Preprocesamiento de texto

Aprendizaje automático

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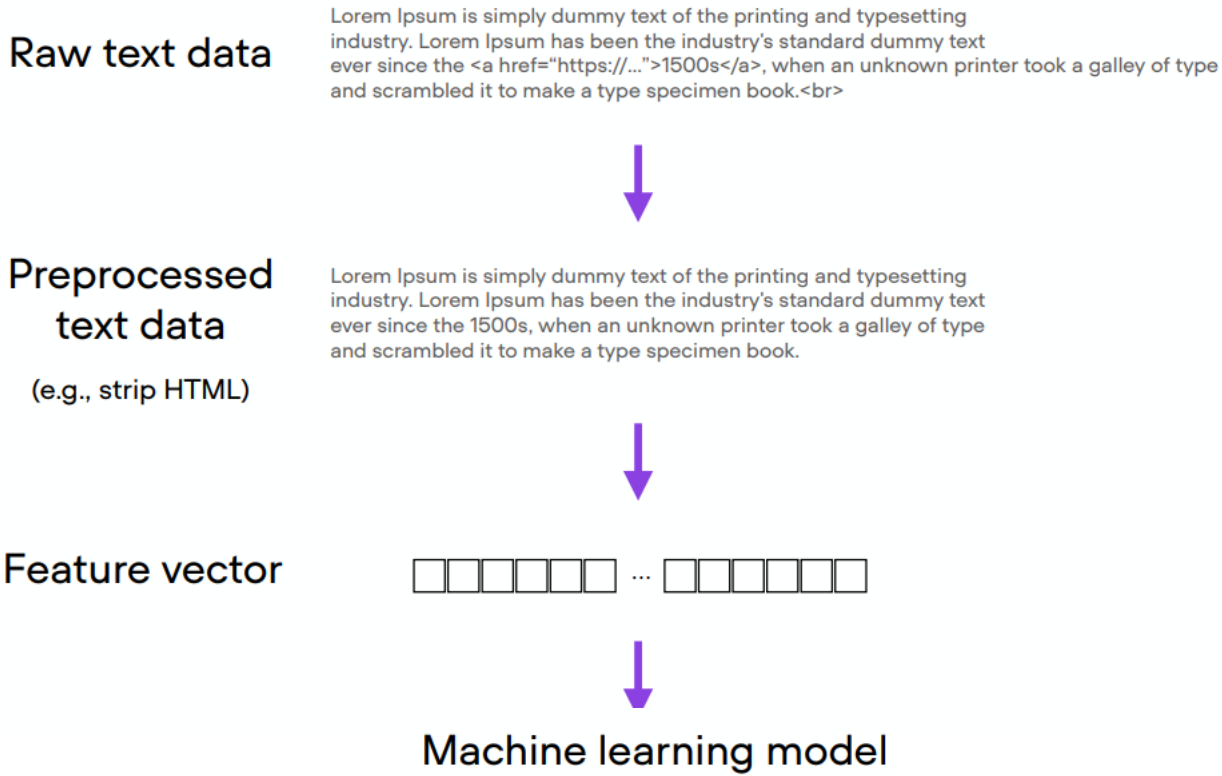
Preprocesamiento de texto



Preprocesamiento de texto

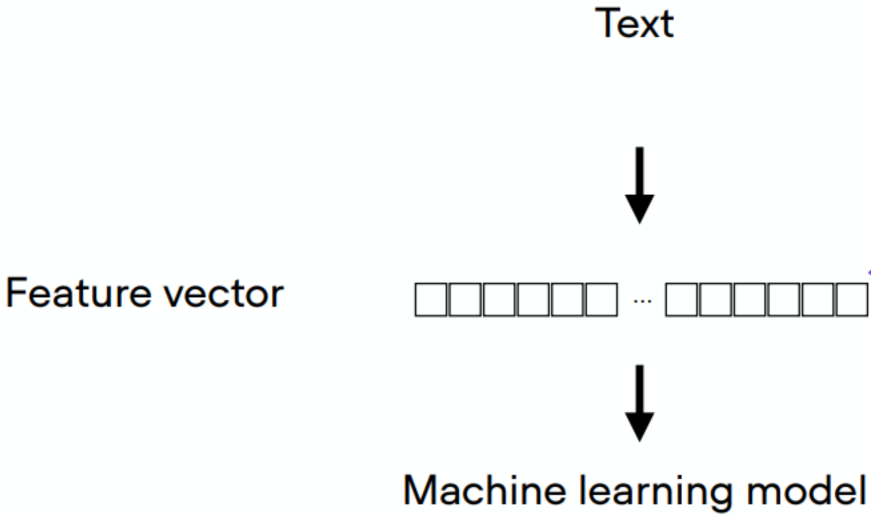
Machine learning model

Classic methods for tabular data:
- Logistic regression
- Multilayer perceptron

Sequence models:
- 1D convolutional network
- Recurrent neural network

Transformers

Preprocesamiento de texto



1. Bag of words
2. Embeddings

Tokenización

Divide el texto/documento en partes pequeñas con espacios en blanco y puntuaciones

Sentence	Tokens
“I don’t like eggs.”	“I”, “do”, “n’t”, “like”, “eggs”, “.”

