ML for SS: Neural Networks for Image Classification

Session 12

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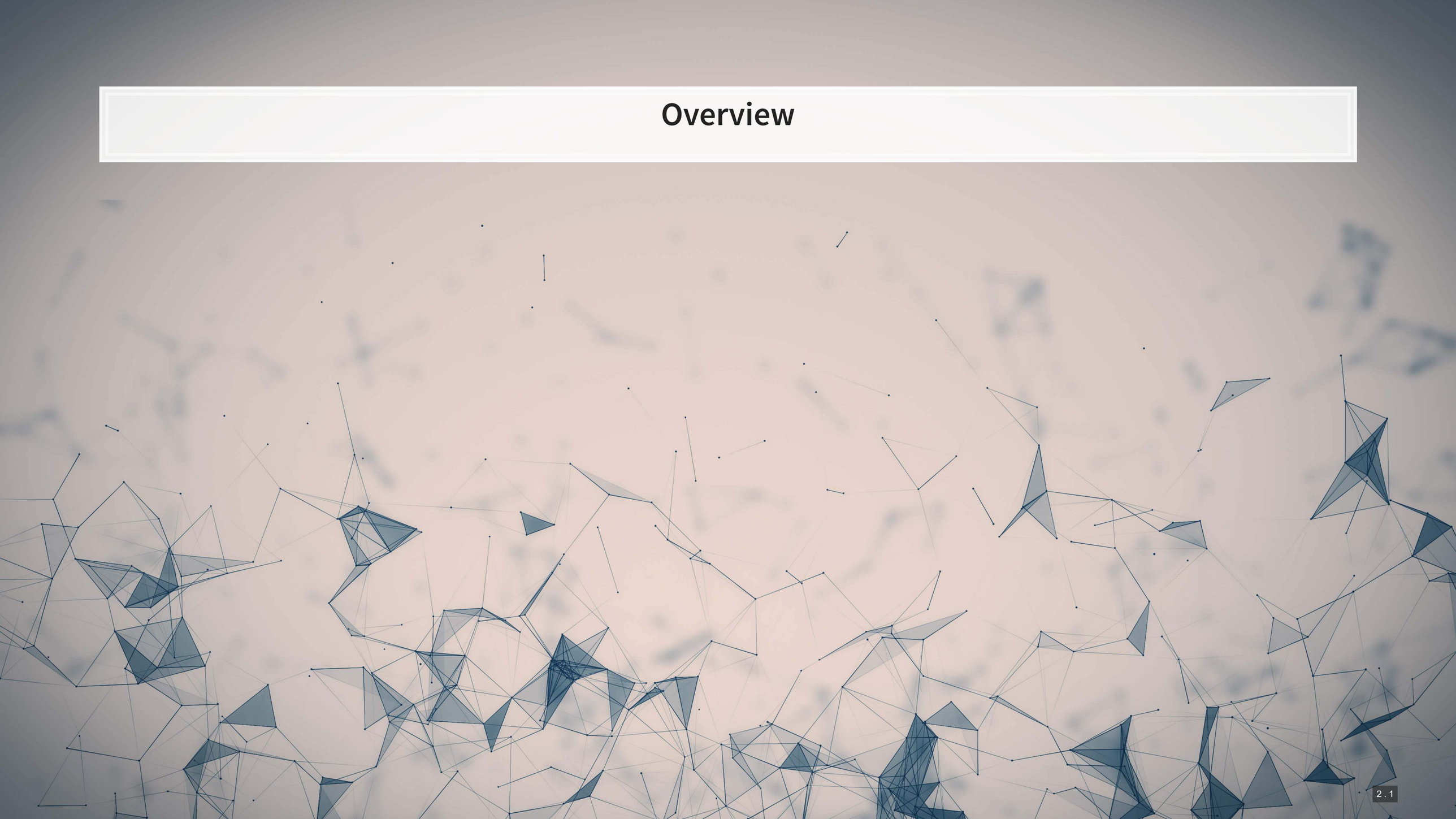
Overview



Papers

- Liu, Dzyabura and Mizik (2020)
  - Examines brand image and how reflective profiles are of the brands
- Zhang, Lee, Singh and Srinivasan (2017)
  - Examines how images in listings impact AirBNB properties
- Aubry, Kraeussl, Manso, and Spaenjers (2022)
  - Estimation errors in art auction listings

Technical Discussion

Focus on Neural Networks for images

Python

- Using Keras with Tensorflow for image classification
  1. Repeat our MNIST example using a proper CNN
  2. Using a premade GAN approach for even higher performance
- Using a 80-class pretrained classifier
- Combining images and text with CLIP

R

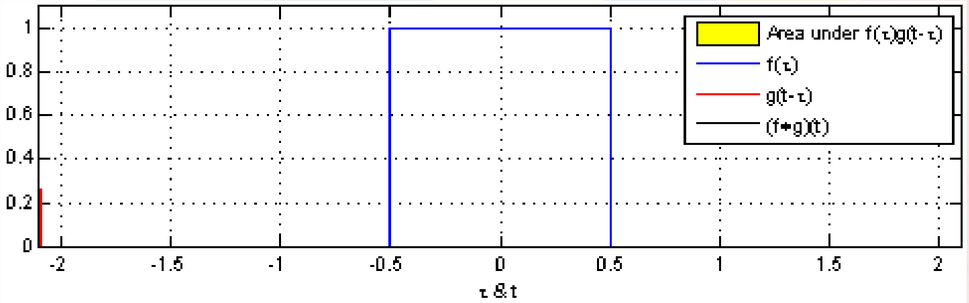
- You can use Keras from R through RStudio's package

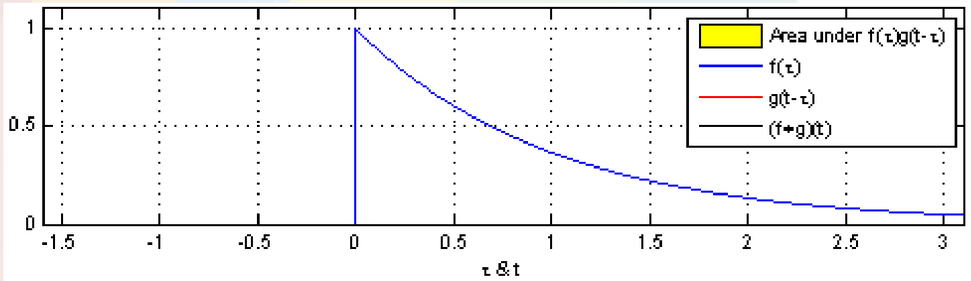
Python's support is a lot better here

MNIST: Extending to a CNN

How CNNs work

- CNNs use repeated convolution, usually looking at slightly bigger chunks of data each iteration
- But what is convolution? It is illustrated by the following graphs (from Wikipedia):





Further reading

Setup

- The setup is similar, except we don't need to reshape our X data
- We do need to add an additional dimension to our images though, which `np.expand_dims()` does for us

```
(train_X, train_Y), (test_X, test_Y) = keras.datasets.mnist.load_data()

train_X = train_X.astype("float32") / 255
test_X  = test_X.astype("float32") / 255

train_X = np.expand_dims(train_X, -1)
test_X = np.expand_dims(test_X, -1)

train_Y = keras.utils.to_categorical(train_Y, 10)
test_Y = keras.utils.to_categorical(test_Y, 10)

print('Train, X:%s, Y:%s' % (train_X.shape, train_Y.shape))
print('Test, X:%s, Y:%s' % (test_X.shape, test_Y.shape))
```

```
## Train, X:(60000, 28, 28, 1), Y:(60000, 10)
## Test, X:(10000, 28, 28, 1), Y:(10000, 10)
```

Build the model

- Here we use `Conv2D()` layers for the convolution
- The `MaxPooling2D()` layers downsample (shrink) the data
- The `Flatten()` layer reshapes the output to a vector
- `Relu` is essentially the same as a call option payoff ("hockey stick")
- `Softmax` is to output the class with the highest weight (argmax)

```python
# Parameters for the model
num_classes = 10
input_shape = (28, 28, 1)

model_cnn = keras.Sequential(
    [
        keras.layers.InputLayer(input_shape=input_shape),
        keras.layers.Conv2D(32, kernel_size=(3, 3), activation="relu"),
        keras.layers.MaxPooling2D(pool_size=(2, 2)),
        keras.layers.Conv2D(64, kernel_size=(3, 3), activation="relu"),
        keras.layers.MaxPooling2D(pool_size=(2, 2)),
        keras.layers.Flatten(),
        keras.layers.Dropout(0.5),
        keras.layers.Dense(num_classes, activation="softmax"),
    ]
)

model_cnn.summary()
```

