```
In [15]: using JSON
using DataFrames
using StatsPlots
using Turing
using LinearAlgebra
using Random
```

Multi-level model using football match simulation as an example

```
In [16]: ## First, import the data and do some data wrangling
    england_league = JSON.parsefile("../data/matches_England.json")
    matches_df = DataFrame(home = [], away = [], score_home = [], score_aw
    O×4 DataFrame
    Row home away score_home score_away
        Any Any Any Any
```

```
In [17]: # example entry for each game in england_league: "label" => "Burnley
matches = []
for match in england_league
    push!(matches, split(match["label"], ",")) # "Burnley - AFC Bourne
end

for match in matches
    home, away = split(match[1], " - ") # "Burnley" # "AFC Bournemout
    score_home, score_away = split(match[2], " - ") # "1" # "2"
    push!(matches_df,[home, away, parse(Int,score_home), parse(Int,score)
end

matches_df

teams = unique(collect(matches_df[:,1]))
```

```
"Burnley"
        "Crystal Palace"
        "Huddersfield Town"
        "Liverpool"
        "Manchester United"
        "Newcastle United"
        "Southampton"
        "Swansea City"
        "Tottenham Hotspur"
        "West Ham United"
        "Manchester City"
        "Leicester City"
        "Chelsea"
        "Arsenal"
        "Everton"
        "AFC Bournemouth"
        "Watford"
        "West Bromwich Albion"
        "Stoke City"
        "Brighton & Hove Albion"
In [ ]: ## Now, our model
         @model function football_matches(home_teams, away_teams, score_home, s
             # Hyper priors
             μatt ~ Normal(0, 0.1)
             \mu def \sim Normal(0, 0.1)
             σatt ∼ Exponential(1)
             odef ∼ Exponential(1)
             home ~ Normal(0, 1)
             # Team-specific effects
             att = zeros(length(teams))
             def = zeros(length(teams))
             for i in 1:length(teams)
                 att[i] ~ Normal(μatt, σatt)
                 def[i] ~ Normal(μdef, σdef)
             end
             #att ~ filldist(Normal(μatt, σatt), length(teams)) # more compact
             #def ~ filldist(Normal(μdef, σdef), length(teams))
             offset = mean(att) + mean(def)
             # the number of matches
             n_matches = length(home_teams)
             # scoring rates \theta
             \theta_{\text{home}} = \text{Vector}\{\text{Real}\}(\text{undef, n_matches}) # or just \theta_{\text{home}} = zer
```

20-element Vector{Any}:

```
\theta_{\text{away}} = \text{Vector}\{\text{Real}\} (\text{undef, n_matches}) # or just \theta_{\text{away}} = zer
             # Modeling score-rate and scores for each match
             for i in 1:n matches
                  # scoring rate
                  home_team_idx = findfirst(isequal(home_teams[i]), teams)
