







Spam Filtering

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Spam filtering

- Spam filtering task
- Naïve Bayes spam filtering
- Feed forward neural network for spam filtering
- Evaluation of spam filters

Spam detection

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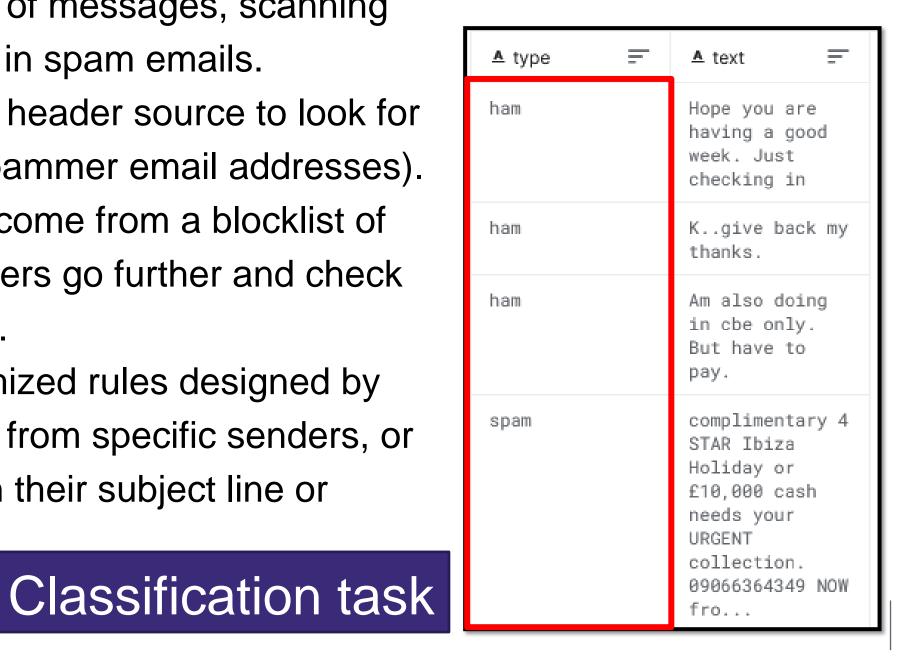
Spam filtering task

- A spam filter is a program that is used to detect unsolicited and unwanted email and prevent those messages from getting to a user's inbox
- The simplest and earliest can be set to watch for particular words in the subject line of messages and to exclude these from the user's inbox

