Crafting Table

Instalación e inicialización

Opcionalmente, creamos un entrono virtual.

```
# Creamos un entorno virtual para instalar las dependencias
!python3 -m venv venv
# Activamos el entorno virtual
!source venv/bin/activate
# Reiniciar notebook y escoger el kernel del venv que se acaba de
crear
```

La librería usa python >=3.10, <3.14.

```
!python --version
```

```
Python 3.10.5
```

Para instalarlo debemos clonar el repositorio donde se encuentra el código e instalar las dependencias necesarias.

```
# Clonamos el repositorio de GitHub con el código
!git clone https://github.com/diegovelilla/TFG.git
```

```
Cloning into 'TFG'...
```

Antes de clonar las dependencias suele ser recomendable actualizar pip.

Las dependencias se han separado en 2 ficheros distintos, dependiendo de si se requiere uso de GPU o no.

Por último, instalamos las dependencias adicionales que usaremos en este notebook.

```
!pip install --upgrade --quiet pip
#!pip install -r TFG/requirements-cpu.txt --quiet
!pip install -r TFG/requirements-gpu.txt --quiet
!pip install ucimlrepo --quiet # opción secundaria para el importe de
datos. A veces da errores.
!pip install matplotlib --quiet
!pip install seaborn --quiet

from sklearn.datasets import load_iris
import pandas as pd

# Cargar desde sklearn
iris_data = load_iris(as_frame=True)
```

```python
# Obtener features y target
iris_x = iris_data.data
iris_y = iris_data.target
iris = pd.concat([iris_x, iris_y.rename("class")], axis=1)

from TFG.CraftingTable import CTGAN, TVAE, TabDDPM, TabSyn
ctgan = CTGAN()
tvae = TVAE()
tabddpm = TabDDPM()
tabsyn = TabSyn()
```

Entrenamiento de los modelos

Para entrenar los modelos es tan sencillo como llamar a la función *fit* de cada modelo con los datos reales y la lista de columnas categóricas.

Adicionalmente, podemos indicar otros parámetros opcionales para personalizar el entrenamiento.

```python
print("Entrenando CTGAN con CPU...")
ctgan.fit(train_data=iris, discrete_columns=['class'], epochs=5000,
batch_size=50, device='cpu', verbose=True)
print("\nEntrenando TVAE con CPU...")
tvae.fit(train_data=iris, discrete_columns=['class'], epochs=5000,
batch_size=50, device='cpu', verbose=True)
print("\nEntrenando TabDDPM con GPU...")
tabddpm.fit(train_data=iris, discrete_columns=['class'], epochs=5000,
batch_size=50, device='cuda', verbose=True)
print("\nEntrenando TabSyn con GPU...")
tabsyn.fit(train_data=iris, discrete_columns=['class'], vae_epochs=50,
mlp_epochs=50, batch_size=50, device='cuda', verbose=True)
```

```
Entrenando CTGAN con CPU...
Using CPU for training.

Gen. (0.44) | Discrim. (0.55): 100%|██████████| 5000/5000
[03:13<00:00, 25.79it/s]


Entrenando TVAE con CPU...
Using CPU for training.

Loss: -20.853: 100%|██████████| 5000/5000 [01:23<00:00, 59.53it/s]


Entrenando TabDDPM con GPU...
Using CUDA for training.

Loss: 0.7715: 100%|██████████| 5000/5000 [00:35<00:00, 140.70it/s]
```

```
Entrenando TabSyn con GPU...
Using CUDA for training.
```

```
VAE Loss: 0.0116: 100%|██████████| 50/50 [03:50<00:00,  4.61s/it]
```

```
Successfully saved pretrained embeddings to disk!
```

```
MLP Loss: 0.3782: 100%|██████████| 50/50 [02:23<00:00,  2.87s/it]
```

Metadatos

Una vez entrenados los modelos, podemos consultar metadatos sobre los datos usados para su entrenamiento.

```python
print(ctgan.get_metadata()['table']['columns']['sepal length (cm)'])
print(tvae.get_metadata()['table']['columns']['sepal width (cm)'])
print(tabddpm.get_metadata()['table']['columns']['petal length (cm)'])
print(tabsyn.get_metadata()['table']['columns']['petal width (cm)'])
```

```
{'dtype': 'float64', 'max': 7.9, 'min': 4.3, 'avg': 5.843333333333334,
'std': 0.8253012917851409, 'median': 5.8}
{'dtype': 'float64', 'max': 4.4, 'min': 2.0, 'avg':
3.0573333333333337, 'std': 0.4344109677354946, 'median': 3.0}
{'dtype': 'float64', 'max': 6.9, 'min': 1.0, 'avg':
3.7580000000000005, 'std': 1.759404065775303, 'median': 4.35}
{'dtype': 'float64', 'max': 2.5, 'min': 0.1, 'avg':
1.1993333333333336, 'std': 0.7596926279021594, 'median': 1.3}
```

```python
print(ctgan.get_metadata()['table']['correlations']['sepal length
(cm)'])
print(tvae.get_metadata()['table']['correlations']['sepal width
(cm)'])
print(tabddpm.get_metadata()['table']['correlations']['petal length
(cm)'])
print(tabsyn.get_metadata()['table']['correlations']['petal width
(cm)'])
```

```
{'petal length (cm)': 0.8717537758865835, 'petal width (cm)':
0.8179411262715758, 'sepal length (cm)': 1.0, 'sepal width (cm)': -
0.11756978413300088}
{'petal length (cm)': -0.4284401043305386, 'petal width (cm)': -
0.3661259325364377, 'sepal length (cm)': -0.11756978413300088, 'sepal
width (cm)': 1.0}
{'petal length (cm)': 1.0, 'petal width (cm)': 0.962865431402796,
'sepal length (cm)': 0.8717537758865835, 'sepal width (cm)': -
0.4284401043305386}
{'petal length (cm)': 0.962865431402796, 'petal width (cm)': 1.0,
'sepal length (cm)': 0.8179411262715758, 'sepal width (cm)': -
0.3661259325364377}
```