Build the model

```
## Model: "sequential_4"
## _________________________________________________________________
## Layer (type)                 Output Shape              Param #
## =================================================================
## conv2d_2 (Conv2D)            (None, 26, 26, 32)        320
## _________________________________________________________________
## max_pooling2d_2 (MaxPooling2 (None, 13, 13, 32)        0
## _________________________________________________________________
## conv2d_3 (Conv2D)            (None, 11, 11, 64)        18496
## _________________________________________________________________
## max_pooling2d_3 (MaxPooling2 (None, 5, 5, 64)          0
## _________________________________________________________________
## flatten_1 (Flatten)          (None, 1600)              0
## _________________________________________________________________
## dropout_2 (Dropout)          (None, 1600)              0
## _________________________________________________________________
## dense_5 (Dense)              (None, 10)                16010
## =================================================================
## Total params: 34,826
## Trainable params: 34,826
## Non-trainable params: 0
```

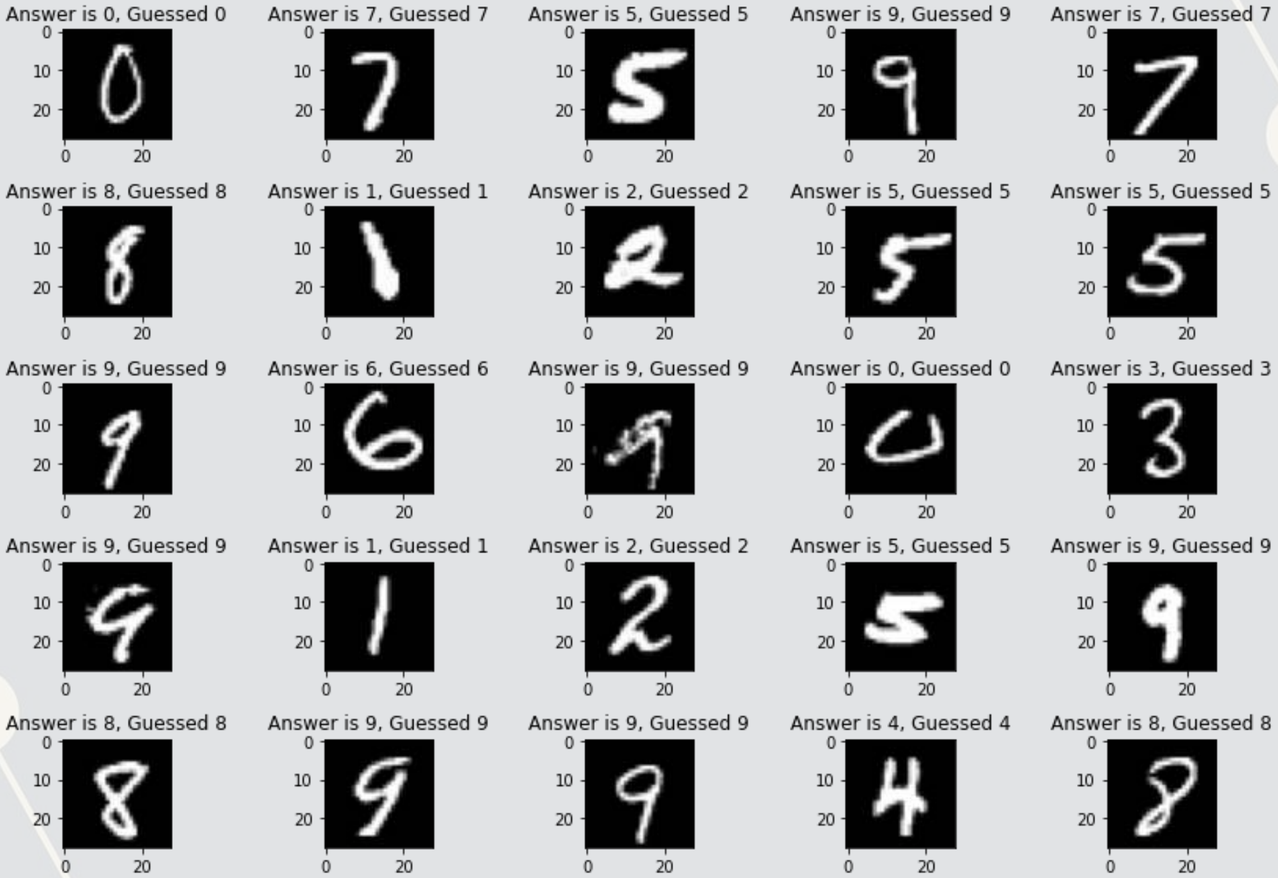
Fit the model and evaluate

- Fitting and evaluating is the same as before

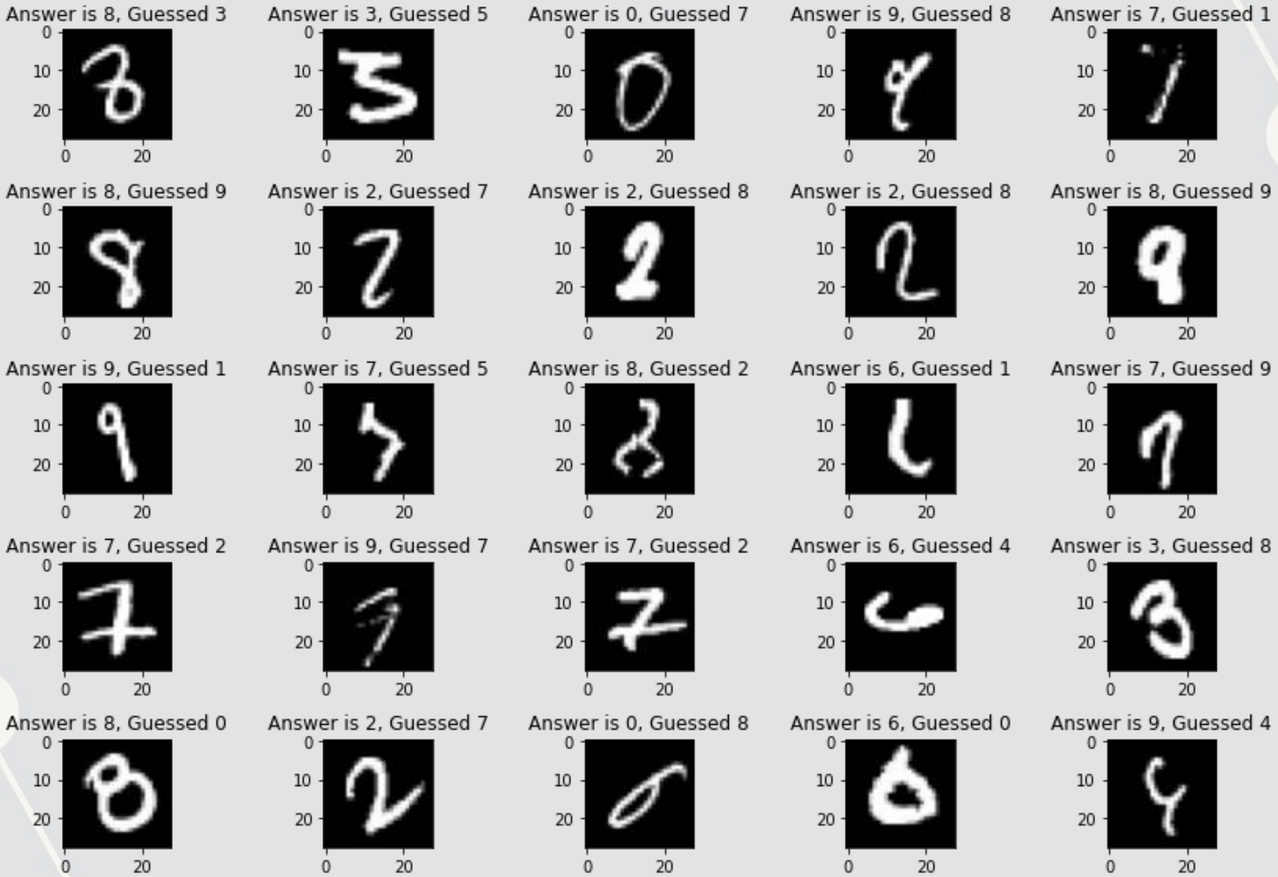
```
batch_size = 128
epochs = 10

model_cnn.compile(loss="categorical_crossentropy", optimizer="adam", metrics=["accuracy"])
model_cnn.fit(train_X, train_Y, batch_size=batch_size, epochs=epochs, validation_split=0.1)

score = model_cnn.evaluate(test_X, test_Y, verbose=0)
print("Test loss:", score[0])
print("Test accuracy:", score[1])
```

```
## Test loss: 0.0291274506598711
## Test accuracy: 0.9897000193595886
```

