

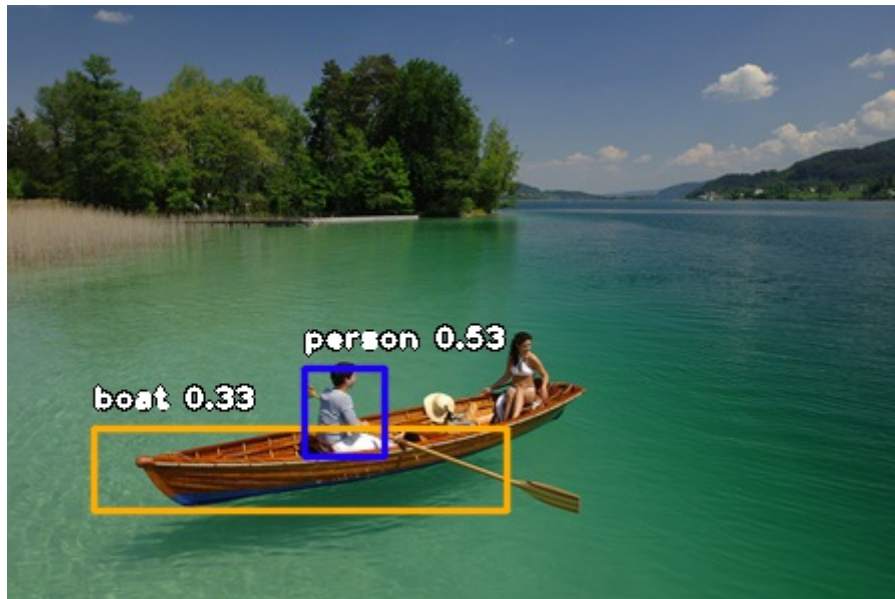
Machine Learning VIII

maXbox Starter 75 - Object Detection

From Document to Recognition?
Detect the Rect!

This tutor puts a trip to the kingdom of object recognition with computer vision knowledge and an image classifier.

Object detection has been witnessing a rapid revolutionary change in some fields of computer vision. Its involvement in the combination of object classification as well as object recognition makes it one of the most challenging topics in the domain of machine learning & vision.



First we need a library with modules. **ImageAI** is a Python library built to empower developers to build applications and systems with self-contained deep learning and Computer Vision capabilities using a few lines of straight forward code. But to use ImageAI you need to install a few dependencies namely:

- TensorFlow
- OpenCV
- Keras and ImageAI itself to install with \$ pip3 install imageAI

Now download the TinyYOLOv3 model file (33.9 MB) that contains a pretrained classification model that will be used for object detection:

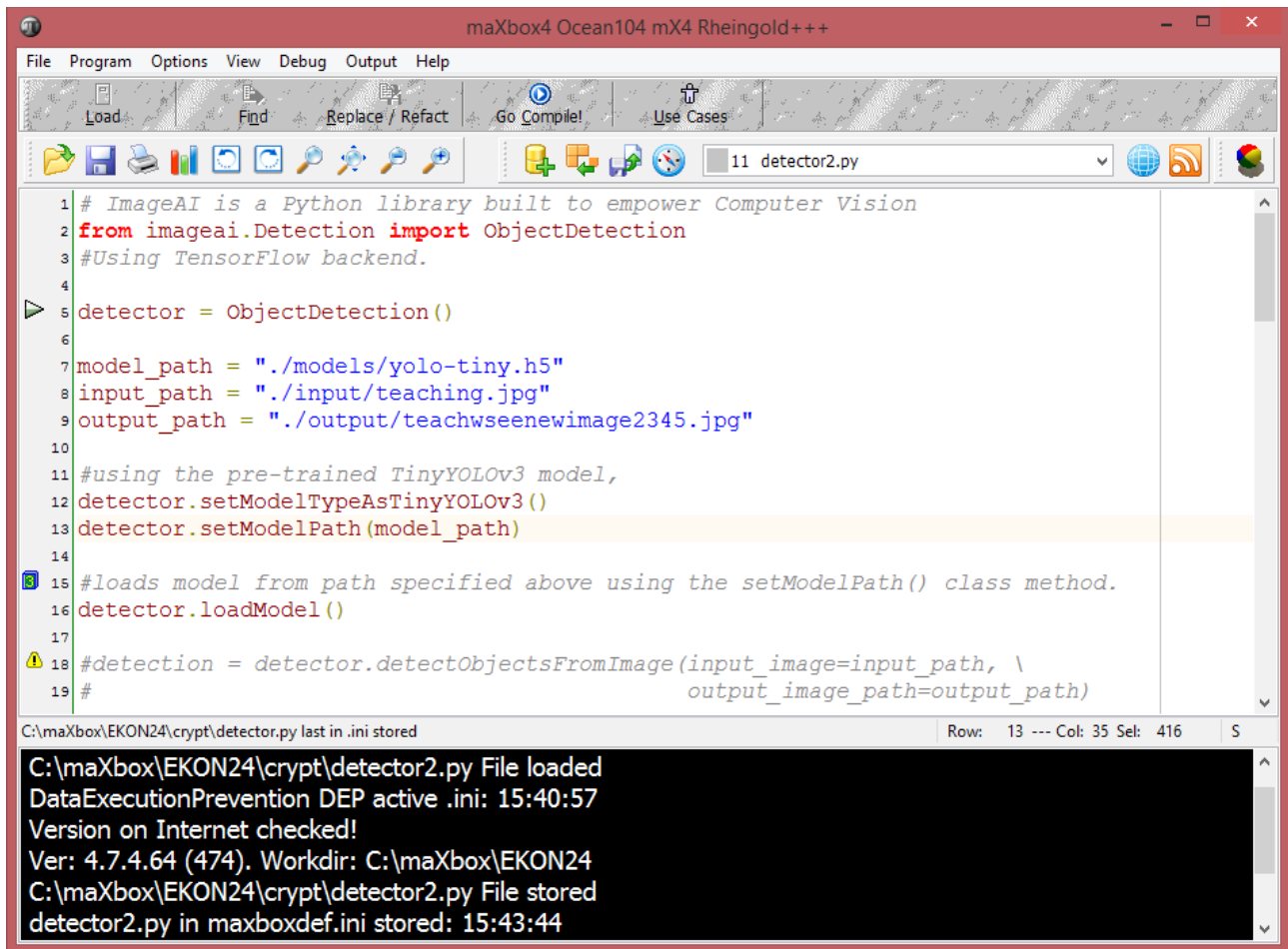
<https://sourceforge.net/projects/maxbox/files/Examples/EKON/EKON24/ImageDetector/yolo-tiny.h5/download>

Then we need 3 necessary folders.

- input\
- models\yolo-tiny.h5
- output

Now put an image for detection in the input folder, for example: teaching.jpg

Open now your preferred text editor for writing Python code (in my case maXbox) and create a new file `detector.py` or some valid file name.



The screenshot shows the maXbox4 IDE interface. The main editor window displays a Python script named `detector2.py`. The script imports the `ObjectDetection` class from the `imageai.Detection` module and initializes an instance. It then sets the model path to `./models/yolo-tiny.h5`, the input path to `./input/teaching.jpg`, and the output path to `./output/teachwseenewimage2345.jpg`. The script uses the pre-trained TinyYOLOv3 model and loads it from the specified path. Finally, it calls the `detectObjectsFromImage` method to perform object detection on the input image.

```
1 # ImageAI is a Python library built to empower Computer Vision
2 from imageai.Detection import ObjectDetection
3 #Using TensorFlow backend.
4
5 detector = ObjectDetection()
6
7 model_path = "./models/yolo-tiny.h5"
8 input_path = "./input/teaching.jpg"
9 output_path = "./output/teachwseenewimage2345.jpg"
10
11 #using the pre-trained TinyYOLOv3 model,
12 detector.setModelTypeAsTinyYOLOv3()
13 detector.setModelPath(model_path)
14
15 #loads model from path specified above using the setModelPath() class method.
16 detector.loadModel()
17
18 #detection = detector.detectObjectsFromImage(input_image=input_path, \
19 #                                              output_image_path=output_path)
```

