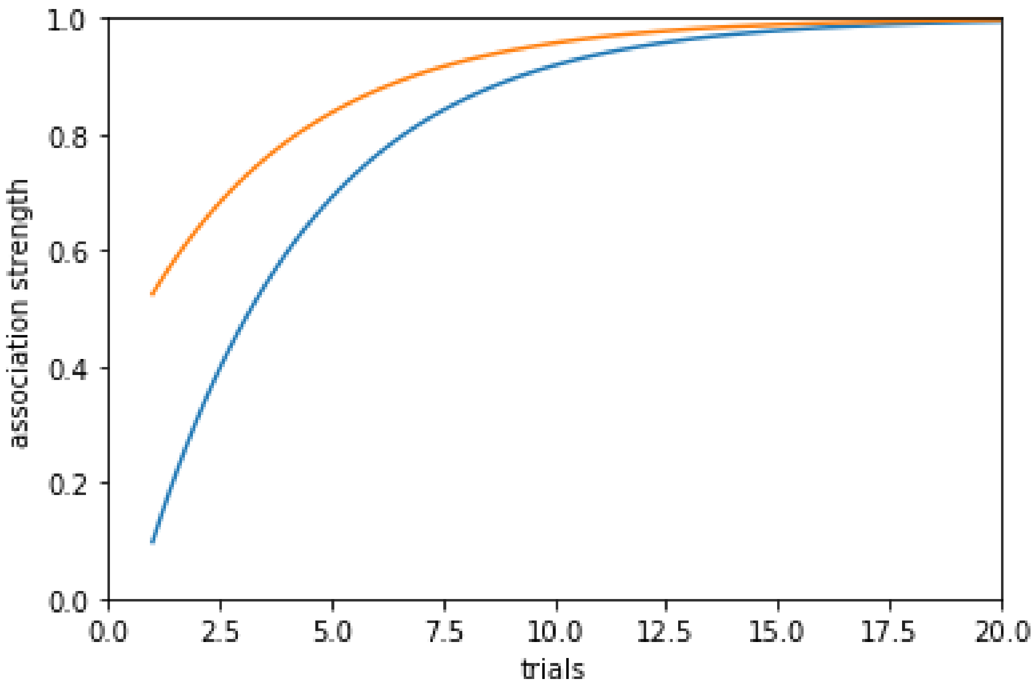
HW_2

February 5, 2020

[184]:
```
import matplotlib
import matplotlib.pyplot as plt
import numpy as np
import random
```

1 QUESTION 1A

[232]:
```
def resc_wagn(x, init, a, b):
    output = []
    for i in x:
        if i == 1:
            output.append(init + ((a*b) * (1 - init)))
        else:
            val = output[-1] + ((a*b) * (1 - output[-1]))
            output.append(val)
    return output

x = np.linspace(1, 20, 100)
y = resc_wagn(x, 0.05, 0.5, 0.1)
z = resc_wagn(x, 0.5, 0.5, 0.1)

plt.plot(x, y)
plt.ylim(0, 1)

plt.plot(x, z)
plt.ylim(0, 1)
plt.xlim(0, 20, 1)

plt.xlabel("trials")
plt.ylabel("association strength")

plt.show()
```



2 QUESTION 1B

At an initial association strength of 0.05, it will take 30 trials to reach an association strength of 0.8.

3 QUESTION 1C

[153]:
```
dat = []
q = np.arange(0, 2, 0.001)
z = np.arange(1, 14)

for i in q:
    dat.append(resc_wagn(z, 0.0, i, 0.1)[-1])
    if round(dat[-1], 3) == 0.8:
        x = int(i * 1000)
        print("")
        print("At an association level of: ")
        print(dat[x])
        print("The expected salience must be: ")
        print(round(i, 3))
```

```
At an association level of:
```

