Keras



Simple. Flexible. Powerful.

Get started

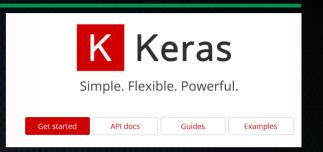
API docs

Guides

Examples

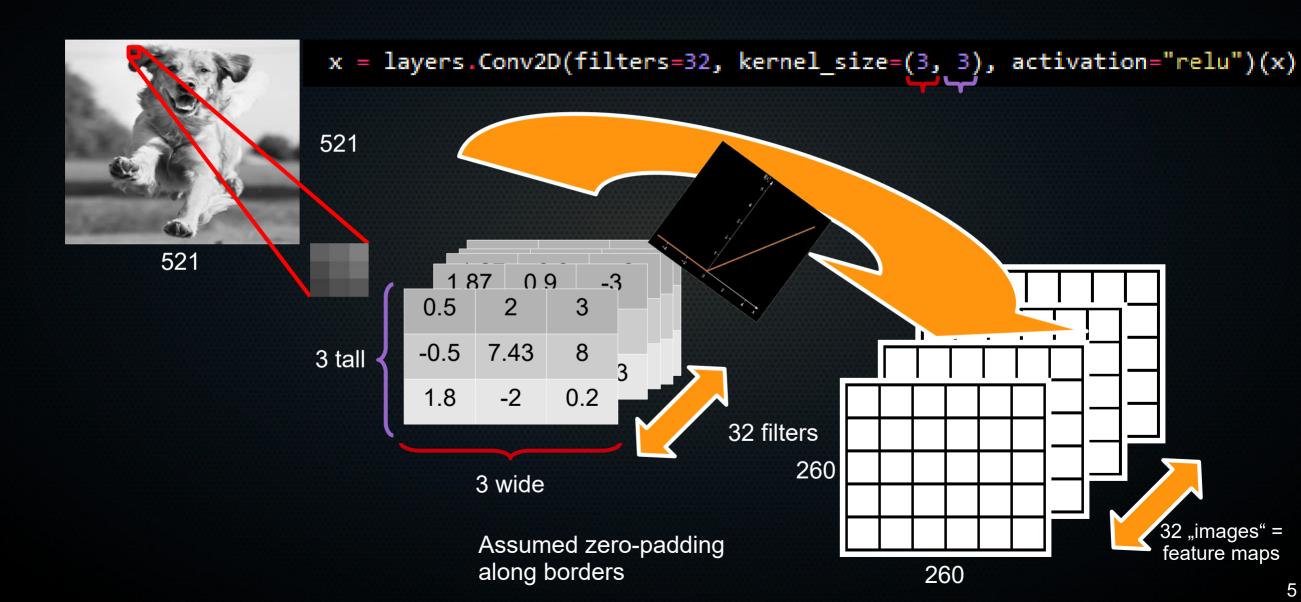
Keras

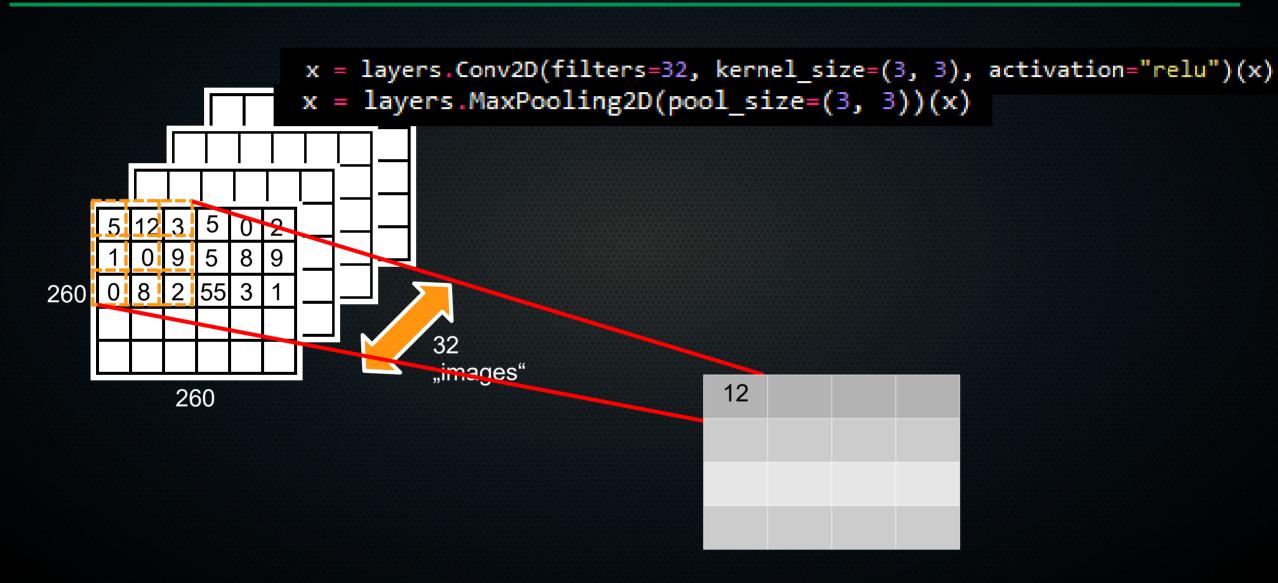
- Similar to Scikitlearn, but for neural networks:
 - Built-in ways to preprocess and load data
 - Many layers available (dense, convolutions, MaxPool, etc.)
 - Cross-validation, dropout, hyperparameter optimalisation all supported.

