Disseminating methodological work to statisticians and researchers using a tweetorial

Emily Granger

Email: *emily.granger@lshtm.ac.uk*
Github: https://github.com/EmilyG602/Presentations
Twitter: *@EGranger90*

What is a #tweetorial?

What is a #tweetorial?

A tutorial that is made by stringing together a series of tweets, with the aim of educating your followers on a particular topic

Why do a #tweetorial?

A tutorial that is made by stringing together a series of tweets, with the aim of educating your followers on a particular topic

Why do a #tweetorial?

A tutorial that is made by stringing together a series of tweets, with the aim of educating your followers on a particular topic

- Promote your own research

Why do a #tweetorial?

A tutorial that is made by stringing together a series of tweets, with the aim of educating your followers on a particular topic
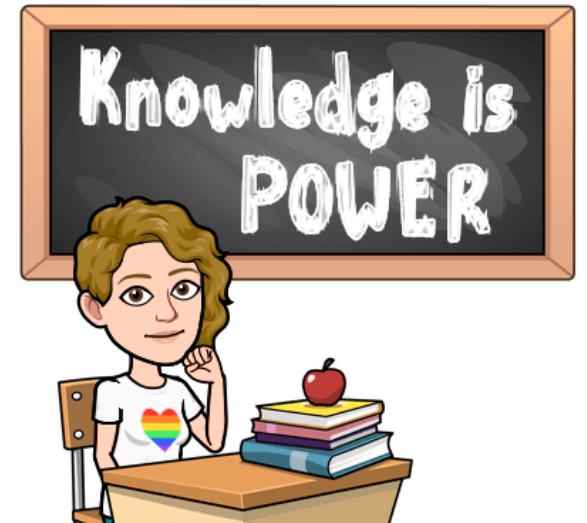
- Promote your own research

- Improve knowledge

Why do a #tweetorial?

Dan Quintana @dsquintana

In my personal experience, papers that are summarized in threads get more reads than blog post equivalents. I'm talking like 10x more reads, at least. I think there are a few reasons for this...

9:40 AM · Mar 19, 2019 · Twitter for iPhone

Grumpy Old Health Stats Dude @healthstatsdude · Aug 12, 2019
Replying to @MaartenvSmeden
i really liked @statsepi 's recent p-value tweetorial. it laid out the ideas more succinctly than i'd seen before, and in way that made sense to analysts at work i shared it with.

💬 1   🔁   ♡ 5   ⬆

Lynn Chiu @drlynnchiu · May 29, 2019
After going through many more exemplars, I've discovered the Ten Reasons I Love Good Paper Threads #listicle

💬 1   🔁   ♡ 3   ⬆

Lynn Chiu @drlynnchiu · May 29, 2019
1. Good paper threads show heart.

They give us a glimpse of the emotions that motivated the paper.

