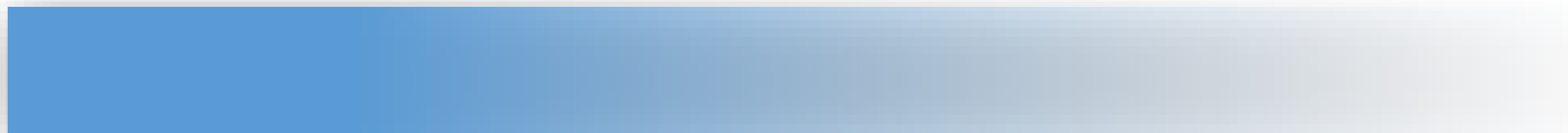




# Image Classification And Object Detection



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*

# OUTLINES

**1**

**Build Networks with High-level API**

**2**

**Classification with  
Convolutional Neural Networks**

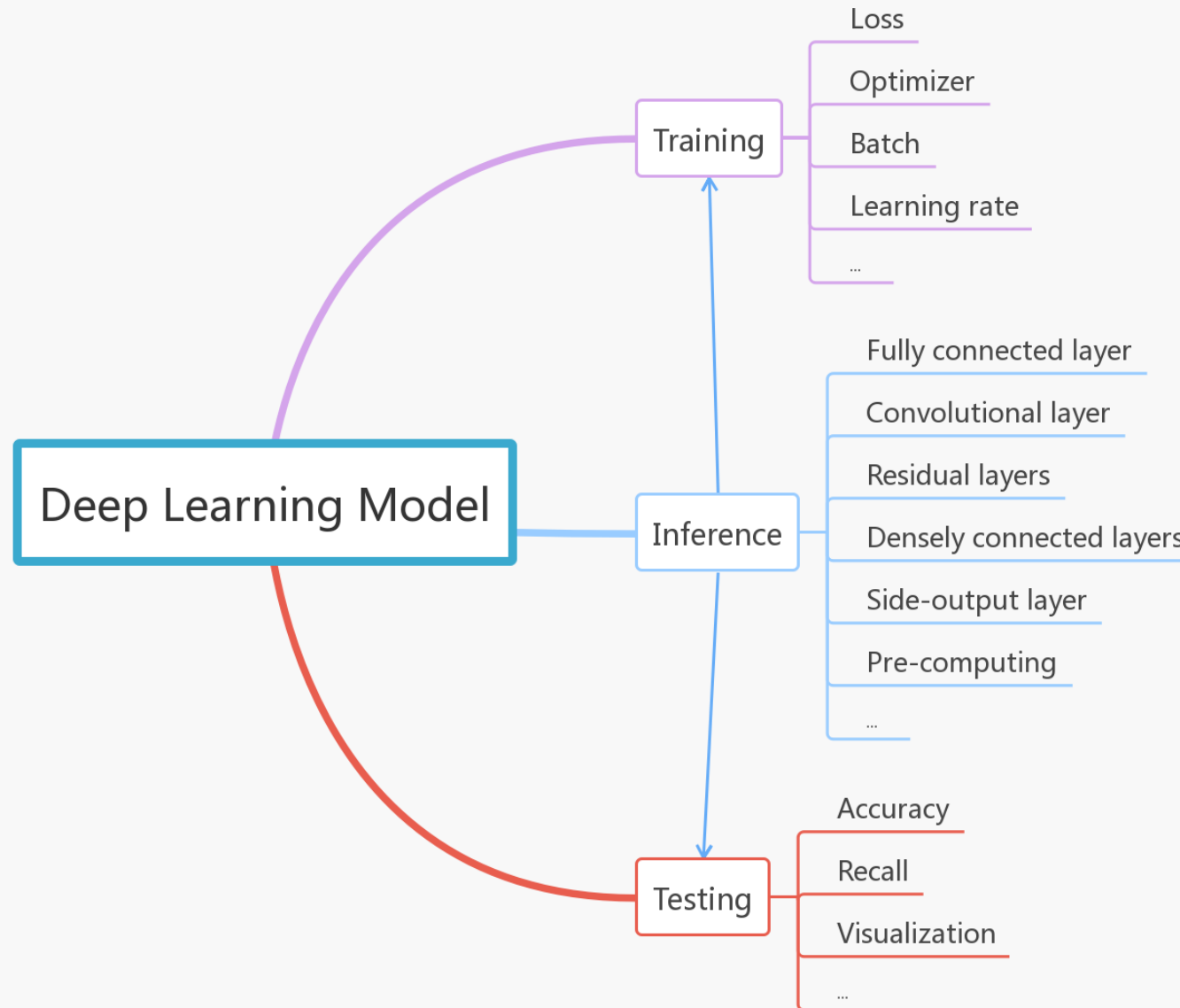
**3**

**Object Detection with Bounding Box**

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**Discussions**

## Build Networks with High-level API



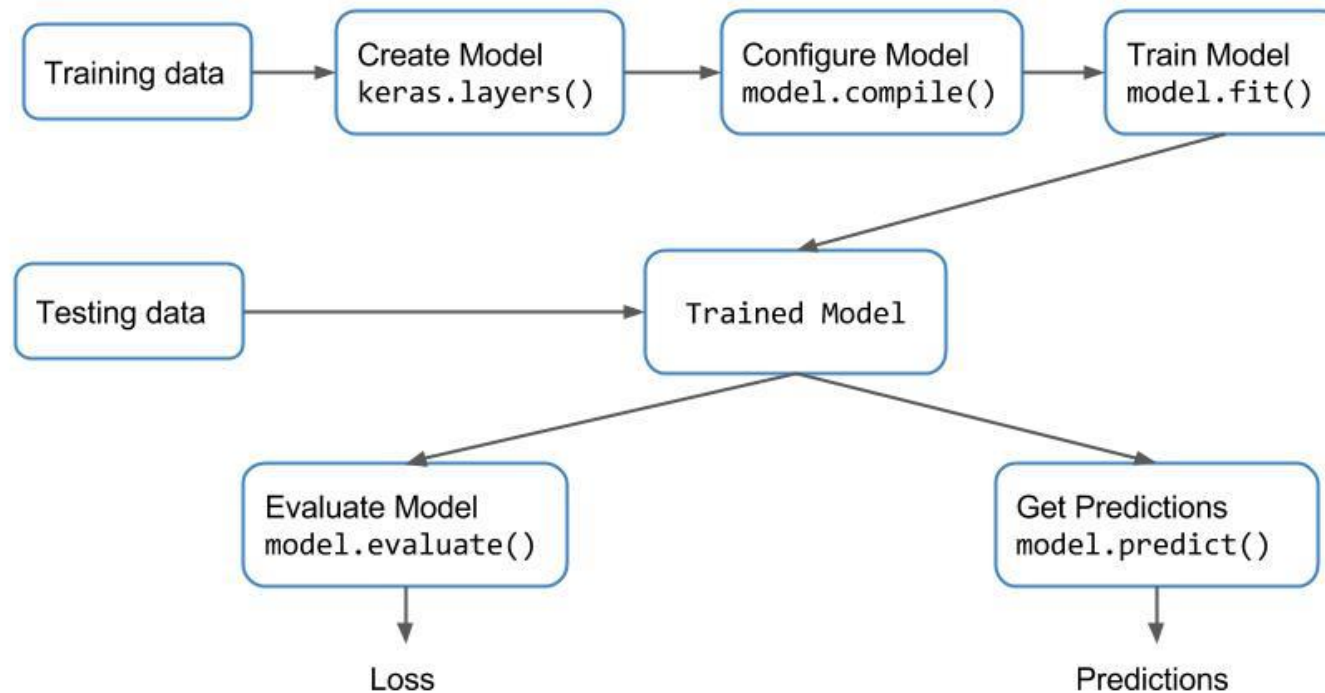


# Keras

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

## Create a model

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

## Add layers

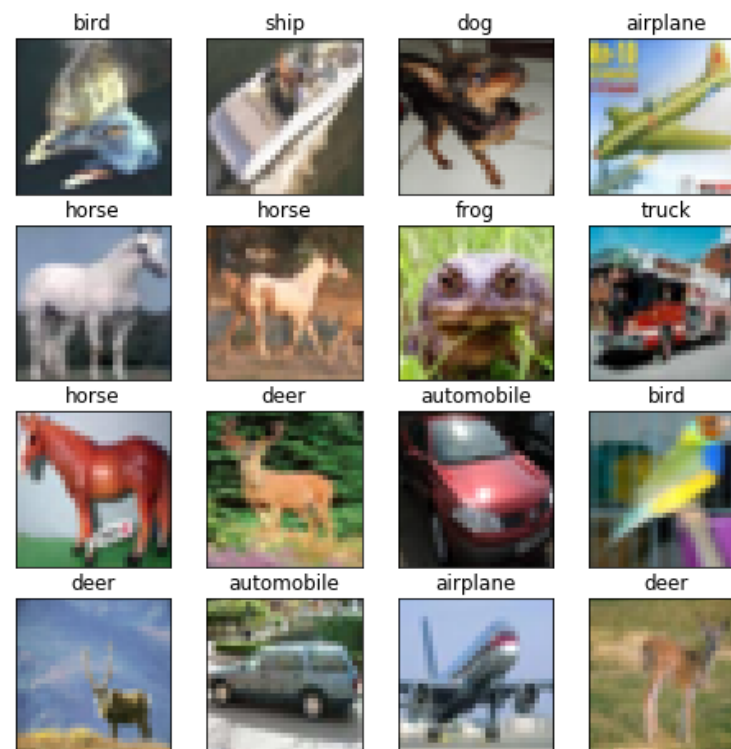
```
In [5]: from tensorflow.keras.layers import Dense, Dropout, Activation, Flatten  
from tensorflow.keras.layers import Conv2D, MaxPooling2D  
#You can also simply add layers via the .add() method  
model.add(Conv2D(32, (3, 3), padding='same', input_shape=x_train.shape[1:],  
                activation='relu'))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

# Getting started with the Keras

### 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()
```



### Getting started with the Keras

#### Initiate optimizer

```
In [8]: opt = tf.keras.optimizers.SGD(lr = 0.1, decay=1e-6, momentum=0.9, nesterov=True)
```

#### Configure model

```
In [9]: #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'])
```

#### Train model

```
In [10]: #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=100,
                   shuffle=True)
```

```
Epoch 1/100
384/50000 [.....] - ETA: 31:54 - loss: 2.3246 - acc: 0.1016
```



## Build Networks with High-level API

### Test model

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

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

### Check predicts

```
In [ ]: 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(50000)
    im = x_test[img_id,:]
    plt.title(class_names[preds[img_id].argmax()])
    plt.imshow(im)
plt.show()
```

