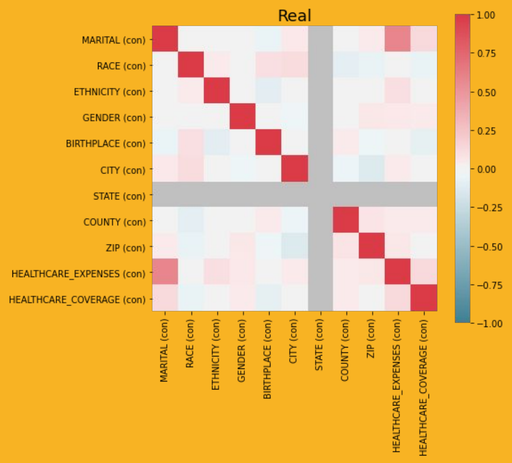
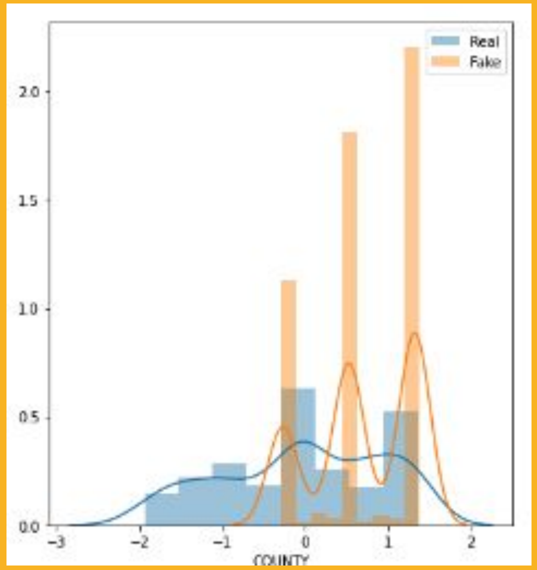


