



# Navigating the Data Privacy Maze

Privacy Considerations for Data Scientists

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# Obligatory GDPR Slide



Credit:

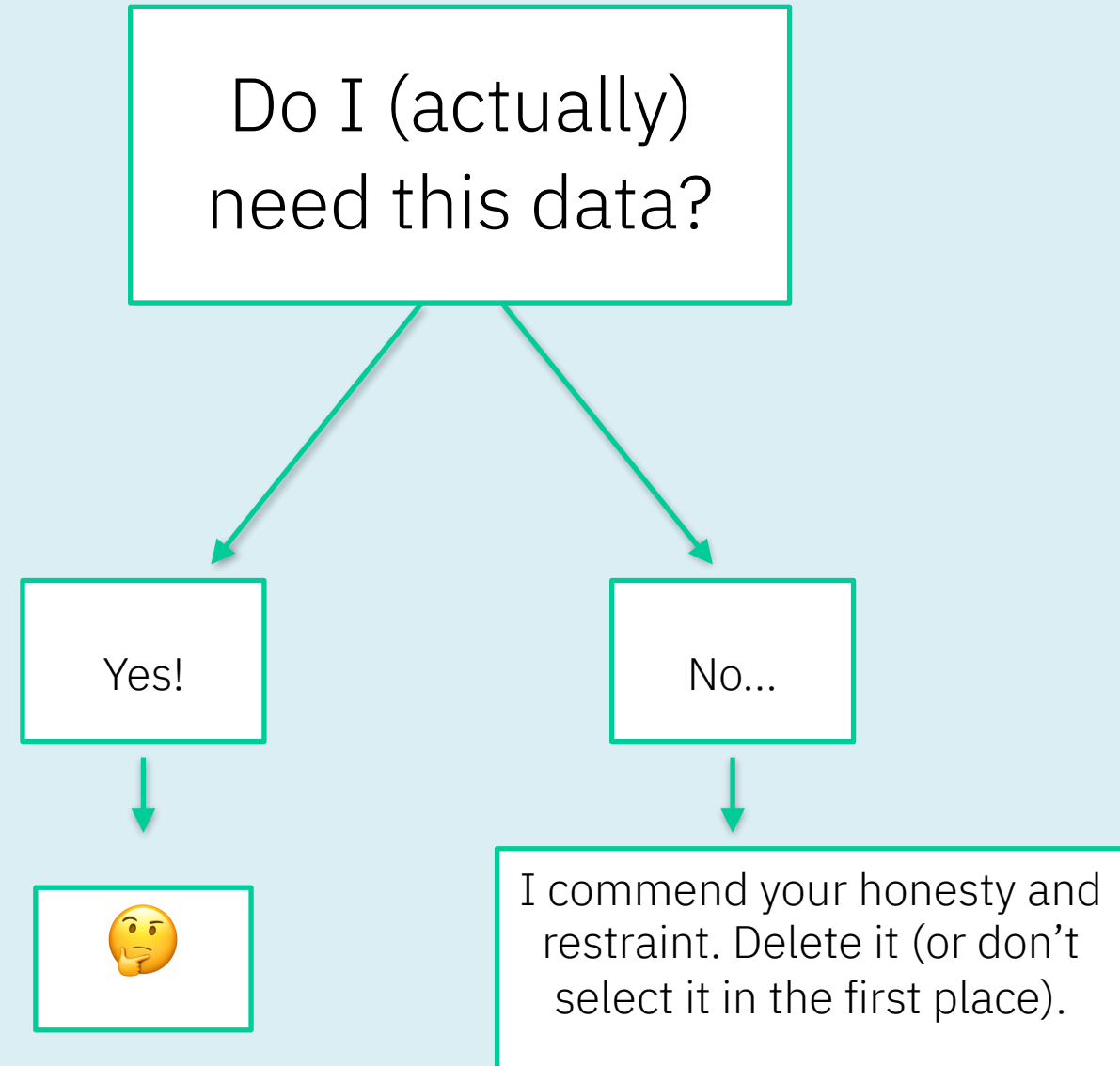
<http://memecollection.net/updated-privacy-policy/>

