Final Project Proposal

MAE 298 (Introduction to Bayesian Statistics for Data-Driven Science and Engineering)

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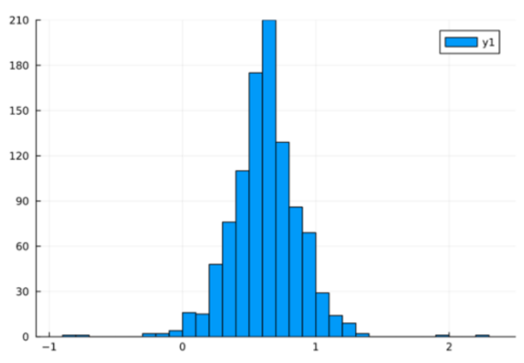
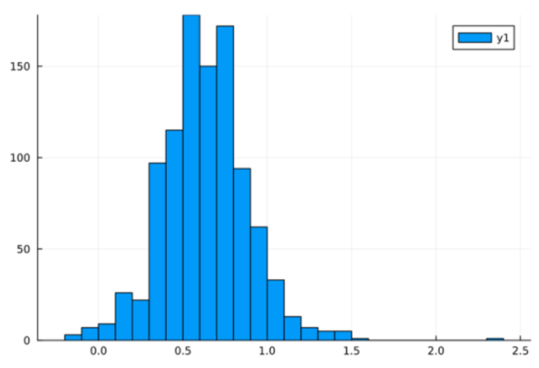
For our final project, we would like to use existing data taken from ASME safety valve testing and apply it to predict the number of valves from a new vendor, in a specific service medium, that will fail subsequent testing. We plan on using a multi-level model to make inferences about a specific vendor while also considering the entire population of sampled valves. The dataset under consideration consists of the results of 560 valves from 19 different vendors tested per ASME BPVC Section VIII, taken from an SRS-PEVT Study by ASME. The overall goal of this would be to try to narrow down the minimum amount of purchased valves required to use on a specific system, assuming a specified vendor and specified service medium (e.g. if 10 working valves are required, we would like to predict how many valves are needed to be bought based on the failure data). The tabulated is shown below, for reference.

Results of New Valve Tests

% Rejected	Rejected for		Vendor	Population	Rejected	High Pop	% Over Set	% Over Limit	Set Pressure	Service
4.6%	leaking		a	9	2	1	10.0%	4.3%	35	steam
4.3%	high pop		b	13	0	0	0.0%	0.0%		air
2.5%	low pop		c	85	1	1	13.0%	9.7%	175	steam
1.1%	stamped wrong		d	108	21	4	4.5%	1.5%	350	air
0.5%	no seel		e	1	0	0	0.0%	0.0%		na
0.4%	wrong valve		f	55	9	2	5.5%	2.5%	400	liquid
0.4%	bad lever		g	41	5	2	6.7%	3.3%	165	steam
0.4%	no oxygen cleen report(?)		h	2	0	0	0.0%	0.0%		air
14.2%	Total		z	40	6	1	24.0%	20.0%	165	steam
79.52	Number of units rejected		k	1	0	0	0.0%	0.0%		steam
			y	66	4	4	6.0%	3.0%	100	air
			m	54	6	1	27.0%	24.0%	75	air/liquid
			m	14	7	3	10.0%	3.0%	80	steam
			n	1	0	0	0.0%	0.0%		na
			o	3	0	0	0.0%	0.0%		air
			p	3	0	0	0.0%	0.0%		liquid
			r	38	7	1	6.8%	4.0%	250	liquid
			s	8	0	0	0.0%	0.0%		air
			x	18	2	1	6.3%	1.2%	175	air
		Total		560	70	21	6.3%	4.0%		
							average	average		

Vendor a	Vendor c
	

The above graphs show normalized posterior distributions where the x axis the success rate for a valve given the vendor. We grouped each set of valves by the vendor and service medium. We then used a beta function with parameters four and two to represent the mean and an exponential function with a lambda of 0.1 for the standard deviation. These were then used in a normal distribution to model our probability of a valve passing a preinstallation pressure test. We had some success using MCMC to obtain a posterior distribution for each vendor. We only tried it on the steam service medium but plan to expand it to air and liquid service mediums.

