ML for SS: Neural Networks for Image Classification

Session 12

Dr. Richard M. Crowley
rcrowley@smu.edu.sg
http://rmc.link/

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

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

R

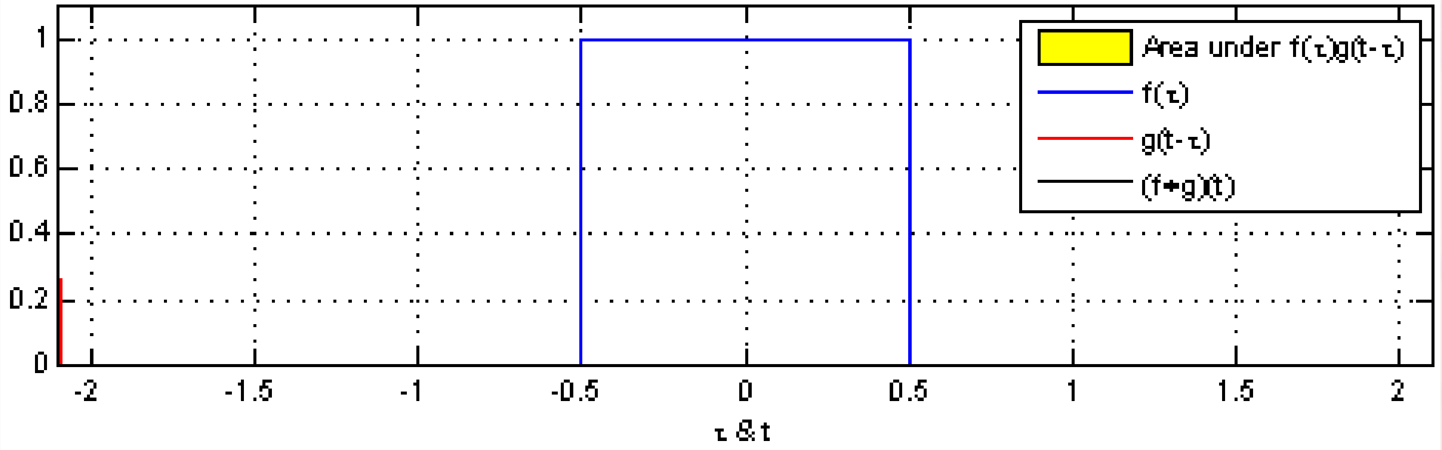
- You can use Keras from R through RStudio's package

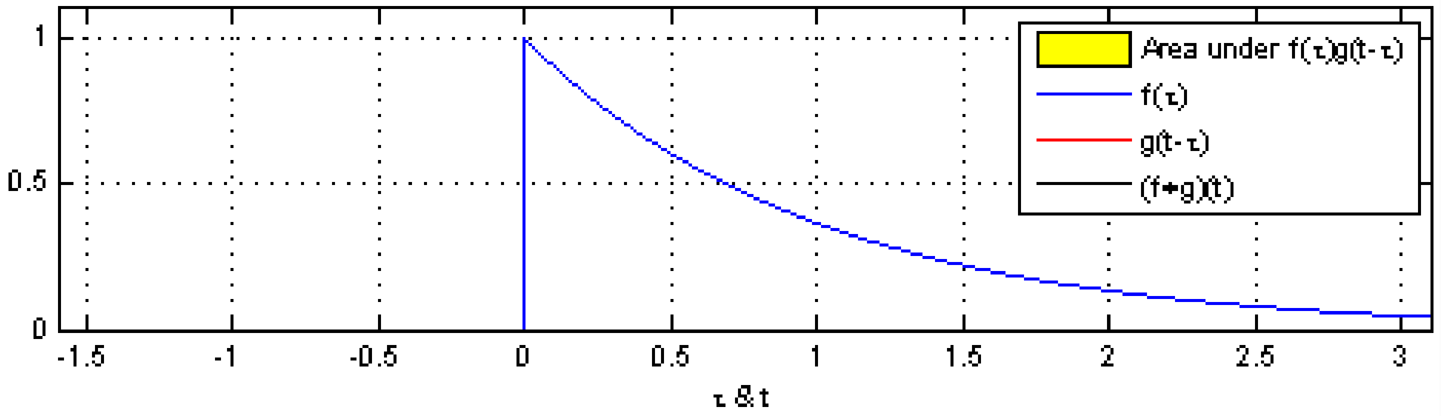
Python's support is a lot better here

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

```python
(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
```

