

Symmetries and Specialized Architectures & Machine Vision

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STScI

| SPACE TELESCOPE
SCIENCE INSTITUTE

How will class work today?

- Three lessons, each with:
 - Learning goals
 - A 15-minute lecture
 - A 45-minute chance to work on coding in teams
 - Links to supplementary instructional materials if you're lost
 - Ideas for extension activities if you're bored
- Lessons cover:
 1. Convolutional Neural Networks
 2. Convolutional Neural Network Interpretability
 3. Graph Neural Networks

INTRO TO MACHINE VISION

Learning goal #0: Explain the benefits and pitfalls of feature engineering in machine vision.

Image Textures: Animal or Food?



Image Textures: Animal or Food?



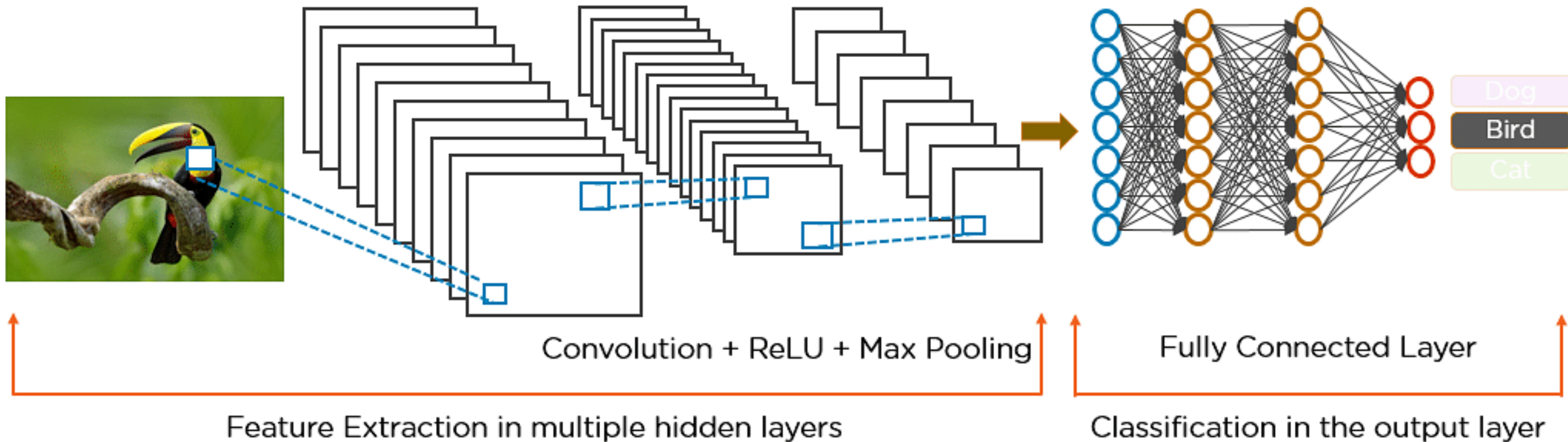
Image Textures: Animal or Food?



CONVOLUTIONAL NEURAL NETWORKS

Learning goal #1: Describe a convolutional neural network's architecture. List the problems that a CNN is well-suited for.

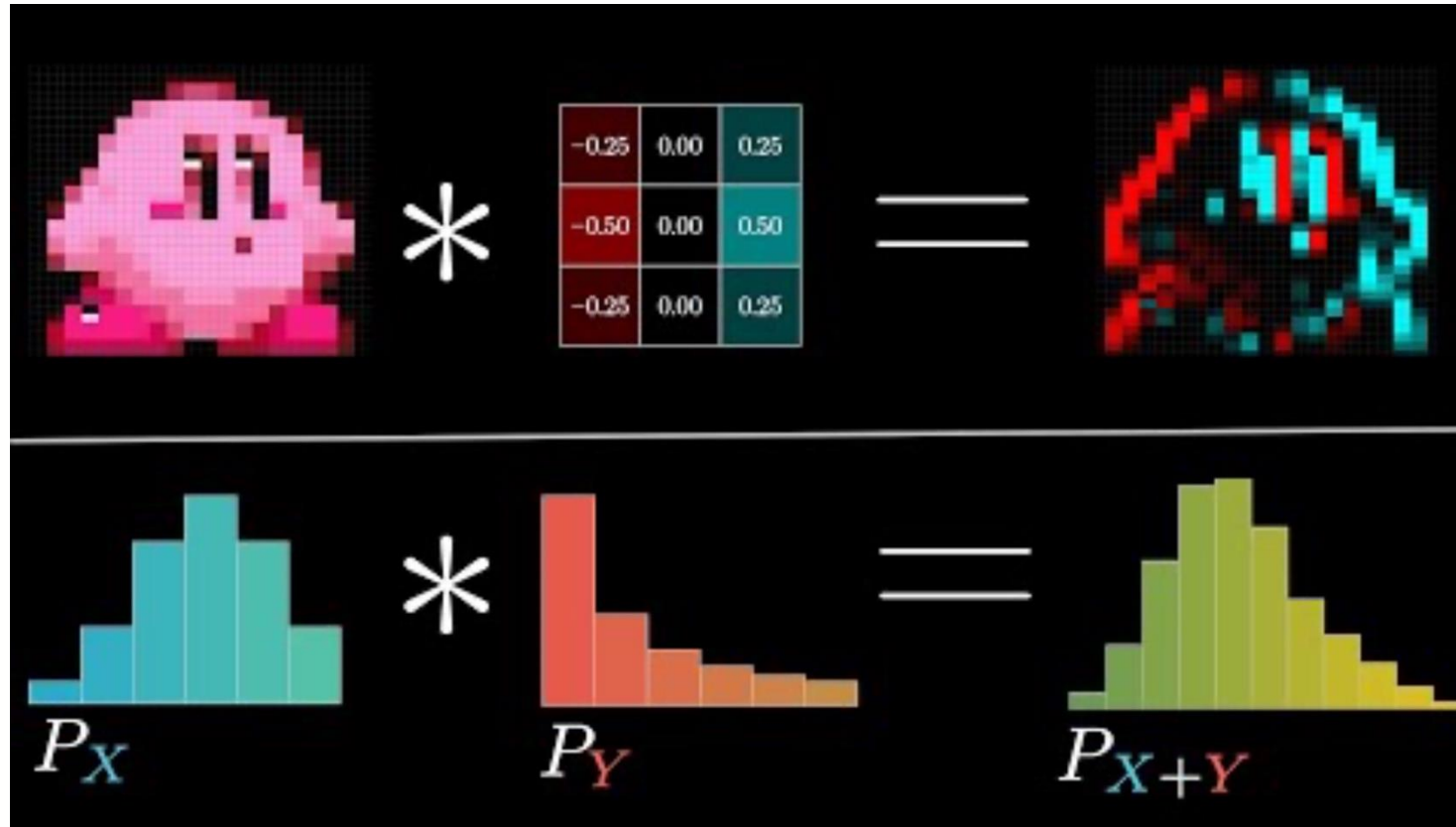
Visit #1 of 2: A Typical CNN Architecture



CONVOLUTIONAL FILTERS

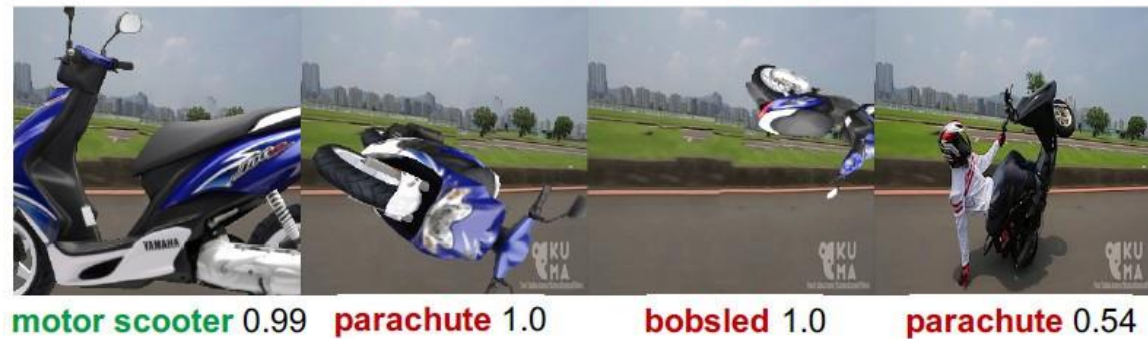
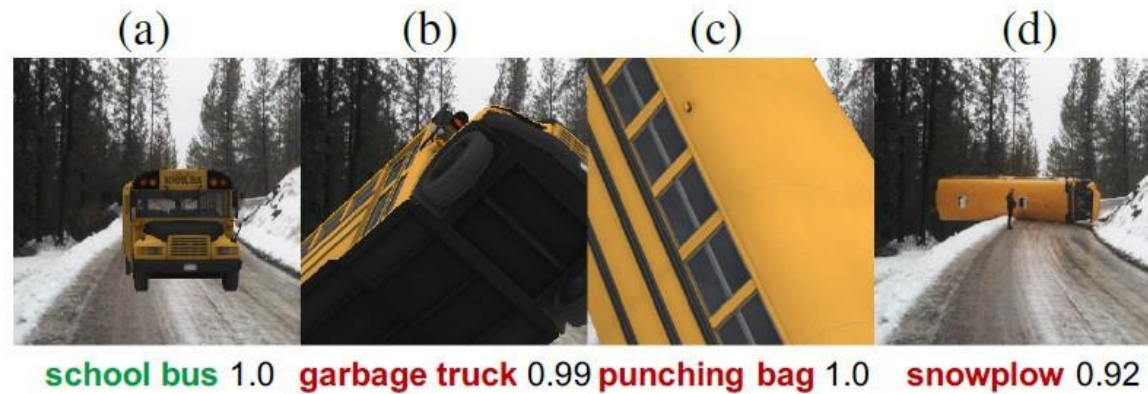
Learning goal #2: Describe a convolutional filter. Build a filter that can find particular shapes.

