Machine Learning Department
School of Computer Science
Carnegie Mellon University

Foundations: RNNs & CNNs

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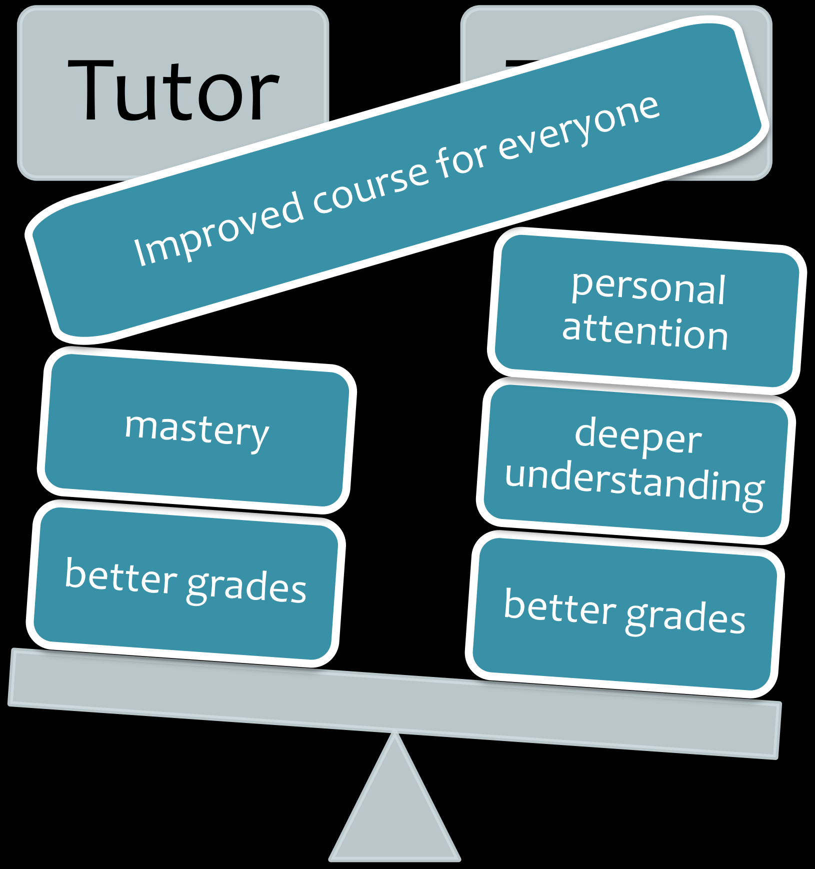
Lecture 17
Oct. 30, 2023

Reminders

- Homework 6: Learning Theory & Generative Models
  - Out: Fri, Oct 27
  - Due: Fri, Nov 3 at 11:59pm

Peer Tutoring



DISCRIMINATIVE AND GENERATIVE CLASSIFIERS

Generative vs. Discriminative

- **Generative Classifiers:**
  - Example: Naïve Bayes
  - Define a joint model of the observations **x** and the labels y: $p(\boldsymbol{x}, y)$
  - Learning maximizes (joint) likelihood
  - Use Bayes' Rule to classify based on the posterior:

$$p(y|\mathbf{x}) = p(\mathbf{x}|y)p(y)/p(\mathbf{x})$$

- **Discriminative Classifiers:**
  - Example: Logistic Regression
  - Directly model the conditional: $p(y|\mathbf{x})$
  - Learning maximizes conditional likelihood

Generative vs. Discriminative

	Gen.	Disc.
MLE	$\prod_i p(\mathbf{x}^{(i)}, y^{(i)} \vert \boldsymbol{\theta})$	$\prod_i p(y^{(i)} \vert \mathbf{x}^{(i)}, \boldsymbol{\theta})$
MAP	$p(\boldsymbol{\theta}) \prod_i p(\mathbf{x}^{(i)}, y^{(i)} \vert \boldsymbol{\theta})$	$p(\boldsymbol{\theta}) \prod_i p(y^{(i)} \vert \mathbf{x}^{(i)}, \boldsymbol{\theta})$

MAP Estimation and Regularization

MAP

$$\begin{aligned}\boldsymbol{\theta}_{\text{MAP}} &= \operatorname*{argmax}_{\boldsymbol{\theta}} \log p(\mathcal{D} \mid \boldsymbol{\theta}) + \log p(\boldsymbol{\theta}) \\ &= \operatorname*{argmin}_{\boldsymbol{\theta}} -\log p(\mathcal{D} \mid \boldsymbol{\theta}) - \log p(\boldsymbol{\theta}) \\ &= \operatorname*{argmin}_{\boldsymbol{\theta}} J_{\mathcal{D}}(\boldsymbol{\theta}) + r(\boldsymbol{\theta})\end{aligned}$$

regularization

fit the data well

keep the model simple

Example: L2 regularization is equivalent to a Gaussian prior

Generative vs. Discriminative

Finite Sample Analysis (Ng & Jordan, 2001)

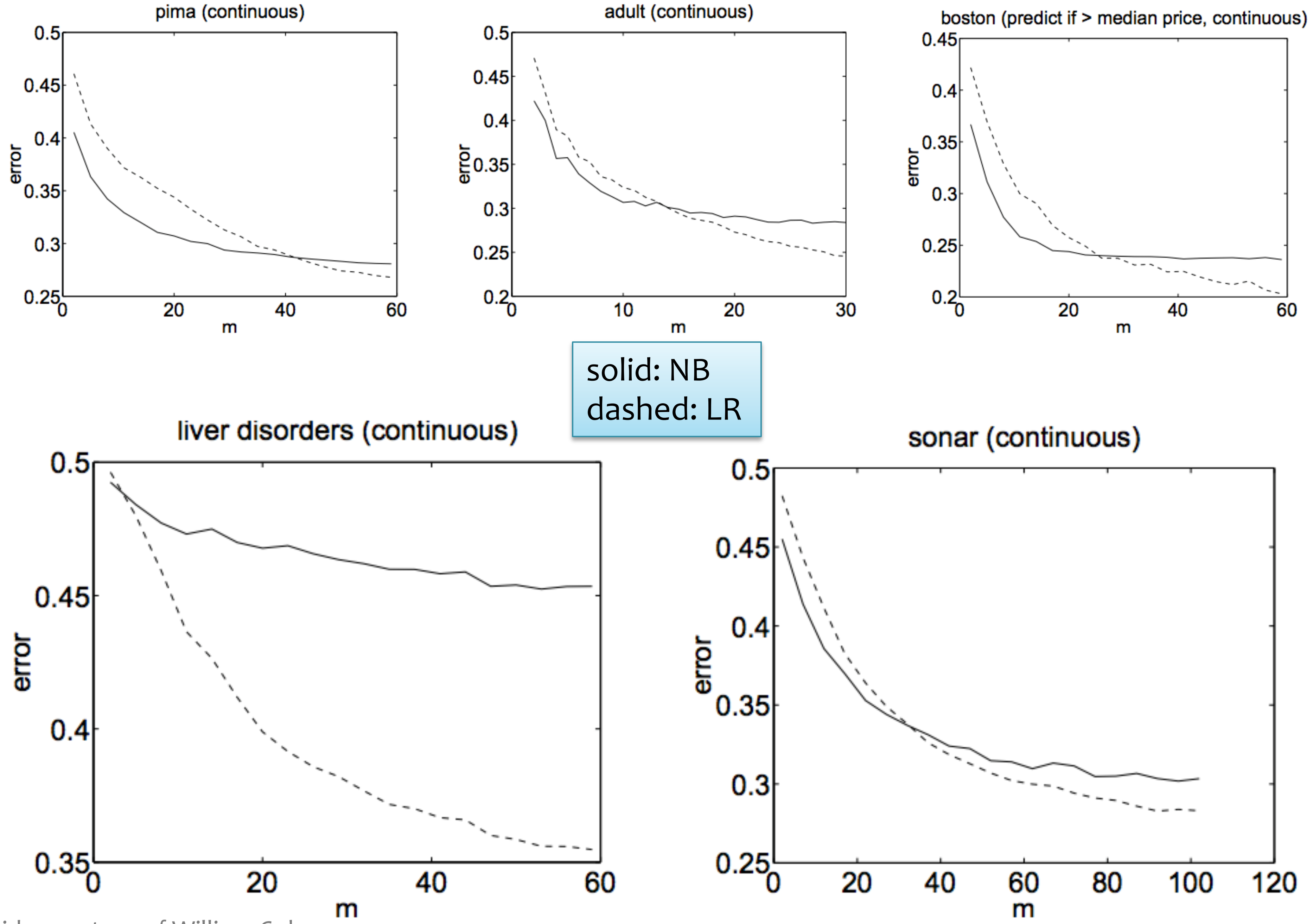
[Assume that we are learning from a finite training dataset]

Naïve Bayes and logistic regression form a *generative-discriminative* model pair:

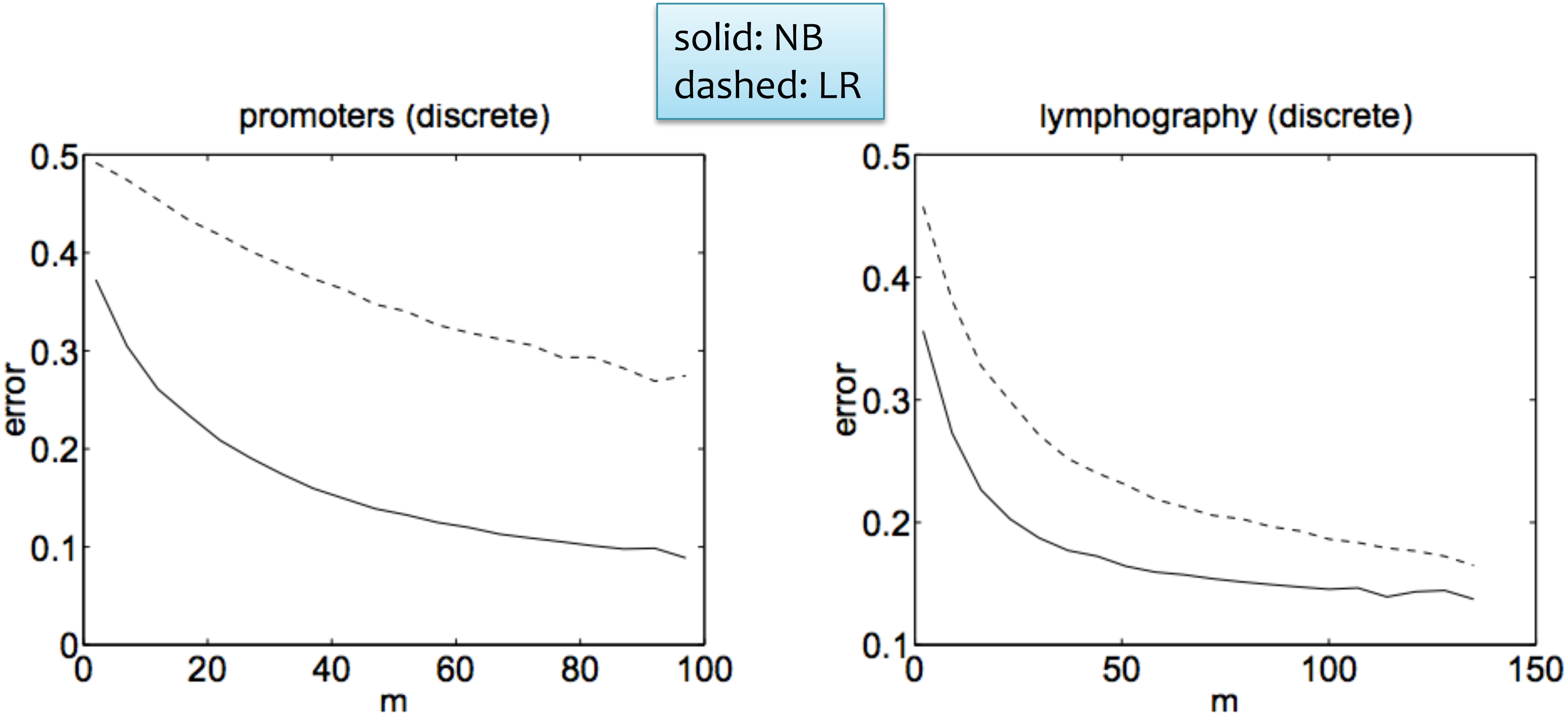
If model assumptions are correct: as the amount of training data increases, Gaussian Naïve Bayes and logistic regression approach the same (linear) decision boundary!

Furthermore, Gaussian Naïve Bayes is a more efficient learner (requires fewer samples) than Logistic Regression

If model assumptions are incorrect: Logistic Regression has lower asymptotic error and does better than Gaussian Naïve Bayes



Slide courtesy of William Cohen



Naïve Bayes makes stronger assumptions about the data but needs fewer examples to estimate the parameters

“On Discriminative vs Generative Classifiers: ….” Andrew Ng and Michael Jordan, NIPS 2001.

Slide courtesy of William Cohen

Naïve Bayes vs. Logistic Reg.

Features

Naïve Bayes:
Features x are assumed to be conditionally independent given y. (i.e. Naïve Bayes Assumption)

Logistic Regression:
No assumptions are made about the form of the features x. They can be dependent and correlated in any fashion.

Naïve Bayes vs. Logistic Reg.

Learning (Parameter Estimation)

Naïve Bayes:
Parameters are decoupled → Closed form solution for MLE

Logistic Regression:
Parameters are coupled → No closed form solution – must use iterative optimization techniques instead

Naïve Bayes vs. Logistic Reg.

Learning (MAP Estimation of Parameters)

Bernoulli Naïve Bayes:
Parameters are probabilities → Beta prior (usually) pushes probabilities away from zero / one extremes

Logistic Regression:
Parameters are not probabilities → Gaussian prior encourages parameters to be close to zero

(effectively pushes the probabilities away from zero / one extremes)

Naïve Bayes vs. Logistic Regression

Question:

You just started working at a new company that manufactures comically large pennies. Your manager asks you to build a binary classifier that takes an image of a penny (on the factory assembly line) and predicts whether or not it has a defect.

What follow-up questions would you pose to your manager in order to decide between using a Naïve Bayes classifier and a Logistic Regression classifier?

Answer:

THE BIG PICTURE

ML Big Picture

Learning Paradigms:

What data is available and when? What form of prediction?

- supervised learning
- unsupervised learning
- semi-supervised learning
- reinforcement learning
- active learning
- imitation learning
- domain adaptation
- online learning
- density estimation
- recommender systems
- feature learning
- manifold learning
- dimensionality reduction
- ensemble learning
- distant supervision
- hyperparameter optimization

Problem Formulation:

What is the structure of our output prediction?

boolean	Binary Classification
categorical	Multiclass Classification
ordinal	Ordinal Classification
real	Regression
ordering	Ranking
multiple discrete	Structured Prediction
multiple continuous	(e.g. dynamical systems)
both discrete & cont.	(e.g. mixed graphical models)

Application Areas

Key challenges?

NLP, Speech, Computer Vision, Robotics, Medicine, Search

Theoretical Foundations:

What principles guide learning?

- ❑ probabilistic
- ❑ information theoretic
- ❑ evolutionary search
- ❑ ML as optimization

Facets of Building ML Systems:

How to build systems that are robust, efficient, adaptive, effective?

1. *Data prep*
2. *Model selection*
3. *Training (optimization / search)*
4. *Hyperparameter tuning on validation data*
5. *(Blind) Assessment on test data*

Big Ideas in ML:

Which are the ideas driving development of the field?

- *inductive bias*
- *generalization / overfitting*
- *bias-variance decomposition*
- *generative vs. discriminative*
- *deep nets, graphical models*
- *PAC learning*
- *distant rewards*

Classification and Regression: The Big Picture

Recipe for Machine Learning

1. Given data $\mathcal{D} = \{\mathbf{x}^{(i)}, y^{(i)}\}_{i=1}^N$
2. (a) Choose a decision function $h_{\boldsymbol{\theta}}(\mathbf{x}) = \cdots$ (parameterized by $\boldsymbol{\theta}$)
   (b) Choose an objective function $J_{\mathcal{D}}(\boldsymbol{\theta}) = \cdots$ (relies on data)
3. Learn by choosing parameters that optimize the objective $J_{\mathcal{D}}(\boldsymbol{\theta})$

$$\hat{\boldsymbol{\theta}} \approx \operatorname*{argmin}_{\boldsymbol{\theta}} J_{\mathcal{D}}(\boldsymbol{\theta})$$

4. Predict on new test example $\mathbf{x}_{\text{new}}$ using $h_{\boldsymbol{\theta}}(\cdot)$

$$\hat{y} = h_{\boldsymbol{\theta}}(\mathbf{x}_{\text{new}})$$

Optimization Method

- Gradient Descent: $\boldsymbol{\theta} \to \boldsymbol{\theta} - \gamma \nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta})$
- SGD: $\boldsymbol{\theta} \to \boldsymbol{\theta} - \gamma \nabla_{\boldsymbol{\theta}} J^{(i)}(\boldsymbol{\theta})$
  for $i \sim$ Uniform$(1, \ldots, N)$
  where $J(\boldsymbol{\theta}) = \frac{1}{N} \sum_{i=1}^N J^{(i)}(\boldsymbol{\theta})$
- mini-batch SGD
- closed form
  1. compute partial derivatives
  2. set equal to zero and solve

Decision Functions

- Perceptron: $h_{\boldsymbol{\theta}}(\mathbf{x}) = \text{sign}(\boldsymbol{\theta}^T \mathbf{x})$
- Linear Regression: $h_{\boldsymbol{\theta}}(\mathbf{x}) = \boldsymbol{\theta}^T \mathbf{x}$
- Discriminative Models: $h_{\boldsymbol{\theta}}(\mathbf{x}) = \operatorname*{argmax}_y p_{\boldsymbol{\theta}}(y \mid \mathbf{x})$
  - Logistic Regression: $p_{\boldsymbol{\theta}}(y = 1 \mid \mathbf{x}) = \sigma(\boldsymbol{\theta}^T \mathbf{x})$
  - Neural Net (classification):
    $p_{\boldsymbol{\theta}}(y = 1 \mid \mathbf{x}) = \sigma((\mathbf{W}^{(2)})^T \sigma((\mathbf{W}^{(1)})^T \mathbf{x} + \mathbf{b}^{(1)}) + \mathbf{b}^{(2)})$
- Generative Models: $h_{\boldsymbol{\theta}}(\mathbf{x}) = \operatorname*{argmax}_y p_{\boldsymbol{\theta}}(\mathbf{x}, y)$
  - Naive Bayes: $p_{\boldsymbol{\theta}}(\mathbf{x}, y) = p_{\boldsymbol{\theta}}(y) \prod_{m=1}^M p_{\boldsymbol{\theta}}(x_m \mid y)$

Objective Function

- MLE: $J(\boldsymbol{\theta}) = -\sum_{i=1}^N \log p(\mathbf{x}^{(i)}, \mathbf{y}^{(i)})$
- MCLE: $J(\boldsymbol{\theta}) = -\sum_{i=1}^N \log p(\mathbf{y}^{(i)} \mid \mathbf{x}^{(i)})$
- L2 Regularized: $J'(\boldsymbol{\theta}) = J(\boldsymbol{\theta}) + \lambda ||\boldsymbol{\theta}||_2^2$
  (same as Gaussian prior $p(\boldsymbol{\theta})$ over parameters)
- L1 Regularized: $J'(\boldsymbol{\theta}) = J(\boldsymbol{\theta}) + \lambda ||\boldsymbol{\theta}||_1$
  (same as Laplace prior $p(\boldsymbol{\theta})$ over parameters)

Backpropagation and Deep Learning

Convolutional neural networks (CNNs) and **recurrent neural networks** (RNNs) are simply fancy computation graphs (aka. hypotheses or decision functions).

Our recipe also applies to these models and (again) relies on the **backpropagation algorithm** to compute the necessary gradients.

BACKGROUND: HUMAN LANGUAGE TECHNOLOGIES

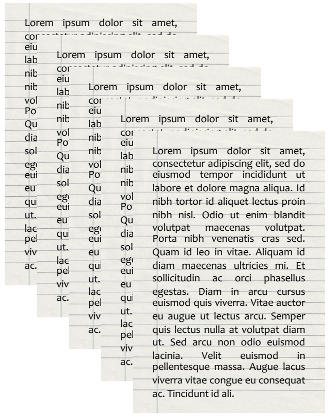
Human Language Technologies

Speech Recognition

Machine Translation

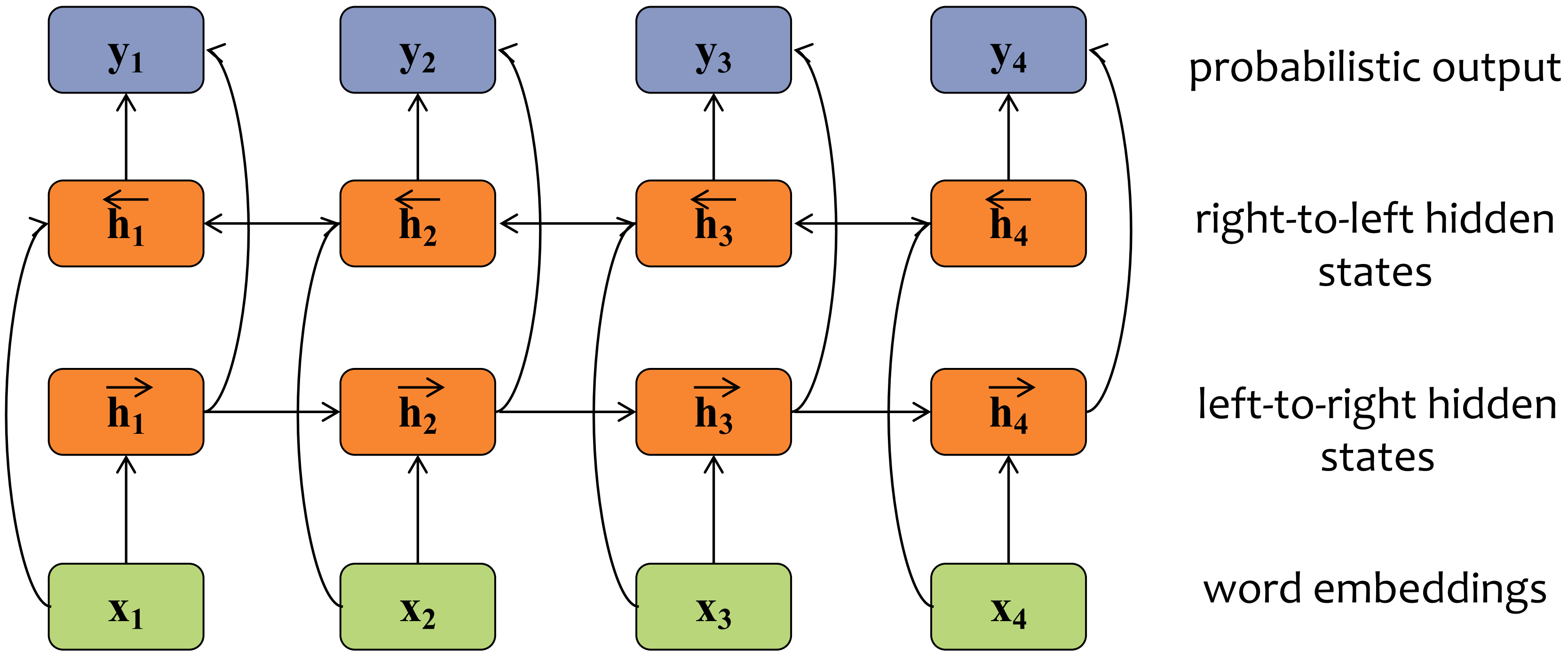
기계 번역은 특히 영어와 한국어와 같은 언어 쌍의 경우 매우 어렵습니다.

Summarization



Bidirectional RNN

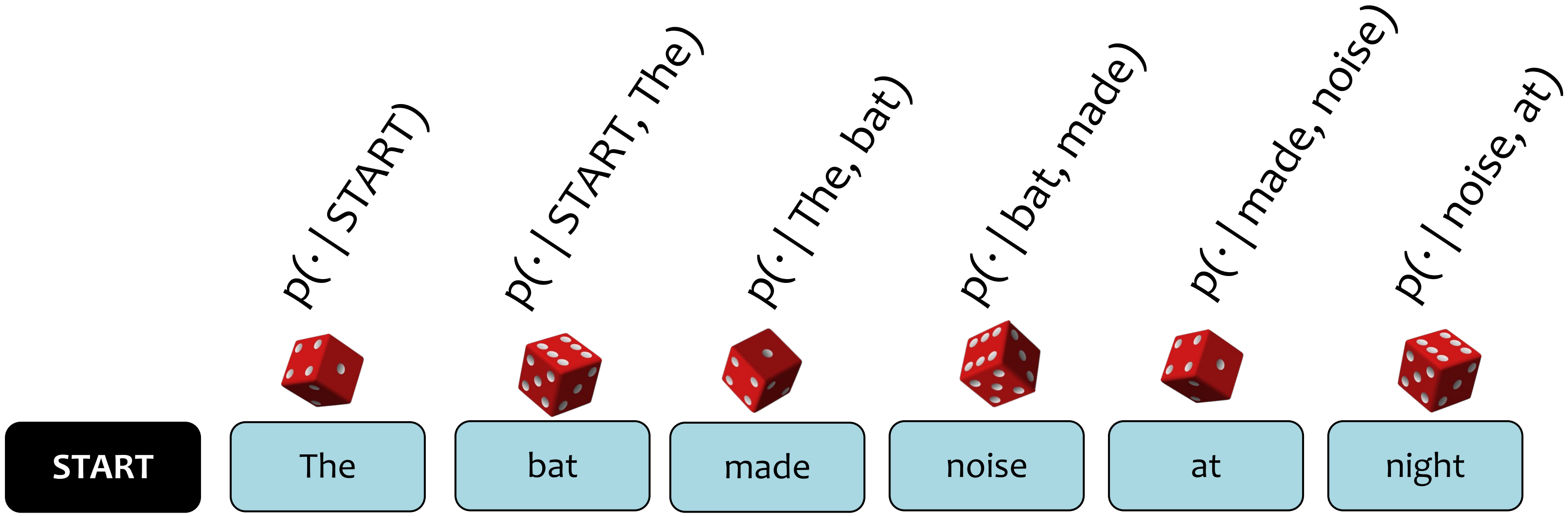
RNNs are a now commonplace backbone in deep learning approaches to natural language processing



BACKGROUND:
N-GRAM LANGUAGE MODELS

n-Gram Language Model

- *Goal*: Generate realistic looking sentences in a human language
- *Key Idea*: condition on the last n-1 words to sample the n^{th} word



n-Gram Language Model

<u>*Question*</u>: How can we **define** a probability distribution over a sequence of length T?

The	bat	made	noise	at	night
w_1	w_2	w_3	w_4	w_5	w_6

n-Gram Model (n=2)

$$p(w_1, w_2, \ldots, w_T) = \prod_{t=1}^{T} p(w_t \mid w_{t-1})$$

$p(w_1, w_2, w_3, \ldots, w_6) =$

The	$p(w_1)$
The bat	$p(w_2 \mid w_1)$
bat made	$p(w_3 \mid w_2)$
made noise	$p(w_4 \mid w_3)$
noise at	$p(w_5 \mid w_4)$
at night	$p(w_6 \mid w_5)$

n-Gram Language Model

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The	bat	made	noise	at	night
w_1	w_2	w_3	w_4	w_5	w_6

n-Gram Model (n=3)

$$p(w_1, w_2, \ldots, w_T) = \prod_{t=1}^{T} p(w_t \mid w_{t-1}, w_{t-2})$$

$p(w_1, w_2, w_3, \ldots, w_6) =$

The — $p(w_1)$

The bat — $p(w_2 \mid w_1)$

The bat made — $p(w_3 \mid w_2, w_1)$

bat made noise — $p(w_4 \mid w_3, w_2)$

made noise at — $p(w_5 \mid w_4, w_3)$

noise at night — $p(w_6 \mid w_5, w_4)$

n-Gram Language Model

Question: How can we **define** a probability distribution over a sequence of length T?

The	bat	made	noise	at	night
w_1	w_2	w_3	w_4	w_5	w_6

n-Gram Model (n=3)

$$p(w_1, w_2, \ldots, w_T) = \prod_{t=1}^{T} p(w_t \mid w_{t-1}, w_{t-2})$$

$p(w_1,$ … $w_3, \ldots, w_6) =$

The

$p(w_1)$

The

The

Note: This is called a **model** because we made some **assumptions** about how many previous words to condition on (i.e. only n-1 words)

Learning an n-Gram Model

<u>Question</u>: How do we **learn** the probabilities for the n-Gram Model?

$p(w_t \mid w_{t-2} = \text{The}, w_{t-1} = \text{bat})$

w_t	$p(\cdot \mid \cdot, \cdot)$
ate	0.015
…	
flies	0.046
…	
zebra	0.000

$p(w_t \mid w_{t-2} = \text{made}, w_{t-1} = \text{noise})$

w_t	$p(\cdot \mid \cdot, \cdot)$
at	0.020
…	
pollution	0.030
…	
zebra	0.000

$p(w_t \mid w_{t-2} = \text{cows}, w_{t-1} = \text{eat})$

w_t	$p(\cdot \mid \cdot, \cdot)$
corn	0.420
…	
grass	0.510
…	
zebra	0.000

Learning an n-Gram Model

<u>Question</u>: How do we **learn** the probabilities for the n-Gram Model?
<u>Answer</u>: From data! Just **count** n-gram frequencies

…the **cows eat** grass…
…our **cows eat hay** daily…
…factory-farm **cows eat** corn…
…on an organic farm, **cows eat hay** and…
…do your **cows eat** grass or corn?...
…what do **cows eat if** they have…
…**cows eat** corn when there is no…
…which **cows eat which** foods depends…
…if **cows eat** grass…
…when **cows eat** corn their stomachs…
…should we let **cows eat** corn?...

$p(w_t \mid w_{t-2} = \text{cows}, w_{t-1} = \text{eat})$

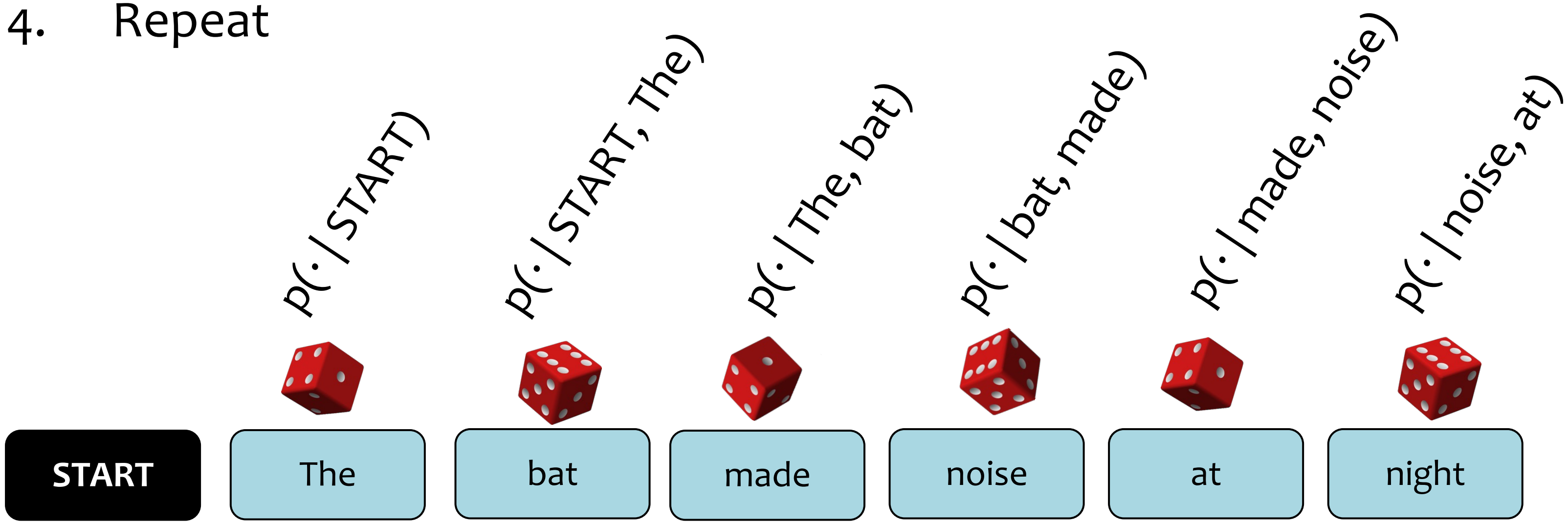
w_t	$p(\cdot \mid \cdot, \cdot)$
corn	4/11
grass	3/11
hay	2/11
if	1/11
which	1/11

Sampling from a Language Model

Question: How do we sample from a Language Model?

