VIReC Database & Methods Cyberseminar Series

WEIGHT, WEIGHT … DO TELL ME!: Comparing algorithms to process and clean CDW weight data

April 6, 2020

Jenny Burns, Laura Damschroder, Richard Evans, Wyndy Wiitala

VA Center for Clinical Management Research

Ann Arbor Michigan

VA CCMR

Poll #1: Data User Role

What is your role?

- Research Investigator
- Methodologist
- Data Manager, Analyst or Programmer
- Project Coordinator
- Other – please describe via the Q&A function

Poll #2: Familiarity with VA weight data

How would you rate your **expertise in** VA **weight** data?

- **High** – Others regard me as an “expert”
- **Progress** – I have experience but am still learning
- **Little/no expertise**

DATA-DRIVEN CARE EVALUATION FOR PREVENTION

- Part of a larger study
- Systematic Literature Review

HOT ON THE PRESS!

Annis A, Freitag MB, Evans R, Wiitala WL, Burns J, Raffa SD, Spohr SA, Damschroder, L. Construction and use of body weight measures from administrative data in a large national health system: A systematic review. *Obesity*, *in press*.

OPERATIONAL PARTNERS

VA National Center for Health Promotion and Disease Prevention

- **Dr. Jane Kim**, Chief Consultant for Preventive Medicine
- **Dr. Michael Goldstein**, Associate Chief Consultant for Preventive Medicine
- **Dr. Sue Raffa**, National Program Director for Weight Management
- **Dr. Sophie Califano,** Deputy Chief Consultant for Preventive Medicine
- **Dr. Stephanie Spohr,** Program Analyst

COLLABORATORS

Durham VAMC
- **Dr. Gene Oddone**
- **Felicia McCant**

DCEP Technical Expert Panel

Indianapolis VAMC
- **Dr. Edward Miech**

OBJECTIVES

1) Compare algorithms for extracting and processing clinical weight measures from CDW databases.

2) Provide guidance and recommendations for choosing algorithms in research and evaluation.

Agenda

- **Background**
- Data Collection
- Algorithms
- Methods & Results
  - Descriptives
  - Weight as a Predictor
  - Weight Change
  - Weight Trajectories
  - Facility-Level Measures
- Findings & Recommendations
- Limitations
- Works in Progress
- Discussion/Q&A

BACKGROUND

- Rapid increase in the use of EHRs has made **vast amounts of clinical information** available for use.
- But, **issues** associated with utilizing EHR data for research & evaluation.
  - **Lack of control** over data definitions and data collection processes.
  - **Methodological challenges** associated with processing and transforming raw, messy EHR data.
- Calls for **increased transparency** regarding data cleaning efforts, methods to assess EHR data quality, and increased reporting and sharing of methods.

- Patient weight is an **important clinical measure.**
- **Frequently measured** resulting in many entries per patient over time.
- Weight can **vary substantially** within patient, may have differing **units**, and may be subject to data **entry errors.**
- **No standard** for processing and cleaning EHR weight.
- Researchers are left to develop their **own algorithms** to define weight, resulting in many different definitions in the published literature.
- Range from **simple** cut-offs for implausible values to more **computationally complex** algorithms requiring significant coding and processing capacity, as well as difficulties in replicating.

Unknown how resulting weight measures may vary based on how researchers process and clean the data, and subsequently, the impact of **algorithm choice on results and research findings is unknown.**

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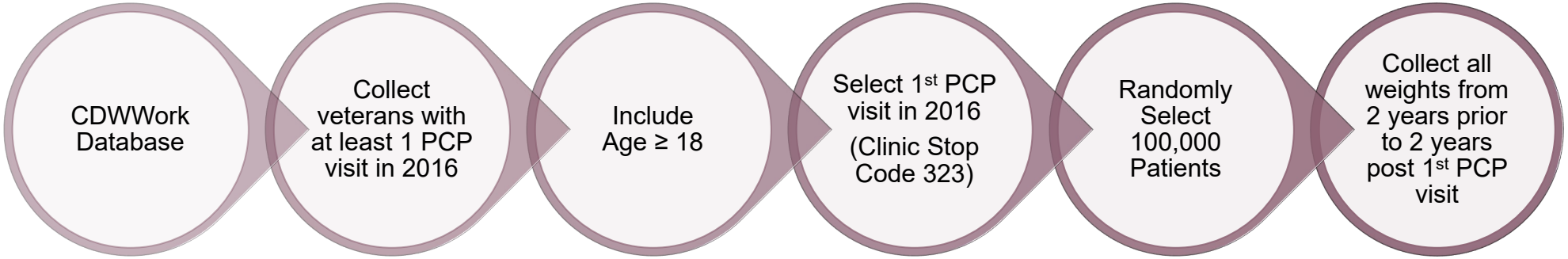
Data Collection – Cohort



Data Collection – Cohort

- SELECT patients FROM Outpat.Workload with a VisitDateTime in 2016 and WHERE Primary or Secondary clinic Stop Code = 323.
- DROP those where the Date of Birth on the Workload record calculates Age < 18.
- Randomly selected 100,000 of resulting patients.
- For each patient, SELECT their first (earliest) visit in the year. This is their Index Date.

Data Collection – Weight Data

- SELECT weight data FROM Vital.VitalSign, WHERE VitalType='Weight' AND VitalSignTakenDateTime is BETWEEN two years before and two years after the Index Date.

This is the "Raw Weight Data".

Data Collection – Exclusions

- Identified women who may have been pregnant during the 4 year time frame by searching for Pregnancy related diagnosis codes in Outpat.VDiagnosis and Inpat.InpatientDiagnosis.

These patients were excluded from the analysis.

Data Collection – Diabetes

- Identified Diabetes Status both 2 years before and 2 years after the index date by searching for diagnosis codes in Outpat.Vdiagnosis and Inpat.InpatientDiagnosis.

- Patients were required to have 2 or more outpatient <u>or</u> 1 inpatient diagnoses to be considered diabetic.

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ALGORITHMS

- Our team conducted a **systematic literature review** to identify studies that utilized patient weight outcome measures from the VHA CDW.
- We identified **39** published studies that used the CDW to define patient weight outcomes.
- Of the 39 studies, **33** included a **weight cleaning algorithm** that could be implemented and replicated in the current work.

ALGORITHMS

We present **12 representative algorithms** here and provide details about the remaining algorithms in the Supplement and within our GitHub repository (github.com/ccmrcodes/WeightAlgorithms).

ALGORITHMS

We divided the 12 algorithms into two conceptual groups:

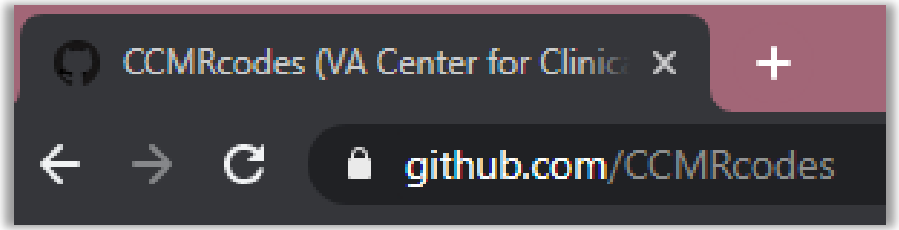
1) Those that include **all weight measurements** during a specified timeframe
2) Those that are **time-period specific**

- **Time-period specific algorithms** selected "baseline, 6-month, and 12-month" **time-periods** and included weight measurements during specified **windows** around those dates.
- Note not all algorithms fit exactly into these groups. For instance, we classified the algorithm utilized in Noel *et al.* 2012 as a "time-period specific" algorithm since it is based on fiscal quarters, but it utilizes all data within each quarter to define median weights.