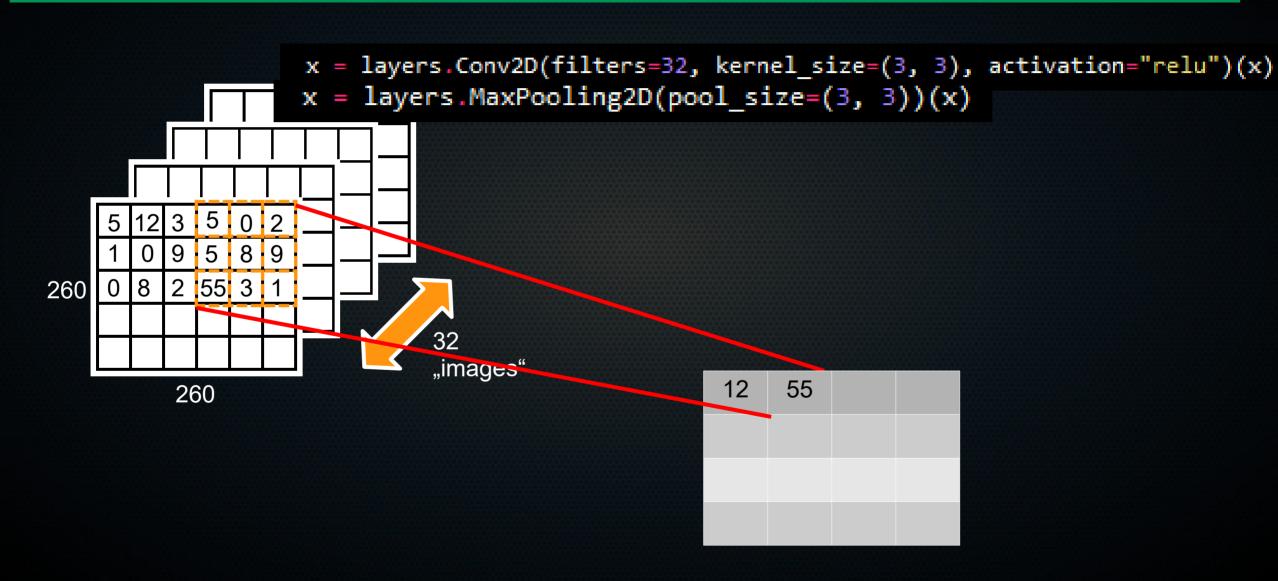


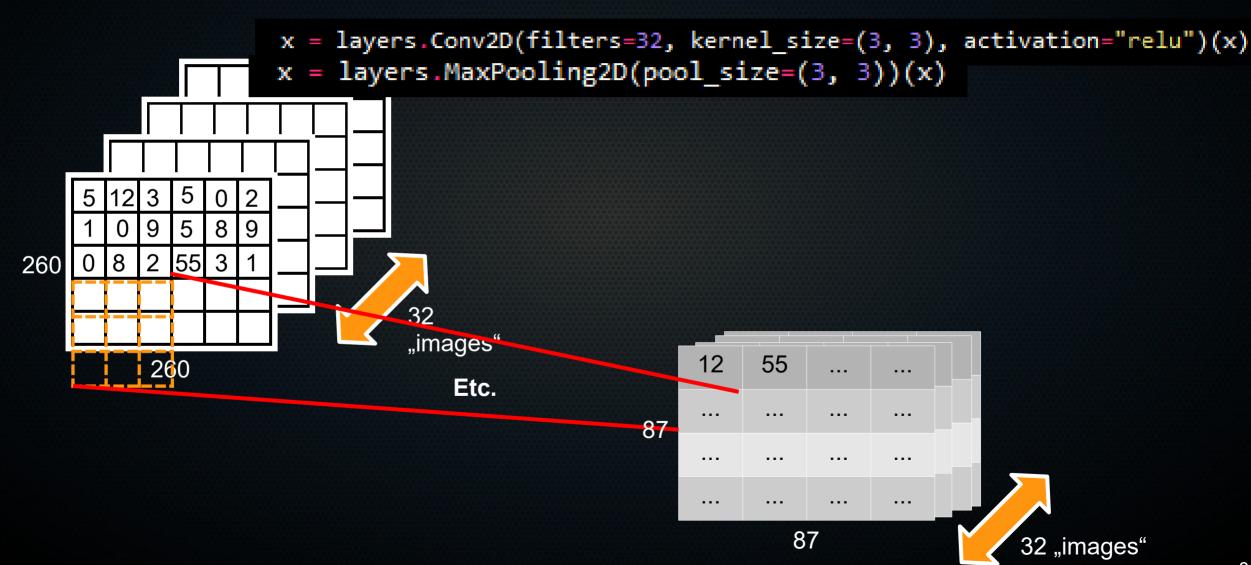
```
# Let's say we expect our inputs to be RGB images of arbitrary size
inputs = keras.Input(shape=(None, None, 3))
from tensorflow.keras import layers
# Center-crop images to 150x150
x = CenterCrop(height=150, width=150)(inputs)
# Rescale images to [0, 1]
x = Rescaling(scale=1.0 / 255)(x)
# Apply some convolution and pooling layers
x = layers.Conv2D(filters=32, kernel size=(3, 3), activation="relu")(x)
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x = layers.Conv2D(filters=32, kernel size=(3, 3), activation="relu")(x)
# Apply global average pooling to get flat feature vectors
x = layers.GlobalAveragePooling2D()(x)
# Add a dense classifier on top
num classes = 10
outputs = layers.Dense(num classes, activation="softmax")(x)
```

