Natural Language Models and Interfaces

BSc Artificial Intelligence

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Institute for Logic, Language, and Computation

2019, week 6, lecture b

Text Classifiers

We have learnt two techniques to design feature-rich models

- naive Bayes classification
- logistic regression

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- naive Bayes classification
- logistic regression

They are both useful to condition on high-dimensional data

- NBC uses Bayes rule and a conditional independence assumption
- LR uses a linear model and the softmax function

Pros and Cons

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- exact MLE solution
- strong independence assumption

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- strong independence assumption

LR

- flexible
- no closed-form MLE
- but gradient ascent converges to global optimum because the log-likelihood function is concave

Applications

1. Text classifiers: predict a categorical target from high-dimensional input
2. Component in a generative model: parameterise a cpd that conditions on high-dimensional input

Text Classification

Task	Description
Sentiment analysis	emotion towards a subject x is a document and y is a binary label
Textual entailment	given a two pieces of text, does one entail or contradict the other? x is a pair of documents and y is a binary label

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In both cases, there are extensions to multiple classes

- Stanford sentiment classification: 5 sentiment levels
- Stanford natural language inference: 3 logical entailment relations

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- LR:

$$P_{Y|X}(y|x) = \frac{\exp\left(w^\top f({\color{red}y, x})\right)}{\sum_{y' \in \mathcal{Y}} \exp(w^\top f(y', x))}$$

Feature functions (cont.)

In NBC a feature is a random variable
while in LR a feature is just input to a log-linear model

Example: NBC for sentiment classification

Consider a sentence like

I did not like the acting, but the plot was decent

Example features are:

- unigrams: I, did, not, like, the, acting, but, the plot, was, decent

See Lab5

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We can pre-process the data to account for negation scope

I did not like-NEG the-NEG acting-NEG, but the plot was decent

---

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We can consider the same types of features and more

- we can pair them with the class: like_{+}, like_{-}
- we can use overlapping features: not like, like acting, plot decent
- with good regularisation, we can have far more features

Evaluation

For binary classification

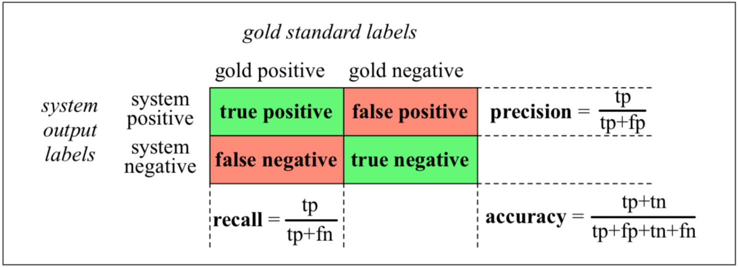

Figure 4.4 Contingency table

- use a training/development/test split
- or, preferably, cross-validation

Image from Ch4 of Jurafsky and Martin (3rd edition)

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For the written assignment, we used **interpolation** to simplify conditioning on high-dimensional outcomes $(X_{\text{prev}} = x', C = c)$

Interpolated CPD

This is a heuristic technique whereby we use a convex combination of simpler CPDs:

$$P_{X|X_{\text{prev}}C}(x|x', c) = \alpha \times P_{X|X_{\text{prev}}}(x|x') + (1 - \alpha) \times P_{X|C}(x|c)$$

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- it requires $0 < \alpha < 1$ for which no closed-form MLE is available
- we need to tune α on held-out data
- and estimate the simpler cpds independently
  $P_{X|X_{\text{prev}}}(x|x') = \frac{\text{count}_{X_{\text{prev}}X}(x',x)}{\text{count}_{X_{\text{prev}}}(x')}$ and $P_{X|C}(x|c) = \frac{\text{count}_{CX}(c,x)}{\text{count}_{C}(c)}$

Naive Bayes CPD

We can use the Naive Bayes assumption to model CPDs!

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Note the denominator needs to be inferred

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Pro: MLE is exact (no need to tune heuristic coefficients)
Con: denominator must be computed $O(|\mathcal{X}|)$ (this scales linearly in vocabulary size)

Logistic CPD

This is a direct application of LR, for example:

$$P_{X|X_{\text{prev}}C}(x|x', c; w) = \frac{\exp\left(w^\top f(x, x', c)\right)}{\mathcal{Z}(x|w)}$$

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- eventually the log-likelihood function stops improving and we have a global optimum

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We can look into exercises (in preparation for final exam) and then you can go work on the final lab ;)

References I