Multi-Level Models

Transferring Knowledge Among Categories

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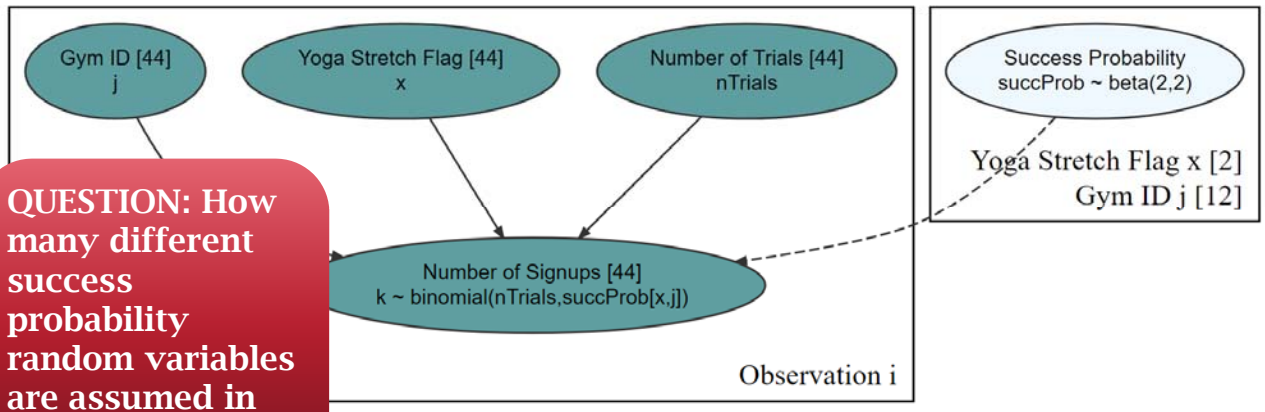
Almost Zero Pooling



QUESTION: How many different success probability random variables are assumed in this model?

No Pooling Model

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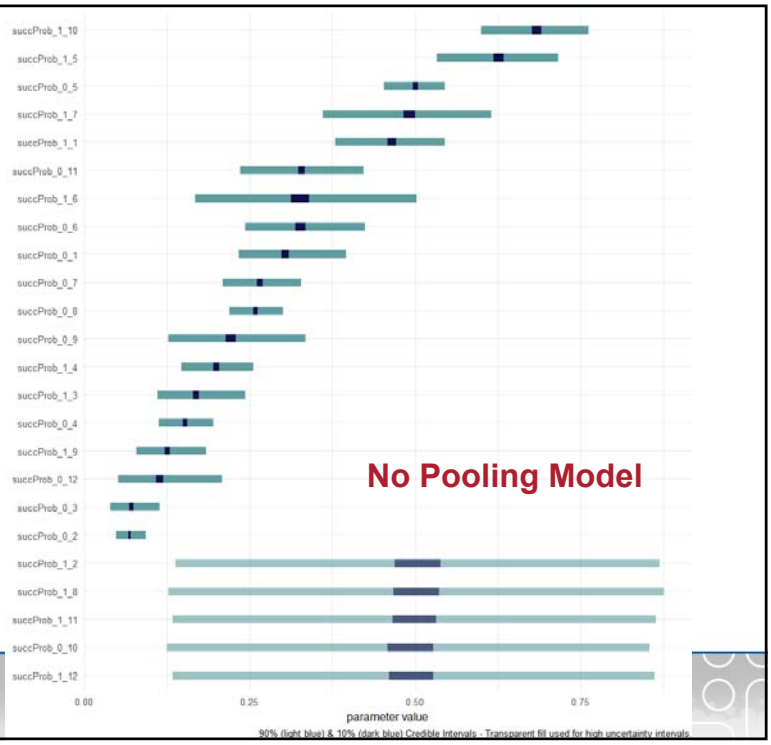
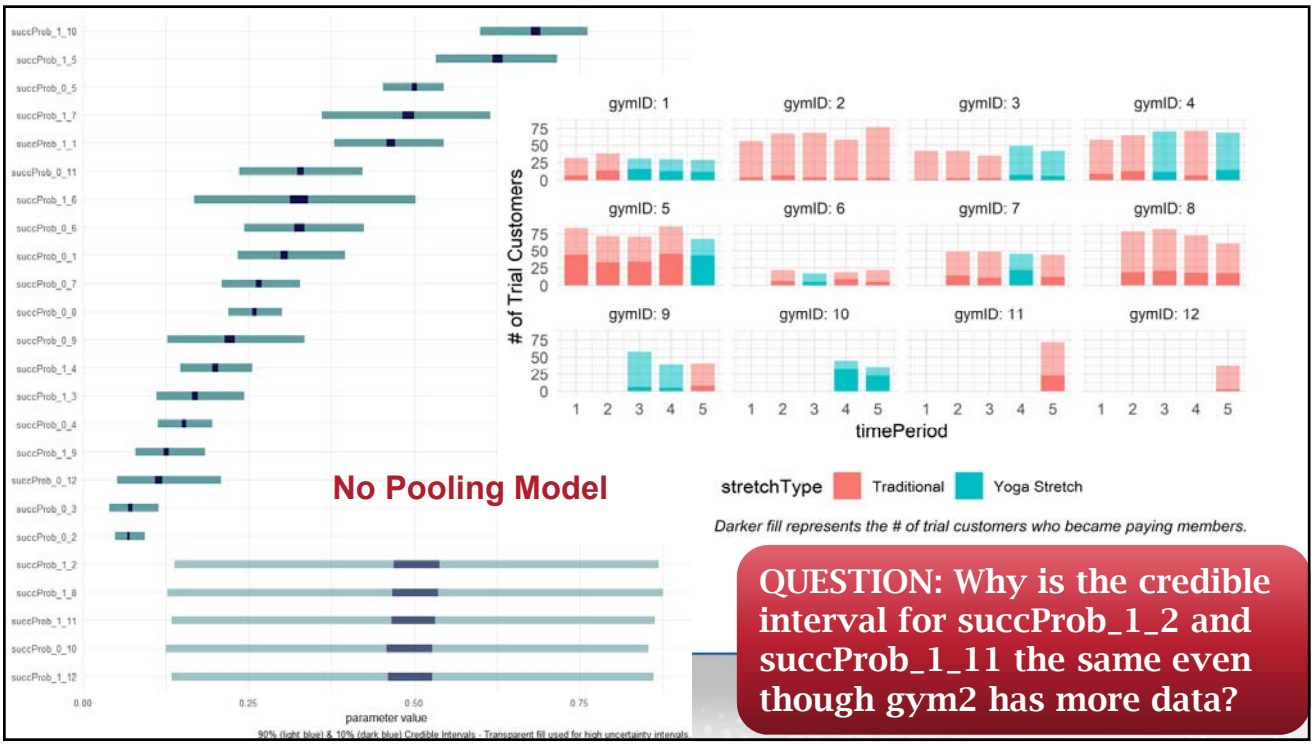
1

Posterior Distribution

QUESTION: What do the numbers mean on the y-axis (e.g. succProb_1_10)?

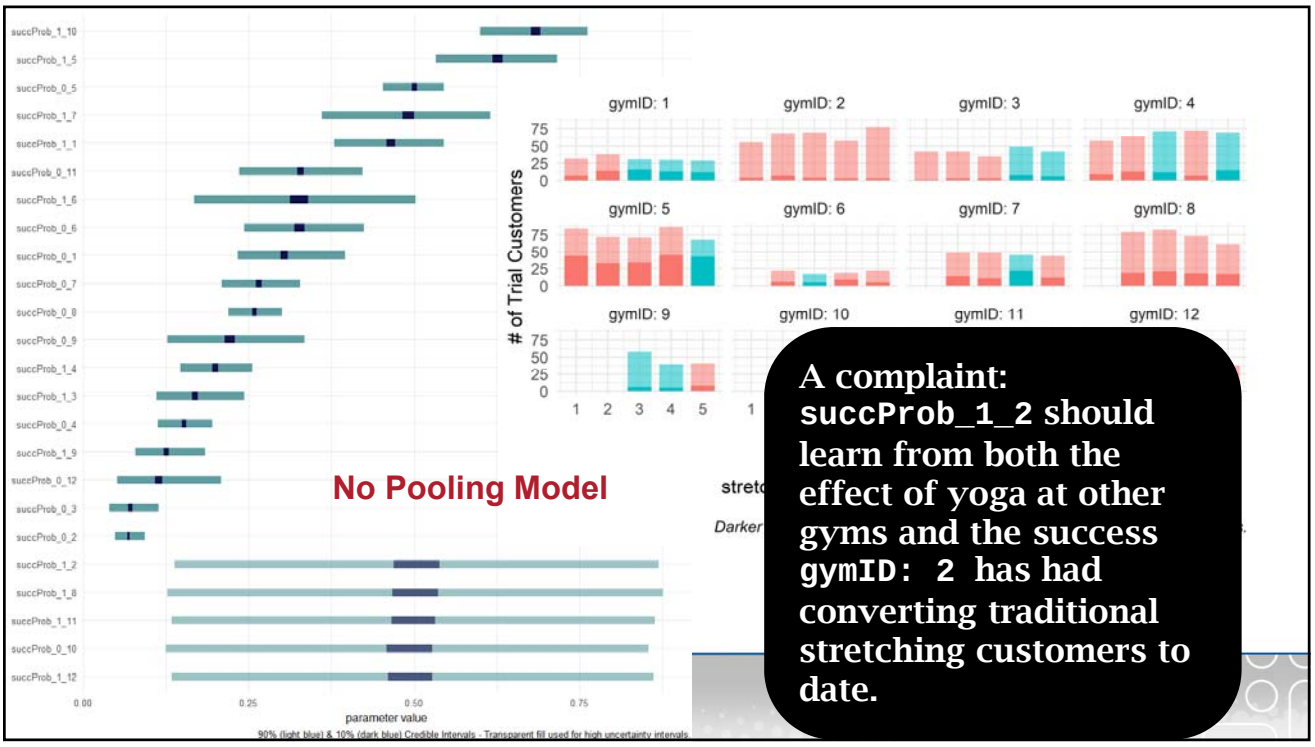


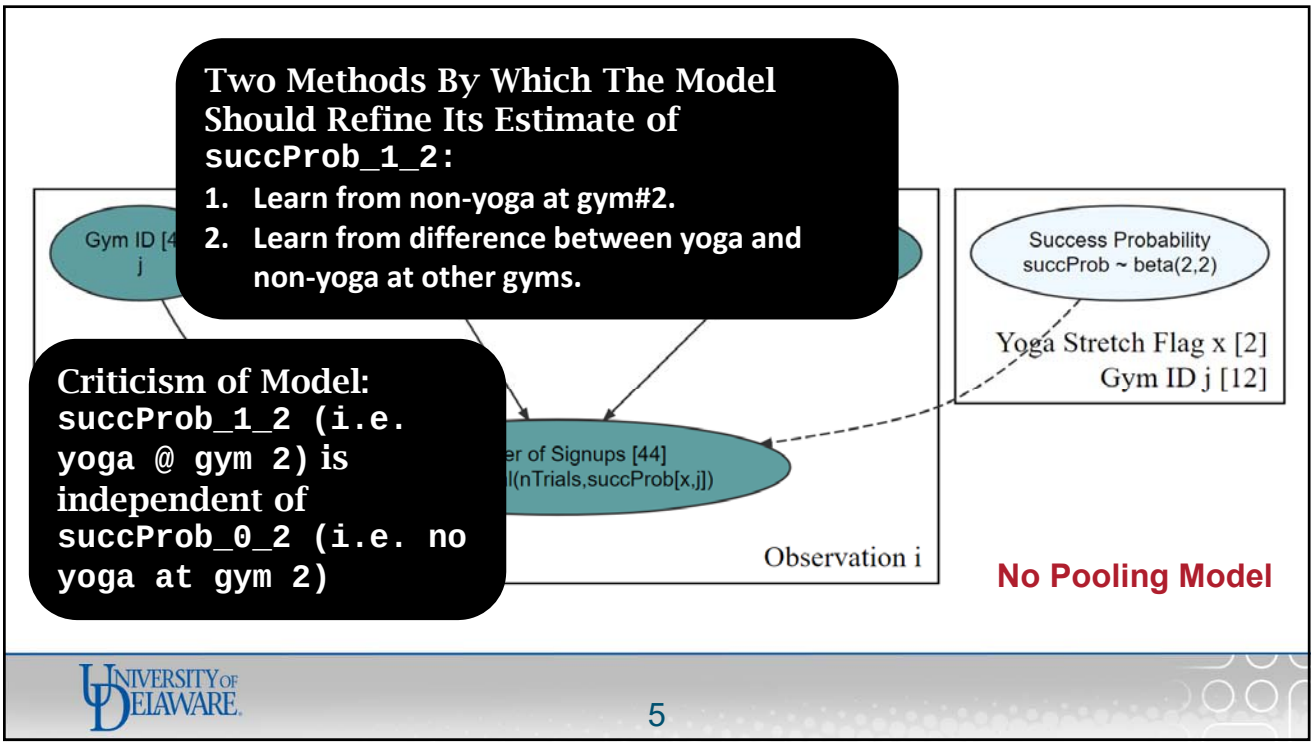
No Pooling Model



No Pooling Model

QUESTION: Why is the credible interval for succProb_1_2 and succProb_1_11 the same even though gym2 has more data?


