

DPFree DATA GENERATION

The future of Data Science

The future of humanity

Sayash Raaj,
IIT Madras
Silver Medalist

Credentials-
IIT Madras

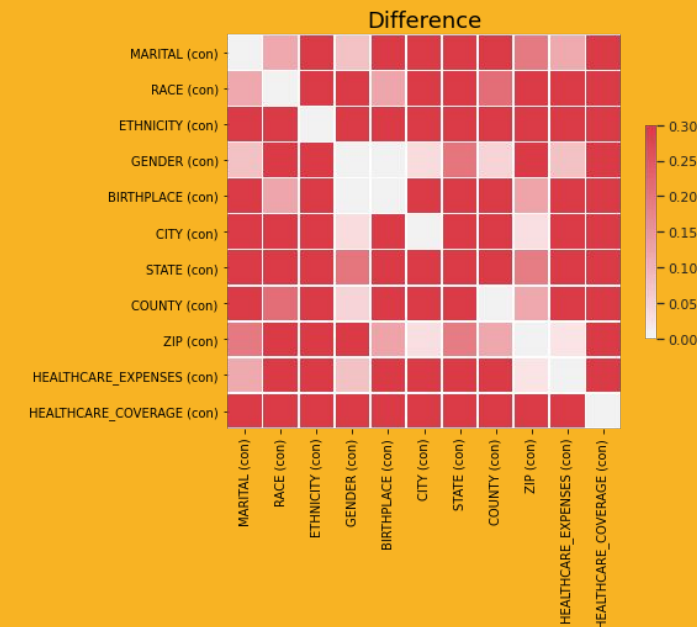
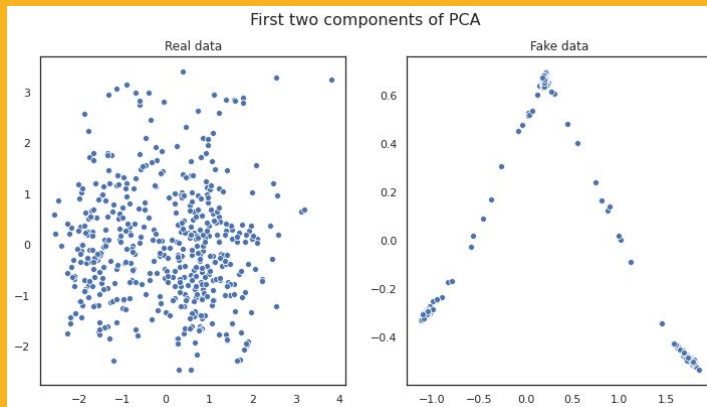
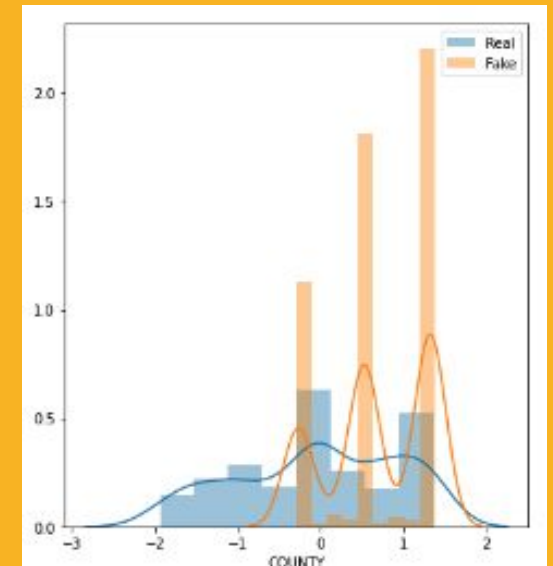
Harvard HPAIR Core Tech Associate

Amazon USA Intl' App Contest Winne

Intel AI Global Impact Festival Winnerr

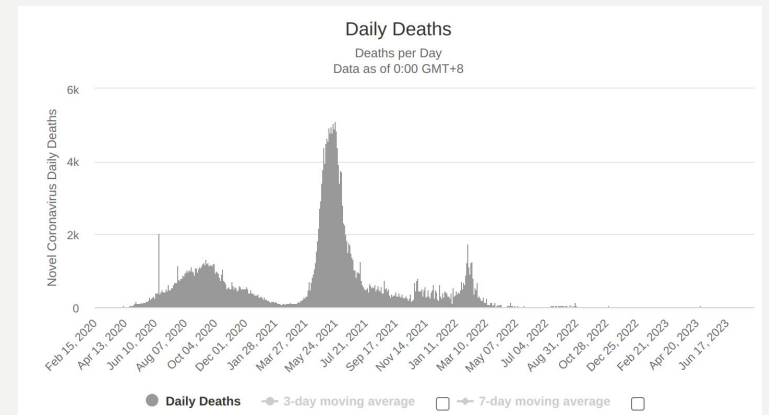
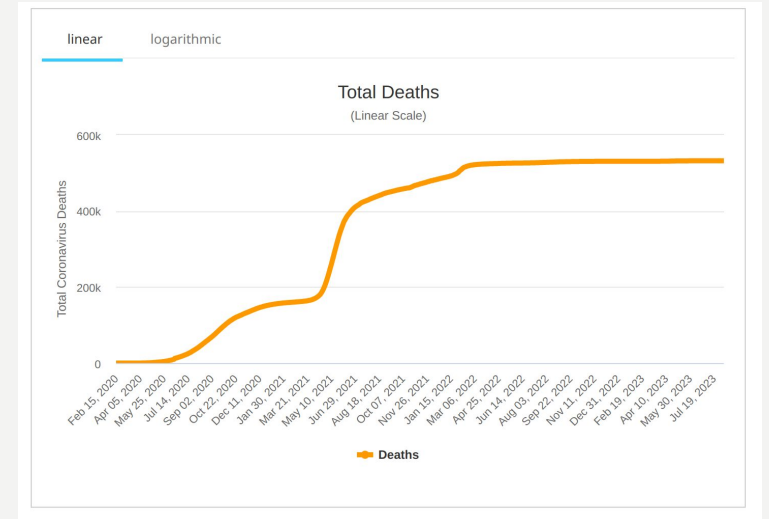
SMEC Indo-Australian **Scholarship'22**

Kalidas Madhavpeddi IITM **Scholarship'22**



Real-Life Use Case: India

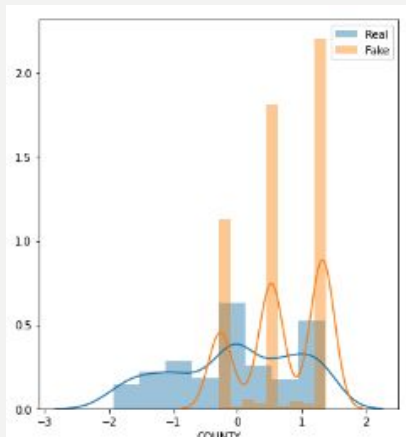
- Covid-19 pandemic disturbed India.
- 531,000 deaths.
- Real-time covid data was inaccessible. Reasons:
 - Privacy of medical data
 - Inefficient logistics (late delivery of data)
 - Lack of manual workforce
- Data-driven solutions could have saved lives
- Data was unavailable, and delayed. It cost real, human lives.