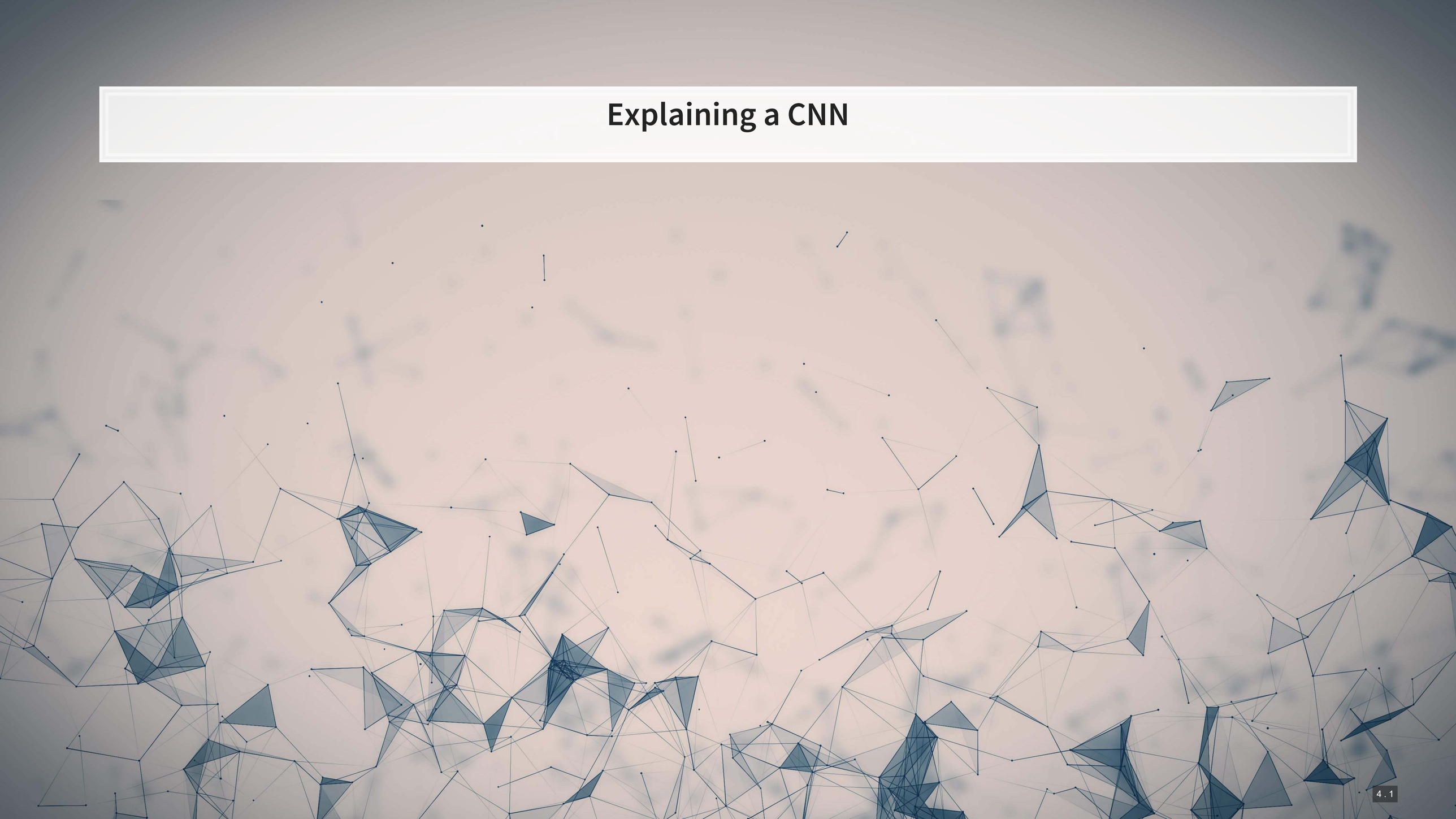
What does the model get right?



What does the model get wrong?



Explaining a CNN



SHAP and TensorFlow

- Recall that Wich, Bauer and Groh (2020 WOAH) used `shap.DeepExplainer()` to analyze a neural network
  - We can do the same!
- First, feed SHAP the model and some sample images

```
images = np.random.randint(0, train_X.shape[0], size=25)
e = shap.DeepExplainer(model_cnn, train_X[images])
```

  - Then we will select 1 of each digit that the CNN got correct and incorrect

```
correct = [np.where((np.argmax(model_cnn.predict(test_X), axis=-1) == np.argmax(test_Y, axis=-1)) & \
                    (np.argmax(test_Y, axis=-1) == i))[0][0] for i in range(0, 10)]
incorrect = [np.where((np.argmax(model_cnn.predict(test_X), axis=-1) != np.argmax(test_Y, axis=-1)) & \
                    (np.argmax(test_Y, axis=-1) == i))[0][0] for i in range(0, 10)]
```

SHAP for correct images

```
shap_values = e.shap_values(test_X[correct])
shap.image_plot(shap_values, -test_X[correct])
```

SHAP for incorrect images

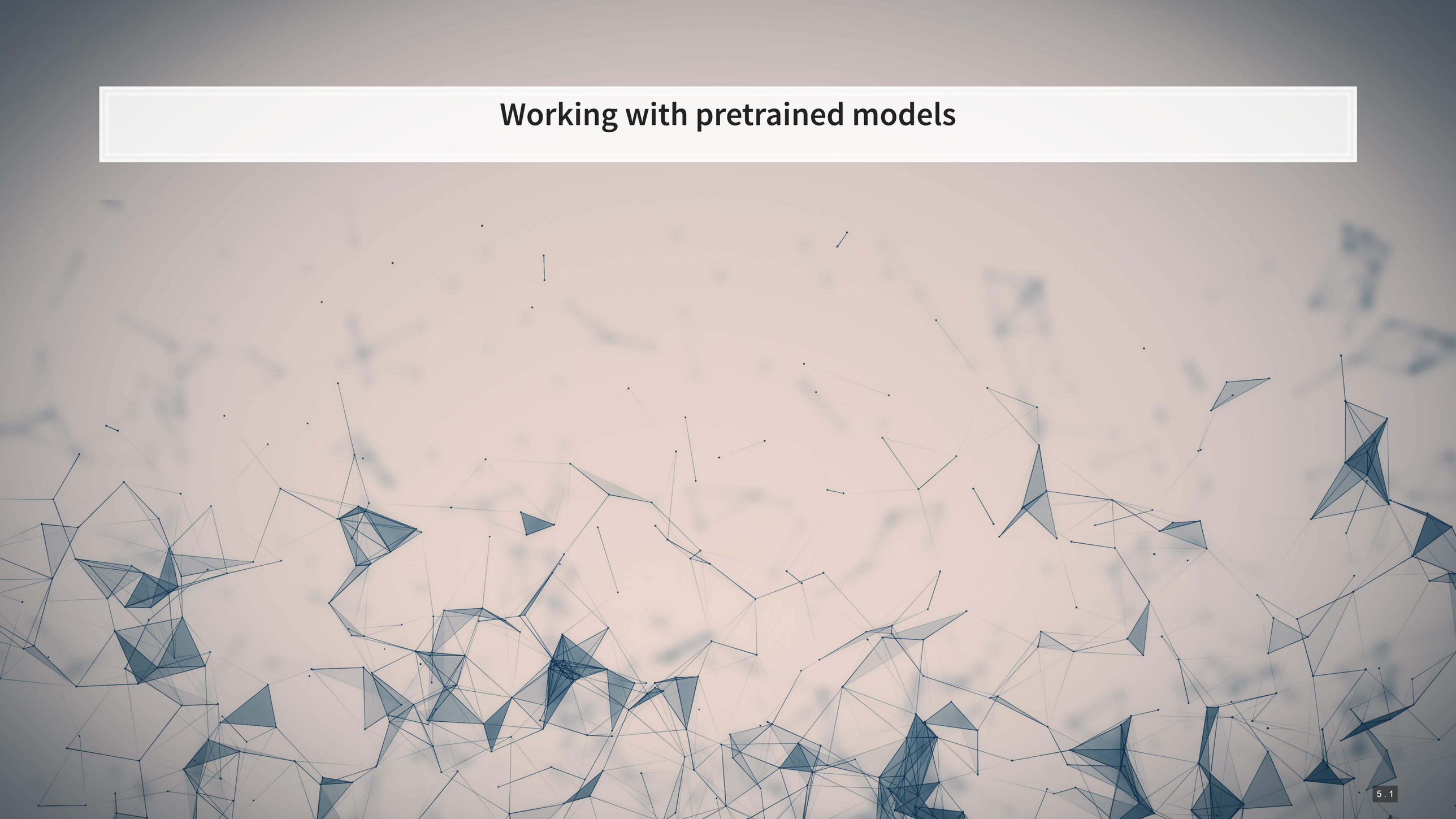
```
shap_values = e.shap_values(test_X[incorrect])
shap.image_plot(shap_values, -test_X[incorrect])
```

Recent attempts at explaining CNNs

- Google & Stanford's "Automated Concept-based Explanation"

Figure 2: **The output of ACE for three ImageNet classes.** Here we depict three randomly selected examples of the top-4 important concepts of each class (each example is shown above the original image it was segmented from). Using this result, for instance, we could see that the network classifies police vans using the van's tire and the police logo.

Working with pretrained models



Where can I find pretrained models?

