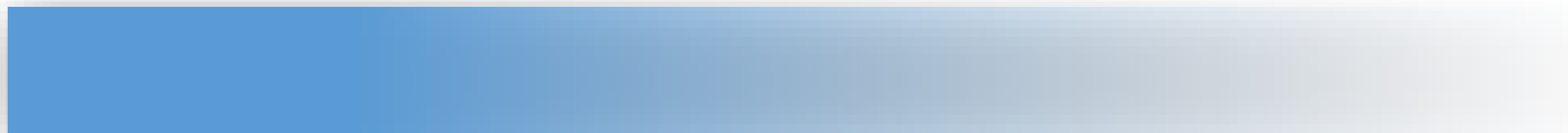




Image Classification And Object Detection



For researchers interested in studying
Earth science with deep learning.

All resources in lectures are available at
<https://github.com/MrXiaoXiao/DLiES>

Deep Learning in Earth Science
Lecture 2
By Xiao Zhuowei

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Build Networks with High-level API

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**Classification with
Convolutional Neural Networks**

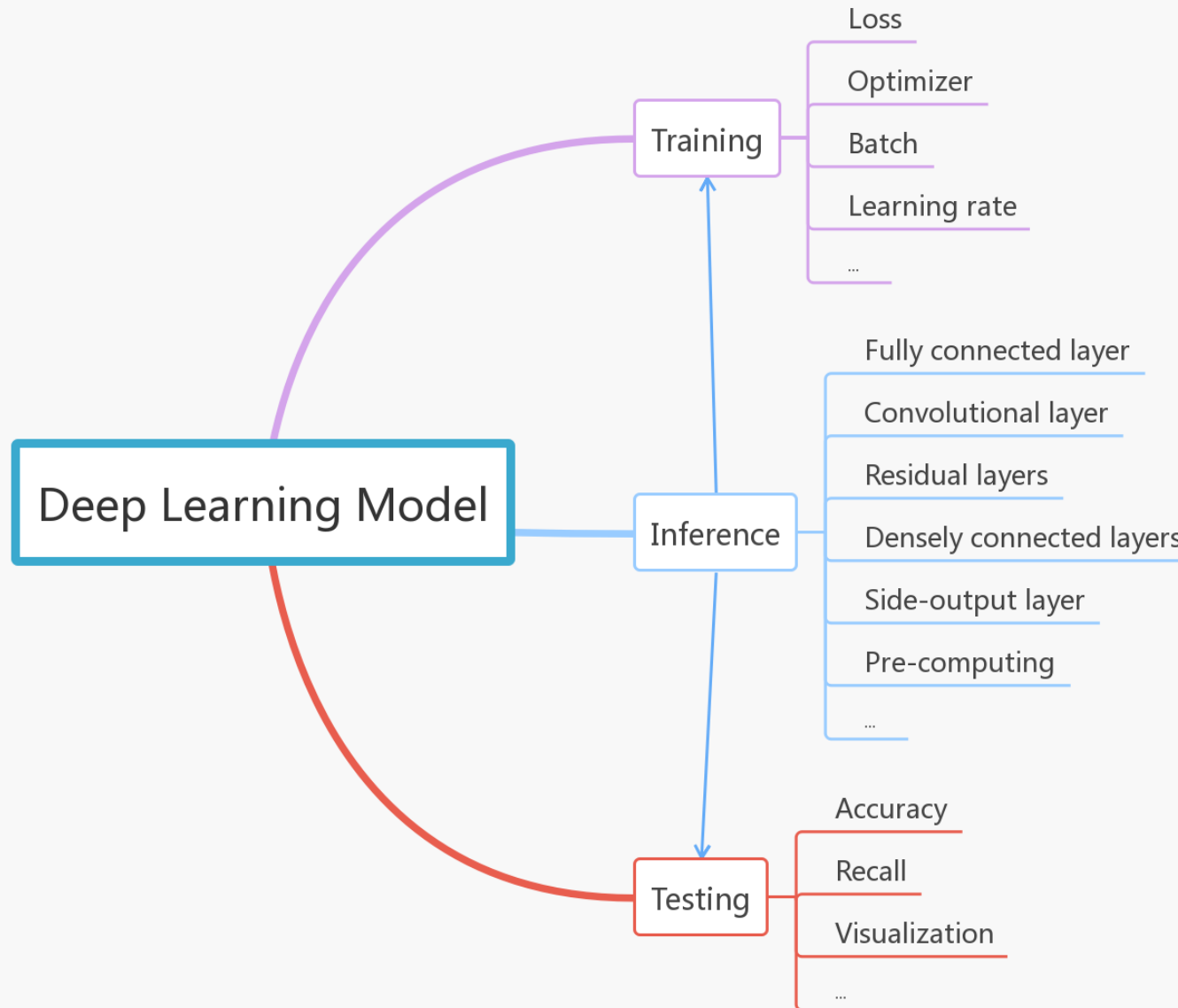
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Build Networks with High-level API



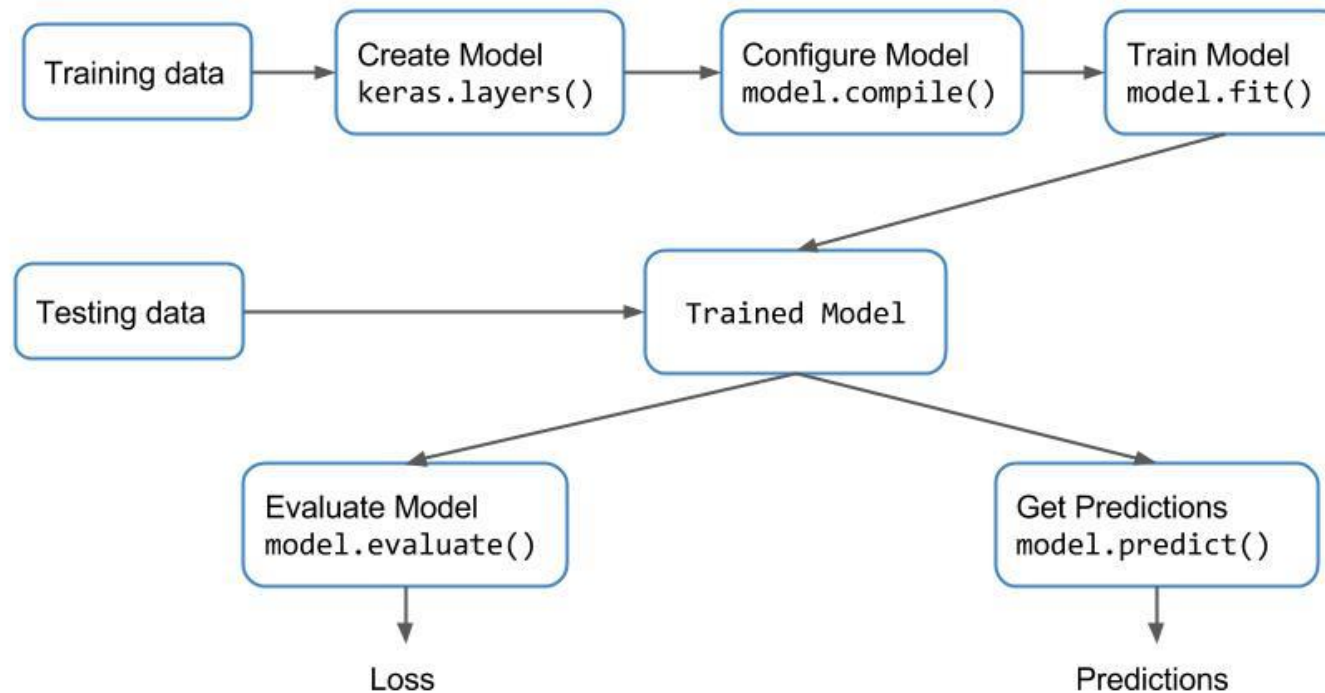


Keras

Keras is a high-level neural networks API, written in Python and capable of running on top of [TensorFlow](#), [CNTK](#), or [Theano](#). It was developed with a focus on enabling fast experimentation.

Being able to go from idea to result with the least possible delay is key to doing good research.

