Image Analysis Workshop: Session 1

Michelle Torres
UCLA

Mar 7, 2024

Welcome!

Welcome!

Thank you for being here

About me (your instructor)

I am a proud Mexican methodologist deeply interested in how people and organizations think, communicate and behave politically. I have a Ph.D. in Political Science, and a M.A. in Statistics from Washington University in St. Louis. My specialty is political methodology, mainly in the fields of computational methods and causal inference, which I apply to substantive questions regarding political communication, public opinion, social movements, and race and ethnicity.

My passions are my (very big) family (in particular my almost-3 year old son, Basti), dancing (no matter the style), food (nearly everything), and traveling. I am also a huge STL sports fan.

Getting to know you

What's your main learning goal/wish/(demand?!)
in this workshop?

GOALS

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6. Have fun! (Yes, yes, I know I am biased!)

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  - Read mathematical notation
- And Clear eyes ◉◉, big hearts ♡ and willingness to work hard

(Cautiously) Optimistic plan

(CAUTIOUSLY) OPTIMISTIC PLAN

Day 1

1. Pre-lunch
   - Motivation
   - Image basics
   - Image features

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1. Pre-lunch
    - Results from yesterday's lab
    - The Bag of Visual Words
    - Visual Structural Topic Model

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4. Lab
   - Run your own Visual STM
   - Wrap-up

Let’s start!

Arizona Daily Star

tucson.com

Saturday, May 30, 2020

$2 plus tax

PHOTOS BY JOHN MINCHILLO / THE ASSOCIATED PRESS

Demonstrators seethe with anger outside a precinct station in Minneapolis that was torched after police abandoned it. Protests over the death of a black man who died in police custody Monday flared up in the city for a fourth straight night Friday.

Cop who knelt on man's neck arrested, charged with murder

Assessing dire economic data, Trump lashes out at WHO, China

By Martin Crutsinger and Dan Sewell

THE ASSOCIATED PRESS

WASHINGTON — With new U.S. economic numbers highlighting the rough road ahead for a hoped-for rebound, President Trump on Friday took aim at the World Health Organization and China, blaming both for their roles in the pandemic's devastation.

Trump announced that the United States will end its support for WHO, charging it didn't respond adequately to the health crisis because of China's "total control" over the global organization. Trump said Chinese officials "ig-

welfare net was showing signs of fraying, as protests erupted for a second day in Spain against layoffs by French carmaker Renault and Italy's chief central banker warned that "uncertainty is rife."

While some U.S. states were moving ahead with steps to reopen businesses and leisure activities needed to spur spending and restore jobs, some were finding relaxed safety measures have been followed by upticks in new cases.

Arkansas over the past week has seen a steady rise in active coronavirus cases, following moves by Gov. Asa Hutchinson to re-

Nation+World: Transcripts released of Michael Flynn's calls with Russian diplomat. A10

THE SUN

AN EDITION OF THE REGISTER

Saturday, May 30, 2020 $2.00 FACEBOOK.COM/SBSUN TWITTER.COM/SBSUN **sbsun.com**

MINNEAPOLIS PROTESTS

EX-OFFICER FACES MURDER CHARGE

GLEN STUBBE — STAR TRIBUNE VIA AP

A member of the Minnesota National Guard stands watch in front of the Capitol in St. Paul on Friday. Minnesota Gov. Tim Walz announced that he asked the Minnesota National Guard to be responsible for the safety of the state Capitol.

EASING OF PANDEMIC ORDER

Hair salons, restaurants have state's OK to open

L.A. County given the go-ahead to allow patrons to dine on-site

By Ryan Carter
rcarter@scng.com
@ryinie on Twitter

Los Angeles County has the green light from the state to allow further easing of shelter-in-place restrictions forced by the coronavirus pandemic and is pushing forward with efforts to reopen a regional economy essentially shut down since March.

The state's approval came Friday after county officials said they've met the criteria to obtain a variance that allows it to move through Stage 2 of the phased-in process that eases restrictions in place since March 19, first on low-risk activities and then to high-risk.

With the state's approval, dine-in restaurants — long left with only curbside sales, takeout and delivery — can now begin allowing customers in with such rules as face masks, major cleaning and social distancing.

OPEN » PAGE 12

NORCO '80, PART 12

Baldy Notch shootout led to

The Gazette

gazette.com

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SATURDAY, MAY 30, 2020 **$2.00**

Protests erupt in U.S.

Officer charged with George Floyd's death as demonstrators nationwide march

PHOTOS BY THE ASSOCIATED PRESS

A protester yells at a member of the Minnesota National Guard on Friday in Minneapolis. Protests continued after the death of George Floyd, who died after being restrained by Minneapolis police officers on Memorial Day.

Akron Beacon Journal
BEACONJOURNAL.COM

Saturday, May 30, 2020 Informing. Engaging. Essential. | @beaconjournal | facebook.com/AkronBeaconJournal | $2

Minneapolis smolders

A protester carries a U.S. flag upside down, a sign of distress, next to a burning building Thursday night in Minneapolis. [JULIO CORTEZ/THE ASSOCIATED PRESS]

Local officials urging peaceful protests

DeWine, area leaders condemn killing of man in Minneapolis police custody

USA TODAY NETWORK Ohio

Gov. Mike DeWine on Friday called the death of George Floyd in the custody of Minneapolis police "horrific," but implored Ohio protesters to assemble peacefully a night after hundreds descended on the Statehouse in Columbus, shattering windows and vandalizing storefronts.

DeWine

"We must not fight violence with more violence. Peaceful protest and the exercise of First Amendment rights are an important part of our civic

Why images?

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- Images are (kind of) universal (e.g. compare them to spoken languages)
- Visuals are frames

USING IMAGES IN SOCIAL SCIENCES

Using images in social sciences

- Studying the effect of presenting information through images
  - Labels vs. Images to signal race/ethnicity (Abrajano, Elmendorf, & Quinn 2018)
  - Visual cues and political knowledge (Prior 2014)

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- Measurement
  - Election incidents in tweets (Wu and Mebane 2022)
  - Electoral fraud (Cantú2018)
  - Displays of emotion (Boussalis et al. 2021)
  - Gender-based ad targeting (Erfort 2023)
  - Rural electrification and service provision (Min 2015)

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  - Gender-based ad targeting (Erfort 2023)
  - Rural electrification and service provision (Min 2015)
- Use images as a vehicle for a complex treatment
  - Masculinity/femininity (Bauer & Carpinella 2018, Bernhard 2023)
  - Police militarization (Mummolo 2018)
  - Level of conflict on attitudes towards protesters (Torres 2022)

WHY COMPUTERS?