DIFFERENTIALLY PRIVATE DATA GENERATION



The future of Data Science

The future of humanity

Sayash Raaj,

IIT Madras

Credentials-

IIT Madras, 4th year student

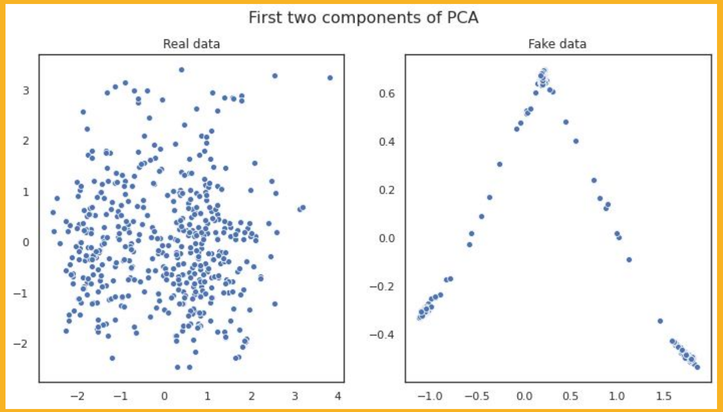
Harvard HPAIR Core Tech Associate

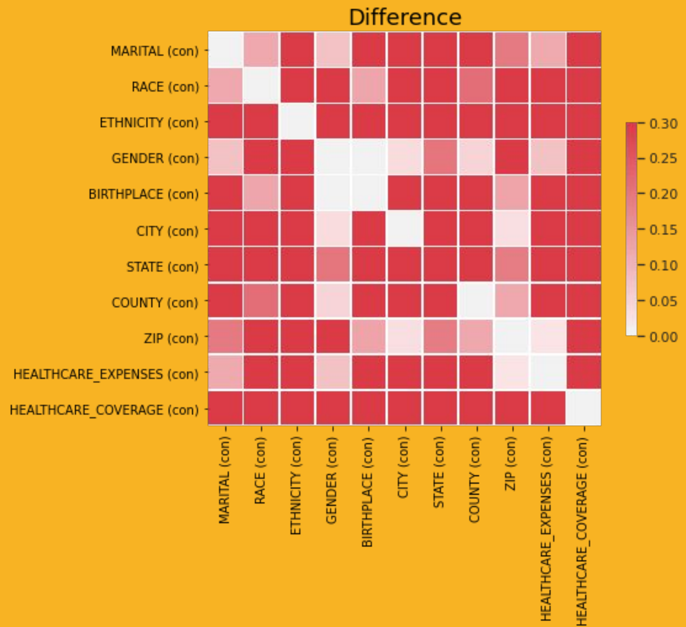
Amazon USA Intl' App Contest Winne

Intel AI Global Impact Festival Winnerr

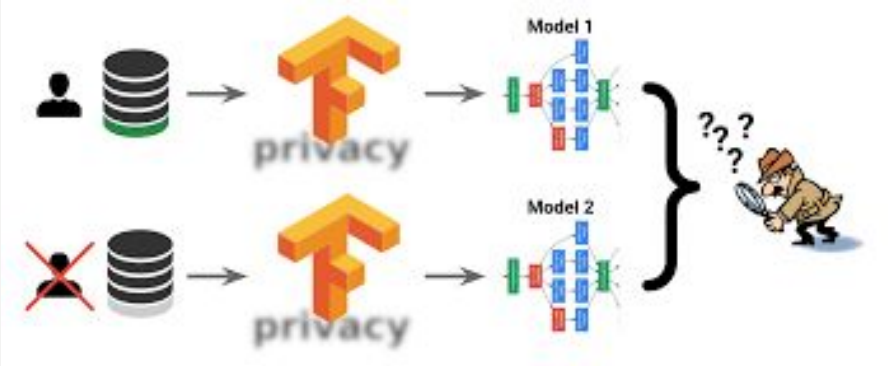
SMEC Indo-Australian **Scholarship'22**

Kalidas Madhavpeddi IITM **Scholarship'22**



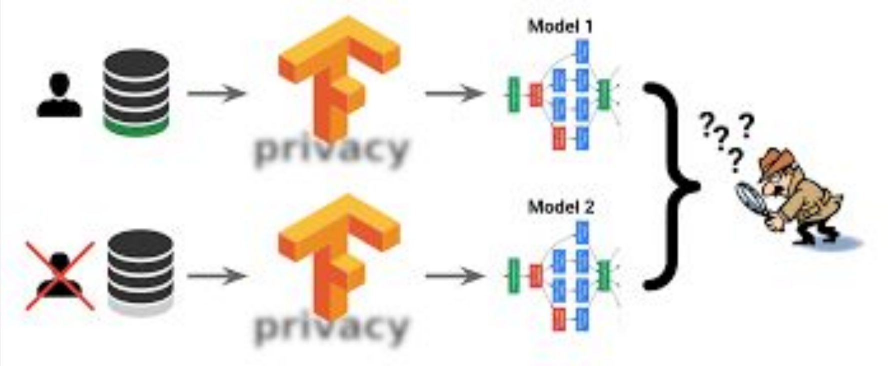


DELIVERABLES



- Differentially Private Data Generation
- GAN based approach
- Customisable for each dataset
- Privacy guaranteed
- Complies with all data privacy regulations including GDPR compliance
- Differential Privacy