The bottom status bar shows the file path: `C:\maXbox\EKON24\crypt\detector.py`. The output window displays the following messages:

```
C:\maXbox\EKON24\crypt\detector2.py File loaded
DataExecutionPrevention DEP active .ini: 15:40:57
Version on Internet checked!
Ver: 4.7.4.64 (474). Workdir: C:\maXbox\EKON24
C:\maXbox\EKON24\crypt\detector2.py File stored
detector2.py in maxboxdef.ini stored: 15:43:44
```

In line 2 we import `ObjectDetection` class from the **ImageAI** library.

```
from imageai.Detection import ObjectDetection
```

As the next thing we create an instance of the class `ObjectDetection`, as shown in line 5 above:

```
detector = ObjectDetection()
```

It goes on with the declaration of the previous created paths:

```
model_path = "./models/yolo-tiny.h5"
input_path = "./input/teaching.jpg"
output_path = "./output/the_newimage.jpg"
```

In this tutorial, as I mentioned we'll be using the pre-trained TinyYOLOv3 model, so I use the `setModelTypeAsTinyYOLOv3()` function to load our model:

```
#using the pre-trained TinyYOLOv3 model,
detector.setModelTypeAsTinyYOLOv3()
detector.setModelPath(model_path)
```

```
#loads model from path specified above using the setModelPath() class method.
detector.loadModel()
```



To detect only some of the objects above, I will need to call the *CustomObjects* method and set the name of the object(s) we want to detect to through. The rest are False by default. In our example, we detect customized only person, laptop and bottle. The boat is to test some negative test (maybe it find some message in the bottle with a boat in it ;-)).

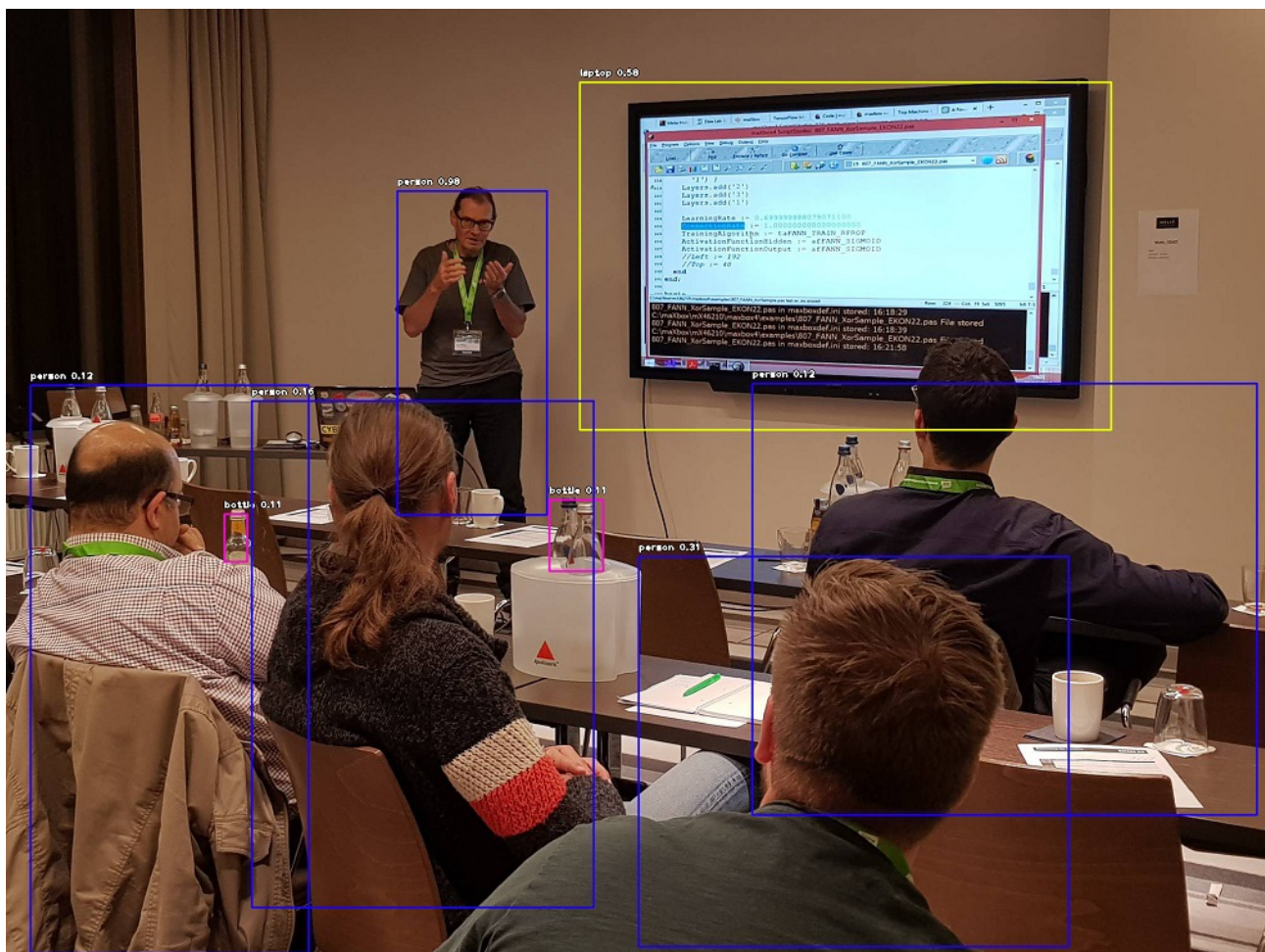
```
custom= detector.CustomObjects(person=True,boat=True,laptop=True,bottle=True)
detections = detector.detectCustomObjectsFromImage(custom_objects=custom, \
                                                    input_image=input_path, output_image_path=output_path,\
                                                    minimum_percentage_probability=10)
```

