

Synthetic Data Use:

Exploring use cases to optimize data utility

Stef James, Senior Director, Clinical Data Insights at AstraZeneca



9th March 2023

What will I cover today?

Peer reviewed paper: James, S., Harbron, C., Branson, J. Sundler, M. Synthetic data use: exploring use cases to optimise data utility. Discov Artif Intell 1, 15 (2021).

https://doi.org/10.1007/s44163-021-00016-y

Acknowledgement: to the PSI Data Sharing Special Interest Group

The definition

'Synthetic data is data generated by simulation, based upon and mirroring properties of an original dataset.'

Uses of synthetic data

7 key use cases we will explore from a pharmaceutical context that

will demonstrate the utility of synthetic data

Techniques to mask data

There are various methods to mask personal data, including

anonymization and data synthesis.

Methods to produce synthetic data

The different methods to produce synthetic data, which can be a

combination, such as embedding or GAN.

Application of utility measurements/ parameters

The measurement, check and balance on the effectiveness and

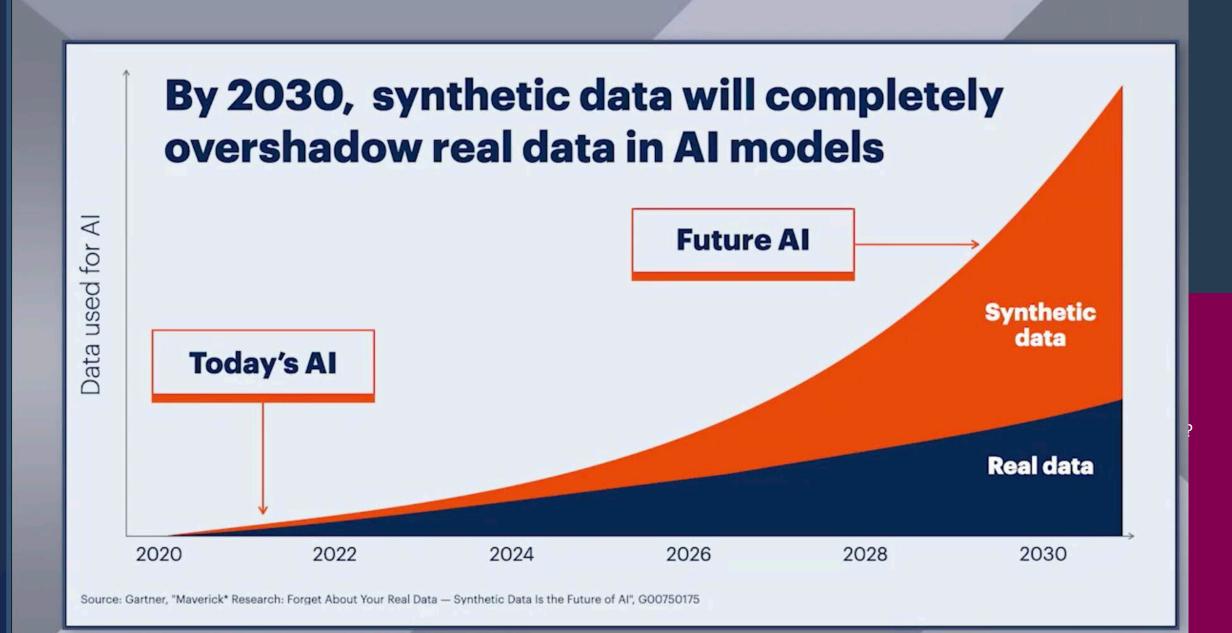
quality of synthetic data generation.

