Advanced Statistical Methods for Observational Studies

LECTURE 06

thick description

QUALIA HUNTING

pre-trial detention

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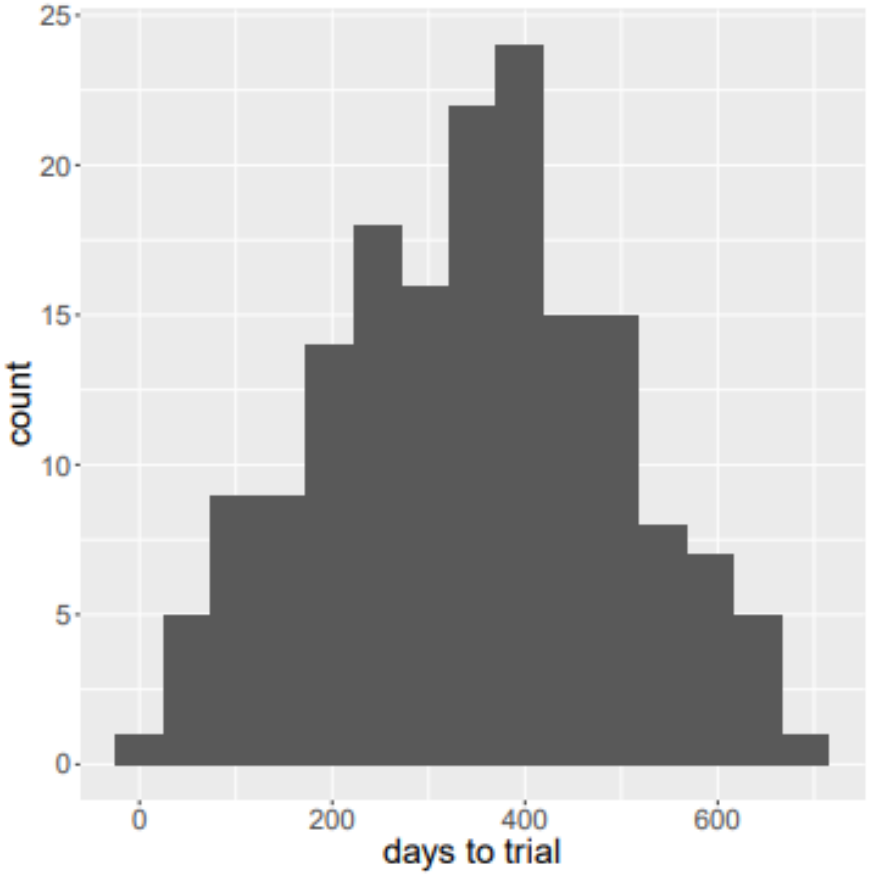

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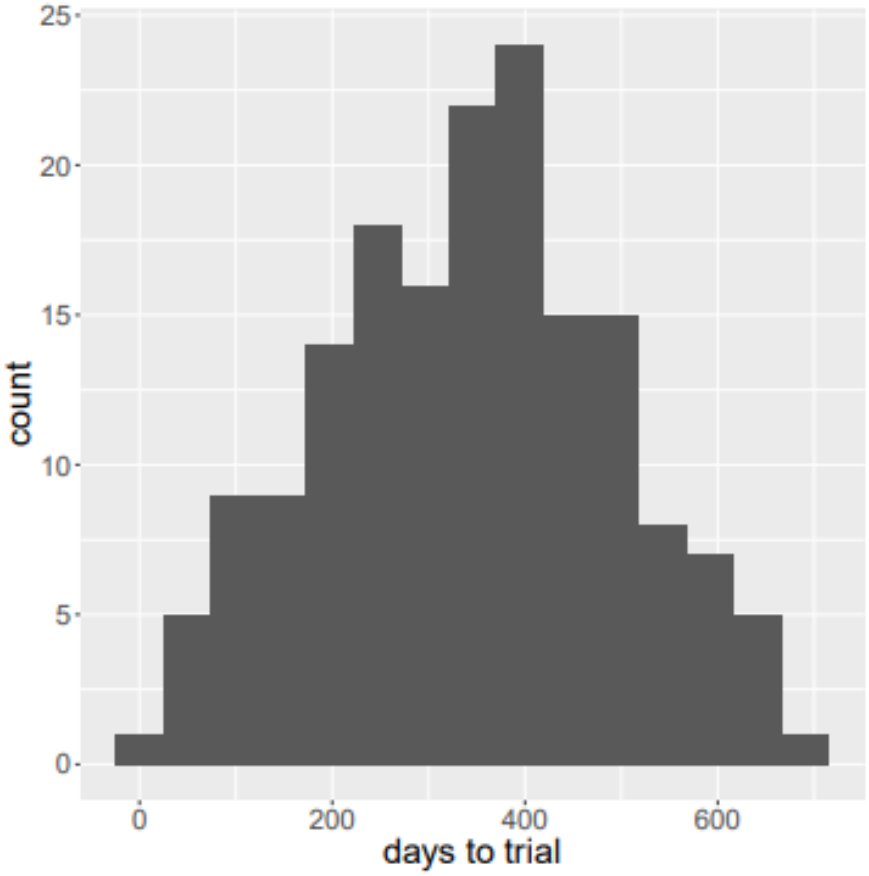

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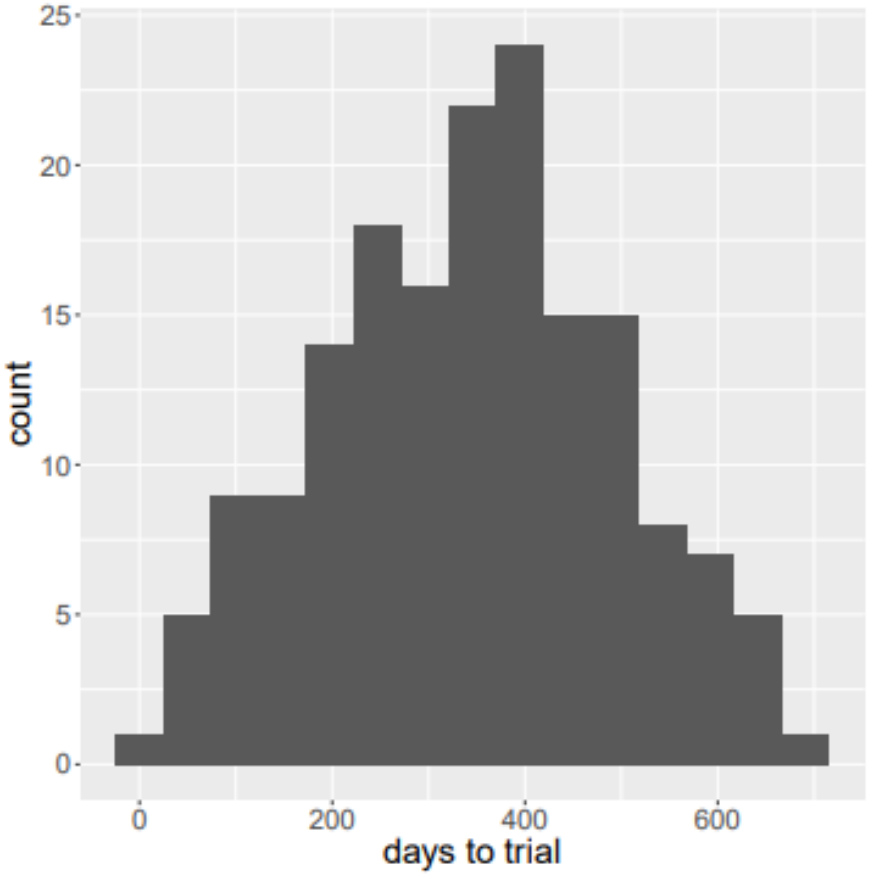

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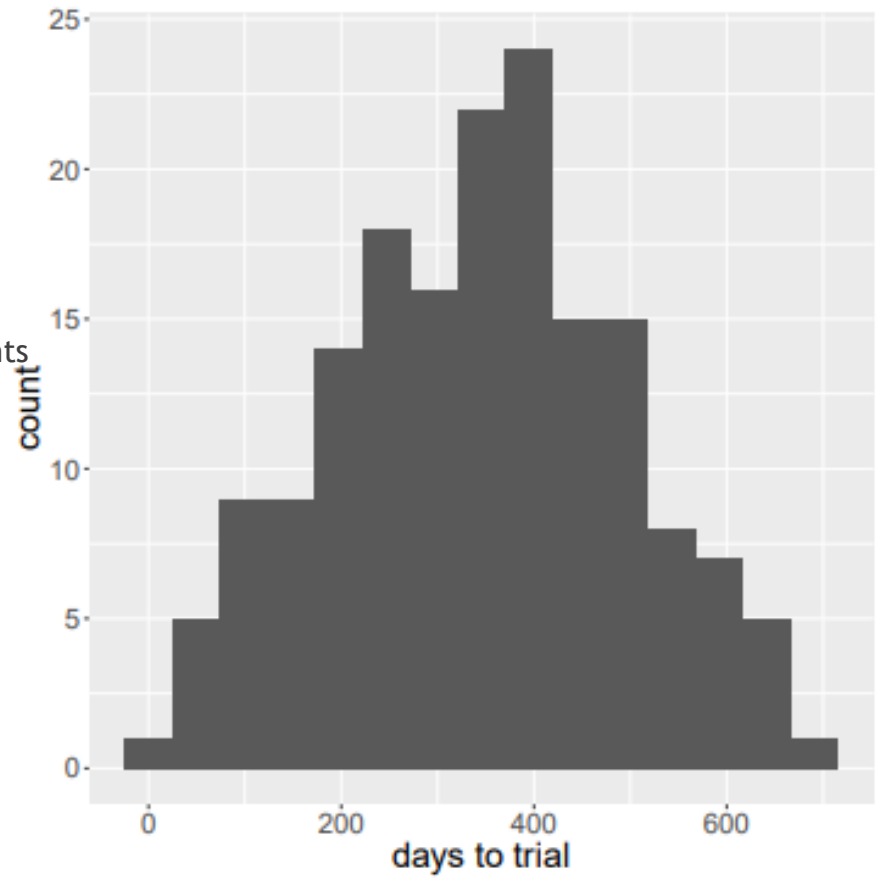

