

# Contextualizing Open and Responsible (Data) Science Citizenship

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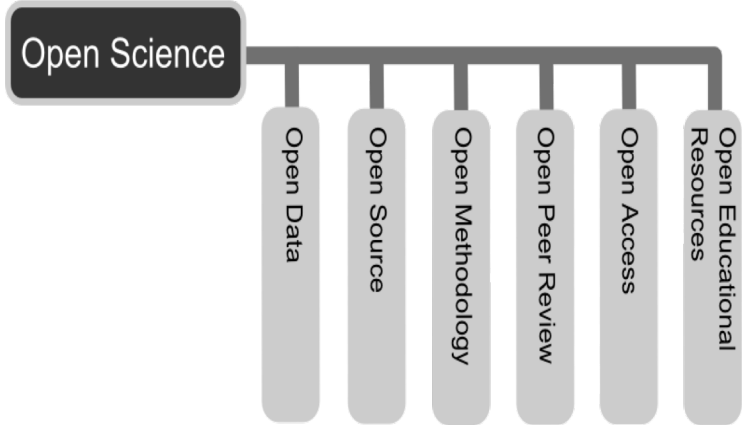
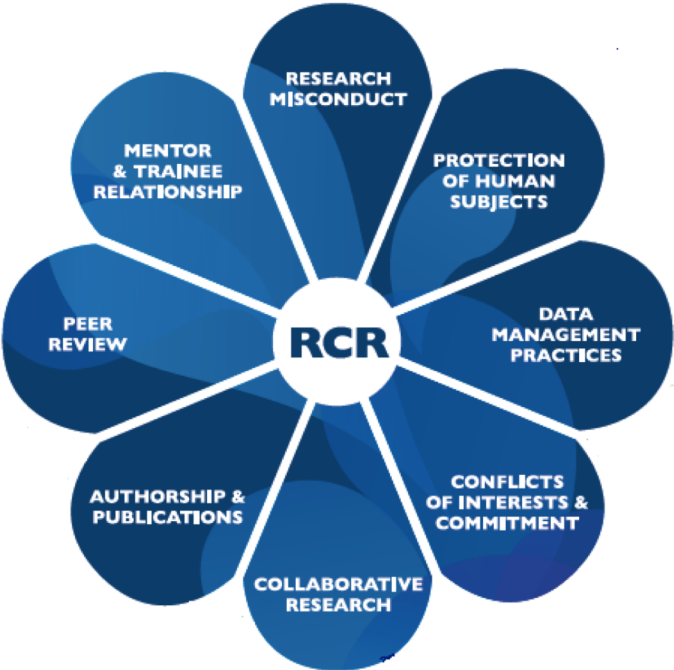
Louise Bezuidenhout

# Plan

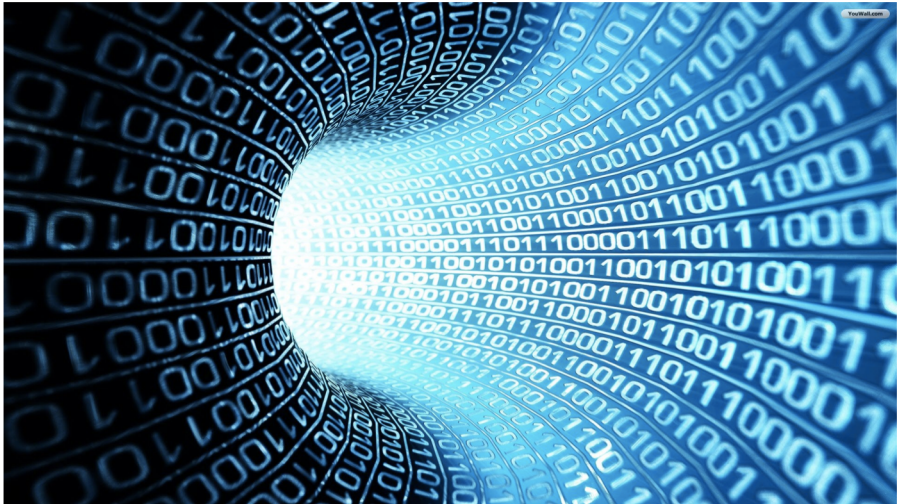
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- Personal concerns and implementing OS practices at home
  - What have we learned this week?
  - What challenges do we have about implementing these in our research environments?
  - What kinds of assistance can we get?
- RCR and the “bigger picture”
  - Designing just systems
  - Avoiding biases and marginalizations