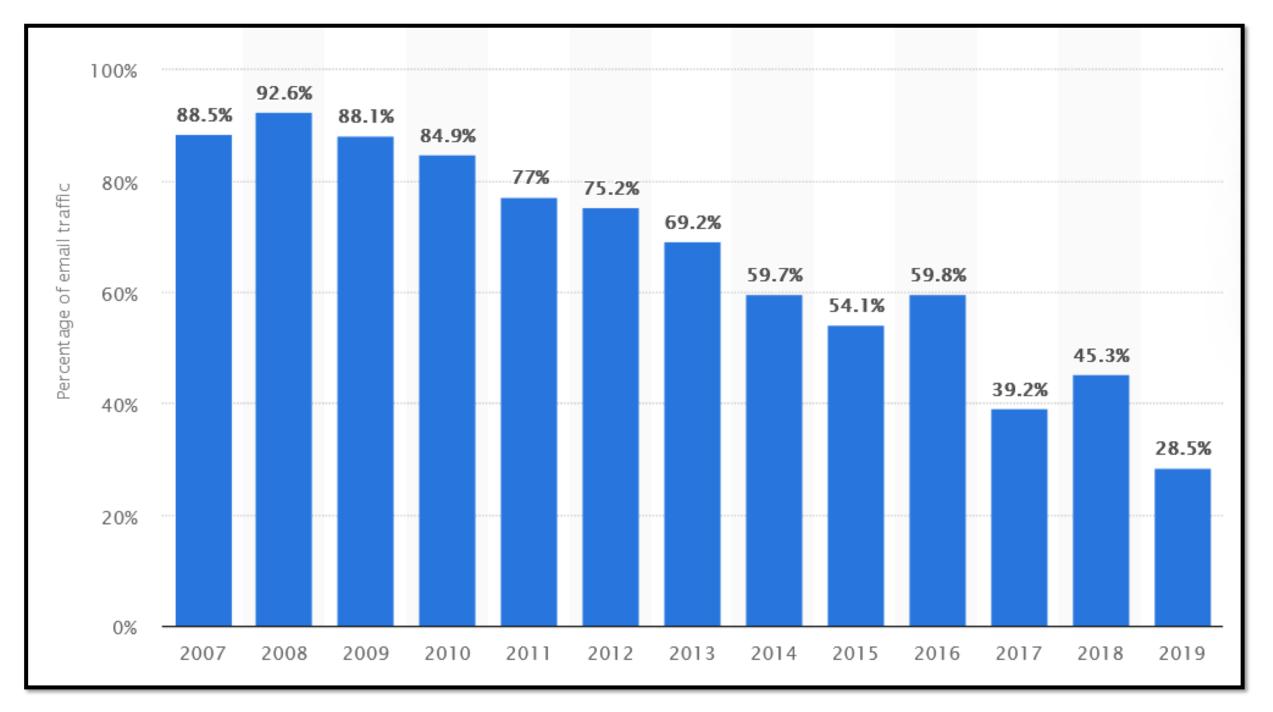


Spam filtering task

- Content filters: parse the content of messages, scanning for words that are commonly used in spam emails.
- **Header filters:** examine the email header source to look for suspicious information (such as spammer email addresses).
- **Blocklist filters:** stop emails that come from a blocklist of suspicious IP addresses. Some filters go further and check the IP reputation of the IP address.
- Rules-based filters: apply customized rules designed by the organization to exclude emails from specific senders, or emails containing specific words in their subject line or body.



Spam filtering task



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- The Naive Bayes classifier is a simple classifier that classifies based on probabilities of events
 - It is the applied commonly to text classification
- Though it is a simple algorithm, it performs well in many text classification problems
- It is a classification technique based on Bayes' theorem with an assumption of independence among predictors
- As with any machine learning model, we need to have an existing set of examples (training set) for each category (spam/non-spam)

congratulations you have won a playstation 5

P(ham|congratulations you have won a playstation 5)

P(spam|congratulations you have won a playstation 5)

 $P(C_k|X)$

 $C_1 = ham$

 $C_2 = spam$

X = congratulations you have won a playstation 5

$$P(C_k|X)$$

 The problem with the above formulation is that if the number of features n is large then basing such a model on probability tables is infeasible

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$
Bayes' theorem

$$P(C_k|X) = \frac{P(C_k)P(X|C_k)}{P(X)}$$

$$P(C_k|X) = \frac{P(C_k)P(X|C_k)}{P(X)}$$

naïve" conditional independence assumptions

$$P(C_k)P(X|C_k) = P(C_k)P(x_1|C_k)P(x_2|C_k) \dots P(x_n|C_k)$$

$$\hat{y} = \underset{k \in \{1, \dots, K\}}{\operatorname{argmax}} P(C_k) \prod_{i=1}^{n} P(x_i | C_k)$$

congratulation you have won a gift card	spam
your package is out for delivery	ham
the event is postponed to the next week	ham
your PlayStation account is temporary locked	spam
congratulation you are hired	spam
congratulation you have won a PlayStation 5	?

congratulation you have won gift card	spam
your PlayStation account is temporary locked	spam
congratulation you are hired	spam
your package is out delivery	ham
event is postponed next week	ham

congratulation you have won a PlayStation 5	?
---	---

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your package is out for delivery	ham
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congratulation you have won a PlayStation 5	?

 $P(C_k)P(X|C_k) = P(C_k)P(congratulation|C_k)P(you|C_k)P(have|C_k)P(won|C_k)P(PlayStation|C_k)$

 $P(C_k)$

$$P(ham) = \frac{2}{5}$$

$$P(ham) = \frac{2}{5}$$
 $P(spam) = \frac{3}{5}$

congratulation you have won a gift card	spam
your package is out for delivery	ham
the event is postponed to the next week	ham
your PlayStation account is temporary locked	spam
congratulation you are hired	spam
congratulation you have won a PlayStation 5	?

	you	account	PlayStation	is	hired	 week	locked	congratulation
S ₁	1	0	0	0	0	0	0	1
S_2	0	0	0	1	0	0	0	0
S_3	0	0	0	0	0	1	0	0
S ₄	0	1	1	1	0	0	1	0
S ₅	1	0	0	0	1	0	0	1

	you	account	PlayStation	is	hired	 week	locked	congratulation
S ₁	1	0	0	0	0	0	0	1
S ₄	0	1	1	1	0	0	1	0
S ₅	1	0	0	0	1	0	0	1
S ₂	0	0	0	1	0	0	0	0
S_3	0	0	0	0	0	1	0	0

 $P(C_k)P(X|C_k) = P(C_k)P(congratulation|C_k)P(you|C_k)P(have|C_k)P(won|C_k)P(PlayStation|C_k)$

 $P(congratulation|spam) = \frac{2}{16}$

	you	account	PlayStation	is	hired	 week	locked	congratulation
S ₁	1	0	0	0	0	0	0	1
S ₄	0	1	1	1	0	0	1	0
S ₅	1	0	0	0	1	0	0	1
S ₂	0	0	0	1	0	0	0	0
S_3	0	0	0	0	0	1	0	0