We did this because I was puzzled by/I was excited about/I was frustrated with/I was angry that.....
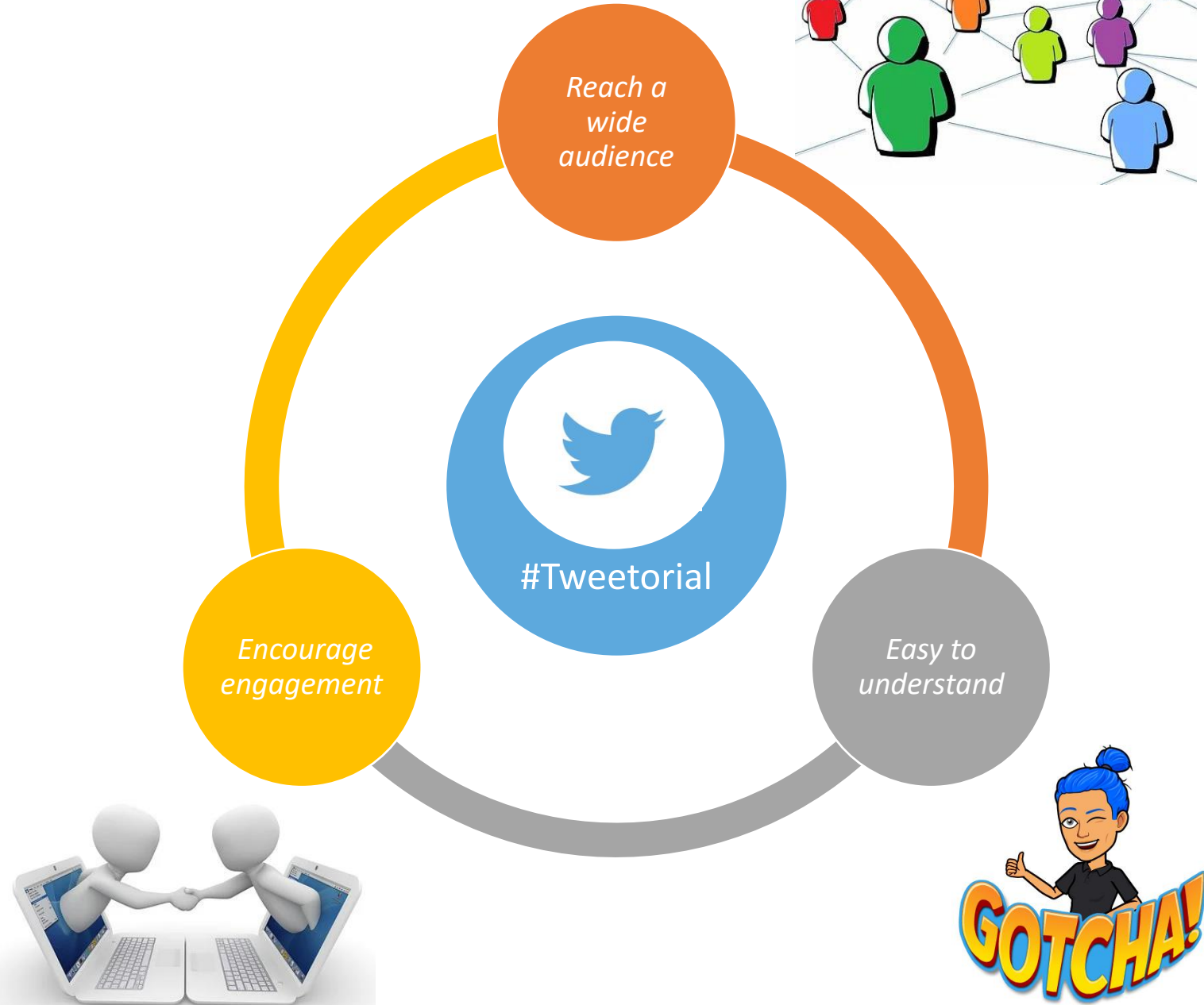
Inquiring minds want to know.

GIF

💬 1   🔁   ♡ 2   ⬆

Relevant Links

- "Why I love [#tweetorials]" by @drlynnchiu : here
- A blog post on "10 Reasons I Love Reading Paper Threads on Twitter": here
- "You should used a Twitter thread to announce new appears instead of a blog post. Here's why..." by @dsquintana : here
- @statsepi #tweetorial on p-values: here

Dr Emily Granger
@EGranger90

Here's a #tweetorial of my first paper😁

This is work I did with @jamiecsergeant and Mark Lunt, comparing different approaches to combining multiple imputation and propensity scores. Hopefully relevant for some of you on #EpiTwitter and #StatsTwitter

👇👇👇

4:52 PM · Sep 14, 2019 · Twitter Web App

View Tweet activity

56 Retweets   **120** Likes

Pinned Tweet

Dr Emily Granger
@EGranger90

Here's a #tweetorial of my first paper😄

This is work I did with @jamiecsergeant and Mark Lunt, comparing different approaches to combining multiple imputation and propensity scores. Hopefully relevant for some of you on #EpiTwitter and #StatsTwitter

👇👇👇

4:52 PM · Sep 14, 2019 · Twitter Web App

|ıl| View Tweet activity

56 Retweets   **120** Likes

- Use hashtags to reach a wider audience

  #MedTwitter
  #AcademicTwitter
  #AcademicChatter
  #PhDChat

Pinned Tweet

Dr Emily Granger
@EGranger90

Here's a #tweetorial of my first p...

This is work I did with @jamiecsergeant and Mark Lunt, comparing different approaches to combining multiple imputation and propensity scores. Hopefully relevant for some of you on #EpiTwitter and #StatsTwitter

👇👇👇

4:52 PM · Sep 14, 2019 · Twitter Web App

ıl View Tweet activity

56 Retweets   **120** Likes

- Use hashtags to reach a wider audience

  #MedTwitter
  #AcademicTwitter
  #AcademicChatter
  #PhDChat

- Tag relevant people and organisations:

  - Co-authors and collaborators
  - Research centres
  - Funders
  - Journal

- Encourage retweets!