Keras Workflow



Getting started with the Keras

Prepare dataset

```
import tensorflow as tf
from tensorflow.keras.datasets import cifar10
#train and test using cifar10 dataset
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
print('x_train shape:', x_train.shape)
print(x_train.shape[0], 'train samples')
print(x_test.shape[0], 'test samples')

#Preprocessing
x_train = x_train.astype('float32')
x_test = x_test.astype('float32')
x_train /= 255
x_test /= 255

num_classes = 10

# Convert class vectors to binary class matrices.
y_train = tf.keras.utils.to_categorical(y_train, num_classes)
y_test = tf.keras.utils.to_categorical(y_test, num_classes)

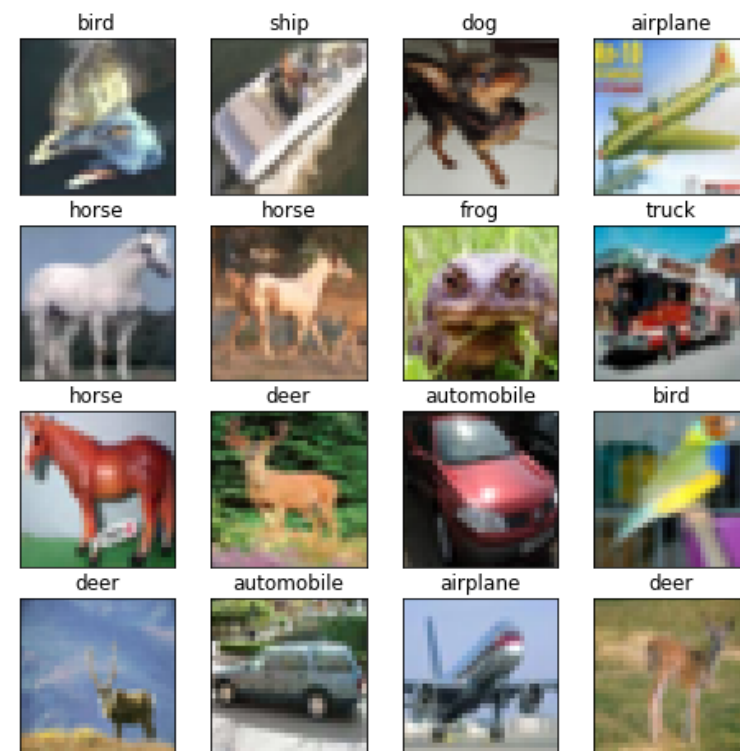
/home/wangj/anaconda3/envs/DLIES/lib/python3.6/importlib/_bootstrap.py:219: RuntimeWarning: numpy.dtype size changed, may indicate binary incompatibility. Expected 88 from C header, got 96 from PyObject
return f(*args, **kwargs)

x_train shape: (50000, 32, 32, 3)
50000 train samples
10000 test samples
```

Check dataset

```
import matplotlib.pyplot as plt
import numpy as np
plt.figure(figsize=(8,8))
class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer',
               'dog', 'frog', 'horse', 'ship', 'truck']

for i in range(16):
    plt.subplot(4, 4, 1 + i, xticks=[], yticks=[])
    img_id = np.random.randint(50000)
    im = x_train[img_id, :]
    plt.title(class_names[y_train[img_id].argmax()])
    plt.imshow(im)
plt.show()
```

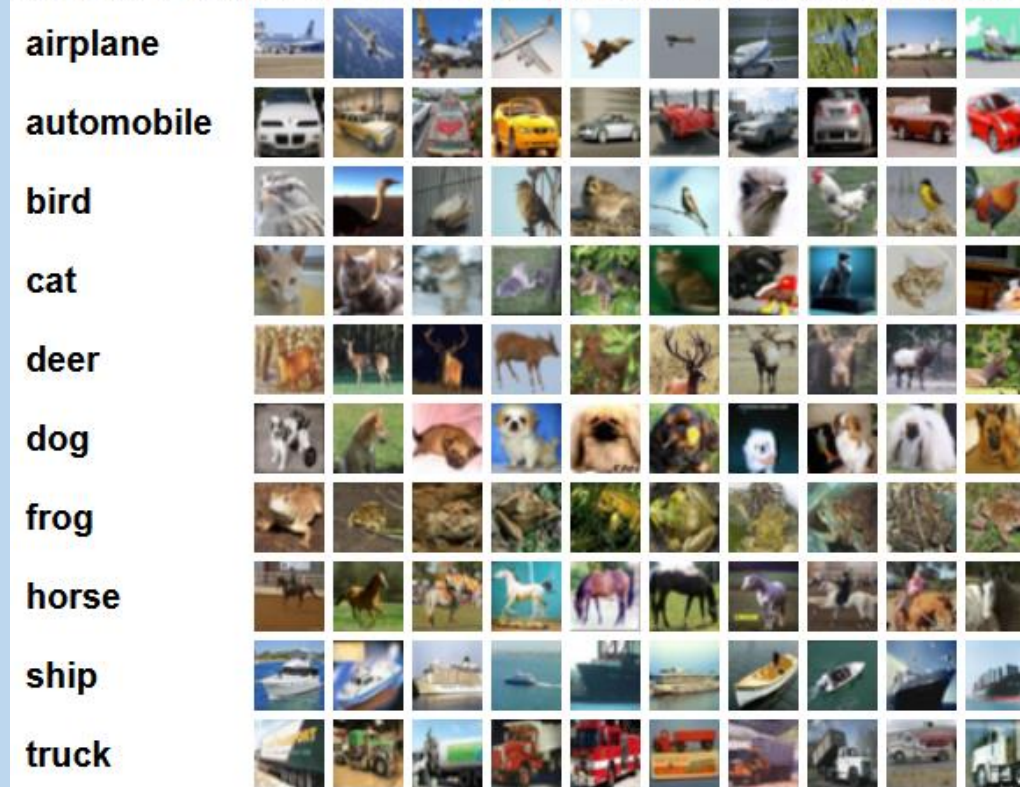


The CIFAR-10 dataset

The CIFAR-10 dataset consists of 60000 32x32 colour images in 10 classes, with 6000 images per class. There are 50000 training images and 10000 test images.

<http://www.cs.toronto.edu/~kriz/cifar.html>

Here are the classes in the dataset, as well as 10 random images from each:



Getting started with the Keras

Create a model

```
In [4]: #The Sequential model is a linear stack of layers.  
model = tf.keras.Sequential()
```

Add layers

```
In [5]: from tensorflow.keras.layers import Dense, Dropout, Activation, Flatten  
from tensorflow.keras.layers import Conv2D, MaxPooling2D  
#You can also simply add layers via the .add() method  
model.add(Conv2D(32, (3, 3), padding='same', input_shape=x_train.shape[1:],  
                activation='relu'))  
model.add(Conv2D(32, (3, 3), activation='relu'))  
model.add(MaxPooling2D(pool_size=(2, 2)))  
model.add(Dropout(0.25))  
model.add(Conv2D(64, (3, 3), padding='same', activation='relu'))  
model.add(Activation('relu'))  
model.add(Conv2D(64, (3, 3), padding='same', activation='relu'))  
model.add(MaxPooling2D(pool_size=(2, 2)))  
model.add(Dropout(0.25))  
  
model.add(Flatten())  
model.add(Dense(512, activation='relu'))  
model.add(Dropout(0.5))  
model.add(Dense(10, activation='softmax'))
```


Build Networks with High-level API

Getting started with the Keras

```
In [6]: print(model.summary())
```

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 32, 32, 32)	896
conv2d_1 (Conv2D)	(None, 32, 32, 32)	9248
max_pooling2d (MaxPooling2D)	(None, 16, 16, 32)	0
dropout (Dropout)	(None, 16, 16, 32)	0
conv2d_2 (Conv2D)	(None, 16, 16, 64)	18496
activation (Activation)	(None, 16, 16, 64)	0
conv2d_3 (Conv2D)	(None, 16, 16, 64)	36928
max_pooling2d_1 (MaxPooling2D)	(None, 8, 8, 64)	0
dropout_1 (Dropout)	(None, 8, 8, 64)	0

Initiate optimizer

```
In [7]: opt = tf.keras.optimizers.Adam()
```

Configure model

```
In [8]: #Before training a model, you need to configure the learning process, which is done via the compile method.
model.compile(loss='categorical_crossentropy',
              optimizer=opt,
              metrics=['accuracy'])
```

Build Networks with High-level API

Train model

```
In [9]: #Keras models are trained on Numpy arrays of input data and labels.
#For training a model, you will typically use the fit function.
history = model.fit(x_train, y_train,
                    batch_size=32,
                    epochs=10,
                    shuffle=True)

Epoch 1/10
50000/50000 [=====] - 21s 424us/step - loss: 1.5485 - acc: 0.4335
Epoch 2/10
50000/50000 [=====] - 14s 285us/step - loss: 1.1393 - acc: 0.5926
Epoch 3/10
50000/50000 [=====] - 14s 283us/step - loss: 0.9782 - acc: 0.6532
Epoch 4/10
50000/50000 [=====] - 14s 277us/step - loss: 0.8747 - acc: 0.6925
Epoch 5/10
50000/50000 [=====] - 14s 281us/step - loss: 0.8105 - acc: 0.7142
Epoch 6/10
50000/50000 [=====] - 14s 277us/step - loss: 0.7452 - acc: 0.7386
Epoch 7/10
50000/50000 [=====] - 14s 278us/step - loss: 0.7060 - acc: 0.7504
Epoch 8/10
50000/50000 [=====] - 14s 276us/step - loss: 0.6683 - acc: 0.7654
Epoch 9/10
50000/50000 [=====] - 13s 266us/step - loss: 0.6360 - acc: 0.7778
Epoch 10/10
50000/50000 [=====] - 14s 273us/step - loss: 0.6098 - acc: 0.7857
```

