Text Classification NER, POS

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https://shala2020.github.io/

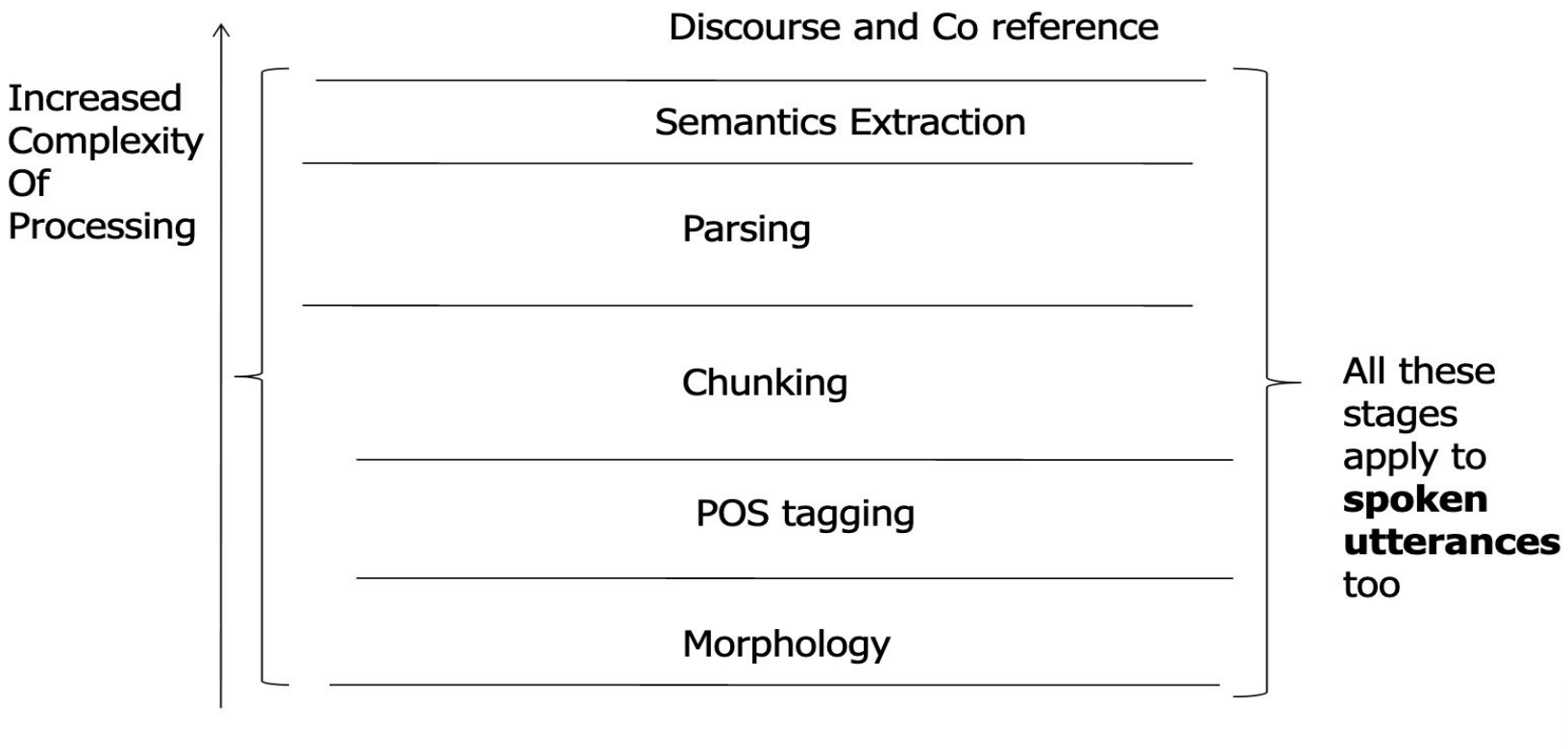
We will start at 09.05 pm

Agenda

- Text Classification
- Classical approaches for text representation
- Modern approaches for text representation
- Challenges in NLP : NER, POS

Introduction to Text Classification

NLP and Speech Layers



Credit: Prof. Pushpak Bhattacharyya

NLP and Speech Layers

- Morphology : karna / try - tried / visible - invisible / create - recreate

  An example

- POS : ram.NN kicked.?? the.?? ball.??
- Chunking : the book has many chapters / noun compounds
- Parsing
- Semantics Extraction - Word Senses / Word Vectors
- Discourse - Coreference Resolution / Sarcasm Detection

Credit: Prof. Pushpak Bhattacharyya

Why do we need to classify Texts ?

- Spam Classification

Why do we need to classify Texts ?

- Sentiment Analysis

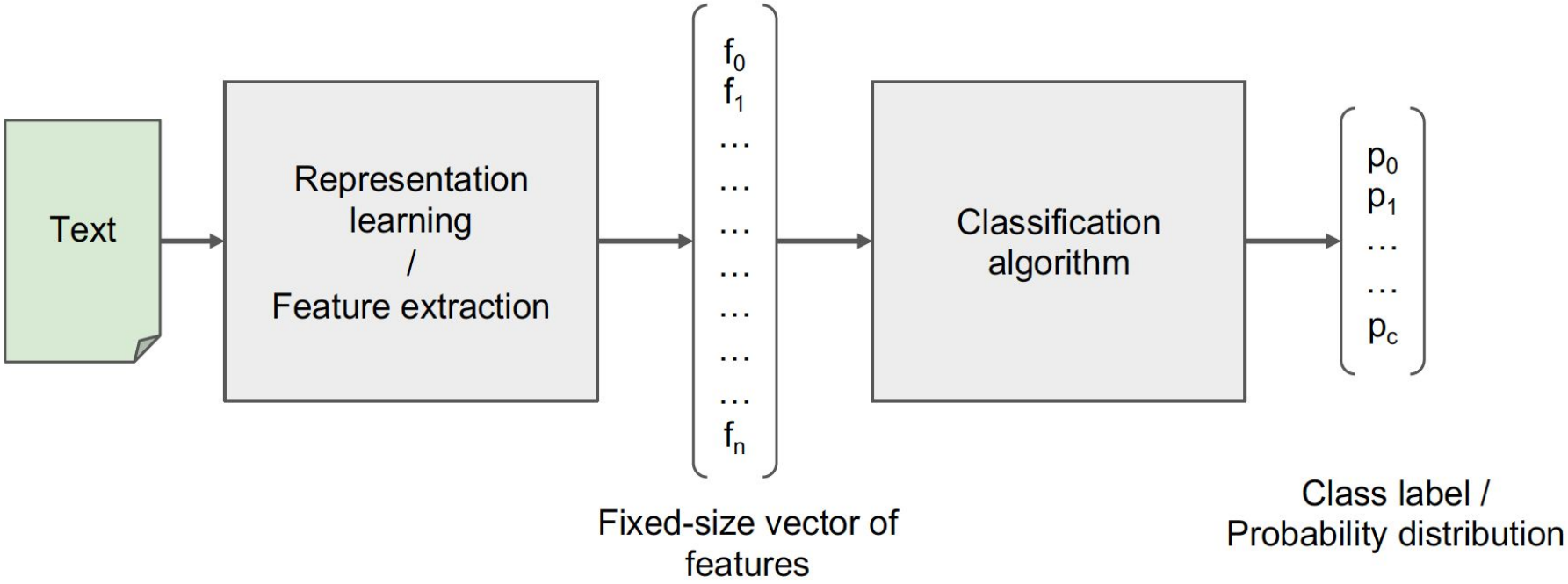
Why do we need to classify Texts ?

- Fake News/Click bait Detection

Why do we need to classify Texts ?

- Data Filtering

Text Classification in general



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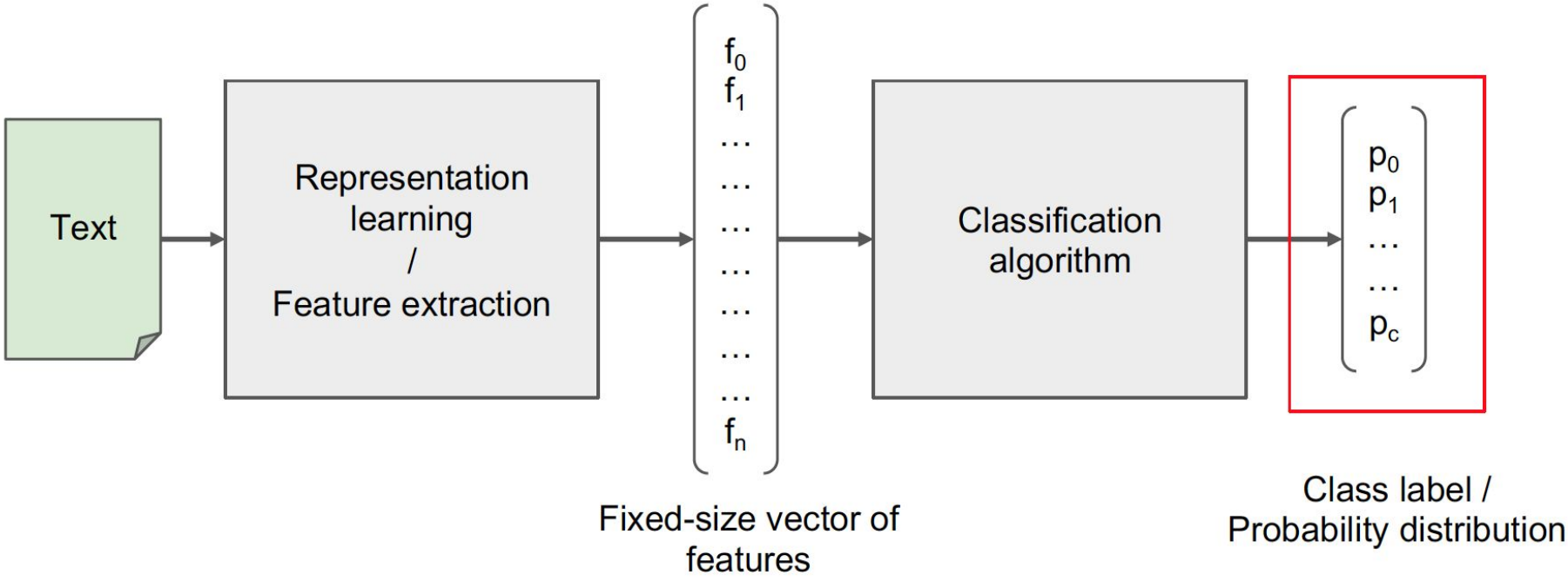
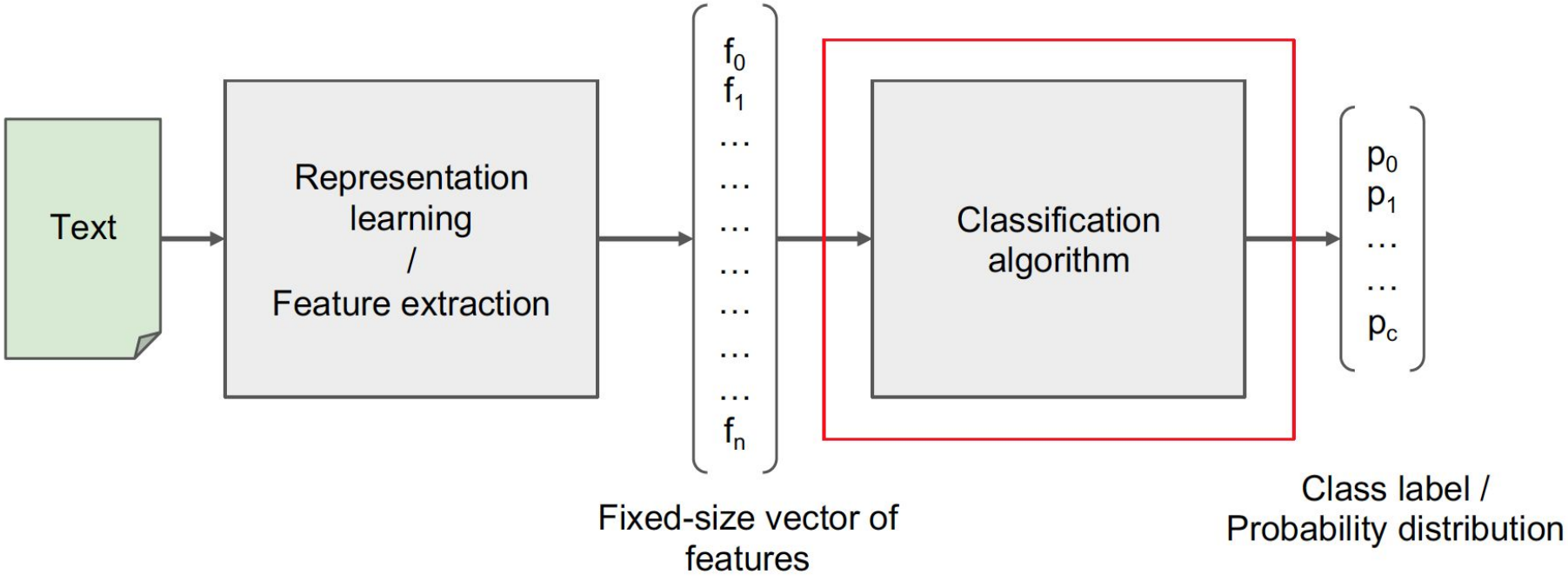


Text Label types

1. Discrete labels:
    a. Label is known:
        i. Binary classification: spam filtering/sentiment analysis
        ii. Multi-class classification: categorization of goods
        iii. Multi-label classification: #hashtag prediction
    b. Label is unknown:
        i. Text clasterization: user intent search
2. Continuous labels: predict a salary by CV, predict a price by a product description

Text Classification in general



Classification Algorithms

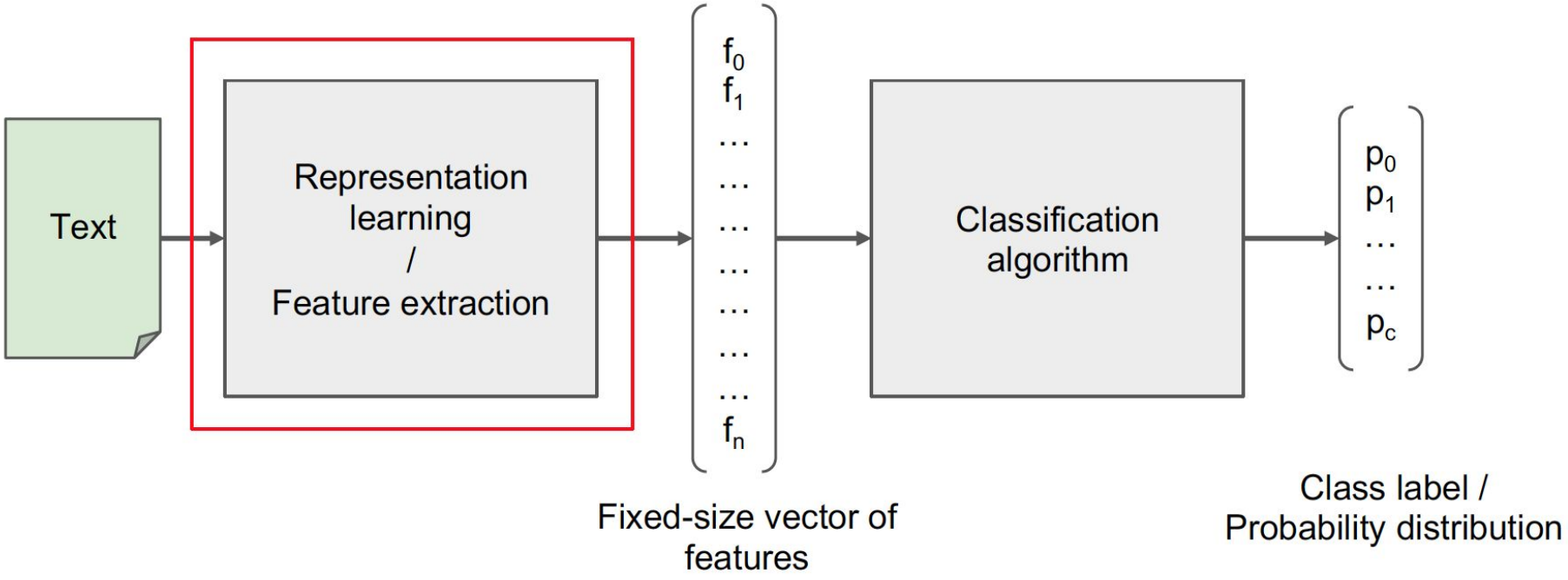
NLP has its own cozy atmosphere when it comes to naming models

TL;DR

Maximum Entropy Method = sklearn.linear_model.LogisticRegression

Multinomial Naive Bayes = sklearn.naive_bayes.MultinomialNB

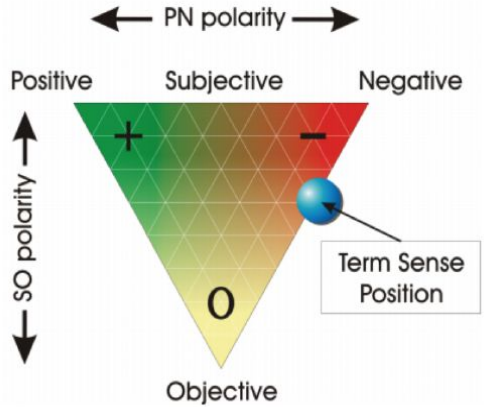
Text Classification in general



Text Representation: Feature Engineering

As for many ML tasks, it is possible to generate useful features by hands.

