Lecture 3:
n-gram LMs and Smoothing
+ Logistic Regression

Instructor: Swabha Swayamdipta

USC CSCI 544 Applied NLP

Sep 3, Fall 2024

Some slides adapted from Dan Jurafsky and Chris Manning and Xuezhe Ma

Lecture Outline

- Announcements + Recap
  - n-gram Language Models
  - Zeros!
- Smoothing
- Basics of Supervised Machine Learning
  - I. Data: Preprocessing and Feature Extraction
  - II. Model:
    - I. Logistic Regression
  - III. Loss
  - IV. Optimization Algorithm
  - V. Inference

Announcements
+
Recap

Logistics and Announcements

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    - TA Office Hours: HW related questions

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Probabilistic Language Modeling

Goal: compute the probability of a sentence or sequence of words:

$$P(\mathbf{w}) = P(w_1, w_2, w_3, \ldots w_n)$$

A model that assigns probabilities to sequences of words is called a language model

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Related task: probability of an upcoming word: $P(w_n \mid w_1, w_2, w_3, w_4, \ldots w_{n-1})$

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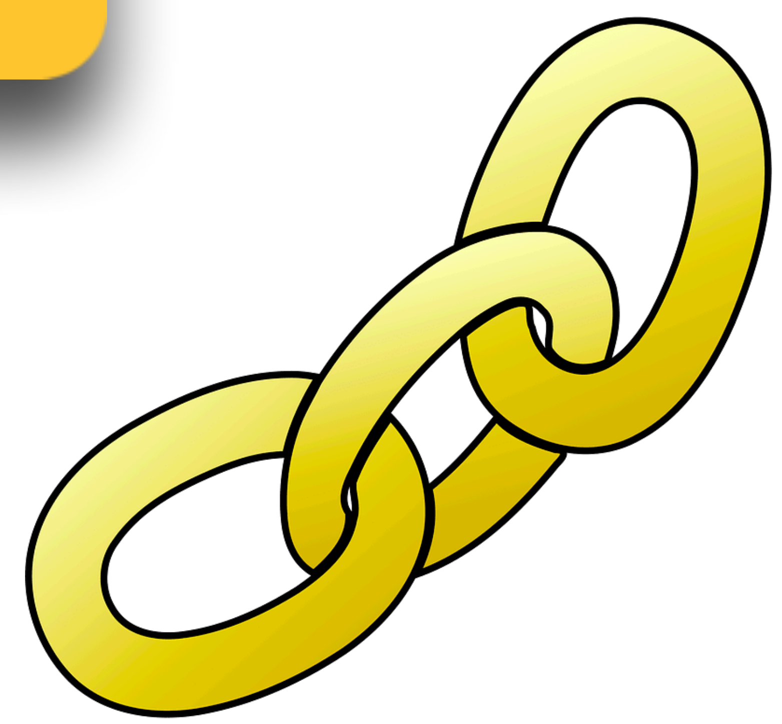
Chain Rule

$$P(w_1, w_2, \dots w_n) = \prod_{i=1}^{n} P(w_i \mid w_{i-1} \dots w_1)$$



How to estimate the probability of the next word?

$$P(\text{that} \mid \text{its water is so transparent}) = \frac{Count(\text{its water is so transparent that})}{Count(\text{its water is so transparent})}$$

Maximum Likelihood Estimate

How to estimate the probability of the next word?

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Maximum Likelihood Estimate

Too many possibilities to count! Too few sentences that look like this…

Need to make some simplifying assumptions…

Markov Assumption

$$P(w_i \mid w_1, w_2, \ldots w_{i-1}) \approx P(w_i \mid w_{i-k+1} \ldots w_{i-1})$$

k-th order Markov Assumption

In other words, we approximate each component in the product such that it is only conditioned on the previous $k-1$ elements

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You think you just fell
out of a coconut tree?


YOU THINK YOU JUST FELL OUT
OF A
COCONUT
TREE?
YOU EXIST IN THE CONTEXT OF ALL IN WHICH
YOU LIVE AND WHAT CAME BEFORE YOU.

Definitely true for tokens in natural language!

n-gram Models: Limitations

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In general this is an insufficient model of language

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Garden Path Sentences

But we can often get away with n-gram models

Language has long-distance dependencies

Estimating bigram probabilities

Maximum Likelihood Estimate

$$P_{MLE}(w_i \mid w_{i-1}) = \frac{count(w_{i-1}, w_i)}{count(w_{i-1})}$$

$$P_{MLE}(w_i \mid w_{i-1}) = \frac{c(w_{i-1}w_i)}{c(w_{i-1})}$$

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We do everything in log space to handle overflow issues

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For the 9222 sentences in the Berkeley Restaurant Corpus:

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i	want	to	eat	chinese	food	lunch	spend
2533	927	2417	746	158	1093	341	278

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Bigram Counts

Next Word

History

	i	want	to	eat	chinese	food	lunch	spend
i	5	827	0	9	0	0	0	2
want	2	0	608	1	6	6	5	1
to	2	0	4	686	2	0	6	211
eat	0	0	2	0	16	2	42	0
chinese	1	0	0	0	0	82	1	0
food	15	0	15	0	1	4	0	0
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Bigram Probabilities

w_i

w_{i-1}

	i	want	to	eat	chinese	food	lunch	spend
i	0.002	0.33	0	0.0036	0	0	0	0.00079
want	0.0022	0	0.66	0.0011	0.0065	0.0065	0.0054	0.0011
to	0.00083	0	0.0017	0.28	0.00083	0	0.0025	0.087
eat	0	0	0.0027	0	0.021	0.0027	0.056	0
chinese	0.0063	0	0	0	0	0.52	0.0063	0
food	0.014	0	0.014	0	0.00092	0.0037	0	0
lunch	0.0059	0	0	0	0	0.0029	0	0
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Most n-grams are never seen!

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$$PPL(\mathbf{w}) = P(w_1, w_2, \ldots, w_N)^{-\frac{1}{N}}$$

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$$= \exp(-\frac{1}{N} \log P(w_1, w_2, \ldots, w_N))$$

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Negative log likelihood

USC Viterbi

Bigram Perplexity

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WSJ Perplexities

N-gram Order	Unigram	Bigram	Trigram
Perplexity	962	170	109

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n-grams do a better and better job of modeling the training corpus as we increase the value of *n*

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- Extrinsic evaluation
  - On an external task (e.g. summarization) that uses an LM
  - More reliable
  - Can be time-consuming; hard to design
    - Which is the best task? How many tasks to try?

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- Extrinsic evaluation
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  - More reliable
  - Can be time-consuming; hard to design
    - Which is the best task? How many tasks to try?
- Therefore, we often use intrinsic evaluation: perplexity
  - Bad approximation (less reliable)
    - Unless the test data looks just like the training data
  - Generally only useful in pilot experiments (faster to compute)

Generating from a bigram model

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- Choose a random bigram (<s>, w) according to its probability
- Now choose a random bigram (w, x) according to its probability
- And so on until we choose </s>
- Then string the words together

```
<s> I
    I want
      want to
           to eat
              eat Chinese
                  Chinese food
                          food  </s>
```

```
I want to eat Chinese food
```

USC Viterbi

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On your own: Sampling from a probability distribution

Shakespearean n-grams

1 gram	–To him swallowed confess hear both. Which. Of save on trail for are ay device and rote life have –Hill he late speaks; or! a more to leg less first you enter
2 gram	–Why dost stand forth thy canopy, forsooth; he is this palpable hit the King Henry. Live king. Follow. –What means, sir. I confess she? then all sorts, he is trim, captain.
3 gram	–Fly, and will rid me these news of price. Therefore the sadness of parting, as they say, ’tis done. –This shall forbid it should be branded, if renown made it empty.
4 gram	–King Henry. What! I will go seek the traitor Gloucester. Exeunt some of the watch. A great banquet serv’d in; –It cannot be but so.

The WSJ is no Shakespeare!

1 gram	Months the my and issue of year foreign new exchange's september were recession exchange new endorsed a acquire to six executives
2 gram	Last December through the way to preserve the Hudson corporation N. B. E. C. Taylor would seem to complete the major central planners one point five percent of U. S. E. has already old M. X. corporation of living on information such as more frequently fishing to keep her
3 gram	They also point to ninety nine point six billion dollars from two hundred four oh six three percent of the rates of interest stores as Mexico and Brazil on market conditions

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Overfitting!

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  - Zero bi-gram counts: Smoothing

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- At test time, we may encounter tokens never seen (unigram with 0 frequency)
  - Very severe yet common problem resulting in undefined probabilities
  - Happens because of new terms, words, different dialects, evolving language
  - These are known as **OOV** for “out of vocabulary”, or <UNK> for **unknown tokens**

N-gram models: Zero Counts

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  - Very severe yet common problem resulting in undefined probabilities
  - Happens because of new terms, words, different dialects, evolving language
  - These are known as **OOV** for "out of vocabulary", or <UNK> for **unknown tokens**
- **Solution:** During training (probability estimation), replace all words that occur fewer than n times in the training set, where n is some small number by <UNK> and re-estimate the counts and probabilities.
  - At test time, any OOV token is automatically mapped to <UNK>

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- Design: Open Vocabulary vs. Closed Vocabulary
  - Closed Vocabulary: predetermine the vocabulary (e.g. using a dictionary)
    - Restricted…why?
  - Open Vocabulary: no predetermination but anticipate new tokens

Open vs. Closed Vocabularies

Smoothing

Intuition for Smoothing

I like to **eat** cake but I want to **eat** pizza right now. Mary told her brother to **eat** pizza too.

→

P(next word = *pizza* | previous word = *eat*) = 2/3

P(next word = *cake* | previous word = *eat*) = 1/3

All other next words = 0 probability

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  - $|V| = ?$ $|V_{\text{bigrams}}| = ?$

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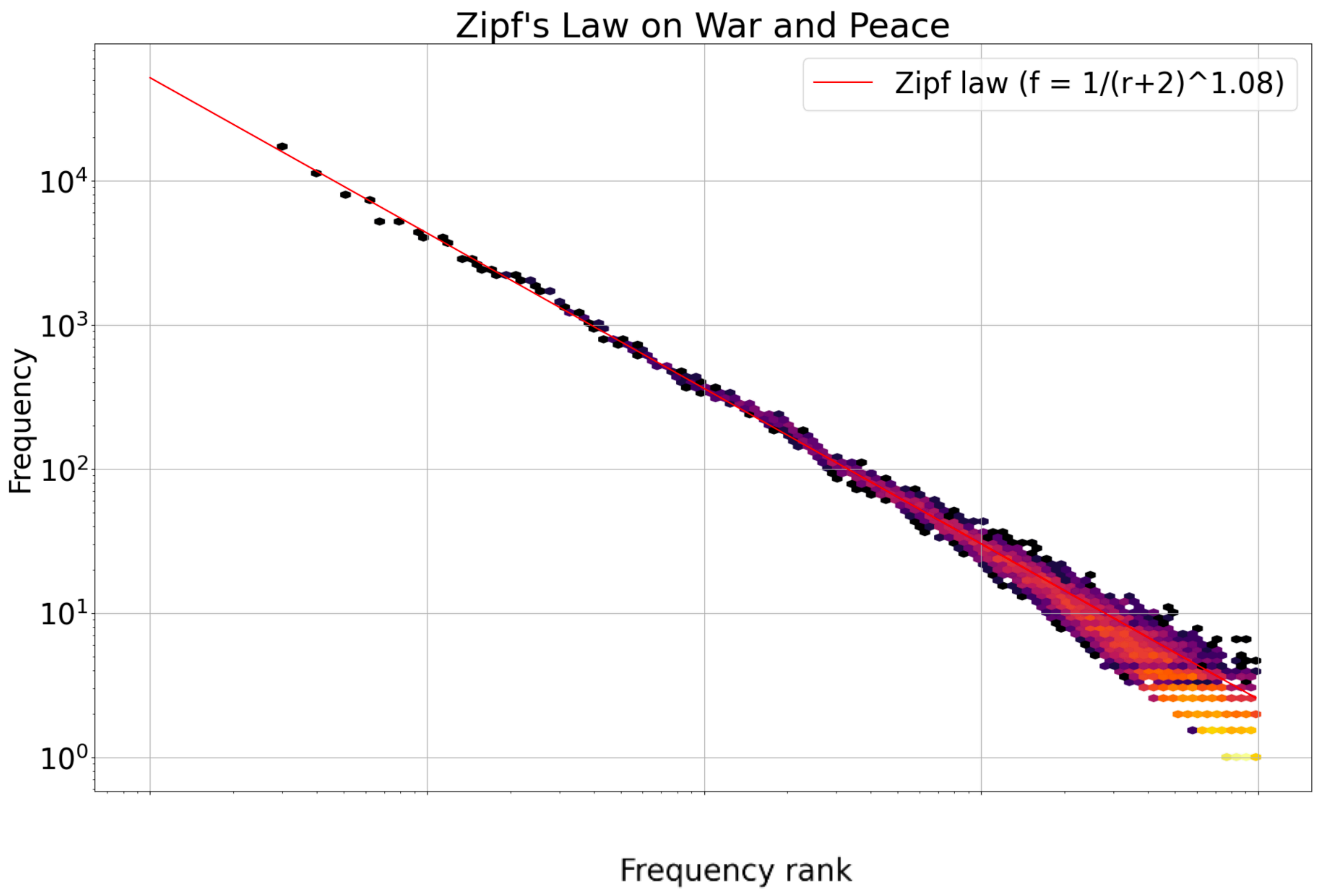
What does a count distribution look like?

Zipf's Law

The distribution over words resembles that of a power law:

- there will be a few words that are very frequent, and a long tail of words that are rare
- $freq_w(r) \approx r^{-s}$, where s is a constant

NLP algorithms must be especially robust to observations that do not occur or rarely occur in the training data

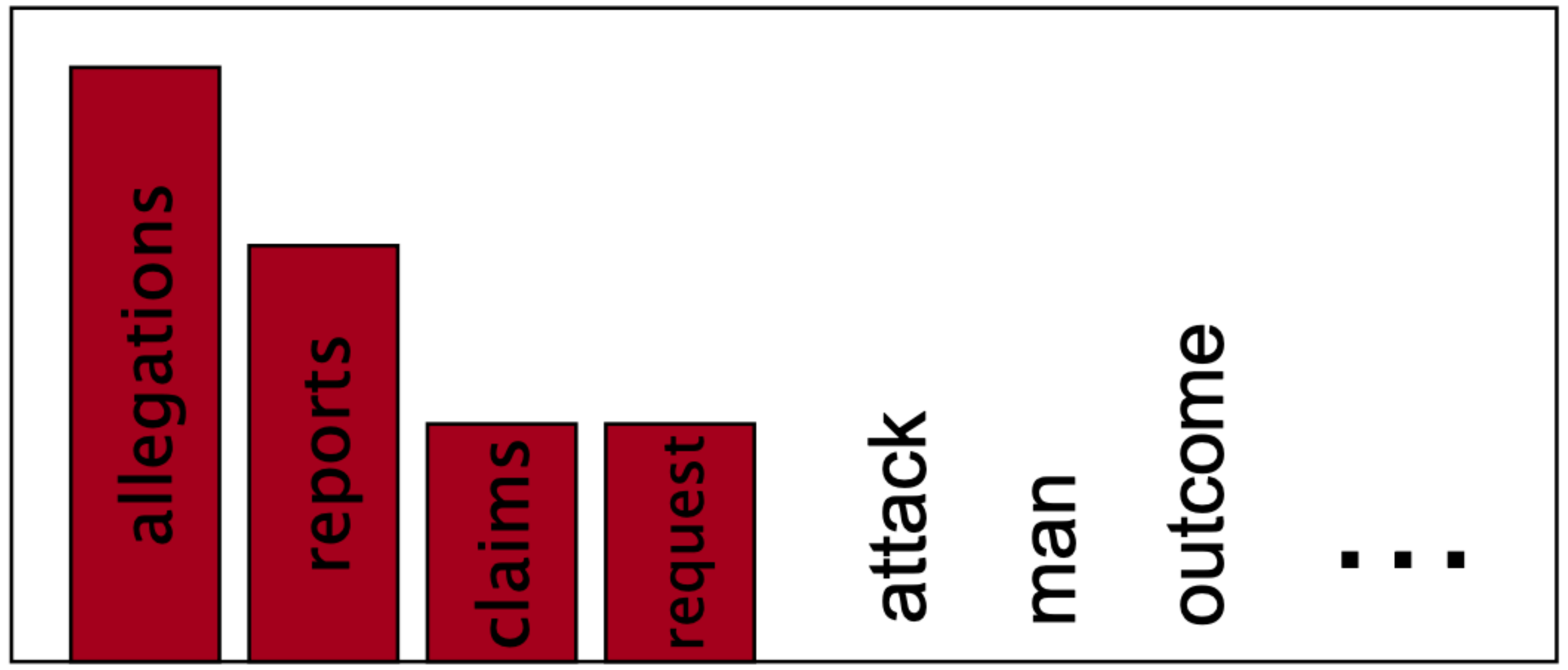


Zipf, G. K. (1949). Human behavior and the principle of least effort.