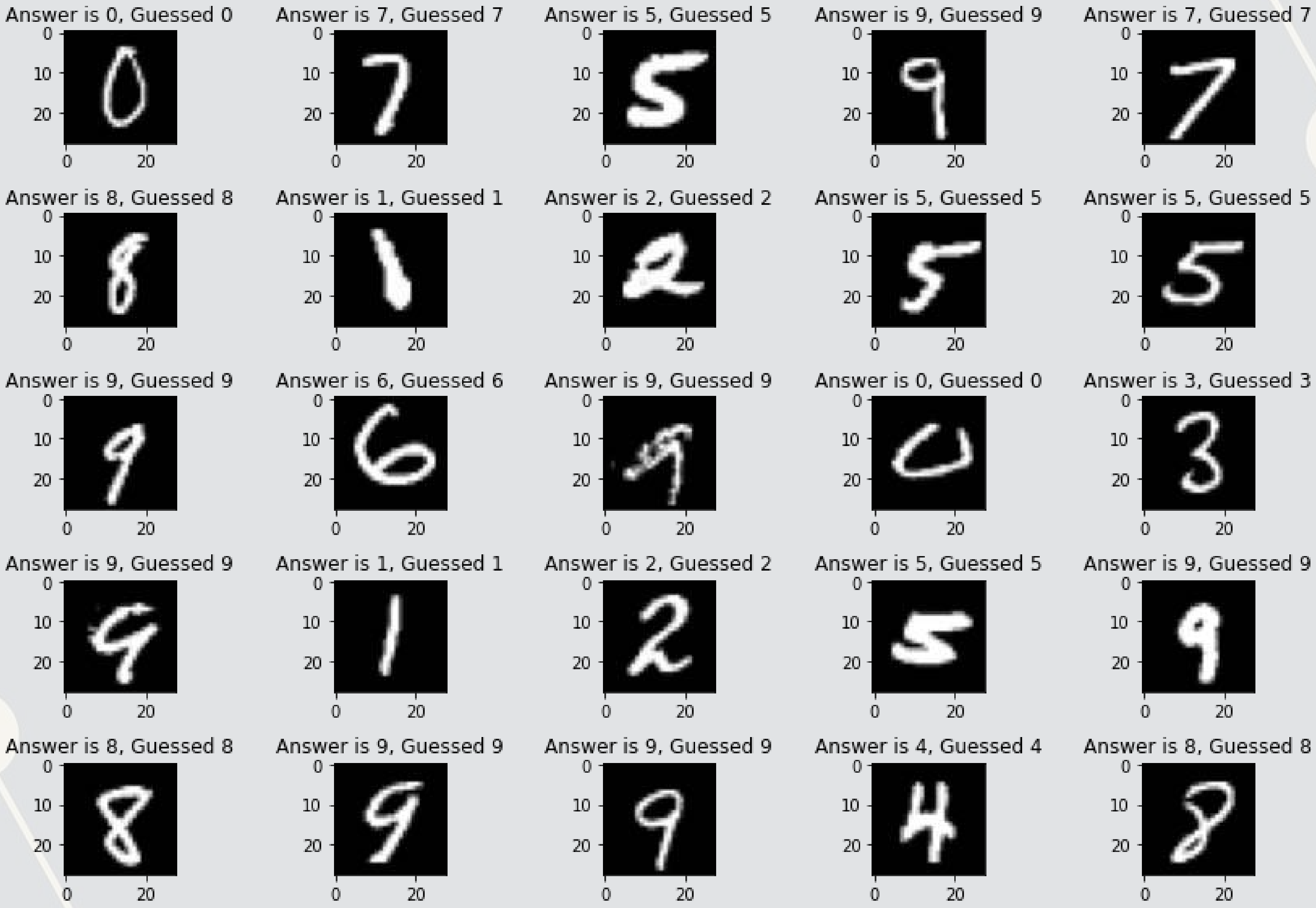
Fit the model and evaluate

- Fitting and evaluating is the same as before

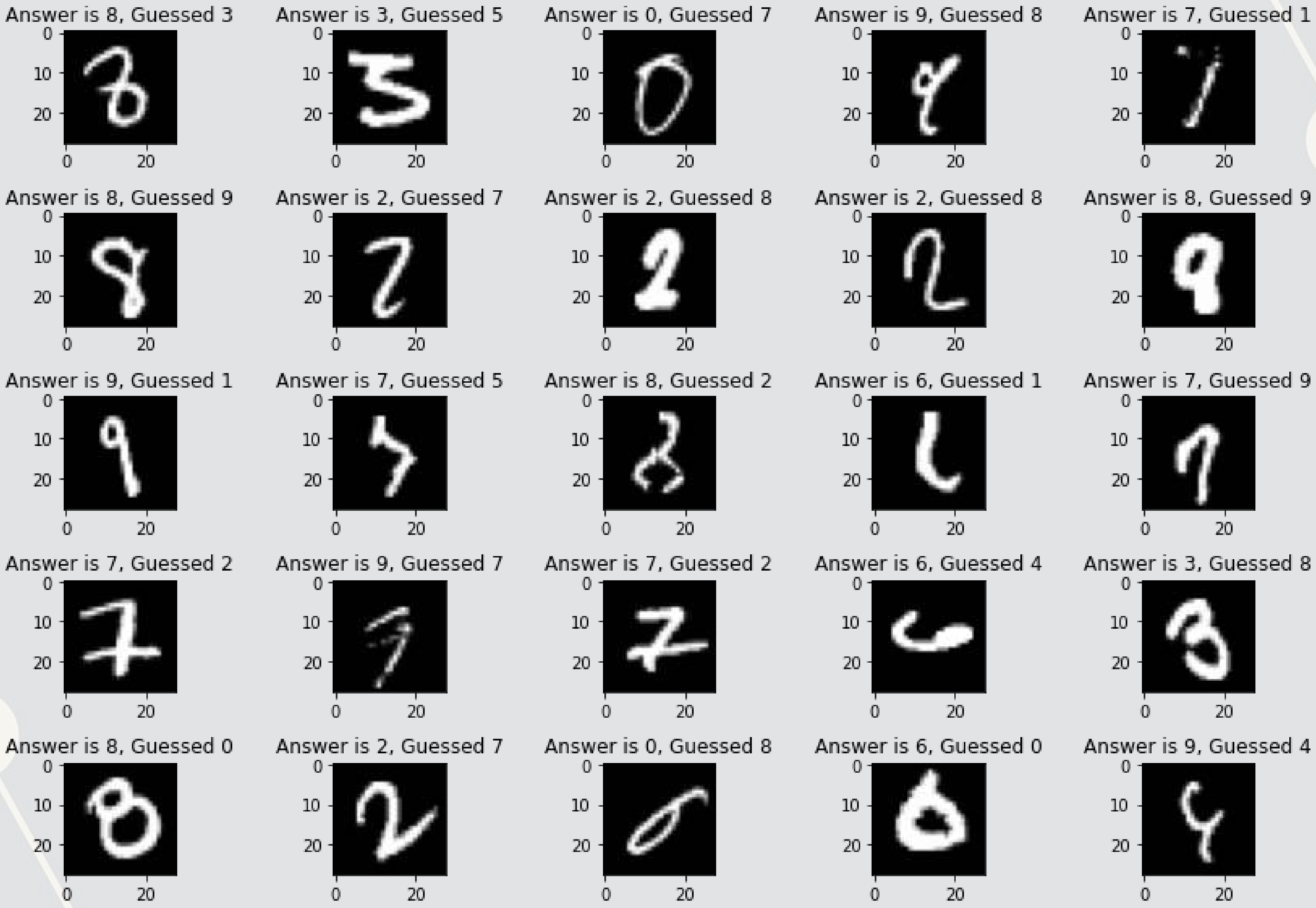
```python
batch_size = 128
epochs = 10

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