Table 1. Conceptual Description of Main Exclusions After Applying Each Algorithm

All Weight Measures		Time-Period Specific	
Algorithm	**Exclusion**	**Algorithm**	**Exclusion**
Buta 2018	Patients with ≤ 1 weight value BMI < 11 or > 70	Rosenberger 2011	Patients with < K number of weight measures, K chosen by researcher Weights outside of 6-month time points
Chan 2017	Weights < 50 lb. or > 750 lb. Weights > 3 SD from mean	Noel 2012	Weights ≤ 70 lb. or ≥ 700 lb. Patients with too few values to compute median within fiscal quarters
Maguen 2013	Weights < 70 lb. or > 700 lb. Weight values where absolute value of conditional residual from linear mixed model ≥ 10	Kazerooni 2016	Weights outside of windows around 3 time periods Patients missing data in any of the 3 time periods
Breland 2017	Weights < 75 lb. or > 700 lb. Weight values that fall outside of specific ratios calculated within patient over time	Jackson 2015	Weights < 75 lb. or > 700 lb. Weights outside of 90-day windows of each time-point
Maciejewski 2016	Weight values associated with large SDs calculated on a rolling basis	Goodrich 2016	Weights < 80 lb. or > 500 lb. Patients with > 100 lb. change between time periods (baseline, 6- and 12-months) Weights outside of 30-day windows for each time point
Littman 2012	Weights < 75 lb. or > 600 lb. Weights where difference from mean > SD Weights where SD was > 10% of the mean	Janney 2016	Weights < 91 lb. or > 600 lb. at baseline Weights outside of 30-day windows of baseline, 60-day windows of 6- and 12-months Weights resulting in > 100 lb. change during study

ALGORITHMS in Github



Overview | **Repositories** 14 | Projects 0 | Packages 0 | Stars 0

Find a repository...

Late-Vasopressor

SAS Updated on Jan 31

Spoon-Knife

Forked from octocat/Spoon-Knife

This repo is for demonstration purposes only.

HTML 108,622 Updated on Jan 14

WeightAlgorithms

DCEP Project - Weight Algorithm Development, Evaluation, and A

SAS Updated on Jan 9

DCEP Project - Weight Algorithm Development, Evaluation, and Analyses

Manage topics

11 commits 1 branch 0 packages 0 releases

Branch: master New pull request Create new file Upload files Find file

CCMRcodes Update README.md Latest com

ClinicalCodes	Add Bariatric and Preg Dx
R	Added R Algorithms
SAS	Added SAS Algorithms
SQL	Create .gitkeep
Stata	Added Stata Facility Analyses
README.md	Update README.md

README.md

Weight Algorithms

DCEP Project - Weight Algorithm Development, Evaluation, and Analyses

Repository for the (in progress) publication, "Development of Standard Algorithms for Weight Outcomes (VHA) Administrative Data."

CCMRcodes / WeightAlgorithms

Unwatch

Code | Issues 0 | Pull requests 0 | Actions | Projects 0

Branch: master

WeightAlgorithms / R /

CCMRcodes Added R Algorithms

..

.gitkeep	C
Breland2017.R	A
Buta2018.R	A
Chan2017.R	A
Goodrich2016.R	A
Jackson2015.R	A
Kazerooni2016.R	A
Littman2012.R	A
Maguen2013.R	A
MeasureRemoveOutliers.R	A
MeasureWindows.R	A
Noel2012.R	Added R Algorithms
Rosenberger2011.R	Added R Algorithms

92 lines (82 sloc) | 3.75 KB

```
#-----------------------------------------------------------------------------#
# US Dept. of Veterans Affairs - Corporate Data Warehouse
# Weight Measurement "Cleaning" Algorithm - Maguen et al. 2013 version
#
# Author: Richard Ryan Evans
# Development Start Date: 11/07/2018
#
# Rationale: For grouped time series, (e.g., per person)
#            remove outliers, then model patients weight trajectories with
#            a linear mixed model with a random slope and intercept, adjusted
#            for age and gender, then remove measurements where the residual
#            meets a certain threshold. Based on work by Maguen et al. 2013
#-----------------------------------------------------------------------------#

#' @title Maguen 2013 Measurment Cleaning Algorithm
#' @param DF object of class data.frame, containing id and measures
#' @param id string corresponding to the name of the column of patient IDs in DF
#' @param measures string corresponding to the name of the column of measurements in DF
#' @param tmeasures string corresponding to the name of the column of measurement collection dates
#' @param outliers object of type 'list' with numeric inputs corresponding to the upper and lower
#' @param variables character vector describing the terms in `DF` to include on the RHS of the int
#' @param ResidThreshold single numeric value to be used as a cut off value for the conditional (
#' @param ... any number of named arguments for the lme4::lmer model
Maguen2013.f <- function(DF,
                         id,
                         measures,
                         tmeasures,
                         outliers = list(LB = 70, UB = 700),
                         variables,
```

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METHODS & RESULTS

Common use of weight measures in research & evaluation

- **Descriptive**
- As a **Predictor** in studies that seek to adjust for the effect of baseline weight when examining the association between another variable and an outcome
- Weight **Change** in studies examining the effects of an independent variable on patient weight or weight change over time
- Patient weight **Trajectories**
- **Facility-Level Effects** in studies examining performance measures across facilities, groups, clusters.

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METHODS

DESCRIPTIVE STATISTICS

All algorithms were applied to the data for each of the two cohorts and **compared based on descriptive statistics**, including the number of measures and patients retained, the mean, standard deviation, median, and range of weight values.

For comparison, we also included the descriptives based on the raw, unprocessed weight data during the timeframe.

RESULTS: DESCRIPTIVES

Algorithm	N pts. Retained (% of Raw)	N Weights Retained (% of Raw)	Mean (SD)	Range (Min, Max)
Raw Weights	98,958 (100)	1,175,995 (100)	207.82 (48.60)	(0, 2423)
Utilize All Data				
Buta (2018)	90,159 (91.1)	1,131,996 (96.3)	207.91 (48.29)	(60, 540)
Chan (2017)	96,132 (97.4)	1,170,114 (99.5)	207.86 (48.27)	(54, 727)
Maguen (2013)	98,352 (99.4)	1,037,293 (88.2)	205.58 (46.37)	(70, 541)
Breland (2017)	98,958 (100)	1,175,177 (99.9)	207.85 (48.25)	(75, 694)
Maciejewski (2016)	98,958 (100)	1,146,995 (97.5)	208.08 (48.13)	(62, 546)
Littman (2012)	96,130 (97.1)	1,161,661 (98.8)	207.97 (48.14)	(75, 546)
Time-Period Specific				
Rosenberger (2011)	63,405 (64.1)	227,215 (19.3)	207.80 (46.23)	(0, 1314)
Kazerooni (2016)	23,987 (24.2)	71,961 (6.1)	209.00 (47.95)	(0, 1233)
Goodrich (2016)	95,748 (95.7)	199,803 (17.0)	206.13 (45.42)	(80, 500)
Janney (2016)	95,742 (96.8)	199,830 (17.0)	206.15 (45.46)	(78, 546)
Jackson (2015)	96,559 (97.6)	251,501 (21.4)	206.31 (45.52)	(76, 553)
Noel (2012)	98,958 (100)	683,008 (58.1)	207.25 (46.13)	(70, 588)

RESULTS: DESCRIPTIVES (CONT.)

