

Brief Contents

I Preliminaries 1

- 1 *Introduction* 3
- 2 *Mathematical Foundations* 39
- 3 *Linguistic Essentials* 81
- 4 *Corpus-Based Work* 117

II Words 149

- 5 *Collocations* 151
- 6 *Statistical Inference: n-gram Models over Sparse Data* 191
- 7 *Word Sense Disambiguation* 229
- 8 *Lexical Acquisition* 265

III Grammar 315

- 9 *Markov Models* 317
- 10 *Part-of-Speech Tagging* 341
- 11 *Probabilistic Context Free Grammars* 381
- 12 *Probabilistic Parsing* 407

IV Applications and Techniques 461

- 13 *Statistical Alignment and Machine Translation* 463
- 14 *Clustering* 495
- 15 *Topics in Information Retrieval* 529
- 16 *Text Categorization* 575

Contents

List of Tables **xv**

List of Figures **xxi**

Table of Notations **xxv**

Preface **xxix**

Road Map **xxxv**

I Preliminaries **1**

1 Introduction **3**

- 1.1 Rationalist and Empiricist Approaches to Language 4
- 1.2 Scientific Content 7
 - 1.2.1 Questions that linguistics should answer 8
 - 1.2.2 Non-categorical phenomena in language 11
 - 1.2.3 Language and cognition as probabilistic phenomena 15
- 1.3 The Ambiguity of Language: Why NLP Is Difficult 17
- 1.4 Dirty Hands 19
 - 1.4.1 Lexical resources 19
 - 1.4.2 Word counts 20
 - 1.4.3 Zipf's laws 23
 - 1.4.4 Collocations 29
 - 1.4.5 Concordances 31
- 1.5 Further Reading 34

1.6	Exercises	35
2	<i>Mathematical Foundations</i>	39
2.1	Elementary Probability Theory	40
2.1.1	Probability spaces	40
2.1.2	Conditional probability and independence	42
2.1.3	Bayes' theorem	43
2.1.4	Random variables	45
2.1.5	Expectation and variance	46
2.1.6	Notation	47
2.1.7	Joint and conditional distributions	48
2.1.8	Determining P	48
2.1.9	Standard distributions	50
2.1.10	Bayesian statistics	54
2.1.11	Exercises	59
2.2	Essential Information Theory	60
2.2.1	Entropy	61
2.2.2	Joint entropy and conditional entropy	63
2.2.3	Mutual information	66
2.2.4	The noisy channel model	68
2.2.5	Relative entropy or Kullback-Leibler divergence	72
2.2.6	The relation to language: Cross entropy	73
2.2.7	The entropy of English	76
2.2.8	Perplexity	78
2.2.9	Exercises	78
2.3	Further Reading	79
3	<i>Linguistic Essentials</i>	81
3.1	Parts of Speech and Morphology	81
3.1.1	Nouns and pronouns	83
3.1.2	Words that accompany nouns: Determiners and adjectives	87
3.1.3	Verbs	88
3.1.4	Other parts of speech	91
3.2	Phrase Structure	93
3.2.1	Phrase structure grammars	96
3.2.2	Dependency: Arguments and adjuncts	101
3.2.3	X' theory	106
3.2.4	Phrase structure ambiguity	107

3.3	Semantics and Pragmatics	109
3.4	Other Areas	112
3.5	Further Reading	113
3.6	Exercises	114
4	<i>Corpus-Based Work</i>	117
4.1	Getting Set Up	118
4.1.1	Computers	118
4.1.2	Corpora	118
4.1.3	Software	120
4.2	Looking at Text	123
4.2.1	Low-level formatting issues	123
4.2.2	Tokenization: What is a word?	124
4.2.3	Morphology	131
4.2.4	Sentences	134
4.3	Marked-up Data	136
4.3.1	Markup schemes	137
4.3.2	Grammatical tagging	139
4.4	Further Reading	145
4.5	Exercises	147
II	Words	149
5	<i>Collocations</i>	151
5.1	Frequency	153
5.2	Mean and Variance	157
5.3	Hypothesis Testing	162
5.3.1	The <i>t</i> test	163
5.3.2	Hypothesis testing of differences	166
5.3.3	Pearson's chi-square test	169
5.3.4	Likelihood ratios	172
5.4	Mutual Information	178
5.5	The Notion of Collocation	183
5.6	Further Reading	187
6	<i>Statistical Inference: n-gram Models over Sparse Data</i>	191
6.1	Bins: Forming Equivalence Classes	192
6.1.1	Reliability vs. discrimination	192
6.1.2	<i>n</i> -gram models	192