Además, la librería también guarda metadatos sobre el propio modelo e hyperparámetros usados.

```
print(ctgan.get_metadata()['model']['model_type'])
print(ctgan.get_metadata()['model']['hyperparameters'])
print()

print(tvae.get_metadata()['model']['model_type'])
print(tvae.get_metadata()['model']['hyperparameters'])
print()

print(tabddpm.get_metadata()['model']['model_type'])
print(tabddpm.get_metadata()['model']['hyperparameters'])
print()

print(tabsyn.get_metadata()['model']['model_type'])
print(tabsyn.get_metadata()['model']['hyperparameters'])
print()
```

```
CTGAN
{'embeddig_dim': 128, 'generator_dim': (256, 256),
'discriminator_dim': (256, 256)}

TVAE
{'embeddig_dim': 128, 'compress_dims': (128, 128), 'decompress_dims':
(128, 128)}

TabDDPM_MLP
{'dim_t': 256, 'd_layers': (8, 16), 'dropout': 0.1}

TabSyn
{'num_layers_vae': 2, 'factor_vae': 32, 'n_head_vae': 1,
'd_token_vae': 4, 'dim_t_mlp': 512}
```

Por último, podemos consultar también información sobre el entrenamiento de cada modelo.

```
print(f"Veces entrenado: {ctgan.get_metadata()['model']
['fit_settings']['times_fitted']}")
print(f"Duración: {ctgan.get_metadata()['model']['fit_settings']
['fit_history'][-1]['duration']}")
print("Parámetros: ",)
for k, v in ctgan.get_metadata()['model']['fit_settings']
['fit_history'][-1]['parameters'].items():
    print(f"    {k}: {v}")
ctgan.get_metadata()['model']['fit_settings']['fit_history'][-1]
['loss'][-15:]
```

```
Veces entrenado: 1
Duración: 0:03:18
```

```
Parámetros:
    device: cpu
    epochs: 5000
    batch_size: 50
    generator_lr: 0.0002
    generator_decay: 1e-06
    discriminator_lr: 0.0002
    discriminator_decay: 1e-06
    discriminator_steps: 1
```

	Epoch	Generator Loss	Discriminator Loss
4985	4985	0.226806	0.489191
4986	4986	-0.086695	-0.608414
4987	4987	-0.409867	0.949151
4988	4988	-0.512807	-1.156794
4989	4989	-0.484479	0.082247
4990	4990	-0.230081	-0.838329
4991	4991	1.158649	-1.124544
4992	4992	0.030039	-0.113346
4993	4993	-0.118749	0.431803
4994	4994	-0.398105	0.344827
4995	4995	0.462802	0.625040
4996	4996	-0.022678	-0.519589
4997	4997	0.864197	-0.306490
4998	4998	0.162486	-0.354396
4999	4999	0.436284	0.550878

```
print(f"Veces entrenado: {tvae.get_metadata()['model']['fit_settings']
['times_fitted']}")
print(f"Duración: {tvae.get_metadata()['model']['fit_settings']
['fit_history'][-1]['duration']}")
print("Parámetros: ",)
for k, v in tvae.get_metadata()['model']['fit_settings']
['fit_history'][-1]['parameters'].items():
    print(f"    {k}: {v}")
tvae.get_metadata()['model']['fit_settings']['fit_history'][-1]
['loss'][-15:]
```

```
Veces entrenado: 1
Duración: 0:01:24
Parámetros:
    batch_size: 50
    epochs: 5000
    device: cpu
    l2_scale: 1e-05
    loss_factor: 2
```

	Epoch	Loss
4985	4985	-19.664181
4986	4986	-19.821409

```
4987   4987 -20.136208
4988   4988 -20.673161
4989   4989 -19.970119
4990   4990 -20.946209
4991   4991 -20.906553
4992   4992 -20.990906
4993   4993 -19.758051
4994   4994 -21.295341
4995   4995 -20.927313
4996   4996 -19.542061
4997   4997 -19.612467
4998   4998 -20.738834
4999   4999 -20.852562
```

```
print(f"Veces entrenado: {tabddpm.get_metadata()['model']
['fit_settings']['times_fitted']}")
print(f"Duración: {tabddpm.get_metadata()['model']['fit_settings']
['fit_history'][-1]['duration']}")
print("Parámetros: ",)
for k, v in tabddpm.get_metadata()['model']['fit_settings']
['fit_history'][-1]['parameters'].items():
    print(f"    {k}: {v}")
tabddpm.get_metadata()['model']['fit_settings']['fit_history'][-1]
['loss'][-15:]
```

```
Veces entrenado: 1
Duración: 0:00:35
Parámetros:
    device: cuda
    epochs: 5000
    lr: 0.005
    weight_decay: 0.0001
    batch_size: 50
    num_timesteps: 1000
```