Answer:

1. Treat each probability distribution like a (50k-sided) weighted die
2. Pick the die corresponding to $p(w_t \mid w_{t-2}, w_{t-1})$
3. Roll that die and generate whichever word w_t lands face up
4. Repeat



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Training Data (Shakespeaere)

I tell you, friends, most charitable care ave the patricians of you. For your wants, Your suffering in this dearth, you may as well Strike at the heaven with your staves as lift them Against the Roman state, whose course will on The way it takes, cracking ten thousand curbs Of more strong link asunder than can ever Appear in your impediment. For the dearth, The gods, not the patricians, make it, and Your knees to them, not arms, must help.

5-Gram Model

```
Approacheth, denay. dungy
Thither! Julius think: grant,--O
Yead linens, sheep's Ancient,
Agreed: Petrarch plaguy Resolved
pear! observingly honourest
adulteries wherever scabbard
guess; affirmation--his monsieur;
died. jealousy, chequins me.
Daphne building. weakness: sun-
rise, cannot stays carry't,
unpurposed. prophet-like drink;
back-return 'gainst surmise
Bridget ships? wane; interim?
She's striving wet;
```

RECURRENT NEURAL NETWORK (RNN) LANGUAGE MODELS

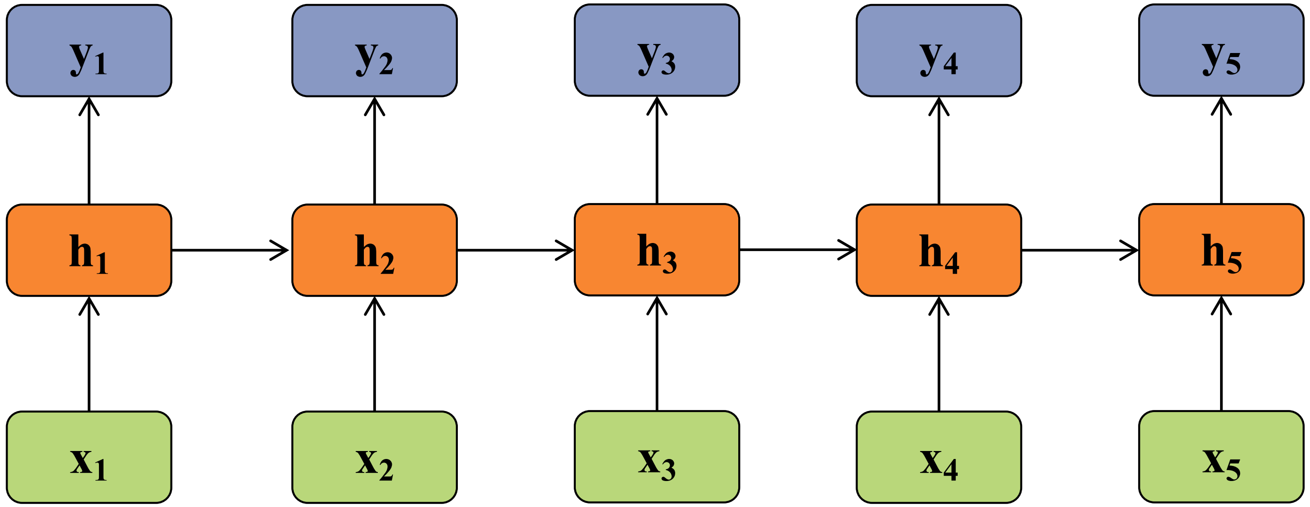
Recurrent Neural Networks (RNNs)

$$\begin{aligned} \text{inputs: } \mathbf{x} &= (x_1, x_2, \ldots, x_T), x_i \in \mathcal{R}^I \\ \text{hidden units: } \mathbf{h} &= (h_1, h_2, \ldots, h_T), h_i \in \mathcal{R}^J \\ \text{outputs: } \mathbf{y} &= (y_1, y_2, \ldots, y_T), y_i \in \mathcal{R}^K \\ \text{nonlinearity: } &\mathcal{H} \end{aligned}$$

Definition of the RNN:

$$h_t = \mathcal{H}\left(W_{xh}x_t + W_{hh}h_{t-1} + b_h\right)$$

$$y_t = W_{hy}h_t + b_y$$



The Chain Rule of Probability

Recall…

Question: How can we **define** a probability distribution over a sequence of length T?

The	bat	made	noise	at	night
w_1	w_2	w_3	w_4	w_5	w_6

Chain rule of probability: $$p(w_1, w_2, \ldots, w_T) = \prod_{t=1}^{T} p(w_t \mid w_{t-1}, \ldots, w_1)$$

$p(w_1, w_2, w_3, \ldots, w_6) =$

The — $p(w_1)$

The — $p(w_2 \mid w_1)$

The

The

The

The bat made noise at night — $p(w_6 \mid w_5, w_4, w_3, w_2, w_1)$

Note: This is called the chain **rule** because it is **always** true for every probability distribution

RNN Language Model

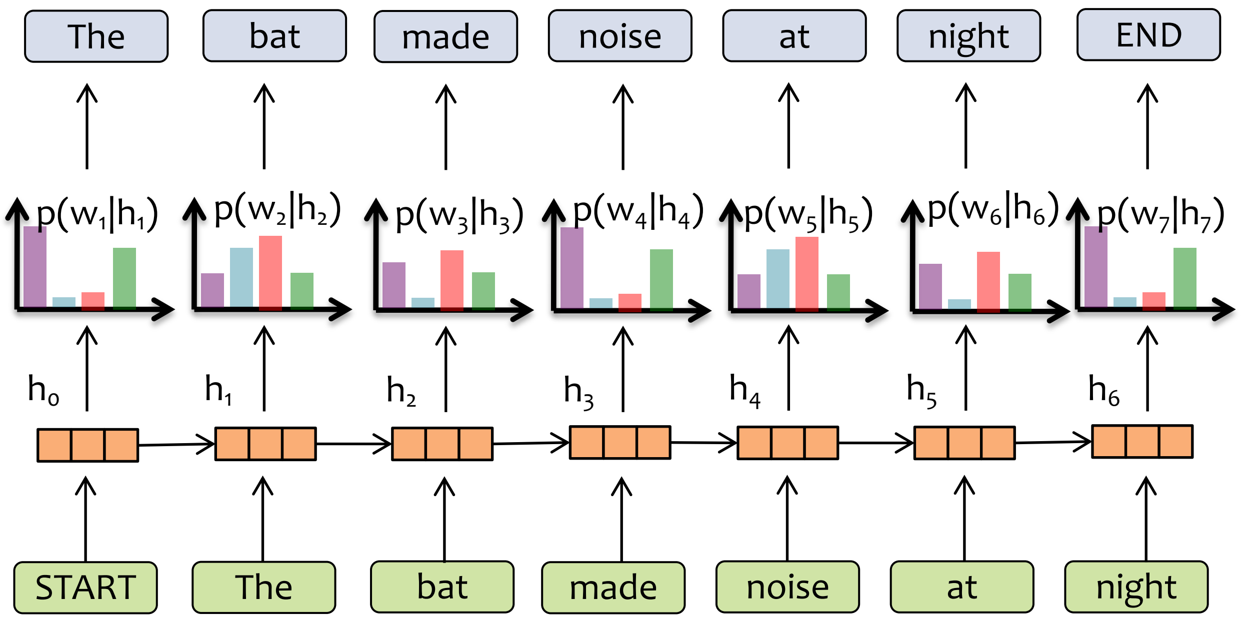
RNN Language Model: $p(w_1, w_2, \ldots, w_T) = \prod_{t=1}^{T} p(w_t \mid f_{\boldsymbol{\theta}}(w_{t-1}, \ldots, w_1))$

$p(w_1, w_2, w_3, \ldots, w_6) =$

The						$p(w_1)$
The	bat					$p(w_2 \mid f_\theta(w_1))$
The	bat	made				$p(w_3 \mid f_\theta(w_2, w_1))$
The	bat	made	noise			$p(w_4 \mid f_\theta(w_3, w_2, w_1))$
The	bat	made	noise	at		$p(w_5 \mid f_\theta(w_4, w_3, w_2, w_1))$
The	bat	made	noise	at	night	$p(w_6 \mid f_\theta(w_5, w_4, w_3, w_2, w_1))$

Key Idea:
(1) convert all previous words to a **fixed length vector**
(2) define distribution $p(w_t \mid f_\theta(w_{t-1}, \ldots, w_1))$ that conditions on the vector

RNN Language Model



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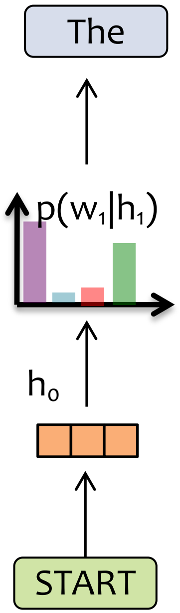

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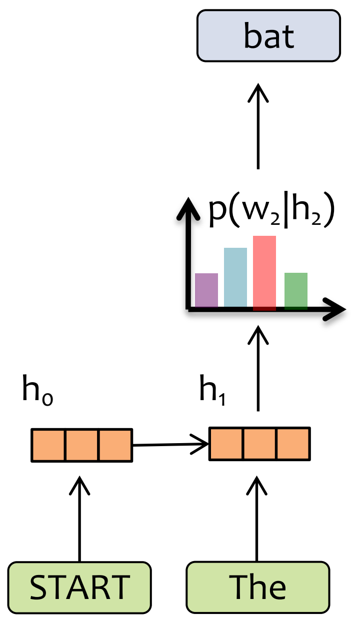

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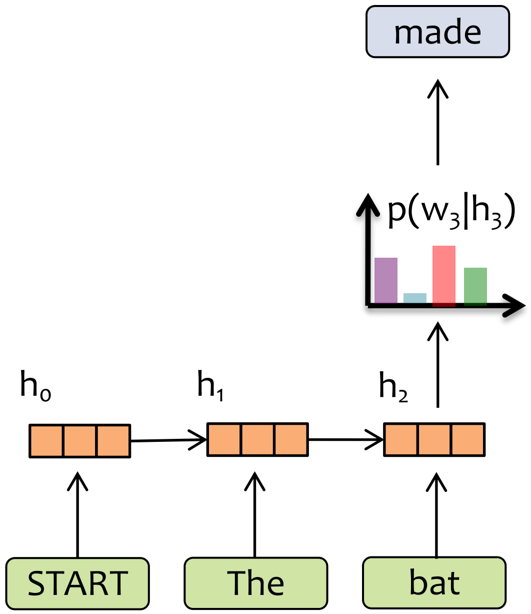
RNN Language Model



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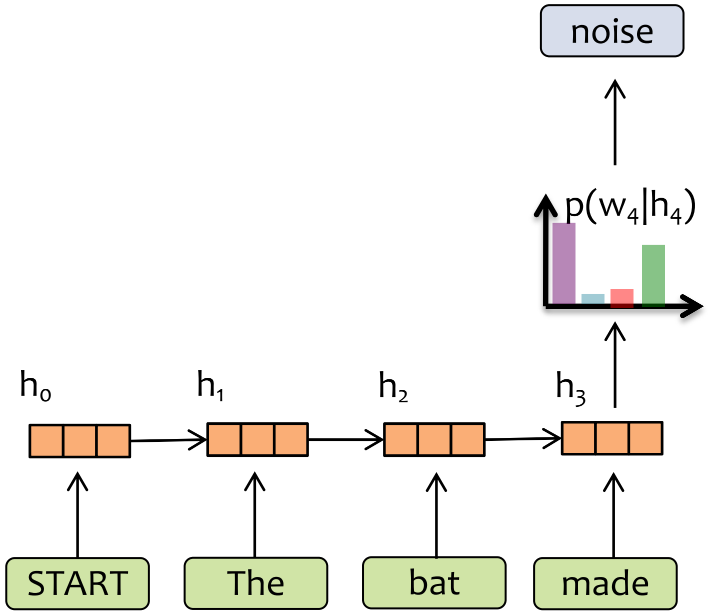
RNN Language Model



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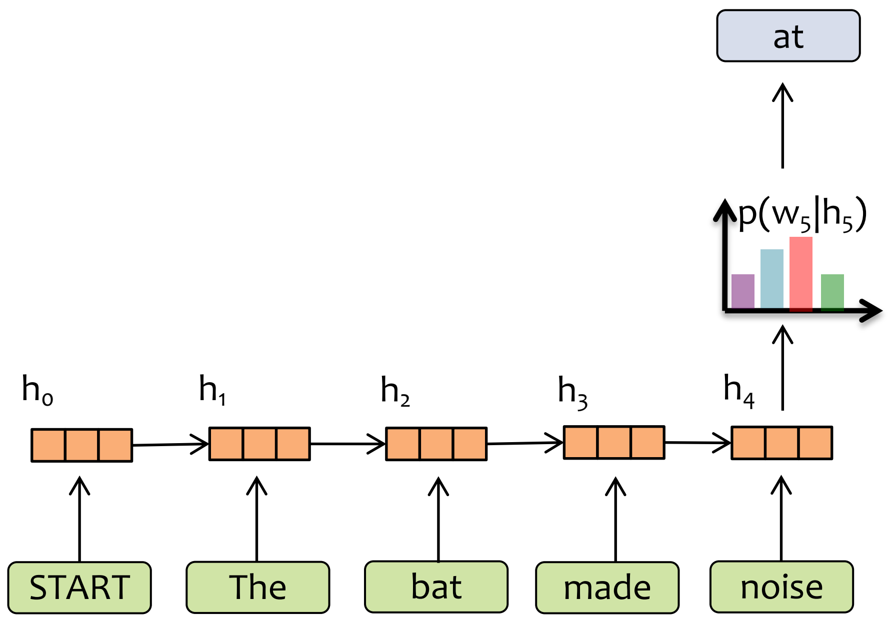
RNN Language Model



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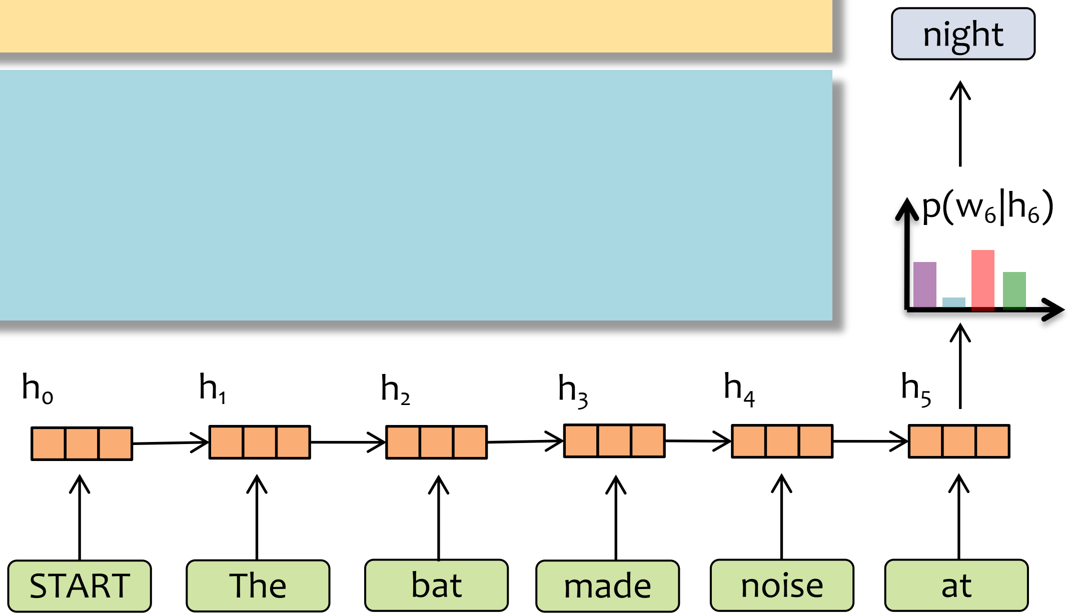
RNN Language Model

Question: How can we create a distribution $p(w_t|h_t)$ from h_t?

Answer:



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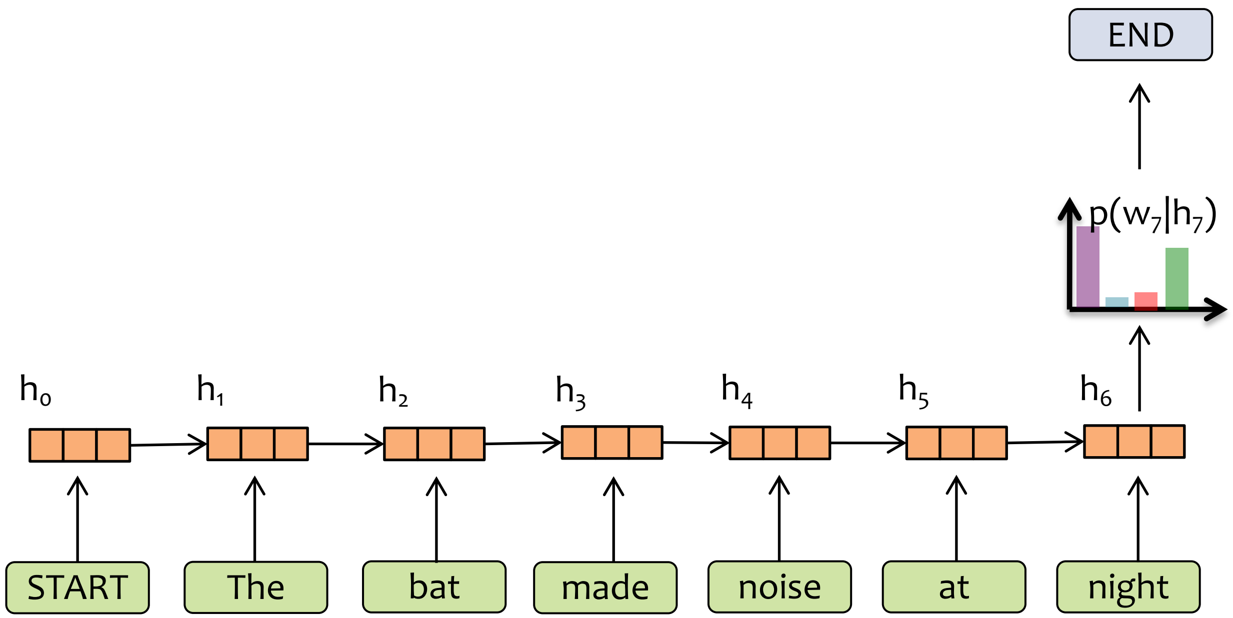
RNN Language Model



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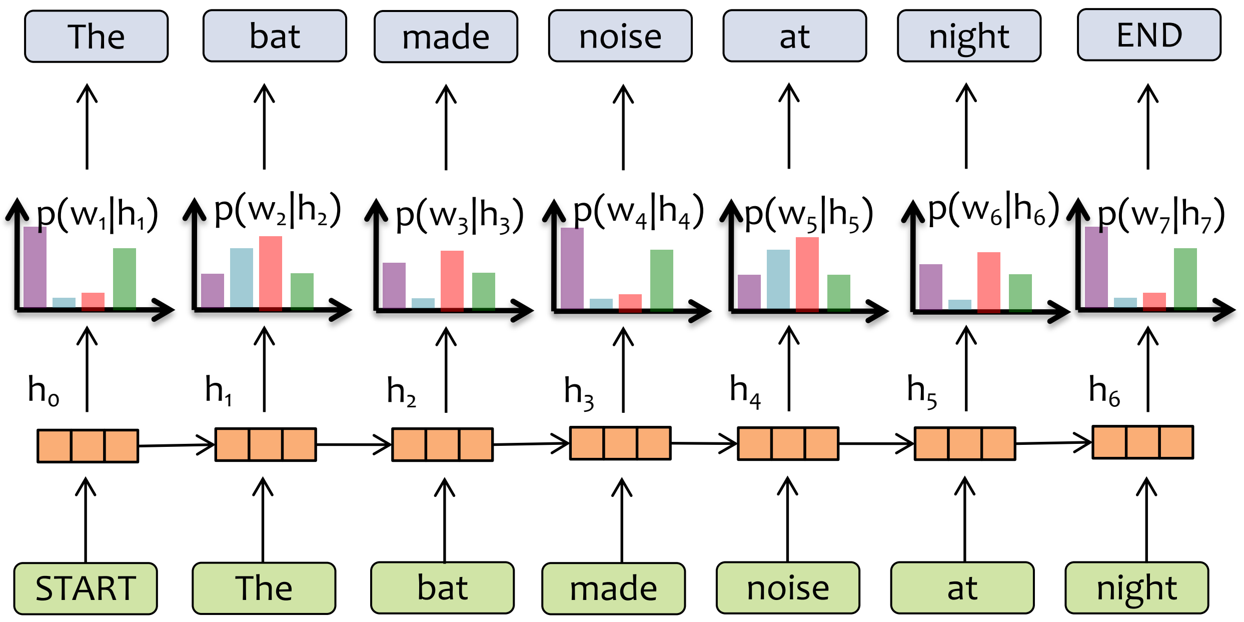
RNN Language Model

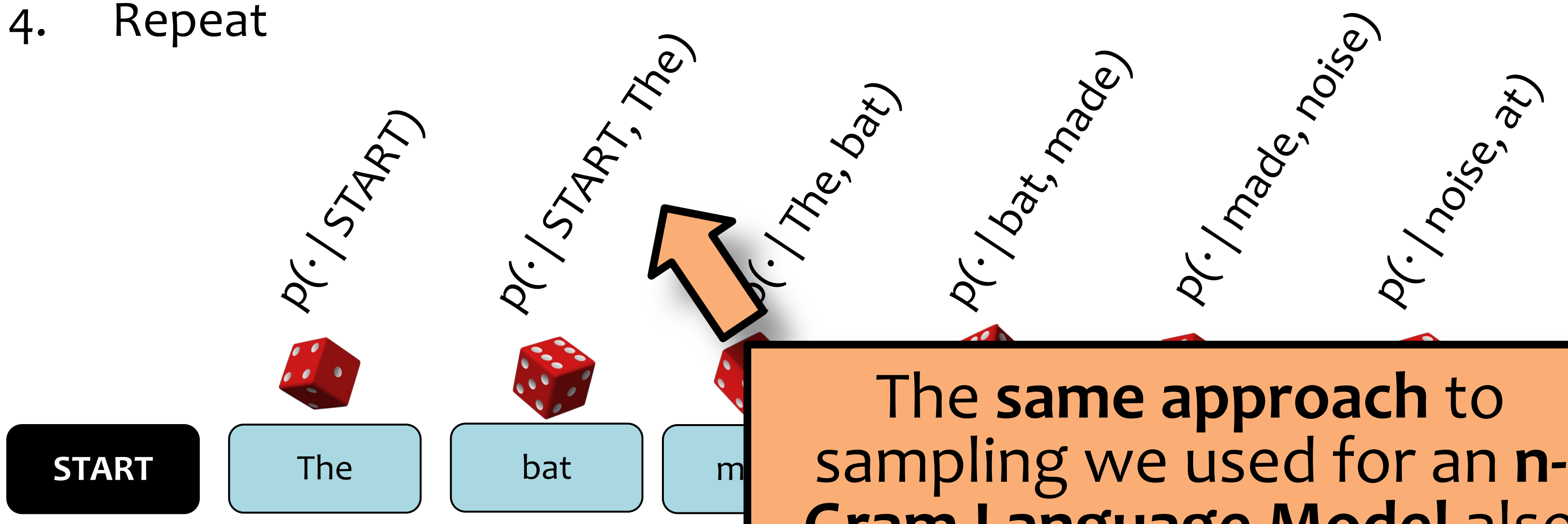


$$p(w_1, w_2, w_3, \ldots, w_T) = p(w_1 \mid h_1)\, p(w_2 \mid h_2) \ldots\, p(w_2 \mid h_T)$$

Sampling from a Language Model

Question: How do we sample from a Language Model?
Answer:

1. Treat each probability distribution like a (50k-sided) weighted die
2. Pick the die corresponding to $p(w_t \mid w_{t-2}, w_{t-1})$
3. Roll that die and generate whichever word w_t lands face up
4. Repeat



The **same approach** to sampling we used for an **n-Gram Language Model** also works here for an **RNN Language Model**

Sampling from an RNN-LM

??

VIOLA: Why, Salisbury must find his flesh and thought That which I am not aps, not a man and in fire, To show the reining of the raven and the wars To grace my hand reproach within, and not a fair are hand, That Caesar and my goodly father's world; When I was heaven of presence and our fleets, We spare with hours, but cut thy council I am great, Murdered and by thy m… there My power to give thee but so much … service in the noble bondman here, Would … her wine.

KING LEAR: O, if you were a feeble sight, the courtesy of your law, Your sight and several breath, will wear the gods With his heads, and my hands are wonder'd at the deeds, So drop upon your lordship's head, and your opinion Shall be against your honour.

??

CHARLES: Marry, do I, sir; and I came to acquaint you with a matter. I am given, sir, secretly to understand that your younger brother Orlando hath a disposition to come in disguised against me to try a fall. To-morrow, sir, I wrestle for my credit; and he that escapes me without some broken limb shall acquit him well. Your brother is …ender; and, for your love, I would be …, as I must, for my own honour, if he …ore, out of my love to you, I came hither to acquaint you withal, that either you might stay him from his intend… or brook such disgrace well as he shall run into, in tha… is a thing of his own search and altogether against my will.

TOUCHSTONE: For my part, I had rather bear with you than bear you; yet I should bear no cross if I did bear you, for I think you have no money in your purse.

Which is the real Shakespeare?!

Example from http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Sampling from an RNN-LM

Shakespeare's As You Like It

VIOLA: Why, Salisbury must find his flesh and thought That which I am not aps, not a man and in fire, To show the reining of the raven and the wars To grace my hand reproach within, and not a fair are hand, That Caesar and my goodly father's world; When I was heaven of presence and our fleets, We spare with hours, but cut thy council I am great, Murdered and by thy master's ready there My power to give thee but so much as hell: Some service in the noble bondman here, Would show him to her wine.

KING LEAR: O, if you were a feeble sight, the courtesy of your law, Your sight and several breath, will wear the gods With his heads, and my hands are wonder'd at the deeds, So drop upon your lordship's head, and your opinion Shall be against your honour.

RNN-LM Sample

CHARLES: Marry, do I, sir; and I came to acquaint you with a matter. I am given, sir, secretly to understand that your younger brother Orlando hath a disposition to come in disguised against me to try a fall. To-morrow, sir, I wrestle for my credit; and he that escapes me without some broken limb shall acquit him well. Your brother is but young and tender; and, for your love, I would be loath to foil him, as I must, for my own honour, if he come in: therefore, out of my love to you, I came hither to acquaint you withal, that either you might stay him from his intendment or brook such disgrace well as he shall run into, in that it is a thing of his own search and altogether against my will.

TOUCHSTONE: For my part, I had rather bear with you than bear you; yet I should bear no cross if I did bear you, for I think you have no money in your purse.

Example from http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Sampling from an RNN-LM

RNN-LM Sample

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Shakespeare's As You Like It

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Example from http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Sampling from an RNN-LM

??

VIOLA: Why, Salisbury must find his flesh and thought That which I am not aps, not a man and in fire, To show the reining of the raven and the wars To grace my hand reproach within, and not a fair are hand, That Caesar and my goodly father's world; When I was heaven of presence and our fleets, We spare with hours, but cut thy council I am great, Murdered and by thy m there My power to give thee but so much service in the noble bondman here, Would her wine.

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Which is the real Shakespeare?!

Example from http://karpathy.github.io/2015/05/21/rnn-effectiveness/

SEQUENCE TO SEQUENCE MODELS

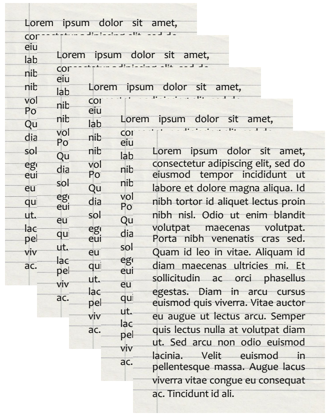
Sequence to Sequence Model

Speech Recognition

Machine Translation

기계 번역은 특히 영어와 한국어와 같은 언어 쌍의 경우 매우 어렵습니다.