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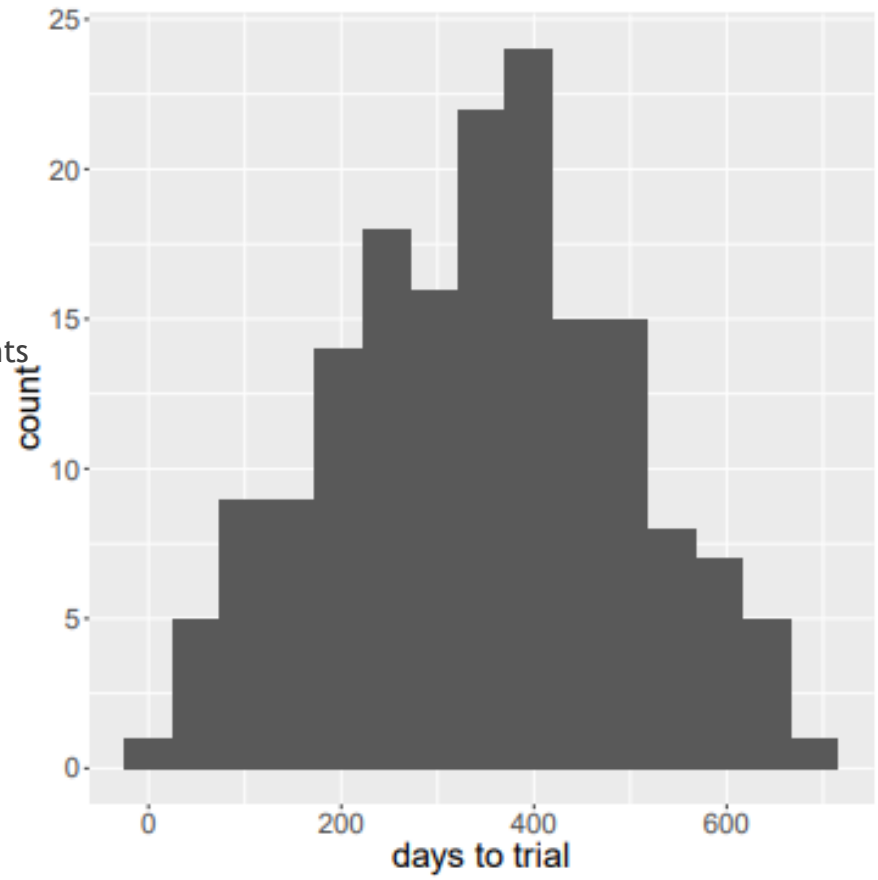

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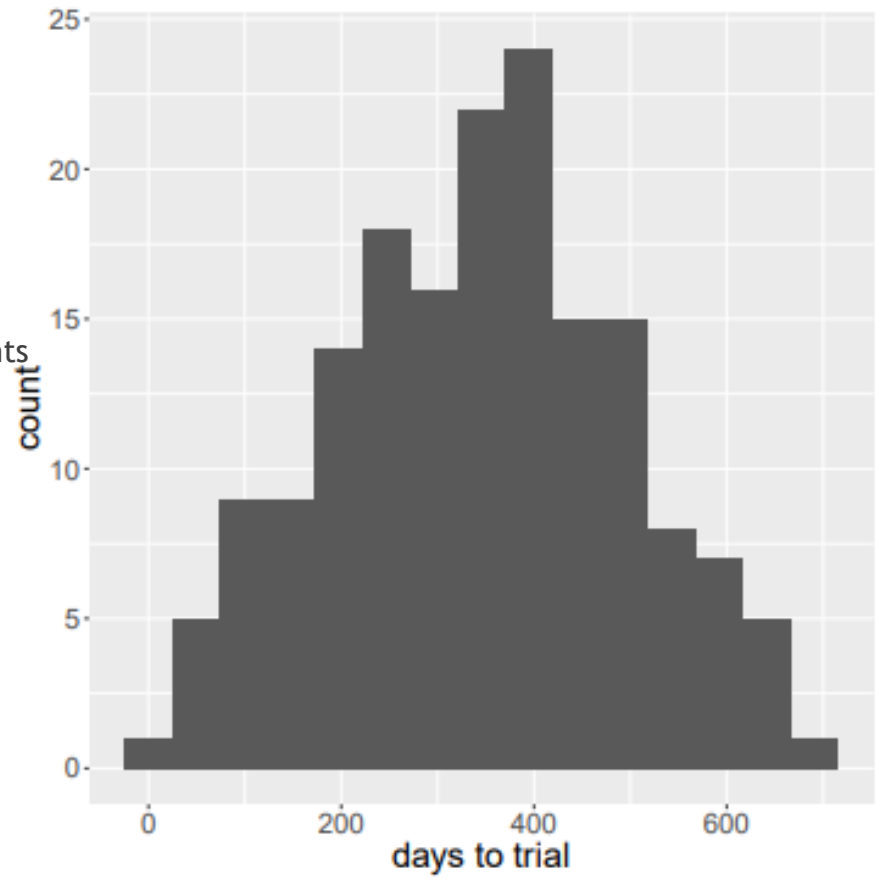

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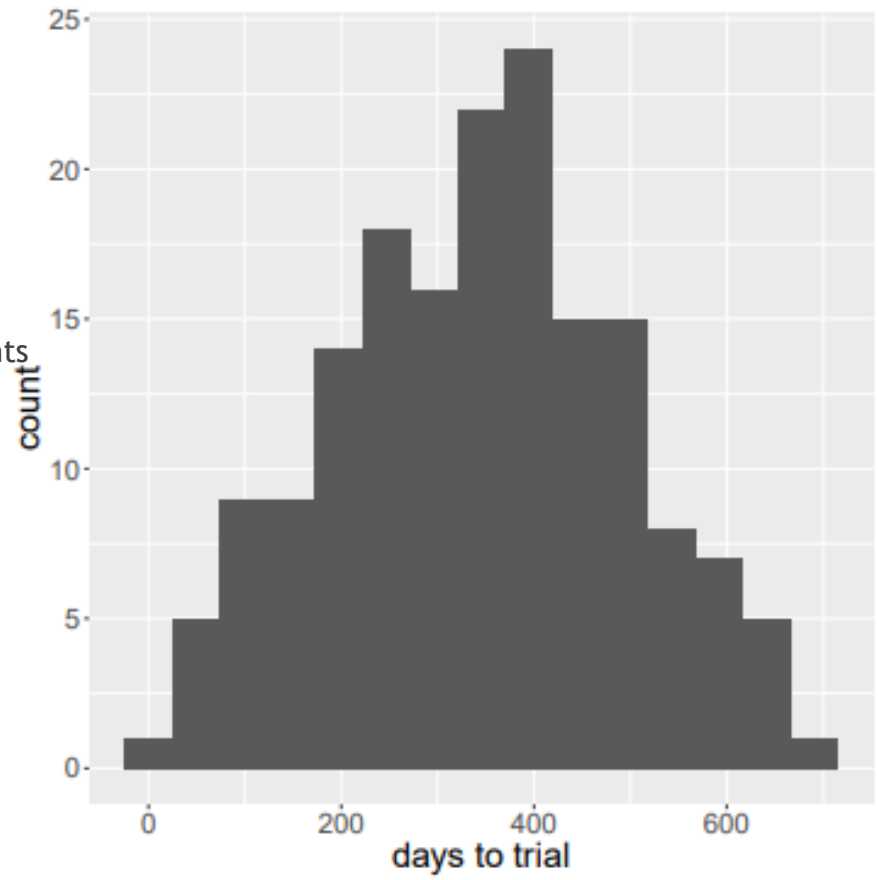

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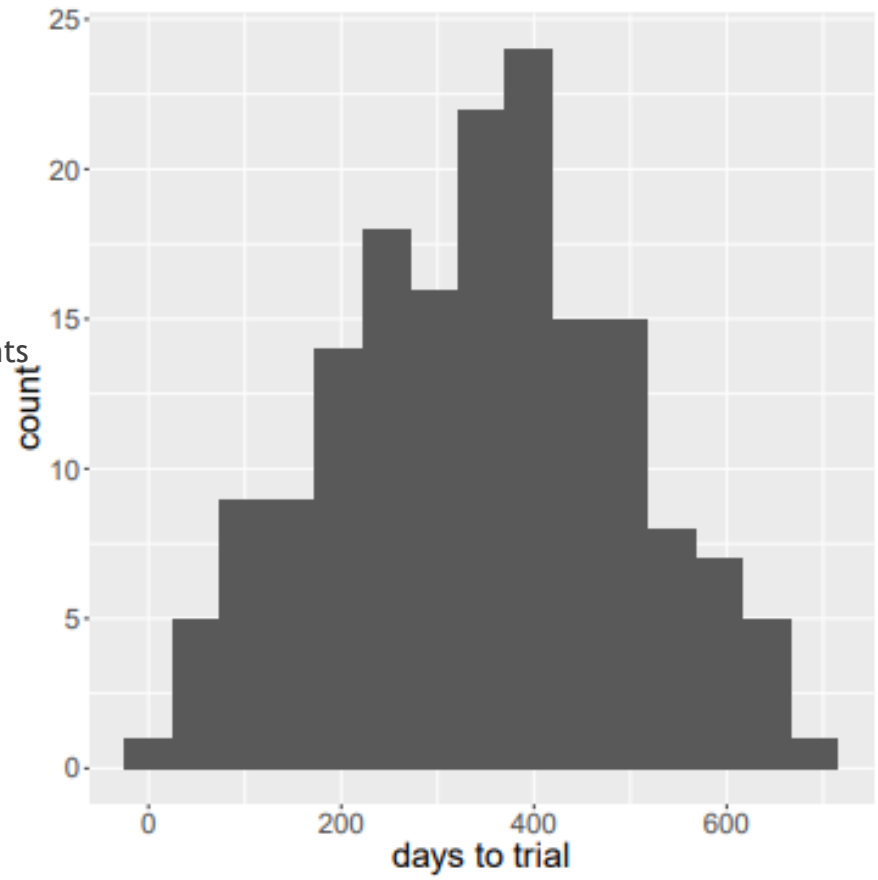
  - That is a quarter of one percent (0.25%)



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- This is known as an “instrumental variable” study design

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Given the linear regression:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon$$

where X_1 is an endogenous variable:

(1) Regress X_1 on Z_1, X_1, and X_3 to obtain $\hat{X}_1$

$$\hat{X}_1 = \gamma_0 + \gamma_1 Z_1 + \gamma_2 X_2 + \gamma_3 X_3 + v$$

where Z_1 is the instrumental variable

(2) Plug in the fitted values of $\hat{X}_1$ derived from equation (1) into the original linear regression equation:

$$Y = \beta_0 + \beta_1 \hat{X}_1 + \beta_2 X_2 + \beta_3 X_3 + v$$

where v is a composite error term that is uncorrelated with $\hat{X}_1, X_2$, and X_3

