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Introduction to the special issue on evaluating word sense disambiguation systems

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- Definición:

  Word sense disambiguation (WSD) is the problem of deciding which sense a word has in any given context.

- Ejemplo:

$$\text{drug} \begin{cases} \rightarrow \text{medicamento} \\ \rightarrow \text{droga} \end{cases}$$

- Bibliografia:

  - Ide and Véronis (1998)
  - Manning and Schütze (1999)
  - Jurafsky and Martin (2000)

EXERCISES

- Recuperación de información → TREC
- Extracción de información → MUC
- Resumen automático → DUC
- Desambiguación de sentidos → SENSEVAL (ACL)
  - SENSEVAL I (1998, Inglés, francés e italiano)
  - SENSEVAL II (2000-2001, 3 tareas en 13 lenguas)
  - SENSEVAL III (2004 en Barcelona –ACL-04-)
  - http://www.senseval.org/

DARPA

A typology of evaluations

Sense inventory	*In vitro* evaluation	*In vivo* evaluation
Explicit application-independent	SENSEVAL	?
Explicit, defined by an application or domain	E.g. senses as translation equivalents	E.g. improvement in machine translation or information extraction as the task
Implicit, defined by application in a domain	E.g. senses as word or context clusters	E.g. improvement of information retrieval as the task

SENSEVAL Tasks

- **all-words** task, systems must tag almost all of the content words in a sample of running text.
- **lexical sample** task, we first carefully select a sample of words from the lexicon; systems must then tag several instances of the sample words in short extracts of text.
- **translation** task (Japanese only) is a lexical sample task in which word sense is defined according to translation distinction.
- http://www.sle.sharp.co.uk/senseval2/archive/call-for-participation.txt

Results of SENSEVAL-2

Table 3. *Results of* SENSEVAL-2, *tabulated from Edmonds and Cotton (2001)*

Language	Task[a]	Systems	Lemmas	Instances[b]	IAA[c]	Baseline[d]	Best score
Czech	AW	1	–[e]	277,986	–	–	0.94
Basque	LS	3	40	5,284	0.75	0.65	0.76
Dutch[f]	AW	1	1,168	16,686	–	0.75	0.84
English	AW	21	1,082	2,473	0.75	0.57	0.69
English	LS	26	73	12,939	0.86	0.48/0.16[g]	0.64/0.40
Estonian	AW	2	4,608	11,504	0.72	0.85	0.67
Italian	LS	2	83	3,900	0.21	–	0.39
Japanese	LS	7	100	10,000	0.86	0.72	0.78
Japanese	TL	9	40	1,200	0.81	0.37	0.79
Korean	LS	2	11	1,733	–	0.71	0.74
Spanish	LS	12	39	6,705	0.64	0.48	0.65
Swedish	LS	8	40	10,241	0.95	–	0.70

SEMCOR corpus

```
<contextfile concordance=brown>
<context filename=br-l11 paras=yes>
<s snum=3>
<wf pos=PRP>He</wf>
<wf pos=VB lemma=demonstrate wnsn=2 lexsn=2:31:00::>demonstrated</wf>
<wf pos=IN>by</wf>
<wf pos=VB lemma=play wnsn=7 lexsn=2:36:01::>playing</wf>
<wf pos=DT>an</wf>
<wf pos=JJ lemma=imaginary wnsn=1 lexsn=5:00:00:unreal:00>imaginary</wf>
<wf pos=NN lemma=piano wnsn=1 lexsn=1:06:00::>piano</wf>
<punc>,</punc>
<wf pos=VB lemma=do wnsn=2 lexsn=2:36:01::>doing</wf>
<wf pos=DT>a</wf>
<wf pos=JJ lemma=staccato wnsn=1 lexsn=3:00:00::>staccato</wf>
<wf pos=NN lemma=passage wnsn=6 lexsn=1:10:01::>passage</wf>
<wf pos=IN>with</wf>
<wf pos=DT>a</wf>
<wf pos=RB lemma=broadly wnsn=1 lexsn=4:02:00::>broadly</wf>
<wf pos=JJ lemma=exaggerated wnsn=1 lexsn=5:00:00:immoderate:00>exaggerated</wf
<wf pos=NN lemma=attack wnsn=8 lexsn=1:04:01::>attack</wf>
<punc>.</punc>
</s>
...
```

English lexical sample

Table 1. *Keyword-itemized performance on* SENSEVAL2 *English lexical sample task*

Model	Num Samples	Num Senses	ML	Entr	FENBayes	BayesRatio	Cosine	DL	TBL
begin.v	557	8	59.1%	0.2	79.4%	79.2%	80.3%	81.3%	**83.1%**
call.v	132	23	25.7%	0.5	**43.9%**	38.6%	35.6%	39.4%	40.2%
carry.v	132	27	23.5%	0.6	37.9%	**43.2%**	43.2%	39.4%	40.1%
collaborate.v	57	2	91.2%	0.1	86.1%	**94.7%**	87.9%	91.2%	**94.7%**
develop.v	133	15	30.1%	0.5	36.9%	38.4%	**41.3%**	40.6%	36.0%
art.n	196	19	38.2%	0.4	59.7%	65.9%	63.8%	61.7%	**67.3%**
authority.n	184	11	33.7%	0.3	**69.1%**	69.0%	64.1%	60.4%	66.4%
bar.n	304	22	41.8%	0.4	**71.4%**	71.0%	69.4%	63.1%	65.1%
bum.n	92	6	70.6%	0.3	69.5%	70.6%	62.0%	71.8%	**73.9%**
chair.n	138	8	82.6%	0.2	**91.3%**	91.3%	88.4%	89.9%	88.4%
channel.n	145	10	40.7%	0.4	60.0%	**62.1%**	61.4%	49.7%	48.3%
child.n	129	9	60.4%	0.2	68.2%	66.6%	64.3%	72.1%	**78.2%**
blind.a	108	9	62.9%	0.3	**74.2%**	71.5%	70.5%	72.3%	72.2%
colourless.a	68	3	77.9%	0.2	80.9%	**82.4%**	82.3%	77.8%	81.0%
cool.a	106	8	50.0%	0.4	**70.7%**	59.4%	52.9%	66.1%	56.6%
faithful.a	47	3	72.2%	0.2	65.6%	67.8%	59.6%	**74.2%**	70.0%

Senses for ‘bank’

Table 1. WordNet *senses and domains for the word ‘bank’*

Sense	Synset and Gloss	Domains	Semcor
#1	depository financial institution, bank, banking concern, banking company (a financial institution . . .)	ECONOMY	20
#2	bank (sloping land . . .)	GEOGRAPHY, GEOLOGY	14
#3	bank (a supply or stock held in reserve . . .)	ECONOMY	–
#4	bank, bank building (a building . . .)	ARCHITECTURE, ECONOMY	–
#5	bank (an arrangement of similar objects . . .)	FACTOTUM	1
#6	savings bank, coin bank, money box, bank (a container . . .)	ECONOMY	–
#7	bank (a long ridge or pile . . .)	GEOGRAPHY, GEOLOGY	2
#8	bank (the funds held by a gambling house . . .)	ECONOMY, PLAY	
#9	bank, cant, camber (a slope in the turn of a road . . .)	ARCHITECTURE	–
#10	bank (a flight maneuver . . .)	TRANSPORT	–

Lexical entry for noun headword "arte"

arte#NCMS#1#Actividad humana o producto de tal actividad que expresa simbólicamente un aspecto de la realidad: el arte de la música; el arte precolombino#SIN:?#00518008n/02980374n#
arte#NCMS#2#Sabiduría, destreza o habilidad de una persona en una actividad o conducta determinada: tiene mucho arte bailando; desplegó todo su arte para convencerle#SIN:?#03850627n#
arte#NCMS#3#Aparato que sirve para pescar#SIN:?#02005770n#

The papers

- Uso de la información de dominio en WSD
- Combinación de clasificadores
- Análisis del espacio de rasgos
- Ajuste de parámetros
- Método semisupervisado para WSD
- Evaluación de recursos léxicos

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The role of domain information in Word Sense Disambiguation

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Introduction

"*The purpose of this paper is to investigate the role of domain information in Word Sense Disambiguation.*

The hypothesis is that domain labels (such as Medicine, Architecture and Sport) provide a powerful way to establish semantic relations among word senses, which can be probably used during the disambiguation process."

chair_1: (F) a seat for one person,...
chair_2: (a) the position of professor
chair_3: (b) the officer who presides at the meeting .
chair_4: (c) an instrument of death ...

