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example

example description

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Contents

1 NLP Classification tasks

Definition 1.1 (Classification).

$$\hat{y} = \arg\max_y P(y|x) \tag{1}$$

Predicting which 'class' an observation belongs to

A Model produces a score (logit), a sigmoid makes this between 0 and 1, and 0.5 is our decision boundary. In multi-class classification we then use softmax.

1.1 Natural Language Inference

a model is presented with a pair of sentences and must classify the relationship between their meanings. For example in the MultiNLI corpus, pairs of sentences are given one of 3 labels: entails, contradicts and neutral. These labels describe a relationship between the meaning of the first sentence (the premise) and the meaning of the second sentence (the hypothesis). Here are representative examples of each class from the corpus:

- **Premise**: The kitten is climbing the curtains again
- **Hypothesis**: The kitten is sleeping
- **Entailment**: If the hypothesis is implied by the premise
- **Contradiction**: If the hypothesis contradicts the premise (in this example, the hypothesis is contradicting)
- **Neutral**: otherwise (neither is necessarily true)

2 Naive Bayes

(Generative Algorithm)

Definition 2.1 (Bayes Rule).

$$\underbrace{P(y|x)}_{\text{Posterior}} = \frac{\overbrace{P(x|y)}^{\text{Likelihood}}\ \overbrace{P(y)}^{\text{Prior}}}{\underbrace{P(x)}_{\text{Evidence}}}$$

Since $P(x)$ won't change for different classes

☞ why?

$$\hat{y} = \arg\max_y P(y|x) = \arg\max_y P(x|y)P(y)$$

We can further state that since x is a set of features $x_1, \ldots, x_I$ we have a independence assumption:

Definition 2.2 (Naiive Bayes Classifier).

$$P(x_1, \ldots, x_I|y) = P(x_1|y) \cdots P(x_I|y)$$

$$\hat{y} = \arg\max_y P(x_1, \ldots, x_I|y)P(y) = \arg\max_y P(y) \prod_{i=1}^{I} P(x_i|y)$$

2.1 Add-one smoothing

Raw input is transformed into a numerical representation - i.e. each input x is represented by a feature vector by using a Bag of Words approach (count of each word in the input) “This was another good movie for holiday watchers. There was a nice little twist at the end” Collect statistics from our training

	a	**about**	**another**	**and**	$\cdots$	**was**	**you**
Review #1	1	0	1	0		2	0

data (find what $P(y|x)$ is) after performing limited data-preprocessing.

Training corpus	**good**	**movie**	**bad**	class
another **good movie** for holiday watchers . a little twist from the ordinary scrooge movie . enjoyable .	1	1	0	+
it seems like just about everybody has made a christmas carol movie . others are just **bad** and the time period seems to be perfect .	0	0	1	+
if you 're looking for the same feel **good** one but in a new setting , this one 's for you .	1	0	0	+
this is a first for me , i didn 't like this **movie** . it was really **bad** .	0	1	1	-
it was **good** but the christmas carol by dickens was emotionally moving .	1	0	0	-

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Figure 1: Example of training corpus. Here, we are only concerned with the words ‘good’, ‘movie’, and ‘bad’ for classes ‘+’ and ‘-’

$$P(y) \rightarrow P(+) = \frac{3}{5}, \quad P(-) = \frac{2}{5}$$

$$P(good|+) = \frac{2}{4} \qquad \text{i.e. } \frac{\text{frequency of word for class}}{\text{total count of words for this class}}$$

this introduces the problem that one of our probabilities could be zero; therefore, adjust naive bayes classifier with ‘Add-one smoothing’

Definition 2.3 (Add-one smoothing)**.**

$$P(x_i|y) = \frac{count(x_i, y) + 1}{\sum_{x \in V}(count(x, y) + 1)} = \frac{count(x_i, y) + 1}{(\sum_{x \in V} count(x, y)) + |V|}$$

$$\begin{aligned} P(good|+) &= \frac{2+1}{4+3} = \frac{3}{7} P(good|-) = \frac{1+1}{3+3} = \frac{2}{6} \\ P(movie|+) &= \frac{1+1}{4+3} = \frac{2}{7} P(movie|-) = \frac{1+1}{3+3} = \frac{2}{6} \\ P(bad|+) &= \frac{1+1}{4+3} = \frac{2}{7} P(bad|-) = \frac{1+1}{3+3} = \frac{2}{6} \end{aligned}$$