Problem Solved

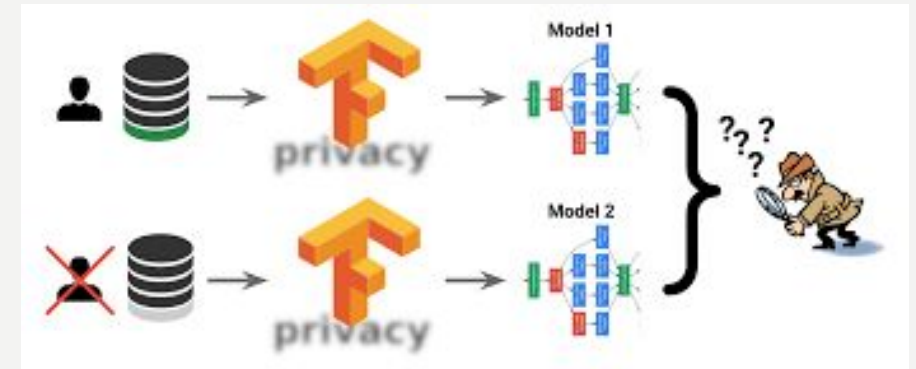
- ~~Privacy of medical data~~
- ~~Inefficient logistics (late delivery of data)~~
- ~~Lack of manual workforce~~

- PII-free, Secure, **GDPR-compliant** shareable data
- **95.83%** Efficient, Faster Data generation
- **100%** Automation achieved

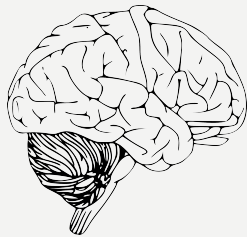
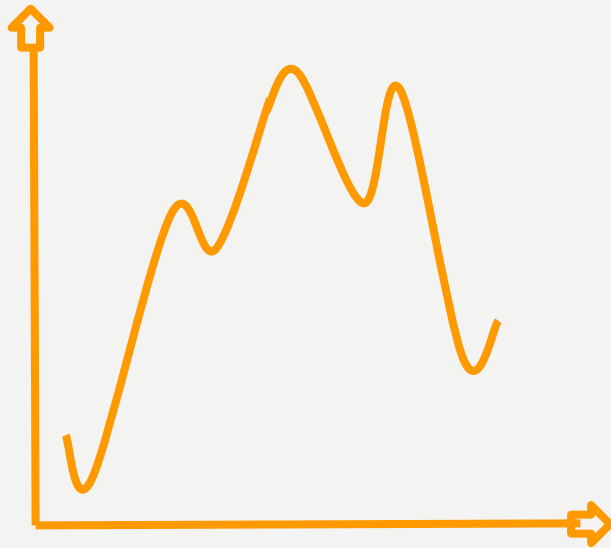


DELIVERABLES

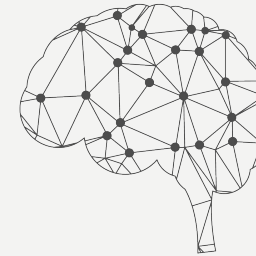
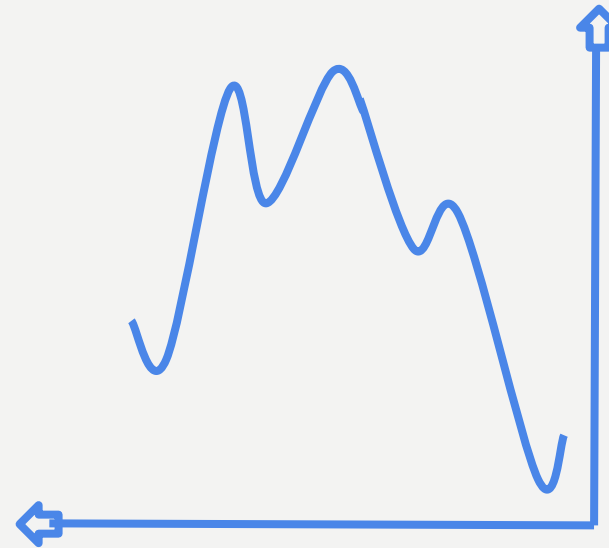
- DPFree Data Generation
- GAN based approach: Modular
- Customisable for each dataset: Domain-agnostic
- Privacy guaranteed
- Complies with all data privacy regulations including GDPR compliance: biggest mark of trust
- Differential Privacy



