Design & Constructs

- Ensemble Learning

- Ensemble Learning
- CNN - Convolutional Neural Networks

- Ensemble Learning
- CNN - Convolutional Neural Networks
- RNN - Recurrent Neural Networks

- Ensemble Learning
- CNN - Convolutional Neural Networks
- RNN - Recurrent Neural Networks
- Reinforcement Learning

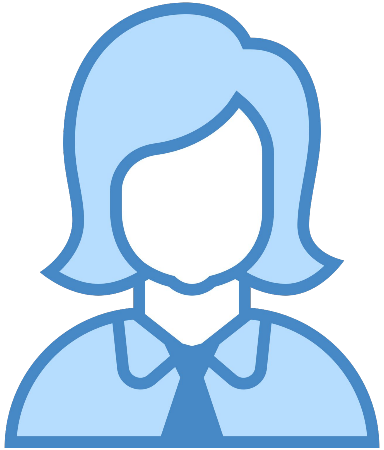
Question - We are all biased. What should we do?

Question - We are all biased. What should we do?

Answer - Create an Ensemble

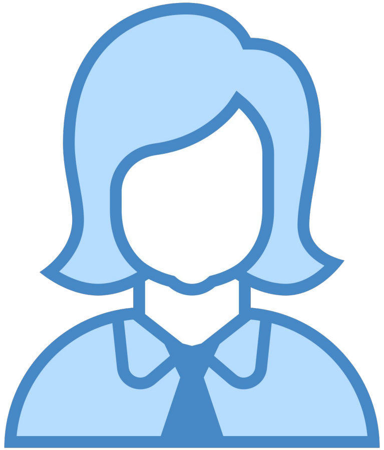

CV

Expert Interviewer



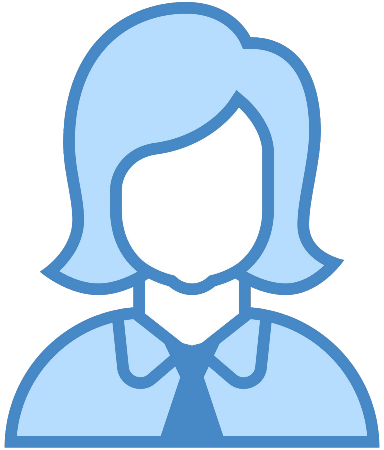
Interviewee

Expert Interviewer



Interviewee

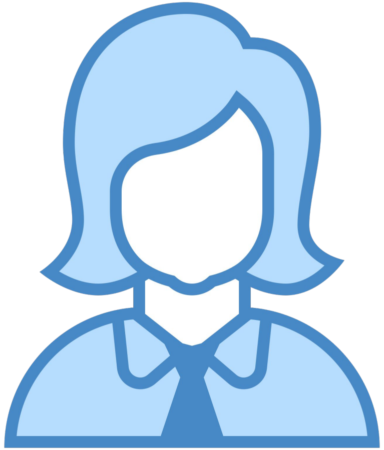
Expert Interviewer



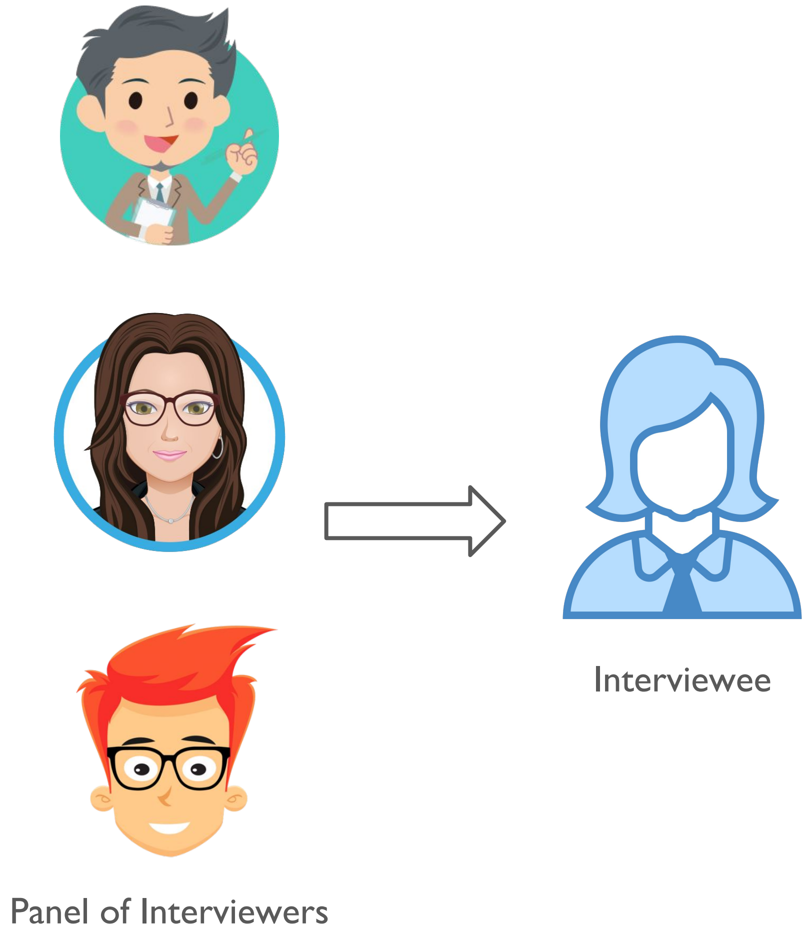
Interviewee

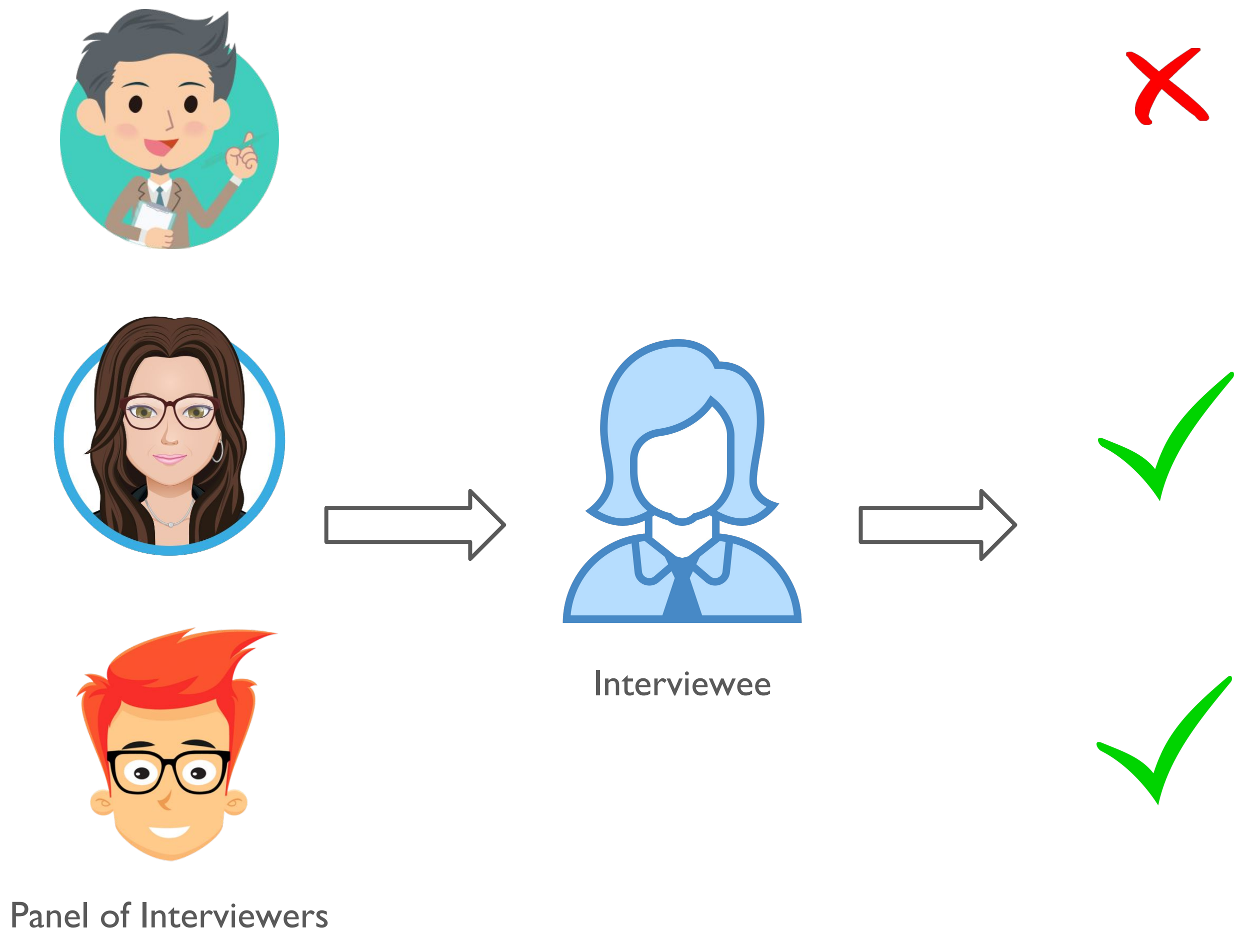
Biased Interviewer

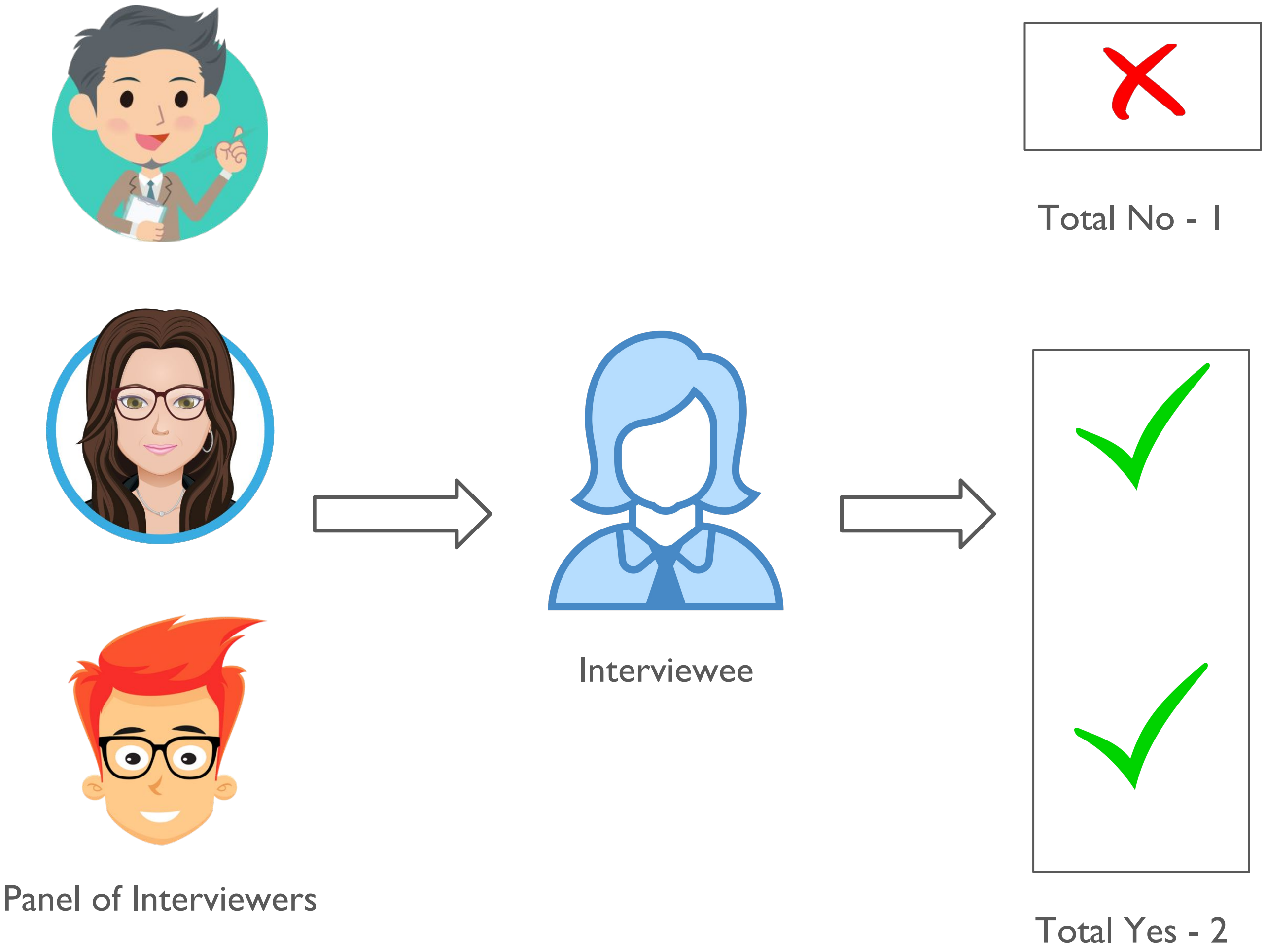
Expert Interviewer

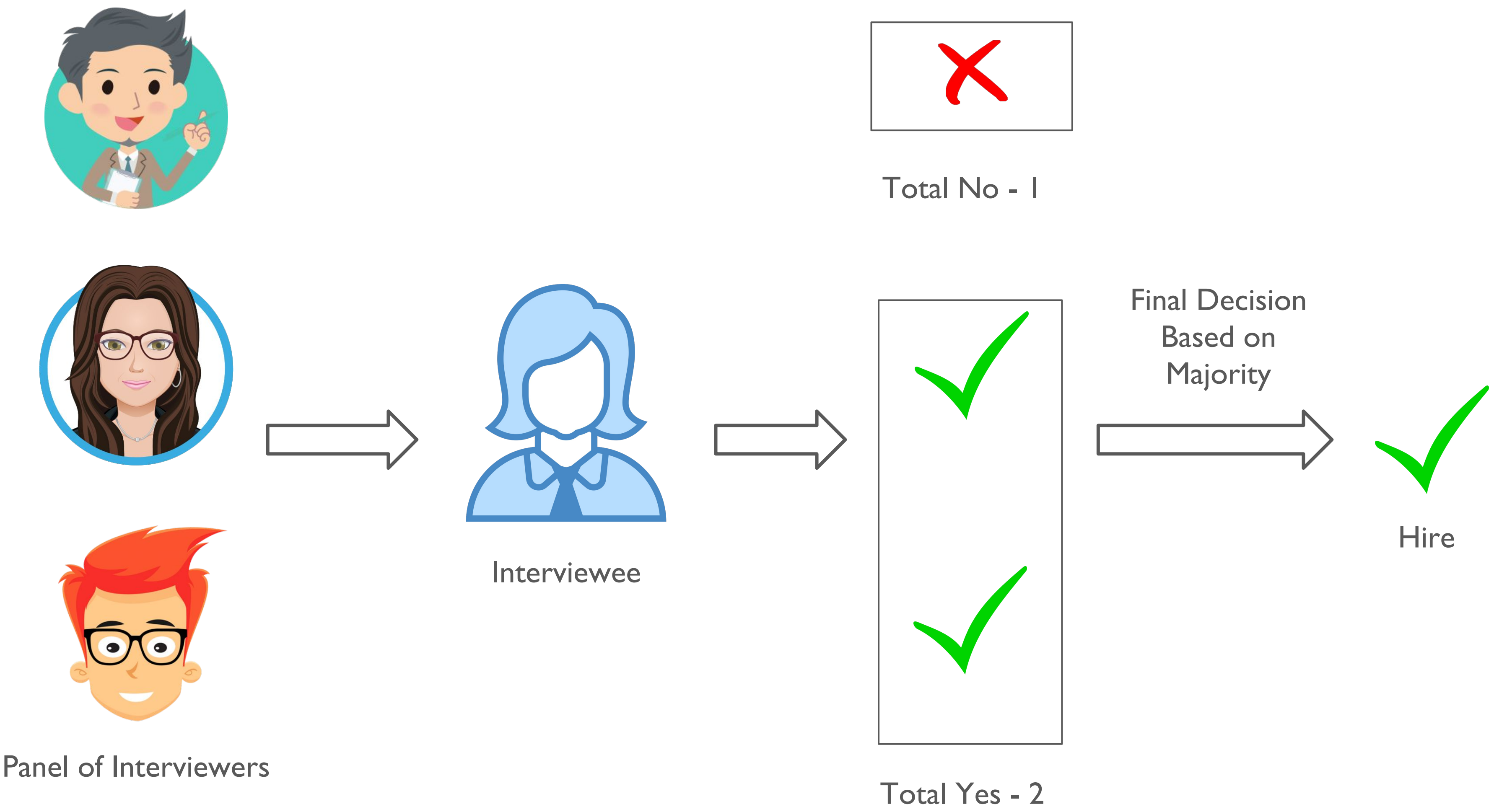


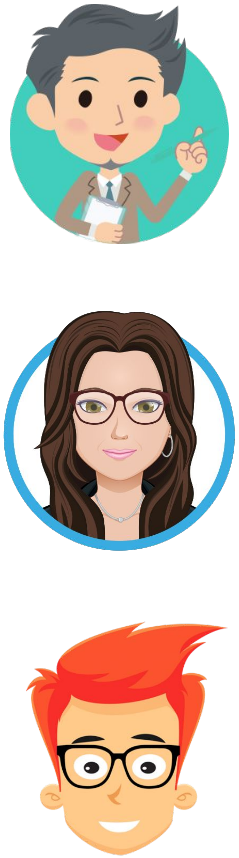
Interviewee


Interviewee
Panel of Interviewers


Interviewee
Panel of Interviewers


Total No - 1
Interviewee
Panel of Interviewers
Total Yes - 2


Total No - 1
Final Decision
Based on
Majority
Interviewee
Hire
Panel of Interviewers
Total Yes - 2

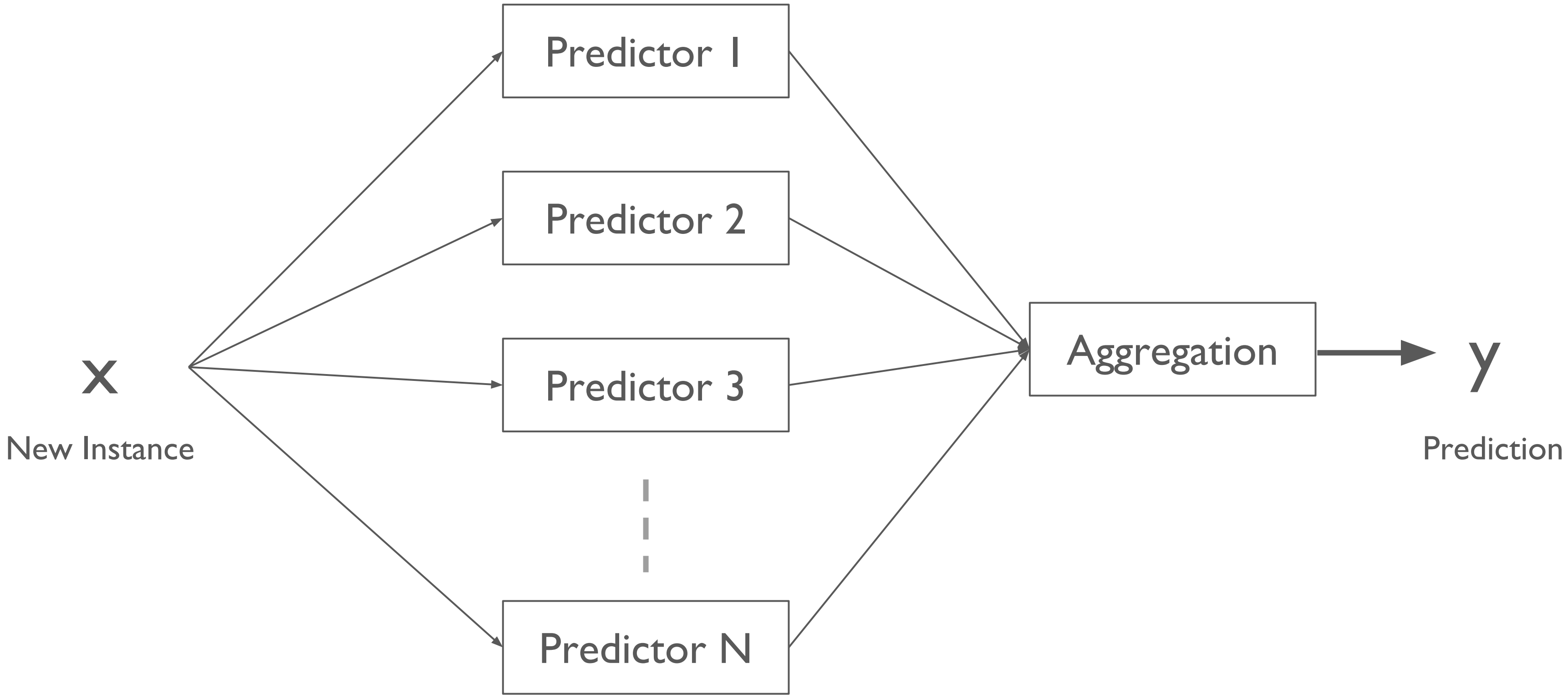


Panel of Interviewers

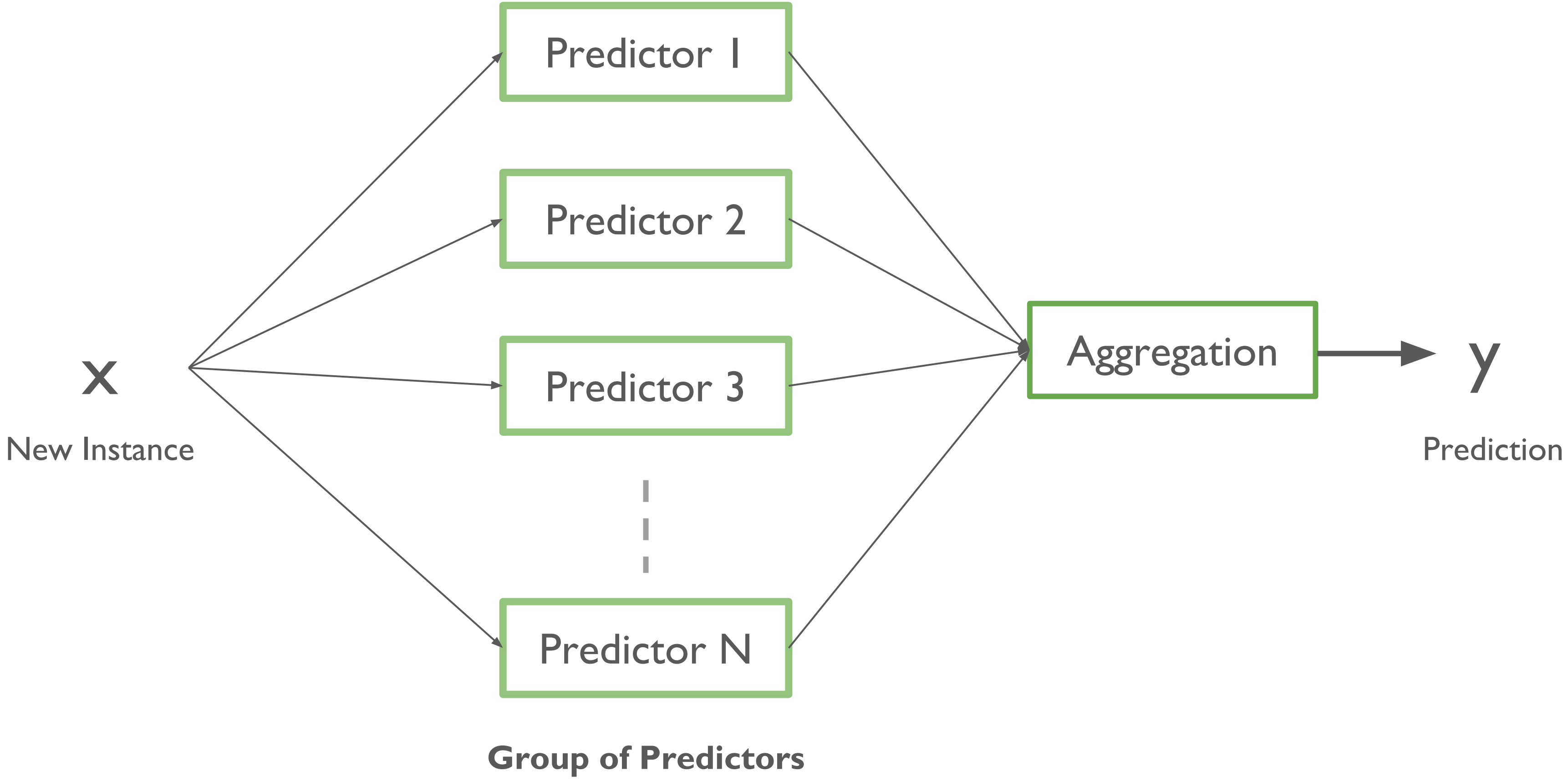
$>$

Better Decision

Expert Interviewer

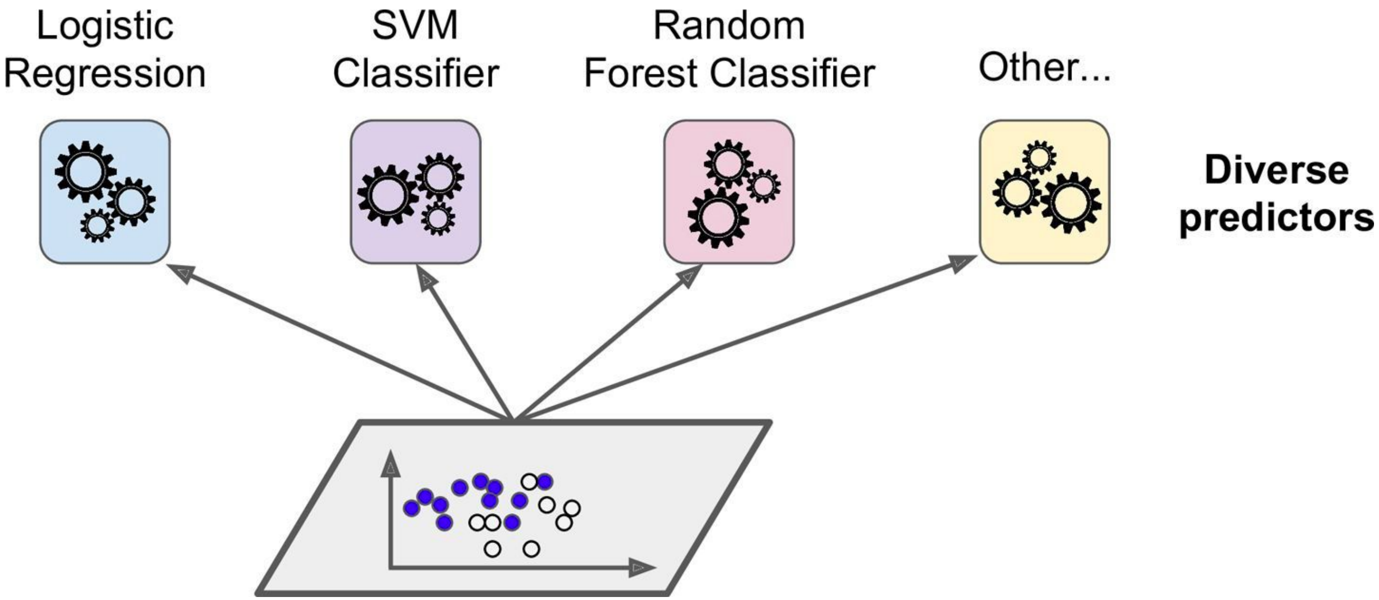


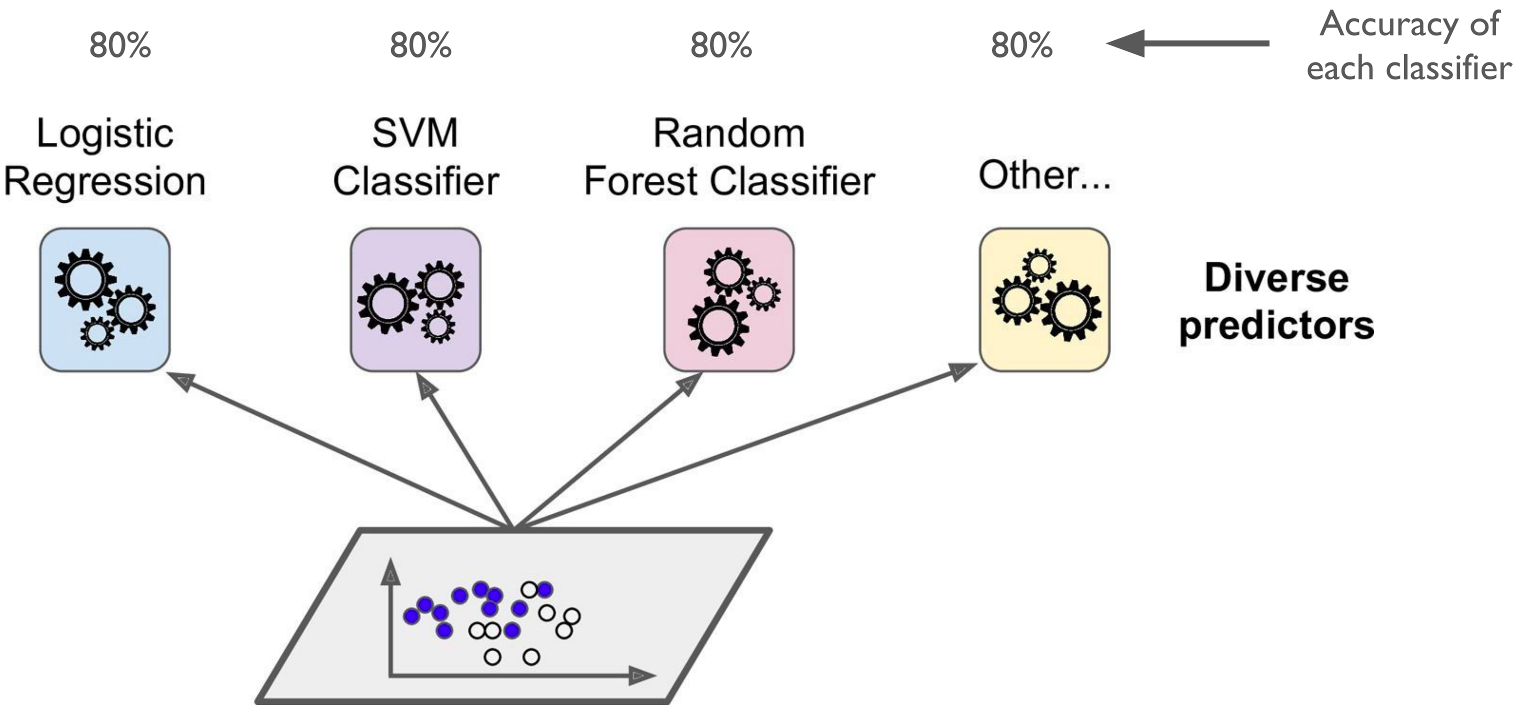
Group of Predictors


x
New Instance
Predictor 1
Predictor 2
Predictor 3
Predictor N
Group of Predictors
Aggregation
y
Prediction