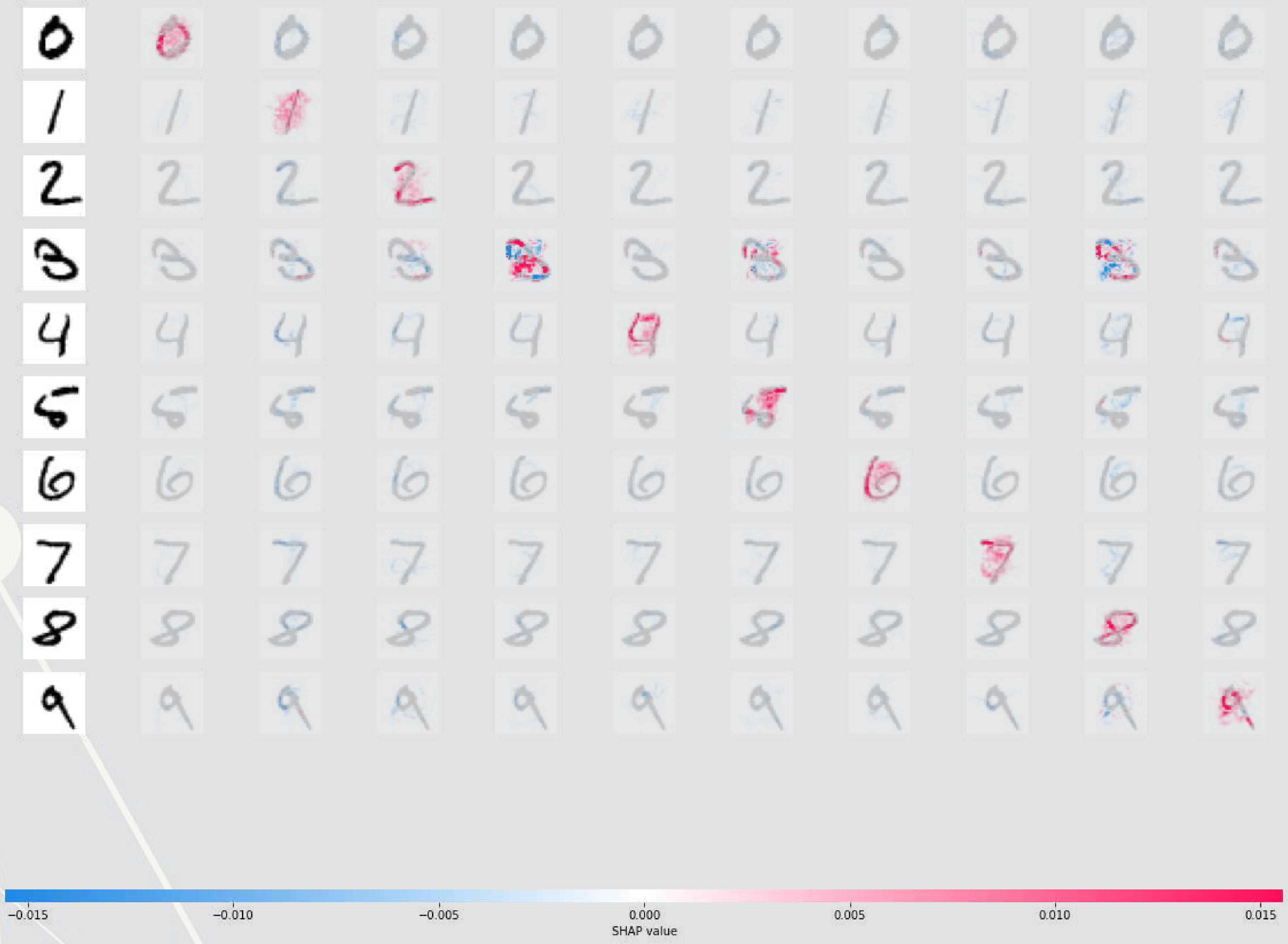
```python
images = np.random.randint(0, train_X.shape[0], size=25)
e = shap.DeepExplainer(model_cnn, train_X[images])
```

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