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- Computer vision: Teaching computers to see

Image as Data: Teaching the computer to see

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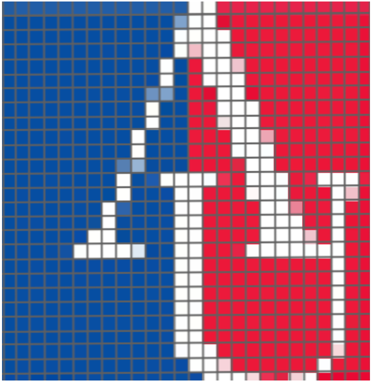
GETTING READY

- Course website, Github: smtorres/AU_Workshop
- Google Colab notebooks
  - Notebook 1: here
  - Notebook 2: here
  - Notebook 3: here
- Follow instructions here
- When doing your own projects:
  - Install Keras (here), with `tensorflow` backend
  - Install the following python libraries: numpy, scipy, cv2, matplotlib, PIL, sklearn ⇒ Look for tutorials for your machine
    - Check tutorials for OpenCV installation here
    - I suggest OpenCV 3.X and its compilation from source for full functionality

Image basics

- An image is a set of pixels:



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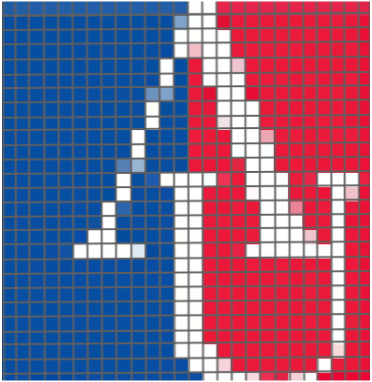

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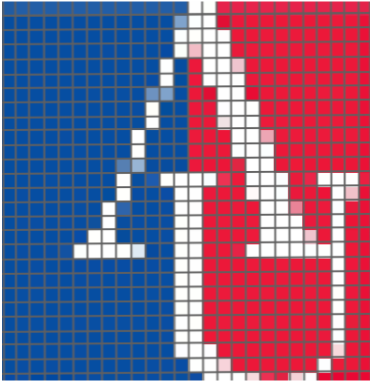

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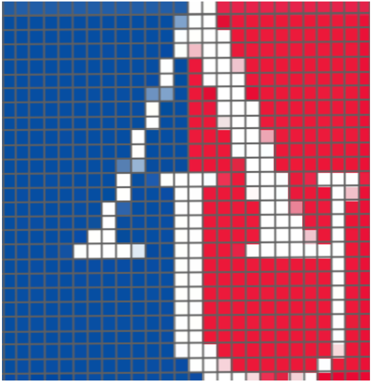

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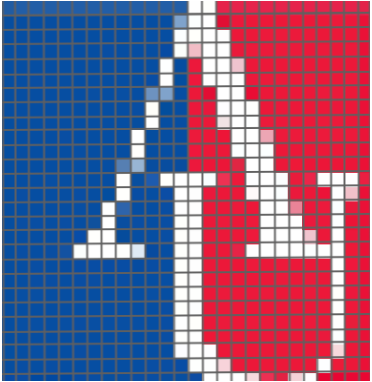

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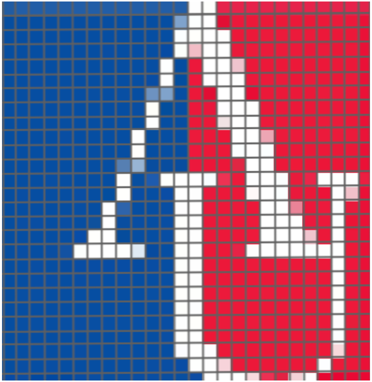

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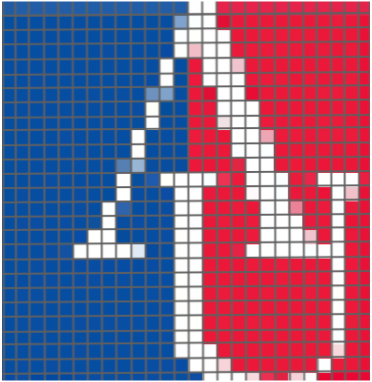

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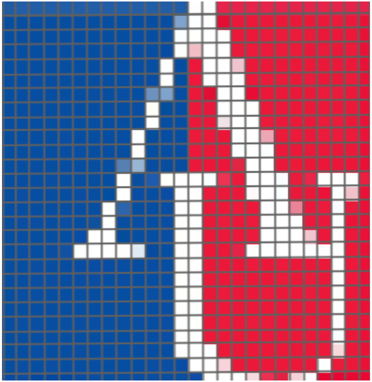

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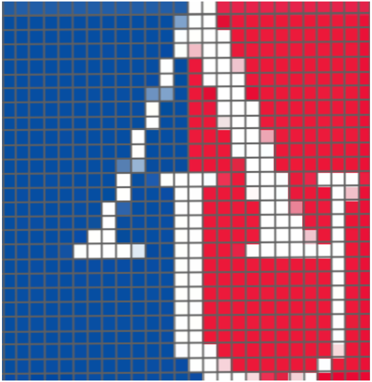

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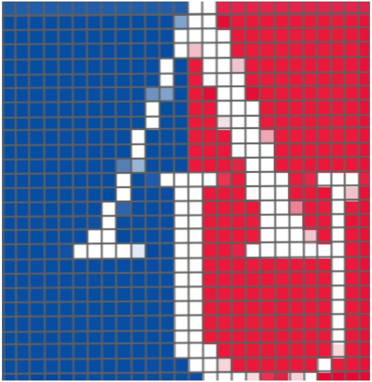
  - In `numpy` you specify the $y-$coordinates of an image first: `X2 = image[y0:y1, x0:x1]`



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  - Color
  - Texture
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  - Pixel intensity change
  - Edges, objects, etc.
- Feature vectors: A series of numbers used to numerically quantify the contents of an image (or regions of it) $\Rightarrow$ WE USE THEM TO CREATE TOKENS!

An example: Color statistics

Channel statistics

- Very intuitive and simple
- Basic statistics of each color channel
  1. Separate channels
  2. Compute moments for each channel

Histograms

- More information based on distribution
- 3D histogram of colors
  1. Convert image to
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COLOR STATISTICS, CONT.

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Color statistics, cont.

Channel	Mean	Median	Std. Dev
Red	135.4	136.5	77.2
Green	143	146	85.7
Blue	147	146	90.8

COLOR STATISTICS, CONT.

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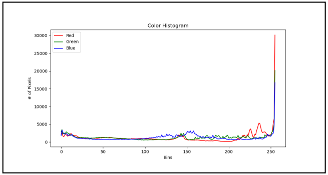
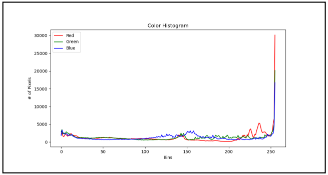
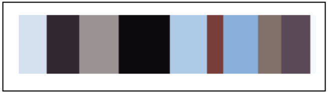


Color statistics, cont.

Channel	Mean	Median	Std. Dev
Red	135.4	136.5	77.2
Green	143	146	85.7
Blue	147	146	90.8





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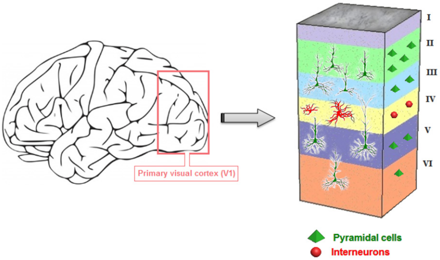
- In other more ambitious words:

How do we teach the computer to *see* like us?