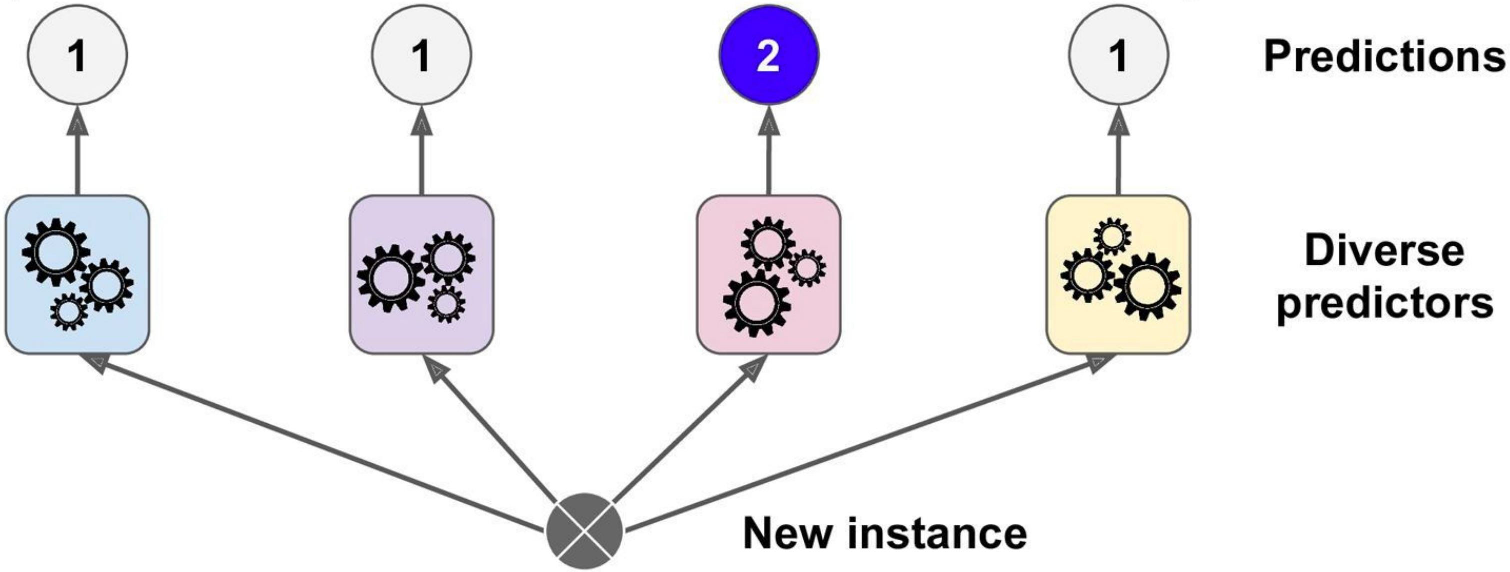
Checklist for Machine Learning Projects

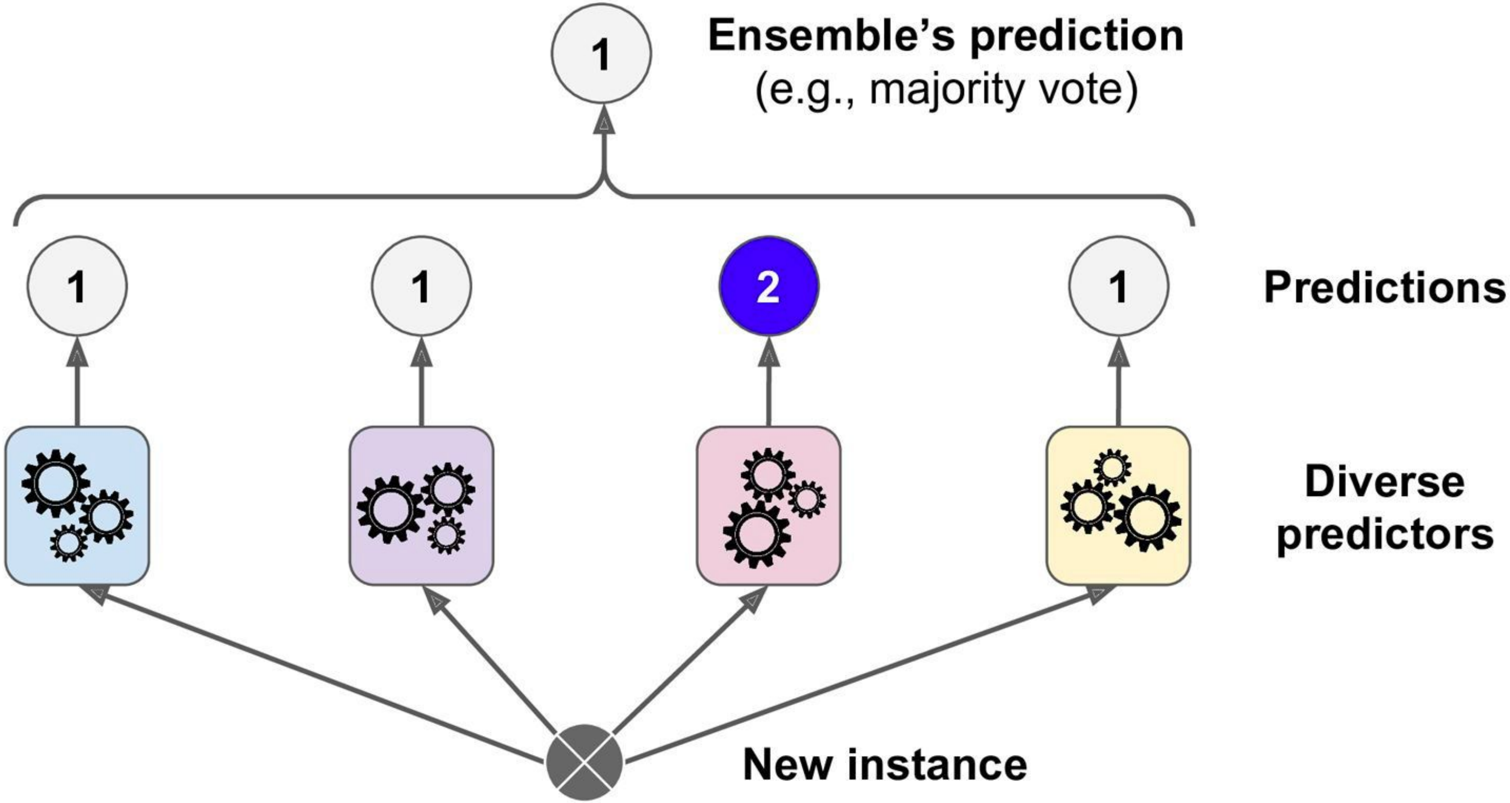
1. Frame the problem and look at the big picture
2. Get the data
3. Explore the data to gain insights
4. Prepare the data for Machine Learning algorithms
5. Explore many different models and short-list the best ones
6. **Fine-tune model**
7. Present the solution
8. Launch, monitor, and maintain the system

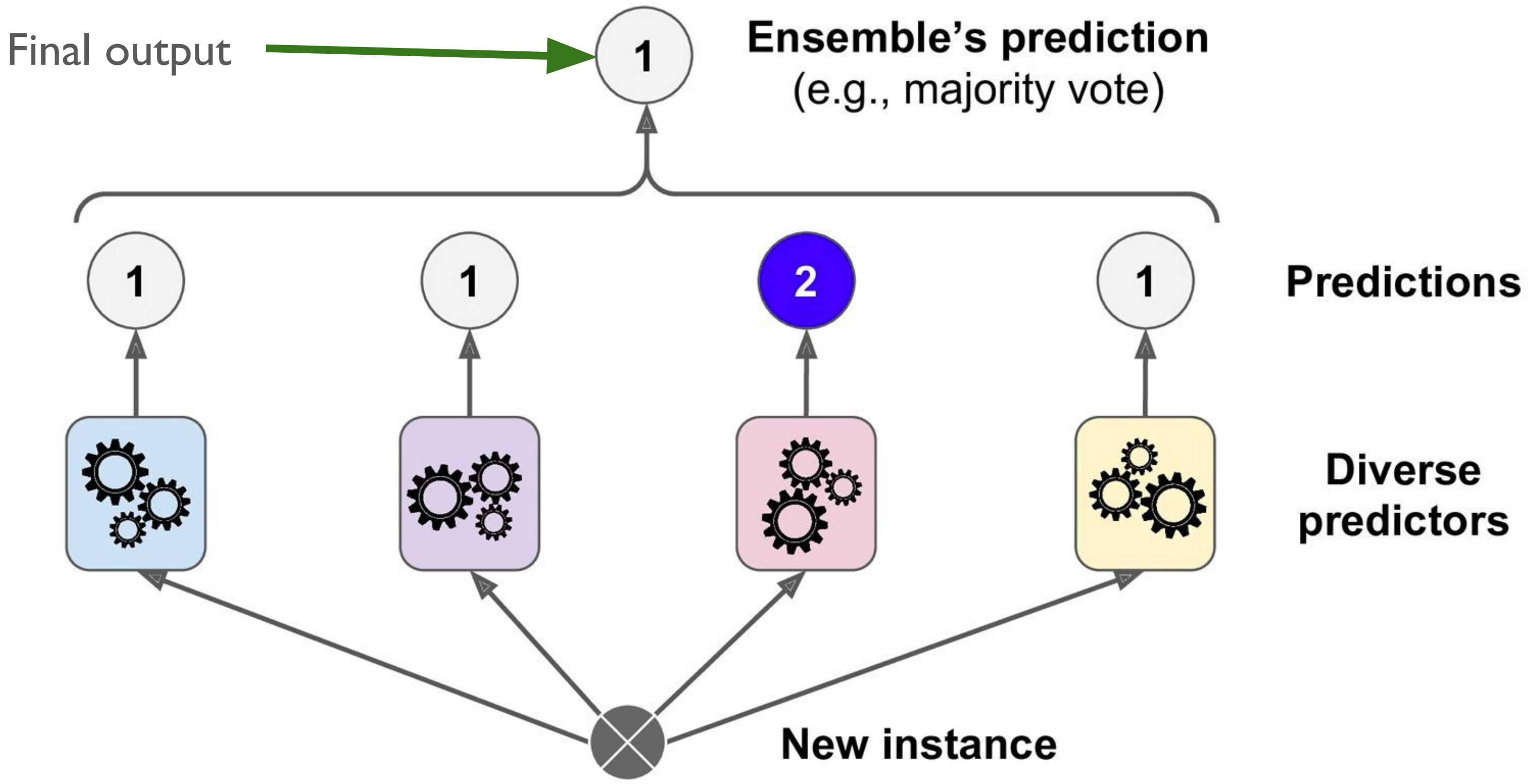

Logistic Regression
SVM Classifier
Random Forest Classifier
Other...
Diverse predictors

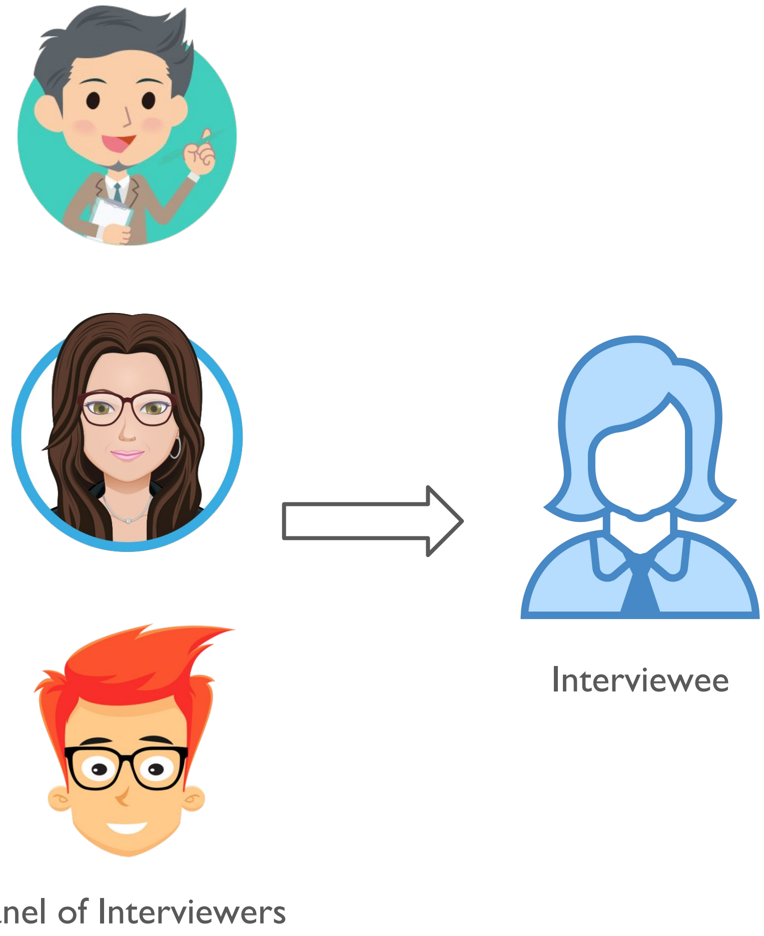

80%
80%
80%
80%
Accuracy of each classifier
Logistic Regression
SVM Classifier
Random Forest Classifier
Other...
Diverse predictors

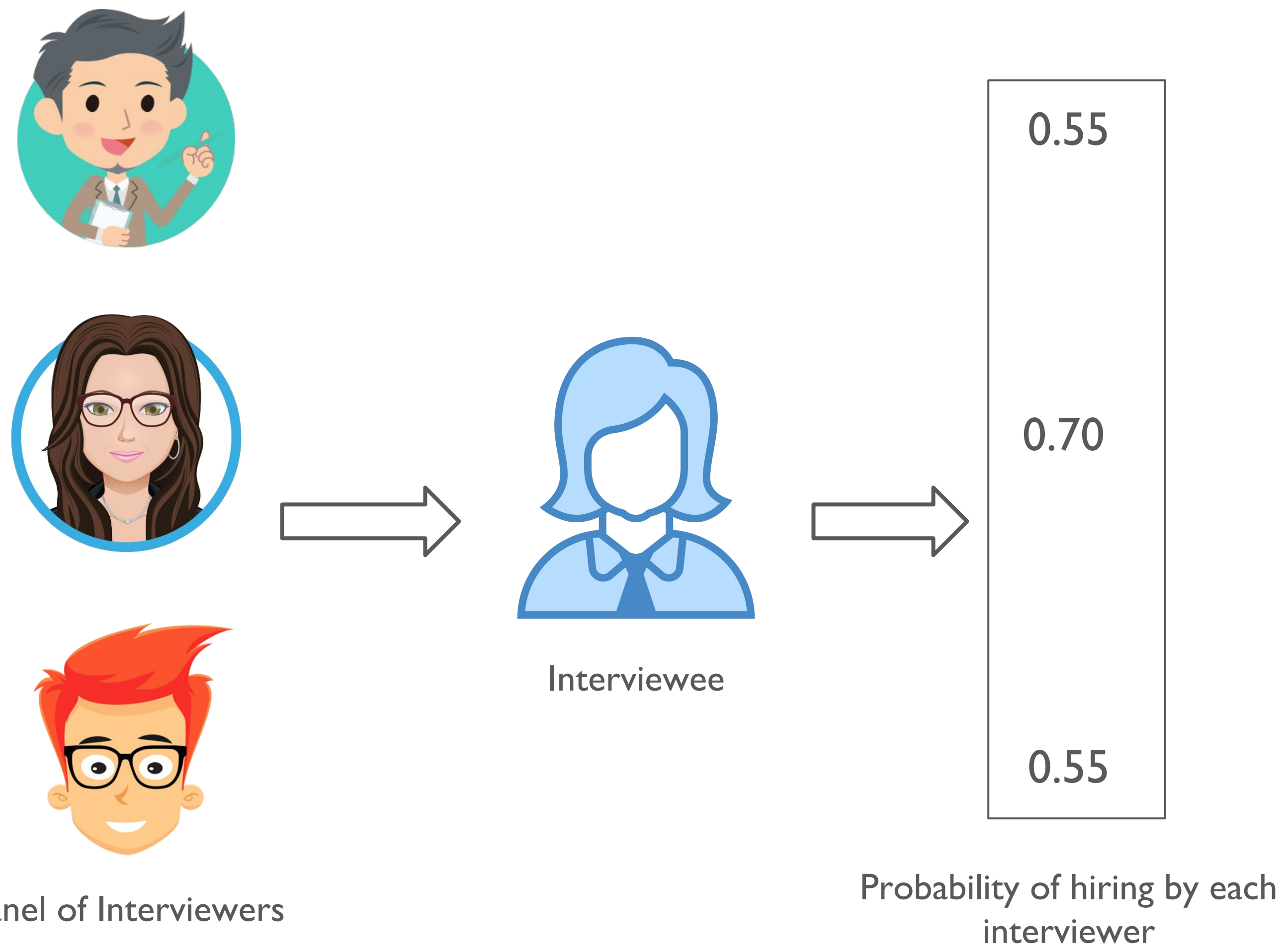
CLOUD x LAB

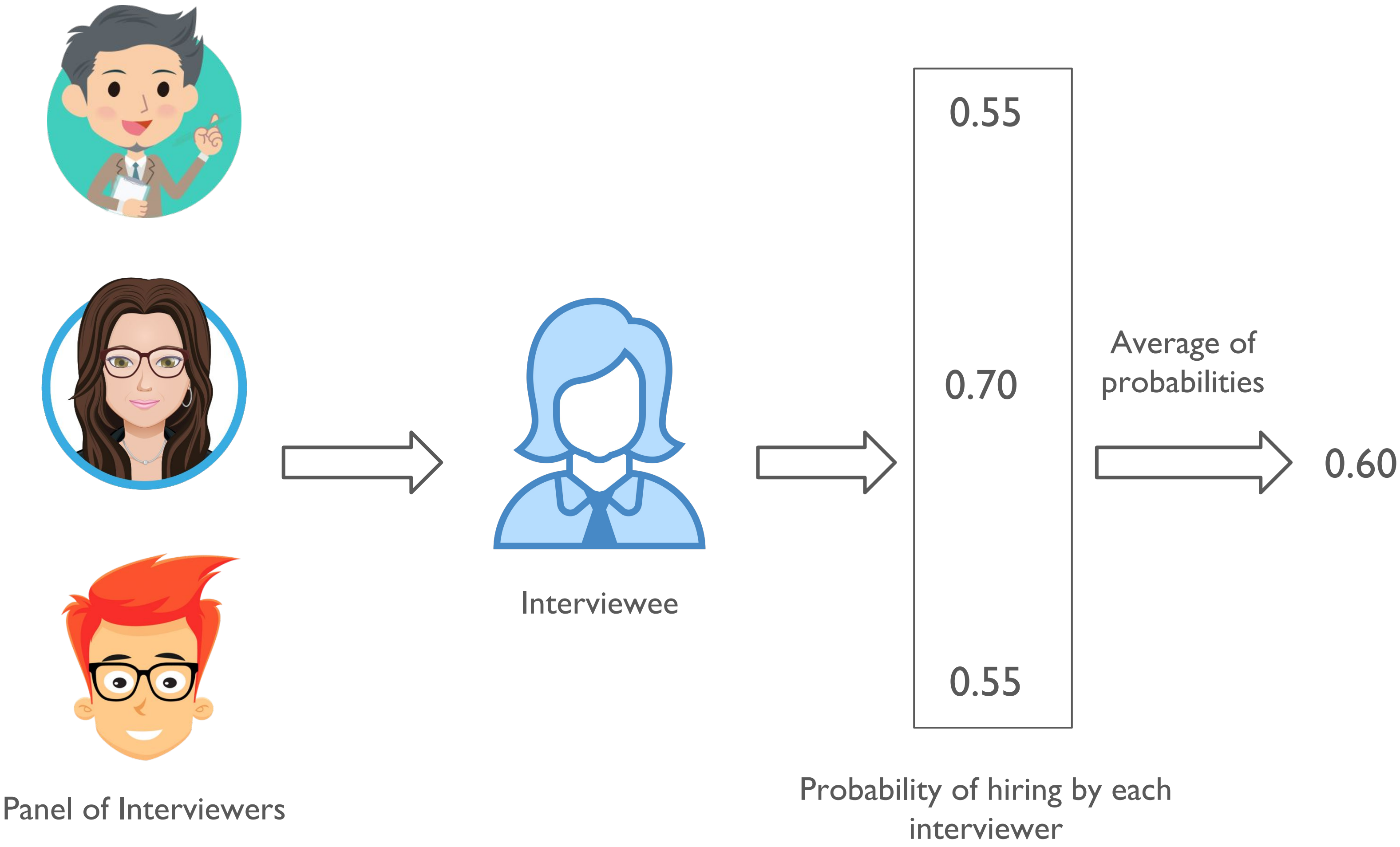

1
1
2
1
Predictions
Diverse predictors
New instance

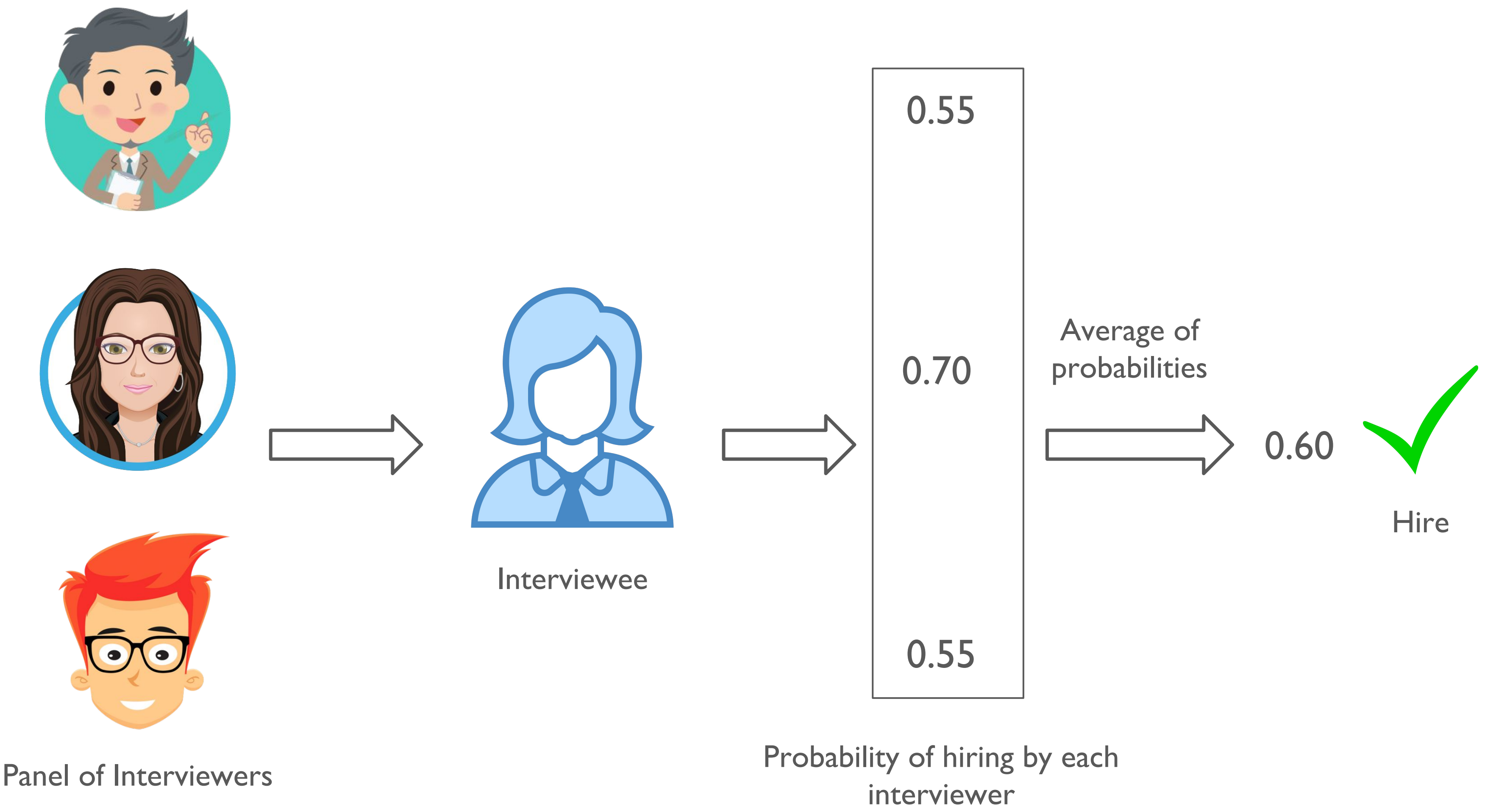

1
Ensemble's prediction
(e.g., majority vote)
1
1
2
1
Predictions
Diverse
predictors
New instance

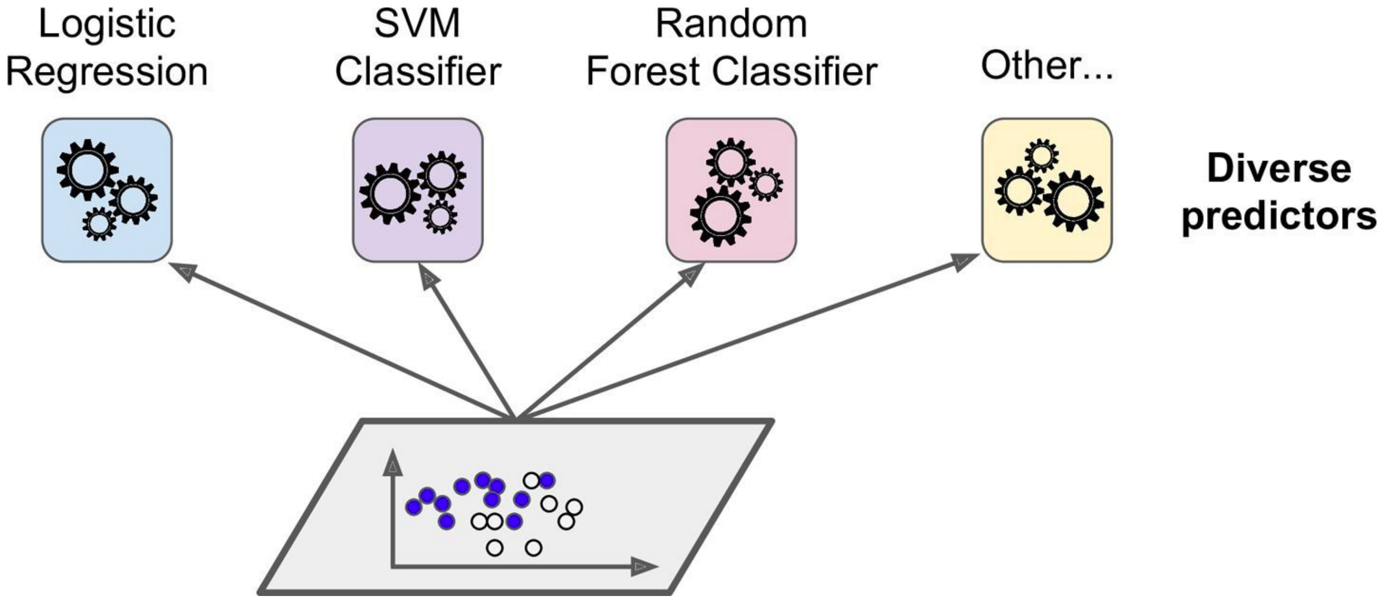

Final output
1
Ensemble's prediction
(e.g., majority vote)
1
1
2
1
Predictions
Diverse
predictors
New instance


Interviewee
Panel of Interviewers

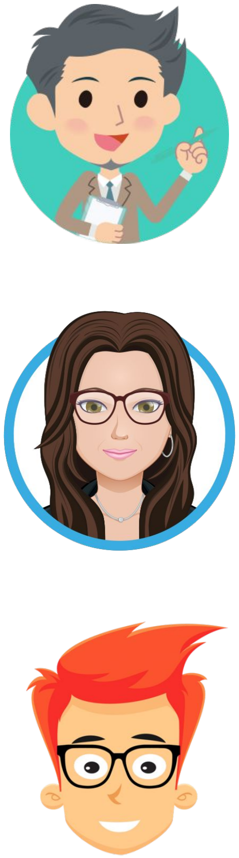

0.55
0.70
0.55
Interviewee
Panel of Interviewers
Probability of hiring by each interviewer


0.55
0.70
0.55
Average of probabilities
0.60
Interviewee
Panel of Interviewers
Probability of hiring by each interviewer

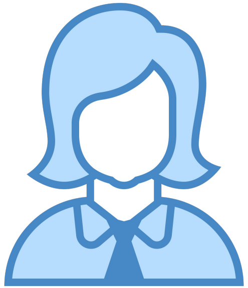

0.55
0.70
0.55
Average of probabilities
0.60
Hire
Interviewee
Panel of Interviewers
Probability of hiring by each interviewer


Logistic
Regression
SVM
Classifier
Random
Forest Classifier
Other...
Diverse
predictors

