## Bayesian\_AB\_Testing\_Slot\_machines

#### August 10, 2020

[8]: import numpy as np

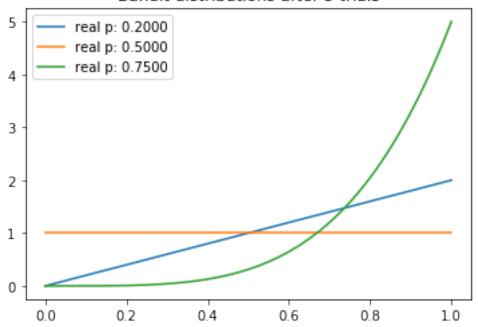
```
import matplotlib.pyplot as plt
     from scipy.stats import beta
[9]: NUM_TRIALS = 2000
     BANDIT_PROBABILITIES = [0.2,0.5,0.75] ## win rates of the Arm bandits(slotu
      \rightarrow machines)
     # Creating a class for the slot machine
     class Bandit:
         def __init__(self, p): # p: probability of winning, a,b: beta parameters
             self.p = p
             self.a = 1
             self.b = 1
         def pull(self):
             return np.random.random() < self.p</pre>
         def sample(self): # sampling from it data (beta) distribution
             return np.random.beta(self.a,self.b)
         def update(self,x): # Updating a and b: Conjugate priors
             self.a += x
             self.b += 1-x
     def plot(bandits, trial): # for plotting the PDF of each bandit
         x = np.linspace(0, 1, 200)
         for b in bandits:
             y = beta.pdf(x, b.a, b.b)
             plt.plot(x, y, label="real p: %.4f" %b.p)
         plt.title("Bandit distributions after %s trials" % trial)
         plt.legend()
         plt.show()
     def experiment(): # function to run these bandits and check which one gives the
      \rightarrow largest sample
         #Initializing an array of bandits
```

```
bandits = [Bandit(p) for p in BANDIT_PROBABILITIES]
   sample_points = [5,10,20,50,100,200,500,1000,1500,1999] #trials
   for i in range(NUM_TRIALS):
       # take a sample from each bandit
       bestb = None #This is going to the bandit whose arm we would eventually __
\rightarrow pull
       maxsample = -1 # to keep a track of maxsample we got
       allsamples = [] # let's collect these just to print for debugging
       for b in bandits:
           sample = b.sample()
           allsamples.append("%.4f" % sample)
           if sample > maxsample:
               maxsample = sample
               bestb = b
       if i in sample points:
           print("current samples: %s" % allsamples)
           plot(bandits, i)
       # pull the arm for the bandit with the largest sample
       x = bestb.pull()
       # update the distribution for the bandit whose arm we just pulled
       bestb.update(x)
```

```
[10]: if __name__ == "__main__":
    experiment()
```

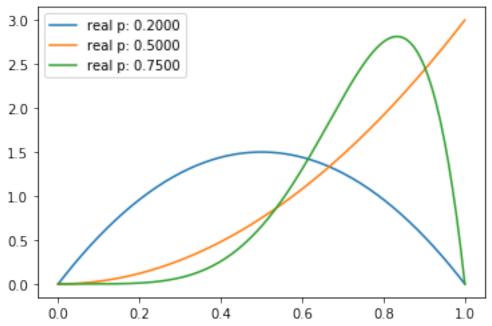
current samples: ['0.6747', '0.0659', '0.7726']

## Bandit distributions after 5 trials



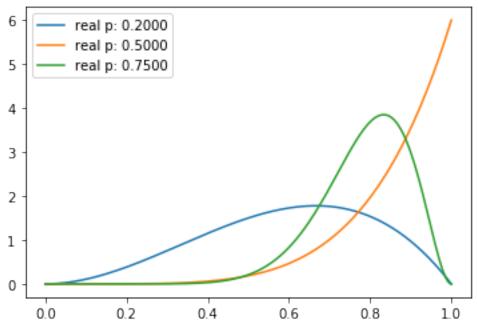
current samples: ['0.3914', '0.6690', '0.8632']

## Bandit distributions after 10 trials



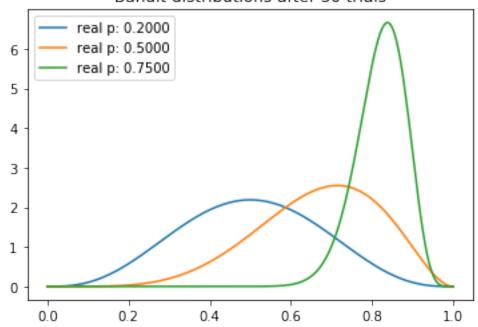
current samples: ['0.8657', '0.6576', '0.5590']



