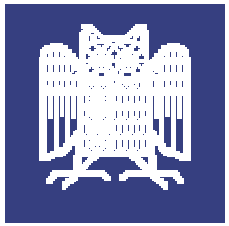


Foundations: Statistical Classification in Natural Language Processing

Dietrich Klakow

What is Classification?

Introduction

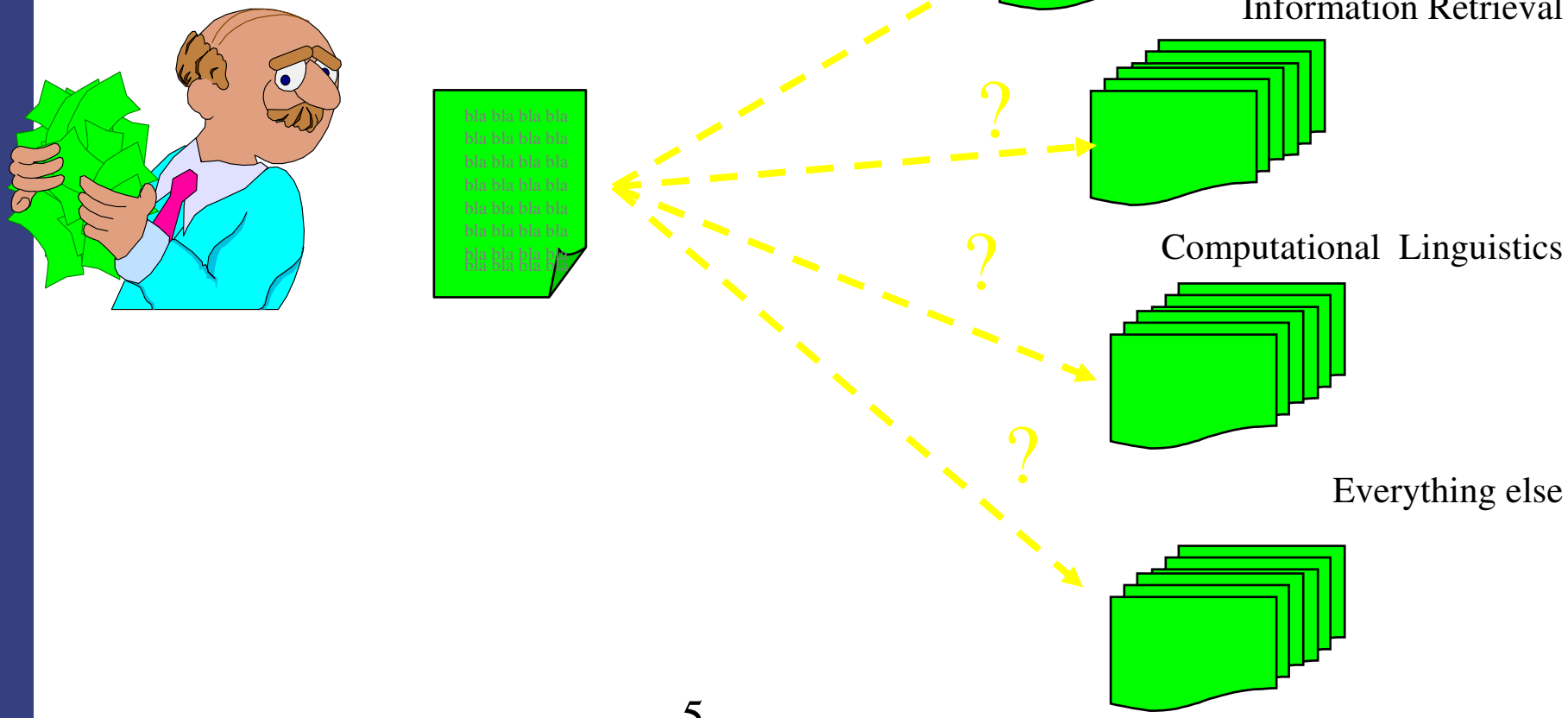
Spam/junk/bulk Emails

- The messages you spend your time with just to delete them
  - Spam: do not want to get, unsolicited messages
  - Junk: irrelevant to the recipient, unwanted
  - Bulk: mass mailing for business marketing (or fill-up mailbox etc.)