# What is Privacy for Data Scientists?

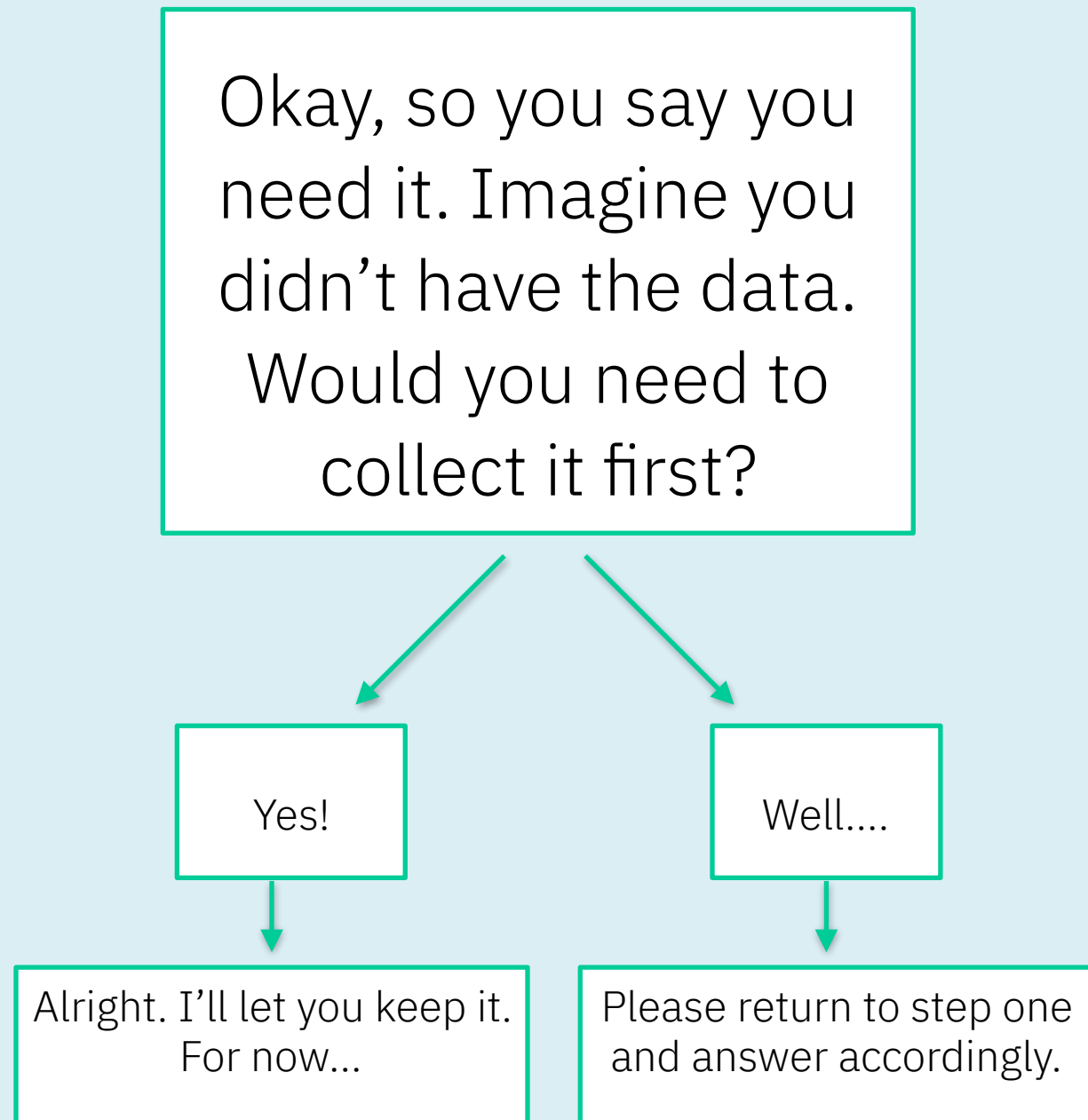


Photo Credits:  
Left: (Lily Martin/CBC)  
Right: (Thor Swift/NYT)