- General statistics: text length, text length variance,...
- Scores from tagged word lists:
  - Sentiment dictionaries: SentiWordNet, SentiWords, ...
  - Subjectivity/objectivity dictionaries: MPQA
  - ...
- Syntactic features:
  - POS tags
- Ad-hoc features: e.g. number of emojis ( or )



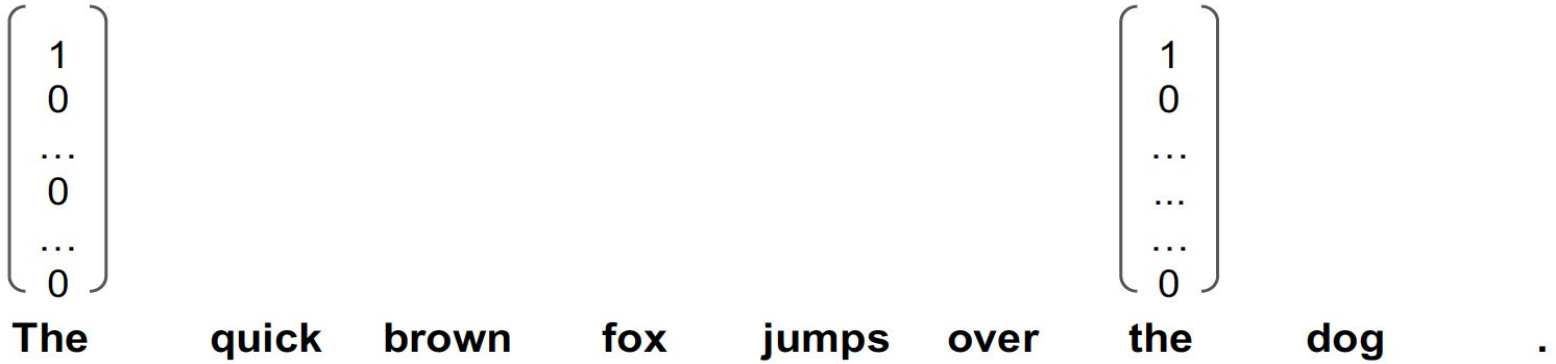
Sparse Text Representation: BOW

The	quick	brown	fox	jumps	over	~~lazy~~ the	dog	.

Sparse Text Representation: BOW

The quick brown fox jumps over the dog .

Sparse Text Representation: BOW



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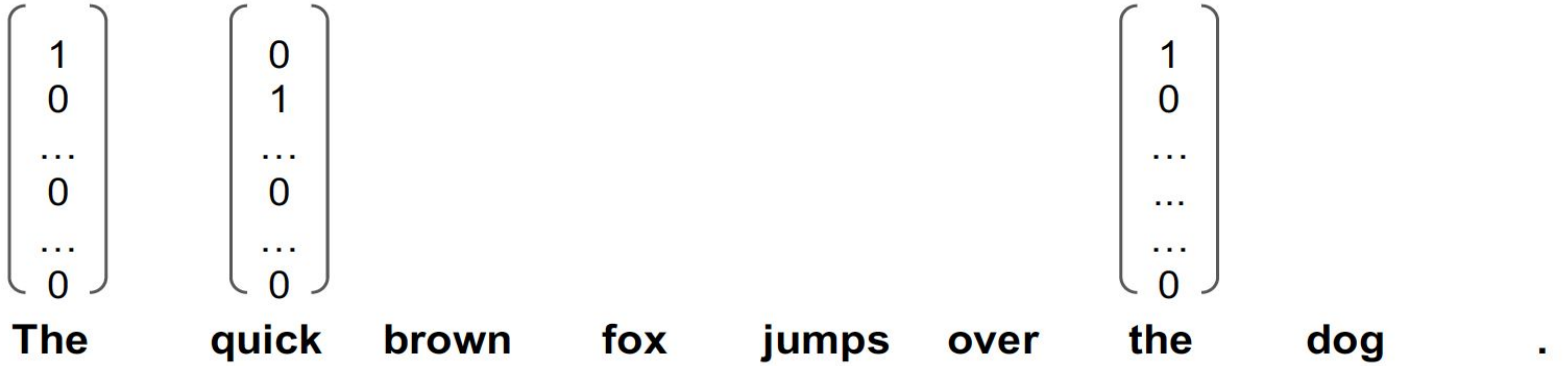

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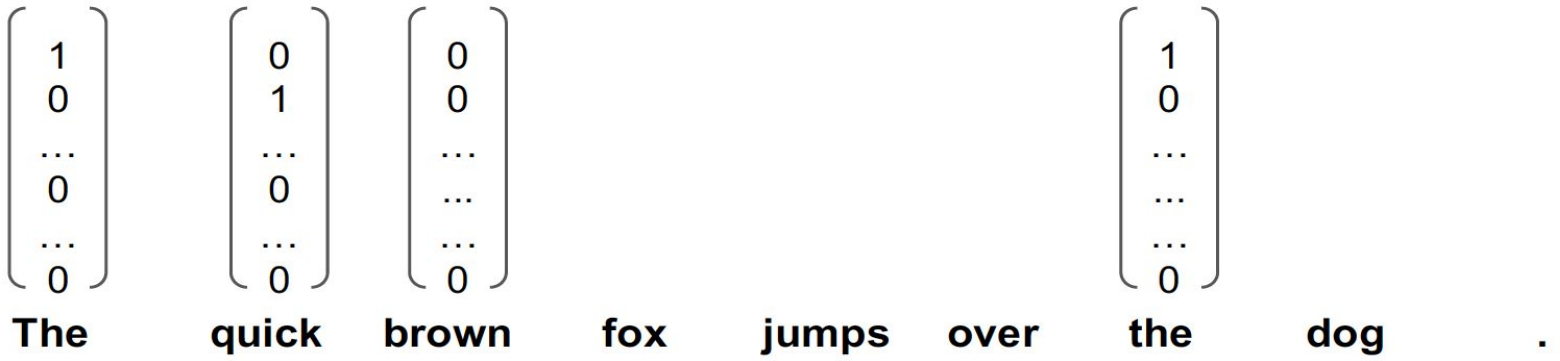

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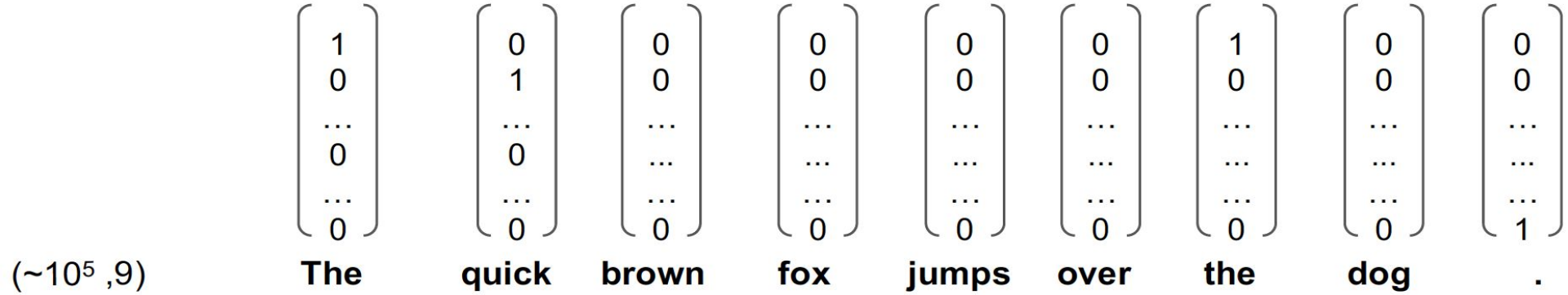

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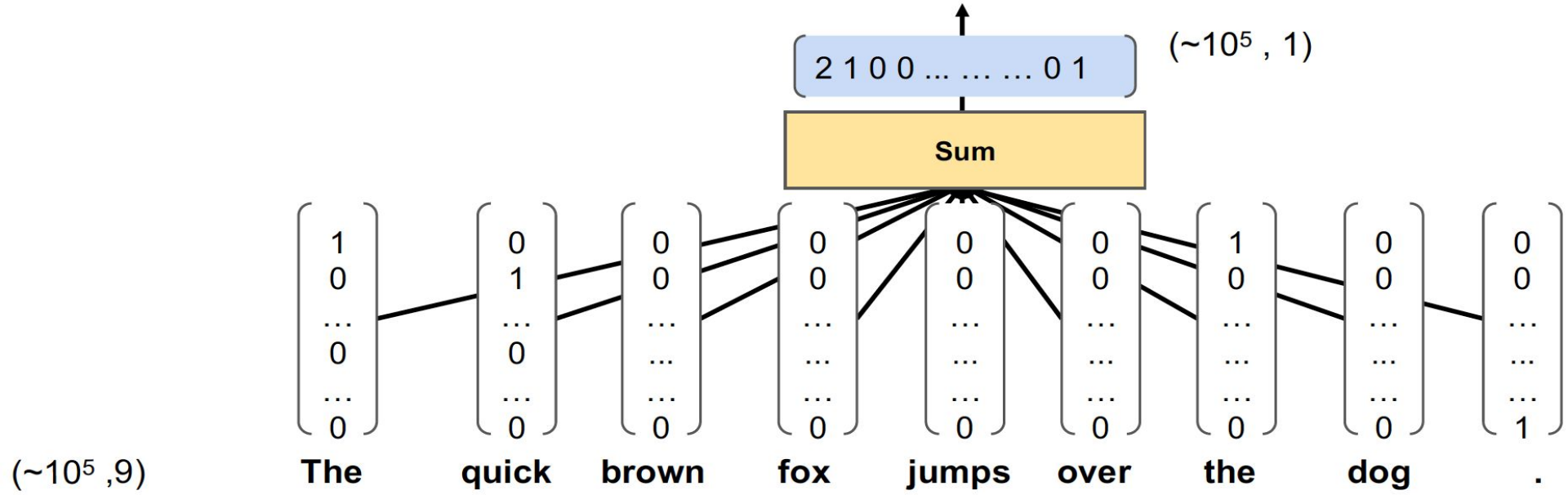

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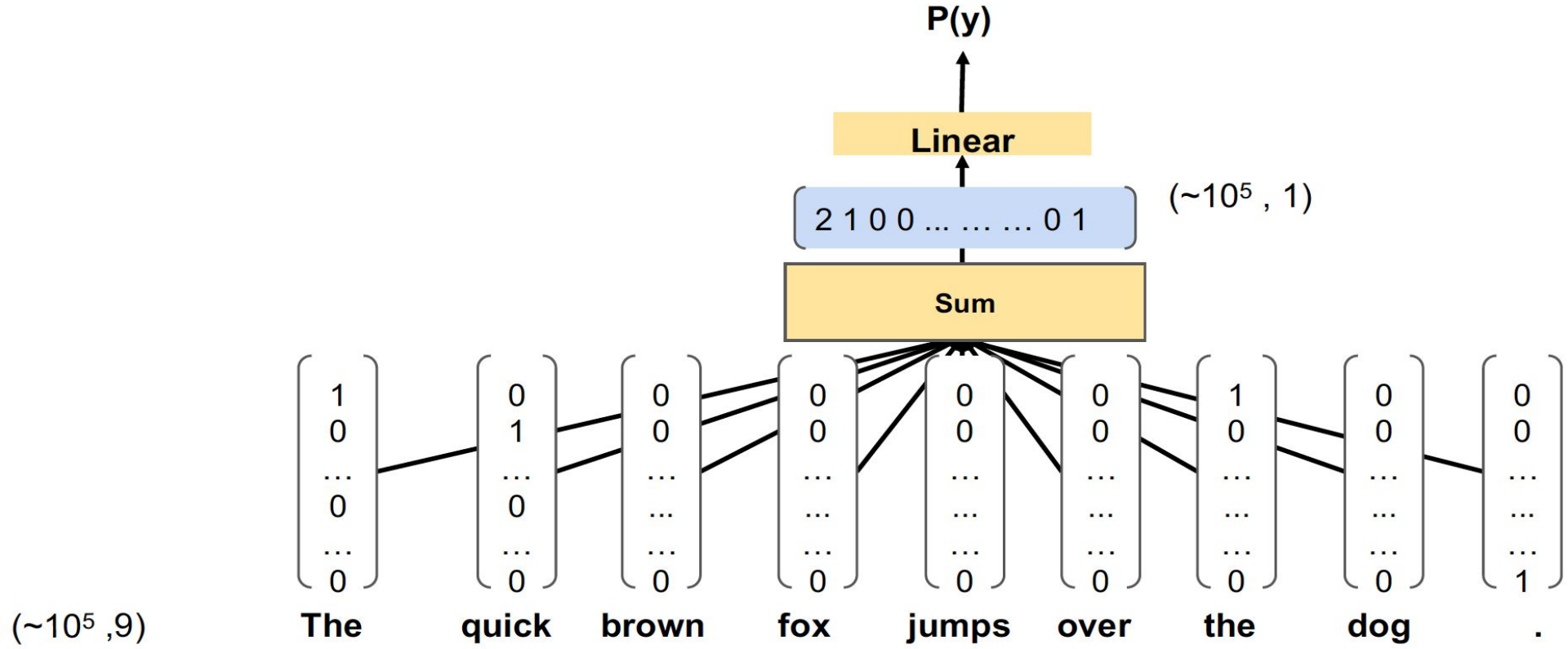
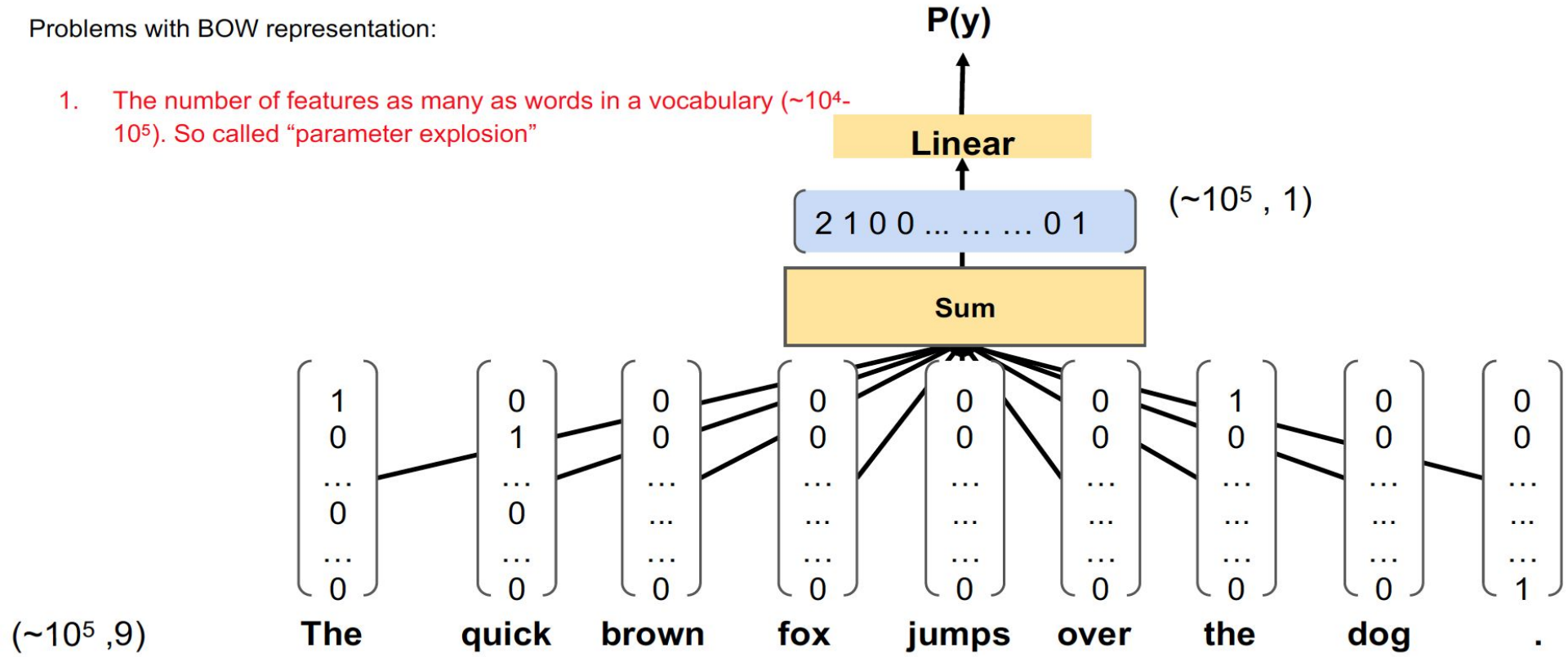


Sparse Text Representation: BOW

Problems with BOW representation:

1. The number of features as many as words in a vocabulary (~10^4-10^5). So called “parameter explosion”



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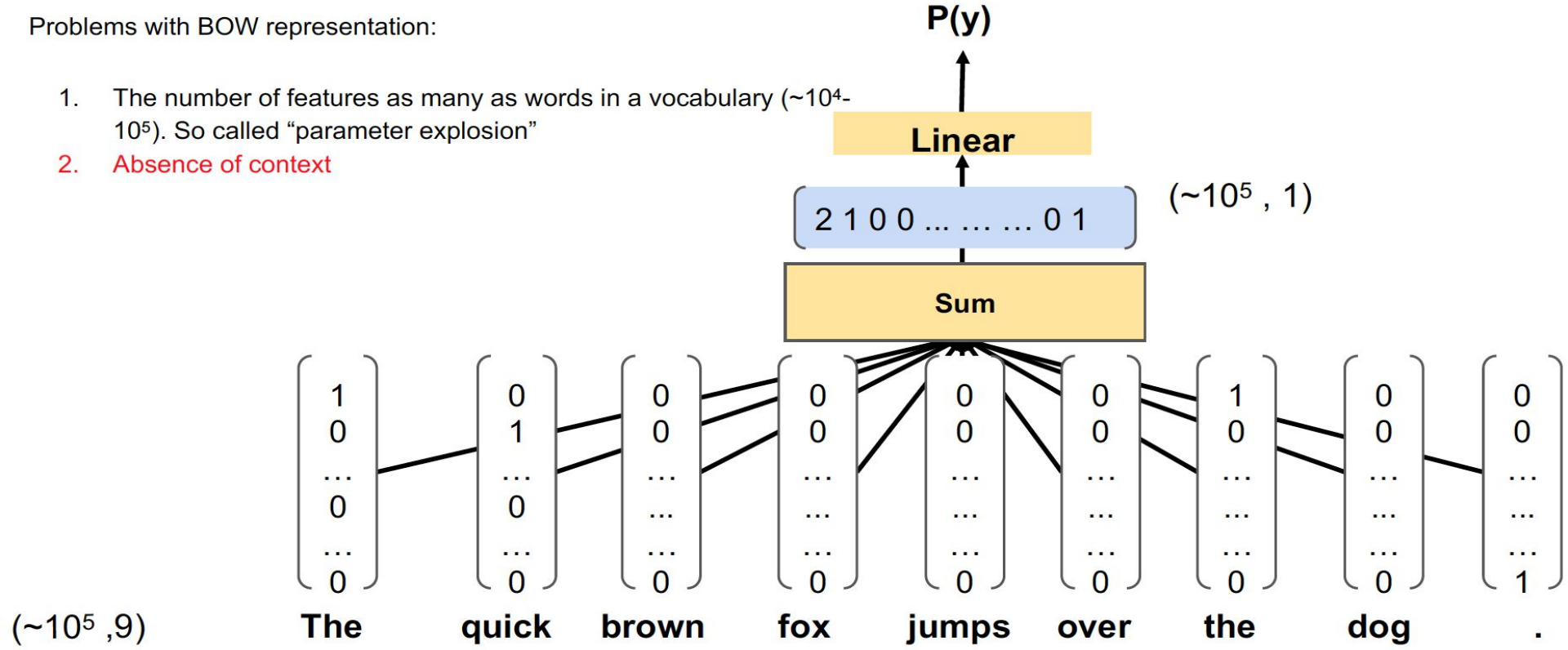