Convolutional Neural Networks

SEEING LIKE A HUMAN



Credit: *Bachatene, Bharmauria and Molotchnikoff (2012).*

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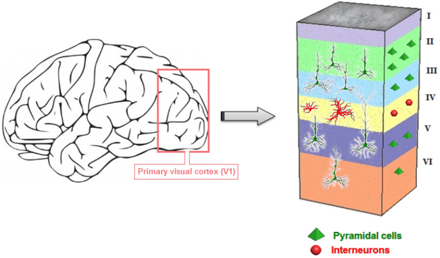

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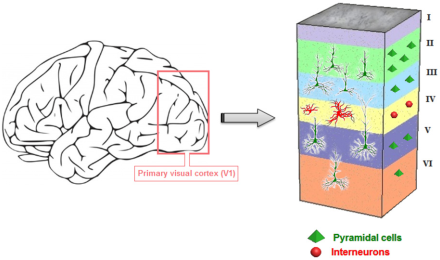

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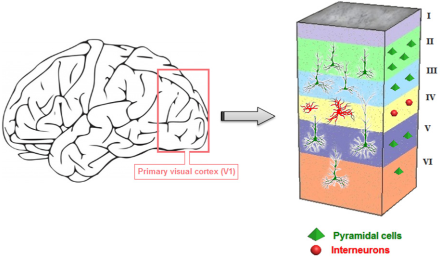

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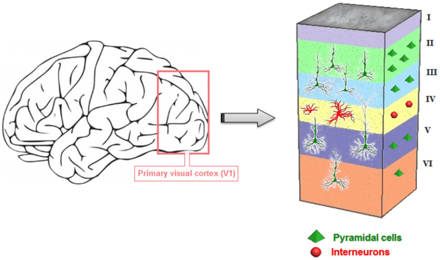

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- Every layer breaks down the signal into small pieces, allowing each of its neurons to focus on a unique piece of information.
- The first layers identify basic visual patterns, intermediate layers transform patterns into shapes, and the last layers convert shapes into objects.

Seeing like a human, cont.

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SEEING LIKE A HUMAN, CONT.

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- This is a TRAINING process (*)

SEEING LIKE A HUMAN, CONT.

- Modern computer vision systems are meant to emulate how human brains transform sensual stimuli into conceptual understanding
- The process allows computers to set their own set of **rules** to classify information based on TRAINING (*)

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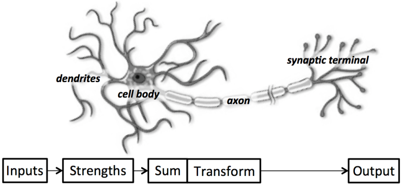

Credit: *Buduma (2017)*

- This process is called Convolutional Neural Network (or CNN)
- A set of “neurons” in charge of identifying unique bits of information...
- ...arranged in a network that allows for information sharing/processing...
- ... to eventually “tag” or “name” the input

Wait... what?

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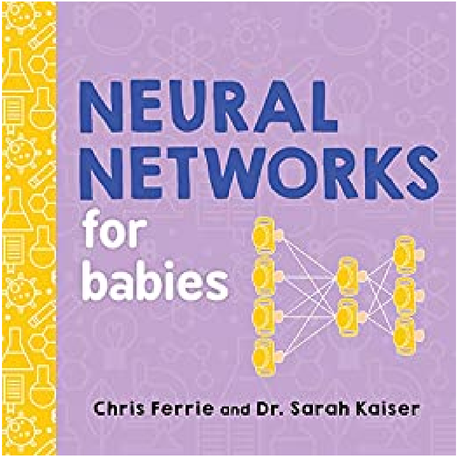

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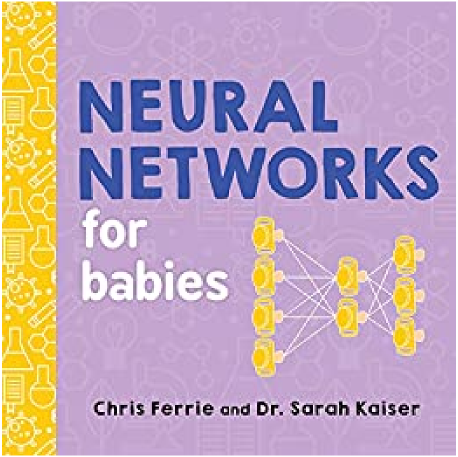
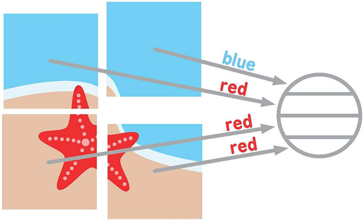


(No... I am not joking)

THE LOGIC OF CNNs

Is there a red animal in this picture?



The neuron can decide based on its input.

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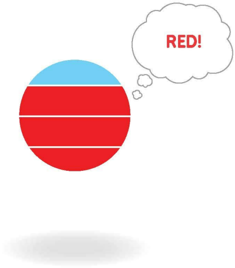
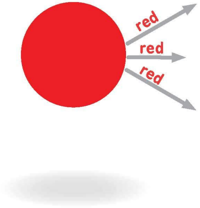


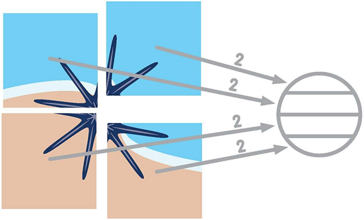
When the neuron has an answer,



it sends its own message.

The logic of CNNs

Does this animal have 8 arms?



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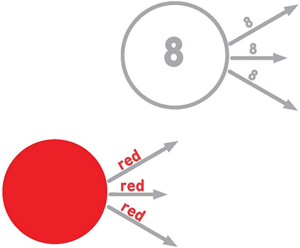
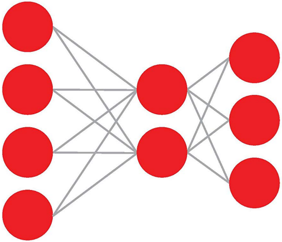


Where do the messages go?



Neurons talk to each other.
They connect together in a network.

Almost like finding Waldo…

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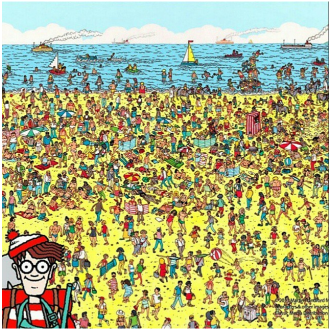
- Ok, not that cartoonish but almost!



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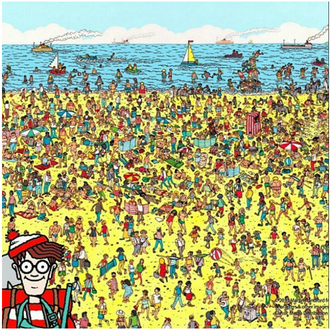

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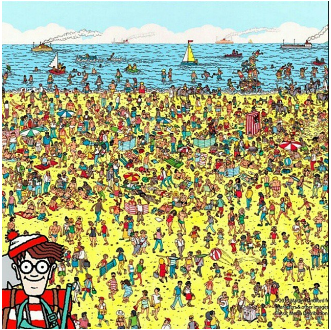

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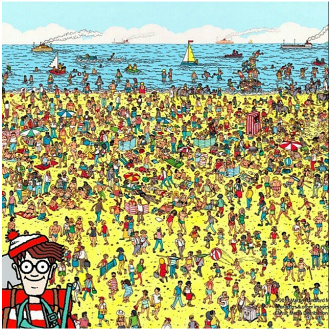

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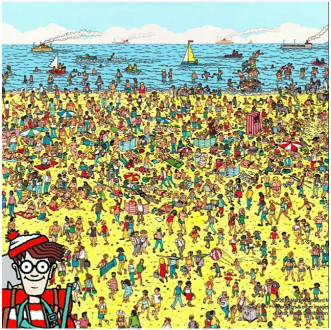

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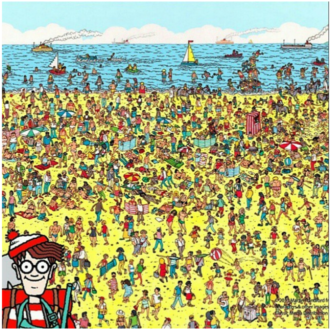