What are convolutions?



This video is available at <https://youtu.be/KuXjwB4LzSA?si=1iErbpMDAatXooCy&t=510>

Translational and Rotational Invariance



Translational and Rotational Invariance

Google sheet implementation of a simple convolution [here](#).

Sample Image #1

0	0	5	5	5	0	0
0	0	5	5	5	0	0
0	0	5	5	5	0	0
0	0	5	5	5	0	0
0	0	5	5	5	0	0
0	0	5	5	5	0	0
0	0	5	5	5	0	0

output #1

15	15	0	-15	-15
15	15	0	-15	-15
15	15	0	-15	-15
15	15	0	-15	-15
15	15	0	-15	-15

Filter

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

Activity (10 minutes)

Translational and Rotational Invariance

Instructions:

1. Make a copy of the google sheet. Change the image and filters to test your ideas.
<https://tinyurl.com/manualCNN>
2. Talk in groups!

Prepare an answer for these two questions

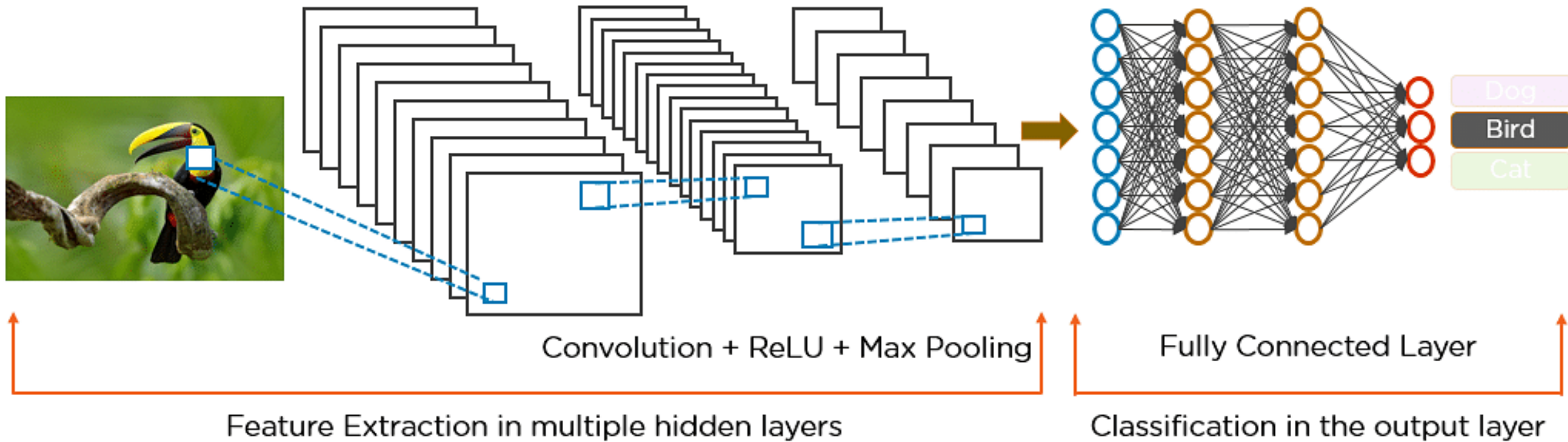
- Do CNNs have translational invariance? Can you move an image to the right or left and still have it be recognized?
- Do CNNs have rotational invariance? Can you turn an image 90 degrees and still have it be recognized?



How do the convolutional filters in CNNs differ from these toy examples?

1. They are data-driven (and less intuitive). They start from random numbers!
2. In sequence, they can find increasingly complex patterns
3. Most of the training time of a CNN is teaching it how to find edges (this is why transfer learning works!)

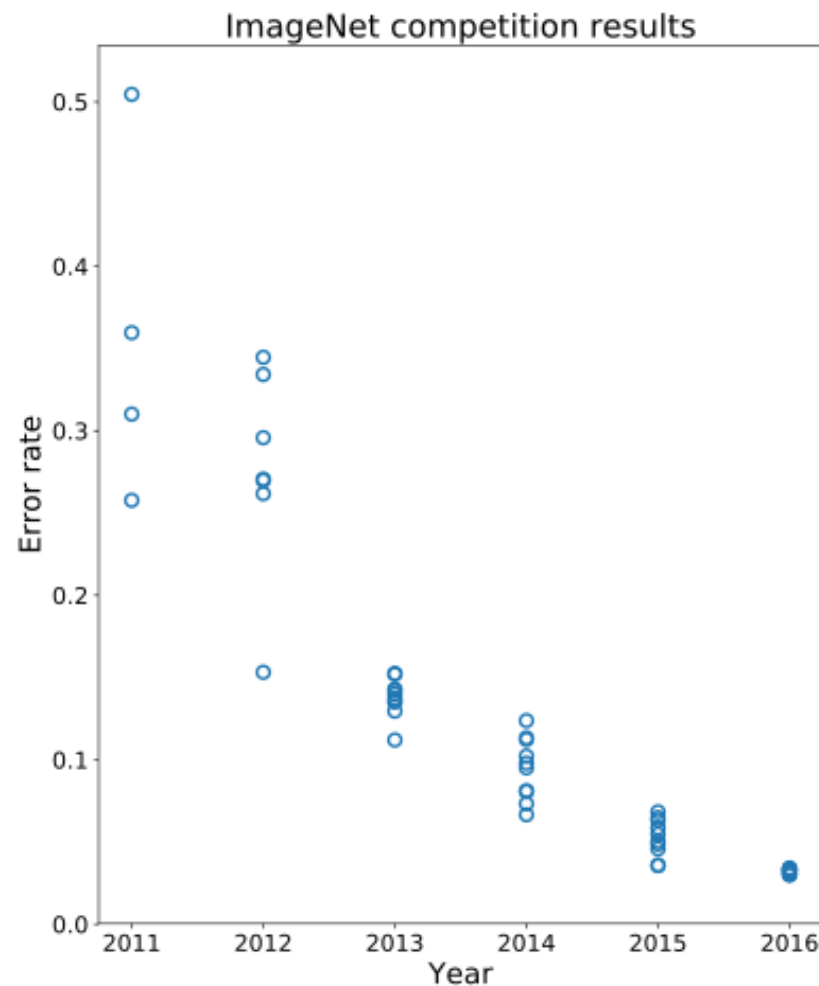
Visit #1 of 2: A Typical CNN Architecture



CNNs changed the game of image recognition



IN CS, IT CAN BE HARD TO EXPLAIN
THE DIFFERENCE BETWEEN THE EASY
AND THE VIRTUALLY IMPOSSIBLE.



CNNS IN KERAS/TENSORFLOW

Learning goal #3: Run a CNN classifier in keras.

Activity (30-45 minutes)

Classify Galaxy Mergers with CNNs

Instructions:

1. Download the notebook at <https://archive.stsci.edu/hello-universe/deepmerge>
2. Change `lr = 0.002` to `learning_rate = 0.002`
3. In teams of 2 or 3, talk and work together through the example tutorial

Did you finish early? Learn more by trying one of these:

1. Learn more about CNN classifiers by working through the extension exercises at the bottom of the notebook
2. Learn more about science platforms at <https://timeseries.science.stsci.edu/> (this notebook is available in “all Jupyter tutorial notebooks”)
3. Learn more about CNN regression by repurposing this notebook with a toy data set to do *regression* rather than classification. (*hint: make images of blurry circles, and ask the CNN to estimate what size the circle is*)

Feeling lost?
Here are two
tutorials!



INTERPRETING CNNs

Learning goal #4: Develop techniques for interpreting CNNs and understanding what pixels are most informative in the model's decision-making

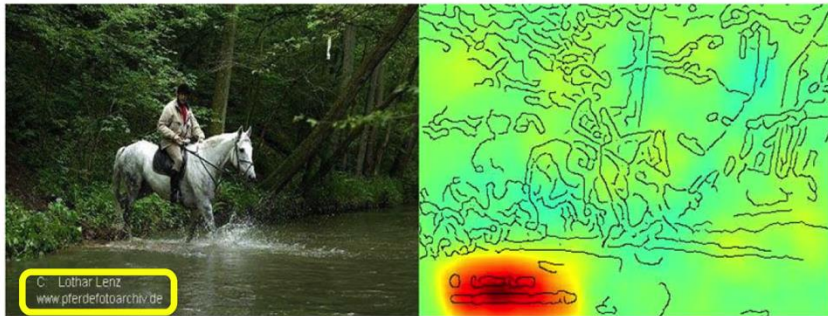


How can you tell that this is a horse? How can ML tell that this is a horse?