Sparse Text Representation: BOW

Problems with BOW representation:

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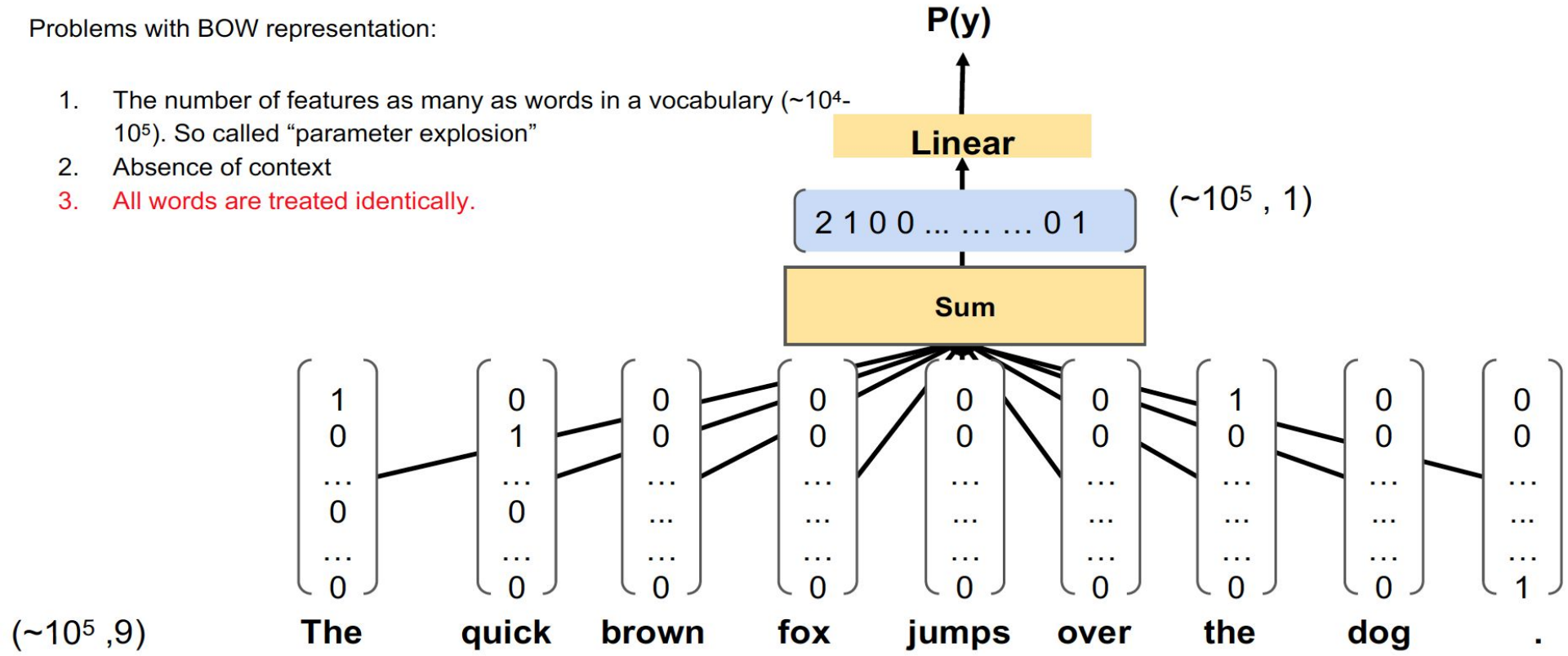
3. All words are treated identically.

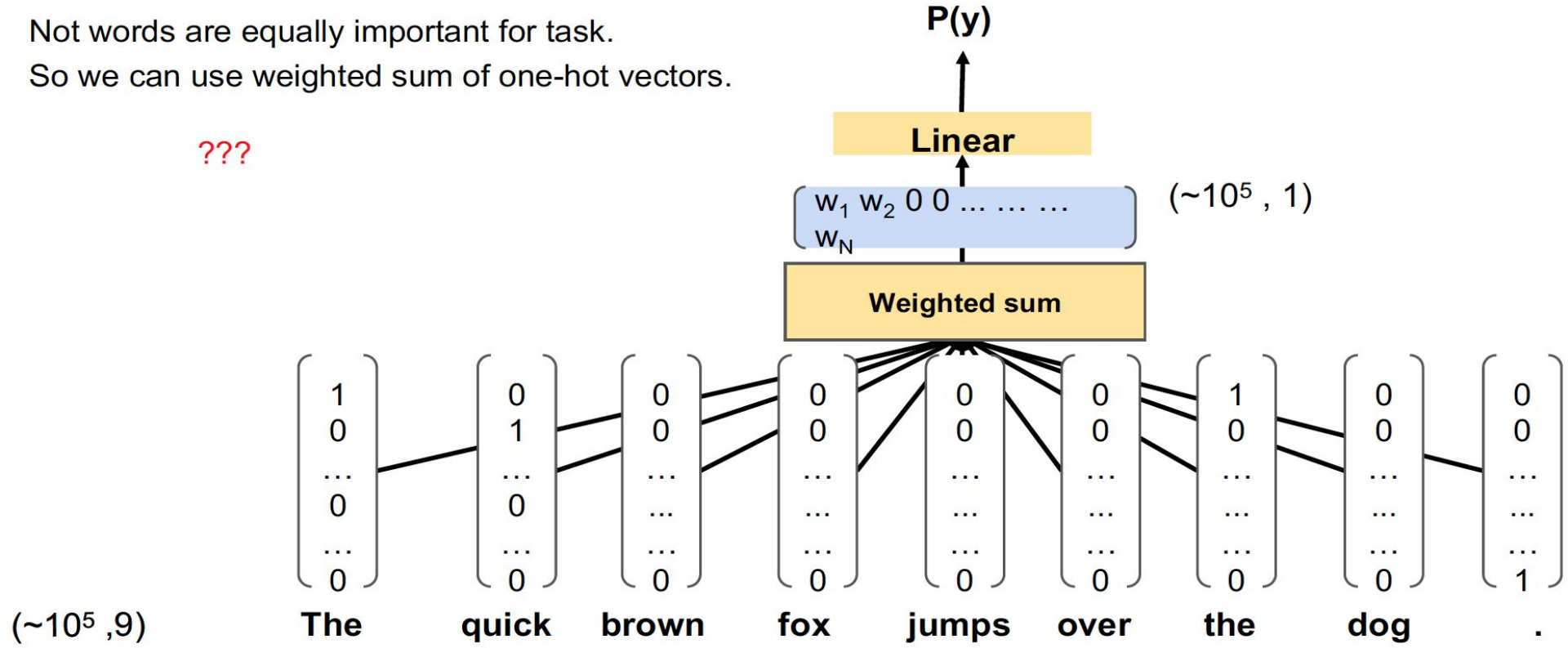


Weighting techniques for BOW

Not words are equally important for task.

So we can use weighted sum of one-hot vectors.

???



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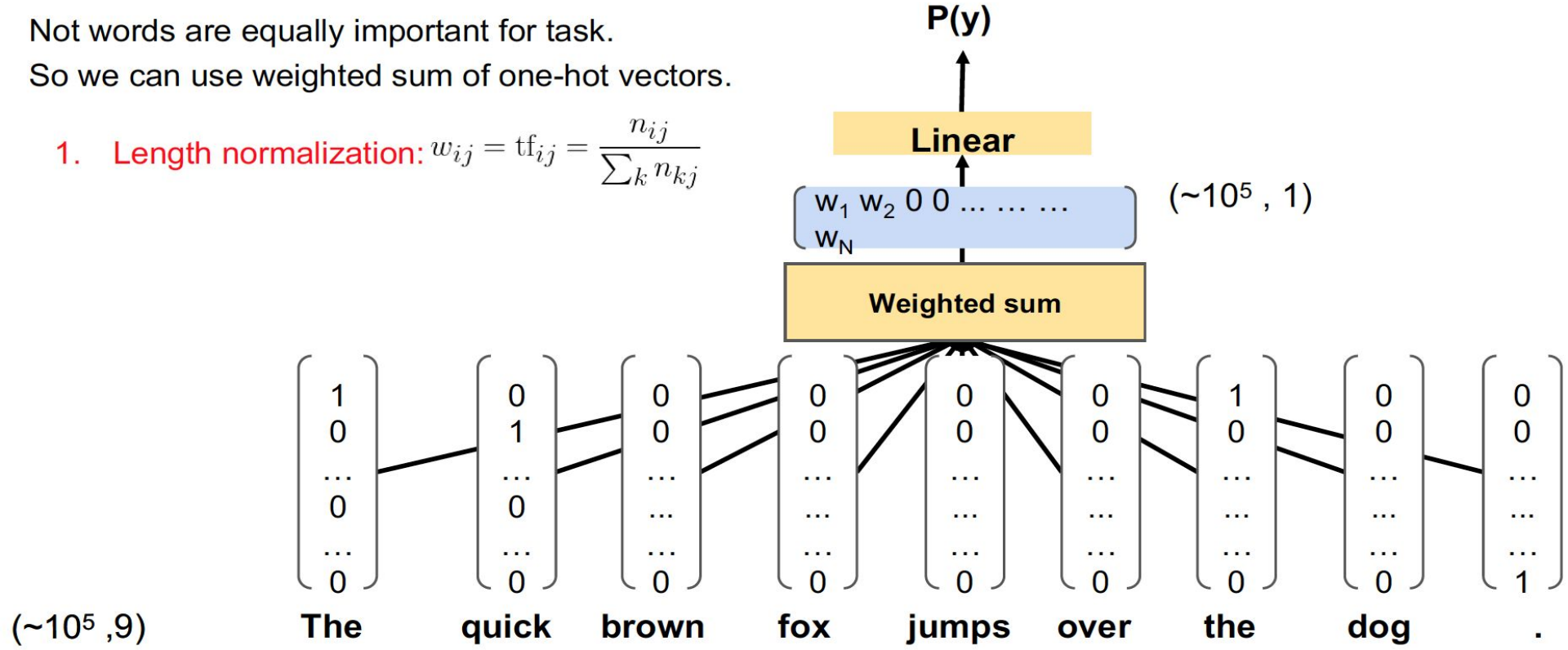

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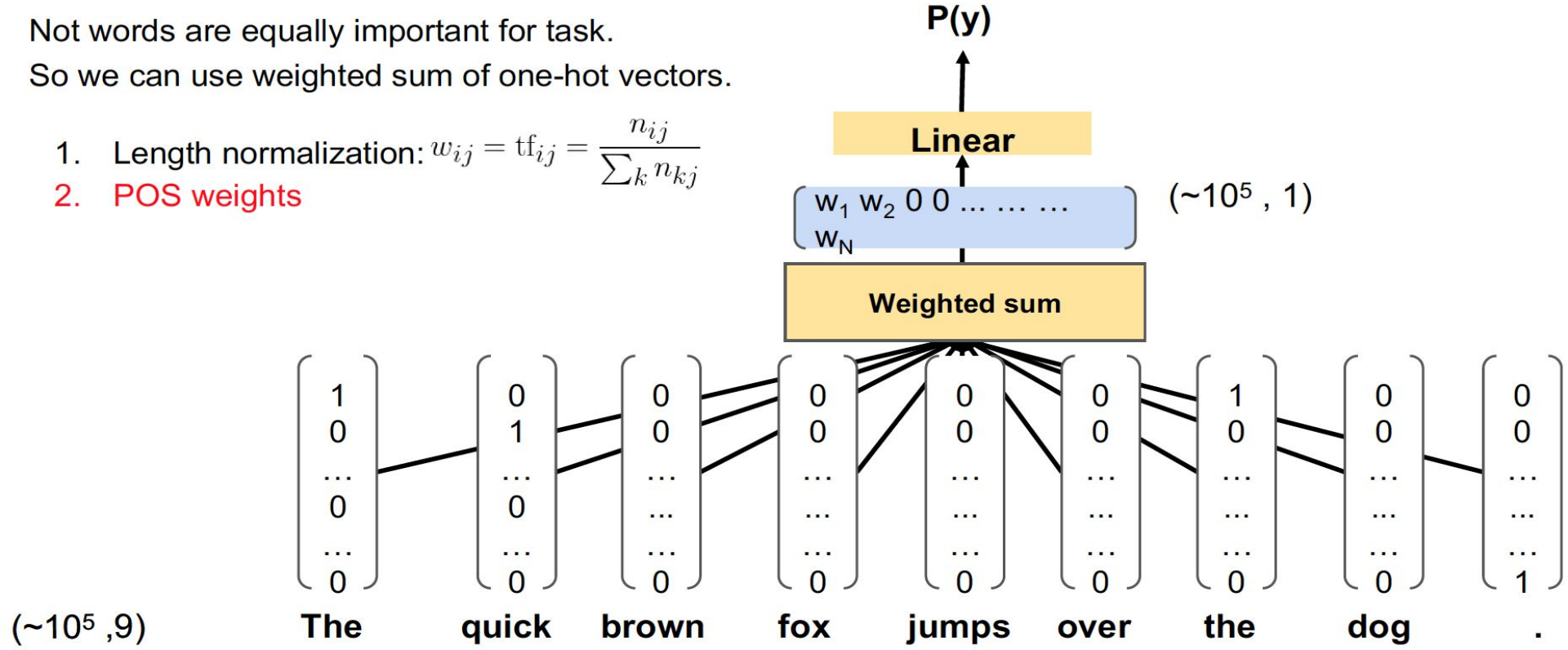