	Epoch	Loss
4985	4985.0	0.5932
4986	4986.0	0.7573
4987	4987.0	0.7824
4988	4988.0	0.6533
4989	4989.0	0.6722
4990	4990.0	0.6935
4991	4991.0	0.6659
4992	4992.0	0.7411
4993	4993.0	0.6593
4994	4994.0	0.6096
4995	4995.0	0.7490
4996	4996.0	0.6356
4997	4997.0	0.5380

```
4998  4998.0  0.7659
4999  4999.0  0.7715
```

```python
print(f"Veces entrenado: {tabsyn.get_metadata()['model']
['fit_settings']['times_fitted']}")
print(f"Duración: {tabsyn.get_metadata()['model']['fit_settings']
['fit_history'][-1]['duration']}")
print("Parámetros: ",)
for k, v in tabsyn.get_metadata()['model']['fit_settings']
['fit_history'][-1]['parameters'].items():
    print(f"    {k}: {v}")
tabsyn.get_metadata()['model']['fit_settings']['fit_history'][-1]
['loss']['vae_loss'][-15:]
```

```
Veces entrenado: 1
Duración: {'vae_duration': '0:03:50', 'mlp_duration': '0:02:23'}
Parámetros:
    device: cuda
    vae_epochs: 50
    mlp_epochs: 50
    batch_size: 50
    lr: 0.001
    max_beta: 0.01
    min_beta: 1e-05
    lambda: 0.7
    weight_decay: 0
```

	Epoch	Vae Loss
35	35	0.013080
36	36	0.011155
37	37	0.009913
38	38	0.010109
39	39	0.009374
40	40	0.009462
41	41	0.007661
42	42	0.007687
43	43	0.007795
44	44	0.006046
45	45	0.006350
46	46	0.006063
47	47	0.005720
48	48	0.005051
49	49	0.005435

```python
tabsyn.get_metadata()['model']['fit_settings']['fit_history'][-1]
['loss']['mlp_loss'][-15:]
```

	Epoch	MLP Loss
35	35	0.350489
36	36	0.377854

```
37      37  0.441902
38      38  0.346506
39      39  0.325930
40      40  0.357212
41      41  0.358664
42      42  0.365620
43      43  0.363711
44      44  0.324463
45      45  0.347781
46      46  0.375827
47      47  0.334102
48      48  0.297414
49      49  0.328264
```

Guardado / Carga de modelos

Una vez entrenados los modelos, podemos guardar estas instancias para poder cargarlas en un futuro.

```
ctgan.save('saves/ctgan.pt')
tvae.save('saves/tvae.pt')
tabddpm.save('saves/tabddpm.pt')
tabsyn.save('saves/tabsyn.pt')

ctgan2 = CTGAN.load('saves/ctgan.pt')
tvae2 = TVAE.load('saves/tvae.pt')
tabddpm2 = TabDDPM.load('saves/tabddpm.pt')
tabsyn2 = TabSyn.load('saves/tabsyn.pt')
```

Esta guardado/carga mantiene tanto los modelos entrenados como sus metadatos anteriores.

```
print(ctgan.get_metadata()['table']['columns']['sepal length (cm)'])
print(ctgan2.get_metadata()['table']['columns']['sepal length (cm)'])
print()

print(tvae.get_metadata()['model']['model_type'])
print(tvae.get_metadata()['model']['hyperparameters'])
print(tvae2.get_metadata()['model']['model_type'])
print(tvae2.get_metadata()['model']['hyperparameters'])
print()

print(f"Veces entrenado: {tabddpm.get_metadata()['model']
['fit_settings']['times_fitted']}")
print(f"Duración: {tabddpm.get_metadata()['model']['fit_settings']
['fit_history'][-1]['duration']}")
print("Parámetros: ",)
for k, v in tabddpm.get_metadata()['model']['fit_settings']
['fit_history'][-1]['parameters'].items():
    print(f"    {k}: {v}")
```

```python
print(f"Veces entrenado: {tabddpm2.get_metadata()['model']
['fit_settings']['times_fitted']}")
print(f"Duración: {tabddpm2.get_metadata()['model']['fit_settings']
['fit_history'][-1]['duration']}")
print("Parámetros: ",)
for k, v in tabddpm2.get_metadata()['model']['fit_settings']
['fit_history'][-1]['parameters'].items():
    print(f"    {k}: {v}")
```

```
{'dtype': 'float64', 'max': 7.9, 'min': 4.3, 'avg': 5.843333333333334,
'std': 0.8253012917851409, 'median': 5.8}
{'dtype': 'float64', 'max': 7.9, 'min': 4.3, 'avg': 5.843333333333334,
'std': 0.8253012917851409, 'median': 5.8}

TVAE
{'embeddig_dim': 128, 'compress_dims': (128, 128), 'decompress_dims':
(128, 128)}
TVAE
{'embeddig_dim': 128, 'compress_dims': (128, 128), 'decompress_dims':
(128, 128)}

Veces entrenado: 1
Duración: 0:00:35
Parámetros:
    device: cuda
    epochs: 5000
    lr: 0.005
    weight_decay: 0.0001
    batch_size: 50
    num_timesteps: 1000
Veces entrenado: 1
Duración: 0:00:35
Parámetros:
    device: cuda
    epochs: 5000
    lr: 0.005
    weight_decay: 0.0001
    batch_size: 50
    num_timesteps: 1000
```

Muestreo

Por supuesto, la librería permite muestrear datos completamente nuevos de los modelos entrenados.