Dr Emily Granger @EGranger90 · Sep 14, 2019
Replying to @EGranger90

Multiple imputation (MI) is often used for missing data and propensity scores (PS) are commonly used to deal with confounding bias.

We may often need to use both MI and PS in an analysis, but combining MI and PS is not straightforward.

💬 1   🔁   ♥ 3   ⬆️   ⅲ

Dr Emily Granger
@EGranger90

In this paper we conducted a simulation study to compare two approaches to combining MI and PS: the Across Approach and the Within Approach.

Dr Emily Granger @EGranger90 · Sep 14, 2019
Replying to @EGranger90

Multiple imputation (MI) is often used for missing data and propensity scores (PS) are commonly used to deal with confounding bias.

We may often need to use both MI and PS in an analysis, but combining MI and PS is not straightforward.

1   3

Dr Emily Granger
@EGranger90

In this paper we conducted a simulation study to compare two approaches to combining MI and PS: the Across Approach and the Within Approach.

4:52 PM · Sep 14, 2019 · Twitter Web App

Dr Emily Granger @EGranger90 · Sep 14, 2019
Both approaches start by imputing missing data (Step 1), then estimating PS's in each imputed dataset (Step 2).

Now the approaches differ. For Across:

Step 3: Average PS's across imputed data.

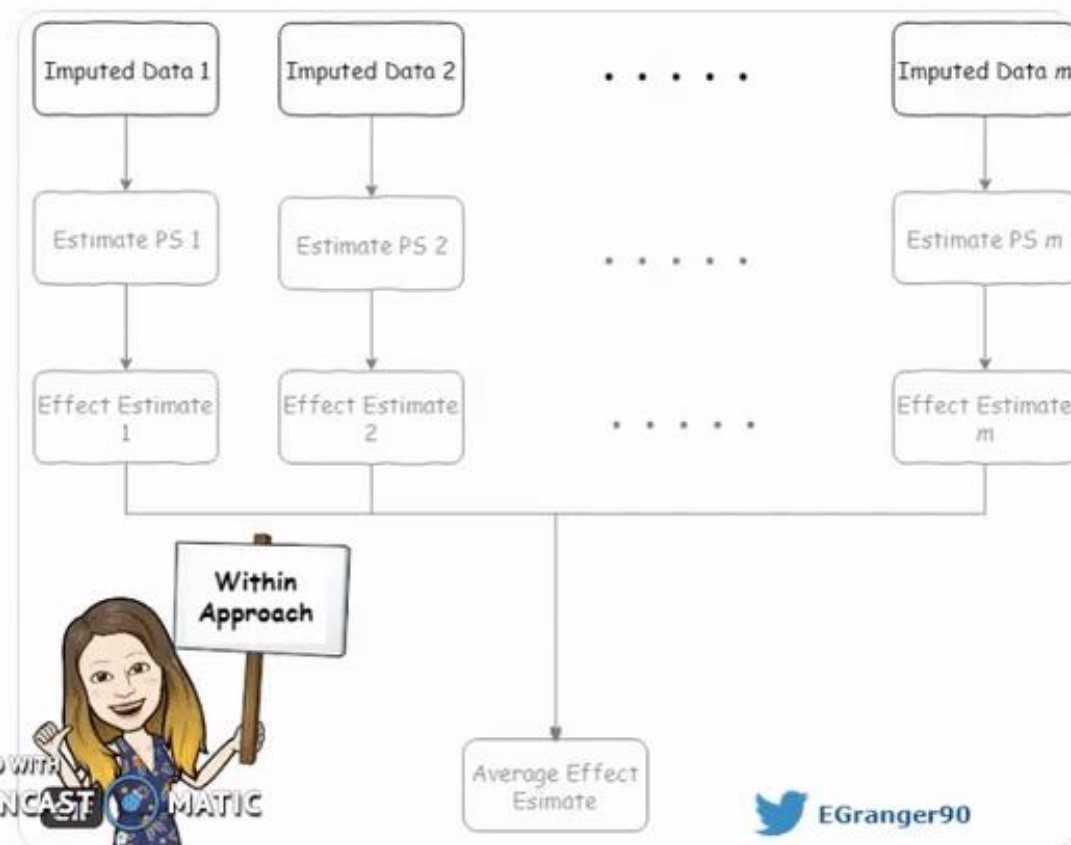Step 4: Use average PS to obtain one effect estimate and one standard error.