We are having trouble finding a good way to set up our model using a binomial distribution since it seemed to be applicable to pass/fail testing. We had problems with our probability of success parameter because when using our hyperparameters we were getting probabilities less than zero and greater than one. Our probabilities between vendors seem to be very similar which is not what we would expect. We attached our code for further information.

Final Project

March 8, 2025

```
[210]: using DataFrames #for data wrangling
       using StatsPlots #for plotting
       using Turing #for MCMC
       using CSV #CSV import
       using Random #data generation (if required)
       using Distributions
```

Import Data

```
[211]: #this is a local document, but i've also saved a slightly cleaned up version in␣
        ↪github with the same "valveTestRaw" title
       valveData = CSV.read("./Results of New Valve Tests.csv", DataFrame)
```

	Vendor	Population	Rejected	High Pop	% Over Set	% Over Limit	Set Pressure	
	String1	Int64	Int64	Int64	String7	String7	Int64?	
1	a	9	2	1	10.00%	4.30%	35	...
2	b	13	0	0	0.00%	0.00%	*missing*	...
3	c	85	1	1	13.00%	9.70%	175	...
4	d	108	21	4	4.50%	1.50%	350	...
5	e	1	0	0	0.00%	0.00%	*missing*	...
6	f	55	9	2	5.50%	2.50%	400	...
7	g	41	5	2	6.70%	3.30%	165	...
8	h	2	0	0	0.00%	0.00%	*missing*	...
9	z	40	6	1	24.00%	20.00%	165	...
10	k	1	0	0	0.00%	0.00%	*missing*	...
11	y	66	4	4	6.00%	3.00%	100	...
12	m	54	6	1	27.00%	24.00%	75	...
13	m	14	7	3	10.00%	3.00%	80	...
14	n	1	0	0	0.00%	0.00%	*missing*	...
15	o	3	0	0	0.00%	0.00%	*missing*	...
16	p	3	0	0	0.00%	0.00%	*missing*	...
17	r	38	7	1	6.80%	4.00%	250	...
18	s	8	0	0	0.00%	0.00%	*missing*	...
19	x	18	2	1	6.30%	1.20%	175	...

Collect Number of Trials & Separate into Service Mediums

```
[212]: # vendors = (collect(valveData[:,1]))
       # n=0
# for i in 1:length(vendors)
#     n = valveData[i, 2] + n
# end
# n

steamDF = []
airDF = []
liquidDF = []
airLiqDF = []

steamDF = filter(:Service => ==("steam"), valveData)
airDF = filter(:Service => ==("air"), valveData)
liquidDF = filter(:Service => ==("liquid"), valveData)
airLiqDF = filter(:Service => ==("air/liquid"), valveData)
naDF = filter(:Service => ==("na"), valveData)

n_steam = 0
n_air = 0
n_liquid = 0
n_airLiq = 0
n_na = 0

steamVend = (collect(steamDF[:,1]))
for i in 1:length(steamVend)
    n_steam = steamDF[i,2] +n_steam
end

airVend = (collect(airDF[:,1]))
for i in 1:length(airVend)
    n_air = airDF[i,2] +n_air
end

liquidVend = (collect(liquidDF[:,1]))
for i in 1:length(liquidVend)
    n_liquid = liquidDF[i,2] +n_liquid
end

airLiqVend = (collect(airLiqDF[:,1]))
for i in 1:length(airLiqVend)
    n_airLiq = airLiqDF[i,2] +n_airLiq
end

naVend = (collect(naDF[:,1]))
for i in 1:length(naVend)
    n_na = naDF[i,2]+n_na
end
```

```
steamDF
```

	Vendor	Population	Rejected	High Pop	% Over Set	% Over Limit	Set Pressure	
	String1	Int64	Int64	Int64	String7	String7	Int64?	
1	a	9	2	1	10.00%	4.30%	35	...
2	c	85	1	1	13.00%	9.70%	175	...
3	g	41	5	2	6.70%	3.30%	165	...
4	z	40	6	1	24.00%	20.00%	165	...
5	k	1	0	0	0.00%	0.00%	*missing*	...
6	m	14	7	3	10.00%	3.00%	80	...

