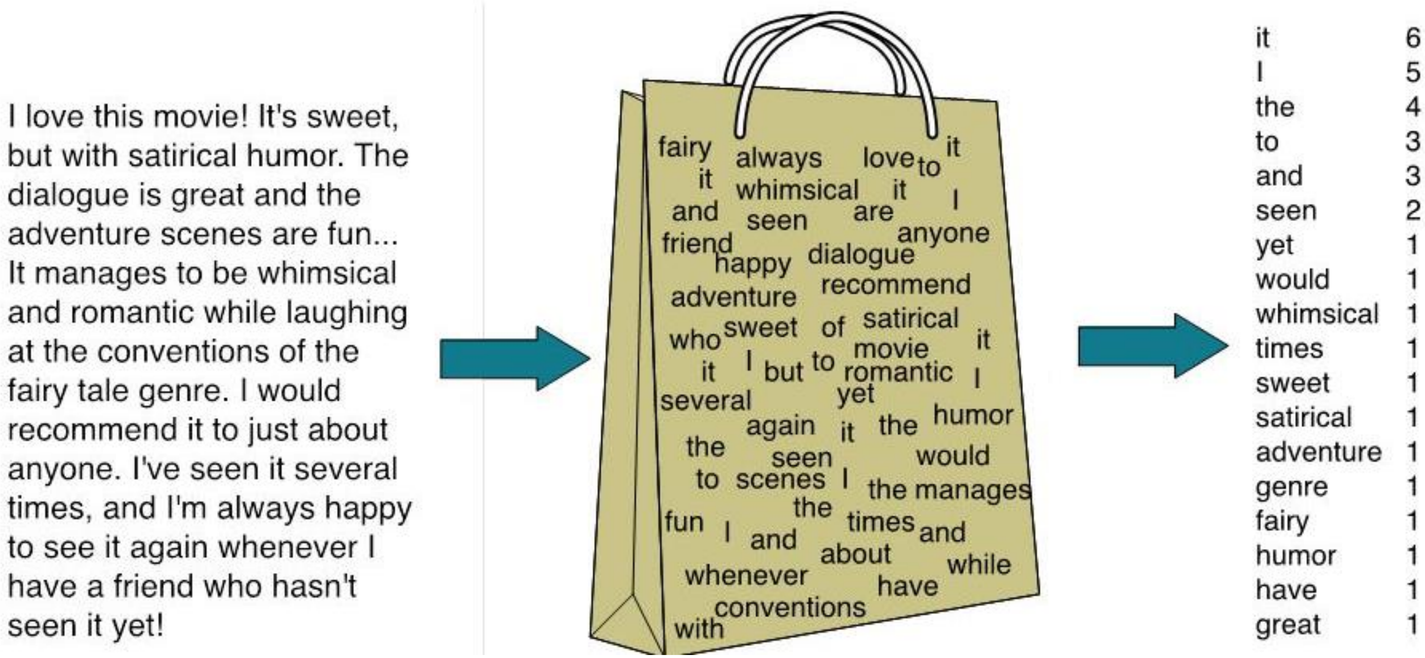


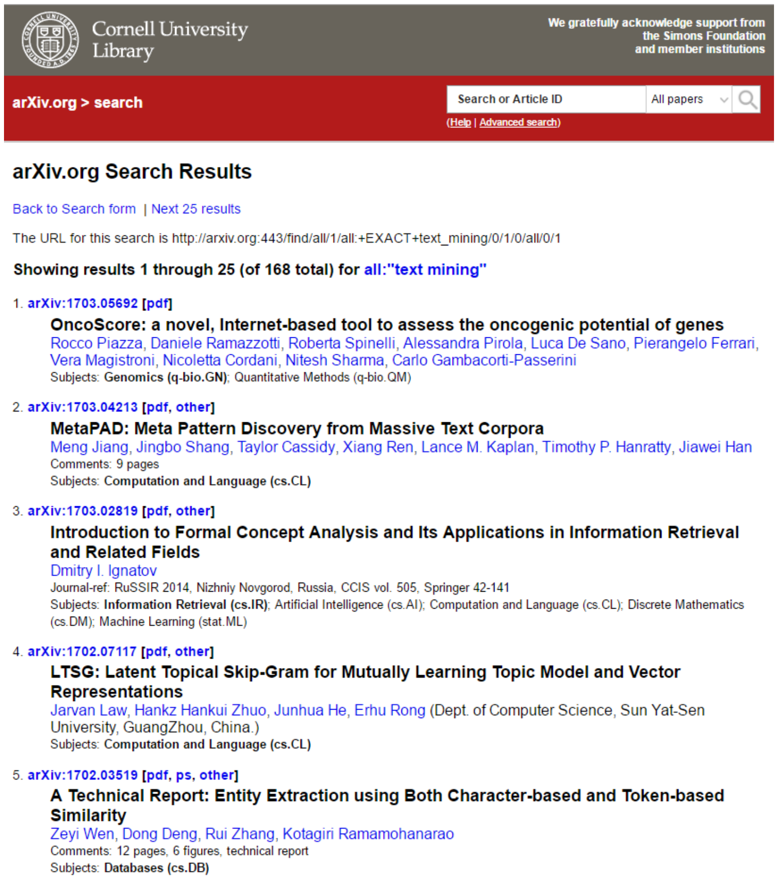
Lecture 5: Document Representation I
Count-based Representations

Pilsung Kang
School of Industrial Management Engineering
Korea University

AGENDA

What We Have Done So Far…

Collecting Text Data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Showing results 1 through 25 (of 168 total) for all:"text mining"

1. arXiv:1703.05692 [pdf]
   OncoScore: a novel, Internet-based tool to assess the oncogenic potential of genes
   Rocco Piazza, Daniele Ramazzotti, Roberta Spinelli, Alessandra Pirola, Luca De Sano, Pierangelo Ferrari, Vera Magistroni, Nicoletta Cordani, Nitesh Sharma, Carlo Gambacorti-Passerini
   Subjects: **Genomics (q-bio.GN)**; Quantitative Methods (q-bio.QM)
2. arXiv:1703.04213 [pdf, other]
   MetaPAD: Meta Pattern Discovery from Massive Text Corpora
   Meng Jiang, Jingbo Shang, Taylor Cassidy, Xiang Ren, Lance M. Kaplan, Timothy P. Hanratty, Jiawei Han
   Comments: 9 pages
   Subjects: **Computation and Language (cs.CL)**
3. arXiv:1703.02819 [pdf, other]
   Introduction to Formal Concept Analysis and Its Applications in Information Retrieval and Related Fields
   Dmitry I. Ignatov
   Journal-ref: RuSSIR 2014, Nizhniy Novgorod, Russia, CCIS vol. 505, Springer 42-141
   Subjects: **Information Retrieval (cs.IR)**; Artificial Intelligence (cs.AI); Computation and Language (cs.CL); Discrete Mathematics (cs.DM); Machine Learning (stat.ML)
4. arXiv:1702.07117 [pdf, other]
   LTSG: Latent Topical Skip-Gram for Mutually Learning Topic Model and Vector Representations
   Jarvan Law, Hankz Hankui Zhuo, Junhua He, Erhu Rong (Dept. of Computer Science, Sun Yat-Sen University, GuangZhou, China.)
   Subjects: **Computation and Language (cs.CL)**
5. arXiv:1702.03519 [pdf, ps, other]
   A Technical Report: Entity Extraction using Both Character-based and Token-based Similarity
   Zeyi Wen, Dong Deng, Rui Zhang, Kotagiri Ramamohanarao
   Comments: 12 pages, 6 figures, technical report
   Subjects: **Databases (cs.DB)**

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Mining textual patterns in news, tweets, papers, and
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pattern quality assessment function, which avoids costly dependency parsing and generates high-quality patterns; (2) it identifies and groups synonymous meta patterns from multiple facets---their types, contexts, and extractions; and (3) it examines type distributions of entities in the instances extracted by each group of patterns, and looks for appropriate type levels to make discovered patterns precise. Experiments demonstrate that our proposed framework discovers high-quality typed textual patterns efficiently from different genres of massive corpora and facilitates information extraction.

This paper is a tutorial on Formal Concept Analysis (FCA) and its applications. FCA is an applied branch of Lattice Theory, a mathematical discipline which enables formalisation of concepts as basic units of human thinking and analysing data in the object-attribute form. Originated in early 80s, during the last three decades, it became a popular human-centred tool for knowledge representation and data analysis with numerous applications. Since the tutorial was specially prepared for RuSSIR 2014, the covered FCA topics include Information Retrieval with a focus on visualisation aspects, Machine Learning, Data Mining and Knowledge Discovery, Text Mining and several others.