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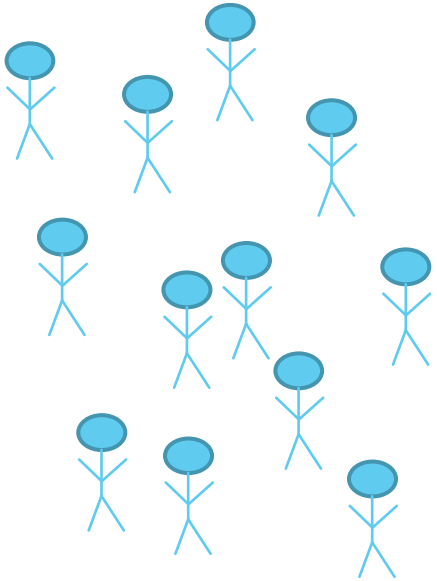

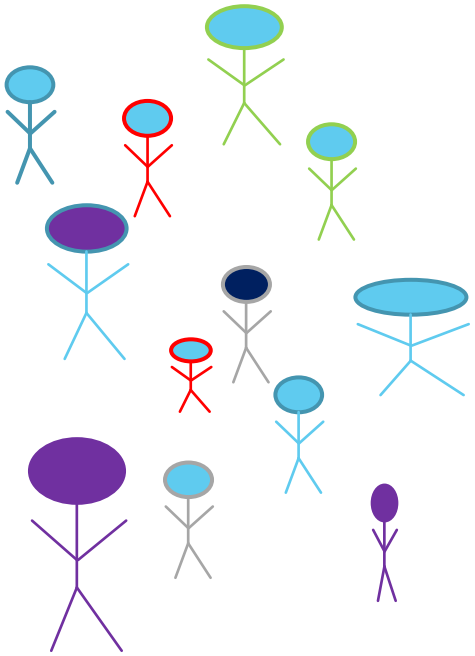

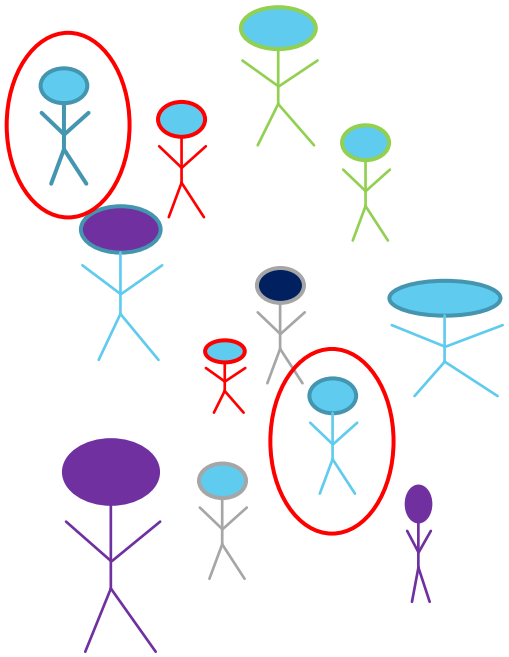

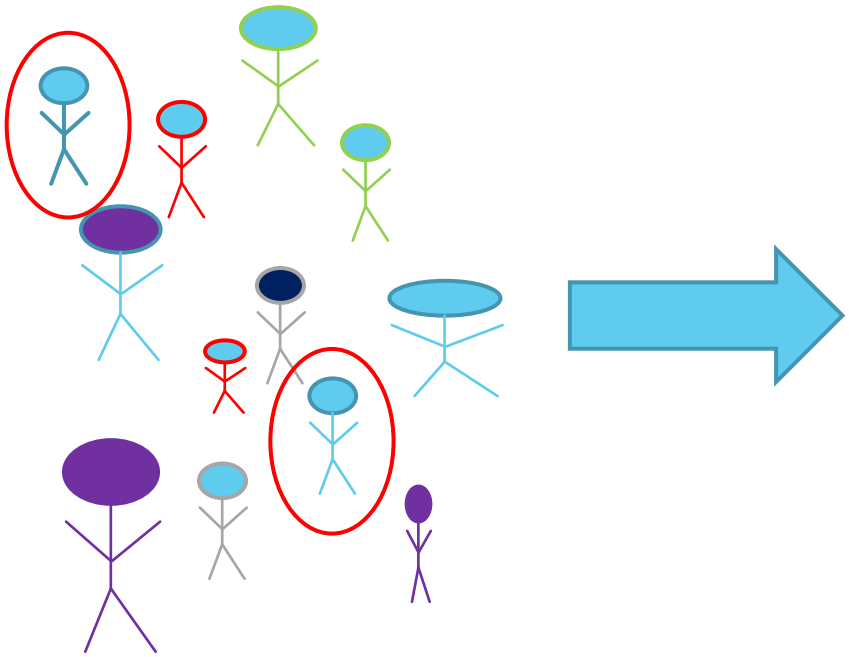

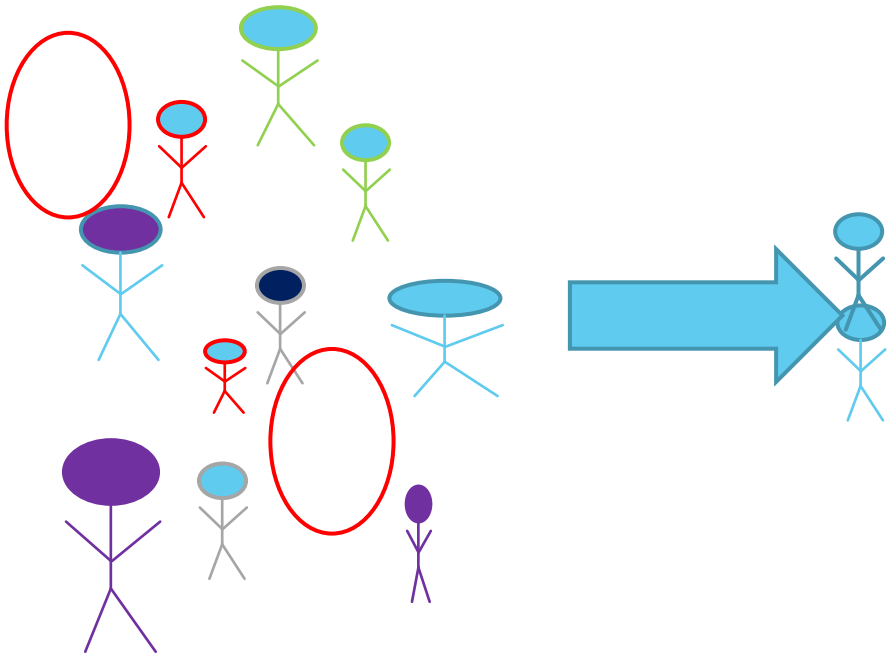

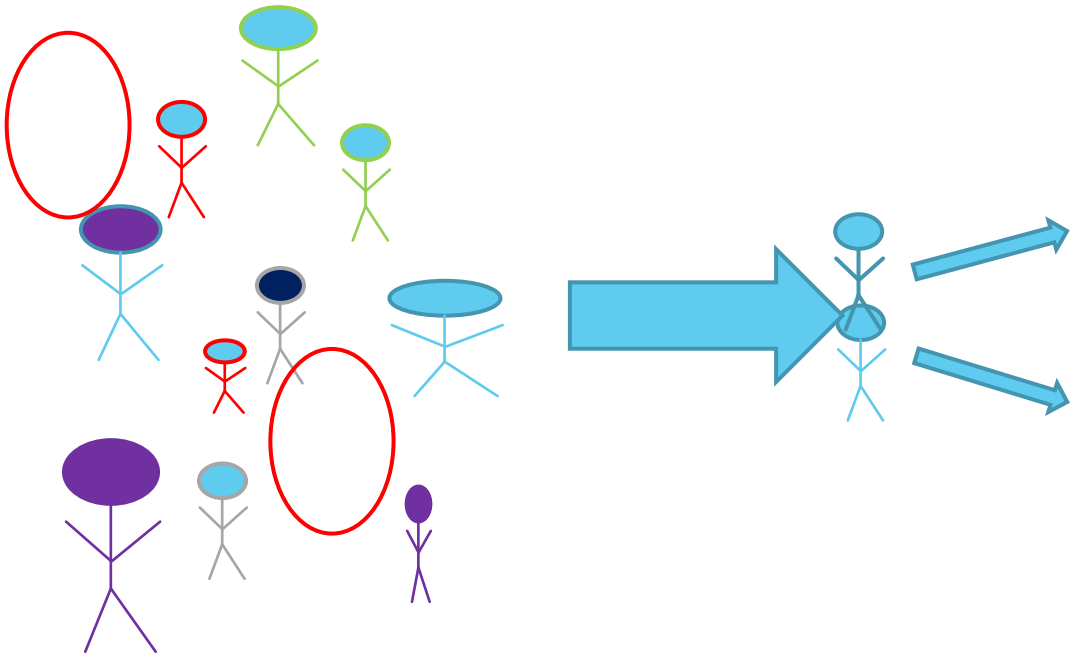

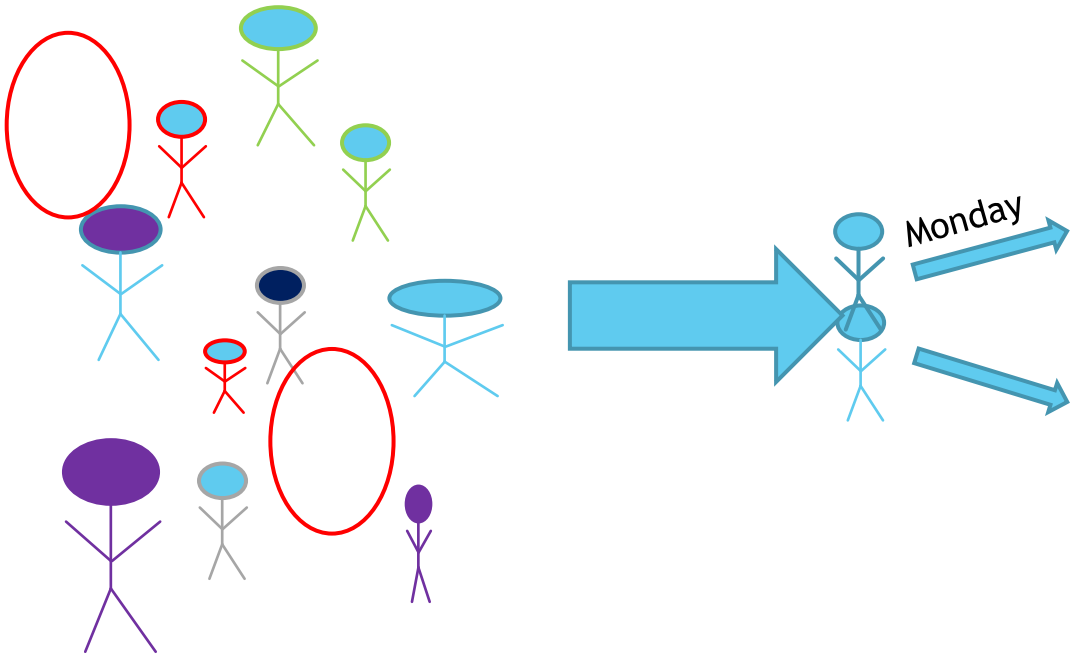