- There are many pretrained models on TensorFlow Hub
- There are also models contained in the TensorFlow Github page:
  - Research models
  - Community models
- Google Brain also maintains a collection of models in trax

> Other platforms also maintain model collections

- PyTorch has PyTorch Hub
- Hugging Face maintains a large collection of text models
- ONNX maintains a collection of framework-agnostic models

> We will look at TensorFlow Hub today

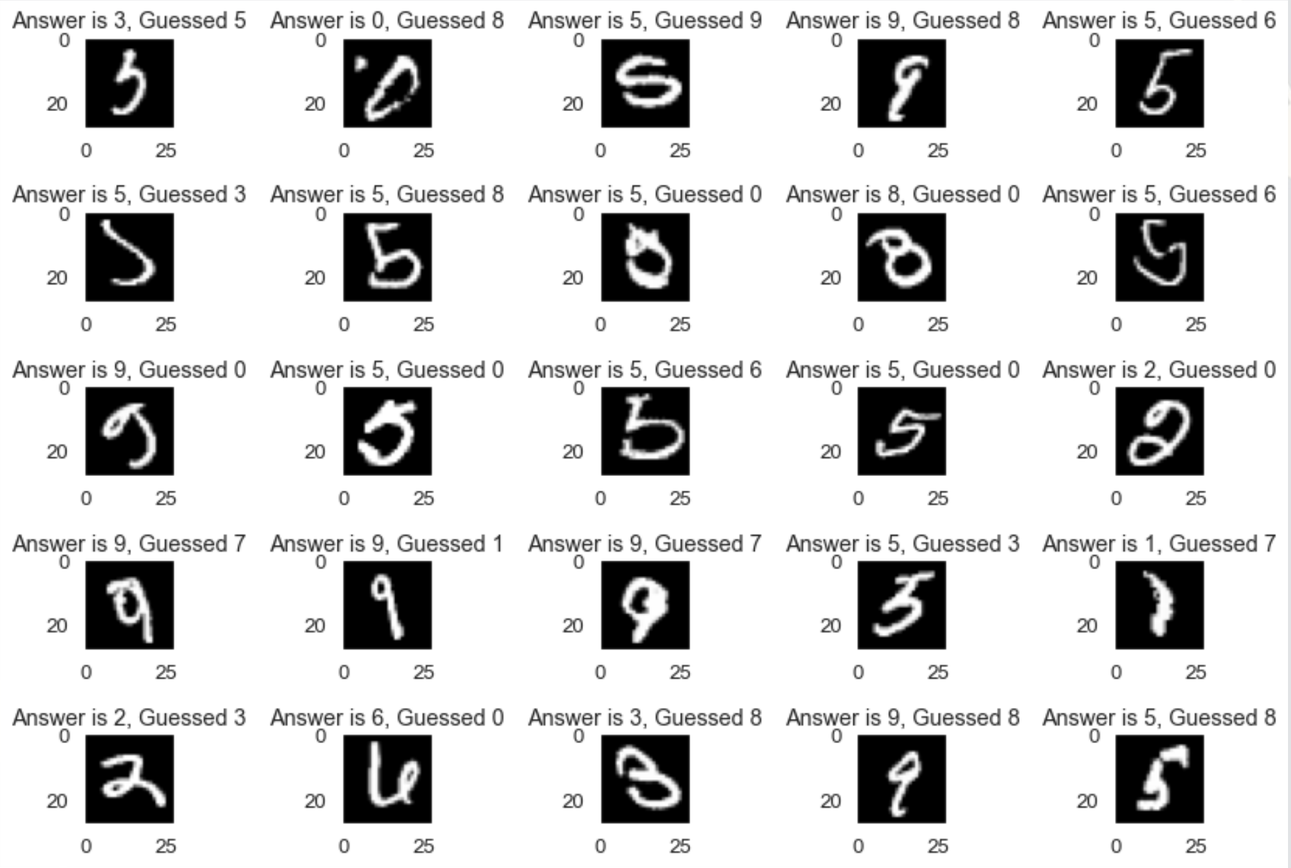
MNIST off-the-shelf

- The model we will be using is GAN-based MNIST classifier
  - tfgan/eval/mnist/logits
- Use `hub.load()` to load in a model
- Apply it to our testing data, same as before
  - Just apply the model to our data

```
model_tfgan = hub.load("https://tfhub.dev/tensorflow/tfgan/eval/mnist/logits/1")
logits = model_tfgan(test_X).numpy()

# Check accuracy
sum(np.argmax(logits,-1) == np.argmax(test_Y, -1))
```

```
## 9822
```

Examine incorrect answers



Object detection off-the-shelf

COCO Classification problem

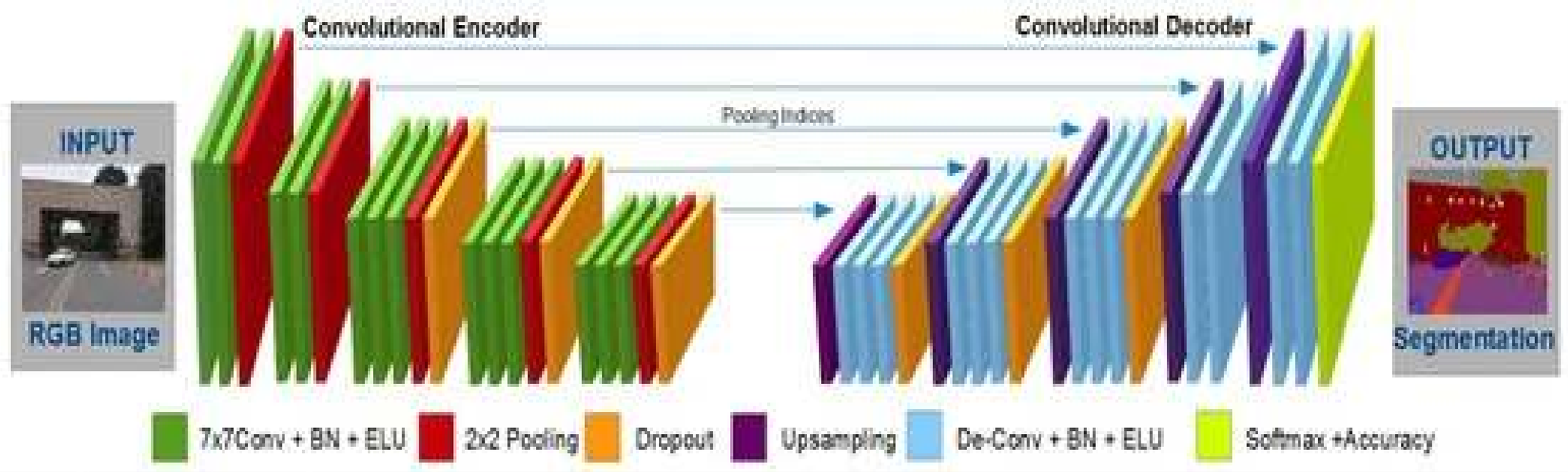
- There are a lot of options for this
- We will use a model trained on COCO from CenterNet
  - centernet/hourglass_512x512
- This can detect 80 different object types, including people

```
# Full list of object types
labels = load_COCO_labelmap()
print(list(labels.values()))
```

```
## ['person', 'bicycle', 'car', 'motorcycle', 'airplane', 'bus', 'train',
## 'truck', 'boat', 'traffic light', 'fire hydrant', 'stop sign', 'parking meter',
## 'bench', 'bird', 'cat', 'dog', 'horse', 'sheep', 'cow', 'elephant', 'bear',
## 'zebra', 'giraffe', 'backpack', 'umbrella', 'handbag', 'tie', 'suitcase',
## 'frisbee', 'skis', 'snowboard', 'sports ball', 'kite', 'baseball bat',
## 'baseball glove', 'skateboard', 'surfboard', 'tennis racket', 'bottle',
## 'wine glass', 'cup', 'fork', 'knife', 'spoon', 'bowl', 'banana', 'apple',
## 'sandwich', 'orange', 'broccoli', 'carrot', 'hot dog', 'pizza', 'donut', 'cake',
## 'chair', 'couch', 'potted plant', 'bed', 'dining table', 'toilet', 'tv',
## 'laptop', 'mouse', 'remote', 'keyboard', 'cell phone', 'microwave', 'oven',
## 'toaster', 'sink', 'refrigerator', 'book', 'clock', 'vase', 'scissors',
## 'teddy bear', 'hair drier', 'toothbrush']
```

What is Centernet/Hourglass?