What We Have Done So Far…

Preprocessing with some NLP techniques

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What We Will Do…

Transform unstructured data into structured data

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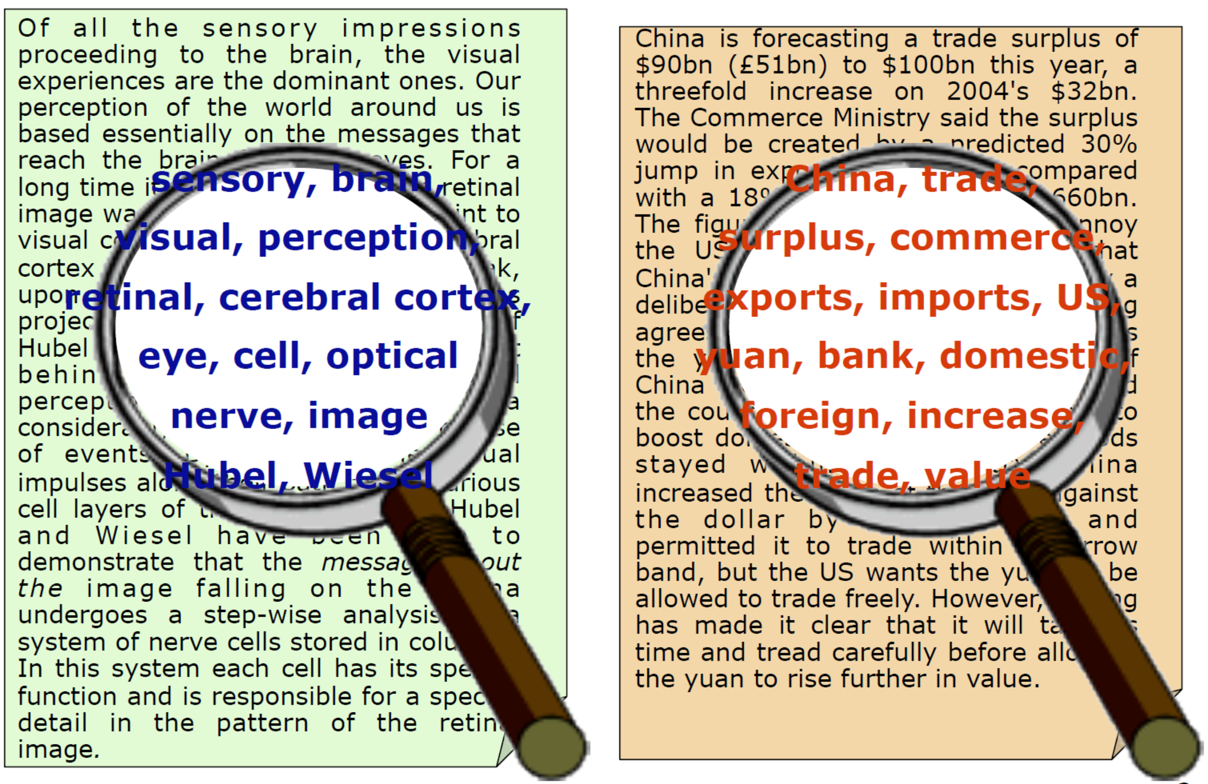
	Var 1	Var 2	…	…	Var P
Doc 1					
Doc 2					
Doc 3					
…					
…					
…					
Doc D					

Bag of Words: Motivation

- Document Representation
  - ✓ How to represent a document in a structured way?
  - ✓ How to convert a unstructured text into a vector/matrix form to apply machine learning algorithms based on a vector space?



Bag of Words: Idea

박은정 (2016)

- Bag-of-words
  - ✓ A simplified representation method for documents where a text is represented in a vector of an unordered collection of words
  - ✓ Consider words as atomic symbols, represented in the discrete space

Ex:

sentences

documents

```
five_random_documents = [
    'i like this movie',
    'the movie hunger games is a trilogy movie',
    'jennifer lawrence is an excellent actor',
    'i would give the film an 8 out of 10',
    'you can observe some jaw-dropping cleverness'
]
```

words

documents

```
bag_of_words = [
    [ 1., 1., 1., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.],
    [ 0., 0., 0., 2., 1., 1., 1., 1., 1., 1., 0., 0., 1., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.],
    [ 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 1., 1., 1., 1., 1., 1., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.],
    [ 1., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 0., 0., 0., 0., 0., 0.],
    [ 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 1., 1., 1., 1., 1.]
]
```

Bag of Words: Idea

- Bag-of-words: Term-Document Matrix
  - ✓ Simplifying representation method for documents where a text is represented in a vector of an unordered collection of words

S1: John likes to watch movies. Mary likes too.

S2: John also likes to watch football game.

Binary representation

Word	S1	S2
John	1	1
Likes	1	1
To	1	1
Watch	1	1
Movies	1	0
Also	0	1
Football	0	1
Games	0	1
Mary	1	0
too	1	0

Frequency representation

Word	S1	S2
John	1	1
Likes	2	1
To	1	1
Watch	1	1
Movies	1	0
Also	0	1
Football	0	1
Games	0	1
Mary	1	0
too	1	0

Bag of Words: Idea

- Bag of words Representation in a Vector Space
  - ✓ The contents can be inferred from the frequency of words
  - ✓ Vector representation does not consider the ordering of words in a document
    - Visual words = independent features
    - John is quicker than Mary = Mary is quicker than John in BOW representation
  - ✓ We cannot reconstruct the original text based on the term-document matrix

Original text	John loves Mary
	↓
BOW	(..., John, ..., loves, ..., Mary, ...)
	(..., 1 , ..., 1 , ..., 1 , ...)
	↓
Reconstruction	John loves Mary? Mary loves John?

Text Preprocessing

- Remove unnecessary information
  - ✓ They vs. they: different words in many systems
    - lower case is commonly used
  - ✓ Punctuation
    - Punctuations do not contain significant information → Remove them!
  - ✓ Numbers
    - Numbers are not critical in some domains but critical in other domains
    - Removing numbers should be carefully determined based on the domain for which a collection of text is about to be analyzed

Stop Words

- What are stop words?
  - ✓ Words that do not carry any information
    - Mainly functional role
    - Usually remove them to help the machine learning algorithms to perform better
  - ✓ Natural language dependent
    - English: a, about, above, across, after, again, against, all, also, etc.
    - 한국어: …습니다, …로서(써), …를 등

[Original text]

Information Systems Asia Web - provides research, IS-related commercial materials, interaction, and even research sponsorship by interested corporations with a focus on Asia Pacific region.

[After removing stop words]

Information Systems Asia Web provides research IS-related commercial materials interaction research sponsorship interested corporations focus Asia Pacific region