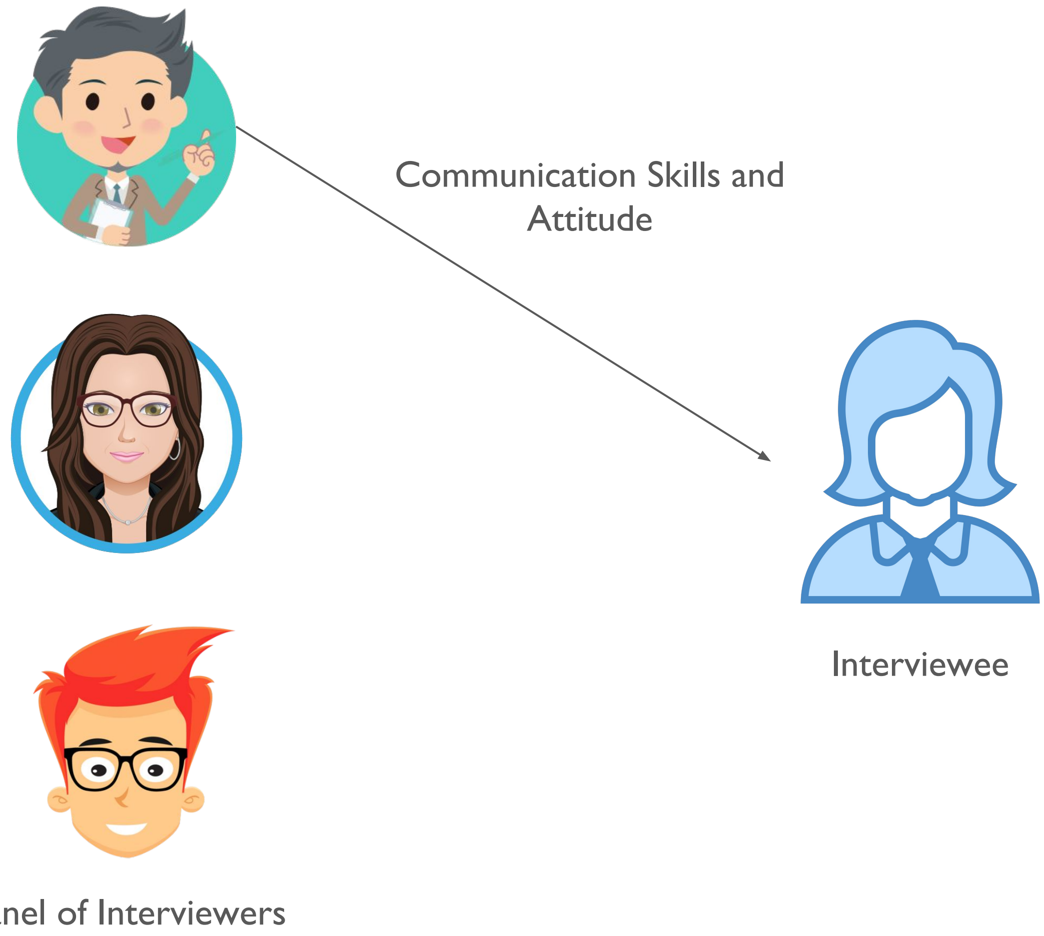
CLOUD x LAB

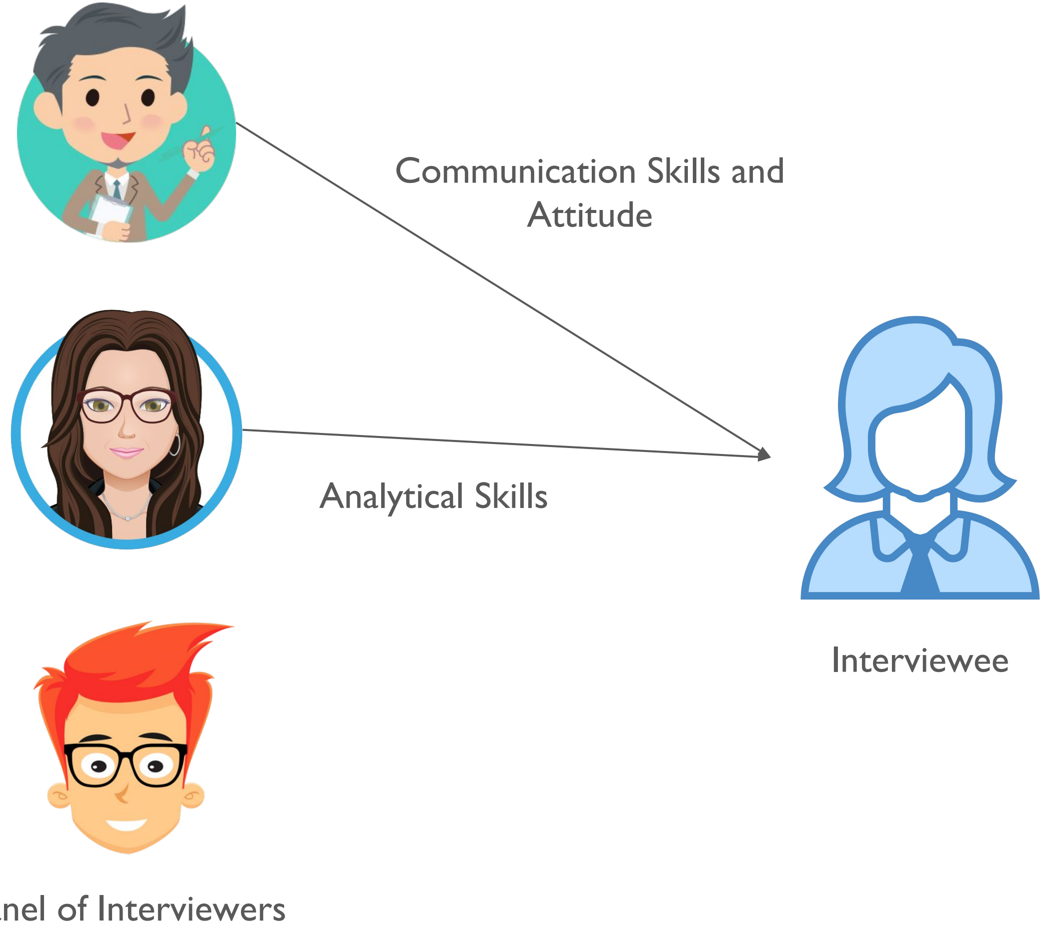


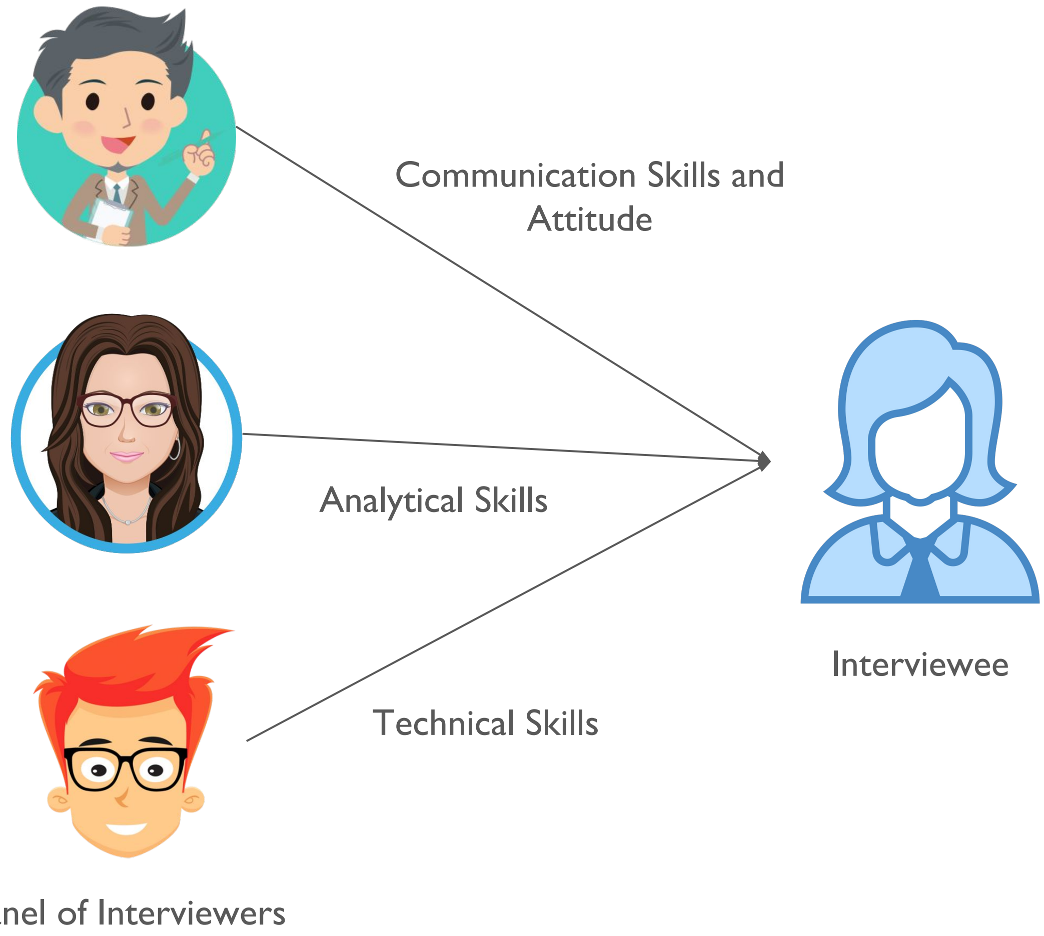
Panel of Interviewers

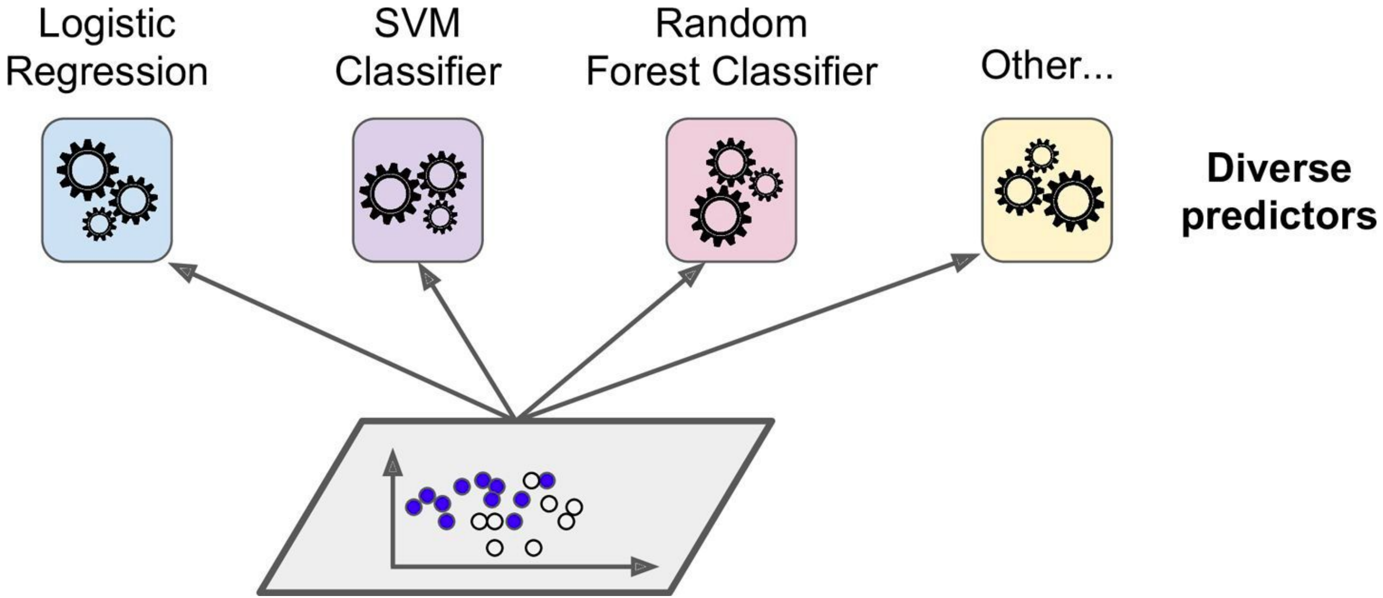


Interviewee


Communication Skills and Attitude
Interviewee
Panel of Interviewers


Communication Skills and Attitude
Analytical Skills
Interviewee
Panel of Interviewers


Communication Skills and Attitude
Analytical Skills
Technical Skills
Interviewee
Panel of Interviewers


Logistic Regression
SVM Classifier
Random Forest Classifier
Other...
Diverse predictors

- In ensemble we use diverse models

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- These diverse models need to be better than random guessing

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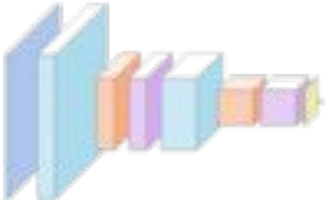
- In ensemble we use diverse models
- These diverse models need to be better than random guessing
- Ensembling can be used for both
    - Classification

- In ensemble we use diverse models
- These diverse models need to be better than random guessing
- Ensembling can be used for both
    - Classification
    - Regression



Convolutional Neural Network

In 1996 IBM’s Deep Blue supercomputer Beat Garry Kasparov

Question - Why are these tasks so effortless to us humans?

Question - Why are these tasks so effortless to us humans?

Answer

Question - Why are these tasks so effortless to us humans?

Answer

- Perception takes places outside the realm of consciousness

Question - Why are these tasks so effortless to us humans?

Answer

- Perception takes places outside the realm of consciousness
    - Visual

Question - Why are these tasks so effortless to us humans?

Answer

- Perception takes places outside the realm of consciousness
  - Visual
  - Auditory

Question - Why are these tasks so effortless to us humans?

Answer

- Perception takes places outside the realm of consciousness
    - Visual
    - Auditory
    - Sensory

Question - Why are these tasks so effortless to us humans?

Answer

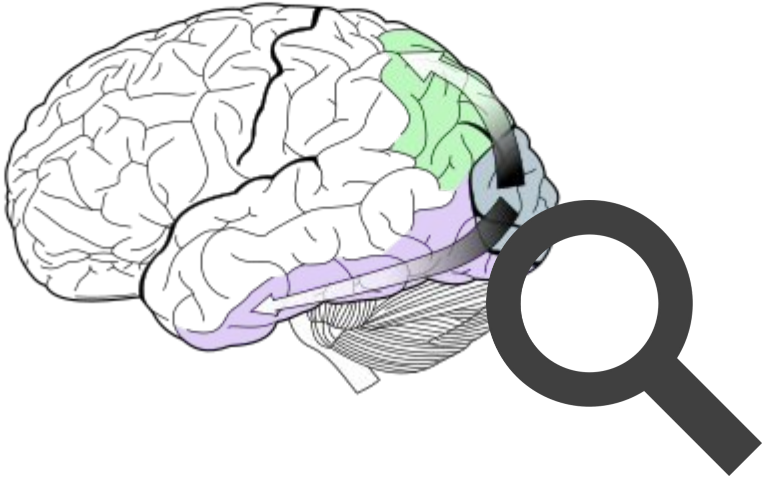
- Perception takes places outside the realm of consciousness
    - Visual
    - Auditory
    - Sensory
- By the time sensory information reaches our consciousness

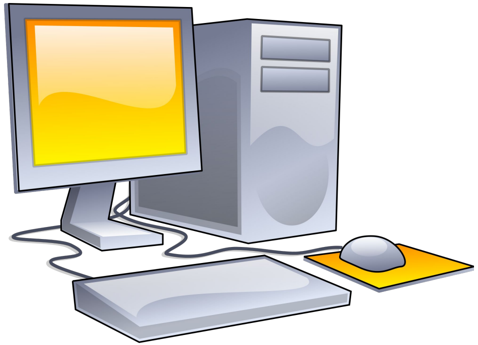
Question - Why are these tasks so effortless to us humans?

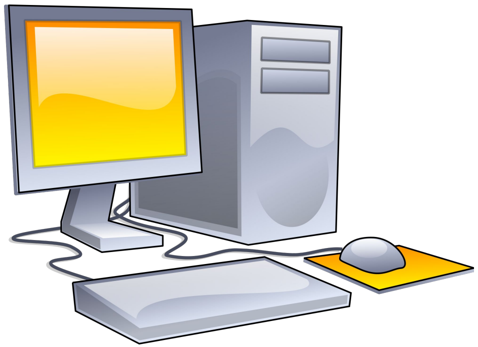
Answer

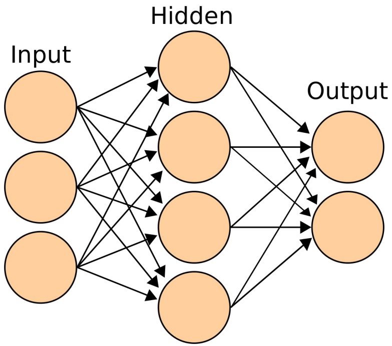
- Perception takes places outside the realm of consciousness
  - Visual
  - Auditory
  - Sensory
- By the time sensory information reaches our consciousness
  - It is already adorned with high-level features

So Cute!

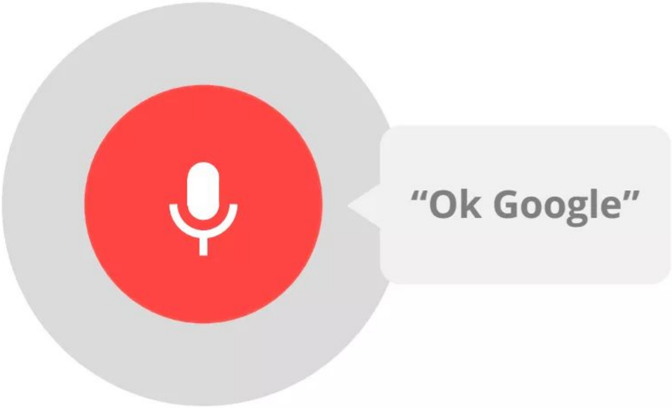






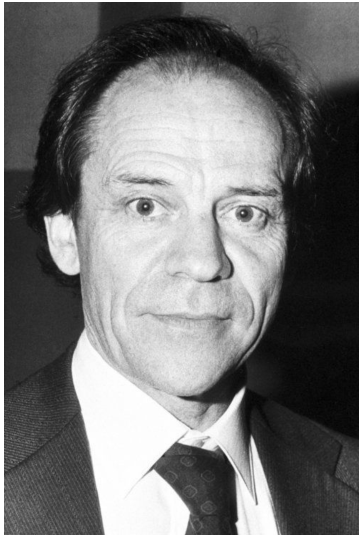

Hidden
Input
Output

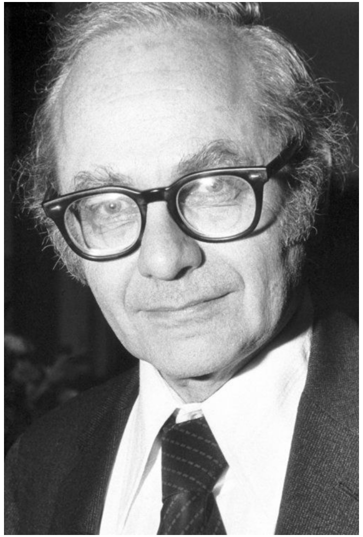
Basketball Video


"Ok Google"

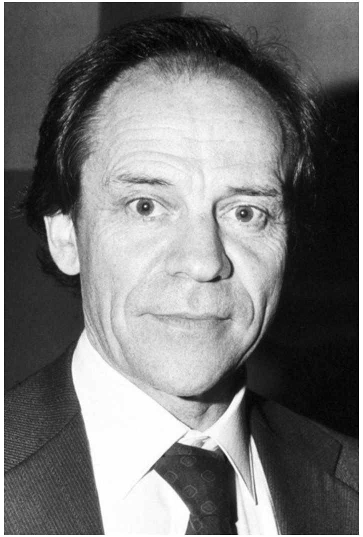

TANTRUM
RESENTMENT
FURY
RAGE
WRATH
HATRED
TEMPER
IMPATIENCE
HISSY FIT
ADRENALINE
OUTRAGE
ILL TEMPER
SLOW BURN
SORENESS
IRRITABILITY
AGGRAVATION
IRRITATION
ANNOYANCE
VEXATION
ENMITY
ANGER
PASSION
VEXATION
FURY
FIGHT OR FLIGHT
VIOLENCE
UMBRAGE
DISPLEASURE
PIQUE
DISAPPROBATION
ANTAGONISM
HOSTILITY
CHAGRIN
DISAPPROBATION
EXASPERATION
AGGRESSION
DANDER
INFURIATION
MAD
MANIPULATION
PETULANCE

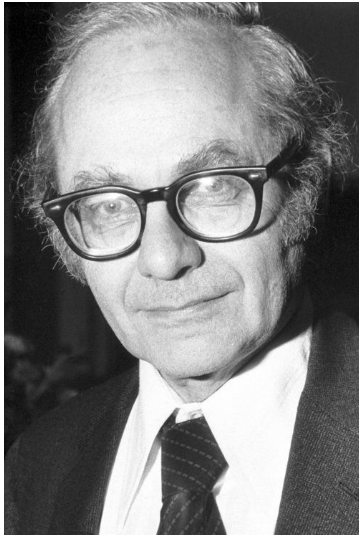
- David H. Hubel and Torsten Wiesel



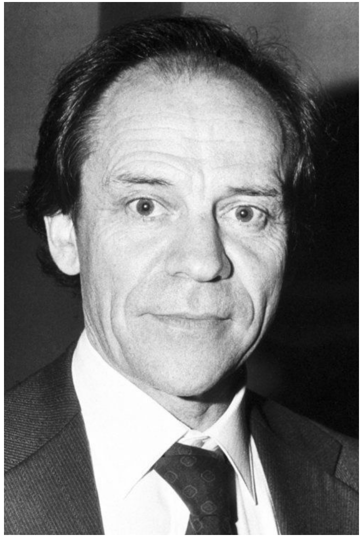


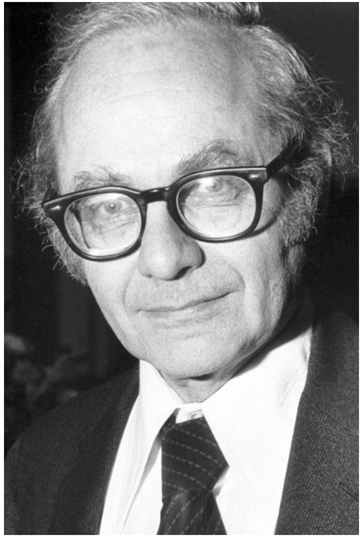
- David H. Hubel and Torsten Wiesel
    - In 1958 and 1959



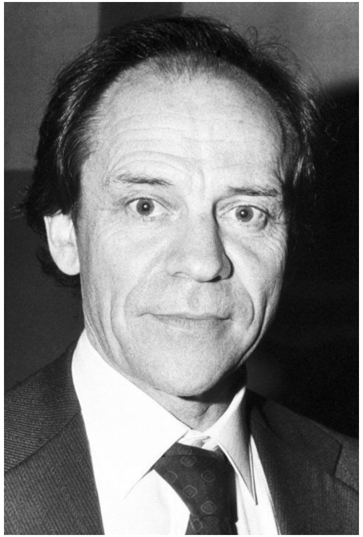


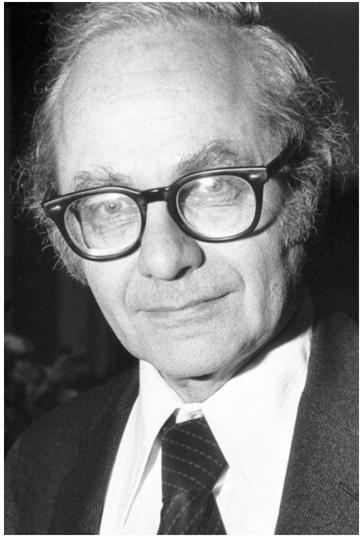
- David H. Hubel and Torsten Wiesel
    - In 1958 and 1959
    - Experimented on animals



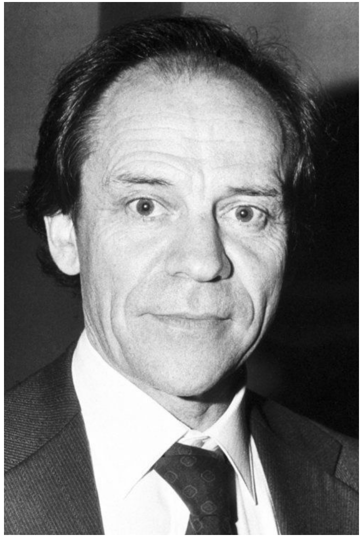


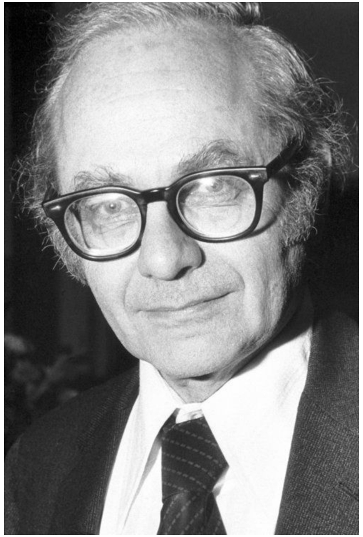
- David H. Hubel and Torsten Wiesel
  - In 1958 and 1959
  - Experimented on animals
  - Gave crucial insights on the

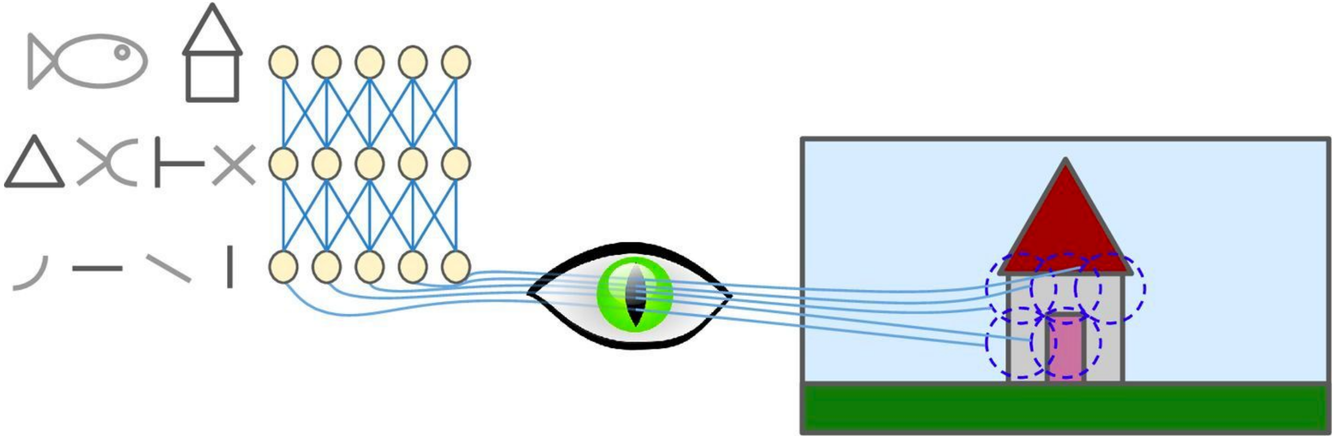


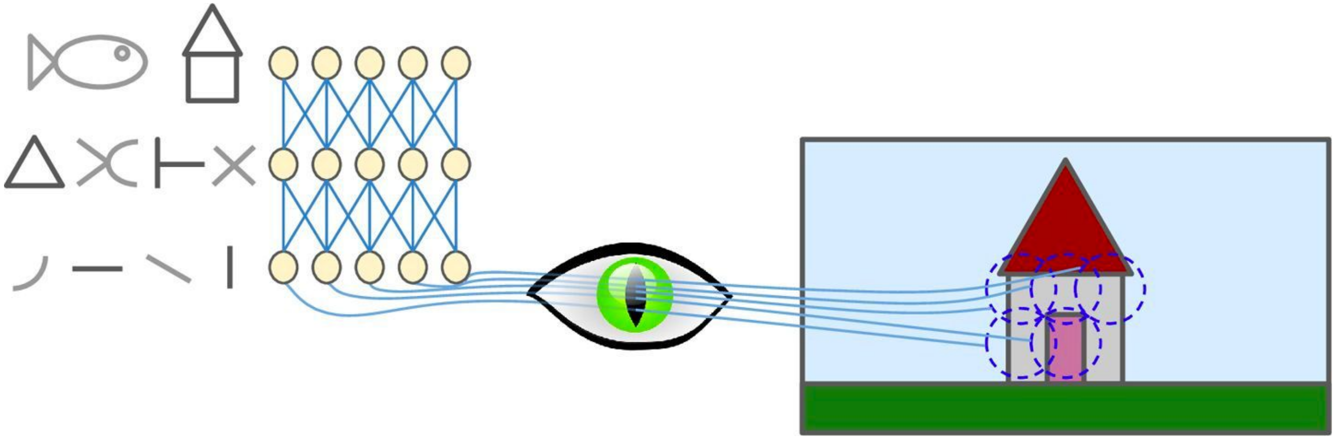


- David H. Hubel and Torsten Wiesel
    - In 1958 and 1959
    - Experimented on animals
    - Gave crucial insights on the
    - Structure of the visual cortex

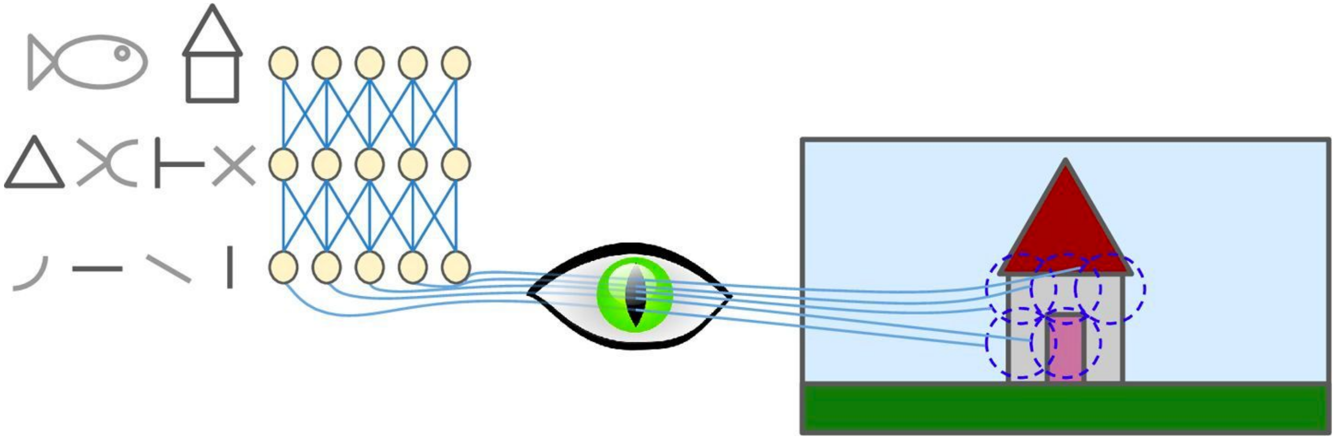




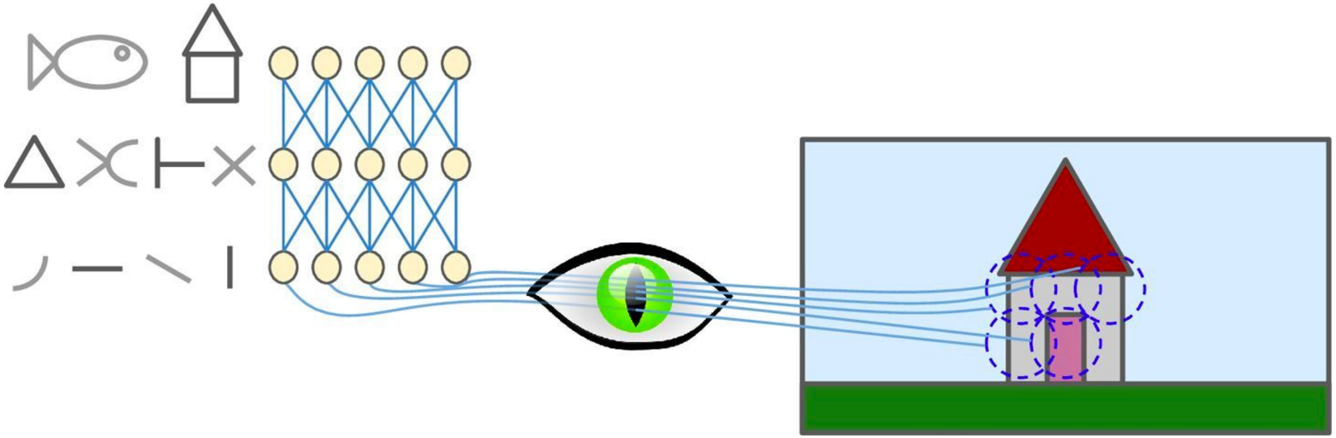




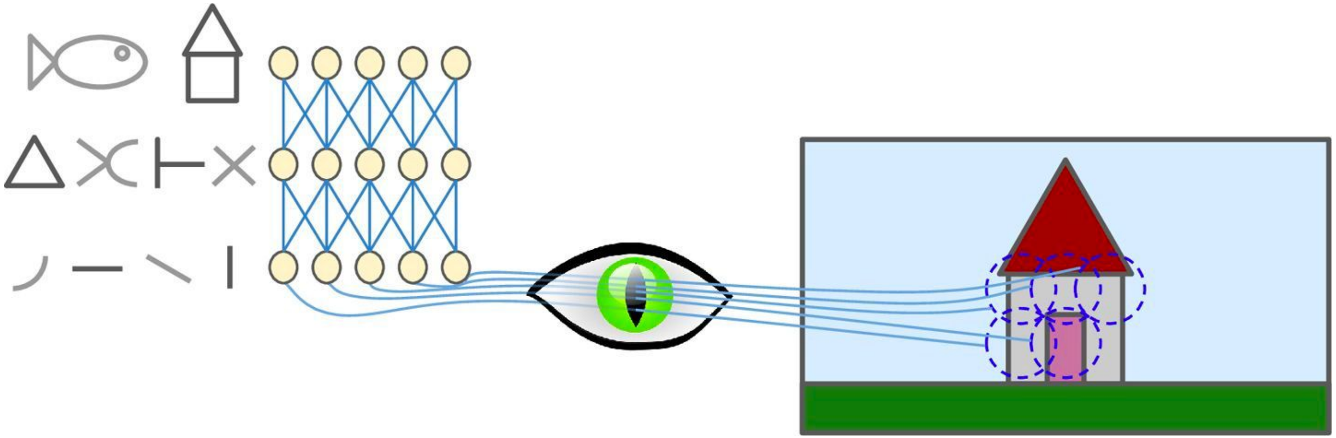
- Many neurons in the visual cortex have a small local receptive field



