Laboratorio_4_Vectorizacion

August 25, 2024

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FECHA: 8/23/2024

Ejercicio 1 Con los datos, cálcule PPMI, pero aplicando Lapace Smoothing.

[ ]:
```python
import numpy as np
import pandas as pd
```

[ ]:
```python
# Cargar el archivo proporcionado
file_path = './pmi_ejercicio.xlsx'
data = pd.read_excel(file_path)

# Mostrar las primeras filas del archivo para entender su estructura
data.head()
```

[ ]:
```
    Unnamed: 0 Unnamed: 1 Unnamed: 2 Unnamed: 3 Unnamed: 4 Unnamed: 5
0          NaN   Computer       data     result        pie      sugar
1       Cherry          2          8          9      44260         25
2   Strawberry          0          0          1          5         19
3      Digital       1670       1683         85          5          4
4  Information       3325       3982        378        512         13
```

[ ]:
```python
# Renombrar columnas para mayor claridad
data.columns = ["Term"] + list(data.iloc[0, 1:])
data = data[1:]

# Convertir los valores numéricos a enteros para realizar los cálculos
for col in data.columns[1:]:
    data[col] = pd.to_numeric(data[col], errors='coerce').fillna(0).astype(int)

# Calcular las frecuencias totales por palabra (sumando filas y columnas)
total_word_frequency = data.set_index("Term").sum(axis=1) + data.
↪drop(columns=["Term"]).sum(axis=0)

# Calcular el total de todas las coocurrencias
```

```
total_cooccurrences = data.drop(columns=["Term"]).values.sum()

# Calcular la probabilidad conjunta y aplicar Laplace Smoothing
laplace_k = 1  # Smoothing factor
vocab_size = len(total_word_frequency)  # Tamaño del vocabulario

# Crear una matriz de probabilidades suavizadas
ppmi_matrix = pd.DataFrame(index=data["Term"], columns=data.columns[1:])
```

[ ]:
```
for term1 in ppmi_matrix.index:
    for term2 in ppmi_matrix.columns:
        cooccurrence = data.loc[data["Term"] == term1, term2].values[0]
        # Probabilidad conjunta suavizada
        p_xy = (cooccurrence + laplace_k) / (total_cooccurrences + laplace_k *␣
↪vocab_size ** 2)
        # Probabilidad marginales suavizadas
        p_x = (total_word_frequency[term1] + laplace_k * vocab_size) /␣
↪(total_cooccurrences + laplace_k * vocab_size ** 2)
        p_y = (total_word_frequency[term2] + laplace_k * vocab_size) /␣
↪(total_cooccurrences + laplace_k * vocab_size ** 2)

        # Calcular PMI
        pmi = np.log2(p_xy / (p_x * p_y)) if p_x * p_y > 0 else 0

        # Calcular PPMI
        ppmi_matrix.loc[term1, term2] = max(pmi, 0)

# Mostrar el resultado
print(ppmi_matrix)
```

```
            Computer data result pie sugar
Term
Cherry             0    0      0   0     0
Strawberry         0    0      0   0     0
Digital            0    0      0   0     0
Information        0    0      0   0     0
```

Ejercicio 2

POC para crear información de entreno

[ ]:
```
# Librerías que necesitarán
import io
import re
import string
import tqdm
import numpy as np
import tensorflow as tf
```

```
from tensorflow.keras import layers
from tensorflow.keras import losses
from tensorflow.keras import preprocessing
from tensorflow.keras import utils
from tensorflow.keras.callbacks import TensorBoard
import datetime

%load_ext tensorboard

SEED = 42
AUTOTUNE = tf.data.AUTOTUNE
```

```
The tensorboard extension is already loaded. To reload it, use:
  %reload_ext tensorboard
```

[ ]:
```
sentence = "The wind crosses the brown land unheard"  # De mis poemas favoritos.
↪ The Waste Land de T.S. Eliot
tokens = sentence.lower().split()  # Tokenizar dividiendo la oración en␣
↪palabras y convirtiendo todo a minúsculas
vocab, index = {}, 1  # Arreglo de vocabulario, empezar el índice en 1
vocab["<pad>"] = 0  # Es importante tener un padding token para que el programa␣
↪no explote

# Llenar el arreglo para vocabulario
for word in tokens:
    if word not in vocab:
        vocab[word] = index
        index += 1

vocab_size = len(vocab)
example_sequence = [vocab[word] for word in tokens]
window_size = 2

# Generar positive skip-grams
positive_skip_grams, _ = tf.keras.preprocessing.sequence.skipgrams(
    example_sequence,
    vocabulary_size=vocab_size,
    window_size=window_size,
    negative_samples=0
)
```

