
# Sequence Modeling

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# ADL x MLDS

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Slides credited from Richard Socher

# How to Frame the Learning Problem?

The learning algorithm $f$ is to map the input domain $X$ into the output domain $Y$

$$f : X \rightarrow Y$$

Input domain: word, word sequence, audio signal, click logs

Output domain: single label, sequence tags, tree structure, probability distribution

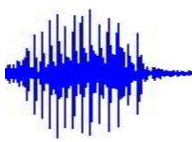
# Output Domain – Classification

## Sentiment Analysis

“這規格有誠意!” → +

“太爛了吧~” → -

## Speech Phoneme Recognition

 → /h/

## Handwritten Recognition

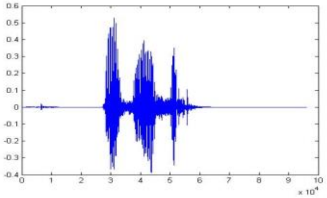
 → 2

# Output Domain – Sequence Prediction

## POS Tagging

"推薦我台大後門的餐廳" → 推薦/VV 我/PN 台大/NR 後門/NN 的/DEG 餐廳/NN

## Speech Recognition



→ "大家好"

## Machine Translation

"How are you doing today?" → "你好嗎?"

Learning tasks are decided by the output domains

# Input Domain –
# How to Aggregate Information

Input: word sequence, image pixels, audio signal, click logs

Property: continuity, temporal, importance distribution

Example

- CNN (convolutional neural network): local connections, shared weights, pooling
  - AlexNet, VGGNet, etc.
- RNN (recurrent neural network): temporal information
- RvNN (recursive neural network): compositionality

Network architectures should consider the input domain properties

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**Input domain:** word, word sequence, audio signal, click logs

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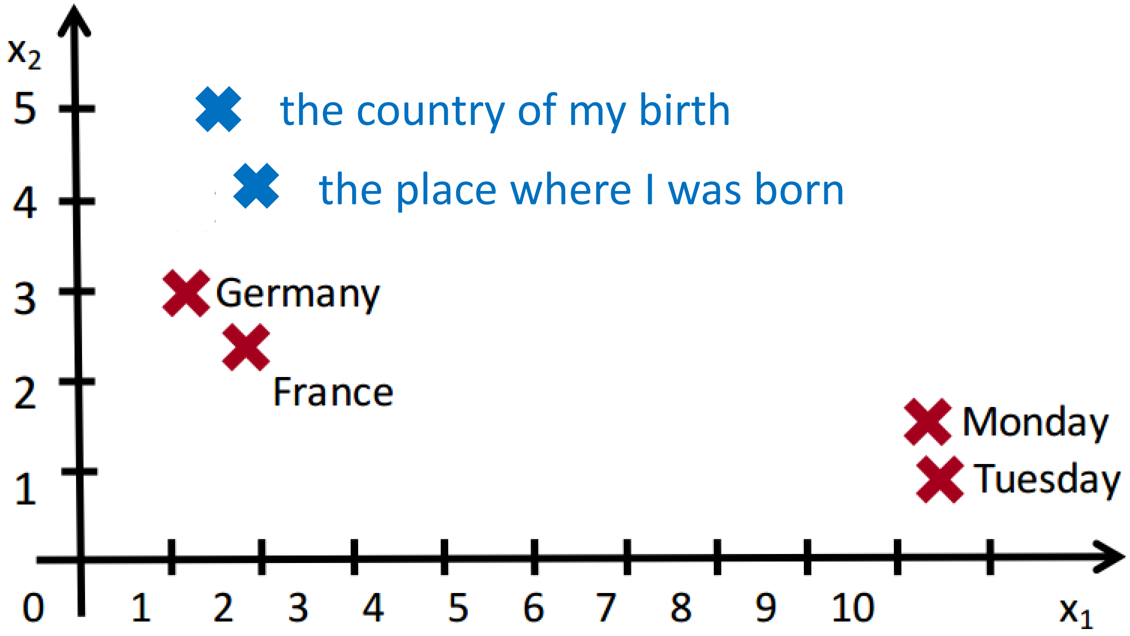
Network design should leverage input and output domain properties

# Review

# Word Vector Space

The words can be represented as vectors in the high-dim space




How can we represent the meaning of longer phrases?

Mapping them into same vector space!!