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KEY TAKEAWAYS

SIMPLE DESCRIPTIVE STATISTICS

- Despite cleaning efforts, **implausible values remain** in the data.
- For large cohorts of patients, the loss of data due to algorithm choice does not appreciably change the overall mean and variance.

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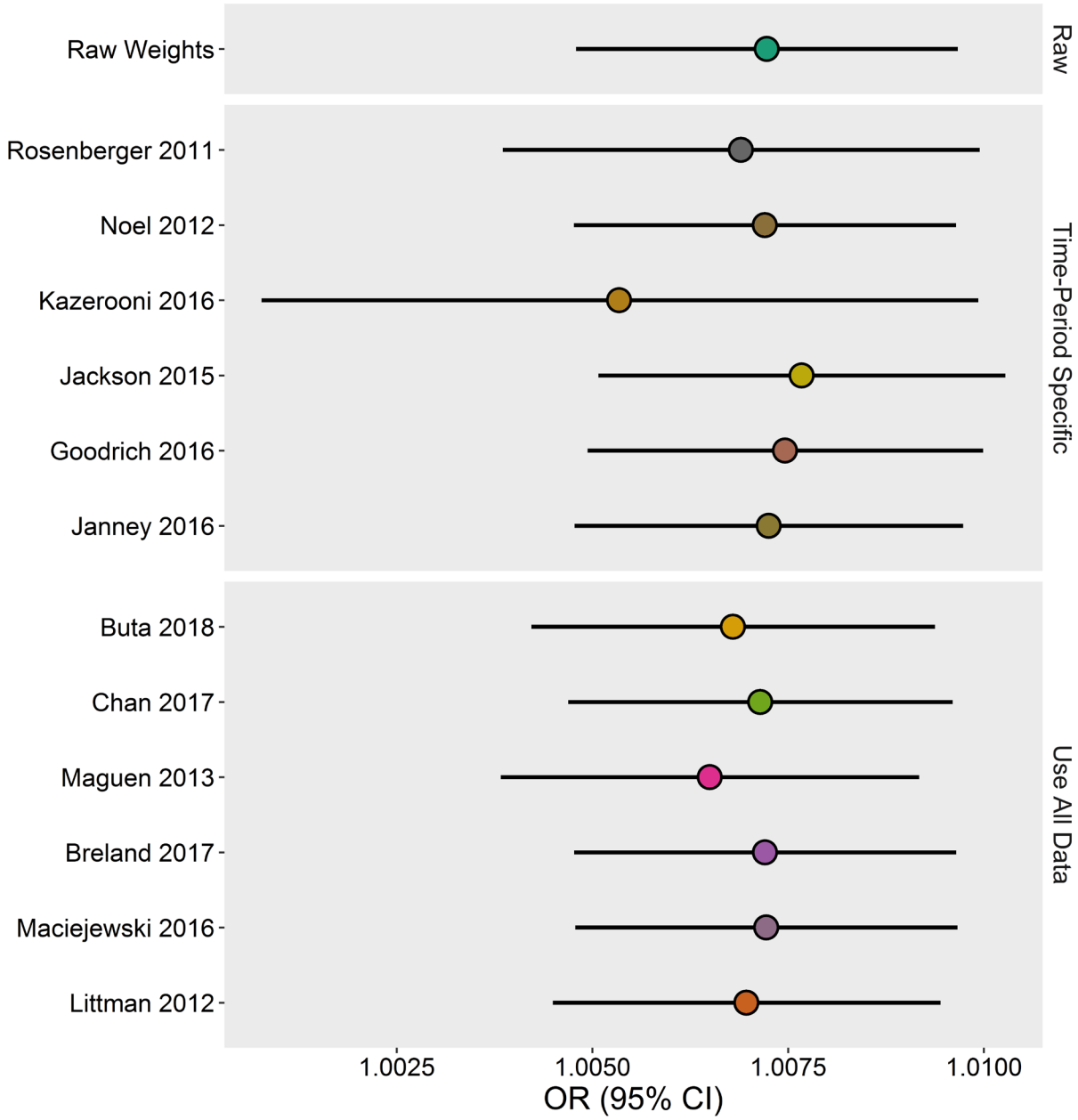
METHODS

WEIGHT AS A PREDICTOR

- To compare algorithms in this context, we present an example showing the **association between baseline weight and "new-onset" diabetes**.
- We excluded patients with diabetes prior to the study index date and we defined new-onset diabetes as the presence of two or more diabetes diagnosis codes after the patient's index date.
- We **applied each of the 12 algorithms to create baseline weight measures** for the patients in our four cohorts, using weight measurements that occurred during a 60-day window on or before the index date.
- The resulting baseline weight measure was the measurement that occurred on the closest day to the index date.
- We used **separate logistic regression models** to obtain odds ratios for the effect of patient weight on new-onset diabetes.

RESULTS: WEIGHT AS A PREDICTOR



KEY TAKEAWAYS

WEIGHT AS A PREDICTOR

- Relatively **small differences** in effect size.
- Across algorithms, 95% CIs overlap substantially; however, **some of the time-period specific algorithms have greater variation**.

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METHODS

WEIGHT CHANGE OUTCOME

- A common metric used in weight loss studies involves one-year **weight loss ≥ 5%**.
- Similarly, we examined **≥ 5% weight gain.**
- To compare algorithms on this metric, we applied each algorithm to our cohorts.
- We used a **60-day window** to definite initial weight values and included the weight measurement taken on the closest day to the index date. To define one-year follow-up weights, we again used a 60-day window around the date one year after baseline, keeping the closest weight measurement.