Test model

```
In [10]: # test trained model.
scores = model.evaluate(x_test, y_test, verbose=1)

print('Test loss:', scores[0])
print('Test accuracy:', scores[1])

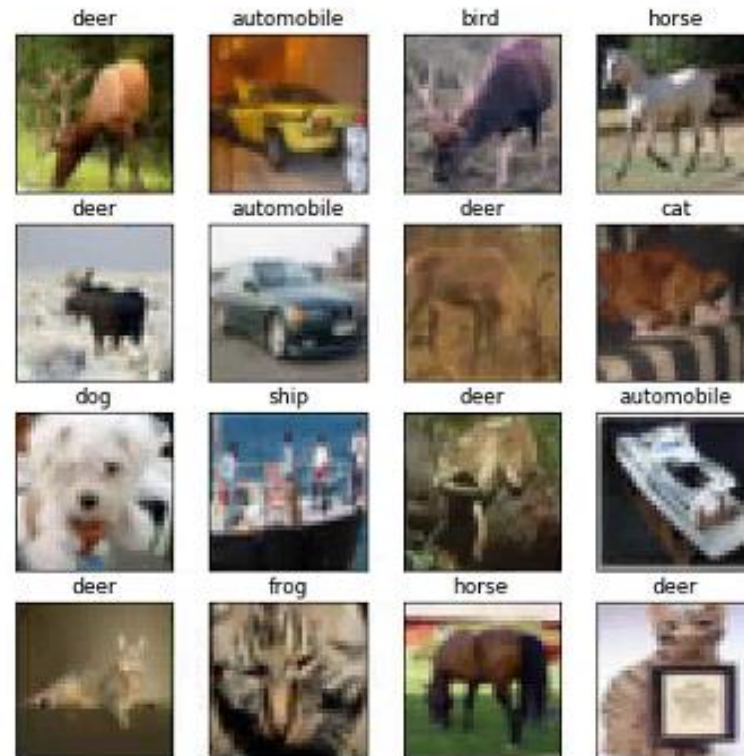
10000/10000 [=====] - 1s 114us/step
Test loss: 0.6621272174358368
Test accuracy: 0.7711
```

Build Networks with High-level API

Check predictions

```
In [11]: preds = model.predict(x_test)
plt.figure(figsize=(8,8))

for i in range(16):
    plt.subplot(4, 4, 1 + i, xticks=[], yticks=[])
    img_id = np.random.randint(10000)
    im = x_test[img_id,:]
    plt.title(class_names[preds[img_id].argmax()])
    plt.imshow(im)
plt.show()
```



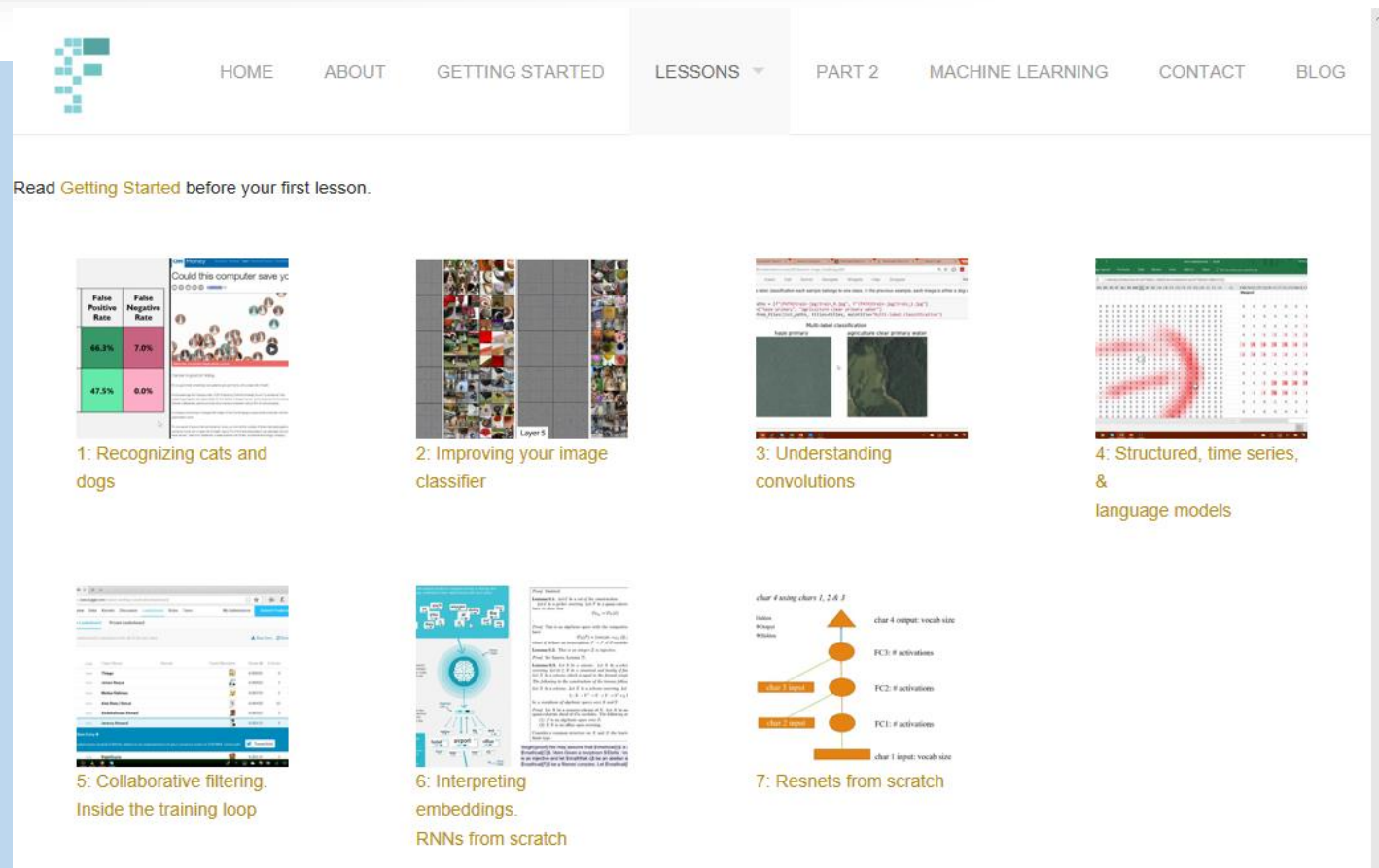
Build Networks with High-level API

fast.ai

Making neural nets
uncool again

<https://www.fast.ai/>

If you can code,
you can do deep learning.



Read [Getting Started](#) before your first lesson.

- 1: Recognizing cats and dogs
- 2: Improving your image classifier
- 3: Understanding convolutions
- 4: Structured, time series, & language models
- 5: Collaborative filtering. Inside the training loop
- 6: Interpreting embeddings. RNNs from scratch
- 7: Resnets from scratch

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DeepSat (SAT-6) Airborne Dataset

405,000 image patches each of size
28x28 and covering 6 landcover
classes

<https://www.kaggle.com/crawford/deepsat-sat6>



Kaggle is an online community of data scientists and machine learners, owned by Google, Inc. Kaggle allows users to find and publish data sets, explore and build models in a web-based data-science environment, work with other data scientists and machine learning engineers, and enter competitions to solve data science challenges

Classifying Satellite Images

Prepare dataset

```
#require panadas
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import numpy as np

# Method to load data and images
def load_data_and_labels(data, labels):
    data_df = pd.read_csv(data, header=None)
    X = data_df.values.reshape((-1, 28, 28, 4)).clip(0, 255).astype(np.uint8)
    labels_df = pd.read_csv(labels, header=None)
    Y = labels_df.values.getfield(dtype=np.int8)
    return X, Y

data_dir = 'F:/deepsat_sat6'

x_train, y_train = load_data_and_labels(data='{}/X_train_sat6.csv'.format(data_dir),
                                         labels='{}/y_train_sat6.csv'.format(data_dir))
x_test, y_test = load_data_and_labels(data='{}/X_test_sat6.csv'.format(data_dir),
                                       labels='{}/y_test_sat6.csv'.format(data_dir))

print(pd.read_csv('{}/sat6annotations.csv'.format(data_dir), header=None))

# Print shape of all training, testing data and labels
# Labels are already loaded in one-hot encoded format
print('x_train_shape : {}'.format(x_train.shape)) # (324000, 28, 28, 4)
print('y_train_shape : {}'.format(y_train.shape)) # (324000, 6)
print('x_test_shape : {}'.format(x_test.shape))   # (81000, 28, 28, 4)
print('y_test_shape : {}'.format(y_test.shape))   # (81000, 6)
```

