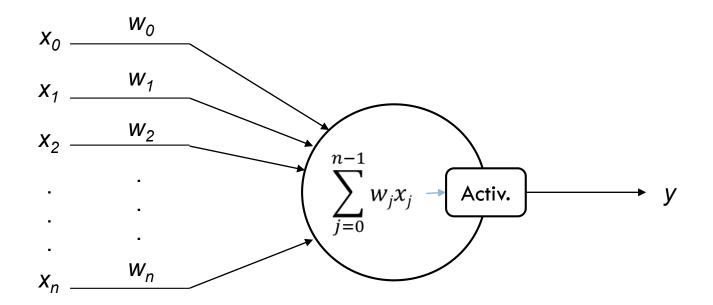
### NEURAL NETWORKS

Instructors: Crista Lopes Copyright © Instructors.

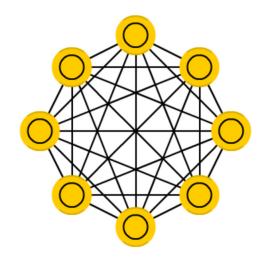
# Artificial Neuron - Perceptron

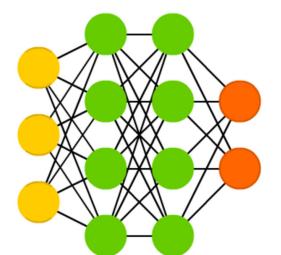


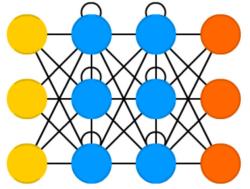
### Neural Networks

 Networks of perceptrons connected to each other in some topology

Hopfield Network (HN) Deep Feed Forward (DFF) Recurrent Neural Network (RNN)



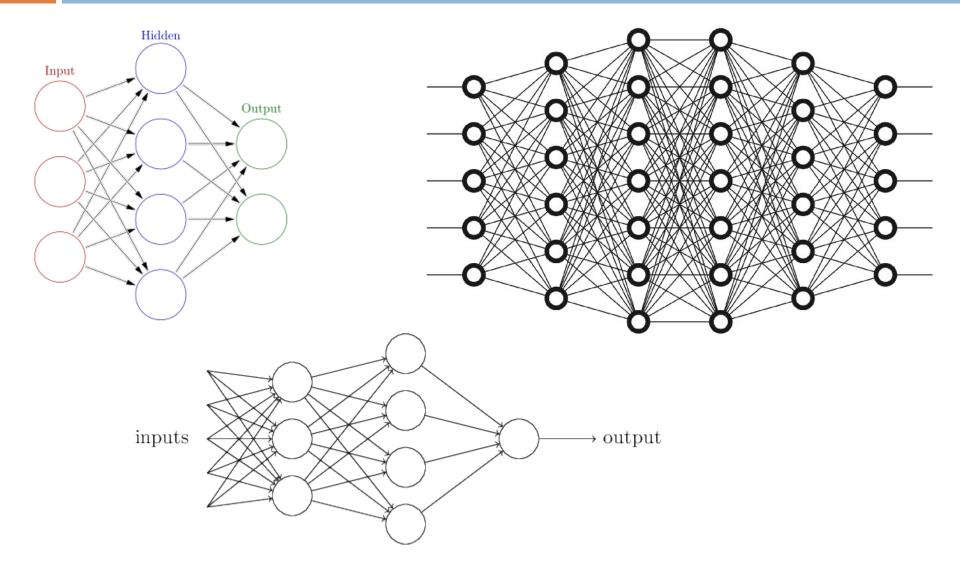




### **Dataflow Programming**

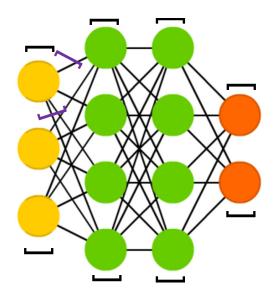
- □ The network implements a <u>function</u>
  - Input neurons get the input
  - Output neurons show the output
- Neurons receive input from other neurons, and send their outputs to the neurons they are connected to
- Neurons are data transformers
- □ No memory again, a <u>pure function</u>

### Feed Forward Neural Networks



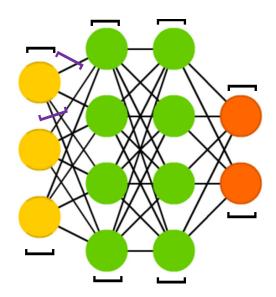
#### How to model NNs?