F *?*

The dinnertable and chairs are elegant yet comfortable,

and you can be assured of the finest tableware and crystal for

F

meals at home.

WordNet domains

- Es una extensión de WordNet donde cada synset tiene asociado una o mas etiquetas de dominio.
- Construcción semimanual basado en criterios sintactico-semánticos (*is-a*, *part-of*, etc.)
- Jerarquia de dominios (200/43)
- FACTOTUM (38620):
  - Synsets genéricos (*man_1*)
  - Bloquear mecanismo de propagación en palabras frecuentes (números, dias de la semana, colores, etc.).

Domains & words

- *Text Related Domain words*: palabras con al menos un sentido en el dominio del texto. Ej 'bank' en Economía
- *Text Unrelated Domain words*: palabras con ningún sentido perteneciente al dominio del texto. Ej. 'churh'
- *Text Unrelated Generics*: palabras cuyo sentido no es significativo. Ej. 'be'. Sense: FACTOTUM

Quantitative distribution

Table 3. *Word distribution in Semcor according to the prevalent domains of the texts*

Word class	Nouns	Verbs	Adjectives	Adverbs	All
TRD words	18732 (34.5%)	2416 (8.7%)	1982 (9.6%)	436 (3.7%)	21%
Polysemy	3.90	9.55	4.17	1.62	4.46
TUD words	13768 (25.3%)	2224 (8.1%)	815 (3.9%)	300 (2.5%)	15%
Polysemy	4.02	7.88	4.32	1.62	4.49
TUG words	21902 (40.2%)	22933 (83.2%)	17987 (86.5%)	11131 (93.8%)	64%
Polysemy	5.03	10.89	4.55	2.78	6.39

One domain per discourse

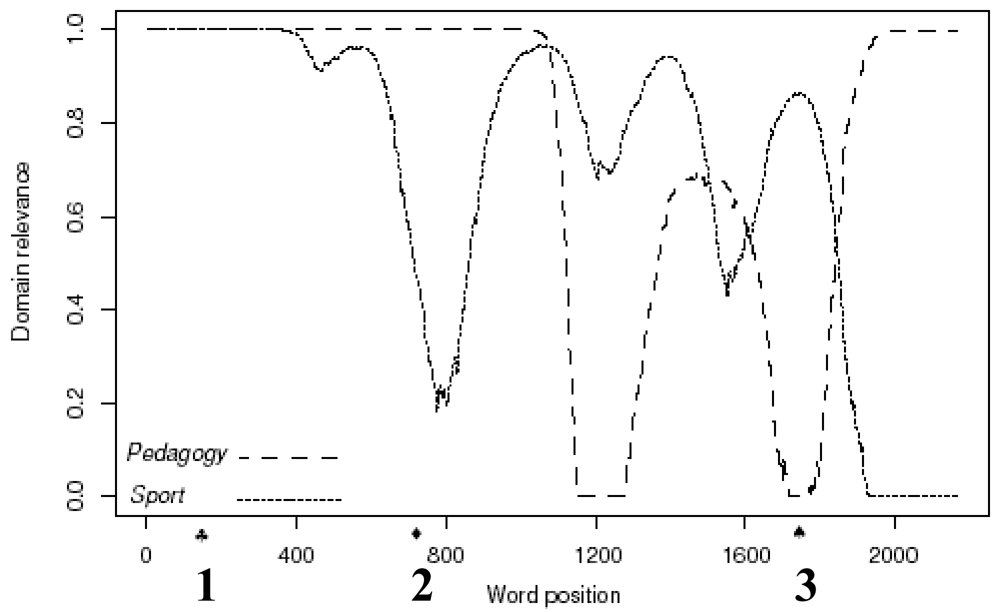
- *One Sense per Discourse hypothesis*: en textos bien escritos existe la tendencia a que los distintos usos de una palabra correspondan a un mismo sentido
  Gale, Church & Yarowsky (1992) vs Krovetz (1998)

- *One Domain per Discourse*: distintos usos de una misma palabra en fragmentos coherentes de texto corresponden a un mismo domino

Table 4. *One Sense per Discourse vs. One Domain per Discourse*

Pos	Cases[a]	Exceptions to OSD[b]	Exceptions to ODD[c]
All	23877	7469 (31%)	2466 (10%)
Nouns	10291	2403 (23%)	1142 (11%)
Verbs	6658	3154 (47%)	916 (13%)
Adjectives	4495	1100 (24%)	391 (9%)
Adverbs	2336	790 (34%)	12 (1%)[d]

Domain variation in a text



1. The Russians are all trained as dancers before they start to study gymnastics . .
2. If we wait until children are in junior-high or high-school, we will never manage it. . . .
3. The backbend is of extreme importance to any form of free gymnastics, and, as with all acrobatics, the sooner begun the better the results. . . .

Domains and WSD

- Metodologia básica: comparación entre los dominios de la palabra a desambiguar y los dominios de las palabras del contexto.
- Estructura de dades: *domain vector*
  - *text vector* relevancia de un fragmento en relación a cada dominio
  - *domain vector* relevancia de cada sentido de cada palabra en relación a cada dominio

Domain relevance

- Número positivo [0,1]
- Cálculo:
  - Define un ventana *v* (≥ 25)
  - Calcula la frecuencia de los dominios
  - Compara el resultado con un corpus balanceado (LOB) suponiendo una distribución normal
- Ej. "*Today I draw money from my bank*"

1/33 + 5/10 + 3/3 = 1,53 > 0,4

LOB (ECONOMY) → 0,2 · σ = 0.1

Text vector & Sense vector

- Text vector: es un vector de dominio calculado a partir de un fragmento de texto
  - Dados T, p y $\{D_1, D_2,...D_n\}$ → $\vec{T}p$

- Sense vector: es un vector de dominio calculado a partir de los sentidos de una palabra.

  Ej. bank_1 → (economy·20, sport·0, ...)

Disambiguation procedure

- Comparación entre el *Text vector* y el *Sense vector* (todos los sentidos)

- Ejemplo

Table 5. *Sense vectors ($\vec{s}_1$ and $\vec{s}_2$) and text vector ($\vec{T}_8$) for the text* T *'Today I have drawn money from my bank', for a subset of domains*

	Sport	Medicine	Economy	Geography
$\vec{s}_1$ (*Bank#1*)	0.02	0.08	1.73	0.04
$\vec{s}_2$ (*Bank#2*)	0.005	0.03	0.04	0.69
$\vec{T}_8$	0.2	0.005	1	0.03

