Extracting Information from Awkward Datasets

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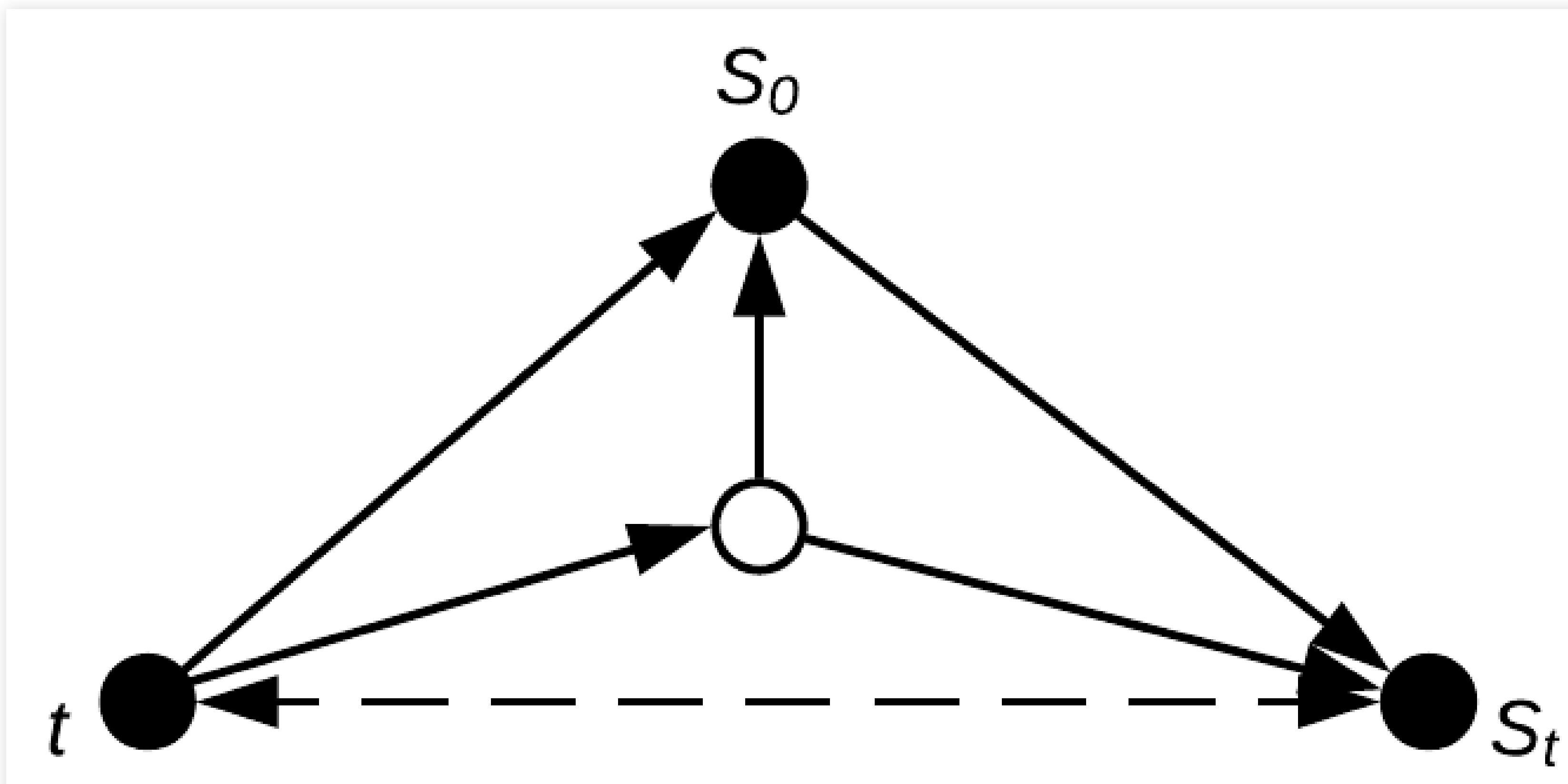
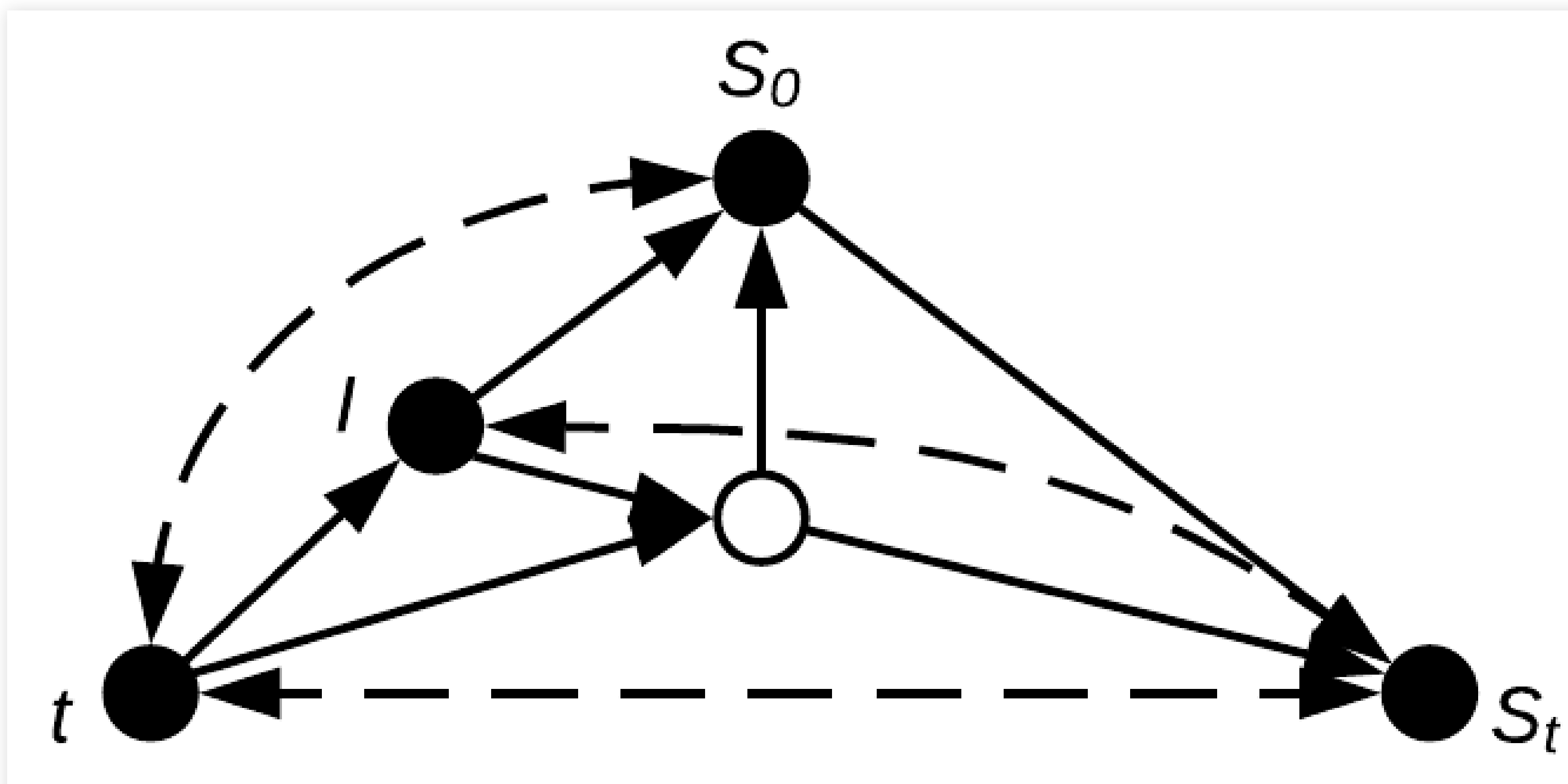
Modeling

