Finding Structure in Time

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Problem

- Speech research
- Usual MLP takes all input at once and returns output all at once
- Speech needs temporal ordering

Past solutions to problem

- Usual approach: sequential representation of events
 - -[011100000]
 - -[000111000]
- Biological Implications
 - How to express parallel computations in terms of human brain?
- Not all input vectors same length
 - Example: translating user speech into text
- Applications: prediction problems

Solution to Problem

- Variable length input
- Analyze batches of events
- Dynamic system
- Remember past events

Algorithm

Solution: give network memory with a recurrent network

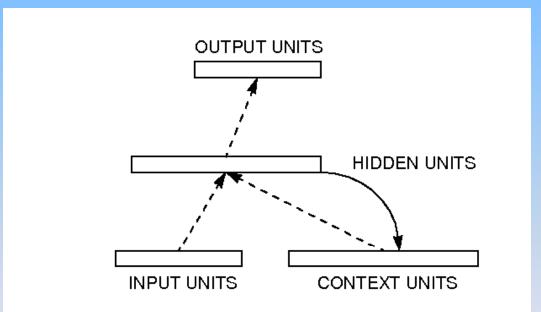


Figure 2. A simple recurrent network in which activations are copied from hidden layer to context layer on a one-for-one basis, with fixed weight of 1.0. Dotted lines represent trainable connections.

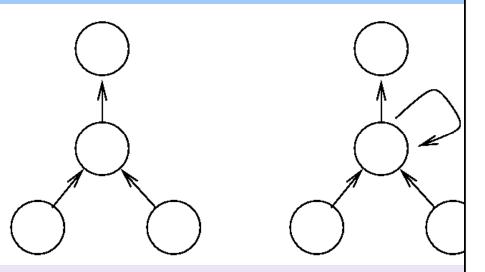
Recurrent Networks Overview

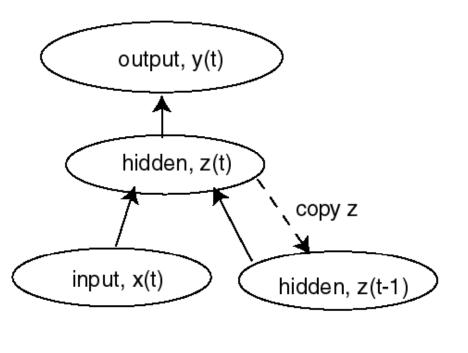
Has a directed cycle

Hopfield is a symmetric recurrent network

Good for: learning grammar, speech recognition, and

music composition





Author's Network

 Why did author use network on left and not the one on the right?

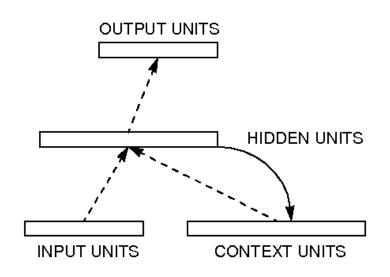
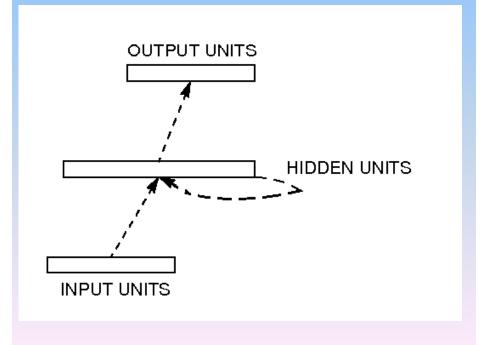


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Results Contents

- XOR
- Letter Sequence
- Words
- Sentences

XOR

- Problem setup:
 - Input: 2 random bits, 3rd bit is XOR of previous 2
 bits
 - Goal: predict next bit
 - Example Input: 10 **1** 0 0 **0** 0 1 **1** 1 1 **0** 1 0 **1**...