Imputed Data 1   Imputed Data 2   · · · · ·   Imputed Data m

Estimate PS 1   Estimate PS 2   · · · · ·   Estimate PS m

Average PS

Across Approach

Effect Estimate
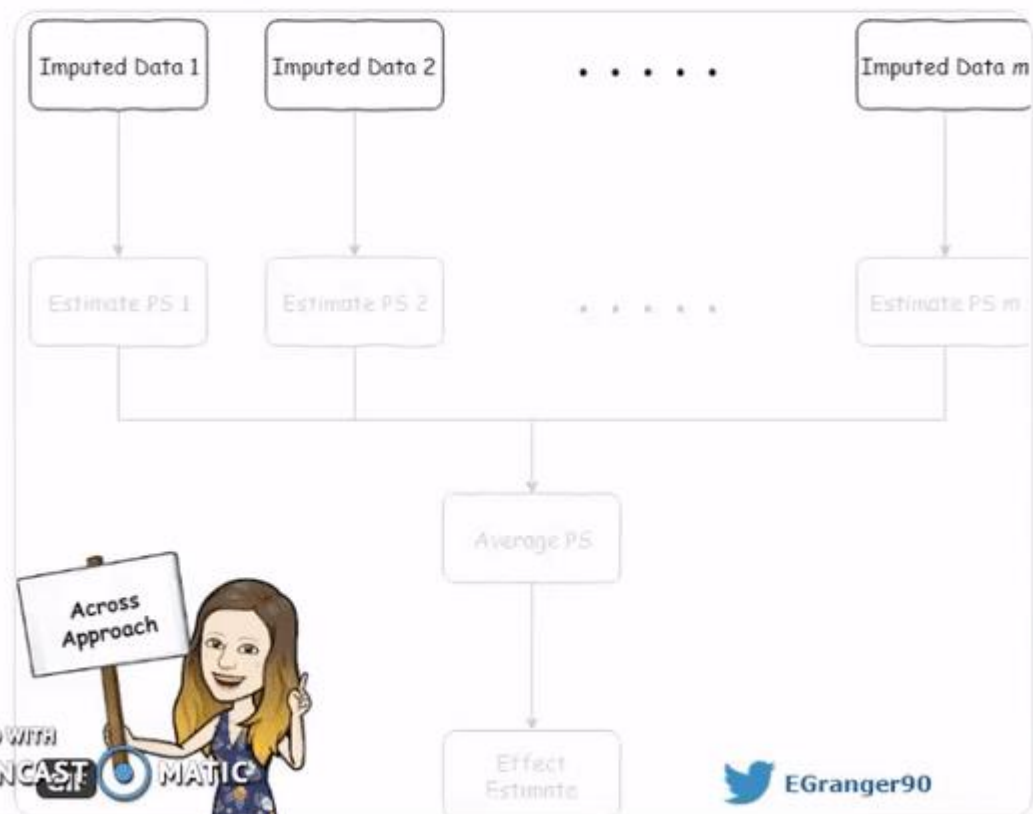
EGranger90

Dr Emily Granger @EGranger90 · Sep 14, 2019
Replying to @EGranger90
For the Within Approach:

Step 3: Obtain multiple estimates of the exposure effect and associated standard error (one from each dataset).

Step 4: Combine results using Rubin's rules.

Imputed Data 1   Imputed Data 2   · · · · ·   Imputed Data m

Estimate PS 1   Estimate PS 2   · · · · ·   Estimate PS m

Effect Estimate 1   Effect Estimate 2   · · · · ·   Effect Estimate m

Within Approach

Average Effect Esimate

EGranger90

Dr Emily Granger
@EGranger90

What about standard error?

In the Across Approach, the estimated SE didn't increase as missing data increases, underestimating the true variance. This is because the estimator fails to take into account the between-imputation variance!
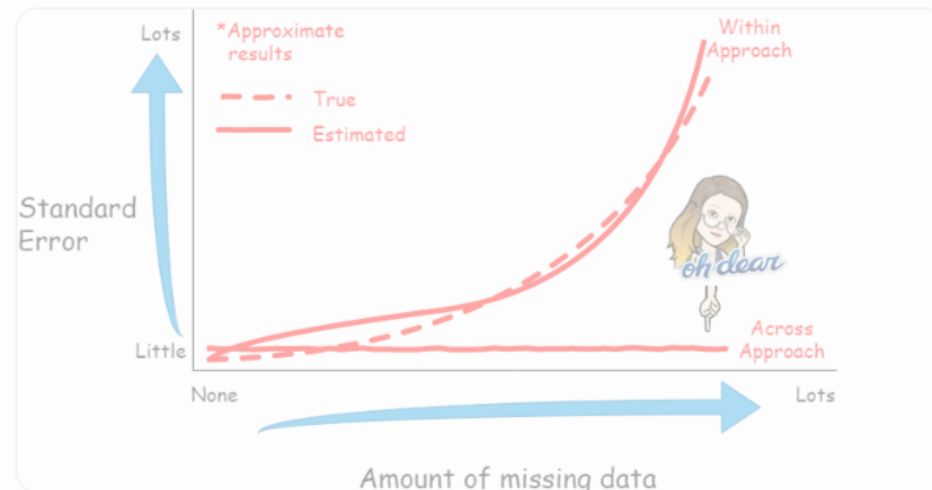
The Within Approach did better 👇

