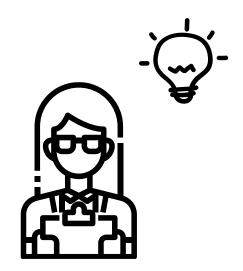
# Fake it 'till you make it Generating synthetic data

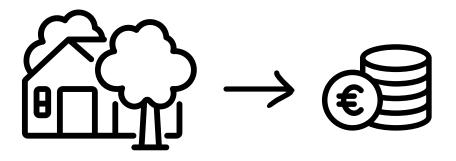
Erik-Jan van Kesteren Thom Volker

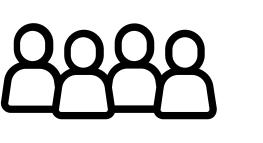
Utrecht University
ODISSEI Social Data Science team

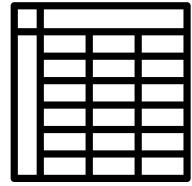
## thomvolker.github.io/OSWS\_Synthetic

# Imagine..

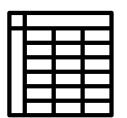


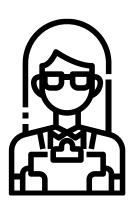


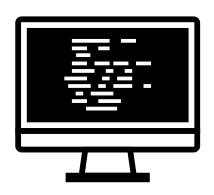




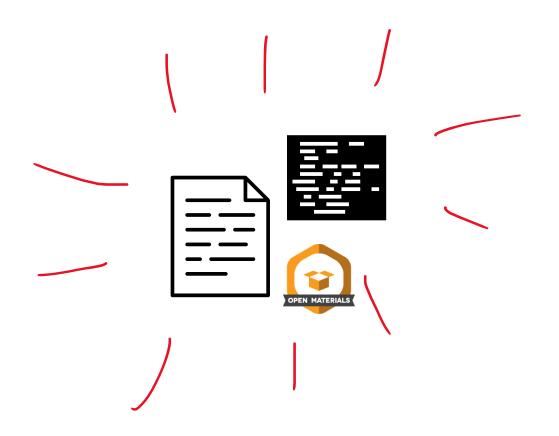
- Where do you live?
- How long have you lived there?
- What do you earn?
- How much do you spend on gifts for your friends?







"More generous gifting behaviour in greener neighbourhoods"





my\_data <- read\_csv("super\_private\_data\_file.csv")</pre>

#### **Open data not allowed, options:**

- Data just not available, good luck
- "Data available upon reasonable request"
- Data is part of a large project with data access procedures

I just want to check out the script to learn from the cool analysis!

Solution: publish open synthetic data with your open materials

## What will we do in this tutorial?

#### Lecture

A primer on synthetic data

#### **Practical**

Creating synthetic data in R

#### Lecture

Privacy & utility for synthetic data

#### **Practical**

Assessing utility & disclosure control in R

# A primer on synthetic data

# Synthetic data (EJ's definition)

Synthetic data is generated from a model
As opposed to real, natural, collected data

fake data generated data simulated data digital twin public use file

# To create synthetic data, you need a generative model

## **Generative model**

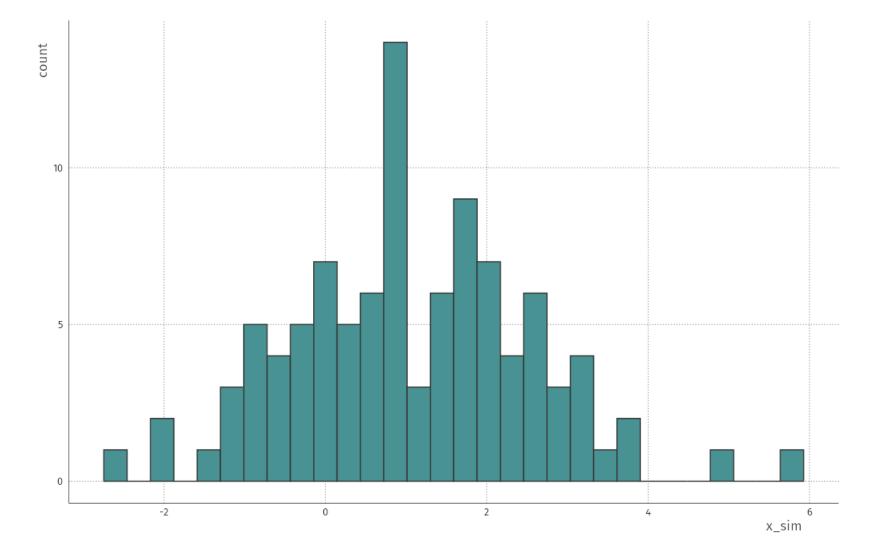
$$p(X|\theta)$$

- A model for data X
- Has parameters  $(\theta)$
- You can fit / estimate / learn  $\theta$  based on real data