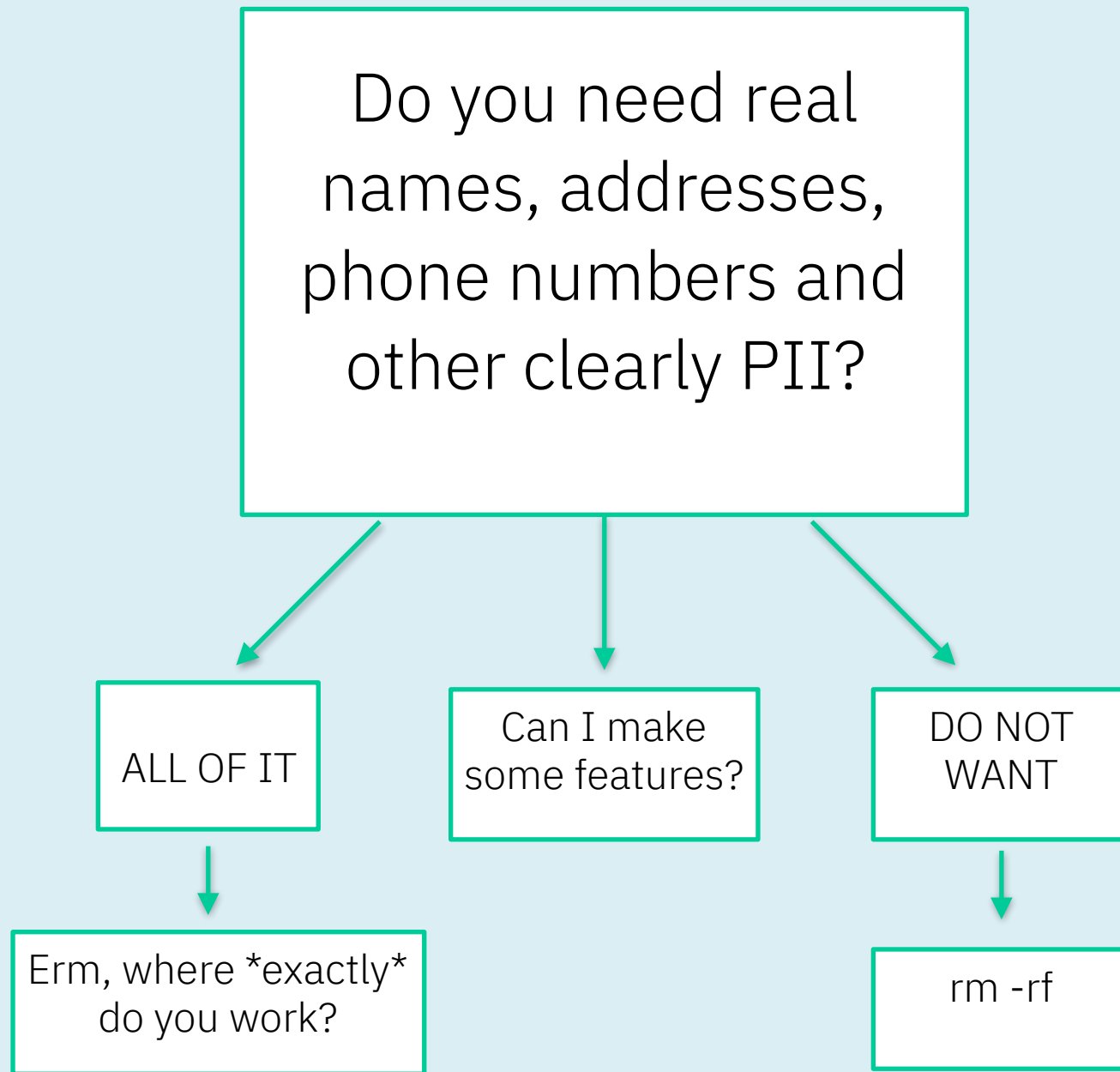
# Navigating Data Privacy



# Gimme the Data (cont.)



# Actually Required Sensitive Data



# The Case for Deletion

- Best possible protection
- Determine if derivative features (i.e. “uses free email” or “name ends with a vowel”) can convey enough info (and still preserve some privacy)