- Neurons-as-objects may seem appropriate
  - Would capture network changes dynamically (creation/deletion of neurons)
- Actors, maybe?



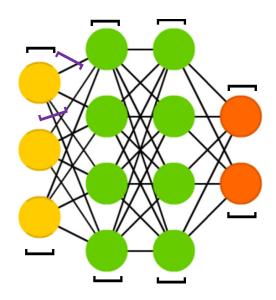
#### How to model NNs?

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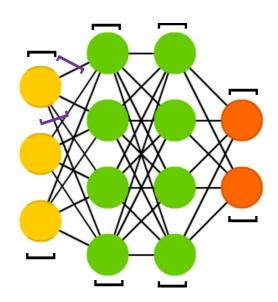
#### How to model NNs?

- Popular frameworks: no dynamicity, everything is static
- Arrays all the way down!



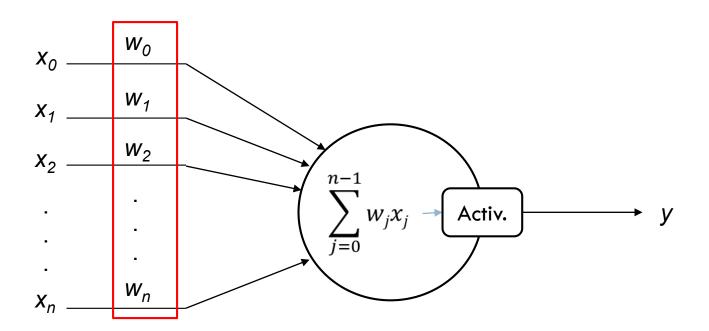
# NNs as Array Programming

- Static network allows for powerful array operations
- Highly parallelizable
- Use of GPUs



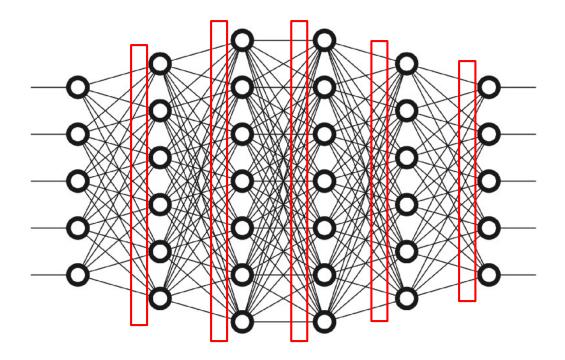
#### **Tensors**

 Multidimensional arrays of numbers representing data transformation functions



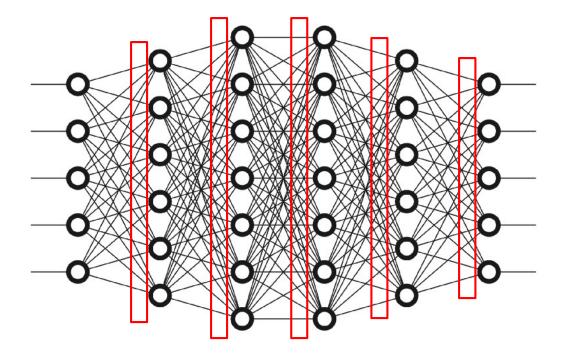
#### **Tensors**

 Multidimensional arrays of numbers representing data transformation functions



### Learning

The values of these tensors are **not** set upfront by the programmer; they are **inferred** (learned) during "training" using input/output examples

