- An important feature of Bayesian inference is the existence of a predictive distribution for new observations.
 - Let \tilde{y} be a new (unseen) observation, and $y_1, \ldots y_n$ the observed data.
 - \circ The Posterior predictive distribution is $p(\tilde{y} \mid y_1, \dots y_n)$

- An important feature of Bayesian inference is the existence of a predictive distribution for new observations.
 - Let \tilde{y} be a new (unseen) observation, and $y_1, \ldots y_n$ the observed data.
 - \circ The Posterior predictive distribution is $p(\tilde{y} \mid y_1, \dots y_n)$
- The predictive distribution does not depend on unknown parameters
- The predictive distribution only depends on observed data
- Asks: what is the probability distribution for new data given observations of old data?

Another Basketball Example

- 3_{mle} = 0.5
- I take free throw shots and make 1 out of 2. How many do you think I will make if I take 10 more?
- If my true "skill" was 50%, then $ilde{Y} \sim \mathrm{Bin}(10,0.50)$
- Is this the correct way to calculate the predictive distribution?

Predictive Duty.

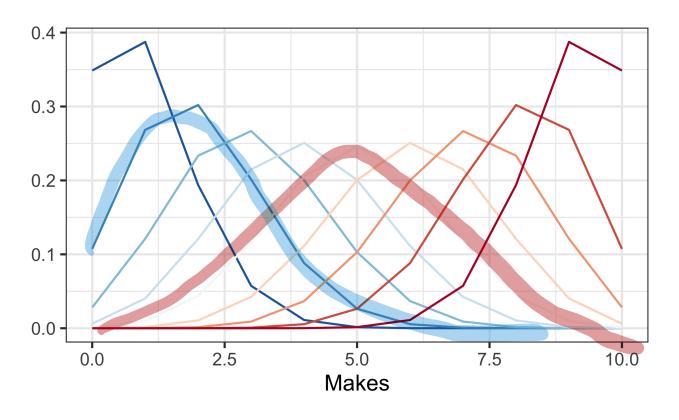
"True Skill" 0, Fraction made W/ as

Somply variety uncertainty about D.

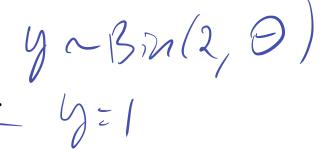
Posterior Prediction

If you know θ , then we know the distribution over future attempts:

$$ilde{Y} \sim ext{Bin}(10, heta)$$



Posterior Prediction



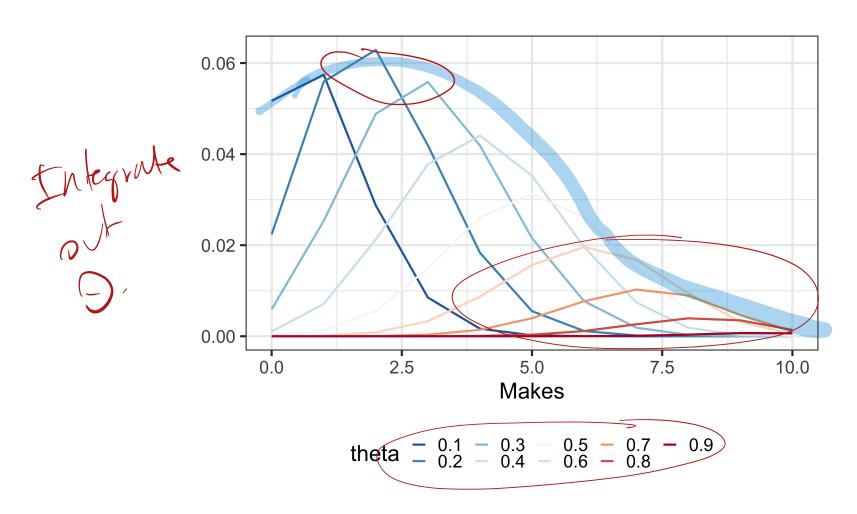
- We already observed 1 make out of 2 tries.
- Assume a Beta(1, 3) prior distribution
 - o e.g. a priori you think I'm more likely to make 25% of my shots
- Then $p(\theta \mid Y=1, n=2)$ is a $\mathrm{Beta}(2,4)$
- Intuition: weight $ilde{Y} \sim ext{Bin}(10, heta)$ by $p(heta \mid Y = 1/, n = 2)$

Men = -25%

45 / 55

Posterior Prediction

If I take 10 more shots how many will I make?