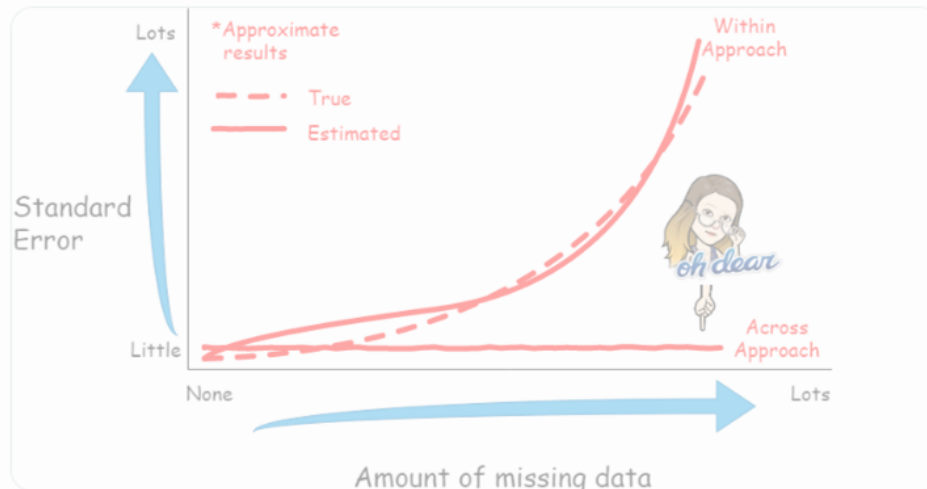4:55 PM · Sep 14, 2019 · Twitter Web App

Dr Emily Granger
@EGranger90

What about standard error?

In the Across Approach, the estimated SE didn't increase as missing data increases, underestimating the true variance. This is because the estimator fails to take into account the between-imputation variance!

The Within Approach did better 👇

Eiko Fried
@EikoFried

7/ Most research add Sx to sum score which is then used as predictor, outcome, moderator. But sum scores for different scales mean different things since based on different Sx → poses threat to replicability/generalizability of depression research (dx.doi.org/10.1016/j.jad....).

ABSTRACT

Background: Depression severity is assessed in numerous research disciplines, ranging from the social sciences to genetics, and used as a dependent variable, predictor, covariate, or to enroll participants. The routine practice is to assess depression severity with one particular depression scale, and draw conclusions about depression in general, relying on the assumption that scales are interchangeable measures of depression. The present paper investigates to which degree 7 common depression scales differ in their item content and generalizability.

Methods: A content analysis is carried out to determine symptom overlap among the 7 scales via the Jaccard index (0=no overlap, 1=full overlap). Per scale, rates of idiosyncratic symptoms, and rates of specific vs. compound symptoms, are computed.

Results: The 7 instruments encompass 52 disparate symptoms. Mean overlap among all scales is low (0.36), mean overlap of each scale with all others ranges from 0.27 to 0.40, overlap among individual scales from 0.26 to 0.61. Symptoms feature across a mean of 3 scales, 40% of the symptoms appear in only a single scale, 12% across all instruments. Scales differ regarding their rates of idiosyncratic symptoms (0–33%) and compound symptoms (22–90%).

Limitations: Future studies analyzing more and different scales will be required to obtain a better estimate of the number of depression symptoms; the present content analysis was carried out conservatively and likely underestimates heterogeneity across the 7 scales.