Working Visuals



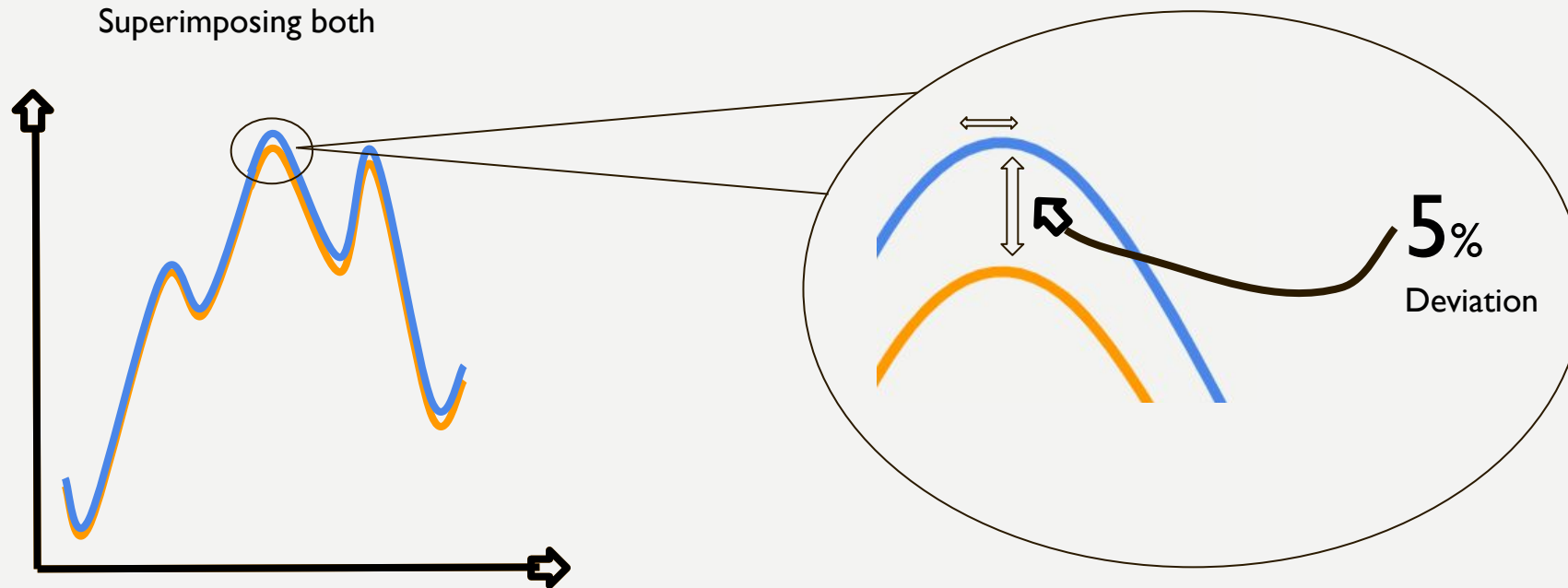
Original Data



My solution: Masked PII, Encrypted data



95% Accuracy



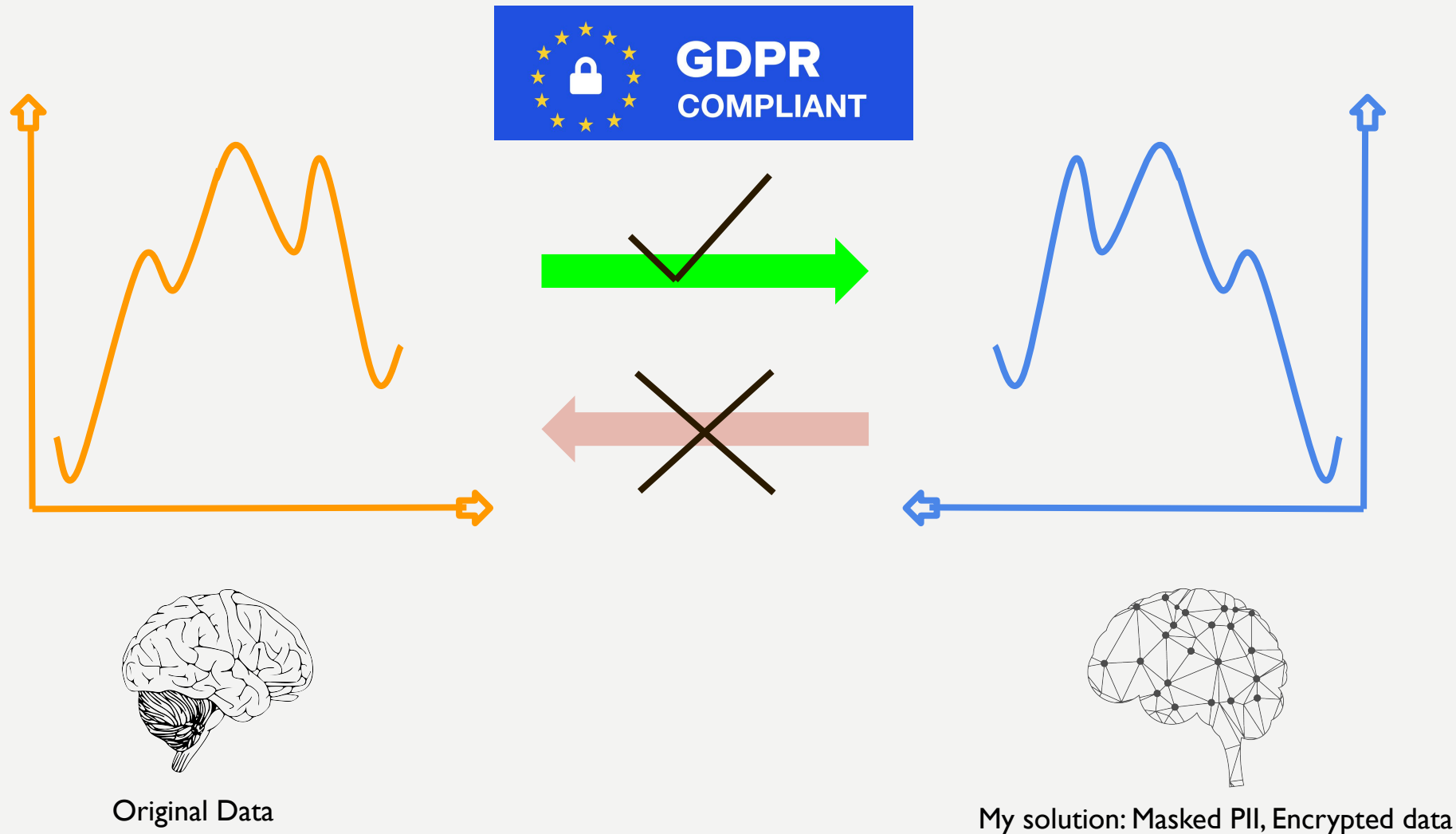
My solution replicates the original data with **95% Accuracy**

5% Deviation gives birth to **Hashing: Irreversible Encryption of Data**
Intrinsically, Masking **PII**, improving **security** with unbreakable encryption

95% Accuracy 5% Deviation: Hashing: Irreversible Encryption of Data

Ensures Privacy

Observations are **untraceable, untracked, backtracking-resistant**



1. EXTRACT COLUMNS TO SIMULATE

▼ Remove unnecessary columns and encode all data

```
[ ] import pandas as pd

df = pd.read_csv('csv/patients.csv')
df.drop(['Id', 'BIRTHDATE', 'DEATHDATE', 'SSN', 'DRIVERS', 'PASSPORT', 'PREFIX',
        'FIRST', 'ADDRESS', 'LAST', 'SUFFIX', 'MAIDEN', 'LAT', 'LON'], axis=1, inplace=True)
print(df.columns)

Index(['MARITAL', 'RACE', 'ETHNICITY', 'GENDER', 'BIRTHPLACE', 'CITY', 'STATE',
        'COUNTY', 'ZIP', 'HEALTHCARE_EXPENSES', 'HEALTHCARE_COVERAGE'],
      dtype='object')
```

Next, read patients data and remove fields such as id, date, SSN, name etc. Note, that we are trying to generate synthetic data which can be used to train our deep learning models for some other tasks. For such a model, we don't require fields like id, date, SSN etc.

```
▶ # data configuration

file_name = "csv/patients.csv"
columns_to_drop = ['Id', 'BIRTHDATE', 'DEATHDATE', 'SSN', 'DRIVERS', 'PASSPORT', 'PREFIX', 'FIRST', 'ADDRESS', 'LAST', 'SUFFIX', 'MAIDEN', 'LAT', 'LON']
categorical_features = ['MARITAL', 'RACE', 'ETHNICITY', 'GENDER', 'BIRTHPLACE', 'CITY', 'STATE', 'COUNTY', 'ZIP']
continuous_features = ['HEALTHCARE_EXPENSES', 'HEALTHCARE_COVERAGE']
col1, col2 = 'num_of_doors', 'price'
col_group_by = 'body_style'
```

- User decides the columns to contain in the simulated dataset
- Customizable as per user needs

- Pre-processing continuous variables- binning

Next, we will encode all [continuous features](#) to equally sized bins. First, lets find the minimum and maximum values for `HEALTHCARE_EXPENSES` and `HEALTHCARE_COVERAGE` and then create bins based on these values.

```
import numpy as np

for column in continuous_features:
    min = df[column].min()
    max = df[column].max()
    feature_bins = pd.cut(df[column], bins=np.linspace(min, max, 21), labels=False)
    df.drop([column], axis=1, inplace=True)
    df = pd.concat([df, feature_bins], axis=1)
    print(df)
```

	MARITAL	RACE	ETHNICITY	...	ZIP	HEALTHCARE_COVERAGE	HEALTHCARE_EXPENSES
0	0	4	0	...	2	1334.88	2.0
1	0	4	1	...	132	3204.49	7.0
2	0	4	1	...	3	2606.40	5.0
3	0	4	1	...	68	8756.19	8.0
4	-1	4	1	...	125	3772.20	5.0
...
1166	0	0	0	...	130	32086.31	15.0
1167	1	4	1	...	80	3130.52	9.0
1168	1	4	1	...	-1	52391.24	14.0
1169	0	4	1	...	98	13157.00	12.0
1170	0	4	1	...	102	26565.65	14.0

Next, we will encode all [categorical features](#) to integer values. We are simply encoding the features to numerical hot encoding as its not required for GANs.

```
[ ] for column in categorical_features:
    df[column] = df[column].astype('category').cat.codes

df.head()
```