	0	1	2	3	4	5	6
0 building	1	0	0	0	0	0	0
1 barren_land	0	1	0	0	0	0	0
2 trees	0	0	1	0	0	0	0
3 grassland	0	0	0	1	0	0	0
4 road	0	0	0	0	1	0	0
5 water	0	0	0	0	0	0	1

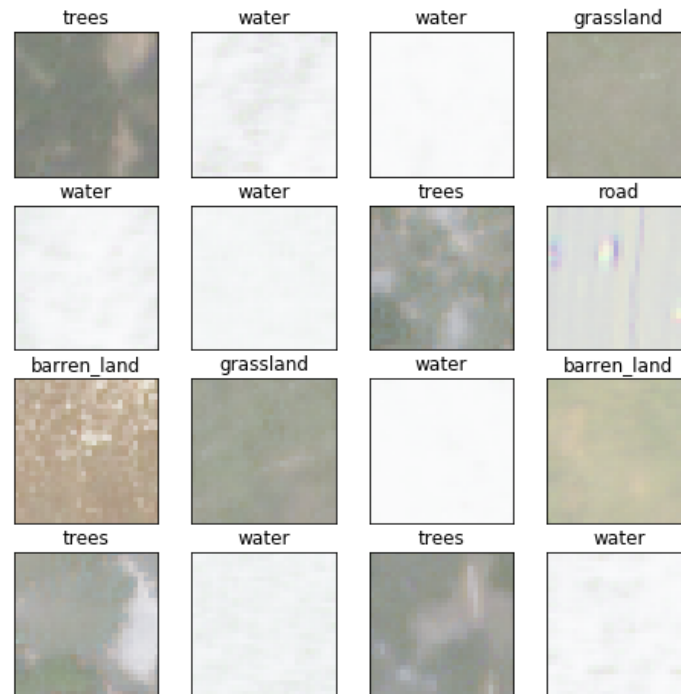
```
x_train_shape : (324000, 28, 28, 4)
y_train_shape : (324000, 6)
x_test_shape : (81000, 28, 28, 4)
y_test_shape : (81000, 6)
```

Classifying Satellite Images

Check dataset

```
import matplotlib.pyplot as plt
plt.figure(figsize=(8,8))
class_names = ['building', 'barren_land', 'trees',
               'grassland', 'road', 'water']

for i in range(16):
    plt.subplot(4, 4, 1 + i, xticks=[], yticks=[])
    img_id = np.random.randint(324000)
    im = x_train[img_id, :]
    plt.title(class_names[y_train[img_id].argmax()])
    plt.imshow(im)
plt.show()
```



Classifying Satellite Images

Create model

```
import tensorflow as tf
from tensorflow.keras.layers import Conv2D, MaxPool2D, Dense, Dropout, Flatten
from tensorflow.keras.models import Sequential

#Create model
model = Sequential()

#Add layers
model.add(Conv2D(16, (3,3), activation='relu', input_shape=(28,28,4)))
model.add(Conv2D(32, (3,3), activation='relu'))
model.add(MaxPool2D(pool_size=(2,2)))
model.add(Dropout(0.5))
model.add(Conv2D(32, (3,3), activation='relu'))
model.add(Conv2D(64, (3,3), activation='relu'))
model.add(MaxPool2D(pool_size=(2,2)))
model.add(Dropout(0.5))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(6, activation='softmax'))

#configure model
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

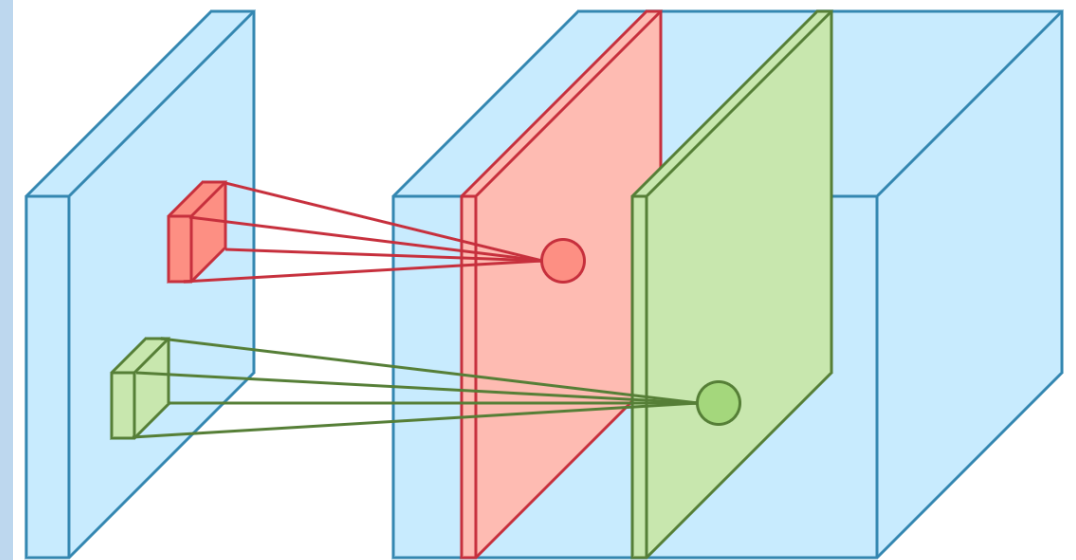
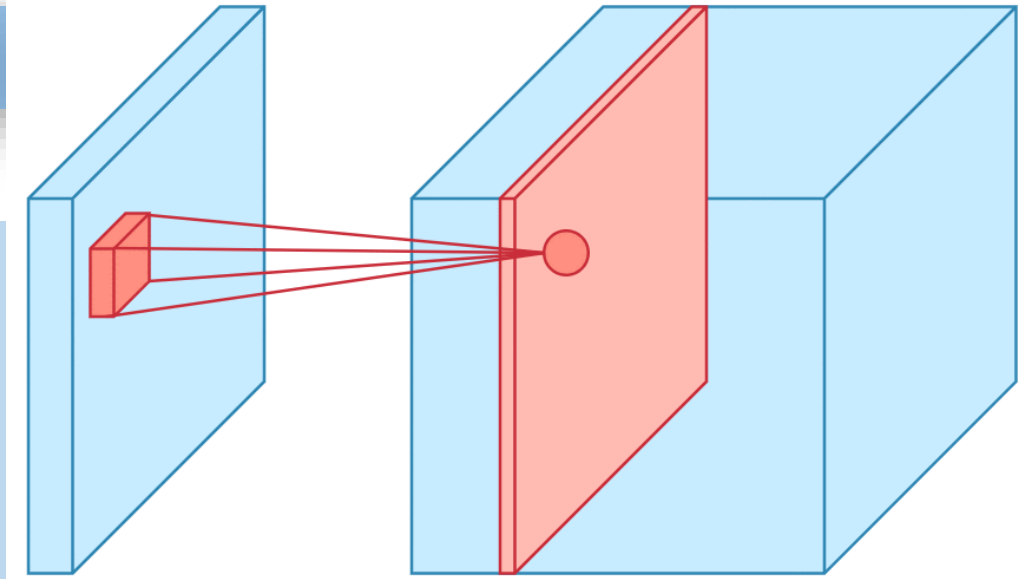
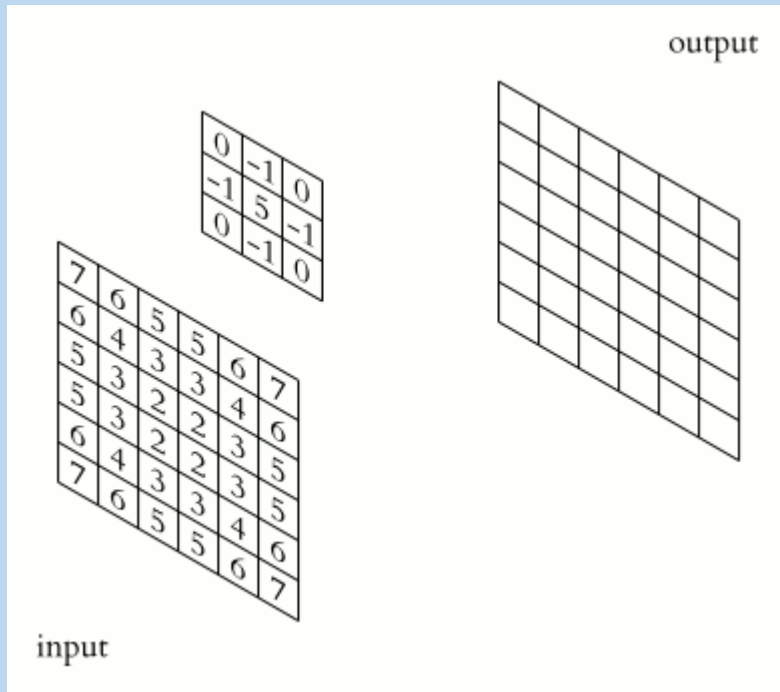
print(model.summary())
```

