



# BWF Badminton

Bayesian Data Analysis Project

Team: TheSurvivors

# Introduction

- **Goal:** distribution of the outcomes in a badminton tournament
- **Approach:** Bayesian data analysis on historical data



Tanongsak  
SAENSOMBOONSUK [1]

21-14, 21-12



Kantaphon  
WANGCHAROEN

21-19, 11-4 Retirement



Kantaphon  
WANGCHAROEN

20-22, 21-10, 21-4



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Cao Cuong  
PHAM

21-15, 21-17



Ihsan Maulana  
MUSTOFA

21-17, 21-14



Ihsan Maulana  
MUSTOFA

23-21, 21-6

# Ranking spread

- Ranking spreads =  $\text{rank}(2^{\text{nd}} \text{ player}) - \text{rank}(1^{\text{st}} \text{ player})$
- For example:
  - Spread(from 1st rank player to 8th rank player) =  $8 - 1 = 7$
  - Spread(from 2nd rank player to unrank player) =  $12 - 2 = 10$

# Win degree

- Win degrees =  $\{1, 2, 3, 4, 5, 6\}$

1 Lose Lose  $\rightarrow$  Lose

2 Lose Win Lose  $\rightarrow$  Lose

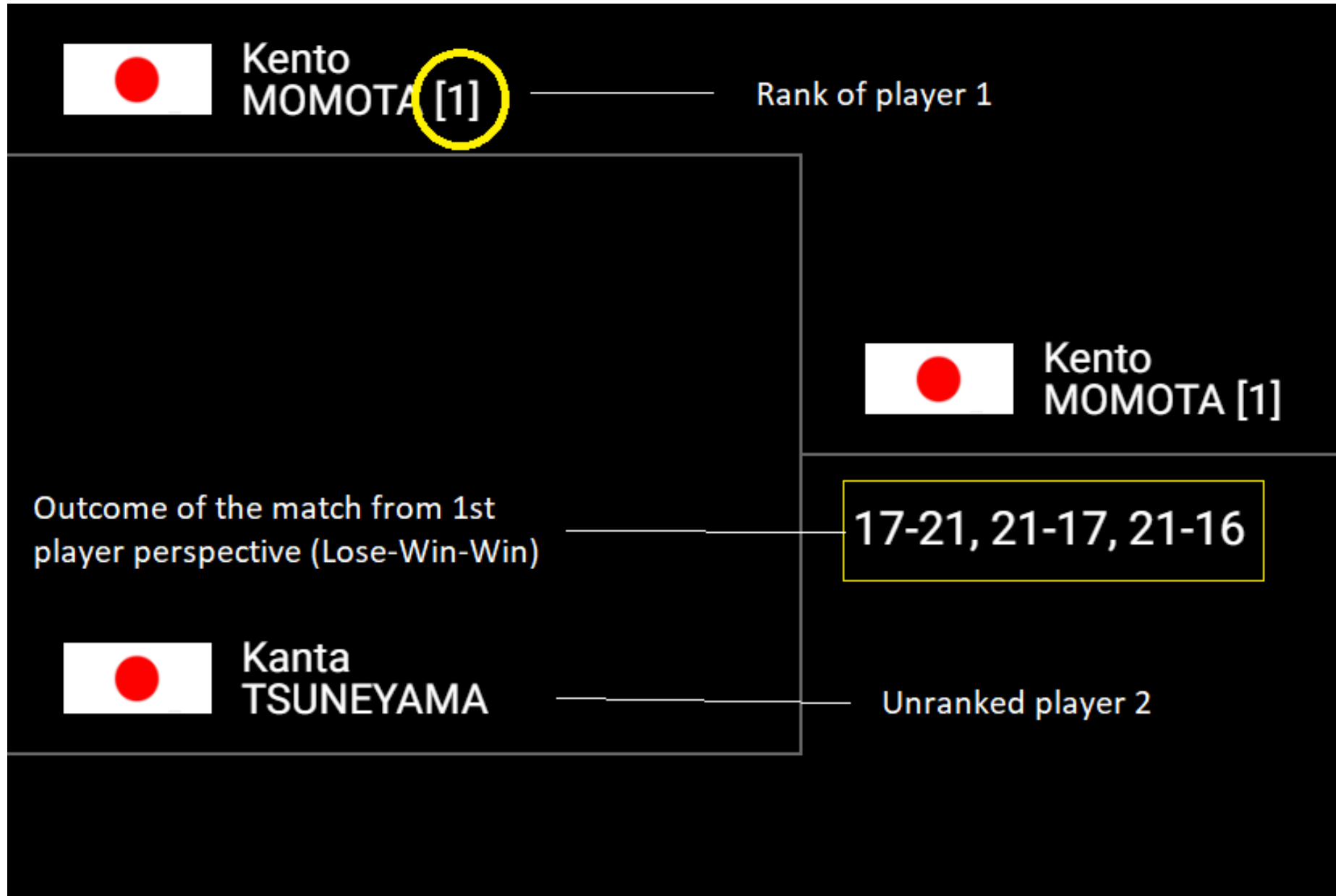
3 Win Lose Lose  $\rightarrow$  Lose

4 Lose Win Win  $\rightarrow$  Win

5 Win Lose Win  $\rightarrow$  Win

6 Win Win  $\rightarrow$  Win