### Save model

```
In [ ]: # Save model and weights
if not os.path.isdir(save_dir):
    os.makedirs(save_dir)

model_path = os.path.join(save_dir, model_name)
model.save(model_path)
print('Saved trained model at %s ' % model_path)
```

## Build Networks with High-level API

### Test model

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

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

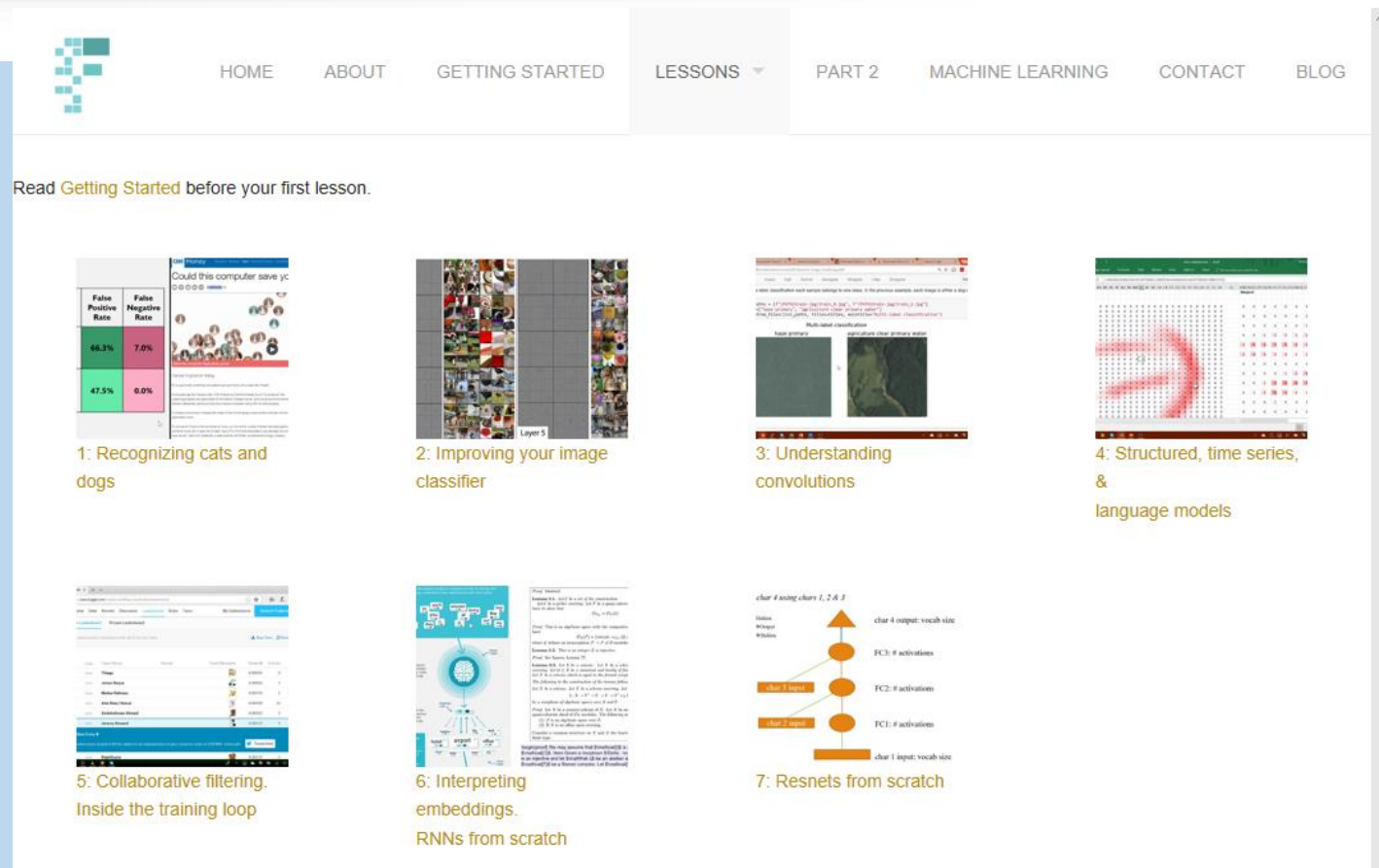
## Build Networks with High-level API

**fast.ai**

Making neural nets  
uncool again

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

If you can code,  
you can do deep learning.



The screenshot shows the fast.ai website with a navigation menu at the top: HOME, ABOUT, GETTING STARTED, LESSONS (selected), PART 2, MACHINE LEARNING, CONTACT, and BLOG. Below the menu, a message reads: "Read **Getting Started** before your first lesson."

Seven lessons are listed with corresponding images:

- 1: Recognizing cats and dogs (Image: A grid of cat and dog photos with a classification table showing False Positive Rate of 66.3% and False Negative Rate of 7.0%.)
- 2: Improving your image classifier (Image: A grid of various images with a classification table showing False Positive Rate of 47.5% and False Negative Rate of 0.0%.)
- 3: Understanding convolutions (Image: A diagram showing a 3x3 convolution kernel applied to a 5x5 input grid.)
- 4: Structured, time series, & language models (Image: A diagram showing a sequence of characters being processed by a model.)
- 5: Collaborative filtering. Inside the training loop (Image: A screenshot of a recommendation system interface showing user ratings for various items.)
- 6: Interpreting embeddings. RNNs from scratch (Image: A diagram showing a sequence of characters being processed by a model.)
- 7: Resnets from scratch (Image: A diagram showing a ResNet architecture with multiple layers and residual connections.)