Smoothing ~ Massaging Probability Masses

When we have sparse statistics: $Count(w \mid \text{denied the})$

3 allegations
2 reports
1 claims
1 request
7 total



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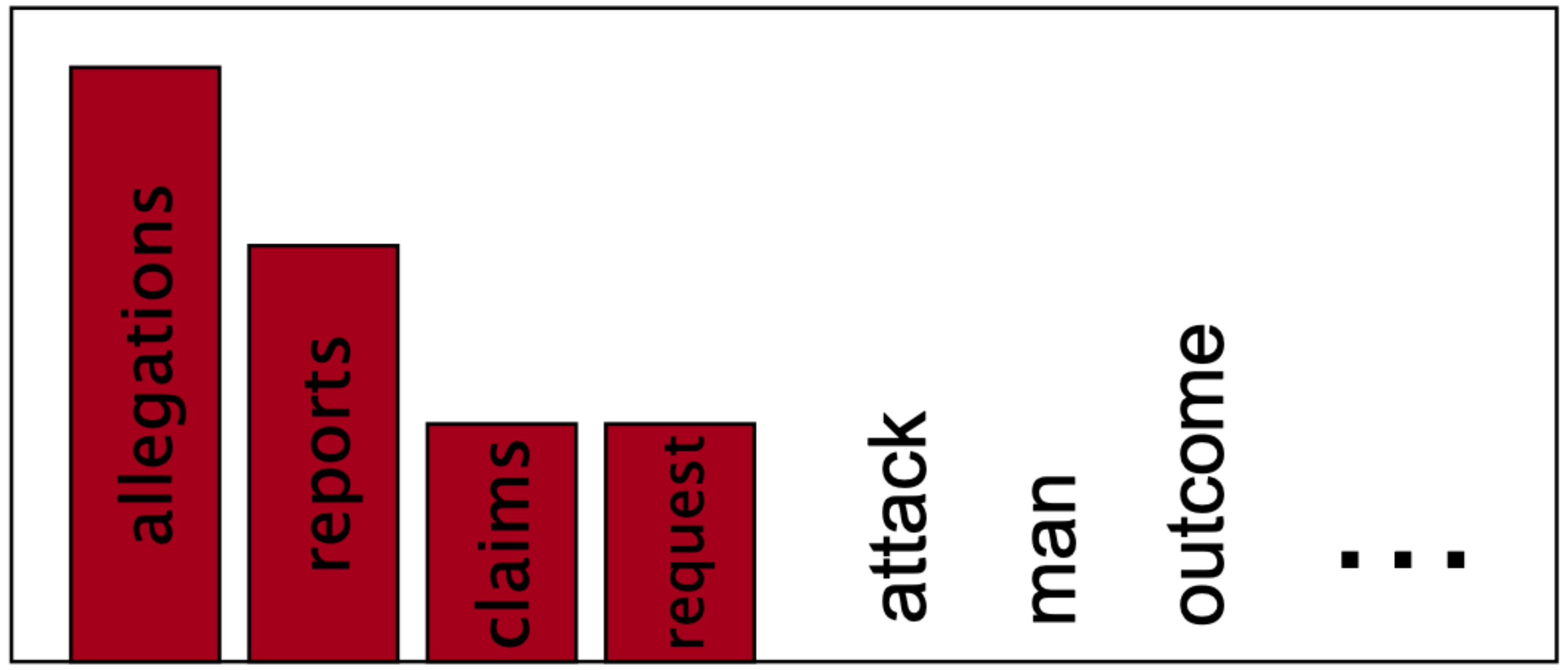
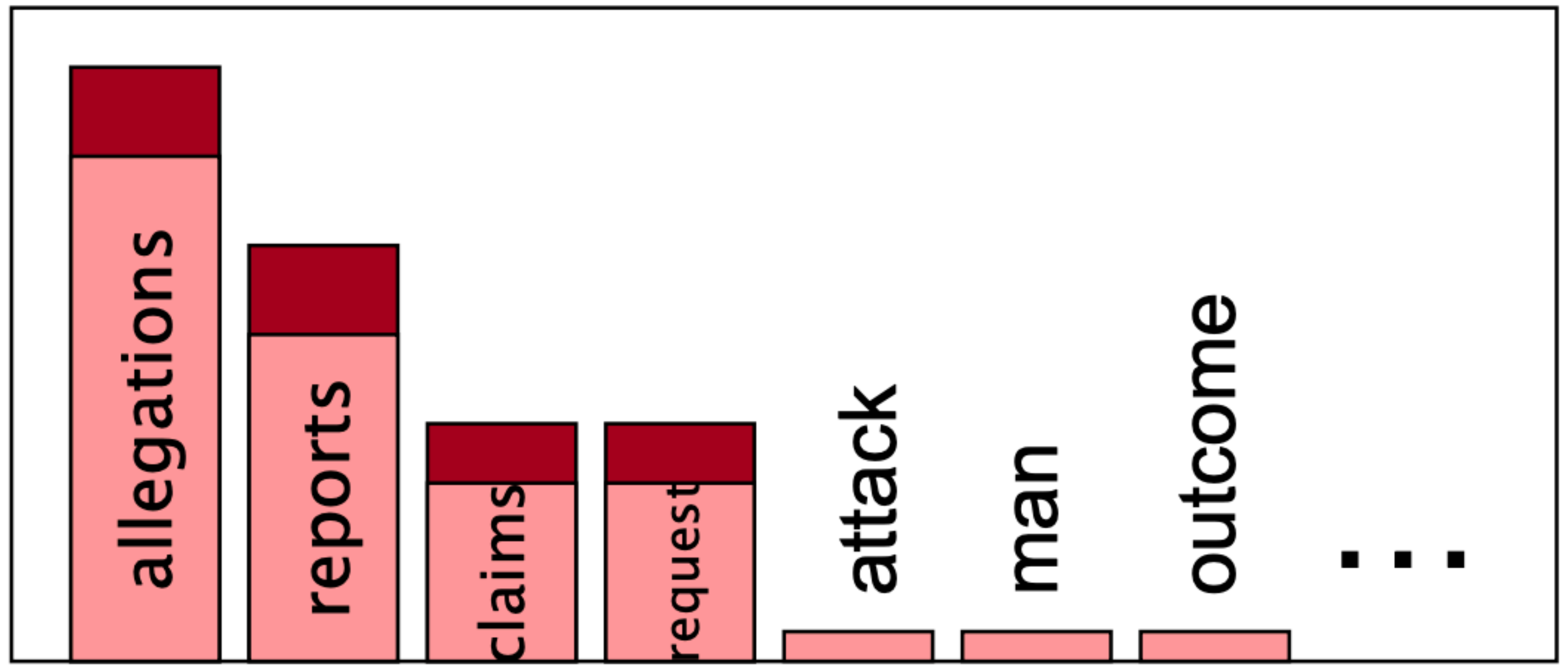
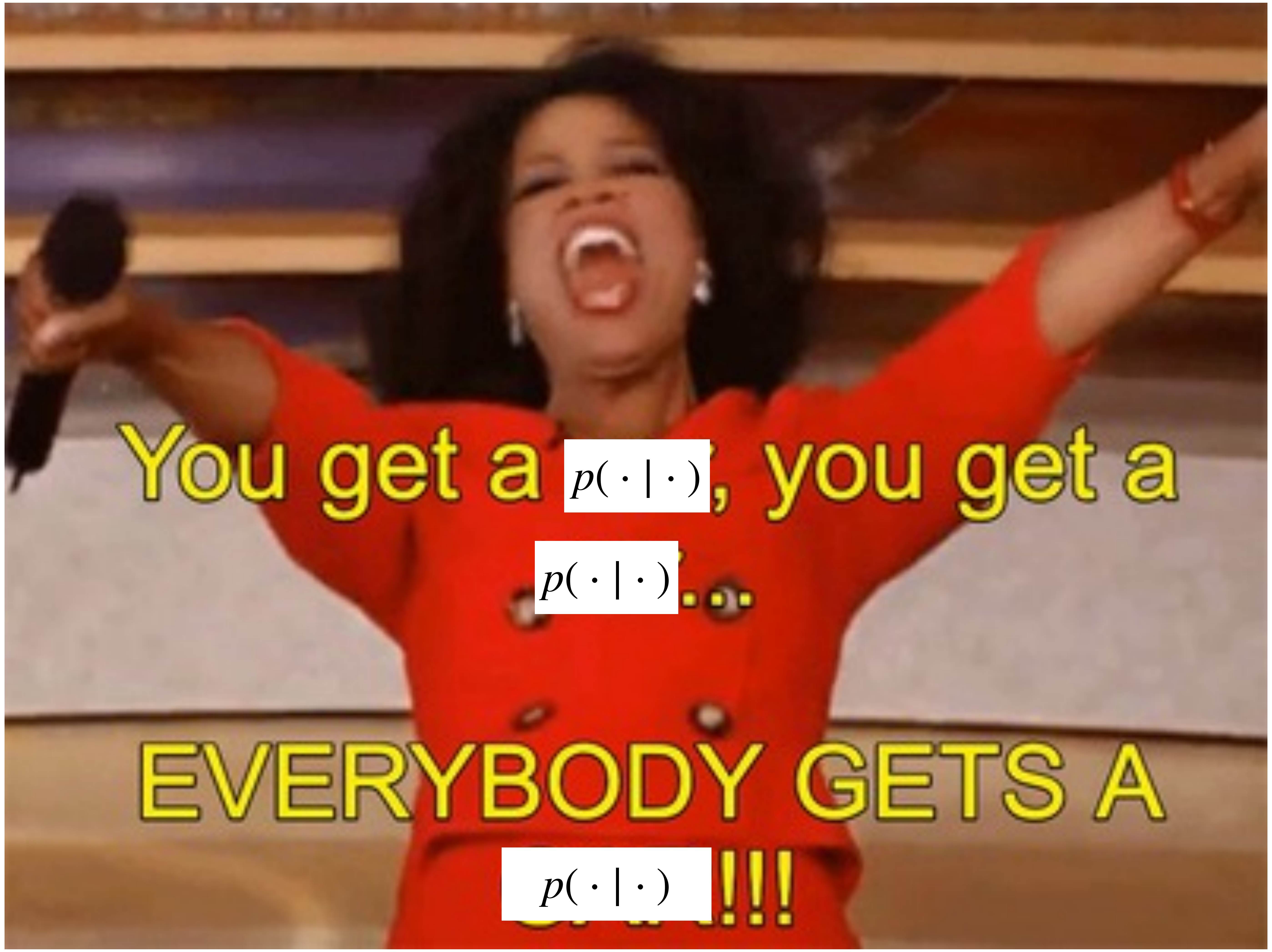


Steal probability mass to generalize better: $Count(w \mid \text{denied the})$

2.5 allegations
1.5 reports
0.5 claims
0.5 request
2 other
7 total




You get a $p(\cdot \mid \cdot)$, you get a
$p(\cdot \mid \cdot)$...
EVERYBODY GETS A
$p(\cdot \mid \cdot)$!!!

Add-One Estimation

MLE estimate

$$P_{MLE}(w_i) = \frac{c(w_i)}{\sum_w c(w)}$$

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$$P_{Add-1}(w_i) = \frac{c(w_i)+1}{\sum_w (c(w)+1)} = \frac{c(w_i)+1}{V + \sum_w c(w)}$$

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What happens to our P if we don't increase the denominator?

Add-1 Estimation Bigrams

MLE estimate

$$P_{MLE}(w_i \mid w_{i-1}) = \frac{c(w_{i-1}w_i)}{c(w_{i-1})}$$

Pretend we saw each **bigram** one more time than we did

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Keep the same denominator as before and reconstruct bigram counts

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$$= \frac{c^*(w_{i-1}w_i)}{c(w_{i-1})}$$

Recall: BRP Corpus

- can you tell me about any good cantonese restaurants close by
- mid priced thai food is what i'm looking for
- tell me about chez panisse
- can you give me a listing of the kinds of food that are available
- i'm looking for a good place to eat breakfast
- when is caffe venezia open during the day

Unigrams

i	want	to	eat	chinese	food	lunch	spend
2533	927	2417	746	158	1093	341	278

Bigrams

w_i

w_{i-1}

	i	want	to	eat	chinese	food	lunch	spend
i	5	827	0	9	0	0	0	2
want	2	0	608	1	6	6	5	1
to	2	0	4	686	2	0	6	211
eat	0	0	2	0	16	2	42	0
chinese	1	0	0	0	0	82	1	0
food	15	0	15	0	1	4	0	0
lunch	2	0	0	0	0	1	0	0
spend	1	0	1	0	0	0	0	0

Laplace-smoothed bigram counts

Just add one to all the counts!

USC Viterbi

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w_i (columns); w_{i-1} (rows)

	i	want	to	eat	chinese	food	lunch	spend
i	6	828	1	10	1	1	1	3
want	3	1	609	2	7	7	6	2
to	3	1	5	687	3	1	7	212
eat	1	1	3	1	17	3	43	1
chinese	2	1	1	1	1	83	2	1
food	16	1	16	1	2	5	1	1
lunch	3	1	1	1	1	2	1	1
spend	2	1	2	1	1	1	1	1

Laplace-smoothed bigram probabilities

$$P_{Add-1}\left(w_i \mid w_{i-1}\right) = \frac{c(w_{i-1}w_i) + 1}{c(w_{i-1}) + V}$$

	i	want	to	eat	chinese	food	lunch	spend
i	0.0015	0.21	0.00025	0.0025	0.00025	0.00025	0.00025	0.00075
want	0.0013	0.00042	0.26	0.00084	0.0029	0.0029	0.0025	0.00084
to	0.00078	0.00026	0.0013	0.18	0.00078	0.00026	0.0018	0.055
eat	0.00046	0.00046	0.0014	0.00046	0.0078	0.0014	0.02	0.00046
chinese	0.0012	0.00062	0.00062	0.00062	0.00062	0.052	0.0012	0.00062
food	0.0063	0.00039	0.0063	0.00039	0.00079	0.002	0.00039	0.00039
lunch	0.0017	0.00056	0.00056	0.00056	0.00056	0.0011	0.00056	0.00056
spend	0.0012	0.00058	0.0012	0.00058	0.00058	0.00058	0.00058	0.00058

Reconstituted Counts

$$c*(w_{i-1}w_i) = \frac{[c(w_{i-1}w_i)+1]c(w_{i-1})}{c(w_{i-1})+V}$$

	i	want	to	eat	chinese	food	lunch	spend
i	3.8	527	0.64	6.4	0.64	0.64	0.64	1.9
want	1.2	0.39	238	0.78	2.7	2.7	2.3	0.78
to	1.9	0.63	3.1	430	1.9	0.63	4.4	133
eat	0.34	0.34	1	0.34	5.8	1	15	0.34
chinese	0.2	0.098	0.098	0.098	0.098	8.2	0.2	0.098
food	6.9	0.43	6.9	0.43	0.86	2.2	0.43	0.43
lunch	0.57	0.19	0.19	0.19	0.19	0.38	0.19	0.19
spend	0.32	0.16	0.32	0.16	0.16	0.16	0.16	0.16

Compare with raw bigram counts

Original, Raw

	i	want	to	eat	chinese	food	lunch	spend
i	5	827	0	9	0	0	0	2
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Add-k smoothing

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Add-k smoothing

k is a hyperparameter

Add-1 Estimation: Last thoughts

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- One-size-fits-all

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So add-1 isn't used for n-grams, being something of a blunt instrument

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Add-1 is used to smooth other NLP models though…

- For text classification (Naïve Bayes)
- In domains where the number of zeros isn't so huge

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- Condition on less context for contexts you haven’t learned much about

Interpolation

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Interpolation works better than Add-1 / Laplace

Linear Interpolation

Linear Interpolation

$$\hat{P}(w_i \mid w_{i-2}w_{i-1}) = \lambda_1 P(w_i)$$
$$+\lambda_2 P(w_i \mid w_{i-1})$$
$$+\lambda_3 P(w_i \mid w_{i-2}w_{i-1})$$

Linear Interpolation

Simple Interpolation

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USC Viterbi

Linear Interpolation

Simple Interpolation

$$\hat{P}(w_i \mid w_{i-2}w_{i-1}) = \lambda_1 P(w_i) + \lambda_2 P(w_i \mid w_{i-1}) + \lambda_3 P(w_i \mid w_{i-2}w_{i-1})$$

$$\sum_k \lambda_k = 1$$

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Context-Conditional Interpolation

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Different for every unique context

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Hyperparameters!

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Different for different bigrams!
Serve as Reconstituted Counts

Different for every unique context

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n-grams Today

Infini-gram: Scaling Unbounded *n*-gram Language Models to a Trillion Tokens

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Luke Zettlemoyer[♡] **Yejin Choi**[♡♠] **Hannaneh Hajishirzi**[♡♠]
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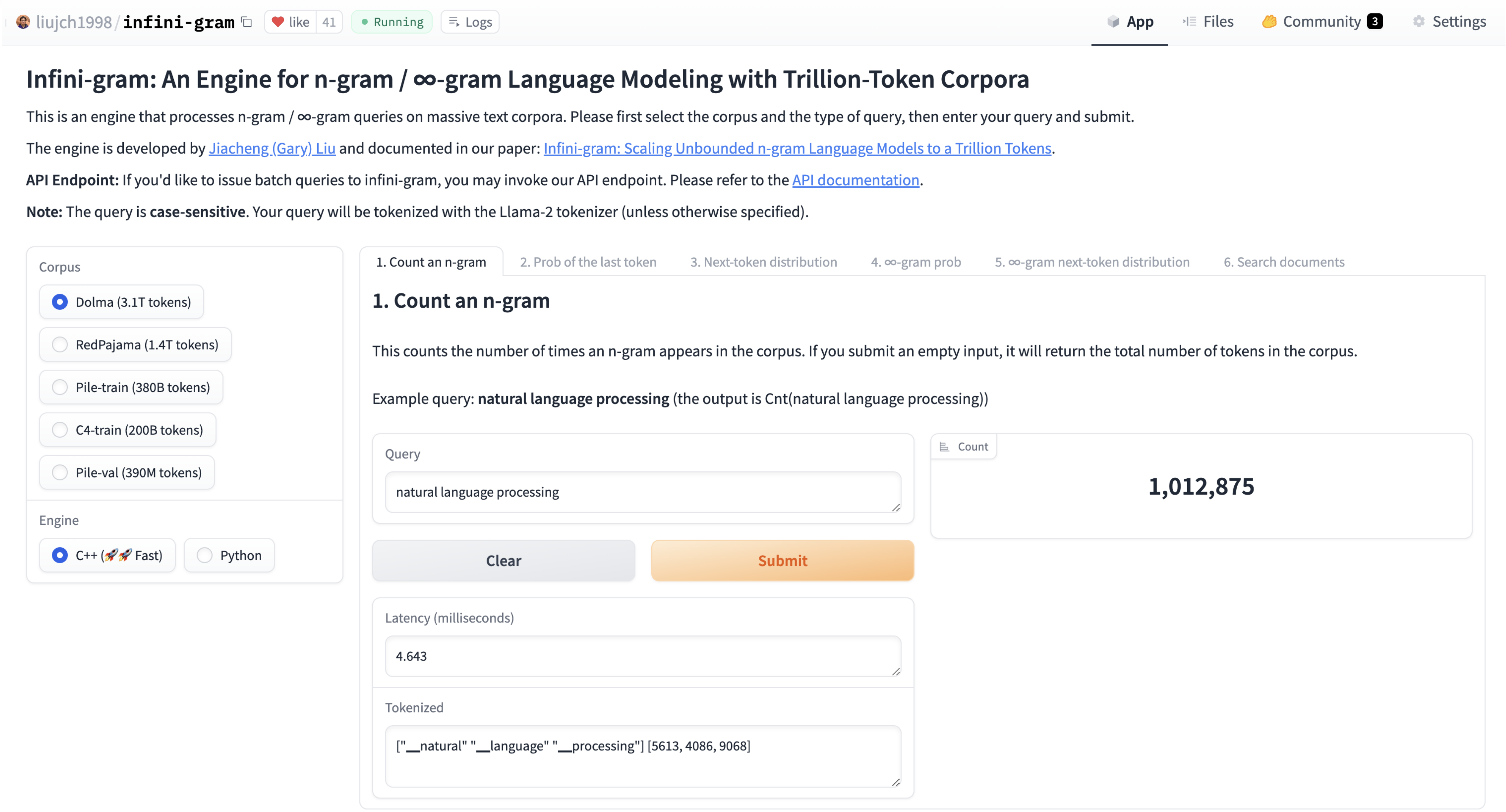

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Lecture Outline

- Announcements
- Recap
  - n-gram Language Models
  - Zeros!
- Smoothing
- Basics of Supervised Machine Learning
  I. Data: Preprocessing and Feature Extraction
  II. Model:
      I. Logistic Regression
  III. Loss
  IV. Optimization Algorithm
  V. Inference

Basics of Supervised Machine Learning

Ingredients of Supervised Machine Learning

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  - A classification function that computes $\hat{y}$, the estimated class, via $p(y \mid x)$