Classification task: decide for each e-mail whether it is spam/not-spam

Text Classification

e.g. text classification



Question type classification in question answering

Question	Type	Sub-type
Who killed Gandhi ?	HUMAN	individual
Who has won the most Super Bowls ?	HUMAN	group
What city did Duke Ellington live in?	LOCATION	city
Where is the highest point in Japan ?	LOCATION	mountain
What do sailors use to measure time ?	ENTITY	technique
Who is Desmond Tutu ?	DESCRIPTION	human

50 different question types

Most frequent question types:

Human:individual	18%
Location:other	9%
Decription:definition	8%

Examples of Senses of the Word "Band" from SENSEVAL

band 532732 strip n band/2/1
band 532733 stripe n band/2/1.2
band 532734 range n band/2/2
band 532735 group n band/1/2
band 532736 mus n band/1/1
band 532744 brass n brass_band
band 532745 radio n band/2/2.1
band 532746 vb v band/1/3
band 532747 silver n silver_band
band 532756 steel n steel_band
band 532765 big n big_band
band 532782 dance n dance_band
band 532790 elastic n elastic_band
band 532806 march n marching_band
band 532814 man n one-man_band
band 532838 rubber n rubber_band
band 532903 ed n band/2/3
band 532949 saw n band_saw
band 532963 course n band_course
band 532979 pl n band/2/4
band 533487 vb2 a band/2/5
band 533495 portion n band/2/1.3
band 533508 waist n waistband
band 533520 ring n band/2/1.4
band 533522 sweat n sweat_band
band 533580 wrist n wristband//1
band 533705 vb3 v band/2/6
band 533706 vb4 v band/2/7

Example 1:

The incidence of accents and rests, permuted through a regular space-time grid, becomes rhythmic in itself as it modifies, defines and enriches the grouping procedure. For example, a traditional American jazz <tag ???? >band</> was subdivided into a front line (melodic) section, usually led by trumpet, and rhythm section, usually based on drums.

Example 1:

The incidence of accents and rests, permuted through a regular space-time grid, becomes rhythmic in itself as it modifies, defines and enriches the grouping procedure. For example, a traditional American jazz <tag "532736">band</> was subdivided into a front line (melodic) section, usually led by trumpet, and rhythm section, usually based on drums.

band 532736 mus n band/1/1

Example 2:

The headsail wardrobe currently consists of a non-overlapping working jib set on a furler, originally designed to cope with wind speeds between 10 and 35 knots plus. But Mary feels it is too small for the lower wind speeds, so she may introduce an overlapping furler for the 10 to 18 knot ???? band</>.

Example 2:

The headsail wardrobe currently consists of a non-overlapping working jib set on a furler, originally designed to cope with wind speeds between 10 and 35 knots plus. But Mary feels it is too small for the lower wind speeds, so she may introduce an overlapping furler for the 10 to 18 knot <tag "532734">band</>.

band 532734 range n band/2/2

Example 3:

The Moorsee Lake, on the edge of town, is ideal for swimming. rowing boats are also available for hire. Don't leave without hearing the village brass <tag

???? >band</> which plays three times a week.

Example 3:

The Moorsee Lake, on the edge of town, is ideal for swimming. rowing boats are also available for hire. Don't leave without hearing the village brass <tag "532744">band</> which plays three times a week.

band 532744 brass n brass_band

Example 4:

Here, suspended from Lewis's person, were pieces of tubing held on by rubber <tag ???? bands</>, an old wooden peg, a bit of cork.

