

Images are self-made, part of the IAM Dataset, or credited in the slides.

# Horizontally Variable OCR

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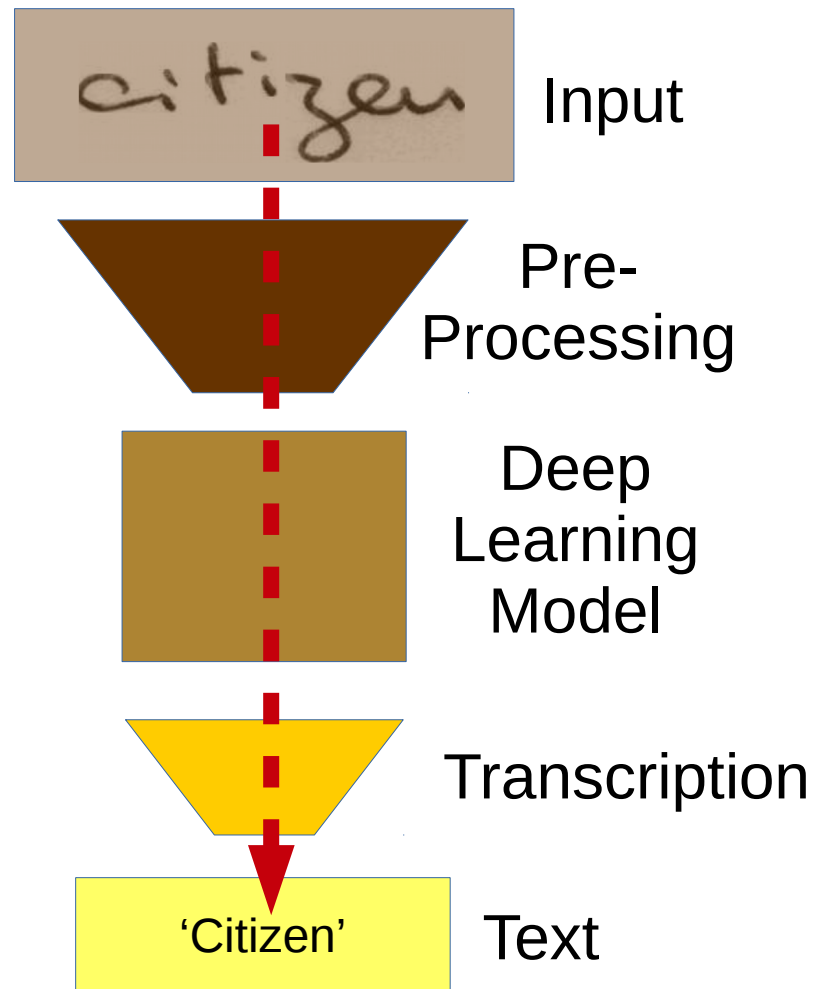
*Or something....*

# Goal: Transcription of Images to Text, without letter segmentation

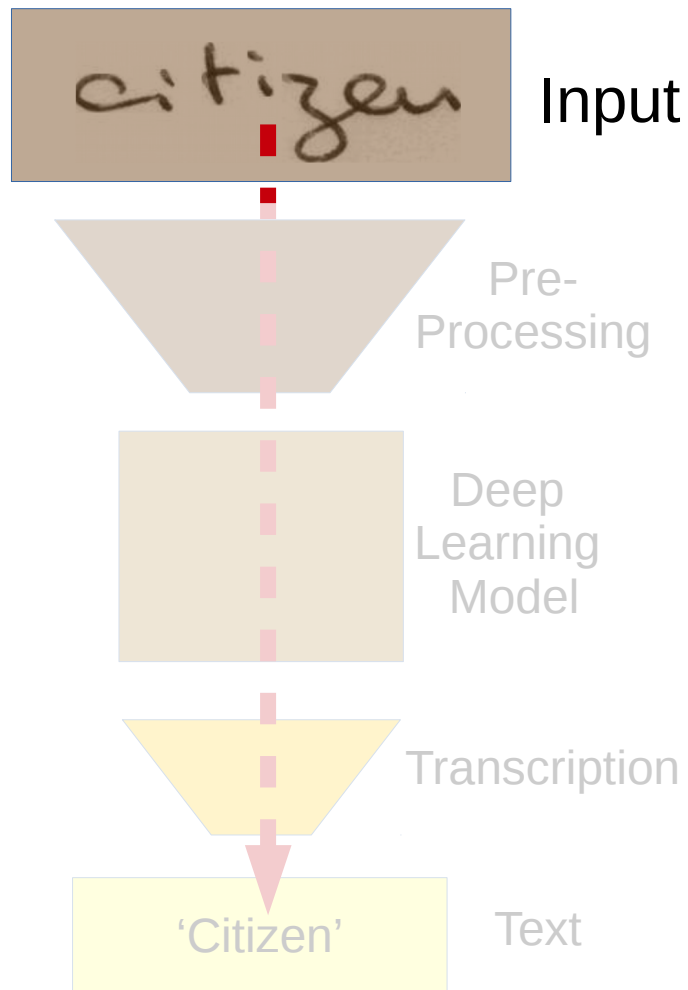
- Examine a lot of different datasets, and found one which had the closest resemblance to my problem.
- Ended up with the IAM (offline, i.e. handwritten) dataset with **word segmentation**\*
- I'll skip over the first few months of research :)
- First let's see what the ML model is supposed to do:

\*The IAM dataset contains variations with word, sentence and line segmentation.

# Black Box Illustration



# Black Box Illustration

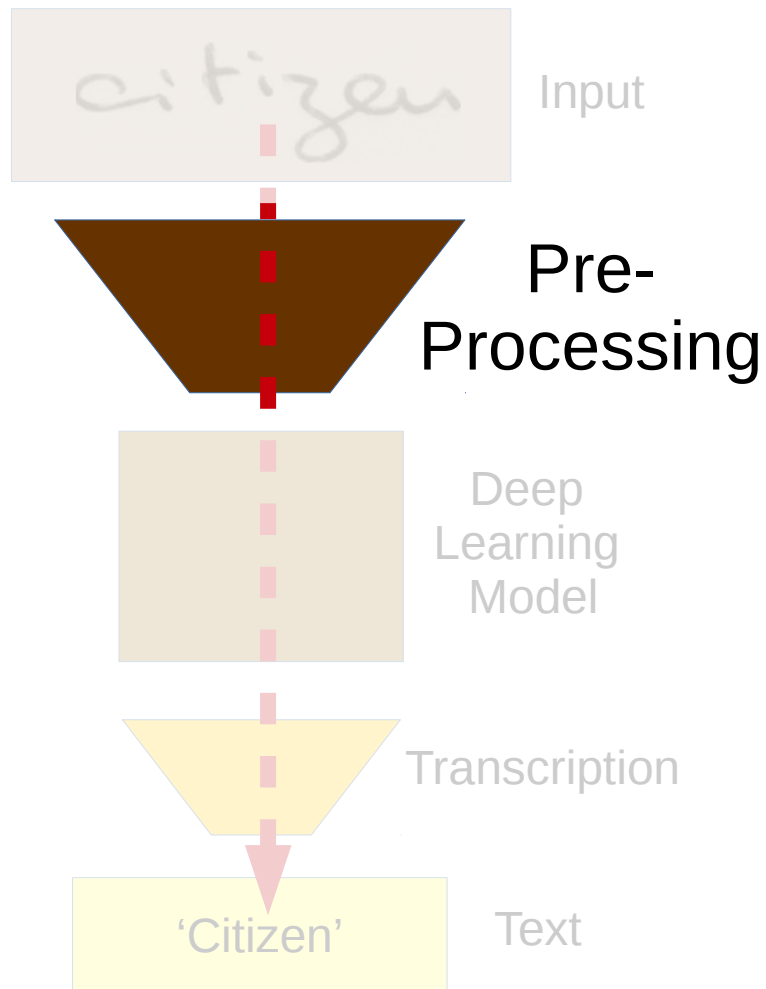


Text Examples from IAM:

And as the British  
government  
stepped up

Labels from the Dataset:  
'And' 'as' 'the' 'British'  
'Government'  
'stepped' 'up'

# Black Box Illustration



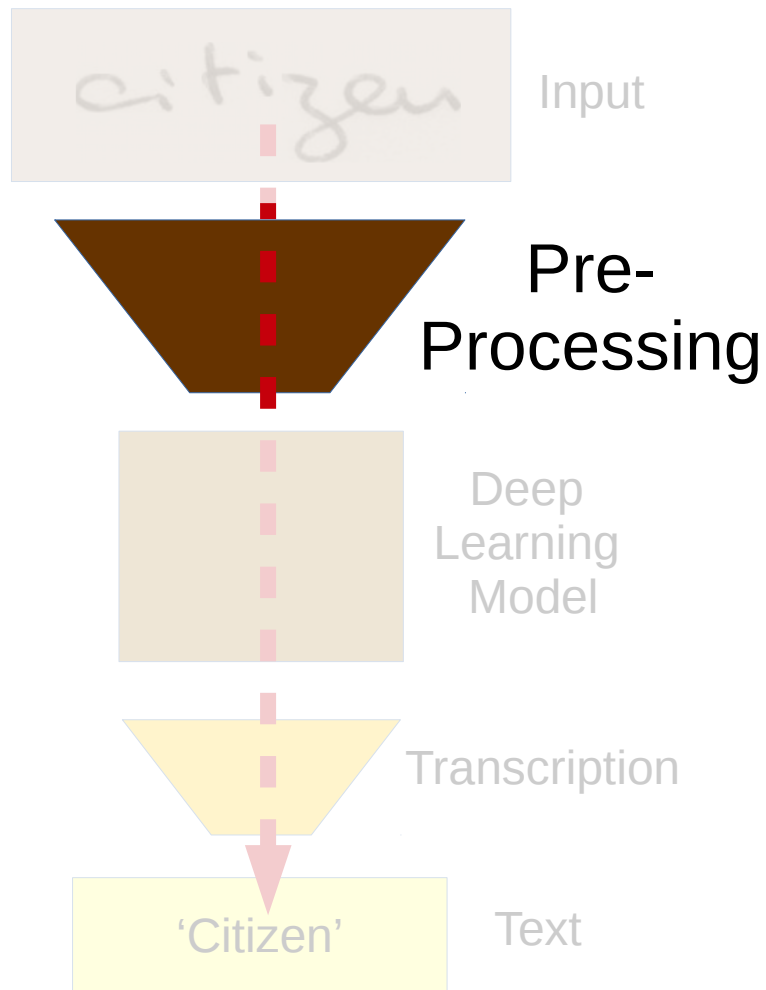
And as the British

Text had to be normalized to a fixed height:

And AS the British

Not ideal, but the letters should be recognized regardless of size anyway.

# Black Box Illustration



And as the British

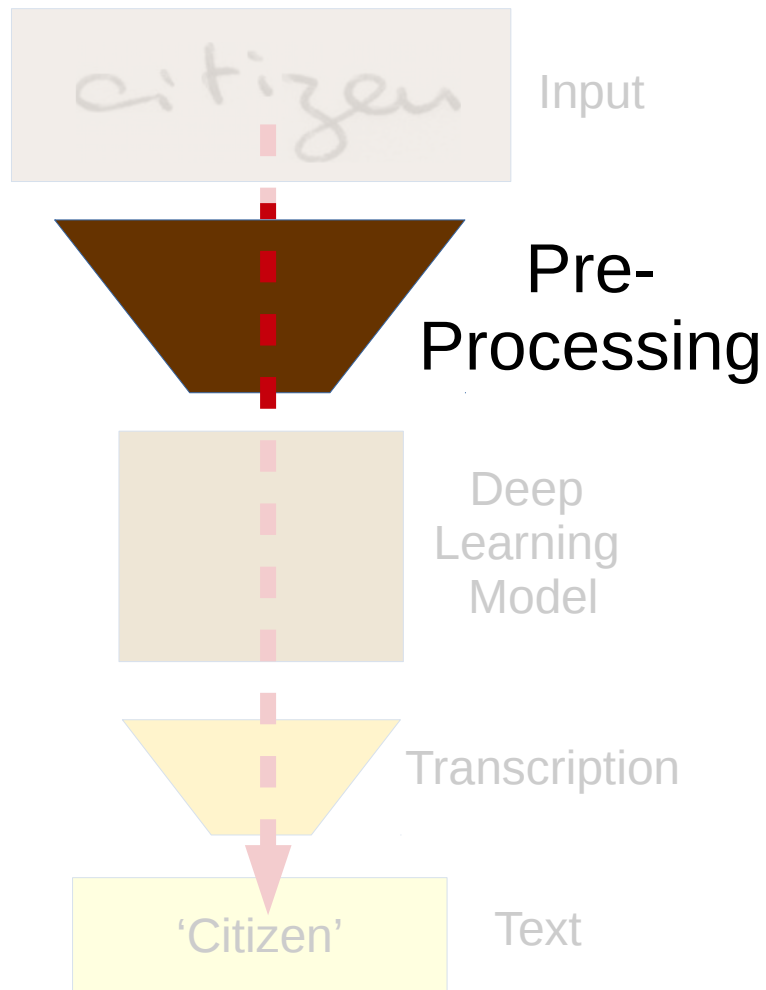
Why not just pad the words?

