Natural Language Processing

Lectures 2: Language Classification. Probability Review. Machine Learning Background. Naive Bayes' Classifier.

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COMS W4705
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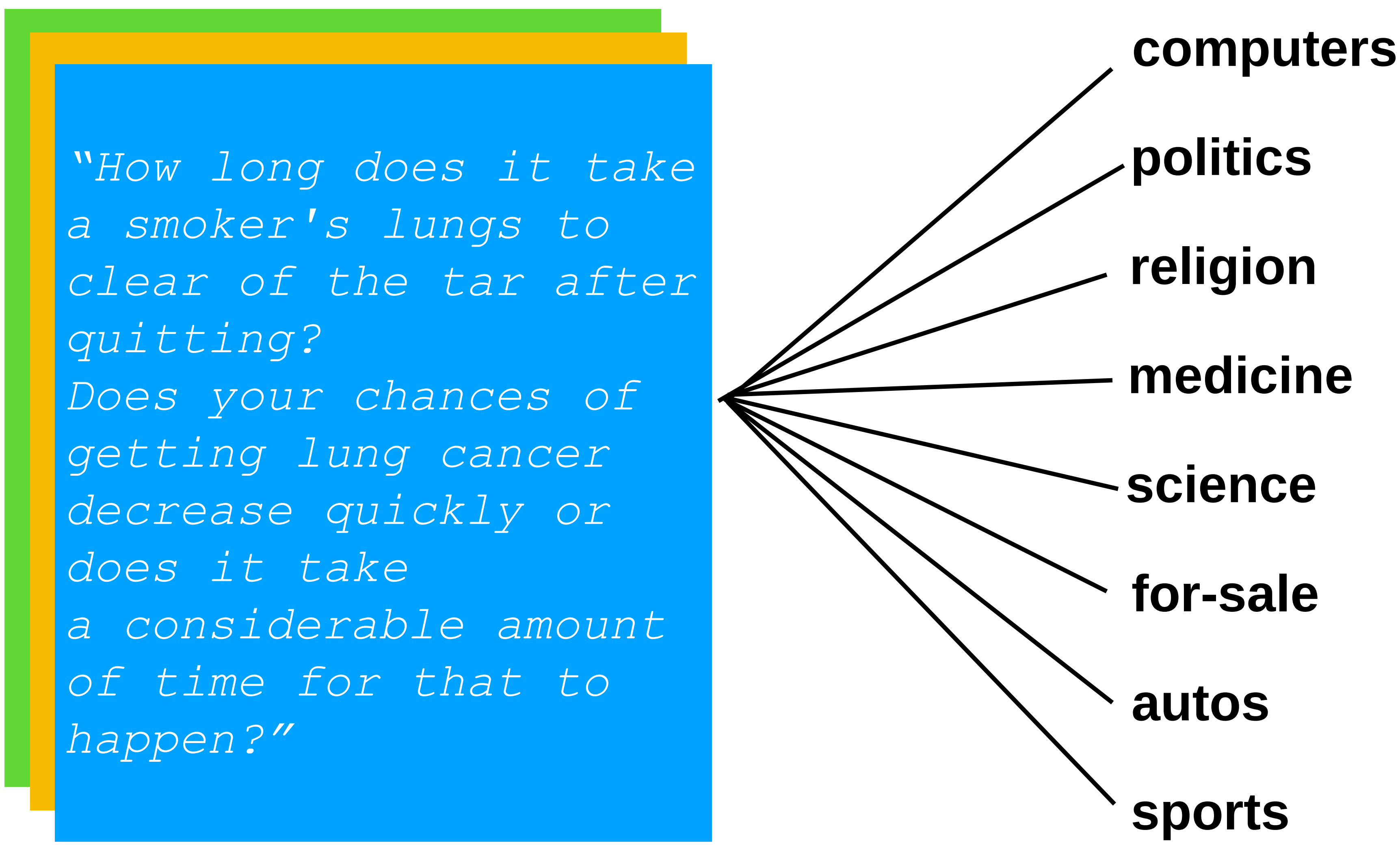
Text Classification

- Given a representation of some document d, identify which class $c \in C$ the document belongs to.