```python
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

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



SHAP for incorrect images

```python
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

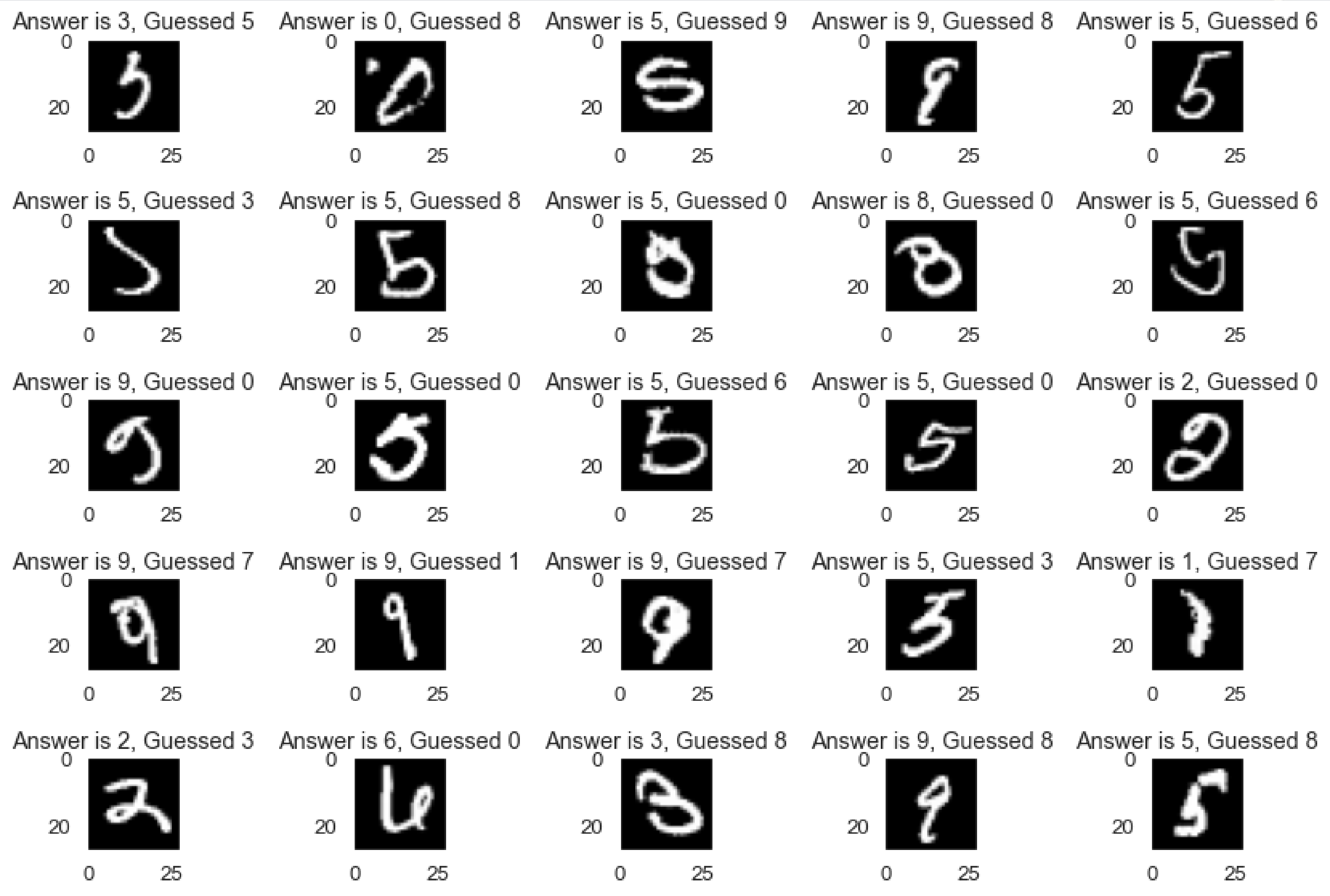
> We will look at TensorFlow Hub today

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))
```