succProb_1_10
succProb_1_5
succProb_0_5
succProb_1_7
succProb_1_1
succProb_0_11
succProb_1_6
succProb_0_6
succProb_0_1
succProb_0_7
succProb_0_8
succProb_0_9
succProb_1_4
succProb_1_3
succProb_0_4
succProb_1_9
succProb_0_12
succProb_0_3
succProb_0_2
succProb_1_2
succProb_1_8
succProb_1_11
succProb_0_10
succProb_1_12
0.00
0.25
0.50
0.75
parameter value
90% (light blue) & 10% (dark blue) Credible Intervals - Transparent fill used for high uncertainty intervals
gymID: 1
gymID: 2
gymID: 3
gymID: 4
gymID: 5
gymID: 6
gymID: 7
gymID: 8
gymID: 9
gymID: 10
gymID: 11
gymID: 12
# of Trial Customers
75
50
25
0
1 2 3 4 5
No Pooling Model
A complaint: succProb_1_2 should learn from both the effect of yoga at other gyms and the success gymID: 2 has had converting traditional stretching customers to date.


Two Methods By Which The Model Should Refine Its Estimate of succProb_1_2:
1. Learn from non-yoga at gym#2.
2. Learn from difference between yoga and non-yoga at other gyms.
Criticism of Model: succProb_1_2 (i.e. yoga @ gym 2) is independent of succProb_0_2 (i.e. no yoga at gym 2)
Gym ID [4
j
Success Probability
succProb ~ beta(2,2)
Yoga Stretch Flag x [2]
Gym ID j [12]
er of Signups [44]
l(nTrials,succProb[x,j])
Observation i
No Pooling Model
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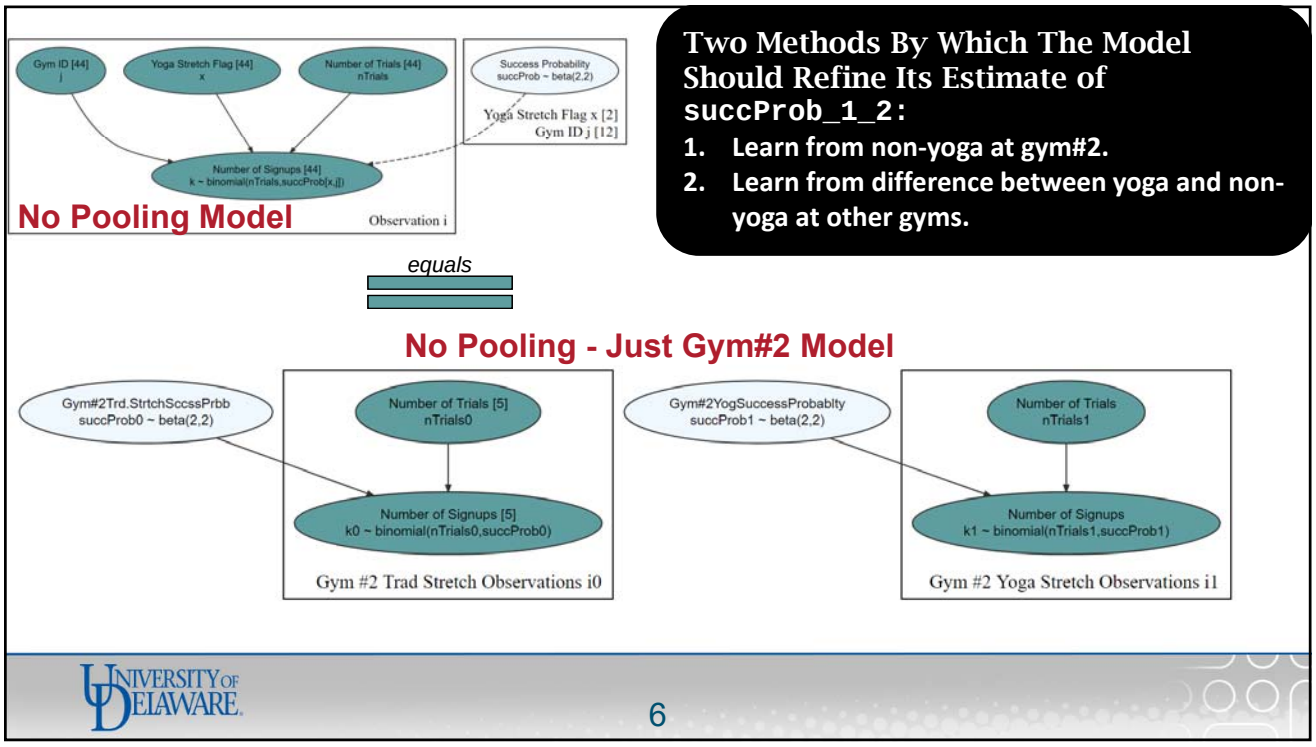
5


Gym ID [44] j
Yoga Stretch Flag [44] x
Number of Trials [44] nTrials
Number of Signups [44] k ~ binomial(nTrials,succProb[x,j])
Success Probability succProb ~ beta(2,2)
Yoga Stretch Flag x [2] Gym ID j [12]
No Pooling Model
Observation i
Two Methods By Which The Model Should Refine Its Estimate of succProb_1_2:
1. Learn from non-yoga at gym#2.
2. Learn from difference between yoga and non-yoga at other gyms.
equals
No Pooling - Just Gym#2 Model
Gym#2Trd.StrtchSccssPrbb succProb0 ~ beta(2,2)
Number of Trials [5] nTrials0
Number of Signups [5] k0 ~ binomial(nTrials0,succProb0)
Gym #2 Trad Stretch Observations i0
Gym#2YogSuccessProbablty succProb1 ~ beta(2,2)
Number of Trials nTrials1
Number of Signups k1 ~ binomial(nTrials1,succProb1)
Gym #2 Yoga Stretch Observations i1
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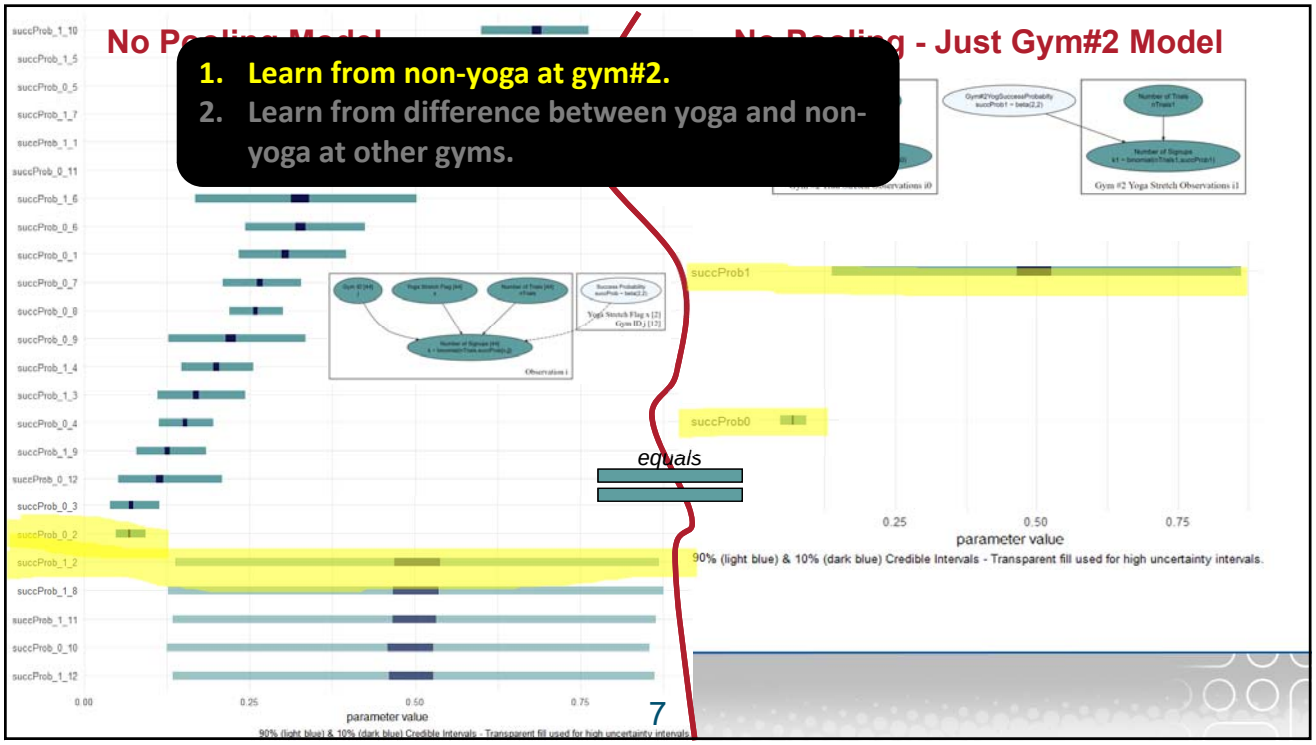
6

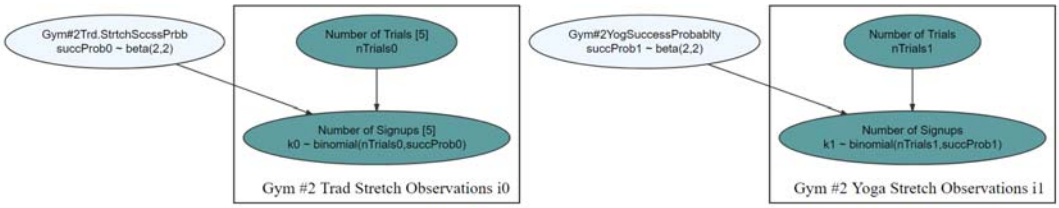

No Pooling - Just Gym#2 Model
1. Learn from non-yoga at gym#2.
2. Learn from difference between yoga and non-yoga at other gyms.
succProb1
succProb0
equals
0.25
0.50
0.75
parameter value
90% (light blue) & 10% (dark blue) Credible Intervals - Transparent fill used for high uncertainty intervals.
7