RESULTS: WEIGHT CHANGE OUTCOME

	Patients Retained*	Weight loss ≥ 5% from baseline	Weight gain ≥ 5% from baseline
	N (%)	N (%)	N (%)
Raw Weights	60,286 (60.9)	8,162 (13.5)	6,977 (11.6)
Utilize All Data			
Buta 2018	57,014 (57.6)	7,762 (13.6)	6,642 (11.6)
Chan 2017	60,175 (60.8)	8,069 (13.4)	6,902 (11.5)
Maguen 2013	52,642 (53.2)	4,933 (9.4)	4,088 (7.8)
Breland 2017	60,225 (60.9)	8,124 (13.5)	6,936 (11.5)
Maciejewski 2016	58,457 (59.1)	7,985 (13.7)	6,810 (11.6)
Littman 2012	59,773 (60.4)	7,851 (13.1)	6,787 (11.4)
Time-Period Specific			
Rosenberger 2011	38,875 (39.3)	5,425 (14.0)	4,725 (12.2)
Noel 2012	58,525 (59.1)	7,786 (13.3)	6,624 (11.3)
Kazerooni 2016	23,987 (24.2)	3,355 (14.0)	2,503 (10.4)
Jackson 2015	59,770 (60.4)	7,973 (13.3)	6,494 (10.9)
Goodrich 2016	58,142 (58.8)	7,828 (13.5)	6,668 (11.5)
Janney 2016	58,171 (58.8)	7,842 (13.5)	6,679 (11.5)

* Number of patients retained after applying the algorithm. Denominator = 98,958 (number of veterans in 2016 cohort)

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Kazerooni 2016	23,987 (24.2)	3,355 (14.0)	2,503 (10.4)
Jackson 2015	59,770 (60.4)	7,973 (13.3)	6,494 (10.9)
Goodrich 2016	58,142 (58.8)	7,828 (13.5)	6,668 (11.5)
Janney 2016	58,171 (58.8)	7,842 (13.5)	6,679 (11.5)

* Number of patients retained after applying the algorithm. Denominator = 98,958 (number of veterans in 2016 cohort)

RESULTS: WEIGHT CHANGE OUTCOME

	Average Weight Change from Baseline (lbs.)	
	Mean (SD)	**[Min, Max]**
Raw Weights	-0.29 (16.10)	[-1006, 1069]
Utilize All Data		
Buta 2018	-0.60 (12.01)	[-245, 278]
Chan 2017	-0.58 (11.95)	[-510, 278]
Maguen 2013	-0.37 (7.78)	[-73, 98]
Breland 2017	-0.60 (11.54)	[-259, 207]
Maciejewski 2016	-0.61 (11.26)	[-117, 195]
Littman 2012	-0.49 (10.76)	[-118, 108]
Time-Period Specific		
Rosenberger 2011	-0.68 (14.14)	[-1002, 298]
Noel 2012	-0.57 (11.48)	[-245, 195]
Kazerooni 2016	-0.95 (12.44)	[-534, 299]
Jackson 2015	-0.70 (11.31)	[-245, 230]
Goodrich 2016	-0.60 (11.51)	[-117, 205]
Janney 2016	-0.61 (12.03)	[-291, 281]

KEY TAKEAWAYS

WEIGHT CHANGE

- Weight gain and loss proportions are fairly **consistent** across algorithms.
- **Implausible values remain** even after applying a - possibly complicated - algorithm.