Examine incorrect answers



Object detection off-the-shelf

COCO Classification problem

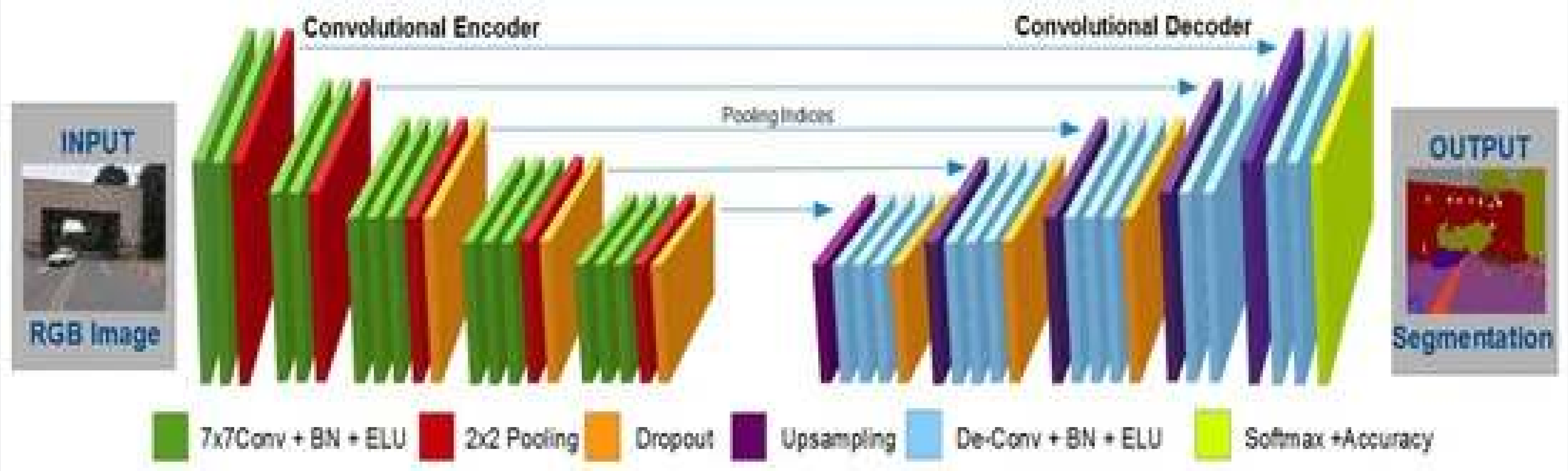
- There are a lot of options for this
- We will use a model trained on COCO from CenterNet
  - centernet/hourglass_512x512
- This can detect 80 different object types, including people

```python
# 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']
```