No Pooling Model

No Pooling - Just Gym#2 Model

1. Learn from non-yoga at gym#2.
2. Learn from difference between yoga and non-yoga at other gyms.

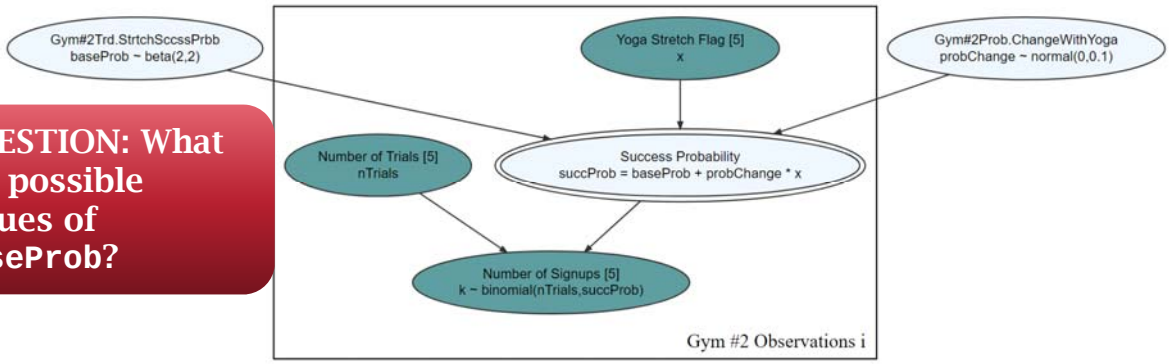
No Pooling - Just Gym#2 Model



Linking Non-Yoga and Yoga at A Gym

first attempt (might not be good)

Gym#2 Model where Yoga Treated as Random Variable that increases/decreases the base customer signup rate



QUESTION: What are possible values of `baseProb`?

Linking Non-Yoga and Yoga at A Gym

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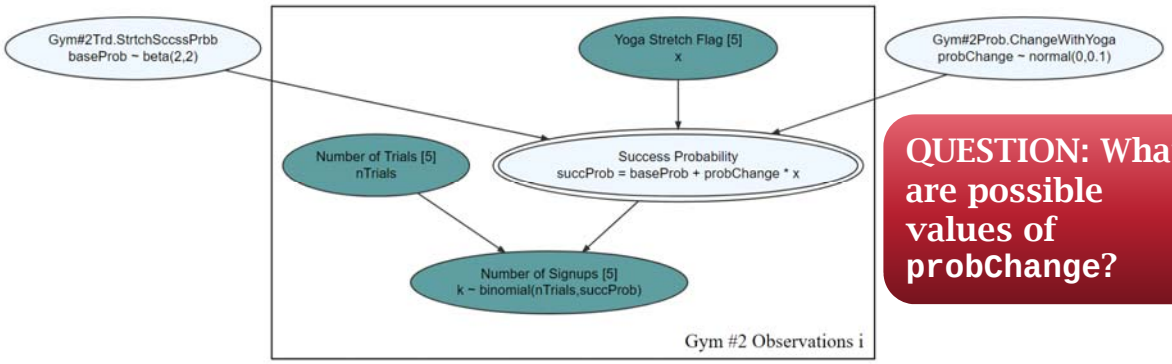
Gym#2 Model where Yoga Treated as Random Variable that increases/decreases the base customer signup rate



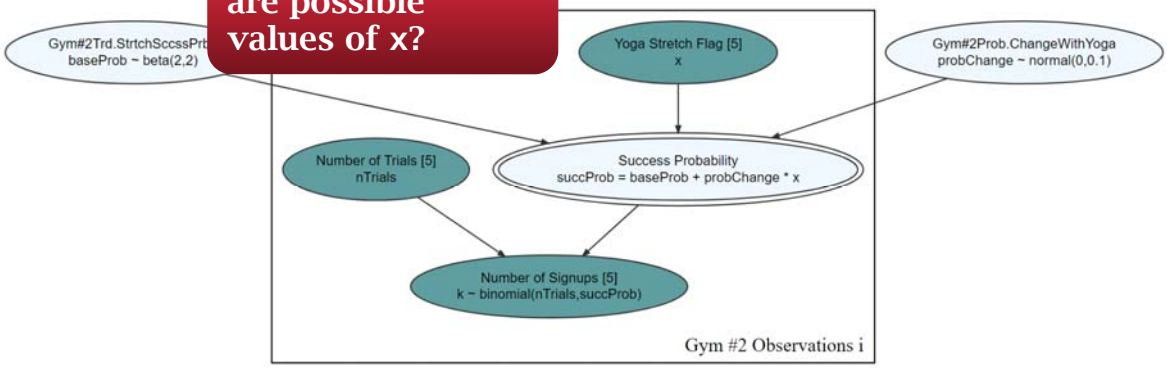
QUESTION: What are possible values of `probChange`?

Linking Non-Yoga and Yoga at A Gym

first attempt (might not be good)

Gym#2 Model where Yoga Treated as Random Variable that increases/decreases the base customer signup rate

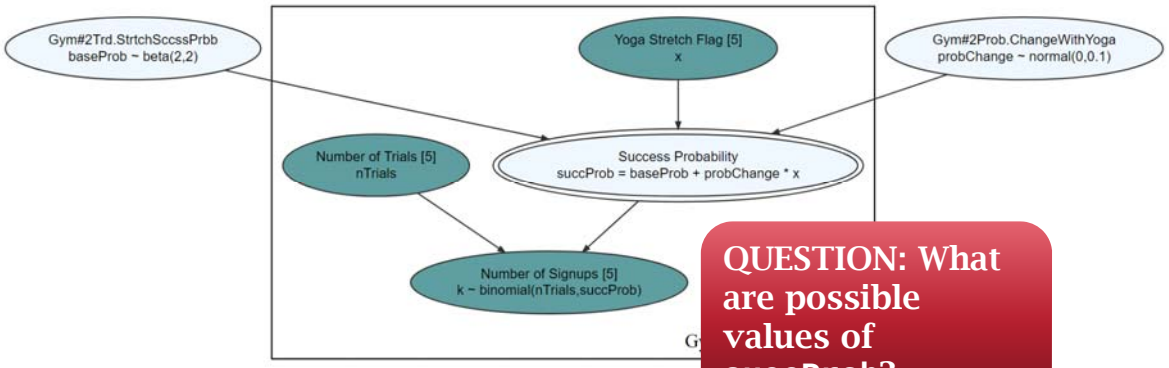
QUESTION: What are possible values of x?



Linking Non-Yoga and Yoga at A Gym

first attempt (might not be good)

Gym#2 Model where Yoga Treated as Random Variable that increases/decreases the base customer signup rate

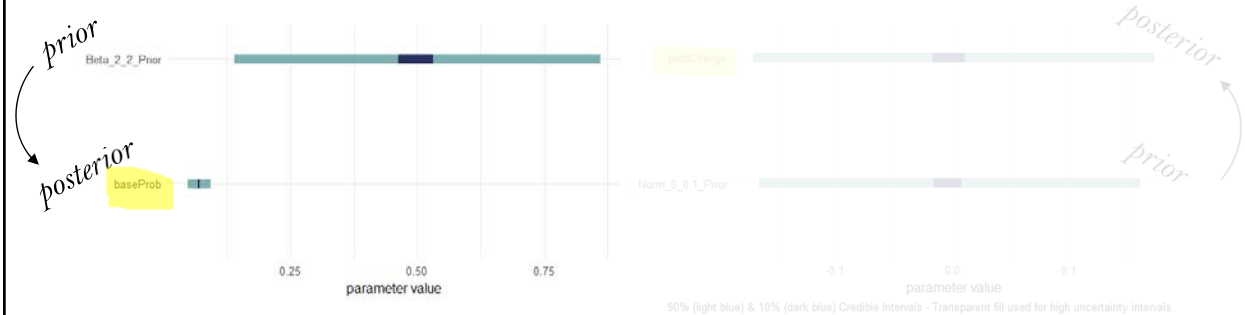


QUESTION: What are possible values of `succProb`?

Linking Non-Yoga and Yoga at A Gym

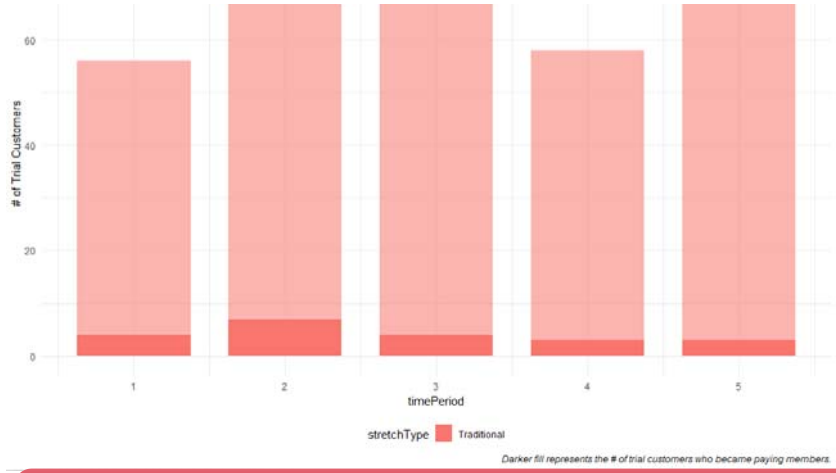
first attempt (might not be good)

Gym#2 Model where Yoga Treated as Random Variable that increases/decreases the base customer signup rate



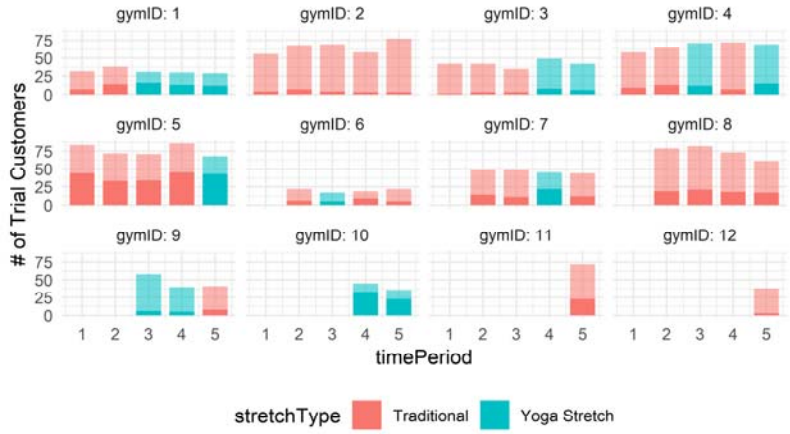
QUESTION: Why do the prior and posterior look the same for `probChange`, but not `baseProb`?