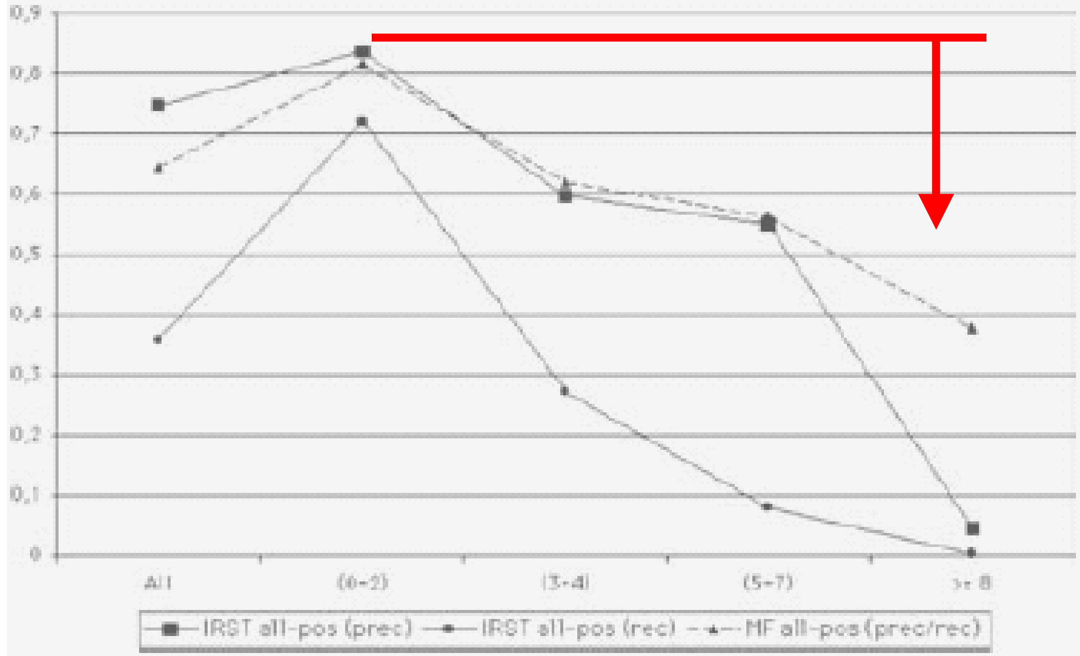
Ts · s1 = 1,73

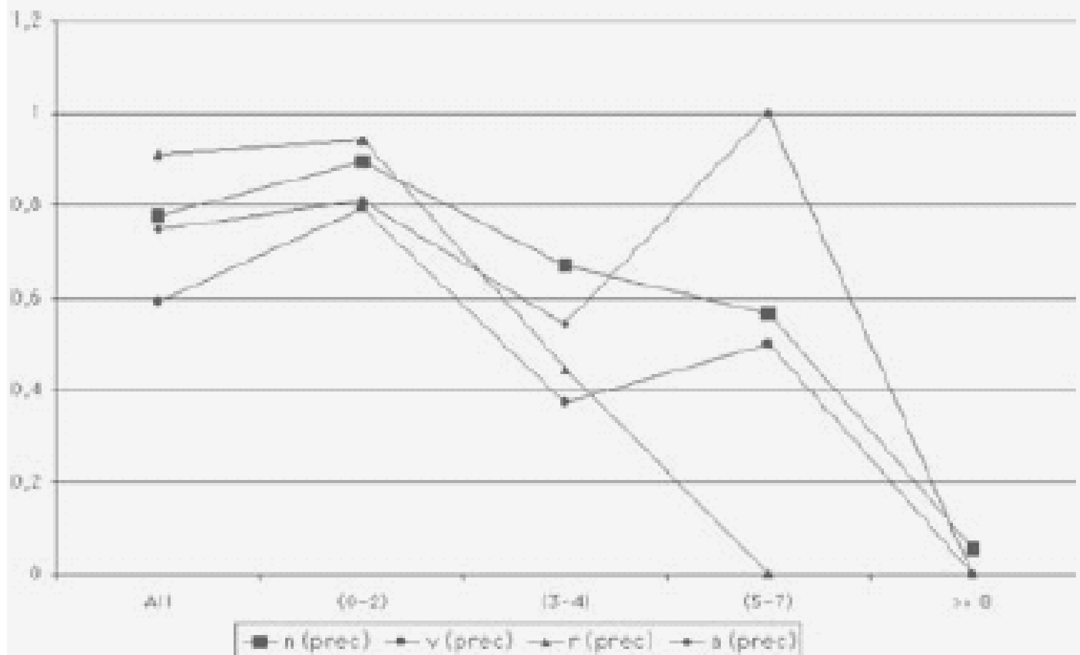
Ts · s2 = 0.06

Results

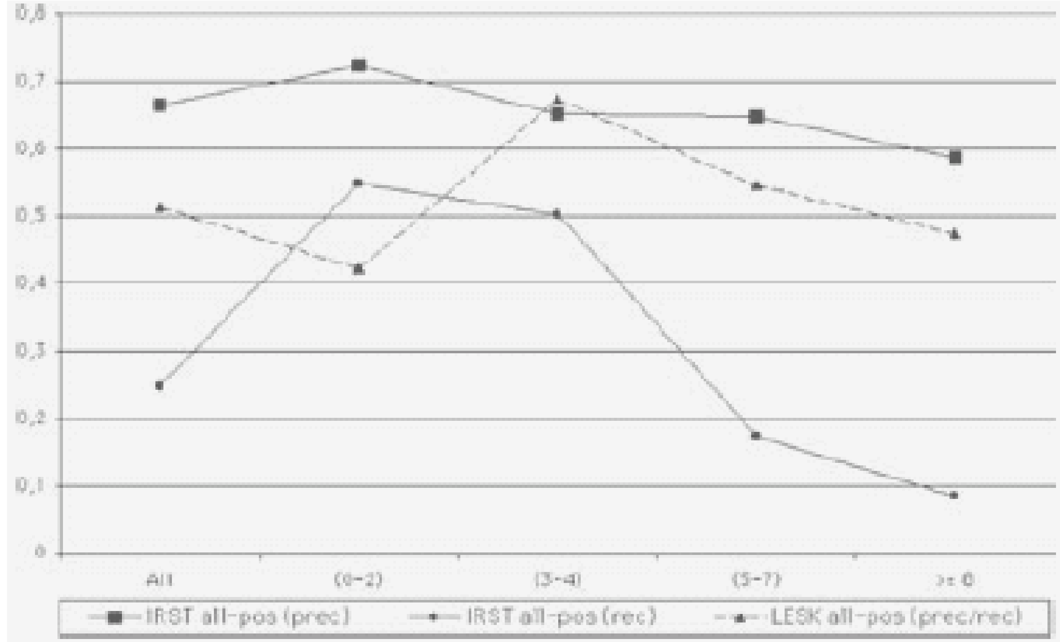
- El sistema participó en dos tareas:
  - *English_all_words* (desambiguar todas las palabras de un texto)
  - *English_lexical_sample* (una palabra y su contexto)
- ds

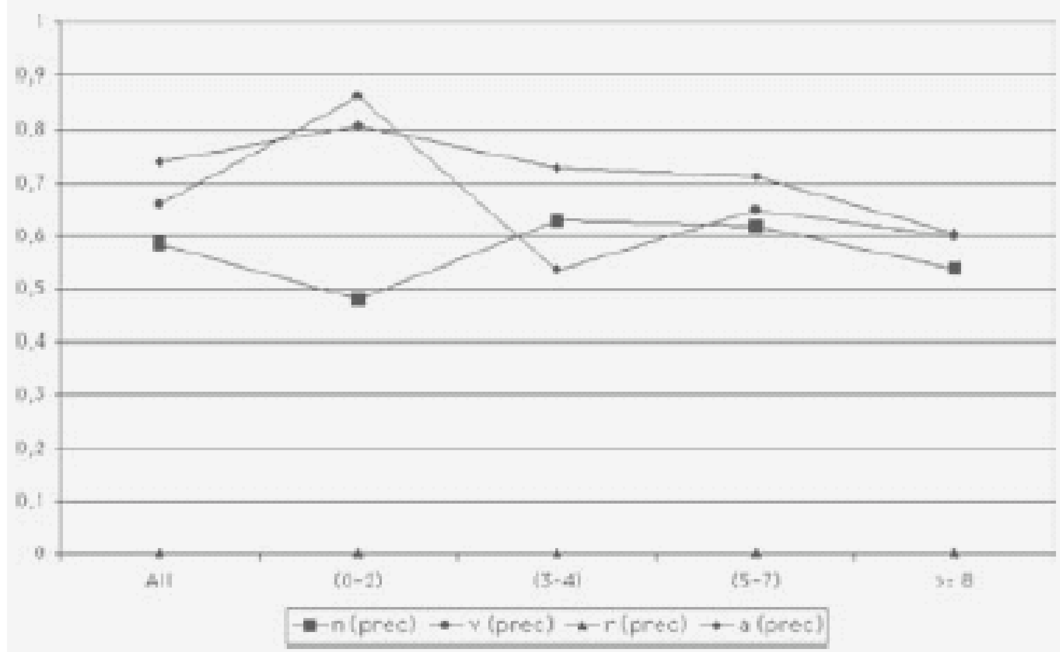
all_words Task





lexical_sample_words Task





Conclusions

- El algoritmo de desambiguación propuesto aprovecha la información de dominio y
- Para un subconjunto importante de palabras obtiene un alto grado de precisión .

