# Garden of Forking paths part 2

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```
i Listening

renv::install("khroma")

library(tidyverse)
library(khroma)
library(gt)
library(patchwork)
```

#### A nicer table version.

library(here)

I'd like to re-represent the Bayesian Update in a nicer GT table. Some options are

1. Plotting extensions from {gtExtras}

source(here("\_defaults.R"))

2. Emojis

```
renv::install("gtExtras")
renv::install("svglite")
renv::install("emoji")

library(gtExtras)
library(emoji)
```

First, trying the "win/losses" column plot from {gtExtra} to illustrate the blue vs white marbles.

The cell background will have to be off-white for the white ticks to show I'm not overwhelmed by the result. I'll try emojis instead.

```
blue_marb <- emojis |>
    filter(str_detect(name, "blue"),
           str_detect(name, "circle")) |>
    pull(emoji)
  blue_marb
[1] ""
  white_marb <- emojis |>
    filter(str_detect(name, "white"),
           str_detect(name, "circle")) |>
    pull(emoji)
  white_marb
[1] ""
  tibble(
    blue_marbs = 0:4,
    white_marbs = 4 - blue_marbs
  ) |>
    rowwise() |>
    mutate(
      marbles = list(c(rep(blue_marb, blue_marbs),
```

```
rep(white_marb, white_marbs)))
) ->
marbles_emoji
```

**Update:** As it turns out, getting tables with emoji and the plots with gt\_plt\_\*() do not play nice with LaTeX. For now, I'm saving the tables to png with gtsave() just for the pdf output.

```
fs::dir_create("tables/")
renv::install("webshot2")

marbles_emoji |>
   gt() |>
   gtsave(filename = "tables/marb1.png")
```

blue_marbs	white_marbs	marbles
0	4	<b>, , , ,</b>
1	3	•, •, •, •
2	2	<b>, , , ,</b>
3	1	•, •, •, •
4	0	•, •, •, •

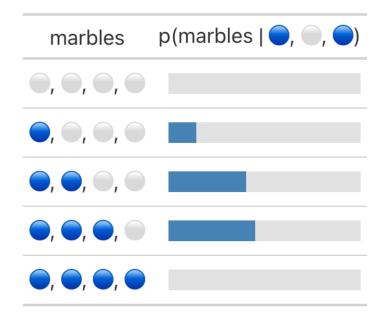
Yes, this is it.

#### Rerunning the sampling

I'll re-run the sampling from the previous post.

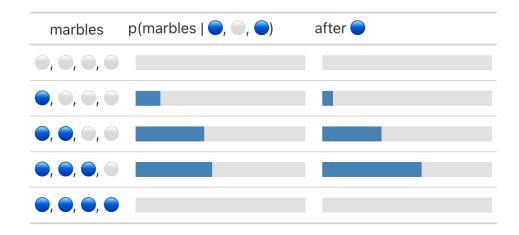
```
pattern = c(blue_marb, white_marb, blue_marb)){
    sampling_tibble <- tibble(samp = 1:n)</pre>
    sampling_tibble |>
      mutate(
         chosen = map(samp,
                       ~sample(marbles,
                               size = 3,
                               replace = T)),
        match = map_lgl(chosen,
                         ~all(.x == pattern))
       ) |>
       summarise(prop_match = mean(match))->
       sampling_tibble
    return(sampling_tibble)
  marbles_emoji |>
   ungroup() |>
    mutate(
      prob = map(marbles, ~sampling_df(.x, n = 10000))
    ) |>
    unnest(prob) |>
    mutate(norm_probs = prop_match/sum(prop_match))->
    marble_probs
I want to label the column of probabilities with the key sequence.
  key_seq <- str_glue("{blue_marb}, {white_marb}, {blue_marb}")</pre>
gtExtras::gt_plt_bar_pct() will plot a bar chart within the table.
  marble_probs |>
    select(marbles, norm_probs) |>
    mutate(norm_probs = norm_probs * 100) |>
    gt() |>
    cols_label(
      norm_probs = str_glue("p(marbles | {key_seq})")
    ) |>
    gt_plt_bar_pct(norm_probs,
                    scaled = T,
                    fill = "steelblue")->
```

```
update_1
gtsave(update_1, filename = "tables/update1.png")
```



There we go!

#### With the Bayesian Update



## **Bayesian Updating**

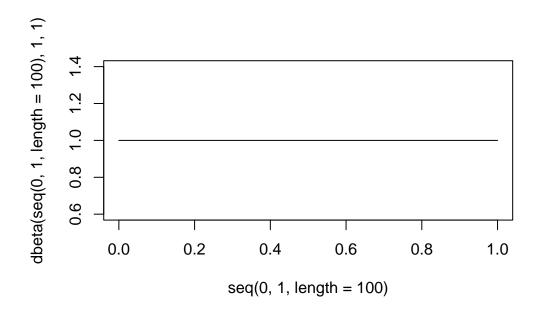
I'll try to illustrate Baysian updating with an animated plotly plot.

```
renv::install("plotly")
renv::install("slider")

library(plotly)
library(slider)
```

I know enough to know that the distribution that's being updated is the beta. (Apparently is the binomial. Still a but lost on their distinction!) So I'll get the density for each update.