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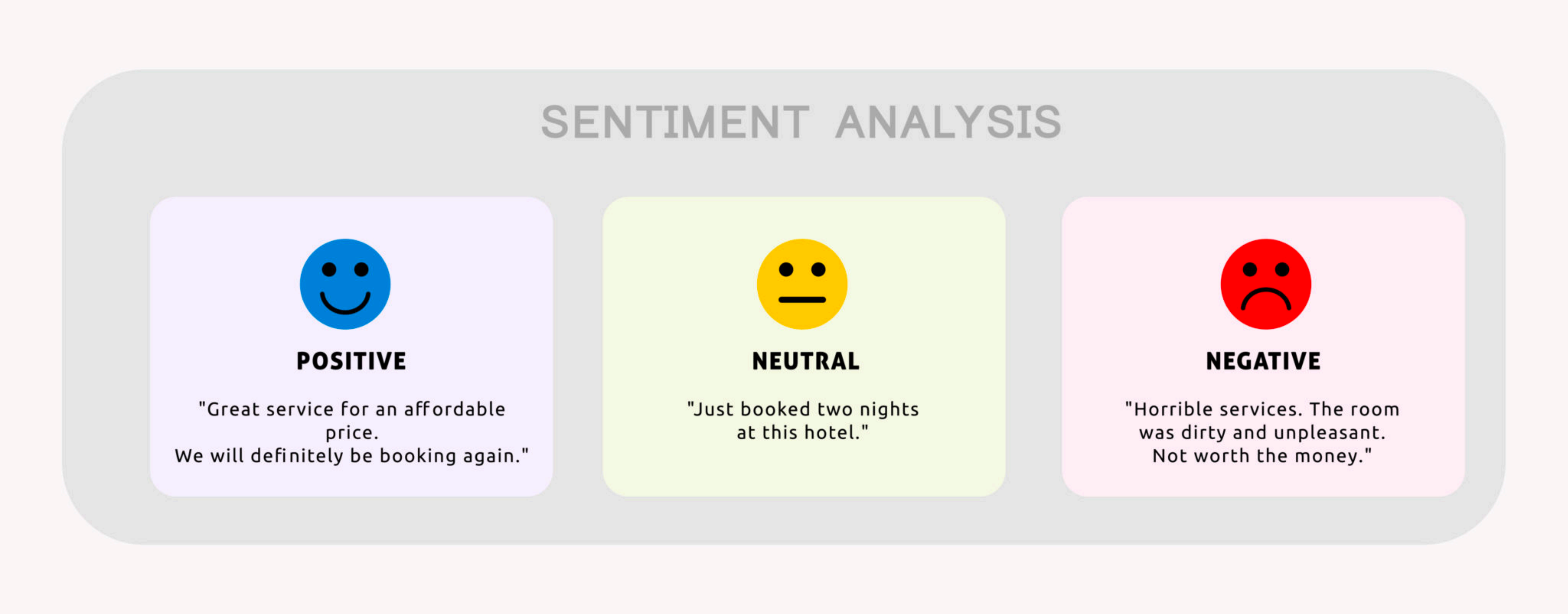
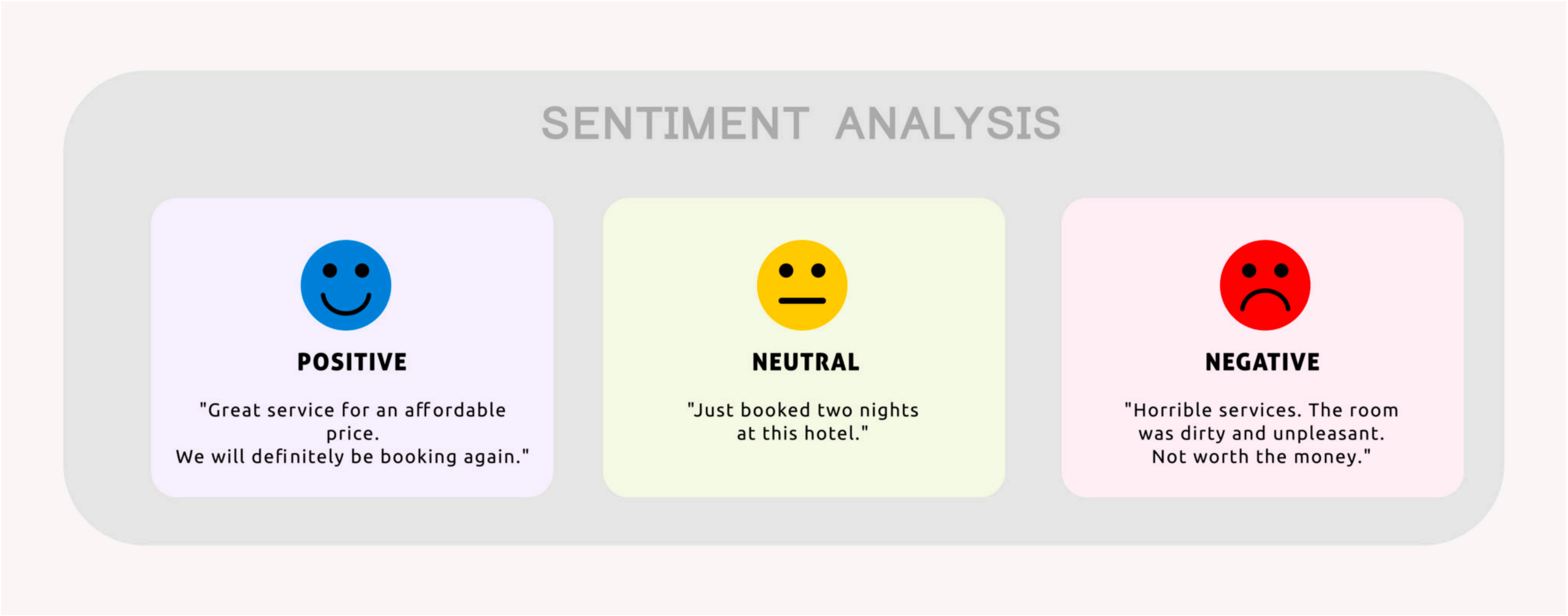
Learning Phase

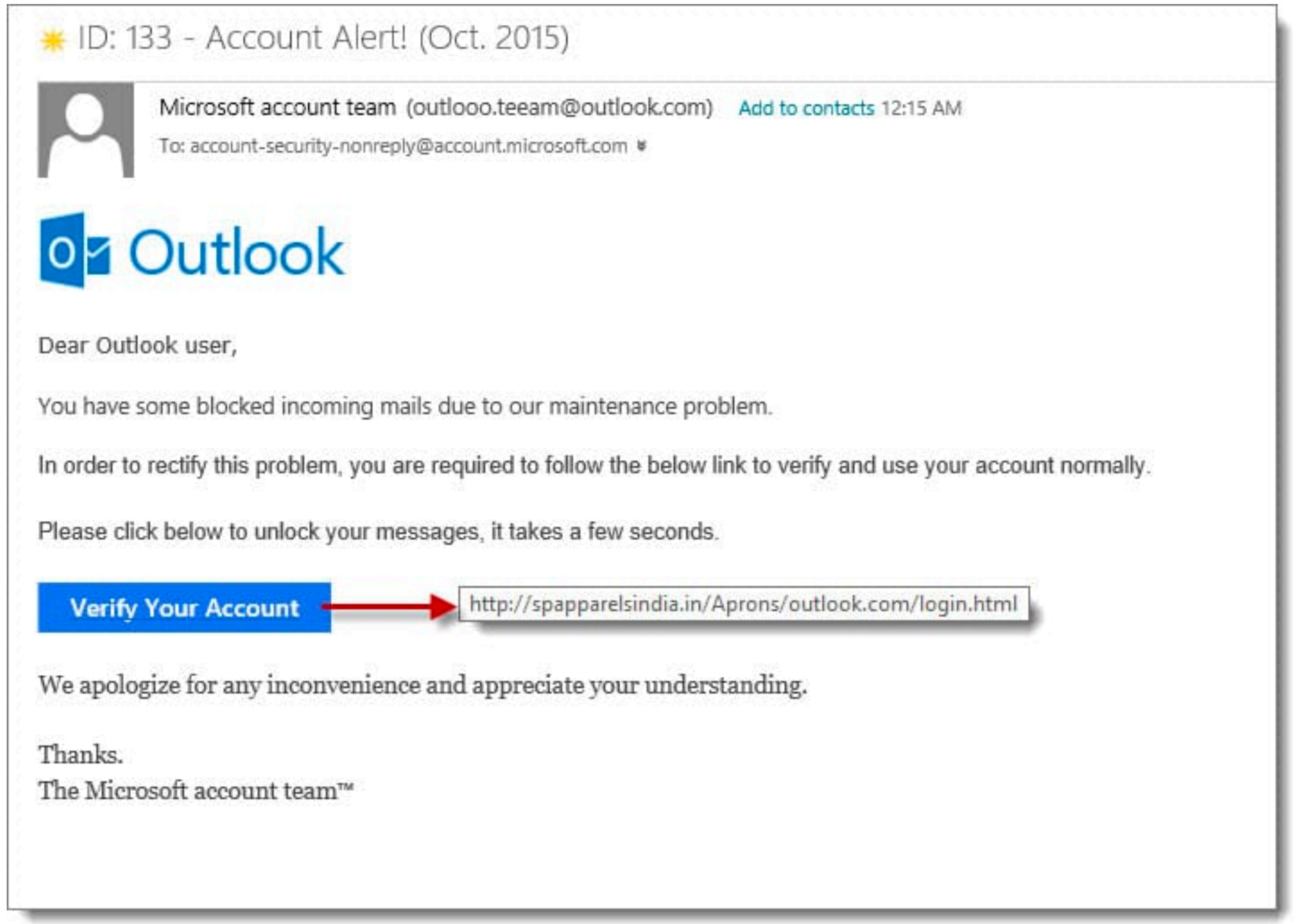
Text Classification Tasks

Text Classification Tasks



Text Classification Tasks





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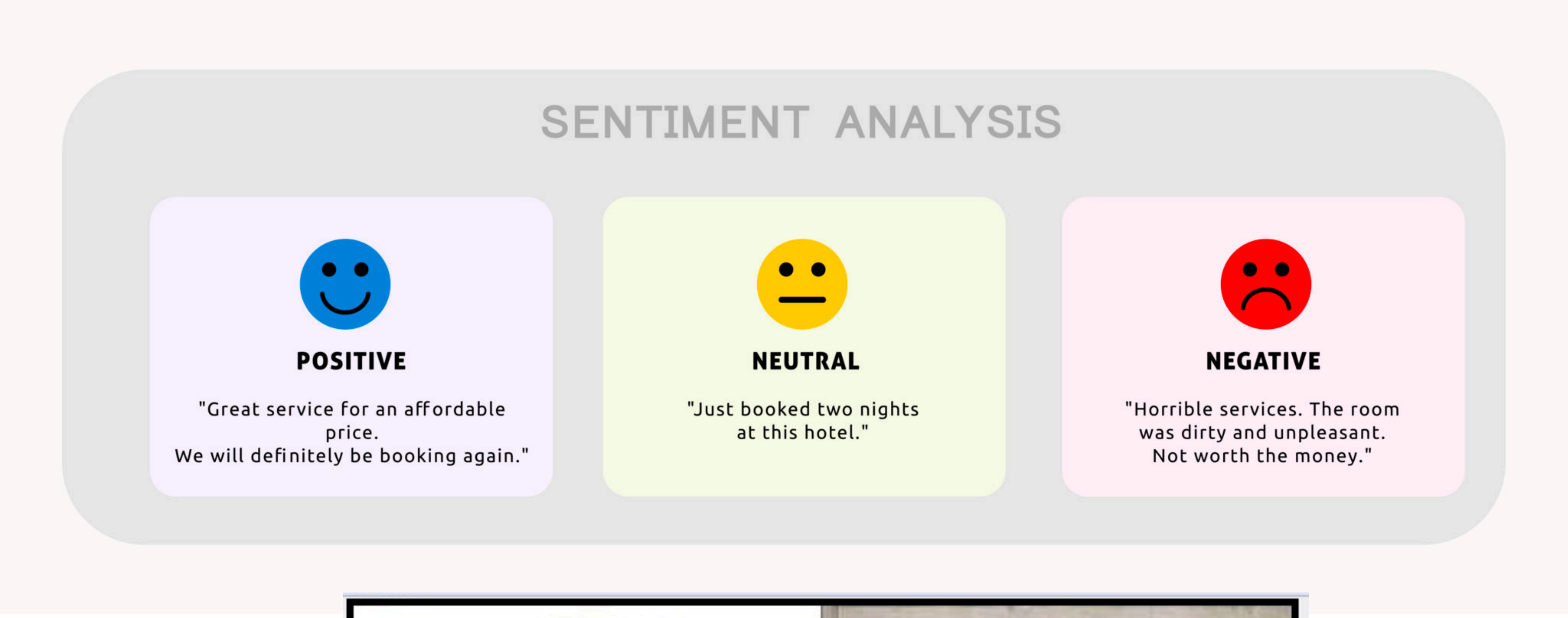

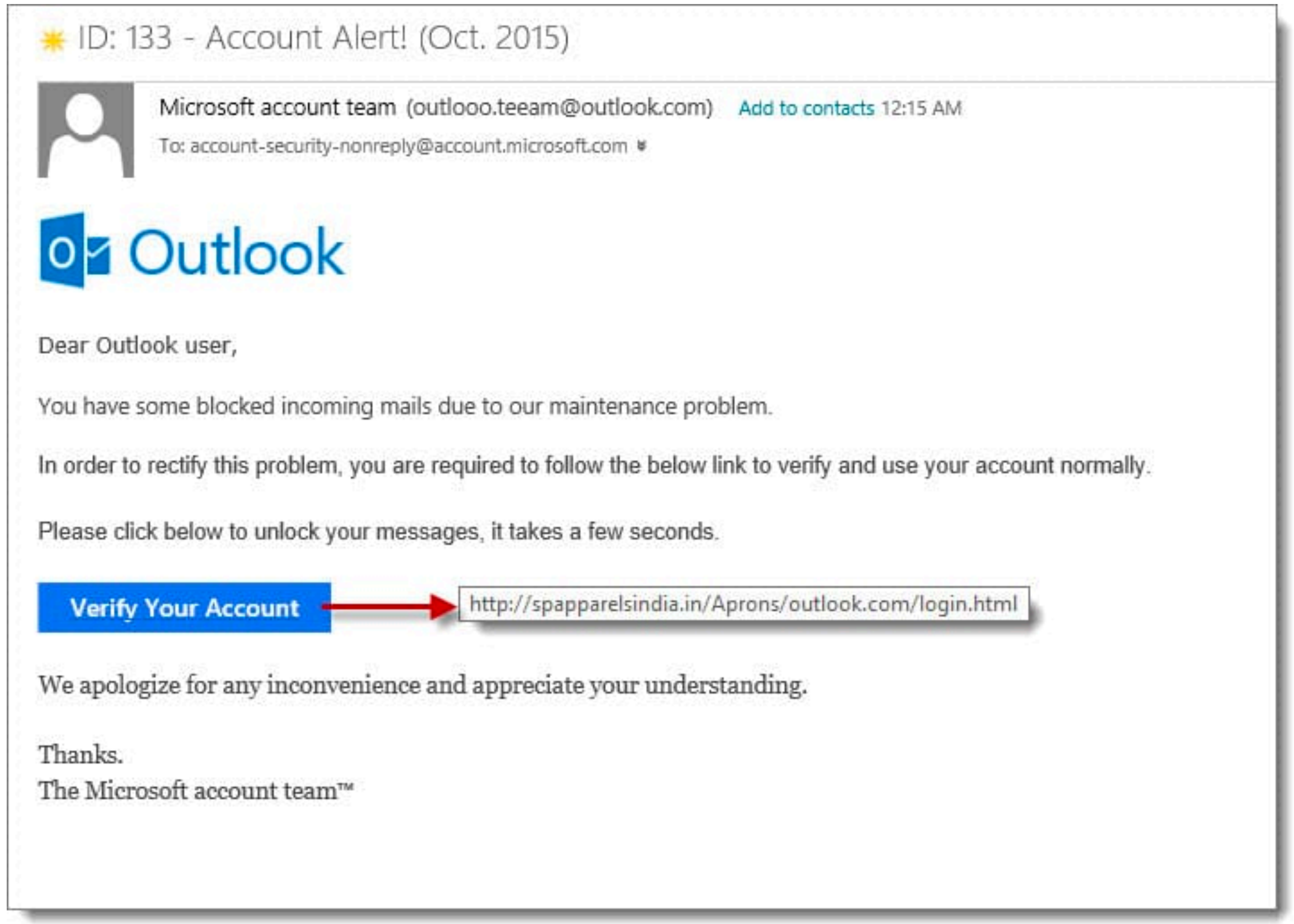

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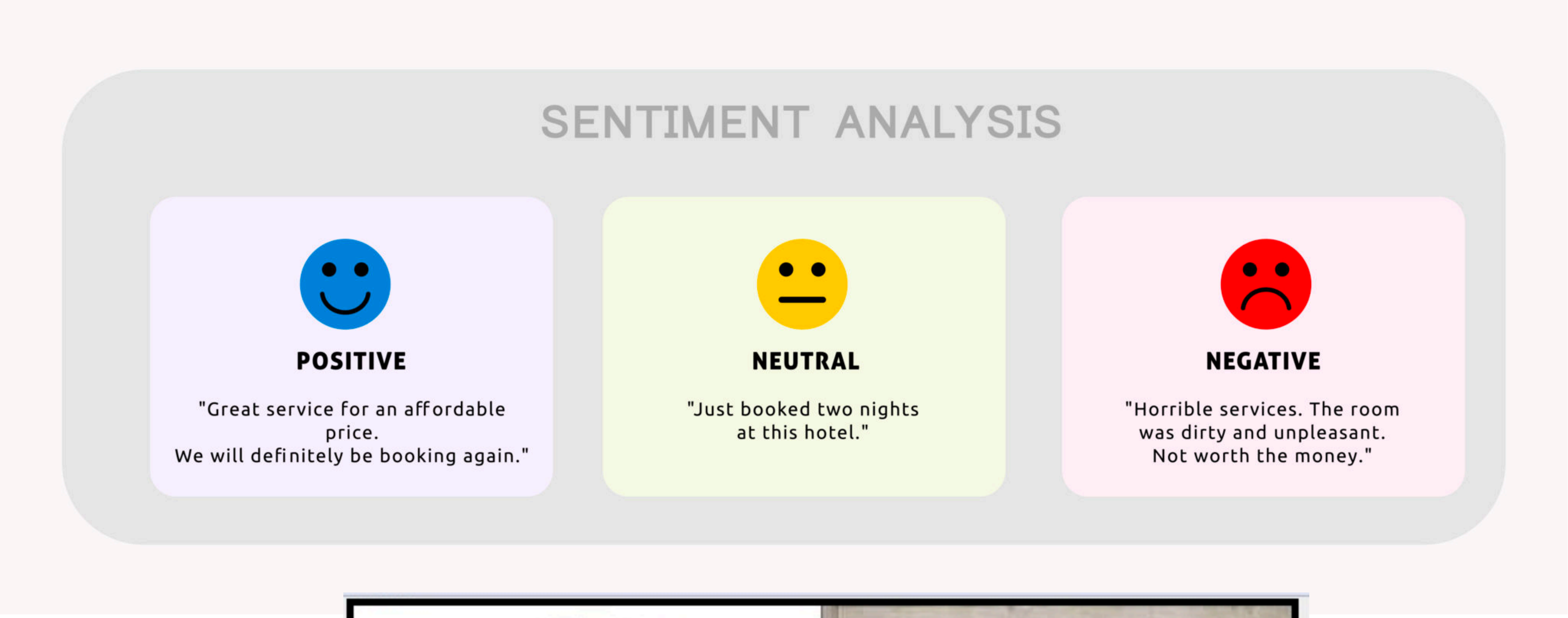

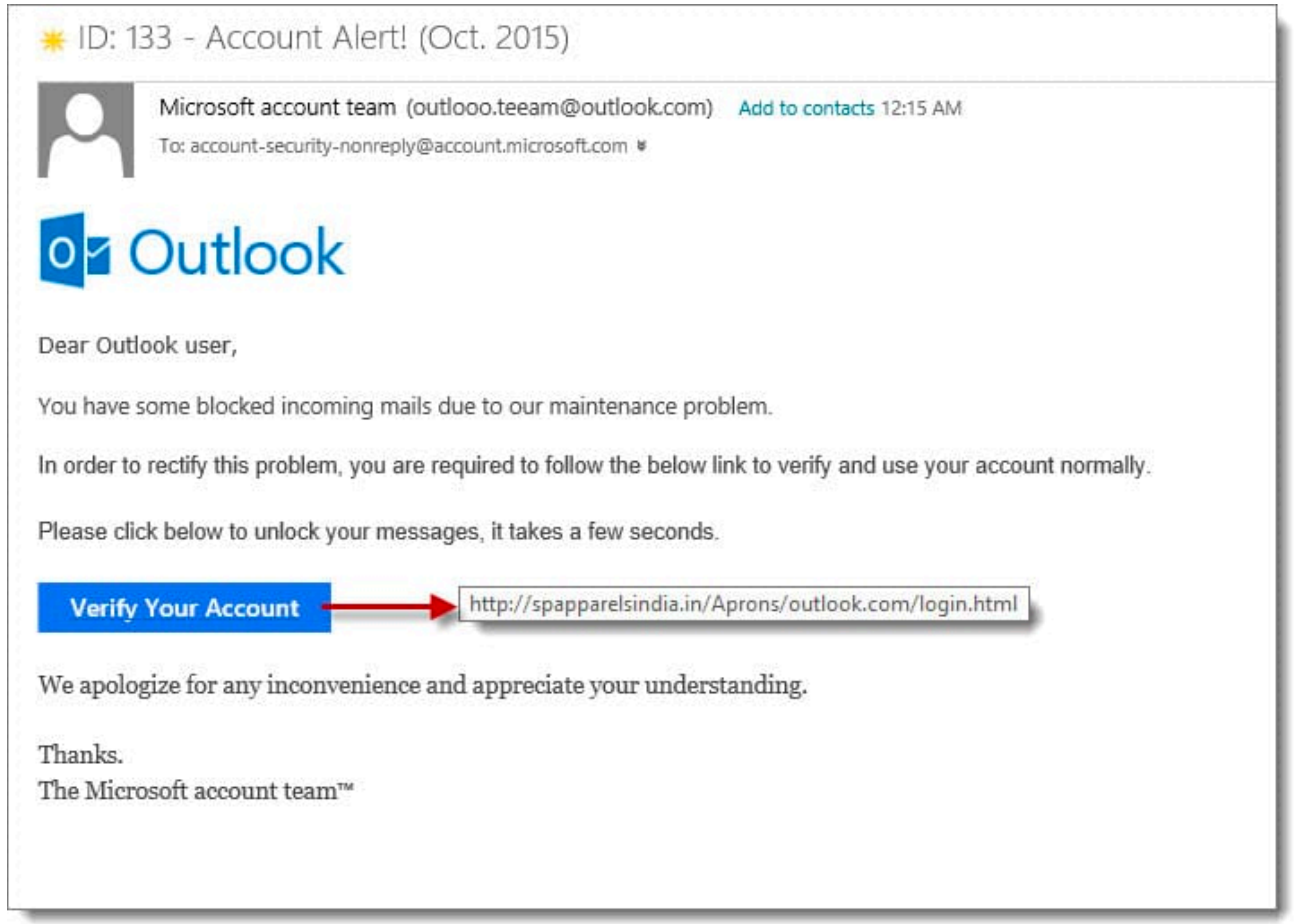

Not just NLP, classification is a general ML technique often applied across a wide variety of prediction tasks!