- A patient P presents with initial state S_0, evolving under the influence of time t and an unmeasured confounding variable into S_t.[a]



Psychomotor Task Model

- An intervention I confounds the relationship of t, S_0, S_t, and the unmeasured variable in *predictable and unpredictable* ways.[b]



Data

- Filmed study participants during simulated case
- Two (2) raters reviewed footage
- Created a psychomotor event log for each case

t	event	code	state	result	notes
0.0	start				
56.0	drug	Fentanyl	bolus	100mcg	Stated ‘2.0mcg/kg’
97.0	drug	Lidocaine	bolus	70mg	
101.0	drug	Propofol	bolus	150mg	Stated ‘2mg/kg’
119.0	drug	Succinylcholine	bolus	70mg	Stated ‘1mg/kg’
160.0	laryngoscopy	start	manual		
192.0	eti	start			
212.0	laryngoscopy	stop	manual		
232.0	eti	stop			
243.0	ventilations	start	manual		
249.0	check	breath sounds		bilateral	
257.0	recognize	monitor	etCO2	active	
259.0	end				

Data Integrity

A minority of orderings are valid, and raters "blind" downstream consumers

- Essential items
  - Chronology, pairing of events
  - Coding and spelling
  - Drug dosing

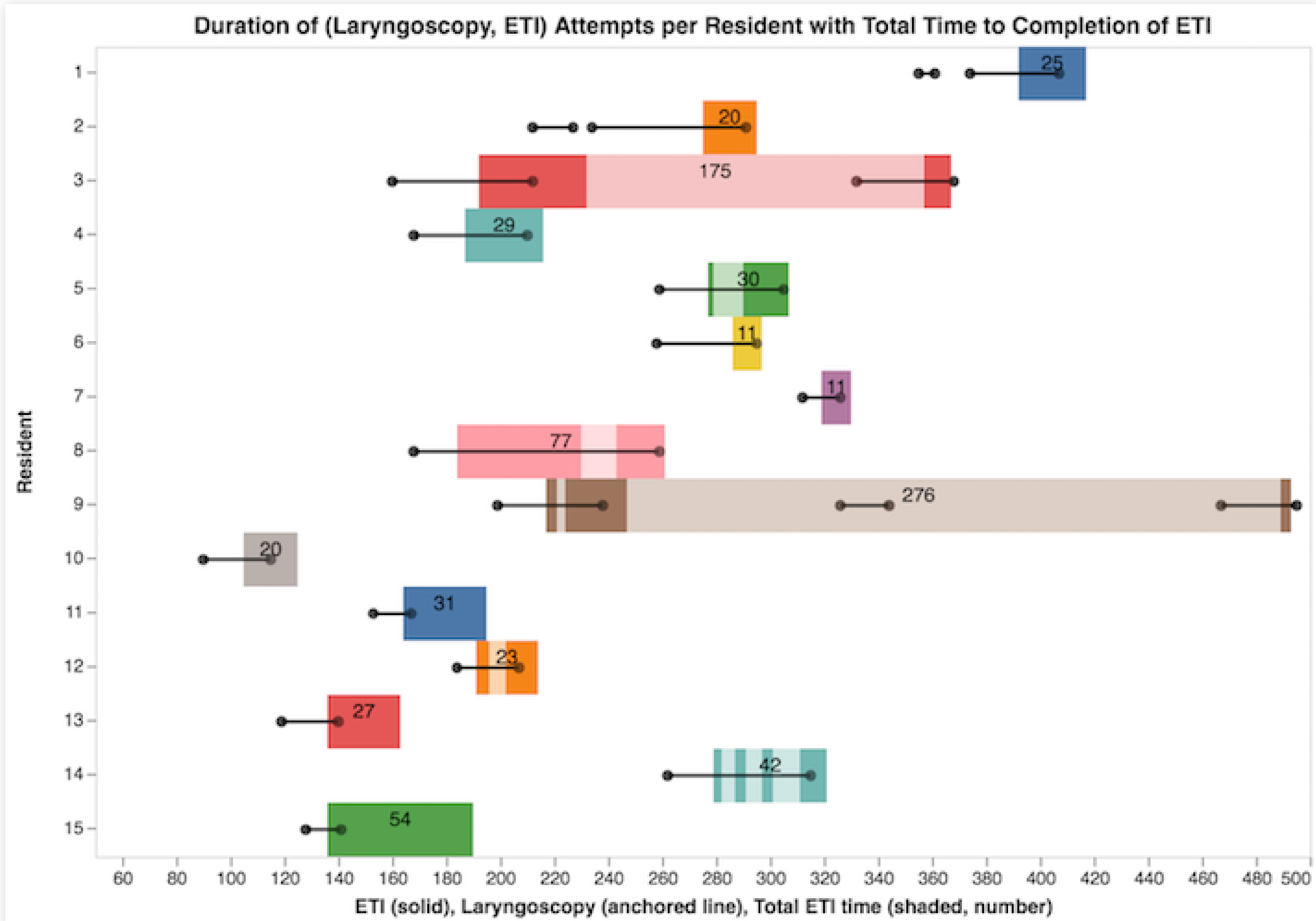
Key Algorithms

- `countunique`
  - Coding and spelling errors
  - Provides rough measure of set “orthodoxy”