6.1.3	Building n -gram models	195
6.2	Statistical Estimators	196
6.2.1	Maximum Likelihood Estimation (MLE)	197
6.2.2	Laplace's law, Lidstone's law and the Jeffreys-Perks law	202
6.2.3	Held out estimation	205
6.2.4	Cross-validation (deleted estimation)	210
6.2.5	Good-Turing estimation	212
6.2.6	Briefly noted	216
6.3	Combining Estimators	217
6.3.1	Simple linear interpolation	218
6.3.2	Katz's backing-off	219
6.3.3	General linear interpolation	220
6.3.4	Briefly noted	222
6.3.5	Language models for Austen	223
6.4	Conclusions	224
6.5	Further Reading	225
6.6	Exercises	225
7	<i>Word Sense Disambiguation</i>	229
7.1	Methodological Preliminaries	232
7.1.1	Supervised and unsupervised learning	232
7.1.2	Pseudowords	233
7.1.3	Upper and lower bounds on performance	233
7.2	Supervised Disambiguation	235
7.2.1	Bayesian classification	235
7.2.2	An information-theoretic approach	239
7.3	Dictionary-Based Disambiguation	241
7.3.1	Disambiguation based on sense definitions	242
7.3.2	Thesaurus-based disambiguation	244
7.3.3	Disambiguation based on translations in a second-language corpus	247
7.3.4	One sense per discourse, one sense per collocation	249
7.4	Unsupervised Disambiguation	252
7.5	What Is a Word Sense?	256
7.6	Further Reading	260
7.7	Exercises	262

8	<i>Lexical Acquisition</i>	265
8.1	Evaluation Measures	267
8.2	Verb Subcategorization	271
8.3	Attachment Ambiguity	278
8.3.1	Hindle and Rooth (1993)	280
8.3.2	General remarks on PP attachment	284
8.4	Selectional Preferences	288
8.5	Semantic Similarity	294
8.5.1	Vector space measures	296
8.5.2	Probabilistic measures	303
8.6	The Role of Lexical Acquisition in Statistical NLP	308
8.7	Further Reading	312
III	Grammar	315
9	<i>Markov Models</i>	317
9.1	Markov Models	318
9.2	Hidden Markov Models	320
9.2.1	Why use HMMs?	322
9.2.2	General form of an HMM	324
9.3	The Three Fundamental Questions for HMMs	325
9.3.1	Finding the probability of an observation	326
9.3.2	Finding the best state sequence	331
9.3.3	The third problem: Parameter estimation	333
9.4	HMMs: Implementation, Properties, and Variants	336
9.4.1	Implementation	336
9.4.2	Variants	337
9.4.3	Multiple input observations	338
9.4.4	Initialization of parameter values	339
9.5	Further Reading	339
10	<i>Part-of-Speech Tagging</i>	341
10.1	The Information Sources in Tagging	343
10.2	Markov Model Taggers	345
10.2.1	The probabilistic model	345
10.2.2	The Viterbi algorithm	349
10.2.3	Variations	351
10.3	Hidden Markov Model Taggers	356

10.3.1	Applying HMMs to POS tagging	357	
10.3.2	The effect of initialization on HMM training	359	
10.4	Transformation-Based Learning of Tags	361	
10.4.1	Transformations	362	
10.4.2	The learning algorithm	364	
10.4.3	Relation to other models	365	
10.4.4	Automata	367	
10.4.5	Summary	369	
10.5	Other Methods, Other Languages	370	
10.5.1	Other approaches to tagging	370	
10.5.2	Languages other than English	371	
10.6	Tagging Accuracy and Uses of Taggers	371	
10.6.1	Tagging accuracy	371	
10.6.2	Applications of tagging	374	
10.7	Further Reading	377	
10.8	Exercises	379	
11	Probabilistic Context Free Grammars	381	
11.1	Some Features of PCFGs	386	
11.2	Questions for PCFGs	388	
11.3	The Probability of a String	392	
11.3.1	Using inside probabilities	392	
11.3.2	Using outside probabilities	394	
11.3.3	Finding the most likely parse for a sentence	396	
11.3.4	Training a PCFG	398	
11.4	Problems with the Inside-Outside Algorithm	401	
11.5	Further Reading	402	
11.6	Exercises	404	
12	Probabilistic Parsing	407	
12.1	Some Concepts	408	
12.1.1	Parsing for disambiguation	408	
12.1.2	Treebanks	412	
12.1.3	Parsing models vs. language models	414	
12.1.4	Weakening the independence assumptions of PCFGs	416	
12.1.5	Tree probabilities and derivational probabilities	421	
12.1.6	There's more than one way to do it	423	