Due to the large variation between the images padding might end up being very large, which would cause a visible break between the images and the padding. This is already a problem in some of the images:

TODAY



# Black Box Illustration



And as the British

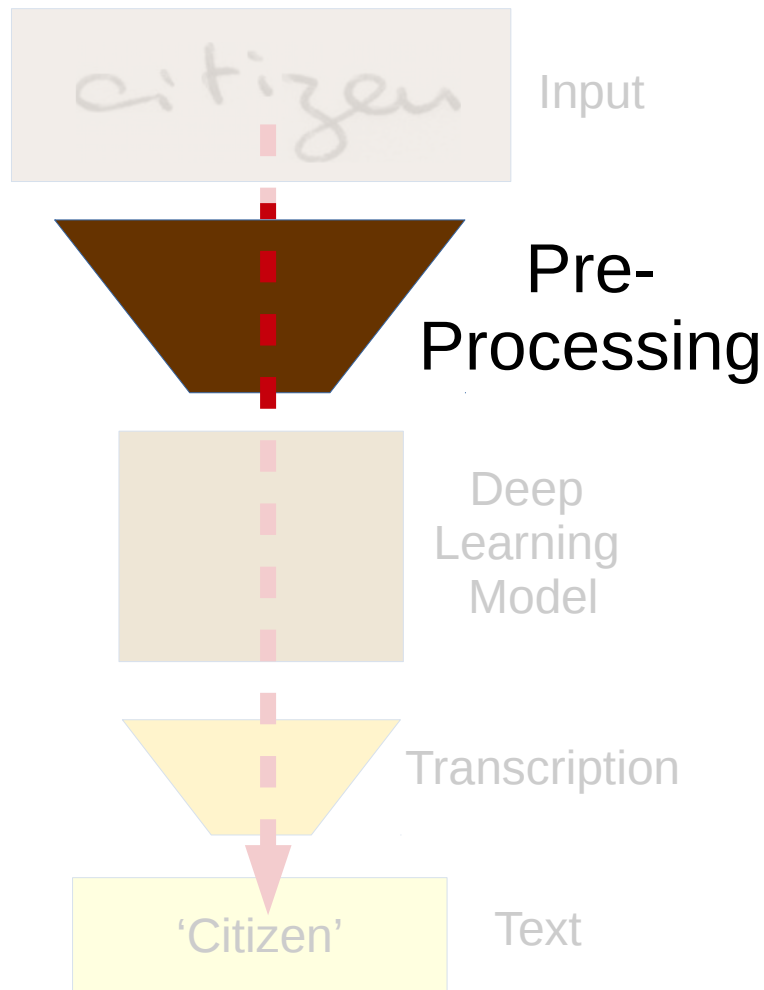
Different checks were made, the dataset was cleaned of the biggest errors in labels or images:

Some words were not segmented so that an entire sentence was labeled as one word, and sometimes the labels were wrong.

And the British

'And'

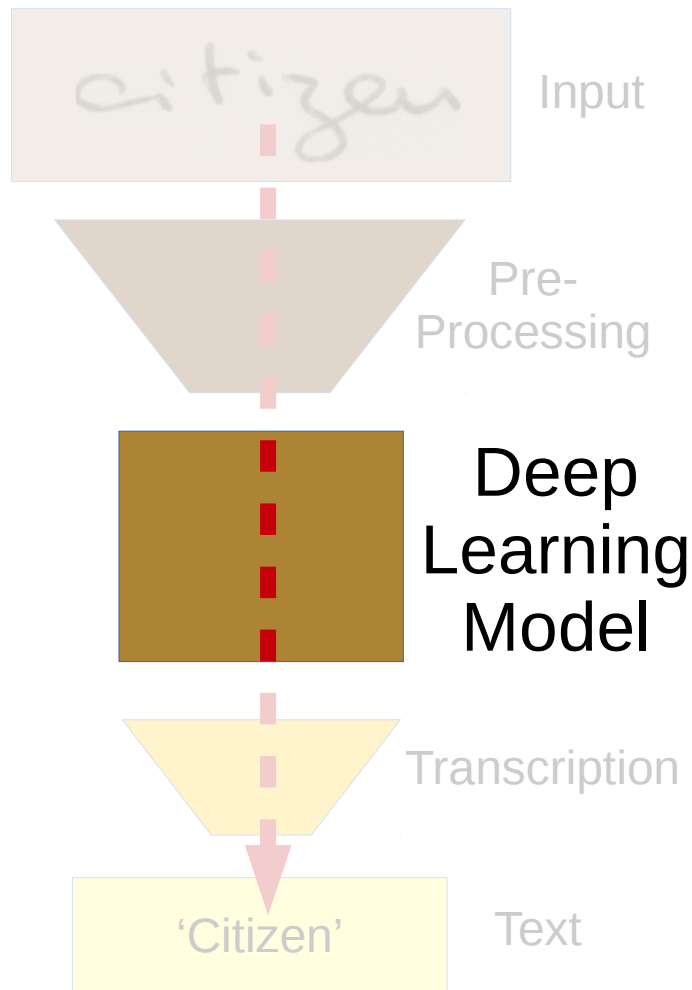
# Black Box Illustration



Images were pickled after preprocessing for easier and faster loading, as well as for the convenience of loading a single file instead of 115.276



# Black Box Illustration

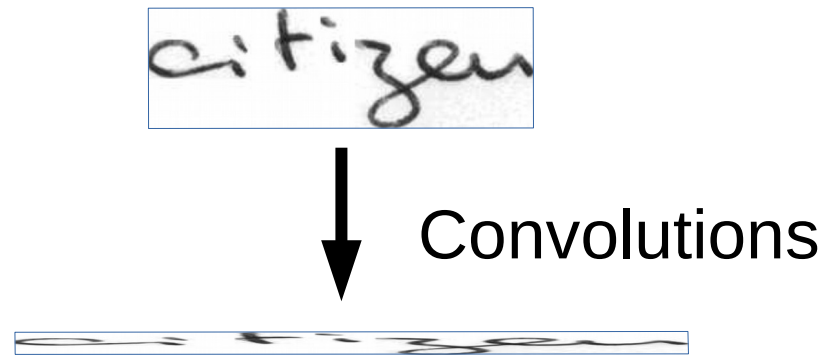
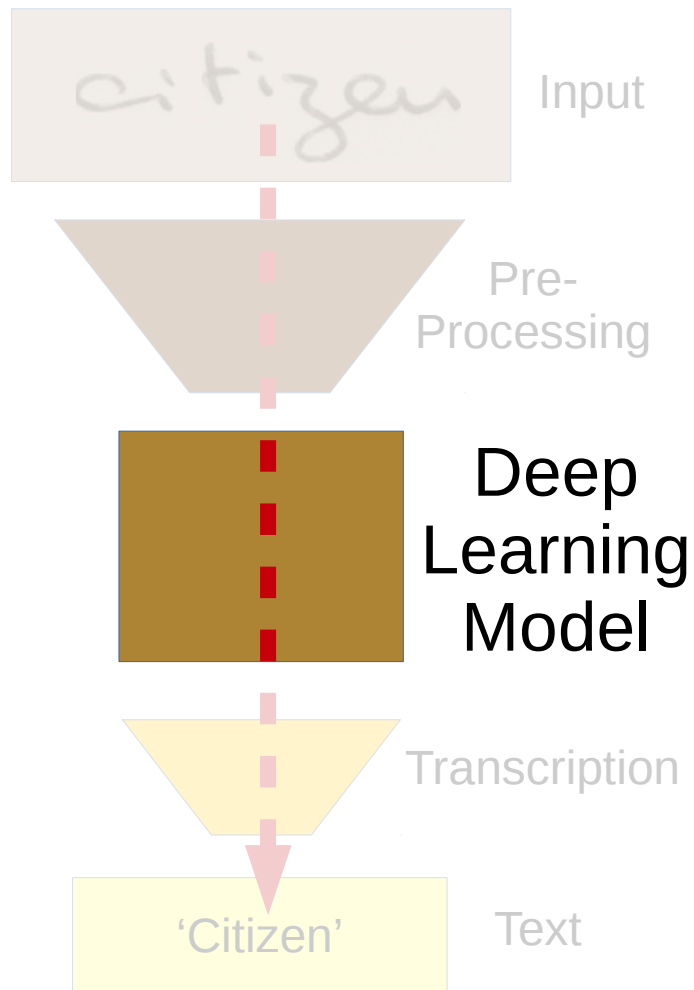


After some research, I found this paper:

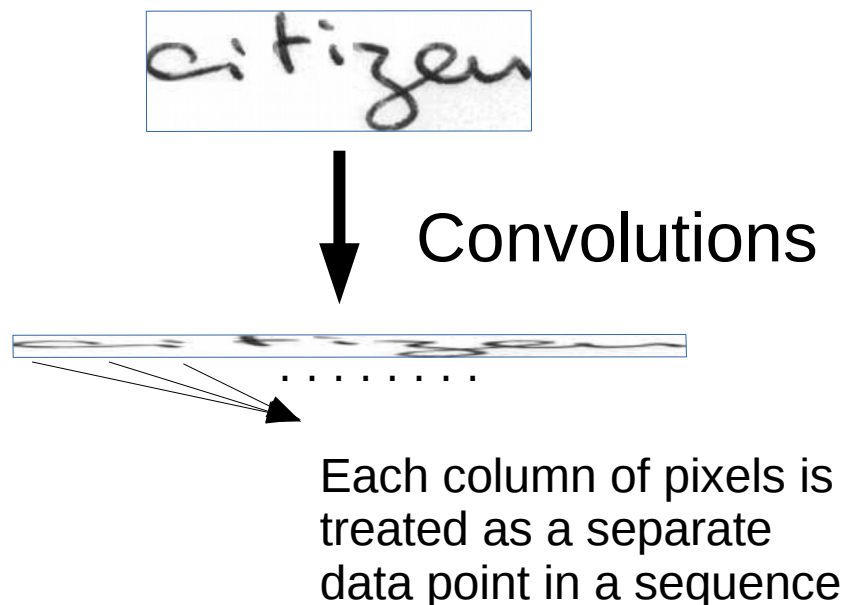
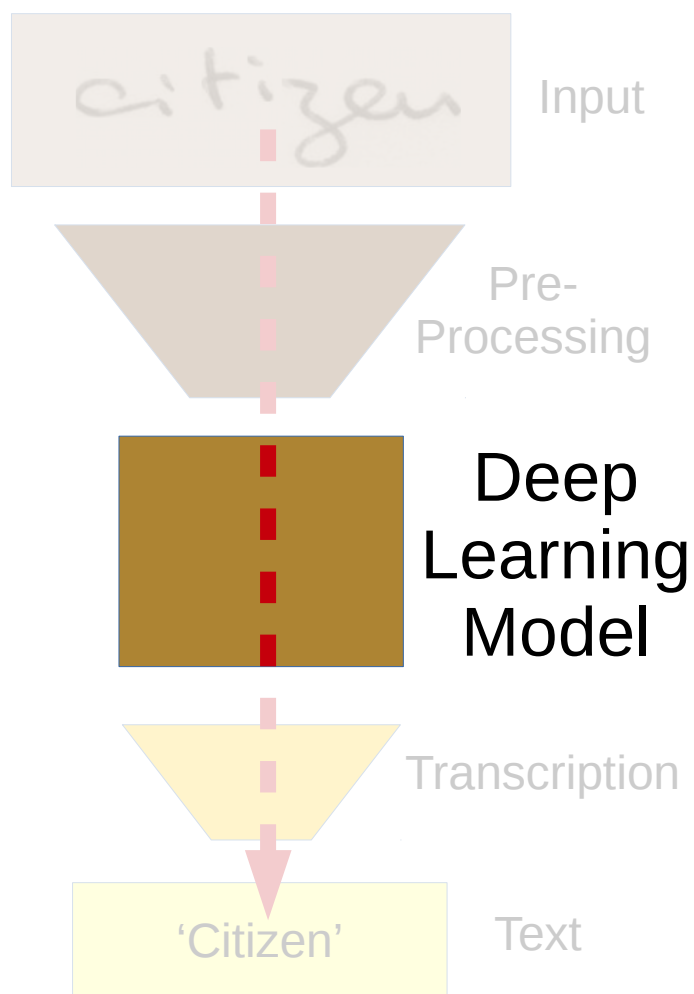
'An End-to-End Trainable NN for Image-based Sequence Recognition and it's application to Scene Text Recognition'.

What this paper, in a rather complicated fashion, describes, is a model where Convolutional Layers are used to extract information from an image, and then a RNN is used to process that data to be transcribed into text.

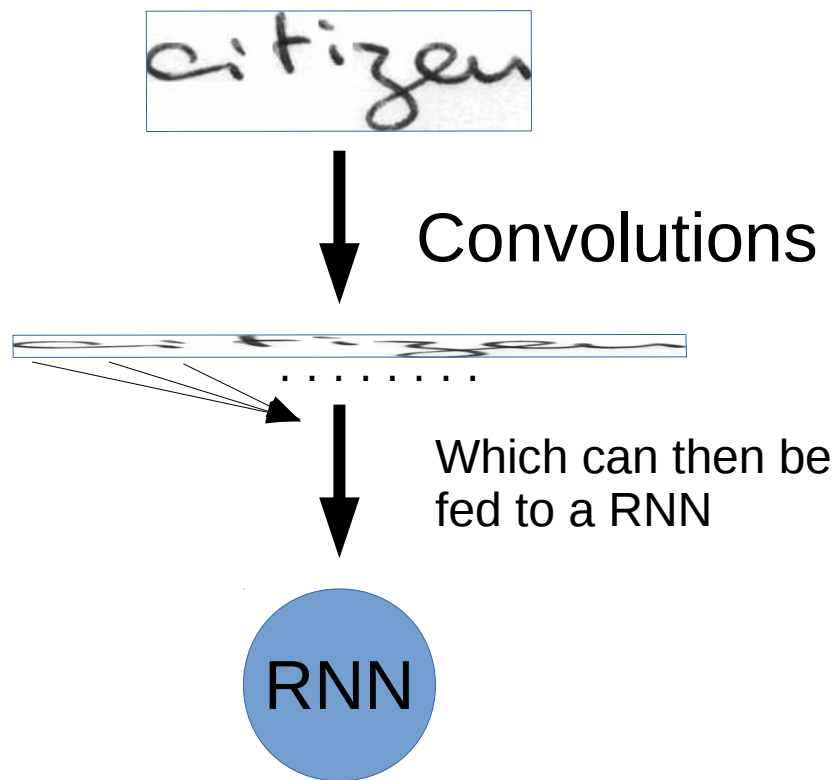
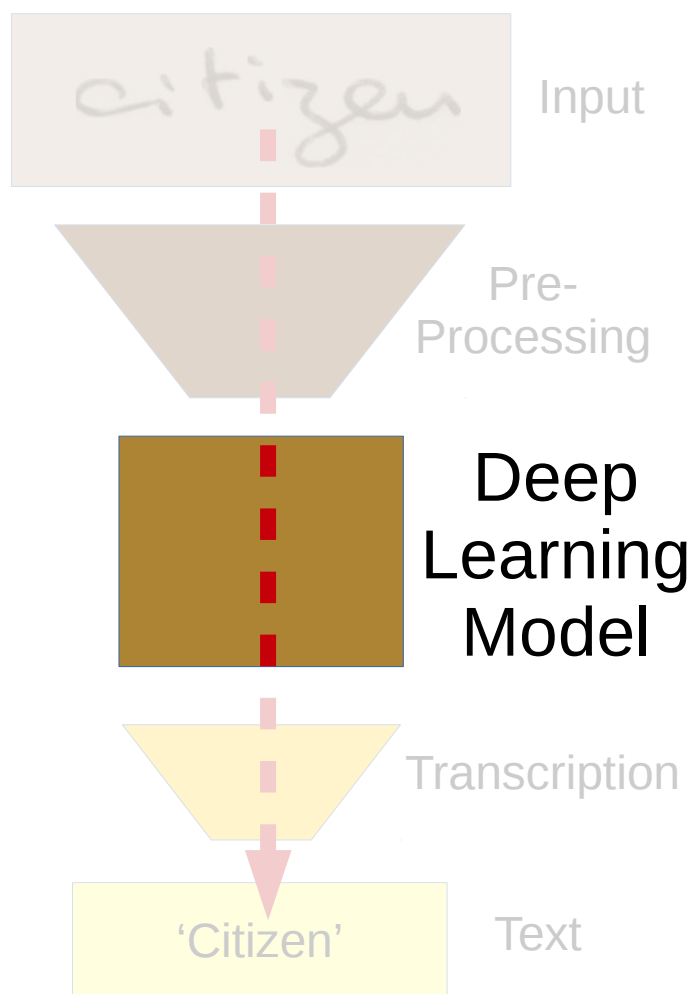
# Black Box Illustration



