Computational Psycholinguistics

Lecture 11: Learning Phonology and Morphology

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References: McLeod et al, Chapter 8 & 9, pages 155-194
Elman et al, Chapter 3, pages 130-147

Overview

- Reading Aloud: Mapping Orthography to Phonology
  - Sejnowski & Rosenberg: NETtalk
  - Seidenberg & McClelland, Plaut *et al* models of adult performance
    - Good performance on known and unknown words
    - Models (normal) human behaviour
    - Fails to replicate the double-dissociation (in acquired dyslexics)
    - Importance of input and output representations

- Language Acquisition: how do children acquire language?

- English past-tense: Morphology
  - Forming the past tense from the present
  - Similarity: dual-route models to explain a double dissociation
  - Connectionist account: a single mechanism

- Learning vocabulary: Lexical development

Reading Aloud

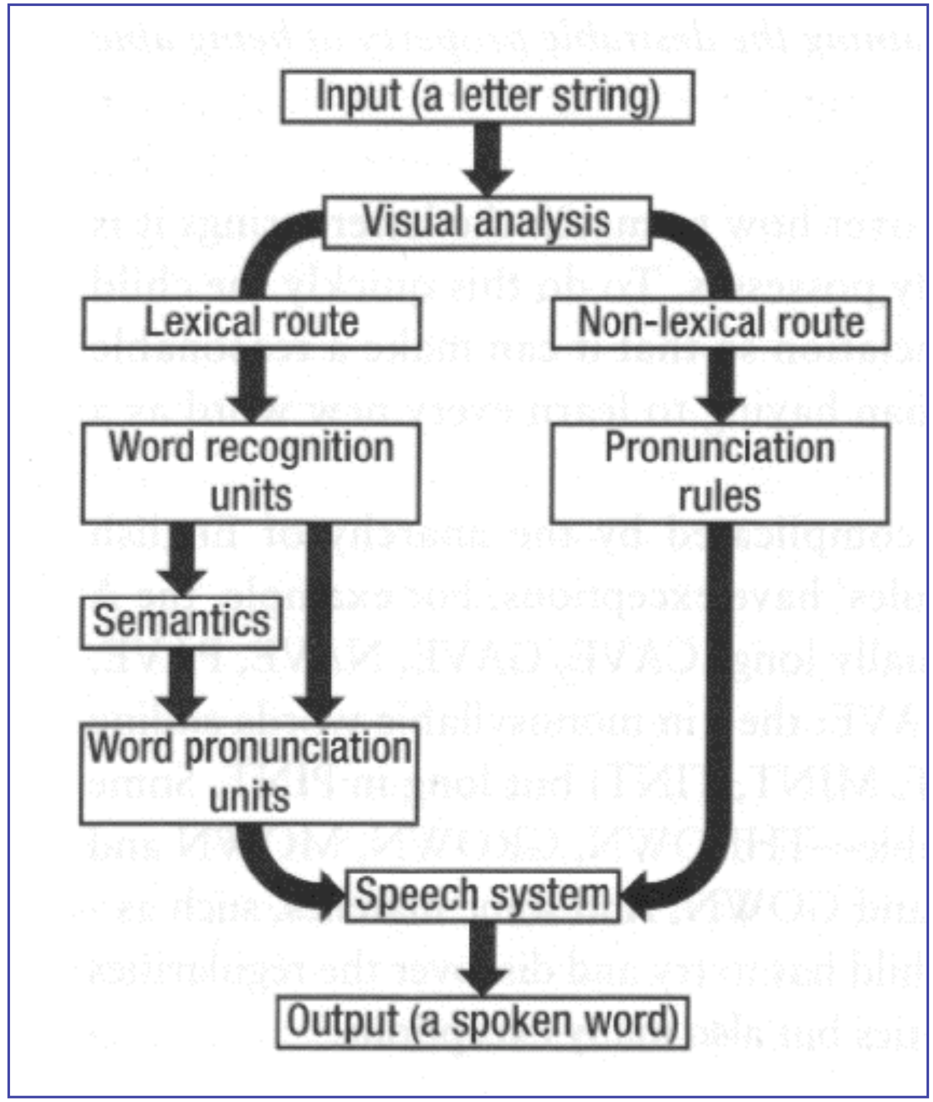
- Task: produce correct pronunciation for a word, given its printed form

- Suited to connectionist modelling:
  - Need to learn mappings from one domain (print) to another (sound)
  - Multi-layer networks are good at this, even when mappings are somewhat arbitrary
  - Human learning is similar to network learning:
    - Learning takes place gradually over time
    - Incorrect attempts are often corrected

- If a network can't model this linguistic task successfully, it would be a serious blow to connectionist modelling. But …

Dual Route Model

- The standard model of reading posits two independent routes leading to pronunciation of a word, because …
  - People can easily pronounce words they have never seen:
    - SLINT or MAVE
  - People can pronounce words which break the “rules”:
    - PINT or HAVE
- One mechanism uses general rules for pronunciation
- The other mechanism stores pronunciation information with specific words



Behaviour of Dual-Route Models

- Consider: MINT, PINT, and KINT

- MINT is a regular word:
  - Can be pronounced using the “rule-based” mechanism
  - But also exists in the lexicon, so can be pronounced by the “lexical” route
- PINT is a word, but irregular
  - Can only be correctly pronounced by the lexical route
  - Otherwise, it would rhyme with MINT
- KINT is not a word:
  - No entry in the lexicon
  - Can only be pronounced using the “rule-based” mechanism
  - So it should rhyme with MINT

Evidence for the Dual-Route Model

- Evidence from neuropsychology shows different patterns of behaviour for two types of brain damage (acquired *after* learning):

- Phonological dyslexia
  - Symptom: Read regular words without difficulty, but cannot produce pronunciations for non-words
  - Explanation: Damage to rule-based route; lexical route intact
- Surface dyslexia
  - Symptom: Can pronounce regular words and non-words correctly, but make errors on irregulars (tendency to regularise)
  - Explanation: Damage to the lexical route; rule-based route intact

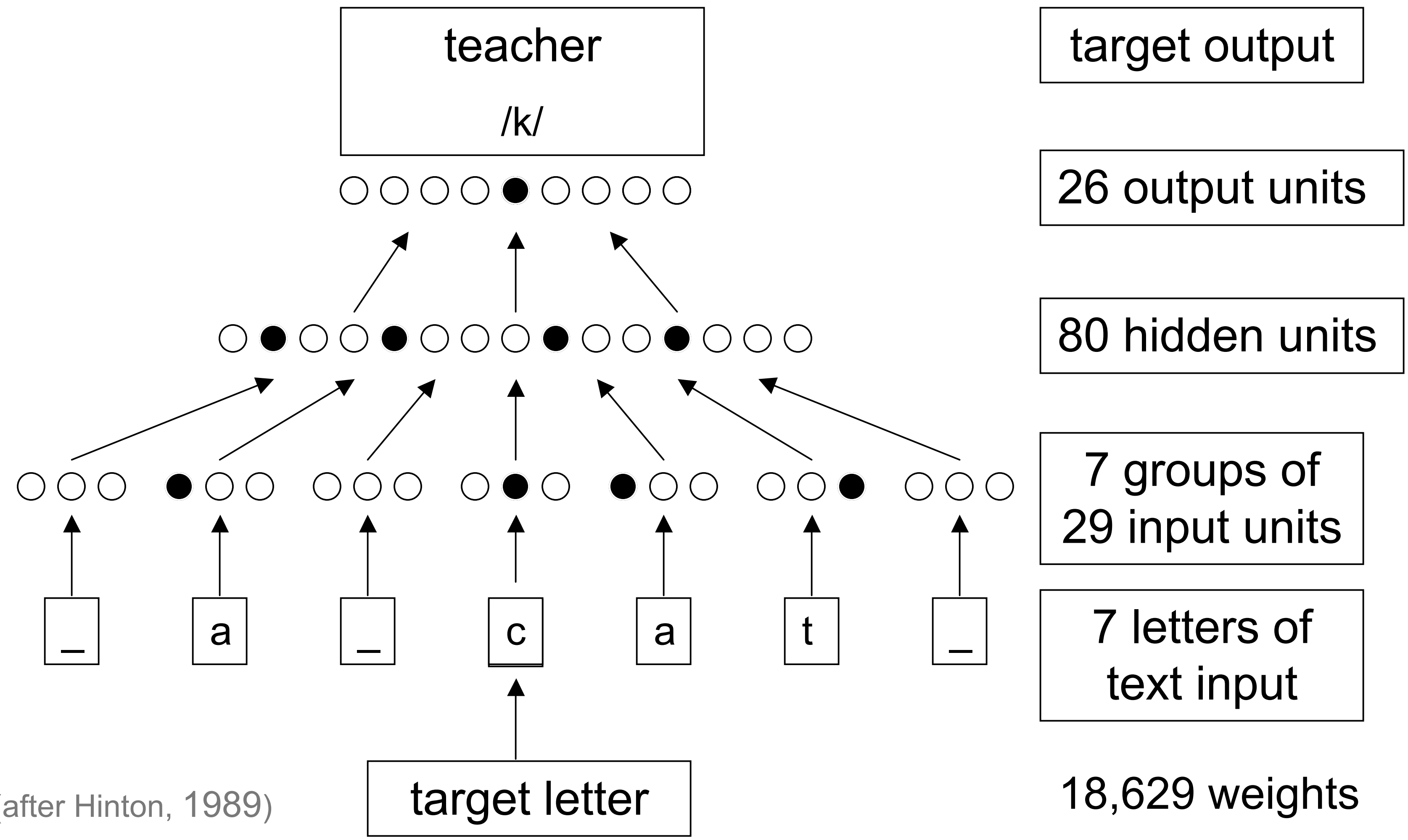
- All Dual-Route models share:
  - A lexicon for known words, with specific pronunciation information
  - A rule mechanism for the pronunciation of unknown words

Towards a Connectionist Model

- It is unclear how a connectionist model could naturally implement a dual-route model:
  - No obvious way to implement a lexicon to store information about *particular* words; storage is typically *distributed*
  - No clear way to distinguish "specific information" from "general rules"; only one uniform way to store information: connection weights

- Examine the behaviour of standard 2-layer feedforward models
  - NETTalk: Sejnowski & Rosenberg (1987)
  - Seidenberg & McClelland (1989)
    - Trained to pronounce all the monosyllabic words of English
    - Learning is implemented using the backpropagation algorithm

NETTalk (Sejnowski & Rosenberg, 1987)



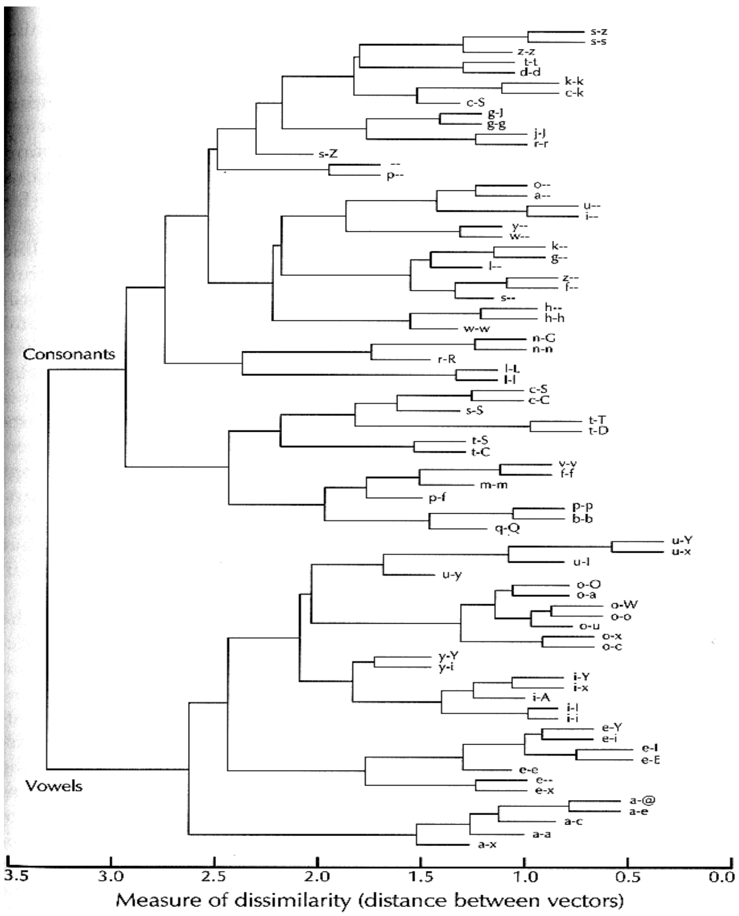
(after Hinton, 1989)

NETTalk Performance, Learning and Behavior

- Performance
  - 90% success rate during training.
  - 80%-87% when tested on a set of novel inputs
- Learning
  - Initially (with random weights) NETTalk babbled incoherently
  - Target phoneme was produced more often as weights were altered
  - Generalisation of learned pronunciations (e.g., the “a” sound in cat)
    - Often useful (e.g., the “a” sound in hat)
    - Exceptions (e.g., the “a” sound in hate)
  - Learned to use letter’s context

friends	soon
sent	doubt
around	keep
not	attention
let	loss

NETTalk's Hidden Unit Subspaces



NETtalk uses the same trick.

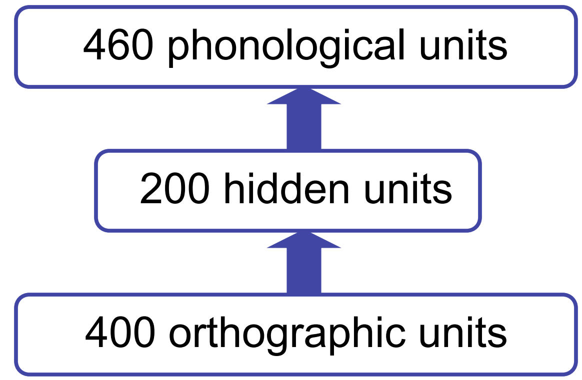
It uses the hidden units to detect 79 different features…

In other words, its weights divide its input space into 79 regions

There are 79 regions because there are 79 English letter-to-phoneme relationships.

Examining the weights allows us to cluster these features/regions, grouping similar ones together…

Seidenberg and McClelland (1989)



- 2-layer feed-forward model:
  - Distributed representations at input and output
  - Distributed knowledge within the net
  - Gradient descent learning
- Input and Output
  - Inputs are activated by the letters of the words
    - 20% activated, on average
  - Outputs represent the phonological features
    - 12% activated, on average
  - Encoding of features does not affect the success
- Processing:

$$\text{netinput}_i = \sum_j a_j w_{ij} + \text{bias}_i$$

  - Activation of a node is calculated using the logistic function

Training the Model

- Learning
  - Weights and bias are initially random
  - Words are presented and outputs are computed
  - Connection weights are adjusted based on backpropagation of error
- Training
  - All monosyllabic words of 3 or more letters (about 3000) words
  - In each epoch, a subset was presented
    - Frequent words appeared more often
  - Over 250 epochs, (THE) was presented 230 times, least common 7 times
    - (THE) is actually 100000 times more likely, but this doesn't change learning
- Performance
  - Outputs were considered correct if the pattern was closer to the correct pronounciation than that of any other word
  - After 250 epochs, accuracy was 97%

Results: Seidenberg & McClelland

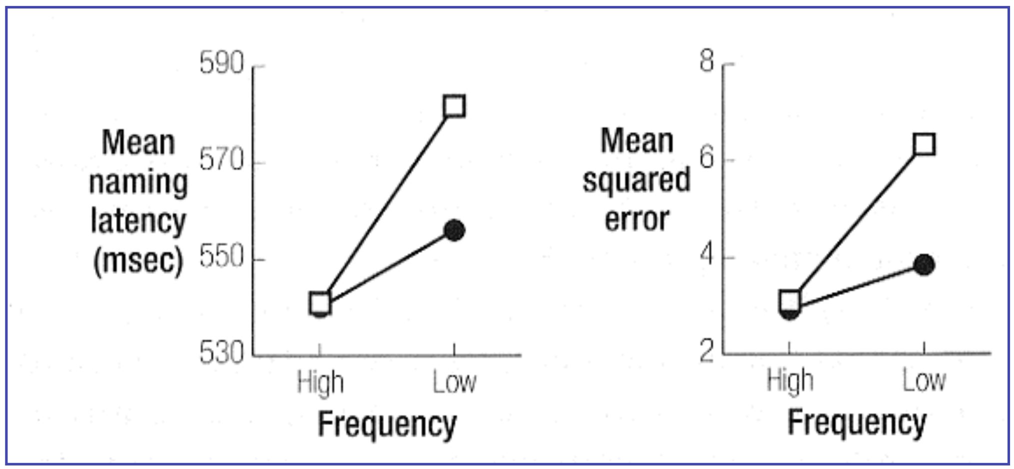
- The model does successfully learn to map most regular and irregular word forms to their correct pronunciation
  - It does this without separate routes for lexical or rule based processing
  - There is no word specific memory
- It does not perform as well as humans in pronouncing non-words
- Naming Latency:
  - Experiments have shown that adult reaction times for naming a word is a function of variables such as word frequency and spelling regularity
- The current model cannot directly mimic latencies, since the computation of outputs is constant
- The model can be seen as simulating this observation if we relate the output error score to latency
  - Phonological error score is the difference between the actual pattern and the correct pattern
  - Hypothesis: high error should correlate with longer latencies

Word Frequency Effects

- Common words are pronounced more quickly than uncommon words
  - This is true for almost all aspects of human information processing
- Conventional (localist) explanation:
  - Frequent words require a lower threshold of activity for “the word recognition device” to “fire”
  - Infrequent words require a higher threshold of activity
- In the Seidenberg & McClelland model, naming latency is modelled by the error:
  - Word frequency is reflected in the training procedure
  - Phonological error is reduced by training, and therefore lower for high frequency words
- The explanation of latencies in terms of error follows directly from the network’s architecture and the training regime

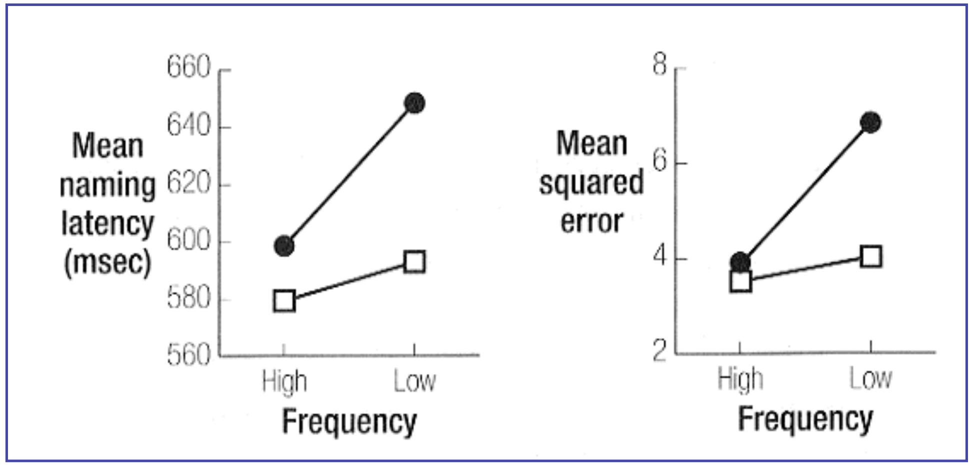
Frequency x Regularity

- In addition to faster naming of frequent words, human subjects exhibit:
  - Faster pronunciation of regular words (e.g GAVE or MUST) than irregular words (e.g. HAVE or PINT)
  - But this effect interacts with frequency: it is only observed with low frequency words
- For regulars (filled circle) we observe a small effect of frequency
  - It takes slightly longer to pronounce the low frequency regulars
- For irregulars (open square) we observe a large effect of frequency
- The model precisely mimics this pattern of behavior in the error
- 2-route: the confusion of the lexical and rule outcome requires resolution
  - Lexical route wins faster for high frequency words



Frequency x Neighborhood Size

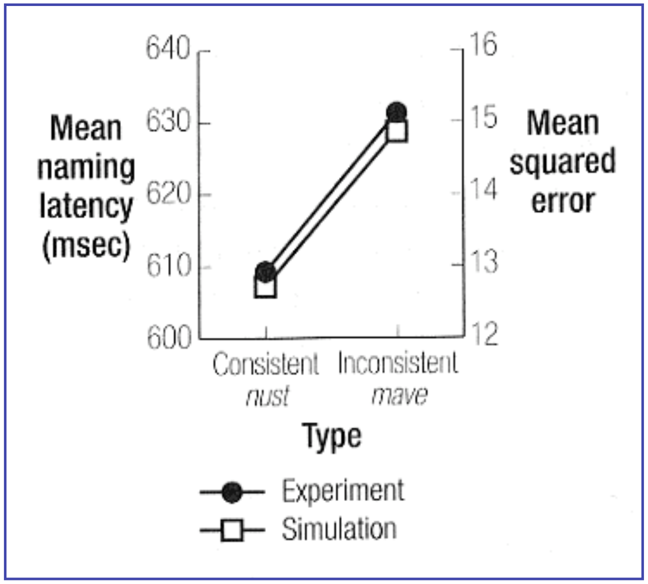
- The "neighborhood size" of a word is defined as the number of words that differ by changing one letter (in orthographic representation)
- Neighborhood size has been shown to also affect naming latency in much the same way as with regularity:
  - Not much influence for high frequency words
  - Low frequency words with small neighborhoods (filled circles) are read much more slowly than words with large neighborhoods (open squares)
- Shows "cooperation" of the information learnt in response to different (but similar) inputs
- Again, the connectionist model directly predicts this
- The 2 route model requires a more *ad hoc* explanation, grouping across localist representations of the lexicon



Spelling-to-Sound Consistency

- Consistent spelling patterns: _UST
  - All words have the same pronunciation
- Inconsistent patterns are those with more than one: _AVE

- Observation: adult readers produce pronunciations more quickly for non-words derived from consistent patterns (NUST) than from inconsistent patterns (MAVE)
- This is difficult for 2-route models:
  - Since both are processed by the rule-based route
  - Consistent and inconsistent rules would need to be distinguished
- The error in the connectionist model predicts this latency effect perfectly



Summary of Seidenberg & McClelland (1989)

- What has the model achieved?
  - The model is a single mechanism with no lexical entries or explicit rules
  - Response to an input is a function of the network's entire experience
    - Reflects previous experience on a particular word
    - Experience with words resembling that string
- E.g. <u>specific</u> experience with HAVE is sufficient to overcome the <u>general</u> information that _AVE is usually a long vowel
- The network can produce a plausible pronunciation for MAVE, but error is introduced by experience with inconsistent words like HAVE
- Performance
  - 97% accuracy on pronouncing learned words
  - Models: frequency & interaction with regularity, neighborhood, consistency
- Limitations: It is not as good as humans at
  - Reading non-words (model gets 60%, humans 90%)
  - Lexical decision (FRAME is a word, but FRANE is not)

Representations are important

- Position specific: for inputting words of maximum length N:
  - N groups of 26 binary inputs = word
- But consider: LOG, GLAD, SPLIT, GRILL, CRAWL
  - The model needs to learn the correspondence between L and /l/
  - But L always appears in different positions
  - Learning different pronunciations for different positions should be straightforward
  - Alignment: letters and phonemes are not in 1-to-1 correspondence
- Problem: non-position-specific loses important order information:
  - RAT = ART = TAR
- Solution: S&M decompose word and phoneme strings into "triples"
  - FISH = _FI SH_ ISH FIS
  - Each input unit is associated with 1000 random triples
  - Active if that triple appears in the input word

Wickelfeatures

- S&M still suffer some specific effects
  - Information learned about a letter in one context is not easily generalised

Improving the Model: Plaut *et al* (1996)

- Plaut *et al* (1996) solution: non-position-specific + linguistic constraints
  - Monosyllabic word = onset + vowel + coda
  - Strong constraints on order within these clusters
    - E.g, if ‘t’ and ‘s’ are together, ‘s’ always precedes ‘t’
  - Only one set of grapheme-to-phoneme units is required for the letters in each group
  - Correspondences can be pooled across different words, even when letters appear in different positions
- Input representations:
  - Onset: first letter or consonant cluster (30)
    - y s p t k q c b d g f v j z l m n r w h ch gh gn ph ps rh sh th ts wh
  - Vowel (27)
    - e I o u a y ai au aw ay ea ee ei eu ew ey ie oa oe oi oo ou ow oy ue ui uy
  - Coda: final letter or consonant cluster (48)
    - h r l m n b d g cxf v j s z p t k q bb ch ck dd dg ff gg gh gn ks ll ng nn ph pp ps rr sh sl ss tch th ts tt zz u e es ed
- Monosyllabic words are spelt by choosing one or more candidates from each of the 3 possible groups:
  - THROW: (‘th’ + ‘r’), (‘o’), (‘w’)

Output representations

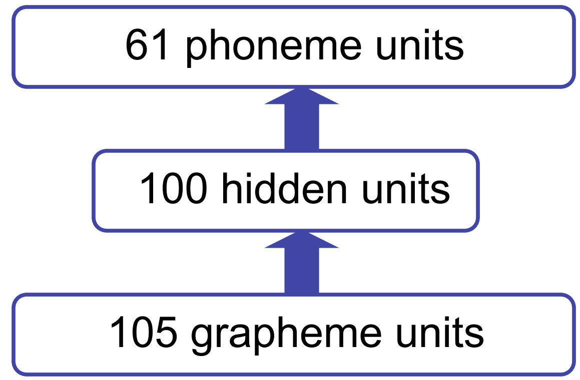
- Phonology: groups of mutually exclusive members
  - Onset (23)
    - s S C
    - z Z j f v T D p b t d k g m n h
    - l r w y
  - Vowel (14)
    - a e i o u @ ^ A E I O U W Y
  - Coda (24)

r	s z
l	f v p k
m n N	t
b g d	S Z T D C j
ps ks ts	

- “Scratch” = ‘s k r a _ _ _ _ _ _ _ _ _ C’

The network architecture

- The architecture of the Plaut *et al* network:
  - The are a total 105 possible orthographic onsets, vowels, and codas
  - The are 61 possible phonological onsets, vowels and codas



- Performance of the Plaut *et al* model:
  - Succeeds in learning both regular and exception words
  - Produces the frequency x regularity interaction
  - Demonstrates the influences of frequency and neighbourhood size
- What is the performance on non-words?
  - For consistent words (HEAN/DEAN): model (98%) *versus* human (94%)
  - For inconsistent words (HEAF/DEAF/LEAF): model (72%), human (78%)
    - This reflects production of regular forms: both human & model produced both
- Highlights the importance of encoding … how much knowledge is implicit in the coding scheme

Summary

- Word frequencies:
  - Seidenberg & McClelland presented training materials according to the log frequencies of words
  - People must deal with absolute frequencies which might lead the model to see low frequency items too rarely
  - Plaut *et al* model, however, succeeds with absolute frequencies
- Representations:
  - The right encoding scheme is essential for modelling the findings
    - How much linguistic knowledge is “given” to the network by Plaut’s encoding?
  - They assume this knowledge could be partially acquired prior to reading
    - I.e. children learn to pronounce “talk” before they can read it
  - Doesn’t scale to polysyllabic words
- Does not explain the double dissociation:
  - ✓ Surface dyslexics (can read exceptions, but not non-words)
  - ✗ Phonological (can pronounce non-words, but not irregulars)

Connectionist models of Acquisition

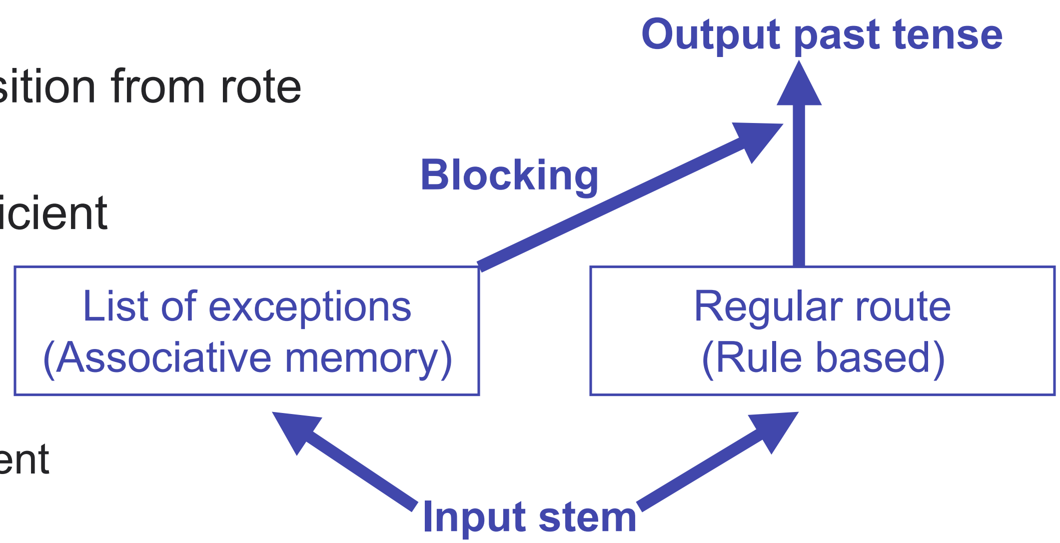
- Symbolic models emphasise the learning of rules and exceptions
- Connectionist models have no direct correlate to such mechanisms
  - Knowledge is stored in a distributed weight matrix
- Models of learning:
  - Start state of the cognitive system
  - Learning mechanism
  - Training environment
  - Acquired skill
- Connectionist models provide an opportunity to model the learning process itself, not just the resulting acquired skill
  - We can test connectionist models against developmental data, at various points during learning
  - Discontinuities in performance (sudden changes in behaviour) can be explained by “emergent properties” of a single, continuous mechanism

Learning the Past Tense

- The problem of past tense formation:
  - Regular formation: *stem* + ‘ed’
  - Irregulars do show some patterns:
    - No-change: hit » hit (all end in a ‘t’ or ‘d’)
    - Vowel-change: ring » rang, sing » sang (rhymes often share vowel-change)
    - Arbitrary: go » went
- Young children often form the past tense of irregular verbs (like GO) by adding ED: <u>overregularisations</u>
  - *“go”+”ed” » “goed”*
- This suggests incorrect application of a <u>learned rule</u>, not just rote learning or imitation
- Overregularisations often occur after the child has already succeeded in producing the correct irregular form: “*went”*
- Thus we need to explain this “U-shaped” learning curve

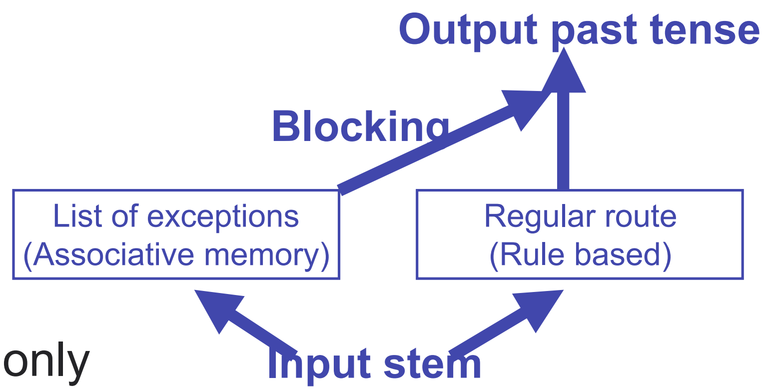
A Symbolic Account: Dual-Route Model

- General pattern of behaviour:
  - Early: children learn past tenses by rote (forms are stored in memory)
  - Later: recognise regularities, add general device to add ‘ed’ suffix
  - Now: no need to memorise forms, but this leads to incorrect generalisation of the regular rule to irregulars
  - Finally: distinguish which forms can be generated by the rule, and which must be stored (and accessed) as exceptions
- A Dual Route Model:
  - Errors result from the transition from rote learning to rule-governed
  - Recovery occurs after sufficient exposure to irregulars:
    - Increased “strength”
    - Frequency based
    - Faster recovery for frequent irregulars



The Dual-Route Model

- As with reading aloud, this proposal requires two qualitatively different types of mechanism



- Accounts for the observed dissociation:
  - Children make mistakes on irregulars only
- Evidence for double dissociation (Pinker 1994)
  - In some language disorders, children preserve performance on irregulars but not regulars
  - In other disorders, the opposite pattern is observed
- Accounts for the U-shaped learning curve
  - And since irregulars differ in “representational strength” it explains why overregularisation of high frequency irregulars is uncommon
- No explicit account of how the “+ed” rule is learned

Language Acquisition

- Perhaps the notion of inflection is innately specified, and need not itself be learned:
  - The inflectional mechanism is triggered by the environment or maturation
  - Then the exact (language specific) manifestation must be learned

- Criticisms:
  - Early learning tends to be focussed on irregular verbs
  - Irregular sub-classes (hit, sing, ring) might lead to incorrect rule learning
    - These do occur, but typically late in learning
    - How are good/spurious rules distinguished and selected
  - English is unusual in possessing a large class of regular verbs
    - Only 180 irregulars
  - Only 20% of plurals in Arabic are regular
  - Norwegian has 2 regular forms for verbs: 3-route model ?

Towards a Connectionist Model

- No distinct mechanisms for regular and irregular forms
- No innately specified maturation stage or rules to be triggered

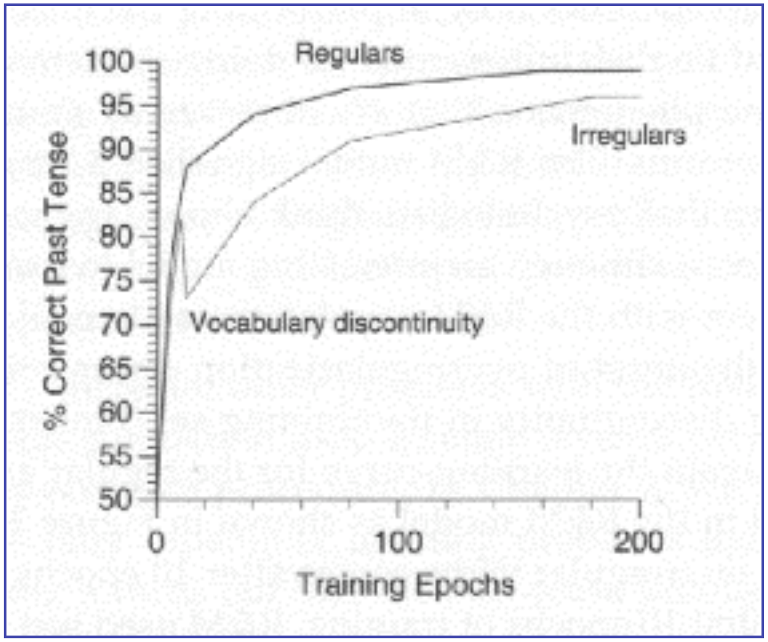
- Parsimonious:
  - Simplifies the structural complexity of the starting state
  - Learning exploits the structure of the learning environment

- Rummelhart and McClelland (1986)
  - First attempt to model this problem (or any development system)
  - Modelled U-shaped learning, but heavily criticised (Pinker & Prince 1988)

- Plunkett & Marchman
  - Use a feed-forward network, one hidden layer

Rummelhart and McClelland (1986)

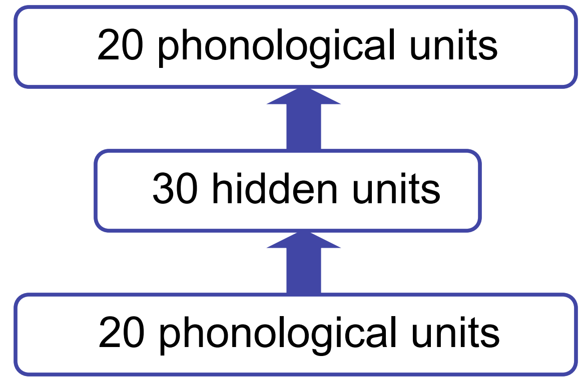
- A single-layer feed-forward network (perceptron)
  - Input: a phonological representation of the stem (wickelfeatures)
  - Output: a phonological representation of the past tense (wickelfeatures)
  - Trained using the perceptron learning rule
- Training:
  - First trained on 10 high frequency verbs (8 irregular, 2 regular), 10 epochs
  - Perfect performance
  - Then 420 (medium frequency) verbs (80% regular), 190 epochs
  - Early in training, shows tendency to overregularise, i.e. modelling stage 2
  - End of training, exhibits “adult” (near perfect) performance
  - Generalised reasonably well to 86 low frequency verbs in test set



Performance of R&M (1986)

- Criticisms:
  - Problems with representation using wickelphones/wickelfeatures
  - U-shape performance depends on sudden changes from 10-420 in the training regime
  - Rote learning of first 10 verbs: there was no generalisation to novel stems after 10 epochs
  - Most of the 410 new verbs are regular, overwhelming the network and leading to overregularisation
- Justification: children do exhibit vocabulary spurt at end of year 2
  - But overregularisation errors typically occur at end of year 3
  - Vocabulary spurt is mostly due to nouns
- Single-layer Perceptron only works for linearly separable problems
  - Plunkett & Marchman (1991) show residual error remains after extensive training
  - Suggests a hidden-layer network

Plunkett and Marchman (1993)



- A standard feedforward network with one hidden layer
- Maps a phonological representation of the stem to a phonological representation of the past tense
- Initially, the model is trained to learn the past tense of 10 regular and 10 irregular verbs
  - Represents current estimates of children’s early vocabulary
- Training proceeds using the standard backprop algorithm, in response to error between actual and desired output
  - Is this plausible?
- Learning must configure the network for both regulars and irregulars
  - Consider: *hit » hit*, but *pit » pitted*
  - We know multi-layer networks can do this, but considerable training may be required

Plunkett and Marchman (continued)

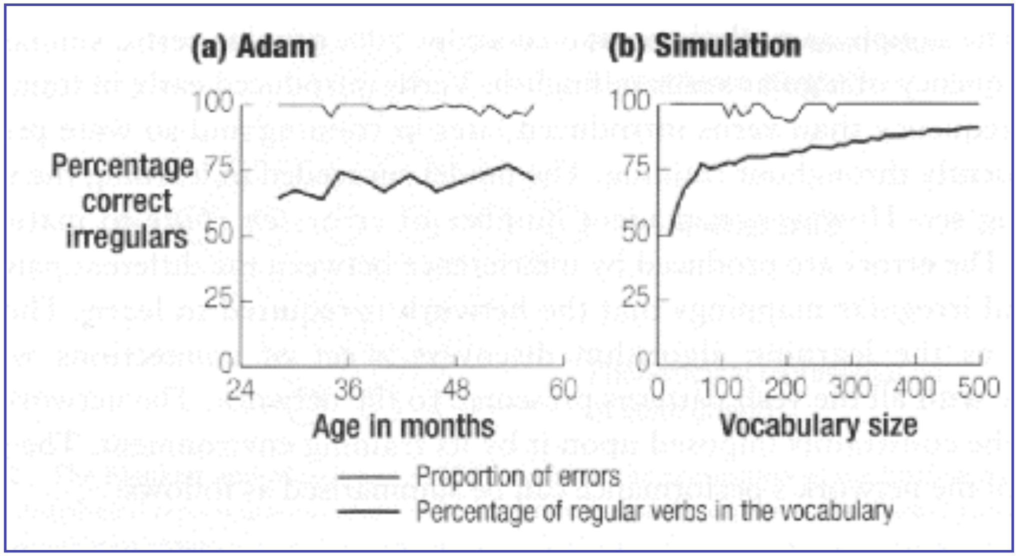
- Training:
  - Initial period of 10 regular and 10 irregular verbs
  - Then vocabulary was gradually increased to mimic the gradual uptake of words in children
  - Total: 500 word stems, 90% regular (similar to the relative frequency of regulars in English)
  - Higher frequency verbs were introduced earlier in training, and so were also presented to the network more often
    - Irregulars are more frequent, so appear more often in training
    - This is essential, otherwise the regulars swamp the network
    - Arguably more accurately reflects the child's learning environment

- The final model successfully learned the 500 verbs in the training set
  - But errors were made *during* the learning phase
  - Caused by interference between mappings for regulars and irregulars before mature connection weights have been discovered

Performance of P&M

- Early acquisition is characterised by a period of error free performance
- Low overall rate (5-10%) of overregularisation errors
- Overregularisation is not restricted to a particular period of development
- Common irregulars do not exhibit overregularisation (e.g. ‘goed’ is rare)
- Errors are phonologically conditioned: No change verbs (hit) are robust to overregularisation (e.g ‘hitted’ is rare)
- Only a very small number of irregularisation errors are observed (e.g. where the network produces ‘bat’ for ‘bite’)

- Generally compatible with the results of studies by Marcus *et al* (1992):
  - Early performance is error free, and then low error is more or less random



Discussion

- Performance is closely tied to the training environment:
  - Onset of overregularisation is closely bound to a “critical mass” of regular verbs entering the child vocabulary
  - This subsides as the training learns the final solution for the task
- Highly sensitive to training environment:
  - Requires more training on arbitrary irregulars (go/went), which are highly frequent in the language
  - More robust for no-change verbs (hit, put) which are more numerous (type) and less frequent (token)
- Models the frequency x regularity interaction:
  - Faster reaction time for high frequency irregulars than low frequency ones
  - No advantage for regulars
- Differential behaviour for regulars and irregulars result from lesioning
- Suggests it is dangerous to infer dissociations in mechanisms due to observed dissociations in behaviour
  - Critical mass effect can have the appearance of a distinct mechanism

Criticism

- We know multi-layered networks can learn such mappings in general; not proof that children use the same type of mechanism

- Pinker & Prasada argue that the (idiosyncratic) statistical properties of English help the model:
  - Regulars have low token frequency but high type frequency: facilitates the generalisation across this class of items
  - Irregulars have low type frequency but high token frequency: facilitates rote learning mechanism for these words

- They argue no connectionist model can accommodate default generalisation for a class which has both low type and token frequency
  - Default inflection of plural nouns in German appear to have this property (Clahsen, *Monographs of the Society for Research in Child Development, 57,* 1992)

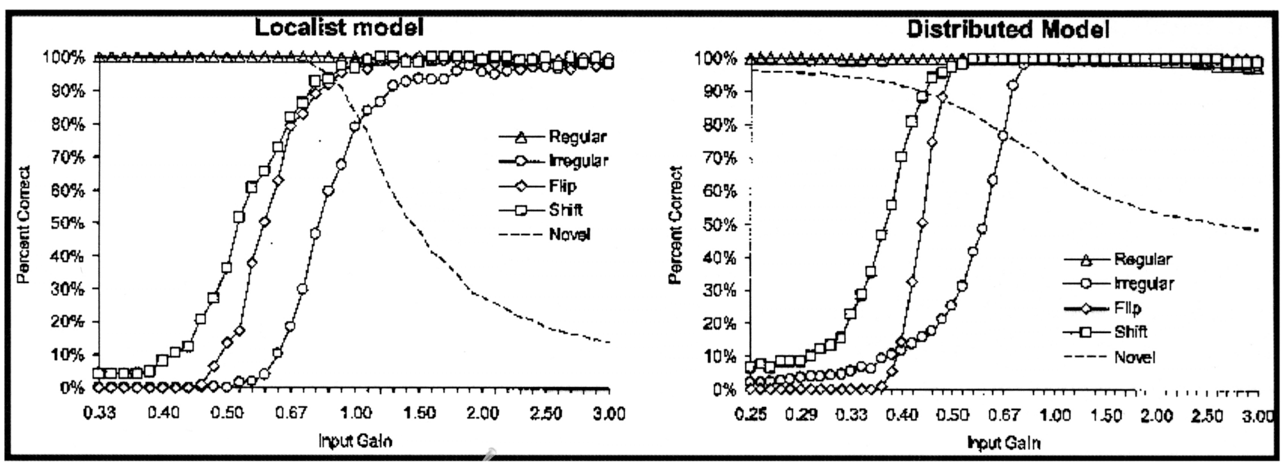
- No explanation of the double-dissociation observed by Pinker (1994)

Double Dissociations and Input Gain (Kello, Sibley, & Plaut, 2005)

- Motivated by a study that used representations that mediate both semantics and phonology, in which orthography was processed into the junction between semantics and phonology.
- Basic characteristics of surface and phonological dyslexia were manipulated by the input-gain parameter that modulated sensitivity of a unit's activation to its net input.
- To isolate the source of the dissociative effects observed in the model, simple connectionist models were build to compute simple quasi-regular mappings based on linguistic phenomena.
- Both localist and distributed models were investigated.
  - In the localist models, input modulated competition among units
  - In the distributed models, input-output pairings activated multiple units in a hidden layer that mediated quasi-regular mappings.
- Four pairs of simulations explored both basic effect of input gain on localist and distributed models types, as well as model two basic aspects of quasi-regularity.

Results

- We will focus on the fourth experiment, built up on the other three
  - Sub-regularities of quasi-regular domains
    - One large-scale regularity (the identity mapping)
    - Two small-scale subregularities (flipping and shifting four target values)
      - *Flip*: CHAT-CHATTED, DOT-DOTTED vs HIT, FIT, QUIT, LET, BET, SET
      - *Shift*: BAT-BATTED (/æ/) vs BATE-BATED (/ɛ/)
- Method: 1024 known items, 3072 novel (12 dimensions)
  - Target items were first copied and exceptions applied for flip, shift, and random irregularities.



Main conclusions

- Dissociations in performance do not necessarily entail distinct mechanisms:
  - Reading aloud: a single mechanism explains regular and irregular pronunciation of monosyllabic rules
  - Past tense: a single model of regular and irregular past tense formation
- But, explaining <u>double dissociations</u> is difficult
  - Has been shown to be possible on small networks, but unclear if larger (more plausible) networks can demonstrate double dissociations
- Connectionist models excel at finding structure and patterns in the environment: "statistical inference machines"
  - The start state for learning may be relatively simple, unspecified
  - Necessary constraints to aid learning come from the environment
- Can such models scale up? Are they successful for languages with different distributional properties?