Classifying Satellite Images

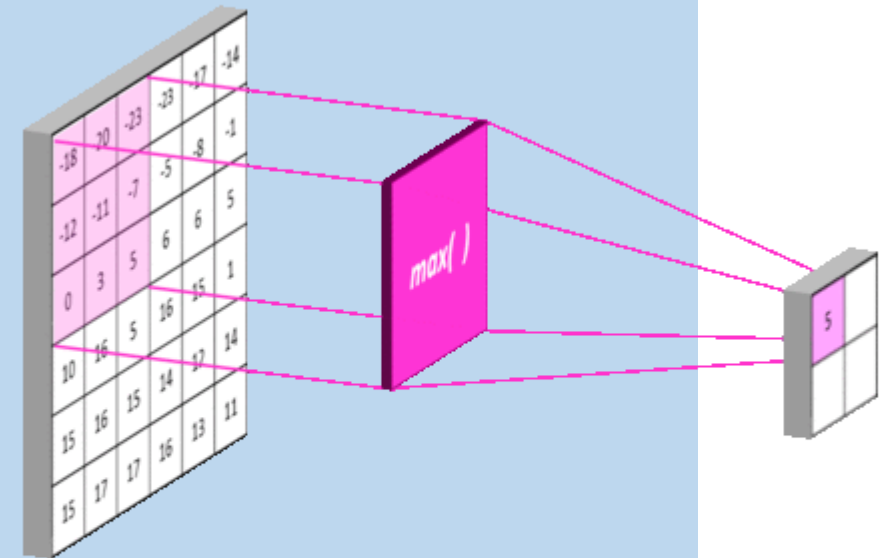
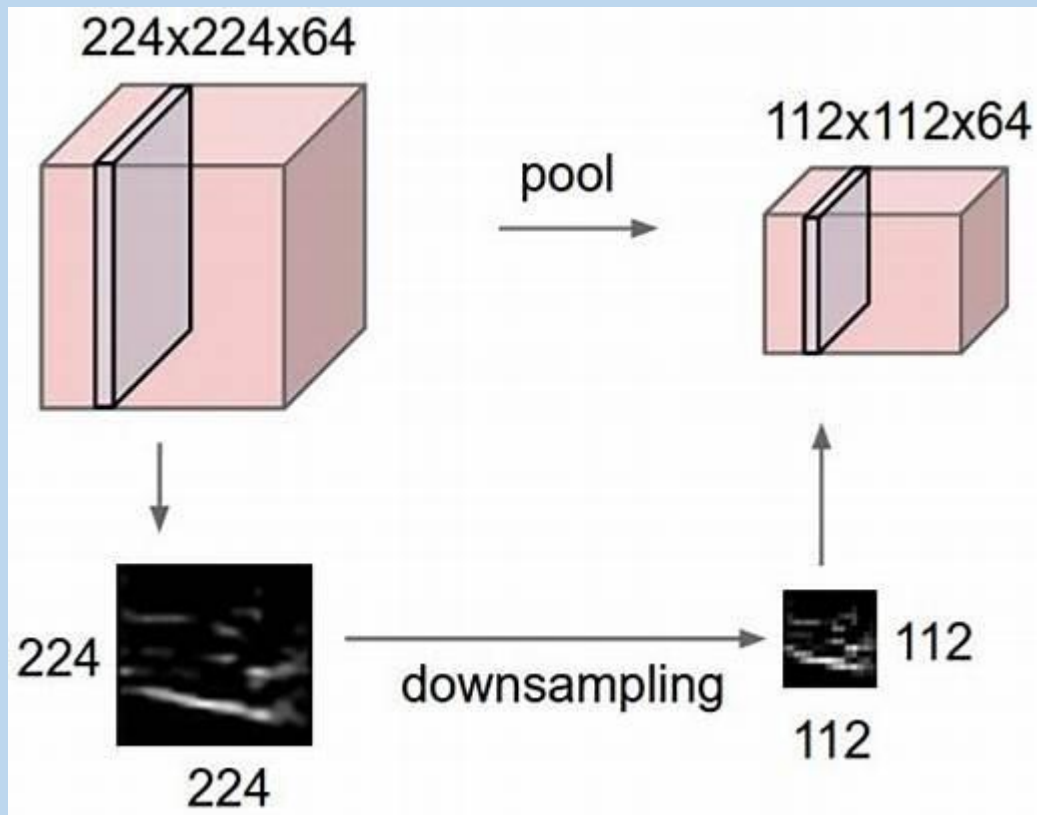
Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 26, 26, 16)	592
conv2d_1 (Conv2D)	(None, 24, 24, 32)	4640
max_pooling2d (MaxPooling2D)	(None, 12, 12, 32)	0
dropout (Dropout)	(None, 12, 12, 32)	0
conv2d_2 (Conv2D)	(None, 10, 10, 32)	9248
conv2d_3 (Conv2D)	(None, 8, 8, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 4, 4, 64)	0
dropout_1 (Dropout)	(None, 4, 4, 64)	0
flatten (Flatten)	(None, 1024)	0
dense (Dense)	(None, 128)	131200
dropout_2 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 6)	774
Total params: 164,950		
Trainable params: 164,950		
Non-trainable params: 0		
None		

Classification with Convolutional Neural Networks

Convolutional Layer



Pooling Layer



Dropout

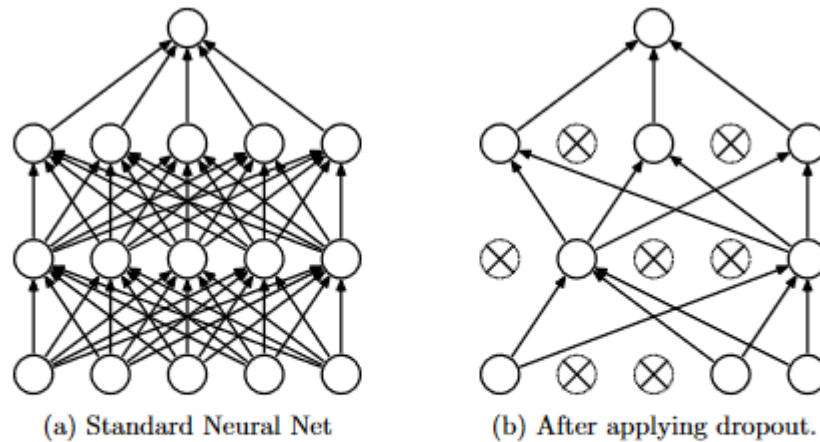
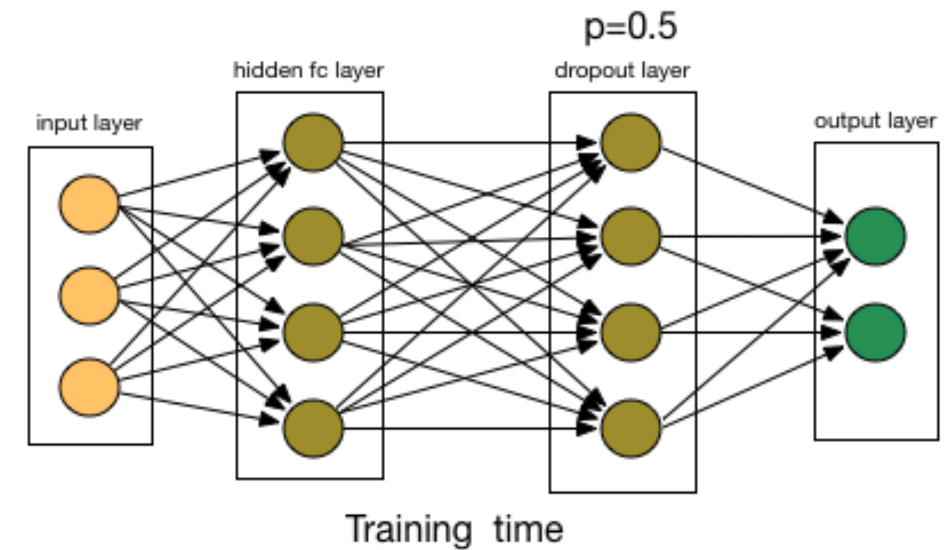


Figure 1: Dropout Neural Net Model. **Left:** A standard neural net with 2 hidden layers. **Right:** An example of a thinned net produced by applying dropout to the network on the left. Crossed units have been dropped.