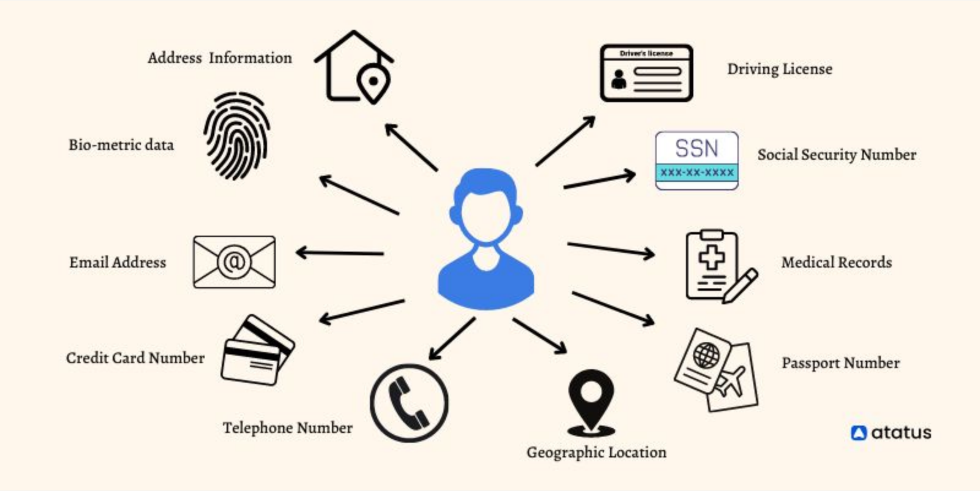
DIFFERENTIAL PRIVACY



- 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

PII Detection

- Regular Expressions or other pattern matching techniques used for detection of PII
- PII eg - names, social security numbers (###-##-####), email addresses ([a-zA-Z0-9._%+-]+@[a-zA-Z0-9.-]+.[a-zA-Z]{2,}) and credit card numbers (####-####-####-####)
- Supervised Machine Learning algorithms on labelled datasets can be used to increase the accuracy of PII detection
- Using the ML model, PII in the actual data can be detected easily



PII Masking

- Regular Expressions ReGex transformations can be applied to the PII columns
- Post detection of PII, type of PII can be determined using ReGex templating
- After a template matches the PII column, masking using the appropriate template used is done easily
- PII eg - names, social security numbers (###-##-####), email addresses ([a-zA-Z0-9._%+-]+@[a-zA-Z0-9.-]+.[a-zA-Z]{2,}) and credit card numbers (####-####-####-####)

1. EXTRACT COLUMNS TO SYNTHESIZE

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 synthesized dataset
- Customizable as per user needs

- Pre-processing continuous variables- binning

- Pre-processing categorical variables- encoding

Next, we will encode all continious 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

[1171 rows x 11 columns]
      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]
```

Next, we will encode all categorical features to integer values. We are simply encoding the features to numerica 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_EXPEN	
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

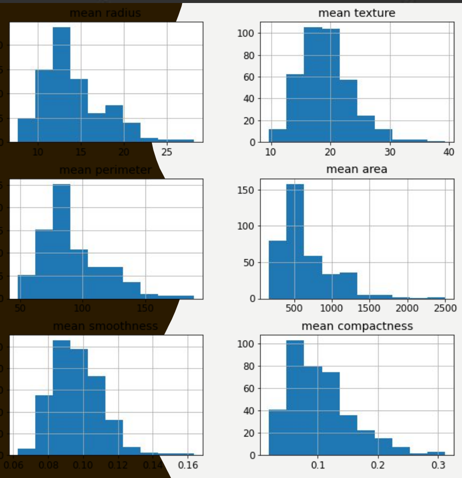
Transform the data

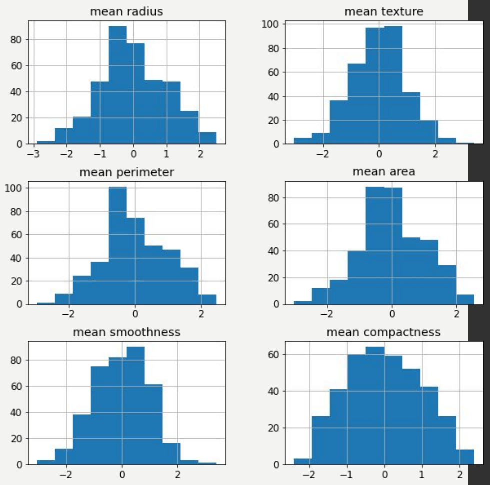
Next, we apply `PowerTransformer` on all the fields to get a Gaussian distribution for the data.