	MARITAL	RACE	ETHNICITY	GENDER	BIRTHPLACE	CITY	STATE	COUNTY	ZIP	HEALTHCARE_EXPENSES	HEALTHCARE_COVERAGE
0	0	4	0	1	136	42	0	6	2	271227.08	1334.88
1	0	4	1	1	61	186	0	8	132	793946.01	3204.49
2	0	4	1	1	236	42	0	6	3	574111.90	2606.40
3	0	4	1	0	291	110	0	8	68	935630.30	8756.19
4	-1	4	1	1	189	24	0	12	125	598763.07	3772.20

	MARITAL	RACE	ETHNICITY	...	ZIP	HEALTHCARE_EXPENSES	HEALTHCARE_COVERAGE
0	0	4	0	...	2	2.0	0.0
1	0	4	1	...	132	7.0	0.0
2	0	4	1	...	3	5.0	0.0
3	0	4	1	...	68	8.0	0.0
4	-1	4	1	...	125	5.0	0.0
...
1166	0	0	0	...	130	15.0	0.0
1167	1	4	1	...	80	9.0	0.0
1168	1	4	1	...	-1	14.0	1.0
1169	0	4	1	...	98	12.0	0.0
1170	0	4	1	...	102	14.0	0.0

[1171 rows x 11 columns]

- Pre-processing categorical variables- encoding

Transform the data

Next, we apply `PowerTransformer` on all the fields to get a Gaussian distribution for the data.

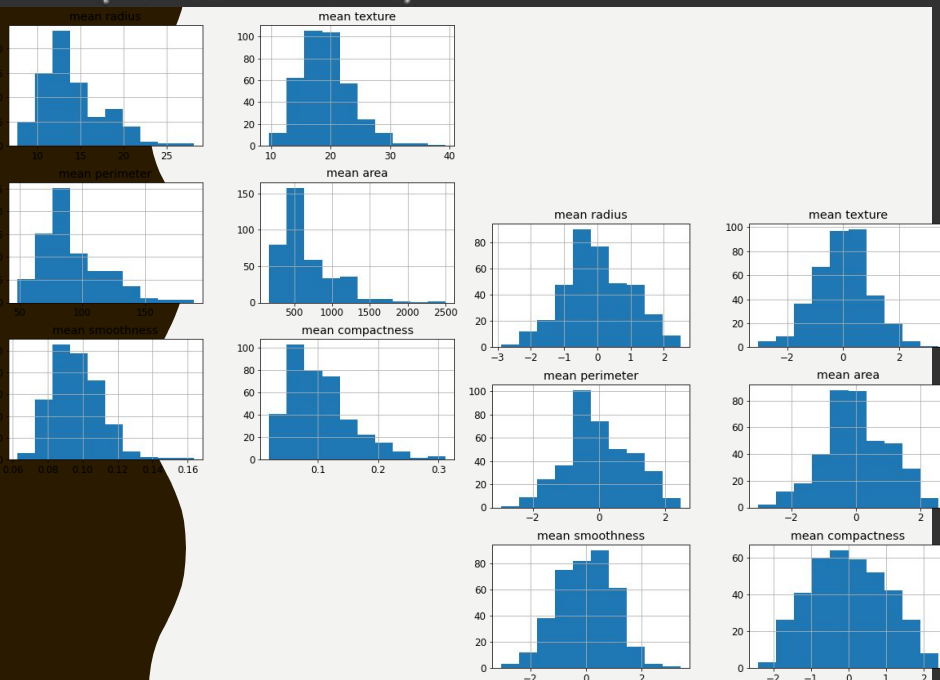
```
[ ] from sklearn.preprocessing import PowerTransformer

df[df.columns] = PowerTransformer(method='yeo-johnson', standardize=True, copy=True).fit_transform(df[df.columns])

print(df)
```

	MARITAL	RACE	...	HEALTHCARE_EXPENSES	HEALTHCARE_COVERAGE
0	0.334507	0.461541	...	-0.819522	-0.187952
1	0.334507	0.461541	...	0.259373	-0.187952
2	0.334507	0.461541	...	-0.111865	-0.187952
3	0.334507	0.461541	...	0.426979	-0.187952
4	-1.275676	0.461541	...	-0.111865	-0.187952
...
1166	0.334507	-2.207146	...	1.398831	-0.187952
1167	1.773476	0.461541	...	0.585251	-0.187952
1168	1.773476	0.461541	...	1.275817	5.320497
1169	0.334507	0.461541	...	1.016430	-0.187952
1170	0.334507	0.461541	...	1.275817	-0.187952

[1171 rows x 11 columns]



```
[ ] df
```

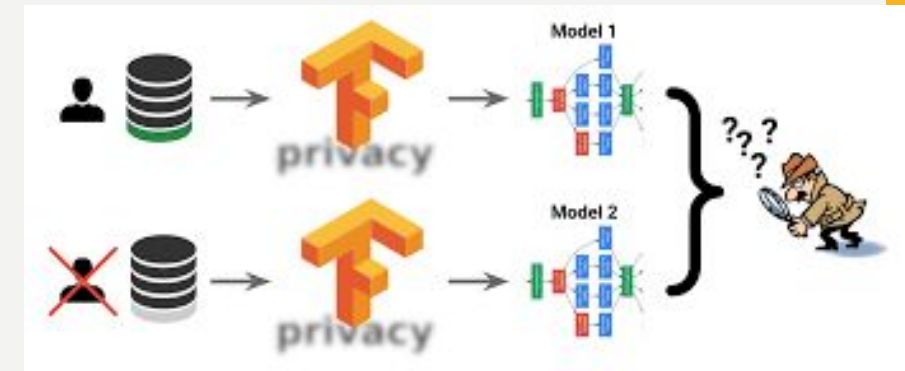
	MARITAL	RACE	ETHNICITY	GENDER	BIRTHPLACE	CITY	STATE	COUNTY	ZIP	HEALTHCARE_EXPENSES	HEALTHCARE_COVERAGE
0	0.323410	0.462029	-3.059874	1.040975	0.080041	-0.953186	0.0	-0.603714	-0.329374	-0.852459	-0.187952
1	0.323410	0.462029	0.326811	1.040975	-0.781806	1.009515	0.0	-0.108844	1.084032	0.178401	-0.187952
2	0.323410	0.462029	0.326811	1.040975	1.086562	-0.953186	0.0	-0.603714	-0.240309	-0.201706	-0.187952
3	0.323410	0.462029	0.326811	-0.960637	1.596780	0.025263	0.0	-0.108844	0.798438	0.359778	-0.187952
4	-1.266799	0.462029	0.326811	1.040975	0.627873	-1.276494	0.0	1.132069	1.059763	-0.201706	-0.187952
...
1166	0.323410	-2.165654	-3.059874	-0.960637	-0.180194	-1.107466	0.0	-0.108844	1.077217	1.504460	-0.187952
1167	1.797699	0.462029	0.326811	1.040975	1.265789	-1.337494	0.0	-1.035152	0.866443	0.535933	-0.187952
1168	1.797699	0.462029	0.326811	-0.960637	-0.593921	0.604114	0.0	0.472068	-1.037056	1.351976	5.320497
1169	0.323410	0.462029	0.326811	-0.960637	1.086562	0.604114	0.0	0.472068	0.953153	1.037127	-0.187952
1170	0.323410	0.462029	0.326811	-0.960637	1.578669	0.604114	0.0	0.472068	0.970481	1.351976	-0.187952