Summarization



Sequence to Sequence Model

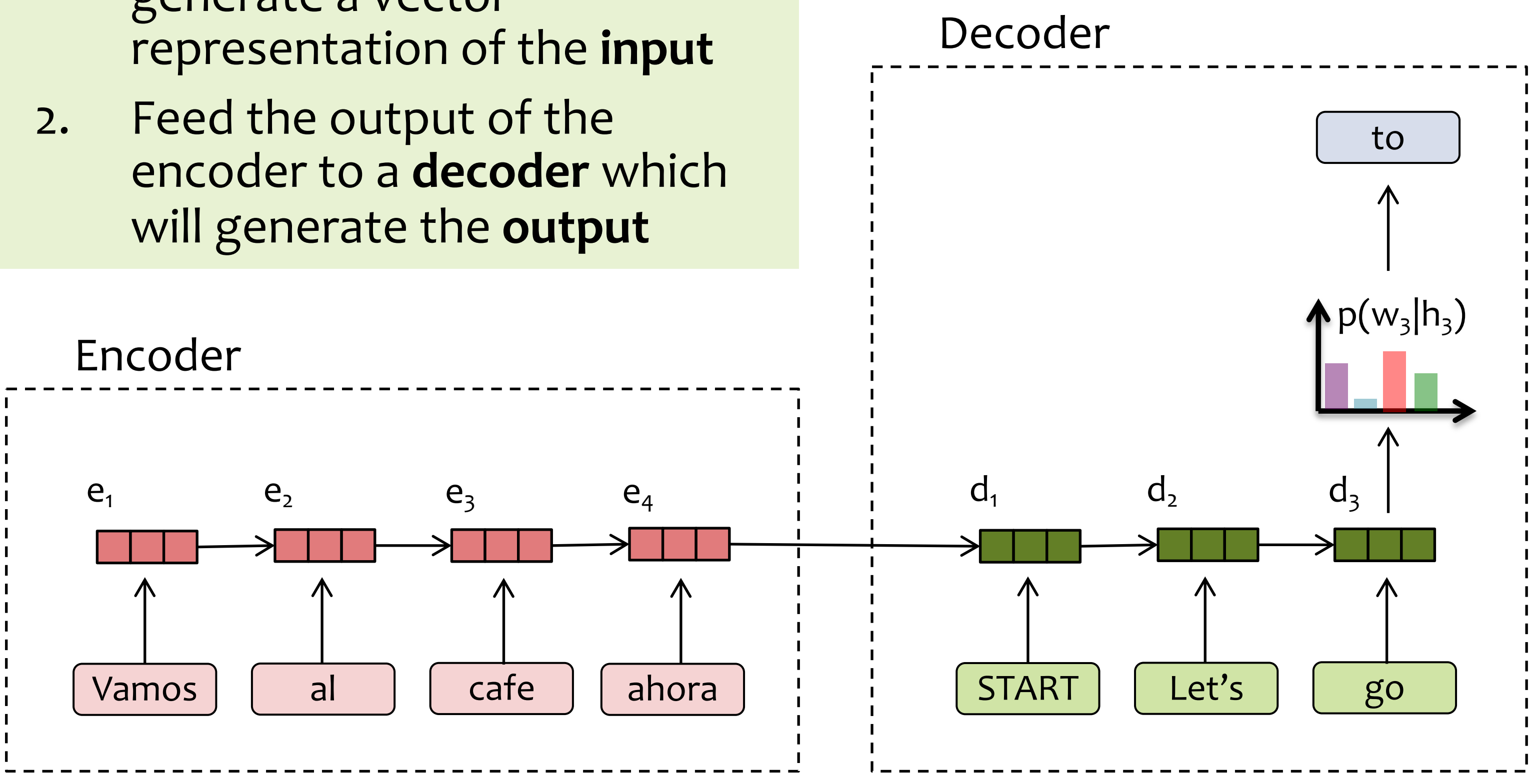
Now suppose you want generate a sequence conditioned on another input

Key Idea:

1. Use an **encoder** model to generate a vector representation of the **input**
2. Feed the output of the encoder to a **decoder** which will generate the **output**

Applications:

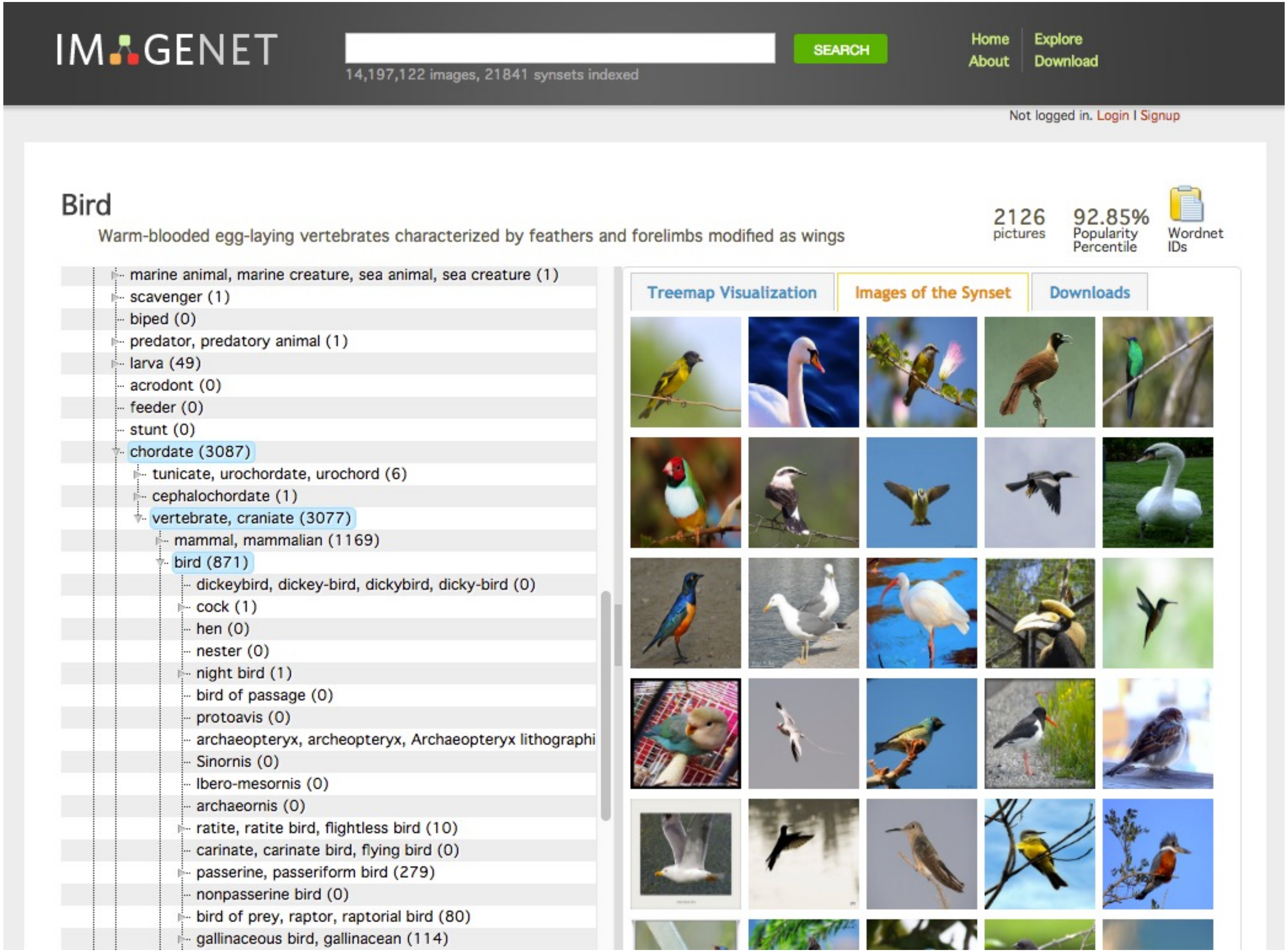
- translation:
  Spanish → English
- summarization:
  article → summary
- speech recognition:
  speech signal → transcription



BACKGROUND: COMPUTER VISION

Example: Image Classification

- ImageNet LSVRC-2011 contest:
  - **Dataset:** 1.2 million labeled images, 1000 classes
  - **Task:** Given a new image, label it with the correct class
  - **Multiclass** classification problem
- Examples from http://image-net.org/


IMAGENET
SEARCH
14,197,122 images, 21841 synsets indexed
Home
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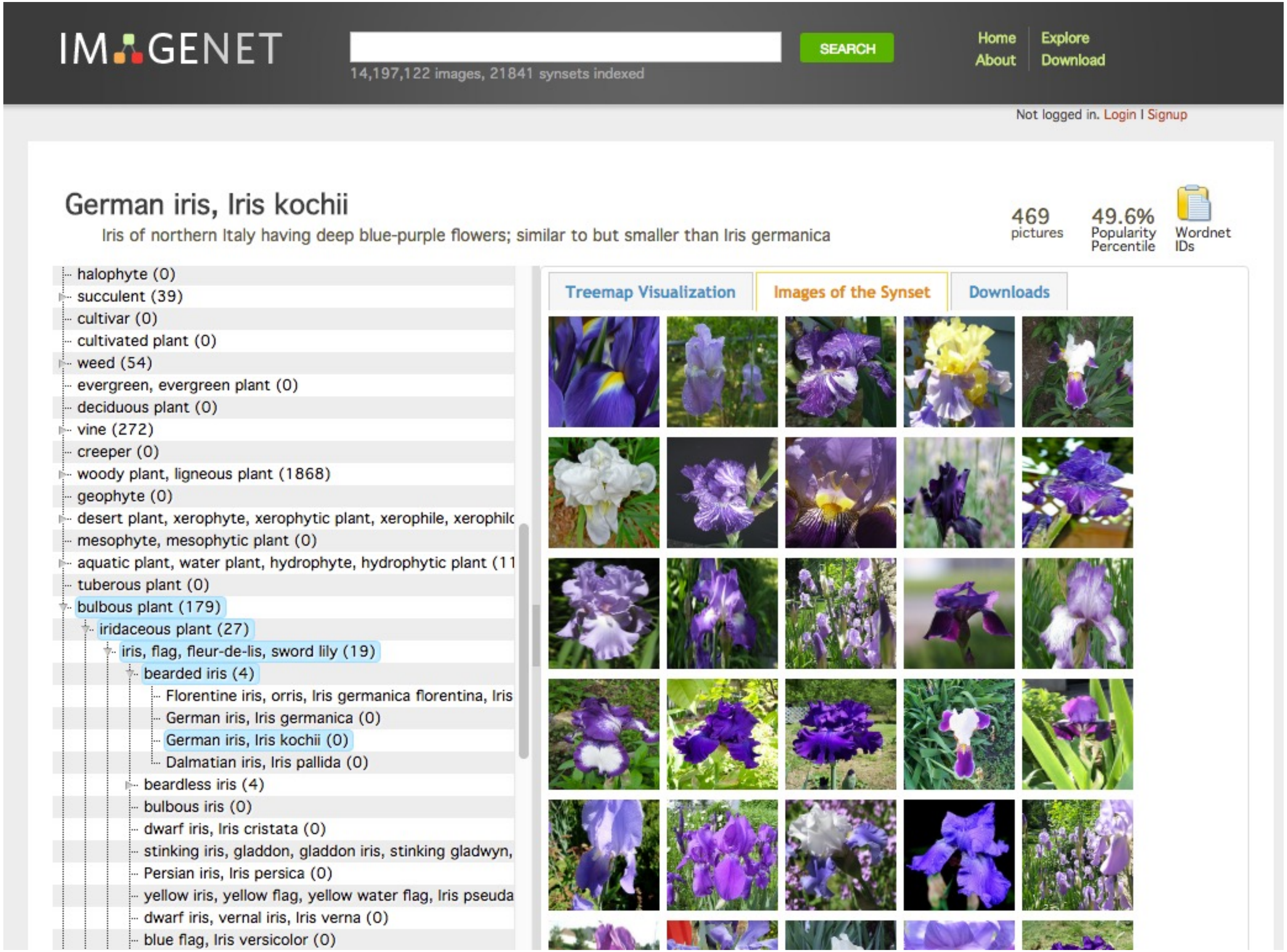
Bird
Warm-blooded egg-laying vertebrates characterized by feathers and forelimbs modified as wings
2126 pictures
92.85% Popularity Percentile
Wordnet IDs
marine animal, marine creature, sea animal, sea creature (1)
scavenger (1)
biped (0)
predator, predatory animal (1)
larva (49)
acrodont (0)
feeder (0)
stunt (0)
chordate (3087)
tunicate, urochordate, urochord (6)
cephalochordate (1)
vertebrate, craniate (3077)
mammal, mammalian (1169)
bird (871)
dickeybird, dickey-bird, dickybird, dicky-bird (0)
cock (1)
hen (0)
nester (0)
night bird (1)
bird of passage (0)
protoavis (0)
archaeopteryx, archeopteryx, Archaeopteryx lithographi
Sinornis (0)
Ibero-mesornis (0)
archaeornis (0)
ratite, ratite bird, flightless bird (10)
carinate, carinate bird, flying bird (0)
passerine, passeriform bird (279)
nonpasserine bird (0)
bird of prey, raptor, raptorial bird (80)
gallinaceous bird, gallinacean (114)
Treemap Visualization
Images of the Synset
Downloads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SEARCH
14,197,122 images, 21841 synsets indexed
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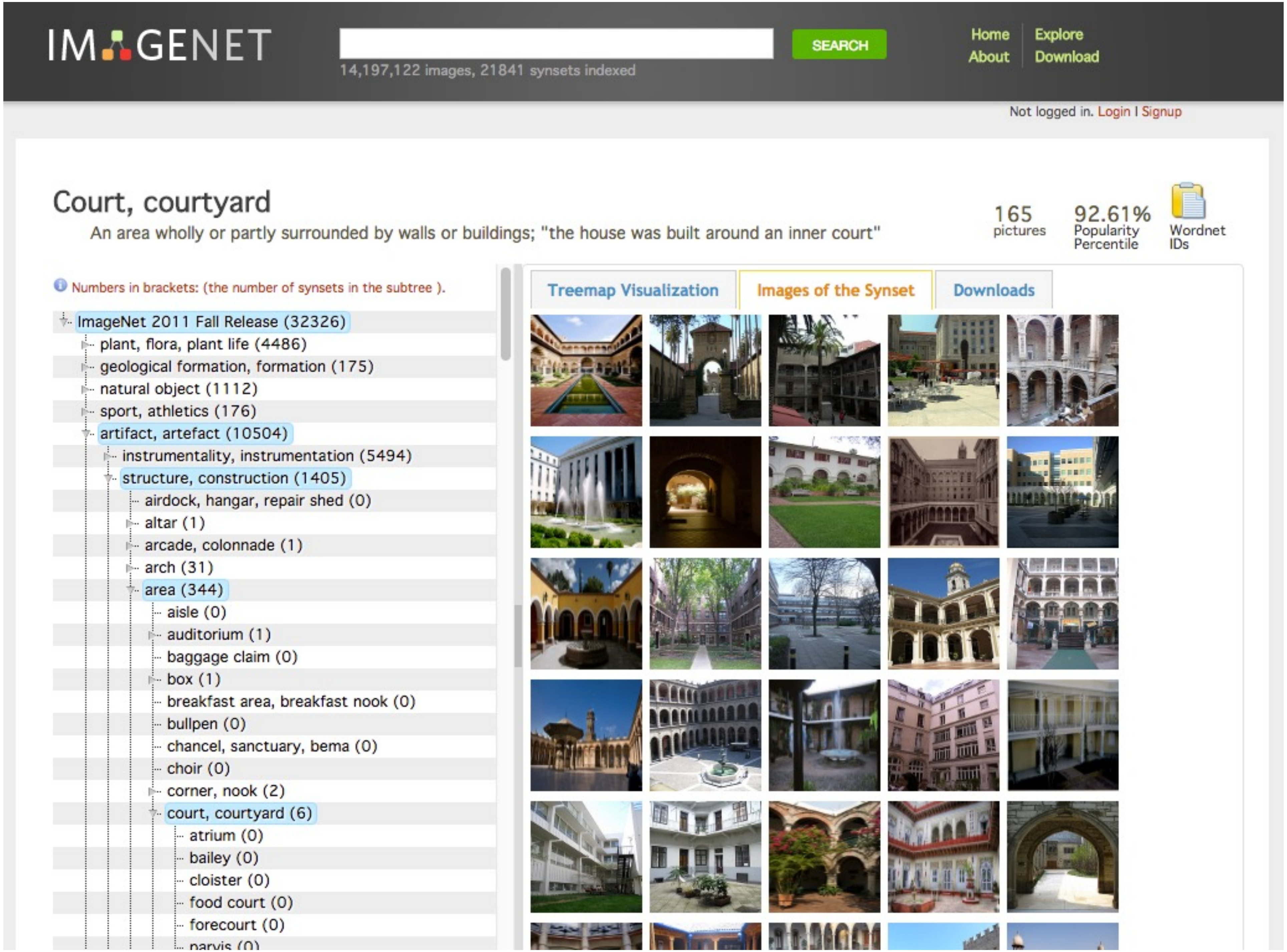
German iris, Iris kochii
Iris of northern Italy having deep blue-purple flowers; similar to but smaller than Iris germanica
469
pictures
49.6%
Popularity Percentile
Wordnet IDs
halophyte (0)
succulent (39)
cultivar (0)
cultivated plant (0)
weed (54)
evergreen, evergreen plant (0)
deciduous plant (0)
vine (272)
creeper (0)
woody plant, ligneous plant (1868)
geophyte (0)
desert plant, xerophyte, xerophytic plant, xerophile, xerophilc
mesophyte, mesophytic plant (0)
aquatic plant, water plant, hydrophyte, hydrophytic plant (11
tuberous plant (0)
bulbous plant (179)
iridaceous plant (27)
iris, flag, fleur-de-lis, sword lily (19)
bearded iris (4)
Florentine iris, orris, Iris germanica florentina, Iris
German iris, Iris germanica (0)
German iris, Iris kochii (0)
Dalmatian iris, Iris pallida (0)
beardless iris (4)
bulbous iris (0)
dwarf iris, Iris cristata (0)
stinking iris, gladdon, gladdon iris, stinking gladwyn,
Persian iris, Iris persica (0)
yellow iris, yellow flag, yellow water flag, Iris pseuda
dwarf iris, vernal iris, Iris verna (0)
blue flag, Iris versicolor (0)
Treemap Visualization
Images of the Synset
Downloads


IMAGENET
SEARCH
14,197,122 images, 21841 synsets indexed
Home
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Explore
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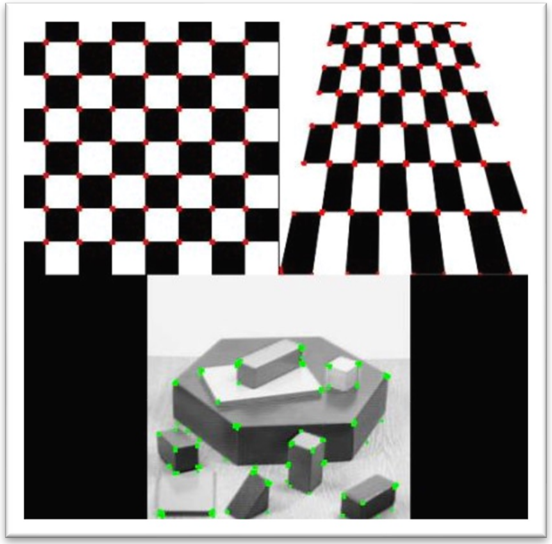
Not logged in. Login I Signup
Court, courtyard
An area wholly or partly surrounded by walls or buildings; "the house was built around an inner court"
165 pictures
92.61% Popularity Percentile
Wordnet IDs
Numbers in brackets: (the number of synsets in the subtree).
ImageNet 2011 Fall Release (32326)
plant, flora, plant life (4486)
geological formation, formation (175)
natural object (1112)
sport, athletics (176)
artifact, artefact (10504)
instrumentality, instrumentation (5494)
structure, construction (1405)
airdock, hangar, repair shed (0)
altar (1)
arcade, colonnade (1)
arch (31)
area (344)
aisle (0)
auditorium (1)
baggage claim (0)
box (1)
breakfast area, breakfast nook (0)
bullpen (0)
chancel, sanctuary, bema (0)
choir (0)
corner, nook (2)
court, courtyard (6)
atrium (0)
bailey (0)
cloister (0)
food court (0)
forecourt (0)
parvis (0)
Treemap Visualization
Images of the Synset
Downloads

Feature Engineering for CV

Edge detection (Canny)

Corner Detection (Harris)



Figures from http://opencv.org

Scale Invariant Feature Transform (SIFT)

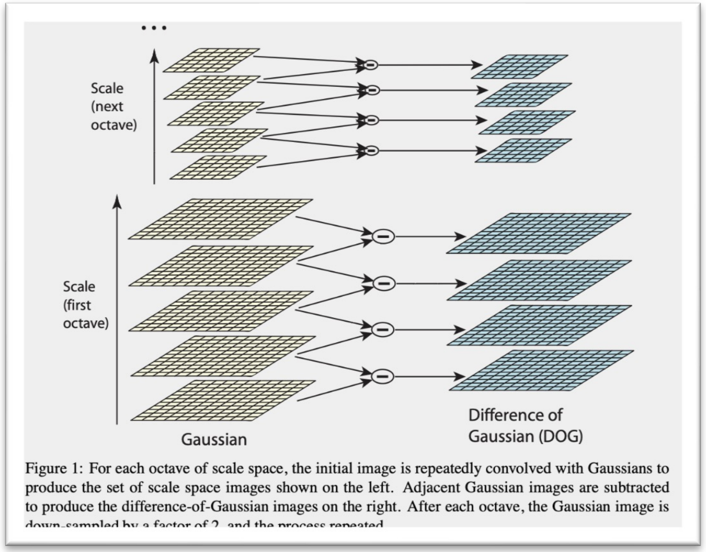


Figure from Lowe (1999) and Lowe (2004)

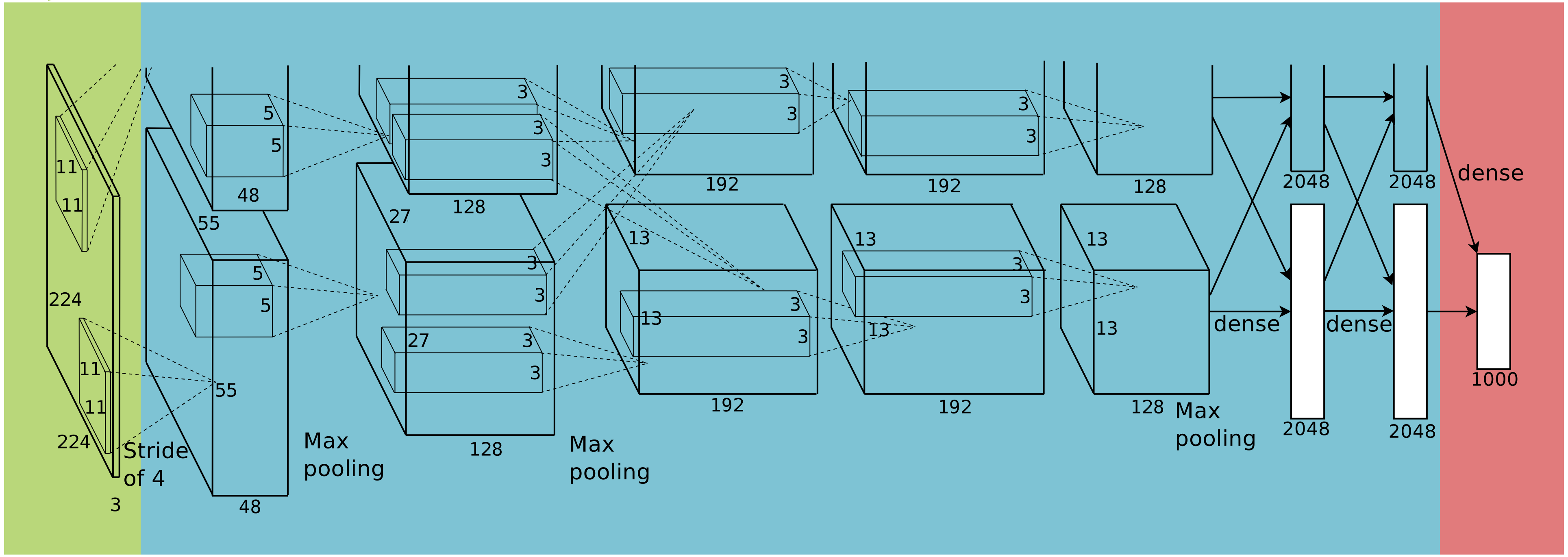
Example: Image Classification

CNN for Image Classification
(Krizhevsky, Sutskever & Hinton, 2012)
15.3% error on ImageNet LSVRC-2012 contest

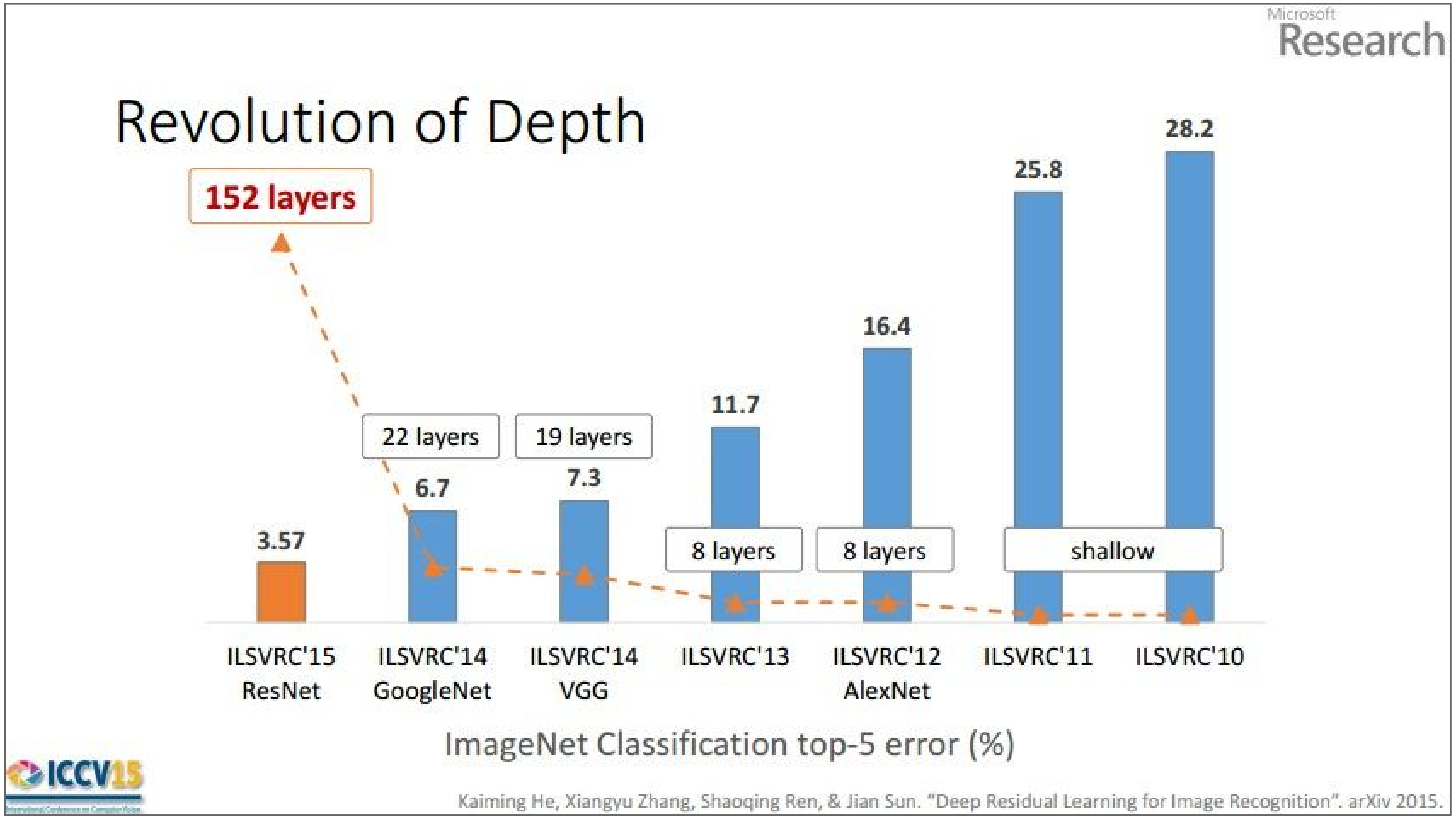
Input image (pixels)

- Five convolutional layers (w/max-pooling)
- Three fully connected layers

1000-way softmax



CNNs for Image Recognition



Slide from Kaiming He

Backpropagation and Deep Learning

Convolutional neural networks (CNNs) and **recurrent neural networks** (RNNs) are simply fancy computation graphs (aka. hypotheses or decision functions).

Our recipe also applies to these models and (again) relies on the **backpropagation algorithm** to compute the necessary gradients.

CONVOLUTION

What’s a convolution?

- Basic idea:
  - Pick a 3x3 matrix F of weights
  - Slide this over an image and compute the “inner product” (similarity) of F and the corresponding field of the image, and replace the pixel in the center of the field with the output of the inner product operation
- Key point:
  - Different convolutions extract different types of low-level “features” from an image
  - All that we need to vary to generate these different features is the weights of F

Ex: 1 input channel, 1 output channel

$$\underset{\text{Input}}{\begin{bmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{32} & x_{33} \end{bmatrix}} \longrightarrow \underset{\text{Conv}}{\begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}} \longrightarrow \underset{\text{Output}}{\begin{bmatrix} y_{11} & y_{12} \\ y_{21} & y_{22} \end{bmatrix}}$$

$$y_{11} = \alpha_{11} x_{11} + \alpha_{12} x_{12} + \alpha_{21} x_{21} + \alpha_{22} x_{22} + \alpha_0$$
$$y_{12} = \alpha_{11} x_{12} + \alpha_{12} x_{13} + \alpha_{21} x_{22} + \alpha_{22} x_{23} + \alpha_0$$
$$y_{21} = \alpha_{11} x_{21} + \alpha_{12} x_{22} + \alpha_{21} x_{31} + \alpha_{22} x_{32} + \alpha_0$$
$$y_{22} = \alpha_{11} x_{22} + \alpha_{12} x_{23} + \alpha_{21} x_{32} + \alpha_{22} x_{33} + \alpha_0$$

Background: Image Processing

A **convolution matrix** is used in image processing for tasks such as edge detection, blurring, sharpening, etc.

Input Image

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

Convolution

0	0	0
0	1	1
0	1	0

Convolved Image

3	2	2	3	1
2	0	2	1	0
2	2	1	0	0
3	1	0	0	0
1	0	0	0	0

Background: Image Processing

A **convolution matrix** is used in image processing for tasks such as edge detection, blurring, sharpening, etc.

Input Image

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

Convolution

0	0	0
0	1	1
0	1	0

Convolved Image

3	2	2	3	1
2	0	2	1	0
2	2	1	0	0
3	1	0	0	0
1	0	0	0	0

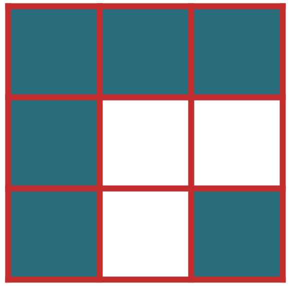
Background: Image Processing

A **convolution matrix** is used in image processing for tasks such as edge detection, blurring, sharpening, etc.

Input Image

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

Convolution



Convolved Image

3	2	2	3	1
2	0	2	1	0
2	2	1	0	0
3	1	0	0	0
1	0	0	0	0

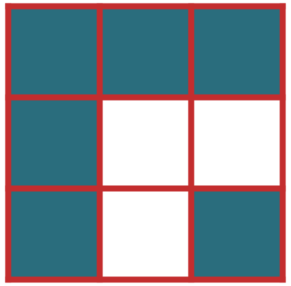
Background: Image Processing

A **convolution matrix** is used in image processing for tasks such as edge detection, blurring, sharpening, etc.

Input Image

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

Convolution

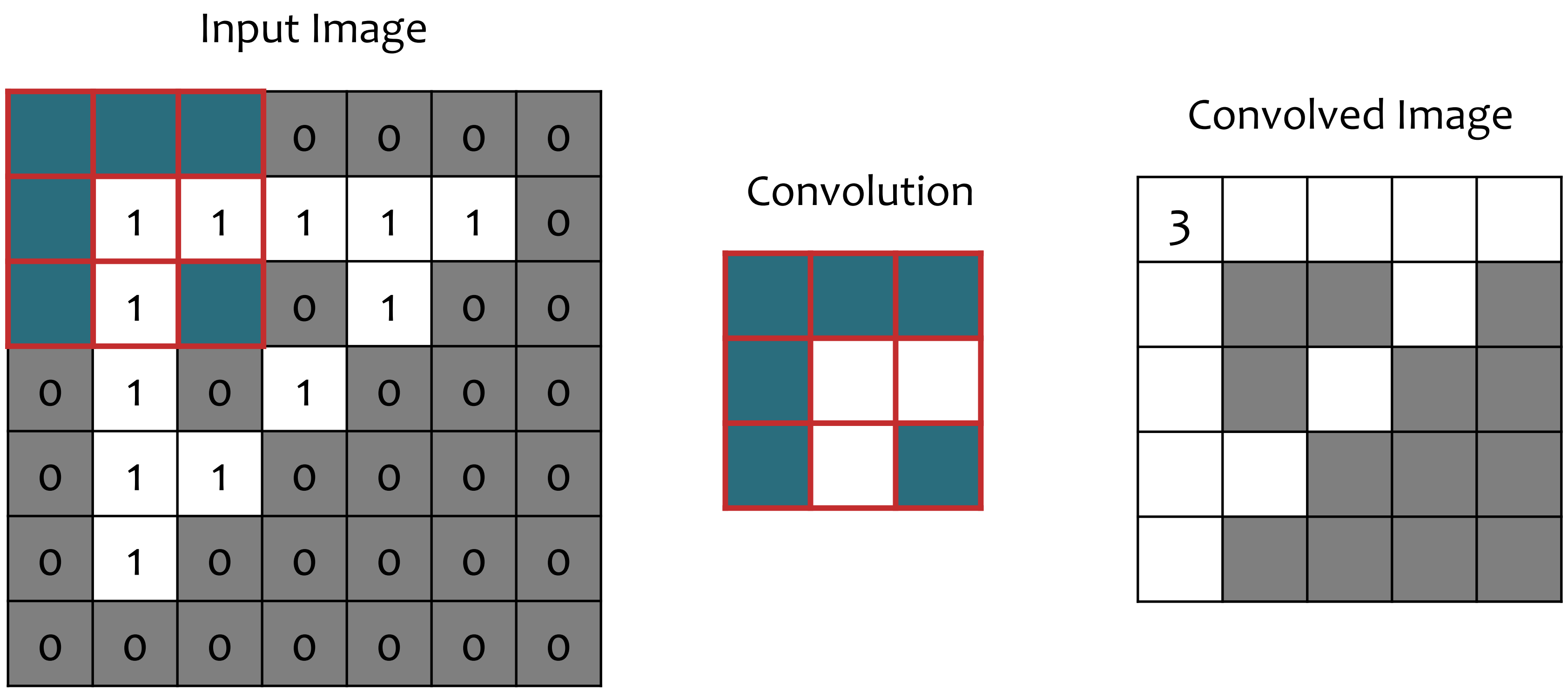


Convolved Image

3	2	2	3	1
2	0	2	1	0
2	2	1	0	0
3	1	0	0	0
1	0	0	0	0

Background: Image Processing

A **convolution matrix** is used in image processing for tasks such as edge detection, blurring, sharpening, etc.