Stop Words

- Example 1: SMART stop words list
  - ✓ SMART: **S**ystem for the **M**echanical **A**nalysis and **R**etrieval of **T**ext
    - A total of 571 stop words

```
  [1] "a"            "a's"          "able"         "about"        "above"         "according"    "accordingly"  "across"       "actually"     "after"         "afterwards"
 [12] "again"        "against"      "ain't"        "all"          "allow"         "allows"       "almost"       "alone"        "along"        "already"       "also"
 [23] "although"     "always"       "am"           "among"        "amongst"       "an"           "and"          "another"      "any"          "anybody"       "anyhow"
 [34] "anyone"       "anything"     "anyway"       "anyways"      "anywhere"      "apart"        "appear"       "appreciate"   "appropriate"  "are"           "aren't"
 [45] "around"       "as"           "aside"        "ask"          "asking"        "associated"   "at"           "available"    "away"         "awfully"       "b"
 [56] "be"           "became"       "because"      "become"       "becomes"       "becoming"     "been"         "before"       "beforehand"   "behind"        "being"
 [67] "believe"      "below"        "beside"       "besides"      "best"          "better"       "between"      "beyond"       "both"         "brief"         "but"
 [78] "by"           "c"            "c'mon"        "c's"          "came"          "can"          "can't"        "cannot"       "cant"         "cause"         "causes"
 [89] "certain"      "certainly"    "changes"      "clearly"      "co"            "com"          "come"         "comes"        "concerning"   "consequently"  "consider"
[100] "considering"  "contain"      "containing"   "contains"     "corresponding" "could"        "couldn't"     "course"       "currently"    "d"             "definitely"
[111] "described"    "despite"      "did"          "didn't"       "different"     "do"           "does"         "doesn't"      "doing"        "don't"         "done"
[122] "down"         "downwards"    "during"       "e"            "each"          "edu"          "eg"           "eight"        "either"       "else"          "elsewhere"
[133] "enough"       "entirely"     "especially"   "et"           "etc"           "even"         "ever"         "every"        "everybody"    "everyone"      "everything"
[144] "everywhere"   "ex"           "exactly"      "example"      "except"        "f"            "far"          "few"          "fifth"        "first"         "five"
[155] "followed"     "following"    "follows"      "for"          "former"        "formerly"     "forth"        "four"         "from"         "further"       "furthermore"
[166] "g"            "get"          "gets"         "getting"      "given"         "gives"        "go"           "goes"         "going"        "gone"          "got"
[177] "gotten"       "greetings"    "h"            "had"          "hadn't"        "happens"      "hardly"       "has"          "hasn't"       "have"          "haven't"
[188] "having"       "he"           "he's"         "hello"        "help"          "hence"        "her"          "here"         "here's"       "hereafter"     "hereby"
[199] "herein"       "hereupon"     "hers"         "herself"      "hi"            "him"          "himself"      "his"          "hither"       "hopefully"     "how"
[210] "howbeit"      "however"      "i"            "i'd"          "i'll"          "i'm"          "i've"         "ie"           "if"           "ignored"       "immediate"
[221] "in"           "inasmuch"     "inc"          "indeed"       "indicate"      "indicated"    "indicates"    "inner"        "insofar"      "instead"       "into"
[232] "inward"       "is"           "isn't"        "it"           "it'd"          "it'll"        "it's"         "its"          "itself"       "j"             "just"
[243] "k"            "keep"         "keeps"        "kept"         "know"          "knows"        "known"        "l"            "last"         "lately"        "later"
[254] "latter"       "latterly"     "least"        "less"         "lest"          "let"          "let's"        "like"         "liked"        "likely"        "little"
[265] "look"         "looking"      "looks"        "ltd"          "m"             "mainly"       "many"         "may"          "maybe"        "me"            "mean"
[276] "meanwhile"    "merely"       "might"        "more"         "moreover"      "most"         "mostly"       "much"         "must"         "my"            "myself"
[287] "n"            "name"         "namely"       "nd"           "near"          "nearly"       "necessary"    "need"         "needs"        "neither"       "never"
[298] "nevertheless" "new"          "next"         "nine"         "no"            "nobody"       "non"          "none"         "noone"        "nor"           "normally"
[309] "not"          "nothing"      "novel"        "now"          "nowhere"       "o"            "obviously"    "of"           "off"          "often"         "oh"
[320] "ok"           "okay"         "old"          "on"           "once"          "one"          "ones"         "only"         "onto"         "or"            "other"
[331] "others"       "otherwise"    "ought"        "our"          "ours"          "ourselves"    "out"          "outside"      "over"         "overall"       "own"
[342] "p"            "particular"   "particularly" "per"          "perhaps"       "placed"       "please"       "plus"         "possible"     "presumably"    "probably"
[353] "provides"     "q"            "que"          "quite"        "qv"            "r"            "rather"       "rd"           "re"           "really"        "reasonably"
[364] "regarding"    "regardless"   "regards"      "relatively"   "respectively"  "right"        "s"            "said"         "same"         "saw"           "say"
[375] "saying"       "says"         "second"       "secondly"     "see"           "seeing"       "seem"         "seemed"       "seeming"      "seems"         "seen"
[386] "self"         "selves"       "sensible"     "sent"         "serious"       "seriously"    "seven"        "several"      "shall"        "she"           "should"
[397] "shouldn't"    "since"        "six"          "so"           "some"          "somebody"     "somehow"      "someone"      "something"    "sometime"      "sometimes"
[408] "somewhat"     "somewhere"    "soon"         "sorry"        "specified"     "specify"      "specifying"   "still"        "sub"          "such"          "sup"
[419] "sure"         "t"            "t's"          "take"         "taken"         "tell"         "tends"        "th"           "than"         "thank"         "thanks"
[430] "thanx"        "that"         "that's"       "thats"        "the"           "their"        "theirs"       "them"         "themselves"   "then"          "thence"
[441] "there"        "there's"      "thereafter"   "thereby"      "therefore"     "therein"      "theres"       "thereupon"    "these"        "they"          "they'd"
[452] "they'll"      "they're"      "they've"      "think"        "third"         "this"         "thorough"     "thoroughly"   "those"        "though"        "three"
[463] "through"      "throughout"   "thru"         "thus"         "to"            "together"     "too"          "took"         "toward"       "towards"       "tried"
[474] "tries"        "truly"        "try"          "trying"       "twice"         "two"          "u"            "un"           "under"        "unfortunately" "unless"
[485] "unlikely"     "until"        "unto"         "up"           "upon"          "us"           "use"          "used"         "useful"       "uses"          "using"
[496] "usually"      "uucp"         "v"            "value"        "various"       "very"         "via"          "viz"          "vs"           "w"             "want"
[507] "wants"        "was"          "wasn't"       "way"          "we"            "we'd"         "we'll"        "we're"        "we've"        "welcome"       "well"
[518] "went"         "were"         "weren't"      "what"         "what's"        "whatever"     "when"         "whence"       "whenever"     "where"         "where's"
[529] "whereafter"   "whereas"      "whereby"      "wherein"      "whereupon"     "wherever"     "whether"      "which"        "while"        "whither"       "who"
[540] "who's"        "whoever"      "whole"        "whom"         "whose"         "why"          "will"         "willing"      "wish"         "with"          "within"
[551] "without"      "won't"        "wonder"       "would"        "would"         "wouldn't"     "x"            "y"            "yes"          "yet"           "you"
[562] "you'd"        "you'll"       "you're"       "you've"       "your"          "yours"        "yourself"     "yourselves"   "z"            "zero"
```

Stop Words

- Example 2: MySQL Stop words list
  - ✓ http://dev.mysql.com/doc/refman/5.1/en/fulltext-stopwords.html
    - A total of 543 stop words

a's	able	about	above	according	her	here	here's	hereafter	hereby	serious	seriously	seven	several	shall
accordingly	across	actually	after	afterwards	herein	hereupon	hers	herself	hi	she	should	shouldn't	since	six
again	against	ain't	all	allow	him	himself	his	hither	hopefully	so	some	somebody	somehow	someone
allows	almost	alone	along	already	how	howbeit	however	i'd	i'll	something	sometime	sometimes	somewhat	somewhere
also	although	always	am	among	i'm	i've	ie	if	ignored	soon	sorry	specified	specify	specifying
amongst	an	and	another	any	immediate	in	inasmuch	inc	indeed	still	sub	such	sup	sure
anybody	anyhow	anyone	anything	anyway	indicate	indicated	indicates	inner	insofar	t's	take	taken	tell	tends
anyways	anywhere	apart	appear	appreciate	instead	into	inward	is	isn't	th	than	thank	thanks	thanx
appropriate	are	aren't	around	as	it	it'd	it'll	it's	its	that	that's	thats	the	their
aside	ask	asking	associated	at	itself	just	keep	keeps	kept	theirs	them	themselves	then	thence
available	away	awfully	be	became	know	known	knows	last	lately	there	there's	thereafter	thereby	therefore
because	become	becomes	becoming	been	later	latter	latterly	least	less	therein	theres	thereupon	these	they
before	beforehand	behind	being	believe	lest	let	let's	like	liked	they'd	they'll	they're	they've	think
below	beside	besides	best	better	likely	little	look	looking	looks	third	this	thorough	thoroughly	those
between	beyond	both	brief	but	ltd	mainly	many	may	maybe	though	three	through	throughout	thru
by	c'mon	c's	came	can	me	mean	meanwhile	merely	might	thus	to	together	too	took
can't	cannot	cant	cause	causes	more	moreover	most	mostly	much	toward	towards	tried	tries	truly
certain	certainly	changes	clearly	co	must	my	myself	name	namely	try	trying	twice	two	un
com	come	comes	concerning	consequently	nd	near	nearly	necessary	need	under	unfortunately	unless	unlikely	until
consider	considering	contain	containing	contains	needs	neither	never	nevertheless	new	unto	up	upon	us	use
corresponding	could	couldn't	course	currently	next	nine	no	nobody	non	used	useful	uses	using	usually
definitely	described	despite	did	didn't	none	noone	nor	normally	not	value	various	very	via	viz
different	do	does	doesn't	doing	nothing	novel	now	nowhere	obviously	vs	want	wants	was	wasn't
don't	done	down	downwards	during	of	off	often	oh	ok	way	we	we'd	we'll	we're
each	edu	eg	eight	either	okay	old	on	once	one	we've	welcome	well	went	were
else	elsewhere	enough	entirely	especially	ones	only	onto	or	other	weren't	what	what's	whatever	when
et	etc	even	ever	every	others	otherwise	ought	our	ours	whence	whenever	where	where's	whereafter
everybody	everyone	everything	everywhere	ex	ourselves	out	outside	over	overall	whereas	whereby	wherein	whereupon	wherever
exactly	example	except	far	few	own	particular	particularly	per	perhaps	whether	which	while	whither	who
fifth	first	five	followed	following	placed	please	plus	possible	presumably	who's	whoever	whole	whom	whose
follows	for	former	formerly	forth	probably	provides	que	quite	qv	why	will	willing	wish	with
four	from	further	furthermore	get	rather	rd	re	really	reasonably	within	without	won't	wonder	would
gets	getting	given	gives	go	regarding	regardless	regards	relatively	respectively	wouldn't	yes	yet	you	you'd
goes	going	gone	got	gotten	right	said	same	saw	say	you'll	you're	you've	your	yours
greetings	had	hadn't	happens	hardly	saying	says	second	secondly	see	yourself	yourselves	zero		
has	hasn't	have	haven't	having	seeing	seem	seemed	seeming	seems					
he	he's	hello	help	hence	seen	self	selves	sensible	sent					

