Proyecto Final Statistical Learning 2

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Abstract

- A continuación se presenta la información del proyecto final de Statistcal Learning,
- en el cual se desarrollaron tres problemas MLP, CNN y Análisis de sentimientos.

3 1 Feed Forward Network

- 4 Para feedforward se trabajo con un dataset para la detección de malware en base a sequencias de
- 5 llamadas API.

```
SM_filepath = './MLP'
ds_Malware0 = pd.read_csv("./dynamic_api_call_sequence_per_malware_100_0_306.csv")
ds_MalwareO.head()
                        hash t_0 t_1 t_2 t_3 t_4 t_5 t_6 t_7 t_8 ... t_91 t_92 t_93 t_94 t_95 t_96 t_97
0 071e8c3f8922e186e57548cd4c703a5d 112 274 158 215 274 158 215 298 76 ...
                                                                   71 297
                                                                                    215
                                                                           135
                                                                                171
                                                                                          35
1 33f8e6d08a6aae939f25a8e0d63dd523 82 208 187 208 172 117 172 117 172 ...
                                                                   81 240
                                                                                         135
65
                                                                      112
                                                                           123
                                                                                 65
                                                                                    112
3 72049be7bd30ea61297ea624ae198067 82 208 187 208 172 117 172 117 172 ... 208
                                                                       302
                                                                           208
                                                                                302
                                                                                    187
    c9b3700a77facf29172f32df6bc77f48 82 240 117 240 117 240 117 240 117 ... 209
5 rows × 102 columns
```

7 1.1 Limpieza de Dataset

- 8 Antes de procesar la información en el modelo, se procedio a eliminar la inforamción que no aporta
- 9 nada a el modelo.

```
#ELIMINACION DE FEATURES QUE NO APORTAN INFORMACION
ds_Malware = ds_Malware0.drop(columns=["hash"],axis=1)
ds_Malware.shape

(43876, 101)

Y= ds_Malware["malware"]
X = ds_Malware.drop(columns=["malware"])
X Train, X Test, Y Train, Y Test = TTS(X,Y,test size=0.2,random state=9)
```

1.2 Definición del Modelo

- 12 Se utilizaron dos metodos para la generación del modelo Keras y Sklearn con MLP (Multi Layer
- 13 Perceptron).
- Función de activacion = relu y sigmoid Optimizador = Adam Loss = Binary Cross Entropy

 UTILIZANDO KERAS

```
: model = Sequential()
    model.add(Dense(128, input_shape=(100,), activation='relu')),
    model.add(Dropout(0.5)),
    model.add(Dense(64, activation='relu')),
    model.add(Dropout(0.5)),
    model.add(Dense(32, activation='relu')),
    model.add(Dropout(0.5)),
    model.add(Dense(16, activation='relu')),
    model.add(Dropout(0.5)),
    model.add(Dense(8, activation='relu')),
    model.add(Dropout(0.5)),
    model.add(Dense(4, activation='relu')),
    model.add(Dropout(0.5)),
    model.add(Dense(1, activation='sigmoid'))
    #model.add(Dense(2, activation='softmax'))
:]: | Model_Optimizer = tf.keras.optimizers.Adam(learning_rate=0.01)
    model.compile(optimizer=Model_Optimizer, loss=tf.keras.losses.BinaryCrossentropy(), metrics=[
    Model_EarlyStop = tf.keras.callbacks.EarlyStopping(monitor='val_accuracy', min_delta=0, patien
    Model_checkpoint= tf.keras.callbacks.ModelCheckpoint(filepath=SM_filepath,save_weights_only=Fa
```

16 1.3 Resultados

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Se puede observar que al correr el modelo se obtiene un accuracy del 97

```
[29]: Pred_K_P = model.predict(X_Test)
Accuracy_K =metrics.average_precision_score(Y_Test, Pred_K_P)
MLP_K = pd.DataFrame({
        'MLP': ['MLP Keras'],
        'Acurracy': [Accuracy_K]
})
MLP_K
```

[29]: MLP Acurracy

0 MLP Keras 0.971399

```
: Model_Fit = model.fit(X_Train.values, Y_Train.values, epochs = 10, batch_size=1000, validation
  Model_Fit_History = Model_Fit.history
  save_model(model, SM_filepath)
  INFO:tensorflow:Assets written to: ./MLP\assets
: Loss = Model_Fit_History['loss']
  Val_Loss = Model_Fit_History['val_loss']
  plt.plot(Loss,'g',label='Model - Training Loss')
  plt.plot(Val_Loss,'r',label='Model - Val Training Loss')
  plt.legend()
  plt.xlabel("Epochs")
: Text(0.5, 0, 'Epochs')
  0.118
  0.117
  0.116
  0.115
                                      Model - Training Loss
```