© Horse Photographer

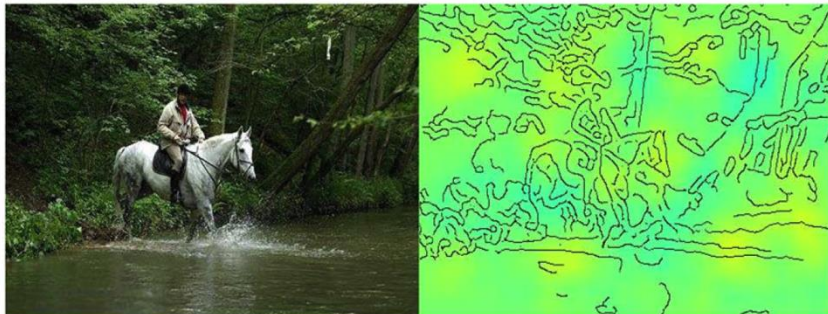
Horse-picture from Pascal VOC data set



Source tag
present



Classified
as horse

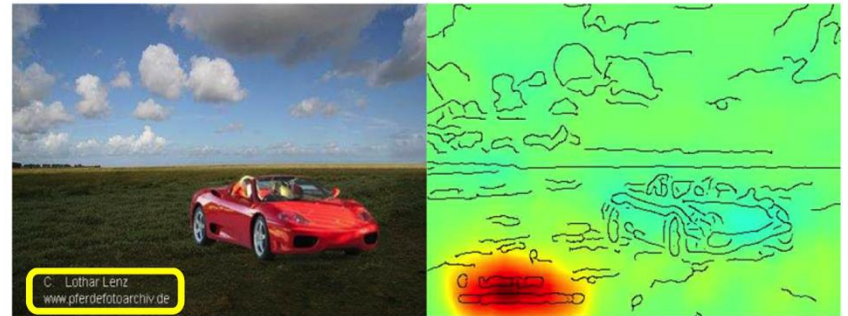


No source
tag present

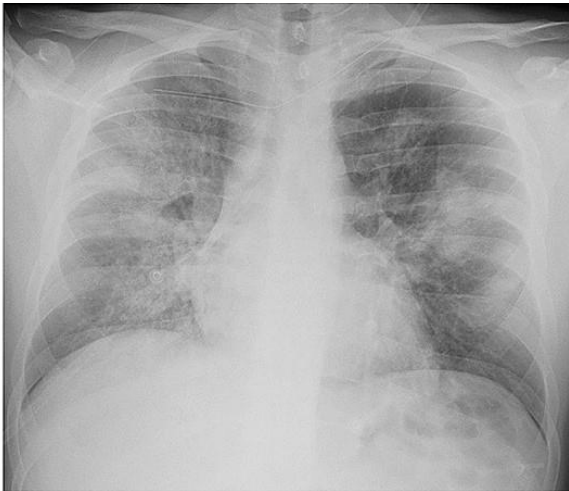


Not classified
as horse

Artificial picture of a car

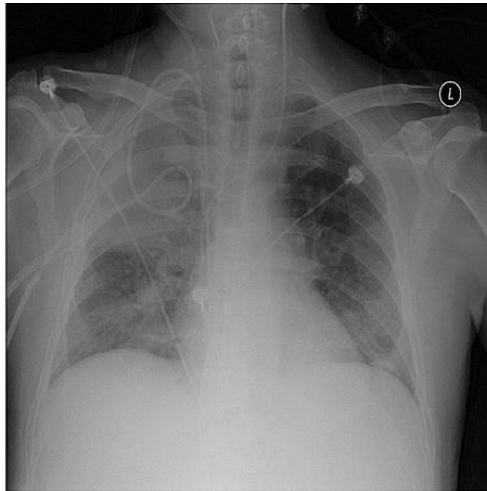


(A)



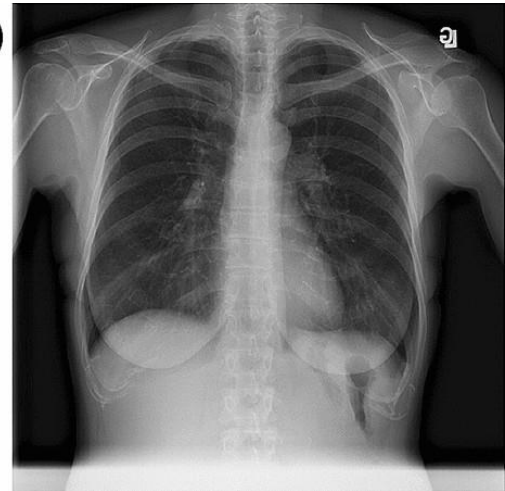
Covid

(B)



Pneumonia

(C)



Healthy

Hundreds of AI tools have been built to catch covid. None of them helped.

Some have been used in hospitals, despite not being properly tested. But the pandemic could help make medical AI better.