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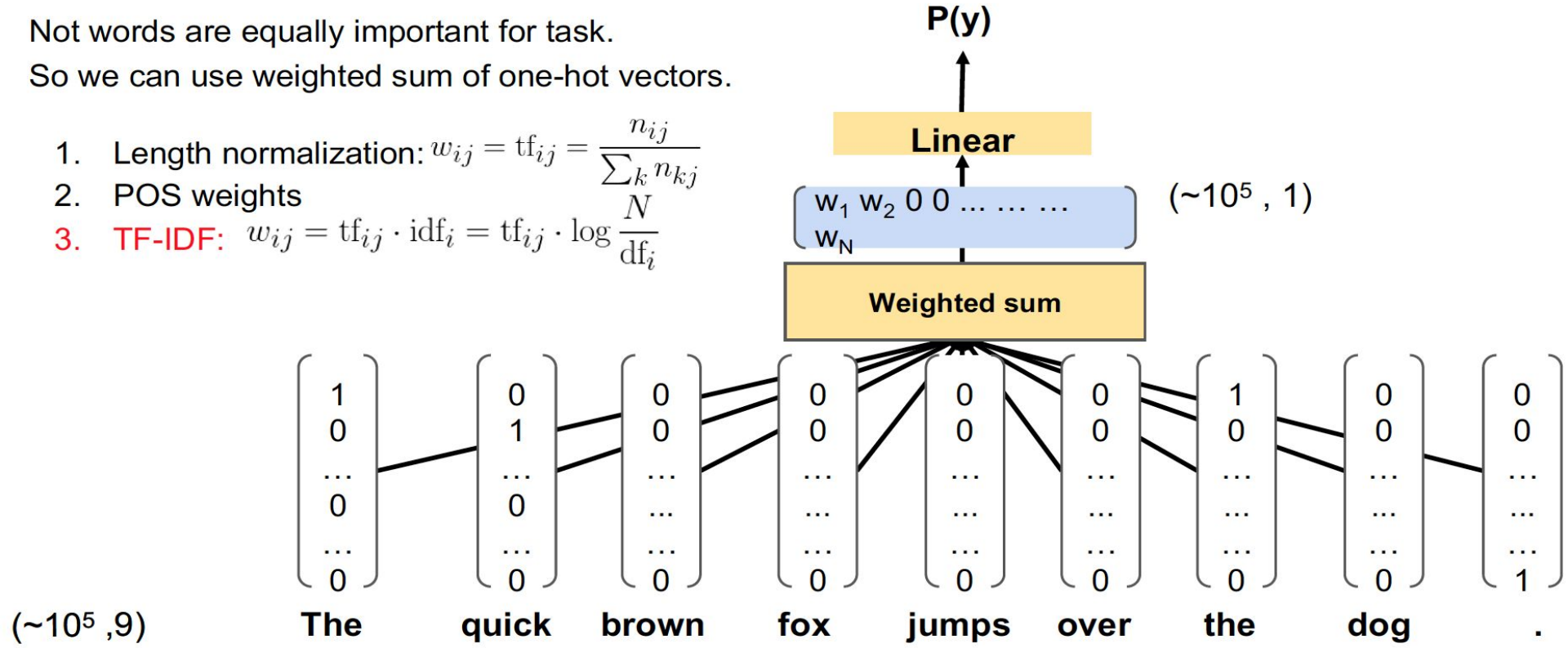
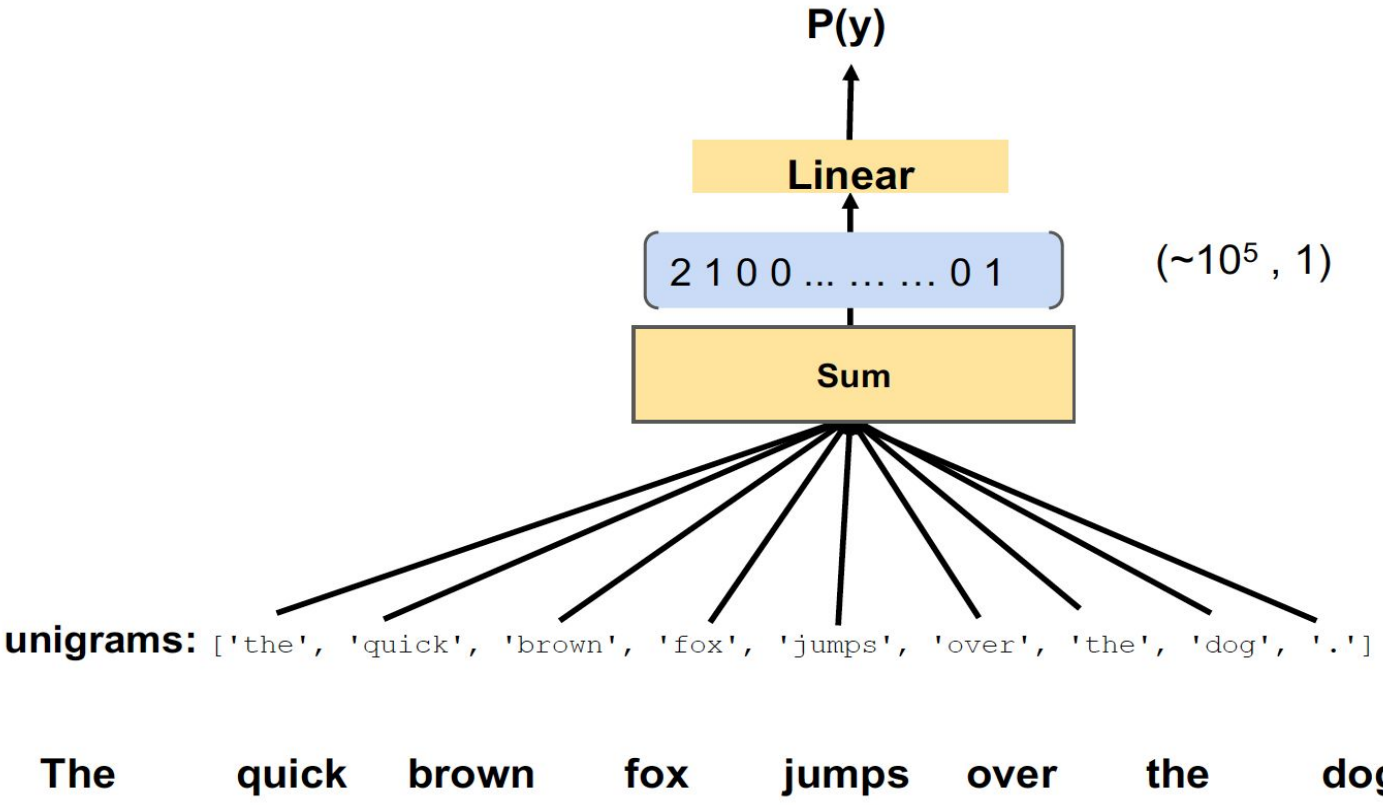
3. TF-IDF: $w_{ij} = \mathrm{tf}_{ij} \cdot \mathrm{idf}_i = \mathrm{tf}_{ij} \cdot \log \frac{N}{\mathrm{df}_i}$

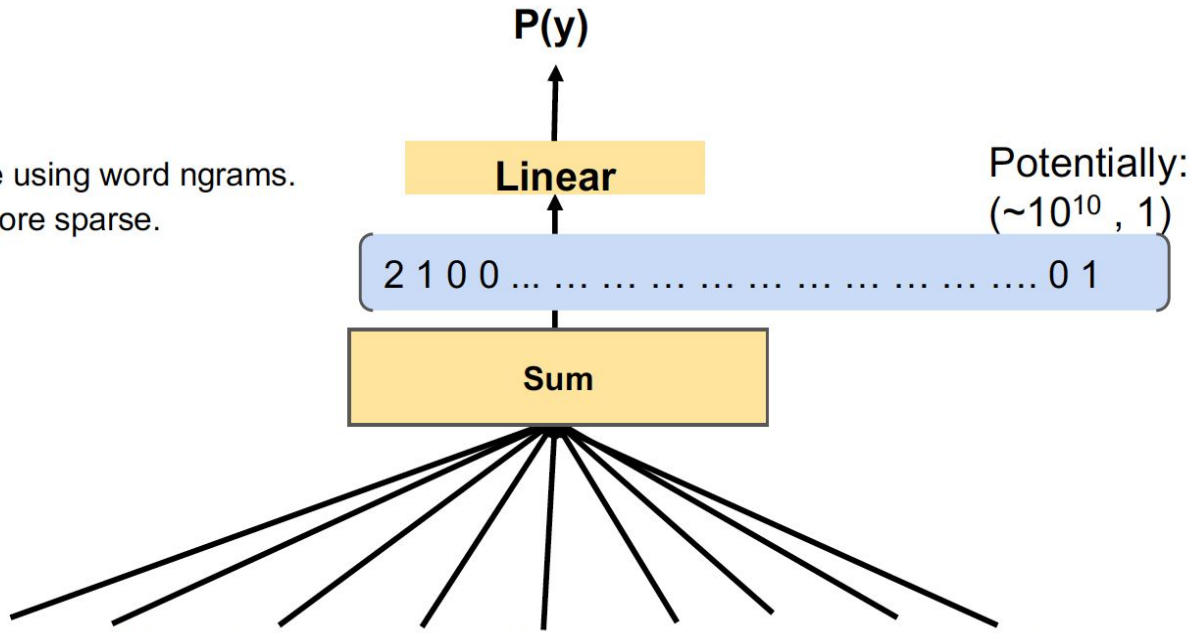


Context Importance



Context Importance

We can improve BOW context usage using word ngrams.
But it makes a feature space even more sparse.



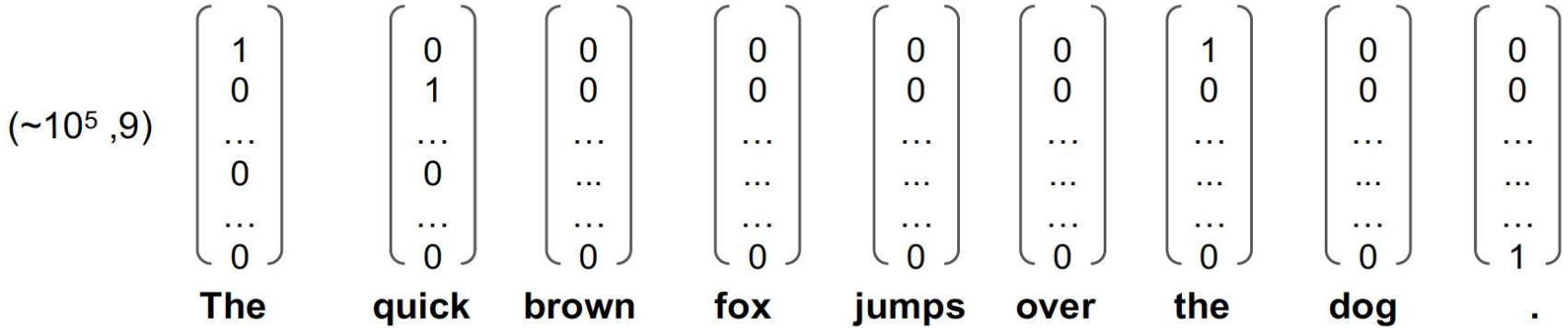
unigrams: `['the', 'quick', 'brown', 'fox', 'jumps', 'over', 'the', 'dog', '.']`

bigrams: `['the quick', 'quick brown', 'brown fox', 'fox jumps', 'jumps over', 'over the', 'the dog', 'dog .']`

The quick brown fox jumps over the dog .

Dense Text Representation: NBOW

Instead of sparse one-hot encoding we can you use pre-trained word embeddings. It is so-called "**neural bag-of-words**".



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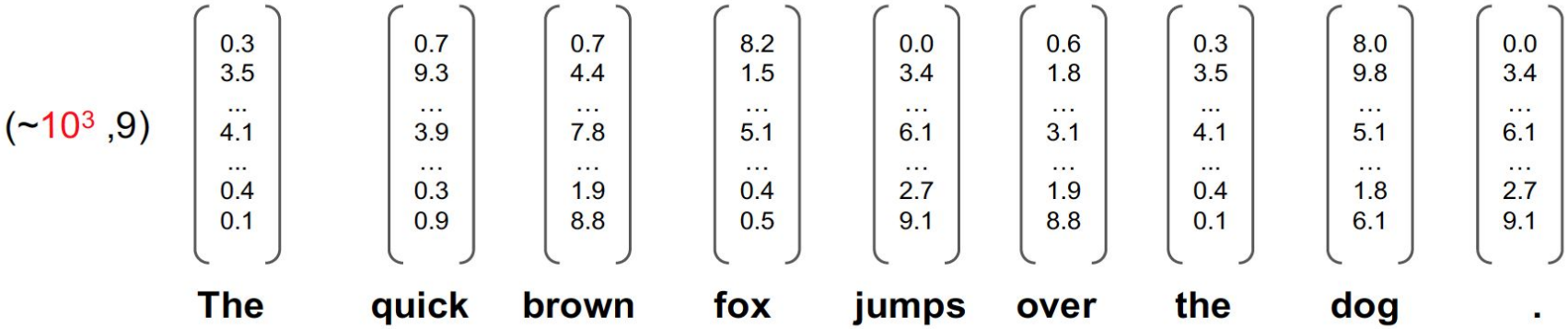

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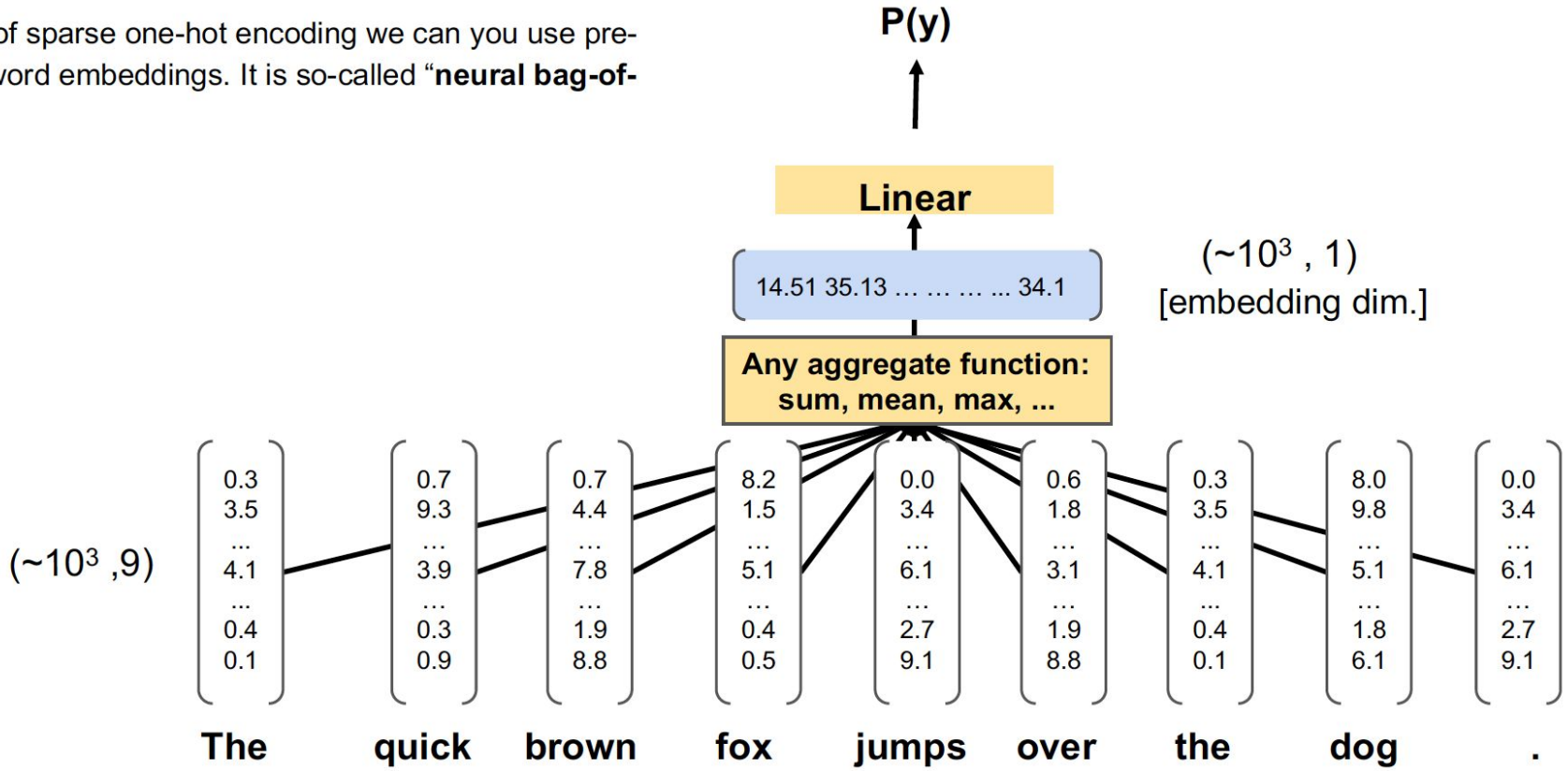

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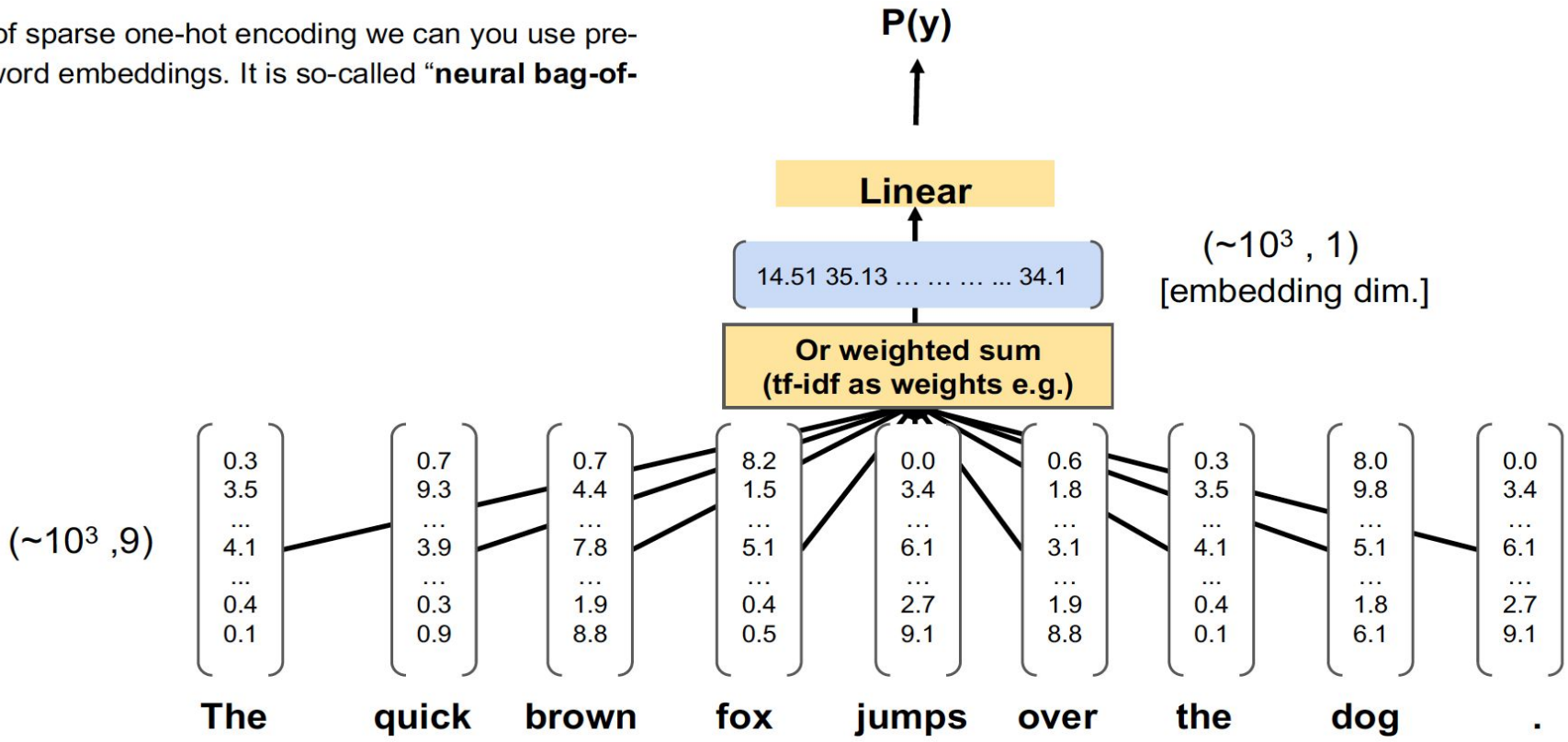