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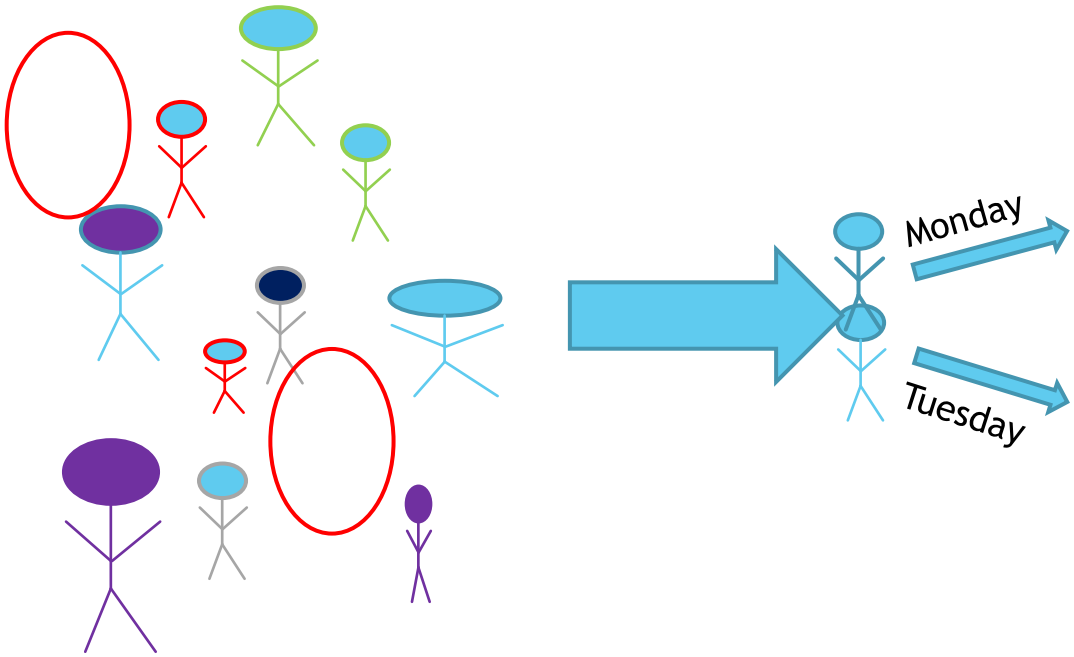
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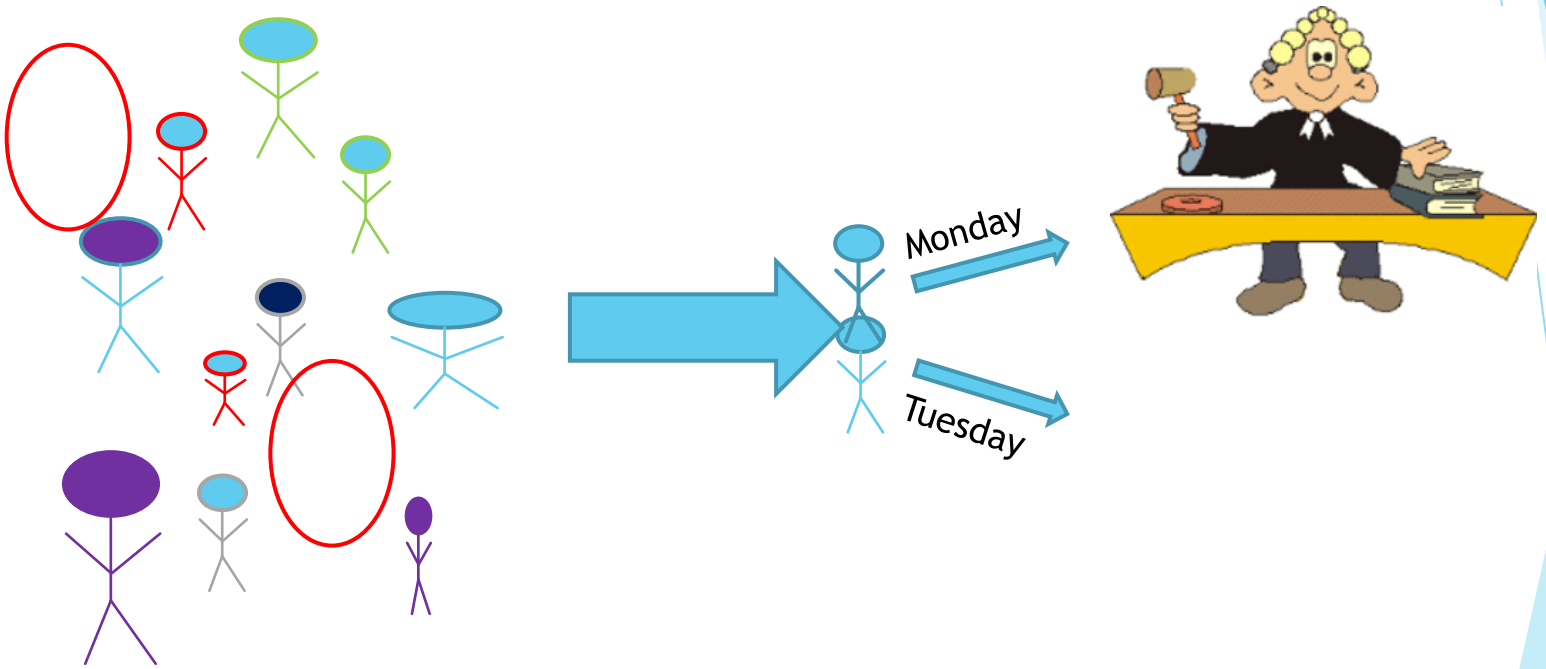
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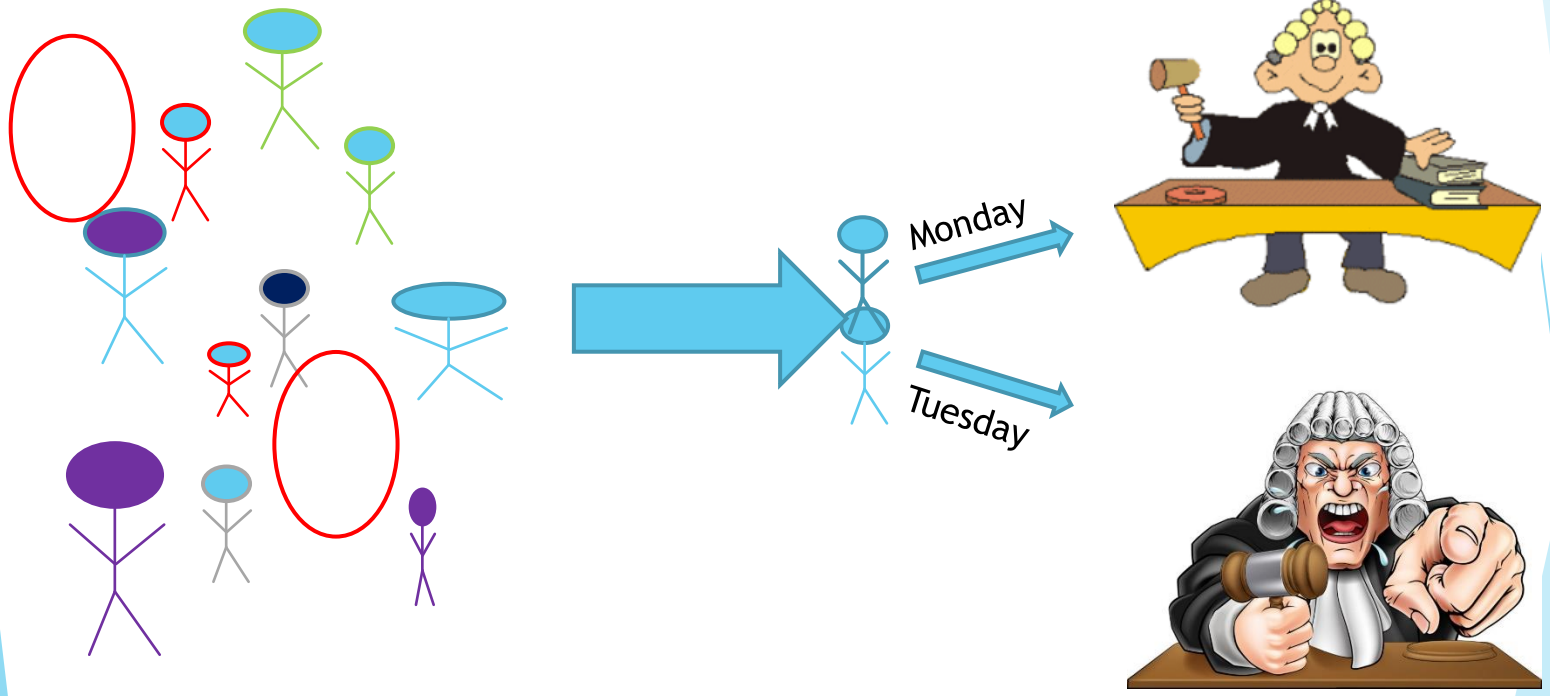
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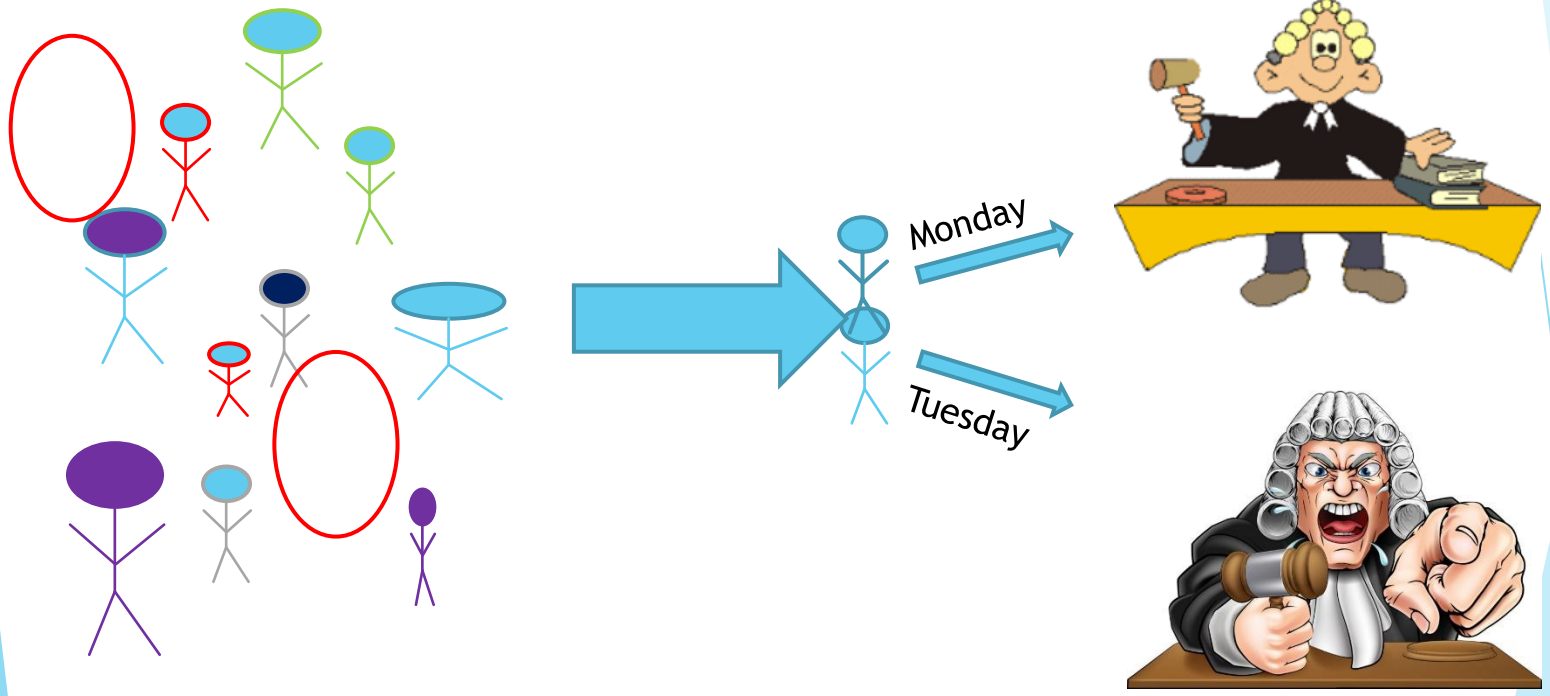

