Effect sizes from predictive models

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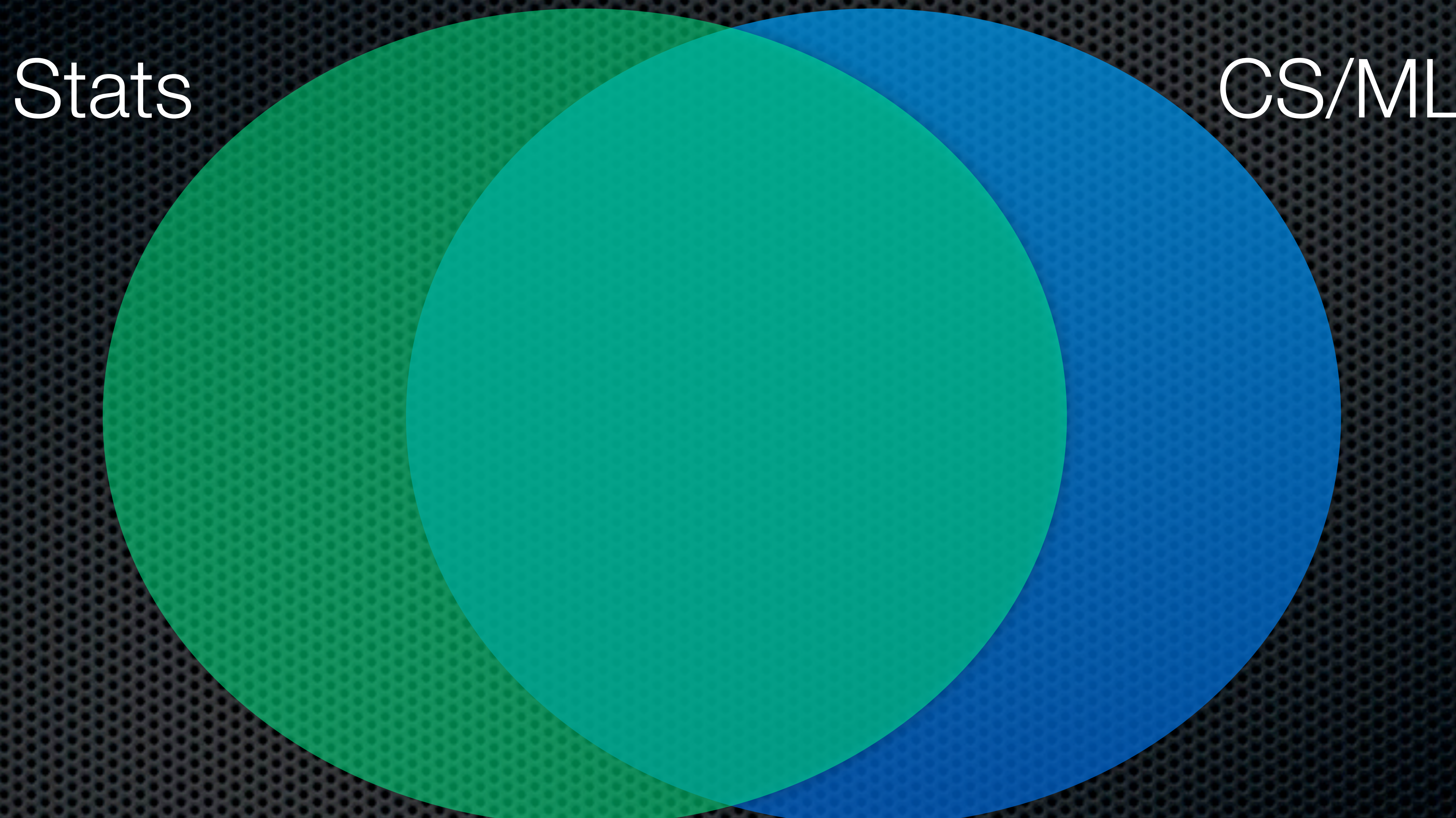
Statistics

- Parametric models
- Emphasis on explanation or “causality”
- Often hypothesis-driven
- End product is often a series of p-values

CS/ML

- Nonparametric models
- Emphasis on prediction
- Often hypothesis-generating
- End product is a set of predictions


Stats
CS/ML


Stats
CS/ML
I play here

We’ve trained our clients too well

Effect sizes and p-values

- In a supervised learning setting, demands are often
  - What is the effect of a feature?
  - Is it significant?
- The question is not
  - How well can I predict the outcome in new data?

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  - Is it significant?

Associative

- The question is not
  - How well can I predict the outcome in new data?

Predictive

My experience/belief/faith

- Many good machine learning algorithms reflect patterns in the data very well, capturing structure in a “black box”
- Classical parametric models are limited by requirements of explicit structural specification and resulting mis-specification
- This affects both the associative and predictive views

Prediction

- Associative models are used for prediction
  - Linear regression
  - Logistic regression
  - Structural equations