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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 pandas
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 | 0 | 1 | 0 | 0 |
| 4 road        | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| 5 water       | 0 | 0 | 0 | 0 | 0 | 0 | 1 |

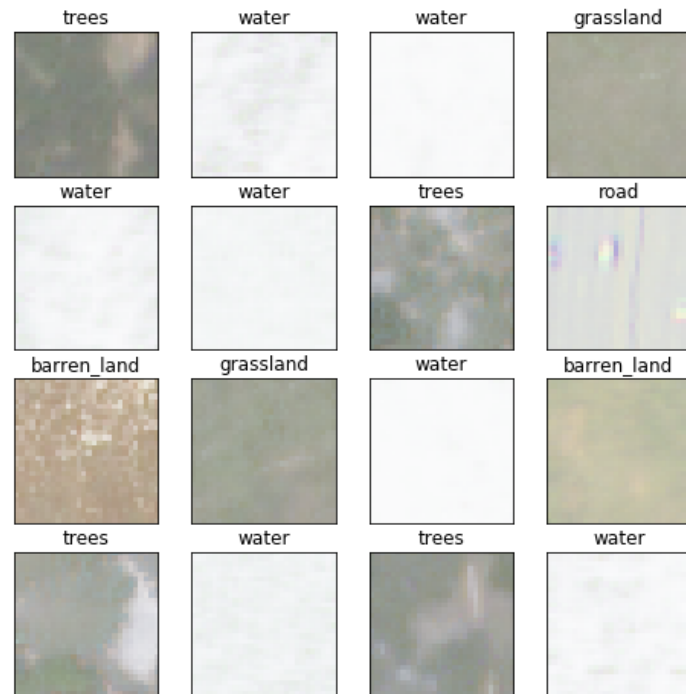
```
x_train_shape : (324000, 28, 28, 4)
y_train_shape : (324000, 6)
x_test_shape : (81000, 28, 28, 4)
y_test_shape : (81000, 6)
```