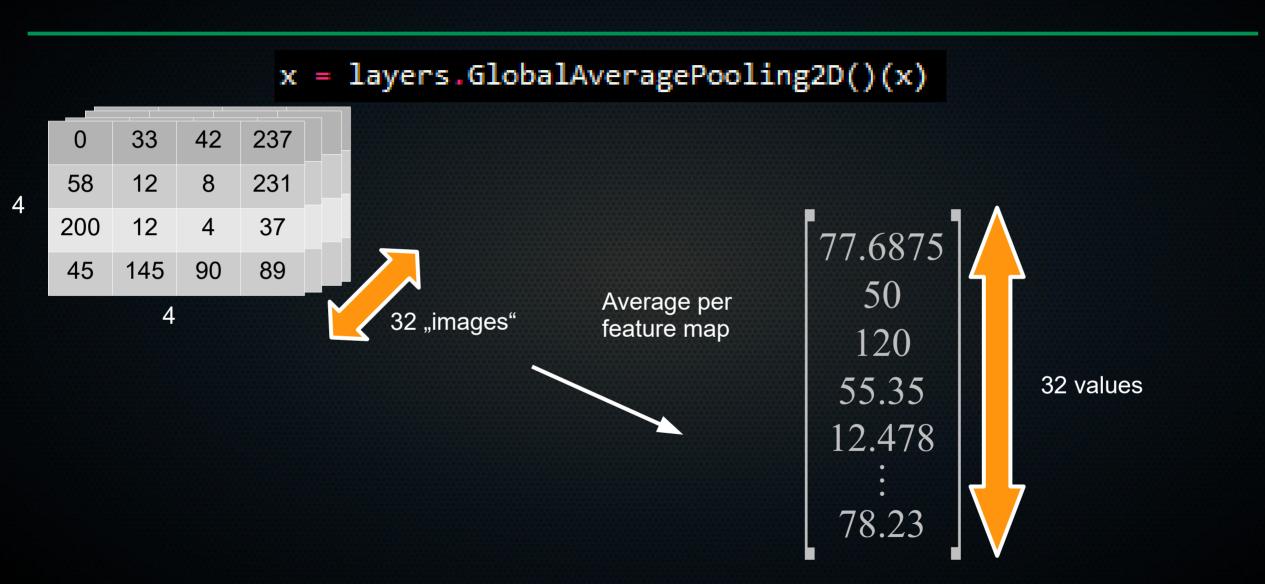


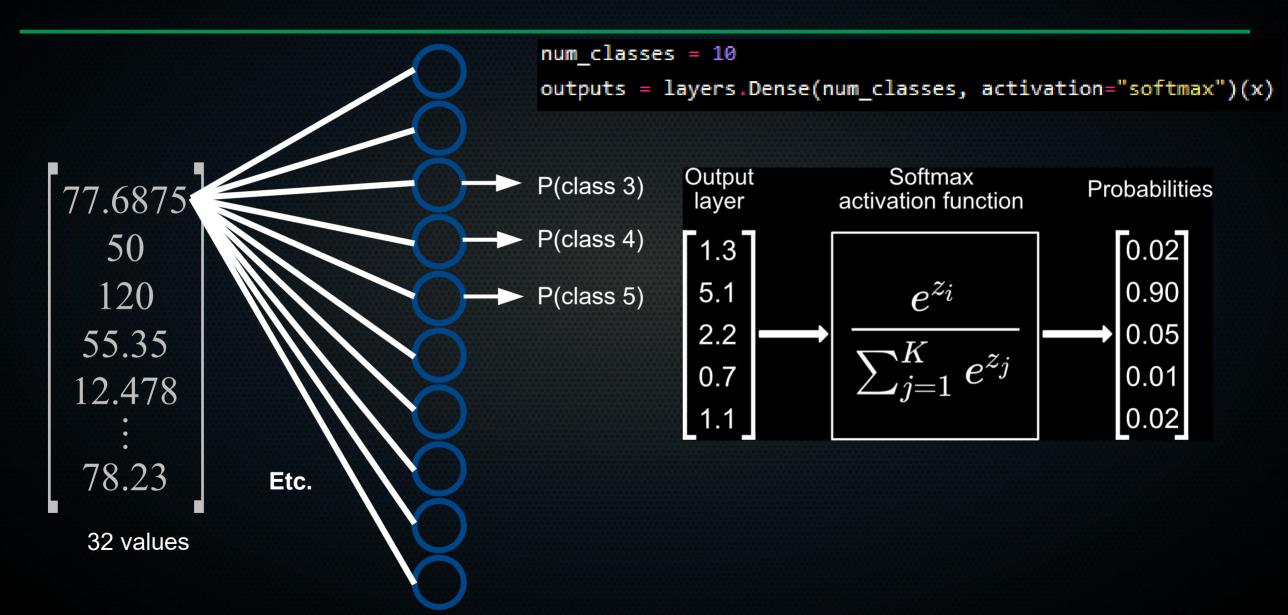












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```

```
model = keras.Model(inputs=inputs, outputs=outputs)

data = np.random.randint(0, 256, size=(64, 200, 200, 3)).astype("float32")
processed_data = model(data)
print(processed_data.shape)

(64, 10)
```

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```

model.summary()

Layer (type)		Shape	Param #
input_1 (InputLayer)		, None, None, 3)]	
center_crop_1 (CenterCrop)	(None,	150, 150, 3)	0
rescaling_1 (Rescaling)	(None,	150, 150, 3)	0
conv2d (Conv2D)	(None,	148, 148, 32)	896
max_pooling2d (MaxPooling2D)	(None,	49, 49, 32)	0
conv2d_1 (Conv2D)	(None,	47, 47, 32)	9248
max_pooling2d_1 (MaxPooling2	(None,	15, 15, 32)	0
conv2d_2 (Conv2D)	(None,	13, 13, 32)	9248
global_average_pooling2d (Gl	(None,	32)	0
dense (Dense)	(None,	10)	330
			======
Total params: 19,722			
Trainable params: 19,722 Non-trainable params: 0			

Step size adapative to prevent updates from exploding for large gradients or slowing to a crawl for small gradients

For each Parameter w^{j}

 $(j\ subscript\ dropped\ for\ clarity)$

$$\nu_t = \rho \nu_{t-1} + (1 - \rho) * g_t^2$$

$$\Delta \omega_t = -\frac{\eta}{\sqrt{\nu_t + \epsilon}} * g_t$$

$$\omega_{t+1} = \omega_t + \Delta \omega_t$$

 $\eta: Initial\ Learning\ rate$

 ν_t : Exponential Average of squares of gradients

 g_t : Gradient at time t along ω^j

Use mini-batch gradient updating: calculate gradient not using average error on *all* training examples, but average error on *32* training examples.