Set Up Model

[213]:
```
@model function valveTesting(Vendors, Population, highPops) # rejects␣
↪serviceMedium)
    #additional functionality can be added to this, especially when considering␣
↪that the probability of failing (p-1) is the sum of the probability of␣
↪failing on a low pop (less dangerous) & a high pop (more dangerous)



    #hyper prior
          ~ Beta(4, 2)
          ~ Exponential(0.1)

        p = Vector{Real}(undef, length(Vendors))
        n = Vector{Real}(undef, length(Vendors))
        valvePass = Vector{Real}(undef, length(Vendors))
    for i in 1:length(Vendors)

        #prior
        n[i] = Population[i]
        valvePass[i] ~ Normal( ,  )
        #distribution of valves passing given pass probability p and n trials
        #valvePass[i] ~ Binomial(n[i], p[i])
        #valvePass[i] ~ Normal( ,  )
    end
end
```

```
valveTesting (generic function with 6 methods)
```

[214]:
```
steam_model = valveTesting(steamDF[:,1], steamDF[:,2], steamDF[:,3])

steam_posterior = sample(steam_model, NUTS(), 1000)
```

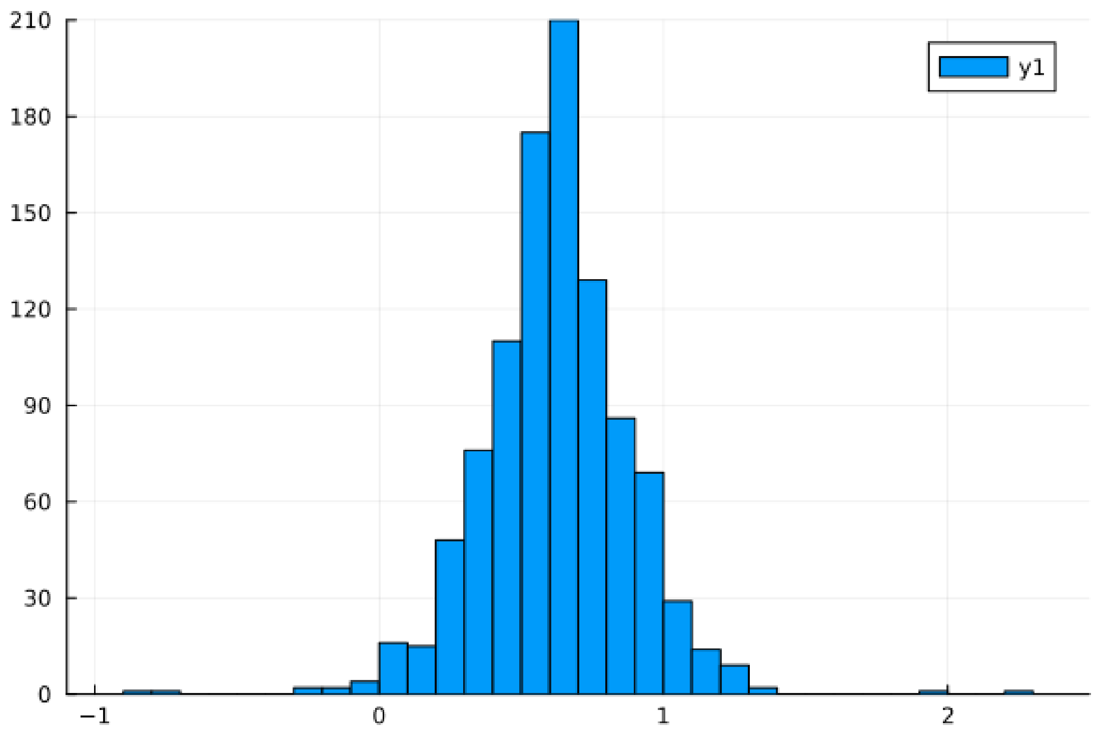
```
Sampling    0%|                                          |  ETA: N/A
  Info: Found initial step size
    = 0.2
  @ Turing.Inference
/Users/user/.julia/packages/Turing/NQDYt/src/mcmc/hmc.jl:207
```

```
Number of chains  = 1
Samples per chain = 1000
Wall duration     = 0.82 seconds
Compute duration  = 0.82 seconds
parameters        =  ,  , valvePass[1], valvePass[2], valvePass[3], valvePass[4],␣
 ↪valvePass[5], valvePass[6]
internals         = lp, n_steps, is_accept, acceptance_rate, log_density,␣
 ↪hamiltonian_energy, hamiltonian_energy_error, max_hamiltonian_energy_error,␣