Conclusion: The substantial heterogeneity of the depressive syndrome and low overlap among scales may lead to research results idiosyncratic to particular scales used, posing a threat to the replicability and generalizability of depression research. Implications and future research opportunities are discussed.
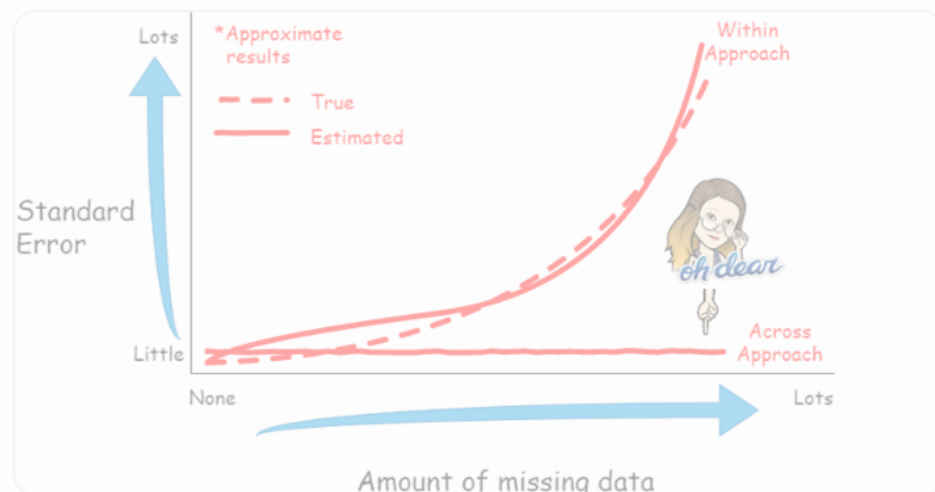
Dr Emily Granger
@EGranger90

What about standard error?

In the Across Approach, the estimated SE didn't increase as missing data increases, underestimating the true variance. This is because the estimator fails to take into account the between-imputation variance!
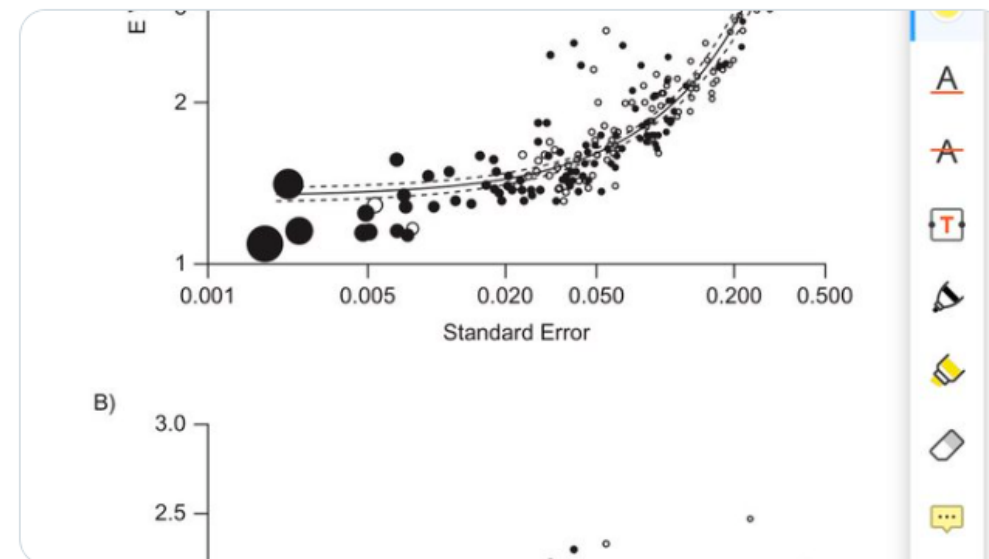
The Within Approach did better 👇

4:55 PM · Sep 14, 2019 · Twitter Web App

The result? Nutritional epi had higher e-values than air pollution epi!

Am J Epidemiology ✔ @AmJEpi · Jan 2

Does that mean nutritional epi studies *really* give more evidence for true effects than air pollution epi studies?

(Expand to vote in poll!)

Yes that's how it works — 2.1%

Not necessarily — **87.4%**

Show me 💁 — 10.5%

95 votes · Final results

Dr Emily Granger
@EGranger90

Based on these results, we recommend using the Within Approach when combining multiple imputation and propensity scores!

Here's a link to the paper: doi.org/10.1002/sim.83...