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Combining classifiers for word sense disambiguation

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Introduction

- La combinación de clasificadores es una manera de mejorar el rendimiento de ciertas aplicaciones
- Cada método tiene sus puntos fuertes y funciona bien sobre diferentes tipos de datos de prueba. Existen:
  - Características inherentes a cada método
  - Diferencias en los métodos de selección de los rasgos
  - Uso de diferentes fuentes de conocimiento en la fase de entrenamiento.
- Métodos aprendizaje (supervisado): *Naïve Bayes* (variantes), *Cosine* y *Decision lists*
- Tarea: *lexical-sample task*
- Idiomas: inglés, español, vasco y sueco

The feature space

- Aspecto crítico en el diseño de un clasificador
- Rasgos morfológicos: lema + categoría
- Rasgos sintácticos :
  - Verbos: núcleo nominal del objeto, preposición y PP
  - Nombres: función sintáctica (sujeto, objeto, ...)
  - Adjetivos: núcleo nominal que modifica

Example sentence

Table 1. *Example sentence and sample of extracted features*

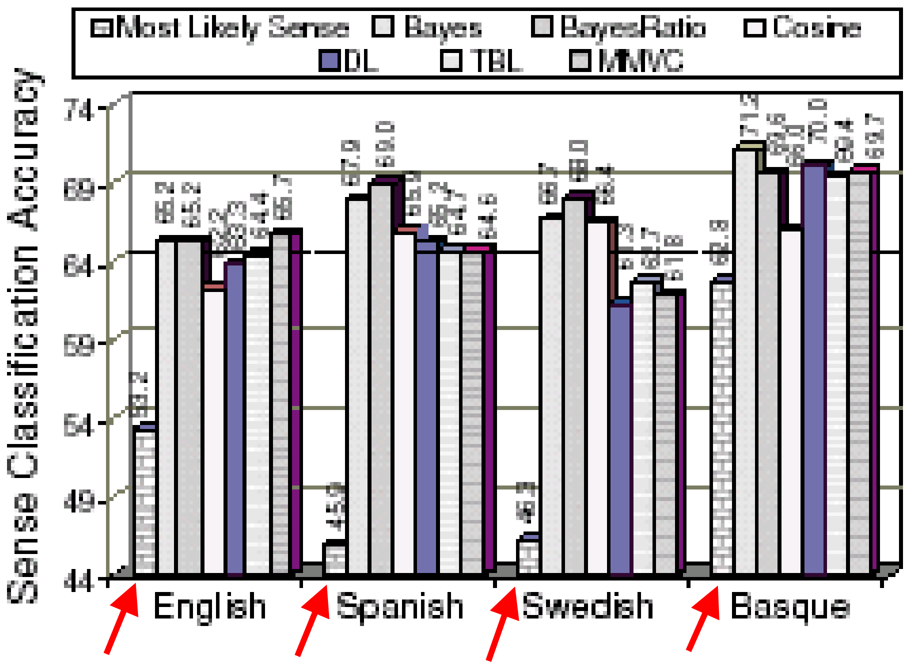
Many mothers do not even try to toilet **train** their children until the age of 2 years or later ..

Feature type	Word	POS	Lemma	Feature type	Word	POS	Lemma
Context	...	...	...	*Syntactic (predicate-argument) features*			
Context	try	VB	try/N	Object	children	NNS	child/N
Context	to	TO	to/T	Prep	until	IN	until/I
Context	toilet	NN	toilet/N	ObjPrep	age	NN	age/N
Context	train	VBP	train/V	*Ngram collocational features*			
Context	their	DT	their/D	−1 bigram	toilet	NN	toilet/N
Context	children	NN	child/N	+1 bigram	their	DT	their/D
Context	...	...	...	−1/+1 trigram	to * their	TO-DT	to/T * their/D
Context	...	...	...	+1/+2 trigram	their children	DT-NN	their/D child/N

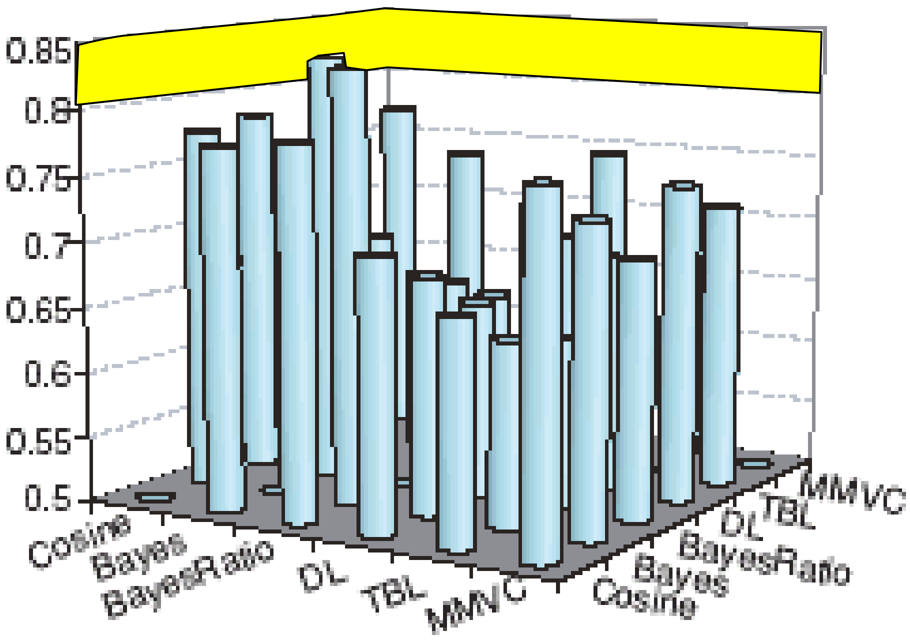
WSD classifier combination

- Classifer combination has been theoretically and practically shown to be beneficial in terms of improving system accuracy. Perrone (1993) shows that, under the restrictive assumption that the n input classifers are uncorrelated and have unbiased binary output, the expected error is reduced by a factor of n when combining their classications through averaging.

