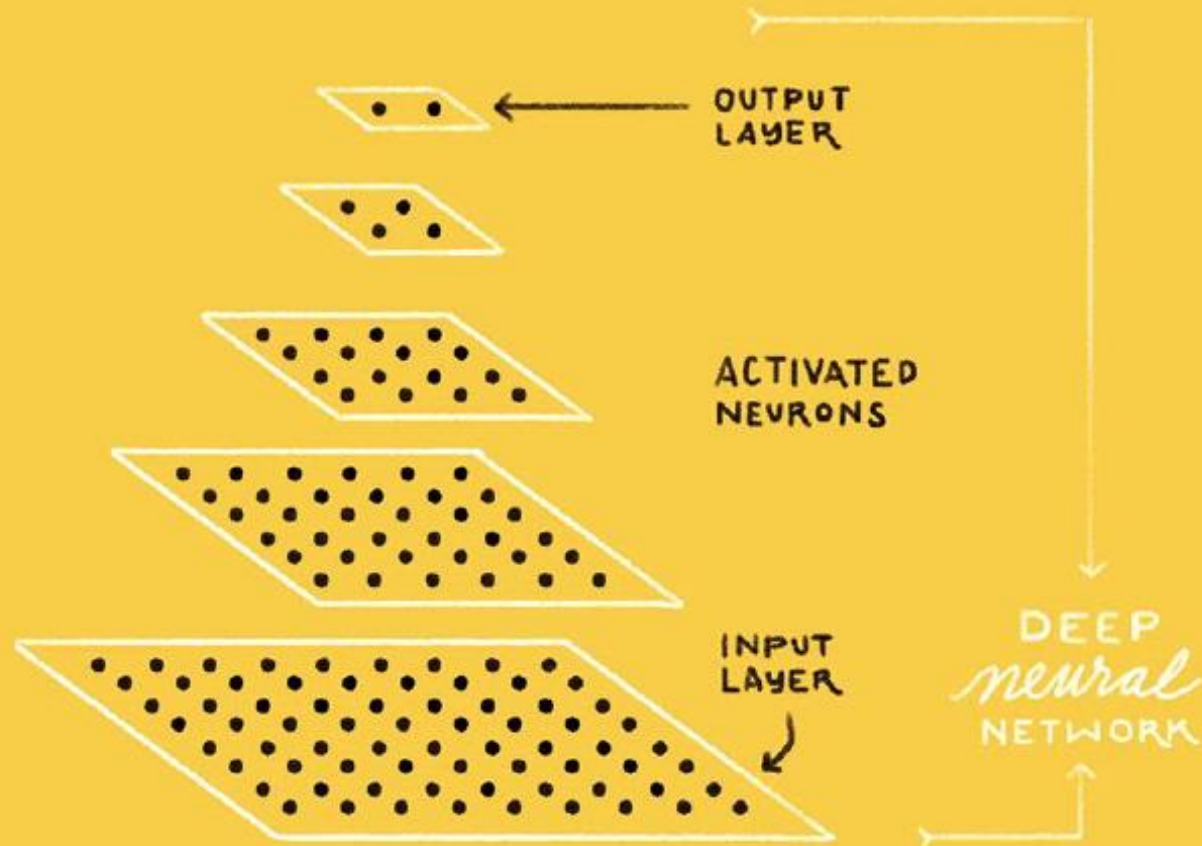
- Loosely based on (what little) we know about the brain



IS THIS A
CAT or **DOG**?



CAT **DOG**



Learning Algorithm

While not done:

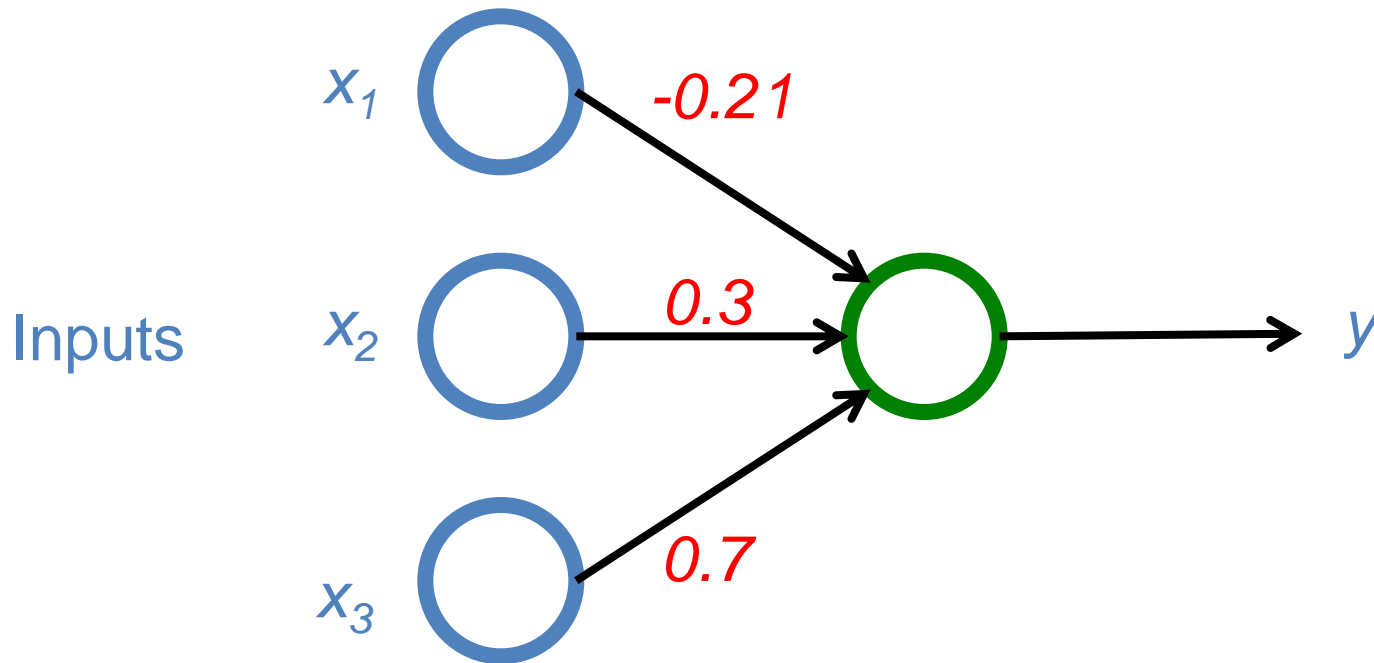
Pick a random training example “(input, label)”

Run neural network on “input”

Adjust weights on edges to make output closer to “label”

$$y = \max (0, -0.21 * x_1 + 0.3 * x_2 + 0.7 * x_3)$$

Weights

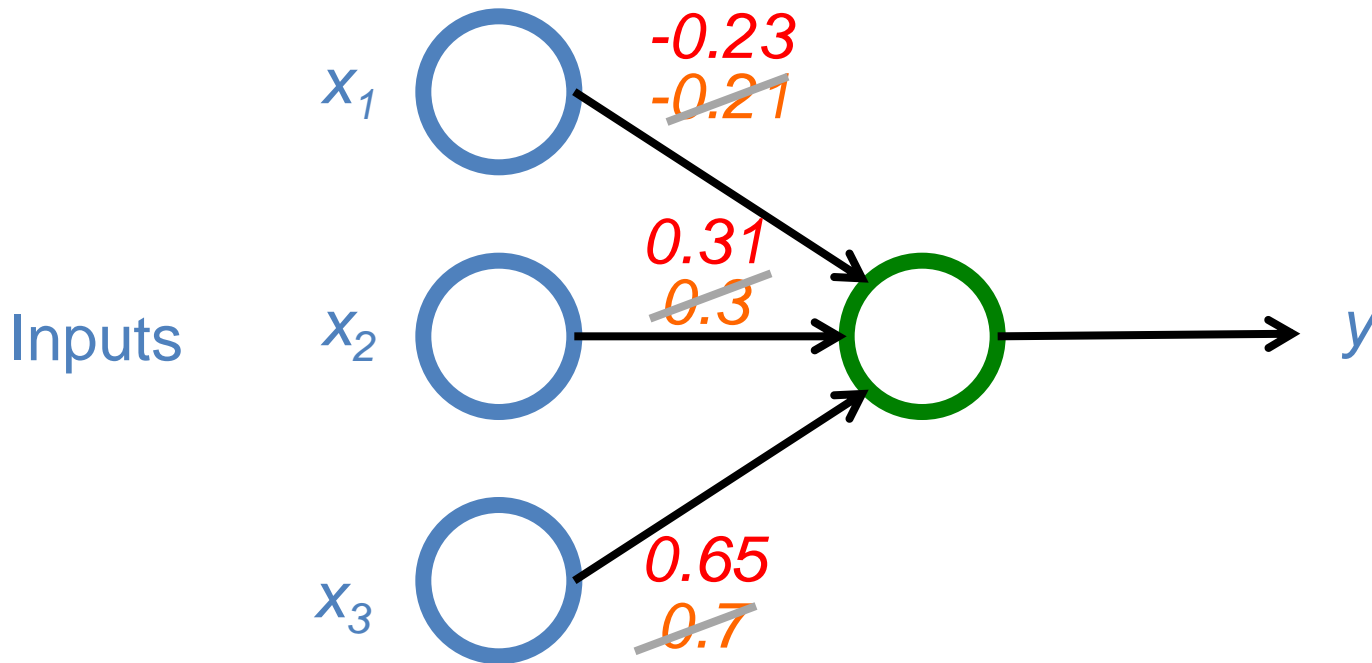


Next time:

$$y = \max(0, -0.23 * x_1 + 0.31 * x_2 + 0.65 * x_3)$$

~~$$y = \max(0, -0.21 * x_1 + 0.3 * x_2 + 0.7 * x_3)$$~~

Weights

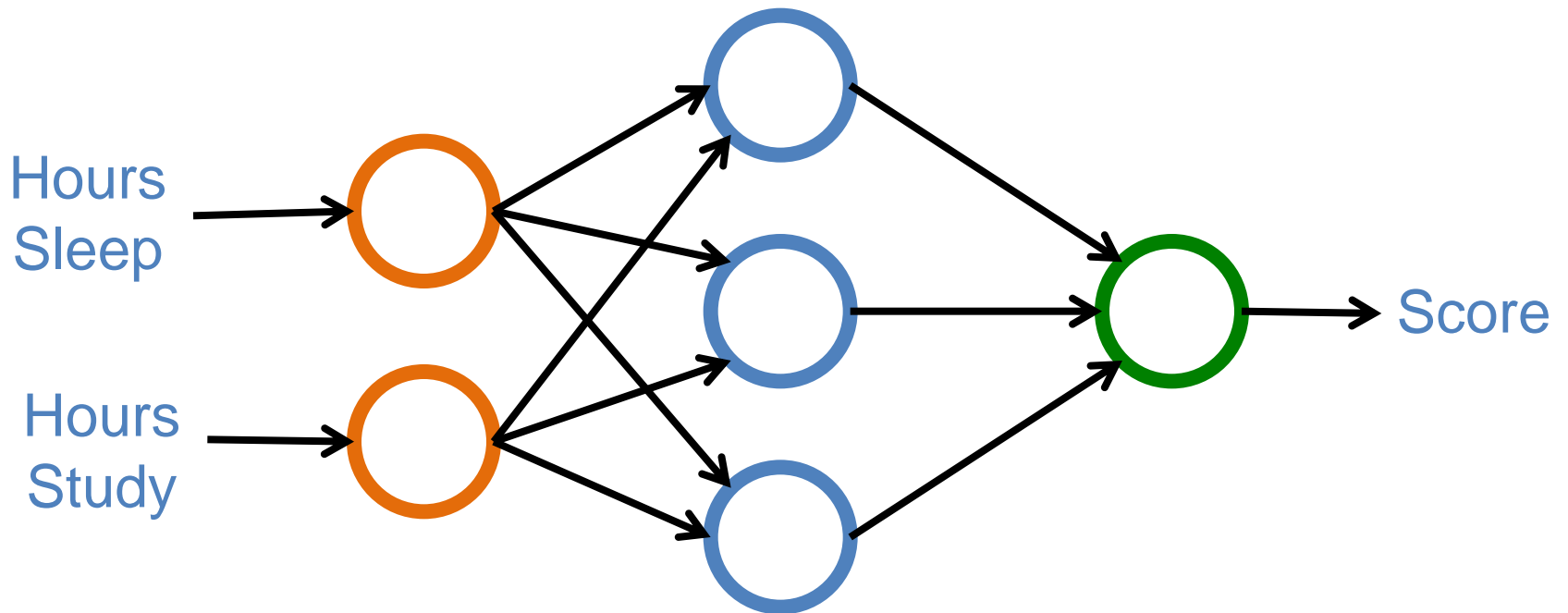


Neural Networks

Input Layer
(X)

Hidden Layer
(H)

Output Layer
(Y)

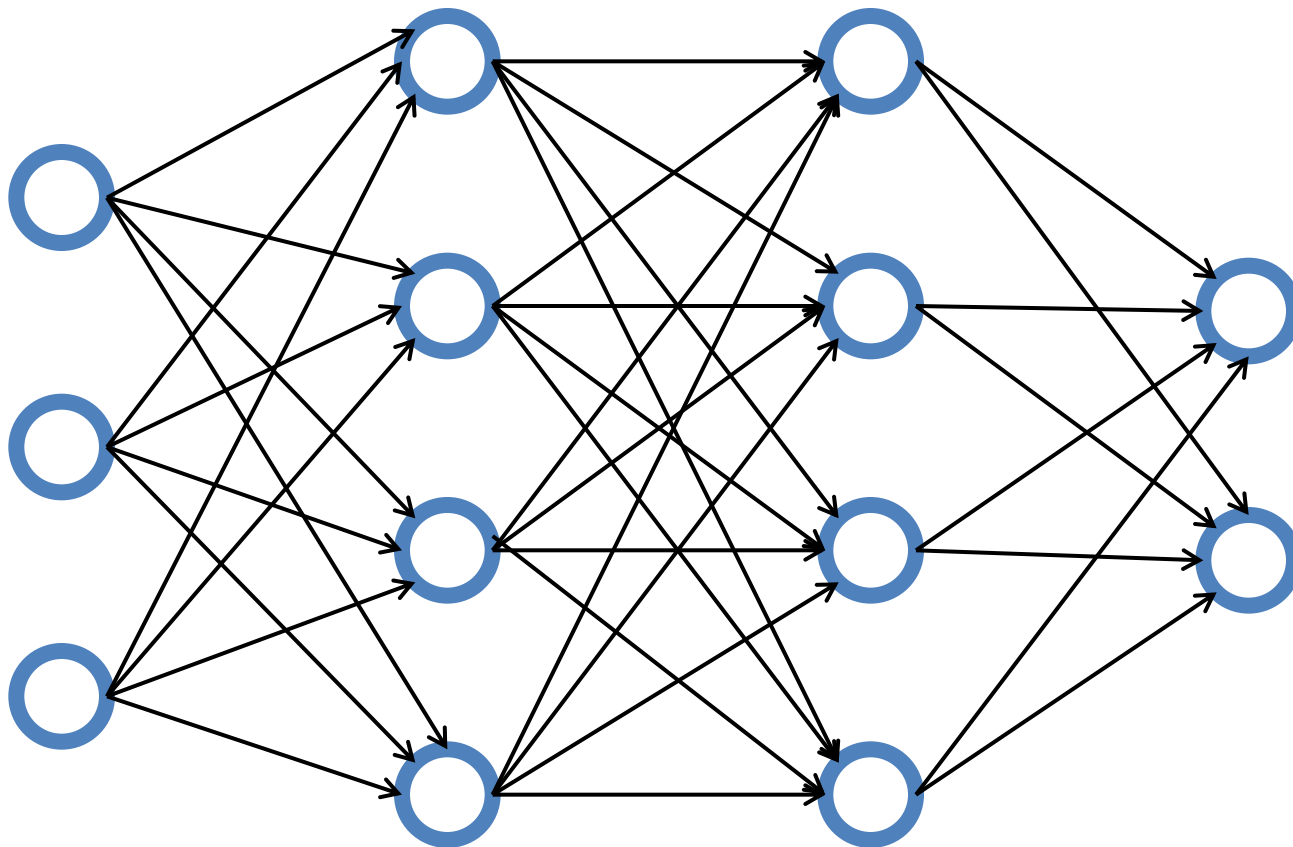


Neural Networks

Input Layer
(X)

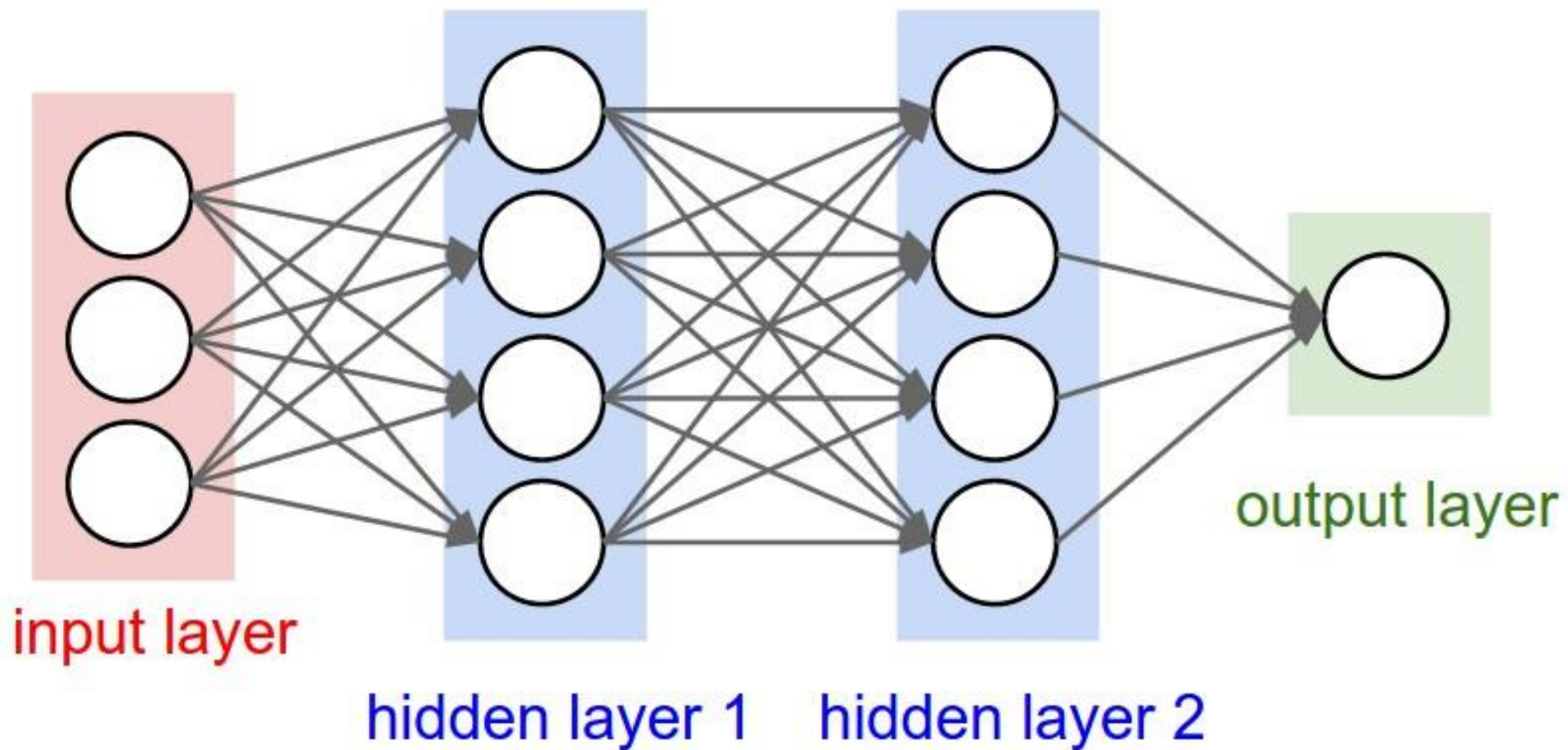
Hidden Layer
(H)

Output Layer
(Y)