From the 20-Newsgroups data set: http://www.cs.cmu.edu/afs/cs/project/theo-11/www/naive-bayes.html

Text Classification

- Applications:
  - Spam detection.
  - Mood / Sentiment detection.
  - Author identification.
  - Identifying political affiliation.
  - Word Sense Disambiguation.
  - …

Text Classification

- This is a machine learning problem.
  - How do we represent each document?
    (feature representation).
  - Can use different ML techniques.
    - **Supervised ML:** Fixed set of classes C.
      Train a classifier from a set of labeled <document,class> pairs.
      - Discriminative vs. Generative models.
    - Unsupervised ML: Unknown set of classes C.
      Topic modeling.

Types of Feedback

- **Supervised learning:** Given a set of input-output pairs, learn a function that maps inputs to outputs.
- **Unsupervised learning:** Learn patterns in the input without any explicit feedback.
  One typical approach: clustering, identify clusters of input examples.
- **Semi-supervised learning:** Start with a few labeled input/output pairs, then use a lot of unlabeled data to improve.
- **Reinforcement learning:** Start with a *policy* determining the agent's actions. Feedback in the form of reward or punishment.

Supervised Learning

- Given: Training data consisting of training examples $(\mathbf{x_1}, y_1), \ldots, (\mathbf{x_n}, y_n)$, where $\mathbf{x_i}$ is an input example (a d-dimensional vector of attribute values) and y_i is the label.

example					label
1	x_{11}	x_{12}	…	x_{1d}	y_1
…	…	…	…	…	…
i	x_{i1}	x_{i2}	…	x_{id}	y_i
…	…	…	…	…	…
n	x_{n1}	x_{n2}	…	x_{nd}	y_n

- Goal: learn a hypothesis function h(x) that approximates the true relationship between x and y. This function should: 1) ideally be consistent with the training data. 2) generalize to unseen examples.

- In NLP y_i typically form a finite, discrete set.

Running Machine Learning Experiments

- When running machine learning experiments we typically split the labeled data in three sections:

- For example: 80% Training, 10% Validation (development), 10% Test or 90/5/5

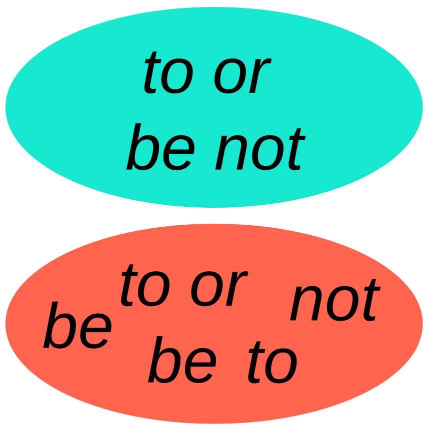
- Validation set is used to tune model parameters (for example smoothing parameters), but cannot be used for training. This can help with overfitting.

- Test set is used to assess the performance of the final model and provide an estimation of the test error.

Note: Never train or tune parameters on the test set!

Representing Documents

to be, or not to be



- Set-of-words representation.
- Bag-of-words representation (Multi-set).
- Vector-space model: Each word corresponds to one dimension in vector space. Entries are either:
    - Binary (Word appears / does not appear)
    - Raw or normalized frequency counts.
    - Weighted frequency counts
    - Probabilities.

$$\begin{array}{c} \text{be} \\ \vdots \\ \text{not} \\ \vdots \\ \text{or} \\ \vdots \\ \text{to} \end{array} \left[\begin{array}{c} \mathbf{2} \\ \vdots \\ \mathbf{1} \\ \vdots \\ \mathbf{1} \\ \vdots \\ \mathbf{2} \end{array} \right]$$

What is a Word?