# Example of spread 11 and win degree 4



# Preprocess

- Objective: 1-d space collection
- Reduction rules:
  - Same spreads, higher win degree correlates to higher value (arrow A)
  - Same win degrees, lower spread correlates to higher value (arrow B)
- How:
  - Starts with an extreme value
  - Increase by step 1

		6	5	4	3	2	1
-11		28	27	26	25	24	23
-10		27	26	25	24	23	22
-9		26	25	24	23	22	21
-8		25	24	23	22	21	20
⋮		⋅	⋅	⋅	⋅	⋅	⋅
⋮		⋅	⋅	⋅	⋅	⋅	⋅
⋮		⋅	⋅	⋅	⋅	⋅	⋅
8		9	8	7	6	5	4
9		8	7	6	5	4	3
10		7	6	5	4	3	2
11		6	5	4	3	2	1

# Dataset

- Outcome of the dataset after preprocessing (67x5)

	Tournament 1	Tournament 2	Tournament 3	Tournament 4	Tournament 5
Match 1	6.0	17.0	16.0	6.0	1.0
Match 2	15.0	15.0	17.0	13.0	17.0
Match 3	16.0	7.0	4.0	17.0	5.0
Match 4	15.0	13.0	17.0	17.0	13.0
Match 5	19.0	20.0	20.0	15.0	17.0



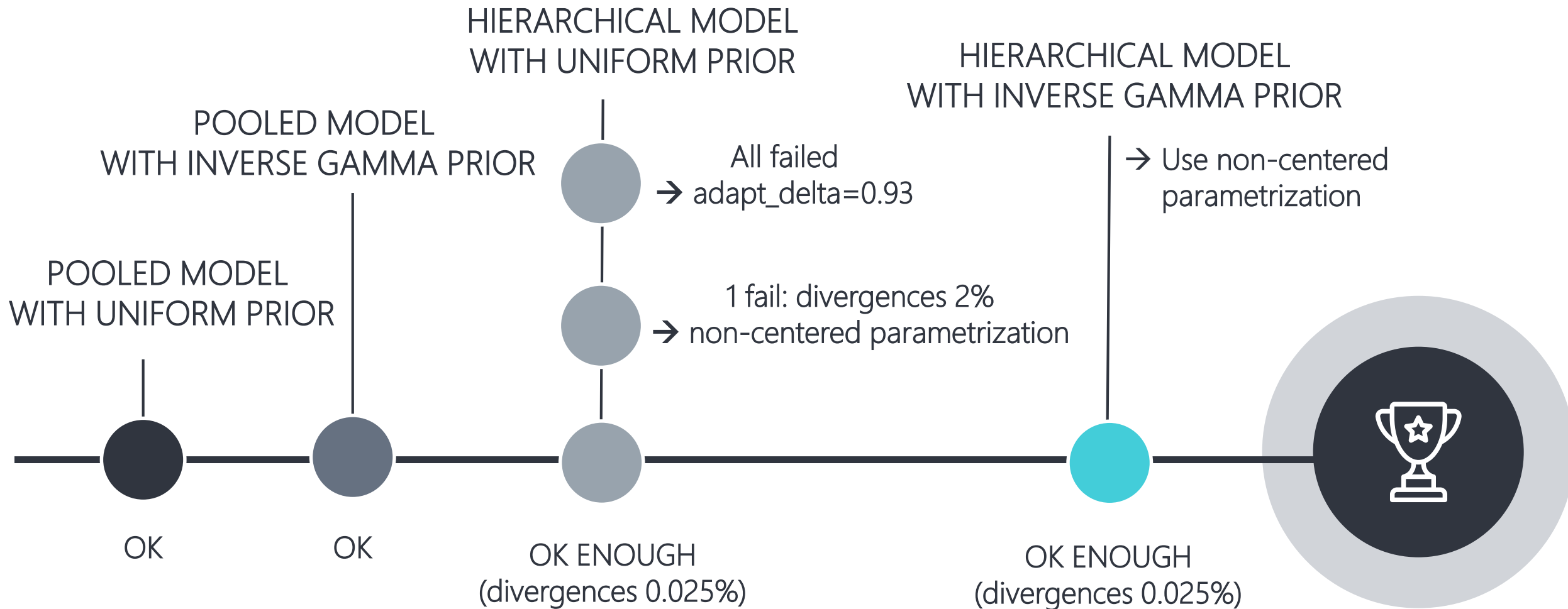
# Models

- Priors
  - Uniform (weak prior)
  - Inverse Gamma (on variance, conjugate prior to the normal likelihood)
- Likelihood
  - Normal
- Models
  - Pooled with uniform prior
  - Pooled with inverse gamma prior
  - Hierarchical with uniform prior
  - Hierarchical with inverse gamma prior