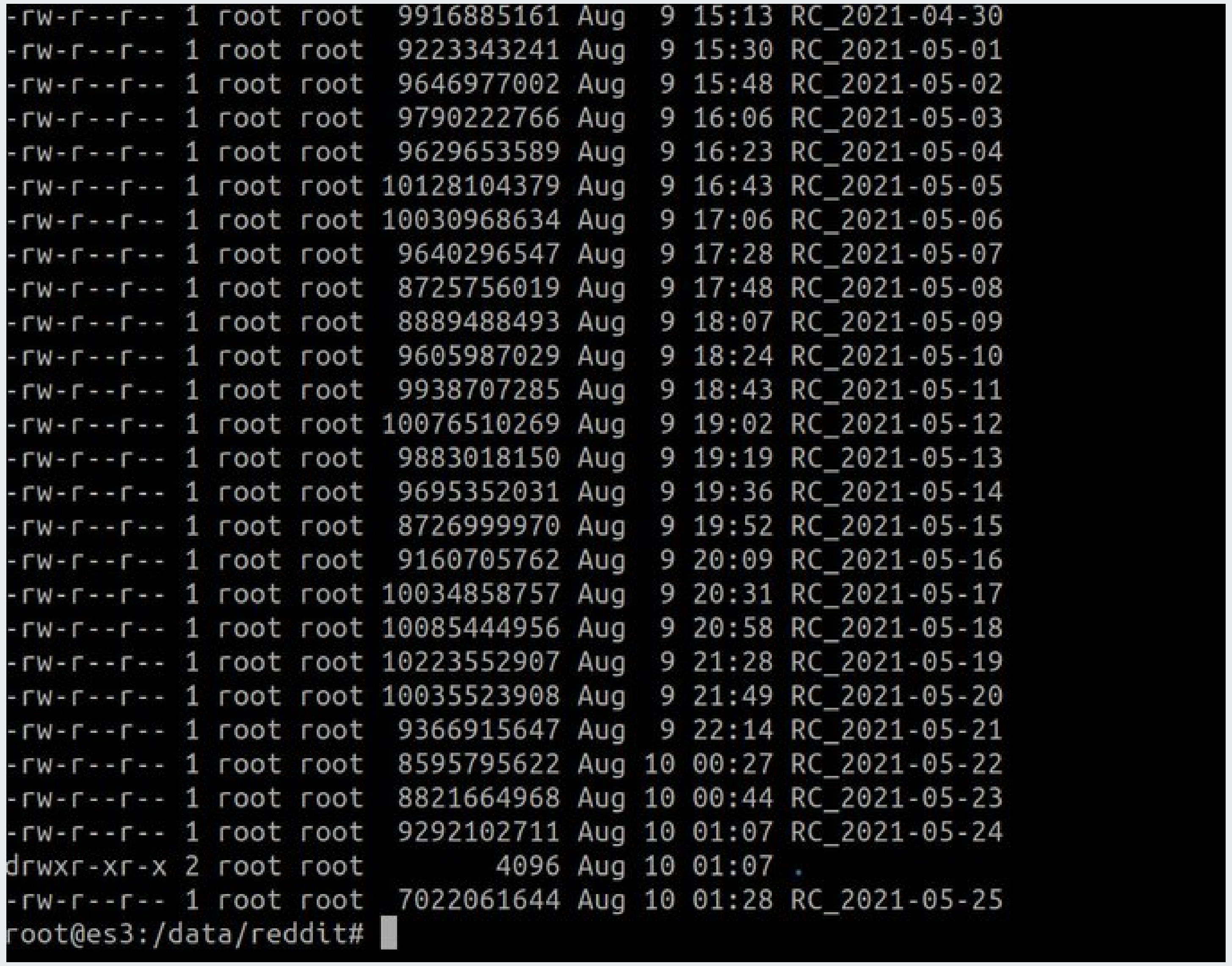
What is Centernet/Hourglass?

- 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

```python
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

```python
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

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

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

```python
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

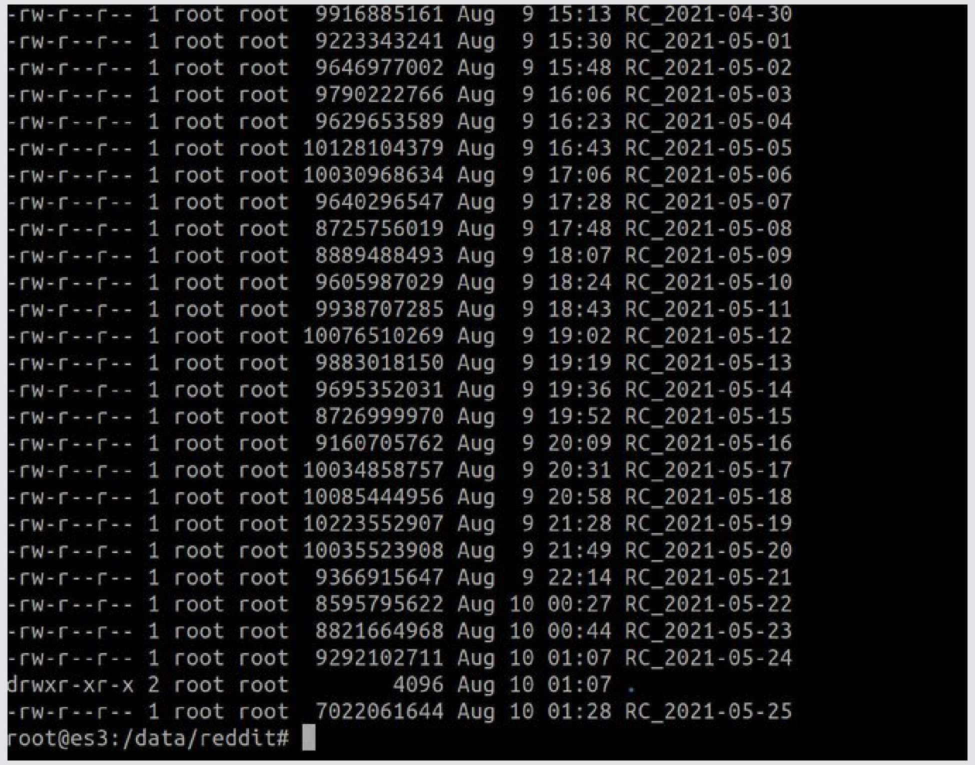
```python
results = centernet(image2_np)
result = {key:value.numpy() for key,value in results.items()}
```

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

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