En el caso de la CTGAN podemos condicionar esta generación.

```
ctgan2.sample(10, condition_column='class', condition_value=1,
force_value=False)
```

```
   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width
(cm)  \
0           5.156375          3.048959           0.969575
0.455050
1           6.953641          2.345448           4.840564
1.456826
2           6.377283          2.666385           5.739253
2.187563
3           4.811180          2.351812           3.911719
1.092592
4           4.981969          3.057930           5.063562
1.360918
5           6.054386          2.213790           4.443929
1.212013
6           6.691280          2.688192           5.270552
1.856599
7           5.473180          2.144689           3.688999
0.743934
8           6.054203          2.682227           4.524225
1.944946
9           6.076236          2.474134           3.888033
1.530123

   class
0      0
1      2
2      2
3      1
4      1
5      1
6      0
7      1
8      1
9      2
```

```
ctgan2.sample(10, condition_column='class', condition_value=1,
force_value=True)
```

```
   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width
(cm)  \
0           6.716820          2.749882           5.224749
2.000724
1           5.497083          2.863173           3.909284
1.032653
2           6.149627          2.608503           5.617725
2.190987
3           5.257764          2.919788           4.166039
```

```
1.698968
4               6.409065            2.755739              3.231584
1.285404
5               5.074476            2.393885              5.155053
1.243100
6               5.826121            2.216662              4.878452
1.406717
7               5.717939            3.168056              4.960400
1.606056
8               5.415207            2.637214              5.437849
1.439062
9               6.278382            2.636938              4.980806
1.559967

   class
0      1
1      1
2      1
3      1
4      1
5      1
6      1
7      1
8      1
9      1
```

Evaluación estadística

La librería también permite evaluar la calidad de generación de los datos mediante tests estadísticos y medidas de distancia.

```
fake_data = ctgan2.sample(150)
print(f"Distancia CTGAN: {ctgan2.eval_stat(real_data=iris, 
test='mahalanobis', fake_data=fake_data)['value']:.3f}\n")
print(f"Distancia TVAE: {tvae2.eval_stat(real_data=iris, 
test='mahalanobis')['value']:.3f}\n")
print(f"Distancia TabDDPM: {tabddpm2.eval_stat(real_data=iris, 
test='mahalanobis')['value']:.3f}\n")
print(f"Distancia TabSyn: {tabsyn2.eval_stat(real_data=iris, 
test='mahalanobis')['value']:.3f}\n")

Distancia CTGAN: 0.793

No fake data provided, sampling from the model...
Sampled 150 rows of fake data.
Distancia TVAE: 0.204

No fake data provided, sampling from the model...
```

```
Sampled 150 rows of fake data.
Distancia TabDDPM: 3.781

No fake data provided, sampling from the model...
Sampled 150 rows of fake data.
Distancia TabSyn: 17.145
```

```python
res = ctgan2.eval_stat(real_data=iris, test='wasserstein_distance')
resl = []
for value in res['value']:
    resl.append(value['value'])
print("Distancia CTGAN:")
print(sum(resl)/len(resl))
print()

res = tvae2.eval_stat(real_data=iris, test='wasserstein_distance')
resl = []
for value in res['value']:
    resl.append(value['value'])
print("Distancia TVAE:")
print(sum(resl)/len(resl))
print()

res = tabddpm2.eval_stat(real_data=iris, test='wasserstein_distance')
resl = []
for value in res['value']:
    resl.append(value['value'])
print("Distancia TabDDPM:")
print(sum(resl)/len(resl))
print()

res = tabsyn2.eval_stat(real_data=iris, test='wasserstein_distance')
resl = []
for value in res['value']:
    resl.append(value['value'])
print("Distancia TabSyn:")
print(sum(resl)/len(resl))
```

```
No fake data provided, sampling from the model...
Sampled 150 rows of fake data.
Distancia CTGAN:
0.07594086651297098

No fake data provided, sampling from the model...
Sampled 150 rows of fake data.
Distancia TVAE:
0.06431663743524751

No fake data provided, sampling from the model...
```

```
Sampled 150 rows of fake data.
Distancia TabDDPM:
0.8429494541164431

No fake data provided, sampling from the model...
Sampled 150 rows of fake data.
Distancia TabSyn:
1.0172984713857287
```

```python
print(f"Distancia CTGAN: {ctgan2.eval_stat(real_data=iris,
test='energy_distance')['value']:.3f}\n")
print(f"Distancia TVAE: {tvae2.eval_stat(real_data=iris,
test='energy_distance')['value']:.3f}\n")
print(f"Distancia TabDDPM: {tabddpm2.eval_stat(real_data=iris,
test='energy_distance')['value']:.3f}\n")
print(f"Distancia TabSyn: {tabsyn2.eval_stat(real_data=iris,
test='energy_distance')['value']:.3f}\n")
```

```
No fake data provided, sampling from the model...
Sampled 150 rows of fake data.
Distancia CTGAN: 0.060

No fake data provided, sampling from the model...
Sampled 150 rows of fake data.
Distancia TVAE: 0.019

No fake data provided, sampling from the model...

Sampled 150 rows of fake data.
Distancia TabDDPM: 1.299

No fake data provided, sampling from the model...
Sampled 150 rows of fake data.
Distancia TabSyn: 3.275
```

```python
from sklearn.tree import DecisionTreeClassifier
print(f"Accuracy CTGAN: {ctgan2.eval_stat(real_data=iris,
test='two_sample_classifier', classifier=DecisionTreeClassifier())
['value']*100}%\n")
print(f"Accuracy TVAE: {tvae2.eval_stat(real_data=iris,
test='two_sample_classifier', classifier=DecisionTreeClassifier())
['value']*100}%\n")
print(f"Accuracy TabDDPM: {tabddpm2.eval_stat(real_data=iris,
test='two_sample_classifier', classifier=DecisionTreeClassifier())
['value']*100}%\n")
print(f"Accuracy TabSyn: {tabsyn2.eval_stat(real_data=iris,
test='two_sample_classifier', classifier=DecisionTreeClassifier())
['value']*100}%\n")
```

```
No fake data provided, sampling from the model...
Sampled 150 rows of fake data.
Accuracy CTGAN: 75.0%

No fake data provided, sampling from the model...
Sampled 150 rows of fake data.
Accuracy TVAE: 65.0%

No fake data provided, sampling from the model...

Sampled 150 rows of fake data.
Accuracy TabDDPM: 100.0%

No fake data provided, sampling from the model...
Sampled 150 rows of fake data.
Accuracy TavSyn: 100.0%
```

```
print(f"KS-test CTGAN {ctgan2.eval_stat(real_data=iris, test='ks')
['global']['statistic']:.3f}\n")
print(f"KS-test TVAE {tvae2.eval_stat(real_data=iris, test='ks')
['global']['statistic']:.3f}\n")
print(f"KS-test TabDDPM {tabddpm2.eval_stat(real_data=iris, test='ks')
['global']['statistic']:.3f}\n")
print(f"KS-test TabSyn {tabsyn2.eval_stat(real_data=iris, test='ks')
['global']['statistic']:.3f}\n")
```

```
No fake data provided, sampling from the model...
Sampled 150 rows of fake data.
KS-test CTGAN 34.865

No fake data provided, sampling from the model...
Sampled 150 rows of fake data.
KS-test TVAE 13.749

No fake data provided, sampling from the model...

Sampled 150 rows of fake data.
KS-test TabDDPM 307.662

No fake data provided, sampling from the model...
Sampled 150 rows of fake data.
KS-test TabSyn 1060.376
```