Stop Words

- Example 3: Stop words list in Korean
  - ✓ http://www.ranks.nl/stopwords/korean
    - A total of 677 stop words

아	어찌됐든	하기보다는
휴	그위에	차라리
아이구	게다가	하는 편이 낫다
아이쿠	점에서 보아	흐흐
아이고	비추어 보아	놀라다
어	고려하면	상대적으로 말하
나	하게될것이다	자면
우리	일것이다	마치
저희	비교적	아니라면
따라	좀	쉿
의해	보다더	그렇지 않으면
을	비하면	그렇지 않다면
를	시키다	안 그러면
에	하게하다	아니었다면
의	할만하다	하든지
가	의해서	아니면
으로	연이서	이라면
로	이어서	좋아
에게	잇따라	알았어
뿐이다	뒤따라	하는것도
의거하여	뒤이어	그만이다
근거하여	결국	어쩔수 없다
입각하여	의지하여	하나
기준으로	기대여	일
예하면	통하여	일반적으로
예를 들면	자마자	일단
예를 들자면	더욱더	한켠으로는
저	불구하고	오자마자
소인	얼마든지	이렇게되면
소생	마음대로	이와같다면
저희	주저하지 않고	전부
지말고	곧	한마디
하지마	즉시	한항목
하지마라	바로	근거로
다른	당장	하기에
물론	하자마자	아울러
또한	밖에 안된다	하지 않도록
그리고	하면된다	않기 위해서
비길수 없다	그래	이르기까지
해서는 안된	그렇지	이 되다
다	요컨대	로 인하여

뿐만 아니라	다시 말하자면	까닭으로
만이 아니다	바꿔 말하면	이유만으로
만은 아니다	즉	이로 인하여
막론하고	구체적으로	그래서
관계없이	말하자면	이 때문에
그치지 않다	시작하여	그러므로
그러나	시초에	그런 까닭에
그런데	이상	알 수 있다
하지만	허	결론을 낼 수 있
든간에	헉	다
논하지 않다	허걱	으로 인하여
따지지 않다	바와같이	있다
설사	해도좋다	어떤것
비록	해도된다	관계가 있다
더라도	게다가	관련이 있다
아니면	더구나	연관되다
만 못하다	하물며	어떤것들
하는 편이 낫	와르르	에 대해
다	팍	이리하여
불문하고	퍽	그리하여
향하여	펄렁	여부
향해서	동안	하기보다는
향하다	이래	하느니
쪽으로	하고있었다	하면 할수록
틈타	이었다	운운
이용하여	에서	이러이러하다
타다	로부터	하구나
오르다	까지	하도다
제외하고	예하면	다시말하면
이 외에	했어요	다음으로
이 밖에	해요	에 있다
하여야	함께	에 달려 있다
비로소	같이	우리
한다면 몰라	더불어	우리들
도	마저	오히려
외에도	마저도	하기는한데
이곳	양자	어떻게
여기	모두	어떻해
부터	습니다	어찌됐어
기점으로	가까스로	어때
따라서	하려고하다	어째서

할 생각이다	즈음하여	본대로
하려고하다	다른	자
이리하여	다른 방면으로	이
그리하여	해봐요	이쪽
그렇게 함으	습니까	여기
로써	했어요	이것
하지만	말할것도 없고	이번
일때	무릎쓰고	이렇게말하자면
할때	개의치않고	이런
앞에서	하는것만 못하다	이러한
중에서	하는것이 낫다	이와 같은
보는데서	매	요만큼
으로써	매번	요만한 것
로써	들	얼마 안 되는 것
까지	모	이만큼
해야한다	어느것	이 정도의
일것이다	어느	이렇게 많은 것
반드시	로써	이와 같다
할줄알다	갖고말하자면	이때
할수있다	어디	이렇구나
할수있어	어느쪽	것과 같이
임에 틀림없	어느것	끼익
다	어느해	삐걱
한다면	어느 년도	따위
등	라 해도	와 같은 사람들
등등	언젠가	부류의 사람들
제	어떤것	왜냐하면
겨우	어느것	중의하나
단지	저기	오직
다만	저쪽	오로지
할뿐	저것	에 한하다
딩동	그때	하기만 하면
댕그	그럼	도착하다
대해서	그러면	까지 미치다
대하여	요만한걸	도달하다
대하면	그래	정도에 이르다
훨씬	그때	할 지경이다
얼마나	저것만큼	결과에 이르다
얼마만큼	그저	관해서는
얼마큼	이르기까지	여러분
남짓	할 줄 안다	하고 있다
여	할 힘이 있다	한 후

얼마간	너	혼자
약간	너희	자기
다소	당신	자기집
좀	어찌	자신
조금	설마	우에 종합한것과
다수	차라리	같이
몇	할지언정	총적으로 보면
얼마	할지라도	총적으로 말하면
지만	할망정	총적으로
하물며	할지언정	대로 하다
또한	구토하다	으로서
그러나	게우다	참
그렇지만	토하다	그만이다
하지만	메쓰겁다	할 따름이다
이외에도	옆사람	쿵
대해 말하자	퉤	탕탕
면	쳇	쾅쾅
뿐이다	의거하여	둥둥
다음에	근거하여	봐
반대로	의해	봐라
반대로 말하	따라	아이야
자면	힘입어	아니
이와 반대로	그	와아
바꾸어서 말	다음	응
하면	버금	아이
바꾸어서 한	두번째로	참나
다면	기타	년
만약	첫번째로	월
그렇지않으	나머지는	일
면	그중에서	령
까악	견지에서	영
툭	형식으로 쓰여	일
딱	입장에서	이
삐걱거리다	위해서	삼
보드득	단지	사
비걱거리다	의해되다	오
꽈당	하도록시키다	육
응당	뿐만아니라	륙
해야한다	반대로	칠
에 가서	전후	팔
각	전자	구

…

AGENDA

Word Weighting: Term-Frequency (TF)

Nayak & Raghavan (2014)

- Term frequency $tf_{t,d}$
  - ✓ The number of times that the term **t** occurs in the document **d**

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
Antony	157	73	0	0	0	0
Brutus	4	157	0	1	0	0
Caesar	232	227	0	2	1	1
Calpurnia	0	10	0	0	0	0
Cleopatra	57	0	0	0	0	0
mercy	2	0	3	5	5	1
worser	2	0	1	1	1	0

Word Weighting: Term-Frequency (TF)

이재천, 김수경, 홍성연 (2015)

- Term frequency $tf_{t,d}$
  - ✓ The more frequently occurs, the more important it is

<산공 강의 상위 25%>

<산공 강의 하위 25%>

Word Weighting: Document Frequency (DF)

- Document frequency df_t
  - ✓ The number of documents in which the term **t** appears.
- Issues on DF
  - ✓ Rare terms are more informative than frequent terms across the document collection
    - is, can, the, of, …
  - ✓ Consider a term in the query that is rare in the collection (e.g., Pneumonoultramicroscopicsilicovolcanoconiosis (longest word in English,))
  - ✓ A document containing this term is very likely to be relevant to the query
  - ✓ We should give a high weight for rare terms than common terms

Word Weighting: Inverse Document Frequency (IDF)

- Inverse document frequency idf_t
  - ✓ $idf_t = \log_{10}(N/df_t)$
  - ✓ We use $\log(N/df_t)$ instead of N/df_t to "dampen" the effect of idf
- IDF example with N = 1 million

term	**df_t**	**idf_t**
calpurnia	1	6
animal	100	4
sunday	1,000	3
fly	10,000	2
under	100,000	1
the	1,000,000	0