Another reason for the custom instance is that I can define the threshold to find things. Unlike the normal *detectObjectsFromImage()* function, this needs an extra parameter which is "custom_object" which accepts the dictionary returned by the *CustomObjects()* function. In the sample below, we set the detection function to report only detections we want:

```
for eachItem in detections:
    print(eachItem["name"] , " : ", eachItem["percentage_probability"])
```

```
laptop   : 57.53162503242493
bottle   : 10.687477886676788
bottle   : 11.373373866081238
person   : 11.838557571172714
person   : 12.098842114210129
person   : 15.951324999332428
person   : 31.1357319355011
person   : 98.0242371559143
image detector compute ends...
```

With the parameter `minimum_percentage_probability=30` it could not find the 2 bottles, and yes we got an output!:



So we get 8 objects with color frames and corresponding probability. The 2 bottles by lila color and astonishing the yellow frame is the laptop. Funny but really effective!

This is the function (`detectCustomObjectsFromImage`) that performs object detection task after the model as loaded. It can be called many times to detect objects in any number of images.

Script `detector2.py`

```
# ImageAI is a Python library built to empower Computer Vision
from imageai.Detection import ObjectDetection
#Using TensorFlow backend.

detector = ObjectDetection()

model_path = "./models/yolo-tiny.h5"
input_path = "./input/teaching.jpg"
output_path = "./output/teachwseewimimage2345.jpg"

#using the pre-trained TinyYOLOv3 model,
detector.setModelTypeAsTinyYOLOv3()
detector.setModelPath(model_path)

detector.loadModel()
```



```
#detection = detector.detectObjectsFromImage(input_image=input_path, \
#                                              output_image_path=output_path)

custom= detector.CustomObjects(person=True, boat=True, laptop=True, bottle=True)
detections = detector.detectCustomObjectsFromImage(custom_objects=custom, \
                                                    input_image=input_path, output_image_path=output_path, \
                                                    minimum_percentage_probability=10)

for eachItem in detections:
    print(eachItem["name"] , " : ", eachItem["percentage_probability"])

print('image detector compute ends...')

#https://stackabuse.com/object-detection-with-imageai-in-python/
#https://github.com/OlafenwaMoses/ImageAI/releases/download/1.0/yolo-tiny.h5
#https://imageai.readthedocs.io/en/latest/detection/index.html
```

