

# Using EEG to Decode Semantics During an Artificial Language Learning Task

*Thesis Oral Defense*

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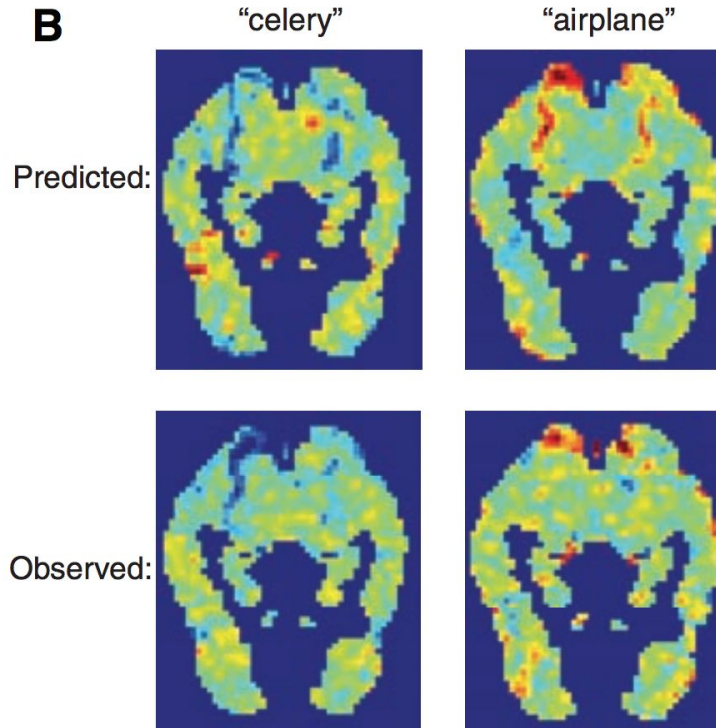


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Can machine learning algorithms be used to track the acquisition of a new language in adults, based solely on electrical signals from the brain?



# Predicting fMRI activity



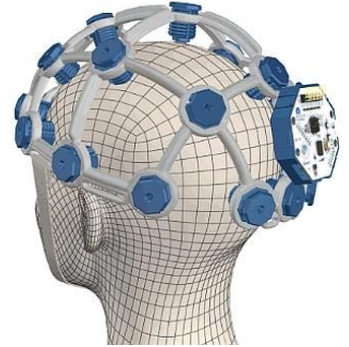
# Can we do this with EEG?

EEG is great due to its:

- Low cost of collection
- Mobility for collecting in various environments
- High time resolution

But, EEG has:

- Generally poorer spatial resolution
- Lower signal-to-noise ratio



# Experiment paradigm



A black Tamil character 'ம' (Ma) is centered on a gray square background.

MARKET

A black Tamil character 'பி' (Pi) is centered on a gray square background.

CINEMA

A black Tamil character 'ஐ' (Ai) is centered on a gray square background.

WE

A black Tamil character 'ஐ' (Ai) is centered on a gray square background.

TIRED

A black Tamil character 'ஈ' (Ii) is centered on a gray square background.

HUNGRY

A black Tamil character 'து' (Tu) is centered on a gray square background.

PENCIL

A black Tamil character 'ஸ' (Sa) is centered on a gray square background.

YOU

A black Tamil character 'உ' (U) is centered on a gray square background.

WORK

A black Tamil character 'ஈ' (Ii) is centered on a gray square background.

SALESMAN

A black Tamil character 'ஈ' (Ii) is centered on a gray square background.

CAMPING

# Machine learning analysis of brain data

Three components to discuss

1. Input features
2. Regression model
3. Prediction target



## Source Text

## Training Samples

The quick brown fox jumps over the lazy dog. →

(the, quick)  
(the, brown)

The quick brown fox jumps over the lazy dog. →

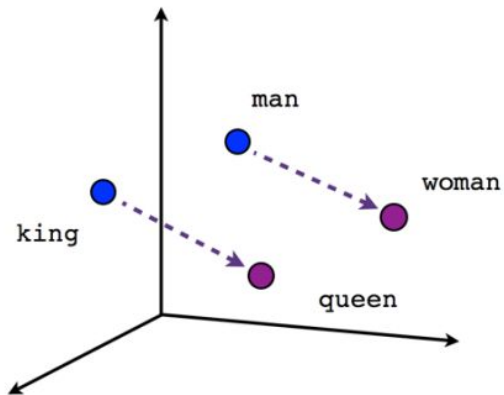
(quick, the)  
(quick, brown)  
(quick, fox)