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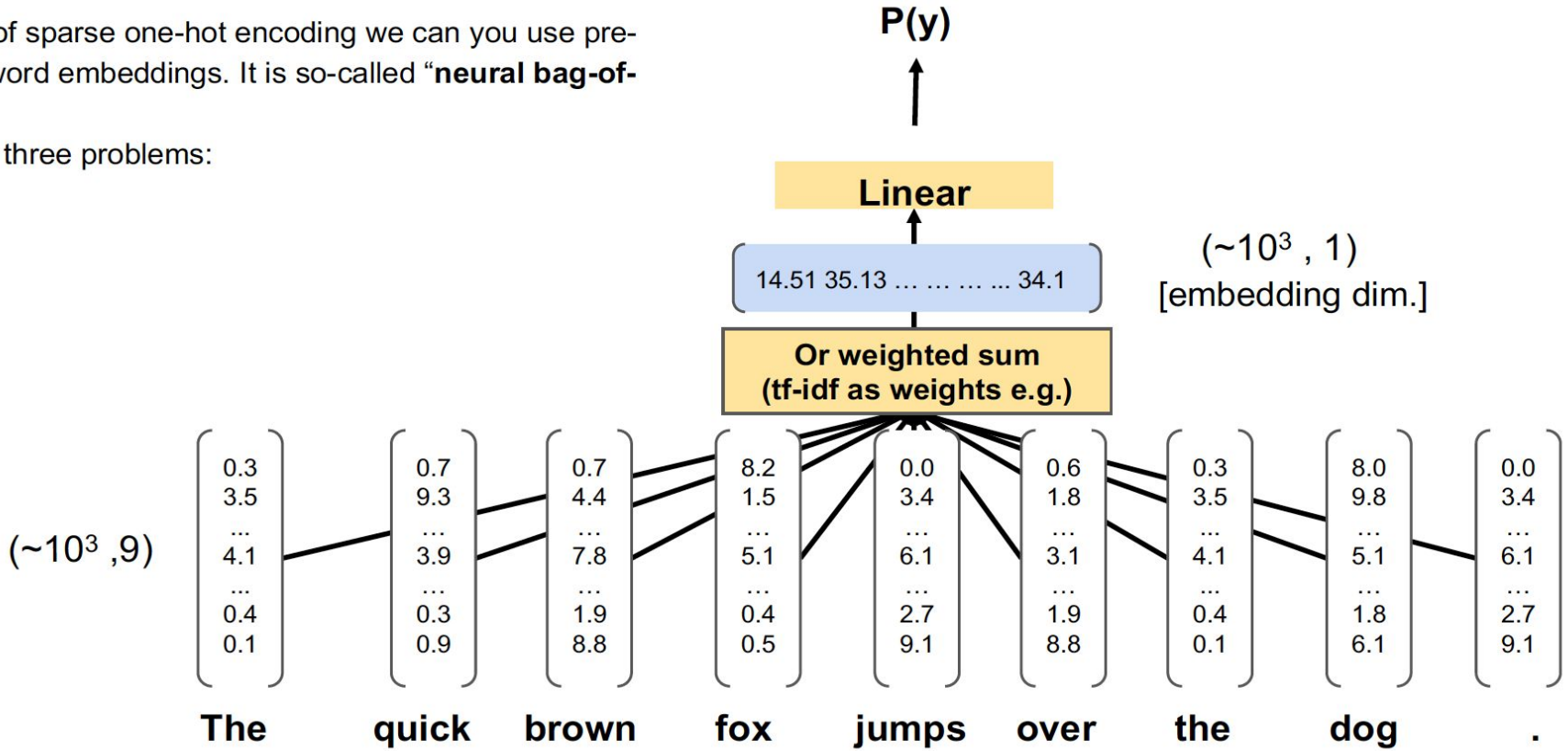

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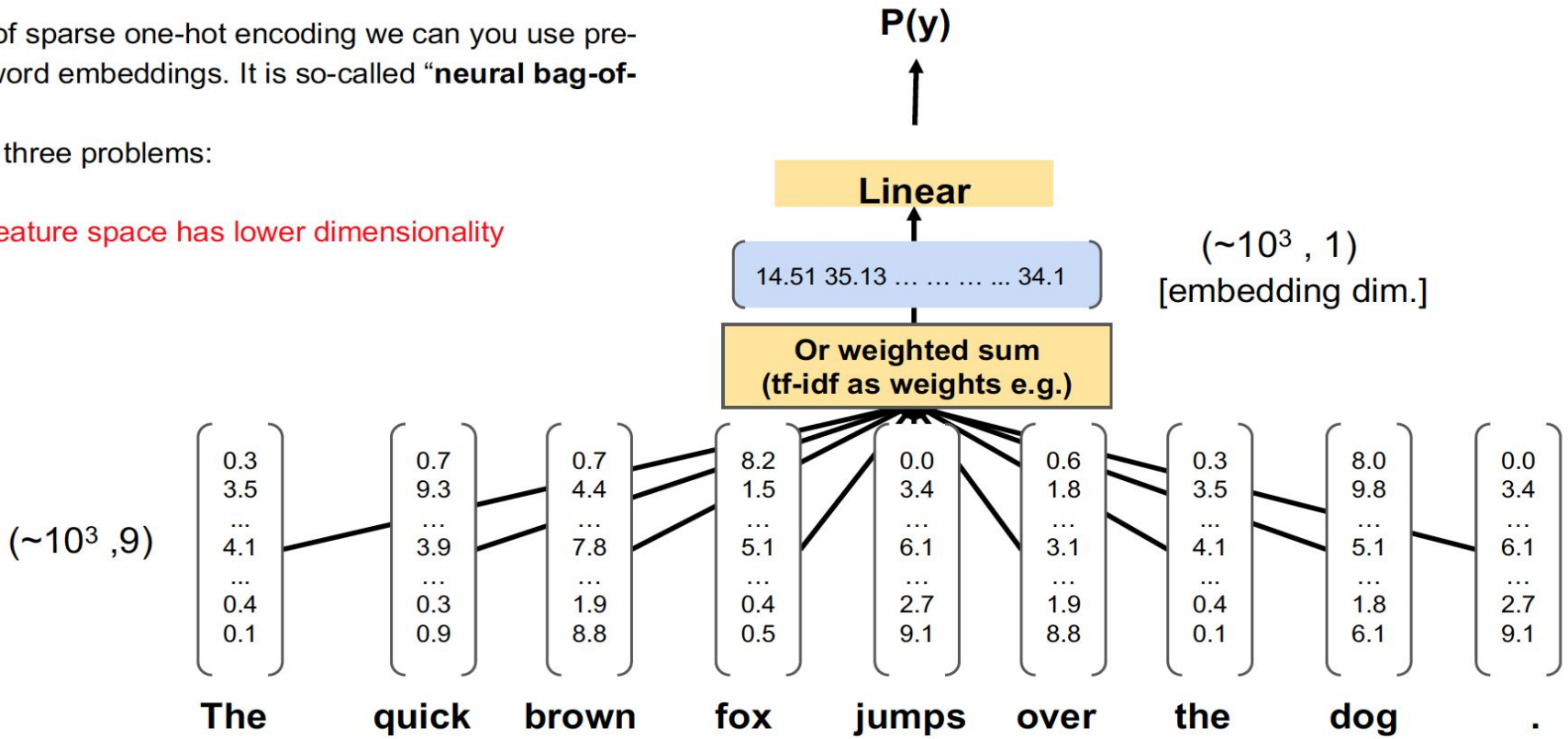

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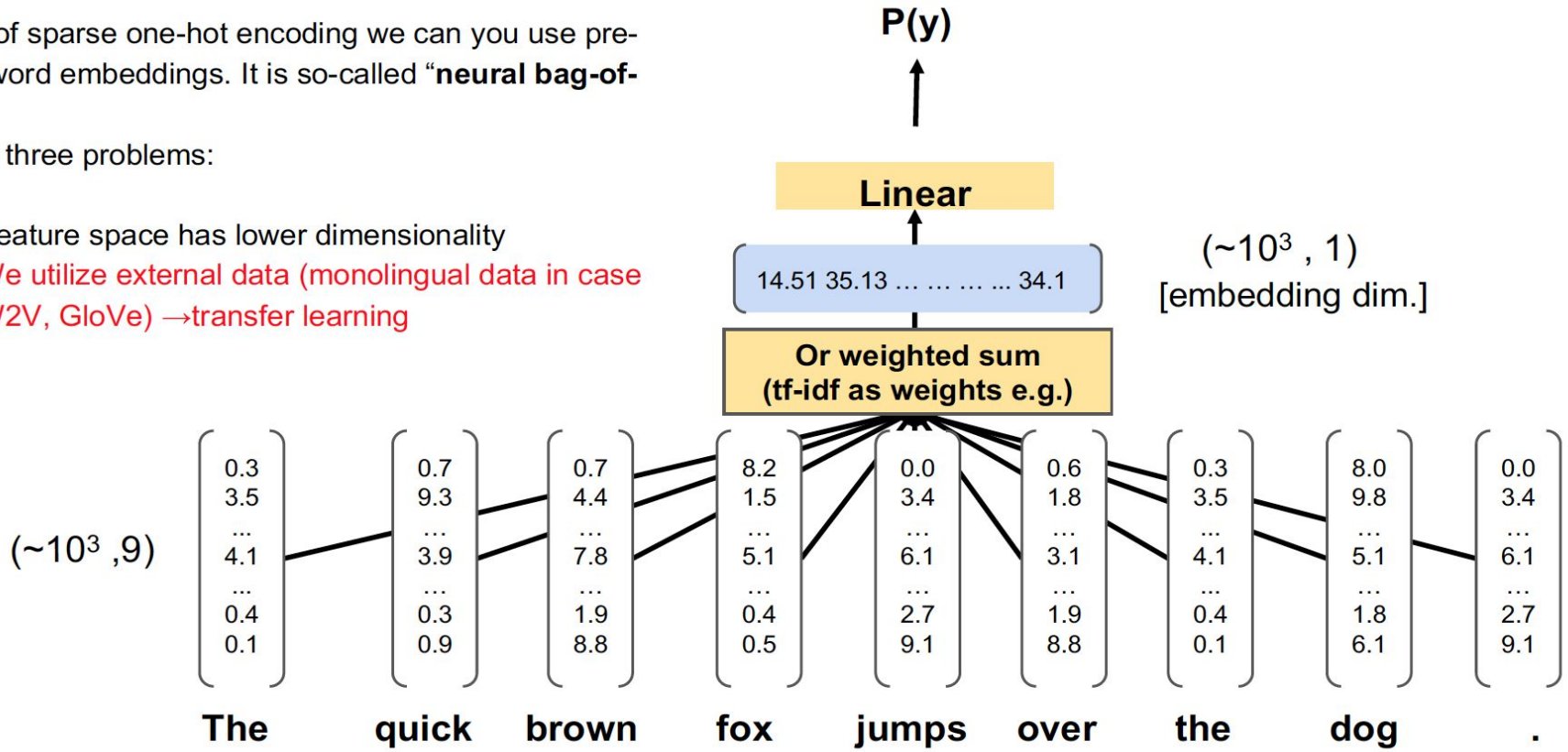

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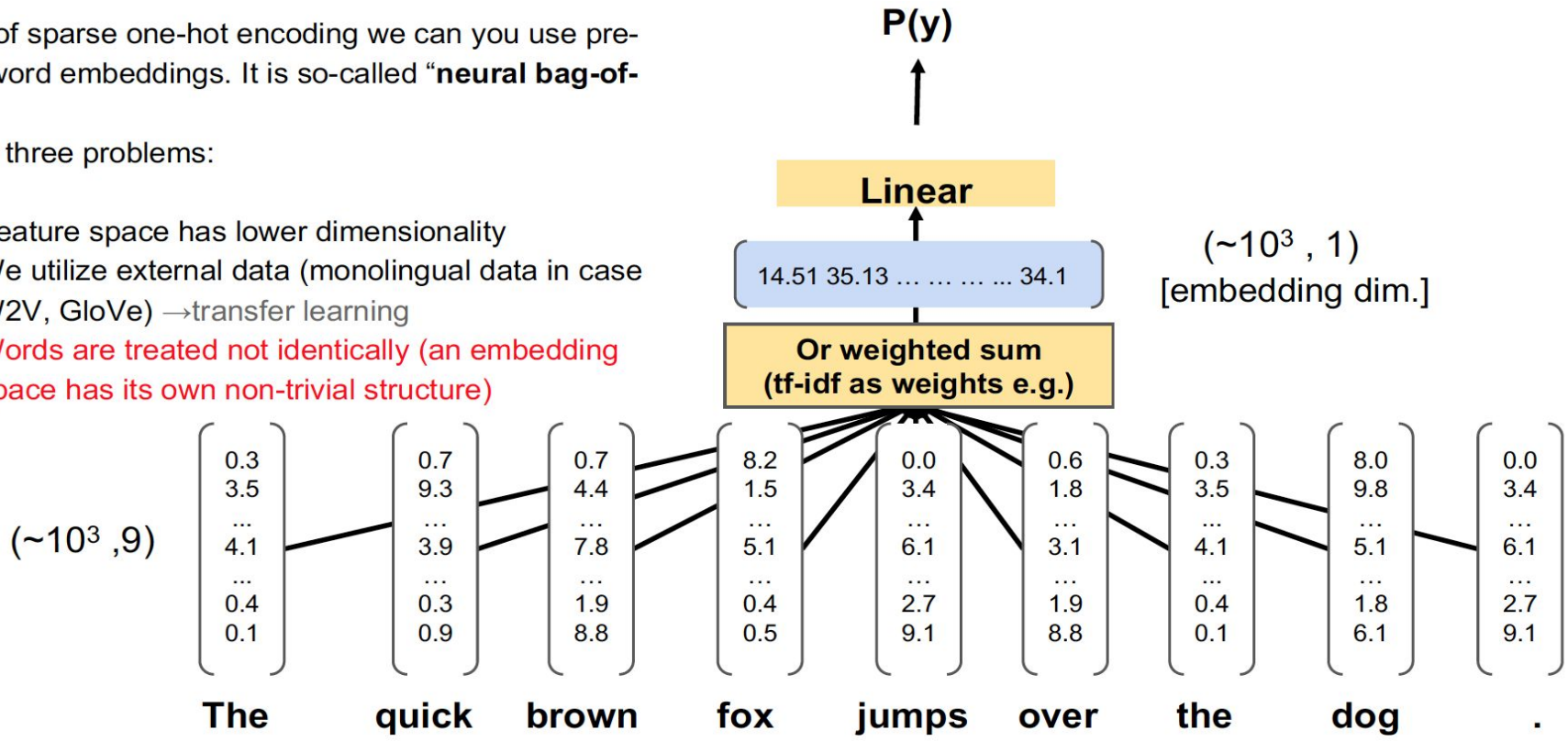

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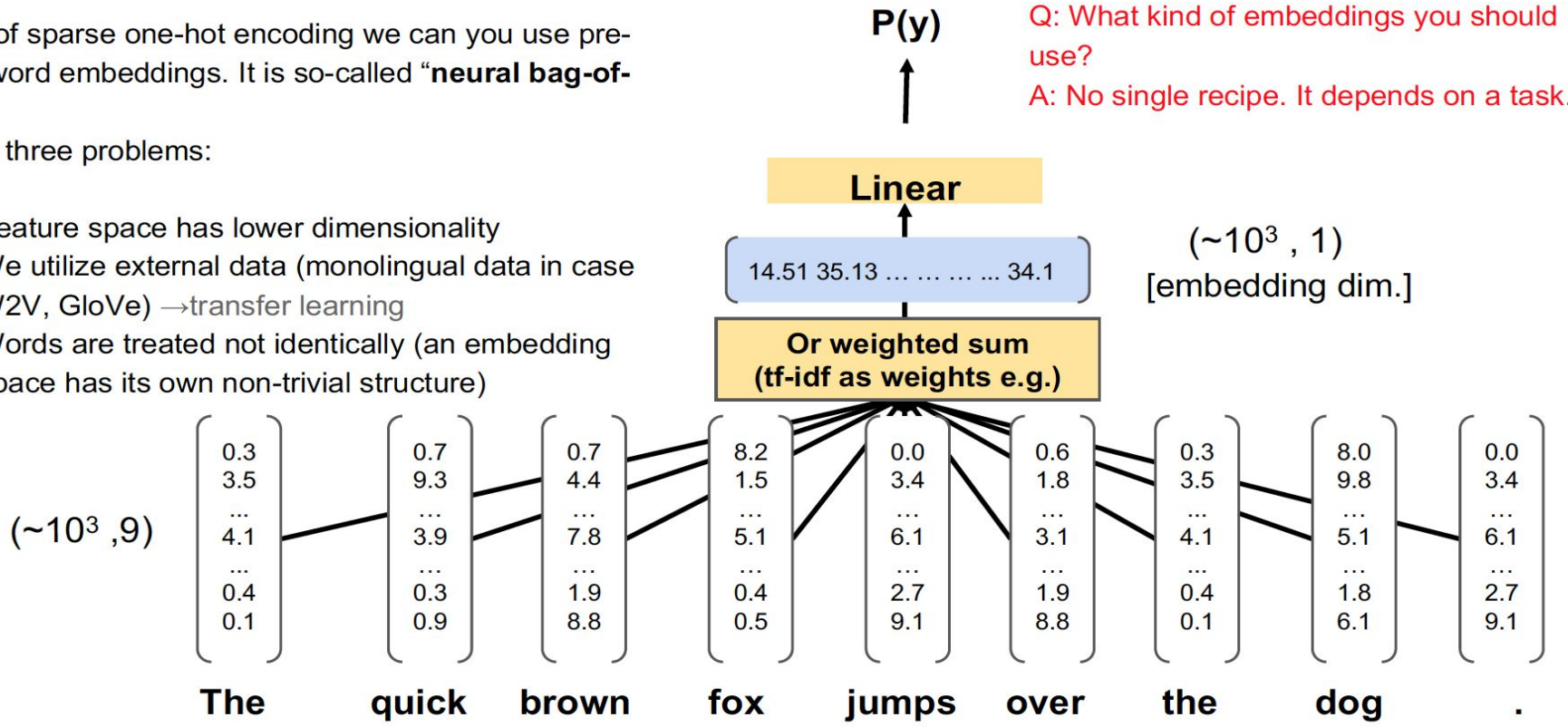