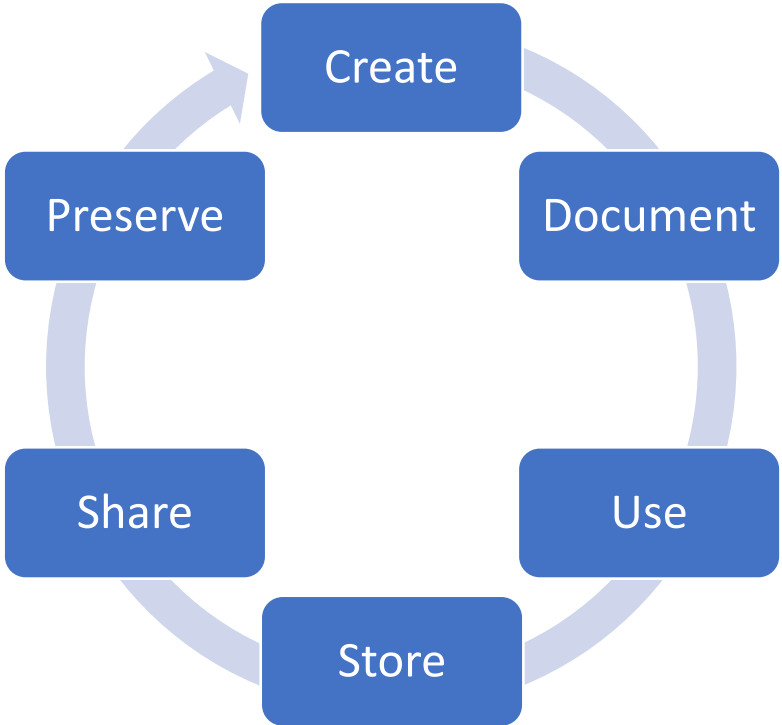
How to be a responsible and open data scientist



Tools for responsible and open data science



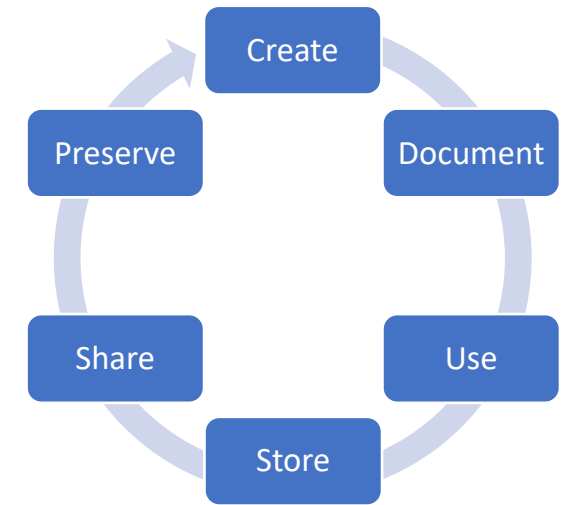
Doing responsible and open data science research



# Being Open and Responsible at Home

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- Institutional cultures
  - Promotion criteria
  - Incentivization schemes
  - Cultural specificities
- Institutional support
  - Facilities
  - Traditions
  - Lack of whistleblowing protection



# Being Responsible at Home

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- Resources
  - Time
  - Money
  - Infrastructure
- Copyright, ownership and agency
  - IP
- Training



# Personal Concerns

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- Lack of awareness and training
- Cultural inertia and misinformation
- Challenging the establishment
- Following status quo
- Lack of reward
- Publication bias towards novel findings
- Resources
- Fear – of being scooped, scrutinized, reduced scientific quality, risk to reputation
- Career pressures

