Lecture 11

Introduction to Deep Learning

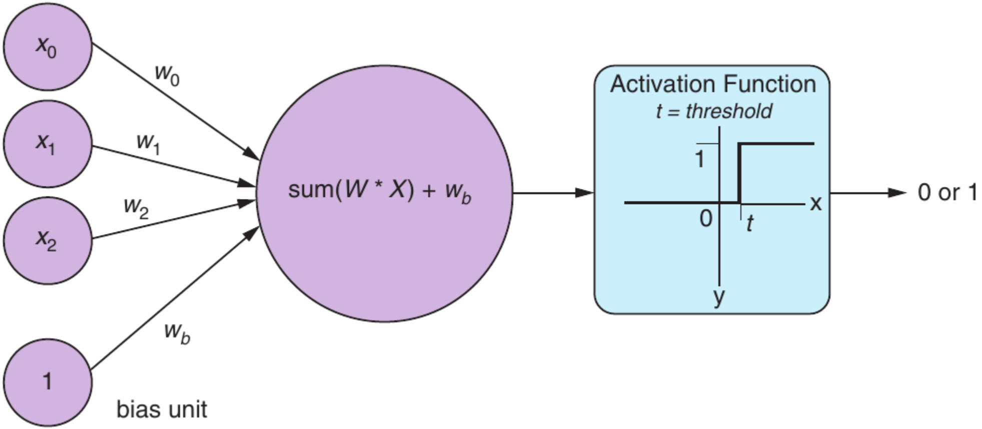
COMP 474/6741, Winter 2022

René Witte
Department of Computer Science
and Software Engineering
Concordia University

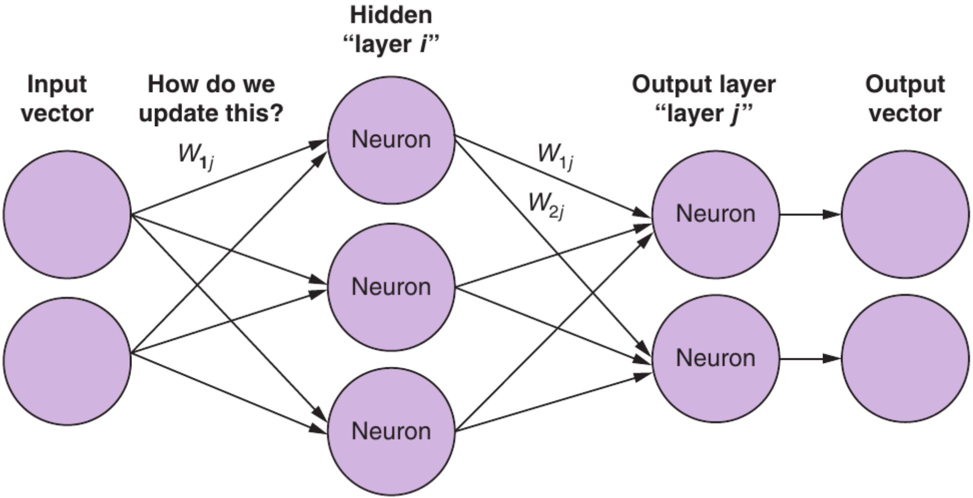
Outline

1. Introduction
2. Deep Learning Architectures
3. Notes and Further Reading

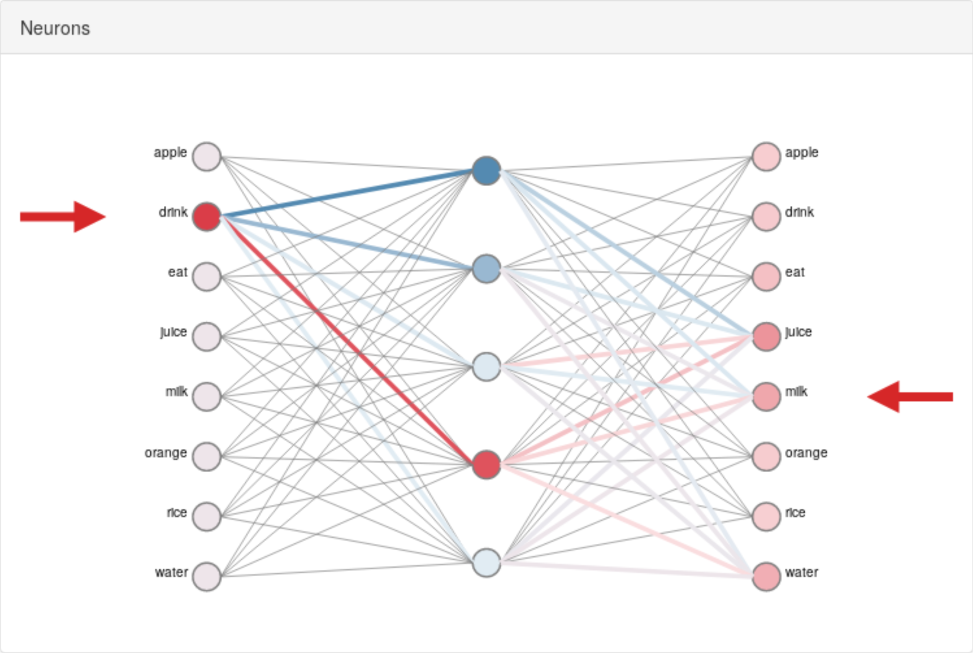
Single Neuron (Perceptron)



Multi-layer neural networks with hidden weights



Feedforward Network (Word2vec)