 $P(C_k)P(X|C_k) = P(C_k)P(congratulation|C_k)P(you|C_k)P(have|C_k)P(won|C_k)P(PlayStation|C_k)$

 $P(congratulation|spam) = \frac{2}{16}$

 $P(congratulation|ham) = \frac{0}{10}$

	you	account	PlayStation	is	hired	 week	locked	congratulation
S ₁	1	0	0	0	0	0	0	1
S ₄	0	1	1	1	0	0	1	0
S ₅	1	0	0	0	1	0	0	1
S ₂	0	0	0	1	0	0	0	0
S_3	0	0	0	0	0	1	0	0

 $P(C_k)P(X|C_k) = P(C_k)P(congratulation|C_k)P(you|C_k)P(have|C_k)P(won|C_k)P(PlayStation|C_k)$

 $P(congratulation|spam) = \frac{2}{16}$

 $P(congratulation|ham) = \frac{0}{10}$

 $P(is|spam) = \frac{1}{16}$

 $P(is|ham) = \frac{1}{10}$

$$P(C_k)P(X|C_k) = P(C_k)P(congratulation|C_k)P(you|C_k)P(have|C_k)P(won|C_k)P(PlayStation|C_k)$$

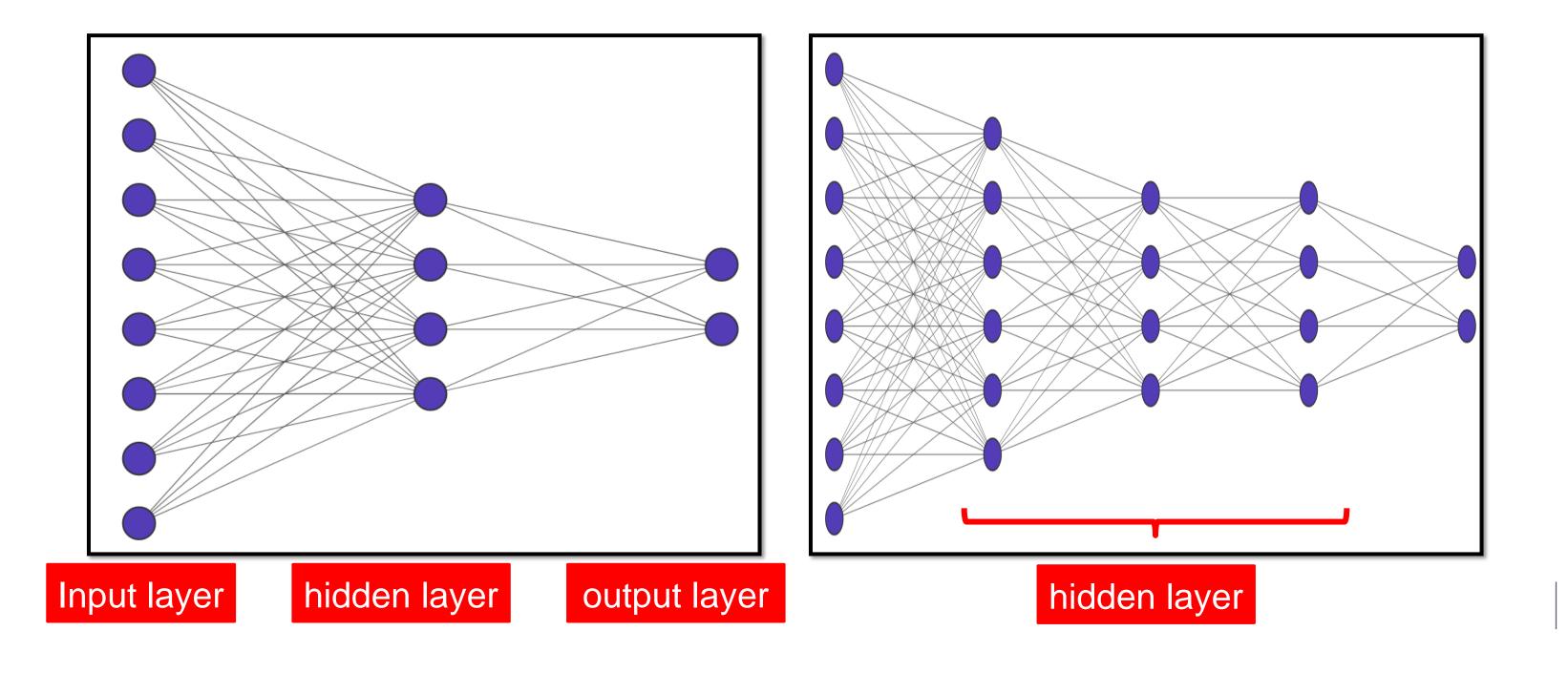
$$P(ham|X) = \frac{2}{5} \times \frac{1}{10} \times \cdots$$

