We're going to play with very simple layer ANNs. Even with just one layer we'll be able to do some fun stuff!

In [2]:
```
import numpy as np
from matplotlib import pyplot
```

This is our activation function, just a simple sigmoidal curve called the logistic function

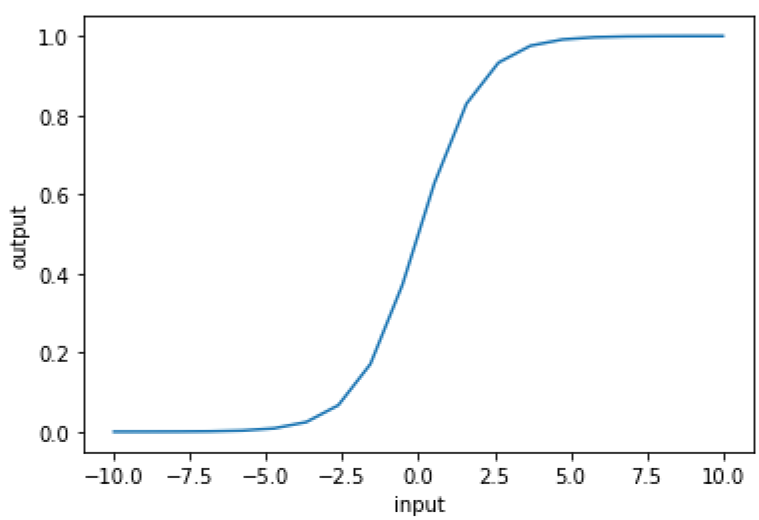
In [3]:
```
def logistic_func(x):
    return 1/(1+np.exp(-x))
```

Let's take a look at the logistic function by plotting in in the range of -10 to 10 using this handy built-in numpy function *linspace*. This function takes the lower bound, the upper bound, and the number of values, and returns a *linearly spaced* vector including the lower and upper bounds. **Neat!**

In [4]:
```
x = np.linspace(-10, 10,20)
print(x)
```

```
[-10.          -8.94736842  -7.89473684  -6.84210526  -5.78947368
  -4.73684211  -3.68421053  -2.63157895  -1.57894737  -0.52631579
   0.52631579   1.57894737   2.63157895   3.68421053   4.73684211
   5.78947368   6.84210526   7.89473684   8.94736842  10.        ]
```

In [5]:
```
#Now plot it!
pyplot.plot(x, logistic_func(x))
pyplot.xlabel("input")
pyplot.ylabel("output")
pyplot.show()
```



Let's try to make a simple network that generates the following truth table

Input 1	Output
0	0
1	1

In [6]:
```
# Since we're only using one value, our input
# is a single value
input_vector = np.array([1])
input_weights = np.array([5])

# because we're using numpy arrays, when we do multiplication
# it will automatically perform it element-by-element
input_x_weights = input_vector * input_weights
neuron_sum = sum(input_x_weights)

# Now apply our activation function to the
# sum of the inputs*weights vector
activation = logistic_func(neuron_sum)

print(activation)
```

```
0.9933071490757153
```

In [7]:
```
# Since we're only using one value, our input
# is a single value
input_vector = np.array([0])
input_weights = np.array([5])

# because we're using numpy arrays, when we do multiplication
# it will automatically perform it element-by-element
input_x_weights = input_vector * input_weights
neuron_sum = sum(input_x_weights)
activation = logistic_func(neuron_sum)

print(activation)
```

```
0.5
```

Hmm, we're going to have a hard time multipling 0 by something to get a lower value...

To fix this problem, we use something called a **bias node**. Basically, we give the neural network a constant value to use for situations exactly like this. This is typically set at 1, though -1 is also a common choice.

In [8]:

```
# Now we're passing in a bias node with value set to 1
# so we'll also have to give it's synapse a weight!
input_vector = np.array([0, 1])

# I just picked a few big values that will pull the
# logistic function close to either 0 or 1 depending on
# the value of the input.
input_weights = np.array([6, -3])

# because we're using numpy arrays, when we do multiplication
# it will automatically perform it element-by-element
input_x_weights = input_vector * input_weights
neuron_sum = sum(input_x_weights)
activation = logistic_func(neuron_sum)

print(activation)
```

```
0.04742587317756678
```

We can shorten this a lot using some nice numpy built in functions!

Spend some time making sure you understand this bit of code, it's going to come back!

In [9]:

```
input_vector = np.array([0, 1])
input_weights = np.array([6, -3])

# https://docs.scipy.org/doc/numpy/reference/generated/numpy.dot.html
# numpy's dot function computes the inner product
# e.g., [a,b].[c,d] = [a*c + b*d]
activation = logistic_func(np.dot(input_vector, input_weights))
print(activation)
```

```
0.04742587317756678
```

1. Try your hand at choosing weights for a network that can compute this function

Input 1	Output
0	1
1	0

In [ ]:

```
```

2. Let's make it a bit more complex and add a second input!

Input 1	Input 2	Output
0	0	0
0	1	1
1	0	1
1	1	1

In [ ]:

```

```

You should make sure your weights handle all the possible binary inputs we can give this function -- like the following input vectors!

In [82]:

```
input_vector = np.array([0, 0, 1])
input_vector = np.array([0, 1, 1])
input_vector = np.array([1, 0, 1])
input_vector = np.array([1, 1, 1])
```

3. What would you have to do if we wanted to have more than one output?

Let's try to replicate the following truth table (i.e., mirror the bits)

Input 1	Input 2	Output 1	Output 2
0	0	0	0
0	1	1	0
1	0	0	1
1	1	1	1

NOTE: Because now each input node has more than one output node to connect to, we'll need more weights.

We can store these weights as a matrix with 3 rows (one for each input plus the bias) and 2 columsn (one for each output). Thus, each value is a weight from the row's input node to the column's output node.

In [10]:
```
input_vector = np.array([1, 0, 1])

#TODO: You'll have to change these weights!
input_weights = np.array( [[1, 1],
                           [1, 1],
                           [1, 1]])


# https://docs.scipy.org/doc/numpy/reference/generated/numpy.dot.html
# we get to take advantage of more numpy fancyness here,
# when np.dot is given a matrix, it performs matrix multiplication!
activation = logistic_func(np.dot(input_vector, input_weights))
print(np.round(activation, decimals=3))
```

```
[0.881 0.881]
```

You'll want to check all the possible combinations of 2-bit inputs again, like you did in Question 3.

In [ ]:
```
```

4. If you're feeling brave, try your hand at this one.

Hint: It's not as simple as it looks... You'll need more **layers** for this one!

Input 1	Input 2	Output
0	0	0
0	1	1
1	0	1
1	1	0

In [ ]:
```
```