

Testing exchangeability between Real and Synthetic data

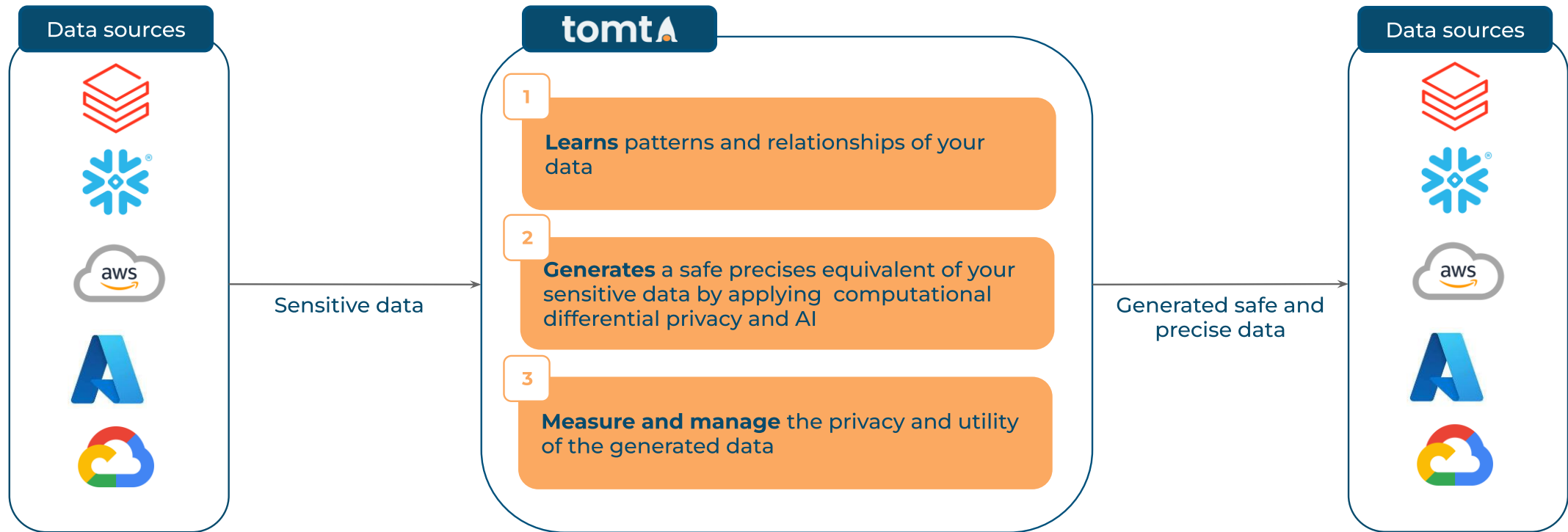
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Outline

- Introduction
- Methodology
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- Conclusion
- Future work