```
plot(
    seq(0,1, length =100),
    dbeta(seq(0,1, length =100), 1, 1),
    type = 'l'
)
```



```
water_land_sequence <- c("\dagger", "L", "\dagger", "\dagger", "\dagger", "\dagger", "\dagger", "\dagger")</pre>
```

I'll use slider::slide() to generate a data frame of sample updates. I'll need a function that takes a sequence of W and L and converts them into counts.

```
w_l_count <- function(x){
  tibble(
    water = sum(x == "W"),
    land = sum(x == "L")
)
}

slide(water_land_sequence,
    .f = w_l_count,
    .before = Inf,
    .after = 0) |>
  bind_rows() |>
  mutate(seq = row_number()) |>
  bind_rows(
    tibble(
    water = 0,
```

```
land = 0,
    seq = 0
)
) |>
arrange(seq) ->
sequence_counts

sequence_counts |>
gt()
```

Table 1: Table of water, land count updates

water	land	seq
0	0	0
1	0	1
1	1	2
2	1	3
3	1	4
3	2	5
4	2	6
4	3	7
5	3	8

Now to get the densities.

```
sequence_counts |>
  rowwise() |>
  mutate(
    density = map2(
        water, land, ~tibble(
        prop = seq(0.0001, 0.9999, length = 100),
        density_unstd = dbinom(water, size = water + land, prob = prop),
        density = density_unstd/sum(density_unstd)
        )
    )
    )
    )
    unnest(density)->
    density_updates
```

```
density_updates |>
  ggplot(aes(prop, density))+
  geom_line(aes(group = seq, color = seq))
```

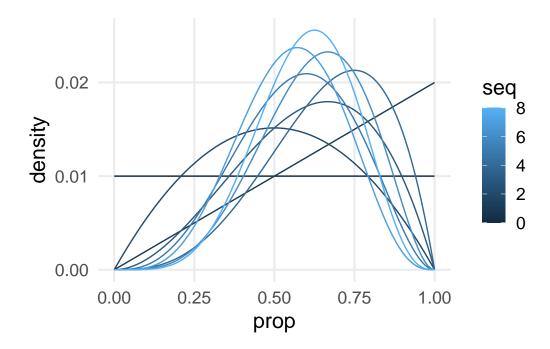


Figure 1: beta distribution updates

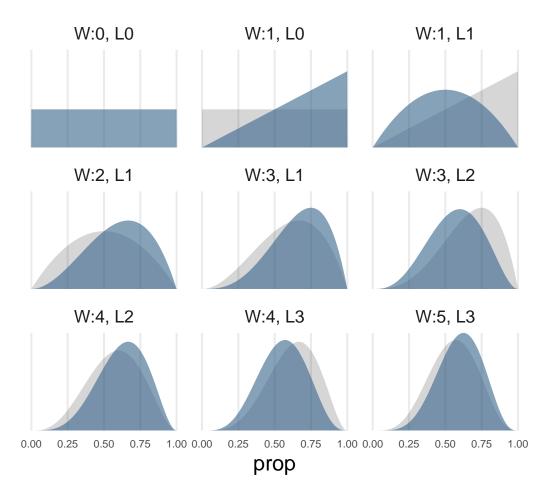
#### Good first step.

I had to turn to the plotly book to get the animated lines correct https://plotly-r.com/animating-views.html.

```
sequence_counts |>
mutate(
   annotation = str_glue("W:{water}, L:{land}")
) ->
wl_annotate
```

**Update**: I started making this just for the pdf, which can't have the animation, but it's actually kind of nice enough to include in the html.

```
density_updates |>
 group_by(prop) |>
 arrange(seq) |>
 mutate(
   prev_density = lag(density),
   facet_lab = str_glue("W:{water}, L{land}")
  ggplot(aes(prop, density))+
    geom_area(aes(y = prev_density), linetype = 2, alpha = 0.2)+
    geom_area(alpha = 0.6, fill = "steelblue4")+
    scale_y_continuous(expand = expansion(mult = c(0,0)))+
    facet_wrap(~facet_lab)+
    theme(
      axis.title.y = element_blank(),
      axis.text.y = element_blank(),
     axis.text.x = element_text(size = 8),
     panel.grid.major.y = element_blank()
```



## On priors

The fact that statistical inference uses mathematics does not imply that there is only one reasonable or useful way to conduct an analysis.

## **Grid approximation**

Ok, I'll do one grid approximation for the hell of it.

•••

Got distracted and went down a rabbit hole on the beta vs binomial distributions.