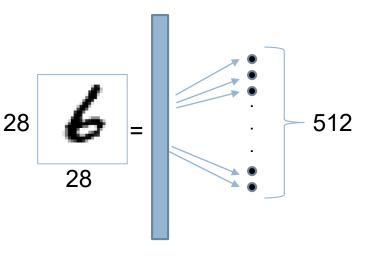


### Anatomy of Neural Network Programs

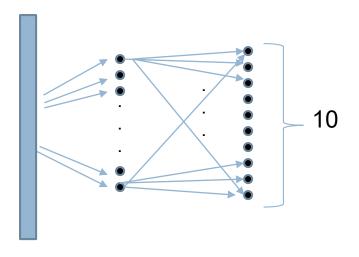
Using Keras

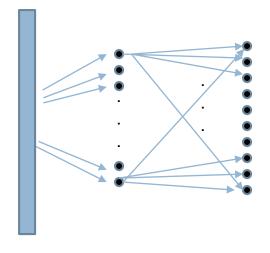
# Anatomy of a NN Program

- Prepare the data
- Define the network model
- 3. "Compile" the network model along with certain operational parameters (loss function, optimizer, evaluation metrics)
- 4. Train the model using the training data (aka fit)
- 5. Use the network on new data (aka predict)
  - Evaluate it using given metrics



```
from keras import models
                                                                 ReLU
                                                           R(z) = max(0, z)
from keras import layers
network = models.Sequential()
network.add(layers.Dense(512, activation='relu',
                             input shape=(28 * 28,)))
            W_0
            W_1
            W_2
                                        Activ.
            W_n
```





Softmax([1, 43, 21]) = [0.000001, 0.999997, 0.000002]

```
from keras import models
from keras import layers
network = models.Sequential()
network.add(layers.Dense(512, activation='relu',
                         input shape=(28 * 28,)))
network.add(layers.Dense(10, activation='softmax'))
network.compile(optimizer='rmsprop',
                loss='categorical crossentropy',
                metrics=['accuracy'])
network.fit(train images, train labels, epochs=5, batch size=128)
```

Training phase: inferring the weights (aka parameter values) of the model. Backpropagation.

```
from keras import models
from keras import layers
network = models.Sequential()
network.add(layers.Dense(512, activation='relu',
                         input shape=(28 * 28,)))
network.add(layers.Dense(10, activation='softmax'))
network.compile(optimizer='rmsprop',
                loss='categorical crossentropy',
                metrics=['accuracy'])
network.fit(train images, train_labels,epochs=5,batch_size=128)
predictions = network.predict(test images)
```

The actual "program"

# Keras Example: without learning?

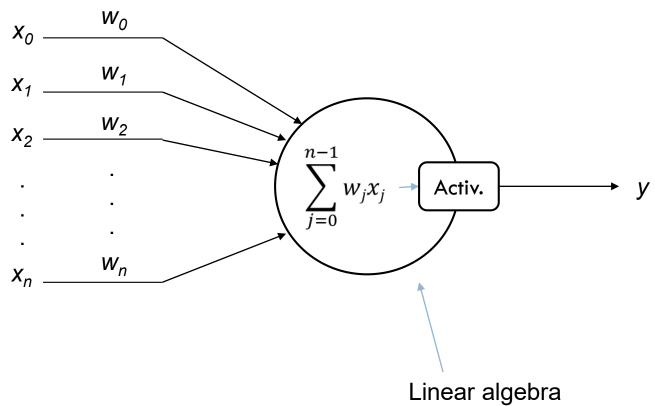
Very high-level array programming style!

#### Network Models as Monadic Structures

- Each layer is a function
- Pure function: side effects are held off
- Many layers = chain of functions
- Chain is manipulated as an object (compile)
- □ Predict = run on given input

# Data Representations

### Artificial Neuron



**Numbers only!** 

# Types of Data

- □ Numerical: images, videos, scalar variables, etc.
- Categorical: strings, text, symbols, etc.
  - Must be converted to numbers before they are fed into a DNN

### Data Representations

- All data is encoded as vectors of numbers
- These encodings are an important part of solving problems in this style
  - Some encodings make the problem easy to solve
  - Others make the problem hard
- Deep neural nets can be seen as a sequence of data representation transformations
- The "learning" part is about searching for suitable representations of the data

### One Hot Encodings for categorical data

- Popular and simple, but quite expensive
- Given N different things, use N bits, where only one bit is 1 and all others are 0
  - Excellent orthogonality
- □ E.g. one-hot encoding of the alphabet, 26 letters:

  - Etc.