- e.g., are *“Cat”*, *“cat”* and *“cats”* the same word?
- *“September”* and *“Sept”*?
- *“zero”* and *“oh”*?
- Is *“_”* a word? *“.”*? *“*”*? *‘(‘*?
- How many words are there in *“don’t”* ? *“Gonna”* ? *“I.B.M.”*?
- In Japanese and Chinese text -- how do we identify a word?
- …

Text Normalization

- Every NLP task needs to do some text normalization.
  - Segmenting / tokenizing words in running text.
  - Normalizing word forms (lemmatization or stemming, possibly replacing named-entities).
  - Sentence splitting.

Linguistic Terminology

- **Sentence**: Unit of written language.
- **Utterance**: Unit of spoken language.
- Word **Form:** the inflected form as it actually appears in the corpus. *“produced”*
- Word **Stem**: The part of the word that never changes between morphological variations. *“produc”*
- **Lemma**: an abstract base form, shared by word forms, having the same stem**,** part of speech, and word sense – stands for the **class** of words with stem. *“produce”*
- **Type**: number of distinct words in a corpus (vocabulary size).
- **Token**: Total number of word occurrences**.**

Tokenization

- Tokenization: The process of segmenting text (a sequence of characters) into a sequence of tokens (words).

"Mr. O'Neill thinks that the boys' stories about Chile's capital aren't amusing."

$\boxed{\textit{mr.}}$ $\boxed{\textit{o'neill}}$ $\boxed{\textit{thinks}}$ $\boxed{\textit{that}}$ $\boxed{\textit{the}}$ $\boxed{\textit{boys}}$ $\boxed{\textit{'}}$ $\boxed{\textit{stories}}$ $\boxed{\textit{about}}$ $\boxed{\textit{Chile}}$ $\boxed{\textit{'s}}$ $\boxed{\textit{capital}}$ $\boxed{\textit{are}}$ $\boxed{\textit{n't}}$ $\boxed{\textit{amusing}}$ $\boxed{\textit{.}}$

- Simple (but weak) approach: Separate off punctuation. Then split on whitespaces.

- Typical implementations use regular expressions (finite state automata).

Tokenization Issues

- Dealing with punctuation (some may be part of a word)
  “Ph.D.”, “O’Reilly”, “pick-me-up”

- Which tokens to include (punctuation might be useful for parsing, but not for text classification)?

- Language dependent: Some languages don’t separate words with whitespaces.
  de: *“Lebensversicherungsgesellschaftsangestellter”*

  zh: 日文章鱼怎么说? - Japanese Octopus how say?

  日文章鱼怎么说? - Sun article fish how say?

Chinese example from Sproat (1996)

Lemmatization

- Converting Lemmas into their base form.

"Mr. O'Neill thinks that the boys' stories about Chile's capital aren't amusing."

mr.	o'neill	think	that	the	boy	story	about	chile	's	capital	are	n't	amusing	.

PER	PER	think	that	the	boy	story	about	LOC	's	capital	are	n't	amusing	.

Probabilities in NLP

- Ambiguity is everywhere in NLP. There is often *uncertainty* about the "correct" interpretation. Which is more likely:
  - Speech recognition: *"recognize speech"* vs. *"wreck a nice beach"*
  - Machine translation: *"l'avocat general"*: *"the attorney general"* vs. *"the general avocado"*
  - Text classification: is a document that contains the word *"rice"* more likely to be about politics or about agriculture?
    What if it also includes several occurrences of the word *"stir"*?
- Probabilities make it possible to combine evidence from multiple sources systematically to (using Bayesian statistics)

Bayesian Statistics

- Typically, we observe some evidence (for example, words in a document) and the goal is to infer the “correct” interpretation (for example, the topic of a text).

- Probabilities express the degree of belief we have in the possible interpretations.

  - **Prior probabilities:** Probability of an interpretation prior to seeing any evidence.

  - **Conditional (Posterior) probability:** Probability of an interpretation after taking evidence into account.