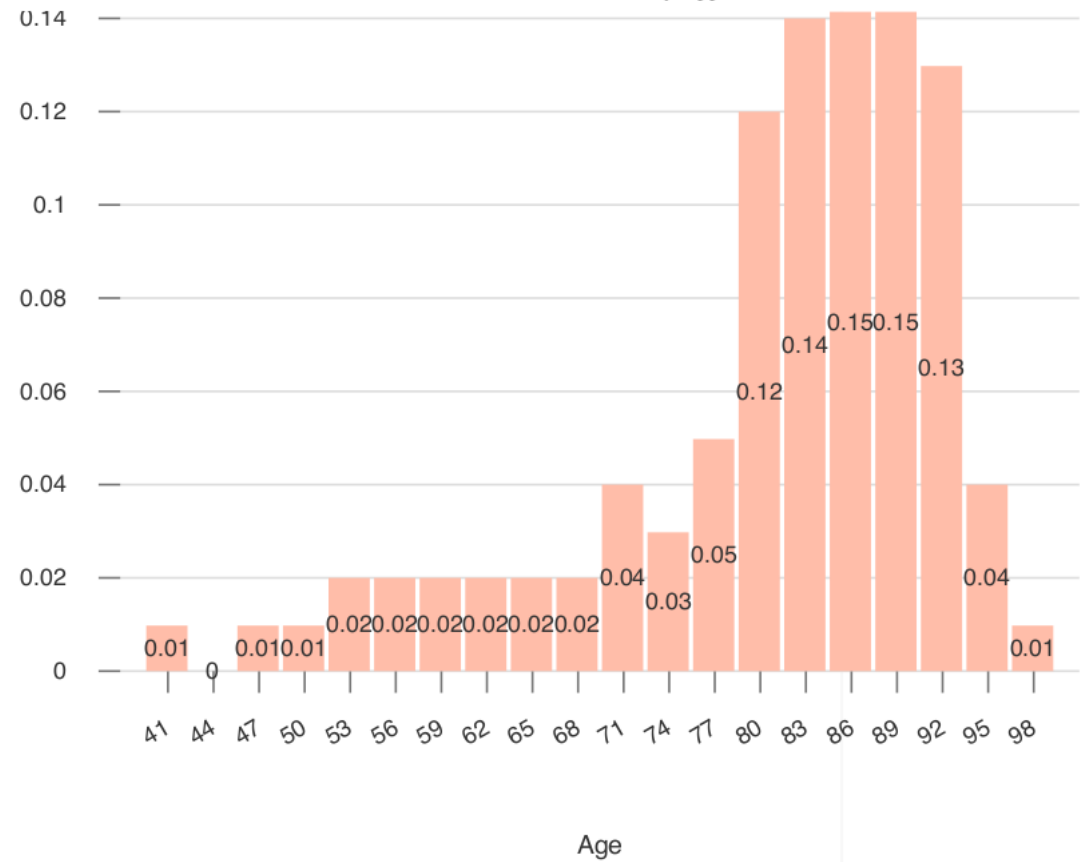
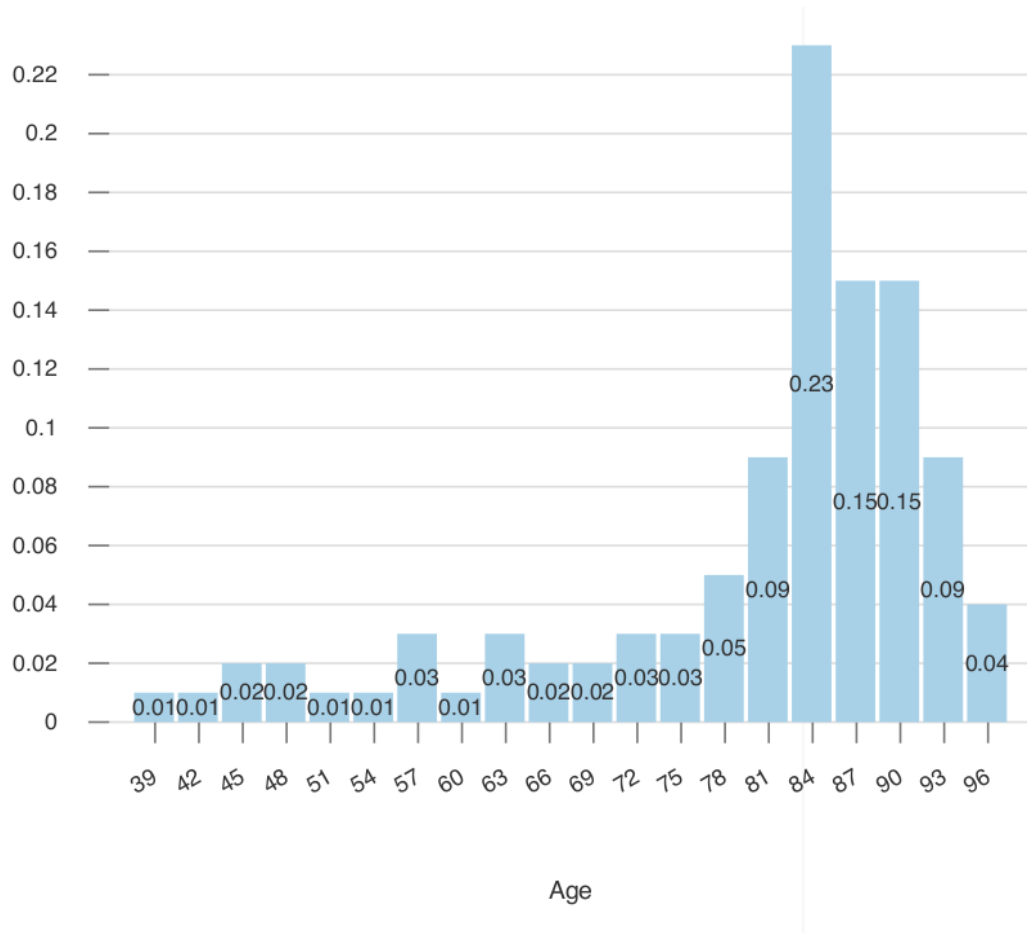
Why synthetic data?