[ ]:
```
# Resultados
inverse_vocab = {index: token for token, index in vocab.items()}
for target, context in positive_skip_grams[:5]:
    print(f"({target}, {context}): ({inverse_vocab[target]},␣
↪{inverse_vocab[context]})")
```

```
(5, 6): (land, unheard)
```

```
(6, 5): (unheard, land)
(1, 4): (the, brown)
(3, 1): (crosses, the)
(4, 6): (brown, unheard)
```

[ ]:
```
target_word, context_word = positive_skip_grams[0]
# Escoger un número para muestras negativas (que no pertenece al contexto)
num_ns = 4  # Número de muestras negativas

context_class = tf.reshape(tf.constant(context_word, dtype="int64"), (1, 1))
negative_sampling_candidates, _, _ = tf.random.log_uniform_candidate_sampler(
    true_classes=context_class,  # Clase que debe ser muestreada como positiva␣
 ↪(que pertenece al contexto)
    num_true=1,
    num_sampled=num_ns,
    unique=True,
    range_max=vocab_size,  # [0, vocab_size]
    seed=SEED,
    name="negative_sampling"
)
```

[ ]:
```
print(negative_sampling_candidates)
print([inverse_vocab[index.numpy()] for index in negative_sampling_candidates])
```

```
tf.Tensor([1 6 2 4], shape=(4,), dtype=int64)
['the', 'unheard', 'wind', 'brown']
```

[ ]:
```
sampling_table = tf.keras.preprocessing.sequence.
 ↪make_sampling_table(vocab_size)  # Función que construye la tabla de␣
 ↪muestreo en forma de frecuencias
print(sampling_table)
```

```
[0.00315225 0.00315225 0.00547597 0.00741556 0.00912817 0.01068435
 0.01212381]
```

[ ]:
```
negative_sampling_candidates = tf.expand_dims(negative_sampling_candidates, 1) ␣
 ↪# Se agrega una dimensión para poder concatenar
context = tf.concat([context_class, negative_sampling_candidates], 0)
label = tf.constant([1] + [0] * num_ns, dtype="int64")
target = tf.squeeze(target_word)
context = tf.squeeze(context)
label = tf.squeeze(label)

# ¡Listo! Así se prepara la información para entrenar
```

[ ]:
```
# Información a utilizar:
path_to_file = tf.keras.utils.get_file('shakespeare.txt', 'https://storage.
 ↪googleapis.com/download.tensorflow.org/data/shakespeare.txt')
```

```
text_ds = tf.data.TextLineDataset(path_to_file).filter(lambda x: tf.cast(tf.
↪strings.length(x), bool))
```

[ ]:
```
#Paso 1: cree una funcion que estandarice el texto como ya hemos hecho e␣
↪incrustela en una capa de Tensorflow (TextVectorization)
from tensorflow.keras.layers import TextVectorization


# Define la función de estandarización personalizada para la capa de␣
↪vectorización
def custom_standardization(input_text):
    lowercase = tf.strings.lower(input_text)
    stripped_html = tf.strings.regex_replace(lowercase, '<br />', ' ')
    return tf.strings.regex_replace(stripped_html, '[%s]' % re.escape(string.
↪punctuation), '')

# Crear la capa de vectorización
vectorize_layer = TextVectorization(
    standardize=custom_standardization,
    max_tokens=10000,
    output_mode='int',
    output_sequence_length=250
)

# Descargar y preparar el dataset
path_to_file = tf.keras.utils.get_file('shakespeare.txt', 'https://storage.
↪googleapis.com/download.tensorflow.org/data/shakespeare.txt')
text_ds = tf.data.TextLineDataset(path_to_file).filter(lambda x: tf.cast(tf.
↪strings.length(x), bool))

# Adaptar la capa con los datos
vectorize_layer.adapt(text_ds.batch(1024))

# Visualizar el texto nuevamente
for line in text_ds.take(5):
    print(line.numpy().decode('utf-8'))
```

```
First Citizen:
Before we proceed any further, hear me speak.
All:
Speak, speak.
First Citizen:
```

