

See chapter 9 in Regression and Other Stories.

=====

```
• html"""  
• <style>  
•     main {  
•         margin: 0 auto;  
•         max-width: 2000px;  
•         padding-left: max(160px, 10%);  
•         padding-right: max(160px, 10%);  
•     }  
• </style>  
• """  
•
```

```
• using Pkg ✓ , DrWatson ✓
```

```
• begin  
•     # Specific to this notebook  
•     using GLM ✓  
•  
•     # Specific to ROSTuringPluto  
•     using Optim ✓  
•     using Logging ✓  
•     using Turing ✓  
•  
•     # Graphics related  
•     using GLMakie ✓  
•  
•     # Common data files and functions  
•     using RegressionAndOtherStories ✓  
•     import RegressionAndOtherStories: link  
•  
•     Logging.disable_logging(Logging.Warn)  
• end;
```

```
Replacing docs for `RegressionAndOtherStories.tr  
DataFrame, AbstractString}` in module `Regressio
```

9.1 Propagating uncertainty in inference using posterior simulations.

`hibbs =`

	year	growth	vote	inc_party_candidate
1	1952	2.4	44.6	"Stevenson"
2	1956	2.89	57.76	"Eisenhower"
3	1960	0.85	49.91	"Nixon"
4	1964	4.21	61.34	"Johnson"
5	1968	3.02	49.6	"Humphrey"
6	1972	3.62	61.79	"Nixon"
7	1976	1.08	48.95	"Ford"
8	1980	-0.39	44.7	"Carter"
9	1984	3.86	59.17	"Reagan"
10	1988	2.27	53.94	"Bush, Sr."
⋮ more				
16	2012	0.95	52.0	"Obama"

```
• hibbs =  
  CSV.read(ros_datadir("ElectionsEconomy",  
    "hibbs.csv"), DataFrame)
```

UndefVarError: hibbs_lm not defined

1. top-level scope @ Local: 18

```
• let
•     fig = Figure()
•     hibbs.label = string.(hibbs.year)
•     xlabel = "Average growth personal
•     income [%]"
•     ylabel = "Incumbent's party vote share"
•     let
•         title = "Forecasting the election
•         from the economy"
•         ax = Axis(fig[1, 1]; title, xlabel,
•         ylabel)
•         for (ind, yr) in
•         enumerate(hibbs.year)
•             annotations!("$ (yr)"; position=
•             (hibbs.growth[ind],
•             hibbs.vote[ind]), fontsize=10)
•         end
•     end
•     let
•         x = LinRange(-1, 4, 100)
•         title = "Data and linear fit"
•         ax = Axis(fig[1, 2]; title, xlabel,
•         ylabel)
•         scatter!(hibbs.growth, hibbs.vote)
•         lines!(x, coef(hibbs_lm)[1] .+
•         coef(hibbs_lm)[2] .* x;
•         color=:darkred)
•         annotations!("vote = 46.2 + 3.0 *
•         growth"; position=(0, 41))
•     end
•     fig
• end
```

ppl7_1 (generic function with 2 methods)

```
• @model function ppl7_1(x, y)
•     a ~ Normal(50, 20)
•     b ~ Normal(2, 10)
•     σ ~ Exponential(1)
•     μ = a .+ b .* x
•     for i in eachindex(y)
•         y[i] ~ Normal(μ[i], σ)
•     end
• end
```