The quick brown fox jumps over the lazy dog. →

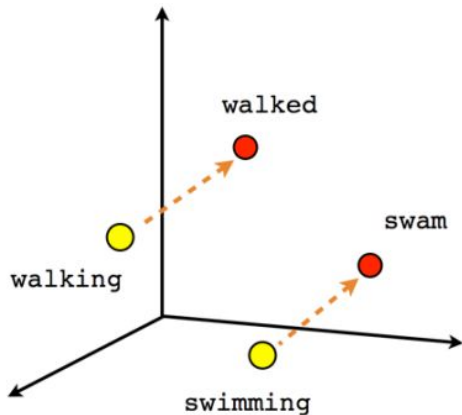
(brown, the)  
(brown, quick)  
(brown, fox)  
(brown, jumps)

The quick brown fox jumps over the lazy dog. →

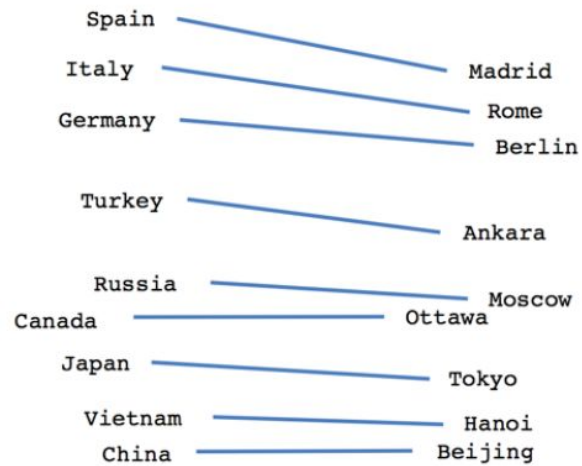
(fox, quick)  
(fox, brown)  
(fox, jumps)  
(fox, over)



