Inefficacité du Perceptron

In [406]:
```python
import pandas as pd
import numpy as np
import itertools

from nltk.corpus import stopwords
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences

from keras.models import Sequential
from keras.layers import Conv2D, Dropout, Dense, Embedding, Flatten, Reshape
from keras.optimizers import Adam
```

Boite à outils

In [407]:
```python
def plot_confusion_matrix(cm, classes, cmap=plt.cm.Blues):

    cm = cm.astype("float") / cm.sum(axis=1)

    plt.figure(figsize=(10,10))
    plt.imshow(cm, interpolation="nearest", cmap=cmap)
    plt.colorbar()
    tick_marks = np.arange(len(classes))

    plt.xticks(tick_marks, classes, fontsize=20, rotation=45)
    plt.yticks(tick_marks, classes, fontsize=20)

    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        color = "white" if cm[i,j] > 0.5 else "black"
        plt.text(j, i, format(cm[i, j], ".2f"), horizontalalignment="center", verticalalignm
ent="center", color=color, fontsize=40)

    plt.ylabel("Correction", fontsize=15)
    plt.xlabel("Prédiction", fontsize=15)
```

In [408]:
```python
# nettoyage des données (ponctuations)

stopWords = set(stopwords.words("english"))

def cleanText(text):
    forbidden = {",","@",";","/","-",":",".","!","?", "#","\"","(",")","\'","’","‘","–",
"...","&"}
    res = str(text)

    if res is None:
        return ""

    for elm in forbidden:
        res = res.replace(elm, "")

    if len(res.split()) >= 30:
        res = " ".join(res.split()[0:30])

    for elm in forbidden:
        res = res.replace("  ", " ")

    return res
```

Traitement des données

Dataset 1

In [409]:
```python
# chargement des deux tables
real_news = pd.read_csv("./dataset1/True.csv")
fake_news = pd.read_csv("./dataset1/Fake.csv")

# vrai = 1, faux = 0
real_news["label"] = 1
fake_news["label"] = 0

# création du dataset complet
dataframe1 = pd.concat([real_news, fake_news])

print(f"Nombre de références : {dataframe1.title.count()}")
print(f"Nombre de fake news : {fake_news.title.count()}")
print(f"Nombre de vraies news : {real_news.title.count()}")

# ici on ne s'intéresse qu'au titre et au label
del dataframe1["title"]
del dataframe1["subject"]
del dataframe1["date"]
dataframe1["text"] = dataframe1["text"].apply(cleanText)

dataframe1.sample(10)
```

```
Nombre de références : 44898
Nombre de fake news : 23481
Nombre de vraies news : 21417
```

Out[409]:

	text	label
13047	I know there are only 60 days left to make our...	0
7876	Marijuana legalization is on the cusp in Ameri...	0
2739	WASHINGTON Reuters With talks to renegotiate t...	1
1860	WASHINGTON Reuters President Donald Trumps cal...	1
18764	BARCELONA Reuters Catalan separatists urged su...	1
1842	WASHINGTON Reuters US President Donald Trump s...	1
16893	The Transportation Security Administration TSA...	0
14516	JOHANNESBURG Reuters South Africa s Justice Mi...	1
9780	During game 1 of the WNBA Finals the LA Sparks...	0
3038	COLORADO SPRINGS Colo Reuters Officials with t...	1

Dataset 2

In [410]:
```python
dataframe2 = pd.read_csv("./dataset2/train.csv")
del dataframe2["id"]
del dataframe2["author"]
del dataframe2["title"]

dataframe2["text"] = dataframe2["text"].apply(cleanText)

dataframe2.sample(10)
```

Out[410]:

	text	label
5801	WASHINGTON — Attorney General Jeff Sessions fa...	0
16070	20 Views November 03 2016 GOLD KWN King World ...	1
11234	Print Protesters blocked the upper level of th...	1
2134	« on Today at 083635 PM » AIG Quadruples Limit...	1
4578	Wed 26 Oct 2016 1945 UTC © The Canary Leaked d...	1
15668	Good morning Were trying something new this we...	0
17032	License DMCA With the US more interested in fi...	1
3190	STAFFORD SPRINGS Conn — Sandra Miller was at w...	0
4575	Veteran political strategist Pat Caddell talke...	0
10752	Leaked Podestas Satanic Spirit Cooking Dinner ...	1