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- Input:
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    - Each observation $x^{(i)}$ is represented by a feature vector $\mathbf{x}^{(i)} = [x_1^{(i)}, x_2^{(i)}, \ldots, x_d^{(i)}]$

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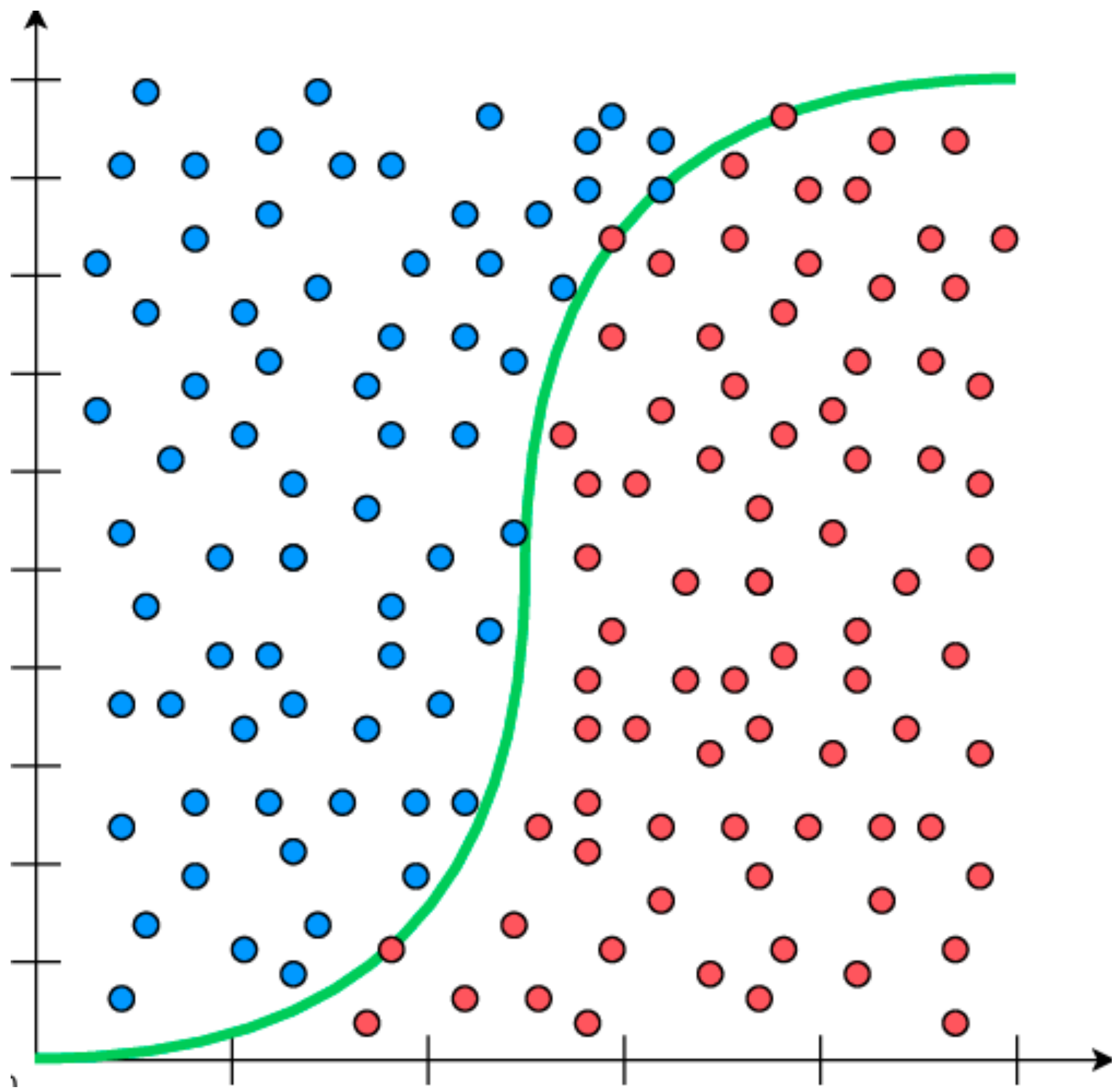

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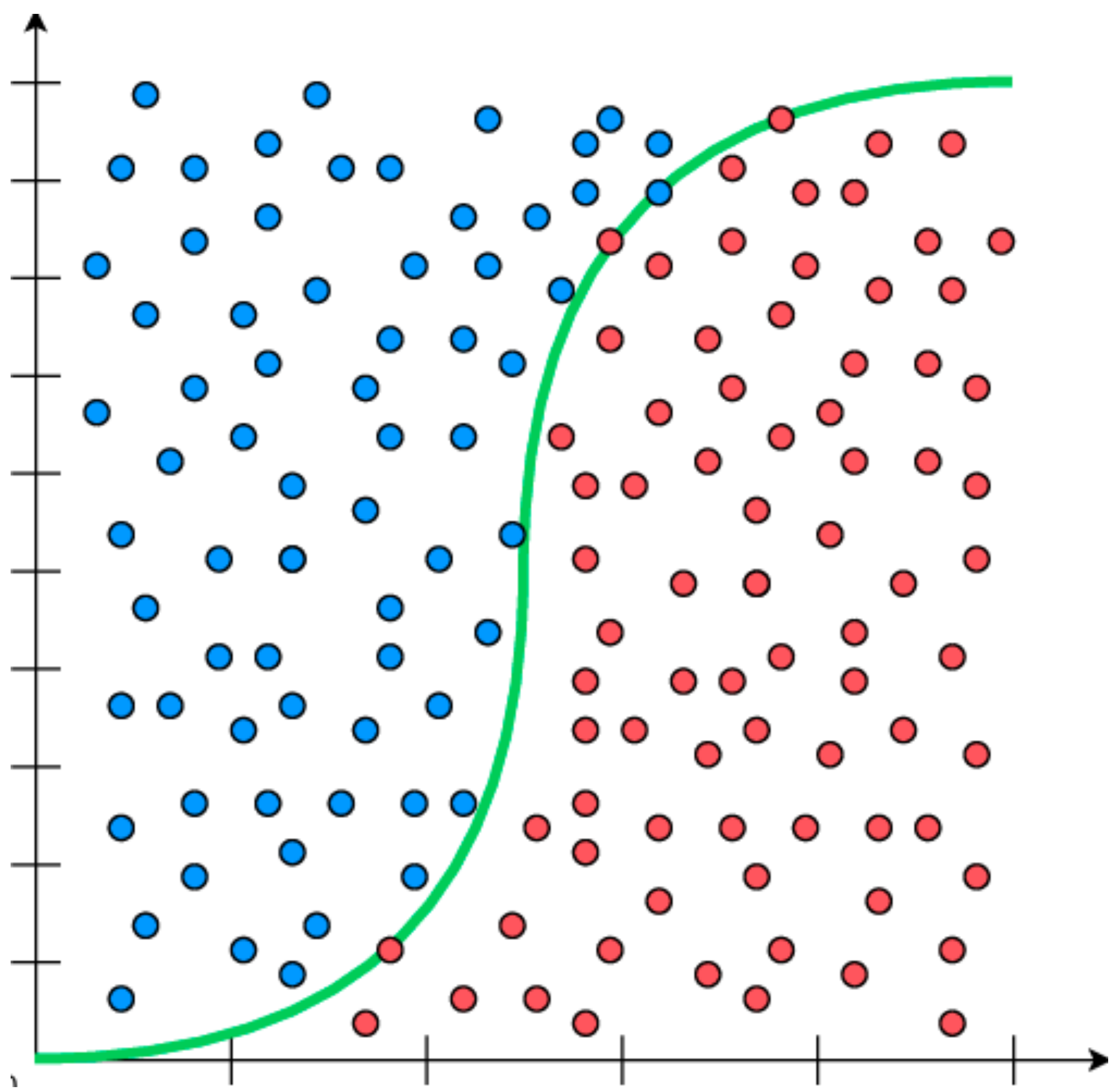

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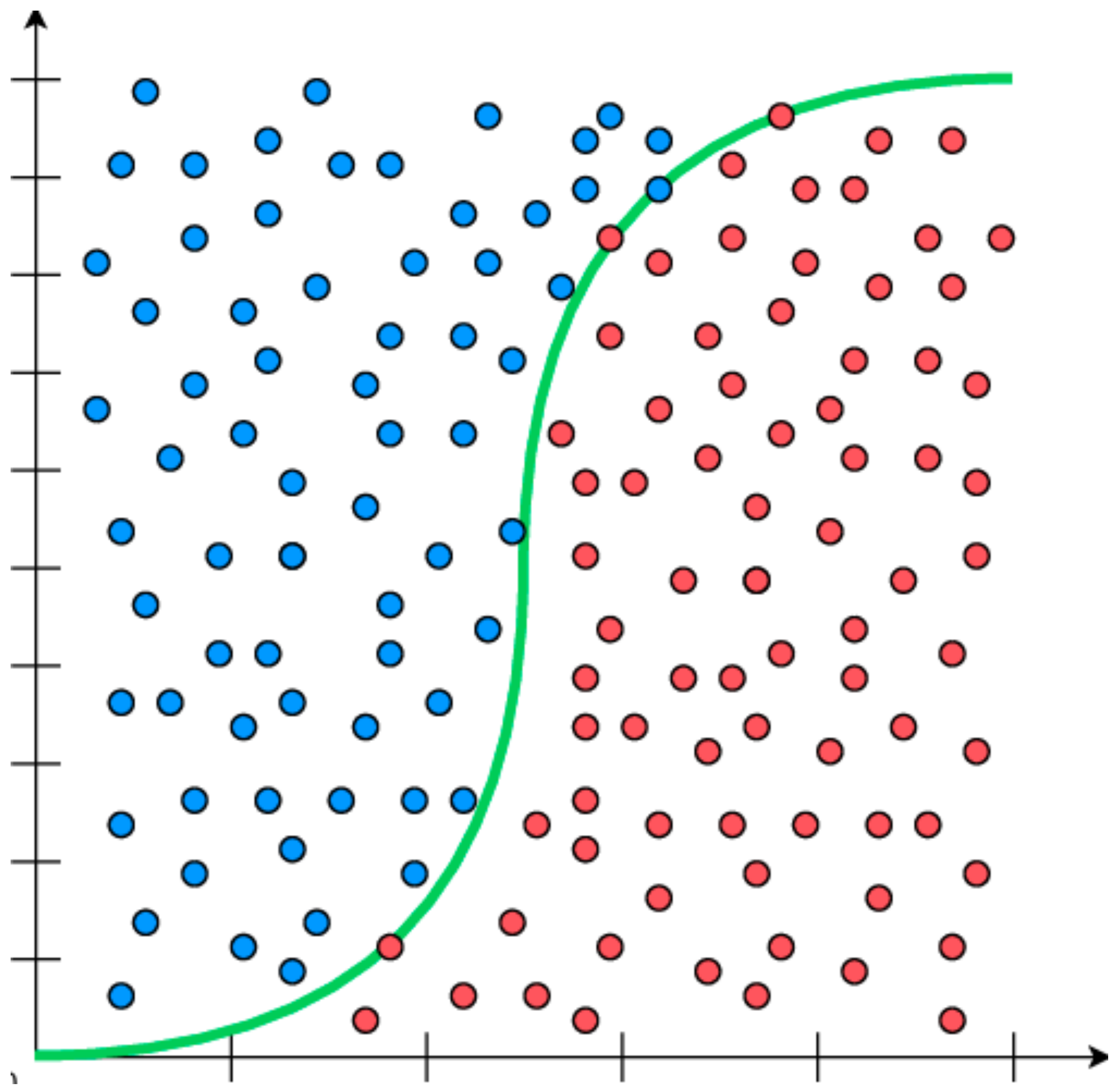

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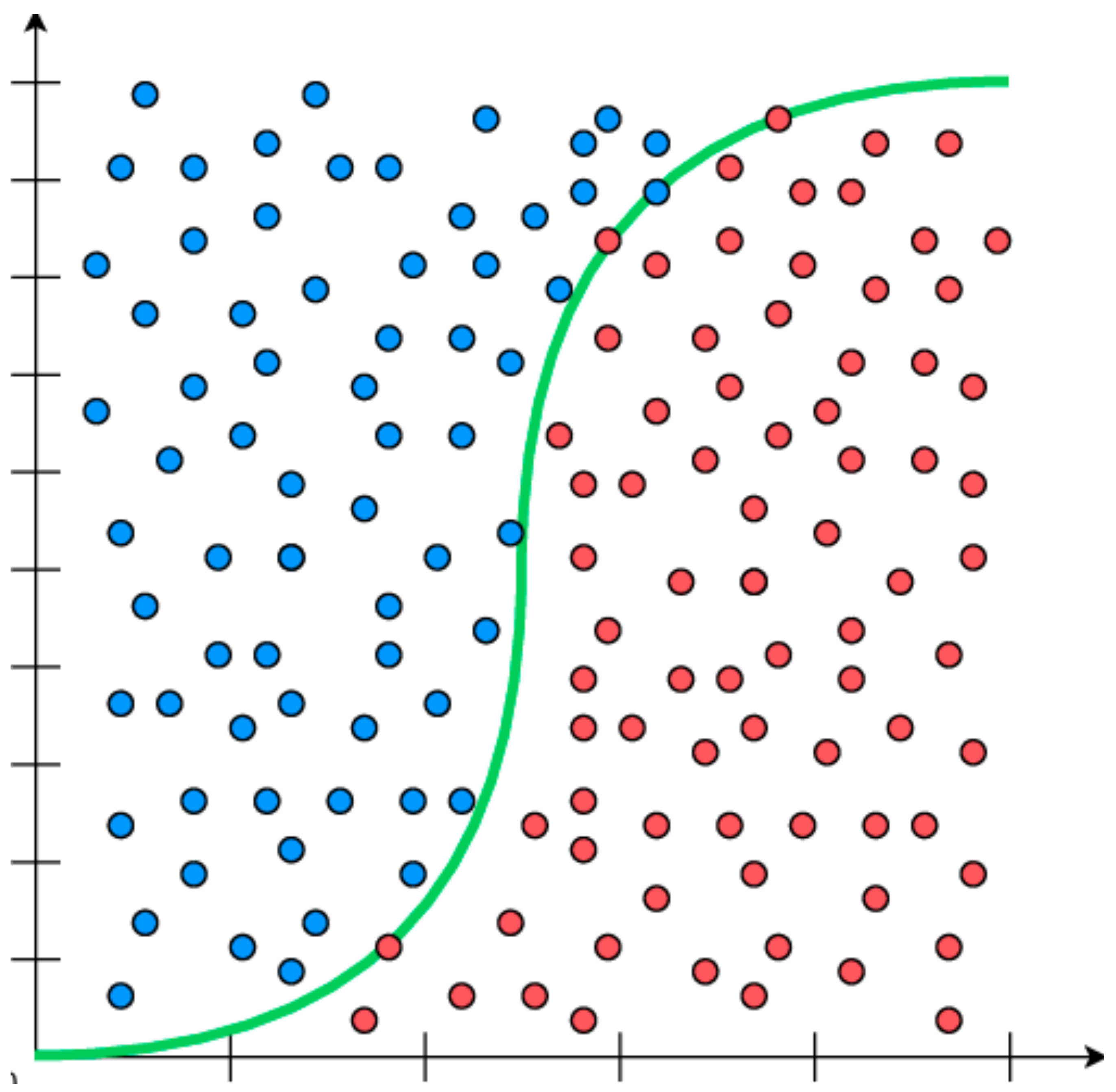

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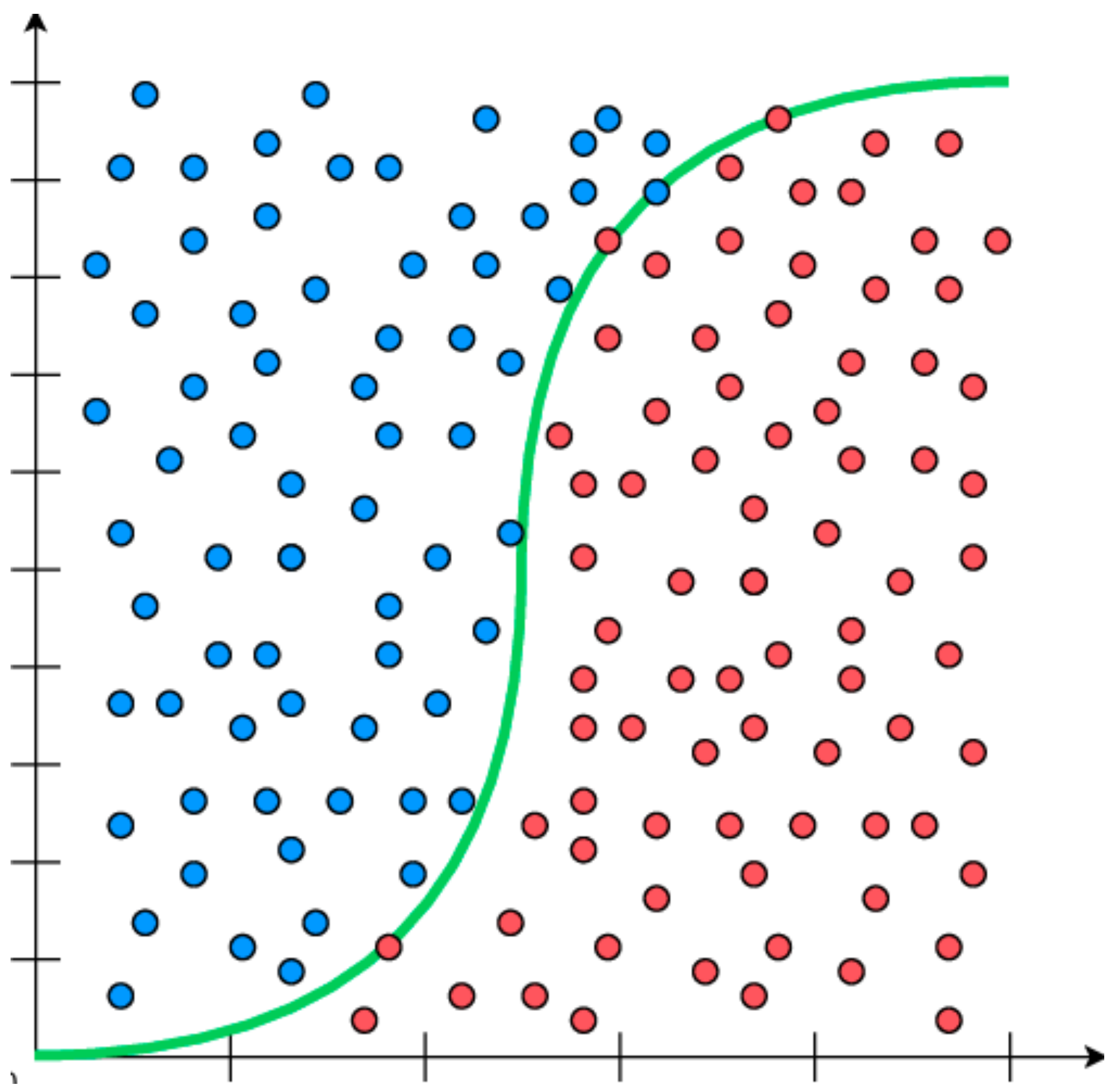
- Goal of Binary Classification
  - At test time, for input x^{test}, compute an output: a predicted class $\hat{y}^{test} \in \{0,1\}$