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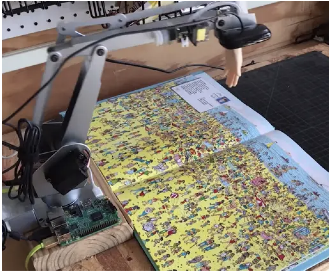
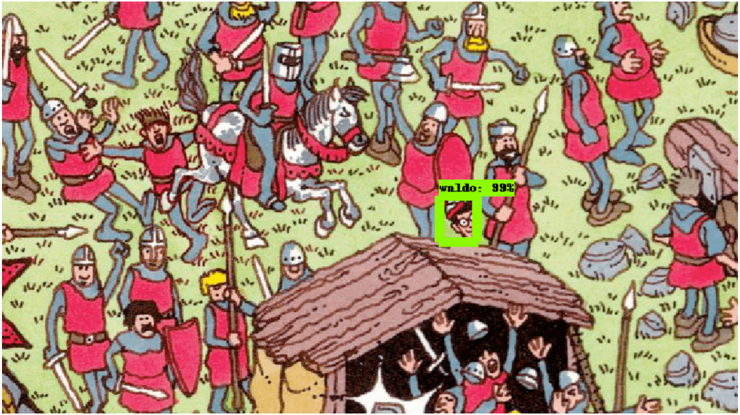
  - Glasses
  - Hat
- There is a robot who finds him in less than 5 seconds



For real

And it's based on CNN code (see here)



SPEED BUMP: A HEALTHY DOSE OF SKEPTICISM

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Speed bump: a healthy dose of skepticism

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- This has important implications for their usage and applicability

Back to business...

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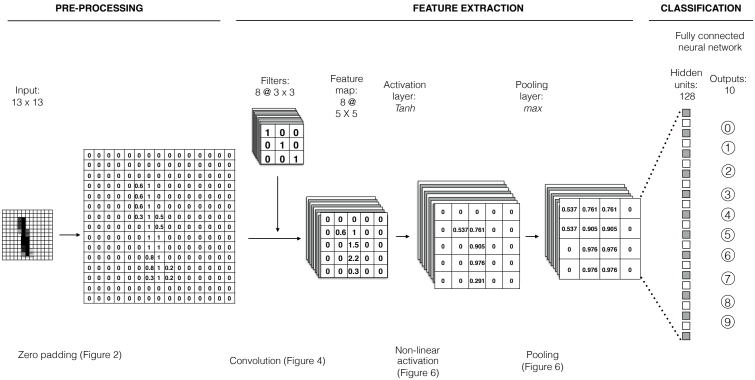
- CNNs are organized into multiple layers. Each layer contains multiple representations of the original image through maps of visual features such as edges, blobs or color combinations.
- The part of learning and reaching a semantic concept that humans conduct by trial and error is achieved through the training, validation and testing procedures in CNNs.

NETWORK STRUCTURE

- GOAL: learn the features associated w/ outcomes



NETWORK STRUCTURE

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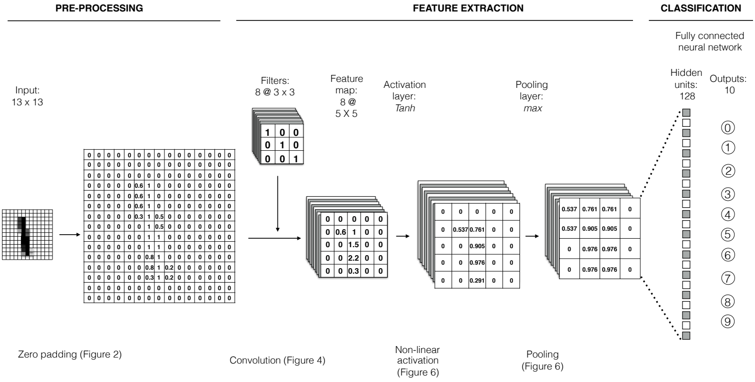

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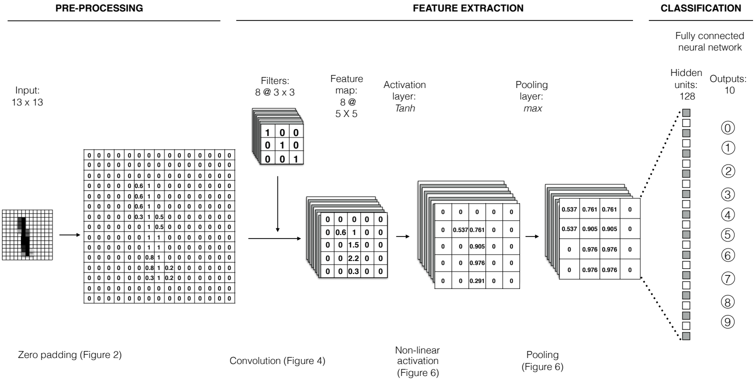

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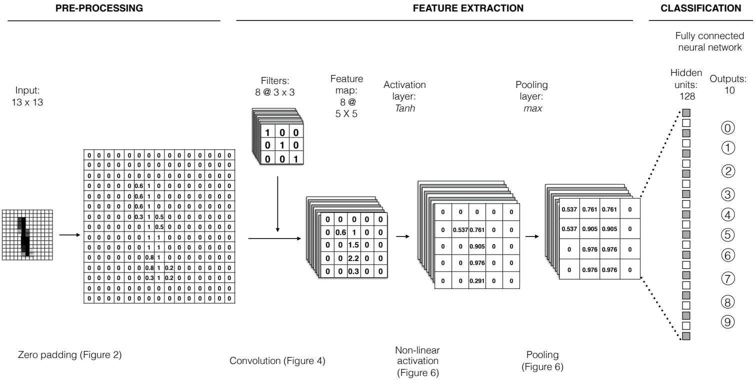
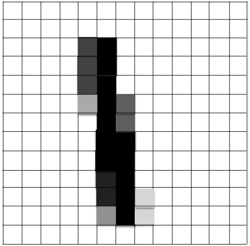
- Not a black-box! → Optimization of error



REPRESENTING IMAGES

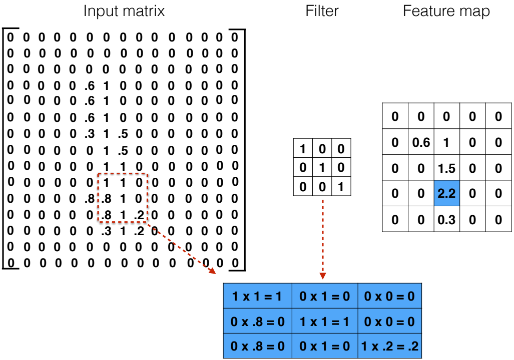


$$\begin{bmatrix}
0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&.6&1&0&0&0&0&0&0&0\\
0&0&0&0&.6&1&0&0&0&0&0&0&0\\
0&0&0&0&.6&1&0&0&0&0&0&0&0\\
0&0&0&0&.3&1&.5&0&0&0&0&0&0\\
0&0&0&0&0&1&.5&0&0&0&0&0&0\\
0&0&0&0&0&1&1&0&0&0&0&0&0\\
0&0&0&0&0&1&1&0&0&0&0&0&0\\
0&0&0&0&.8&.8&1&0&0&0&0&0&0\\
0&0&0&0&0&.8&1&.2&0&0&0&0&0\\
0&0&0&0&0&.3&1&.2&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0
\end{bmatrix}$$

The image is transformed into a numerical matrix, where each element represents the value of a specific pixel of the image measured as light intensity (in grayscale images) or color intensity (in color images).

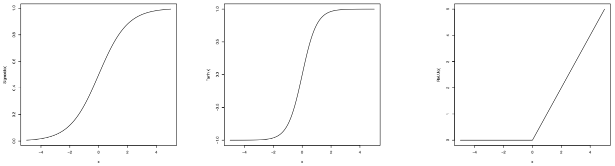
FEATURE EXTRACTION

It's all about feature extraction!