Probability Basics

- Begin with a **sample space** Ω
  - Each $\omega \in \Omega$ is a possible basic outcome / “possible world” (e.g. the 6 possible rolls of a die).
- A **probability distribution** assigns a probability to each basic outcome.

$$P(\omega) \leq 1.0 \text{ for every } \omega \in \Omega$$

$$\sum_{\omega \in \Omega} P(\omega) = 1.0$$

- E.g: six-sided die

$$P(1) + P(2) + P(3) + P(4) + P(5) + P(6) = 1.0$$

Events

- An *event A* is any subset of Ω .

$$P(A) = \sum_{\omega \in A} P(\omega)$$

- Example:

$$P(\text{die roll} < 4) = P(1) + P(2) + P(3) = 1/6 + 1/6 + 1/6 = 1/2$$

Random Variables

- A random variable is a function from basic outcomes to some range, e.g. real numbers or booleans.

$$Odd(1) = true$$

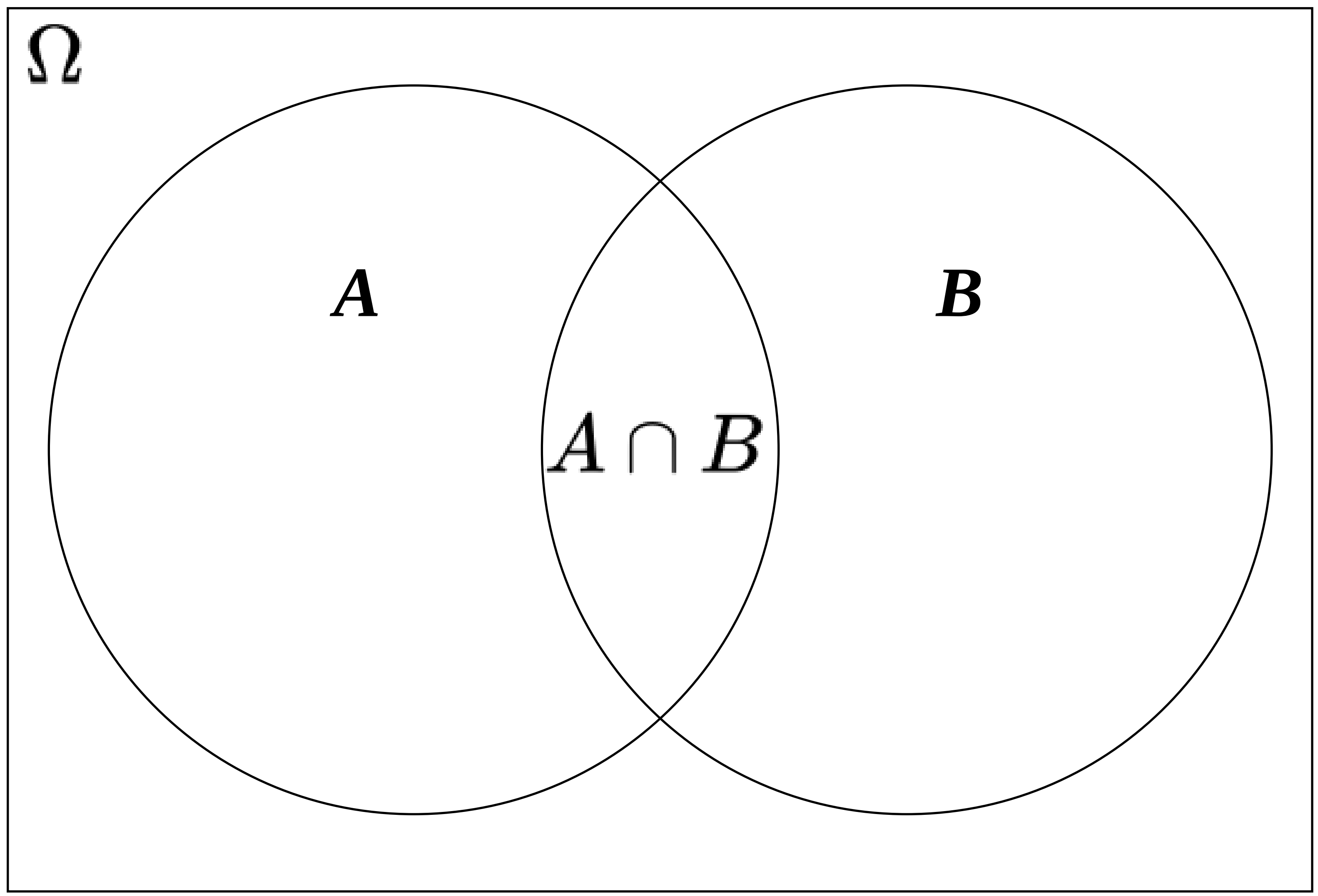
- A distribution P induces a probability distribution for any random variable.