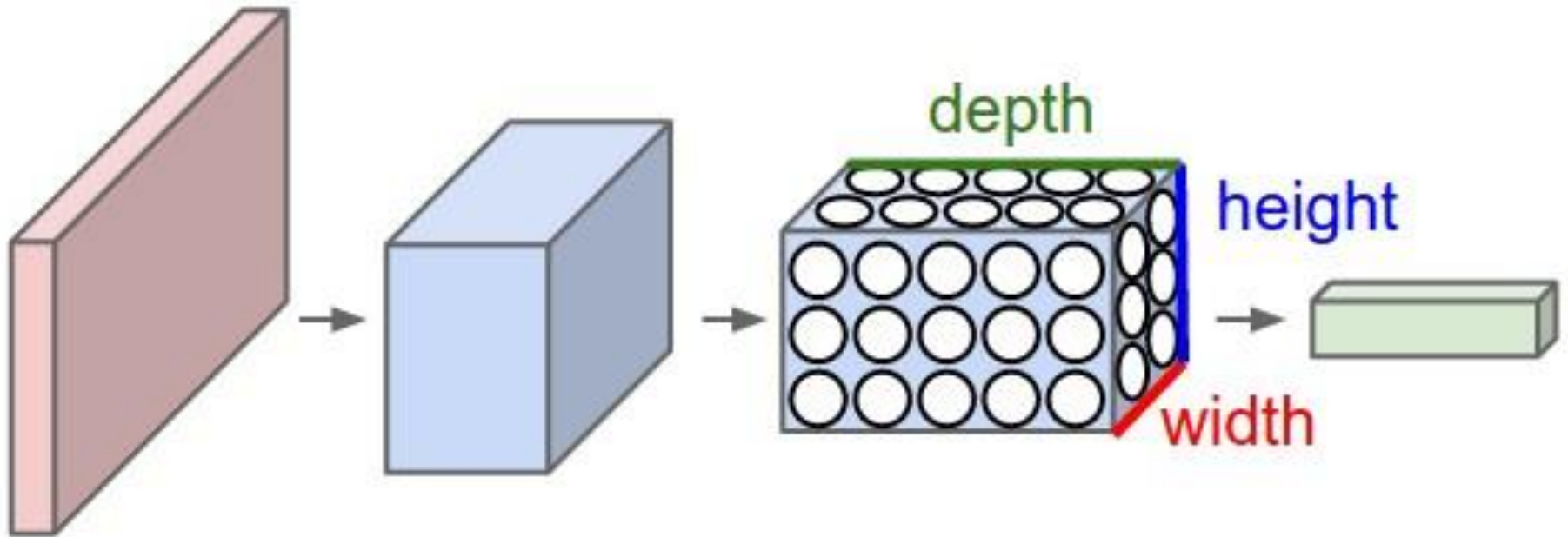


Convolutional Neural Networks (CNNs / ConvNets)

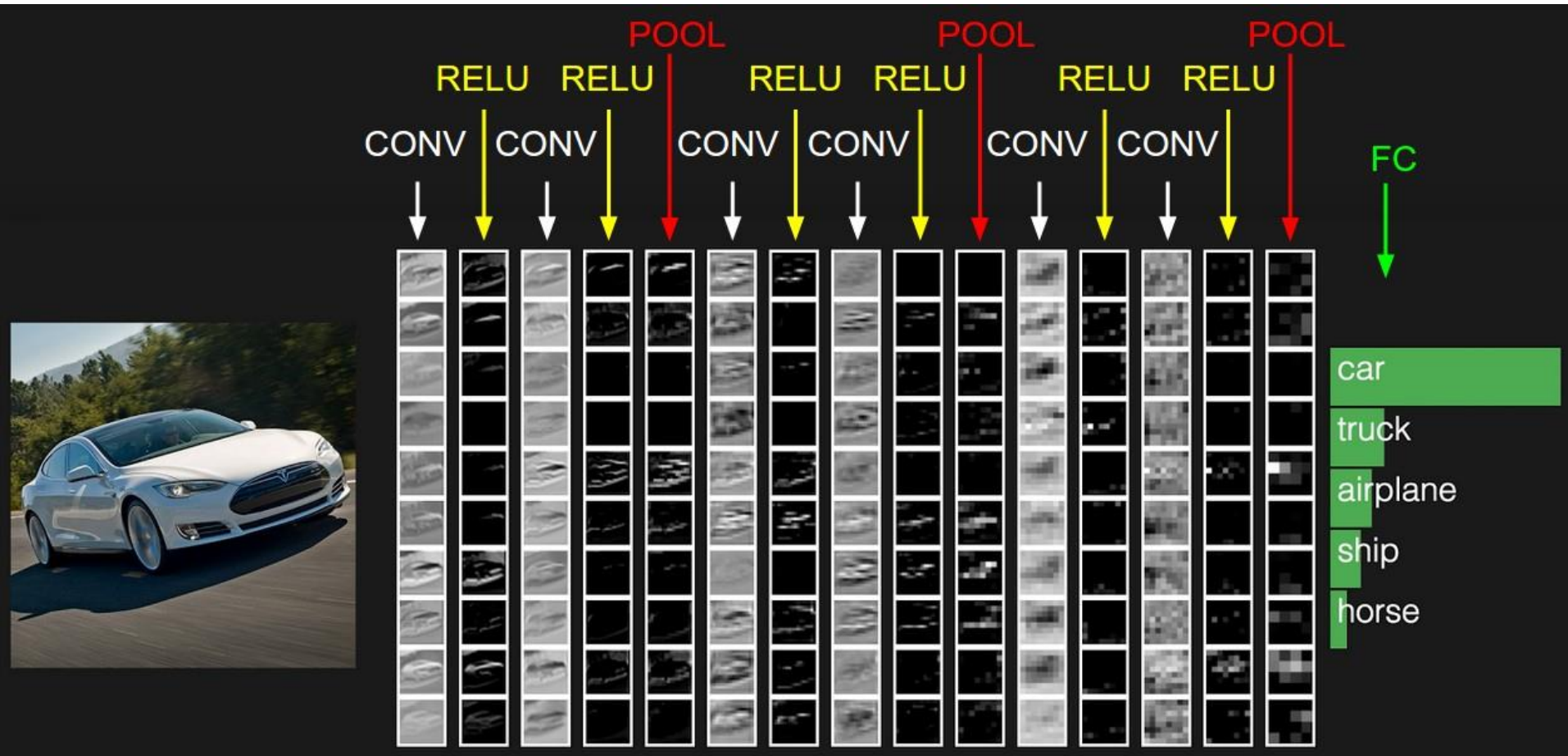
A regular 3-layer Neural Network



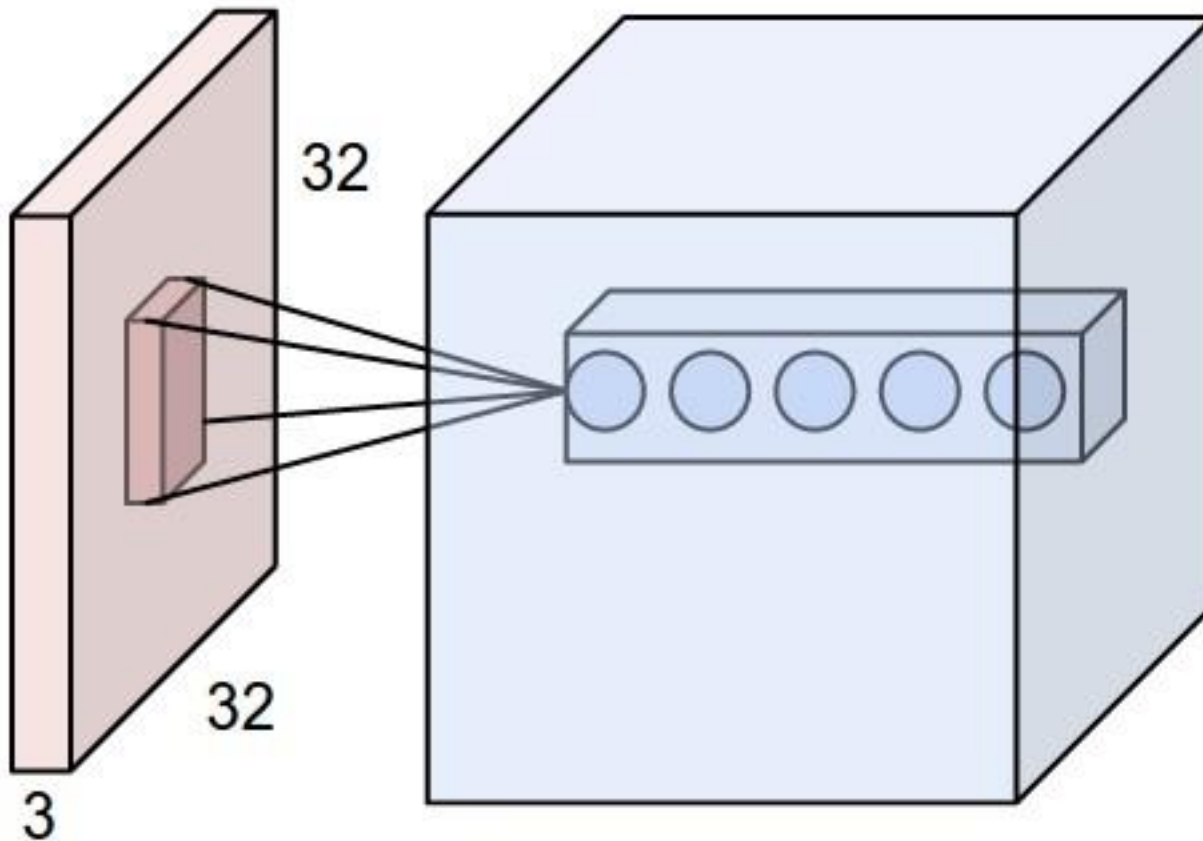
A ConvNet arranges its neurons in three dimensions (width, height, depth)



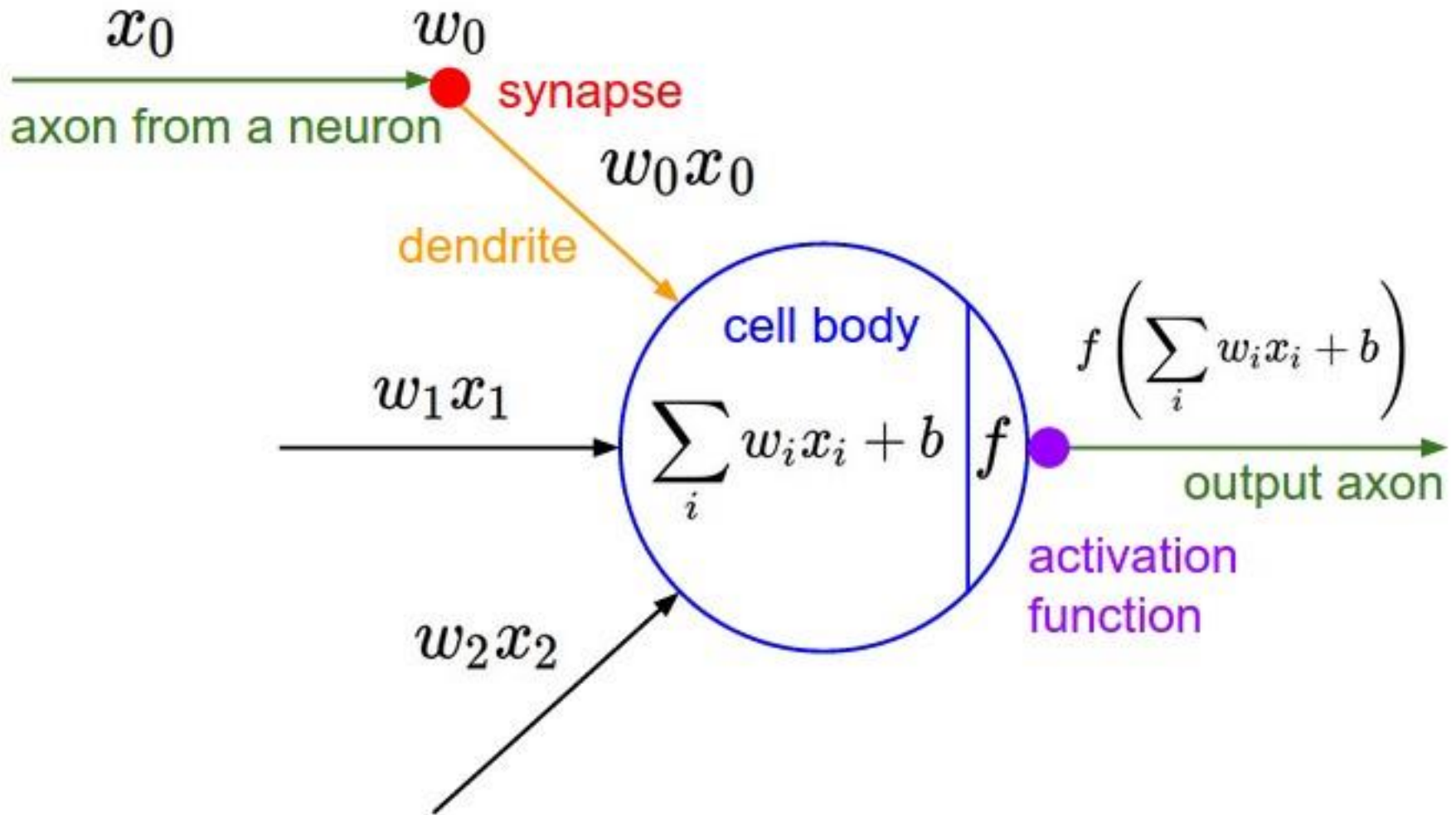
The activations of an example ConvNet architecture.