$$P(spam|X) = \frac{3}{5} \times \frac{2}{16} \times \cdots$$

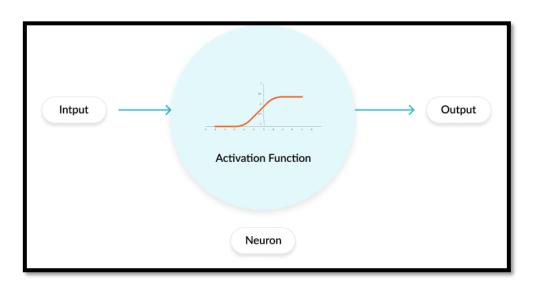
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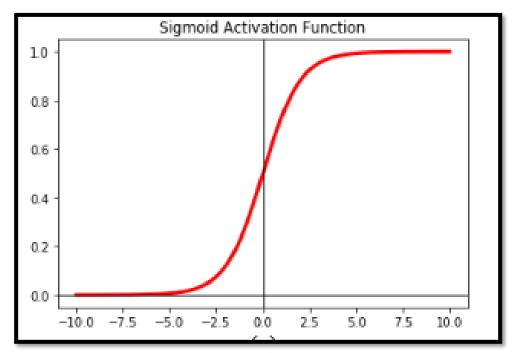
Spam detection

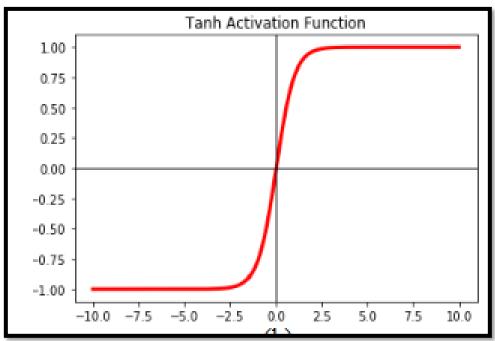
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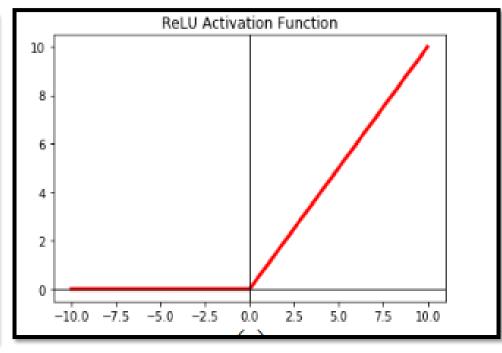