## 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()
```



## Classification with Convolutional Neural Networks

### Classifying Satellite Images

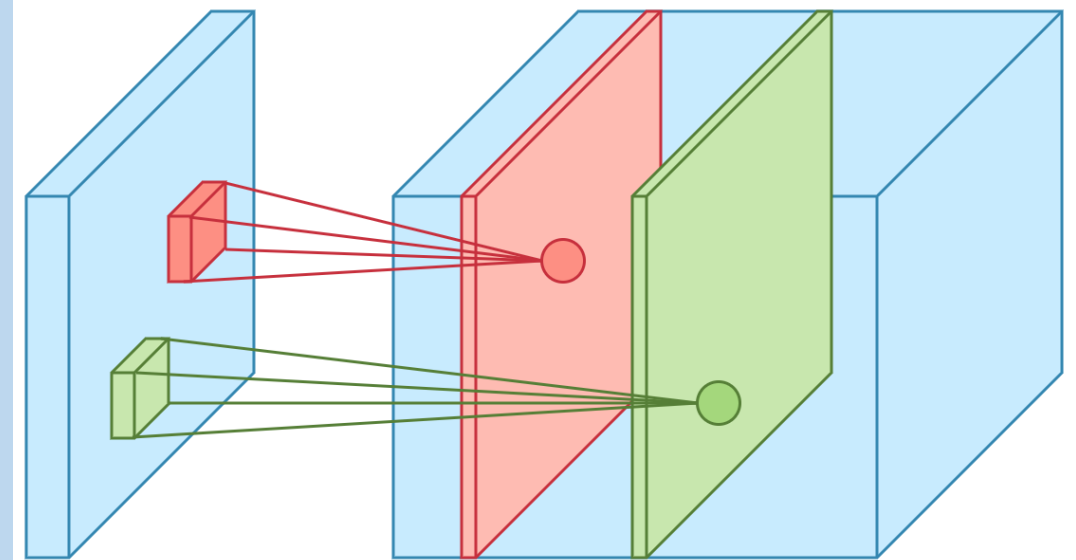
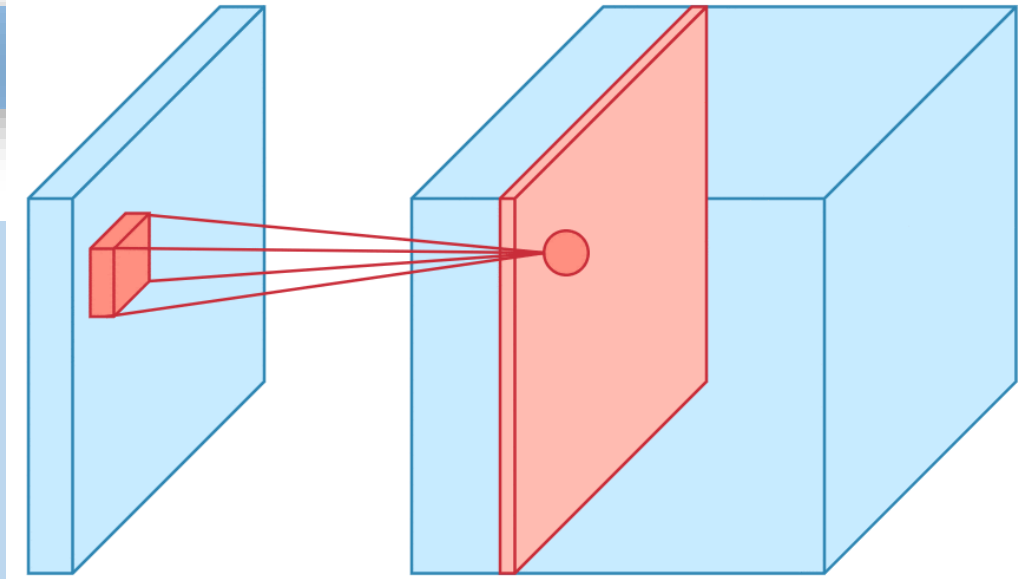
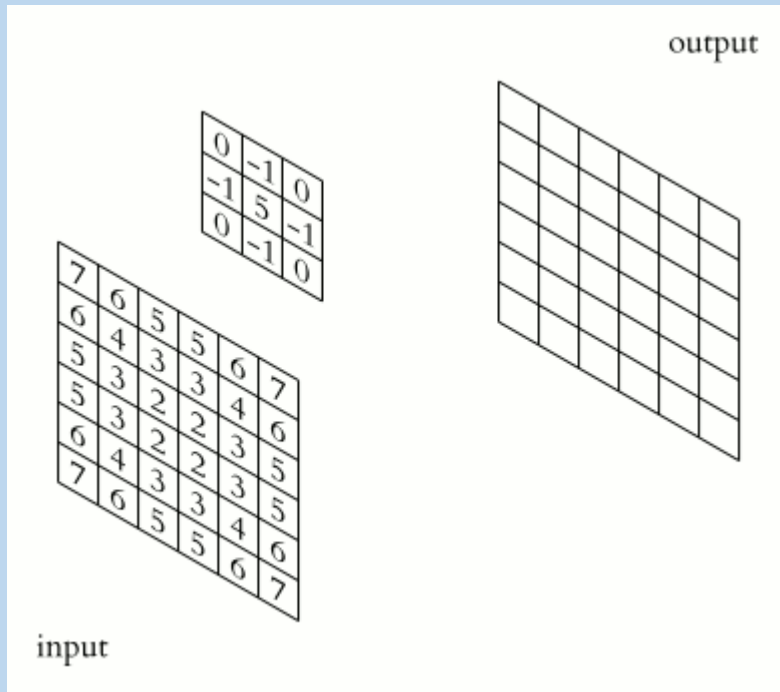
| Layer (type)                   | Output Shape       | Param # |
|--------------------------------|--------------------|---------|
| conv2d (Conv2D)                | (None, 26, 26, 16) | 592     |
| conv2d_1 (Conv2D)              | (None, 24, 24, 32) | 4640    |
| max_pooling2d (MaxPooling2D)   | (None, 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

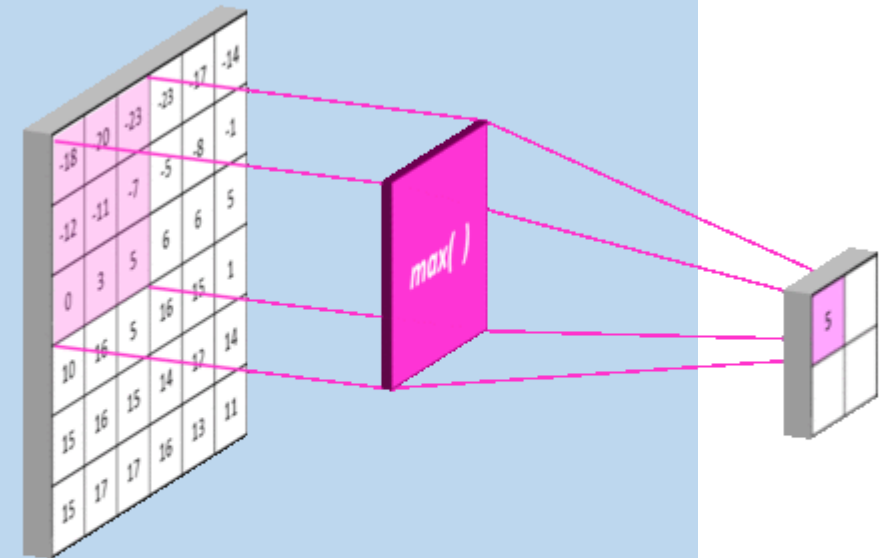