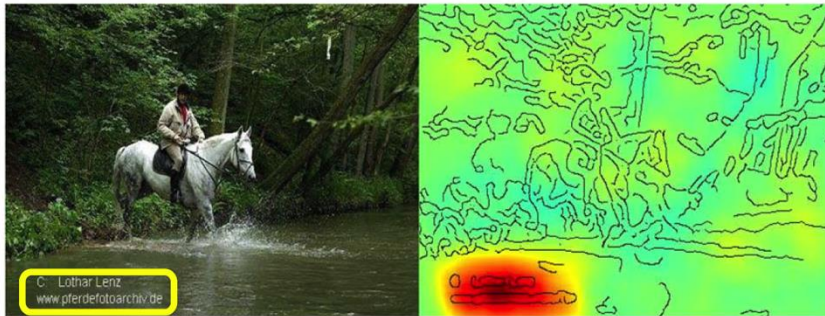
By Will Douglas Heaven

July 30, 2021



Saliency Maps

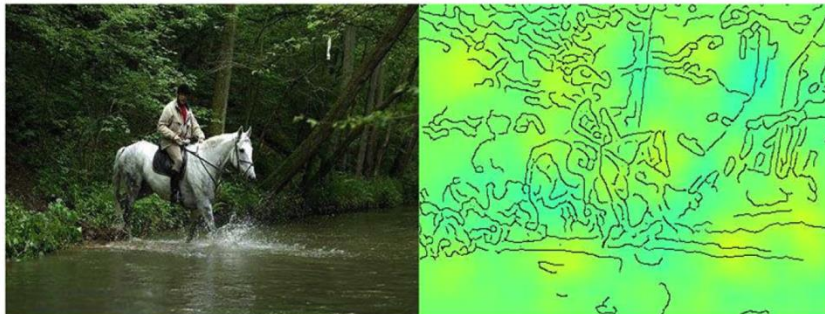
Horse-picture from Pascal VOC data set



Source tag
present



Classified
as horse



No source
tag present



Not classified
as horse

Artificial picture of a car



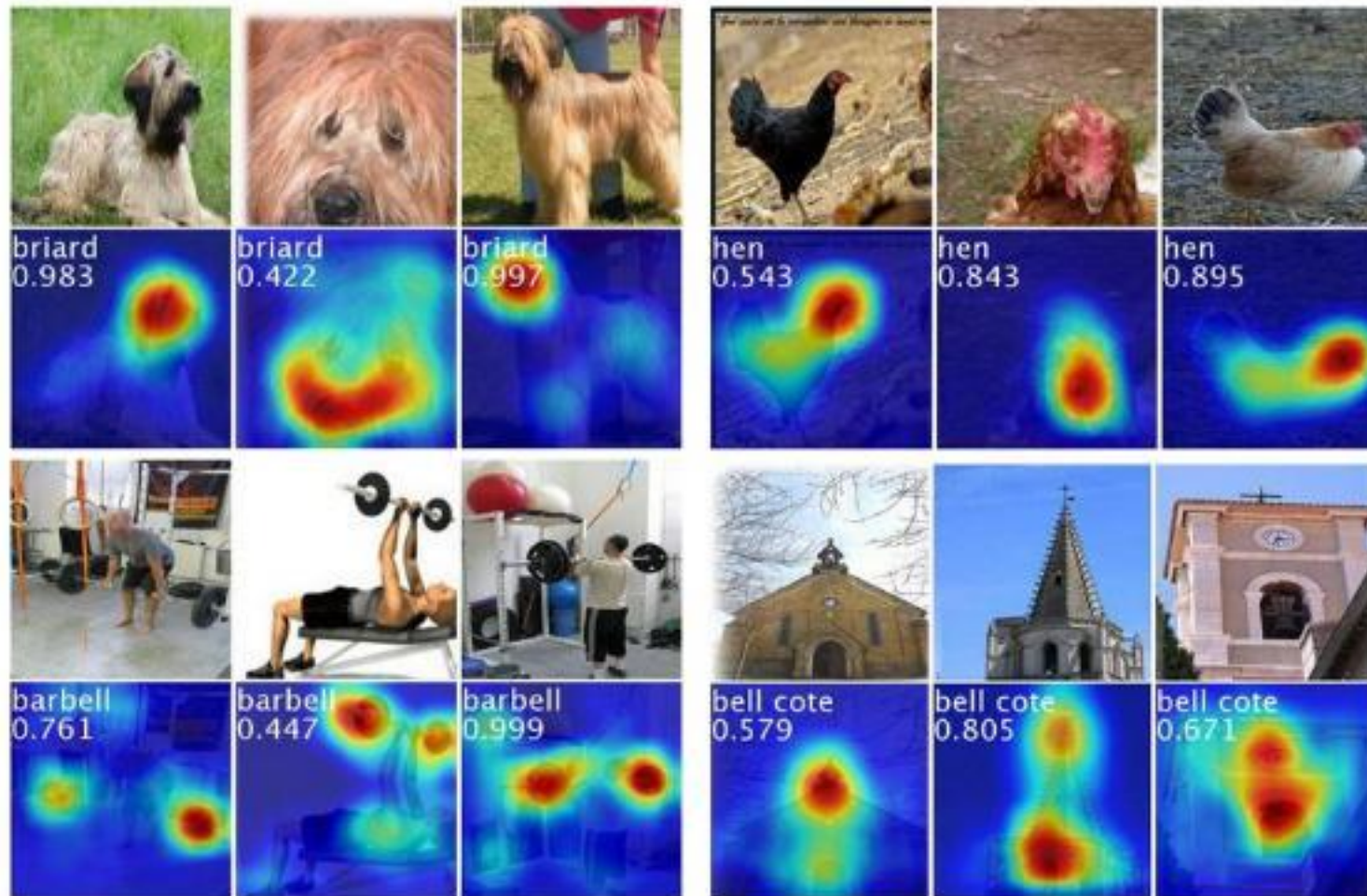
Saliency Maps

$$S = \frac{\delta y}{\delta x}$$

where

- y is the model output
- x is the pixel of interest

Saliency Maps

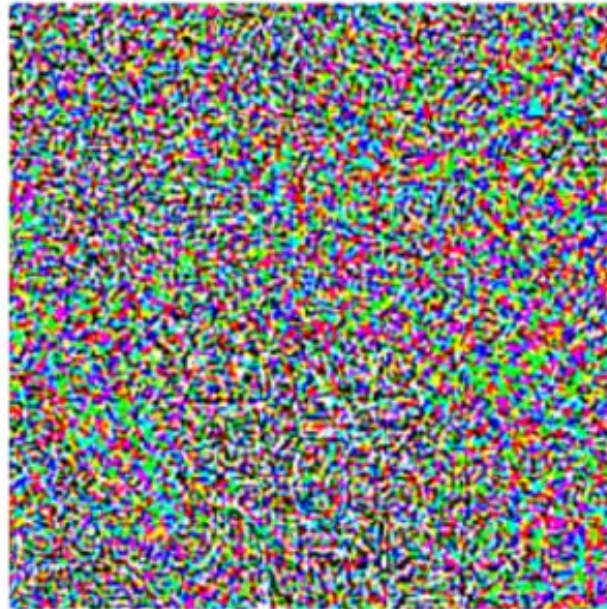


Adversarial Attacks

Panda 57.7%



+ .007 ×



=

Gibbon 99.3%

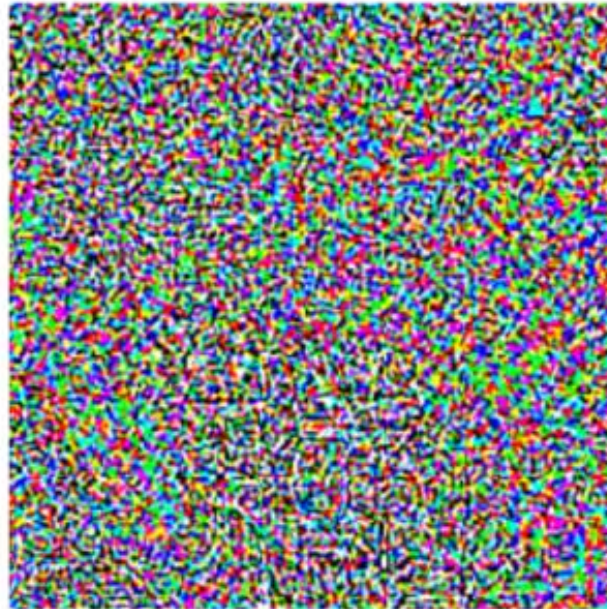


Adversarial Attacks

Panda 57.7%



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=

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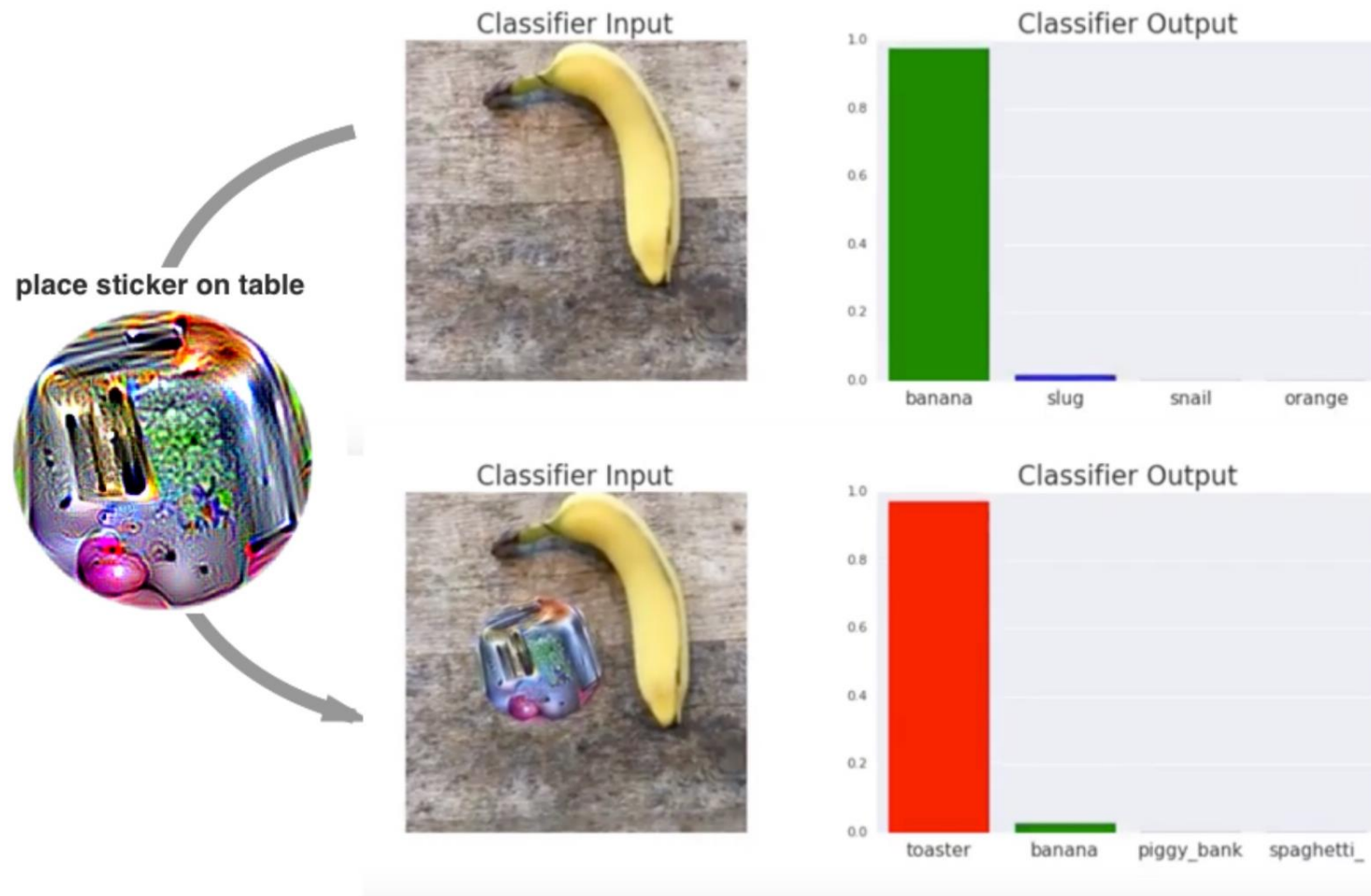


Figure 1: A real-world attack on VGG16, using a physical patch generated by the white-box ensemble method described in Section 3. When a photo of a tabletop with a banana and a notebook (top photograph) is passed through VGG16, the network reports class 'banana' with 97% confidence (top plot). If we physically place a sticker targeted to the class "toaster" on the table (bottom photograph), the photograph is classified as a toaster with 99% confidence (bottom plot). See the following video for a full demonstration: <https://youtu.be/i1sp4X57TL4>

Activity (45 minutes)

Classify Galaxy Mergers with CNNs

Feeling lost?
Start here!



