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# Conformalized Generative Adversarial Network

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# 1 Class Diagram

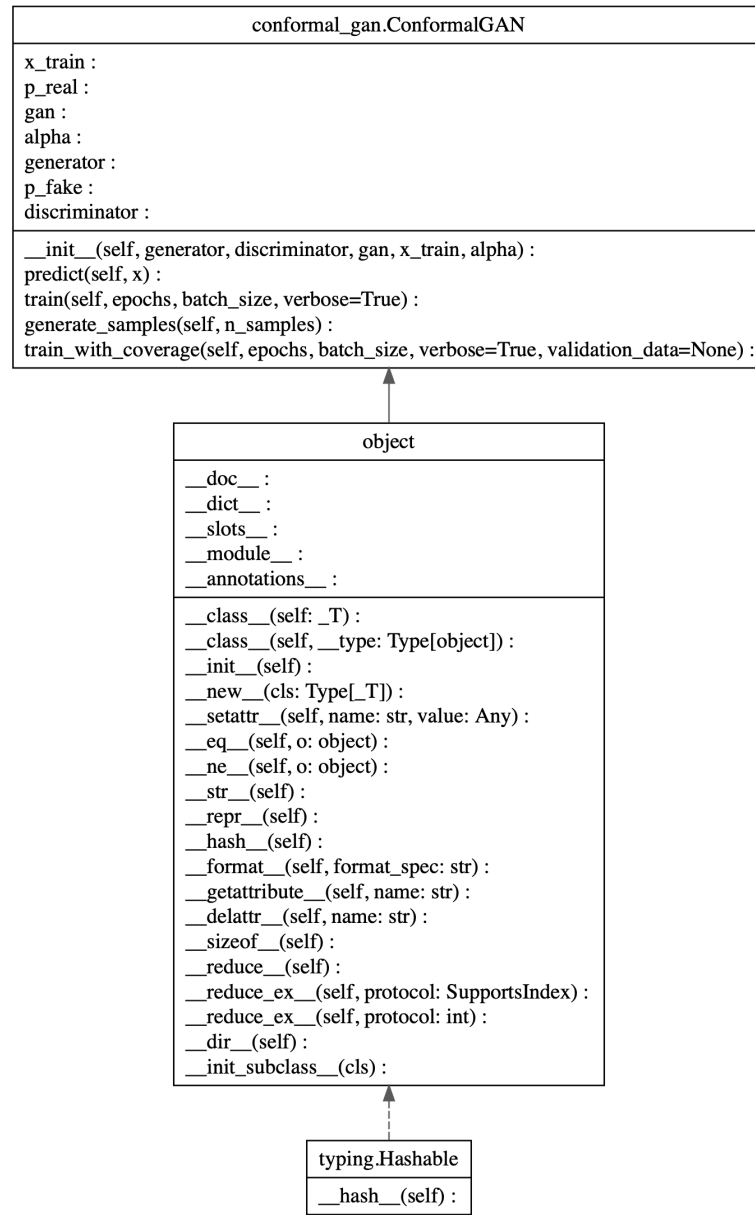


Figure 1: Class diagram for ConformalizedGAN

## 2 Sequence diagram

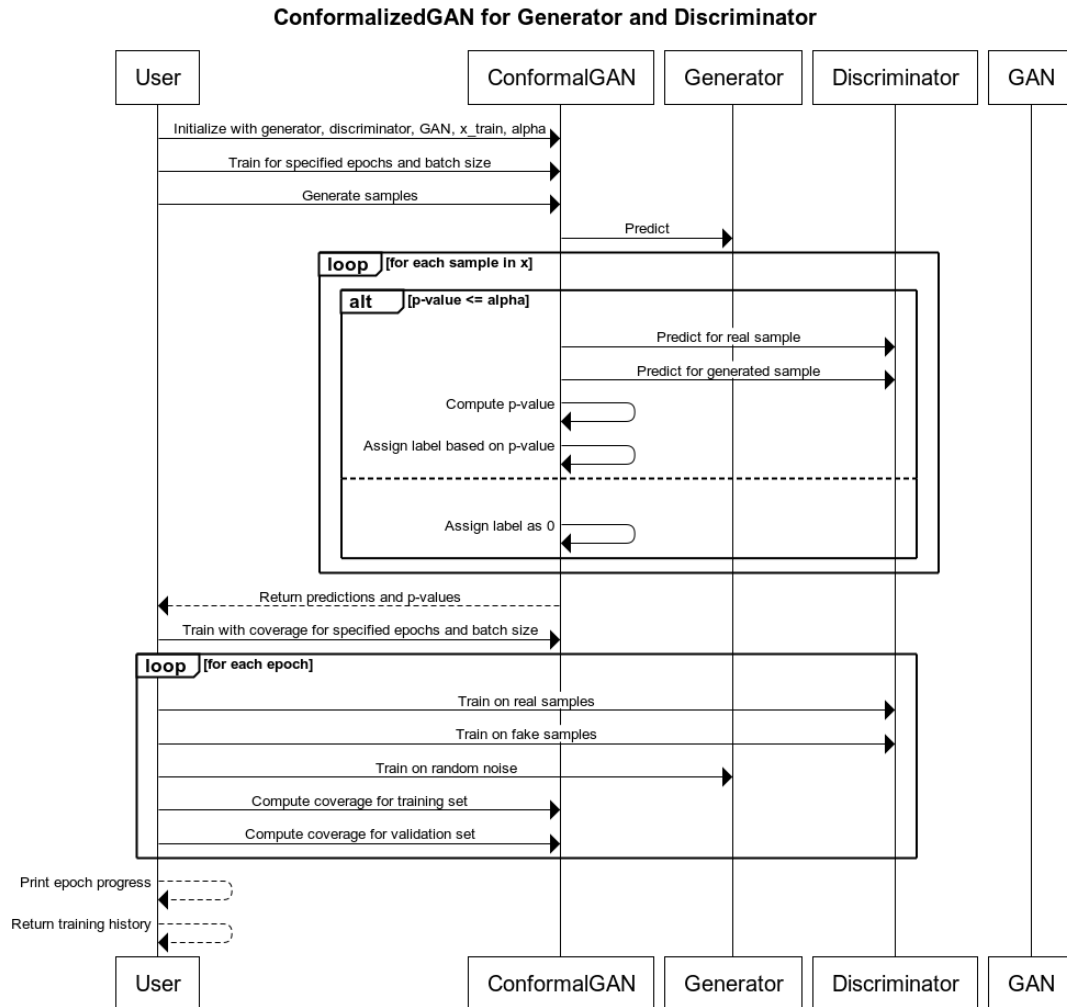


Figure 2: Sequence diagram for ConformalizedGAN

## 3 Source code

### 3.1 Conformal GAN

```
1
2 import numpy as np
3 import tensorflow as tf
4 from tensorflow.keras.layers import Input, Dense, Reshape,
    Flatten, Dropout, BatchNormalization, LSTM, LeakyReLU
5 from tensorflow.keras.models import Sequential, Model
6 from tensorflow.keras.optimizers import Adam
7
8 class ConformalGAN:
9     def __init__(self, generator, discriminator, gan, x_train,
10         alpha):
11         self.generator = generator
12         self.discriminator = discriminator
13         self.gan = gan
14         self.x_train = x_train
15         self.alpha = alpha
16
17     def predict(self, x):
18         p_values = np.zeros((len(x), 2))
19         y_pred = np.zeros((len(x),))
20         for i, x_i in enumerate(x):
21             # Generate a sample from the generator
22             z = np.random.normal(size=(1, self.generator.
23 input_shape[1]))
24             x_gen = self.generator.predict(z)
25             # Compute the p-value for the sample
26             d_real = self.discriminator.predict(x_i.reshape(1,
27 -1))[0]
28             d_gen = self.discriminator.predict(x_gen.reshape(1,
29 -1))[0]
30             p_value = (np.sum(d_gen >= d_real) + 1) / (self.
31 x_train.shape[0] + 1)
32             p_values[i] = [1 - p_value, p_value]
33             # Predict the label for the sample
34             if p_value <= self.alpha:
35                 y_pred[i] = 1
36         return y_pred, p_values
37
38     def train(self, epochs, batch_size, verbose=True):
39         # Compute p-values for real and fake samples
40         D_real = self.discriminator.predict(self.X_train)
41         D_fake = self.discriminator.predict(self.generator.
42 predict(np.random.normal(0, 1, (len(self.X_train), 100)))).
43 ravel()
44
45         # Compute conformal prediction intervals
46         self.p_real = np.zeros_like(D_real)