In [411]:
```python
# on sépare les données en données d'entraînement et données de test (80% et 20%)
x_train, x_test, y_train, y_test = train_test_split(dataframe1["text"], dataframe1["label"],
test_size=0.99, random_state = 42)
print(f"Données d'entrainement : {len(x_train)}")
print(f"Données de test : {len(x_test)}")
```

```
Données d'entrainement : 448
Données de test : 44450
```

In [412]:
```python
max_features = 10000 # taille max du vocab
maxlen = 70 # taille max de séquence
```

In [413]:
```python
# vectorisation naïve en "one-hot"
tokenizer = Tokenizer(num_words=max_features)
tokenizer.fit_on_texts(pd.concat([dataframe1["text"], dataframe2["text"]]))
```

In [414]:
```python
# vectorisation des données d'entraînement
x_train = tokenizer.texts_to_sequences(x_train)
x_train = pad_sequences(x_train, maxlen=maxlen)
```

In [415]:
```python
# vectorisation des données de test
x_test = tokenizer.texts_to_sequences(x_test)
x_test = pad_sequences(x_test, maxlen=maxlen)
```

Modèle Perceptron

In [416]:
```python
batch_size = 128 # la batch_size n'influe pas sur le résultat non plus
nb_epochs = 100 # le nombre d'époques n'influe pas sur le résultat
embedded_dim = 100 # idem
```

In [417]:
```python
model = Sequential()
model.add(Embedding(max_features, output_dim=embedded_dim, input_length=maxlen, trainable=Tr
ue))
model.add(Flatten())
model.add(Dense(256, activation="relu"))
model.add(Dropout(0.1))
model.add(Dense(128, activation="relu"))
model.add(Dense(1, activation="sigmoid"))
model.compile(loss="binary_crossentropy", optimizer=Adam(lr=0.0002), metrics=["accuracy"])
model.summary()
```

```
Model: "sequential_16"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_16 (Embedding)     (None, 70, 100)           1000000
_________________________________________________________________
flatten_14 (Flatten)         (None, 7000)              0
_________________________________________________________________
dense_25 (Dense)             (None, 256)               1792256
_________________________________________________________________
dropout_15 (Dropout)         (None, 256)               0
_________________________________________________________________
dense_26 (Dense)             (None, 128)               32896
_________________________________________________________________
dense_27 (Dense)             (None, 1)                 129
=================================================================
Total params: 2,825,281
Trainable params: 2,825,281
Non-trainable params: 0
_________________________________________________________________
```