	parameters	mean	std	naive_se
1	:a	46.2708	1.55608	0.0246038
2	:b	3.05463	0.663403	0.0104893
3	: σ	3.57383	0.620971	0.00981841

```

• begin
•   m7_1t = ppl7_1(hibbs.growth, hibbs.vote)
•   chns7_1t = sample(m7_1t, NUTS(),
•     MCMCThreads(), 1000, 4)
•   describe(chns7_1t)
• end

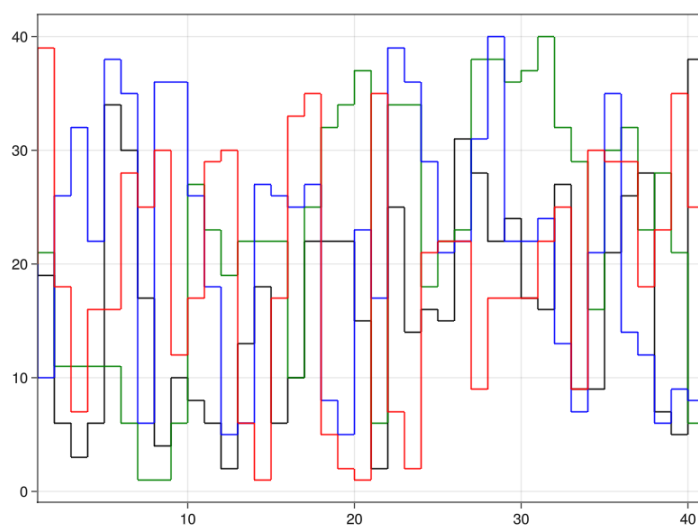
```

	parameters	median	mad_sd	mean	std
1	"a"	46.273	1.554	46.271	1.556
2	"b"	3.049	0.66	3.055	0.663

```

• begin
•   post7_1t = DataFrame(chns7_1t)[: , 3:5]
•   ms7_1t = model_summary(post7_1t, [:a,
•     :b, :sigma])
• end

```



```

• trankplot(post7_1t, "b")

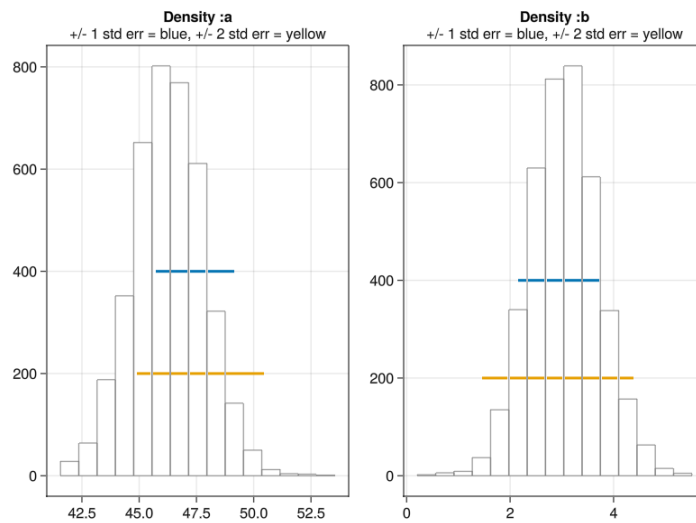
```

```
sims = 4000x3 Matrix{Float64}:  
 46.9655  2.92837  4.19874  
 48.2228  2.33301  2.98444  
 48.531   2.08068  2.57154  
 48.4329  2.33537  3.76951  
 45.4511  3.68536  2.99814  
 43.5968  3.45706  3.77984  
 45.6401  2.84532  3.23996  
  ⋮  
 46.0638  3.33481  3.41148  
 44.1948  3.35263  3.12854  
 45.7716  2.73001  4.02867  
 47.5026  2.25395  3.93305  
 45.5372  3.39224  3.18888  
 48.2702  2.82634  2.85088
```

```
• sims = Array(post7\_1t)
```

```
1x3 Matrix{Float64}:  
 46.2726  3.04927  3.50379
```