 ↪tree_depth, numerical_error, step_size, nom_step_size

Summary Statistics
    parameters      mean       std      mcse   ess_bulk   ess_tail      rhat
        Symbol   Float64   Float64   Float64    Float64    Float64   Float64

                  0.6261    0.1734    0.0204    72.4505   211.2309    1.0308
                  0.1465    0.0947    0.0139    27.0439    20.8341    1.0076
  valvePass[1]    0.6231    0.2538    0.0233    92.4972   299.8958    1.0054
  valvePass[2]    0.6332    0.2526    0.0241    92.7321   294.9325    1.0327
  valvePass[3]    0.6325    0.2277    0.0182   142.0857   340.5463    1.0065
  valvePass[4]    0.6192    0.2393    0.0210   127.0519   236.7808    1.0239
  valvePass[5]    0.6172    0.2344    0.0177   143.4016   386.8376    1.0189
  valvePass[6]    0.6140    0.2536    0.0237   101.1608   437.3298    1.0277
                                                                1 column omitted

Quantiles
    parameters      2.5%     25.0%     50.0%     75.0%     97.5%
        Symbol   Float64   Float64   Float64   Float64   Float64

                  0.2821    0.5029    0.6416    0.7477    0.9312
                  0.0450    0.0769    0.1195    0.1934    0.3898
  valvePass[1]    0.0958    0.4840    0.6240    0.7656    1.1022
  valvePass[2]    0.1325    0.4747    0.6419    0.7739    1.1489
  valvePass[3]    0.1837    0.4939    0.6320    0.7523    1.1059
  valvePass[4]    0.1396    0.4555    0.6274    0.7705    1.0622
  valvePass[5]    0.1448    0.4896    0.6439    0.7500    1.0654
  valvePass[6]    0.1153    0.4474    0.6180    0.7697    1.1252
```