- Centernet is an approach that's intended to be used for drawing bounding boxes around objects
  - From Zhou, Wang, and Krähenbühl (2019)
  - The second stage in the classification problem for computer vision:
    1. Detect objects
    2. Locate them in the image
- Hourglass is a neural network structure based on CNNs



Using the model

```
centernet = hub.load('https://tfhub.dev/tensorflow/centernet/hourglass_512x512/1')

image1, image1_np = load_image('../Data/S6_1.jpeg')
image2, image2_np = load_image('https://pbs.twimg.com/media/E8ZIIKGXIAAipIh?format=jpg&name=small')
```


```
-rw-r--r-- 1 root root  9916885161 Aug  9 15:13 RC_2021-04-30
-rw-r--r-- 1 root root  9223343241 Aug  9 15:30 RC_2021-05-01
-rw-r--r-- 1 root root  9646977002 Aug  9 15:48 RC_2021-05-02
-rw-r--r-- 1 root root  9790222766 Aug  9 16:06 RC_2021-05-03
-rw-r--r-- 1 root root  9629653589 Aug  9 16:23 RC_2021-05-04
-rw-r--r-- 1 root root 10128104379 Aug  9 16:43 RC_2021-05-05
-rw-r--r-- 1 root root 10030968634 Aug  9 17:06 RC_2021-05-06
-rw-r--r-- 1 root root  9640296547 Aug  9 17:28 RC_2021-05-07
-rw-r--r-- 1 root root  8725756019 Aug  9 17:48 RC_2021-05-08
-rw-r--r-- 1 root root  8889488493 Aug  9 18:07 RC_2021-05-09
-rw-r--r-- 1 root root  9605987029 Aug  9 18:24 RC_2021-05-10
-rw-r--r-- 1 root root  9938707285 Aug  9 18:43 RC_2021-05-11
-rw-r--r-- 1 root root 10076510269 Aug  9 19:02 RC_2021-05-12
-rw-r--r-- 1 root root  9883018150 Aug  9 19:19 RC_2021-05-13
-rw-r--r-- 1 root root  9695352031 Aug  9 19:36 RC_2021-05-14
-rw-r--r-- 1 root root  8726999970 Aug  9 19:52 RC_2021-05-15
-rw-r--r-- 1 root root  9160705762 Aug  9 20:09 RC_2021-05-16
-rw-r--r-- 1 root root 10034858757 Aug  9 20:31 RC_2021-05-17
-rw-r--r-- 1 root root 10085444956 Aug  9 20:58 RC_2021-05-18
-rw-r--r-- 1 root root 10223552907 Aug  9 21:28 RC_2021-05-19
-rw-r--r-- 1 root root 10035523908 Aug  9 21:49 RC_2021-05-20
-rw-r--r-- 1 root root  9366915647 Aug  9 22:14 RC_2021-05-21
-rw-r--r-- 1 root root  8595795622 Aug 10 00:27 RC_2021-05-22
-rw-r--r-- 1 root root  8821664968 Aug 10 00:44 RC_2021-05-23
-rw-r--r-- 1 root root  9292102711 Aug 10 01:07 RC_2021-05-24
drwxr-xr-x 2 root root        4096 Aug 10 01:07 .
-rw-r--r-- 1 root root  7022061644 Aug 10 01:28 RC_2021-05-25
root@es3:/data/reddit#
```

Applying the model

- We apply the model to the numpy matrix representation of the image
- `result` is just a numpy version of `results`
  - This contains four types of information

```
results = centernet(image1_np)
result = {key:value.numpy() for key,value in results.items()}
print(result.keys())
```

```
## dict_keys(['detection_scores', 'num_detections', 'detection_boxes', 'detection_classes'])
```

Applying the model

- The below functions are defined out of convenience

```python
def top_k_objects(result, k=3):
    top_scores = result['detection_scores'][0][0:k]
    top_ids = [labels[str(int(i))] for i in result['detection_classes'][0]][0:k]
    for row in zip(top_scores, top_ids):
        print('Object: ' + row[1] + ', score: ' + str(row[0]))


def prob_person(result):
    id_person = 1
    if len(np.where(result['detection_classes'][0] == 1)[0]):
        top_person_loc = np.where(result['detection_classes'][0] == 1)[0][0]
        people = np.where(result['detection_classes'][0] == 1)[0]
        max_prob = result['detection_scores'][0][top_person_loc]
        implied_prob = 1-np.prod(1-result['detection_scores'][0][people])
        print('Maximum probability of an object in the photo being a person: ' + str(max_prob) +\
              '\nProbability of at least 1 person: ' + str(implied_prob))
    else:
        print('No person found')
```

- The first function reports the top k objects detected, based on weights assigned by the model
- The second function reports the highest probability that a person was included in the image as well as an aggregate probability measure

Analyzing the first image

```
top_k_objects(result, 3)
```

```
## Object: tie, score: 0.56596684
## Object: person, score: 0.45707893
## Object: tv, score: 0.3345726
```

```
prob_person(result)
```

```
## Maximum probability of an object in the photo being a 
## Probability of at least 1 person: 0.5256033539772034
```

Applying to the second image

```
results = centernet(image2_np)
result = {key:value.numpy() for key,value in results.items()}
```

```
top_k_objects(result, 3)
```

```
## Object: book, score: 0.7087656
## Object: tv, score: 0.10406752
## Object: book, score: 0.07747121
```

```
prob_person(result)
```

```
## No person found
```

```
-rw-r--r-- 1 root root  9916885161 Aug  9 15:13 RC_2021-04-30
-rw-r--r-- 1 root root  9223343241 Aug  9 15:30 RC_2021-05-01
-rw-r--r-- 1 root root  9646977002 Aug  9 15:48 RC_2021-05-02
-rw-r--r-- 1 root root  9790222766 Aug  9 16:06 RC_2021-05-03
-rw-r--r-- 1 root root  9629653589 Aug  9 16:23 RC_2021-05-04
-rw-r--r-- 1 root root 10128104379 Aug  9 16:43 RC_2021-05-05
-rw-r--r-- 1 root root 10030968634 Aug  9 17:06 RC_2021-05-06
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drwxr-xr-x 2 root root        4096 Aug 10 01:07 .
-rw-r--r-- 1 root root  7022061644 Aug 10 01:28 RC_2021-05-25
root@es3:/data/reddit#
```
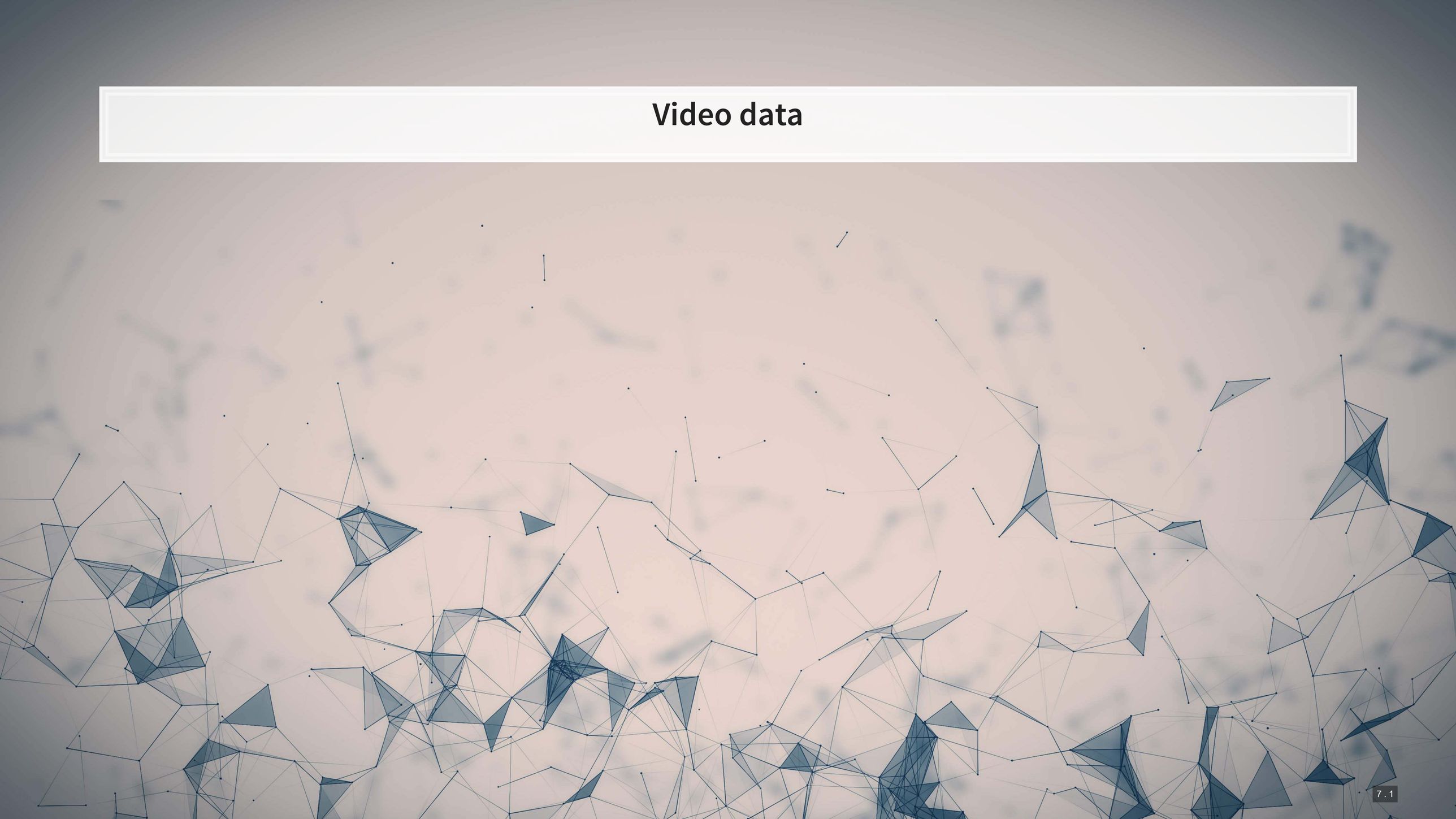