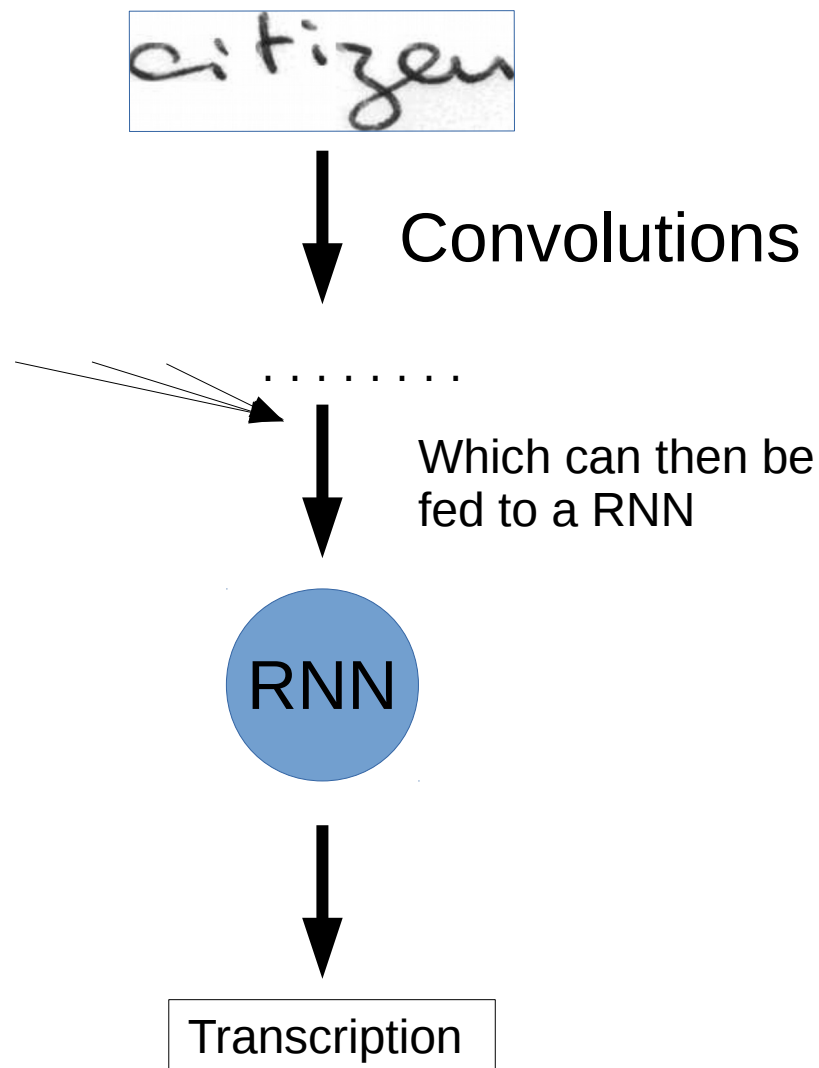
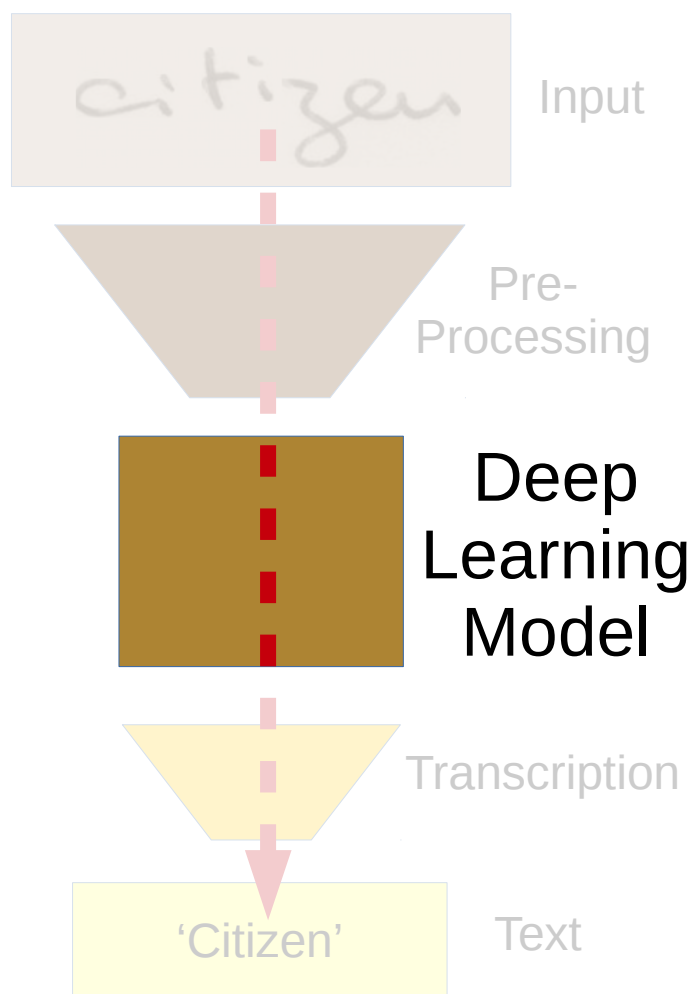
# Black Box Illustration



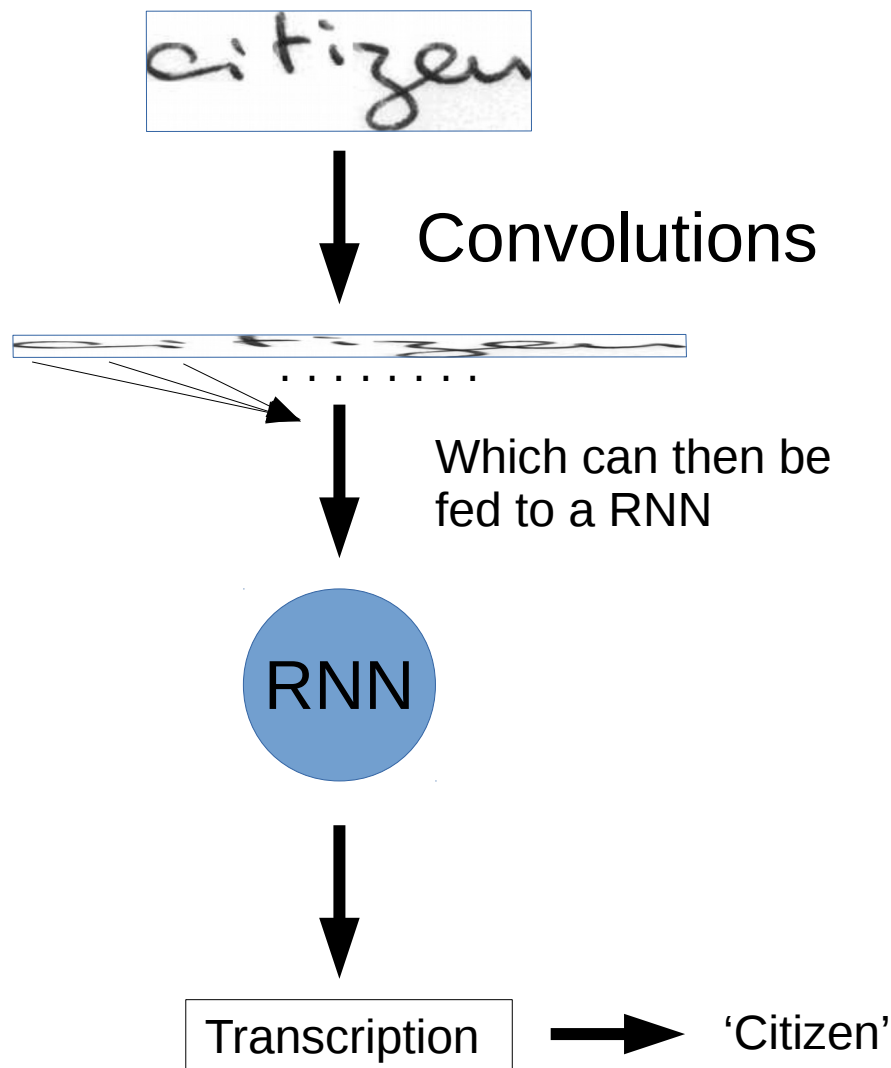
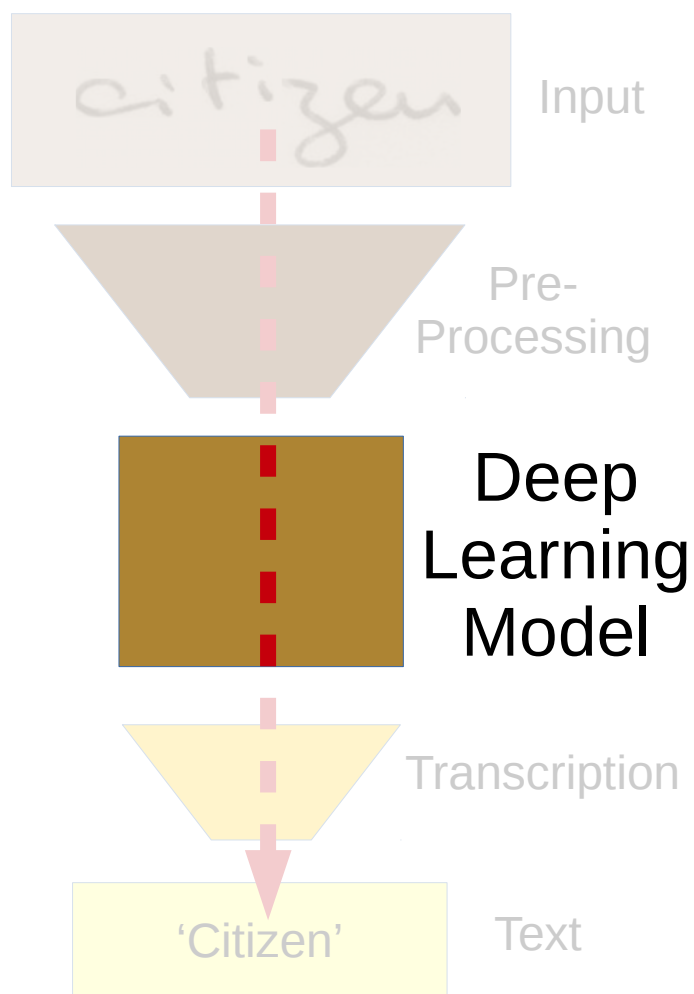
# Black Box Illustration



# Black Box Illustration

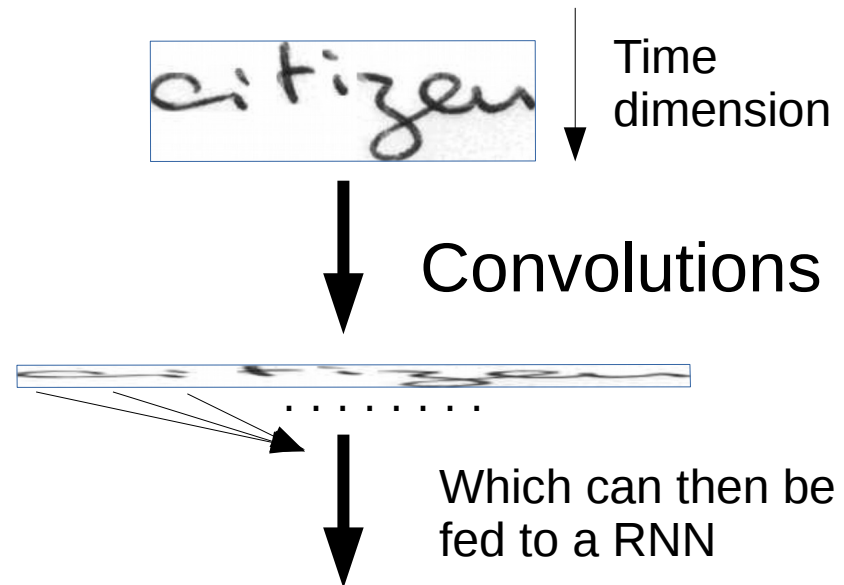
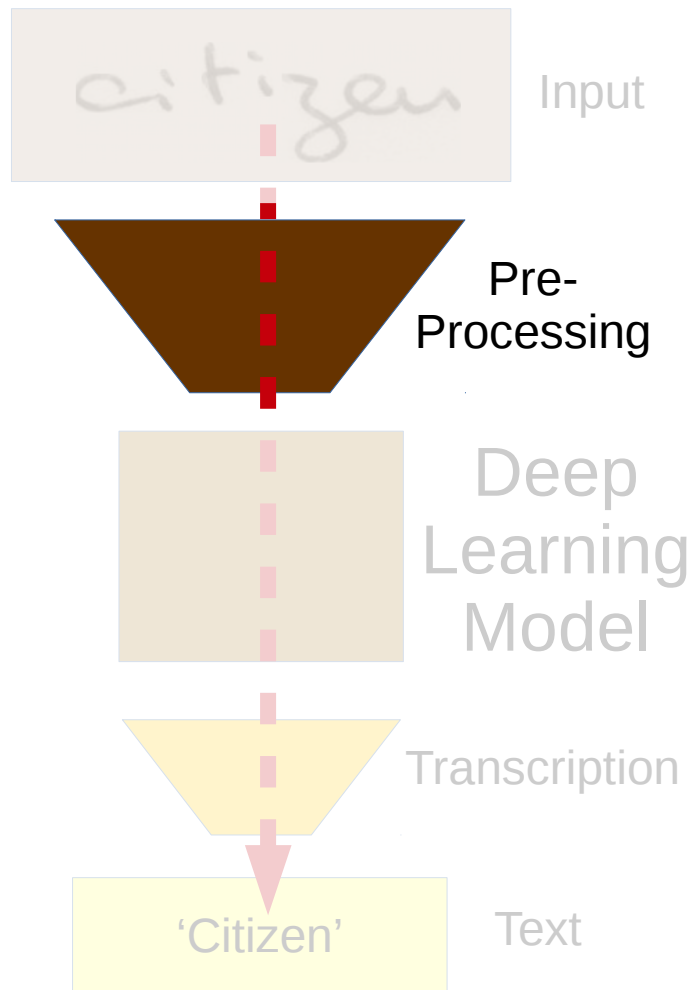


# Black Box Illustration

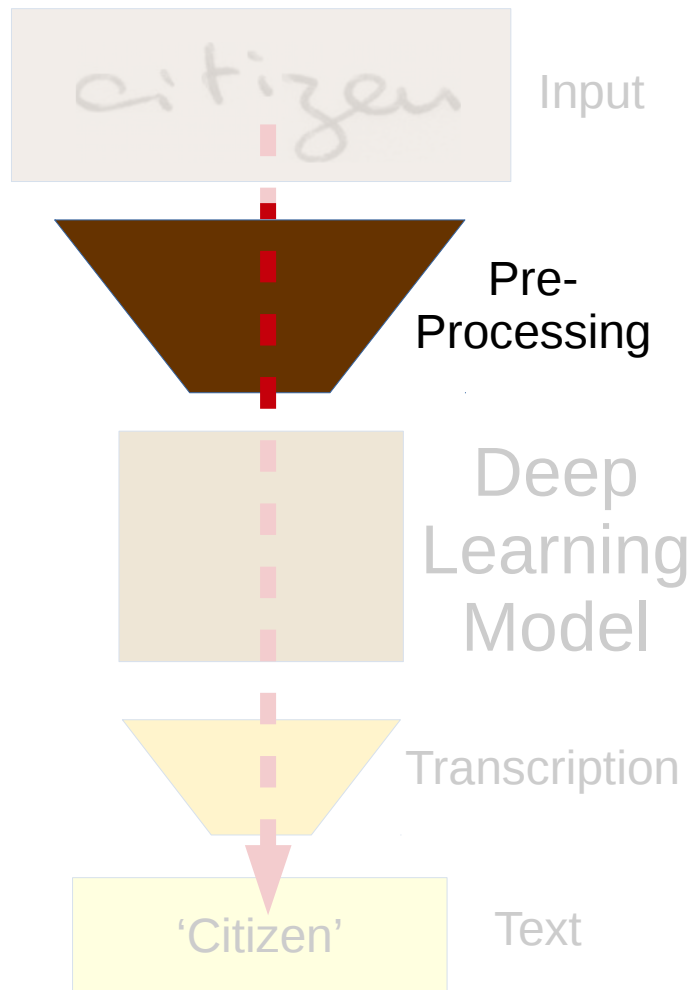




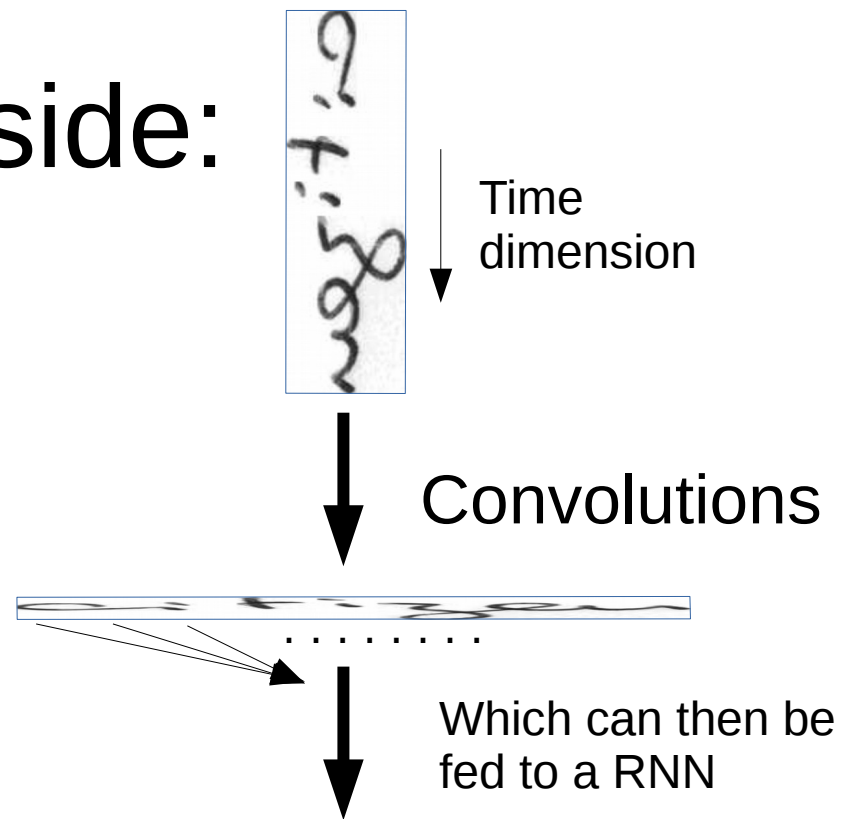
# Aside:



Since the RNNs take data in which the 'Time Dimension'\* is the first dimension, the dimensions for the images were flipped.

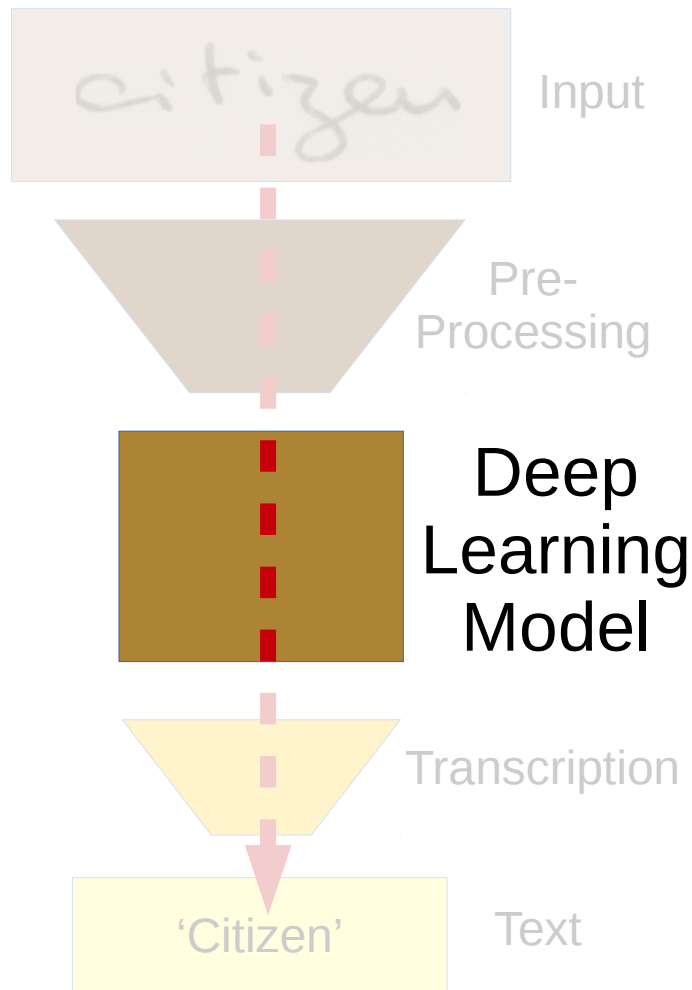


# Aside:



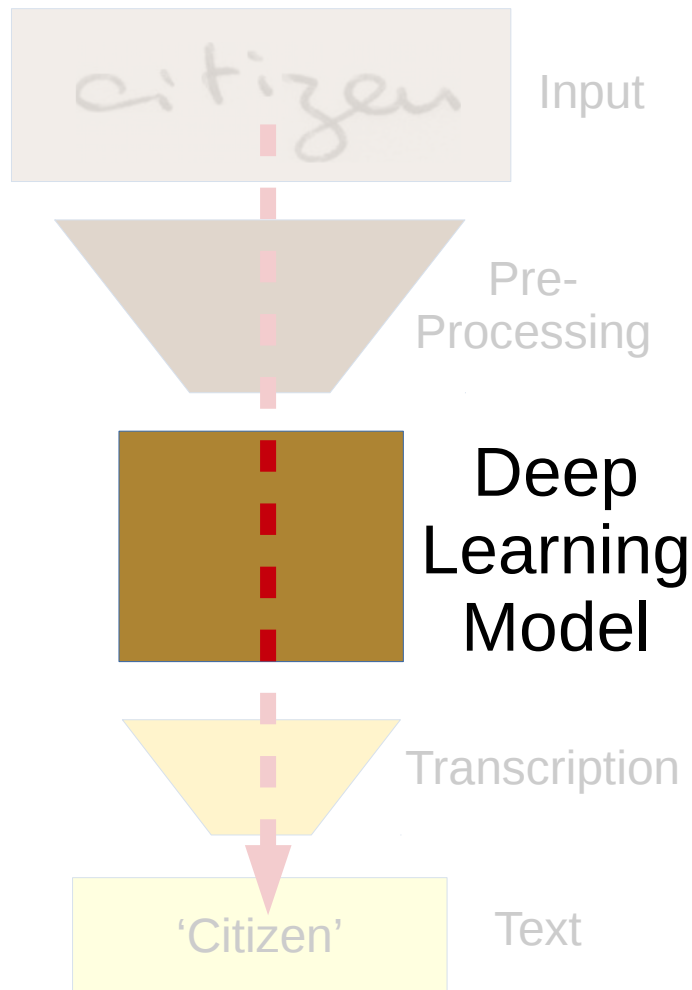
Since the RNNs take data in which the 'Time Dimension'\* is the first dimension, the dimensions for the images were flipped.

# Black Box Illustration

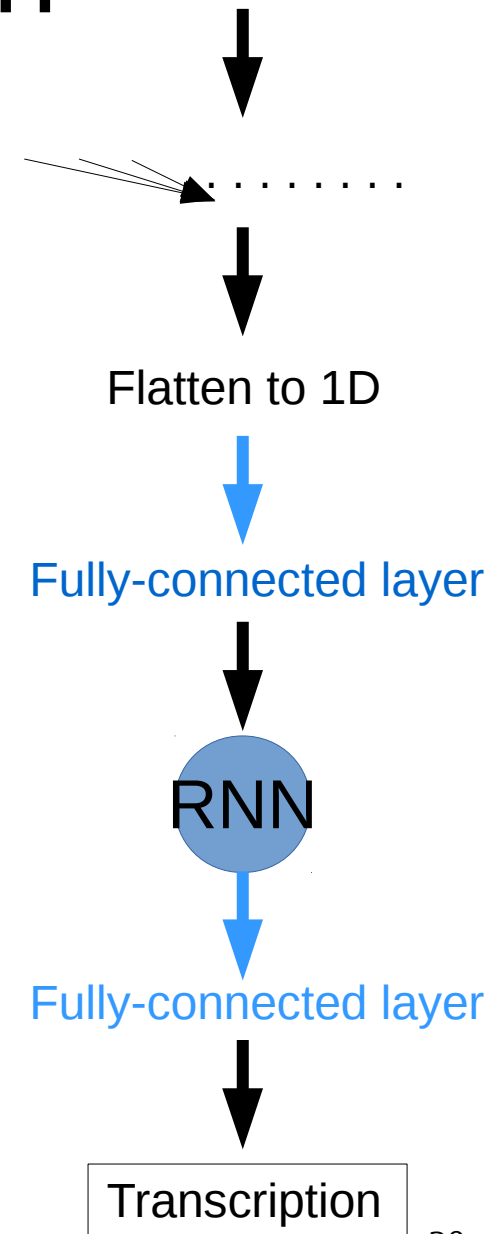


Since the paper was coded in Torch I looked for any implementations that used Tensorflow and ideally the Keras frontend. While the architecture was relatively easy to understand, the puzzle piece missing was how to calculate the loss function for this type of output.

# Black Box Illustration

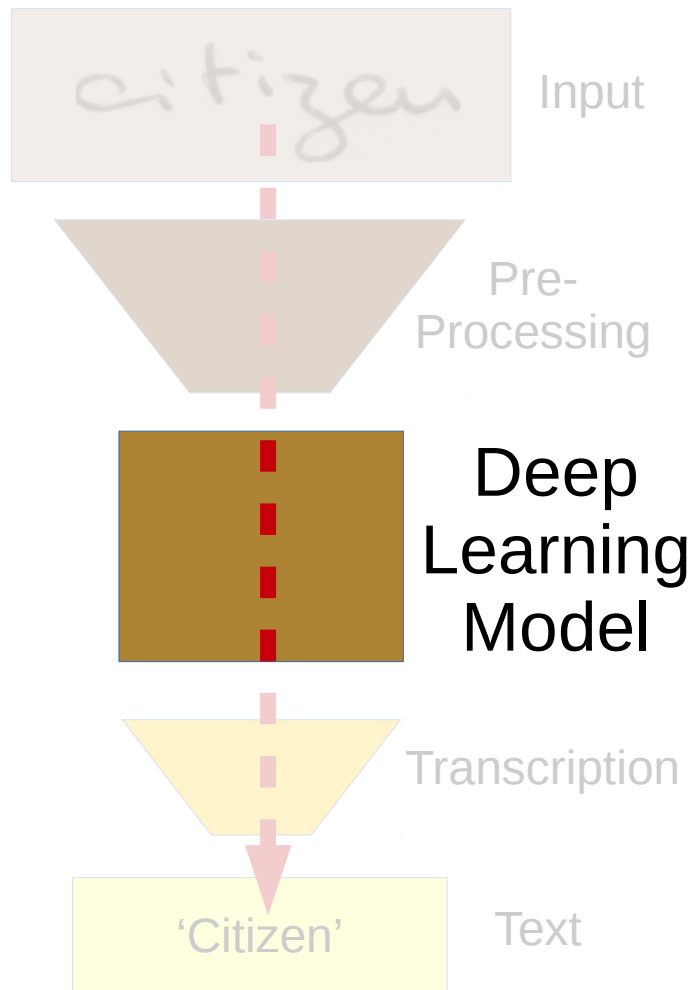


I found the keras-image-ocr repository\* which (as a demonstration) used a similar architecture.



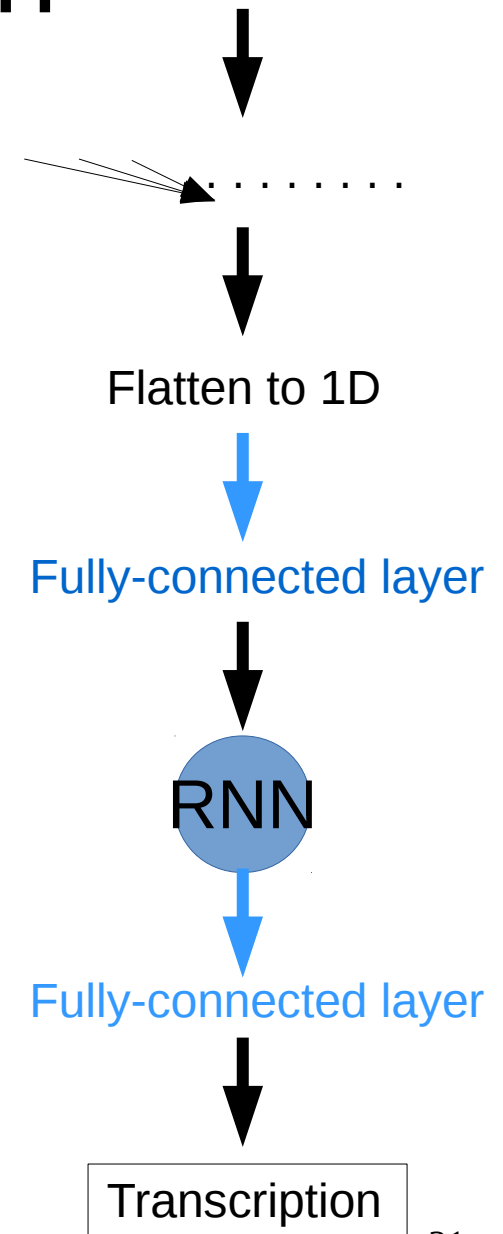
\*<https://github.com/Tony607/keras-image-ocr>

# Black Box Illustration

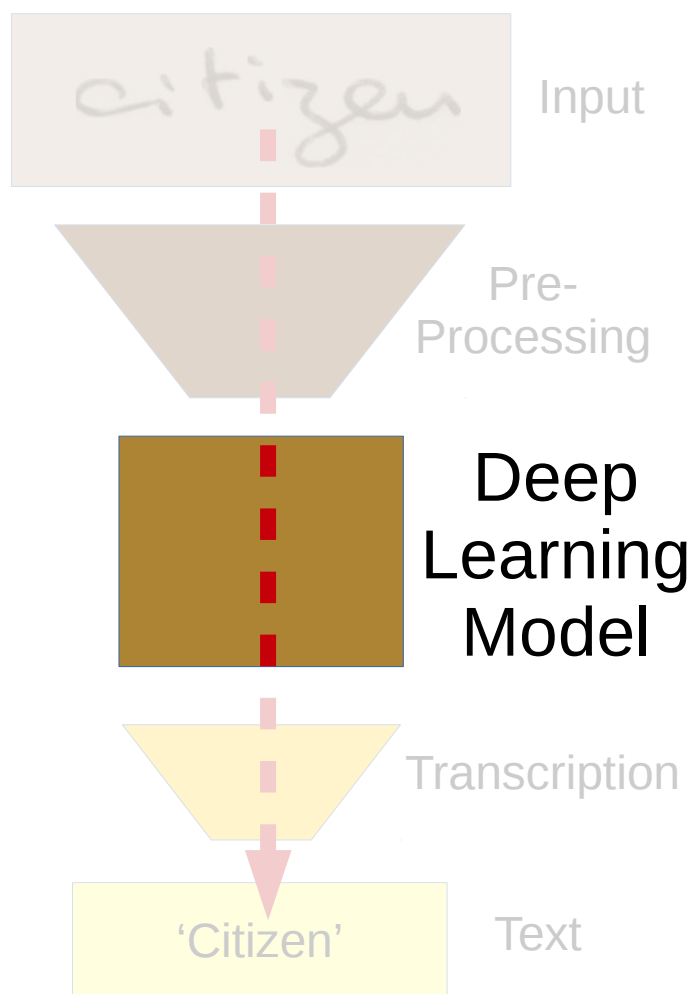


I found the keras-image-ocr repository which (as a demonstration) used a similar architecture. This demo used Automatically generated images to train the network.

Example image\*:

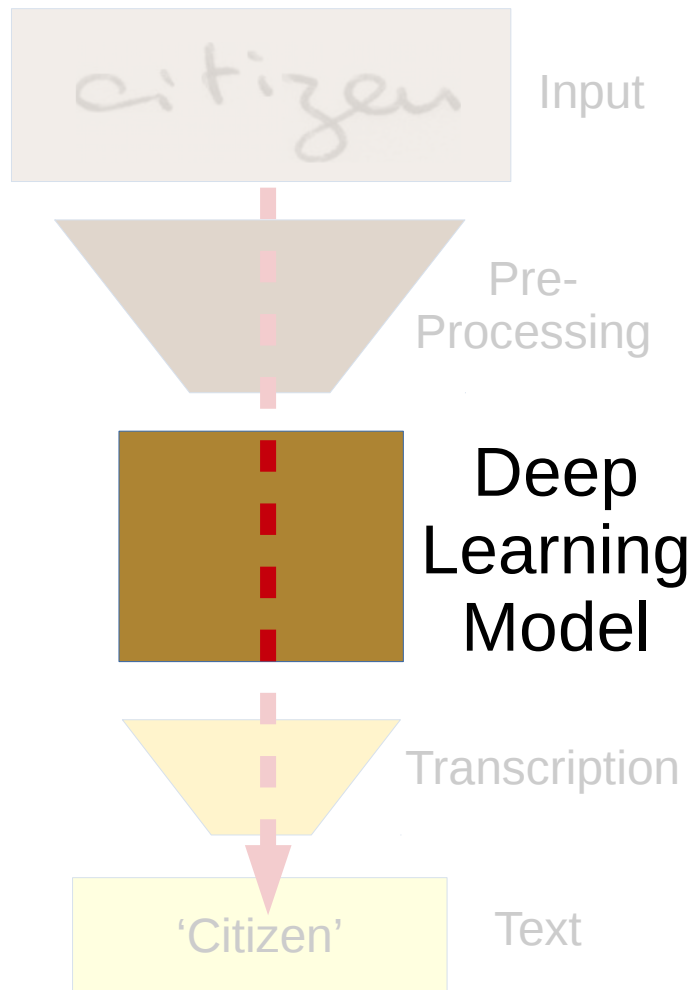


# Black Box Illustration



Most importantly it used a working implementation of the CTC loss function.

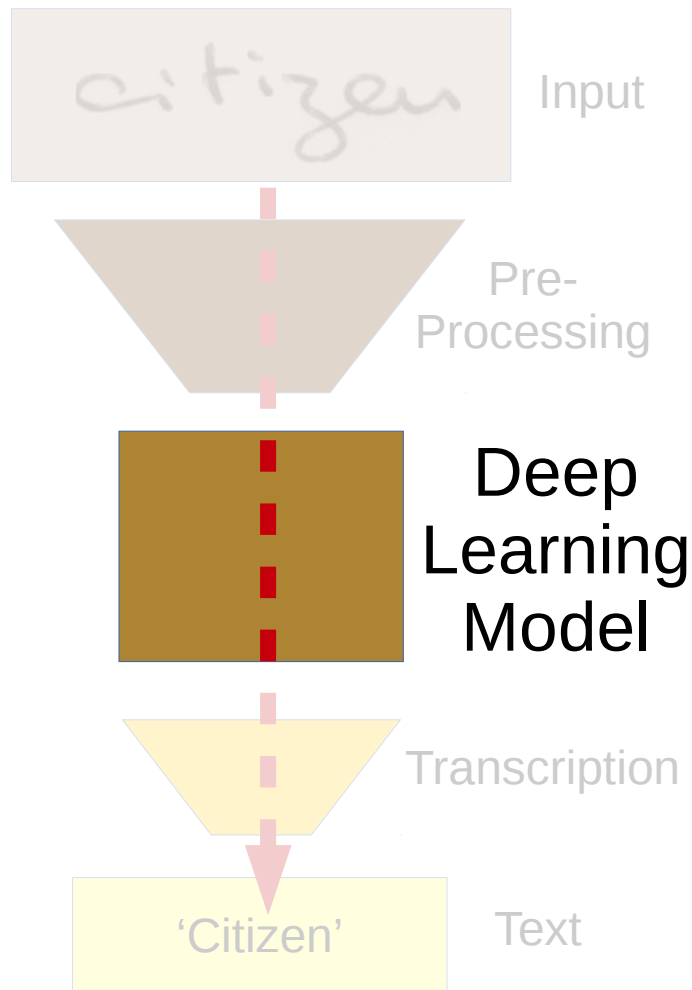
# Black Box Illustration



The CTC loss function is able to calculate Loss for unsynchronized input and output.

Since every letter is not the same number of pixels wide, you cannot apply a n-number of pixels per letter algorithm. This is where CTC comes into play. It was originally developed for audio data, but works for any kind of sequential data. I won't go into details as to how it works, see the paper at [http://www.cs.toronto.edu/~graves/icml\\_2006.pdf](http://www.cs.toronto.edu/~graves/icml_2006.pdf) for more. (warning: Math!)

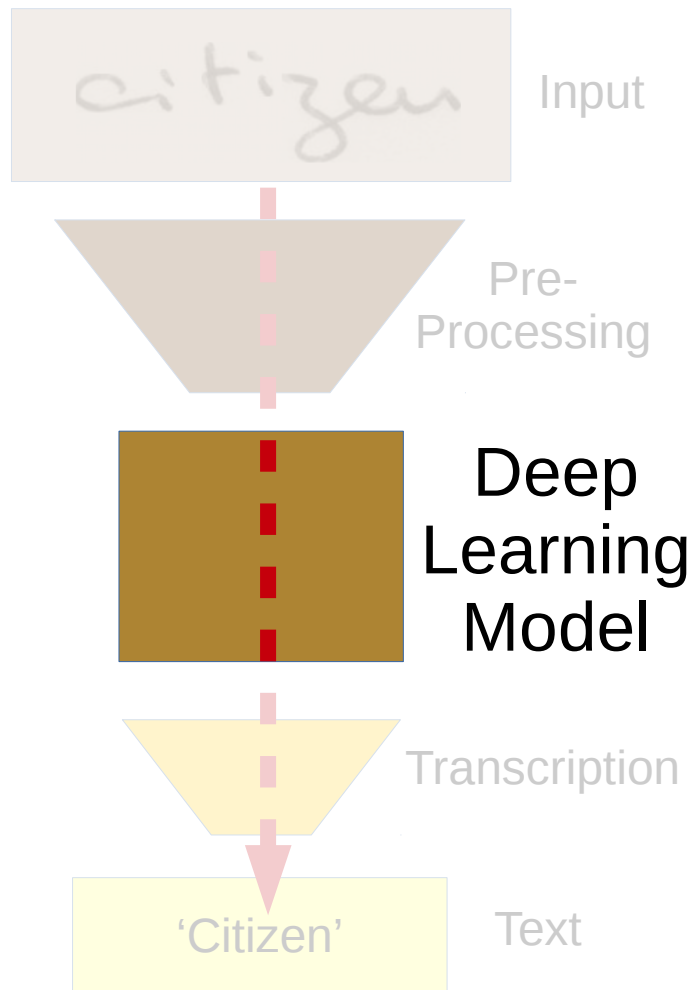
# Black Box Illustration



While CTC Loss has been implemented in Tensorflow, the documentation is not particularly clear, so I had to take the data generator from the demo apart to see the data it was generating, then format the IAM dataset into that format.



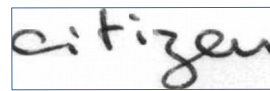
# Black Box Illustration



CTC loss requires for each sample:

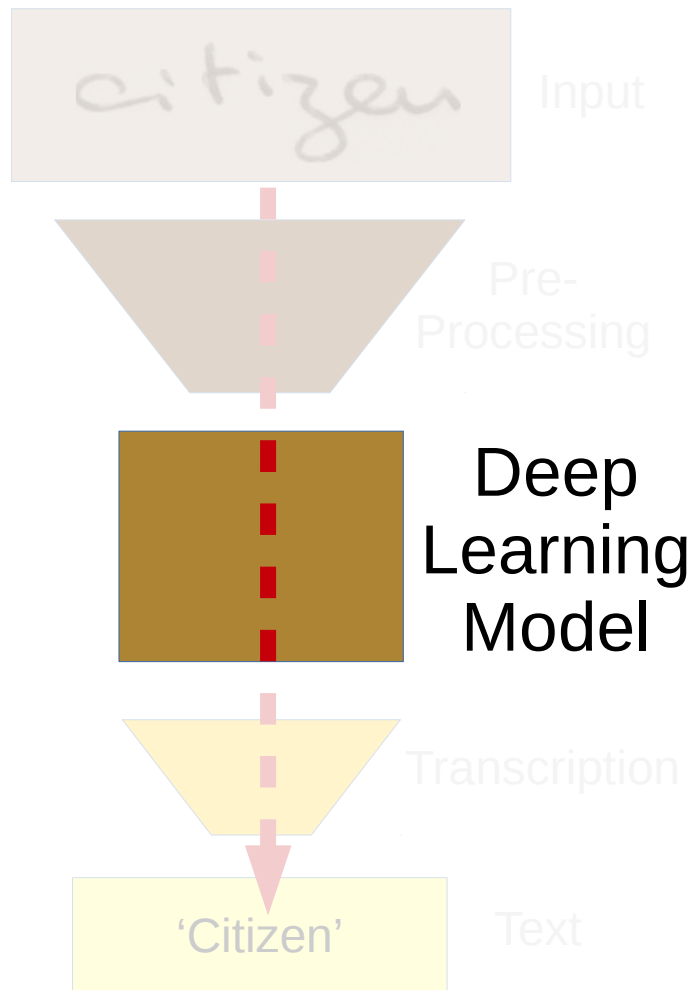
- the output Data from the model,
- Labels encoded in integer form and padded with an encoding for 'blank' to a certain max length,
- The size of the input in the time dimension,
- The length of the label without the 'blank' padding.