Individual classifier properties

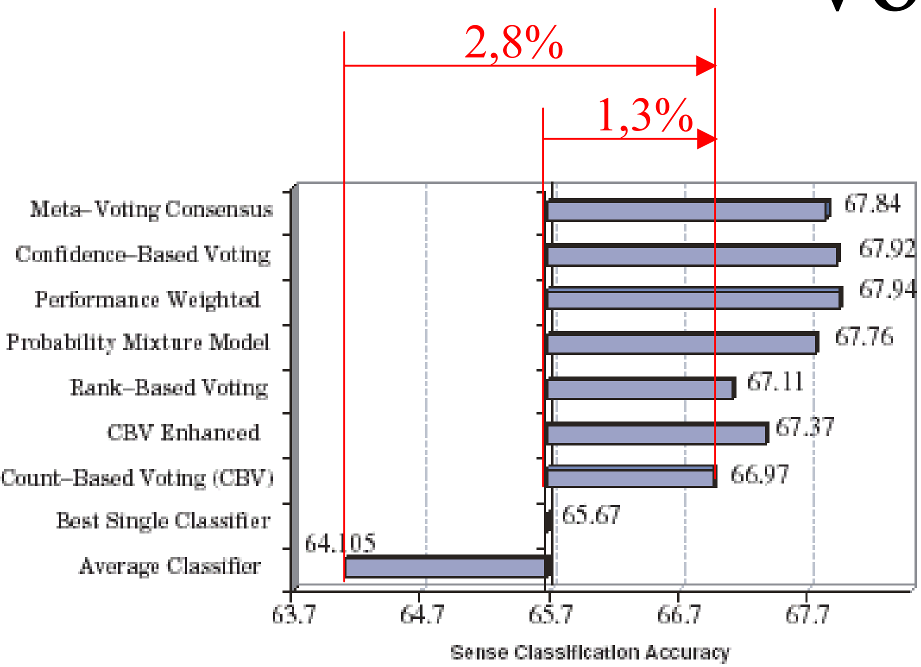


(a) Individual classifer performance,

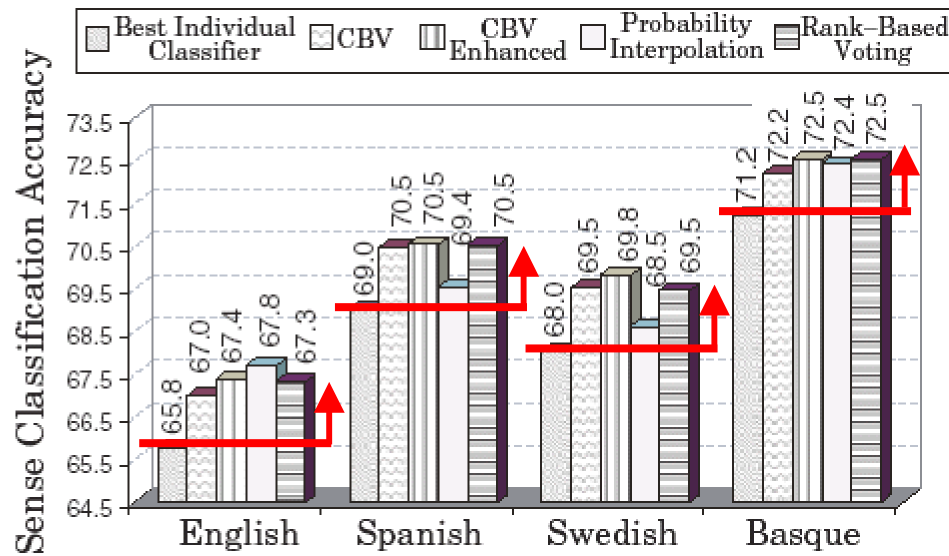


(b) Classifier inter-agreement.

Count-based and probability-based voting



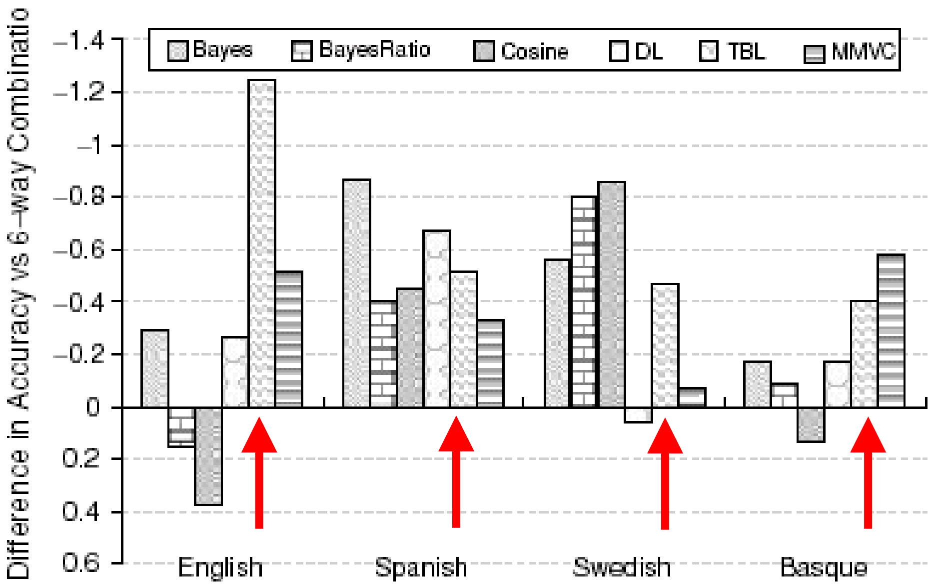
(a) English lexical choice WSD performance,



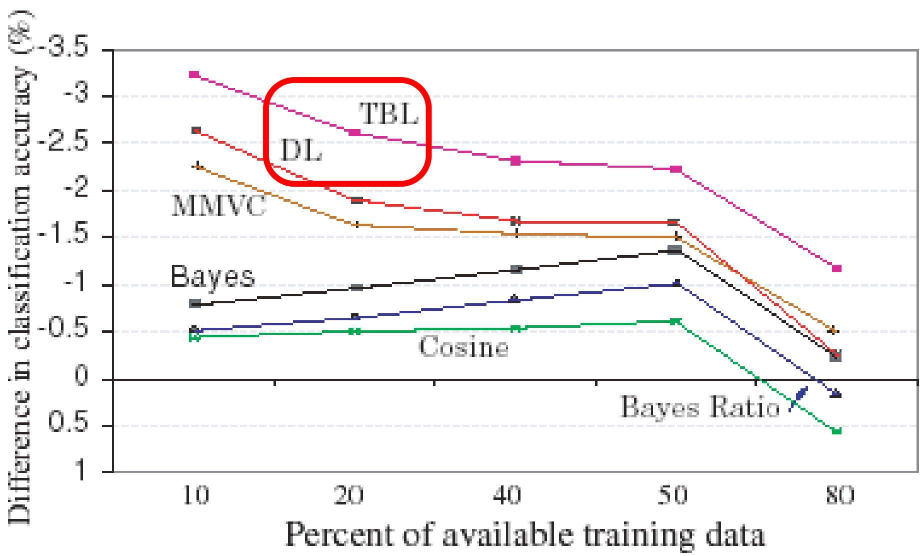
(b) WSD performance across four languages.

CBV enhanced= CBV + probabilidades
Probability mixture= voto ponderado
Rank Based Voting= voto ponderado
Metavoting= CBV sobre los *k* mejores métodos

Individual classifers' contribution to combination



(a) Performance drop when eliminating one classifer



(b) Performance when eliminating one classifer, by training data size.

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Evaluating sense disambiguation across diverse parameter spaces

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Introduction

- Es un estudio comparativo y detallado de la influencia que tienen algunos parámetros utilizados en diferentes algoritmos de WSD
- Algoritmos: variantes de *Naïve Bayes*, *cosine model*, *TBL* y *decision lists*
- Parámetros analizados:
  - Idioma
  - POS
  - Granularidad
  - Ancho de contexto
  - Núm. de ejemplos de entranamiento
  - Entropia en la distribución de los sentidos
  - Efecto del ruido
  - Divergencia entre datos de entrenamiento/prueba

Algorithm classification

- Aggregative:

  integrate all available evidence in favor of a sense and then select the sense with the maximum cumulative support (*cosine*, *FENBayes* and *BR*)