47         self.p_fake = np.zeros_like(D_fake)
48
49         for i in range(len(D_real)):
50             self.p_real[i] = np.sum(D_real >= D_real[i]) / (len(
```

```

D_real) + 1)
43         self.p_fake[i] = np.sum(D_fake >= D_fake[i]) / (len(
D_fake) + 1)
44
45     # Train the GAN
46     for epoch in range(epochs):
47         # Train discriminator on real samples
48         idx = np.random.randint(0, len(self.X_train),
batch_size)
49         X_real = self.X_train[idx]
50         y_real = np.ones((batch_size, 1))
51         d_loss_real = self.discriminator.train_on_batch(
X_real, y_real)
52
53         # Train discriminator on fake samples
54         z = np.random.normal(0, 1, (batch_size, 100))
55         X_fake = self.generator.predict(z)
56         y_fake = np.zeros((batch_size, 1))
57         d_loss_fake = self.discriminator.train_on_batch(
X_fake, y_fake)
58
59         # Train generator
60         z = np.random.normal(0, 1, (batch_size, 100))
61         y = np.ones((batch_size, 1))
62         g_loss = self.gan.train_on_batch(z, y)
63
64         # Print progress
65         if verbose and epoch % 100 == 0:
66             print(f"Epoch {epoch}: D_loss_real={d_loss_real
[0]}, D_loss_fake={d_loss_fake[0]}, G_loss={g_loss}")
67
68     def generate_samples(self, n_samples):
69         z = np.random.normal(0, 1, (n_samples, 100))
70         samples = self.generator.predict(z)
71
72         # Compute prediction intervals for samples
73         p_values = np.zeros((n_samples,))
74         for i in range(n_samples):
75             D = self.discriminator.predict(np.expand_dims(samples
[i], axis=0)).ravel()
76             p_values[i] = np.sum(D >= D.real[i]) / (len(D) + 1)
77
78             lower_bound = np.percentile(samples, (self.alpha / 2) *
100, axis=0)
79             upper_bound = np.percentile(samples, (1 - (self.alpha /
2)) * 100, axis=0)
80             in_prediction_interval = (p_values > self.alpha / 2) & (
p_values < 1 - self.alpha / 2)
81
82         return samples, lower_bound, upper_bound,
in_prediction_interval
83
84
85

```

```

86     def train_with_coverage(self, epochs, batch_size, verbose=
True, validation_data=None):
87         train_loss = []
88         train_coverage = []
89         if validation_data is not None:
90             test_loss = []
91             test_coverage = []
92         for epoch in range(epochs):
93             # Train the discriminator
94             idx = np.random.randint(0, self.x_train.shape[0],
batch_size)
95             x_real = self.x_train[idx]
96             y_real = np.ones((batch_size,))
97             x_gen = self.generator.predict(np.random.normal(size
=(batch_size, self.generator.input_shape[1])))
98             y_gen = np.zeros((batch_size,))
99             x = np.concatenate([x_real, x_gen], axis=0)
100            y = np.concatenate([y_real, y_gen], axis=0)
101            d_loss, d_acc = self.discriminator.train_on_batch(x,
y)
102            # Train the generator
103            z = np.random.normal(size=(batch_size, self.generator
.input_shape[1]))
104            y = np.ones((batch_size,))
105            g_loss = self.gan.train_on_batch(z, y)
106            # Compute the coverage for the training set
107            y_pred, p_values = self.predict(self.x_train)
108            train_loss.append([d_loss, g_loss])
109            train_coverage.append(np.mean(y_pred == y_real))
110            # Compute the coverage for the validation set
111            if validation_data is not None:
112                x_val, y_val = validation_data
113                y_pred_val, p_values_val = self.predict(x_val)
114                d_loss_val, d_acc_val = self.discriminator.
evaluate(x_val, y_val, verbose=0)
115                g_loss_val = self.gan.evaluate(z, y, verbose=0)
116                test_loss.append([d_loss_val, g_loss_val])
117                test_coverage.append(np.mean(y_pred_val == y_val)
)
118
119            if verbose:
120                print("Epoch {}/{} - Discriminator Loss: {:.4f} -
Discriminator Accuracy: {:.4f} - Generator Loss: {:.4f} -
Train Coverage: {:.4f}".format(epoch+1, epochs, d_loss, d_acc
, g_loss , train_coverage[-1]))
121            # Return the training history
122            history = {"train_loss": train_loss, "train_coverage":
train_coverage}
123            if validation_data is not None:
124                history["test_loss"] = test_loss
125                history["test_coverage"] = test_coverage
126            return history

```

Listing 1: Python implementation for conformalized GAN.