# Experiencing Challenges is Normal

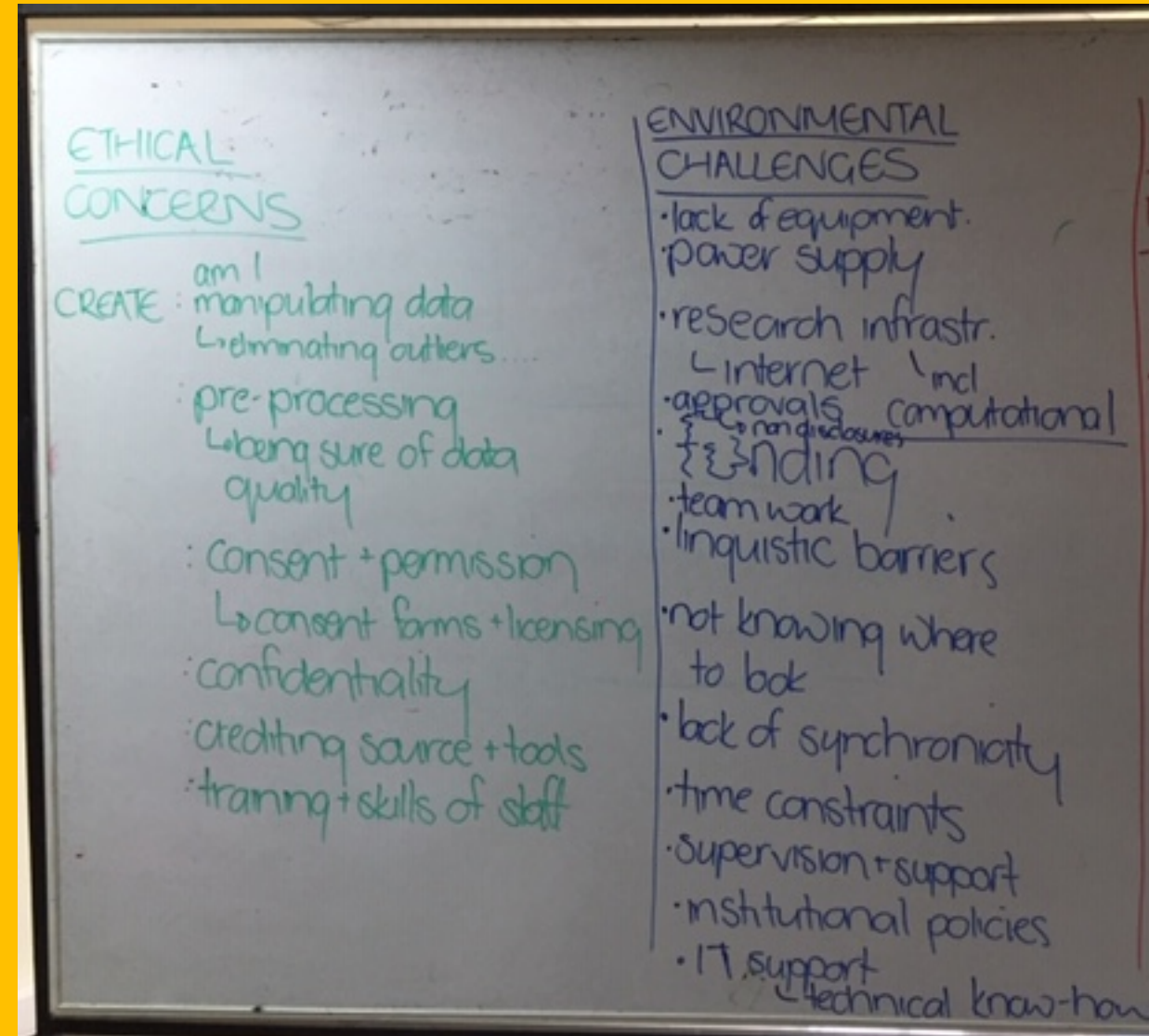
## Discussion

What specific challenges do you anticipate encountering when you return home in terms of your data work?

- Think about specific, or general challenges.  
Write down 3 on post-its

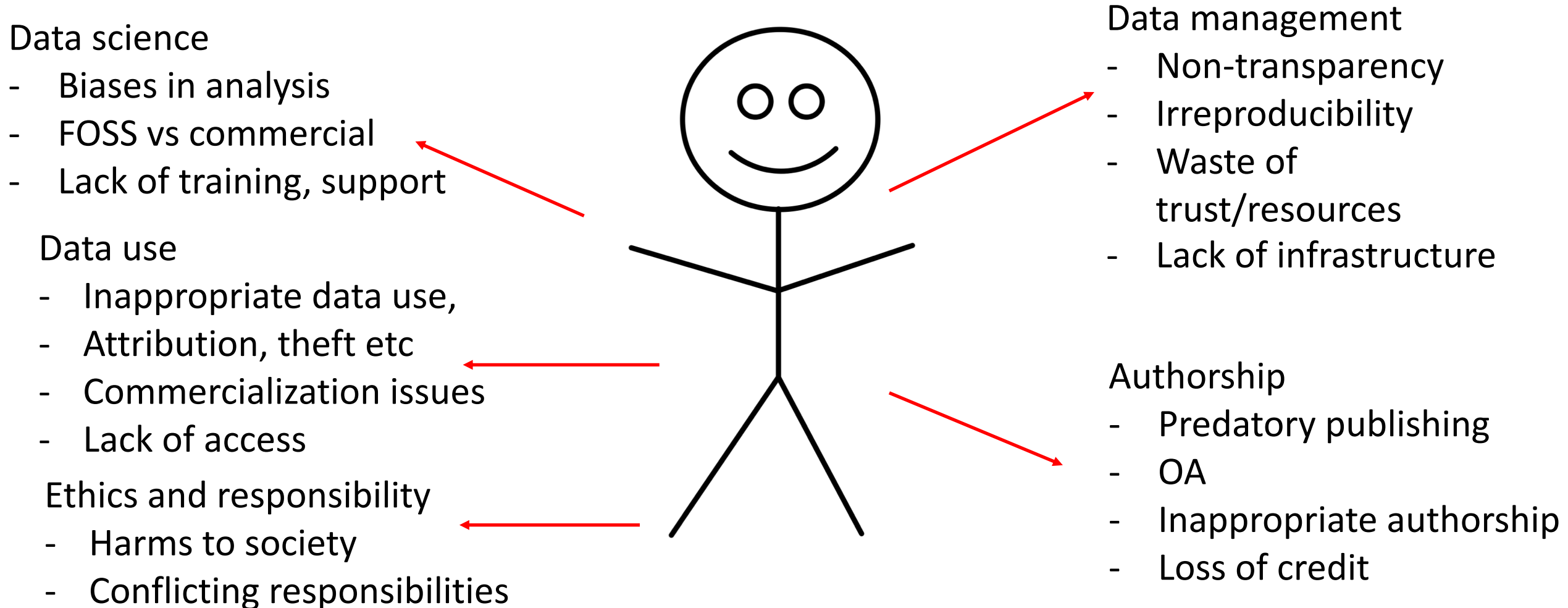
We have learnt quite a few tools that could help with these challenges.