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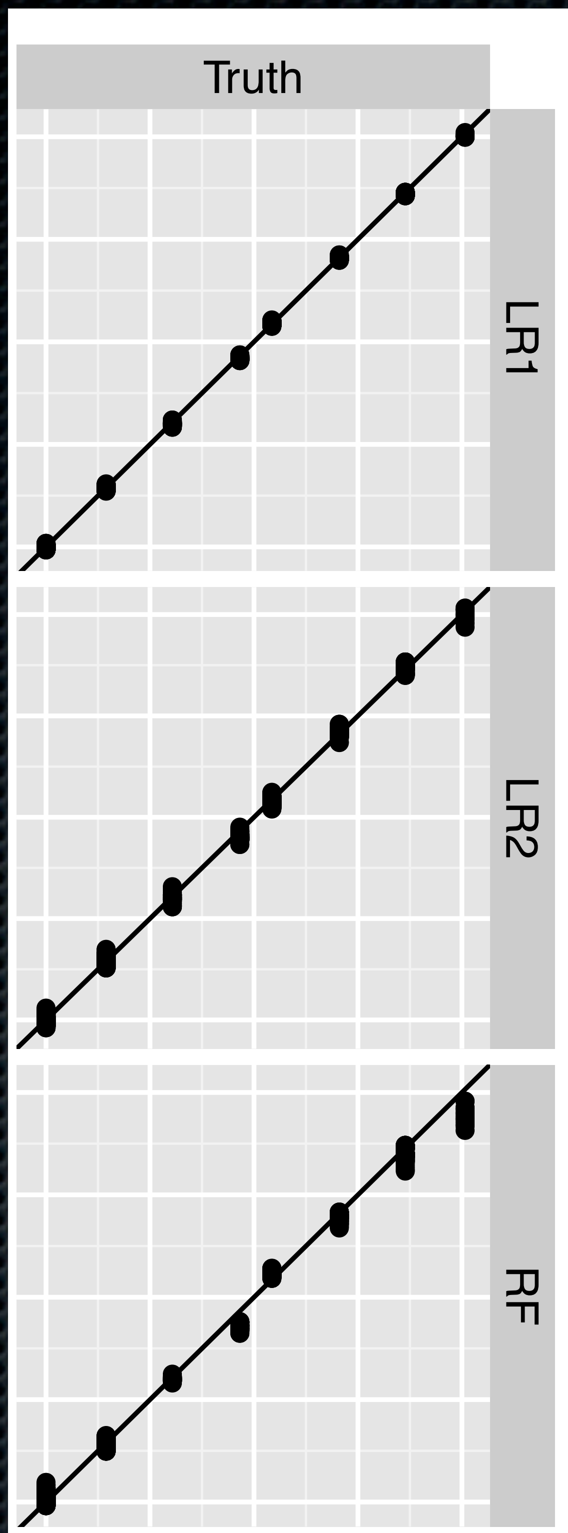
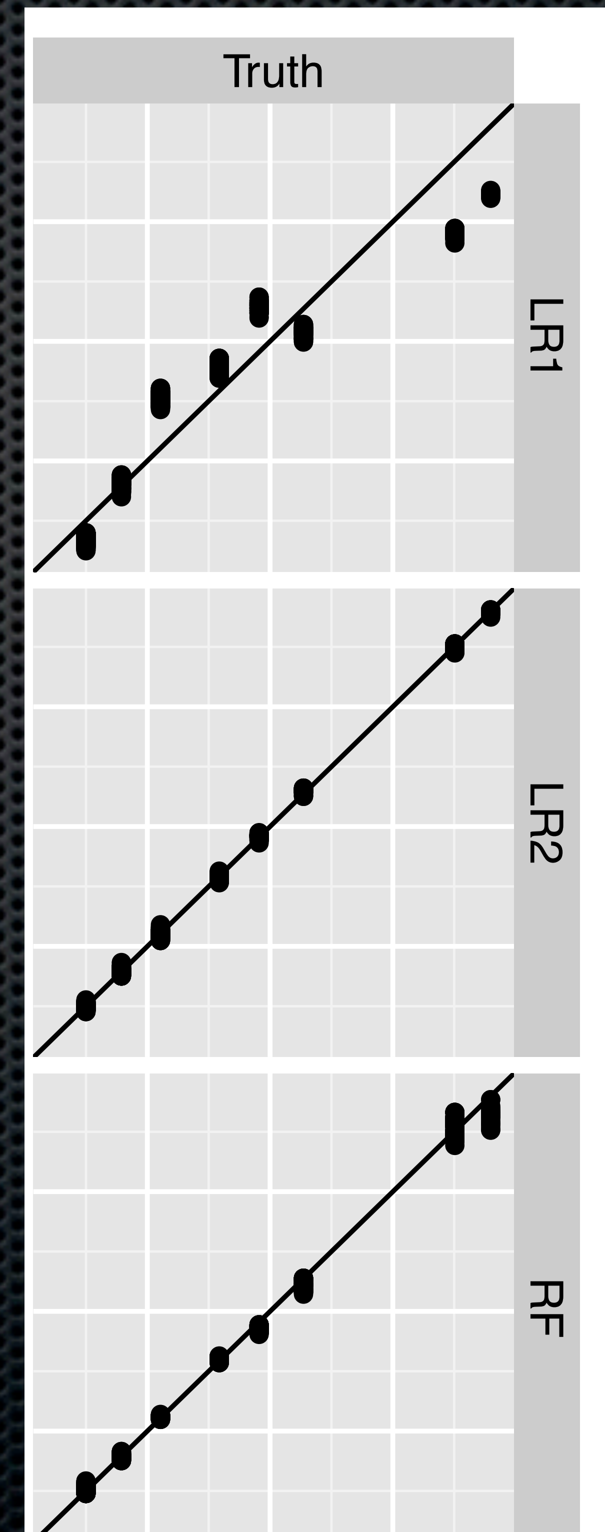
They require more careful model building to do well