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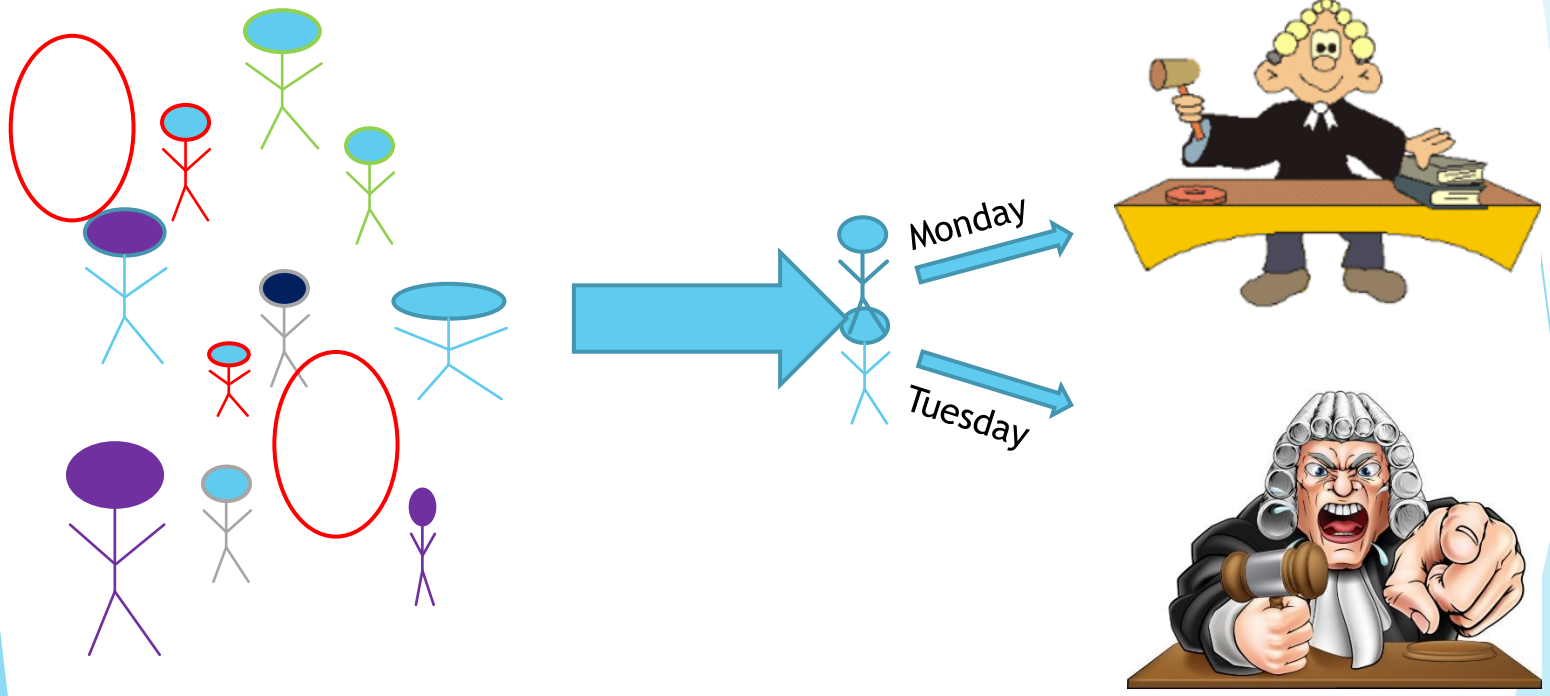

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- This is an improvement upon propensity score matching

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post-matching

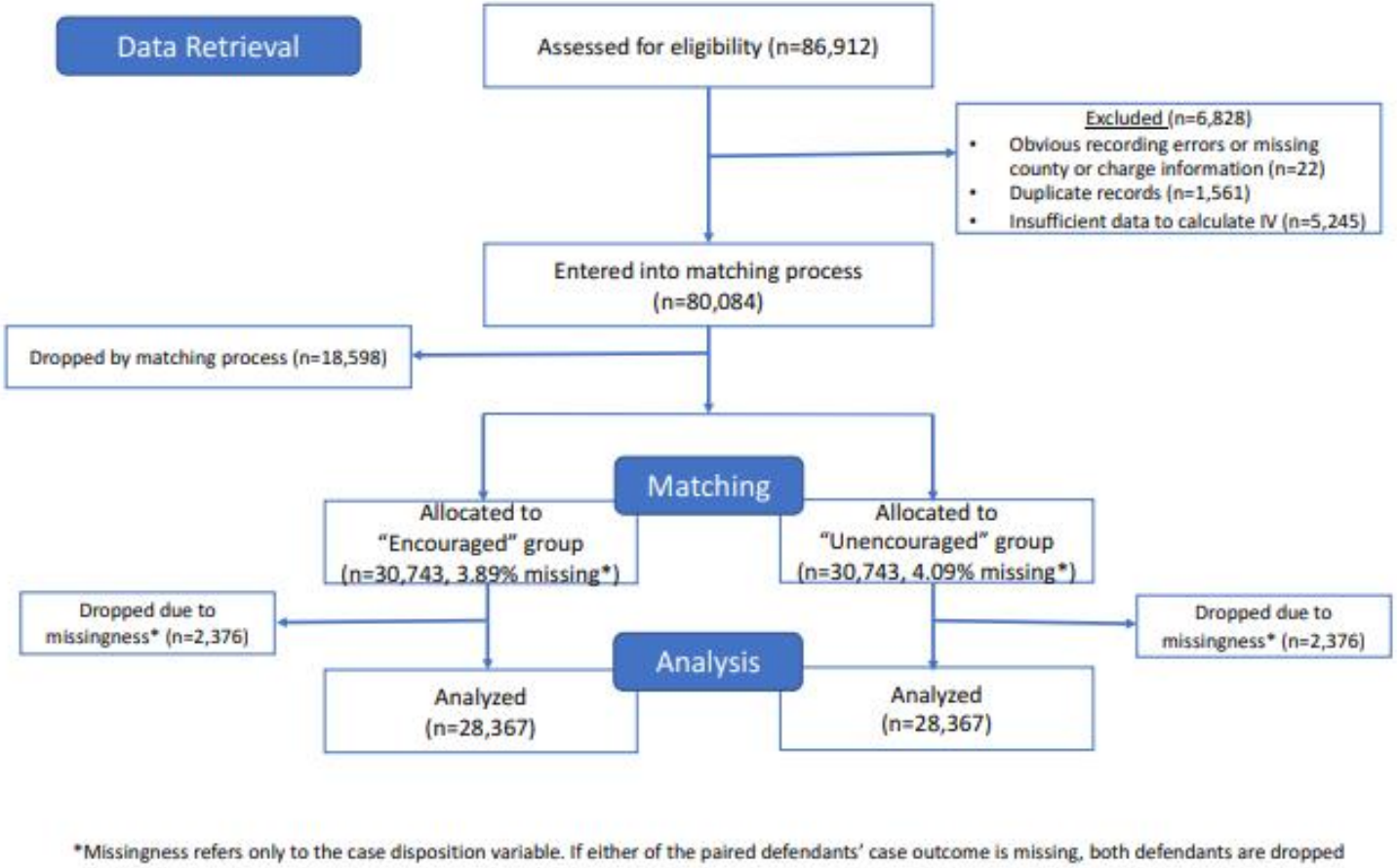

Figure 3: CONSORT flow diagram which shows the number of records dropped from the final analysis at each stage of the procedure.