Gym #2 Data

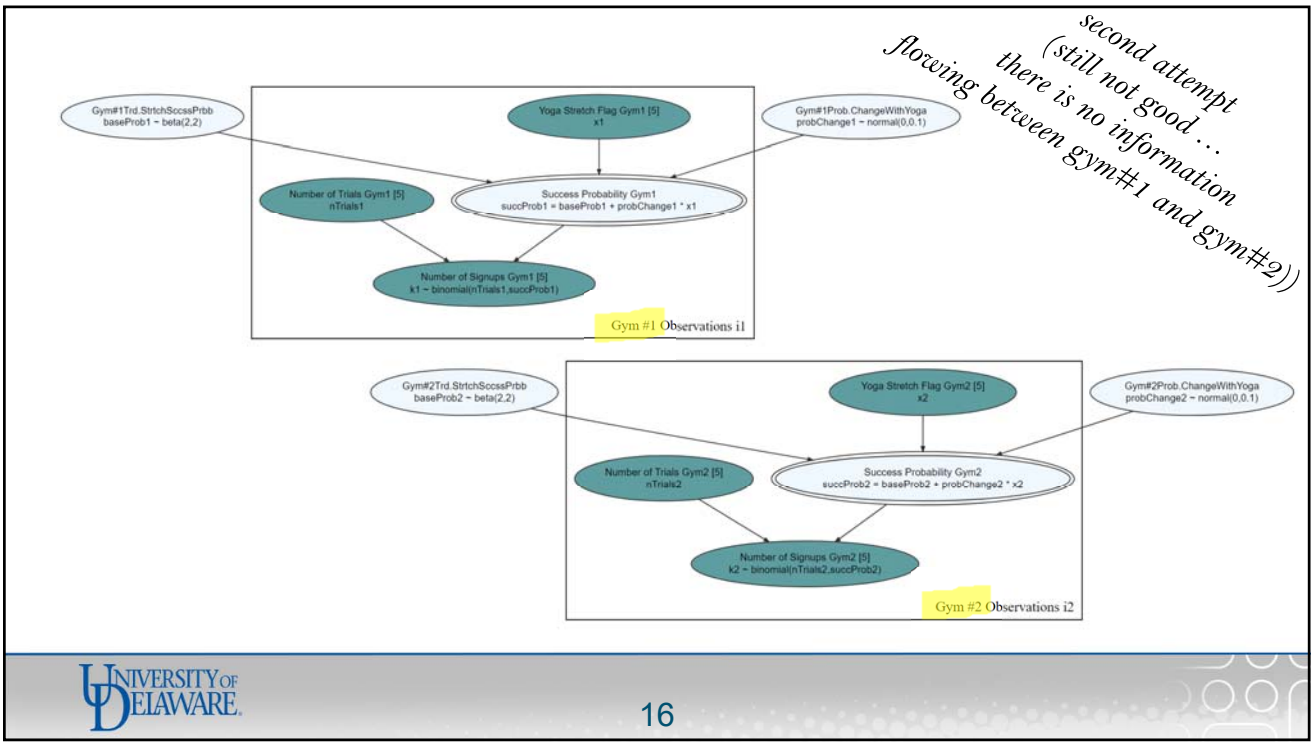


QUESTION: Why do the prior and posterior look the same for `probChange`, but not `baseProb`?

Model After Next Model Will Learn About Yoga at Gym#2 By Incorporating Gym#1's experience

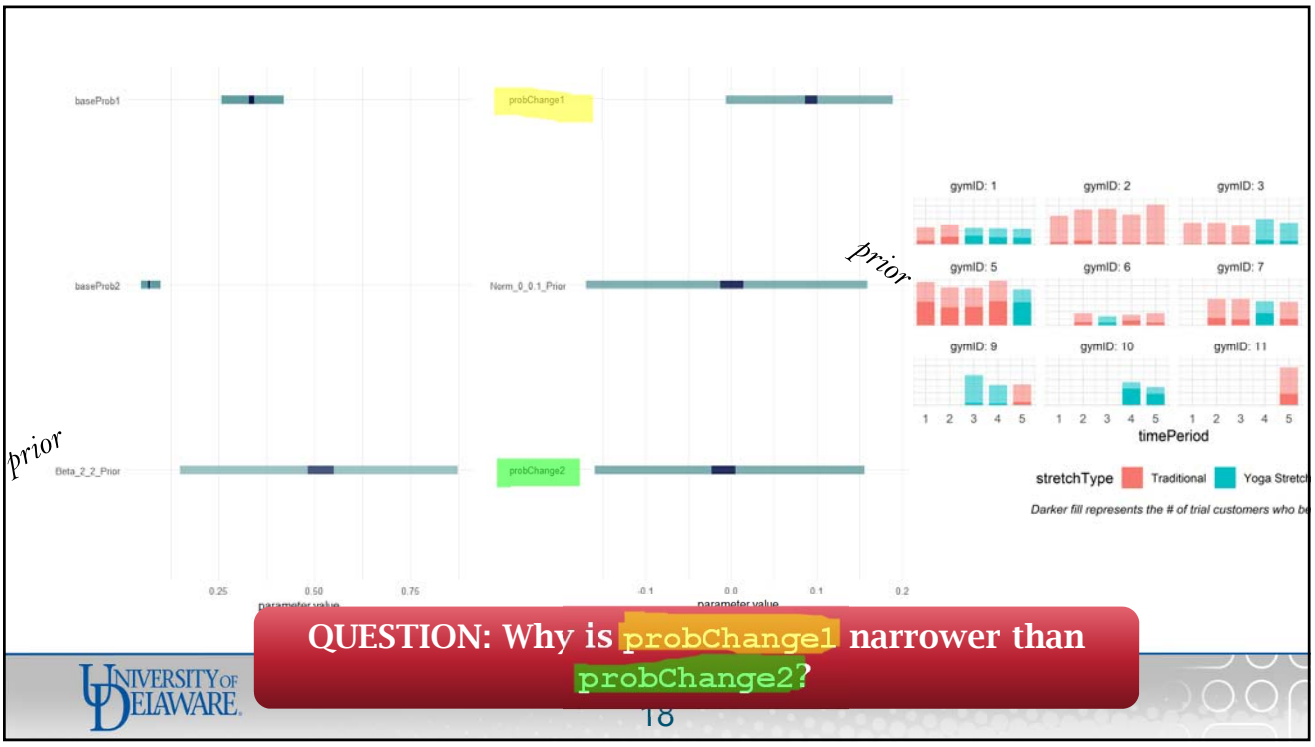


QUESTION: Has gym#1's experience with yoga stretching been positive or negative?



second attempt (still not good … there is no information flowing between gym#1 and gym#2))

QUESTION: Why is `baseProb1` wider than `baseProb2`?



QUESTION: Why is probChange1 narrower than probChange2?

Modelling the Transfer of Info

Base Probability

1-New York

2-Philly

Probability Change Due To Yoga

1-New York

2-Philly

No Knowledge Transfer (no pooling)

Base Probability

1-New York

2-Philly

Probability Change Due To Yoga

1-New York

2-Philly

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Transfer BaseProb Info – Random Intercepts

Base Probability

1-New York

2-Philly

Probability Change Due To Yoga

1-New York

2-Philly

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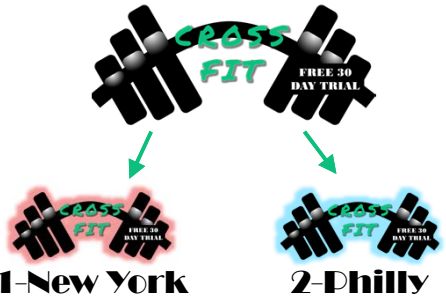
Transfer Yoga Impact Info – Random Slopes

Base Probability

Probability Change Due To Yoga



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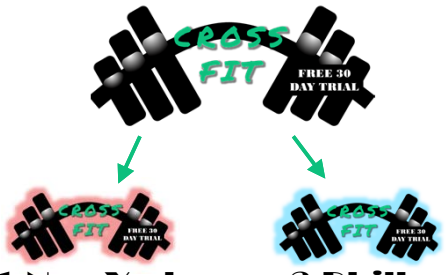
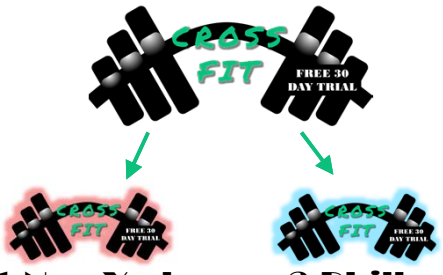
Transfer Intercepts and Slopes

Base Probability



Probability Change Due To Yoga



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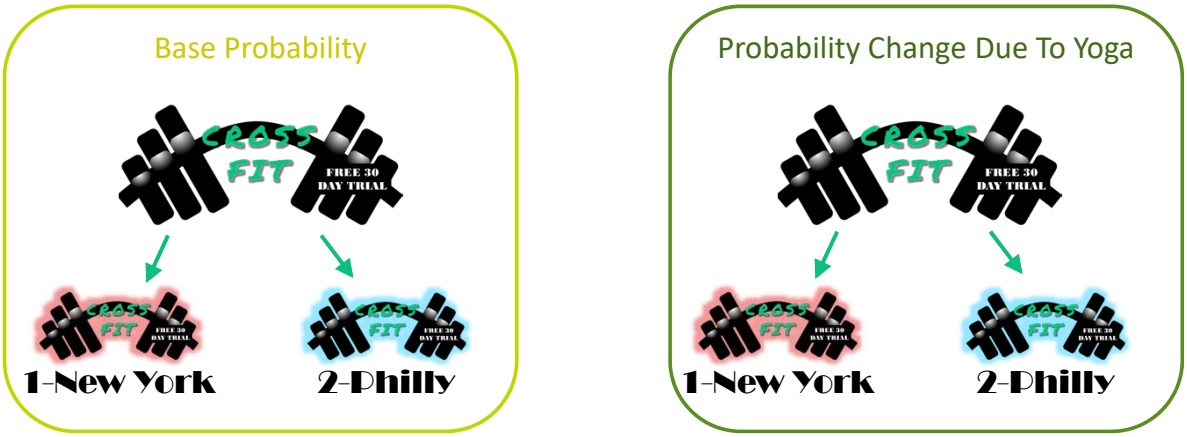
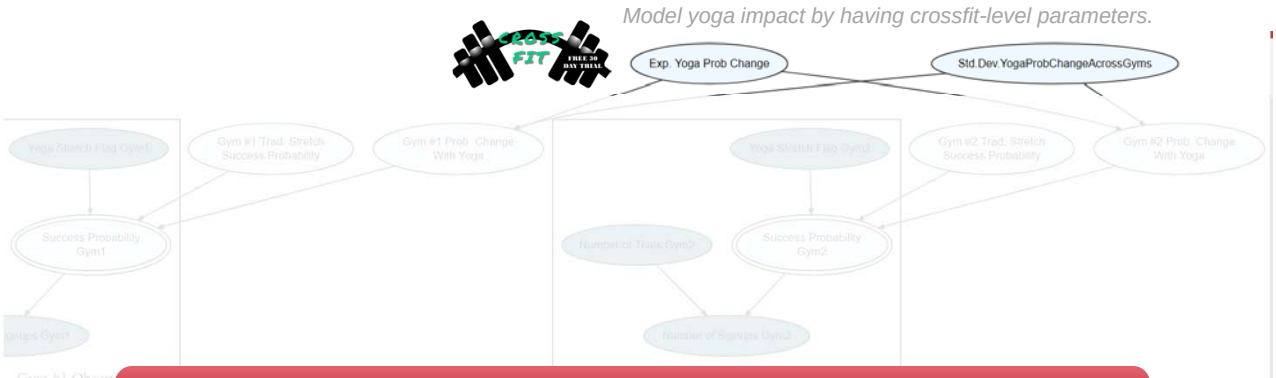
Tell the Generative Story