Background: Image Processing

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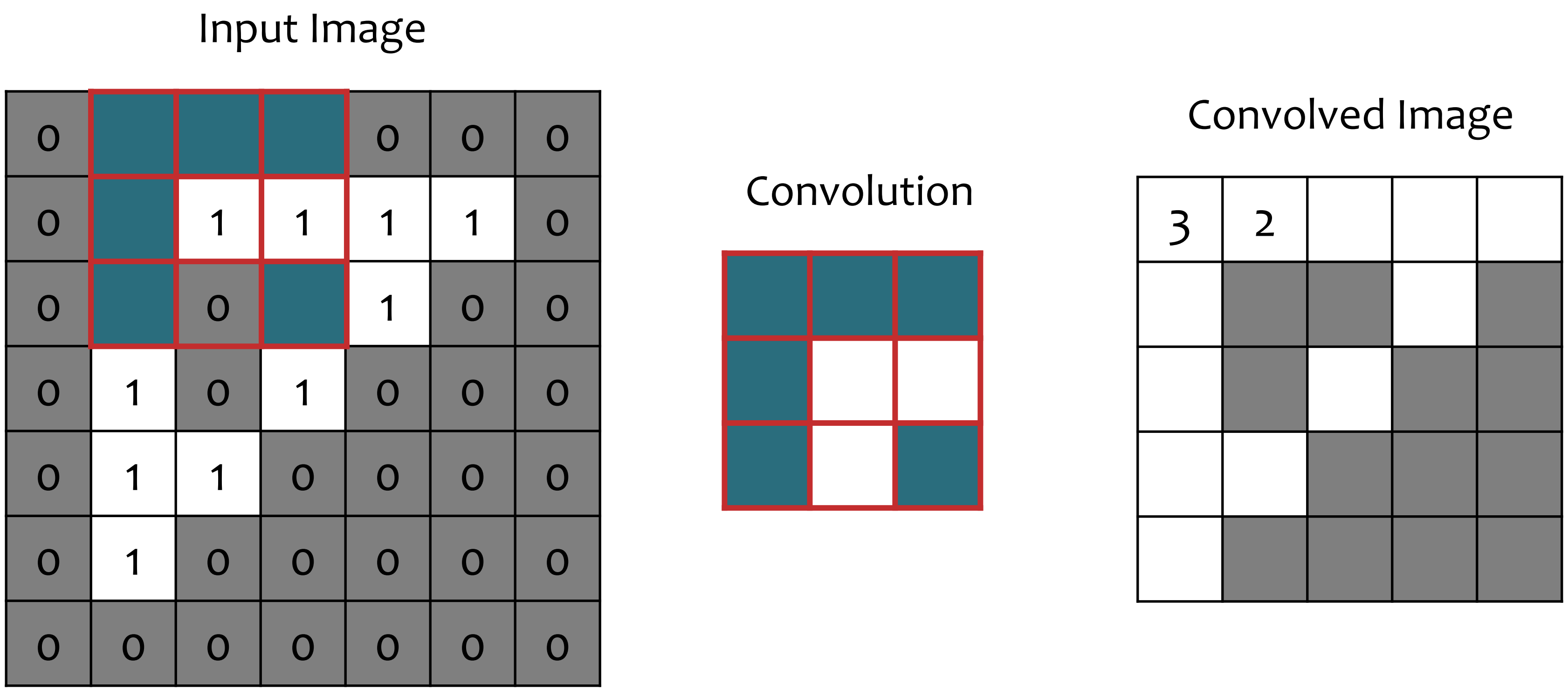

Background: Image Processing

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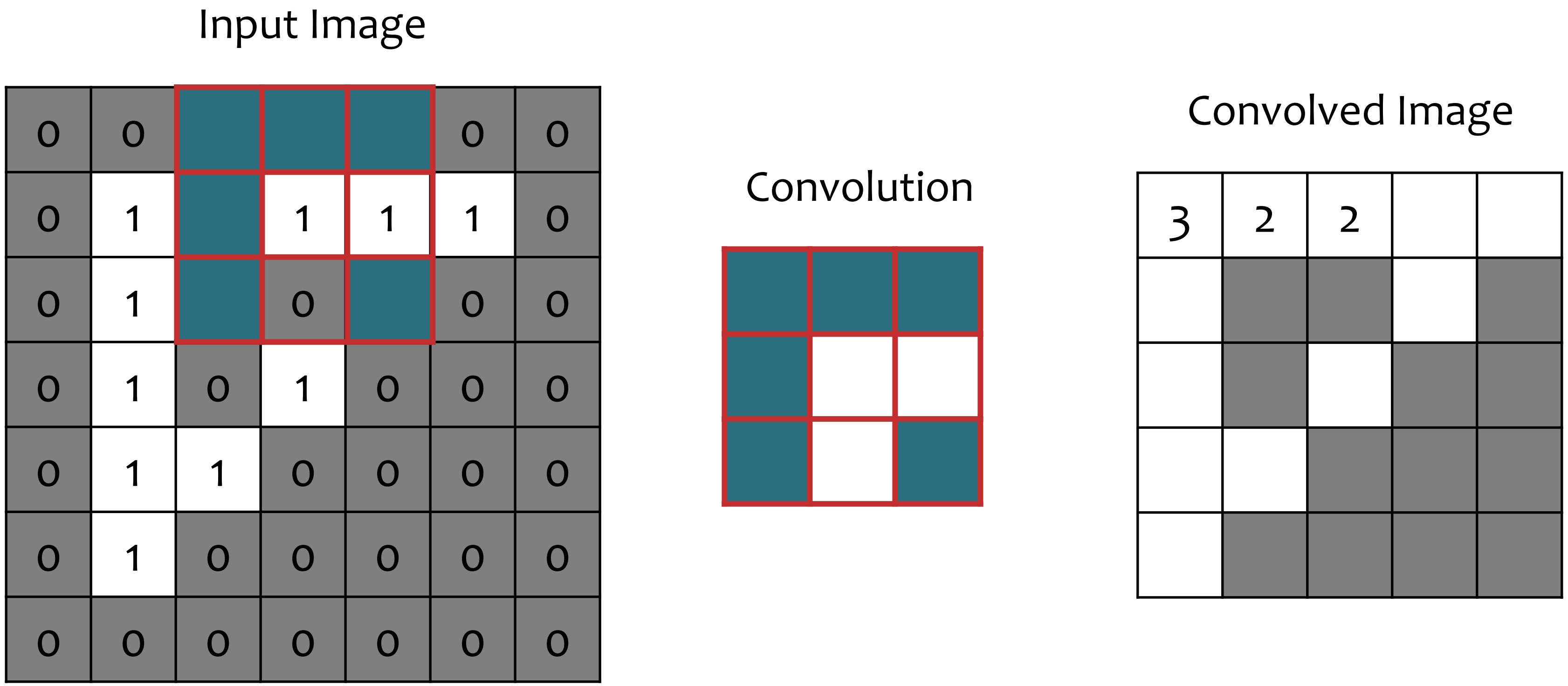
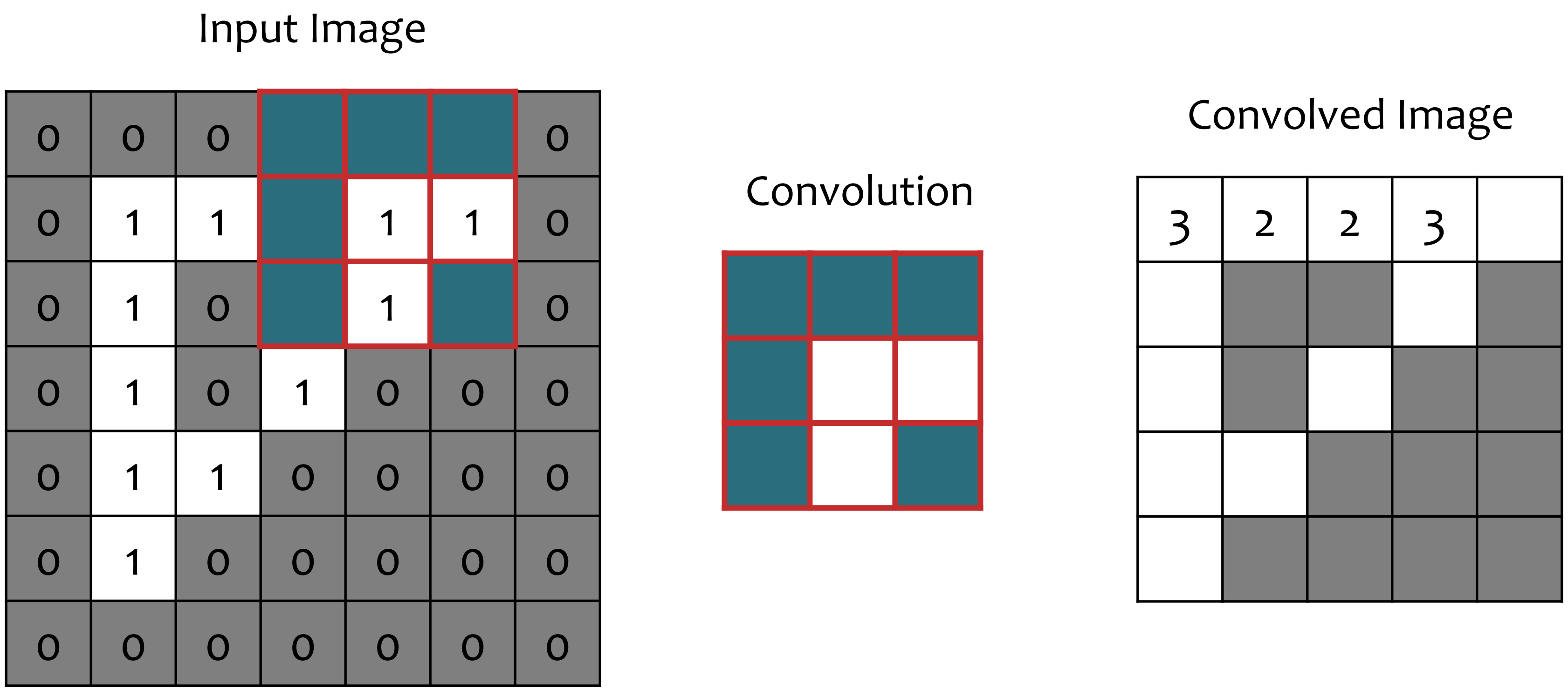


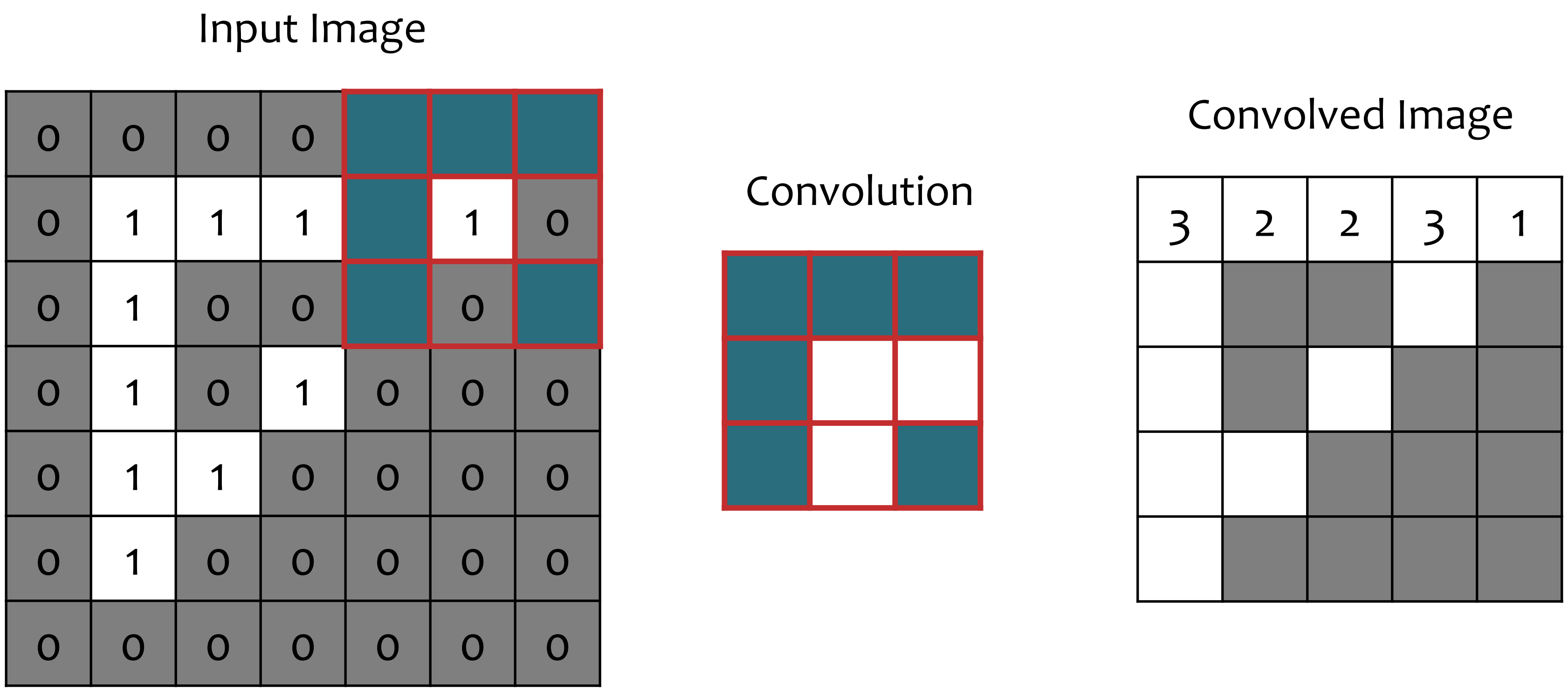
Background: Image Processing

A **convolution matrix** is used in image processing for tasks such as edge detection, blurring, sharpening, etc.



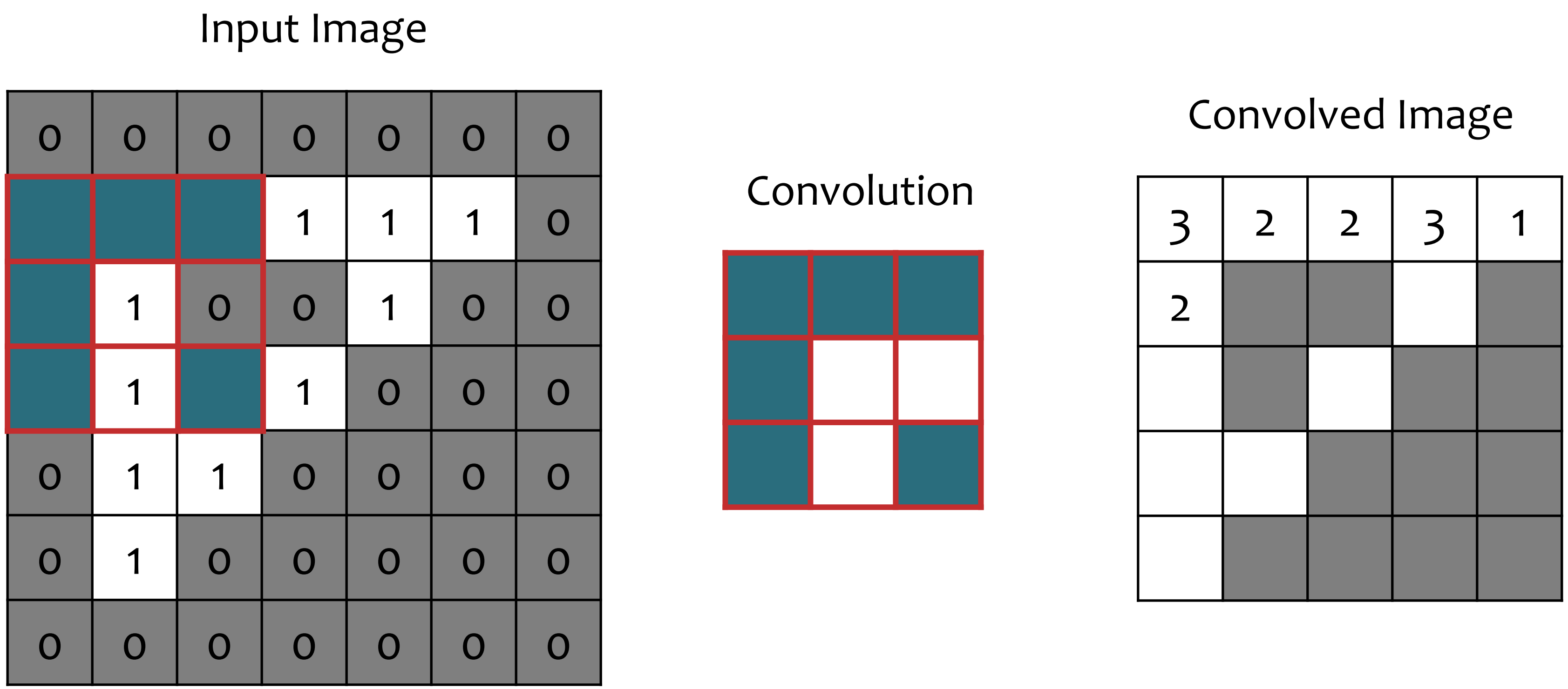
Background: Image Processing

A **convolution matrix** is used in image processing for tasks such as edge detection, blurring, sharpening, etc.



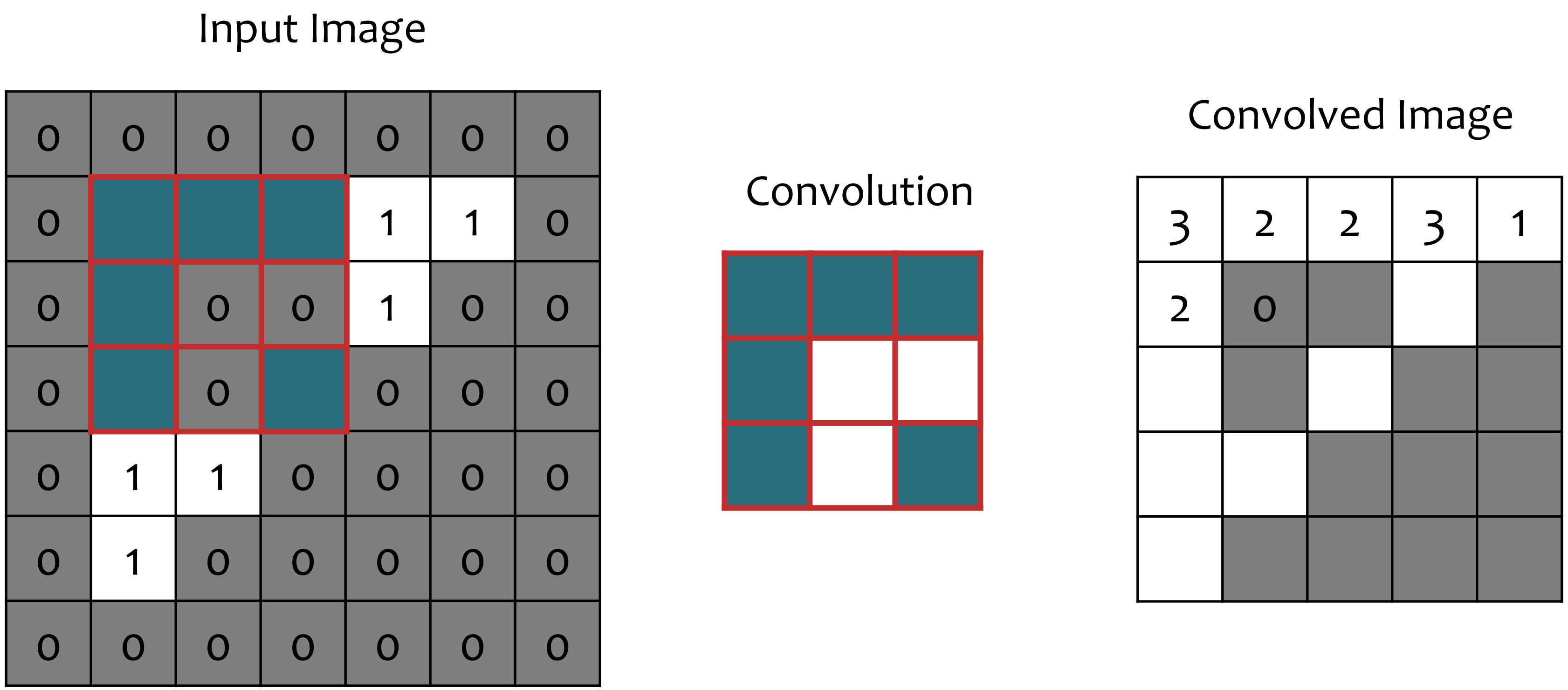
Background: Image Processing

A **convolution matrix** is used in image processing for tasks such as edge detection, blurring, sharpening, etc.



Background: Image Processing

A **convolution matrix** is used in image processing for tasks such as edge detection, blurring, sharpening, etc.



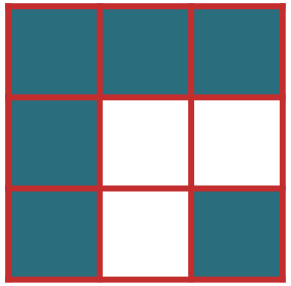
Background: Image Processing

A **convolution matrix** is used in image processing for tasks such as edge detection, blurring, sharpening, etc.

Input Image

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

Convolution



Convolved Image

3	2	2	3	1
2	0	2	1	0
2	2	1	0	0
3	1	0	0	0
1	0	0	0	0

Background: Image Processing

A **convolution matrix** is used in image processing for tasks such as edge detection, blurring, sharpening, etc.

Input Image

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

Identity Convolution

0	0	0
0	1	0
0	0	0

Convolved Image

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

Background: Image Processing

A **convolution matrix** is used in image processing for tasks such as edge detection, blurring, sharpening, etc.

Input Image

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

Blurring Convolution

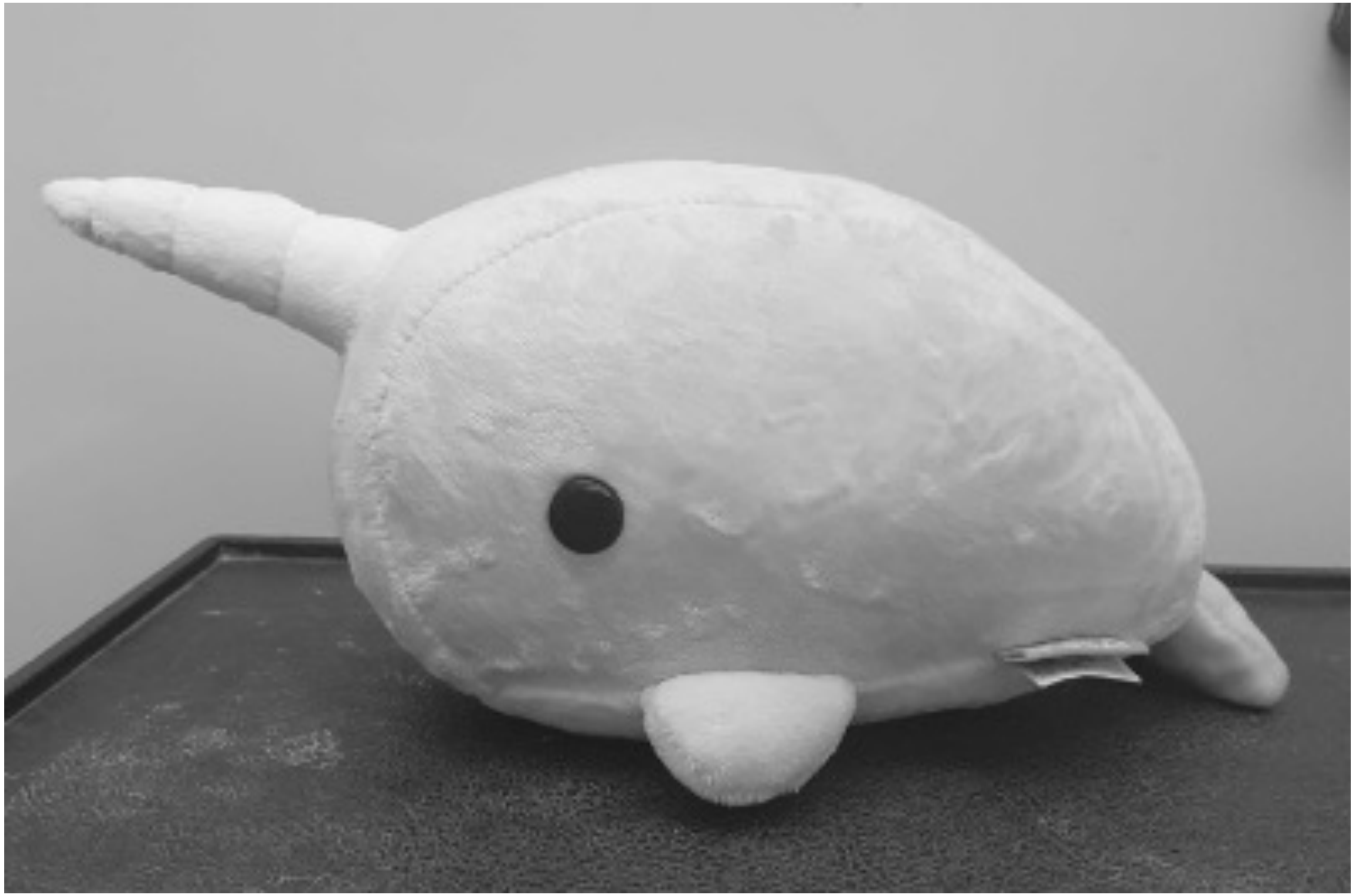
.1	.1	.1
.1	.2	.1
.1	.1	.1

Convolved Image

.4	.5	.5	.5	.4
.4	.2	.3	.6	.3
.5	.4	.4	.2	.1
.5	.6	.2	.1	0
.4	.3	.1	0	0

Convolution Examples

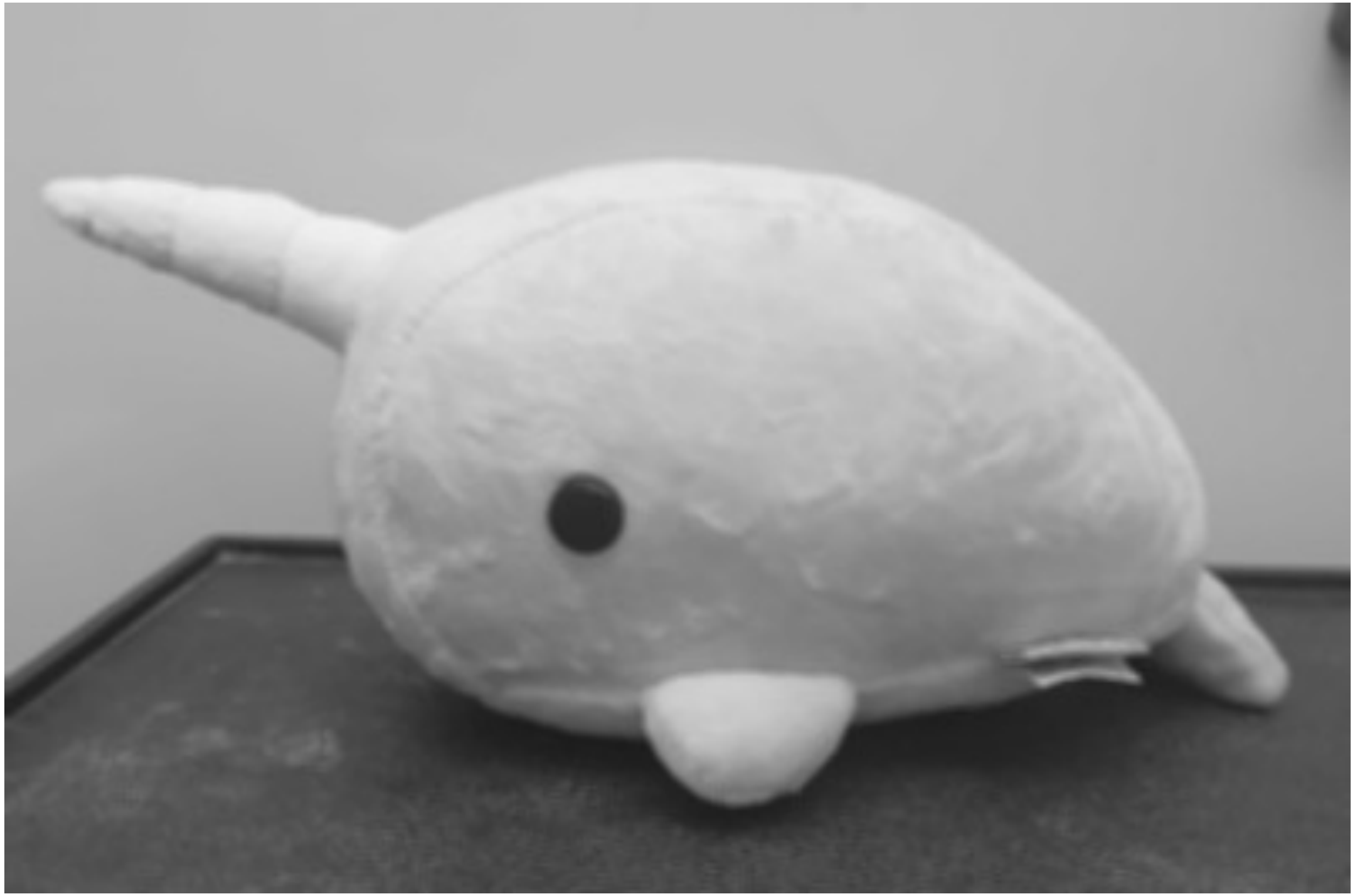
Original
Image



Convolution Examples

Smoothing Convolution

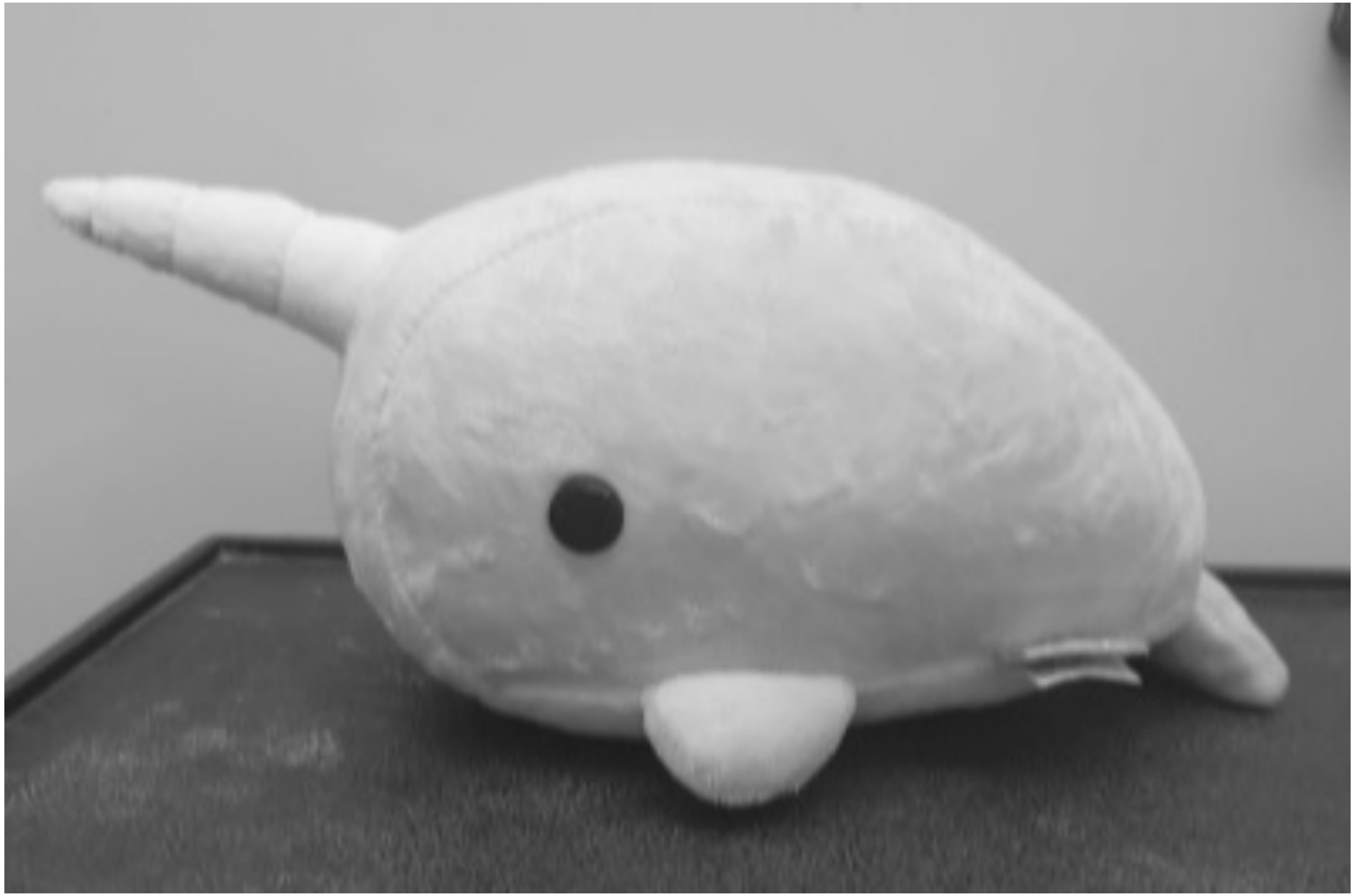
1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9