Evaluación de aprendizaje automático

Como otra forma de evaluación, la librería también ofrece tests de aprendizaje automático.

```
print(f"Real: {ctgan2.eval_ml(real_data=iris, target_name='class',
task='classification', model=DecisionTreeClassifier(),
metrics=['accuracy'])['real']['accuracy']*100:.3f}")
print(f"CTGAN: {ctgan2.eval_ml(real_data=iris, target_name='class',
task='classification', model=DecisionTreeClassifier(),
metrics=['accuracy'])['fake']['accuracy']*100:.3f}")
print(f"TVAE: {tvae2.eval_ml(real_data=iris, target_name='class',
task='classification', model=DecisionTreeClassifier(),
metrics=['accuracy'])['fake']['accuracy']*100:.3f}")
print(f"TabDDPM: {tabddpm2.eval_ml(real_data=iris,
target_name='class', task='classification',
model=DecisionTreeClassifier(), metrics=['accuracy'])['fake']
['accuracy']*100:.3f}")
print(f"TabSyn: {tabsyn2.eval_ml(real_data=iris, target_name='class',
task='classification', model=DecisionTreeClassifier(),
metrics=['accuracy'])['fake']['accuracy']*100:.3f}")
```

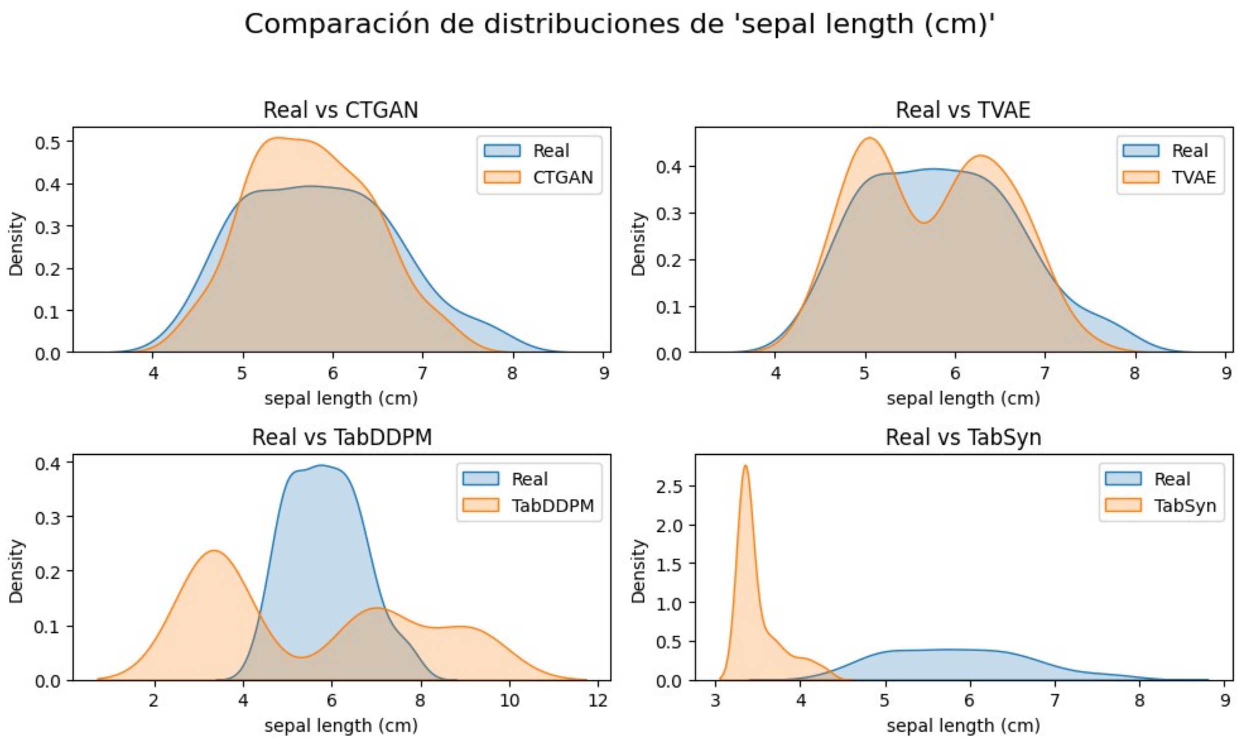
```
Real: 93.333
CTGAN: 95.556
TVAE: 97.778

TabDDPM: 17.778
TabSyn: 44.444
```