Therefore for a test example: “Not as **good** as the old **movie**, rather **bad**” we use Equation 2.2 to get $P(+)P(x|+) = \frac{3}{5} \times \frac{3 \times 2 \times 2}{7^3} = 0.021$ and $P(-)P(x|-) = \frac{2}{5} \times \frac{2 \times 2 \times 2}{6^3} = 0.014$. So final outcome of the model is $+$. However, this sentence is clearly negative, yet we classify as positive.

2.2 Binary Naive Bayes

Within binary naive bayes, we only consider if a feature is present, rather than considering every time it occurs. Note, this means re-calculating the conditional probabilities from the training data.

E.g. "Not as **good** as the old **movie**, rather **bad movie**" we have $P(+)P(x|+) = \frac{3}{5} \times \frac{3 \times 2 \times 2}{7^3} = 0.021$ and $P(-)P(x|-) = \frac{2}{5} \times \frac{2 \times 2 \times 2}{6^3} = 0.014$. If we were still operating under the same formula in Equation 2.2 then we would have iterated over the label 'movie' twice, and thus multiplied by $P(good|+)$ twice (in the positive case).

2.3 Controlling for negation

We append 'Not_' after any logical negation (e..g n't, not, no, never) until the next punctuation mark.

"I didn't like the movie, but it was better than Top Gun" becomes "I didn't NOT_like NOT_the NOT_movie, but it was better than Top Gun"

2.4 Problems

- Conditional independence assumption
- Features considered equally important
- Context of words not taken into account
- New words (not seen at training) cannot be used

2.5 Summary

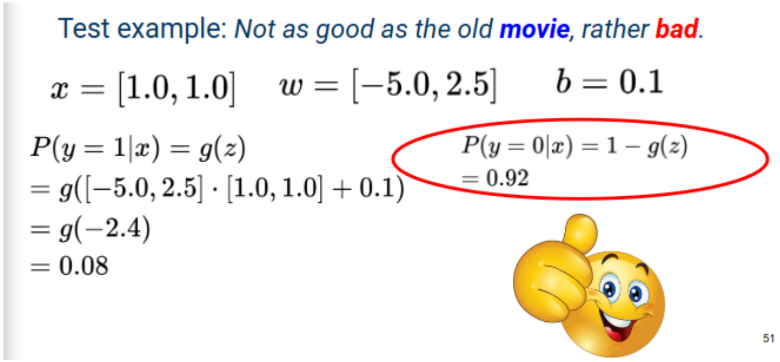
Very quick to train, Some evidence it works well on very small datasets.

3 Logistic Regression

(Discriminative Algorithm) because we directly learn $P(Y|X)$ since we don't care about $P(Y)$ or $P(X)$. They learn the input feauters most useful to discriminate between the different classes, without considering the likelihood of the input itself.

$$y(x) = g(z) = \frac{1}{1 + e^{-z}}$$
$$z = w \cdot x + b$$
$$P(y = 1) = \frac{1}{1 + e^{-(w \cdot x + b)}}$$

where w is how important an input feature is to the classification decision and we have a threshold at 0.5 for decision making.



If we don't have the w, then we learn parameters to make the model predictions close to our labels by using a loss function (to measure the distance between the true and predicted labels) and optimization algorithm (to minimize the function usually through gradient descent.)

Definition 3.1 (Logistic Regression).

$$H(P, Q) = -\sum_i P(y_i) \log Q(y_i)$$

3.1 Multiple Classes

Weights and bias are learnt per class, then use a softmax function over the result of finding z_i.

$$y = g(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}}$$

3.2 Summary

Logistic Regression considers the importance of feautres, so is better (than Naive Bayes) at dealing with correlated feautres, also better (than Naive Bayes) with larger datasets.