AI, ML, DL

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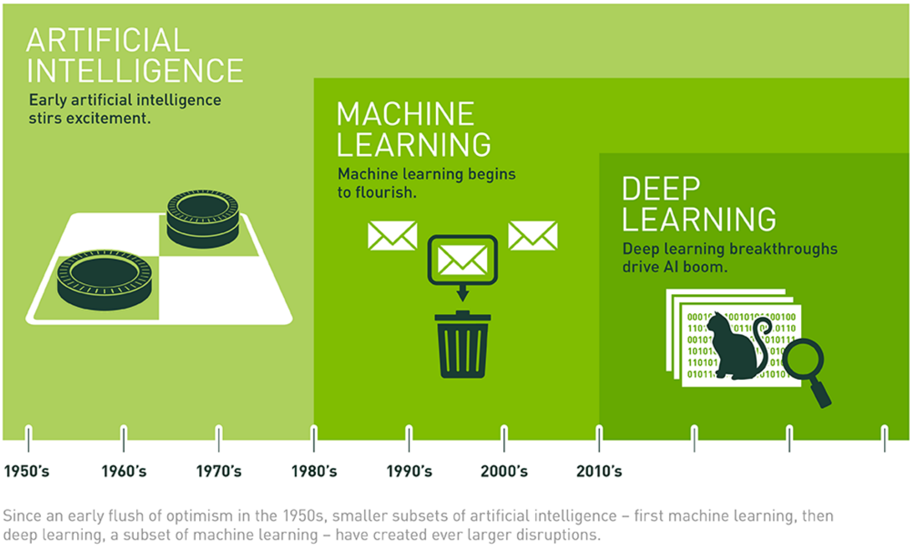
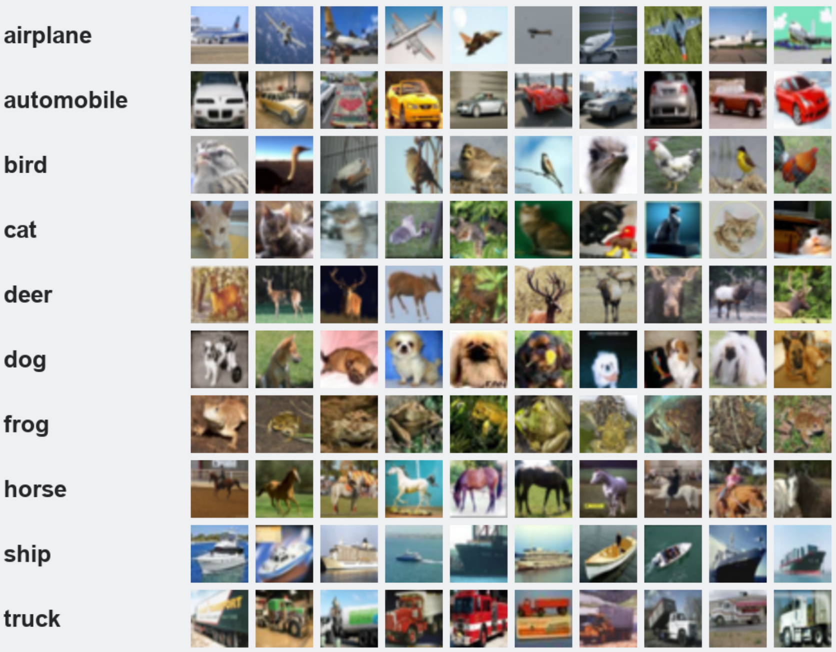


https://medium.com/machine-learning-for-humans/neural-networks-deep-learning-cdad8aeae49b

Classification Example: The CIFAR-10 Dataset



60000 32x32 colour images in 10 classes: https://www.cs.toronto.edu/~kriz/cifar.html

Loading the data (Keras/TensorFlow)


```
import numpy as np
from keras.utils import to_categorical
from keras.datasets import cifar10

(x_train, y_train), (x_test, y_test) = cifar10.load_data()

NUM_CLASSES = 10

x_train = x_train.astype('float32') / 255.0
x_test = x_test.astype('float32') / 255.0

y_train = to_categorical(y_train, NUM_CLASSES)
y_test = to_categorical(y_test, NUM_CLASSES)
```

See https://github.com/davidADSP/GDL_code/blob/master/02_01_deep_learning_deep_neural_network.ipynb

Image Data Shape

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Training data

We use 50000 images for training (and 10000 for testing):

- `x_train` is an array of shape `[50000, 32, 32, 3]`
- First dimension: index of the image in the dataset
- Second, third dimension: size of the image
- Fourth dimension: RGB channels
- We normalized the RGB values from `[0, 255]` to `[0, 1]`

This is called a (four-dimensional) tensor

Example

`x_train[54, 12, 13, 1]` is `0.36862746`

- Image 54, pixel at (12, 13), green channel

Tensors: n-dimensional arrays with $n > 2$

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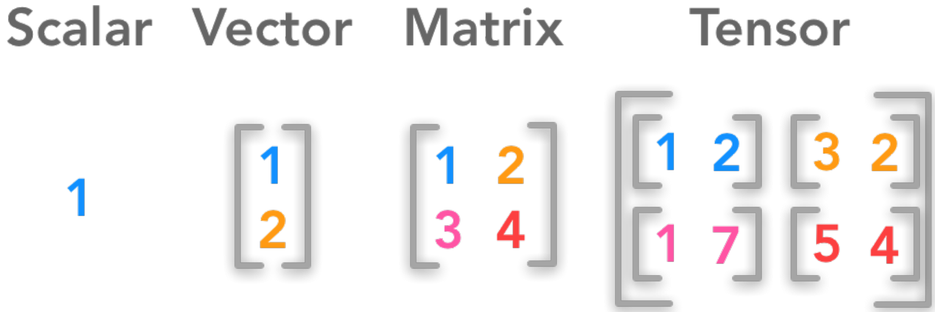
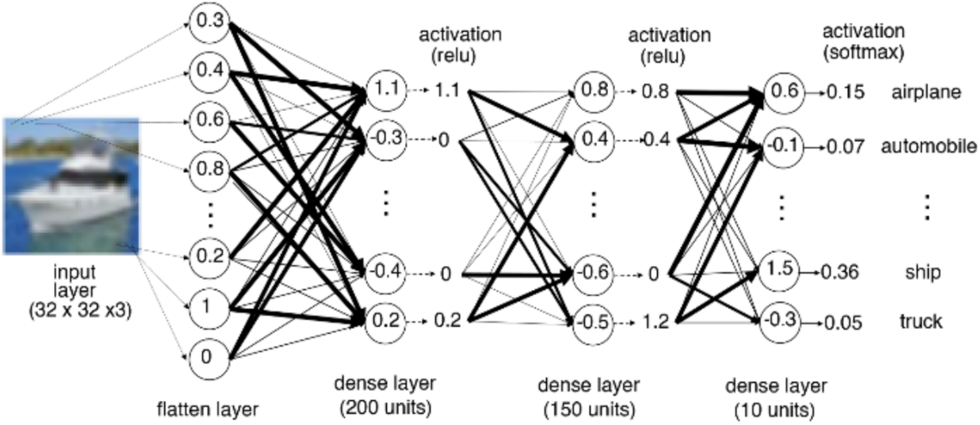


https://hadrienj.github.io/posts/Deep-Learning-Book-Series-2.1-Scalars-Vectors-Matrices-and-Tensors/