Thank you to everyone who read this (or parts of this) #tweetorial! ☺

Statistics in Medicine
Avoiding pitfalls when combining multiple imputation and pr...
Overcoming bias due to confounding and missing data is challenging when analyzing observational data. Propensity ...
🔗 onlinelibrary.wiley.com

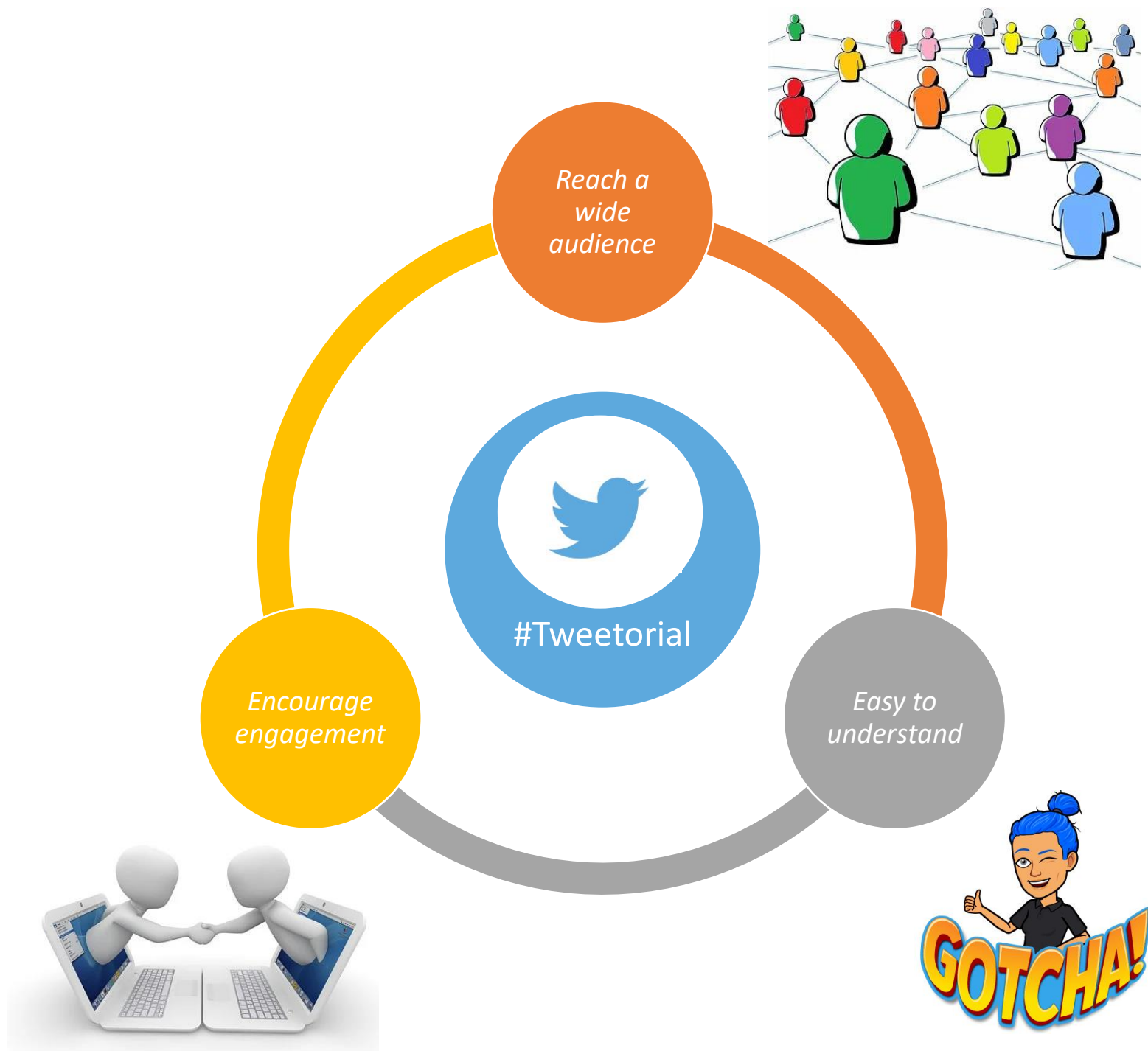4:55 PM · Sep 14, 2019 · Twitter Web App

View Tweet activity

5 Retweets   **47** Likes

- Include link to your paper
  - Better to do this in the first tweet!
  - Can shorten weblinks to save space

- Thank your readers and those who helped you with the research

DONE
and
DONE

What makes a great #tweetorial?

Reach a wide audience

#Tweetorial

Encourage engagement

Easy to understand

GOTCHA!