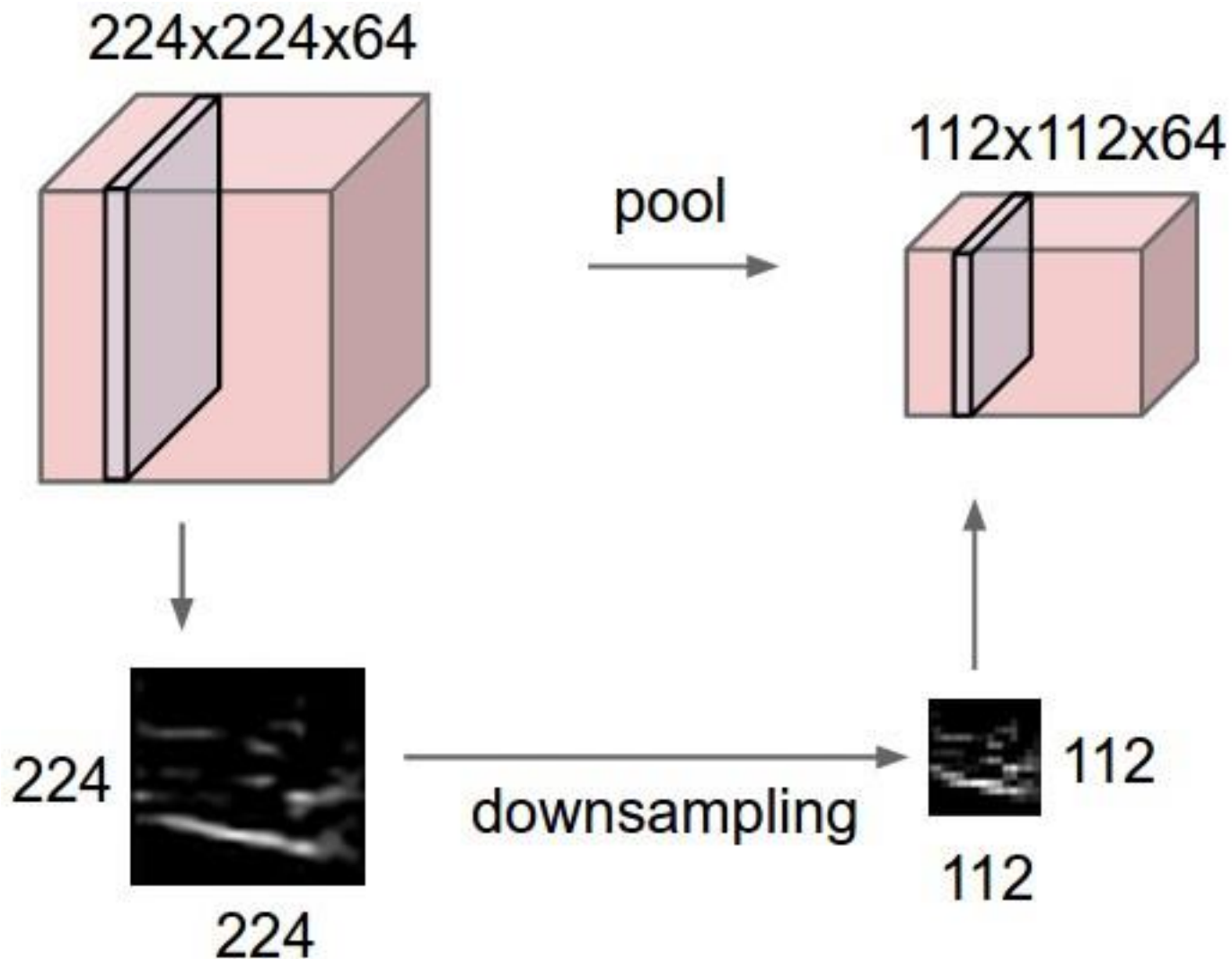
ConvNets



ConvNets



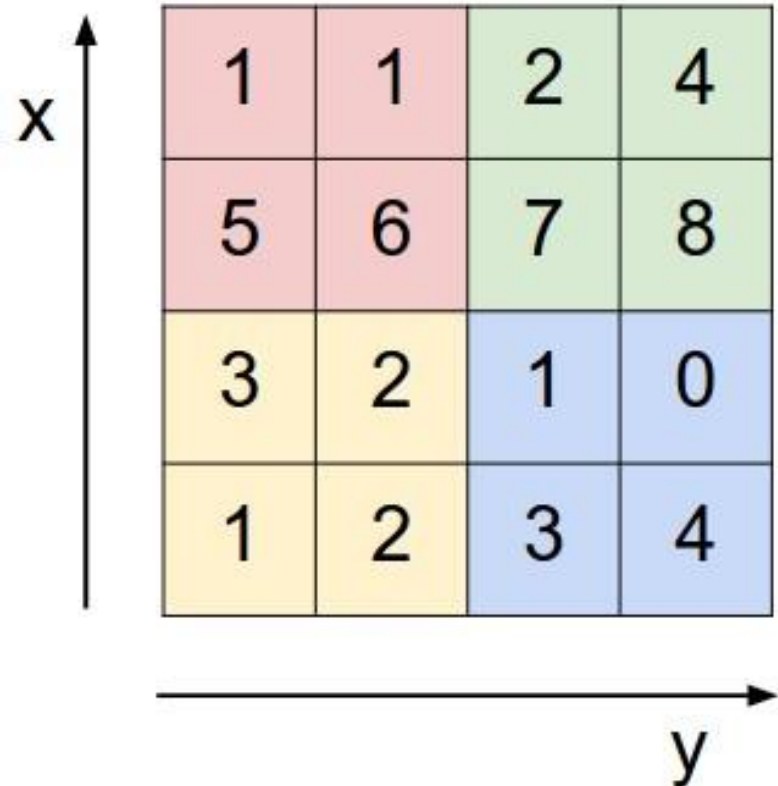
ConvNets



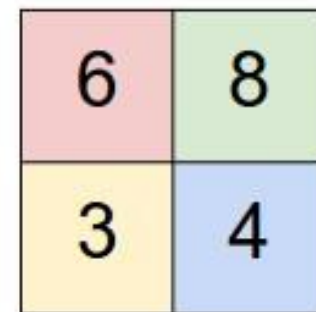
ConvNets

max pooling

Single depth slice



max pool with 2x2 filters
and stride 2

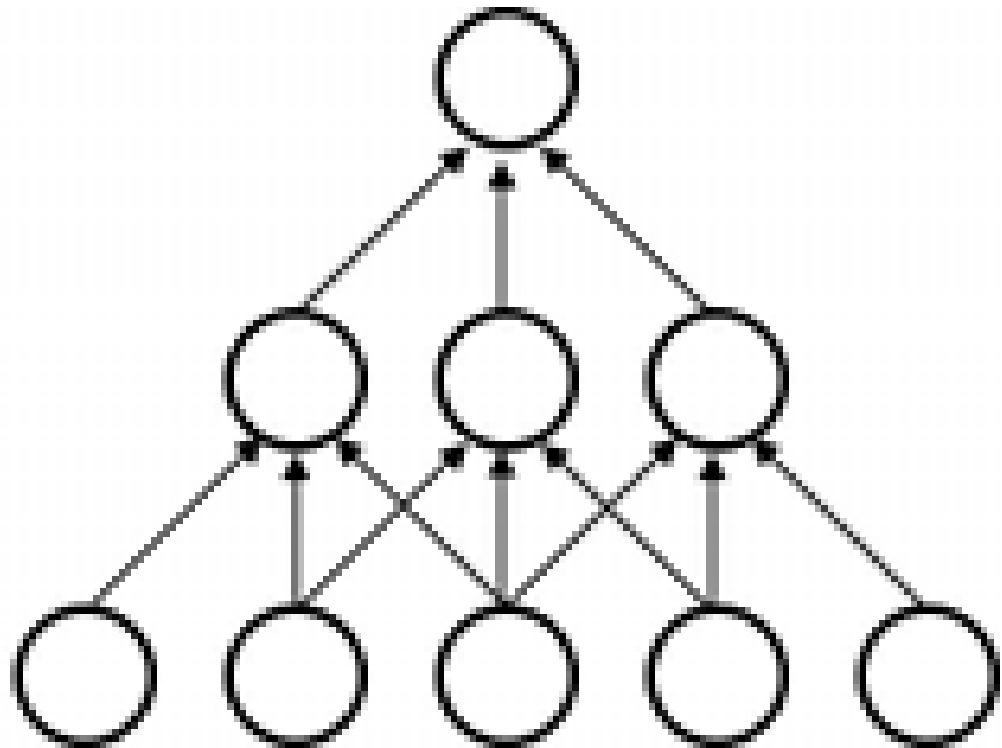


Convolutional Neural Networks (CNN) (LeNet) Sparse Connectivity

layer $m+1$

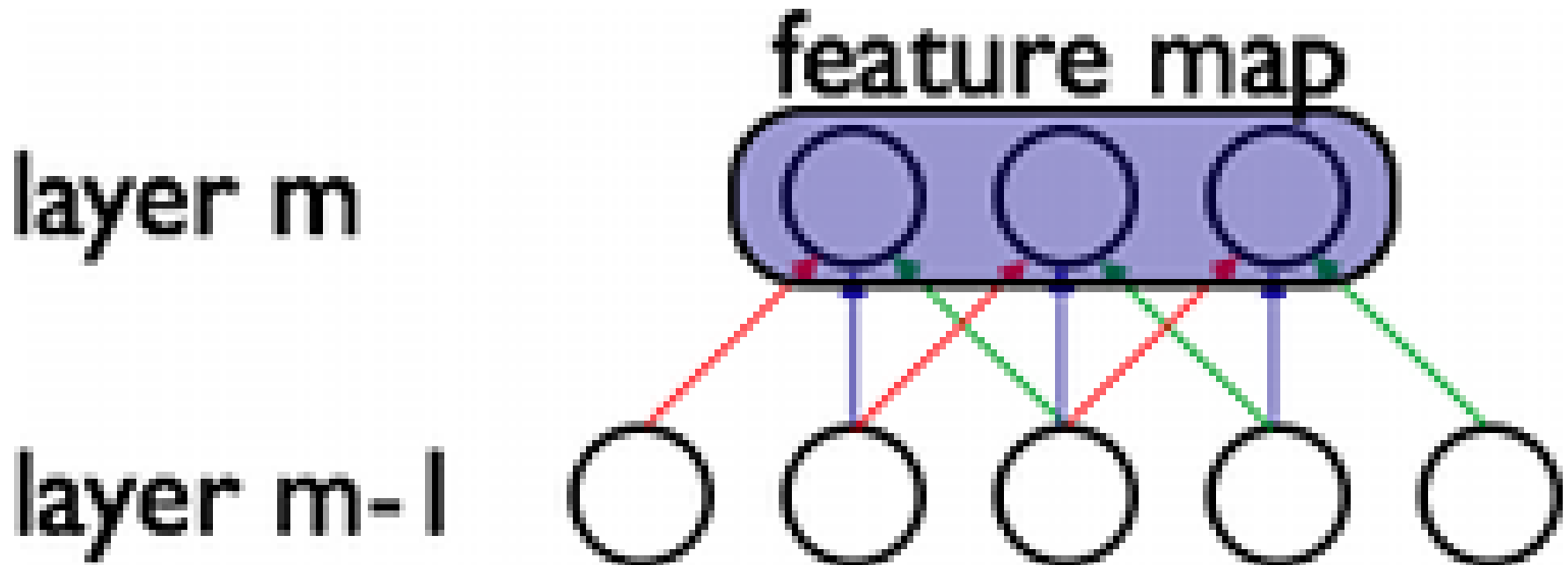
layer m

layer $m-1$



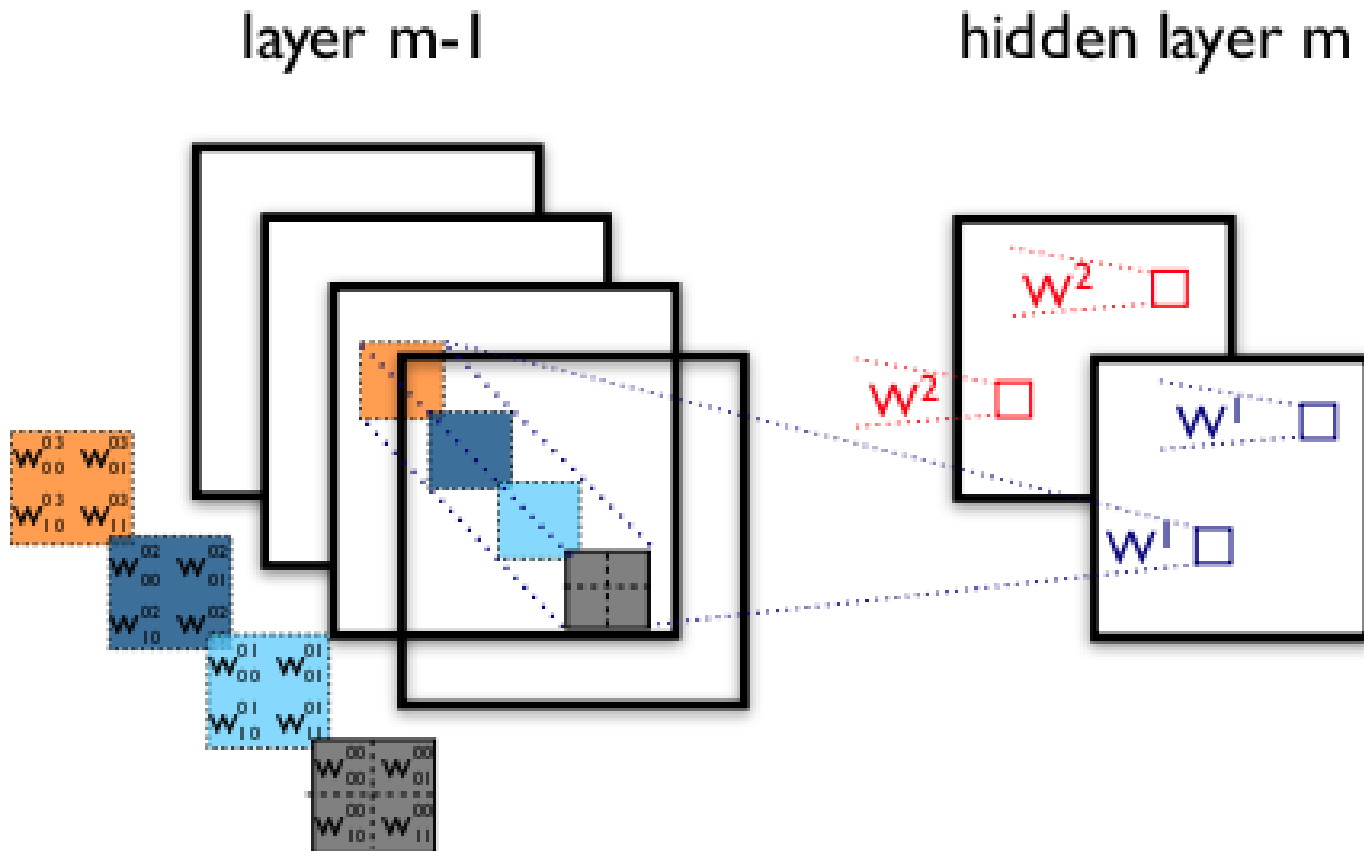
Convolutional Neural Networks (CNN) (LeNet)

Shared Weights



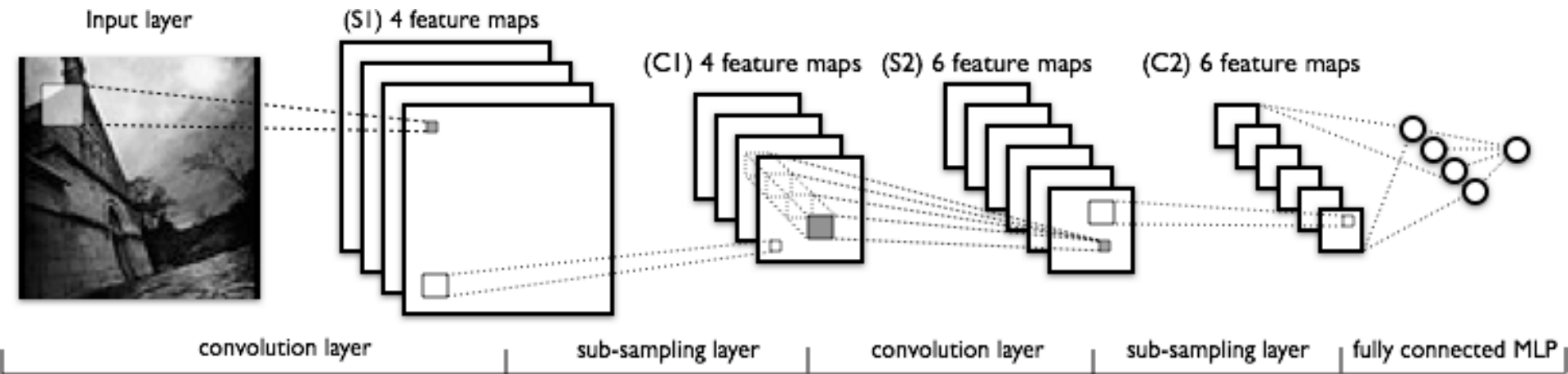
Convolutional Neural Networks (CNN) (LeNet)

example of a convolutional layer



Source: <http://deeplearning.net/tutorial/lenet.html>

Convolutional Neural Networks (CNN) (LeNet)



show flights from Boston to New York today

Recurrent Neural Networks with Word Embeddings

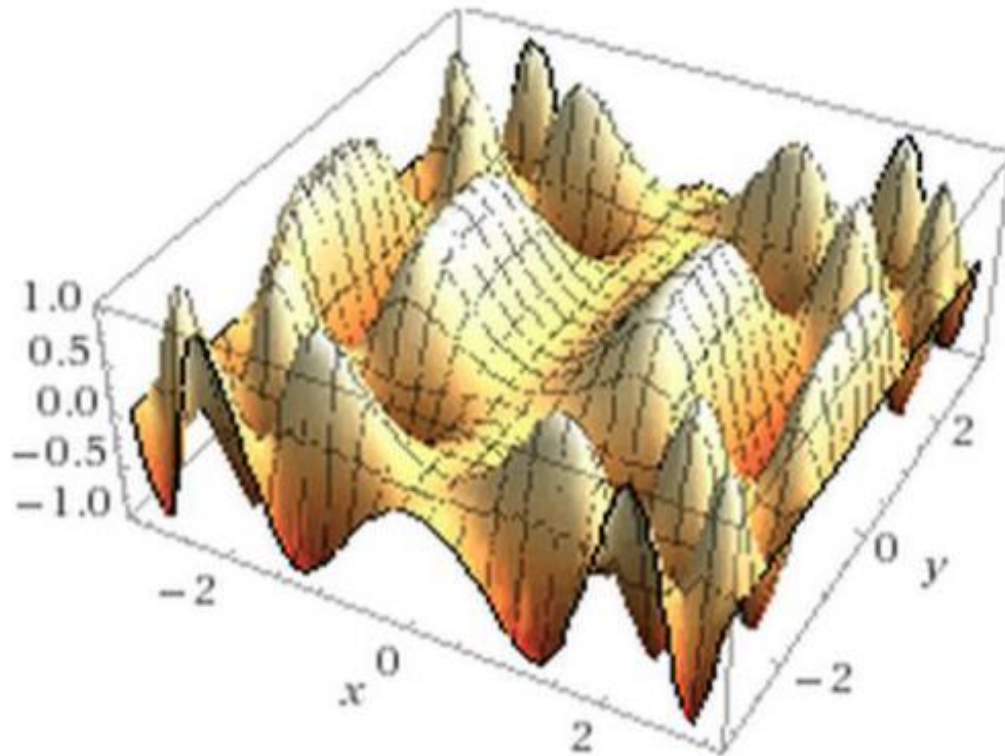
Semantic Parsing / Slot-Filling (Spoken Language Understanding)

Input (words)	show	flights	from	Boston	to	New	York	today
Output (labels)	O	O	O	B-dept	O	B-arr	I-arr	B-date

show flights from Boston to New York today

show flights from Boston to New York today

Input (words)	show	flights	from	Boston	to	New	York	today
Output (labels)	0	0	0	B-dept	0	B-arr	I-arr	B-date



This shows a function of 2 variables: real neural nets are functions of hundreds of millions of variables!

Important Property of Neural Networks

Results get better with

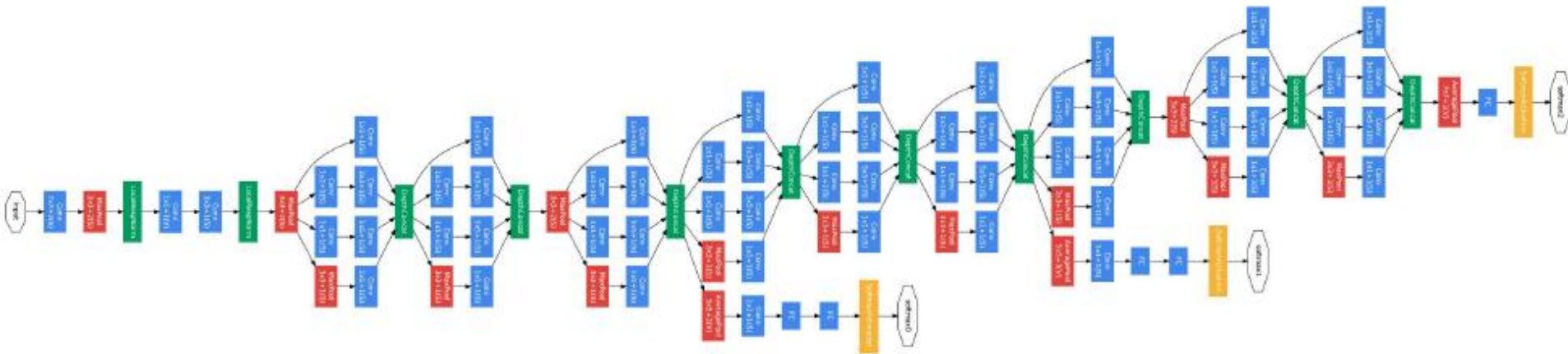
More data +

Bigger models +

More computation

(Better algorithms, new insights
and improved techniques always help, too!)

The Inception Architecture (GoogLeNet, 2014)



Going Deeper with Convolutions

Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, Andrew Rabinovich

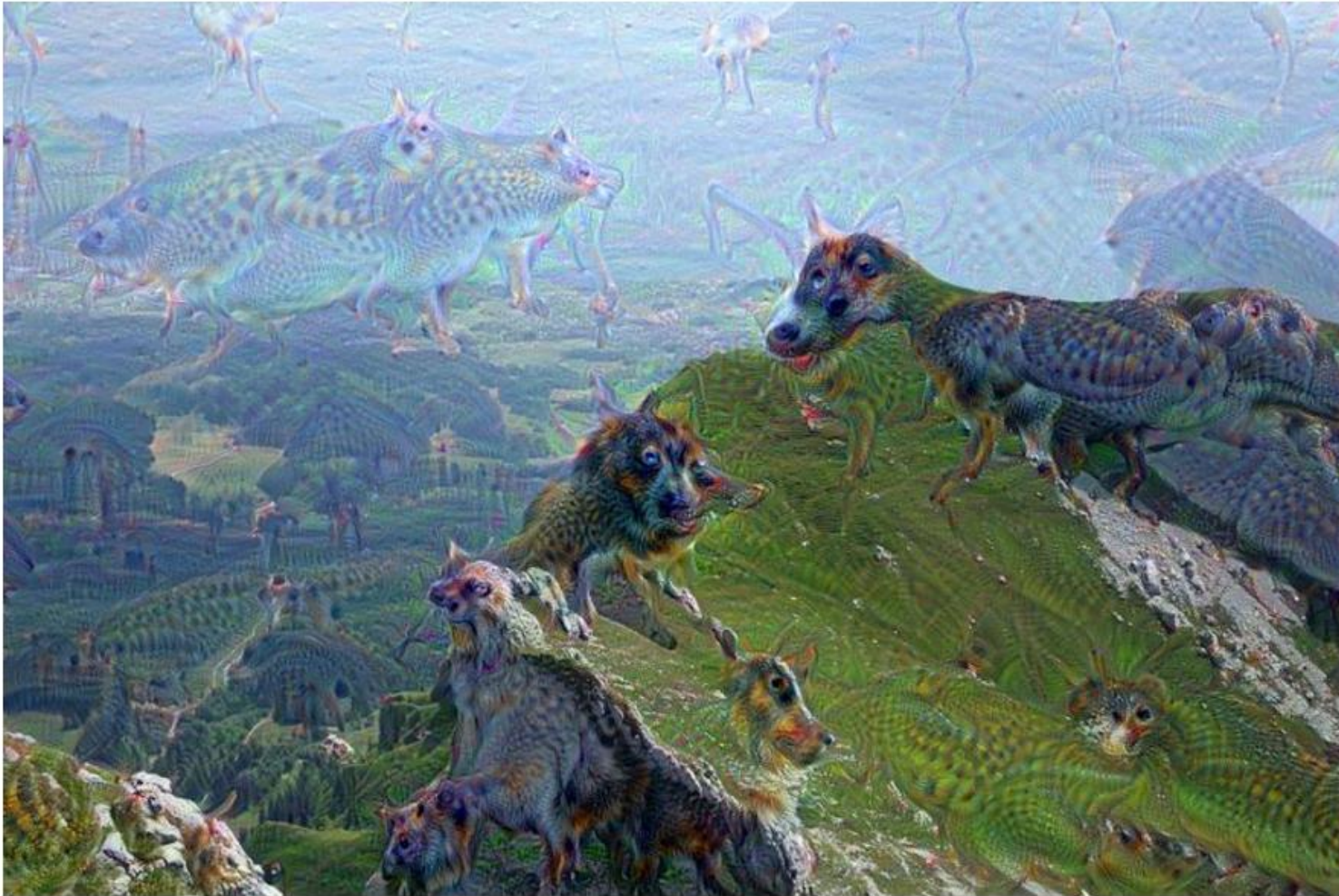
ArXiv 2014, CVPR 2015



DeepDream

GitHub, Inc. [US] <https://github.com/tensorflow/tensorflow/blob/master/tensorflow/examples/tutorials/deepdream/deepdream.ipynb>

```
In [15]: render_deepdream(tf.square(T('mixed4c')), img0)
```



Note that results can differ from the [Caffe's](#) implementation, as we are using an independently trained network. Still, the network seems to like dogs and animal-like features due to the nature of the ImageNet dataset.

Source: <https://github.com/tensorflow/tensorflow/blob/master/tensorflow/examples/tutorials/deepdream/deepdream.ipynb>

Deep Learning Software

- **Theano**
 - CPU/GPU symbolic expression compiler in python (from MILA lab at University of Montreal)
- **Keras**
 - A theano based deep learning library.
- **Tensorflow**
 - TensorFlow™ is an open source software library for numerical computation using data flow graphs.



TensorFlow

Google TensorFlow

TensorFlow™

GET STARTED TUTORIALS HOW TO API RESOURCES ABOUT

Fork me on GitHub

TensorFlow is an Open Source Software Library for Machine Intelligence

GET STARTED

About TensorFlow

TensorFlow™ is an open source software library for numerical computation using data flow graphs. Nodes in the graph represent mathematical operations, while the graph edges represent the multidimensional data arrays (tensors) communicated between them. The flexible architecture allows you to deploy computation to one or more CPUs or GPUs in a desktop, server, or mobile device with a single API.



<https://www.tensorflow.org/>

TensorFlow
is an
Open Source
Software Library
for
Machine Intelligence

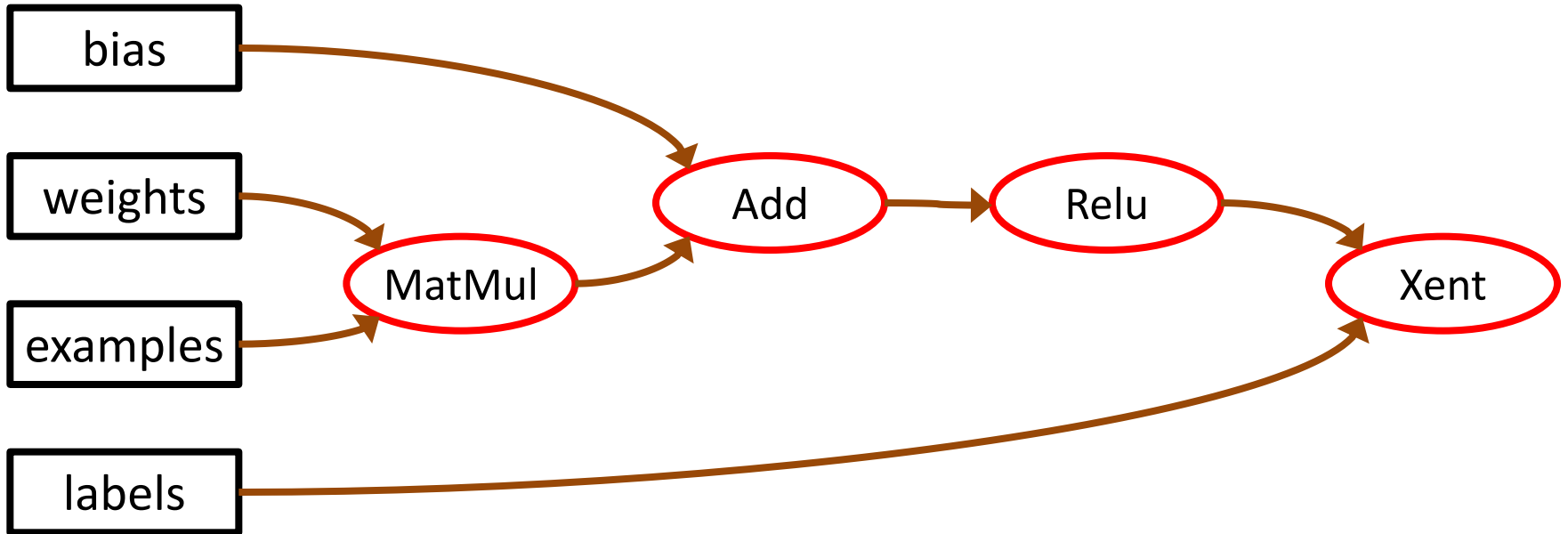
numerical computation using data flow graphs

Nodes:
mathematical operations

edges:
multidimensional data arrays
(tensors)
communicated between nodes

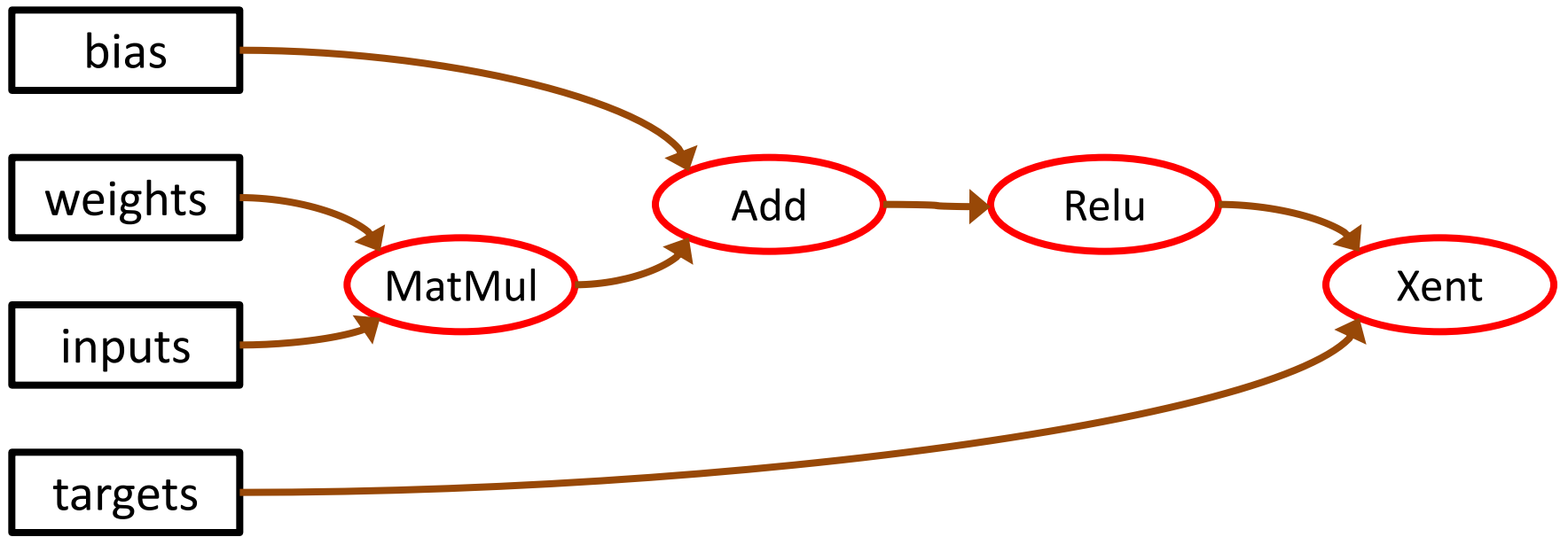
Computation is a Dataflow Graph

Graph of **Nodes**,
also called **Operations** or **ops**.

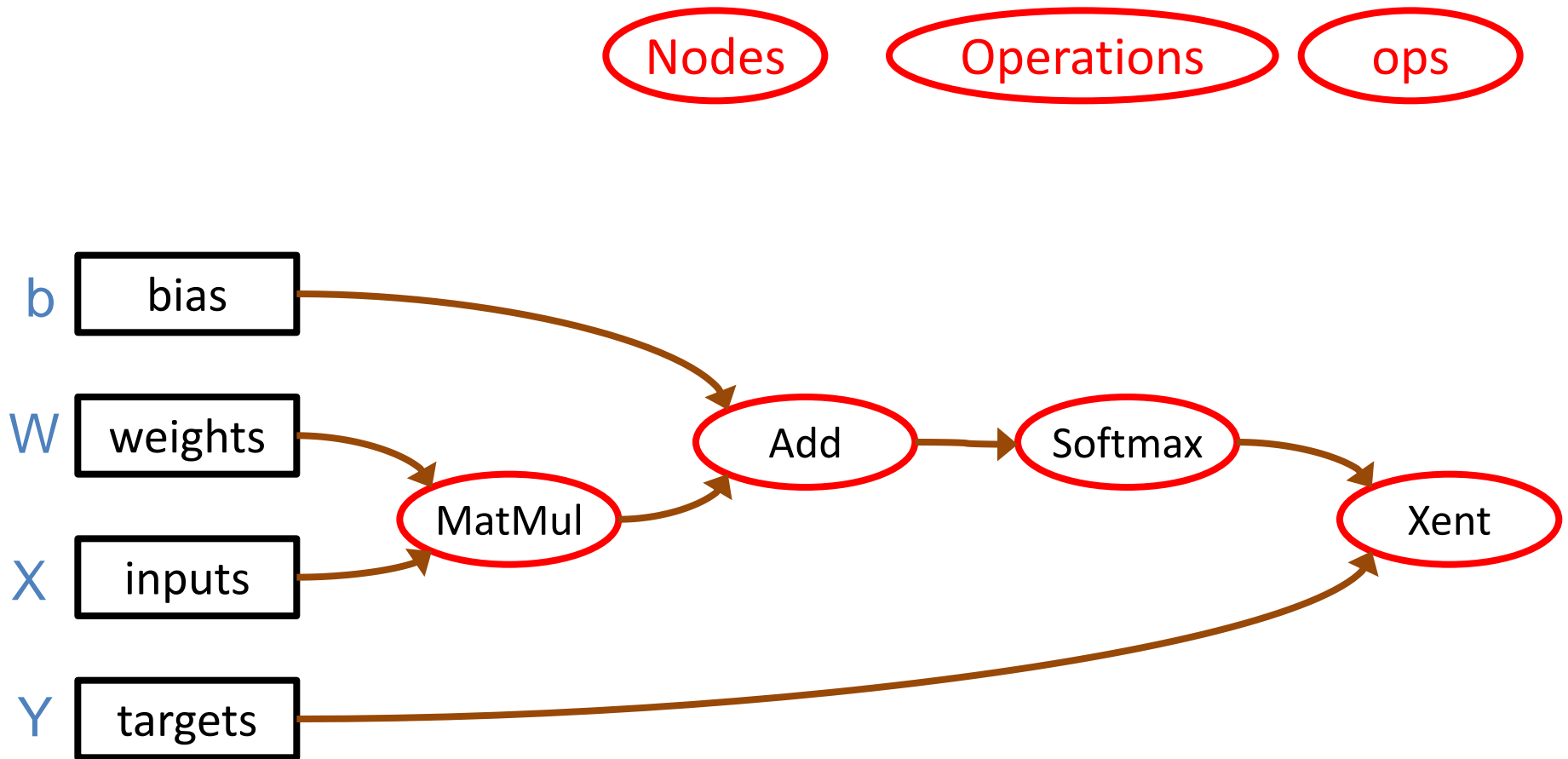


Computation is a Dataflow Graph

Edges are N-dimensional arrays: **Tensors**



Logistic Regression as Dataflow Graph

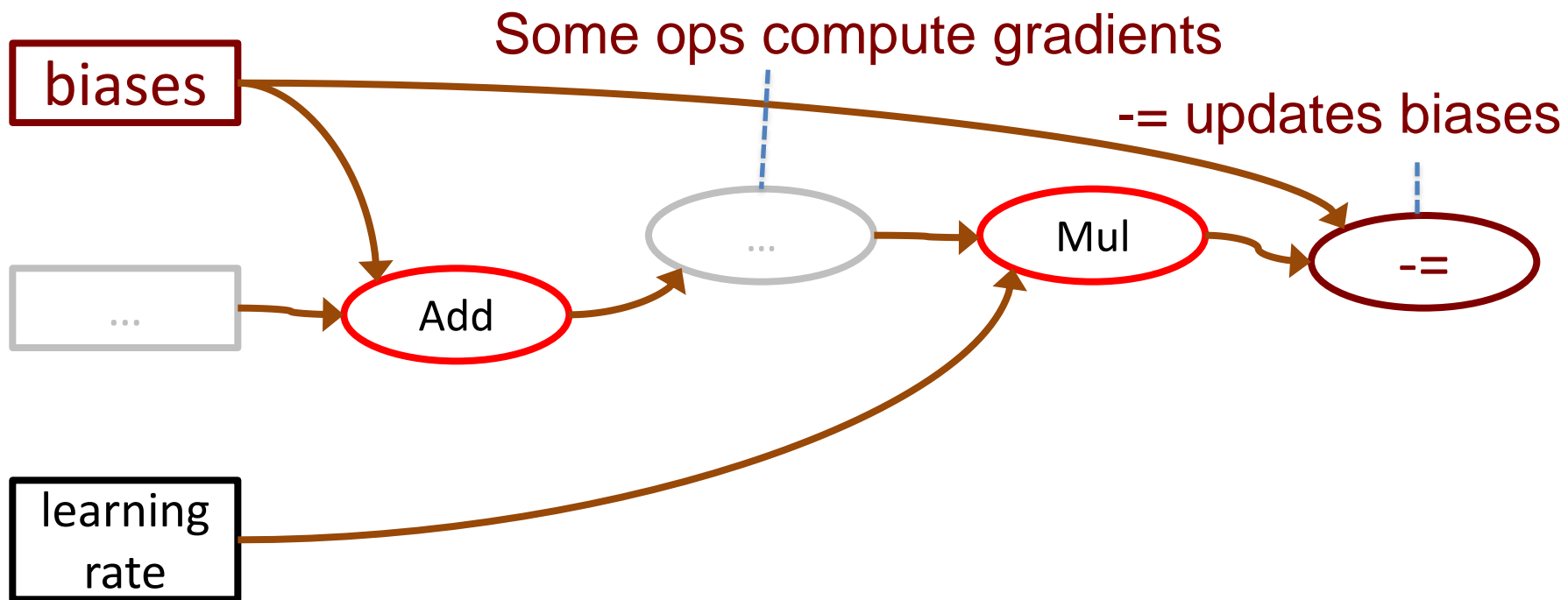


Edges are N-dimensional arrays: **Tensors**

Computation is a Dataflow Graph

with state

'Biases' is a variable

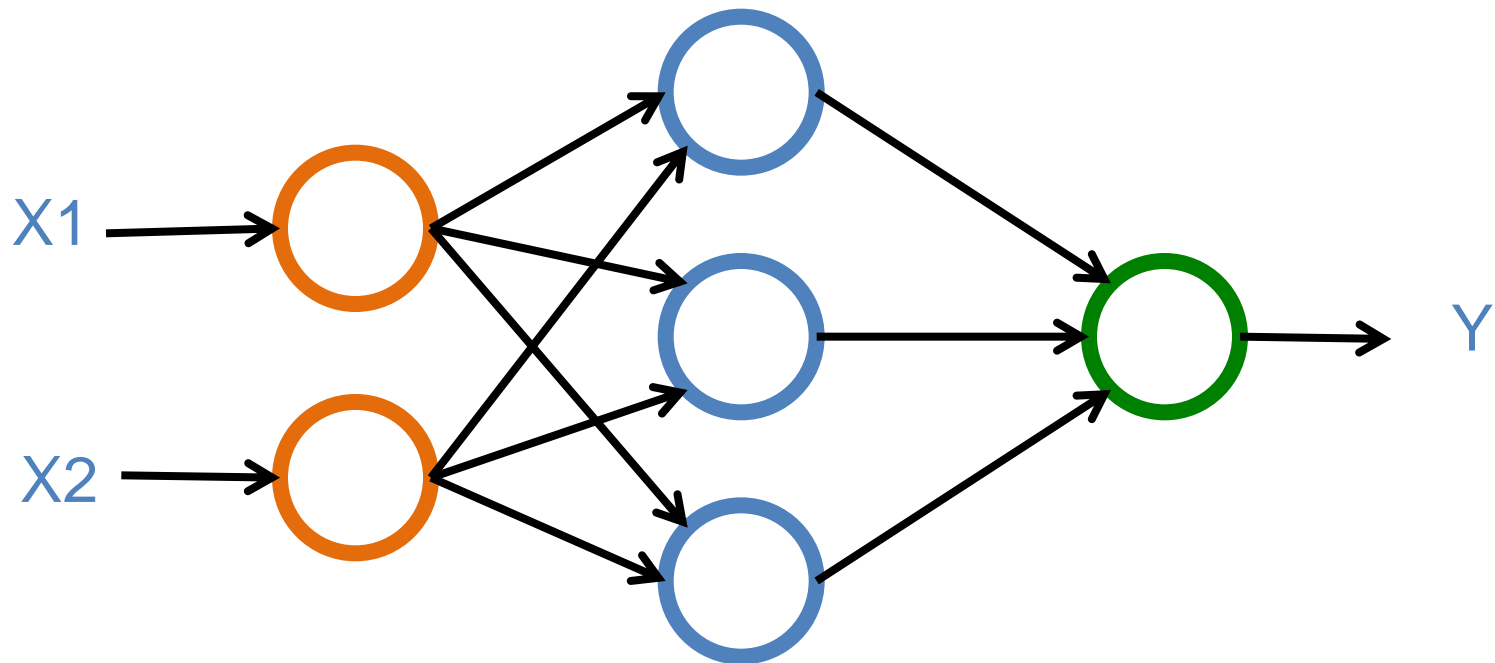


Neural Networks

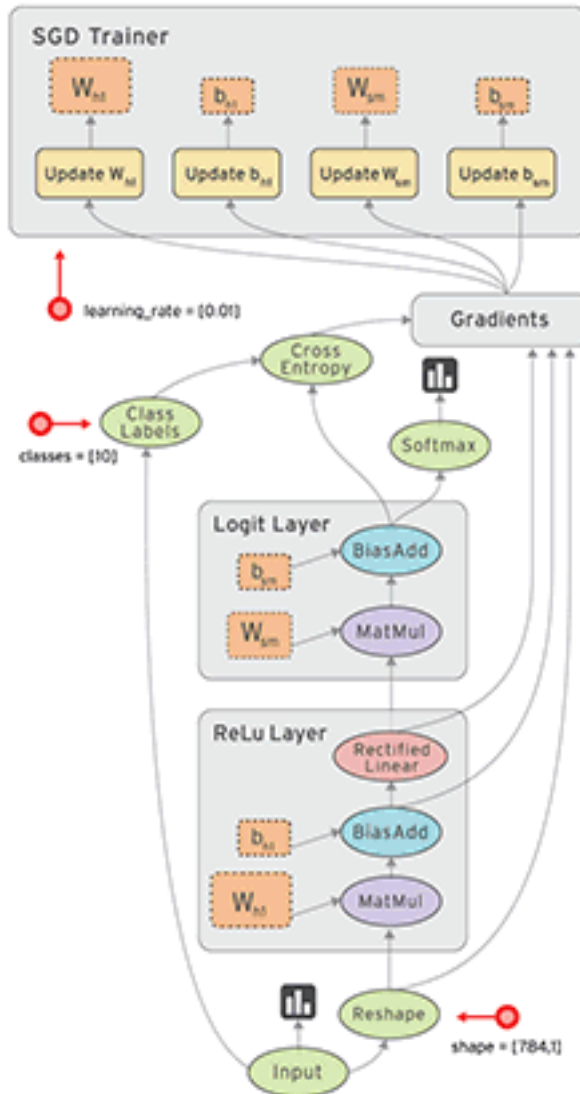
Input Layer
(X)

Hidden Layer
(H)

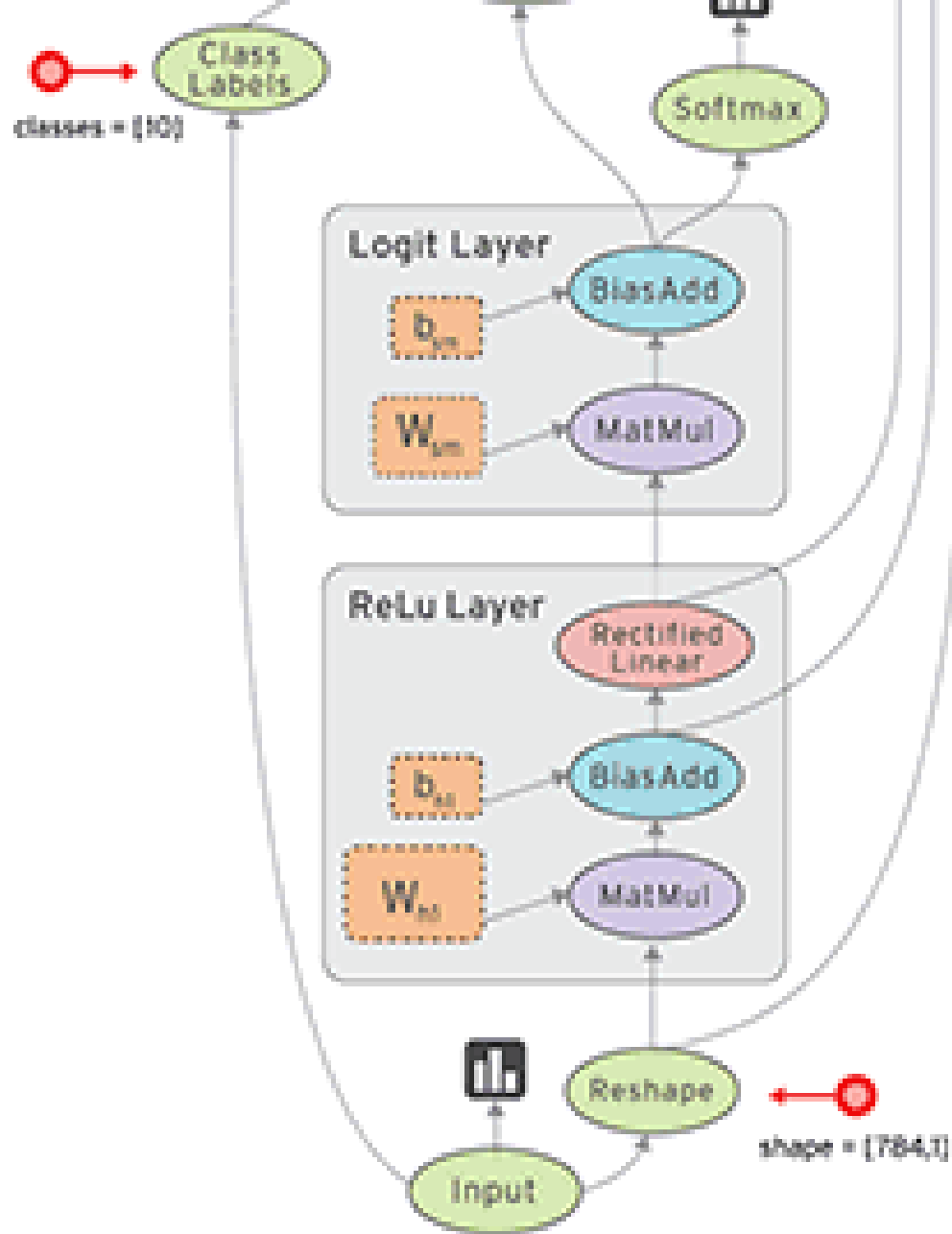
Output Layer
(Y)



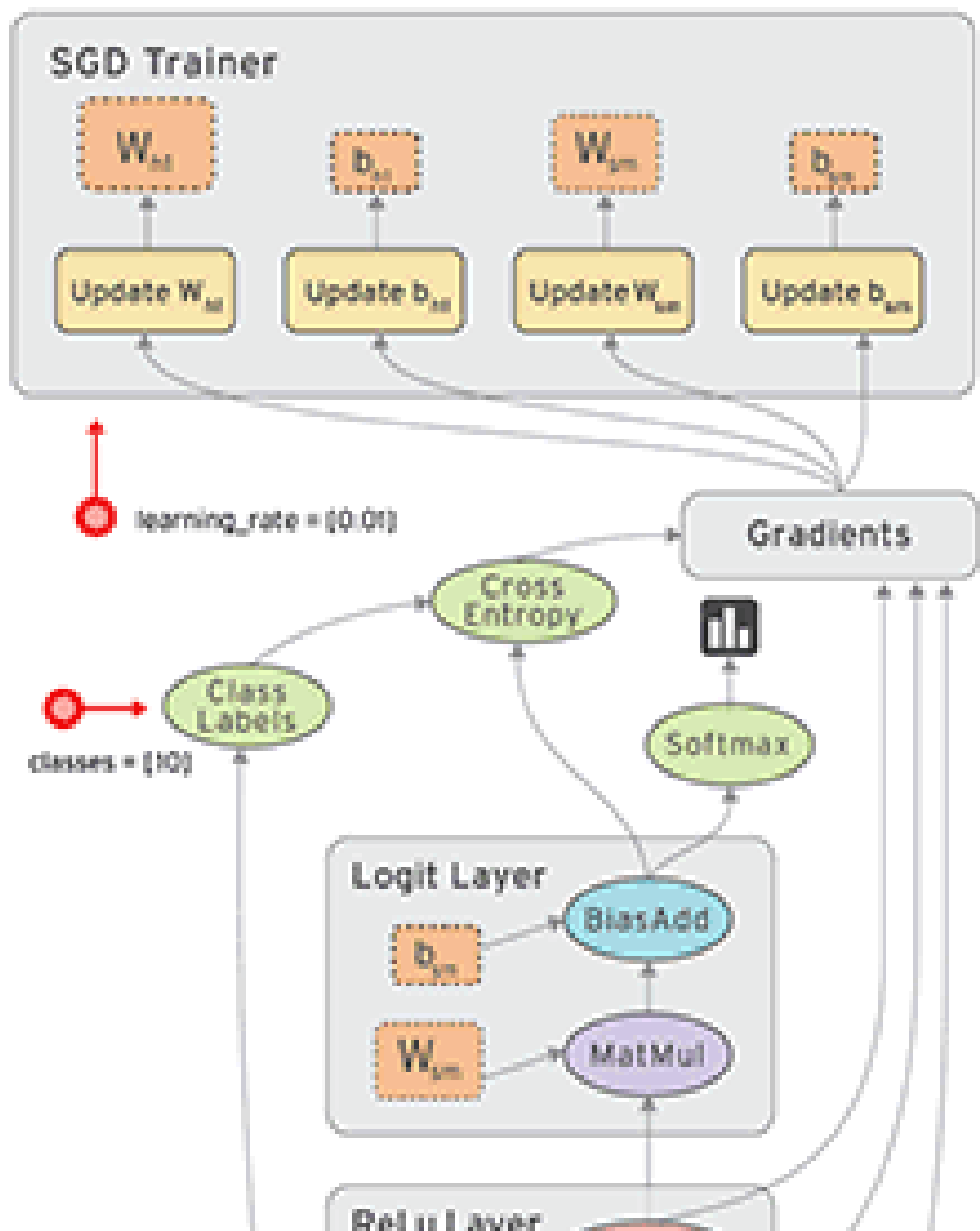
Data Flow Graph



Data Flow Graph



Data Flow Graph



TensorFlow Playground

Tinker With a **Neural Network** Right Here in Your Browser.
Don't Worry, You Can't Break It. We Promise.



Iterations
000,582

Learning rate
0.03

Activation
Tanh

Regularization
None

Regularization rate
0

Problem type
Classification

DATA

Which dataset do you want to use?



Ratio of training to test data: 50%



Noise: 0



Batch size: 10

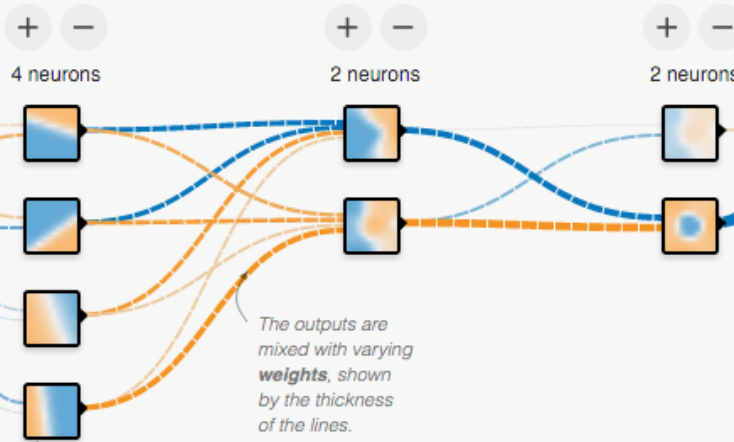


INPUT

Which properties do you want to feed in?



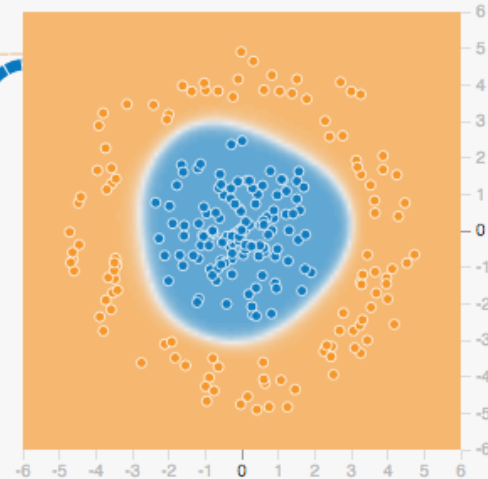
3 HIDDEN LAYERS



This is the output from one **neuron**. Hover to see it larger.

OUTPUT

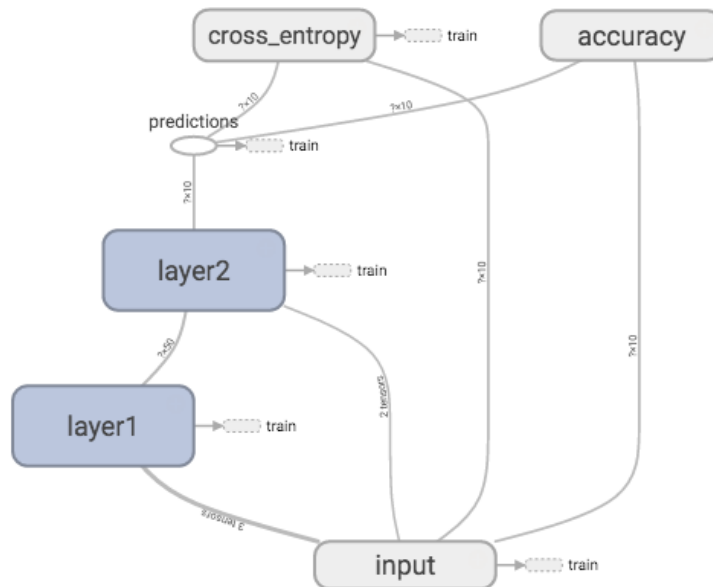
Test loss 0.000
Training loss 0.000



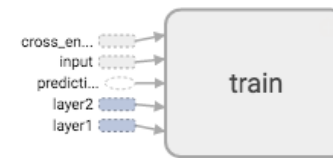
TensorBoard

Fit to screen
 Download PNG
 Run train (1)
 Session runs (0)
 Upload
 Color Structure
 Device
 color: same substructure
 gray: unique substructure
 Graph (* = expandable)
 Namespace*
 OpNode
 Unconnected series*
 Connected series*
 Constant
 Summary
 Dataflow edge
 Control dependency edge
 Reference edge

Main Graph



Auxiliary nodes

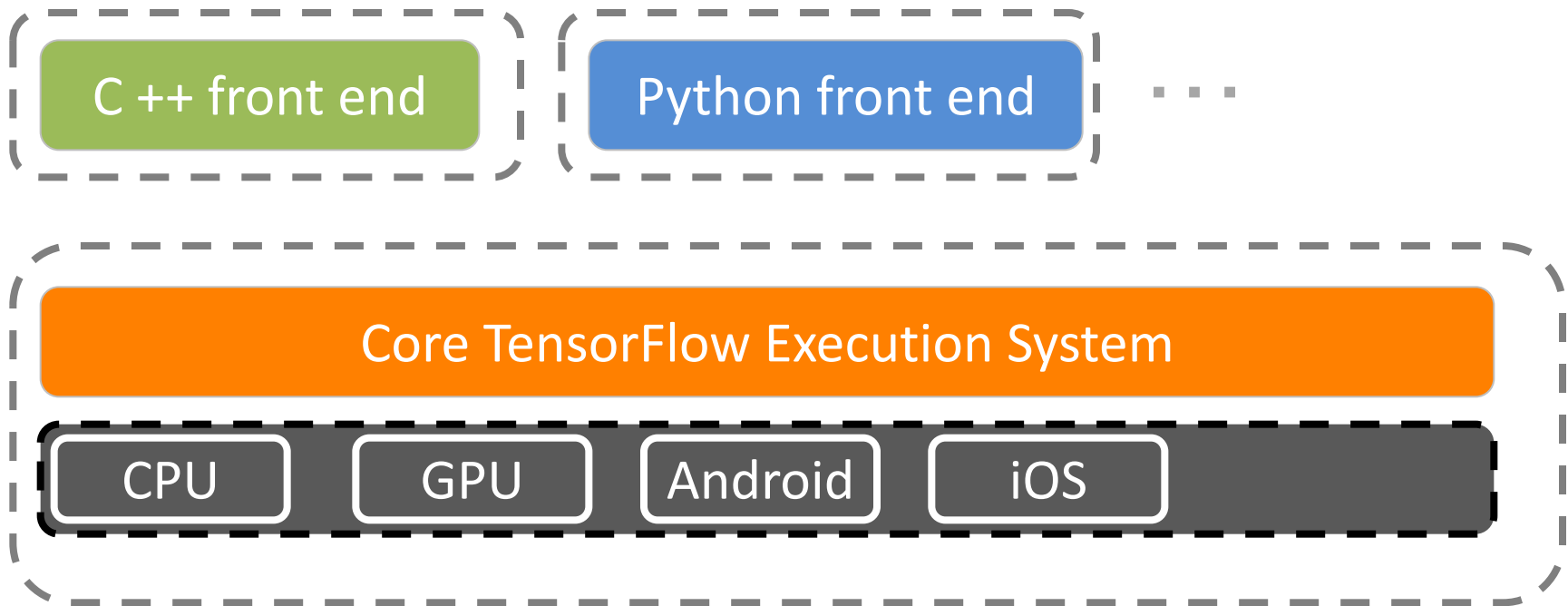


Try your first TensorFlow

```
$ python
```

```
>>> import tensorflow as tf
>>> hello = tf.constant('Hello, TensorFlow!')
>>> sess = tf.Session()
>>> sess.run(hello)
Hello, TensorFlow!
>>> a = tf.constant(10)
>>> b = tf.constant(32)
>>> sess.run(a+b)
42
>>>
```

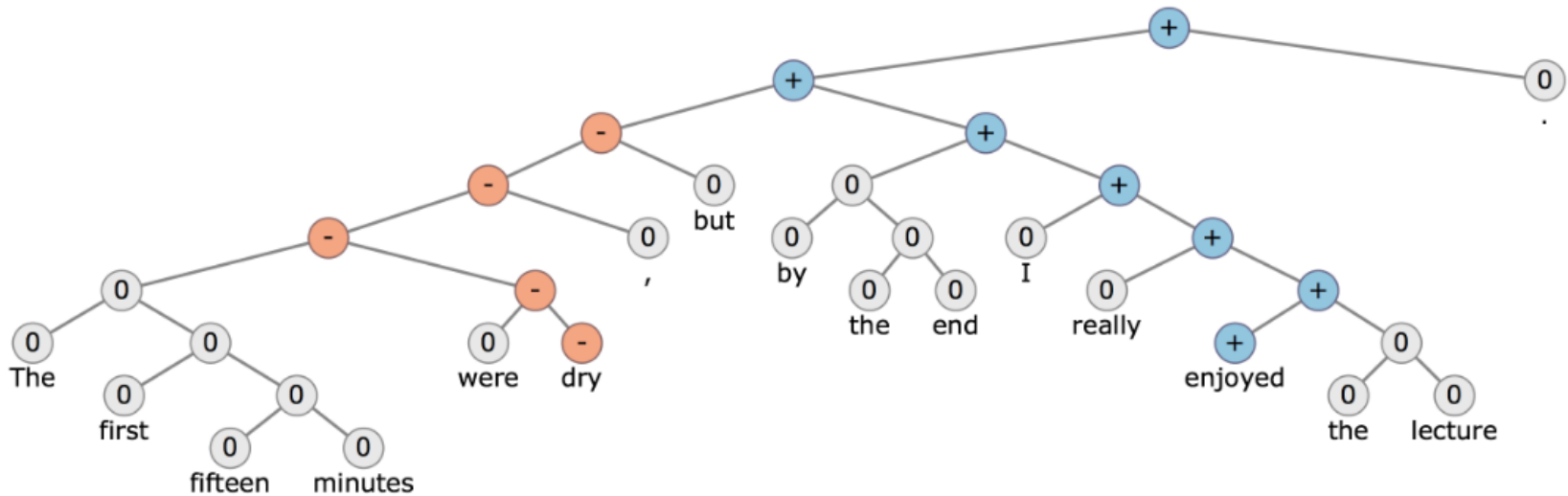
Architecture of TensorFlow



CS224d: Deep Learning for Natural Language Processing



CS224d: Deep Learning for Natural Language Processing



Course Description

Natural language processing (NLP) is one of the most important technologies of the information age. Understanding complex language utterances is also a crucial part of artificial intelligence. Applications of NLP are everywhere because people communicate most everything in language: web search, advertisement, emails, customer service, language translation, radiology reports, etc. There are a large variety of underlying tasks and machine learning models powering NLP applications. Recently, deep learning approaches

<http://cs224d.stanford.edu/>

Deeply Moving: Deep Learning for Sentiment Analysis



Sentiment Analysis

[Information](#)[Live Demo](#)[Sentiment Treebank](#)[Help the Model](#)[Source Code](#)

Deeply Moving: Deep Learning for Sentiment Analysis

This website provides a [live demo](#) for predicting the sentiment of movie reviews. Most sentiment prediction systems work just by looking at words in isolation, giving positive points for positive words and negative points for negative words and then summing up these points. That way, the order of words is ignored and important information is lost. In contrast, our new deep learning model actually builds up a representation of whole sentences based on the sentence structure. It computes the sentiment based on how words compose the meaning of longer phrases. This way, the model is not as easily fooled as previous models. For example, our model learned that *funny* and *witty* are positive but the following sentence is still negative overall:

This movie was actually neither that funny, nor super witty.

The underlying technology of this demo is based on a new type of *Recursive Neural Network* that builds on top of grammatical structures. You can also browse the [Stanford Sentiment Treebank](#), the dataset on which this model was trained. The model and dataset are described in an upcoming [EMNLP paper](#). Of course, no model is perfect. You can help the model learn even more by [labeling sentences](#) we think would help the model or those you try in the live demo.

Paper Title and Abstract

Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank

Paper: [Download pdf](#)

Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher Manning, Andrew Ng and Christopher Potts

Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank

Conference on Empirical Methods in Natural Language Processing (EMNLP 2013)

Dataset Downloads:

Main zip file with readme (6mb)
Dataset raw counts (5mb)
Train,Dev,Test Splits in PTB Tree Format

Code: [Download Page](#)

Press: [Stanford Press Release](#)

Dataset visualization and web design by Jason Chuang. Live demo by Jean Wu, Richard Socher, Rukmani Ravisundaram and Tayyab Tariq.

Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank

Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank

Richard Socher, Alex Perelygin, Jean Y. Wu, Jason Chuang,
Christopher D. Manning, Andrew Y. Ng and Christopher Potts

Stanford University, Stanford, CA 94305, USA

richard@socher.org, {aperelyg, jcchuang, ang}@cs.stanford.edu

{jeaneis, manning, cgpotts}@stanford.edu

Abstract

Semantic word spaces have been very useful but cannot express the meaning of longer phrases in a principled way. Further progress towards understanding compositionality in tasks such as sentiment detection requires richer supervised training and evaluation resources and more powerful models of composition. To remedy this, we introduce a Sentiment Treebank. It includes fine grained sentiment labels for 215,154 phrases in the parse trees of 11,855 sentences and presents new challenges for sentiment compositionality. To address them, we introduce the Recursive Neural Tensor Network. When trained on the new treebank, this model out-

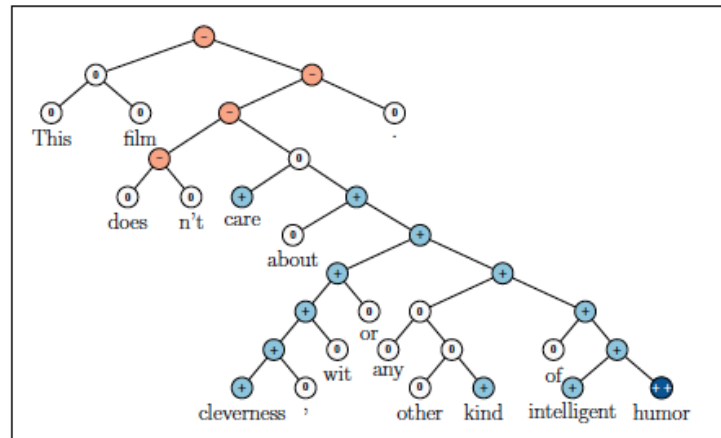
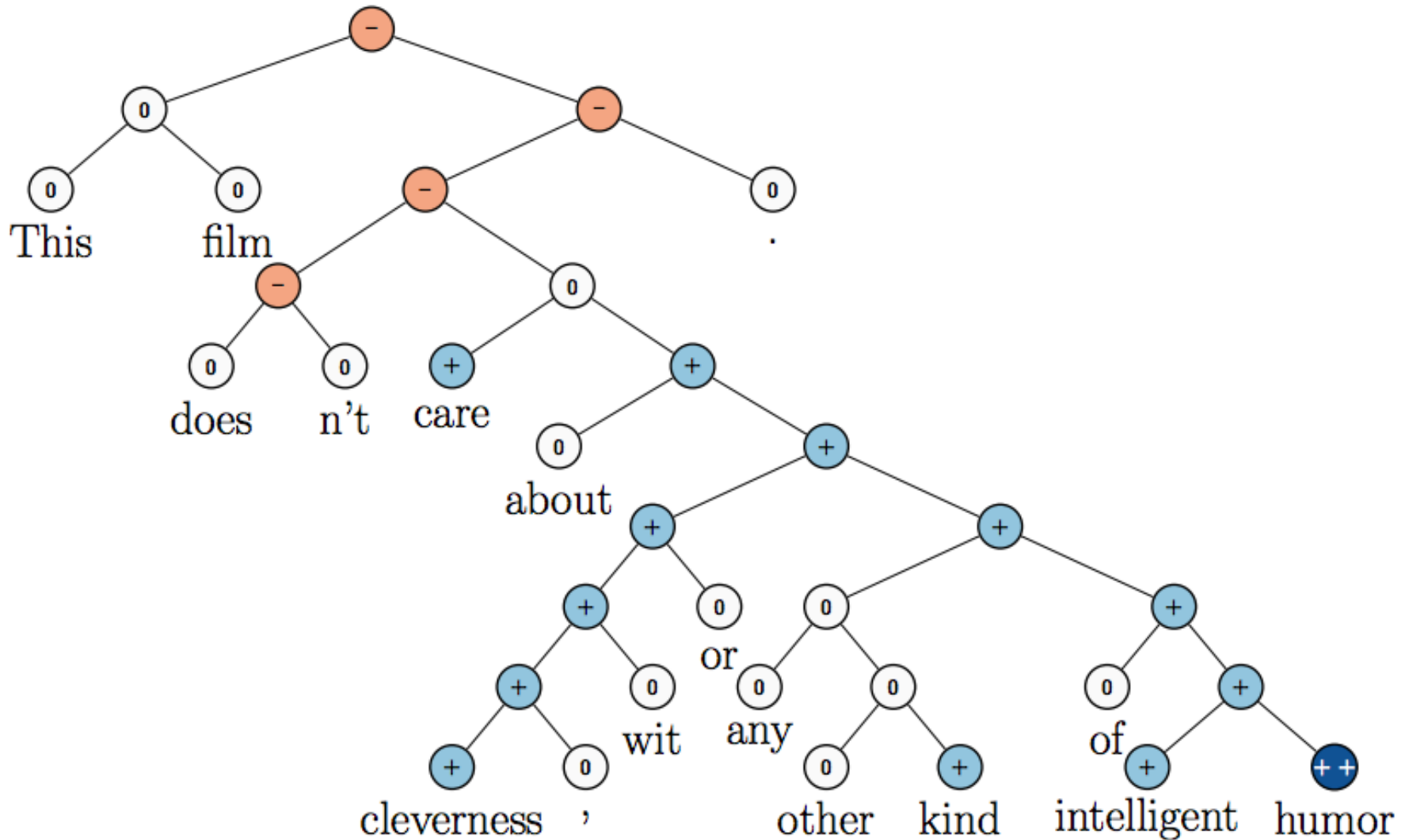


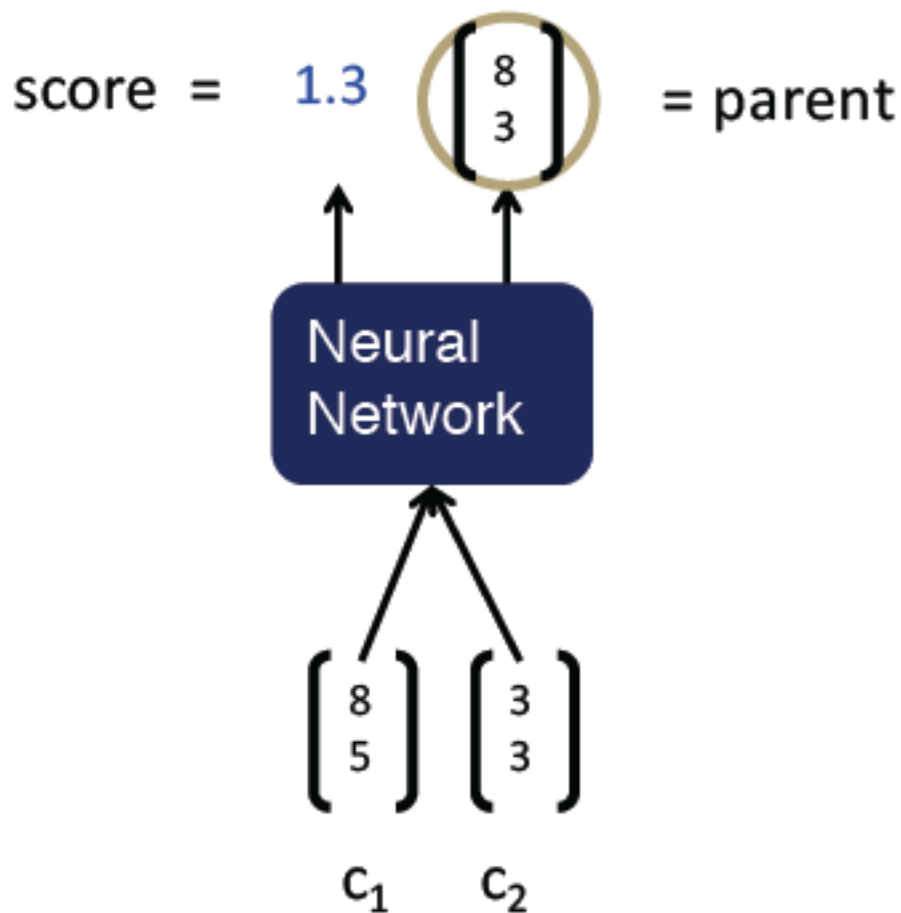
Figure 1: Example of the Recursive Neural Tensor Network accurately predicting 5 sentiment classes, very negative to very positive ($--$, $-$, 0 , $+$, $++$), at every node of a parse tree and capturing the negation and its scope in this sentence.

Recursive Neural Tensor Network (RNTN)



Source: Richard Socher et al. (2013) "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank", EMNLP 2013

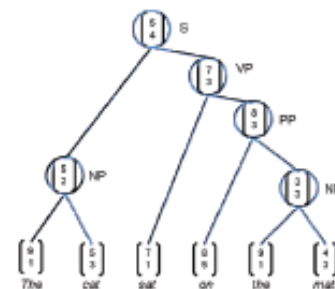
Recursive Neural Network Definition



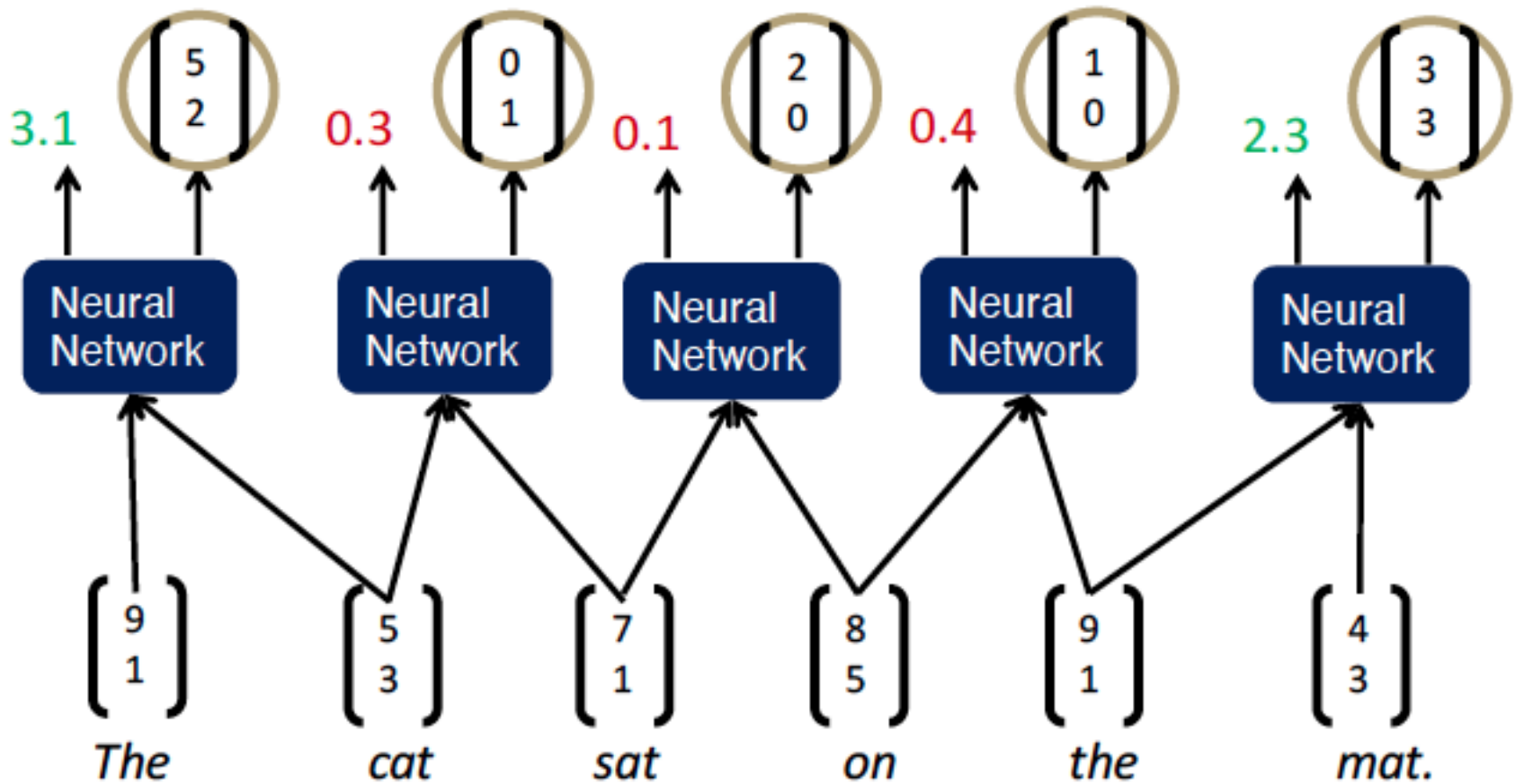
$$\text{score} = U^T p$$

$$p = \tanh\left(W \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + b\right),$$

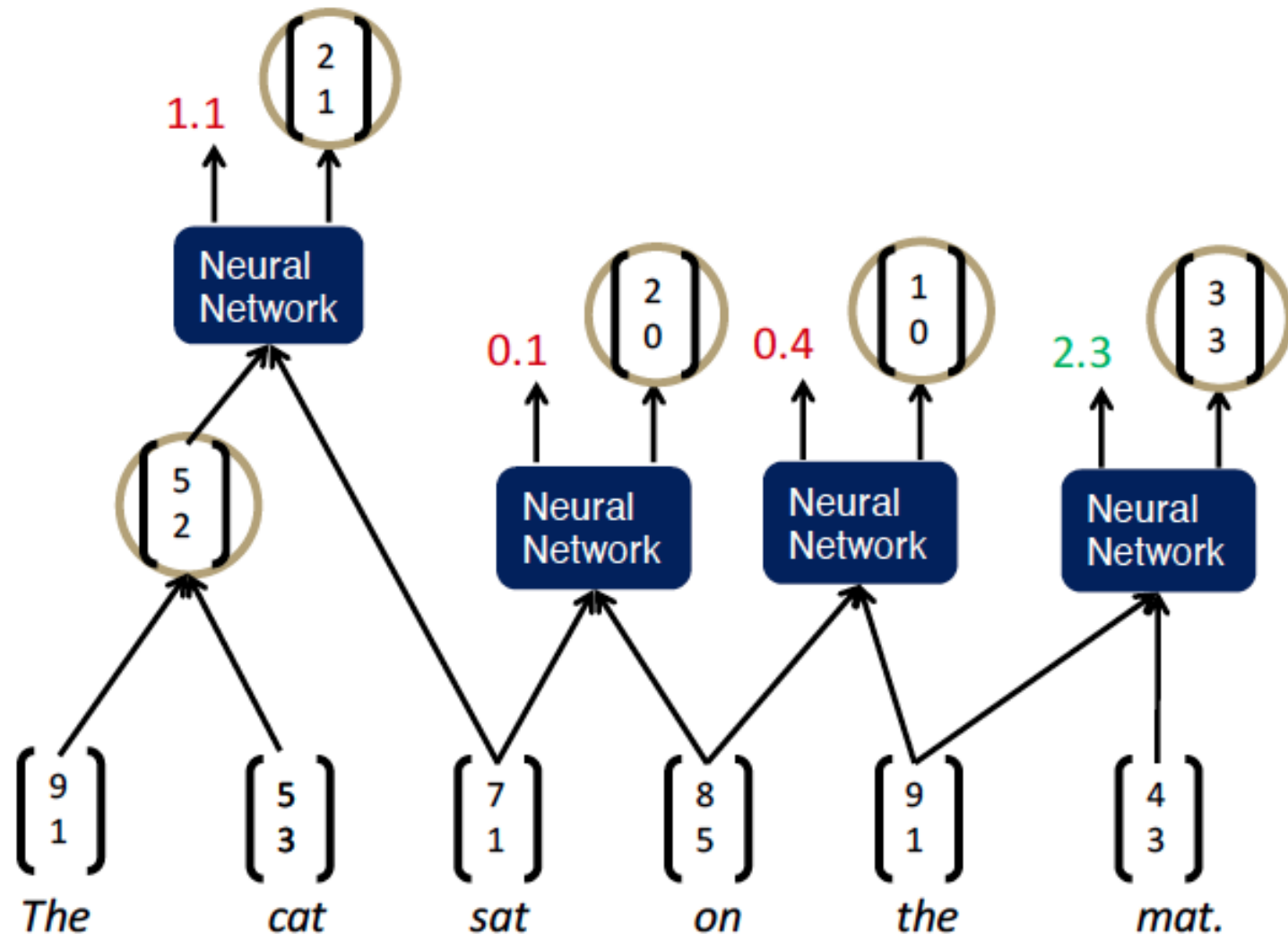
Same W parameters at all nodes of the tree



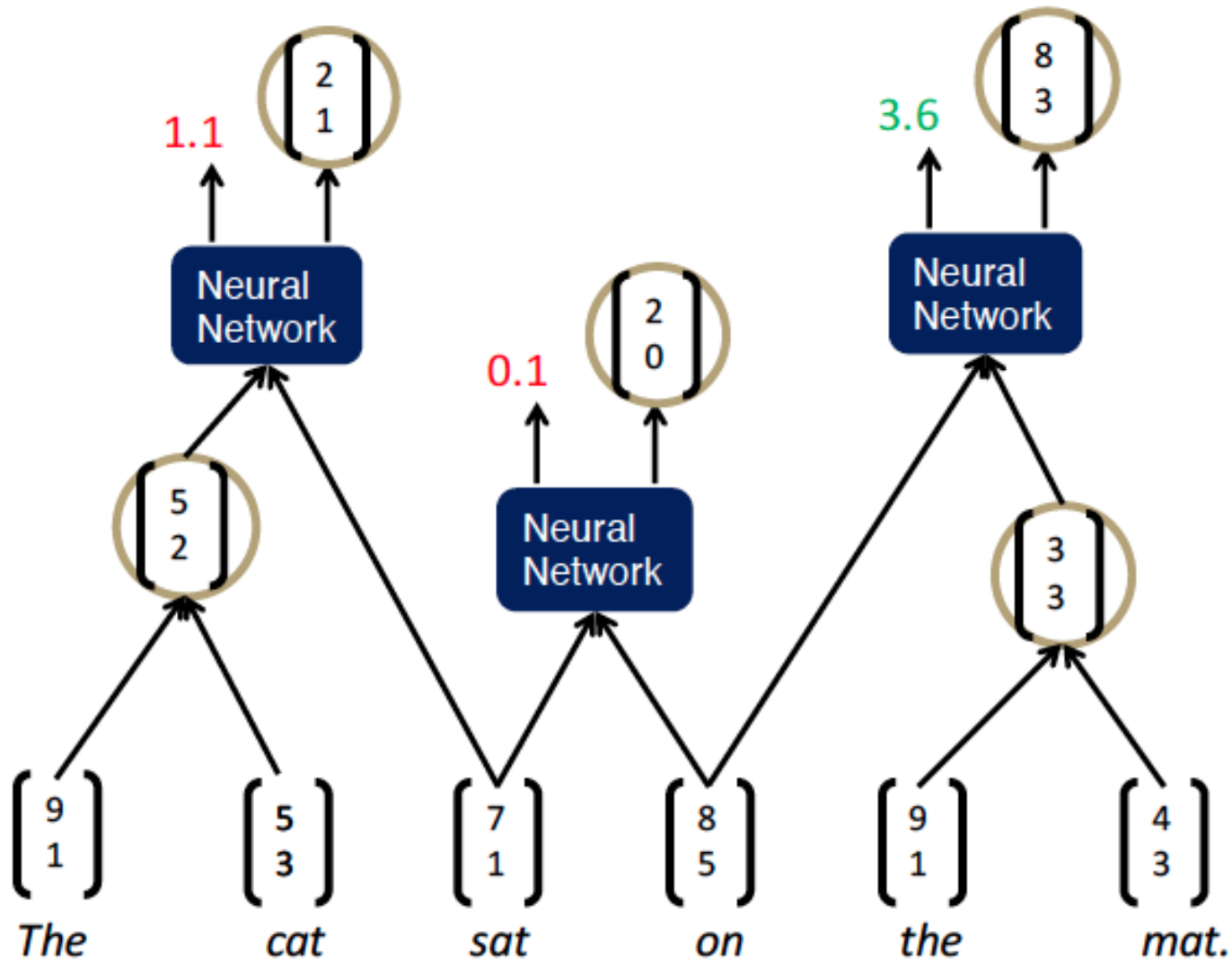
Parsing a sentence with an RNN



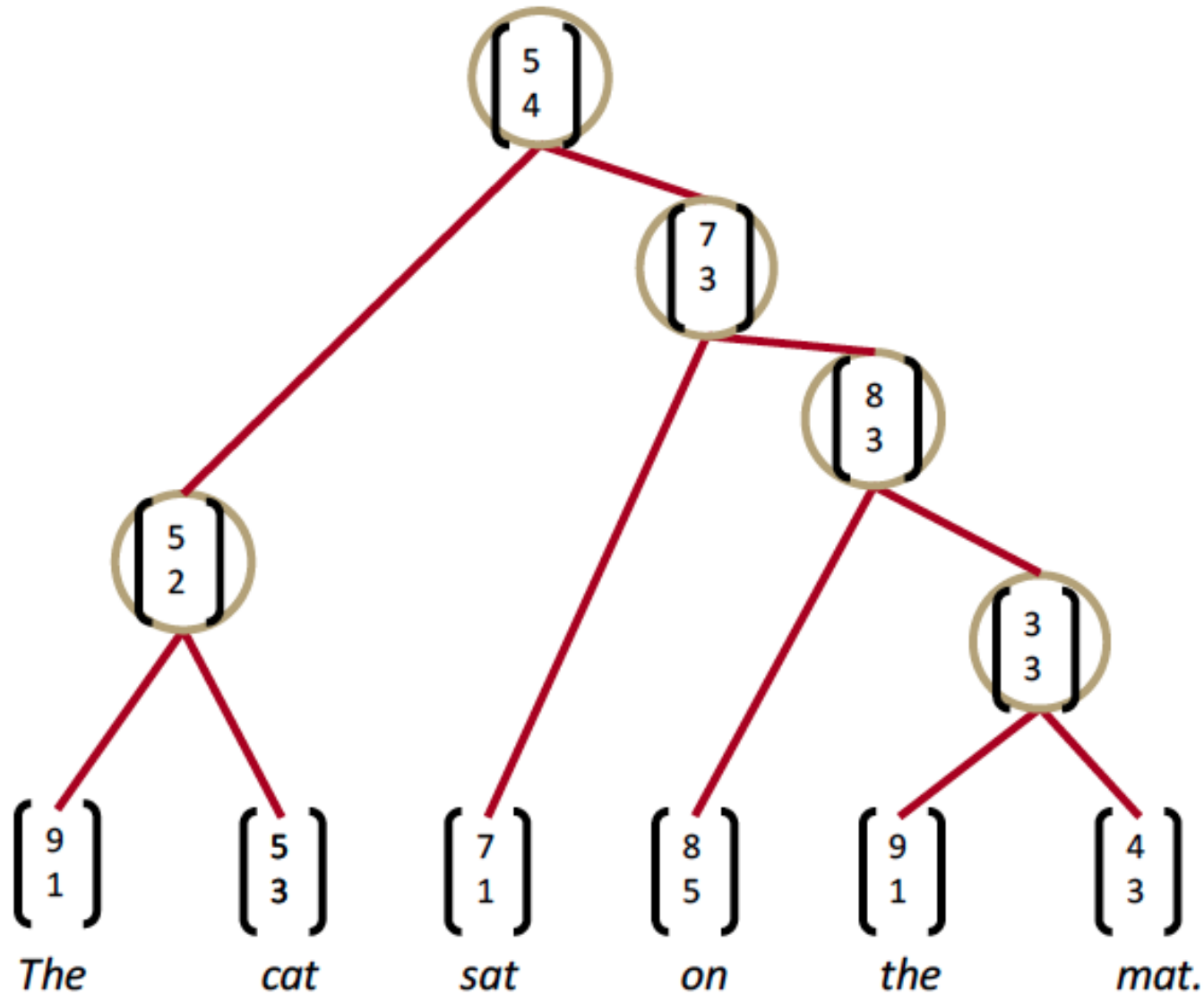
Parsing a sentence with an RNN



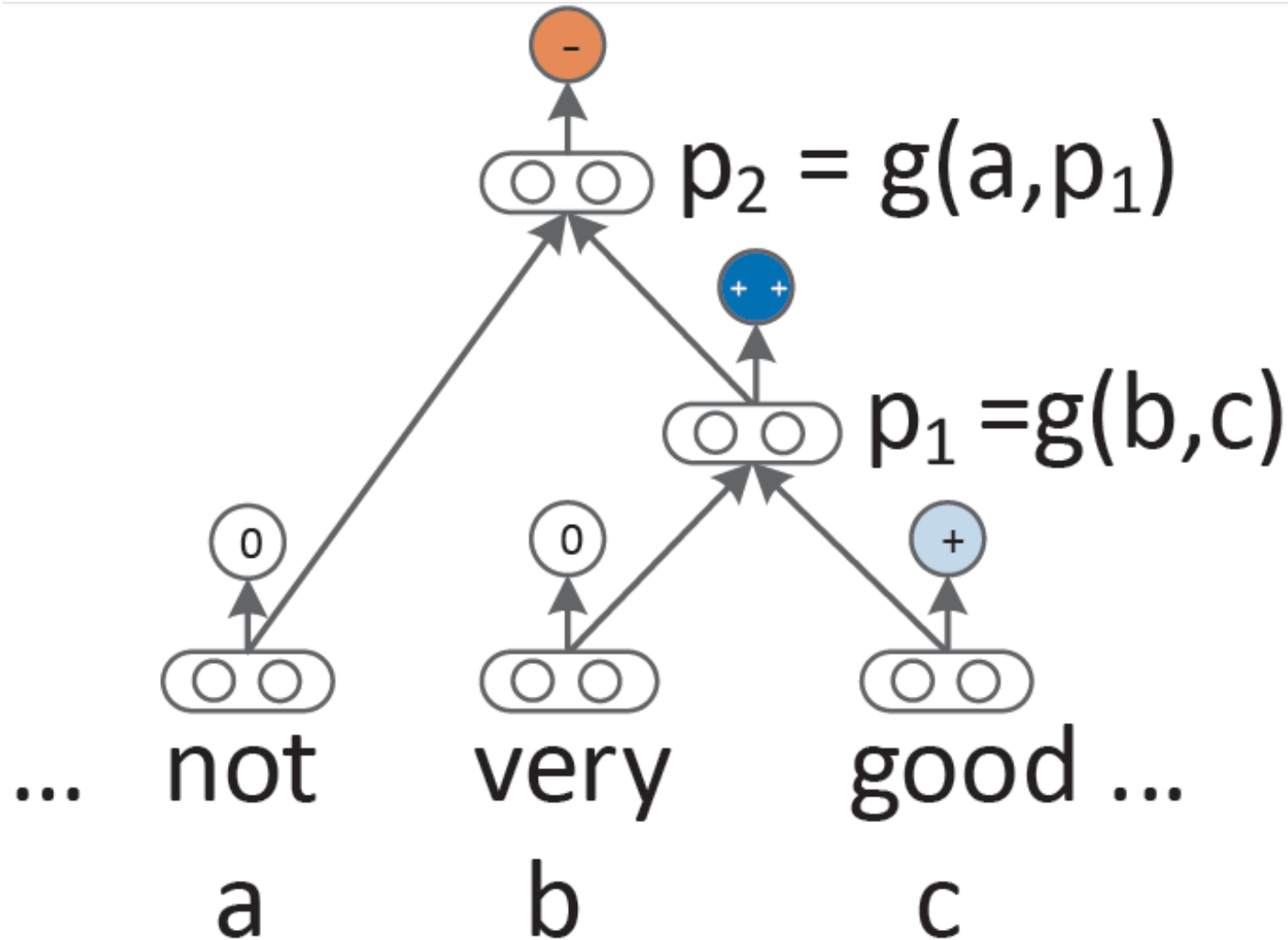
Parsing a sentence with an RNN



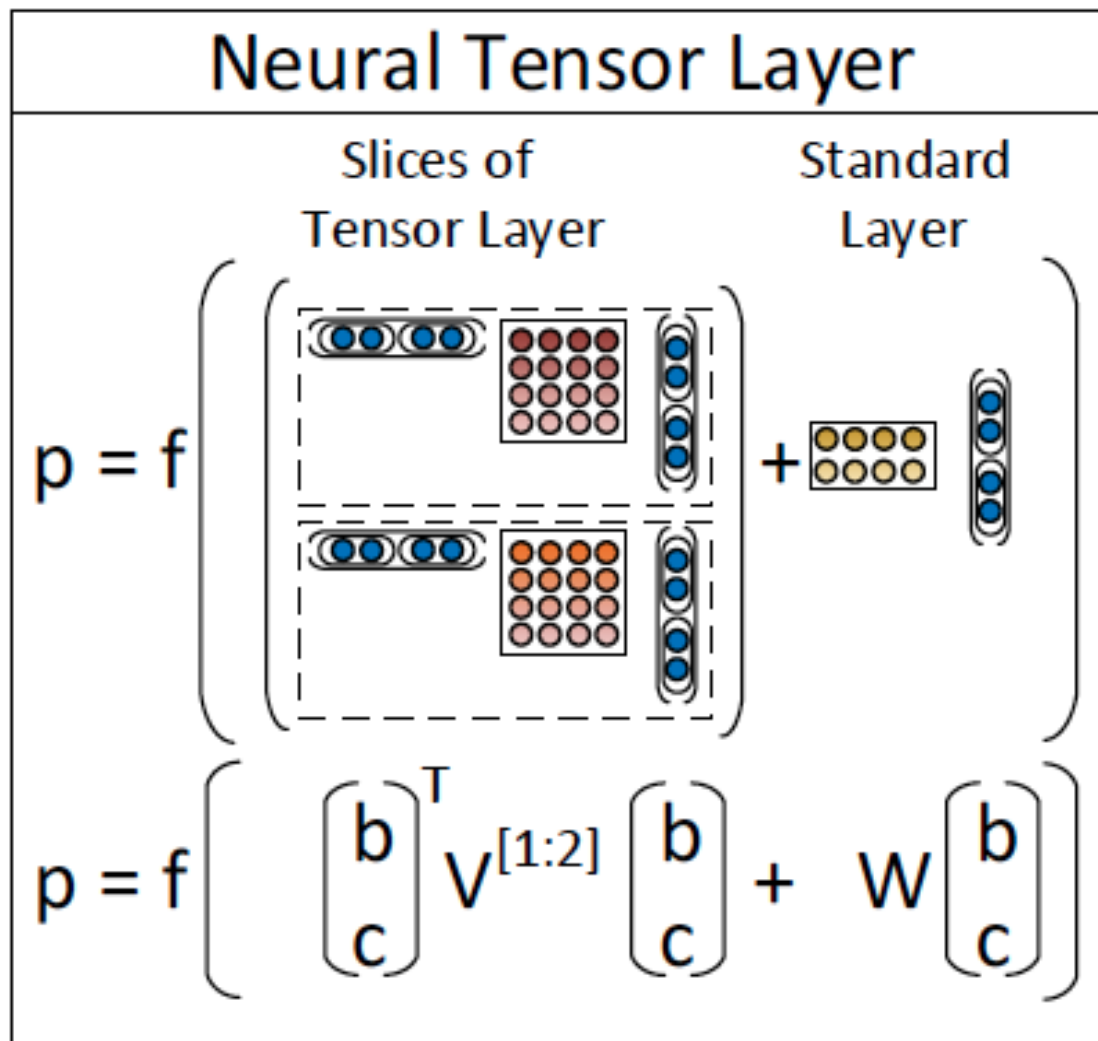
Parsing a sentence with an RNN



Recursive Neural Network (RNN) models for sentiment



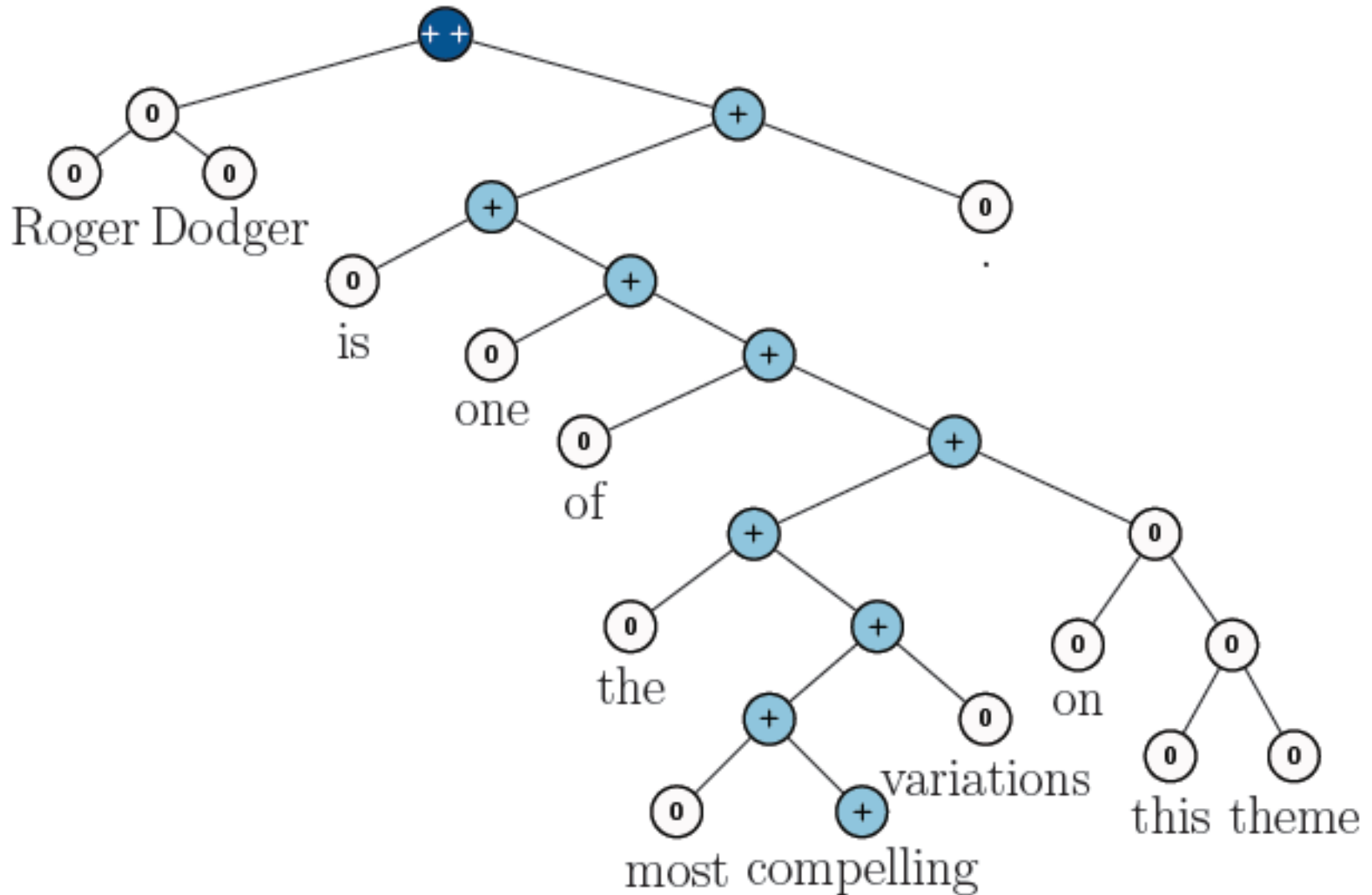
Recursive Neural Tensor Network (RNTN)



Roger Dodger is one of the **most compelling variations on this theme.**

Roger Dodger is one of the **least compelling variations on this theme.**

RNTN for Sentiment Analysis



Roger Dodger is one of the **most** compelling variations on this theme.

Source: Richard Socher et al. (2013) "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank", EMNLP 2013

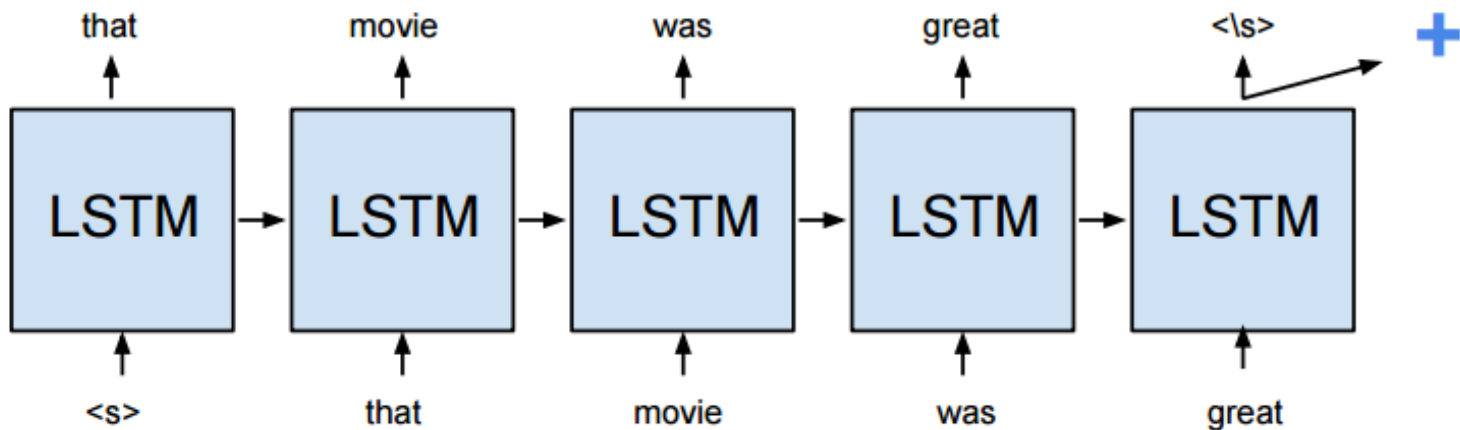
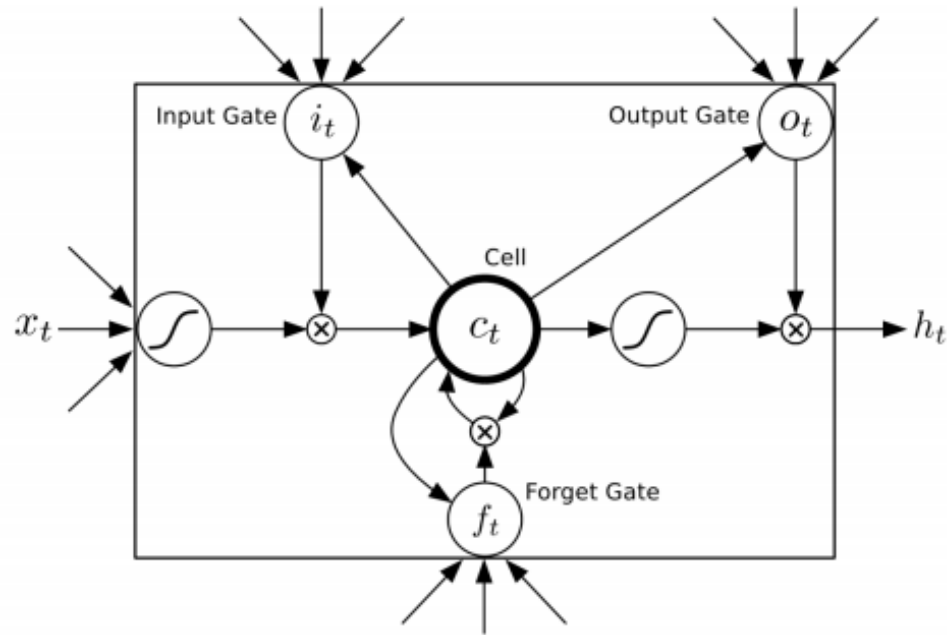
Accuracy for fine grained (5-class) and binary predictions at the sentence level (root) and for all nodes

Model	Fine-grained		Positive/Negative	
	All	Root	All	Root
NB	67.2	41.0	82.6	81.8
SVM	64.3	40.7	84.6	79.4
BiNB	71.0	41.9	82.7	83.1
VecAvg	73.3	32.7	85.1	80.1
RNN	79.0	43.2	86.1	82.4
MV-RNN	78.7	44.4	86.8	82.9
RNTN	80.7	45.7	87.6	85.4

Accuracy of negation detection

Model	Accuracy	
	Negated Positive	Negated Negative
biNB	19.0	27.3
RNN	33.3	45.5
MV-RNN	52.4	54.6
RNTN	71.4	81.8

Long Short-Term Memory (LSTM)



Deep Learning for Sentiment Analysis

CNN RNTN LSTM

Model	Fine (5-class)	Binary
DCNN (Blunsom, et al. 2014)	0.485	0.868
RNTN (Socher, et al. 2013)	0.457	0.854
CNN-non-static (Kim, 2014)	0.480	0.872
CNN-multi-channel (Kim, 2014)	0.474	0.881
DRNN w. pretrained word-embeddings (Irsoy and Cardie, 2014)	0.498	0.866
Paragraph Vector (Le and Mikolov. 2014)	0.487	0.878
Dependency Tree-LSTM (Tai, et al, 2015)	0.484	0.857
Constituency Tree-LSTM (Tai, et al, 2015)	0.439	0.820
Constituency Tree-LSTM (Glove vectors) (Tai, et al, 2015)	0.510	0.880
Paragraph Vector	0.391	0.798
LSTM	0.456	0.843
Deep Recursive-NN	0.469	0.847

Performance Comparison of Sentiment Analysis Methods

	Method	Data Set	Acc.	Author
Machine Learning	SVM	Movie reviews	86.40%	Pang, Lee[23]
	CoTraining SVM	Twitter	82.52%	Liu[14]
	Deep learning	Stanford Sentiment Treebank	80.70%	Richard[18]
Lexical based	Corpus	Product reviews	74.00%	Turkey
	Dictionary	Amazon's Mechanical Turk	---	Taboada[20]
Cross-lingual	Ensemble	Amazon	81.00%	Wan,X[16]
	Co-Train	Amazon, ITI68	81.30%	Wan,X.[16]
	EWGA	IMDb movie review	>90%	Abbasi,A.
	CLMM	MPQA, NTCIR, ISI	83.02%	Mengi
Cross-domain	Active Learning	Book, DVD, Electronics, Kitchen	80% (avg)	Li, S
	Thesaurus			Bollegala[22]
	SFA			Pan S J[15]

Social Media Monitoring/Analysis

Existing Tools

("Social Media Monitoring/Analysis")

- Radian 6
- Social Mention
- Overtone OpenMic
- Microsoft Dynamics Social Networking Accelerator
- SAS Social Media Analytics
- Lithium Social Media Monitoring
- RightNow Cloud Monitor

Word-of-mouth

Voice of the Customer

- 1. Attensity
 - Track social sentiment across brands and competitors
 - <http://www.attensity.com/home/>
- 2. Clarabridge
 - Sentiment and Text Analytics Software
 - <http://www.clarabridge.com/>

Attensity: Track social sentiment across brands and competitors

<http://www.attensity.com/>

The screenshot displays the Attensity website homepage. At the top, there is a navigation bar with the Attensity logo on the left, a language selector set to 'English', and links for 'Contact', 'Resources', 'Support', and 'Blog'. A search bar is located on the right. Below the navigation bar, a secondary menu lists 'Products', 'Solutions', 'Services', 'Customers', and 'Partners'. The main content area features a large central banner with the headline 'Your real-time window into the social web.' and a quote from Yahoo! stating, 'Teaming with a leading analytics provider like Attensity offers Yahoo! a great opportunity to deliver the key news and analysis that matter.' A 'Learn More' button is positioned below the quote. To the left of the banner is a vertical menu with categories: 'Social Analytics', 'Social Response', 'Customer Analytics', 'Industry Solutions', and 'Why Attensity'. To the right, there are several overlapping images of the Attensity dashboard, showing various charts and graphs. Below the main banner, there are four distinct sections: 'Attensity for Marketing', 'Attensity for Customer Service', 'Success Story' (highlighting JetBlue Airways), and 'Watch Video' (featuring a 'Command Center Video' player). The footer contains the URL 'www.attensity.com/home/#fragment-1' and a 'DOWNLOAD NOW' button.