Convolution Examples

Gaussian
Blur

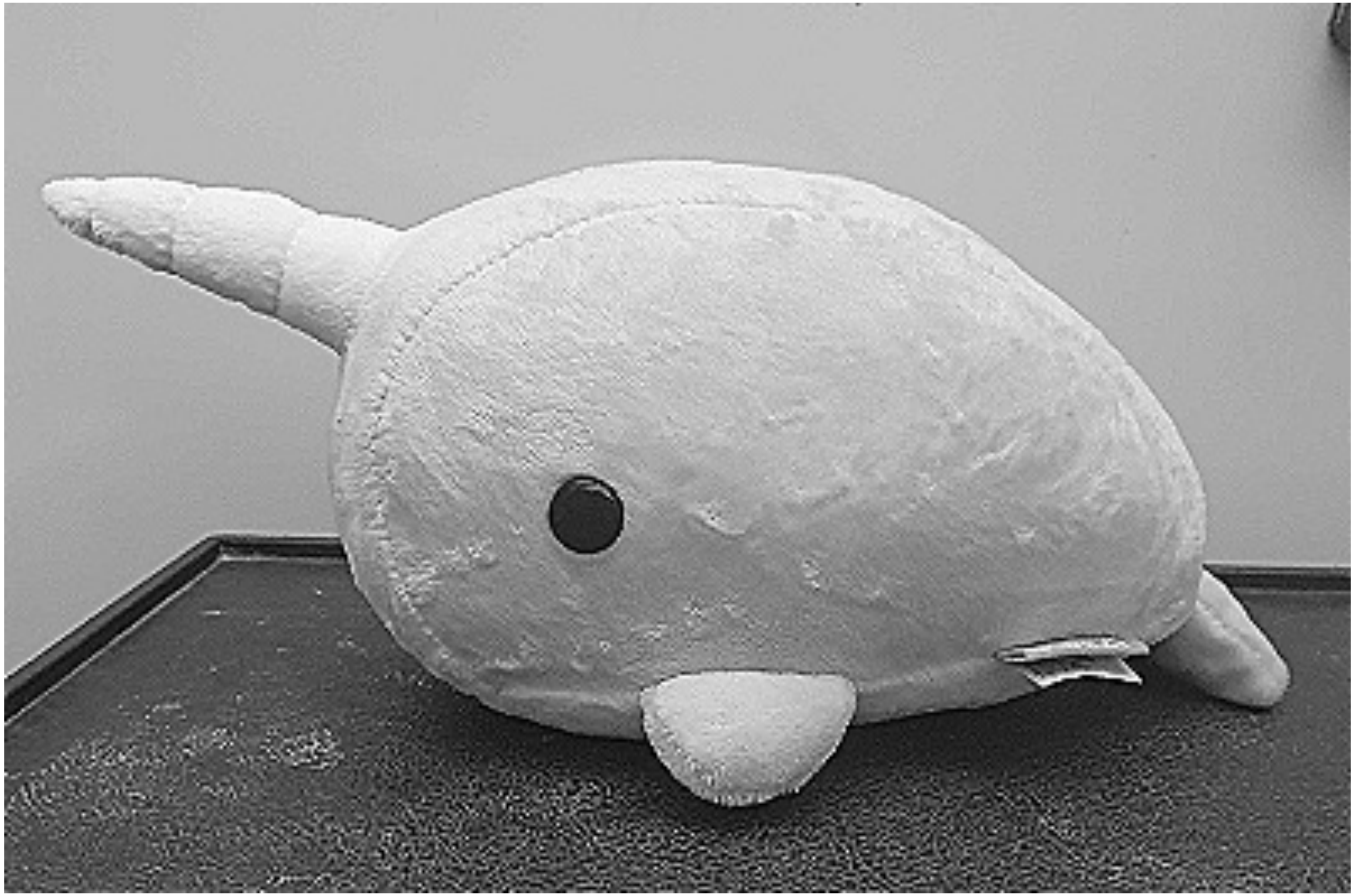
.01	.04	.06	.04	.01
.04	.19	.25	.19	.04
.06	.25	.37	.25	.06
.04	.19	.25	.19	.04
.01	.04	.06	.04	.01



Convolution Examples

Sharpening
Kernel

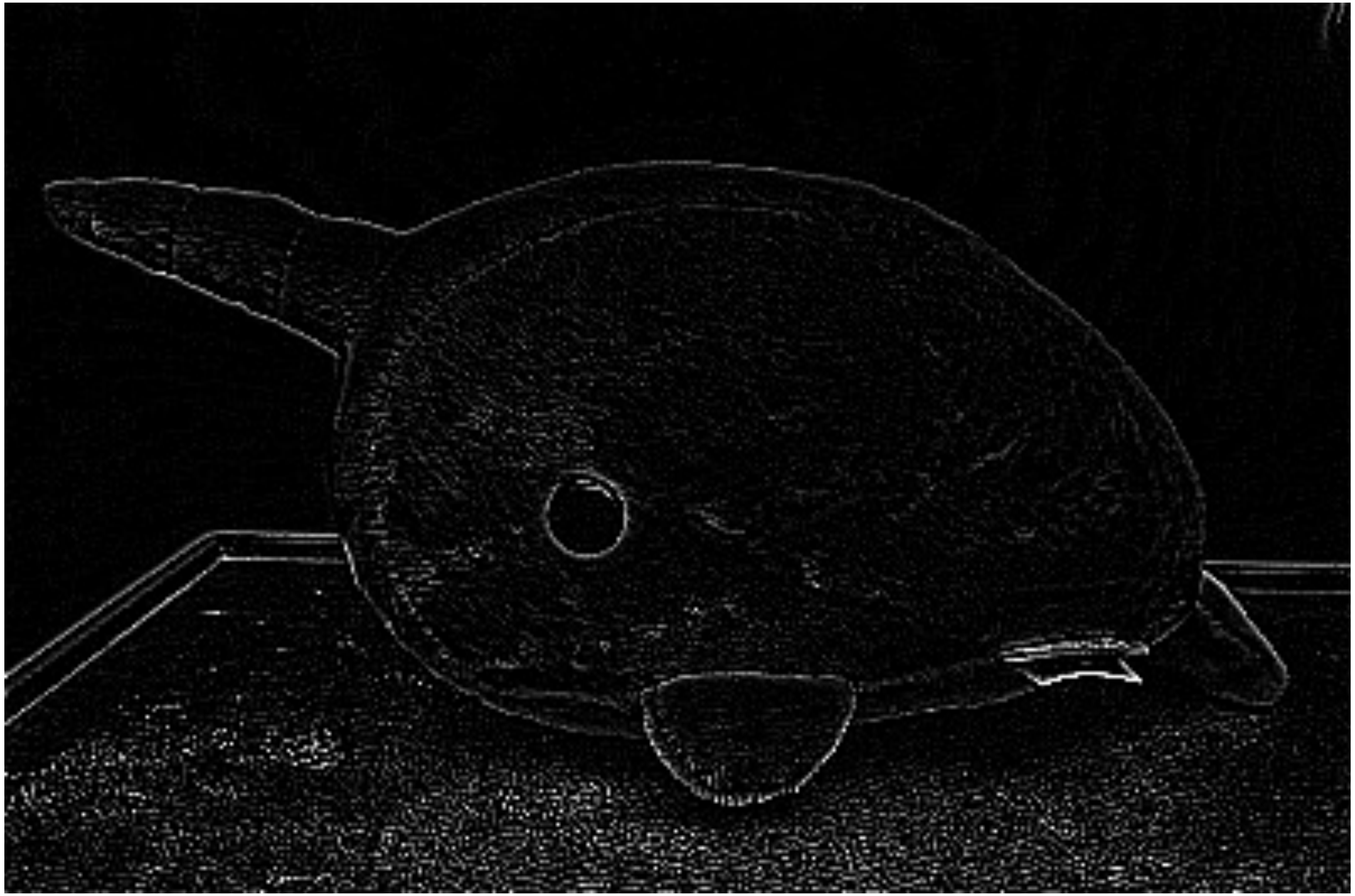
0	-1	0
-1	5	-1
0	-1	0



Convolution Examples

Edge
Detector

-1	-1	-1
-1	8	-1
-1	-1	-1



What's a convolution?

- Basic idea:
  - Pick a 3x3 matrix F of weights
  - Slide this over an image and compute the "inner product" (similarity) of F and the corresponding field of the image, and replace the pixel in the center of the field with the output of the inner product operation
- Key point:
  - Different convolutions extract different types of low-level "features" from an image
  - All that we need to vary to generate these different features is the weights of F

Ex: 1 input channel, 1 output channel

$$\underset{\text{Input}}{\begin{bmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{32} & x_{33} \end{bmatrix}} \longrightarrow \underset{\text{Conv}}{\begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}} \longrightarrow \underset{\text{Output}}{\begin{bmatrix} y_{11} & y_{12} \\ y_{21} & y_{22} \end{bmatrix}}$$

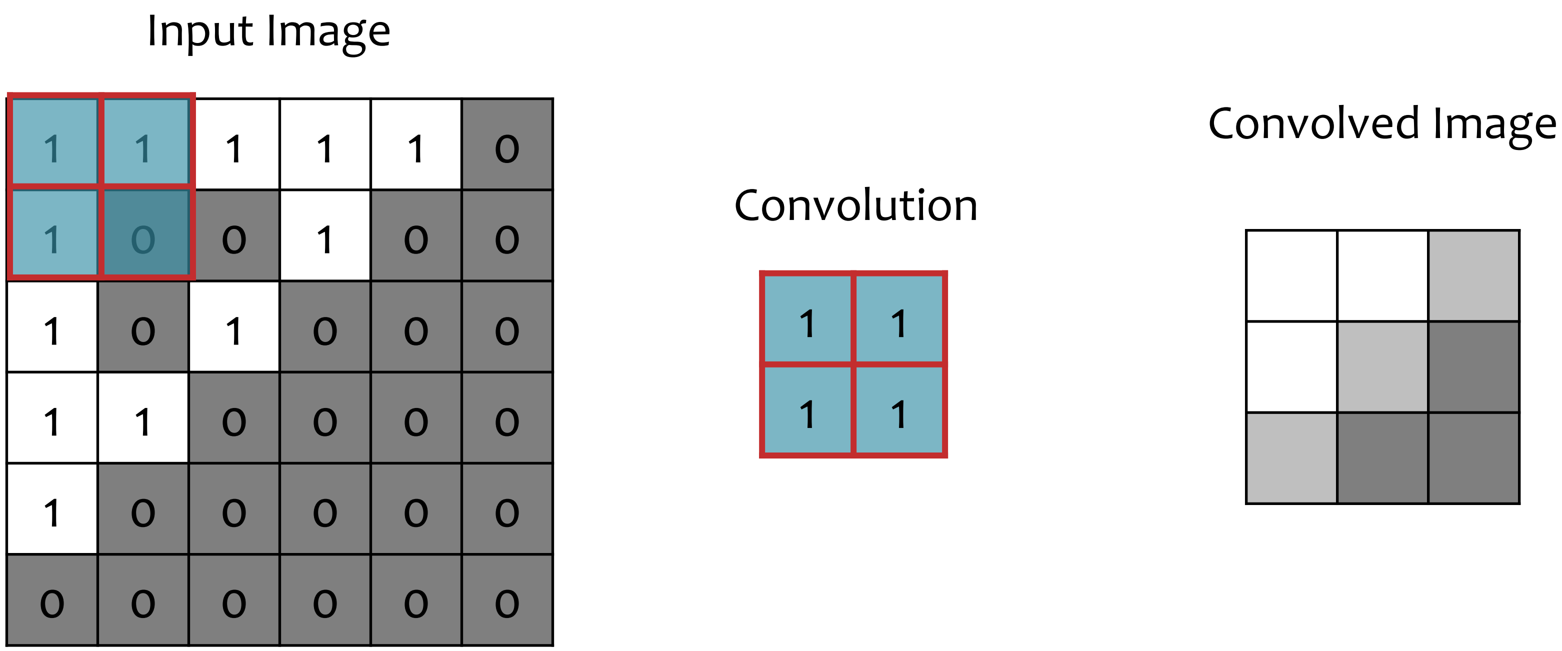
$$y_{11} = \alpha_{11} x_{11} + \alpha_{12} x_{12} + \alpha_{21} x_{21} + \alpha_{22} x_{22} + \alpha_0$$
$$y_{12} = \alpha_{11} x_{12} + \alpha_{12} x_{13} + \alpha_{21} x_{22} + \alpha_{22} x_{23} + \alpha_0$$
$$y_{21} = \alpha_{11} x_{21} + \alpha_{12} x_{22} + \alpha_{21} x_{31} + \alpha_{22} x_{32} + \alpha_0$$
$$y_{22} = \alpha_{11} x_{22} + \alpha_{12} x_{23} + \alpha_{21} x_{32} + \alpha_{22} x_{33} + \alpha_0$$

Slide adapted from William Cohen

DOWNSAMPLING

Downsampling

- Suppose we use a convolution with stride 2
- Only 9 patches visited in input, so only 9 pixels in output



Downsampling

- Suppose we use a convolution with stride 2
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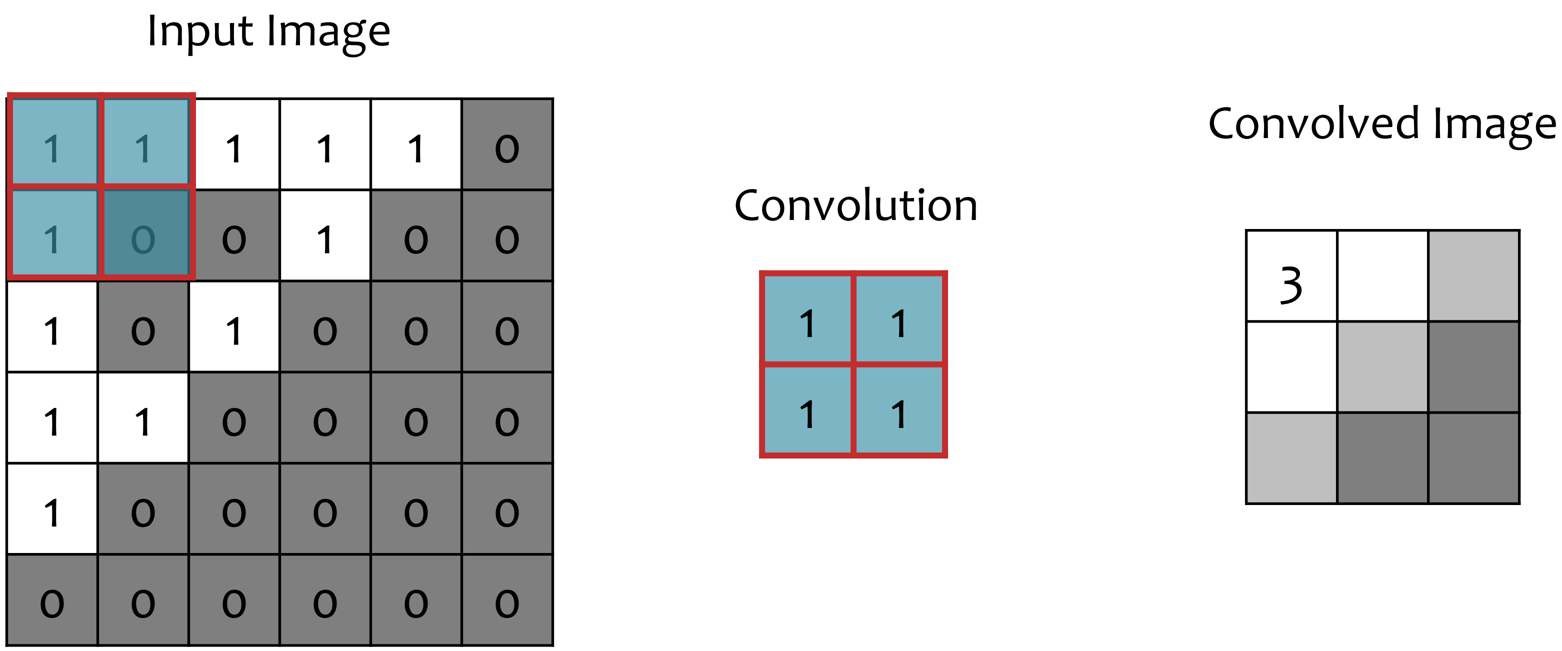

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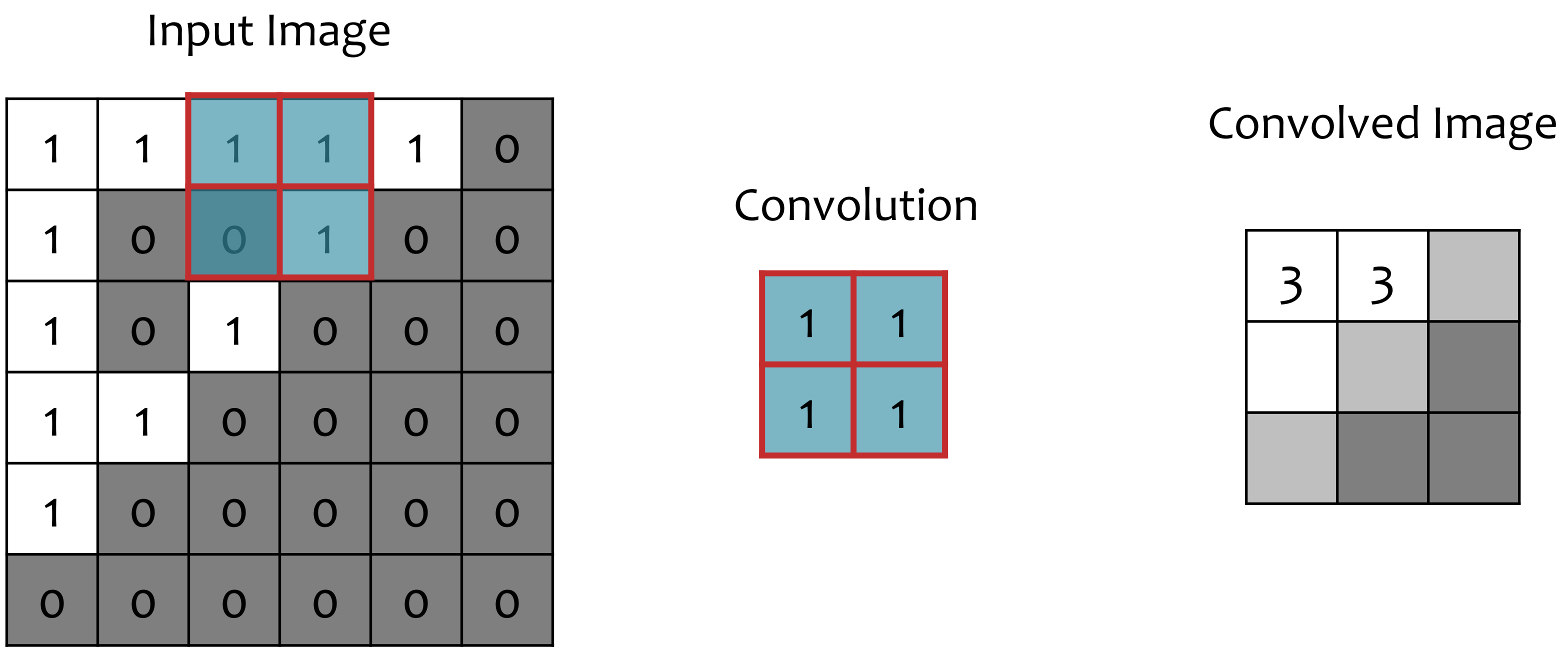
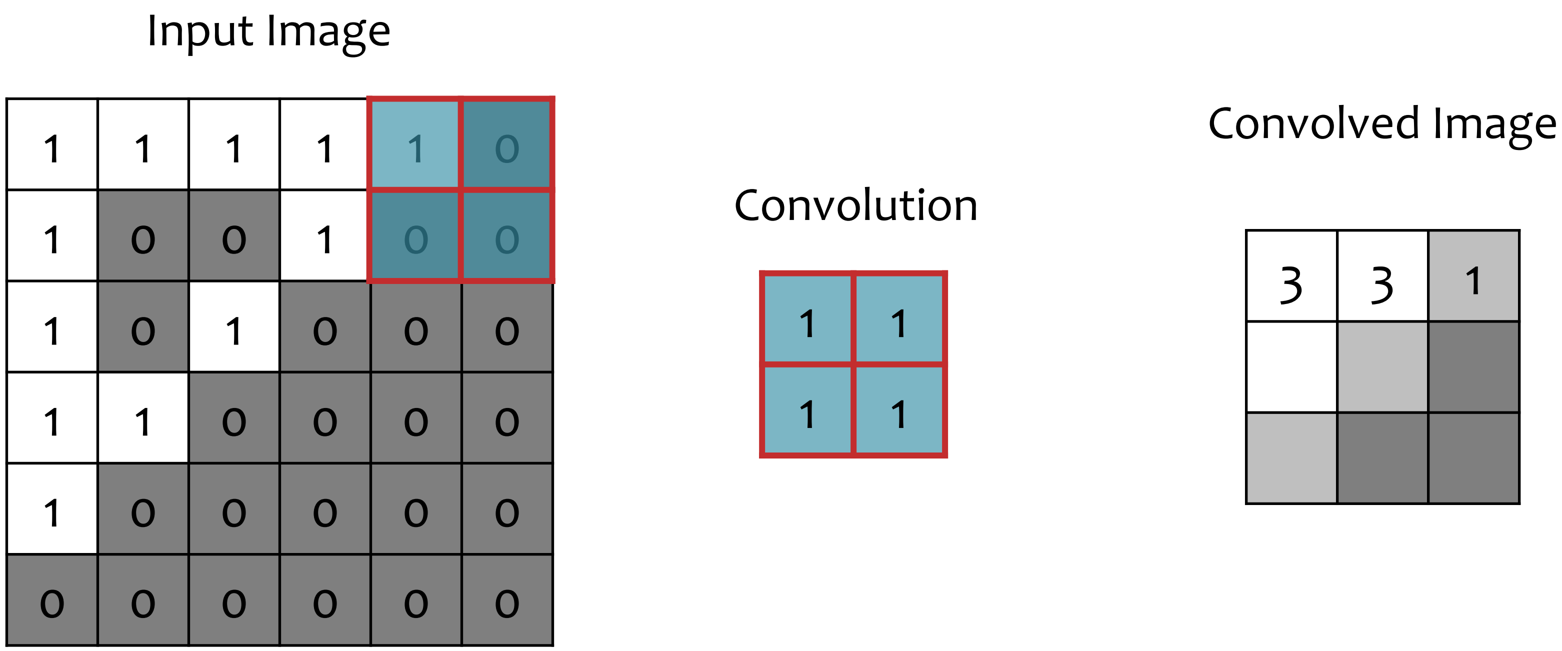


Downsampling

- Suppose we use a convolution with stride 2
- Only 9 patches visited in input, so only 9 pixels in output



Downsampling

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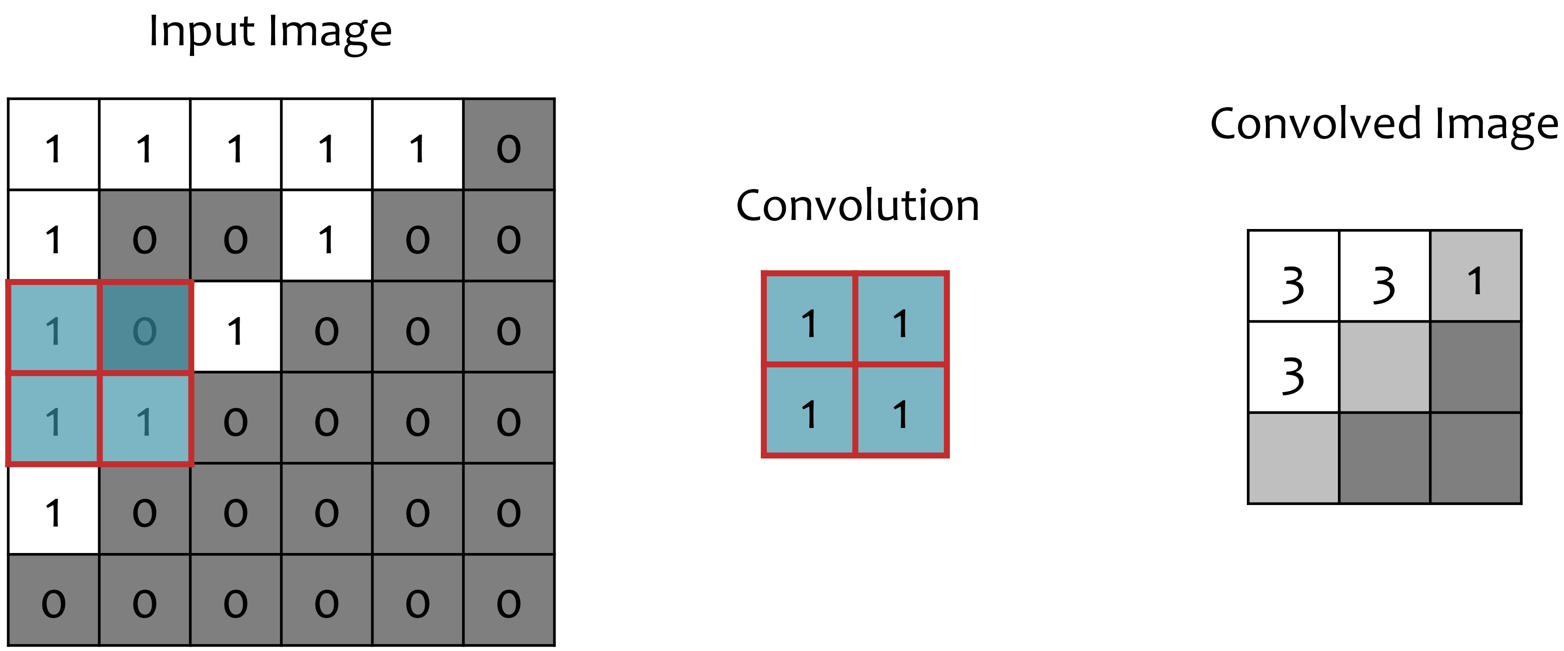
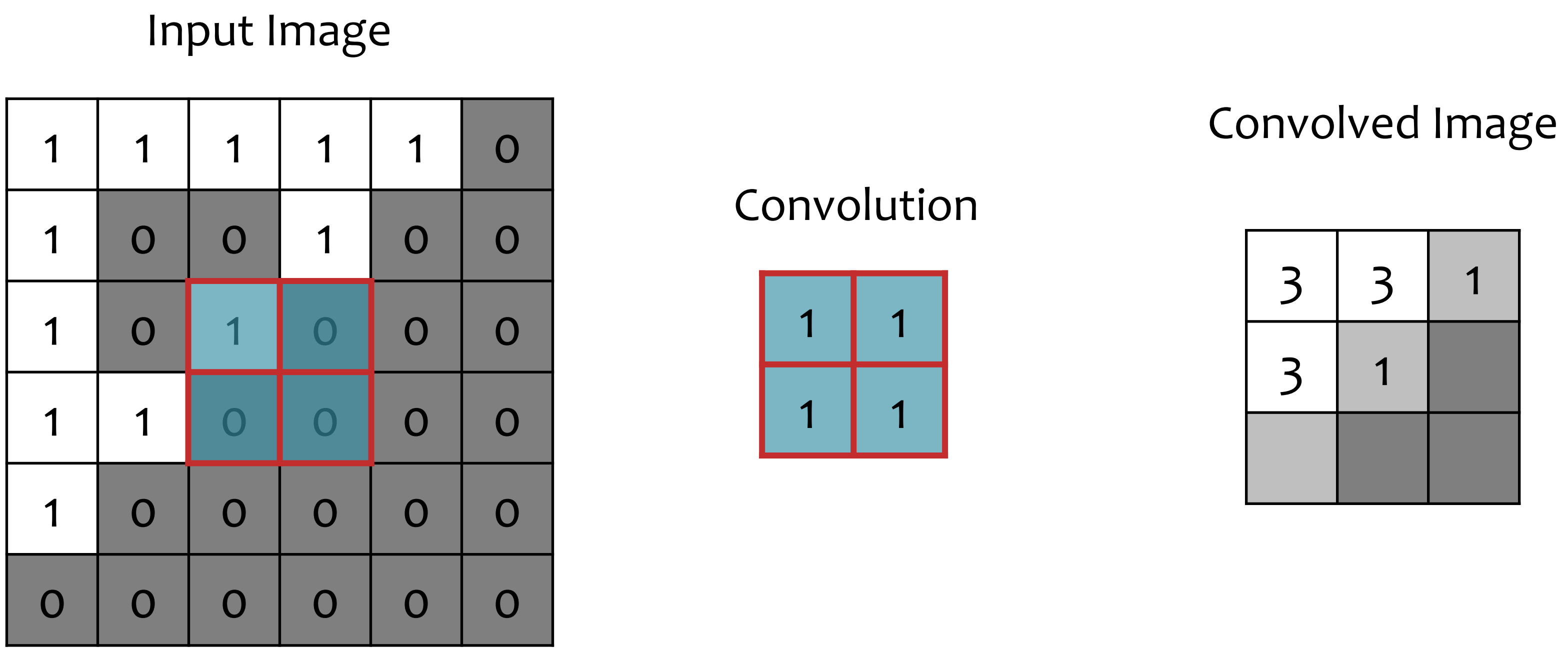
- Only 9 patches visited in input, so only 9 pixels in output