In [418]:
```python
progress = model.fit(x_train, y_train, batch_size=batch_size, epochs=nb_epochs)
```

```
C:\Users\Shadow\AppData\Roaming\Python\Python37\site-packages\tensorflow\python\framework\ind
exed_slices.py:434: UserWarning: Converting sparse IndexedSlices to a dense Tensor of unknown
shape. This may consume a large amount of memory.
  "Converting sparse IndexedSlices to a dense Tensor of unknown shape. "
```

```
Epoch 1/100
448/448 [==============================] - 0s 530us/step - loss: 0.6924 - accuracy: 0.5134
Epoch 2/100
448/448 [==============================] - 0s 59us/step - loss: 0.6800 - accuracy: 0.6071
Epoch 3/100
448/448 [==============================] - 0s 65us/step - loss: 0.6642 - accuracy: 0.7143
Epoch 4/100
448/448 [==============================] - 0s 65us/step - loss: 0.6397 - accuracy: 0.8326
Epoch 5/100
448/448 [==============================] - 0s 59us/step - loss: 0.6102 - accuracy: 0.9107
Epoch 6/100
448/448 [==============================] - 0s 60us/step - loss: 0.5773 - accuracy: 0.9286
Epoch 7/100
448/448 [==============================] - 0s 61us/step - loss: 0.5370 - accuracy: 0.9821
Epoch 8/100
448/448 [==============================] - 0s 63us/step - loss: 0.4827 - accuracy: 0.9911
Epoch 9/100
448/448 [==============================] - 0s 61us/step - loss: 0.4277 - accuracy: 0.9933
Epoch 10/100
448/448 [==============================] - 0s 62us/step - loss: 0.3599 - accuracy: 0.9978
Epoch 11/100
448/448 [==============================] - 0s 64us/step - loss: 0.2933 - accuracy: 1.0000
Epoch 12/100
448/448 [==============================] - 0s 63us/step - loss: 0.2248 - accuracy: 1.0000
Epoch 13/100
448/448 [==============================] - 0s 61us/step - loss: 0.1685 - accuracy: 1.0000
Epoch 14/100
448/448 [==============================] - 0s 66us/step - loss: 0.1195 - accuracy: 1.0000
Epoch 15/100
448/448 [==============================] - 0s 81us/step - loss: 0.0829 - accuracy: 1.0000
Epoch 16/100
448/448 [==============================] - 0s 62us/step - loss: 0.0566 - accuracy: 1.0000
Epoch 17/100
448/448 [==============================] - 0s 65us/step - loss: 0.0390 - accuracy: 1.0000
Epoch 18/100
448/448 [==============================] - 0s 61us/step - loss: 0.0268 - accuracy: 1.0000
Epoch 19/100
448/448 [==============================] - 0s 63us/step - loss: 0.0199 - accuracy: 1.0000
Epoch 20/100
448/448 [==============================] - 0s 64us/step - loss: 0.0144 - accuracy: 1.0000
Epoch 21/100
448/448 [==============================] - 0s 64us/step - loss: 0.0118 - accuracy: 1.0000
Epoch 22/100
448/448 [==============================] - 0s 60us/step - loss: 0.0090 - accuracy: 1.0000
Epoch 23/100
448/448 [==============================] - 0s 67us/step - loss: 0.0074 - accuracy: 1.0000
Epoch 24/100
448/448 [==============================] - 0s 64us/step - loss: 0.0063 - accuracy: 1.0000
Epoch 25/100
448/448 [==============================] - 0s 62us/step - loss: 0.0053 - accuracy: 1.0000
Epoch 26/100
448/448 [==============================] - 0s 64us/step - loss: 0.0048 - accuracy: 1.0000
Epoch 27/100
448/448 [==============================] - 0s 62us/step - loss: 0.0043 - accuracy: 1.0000
Epoch 28/100
448/448 [==============================] - 0s 61us/step - loss: 0.0038 - accuracy: 1.0000
Epoch 29/100
448/448 [==============================] - 0s 67us/step - loss: 0.0034 - accuracy: 1.0000
Epoch 30/100
448/448 [==============================] - 0s 61us/step - loss: 0.0031 - accuracy: 1.0000
Epoch 31/100
448/448 [==============================] - 0s 66us/step - loss: 0.0028 - accuracy: 1.0000
Epoch 32/100