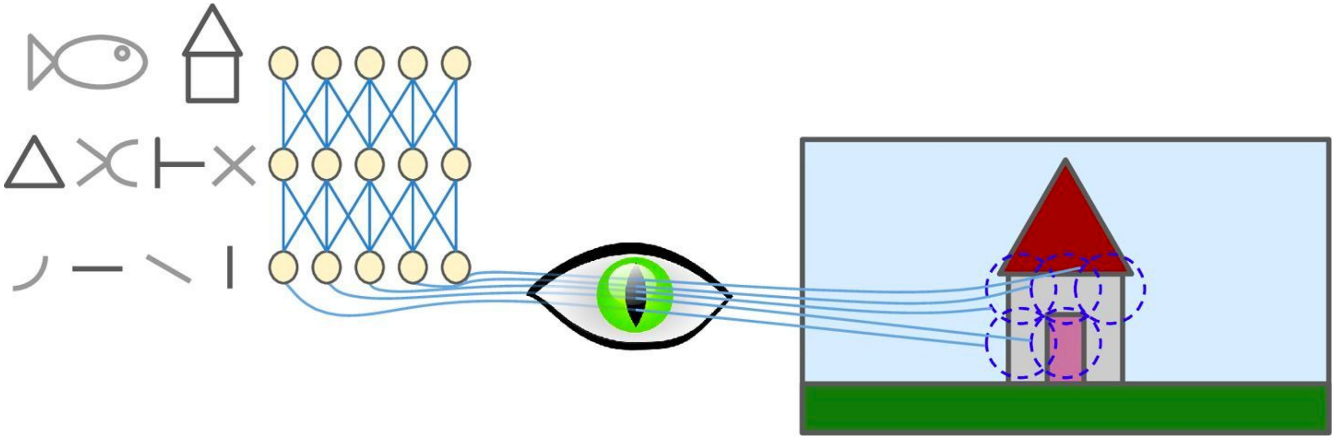
- Many neurons in the visual cortex have a small local receptive field
- React only to Visual stimuli located in a limited region of the visual field



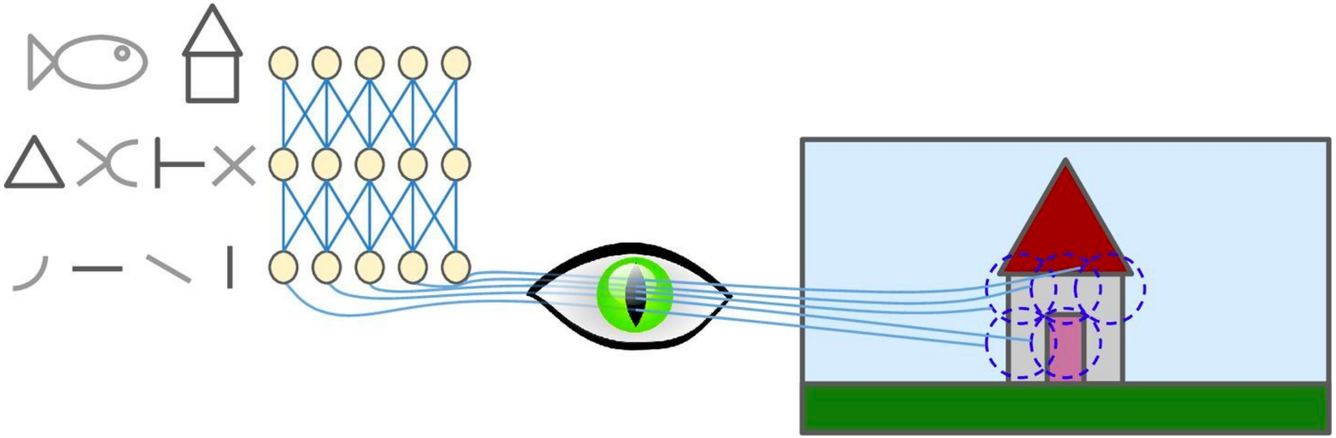
- Some neurons react only to images of horizontal lines



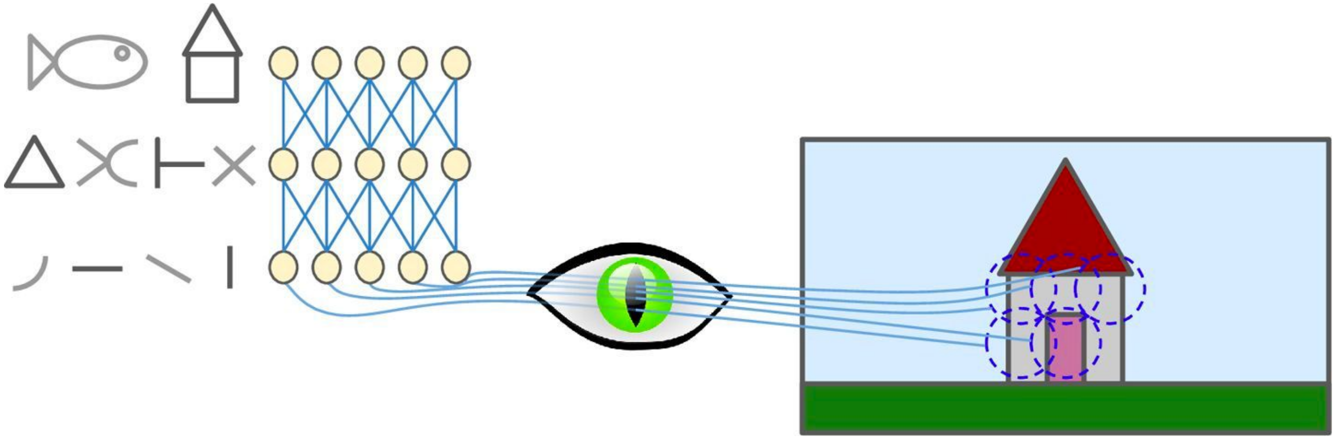
- Some neurons react only to images of horizontal lines
- While others react only to lines with different orientations



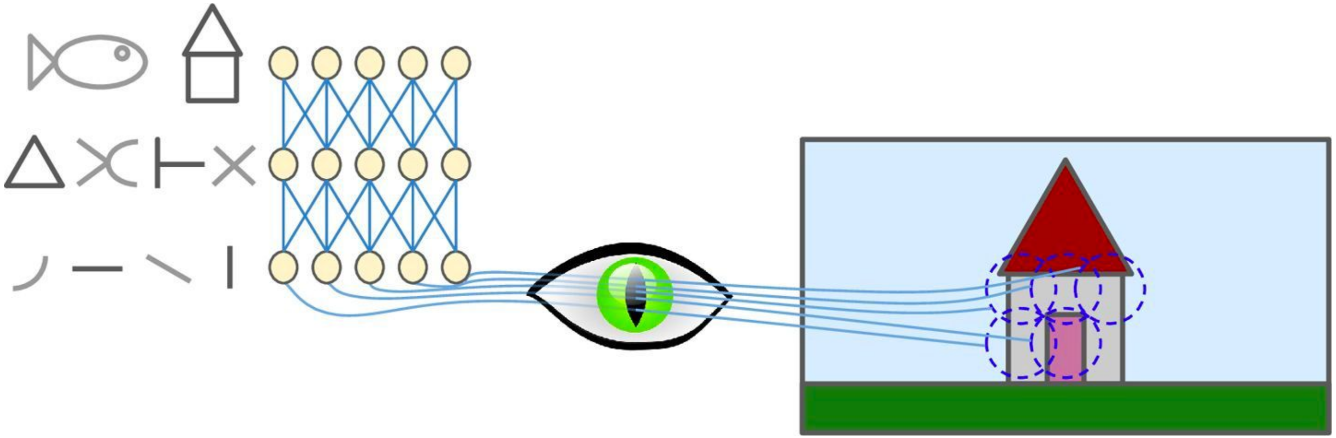
- Some neurons have larger receptive fields



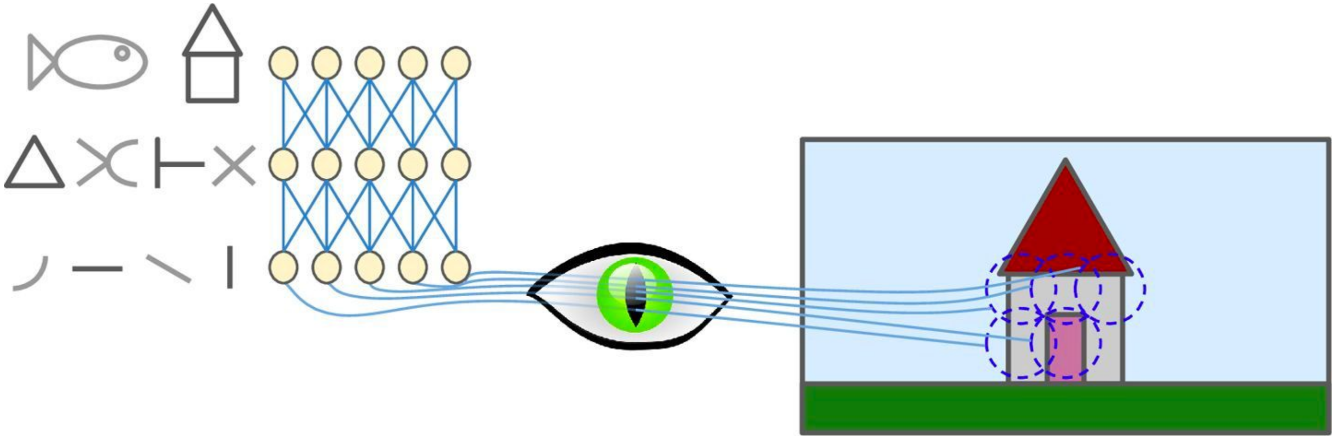
- Some neurons have larger receptive fields
- They react to more complex patterns that are combinations of the lower-level patterns



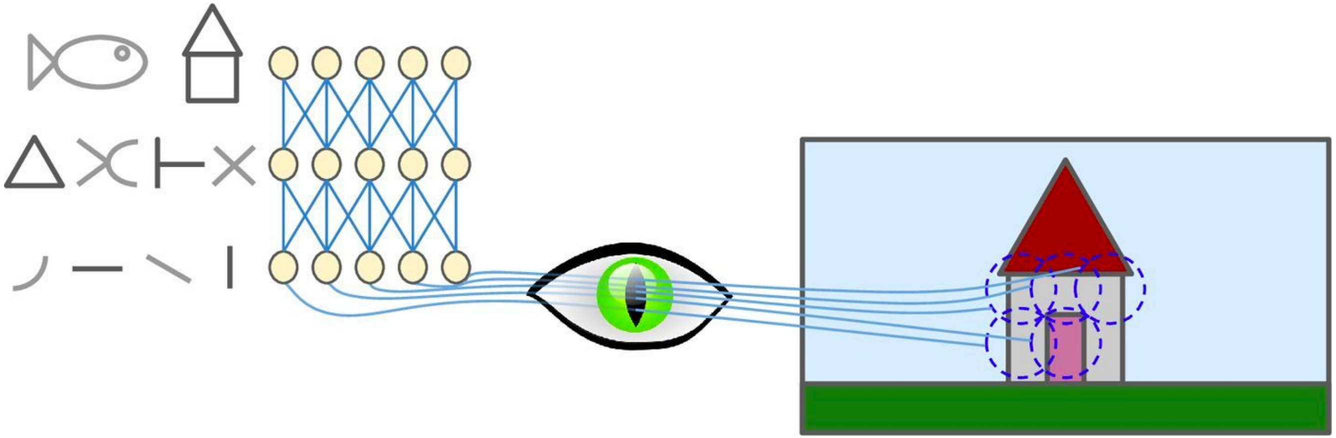
- Higher level neurons are based on the outputs of neighboring lower-level neurons



- This powerful architecture is able to detect all sorts of complex patterns in any area of the visual field



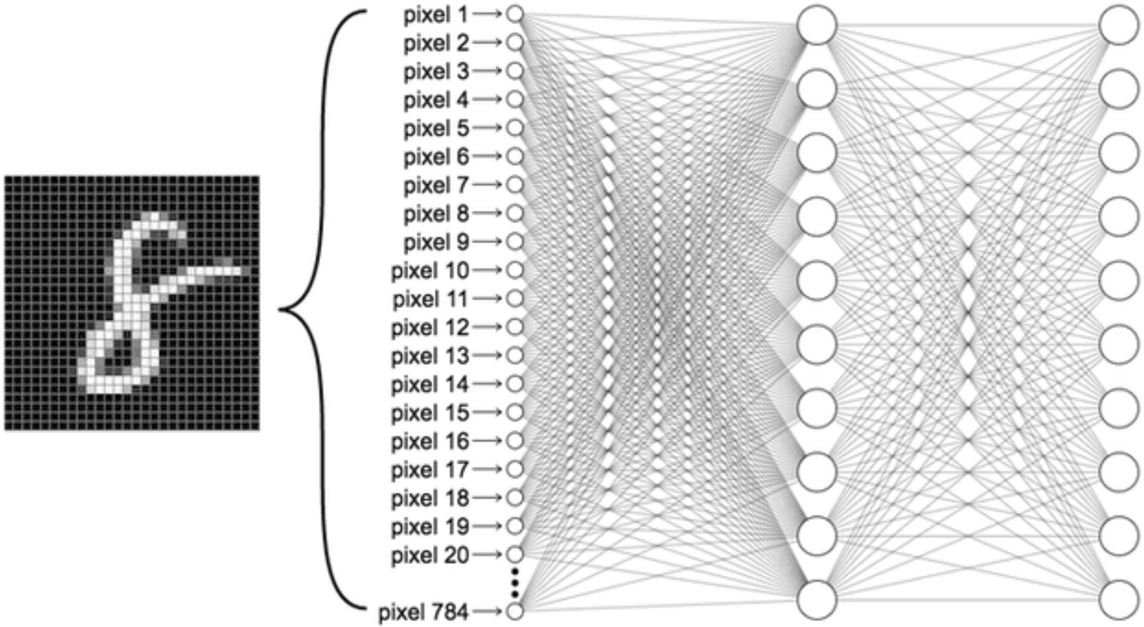
- These studies of the visual cortex inspired the neocognitron



- These studies of the visual cortex inspired the neocognitron
- Which gradually evolved into Convolutional Neural Networks

Question

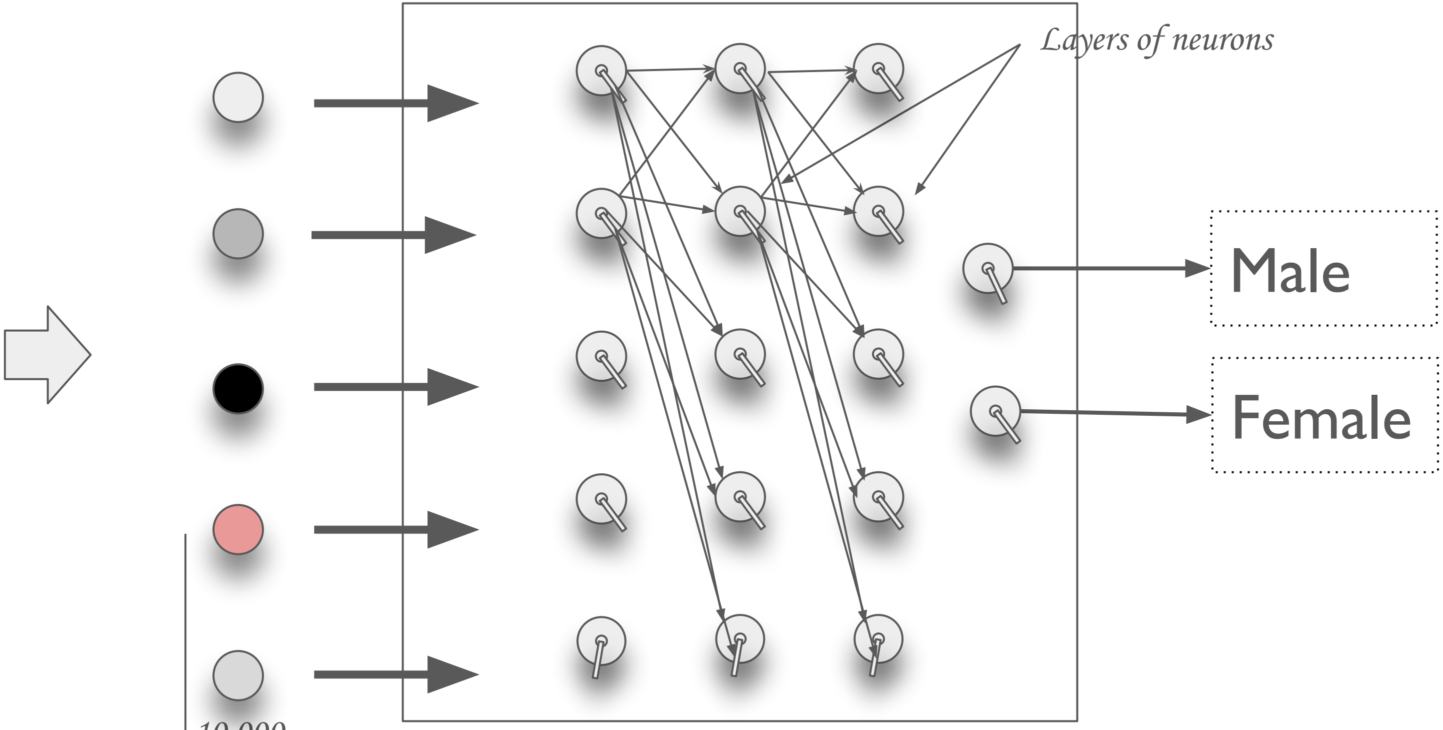
Why not simply use a regular deep network with fully connected layers for image recognition tasks instead of CNN?



Deep neural network may work fine for small images such as MNIST

3 layers each with 10000 weights and 2 last
Total connections: 10000x10000 + 10000x10000 + 10000x2 ~ 200 million

100x100

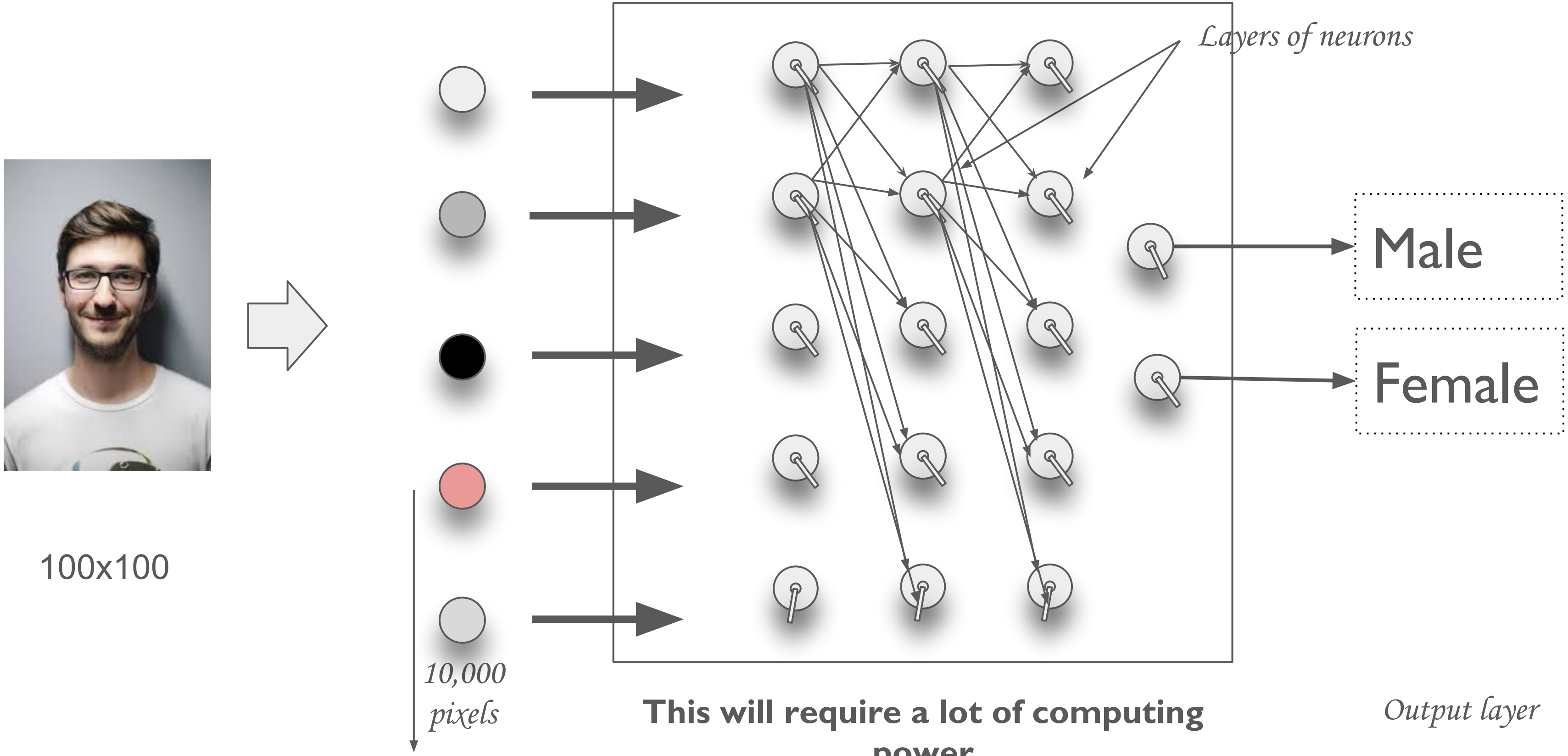


10,000 pixels

This will require a lot of computing power

Output layer

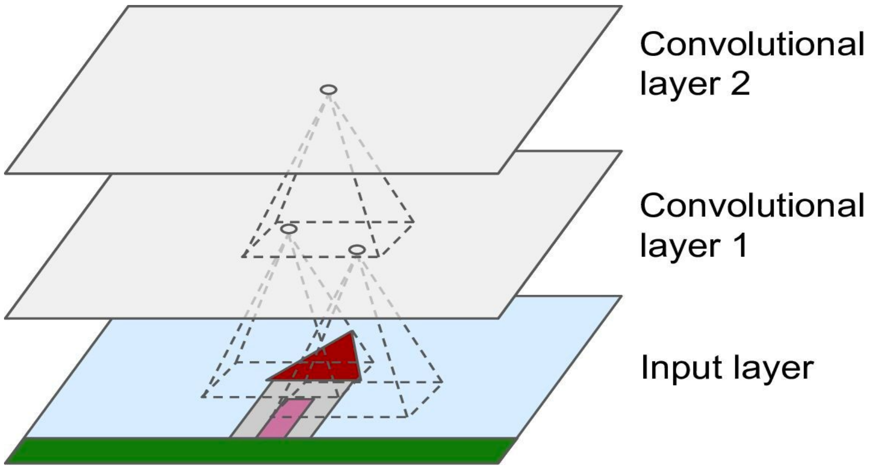
Also notice that the adjacent pixels at 0,0 and 1,1 would go far away.



This will require a lot of computing power

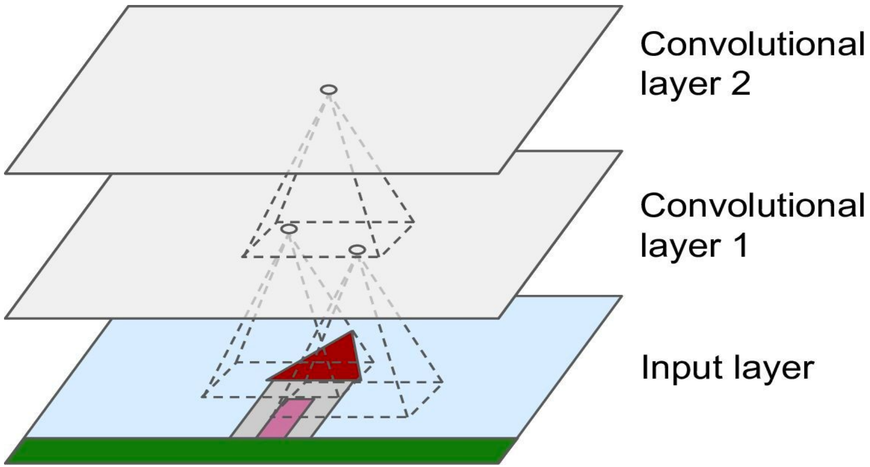
CNNs solve this problem by using partially connected layers called

Convolutional Layers



Convolutional Layer

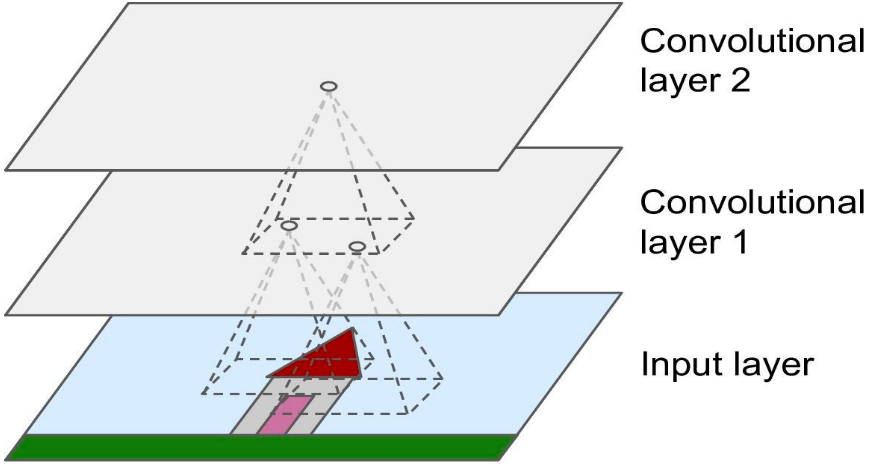
- Neurons in the first convolutional layer are connected only to pixels in their receptive fields.



Convolutional Layer

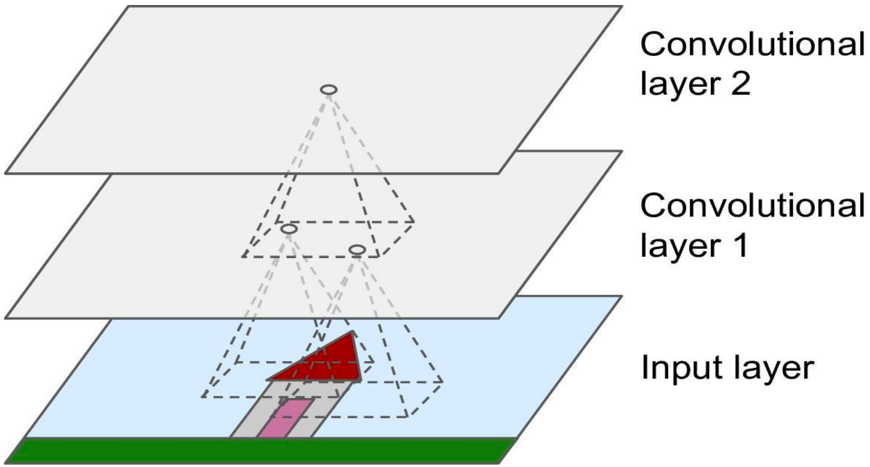
Receptive Field

- Neurons in the first convolutional layer are connected only to pixels in their receptive fields.



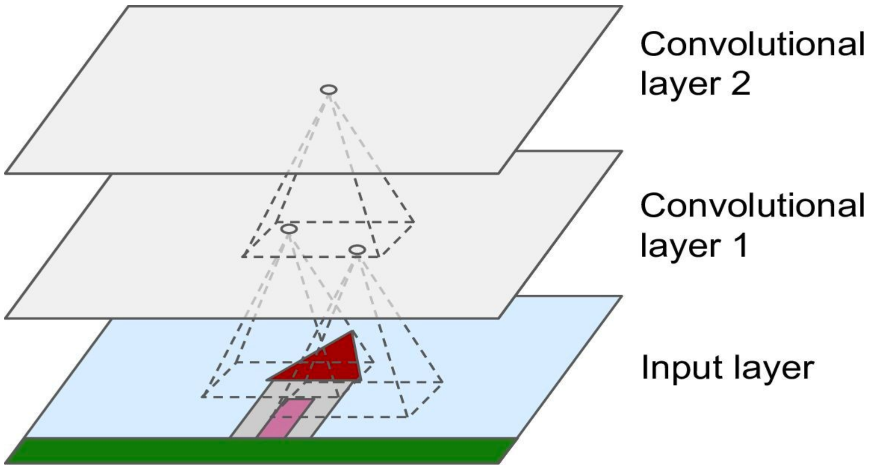
Convolutional Layer

- Neurons in the first convolutional layer are connected only to pixels in their receptive fields.
- Each neuron in the second convolutional layer is connected only to neurons located within a small rectangle in the first layer



Convolutional Layer

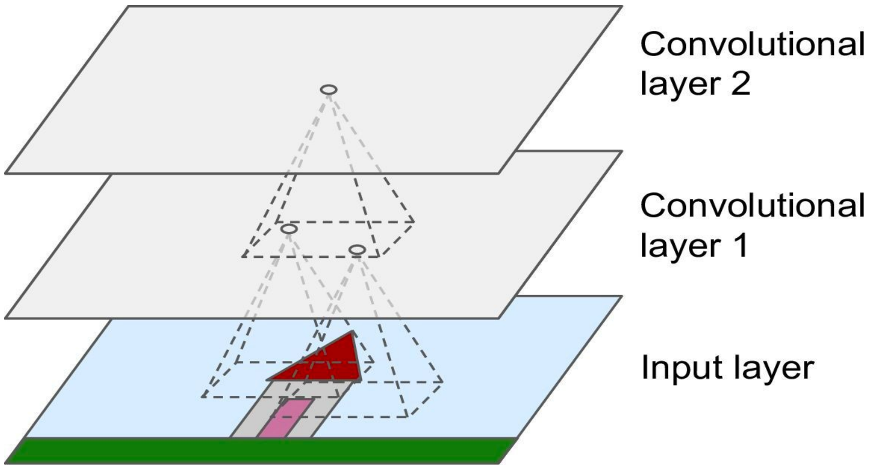
- The network concentrates on low-level features in the first hidden layer



Convolutional Layer

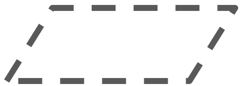
- The network concentrates on low-level features in the first hidden layer
- Then assemble them into higher-level features in the next hidden layer and so on.