12.1.7	Phrase structure grammars and dependency grammars	428
12.1.8	Evaluation	431
12.1.9	Equivalent models	437
12.1.10	Building parsers: Search methods	439
12.1.11	Use of the geometric mean	442
12.2	Some Approaches	443
12.2.1	Non-lexicalized treebank grammars	443
12.2.2	Lexicalized models using derivational histories	448
12.2.3	Dependency-based models	451
12.2.4	Discussion	454
12.3	Further Reading	456
12.4	Exercises	458

IV Applications and Techniques 461

13 Statistical Alignment and Machine Translation 463

13.1	Text Alignment	466
13.1.1	Aligning sentences and paragraphs	467
13.1.2	Length-based methods	471
13.1.3	Offset alignment by signal processing techniques	475
13.1.4	Lexical methods of sentence alignment	478
13.1.5	Summary	484
13.1.6	Exercises	484
13.2	Word Alignment	484
13.3	Statistical Machine Translation	486
13.4	Further Reading	492

14 Clustering 495

14.1	Hierarchical Clustering	500
14.1.1	Single-link and complete-link clustering	503
14.1.2	Group-average agglomerative clustering	507
14.1.3	An application: Improving a language model	509
14.1.4	Top-down clustering	512
14.2	Non-Hierarchical Clustering	514
14.2.1	K-means	515
14.2.2	The EM algorithm	518
14.3	Further Reading	527

14.4 Exercises	528
15 Topics in Information Retrieval	529
15.1 Some Background on Information Retrieval	530
15.1.1 Common design features of IR systems	532
15.1.2 Evaluation measures	534
15.1.3 The probability ranking principle (PRP)	538
15.2 The Vector Space Model	539
15.2.1 Vector similarity	540
15.2.2 Term weighting	541
15.3 Term Distribution Models	544
15.3.1 The Poisson distribution	545
15.3.2 The two-Poisson model	548
15.3.3 The K mixture	549
15.3.4 Inverse document frequency	551
15.3.5 Residual inverse document frequency	553
15.3.6 Usage of term distribution models	554
15.4 Latent Semantic Indexing	554
15.4.1 Least-squares methods	557
15.4.2 Singular Value Decomposition	558
15.4.3 Latent Semantic Indexing in IR	564
15.5 Discourse Segmentation	566
15.5.1 TextTiling	567
15.6 Further Reading	570
15.7 Exercises	573
16 Text Categorization	575
16.1 Decision Trees	578
16.2 Maximum Entropy Modeling	589
16.2.1 Generalized iterative scaling	591
16.2.2 Application to text categorization	594
16.3 Perceptrons	597
16.4 <i>k</i> Nearest Neighbor Classification	604
16.5 Further Reading	607
Tiny Statistical Tables	609
Bibliography	611
Index	657

List of Tables

1.1	Common words in <i>Tom Sawyer</i> .	21
1.2	Frequency of frequencies of word types in <i>Tom Sawyer</i> .	22
1.3	Empirical evaluation of Zipf's law on <i>Tom Sawyer</i> .	24
1.4	Commonest bigram collocations in the <i>New York Times</i> .	30
1.5	Frequent bigrams after filtering.	32
2.1	Likelihood ratios between two theories.	58
2.2	Statistical NLP problems as decoding problems.	71
3.1	Common inflections of nouns.	84
3.2	Pronoun forms in English.	86
3.3	Features commonly marked on verbs.	90
4.1	Major suppliers of electronic corpora with contact URLs.	119
4.2	Different formats for telephone numbers appearing in an issue of <i>The Economist</i> .	131
4.3	Sentence lengths in newswire text.	137
4.4	Sizes of various tag sets.	140
4.5	Comparison of different tag sets: adjective, adverb, conjunction, determiner, noun, and pronoun tags.	141
4.6	Comparison of different tag sets: Verb, preposition, punctuation and symbol tags.	142
5.1	Finding Collocations: Raw Frequency.	154
5.2	Part of speech tag patterns for collocation filtering.	154
5.3	Finding Collocations: Justeson and Katz' part-of-speech filter.	155