Video data



Working with video

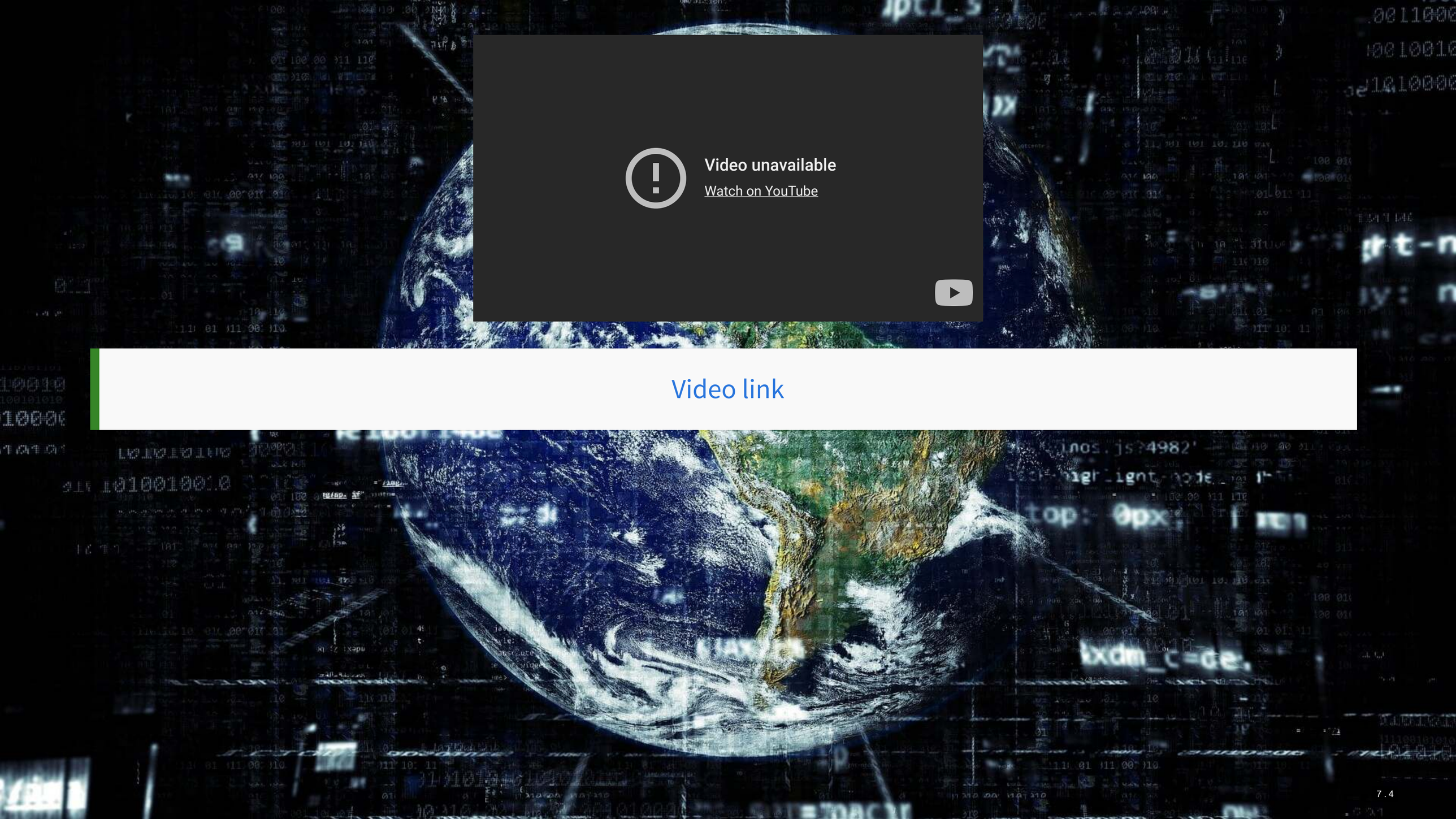
- Video data is challenging – very storage intensive
  - Ex.: Uber's self driving cars would generate >100GB of data *per hour* **per car**
- Video data is very promising
  - Think of how many task involve vision!
    - Driving
    - Photography
    - Warehouse auditing…
- At the end of the day though, video is just a sequence of images

One method for video

YOLOv3

- You
- Only
-

- Once

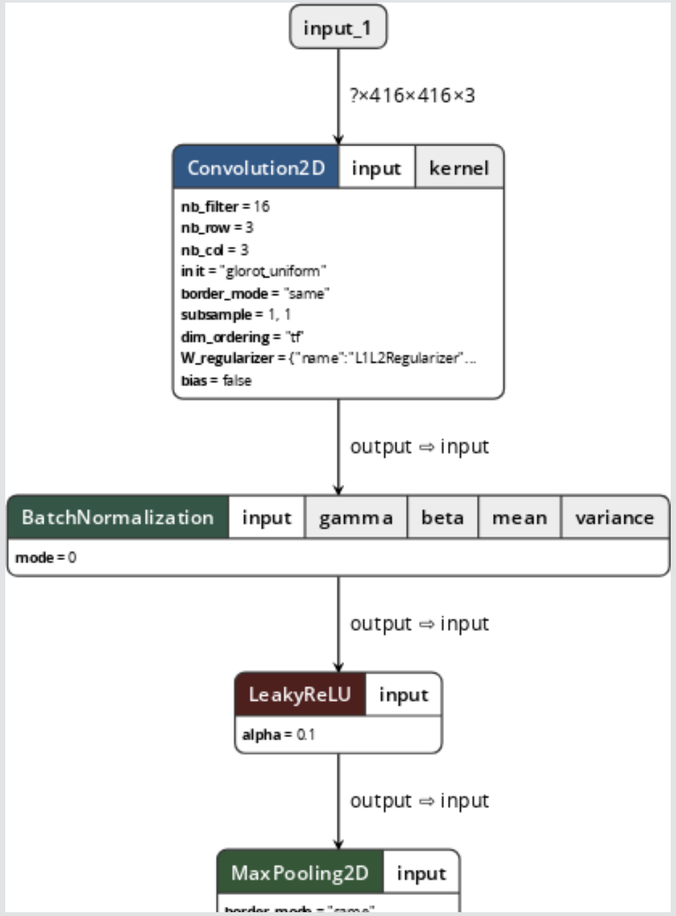


Video link

What does YOLO do?

- It spots objects in videos and labels them
  - It also figures out a *bounding box* – a box containing the object inside the video frame
- It can spot *overlapping* objects
- It can spot multiple of the same or different object types
- The baseline model (using the COCO dataset) can detect 80 different object types
  - There are other datasets with more objects

How does Yolo do it? Map of Tiny YOLO



Yolo model and graphing tool from lutzroeder/netron

How does Yolo do it?