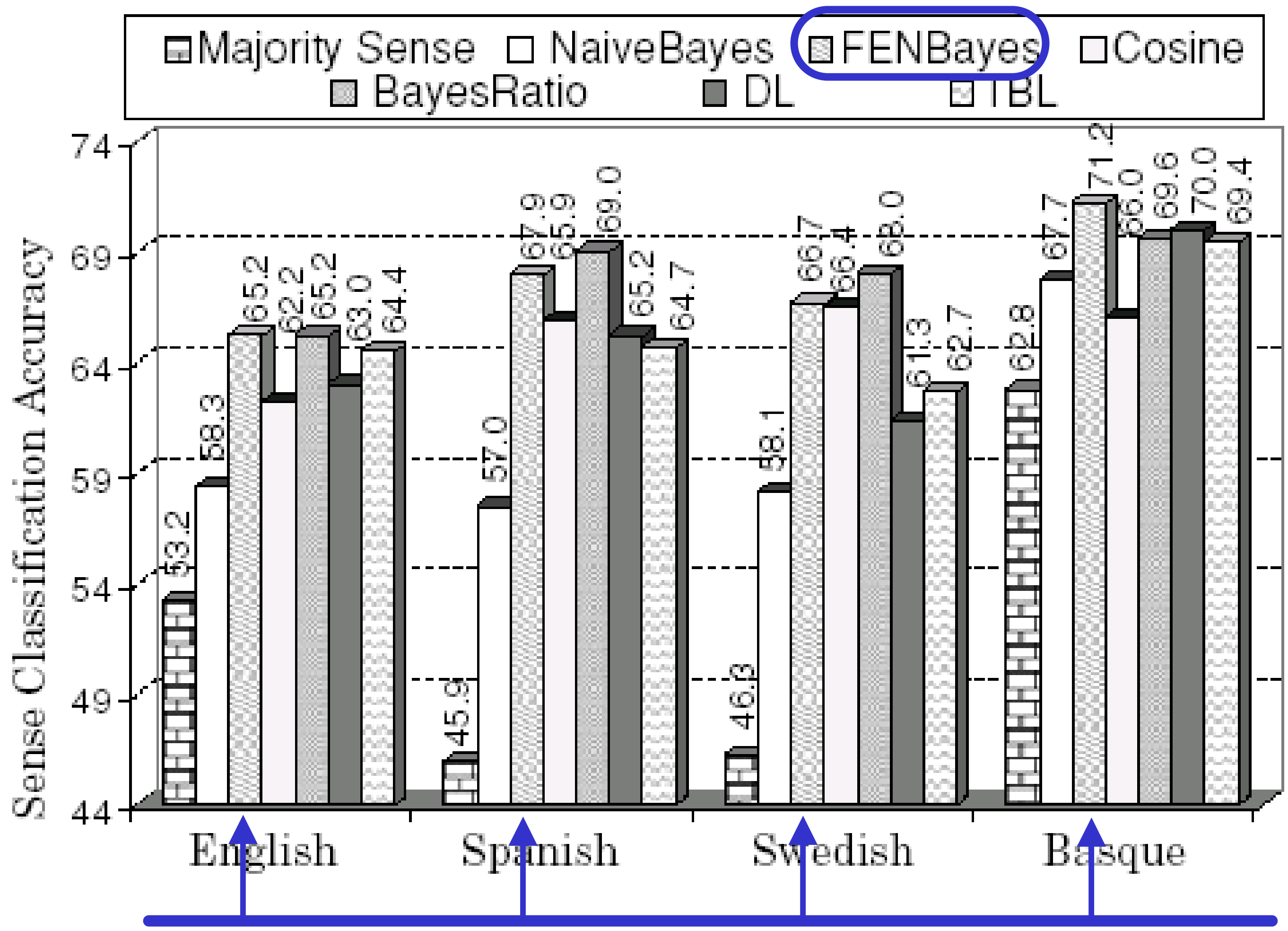
- Discriminative:

  rely on one or a few features in any given context that most efficiently partition or discriminate the candidate sense space (*DL* and *TBL*).

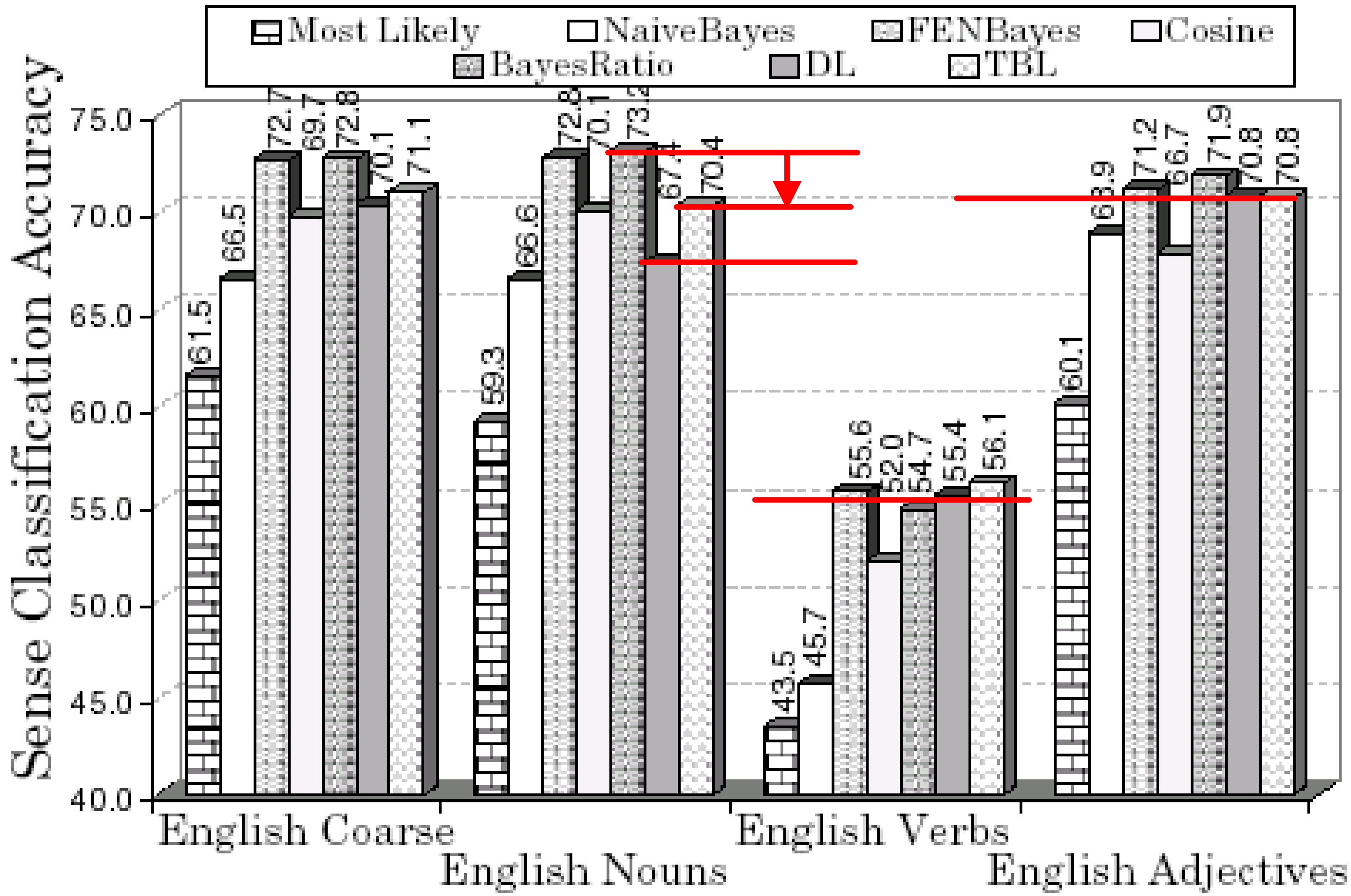
Feature space

- Forma/lema/etiqueta para conjuntos de palabras o colocaciones tipo n-gram.
- Relaciones sintácticas relevantes (sujeto, objeto, modificador, etc.)
- Agrupaciones:
  - *BagOfWordsContext*
  - *LocalContext*
  - *SyntacticFeatures*