Truth

No interactions



Interactions



Main effects only

$$y=\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots$$

Main effects + interactions

$$y=\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_{12} x_1 x_2+\ldots$$

Same specification

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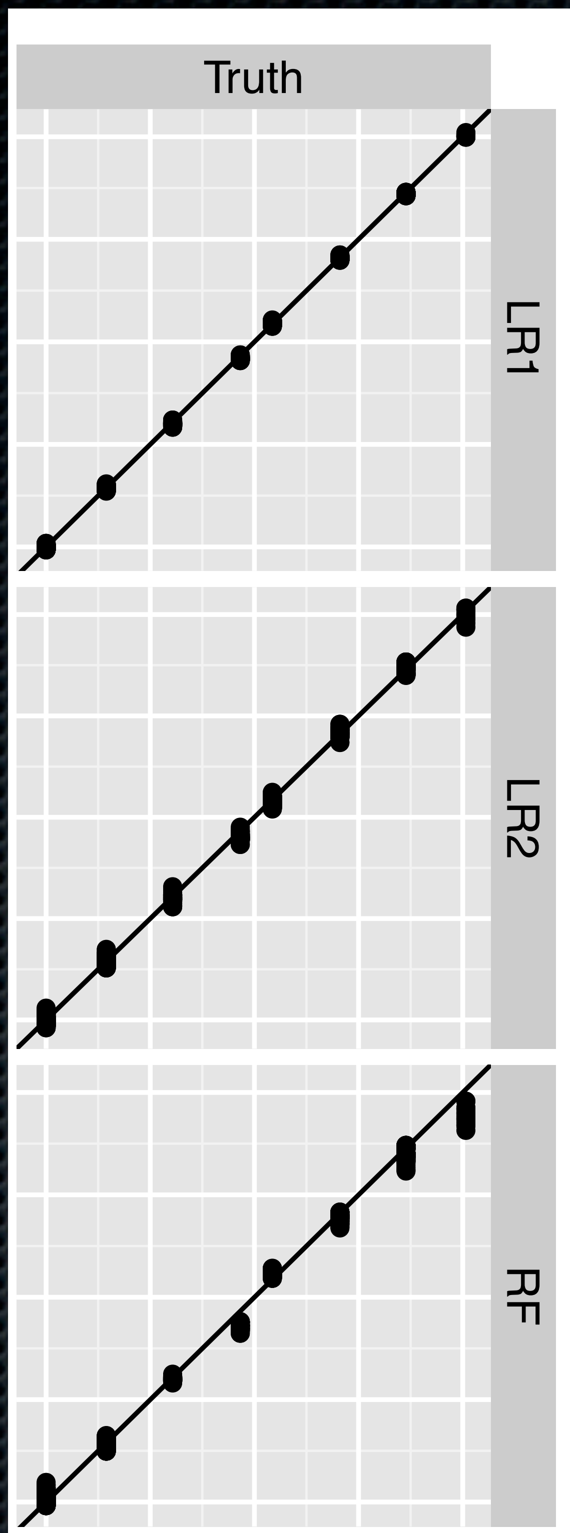

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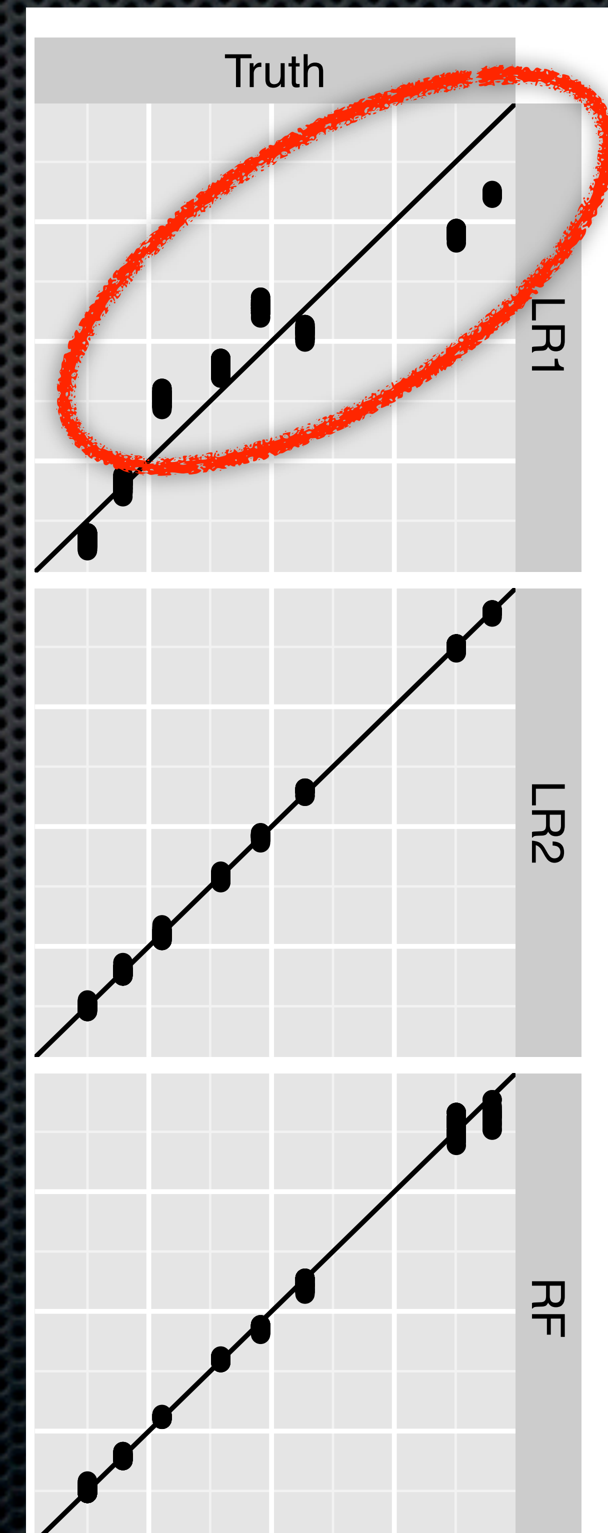
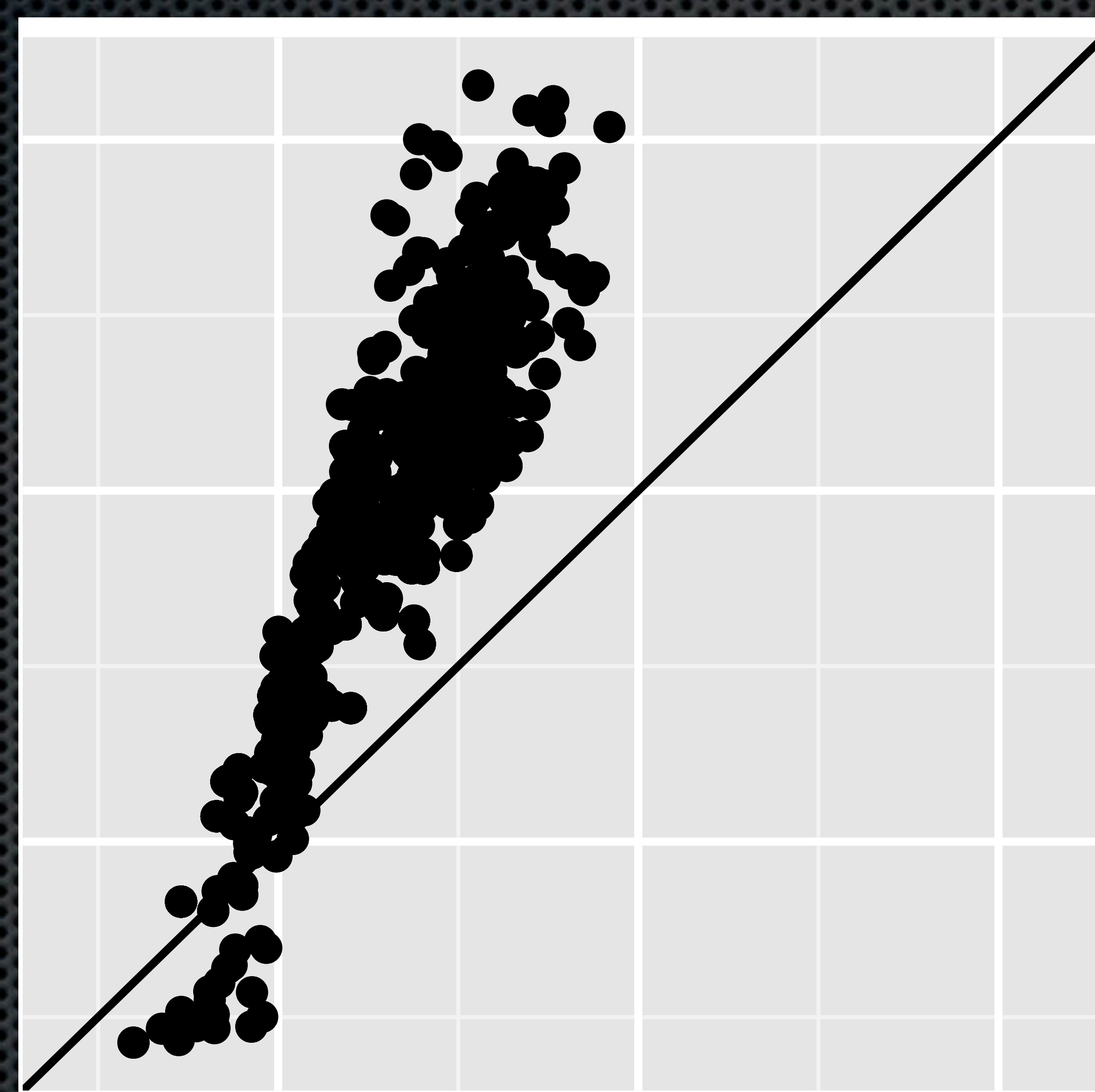