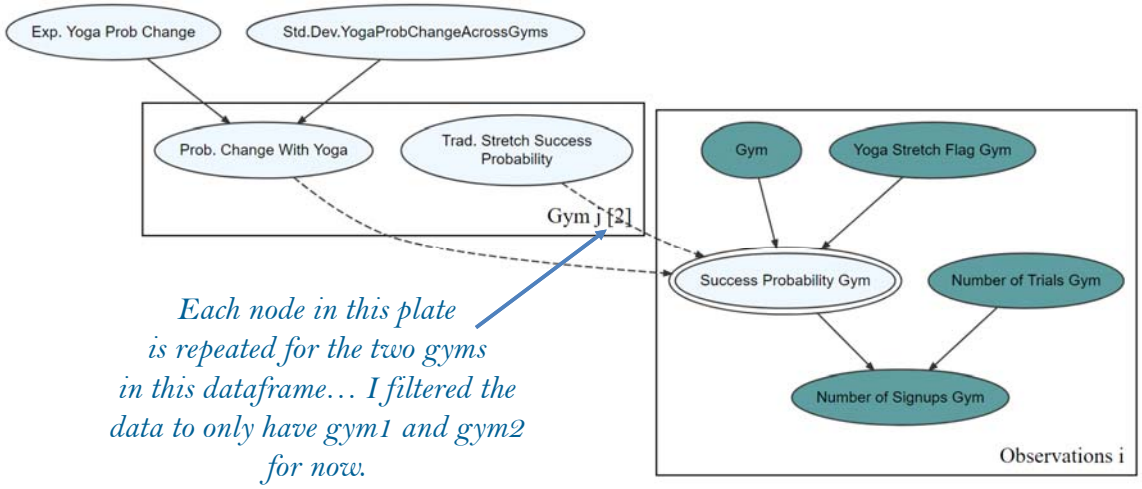


Learn About Yoga at Gym#2 By Incorporating Gym#1's experience



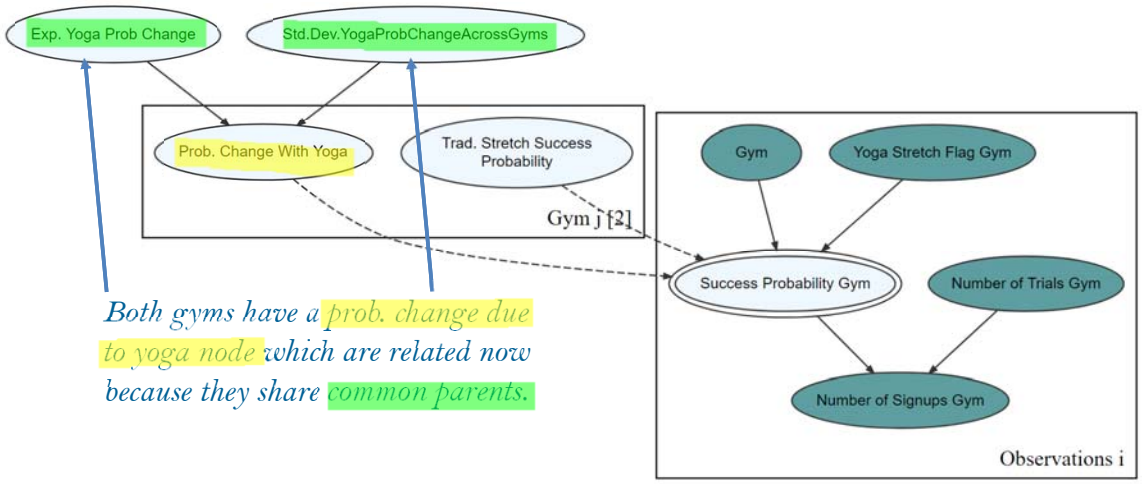
QUESTION: Is this a random slopes model, random intercepts model, or random slope/intercept model?

Same Model Using Plate Notation



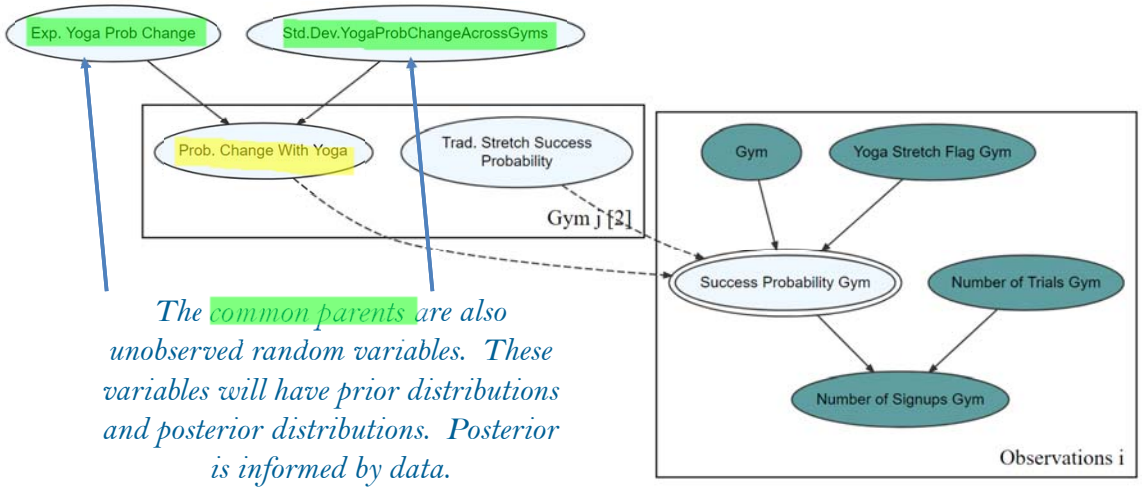
Each node in this plate is repeated for the two gyms in this dataframe… I filtered the data to only have gym1 and gym2 for now.

Same Model Using Plate Notation



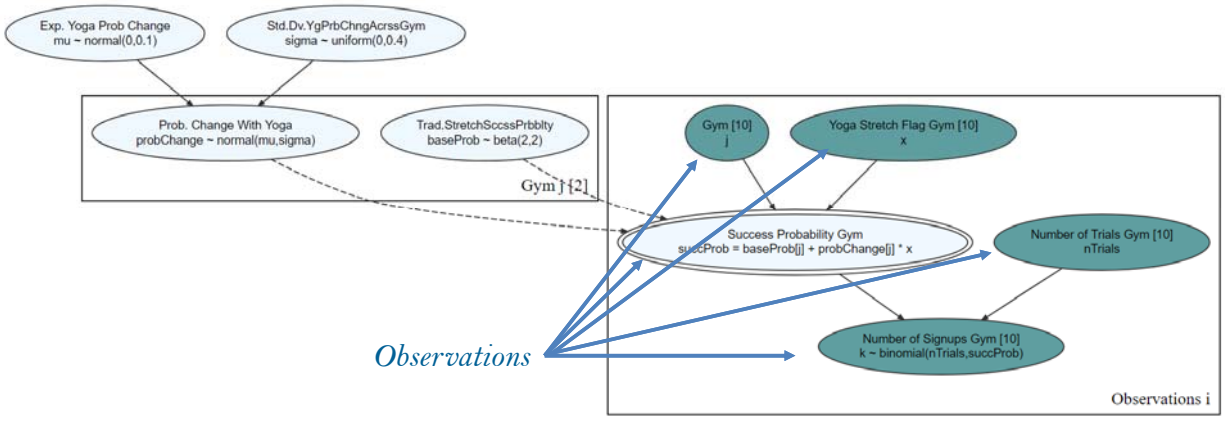
Both gyms have a prob. change due to yoga node which are related now because they share common parents.

Same Model Using Plate Notation



The common parents are also unobserved random variables. These variables will have prior distributions and posterior distributions. Posterior is informed by data.

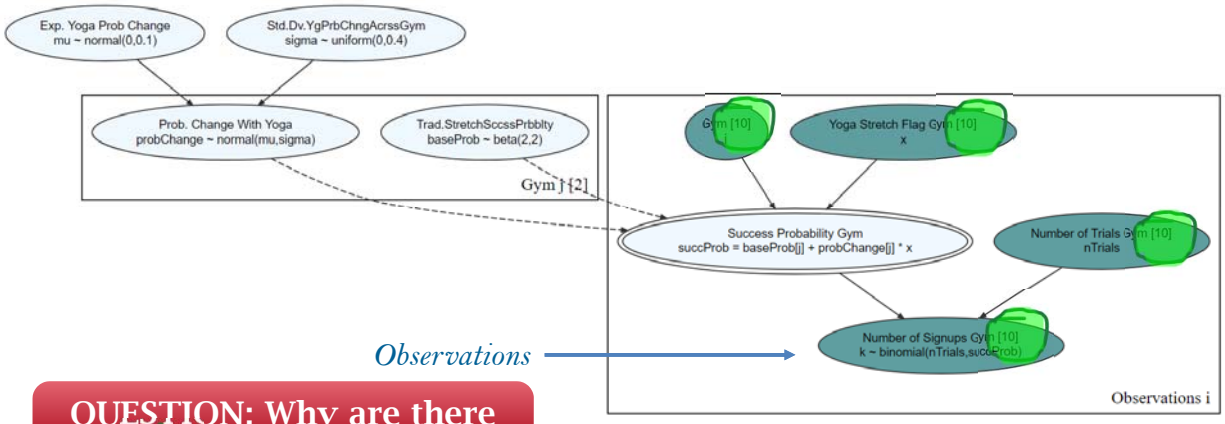
The Multi-Levels of this Multi-Level Model



Observations

use these nodes to answer questions about specific observations

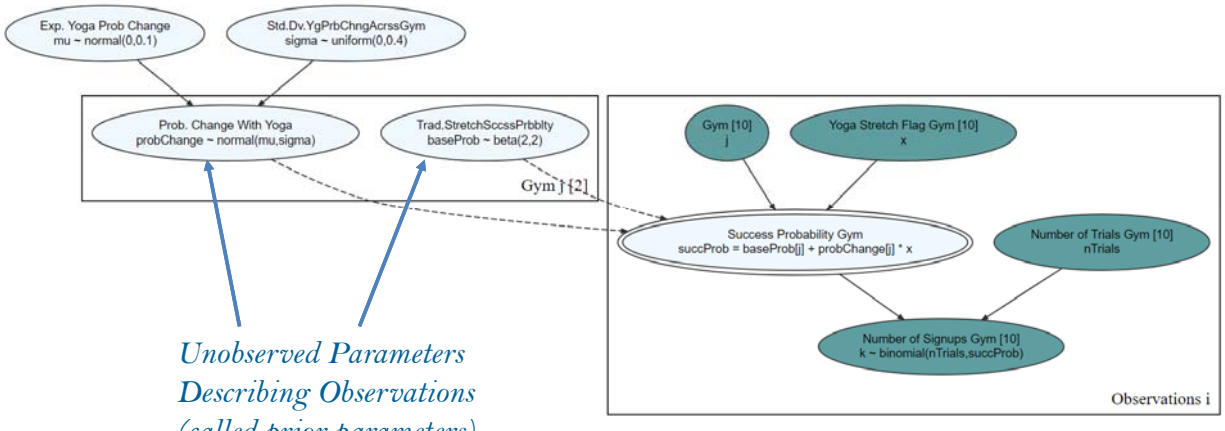
The Multi-Levels of this Multi-Level Model



Observations

QUESTION: Why are there 10 observations?