Downsampling

- Suppose we use a convolution with stride 2
- Only 9 patches visited in input, so only 9 pixels in output



Downsampling

- Suppose we use a convolution with stride 2
- Only 9 patches visited in input, so only 9 pixels in output

Input Image

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

Convolution

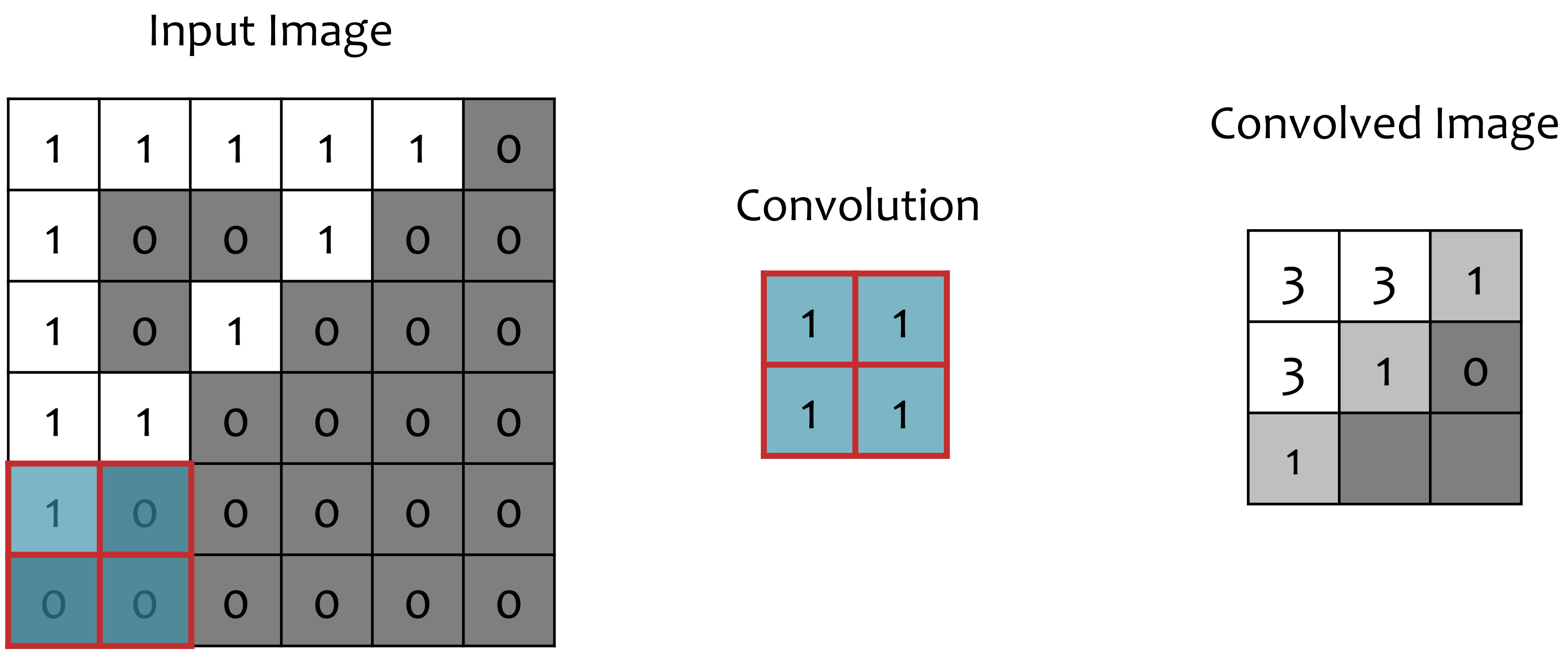
1	1
1	1

Convolved Image

3	3	1
3	1	0

Downsampling

- Suppose we use a convolution with stride 2
- Only 9 patches visited in input, so only 9 pixels in output



Downsampling

- Suppose we use a convolution with stride 2
- Only 9 patches visited in input, so only 9 pixels in output

Input Image

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

Convolution

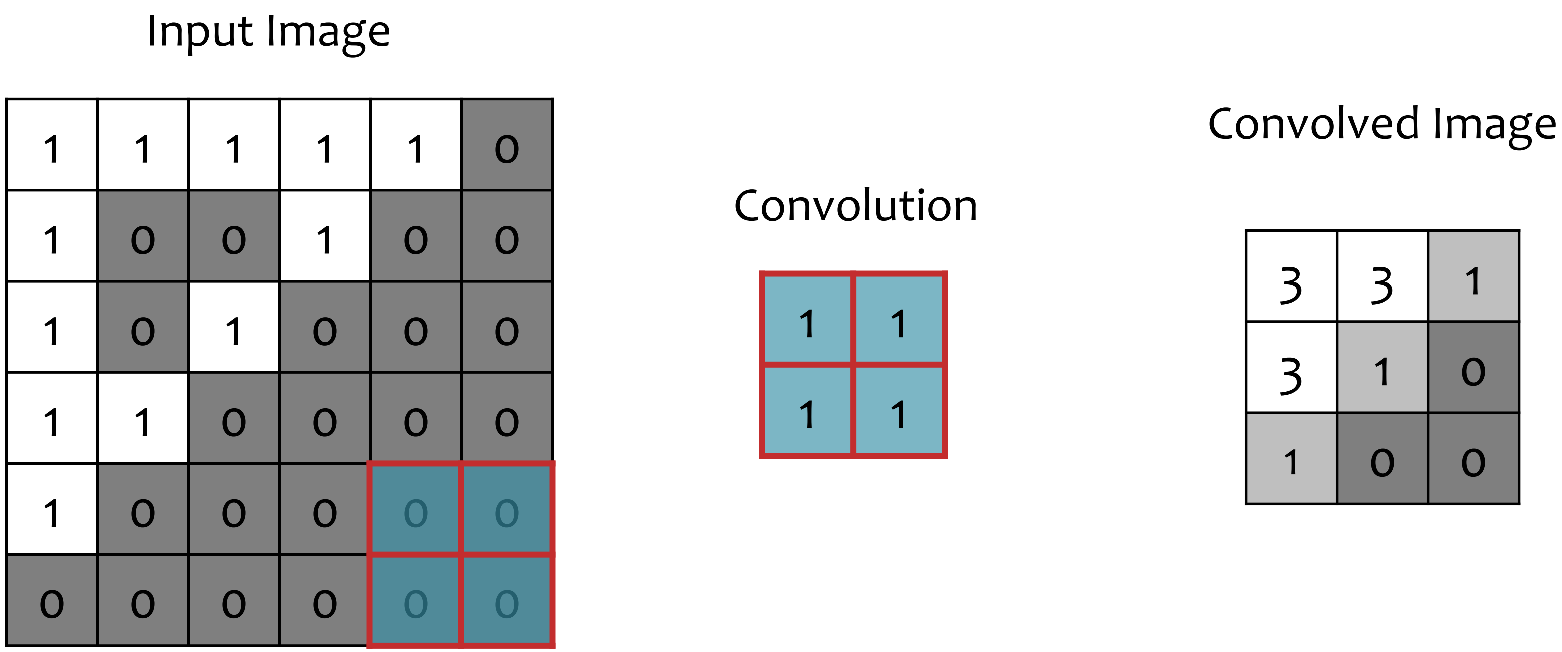
1	1
1	1

Convolved Image

3	3	1
3	1	0
1	0	

Downsampling

- Suppose we use a convolution with stride 2
- Only 9 patches visited in input, so only 9 pixels in output



Downsampling by Averaging

- Downsampling by averaging is a special case of convolution where the weights are fixed to a uniform distribution
- The example below uses a stride of 2

Input Image

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

Convolution

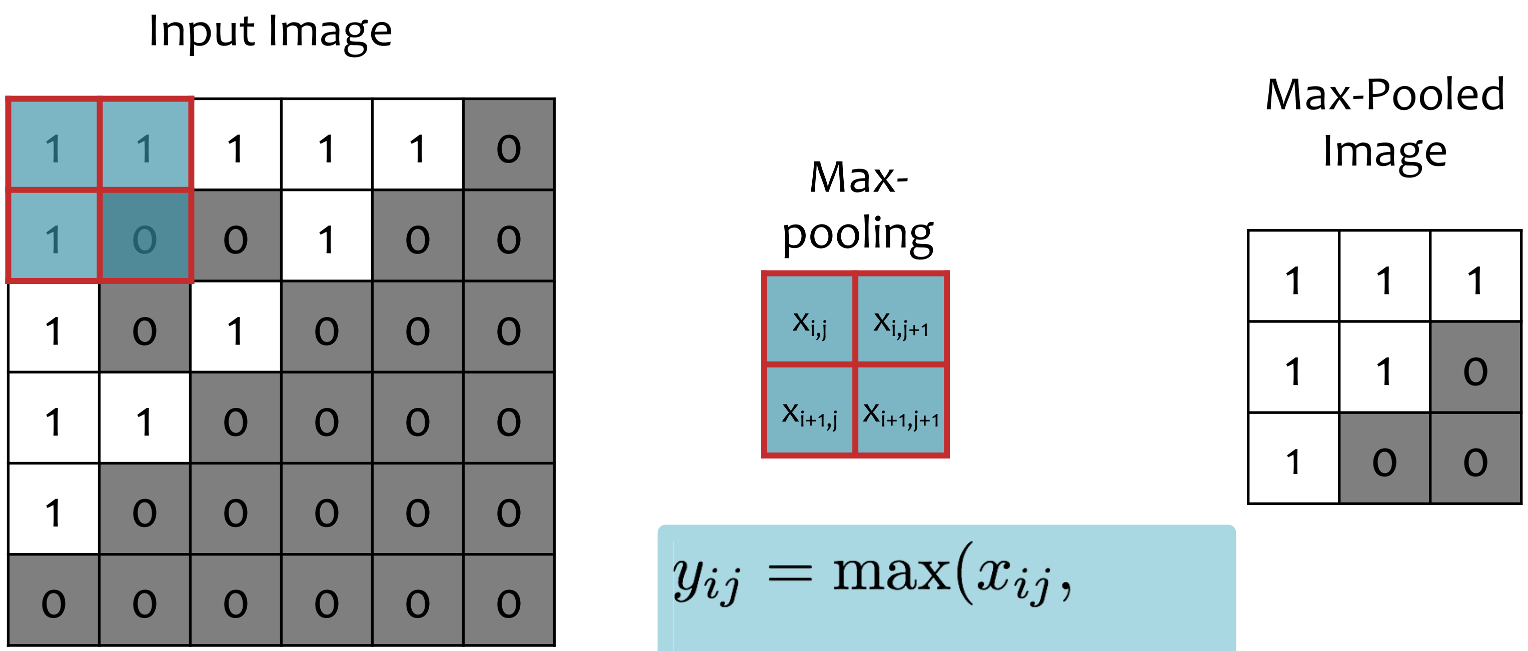
1/4	1/4
1/4	1/4

Convolved Image

3/4	3/4	1/4
3/4	1/4	0
1/4	0	0

Max-Pooling

- Max-pooling with a stride > 1 is another form of downsampling
- Instead of averaging, we take the max value within the same range as the equivalently-sized convolution
- The example below uses a stride of 2



$$\begin{aligned} y_{ij} = \max(x_{ij}, \\ x_{i,j+1}, \\ x_{i+1,j}, \\ x_{i+1,j+1}) \end{aligned}$$

CONVOLUTIONAL NEURAL NETS

A Recipe for Machine Learning

1. Given training data:

$$\{\boldsymbol{x}_i, \boldsymbol{y}_i\}_{i=1}^N$$

2. Choose each of these:
   - Decision function

$$\hat{\boldsymbol{y}} = f_{\boldsymbol{\theta}}(\boldsymbol{x}_i)$$

   - Loss function

$$\ell(\hat{\boldsymbol{y}}, \boldsymbol{y}_i) \in \mathbb{R}$$

3. Define goal:

$$\boldsymbol{\theta}^* = \arg\min_{\boldsymbol{\theta}} \sum_{i=1}^N \ell(f_{\boldsymbol{\theta}}(\boldsymbol{x}_i), \boldsymbol{y}_i)$$

4. Train with SGD:

(take small steps opposite the gradient)

$$\boldsymbol{\theta}^{(t+1)} = \boldsymbol{\theta}^{(t)} - \eta_t \nabla \ell(f_{\boldsymbol{\theta}}(\boldsymbol{x}_i), \boldsymbol{y}_i)$$

A Recipe for Machine Learning

1.

- Convolutional Neural Networks (CNNs) provide another form of **decision function**
- Let's see what they look like…

2. Choose each of these:
   - Decision function

$$\hat{y} = f_{\boldsymbol{\theta}}(\boldsymbol{x}_i)$$

   - Loss function

$$\ell(\hat{\boldsymbol{y}}, \boldsymbol{y}_i) \in \mathbb{R}$$

4. Train with SGD:
(take small steps opposite the gradient)

$$\boldsymbol{\theta}^{(t+1)} = \boldsymbol{\theta}^{(t)} - \eta_t \nabla \ell(f_{\boldsymbol{\theta}}(\boldsymbol{x}_i), \boldsymbol{y}_i)$$

Convolutional Layer

CNN key idea:
Treat convolution matrix as parameters and learn them!

Input Image

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

Learned Convolution

θ_{11}	θ_{12}	θ_{13}
θ_{21}	θ_{22}	θ_{23}
θ_{31}	θ_{32}	θ_{33}

Convolved Image

.4	.5	.5	.5	.4
.4	.2	.3	.6	.3
.5	.4	.4	.2	.1
.5	.6	.2	.1	0
.4	.3	.1	0	0

Convolutional Neural Network (CNN)

- Typical layers include:
  - Convolutional layer
  - Max-pooling layer
  - Fully-connected (Linear) layer
  - ReLU layer (or some other nonlinear activation function)
  - Softmax
- These can be arranged into arbitrarily deep topologies

Architecture #1: LeNet-5

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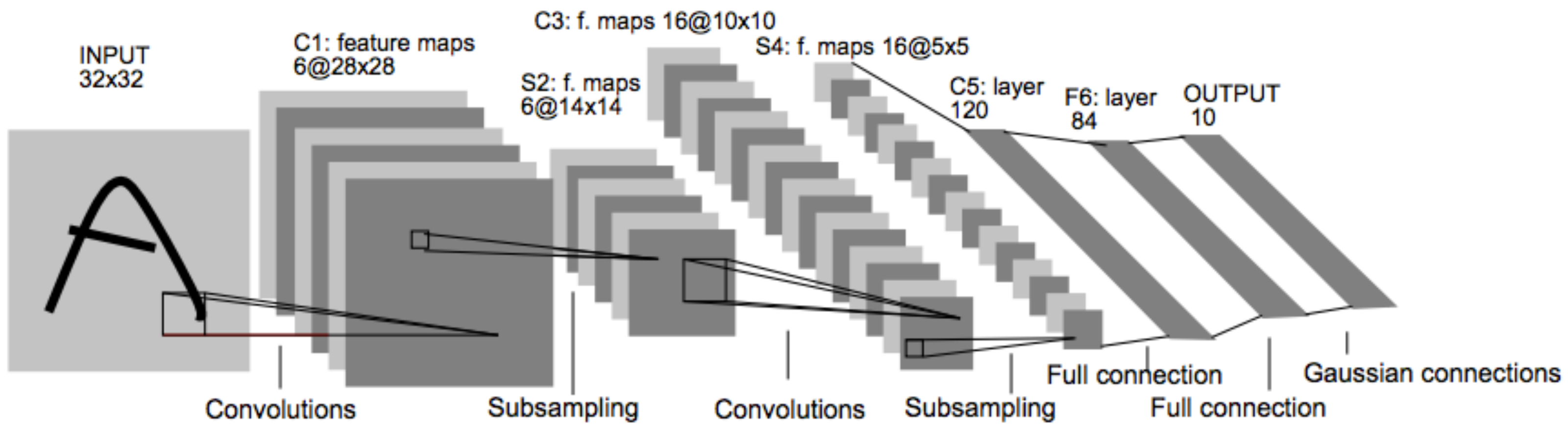


Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

TRAINING CNNS

A Recipe for Machine Learning

1. Given training data:

$$\{\boldsymbol{x}_i, \boldsymbol{y}_i\}_{i=1}^N$$

2. Choose each of these:

– Decision function

$$\hat{\boldsymbol{y}} = f_{\boldsymbol{\theta}}(\boldsymbol{x}_i)$$

– Loss function

$$\ell(\hat{\boldsymbol{y}}, \boldsymbol{y}_i) \in \mathbb{R}$$

3. Define goal:

$$\boldsymbol{\theta}^* = \arg\min_{\boldsymbol{\theta}} \sum_{i=1}^N \ell(f_{\boldsymbol{\theta}}(\boldsymbol{x}_i), \boldsymbol{y}_i)$$

4. Train with SGD:

(take small steps opposite the gradient)

$$\boldsymbol{\theta}^{(t+1)} = \boldsymbol{\theta}^{(t)} - \eta_t \nabla \ell(f_{\boldsymbol{\theta}}(\boldsymbol{x}_i), \boldsymbol{y}_i)$$

A Recipe for Machine Learning

1. Given training data:

$$\{\boldsymbol{x}_i, \boldsymbol{y}_i\}_{i=1}^N$$

2. Choose each of t

– Decision functio

$$\hat{y} = f_{\boldsymbol{\theta}}(\boldsymbol{x}_i)$$

– Loss function

$$\ell(\hat{\boldsymbol{y}}, \boldsymbol{y}_i) \in \mathbb{R}$$

3. Define goal:

opp site the gradient)

$$\boldsymbol{\theta}^{(t} \quad {}^{(t)} - \eta_t \nabla \ell(f_{\boldsymbol{\theta}}(\boldsymbol{x}_i), \boldsymbol{y}_i)$$

- Q: Now that we have the CNN as a decision function, how do we compute the gradient?
- A: Backpropagation of course!

SGD for CNNs

SGD for CNNs

Ex: Architecture: Given $\vec{x}, y^*$

$J = \ell(y, y^*)$

$y = \text{softmax}(z^{(5)})$

$z^{(5)} = \text{linear}(z^{(4)}, W)$

$z^{(4)} = \text{relu}(z^{(3)})$

$z^{(3)} = \text{conv}(z^{(2)}, \beta)$

$z^{(2)} = \text{max-pool}(z^{(1)})$

$z^{(1)} = \text{conv}(\vec{x}, \alpha)$

Parameters $\vec{\Theta} = [\alpha, \beta, W]$

SGD:

① Init $\vec{\Theta}$

② While not converged:

Sample $i \in \{1, \dots, N\}$

Forward: $y = h_\Theta(\vec{x}^{(i)})$, $J_i(\Theta) = \ell(y, y^*)$

Backward: $\nabla_{\vec{\Theta}} J_i(\Theta) = \dots$

Update: $\vec{\Theta} \leftarrow \vec{\Theta} - \lambda \nabla_{\vec{\Theta}} J_i(\Theta)$

LAYERS OF A CNN

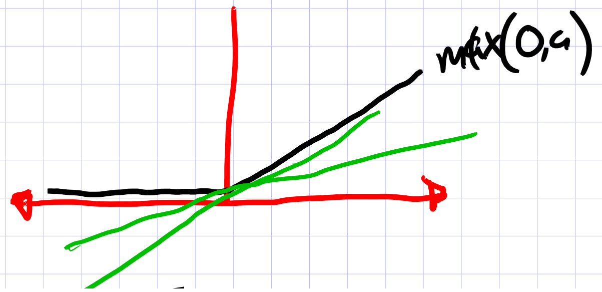
ReLU Layer

ReLU Layer Input: $\vec{x} \in \mathbb{R}^K$ Output: $\vec{y} \in \mathbb{R}^K$

Forward:

$\vec{y} = \sigma(\vec{x})$ ← element-wise

$\sigma(a) = \max(0, a)$



Backward:

$$\frac{dJ}{dx_i} = \frac{dJ}{dy_i} \frac{dy_i}{dx_i}$$

where $\frac{dy_i}{dx_i} = \begin{cases} 1 & \text{if } x_i > 0 \\ 0 & \text{otherwise} \end{cases}$ subderivative

Softmax Layer

Softmax Layer

Input: $\vec{x} \in \mathbb{R}^K$ Output: $\vec{y} \in \mathbb{R}^K$

Forward:

$$y_i = \frac{\exp(x_i)}{\sum_{k=1}^{K} \exp(x_k)}$$

Backward:

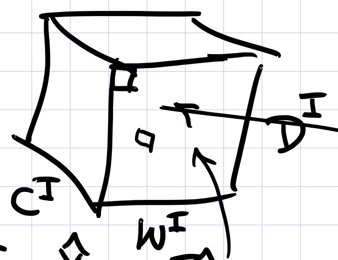
$$\frac{dJ}{dx_j} = \sum_{i=1}^{K} \frac{dJ}{dy_i} \frac{dy_i}{dx_j}$$

where $\frac{dy_i}{dx_j} = \begin{cases} y_i(1-y_i) & \text{if } i=j \\ -y_i y_j & \text{otherwise} \end{cases}$

Fully-Connected Layer

$\boxed{\text{Fully Connected Layer}}$ (w/ tensor input)

- Suppose input is a 3D Tensor: $X =$



- Stretch out into a long vector. $\hat{X} = [\hat{x}_1, \ldots, \hat{x}_{(C\times H\times W)}]$
- then standard linear layer:

$$y = \alpha^T \hat{x} + \alpha_0 \quad \text{where } \alpha \in \mathbb{R}^{A\times B}$$

$$|\hat{x}| = A, \; |y| = B$$

Convolutional Layer

<u>Ex:</u> 1 input channel, 1 output channel

$$\underbrace{\begin{bmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{32} & x_{33} \end{bmatrix}}_{\text{Input}} \longrightarrow \underbrace{\begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}}_{\text{Conv}} \longrightarrow \underbrace{\begin{bmatrix} y_{11} & y_{12} \\ y_{21} & y_{22} \end{bmatrix}}_{\text{Output}}$$

$$y_{11} = \alpha_{11} x_{11} + \alpha_{12} x_{12} + \alpha_{21} x_{21} + \alpha_{22} x_{22} + \alpha_0$$
$$y_{12} = \alpha_{11} x_{12} + \alpha_{12} x_{13} + \alpha_{21} x_{22} + \alpha_{22} x_{23} + \alpha_0$$
$$y_{21} = \alpha_{11} x_{21} + \alpha_{12} x_{22} + \alpha_{21} x_{31} + \alpha_{22} x_{32} + \alpha_0$$
$$y_{22} = \alpha_{11} x_{22} + \alpha_{12} x_{23} + \alpha_{21} x_{32} + \alpha_{22} x_{33} + \alpha_0$$

<u>Ex:</u> 1 input channel, 2 output channels

$$\underbrace{\begin{bmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{32} & x_{33} \end{bmatrix}}_{\text{Input}} \longrightarrow \underbrace{\begin{bmatrix} \alpha^{(1)}_{11} & \alpha^{(1)}_{12} \\ \alpha^{(1)}_{21} & \alpha^{(1)}_{22} \end{bmatrix}}_{\text{Conv\#1}} \longrightarrow \underbrace{\begin{bmatrix} y^{(1)}_{11} & y^{(1)}_{12} \\ y^{(1)}_{21} & y^{(1)}_{22} \end{bmatrix}}_{\text{Output\#1}}$$

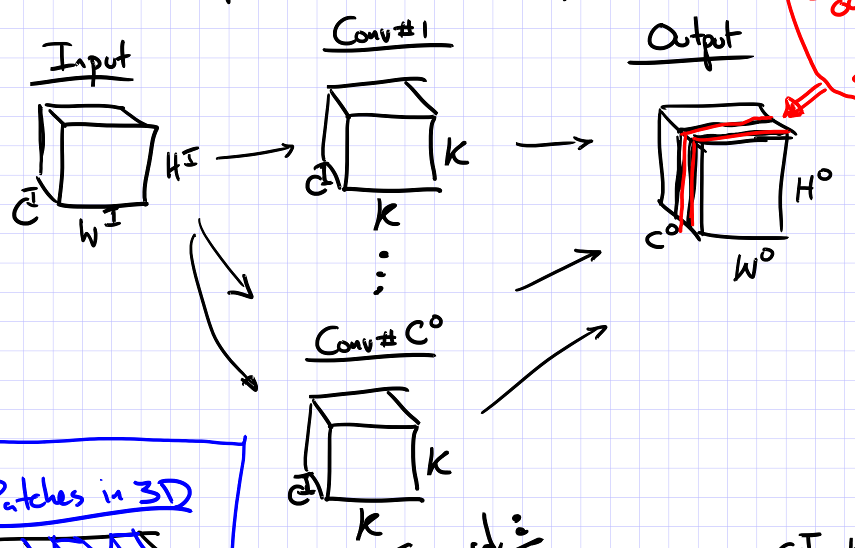
$$\text{Input} \longrightarrow \underbrace{\begin{bmatrix} \alpha^{(2)}_{11} & \alpha^{(2)}_{12} \\ \alpha^{(2)}_{21} & \alpha^{(2)}_{22} \end{bmatrix}}_{\text{Conv\#2}} \longrightarrow \underbrace{\begin{bmatrix} y^{(2)}_{11} & y^{(2)}_{12} \\ y^{(2)}_{21} & y^{(2)}_{22} \end{bmatrix}}_{\text{Output\#2}}$$

$$y^{(1)}_{11} = \alpha^{(1)}_{11} x_{11} + \alpha^{(1)}_{12} x_{12} + \alpha^{(1)}_{21} x_{21} + \alpha^{(1)}_{22} x_{22} + \alpha^{(1)}_0$$
$$y^{(1)}_{12} = \dots$$
$$y^{(1)}_{21} = \dots$$
$$y^{(1)}_{22} = \alpha^{(1)}_{11} x_{22} + \alpha^{(1)}_{12} x_{23} + \alpha^{(1)}_{21} x_{32} + \alpha^{(1)}_{22} x_{33} + \alpha^{(1)}_0$$

$$y^{(2)}_{11} = \alpha^{(2)}_{11} x_{11} + \alpha^{(2)}_{12} x_{12} + \alpha^{(2)}_{21} x_{21} + \alpha^{(2)}_{22} x_{22} + \alpha^{(2)}_0$$
$$y^{(2)}_{12} = \dots$$
$$y^{(2)}_{21} = \dots$$
$$y^{(2)}_{22} = \alpha^{(2)}_{11} x_{22} + \alpha^{(2)}_{12} x_{23} + \alpha^{(2)}_{21} x_{32} + \alpha^{(2)}_{22} x_{33} + \alpha^{(2)}_0$$

Convolutional Layer

Ex: C^I input channels, C^I output channels

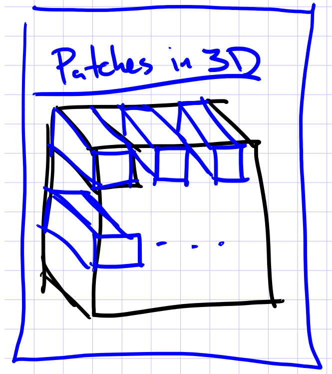


jth slice is output from jth convolution matrix

$$H^O = \lfloor (H^I + 2p - K)/s + 1 \rfloor$$

$$W^O = \lfloor (W^I + 2p - K)/s + 1 \rfloor$$

where p = # pixels of padding on input
k = size of conv. matrix
s = stride length



Forward:

$$y_{ij}^{(k)} = \alpha_0^{(k)} + \sum_{c=1}^{C^I} \sum_{q=1}^{K} \sum_{r=1}^{K} \alpha_{qr}^{(k)} x_{mn}^{(c)} \quad \text{where } \begin{array}{l} m = s(i-1)+q \\ n = s(j-1)+r \end{array}$$

Backward:

$$\frac{dJ}{d\alpha_0^{(k)}} = \sum_i \sum_j \frac{dJ}{dy_{ij}^{(k)}} \frac{dy_{ij}^{(k)}}{d\alpha_0^{(k)}}$$

$$\frac{dJ}{d\alpha_{qr}^{(k)}} = \sum_i \sum_j \frac{dJ}{dy_{ij}^{(k)}} \frac{dy_{ij}^{(k)}}{d\alpha_{qr}^{(k)}}$$

$$\frac{dJ}{dx_{mn}^{(c)}} = \sum_i \sum_j \sum_k \frac{dJ}{dy_{ij}^{(k)}} \frac{dy_{ij}^{(k)}}{dx_{mn}^{(c)}}$$

just some calculus

Max-Pooling Layer

Ex: 1 input channel, 1 output channel, stride of 1

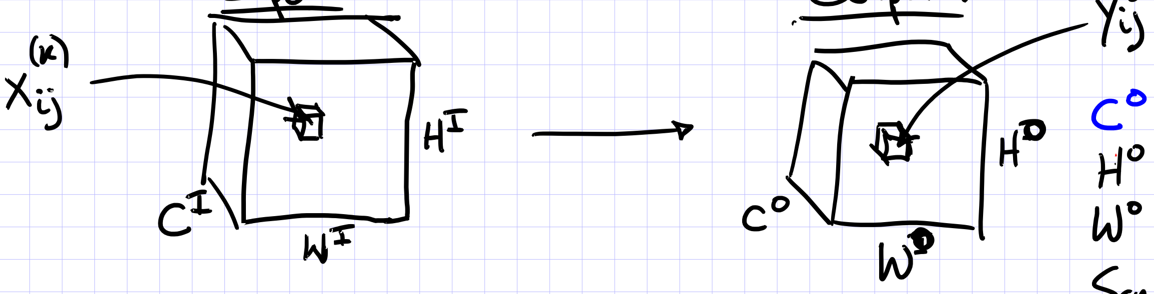
$$\underset{\text{Input}}{\begin{bmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{32} & x_{33} \end{bmatrix}} \longrightarrow \underset{\text{Pool Size}}{\begin{bmatrix} & \\ & \end{bmatrix}} \longrightarrow \underset{\text{Output}}{\begin{bmatrix} y_{11} & y_{12} \\ y_{21} & y_{22} \end{bmatrix}}$$

$$y_{11} = \max(x_{11}, x_{12}, x_{21}, x_{22})$$
$$y_{12} = \max(x_{12}, x_{13}, x_{22}, x_{23})$$
$$y_{21} = \max(x_{21}, x_{22}, x_{31}, x_{32})$$
$$y_{22} = \max(x_{22}, x_{23}, x_{32}, x_{33})$$

Max-Pooling Layer

Max-Pooling Layer

Input: Output:



$C^O = C^I$

$H^O = \ldots$ } same as conv. layer
$W^O = \ldots$

Same hyperparams too.

Forward:

$$y_{ij}^{(k)} = \max_{\substack{q \in \{1,\ldots,K\} \\ r \in \{1,\ldots,K\}}} x_{mn}^{(k)} \quad \text{where} \quad \begin{array}{l} m = s(i-1)+q \\ n = s(j-1)+r \end{array}$$

Backward:

$$\frac{dJ}{dx_{mn}^{(k)}} = \sum_i \sum_j \frac{dJ}{dy_{ij}^{(k)}} \frac{dy_{ij}^{(k)}}{dx_{mn}^{(k)}}$$

Subderivatives

+ Max() is not differentiable, but subdifferentiable.
+ There are a set of derivatives and we can just choose one for SGD.