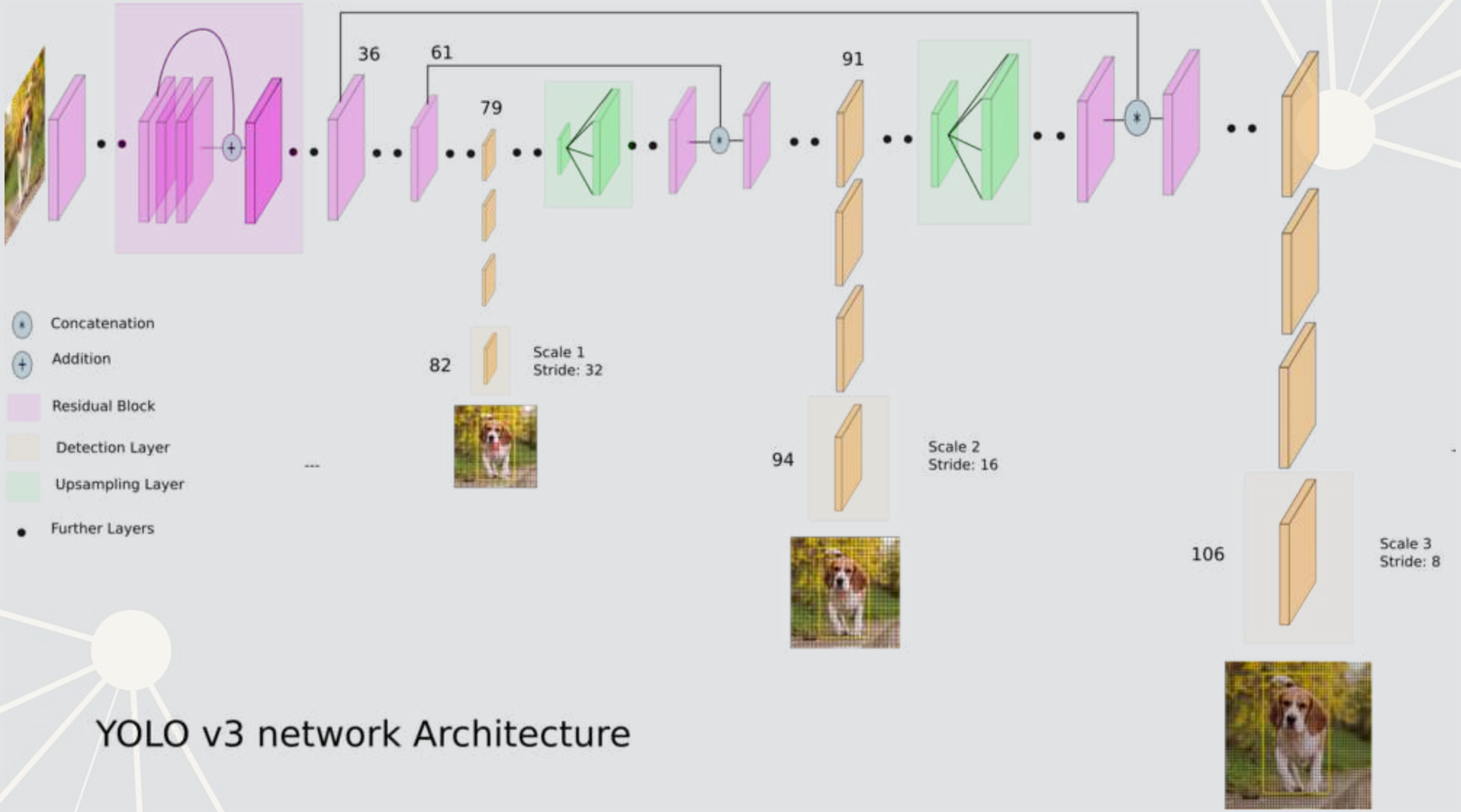


Diagram from *What's new in YOLO v3* by Ayoosh Kathuria

Where to get video data

- One extensive source is Youtube-8M
  - 6.1M videos, 3-10 minutes each
  - Each video has >1,000 views
  - 350,000 hours of video
  - 237,000 labeled 5 second segments
  - 1.3B video features that are machine labeled
  - 1.3B audio features that are machine labeled

Object detection in practice

- An algorithm like YOLO v3 is somewhat tricky to run
- Preparing the algorithm takes a long time
  - The final output, though, can run on much cheaper hardware
- These algorithms just recently became feasible so their impact has yet to be felt so strongly

> Think about how facial recognition showed up everywhere for images over the past few years

A word on ethics of object detection

But maybe a better question is: "What are we going to do with these detectors now that we have them?" A lot of the people doing this research are at Google and Facebook. I guess at least we know the technology is in good hands and definitely won't be used to harvest your personal information and sell it to.... wait, you're saying that's exactly what it will be used for?? Oh.

Well the other people heavily funding vision research are the military and they've never done anything horrible like killing lots of people with new technology oh wait.....[1]

I have a lot of hope that most of the people using computer vision are just doing happy, good stuff with it, like counting the number of zebras in a national park [13], or tracking their cat as it wanders around their house [19]. But computer vision is already being put to questionable use and as researchers we have a responsibility to at least consider the harm our work might be doing and think of ways to mitigate it. We owe the world that much.

In closing, do not @ me. (Because I finally quit Twitter).

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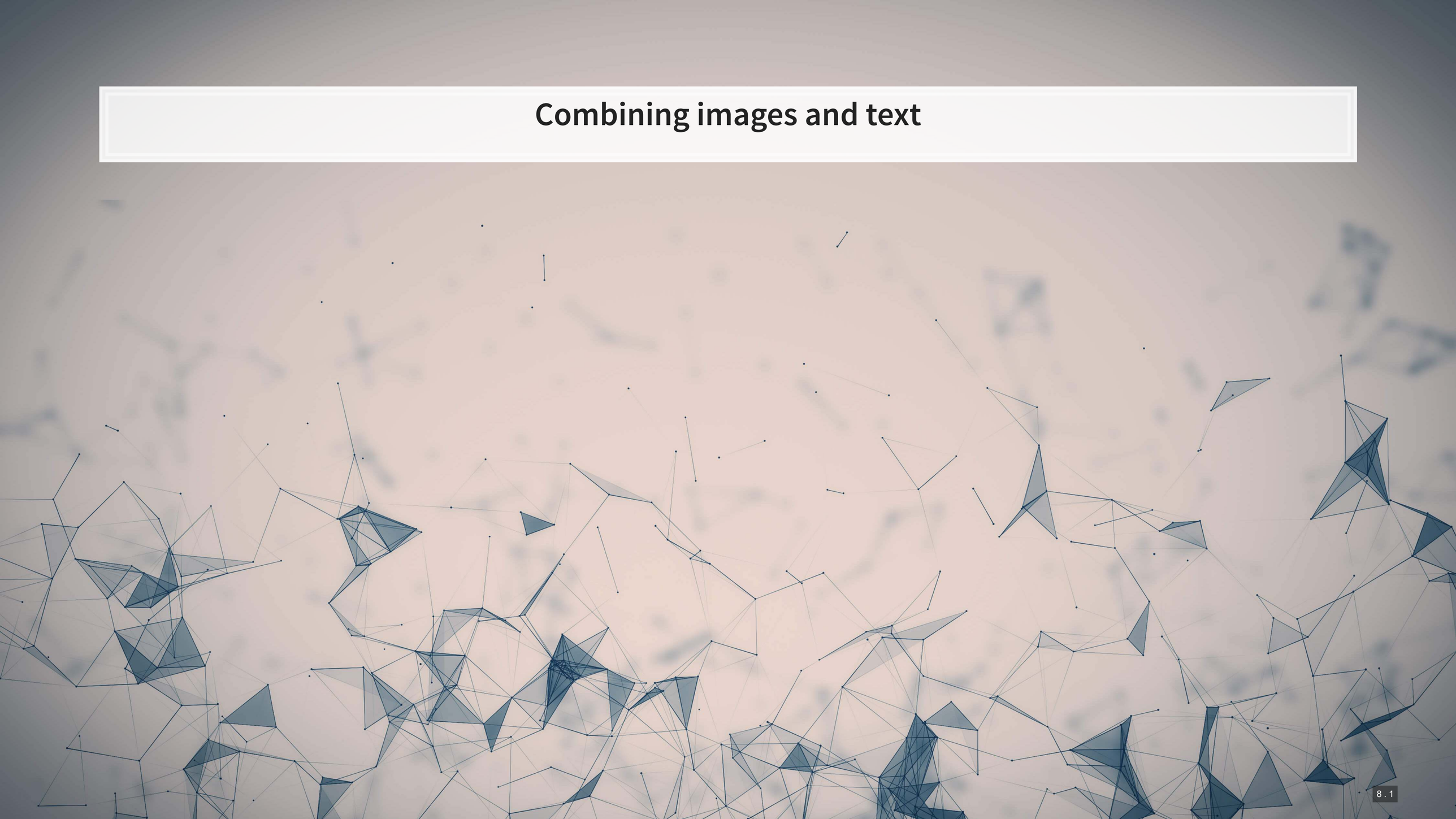
[1] The author is funded by the Office of Naval Research and Google.

From Redmon and Farhadi (2018) [The YOLO v3 paper]

Combining images and text



Large language models + Images

- Multiple impactful models were released since 2021 that merge text and image processing into a single model
  - CLIP: Contrastive Language-Image Pre-training
    - Pairs images with captions
  - Stable Diffusion
    - Image generation from text

> These work by embedding images and text into the same embedding space

CLIP

- Code for this is available at: rmc.link/colab_clip

Stable diffusion: Content

- Code to implement as a Telegram bot: https://github.com/rmcrowley2000/StableDiffBot

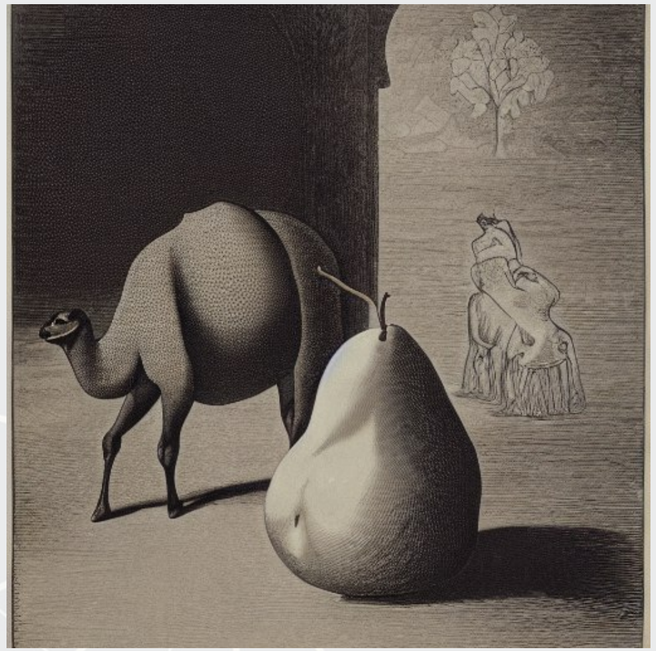
"A photo of the Singapore skyline including Marina Bay Sands"