pre-matching differences

	No Bail n=62826	Bail n=14057	Abs St Dif
Guilty	0.33	0.73	1.04
Bail Set	0.00	1.00	2.04
IV	0.01	-0.02	0.22
Age	31.93	35.94	0.32
White	0.29	0.28	0.02
Black	0.48	0.61	0.26
Non-Hispanic	0.63	0.66	0.08
Male	0.79	0.90	0.30
Prior Records 2014	0.38	1.36	0.70
Weekly Income	67.41	63.94	0.02
Any Income	0.15	0.14	0.02
Reported Employer	0.21	0.21	0.00
Reported Phone Number	0.18	0.19	0.04
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	Strict n=28367	Lenient n=28367	Abs St Dif
Guilty	0.41	0.40	0.03
Bail Set	0.21	0.16	0.12
IV	-0.07	0.07	1.18
Age	32.69	32.71	0.00
White	0.28	0.28	0.00
Black	0.52	0.52	0.00
Non-Hispanic	0.65	0.65	0.00
Male	0.81	0.81	0.00
Prior Records 2014	0.54	0.53	0.00
Weekly Income	53.00	52.75	0.00
Any Income	0.12	0.12	0.00
Reported Employer	0.17	0.17	0.00
Reported Phone Number	0.15	0.15	0.00
Reported Address	0.91	0.91	0.00

Table 5: Table of post-match standardized differences. Summary of data analyzed.

what happens next?

results and making a difference

results

results

Stratification	Stratum	Estimate	Lower	Upper	n	Signif
Aggregate	total	0.34	0.2	0.49	56734	*
County	New York	0.43	0.23	0.63	17010	*
	Kings	0.34	0.14	0.54	17936	*
	Bronx	-0.07	-0.52	0.33	7290	
	Queens	0.66	0.13	1.35	12174	*
	Richmond	0.88	0.11	2.89	2324	*
Crime Type	Felony	0.22	-0.12	0.58	8448	
	Misdemeanor	0.37	0.22	0.53	48286	*
Gender	Male	0.31	0.16	0.45	46118	*
	Female	0.65	0.12	1.27	10532	*

Table 6: Estimated causal impact of setting bail on judicial outcome

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If you had a 5% chance of “guilty” then bail would change that to 39%.

results

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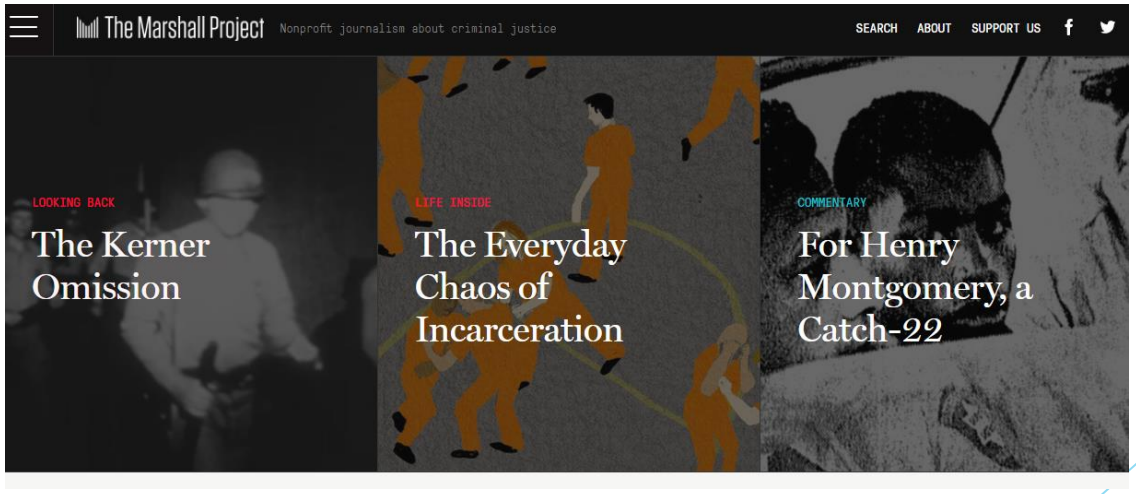

near-far matching

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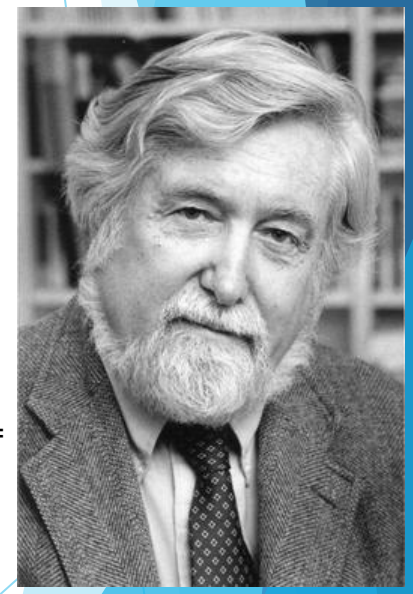
“thick description” =



Clifford Geertz

Did having bail set make you more likely to plead guilty?

Yes I believe so, because not being able to afford the bail money set, requires being remanded in county jail. Sitting in jail going back & forth to court with 2-3 months adjournments. After so many unjustified continuances time accumulating or frustrations wears out your resolve to fight for your freedom.

Did having bail set make you more likely to plead guilty?

At this point in my life No! Why? because this system has completed destroied my life, so really there's nothing left for them to take. We as a nation lock more people up for crime that have not even been committed and the blame is still on us.

Primary Contact:
Joshua Norkin
199 Water Street
New York, NY 10038
(212) 577-3509
jnorkin@legal-aid.org
www.legal-aid.org

MEMORANDUM OF SUPPORT

Comprehensive Bail Reform
A.09955 (Quart)

My bail was set at $25k, and I am a father of four, and only collect SSI disability. There is no way I could afford to take that money out of my kids mouth and still consider myself a decent man. - W.F., Legal Aid Client

Dear Legislator,

The Legal Aid Society supports A.09955 ("the Quart Bill"), and the New York State Assembly's efforts to reform our broken bail system. As you are well aware, Rikers Island and pretrial incarceration present an ongoing humanitarian crisis that requires urgent action.

In October 2017, Legal Aid released a ground-breaking report with the Human Rights Data Analysis Group and a Stanford University researcher on the impact that money bail has on our clients. The report definitively proved that New York's criminal justice system destroys the presumption of innocence. Specifically, the report found that "a strong causal relationship between setting bail and the outcome of a case for the [Legal Aid] clients. . . **setting bail results in a 34% increase in the chances that they will be found guilty.**" (Report found here: https://arxiv.org/pdf/1707.04666.pdf)

As part of this study, Legal Aid reached out to hundreds of our clients throughout New York to better understand how bail impacted their lives, their families, and their case. **Attached to this memorandum you will find 9 letters from Legal Aid clients detailing in vivid detail why the bail system must be reformed immediately.**

These stories are just one of many reasons why the Legal Aid Society strongly supports the Assembly's efforts to reform the system and the Quart Bill specifically. We remain opposed to the Governor's proposed bail legislation, which greatly expands the category of people eligible for remand, creates a presumption of detention, eliminates meaningful speedy trial release mechanisms, and permits courts to detain individuals for five days based on the mere request of the prosecutor—without any evidentiary showing or burden of proof.

Sincerely,

Justine Luongo
Attorney-in-Charge
Criminal Defense Practice
The Legal Aid Society

Sir Austin Bradford Hill

ENVIRONMENT AND DISEASE: ASSOCIATION OR CAUSATION?

Reprint with commentary

the criteria

The means of reasoning

- strength,
- consistency,
- specificity,
- temporality,
- biological gradient,
- plausibility,
- coherence,
- experiment,
- and analogy.

scorching hot takes still being served

- Phillips, C. and Goodman, K. (2004). The missed lessons of Sir Austin Bradford Hill. Epidemiologic Perspectives & Innovations, 1(1).
- Hofler, M. (2005). The Bradford Hill considerations on causality: a counterfactual perspective. Emerging Themes in Epidemiology, 2(1).
- Phillips, C. and Goodman, K. (2006). Causal criteria and counterfactuals; nothing more (or less) than scientific common sense. Emerging Themes in Epidemiology, 3(1).
- Hofler, M. (2006). Getting causal considerations back on the right track. Emerging Themes in Epidemiology, 3(1).

the criteria

- Strength: the observed association (e.g., correlation).
- Consistency: the relationship has been repeatedly observed by different persons, in different places, circumstances and times.
- Specificity: the association can be identified with particular people, locations, and outcomes.
- Temporality: cause precedes effect.
- Biological gradient: dose-response relationship.

the criteria

- Plausibility: biologically (physically, socially…) reasonable or probable.
- Coherence: does not conflict (too severely) with our present beliefs about related cause-and-effect relationships.
- Experiment: RCTs or observational studies to establish empirically rigorous associations.
- Analogy: the association is similar to existing associations, potentially sharing similar structures.

heuristics

- These are not presented as “rules” or “criteria” in the paper, rather they’re offered as ways of reasoning or moving toward taking action.
- This was a speech given to the first ever meeting of the occupational medicine group.
- A lot of times people talk about BH Criteria, they’ll introduce these as flawed. That’s fine. Impressionist paintings still help me think about light.

the criteria

- Several of these ideas have been modernized
  - Strength: sensitivity analysis
  - Consistency: reproducibility and meta-analysis
  - Specificity: treatment heterogeneity and transportability
  - Coherence: coherence statistics and the “known null” type designs
  - Analogy: transfer learning (in machine learning)

- It’s funny: he has a section in his paper where he rags on “t-tests.” Obscures decision making.

the criteria

- What is he trying to do?
- He’s trying to convince people.

Machine Learning

A NEW WAY OF REASONING ABOUT DATA

(PLAYER 2 HAS ENTERED THE GAME)

a principled prediction-problem ontology

modern algorithms

Blog \ Artifical intelligence \ Turing-NLG: A 17-billion-parameter language model by Microsoft

Turing-NLG: A 17-billion-parameter language model by Microsoft

February 13, 2020 | By Corby Rosset, Applied Scientist

How do we decide if this model is good?

do details help?

Pretraining T-NLG: Hardware and software breakthroughs

Any model with more than 1.3 billion parameters cannot fit into a single GPU (even one with 32GB of memory), so the model itself must be parallelized, or broken into pieces, across multiple GPUs. We took advantage of several hardware and software breakthroughs to achieve training T-NLG:

1. We leverage a NVIDIA DGX-2 hardware setup, with InfiniBand connections so that communication between GPUs is faster than previously achieved.