# Convergence diagnostics 1/2

- Pre-conditions
  - Stan's default parameters
  - `adapt_delta=0.9`
- Validation criteria
  - $R_{\text{hat}} < 1.1$
  - Effective sample size high
  - Divergences 0

# Convergence diagnostics 2/2



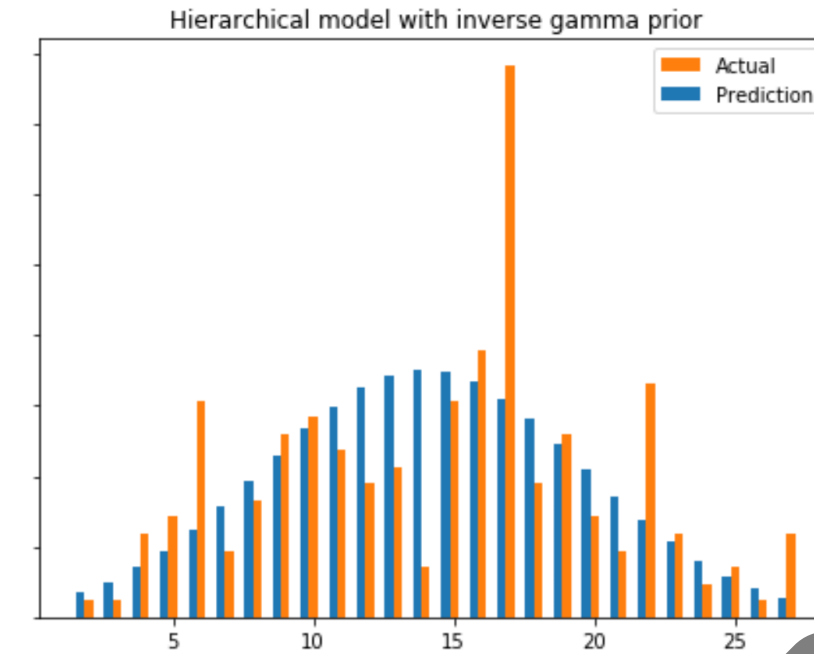
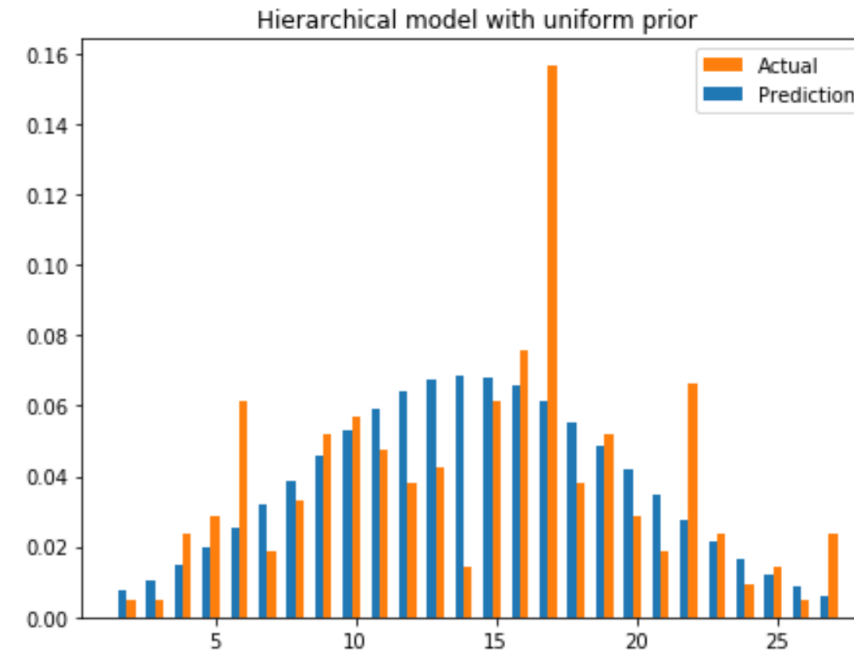
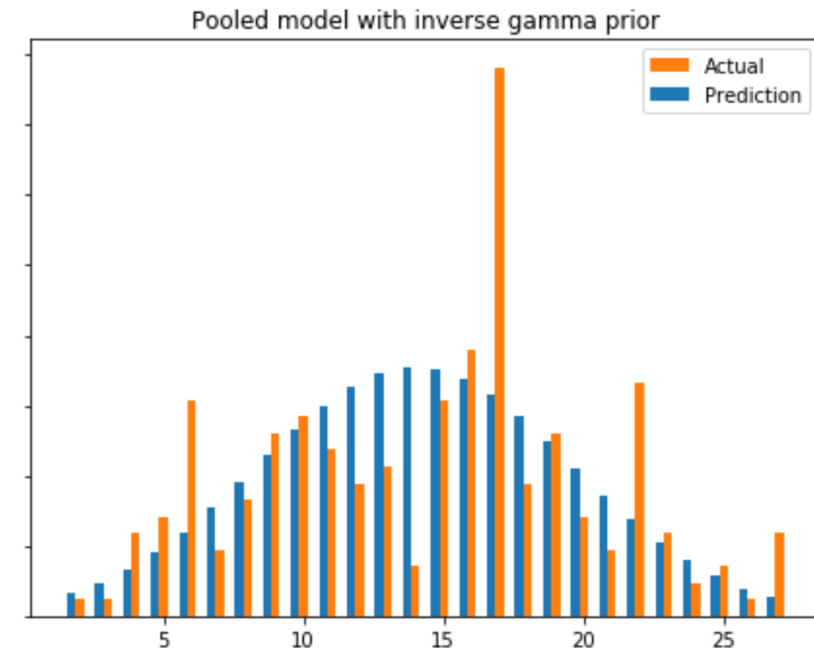
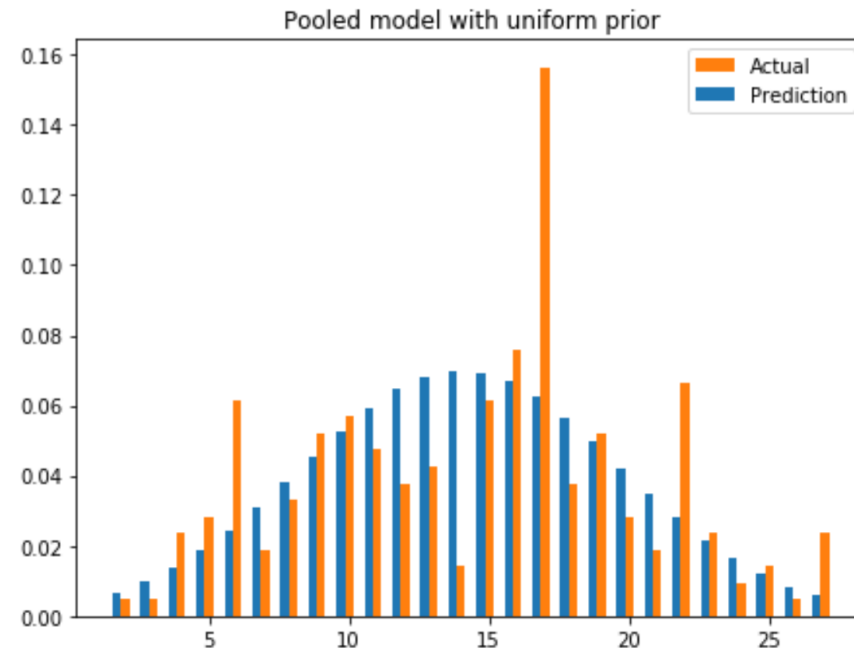
# Model comparison with PSIS-LOO