(Srivastava et al., 2014)

<https://chatbotslife.com/regularization-in-deep-learning-f649a45d6e0>

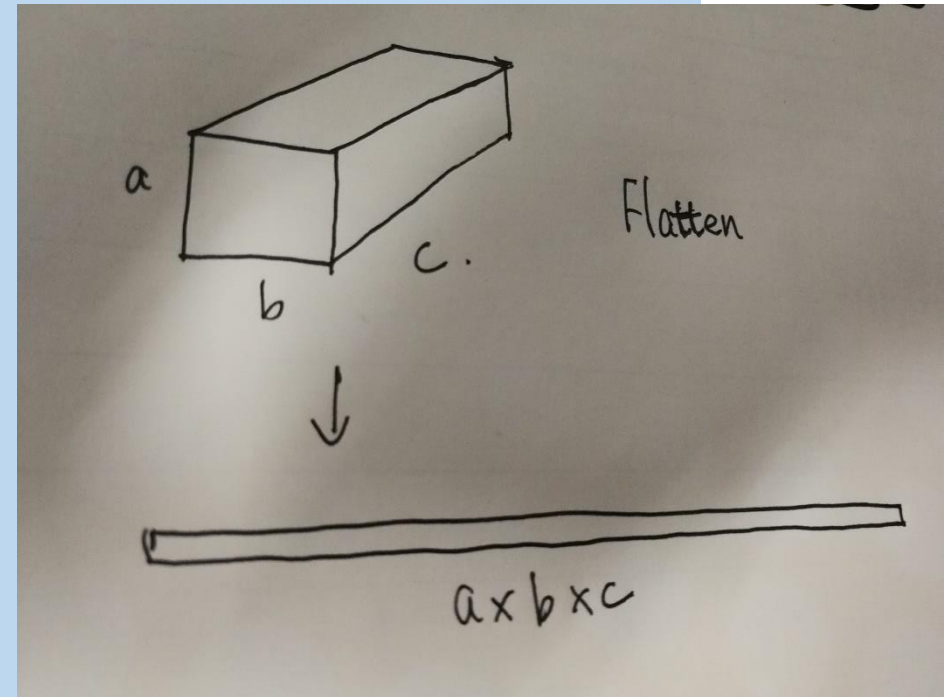
Flatten Layer

Example:

```
model = Sequential()
model.add(Convolution2D(64, 3, 3,
                        border_mode='same',
                        input_shape=(3, 32, 32)))
# now: model.output_shape == (None, 64, 32, 32)

model.add(Flatten())
# now: model.output_shape == (None, 65536)
```

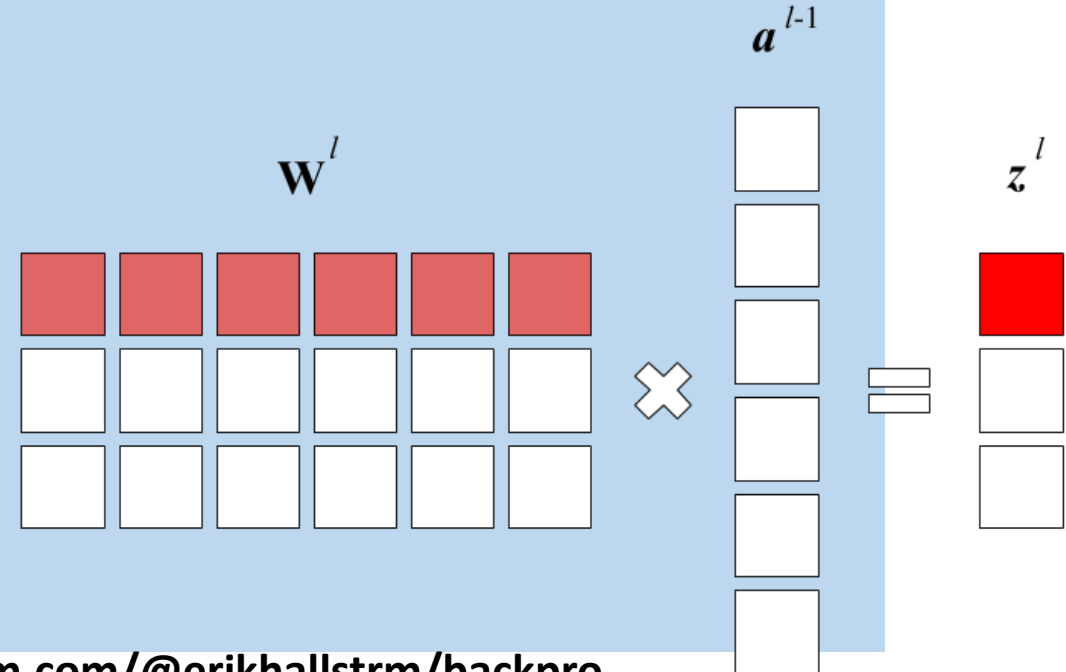
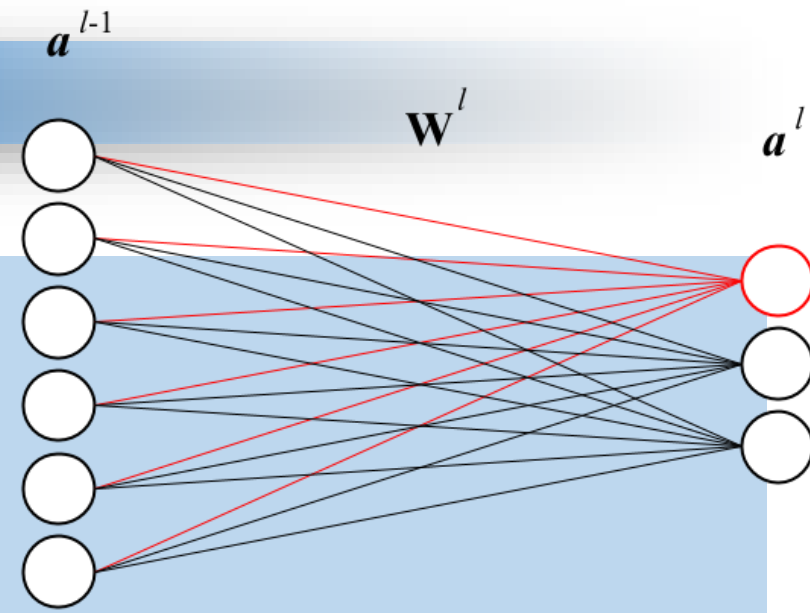
https://www.tensorflow.org/api_docs/python/tf/keras/layers/Flatten



Classification with Convolutional Neural Networks

Densely(Fully) Connected Layer

$$\mathbf{a}^l = \sigma(\mathbf{W}^l \mathbf{a}^{l-1} + \mathbf{b}^l)$$



Images From
<https://medium.com/@erikhallstrm/backpropagation-from-the-beginning-77356edf427d>

Classifying Satellite Images

Train model

```
In [5]: model.fit(x_train, y_train, batch_size=200,  
                 epochs=6, verbose=1)
```

```
Epoch 1/6  
324000/324000 [=====] - 23s 72us/step - loss: 0.4426 - acc: 0.9147  
Epoch 2/6  
324000/324000 [=====] - 17s 54us/step - loss: 0.1044 - acc: 0.9625  
Epoch 3/6  
324000/324000 [=====] - 17s 51us/step - loss: 0.0762 - acc: 0.9736  
Epoch 4/6  
324000/324000 [=====] - 17s 52us/step - loss: 0.0676 - acc: 0.9767  
Epoch 5/6  
324000/324000 [=====] - 17s 52us/step - loss: 0.0636 - acc: 0.9781  
Epoch 6/6  
324000/324000 [=====] - 17s 52us/step - loss: 0.0597 - acc: 0.9797
```

```
Out[5]: <tensorflow.python.keras.callbacks.History at 0x7f306842a438>
```

Test model

```
In [7]: # test trained model.  
scores = model.evaluate(x_test, y_test, verbose=1)  
  
print('Test loss:', scores[0])  
print('Test accuracy:', scores[1])
```

```
81000/81000 [=====] - 6s 80us/step  
Test loss: 0.1474194964328666  
Test accuracy: 0.9246296296296296
```


Classifying Satellite Images

Check predictions

```
: preds = model.predict(x_test)
plt.figure(figsize=(8,8))

for i in range(16):
    plt.subplot(4, 4, 1 + i, xticks=[], yticks=[])
    img_id = np.random.randint(81000)
    im = x_test[img_id,:]
    plt.title(class_names[preds[img_id].argmax()])
    plt.imshow(im)
plt.show()
```



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Object Detection with Bounding Box

Bounding Box Example

In geometry, the **minimum** or smallest **bounding** or enclosing **box** for a point set (S) in N dimensions is the **box** with the smallest measure (area, volume, or hypervolume in higher dimensions) within which all the points lie.