<http://www.youtube.com/watch?v=4goxmBEg2lw#/>

Clarabridge: Sentiment and Text Analytics Software

<http://www.clarabridge.com/>

The image shows a screenshot of a web browser displaying the Clarabridge website. The browser's address bar shows the URL www.clarabridge.com. The website features a navigation menu with links for Home, About Us, News & Events, Blog, Login, and Contact Us. Below the navigation is a main banner with the headline "The First Sentiment and Text Analytics Solution Built Specifically for Business." and a sub-headline "The Clarabridge sentiment and text analytics software provides enterprises with a universal view of their customers." A "Learn more about how Clarabridge works >" link is positioned at the bottom right of the banner. A horizontal strip of logos for various customers, including Nissan, Best Buy, Marriott, Sage, H&R Block, Choice Hotels International, Wendy's, GWLORD HOTELS, and Dell, is located below the banner. The footer contains three sections: "Clarabridge Text Analytics", "Choose Your Edition" (with a sub-section for "Clarabridge for Enterprises" described as ideal for enterprise-class text analytics solutions), and "Clarabridge Webinar" presented by Hypatia Research Group on social media.

<http://www.youtube.com/watch?v=IDHudt8M9P0>

<http://www.radian6.com/>

Social Media Monitoring x
www.radian6.com

Country 1 888 672 3426 About Radian6 Contact CUSTOMER LOGIN Search GO

salesforce **radian6**

How We Help What We Sell See Demo Free Resources Training & Support

The Social Enterprise.
Get closer to your customer.
Learn how >

Have Us Contact You
Live Demo
Free Trial

Chat & find out more.
Offline. Leave us a message.

Sales The social web is a goldmine of untapped sales opportunities. Let us help you realize your potential. [Learn more >](#)

Marketing Brands are now the sum of the conversations about them. We can help you hear what's being said. [Learn more >](#)

Customer Service Take your customer service where your consumers are gathering. Respond to issues voiced on the social web. [Learn more >](#)

Newsletter Sign up and get the regular Radian6 goods.
Enter email address GO

Mashable named Radian6's Co-founder Chris Ramsey one of five masterminds redefining social media

JUST Get the Skinny
WEBINAR / June 7th at 2pm est
CASE STUDY

radian6 Community

http://www.youtube.com/watch?feature=player_embedded&v=8i6Exg3Urg0

Social Media Monitoring x

www.sas.com/software/customer-intelligence/social-media-analytics/

Log In Worldwide Sites Contact Us Follow Us

NEWS EVENTS CONSULTING CAREERS RESOURCE CENTER

SEARCH

Home Products & Solutions Customer Success Partners Company Support & Training

PRODUCTS & SOLUTIONS / SOCIAL MEDIA ANALYTICS

Products and Solutions

- Industries
- Small and Midsize Business
- Nonprofit Organizations
- Analytics
 - Business Analytics
 - Business Intelligence
 - Customer Intelligence
 - Strategy & Planning
 - Information & Analytics
 - Orchestration & Interaction
 - Customer Experience
 - Customer Experience Analytics
 - Social Media Analytics
 - Web Analytics
 - Financial Intelligence
 - Foundation Tools
 - Fraud & Financial Crimes
 - Governance, Risk & Compliance
 - High-Performance Analytics
 - Human Capital Intelligence
 - Information Management
 - IT & CIO Enablement

SAS® Social Media Analytics
Integrate, archive, analyze and act on online conversations

Overview Benefits Features Demos & Screenshots System Requirements

SAS Social Media Analytics is an enterprise-hosted, on-demand solution that integrates, archives, analyzes and enables organizations to act on intelligence gleaned from online conversations on professional and consumer-generated media sites. It enables you to attribute online conversations to specific parts of your business, allowing accelerated responses to marketplace shifts.

Based on your unique business challenges and enterprise goals, SAS can provide a tailored implementation that's hosted and managed by [SAS Solutions OnDemand](#).

Benefits

- Analyze conversation data.
- Identify advocates of, and threats to, corporate reputation and brand.
- Quantify interaction among traditional media/campaigns and social media activity.
- Establish a platform for social CRM strategy.

“ The great thing about SAS is that it's so powerful and has such a broad offering. ”

—Jonathan Prantner
Manager of Statistics
Organic

[Read full story](#)

Product Demo

Questions?

Phone
Contact Form

White Paper

Text Analytics for Social Media: Evolving Tools for an Evolving Environment

[Download Now](#)

SAS® Social Media Analytics

[Overview](#)

RESOURCES


- [Fact Sheet \(PDF\)](#)
- [Solution Brief \(PDF\)](#)
- [White Papers](#)

The screenshot shows a web browser window with the URL www.tweetfeel.com/index.php#iPhone4s. The page features the 'tweetfeel' logo with a blue bird icon. A search bar contains the text 'iPhone4s' and a yellow 'Search' button. Below the search bar, it displays 'Try some Twitter trends: [Tomorrow is June](#) [H&M](#) [Defense of Marriage Act](#) [Diddy's](#) [Bloomberg](#) [UCLA](#) [ESPN](#)'. A sentiment analysis graphic shows a green smiley face with '40' below it, a red frowny face with '41' below it, an equals sign, and '51%' in red. A text block reads: 'Those are all the results available right now. Try again or try another term to see how people feel towards it. Got questions? [Read our FAQ.](#)' Below this are six tweet snippets, each with a small profile picture and text mentioning 'iPhone4s' and 'wtf'. The footer contains links for 'Read our FAQ', 'Legal Stuff', '100% Guarantee', and 'Share', along with social media icons and logos for 'conversion' and 'Powered by twitter'.

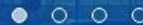
eLand

<http://www.eland.com.tw/>



關於意藍 產品與雲端服務 ▾ 新聞與活動 聯絡資訊 

◀ 巨量搜尋。語意分析。社群大數據 ▶



 OpView社群口碑資料庫

OpView

<http://www.opview.com.tw/>



OpView 介紹 ▾

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新聞與活動

分析報告

資源與課程 ▾

聯絡資訊



社群大數據

觀測 · 分析 · 探索 · 預警



FOCUS

i-Buzz
VOC口碑分析平台
自動化海量資料分析
迅速掌握網路口碑動態



母親節好禮大比拼 聽聽網友怎麼說

這個周末就是母親節了，大家有想好要如何慶祝了嗎？吃大餐、送好禮已成了節慶的基本盤，再加上百貨針對母親節紛紛推出特賣優惠，不僅讓孝子孝女省下荷包，也讓平常有在觀望檔期活動的網友殺紅了眼，更增添了其口碑豐富性...

i-Buzz
專業口碑客服團隊
公關危機處理，扭轉話題關鍵
提供具有科學性的策略方針



熱門文章



Resources of Opinion Mining

Datasets of Opinion Mining

- Blog06
 - 25GB TREC test collection
 - [http://ir.dcs.gla.ac.uk/test collections/access to data.html](http://ir.dcs.gla.ac.uk/test%20collections/access%20to%20data.html)
- Cornell movie-review datasets
 - <http://www.cs.cornell.edu/people/pabo/movie-review-data/>
- Customer review datasets
 - <http://www.cs.uic.edu/~liub/FBS/CustomerReviewData.zip>
- Multiple-aspect restaurant reviews
 - <http://people.csail.mit.edu/bsnyder/naacl07>
- NTCIR multilingual corpus
 - NTCIR Multilingual Opinion-Analysis Task (MOAT)

Lexical Resources of Opinion Mining

- SentiWordnet
 - <http://sentiwordnet.isti.cnr.it/>
- General Inquirer
 - <http://www.wjh.harvard.edu/~inquirer/>
- OpinionFinder's Subjectivity Lexicon
 - <http://www.cs.pitt.edu/mpqa/>
- NTU Sentiment Dictionary (NTUSD)
 - <http://nlg18.csie.ntu.edu.tw:8080/opinion/>
- HowNet Sentiment
 - http://www.keenage.com/html/c_bulletin_2007.htm

Example of SentiWordNet

POS	ID	PosScore	NegScore	SynsetTerms	Gloss
a	00217728	0.75	0	beautiful#1	delighting the senses or exciting intellectual or emotional admiration; "a beautiful child"; "beautiful country"; "a beautiful painting"; "a beautiful theory"; "a beautiful party"
a	00227507	0.75	0	best#1	(superlative of `good') having the most positive qualities; "the best film of the year"; "the best solution"; "the best time for planting"; "wore his best suit"
r	00042614	0	0.625	unhappily#2	sadly#1 in an unfortunate way; "sadly he died before he could see his grandchild"
r	00093270	0	0.875	woefully#1	sadly#3 lamentably#1 deplorably#1 in an unfortunate or deplorable manner; "he was sadly neglected"; "it was woefully inadequate"
r	00404501	0	0.25	sadly#2	with sadness; in a sad manner; "'She died last night,' he said sadly"

《知網》情感分析用詞語集 (beta版)

- “中英文情感分析用詞語集”
 - 包含詞語約 17887
- “中文情感分析用詞語集”
 - 包含詞語約 9193
- “英文情感分析用詞語集”
 - 包含詞語 8945

中文情感分析用詞語集

中文正面情感詞語	836
中文負面情感詞語	1254
中文正面評價詞語	3730
中文負面評價詞語	3116
中文程度級別詞語	219
中文主張詞語	38
Total	9193

中文情感分析用詞語集

- “正面情感” 詞語

— 如：

愛，讚賞，快樂，感同身受，好奇，
喝彩，魂牽夢縈，嘉許 ...

- “負面情感” 詞語

— 如：

哀傷，半信半疑，鄙視，不滿意，不是滋味兒
，後悔，大失所望 ...

中文情感分析用詞語集

- “正面評價” 詞語

— 如：

不可或缺，部優，才高八斗，沉魚落雁，
催人奮進，動聽，對勁兒 ...

- “負面評價” 詞語

— 如：

醜，苦，超標，華而不實，荒涼，混濁，
畸輕畸重，價高，空洞無物 ...

中文情感分析用詞語集

- “程度級別” 詞語
 - 1. “極其|extreme / 最|most”
 - 非常，極，極度，無以倫比，最為
 - 2. “很|very”
 - 多麼，分外，格外，著實
 - ...
- “主張” 詞語
 - 1. {perception|感知}
 - 感覺，覺得，預感
 - 2. {regard|認為}
 - 認為，以為，主張

Opinion Spam Detection

Opinion Spam Detection

- Opinion Spam Detection: Detecting Fake Reviews and Reviewers
 - Spam Review
 - Fake Review
 - Bogus Review
 - Deceptive review
 - Opinion Spammer
 - Review Spammer
 - Fake Reviewer
 - Shill (Stooge or Plant)

Opinion Spamming

- Opinion Spamming
 - "illegal" activities
 - e.g., writing fake reviews, also called shilling
 - try to mislead readers or automated opinion mining and sentiment analysis systems by giving undeserving positive opinions to some target entities in order to promote the entities and/or by giving false negative opinions to some other entities in order to damage their reputations.

Forms of Opinion spam

- fake reviews (also called bogus reviews)
- fake comments
- fake blogs
- fake social network postings
- deceptions
- deceptive messages

Fake Review Detection

- Methods
 - supervised learning
 - pattern discovery
 - graph-based methods
 - relational modeling
- Signals
 - Review content
 - Reviewer abnormal behaviors
 - Product related features
 - Relationships

Professional Fake Review Writing Services (some Reputation Management companies)

- Post positive reviews
- Sponsored reviews
- Pay per post
- Need someone to write positive reviews about our company (budget: \$250-\$750 USD)
- Fake review writer
- Product review writer for hire
- Hire a content writer
- Fake Amazon book reviews (hiring book reviewers)
- People are just having fun (not serious)

SponsoredReviews.com x

www.sponsoredreviews.com

 **SponsoredReviews.com**
Bloggers Earn Cash, Advertisers Build Buzz!

[Members Login](#)

Sales Toll-Free (877) 360-3683

[Home](#) [Sign-Up](#) [FAQs](#) [Our Blog](#) [Contact Us](#)

SponsoredReviews connects bloggers with SEO's, Marketers, and Advertisers looking to build Links, Traffic and Buzz.

Direct Traffic.

Millions of people read blogs every day. Paying for posts puts the spotlight on your company and will generate tons of targeted traffic.

Buzz & Branding.

The more bloggers talk about your site the better. Many blogs syndicate stories they see on other sites. A couple well timed sponsored posts has the potential to generate a flurry of other post being written.

Search Engine Rankings.

Every post has links back to your site. Getting links from quality blogs will increase your link popularity and will help your site rank better in the search engines.

Valuable Feedback.

Getting Reviewed by bloggers will provide you with valuable feedback that you can use to better understand your audience and customers.

Advertisers
Start Here.



- Announce your products, services, websites, and ideas to the world!
- Tap into the power of the blogosphere to build traffic, links and valuable feedback.

[Free Sign Up](#)

[Read More](#)

Bloggers
Earn Cash.



- Earn cash by writing honest posts about our advertiser's products and services.
- Write posts in your own tone and style, and gear them to your audience's interest.

[Free Sign Up](#)


[Read More](#)

How it works:  Advertiser  Blogger

PayPerPost : Blog Marke x
https://payperpost.com

payperpost


advertisers bloggers ethics about login



advertisers

Hire bloggers to blog about your company, service or website. PayPerPost gives you access to a diverse pool of bloggers from all over the world. Make offers, negotiate deals and approve posts.

[signup now](#)




bloggers

Make money blogging! PayPerPost lets you pick your advertisers, name your own price and negotiate your own deals. You can get paid to blog on virtually any subject. Sign up below!


[signup now](#)

see how it works



[click here and watch the video](#)

customer testimonial



"PayPerPost has been instrumental in helping our company streamline our various product awareness campaigns."
-C. Litchfield

1 (877) 916 POST



Post Project

Find Freelancers

Browse Projects

Post Contest

Search for Freelancers, Projects...

Need someone to write and post positive reviews

f Like 0 f Send t Tweet 0 g +1 0 + Share

Bids	Avg Bid (USD)	Project Budget (USD)
10	N/A	\$250 - \$750

Featured Sealed

CLOSED

Project Description:

We need someone to write and post positive reviews about our company on websites. Please send an example of a review you would post for any company. We can also send examples of comments our customers have sent us to use and refer too as well

This is a long term project, so if it works out there will be a healthy amount of work. Please reply back with all your experience and how much you would charge per post.

thank you.

Skills required:

Publicación en foros, Opiniones



Follow

Project posted by:

dvel 5.0 (1 Review) VERIFIED

Your ad could From \$100/week

Papers on Opinion Spam Detection

1. Arjun Mukherjee, Bing Liu, and Natalie Glance. Spotting Fake Reviewer Groups in Consumer Reviews. International World Wide Web Conference (WWW-2012), Lyon, France, April 16-20, 2012.
2. Guan Wang, Sihong Xie, Bing Liu, Philip S. Yu. Identify Online Store Review Spammers via Social Review Graph. ACM Transactions on Intelligent Systems and Technology, accepted for publication, 2011.
3. Guan Wang, Sihong Xie, Bing Liu, Philip S. Yu. Review Graph based Online Store Review Spammer Detection. ICDM-2011, 2011.
4. Arjun Mukherjee, Bing Liu, Junhui Wang, Natalie Glance, Nitin Jindal. Detecting Group Review Spam. WWW-2011 poster paper, 2011.
5. Nitin Jindal, Bing Liu and Ee-Peng Lim. "Finding Unusual Review Patterns Using Unexpected Rules" Proceedings of the 19th ACM International Conference on Information and Knowledge Management (CIKM-2010, short paper), Toronto, Canada, Oct 26 - 30, 2010.
6. Ee-Peng Lim, Viet-An Nguyen, Nitin Jindal, Bing Liu and Hady Lauw. "Detecting Product Review Spammers using Rating Behaviors." Proceedings of the 19th ACM International Conference on Information and Knowledge Management (CIKM-2010, full paper), Toronto, Canada, Oct 26 - 30, 2010.
7. Nitin Jindal and Bing Liu. "Opinion Spam and Analysis." Proceedings of First ACM International Conference on Web Search and Data Mining (WSDM-2008), Feb 11-12, 2008, Stanford University, Stanford, California, USA.
8. Nitin Jindal and Bing Liu. "Review Spam Detection." Proceedings of WWW-2007 (poster paper), May 8-12, Banff, Canada.

References

- Bing Liu (2011) , “Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data,” 2nd Edition, Springer.
<http://www.cs.uic.edu/~liub/WebMiningBook.html>
- Bing Liu (2013), Opinion Spam Detection: Detecting Fake Reviews and Reviewers,
<http://www.cs.uic.edu/~liub/FBS/fake-reviews.html>
- Bo Pang and Lillian Lee (2008), "Opinion mining and sentiment analysis," Foundations and Trends in Information Retrieval 2(1-2), pp. 1–135, 2008.
- Wiltrud Kessler (2012), Introduction to Sentiment Analysis,
http://www.ims.uni-stuttgart.de/~kesslewd/lehre/sentimentanalysis12s/introduction_sentimentanalysis.pdf
- Z. Zhang, X. Li, and Y. Chen (2012), "Deciphering word-of-mouth in social media: Text-based metrics of consumer reviews," ACM Trans. Manage. Inf. Syst. (3:1) 2012, pp 1-23.
- Efraim Turban, Ramesh Sharda, Dursun Delen (2011), Decision Support and Business Intelligence Systems, Ninth Edition, 2011, Pearson.
- Guandong Xu, Yanchun Zhang, Lin Li (2011), Web Mining and Social Networking: Techniques and Applications, 2011, Springer

References

- Richard Socher, Alex Perelygin, Jean Y. Wu, Jason Chuang, Christopher D. Manning, Andrew Y. Ng, and Christopher Potts (2013), "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank," In Proceedings of the conference on empirical methods in natural language processing (EMNLP), vol. 1631, p. 1642
http://nlp.stanford.edu/~socherr/EMNLP2013_RNTN.pdf
- Kumar Ravi and Vadlamani Ravi (2015), "A survey on opinion mining and sentiment analysis: tasks, approaches and applications." Knowledge-Based Systems, 89, pp.14-46.
- Vishal Kharde and Sheetal Sonawane (2016), "Sentiment Analysis of Twitter Data: A Survey of Techniques," International Journal of Computer Applications, vol 139, no. 11, 2016. pp.5-15.
- Jesus Serrano-Guerrero, Jose A. Olivas, Francisco P. Romero, and Enrique Herrera-Viedma (2015), "Sentiment analysis: A review and comparative analysis of web services," Information Sciences, 311, pp. 18-38.
- Steven Struhl (2015), Practical Text Analytics: Interpreting Text and Unstructured Data for Business Intelligence (Marketing Science), Kogan Page
- Bing Liu (2015), Sentiment Analysis: Mining Opinions, Sentiments, and Emotions, Cambridge University Press

References

- Sunila Gollapudi (2016), Practical Machine Learning, Packt Publishing
- Sebastian Raschka (2015), Python Machine Learning, Packt Publishing
- TensorFlow: <https://www.tensorflow.org/>
- Rajat Monga (2016), TensorFlow: Machine Learning for Everyone, https://www.youtube.com/watch?v=wmw8Bbb_eIE
- Jeff Dean (2016), Large-Scale Deep Learning For Building Intelligent Computer Systems, The 9th ACM International Conference on Web Search and Data Mining (WSDM 2016), San Francisco, California, USA., February 22-25, 2016. <http://www.wsdm-conference.org/2016/slides/WSDM2016-Jeff-Dean.pdf>
- Deep Learning Basics: Neural Networks Demystified, <https://www.youtube.com/playlist?list=PLiaHhY2iBX9hdHaRr6b7XevZtgZRa1PoU>
- Deep Learning SIMPLIFIED, <https://www.youtube.com/playlist?list=PLjJh1vISEYgvGod9wWiydumYl8hOXixNu>
- Theano: <http://deeplearning.net/software/theano/>
- Keras: <http://keras.io/>