Male-Female



Verb tense



Country-Capital

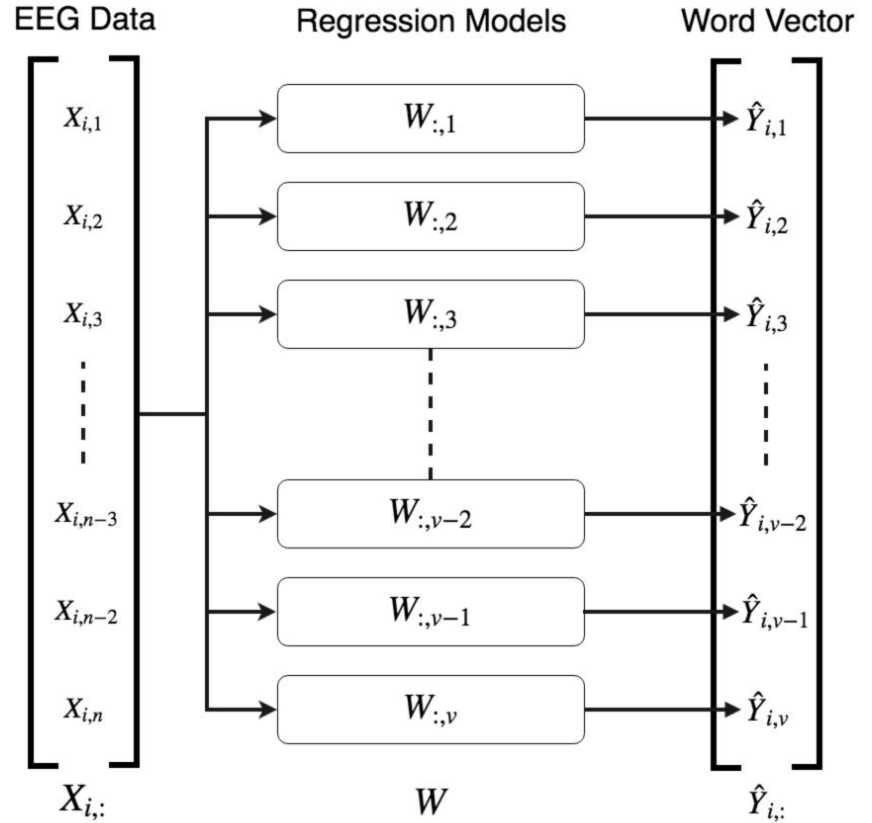
# Ridge regression

Linear regression model with regularization via weight decay

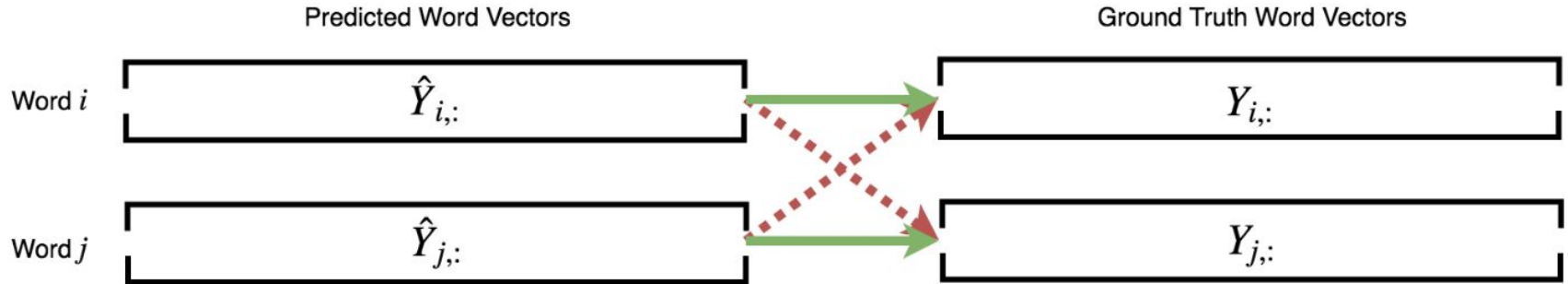
Basic linear regression:  $y = w_0x_0 + w_1x_1 + \dots + w_mx_m = \sum_{j=0}^m = \mathbf{w}^T \mathbf{x}$

Gradient descent using a loss function:  $J(\mathbf{w}) = \frac{1}{2} \sum_i (\text{target}^{(i)} - \text{output}^{(i)})^2$

# Multivariate regression model



# Model evaluation



# Research questions

1. Can we identify the semantics of the English word?
2. How much participant practice is needed to identify semantics?
3. How long does the brain take to process the semantics?
4. Are there areas of the brain that contribute more to identifying semantics?

# Can we identify the semantics of the English word?

Our machine learning model shows an accuracies of:

- **79.54%** over 0 - 700ms
- **69.15%** over 0 - 500ms

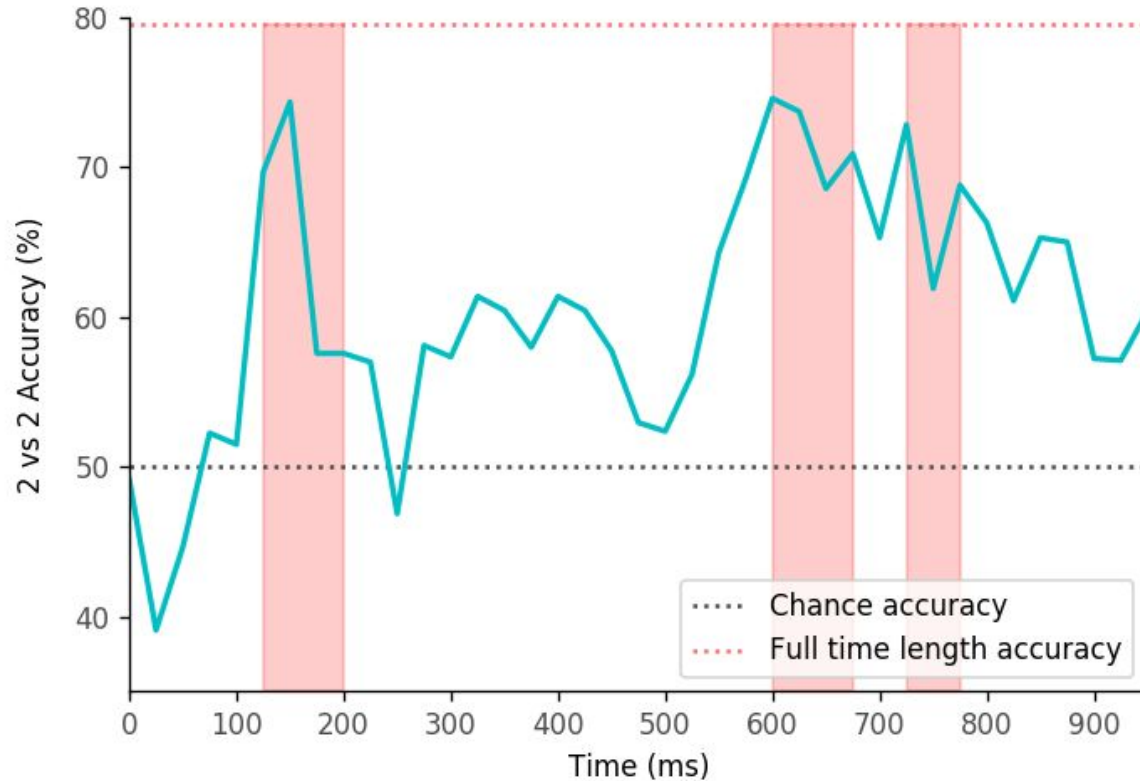
This provides evidence that EEG activity is correlated with the representation of word semantics in the brain