XOR Results

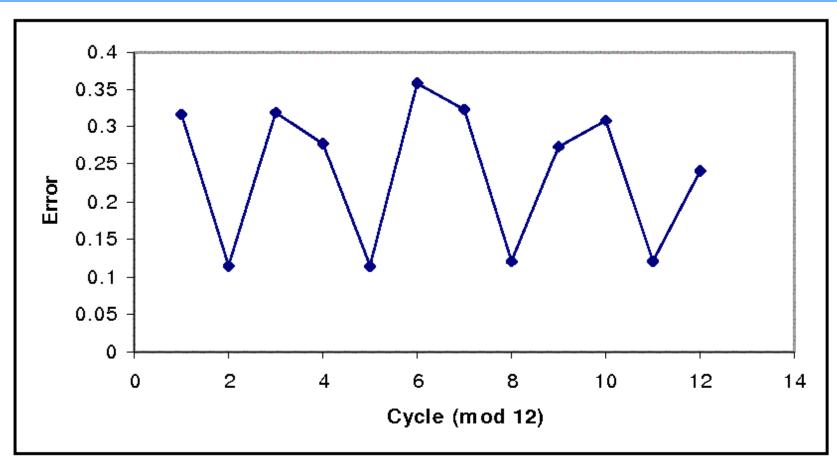


Figure 3. Graph of root mean squared error over 12 consecutive inputs in sequential XOR task. Data points are averaged over 1200 trials.

Letter Sequence

- Problem setup:
 - Input: Random consonants (b,d,g), then random consonants replaced with: b->ba, d->dii, g->guuu
 - Each letter given unique 1x6 vector
 - Goal: predict next letter

Table 4: Vector Definitions of Alphabet

| | Consonant | Vowel | Interrupted | High | Back | Voiced |
|---|-----------|-------|-------------|------|------|--------|
| b | [1 | 0 | 1 | 0 | 0 | 1] |
| d | [1 | 0 | 1 | 1 | 0 | 1] |
| g | [1 | 0 | 1 | 0 | 1 | 1] |
| a | 0] | 1 | 0 | 0 | 1 | 1] |
| i | 0] | 1 | 0 | 1 | 0 | 1] |
| u | 0] | 1 | 0 | 1 | 1 | 1] |

Letter Sequence Results

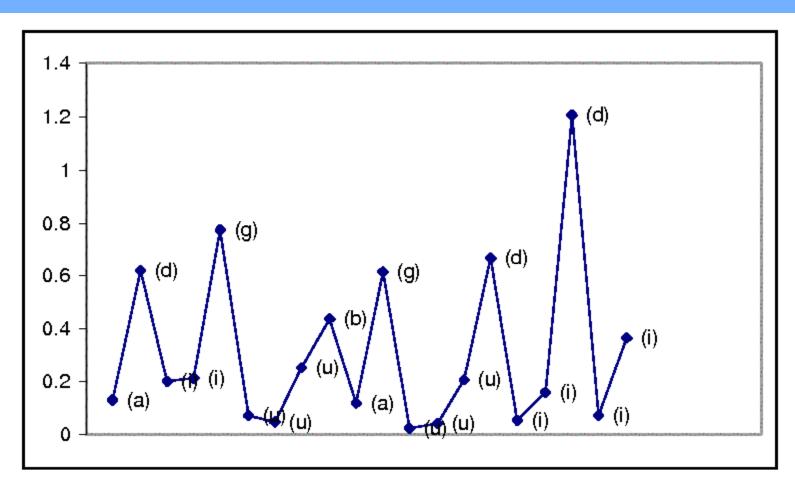


Figure 4. Graph of root mean squared error in letter prediction task. labels indicate the correct output prediction at each point in time. Error is computed over the entire output vector.

Words

- Problem Setup:
 - Input: String of sentences with no breaks between words or sentences
 - Goal: predict next letter of sequence

Words Results

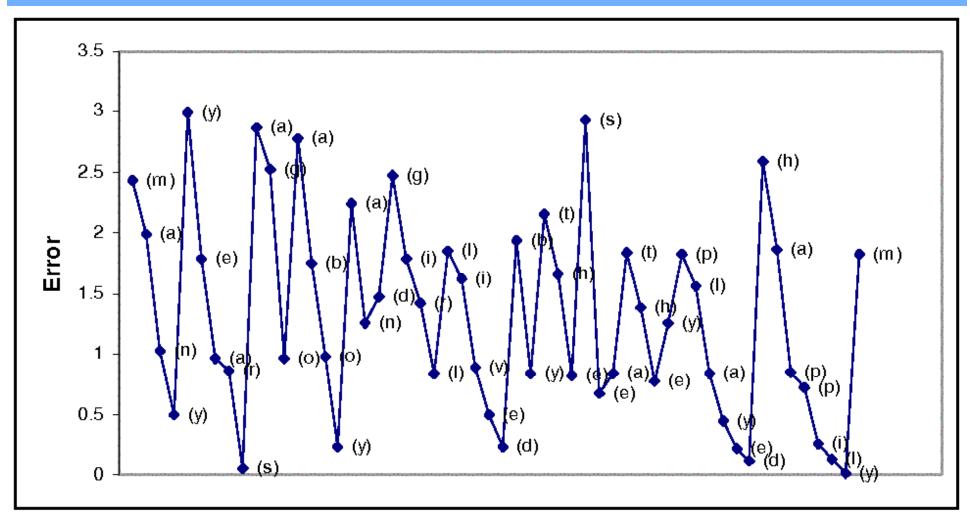


Figure 6. (a) Graph of root mean squared error in letter-in-word prediction task.