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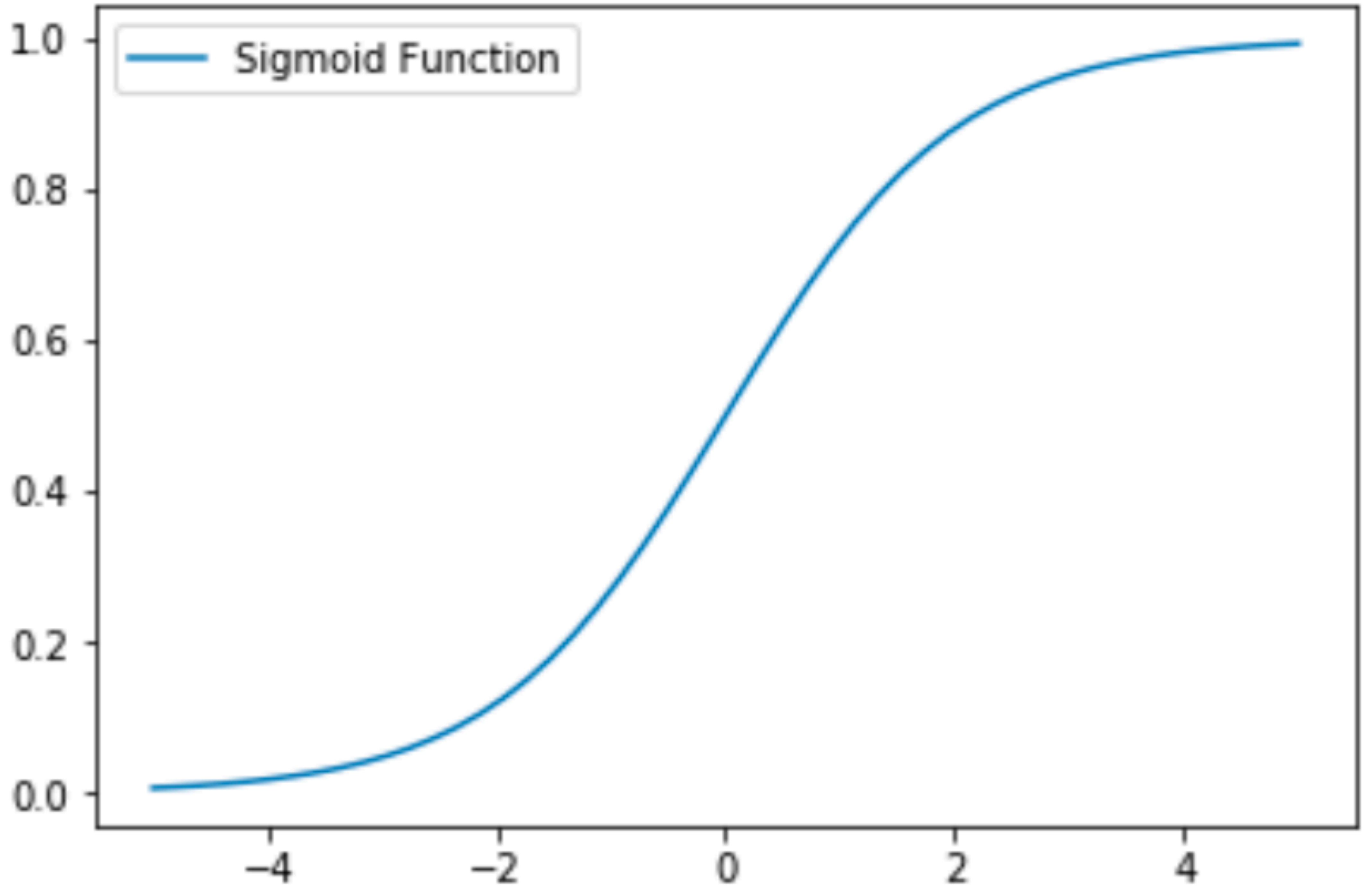
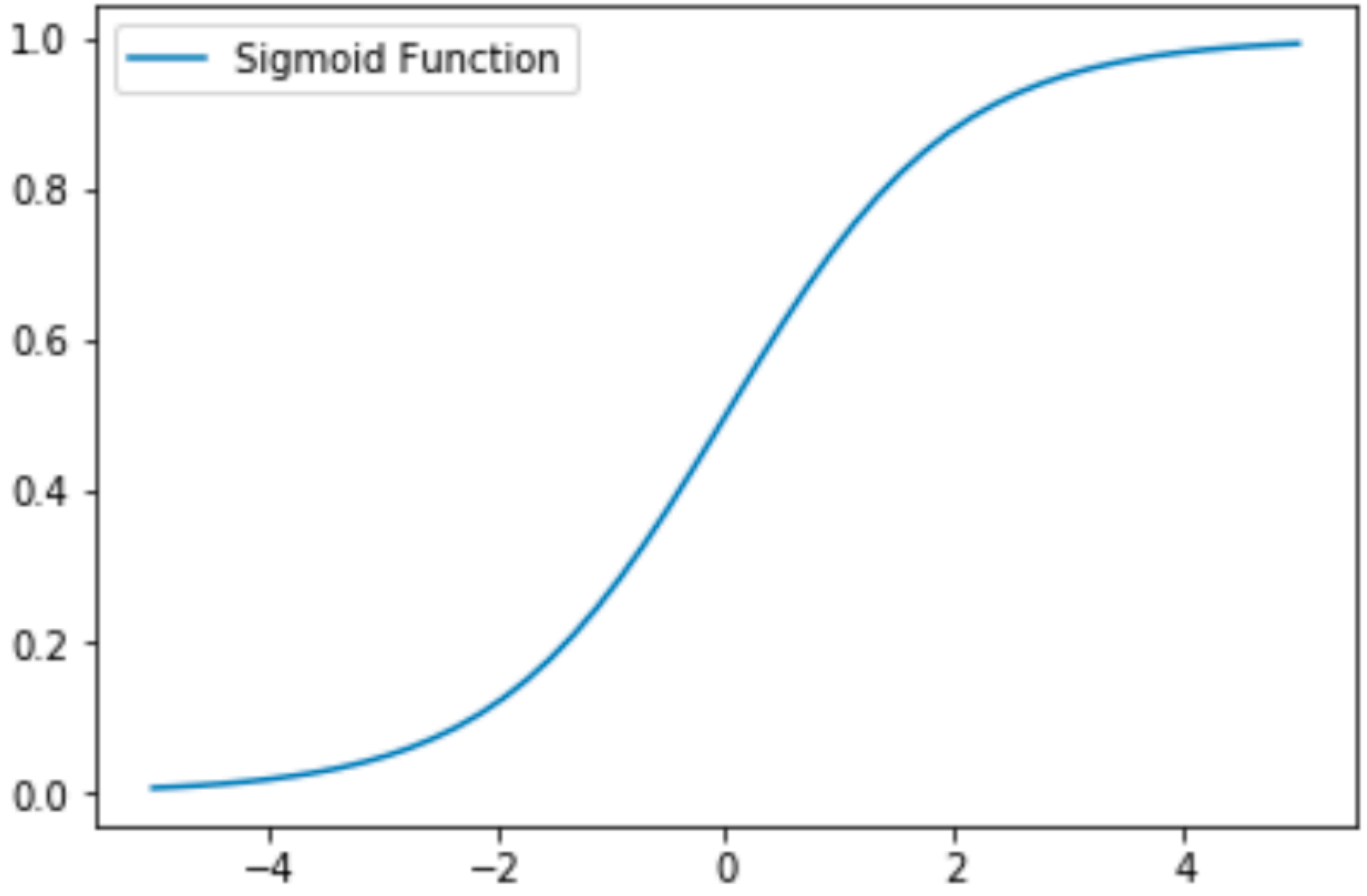


Example: Logistic Regression

- Important analytic tool in natural and social sciences



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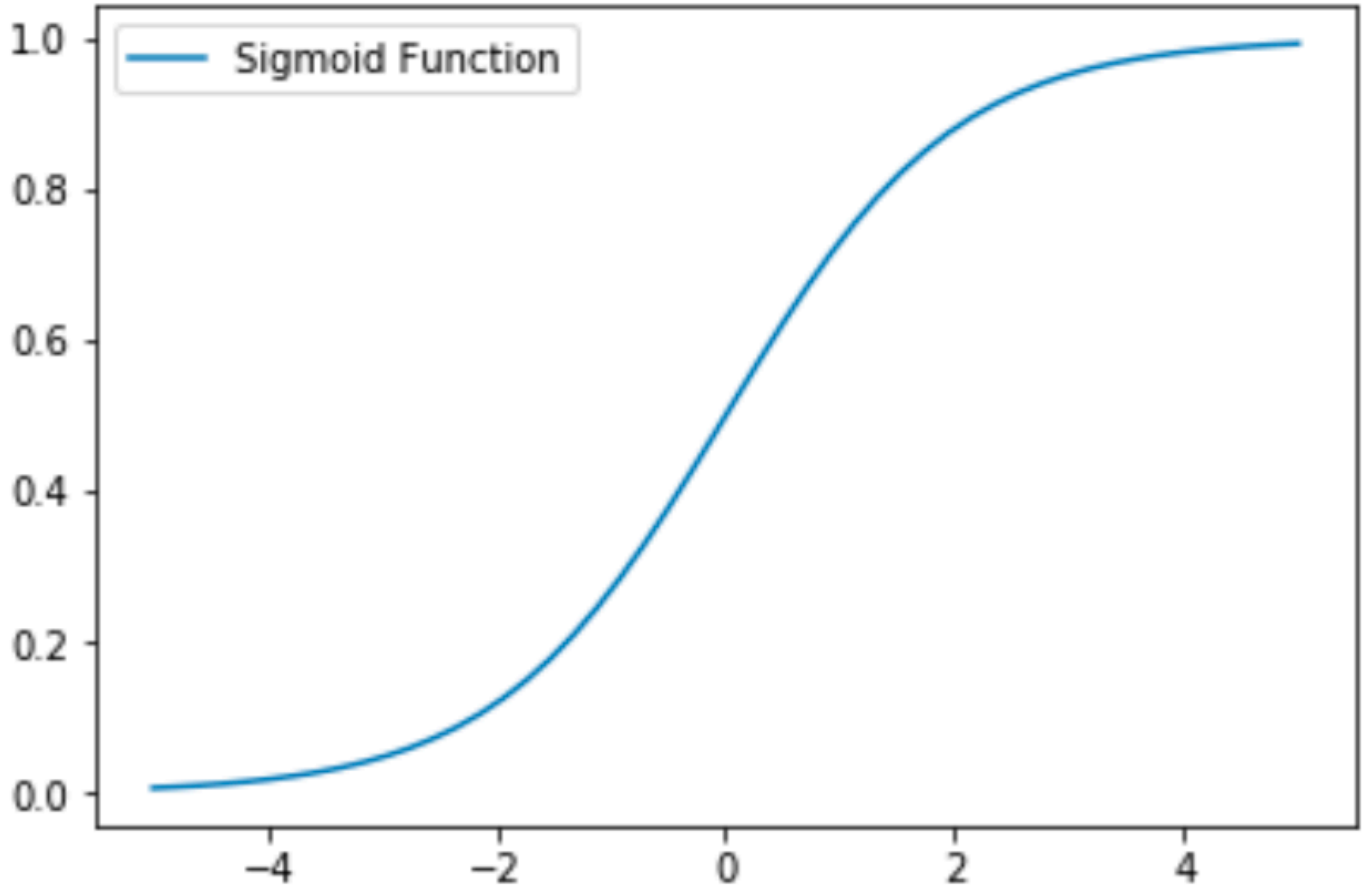
- Important analytic tool in natural and social sciences
- Baseline supervised machine learning tool for classification



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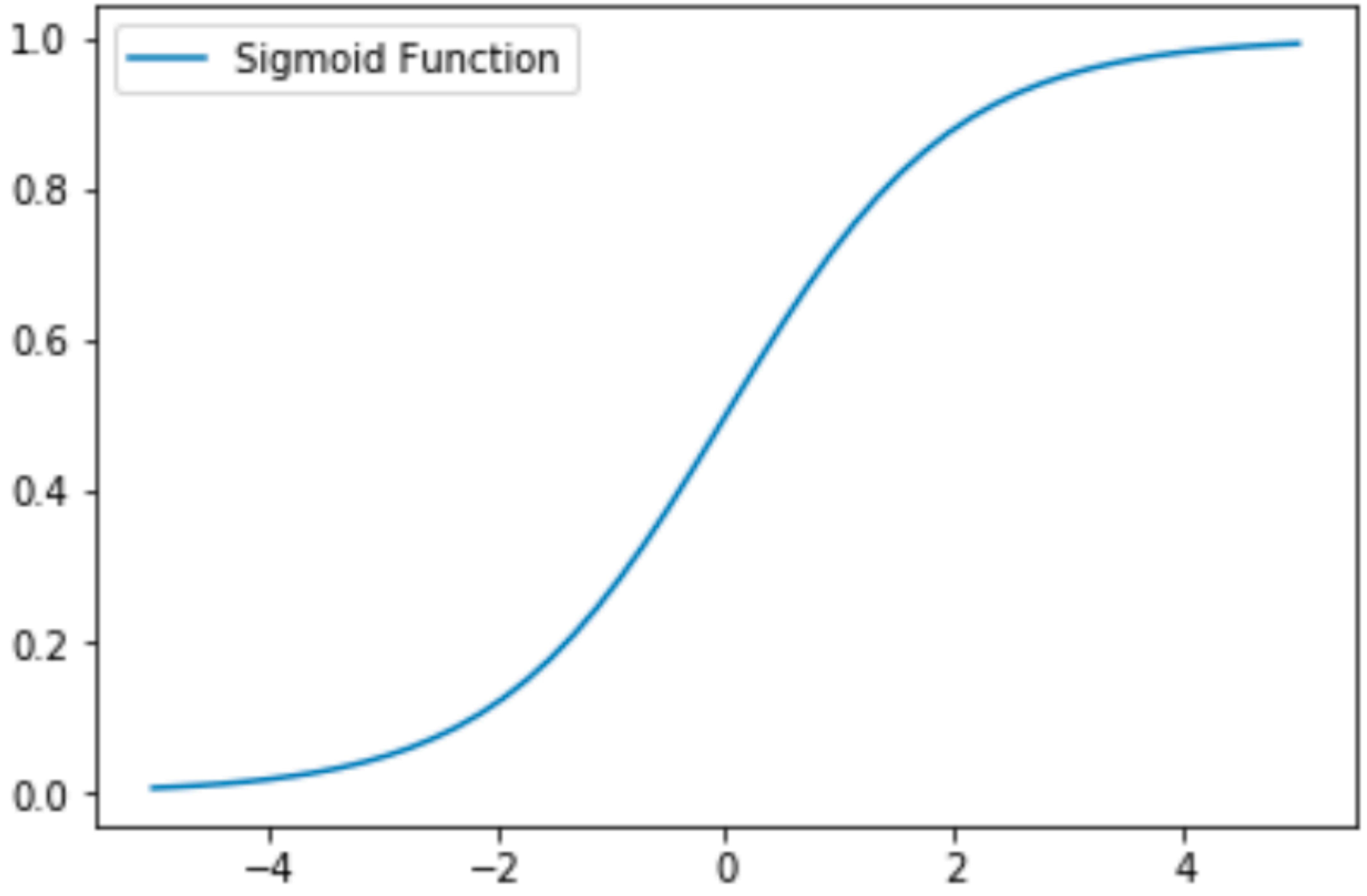

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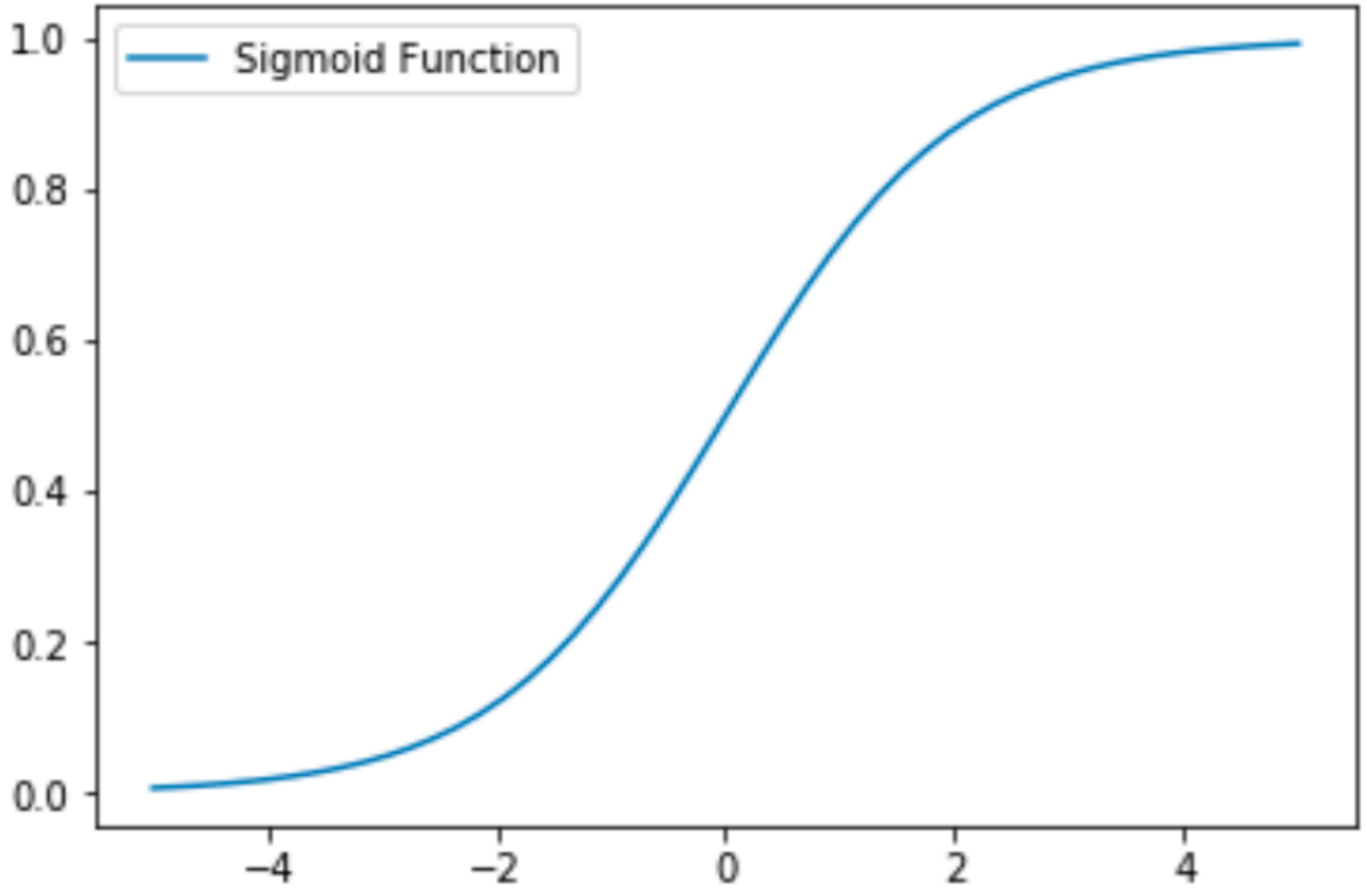