$y = \max(a, b)$

$$\Rightarrow \frac{dJ}{da} = \frac{dJ}{dy}\frac{dy}{da} \quad \text{where} \quad \frac{dy}{da} = \begin{cases} 1 & \text{if } a > b \\ 0 & \text{otherwise} \end{cases}$$

Convolutional Neural Network (CNN)

- Typical layers include:
  - Convolutional layer
  - Max-pooling layer
  - Fully-connected (Linear) layer
  - ReLU layer (or some other nonlinear activation function)
  - Softmax
- These can be arranged into arbitrarily deep topologies

Architecture #1: LeNet-5

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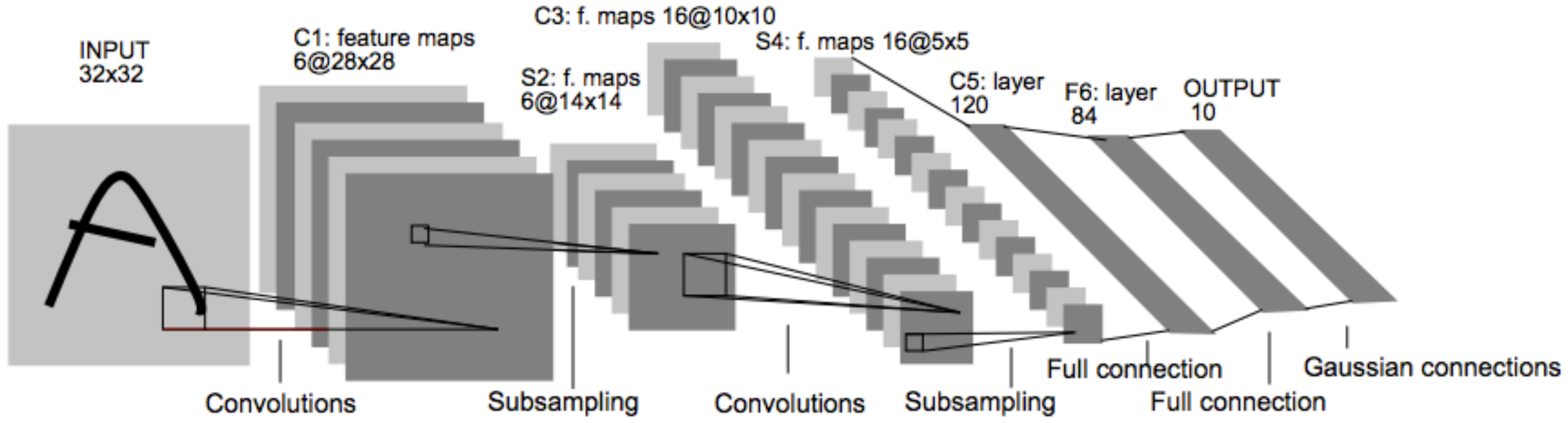


Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

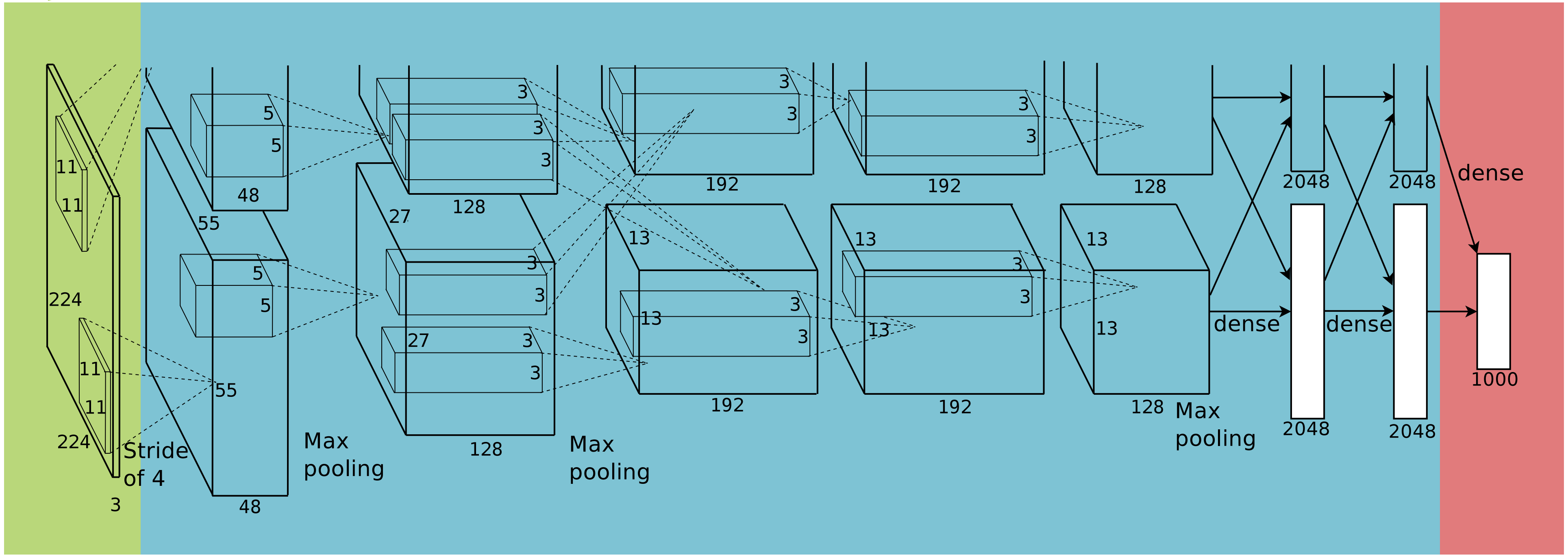
Architecture #2: AlexNet

CNN for Image Classification
(Krizhevsky, Sutskever & Hinton, 2012)
15.3% error on ImageNet LSVRC-2012 contest

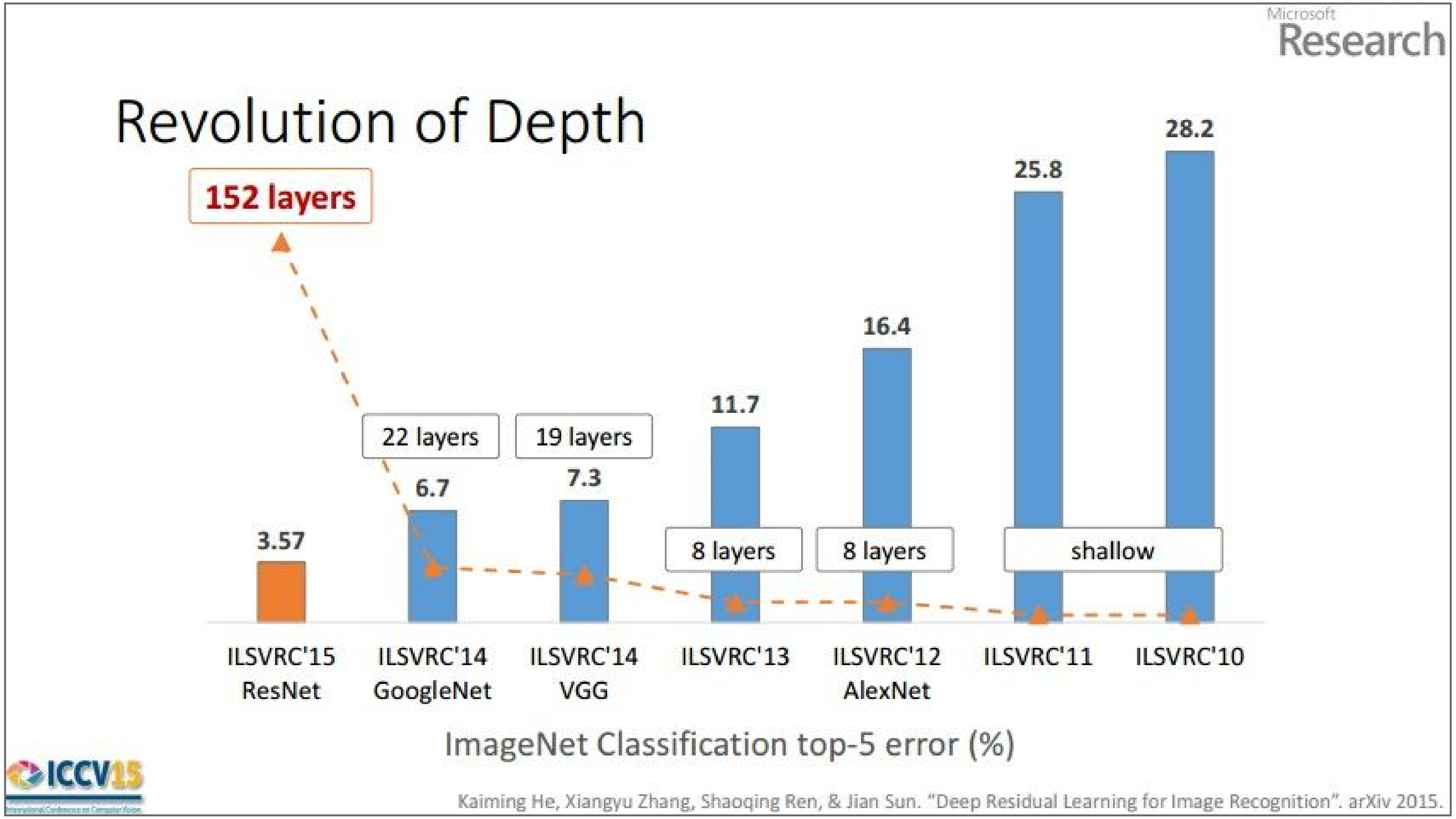
Input image (pixels)

- Five convolutional layers (w/max-pooling)
- Three fully connected layers

1000-way softmax



CNNs for Image Recognition



Slide from Kaiming He

Convolutional Neural Network (CNN)

Typical Architectures

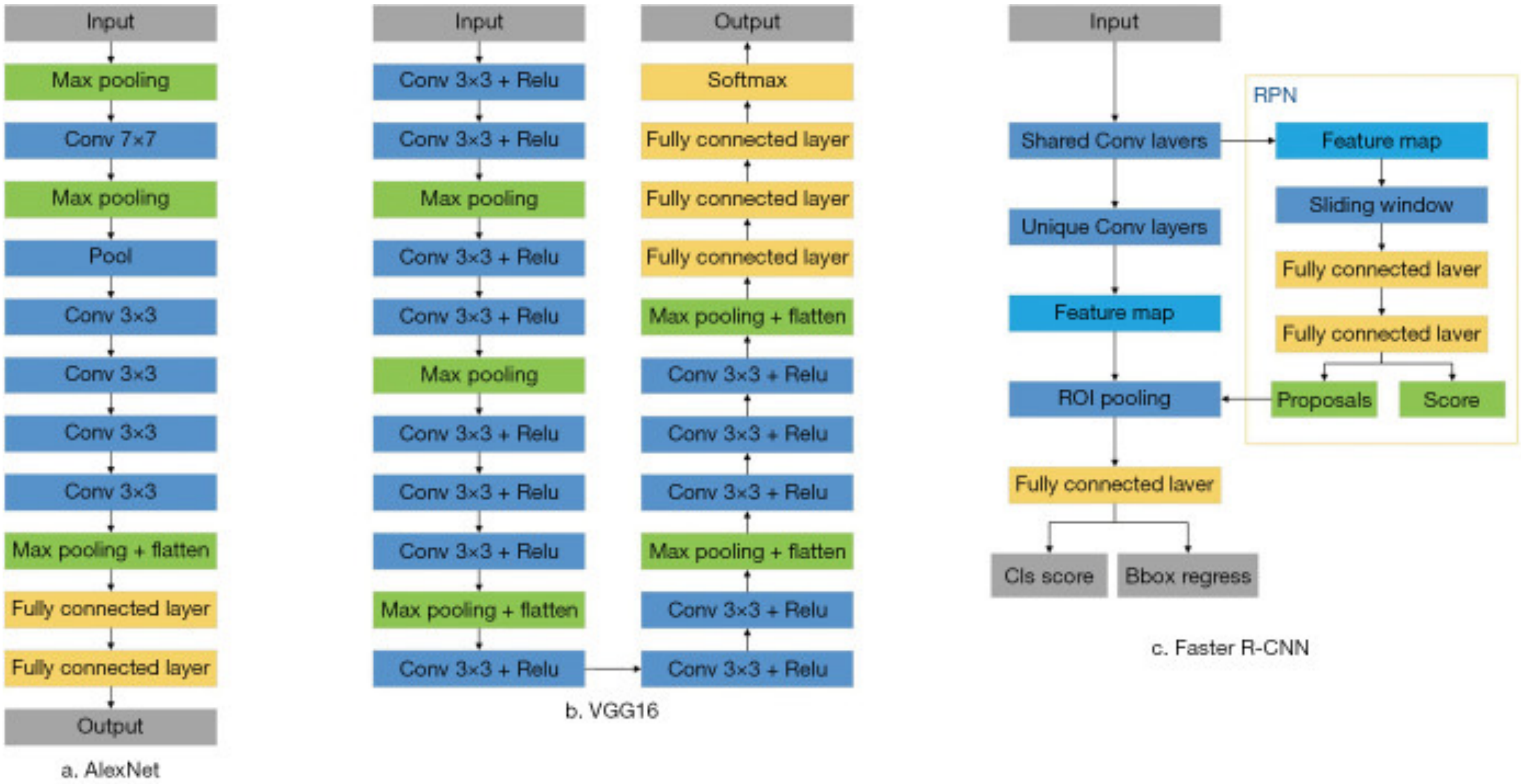


Figure from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7327346/

Convolutional Neural Network (CNN)

Typical Architectures

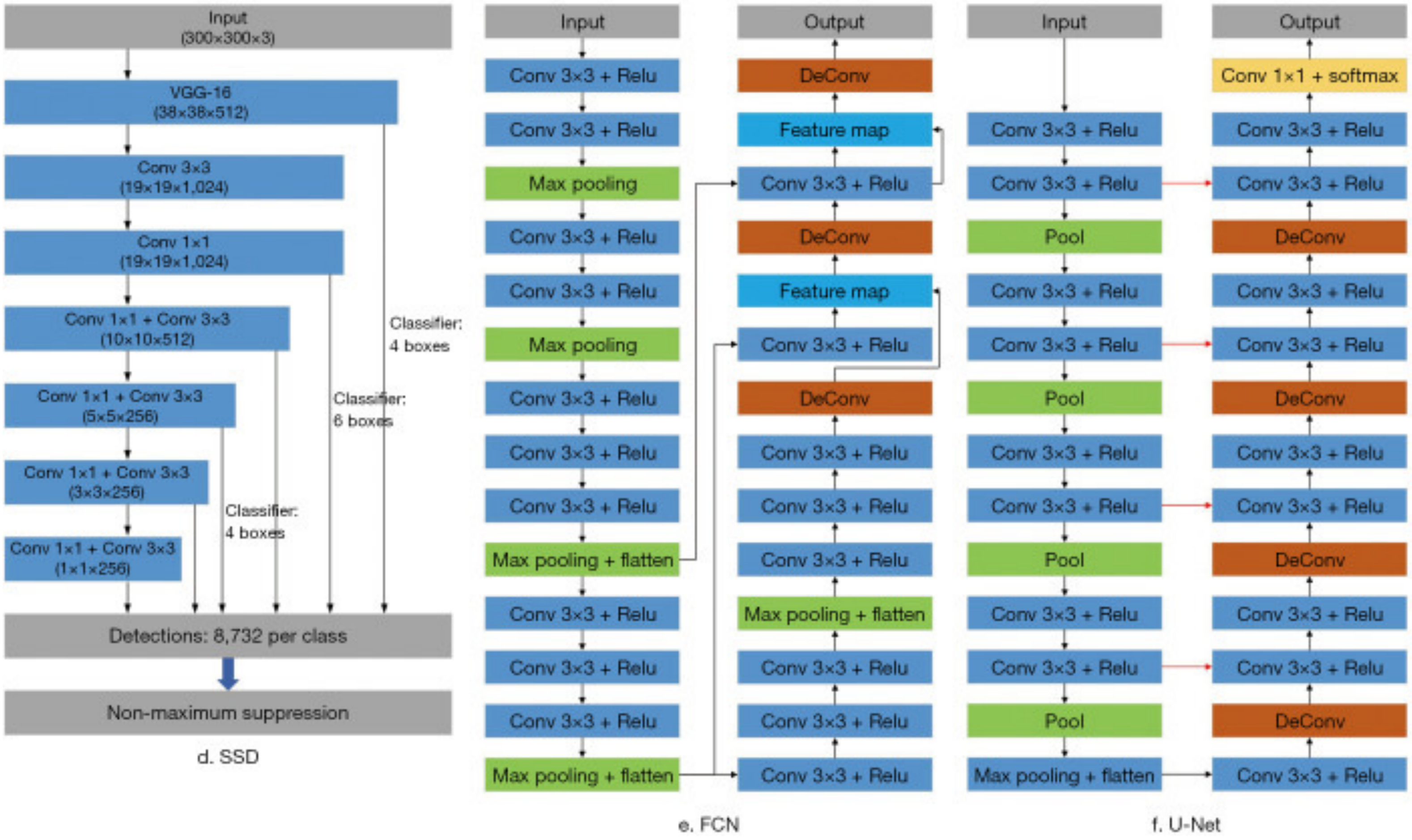
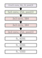


Figure from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7327346/

Convolutional Neural Network (CNN)

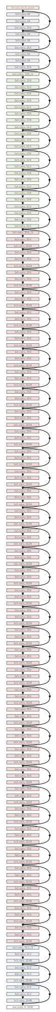
Typical Architectures

AlexNet, 8 layers
(ILSVRC 2012)



VGG, 19 layers
(ILSVRC 2014)

ResNet, 152 layers
(ILSVRC 2015)



Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. arXiv 2015.

In-Class Poll

Question:

Why do many layers used in computer vision *not have* location specific parameters?

Answer:

Convolutional Layer

For a convolutional layer, how do we pick the kernel size (aka. the size of the convolution)?

Input Image

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

2x2 Convolution

θ_{11}	θ_{12}
θ_{21}	θ_{22}

3x3 Convolution

θ_{11}	θ_{12}	θ_{13}
θ_{21}	θ_{22}	θ_{23}
θ_{31}	θ_{32}	θ_{33}

4x4 Convolution

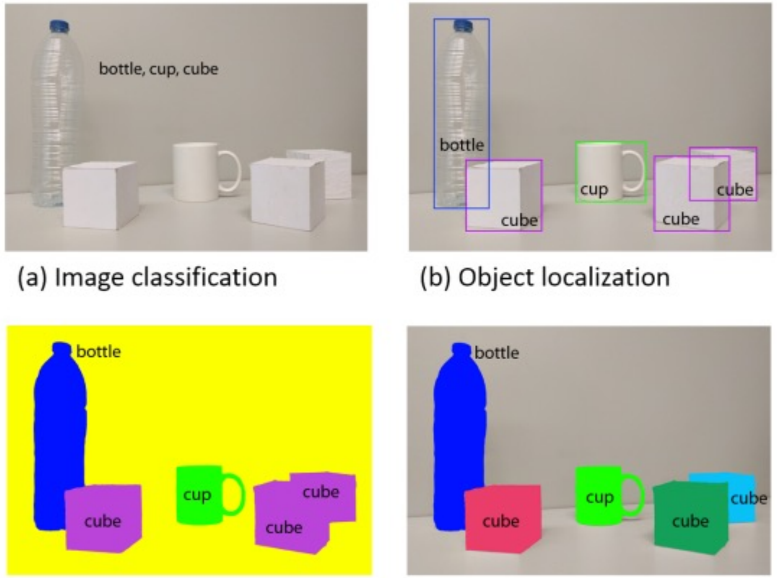
θ_{11}	θ_{12}	θ_{13}	θ_{14}
θ_{21}	θ_{22}	θ_{23}	θ_{24}
θ_{31}	θ_{32}	θ_{33}	θ_{34}
θ_{41}	θ_{42}	θ_{43}	θ_{44}

- A small kernel can only see a very small part of the image, but is fast to compute
- A large kernel can see more of the image, but at the expense of speed

COMPUTER VISION

Common Tasks in Computer Vision

1. Image Classification
2. Image Classification + Localization
3. Human Pose Estimation
4. Semantic Segmentation
5. Object Detection
6. Instance Segmentation
7. Image Captioning

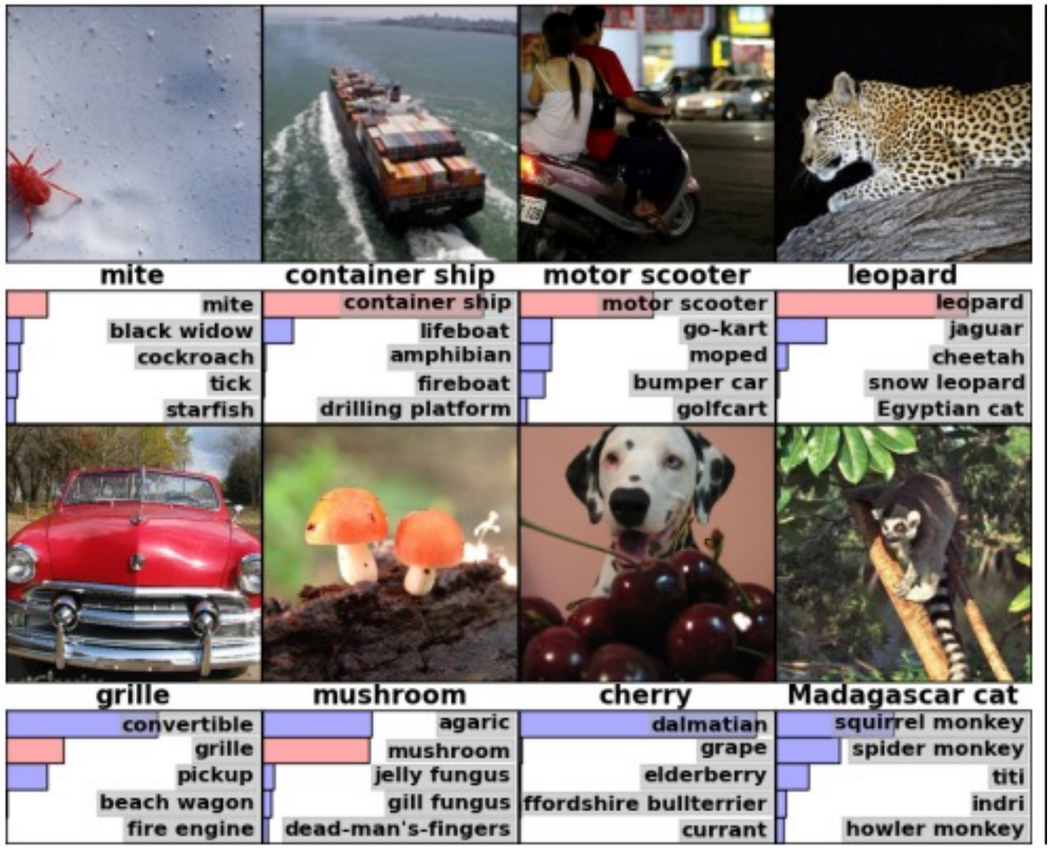


(a) Image classification (b) Object localization
(c) Semantic segmentation (d) Instance segmentation

Figure from https://arxiv.org/pdf/1704.06857.pdf

Image Classification

- Given an image, predict a single label
- A multi-class classification problem



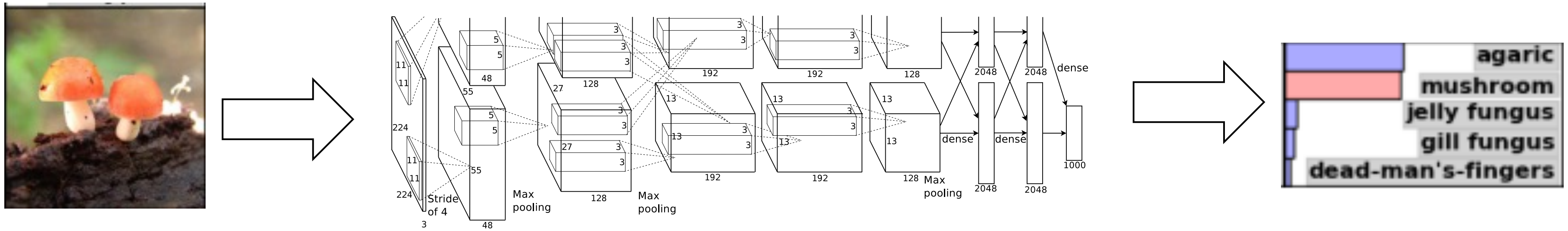


Figure from https://proceedings.neurips.cc/paper/2012/file/c399862d3b9d6b76c8436e924a68c45b-Paper.pdf

Image Classification + Localization

- Given an image, predict a single label and a bounding box for the object
- Bounding box is represented as (x, y, h, w), position (x,y) and height/width (h,w)

(a) Good localizations
(b) Strong false positive
(c) Missed objects

Figure from https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=5459257

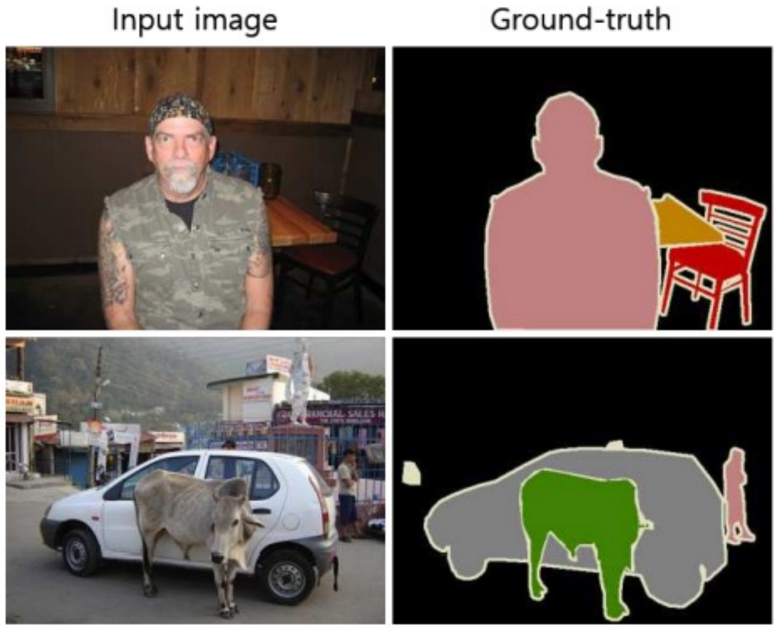
Human Pose Estimation

- Given an image of a human, predict the position of several keypoints (left hand, right hand, left elbow, …, right foot)
- This is a multiple regression problem, where each keypoint has a corresponding position (x_i,y_i)

Figure from
https://openaccess.thecvf.com/content_cvpr_2014/papers/Toshev_DeepPose_Human_Pose_2014_CVPR_paper.pdf

Semantic Segmentation

- Given an image, predict a label for every pixel in the image
- Not merely a classification problem, because there are strong correlations between pixel-specific labels



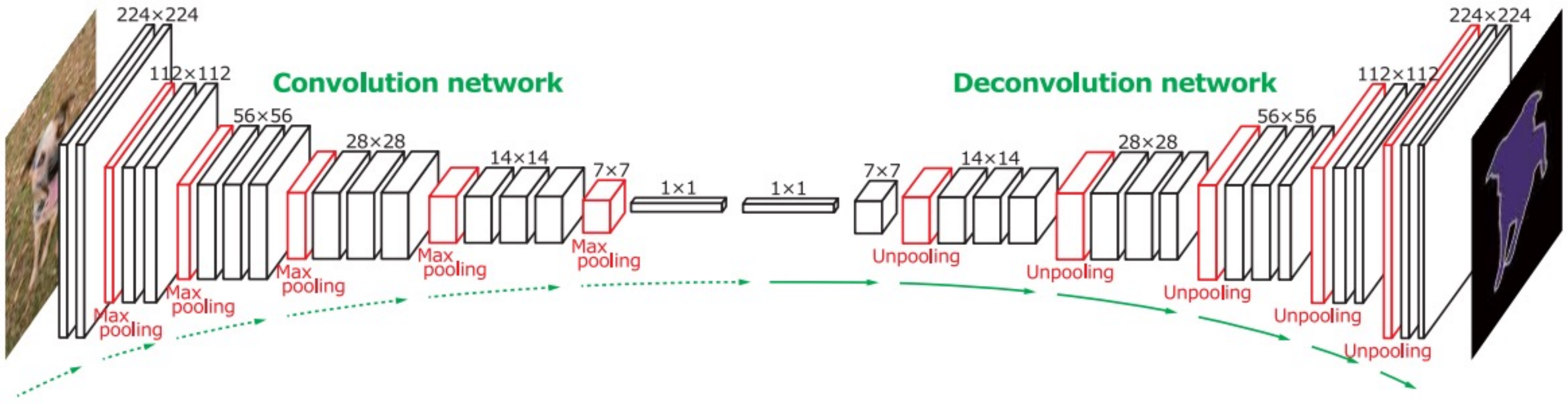


Figure from https://openaccess.thecvf.com/content_iccv_2015/papers/Noh_Learning_Deconvolution_Network_ICCV_2015_paper.pdf

Object Detection

- Given an image, for each object predict a bounding box and a label (x,y,w,h,l)
- Example: R-CNN
  - (x=110, y=13, w=50, h=72, l=person)
  - (x=90, y=55, w=81, h=87, l=horse)
  - (x=421, y=533, w=24, h=30, l=chair)
  - (x=2, y=25, w=51, h=121, l=gate)

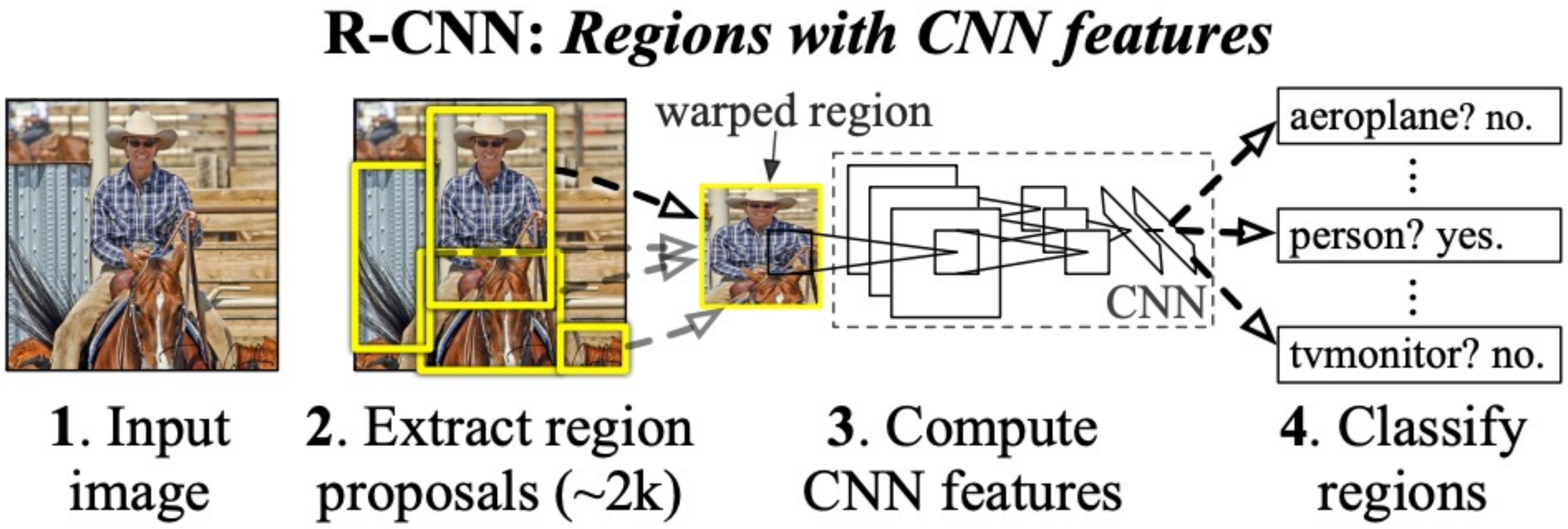


Figure from https://openaccess.thecvf.com/content_cvpr_2014/papers/Girshick_Rich_Feature_Hierarchies_2014_CVPR_paper.pdf

Instance Segmentation

- Predict per-pixel labels as in semantic segmentation, but differentiate between different instances of the same label
- *Example*: if there are two people in the image, one person should be labeled **person-1** and one should be labeled **person-2**

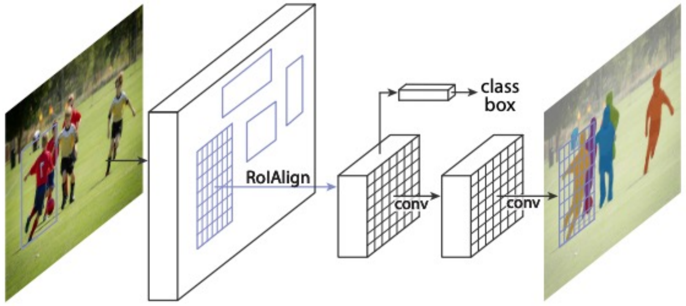


Figure 1. The **Mask R-CNN** framework for instance segmentation.