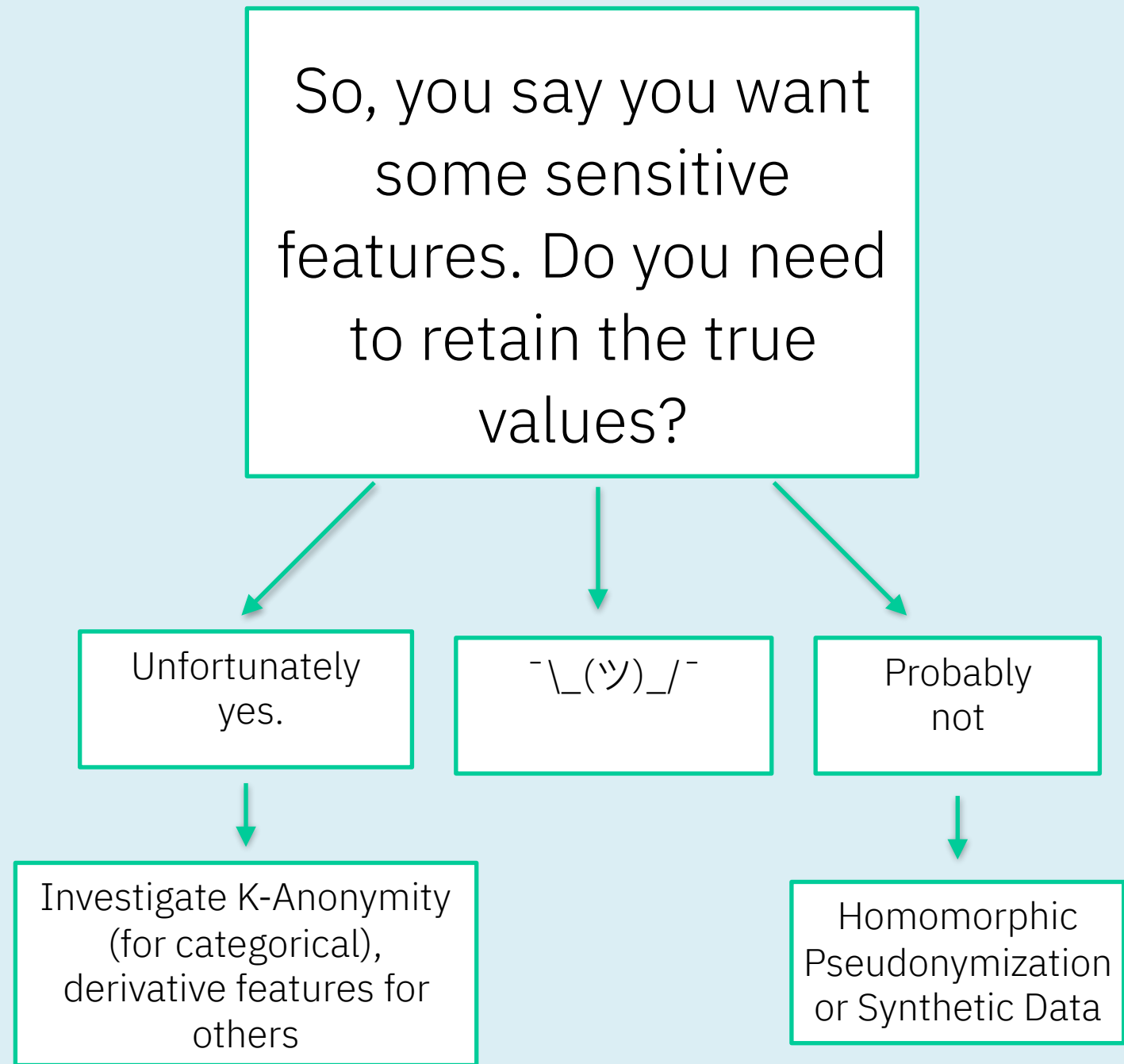
## YOUR PERSONAL INFORMATION

PLEASE DON'T SEND US YOUR PERSONAL INFORMATION. WE DO NOT WANT YOUR PERSONAL INFORMATION. WE HAVE A HARD ENOUGH TIME KEEPING TRACK OF OUR OWN PERSONAL INFORMATION, LET ALONE YOURS.

IF YOU TELL US YOUR NAME, OR ANY IDENTIFYING INFORMATION, WE WILL FORGET IT IMMEDIATELY. THE NEXT TIME WE SEE YOU, WE'LL STRUGGLE TO REMEMBER WHO YOU ARE, AND TRY DESPERATELY TO GET THROUGH THE CONVERSATION SO WE CAN GO ONLINE AND HOPEFULLY FIGURE IT OUT.