Instructions:

1. Download the notebook at <https://archive.stsci.edu/hello-universe/interpretability>
2. Change from `keras.models import Model` to `from tensorflow.keras.models import Model`
3. In teams of 2 or 3, talk and work together through the tutorial

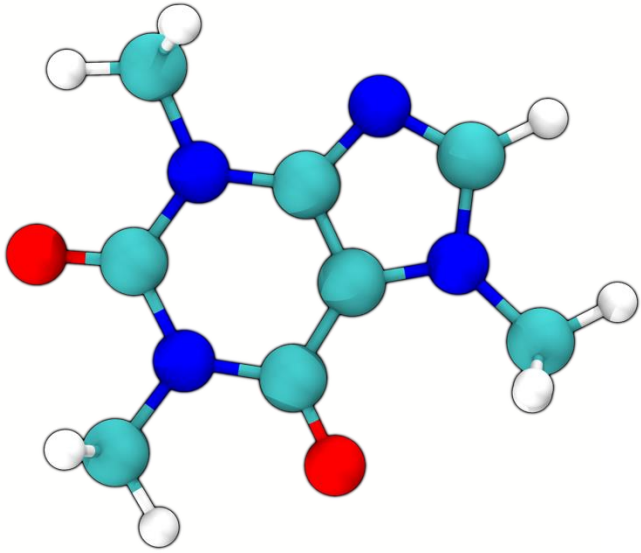
Did you finish early? Learn more by trying one of these:

1. Learn more about adversarial patches ([arxiv 1712.09665](#))
2. Repurpose this notebook with a toy data set to do *regression* rather than classification. (*hint: make images of blurry circles, and ask the CNN to estimate what size the circle is, then look for where it finds the information. Try offsetting the blurry circles from the center of your image.*)

GRAPH NEURAL NETWORKS

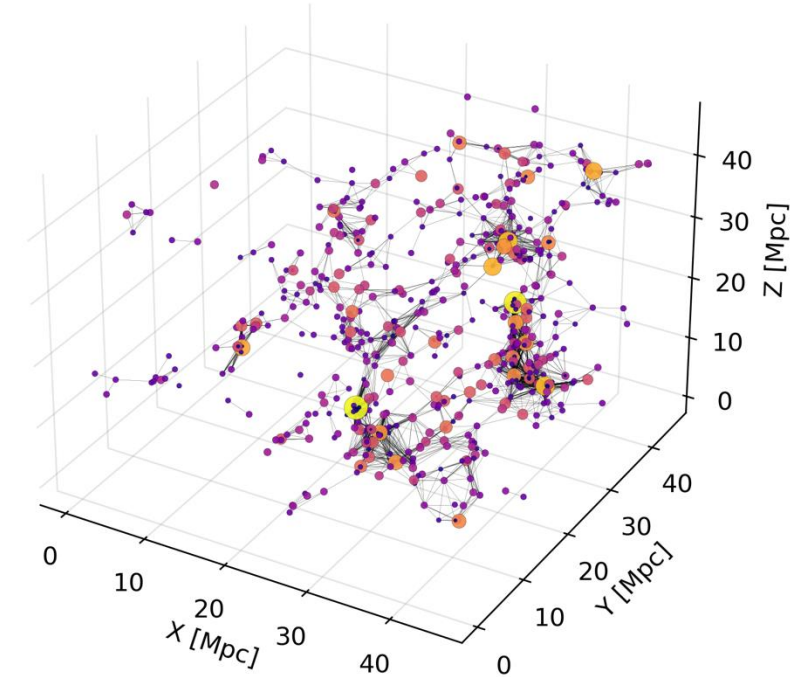
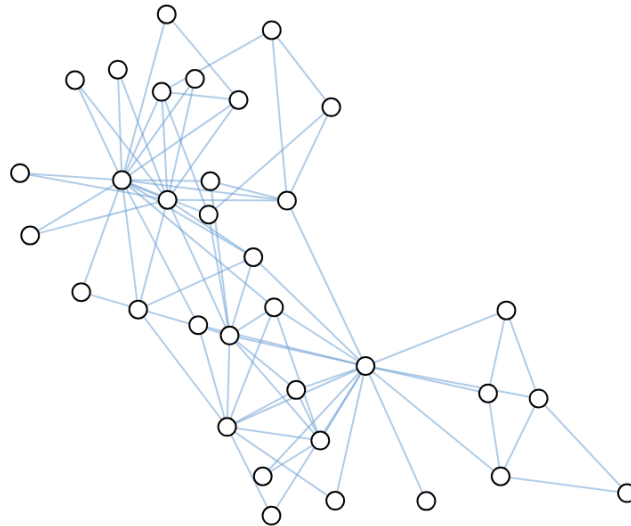
Learning goal #5: Describe a graph. Describe pooling. List the types of problems that a GNN is well-suited for.

GNNs are good for Heterogeneously Structured Data



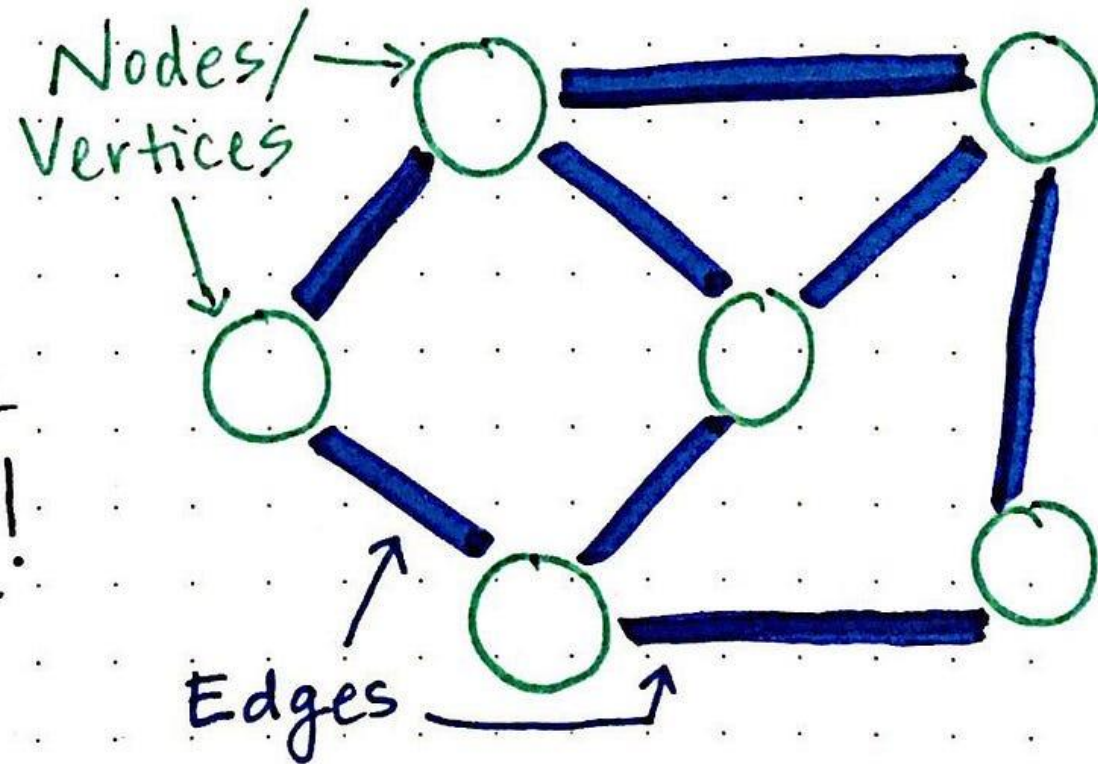
Graphs → are → all → around → us

	Graphs	are	all	around	us
Graphs					
are					
all					
around					
us					



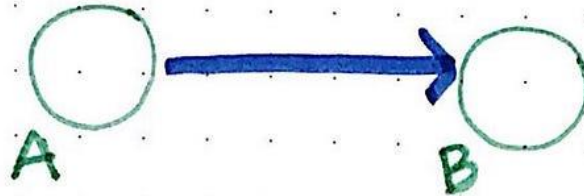
What is a graph?

Edges can
connect nodes
in any possible
way! No rules!

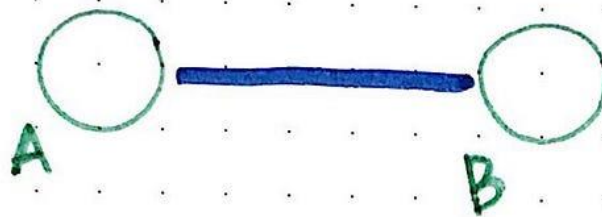


What is a graph?

