# 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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We have learnt two techniques to design feature-rich models

- 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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- exact MLE solution
- 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<br><br>$x$ is a document and $y$ is a binary label |
| Textual entailment | given a two pieces of text, does one entail or contradict the other?<br><br>$x$ 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

# Feature functions

A feature function in NBC is a little different from a feature function in LR

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- NBC:

$$P_{Y|X}(y|x) \stackrel{\text{def}}{=} P_{Y|F_1^n}(y|f_1^n = h(x))$$

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- NBC:

$$P_{Y|X}(y|x) \stackrel{\text{def}}{=} P_{Y|F_1^n}(y|f_1^n = h(x)) \propto P_Y(y) \prod_{i=1}^{n} P_{F|Y}(f_i|y)$$

- LR:

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

# 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 pair them with the class: $\text{like}_+$, $\text{like}_-$

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We can consider the same types of features and more

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

# Evaluation

For binary classification

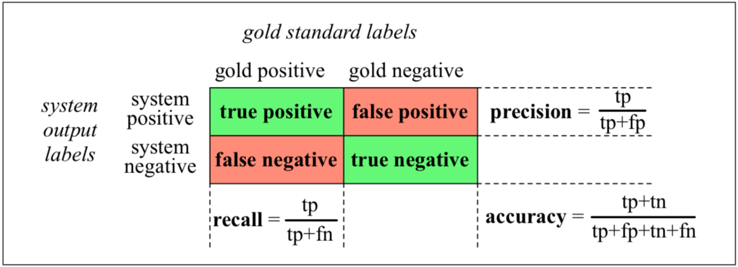


**Figure 4.4** Contingency table

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

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

# Component in Generative Model

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

# 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 $\alpha$ on held-out data
- and estimate the simpler cpds independently

# Naive Bayes CPD

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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 $O(|\mathcal{Y}|)$

# Logistic CPD

This is a direct application of LR, for example:

$$P_{X|X_{\mathsf{prev}}C}(x|\color{red}{x', c}; w) = \frac{\exp\Big(w^\top f(x, x', c)\Big)}{\mathcal{Z}(x|w)}$$

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

# This is it!

We reached the end of the course

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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