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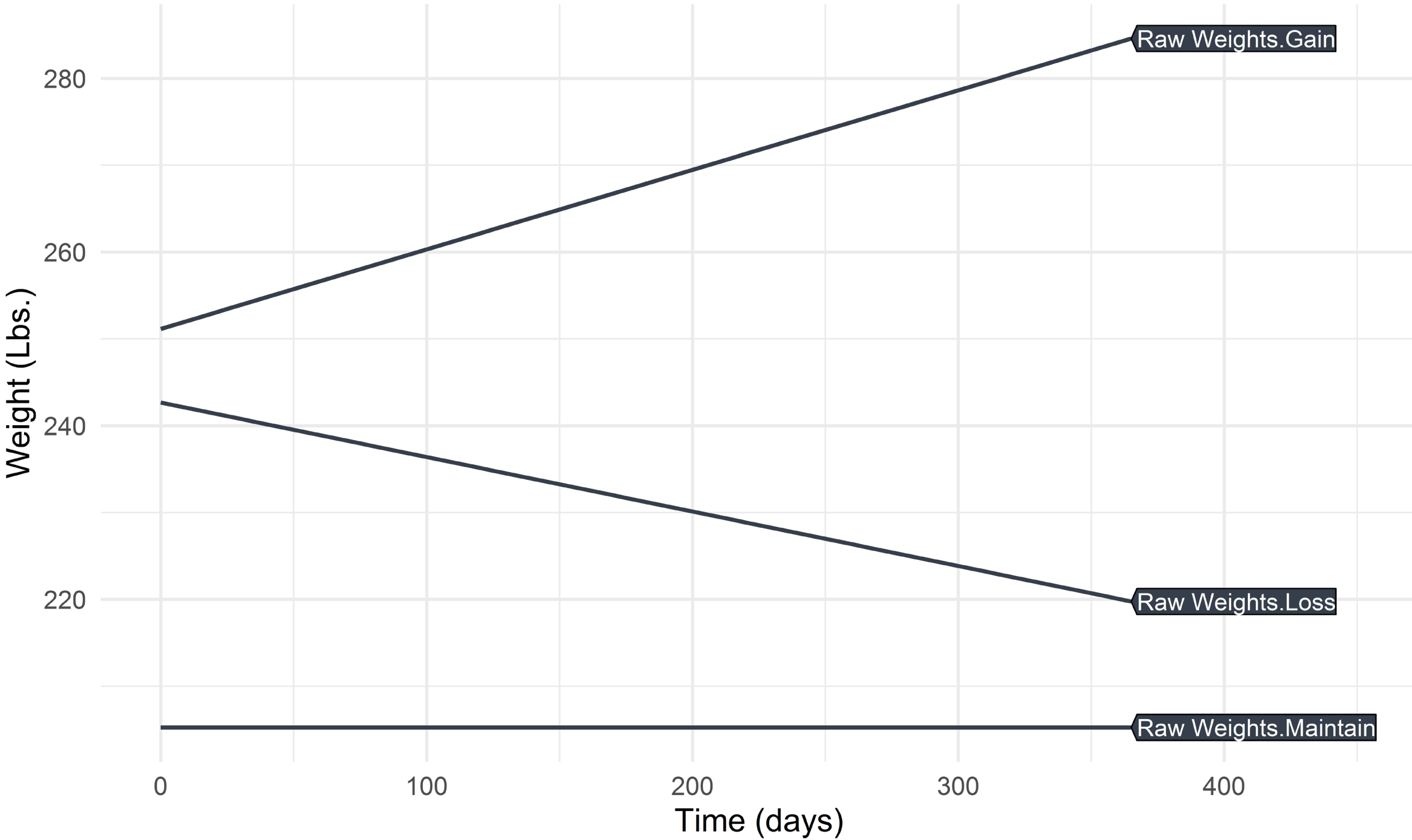
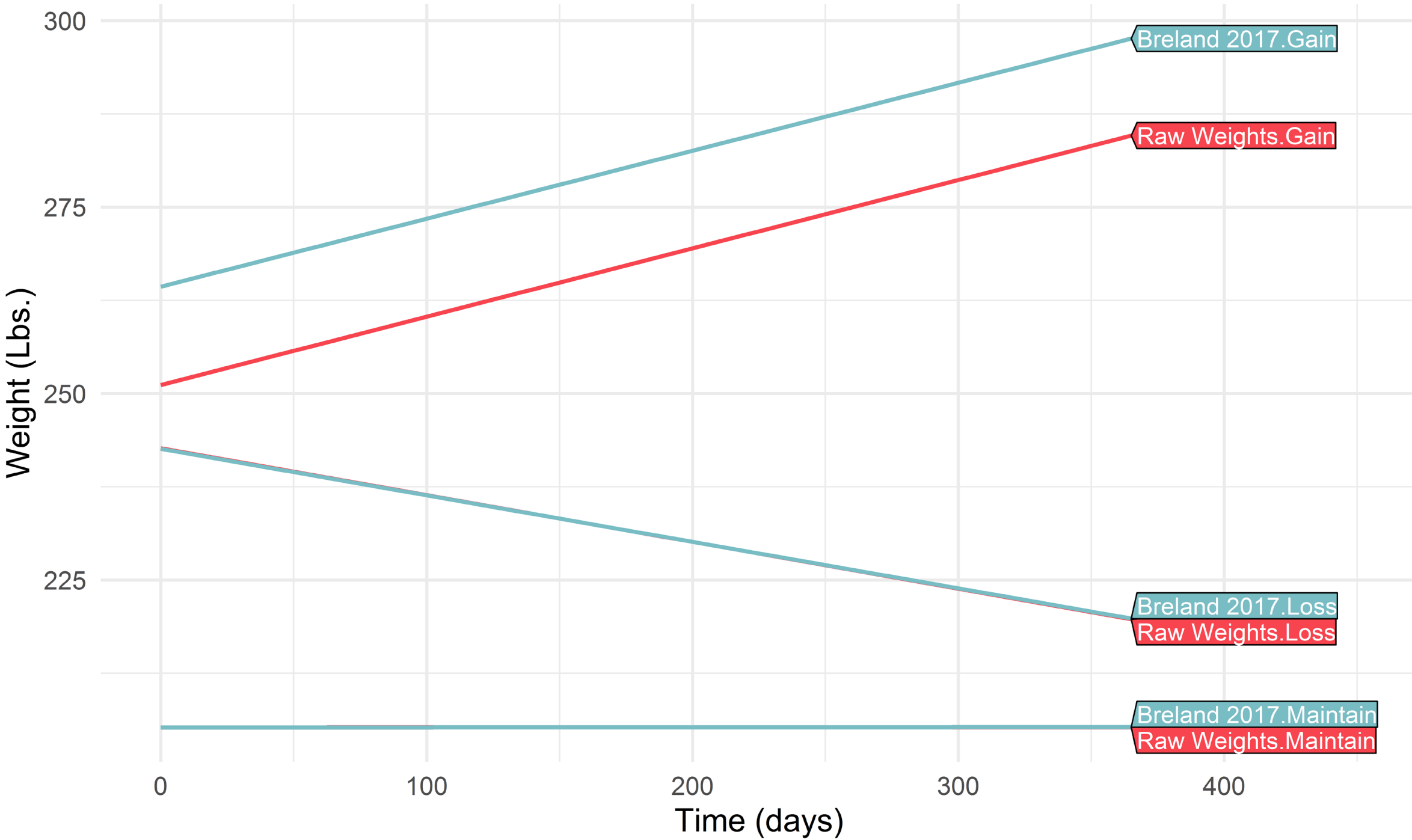
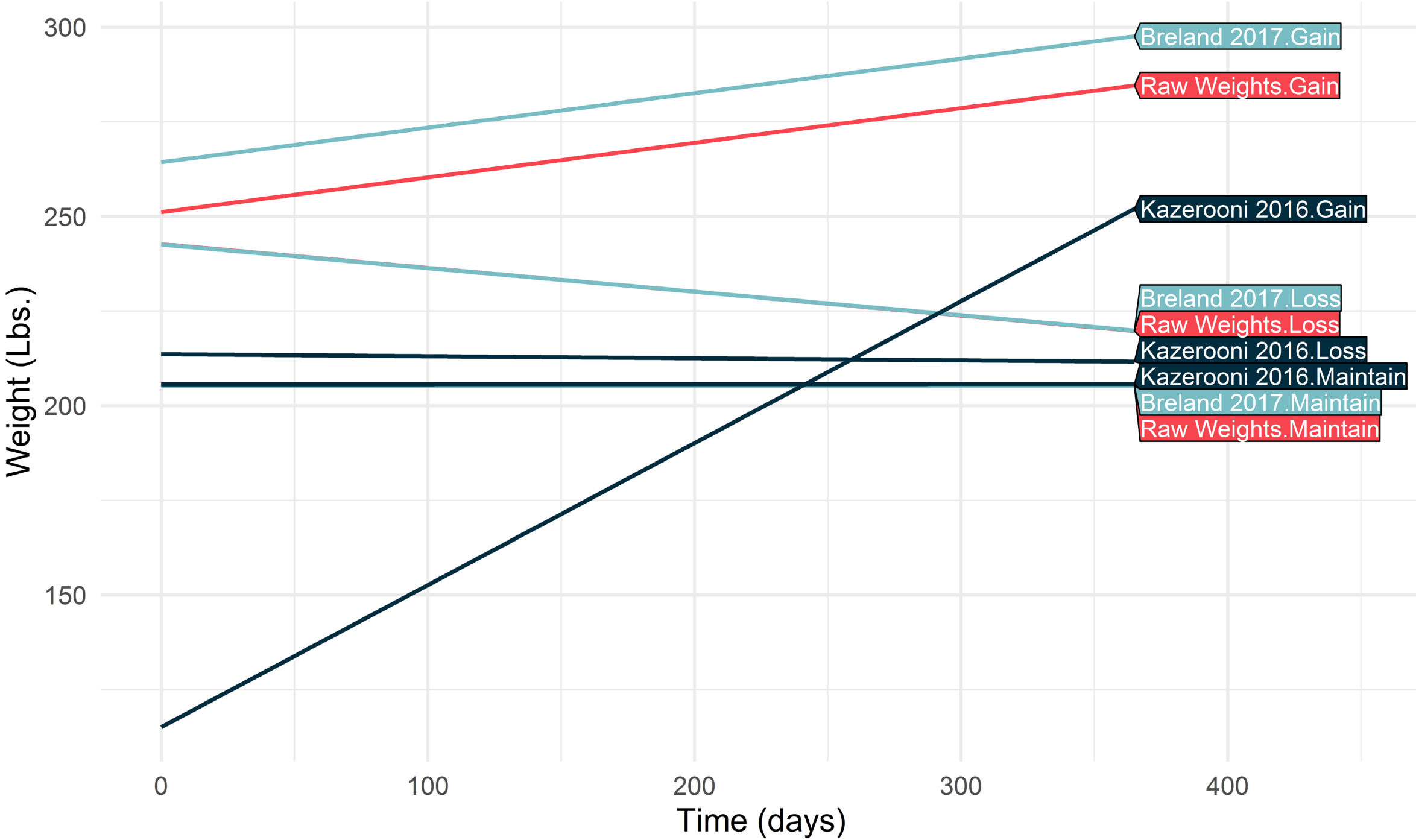
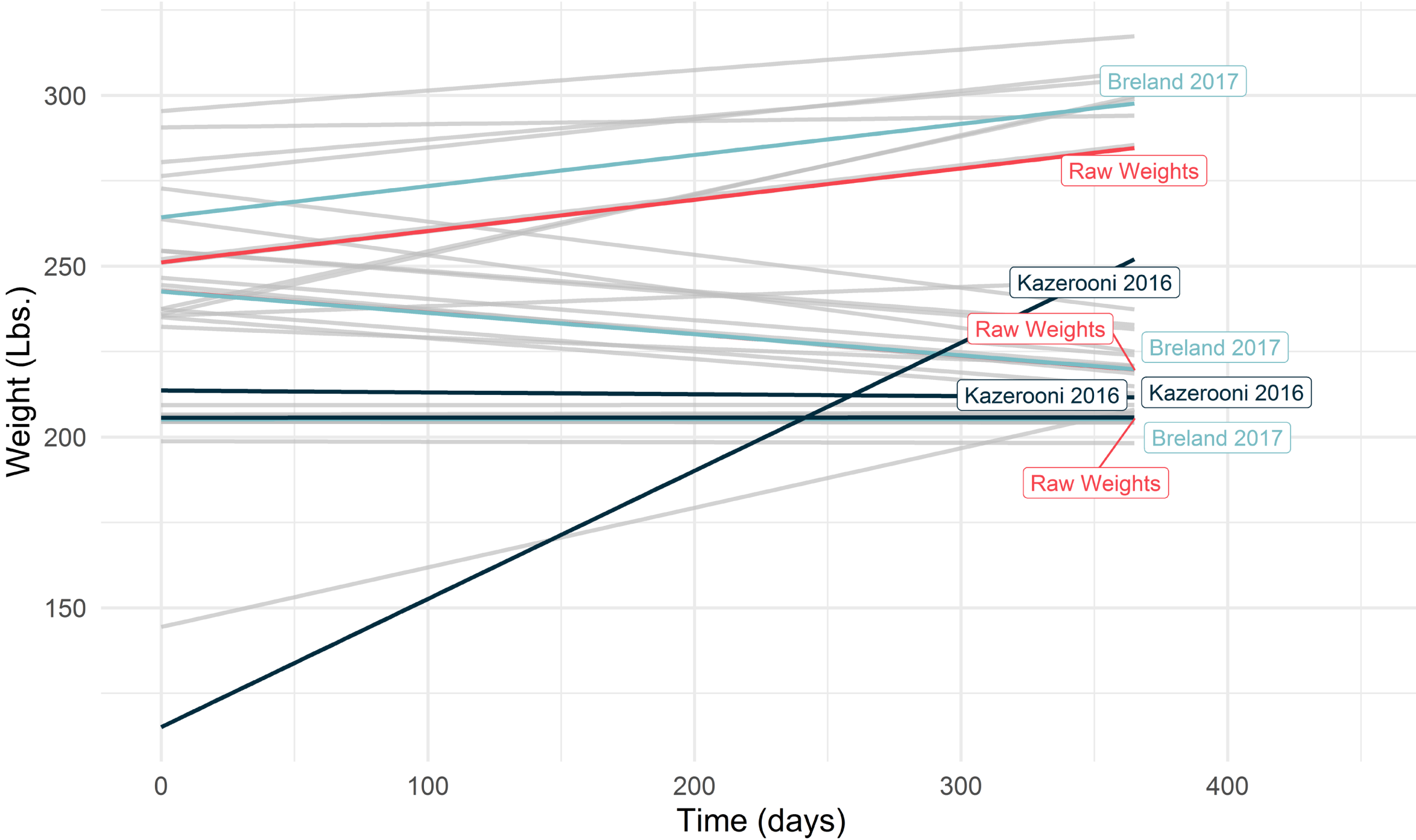
METHODS
LONGITUDINAL WEIGHT TRAJECTORY