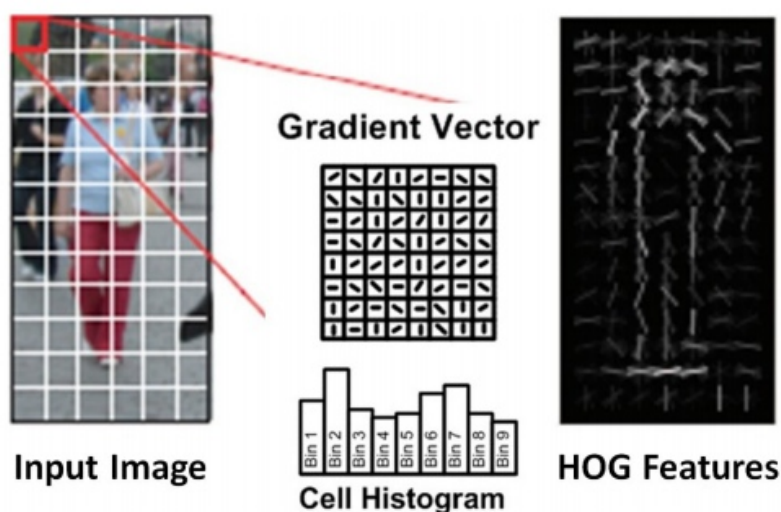
There are 80 possible objects that you can detect with the ObjectDetection class, and they are as seen below (not ordered).

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 dryer, toothbrush.

To detect only some of the objects above, you will need to call the *CustomObjects* function and set the name of the object(s) you want to detect.

Note:

Histogram of oriented gradients (HOG) is basically a feature descriptor that is used to detect objects in image processing and other computer vision techniques. The Histogram of oriented gradients descriptor technique includes occurrences of gradient orientation in localised portions of an image, such as detection window, region of interest (ROI), among others. Advantage of HOG-like features is their simplicity, and it is easier to understand information they carry.



Appendix: See also two other classifiers

[SGDClassifier](#)

[LogisticRegressionCV](#)

SGDClassifier

incrementally trained logistic regression (when given parameter `loss="log"`).

LogisticRegressionCV

Logistic regression with built-in cross validation

Notes:

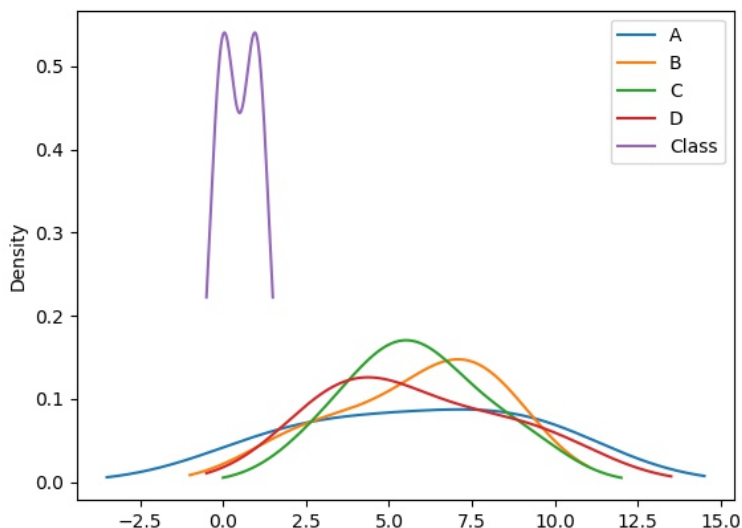
The underlying C implementation uses a random number generator to select features when fitting the model. It is thus not uncommon, to have slightly different results for the same input data. If that happens, try with a smaller `tol` parameter or set random state to 0.

Mathematically, a histogram is a mapping of bins (intervals or numbers) to frequencies. More technically, it can be used to approximate a probability density function (PDF) of the underlying variable that we see later on.

Moving on from a frequency table above (`density=False` counts at y-axis), a true histogram first <bins> the range of values and then counts the number of values that fall into each bin or interval. A plot of a histogram uses its bin edges on the x-axis and the corresponding frequencies on the y-axis.

Sticking with the Pandas library, you can create and overlay density plots using `plot.kde()`, which is available for both [Series] and [DataFrame] objects.