5.4	The nouns <i>w</i> occurring most often in the patterns 'strong <i>w</i> ' and 'powerful <i>w</i> .'	156
5.5	Finding collocations based on mean and variance.	161
5.6	Finding collocations: The <i>t</i> test applied to 10 bigrams that occur with frequency 20.	166
5.7	Words that occur significantly more often with <i>powerful</i> (the first ten words) and <i>strong</i> (the last ten words).	167
5.8	A 2-by-2 table showing the dependence of occurrences of <i>new</i> and <i>companies</i> .	169
5.9	Correspondence of <i>vache</i> and <i>cow</i> in an aligned corpus.	171
5.10	Testing for the independence of words in different corpora using χ^2 .	171
5.11	How to compute Dunning's likelihood ratio test.	172
5.12	Bigrams of <i>powerful</i> with the highest scores according to Dunning's likelihood ratio test.	174
5.13	Damerau's frequency ratio test.	176
5.14	Finding collocations: Ten bigrams that occur with frequency 20, ranked according to mutual information.	178
5.15	Correspondence of <i>chambre</i> and <i>house</i> and <i>communes</i> and <i>house</i> in the aligned Hansard corpus.	179
5.16	Problems for Mutual Information from data sparseness.	181
5.17	Different definitions of <i>mutual information</i> in (Cover and Thomas 1991) and (Fano 1961).	182
5.18	Collocations in the BBI Combinatory Dictionary of English for the words <i>strength</i> and <i>power</i> .	185
6.1	Growth in number of parameters for <i>n</i> -gram models.	194
6.2	Notation for the statistical estimation chapter.	197
6.3	Probabilities of each successive word for a clause from <i>Persuasion</i> .	200
6.4	Estimated frequencies for the AP data from Church and Gale (1991a).	203
6.5	Expected Likelihood Estimation estimates for the word following <i>was</i> .	205
6.6	Using the <i>t</i> test for comparing the performance of two systems.	209
6.7	Extracts from the frequencies of frequencies distribution for bigrams and trigrams in the Austen corpus.	214

6.8	Good-Turing estimates for bigrams: Adjusted frequencies and probabilities.	215
6.9	Good-Turing bigram frequency estimates for the clause from <i>Persuasion</i> .	215
6.10	Back-off language models with Good-Turing estimation tested on <i>Persuasion</i> .	223
6.11	Probability estimates of the test clause according to various language models.	224
7.1	Notational conventions used in this chapter.	235
7.2	Clues for two senses of <i>drug</i> used by a Bayesian classifier.	238
7.3	Highly informative indicators for three ambiguous French words.	239
7.4	Two senses of <i>ash</i> .	243
7.5	Disambiguation of <i>ash</i> with Lesk's algorithm.	243
7.6	Some results of thesaurus-based disambiguation.	247
7.7	How to disambiguate <i>interest</i> using a second-language corpus.	248
7.8	Examples of the one sense per discourse constraint.	250
7.9	Some results of unsupervised disambiguation.	256
8.1	The F measure and accuracy are different objective functions.	270
8.2	Some subcategorization frames with example verbs and sentences.	271
8.3	Some subcategorization frames learned by Manning's system.	276
8.4	An example where the simple model for resolving PP attachment ambiguity fails.	280
8.5	Selectional Preference Strength (SPS).	290
8.6	Association strength distinguishes a verb's plausible and implausible objects.	292
8.7	Similarity measures for binary vectors.	299
8.8	The cosine as a measure of semantic similarity.	302
8.9	Measures of (dis-)similarity between probability distributions.	304
8.10	Types of words occurring in the LOB corpus that were not covered by the OALD dictionary.	310
9.1	Notation used in the HMM chapter.	324
9.2	Variable calculations for $O = (\text{lem}, \text{ice}_t, \text{cola})$.	330
10.1	Some part-of-speech tags frequently used for tagging English.	342