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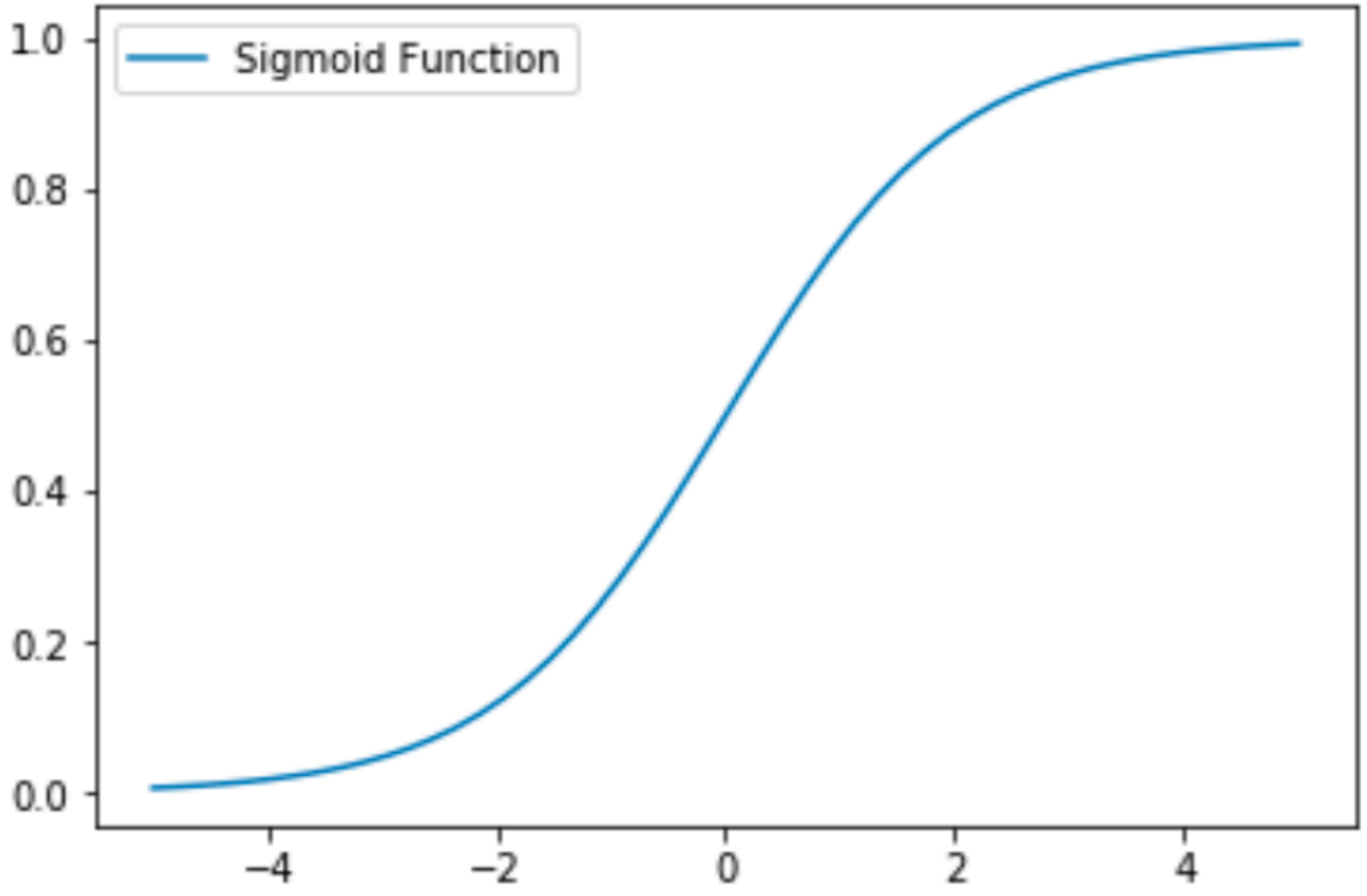

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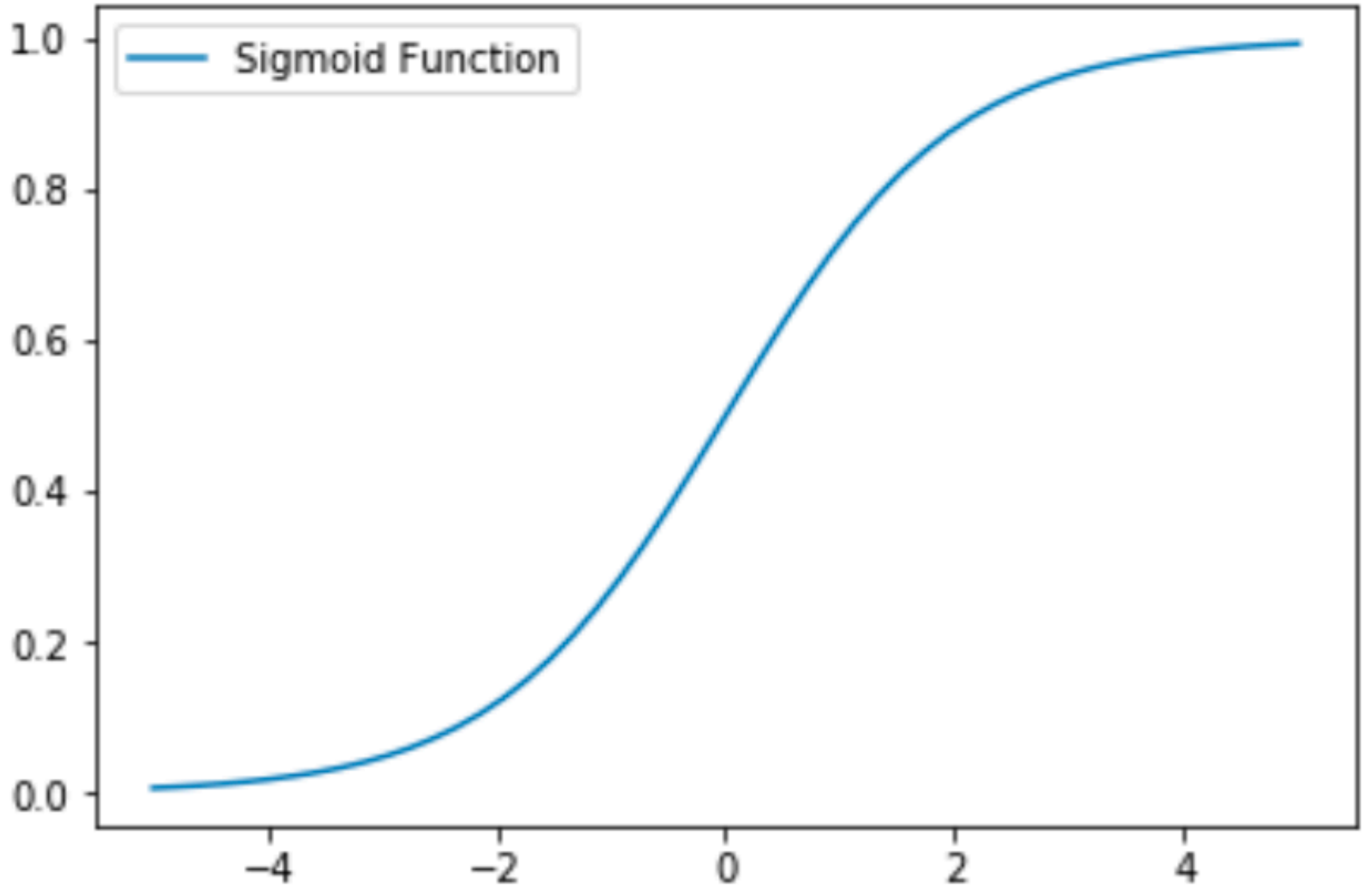

Is language modeling a classification task?

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  - Multinomial logistic regression (e.g. 5 classes): $\hat{y} \in \{0,1,2,3,4\}$

Parametric Model

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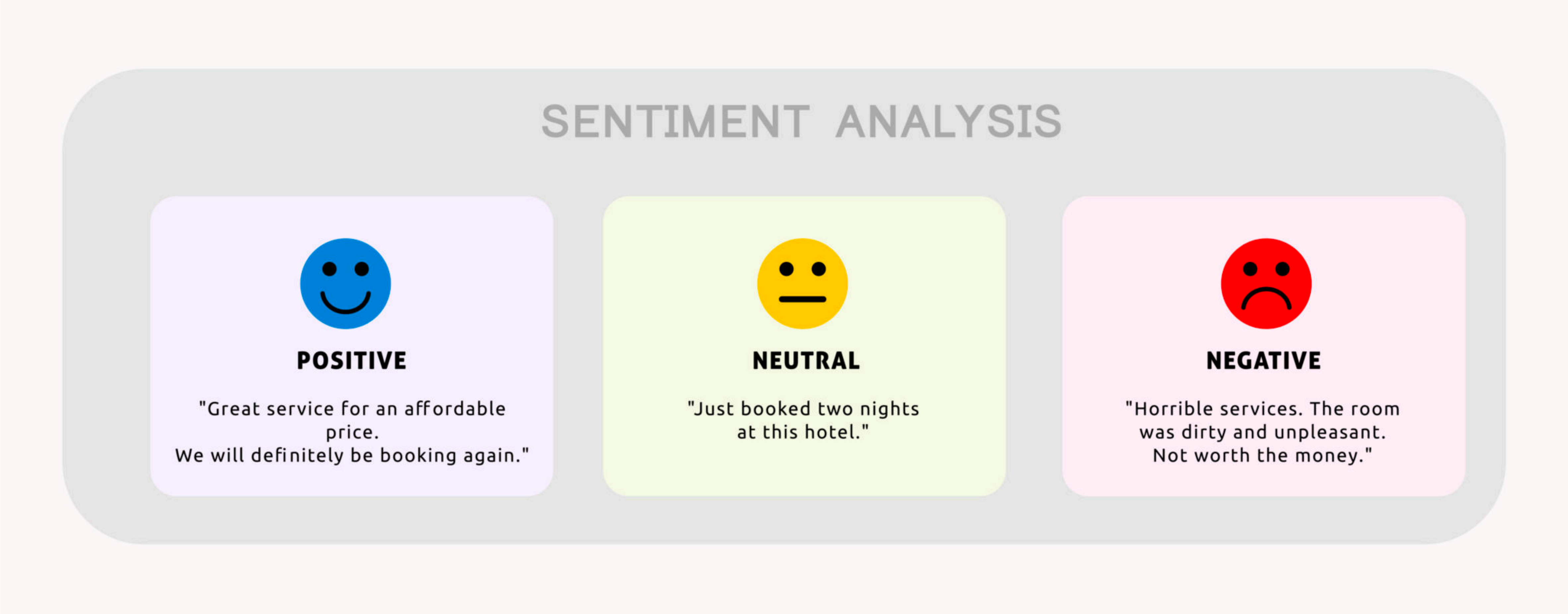
I. Data:
Preprocessing and Feature Extraction

Features in Classification



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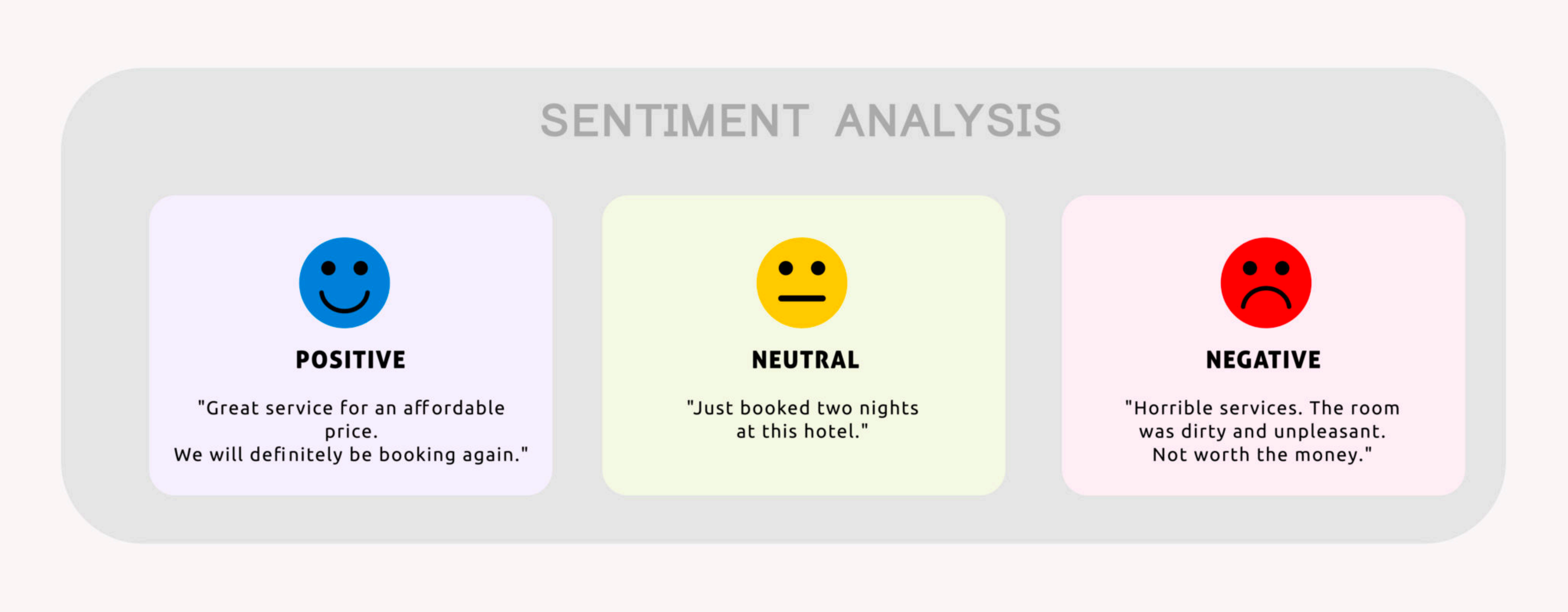

- Examples of feature x_i
  - x_i = "review contains 'awesome'"; $w_i = +10$
  - x_j = "review contains 'abysmal'"; $w_j = -10$
  - x_k = "review contains 'mediocre'"; $w_k = -2$

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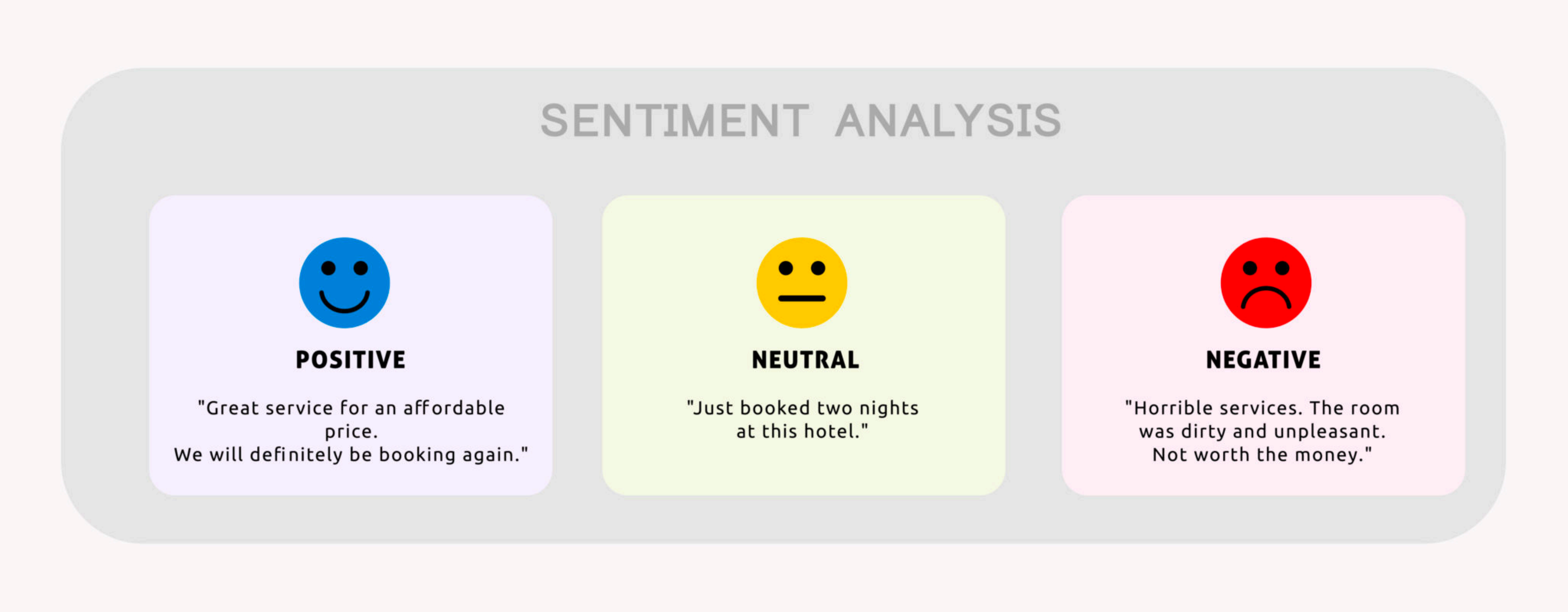

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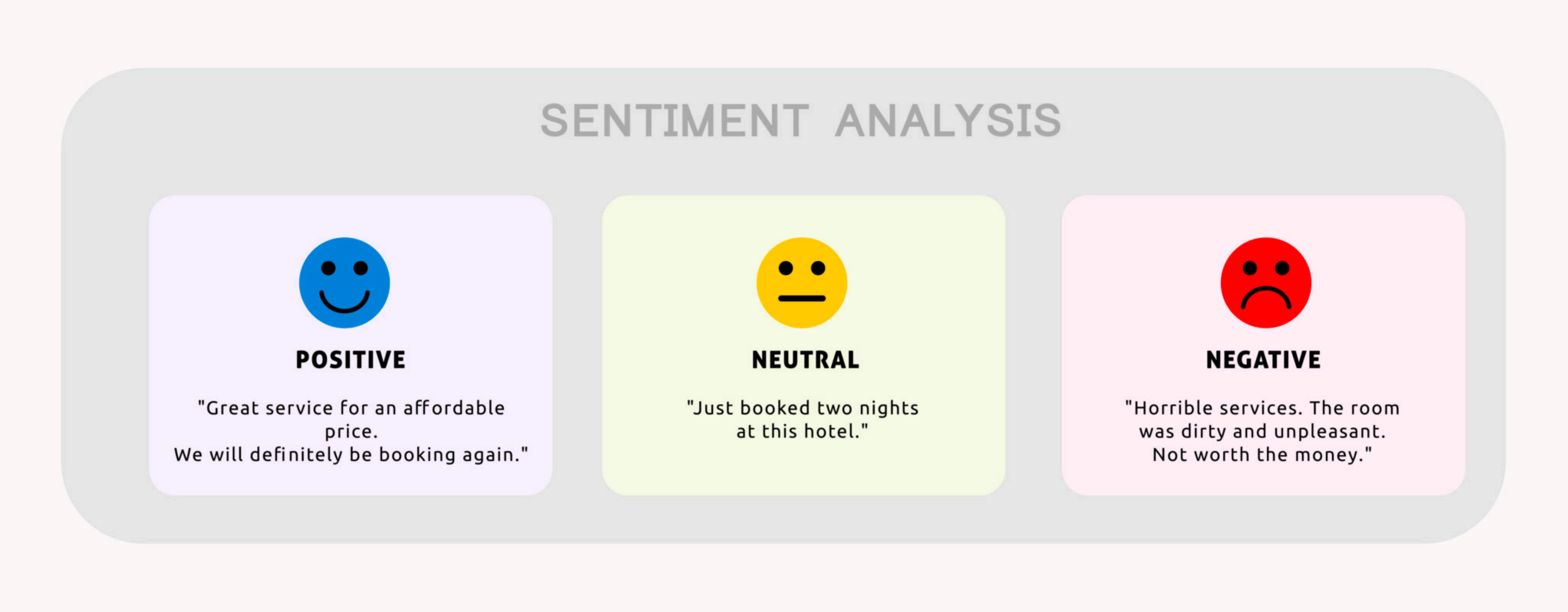

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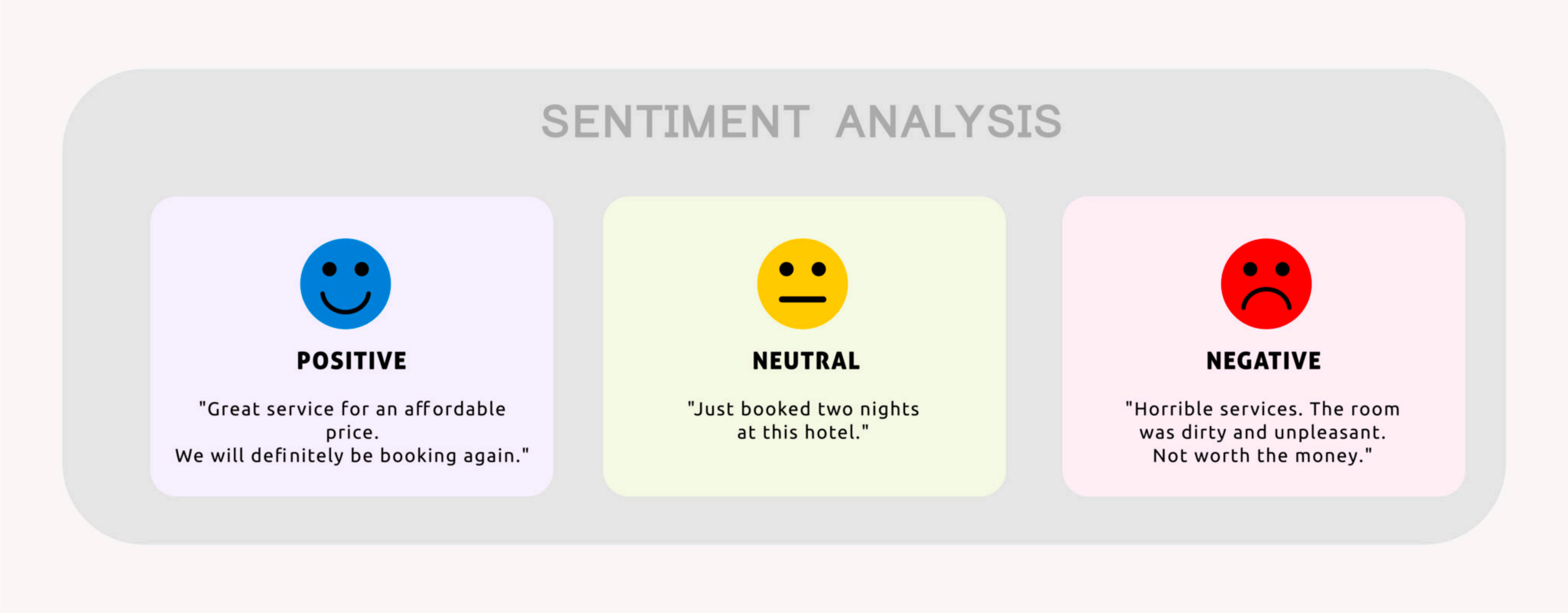

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Can you guess the w for x_l = "review contains 'restaurant'"?