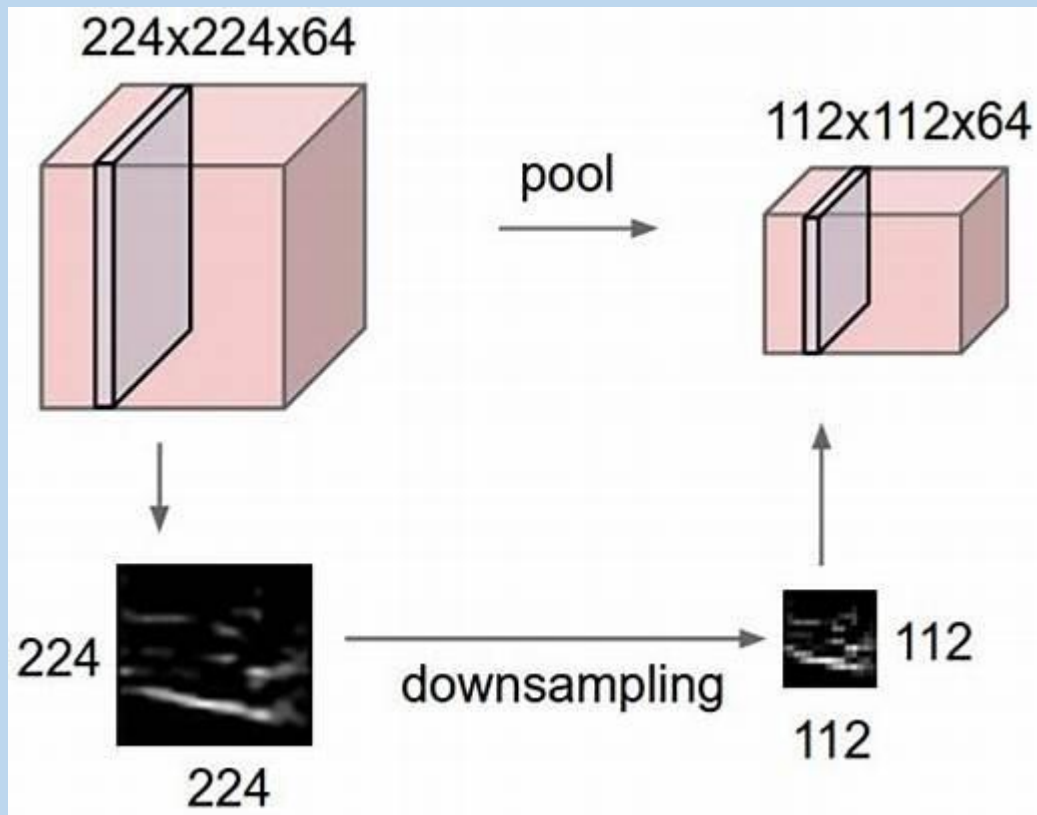


## Classification with Convolutional Neural Networks

### Convolutional Layer



## Pooling Layer



## Dropout

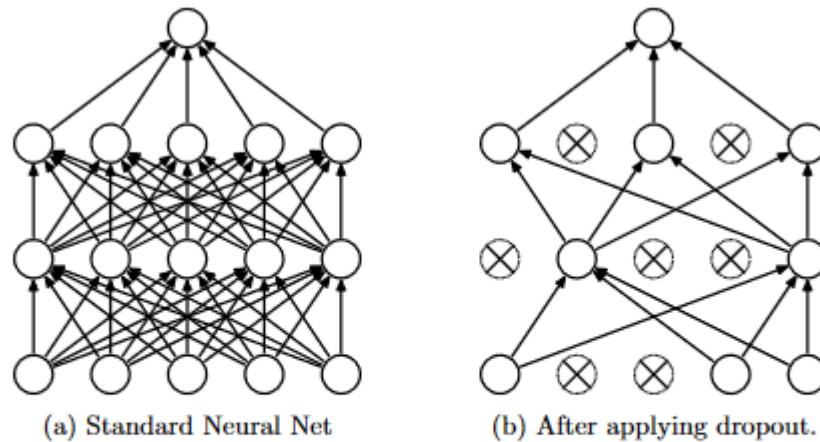
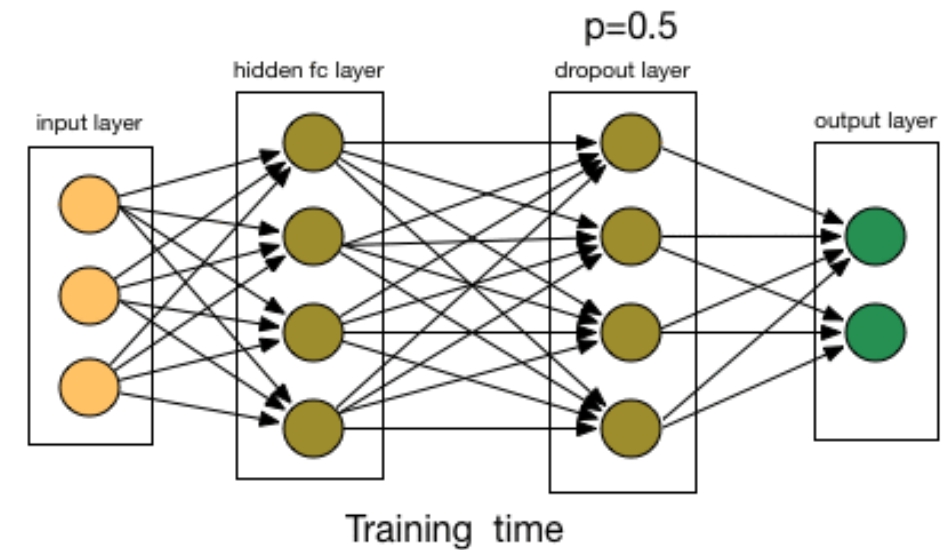


Figure 1: Dropout Neural Net Model. **Left:** A standard neural net with 2 hidden layers. **Right:** An example of a thinned net produced by applying dropout to the network on the left. Crossed units have been dropped.



(Srivastava et al., 2014)

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

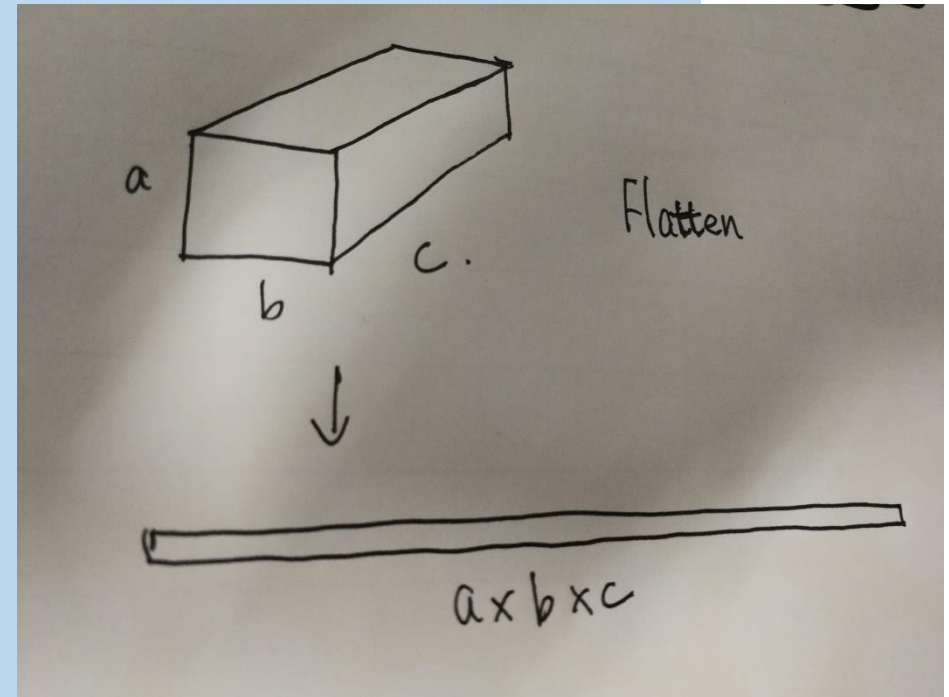
## Flatten Layer

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)
```