The Multi-Levels of this Multi-Level Model

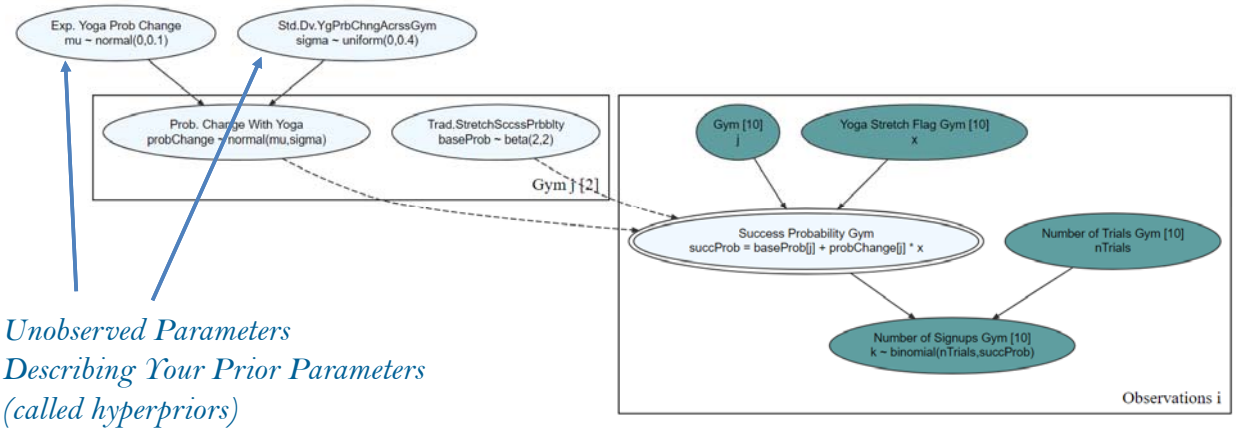


Unobserved Parameters Describing Observations (called prior parameters)

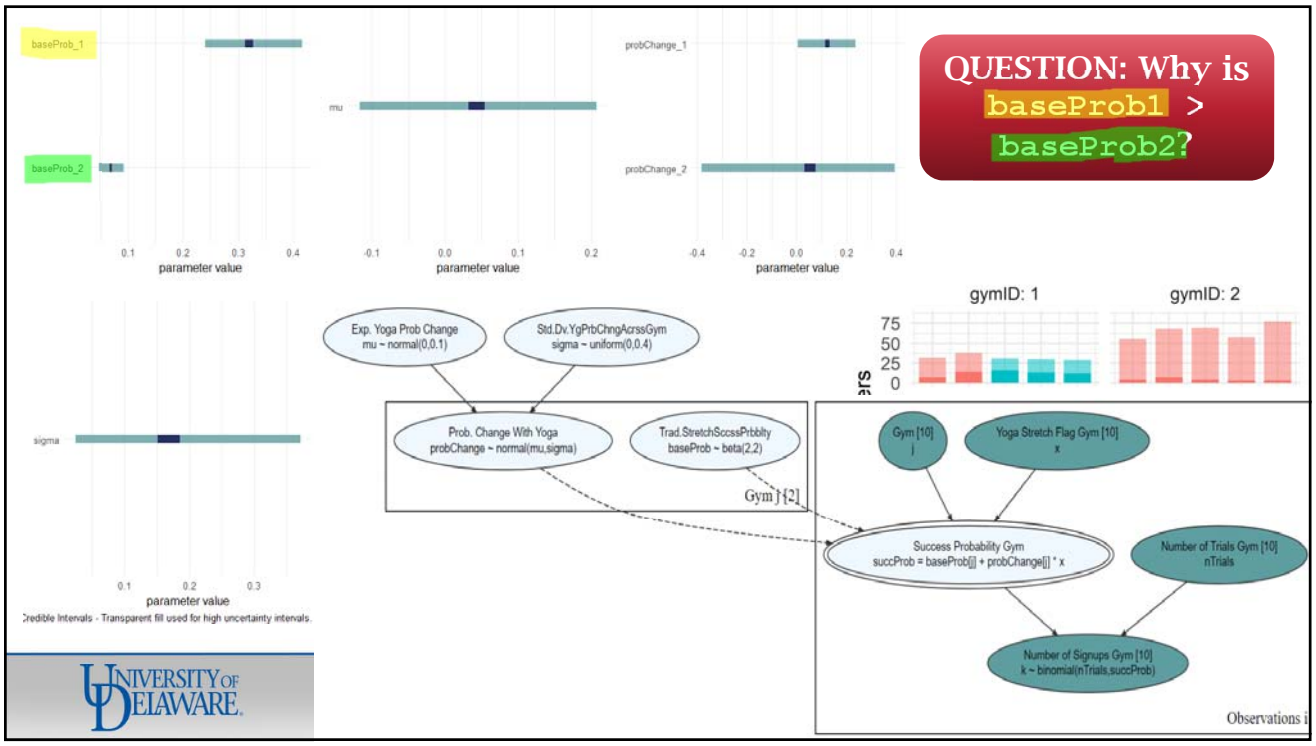
use these nodes to answer questions about a specific gym

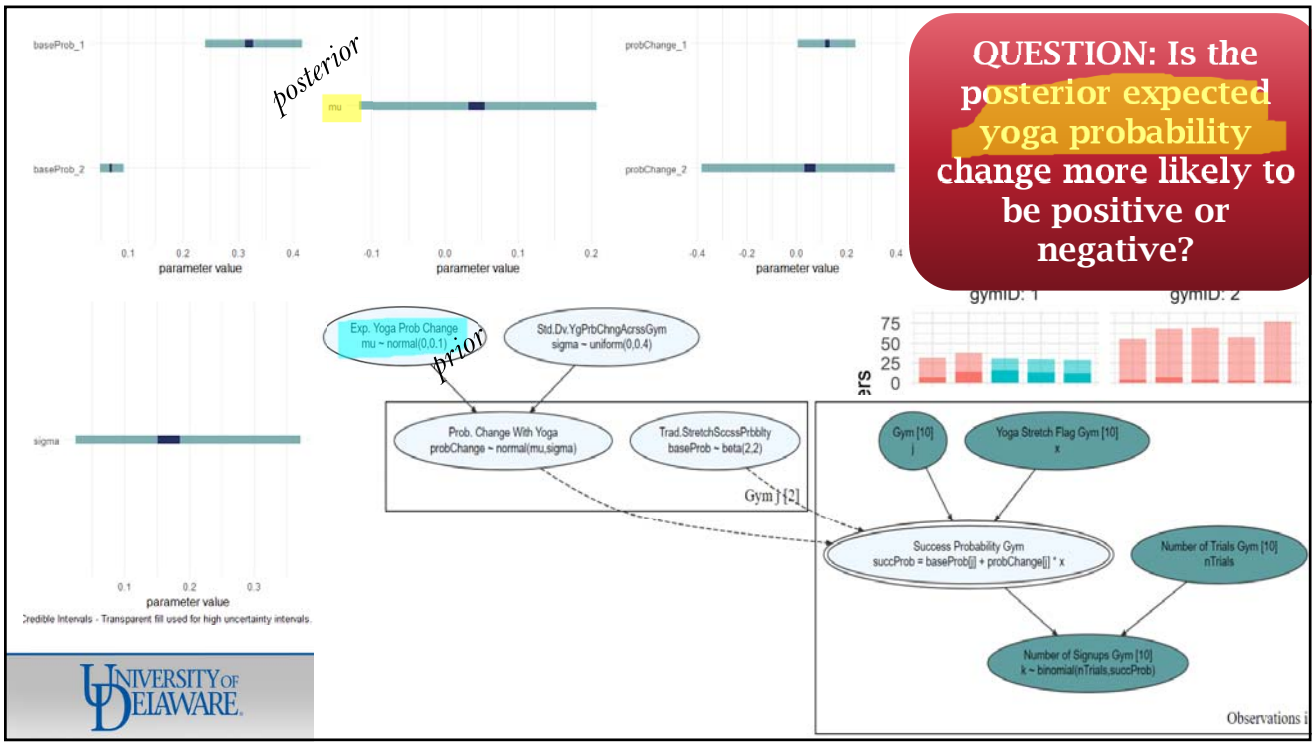
The Multi-Levels of this Multi-Level Model

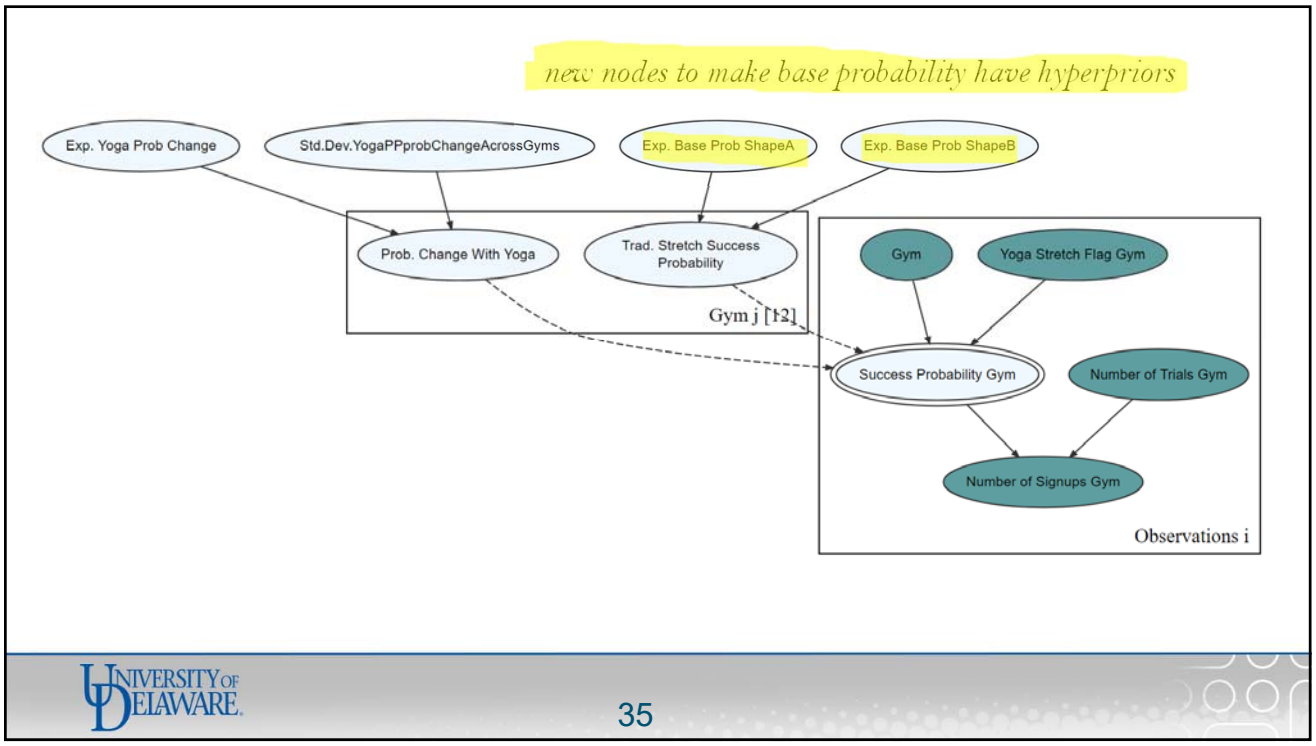
use these nodes to answer questions about new Crossfit Gyms