448/448 [==============================] - 0s 60us/step - loss: 0.0027 - accuracy: 1.0000
Epoch 33/100
448/448 [==============================] - 0s 64us/step - loss: 0.0024 - accuracy: 1.0000
Epoch 34/100
448/448 [==============================] - 0s 61us/step - loss: 0.0023 - accuracy: 1.0000
Epoch 35/100
448/448 [==============================] - 0s 66us/step - loss: 0.0022 - accuracy: 1.0000
Epoch 36/100
448/448 [==============================] - 0s 61us/step - loss: 0.0021 - accuracy: 1.0000
Epoch 37/100
448/448 [==============================] - 0s 62us/step - loss: 0.0019 - accuracy: 1.0000
Epoch 38/100
448/448 [==============================] - 0s 60us/step - loss: 0.0019 - accuracy: 1.0000
Epoch 39/100
448/448 [==============================] - 0s 59us/step - loss: 0.0017 - accuracy: 1.0000
Epoch 40/100
448/448 [==============================] - 0s 65us/step - loss: 0.0016 - accuracy: 1.0000
Epoch 41/100
448/448 [==============================] - 0s 65us/step - loss: 0.0015 - accuracy: 1.0000
Epoch 42/100
448/448 [==============================] - 0s 60us/step - loss: 0.0014 - accuracy: 1.0000
Epoch 43/100
448/448 [==============================] - 0s 64us/step - loss: 0.0014 - accuracy: 1.0000
Epoch 44/100
448/448 [==============================] - 0s 64us/step - loss: 0.0013 - accuracy: 1.0000
Epoch 45/100
448/448 [==============================] - 0s 65us/step - loss: 0.0012 - accuracy: 1.0000
Epoch 46/100
448/448 [==============================] - 0s 59us/step - loss: 0.0012 - accuracy: 1.0000
Epoch 47/100
448/448 [==============================] - 0s 65us/step - loss: 0.0011 - accuracy: 1.0000
Epoch 48/100
448/448 [==============================] - 0s 65us/step - loss: 0.0011 - accuracy: 1.0000
Epoch 49/100
448/448 [==============================] - 0s 61us/step - loss: 0.0011 - accuracy: 1.0000
Epoch 50/100
448/448 [==============================] - 0s 63us/step - loss: 0.0010 - accuracy: 1.0000
Epoch 51/100
448/448 [==============================] - 0s 66us/step - loss: 9.3519e-04 - accuracy: 1.0000
Epoch 52/100
448/448 [==============================] - 0s 61us/step - loss: 8.8057e-04 - accuracy: 1.0000
Epoch 53/100
448/448 [==============================] - 0s 66us/step - loss: 8.9056e-04 - accuracy: 1.0000
Epoch 54/100
448/448 [==============================] - 0s 63us/step - loss: 8.3335e-04 - accuracy: 1.0000
Epoch 55/100
448/448 [==============================] - 0s 62us/step - loss: 7.5604e-04 - accuracy: 1.0000
Epoch 56/100
448/448 [==============================] - 0s 65us/step - loss: 7.7232e-04 - accuracy: 1.0000
Epoch 57/100
448/448 [==============================] - 0s 59us/step - loss: 7.2607e-04 - accuracy: 1.0000
Epoch 58/100
448/448 [==============================] - 0s 60us/step - loss: 6.9385e-04 - accuracy: 1.0000
Epoch 59/100
448/448 [==============================] - 0s 61us/step - loss: 7.0591e-04 - accuracy: 1.0000
Epoch 60/100
448/448 [==============================] - 0s 63us/step - loss: 6.6530e-04 - accuracy: 1.0000
Epoch 61/100
448/448 [==============================] - 0s 64us/step - loss: 6.3672e-04 - accuracy: 1.0000
Epoch 62/100
448/448 [==============================] - 0s 60us/step - loss: 6.3992e-04 - accuracy: 1.0000
Epoch 63/100
448/448 [==============================] - 0s 61us/step - loss: 5.8644e-04 - accuracy: 1.0000
Epoch 64/100
448/448 [==============================] - 0s 65us/step - loss: 5.8675e-04 - accuracy: 1.0000
Epoch 65/100
448/448 [==============================] - 0s 63us/step - loss: 5.7210e-04 - accuracy: 1.0000
Epoch 66/100
448/448 [==============================] - 0s 66us/step - loss: 5.1201e-04 - accuracy: 1.0000