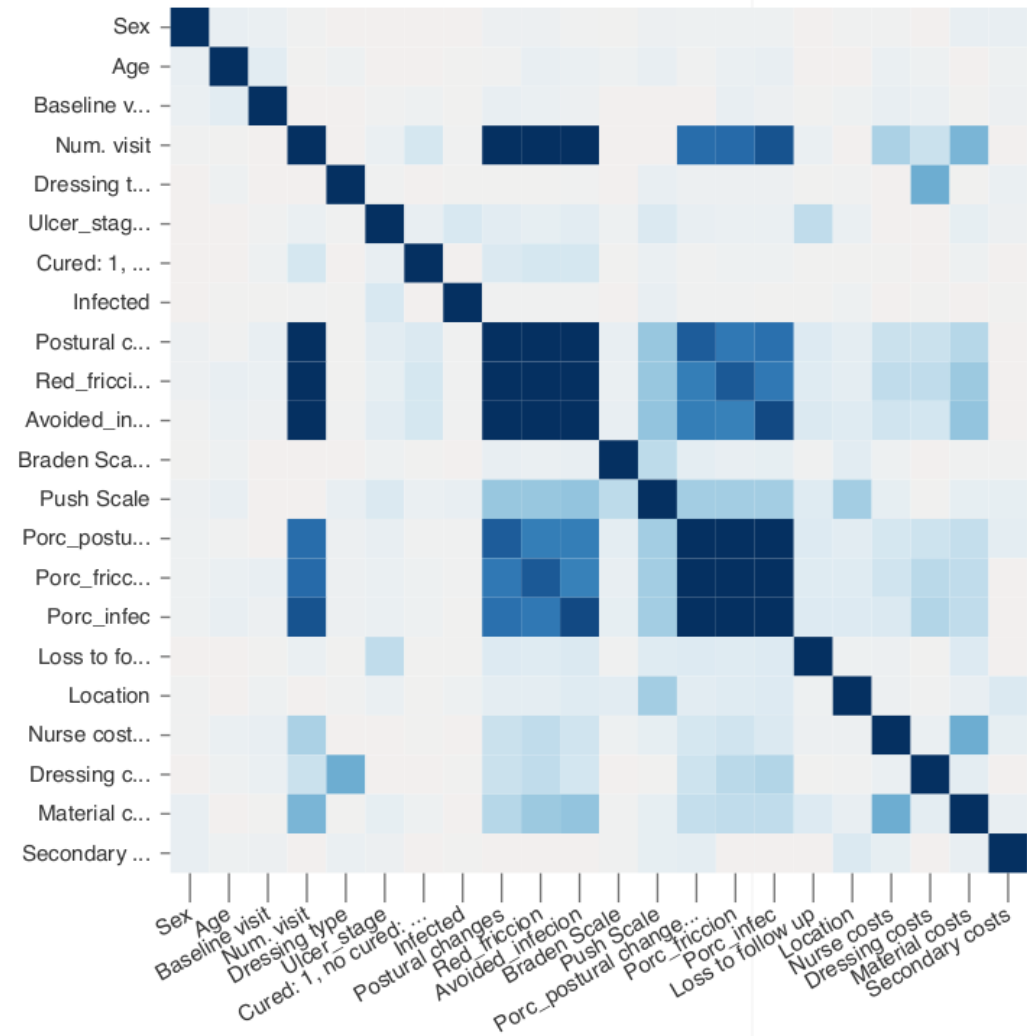
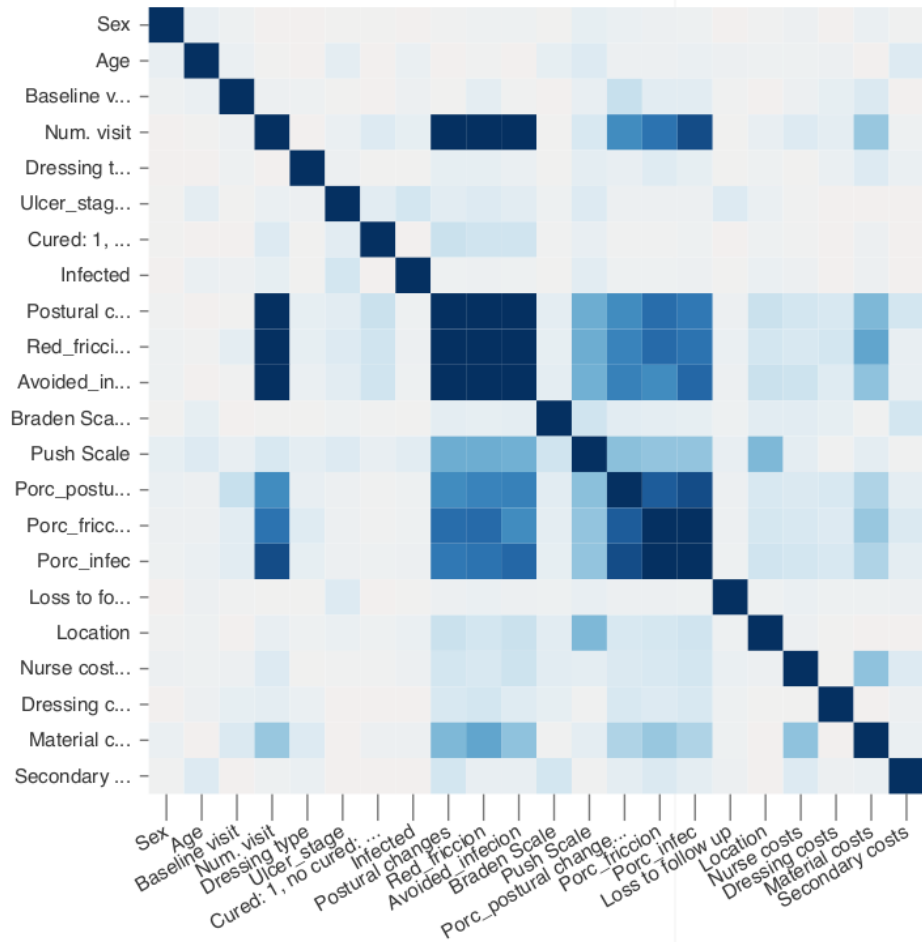
The Challenge – can synthetic data be taken as real data?