Word Weighting: TF-IDF

- TF-IDF
  - ✓ TF-IDF weight of a term is the product of its tf weight and its idf weight

$$TF-IDF(w) = \underbrace{tf(w)}_{\text{More important if the term occur more frequently in a document}} \times \log\left(\frac{N}{\underbrace{df(w)}_{\text{More important if the term occur less frequently in the other document}}}\right)$$

  - ✓ Best known weighting scheme in information retrieval
  - ✓ Increases with the number of occurrences within a document
  - ✓ Increases with the rarity of the term in the collection

Word Weighting: TF-IDF

Nayak & Raghavan (2014)

- Example revisited

  ✓ Each document is now represented by a real-valued vector of tf-idf weights in $R^{|V|}$

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
Antony	5.25	3.18	0	0	0	0
Brutus	1.21	6.1	0	1	0	0
Caesar	8.59	2.54	0	1.51	0.25	0.35
Calpurnia	0	1.54	0	0	0	0
Cleopatra	2.85	0	0	0	0	0
mercy	1.51	0	1.9	0.12	5.25	0.88
worser	1.37	0	0.11	4.15	0.25	1.95

  ✓ So, we have a |V|-dimensional vector space

  - Terms are axes of the space
  - Documents are points or vectors in this space
  - Very high dimensional: need to reduce the number of features!
  - Sparseness: most entries are zero

Word Weighting: TF-IDF

- TF-IDF Example
  - ✓ Q1: Which term is the most important for the document 1?
  - ✓ Q2: Which term is the least important for the document 1?

	Doc1	Doc2	Doc3
Term1	5	0	0
Term2	1	0	0
Term3	5	5	5
Term4	3	3	3
Term5	3	0	1

Doc1	TF	DF	IDF	TF-IDF
Term1	5	1	Log3	5log3
Term2	1	1	Log3	1log3
Term3	5	3	Log1	0
Term4	3	3	Log1	0
Term5	3	2	Log(3/2)	3log(3/2)

Word weighting: Term 1 > Term 5 > Term 2 > Term 3 = Term 4

TF Variants

Roelleke (2013)

- TF Variants

Definition 2.1 TF Variants: $\mathrm{TF}(t,d)$. $\mathrm{TF}(t,d)$ is a quantification of the within-document term frequency, tf_d. The main variants are:

$$\mathrm{tf}_d := \mathrm{TF}_{\text{total}}(t,d) := \mathrm{lf}_{\text{total}}(t,d) := n_L(t,d) \tag{2.1}$$

$$\mathrm{TF}_{\text{sum}}(t,d) := \mathrm{lf}_{\text{sum}}(t,d) := \frac{n_L(t,d)}{N_L(d)} \quad \left(= \frac{\mathrm{tf}_d}{\mathrm{dl}}\right) \tag{2.2}$$

$$\mathrm{TF}_{\text{max}}(t,d) := \mathrm{lf}_{\text{max}}(t,d) := \frac{n_L(t,d)}{n_L(t_{\text{max}},d)} \tag{2.3}$$

$$\mathrm{TF}_{\text{log}}(t,d) := \mathrm{lf}_{\text{log}}(t,d) := \log(1 + n_L(t,d)) \quad (= \log(1 + \mathrm{tf}_d)) \tag{2.4}$$

$$\mathrm{TF}_{\text{frac},K}(t,d) := \mathrm{lf}_{\text{frac},K}(t,d) := \frac{n_L(t,d)}{n_L(t,d) + K_d} \quad \left(= \frac{\mathrm{tf}_d}{\mathrm{tf}_d + K_d}\right) \tag{2.5}$$

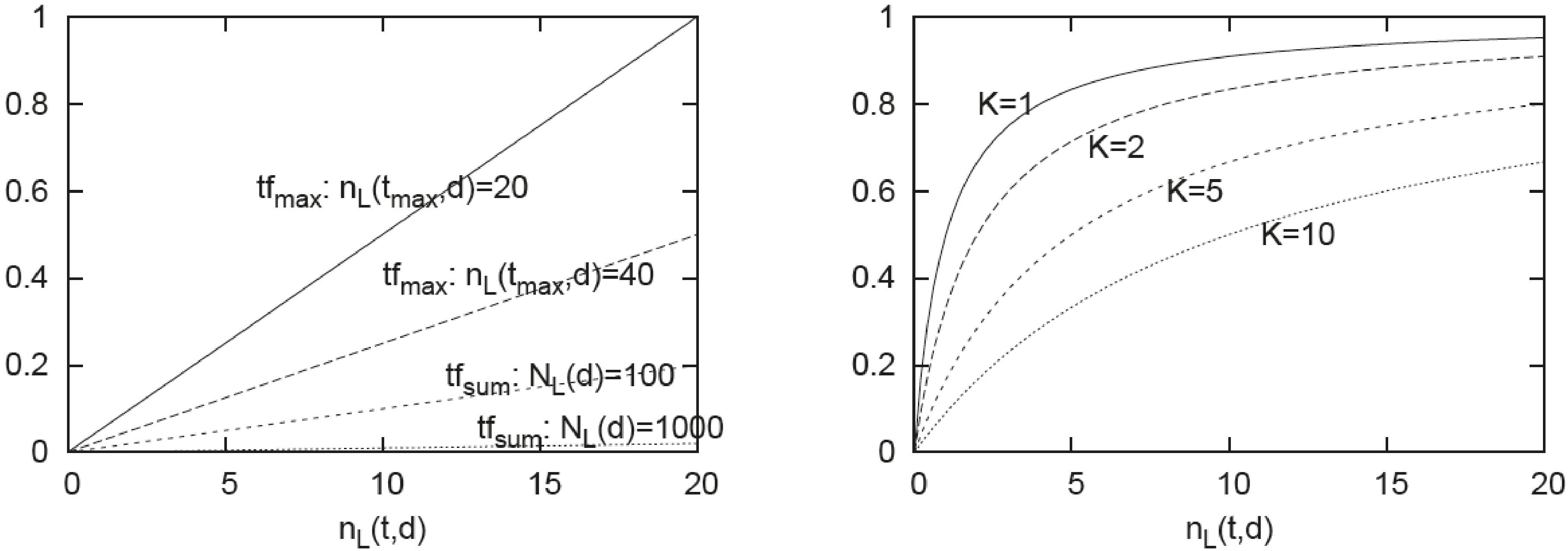
$$\mathrm{TF}_{\text{BM25},k_1,b}(t,d) := \mathrm{lf}_{\text{BM25},k_1,b}(t,d) := \frac{n_L(t,d)}{n_L(t,d) + k_1 \cdot (b \cdot \mathrm{pivdl}(d,c) + (1-b))} \tag{2.6}$$

- K_d: (document length)/(average document length)

TF Variants

Roelleke (2013)

- TF Variants



(a) TF_{sum} and TF_{max} (b) TF_{frac}

DF & IDF Variants

Roelleke (2013)

- DF & IDF Variants

Definition 2.3 DF Variants. $\mathrm{DF}(t,c)$ is a quantification of the document frequency, $\mathrm{df}(t,c)$. The main variants are:

$$\mathrm{df}(t,c) := \mathrm{df}_{\mathrm{total}}(t,c) := n_D(t,c) \tag{2.18}$$

$$\mathrm{df}_{\mathrm{sum}}(t,c) := \frac{n_D(t,c)}{N_D(c)} \quad \left(= \frac{\mathrm{df}(t,c)}{N_D(c)}\right) \tag{2.19}$$

$$\mathrm{df}_{\mathrm{sum,smooth}}(t,c) := \frac{n_D(t,c)+0.5}{N_D(c)+1} \tag{2.20}$$

$$\mathrm{df}_{\mathrm{BIR}}(t,c) := \frac{n_D(t,c)}{N_D(c)-n_D(t,c)} \tag{2.21}$$

$$\mathrm{df}_{\mathrm{BIR,smooth}}(t,c) := \frac{n_D(t,c)+0.5}{N_D(c)-n_D(t,c)+0.5} \tag{2.22}$$