# One-hot vs. binary

- A = 01000001 B = 01000010 A = 01000010

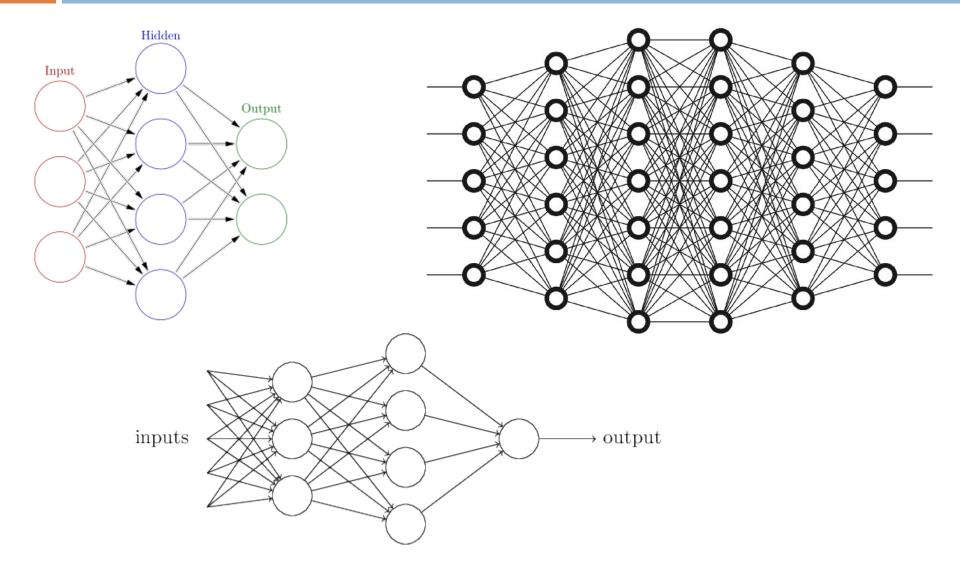
- One hot has less rules than ASCII
- □ The ASCII rules don't mean anything in vector space

### Encodings vs. Embeddings

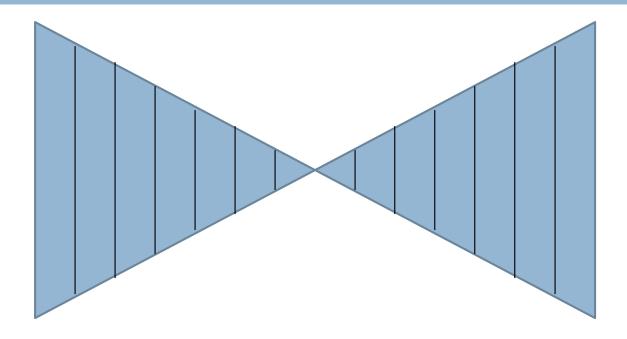
- Both represent data in as numerical vectors
- Embeddings are encodings where the proximity in the space is meaningful
  - E.g. word2vec embeddings place words with similar meaning in close proximity of each other
- For certain problems, it helps using embeddings to start with

# Popular Network Architectures

### Feed Forward Neural Networks



### Encoder-Decoder Architectures

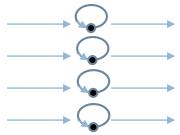


We're dealing with real numbers!

#### Recurrent Neural Networks

- Problem: NNs don't have memory, they are stateless, but many functions depend on prior values
  - E.g. regex \w+
    input: sequence of characters
    output: sequence of words

Solution: Networks "with loops"

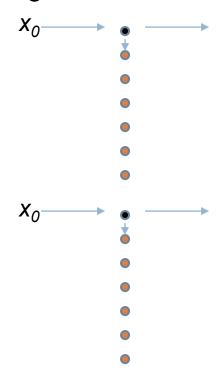


# Loops and Arrays

 Problem: loops break the fixed-sized constraint of this style

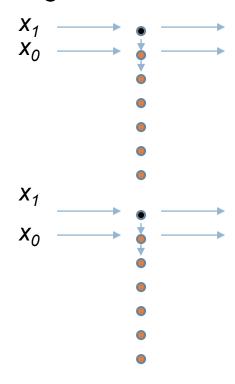
# Loops and Arrays

- Problem: loops break the fixed-sized constraint of this style
- Solution: fixed-length loop unrolling



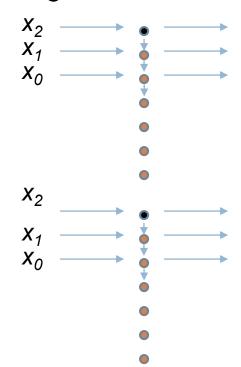
# Loops and Arrays

- Problem: loops break the fixed-sized constraint of this style
- Solution: fixed-length loop unrolling