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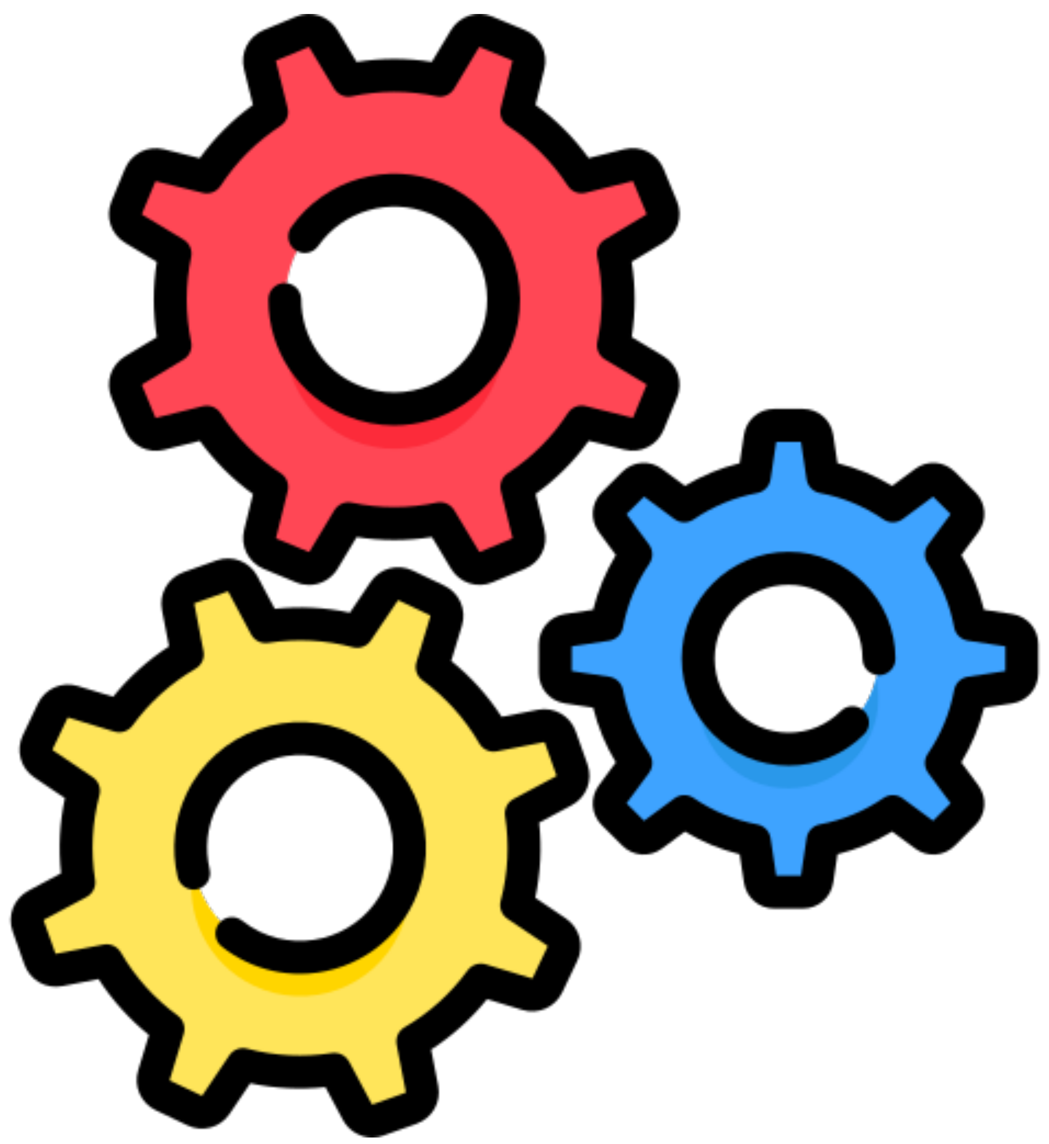

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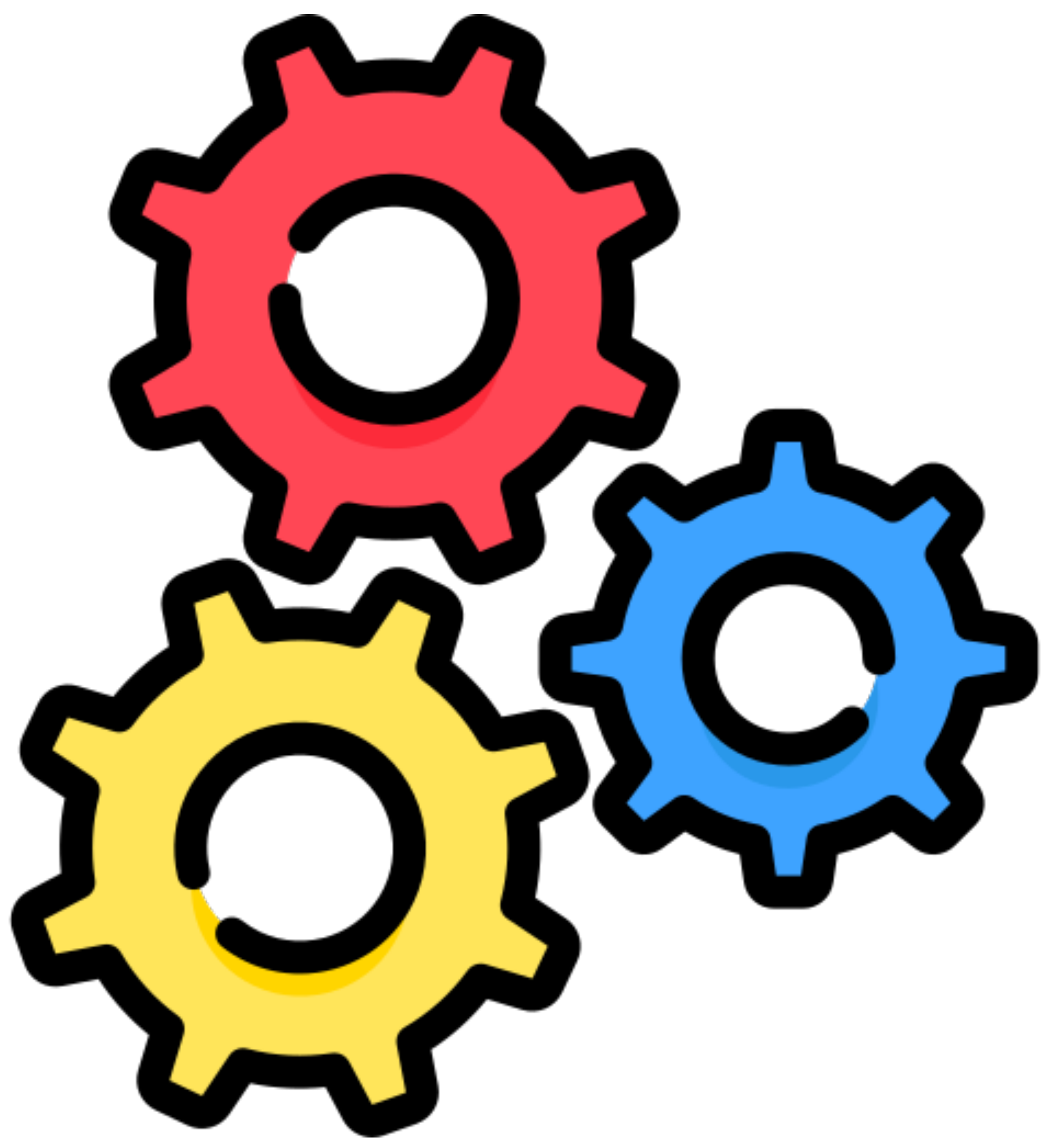

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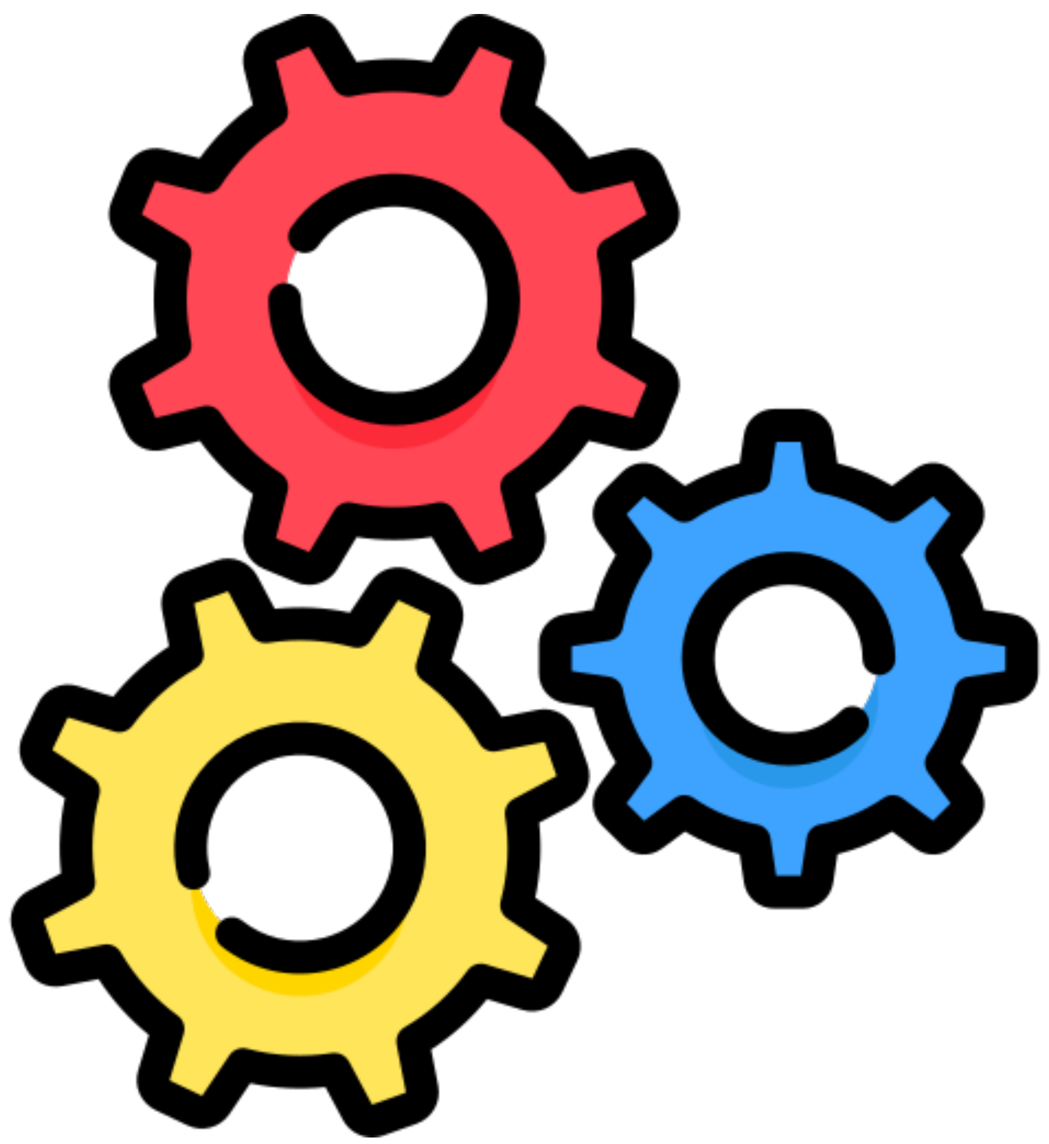

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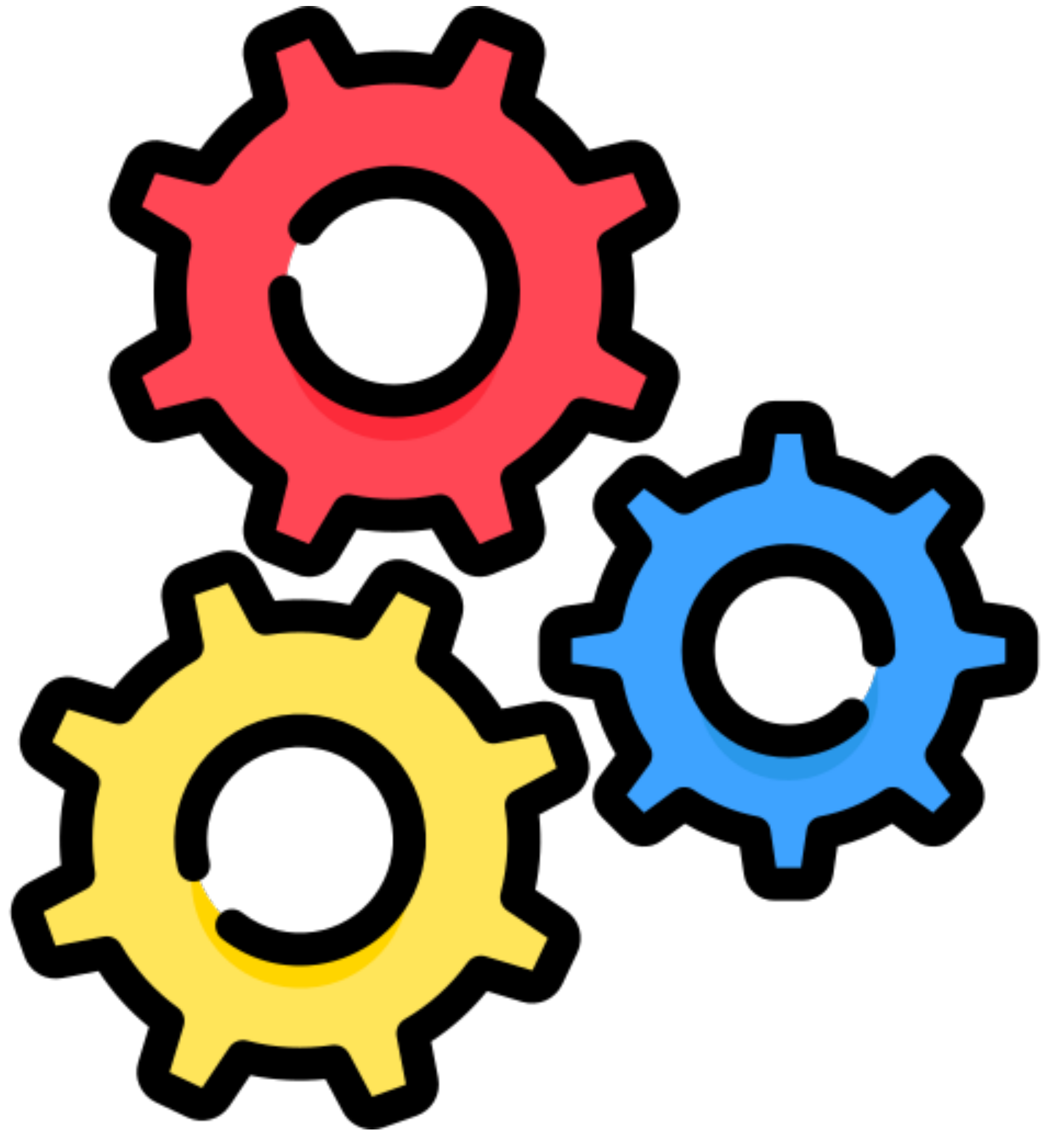

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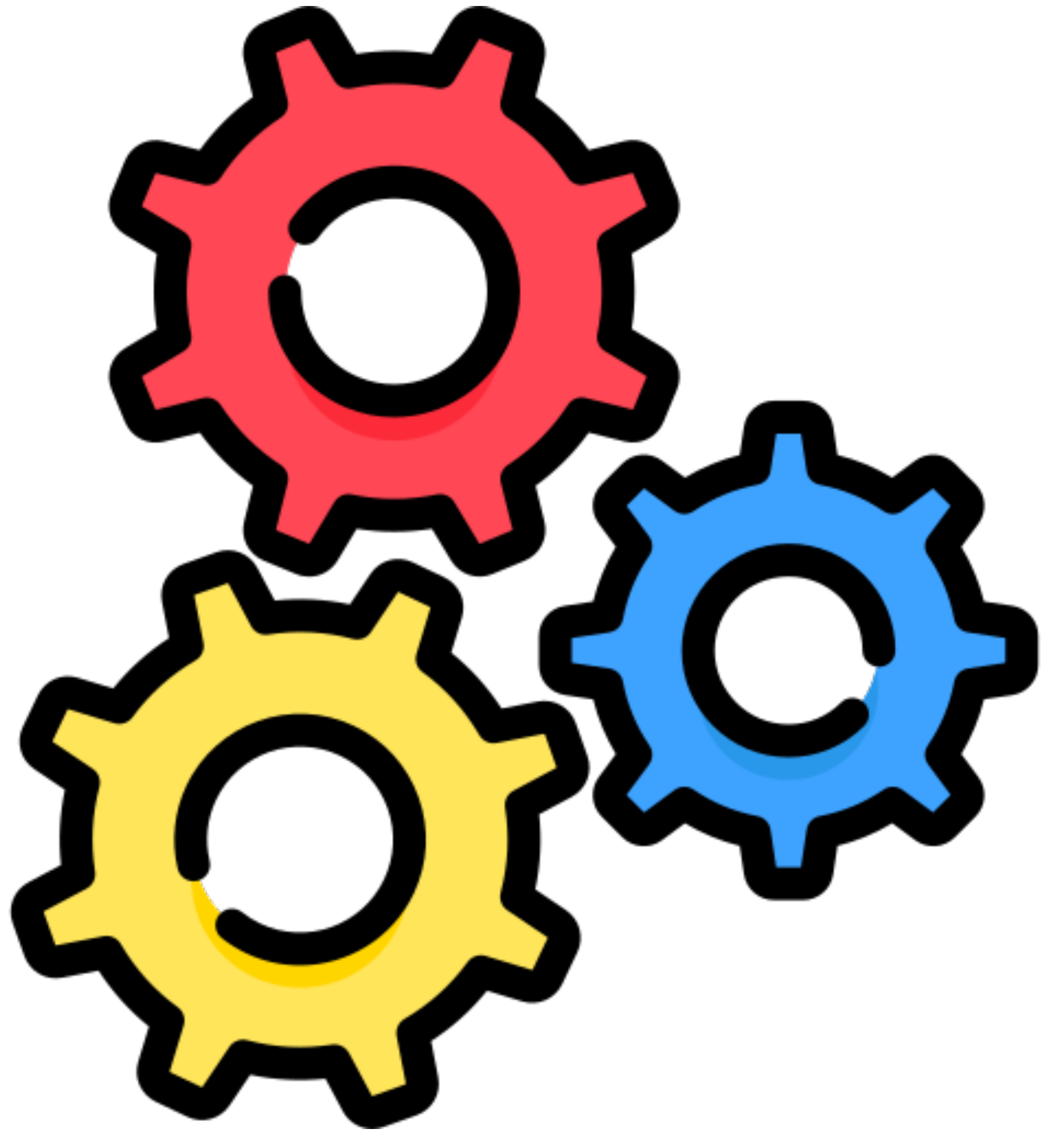
    - Contracting and standardizing: won't -> will not