  - Histograms, other frequency statistics
- `destructure`
  - Deconstructs `DataFrame` into `Array{Tuple{Symbol, Array}}`
- `tuplesbykey`
  - Extracts combinations

Pairing, coding and spelling errors

	event:code	count	representation		event:code	count	representation
1	ask:equipment	1	0.07	19	check:breath sounds	10	0.67
2	check:monitor	1	0.07	20	check:equipment	10	0.67
3	drug:Phenylephrine	1	0.07	21	preoxygenate:start	12	0.80
4	eti:adjust	1	0.07	22	preoxygenate:stop	12	0.80
5	recognize:eti	1	0.07	23	drug:Lidocaine	13	0.87
6	suction:start	1	0.07	24	drug:Succinylcholine	13	0.87
7	suction:stop	1	0.07	25	recognize:monitor	14	0.93
8	ask:monitor	2	0.13	26	end:missing	15	1.00
9	check:medications	2	0.13	27	start:missing	15	1.00
10	check:reflex	2	0.13	28	drug:Propofol	16	1.07
11	extubation:missing	2	0.13	29	ventilations:start	17	1.13
12	ventilations:stop	2	0.13	30	cricoid pressure:start	20	1.33
13	ask:patient	3	0.20	31	cricoid pressure:stop	20	1.33
14	cricoid pressure:switch	3	0.20	32	laryngoscopy:start	20	1.33
15	drug:Rocuronium	4	0.27	33	laryngoscopy:stop	20	1.33
16	ask:assistant	7	0.47	34	eti:stop	23	1.53
17	drug:Fentanyl	8	0.53	35	eti:start	24	1.60
18	recognize:fasciculations	9	0.60				

