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Machine Learning with Python-From Linear Models to Deep Learning

<u>Help</u>



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Lecture 10. Recurrent Neural

Course > Unit 3 Neural networks (2.5 weeks) > Networks 1

> 3. Why we need RNNs

3. Why we need RNNs Why we need RNNs



What are we missing?

- · Sequence prediction problems can be recast in a form amenable to feed-forward neural networks
- · But we have to engineer how "history" is mapped to a vector (representation). This vector is then fed into, e.g., a neural network
 - how many steps back sho
 - look at? - how to retain important it ntioned far back?
- · Instead, we would like to learn how to encode the "history" into a vector

Start of transcript. Skip to the end.

So let's look at a few instances of the prediction tasks,

where this type of flexible way of encoding sequences

is quite relevant.

One we have already seen, predicting the next

in the sentence, what happens next.

We have here already a part of the sentence.

We need to turn that into a feature vector, such

that we can use standard prediction tools to

0:00 / 0:00

▶ Speed 1.50x





CC

Video Download video file **Transcripts** Download SubRip (,srt) file Download Text (.txt) file

Video Quiz: Why We Need RNNs

1/1 point (graded)

As we saw in the previous problem, it is possible to use feed-forward networks for predicting future values of temporal sequences. However, there is a reason why recurrent neural networks can be more useful than feed-forward networks when it comes to temporal sequences. In general, RNNs automatically address some issues that need to be engineered with feed-forward networks. What are some of these issues?

■ How do we deal with the time complexity if the feature vector is very long?
✓ How many time steps back should we look at in the feature vector? ✓
■ How do we calculate the mean and the variance inside the sliding window?

Solution:

As discussed in the lecture, an inconvenient aspect of feed-forward networks is that we have to manually engineer how history is mapped to a feature vector (representation). However, in fact, this mapping into feature vectors (encoding) is also what we would like to learn. RNN's learn the encoding into a feature vector, unlike feed-forward networks.

Submit

You have used 2 of 2 attempts

1 Answers are displayed within the problem

Understanding RNNs

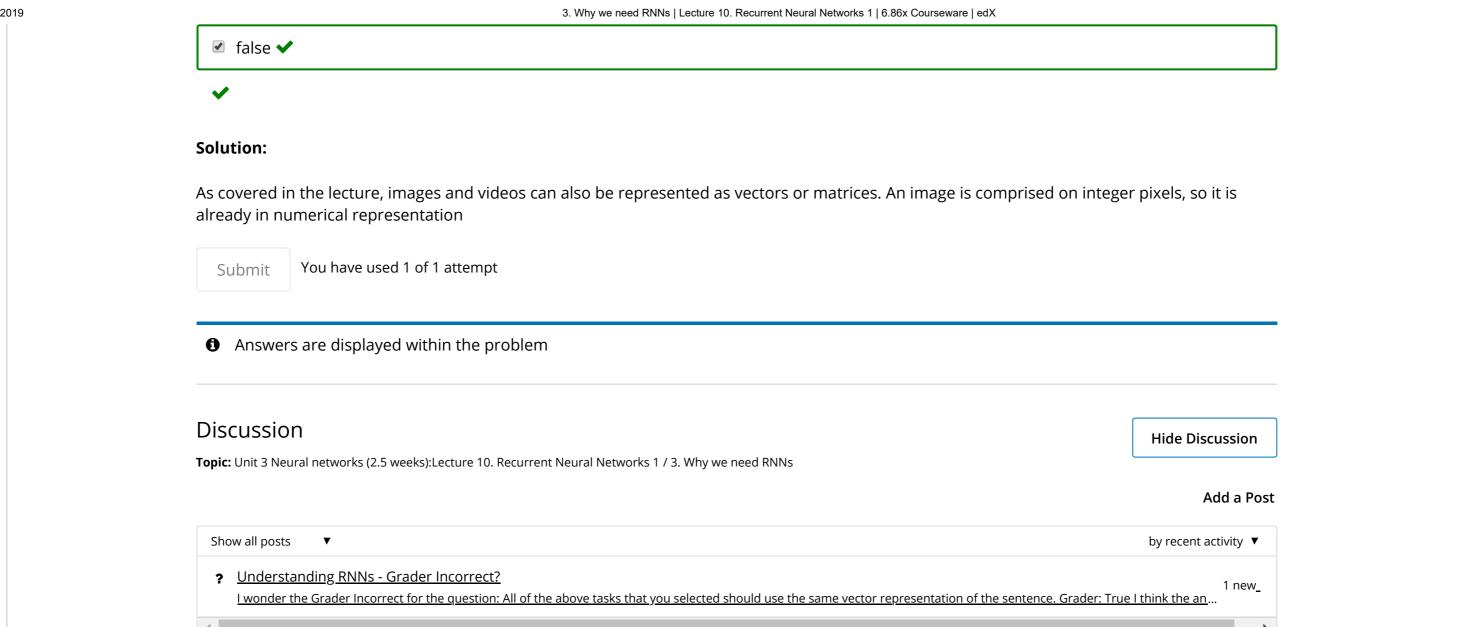
3/3 points (graded)

You can use a vector representation of a sentence to...

- ✓ predict whether the sentence is positive or negative
 ✓
- lacktriangledown translate the sentence to another language \checkmark
- lacksquare to predict the next word in the sentence \checkmark

~

All of the above tasks that you selected should use the same vector representation of the sentence.
true
✓ false ✓
✓
In order to accomplish the tasks you selected above, which two steps are necessary?
✓ mapping a sequence to a vector ✓
■ mapping a vector to a prediction ✓
mapping a prediction to a sequence
✓
Solution:
All of the above tasks are possible. Sentiment analysis, language translation, and language modelling are covered in the lecture video. However, each task requires a different sentence representation as they focus on different parts of the sentence. One example is that sentiment analysis focuses on the holistic meaning of a sentence, where translation focuses more on individual words. Thirdly, the lecture explains that we need encoding, or mapping a sequence to a vector, and decoding, or mapping a vector to a prediction. A prediction is our end goal, we don't need to map it to a sequence.
Submit You have used 1 of 2 attempts
• Answers are displayed within the problem
Vector Representations
1/1 point (graded) Only textual information, such as words and sentences, can be turned into vectors or matrices.
true



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