Neural Network for CIFAR-10



Neural Network in Keras

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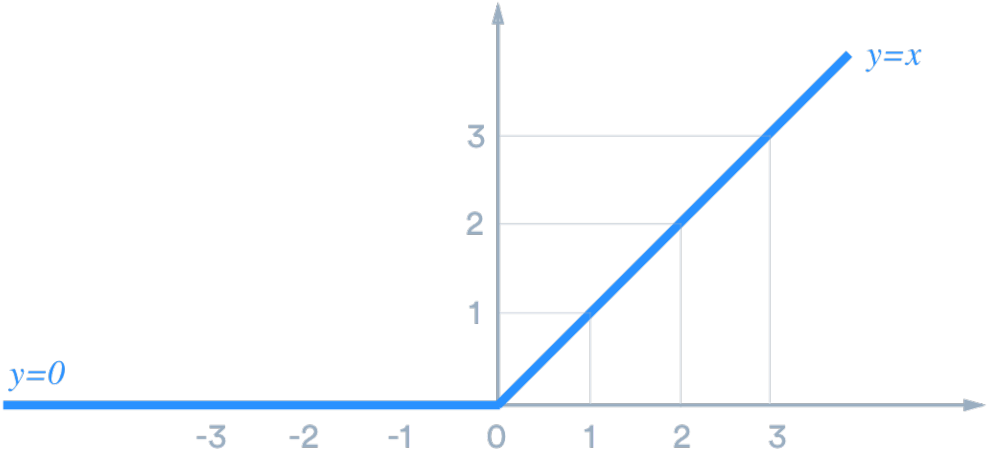
```python
from keras.layers import Input, Flatten, Dense
from keras.models import Model

input_layer = Input((32,32,3))

x = Flatten()(input_layer)

x = Dense(200, activation = 'relu')(x)
x = Dense(150, activation = 'relu')(x)

output_layer = Dense(NUM_CLASSES, activation = 'softmax')(x)

model = Model(input_layer, output_layer)
```

ReLU (Rectified Linear Unit) Activation Function



https://medium.com/@danqing/a-practical-guide-to-relu-b83ca804f1f7

Keras: Building the model

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```python
from keras.optimizers import Adam

opt = Adam(lr=0.0005)
model.compile(loss='categorical_crossentropy',
              optimizer=opt,
              metrics=['accuracy'])
```

Keras: Model Summary


```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_2 (InputLayer)         (None, 32, 32, 3)         0
_________________________________________________________________
flatten_2 (Flatten)          (None, 3072)              0
_________________________________________________________________
dense_4 (Dense)              (None, 200)               614600
_________________________________________________________________
dense_5 (Dense)              (None, 150)               30150
_________________________________________________________________
dense_6 (Dense)              (None, 10)                1510
=================================================================
Total params: 646,260
Trainable params: 646,260
Non-trainable params: 0
_________________________________________________________________
```

Training the Model


```
model.fit(x_train,
          y_train,
          batch_size = 32,
          epochs = 10,
          shuffle = True)
```

Training: Output


```
Epoch 1/10
50000/50000 [==========================] - 13s 262us/step - loss: 1.8490 - accuracy: 0.3361
Epoch 2/10
50000/50000 [==========================] - 13s 257us/step - loss: 1.6592 - accuracy: 0.4104
Epoch 3/10
50000/50000 [==========================] - 13s 259us/step - loss: 1.5827 - accuracy: 0.4372
Epoch 4/10
50000/50000 [==========================] - 13s 256us/step - loss: 1.5290 - accuracy: 0.4571
Epoch 5/10
50000/50000 [==========================] - 13s 261us/step - loss: 1.4882 - accuracy: 0.4725
Epoch 6/10
50000/50000 [==========================] - 13s 257us/step - loss: 1.4537 - accuracy: 0.4847
Epoch 7/10
50000/50000 [==========================] - 13s 257us/step - loss: 1.4293 - accuracy: 0.4940
Epoch 8/10
50000/50000 [==========================] - 13s 263us/step - loss: 1.4056 - accuracy: 0.4988
Epoch 9/10
50000/50000 [==========================] - 12s 246us/step - loss: 1.3849 - accuracy: 0.5086
Epoch 10/10
50000/50000 [==========================] - 12s 244us/step - loss: 1.3659 - accuracy: 0.5150
```

Evaluating the model

Training for 10 epochs:

```
model.evaluate(x_test, y_test)
[1.4283625371932984, 0.4955999851226806б]
```

Training for 100 epochs:

```
model.evaluate(x_test, y_test)
[1.6529622526168823, 0.5023999810218811]
```

Training for 1000 epochs:

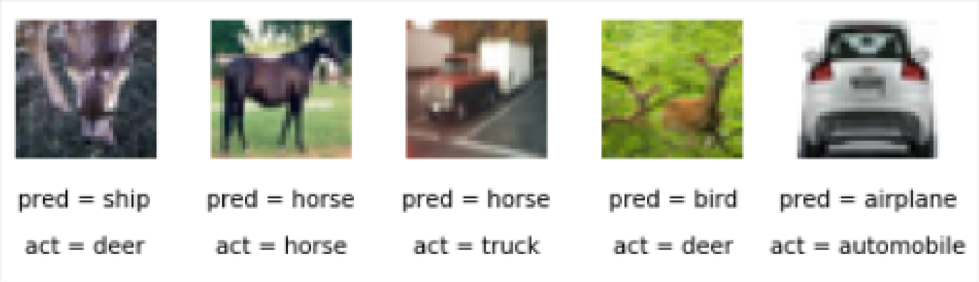
```
...
50000/50000 [==========================] - 13s 255us/step - loss: 0.2840 - accuracy: 0.8986
10000/10000 [==========================] - 0s 47us/step
```

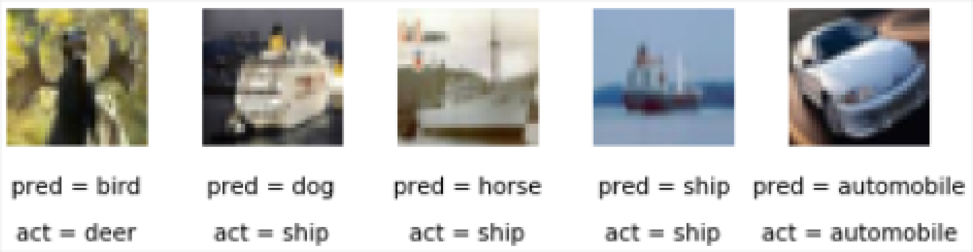
```
model.evaluate(x_test, y_test)
[6.070724856567383, 0.4410000145435333]
```

Show result for some random test images


```
CLASSES = np.array(['airplane', 'automobile', 'bird', 'cat', 'deer',
                    'dog', 'frog', 'horse', 'ship', 'truck'])

preds = model.predict(x_test)
preds_single = CLASSES[np.argmax(preds, axis = -1)]
actual_single = CLASSES[np.argmax(y_test, axis = -1)]

n_to_show = 10
indices = np.random.choice(range(len(x_test)), n_to_show)

fig = plt.figure(figsize=(15, 3))
fig.subplots_adjust(hspace=0.4, wspace=0.4)

for i, idx in enumerate(indices):
    img = x_test[idx]
    ax = fig.add_subplot(1, n_to_show, i+1)
    ax.axis('off')
    ax.text(0.5, -0.35, 'pred = ' + str(preds_single[idx]), fontsize=10,
            ha='center', transform=ax.transAxes)
    ax.text(0.5, -0.7, 'act = ' + str(actual_single[idx]), fontsize=10,
            ha='center', transform=ax.transAxes)
    ax.imshow(img)
```

Some random results. . .





Outline

1. Introduction

2. **Deep Learning Architectures**
   - Convolutional Neural Networks (CNNs)
   - CNN for Text
   - Sentiment Analysis

3. Notes and Further Reading

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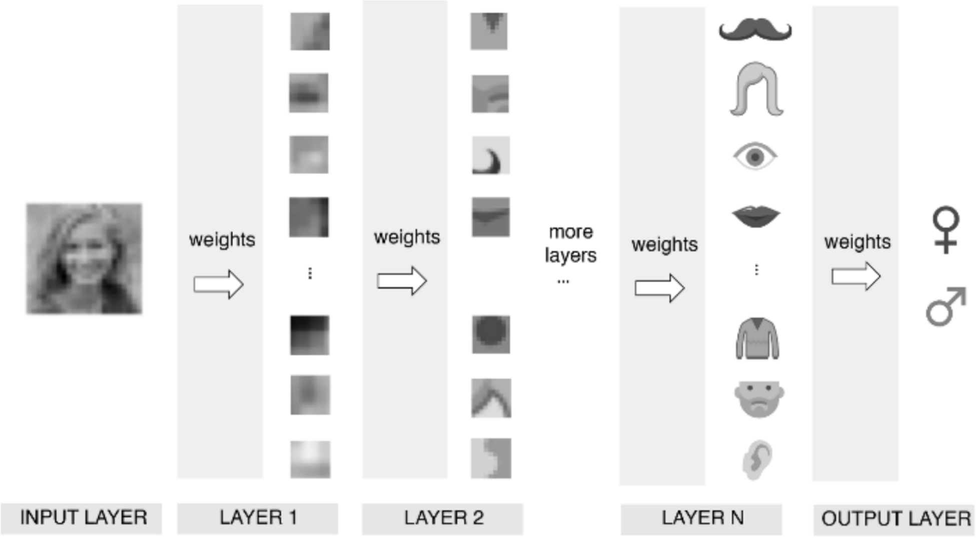
Deep Learning Conceptual Diagram



The Convolution Operation

Applying a $3 \times 3 \times 1$ filter (a.k.a. kernel)

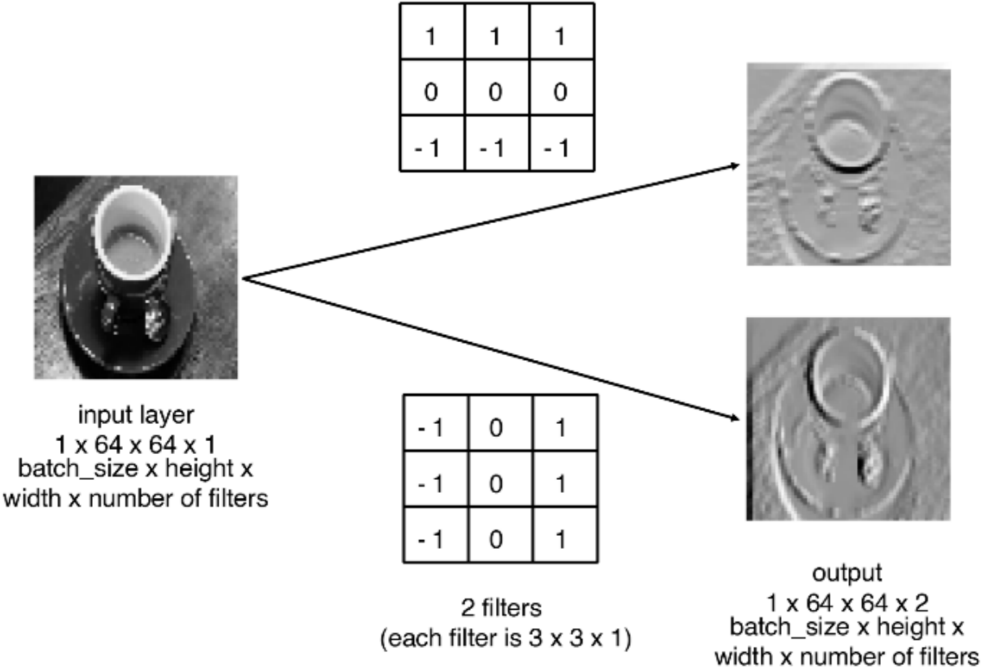
3x3 portion of an image

filter

$$\begin{bmatrix} 0.6 & 0.2 & 0.6 \\ 0.1 & -0.2 & -0.3 \\ -0.5 & -0.1 & -0.3 \end{bmatrix} * \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} = 2.3$$

$$\begin{bmatrix} -0.6 & -0.2 & -0.6 \\ -0.1 & 0.2 & 0.3 \\ 0.5 & 0.1 & 0.3 \end{bmatrix} * \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} = -2.3$$

Applying Two Convolutional Filters to a Grayscale Image



Convolutions in Keras