Activation function

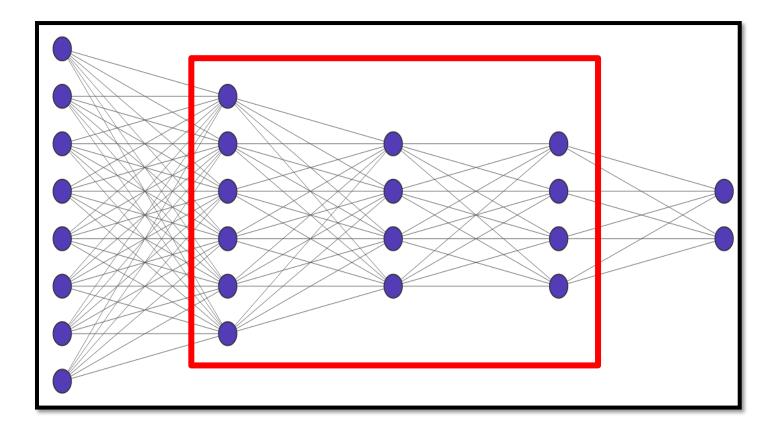


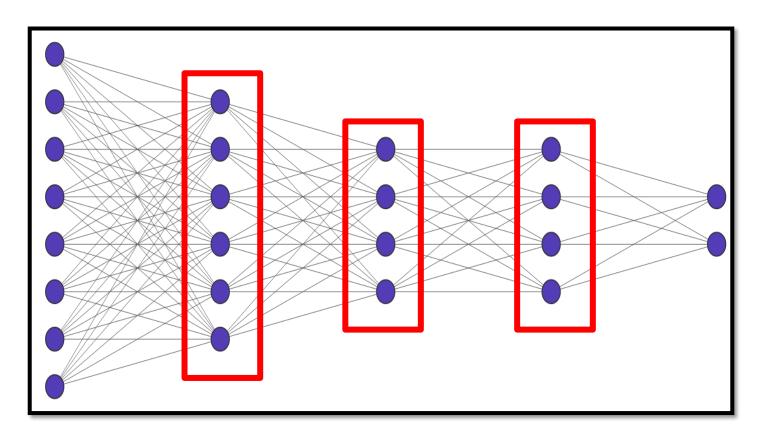




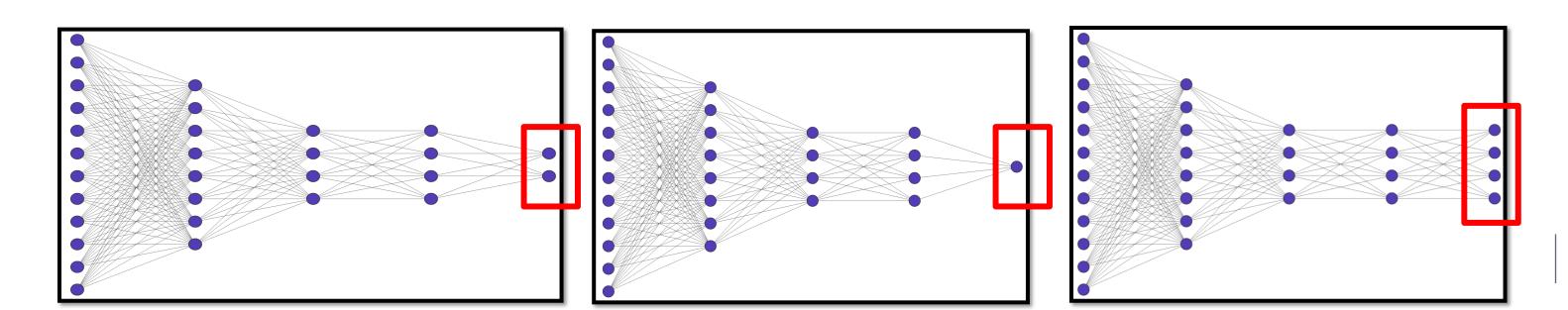


- Activation function
- Loss function
- Number of hidden layers
- Number of neurons in each layer

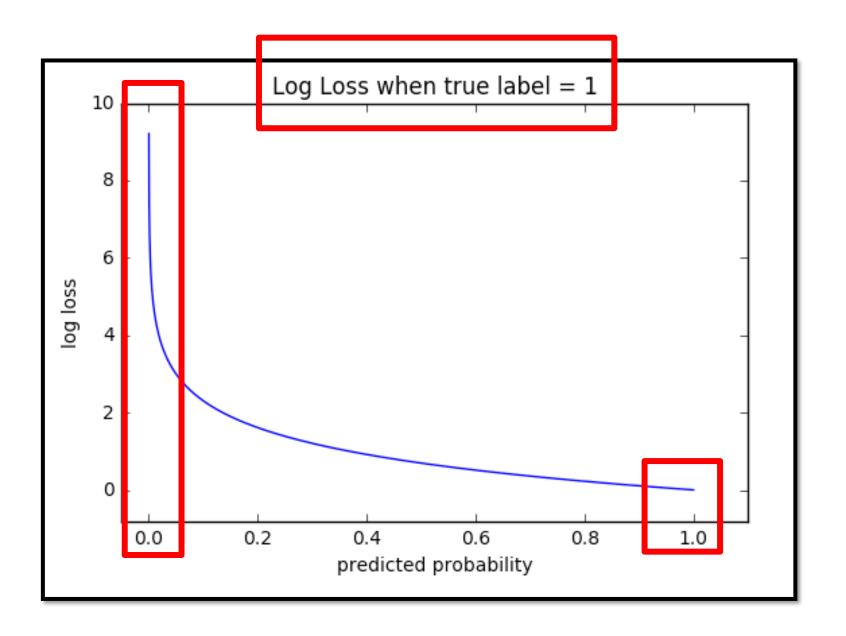




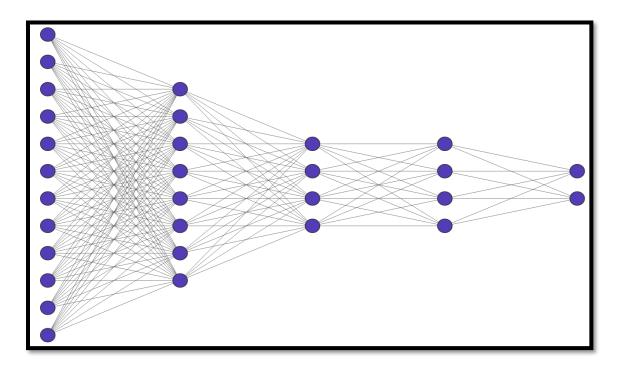
- Activation function
- Loss function
- Number of hidden layers
- Number of neurons in each layer
- Output layer