Epoch 67/100
448/448 [==============================] - 0s 63us/step - loss: 5.3162e-04 - accuracy: 1.0000
Epoch 68/100
448/448 [==============================] - 0s 59us/step - loss: 5.2705e-04 - accuracy: 1.0000
Epoch 69/100
448/448 [==============================] - 0s 61us/step - loss: 4.8150e-04 - accuracy: 1.0000
Epoch 70/100
448/448 [==============================] - 0s 64us/step - loss: 5.0169e-04 - accuracy: 1.0000
Epoch 71/100
448/448 [==============================] - 0s 60us/step - loss: 4.7096e-04 - accuracy: 1.0000
Epoch 72/100
448/448 [==============================] - 0s 61us/step - loss: 4.4432e-04 - accuracy: 1.0000
Epoch 73/100
448/448 [==============================] - 0s 60us/step - loss: 4.3065e-04 - accuracy: 1.0000
Epoch 74/100
448/448 [==============================] - 0s 62us/step - loss: 4.3252e-04 - accuracy: 1.0000
Epoch 75/100
448/448 [==============================] - 0s 59us/step - loss: 3.9517e-04 - accuracy: 1.0000
Epoch 76/100
448/448 [==============================] - 0s 60us/step - loss: 4.1144e-04 - accuracy: 1.0000
Epoch 77/100
448/448 [==============================] - 0s 59us/step - loss: 3.8794e-04 - accuracy: 1.0000
Epoch 78/100
448/448 [==============================] - 0s 63us/step - loss: 3.8222e-04 - accuracy: 1.0000
Epoch 79/100
448/448 [==============================] - 0s 60us/step - loss: 3.6140e-04 - accuracy: 1.0000
Epoch 80/100
448/448 [==============================] - 0s 62us/step - loss: 3.7044e-04 - accuracy: 1.0000
Epoch 81/100
448/448 [==============================] - 0s 58us/step - loss: 3.5860e-04 - accuracy: 1.0000
Epoch 82/100
448/448 [==============================] - 0s 58us/step - loss: 3.4682e-04 - accuracy: 1.0000
Epoch 83/100
448/448 [==============================] - 0s 60us/step - loss: 3.3037e-04 - accuracy: 1.0000
Epoch 84/100
448/448 [==============================] - 0s 60us/step - loss: 3.0957e-04 - accuracy: 1.0000
Epoch 85/100
448/448 [==============================] - 0s 61us/step - loss: 2.9992e-04 - accuracy: 1.0000
Epoch 86/100
448/448 [==============================] - 0s 60us/step - loss: 3.1552e-04 - accuracy: 1.0000
Epoch 87/100
448/448 [==============================] - 0s 62us/step - loss: 2.9025e-04 - accuracy: 1.0000
Epoch 88/100
448/448 [==============================] - 0s 61us/step - loss: 3.0908e-04 - accuracy: 1.0000
Epoch 89/100
448/448 [==============================] - 0s 64us/step - loss: 2.8413e-04 - accuracy: 1.0000
Epoch 90/100
448/448 [==============================] - 0s 59us/step - loss: 2.7812e-04 - accuracy: 1.0000
Epoch 91/100
448/448 [==============================] - 0s 61us/step - loss: 2.7532e-04 - accuracy: 1.0000
Epoch 92/100
448/448 [==============================] - 0s 61us/step - loss: 2.5010e-04 - accuracy: 1.0000
Epoch 93/100
448/448 [==============================] - 0s 62us/step - loss: 2.6070e-04 - accuracy: 1.0000
Epoch 94/100
448/448 [==============================] - 0s 61us/step - loss: 2.6096e-04 - accuracy: 1.0000
Epoch 95/100
448/448 [==============================] - 0s 59us/step - loss: 2.4740e-04 - accuracy: 1.0000
Epoch 96/100
448/448 [==============================] - 0s 58us/step - loss: 2.3809e-04 - accuracy: 1.0000
Epoch 97/100
448/448 [==============================] - 0s 64us/step - loss: 2.4219e-04 - accuracy: 1.0000
Epoch 98/100
448/448 [==============================] - 0s 64us/step - loss: 2.2528e-04 - accuracy: 1.0000
Epoch 99/100
448/448 [==============================] - 0s 63us/step - loss: 2.3656e-04 - accuracy: 1.0000
Epoch 100/100
448/448 [==============================] - 0s 59us/step - loss: 2.2020e-04 - accuracy: 1.0000
```