Visualización

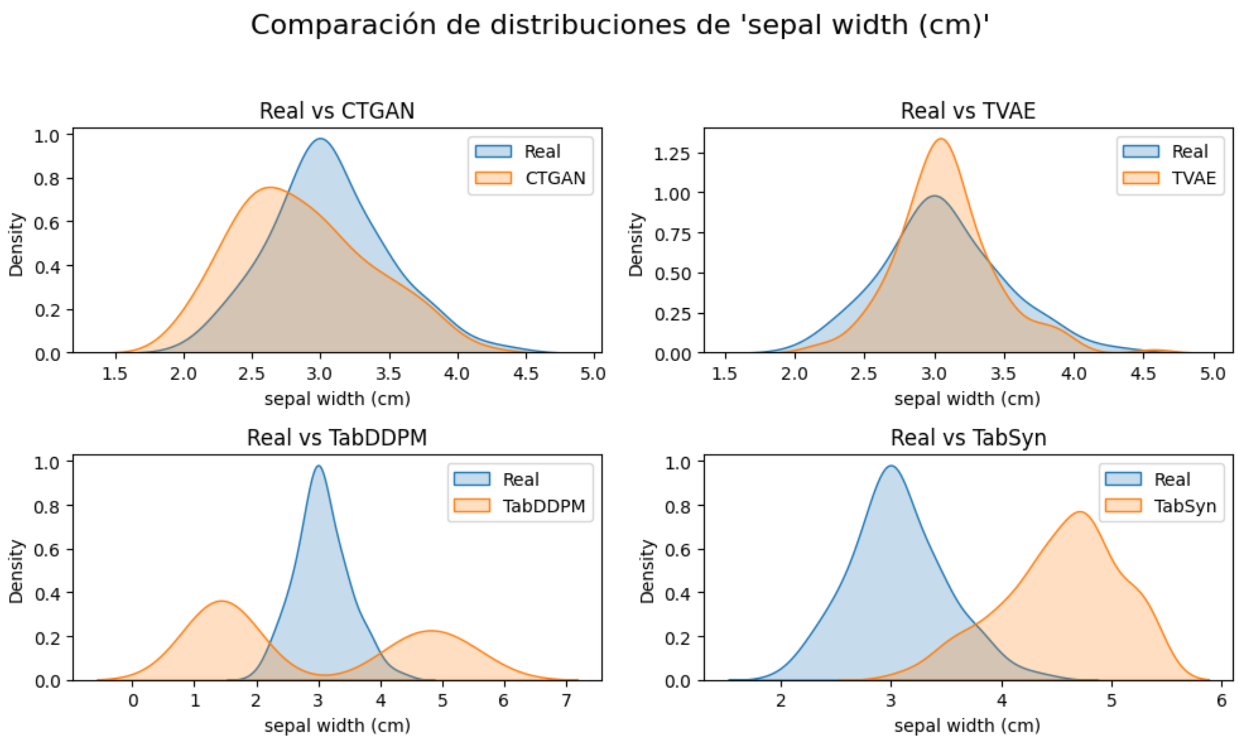
Por último, vamos a visualizar los datos generados respecto a los reales.

```
import matplotlib.pyplot as plt
import seaborn as sns

df_ctgan = ctgan2.sample(150)
df_tvae = tvae2.sample(150)
df_tabddpm = tabddpm2.sample(150)
df_tabsyn = tabsyn2.sample(150)

fig, axes = plt.subplots(2, 2, figsize=(10, 6))
fig.suptitle("Comparación de distribuciones de 'sepal length (cm)'",
fontsize=16)

model_data = [
    (df_ctgan, 'CTGAN'),
    (df_tvae, 'TVAE'),
    (df_tabddpm, 'TabDDPM'),
    (df_tabsyn, 'TabSyn')
]

for ax, (df_model, name) in zip(axes.flatten(), model_data):
    sns.kdeplot(iris['sepal length (cm)'], label='Real', ax=ax,
```