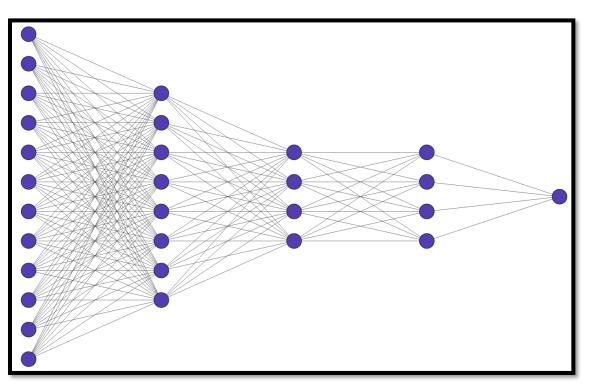


- Setting for spam filtering
 - Loss function
 - Cross entropy loss (log loss)



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 - Output layer
 - Softmax (2 output)
 - Sigmoid (1 output)





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 - Loss function
 - Cross entropy loss (log loss)
 - Output layer
 - Softmax (2 output)
 - Sigmoid (1 output)
 - Input layer

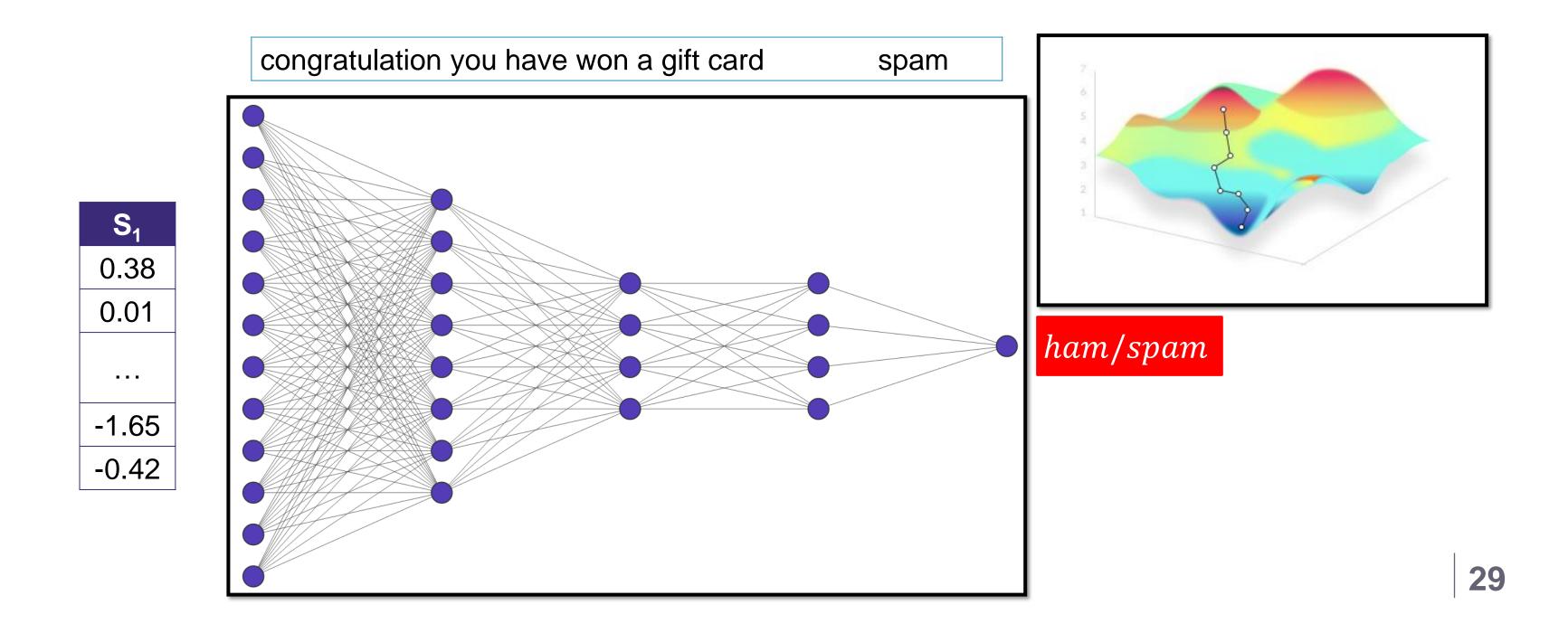
Input layer

congratulation you have won a PlayStation 5	?
congratulation you are hired	spam
your PlayStation account is temporary locked	spam
the event is postponed to the next week	ham
your package is out for delivery	ham
congratulation you have won a gift card	spam



	you	account	PlayStation	is	hired	 week	locked	congratulation
S ₁	1	0	0	0	0	0	0	1
S_2	0	0	0	1	0	0	0	0
S_3	0	0	0	0	0	1	0	0
S ₄	0	1	1	1	0	0	1	0
S ₅	1	0	0	0	1	0	0	1

