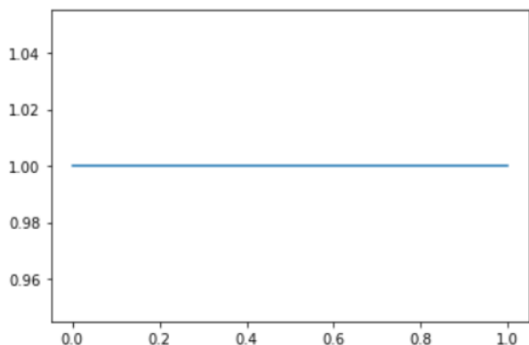


```
In [3]: a=1;b=1 #beta(1,1)
hypos=np.linspace(0,1,101)
x=beta.pdf(hypos,a,b)
prior=Pmf(x,hypos)
```

```
In [4]: plt.plot(hypos,x) #prior plot
```

```
Out[4]: [<matplotlib.lines.Line2D at 0x25d2cb3af70>]
```



• Prob (Yes)

$$\text{Prob}(\text{tail}) \text{Prob}(\text{Yes}|\text{tail}) + \text{Prob}(\text{head}) \text{Prob}(\text{Yes}|\text{head}) \\ = 0.5 \cdot \text{hypo} + 0.5 \cdot 1 = \frac{1}{2} (\text{hypo} + 1)$$

• Prob (No)

$$\text{Prob}(\text{tail}) \text{Prob}(\text{No}|\text{tail}) + \text{Prob}(\text{head}) \text{Prob}(\text{No}|\text{head}) \\ = 0.5 \cdot (1 - \text{hypo}) + 0.5 \cdot 0 = \frac{1}{2} (1 - \text{hypo})$$

```
In [5]: likelihood={'Y':0.5+hypos/2, 'N':(1-hypos)/2} #Q1 WHY?? IS THIS BINOMIAL MODEL?
```

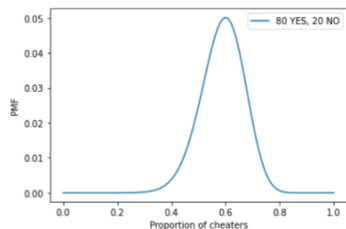
Q1 : Likelihood 함수가 이와 같이 나오는 이유를 설명해주세요. 그리고 이와 같은 sampling model은 binomial model인가요? 왜 그런가요?

```
In [6]: dataset='Y'*80+'N'*20 #DATA 80 YES, 20 NO
posterior1=prior.copy()
for data in dataset:
    posterior1 *= likelihood[data]
posterior1.normalize()
```

```
Out[6]: 3.694513913396701e-21
```

```
In [7]: posterior1.plot(label='80 YES, 20 NO', xlabel='Proportion of cheaters', ylabel='PMF')
plt.legend() #Q2 WHY MODE ON 0.6? DATA IS 80 YES & 20 NO, WHY NOT 0.8?
```

```
Out[7]: <matplotlib.legend.Legend at 0x25d2ad13a90>
```



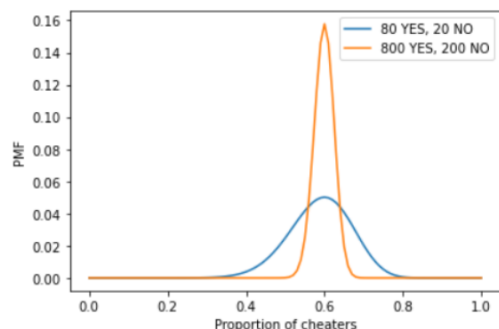
Q2 : 우리가 구한 Posterior 분포의 꼴이 왜 다음과 같이 나왔을까요? prior의 꼴과 data와 관련하여 설명해주세요. 그리고 data는 YES와 NO의 비율이 4:1인데 왜 posterior의 mode는 0.8이 아니라 0.6인걸까요?

$$\Rightarrow \text{적용} : (a=b=1, N=100, Y=80) \Rightarrow \text{beta}(81, 21), E[\theta|Y] = \frac{1+80}{1+1+100} = \frac{81}{102} \approx 0.8$$

⊗ likelihood 설정시 hypo를 그대로 사용하지 않음.

$$E[\theta|Y] = E\left[\frac{1}{2}(1+\text{hypo})|Y\right] = 0.8 \Rightarrow E[\text{hypo}|Y] = 0.6$$

```
<matplotlib.legend.Legend at 0x25d2d3c0760>
```



Q3: 두 posterior 분포는 왜 이렇게 다른 꼴이 나오게 되었을까요?

$$P(\theta|Y) = \frac{P(Y|\theta)P(\theta)}{P(Y)} \quad (P(\theta)=1) \\ = c(Y)\theta^{a+Y}(1-\theta)^{b+N-Y-1} \quad \left(c(Y) = \frac{\Gamma(a+b+N)}{\Gamma(a+Y)\Gamma(b+N-Y)}\right) \\ = \text{beta}(a+Y, b+N-Y)$$

$$E[\theta|Y] = \frac{a+Y}{a+b+N} \\ = \frac{a+b}{a+b+N} \cdot \frac{a}{a+b} + \frac{N}{a+b+N} \cdot \frac{Y}{N} \\ \text{Prior exp} \quad \text{data avg}$$

$$\textcircled{1} N=100, Y=80$$

$$\Rightarrow \text{beta}(101, 21)$$

$$\textcircled{2} N=1000, Y=800$$

$$\Rightarrow \text{beta}(1001, 201)$$

Homework

2. Assume home runs per game at Citizens Bank Park follow a Poisson distribution with parameter θ . Assume for θ a **Gamma prior** distribution with shape **parameter** $\alpha = 4$ and rate parameter $\beta = 2$.

- 1) Write an expression for the prior density $\phi(\theta)$. Find the prior mean and prior SD.
- 2) Suppose a single game with 1 home run is observed. Write the likelihood function.
- 3) Write an expression for the posterior distribution of θ given a single game with 1 home run. Find the posterior mean and posterior SD.

$$1) P(\theta) = \frac{\beta^\alpha}{\Gamma(\alpha)} \theta^{\alpha-1} e^{-\beta\theta} = \frac{2^4}{\Gamma(4)} \theta^3 e^{-2\theta} \quad E[\theta] = \frac{\alpha}{\beta} = \frac{4}{2} = 2 \quad \text{Var}[\theta] = \frac{\alpha}{\beta^2} = 1$$
$$\text{sd}[\theta] = 1$$

$$2) P(y_i | \theta) = \frac{\theta^{y_i} e^{-\theta}}{y_i!} \rightarrow y_i = 1, P(y_i = 1 | \theta) = \theta e^{-\theta}$$

$$3) P(\theta | y_1, \dots, y_n) = \frac{P(\theta) P(y_1, \dots, y_n | \theta)}{P(y_1, \dots, y_n)} = C \cdot \theta^{a + \sum y_i - 1} e^{-(n+b)\theta} \sim \text{gamma}(a + \sum y_i, n+b)$$
$$\Rightarrow \text{योग} (n=1, y_1=1) \Rightarrow \text{gamma}(5, 3) \Rightarrow \begin{cases} \text{mean: } \frac{\alpha}{\beta} = \frac{5}{3} \\ \text{Var: } \frac{\alpha}{\beta^2} = \frac{5}{3^2} \end{cases} \quad \text{sd: } \frac{\sqrt{5}}{3}$$