```
[ ] 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]
```

Normalisation of variables for better sampling from distribution





Final input dataframe output

```
[ ] df
```

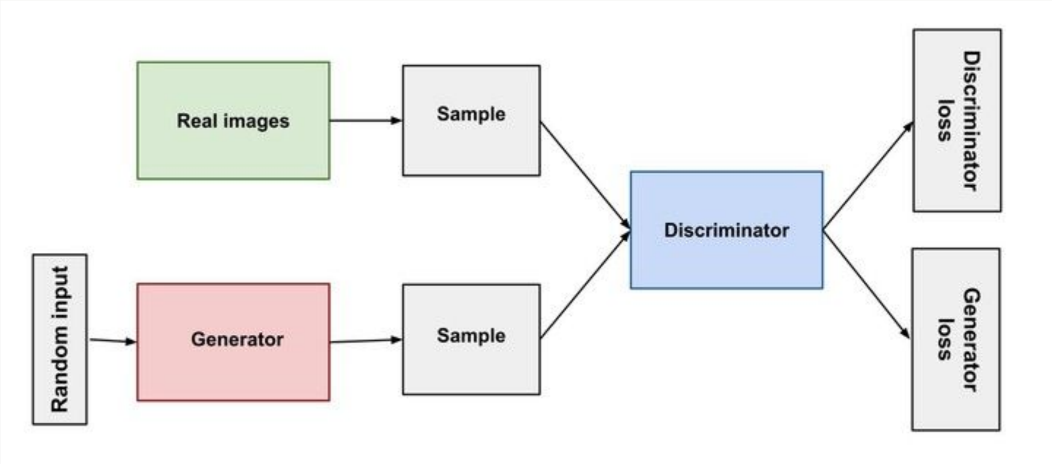
	MARITAL	RACE	ETHNICITY	GENDER	BIRTHPLACE	CITY	STATE	COUNTY	ZIP	HEALTHCARE_EXPENSES	HEALTHCARE_COVERAG
0	0.323410	0.462029	-3.059874	1.040975	0.080041	-0.953186	0.0	-0.603714	-0.329374	-0.852459	-0.18795
1	0.323410	0.462029	0.326811	1.040975	-0.781806	1.009515	0.0	-0.108844	1.084032	0.178401	-0.18795
2	0.323410	0.462029	0.326811	1.040975	1.086562	-0.953186	0.0	-0.603714	-0.240309	-0.201706	-0.18795
3	0.323410	0.462029	0.326811	-0.960637	1.596780	0.025263	0.0	-0.108844	0.798438	0.359778	-0.18795
4	-1.266799	0.462029	0.326811	1.040975	0.627873	-1.276494	0.0	1.132069	1.059763	-0.201706	-0.18795