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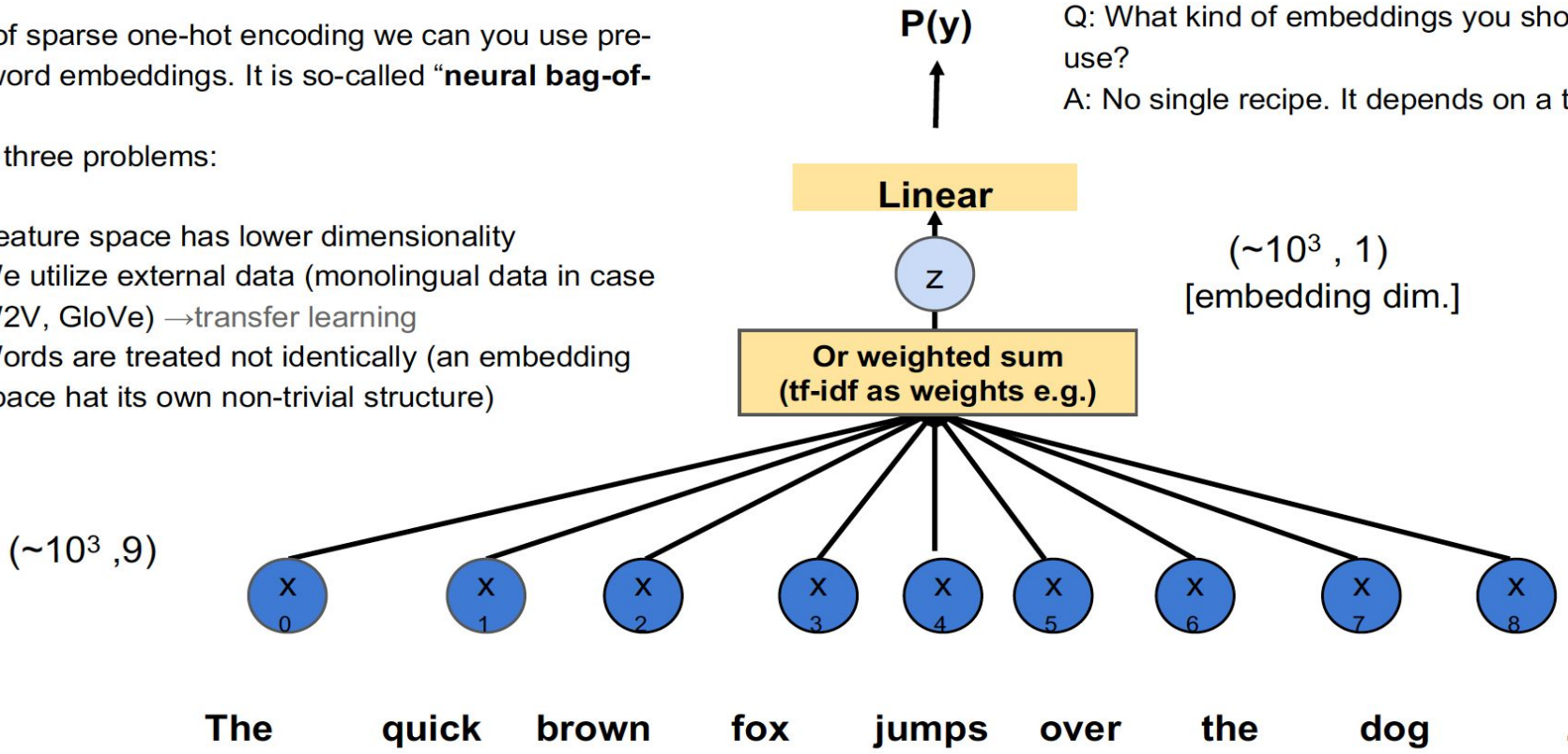


BOW and NBOW: the shared problems

1. The importance weights for the word vectors aren't defined fully.
2. The only way to use context for these models is to utilize word ngrams.

Hmm...

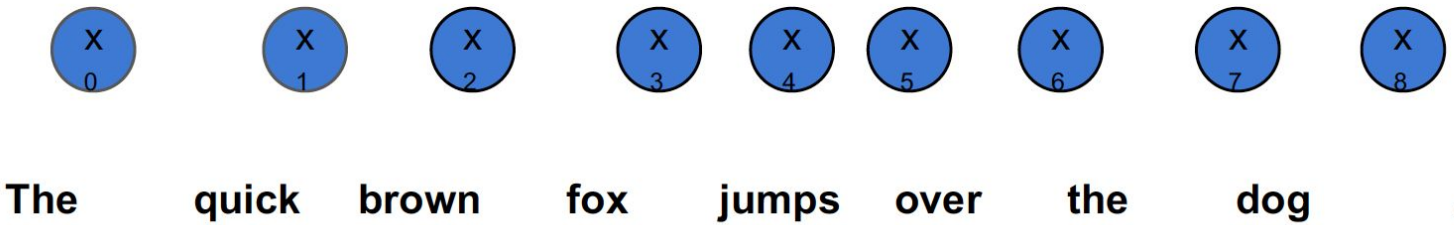
BOW and NBOW: the shared problems

1. The importance weights for the word vectors aren't defined fully.
2. The only way to use context for these models is to utilize word ngrams.

We can use a learnable aggregation function to overcome the difficulties.
The learnable function is a neural network (the universal approximator)

Multilayer perceptron

The simplest learnable aggregation function
is a multilayer perceptron (stacked dense layers).



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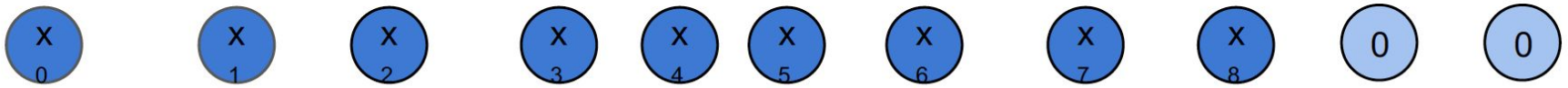

(~10^3 , max_len)

The quick brown fox jumps over the dog . <PAD> <PAD>

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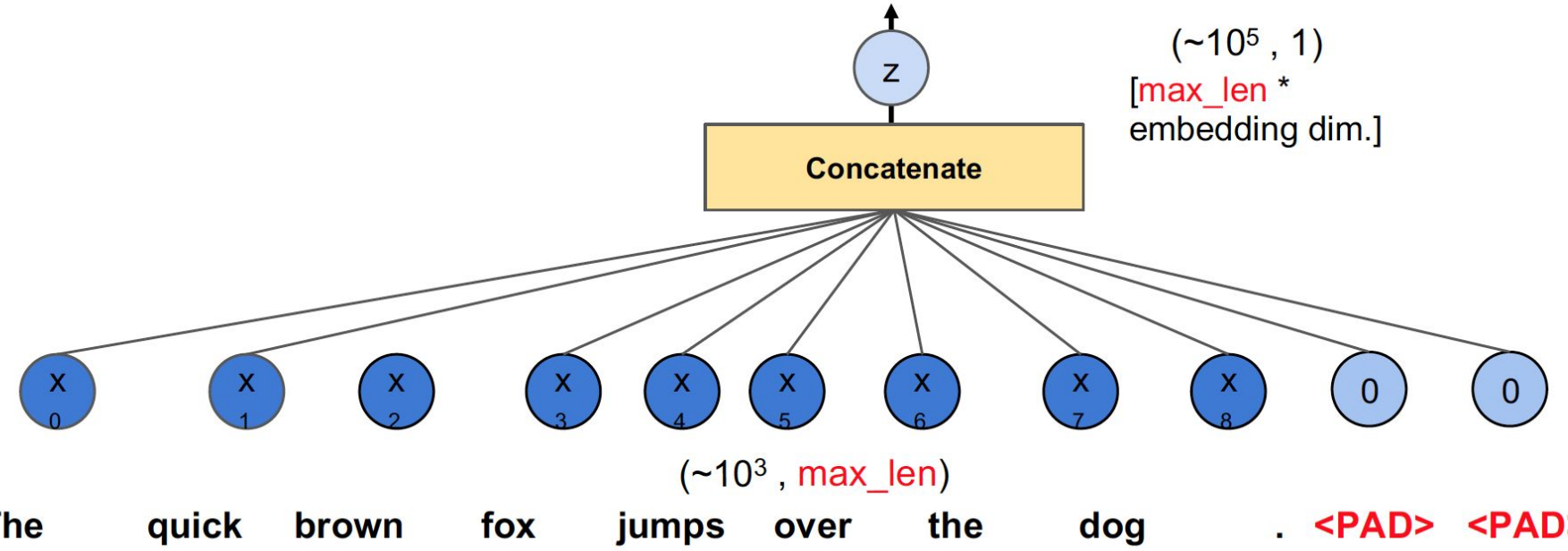

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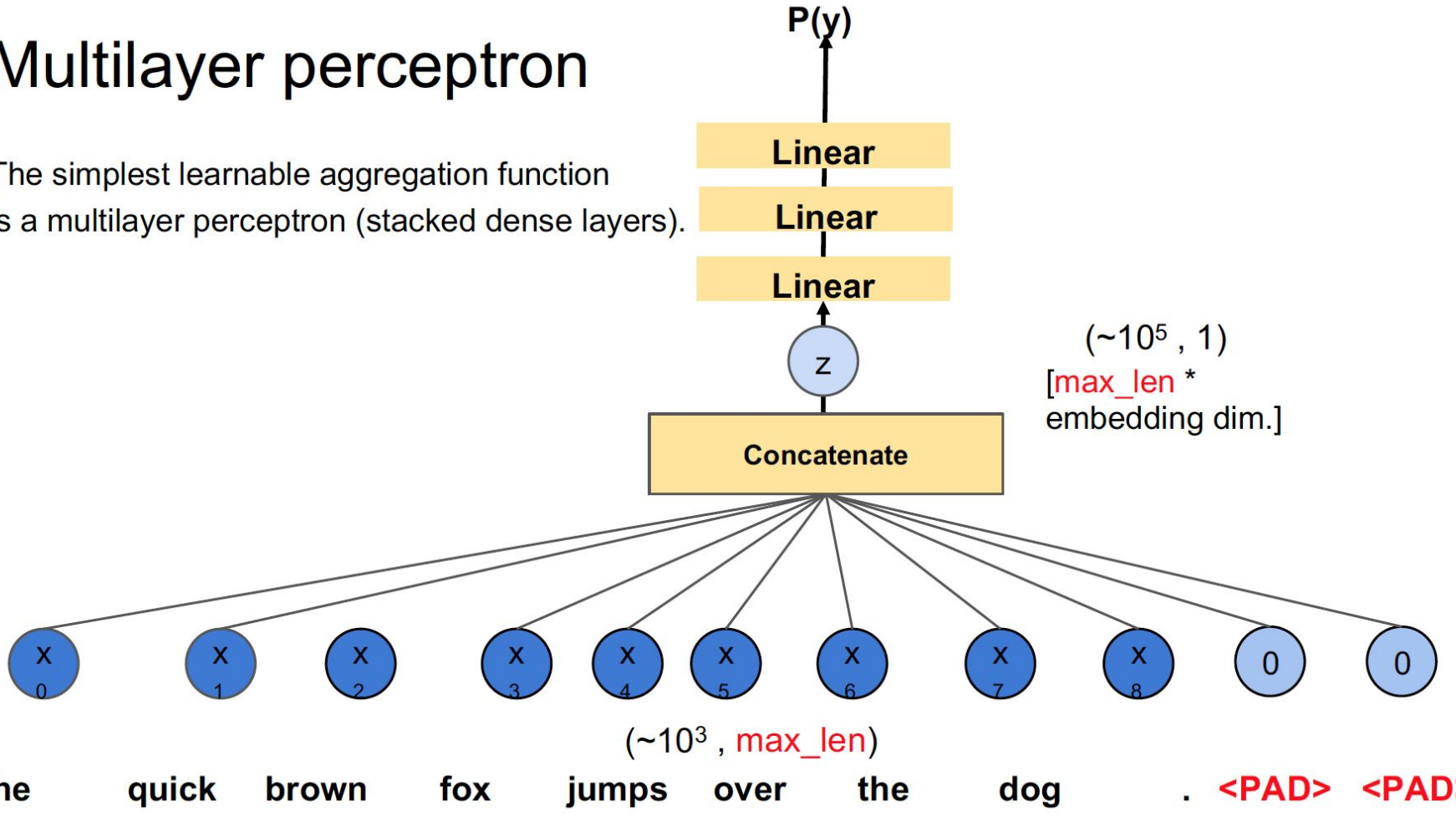

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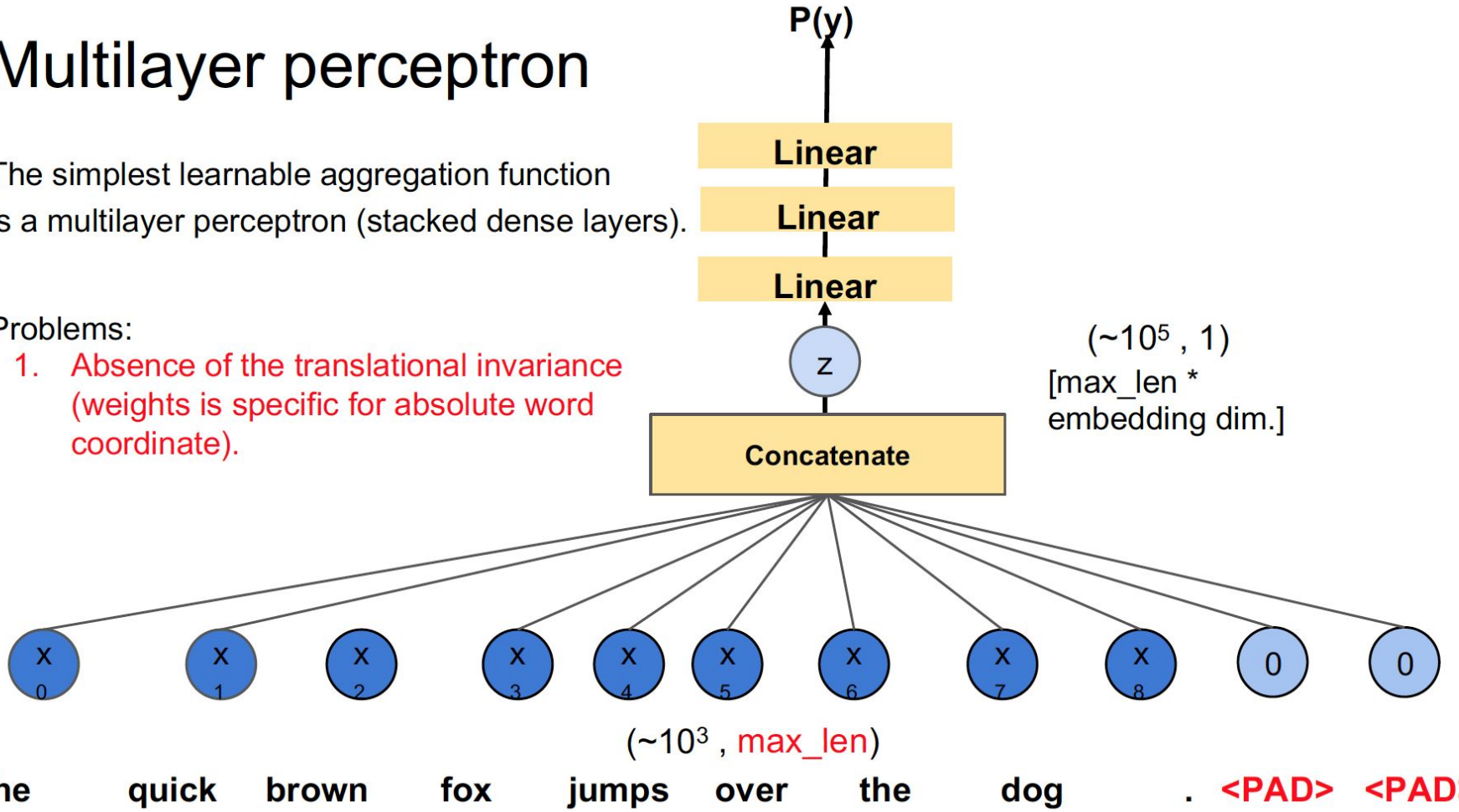