Different types of edges in graphs

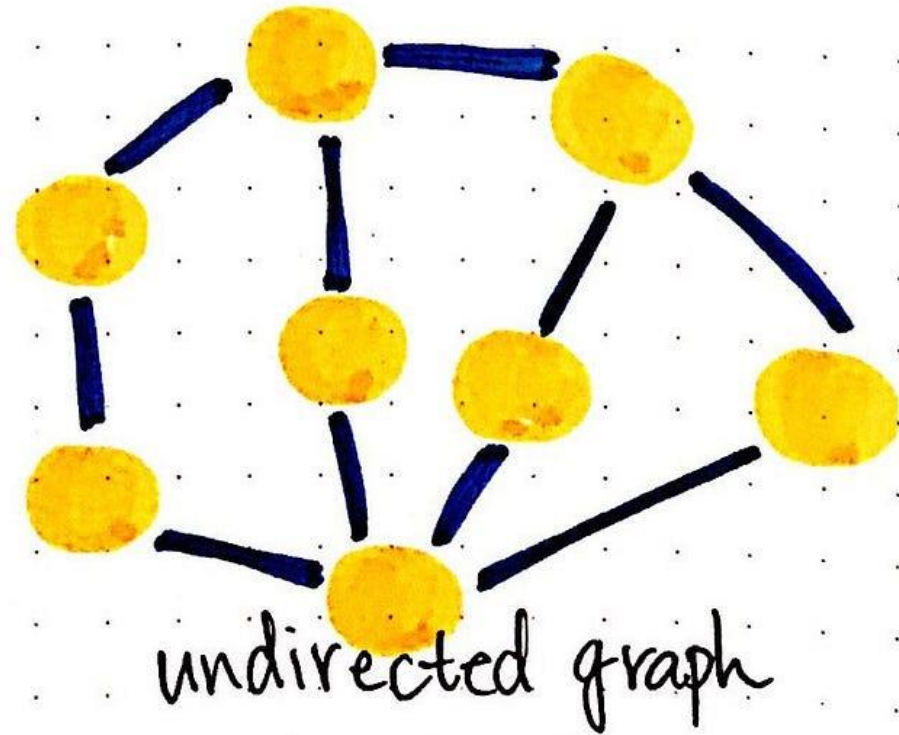
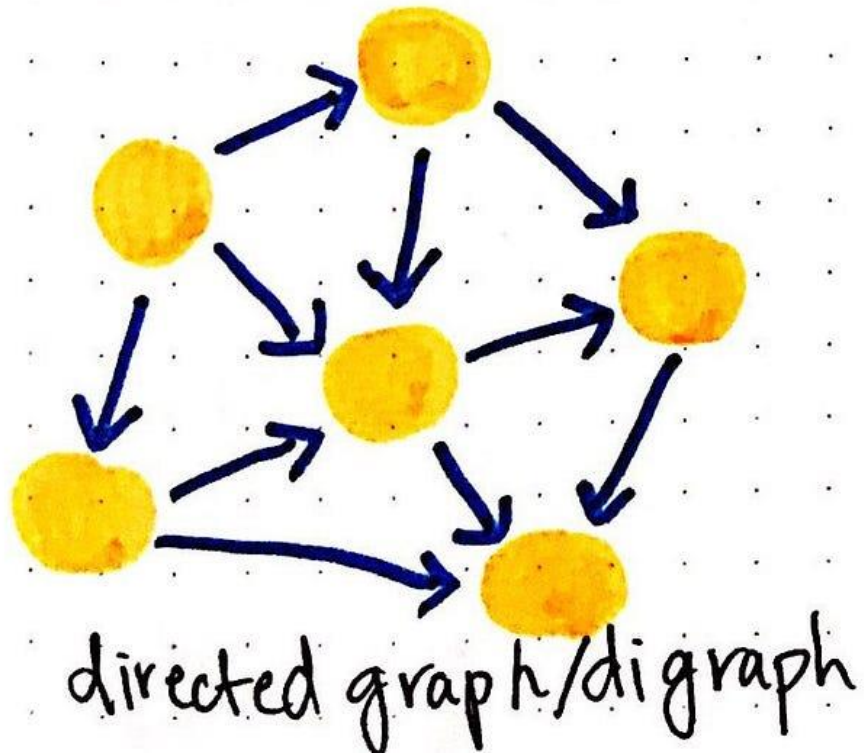


directed edge: There is only a path from A, the origin, to B, the destination



undirected edge: the path between A and B is bidirectional, meaning origin & destination are not fixed.

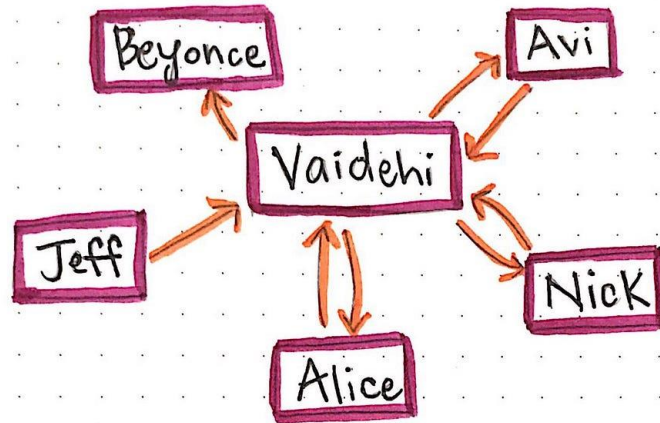
What is a graph?



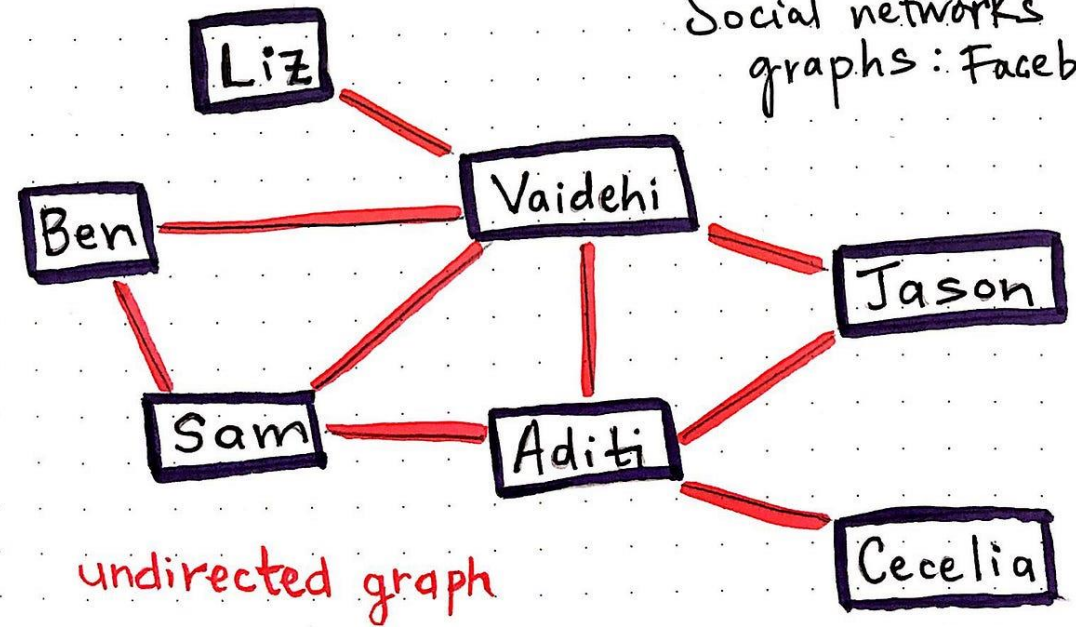
What is a graph?

directed graph

Social networks as
graphs: Twitter



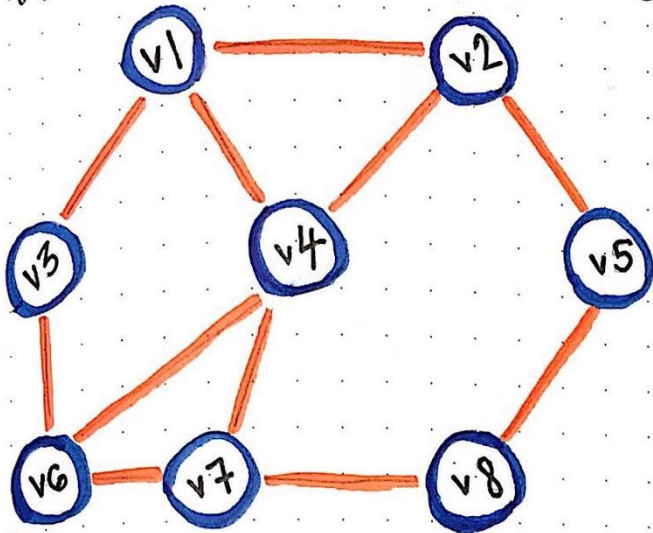
Social networks as
graphs: Facebook



undirected graph

What is a graph?

(Formally) Defining a Graph



8 vertices/nodes

11 edges/links

$$G = (V, E)$$

$$V = \{v1, v2, v3, v4, v5, v6, v7, v8\}$$

$$E = \left\{ \begin{aligned} &\{v1, v2\}, \\ &\{v1, v3\}, \\ &\{v1, v4\}, \\ &\{v2, v4\}, \\ &\{v2, v5\}, \\ &\{v3, v6\}, \\ &\{v4, v6\}, \\ &\{v4, v7\}, \\ &\{v5, v8\}, \\ &\{v6, v7\}, \\ &\{v7, v8\} \end{aligned} \right\}$$

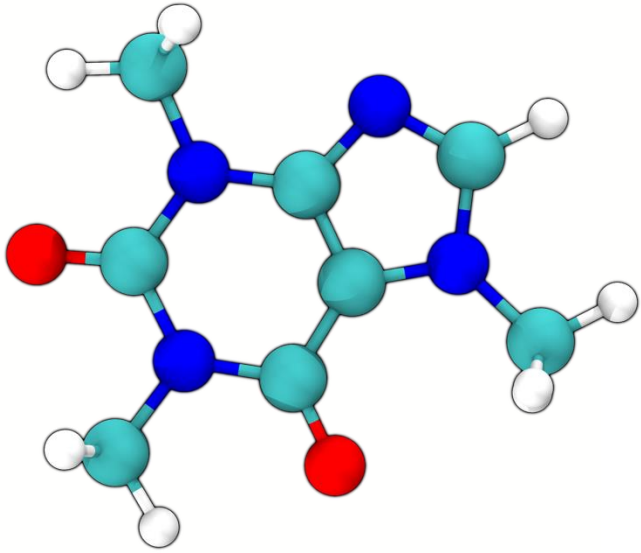
these edge definitions are unordered pairs!