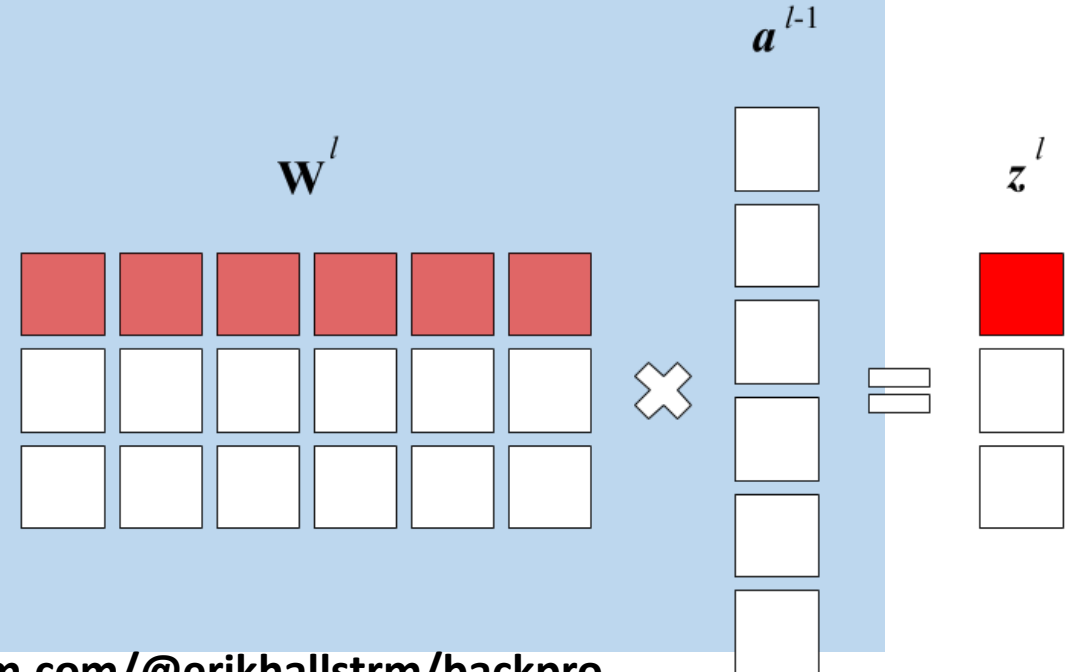
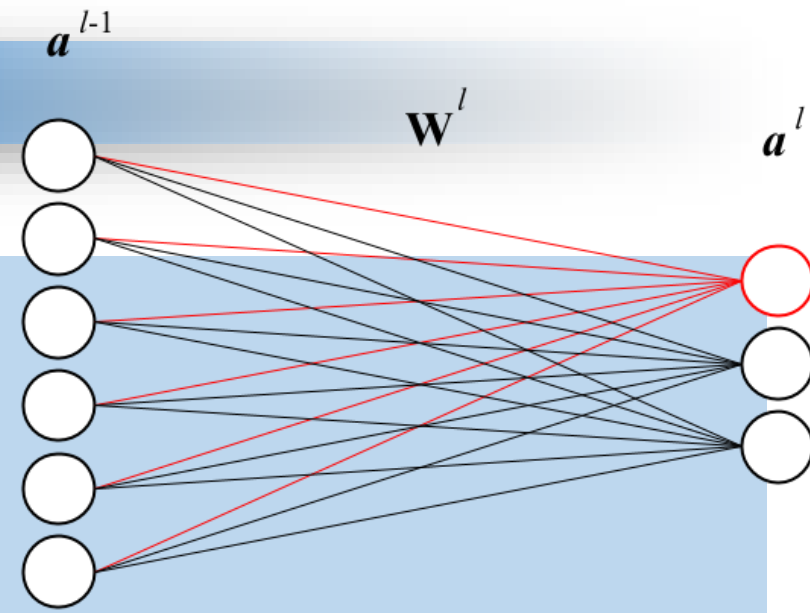
[https://www.tensorflow.org/api\\_docs/python/tf/keras/layers/Flatten](https://www.tensorflow.org/api_docs/python/tf/keras/layers/Flatten)