Model - Val Training Loss

6

Epochs

19 En base al training realizado

0.114 0.113 0.112 0.111

```
: Accuracy = Model_Fit_History['accuracy']
  Val_Accuracy = Model_Fit_History['val_accuracy']
  plt.plot(Accuracy,'-b',label='accuracy')
  plt.plot(Val_Accuracy,'-r',label='val_accuracy')
  plt.legend()
  plt.xlabel("Epochs")
: Text(0.5, 0, 'Epochs')
   0.97675
   0.97650
   0.97625
   0.97600
                                                   accuracy
   0.97575
                                                   val accuracy
   0.97550
   0.97525
   0.97500
   0.97475
                                            6
                                                      8
                                 Epochs
```

21 Ahora utilzando sklearn se obtien de igual manera un accurracy aceptable un poco mayor que con

22 keras

UTILIZANDO SKLEARN

MLP

```
: MLP = MLPC(solver='adam', hidden_layer_sizes=(100,100,100), max_iter=800, random_state=50)
  MLP.fit(X_Train, Y_Train)
  Pred = MLP.predict(X_Test)
  Pred
: array([1, 1, 1, ..., 1, 1, 1], dtype=int64)
: F1 = metrics.f1_score(Y_Test, Pred)
  Accuracy =metrics.accuracy_score(Y_Test, Pred)
  Precission = metrics.precision_score(Y_Test, Pred)
  Recall = metrics.recall_score(Y_Test, Pred)
  MLP_S = pd.DataFrame({
      'MLP': ['MLP Sklearn'],
      'F1': [F1],
      'Acurracy': [Accuracy],
      'Precission': [Precission],
      'Recall': [Recall]
  })
  MLP_S
                    F1 Acurracy Precission Recall
```

0 MLP Sklearn 0.991214 0.982794 0.983376 0.999179

```
average_precision = average_precision_score(Y_Test, Pred)
  disp = plot_precision_recall_curve(MLP,X_Train, Y_Train)
  disp.ax_.set_title('2-class Precision-Recall curve: ''AP={0:0.2f}'.format(average_precision))
  print('Average precision-recall score: {0:0.2f}'.format(average_precision))
  Average precision-recall score: 0.98
                 2-class Precision-Recall curve: AP=0.98
     1.000
  O.9988
0.9996
0.9994
0.9992
               MLPClassifier (AP = 1.00)
     0.990
                    0.2
                             0.4
                                      0.6
                                               0.8
                                                        1.0
           0.0
                          Recall (Positive label: 1)
: ConM = confusion_matrix(Y_Test, Pred)
  f, ax = plt.subplots(figsize=(5,5))
  sns.heatmap(ConM, annot=True, linewidth=0.4, linecolor='black', fmt='g', ax=ax, cmap="BuPu")
  plt.title('MLP- Matriz de Confusion')
plt.xlabel('Y Pred')
  plt.ylabel('Y Test')
  plt.show()
            MLP- Matriz de Confusion
                                              8000
                                              7000
     0
                                              6000
                                              5000
  YTest
                                             4000
                                              3000
                              8518
                                              2000
                                             - 1000
               ó
                               i
                     Y Pred
```

2 Convolutional Network

Para este problema se utilizo un data set para la detección de pacientes que tuvieron o no covid por medio de el analisis de imagenes de los pulmones de los pacientes.

```
: SM_filepath = './MLP'
Directorio = './COVID/'
ds_PulmonCovidP = os.path.join('./CT_COVID/')
ds_PulmonCovidN = os.path.join('./CT_NonCOVID/')
print('Total Casos Positivos :{}'.format(len(os.listdir(ds_PulmonCovidP))))
print('Total Casos Negativos:{}'.format(len(os.listdir(ds_PulmonCovidN))))
        CovPositivo = glob(os.path.join(ds_PulmonCovidP, "*.png"))
CovNegativo = glob(os.path.join(ds_PulmonCovidN, "*.png"))
CovNegativo.extend(glob(os.path.join(ds_PulmonCovidN, "*.jpg")))
         #MUESTA DE IMAGENES
       #MUESTA DE IMAGENES
IMG_P = cv2.imread(os.path.join(CovPositivo[150]))
IMG_N = cv2.imread(os.path.join(CovNegativo[150]))
f = plt.figure(figsize=(20, 20))
f.add_subplot(1, 2, 1)
plt.imshow(IMG_P)
f.add_subplot(1, 2, 2)
plt.imshow(IMS_N)
        plt.imshow(IMG_N)
       Total Casos Positivos :349
Total Casos Negativos:397
```