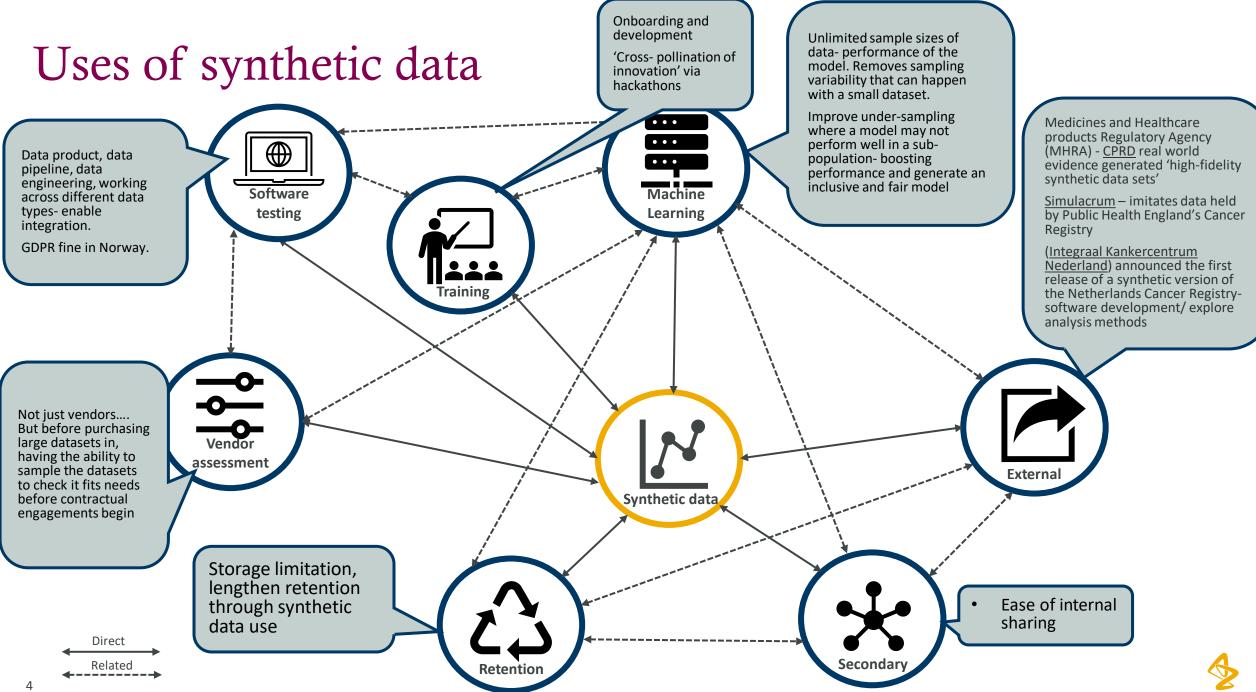
Consideration of the challenges to adoption The considerations specifically for the pharma industry, although this

may transfer to other industries also where sensitive data is a

consideration.







James, S., Harbron, C., Branson, J. et al. Synthetic data use: exploring use cases to optimise data utility. Discov Artif Intell 1, 15 (2021). https://doi.org/10.1007/s44163-021-00016-y

Request form for CPRD database

Training of machine learning algorithms	
Testing/validation of machine learning algorithms	
Developing, populating or testing models	
Methodological research	
Sample size boosting	
Feasibility counts	
To support regulatory submissions	
Building medical software applications	
Trend simulation/analysis	
Sample dataset to understand CPRD Aurum data structure and utility	
Data management teaching/training resource	
Develop/validate/test analytics tools for use with CPRD Aurum	
Improve bespoke CPRD Aurum application interfaces/algorithms	
Develop machine learning workflows for application to anonymised CPRD Aurum data	
Other (please state below)	

Note:

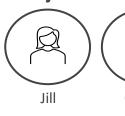
- Training
- Testing
- Machine learning
- Sample size boosting
- Support regulatory submissions

Synthetic datasets are owned by the Medicines and Healthcare products Regulatory Agency (MHRA)

Common techniques adopted to mask data

Unmasked patient data

Real patient data contains sensitive health data which is subject to GDPR



25 years



42 years



62 years

50 years

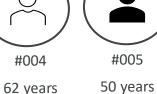
Pseudonymisation

Names and personal information removed or encrypted which is subject to GDPR- must have a legal basis









#005

Anonymisation

31 years

Aggregation and statistics: sanitation applied to remove personally identifiable information, excluded from GDPR



Synthetic data

Artificially generated patients, excluded from GDPR



Methods to produce synthetic data

Embedding

Uses two neural networks to help generate data. Neural networks are **encoder** and **decoder**. There is a need to train the two networks to encode and decode the data. The outcome provides synthetic data Generative adversarial network (GAN)

Uses a **generator** and **discriminator**. The discriminator attempts to figure out what records are real which is produced by the generator. The generator and discriminator are trained over time. This provides a propensity score. This is a machine learning/ deep learning method. Sequential synthesis

This method synthesizes datasets **variable** by **variable**. The more variables in a dataset, the more the sequence of the variables will need to be optimized

More methods exist e.g. tree based or copula based methods, one or several methods can be used and combined to produce a synthetic dataset. There would be a requirement to detail the methods used.