Sentence Setup

- A large number of simple sentences were randomly produced
- Each word was vectorized
- No breaks in between sentences
- Goal: predict the next word

Sentences

| Table 4: Templates for sentence generator | | | | | | |
|---|--------------|-------------|----|--|--|--|
| WORD 1 | WORDS | WORD 3 | | | | |
| NOUN-HUM | VERB-EAT | NOUN-FOOD | | | | |
| NOUN-HUM | VERB-PERCEPT | NOUN-INANIM | Ta | | | |
| NOUN-HUM | VERB-DESTROY | NOUN-FRAG | _ | | | |
| NOUN-HUM | VERB-INTRAN | | | | | |
| NOUN-HUM | VERB-TRAN | NOUN-HUM | = | | | |
| NOUN-HUM | VERB-AGPAT | NOUN-INANIM | | | | |
| NOUN-HUM | VERB-AGPAT | | 1 | | | |
| NOUN-ANIM | VERB-EAT | NOUN-FOOD | 1 | | | |
| NOUN-ANIM | VERB-TRAN | NOUN-ANIM | 1 | | | |
| NOUN-ANIM | VERB-AGPAT | NOUN-INANIM | | | | |
| NOUN-ANIM | VERB-AGPAT | | | | | |
| NOUN-INANIM | VERB-AGPAT | | ſ | | | |
| NOUN-AGRESS | VERB-DESTORY | NOUN-FRAG | ١ | | | |
| NOUN-AGRESS | VERB-EAT | NOUN-HUM | ١ | | | |
| NOUN-AGRESS | VERB-EAT | NOUN-ANIM | ١ | | | |
| NOUN-AGRESS | VERB-EAT | NOUN-FOOD | , | | | |

Table 3: Categories of lexical items used in sentence simulation

| Category | Examples |
|--------------|------------------|
| NOUN-HUM | man, woman |
| NOUN-ANIM | cat, mouse |
| NOUN-INANIM | book, rock |
| NOUN-AGRESS | dragon, monster |
| NOUN-FRAG | glass, plate |
| NOUN-FOOD | cookie, sandwich |
| VERB-INTRAN | think, sleep |
| VERB-TRAN | see, chase |
| VERB-AGPA | move, break |
| VERB-PERCEPT | smell, see |
| VERB-DESTROY | break, smash |
| VERB-EA | eat |
| | |

Sentences: quality measurement

Can't use word-by-word RSS

- Error: 0.88

Solution: use RSS for categories of words

- Error: 0.053

How did the network do this?

Sentence Classification

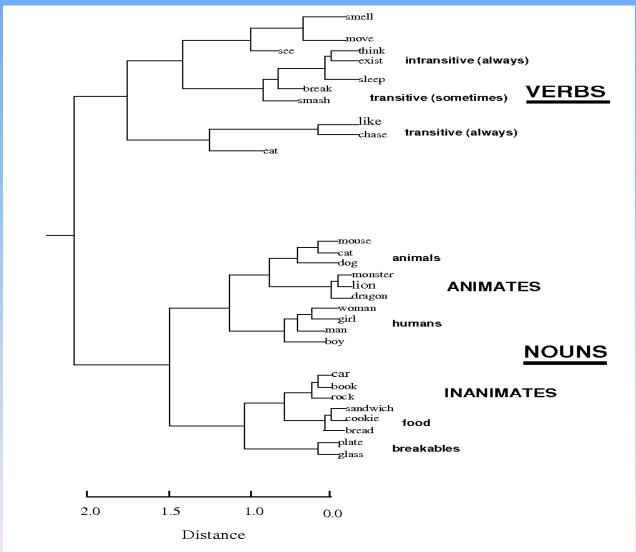


Figure 7. Hierarchical cluster diagram of hidden unit activation vectors in simple sentence prediction task. labels indicate the inputs which produced the hidden unit vectors; inputs were presented in context, and the hidden unit vectors averaged across multiple contexts.

Conclusion

- Some problems are different when expressed as temporal events.
- RSS can be used to analyze the temporal structure.
- Length of sequential dependencies doesn't always worsen performance.
- Representation of time and memory is taskdependant.
- Representations can be structured.

The End