Chronology and pairing of events

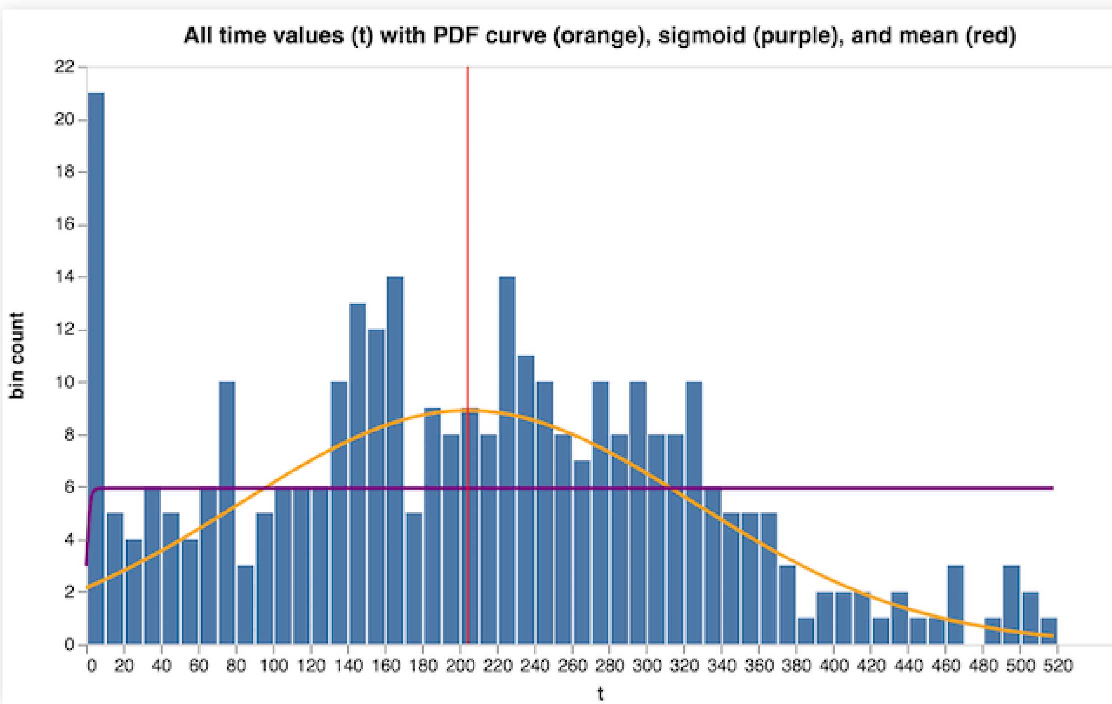


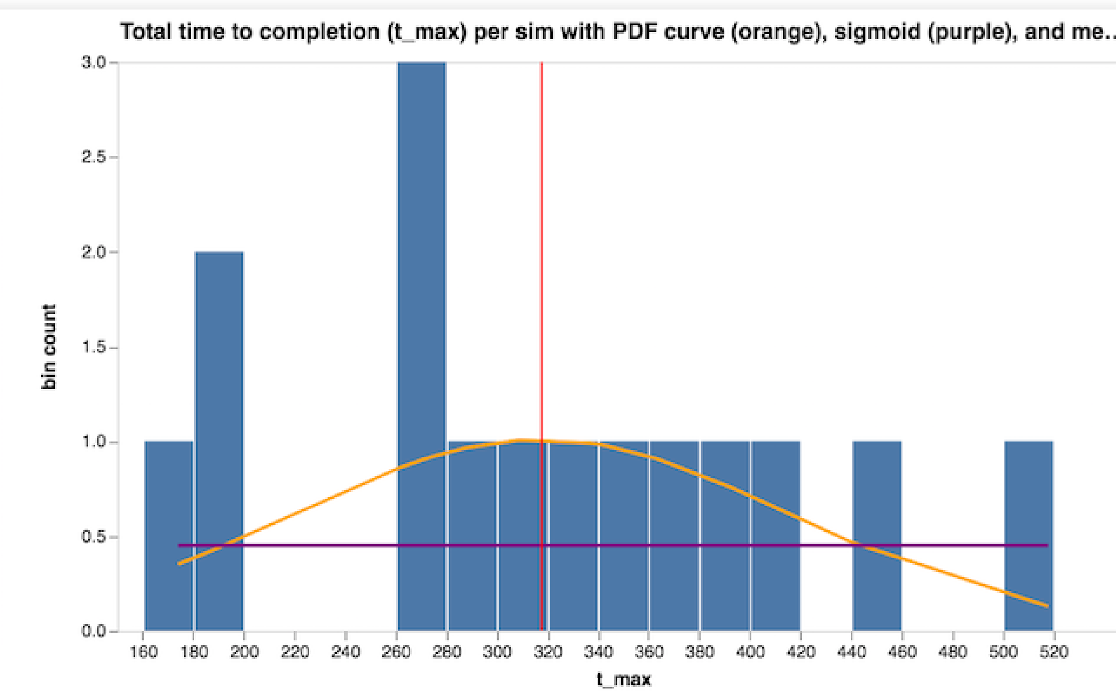
Hypotheses

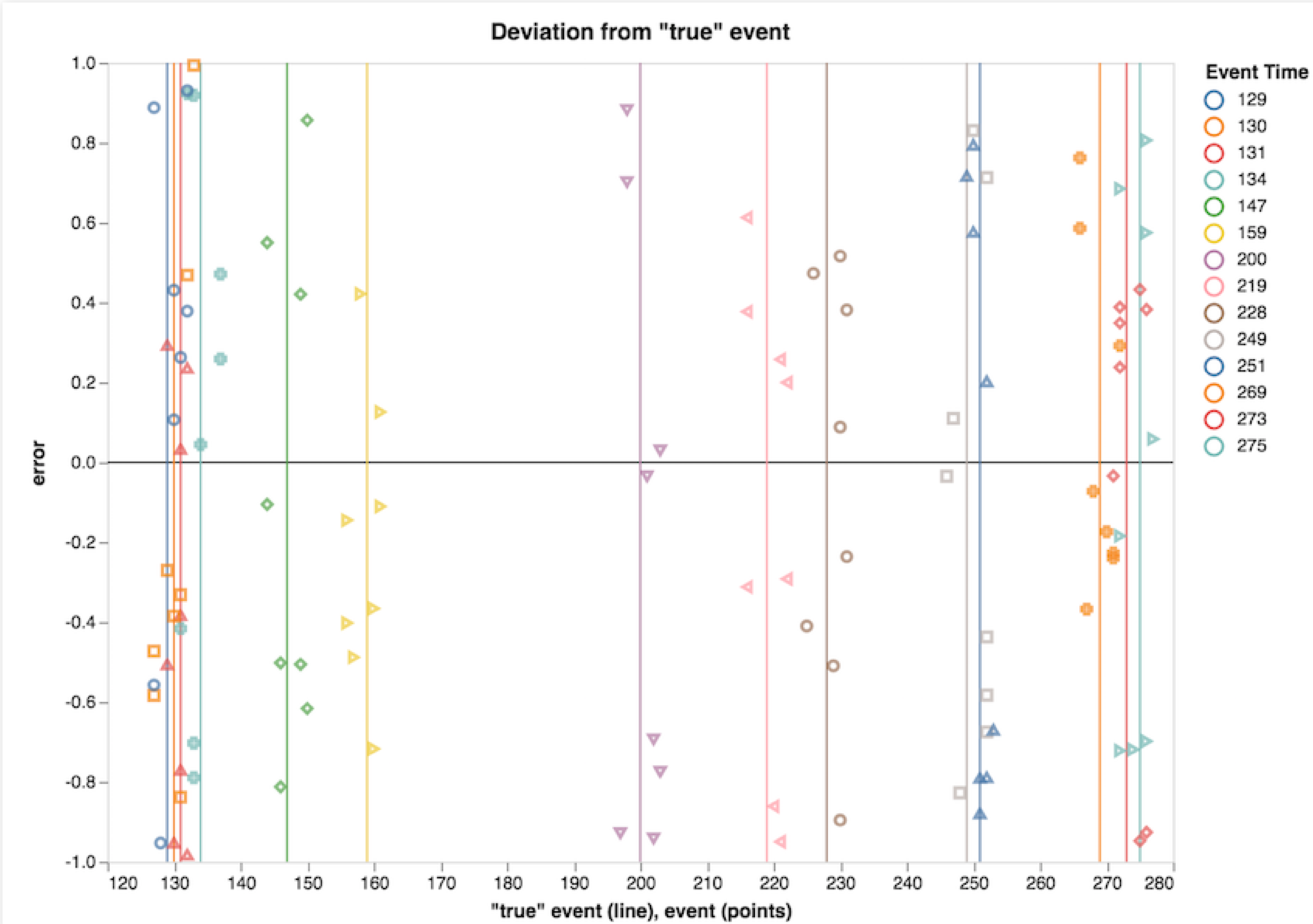
1. Increase in maximum time to completion is proportional to increase in risk of adverse events: $t_{max} \propto risk_{adv}$
2. Specifically, we believe the predominance of risk to the patient lies between the cessation of respirations and the reestablishment of effective ventilatory support.
   - Formally, that the mean risk of adverse events lies within the closed interval between a respiratory rate of 0 and the start of effective ventilatory support: $mean(risk_{adv}) \in [RR_0, vent_{eff}]$
3. The items with $representation > 1.0$ for the set (see table below) increase t_{max}, specifically
   - Number of laryngoscopy attempts
   - Number of ETI attempts
   - Number of ventilation attempts
   - Number of cricoid pressure attempts
4. The confounding influence of unmeasured variables will be greater in sets with higher t_{max}
5. The sequence of events preceding RR_0 correlates with the sequence events following it.