- Researchers may be interested in assessing **weight trajectories** within patient over time, and potentially **classifying patients** according to their trajectory, or examining whether types of patients respond differentially to interventions.
- **Algorithm choice** may impact the trajectory of individuals and their measurements collected over time, especially for algorithms that severely reduce the number of measurements left to analyze.
- Instead of aggregating patient weight over a specific time period, studies analyzing weight measures utilize **repeated measures designs**, such as (generalized) linear mixed models (LMM) or ANOVA/ANCOVAs for estimation.
- To compare algorithms in this context, we used a **latent class mixed model** that assumes the population is heterogeneous and composed of some selected number of latent classes characterized by specific trajectories.


Raw Weights.Gain
Raw Weights.Loss
Raw Weights.Maintain
280
260
240
220
Weight (Lbs.)
0
100
200
300
400
Time (days)


300
275
250
225
Weight (Lbs.)
0
100
200
300
400
Time (days)
Breland 2017.Gain
Raw Weights.Gain
Breland 2017.Loss
Raw Weights.Loss
Breland 2017.Maintain
Raw Weights.Maintain


Breland 2017.Gain
Raw Weights.Gain
Kazerooni 2016.Gain
Breland 2017.Loss
Raw Weights.Loss
Kazerooni 2016.Loss
Kazerooni 2016.Maintain
Breland 2017.Maintain
Raw Weights.Maintain
300
250
200
150
Weight (Lbs.)
0
100
200
300
400
Time (days)


Breland 2017
Raw Weights
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Raw Weights
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Kazerooni 2016
Kazerooni 2016
Breland 2017
Raw Weights
300
250
200
150
Weight (Lbs.)
0
100
200
300
400
Time (days)

KEY TAKEAWAYS

LONGITUDINAL WEIGHT TRAJECTORY

- Algorithms that **use all data** to clean weight measures appear to be more appropriate when analyzing longitudinal trajectories.