Example 4:

Here, suspended from Lewis's person, were pieces of tubing held on by rubber <tag "532838">bands</>, an old wooden peg, a bit of cork.

band 532838 rubber n rubber_band

Example for Part-Of-Speech Tagging

Xinhua News Agency , Guangzhou , March 16 (Reporter Chen Ji) The latest statistics show that from January through February this year , the export of high-tech products in Guangdong Province reached 3.76 billion US dollars , up 34.8% over the same period last year and accounted for 25.5% of the total export in the province .

Example for Part-Of-Speech Tagging

Xinhua/NNP News/NNP Agency/NNP ,/,
Guangzhou/NNP ,/, March/NNP 16/CD (/(
Reporter/NNP Chen/NNP Ji/NNP)/SYM The/DT
latest/JJS statistics/NNS show/VBP that/IN from/IN
January/NNP through/IN February/NNP this/DT
year/NN ,/, the/DT export/NN of/IN high-tech/JJ
products/NNS in/IN Guangdong/NNP
Province/NNP reached/VBD 3.76/CD billion/CD
US/PRP dollars/NNS ,/, up/IN 34.8%/CD over/IN
the/DT same/JJ period/NN last/JJ year/NN and/CC
accounted/VBD for/IN 25.5%/CD of/IN the/DT
total/JJ export/NN in/IN the/DT province/NN ./.

Penn-Tree-Bank Tags-Set

- 45 Tags

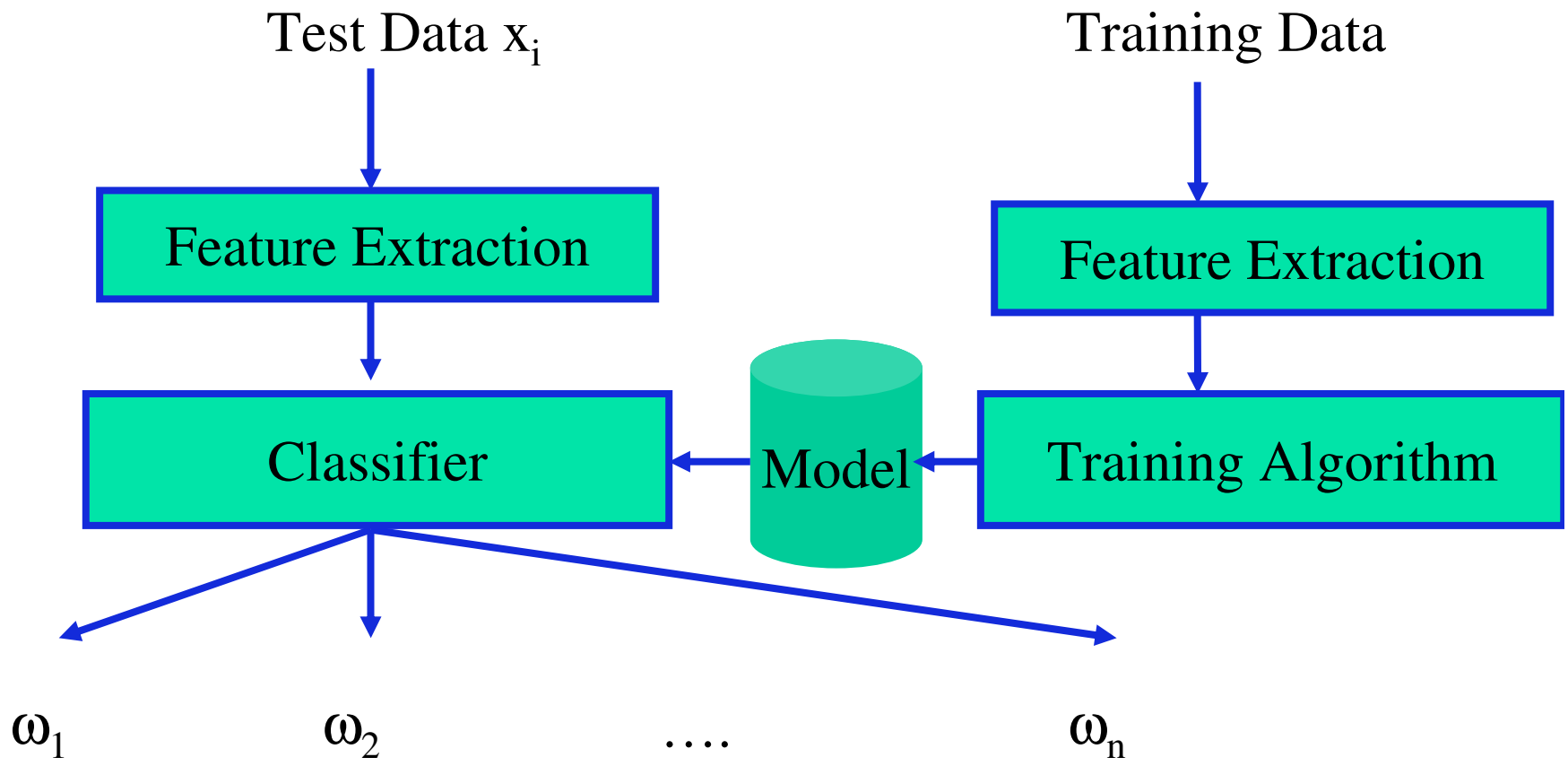
Examples:

Tag	Description	Example
CC	Coordinating Conjunction	and, but, or
CD	Cardinal number	one, two, three
DT	Determiner	a. the
JJ	Adjective	yellow
NN	Noun, sing. or mass	province
NNP	Proper noun, singular	IBM
RB	Adverb	quickly, never
VB	Verb, base form	eat
VBD	Verb, past tense	ate
…	…	…

Definition

Pattern Classification:
Automatic transformation of data x_i (observations, features) into a set of symbols ω_i (classes).

Flow of Data in Pattern Classification



The Bayes Classifier

Classifying e-mail for spam/not-spam

- Simple model:
  - No posterior knowledge (i.e. no measurements)
  - Two classes

    ω_1 ="spam"

    ω_2="not-spam"
  - Given: $P(\omega_1)$ and $P(\omega_2)$
  - Goal:
    - Minimize the number of mails that get the wrong label

How would you set up a decision rule?

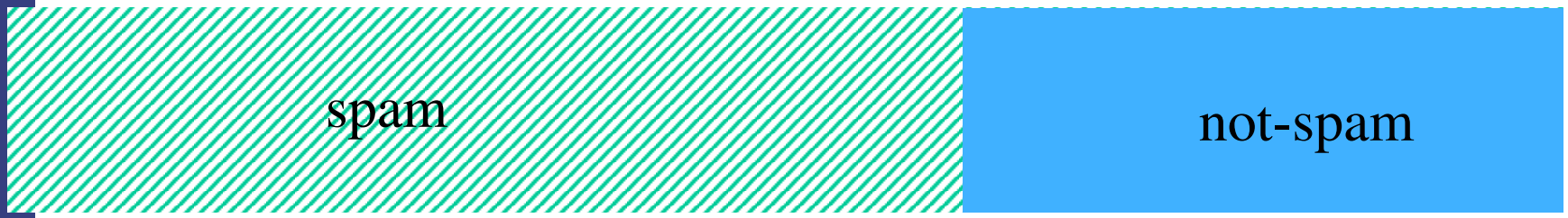
Classifying Mail

$P(\omega_1)$ $P(\omega_2)$

Classify every e-mail as

Classifying Mail

Incorrectly classified



$P(\omega_1)$ $P(\omega_2)$

Classify every e-mail as not-spam

Classifying Mail

$P(\omega_1)$ $P(\omega_2)$

Classify every e-mail as spam

Smaller number of e-mails with wrong label

Generalization

- Minimize number of wrong labels

  $\mapsto$pick class with highest probability

Formal notation:

$$\overline{\omega_i} = \arg\max_{\omega_k} P(\omega_k)$$

Available Measurements x

- Feature vector x from measurement
- Probabilities depend on x $P(\omega_k \mid x)$
- Definition conditional probability:

$$P(\omega_k \mid x) = \frac{P(\omega_k, x)}{P(x)}$$

Bayes Decision Rule: Draft Version

- Bayes decision rule

$$\overline{\omega_i} = \arg\max_{\omega_k} P(\omega_k \mid x)$$

Ugly: usually x is measured for a given class ω_k

Rewrite Bayes Decision Rule

$$\overline{\omega_i} = \arg\max_{\omega_k} P(\omega_k \mid x)$$

$$= \arg\max_{\omega_k} \frac{P(x \mid \omega_k)P(\omega_k)}{P(x)}$$

$$= \arg\max_{\omega_k} P(x \mid \omega_k)P(\omega_k)$$

Use definition of cond. probability

$$P(\omega_k \mid x) = \frac{P(\omega_k, x)}{P(x)}$$

$$= \frac{P(x \mid \omega_k)P(\omega_k)}{P(x)}$$

P(x) does not affect decision

Bayes Decision Rule

$$\overline{\omega_k} = \arg\max_{\omega_k} \left[P(x \mid \omega_k) P(\omega_k) \right]$$

Terminology

Prior: $P(\omega_k)$

Posterior: $P(\omega_k \mid x)$

Naïve Bayes

- x is not a single feature, but a bag of features

  e.g. different key-words for your spam-mail detection system
- Assume statistical independence of features

$$P(\{x_1 \ldots x_N\} \mid \omega_k) \approx \prod_{i=1}^{N} P(x_i \mid \omega_k)$$

Apply Naïve Bayes Classifier to Question Type Classification

What are suitable features to classify questions?

- Question word?
- Key words?
- Head word?

Pointwise Mutual Information

Definition

$$pMI(x_i, \omega_j) = \frac{N(x_i, \omega_j)}{N} \log\left(\frac{N(x_i, \omega_j)N}{N(x_i)N(\omega_j)} \right)$$

with

$N(x_i, \omega_j)$: frequency of co-occurence of feature x_i with class ω_j

$N(x_i)$: frequency of feature x_i

$N(\omega_j)$: frequency of class ω_j

Examples

Type	Feature	pMI(x,ω)	N(x,ω)	P(x|ω)/P(x)
NUM:count	many	0.015	322	13.7
HUM:ind	Who	0.013	498	4.46
NUM:count	How	0.011	336	6.23
LOC:other	Where	0.011	253	11.22
DESC:manner	How	0.010	274	7.52
LOC:country	country	0.007	120	32.01
NUM:date	When	0.007	124	26.23
DESC:def	is	0.006	284	3.48