([Wikipedia](#))



<http://host.robots.ox.ac.uk/pascal/VOC/voc2006/examples/index.html>

SPPNet: Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition

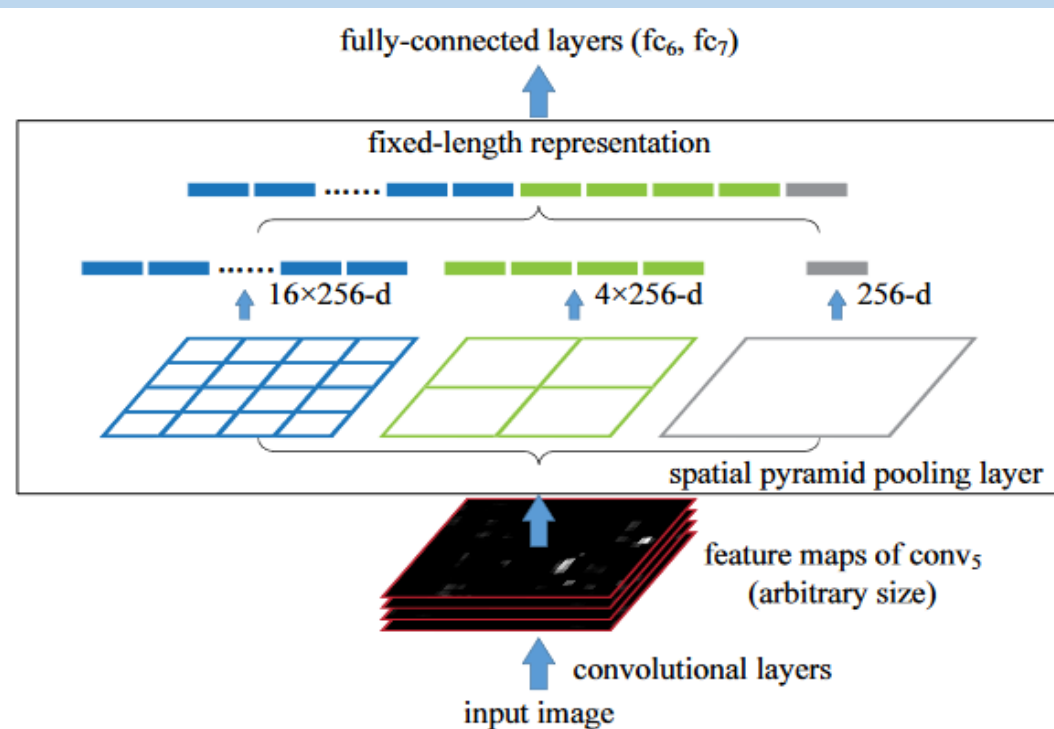
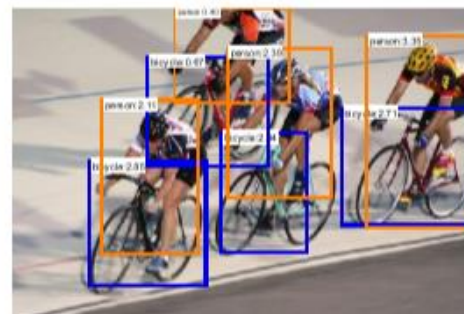
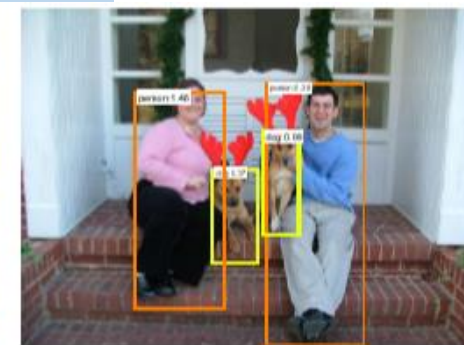


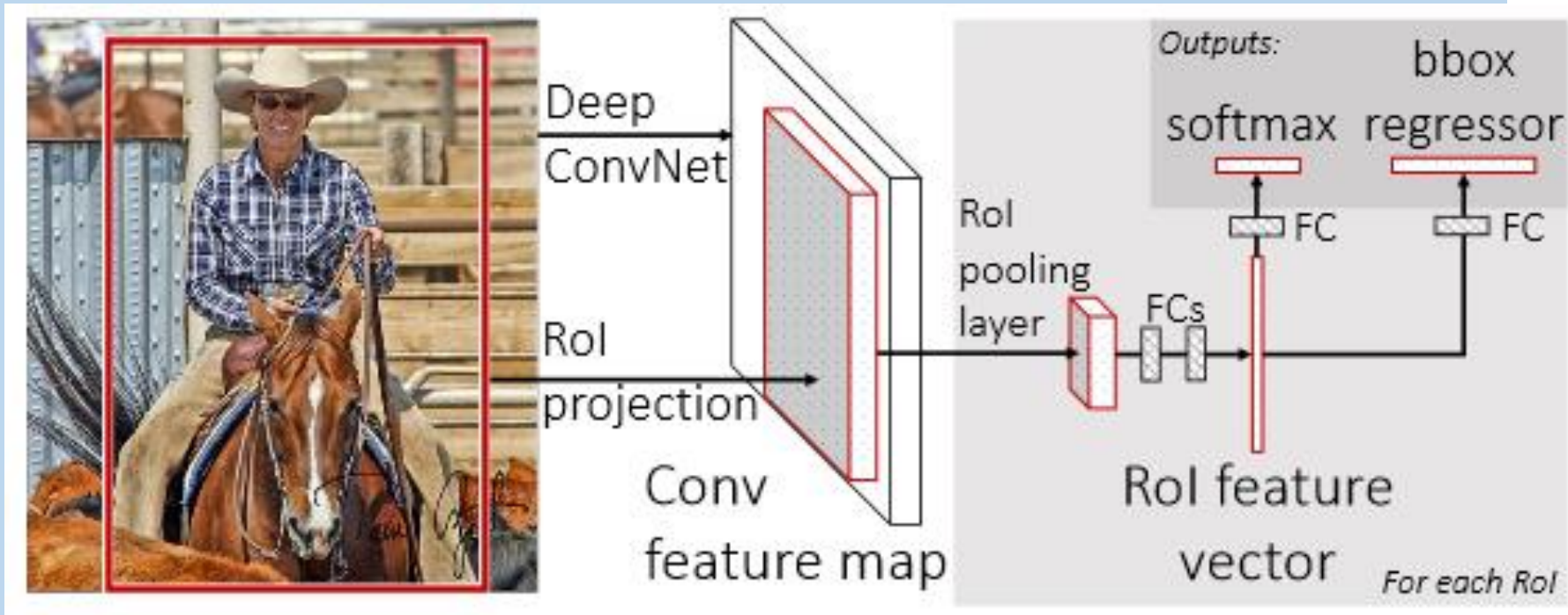
Figure 3: A network structure with a **spatial pyramid pooling layer**. Here 256 is the filter number of the conv₅ layer, and conv₅ is the last convolutional layer.