                  away_team_idx = findfirst(isequal(away_teams[i]), teams)
                  \theta home[i] = home + att[home team idx] + def[away team idx] - o
                  \theta_{\text{away}}[i] = \text{att[away\_team\_idx]} + \text{def[home\_team\_idx]} - \text{offset}
                  # scores
                  score_{home[i]} \sim Poisson(exp(\theta_{home[i]})) # To ensure positive
                  score_away[i] \sim Poisson(exp(\theta_away[i]))
             end
         end
        football_matches (generic function with 2 methods)
In []: model = football matches(matches df[:,1], matches df[:,2], matches df[
         posterior = sample(model, NUTS(), 3000)
        Sampling
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        r Info: Found initial step size
            \epsilon = 0.00625
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        hmc.il:213
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                                                                          ETA: 0:05:25
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```

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ETA: 0:03:13

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ETA: 0:03:06 ETA: 0:03:07

Sampling

Sampling

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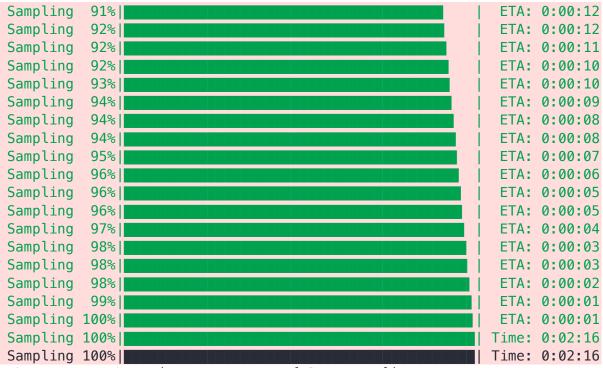
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Chains MCMC chain (3000×57×1 Array{Float64, 3}):

Iterations = 1001:1:4000

Number of chains = 1 Samples per chain = 3000

Wall duration = 136.29 seconds Compute duration = 136.29 seconds

parameters = μ att, μ def, σ att, σ def, home, att[1], def[1], att[2], def[2], att[3], def[3], att[4], def[4], att[5], def[5], att[6], def[6], att[7], def[7], att[8], def[8], att[9], def[9], att[10], def[10], att[11], def[11], att[12], def[12], att[13], def[13], att[14], def[14], att[15], def[15], att[16], def[16], att[17], def[17], att[18], def[18], att[19], def[19], att[20]

internals = lp, n_steps, is_accept, acceptance_rate, log_densit
y, hamiltonian_energy, hamiltonian_energy_error, max_hamiltonian_energy
_error, tree_depth, numerical_error, step_size, nom_step_size

Summary Statistics

	eters 	mean	std	mcse	ess_bulk	ess_tail	
	ymbol 	Float64	Float64	Float64	Float64	Float64	Fl
1.0155	μatt 	-0.0106	0.1006	0.0059	286.0900	721.8933	
1.0031	μdef 	-0.0008	0.0994	0.0059	288.4936	464.7421	
1.0023	σatt 	0.3849	0.0779	0.0035	621.2962	339.6839	
1.0028	σdef 	0.2154	0.0612	0.0034	327.5896	117.0460	
	home	0.3380	0.0425	0.0009	2208.4531	2263.3756	

1.0004						
att[1]	-0.2672	0.2014	0.0100	409.4098	955.1314	
1.0069 ···						
def[1]	-0.1680	0.1656	0.0079	421.9315	441.1022	
1.0004						
att[2]	-0.0720	0.1883	0.0100	355.6188	657.8336	
1.0078						
def[2]	0.0594	0.1556	0.0078	400.4448	1113.5101	