Filters are matrixes made of *weights*, that maximize or minimize the "intensity" of a pixel. Every filter slides through each 3 x 3 pixel area of the image, and computes the dot product of the region. The result is recorded on a smaller matrix to create *feature maps*. Intuitively, we want to detect whether and where a feature represented by a filter is prominent in the image.

ACTIVATION FUNCTIONS



(a) $Sigmoid(x) = \frac{1}{1+e^{-x}}$ (b) $Tanh(x) = \frac{2}{1+e^{-2x}}$ (c)$ReLU(x) = \begin{cases} 0 & \text{if } x < 0, \\ x & \text{otherwise.} \end{cases}$

We add non-linearity by including an *activation layer*.

POOLING STAGE

Non-linear activation:
Tanh(x)

0	0	0	0	0
0	0.6	1	0	0
0	0	1.5	0	0
0	0	2.2	0	0
0	0	0.3	0	0

0	0	0	0	0
0	0.537	0.761	0	0
0	0	0.905	0	0
0	0	0.976	0	0
0	0	0.291	0	0

max pooling

0.537	0.761	0.761	0
0.537	0.905	0.905	0
0	0.976	0.976	0
0	0.976	0.976	0

Once the activation map shows non-linear outputs, we reduce its dimensionality using a *pooling layer*. A pooling layer shrinks the size of the matrix while keeping the most important information in the feature map.

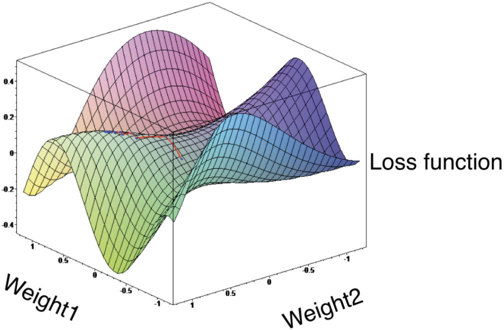
Learning

- The last stage of the network involves the classification of the image. The way in which the CNN learns the features that correlate to each outcome follows a procedure called back-propagation.

More on back-propagation

ACTUALLY, THIS SHOULD BE FAMILIAR...

Loss function



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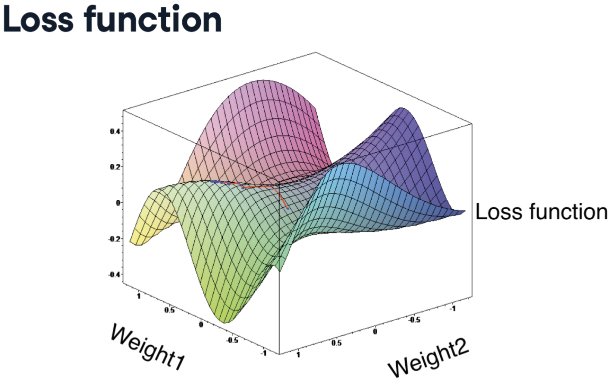

- Minimize multidimensional loss function →

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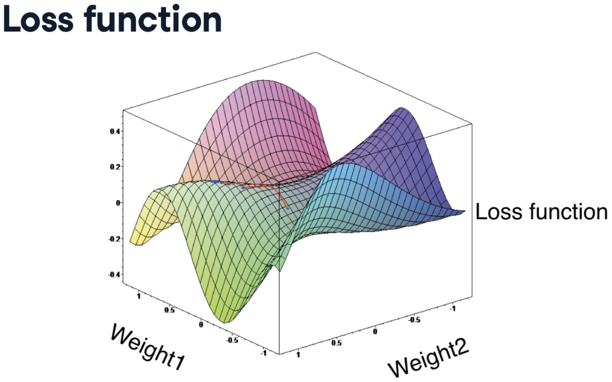
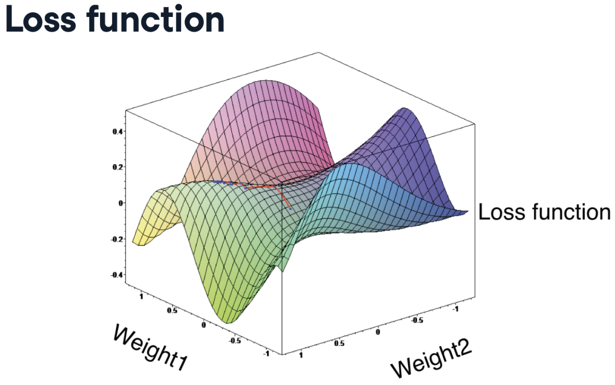


- Minimize multidimensional loss function →

Actually, this should be familiar...



- Minimize multidimensional loss function → (OLS anyone?)
- By finding the minimum point [=minimum prediction error]

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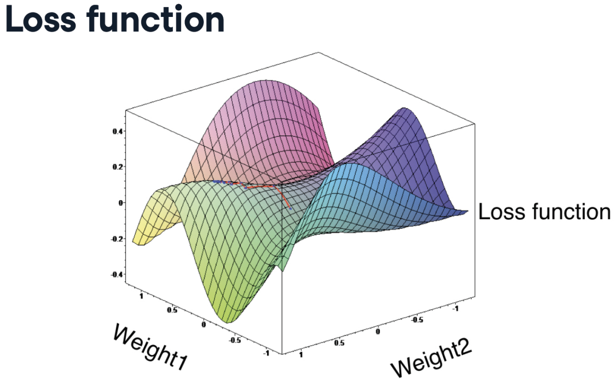
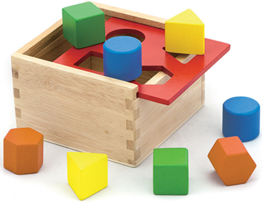


- Minimize multidimensional loss function → (OLS anyone?)
- By finding the minimum point [=minimum prediction error]
- Explore the “field” step by step

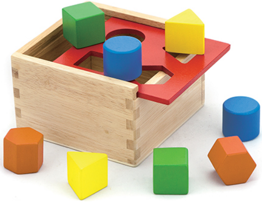
Beyond a CNN: transfer learning

Beyond a CNN: transfer learning

Beyond a CNN: transfer learning



Beyond a CNN: transfer learning



BEYOND A CNN: TRANSFER LEARNING (CONT.)

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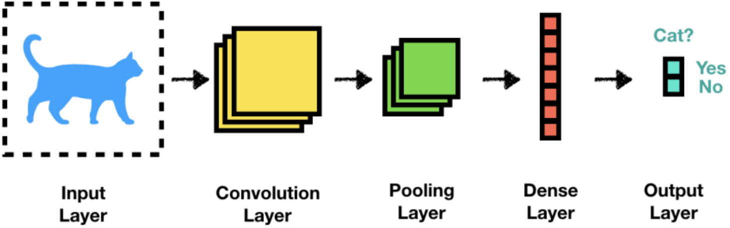
  2. Retrain further layers with new data and new labels

BEYOND A CNN: TRANSFER LEARNING (CONT.)