Width of prediction intervals

Main effects + interactions

$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_{12} x_1 x_2 + \ldots$



Random Forest

The point is….

- With “black box” models you don’t have to worry about data structure explicitly, as long as you trust your “black box”
- With classical models, you spend a lot of time worrying about whether you got close enough to the data structure
- Often we don’t worry enough

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- With “black box” models you don’t have to worry about data structure explicitly, as long as you trust your “black box”
- With classical models, you spend a lot of time worrying about whether you got close enough to the data structure
- Often we don’t worry enough → CONSEQUENCES

But you can’t tell me how my favorite feature affects the outcome

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Whine, whine, whine!!

But you can't tell me how my favorite feature affects the outcome

Whine, whine, whine!!

Like some cheese with that?

Like some cheese with that?

A trip down memory lane ….

Regression

$$y = b_0 + b_1x_1 + b_2x_2 + \ldots + \text{error}$$

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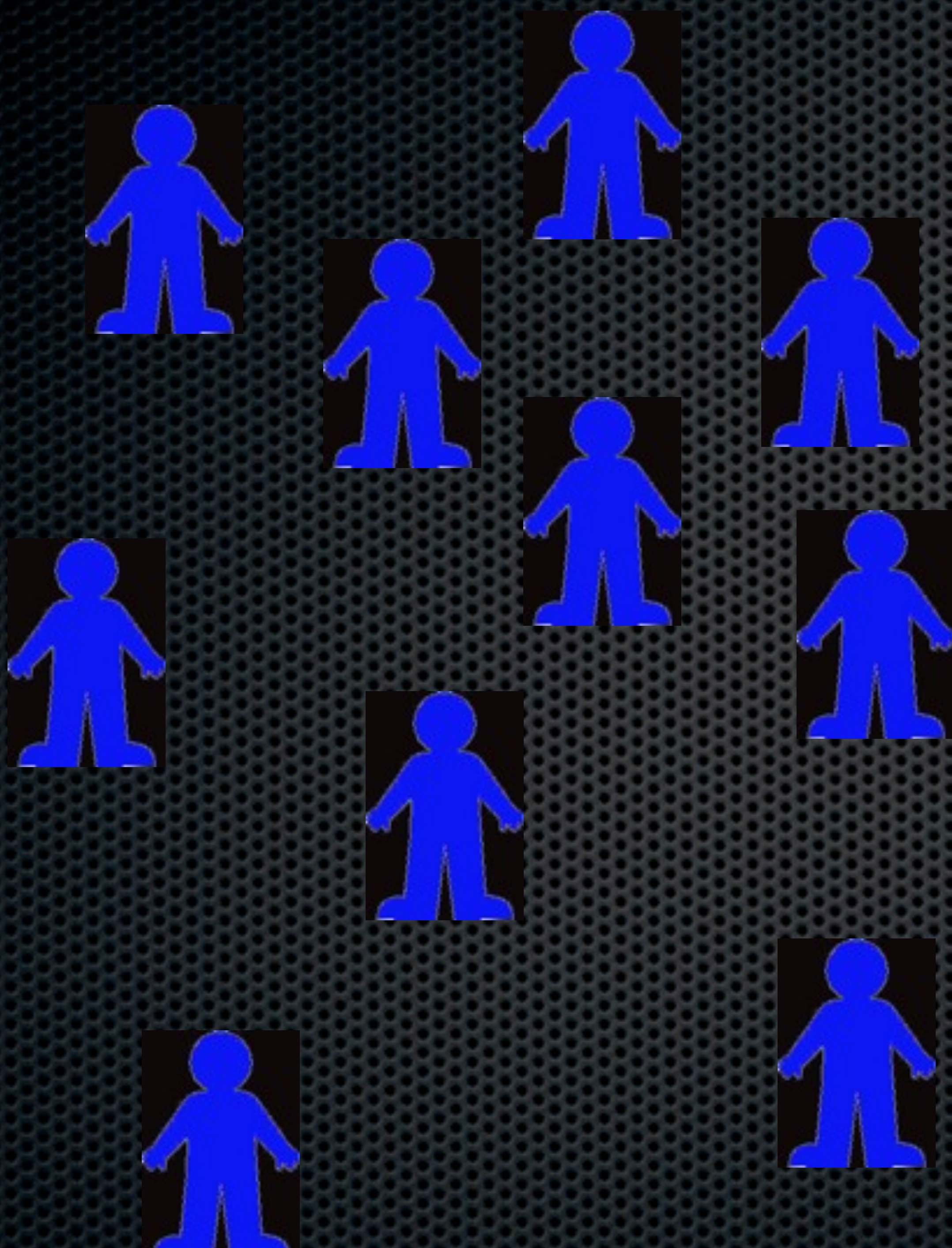
Counterfactual argument