```
input_layer = Input(shape=(64,64,1))

conv_layer_1 = Conv2D(filters = 2,
                      kernel_size = (3,3),
                      strides = 1,
                      padding = "same")(input_layer)
```

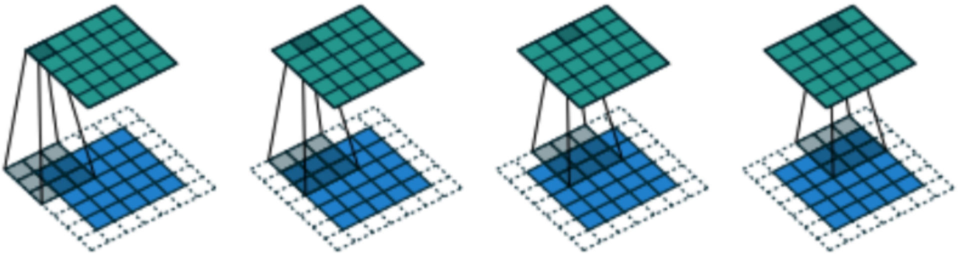
Strides & Padding

Stride (a.k.a. step size)

Distance we move the convolution across the input at each step

Padding

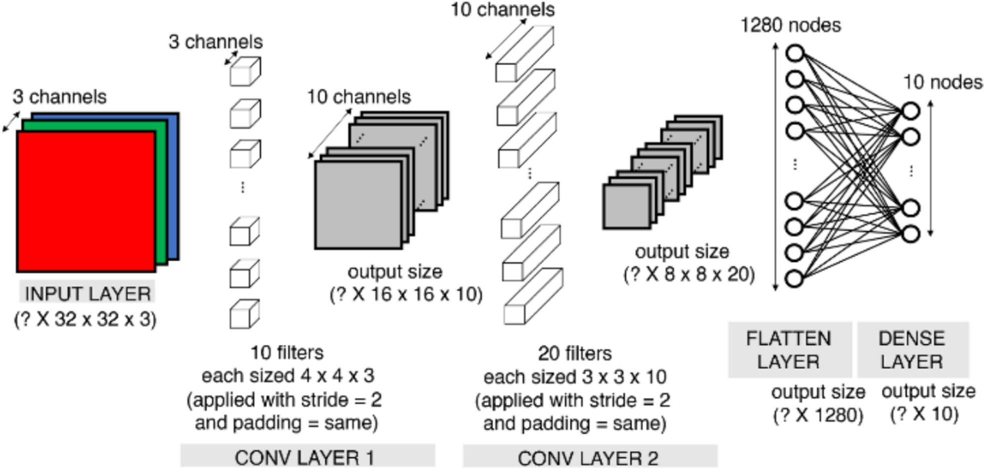
Padding extends the filter over the edges, using zero values



A $3 \times 3 \times 1$ kernel (gray) being passed over a $5 \times 5 \times 1$ input image (blue), with `padding="same"` and `strides=1`, to generate the $5 \times 5 \times 1$ output (green)

→ Worksheet #10: Task 1

Convolutional Neural Network



Our CNN in Keras


```
input_layer = Input(shape=(32,32,3))

conv_layer_1 = Conv2D(filters = 10,
                      kernel_size = (4,4),
                      strides = 2,
                      padding = 'same'
                      )(input_layer)

conv_layer_2 = Conv2D(filters = 20,
                      kernel_size = (3,3),
                      strides = 2,
                      padding = 'same'
                      )(conv_layer_1)
```

https://github.com/davidADSP/GDL_code/blob/master/02_03_deep_learning_conv_neural_network.ipynb

Analysing the Network Architecture

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Concordia University

Input Shape: `(None, 32, 32, 3)` (`None`: can process inputs in batch)

First conv layer: 4×4×3 (`kernel_size = (4,4)`)

- Three channels in preceding layer (red, green, blue)
- Number of weights (parameters) is $(4 \times 4 \times 3 + 1) \times 10 = 490$
- Depth of filters in a layer $=$ number of channels in preceding layer
- General formula (with `padding = "same"`, meaning same size as input, padding with zeros):

$$\text{output\_shape} = \left(\text{None}, \frac{\text{input\_height}}{\text{stride}}, \frac{\text{input\_width}}{\text{stride}}, \text{filters}\right)$$

Second conv layer: 20 filters, 3×3 size, depth 10

Flatten: transform into $8 \times 8 \times 20 = 1280$ unit vector using Keras `Flatten`

Output: 10-unit `Dense` layer with softmax activation

→ Worksheet #10: Task 2

Batch Normalization Layer

Avoiding 'exploding gradient' problem

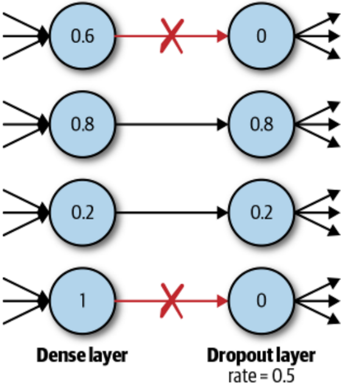
- Over time, calculating the gradient in earlier layers can grow exponentially large
- Loss functions start to return `NaN` $\rightarrow$ overflow error
- Caused by covariance shift in weights
- Reduced in practice through batch normalization
- Added as a separate layer, in Keras: `BatchNormalization(momentum = 0.9)`
- Calculates the mean and standard deviation of each of its input channels across the batch and normalizes by subtracting the mean and dividing by the standard deviation
- Learns two parameters, scale (gamma) and shift (beta)
- Output is normalized input, scaled by gamma and shifted by beta

[Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift, https://arxiv.org/abs/1502.03167]

Dropout Layer

Goal: Avoid Overfitting

- Want a network that can generalize, not just remember the input samples
- We add a regularization technique, here a dropout layer
- Keras: `Dropout(rate = 0.5)`



[Nitish Srivastava et al., “Dropout: A Simple Way to Prevent Neural Networks from Overfitting,” *Journal of Machine Learning Research* 15 (2014): 1929–1958, http://jmlr.org/papers/volume15/srivastava14a/srivastava14a.pdf].

Complete Network in Keras