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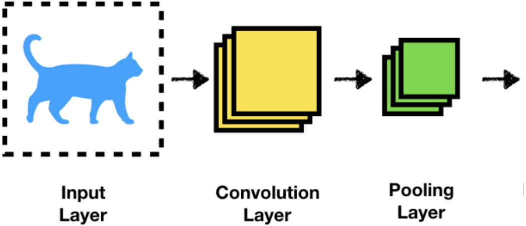

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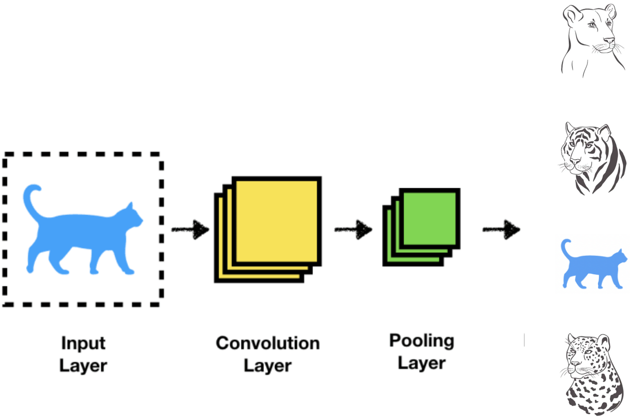

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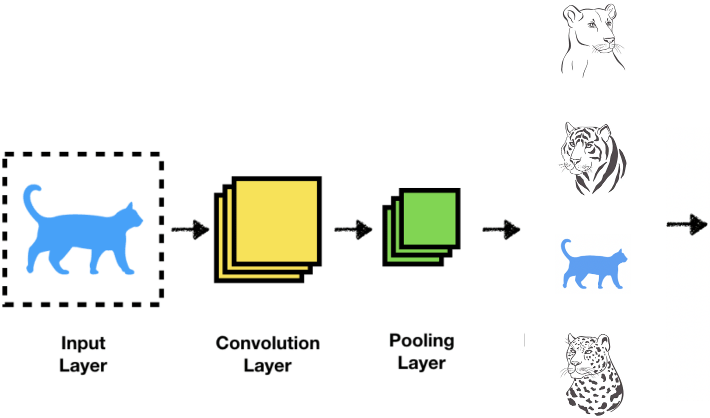
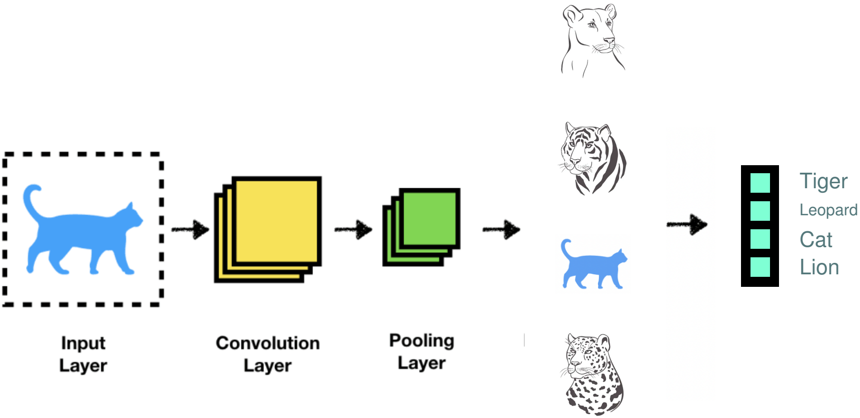
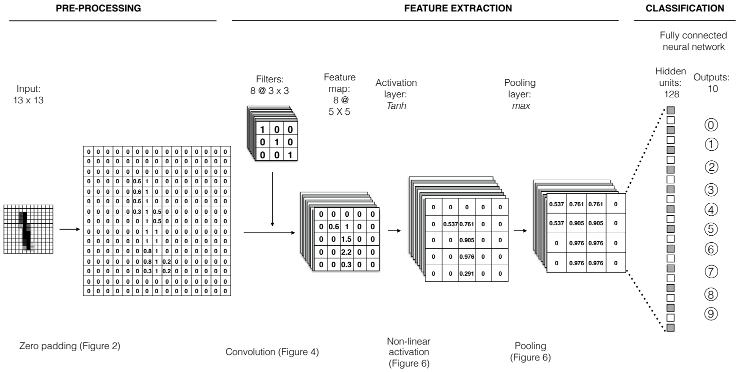


Beyond a CNN: transfer learning (cont.)



BEYOND A CNN: TRANSFER LEARNING (CONT.)

- “Freeze” some layers and retrain the active ones
- Idea: keep useful learned features and fine-tune to account for your labels of interest



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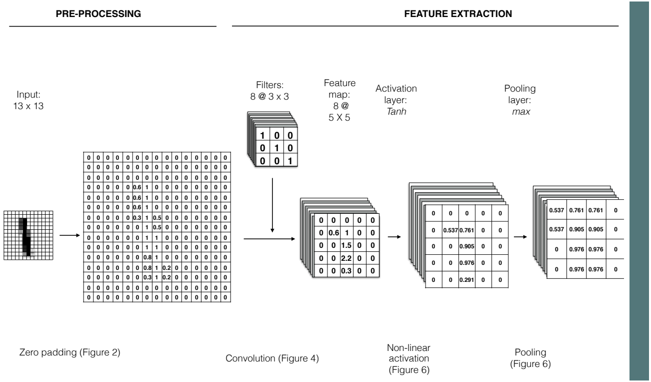

BEYOND A CNN: TRANSFER LEARNING (CONT.)

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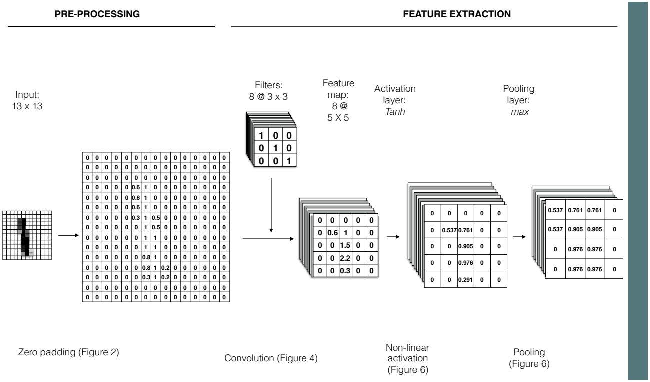

New data

BEYOND A CNN: TRANSFER LEARNING (CONT.)

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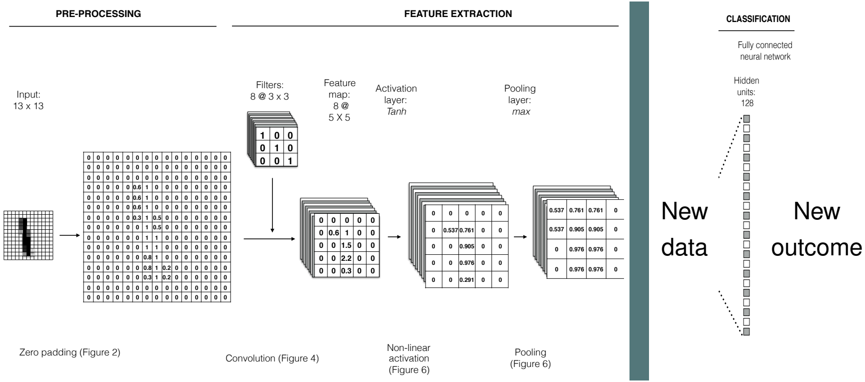

LET'S CODE!

CHALLENGES AND RECOMMENDATIONS

- Prevent overfitting(*)
  - Increase number of training images
  - Data augmentation
  - Dropout random neurons
- Optimize your training set
  - Active learning: Informativeness vs. Representativeness
  - Class balance
  - “Denoise” images
  - Batch normalization
  - CAUTION: Bias training
- Post-CNN diagnosis
  - Know your training, testing and out-of-sample data
  - Always check mislabeled examples: validate, validate, validate...
  - Diagnosis
  - Hyperparameter grid for tuning

LUNCH ASSIGNMENT

- Set up a Google Colab account
- If you don't have Google Drive, sign up for one too
- Copy Notebook 1 and play a bit with the code:
  - Get labels/predictions for 10 images of your choice (gather the links and substitute them)
  - Evaluate the model that we re-trained with our own data:
    - Compute performance statistics: precision, recall, F1, etc. [choose 4]
    - Explore the "correct" and "incorrect" of the model: can you find a pattern?
    - Any suggestions on how to improve it?