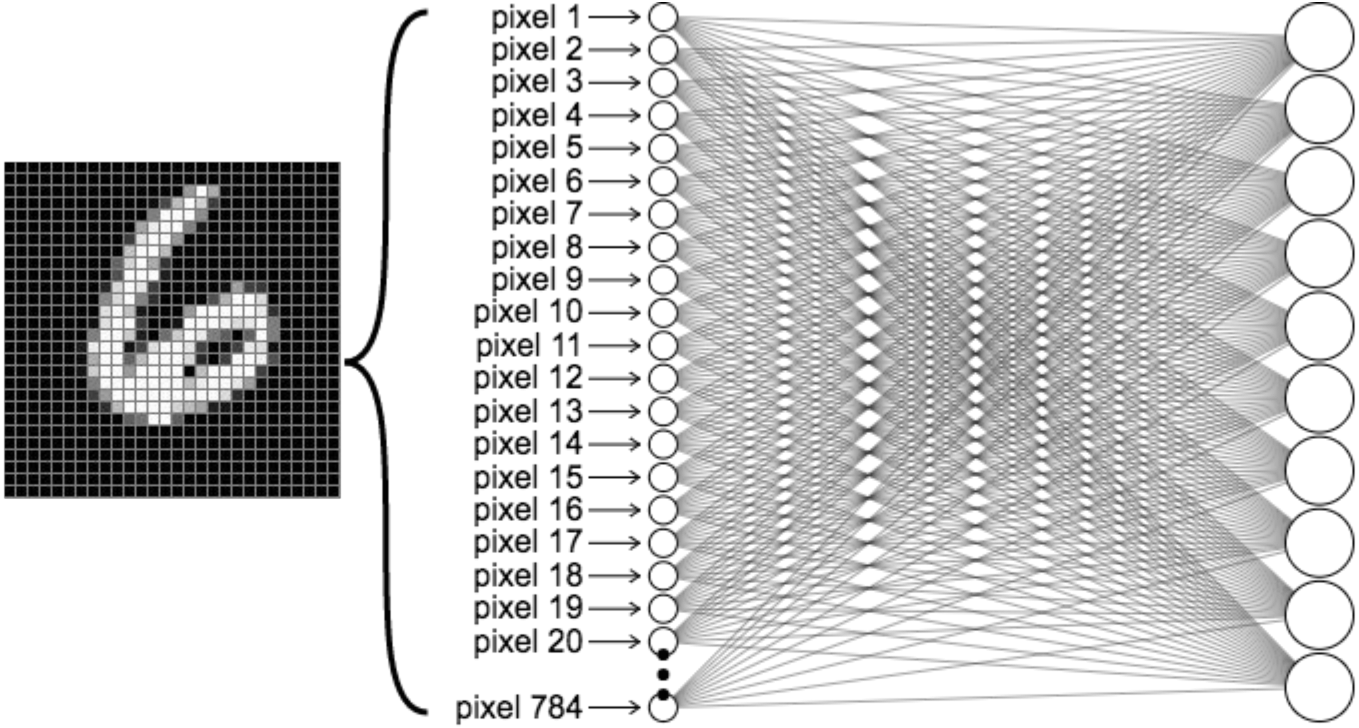

Receptive Field

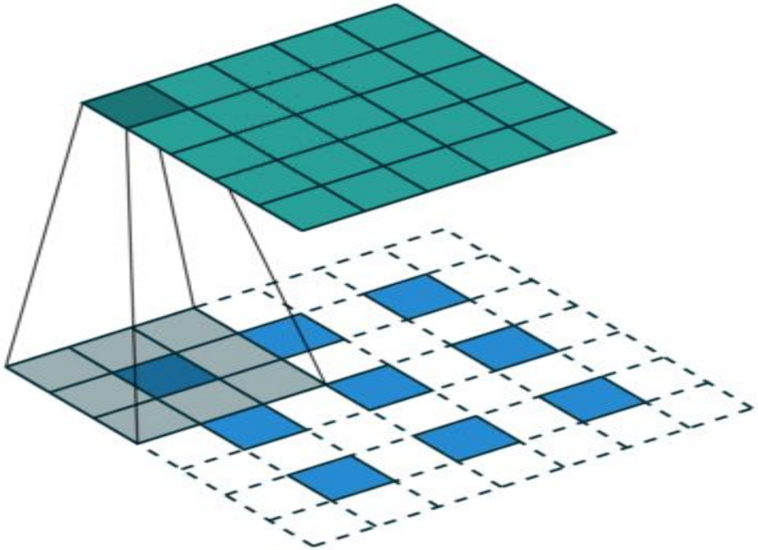


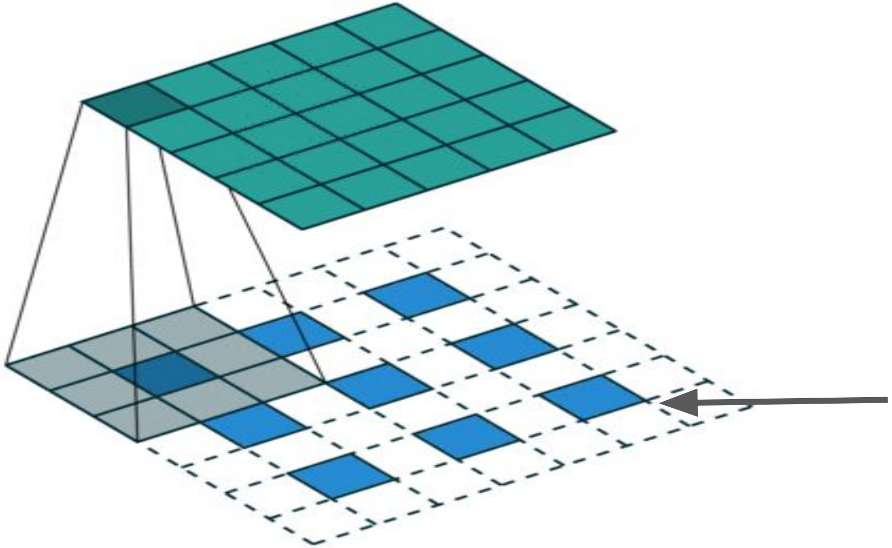
- The network concentrates on low-level features in the first hidden layer
- Then assemble them into higher-level features in the next hidden layer and so on.
- This hierarchical structure is common in real-world images

Convolutional Layer

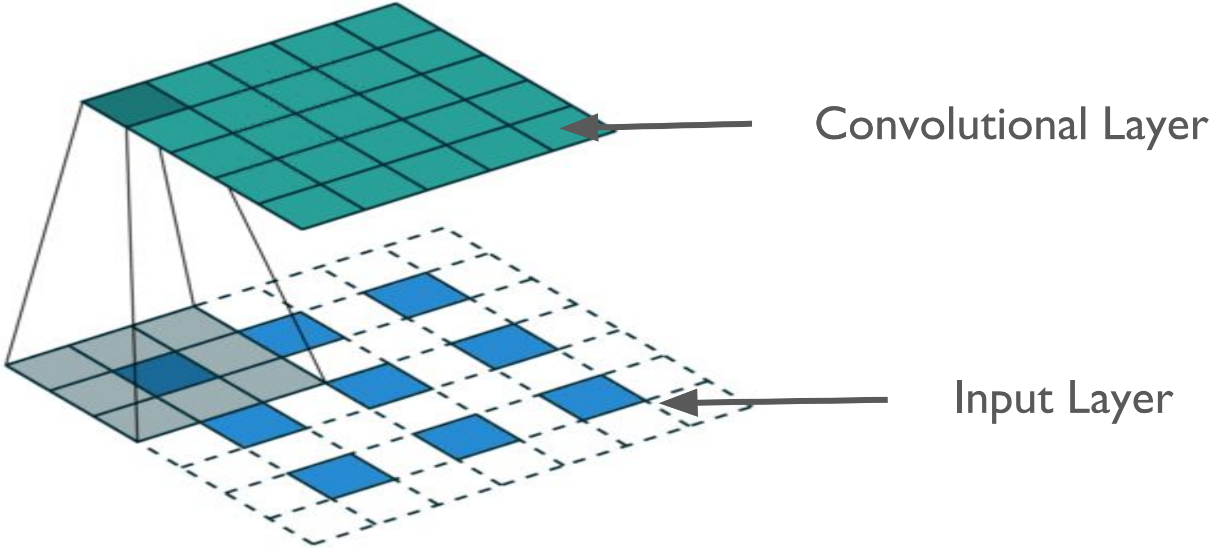



pixel 1
pixel 2
pixel 3
pixel 4
pixel 5
pixel 6
pixel 7
pixel 8
pixel 9
pixel 10
pixel 11
pixel 12
pixel 13
pixel 14
pixel 15
pixel 16
pixel 17
pixel 18
pixel 19
pixel 20
pixel 784

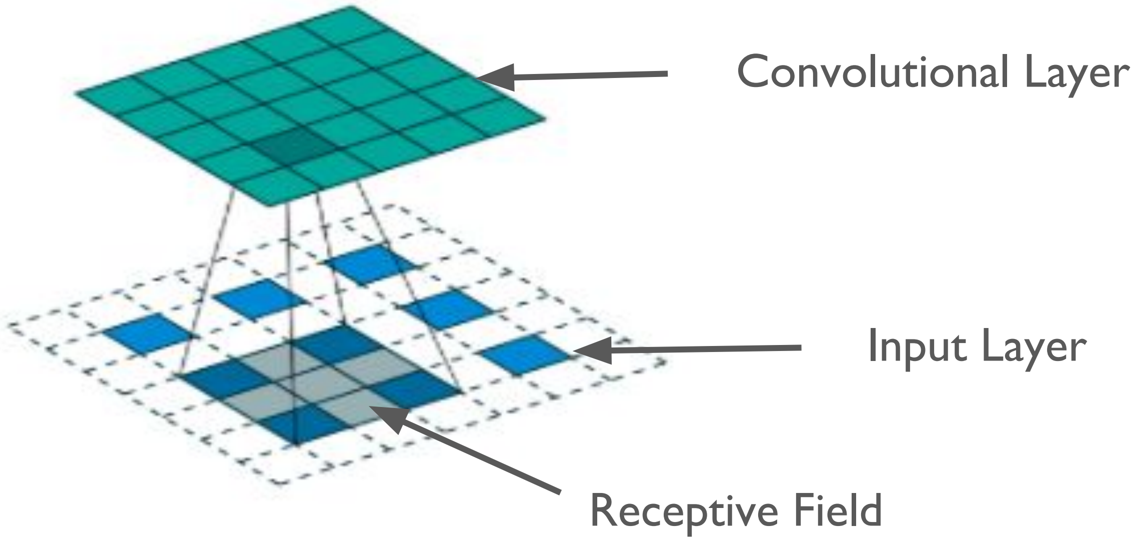




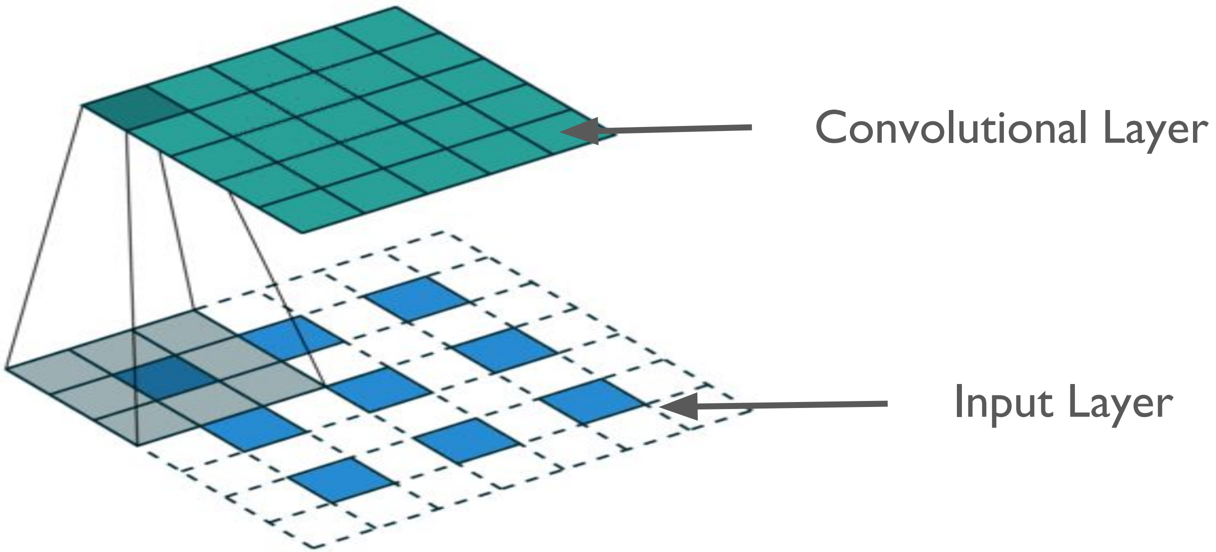
This figure shows how the layers of CNN are formed



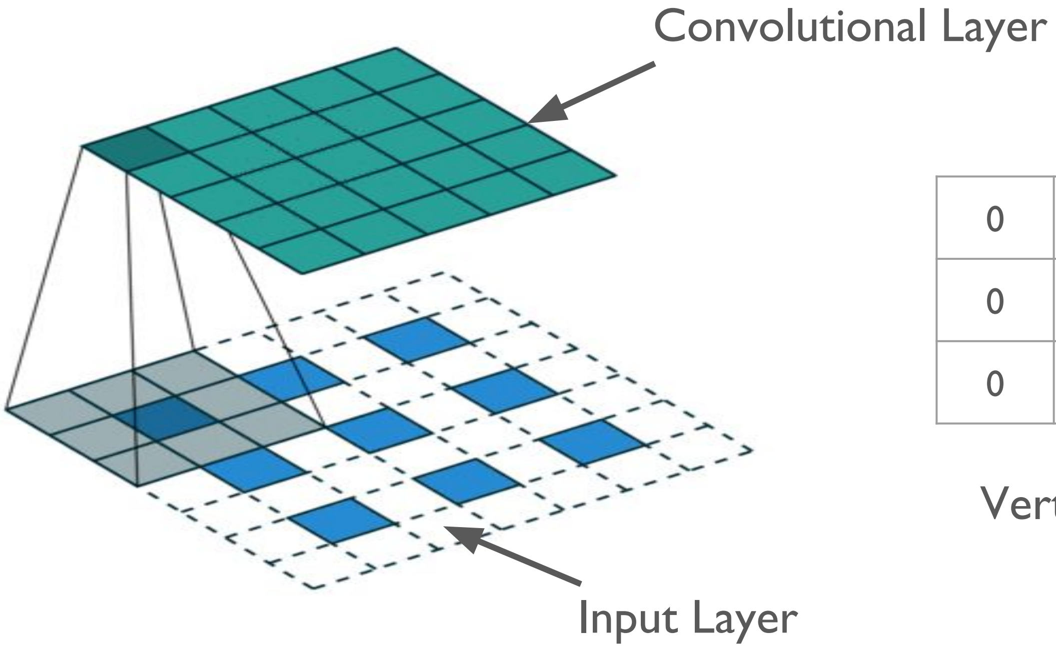
This figure shows how the layers of CNN are formed



This figure shows how the layers of CNN are formed



This figure shows how the layers of CNN are formed



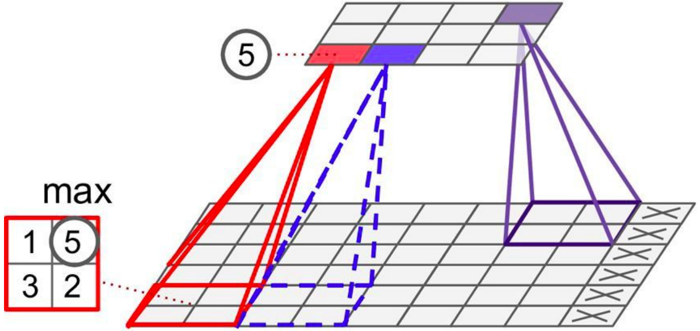
0	1	0
0	1	0
0	1	0

Vertical Filter

0	0	0
1	1	1
0	0	0

Horizontal Filter

This figure shows how the layers of CNN are formed



Shrinked Image

Input Image

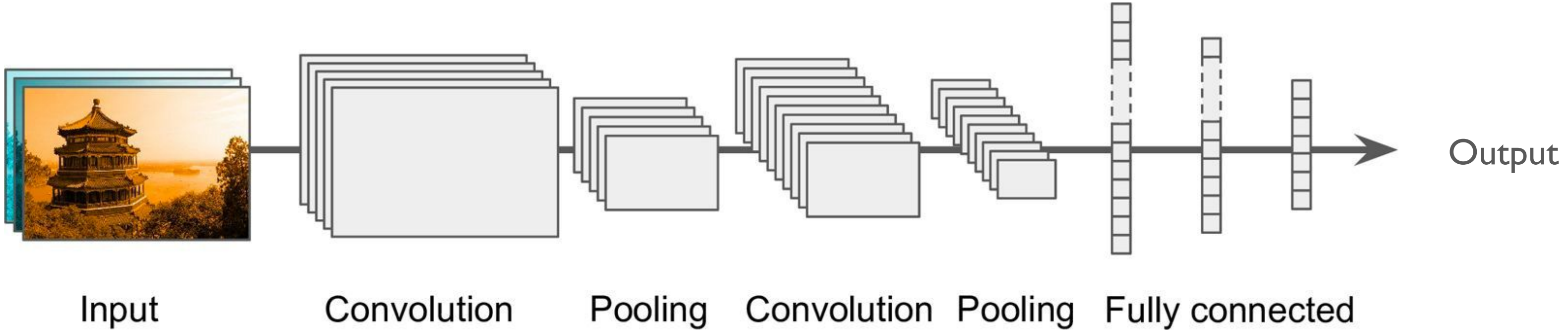
Pooling Layers

- Computes the maximum value of the receptive field - Max pool

Pooling Layers

- Computes the maximum value of the receptive field - Max pool
- Computes the average of all pixels - Average pool