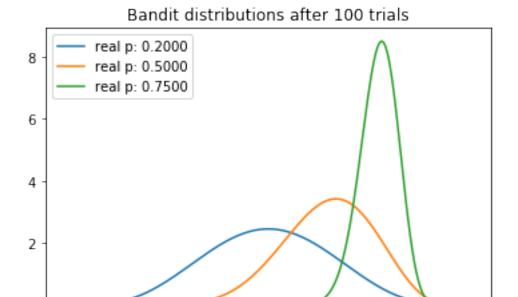


current samples: ['0.5532', '0.8203', '0.8964']

## Bandit distributions after 50 trials



current samples: ['0.7721', '0.6153', '0.8106']



0.4

0.6

0.8

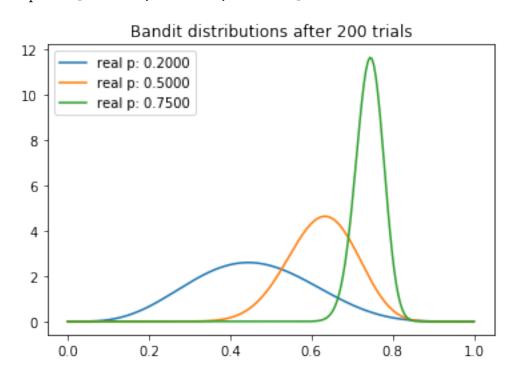
1.0

current samples: ['0.3771', '0.4527', '0.6512']

0.2

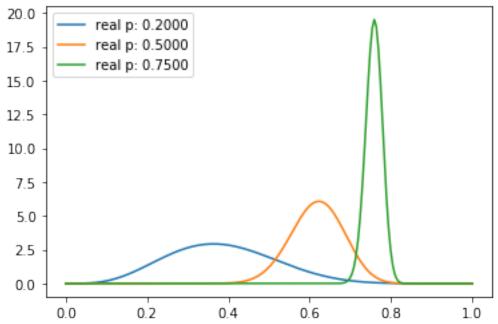
0

0.0



current samples: ['0.6357', '0.7263', '0.7669']





current samples: ['0.3991', '0.6748', '0.7731']

# Bandit distributions after 1000 trials 30 real p: 0.2000 real p: 0.5000 25 real p: 0.7500 20 15 10 5 0 0.2

0.4

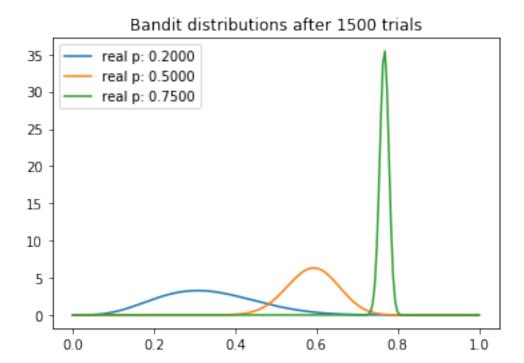
0.6

0.8

1.0

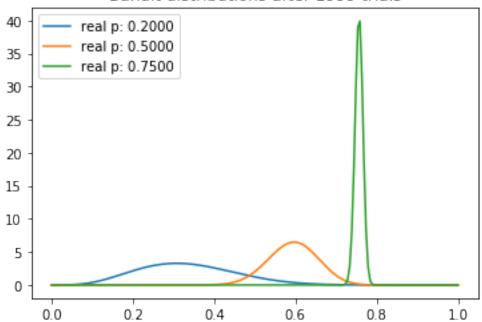
current samples: ['0.3928', '0.5782', '0.7452']

0.0



#### current samples: ['0.2790', '0.4981', '0.7498']





```
[]: # CONCLUSION: We can see that Bandit 3 has its distribution becoming sharper → with more trials

#.... Sharper distribution → Less variance → Less exploration

#.... Thus, arm3 can be exploited

#.... Also, Arm3 is the best performing arm because of the highest CTR

# We need NOT look into the other arms: 1 and 2 for exploration also

#.... Because though these have fatter variances and have scope for → exploration,

# .... They still have less CTR's compared to the Arm3

# Let's blindly go for the Arm3 and exploit it!
```