2. We apply tensor slicing to shard the model across four NVIDIA V100 GPUs on the NVIDIA Megatron-LM framework.

3. DeepSpeed with ZeRO allowed us to reduce the model-parallelism degree (from 16 to 4), increase batch size per node by fourfold, and reduce training time by three times. DeepSpeed makes training very large models more efficient with fewer GPUs, and it trains at batch size of 512 with only 256 NVIDIA GPUs compared to 1024 NVIDIA GPUs needed by using Megatron-LM alone. DeepSpeed is compatible with PyTorch.

The resulting T-NLG model has 78 Transformer layers with a hidden size of 4256 and 28 attention heads. To make results comparable to Megatron-LM, we pretrained the model with the same hyperparameters and learning schedule as Megatron-LM using autoregressive generation loss for 300,000 steps of batch size 512 on sequences of 1024 tokens. The learning schedule followed 3,200 steps of linear warmup up to a maximum learning rate of 1.5×10^{-4} and cosine decay over 500,000 steps, with FP16. We trained the model on the same type of data that Megatron-LM models were trained on.

the leaderboard

We also compared the performance of the pretrained T-NLG model on standard language tasks such as WikiText-103 perplexity (lower is better) and LAMBADA next word prediction accuracy (higher is better). The table below shows that we achieve the new state of the art on both LAMBADA and WikiText-103. Megatron-LM is the publicly released results from the NVIDIA Megatron model.

	LAMBADA (acc) strict	WikiText-103 (test adj. ppl)
Open AI GPT-2 1.5B	52.66 (63.24)*	17.48
Megatron-LM 8.3B	66.51	10.81
T-NLG 17B	67.98	10.21

*Open AI used additional processing (stopword filtering) to achieve higher numbers than the model achieved alone. Neither Megatron nor T-NLG use this stopword filtering technique.

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Basically every six months or so a group with a lot of money comes out with a bigger, better (?) language model

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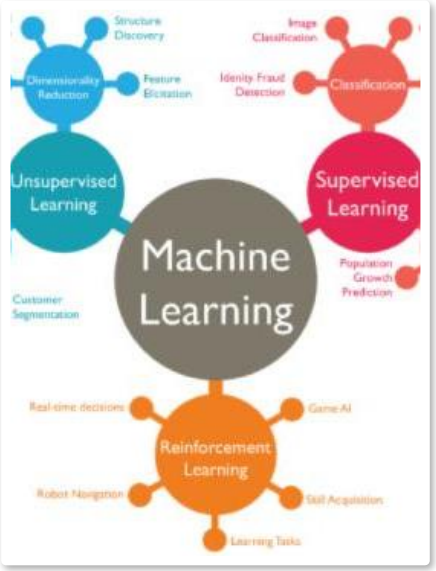
≈ February 2019

≈ September 2019

where we are at

prediction



setting the stage: prediction

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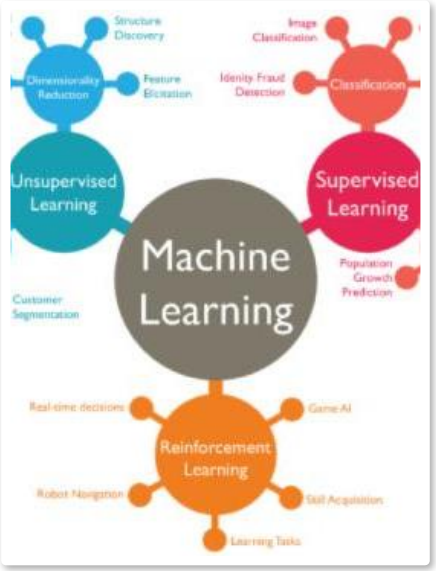
the common task framework

WTF is “the CTF”



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  - A hold out data set is reserved for evaluating performance

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- This has led to wildly complex algorithms which do not rely upon mathematical descriptions of how the algorithms take in variation from covariates and makes use of that variation to variation in the prediction space. ("**black box algorithms**")

what if something goes wrong?

the common task framework: errors post-deployment

- Without a mathematical understanding of how an algorithm links variation in X to variation in Y, we have limited options:

the common task framework: errors post-deployment

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the common task framework: errors post-deployment

- Without a mathematical understanding of how an algorithm links variation in X to variation in Y, we have limited options:
  - Sample more data and retrain.
    If it's black box then we don't know what parts of the covariate space are extrapolation and where to sample for maximal benefit.
  - Brute force patch.
  - Switch to new algorithm(s).
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the common task framework: errors post-deployment

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  - Add a human into the loop.

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    Boeing 737 Super Max: the algorithm kept fighting with the pilot. They've now added an override to give the pilot complete control after a major disagreement.

have we lost control of our analytics?

old thinking becomes new

- While any particular black-box algorithm is extraordinarily hard to understand…

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- While any particular black-box algorithm is extraordinarily hard to understand, what we realized is if we understand how they're developed then we can understand when they can be deployed.

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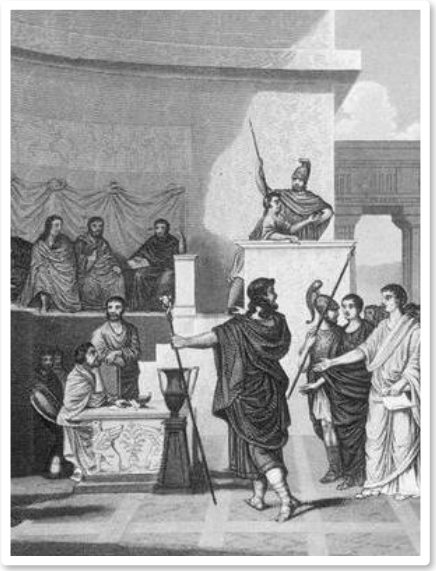
- The rest of the talk I'll offer a framework for guiding our thinking about whether or not a particular prediction problem is suitable for an algorithm that was developed purely under the CTF. That is, are the conditions right for a black box algorithm to be deployed into the real-world, where there are real consequences?

the principled prediction problem ontology

a framework for prediction



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  Given its dependence on stakeholders, we abbreviate: MARA(s)

MARA

examples

2) For some positive real number 'b',
$b - 1$, $b + 4$, $3b + 2$. What is the

a) 16
b) 20
c) 24
d) 28
e) 40

MARA:

MARA: example 1

MARA: example 1 – ad placement

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1. measurement
2. adaptability
3. resilience
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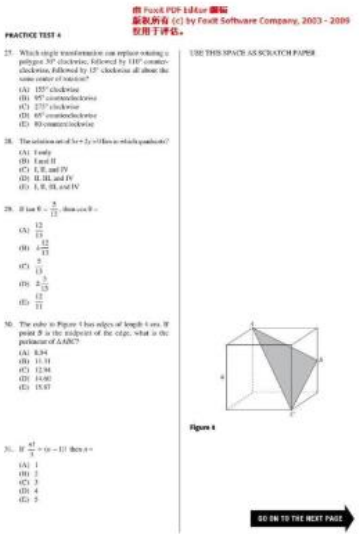

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仅用于评估。

PRACTICE TEST 4

27. Which single transformation can replace rotating a polygon 30° clockwise, followed by 110° counter-clockwise, followed by 15° clockwise all about the same center of rotation?
(A) 155° clockwise
(B) 95° counterclockwise
(C) 235° clockwise
(D) 65° counterclockwise
(E) 80 counterclockwise

28. The solution set of $5x + 2y > 10$ lies in which quadrant(s)?
(A) I only
(B) I and II
(C) I, II, and IV
(D) II, III, and IV
(E) I, II, III, and IV

29. If $\tan\theta = -\frac{5}{12}$, then $\cos\theta =$
(A) $\frac{12}{13}$
(B) $\pm\frac{12}{13}$
(C) $\frac{5}{13}$
(D) $\pm\frac{5}{13}$
(E) $\frac{12}{11}$

30. The cube in Figure 4 has edges of length 4 cm. If point B is the midpoint of the edge, what is the perimeter of $\triangle ABC$?
(A) 8.94
(B) 11.31
(C) 12.94
(D) 14.00
(E) 15.07

31. If $\frac{x^2}{3} = (x-1)^2$ then $x =$
(A) 1
(B) 2
(C) 3
(D) 4
(E) 5

USE THIS SPACE AS SCRATCH PAPER

Figure 4

GO ON TO THE NEXT PAGE

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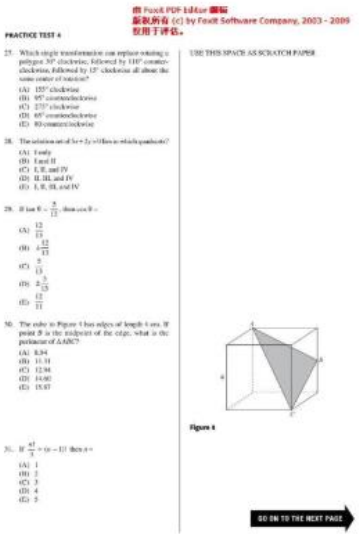

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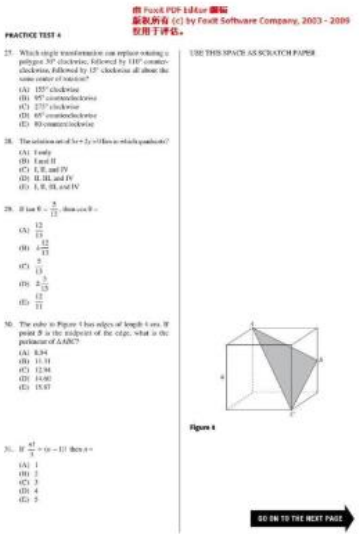

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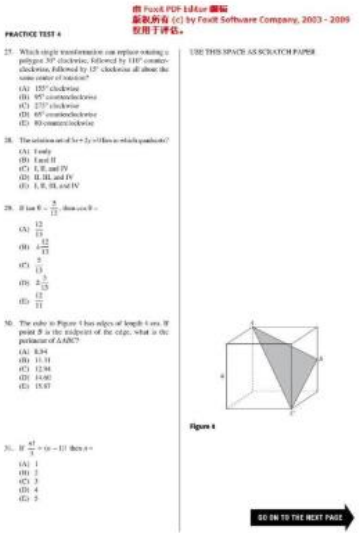

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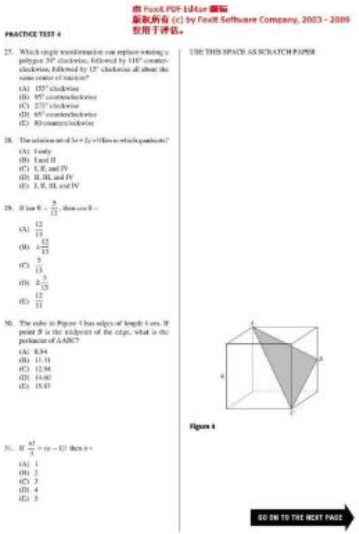

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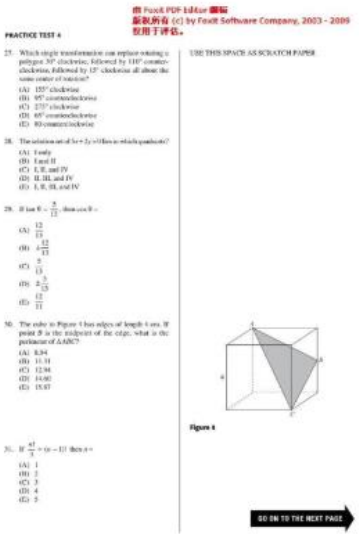

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But what if we change stakeholders?