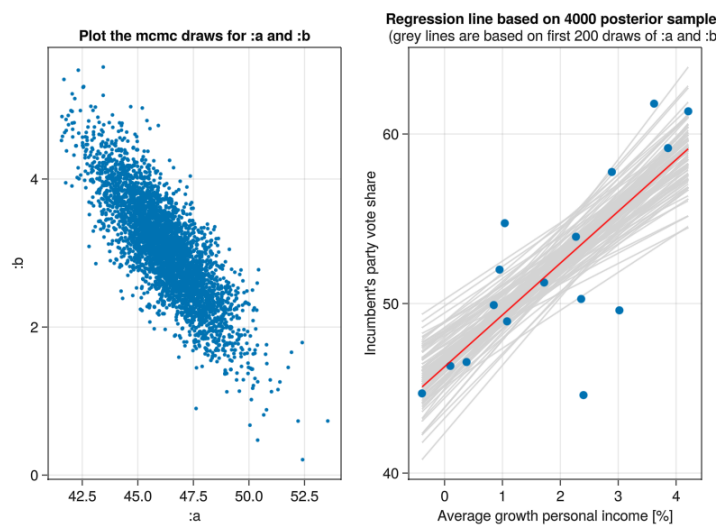
```
• median(sims; dims=1)
```



```

• let
•   f = Figure()
•   ax = Axis(f[1, 1]; title="Density :a",
•         subtitle="+/- 1 std err = blue, +/- 2
•         std err = yellow")
•   hist!(post7_1t.a; bins=15, color =
•         :white, strokewidth = 1, strokecolor =
•         :grey)
•   hlines!(ax, 400; xmin=0.36, xmax=0.62,
•         linewidth=3)
•   hlines!(ax, 200; xmin=0.30, xmax=0.72,
•         linewidth=3)
•
•   ax = Axis(f[1, 2]; title="Density :b",
•         subtitle="+/- 1 std err = blue, +/- 2
•         std err = yellow")
•   hist!(post7_1t.b; bins=15, color =
•         :white, strokewidth = 1, strokecolor =
•         :grey)
•   hlines!(ax, 400; xmin=0.38, xmax=0.65,
•         linewidth=3)
•   hlines!(ax, 200; xmin=0.26, xmax=0.76,
•         linewidth=3)
•   f
• end

```



```

• let
•   growth_range =
•     LinRange(minimum(hibbs.growth),
•       maximum(hibbs.growth), 200)
•   votes = mean.(link(post7_1t, (r,x) ->
•     r.a + x * r.b, growth_range))
•
•   xlabel = "Average growth personal
•     income [%]"
•   ylabel = "Incumbent's party vote share"
•
•   fig = Figure()
•
•   ax = Axis(fig[1, 1]; title="Plot the
•     mcmc draws for :a and :b", xlabel=":a",
•     ylabel=":b")
•   scatter!(post7_1t.a, post7_1t.b;
•     markersize=4)
•
•   xlabel = "Average growth personal
•     income [%]"
•   ylabel="Incumbent's party vote share"
•   ax = Axis(fig[1, 2]; title="Regression
•     line based on 4000 posterior samples",
•     subtitle = "(grey lines are based
•       on first 200 draws of :a and :b)",
•     xlabel, ylabel)
•   for i in 1:100
•     lines!(growth_range, post7_1t.a[i]
•       .+ post7_1t.b[i] .* growth_range,
•       color = :lightgrey)
•   end
•   scatter!(hibbs.growth, hibbs.vote)
•   lines!(growth_range, votes, color =
•     :red)
•   fig

```

```
end
```

9.2 Prediction and uncertainty.

	x	y
1	-2.0	50
2	-1.0	44
3	0.0	50
4	1.0	47
5	2.0	56

```
• let
•   x = LinRange(-2, 2, 5)
•   y = [50, 44, 50, 47, 56]
•   global sexratio = DataFrame(x = x, y =
•   y)
• end
```

ppl9_1 (generic function with 2 methods)

```
• @model function ppl9_1(x, y)
•   a ~ Normal(50, 5)
•   b ~ Normal(0, 5)
•   σ ~ Exponential(1)
•   μ = a .+ b .* x
•   for i in eachindex(y)
•       y[i] ~ Normal(μ[i], σ)
•   end
• end
```


	parameters	mean	std	naive_se
--	------------	------	-----	----------

1	:a	49.4958	1.50676	0.0238239
2	:b	1.38353	1.13322	0.0179178
3	: σ	3.51317	1.00488	0.0158886

```

• begin
•   m9_1t = ppl9_1(sexratio.x, sexratio.y)
•   chns9_1t = sample(m9_1t, NUTS(),
•     MCMCThreads(), 1000, 4)
•   describe(chns9_1t)
• end