...	...	...	...	...	...	...	...	...	...	...	...
1166	0.323410	-2.165654	-3.059874	-0.960637	-0.180194	-1.107466	0.0	-0.108844	1.077217	1.504460	-0.18795
1167	1.797699	0.462029	0.326811	1.040975	1.265789	-1.337494	0.0	-1.035152	0.866443	0.535933	-0.18795
1168	1.797699	0.462029	0.326811	-0.960637	-0.593921	0.604114	0.0	0.472068	-1.037056	1.351976	5.32049
1169	0.323410	0.462029	0.326811	-0.960637	1.086562	0.604114	0.0	0.472068	0.953153	1.037127	-0.18795
1170	0.323410	0.462029	0.326811	-0.960637	1.578669	0.604114	0.0	0.472068	0.970481	1.351976	-0.18795

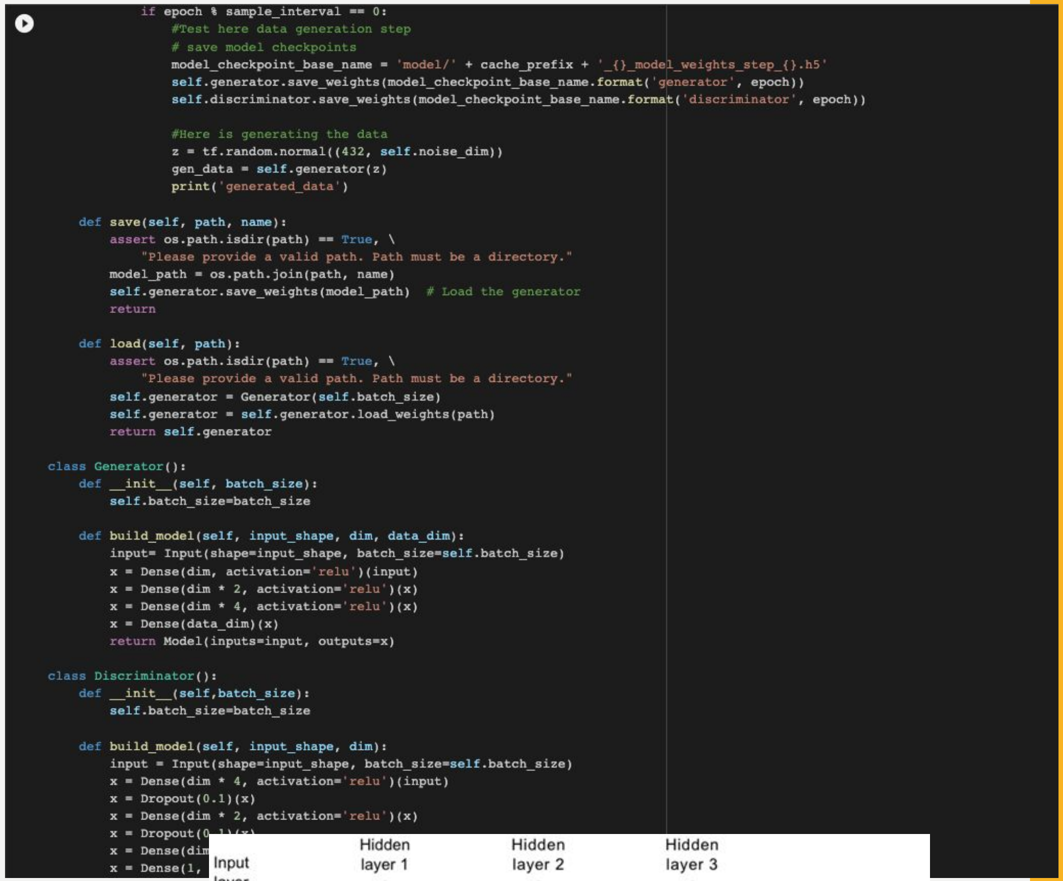
1171 rows × 11 columns

GAN- TRAINING THE MODEL

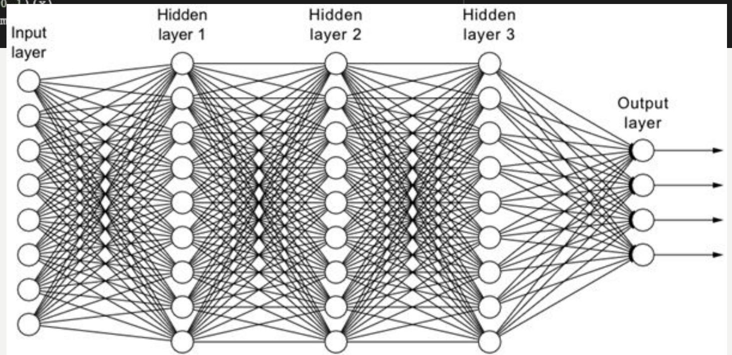
For the first iteration, we have used a classic GAN solution to iterate upon after inspecting and obtaining further results

Other method in progress is using Bayesian Networks