## 3.2 Synthesize data using conformal GAN

```
1
2 import numpy as np
3 import matplotlib.pyplot as plt
4 from tensorflow.keras.layers import Input, Dense, Reshape,
    Flatten
5 from tensorflow.keras.models import Model, Sequential
6 from tensorflow.keras.optimizers import Adam
7 from conformal_gan import ConformalGAN
8
9 # Generate the training data
10 n_samples = 10000
11 seq_length = 50
12 data = np.zeros((n_samples, seq_length))
13 for i in range(n_samples):
14     phase = np.random.uniform(low=0.0, high=2*np.pi)
15     freq = np.random.uniform(low=0.01, high=0.1)
16     amp = np.random.uniform(low=0.1, high=1.0)
17     x = np.linspace(0, seq_length/freq, seq_length, endpoint=
        False)
18     data[i] = amp * np.sin(2*np.pi*freq*x + phase)
19
20 # Normalize the data
21 data = (data - np.mean(data)) / np.std(data)
22
23 # Define the generator model
24 latent_dim = 10
25 generator = Sequential()
26 generator.add(Dense(256, input_dim=latent_dim, activation='relu')
    )
27 generator.add(Dense(512, activation='relu'))
28 generator.add(Dense(1024, activation='relu'))
29 generator.add(Dense(seq_length, activation='tanh'))
30
31 # Define the discriminator model
32 discriminator = Sequential()
33 discriminator.add(Flatten(input_shape=(seq_length,)))
34 discriminator.add(Dense(512, activation='relu'))
35 discriminator.add(Dense(256, activation='relu'))
36 discriminator.add(Dense(1, activation='sigmoid'))
37
38 # Compile the discriminator
39 discriminator.compile(loss='binary_crossentropy', optimizer=Adam
    (0.0002, 0.5), metrics=['accuracy'])
40
41 # Define the GAN
42 z = Input(shape=(latent_dim,))
43 time_series = generator(z)
44 validity = discriminator(time_series)
45 gan = Model(z, validity)
46
47 # Compile the GAN
48 gan.compile(loss='binary_crossentropy', optimizer=Adam(0.0002,
```



```

    0.5))
49
50 # Train the GAN with conformal prediction
51 alpha = 0.05
52 n_train = 8000
53 x_train_subset = data[:n_train]
54 conformal_gan = ConformalGAN(generator, discriminator, gan,
    x_train_subset, alpha=alpha)
55 train_loss, test_loss, train_coverage, test_coverage =
    conformal_gan.train_with_coverage(epochs=5000, batch_size=32,
    verbose=True)
56
57 # Generate synthetic time-series data
58 n_samples = 10
59 z = np.random.normal(size=(n_samples, latent_dim))
60 synthetic_data = generator.predict(z)
61
62 # Plot the training and validation loss
63 plt.plot(train_loss)
64 plt.plot(test_loss)
65 plt.title('Conformal GAN Loss')
66 plt.ylabel('Loss')
67 plt.xlabel('Epoch')
68 plt.legend(['Train', 'Validation'], loc='upper left')
69 plt.show()
70
71 # Plot the training and validation coverage
72 plt.plot(train_coverage)
73 plt.plot(test_coverage)
74 plt.title('Conformal GAN Coverage')
75 plt.ylabel('Coverage')
76 plt.xlabel('Epoch')
77 plt.legend(['Train', 'Validation'], loc='upper left')
78 plt.show()
79
80 # Plot the synthetic time-series data
81 for i in range(n_samples):
82     plt.plot(synthetic_data[i])
83 plt.title('Synthetic Time-Series Data')
84 plt.xlabel('Time')
85 plt.ylabel('Value')
86 plt.show()

```

Listing 2: Python implementation for generating data using conformal GAN.