```

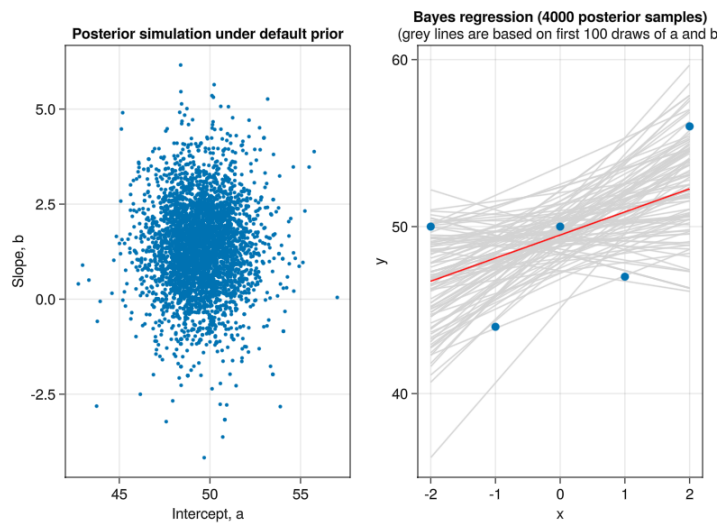
	parameters	median	mad_sd	mean	std
--	------------	--------	--------	------	-----

1	"a"	49.491	1.413	49.496	1.50676
2	"b"	1.397	1.058	1.384	1.13322

```

• begin
•   post9_1t = DataFrame(chns9_1t)[: , 3:5]
•   ms9_1t = model_summary(post9_1t, [:a,
•     :b, :sigma])
• end

```



```

let
  x_range = LinRange(minimum(sexratio.x),
    maximum(sexratio.x), 200)
  y = mean.(link(post9_1t, (r,x) -> r.a +
    x * r.b, x_range))

  xlabel = "x"
  ylabel = "y"

  fig = Figure()

  ax = Axis(fig[1, 1]; title="Posterior
simulation under default prior",
  xlabel="Intercept, a", ylabel="Slope,
b")
  scatter!(post9_1t.a, post9_1t.b;
  markersize=4)

  ax = Axis(fig[1, 2]; title="Bayes
regression (4000 posterior samples)",
  subtitle = "(grey lines are based
on first 100 draws of a and b)",
  xlabel, ylabel)
  for i in 1:100
    lines!(x_range, post9_1t.a[i] .+
      post9_1t.b[i] .* x_range, color =
      :lightgrey)
  end
  scatter!(sexratio.x, sexratio.y)
  lines!(x_range, y, color = :red)
  fig
end

```

ppl9_2 (generic function with 2 methods)

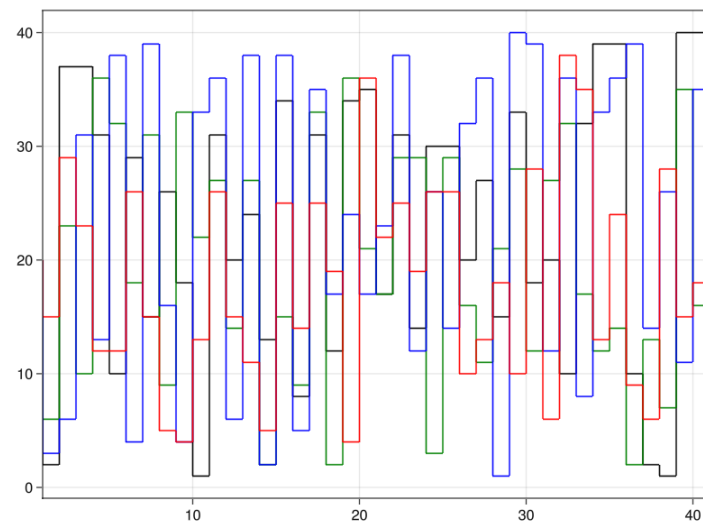
```
• @model function ppl9_2(x, y)
•   a ~ Normal(48.8, 0.2)
•   b ~ Normal(0, 0.2)
•   σ ~ Exponential(1)
•   μ = a .+ b .* x
•   for i in eachindex(y)
•     y[i] ~ Normal(μ[i], σ)
•   end
• end
```