4 Neural Networks (NNs)

Definition 4.1 (Linear Layer).

$$z = w \cdot x + b = \sum_{i=0}^{I} w_i x_i + b$$

Definition 4.2 (Non-linear activation function).

$$y = g(z)$$

Definition 4.3 (Fully-connected layers).

$$FFN(x) = (g^2(g^1(xW^1 + b^1))W^2 + b^2)W^3 + b^3$$

The neural networks allow for automatically learning dense feature representations, not one-hot encodings.

4.1 Docuemnt Representation

How to get a document representation of sentence of fixed dimensionality?

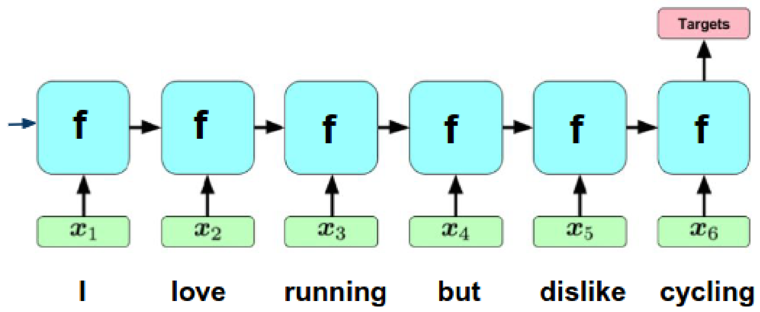
Average of sentence - bad idea:

Model architecutre fixed to sentence length size, model wieghts learnt for specific word positions

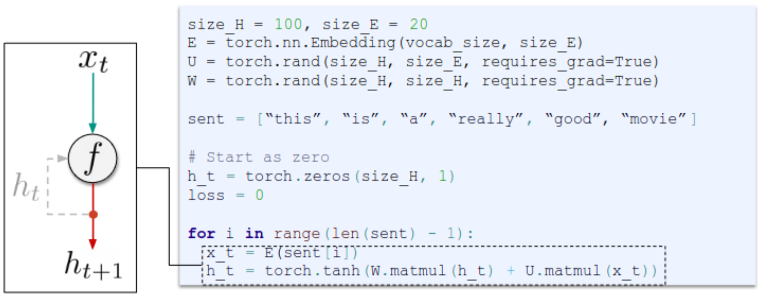
4.2 Neural Networks

Automatically learned features; flexibility to fit highly complex relationships in data, but they require more data to learn more complex patterns.

5 Recurrent neural networks (RNNs)



Natural language data is made up of sequences, so its natural to represent in a RNN; the value of a unit depends on own previous outputs - the last hidden state is the input to the output layer.



5.1 Vanishing gradient problem

The model is less able to learn from earlier inputs (Tanh derivatives are between 0 and 1) (Sigmoid derivatives are between 0 and 0.25) - Gradient for earlier layers involves repeated multiplication of the same matrix W - depending on the dominant eignevalue this can cause gradients to either 'vanish' or 'explode'

☞ RNNs perform better when you need to understand longer range dependencies

6 CNNs

CNNs are composed of a series of convolution layers, pooling layers and fully connected layers. Convolutional layers Detect important patterns in the inputs. Pooling layers Reduce dimensionality of features and transform them into a fixed-size. Fully connected layers Train weights of learned representation for a specific task.

We can stack multiple filters on-top of eachother also.

☞ CNNs can perform well if the task involves key phrase recognition.

7 Accuracy and F1

Definition 7.1 (accuracy).

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

Definition 7.2 (f1-measure).

$$f1 = 2 \times \frac{precision \times recall}{precision + recall} = \frac{TP}{TP + 0.5(FP + FN)}$$

7.1 Macro averaging

averaging of each class F1 scores: increases the emphasis on less frequent classes

7.2 Micro averaging

TPs, TNs, FNs. FPs are summed across each class.
Microaveraged F1

FPs		Predicted		
		Airplane	Boat	Car
Actual	Airplane	2	1	0
	Boat	0	1	0
	Car	1	2	3

FNs		Predicted		
		Airplane	Boat	Car
Actual	Airplane	2	1	0
	Boat	0	1	0
	Car	1	2	3

$$\frac{\sum_i^C TP_i}{\sum_i^C TP_i + 0.5(\sum_i^C FP_i + \sum_i^C FN_i)} = \frac{\sum_i^C TP_i}{|Dataset|} = Accuracy$$