```python
prob_person(result)
```

```
## No person found
```



```
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-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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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 unavailable

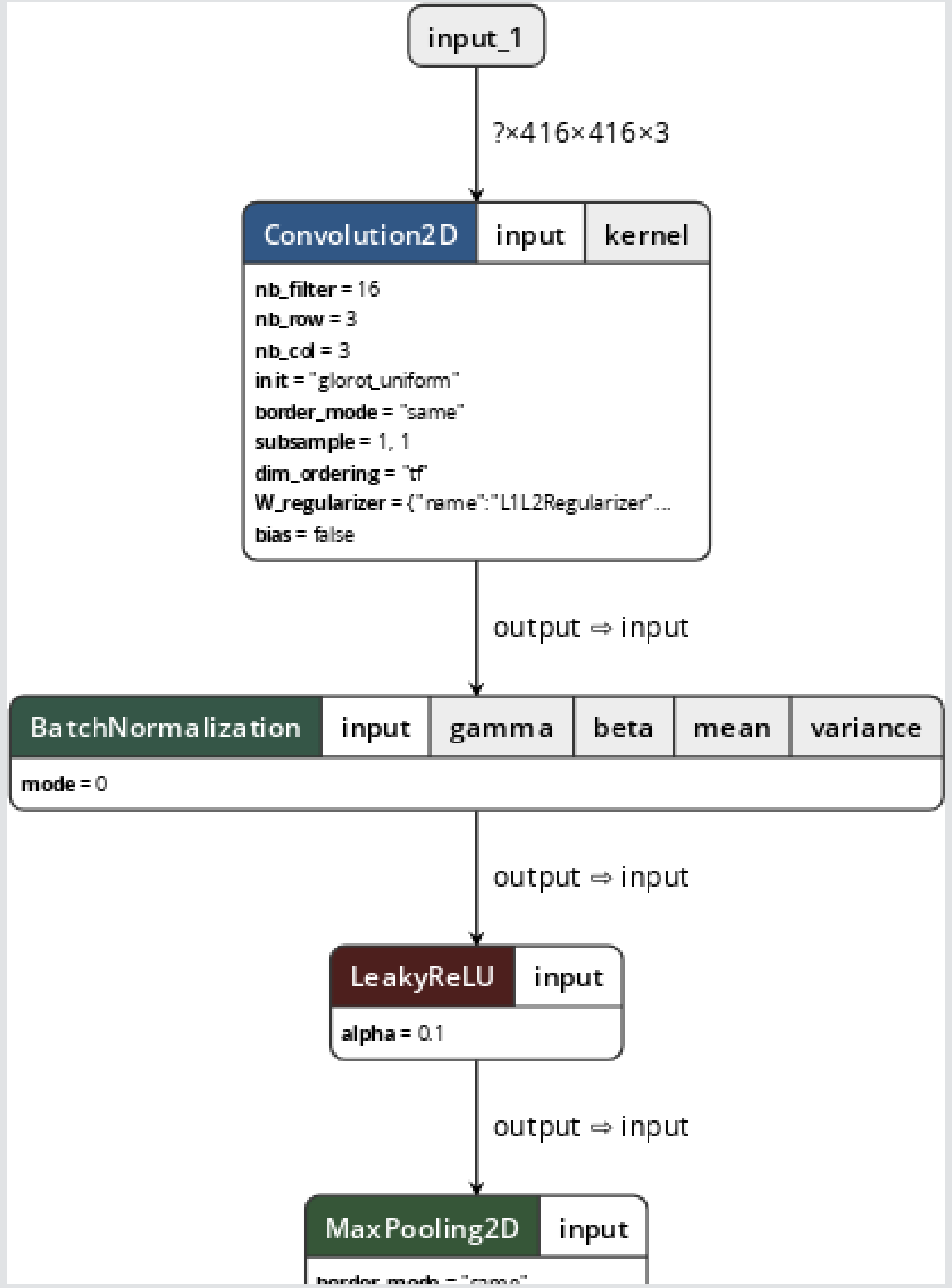
Watch on YouTube

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?