```python
            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
        x = Dense(dim
        x = Dense(1,
```



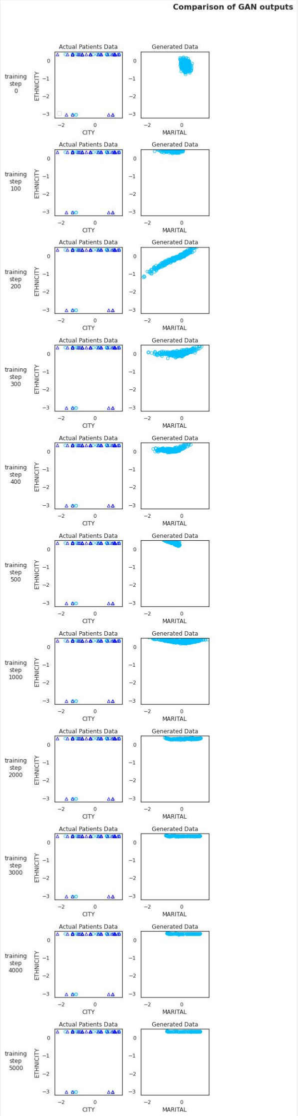
Let's take a look at the Generator and Discriminator models.

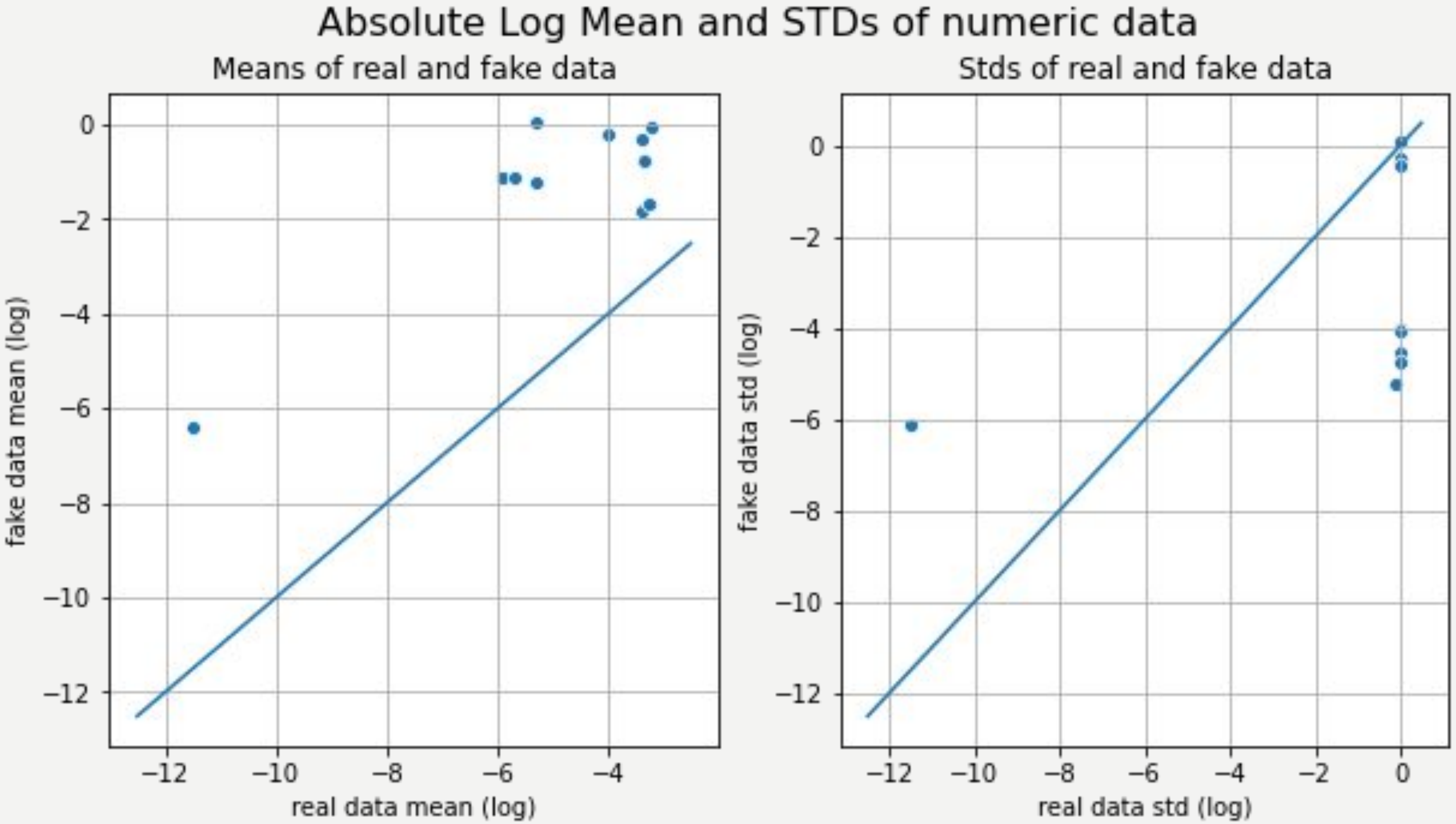
```
[ ] synthesizer.generator.summary()