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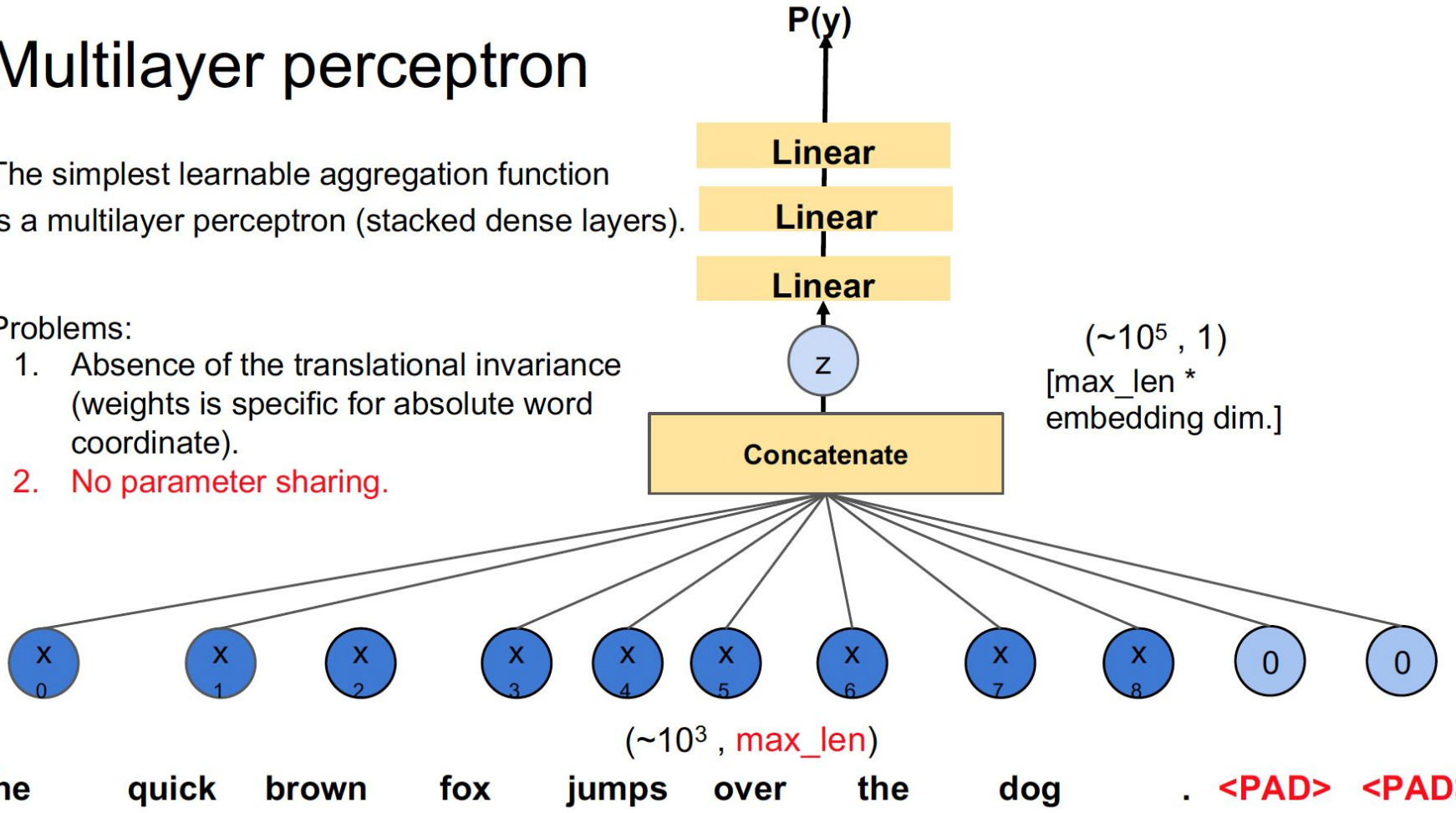
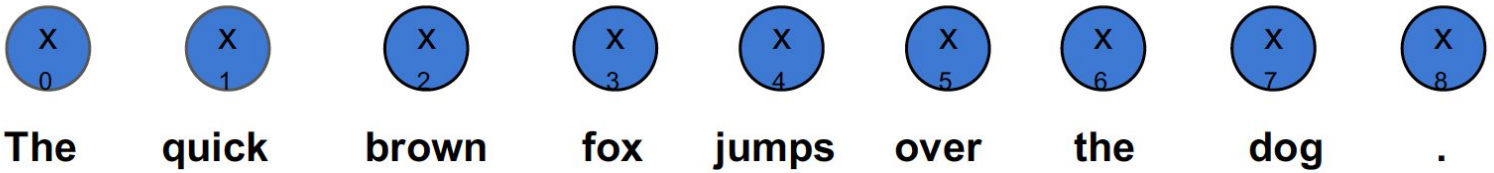
Problems:

1. Absence of the translational invariance (weights is specific for absolute word coordinate).
2. No parameter sharing.



Recurrent NN for text classification

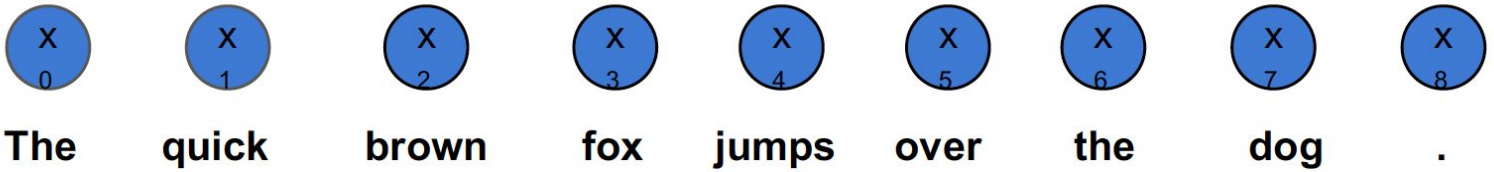
In a RNN Connections between nodes
form a directed graph along a sequence.



Recurrent NN for text classification

In a RNN Connections between nodes
form a directed graph along a sequence.

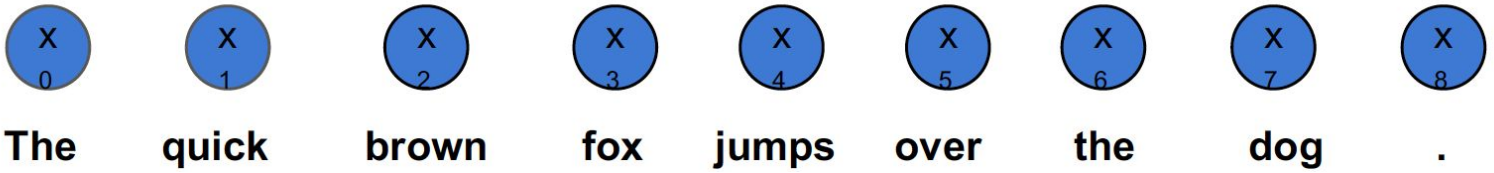
There are different types of recurrent units:
vanilla RNN, LSTM, GRU, MI-LSTM,
peephole LSTM, …
But it's not important this time.



Recurrent NN for text classification

In a RNN Connections between nodes
form a directed graph along a sequence.

$$\mathbf{h}_t = f_w(\mathbf{h}_{t-1}, \mathbf{x}_t)$$



Recurrent NN for text classification

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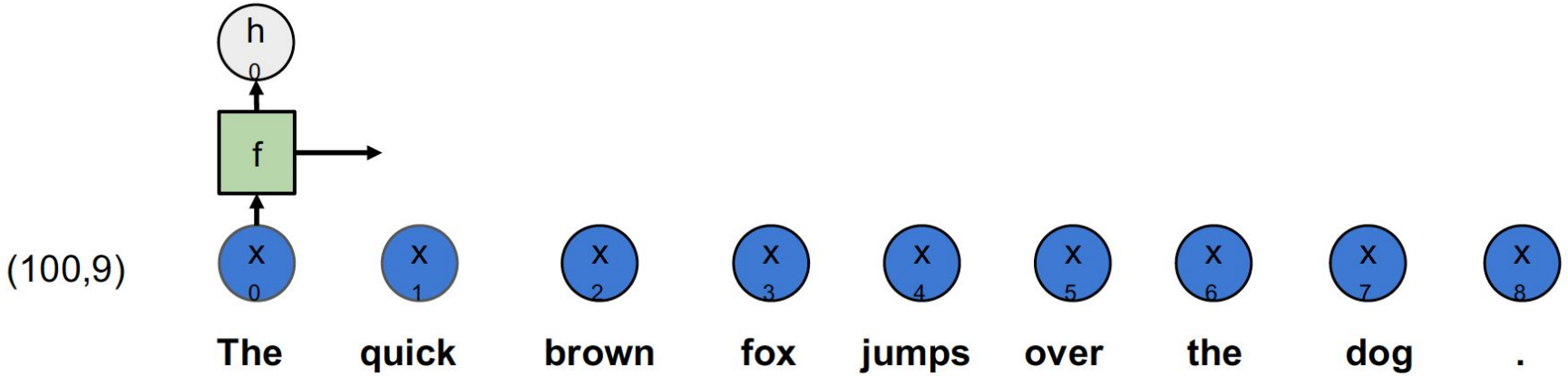

Recurrent NN for text classification

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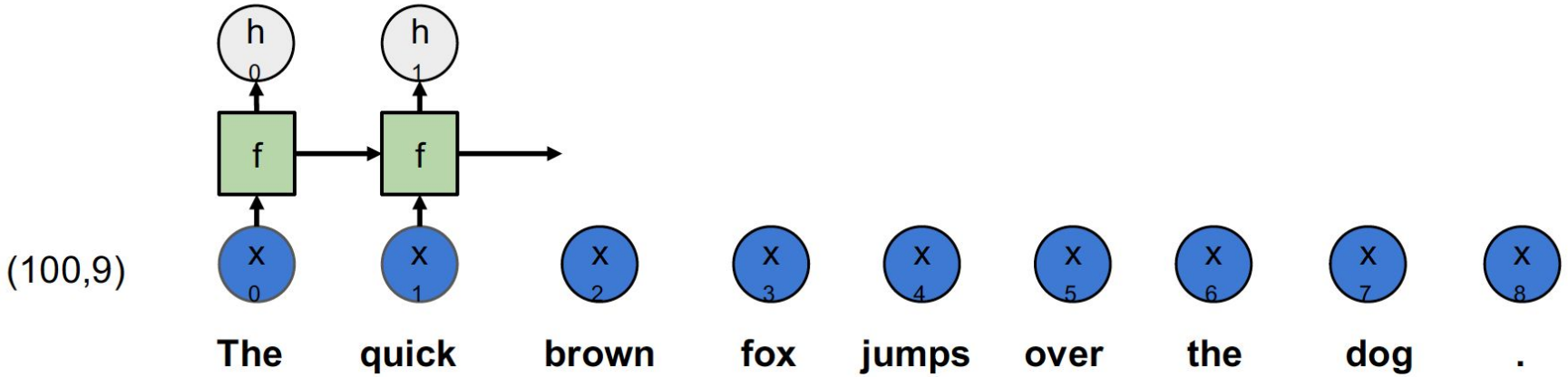

Recurrent NN for text classification

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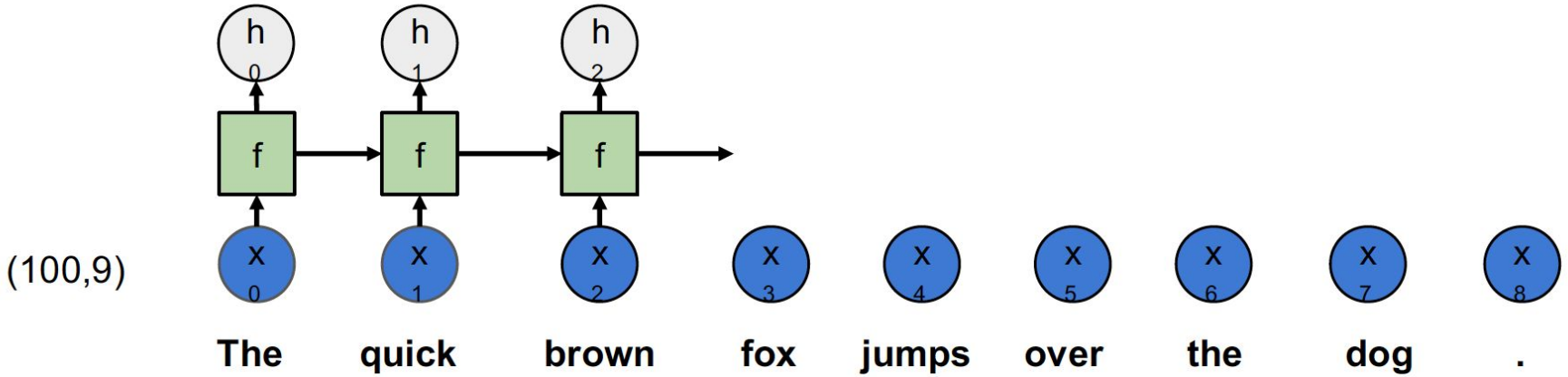

Recurrent NN for text classification

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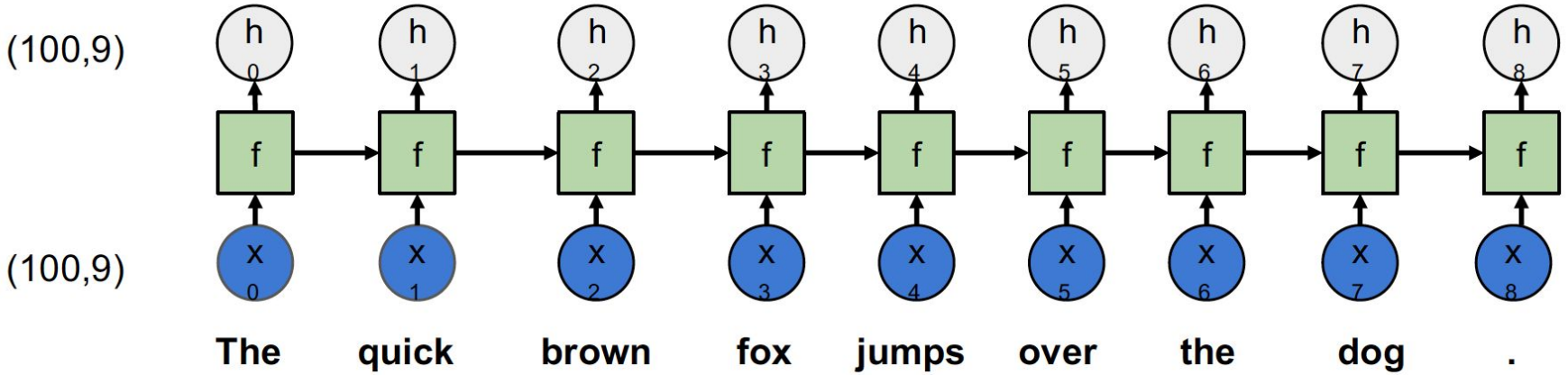
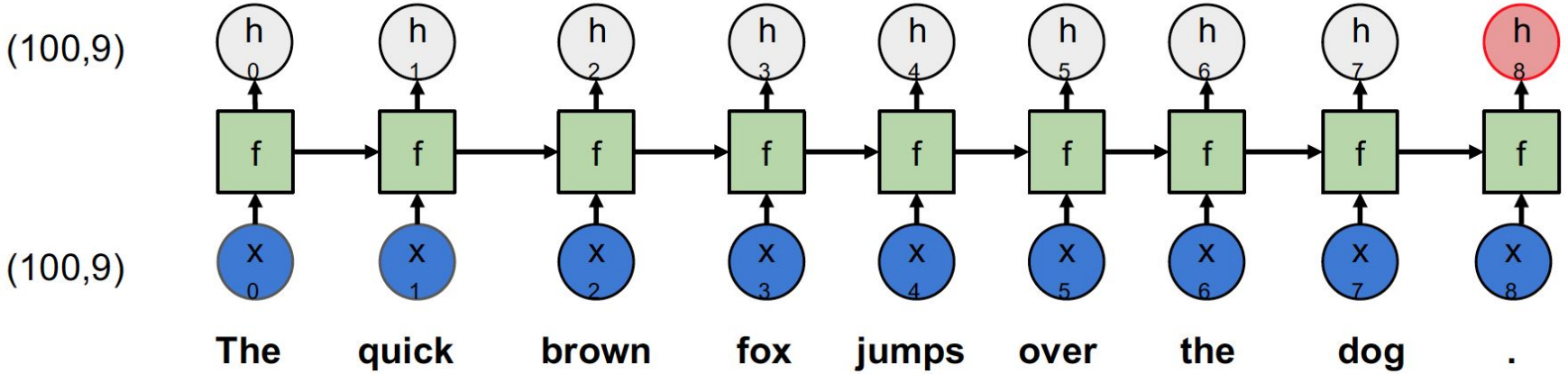


Recurrent NN for text classification

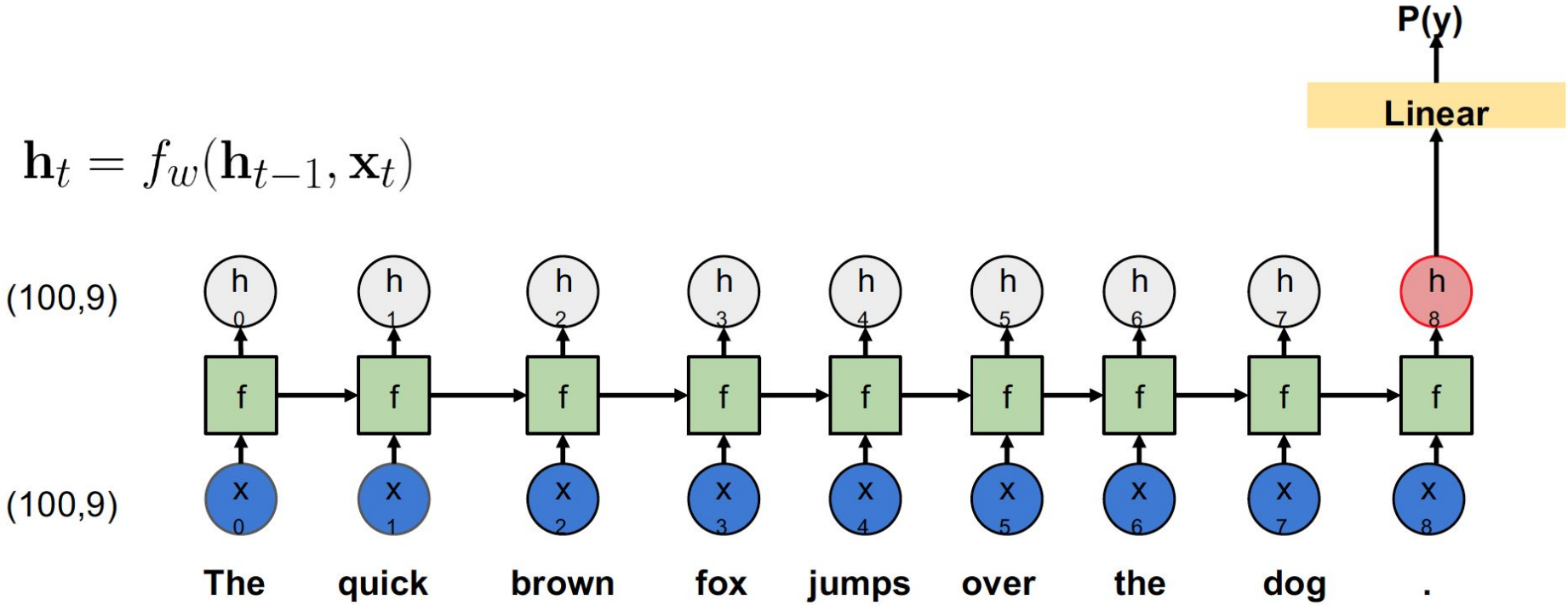
$$\mathbf{h}_8 = f(f(f(...(f(\mathbf{0}, \mathbf{x}_0)), \mathbf{x}_6), \mathbf{x}_7), \mathbf{x}_8)$$

$$\mathbf{h}_t = f_w(\mathbf{h}_{t-1}, \mathbf{x}_t)$$



Recurrent NN for text classification

$$\mathbf{h}_t = f_w(\mathbf{h}_{t-1}, \mathbf{x}_t)$$



Recurrent NN for text classification

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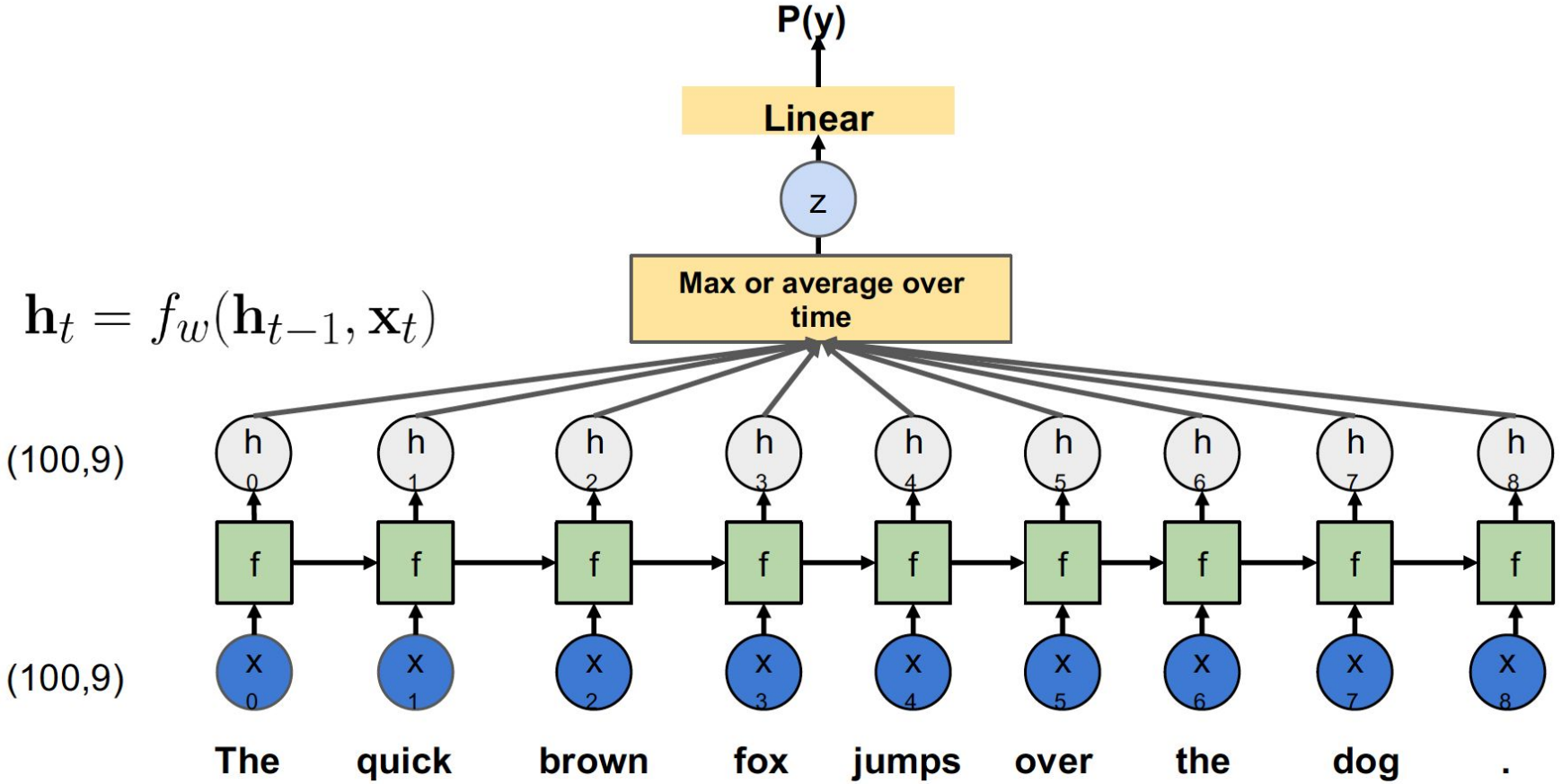
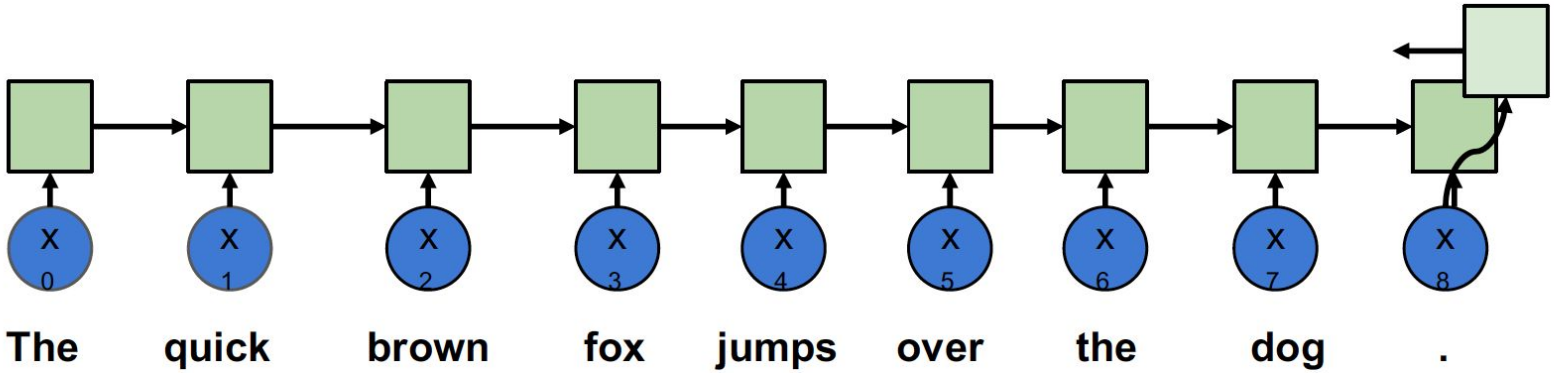


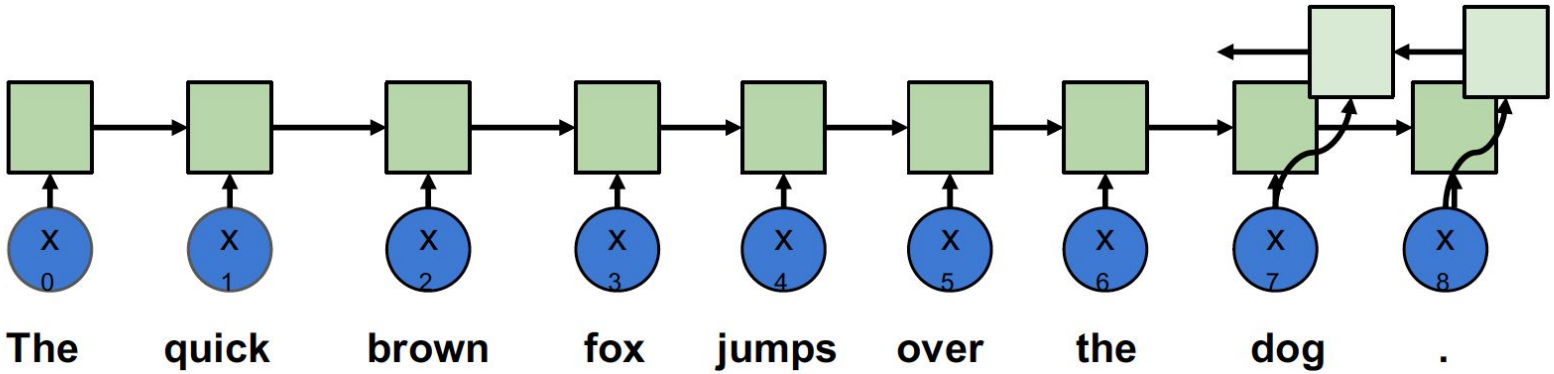
Recurrent NN for text classification

(100,9)



Recurrent NN for text classification

(100,9)



Recurrent NN for text classification

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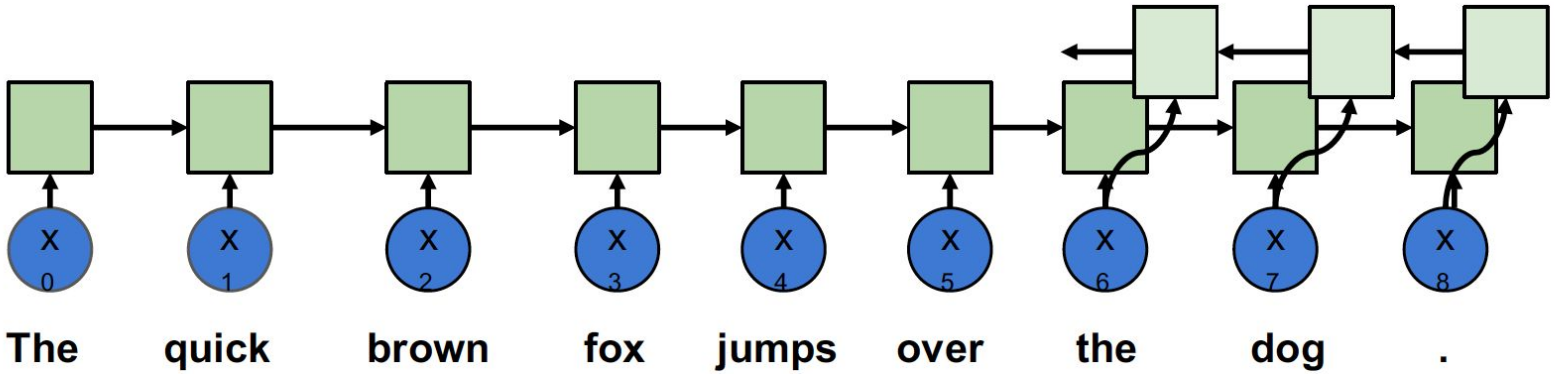

Recurrent NN for text classification

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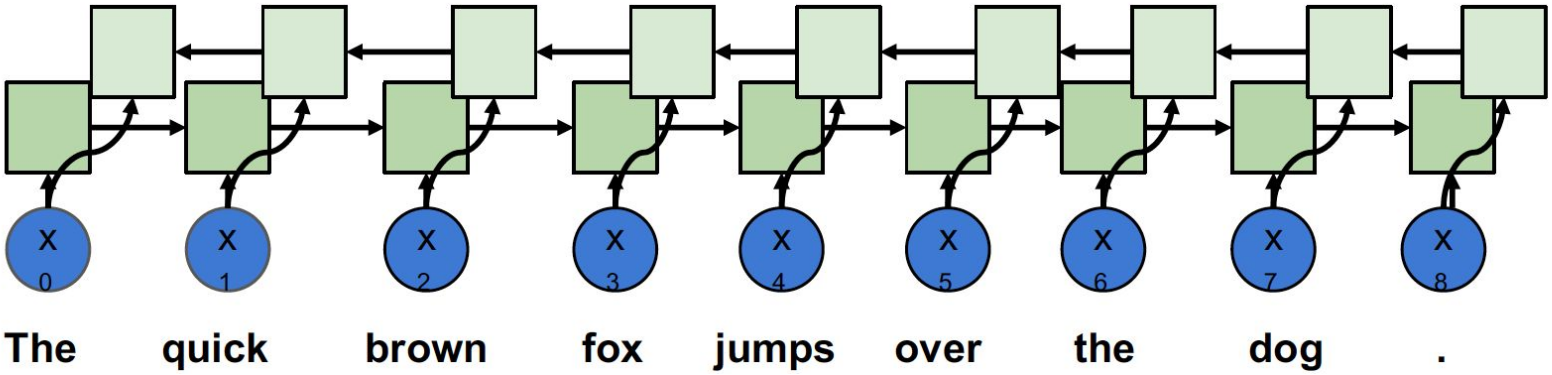
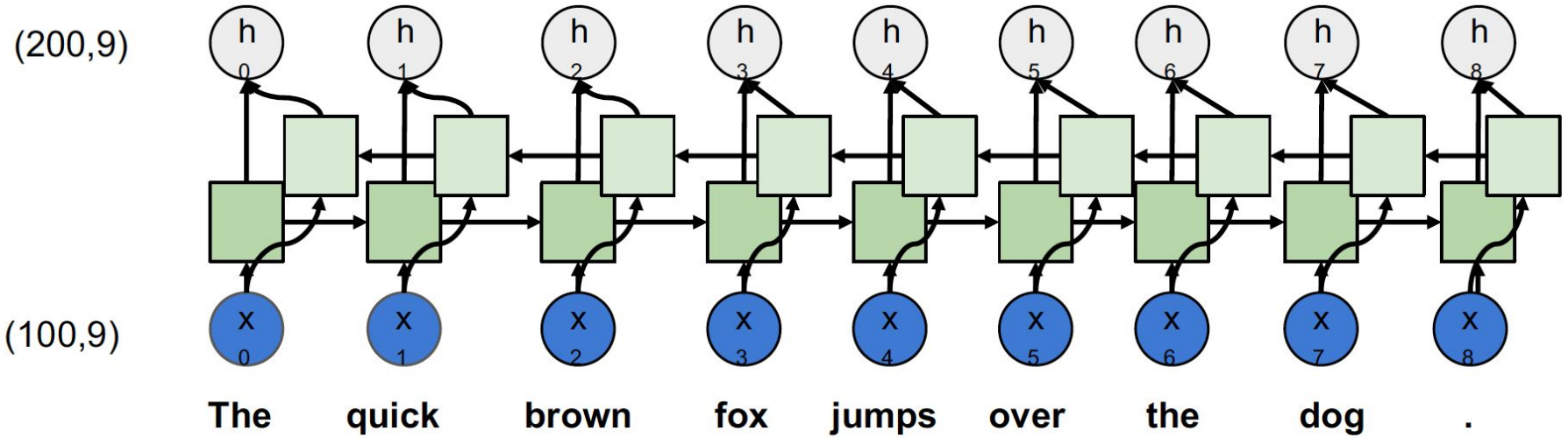
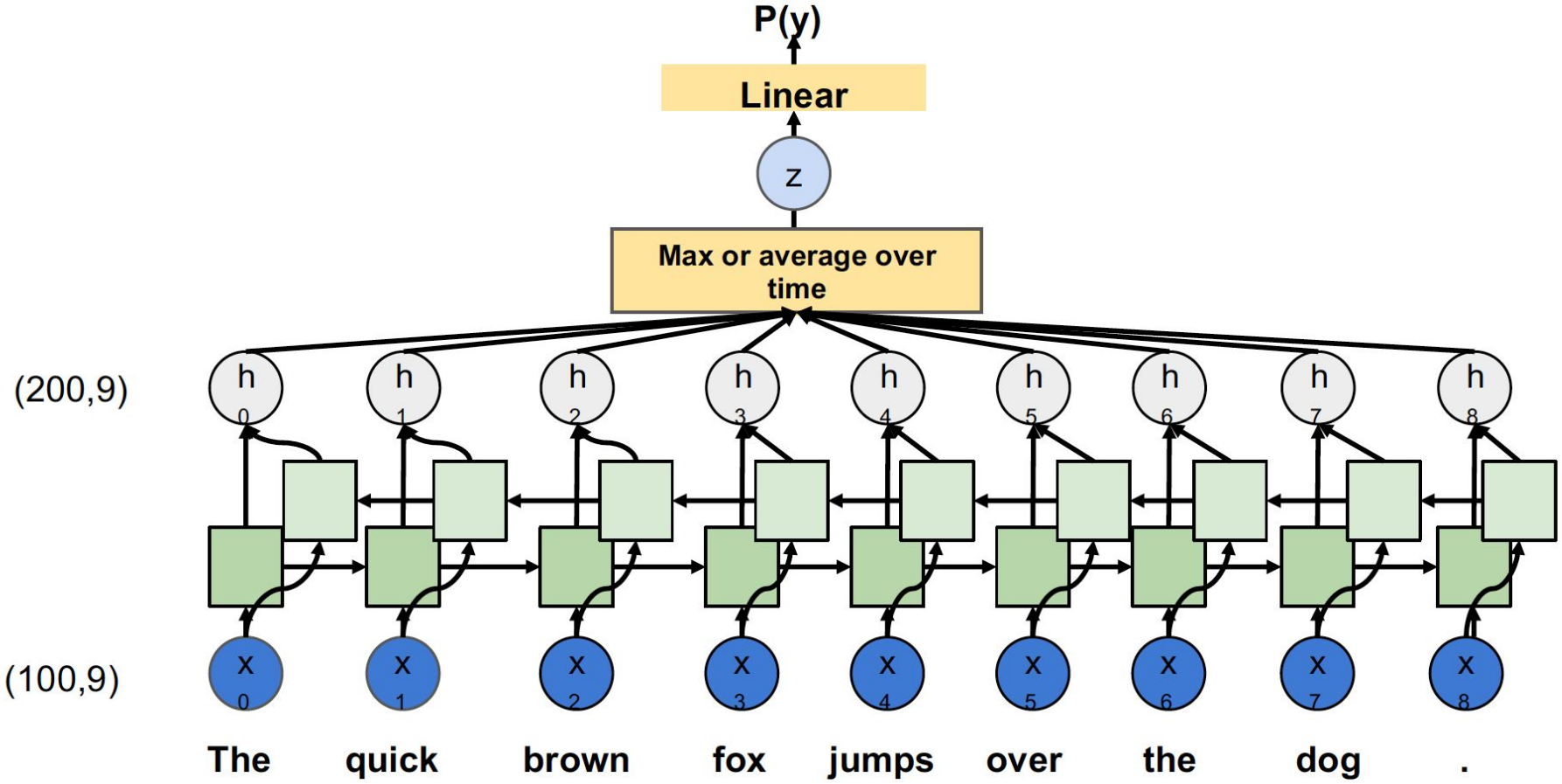


Recurrent NN for text classification



Recurrent NN for text classification



References

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- NLP course by Yandex data school
- https://medium.com/data-from-the-trenches/text-classification-the-first-step-toward-nlp-mastery-f5f95d525d73

Thank You!

The Hitchhiker's Guide to the Galaxy *by* Douglas Adams's

The Hitchhiker's Guide to the Intelligence ™!

Don’t Panic Guide to AI