[ ]:
```
vectorize_layer.adapt(text_ds.batch(1024))
```

[ ]:
```
def prepare_training_data(sentences, window_size=2, num_ns=4, seed=42):
    tokens = [sentence.lower().split() for sentence in sentences]
```

```
    vocab = {word: idx + 1 for idx, word in enumerate(set(sum(tokens, [])))}
    vocab["<pad>"] = 0  # Añadir palabra de padding

    vocab_size = len(vocab) + 1  # Añadir 1 para incluir <pad>

    # Convertir sentencias a secuencias de índices
    sequences = [[vocab[word] for word in token_list] for token_list in tokens]

    sampling_table = tf.keras.preprocessing.sequence.
↪make_sampling_table(vocab_size)
    pairs = []
    labels = []

    for sequence in sequences:
        positive_skip_grams, _ = tf.keras.preprocessing.sequence.skipgrams(
            sequence,
            vocabulary_size=vocab_size,
            window_size=window_size,
            negative_samples=0,
            sampling_table=sampling_table
        )

        for target_word, context_word in positive_skip_grams:
            context_class = tf.reshape(tf.constant(context_word,␣
↪dtype="int64"), (1, 1))
            negative_sampling_candidates, _, _ = tf.random.
↪log_uniform_candidate_sampler(
                true_classes=context_class,
                num_true=1,
                num_sampled=num_ns,
                unique=True,
                range_max=vocab_size,
                seed=seed,
                name="negative_sampling"
            )

            pairs.append([target_word, context_word])
            labels.append(1)

            for neg_word in negative_sampling_candidates:
                pairs.append([target_word, neg_word.numpy()])
                labels.append(0)

    return pairs, labels, vocab_size
```

[ ]:
```
SEED = 42
AUTOTUNE = tf.data.AUTOTUNE
```

```
# Vectorize the data in text_ds.
text_vector_ds = text_ds.batch(1024).prefetch(AUTOTUNE).map(vectorize_layer).
↪unbatch()
sequences = list(text_vector_ds.as_numpy_iterator())
```

[ ]:
```
#El siguiente codigo es el modelo Word2Vec usando lo que ya han hecho. Sin␣
↪embargo, deben agregar la metrica de similitud que vimos en clase, a la cual␣
↪deben llamar dots
class Word2Vec(tf.keras.Model):
  def __init__(self, vocab_size, embedding_dim):
    super(Word2Vec, self).__init__()
    self.target_embedding = layers.Embedding(vocab_size,
                                      embedding_dim,
                                      name="w2v_embedding")
    self.context_embedding = layers.Embedding(vocab_size,
                                       embedding_dim)

  def call(self, pair):
    target, context = pair
    # target: (batch, dummy?)  # The dummy axis doesn't exist in TF2.7+
    # context: (batch, context)
    if len(target.shape) == 2:
      target = tf.squeeze(target, axis=1)
    # target: (batch,)
    word_emb = self.target_embedding(target)
    # word_emb: (batch, embed)
    context_emb = self.context_embedding(context)


    # dots: (batch, context)
    dots = tf.einsum('be,be->b', word_emb, context_emb)
    return dots
```

[ ]:
```
import tensorflow as tf
from tensorflow.keras import layers
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.losses import BinaryCrossentropy
from tensorflow.keras.metrics import BinaryAccuracy
import numpy as np
import matplotlib.pyplot as plt

# 1000 oraciones porque el dataset es muy grande
max_sentences = 1000
sentences = []
for idx, line in enumerate(text_ds):
    if idx < max_sentences:
        sentences.append(line.numpy().decode('utf-8'))
```

```
    else:
        break

# Preparar los datos
pairs, labels, vocab_size = prepare_training_data(sentences, window_size=2,␣
↪num_ns=4, seed=42)
pairs = np.array(pairs)
labels = np.array(labels)

# Crear el dataset de TensorFlow
dataset = tf.data.Dataset.from_tensor_slices(((pairs[:, 0], pairs[:, 1]),␣
↪labels))
dataset = dataset.shuffle(buffer_size=10000).batch(32).prefetch(tf.data.
↪AUTOTUNE)

# Dividir el dataset en entrenamiento y validación
dataset_size = len(pairs)
train_size = int(0.8 * dataset_size)
val_size = dataset_size - train_size

# Dividir los datos en arrays de entrenamiento y validación
train_pairs = pairs[:train_size]
train_labels = labels[:train_size]
val_pairs = pairs[train_size:]
val_labels = labels[train_size:]

# Crear los datasets de TensorFlow
train_dataset = tf.data.Dataset.from_tensor_slices(((train_pairs[:, 0],␣
↪train_pairs[:, 1]), train_labels)).batch(32).prefetch(tf.data.AUTOTUNE)
val_dataset = tf.data.Dataset.from_tensor_slices(((val_pairs[:, 0], val_pairs[:
↪, 1]), val_labels)).batch(32).prefetch(tf.data.AUTOTUNE)
```