```
input_layer = Input((32,32,3))

x = Conv2D(filters=32, kernel_size=3, strides=1, padding='same')(input_layer)
x = BatchNormalization()(x)
x = LeakyReLU()(x)

x = Conv2D(filters = 32, kernel_size = 3, strides = 2, padding = 'same')(x)
x = BatchNormalization()(x)
x = LeakyReLU()(x)

x = Conv2D(filters = 64, kernel_size = 3, strides = 1, padding = 'same')(x)
x = BatchNormalization()(x)
x = LeakyReLU()(x)

x = Conv2D(filters = 64, kernel_size = 3, strides = 2, padding = 'same')(x)
x = BatchNormalization()(x)
x = LeakyReLU()(x)

x = Flatten()(x)
x = Dense(128)(x)
x = BatchNormalization()(x)
x = LeakyReLU()(x)
x = Dropout(rate = 0.5)(x)

x = Dense(NUM_CLASSES)(x)
output_layer = Activation('softmax')(x)
model = Model(input_layer, output_layer)
```

Resulting Model (1/2)


```
Layer (type)                 Output Shape              Param #
=================================================================
input_13 (InputLayer)        (None, 32, 32, 3)         0
_________________________________________________________________
conv2d_11 (Conv2D)           (None, 32, 32, 32)        896
_________________________________________________________________
batch_normalization_6 (Batch (None, 32, 32, 32)        128
_________________________________________________________________
leaky_re_lu_6 (LeakyReLU)    (None, 32, 32, 32)        0
_________________________________________________________________
conv2d_12 (Conv2D)           (None, 16, 16, 32)        9248
_________________________________________________________________
batch_normalization_7 (Batch (None, 16, 16, 32)        128
_________________________________________________________________
leaky_re_lu_7 (LeakyReLU)    (None, 16, 16, 32)        0
_________________________________________________________________
conv2d_13 (Conv2D)           (None, 16, 16, 64)        18496
_________________________________________________________________
batch_normalization_8 (Batch (None, 16, 16, 64)        256
_________________________________________________________________
leaky_re_lu_8 (LeakyReLU)    (None, 16, 16, 64)        0
_________________________________________________________________
conv2d_14 (Conv2D)           (None, 8, 8, 64)          36928
...
```

Resulting Model (2/2)

```
Layer (type)                 Output Shape              Param #
=================================================================
...
conv2d_14 (Conv2D)           (None, 8, 8, 64)          36928
_________________________________________________________________
batch_normalization_9 (Batch (None, 8, 8, 64)          256
_________________________________________________________________
leaky_re_lu_9 (LeakyReLU)    (None, 8, 8, 64)          0
_________________________________________________________________
flatten_13 (Flatten)         (None, 4096)              0
_________________________________________________________________
dense_30 (Dense)             (None, 128)               524416
_________________________________________________________________
batch_normalization_10 (Batc (None, 128)               512
_________________________________________________________________
leaky_re_lu_10 (LeakyReLU)   (None, 128)               0
_________________________________________________________________
dropout_2 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_31 (Dense)             (None, 10)                1290
_________________________________________________________________
activation_2 (Activation)    (None, 10)                0
=================================================================
Total params: 592,554
Trainable params: 591,914
Non-trainable params: 640
_________________________________________________________________
```

Training

```
opt = Adam(lr=0.0005)

model.compile(loss='categorical_crossentropy',
              optimizer=opt,
              metrics=['accuracy'])

model.fit(x_train,
          y_train,
          batch_size=32,
          epochs=10,
          shuffle=True,
          validation_data = (x_test, y_test))
```

Training (output)

```
Train on 50000 samples, validate on 10000 samples
Epoch 1/10
50000/50000 [==============] - 118s 2ms/step - loss: 1.5609 - accuracy: 0.4556 - val_loss: 1.2602 - val_
Epoch 2/10
50000/50000 [==============] - 114s 2ms/step - loss: 1.1528 - accuracy: 0.5914 - val_loss: 1.0027 - val_
Epoch 3/10
50000/50000 [==============] - 112s 2ms/step - loss: 1.0021 - accuracy: 0.6472 - val_loss: 0.9151 - val_
Epoch 4/10
50000/50000 [==============] - 117s 2ms/step - loss: 0.9156 - accuracy: 0.6801 - val_loss: 0.9089 - val_
Epoch 5/10
50000/50000 [==============] - 116s 2ms/step - loss: 0.8517 - accuracy: 0.7018 - val_loss: 0.8910 - val_
Epoch 6/10
50000/50000 [==============] - 112s 2ms/step - loss: 0.8004 - accuracy: 0.7212 - val_loss: 0.8599 - val_
Epoch 7/10
50000/50000 [==============] - 118s 2ms/step - loss: 0.7532 - accuracy: 0.7369 - val_loss: 0.8539 - val_
Epoch 8/10
50000/50000 [==============] - 113s 2ms/step - loss: 0.7111 - accuracy: 0.7502 - val_loss: 0.8647 - val_
Epoch 9/10
50000/50000 [==============] - 113s 2ms/step - loss: 0.6760 - accuracy: 0.7633 - val_loss: 0.8913 - val_
Epoch 10/10
50000/50000 [==============] - 113s 2ms/step - loss: 0.6395 - accuracy: 0.7744 - val_loss: 0.8169 - val_
```

Evaluation

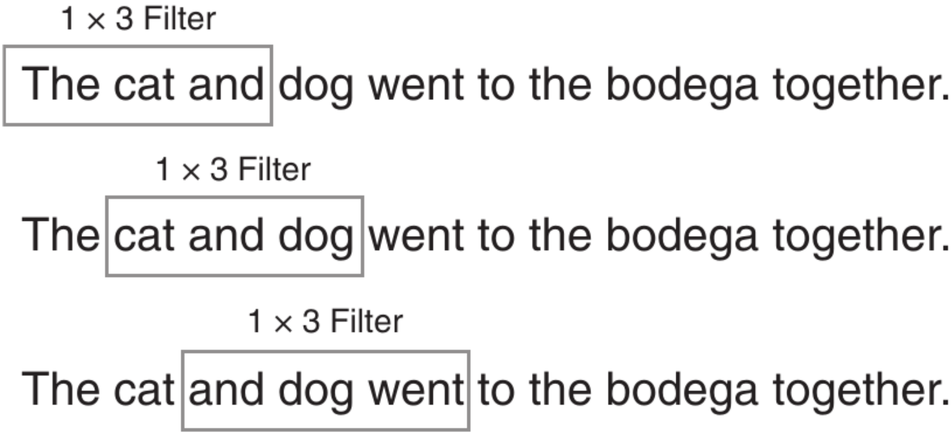