			100 - 300		
congratulation	-0.37	-0.06		0.28	-0.67
You	0.68	-0.05		0.16	0.14
Have	0.53	0.05		-0.36	-0.27
Won	0.21	-0.35		-0.53	0.20
gift	-0.81	0.41		-0.58	-0.29
card	0.14	0.01		-0.62	0.47
			Sum		
S ₁	0.38	0.01		-1.65	-0.42



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- Confusion matrix
 - The Confusion matrix is one of the most intuitive and easiest metrics used for finding the correctness and accuracy of the model. It is used for Classification problem where the output can be of two or more types of classes_______

spam > positive

ham \rightarrow negative

		Actual class	
		Positive	Negative
d class	Positive	TP: True Positive	FP: False Positive
Predicted class	Negative	FN: False Negative	TN: True Negative

Accuracy

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

		Actual class		
		Positive	Negative	
ed class	Positive	TP: True Positive	FP: False Positive	
Predicted class	Negative	FN: False Negative	TN: True Negative	

- Precision
- Recall
- F1

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{2 \times (precision \times Recall)}{(precision + Recall)}$$

		Actual	class
		Positive	Negative
d class	Positive	TP: True Positive	FP: False Positive
Predicted class	Negative	FN: False Negative	TN: True Negative

		Actual class		
		Positive	Negative	
Predicted class	Positive	TP: 1	FP: 2	
	Negative	FN: 2	TN: 3	

Actual	Predicted
ham	ham
ham	spam
spam	spam
spam	ham
spam	ham
ham	ham
ham	ham
ham	spam

		Actual class	
		Positive	Negative
class	Positive	TP: True Positive	FP: False Positive
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Predicted
ham
spam
spam
ham
ham
ham
ham
spam

		Actual class		
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class	Positive	TP: True Positive	FP: False Positive	
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		Actual class				
		Positive	Negative			
Predicted class	Positive	TP: 1	FP: 2			
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Actual	Predicted
ham	ham
ham	spam
spam	spam
spam	ham
spam	ham
ham	ham
ham	ham
ham	spam

		Actual class			
		Positive	Negative		
class	Positive	TP: True Positive	FP: False Positive		
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•
$$accuracy = \frac{4}{8} = 0.5 = 50\%$$

•
$$precision = \frac{1}{3} = 0.33 = 33\%$$

•
$$recall = \frac{1}{3} = 0.33 = 33\%$$

•	f1 =	$2 \times 0.33 \times 0.33 / 0.33 + 0.33$, =	0.33	= 33%
		/ 11 33 + 11 33	.	$\mathbf{O}_{\mathbf{i}}\mathbf{O}_{\mathbf{J}}$	— 33/0

= 33%		Actual class			
		Positive	Negative		
d class	Positive	TP: 1	FP: 2		
Predicted class	Negative	FN: 2	TN: 3		

Actual class Positive Negative TP: 0 FP: 0 FN: 1 TN: 99

imbalanced data

Actual	Predicted
ham	ham
ham	ham
•••	
ham	ham
ham	ham
spam	ham
ham	ham

99% accuracy!

Accuracy is not a good metric for imbalanced data!

Actual class Positive Negative TP: 0 FP: 0 TN: 99

imbalanced data

Actual	Predicted
ham	ham
ham	ham
ham	ham
ham	ham
spam	ham
ham	ham

0% precision

0% recall

0% F1

 A spam filter is a program that is used to detect unsolicited and *unwanted email* and prevent those messages from getting to a user's inbox

$$P(C_k)P(X|C_k) = P(C_k)P(x_1|C_k)P(x_2|C_k) \dots P(x_n|C_k)$$

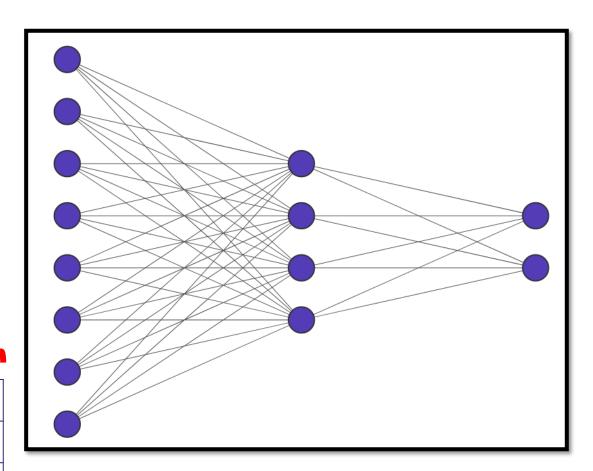
congratulations you have won a playstation 5