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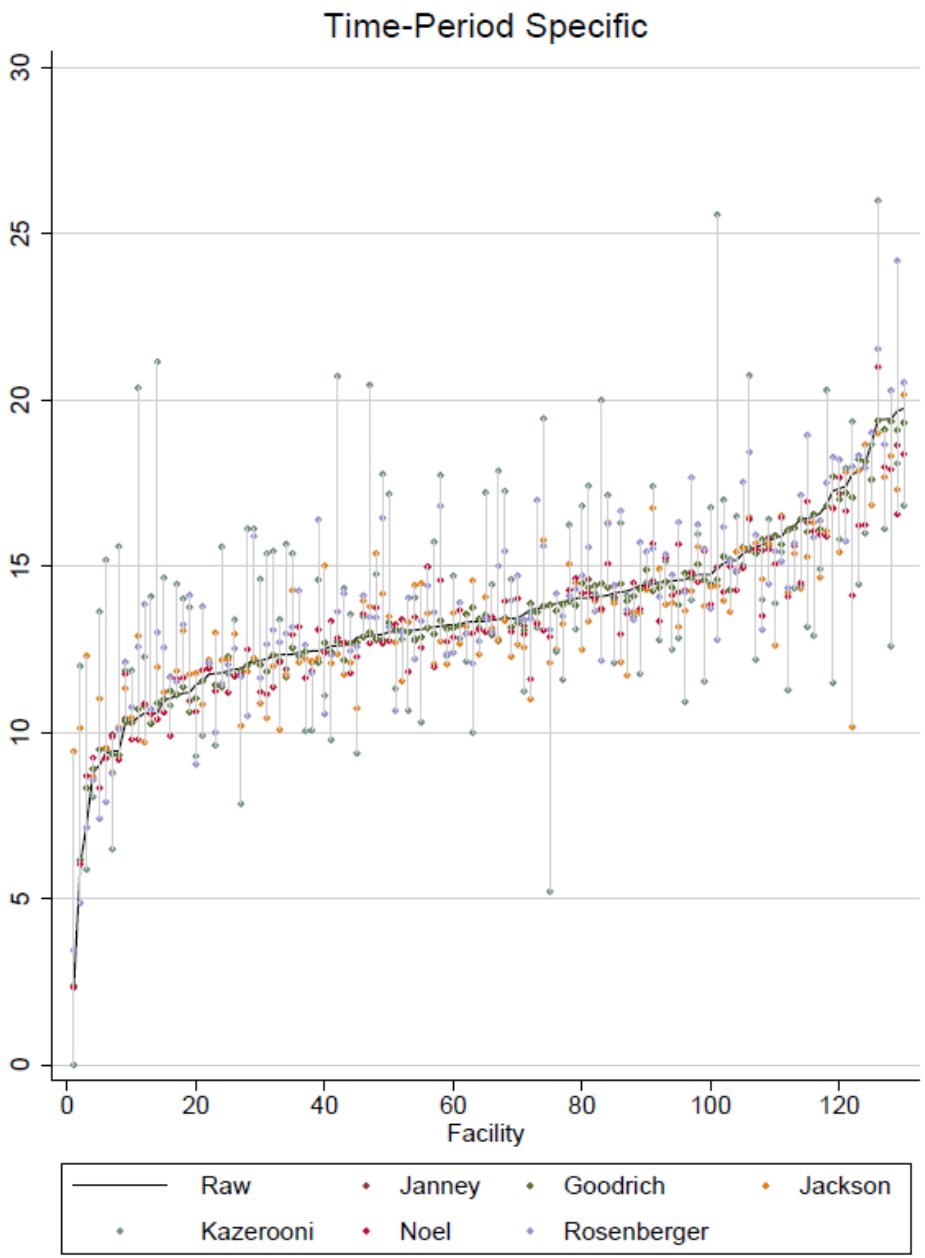
METHODS
FACILITY-LEVEL MEASURES

- Researchers and evaluators are often interested in **comparing facilities** according to the percent of patients meeting a metric of interest.
- We used the raw data and each of the 12 algorithms to calculate the percent of patients at each facility with:
  - **one-year weight loss ≥ 5%**
  - **one-year weight gain ≥ 5%**
- Our objective was to understand the impact of algorithm choice on calculated facility level metrics therefore we examined **unadjusted facility rates**.
- We **rank ordered facilities** based on the percent of patients meeting each metric.
- Compared the differences in the facility level percent of patients based on each algorithm, grouping by those that use all data and time-period specific algorithms.

Weight Loss


Time-Period Specific
30
25
20
15
10
5
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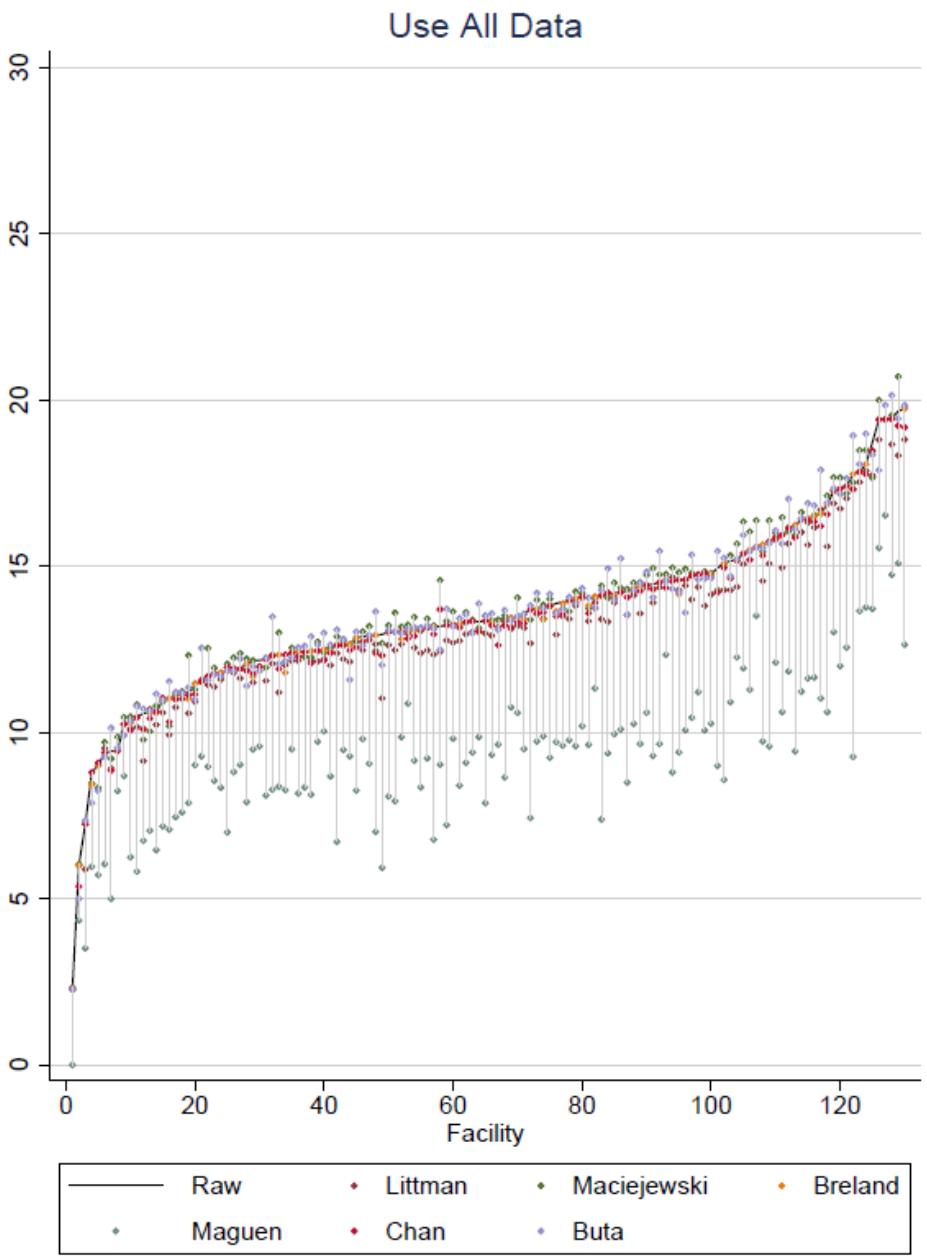
0
20
40
60
80
100
120
Facility
Raw
Janney
Goodrich
Jackson
Kazerooni
Noel
Rosenberger