Lab assignment

1. Copy Notebook 2 and run it chunk by chunk, paying attention to each step of the process
2. Analyze all the pictures in the dataset provided: (i) detect faces in each of them, (ii) extract information from each face idenfitifed
3. Create a new dataset containing the information you consider relevant from the step 2. The unit of analysis is at the picture level
4. Link your new dataset to the original dataset provided (the meta data of the articles)
5. Run an interesting analysis using your new variables

Welcome to day 2!

- Questions?

Welcome to day 2!

- Questions?
- Useful so far?

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- Questions?
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- First: presentations

Welcome to day 2!

- Questions?
- Useful so far?
- First: presentations
- Then: Bag of Visual Words and STM

WHERE ARE WE (GOING)?

- Learned image basics: represent, describe, show them

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- BEFORE WE EVEN BEGIN: This method is not superior, it is just different.

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- Learned image basics: represent, describe, show them
- Learned about Convolutional Neural Networks: a supervised approach
- TODAY: Learn about a *semi-supervised* method that does not require previous labeling
- BEFORE WE EVEN BEGIN: This method is not superior, it is just different.
- Different questions demand different methods

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Latent Treatment Identification

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Latent Treatment Identification

Binary Classification

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Latent Treatment Identification

Binary Classification

Clustering Analysis

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Latent Treatment Identification	Binary Classification	Clustering Analysis	Topic Modeling

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Topic Modeling

Today: A "Visual" Structural Topic Model

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Sky:

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Pavement:

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Sky:

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Flag:

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Sky: 41%

Crowd: 38%

Pavement: 12%

Flag: 9%

But first: Constructing Visual Words

- Why do we need visual words?

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But first: Constructing Visual Words

- Why do we need visual words?
- To build a Document-Term matrix (DTM)!
- Why a DTM?
- Because that's the input of a STM
- Actually, what's a DTM?

But first: Constructing Visual Words, cont.

But first: Constructing Visual Words, cont.

1. Identification of blocks in images

But first: Constructing Visual Words, cont.

1. Identification of blocks in images
2. Extraction of features using a CNN

But first: Constructing Visual Words, cont.

1. Identification of blocks in images
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But first: Constructing Visual Words, cont.

1. Identification of blocks in images
2. Extraction of features using a CNN
3. Construction of visual vocabulary based on clustering features
4. Construction of Image-Visual Word matrix

DIVISION OF IMAGES INTO BLOCKS

(a) Original image (resized)

DIVISION OF IMAGES INTO BLOCKS

(a) Original image (resized)

(b) Image divided into 32 × 32 pixels blocks

Feature Extraction with CNNs

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- Use a **CNN** to extract features from EACH of the “mini” images composing each of the images in our corpus

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(NOT SO) SHORT PAUSE: Brief crash course on Convolutional Neural Networks

FEATURE EXTRACTION WITH CNNS

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(NOT SO) SHORT PAUSE: Brief crash course on Convolutional Neural Networks

(But please hold the "mini" images thought!)

Feature extraction using CNNs

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- Use pre-trained model on each block of an image

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- In our applications, this is 70×2,048

Clustering Features to Build Visual Vocabulary

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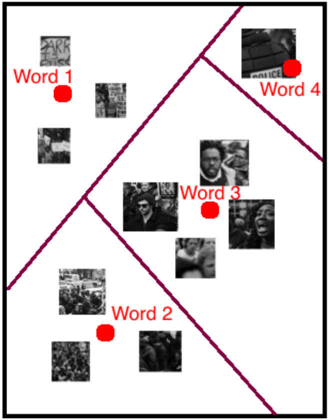

Clustering Features to Build Visual Vocabulary

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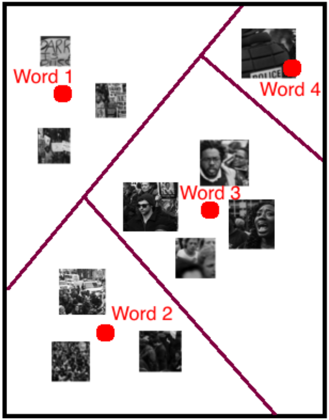

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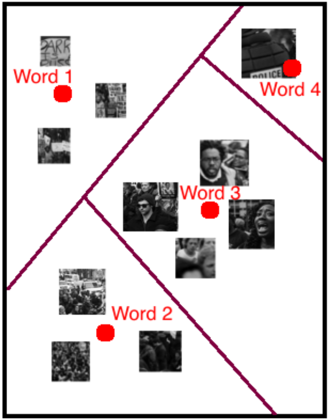

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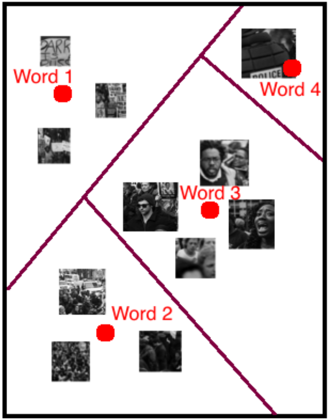

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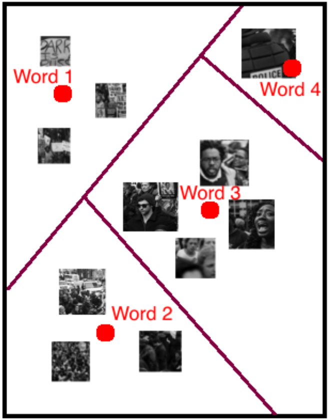
- Why do we do this?



Clustering Features to Build Visual Vocabulary

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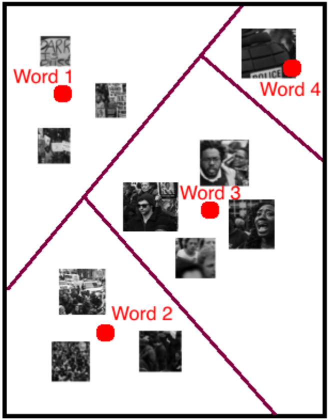
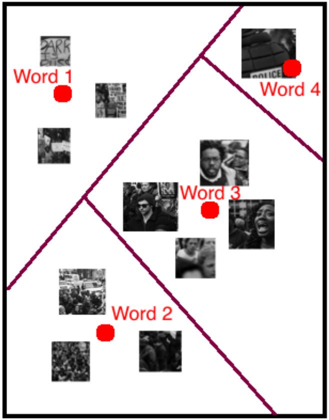
- Centroid of cluster is the "visual word"
- Why do we do this?
  - Similar features = Same concept



CLUSTERING FEATURES TO BUILD VISUAL VOCABULARY

- Need for tokens → Words in columns of a DTM
- Define *v* clusters (= # of desired visual words)
- Cluster randomly selected sample of feature vectors
- Centroid of cluster is the "visual word"
- Why do we do this?
  - Similar features = Same concept
  - Reduce potential sparsity in IVWM



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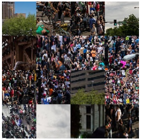

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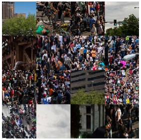


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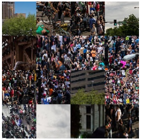