"Singapore Management University"

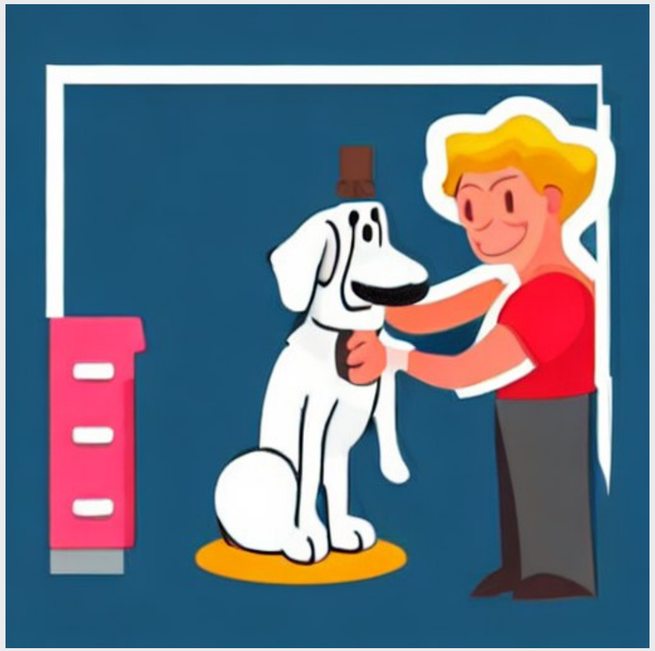
Stable diffusion: Style

- Code to implement as a Telegram bot: https://github.com/rmcrowley2000/StableDiffBot

“Lithograph of a camel eating a pear”



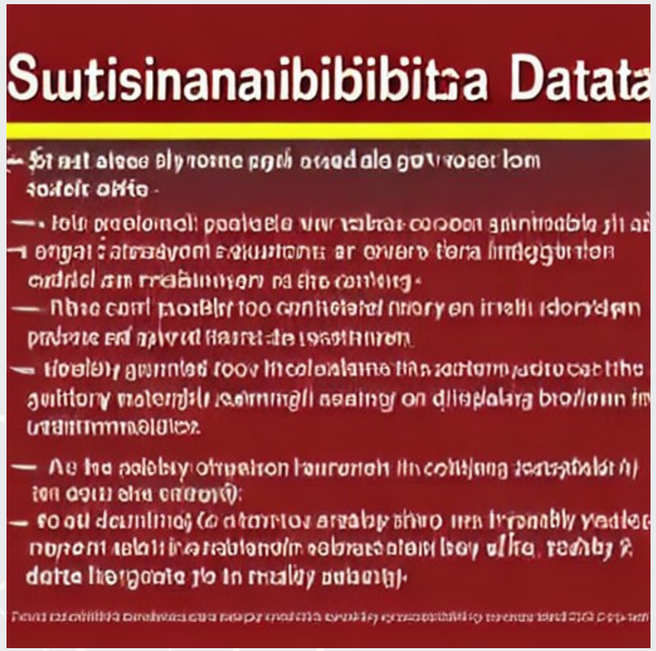
“A cartoon icon of a dog getting a hair cut.”



Stable diffusion: Problems

- Code to implement as a Telegram bot: https://github.com/rmcrowley2000/StableDiffBot

“Sustainability data”



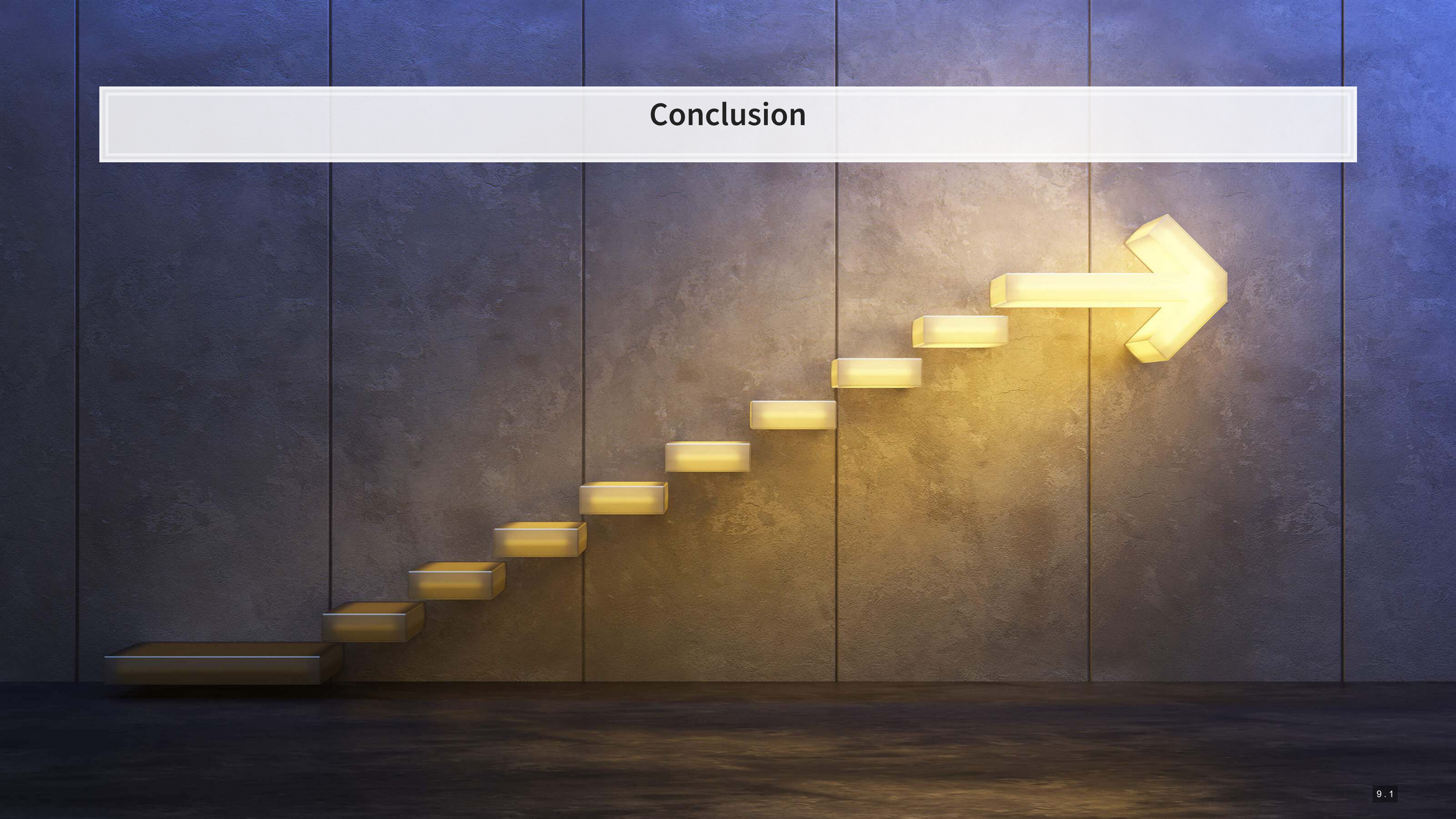
“A cavapoo enjoying a nice warm cup of tea”

Stable diffusion: Compexity

- Code to implement as a Telegram bot: https://github.com/rmcrowley2000/StableDiffBot

“Tiny cute isometric living room in a cutaway box, soft smooth lighting, soft colors, purple and blue color scheme, soft colors, 100mm lens, 3d blender render”

Conclusion



Wrap-up

Neural networks can accurate classify entire images

- Useful for clustering our classifying images

Neural networks can accurately classify or detect objects included in images

- Opens up a lot of possibilities
  - Such as looking at whether a person is wearing a mask or not (related to HW3)

Neural networks can combine text and images into a measure

- Opens up more empirical possibilities and new ways to use image data

What remains

- Assignment 2
  - New due date: **November 17th**
  - You are welcome to submit earlier
- Assignment 3
  - Shorter than the other assignments
  - Focuses on image detection and classification
  - It’s all done on Colab so that you don’t need to worry about getting pytorch to work locally
  - Due: **December 6th**
- Proposal
  - Due: **December 6th**

> Can’t extend past December 6th due to grade deadlines

Packages used for these slides

Python

- matplotlib
- numpy
- pandas
- PIL
- requests
- seaborn
- shap
- tensorflow
- tensorflow_gan
- tensorflow_hub
- transformers

References

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- Yasrab, Robail, Naijie Gu, and Xiaoci Zhang. “An encoder-decoder based convolution neural network (CNN) for future advanced driver assistance system (ADAS).” Applied Sciences 7, no. 4 (2017): 312.
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