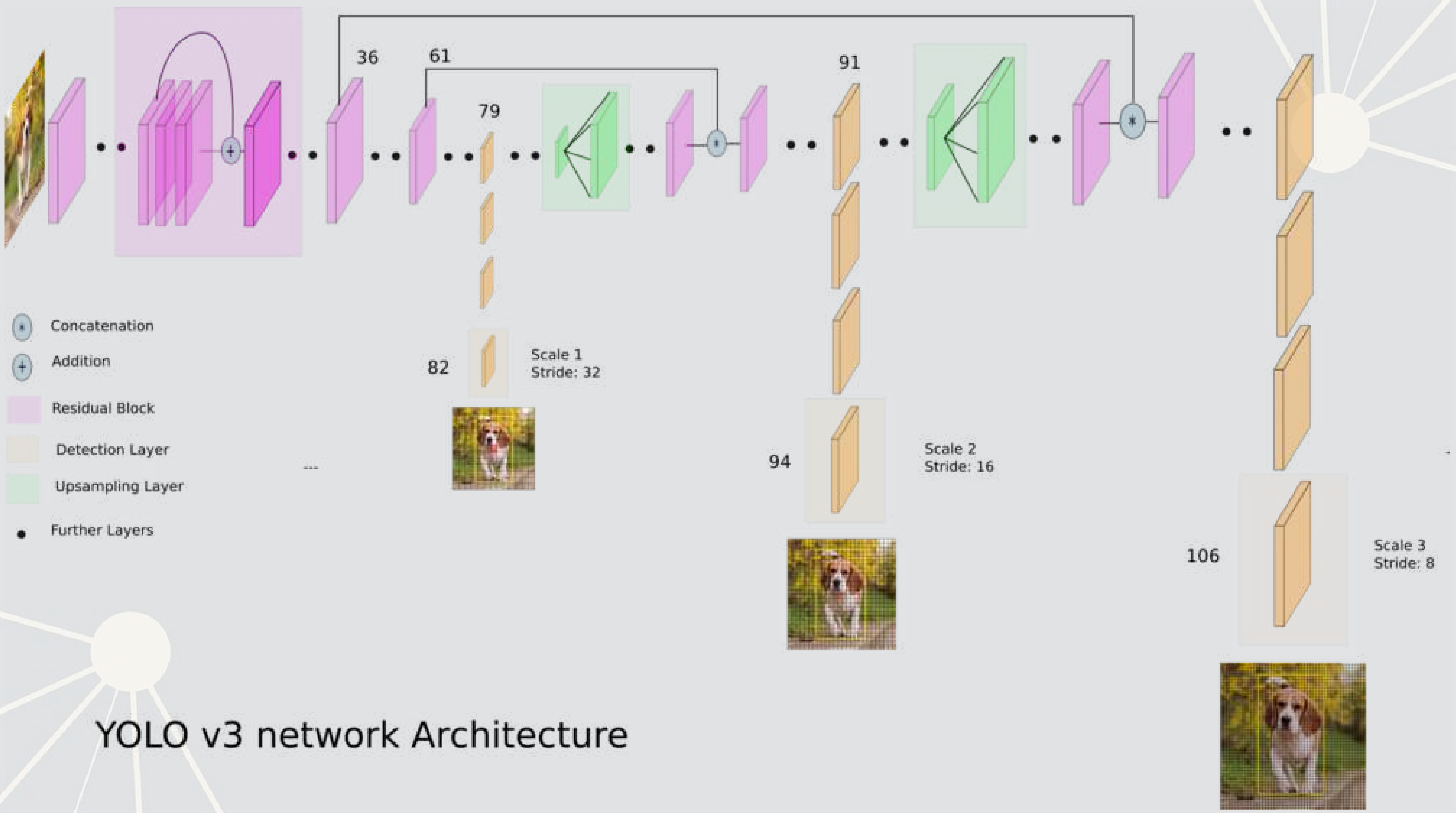


Diagram from *What's new in YOLO v3* by Ayoosh Kathuria

Final word on object detection

- 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

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

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)

What remains

- Assignment 2
  - New due date: **November 30th**
  - You are welcome to submit earlier
    - If you want t finalize your submission and get earlier feedback, email me to let me know
- Assignment 3
  - Will be posted soon
  - Shorter than the other assignments
  - Focuses on image detection and classification
  - Online hosted tools will be available in case you can't get a local copy of tensorflow to work
  - 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

References

- Liu, Liu, Daria Dzyabura, and Natalie Mizik. “Visual listening in: Extracting brand image portrayed on social media.” Marketing Science 39, no. 4 (2020): 669-686.
- Zhang, Shunyuan, Dokyun DK Lee, Param Vir Singh, and Kannan Srinivasan. “How much is an image worth? Airbnb property demand estimation leveraging large scale image analytics.” Airbnb Property Demand Estimation Leveraging Large Scale Image Analytics (May 25, 2021) (2021).
- 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.
- Zhou, Xingyi, Dequan Wang, and Philipp Krähenbühl. “Objects as points.” arXiv preprint arXiv:1904.07850 (2019).