Run through all the training data 10 times

(normally you would stop training when you see that performance on training set goes up but on validation set goes down \rightarrow overfitting)

Keras example: calculating more metrics during training

```
model.compile(
    optimizer="adam",
    loss="sparse_categorical_crossentropy",
    metrics=[keras.metrics.SparseCategoricalAccuracy(name="acc")],
)
history = model.fit(dataset, epochs=1)
```

Keras example: evaluate on test set after training + predicting on unlabeled data

```
loss, acc = model.evaluate(val_dataset) # returns loss and metrics
print("loss: %.2f" % loss)
print("acc: %.2f" % acc)

157/157 [============] - 0s 688us/step - loss: 0.1041 - acc: 0.9692
loss: 0.10
acc: 0.97
```

```
predictions = model.predict(val dataset)
```

```
from sklearn.model selection import RepeatedKFold, cross val score
from tensorflow.keras.models import *
from tensorflow.keras.layers import *
from tensorflow.keras.wrappers.scikit learn import KerasRegressor
def buildmodel():
    model= Sequential([
        Dense(10, activation="relu"),
        Dense(5, activation="relu"),
        Dense(1)
    1)
    model.compile(optimizer='adam', loss='mse', metrics=['mse'])
    return(model)
estimator= KerasRegressor(build fn=buildmodel, epochs=100, batch size=10, verbose=0)
kfold= RepeatedKFold(n splits=5, n repeats=100)
results= cross val score(estimator, x, y, cv=kfold, n jobs=2) # 2 cpus
results.mean() # Mean MSE
```

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Function that returns a valid Keras model

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estimator= KerasRegressor(build fn=buildmodel, epochs=100, batch size=10, verbose=0)
kfold= RepeatedKFold(n splits=5, n repeats=100)
results= cross val score(estimator, x, y, cv=kfold, n_jobs=2) # 2 cpus
results.mean() # Mean MSE
```

Wrapper that instantiates a Keras model as a scikit-learn regressor object (with a .fit() and .predict() method, etc.)

```
from sklearn.model selection import RepeatedKFold, cross val score
from tensorflow.keras.models import *
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results.mean() # Mean MSE
```

Split data in 5 folds 100 times, for each train the model on 4 folds and validate on 1.

Show average mean-squared error over these 100 5-fold cross-validations.

Function that builds your model. Take argument hyperparameter (hp).

For number of neurons, search from 32 to 512 neurons in steps of 32.

Range of numbers = hp.Int()

For learning rate in the Adam optimizer, pick from 3 specific options.

Specific options = hp.Choice()

```
import keras_tuner
tuner = keras_tuner.tuners.Hyperband(
  build_model,
  objective='val_loss',
  max_epochs=100,
  max_trials=200,
  executions_per_trial=2,
  directory='my_dir')
```

max_trials = how many different models you try maximally.

executions_per_trial: how many times you train a model with the same parameters

- → since neural net weights and biases are randomly instantiated, training the same model twice might not get the exact same outcome
- → reduce variance in model performance measure.

```
import keras tuner
                                                                    Get the best fit
tuner = keras tuner.tuners.Hyperband(
  build model,
  objective='val loss',
  max epochs=100,
  max trials=200,
  executions per trial=2,
  directory='my_dir')
tuner.search(x train, y train, epochs=2, validation data=(x val, y val))
models = tuner.get_best_models(num_models=2)
```

tuner.results_summary()

```
Results summary
Results in my dir/helloworld
Showing 10 best trials
Objective(name='val accuracy', direction='max')
Trial summary
Hyperparameters:
units: 480
learning rate: 0.001
Score: 0.9730499982833862
Trial summary
Hyperparameters:
units: 160
learning rate: 0.001
Score: 0.9692499935626984
Trial summary
Hyperparameters:
units: 320
learning rate: 0.0001
Score: 0.9421000182628632
```

See a summary of the (top N) hyperparameter choices

(here for a tuner with max_trials = 3, so just 3)

Break for practical 2

- Guided exercises where they:
 - Reimplement the simple neural network they made on Wednesday the previous week (hopefully) in Keras, train it and predict on some new data
 - Perform hyperparameter optimisation (i.e. full training pipeline with bells and whistles) for MNIST dataset classification (starting from some okay convolutional architecture).