# How much participant practice is needed?

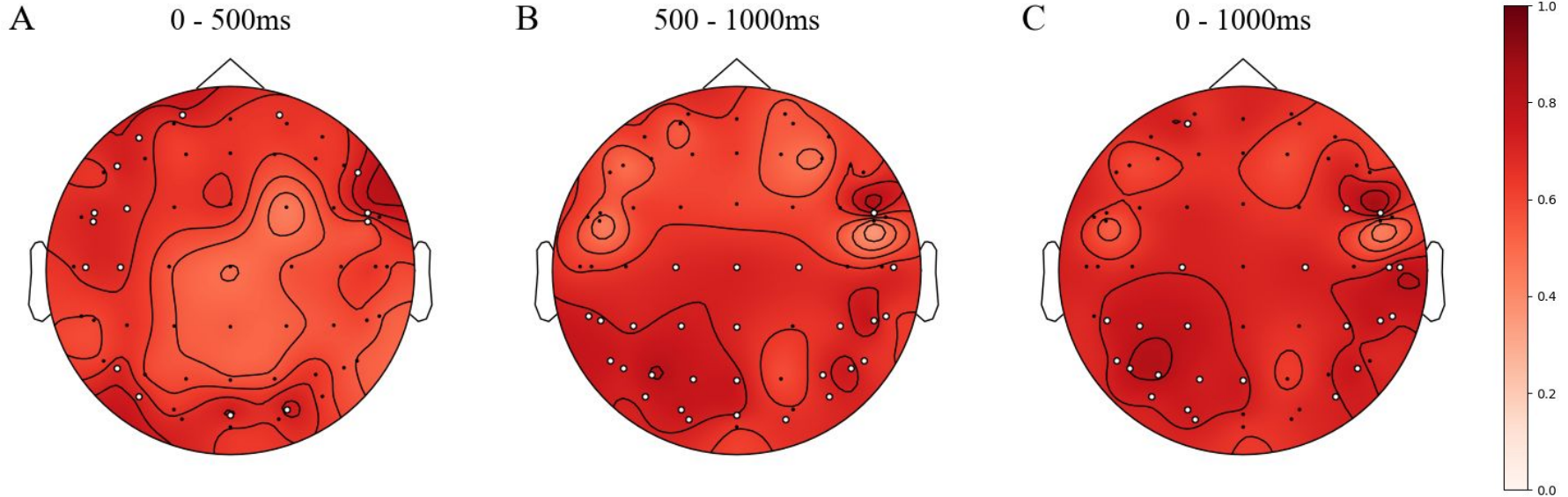




# How long does the brain take to process semantics?



# Are there areas of the brain that contribute more?



# Conclusion

We show that semantics can be detected via EEG, and further that we can detect learning of semantic concepts as they develop a language mapping in the brain

This opens new avenues for studying language semantics and learning via EEG

Thanks!