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Changing stakeholders can change the loadings of the problem-features.

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This is common in text mining, but also "triaging" settings.

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(iii) We get things wrong, but maybe algorithms can do better.
(iv) Serious ethical issues.
What if algorithm tells you to lock up black men?

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If stakeholders include the accused as well:
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1. measurement
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2. adaptability
   yes
3. resilience
   no
4. agnosis
   no

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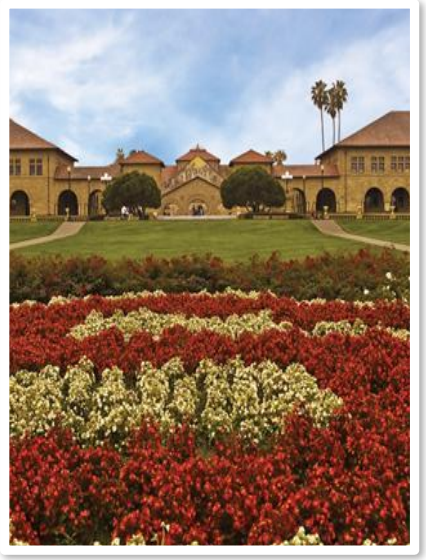
reasoning

outcome- vs model- reasoning



MARA: two types of reasoning

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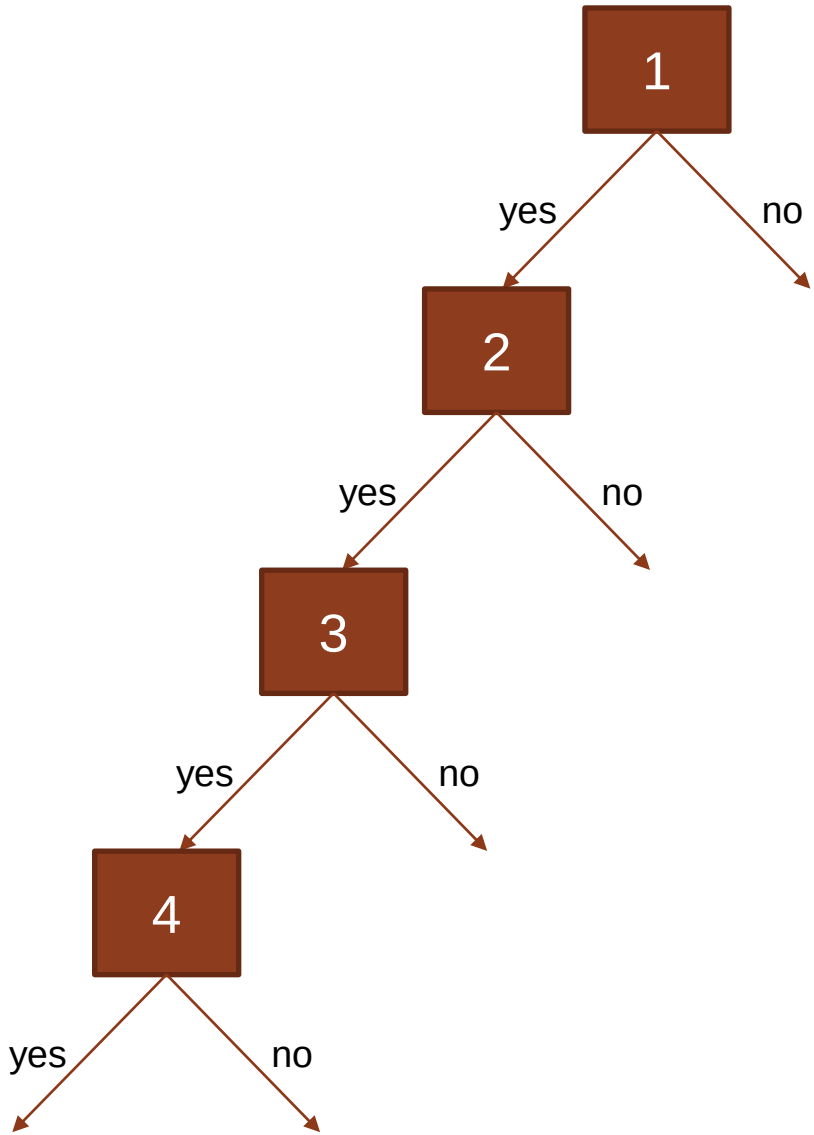
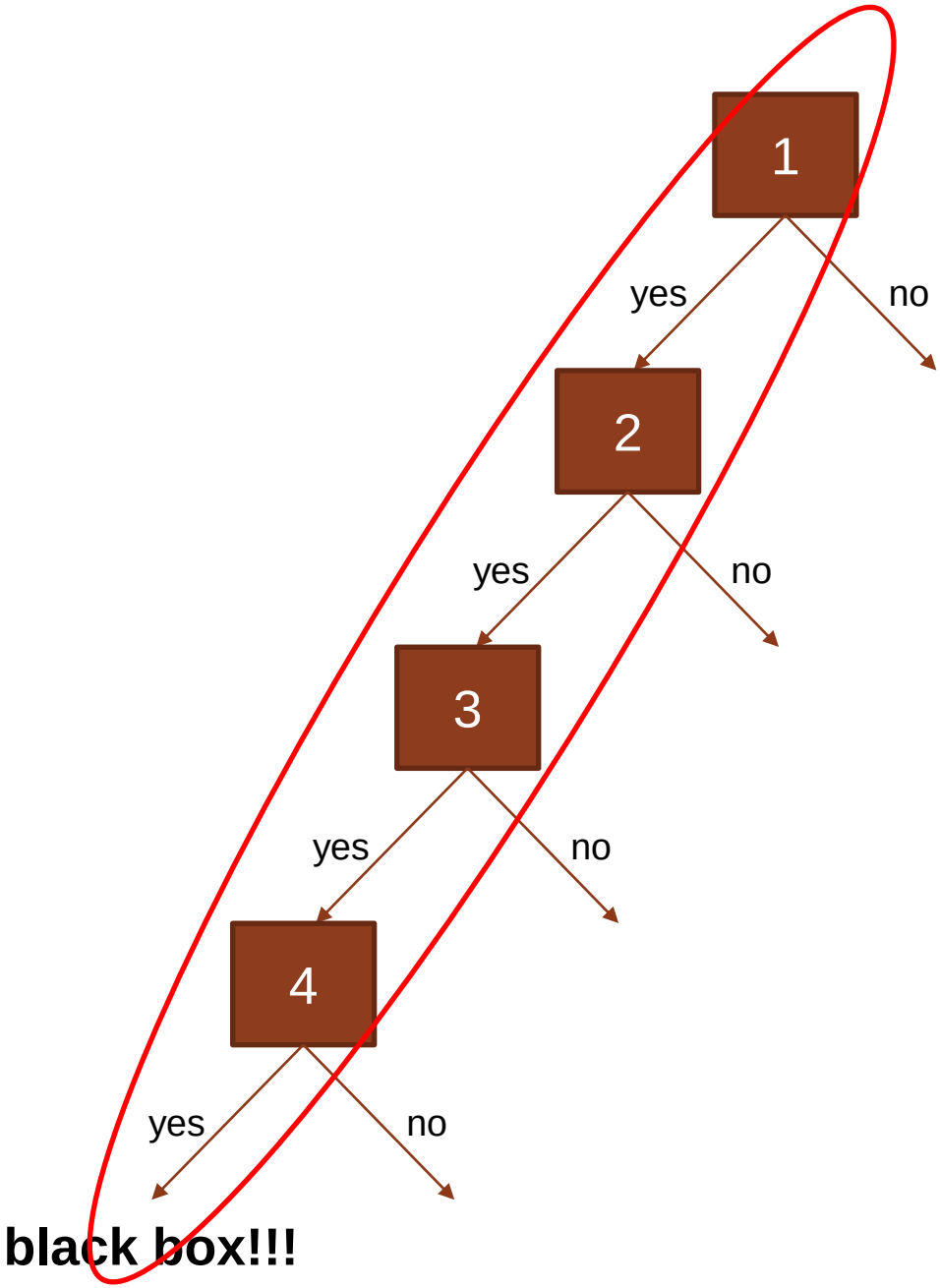
MARA



black box!!!

MARA



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Model reasoning: consider a linear regression with $\hat{\beta}_3 < 0$ but every randomized controlled study finds X_3 causes Y to increase.

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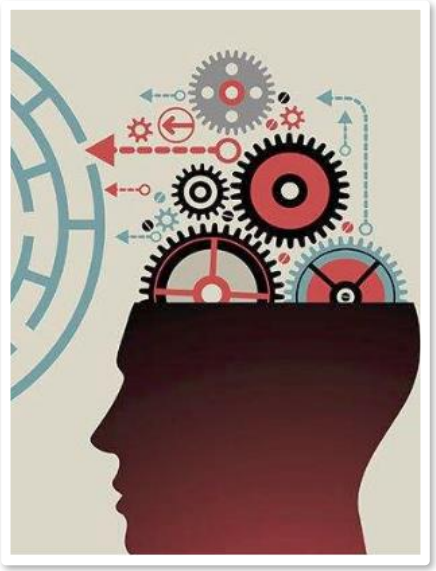
insights

final thoughts



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