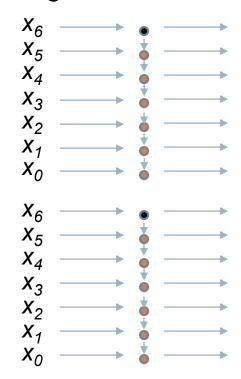
## Loops and Arrays

- Problem: loops break the fixed-sized constraint of this style
- Solution: fixed-length loop unrolling



## Loops and Arrays

- Problem: loops break the fixed-sized constraint of this style
- Solution: fixed-length loop unrolling

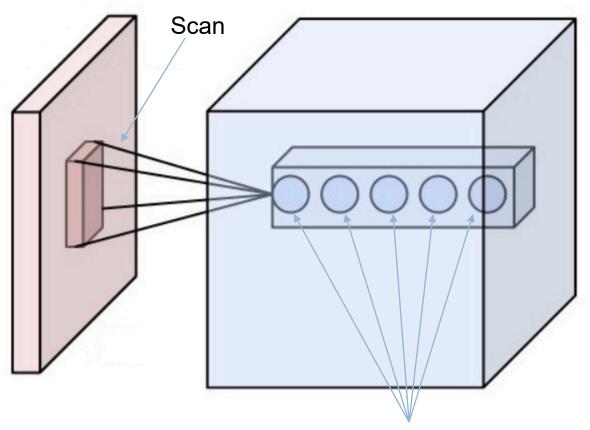


## A simple RNN

```
model = Sequential()
model.add(Embedding(10000, 32))
model.add(SimpleRNN(32, return_sequences=True))
```

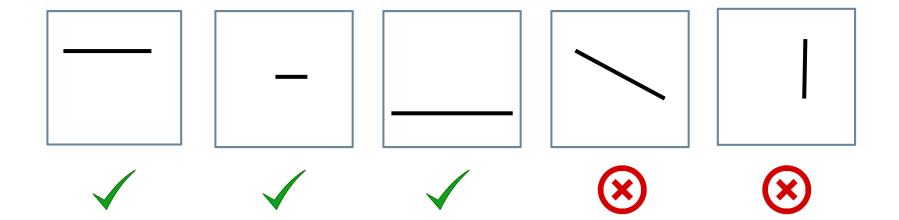
How many "iterations"

#### Convolutional Neural Networks

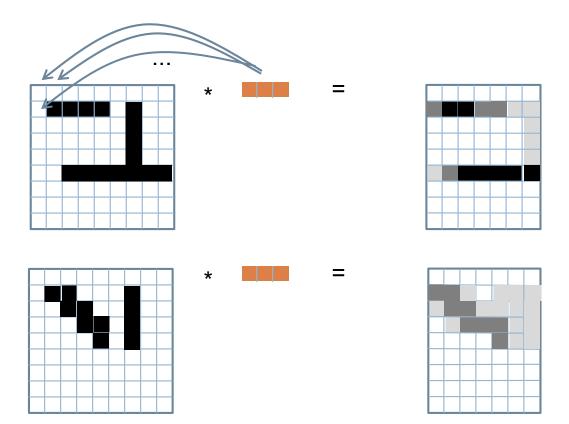


Number of features to extract

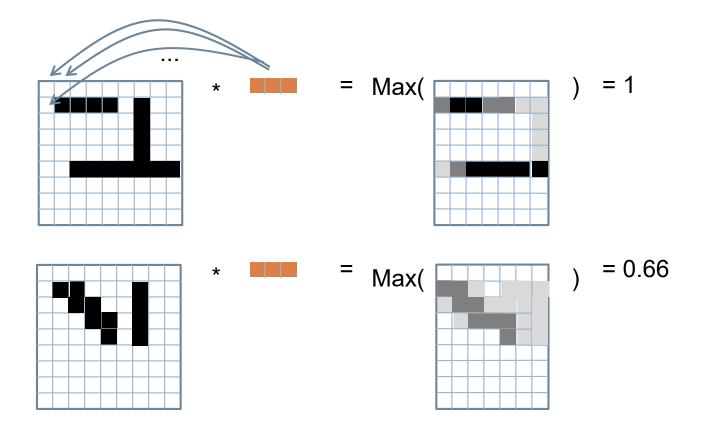
- Example: does the image have an horizontal line?
  - Output: Yes (1) or No (0)