► [parameters	mean	std	naive_sd
1	:a	48.8133	0.197691	0.003125
2	:b	0.0509051	0.198607	0.003140
3	:σ	3.57855	0.922843	0.014591

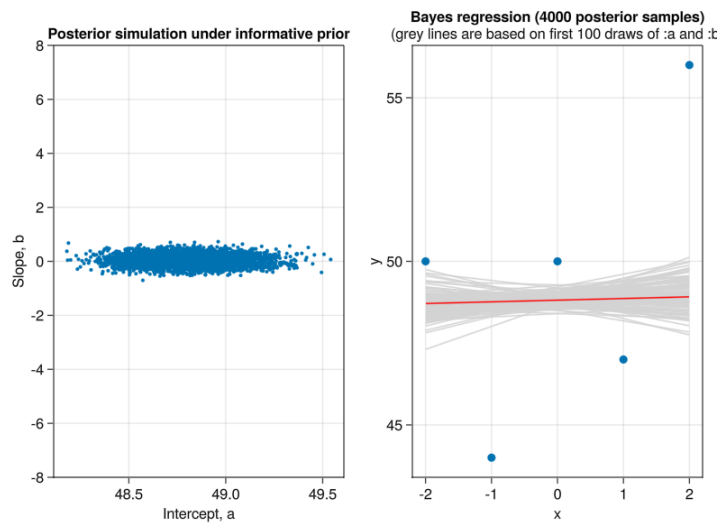
```
• begin
•   m9_2t = ppl9_2(sexratio.x, sexratio.y)
•   chns9_2t = sample(m9_2t, NUTS(),
•   MCMCThreads(), 1000, 4)
•   describe(chns9_2t)
• end
```

	parameters	median	mad_sd	mean	std
1	"a"	48.816	0.198	48.813	0.197
2	"b"	0.052	0.199	0.051	0.198

```
• begin
•   post9_2t = DataFrame(chns9_2t)[: , 3:5]
•   ms9_12 = model_summary(post9_2t, [:a,
•   :b, :sigma])
• end
```



- `trankplot(post9_2t, "b")`



```

let
  x_range = LinRange(minimum(sexratio.x),
    maximum(sexratio.x), 200)
  y = mean.(link(post9_2t, (r,x) -> r.a +
    x * r.b, x_range))

  xlabel = "x"
  ylabel = "y"

  fig = Figure()

  ax = Axis(fig[1, 1]; title="Posterior
simulation under informative prior",
  xlabel="Intercept, a", ylabel="Slope,
b")
  ylims!(ax, -8, 8)
  scatter!(post9_2t.a, post9_2t.b;
  markersize=4)

  ax = Axis(fig[1, 2]; title="Bayes
regression (4000 posterior samples)",
  subtitle = "(grey lines are based
on first 100 draws of :a and :b)",
  xlabel, ylabel)
  for i in 1:100
    lines!(x_range, post9_2t.a[i] .+
      post9_2t.b[i] .* x_range, color =
      :lightgrey)
  end
  scatter!(sexratio.x, sexratio.y)
  lines!(x_range, y, color = :red)
  fig
end

```

9.3 Prior information and Bayesian synthesis.

Prior based on a previously-fitted model using economic and political condition.

```
• begin
•   theta_hat_prior = 0.524
•   se_prior = 0.041
• end;
```

Survey of 400 people, of whom 190 say they will vote for the Democratic candidate.

```
• begin
•   n = 400
•   y = 190
• end;
```

Data estimate.

```
theta_hat_data = 0.475
```

```
• theta_hat_data = y/n
```

```
se_data = 0.02496873044429772
```

```
• se_data =  $\sqrt{((\underline{y/n}) * (1 - \underline{y/n}) / \underline{n})}$ 
```