Pooling Layers


Output
Input
Convolution
Pooling
Convolution
Pooling
Fully connected

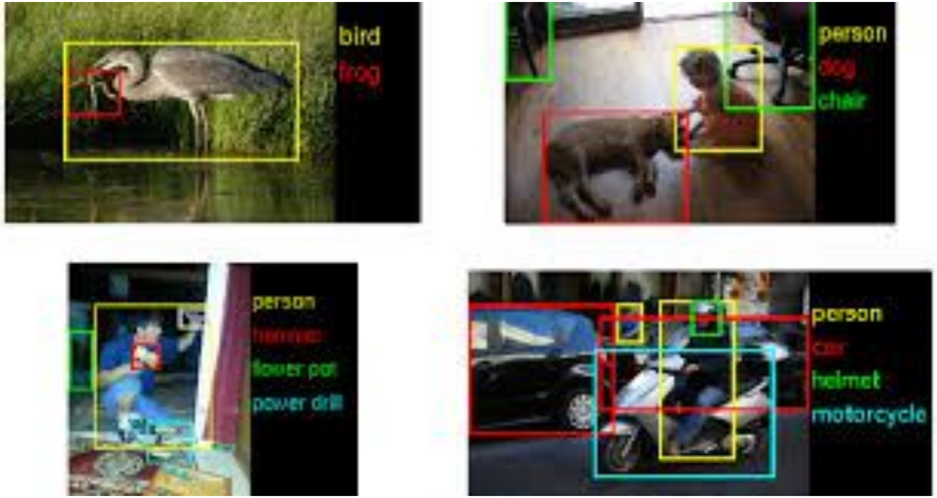
IMAGENET

IMAGENET

Large Scale Visual Recognition Challenge - ILSVRC

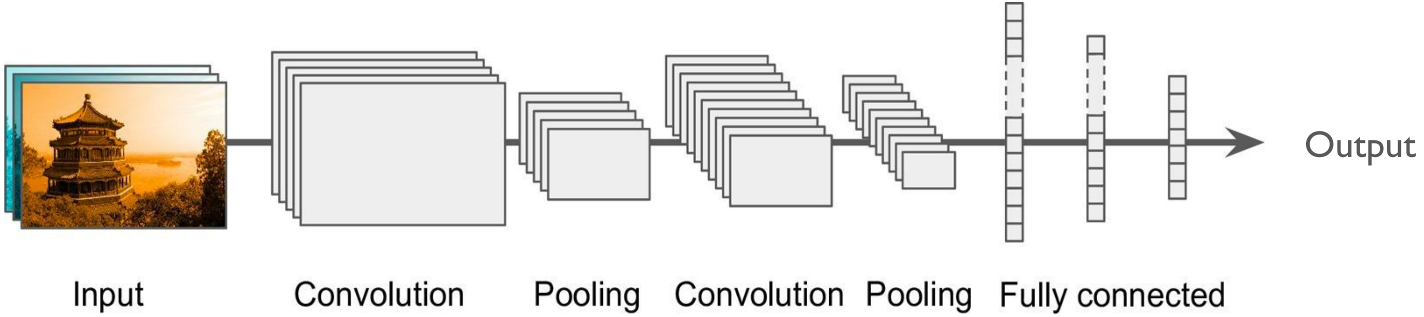
IMAGENET

Large Scale Visual Recognition Challenge - ILSVRC



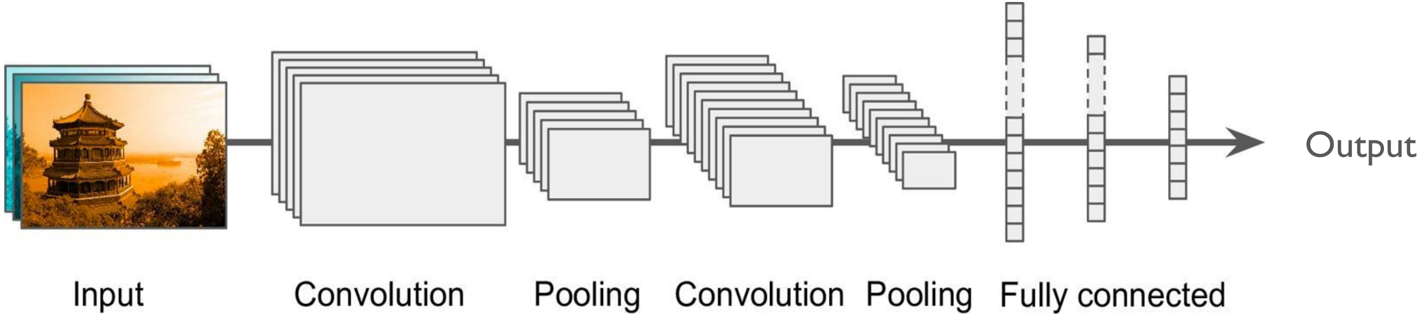
CNN Architectures

- LeNet-5
- AlexNet
- GoogLeNet
- ResNet

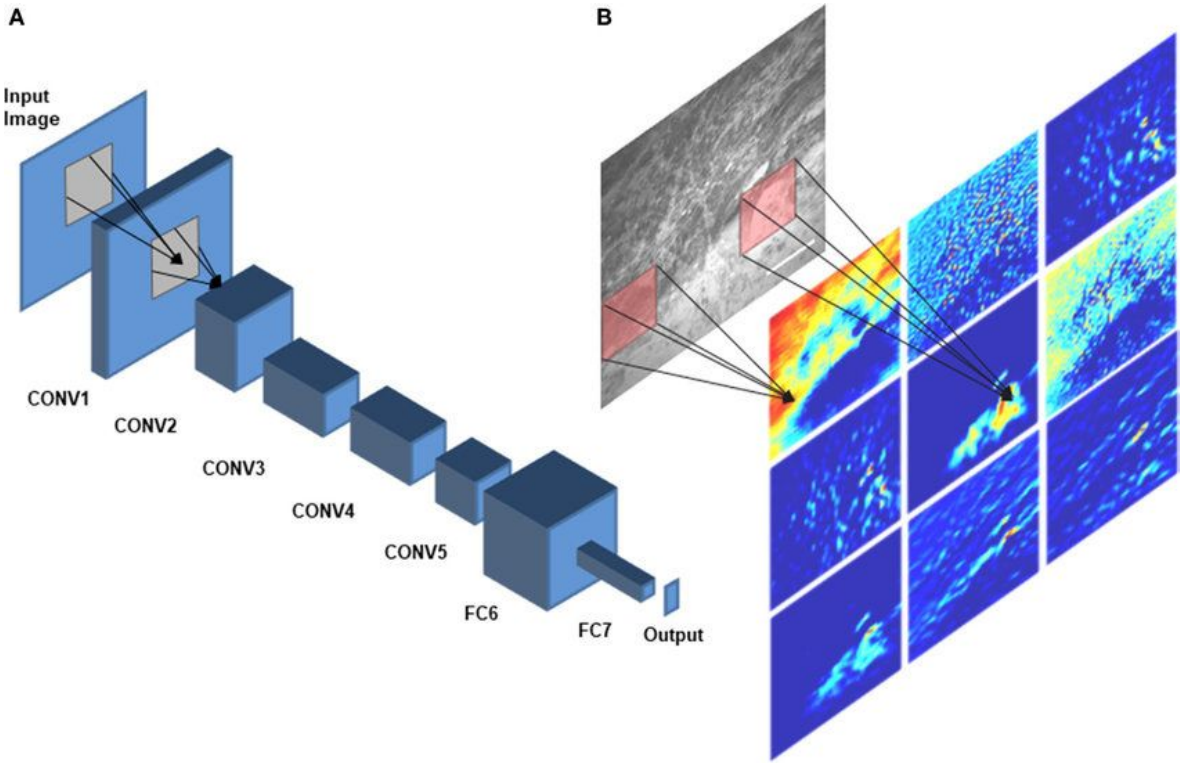

Output
Input
Convolution
Pooling
Convolution
Pooling
Fully connected

LeNet-5

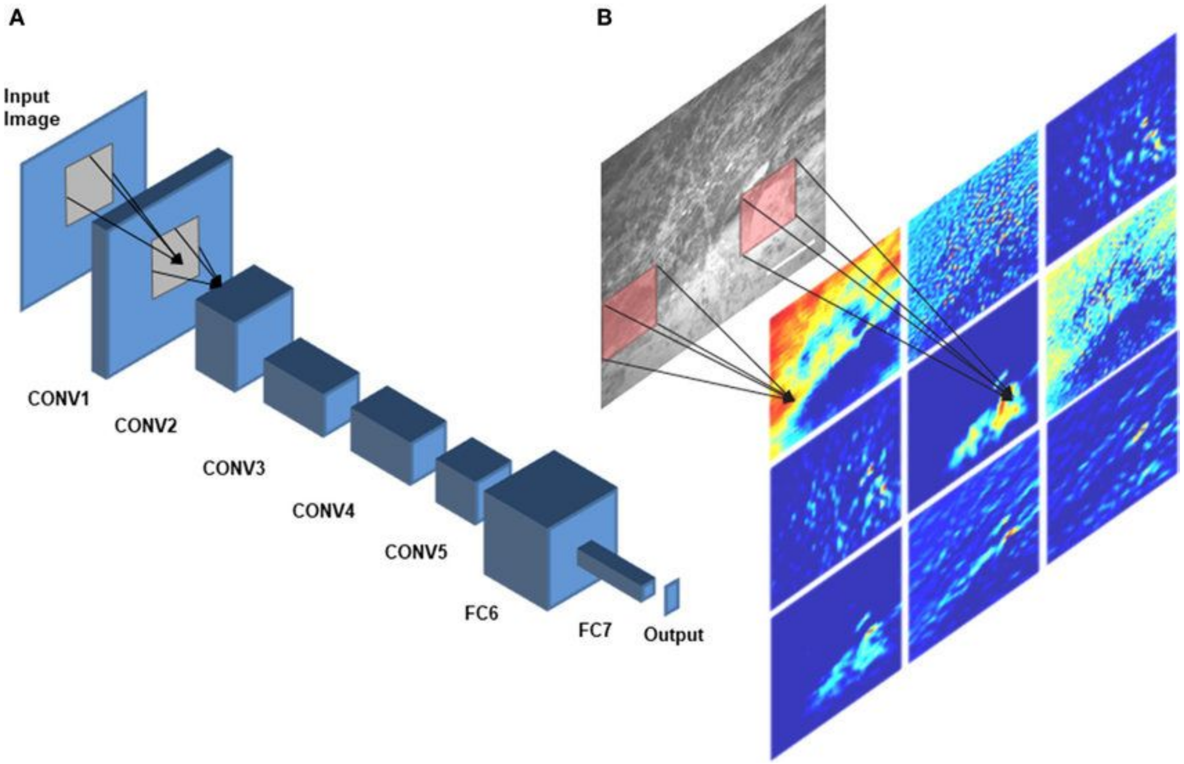
Yann LeCun

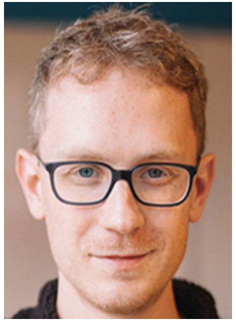


LeNet-5



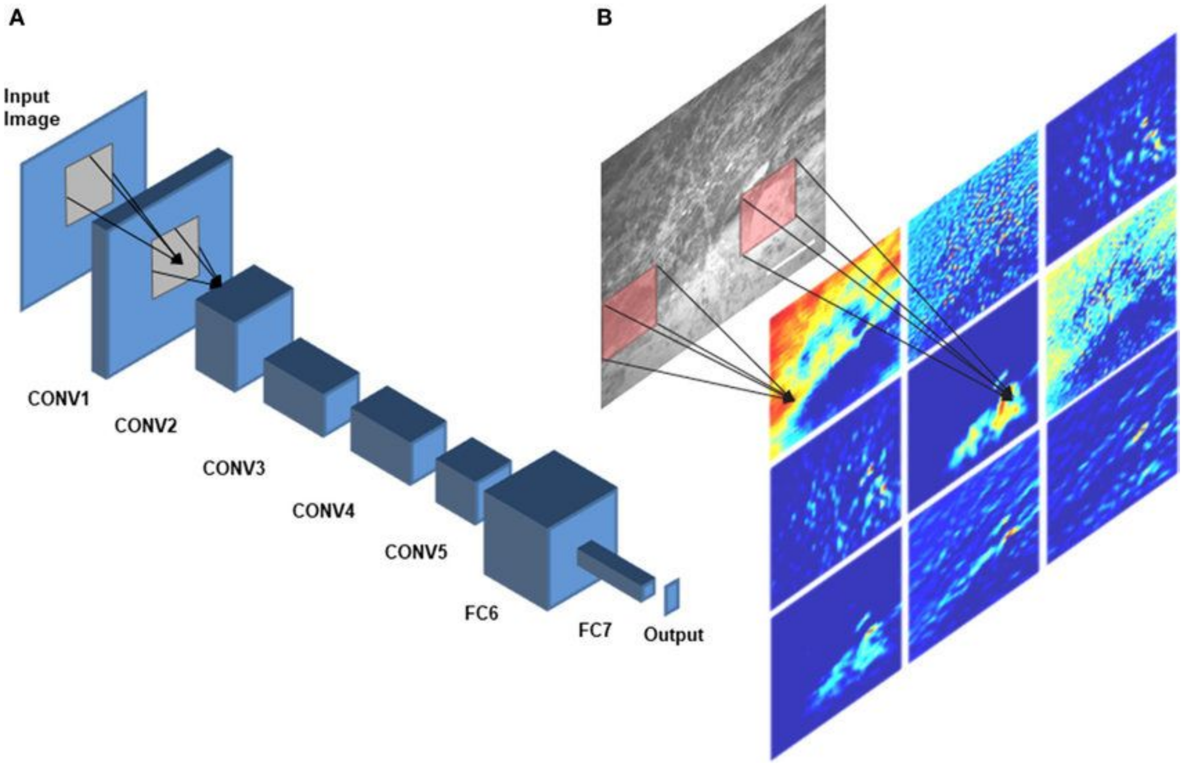
AlexNet - Won 2012 ILSVRC

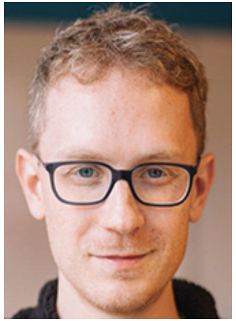




Alex Krizhevsky

AlexNet - Won 2012 ILSVRC

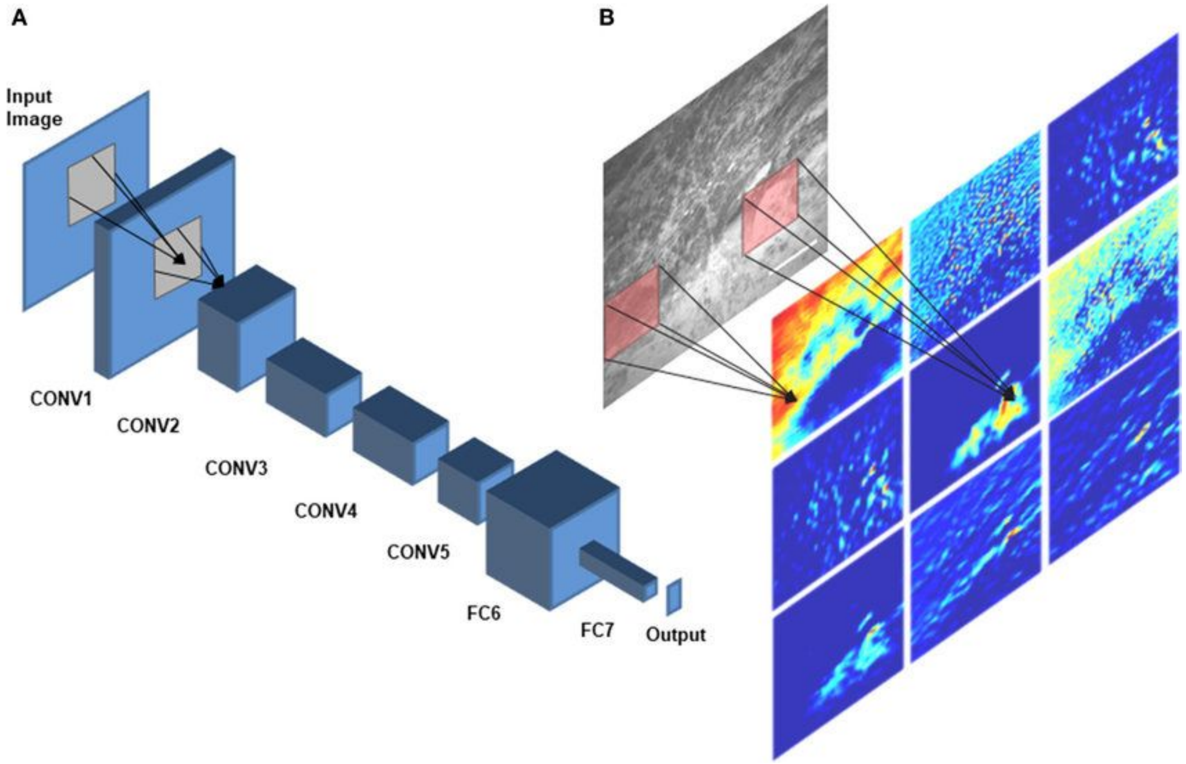


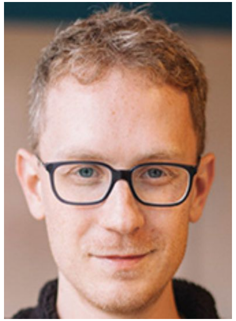


Alex Krizhevsky

Ilya Sutskever

AlexNet - Won 2012 ILSVRC



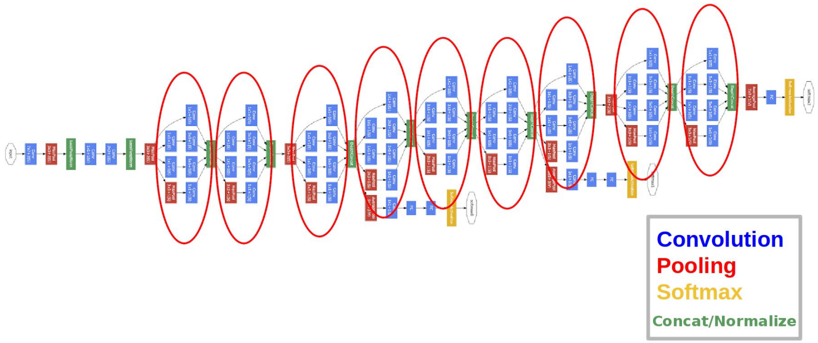


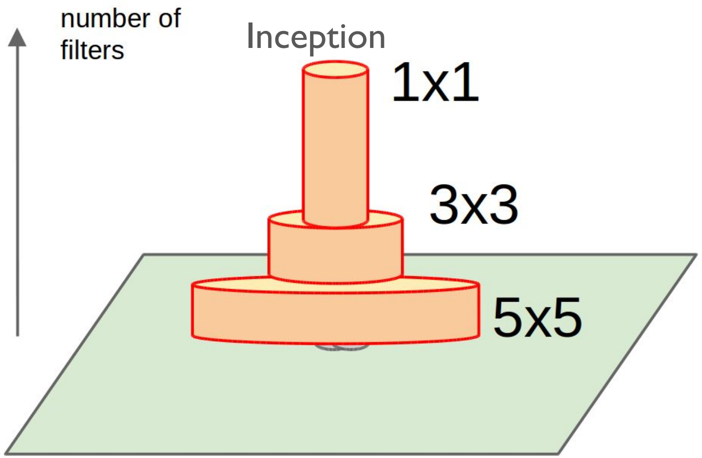
Alex Krizhevsky

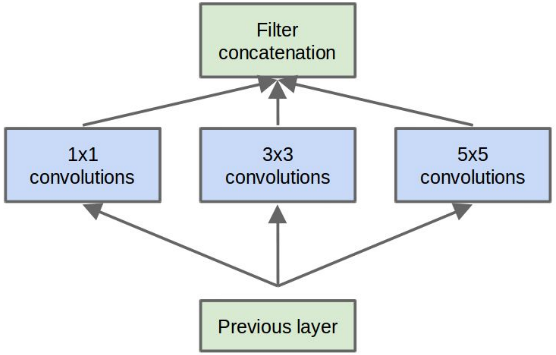
Ilya Sutskever

Geoffrey Hinton

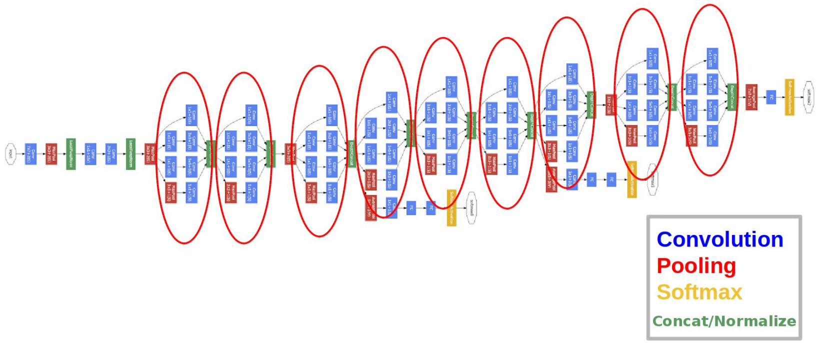
AlexNet - Won 2012 ILSVRC

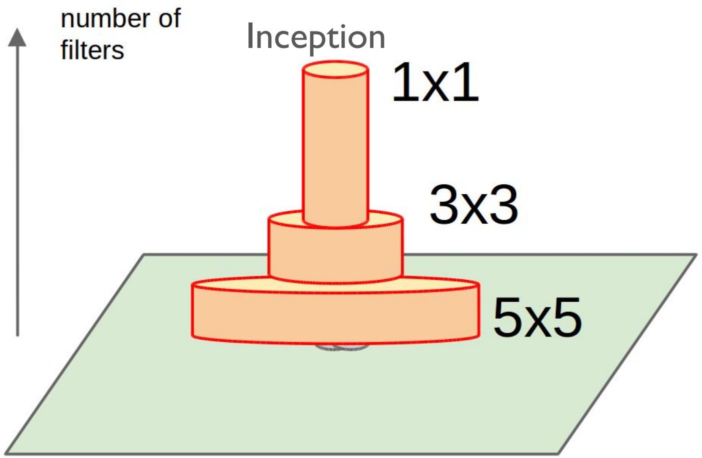

Convolution
Pooling
Softmax
Concat/Normalize

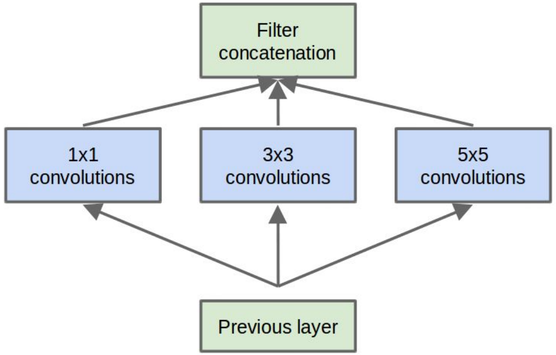

number of filters
Inception
1x1
3x3
5x5


Filter concatenation
1x1 convolutions
3x3 convolutions
5x5 convolutions
Previous layer

GoogLeNet

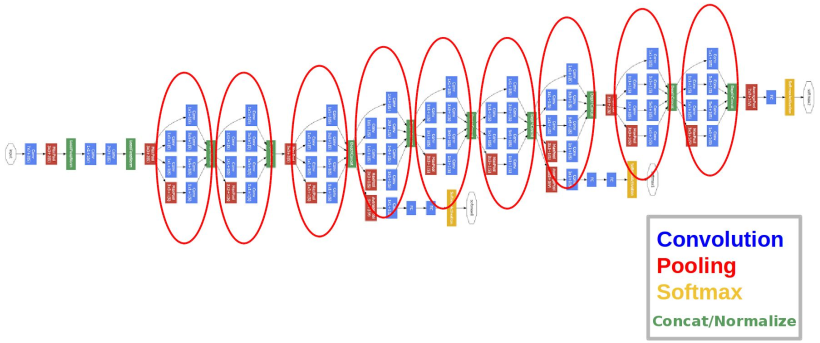


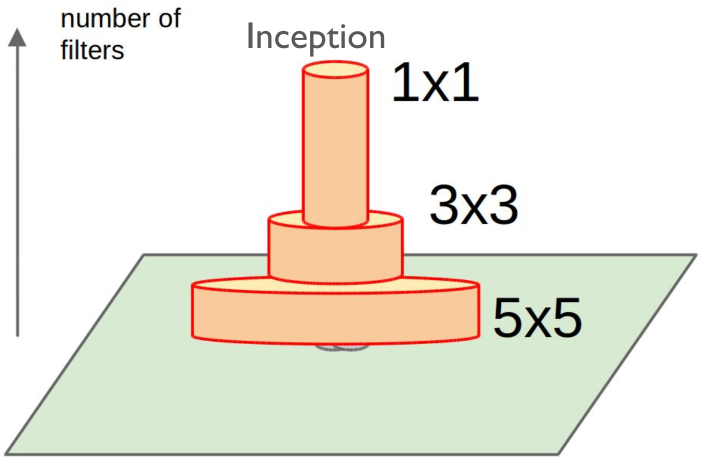


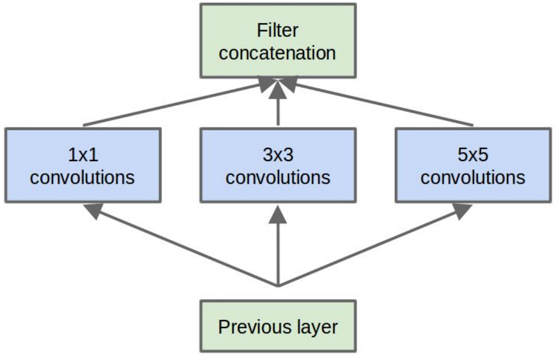


Christian Szegedy

GoogLeNet

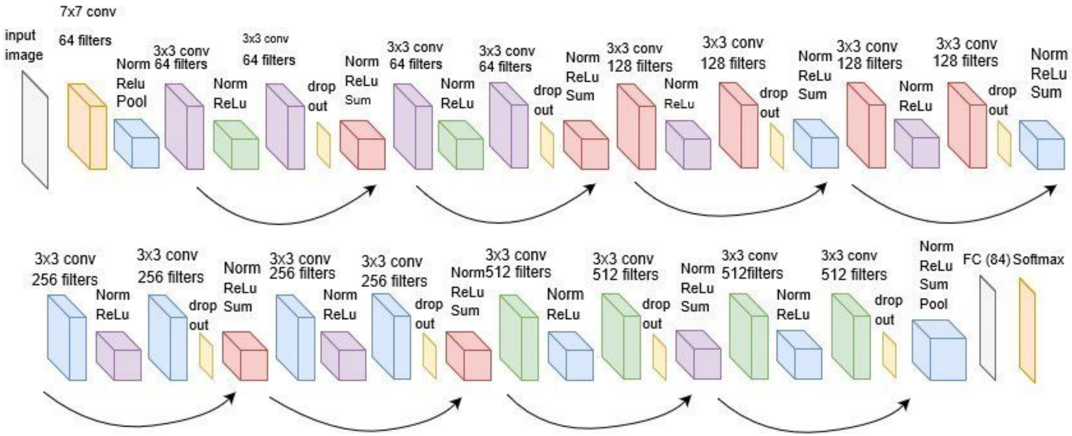


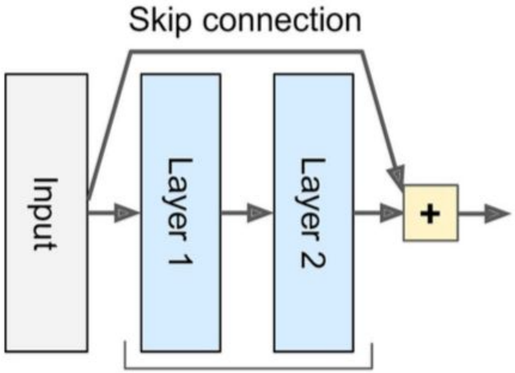


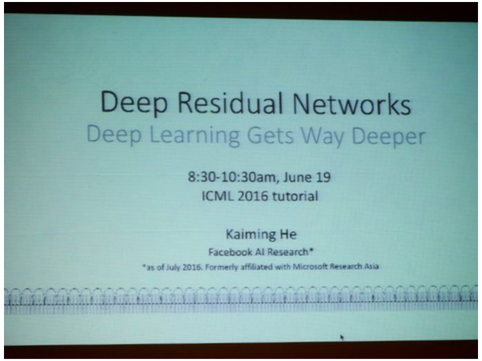


Christian Szegedy

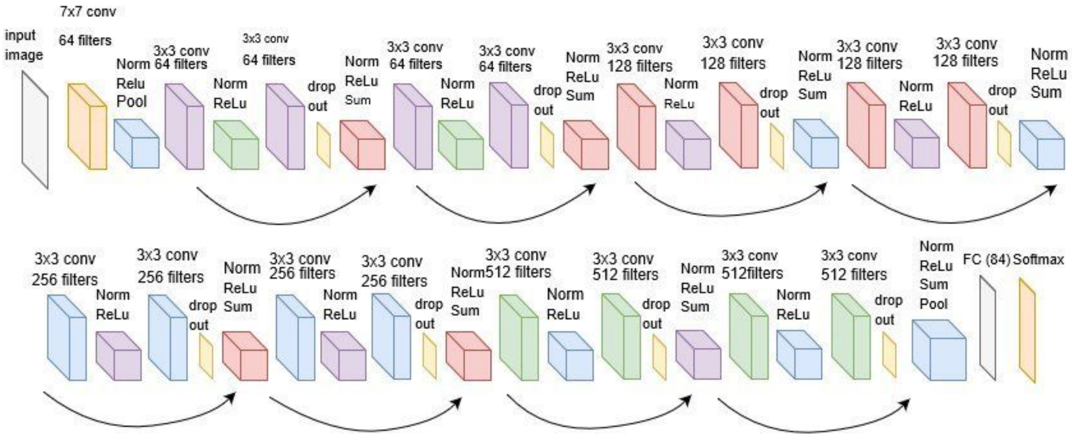
GoogLeNet - Won ILSVRC 2014



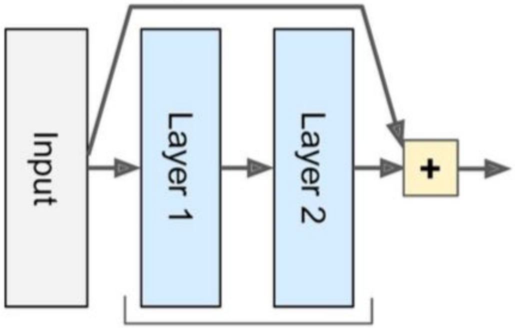




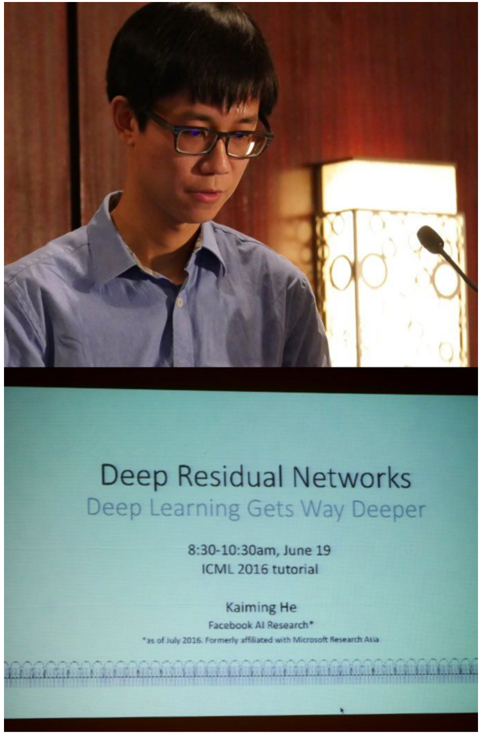
RestNet - Won ILSVRC 2015



Skip connection



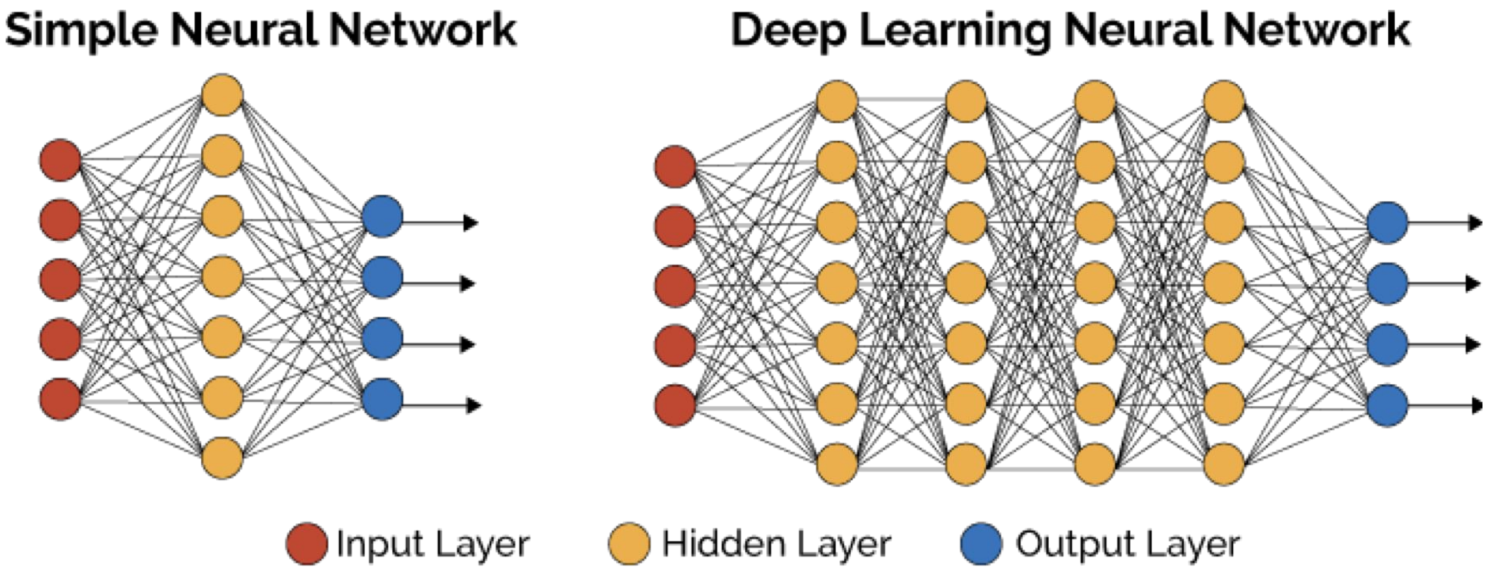
Kaiming He

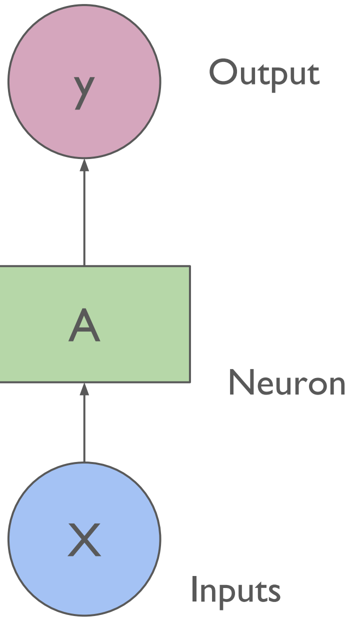


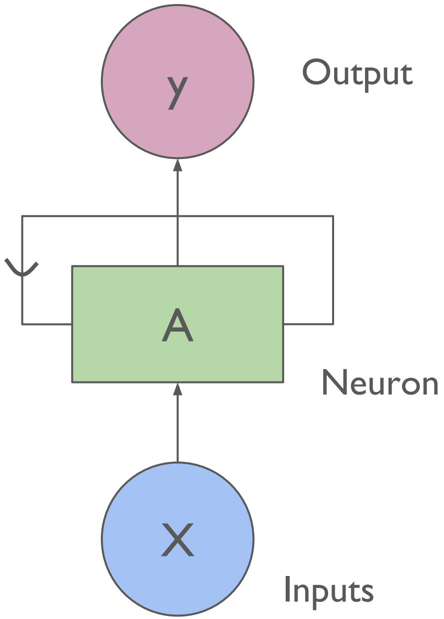
RestNet - Won ILSVRC 2015

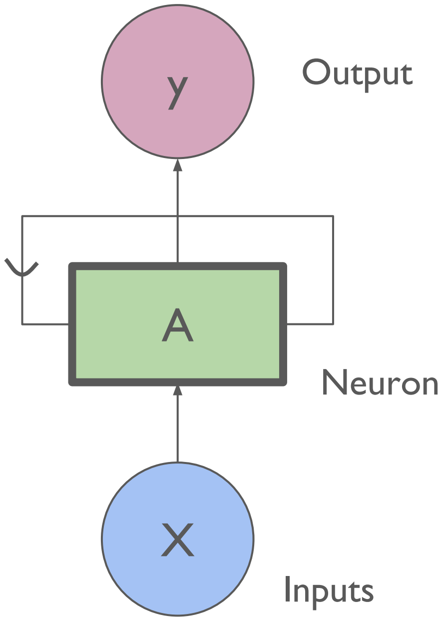
Recurrent Neural Networks - RNN

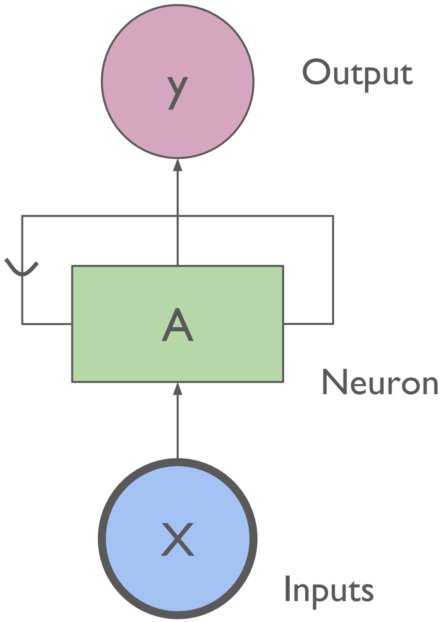

(cloudxlab.com)
Sure,
I'll let you know
Sans Serif

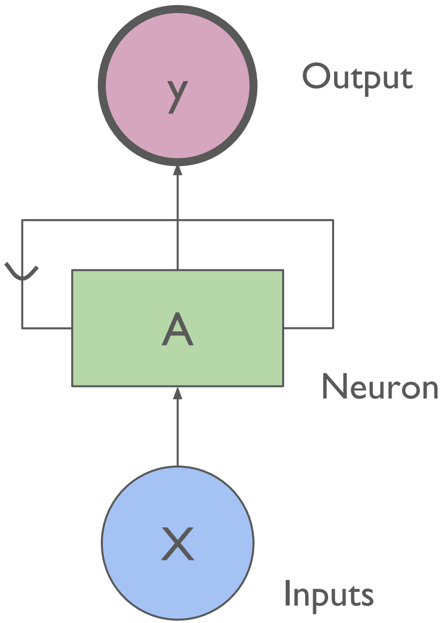

Simple Neural Network
Deep Learning Neural Network
Input Layer
Hidden Layer
Output Layer