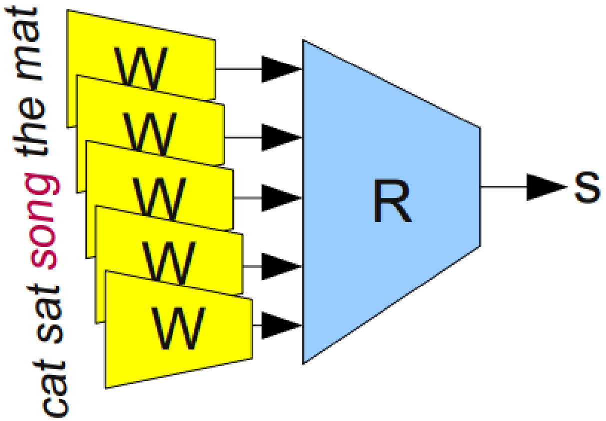
# Word Embedding Benefit

Given an unlabeled training corpus, produce a vector for each word that encodes its semantic information. These vectors are useful because:

① semantic similarity between two words can be calculated as the cosine similarity between their corresponding word vectors

② word vectors as powerful features for various supervised NLP tasks since the vectors contain semantic information

③ propagate any information into them via neural networks and update during training



# Target Function

## Classification Task

$$f(x) = y \quad \Longrightarrow \quad f : R^N \rightarrow R^M$$

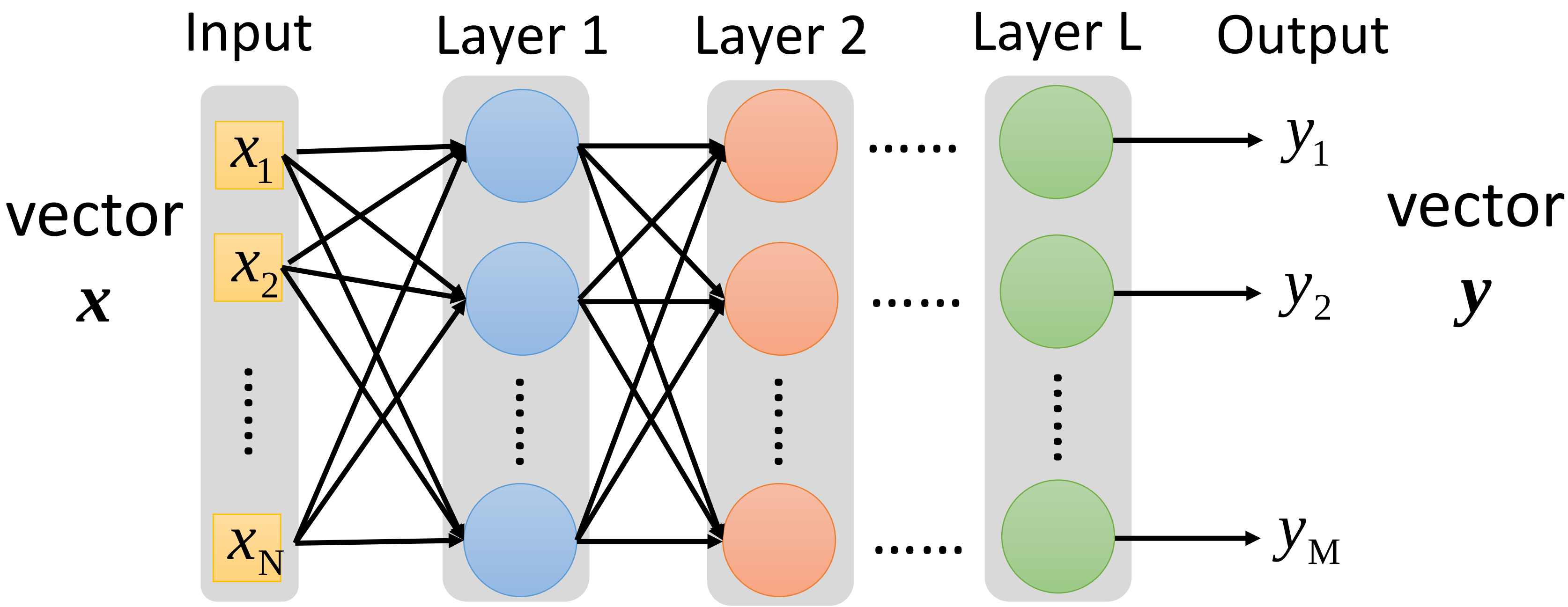
- $x$: input object to be classified → a $N$-dim vector
- $y$: class/label → a $M$-dim vector