Definition 2.4 IDF Variants. $\mathrm{IDF}(t,c)$ is the negative logarithm of a DF quantification. The main variants are:

$$\mathrm{idf}_{\mathrm{total}}(t,c) := -\log \mathrm{df}_{\mathrm{total}}(t,c) \tag{2.23}$$

$$\mathrm{idf}(t,c) := \mathrm{idf}_{\mathrm{sum}}(t,c) := -\log \mathrm{df}_{\mathrm{sum}}(t,c) \tag{2.24}$$

$$\mathrm{idf}_{\mathrm{sum,smooth}}(t,c) := -\log \mathrm{df}_{\mathrm{sum,smooth}}(t,c) \tag{2.25}$$

$$\mathrm{idf}_{\mathrm{BIR}}(t,c) := -\log \mathrm{df}_{\mathrm{BIR}}(t,c) \tag{2.26}$$

$$\mathrm{idf}_{\mathrm{BIR,smooth}}(t,c) := -\log \mathrm{df}_{\mathrm{BIR,smooth}}(t,c) \tag{2.27}$$

TF-IDF Variants Summary

Roelleke (2013)

- The most commonly used TF-IDF in general

Term frequency		Document frequency		Normalization	
n (natural)	$\mathrm{tf}_{t,d}$	n (no)	1	n (none)	1
l (logarithm)	$1 + \log(\mathrm{tf}_{t,d})$	t (idf)	$\log \frac{N}{\mathrm{df}_t}$	c (cosine)	$\frac{1}{\sqrt{w_1^2 + w_2^2 + \ldots + w_M^2}}$
a (augmented)	$0.5 + \frac{0.5 \times \mathrm{tf}_{t,d}}{\max_t(\mathrm{tf}_{t,d})}$	p (prob idf)	$\max\{0, \log \frac{N - \mathrm{df}_t}{\mathrm{df}_t}\}$	u (pivoted unique)	$1/u$
b (boolean)	$\begin{cases} 1 & \text{if } \mathrm{tf}_{t,d} > 0 \\ 0 & \text{otherwise} \end{cases}$			b (byte size)	$1/CharLength^{\alpha}$, $\alpha < 1$
L (log ave)	$\frac{1 + \log(\mathrm{tf}_{t,d})}{1 + \log(\mathrm{ave}_{t \in d}(\mathrm{tf}_{t,d}))}$				

Effects of TF-IDF Variants

- Comparative Study (Paltoglou and Thelwall, 2010)
  - ✓ Task 1: Classification of 2,000 movie reviews: positive vs. negative
  - ✓ Task 2: Multi-Domain Sentiment Data set (MDSD)
    - Four different product types: books, electronics, DVDs, and kitchen appliances
    - 1,000 positive & 1,000 negative for each type, 8,000 in total

Term Frequency

Notation	Term frequency
n (natural)	tf
l (logarithm)	$1 + log(tf)$
a (augmented)	$0.5 + \frac{0.5 \cdot tf}{max_t(tf)}$
b (boolean)	$\begin{cases} 1, & tf > 0 \\ 0, & otherwise \end{cases}$
L (log ave)	$\frac{1+log(tf)}{1+log(avg\_dl)}$
o (BM25)	$\frac{(k_1+1)\cdot tf}{k_1\left((1-b)+b\cdot\frac{dl}{avg\_dl}\right)+tf}$

Inverse Document Frequency

Notation	Inverse Document Frequency
n (no)	1
t (idf)	$log\frac{N}{df}$
p (prob idf)	$log\frac{N-df}{df}$
k (BM25 idf)	$log\frac{N-df+0.5}{df+0.5}$
$\Delta(t)$ (Delta idf)	$log\frac{N_1\cdot df_2}{N_2\cdot df_1}$
$\Delta(t')$ (Delta smoothed idf)	$log\frac{N_1\cdot df_2+0.5}{N_2\cdot df_1+0.5}$
$\Delta(p)$ (Delta prob idf)	$log\frac{(N_1-df_1)\cdot df_2}{df_1\cdot(N_2-df_2)}$
$\Delta(p')$ (Delta smoothed prob idf)	$log\frac{(N_1-df_1)\cdot df_2+0.5}{(N_2-df_2)\cdot df_1+0.5}$
$\Delta(k)$ (Delta BM25 idf)	$log\frac{(N_1-df_1+0.5)\cdot df_2+0.5}{(N_2-df_2+0.5)\cdot df_1+0.5}$

Normalization

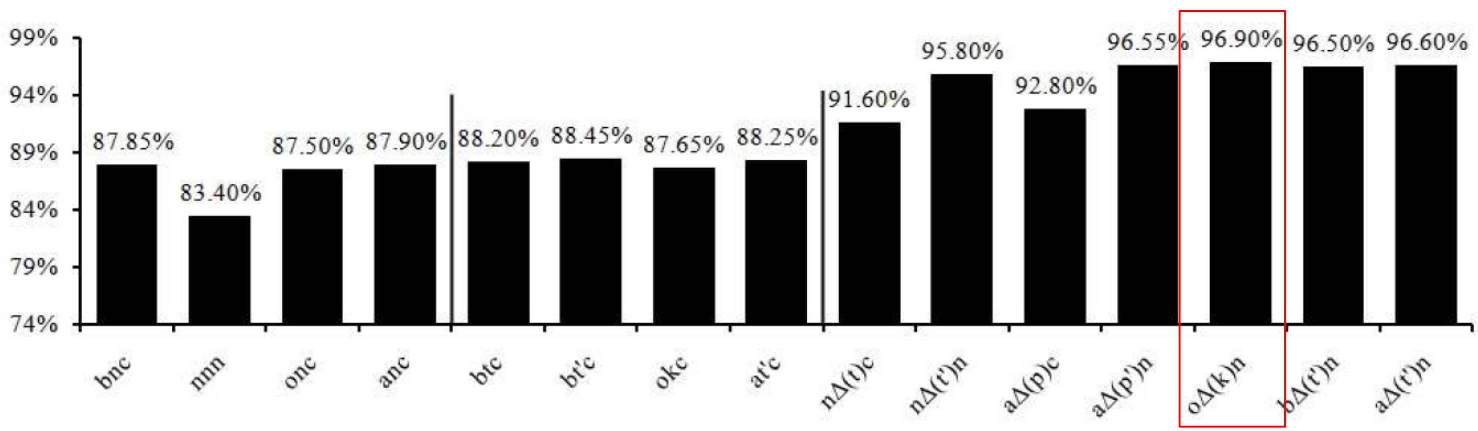
Notation	Normalization
n (none)	1
c (cosine)	$\frac{1}{\sqrt{w_1^2+w_2^2+\ldots+w_n^2}}$

Effects of TF-IDF Variants

Paltoglou and Thelwall (2010)

- Experimental Result 1: Movie Reviews
  - ✓ Base classifier: support vector machine (SVM)

Data set	#Documents	#Terms	#Unique Terms	Average #Terms per Document
Movie Reviews	2,000	1,336,883	39,399	668
Multi-Domain Sentiment Dataset (MDSD)	8,000	1,741,085	455,943	217
BLOGS06	17,898	51,252,850	367,899	2,832



o (BM25)	$\frac{(k_1+1)\cdot tf}{k_1\left((1-b)+b\cdot\frac{dl}{avg\_dl}\right)+tf}$

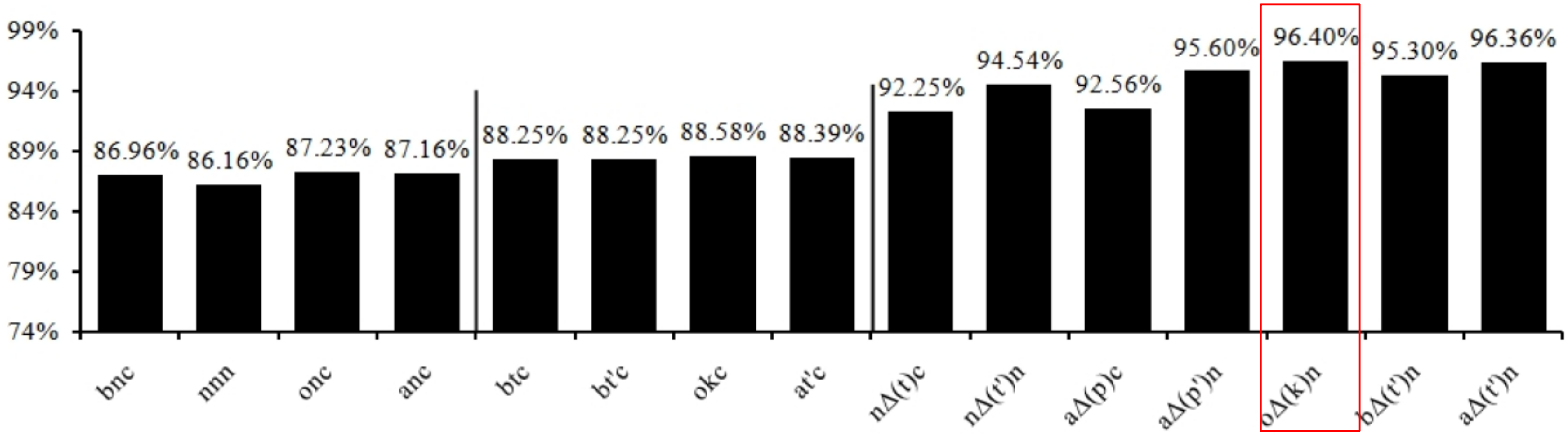
$\Delta(k)$ (Delta BM25 idf)	$log\frac{(N_1-df_1+0.5)\cdot df_2+0.5}{(N_2-df_2+0.5)\cdot df_1+0.5}$

n (none)	1

Effects of TF-IDF Variants

Paltoglou and Thelwall (2010)