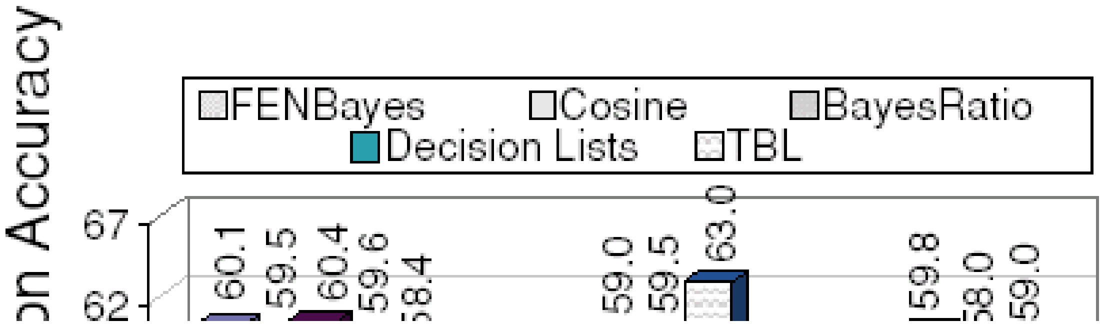
Performance based on language



Performance based on POS



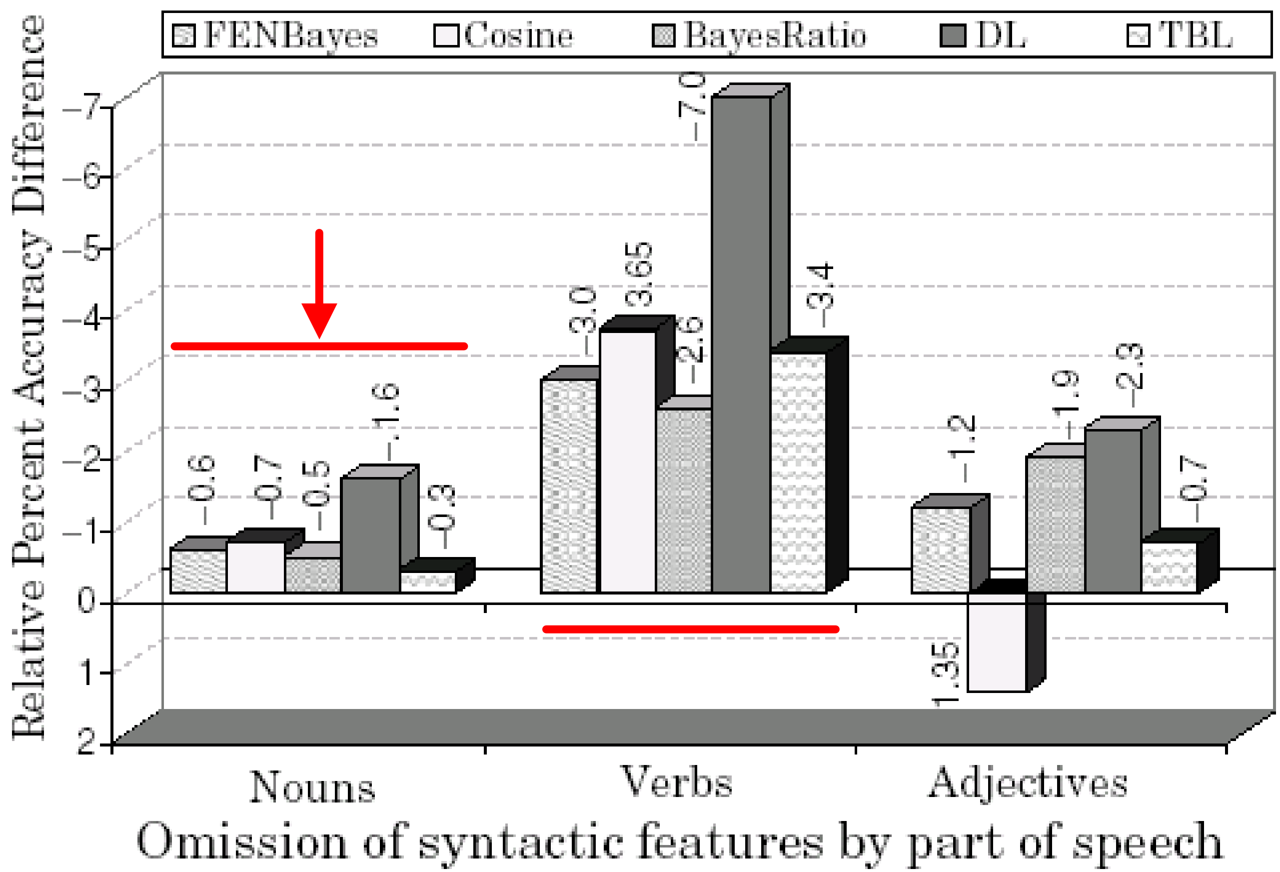
Performance sensitivity to feature type



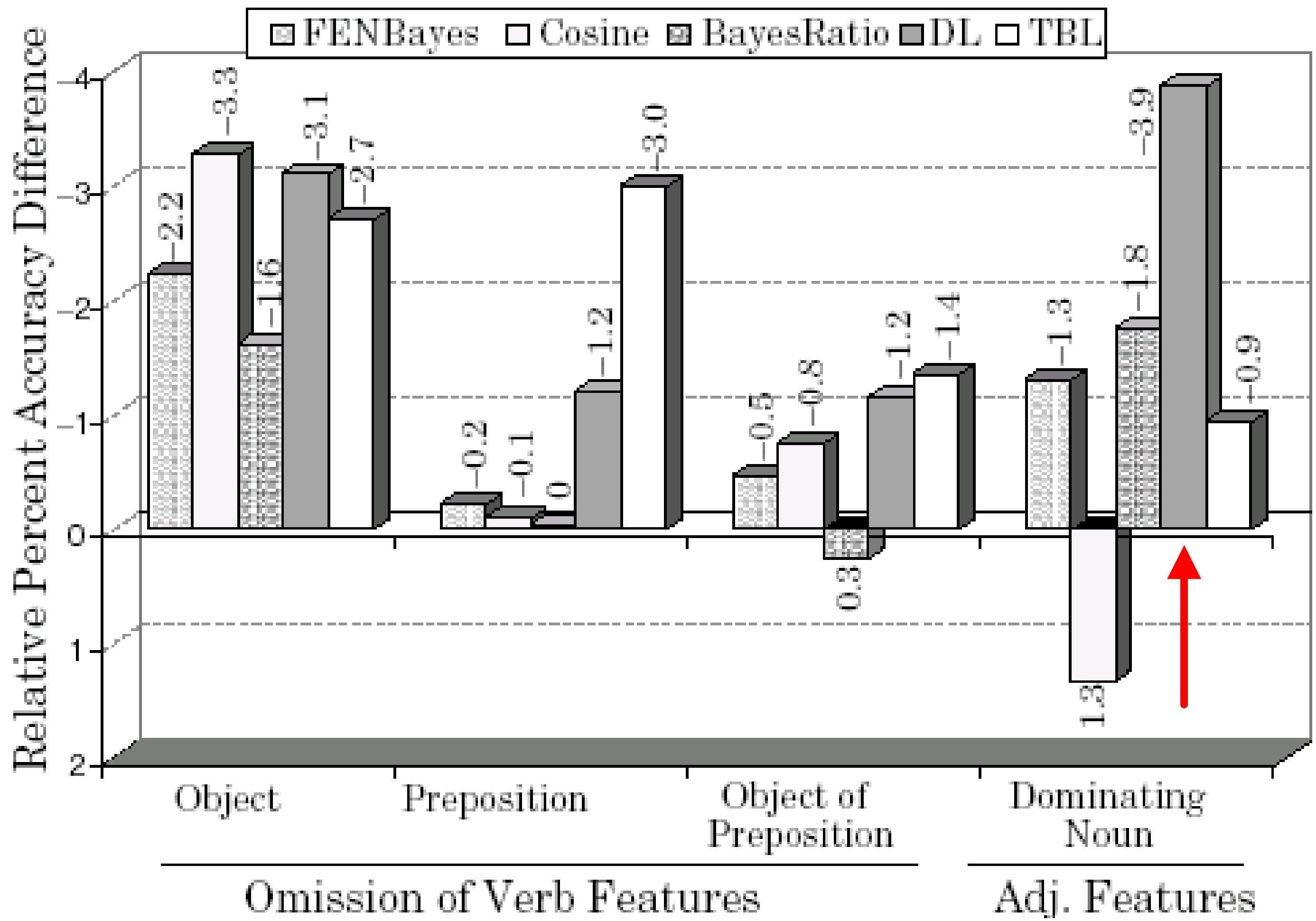
Accuracy drop relative to full system

Features used	Aggregative			Discrimin.	
	FENB	CSN	BR	TBL	DL
Omit Bag-of-words Ftrs	−14.7	−8.1	−5.3	−0.5	−2.0
Omit Local Collocations	−3.5	−0.8	−2.2	−2.9	−4.5
Omit Syntactic Features	−1.1	−0.8	−1.3	−1.0	−2.3
Bag-of-words Ftrs ***Only***	−6.4	−4.8	−4.8	−6.0	−3.2
Local Collocations ***Only***	−18.4	−11.5	−6.1	−1.5	−3.3
Syntactic Features ***Only***	−28.1	−14.9	−5.4	−5.4	−4.8