- Write down three new tools, organizations, practices that you have learnt this week that could help with these challenges



# Challenges of Responsible, Open Science Citizenship

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# Responsible and Open (Data) Science Citizenship

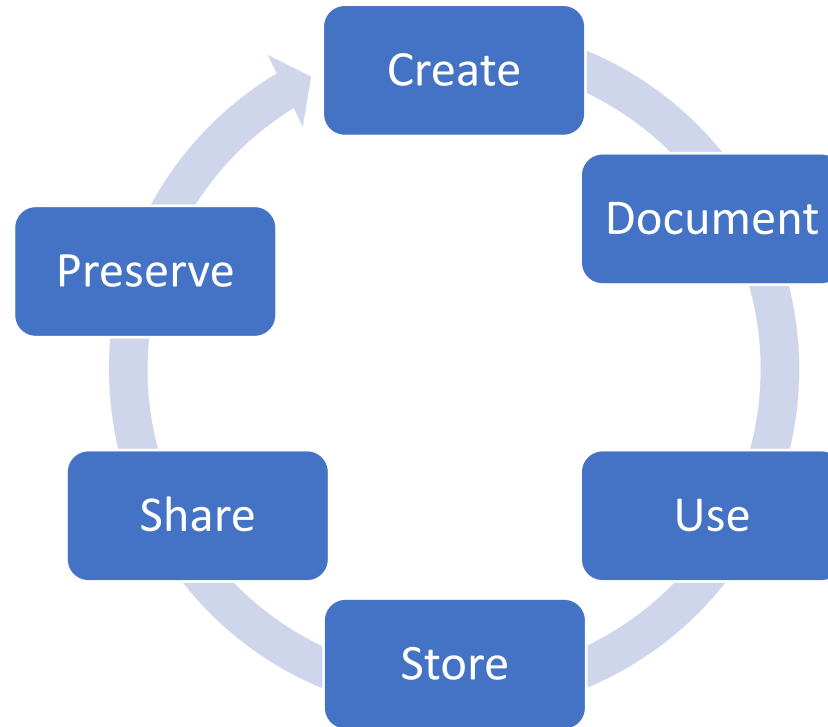
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## Data science