Utility measurements/ parameters



Distribution comparison

Measures the distribution comparison between the real and synthetic data to measure representation per variable



Hellinger distance

Measures the distance between the real dataset and the synthetic data. 0 = equal, 1 = far apart



accuracy

Provides a comparison of future modelling and prediction, comparing machine learning models used on real data versus the synthetic dataset



Distinguishability

A measure which tries to determine in the model developed, whether the data is real or synthetic. 0 = perfect synthesis 1 = easily identified



Area under the receiver operating characteristic (AUROC)

Determines the discrimination in the dataset. ROC measures the probability and AUC measures the degree of separability between the real and synthetic dataset. The higher the AUC the better the model is at distinguishing between patients with the disease and no disease



Lots in the literature And others!



The considerations

The over-arching consideration is to ensure the characteristics between the original and synthetic data set are comparable

Tiers of synthetic data

• **Tiered approach** towards synthetic data, where lower fidelity datasets can be produced for certain use cases.

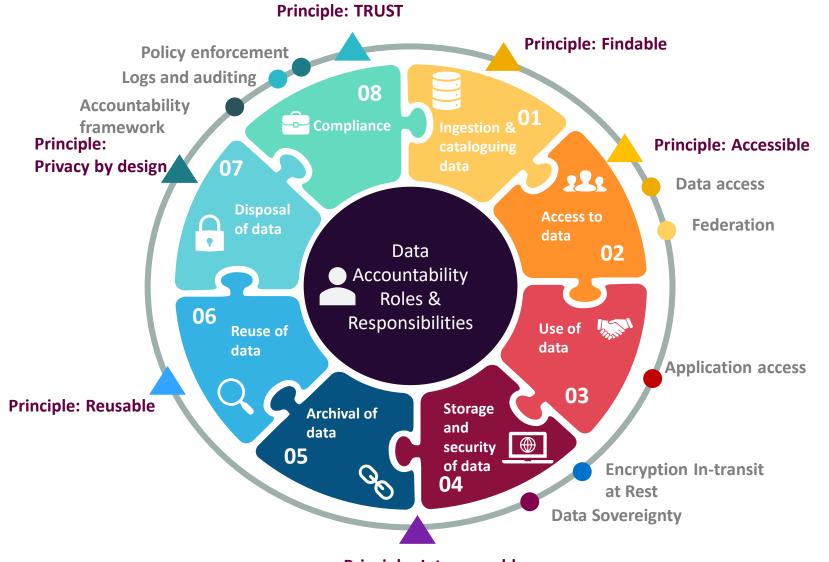
Technical and organizational measures

- **Business processes and skilled individuals** to avoid pitfalls when using synthetic data such as under/over-fitting models.
- Bridge the gap between privacy and utility of the data. This is a specialised skillset which is likely to need several different departments within an organisation.
- Industry and regulatory acceptance.
- **Privacy assurance assessment/report:** data protection by design approach.

Production considerations

- Effort and potential expense in producing representative synthetic data.
- Scientific and medical acceptance- could be used for de-centralised trials, to enlarge the overall cohort size. Aid recruitment in under-represented regions/populations to increase trial diversity as an example. Identification of vulnerabilities in trial design.
- **Agreed industry standard**s towards synthetic data, industry come together and create a central repository/ mechanisms for synthetic data sharing.

Data Protection in the Data Lifecycle: Business Processes



Principle: Interoperable

Remember where we began... **Gartner**: 'Synthetic data will overshadow using real data in AI and models'





What do you think?

Will synthetic data overshadow the use of real data?

Confidentiality Notice

This file is private and may contain confidential and proprietary information. If you have received this file in error, please notify us and remove it from your system and note that you must not copy, distribute or take any action in reliance on it. Any unauthorized use or disclosure of the contents of this file is not permitted and may be unlawful. AstraZeneca PLC, 1 Francis Crick Avenue, Cambridge Biomedical Campus, Cambridge, CB2 0AA, UK, T: +44(0)203 749 5000, www.astrazeneca.com