The counterfactual argument



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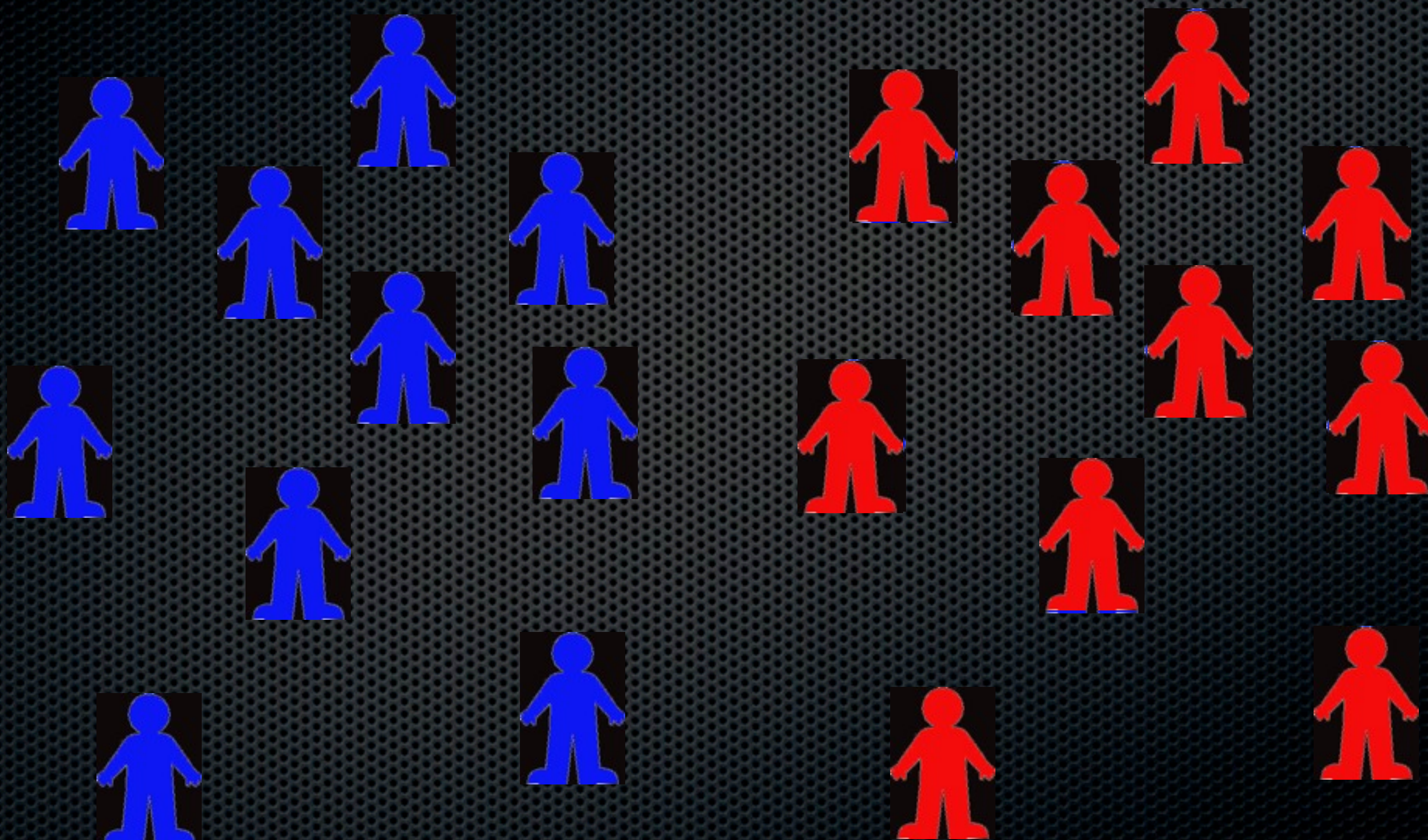

The counterfactual argument

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Can we predict outcome if we change environments?