Comparing distributions



Comparing correlations



Does the exchangeability assumption hold?

Methodology - test

1. Data generation and preprocessing
2. Application of the conformal transducer
3. Application of the martingale test for exchangeability
4. Evaluation of the datasets

Algorithm 1: Simple Jumper $(p_1, p_2, \dots, p_n) \mapsto (S_1, S_2, \dots, S_n)$

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 $C_{-1} := C_0 := C_1 := \frac{1}{3}$   
 $C := 1$   
 $J = 0.01$   
for  $k = 1, 2, \dots, n$  do  
  for  $\varepsilon \in \{-1, 0, 1\}$  do  
     $C_\varepsilon := (1 - J)C_\varepsilon + (J/3)C$   
  end  
  for  $\varepsilon \in \{-1, 0, 1\}$  do  
     $C_\varepsilon := C_\varepsilon(1 + \varepsilon(p_k - 0.5))$   
  end  
   $S_k := C := C_{-1} + C_0 + C_1$   
end
```


Methodology - data and evaluation

- Real on Real (R-R): The conformal transducer is trained and tested on the real dataset to verify that our test works.
- Synthetic on Synthetic (S-S): The conformal transducer is trained and tested on the synthetic dataset, similar to the R-R case.
- Real on Synthetic (R-S): The conformal transducer, trained and calibrated on the real dataset, generates p-values for the synthetic dataset.
- Synthetic on Real (S-R): The conformal transducer, trained and calibrated on the synthetic dataset, generates p-values for the real dataset.

Dataset Name	Instances	Features	Numeric Features	Source
adult-sdv	32561	15	6	(Patki et al., 2016)
credit-g	1000	21	7	(Vanschoren et al., 2013)
spambase	4601	58	58	(Vanschoren et al., 2013)
qsar-biodeg	1055	42	42	(Vanschoren et al., 2013)
adult	48842	15	6	(Vanschoren et al., 2013)
RWI	88588	7	7	(Vanschoren et al., 2013)

Table 1: Additional information on the datasets used in this study.

Results

Dataset	Mean	Std	Min	Max
adult-sdv	-63.61	6.58	-75.52	-45.10
credit-g	-1.40	1.87	-3.49	5.05
spambase	-8.48	2.56	-12.51	-1.85
qsar-biodeg	-2.01	1.84	-3.87	7.06
adult	-96.63	7.09	-109.32	-79.45
RWI	-174.65	7.36	-192.76	-159.12

Table 2: Some metrics on the distribution of the martingale values for the 50 runs in the R-R case.

Dataset	Mean	Std	Min	Max
adult-sdv	-63.34	4.93	-73.59	-48.57
credit-g	-1.81	1.82	-3.49	6.04
spambase	-8.73	2.49	-12.45	-1.68
qsar-biodeg	-1.45	3.04	-3.73	16.17
adult	-96.58	5.53	-106.71	-82.01
RWI	-174.72	10.01	-195.17	-156.26

Table 3: Some metrics on the distribution of the martingale values for the 50 runs in the S-S case.

Results cont'd

Dataset	Mean	Std	Min	Max
adult-sdv	76.50	35.83	8.83	169.04
credit-g	57.72	8.62	36.61	72.18
spambase	519.12	26.78	440.35	579.82
qsar-biodeg	127.23	6.70	111.12	140.12
adult	-8.35	26.97	-62.07	60.97
RWI	709.78	0.00	709.78	709.78

Table 4: Some metrics on the distribution of the martingale values for the 50 runs in the R-S case.

Dataset	Mean	Std	Min	Max
adult-sdv	-65.53	5.26	-73.60	-52.25
credit-g	2.93	6.28	-3.25	26.78
spambase	29.82	14.30	1.04	57.76
qsar-biodeg	13.87	13.68	-3.46	57.60
adult	-79.51	15.20	-99.85	-37.54
RWI	708.55	5.21	684.25	709.78

Table 5: Some metrics on the distribution of the martingale values for the 50 runs in the S-R case.

Conclusion

The synthetic data does not appear to come from the same distribution as the real data.

Future work/considerations

- Extend current scope to regression
- Is it possible to initiate adversarial attacks using synthetic data generation?
- How can we be sure that the underlying relationship remains?