## 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>

## Classification with Convolutional Neural Networks

### Train model

```
In [ ]: model.fit(X_train, y_train, batch_size=200,
                  epochs=6, verbose=1,
                  callbacks=[tbcallback])
```

### Test model

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

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

### Check predictions

```
In [ ]: 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(32400)
    im = X_test[img_id, :]
    plt.title(class_names[preds[img_id].argmax()])
    plt.imshow(im)
plt.show()
```

# Classifying Satellite Images

### Train model

```
In [ ]: model.fit(X_train, y_train, batch_size=200,  
                  epochs=6, verbose=1,  
                  callbacks=[tbcallback])
```

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

### Check predictions

```
In [ ]: 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(32400)  
    im = X_test[img_id, :]  
    plt.title(class_names[preds[img_id].argmax()])  
    plt.imshow(im)  
plt.show()
```

# Classifying Satellite Images

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In [ ]: model.fit(X_train, y_train, batch_size=200,  
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plt.figure(figsize=(8,8))  
  
for i in range(16):  
    plt.subplot(4, 4, 1 + i, xticks=[], yticks=[])  
    img_id = np.random.randint(32400)  
    im = X_test[img_id, :]  
    plt.title(class_names[preds[img_id].argmax()])  
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```



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# Object Detection with Bounding Box

## Bounding Box Example



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

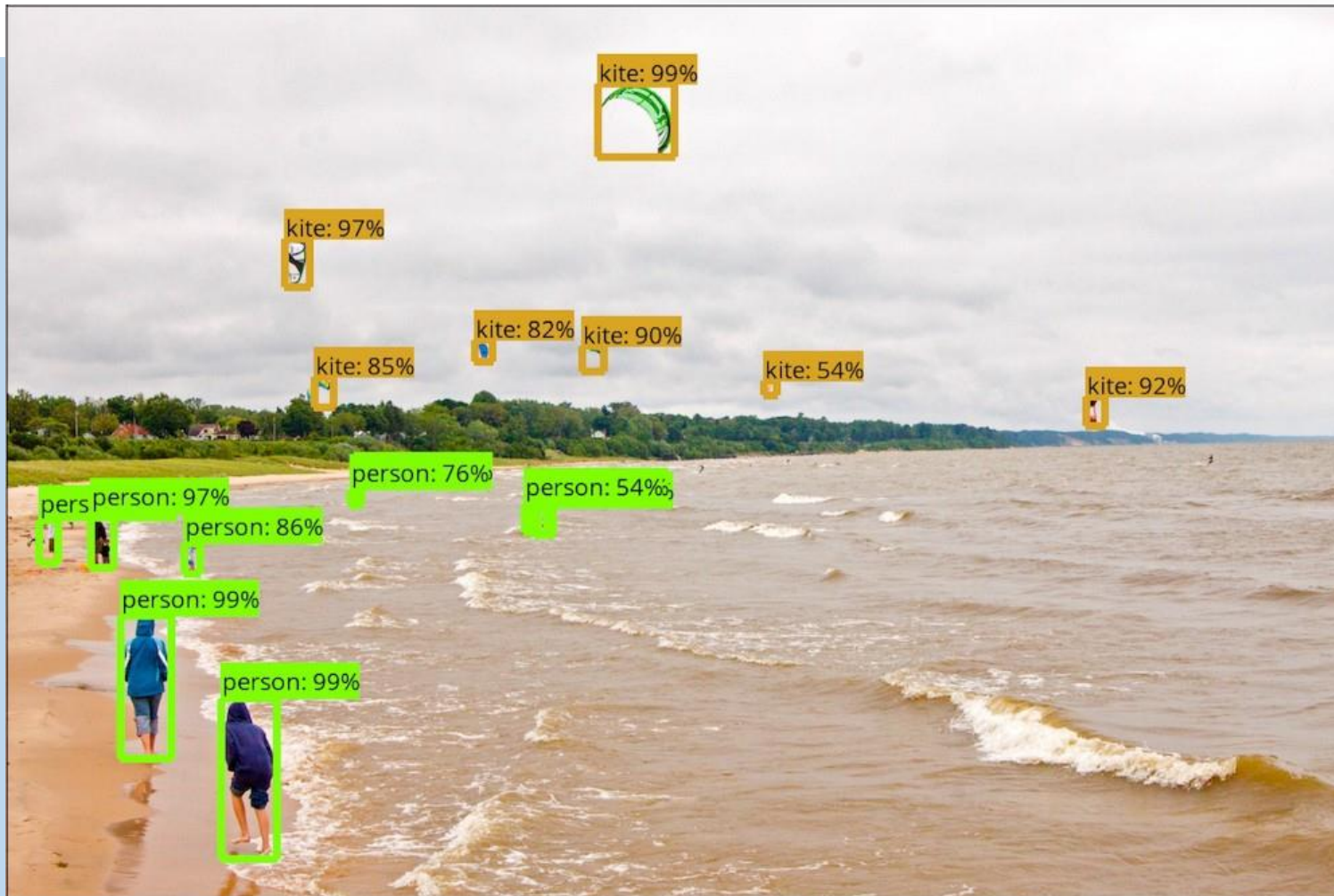
# Object Detection with Bounding Box



<https://pjreddie.com/darknet/yolo/>



## 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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## Discussions





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