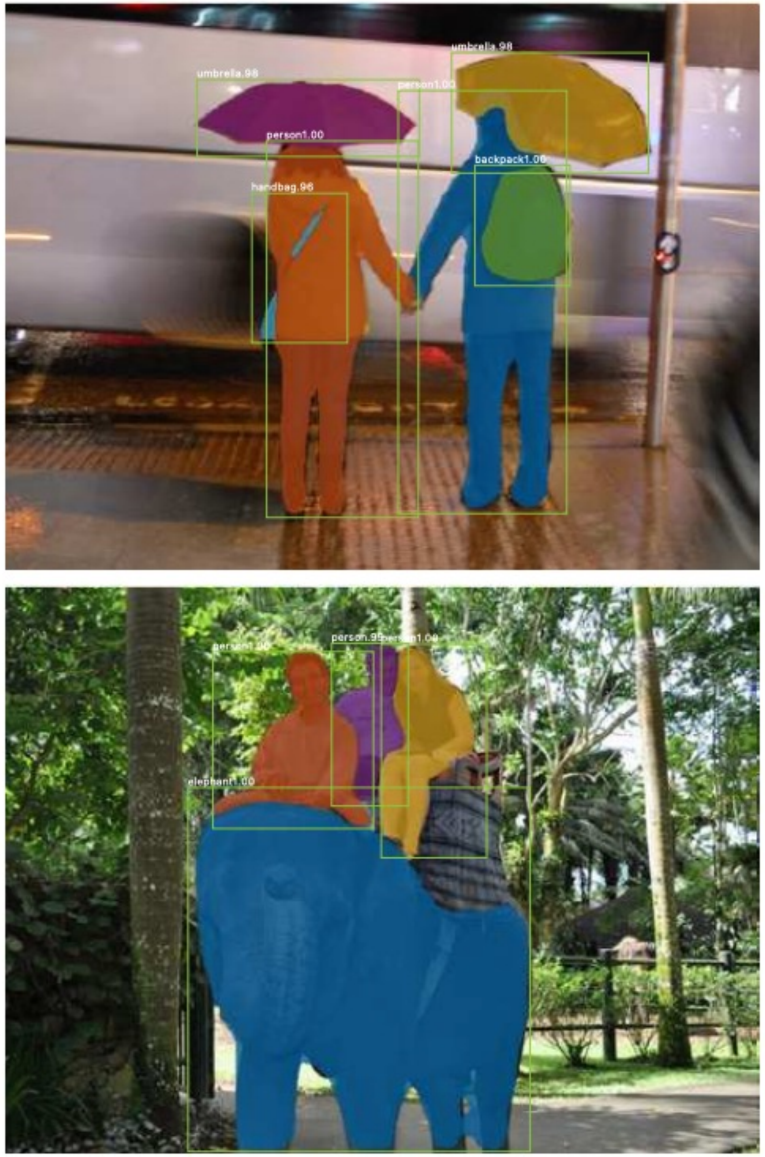
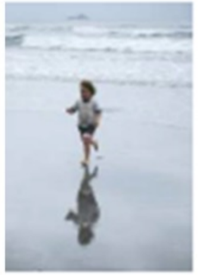


Figure from https://openaccess.thecvf.com/content_ICCV_2017/papers/He_Mask_R-CNN_ICCV_2017_paper.pdf

Image Captioning



Ground Truth Caption: A little boy runs away from the approaching waves of the ocean.

Generated Caption: A young boy is running on the beach.

Ground Truth Caption: A brunette girl wearing sunglasses and a yellow shirt.

Generated Caption: A woman in a black shirt and sunglasses smiles.

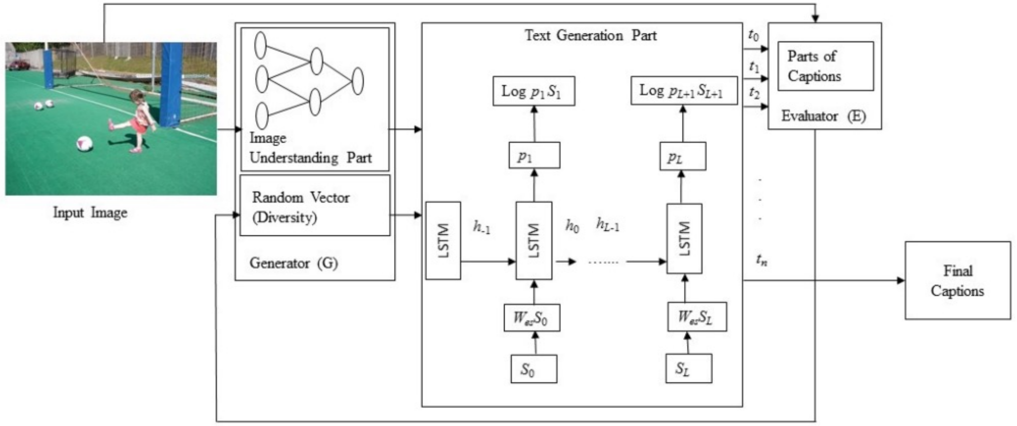


Fig. 3. A block diagram of other deep-learning-based captioning.

- Take an image as input, and generate a sentence describing it as output (i.e. the caption)
- Typical methods include a deep CNN/transformer and a RNN-like language model
- (The task of *Dense Captioning* is to generate one caption per bounding box)

Figure from https://dl.acm.org/doi/pdf/10.1145/3295748

Image Captioning

Table 1. An Overview of the Deep-Learning-Based Approaches for Image Captioning

Reference	Image Encoder	Language Model	Category
Kiros et al. 2014 [69]	AlexNet	LBL	MS, SL, WS, EDA
Kiros et al. 2014 [70]	AlexNet, VGGNet	1. LSTM 2. SC-NLM	MS, SL, WS, EDA
Mao et al. 2014 [95]	AlexNet	RNN	MS, SL, WS
Karpathy et al. 2014 [66]	AlexNet	DTR	MS, SL, WS, EDA
Mao et al. 2015 [94]	AlexNet, VGGNet	RNN	MS, SL, WS
Chen et al. 2015 [23]	VGGNet	RNN	VS, SL, WS, EDA
Fang et al. 2015 [33]	AlexNet, VGGNet	MELM	VS, SL, WS, CA
Jia et al. 2015 [59]	VGGNet	LSTM	VS, SL, WS, EDA
Karpathy et al. 2015 [65]	VGGNet	RNN	MS, SL, WS, EDA
Vinyals et al. 2015 [142]	GoogLeNet	LSTM	VS, SL, WS, EDA
Xu et al. 2015 [152]	AlexNet	LSTM	VS, SL, WS, EDA, AB
Jin et al. 2015 [61]	VGGNet	LSTM	VS, SL, WS, EDA, AB
Wu et al. 2016 [151]	VGGNet	LSTM	VS, SL, WS, EDA, AB
Sugano et at. 2016 [129]	VGGNet	LSTM	VS, SL, WS, EDA, AB
Mathews et al. 2016 [97]	GoogLeNet	LSTM	VS, SL, WS, EDA, SC
Wang et al. 2016 [144]	AlexNet, VGGNet	LSTM	VS, SL, WS, EDA
Johnson et al. 2016 [62]	VGGNet	LSTM	VS, SL, DC, EDA
Mao et al. 2016 [92]	VGGNet	LSTM	VS, SL, WS, EDA
Wang et al. 2016 [146]	VGGNet	LSTM	VS, SL, WS, CA
Tran et al. 2016 [135]	ResNet	MELM	VS, SL, WS, CA
Ma et al. 2016 [90]	AlexNet	LSTM	VS, SL, WS, CA
You et al. 2016 [156]	GoogLeNet	RNN	VS, SL, WS, EDA, SCB
Yang et al. 2016 [153]	VGGNet	LSTM	VS, SL, DC, EDA
Anne et al. 2016 [6]	VGGNet	LSTM	VS, SL, WS, CA, NOB
Yao et al. 2017 [155]	GoogLeNet	LSTM	VS, SL, WS, EDA, SCB
Lu et al. 2017 [88]	ResNet	LSTM	VS, SL, WS, EDA, AB
Chen et al. 2017 [21]	VGGNet, ResNet	LSTM	VS, SL, WS, EDA, AB
Gan et al. 2017 [41]	ResNet	LSTM	VS, SL, WS, CA, SCB
Pedersoli et al. 2017 [112]	VGGNet	RNN	VS, SL, WS, EDA, AB
Ren et al. 2017 [119]	VGGNet	LSTM	VS, ODL, WS, EDA
Park et al. 2017 [111]	ResNet	LSTM	VS, SL, WS, EDA, AB
Wang et al. 2017 [148]	ResNet	LSTM	VS, SL, WS, EDA
Tavakoli et al. 2017 [134]	VGGNet	LSTM	VS, SL, WS, EDA, AB
Liu et al. 2017 [84]	VGGNet	LSTM	VS, SL, WS, EDA, AB
Gan et al. 2017 [39]	ResNet	LSTM	VS, SL, WS, EDA, SC
Dai et al. 2017 [26]	VGGNet	LSTM	VS, ODL, WS, EDA
Shetty et al. 2017 [126]	GoogLeNet	LSTM	VS, ODL, WS, EDA
Liu et al. 2017 [85]	Inception-V3	LSTM	VS, ODL, WS, EDA
Gu et al. 2017 [51]	VGGNet	1. Language CNN 2. LSTM	VS, SL, WS, EDA
Yao et al. 2017 [154]	VGGNet	LSTM	VS, SL, WS, CA, NOB

(Continued)

- Take an image as input, and generate a sentence describing it as output (i.e. the caption)
- Typical methods include a deep CNN/transformer and a RNN-like language model
- (The task of *Dense Captioning* is to generate one caption per bounding box)

Table from https://dl.acm.org/doi/pdf/10.1145/3295748

Medical Image Analysis

Notice that **most** of these tasks are structured prediction problems, not merely classification

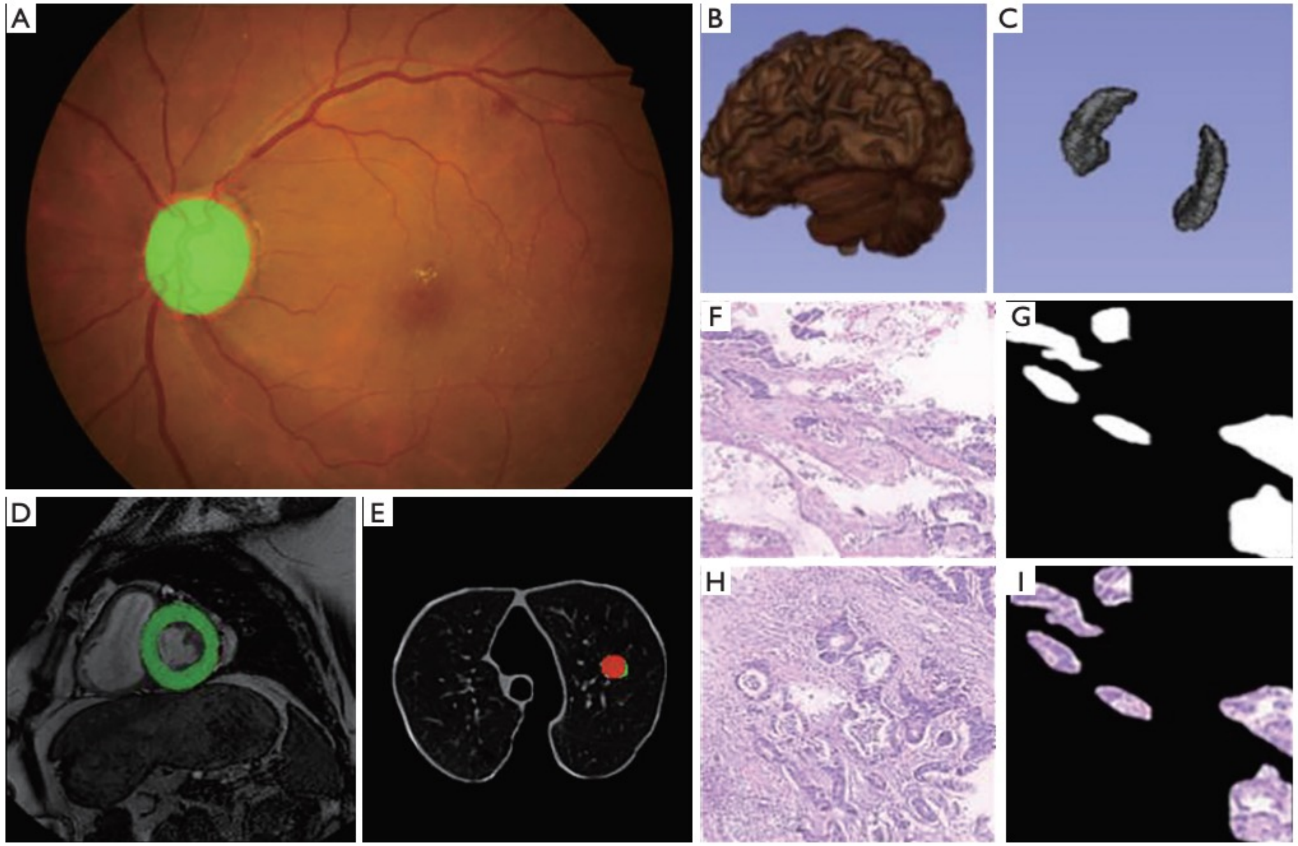


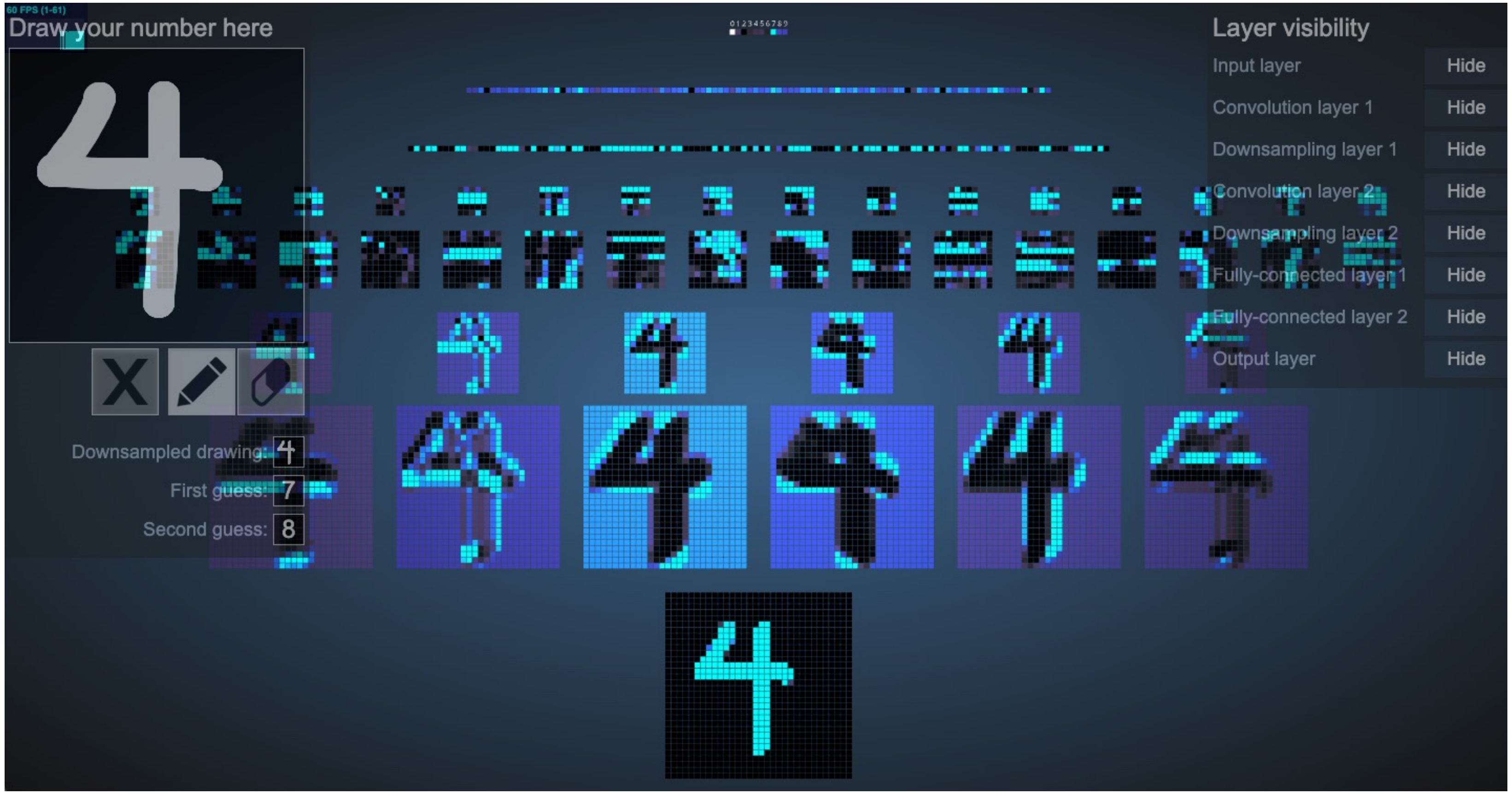
Figure 2 Deep learning application in medical image analysis. (A) Fundus detection; (B,C) hippocampus segmentation; (D) left ventricular segmentation; (E) pulmonary nodule classification; (F,G,H,I) gastric cancer pathology segmentation. The staining method is H&E, and the magnification is ×40.

Figure from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7327346/

CNN VISUALIZATIONS

Visualization of CNN

https://adamharley.com/nn_vis/cnn/2d.html



Convolution of a Color Image

- Color images consist of 3 floats per pixel for RGB (red, green blue) color values
- Convolution must also be 3-dimensional

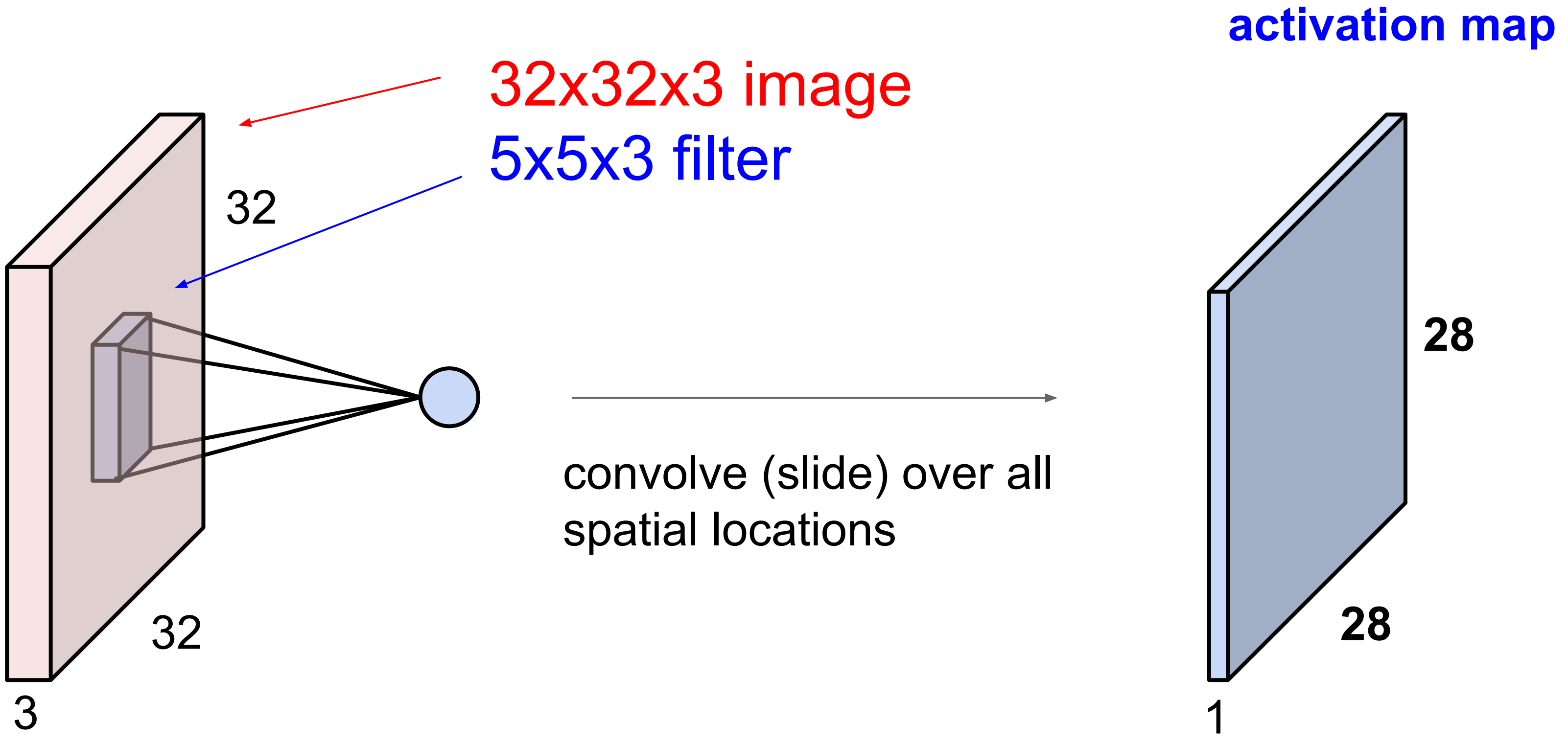


Figure from Fei-Fei Li & Andrej Karpathy & Justin Johnson (CS231N)

Animation of 3D Convolution

http://cs231n.github.io/convolutional-networks/

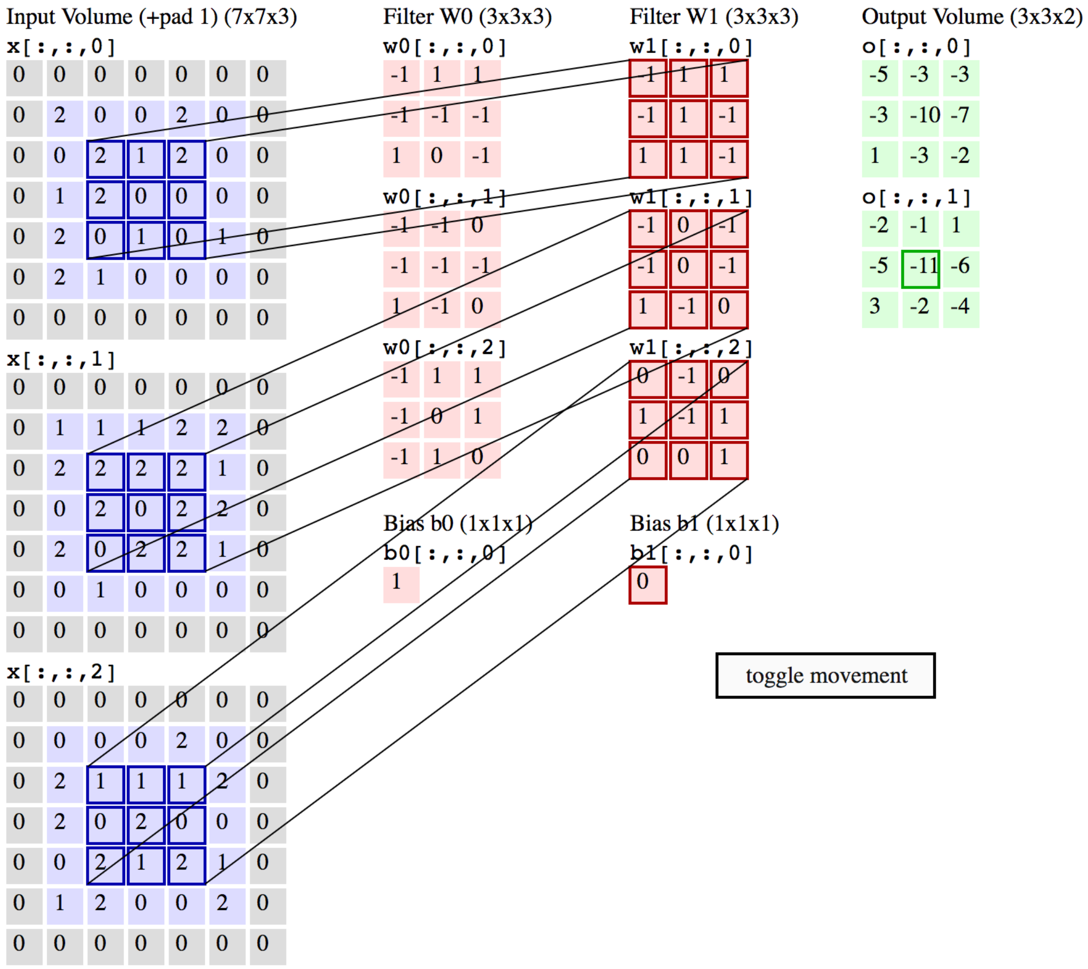


Figure from Fei-Fei Li & Andrej Karpathy & Justin Johnson (CS231N)

MNIST Digit Recognition with CNNs (in your browser)

https://cs.stanford.edu/people/karpathy/convnetjs/demo/mnist.html

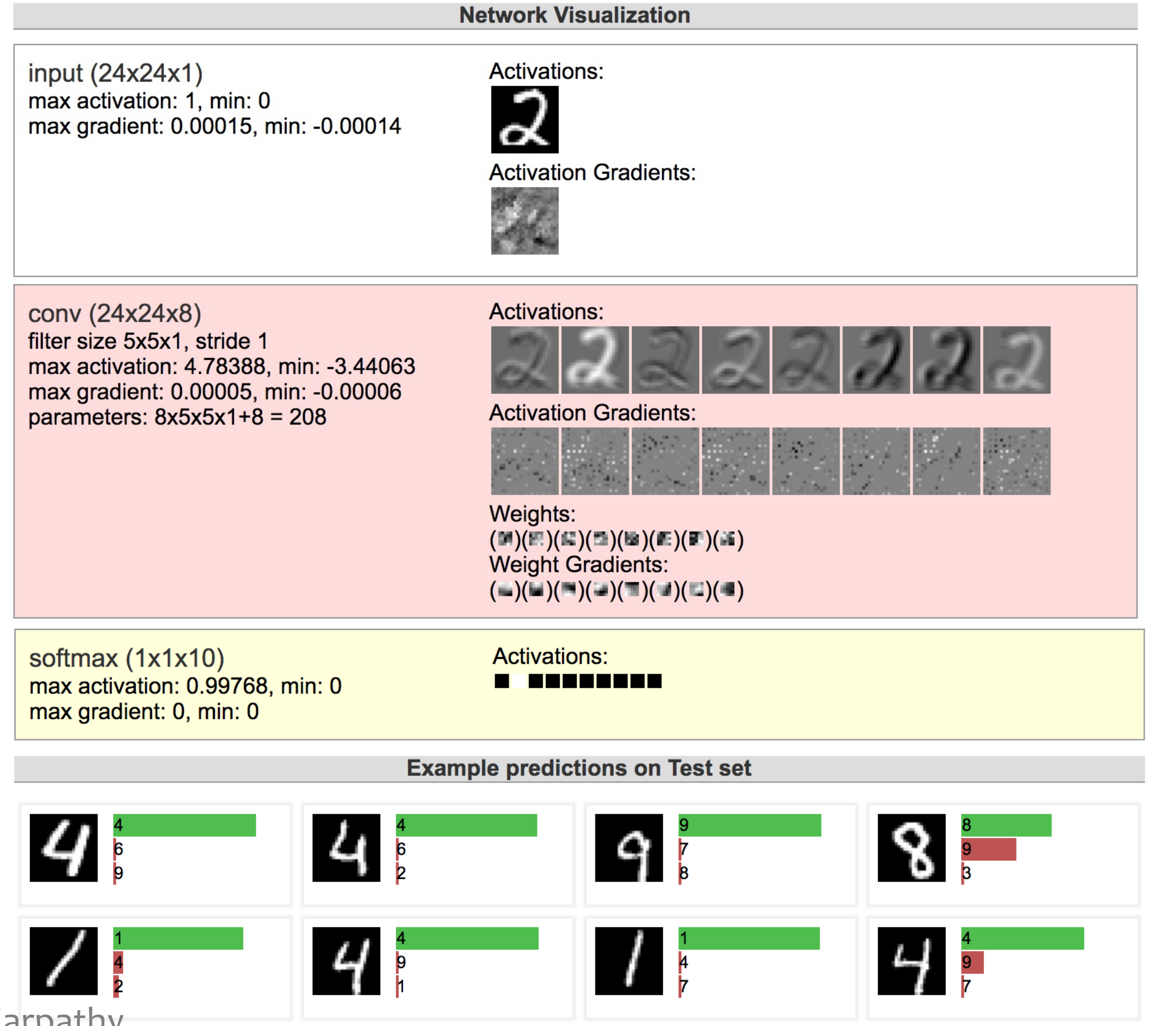


Figure from Andrej Karpathy

CNN Summary

CNNs

– Are used for all aspects of **computer vision**, and have won numerous pattern recognition competitions

– Able learn **interpretable features** at different levels of abstraction

– Typically, consist of **convolution** layers, **pooling** layers, **nonlinearities**, and **fully connected** layers

Deep Learning Objectives

You should be able to…

- Implement the common layers found in Convolutional Neural Networks (CNNs) such as linear layers, convolution layers, max-pooling layers, and rectified linear units (ReLU)
- Explain how the shared parameters of a convolutional layer could learn to detect spatial patterns in an image
- Describe the backpropagation algorithm for a CNN
- Identify the parameter sharing used in a basic recurrent neural network, e.g. an Elman network
- Apply a recurrent neural network to model sequence data
- Differentiate between an RNN and an RNN-LM

ML Big Picture

Learning Paradigms:

What data is available and when? What form of prediction?

- supervised learning
- unsupervised learning
- semi-supervised learning
- reinforcement learning
- active learning
- imitation learning
- domain adaptation
- online learning
- density estimation
- recommender systems
- feature learning
- manifold learning
- dimensionality reduction
- ensemble learning
- distant supervision
- hyperparameter optimization

Problem Formulation:

What is the structure of our output prediction?

boolean	Binary Classification
categorical	Multiclass Classification
ordinal	Ordinal Classification
real	Regression
ordering	Ranking
multiple discrete	Structured Prediction
multiple continuous	(e.g. dynamical systems)
both discrete & cont.	(e.g. mixed graphical models)

Application Areas

Key challenges?

NLP, Speech, Computer Vision, Robotics, Medicine, Search

Facets of Building ML Systems:

How to build systems that are robust, efficient, adaptive, effective?

1. *Data prep*
2. *Model selection*
3. *Training (optimization / search)*
4. *Hyperparameter tuning on validation data*
5. *(Blind) Assessment on test data*

Big Ideas in ML:

Which are the ideas driving development of the field?

- *inductive bias*
- *generalization / overfitting*
- *bias-variance decomposition*
- *generative vs. discriminative*
- *deep nets, graphical models*
- *PAC learning*
- *distant rewards*

Theoretical Foundations:

What principles guide learning?

- ❑ probabilistic
- ❑ information theoretic
- ❑ evolutionary search
- ❑ ML as optimization