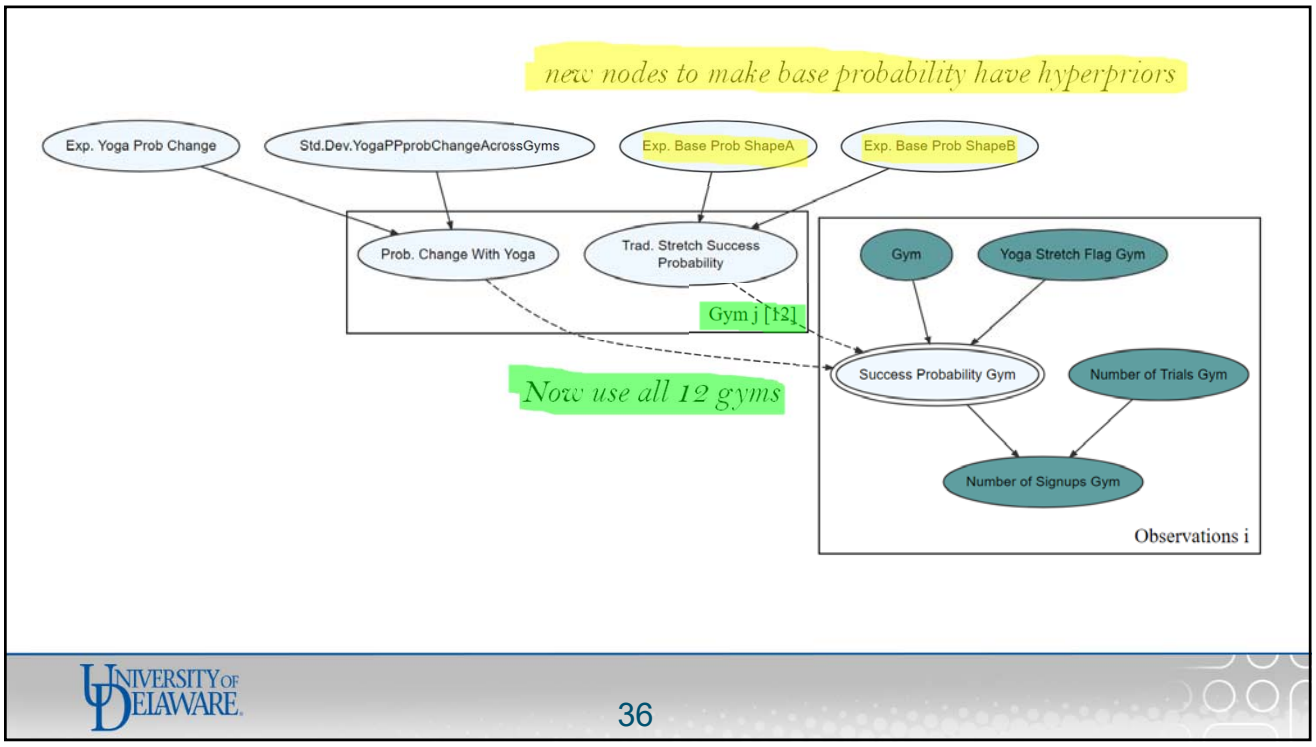


Unobserved Parameters
Describing Your Prior Parameters
(called hyperpriors)

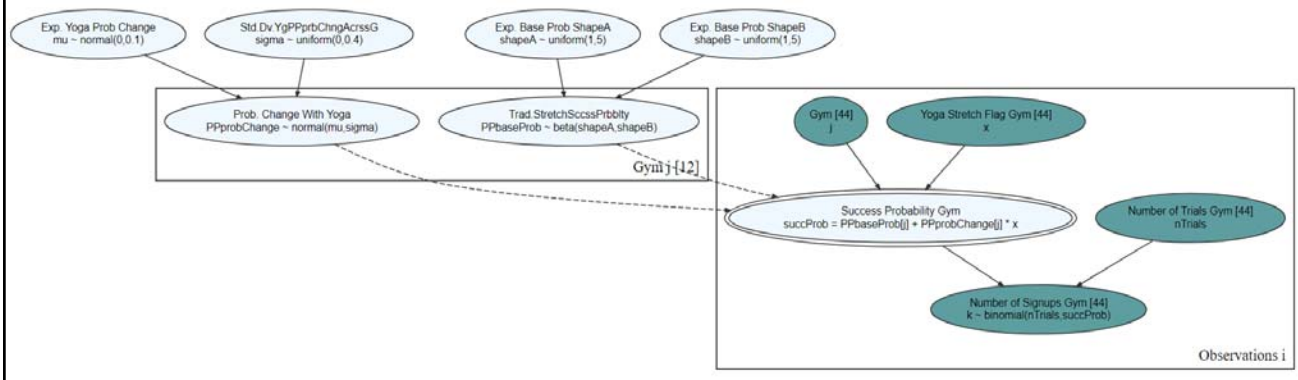



baseProb_1
baseProb_2
mu
probChange_1
probChange_2
sigma
parameter value
posterior
prior
QUESTION: Is the posterior expected yoga probability change more likely to be positive or negative?
Exp. Yoga Prob Change
mu ~ normal(0,0.1)
Std.Dv.YgPrbChngAcrssGym
sigma ~ uniform(0,0.4)
Prob. Change With Yoga
probChange ~ normal(mu,sigma)
Trad.StretchSccssPrbblty
baseProb ~ beta(2,2)
Gym j [2]
gymID: 1
gymID: 2
Gym [10]
j
Yoga Stretch Flag Gym [10]
x
Success Probability Gym
succProb = baseProb[j] + probChange[j] * x
Number of Trials Gym [10]
nTrials
Number of Signups Gym [10]
k ~ binomial(nTrials,succProb)
Observations i
Credible Intervals - Transparent fill used for high uncertainty intervals.


new nodes to make base probability have hyperpriors
Exp. Yoga Prob Change
Std.Dev.YogaPPprobChangeAcrossGyms
Exp. Base Prob ShapeA
Exp. Base Prob ShapeB
Prob. Change With Yoga
Trad. Stretch Success Probability
Gym j [12]
Gym
Yoga Stretch Flag Gym
Success Probability Gym
Number of Trials Gym
Number of Signups Gym
Observations i



Full Partial Pooling Model



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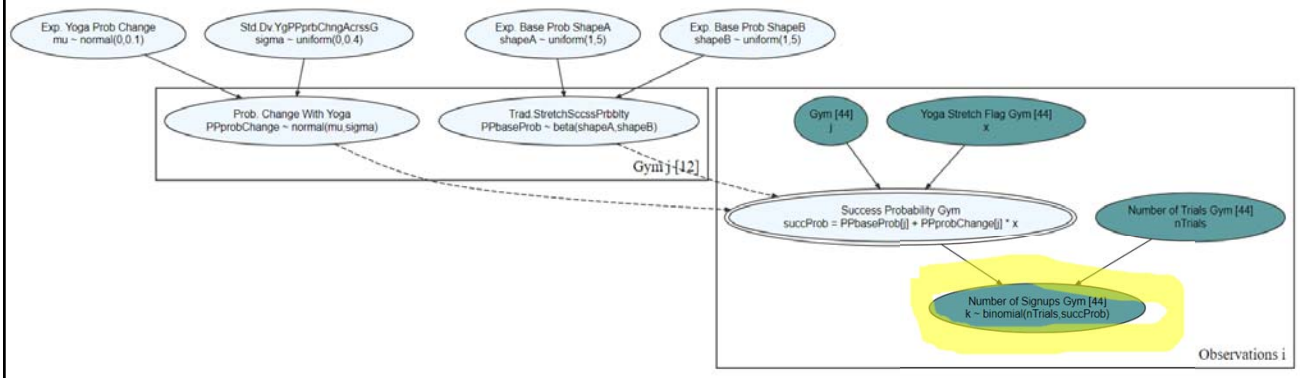

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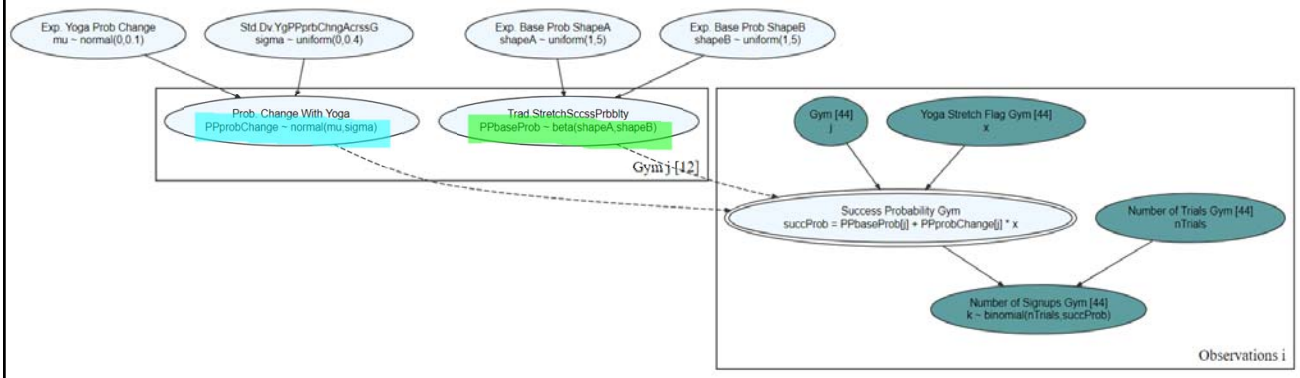