Using predictive models

Counterfactuals as predictions

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- If we drop you down the Red model, it would predict your outcome as if you were red (y_p)

Counterfactuals as predictions

- Consider a binary feature (red/blue)
- Train a model only on the reds (Red model)
  - This captures the red environment
- Suppose you are blue, and have a true outcome y_t
- If we drop you down the Red model, it would predict your outcome as if you were red (y_p)
- Your counterfactual effect would be $y_t - y_p$

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  - Red model trains only on Reds
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We're calling this "counterfactual machines"

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  - the models don't actually use the Red/Blue variable for prediction
  - What these models capture is **everything else** about being Red and Blue
    - Obvious patterns and intangibles
    - The Red and Blue "environment"

Counterfactuals to effect size

- If you want an overall effect measure of Red vs Blue **conditional on everything else**

Average (mean/median) over y_R-y_B

- If you want a subgroup-specific effect measure of Red vs Blue **conditional on everything else**

Average y_R-y_B only over the subgroup

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Try doing this in classical regression

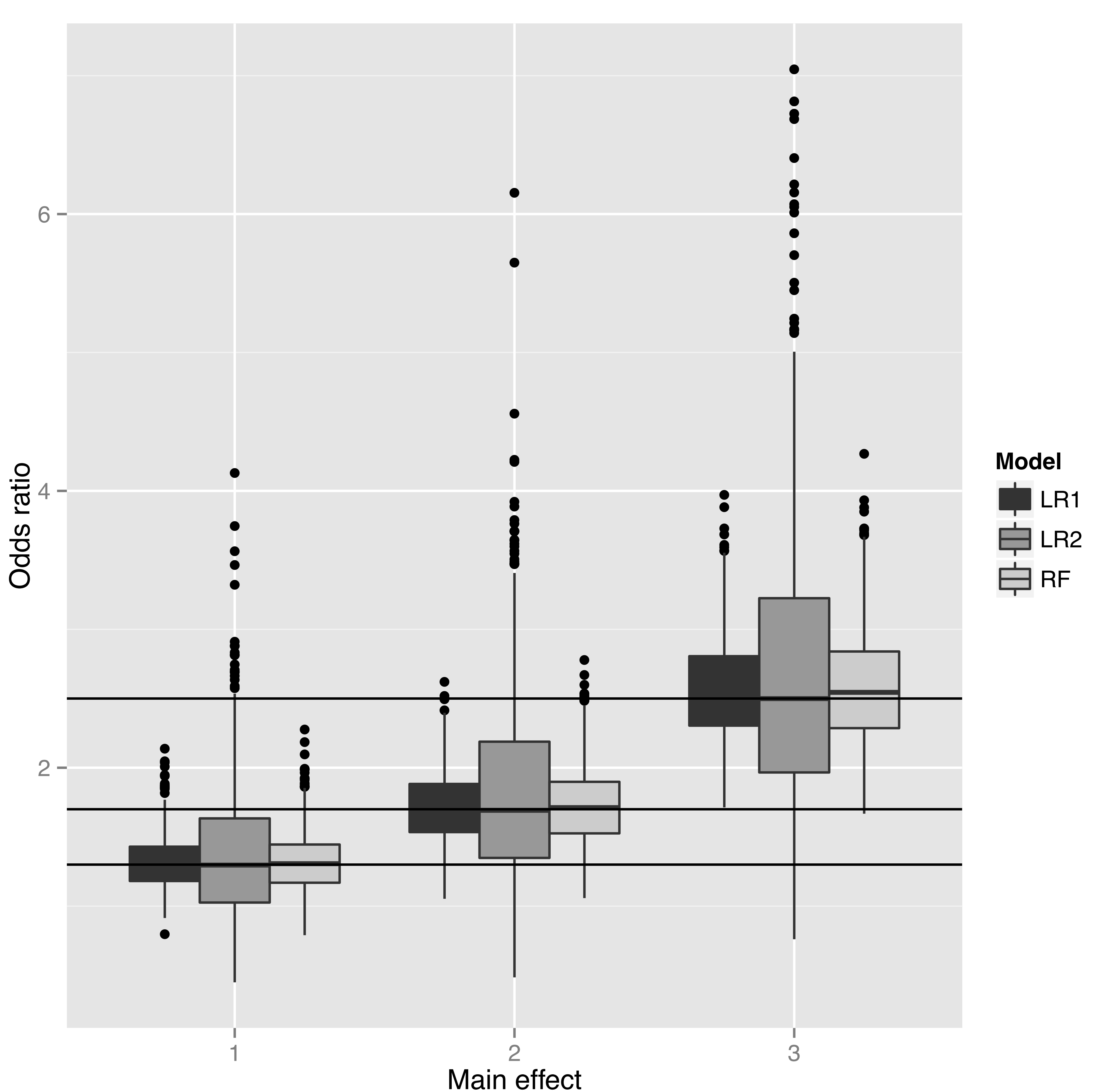
Counterfactuals to effect size

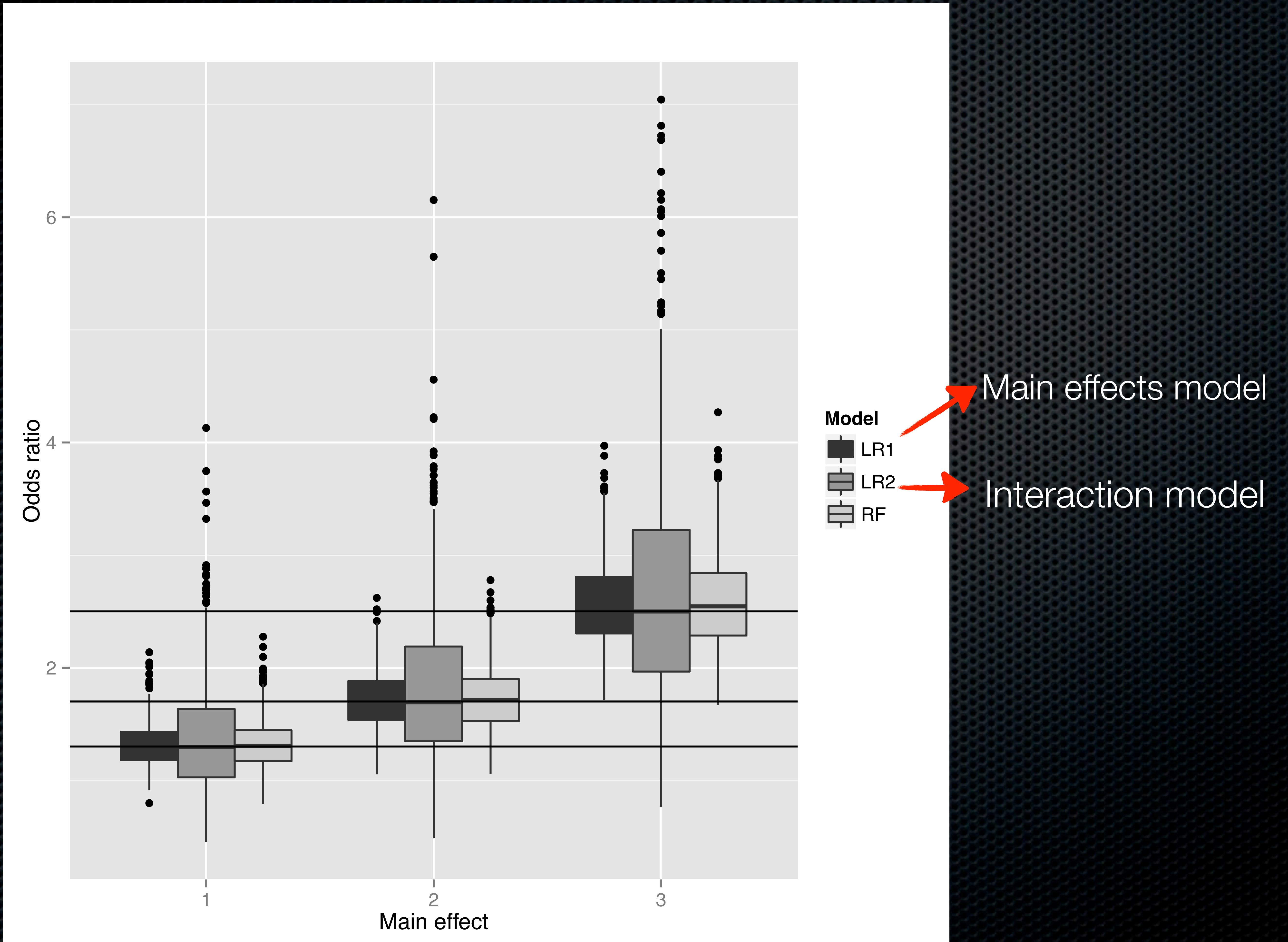