1171 rows x 11 columns

Normalisation of
variables for better
sampling from
distribution

Final input dataframe
output

DIFFERENTIAL PRIVACY



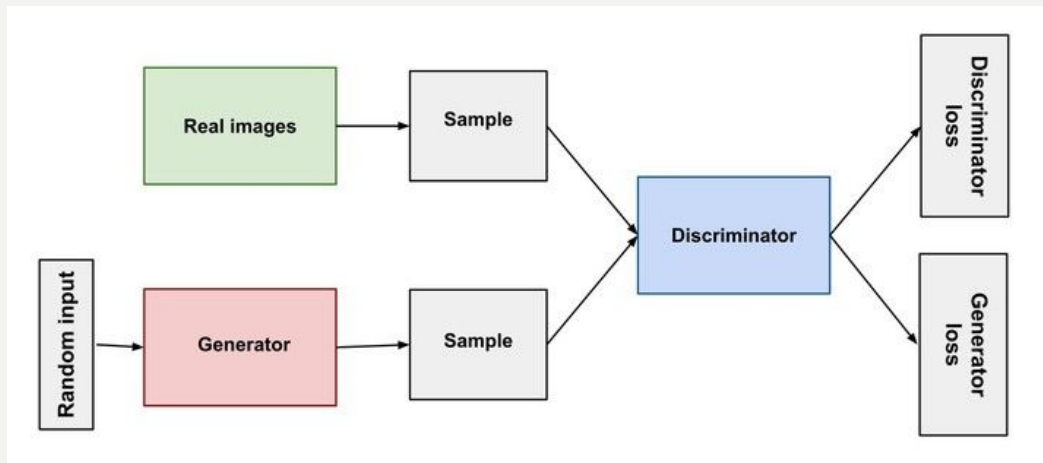
- Differential privacy (DP) is a system for publicly sharing information about a dataset by describing the patterns of groups within the dataset while withholding information about individuals in the dataset
- Describe the statistical properties of data, but abstract individual observations
- Beneficial for sharing private data on-the-go with null restrictions in health domain and other public protected datasets
- Complies with all data privacy regulations including GDPR compliance



GAN- TRAINING THE MODEL

For the first iteration, we have used a classic GAN solution to iterate upon after inspecting and obtaining further results

Other method in progress is using Bayesian Networks



```
if epoch % sample_interval == 0:
    #Test here data generation step
    # save model checkpoints
    model_checkpoint_base_name = 'model/' + cache_prefix + '_{}_model_weights_step_{}.h5'
    self.generator.save_weights(model_checkpoint_base_name.format('generator', epoch))
    self.discriminator.save_weights(model_checkpoint_base_name.format('discriminator', epoch))

    #Here is generating the data
    z = tf.random.normal((432, self.noise_dim))
    gen_data = self.generator(z)
    print('generated_data')

def save(self, path, name):
    assert os.path.isdir(path) == True, \
        "Please provide a valid path. Path must be a directory."
    model_path = os.path.join(path, name)
    self.generator.save_weights(model_path) # Load the generator
    return

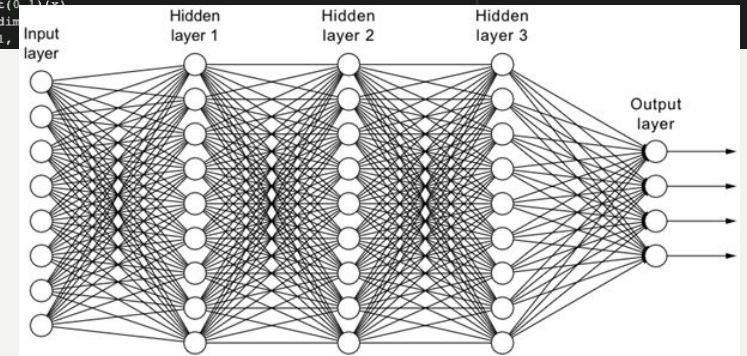
def load(self, path):
    assert os.path.isdir(path) == True, \
        "Please provide a valid path. Path must be a directory."
    self.generator = Generator(self.batch_size)
    self.generator = self.generator.load_weights(path)
    return self.generator

class Generator():
    def __init__(self, batch_size):
        self.batch_size=batch_size

    def build_model(self, input_shape, dim, data_dim):
        input= Input(shape=input_shape, batch_size=self.batch_size)
        x = Dense(dim, activation='relu')(input)
        x = Dense(dim * 2, activation='relu')(x)
        x = Dense(dim * 4, activation='relu')(x)
        x = Dense(data_dim)(x)
        return Model(inputs=input, outputs=x)

class Discriminator():
    def __init__(self, batch_size):
        self.batch_size=batch_size

    def build_model(self, input_shape, dim):
        input = Input(shape=input_shape, batch_size=self.batch_size)
        x = Dense(dim * 4, activation='relu')(input)
        x = Dropout(0.1)(x)
        x = Dense(dim * 2, activation='relu')(x)
        x = Dropout(0.1)(x)
        x = Dense(dim)(x)
        x = Dense(1, activation='sigmoid')(x)
        return Model(inputs=input, outputs=x)
```



Let's take a look at the Generator and Discriminator models.

```
[ ] synthesizer.generator.summary()
```

Model: "functional_13"

Layer (type)	Output Shape	Param #
=====		
input_7 (InputLayer)	[(32, 32)]	0
dense_16 (Dense)	(32, 128)	4224
dense_17 (Dense)	(32, 256)	33024
dense_18 (Dense)	(32, 512)	131584
dense_19 (Dense)	(32, 11)	5643
=====		
Total params: 174,475		
Trainable params: 174,475		
Non-trainable params: 0		

```
[ ] synthesizer.discriminator.summary()
```

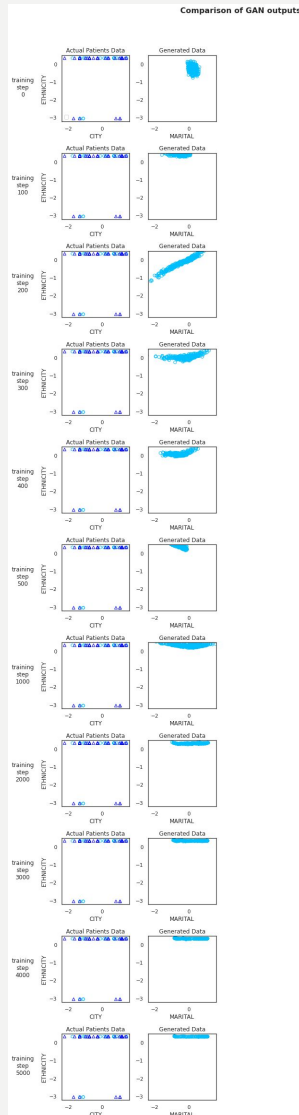
Model: "functional_15"

Layer (type)	Output Shape	Param #
=====		
input_8 (InputLayer)	[(32, 11)]	0
dense_20 (Dense)	(32, 512)	6144
dropout_4 (Dropout)	(32, 512)	0
dense_21 (Dense)	(32, 256)	131328
dropout_5 (Dropout)	(32, 256)	0
dense_22 (Dense)	(32, 128)	32896
dense_23 (Dense)	(32, 1)	129
=====		
Total params: 170,497		
Trainable params: 0		
Non-trainable params: 170,497		

The Generator and Discriminator are neural networks of 3 hidden layers

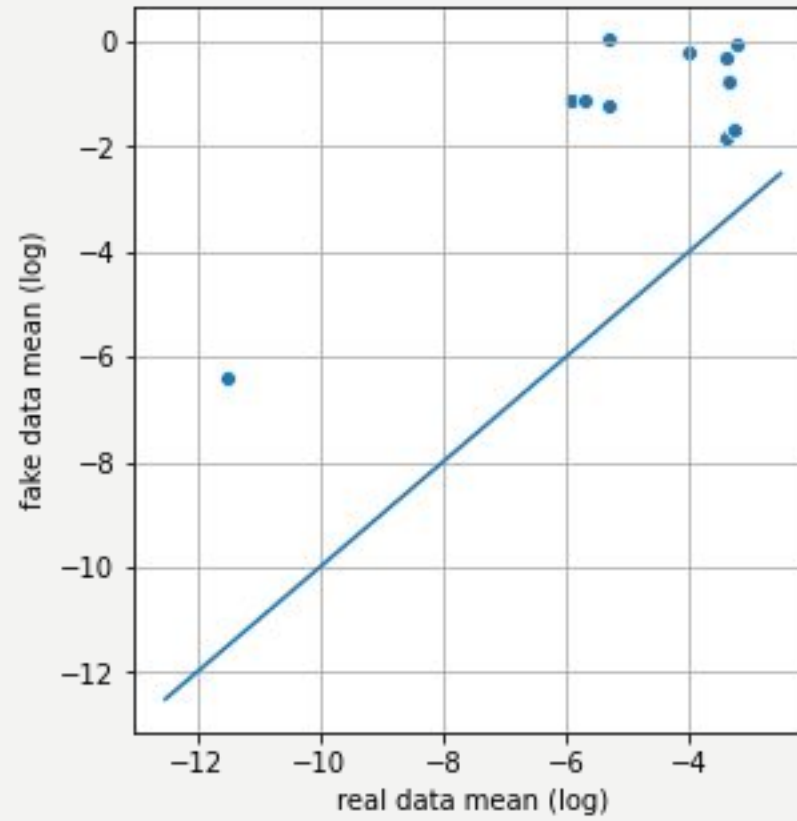
The neural networks are defined in the code and the snippet provided

EVALUATION METRICS

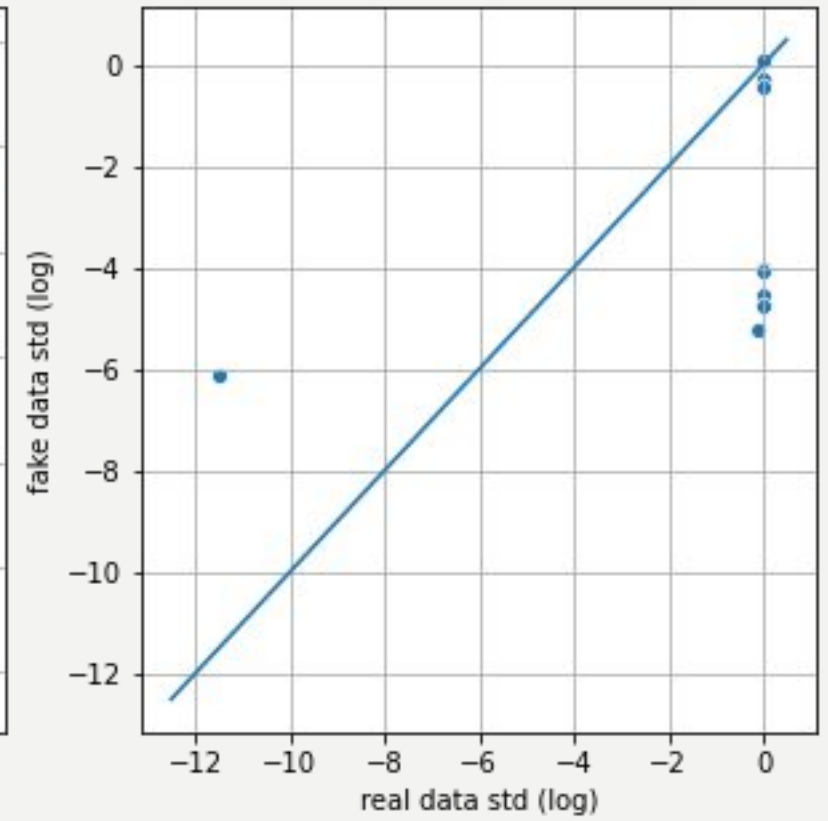


Absolute Log Mean and STDs of numeric data

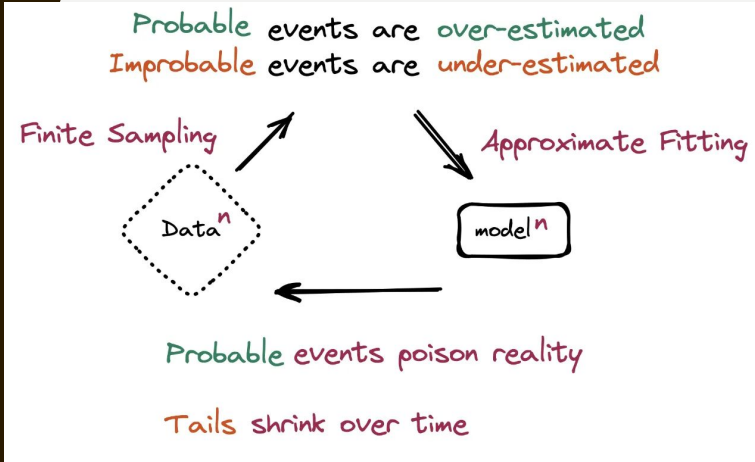
Means of real and fake data



Std of real and fake data



Why DPFree Data is better?

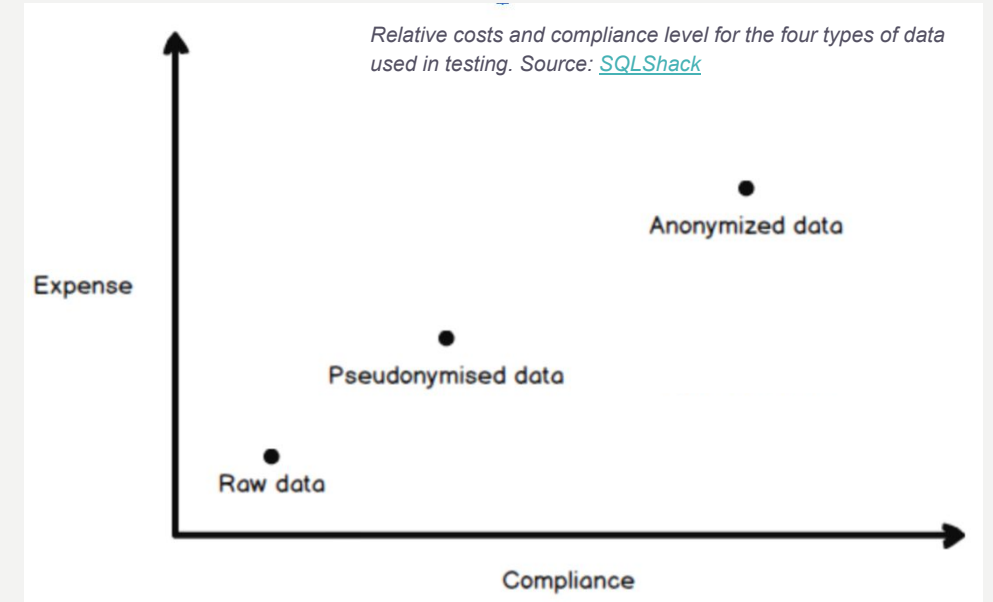


Simulated average accuracy:
90.16%, original: 85.79%.
Average improvement: 4.37%

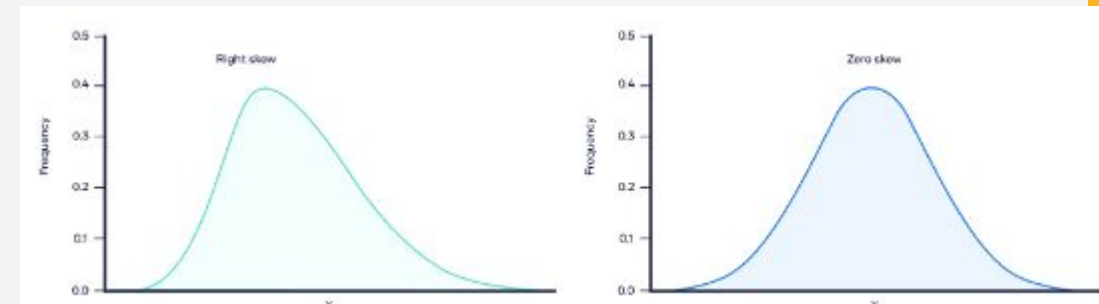
<https://www.kaggle.com/ronitf/heart-disease-uci>

Using a popular Heart Disease dataset that was skewed almost 2-to-1 towards male patients, we added synthetically generated patient records to a training set to boost female representation in the dataset.

Rare cancers, Covid19, Financial data

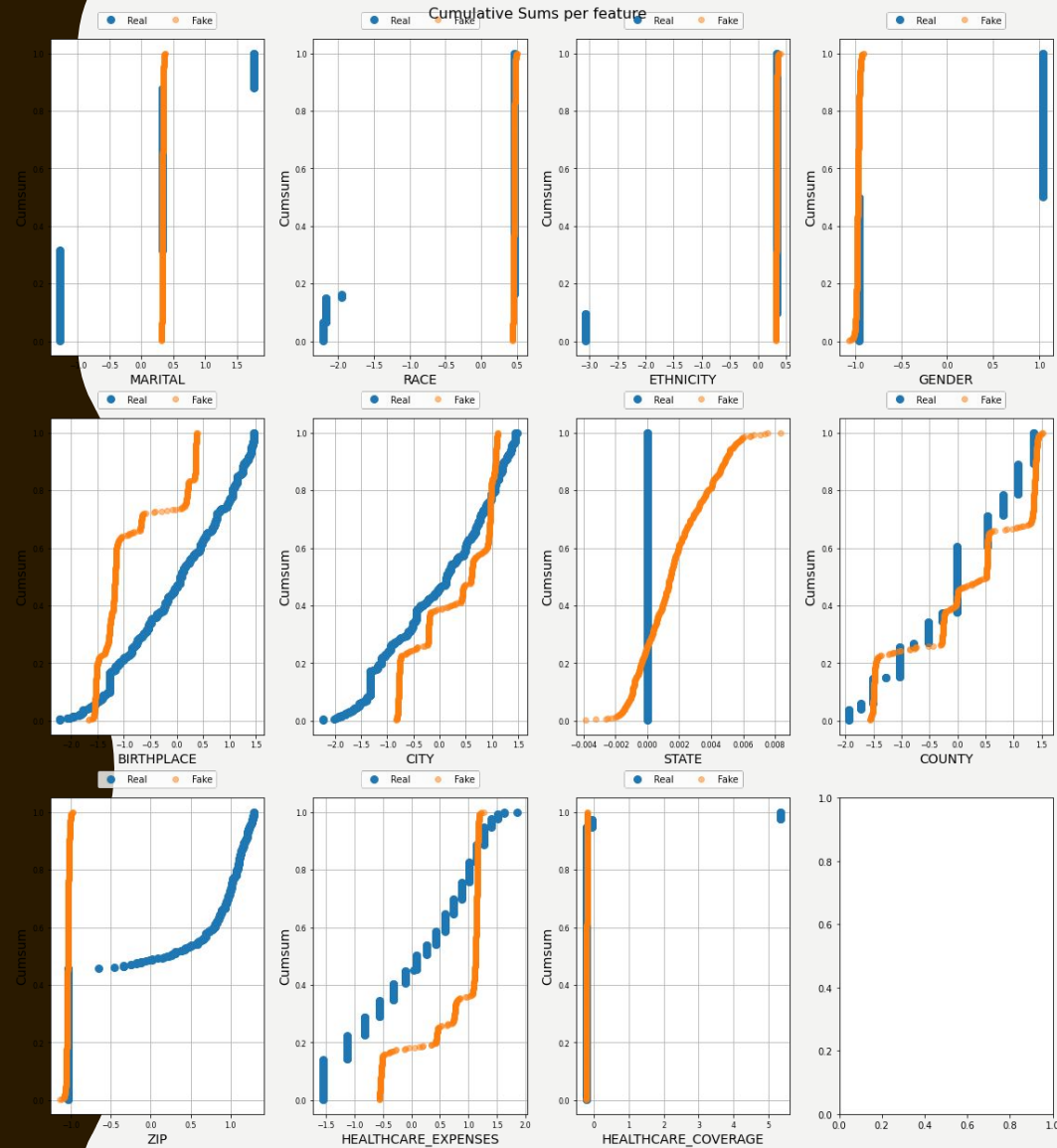


most other solutions mask PII or directly encrypt it, keeping the rest of the data vulnerable. This can be easily reverse engineered causing a data leak



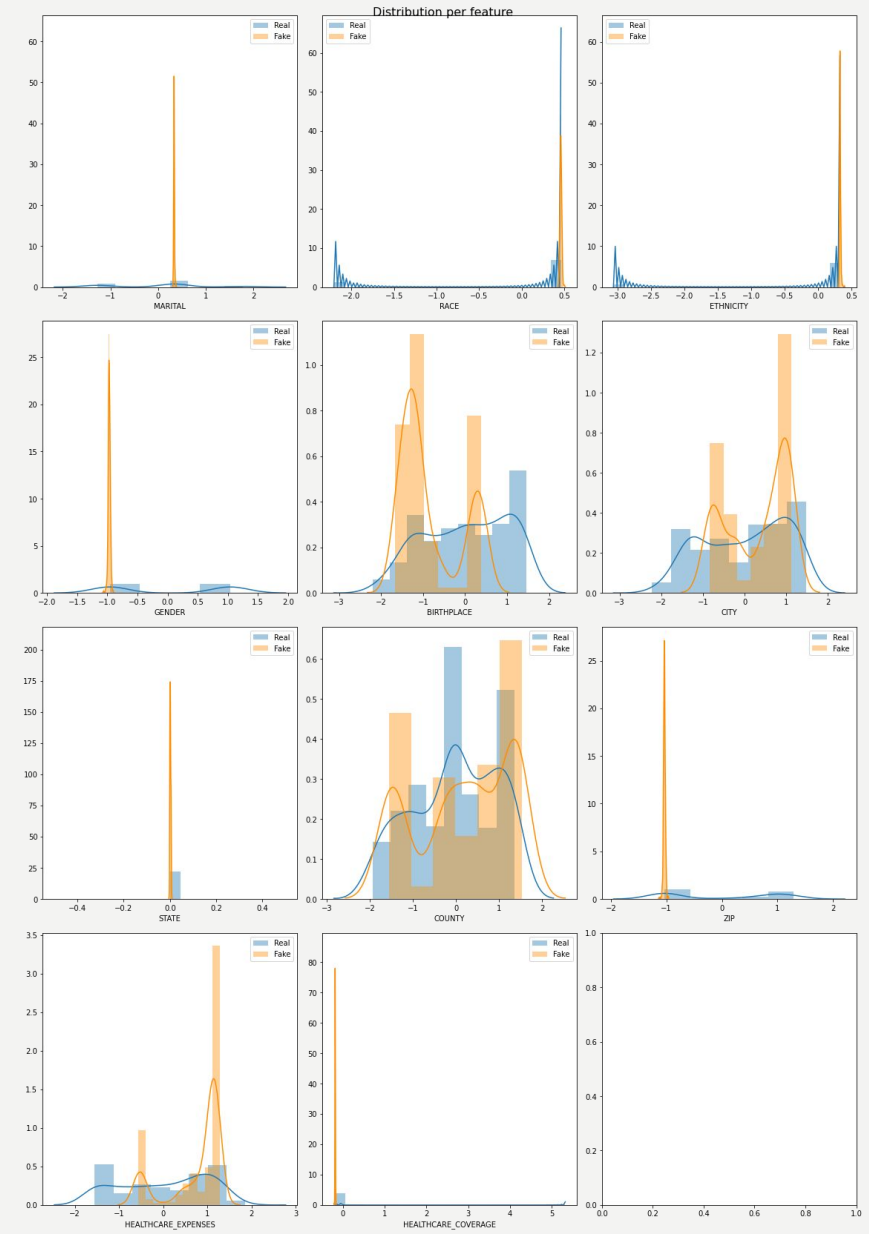
observations from the underlying statistical distribution and correlations.

EVALUATION METRICS



Cumulative
sum

Distributions
visualised



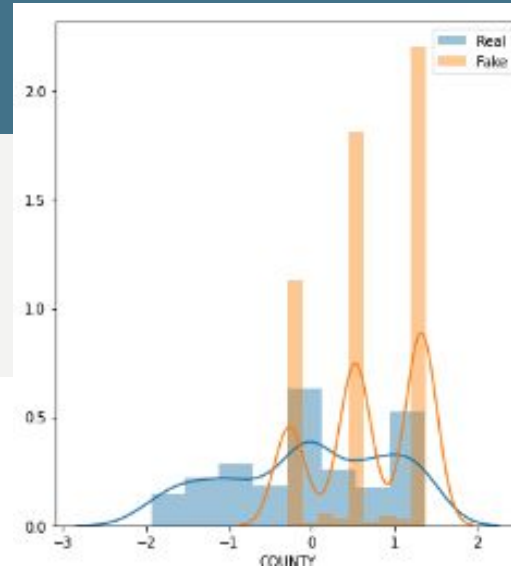
Why My Project Wins

<https://www.bloomberg.com/press-releases/2022-09-21/intel-announces-ai-global-impact-festival-grand-prize-winners>

Intel CEO Pat Gelsinger
Congratulates Global Winners
from Intel® AI Global Impact
Festival 2022

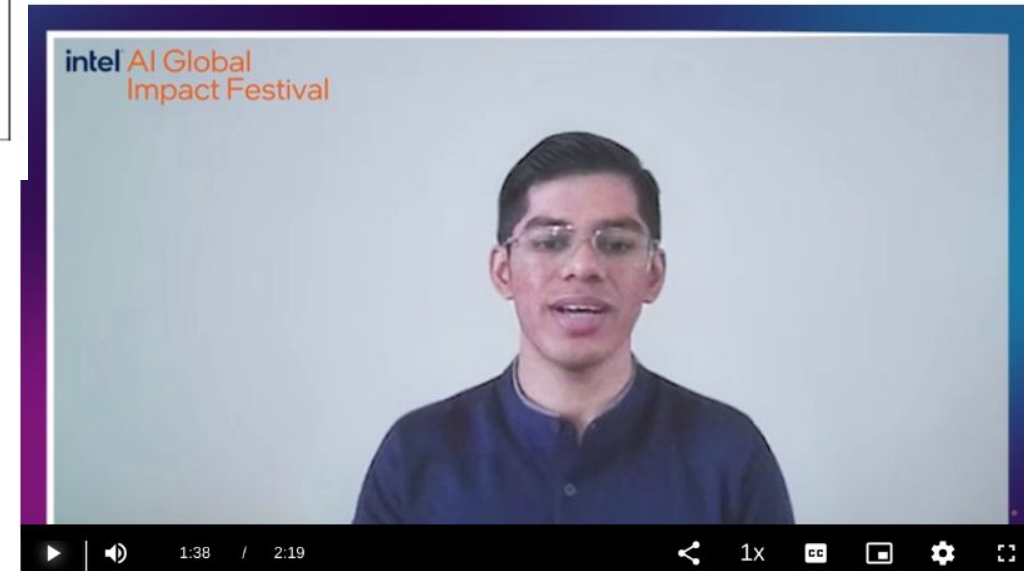


San Jose, California, USA



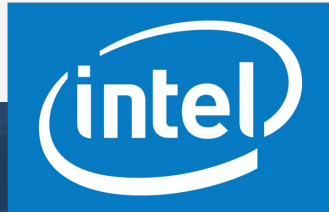
Sayash Raaj – India

This solution generates artificially manufactured data using Intel® technologies that include Intel® Core™ i5, Intel® Optimization for TensorFlow, PyTorch, and Intel® Extension for Scikit-learn. This solution helps in mitigating the unavailability of data due to inefficient logistics, and sensitivity of data.



Global Industrial Testimonials

My claims backed with proofs from global corporations and experts



Intel USA

Global Winner 2022

Represented India



**Broadridge Finance
US**

Global Winner 2023

Integrated a mathematical
approach



Shell AI

Global Winner 2022

Transportational data



OpenText API

```
# Function to authenticate and get a session token
def get_opentext_session_token(api_url, username, password):
    url = f"{api_url}/api/v1/auth"
    payload = {"username": username, "password": password}
    response = requests.post(url, data=json.dumps(payload), headers={"Content-Type": "application/json"})
    if response.status_code == 200:
        return response.json().get('ticket')
    else:
        raise Exception("Authentication failed")

# Function to upload a CSV file to OpenText Content Server
def upload_csv_to_opentext(api_url, session_token, csv_file_path, folder_id):
    url = f"{api_url}/api/v2/nodes"
    headers = {
        "OTCSTicket": session_token,
        "Content-Type": "multipart/form-data"
    }
    files = {
        'type': (None, '144'), # 144 is the type for Document
        'parent_id': (None, folder_id),
        'file': open(csv_file_path, 'rb')
    }
    response = requests.post(url, headers=headers, files=files)
    if response.status_code == 200:
        return response.json()
    else:
        raise Exception("File upload failed")

# Function to download a CSV file from OpenText Content Server
def download_csv_from_opentext(api_url, session_token, file_id, download_path):
    url = f"{api_url}/api/v2/nodes/{file_id}/content"
    headers = {
        "OTCSTicket": session_token
    }
    response = requests.get(url, headers=headers)
    if response.status_code == 200:
        with open(download_path, 'wb') as file:
            file.write(response.content)
        return f"File downloaded successfully to {download_path}"
    else:
        raise Exception("File download failed")
```

opentext™

Using **Content Server REST API** for
uploading and downloading tabular,
relational csv files.

THANK YOU

DPFree DATA GENERATION

The future of Data Science

The future of humanity

Sayash Raaj,

IIT Madras

Special Thanks for conducting this event

The hard work during late nights while balancing academics at IIT Madras has been fueled by
motivation adequately provided

If it saves a life, I will consider my work successful.

<https://www.linkedin.com/in/sayashraaj/>