<matplotlib.image.AxesImage at 0x1e1810cc370>





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2.1 Resultados

Se realizaron distintas pruebas para encontrar el modelo el cual presentarar una mejor predicción

KERAS - Test 1

```
]: Epoch = 40
    Batch = 64
    Img_H, Img_W = 248,248
    opt = tf.keras.optimizers.Adam(lr=0.001,decay=0.001/Epoch)
    es = EarlyStopping(monitor='val_acc', mode='max', verbose=1, patience=10, restore_best_weights=True)
]: Train_D = ImageDataGenerator(rescale=1./255,horizontal_flip=True,rotation_range=5],width_shift_range=0.05,height_shi
    Train_6 = Train_D.flow_from_directory(Directorio, target_size=(Img_H, Img_W),batch_size=Batch,class_mode='binary',col
Val_6 = Train_D.flow_from_directory(Directorio, target_size=(Img_H, Img_W),batch_size=Batch,class_mode='binary',col
    <
    Found 598 images belonging to 2 classes.
Found 148 images belonging to 2 classes.
]: model = Sequential()
     \verb|model.add(Conv2D(32, 3, padding='same', activation='relu', input\_shape=(Img\_H, Img\_W, 1)))| \\
    model.add(MaxPool2D())
    model.add(Conv2D(64, 5, padding='same', activation='relu'))
    model.add(MaxPool2D())
    model.add(Flatten())
    model.add(Dense(128, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
il: model.compile(optimizer=opt, loss=keras.losses.binary_crossentropy, metrics=['accuracy', 'Precision', 'Recall'])
[]: model.summary()
    Model: "sequential_1"
    Layer (type)
                                     Output Shape
                                                                   Param #
    conv2d_2 (Conv2D)
                                     (None, 248, 248, 32)
                                                                   320
    max_pooling2d_2 (MaxPooling2 (None, 124, 124, 32)
    conv2d_3 (Conv2D)
                                     (None, 124, 124, 64)
                                                                   51264
    max_pooling2d_3 (MaxPooling2 (None, 62, 62, 64)
                                                                   0
    flatten_1 (Flatten)
                                     (None, 246016)
    dense_1 (Dense)
                                     (None, 128)
                                                                   31490176
                                     (None, 1)
    dense_2 (Dense)
                                                                   129
                     _____
    Total params: 31,541,889
    Trainable params: 31,541,889
    Non-trainable params: 0
```

```
KFRAS - Test 2
Epoch2 = 50
Batch2 = 70
opt2 = tf.keras.optimizers.Adam(lr=0.001,decay=0.001/Epoch2)
es2 = EarlyStopping(monitor='val_acc', mode='max', verbose=1, patience=10, restore_best_weights=True)
Train_D = ImageDataGenerator(rescale=1./255,horizontal_flip=True,rotation_range=5.width_shift_range=0.05,height_shift_range=0.05,shear_range=0.05,zoom_range=0.05,va
Train_G = Insignostable Boot (Passace-14/2007) in 12014a__Injurity (Votation) alignost production in Injurity (
<
model2 = Sequential()
model2.add(Conv2D(16, 1, padding='same', activation='relu',input_shape=(Img_H, Img_W, 1)))
 model2.add(MaxPool2D())
model2.add(Conv2D(32, 3, padding='same', activation='relu'))
model2.add(MexPool2D())
model2.add(Conv2D(64, 5, padding='same', activation='relu'))
model2.add(MaxPool2D())
model2.add(Flatten())
model2.add(Dense(128, activation='relu'))
model2.add(Dropout(0.5))
model2.add(Dense(64, activation='relu'))
model2.add(Dropout(0.4))
model2.add(Dense(8, activation='relu'))
model2.add(Dropout(0.2))
model2.add(Dense(1, activation='sigmoid'))
model2.compile(optimizer=opt2, loss=keras.losses.binary_crossentropy, metrics=['accuracy', 'Precision', 'Recall'])
model2.summary()
Model: "sequential 4"
Layer (type)
                                                               Output Shape
                                                                                                                          Param #
                                                               (None, 248, 248, 16)
max_pooling2d_11 (MaxPooling (None, 124, 124, 16)
conv2d_12 (Conv2D)
                                                               (None, 124, 124, 32)
max_pooling2d_12 (MaxPooling (None, 62, 62, 32)
conv2d_13 (Conv2D)
                                                             (None, 62, 62, 64)
                                                                                                                         51264
max_pooling2d_13 (MaxPooling (None, 31, 31, 64)
flatten_4 (Flatten)
                                                               (None, 61504)
dense_11 (Dense)
                                                               (None, 128)
                                                                                                                          7872640
dropout_6 (Dropout)
                                                               (None, 128)
dense_12 (Dense)
                                                                 (None, 64)
                                                                                                                          8256
dropout_7 (Dropout)
                                                               (None, 64)
                                                                                                                          0
dense_13 (Dense)
                                                                 (None, 8)
dropout_8 (Dropout)
                                                                 (None, 8)
```