- Practical skills: R, Git

## Data use

- Data providence
- Data re-use and attribution: CC



## Data management

- Norms and values (FAIR)
- Practical tools - RDM

## Authorship

- ORCID
- Open authorship
- Open Access vs predatory publishing

## Ethics and responsibility

- Open Science and RCR
- Norms and values

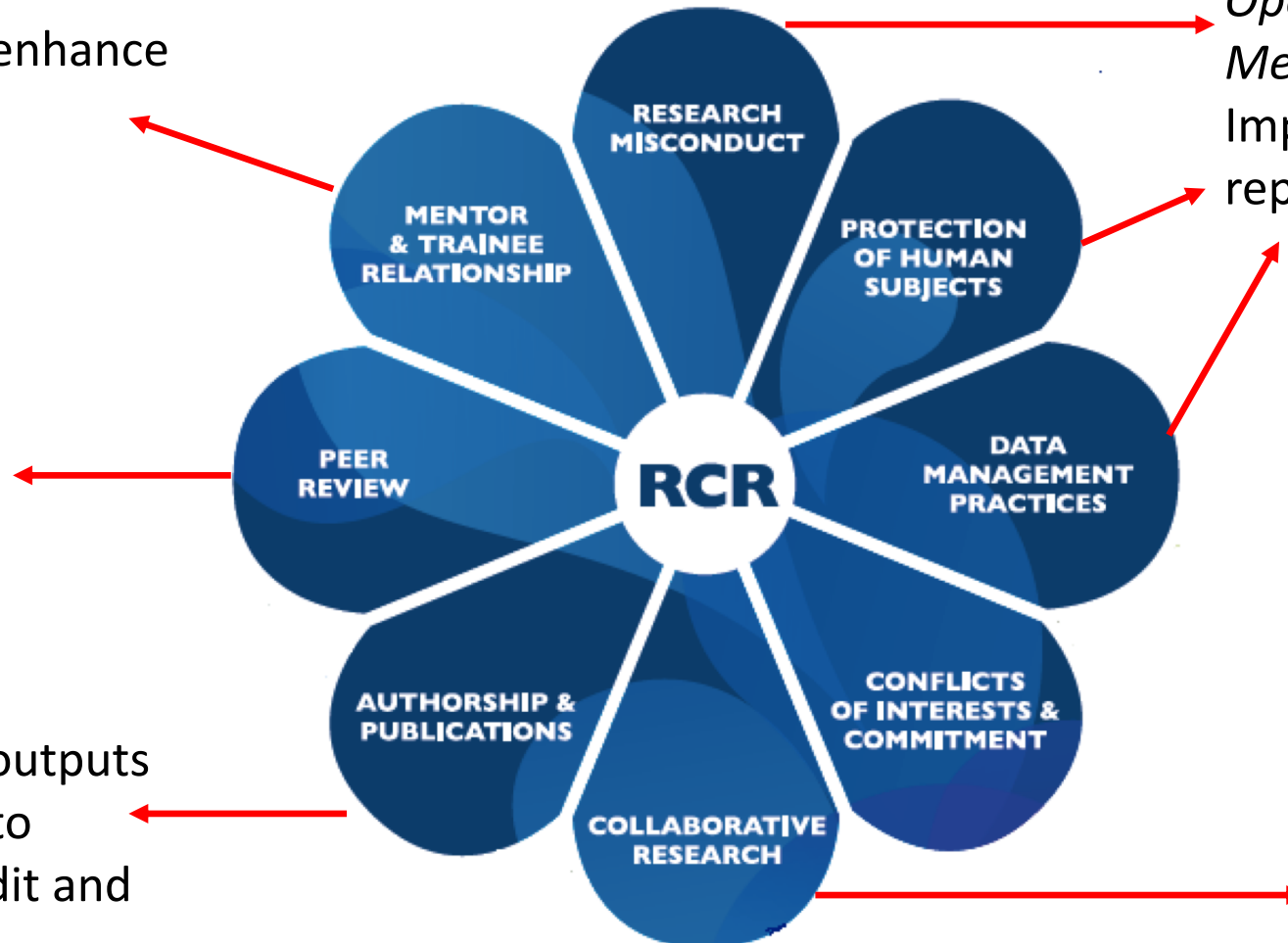
## Open communities, online resources

# Openness in RCR

*Open Lab Books:* Transparency in research practices  
*Sharing and openness:* enhance transmission of values

*Open Peer Review:* Transparency in peer review leads to better dialogue and collegial behaviour

*Open Access:* Improves availability of research outputs  
*Open publishing:* leads to improved citations, credit and collaboration



*Open Data and Open Methodologies:*  
Improve transparency and reproducibility of research

*Open Science Tools:*  
Improve collaboration

# Experiencing Challenges is Normal

## Group discussion

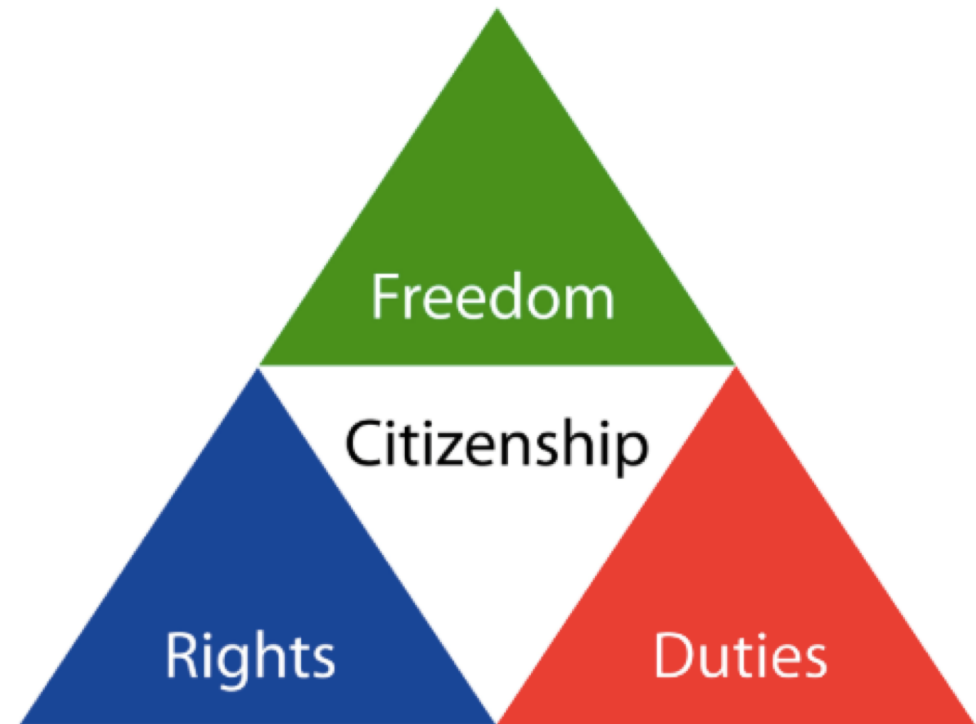
Contextual challenges can affect your ability to be responsible and open. But, there are a range of tools and assistance you can utilize to address some of the problems you have listed.

- Using your hand-out sheets, go through the categories of the research lifecycle and RCR and try and situate some of the challenges you will experience
- Using your hand-out sheets, go through the categories of research lifecycle and RCR and think about how to overcome some of the challenges you have listed
- Discuss these specific, or general solutions in your groups
- How will these resources enhance your ability to be responsible and open?

# Responsible and Open Science Citizenship

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- As a citizen you have duties and expected ways of acting
  - Follow rules
  - Participate in community activities
  - Protect the community and its resources from misuse



# Looking at the Bigger Picture: Ethical Challenges of Data Science



# Challenges Beyond the Lab

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- technology affects communication, collaboration and knowledge exchange within scientific, work and home settings
- need to help people to use those innovations *more productively and safely*
- need to improve ways in which new technologies can be designed and developed to be *more responsive* to societal acceptability and desirability

*Not just about being open/closed. It's about making sure that you use openness as a tool to secure just futures.*

# You Are Part of the Bigger Picture

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- Not just problems of someone else's making"
- The data that you select in your analyses can produce biases
- The algorithms that you design can perpetuate biases and stereotypes
- The websites, platforms, sharing pathways that you design, endorse or populate can perpetuate discrimination
- The data you generate can be re-used, re-combined, re-purposed in unexpected ways

# Bias

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## **Bias**

Inclination or prejudice for or against one person or group, especially in a way considered to be unfair.

## **Discrimination**

Unequal treatment of persons on the basis of 'protected characteristics' such as race, sexual identity etc.