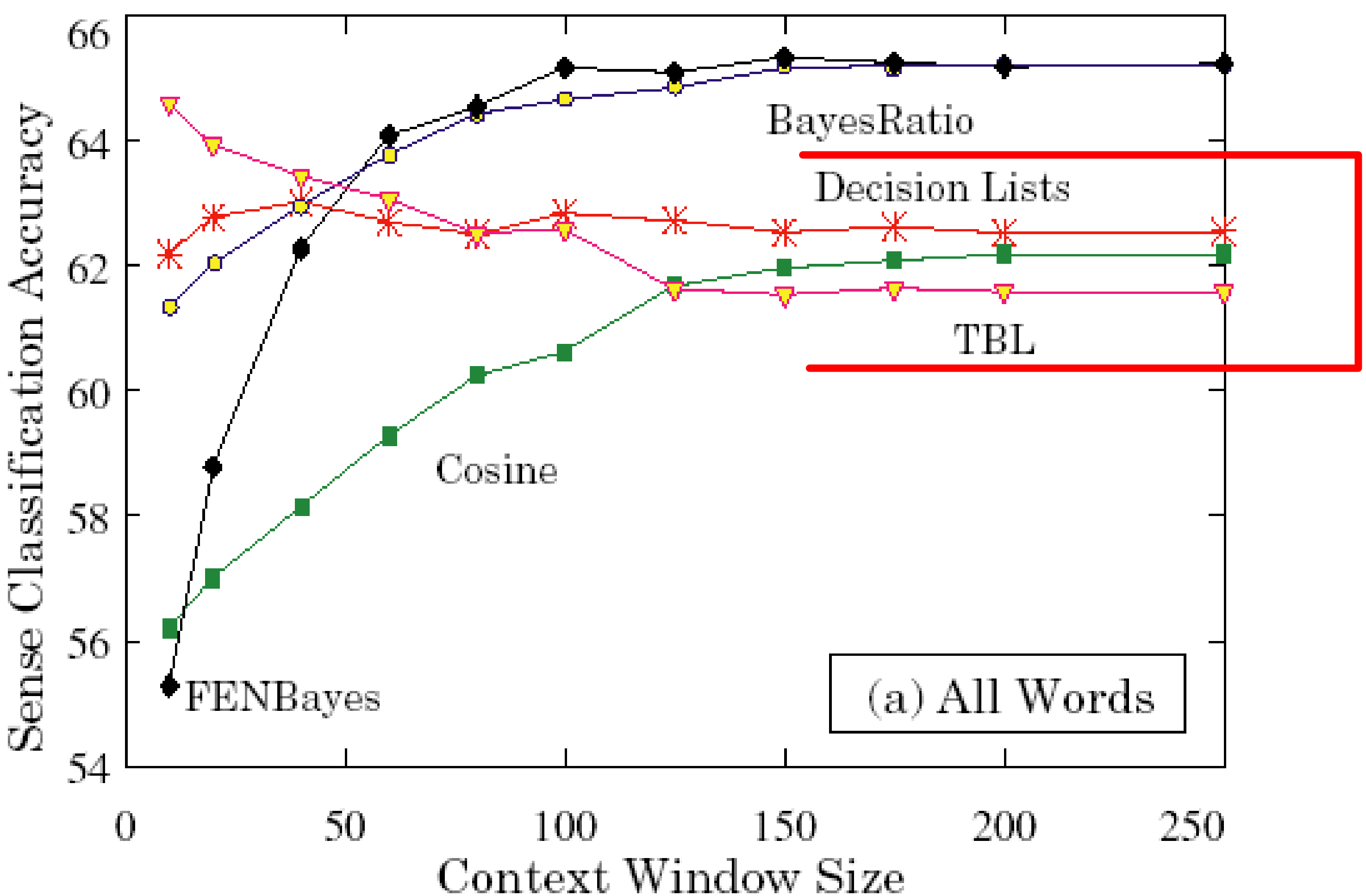
Contribution of syntactic features (I)



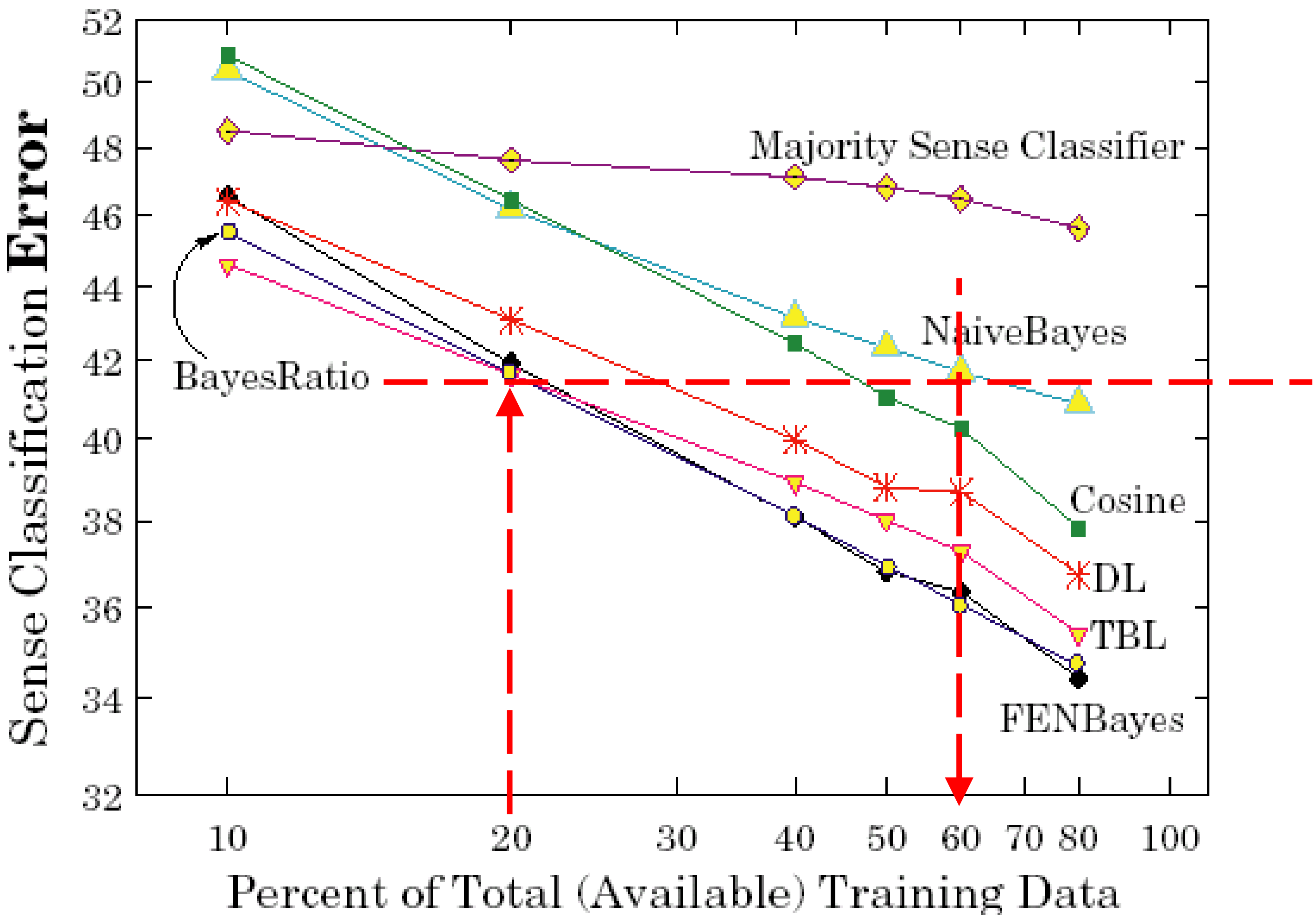
Contribution of syntactic features (II)



Performance sensitivity to context window size



Performance sensitivity to size of training data



Conclusions

- Ningún algoritmo destaca sobre el resto.

Model	Samples	Senses	ML	Entr	FENBayes	BayesRatio	Cosine	DL	TBL
wander.v	100	4	**83.0%**	0.1	78.0%	79.0%	63.0%	81.0%	82.0%
wash.v	25	13	8.0%	0.8	52.0%	52.0%	56.0%	**68.0%**	40.0%
work.v	119	21	27.6%	0.5	44.6%	**46.3%**	40.4%	40.5%	39.6%

- Los algoritmos discriminativos y agregativos tienen comportamientos complementarios → uso de algoritmos de combinación de clasificadores.
- La calidad del espacio de rasgos puede tener un impacto superior al de la elección del algoritmo de desambiguación

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Introduction to the special issue on evaluating word sense disambiguation systems

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