```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import tensorflow as tf
from imblearn.over_sampling import RandomOverSampler
```

```
scaler = StandardScaler()
X = scaler.fit_transform(X)
data = np.hstack((X, np.reshape(y, (-1, 1))))
transformed_df = pd.DataFrame(data, columns=df.columns)
```

```
over = RandomOverSampler()
X, y = over.fit_resample(X, y)
data = np.hstack((X, np.reshape(y, (-1, 1))))
transformed_df = pd.DataFrame(data, columns=df.columns)
```

```
len(transformed_df[transformed_df["Outcome"]==1]), len(transformed_df[transformed_df["Outcome"]==0])
```

```
(500, 500)
```

```
X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.4, random_state=0)
X_valid, X_test, y_valid, y_test = train_test_split(X_temp, y_temp, test_size=0.5, random_state=0)
```

```
model = tf.keras.Sequential([
                             tf.keras.layers.Dense(16, activation='relu'), # if x <= 0 --> 0, x > 0 --> x
                             tf.keras.layers.Dense(16, activation='relu'),
                             tf.keras.layers.Dense(1, activation="sigmoid")
])
```

```
model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.001),
              loss=tf.keras.losses.BinaryCrossentropy(),
              metrics=['accuracy'])
```

```
model.evaluate(X_train, y_train)
```

```
19/19 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.5771 - loss: 0.6951
[0.6951159834861755, 0.5666666626930237]
```

```
model.evaluate(X_valid, y_valid)
```

```
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.5760 - loss: 0.7318
[0.7286570072174072, 0.574999988079071]
```

```
model.fit(X_train, y_train, batch_size=16, epochs=20, validation_data=(X_valid, y_valid))
```

```
Epoch 1/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6082 - loss: 0.6802 - val_accuracy: 0.6450 - val_loss: 0.6563
Epoch 2/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.7082 - loss: 0.6128 - val_accuracy: 0.6950 - val_loss: 0.6138
Epoch 3/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.6972 - loss: 0.5891 - val_accuracy: 0.7150 - val_loss: 0.5787
Epoch 4/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.7467 - loss: 0.5377 - val_accuracy: 0.7100 - val_loss: 0.5526
Epoch 5/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.7082 - loss: 0.5558 - val_accuracy: 0.7250 - val_loss: 0.5346
Epoch 6/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.7212 - loss: 0.5342 - val_accuracy: 0.7350 - val_loss: 0.5244
Epoch 7/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.7231 - loss: 0.5409 - val_accuracy: 0.7500 - val_loss: 0.5147
Epoch 8/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.7325 - loss: 0.5298 - val_accuracy: 0.7350 - val_loss: 0.5088
Epoch 9/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - accuracy: 0.7337 - loss: 0.5130 - val_accuracy: 0.7350 - val_loss: 0.5026
Epoch 10/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7842 - loss: 0.4824 - val_accuracy: 0.7400 - val_loss: 0.4987
Epoch 11/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.7494 - loss: 0.5074 - val_accuracy: 0.7550 - val_loss: 0.4953
Epoch 12/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.7839 - loss: 0.4805 - val_accuracy: 0.7550 - val_loss: 0.4908
Epoch 13/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.7371 - loss: 0.5044 - val_accuracy: 0.7500 - val_loss: 0.4894
Epoch 14/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.7568 - loss: 0.4945 - val_accuracy: 0.7700 - val_loss: 0.4879
Epoch 15/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.7596 - loss: 0.4981 - val_accuracy: 0.7700 - val_loss: 0.4867
Epoch 16/20
```

```
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.7894 - loss: 0.4588 - val_accuracy: 0.7650 - val_loss: 0.4835
Epoch 17/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.7710 - loss: 0.4791 - val_accuracy: 0.7700 - val_loss: 0.4829
Epoch 18/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.7642 - loss: 0.4797 - val_accuracy: 0.7650 - val_loss: 0.4806
Epoch 19/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.7480 - loss: 0.4966 - val_accuracy: 0.7700 - val_loss: 0.4782
Epoch 20/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.7762 - loss: 0.4727 - val_accuracy: 0.7750 - val_loss: 0.4771
<keras.src.callbacks.history.History at 0x7f1e6dc27dd0>
```

```
model.evaluate(X_test, y_test)
```