# Biases in Data Selection and Algorithmic Design

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## **Bias in algorithms**

Unjustified and/or unintended deviation in the distribution of algorithm outputs, with respect to one or more of its parameter dimensions

# Value Ladened Nature of Algorithmic Design

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“Algorithms are inescapably value-laden. Operational parameters are specified by developers and configured by users with desired outcomes in mind that privilege some values and interests over others...[O]peration within accepted parameters does not guarantee ethically acceptable behaviour... for example, profiling algorithms that discriminate against marginalised populations”

(Mittelstadt, Allo, Taddeo, Wachter, Floridi, 2016)

# Current Challenges



## Women less likely to be shown ads for high-paid jobs on Google, study shows

Automated testing and analysis of company's advertising system reveals male job seekers are shown far more adverts for high-paying executive jobs



## Courts use risk algorithms to set bail: A step toward a more just system?

**PROGRESS WATCH** Court systems in more than two dozen US cities and states are using algorithms that assess flight risk without considering race, gender, or socioeconomic status, in an attempt to remove implicit bias from the equation.

By Gretel Kauffman, Staff | AUGUST 3, 2016



# Example 1: Algorithmic Decisions on Bail

## Northpointe and COMPAS

In 2014, then U.S. Attorney General Eric Holder warned that the risk scores might be injecting bias into the courts. He called for the U.S. Sentencing Commission to study their use. "Although these measures were crafted with the best of intentions, I am concerned that they inadvertently undermine our efforts to ensure individualized and equal justice," he said, adding, "they may exacerbate unwarranted and unjust disparities that are already far too common in our criminal justice system and in our society."

The sentencing commission did not, however, launch a study of risk scores. So ProPublica did, as

# Eliminating Human Bias?

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- In the early 2000s the US criminal justice system began using risk assessments to assist decision-making.
- Assessments are based on algorithmic calculations to predict, for instance, how likely an individual is to re-offend or fail to attend court for sentencing.
- Used to determine whether an individual should be granted bail or how long their sentence should be
- 'Low risk' offenders given shorter sentences and perhaps even kept out of jail entirely.
- Overcome human bias, or ...?

# Proprietary Software to Determine Risk?

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- Risk assessments are now used across a wide number of states at all stages of the legal process
- Software and scores provided by for-profit companies such as Northpointe
  - Scores derived from 137 questions, either answered by defendants or pulled from criminal records. These questions related to factors such as personal offender history, family offender history, drug taking amongst friends and personal views on offending. Race was not one of the questions.
- Risk assessment scores are usually made available to the defendant's legal team
- Criteria through which the scores are generated are typically regarded as proprietary to the companies that develop them and are not released.

# The Difficult Nature of Identifying Biases

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- Only 20% of those predicted to commit a violent crime had gone on to do so
- Of those deemed likely to re-offend, 61% went on to be arrested, when misdemeanours such as driving with an expired license were included;
- Black people were almost twice as likely to be falsely labelled as at risk of future offending than white people;
- White people were mislabelled as low risk more often than black people;
- Even when statistical tests were run to isolate the effect of race from criminal history, recidivism, age and gender, black people were:
  - 77% more likely to be labelled as at risk of committing a future violent crime than white people
  - 45% more likely to be labelled as at risk of committing any kind of crime

# Northpointe and COMPAS

Northpointe, the company that sells COMPAS, said in response that the test was racially neutral. To support that assertion, company officials pointed to another of our findings, which was that the rate of accuracy for COMPAS scores — about 60 percent — was the same for black and white defendants. The company said it had devised the algorithm to achieve this goal. A test that is correct in equal proportions for all groups cannot be biased, the company said.

Monkey Cage

## A computer program used for bail and sentencing decisions was labeled biased against blacks. It's actually not that clear.

By Sam Corbett-Davies, Emma Pierson, Avi Feller and Sharad Goel  
October 17, 2016



### Most Read Politics

1 'Poor man's version of Don King': Trump continues his war of words with LeVar Ball



2 Analysis President Trump and accusations of sexual misconduct: The complete list



3 White House military personnel removed amid investigation into contacts with foreign women during Trump's Asia trip



# Even the Smallest Decisions Can Introduce a Bias

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- Unequally wrong for false positives in different populations = unfair (Pro Publica argument)
- Equally right in predicting reoffending = fair (Northpointe argument)
- Base populations have different levels of reoffending so algorithm cannot be equally wrong and equally right for both populations
- Technical measures to 'correct' for societal unevenness?
- **Transparency and accountability is necessary to enable individuals to challenge algorithm-based decision making that affects their lives**

