## **Processing Categorical Features**

Age	Gender	Nationality
35	Male	US
31	Male	China
29	Female	India
27	Male	US

Age	Gender	Nationality
35	Male	US
31	Male	China
29	Female	India
27	Male	US

- Age is a numeric feature because it is ordered.
- 35-year-old is older than 31-year-old.

Age	Gender	Nationality
35	Male	US
31	Male	China
29	Female	India
27	Male	US

- Gender is a binary feature: female or male. (In most people's opinion.)
- Represent ``female'' by 0.
- Represent "male" by 1.

Age	Gender	Nationality
35	1	US
31	1	China
29	0	India
27	1	US

- Gender is a binary feature: female or male. (In most people's opinion.)
- Represent ``female'' by 0.
- Represent "male" by 1.

Age	Gender	Nationality
35	1	US
31	1	China
29	0	India
27	1	US

- Nationality is a categorical feature.
- There are 197 countries (arguably.)
- We need to represent countries by numeric vectors.

Age	Gender	Nationality
35	1	US
31	1	China
29	0	India
27	1	US

- First, build a dictionary that maps countries to indices.
- E.g., US $\rightarrow$ 1, China $\rightarrow$ 2, India $\rightarrow$ 3, Japan $\rightarrow$ 4, Germany $\rightarrow$ 5, ...
- Count from "1" (instead of "0").

Age	Gender	Nationality
35	1	1
31	1	2
29	0	3
27	1	1

- First, build a dictionary that maps countries to indices.
- E.g., US $\rightarrow$ 1, China $\rightarrow$ 2, India $\rightarrow$ 3, Japan $\rightarrow$ 4, Germany $\rightarrow$ 5, ...
- Count from "1" (instead of "0").

Age	Gender	Nationality
35	1	1
31	1	2
29	0	3
27	1	1

- Second, apply one-hot encoding. (Count from "1".)
- US  $\rightarrow$  1  $\rightarrow$  [1, 0, 0, 0, ..., 0].
- China  $\rightarrow$  2  $\rightarrow$  [0, 1, 0, 0, ..., 0].
- •

Age	Gender	Nationality
35	1	$[1, 0, 0, 0, \cdots, 0]$
31	1	$[0, 1, 0, 0, \cdots, 0]$
29	0	$[0, 0, 1, 0, \cdots, 0]$
27	1	$[1, 0, 0, 0, \cdots, 0]$

- Second, apply one-hot encoding. (Count from "1".)
- US  $\rightarrow$  1  $\rightarrow$  [1, 0, 0, 0, ..., 0].
- China  $\rightarrow$  2  $\rightarrow$  [0, 1, 0, 0, ..., 0].
- •

Age	Gender	Nationality
35	1	$[1, 0, 0, 0, \cdots, 0]$
31	1	$[0, 1, 0, 0, \cdots, 0]$
29	0	$[0, 0, 1, 0, \cdots, 0]$
27	1	$[1, 0, 0, 0, \cdots, 0]$

- Why the indices start from "1" (the US) rather than "0"?
- Reserve "0" (whose one-hot encode is  $[0, 0, \cdots, 0]$ ) for unknown or missing nationalities.

#### **Data Processing**

- Represent a person's feature (age, gender, nationality) using a 199dim numeric vector.
- For example, convert (28, Female, China) to vector

$$[28, 0, 0, 1, 0, 0, \dots, 0].$$

a 197-dim vector for nationality.

#### **Data Processing**

- Represent a person's feature (age, gender, nationality) using a 199dim numeric vector.
- For example, convert (28, Female, China) to vector

$$[28, 0, 0, 1, 0, 0, \dots, 0].$$

a 197-dim vector for nationality.

• For example, convert (36, Male, unknown) to vector [36, 1, 0, 0, 0, 0, 0, ..., 0].

### Why using one-hot vectors?

We represent nationalities using one hot vectors:

```
• US: [1, 0, 0, 0, \cdots, 0]
```

- China:  $[0, 1, 0, 0, \dots, 0]$
- India:  $[0, 0, 1, 0, \dots, 0]$

- Why not representing nationalities using scalars?
  - 1 for "US", 2 for "China", and 3 for "India".
  - This saves 197x space and computation.

### Why using one-hot vectors?

- What if we use 1 for "US", 2 for "China", and 3 for "India"?
- Then "US"+ "China" = 3 = "India".

- What if we represent nationalities using one hot vectors?
  - US:  $[1, 0, 0, 0, \dots, 0]$ .
  - China:  $[0, 1, 0, 0, \dots, 0]$ .
  - India:  $[0, 0, 1, 0, \dots, 0]$ .
- Then "US"+ "China" =  $[1, 1, 0, 0, \dots, 0]$ .
  - Both US and China nationalities.

## **Processing Text Data**

### Step 1: Tokenization (Text to Words)

• We are given a piece of text (string), e.g.,

$$S =$$
"... to be or not to be...".

• Break the string (string) into a list of words:

```
L = [..., to, be, or, not, to, be, ...],
```

- Build a dictionary (e.g., hash table) to count words' frequencies.
- Initially, the dictionary is empty.

Key (word)	Value (frequency)

- Update the dictionary in this way:
  - If word w is **not** in the dictionary, add (w, 1) to the dictionary.
  - If word w is in the dictionary, increase its frequency counter.