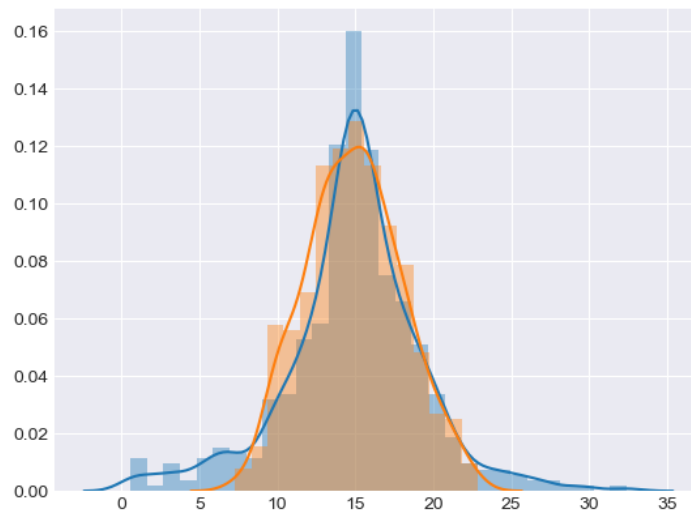
```
df.iloc[0:,0:4].plot.kde()
```



This is also possible for our binary targets to see a probabilistic distribution of the target class values (labels in supervised learning): `[0. 0. 1. 1. 0. 1.]` Consider at last a sample of floats drawn from the Laplace and Normal distribution together. This distribution graph has fatter tails than a normal distribution and has two descriptive parameters (location and scale):

```
>>> d = np.random.laplace(loc=15, scale=3, size=500)
```

```
>>> d = np.random.normal(loc=15, scale=3, size=500)
```



The script and data can be found:

<http://www.softwareschule.ch/examples/detector2.htm>

<https://sourceforge.net/projects/maxbox/files/Examples/EKON/EKON24/ImageDetector/>

http://www.softwareschule.ch/examples/classifier_compare2confusion2.py.txt

Author: Max Kleiner

Ref:

<http://www.softwareschule.ch/box.htm>

<https://scikit-learn.org/stable/modules/>

<https://realpython.com/python-histograms/>

<https://imageai.readthedocs.io/en/latest/detection/index.html>

Doc:

<https://maxbox4.wordpress.com>

How a Human sees an image



How a computer sees an image

[9	1	29	70	114	76	0	8	4	5	5	0	111	162	9	8	62	62]
[3	0	33	61	102	106	34	0	0	0	0	49	182	150	1	12	65	62]
[1	0	40	54	123	90	72	77	52	51	49	121	205	98	0	15	67	59]
[3	1	41	57	74	54	96	181	220	170	90	149	208	56	0	16	69	59]
[6	1	32	36	47	81	85	90	176	206	140	171	186	22	3	15	72	63]
[4	1	31	39	66	71	71	97	147	214	203	190	198	22	6	17	73	65]
[2	3	15	30	52	57	68	123	161	197	207	200	179	8	8	18	73	66]
[2	2	17	37	34	40	78	103	148	187	205	225	165	1	8	19	76	68]
[2	3	20	44	37	34	35	26	78	156	214	145	200	38	2	21	78	69]
[2	2	20	34	21	43	70	21	43	139	205	93	211	70	0	23	78	72]
[3	4	16	24	14	21	102	175	120	130	226	212	236	75	0	25	78	72]
[6	5	13	21	28	28	97	216	184	90	196	255	255	84	4	24	79	74]
[6	5	15	25	30	39	63	105	140	66	113	252	251	74	4	28	79	75]
[5	5	16	32	38	57	69	85	93	120	128	251	255	154	19	26	80	76]
[6	5	20	42	55	62	66	76	86	104	148	242	254	241	83	26	80	77]
[2	3	20	38	55	64	69	80	78	109	195	247	252	255	172	40	78	77]
[10	8	23	34	44	64	88	104	119	173	234	247	253	254	227	66	74	74]
[32	6	24	37	45	63	85	114	154	196	226	245	251	252	250	112	66	71]