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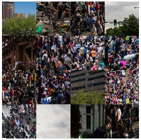


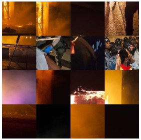

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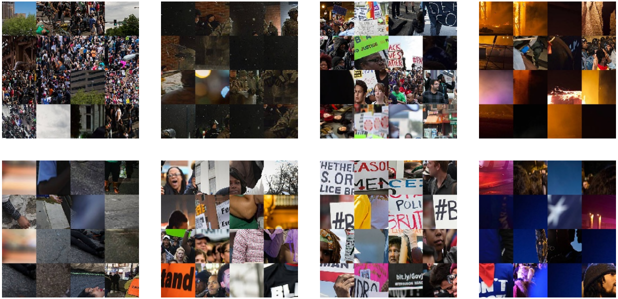

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"Looks more like an invasion than anything"

"See them as they are: Desperate, leaving behind whatever they had, and whomever they knew, all for a better chance at life"

Identifying political components in the data generation process of images

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  - Border/Fence, Small group/Portrait, Water/Sky, Camps, Darkness

Underlying topics in the caravan: FREX words

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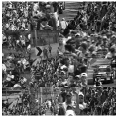
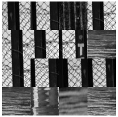
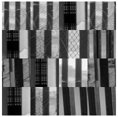
Topic 1: Crowds

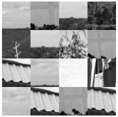


Topic 2: Border/Fence





Topic 3: Water/Sky



UNDERLYING TOPICS IN THE CARAVAN: REPRESENTATIVE IMAGES

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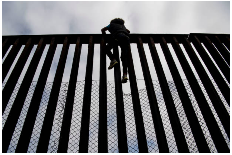
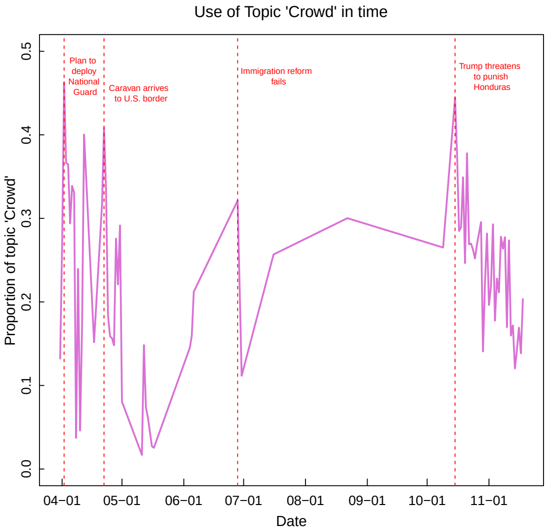
Crowd

Border/ Fence



Water/ Sky

Crowd topic in time



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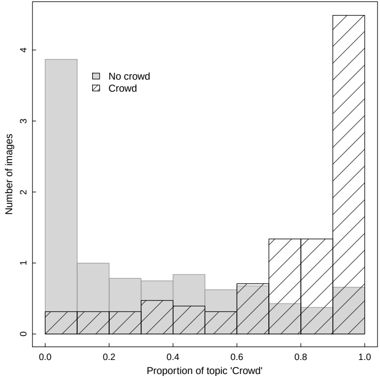

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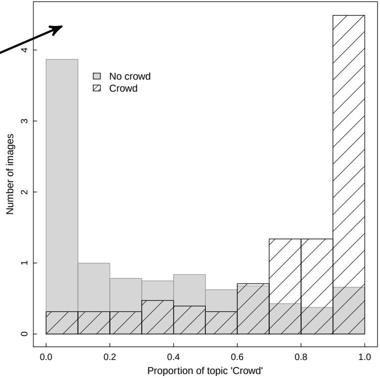

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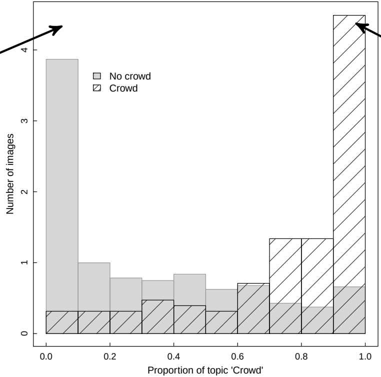
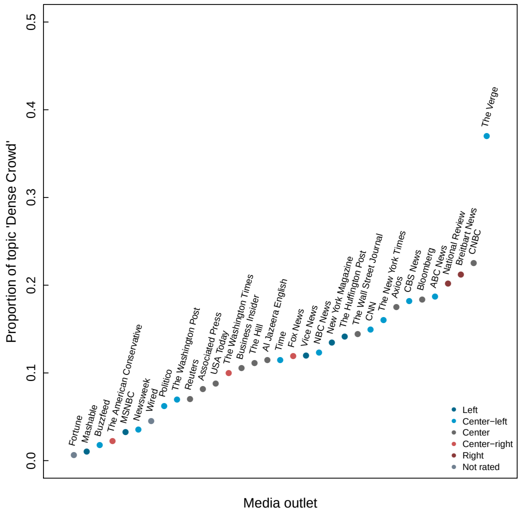


TOPIC "CROWD" BY MEDIA OUTLET



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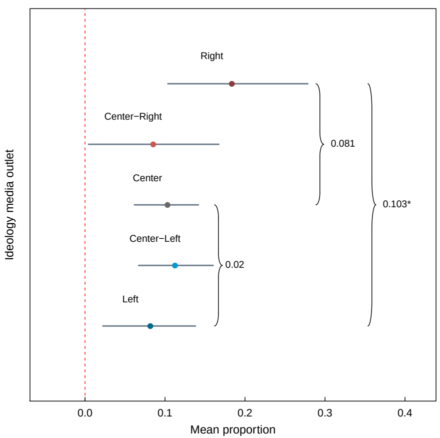

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  - Time?

What else is out there?

A POOL OF OPTIONS

- Create high quality training data and use transfer learning
  - AWS machines, HPC or GPUs [computational power needed]
  - Pre-trained architectures in Google, Amazon, etc.
  - Creating training data: `imglab`
- Pre-canned image detection with API access
  - GoogleVision: `https://cloud.google.com/vision/`, Amazon, Microsoft
    - Labels found in each picture
    - Face detection
    - Emotions
    - Sensitive content (e.g. violence, nudity, etc.)
    - Object detection

Object detection: Covers of Newspapers

Full set of images

Only Women’s March images

Face detection and emotional content

Good results with little effort...

FACE DETECTION AND EMOTIONAL CONTENT

Good results with little effort...

...but also tons of errors(*)

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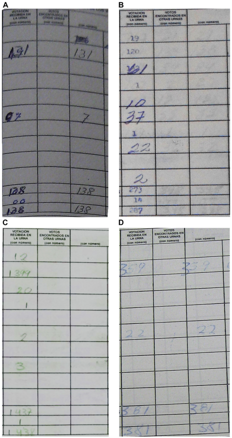
  (Cantú 2019)



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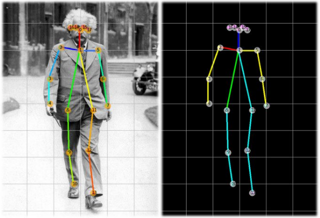
- Nature and reactions/attention to female and male politicians' body language using key points and vocal pitch (Rittman et al. 2023)



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- Keep learning and let the creativity take you to infinity and beyond!

Appendix

L*A*B COLOR SPACE

- L* = lightness
- a* = chromaticity coordinate (red axis)
- b* = chromaticity coordinate (blue axis)