# Actually Required PII

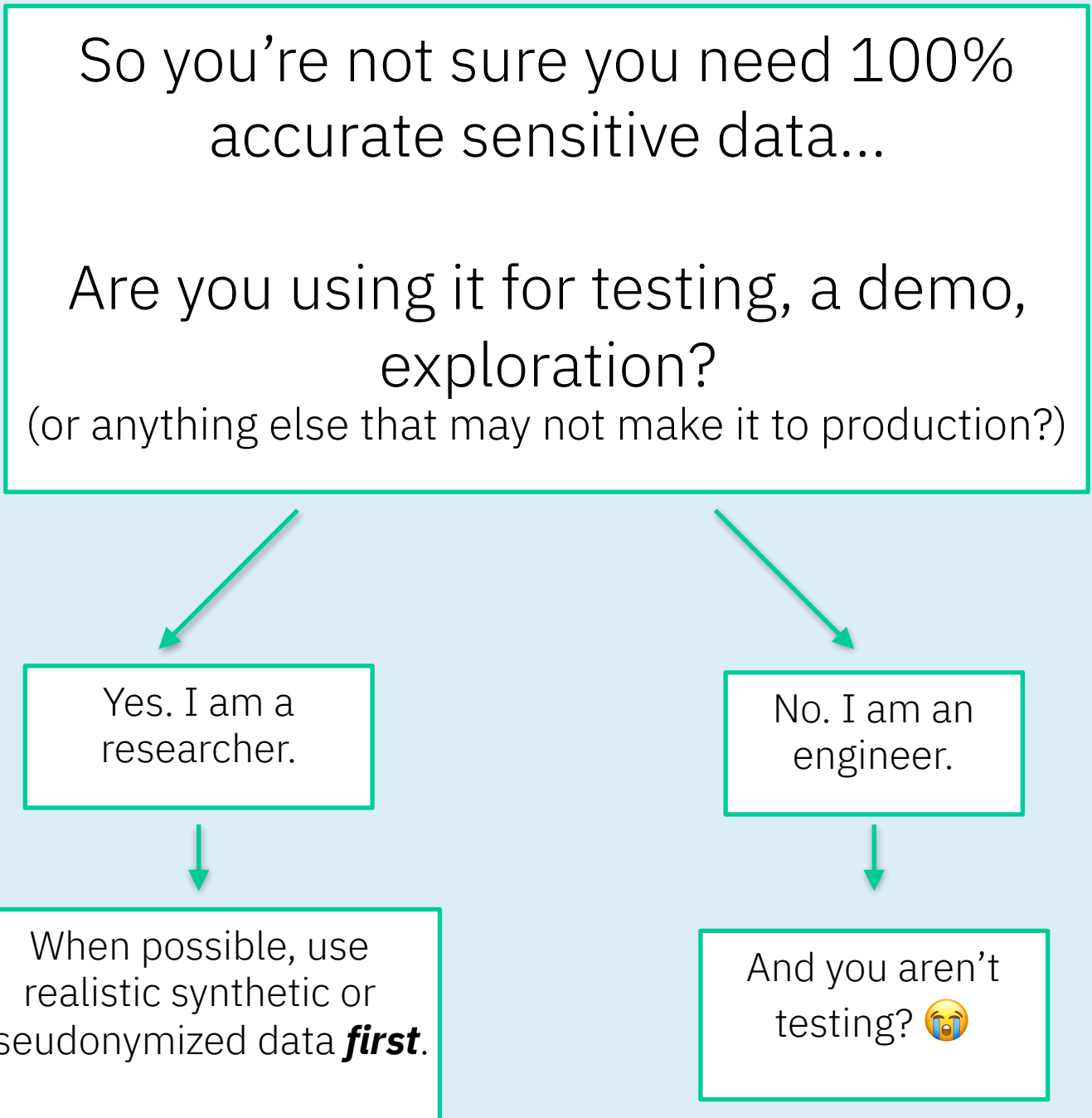




# The Case for K-Anonymity

- Create groups / blocks which allow us to cluster similar individuals together, preserving individual privacy for the grouping (i.e. age: 30-40, larger region vs zip code)
- Usefulness depends on the diversity of your overall dataset and the diversity of the groups
- Does not automatically guarantee against information disclosure about a person or group
  - l-diversity and t-closeness can help with this