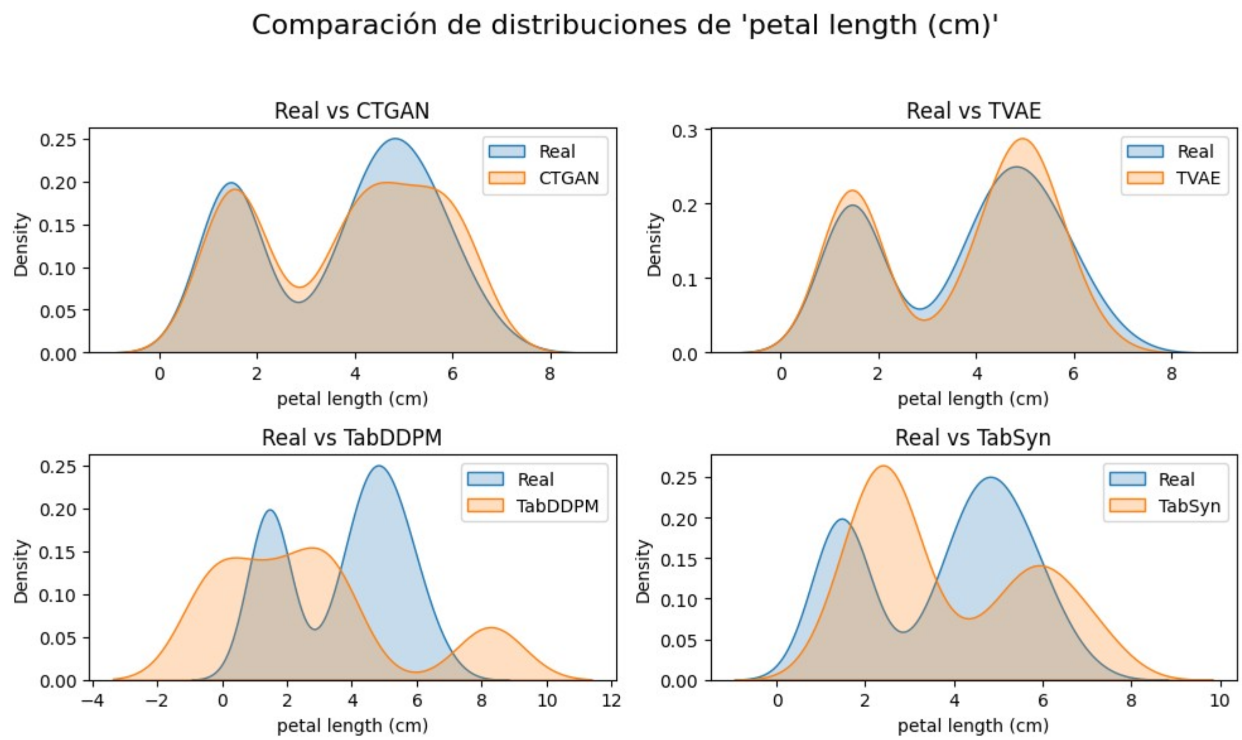
```
fill=True)
    sns.kdeplot(df_model['sepal length (cm)'], label=f'{name}', ax=ax,
fill=True)
    ax.set_title(f'Real vs {name}')
    ax.legend()

plt.tight_layout(rect=[0, 0, 1, 0.95])
plt.show()
```



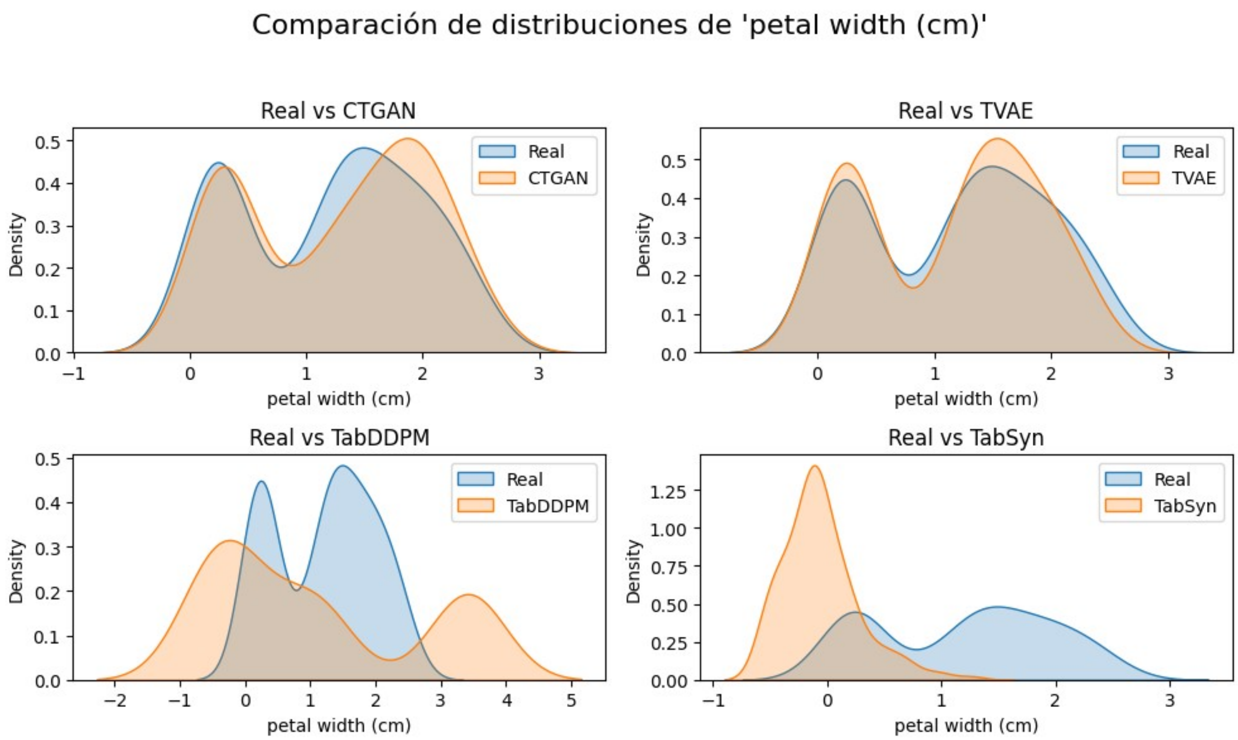

```
fig, axes = plt.subplots(2, 2, figsize=(10, 6))
fig.suptitle("Comparación de distribuciones de 'sepal width (cm)'",
fontsize=16)

for ax, (df_model, name) in zip(axes.flatten(), model_data):
    sns.kdeplot(iris['sepal width (cm)'], label='Real', ax=ax,
fill=True)
    sns.kdeplot(df_model['sepal width (cm)'], label=f'{name}', ax=ax,
fill=True)
    ax.set_title(f'Real vs {name}')
    ax.legend()

plt.tight_layout(rect=[0, 0, 1, 0.95])
plt.show()
```



