Sequence Modeling

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Applied Deep Learning

Yun-Nung (Vivian) Chen WWW.CSIE.NTU.EDU.TW/~YVCHEN/F105-ADL

National Taiwan University

Slide credit 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

$$f : X \to Y$$

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

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

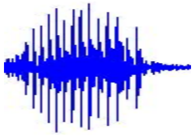
Output Domain – Classification

Sentiment Analysis

"這規格有誠意!" → +

"太爛了吧~" → -

Speech Phoneme Recognition

 → /h/

Handwritten Recognition

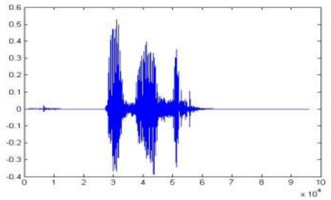
 → 2

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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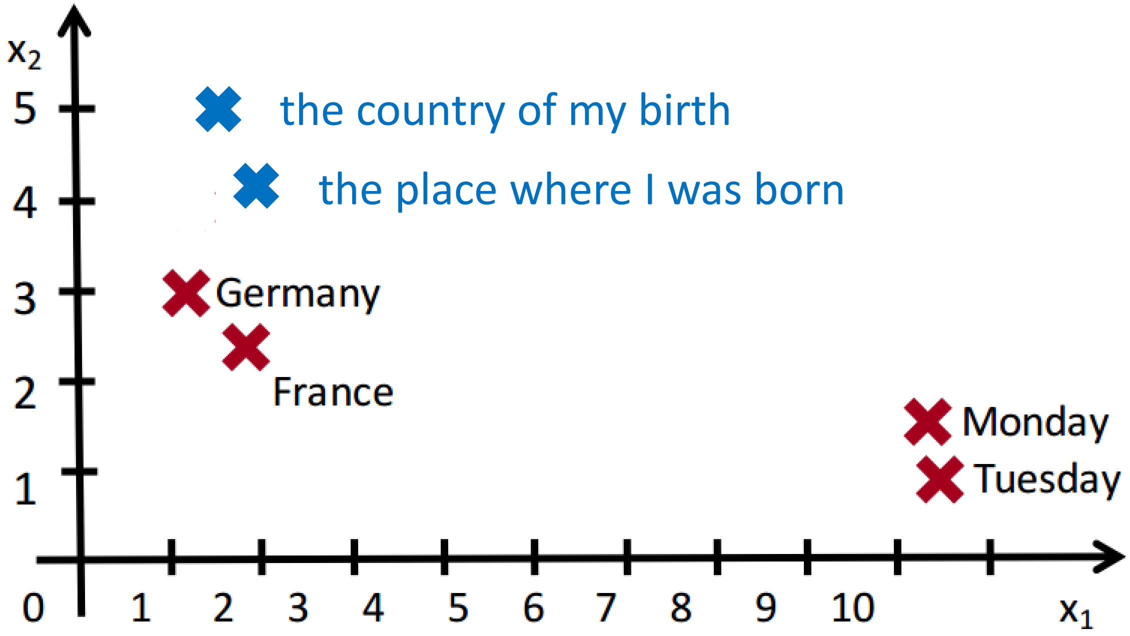
Network design should leverage input and output domain properties

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!!