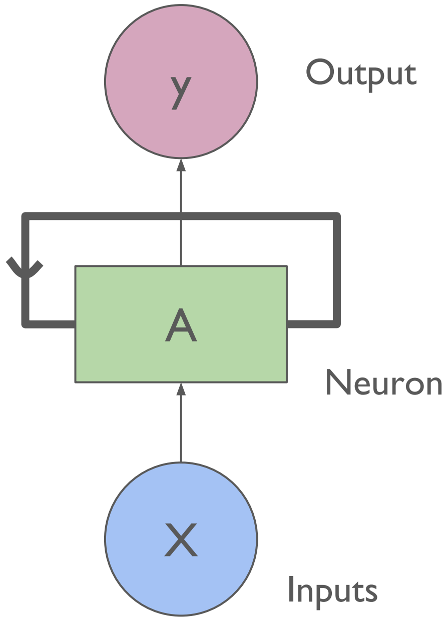

y
Output
A
Neuron
X
Inputs

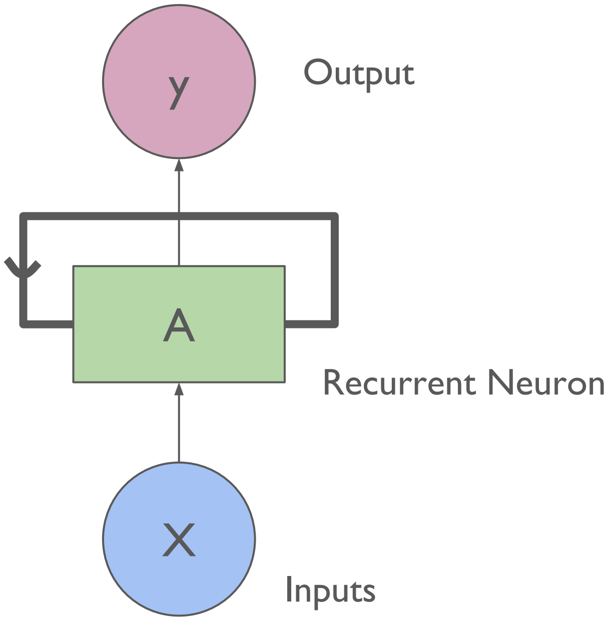

y
Output
A
Neuron
X
Inputs

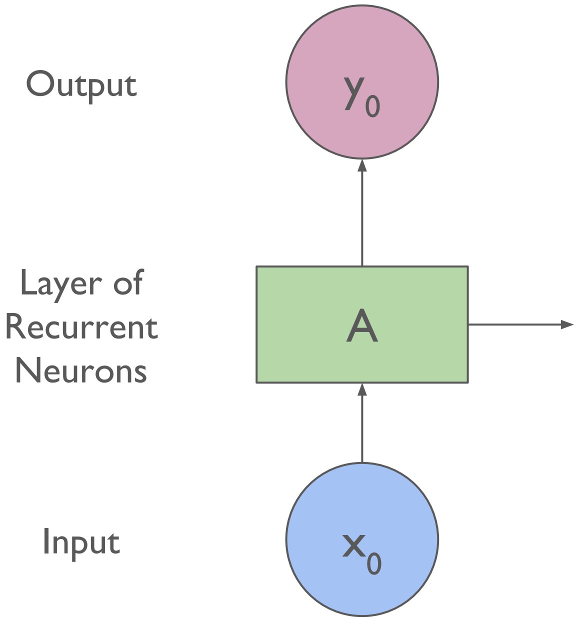

y
Output
A
Neuron
X
Inputs


y
Output
A
Neuron
X
Inputs

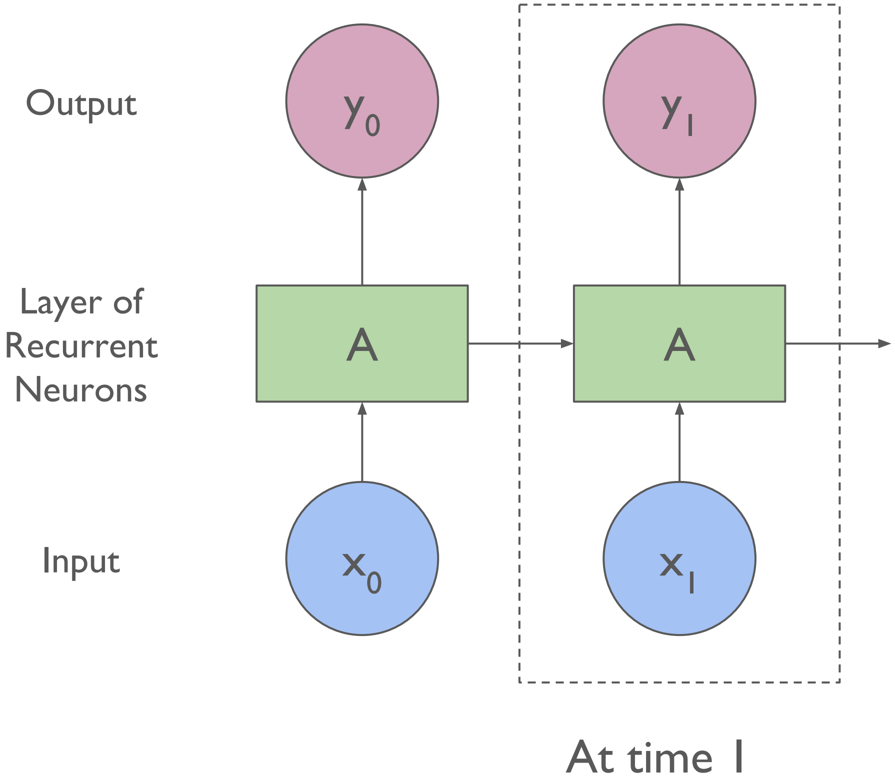

y
Output
A
Neuron
X
Inputs


y
Output
A
Neuron
X
Inputs

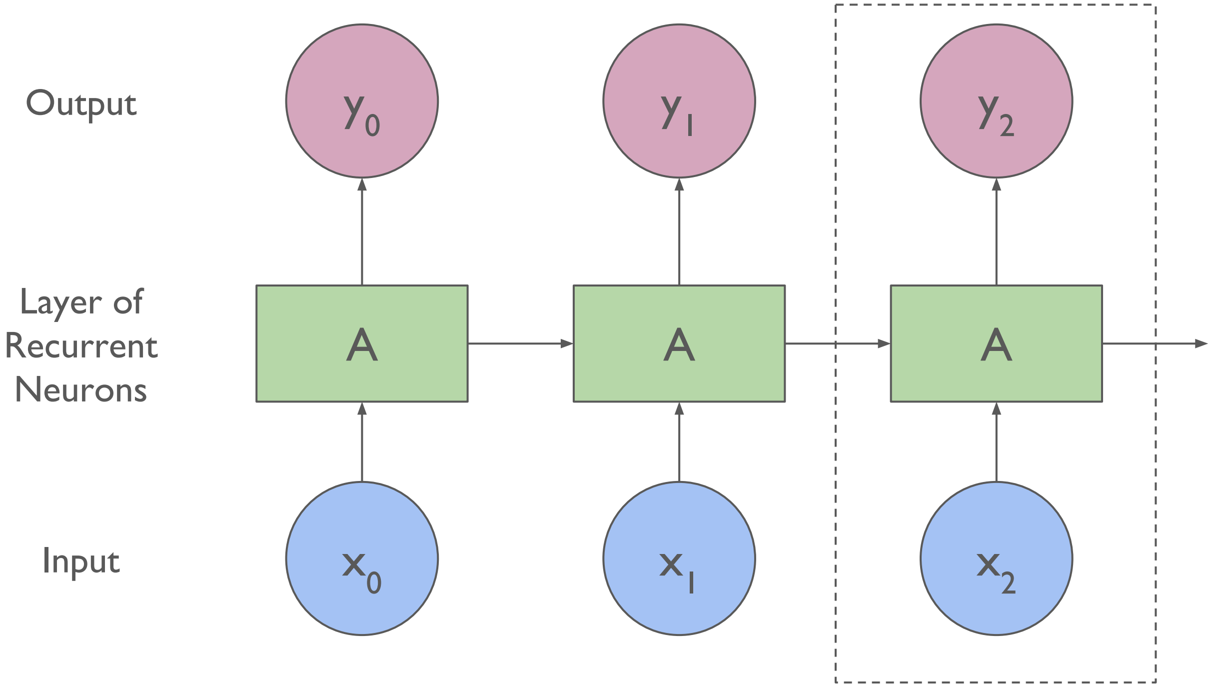

y
Output
A
Recurrent Neuron
X
Inputs



At time 0

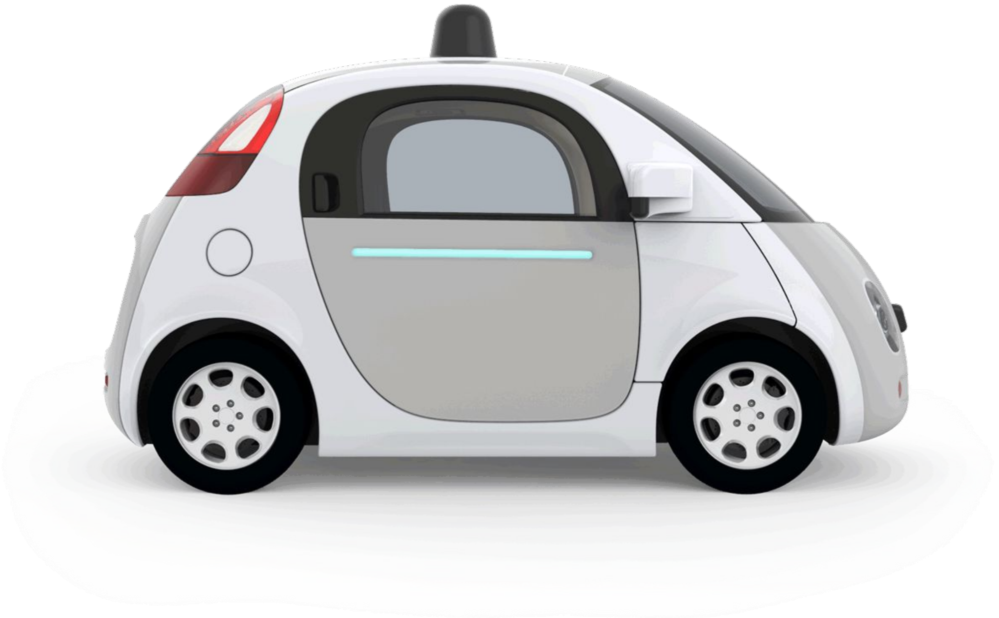


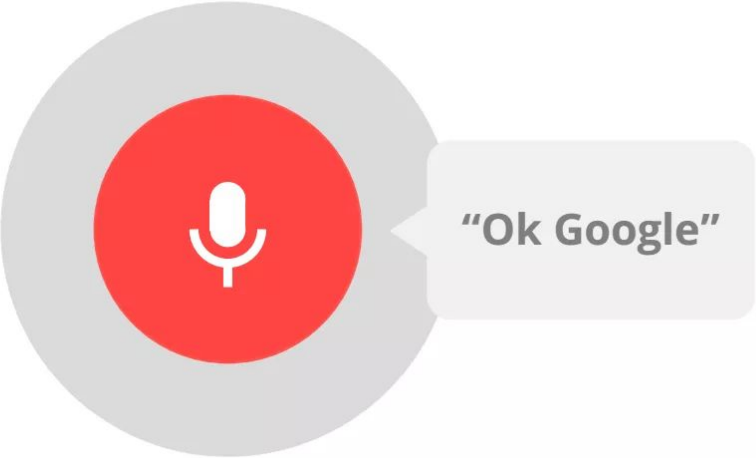
Output
Layer of Recurrent Neurons
Input
y_0
y_1
A
A
x_0
x_1
At time 1

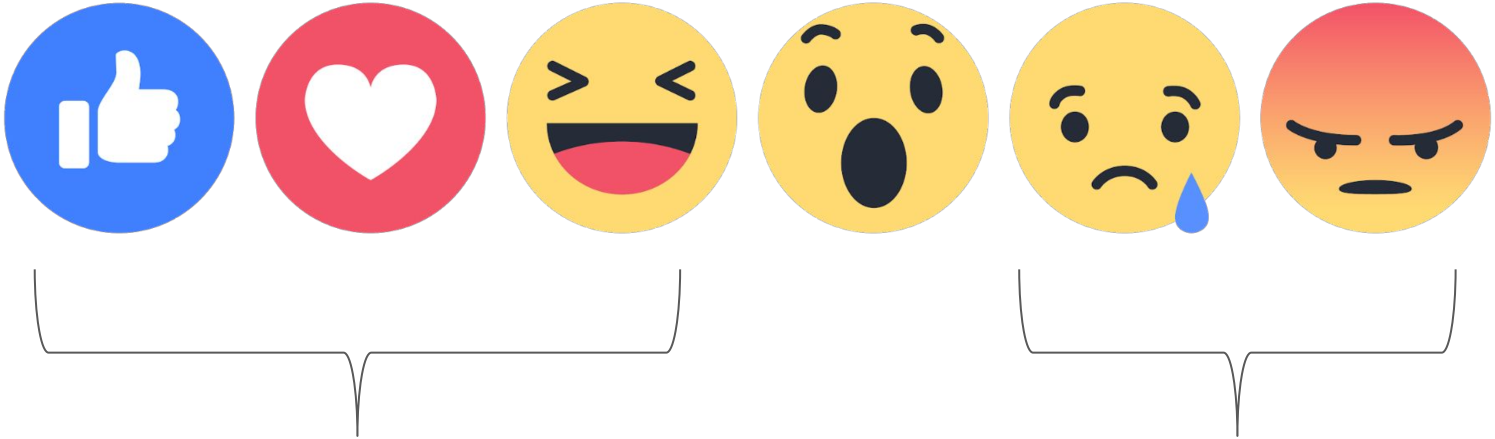


At time 2


S&P BSE SENSEX
25000
20000
15000
10000
5000
0
1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013

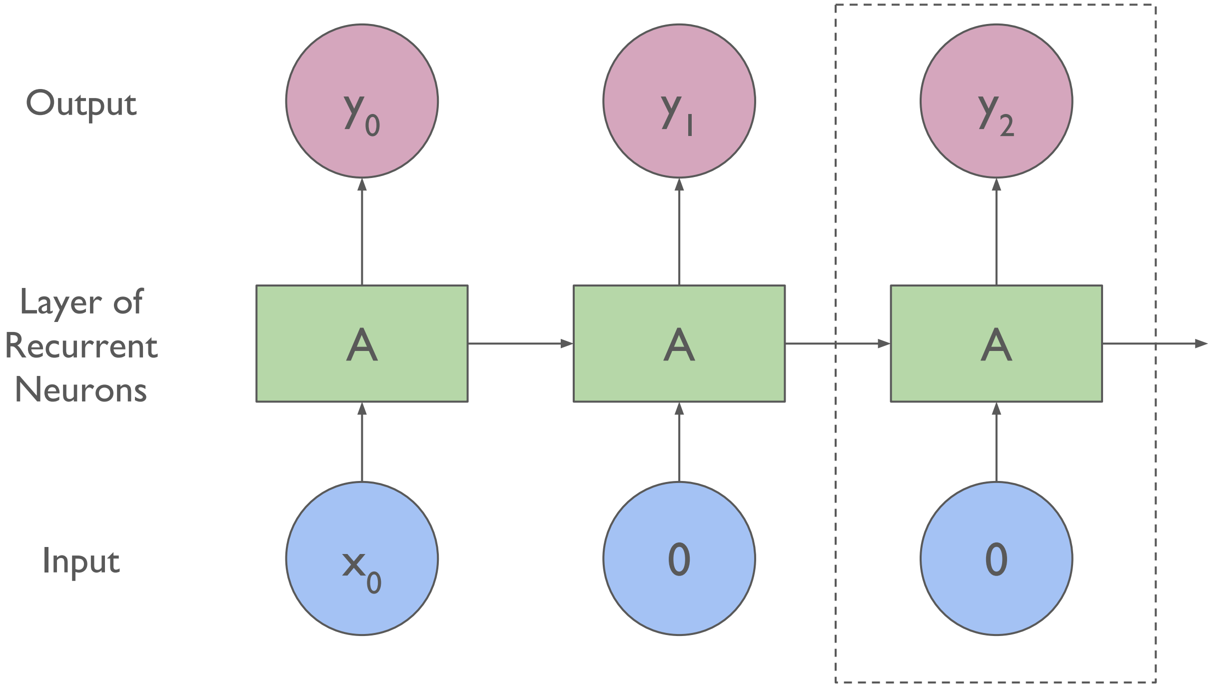



“Ok Google”



Positive Sentiment

Negative Sentiment



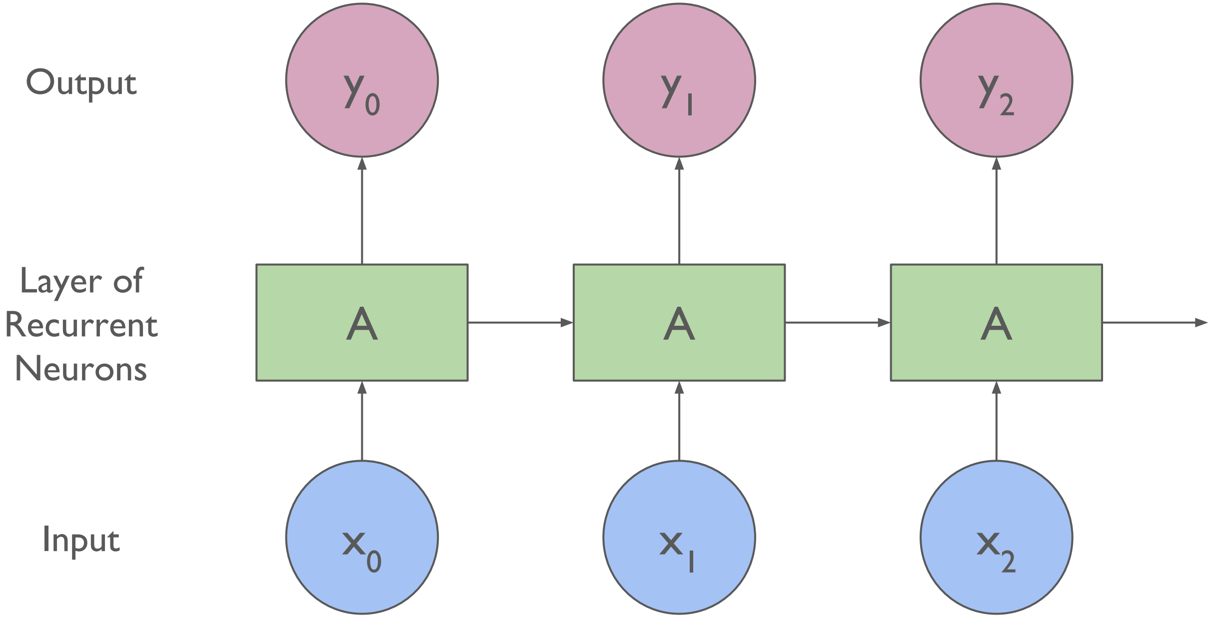
Some inputs skipped

magenta

magenta

Example melody produced by Google's Magenta project

https://www.youtube.com/watch?v=G5JT16flZwM


Output
y_0
y_1
y_2
Layer of Recurrent Neurons
A
A
A
Input
x_0
x_1
x_2

I’ve lived for 25 years in Spain before coming to US to pursue my masters……………………………….

………………………………………………

I can speak fluent ___________

Predict the next word

I've lived for 25 years in Spain before coming to US to pursue my masters……………………………….

……………………………………….

I can speak fluent Spanish

Predict the next word

Relevant information for prediction

<u>I've lived for 25 years in Spain</u> before coming to US to pursue my masters..................................

....

I can speak fluent ____________

Predict the next word

Vanishing Gradient

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

Relevant information for prediction

I’ve lived for 25 years in Spain before coming to US to pursue my masters..................................

....

I can speak fluent ___________

Predict the next word

1. Long Short-Term Memory - LSTM

1. Long Short-Term Memory - LSTM

2. Gated Recurrent Unit - GRU

Relevant information for prediction

I’ve lived for 25 years in Spain before coming to US to pursue my masters……………………………………

…………………………………………

I can speak fluent ____________

Predict the next word

Excellent phone! Camera quality is too good. I’m using this phone from last one month and no complaints so far. I recommend this device to everyone. I will definitely be buying again for my wife.

Excellent phone! Camera quality is too good. I’m using this phone from last one month and no complaints so far. I recommend this device to everyone. I will definitely be buying again for my wife.

Excellent phone! Camera quality is too good. I'm using this phone from last one month and no complaints so far. I recommend this device to everyone. I will definitely be buying again for my wife.

Excellent phone! Camera quality is too good. I'm using this phone from last one month and **no complaints** so far. I recommend this device to everyone. I will definitely be buying again for my wife.

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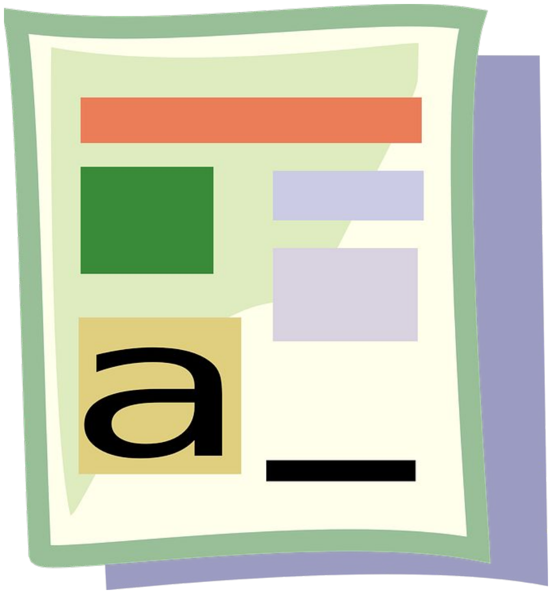
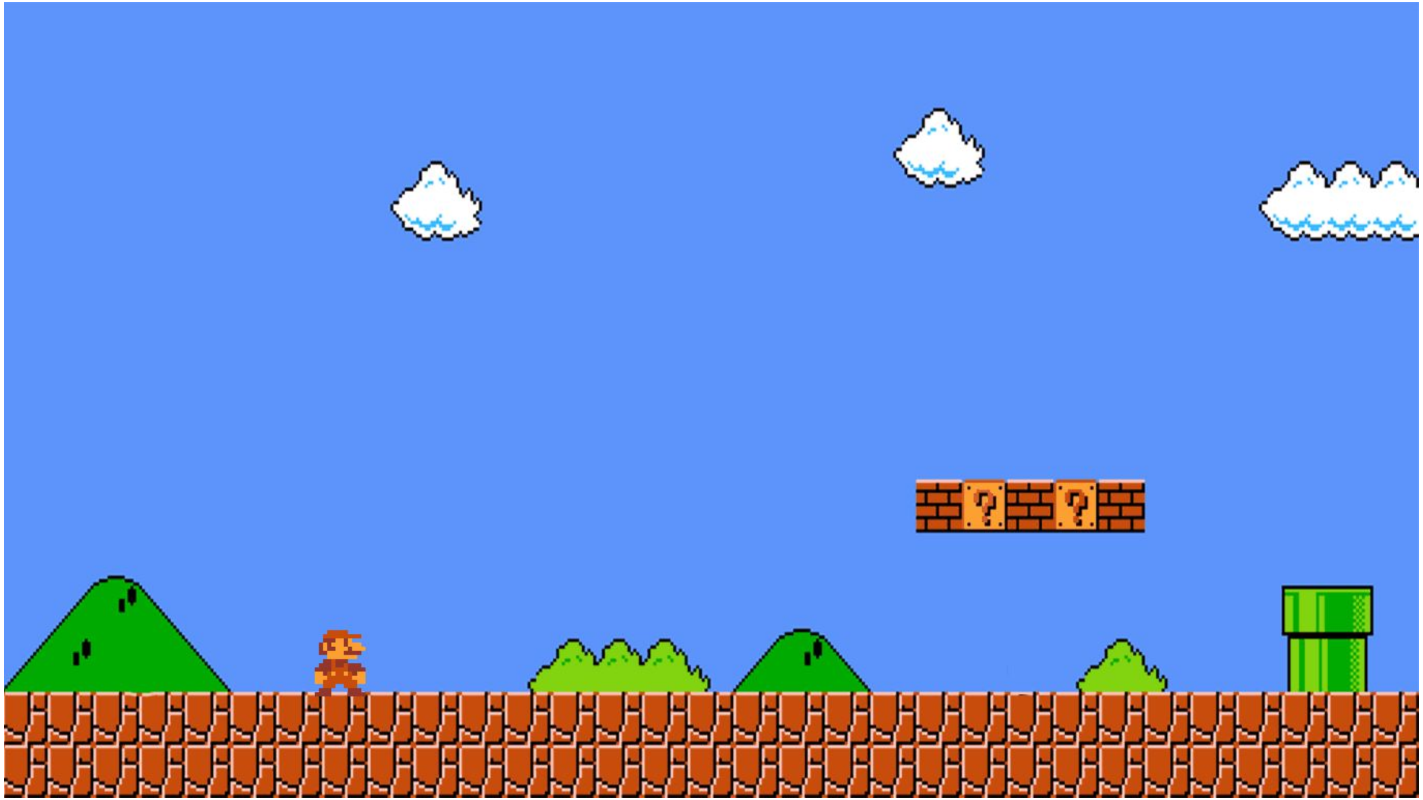
Excellent phone! Camera quality is too good. I'm using this phone from last one month and no complaints so far. I recommend this device to everyone. I will **definitely be buying again** for my wife.



Natural Language Processing

Reinforcement Learning




002
5
1

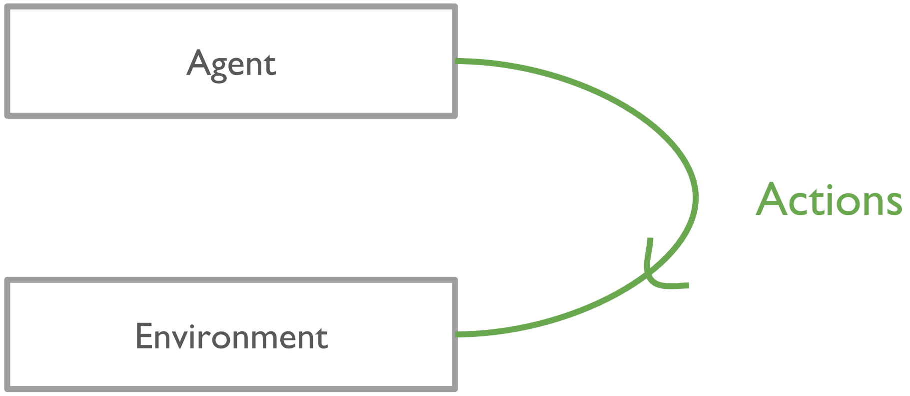
AlphaGo

AlphaGo

Learning to Optimize Rewards

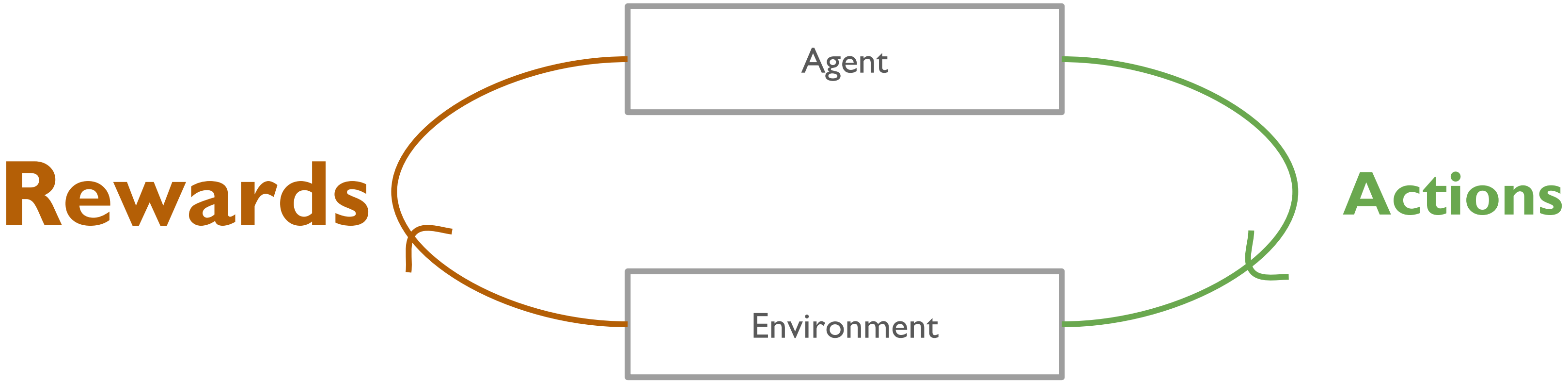
Agent

Environment


Agent
Environment
Actions


Agent
Rewards
Actions
Environment

CLOUD x LAB

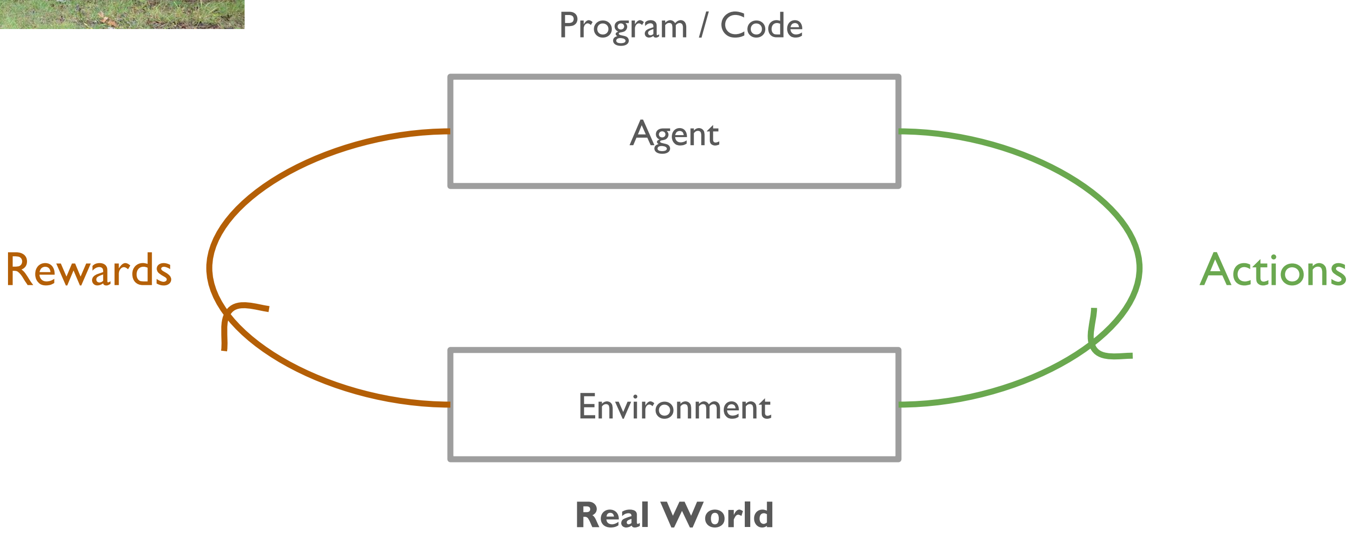

Rewards
Agent
Environment
Actions


Agent
Rewards
Actions
Environment

So how can we apply this in real-life applications?