Analyse des résultats

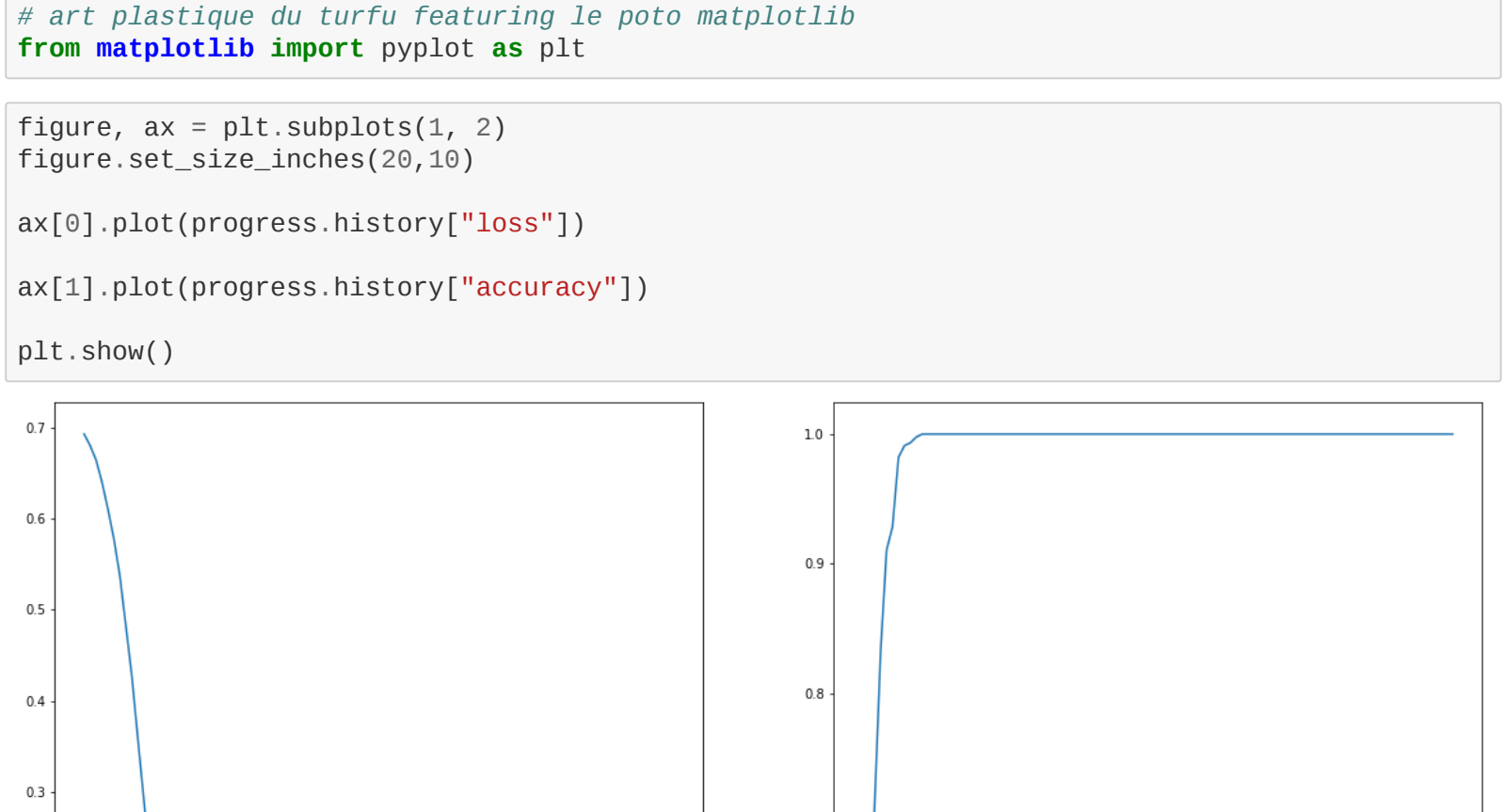
In [419]:
```python
# art plastique du turfu featuring le poto matplotlib
from matplotlib import pyplot as plt
```

In [420]:
```python
figure, ax = plt.subplots(1, 2)
figure.set_size_inches(20,10)

ax[0].plot(progress.history["loss"])

ax[1].plot(progress.history["accuracy"])

plt.show()
```



Ci dessus : mise en évidence que le nombre d'époques influe peu : le modèle devient très précis sur le dataset au bout de 20 époques