Remoción de stop words

Stop words: Palabras que aparecen frecuentemente en textos pero no contribuyen mucho al significado de las oraciones

- Stop words comunes (eng): “a”, “the”, “so”, “is”, “it”, “at”, “in”, “this”, “there”, “that”, “my”

Original sentence	Without stop words
“There is a tree near the house”	“tree near house”

Bag of words

Text	Label
The ghost pepper is so spicy, it is hauntingly hot	1
I tried to hug the sun today, but it was too hot to handle	1
I cannot handle spicy food	0

Bag of words

Text	Label
The ghost pepper is so spicy, it is hauntingly hot	1
I tried to hug the sun today, but it was too hot to handle	1
I cannot handle spicy food	0

→

Vocabulary

```
but
cannot
food
ghost
handle
hauntingly
hot
hug
i
is
it
pepper
so
spicy
sun
the
to
today
too
tried
was
```

Bag of words

- El número de palabras determina el número de características
- El número de veces que aparece cada palabra en cada ejemplo determina el valor de cada característica

Text
The ghost pepper is so spicy, it is hauntingly hot
I tried to hug the sun today, but it was too hot to handle
I cannot handle spicy food

but	cannot	food	ghost	handle	hauntingly	hot	hug	i	is	it	pepper	so	spicy	sun	the	to	today	too	tried	was
0	0	0	1	0	1	1	0	0	1	1	1	1	1	0	1	0	0	0	0	0
1	0	0	0	1	0	1	1	1	0	1	0	0	0	1	1	2	1	1	1	1
0	1	1	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0

BoW vectors

Bag of words

but	cannot	food	ghost	handle	hauntingly	hot	hug	i	is	it	pepper	so	spicy	sun	the	to	today	too	tried	was
0	0	0	1	0	1	1	0	0	1	1	1	1	1	0	1	0	0	0	0	0
1	0	0	0	1	0	1	1	1	0	1	0	0	0	1	1	2	1	1	1	1
0	1	1	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0

Feature vectors

Machine
learning model

Modificaciones de Bag of Words

- N - gramas

Text	Label
The ghost pepper is so spicy, it is hauntingly hot	1
I tried to hug the sun today, but it was too hot to handle	1
I cannot handle spicy food	0

"The"
"ghost"
"pepper"
"is"
"so"
"spicy"
...

1-gram

"The ghost"
"ghost pepper"
"pepper is"
"is so"
"so spicy"
...

2-gram
(bigram)

Modificaciones de Bag of Words

tf-idf: Term frequency – inverse document frequency

Qué tan a menudo aparece una palabra, **ponderado** por el número de documentos en el que la palabra aparece:

- Frecuencia alta de aparición de la palabra: palabra importante
- Frecuencia alta de aparición en documentos: no tan informativa

Embeddings

One-hot encoded ("sparse") representation of "S U N N Y"

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
S	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
N	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
N	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Y	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0

Embedded ("dense") representation of "S U N N Y"

```
[[0.9816, 0.7363, 0.5899],
 [0.2605, 0.3766, 0.3502],
 [0.7382, 0.9807, 0.4762],
 [0.6231, 0.8825, 0.8836]]
```

Embedding layer

```
  [[0.6912, 0.8765, 0.4939],
   [0.6342, 0.7481, 0.7717],
   [0.8395, 0.2128, 0.3696],
   [0.4900, 0.1509, 0.0689],
   [0.2587, 0.9171, 0.8670],
   [0.7213, 0.9922, 0.5701],
   [0.7598, 0.5231, 0.3666],
   [0.5150, 0.5216, 0.9682],
   [0.2248, 0.0261, 0.4427],
   [0.1818, 0.6863, 0.8713],
   [0.4192, 0.1566, 0.9004],
   [0.8102, 0.5741, 0.4241],
   [0.1116, 0.0466, 0.2786],
S  [0.9816, 0.7363, 0.5899],
   [0.9224, 0.3672, 0.6972],
   [0.1207, 0.3372, 0.2128],
   [0.0660, 0.1524, 0.8440],
   [0.2162, 0.5640, 0.0988],
U  [0.2605, 0.3766, 0.3502],
   [0.2334, 0.4757, 0.7581],
N  [0.7382, 0.9807, 0.4762],
   [0.2369, 0.8102, 0.8798],
   [0.6932, 0.2671, 0.8018],
   [0.9593, 0.5302, 0.4290],
Y  [0.6231, 0.8825, 0.8836],
   [0.4623, 0.8503, 0.7279]]
```

HuggingFace (pytorch) Embedding layer

Embedding layers: Forma eficiente de multiplicación de matrices cuando se trabaja con vectores codificados de forma one-hot

```python
import torch

torch.manual_seed(123);
```

```python
idx = torch.tensor([2, 3, 1]) # 3 training examples

num_idx = max(idx)+1
out_dim = 5
```

Input dimension of a one-hot encoded vector is the number of indices (the highest index + 1)

Suppose we want embeddings of size 5

HuggingFace (pytorch) Embedding layer

```
import torch

torch.manual_seed(123);
```

```
idx = torch.tensor([2, 3, 1]) # 3 training examples

num_idx = max(idx)+1
out_dim = 5

embedding = torch.nn.Embedding(num_idx, out_dim)
embedding(idx)
```

```
tensor([[ 0.6957, -1.8061, -1.1589,  0.3255, -0.6315],
        [-2.8400, -0.7849, -1.4096, -0.4076,  0.7953],
        [ 1.3010,  1.2753, -0.2010, -0.1606, -0.4015]],
       grad_fn=<EmbeddingBackward0>)
```

Each training example has
5 feature values