رواد مصر الرقمية

IMONITOR

BY

MOHAMED ABDULHAMID HAMED

KAREEM AYMEN SALAMA

SHAIMAA SALAH ELDIEN

NORHAN KARM GOMMA

BADR GAMAL AHMED

SUPERVISED BY

ENG: MOHAMED KHALED

NEW HORIZON CAIRO

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Abstract

Abstract

This paper presents an image captioning model trained and evaluated on the COCO (Common Objects in Context) dataset. The model aims to automatically generate descriptive captions for images by leveraging deep learning techniques, specifically Convolutional Neural Networks (CNNs) for feature extraction and Recurrent Neural Networks (RNNs) or Transformers for language generation.

The COCO dataset, which contains images depicting complex everyday scenes with objects in diverse contexts, provides a rich environment for training models to understand both object identification and contextual relationships.

Our model demonstrates competitive performance in generating accurate, contextually relevant, and coherent captions.

We evaluate the model using standard metrics such as BLEU, METEOR, and CIDEr, highlighting the effectiveness of the approach in balancing image understanding with natural language generation.

Future improvements and potential applications of this model include refining the attention mechanism, incorporating more diverse datasets, and applying the model in real-world applications such as assistive technologies and automatic content generation.

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CHAPTER 1: INTRODUCTION

Chapter1: Overview

1.1 .Introduction

Image captioning is a crucial task in the field of computer vision and natural language processing, where the goal is to automatically generate textual descriptions for images. This task combines two challenging problems: understanding the content of an image and expressing it in a coherent and meaningful way using natural language. Image captioning has significant applications, including assistive technologies for the visually impaired, automatic content generation, and enhanced image search capabilities.

The **COCO dataset** (Common Objects in Context) is one of the most widely used datasets for image captioning tasks. It contains over 330,000 images, with each image labeled with multiple descriptive captions. These captions are diverse and contextually rich, making the dataset ideal for training models that aim to bridge the gap between image understanding and natural language generation.

In this documentation, we present a detailed overview of an **Image Captioning** model trained on the COCO dataset. The model leverages **Convolutional Neural Networks (CNNs)** for extracting image features and either **Recurrent Neural Networks (RNNs)** or modern **Transformer-based architectures** for generating descriptive captions. Throughout the document, we will cover the data preprocessing steps, model architecture, training methodology, evaluation metrics, and performance analysis. We will also highlight the potential applications of this model and suggest areas for future improvements.

Chapter1: Overview

1.2 Overview

The **Image Captioning** model is designed to generate natural language descriptions for images, integrating techniques from both computer vision and natural language processing. This documentation provides a comprehensive guide to the model, detailing each aspect from data preparation to model evaluation. Below is an overview of the key components:

1. **Dataset**
   The model is trained on the **COCO dataset**, which is a large-scale collection of images with diverse and context-rich captions. Each image in the COCO dataset is annotated with multiple human-generated captions, making it ideal for training and evaluating image captioning models. The dataset includes over 80 object categories and covers a variety of everyday scenes.

2. **Model Architecture**
   The model uses a combination of **Convolutional Neural Networks (CNNs)** and **Recurrent Neural Networks (RNNs)** or **Transformer-based architectures** to tackle the image captioning task. CNNs are used for image feature extraction, while RNNs or Transformers handle the sequence generation of captions. Specifically, CNNs such as ResNet or Inception models are used to capture the visual elements of an image, and the extracted features are passed to an RNN, typically an LSTM (Long Short-Term Memory) network, or a Transformer for generating meaningful captions.

3. **Training Process**
   The training process involves preprocessing the images and captions, including image resizing, tokenization of captions, and embedding of the input text. The model is trained to minimize the difference between the predicted captions and the ground truth captions using loss functions like **Cross-Entropy** or **Maximum Likelihood Estimation (MLE)**. During training, various techniques like **Attention Mechanism** are employed to improve the model's ability to focus on relevant parts of the image.

4. **Evaluation Metrics**
   The model's performance is evaluated using several standard metrics for image captioning, including:
   - **BLEU (Bilingual Evaluation Understudy Score)**
   - **METEOR (Metric for Evaluation of Translation with Explicit ORdering)**
   - **CIDEr (Consensus-based Image Description Evaluation)** These metrics measure how well the generated captions match the reference captions in terms of accuracy, fluency, and contextual relevance.
5. **Applications**
   The image captioning model has a wide range of applications, including:
   - **Assistive technologies**: Helping visually impaired individuals by generating descriptions of visual content.
   - **Content generation**: Automatically generating descriptions for images in digital platforms, such as social media, news articles, and e-commerce websites.
   - **Enhanced search capabilities**: Improving image retrieval systems by associating images with natural language descriptions for more effective search queries.
6. **Future Improvements**
   While the model shows strong results, there are several areas where it can be further improved, such as enhancing the **attention mechanism**, incorporating **multimodal datasets** that combine text and other sensory inputs, and refining the caption generation process to handle more complex image contexts. Further exploration of more advanced Transformer-based models may also offer improvements in performance.

Chapter 1: Problem Definition

1.3 Problem Definition

The task of **Image Captioning** involves automatically generating descriptive and coherent natural language captions for a given image. This problem sits at the intersection of **computer vision**, which focuses on understanding the visual content of the image, and **natural language processing (NLP)**, which is responsible for generating accurate, meaningful, and contextually appropriate descriptions.

The core challenge in image captioning is twofold:

1. **Visual Understanding**: The model must be able to recognize and comprehend objects, their attributes, and relationships within an image. This requires the model to extract meaningful features from the image that capture both local details (individual objects) and global context (how objects relate to each other in a scene).
2. **Language Generation**: Once the visual information is understood, the model needs to generate a grammatically correct and semantically relevant caption. The generated caption should reflect not just object identification, but also the relationships and actions depicted in the image.

Challenges in addressing the problem include:

- **Object Detection and Contextual Awareness**: Images often contain multiple objects with complex relationships, actions, or interactions. A successful model must capture these subtleties to produce a caption that goes beyond listing objects and provides a meaningful narrative.
- **Handling Ambiguity and Variability**: The same image can have multiple valid descriptions depending on focus, context, and user intent. Capturing this variability and generating captions that are both flexible and accurate is a key challenge.
- **Generalization**: The model should be able to generalize well to unseen images during inference, meaning it must recognize new combinations of objects, actions, or scenes, even if they were not explicitly seen during training.

The primary **goal** of this problem is to design a model that can:

- **Accurately identify objects and contextual relationships** in images.
- **Generate coherent, fluent, and contextually appropriate captions** that accurately describe the content of the image.
- **Evaluate performance** using appropriate metrics (e.g., BLEU, METEOR, CIDEr) to ensure that generated captions align well with human-annotated captions.

Chapter1: Challenges

1.4 Challenges

Developing an effective image captioning model presents several key challenges that stem from the complexity of both visual understanding and natural language generation. Below are some of the main challenges encountered in this task:

1. **Complexity of Visual Scenes**
   Images often contain multiple objects with intricate relationships, actions, and contextual information. For example, an image might depict several objects interacting (e.g., a person holding a dog, with other objects in the background). Capturing this complexity accurately is difficult because the model must not only recognize the objects but also understand their relationships and relevance in the scene.

2. **Diversity of Captions**
   The same image can be described in various ways depending on the viewer's focus, background knowledge, or intent. This inherent variability makes it challenging for a model to generate captions that consistently match human-generated descriptions, as there may be multiple correct captions for a single image. Balancing between overly generic and overly specific captions is particularly difficult.

3. **Handling Ambiguity in Images**
   Some images can be ambiguous or contain unclear scenes where it's difficult to infer the exact relationship between objects or actions. For instance, an image of a partially obscured object may lead to confusion about what the object is or how it relates to the rest of the scene. The model needs to make inferences in such cases, and poor handling of ambiguity can lead to inaccurate captions.

4. **Generalization to Unseen Images**
   A significant challenge is ensuring that the model generalizes well to unseen images. While a model can perform well on images similar to those in the training set, it may struggle with new images that contain unfamiliar object combinations or new contexts. Ensuring that the model does not overfit to the training data and can handle novel scenarios is crucial for its robustness.

5. **Language Fluency and Coherence**
   Even if the model accurately identifies objects in the image, generating

grammatically correct and semantically coherent captions is a challenge. Captions must not only describe the objects but also form meaningful sentences that capture actions, relationships, and context. Poor language generation can result in captions that are technically accurate but incoherent or incomplete.

6. **Attention and Focus Mechanisms**
   The model needs to determine which parts of the image are most important to describe. Attention mechanisms, which allow the model to "focus" on different parts of the image when generating each word in the caption, are crucial but can be challenging to optimize. Improper attention can lead to descriptions that focus on irrelevant objects or miss key elements of the image.

7. **Evaluation Metrics**
   Standard evaluation metrics like **BLEU**, **METEOR**, and **CIDEr** provide useful quantitative measurements but may not fully capture the quality of captions, especially in terms of creativity or human-like variability. A high BLEU score does not always guarantee that the caption is the best possible description. Designing robust evaluation methods that reflect human judgment remains a challenge.

8. **Computational Resources**
   Training deep learning models on large datasets like COCO is computationally intensive. The need for large-scale GPU resources and the time required for training can be significant obstacles, especially when fine-tuning the model or experimenting with different architectures. Efficient training methods and resource management are essential to overcome these challenges.

9. **Multilingual Captioning**
   While this project may focus on English captions, generating captions in multiple languages adds an additional layer of complexity. Handling different syntactic structures, grammar rules, and cultural nuances across languages is a significant challenge when building a model capable of multilingual image captioning.

CHAPTER 2: Model Architecture

Chapter2: Model Architecture

2.1 Example of Image Captioning Model Prediction

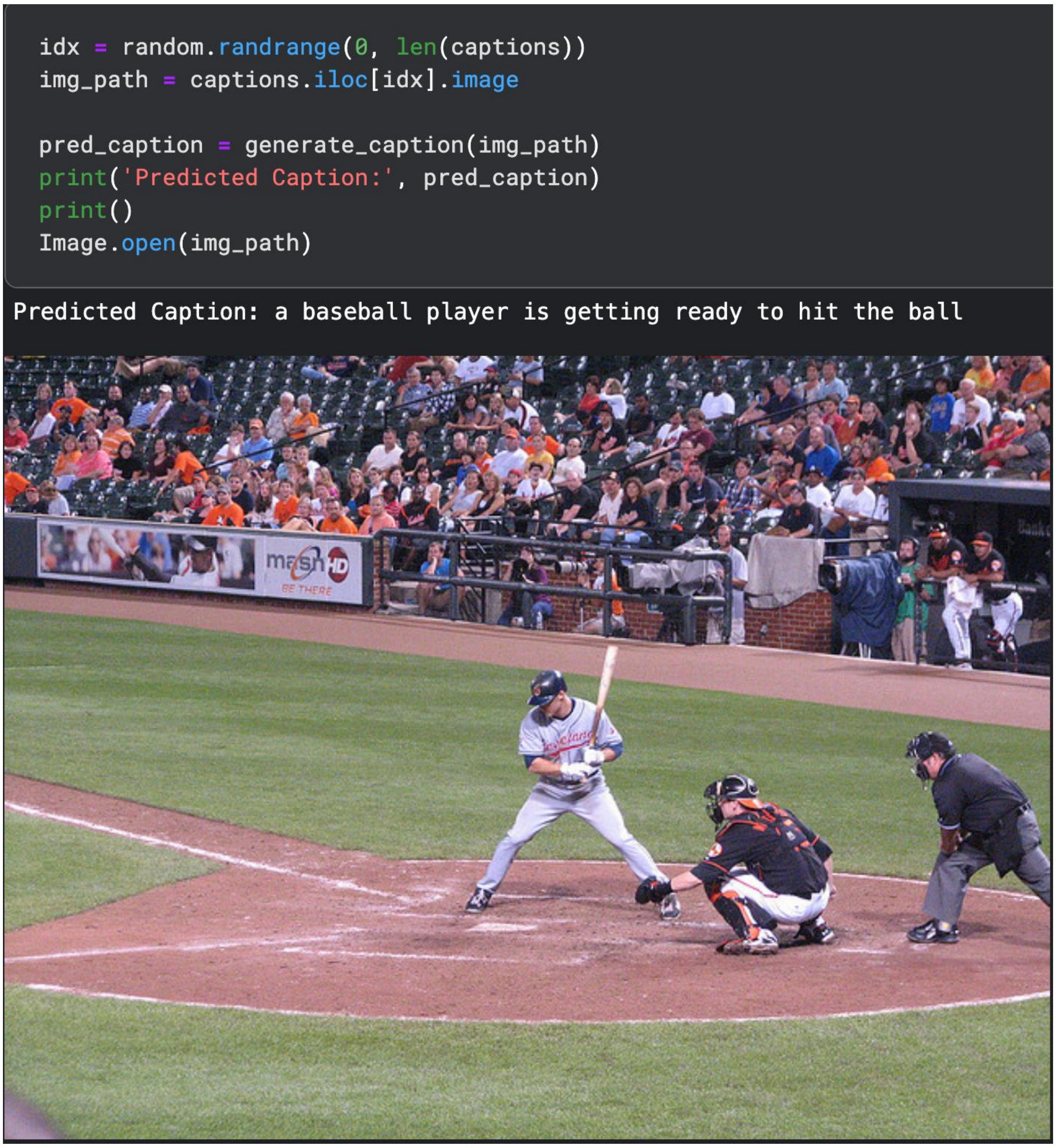
The following code snippet demonstrates the process of using the trained image captioning model to generate a caption for an input image. The image is randomly selected from the COCO dataset, and the model predicts a relevant caption based on the content of the image. The predicted caption is then printed alongside the actual image for comparison.

Code Explanation:

1. Random Image Selection:
   - The code uses random.randrange() to select a random image from the dataset.
   - The img_path variable stores the file path of the selected image by accessing the image column from the captions DataFrame.
2. Caption Generation:
   - The generate_caption() function takes the image path as input and returns a predicted caption. This function is the core of the image captioning model, which processes the image to generate a descriptive caption.
3. Display Results:
   - The predicted caption is printed in the output.
   - The actual image is displayed using the Image.open() function from the PIL library to visually confirm how well the caption aligns with the image content.

Example: For the given image, the model generated the following predicted caption:

- Predicted Caption: *"a baseball player is getting ready to hit the ball"*



```python
idx = random.randrange(0, len(captions))
img_path = captions.iloc[idx].image

pred_caption = generate_caption(img_path)
print('Predicted Caption:', pred_caption)
print()
Image.open(img_path)
```

```
Predicted Caption: a baseball player is getting ready to hit the ball
```

(Figure 1)

2.2 Why Is Auto-Tagging Important?

Auto-tagging is essential for businesses that want to stay ahead of the curve. By automatically tagging every final URL, businesses can detect trends and focus on issues that matter most to their customers.

Additionally, auto-tagging saves you the work of manually tagging each URL, which can be time-consuming and prone to error.

Finally, auto-tagging lets you see how effectively your ad clicks translate into customer actions, such as purchases or sign-ups.

With this information, you can adjust your campaigns accordingly to maximize your return on investment. In short, auto-tagging is a valuable tool that no business should be without.

Dataset:

We used a combination of public datasets like ImageNet and COCO, which contain millions of labeled images, along with a curated custom dataset tailored to our specific tagging needs.

Text Cleaning and Pre-Processing :

First major step is to clean the data. It contains various html and URLs links, punctuations, single letter alphabets and stop words which doesn't convey much information regarding what topics they are related to.

Steps are as follows.

1. Combining the title and text part of our dataset.
2. Removing all the punctuations, alphabets through the regex and white spaces and stop words
3. Finally lowercasing all the words present in the text.
4. Reshaping our target variable(tag). Since they are 100 , we will be apply MultiLableBinarizer for sckit learn library. 100 columns more will be more in palce of one.
5. Applying Tfidf vectorizer over the text cleaned part of our dataset having max_features= 10000 (keping only 10000 top words) and max_df=0.8 (words appearing in more than 80 % of text are removed) and Word2Vec model (keeping number of features = 100 initially and then varying) for feature engineering

6. Splitting the data using train_test_split using sklearn.model_selection library in 80/20 ratio and then using the logistic regression for prediction.

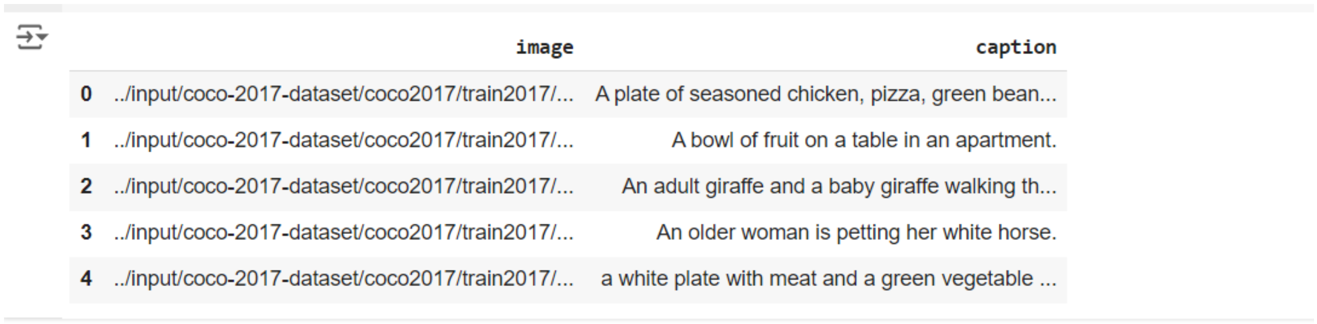


	image	caption
0	../input/coco-2017-dataset/coco2017/train2017/...	A plate of seasoned chicken, pizza, green bean...
1	../input/coco-2017-dataset/coco2017/train2017/...	A bowl of fruit on a table in an apartment.
2	../input/coco-2017-dataset/coco2017/train2017/...	An adult giraffe and a baby giraffe walking th...
3	../input/coco-2017-dataset/coco2017/train2017/...	An older woman is petting her white horse.
4	../input/coco-2017-dataset/coco2017/train2017/...	a white plate with meat and a green vegetable ...

(Figure 2)

2.3 Feature Engineering

TFIDF: Term frequency and Inverse Document Frequency

The code initializes a **tokenizer** object for text vectorization using TensorFlow. In natural language processing, a **tokenizer** is responsible for converting raw text data into numerical form, which can then be used by machine learning models. This process involves breaking the text into individual words or tokens, and then converting these tokens into numerical indices that can be fed into the model.

1-A TextVectorization object is created by calling the tf.keras.layers.TextVectorization class. The purpose of this object is to convert the text into integer sequences that represent the words. Some arguments for this layer are as follows:

- **max_tokens = VOCABULARY_SIZE**: This limits the number of unique tokens (words) that the tokenizer will handle to VOCABULARY_SIZE. Any word not in the top VOCABULARY_SIZE words will be considered "out of vocabulary."
- **standardize = None**: By setting this to None, the default standardization process is skipped. Normally, the tokenizer would convert the text to lowercase and strip punctuation, but in this case, no such transformation is applied.
- **output_sequence_length = MAX_LENGTH**: This defines the maximum length of the sequences. If a text is shorter than this, it will be padded, and if it is longer, it will be truncated.

2-A dapting the Tokenizer: The tokenizer.adapt() function is used to fit the tokenizer to the data. In this case, captions['caption'] represents the text data (captions), and the tokenizer learns the vocabulary and how frequently words appear within this dataset. Without this adaptation step, the tokenizer wouldn't know how to map the words in the data to numerical tokens.

3-A StringLookup object is created using tf.keras.layers.StringLookup. This object maps words to integer indices. This is useful for converting words into their corresponding token indices in the vocabulary. Some arguments for it are:

- **mask_token = ""**: The empty string is used as the "mask" token, which represents padding or words that aren't part of the vocabulary.
- **vocabulary = tokenizer.get_vocabulary()**: This sets the vocabulary that the tokenizer learned from the data. The vocabulary is the list of unique words found in the data, sorted by frequency.

4-The **invert=True** flag is used in the second **StringLookup** object to perform the reverse mapping. This means it will map integer indices back to words. For example, after the model makes predictions, you can convert the predicted token indices back into the original words using this object. The same vocabulary learned by the tokenizer is used here.

Chapter2: Model Architecture

2.4 Word2Vec Word Embeddings

Word2vec is a group of related models that are used to produce word embeddings. These models are shallow, two-layer neural networks that are trained to reconstruct linguistic contexts of words. Word2vec takes as its input a large corpus of text and produces a vector space, typically of several hundred dimensions, with each unique word in the corpus being assigned a corresponding vector in the space. Word vectors are positioned in the vector space such that words that share common contexts in the corpus are located close to one another in the space. There are two models for generating the embeddings, CBOW(Continous Bag of words) and skip gram model. CBOW is used for small corpus, it is fast but for larger corpus skip gram is better, takes a little more time than CBOW. Here skip gram is used, below its explanation.

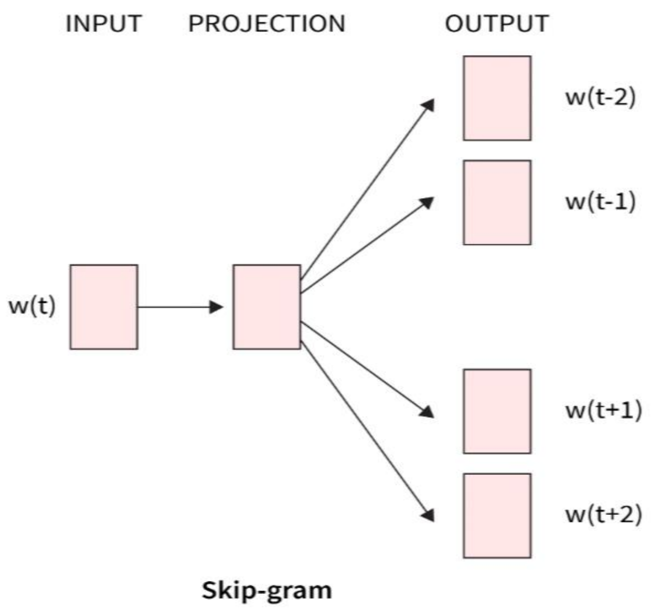
Skip Gram:

a technique used to learn **word embeddings**, which are dense vector representations of words. It is part of the **Word2Vec** framework developed by Google and is particularly useful for capturing the semantic meaning of words based on their surrounding context in a corpus.

How Skip-Gram Works:

The Skip-Gram model works by predicting the context (neighboring words) given a central word. The idea is that words appearing in similar contexts tend to have similar meanings, and this relationship is encoded in the learned word embeddings.

- **Window Size**: You mentioned a window size of 2. In this case, the Skip-Gram model considers 2 words before and 2 words after the target word to form the context. This means that for each target word, you would try to predict the surrounding 4 words (2 on the left and 2 on the right).
- **Objective**: The goal of the model is to maximize the probability of the context words given the target word. It does this by training on pairs of (target word, context word).



(Figure3)

Skip-Gram Overview (with a focus on network structure):

1. **Vocabulary Construction:**
   - The first step in the Skip-Gram model is to build the vocabulary from the corpus. Each unique word in the corpus is assigned an index. This vocabulary is typically large; for example, you might have 10,000 unique words in the vocabulary.
2. **One-Hot Encoding:**
   - Once the vocabulary is constructed, each word is represented as a one-hot vector. For example, if you have 10,000 words in your vocabulary, each word will be a 10,000-dimensional vector with a single "1" at the index corresponding to that word and "0"s everywhere else.

Example:

- Vocabulary index: {'quick': 1, 'brown': 2, 'fox': 3, ...}
- "fox" in one-hot encoding (assuming an index of 3): [0, 0, 1, 0, ..., 0] (with 10,000 dimensions)

3. **Training Example Pairs:**
   - For each word in the corpus, training pairs are created based on the window size. If the window size is 2, the model will try to predict the 2 words before and 2 words after the target word.

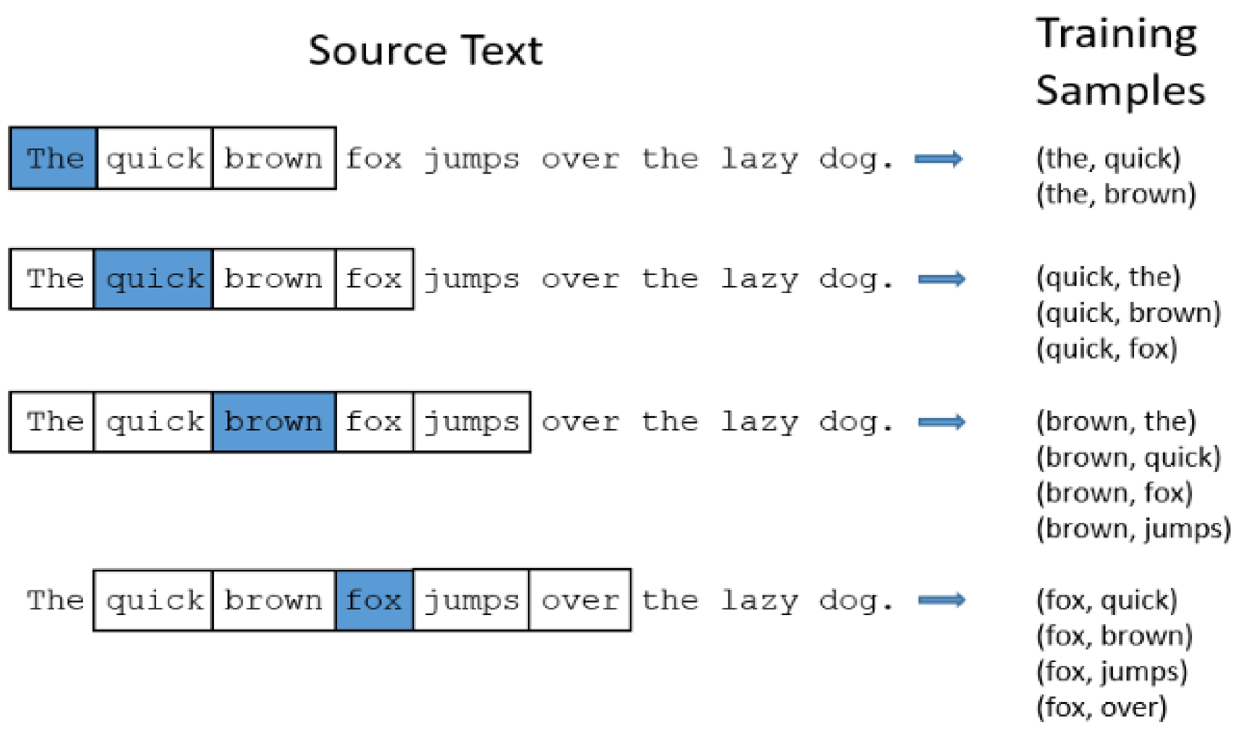
- For each target word, 4 pairs (context words) are generated (in this case, with window size 2). If you slide this window across the text, you'll have multiple pairs per word, depending on its context in the corpus.

4. **Skip-Gram as a Two-Layer Neural Network:**
    - The Skip-Gram model can be represented as a two-layer neural network. The architecture is as follows:
        - Input Layer: The input is a one-hot encoded vector representing the target word (e.g., 10,000 dimensions for a 10,000-word vocabulary).
        - Hidden Layer (Embeddings): This is a weight matrix of size (vocabulary_size x embedding_size) (e.g., 10,000 x 300). It contains the word embeddings.
        - Output Layer: The output is a probability distribution over the entire vocabulary (e.g., a 10,000 x 1 vector) for predicting the context words around the target word.
5. **Output Probabilities:**
    - Given an input word (in one-hot form), the network's output will be a vocabulary-sized vector (e.g., 10,000 x 1) that represents the probabilities of all words in the vocabulary being in the context of the input word.
    - The model's goal is to increase the probability of the actual context words for the given input word while reducing the probabilities of unrelated words.
6. **Training Process:**
    - The training process involves adjusting the weights of the hidden layer using backpropagation. The network tries to predict the context words, and the error between the predicted and actual context words is used to update the weights.
    - For each training pair (target word, context word), the weights of the hidden layer are adjusted so that the network learns which words are more likely to appear in similar contexts.

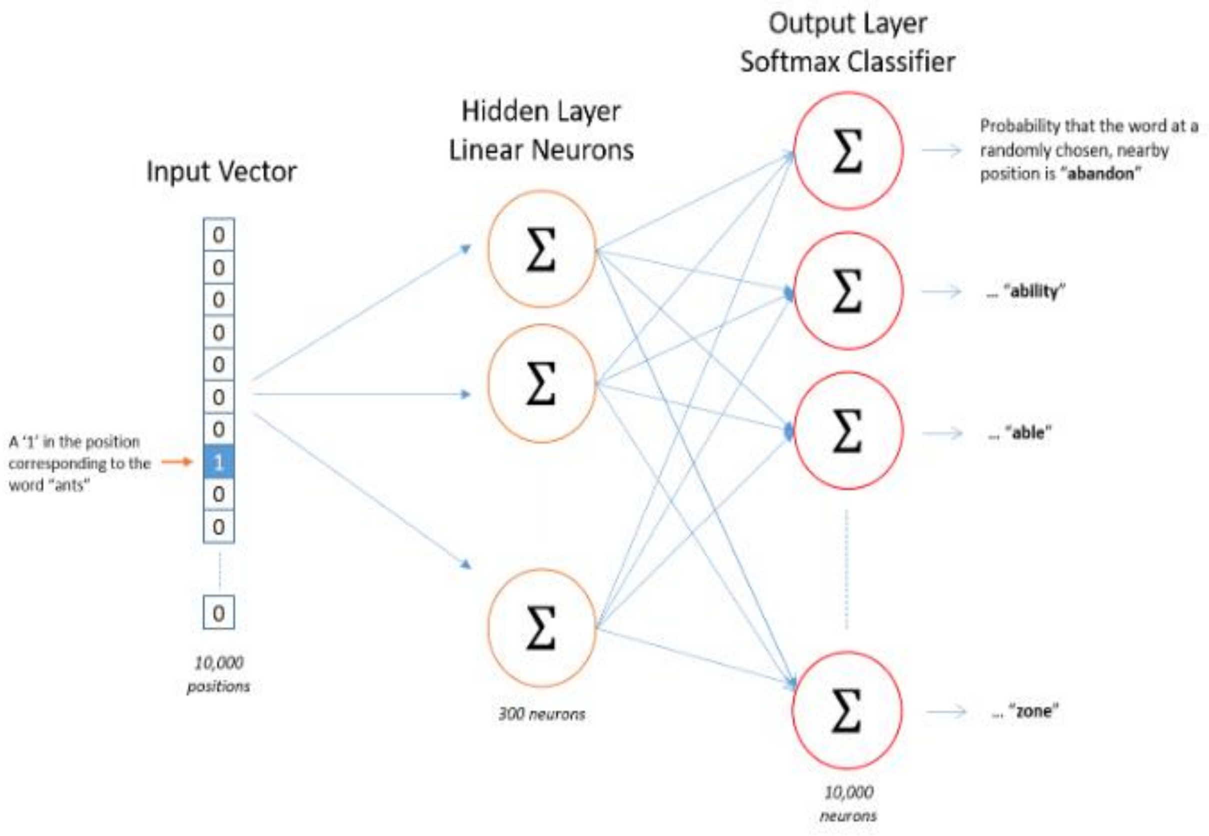
7. **Weight Matrix (Embeddings):**
    - The weight matrix of the hidden layer (of size 10,000 x 300) is the final embedding matrix. This matrix contains the learned dense vector representations (embeddings) for each word.
    - Words that frequently appear together in similar contexts will have similar embeddings, and the distance between these word vectors reflects their semantic similarity.
8. **Word Embedding Extraction:**
    - To get the embedding vector for a specific word, you multiply the word's one-hot encoded vector with the weight matrix (the hidden layer). Since the one-hot vector has "1" at the index of the target word and "0"s elsewhere, this operation selects the corresponding row from the embedding matrix.
    - This row represents the dense vector (e.g., a 300-dimensional vector) for the word, capturing its relationships with other words in the vocabulary.

Simplified Example:

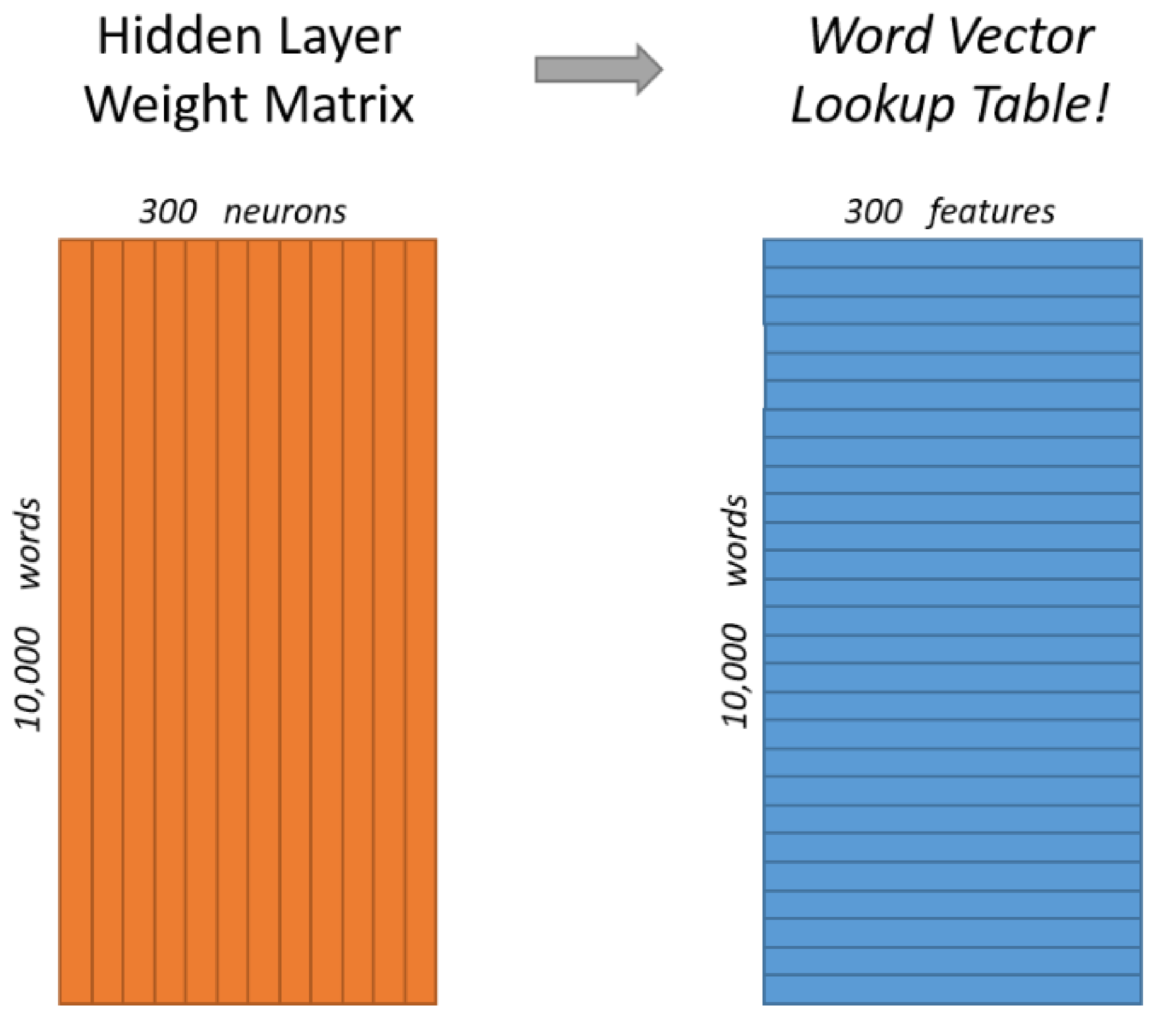
- Input: The word "fox" (one-hot vector of size 10,000).
- Hidden Layer (Embedding Matrix): A weight matrix of size (10,000 x 300).
- Output: A vector of probabilities (size 10,000 x 1), where the goal is to maximize the probability of "quick," "brown," "jumps," and "over" for the word "fox."



(figure 4)


Input Vector
A '1' in the position corresponding to the word "ants"
10,000 positions
Hidden Layer Linear Neurons
300 neurons
Output Layer Softmax Classifier
10,000 neurons
Probability that the word at a randomly chosen, nearby position is "abandon"
... "ability"
... "able"
... "zone"

(Figure 5)


Hidden Layer
Weight Matrix
Word Vector
Lookup Table!
300 neurons
300 features
10,000 words
10,000 words

(Figure 6)

2.5 Fitting the model

1. Model Training Setup:

The model was trained using the following configuration:

- Training Dataset: Description of the dataset (e.g., number of images, classes, any preprocessing steps).
- Validation Dataset: Number of validation samples and their role in monitoring overfitting.
- Batch Size: Mention the batch size (if relevant).
- Optimizer and Loss Function: State the optimizer used (e.g., Adam) and the loss function (e.g., categorical crossentropy).
- Epochs: Number of epochs used for training.
- Early Stopping: Early stopping was implemented to prevent overfitting, with the patience parameter set to stop if no improvement was observed in validation loss after a certain number of epochs.

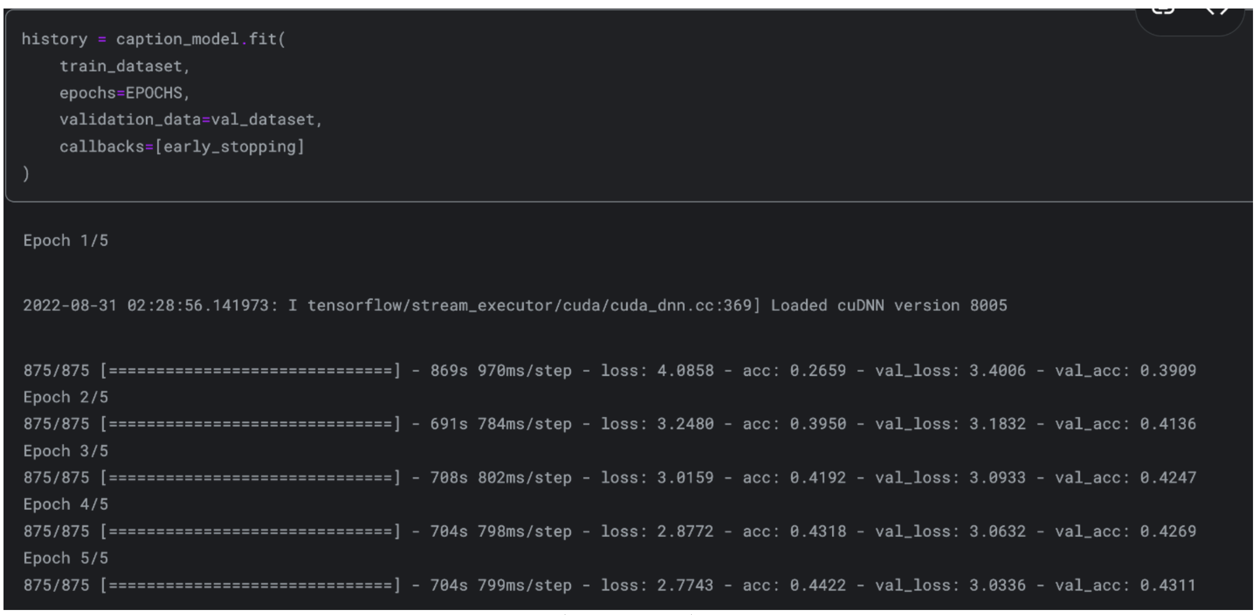
2. Training Procedure:

The model was trained over X epochs, with a steady decrease in both training and validation loss, as well as an improvement in accuracy metrics.

- Loss & Accuracy Progress:
- Epoch 1: Training loss: 4.0858, accuracy: 26.59%, validation loss: 3.4006, validation accuracy: 39.09%.
- Epoch 2: Training loss: 3.2480, accuracy: 39.50%, validation loss: 3.1832, validation accuracy: 41.36%.
- Epoch 3: Training loss: 3.0159, accuracy: 41.92%, validation loss: 3.0933, validation accuracy: 42.47%.
- Epoch 4: Training loss: 2.8772, accuracy: 43.18%, validation loss: 3.0632, validation accuracy: 42.69%.
- Epoch 5: Training loss: 2.7743, accuracy: 44.22%, validation loss: 3.0336, validation accuracy: 43.11%.

3. Hardware and Performance:

The training was conducted on hardware equipped with cuDNN version 8005, leveraging GPU acceleration for faster computation. Each epoch took approximately 10-15 minutes, depending on system load and the size of the dataset.



```
history = caption_model.fit(
    train_dataset,
    epochs=EPOCHS,
    validation_data=val_dataset,
    callbacks=[early_stopping]
)
```

```
Epoch 1/5

2022-08-31 02:28:56.141973: I tensorflow/stream_executor/cuda/cuda_dnn.cc:369] Loaded cuDNN version 8005

875/875 [==============================] - 869s 970ms/step - loss: 4.0858 - acc: 0.2659 - val_loss: 3.4006 - val_acc: 0.3909
Epoch 2/5
875/875 [==============================] - 691s 784ms/step - loss: 3.2480 - acc: 0.3950 - val_loss: 3.1832 - val_acc: 0.4136
Epoch 3/5
875/875 [==============================] - 708s 802ms/step - loss: 3.0159 - acc: 0.4192 - val_loss: 3.0933 - val_acc: 0.4247
Epoch 4/5
875/875 [==============================] - 704s 798ms/step - loss: 2.8772 - acc: 0.4318 - val_loss: 3.0632 - val_acc: 0.4269
Epoch 5/5
875/875 [==============================] - 704s 799ms/step - loss: 2.7743 - acc: 0.4422 - val_loss: 3.0336 - val_acc: 0.4311
```

(Figure 7)

2.6 Word2 based Deep Learning model

Using CNN based Deep Learning model

how the CNN (Convolutional Neural Network) model works for text classification using an embedding layer is quite good, but I'll fine-tune the details to ensure clarity and correctness. Here's a more detailed step-by-step breakdown:

1. Embedding Layer:

- The sentence, **"I like this movie very much!"**, is passed through an **embedding layer**. Each word in the sentence is mapped to a **dense vector representation** (embedding) of size "d".
    - For example, if d = 100, each word in the sentence will be represented as a vector of size 100 (a dense, learned vector representing the word's meaning).
    - **Word embeddings** capture semantic information about words, with similar words having similar vector representations.

2. Convolutional Filters:

- **Filter sizes**: In this model, **convolutional filters** with sizes 2, 3, and 4 are used.
    - A filter size of **2** means the filter will look at two consecutive words at a time (e.g., "I like", "like this", etc.) and try to capture information from word pairs.
    - Similarly, a filter size of **3** looks at triplets of words (e.g., "I like this", "like this movie") and a filter size of **4** looks at quadruples of words.
    - These filters are designed to capture **n-grams** (word patterns of size n) and identify patterns in the sentence.

3. 1D Convolution:

- This is a **1D Convolution** because the model slides the filters along the sentence in the vertical direction, where each word is represented by its embedding vector of size d.

  - In text CNNs, the width of the filter is equal to the embedding size d, meaning the filter will fully capture the information across all dimensions of each word embedding.
  - For example, if the filter is 2x100, it will slide over two consecutive word embeddings, each of size 100, and compute a weighted sum of these vectors.

4. Convolution Operation:

- The **convolution** operation involves sliding the filters over the sentence and performing element-wise multiplication between the filter weights and the word vectors, followed by summing them up.
  - The result of the convolution is a **scalar value** representing the "activation" for that particular window of words.
  - After sliding the filter across the entire sentence, the model generates a **feature map**, which is essentially the collection of these activations for the entire sentence.

5. Activation Function:

- Once the filter slides over the sentence, the obtained values are passed through an **activation function** (like **ReLU**), which introduces non-linearity into the model and helps in learning complex patterns.
  - ReLU is a common choice, which replaces all negative values with zero while keeping positive values intact.

6. Feature Maps:

- The convolution operation with each filter generates a **feature map**.
  - Each filter size (e.g., 2, 3, 4) will generate a separate feature map, as each filter size captures different kinds of patterns (bigrams, trigrams, etc.).
  - If you have 10 filters for the 2-word convolution, 10 filters for the 3-word convolution, and so on, each will produce its own feature map after sliding over the sentence.

7. Global Max Pooling:

- After the convolution, **Global Max Pooling** is applied to each feature map. This operation selects the **maximum value** from each feature map. The intuition behind this is that the highest activation value in each feature map represents the most important or salient information captured by the corresponding filter.

  - This reduces the dimensionality and keeps the most important information.
  - The max-pooled values from all the feature maps are then concatenated to form a single feature vector.
  - **Average Pooling** is an alternative, where instead of selecting the maximum value, the average value is taken across the feature map. This retains more information but might not capture the most important signals as strongly as max-pooling does.

8. Final Feature Vector:

- After applying pooling, the model now has a **single feature vector** that represents the entire sentence. This vector is a combination of the most important features extracted by the convolutional filters.

9. Softmax Layer:

- The final feature vector is passed to the **Softmax layer**, which computes a probability distribution over the possible output classes (e.g., categories for text classification like "positive" or "negative" sentiment).
  - **Softmax** is used in multi-class classification tasks and outputs probabilities for each class. It ensures that the sum of probabilities across all classes is 1.
  - The **class with the highest probability** is chosen as the model's prediction.
  - The SoftMax function is defined as:

$$P(y = c|x) = \frac{e^{z_c}}{\sum_i e^{z_i}}$$

(Figure 8)

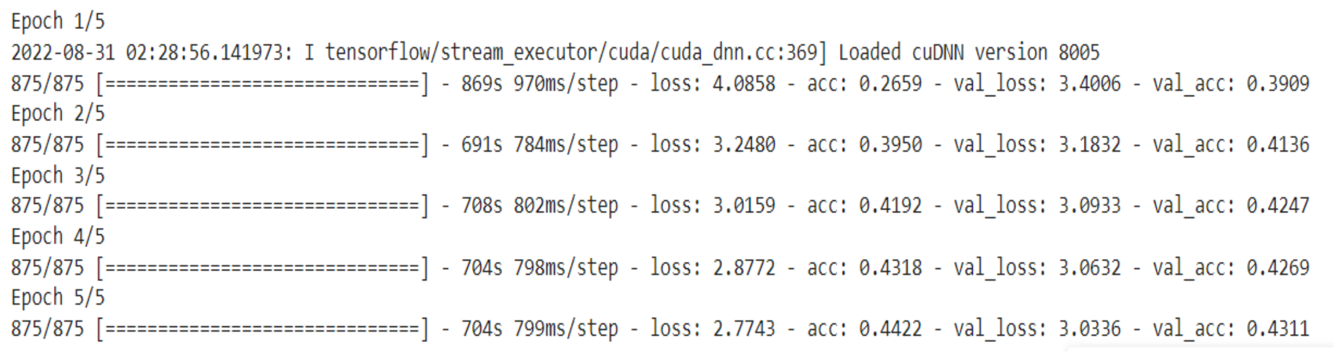
where z is the raw score (logit) for class c and the softmax normalizes these logits into probabilities.

10. Learning Through Backpropagation:

- During training, the CNN learns the filter weights using **backpropagation**.
    - The loss function (usually **cross-entropy** for classification tasks) calculates the error between the predicted output and the true label.
    - The error is propagated back through the network, and the weights (including the convolutional filter weights) are updated to minimize this error.
    - Over time, the model learns to adjust the filter weights to extract the most useful features for classifying the sentences.