**CIFAR**

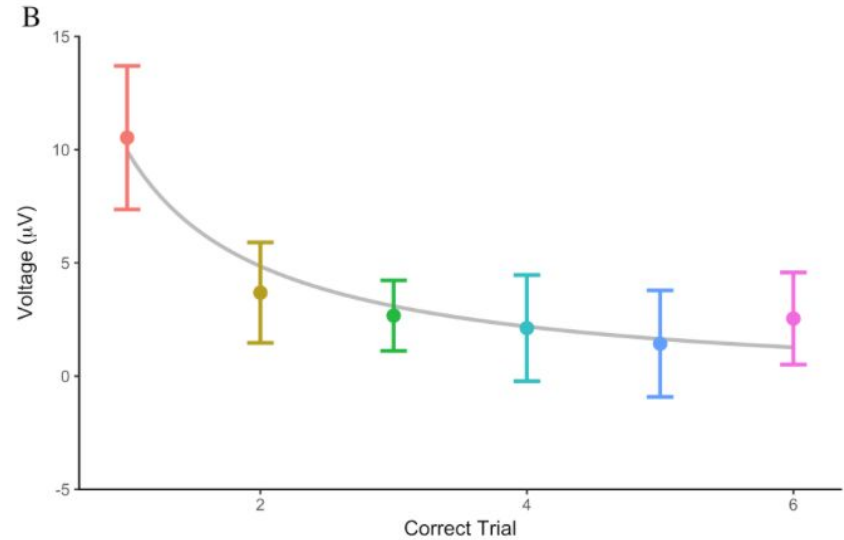
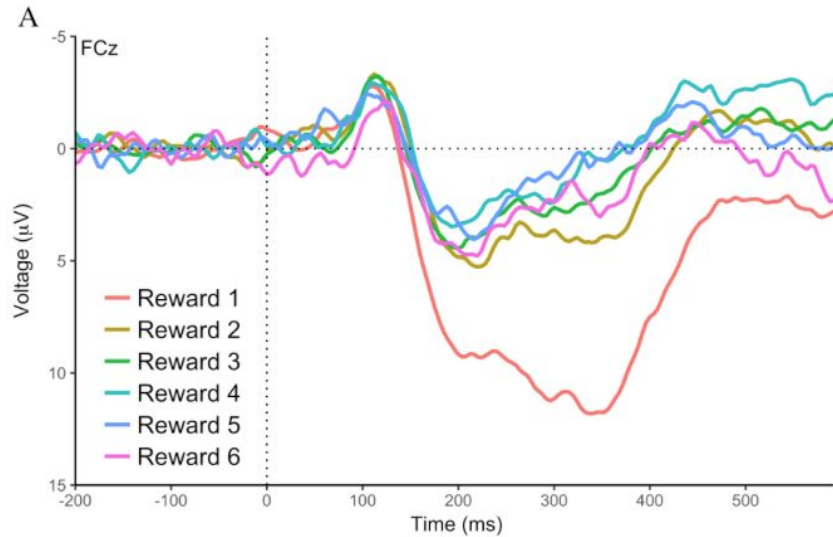


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# How does this compare to traditional methods?



# Is there a relationship to the participant's choices?

Our machine learning model shows an accuracies of:

- **65.13% vs 59.71%** over 0 - 700ms
- **57.55% vs 57.47%** over 0 - 500ms

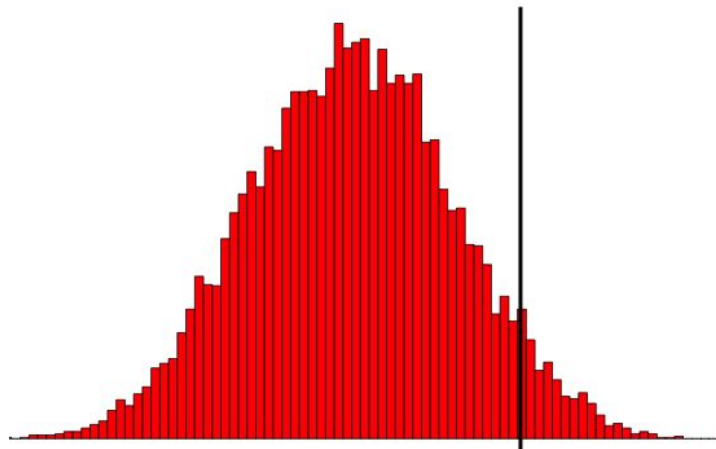
This effect might not be very powerful due to the tasks repetition of blocks with lower participant accuracy