Danod mejores resutlados el segundo test de keras

```
pit.titie( model - Accuracy )
pit.plot(%odel_Fit.history['accuracy'])
pit.plot(%odel_Fit.history['val_accuracy'])
pit.ylabel("foct")
pit.vlabel("foct")
pit.label("foct")
pit.legend(['Train', 'Val'], loc='upper left')
pit.show()
                                                                            Accuracy
                 0.90
                  0.85
             0.80
0.75
                 0.70
                                                                                                  25
                                                                                                                30
i): pit.title('Model - Loss')
  pit.plot(Model_Fit.history['loss'])
  pit.plot(Model_Fit.history['val_loss'])
  pit.ylabel('loss')
  pit.ylabel('loss')
  pit.legend(['Train', 'val'], loc='upper left')
  pit.show()
                                                                               Loss
                 1.0
              1055
                  0.6
                  0.4
                  0.2
                                                                              20
epoch
                                                                                                                           35
                                                        10
                                                                      15
                                                                                                25
                                                                                                             30
 5]: y_pred = (model.predict_generator(Val_G) > 0.5).astype(int)
y_true = Val_G.classes
            for name, value in zip(model.metrics_names, model.evaluate_generator(Val_G)):
    print(f'{name}: {value}')
            print(f'F1 score: {sklearn.metrics.f1_score(y_true, y_pred)}')
      loss: 0.9671728610992432
accuracy: 0.662162184715271
precision: 0.664948451519901245
recall: 0.797468364235739
F1 score: 0.576271186440678
dense 14 /Pense
```

```
plt.title('Accuracy')
plt.plot(hist2.history['accuracy'])
plt.plot(hist2.history['val_accuracy'])
pht.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
                                            Accuracy
    0.85
    0.80
    0.75
 0.70
0.65
    0.60
    0.55
    0.50
plt.title('Loss')
plt.plot(hist2.history['loss'])
plt.plot(hist2.history['val_loss'])
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
    0.75
    0.70
    0.65
S 0.60
    0.55
    0.50
y_pred2 = (model2.predict_generator(Val_G) > 0.5).astype(int)
y_true2 = Val_G.classes
      print(f'{name}: {value}')
print(f'F1 score: {sklearn.metrics.f1_score(y_true, y_pred)}')
loss: 0.6191083192825317
accuracy: 0.7432432174682617
precision: 0.7252747416496277
precision: 0.72274/410490277
recall: 0.8354430198669434
F1 score: 0.576271186440678
```

3 Recurrent Neuronal Network

- Para la red recurrente se utilizo un data set de Yelp, con comentarios de usuarios en donde 1 es
- Negativo y 2 representa Positivo.

```
train = pd.read_csv('./train.csv', names = ['sentiment', 'text'] )
test = pd.read_csv('./test.csv', names = ['sentiment', 'text'] )
train.head()
```

	sentiment	text
0	1	Unfortunately, the frustration of being Dr. Go
1	2	Been going to Dr. Goldberg for over 10 years
2	1	I don't know what Dr. Goldberg was like before
3	1	I'm writing this review to give you a heads up
4	2	All the food is great here. But the best thing

⁴⁰ Se procedio procesar la informacion y a definir el modelo para predecir.