1.0011	0.4504	0 2072	0.0102	402 0100	1040 0410	
att[3] 1.0095 …	-0.4594	0.2072	0.0103	402.8109	1040.9419	
def[3]	0 0062	0 1562	0 0079	406.0630	531.2944	
1.0042 ···		0.1303	0.0076	400.0030	331.2944	
att[4]		0.1743	0.0101	295.1097	771.1988	
1.0159	013000	011743	0.0101	23311037	77111300	
def[4]	-0.1551	0.1678	0.0081	425.6426	571.6784	
0.9998						
att[5]	0.2910	0.1777	0.0102	306.1388	709.1792	
1.0109						
def[5]	-0.3300	0.1843	0.0084	445.9616	167.5677	
0 . 9999						
att[6]	-0.1918	0.1969	0.0104	360.3907	940.1000	
1.0115 ···						
def[6]	-0.0497	0.1541	0.0069	500.0782	991.6641	
1.0016 ···						
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··.				4	1 1 22	
				1 00	olumn and 28	row

s omitted

Quantiles					
parameters	2.5%	25.0%	50.0%	75.0%	97.5%
Symbo	l Float64	Float64	Float64	Float64	Float64
μati	t -0.2005	-0.0769	-0.0106	0.0569	0.1855
μdet	f -0.2022	-0.0655	0.0009	0.0668	0.1866
σati	t 0.2633	0.3281	0.3729	0.4302	0.5561
σdet	f 0.0804	0.1757	0.2123	0.2506	0.3494
home	e 0.2516	0.3101	0.3398	0.3673	0.4177
att[1]	-0.6797	-0.3978	-0.2636	-0.1333	0.1242
def[1]	_0 . 4877	-0.2831	-0.1685	-0.0515	0.1470
att[2]	_0 . 4397	-0.1989	-0.0713	0.0565	0.2913
def[2]	-0.2495	-0.0467	0.0640	0.1688	0.3637
att[3]	-0.8748	-0.5914	-0.4588	-0.3222	-0.0598
def[3]	-0.2396	-0.0133	0.0914	0.1876	0.3825
att[4]	0.1529	0.3881	0.5069	0.6142	0.8376
def[4]	-0.4933	-0.2669	-0.1504	-0.0392	0.1603
att[5]	-0.0623	0.1790	0.2905	0.4048	0.6297
def[5]	-0.6938	-0.4537	-0.3274	-0.2027	0.0213
att[6]	-0.5740	-0.3206	-0.1891	-0.0596	0.1925
def[6]	-0.3658	-0.1516	-0.0457	0.0545	0.2445
:	:	:	:	:	÷

In [20]: posterior_df=DataFrame(posterior)

Row	iteration	chain	μatt	μdef	σatt	σdef	home
	Int64	Int64	Float64	Float64	Float64	Float64	Float
1	1001	1	-0.0340967	0.0488872	0.371805	0.341548	0.41
2	1002	1	0.120224	0.0379764	0.442336	0.104175	0.318
3	1003	1	0.120224	0.0379764	0.442336	0.104175	0.318
4	1004	1	0.14776	0.0602034	0.431715	0.100922	0.329
5	1005	1	0.14776	0.0602034	0.431715	0.100922	0.329
6	1006	1	0.14776	0.0602034	0.431715	0.100922	0.329
7	1007	1	0.132189	0.0570596	0.422664	0.106005	0.358
8	1008	1	0.140849	0.0218837	0.340951	0.149594	0.302
9	1009	1	0.000211701	0.00791739	0.55847	0.0972845	0.407
10	1010	1	-0.0436966	-0.0107217	0.500536	0.108407	0.4
11	1011	1	0.198782	0.0145961	0.331272	0.195929	0.260
12	1012	1	-0.00990157	0.133114	0.629202	0.263415	0.343
13	1013	1	0.143073	0.0929881	0.423556	0.258046	0.315
:	:	÷	:	:	:	:	
2989	3989	1	-0.152038	0.000856577	0.322627	0.227176	0.2
2990	3990	1	0.0130078	0.0471447	0.487366	0.20001	0.379
2991	3991	1	-0.120245	-0.0915178	0.35016	0.21365	0.365
2992	3992	1	-0.0803213	-0.0308569	0.334981	0.158142	0.40
2993	3993	1	-0.0574519	-0.0464465	0.347634	0.225209	0.308
2994	3994	1	0.10894	-0.106624	0.42737	0.23224	0.381