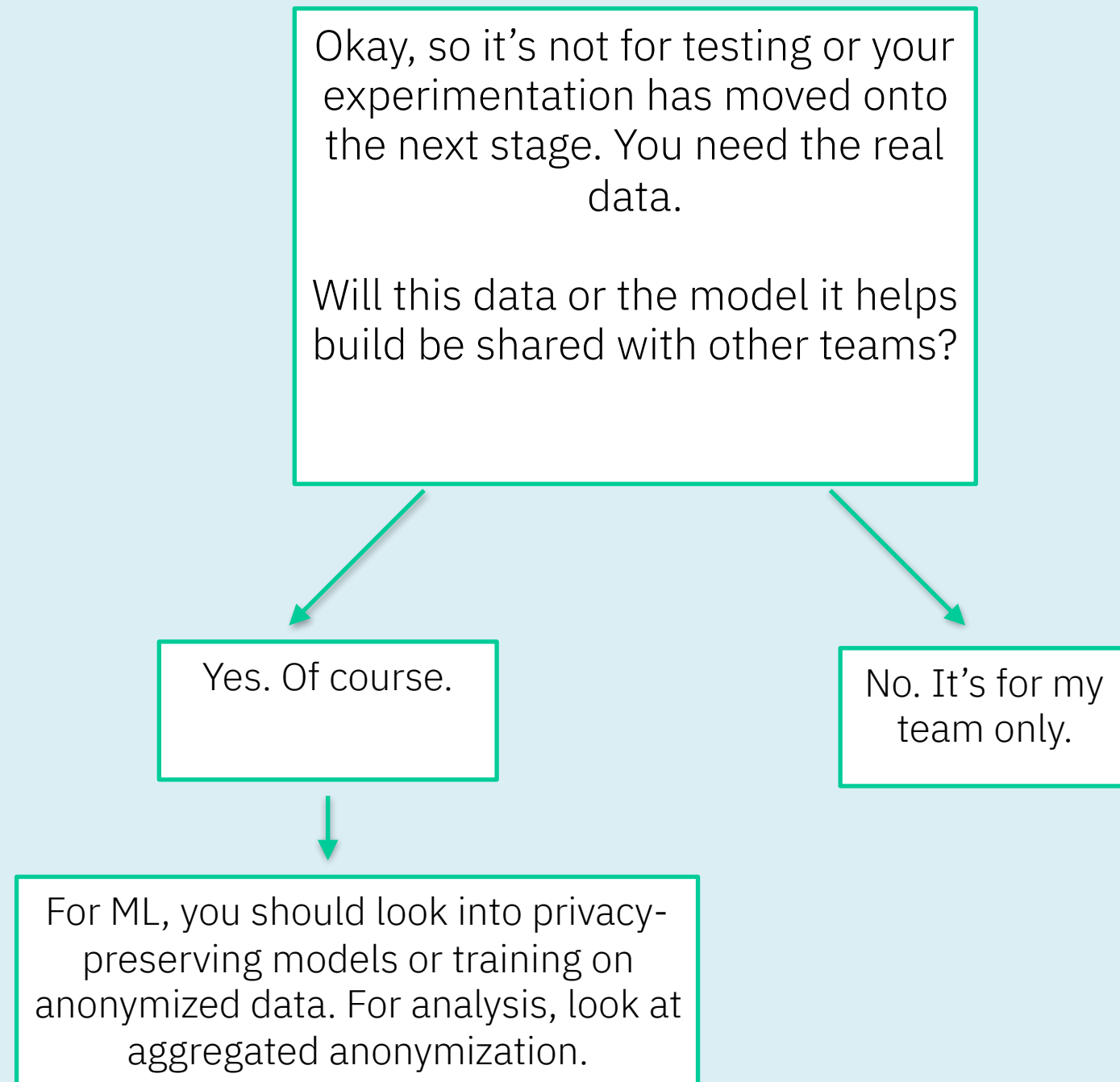
# Determining Your Data Needs



# The Case for Pseudonymization

- Pseudonymization (depending on method) can allow you to preserve individual privacy while still retaining information based on the attribute
- KIProtect Pseudonymization API allows for homomorphic pseudonymization (structure-preserving mechanism)
- Does not protect against statistical attacks or linkage attacks (using outside information to determine identity)