$$P(X = x_i) = \sum_{\{\omega : X(\omega) = x_i\}} P(\omega)$$

- E.g $P(Odd = true) = P(1) + P(3) + P(5) = 1/2$

Joint and Conditional Probability

Joint probability: $P(A \cap B)$ also written as $P(A, B)$



Conditional probability: $$P(A|B) = \frac{P(A,B)}{P(B)}$$

Rules for Conditional Probability

- Product rule: $P(A, B) = P(B) \cdot P(A|B) = P(A) \cdot P(B|A)$

- Chain rule (generalization of product rule):

$$P(A_n, \ldots, A_1) = P(A_n | A_{n-1}, \ldots, A_1) \cdot P(A_{n-1}, \ldots, A_1)$$

- **Bayes' Rule:**

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}$$

Independence

- Two events are independent if $P(A) = P(A|B)$

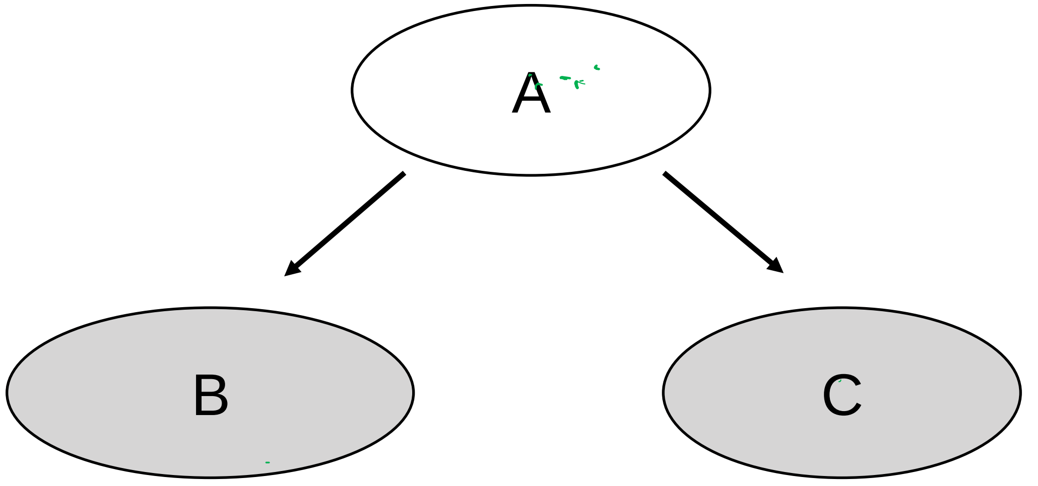
  or equivalently $P(A,B) = P(A) \cdot P(B)$ (if $P(B) > 0$)

- Two events are **conditionally independent** if:

$$P(B,C|A) = P(B|A)P(C|A)$$

  or equivalently

$$P(B|A,C) = P(B|A) \text{ and } P(C|A,B) = P(C|A)$$



Probabilities and Supervised Learning

- Given: Training data consisting of training examples
  data = $(\mathbf{x_1}, y_1), \ldots, (\mathbf{x_n}, y_n)$,
  Goal: Learn a mapping h from x to y.

- We would like to learn this mapping using $P(y|x)$.