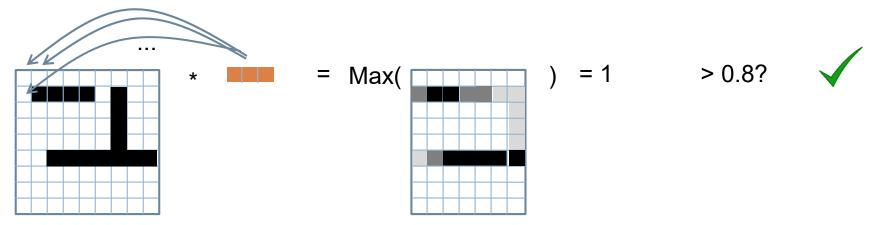
- Example: does the image have an horizontal line?
- Scan the image with a filter (aka convolution)

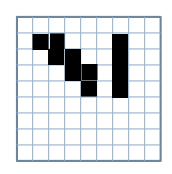


- Example: does the image have an horizontal line?
- □ Then pool

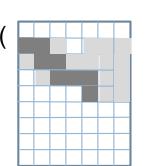


- Example: does the image have an horizontal line?
- Then threshold





= Max(



= 0.66 > 0.8?



#### Convolution Neural Networks

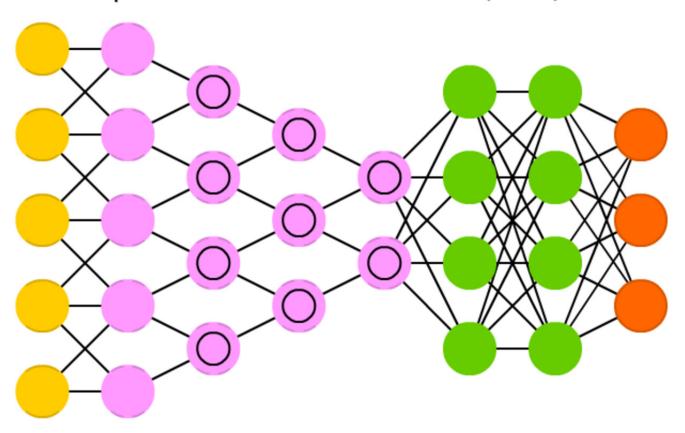
- The number and shape of filters is specified by programmer (aka hyperparameters)
- The exact values of the weights are learned

## Typical CNN

```
from keras import layers
from keras import models
model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu',
                        input shape=(150, 150, 3))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(128, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(128, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Flatten())
model.add(layers.Dense(512, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))
```

## Typical CNN

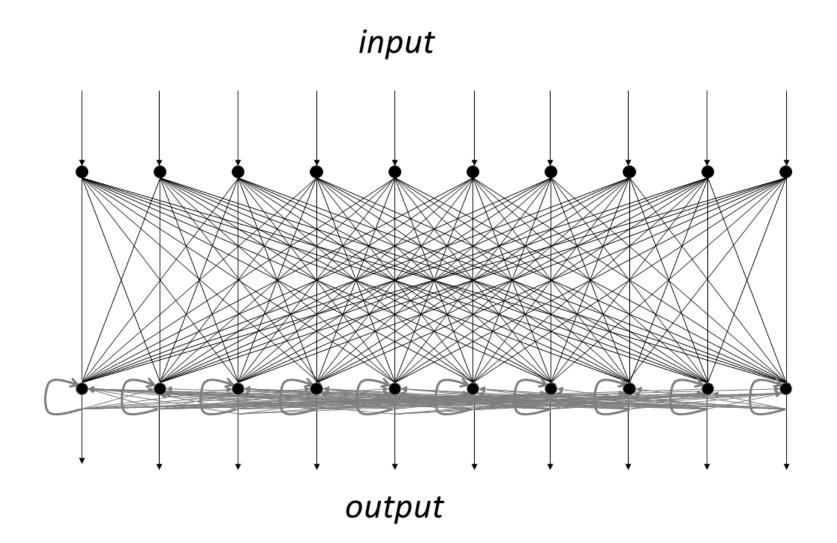
#### Deep Convolutional Network (DCN)