(He et al. 2014)

Object Detection with Bounding Box

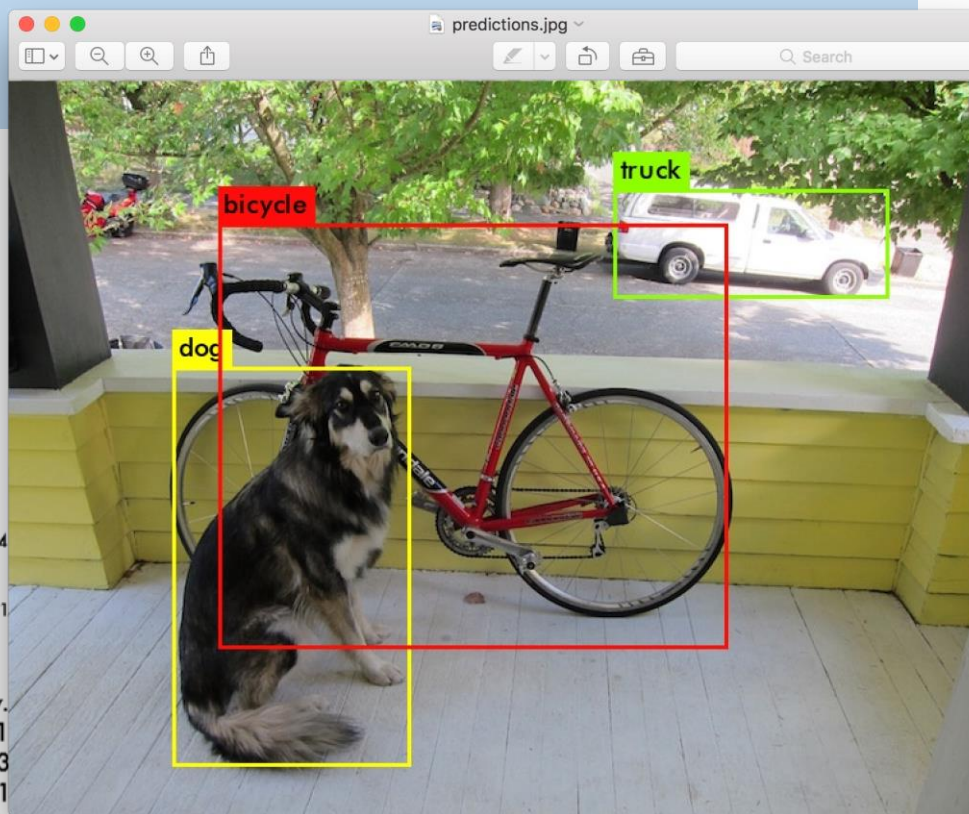
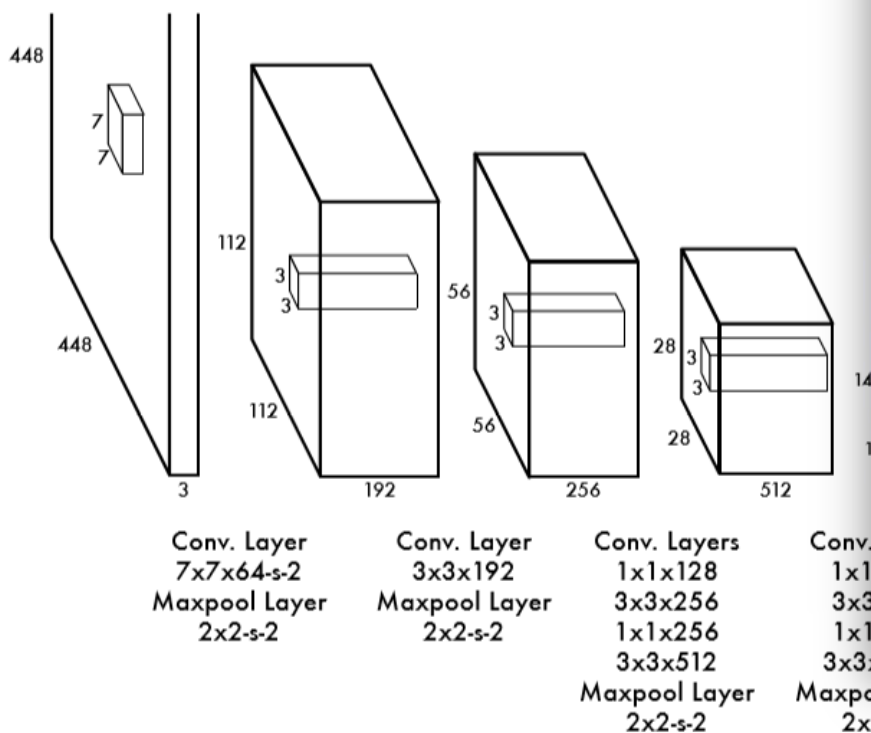
Fast-RCNN: Fast Region-based Convolutional Network method



(Girshick, 2015)

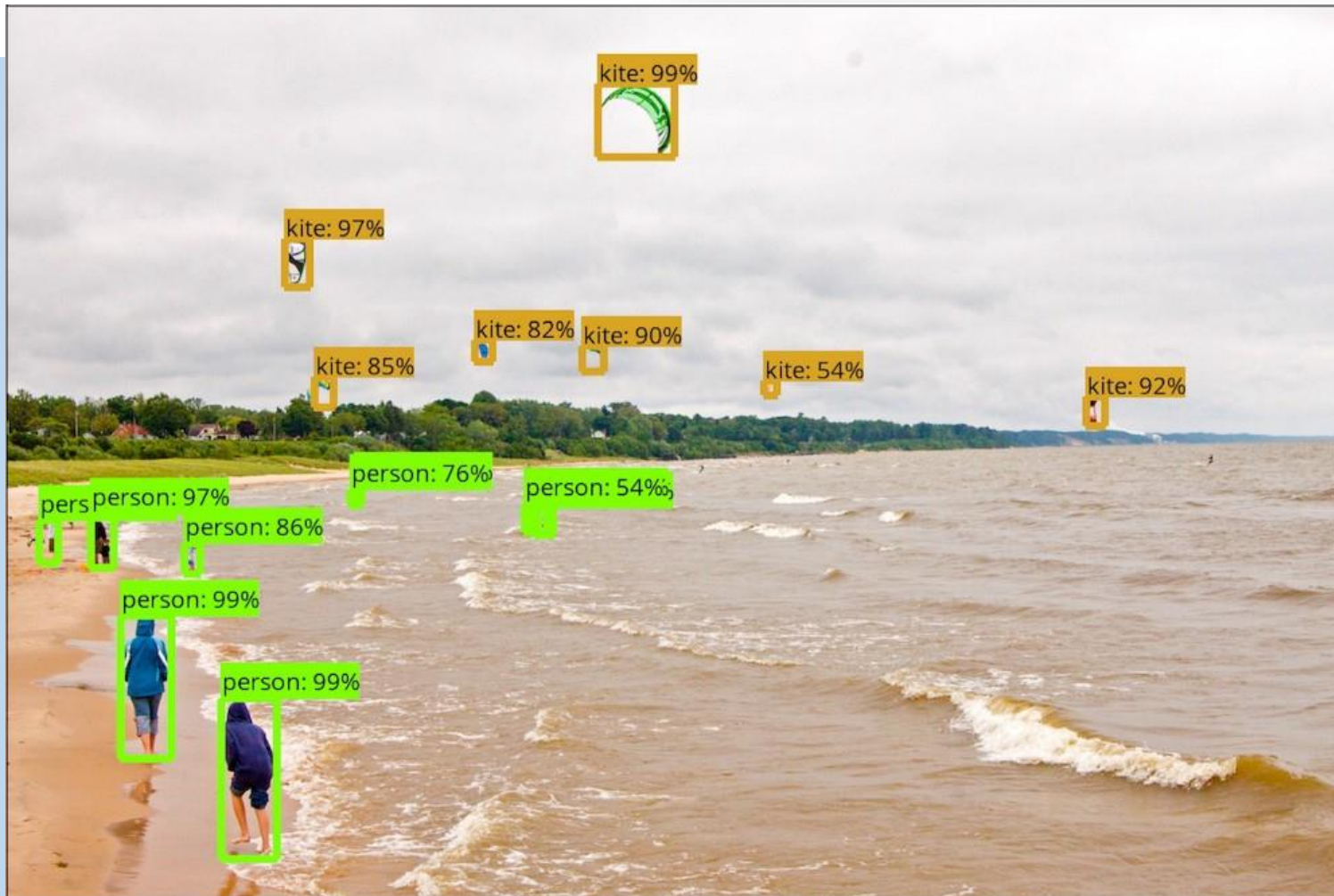
Object Detection with Bounding Box

YOLO model: You Only Look Once



(Redmon et al. 2016)

Object Detection with Bounding Box



<https://towardsdatascience.com/is-google-tensorflow-object-detection-api-the-easiest-way-to-implement-image-recognition-a8bd1f500ea0>

Object Detection with Bounding Box



<https://towardsdatascience.com/is-google-tensorflow-object-detection-api-the-easiest-way-to-implement-image-recognition-a8bd1f500ea0>

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References

- [1] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, “Dropout: A Simple Way to Prevent Neural Networks from Overfitting,” *Journal of Machine Learning Research*, vol. 15, pp. 1929–1958, 2014.
- [2] K. He, X. Zhang, S. Ren, and J. Sun, “Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition,” *arXiv:1406.4729 [cs]*, vol. 8691, pp. 346–361, 2014.
- [3] R. Girshick, “Fast R-CNN,” *arXiv:1504.08083 [cs]*, Apr. 2015.
- [4] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, “You Only Look Once: Unified, Real-Time Object Detection,” in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, USA, 2016, pp. 779–788.
- [5] J. Redmon and A. Farhadi, “YOLOv3: An Incremental Improvement,” p. 6.