For example:



(processed through the network),  
'[5, 11, 22, 11, 28, 7, 16,-1,-1,-1]',  
30 pixels,  
7 letters long

# Black Box Illustration



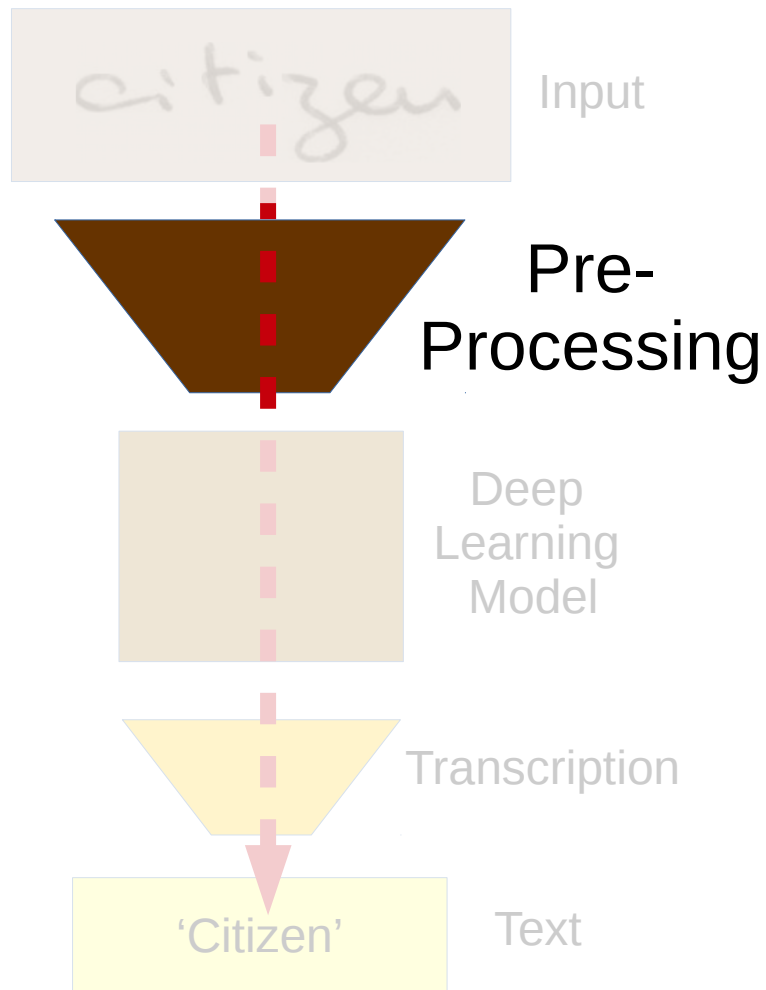
Now the model can process images of variable width, however during training, image dimensions have to be defined, this is a restriction since gpu memory has to be reserved as well as computation optimizations needing a defined input format.

Solution: Padding?

Nope!

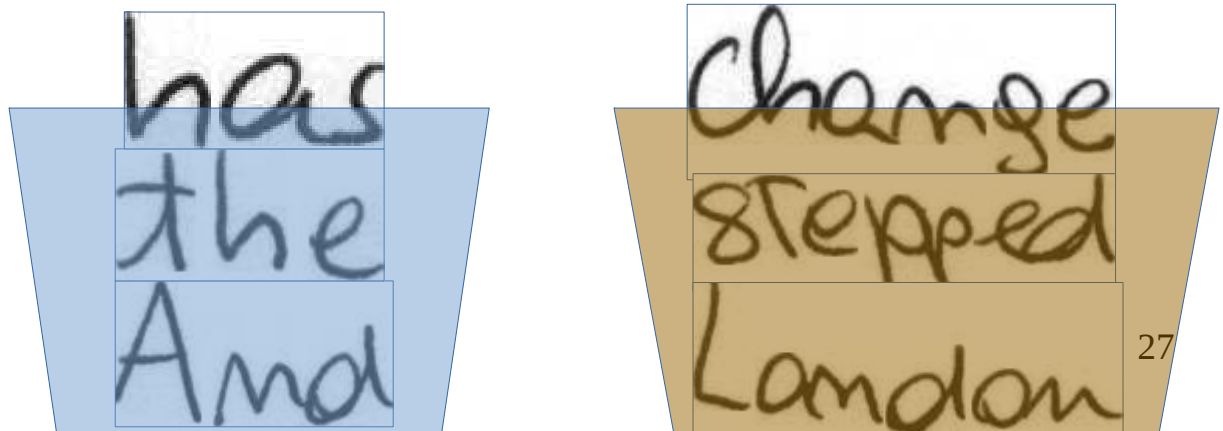
Back to data Pre-processing!

# Buckets!



And as the British

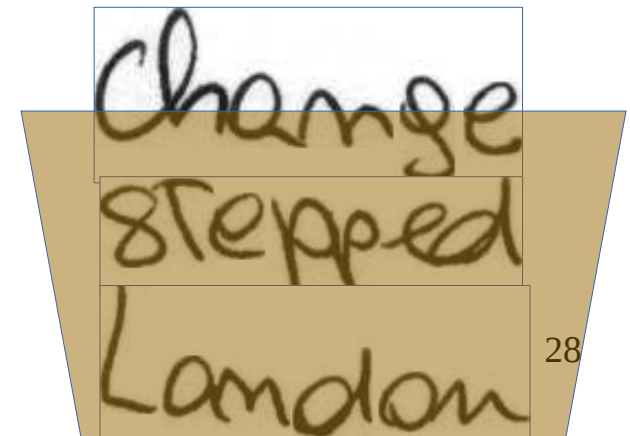
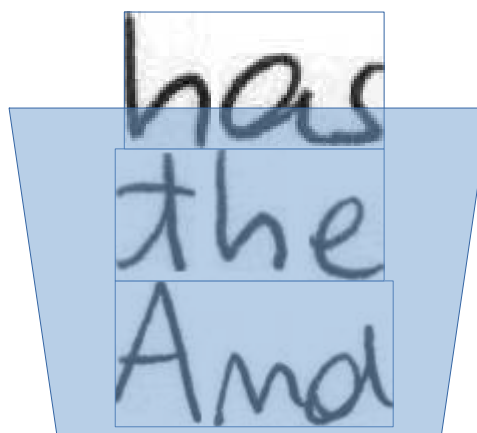
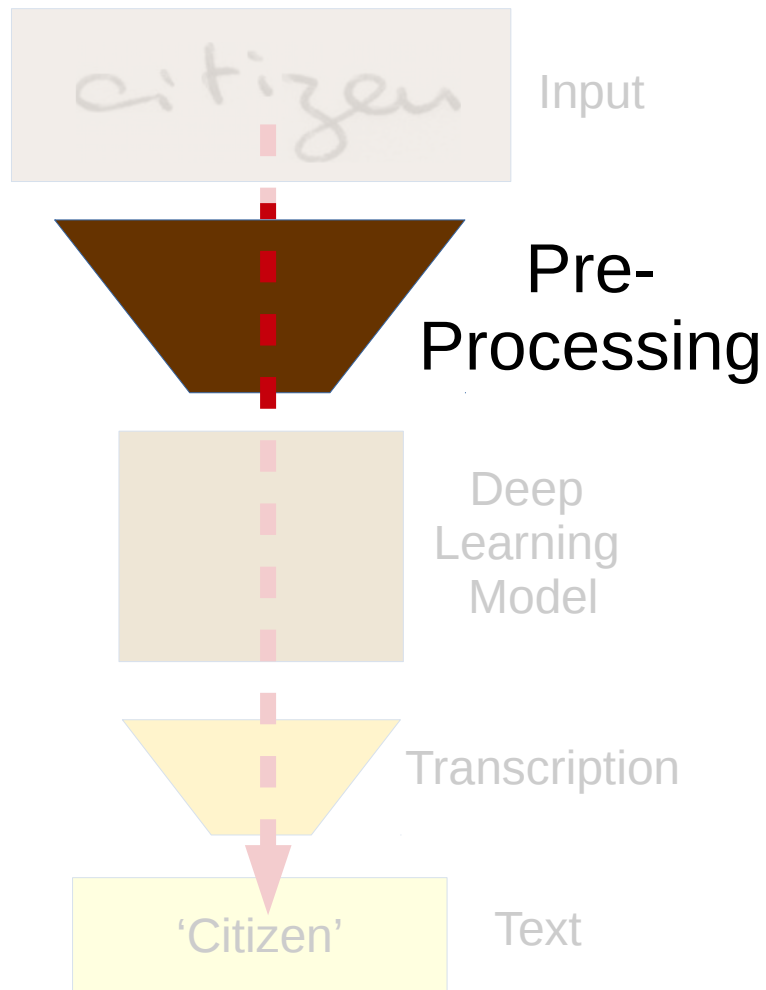
Padding was not necessary since **Bucketing** was implemented. **Bucketing** is the grouping of images based on a criterion, in this case **Image Length**. Image height was already normalized as explained before.



# Buckets!

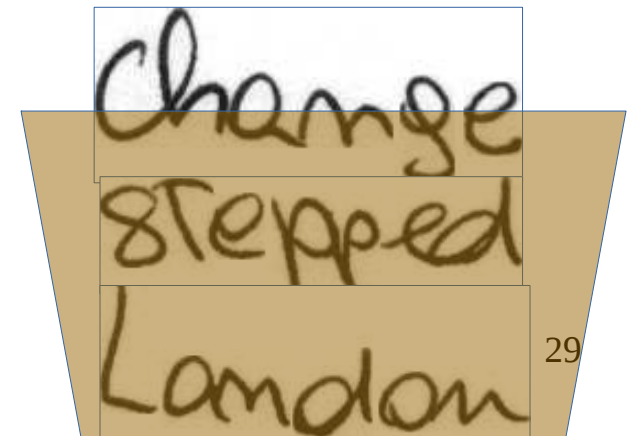
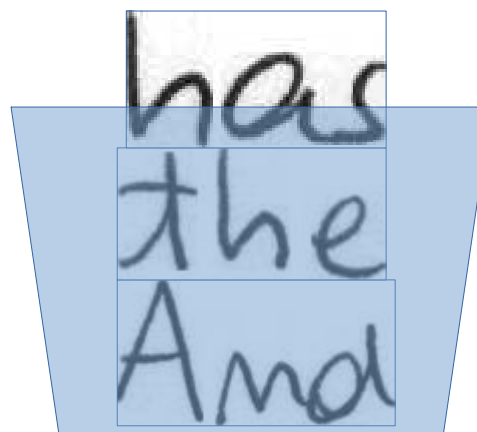
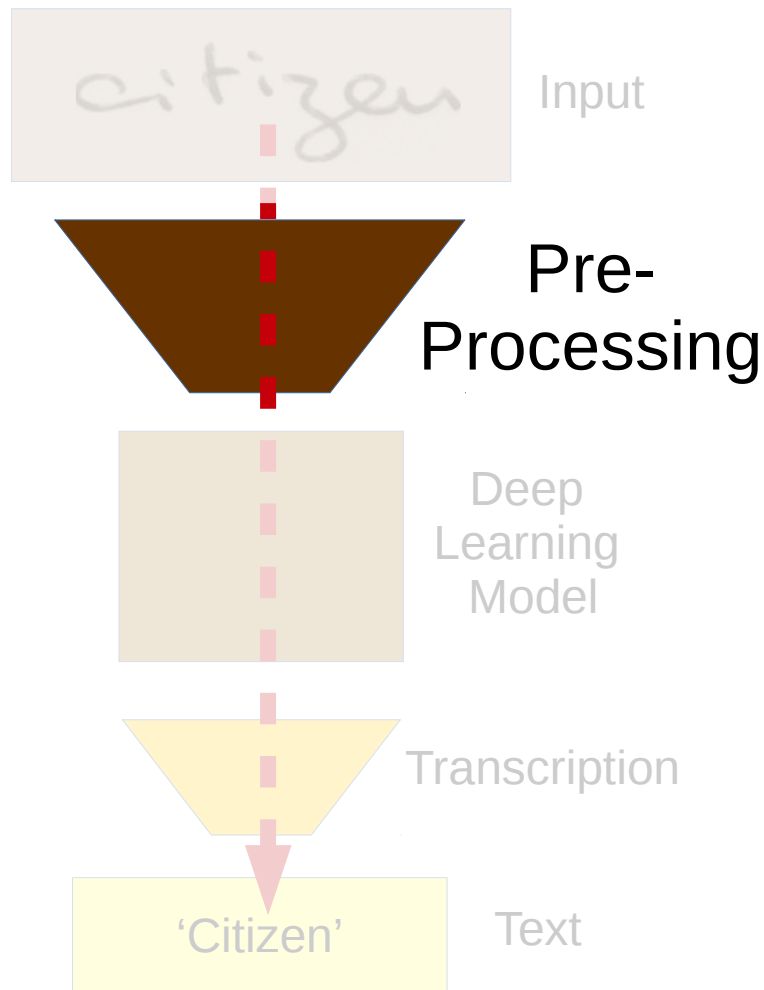
Now we can feed a bucket at a time to the model and since all the images have the same width, the model can be trained on a bucket at a time.

All that is left is writing a generator which supplies the model with a bucket at a time. This can probably be improved with Queues, but it works well enough for now.