- Two approaches:

  - Discriminative algorithms learn $P(y|x)$ directly.

  - Generative algorithms use Bayes rule

$$P(y|x) = \frac{P(x|y) \cdot P(y)}{P(x)}$$

Discriminative Algorithms

- Model conditional distribution of the label given the data
  $P(y|x)$
- Learns decision boundaries that separate instances of the different classes.
- To predict a new example, check on which side of the decision boundary it falls.
- Examples:
  support vector machine (SVM), decision trees, random forests, neural networks, log-linear models.

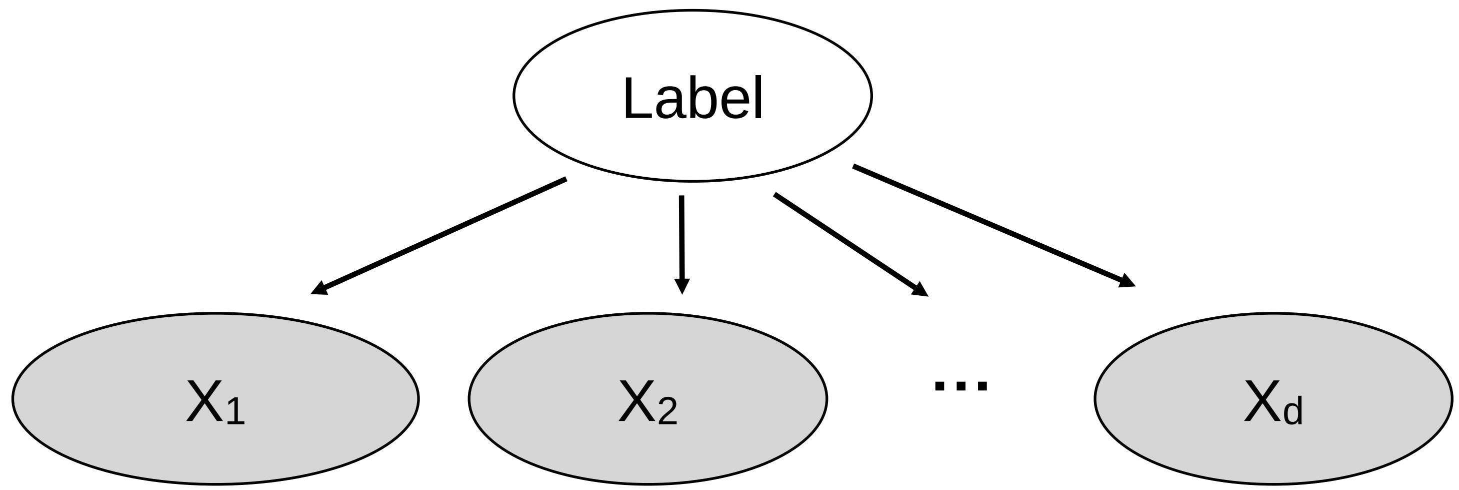
Generative Algorithms

- Assume the observed data is being “generated” by a “hidden” class label.
- Build a **different model** for each class.
- To predict a new example, check it under each of the models and see which one matches best.
- Estimate $P(x|y)$ and $P(y)$. Then use bases rule