10.2	Notational conventions for tagging.	346
10.3	Idealized counts of some tag transitions in the Brown Corpus.	348
10.4	Idealized counts of tags that some words occur within the Brown Corpus.	349
10.5	Table of probabilities for dealing with unknown words in tagging.	352
10.6	Initialization of the parameters of an HMM.	359
10.7	Triggering environments in Brill's transformation-based tagger.	363
10.8	Examples of some transformations learned in transformation-based tagging.	363
10.9	Examples of frequent errors of probabilistic taggers.	374
10.10	A portion of a confusion matrix for part of speech tagging.	375
11.1	Notation for the PCFG chapter.	383
11.2	A simple Probabilistic Context Free Grammar (PCFG).	384
11.3	Calculation of inside probabilities.	394
12.1	Abbreviations for phrasal categories in the Penn Treebank.	413
12.2	Frequency of common subcategorization frames (local trees expanding VP) for selected verbs.	418
12.3	Selected common expansions of NP as Subject vs. Object, ordered by log odds ratio.	420
12.4	Selected common expansions of NP as first and second object inside VP.	420
12.5	Precision and recall evaluation results for PP attachment errors for different styles of phrase structure.	436
12.6	Comparison of some statistical parsing systems.	455
13.1	Sentence alignment papers.	470
14.1	A summary of the attributes of different clustering algorithms.	500
14.2	Symbols used in the clustering chapter.	501
14.3	Similarity functions used in clustering.	503
14.4	An example of K-means clustering.	518
14.5	An example of a Gaussian mixture.	521
15.1	A small stop list for English.	533
15.2	An example of the evaluation of rankings.	535

15.3	Three quantities that are commonly used in term weighting in information retrieval.	542
15.4	Term and document frequencies of two words in an example corpus.	542
15.5	Components of tf.idf weighting schemes.	544
15.6	Document frequency (df) and collection frequency (cf) for 6 words in the <i>New York Times</i> corpus.	547
15.7	Actual and estimated number of documents with k occurrences for six terms.	550
15.8	Example for exploiting co-occurrence in computing content similarity.	554
15.9	The matrix of document correlations $B^T B$.	562
16.1	Some examples of classification tasks in NLP.	576
16.2	Contingency table for evaluating a binary classifier.	577
16.3	The representation of document 11, shown in figure 16.3.	581
16.4	An example of information gain as a splitting criterion.	582
16.5	Contingency table for a decision tree for the Reuters category “earnings.”	586
16.6	An example of a maximum entropy distribution in the form of equation (16.4).	593
16.7	An empirical distribution whose corresponding maximum entropy distribution is the one in table 16.6.	594
16.8	Feature weights in maximum entropy modeling for the category “earnings” in Reuters.	595
16.9	Classification results for the distribution corresponding to table 16.8 on the test set.	595
16.10	Perceptron for the “earnings” category.	601
16.11	Classification results for the perceptron in table 16.10 on the test set.	602
16.12	Classification results for an 1NN categorizer for the “earnings” category.	606

List of Figures

1.1	Zipf's law.	26
1.2	Mandelbrot's formula.	27
1.3	Key Word In Context (KWIC) display for the word <i>showed</i> .	32
1.4	Syntactic frames for <i>showed</i> in <i>Tom Sawyer</i> .	33
2.1	A diagram illustrating the calculation of conditional probability $P(A B)$.	42
2.2	A random variable X for the sum of two dice.	45
2.3	Two examples of binomial distributions: $b(r; 10, 0.7)$ and $b(r; 10, 0.1)$.	52
2.4	Example normal distribution curves: $n(x; 0, 1)$ and $n(x; 1.5, 2)$.	53
2.5	The entropy of a weighted coin.	63
2.6	The relationship between mutual information I and entropy H .	67
2.7	The noisy channel model.	69
2.8	A binary symmetric channel.	69
2.9	The noisy channel model in linguistics.	70
3.1	An example of recursive phrase structure expansion.	99
3.2	An example of a prepositional phrase attachment ambiguity.	108
4.1	Heuristic sentence boundary detection algorithm.	135
4.2	A sentence as tagged according to several different tag sets.	140
5.1	Using a three word collocational window to capture bigrams at a distance.	158