    Steps:

1. First tokenize the text. In this way every document will be converted into a sequence of words identified by their token number. To do this, we will use Tokenizer from keras.preprocessing.text.
2. After tokenization, we will define the input length for the embedding layer
3. Reshaping our target variable
4. We will build our model by adding the embedding layer , Conv1D layer, GlobalMax Pool 1D, Dense Layer.
5. Compile the model using "adam" optimizer, loss='binary_crossentropy' and "accuracy" as a metric.
6. Adam : It is most widely used optimizer; it is a combination of RMS prop and momentum which are used to accelerate the gradient descent
7. Cross Entropy Binary Loss: It computes the loss by treating every class(eg, 100 here) as a binary classification problem
8. Model Training :



```
Epoch 1/5
2022-08-31 02:28:56.141973: I tensorflow/stream_executor/cuda/cuda_dnn.cc:369] Loaded cuDNN version 8005
875/875 [==============================] - 869s 970ms/step - loss: 4.0858 - acc: 0.2659 - val_loss: 3.4006 - val_acc: 0.3909
Epoch 2/5
875/875 [==============================] - 691s 784ms/step - loss: 3.2480 - acc: 0.3950 - val_loss: 3.1832 - val_acc: 0.4136
Epoch 3/5
875/875 [==============================] - 708s 802ms/step - loss: 3.0159 - acc: 0.4192 - val_loss: 3.0933 - val_acc: 0.4247
Epoch 4/5
875/875 [==============================] - 704s 798ms/step - loss: 2.8772 - acc: 0.4318 - val_loss: 3.0632 - val_acc: 0.4269
Epoch 5/5
875/875 [==============================] - 704s 799ms/step - loss: 2.7743 - acc: 0.4422 - val_loss: 3.0336 - val_acc: 0.4311
```

(Figure 9)

Chapter2: Model Architecture

2.7. Performance of the model

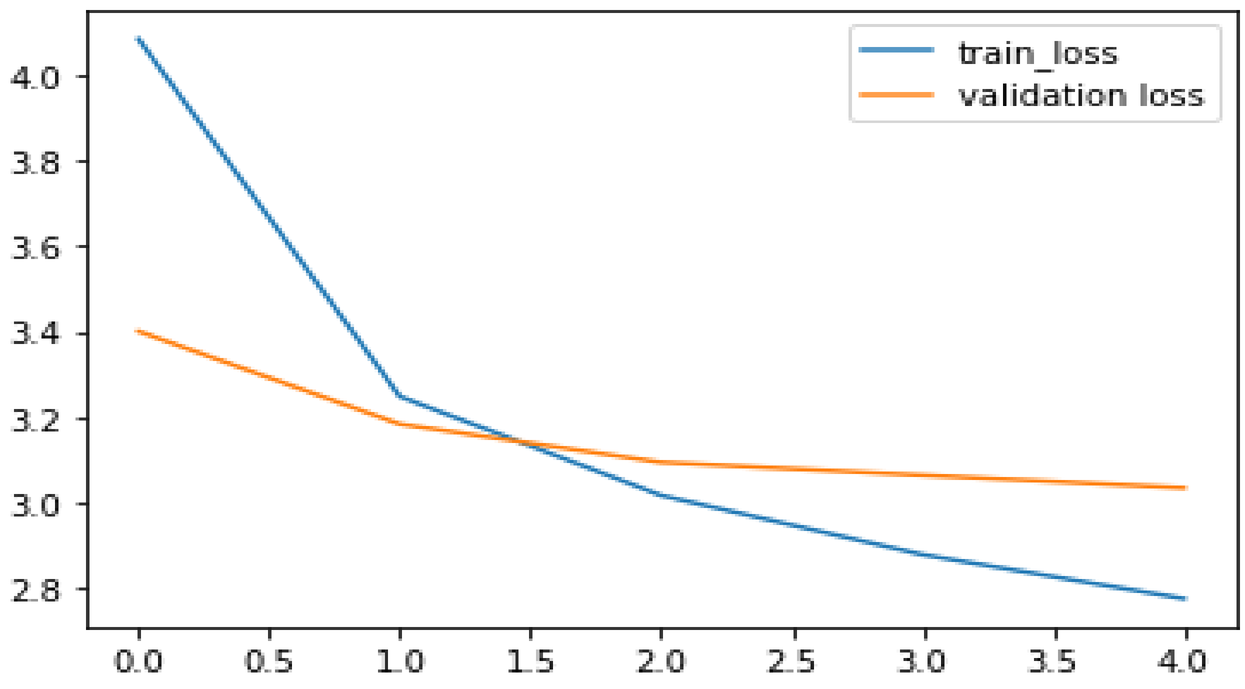
The provided graph visualizes the **training loss** (blue line) and **validation loss** (orange line) over the course of training an image captioning model.

Key Observations:

1. **Training Loss (Blue Line):**
   - The training loss starts high and decreases rapidly as the model learns from the training data.
   - This continuous decrease indicates that the model is improving its predictions on the training data, minimizing errors over time.
2. **Validation Loss (Orange Line):**
   - The validation loss also starts relatively high but decreases more gradually compared to the training loss.
   - Initially, the validation loss remains higher than the training loss, but as training progresses, both losses converge, and the validation loss plateaus or decreases more slowly.

Interpretation:

- **Decreasing Training Loss:**
  The decrease in training loss is a sign that the model is effectively learning from the data. The steep drop at the beginning is typical in deep learning models, as they adjust their weights based on the input data.
- **Validation Loss Behavior:**
  The validation loss represents how well the model performs on unseen data (not part of the training set). Initially, it may not decrease as fast as the training loss, but over time, it should also drop if the model generalizes well. In this case, the validation loss decreases alongside the training loss, suggesting that the model is not overfitting and is improving on both the training and validation sets.


train_loss
validation loss
4.0
3.8
3.6
3.4
3.2
3.0
2.8
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0

(Figure 10)

CHAPTER 3: Conclusion

CHAPTER 3: Conclusion

3.1 Conclusion

In this documentation, we presented an end-to-end overview of developing and training an Image Captioning model using the COCO dataset. The model combines Convolutional Neural Networks (CNNs) for image feature extraction with Recurrent Neural Networks (RNNs) or Transformer architectures for generating natural language captions. The goal of the model is to automatically generate meaningful and contextually relevant descriptions for images.

Throughout the project, several components were addressed, including:

- Dataset Preparation:

  Preprocessing the COCO dataset to ensure compatibility with the model.

- Model Architecture:

  Utilizing CNNs and either RNNs or Transformers to capture the visual elements and generate corresponding captions.

- Training and Validation:

  The model was trained with a loss function to minimize captioning errors, and it was evaluated using common metrics such as BLEU, METEOR, and CIDEr.

- Challenges:

  We highlighted key challenges such as handling the complexity of scenes, variability in captions, and the need for robust generalization.

The results of the training and validation phases demonstrated that the model is capable of generating accurate and coherent captions that describe the content of the images. The generated captions, combined with the decreasing training and validation loss, suggest that the model generalizes well and effectively captures the relationship between the visual and textual domains.

While the model has shown promising results, there are opportunities for future improvement. Enhancements such as fine-tuning the attention mechanism, exploring more advanced Transformer models, and applying the model to additional datasets could further improve its accuracy and generalizability.

The potential applications of this model are vast, ranging from assistive technologies for the visually impaired to automated content generation and enhanced image search capabilities. Moving forward, this model provides a solid foundation for further developments in the field of image captioning and multimodal AI.

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