```
tibble(
  prob = seq(0.0001, 0.9999, length = 50),
  prior_unstd = case_when(
    prob < 0.5 \sim 0,
    .default = 1
  ),
  prior_std = prior_unstd/sum(prior_unstd),
  likelihood_binom = dbinom(6, size = 9, prob = prob),
  l_binom_std = likelihood_binom/sum(likelihood_binom),
  likelihood_beta = dbeta(prob, 6, 9-6),
  l_beta_std = likelihood_beta/sum(likelihood_beta)
) |>
  ggplot(aes(prob))+
    geom_point(aes(y = l_binom_std, color = "binom"))+
    geom_point(aes(y = l_beta_std, color = "beta"))+
    scale_color_bright()+
    labs(
      x = "probability",
      color = "distribution",
     y = NULL
```

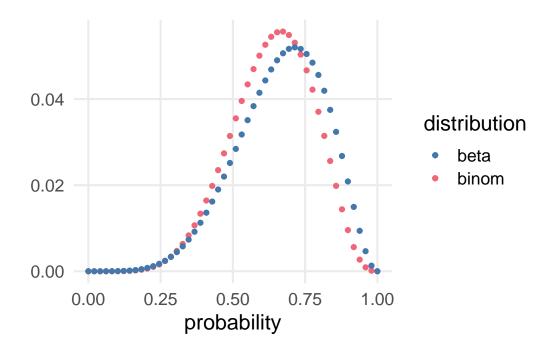


Figure 2: Comparing normalized densities for beta(6,3) and binom(6, 9, p)

Glad I did this. I guess

- dbinom  $\propto P(O, S|p)$
- dbeta  $\propto P(p|O,S)$

I guess I'd want to see dbinom plotted out with O on the x axis?

```
binomial_densities |>
  ggplot(aes(obs, density, color = probability))+
  geom_point()+
  geom_line(aes(group = probability)) +
  geom_rect(
    color = "red",
    fill = NA,
    xmin = 5.5,
    xmax = 6.5,
    ymin = 0,
    ymax = 1
  )+
  scale_color_batlow()
```

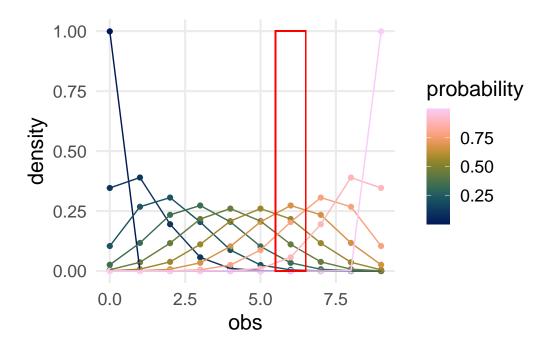


Figure 3: Binomial distributions of various successes out of 9 trials, for various p

What we're plotting out is what's in the red box, flipped on its side.

```
binomial_densities |>
  filter(obs == 6) |>
  ggplot(aes(probability, density))+
```

```
geom_line()+
geom_point(aes(color = probability))+
scale_color_batlow()
```

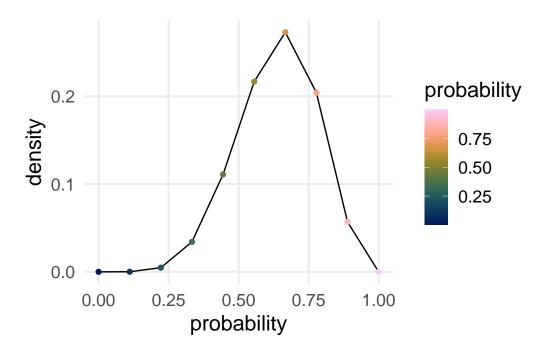


Figure 4: Normalized binomial density for 6 successes out of 9 trials for various p.

## Update!

```
Thanks TJ!
```

i forgot how i know this but they are the same if you plug in likelihood\_beta = dbeta(prob, 1 + 6, 1 + 9-6),

```
— tj mahr (@tjmahr) May 10, 2023
```

```
tibble(
  prob = seq(0.0001, 0.9999, length = 50),
  prior_unstd = case_when(
    prob < 0.5 ~ 0,
    .default = 1
  ),
  prior_std = prior_unstd/sum(prior_unstd),</pre>
```

```
likelihood_binom = dbinom(6, size = 9, prob = prob),
l_binom_std = likelihood_binom/sum(likelihood_binom),
likelihood_beta = dbeta(prob, (6+1), (9-6)+1),
l_beta_std = likelihood_beta/sum(likelihood_beta)
) |>
ggplot(aes(prob))+
geom_point(aes(y = l_binom_std, color = "binom", size = "binom"))+
geom_point(aes(y = l_beta_std, color = "beta", size = "beta"))+
scale_color_bright()+
labs(
    x = "probability",
    color = "distribution",
    size = "distribution",
    y = NULL
)
```

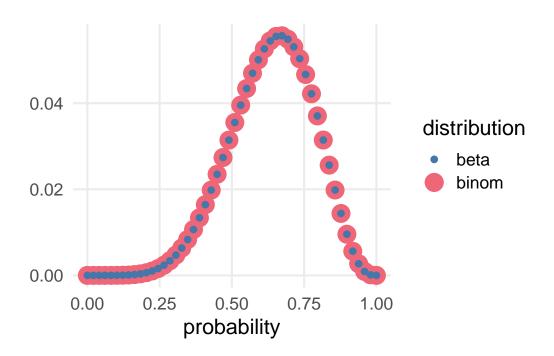


Figure 5: Comparing normalized densities for beta(6+1,3+1) and binom(6, 9, p)