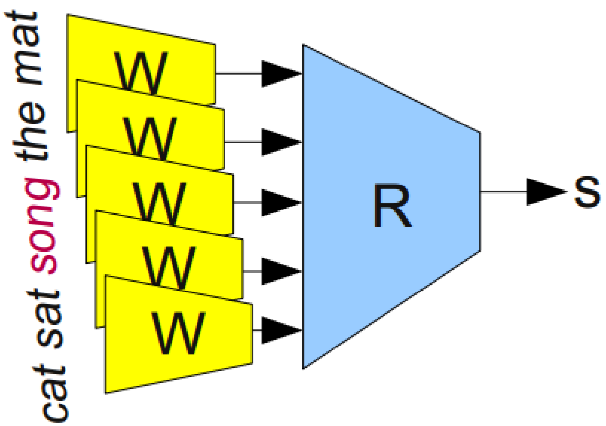
Word Embedding Benefit

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

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

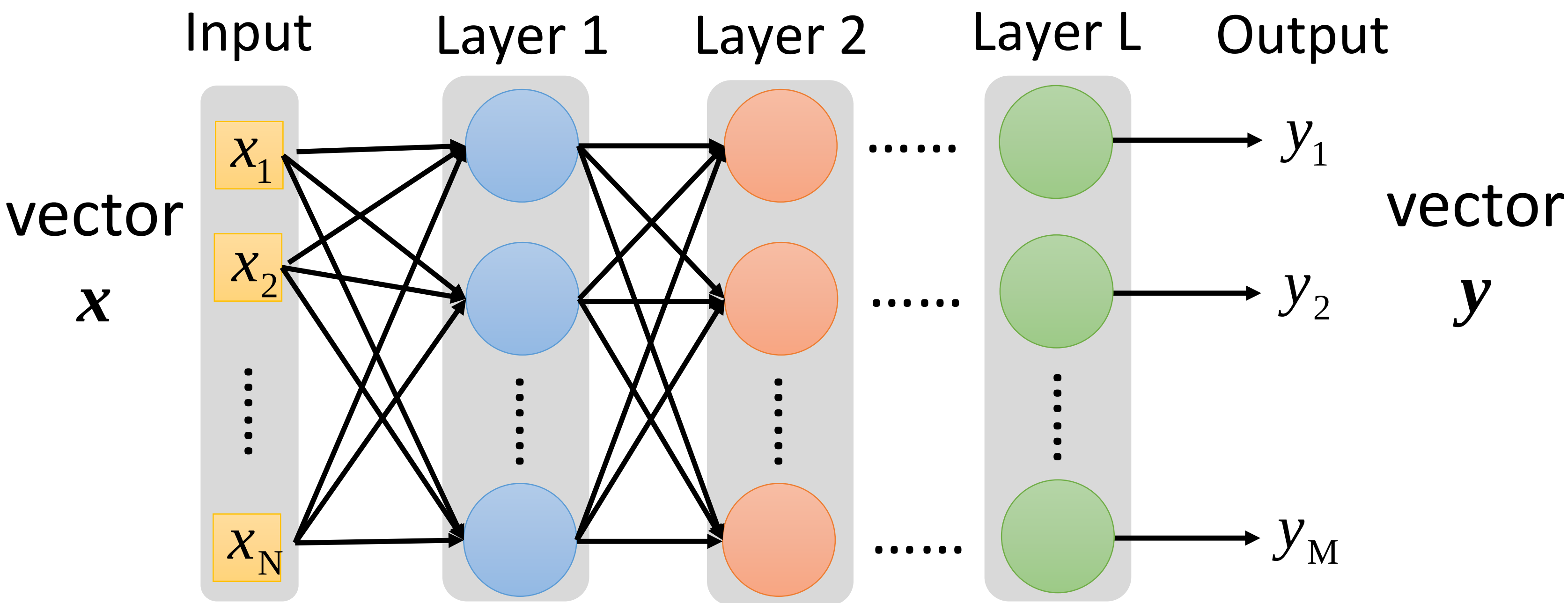
- x: input object to be classified → a N-dim vector
- y: class/label → a M-dim vector

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

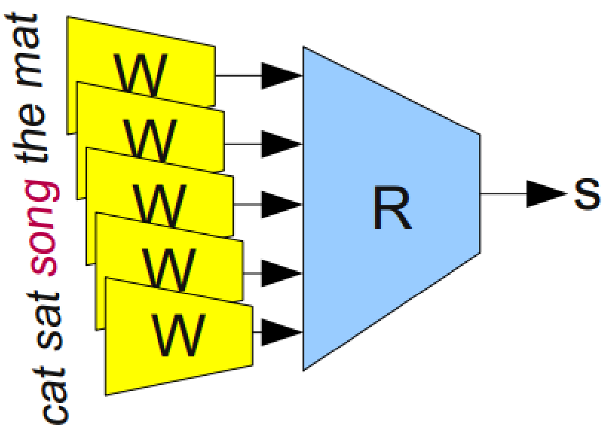
Word Sequence as a Vector

Combine word embeddings into a single input vector

“這規格有誠意!” ⟶ +

“太爛了吧~” ⟶ -

這 (this)	$[0.2\ \ 0.6\ \ 0.3\ \ \cdots\ \ 0.4]$
規格 (specification)	$[0.9\ \ 0.8\ \ 0.1\ \ \cdots\ \ 0.1]$
有 (have)	$[0.1\ \ 0.3\ \ 0.1\ \ \cdots\ \ 0.7]$
誠意 (sincerity)	$[0.5\ \ 0.0\ \ 0.6\ \ \cdots\ \ 0.4]$



$$\vec{x} = [x_1\ \ x_2\ \ x_3\ \ \cdots\ \ x_N]$$

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