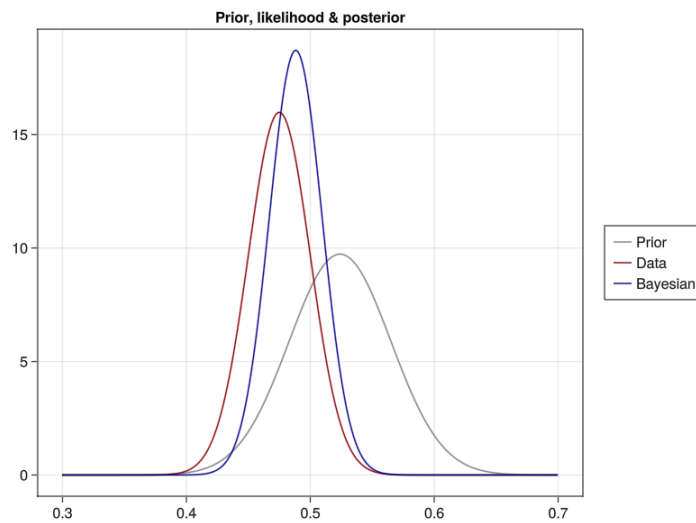
Bayes estimate.

```
theta_hat_bayes = 0.48825635323153693
```

```
• theta_hat_bayes =
•   (theta_hat_prior/se_prior2 +
•    theta_hat_data/se_data2) / (1/se_prior2
•    + 1/se_data2)
```

```
se_bayes = 0.02132543263776925
```

```
• se_bayes =  $\sqrt{1 / (1 / \underline{se\_prior}^2 +$ 
•    $1 / \underline{se\_data}^2))}$ 
```

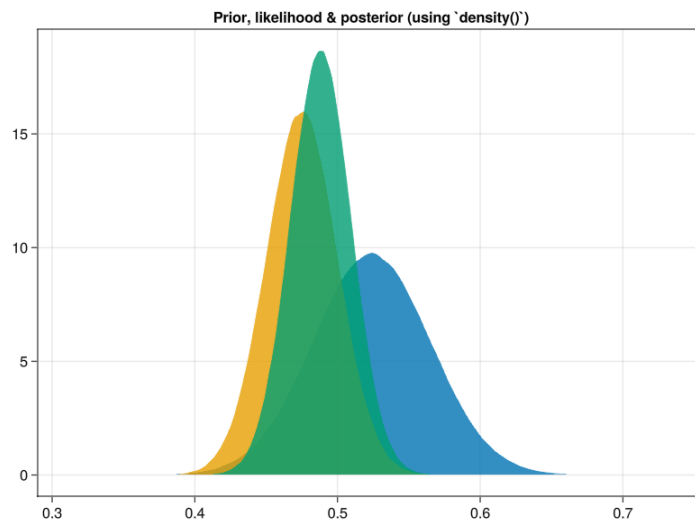


```

• let
•   x = 0.3:0.001:0.7
•   f = Figure()
•   ax = Axis(f[1, 1], title="Prior,
•   likelihood & posterior")
•   prior = lines!(f[1, 1], x, pdf.
•   (Normal(theta_hat_prior, se_prior), x),
•   color=:gray)
•   data = lines!(x, pdf.
•   (Normal(theta_hat_data, se_data),
•   x), color=:darkred)
•   bayes = lines!(x, pdf.
•   (Normal(theta_hat_bayes, se_bayes), x),
•   color=:darkblue)
•   Legend(f[1, 2], [prior, data, bayes],
•   ["Prior", "Data", "Bayesian"])

•   current_figure()
end

```



```

• let
•   f = Figure()
•   ax = Axis(f[1, 1], title="Prior,
•   likelihood & posterior (using
•   `density()`)" )
•   density!(rand(Normal(theta_hat_prior,
•   se_prior), Int(1e6)), lab="prior")
•   density!(rand(Normal(theta_hat_data,
•   se_data), Int(1e6)), lab="likelihood")
•   density!(rand(Normal(theta_hat_bayes,
•   se_bayes), Int(1e6)), lab="bayes")
•   current_figure()
• end

```

9.4 Example of Bayesian inference: beauty and sex ratio.