Statistics

	count	unique	missing	mean	minimum	1st	median	3rd	maximum	σ	σ^2	skew	kurtosis
t	325	223	0	204.27	0.00	122.00	206.00	290.00	518.00	121.10	14666.22	0.22	-0.44
t_{max}	15	15	0	317.60	174.00	266.50	309.0	378.00	518.00	98.77	9754.97	0.28	-0.59






Deviation from "true" event
error
"true" event (line), event (points)
Event Time
129
130
131
134
147
159
200
219
228
249
251
269
273
275
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
120
130
140
150
160
170
180
190
200
210
220
230
240
250
260
270
280

Validity

Given S_t, biomedicine can often predict a range of potential future states and assign a probability to most

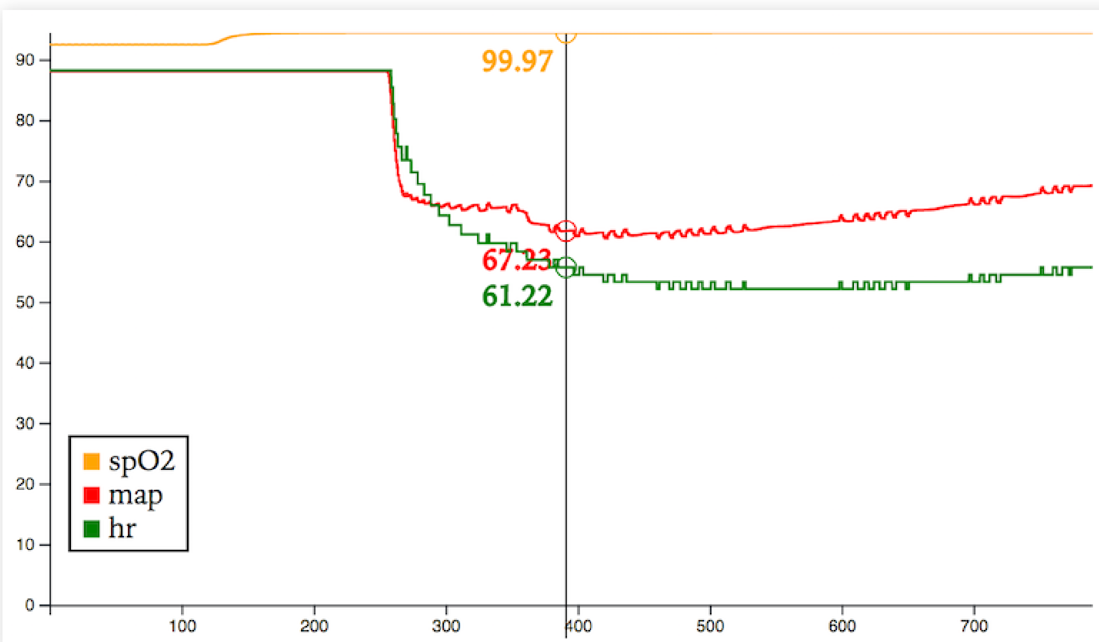
$$range((P_{S(t+n)_a}, S(t+n)_a) \rightarrow (P_{S(t+m)_{\dots}}, S(t+m)_{\dots}))$$

