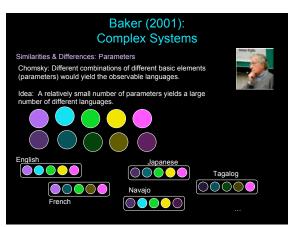
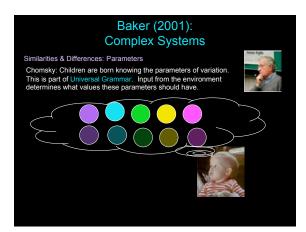


Lecture 20 Syntax Learning







### Baker (2001): Complex Systems

Similarities: Greenberg's Generalizations Word Order Generalizations

Navajo

Basic word order: Subject Object Verb

Postpositions: Noun Phrase Postposition

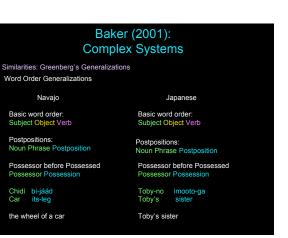
'éé' biih náásdzá clothing into I-got-back I got back into (my) clothes. Japanese Basic word order: Subject Object Verb

Postpositions: Noun Phrase Postposition

Jareth-ga Sarah to kuruma da Jareth Sarah with car by

London ni itta London to went

Jareth went to London with Sarah by car.



### Baker (2001): Complex Systems

Similarities: Greenberg's Generalizations Word Order Generalizations

Navajo

Basic word order: Subject Object Verb

Postpositions: Noun Phrase Postposition

Possessor before Possessed Possessor Possession Basic word order: Subject Object Verb

Japanese

Postpositions: Noun Phrase Postposition

Possessor before Possessed Possessor Possession

# Baker (2001):<br/>Complex SystemsSimilarities: Greenberg's GeneralizationsWord Order GeneralizationsEnglishEdo (Nigeria)Basic word order:<br/>Subject Verb ObjectBasic word order:<br/>Subject Verb ObjectSarah found Toby.Özó mién Adésuwá<br/>Ozo found Adesuwa.

### Baker (2001): Complex Systems

Similarities: Greenberg's Generalizations Word Order Generalizations

ord order Generalizations

English

Basic word order: Subject Verb Object

Prepositions: Preposition Noun Phrase

Jareth gave the crystal to Sarah.

Edo (Nigeria) Basic word order: Subject Verb Object Prepositions: Preposition Noun Phrase

Preposition Noun Phrase

Òzó rhié néné ebé né Adésuwá Ozo gave the book to Adesuwa.



Ozo's child

### Baker (2001): Complex Systems

Similarities: Greenberg's Generalizations Word Order Generalizations

English

Basic word order: Subject Verb Object

Prepositions: Preposition Noun Phrase

Possessed before Possessor Possession Possessor Edo (Nigeria) Basic word order: Subject Verb Object

Prepositions: Preposition Noun Phrase

Freposition Noull Fillas

Possessed before Possessor Possession Possessor

### Baker (2001): Complex Systems

Similarities: Greenberg's Generalizations

Word Order Generalizations

Point: Forty-five "universals" of languages found - patterns overwhelmingly followed by languages with unshared history (Navajo & Japanese, English & Edo)

Not all combinations are possible - some patterns rarely appear Ex: Subject Verb Object language (English/Edo-like) + postpositions (Navajo/Japanese-like)

2

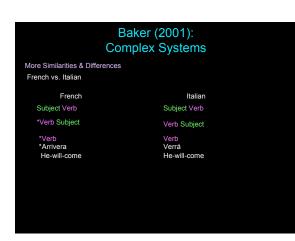
### Baker (2001): Complex Systems

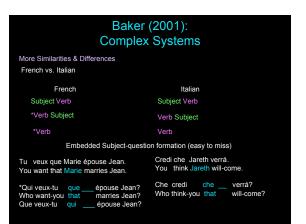
### More Similarities & Differences

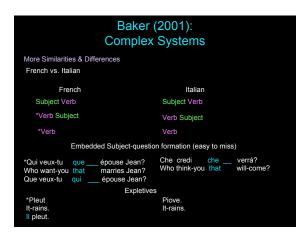
French vs. Italian

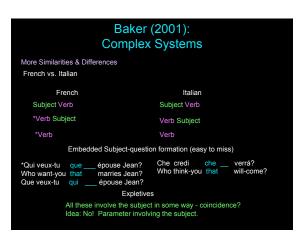
French Subject Verb Jareth arrivera. Jareth will-come. Italian Subject Verb Jareth verrá. Jareth will-come.

# Baker (2001):<br/>Complex SystemsMore Similarities & DifferencesFrench vs. ItalianMore Subject VarbSubject Varb\*Verb Subject\*Verb Subject\*Verly Subject\*Will-arrive Jareth.\*Will-arrive Jareth.

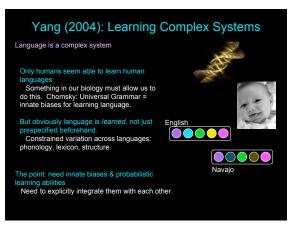








	(2001): Systems
The Value of Parameters for Learning: Le French vs. Italian: Subject Parameter	arn the Hard Stuff from the Easy Stuff
French	Italian Easy to notice
Subject Verb	Subject Verb
*Verb Subject	Verb Subject
*Verb	Verb
Embedded Subject-questi	on formation (easy to miss)
*Qui veux-tu queépouse Jean? Who want-you thatmarries Jean? Que veux-tu quiépouse Jean?	Che credi che /verrá? Who think-you that /will-come?
Expletive	
*Pleut It-rains. Il pleut.	Piove. It-rains.





Stephen Crain



### Yang (2004): Learning Complex Systems

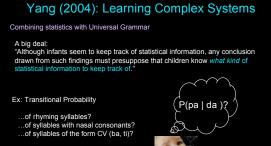
Statistics for word segmentation (remember Gambell & Yang (2006))

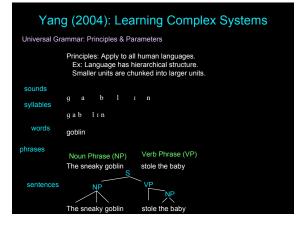
"Modeling shows that the statistical learning (Saffran et al. 1996) does not reliably segment words such as those in child-directed English. Specifically, precision is 41.6%, recall is 23.3%. In other words, about 60% of words postulated by the statistical learner are not English words, and almost 80% of actual English words are not extracted. This is so even under favorable learning conditions".

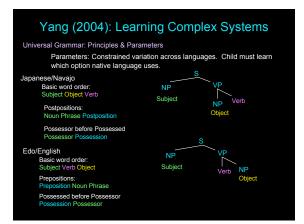
Unconstrained (simple) statistics: not so good.

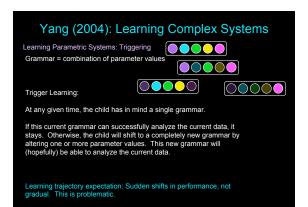


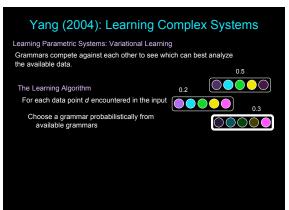
If statistical measure is constrained by language-specific knowledge (words have only one main stress), performance increases dramatically: 73.5% precision, 71.2% recall. Constrained statistics - much better!

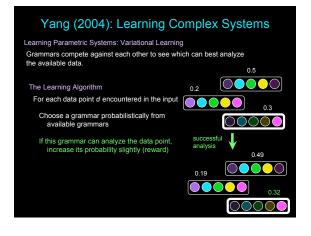


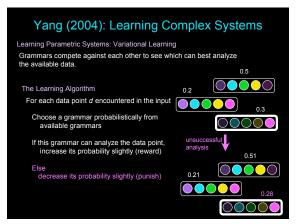


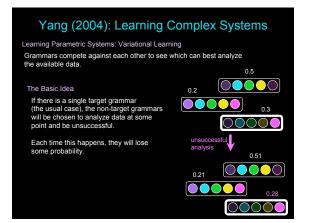


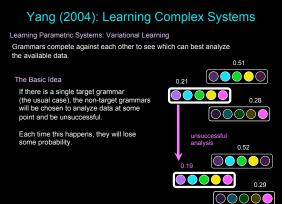


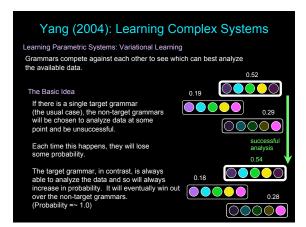












### Yang (2004): Learning Complex Systems

Learning Parametric Systems: Variational Learning Grammars compete against each other to see which can best analyze the available data.

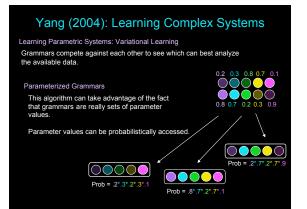
The Main Force

The crucial data is that which is unambiguous for the target grammar: this data is incompatible with non-target grammars.

The more unambiguous data there is, the faster the target grammar will win.

Added perk: Learning is then gradual (probabilistic).

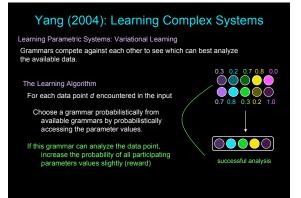
Problem: Does unambiguous data exist for entire grammars? This requires data that is incompatible with every other possible parameter of every other possible grammar....

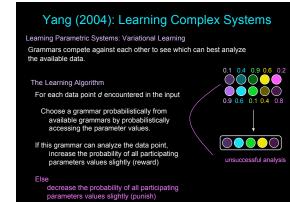


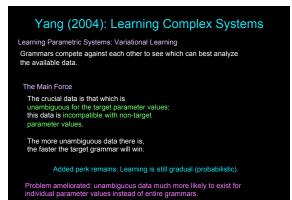


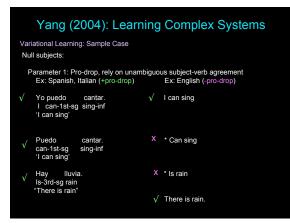
Choose a grammar probabilistically from available grammars by probabilistically accessing the parameter values.

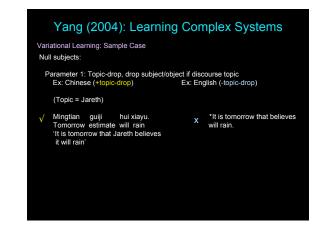


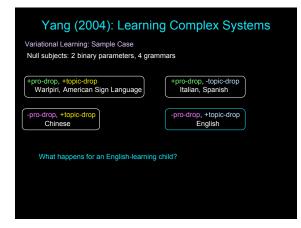


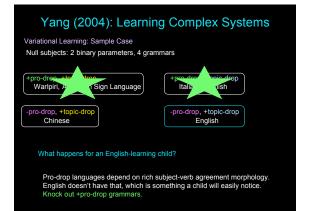


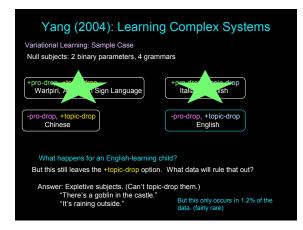


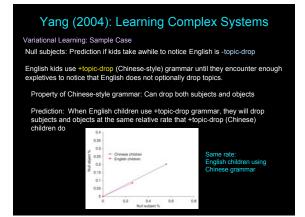


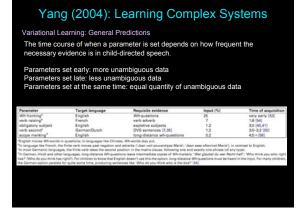












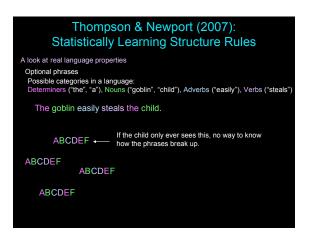
### Thompson & Newport (2007): Statistically Learning Structure Rules

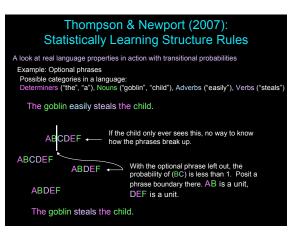
Transitional probability: segmenting words into phrases? Snapshot summary.

Artificial language paradigm, adult subjects, 20 minutes of exposure per session. TPs: high within phrases, low across phrases

Properties of the artificial language: similar to real language properties optional phrases (the goblin *in the castle* chased a chicken) repeated phrases (Noun-Phrase Verb Noun-Phrase) moved phrases (A chicken was chased by the goblin in the castle) different-sized form classes (many nouns, few determiners)

Learning best when all of these properties are present ("structured complexity")





S	I nomp tatisticall		ng Struc		les
tificial lang Baseline j	uage pattern: ABCDE	F			
	Nonser	nse Words Assig	ned to Each For	m Class	
A Words	B Words	C Words	D Words	E Words	F Words

SOT (coat) ZOR (core) LUM (bum) FAL (pal) TAF (waif) RUD (bud)

KER (her) NAV (have) SIB (bib)

JES (dress) REL (fell) TID (bid)

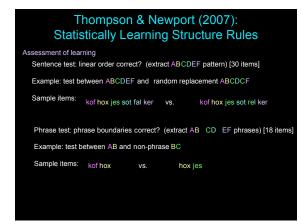
Artific Ba

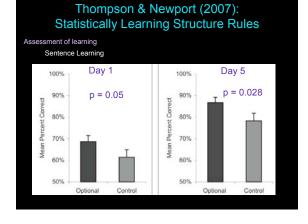
> KOF (oaf) DAZ (has) MER (her)

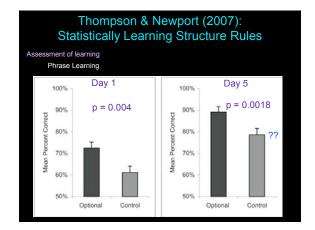
HOX (box) NEB (web) LEV (rev)

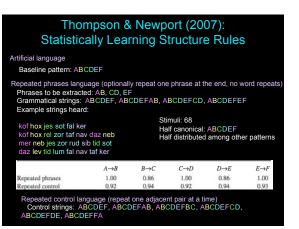
rtificial language Baseline pattern: ABCDE	F				
Optional language (remove Phrases to be extracted Grammatical strings: A Example strings heard:	I: AB, ĊD,	EF			
kof hox jes sot fal ker rel zor taf nav mer neb rud sib daz lev tid lum		Ha	imuli: 96 of p alf canonical alf distributed		er patterr
	$A \rightarrow B$	$B \rightarrow C$	$C \rightarrow D$	$D \rightarrow E$	$E \rightarrow F$
Optional phrases	1.00	0.80	1.00	0.80	1.00

Thompson & Newport (2007)



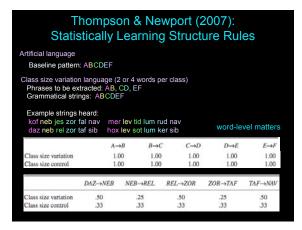


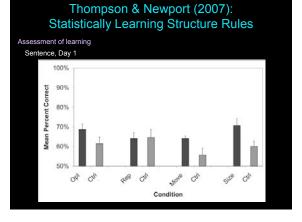


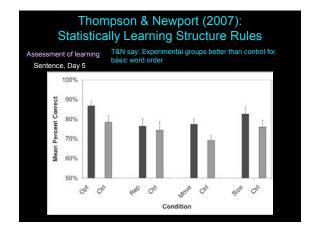


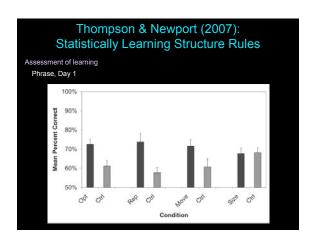
Thom Statistica	•	& Newp rning S			6
Artificial language Baseline pattern: ABCD	EF				
Moved phrases language Phrases to be extracted: Grammatical strings: AE	AB, CD, E	F EFCD, CDA		AB,	
Example strings heard: kof hox jes sot fal ker daz neb rel taf nav zor 		Ha	imuli: 80 alf canonical alf distributed	: ABCDEF d among othe	er patterns
	$A \rightarrow B$	$B \rightarrow C$	$C \rightarrow D$	$D \rightarrow E$	$E \rightarrow F$
Moved phrases Moved control	1.00 0.78	0.60 0.78	1.00 0.78	0.60 0.78	1.00 0.78
Moved control languag Control strings: ABC EFC	DEF, ABER	FCD, CDAB	EF, CDEFA		

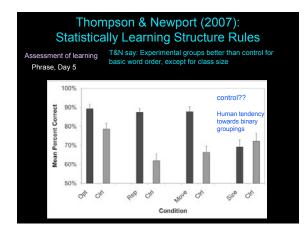
Artificial language Baseline pattern: ABCDEF Class size variation language (2 or 4 words per class) Phrases to be extracted: AB, CD, EF Grammatical strings: ABCDEF Example strings heard: kof reb jes zor fal nav daz neb rel zor taf sib Nox lev sot lum rud nav daz neb rel zor taf sib Nox lev sot lum ker sib MER (har) DAZ (has) NEB (web) MER (fel) ZOR (core) MER (her) EXAMPLE Strings NAV (have) REL (fel) AC (core) MER (her) Core (ther) Core (ther)	S		•	Newport		lles
Grammatical strings: ABCDEF       Example strings heard: kof neb jes zor fal nav daz neb rel zor taf sib     mer lev tid lum rud nav hox lev sot lum ker sib       A words     B words     C words     D words     E words       A words     B words     C words     D words     FAL (pal)       KOF (oaf)     JES (dress)     FAL (pal)     NAV (have)       DAZ (has)     NEB (web)     REL (feli)     ZOR (core)     TAT (waif)     NAV (have)	0	0	EF			
kof neb jes zor fal nav mer lev tid lum rud nav daz neb rel zor taf sib hox lev sot lum ker sib A words B words C words D words E words F words KOF (oaf) JES (dress) FAL (pal) DAZ (has) NEB (web) REL (feil) ZOR (core) TAF (waif) NAV (have) MER (her) LEV (rev) TID (bid) LUM (bum) RUD (bud) SIB (bib)			AB, CD, EF	rds per class)		
KOF (oaf)         JES (dress)         FAL (pal)           DAZ (has)         NEB (web)         REL (fell)         ZOR (core)         TAF (waif)         NAV (have)           MER (her)         LEV (rev)         TID (bid)         LUM (bum)         RUD (bud)         SIB (bib)		al strings: AE	CDEF			
DAZ (has)         NEB (web)         REL (fell)         ZOR (core)         TAF (waif)         NAV (have)           MER (her)         LEV (rev)         TID (bid)         LUM (bum)         RUD (bud)         SIB (bib)	Grammatio Example s kof neb jes	trings heard: zor fal nav	mer lev tid lu			
MER (her) LEV (rev) TID (bid) LUM (burn) RUD (bud) SIB (bib)	Grammatio Example s kof neb jes daz neb re	trings heard: zor fal nav el zor taf sib	mer lev tid lu hox lev sot lu	um ker sib	E words	F words
	Grammation Example s kof neb jes daz neb ro A words	trings heard: zor fal nav el zor taf sib	mer lev tid lu hox lev sot lu C words	um ker sib		F words
HOX (box) SOT (coat) KER (her)	Grammation Example s kof neb jes daz neb ro A words KOF (oaf)	trings heard: zor fal nav el zor taf sib <i>B words</i>	mer lev tid lu hox lev sot lu <i>C words</i> JES (dress)	um ker sib D words	FAL (pal)	
	Grammatid Example s kof neb jes daz neb ro A words KOF (oaf) DAZ (has)	trings heard: zor fal nav el zor taf sib <i>B words</i> NEB (web)	mer lev tid lu hox lev sot lu <i>C words</i> JES (dress) REL (fell)	D words ZOR (core)	FAL (pal) TAF (waif)	NAV (have)



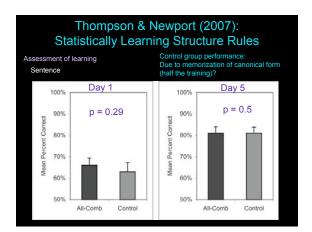


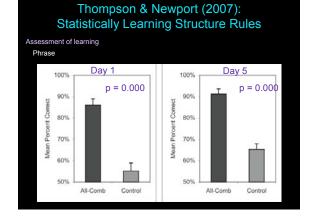


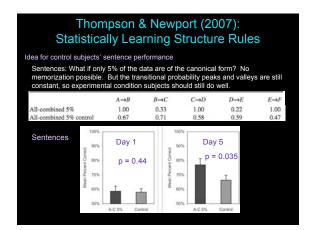


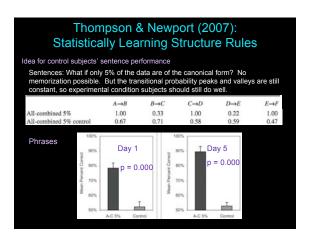


Statistic			port (20 Structu		es
Artificial language					
Baseline pattern: A	BCDEF				
	CDEFAB,				
	$A \rightarrow B$	$B \rightarrow C$	$C \rightarrow D$	$D \rightarrow E$	$E \rightarrow F$
All-combined All-combined control	A→B 1.00 0.80	$B \rightarrow C$ 0.56 0.83	C→D 1.00 0.74	D→E 0.52 0.77	$E \rightarrow F$ 1.00 0.74
	1.00 0.80	0.56	1.00 0.74	0.52	1.00
All-combined control	1.00 0.80	0.56	1.00 0.74 iguage = harde	0.52	1.00
All-combined control More informationbu	1.00 0.80	0.56 0.83 embers of lan	1.00 0.74 iguage = harde	0.52	1.00 0.74
All-combined control More informationbu	1.00 0.80	0.56 0.83 embers of lan	1.00 0.74 iguage = harde	0.52	1.00 0.74 Sentences
All-combined control More informationbu Language Optional phrases Repeated phrases Moved phrases	1.00 0.80	0.56 0.83 embers of lan	1.00 0.74 iguage = harde	0.52	1.00 0.74 Sentences 972
All-combined control More informationbu Language Optional phrases Repeated phrases	1.00 0.80	0.56 0.83 embers of lan	1.00 0.74 iguage = harde	0.52	1.00 0.74 Sentences 972 20,412









## Thompson & Newport (2007): Statistically Learning Structure Rules

Discussion: Do we believe that this is strong evidence for the discovery of grammatical structure (and rules) via transitional probability?