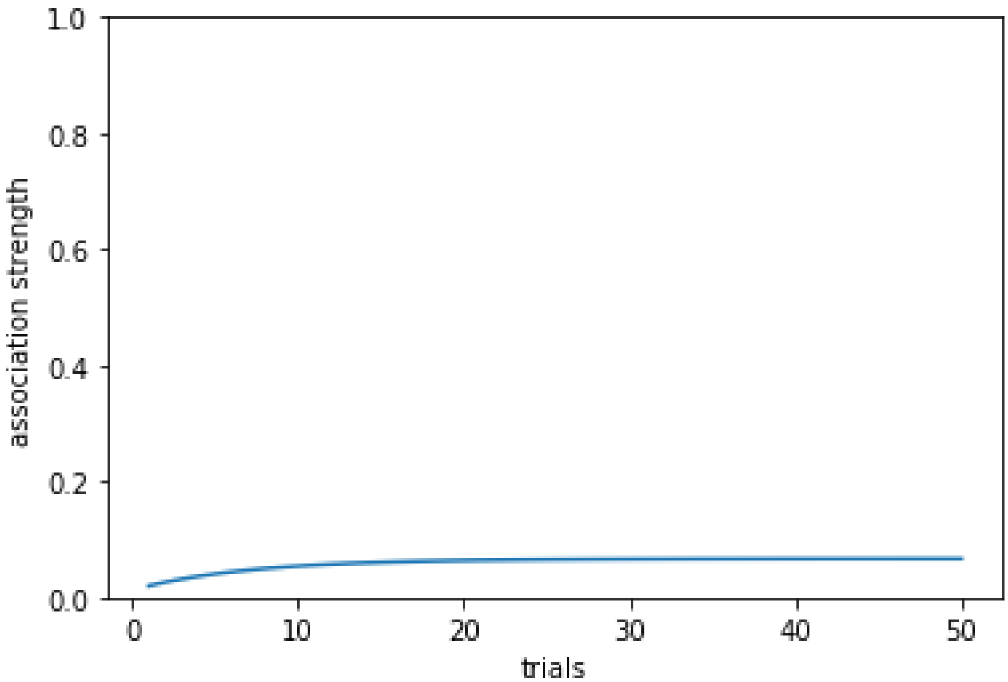
```
0.7995698207312544
The expected salience must be:
1.163

At an association level of:
0.7998644709476593
The expected salience must be:
1.164

At an association level of:
0.8001587212769328
The expected salience must be:
1.165

At an association level of:
0.8004525722166155
The expected salience must be:
1.166
```

The expected salience at an association level of **0.8** is **1.165**

4 QUESTION 2

[231]:
```
def resc_wagn_blocking(x, bell_init, light_init, a_bell, a_light, b):
    output_light = []
    output_bell = []
    for i in x:
        if i == 1:
            output_light.append(light_init + ((a_light*b) * (1 - light_init)))
            output_bell.append(bell_init + ((a_bell*b) * (1 - bell_init)))
        else:
            val1 = output_light[-1] + ((a_light*b) * (1 - (output_light[-1] +
 ↪output_bell[-1])))
            output_light.append(val1)
            val2 = output_bell[-1] + ((a_bell*b) * (1 - (output_bell[-1] +
 ↪output_light[-1])))
            output_bell.append(val2)
    return output_bell

q = np.linspace(1, 50, 100)

data = resc_wagn_blocking(q, 0.0, 0.8, 0.2, 0.5, 0.1)

plt.plot(q, data)
plt.ylim(0, 1)
plt.ylabel("association strength")
plt.xlabel("trials")
```

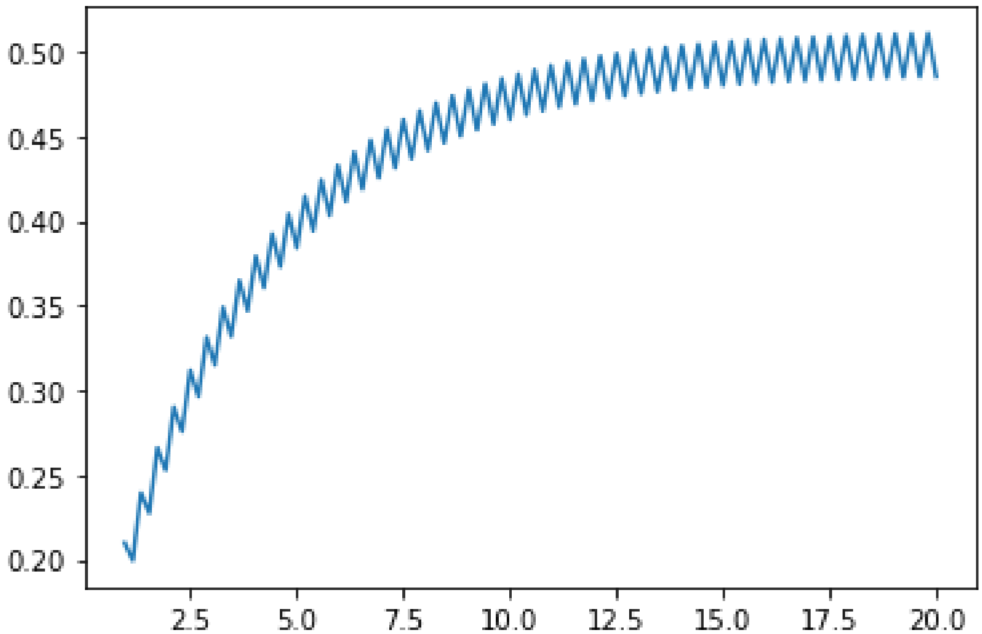
```
plt.show()
```



5 QUESTION 3A

[228]:
```
dat = np.linspace(1, 20, 100)

def alternate(x, init, a, b):
    output = []
    count = 1
    for i in x:
        if count == 1:
            output.append(init + ((a*b) * (init)))
            count += 1
        elif count % 2 == 0:
            output.append(output[-1] - ((a*b) * (output[-1])))
            count += 1
        elif count % 2 != 0:
            output.append(output[-1] + ((a*b) * (1 - output[-1])))
            count += 1
    return output
```

```
## We will make an assumption of an initial association of 0.2, an a(bell) of 0.
↪5, and a learning rate of 0.1 ##

plotdat = alternate(dat, 0.2, 0.5, 0.1)

plt.plot(dat, plotdat)
plt.show()
```