- Experimental Result 2: MDSD
  - ✓ Base classifier: support vector machine (SVM)



o (BM25)	$\frac{(k_1+1)\cdot tf}{k_1\left((1-b)+b\cdot\frac{dl}{avg\_dl}\right)+tf}$

$\Delta(k)$ (Delta BM25 idf)	$log\frac{(N_1-df_1+0.5)\cdot df_2+0.5}{(N_2-df_2+0.5)\cdot df_1+0.5}$

n (none)	1

AGENDA

N-Grams

- N-Gram-based Language Models in NLP
  - ✓ Use the previous N-1 words in a sequence to predict the next word

$$P(w_n | w_{n-1}, w_{n-2}, \ldots, w_1) = \frac{P(w_n, w_{n-1}, w_{n-2}, \ldots, w_1)}{P(w_{n-1}, w_{n-2}, \ldots, w_1)}$$

  - ✓ Q) One of the hottest topics in artificial intelligence is deep ______
    - blue vs. frying vs. learning ?
- N-Gram in Text Mining
  - ✓ Some phrases are very useful in text clustering/categorization!
    - Six sigma, supply chain management, big data, etc.
  - ✓ Term-frequency for n-grams can be utilized.
  - ✓ Domain-dependent.

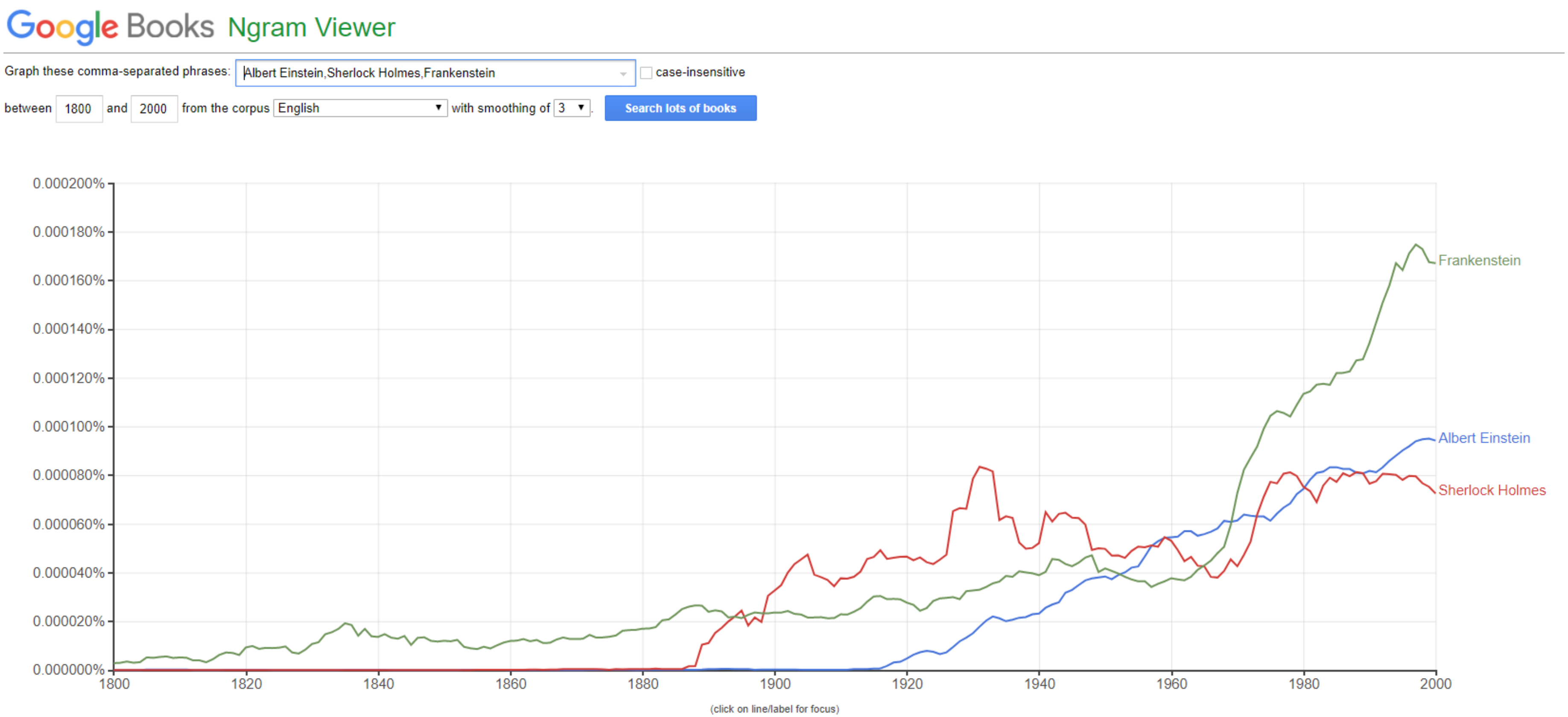
N-Grams

- Bigram example
  - ✓ Total counts in a corpus

	i	want	to	eat	chinese	food	lunch	spend
i	5	827	0	9	0	0	0	2
want	2	0	608	1	6	6	5	1
to	2	0	4	686	2	0	6	211
eat	0	0	2	0	16	2	42	0
chinese	1	0	0	0	0	82	1	0
food	15	0	15	0	1	4	0	0
lunch	2	0	0	0	0	1	0	0
spend	1	0	1	0	0	0	0	0

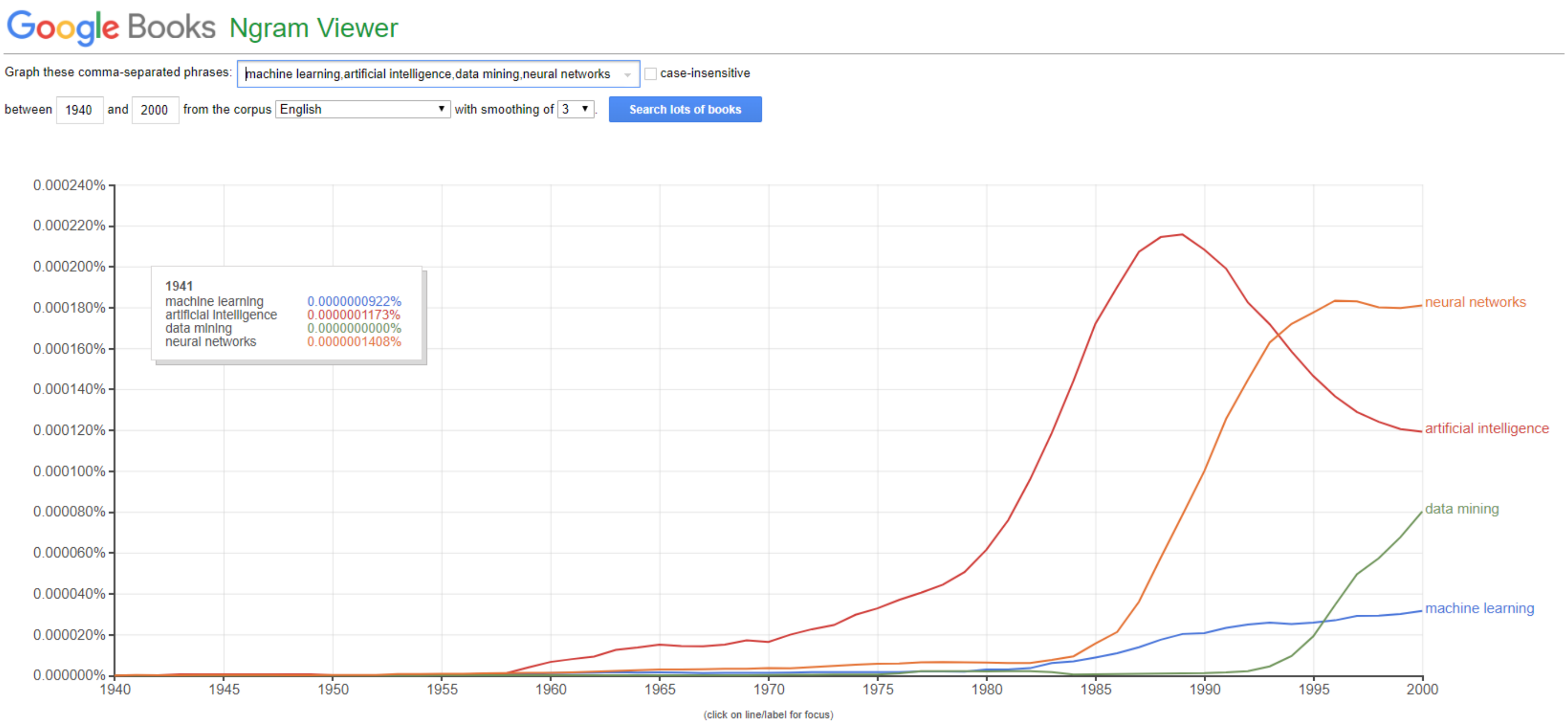
N-Grams

- Google Books Ngram Viewer (https://books.google.com/ngrams)