→ $G = (V, E)$ is the formal mathematical notation for defining graphs.

→ A graph G is an ordered pair of a set V vertices and E , a set of edges.

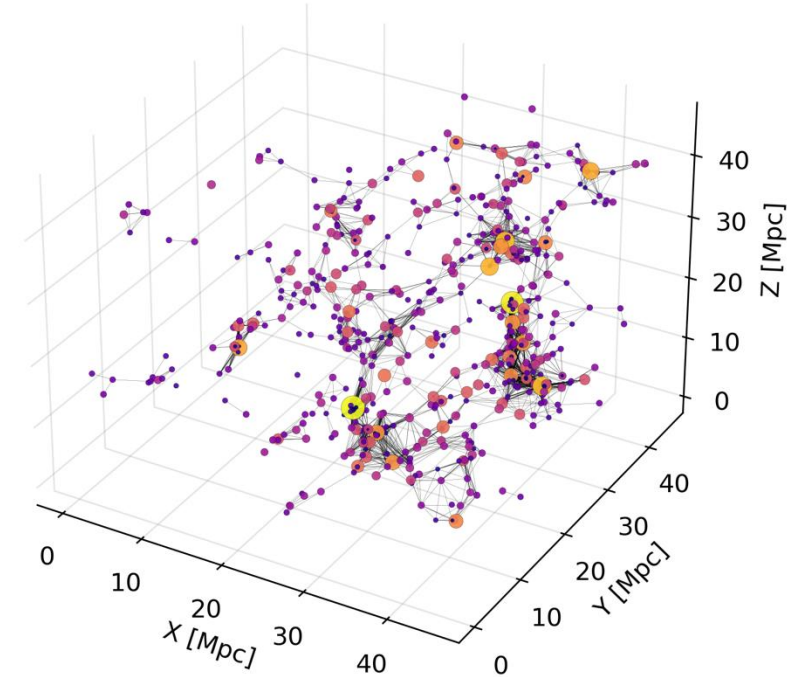
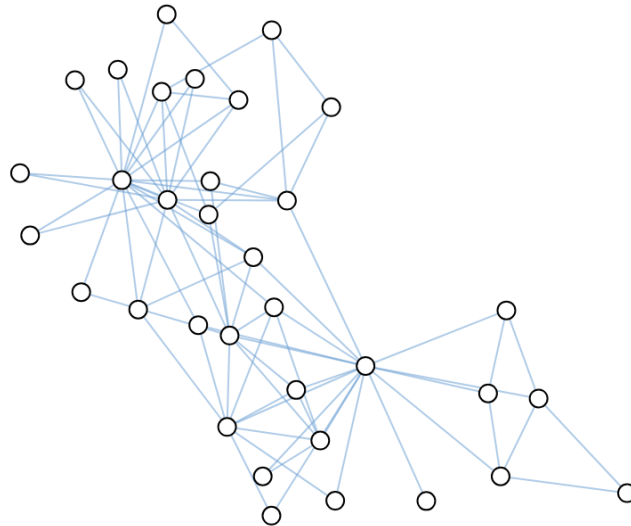
→ An ordered pair is a pair of mathematical objects in which the order of objects in the pair matters.

GNNs are good for Heterogeneously Structured Data



Graphs → are → all → around → us

	Graphs	are	all	around	us
Graphs	■				
are		■			
all			■		
around				■	
us					■



Activity (10 minutes)

Graphs and Networks

Build the authorship network for yourself or a collaborator!

1. Learn more at <https://ui.adsabs.harvard.edu/help/actions/visualize>
2. Build yours at ui.ads.harvard.edu

ads

Feedback ORCID About Sign Up Log In

QUICK FIELD: Author First Author Abstract All Search Terms

Start New Search

author:"ntampaka"

Your search returned 50 results

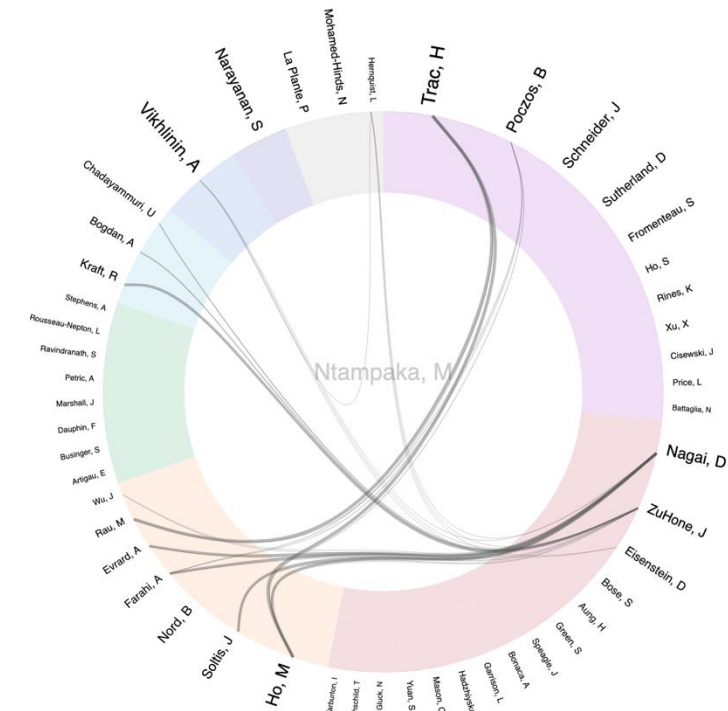
Collection astronomy Collection physics

Authors: Ntampaka, M (50), Nagai, D (11), Trac, H (11), Poczos, B (8), Ho, M (7)

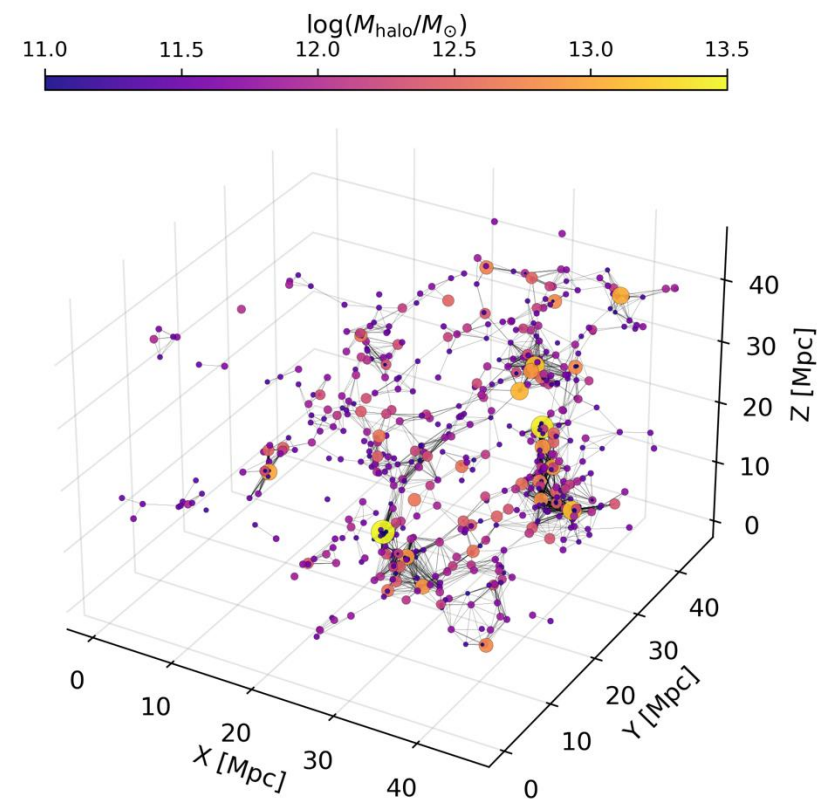
2024eas..conf.2315W 2024/07
Cosmological Dependence of Cluster Evolution with AbacusSummit
Warburton, Iver; Gluck, Naomi; Nagai, Daisuke and 3 more

2024eas..conf..446C 2024/07
Incorporating baryon physics into cosmological inference with neural-network-based baryon painting (Remote)
Chadayammuri, Urmila; Ntampaka, Michelle; Bogdan, Akos and 1 more

Visualizations
Citation Metrics
Author Network
Paper Network
Concept Cloud
Results Graph