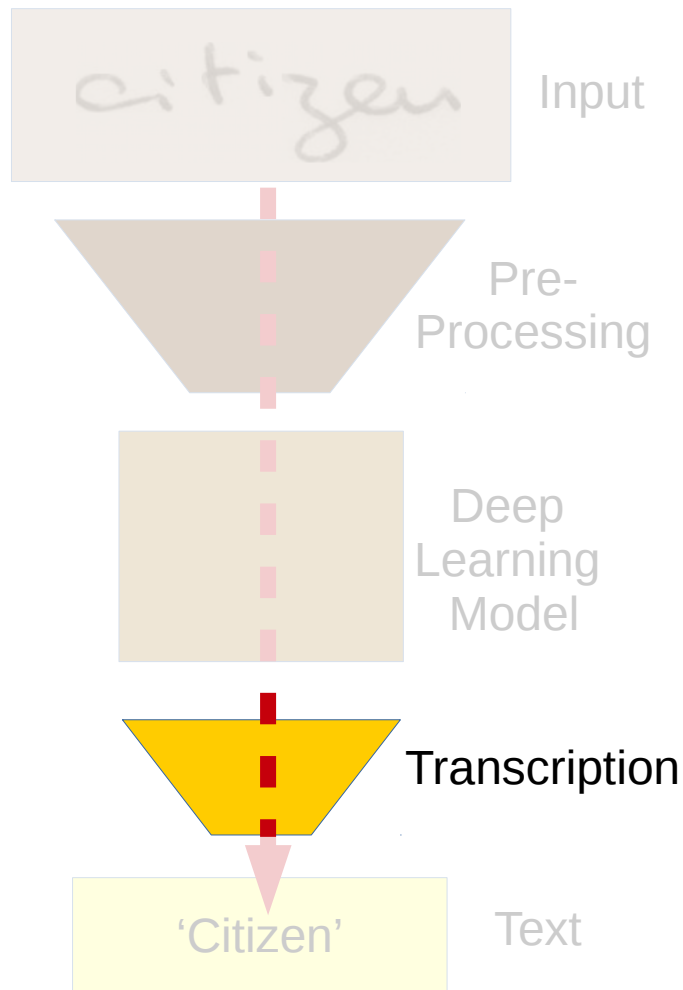


# Buckets!

One last thing about the generator:  
Keras runs the generator in the background on the CPU, while the Model is training. This saves time by pre-fetching data. So even if the generator only supplies a single bucket,



# Black Box Illustration



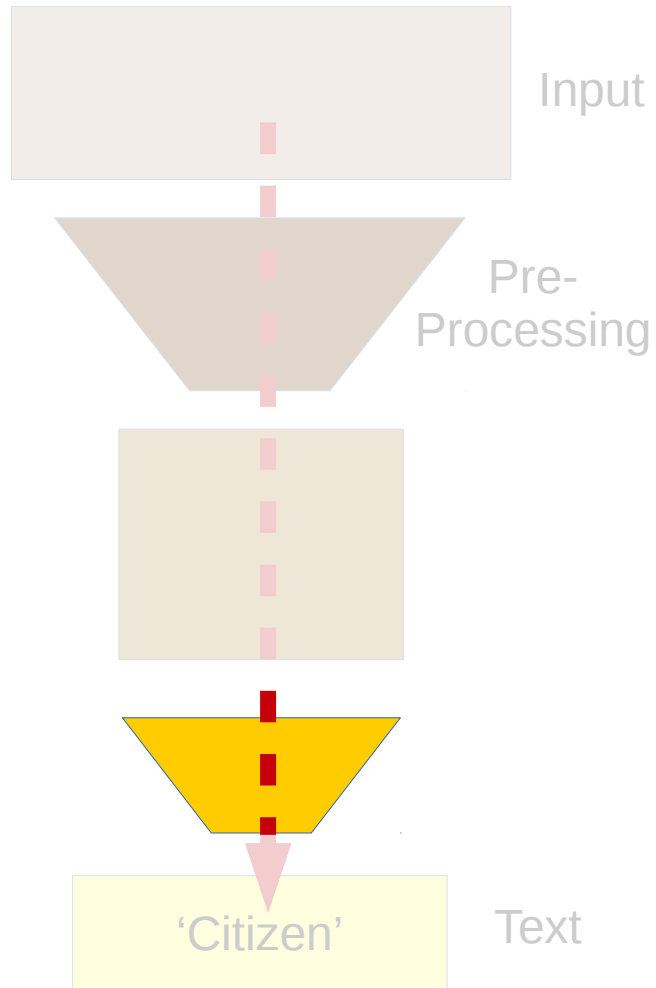
Transcription is done via a CTC decode function from the Keras frontend, which uses Beam Search.

Beam search is a transcription method where the most probable paths are explored and the highest scoring end path is used.

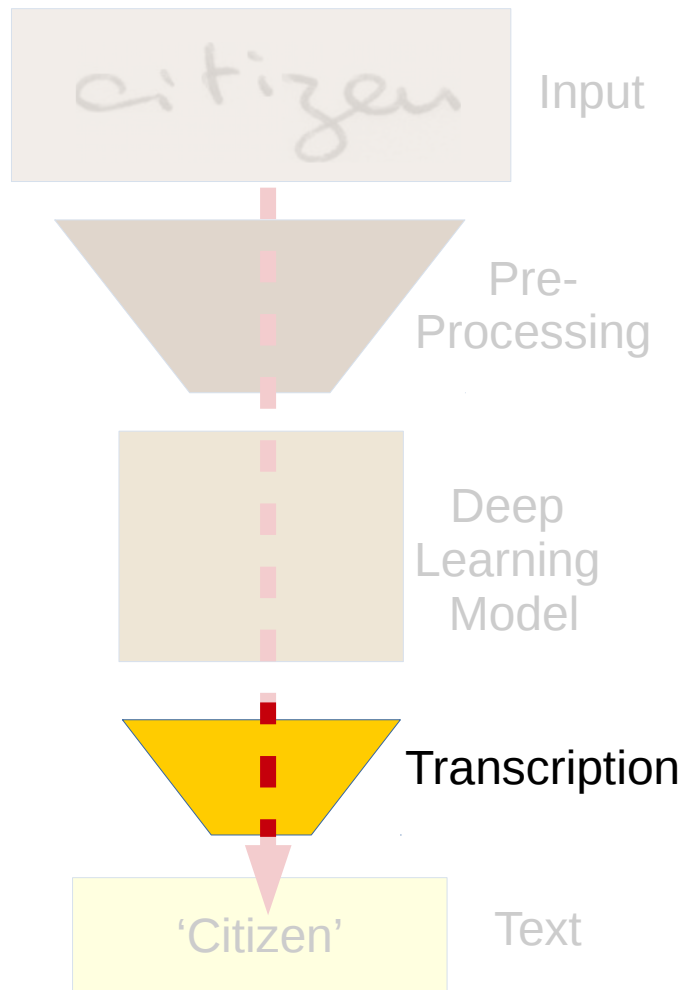
# Beam Search, top\_paths = 3

Example: 'The dog walked'

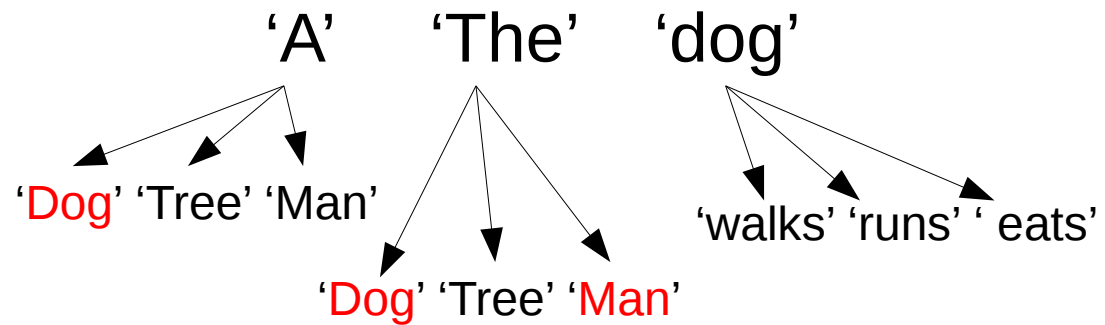
'A' 'The' 'dog'



# Beam Search, top\_paths = 3

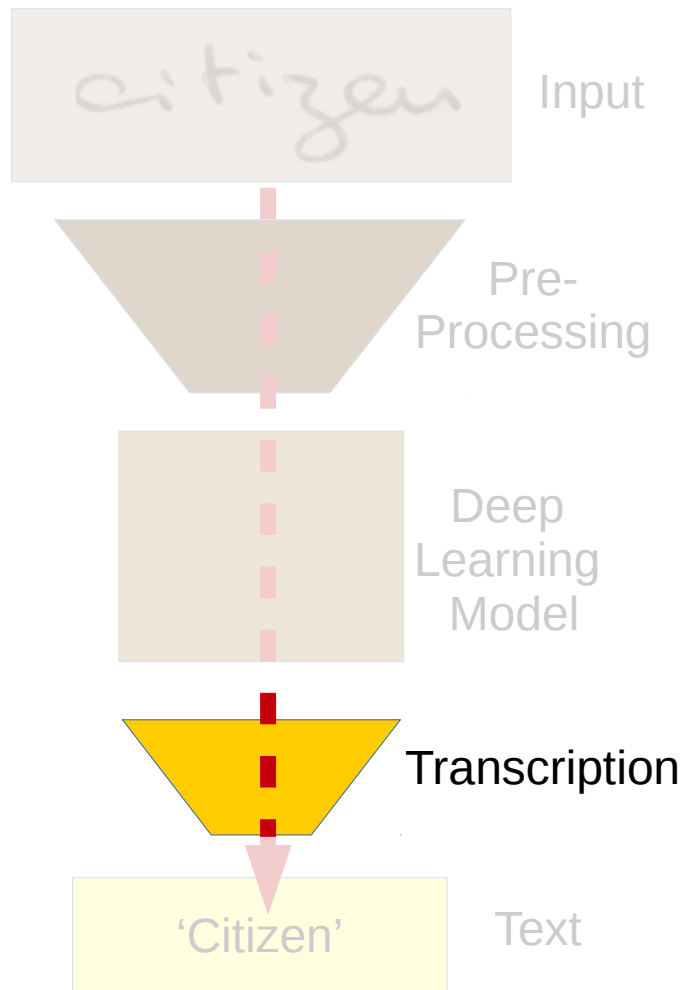


Example: 'The dog walked'

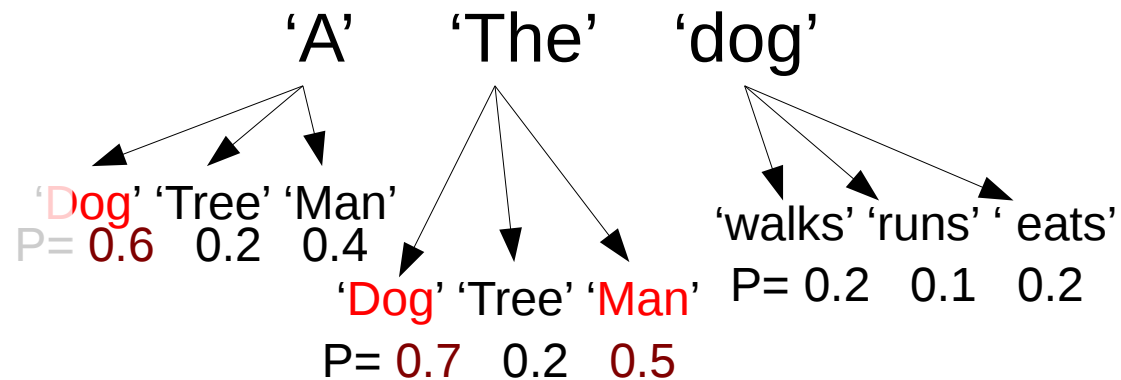




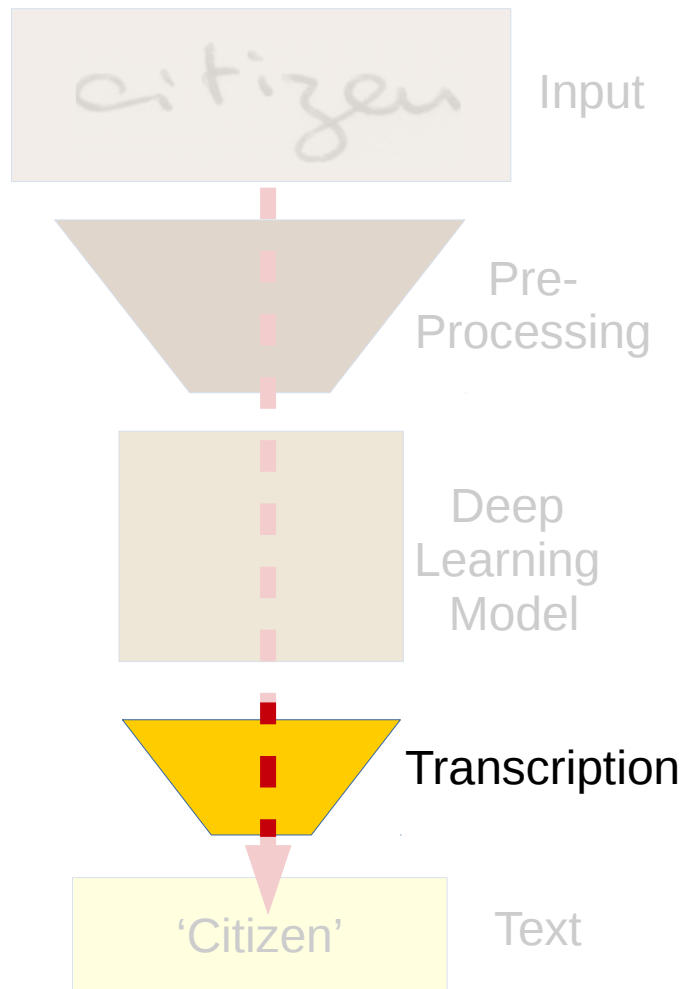
# Beam Search, top\_paths = 3



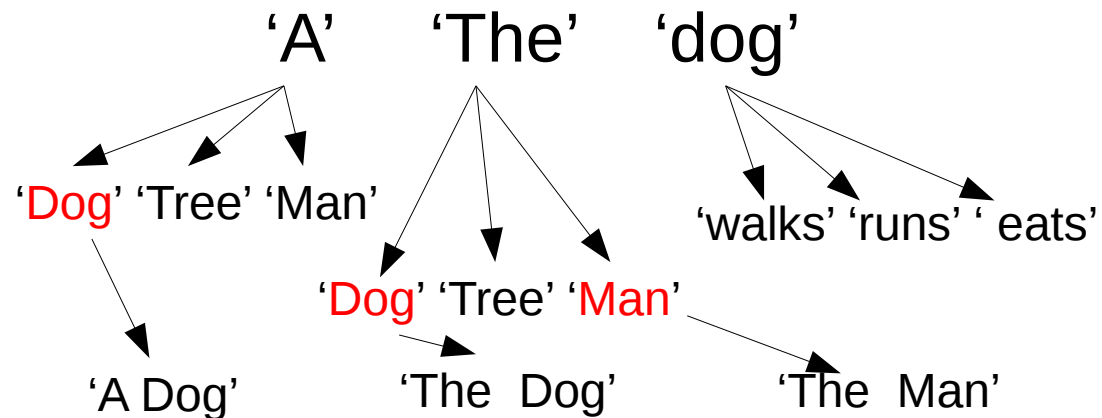
Example: 'The dog walked'