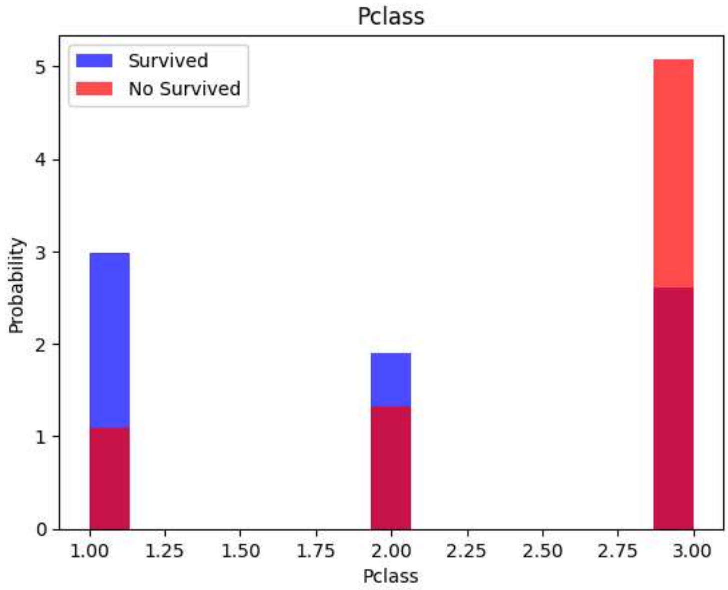
```
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8115 - loss: 0.4616
[0.47945427894592285, 0.7900000214576721]
```

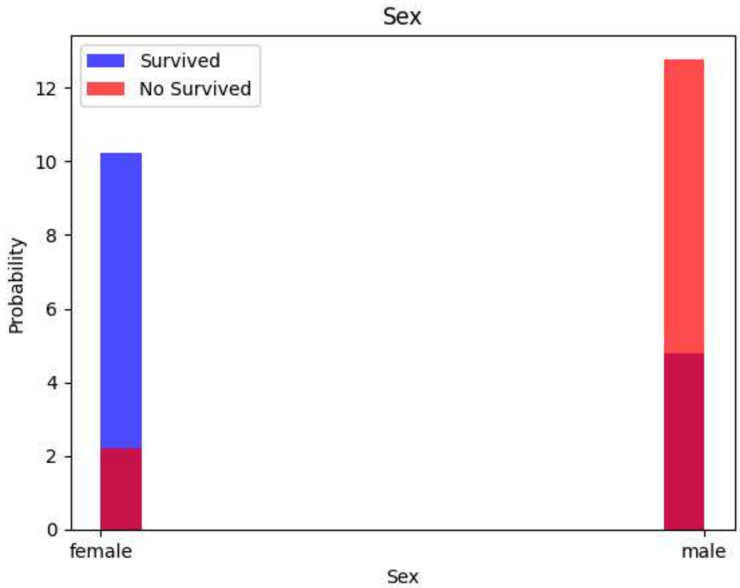
```
dfb = pd.read_csv('Titanic-Dataset.csv')
dfb.head()
dfb[['Pclass','Sex','Age','Fare','Survived']].describe()
```

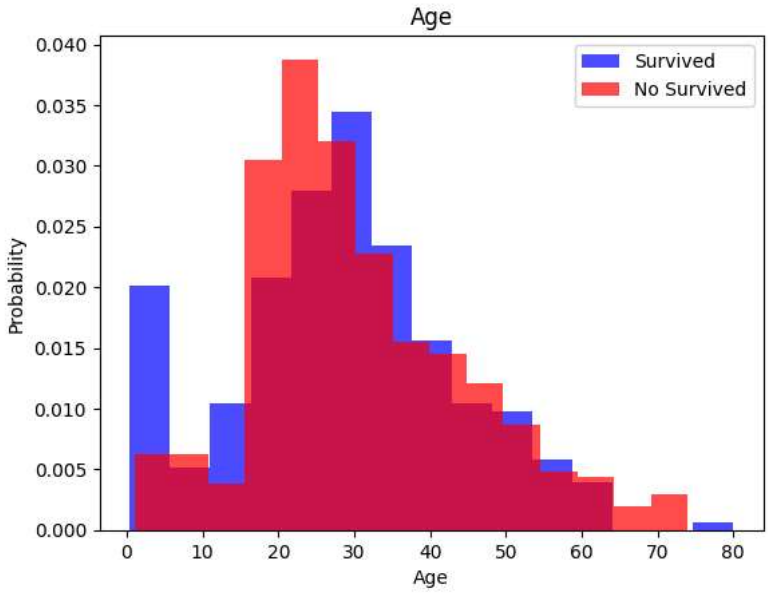
	Pclass	Age	Fare	Survived
count	891.000000	714.000000	891.000000	891.000000
mean	2.308642	29.699118	32.204208	0.383838
std	0.836071	14.526497	49.693429	0.486592
min	1.000000	0.420000	0.000000	0.000000
25%	2.000000	20.125000	7.910400	0.000000
50%	3.000000	28.000000	14.454200	0.000000
75%	3.000000	38.000000	31.000000	1.000000
max	3.000000	80.000000	512.329200	1.000000

```
dfb = dfb[['Pclass','Sex','Age','Fare','Survived']]
```