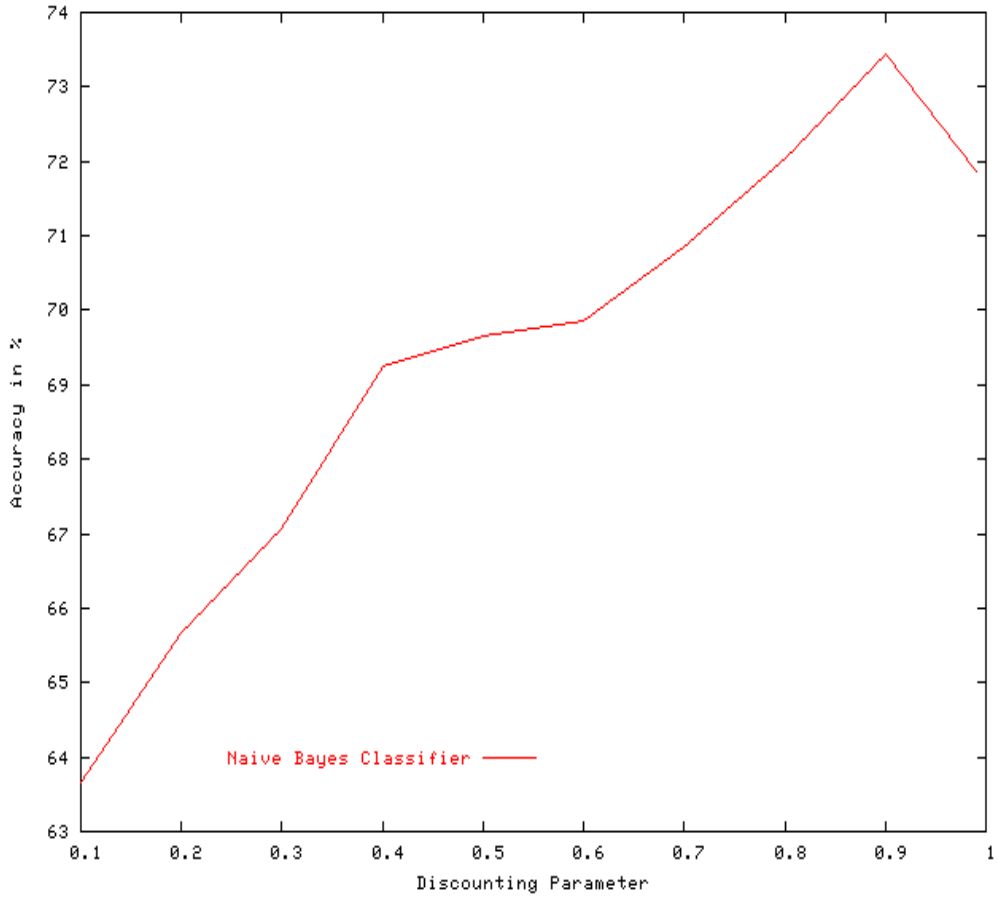
Use Language Models to estimate Probabilities

Absolute discounting:

$$P(x_i \mid \omega_k) = \begin{cases} \dfrac{N_{\omega_k}(x_i) - d}{N_{\omega_k}} + \alpha \dfrac{1}{V} & \text{if } N_{\omega_k}(x_i) > 0 \\ \alpha \dfrac{1}{V} & \text{else} \end{cases}$$

V : size of "feature vocabulary"

Results



Proper smoothing important

Alternative Classifiers

- Nearest Neighbor
- Support Vector Machines
- Neural Networks
- Decision Trees
- Boosting

Summary

- Many NLP problems can be cast as a classification problem
- Naïve Bayes Classifier often serves as a baseline in statistical NLP

How to build a part of speech tagger

HMM Tagger

Specific classification task:

Features: sentence $W=w_1 \ldots w_n$

Class: tag sequence $T=t_1 \ldots t_n$

Bayes classifier:

$$\text{argmax}_T P(W|T)P(T)$$

or

$$\text{argmax}_T P(w_1 \ldots w_n|t_1 \ldots t_n)P(t_1 \ldots t_n)$$

Simplification of HMM Tagger

Assumptions:

word is dependent only on its own POS tag

POS tag depends only on predecessor tag (bigram)

$$\text{argmax}_T[P(w_1|t_1)P(w_2|t_2)\ldots P(w_n|t_n)][P(t_1)P(t_2|t_1)\ldots P(t_n|t_{n-1})]$$

Bigram HMM Tagger

Estimate

$$P(t_i|t_{i-1}) = N(t_{i-1}t_i)/N(t_{i-1})$$

$$P(w_i|t_i) = N(w_i,t_i)/N(t_i)$$

(or use backing-off-model/absolute discounting)

Compute the most likely sequence using Viterbi algorithm

Alternative for POS-Tagging: Transformation based learning

- Assign each word its most frequent tag ignoring context
- Now apply sequence of transformation rules to correct typical mistakes

“Brill-tagger”