- All the models are reliable (very low k-values)
- Model with best predictive accuracy is Pooled model with inverse gamma prior (highest PSIS-LOO value)

	Models	Psisloo	P_eff	Max k value	Min k value	Mean k value
0	Pooled model with uniform prior	-1056.45	1.67	-0.07	-0.25	-0.18
1	Pooled model with inverse gamma prior	-1056.38	1.64	-0.01	-0.16	-0.11
2	Hierarchical model with uniform prior	-1057.25	2.96	0.10	-0.14	-0.05
3	Hierarchical model with inverse gamma prior	-1057.39	3.10	0.11	-0.18	-0.04

# Posterior predictive checking

- Similar trend
- Errors are considerable why?



# Conclusions 1/2

- Problems
  - Direct inference of a single match
  - Divergences in hierarchical model
- Improvements
  - Alternative models: Binomial, Multinomial
  - Joint distribution of some parameters (absolute ranking + win degree)
  - Sensitivity analysis for the prior and model

# Conclusions 2/2

- Badminton domain perspective:
  - Visible correlation between spread and win degree
  - Extreme outcome (towards 1 or 28) not expected
- Statistical inference perspective
  - Given the domain knowledge, one would expect the distribution of the estimand to be a normal distribution
  - Highly data-driven
  - Hierarchical model ends up as pooled model



THANK YOU