[ ]:

```
tensorboard_callback = TensorBoard(log_dir="./")

# Crear el modelo
model = Word2Vec(
    vocab_size,
    embedding_dim=128
)

# Compilar el modelo
model.compile(optimizer=Adam(learning_rate=0.001),
              loss=BinaryCrossentropy(from_logits=True),
              metrics=[BinaryAccuracy(name='accuracy')])

# Entrenar el modelo
```

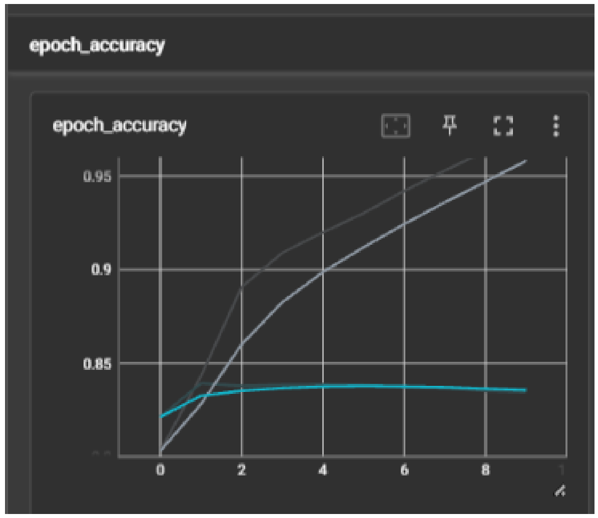
```
history = model.fit(train_dataset, epochs=10, validation_data=val_dataset,␣
↪callbacks=[tensorboard_callback])
```

```
Epoch 1/10
616/616 [==============================] - 5s 7ms/step - loss: 0.6504 -
accuracy: 0.8029 - val_loss: 0.5494 - val_accuracy: 0.8212
Epoch 2/10
616/616 [==============================] - 5s 7ms/step - loss: 0.4408 -
accuracy: 0.8429 - val_loss: 0.4616 - val_accuracy: 0.8390
Epoch 3/10
616/616 [==============================] - 5s 7ms/step - loss: 0.2960 -
accuracy: 0.8906 - val_loss: 0.4606 - val_accuracy: 0.8376
Epoch 4/10
616/616 [==============================] - 5s 7ms/step - loss: 0.2311 -
accuracy: 0.9089 - val_loss: 0.4727 - val_accuracy: 0.8382
Epoch 5/10
616/616 [==============================] - 4s 7ms/step - loss: 0.1938 -
accuracy: 0.9198 - val_loss: 0.4847 - val_accuracy: 0.8384
Epoch 6/10
616/616 [==============================] - 4s 7ms/step - loss: 0.1641 -
accuracy: 0.9301 - val_loss: 0.4968 - val_accuracy: 0.8380
Epoch 7/10
616/616 [==============================] - 5s 7ms/step - loss: 0.1377 -
accuracy: 0.9420 - val_loss: 0.5101 - val_accuracy: 0.8370
Epoch 8/10
616/616 [==============================] - 5s 7ms/step - loss: 0.1137 -
accuracy: 0.9530 - val_loss: 0.5248 - val_accuracy: 0.8364
Epoch 9/10
616/616 [==============================] - 4s 7ms/step - loss: 0.0923 -
accuracy: 0.9634 - val_loss: 0.5406 - val_accuracy: 0.8350
Epoch 10/10
616/616 [==============================] - 5s 8ms/step - loss: 0.0736 -
accuracy: 0.9747 - val_loss: 0.5570 - val_accuracy: 0.8343
```

[ ]:

```
from IPython.display import Image
Image("./epoch_accuracy.png")
```

[ ]:



[ ]: `Image("./epoch_loss.png")`

[ ]: