Simulating the Early Evolution of Writing

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The problem

- There have been only four (more or less unequivocal) cases of the independent discovery of writing:
  - Mesopotamia
  - Egypt
  - China
  - Mesoamerica
- *With only four data points, it is hard to make any generalizations about the conditions that might favor (or disfavor) the discovery.*

Computational simulation

- Computational simulation has been used in a number of areas of linguistics to model phenomena that are hard to test in the laboratory or in the field:
  - Spread of linguistic features in social networks (e.g. Steels, 2012)
  - Historical change (e.g. Niyogi, 2006)
  - Emergence of linguistic properties (e.g. Kirby, 1999 and much subsequent work)
- *The present research seeks to model the emergence of writing from non-linguistic symbol systems*

Phenomena of interest

- The non-linguistic symbol systems in use in the culture, and the existence of combinatorial systems where symbols occur in “texts”.
- Linguistic properties favoring the discovery of writing, and favoring a particular kind of writing system over another (e.g. a consonantary versus a syllabary).
- Economic or other factors that would encourage the development of better means of record keeping.
- The development of lightweight materials encouraging the wider use of writing (Farmer et al. 2002).

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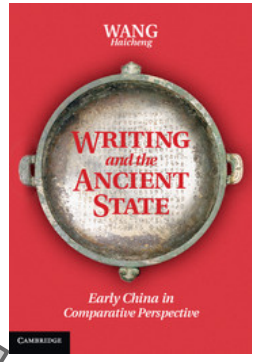


Summary of Chicago Presentation

Goals

- Generate a writing system for a language from a non-linguistic symbol system. Symbols are assigned to morphemes, spreading to new morphemes by:
  - Semantic similarity
  - Phonetic similarity
- Determine how many spellings for morphemes are purely semantic, purely phonetic, or mixed
  - Compare these with the situation in true ancient writing systems
- Determine which linguistic properties make phonetic spread easiest.

Parameters: phonotactics

Basic phonotactics for morphemes

Monosyllabic language	σ = C? V R? C?	[R= sonorant]
Disyllabic language	σσ?	

C = p, t, k, b, d, g

V = a, e, i, o, u

R = N, r

Randomly generate ≈1K morphemes from these templates

Parameters: what's phonetically close?

- CLOSE:
  - obstruents match on place of articulation
  - vowels must match
  - sonorants optional
  - **Ex: *daNg* matches *tak***
- CLOSE_RHYME:
  - as above, but "rhyming" is sufficient
  - **Ex: *daNg* matches *bak***
- CLOSE_V_FREE:
  - same as CLOSE, but vowels don't need to match, and V matches ∅
  - **Ex: *donek* matches *dink***
- STRICT:
  - Exact match required

Parameters: semantics

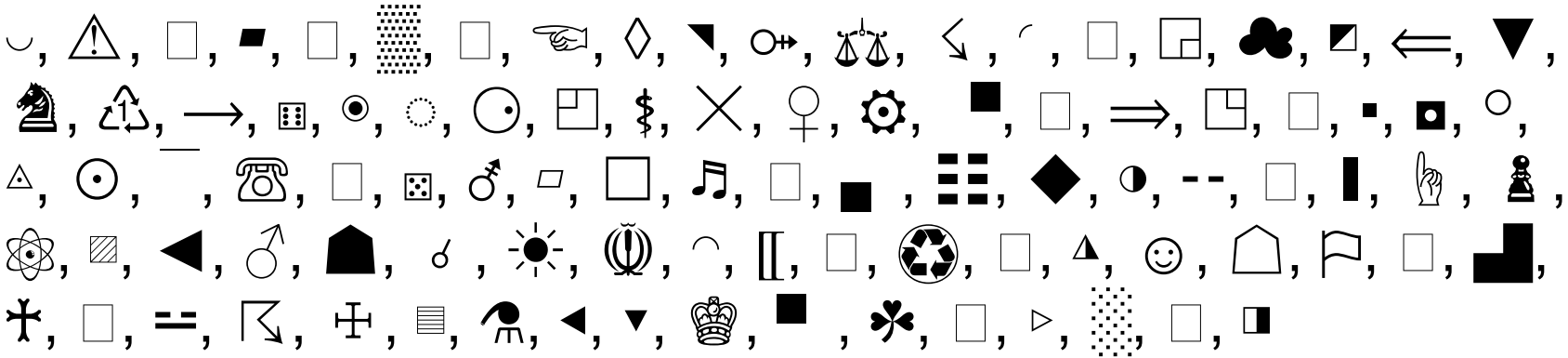
100 basic “concepts”:

PERSON, MAN, WOMAN, HOUSE, BRONZE, SWORD, MEAT, SHEEP, OX, GOAT, FISH, TREE, BARLEY, WHEAT, WATER, STONE, CLAY, THREAD, CLOTHING, FIELD, TEMPLE, GOD, AXE, SCYTHE, DOG, LION, WOLF, DEMON, SNAKE, TURTLE, FRUIT, HILL, CAVE, TOWN, ENCLOSURE, FLOWER, RAIN, THUNDER, CLOUD, SUN, MOON, HEART, LUNG, LEG, ARM, FINGER, HEAD, TONGUE, EYE, EAR, NOSE, GUTS, PENIS, VAGINA, HAIR, SKIN, SHELL, BONE, BLOOD, LIVER, FARM, LOCUST, STICK, STAR, EARTH, ASS, DEATH, BIRTH, WOMB, MILK, COAL, SEED, LEAF, CHILD, ANTELOPE, BEAR, BEE, MOUSE, DUNG, PLOUGH, SPROUT, ICE, DAY, NIGHT, WINTER, SUMMER, AUTUMN, SPRING, KING, GOOSE, PRIEST, ROAD, CART, GRASS, FIRE, WIND, NAIL, BREAST, BOWL, CUP

Randomly associate these with “morphemes” and for remaining morphemes associate those with **random combinations of up to 3 of these**

Parameters: symbols

Each basic concept is associated with a symbol. We used dingbats and other mostly non-script symbols from the Unicode Basic Multilingual Plane.* Some examples:



*Expanded in the current system to include other sets such as Yi symbols

Parameters: “languages”

- Initial parameters:
  - MONOSYLLABIC / DISYLLABIC
  - CLOSE / CLOSE_RHYME / CLOSE_V_FREE / STRICT
- For each pair of the above
  - Generate a “language” 5 times: a language consists of about 1,000 morphemes generated from the grammar
  - Run 5 simulations for each of these

Steps in simulation

1. Assign simplex concepts and symbols to morphemes
   a. **From a set of morphemes associated with a symbol, pick *one* morpheme to associate to the symbol**
2. Assign complex concepts to remaining morphemes
3. Assign spellings to morphemes that do not have one
   a. Symbols associated with shared semantic components, and/or
   b. **Symbols associated with similar sound ⇐ *"eureka" moment***
4. Extend the phonetic coverage with *telescoping*:
   a. *ba* + *ad* → *bad*
5. Result is a mix of semantic and phonetic components

MONOSYLLABIC, CLOSE

toN	PERSON	S(emantic){🏵}
kerg	PERSON	S{🏵}+P(honetic){☆}
gib	PERSON	S{🏵}+P{□}
kak	MAN	S{ ♂ }
gab	WOMAN	S{▫}
pet	WOMAN	S{▫}+P{◺}
urb	HOUSE	S{▲}
kuNt	HOUSE	S{▲}+P{◷}
a	BRONZE	S{☞}
dep	BRONZE	S{☞}+P{☞}
keg	BRONZE	S{☞}+P{☆}

Results from previous simulations

	# entries	w/ spelling	w/out spelling	phon	sem+phon	purephon	sem
DI, CLOSE	661	462 (0.70)	198 (0.30)	47 (0.07)	35 (0.05)	11 (0.02)	451 (0.68)
DI, CLOSE-RHYME	648	508 (0.79)	139 (0.21)	127 (0.20)	100 (0.15)	26 (0.04)	482 (0.74)
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MONO, STRICT	640	487 (0.76)	152 (0.24)	95 (0.15)	71 (0.11)	23 (0.04)	464 (0.73)

DeFrancis, 1984

Table 3 Structural Classification of Characters

Principle	Oracle Bones (Shang dynasty)	Xu Shen (2nd century)	Zheng Qiao (12th century)	Kang Xi (18th century)
Pictographic	227 (23%)	364 (4%)	608 (3%)	
Simple indicative	20 (2%)	125 (1%)	107 (1%)	±1,500 (3%)
Compound indicative	396 (41%)	1,167 (13%)	740 (3%)	
Semantic-phonetic	334 (34%)	7,697 (82%)	21,810 (93%)	47,141 (97%)
Total	977	9,353	23,265	48,641

Take away points

- Strict matches are not very effective.
- Close consonant matches useful for largely “monosyllabic” languages; less so for “disyllabic” languages.
- Allowing vowels to be free is useful in “disyllabic” languages.
- The rate of semantic-phonetic compounds in “monosyllabic” languages with close consonant matches is broadly similar to the rate of semantic-phonetic compounds in Oracle Bone texts.
- But we don’t really provide much evaluation of how well the system works

Note: some details of the simulation

- Currently about 1100 lines of Python code
- Uses the *pyfst* interface to OpenFst
- Grammars written in *Thrax* finite-state grammar compiler (http://www.openfst.org/twiki/bin/view/GRM/Thrax)

Evaluating the Similarity to Known Systems

Problems with the previous work

- Letting a symbol inherit the phonology from just *one* morpheme is not a good model of how some ancient systems apparently worked.
- We need some way of quantifying how good a fit the models are to (the few) documented cases of *ex nihilo* evolution of writing.

Similarity within a phonetic class

- For a set of ancient writing systems, we want to measure how phonologically similar the morphemes are within a phonetic class
- For example in Chinese, those morphemes that share the same phonetic radical

Ancient Chinese

- Source: Baxter-Sagart list. (http://en.wiktionary.org/wiki/Appendix:Baxter-Sagart_Old_Chinese_reconstruction)
- Intersect with characters with semantic-phonetic decomposition from http://www.zhongwen.com/.
- Results in 902 entries. Some examples:

丘	丘	qiu1	khjuw	kʷʰə
蚯	丘	qiu1	khjuw	kʷʰə
虛	丘	xu1	khjo	qʰa
虛	丘	xu1	xjo	qʰa
岳	丘	yue4	ngæwk	ŋˁrok

Edit distance (ED)

	a	b	c	d
c	a		e	d

$$\text{Normalized Edit Distance} = \frac{\text{Insertions} + \text{Deletions} + \text{Substitutions}}{\frac{\text{Length}_1 + \text{Length}_2}{2}}$$

- Efficient to compute: $\mathcal{O}(\text{Length}_1 \times \text{Length}_2)$
- Operations could be weighted by phonetic distance.

Ancient Chinese

- 156 equivalence classes (out of 198 — 79%) with >1 member
  - qʷək ɢʷək ɢʷəʔ
  - gˤaŋ gˤraŋ
  - muʔ tʰaʔ tʰˤaʔ tˤaʔ
  - ləp mˤroŋ rˤoŋ
- Compute mean NED for each equivalence class with >1 member; average over all equivalence classes. Smaller is better.

	Mean edit distance
Ancient Chinese	0.54
Middle Chinese	0.60
Modern Mandarin	0.57

Sumerian

- Source: Electronic Text Corpus of Sumerian Literature sign list (http://etcsl.orinst.ox.ac.uk/edition2/signlist.php)

Sign names	Signs	ETCSL values
A		a, dur_5, $duru_5$
A.AN		am_3, em_x, $še\hat{g}_3$
A.EDIN.LAL		ummud
A.HA.TAR.DU		$girim_3$
A.IGI		er_2, $še_x$
A.KA		ugu_2
A.KAL		illu

- Kept all lower-case (phonetic) values, without subscripts.

Sumerian

- 212 equivalence classes (out of 617 — 34%) with >1 member
- Same procedure as with Chinese

	Mean edit distance
Ancient Chinese	0.54
Middle Chinese	0.60
Modern Mandarin	0.57
Sumerian	0.89

Middle Egyptian

- 21 equivalence classes (out of 256 — 8%) with more than one member from Gardiner's sign list (via http://wwwegyptianhieroglyphsnet/gardiners-sign-list/low-narrow-signs/),

	Mean edit distance
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Two neurological routes to grammatogenesis

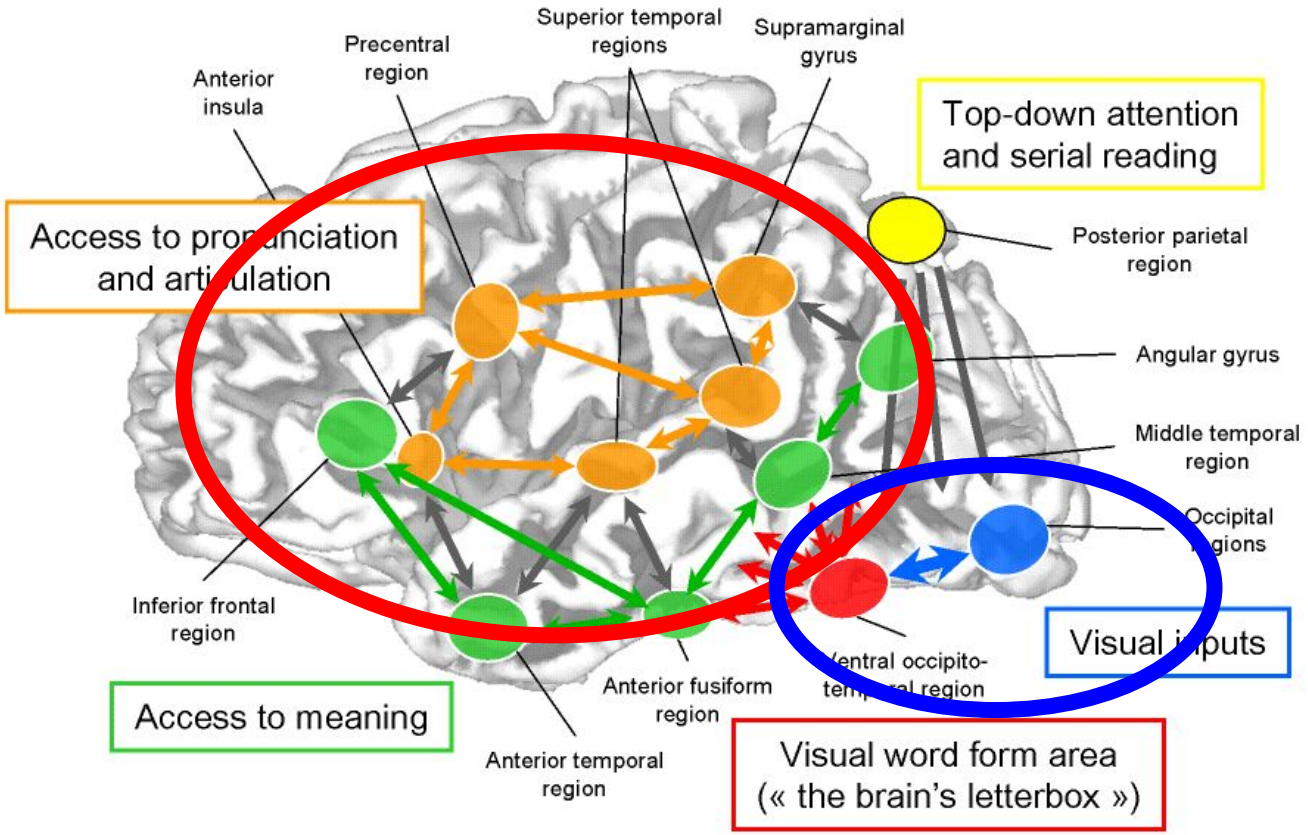


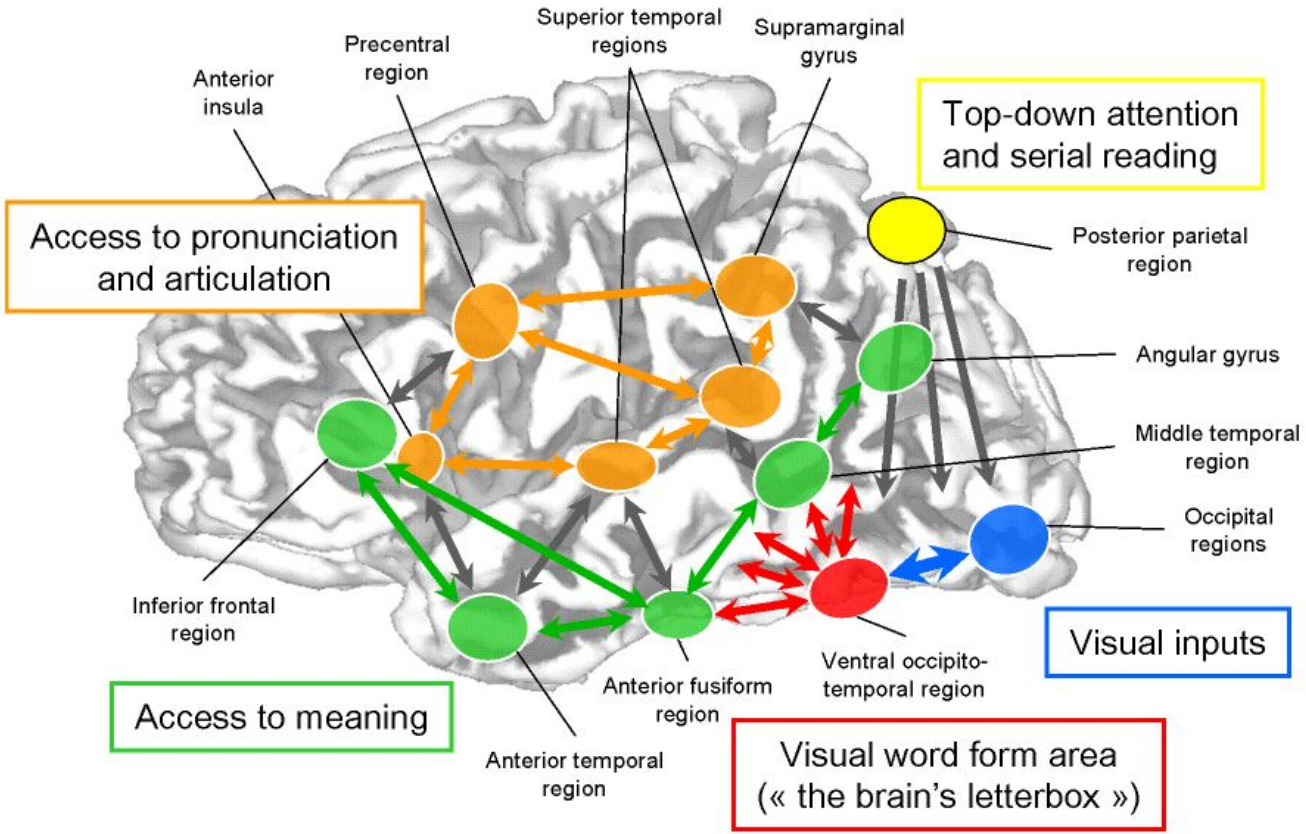
Image from:

Dehaene, Stanislas. 2010. *Reading in the Brain.* New York, Penguin. Fig 2.2. p. 63

Language and speech

Visual processing

Two neurological routes to grammatogenesis



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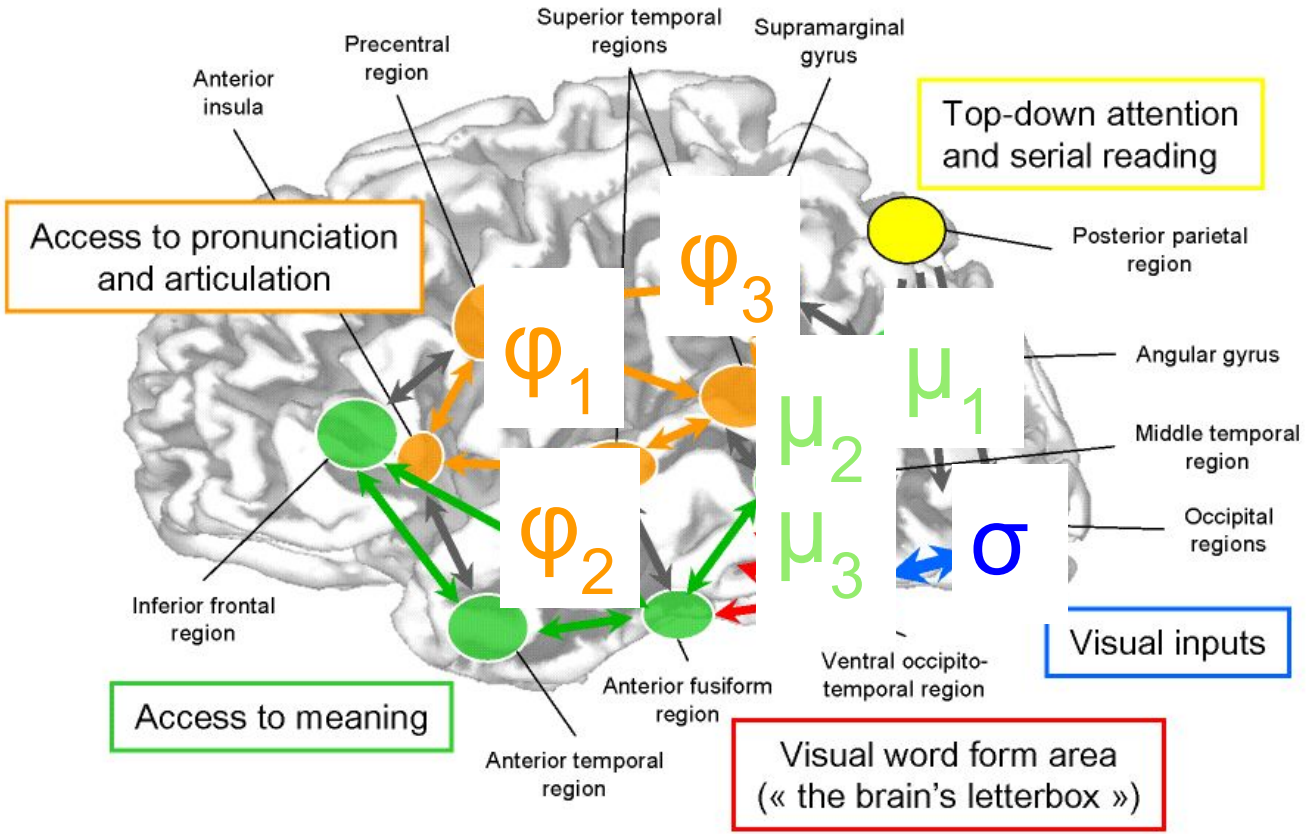

Symbol σ associated with concept and thence a set of related meanings/morphemes μ_k

Via the morphemes becomes associated to set of pronunciations φ_k

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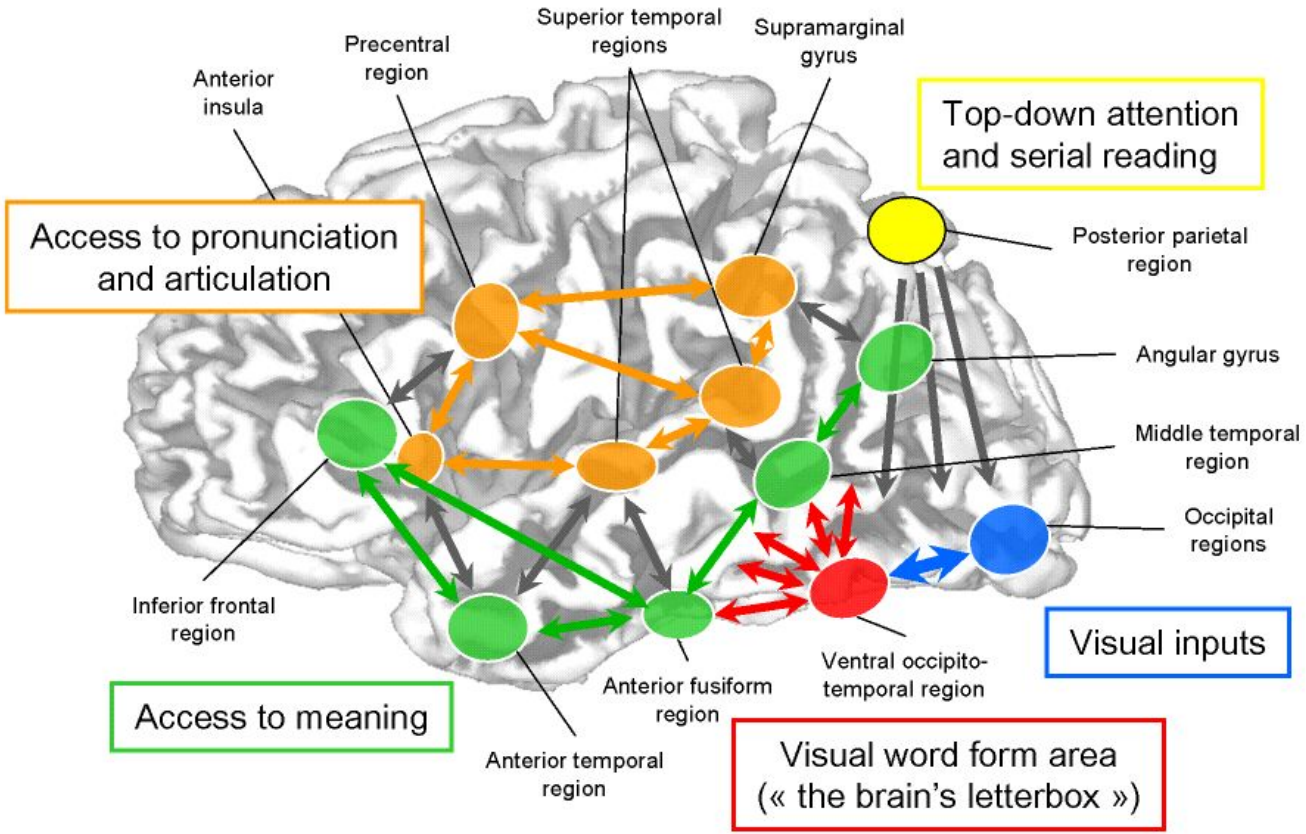

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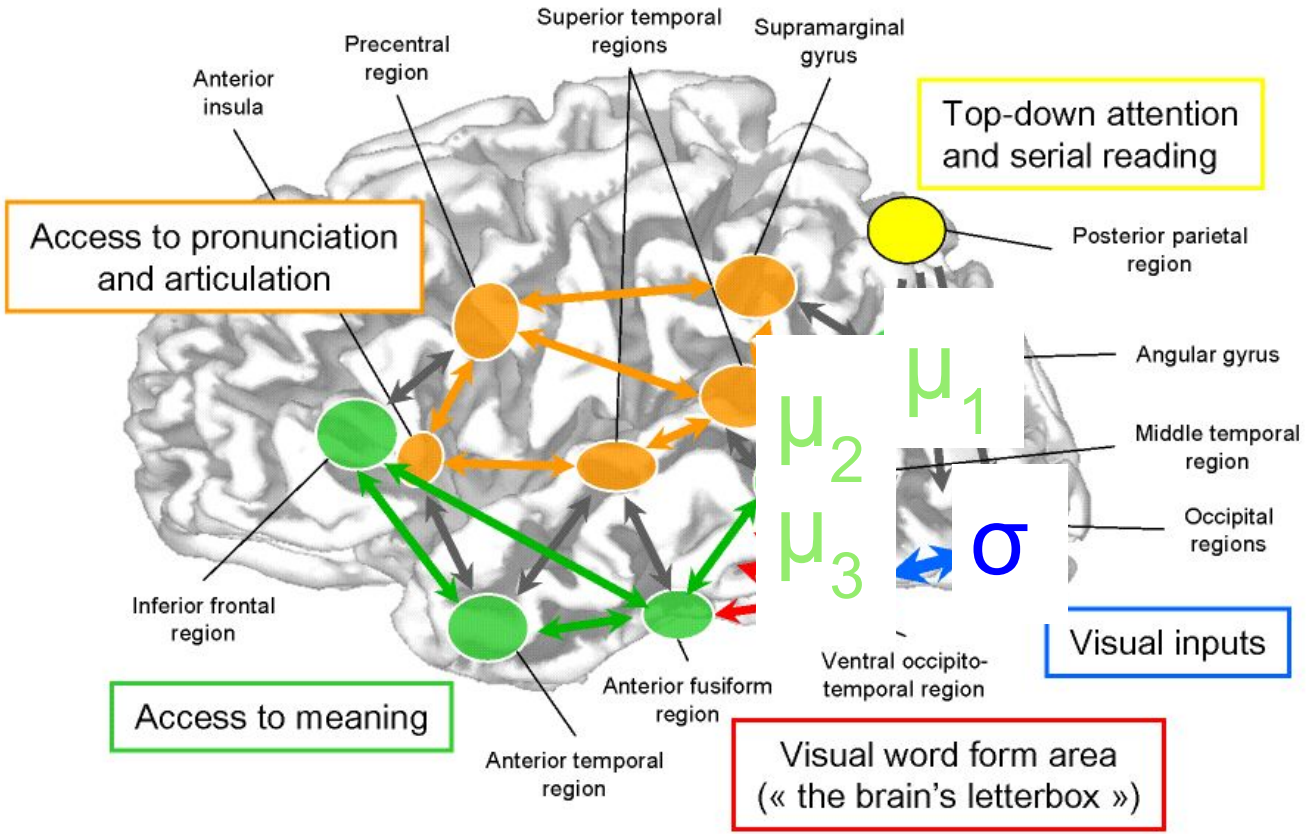
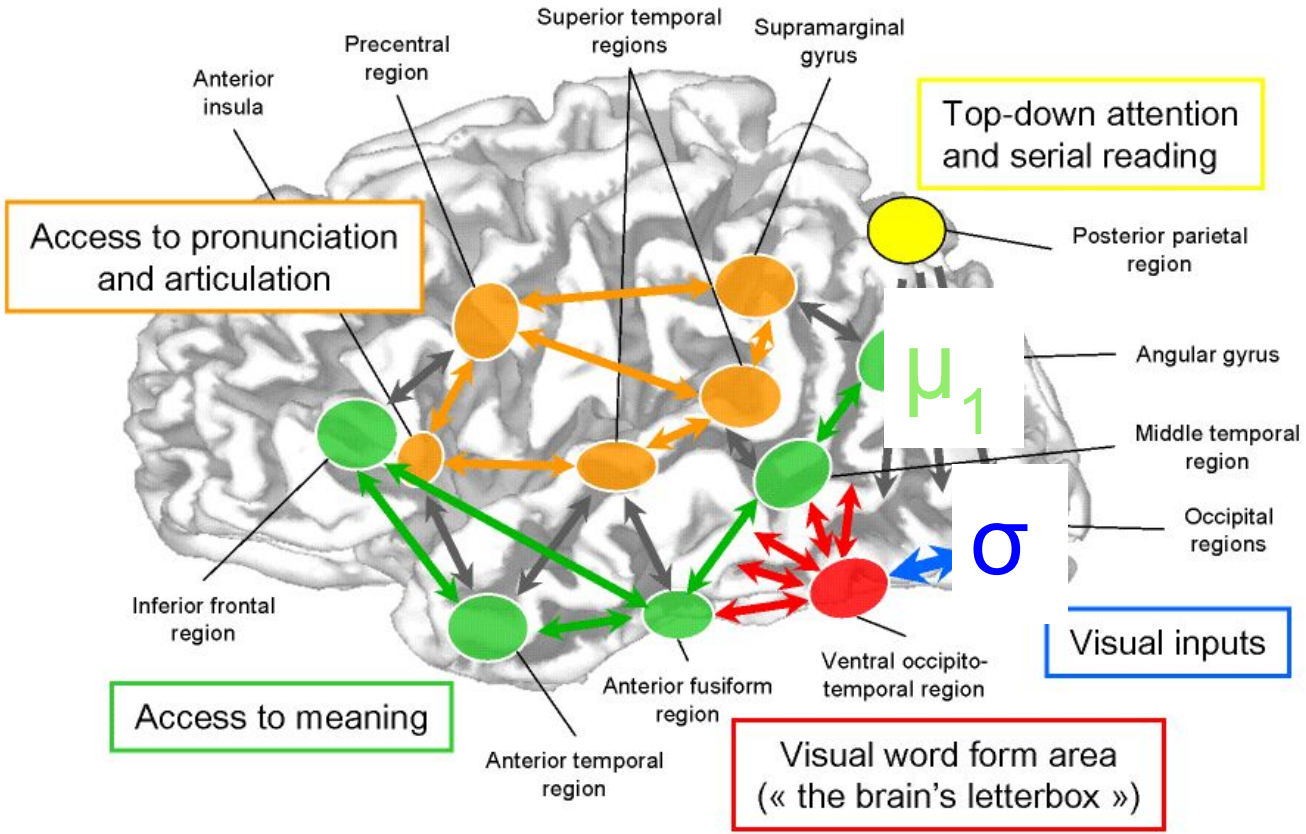


Symbol σ associated with concept and thence a set of related meanings/morphemes μ_k

One morpheme μ_1 becomes most strongly associated with the symbol.

Via this morpheme becomes associated to pronunciation φ_1

Two neurological routes to grammatogenesis



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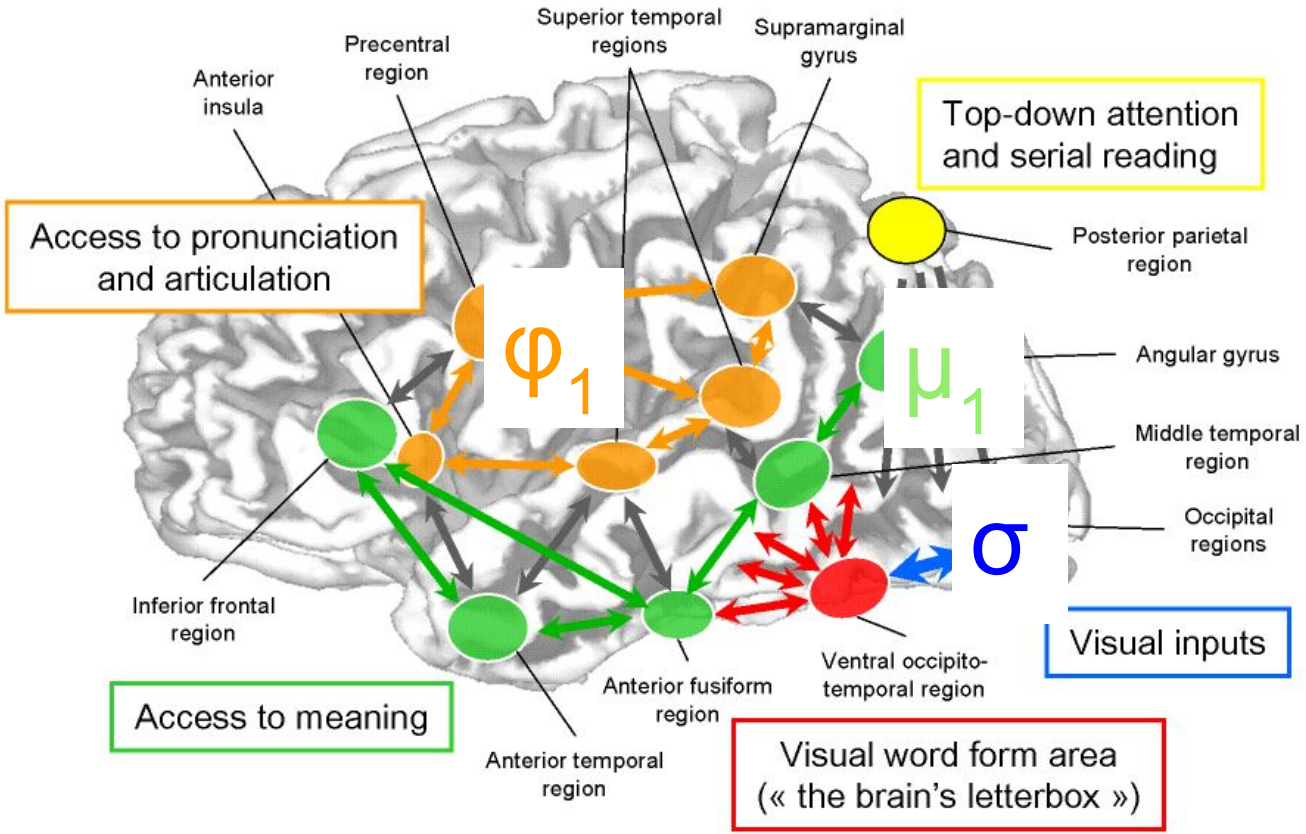

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Two neurological routes to grammatogenesis

- The first effectively “fossilizes” the non-linguistic origin of the sign, preserving it through to multiple phonetic functions. **This is like Sumerian.**
- The second treats the sign as linguistic earlier by associating it to a particular morpheme and thence to a particular sound. **This is like Chinese or Egyptian.**
    - *The second seems to reflect a more advanced stage: the inventors of the system realize that a sign can stand for a particular abstract linguistic unit.*

Simulation

Parameterize with two options:

- As in previous simulations, pick just one morpheme per semantic group and base phonetics on that morpheme (Chinese, Egyptian)
- Use all morphemes in a semantic group (Sumerian)

Coverage results

	# entries	w/ spelling	w/out spelling	phon	sem+phon	purephon	sem
DI, CLOSE	661	462 (0.70)	198 (0.30)	47 (0.07)	35 (0.05)	11 (0.02)	451 (0.68)
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	# entries	w/ spell	w/out sp	phon	sem+phon	purephon	sem
MONO CLOSE 1 morph	638	587 (0.92)	**50 (0.08)****	**235 (0.40)****	**203 (0.32)***	**50 (0.08)****	**537 (0.84)****
MONO CLOSE all morphs	645	636 (0.99)	**8 (0.01)****	**222 (0.34)****	**187 (0.29)***	**34 (0.05)****	**601 (0.93)****

Comparison with extant systems

	Mean edit distance	Standard deviation
Ancient Chinese	0.54	
Middle Chinese	0.60	
Modern Mandarin	0.57	
Middle Egyptian	0.60	
MONOSYLLABIC_CLOSE: 1 morph*	0.52	0.026
MONOSYLLABIC_CLOSE: all morphs*	0.78	0.026
Sumerian	0.89	

*In both cases the percentage of signs with multiple pronunciations is about 64% — less than Chinese but more than Sumerian or Egyptian

Simulation using OC syllables

- 404 Old Chinese reconstructed syllables:
  - *ba, baŋ, ben, but, bˁa, bˁawk, bˁaŋ, bˁrak…*
- 198 equivalence classes used to define “CLOSE”
- One morpheme per group

Example: ☘

lrə LEAF S{☘}

lek LEAF,BIRTH S{☘,㋮}

dʕak CUP,LEAF S{☘}+P{⚜}

paʔ NIGHT,HOUSE,LEAF S{☘, ☾ }

dʕək DEATH,FIRE,LEAF S{☠,☲,☘}

lek NIGHT,HOUSE,LEAF S{☘, ☾ ,☖}

lʕəʔ ENCLOSURE,SKIN,EYE S{⚲ ,◎}+P{☘}

lə GOD,DEMON,OX S{ ☿ ,♉}+P{☘}

Example: ☽

n̥ij	MOON S{ ☽ }
mət	THUNDER,FIRE,MOON S{䷳, ☽ }
rˁew	WOMB,ARM,MOON S{ ☽ , ⚕}
nij	COAL S{■}+P{ ☽ }
nij	CLOTHING,SUMMER,THUNDER S{⚡}+P{ ☽ }
nij	SILVER,FISH S{𓆛 }+P{ ☽ }

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“Ancient Chinese” 1 morph	650	533 (0.82)	116 (0.25)	163 (0.25)	130 (0.20)	32 (0.05)	500 (0.77)

Comparison with simulations

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Middle Egyptian	0.60	
MONOSYLLABIC_CLOSE: 1 morph	0.52	0.03
“Ancient Chinese”-based: 1 morph	0.67	0.08
MONOSYLLABIC_CLOSE: all morphs	0.78	0.03
Sumerian	0.89	

Synopsis and conclusions

- A model where pronunciations spread from all morphemes associated with a concept fits Sumerian better.
- A model where one morpheme is picked as *the* denotation of the symbol fits Chinese (or Egyptian) better.
- Modeling based on “actual” Ancient Chinese syllables and limiting ourselves to reconstructed phonetic equivalence classes does not work well — but that is probably because the phonetic equivalence classes are too limiting.
- Proportion of signs with multiple pronunciations also differs significantly from known systems. This could partly reflect standardization in real systems, which we are not modeling.

Synopsis and conclusions

- Does this reflect a difference in the evolution of the scripts?
- Sumerian developed from a raw “ideographic” system.
- But Chinese had symbols already associated with specific morphemes — a later phase in the evolution of writing? Either:
  - Phonetics were standardized from an earlier system...
  - or maybe Chinese got the idea of writing from elsewhere...

Further work

- Link consonantal systems to ablaut-like processes
  - *We already have some results but no time to report here.*
- Simulate writing full sentences and affixal morphology
  - *We already have some results but no time to report here.*
- Simulate a wider range of phonetic shapes for morphemes, and a wider range of phonetic closeness
- Provide a more plausible model of lexical statistics
- Model of standardization processes
- Set of symbols is currently static: but new symbols are invented in real writing systems