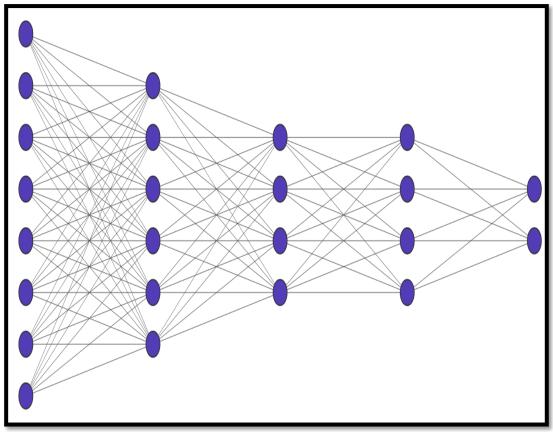
▲ type =	▲ text =
ham	Hope you are having a good week. Just checking in
ham	Kgive back my thanks.
ham	Am also doing in cbe only. But have to pay.
spam	complimentary 4 STAR Ibiza Holiday or £10,000 cash needs your URGENT collection. 09066364349 NOW fro

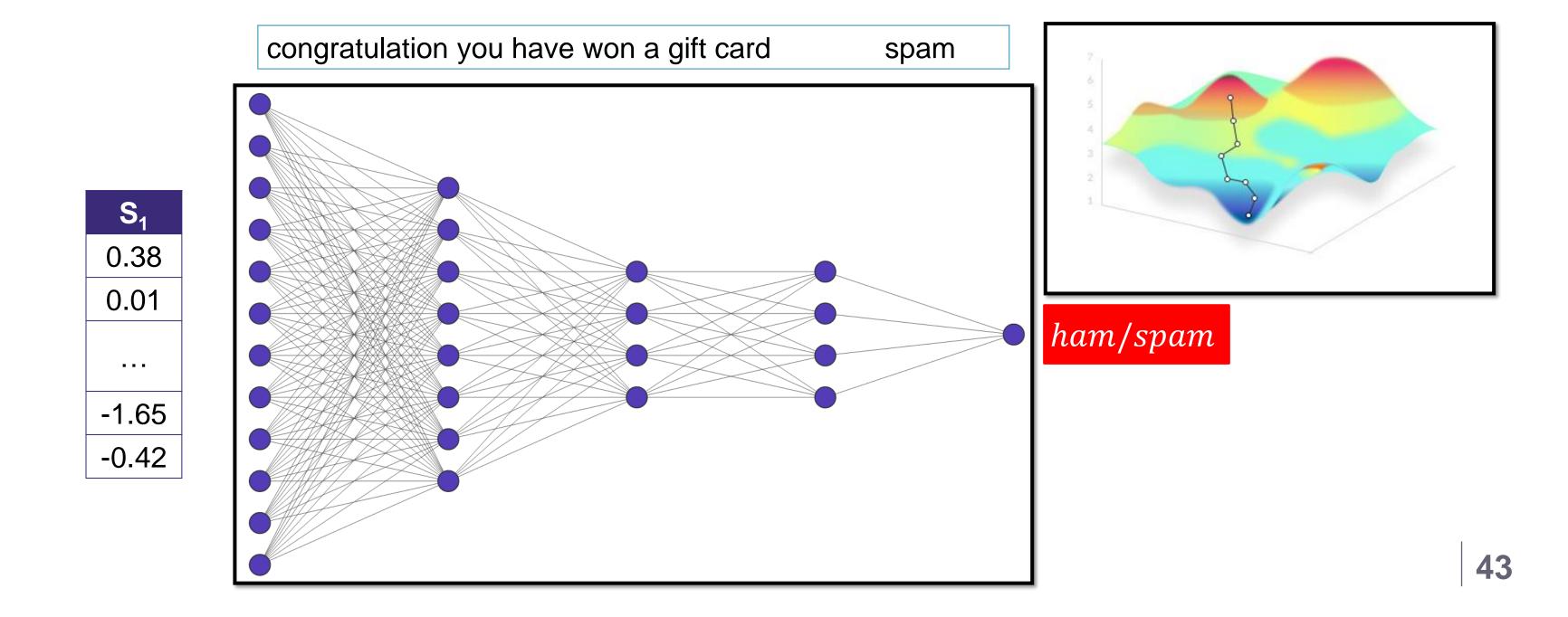
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your package is out delivery	ham
event is postponed next week	ham

100 - 300

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$$Precision = \frac{TP}{TP + FP}$$

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$$F1 = \frac{2 \times (precision \times Recall)}{(precision + Recall)}$$

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