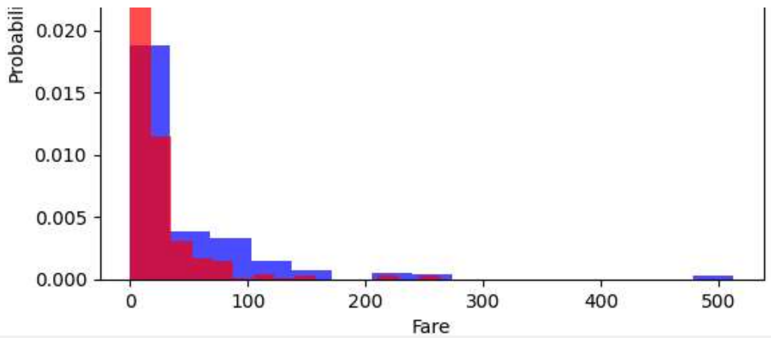
```
for i in range(len(dfb.columns[:-1])):
  label = dfb.columns[i]
  plt.hist(dfb[dfb['Survived']==1][label], color='blue', label="Survived", alpha=0.7, density=True, bins=15)
  plt.hist(dfb[dfb['Survived']==0][label], color='red', label="No Survived", alpha=0.7, density=True, bins=15)
  plt.title(label)
  plt.ylabel("Probability")
  plt.xlabel(label)
  plt.legend()
  plt.show()
```


Pclass
Survived
No Survived
Probability
0
1
2
3
4
5
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
Pclass


Sex
Survived
No Survived
Probability
0
2
4
6
8
10
12
female
male
Sex


Age
Survived
No Survived
Probability
0.000
0.005
0.010
0.015
0.020
0.025
0.030
0.035
0.040
0
10
20
30
40
50
60
70
80
Age


Fare
Survived
No Survived
0.025
0.030
0.035




```
target = dfb['Survived']
inputs = dfb.drop('Survived', axis=1)
inputs.Age = inputs.Age.fillna(inputs.Age.mean())
```

```
dumnies = pd.get_dummies(inputs.Sex,dtype=int)
dumnies.head()
inputs = pd.concat([inputs,dumnies],axis=1).drop('Sex', axis=1)
scaler = StandardScaler()
inputs[['Fare', 'Age']] = scaler.fit_transform(inputs[['Fare', 'Age']])
inputs
```

	Pclass	Age	Fare	female	male
0	3	-0.592481	-0.502445	0	1
1	1	0.638789	0.786845	1	0
2	3	-0.284663	-0.488854	1	0
3	1	0.407926	0.420730	1	0
4	3	0.407926	-0.486337	0	1
...	...	...	...	...	...
886	2	-0.207709	-0.386671	0	1
887	1	-0.823344	-0.044381	1	0
888	3	0.000000	-0.176263	1	0
889	1	-0.284663	-0.044381	0	1
890	3	0.177063	-0.492378	0	1