```
model.evaluate(x_test, y_test)
[0.8298392653465271, 0.7210999727249146]
```

Some more random results...

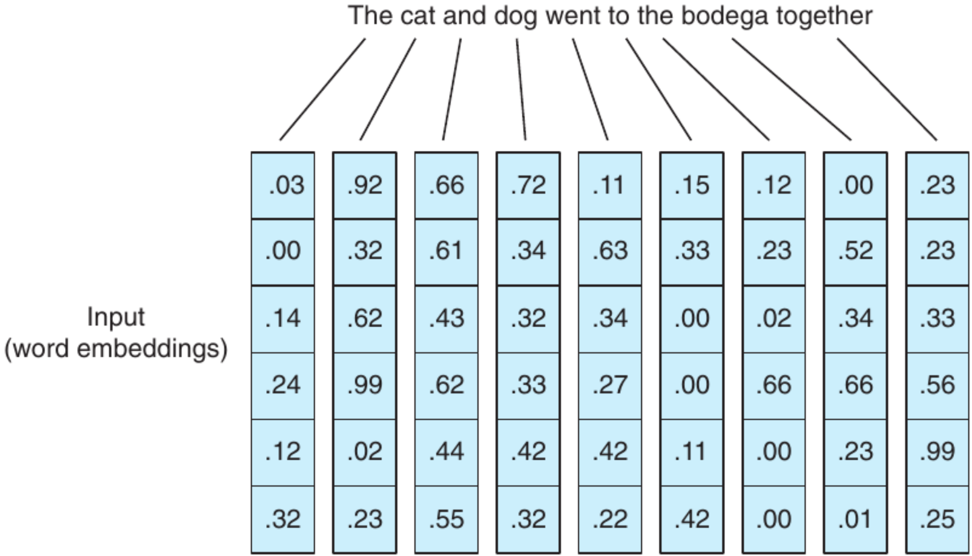
Ok, so what about text?

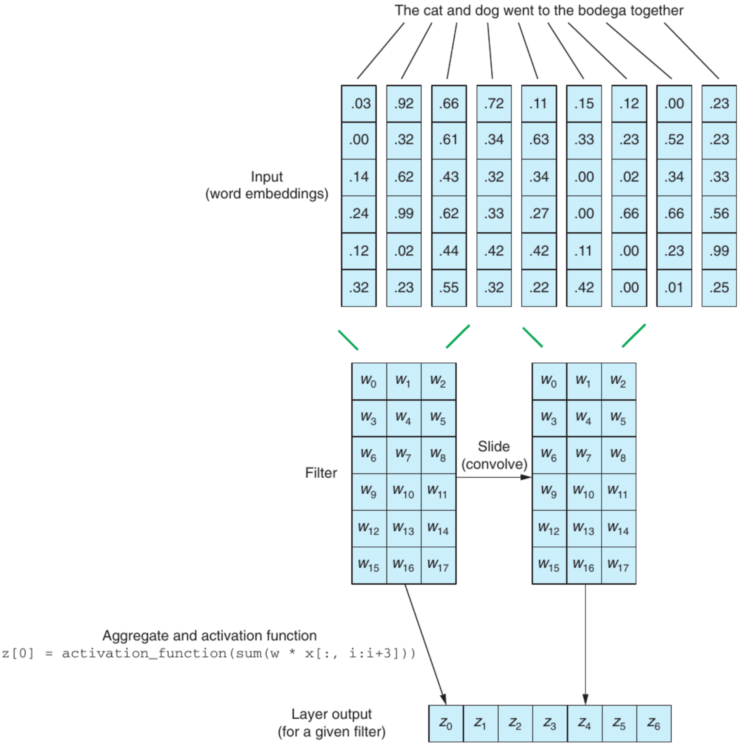
CNN for Text

- No “vertical” information like in an image, but “horizontal” (left-to-right sequence)
- Instead of 2D convolutions, we have 1D convolutions

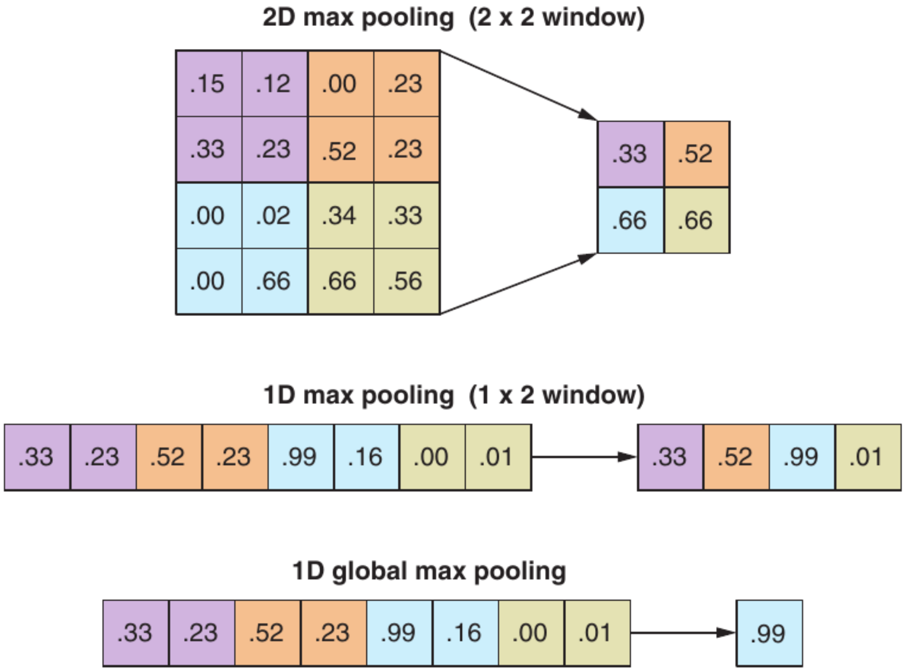


Encoding Input Text using Word Embeddings




The cat and dog went to the bodega together
Input
(word embeddings)
.03 .92 .66 .72 .11 .15 .12 .00 .23
.00 .32 .61 .34 .63 .33 .23 .52 .23
.14 .62 .43 .32 .34 .00 .02 .34 .33
.24 .99 .62 .33 .27 .00 .66 .66 .56
.12 .02 .44 .42 .42 .11 .00 .23 .99
.32 .23 .55 .32 .22 .42 .00 .01 .25
Filter
w_0 w_1 w_2
w_3 w_4 w_5
w_6 w_7 w_8
w_9 w_{10} w_{11}
w_{12} w_{13} w_{14}
w_{15} w_{16} w_{17}
Slide
(convolve)
Aggregate and activation function
z[0] = activation_function(sum(w * x[:, i:i+3]))
Layer output
(for a given filter)
z_0 z_1 z_2 z_3 z_4 z_5 z_6

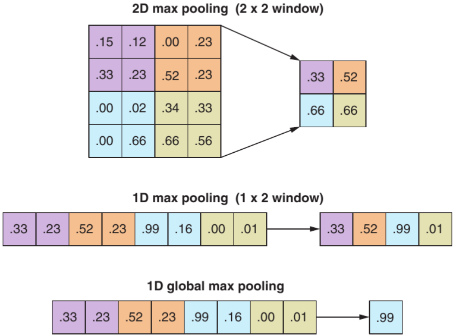
Pooling Layers



Pooling

Dimensionality Reduction

- Filtering results in new (filtered) versions of each data sample
- We can “throw away” some data by reducing the size
- Choose a representative, e.g., maximum in a 2×2 window
- For text: `max` in a 1D (e.g., 1×2 window)
- Keras: `model.add(GlobalMaxPooling1D())` (default size is 2)



→ Worksheet #10: Task 3

Task: Sentiment Analysis

Dataset

Stanford AI movie dataset from https://ai.stanford.edu/~amaas/data/sentiment/

- 50,000 reviews from IMDB; upto 30 reviews/movie
- contains an even number of positive and negative reviews (so randomly guessing yields 50% accuracy)
- A negative review has a score $\leq$ 4 out of 10
- A positive review has a score $\geq$ 7 out of 10
- Neutral reviews are not included in the dataset

Positive Example `6587_9.txt`, so id 6587, rating 9 stars

The Master Blackmailer, based off of Sir Arthur Conan Doyle's short story, "the Adventure of Charles Augustus Milverton," is the first feature length Sherlock Holmes story with Jeremy Brett that I have seen. The story is interesting and dark...

Negative Example `(9985_1.txt)`, id 9985, rating 1 star

Have I ever seen a film more shockingly inept? I can think of plenty that equal this one, but none which manage to outdo it. The cast are all horrible stereotypes lumbered with flat dialogue. I am ashamed for all of the people involved ...

[Maas, Andrew L. et al., Learning Word Vectors for Sentiment Analysis, *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, June 2011, ACL*]

CNN for classifying IMDB movie reviews