In [421]:
```python
dataframe = pd.concat([dataframe1, dataframe2])
```

In [434]:
```python
to_predict = dataframe2.sample(10000)
```

In [435]:
```python
X_test = to_predict["text"]
```

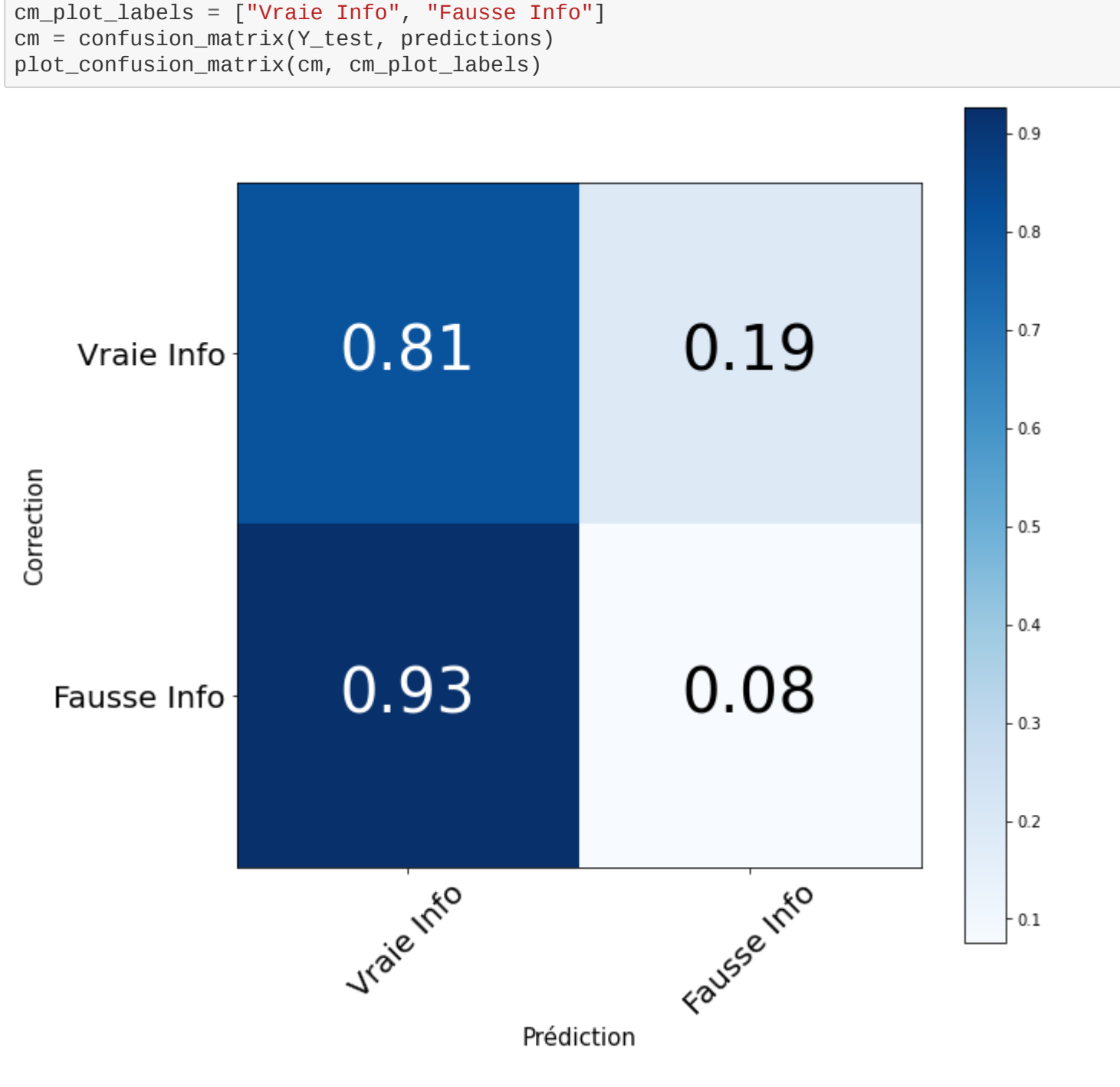
In [436]:
```python
Y_test = to_predict["label"]
```

In [437]:
```python
X_test = tokenizer.texts_to_sequences(X_test)
X_test = pad_sequences(X_test, maxlen=maxlen)
```

In [438]:
```python
predictions = model.predict(X_test)

threshold = 0.5 #la valeur du threshold n'a pas d'importance, les réseaux perceptrons ne fon
ctionnent pas sur ce problème
predictions[predictions > threshold] = 1
predictions[predictions <= threshold] = 0
```

In [439]:
```python
cm_plot_labels = ["Vraie Info", "Fausse Info"]
cm = confusion_matrix(Y_test, predictions)
plot_confusion_matrix(cm, cm_plot_labels)
```



Cela démontre bien qu'un réseau perceptron n'est pas capable de généraliser la notion de fake news sur un dataset sur lequel il n'a pas été entraîné.