2995	3995	1	0.00348895	-0.0755697	0.39041	0.162871	0.317
2996	3996	1	0.0239133	-0.128041	0.357514	0.194984	0.395
2997	3997	1	0.180213	-0.0651568	0.314539	0.16265	0.37
2998	3998	1	0.0579803	0.0572436	0.451031	0.199167	0.369
2999	3999	1	0.176402	0.0165819	0.444763	0.227071	0.329
3000	4000	1	-0.0406021	-0.0143352	0.464827	0.241888	0.33
	-						

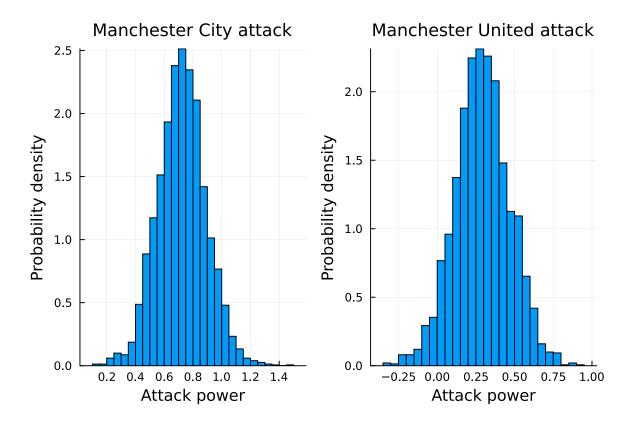
In [21]: DataFrames.transform!(posterior_df, AsTable(Between("att[1]","att[20]"

DataFrames.transform!(posterior_df, AsTable(Between("def[1]","def[20]"
DataFrames.transform!(posterior_df, AsTable([:att_mean,:def_mean]) =>

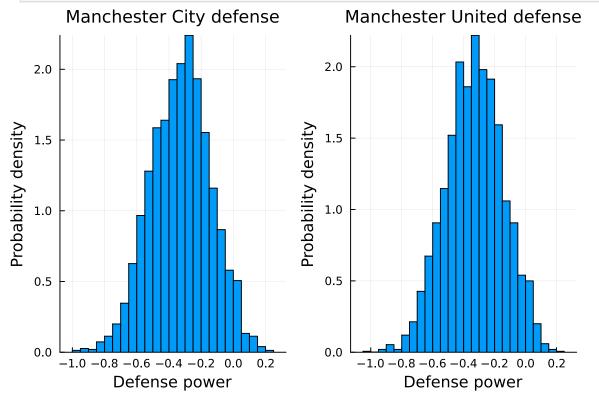
Row	iteration	chain	μatt	μdef	σatt	σdef	home
	Int64	Int64	Float64	Float64	Float64	Float64	Float
1	1001	1	-0.0340967	0.0488872	0.371805	0.341548	0.41
2	1002	1	0.120224	0.0379764	0.442336	0.104175	0.318
3	1003	1	0.120224	0.0379764	0.442336	0.104175	0.318
4	1004	1	0.14776	0.0602034	0.431715	0.100922	0.329
5	1005	1	0.14776	0.0602034	0.431715	0.100922	0.329
6	1006	1	0.14776	0.0602034	0.431715	0.100922	0.329
7	1007	1	0.132189	0.0570596	0.422664	0.106005	0.358
8	1008	1	0.140849	0.0218837	0.340951	0.149594	0.302
9	1009	1	0.000211701	0.00791739	0.55847	0.0972845	0.407
10	1010	1	-0.0436966	-0.0107217	0.500536	0.108407	0.4
11	1011	1	0.198782	0.0145961	0.331272	0.195929	0.260
12	1012	1	-0.00990157	0.133114	0.629202	0.263415	0.343
13	1013	1	0.143073	0.0929881	0.423556	0.258046	0.315
:	÷	÷	:	:	:	÷	
2989	3989	1	-0.152038	0.000856577	0.322627	0.227176	0.2
2990	3990	1	0.0130078	0.0471447	0.487366	0.20001	0.379
2991	3991	1	-0.120245	-0.0915178	0.35016	0.21365	0.365
2992	3992	1	-0.0803213	-0.0308569	0.334981	0.158142	0.40
2993	3993	1	-0.0574519	-0.0464465	0.347634	0.225209	0.308
2994	3994	1	0.10894	-0.106624	0.42737	0.23224	0.381
2995	3995	1	0.00348895	-0.0755697	0.39041	0.162871	0.317
2996	3996	1	0.0239133	-0.128041	0.357514	0.194984	0.395
2997	3997	1	0.180213	-0.0651568	0.314539	0.16265	0.37
2998	3998	1	0.0579803	0.0572436	0.451031	0.199167	0.369
2999	3999	1	0.176402	0.0165819	0.444763	0.227071	0.329
3000	4000	1	-0.0406021	-0.0143352	0.464827	0.241888	0.33
	b						

In [22]: # For this example, we are interested in a pair of teams (no need to u

```
teamA = "Manchester City"
         teamB = "Manchester United"
         teamA_id = findfirst(isequal(teamA), teams)
         teamB_id = findfirst(isequal(teamB), teams)
         teamA att post = posterior df[:,"att[$teamA id]"]
         teamA_def_post = posterior_df[:,"def[$teamA_id]"]
         teamB_att_post = posterior_df[:,"att[$teamB_id]"]
         teamB_def_post = posterior_df[:,"def[$teamB_id]"]
        3000-element Vector{Float64}:
         -0.31659686077845584
          0.010909344846748792
          0.010909344846748792
         -0.005602923863187977
         -0.005602923863187977