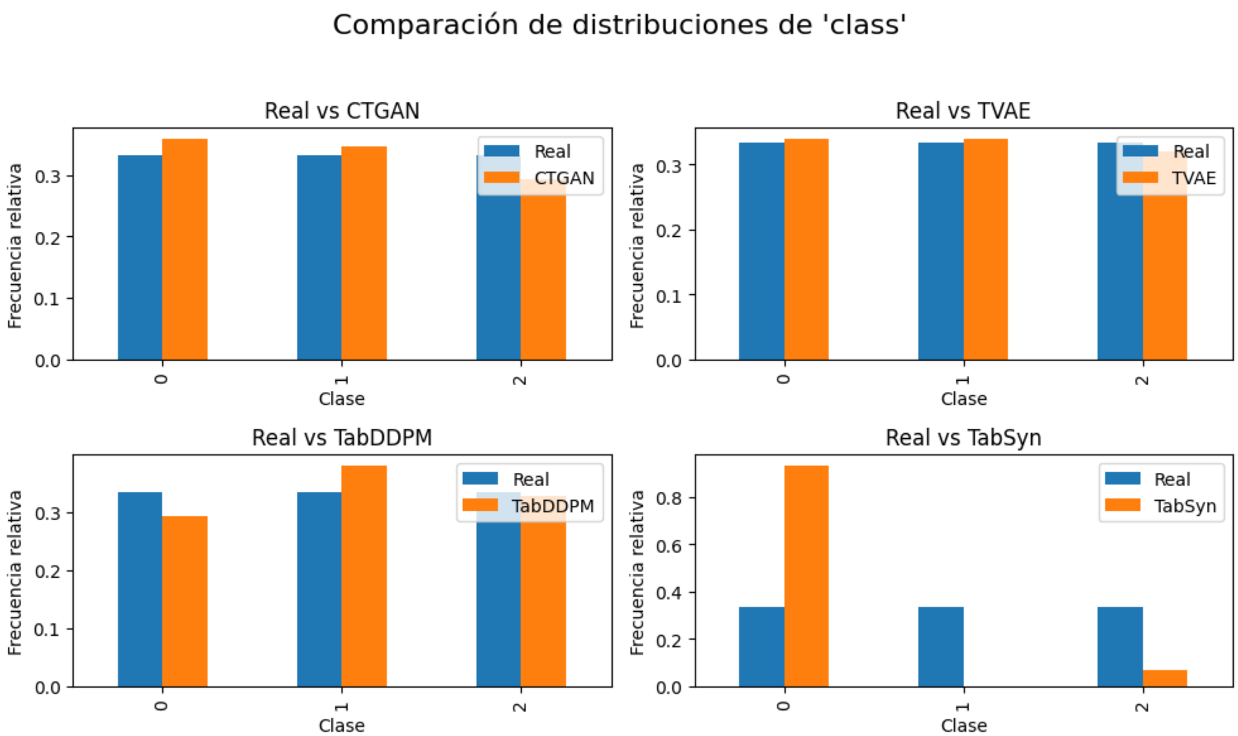

```
fig, axes = plt.subplots(2, 2, figsize=(10, 6))
fig.suptitle("Comparación de distribuciones de 'petal length (cm)'",
fontsize=16)

for ax, (df_model, name) in zip(axes.flatten(), model_data):
    sns.kdeplot(iris['petal length (cm)'], label='Real', ax=ax,
fill=True)
    sns.kdeplot(df_model['petal length (cm)'], label=f'{name}', ax=ax,
fill=True)
    ax.set_title(f'Real vs {name}')
    ax.legend()

plt.tight_layout(rect=[0, 0, 1, 0.95])
plt.show()
```




```
fig, axes = plt.subplots(2, 2, figsize=(10, 6))
fig.suptitle("Comparación de distribuciones de 'petal width (cm)'",
fontsize=16)

for ax, (df_model, name) in zip(axes.flatten(), model_data):
    sns.kdeplot(iris['petal width (cm)'], label='Real', ax=ax,
fill=True)
    sns.kdeplot(df_model['petal width (cm)'], label=f'{name}', ax=ax,
fill=True)
    ax.set_title(f'Real vs {name}')
    ax.legend()

plt.tight_layout(rect=[0, 0, 1, 0.95])
plt.show()
```




```
fig, axes = plt.subplots(2, 2, figsize=(10, 6))
fig.suptitle("Comparación de distribuciones de 'class'", fontsize=16)

for ax, (df_model, name) in zip(axes.flatten(), model_data):
    real_counts =
iris['class'].value_counts(normalize=True).sort_index()
    gen_counts =
df_model['class'].value_counts(normalize=True).sort_index()

    df_plot = pd.DataFrame({
        'Real': real_counts,
        name: gen_counts
    })

    df_plot.plot(kind='bar', ax=ax)
    ax.set_title(f"Real vs {name}")
    ax.set_ylabel("Frecuencia relativa")
    ax.set_xlabel("Clase")
    ax.legend()

plt.tight_layout(rect=[0, 0, 1, 0.95])
plt.show()
```


Comparación de distribuciones de 'class'
Real vs CTGAN
Real vs TVAE
Real vs TabDDPM
Real vs TabSyn
Real
CTGAN
TVAE
TabDDPM
TabSyn
Frecuencia relativa
Clase