Wide audience:

- Use hashtags
- Tag authors and collaborators
- Tag funders and journal
- Encourage authors to retweet

Easy to understand:

- Plain language
- Define your acronyms
- One point per tweet
- Informative visuals

Engagement:

- Use of GIFs
- Twitter polls
- Link to other relevant research
- Link to paper in the first tweet

Reach a wide audience

#Tweetorial

Encourage engagement

Easy to understand

GOTCHA!
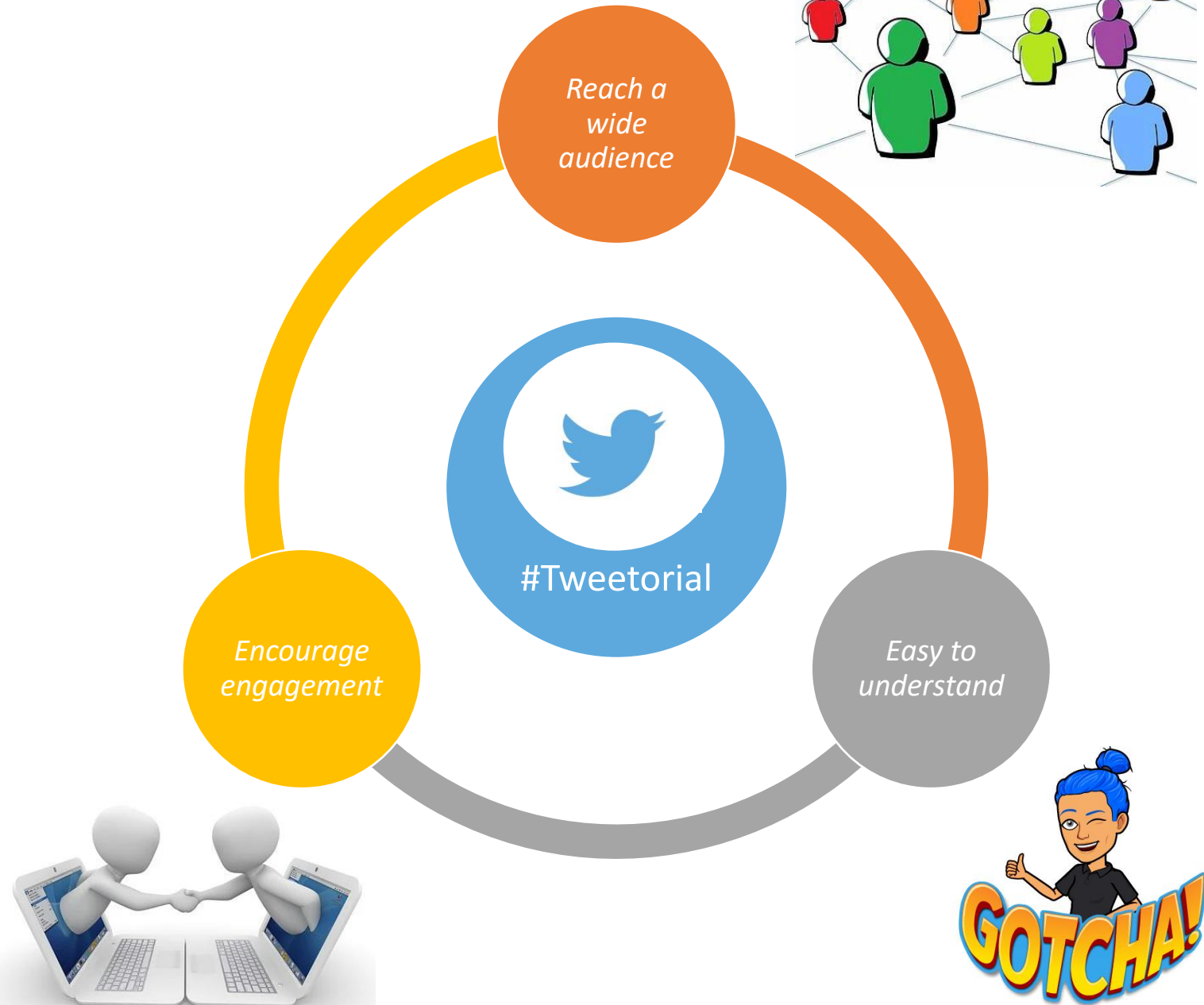
#Tweetorial examples

@Jsheltzer:survival analysis
@EikoFried:clinical psychology
@AmJEpi: e-values
@Epi_D_Nique: collider bias
@drlynnchiu's collection of #tweetorials here

Search #Tweetorial in Twitter for more examples

#Resources

-Twitter for scientists: https://t4scientists.com/
-Create your own GIFs:
https://giphy.com/create/gifmaker
-Create a bitmoji: https://www.bitmoji.com/
-Shorten website links: https://www.shorturl.at/