Walking Robot

CLOUD x LAB


Program / Code
Agent
Rewards
Actions
Environment
Real World

Program / Code

Agent

Rewards

Sensors

Actions

Environment

Real World

Program / Code

Agent

Sensors

Environment

Real World

Rewards

Actions

Sending Signals to Motor

Program / Code

Agent

Rewards

Sensors

Actions

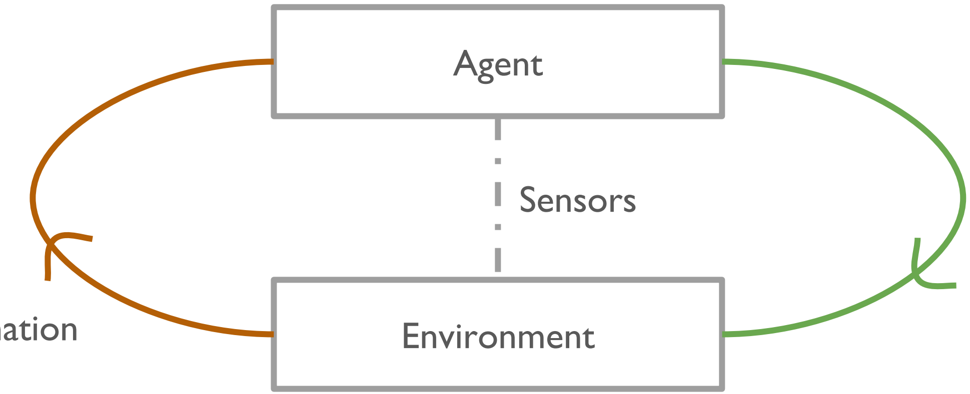
Sending Signals to Motor

\+ Approaching to Destination

Environment

Real World

Program / Code



Rewards

Actions

Sending Signals to Motor

- \+ Approaching to Destination
- \- Wasting Time

Real World

Program / Code

Agent

Sensors

Environment

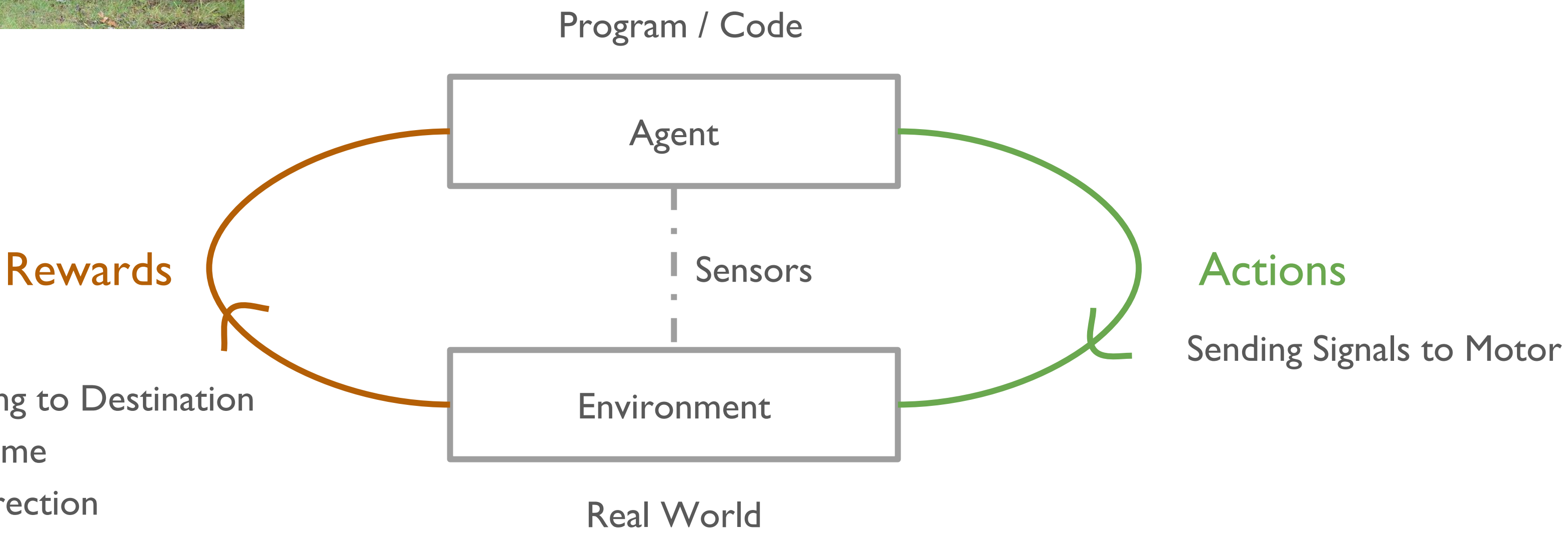
Real World

Rewards

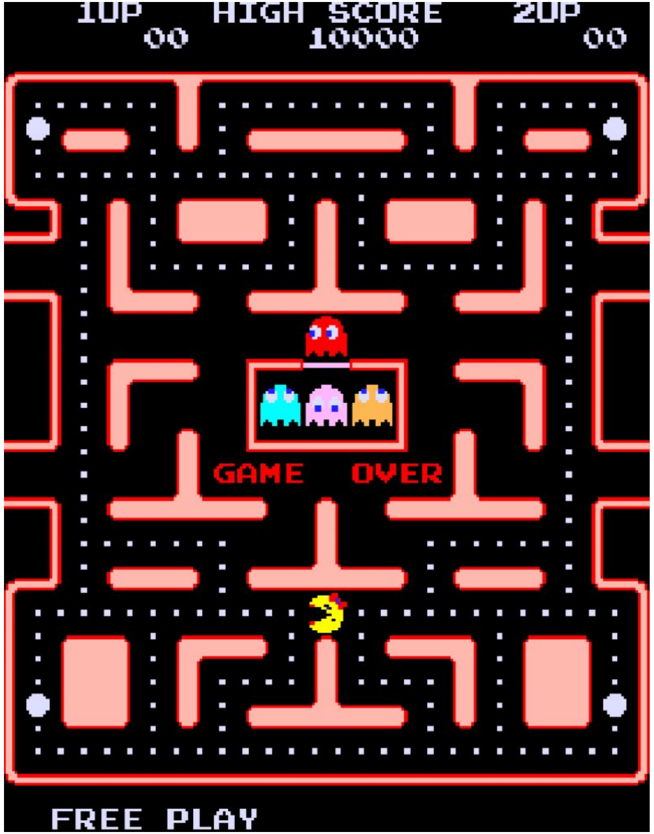
- \+ Approaching to Destination
- \- Wasting Time
- \- Wrong Direction

Actions

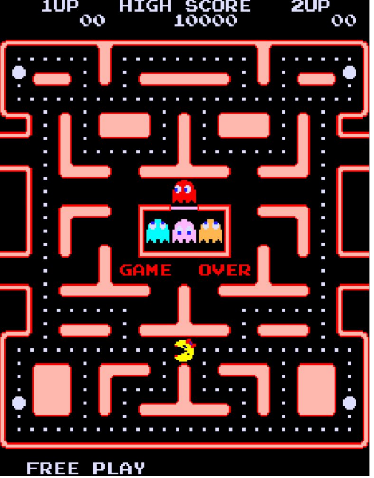
Sending Signals to Motor



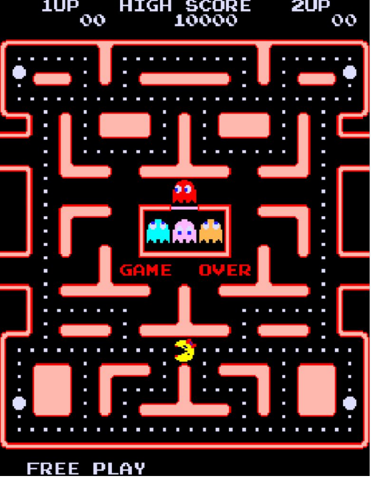
+ Approaching to Destination
- Wasting Time
- Wrong Direction
- Falls Down



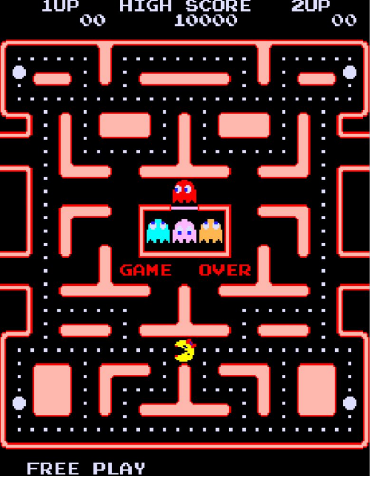
Ms. Pac-Man


1UP
00
HIGH SCORE
10000
2UP
00
GAME OVER
FREE PLAY


Program / Code
Agent
Rewards
Actions
Environment



Simulation of Atari Game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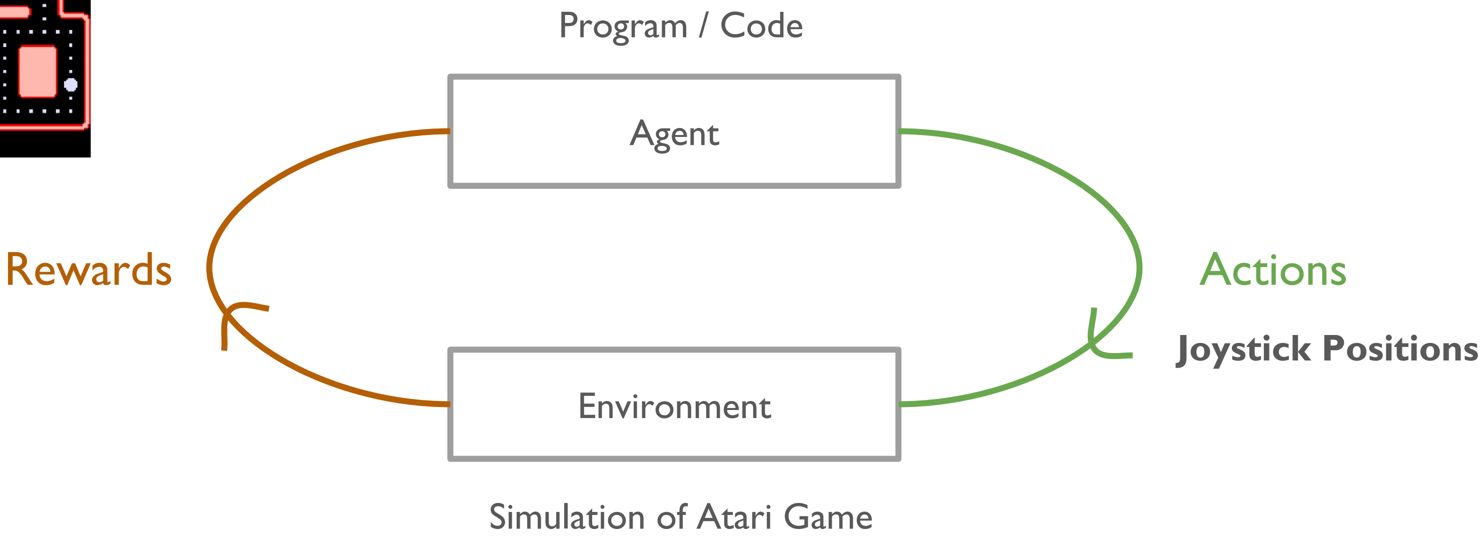
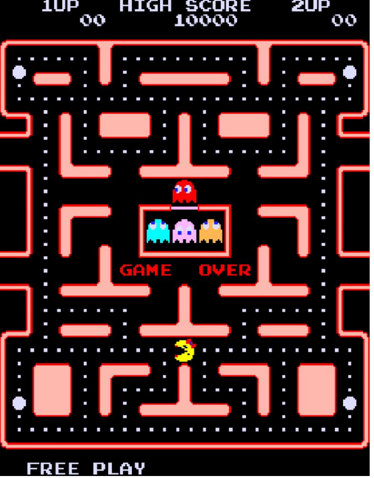
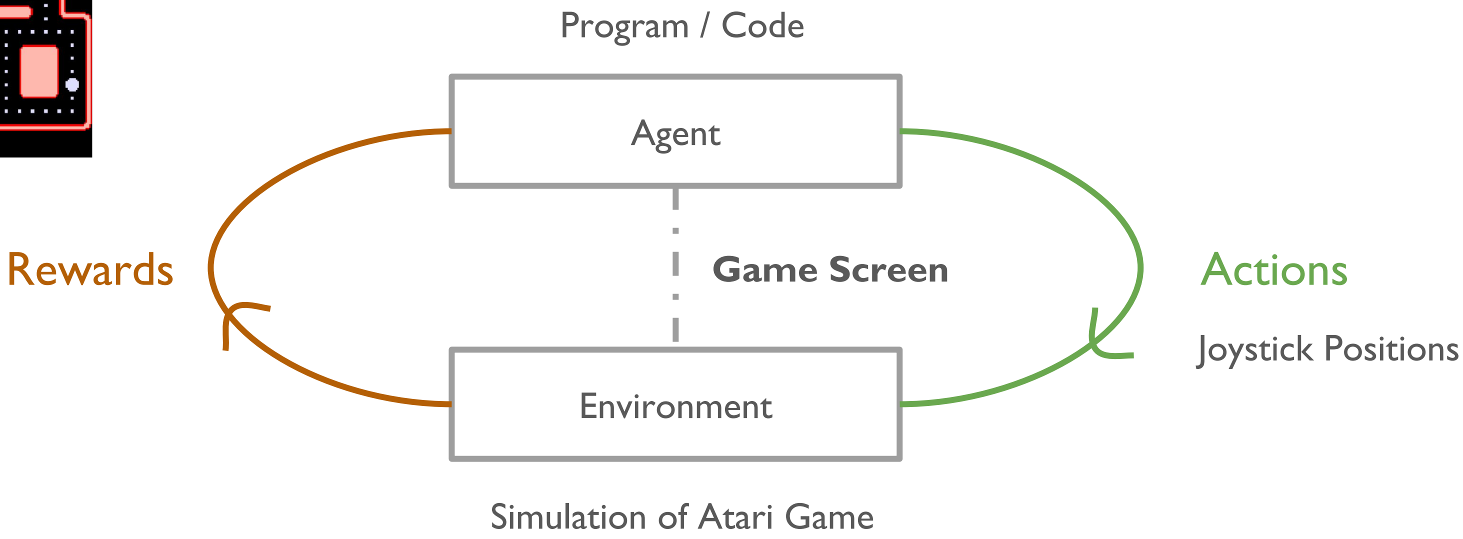
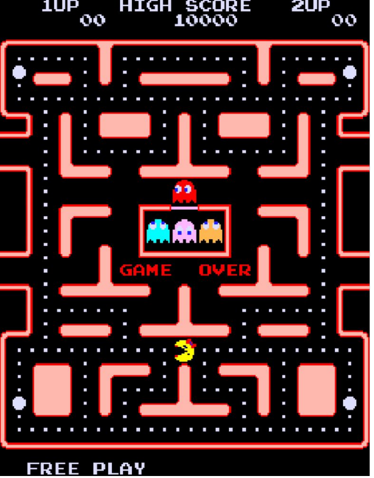

Program / Code
Agent
Rewards
Actions
Joystick Positions
Environment
Simulation of Atari Game


1UP HIGH SCORE 2UP
00 10000 00
GAME OVER
FREE PLAY


Program / Code
Agent
Rewards
Game Screen
Actions
Joystick Positions
Environment
Simulation of Atari Game


1UP
00
HIGH SCORE
10000
2UP
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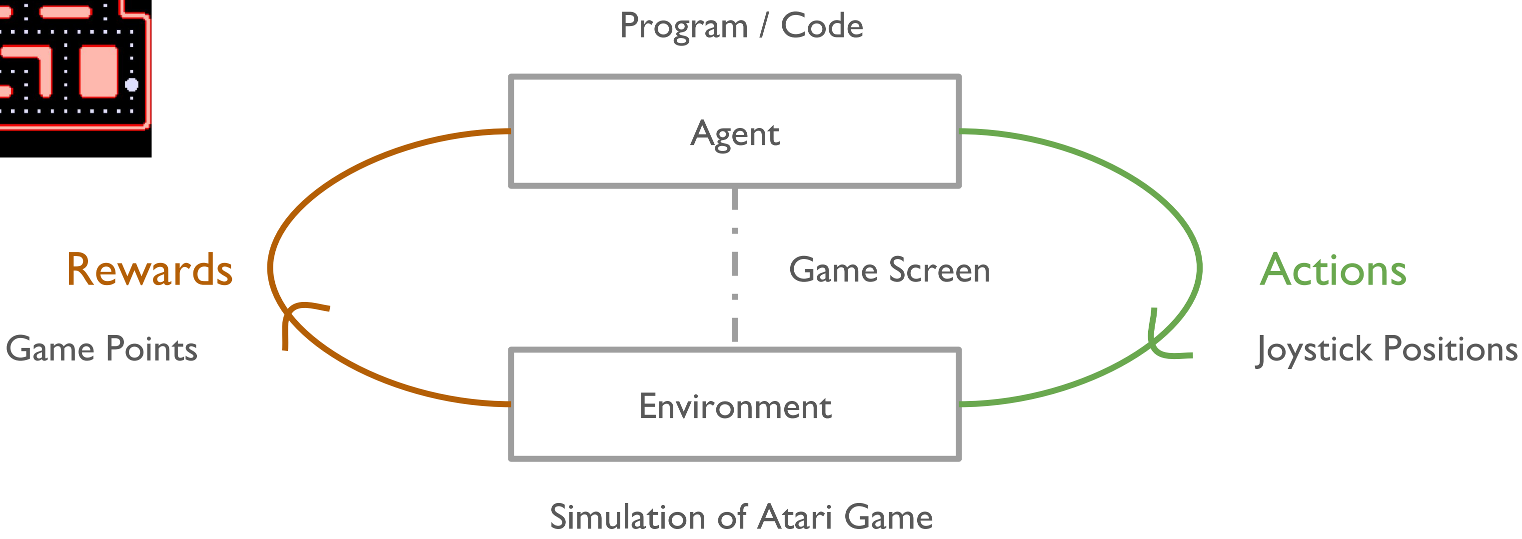
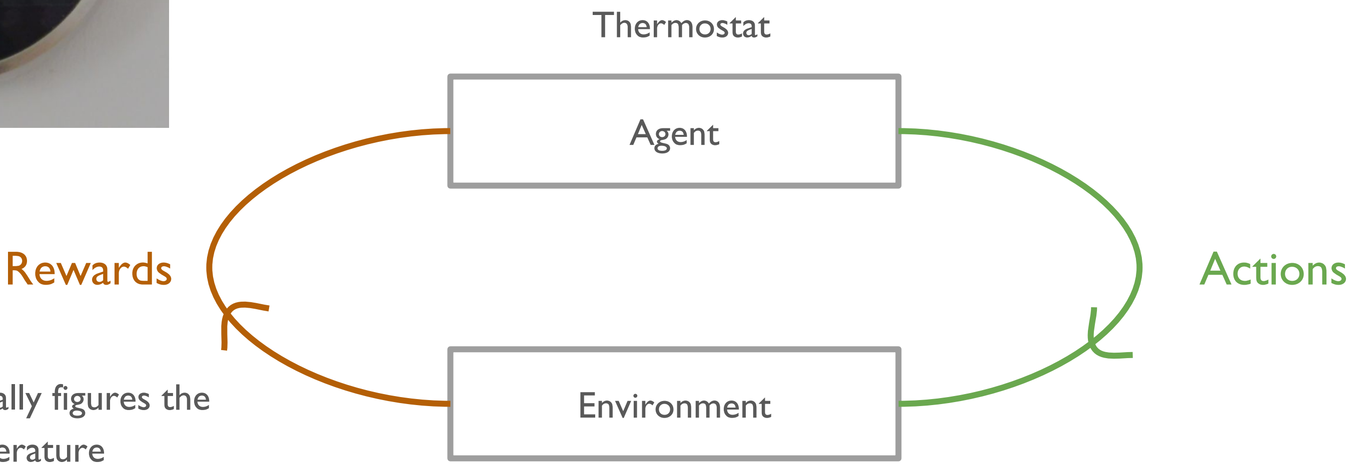
GAME OVER
FREE PLAY


Program / Code
Agent
Rewards
Game Points
Game Screen
Actions
Joystick Positions
Environment
Simulation of Atari Game

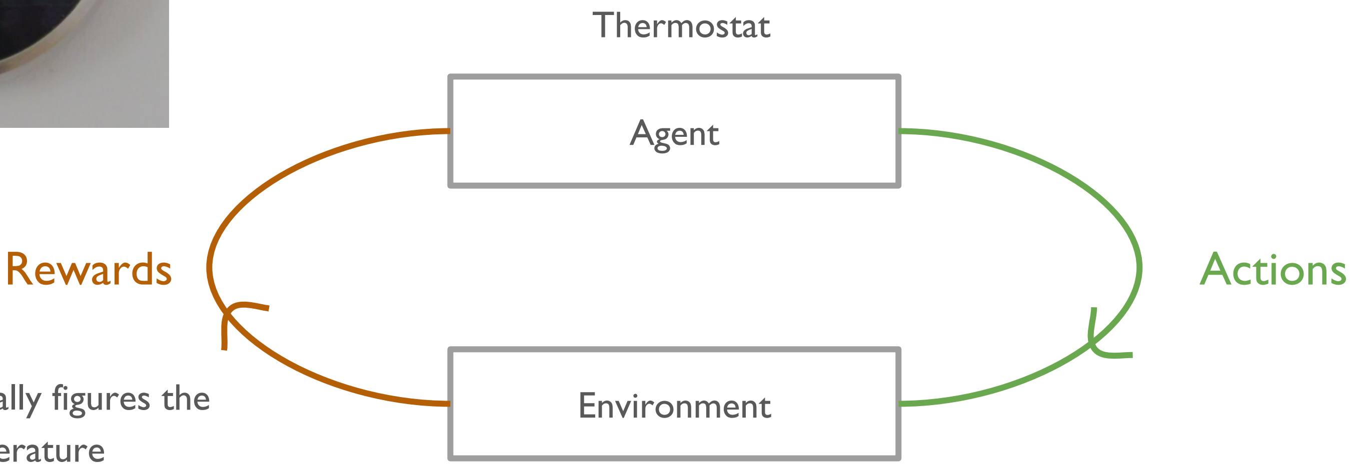
CLOUD x LAB

Smart Thermostat

Thermostat



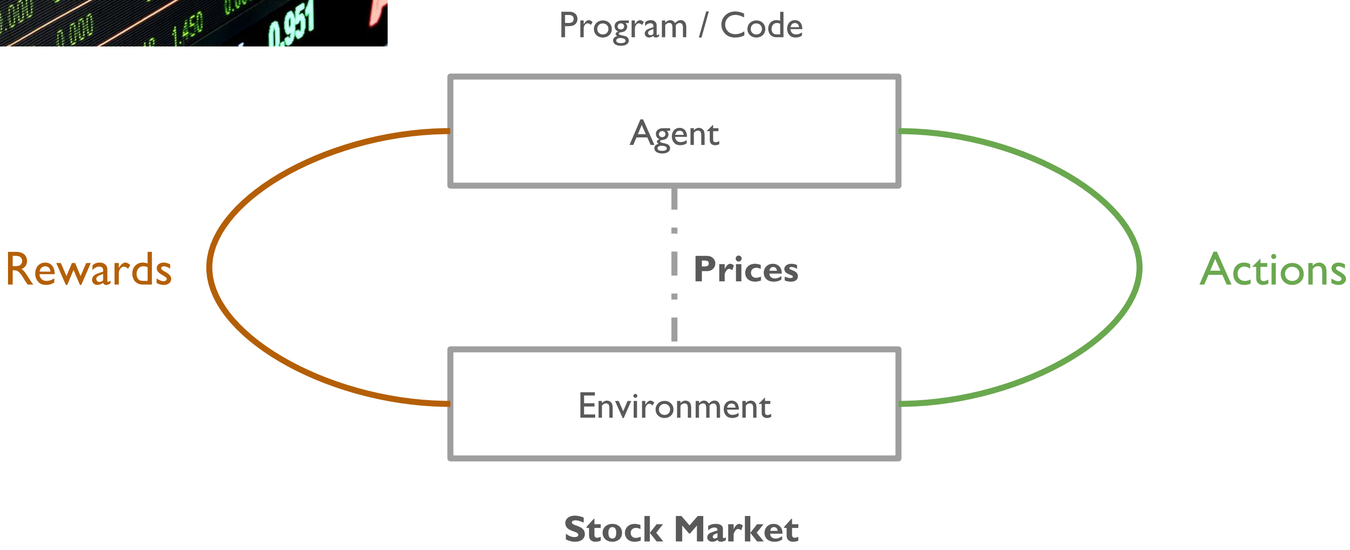
+ Automatically figures the right temperature

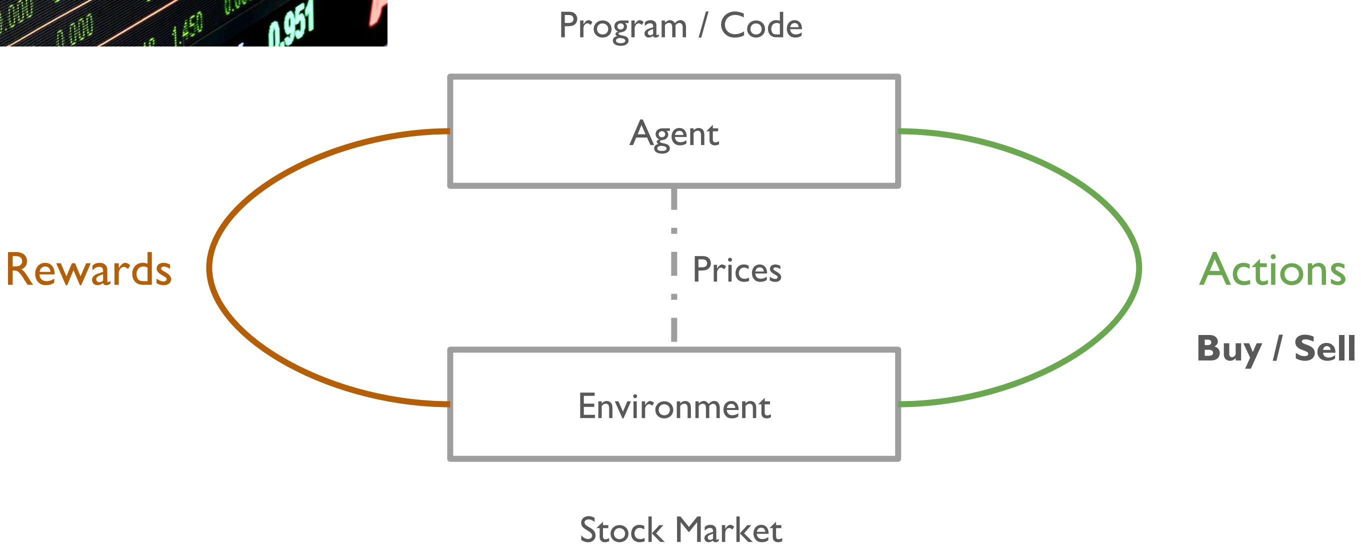


- \+ Automatically figures the right temperature
- \- Humans tweak the temperature manually

Automatic Trader

Program / Code
Agent
Rewards
Actions
Environment


Program / Code
Agent
Rewards
Prices
Actions
Environment
Stock Market


Program / Code
Agent
Rewards
Prices
Actions
Buy / Sell
Environment
Stock Market

Program / Code

Agent

Prices

Environment

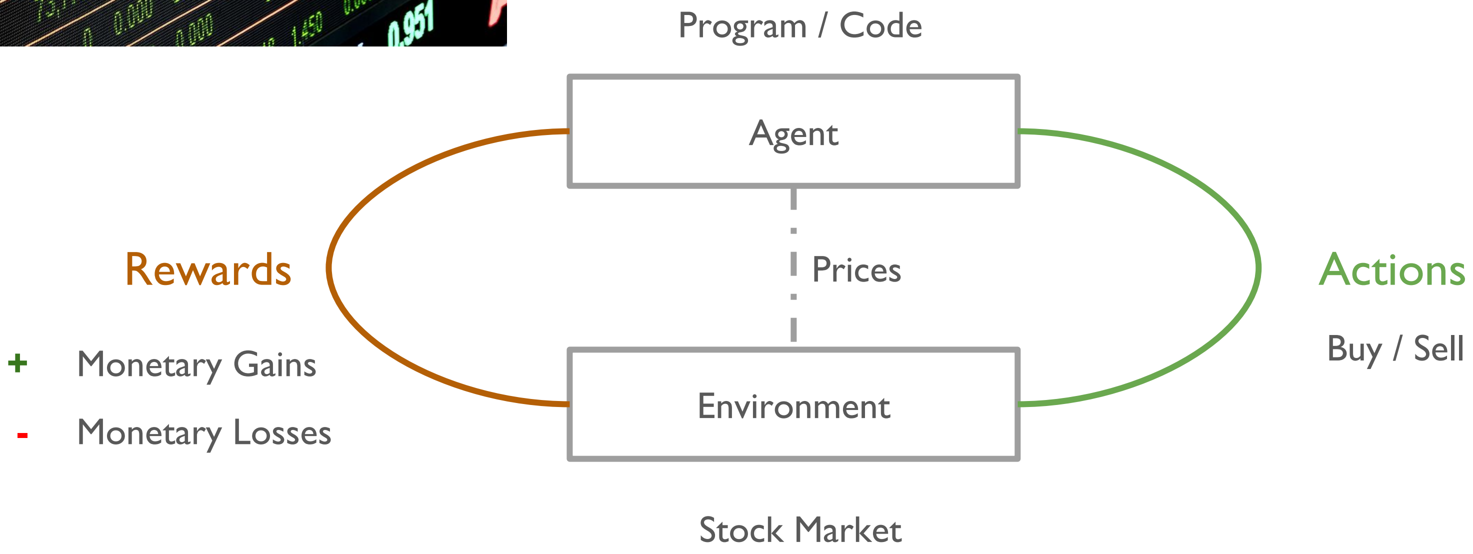
Stock Market

Rewards

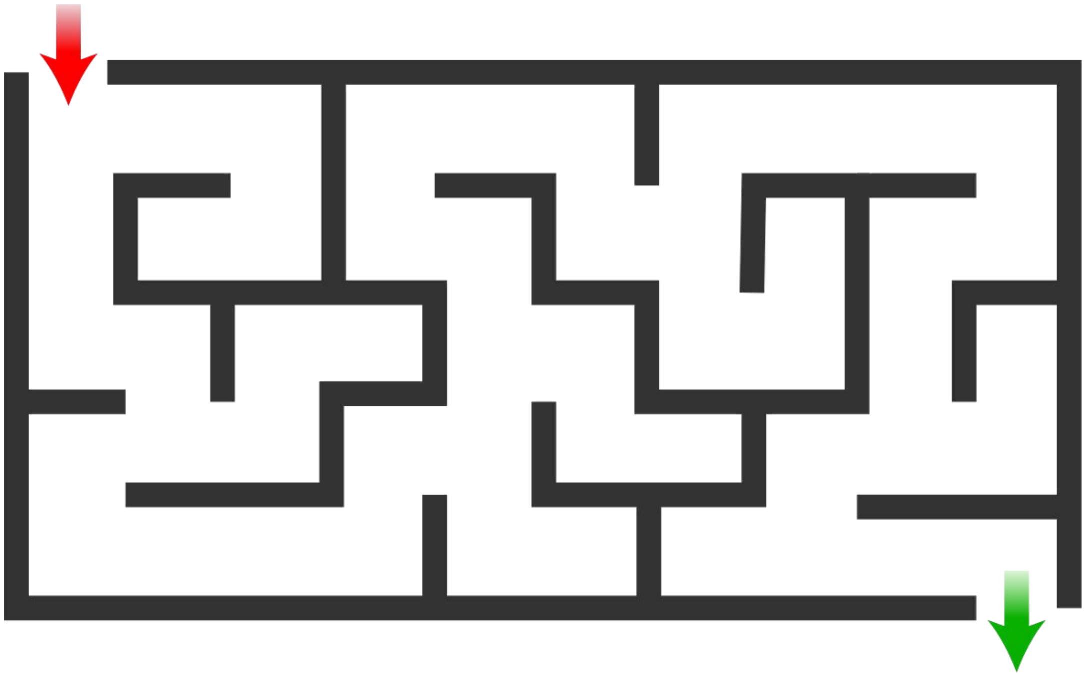
+ Monetary Gains

Actions

Buy / Sell


Program / Code
Agent
Prices
Environment
Stock Market
Rewards
+ Monetary Gains
- Monetary Losses
Actions
Buy / Sell

CLOUD x LAB



Maze

Summary

- Ensemble learning

- Ensemble learning
- Why ensemble learning gives better predictions

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- Why ensemble learning gives better predictions
- Hard voting classifiers

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- Why ensemble learning gives better predictions
- Hard voting classifiers
- Soft voting classifiers

- Convolutional Neural Networks - CNN

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- Convolutional layer

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- Pooling layers

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- Convolutional layer
- Pooling layers
- Various architectures

- Recurrent Neural Networks - RNN

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- Why RNNs?

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- Why RNNs?
- Applications of RNNs

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- Shortcoming of RNNS
- Improvements
    - Long Short-Term Memory - LSTM

- Recurrent Neural Networks - RNN
- Why RNNs?
- Applications of RNNs
- Shortcoming of RNNS
- Improvements
    - Long Short-Term Memory - LSTM
    - Gated Recurrent Unit - GRU

- Reinforcement Learning

- Reinforcement Learning
- Applications of reinforcement learning

- Reinforcement Learning
- Applications of reinforcement learning
- Learning to optimize the rewards

Questions?

https://discuss.cloudxlab.com

reachus@cloudxlab.com