Use All Data
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25
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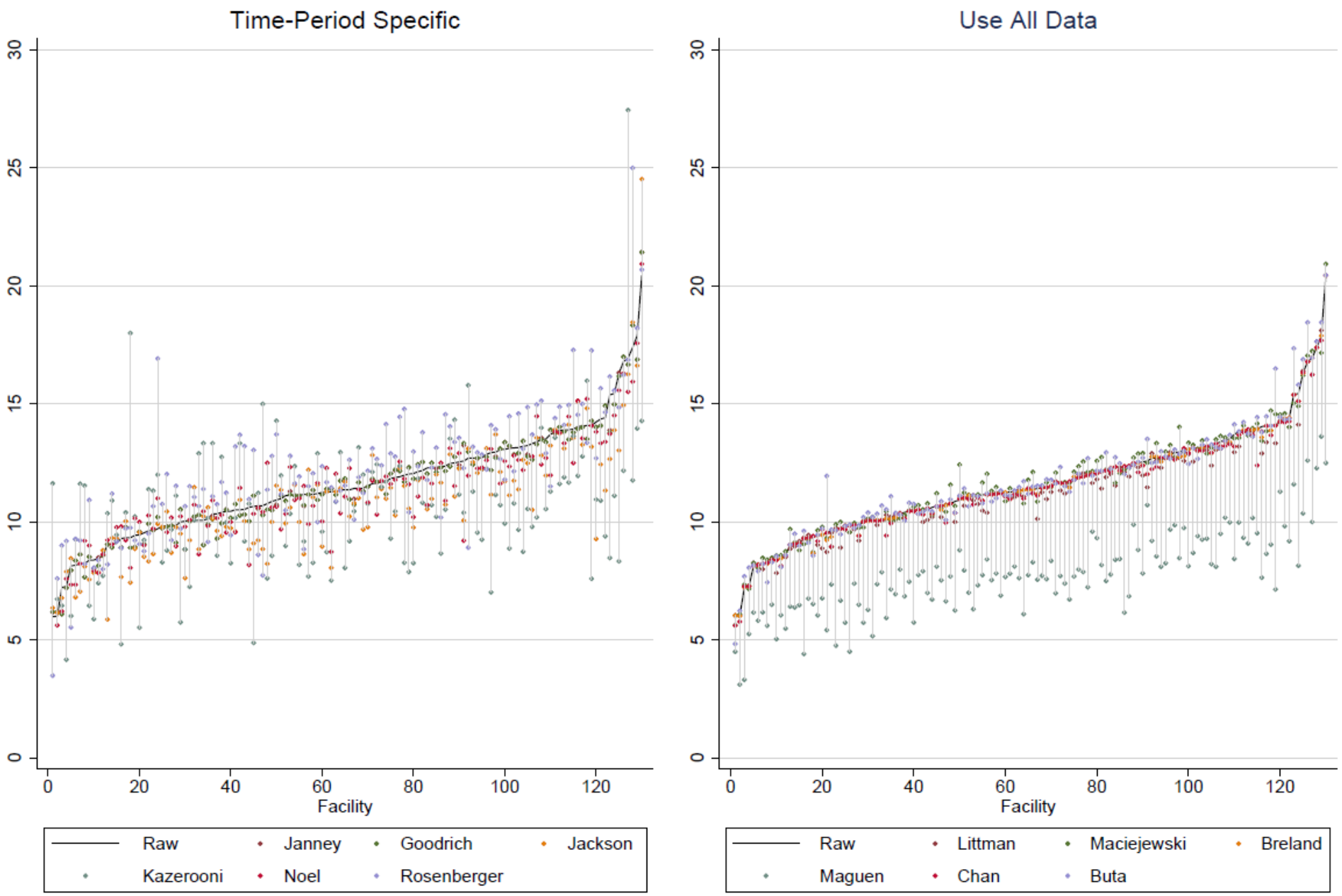
0
20
40
60
80
100
120
Facility
Raw
Littman
Maciejewski
Breland
Maguen
Chan
Buta

Weight Gain


Time-Period Specific
Use All Data
0
5
10
15
20
25
30
0
20
40
60
80
100
120
Facility
Raw
Janney
Goodrich
Jackson
Kazerooni
Noel
Rosenberger
Raw
Littman
Maciejewski
Breland
Maguen
Chan
Buta

KEY TAKEAWAYS

FACILITY-LEVEL MEASURES

- With some exceptions, algorithms **using all data** exhibit less variation in measurement.

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PRINCIPAL FINDINGS

- Differences between algorithms are minor, implying that for many studies, **a simpler algorithm design may be computationally more efficient**.

- In some cases, the results are **not different than using raw**, **unprocessed data**, despite algorithm complexity.

RECOMMENDATIONS

- Studies using **point estimates of weight** and **weight change** may benefit from a **simple cleaning rule** based on cut-offs of implausible values.
- For **trajectory analyses**, time-period specific algorithms may not be appropriate.
- For **facility-level measures**, all time-period specific algorithms result in inconsistent results compared to algorithms that use all data.

RECOMMENDATIONS

- We recommend including detailed information on how measures are constructed in publications and/or share code via open source repositories.

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LIMITATIONS

- Algorithms were **reconstructed** from published methods.
  - Potential for misinterpretation.
- **Lack of a gold standard** to assess accuracy of algorithms.
- VA data, non-intervention/clinical **sample**

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WORKS IN PROGRESS

- **Simulation study** to address the lack of a gold standard and large sample biases.

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Poll #3: How useful are these recommendations for your work?

- **Extremely useful**
- **Very**
- **Moderately**
- **Slightly**
- **Not at all useful**

THANK YOU!

ADDITIONAL QUESTIONS OR COMMENTS?

Contact Rich Evans at Richard.Evans8@va.gov

Additional Resources

VIReC Options for Specific Questions

HSRData Listserv

- Community knowledge sharing
- ~1,400 VA data users
- Researchers, operations, data stewards, managers
- Subscribe by visiting http://vaww.virec.research.va.gov/Support/HSRData-L.htm (VA Intranet)

HelpDesk

- Individualized support

virec@va.gov

(708) 202-2413

Quick links for VA data resources

Quick Guide: Resources for Using VA Data
http://vaww.virec.research.va.gov/Toolkit/QG-Resources-for-Using-VA-Data.pdf (VA Intranet)

VIReC: http://vaww.virec.research.va.gov/Index.htm (VA Intranet)

VIReC Cyberseminars: http://www.virec.research.va.gov/Resources/Cyberseminars.asp

VHA Data Portal: http://vaww.vhadataportal.med.va.gov/Home.aspx (VA Intranet)

VINCI: http://vaww.vinci.med.va.gov/vincicentral/ (VA Intranet)

Health Economics Resource Center (HERC): http://vaww.herc.research.va.gov (VA Intranet)

CDW: https://vaww.cdw.va.gov/Pages/CDWHome.aspx (VA Intranet)

Archived cyberseminar: What can the HSR&D Resource Centers do for you?
http://www.hsrd.research.va.gov/for_researchers/cyber_seminars/archives/video_archive.cfm?SessionID=101

Next session:
May 4th at 1 pm Eastern

Database & Methods Cyberseminar Series

Ascertaining Veterans' Vital Status: Data Sources for Mortality Ascertainment and Cause of Death

Charles Maynard, PhD

Register at
https://www.hsrd.research.va.gov/cyberseminars/catalog-upcoming-session.cfm?UID=3783

VIReC
RESEARCHERS' GUIDE TO VA DATA