- In fact, since you now have individual “effects”
  - You can see how these change against a second variable
  - You can look at arbitrary subgroups
- You can extend this idea to look at interactions **at an individual level**

Can this possibly work?!!!

A simulation of binary regression

- Simulated binary outcomes under a logistic regression model with binary features
- Fit both a logistic regression model and a random forest model to the simulated data
- Used regression estimates from the logistic model and random forest based counterfactual machines


Odds ratio
6
4
2
1
2
3
Main effect
Model
LR1
LR2
RF



Odds ratio
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4
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3
Main effect
Model
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LR2
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Main effects model
Interaction model

But wait, there’s more!!

Interactions

- In genetics there is a great deal of interest in gene-gene and gene-environment interactions
- Similarly, I'm sure, in other domains, there are situations where joint effects are interesting

Interactions

Interactions

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  - $(y_{RM}, y_{RF}, y_{BM}, y_{BF})$
- Interaction effect : $y_{RM}-y_{RF} - (y_{BM}-y_{BF})$
- Average over everyone to get overall interaction effect

But this gets tiring fast!!!

The Interactor

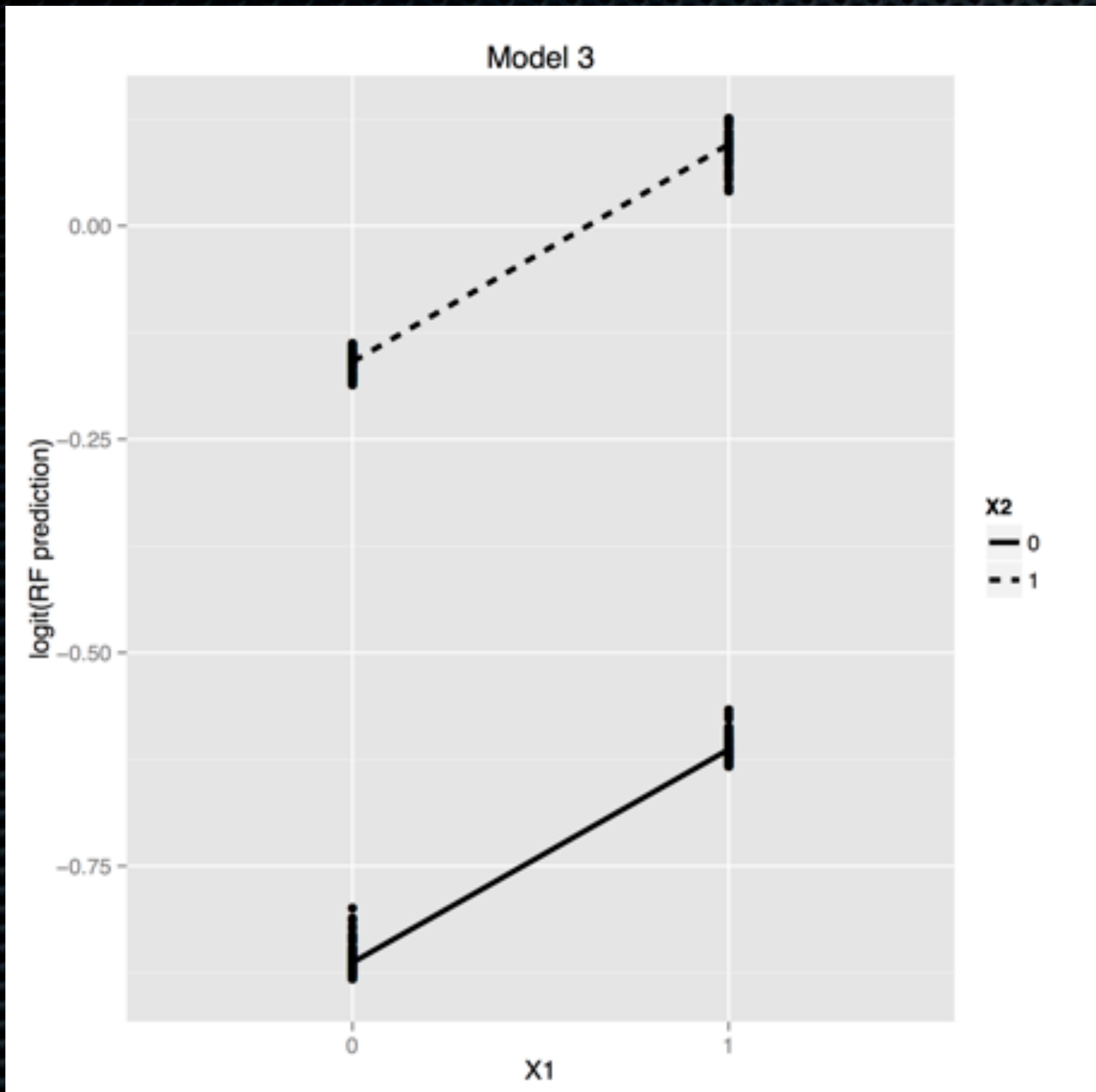
- Fit a <u>single</u> predictive model to your data
- Compute