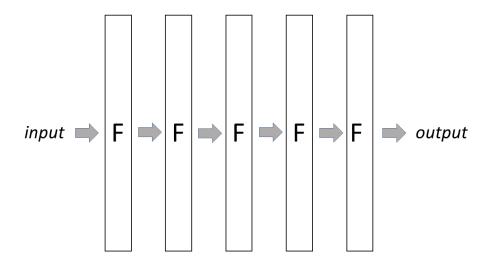
#### Recurrent Neural Networks

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  - E.g. regex \w+
    input: sequence of characters
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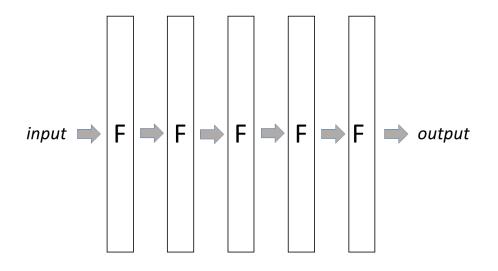
## **RNNs**



```
for (i=0; i<5; i++) {
  doSomething();
  doSomething();
  doSomething();
  doSomething();
  doSomething();</pre>
```



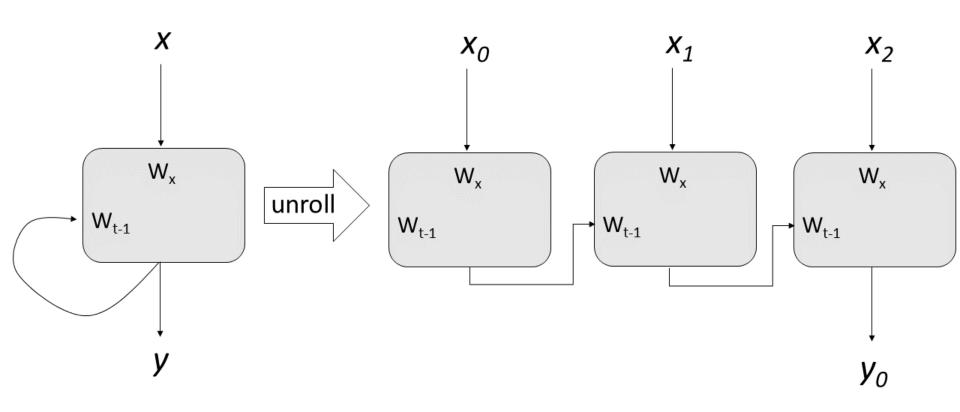
```
for (i=0; i<5; i++) {
    doSomething(0);
    doSomething(1);
    doSomething(2);
    doSomething(3);
    doSomething(4);</pre>
```



```
double d = someCalc();
for (i=0; i<5; i++) {
    d = doSomething(0, d);
    d = doSomething(1, d);
    d = doSomething(2, d);
    d = doSomething(3, d);
    d = doSomething(4, d);</pre>
```

```
double[] d = initArray();
for (i=0; i<5; i++) {
  d[i] = doSomething(i,
                     d[i-1],
                     d[i],
                     d[i+1]);
                double d = someCalc();
                d[0] = doSomething(0, -, d[0], d[1]);
                d[1] = doSomething(1, d[0], d[1], d[2]);
                d[2] = doSomething(2, d[1], d[2], d[3]);
                d[3] = doSomething(3, d[2], d[3], d[4]);
                d[4] = doSomething(4, d[3], d[4], d[5]);
```

## Loop unrolling in NNs



# Who defines N, number of iterations?

□ The shape of the input!

## Neural Network Programming Style

#### Constraints

- All data is represented as vectors of numbers
- A network is a chain of pure functions
  - Each layer is a function over the vectorized data
- These functions are linear algebra transformations expressed as multi-dimensional vectors (tensors)
- Typically, the network architecture and hyperparameters are explicitly specified
- [with learning] the exact values of the weights are inferred during a training phase with in/out examples

#### Observations

- Neural Networks are machines for analog computing – not {0, 1} but [0, 1]
- Well-known programming concepts can be reinvented in this style
  - Containment verification → convolution
  - Loops → recurrence
  - What else?