Key	Value
(word)	(frequency)
a	219
to	398
hamlet	5
be	131
not	499
prince	12
kill	31

- Update the dictionary in this way:
  - If word w is **not** in the dictionary, add (w, 1) to the dictionary.
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#### • Example:

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#### • Example:

to be or not to be
--------------------

Word "to" is in the dictionary.

Key (word)	Value (frequency)
a	219
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- Update the dictionary in this way:
  - If word w is **not** in the dictionary, add (w, 1) to the dictionary.
  - If word w is in the dictionary, increase its frequency counter.

#### • Example:

be or not to be	• • •	to	be	or	not	to	be	
-----------------	-------	----	----	----	-----	----	----	--

- Word "to" is in the dictionary.
- Increase its counter.

Key	Value
(word)	(frequency)
a	219
to	399
hamlet	5
be	131
not	499
prince	12
kill	31

- Update the dictionary in this way:
  - If word w is **not** in the dictionary, add (w, 1) to the dictionary.
  - If word w is in the dictionary, increase its frequency counter.

#### • Example:

to be or not to be	• •		be	to	not	or	be	to	• • •
--------------------	-----	--	----	----	-----	----	----	----	-------

Word "be" is in the dictionary.

Key	Value
(word)	(frequency)
a	219
to	399
hamlet	5
be	131
not	499
prince	12
kill	31

- Update the dictionary in this way:
  - If word w is **not** in the dictionary, add (w, 1) to the dictionary.
  - If word w is in the dictionary, increase its frequency counter.

#### • Example:

• • •	to	be	or	not	to	be	
-------	----	----	----	-----	----	----	--

- Word "be" is in the dictionary.
- Increase its counter.

Key	Value
(word)	(frequency)
a	219
to	399
hamlet	5
be	132
not	499
prince	12
kill	31

- Update the dictionary in this way:
  - If word w is **not** in the dictionary, add (w, 1) to the dictionary.
  - If word w is in the dictionary, increase its frequency counter.

#### • Example:



Word "or" is not in the dictionary.

Key	Value
(word)	(frequency)
a	219
to	399
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kill	31

- Update the dictionary in this way:
  - If word w is **not** in the dictionary, add (w, 1) to the dictionary.
  - If word w is in the dictionary, increase its frequency counter.

#### • Example:

to be or	not to	be	
----------	--------	----	--

- Word "or" is not in the dictionary.
- Add ("or", 1) to the dictionary.

Key	Value
(word)	(frequency)
a	219
to	399
hamlet	5
or	1
be	132
not	499
prince	12
kill	31

• Sort the table so that the frequency is in the descending order.

Key	Value
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or	1

- Sort the table so that the frequency is in the descending order.
- Replace "frequency" by "index" (starting from 1.)

Key (word)	Value (frequency)
not	499
to	399
a	219
be	131
kill	31
prince	12
hamlet	5
or	1

- Sort the table so that the frequency is in the descending order.
- Replace "frequency" by "index" (starting from 1.)
- The number of unique words is called "vocabulary".

Key (word)	Value (index)
not	1
to	2
a	3
be	4
kill	5
prince	6
hamlet	7
or	8

- If the vocabulary is too big, e.g., greater than 10K, then keep only the 10K most frequent words.
- Why removing infrequent words?

Key (word)	Value (index)
not	1
to	2
a	3
be	4
kill	5
prince	6
hamlet	7
or	8

- If the vocabulary is too big, e.g., greater than 10K, then keep only the 10K most frequent words.
- Why removing infrequent words?
- 1. Infrequent words are usually meaningless, e.g.,
  - Name entities, e.g., "Shusen".
  - Typos, e.g., "prinse" and "hemlat".
- 2. Bigger vocabulary → higher-dim one-hot vectors.
  - Slower computation.
  - More parameters in word-embedding layer.

Key	Value
(word)	(index)
not	1
to	2
a	3
be	4
kill	5
prince	6
hamlet	7
or	8

### Step 3: One-Hot Encoding

- Map every word to its index.
- For example,

```
Words: [to, be, or, not, to, be]
```



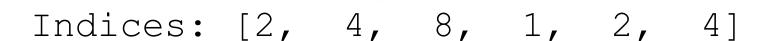
```
Indices: [2, 4, 8, 1, 2, 4]
```

Key (word)	Value (index)
not	1
to	2
a	3
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kill	5
prince	6
hamlet	7
or	8

### Step 3: One-Hot Encoding

- Map every word to its index.
- For example,

```
Words: [to, be, or, not, to, be]
```



- If necessary, convert every index to a one-hot vector.
  - The one-hot vector' dimension is the vocabulary.
  - Vocabulary means # of unique words in the dictionary.

Key (word)	Value (index)
not	1
to	2
a	3
be	4
kill	5
prince	6
hamlet	7
or	8

### Step 3: One-Hot Encoding

• If a word (e.g., typo) cannot be found in the dictionary, then simply ignore it, or encode it as 0.

```
• Example:
```

```
a typo:
Words: [to, bi, or]
Indices: [2, 8]
```

Key (word)	Value (index)
not	1
to	2
a	3
be	4
kill	5
prince	6
hamlet	7
or	8

# Thank you!