    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

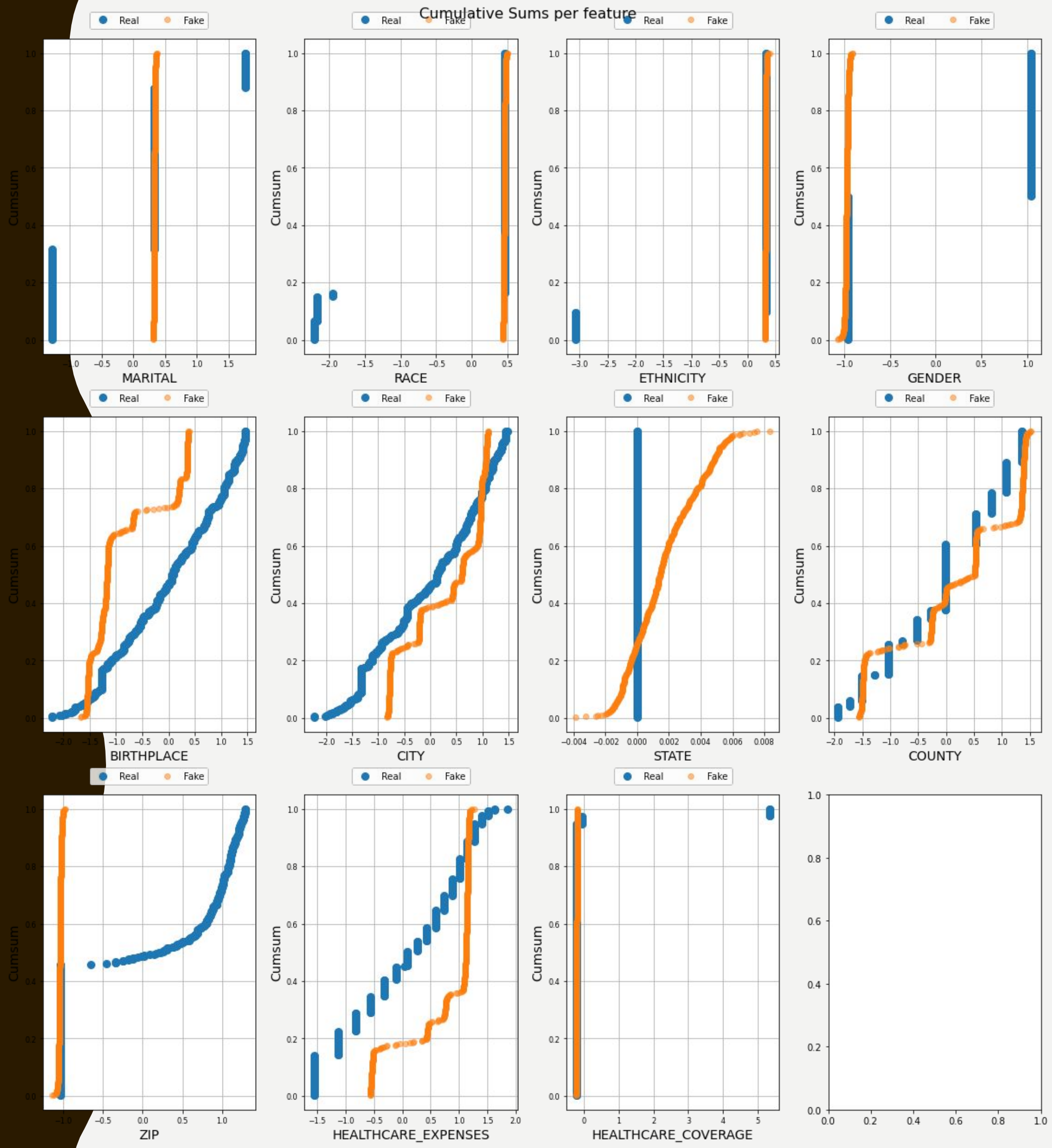
The neural networks are defined in the code and the snippet provided

EVALUATION METRICS



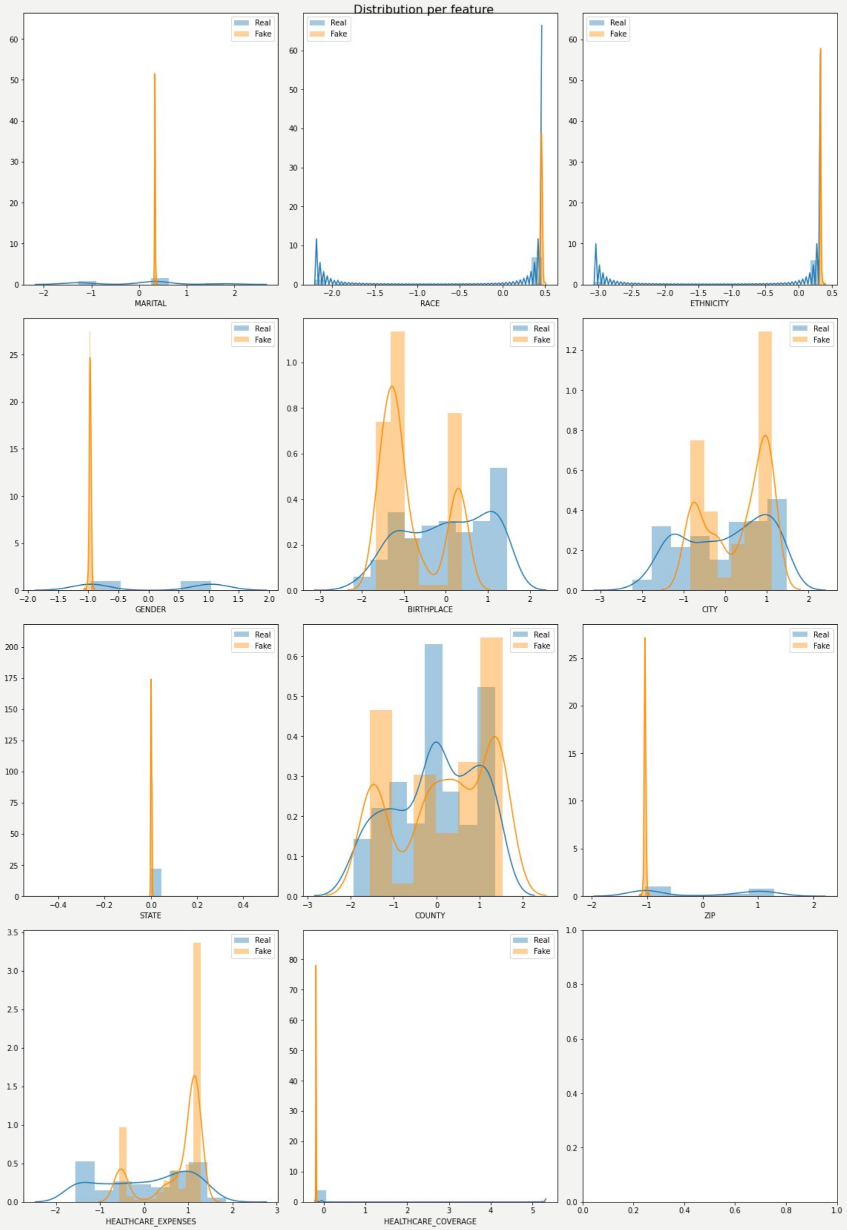


EVALUATION METRICS



Cumulative sum

Distributions visualised



THANK YOU

DIFFERENTIALLY PRIVATE 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

Thank you for the opportunity to present a solution for a real-world business case

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