Assume both x and y can be represented as fixed-size vectors

How to use word embeddings for the subsequent tasks

# Deep Neural Networks (DNN) $f : R^N \rightarrow R^M$

Fully connected feedforward network




From input vector x to output class vector y

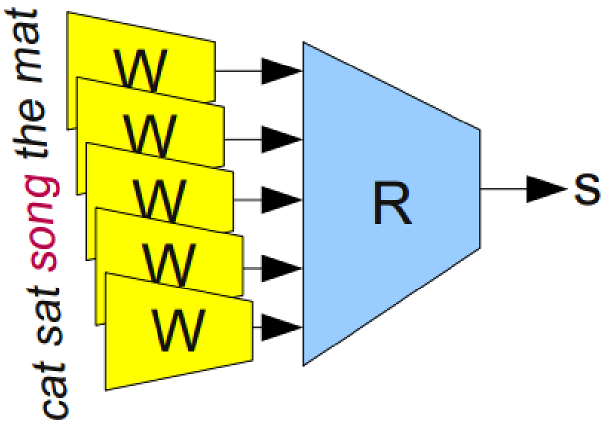
# Word Sequence as a Vector

Combine word embeddings into a single input vector

"這規格有誠意!" ⟶ +

"太爛了吧~" ⟶ -

| | |
|---|---|
| 這 (this) | $\begin{bmatrix} 0.2 & 0.6 & 0.3 & \cdots & 0.4 \end{bmatrix}$ |
| 規格 (specification) | $\begin{bmatrix} 0.9 & 0.8 & 0.1 & \cdots & 0.1 \end{bmatrix}$ |
| 有 (have) | $\begin{bmatrix} 0.1 & 0.3 & 0.1 & \cdots & 0.7 \end{bmatrix}$ |
| 誠意 (sincerity) | $\begin{bmatrix} 0.5 & 0.0 & 0.6 & \cdots & 0.4 \end{bmatrix}$ |




$$\vec{x} = \begin{bmatrix} x_1 & x_2 & x_3 & \cdots & x_N \end{bmatrix}$$

How to compute $x$?

# Semantic Vector Space

single word vector ⟷ document vector

Single word vector

- Distributional representation
- Useful features inside models
- Cannot capture meaning of longer phrases

Document vector

- Bag of words models
- PCA/LSA/LDA
- Great for IR, document exploration
- Ignore word ordering, no detail understanding

Vectors representing *Phrases* and *Sentences* with word order and capture semantics for NLP tasks

# Sequence Modeling

Idea: aggregate the meaning from all words into a vector

→ ***Compositionality***

Method:

- Basic combination: average, sum
- Neural combination:
  - ✓Recursive neural network (RvNN)
  - ✓Recurrent neural network (RNN)
  - ✓Convolutional neural network (CNN)

$$\begin{array}{cc} & \overbrace{\hphantom{[0.2\ 0.6\ 0.3\ \cdots\ 0.4]}}^{N\text{-dim}} \\ \text{這 (this)} & \begin{bmatrix}0.2 & 0.6 & 0.3 & \cdots & 0.4\end{bmatrix} \\ \text{規格 (specification)} & \begin{bmatrix}0.9 & 0.8 & 0.1 & \cdots & 0.1\end{bmatrix} \\ \text{有 (have)} & \begin{bmatrix}0.1 & 0.3 & 0.1 & \cdots & 0.7\end{bmatrix} \\ \text{誠意 (sincerity)} & \begin{bmatrix}0.5 & 0.0 & 0.6 & \cdots & 0.4\end{bmatrix} \end{array}$$

How to compute $\vec{x} = \begin{bmatrix}x_1 & x_2 & x_3 & \cdots & x_N\end{bmatrix}$

# Concluding Remarks

Sequence Modeling

- aggregate information from the input

Method

- basic combination: average, sum
- neural combination: network architectures should consider input domain properties
  - ✓ Convolutional neural network (CNN): local connections, shared weights, pooling
  - ✓ Recurrent neural network (RNN): temporal information
  - ✓ Recursive neural network (RvNN): compositionality