*Even the smallest technical decisions can influence biases*

*Using a single assessment of "right" or "just" can cause biases to perpetuate*

# Campaigning for Justice: ProPublica

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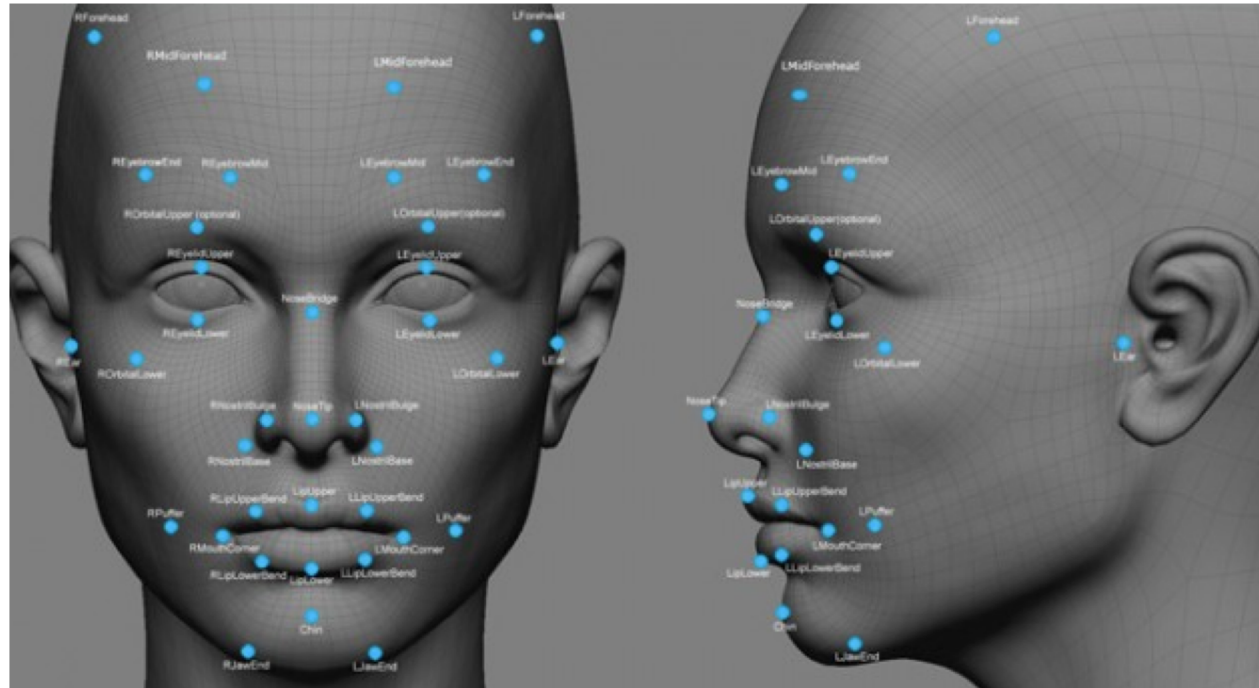
- Increasing amount of discussion about use of Northpointe COMPAS in judiciary
  - Proprietary algorithms determining individual futures
  - Inability to scrutinize processes through which decisions are made unjust
  - Uncritically accepting algorithmic decisions can mean that the justice system is failing in duty of care



# Example 2: Facial Recognition Software

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- Joy Buolamwini (MIT)
- software created by brand-name tech firms such as Amazon uncovered much higher error rates in classifying the gender of darker-skinned women than for lighter-skinned men.
- Other problems – unable to reliably detect Asian eyes
- Location of software companies and demographics = non-representative datasets used in algorithm development



# Significant Harms From Deployment of Algorithms

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- Called on Amazon to stop selling its facial recognition software to police.
- Caution about the fast-moving adoption of facial recognition by police, government agencies and businesses from stores to apartment complexes
- Computer vision systems that enable self-driving cars to “see” the road shows they have a harder time detecting pedestrians with darker skin tones.

# Algorithmic Justice League

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- Algorithmic activism
- Name and shame companies
- “Safe Face Pledge” – address bias, facilitate transparency, promote dignity and human rights



# On Correcting for 'Real World' Bias

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*algorithms are inherently politicised [as connected to social policy and political power]... and reflect our current world view, our current social policy ... If we are not explicit about that as well, if we are not transparent about that, that we value equality between men and women, then we are again creating bias at another level of the system (Jirotko 2016)*

# What Causes Bias?

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*.... among the major factors that contribute to bias in the results that [systems] produce is because there is bias in the data. So you actually have to look at the data as far as the performance is concerned, to make sure you have a representative sample of the population you are trying to model (Mittelstadt, Allo, Taddeo, Wachter, Floridi, 2016)*

## **Bias in data selection**

Use of unrepresentative datasets in algorithm development

## Women less likely to be shown ads for high-paid jobs on Google, study shows

Automated testing and analysis of company's advertising system reveals male job seekers are shown far more adverts for high-paying executive jobs



*we have to think about how to rebalance the data so that that discrimination is not propagated through the algorithms. How does one come up with a fair set of data, which can actually challenge the biases that might naturally be there ...*

*Not as easy as it sounds ...*

# A Vision for Algorithmic Design

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*We want our algorithms in a sense to follow a higher values, **moral values** that we think are more important than giving an exact reflection of the world. And that I think is a very interesting, but also in a sense very shady area in which, are we going to use the data as it is? Or are we going to change the data, or not change but adapt the way we look at the data to serve our purpose of being non-discriminatory...*

# What Can I Do?

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- Get independent researchers to check your code/data selection/results to expose biases
- Always critically examine the decisions you're making in your research and ask "why do I think that way"?
- Be critical of the code and results you're using – how did they get to the point they did?
- Think about how other cultures will respond to your decisions

Do the data/coding choices you made contribute to just present and futures? Are you upholding the moral values of societies?

# Individual Activities ... Global Impact

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- Being a responsible and open science citizen involves more than just making sure that your own data practices are ethical
- Being part of the data community comes with responsibilities to the scientific community, public and future
- Not just about responsible and critical use of data, also about scrutinizing evolving systems

# Open Science as a Means of Minimizing Biases

## Group discussion

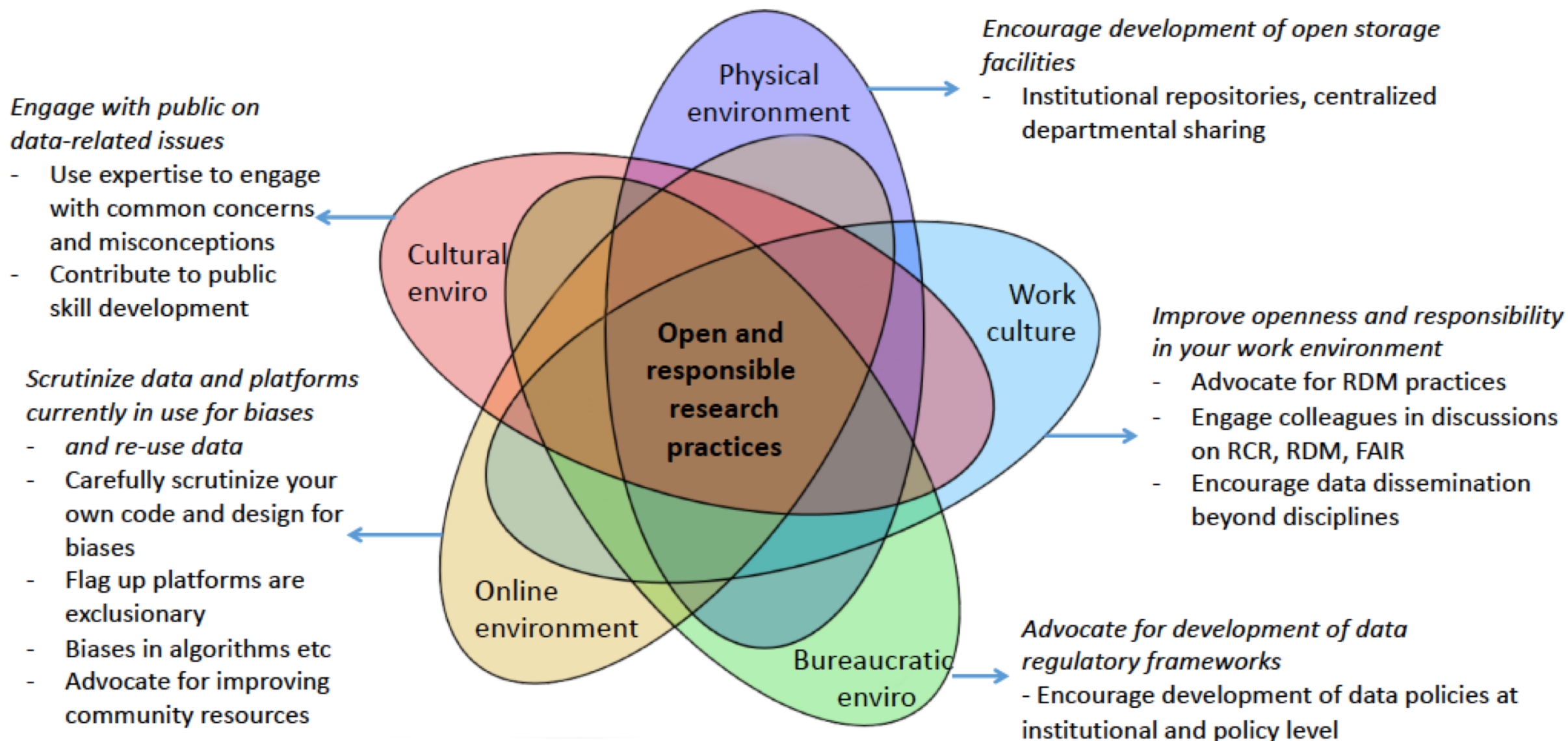
- When you go home, how can YOU, as an open and responsible data science citizen, contribute towards ensuring that digital infrastructures, tools and practices are safeguarding ethical priorities such as:
  - non-discrimination
  - Just distribution of resources
  - non-maleficence (not causing harm)

# The Pivotal Role of Open and Responsible Data Science Citizens

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- Data scientists play a crucial role in Open Data, as they not only work with data but also build, monitor and facilitate the structures that enable openness
- In all aspects, they must consider how best to advance the ideals of Open Science – justice, beneficence, non-maleficence, responsibility
- This must transcend their multiple roles:
  - Training others to work with data
  - Building data infrastructures
  - Contributing data
  - Using data
  - Communicating data to public

# Extending Data Science Citizenship Responsibilities



# Outline for Next Week

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Over the course of next week, reflect on the tools that you are going to be taught. Think about:

1. How you can safeguard *beneficial* outcomes of your activities in data gathering, infrastructure building and data dissemination?
2. How can you discuss these issues with your colleagues and peers?
3. How can you scrutinize the systems/datasets you will work with to make sure that biases do not creep into your research systems?
4. How can responsible and open science citizen strengthen these activities?

# Thank You

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Please feel free to contact me with any further questions!

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