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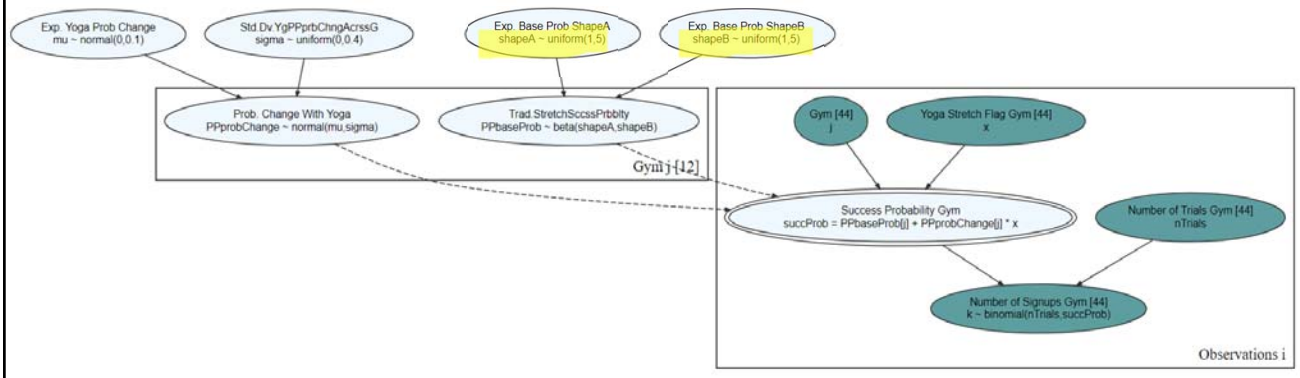
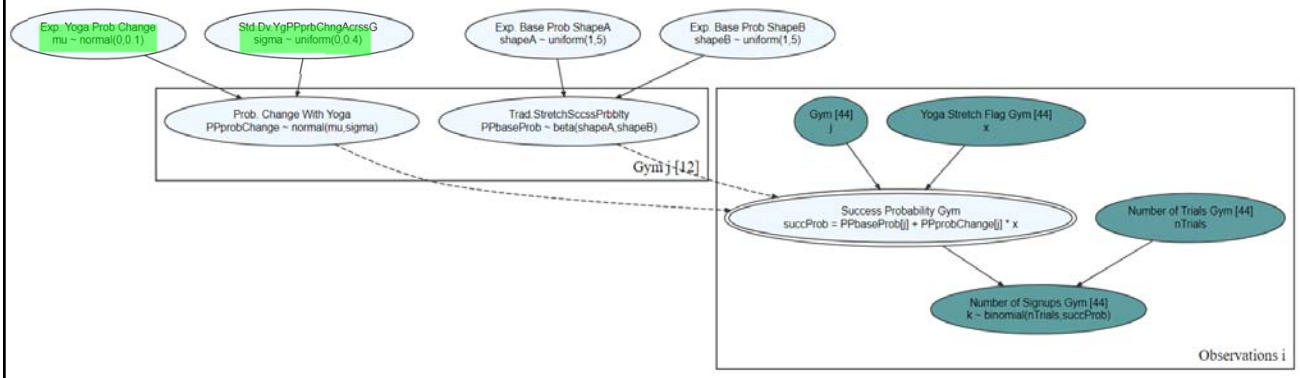
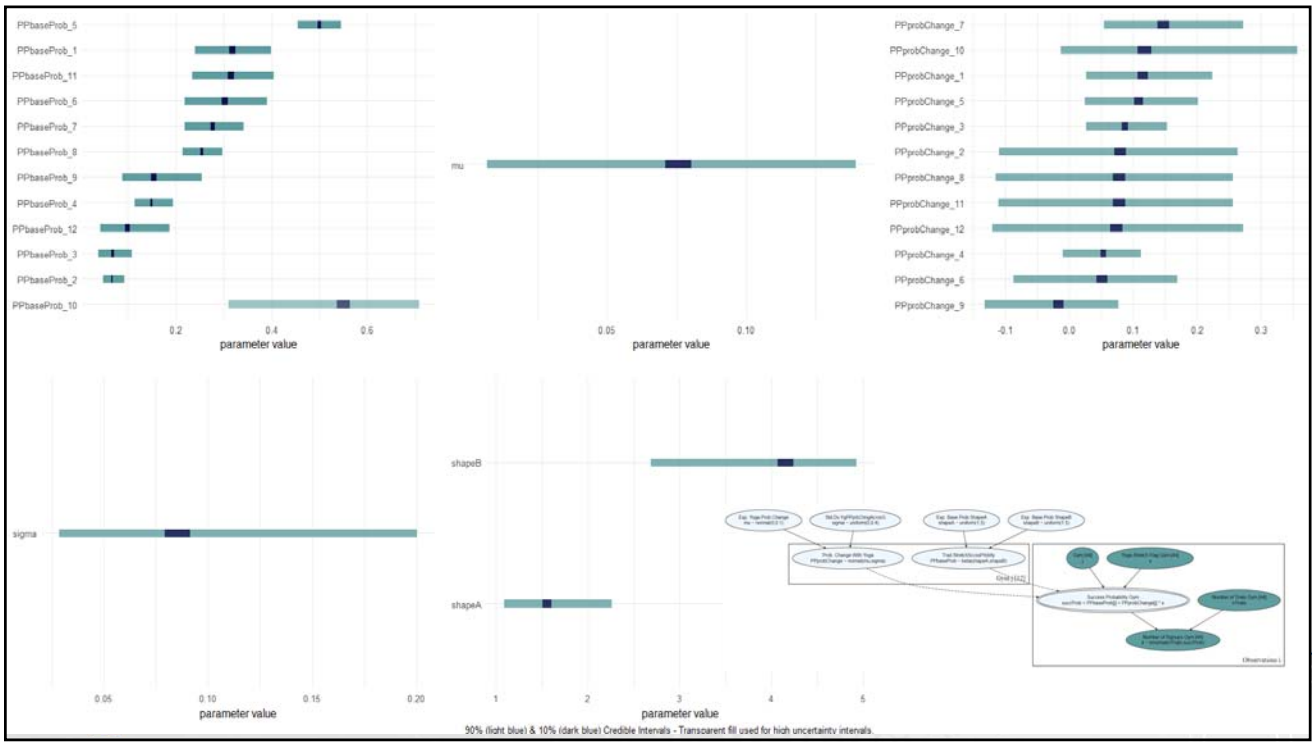
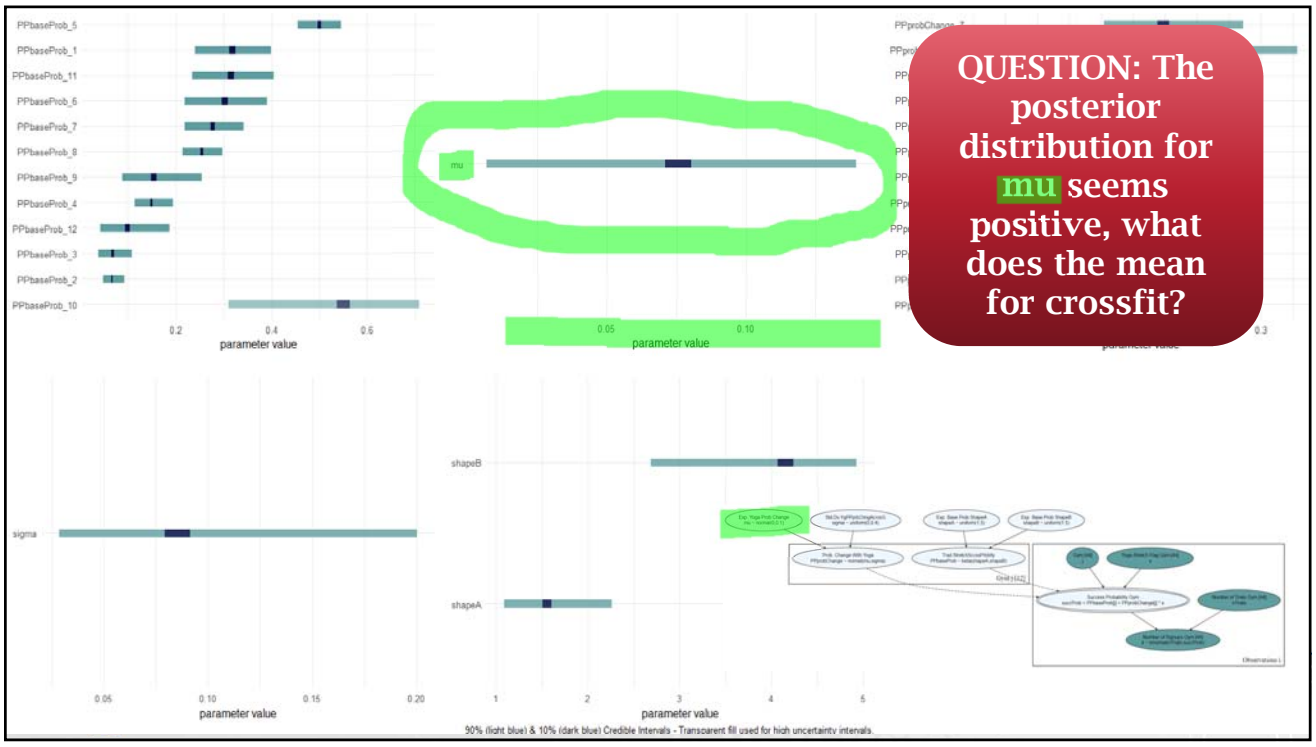


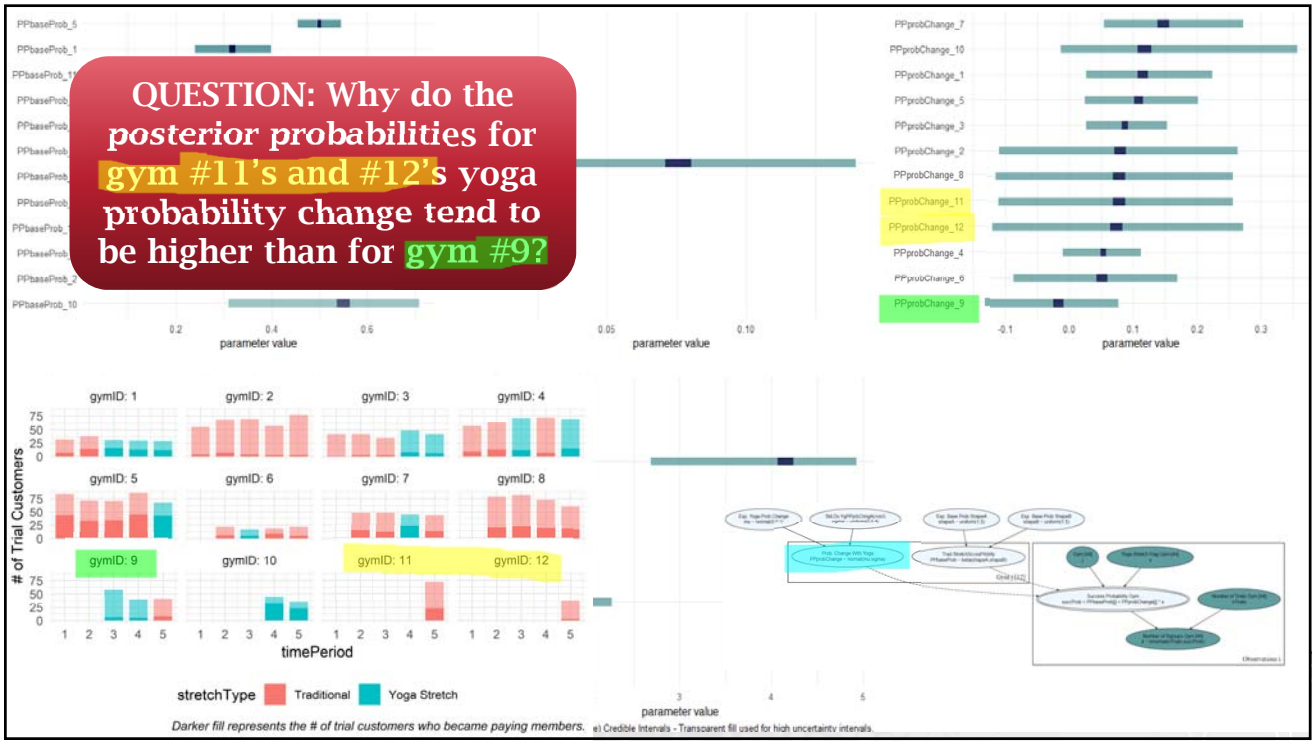
Full Partial Pooling Model




PPbaseProb_5
PPbaseProb_1
PPbaseProb_11
PPbaseProb_6
PPbaseProb_7
PPbaseProb_8
PPbaseProb_9
PPbaseProb_4
PPbaseProb_12
PPbaseProb_3
PPbaseProb_2
PPbaseProb_10
parameter value
mu
parameter value
PPprobChange_7
PPprobChange_10
PPprobChange_1
PPprobChange_5
PPprobChange_3
PPprobChange_2
PPprobChange_8
PPprobChange_11
PPprobChange_12
PPprobChange_4
PPprobChange_6
PPprobChange_9
parameter value
sigma
parameter value
shapeB
shapeA
parameter value
90% (light blue) & 10% (dark blue) Credible Intervals - Transparent fill used for high uncertainty intervals.

PPbaseProb_5
PPbaseProb_1
PPbaseProb_11
PPbaseProb_6
PPbaseProb_7
PPbaseProb_8
PPbaseProb_9
PPbaseProb_4
PPbaseProb_12
PPbaseProb_3
PPbaseProb_2
PPbaseProb_10
parameter value
gymID: 1
gymID: 2
gymID: 3
gymID: 4
gymID: 5
gymID: 6
gymID: 7
gymID: 8
gymID: 9
gymID: 10
gymID: 11
gymID: 12
# of Trial Customers
timePeriod
stretchType
Traditional
Yoga Stretch
Darker fill represents the # of trial customers who became paying members.
parameter value
PPprobChange_7
PPprobChange_10
PPprobChange_1
PPprobChange_5
PPprobChange_3
PPprobChange_2
PPprobChange_8
PPprobChange_11
PPprobChange_12
PPprobChange_4
PPprobChange_6
PPprobChange_9
parameter value
QUESTION: Why does gym 10 have the widest interval for base probability?
shapeB
shapeA
parameter value
90% (light blue) & 10% (dark blue) Credible Intervals - Transparent fill used for high uncertainty intervals.


QUESTION: The posterior distribution for mu seems positive, what does the mean for crossfit?
parameter value
parameter value
parameter value
parameter value
90% (light blue) & 10% (dark blue) Credible Intervals - Transparent fill used for high uncertainty intervals.


QUESTION: Why do the posterior probabilities for gym #11's and #12's yoga probability change tend to be higher than for gym #9?
parameter value
parameter value
parameter value
gymID: 1
gymID: 2
gymID: 3
gymID: 4
gymID: 5
gymID: 6
gymID: 7
gymID: 8
gymID: 9
gymID: 10
gymID: 11
gymID: 12
# of Trial Customers
timePeriod
stretchType
Traditional
Yoga Stretch
Darker fill represents the # of trial customers who became paying members.
parameter value
e) Credible Intervals - Transparent fill used for high uncertainty intervals.