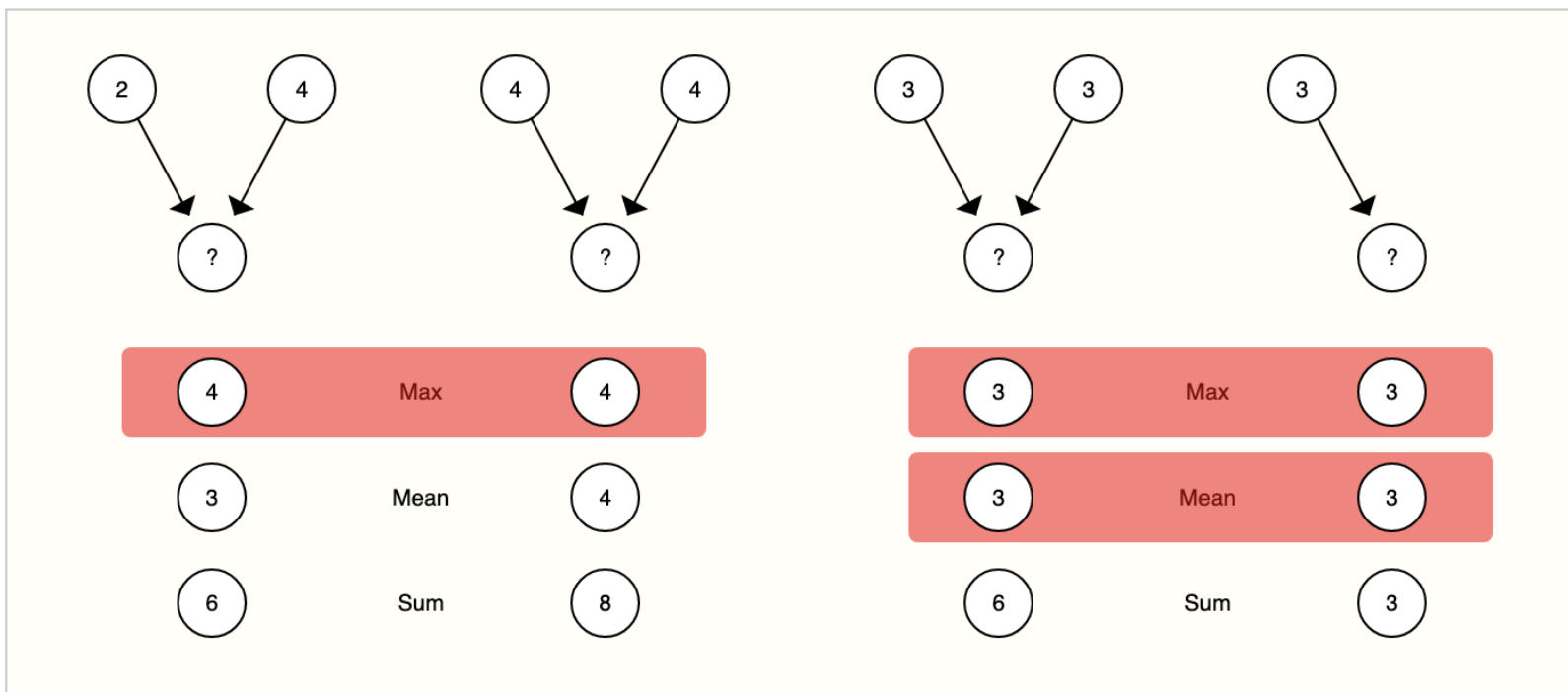


- In a graph-level task, we predict a single property for a whole graph.
- For a node-level task, we predict some property for each node in a graph.
- For an edge-level task, we want to predict the property or presence of edges in a graph.



Pooling

The building block of GNNs is *pooling*: nearby graph attributes are combined and summarized.



No pooling type can always distinguish between graph pairs such as max pooling on the left and sum / mean pooling on the right.

GNNS IN PYTORCH

Learning goal #6: Run a GNN regressor in pytorch.

Activity (45 minutes)

More on GNNs

Feeling lost?
Start here!



Instructions: Estimate Stellar Mass with GNNs

1. Open the GNN notebook on colab at <https://tinyurl.com/john-wu-gnn>
2. In teams of 2 or 3, talk and work together through the example tutorial

Did you finish early?

1. Revisit some key ideas of NNs and CNNs (or learn about transformers and attention!) at the 3blue1brown youtube page:



CONCLUSION & REVIEW

Learning Goals:

- 0: Explain the benefits and pitfalls of feature engineering in machine vision.
- 1: Describe a convolutional neural network's architecture. List the problems that a CNN is well-suited for.
- 2: Describe a convolutional filter. Build a filter that can find particular shapes.
- 3: Run a CNN classifier in keras.
- 4: Develop techniques for interpreting CNNs and understanding what pixels are most informative in the model's decision-making
- 5: Describe a graph. Describe pooling. List the types of problems that a GNN is well-suited for.
- 6: Run a GNN regressor in pytorch.

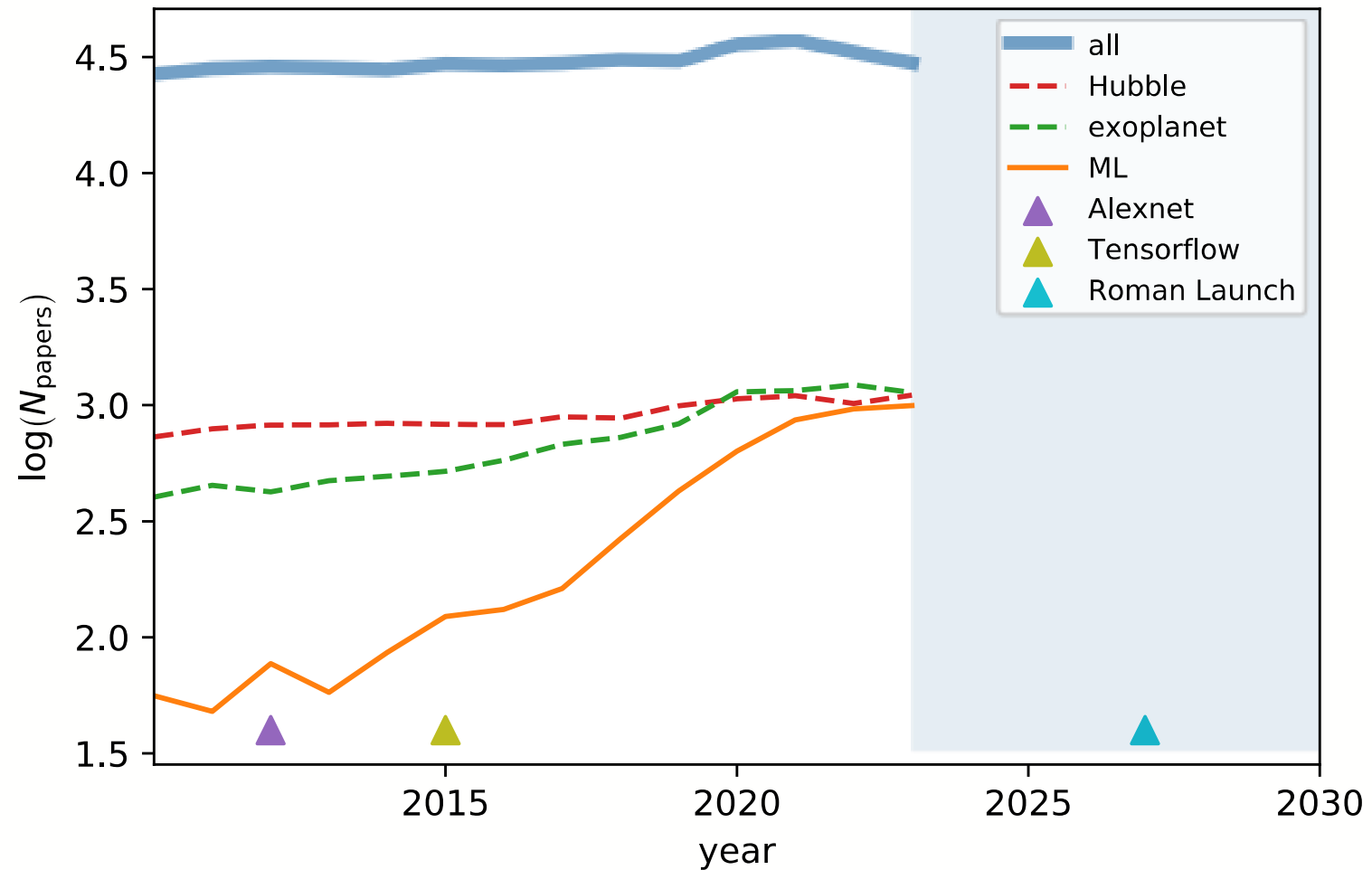
Astro2020 Decadal Report:

Machine learning has already shown significant success at providing tools for identifying anomalies in data, and can speed up parameter estimation in large data sets by significant factors... These techniques could lead to **transformative discoveries** from the new data sets available in the 2020s.

Astronomy a perfect sandbox for machine learning.

- Minimal privacy concerns.
- Culture of sharing data.
- Well-posed questions.
- Public interest and support.
- Data are non-monetizable.
- *This does not exempt us from ethical concerns!*

MLxAstro is Fast-Moving



Rewrite the plans for A3Net Summer School, in the style of "This is Just to Say," the William Carlos Williams poem about the plums and the icebox.



This is just to say

We have set up
the summer school
in Osaka
this fall

to teach you
the ways
of machines
and galaxies

Forgive us
it will be demanding
but rich
and full of light