```python
model = Sequential()

# we add a Convolution1D, which will learn filters
# word group filters of size filter_length:
model.add(Conv1D(filters,
                 kernel_size,
                 padding='valid',
                 activation='relu',
                 strides=1,
                 input_shape=(maxlen, embedding_dims)))

# we use max pooling:
model.add(GlobalMaxPooling1D())

# We add a vanilla hidden layer:
model.add(Dense(hidden_dims))
model.add(Dropout(0.2))
model.add(Activation('relu'))

# We project onto a single unit output layer, and squash it with a sigmoid:
model.add(Dense(1))
model.add(Activation('sigmoid'))

model.compile(loss='binary_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
```

Applying the trained model


```
>>> sample_1 = "I␣hate␣that␣the␣dismal␣weather␣had␣me␣down␣for␣so␣long,
when␣will␣it␣break!␣Ugh,␣when␣does␣happiness␣return?␣The␣sun␣is␣blinding
and␣the␣puffy␣clouds␣are␣too␣thin.␣I␣can't␣wait␣for␣the␣weekend."
...
```

(vectorize and shape input, see [LHH19])

```
...
>>> model.predict(test_vec)
array([[ 0.12459087]], dtype=float32)
```

Outline

1. Introduction
2. Deep Learning Architectures
3. **Notes and Further Reading**

Reading Material

Required

- [Fos19, Chapter 2] (CNNs for images)
- [LHH19, Chapter 7] (CNNs for text)

References

[Fos19] David Foster.
Generative Deep Learning: Teaching Machines to Paint, Write, Compose, and Play.
O'Reilly, 2019.
https://concordiauniversity.on.worldcat.org/oclc/1136155457.

[LHH19] Hobson Lane, Cole Howard, and Hannes Max Hapke.
Natural Language Processing in Action.
Manning Publications Co., 2019.
https://concordiauniversity.on.worldcat.org/oclc/1102387045.