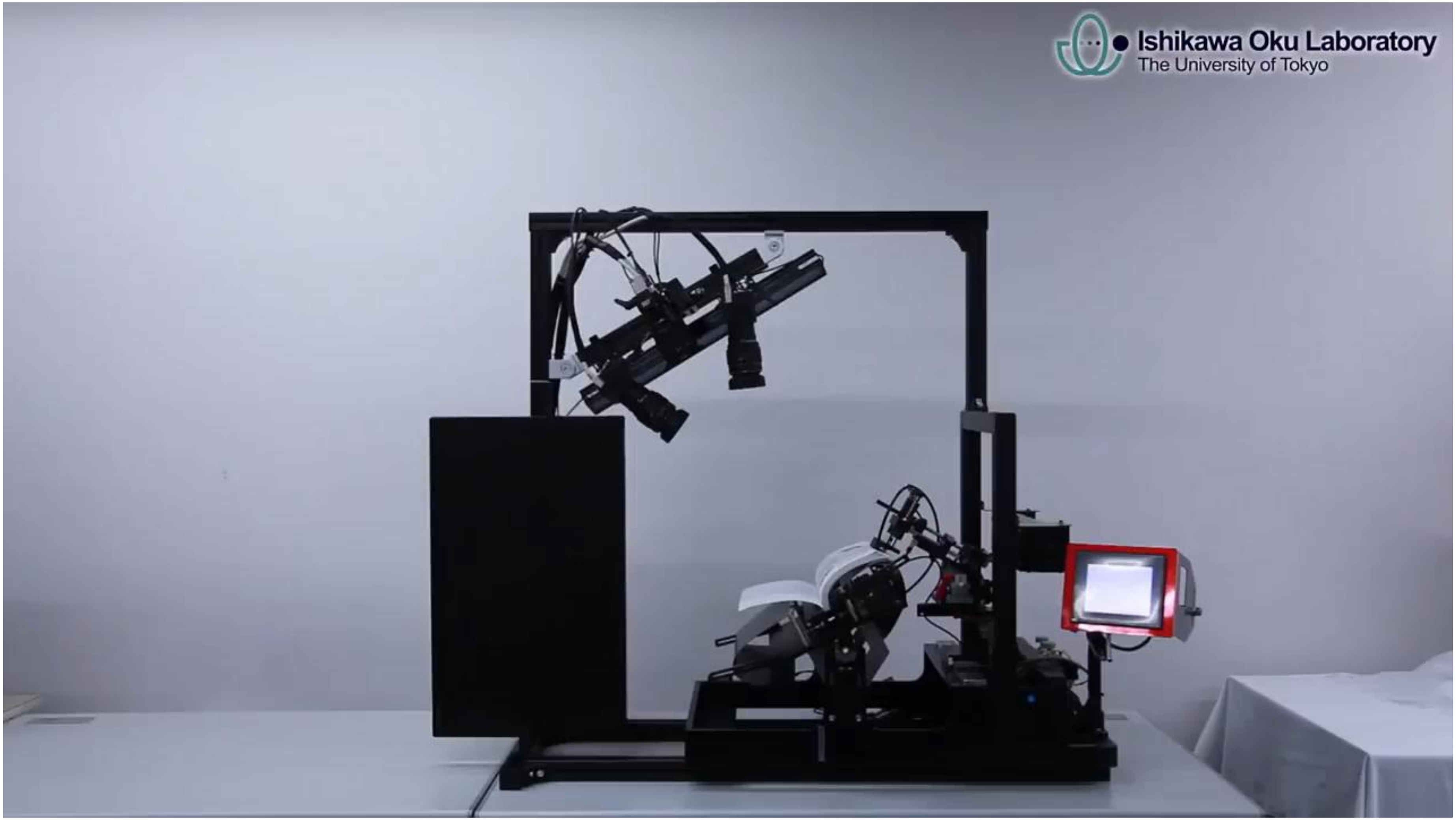


N-Grams

- Google Books Ngram Viewer (https://books.google.com/ngrams)
  - ✓ Ngram frequencies for "artificial intelligence", "machine learning", "data mining", and "neural networks"



N-Grams



N-Grams

Furnkranz (1998)

- Empirical evaluation
  - ✓ Data sets
    - 20 newsgroup data set: 20,000 articles (1,000 for each category)
    - 21578 REUTERS newswire articles: 21,578 articles with 90 categories
  - ✓ Classification algorithm: RIPPER
- Results for 20 newsgroup dataset

Pruning	n-grams	Error rate	CPU secs.	No. Features
set-of-words		47.07 ± 0.92	n.a.	71,731
DF: 3 TF: 5	1	46.18 ± 0.94	12686.12	36,534
	2	45.28 ± 0.51	15288.32	113,716
	3	45.05 ± 1.22	15253.27	155,184
	4	45.18 ± 1.17	14951.17	189,933
DF: 5 TF: 10	1	45.51 ± 0.83	12948.31	22,573
	2	45.34 ± 0.68	13280.73	44,893
	3	46.11 ± 0.73	12995.66	53,238
	4	46.11 ± 0.72	13063.68	59,455
DF: 10 TF: 20	1	45.88 ± 0.89	10627.10	13,805
	2	45.53 ± 0.86	13080.32	20,295
	3	45.58 ± 0.87	11640.18	22,214
	4	45.74 ± 0.62	11505.92	23,565

DF: 25 TF: 50	1	48.23 ± 0.69	10676.43	n.a.
	2	48.97 ± 1.15	8870.05	n.a.
	3	48.69 ± 1.04	10141.25	n.a.
	4	48.36 ± 1.01	10436.58	n.a.
	5	48.36 ± 1.01	10462.65	n.a.
DF: 50 TF: 100	1	51.54 ± 0.60	8547.43	n.a.
	2	49.71 ± 0.53	8164.27	n.a.
	3	51.21 ± 1.26	8079.59	n.a.
	4	51.21 ± 1.26	8078.55	n.a.
	5	51.21 ± 1.26	8147.75	n.a.
DF: 75 TF: 150	1	52.59 ± 0.71	6609.05	n.a.
	2	52.83 ± 0.25	6532.80	n.a.
	3	52.36 ± 0.48	6128.49	n.a.
	4	52.36 ± 0.48	6128.49	n.a.
	5	52.36 ± 0.48	6119.27	n.a.

N-Grams

Furnkranz (1998)

- Results for 21578 REUTERS
  - ✓ Classification accuracy is the highest with bigram features

Pruning	n-grams	Recall	Precision	F1	Accuracy	No. Features
set-of-words		76.71	83.42	79.92	99.5140	n.a.
DF: 3 TF: 5	1	77.22	83.55	80.26	99.5211	9,673
	2	80.34	82.03	81.18	99.5302	28,045
	3	77.56	82.74	80.07	99.5130	38,646
	4	78.18	82.31	80.19	99.5130	45,876
DF: 5 TF: 10	1	77.19	83.65	80.29	99.5221	6,332
	2	80.05	82.06	81.04	99.5278	13,598
	3	77.96	82.29	80.07	99.5106	17,708
	4	78.21	82.13	80.12	99.5106	20,468
DF: 10 TF: 20	1	76.92	83.99	80.30	99.5241	4,068
	2	79.06	82.04	80.52	99.5177	7,067
	3	77.32	82.67	79.91	99.5096	8,759
	4	76.98	82.91	79.84	99.5096	9,907


ANY
questions?

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