         -0.005602923863187977
         -0.12470192624633054
         -0.23946056821044293
         -0.17673201401029642
         -0.12582298768177858
         -0.28907656726617503
         -0.600319104560645
         -0.25490945685899014
         -0.4968341292721567
         -0.2274802264310944
         -0.7068032570364412
         -0.04770233420003743
         -0.03970682618439173
         -0.5052118038597926
In [23]: ha1 = histogram(teamA_att_post, title=teamA*" attack", titlefontsize =
         ha2 = histogram(teamB_att_post, title=teamB*" attack", titlefontsize =
         plot(ha1, ha2, layout=(1,2));
         xlabel!("Attack power");
         ylabel!("Probability density")
```





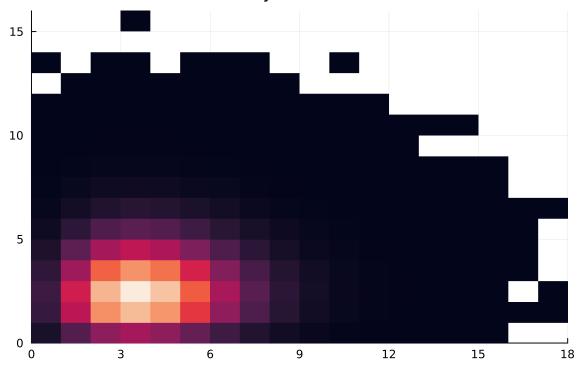


Mini Project

Consult the lecture notes.

```
In [ ]: Random.seed!(205579184)
        # hint: let's simulate 500 hypothetical finals (then you will have a t
        # first leg: teamA is the home team and teamB is the away team
        θ home = posterior df[:,:home] + posterior df[:,"att[$teamA id]"] + po
        θ_away = posterior_df[:,"att[$teamB_id]"] + posterior_df[:,"def[$teamA
        teamA_score = rand.(Poisson.(exp.(\theta_home)),500)
        teamB_score = rand.(Poisson.(exp.(\theta_away)),500)
        # second leg: teamA is the away team and teamB is the home team
        θ_home = posterior_df[:,:home] + posterior_df[:,"att[$teamB_id]"] + po
        0_away = posterior_df[:,"att[$teamA_id]"] + posterior_df[:,"def[$teamB
        teamA_score += rand.(Poisson.(exp.(\theta_away)),500) # add the first-leg
        teamB_score += rand.(Poisson.(exp.(\theta_home)),500)
        # transform into long column vectors
        teamA score = vcat(teamA score...)
        teamB_score = vcat(teamB_score...)
        display(histogram2d(teamA_score, teamB_score, title=teamA*" vs "*teamB
        # https://docs.juliaplots.org/dev/generated/colorschemes/
        # Winning probabilities
        winning_prob_A = sum(teamA_score .> teamB_score) / length(teamA_score)
        println("Winning probability of "*teamA*" against "*teamB*" is "*strin
        winning_prob_B = sum(teamA_score .< teamB_score) / length(teamA_score)</pre>
        println("Winning probability of "*teamB*" against "*teamA*" is "*strin
        draw prob = sum(teamA score .== teamB score) / length(teamA score)
        println("Draw probability between "*teamA*" and "*teamB*" is "*string(
        println("Sum of probabilities (sanity check): "*string((winning_prob_A)
```

Manchester City vs Manchester United



Winning probability of Manchester City against Manchester United is 61. 504%

Winning probability of Manchester United against Manchester City is 24.09%

Draw probability between Manchester City and Manchester United is 14.40 5%

Sum of probabilities (sanity check): 100.0%