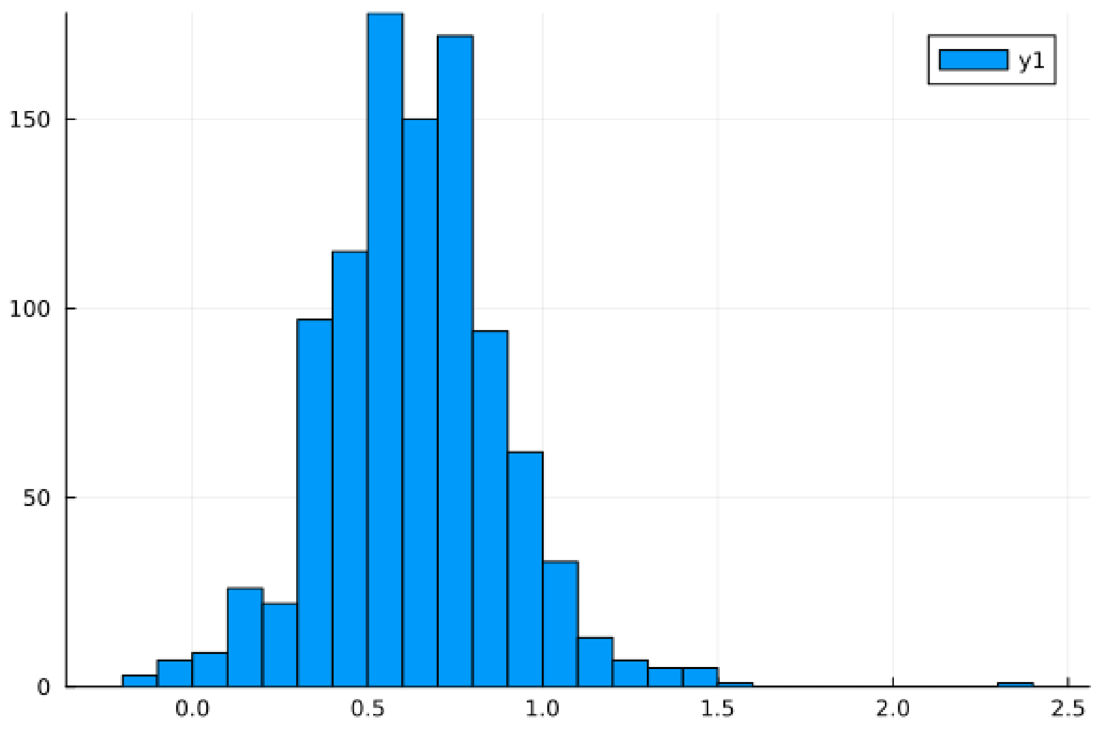
[215]:
```
postDF = DataFrame(steam_posterior)
```

	iteration	chain			valvePass[1]	valvePass[2]	valvePass[3]	
	Int64	Int64	Float64	Float64	Float64	Float64	Float64	
1	501	1	0.624363	0.101732	0.621401	0.676699	0.682054	...
2	502	1	0.638855	0.0943729	0.69544	0.636279	0.608389	...
3	503	1	0.631277	0.162388	0.805922	0.572874	0.499749	...
4	504	1	0.725277	0.17159	0.745444	0.902084	0.631404	...
5	505	1	0.768456	0.123373	0.746789	0.740318	0.923238	...
6	506	1	0.844632	0.143884	1.02434	0.79383	0.994382	...
7	507	1	0.876712	0.136271	0.646383	0.847353	0.821888	...
8	508	1	0.743402	0.123898	0.928348	0.650311	0.81534	...
9	509	1	0.746138	0.0714451	0.662507	0.851967	0.786254	...
10	510	1	0.953225	0.0889042	1.13765	0.936168	1.02415	...
11	511	1	0.919838	0.162016	0.703202	0.921017	0.699027	...
12	512	1	0.831178	0.131615	0.856382	0.89783	0.87989	...
13	513	1	0.839883	0.125637	0.932323	0.922863	0.707186	...
14	514	1	0.593754	0.140075	0.480825	0.50159	0.762223	...
15	515	1	0.765232	0.0961476	0.705133	0.791697	0.570825	...
16	516	1	0.724821	0.108031	0.771887	0.763367	0.647144	...
17	517	1	0.724821	0.108031	0.771887	0.763367	0.647144	...
18	518	1	0.724821	0.108031	0.771887	0.763367	0.647144	...
19	519	1	0.790564	0.101784	0.631645	0.93898	0.848137	...
20	520	1	0.817293	0.0784538	0.99265	0.833883	0.819455	...
21	521	1	0.833972	0.0912988	0.854417	0.773157	0.864878	...
22	522	1	0.833972	0.0912988	0.854417	0.773157	0.864878	...
23	523	1	0.842019	0.0916136	0.978067	0.838782	0.737009	...
24	524	1	0.627328	0.135182	0.515388	0.65372	0.704575	...
...	...	...	...	...	...	...	...	

```
[216]: histogram(postDF[:, 5])
```



```
[217]: histogram(postDF[:, 6])
```


150
100
50
0
0.0
0.5
1.0
1.5
2.0
2.5
y1