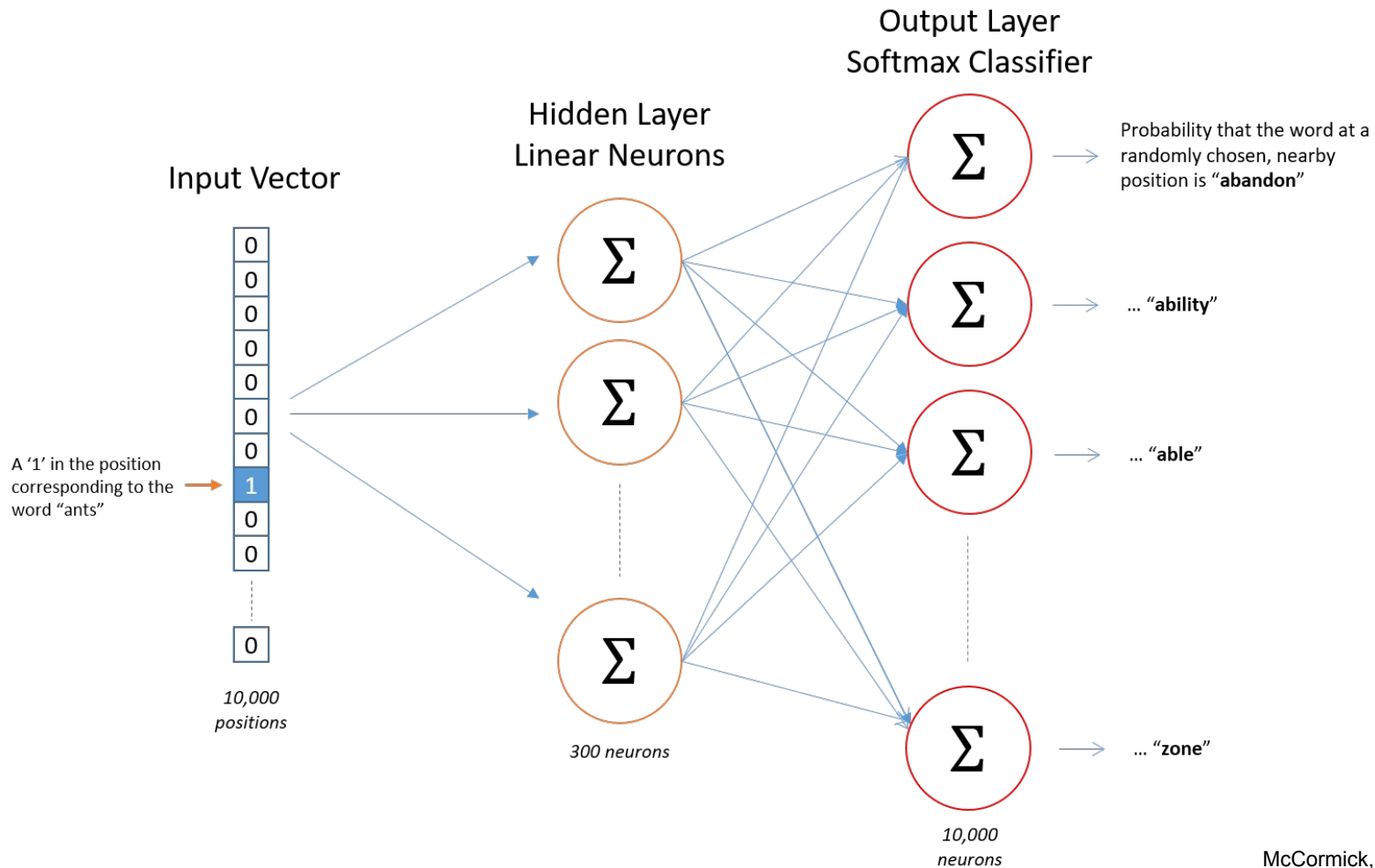
# Measuring significance

Significant is measured with a permutation test

1. Randomly permute the word vectors so that they no longer pair to the correct EEG
2. Run the entire model on the permuted data
3. Repeat 1,000 times

This creates a null distribution we can use







Hidden Layer  
Weight Matrix



*Word Vector  
Lookup Table!*