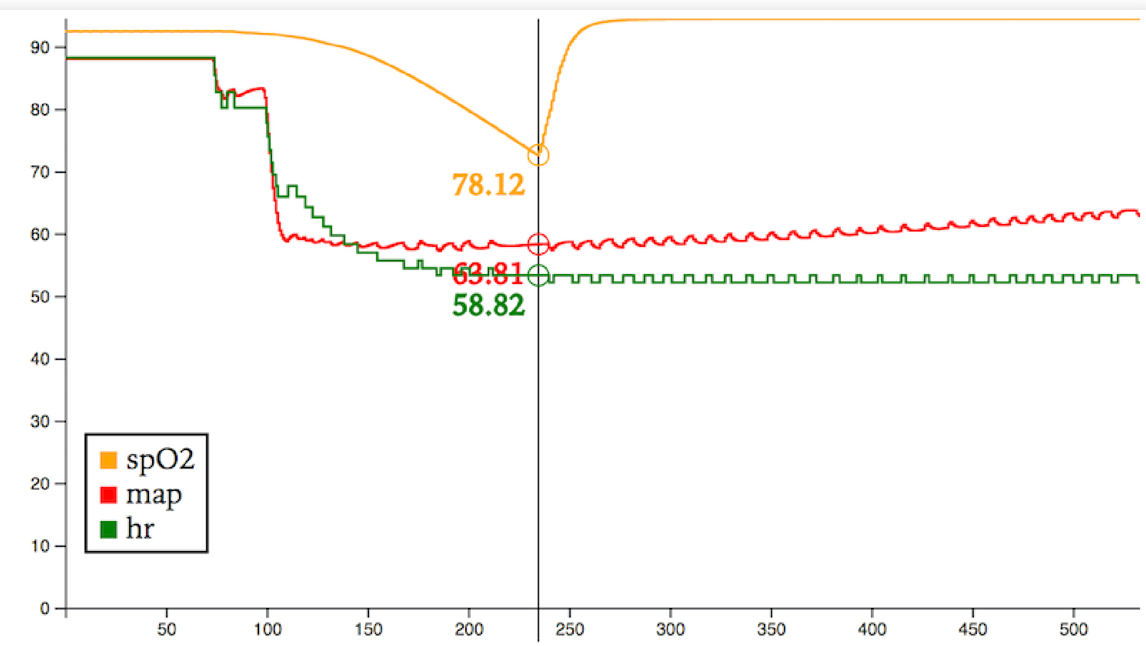
A well-curated set of heuristics for composing empirical evidence guides this process. ***Mechanical ones must match.***[c]

Next Steps

- Asserting meaningful causality from these data necessitates integrating metatdata
  - Clinical
  - Physiologic
  - Expert opinion
  - **Expert practice**
  - Biometric

BioGears Physiology Simulation Engine Output Plots





Machine Learning

- Data programming[1,2]
- Formalization in *do*-Calculus[3,4]
- Modeling of expert heuristic bias[5,6]
- Logical value of “data generation” techniques
- Models for integration of biometric, clinical, physiologic, and expert opinion and practice

Thank you!!

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Endnotes

[a] $S_0, \ldots, S_t$ are likely posets. Reflexivity and transitivity are relatively easy to demonstrate in the physical models of biomedicine. I suspect antisymmetry holds as well, but have not investigated this property.

[b] In biomedicine, it is helpful to understand all applications as partial.

[c] In essence, aggressive data collection and review has facilitated valid association of inputs with outputs, providing some way of calculating the "other end" of a black-box model given a left or right input.

References

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5. Taniguchi H, Sato H, Shirakawa T. A machine learning model with human cognitive biases capable of learning from small and biased datasets. *Scientific Reports*. 2018;8(1):7397. doi:10.1038/s41598-018-25679-z
6. Battaglia PW, Hamrick JB, Bapst V, et al. Relational inductive biases, deep learning, and graph networks. June 2018. https://arxiv.org/abs/1806.01261. Accessed October 2, 2018.