891 rows × 5 columns

Étapes suivantes : Afficher les graphiques recommandés | New interactive sheet

```
X_train, X_temp, y_train, y_temp = train_test_split(inputs, target, test_size=0.4, random_state=0)
X_valid, X_test, y_valid, y_test = train_test_split(X_temp, y_temp, test_size=0.5, random_state=0)
```

```
model = tf.keras.Sequential([
                             tf.keras.layers.Dense(8, activation='sigmoid'),
                             tf.keras.layers.Dense(8, activation='sigmoid'),
                             tf.keras.layers.Dense(1, activation="sigmoid")
])
```

```
model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.01),
              loss=tf.keras.losses.BinaryCrossentropy(),
              metrics=['accuracy'])
```

```
model.evaluate(X_train, y_train)
```

```
17/17 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7916 - loss: 0.4689
[0.4817565381526947, 0.795880138874054]
```

```
model.evaluate(X_valid, y_valid)
```

```
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.7598 - loss: 0.5249
[0.5064712762832642, 0.7808988690376282]
```

```
model.fit(X_train, y_train, batch_size=15, epochs=30, validation_data=(X_valid, y_valid))
```

```
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.8072 - loss: 0.4384 - val_accuracy: 0.7472 - val_loss: 0.5032
Epoch 4/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.7633 - loss: 0.5063 - val_accuracy: 0.7528 - val_loss: 0.4980
Epoch 5/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.8150 - loss: 0.4333 - val_accuracy: 0.7584 - val_loss: 0.5020
Epoch 6/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - accuracy: 0.8011 - loss: 0.4459 - val_accuracy: 0.7472 - val_loss: 0.4871
Epoch 7/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 1s 11ms/step - accuracy: 0.8061 - loss: 0.4485 - val_accuracy: 0.7584 - val_loss: 0.4935
Epoch 8/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.7945 - loss: 0.4483 - val_accuracy: 0.7472 - val_loss: 0.4838
Epoch 9/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.7976 - loss: 0.4456 - val_accuracy: 0.7809 - val_loss: 0.4679
Epoch 10/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8194 - loss: 0.4375 - val_accuracy: 0.7921 - val_loss: 0.4654
Epoch 11/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8144 - loss: 0.4264 - val_accuracy: 0.7809 - val_loss: 0.4626
Epoch 12/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8206 - loss: 0.3935 - val_accuracy: 0.7472 - val_loss: 0.4801
Epoch 13/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.7938 - loss: 0.4393 - val_accuracy: 0.7865 - val_loss: 0.4609
Epoch 14/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8069 - loss: 0.4331 - val_accuracy: 0.7865 - val_loss: 0.4598
Epoch 15/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8147 - loss: 0.4339 - val_accuracy: 0.7978 - val_loss: 0.4592
Epoch 16/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8194 - loss: 0.4495 - val_accuracy: 0.7472 - val_loss: 0.4712
Epoch 17/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.8337 - loss: 0.4256 - val_accuracy: 0.7865 - val_loss: 0.4569
Epoch 18/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.7792 - loss: 0.4528 - val_accuracy: 0.7865 - val_loss: 0.4564
Epoch 19/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8055 - loss: 0.4373 - val_accuracy: 0.7921 - val_loss: 0.4567
Epoch 20/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8238 - loss: 0.4421 - val_accuracy: 0.7528 - val_loss: 0.4756
Epoch 21/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8005 - loss: 0.4485 - val_accuracy: 0.8034 - val_loss: 0.4538
Epoch 22/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.8023 - loss: 0.4730 - val_accuracy: 0.7472 - val_loss: 0.4652
Epoch 23/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.7930 - loss: 0.4433 - val_accuracy: 0.7584 - val_loss: 0.4631
Epoch 24/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.7821 - loss: 0.4753 - val_accuracy: 0.7753 - val_loss: 0.4772
Epoch 25/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.7823 - loss: 0.4814 - val_accuracy: 0.7640 - val_loss: 0.4563
Epoch 26/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 0.8122 - loss: 0.4301 - val_accuracy: 0.7865 - val_loss: 0.4516
Epoch 27/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.8362 - loss: 0.4093 - val_accuracy: 0.7978 - val_loss: 0.4491
Epoch 28/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - accuracy: 0.8238 - loss: 0.4367 - val_accuracy: 0.7528 - val_loss: 0.4558
Epoch 29/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - accuracy: 0.8332 - loss: 0.3995 - val_accuracy: 0.7584 - val_loss: 0.4572
Epoch 30/30
36/36 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.8228 - loss: 0.3926 - val_accuracy: 0.8090 - val_loss: 0.4471
<keras.src.callbacks.history.History at 0x7f1e76534890>
```

```
model.evaluate(X_test, y_test)
```

```
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - accuracy: 0.7904 - loss: 0.4192
[0.41630882024765015, 0.7932960987091064]
```

Double-cliquez (ou appuyez sur Entrée) pour modifier

Conclusion de l'Étude sur la Prédiction de la Survie des Passagers du Titanic

Dans cette étude, nous avons exploré l'utilisation d'un réseau de neurones pour prédire la survie des passagers du Titanic en nous basant sur les caractéristiques suivantes : sexe, âge, tarif du billet, et classe de voyage (`pclass`).

1. **Performance du Modèle** :
   - Le réseau de neurones a atteint une précision (accuracy) d'environ 79 % sur l'ensemble de test, ce qui est comparable aux résultats obtenus avec d'autres méthodes comme Naive Bayes dans notre étude précédente.
   - La perte (loss) sur l'ensemble de test est de 0,4192, indiquant un bon ajustement du modèle aux données.
2. **Optimisation des Hyperparamètres** :
   - Plusieurs essais ont été effectués pour déterminer le nombre optimal de couches et de neurones dans le réseau.
   - Le taux d'apprentissage initial de 0,001 a été ajusté pour améliorer la performance du modèle, ce qui a conduit à une meilleure convergence.
3. **Prétraitement des Données** :

- La standardisation des caractéristiques `age` et `fare` a été cruciale en raison de la grande disparité dans leurs valeurs. Cela a permis au modèle de mieux apprendre les relations sous-jacentes dans les données.

4. **Comparaison avec d'autres Méthodes** :