5.2	Histograms of the position of <i>strong</i> relative to three words.	160
7.1	Bayesian disambiguation.	238
7.2	The Flip-Flop algorithm applied to finding indicators for disambiguation.	240
7.3	Lesk's dictionary-based disambiguation algorithm.	243
7.4	Thesaurus-based disambiguation.	245
7.5	Adaptive thesaurus-based disambiguation.	246
7.6	Disambiguation based on a second-language corpus.	249
7.7	Disambiguation based on "one sense per collocation" and "one sense per discourse."	252
7.8	An EM algorithm for learning a word sense clustering.	254
8.1	A diagram motivating the measures of precision and recall.	268
8.2	Attachments in a complex sentence.	285
8.3	A document-by-word matrix <i>A</i> .	297
8.4	A word-by-word matrix <i>B</i> .	297
8.5	A modifier-by-head matrix <i>C</i> .	297
9.1	A Markov model.	319
9.2	The crazy soft drink machine, showing the states of the machine and the state transition probabilities.	321
9.3	A section of an HMM for a linearly interpolated language model.	323
9.4	A program for a Markov process.	325
9.5	Trellis algorithms.	328
9.6	Trellis algorithms: Closeup of the computation of forward probabilities at one node.	329
9.7	The probability of traversing an arc.	334
10.1	Algorithm for training a Visible Markov Model Tagger.	348
10.2	Algorithm for tagging with a Visible Markov Model Tagger.	350
10.3	The learning algorithm for transformation-based tagging.	364
11.1	The two parse trees, their probabilities, and the sentence probability.	385
11.2	A Probabilistic Regular Grammar (PRG).	390
11.3	Inside and outside probabilities in PCFGs.	391
12.1	A word lattice (simplified).	408

12.2	A Penn Treebank tree.	413
12.3	Two CFG derivations of the same tree.	421
12.4	An LC stack parser.	425
12.5	Decomposing a local tree into dependencies.	430
12.6	An example of the PARSEVAL measures.	433
12.7	The idea of crossing brackets.	434
12.8	Penn trees versus other trees.	436
13.1	Different strategies for Machine Translation.	464
13.2	Alignment and correspondence.	469
13.3	Calculating the cost of alignments.	473
13.4	A sample dot plot.	476
13.5	The pillow-shaped envelope that is searched.	480
13.6	The noisy channel model in machine translation.	486
14.1	A single-link clustering of 22 frequent English words represented as a dendrogram.	496
14.2	Bottom-up hierarchical clustering.	502
14.3	Top-down hierarchical clustering.	502
14.4	A cloud of points in a plane.	504
14.5	Intermediate clustering of the points in figure 14.4.	504
14.6	Single-link clustering of the points in figure 14.4.	505
14.7	Complete-link clustering of the points in figure 14.4.	505
14.8	The K-means clustering algorithm.	516
14.9	One iteration of the K-means algorithm.	517
14.10	An example of using the EM algorithm for soft clustering.	519
15.1	Results of the search ‘‘glass pyramid’’ Pei Louvre’ on an internet search engine.	531
15.2	Two examples of precision-recall curves.	537
15.3	A vector space with two dimensions.	540
15.4	The Poisson distribution.	546
15.5	An example of a term-by-document matrix A .	555
15.6	Dimensionality reduction.	555
15.7	An example of linear regression.	558
15.8	The matrix T of the SVD of the matrix in figure 15.5.	560
15.9	The matrix of singular values of the SVD of the matrix in figure 15.5.	560
15.10	The matrix D^T of the SVD of the matrix in figure 15.5.	561

15.11	The matrix $B_{2 \times d} = S_{2 \times 2} D^T_{2 \times d}$ of documents after rescaling with singular values and reduction to two dimensions.	562
15.12	Three constellations of cohesion scores in topic boundary identification.	569
16.1	A decision tree.	578
16.2	Geometric interpretation of part of the tree in figure 16.1.	579
16.3	An example of a Reuters news story in the topic category "earnings."	580
16.4	Pruning a decision tree.	585
16.5	Classification accuracy depends on the amount of training data available.	587
16.6	An example of how decision trees use data inefficiently from the domain of phonological rule learning.	588
16.7	The Perceptron Learning Algorithm.	598
16.8	One error-correcting step of the perceptron learning algorithm.	600
16.9	Geometric interpretation of a perceptron.	602