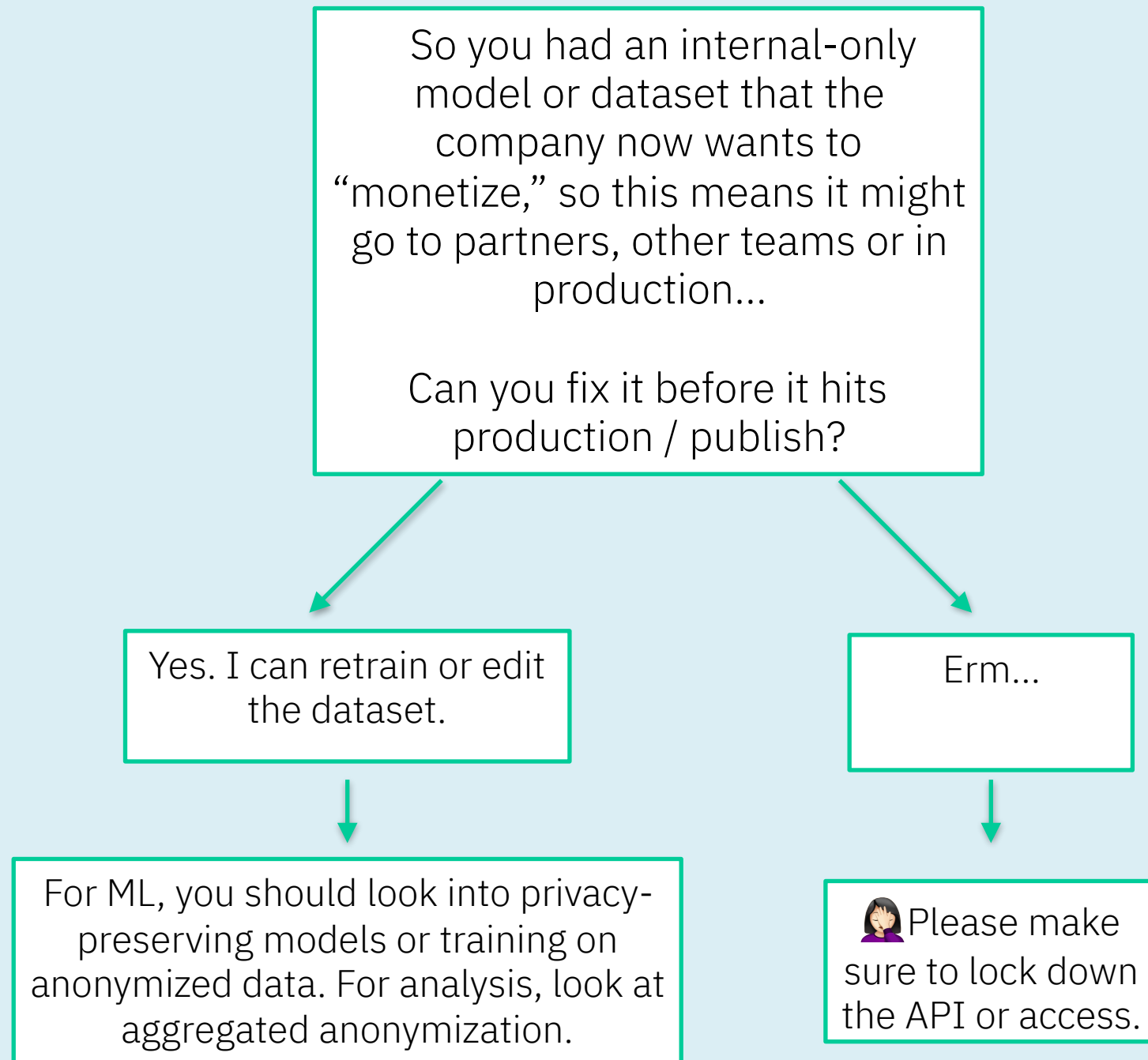
# Sharing Your Data / Models



# The Case for Privacy-Preserving ML

- If you must learn on private data, please utilize privacy-preserving mechanisms
- Determine what the attack vector is:
  - Do you trust your MLaaS provider?
  - Do you trust your API users? (i.e. black box access)
  - Do you trust people with access to the model or training mechanism itself? (i.e. white box access)
- Active area of research!

# Data and Model Security, Anyone?



# The Case for Anonymization

- If you are releasing data to an untrusted audience or public audience, please employ anonymization!
- Deletion of sensitive fields can help, but is not enough (long-tail distribution / linkage)
- Differential privacy can be used to regulate the amount of information w.r.t. a single variable or attribute
- Aggregated anonymization can help preserve privacy but still allow for group insights (i.e. Apple Differential Privacy for Emoji Use)



# End Story: Treat Your Data Like Radiation

- Try to remove as much extraneous data as possible.
- Think: Do I really need this much radiation? Probably not, let's just have the minimal amount of radiation we need.
- Use techniques to make the radiation less harmful — understanding there are a wide variety of options and levels and you can use to determine the range of exposure.
- (raw data → pseudonymization → anonymization → deletion)

# Thank you for your time!

Questions? I'd Love to hear them!

Or reach out anytime:

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