$$\overline{y_{RM}} - \overline{y_{RF}} - (\overline{y_{BM}} - \overline{y_{BF}})$$

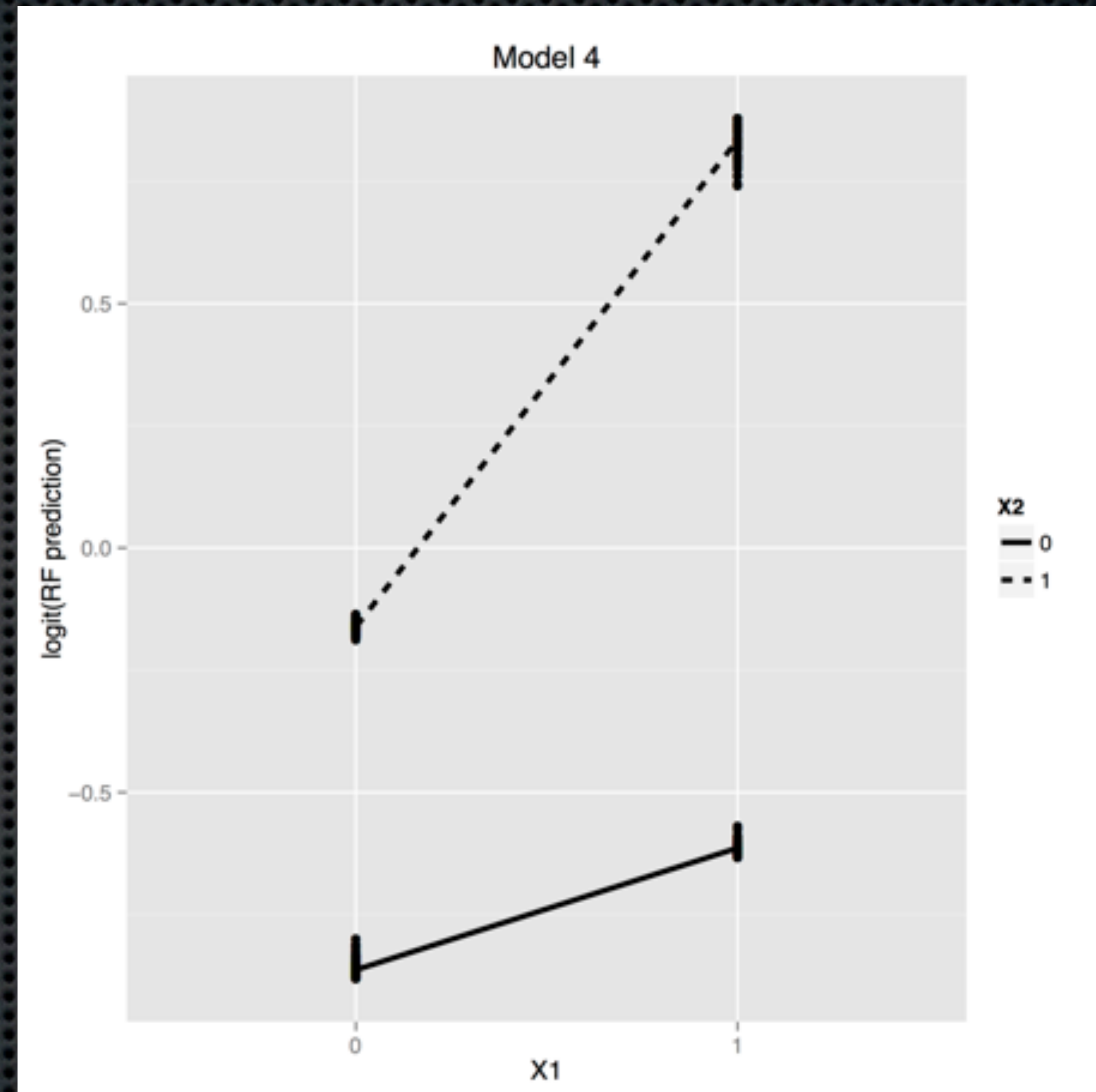
- This isn't a true interaction effect since it doesn't compute the counterfactuals
- It can be used to scan a large set of variables to see if interactions might exist

The Interactor

- This is of course trivial for continuous outcomes
- For binary outcomes, our models give us probability estimates, and so we can look at interactions in the predicted probabilities
  - Note, these probabilities aren't observed
  - In logistic regression, the predicted probabilities reflect the model, not necessarily what the data is saying.



Model 3
logit(RF prediction)
0.00
-0.25
-0.50
-0.75
X1
0
1
X2
0
1



Model 4
logit(RF prediction)
0.5
0.0
-0.5
X1
0
1
X2
0
1

Some notes

- Doing counterfactuals using classical parametric models only reflect the model, not the data
- Your effect size estimates will be only as good as the machine you use as your predictive model
- You can get standard errors by either bootstrapping or using bagged machines
- What I've described is straightforward for binary or categorical features
- You can get similar counterfactual machines for continuous features, but it is not so easy (ongoing research)

Using counterfactual machines

you **can** get conditional effects for particular features

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No more whining