$$P(y|x) = \frac{P(x|y) \cdot P(y)}{P(x)}$$

- Examples:
  Naive Bayes, Hidden Markov Models, Gaussian Mixture Models, PC

Naive Bayes



Label

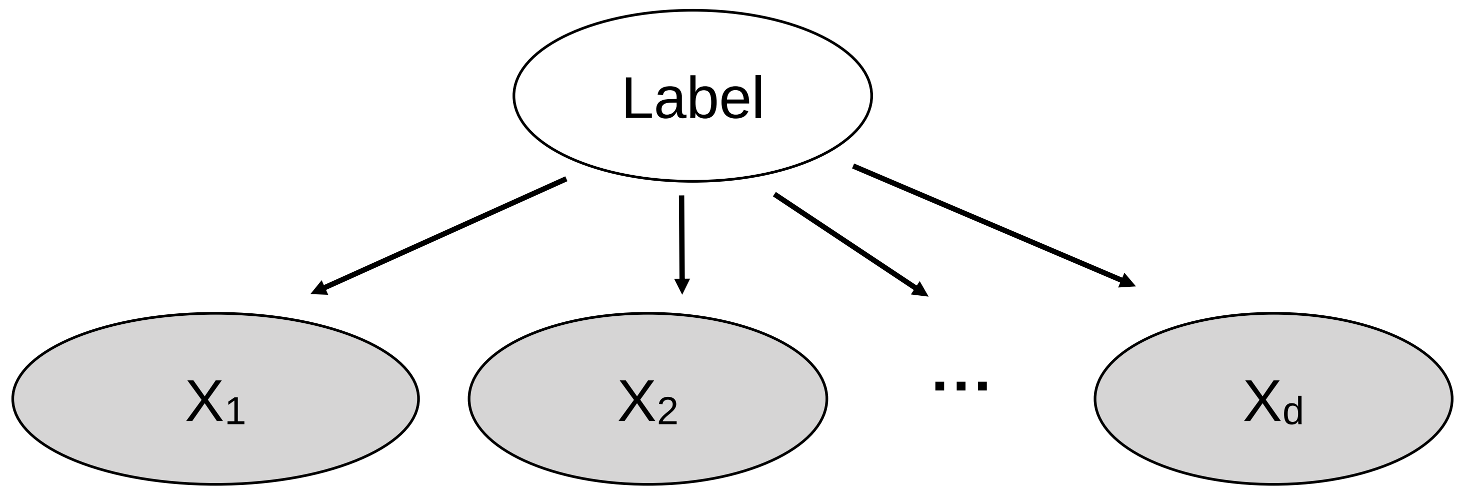
Attributes

$$\mathbf{P}(Label, X_1, \ldots X_d) = \mathbf{P}(Label) \prod_i P(X_i | Label)$$

$$\mathbf{P}(Label | X_1, \ldots X_d) = \frac{\mathbf{P}(Label) \prod_i P(X_i | Label)}{\prod_i P(X_i)}$$

$$= \alpha [\mathbf{P}(Label) \prod_i P(X_i | Label)]$$

Naive Bayes Classifier



$$\mathbf{P}(Label|X_1,\ldots X_d) = \alpha[\mathbf{P}(Label)\prod_i P(X_i|Label)]$$

$$y* = \arg\max_y P(y)\prod_i P(x_i|y)$$

Note that the normalizer α does no longer matter for the argmax because α is independent of the class label.

Training the Naive Bayes' Classifier

- Goal: Use the training data to estimate **P**(Label) and **P**(X_i|Label) from training data.

- Estimate the prior and posterior probabilities using **Maximum Likelihood Estimates (MLE):**

$$P(y) = \frac{Count(y)}{\sum_{y' \in Y} Count(y')}$$

$$P(x_i|y) = \frac{Count(x_i, y)}{\sum_{x'} Count(x', y)} = \frac{Count(x_i, y)}{Count(y)}$$

- I.e. we just count how often each token in the document appears together with each class label.

Why the Independence Assumption Matters

- Without the independence assumption we would have to estimate $\mathbf{P}(X_1, \ldots X_d | Label)$

- There would be many combinations of $x_1, \ldots, x_d$ that are never seen (sparse data).

- The independence assumption allows us to estimate each $\mathbf{P}(X_1 | label)$ independently.

Is this a safe assumption for documents?
Are the words really independent of each other?

Training the Naive Bayes' Classifier

- Ways to improve this model?
- Some issues to consider...
  - What if there are words that do not appear in the training set? What if it appears only once?
  - What if the plural of a word never appears in the training set?
  - How are extremely common words (e.g., “the”, “a”) handled?

Acknowledgments

- Some slides and examples from:
  - Kathy McKeown, Dragomir Radev