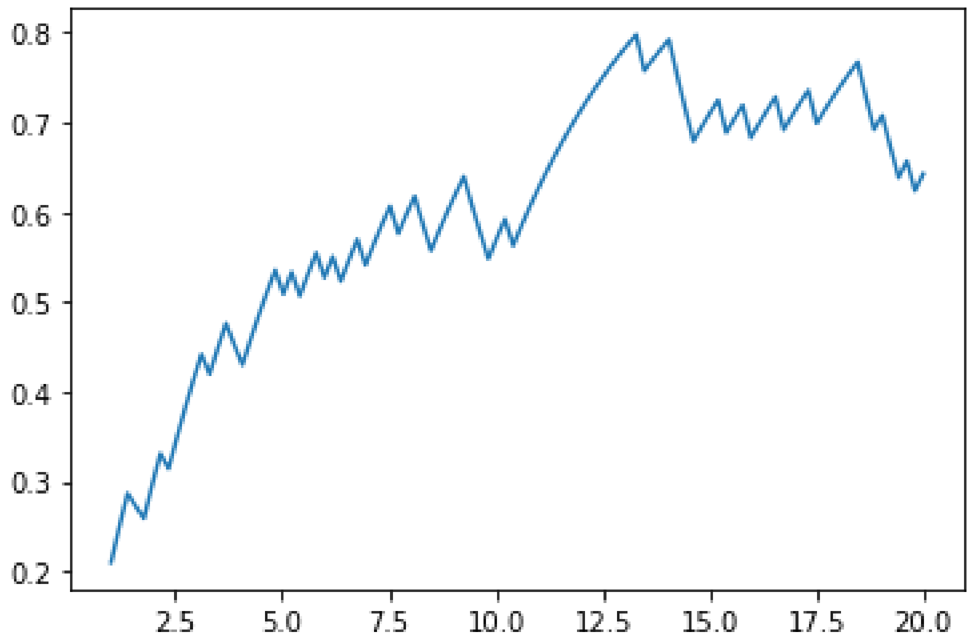
Based on the plot, we can conclude that while association fluctuates slightly between individual trials, there is an overall trend across trials in which association strength between bell and food increases.

Intuitively, it makes sense that over a long period of time, the alternating trials still build an association. There are not enough consecutive extinction trials to decrease association strength developed by the positive conditioning trials.

6 QUESTION 3B

[215]:
```
dat = np.linspace(1, 20, 100)

def alternate_prob(x, init, a, b, prob):
    output = []
    for i in x:
        sample = random.randrange(1, prob, 1) / 100
        if i == 1:
            output.append(init + ((a*b) * (init)))
```

```
        elif sample <= (100 - prob) / 100  :
            output.append(output[-1] - ((a*b) * (output[-1])))
        elif sample > (100 - prob) / 100:
            output.append(output[-1] + ((a*b) * (1 - output[-1])))
    return output

## We will make an assumption of an initial association of 0.2, an a(bell) of 0.
↪5, a learning rate of 0.1, and a P of 0.75 ##

dat2 = alternate_prob(dat, 0.2, 0.5, 0.1, 75)

plt.plot(dat, dat2)
plt.show()
```



Consider a probability of **75%** that the trial will be a bell and food (meaning there is a **25%** probability the trial will be a bell and no food).

At the **computational level** of Marr's analysis, we can posit that it is more probable we present consecutive trials of a bell and food than consecutive trials of a bell with no food. Therefore, by the logic of our previous problem (3A), we observe that the association strength of bell and food continues to strengthen over a series of trials as the subject determines it is overall more likely to receive food with the sound of the bell, despite infrequent extinction trials.

7 QUESTION 4

When considering salience and learning rate, there is the psychological impression that the learning rate is some intrinsic coefficient for our ability to adapt to new information, while we tend to consider the "salience" of a stimulus as the strength of its relationship to our learning rate.

One possible experiment to separate salience from learning rate would be to present a subject with the same stimulus at varying degrees of salience, such as a light presented at brighter intervals or a bell with louder intervals. Intuitively, we should find that if learning rate and salience are different factors, then stronger salience should lead to a faster learning curve.

[ ]:

```

```