$$\Gamma(n) = (n-1)!$$

$$P(\tilde{9}|9) \sim Bin(l0, 9)$$

 $P(9/9) \sim Beta(2, 4)$

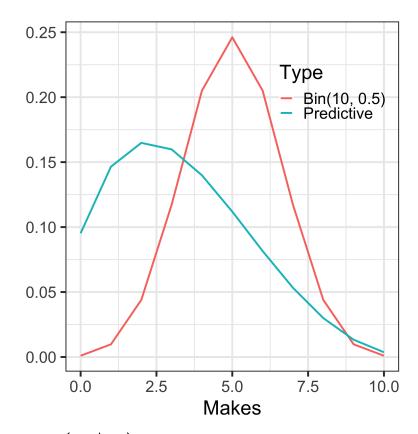
$$P(5/5) = \int (5/5) \frac{10}{5} \frac{$$

$$= \left(\frac{10}{5}\right) \frac{\Gamma(\lambda+1)}{\Gamma(\lambda)\Gamma(5)} = \frac{5+1}{0} (1-9)^{13-\frac{5}{3}} d\theta$$

100ks /1/6 Bch (g+2,14-g)47/55

 $\int_{0}^{\infty} \frac{1}{9} \left(1-9\right)^{13} ds = \frac{1}{9$ $\frac{\Gamma(\tilde{g}+2)\Gamma(14-\tilde{g})}{\Gamma(2)\Gamma(4)} \frac{\Gamma(6)}{\Gamma(16)}$ Beta-Binomial Distribution

$$p(heta) = \mathrm{Beta}(1,3), p(heta \mid y) = \mathrm{Beta}(2,4)$$



The predictive density, $p(\tilde{y} \mid y)$, answers the question "if I take 10 more shots how many will I make, given that I already made 1 of 2".

Y~ Pois() P(1) ~ Can (a, 6) S P(7/X) P(X/Y) d/ POIS (Somma P(5/6) - Negative-Bin.

$$egin{aligned} p(ilde{y} \mid y_1, \ldots y_n) &= \int p(ilde{y}, heta \mid y_1, \ldots y_n) d heta \ &= \int p(ilde{y} \mid heta) p(heta \mid y_1, \ldots y_n) d heta \end{aligned}$$

- The posterior predictive distribution describes our uncertainty about a new observation after seeing *n* observations
- It incorporates uncertainty due to the sampling in a model $p(\tilde{y} \mid \theta)$ and our posterior uncertainty about the data generating parameter, $p(\theta \mid y_1, \dots y_n)$

Posterior Predictive Density P(Y=y 19) = L(9) probability (sampling distribution) data "statistic" population inference (estimation, hypothesis testing) P(9/9) 2 L(0) P(0)

The prior predictive distribution

$$egin{aligned} p(ilde{y}) &= \int p(ilde{y}, heta) d heta \ &= \int p(ilde{y} \mid heta) p(heta) d heta \end{aligned}$$

• The prior predictive distribution describes our uncertainty about a new observation before seeing data

The prior predictive distribution

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- The prior predictive distribution describes our uncertainty about a new observation before seeing data
- It incorporates uncertainty due to the sampling in a model $p(\tilde{y} \mid \theta)$ and our prior uncertainty about the data generating parameter, $p(\theta)$

Homework 1

- $\lambda \sim \operatorname{Gamma}(\alpha, \beta)$
- $ullet \; ilde Y \sim \mathrm{Pois}(\lambda)$
- $p(\tilde{y}) = \int p(\tilde{y} \mid \lambda)p(\lambda)d\lambda$ is a prior predictive distribution!
- "A Gamma-Poisson mixture is a Negative-Binomial Distribution"

Homework 1 Extra Credit

$$egin{aligned} p(ilde{y}) &= \int p(ilde{y} \mid \lambda) p(\lambda) d\lambda \ &= \int (rac{\lambda^{ ilde{y}}}{y!} e^{-\lambda}) (rac{eta^{lpha}}{\Gamma(lpha)} \lambda^{(lpha-1)} e^{-eta \lambda}) d\lambda \ &= rac{eta^{lpha}}{\Gamma(lpha) y!} \int (\lambda^{(lpha+y-1)} e^{-(eta+1)\lambda}) d\lambda \end{aligned}$$

 $\int (\lambda^{(\alpha+y-1)}e^{-(\beta+1)\lambda})d\lambda$ looks like an unormalized $\operatorname{Gamma}(\alpha+y,\beta+1)$

Summary

- Bayesian credible intervals
 - Posterior probability that the value falls in the interval
 - Still strive for well-calibrated intervals (in the frequentist sense)
- Non-informative prior distributions
- Posterior predictive distributions
 - Estimated distribution for new data our uncertainty about the parameters