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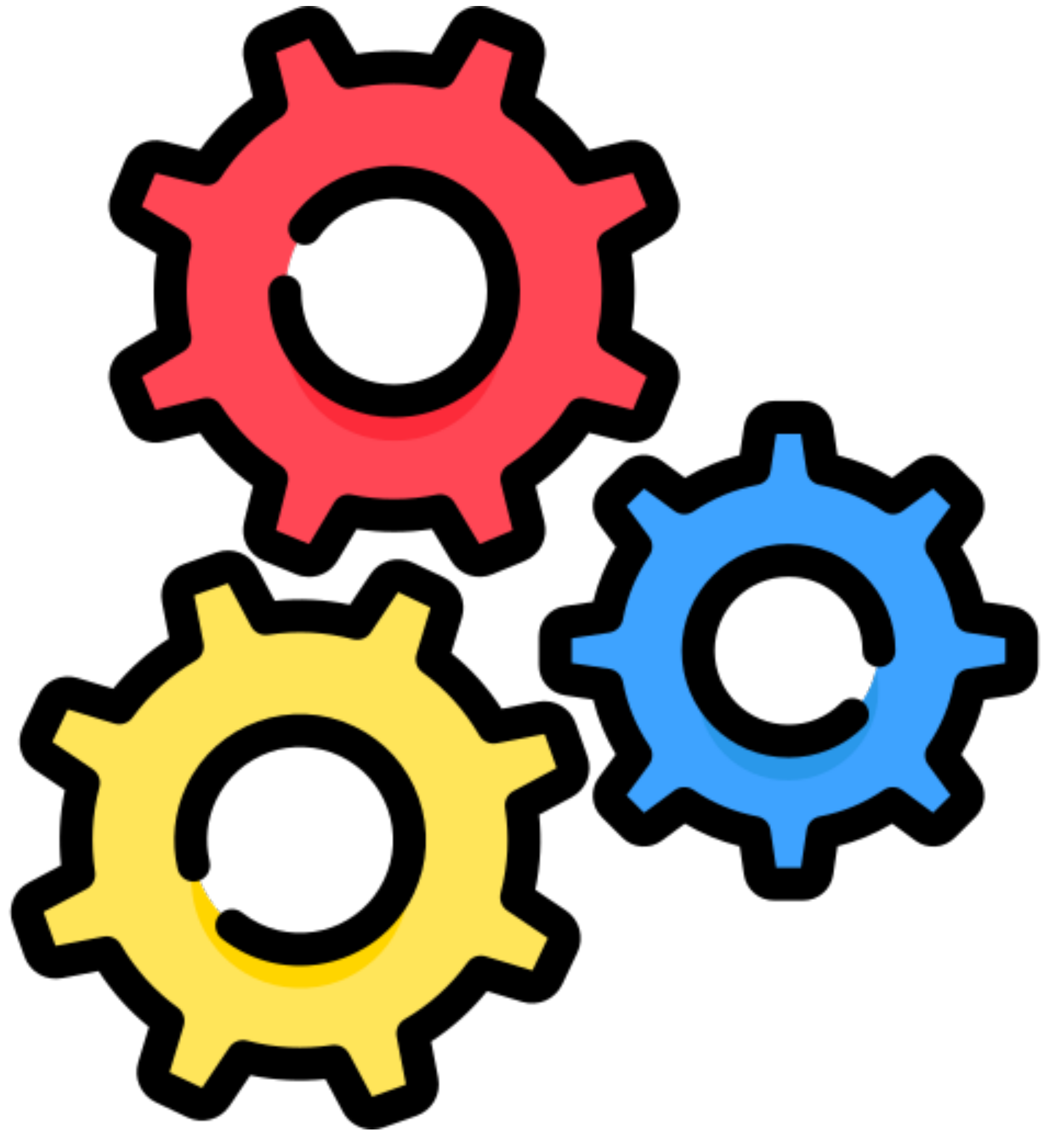

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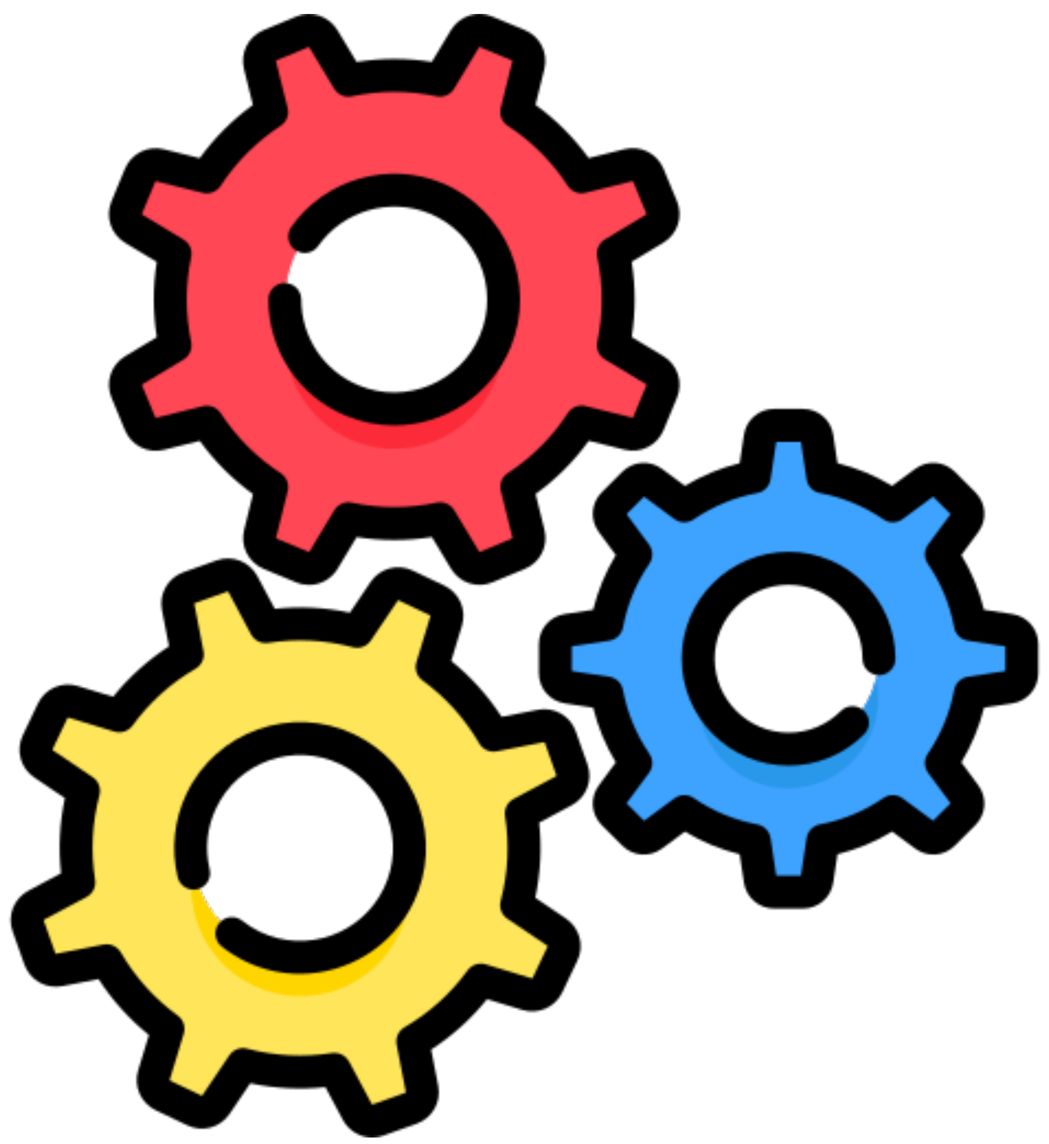

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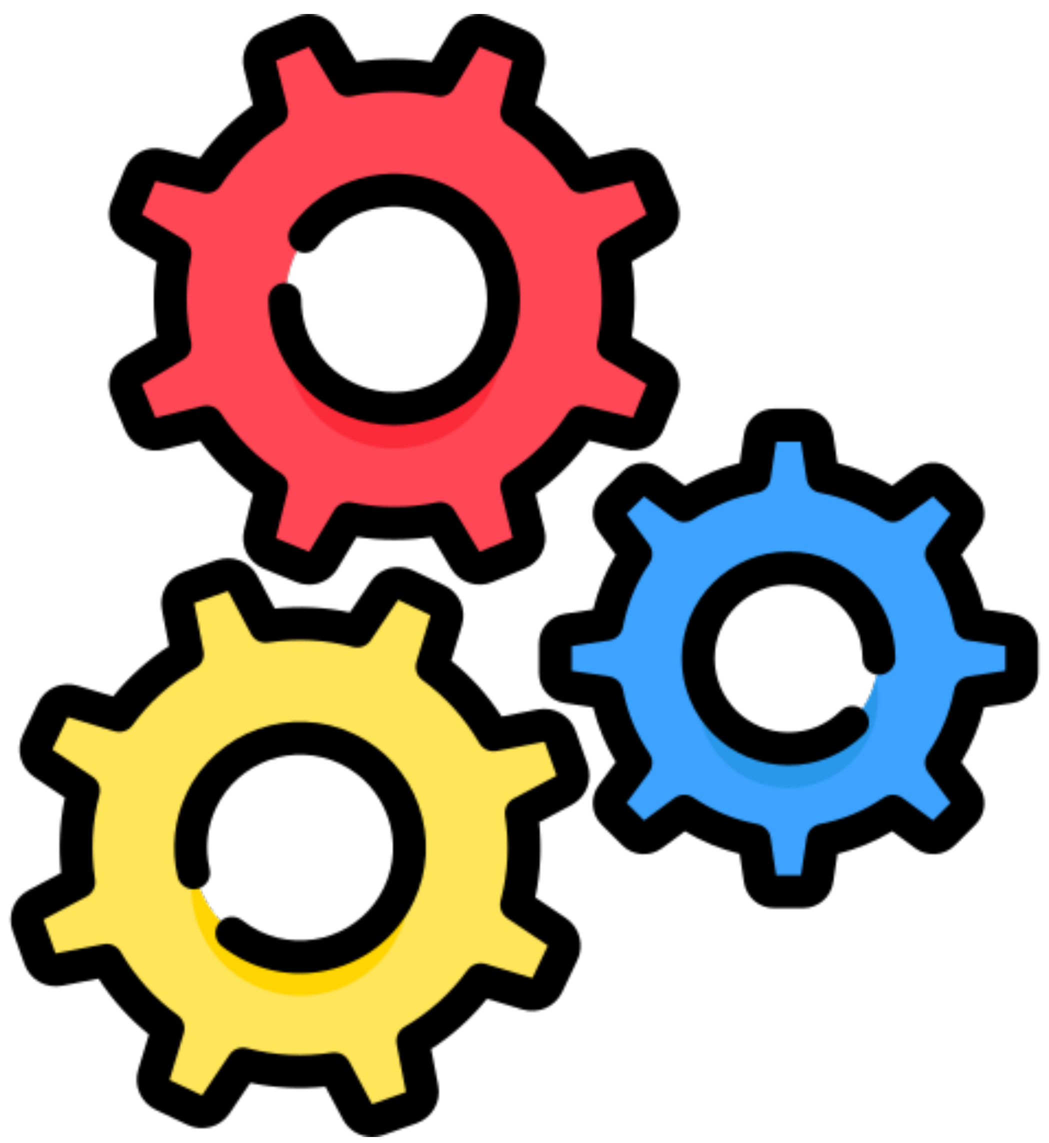

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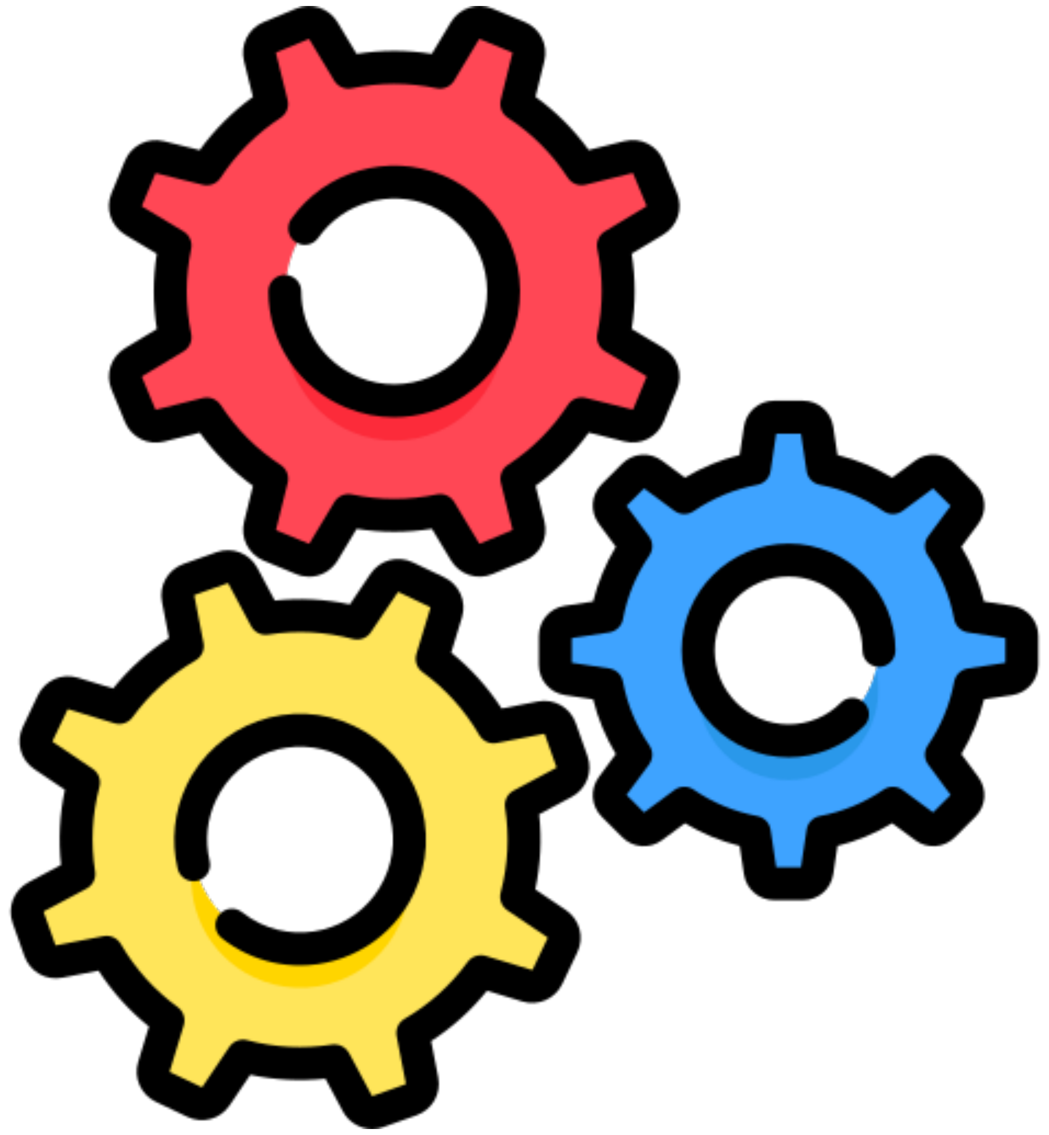

Still relevant, especially for you to understand what current LLMs can automate!

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- Vocabulary Creation
  - A dictionary of all the words we care about
    - Excluding stop words from dictionary as they are useless for the task at hand
  - Mapping each word to a word id: are -> 2
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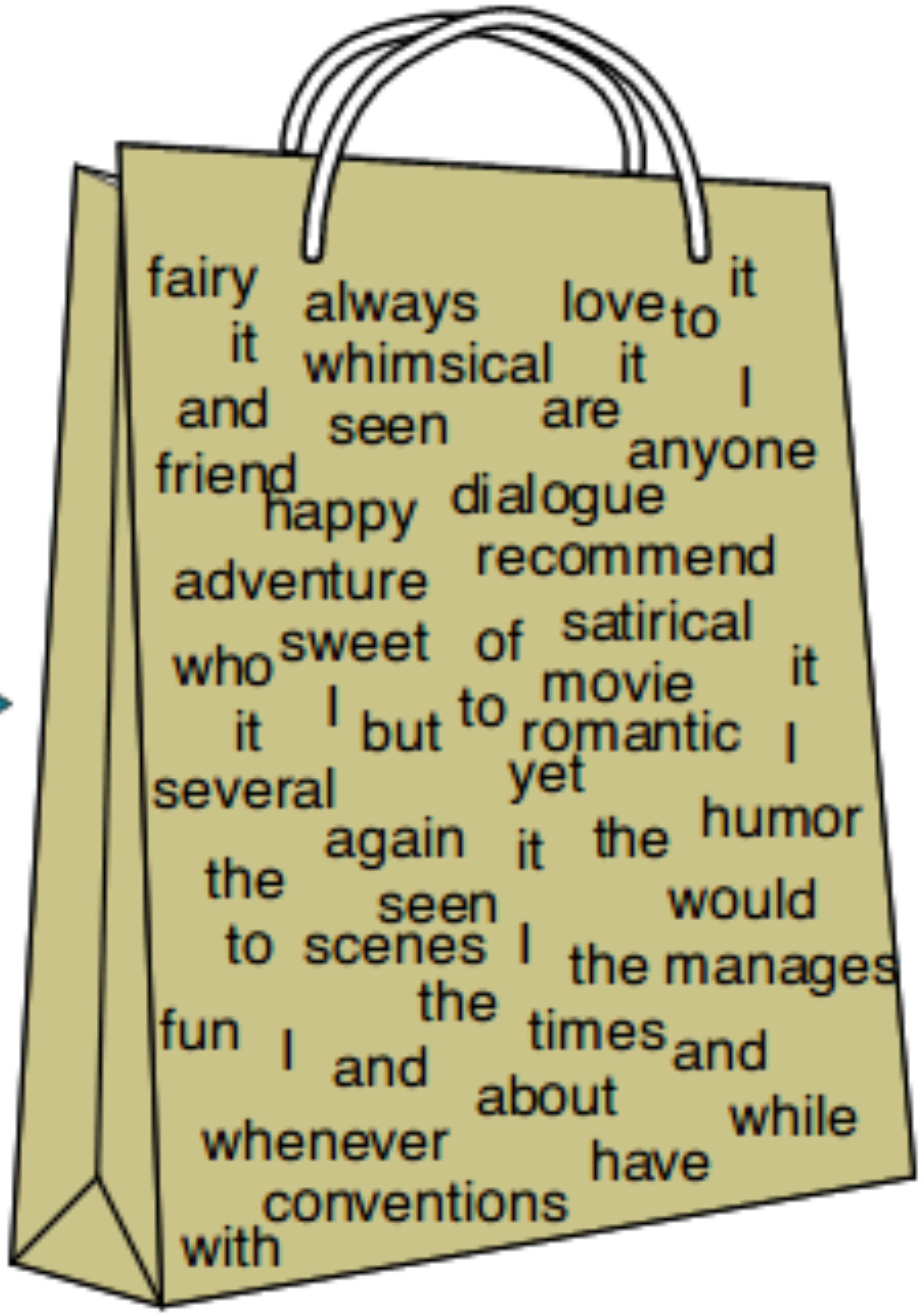
What happens when we see OOV words at test time?

Feature Representation: Bag of Words

I love this movie! It's sweet, but with satirical humor. The dialogue is great and the adventure scenes are fun... It manages to be whimsical and romantic while laughing at the conventions of the fairy tale genre. I would recommend it to just about anyone. I've seen it several times, and I'm always happy to see it again whenever I have a friend who hasn't seen it yet!



it	6
I	5
the	4
to	3
and	3
seen	2
yet	1
would	1
whimsical	1
times	1
sweet	1
satirical	1
adventure	1
genre	1
fairy	1
humor	1
have	1
great	1
...	...

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- $\mathbf{x} = [x_1, \ldots, x_k], \quad x_i \in 0,1,2,\ldots$
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Is k the number of types or tokens?

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Solutions?

- Pros:
  - Simple!
  - Leads to acceptable performance in quite a few settings

Next Class:
II. Model:
(a) Logistic Regression