- Examples:
  - A normal distribution with parameters  $\theta = \mu, \sigma$
  - A histogram with bins and proportions
  - A generative adversarial network with a million parameters

### Generative model

```
In R code:
# parameters
mu <- 1.0
sigma <- 1.5
# generate data
x_sim <- rnorm(100, mean = mu, sd = sigma)</pre>
```



## **Generative model**

Today we will fit two types of generative models:

**Parametric:** Assume that variables (conditionally) follow a certain distributions (e.g., Bernoulli, Normal, Exponential, ...)

**Non-parametric:** Do not assume certain distributions, use a machine learning® method

There are infinitely many more generative models. This is an active field of research

## Software

There are many ways creating generative models & synthetic data

- Manually creating a csv file ©
- Metasynth (<a href="https://github.com/sodascience/metasynth">https://github.com/sodascience/metasynth</a>)
- Synthpop (<a href="https://synthpop.org.uk/">https://synthpop.org.uk/</a>)
- MICE (<a href="https://amices.org/mice/">https://amices.org/mice/</a>)
- Synthetic Data Vault (<a href="https://sdv.dev/">https://sdv.dev/</a>)
- DataSynthesizer (https://github.com/DataResponsibly/DataSynthesizer)

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# The MICE generative model

# The MICE generative model

- MICE: Multiple Imputation by Chained Equations
- Trick to create multivariate generative model through univariate prediction models

$$p(X_1, X_2, X_3) = p(X_1|X_2, X_3)p(X_2|X_1, X_3)p(X_3|X_1, X_2)$$

Focus on making good univariate predictions

# The MICE generative model

Many prediction methods available in MICE, we will use two types:

#### **Parametric**

Linear & Logistic regression

#### Nonparametric

Classification and regression trees

Built-in univariate imputation methods are:			
pmm	any	Predictive mean matching	
midastouch	any	Weighted predictive mean matching	
sample	any	Random sample from observed values	
cart	any	Classification and regression trees	
rf	any	Random forest imputations	
mean	numeric	Unconditional mean imputation	
norm	numeric	Bayesian linear regression	
norm.nob	numeric	Linear regression ignoring model error	
norm.boot	numeric	Linear regression using bootstrap	
norm.predict	numeric	Linear regression, predicted values	
lasso.norm	numeric	Lasso linear regression	
lasso.select.norm	numeric	Lasso select + linear regression	
quadratic	numeric	Imputation of quadratic terms	
ri	numeric	Random indicator for nonignorable data	
logreg	binary	Logistic regression	
logreg.boot	binary	Logistic regression with bootstrap	
lasso.logreg	binary	Lasso logistic regression	
lasso.select.logreg	binary	Lasso select + logistic regression	
polr	ordered	Proportional odds model	
polyreg	unordered	Polytomous logistic regression	
lda	unordered	Linear discriminant analysis	
21.norm	numeric	Level-1 normal heteroscedastic	
21.lmer	numeric	Level-1 normal homoscedastic, Imer	
21.pan	numeric	Level-1 normal homoscedastic, pan	
21.bin	binary	Level-1 logistic, glmer	
21only.mean	numeric	Level-2 class mean	
2lonly.norm	numeric	Level-2 class normal	
21only.pmm	any	Level-2 class predictive mean matching	

# Let's get started!

## Icons from the noun project

```
Scientist by Justicon
Idea by Icon
house tree by LUTFI GANI AL ACHMAD
Euro by Larea
people by Alice Design
Table by Alex Burte
Hacking by Alfredo
Paper by Egi Maulana
Scientist 2 by Justicon
Question by Anggara Putra
```

https://thenounproject.com/