# Beam Search, top\_paths = 3

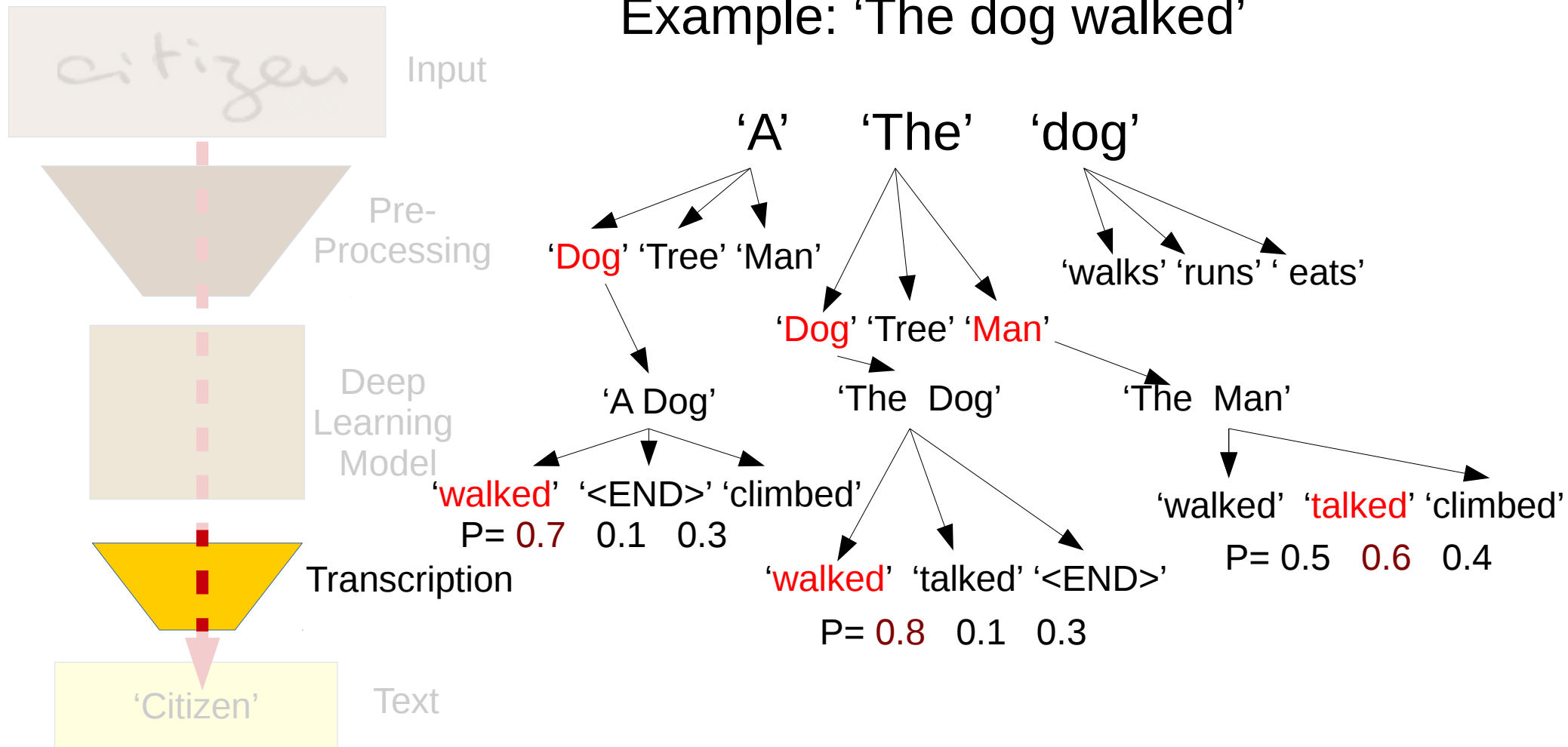


Example: 'The dog walked'



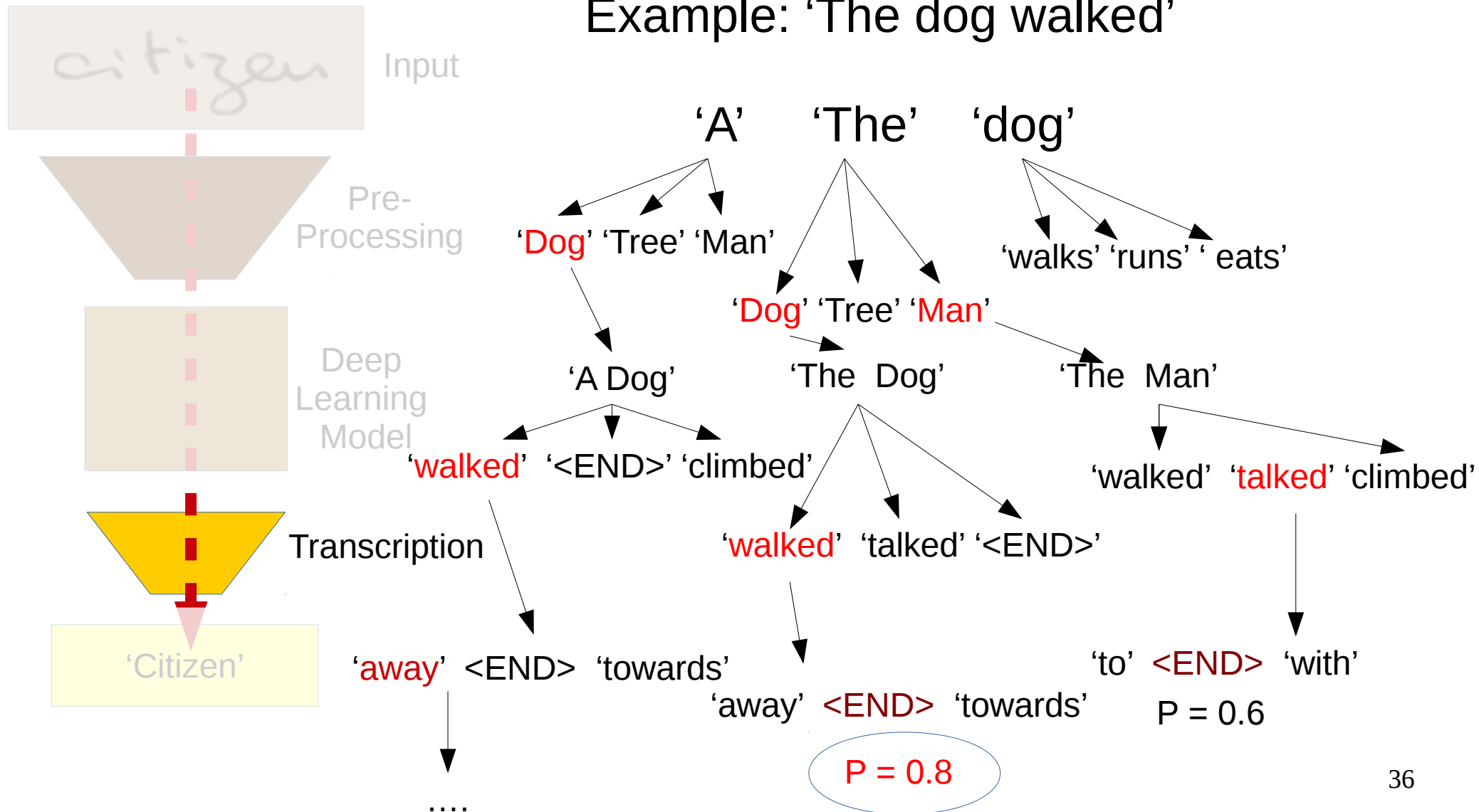
# Beam Search, top\_paths = 3

Example: 'The dog walked'

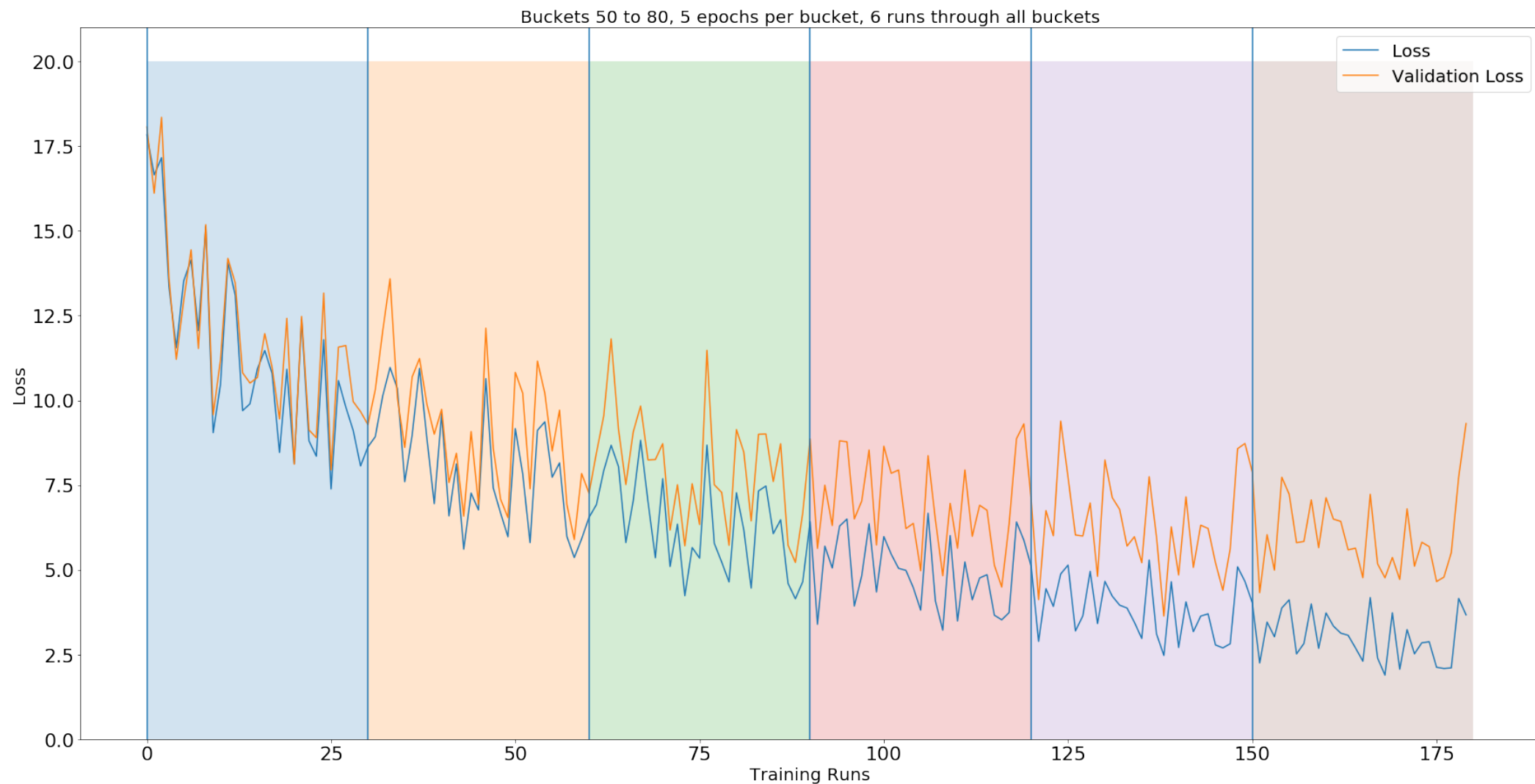


# Beam Search, top\_paths = 3

Example: 'The dog walked'



# Training



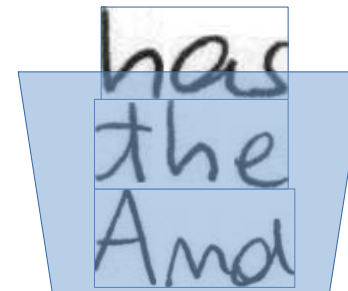
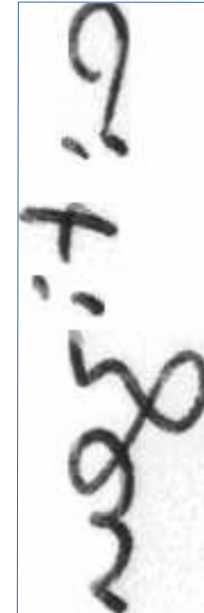
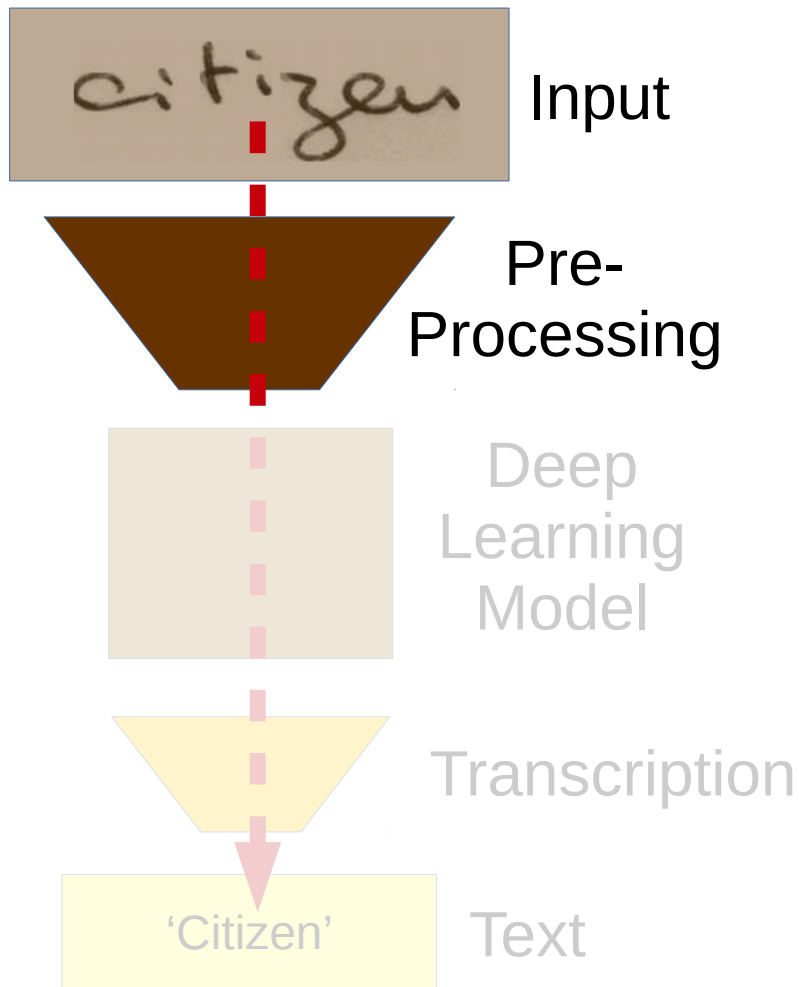
Small bucket number causes the model to quickly begin to overfit

# Training

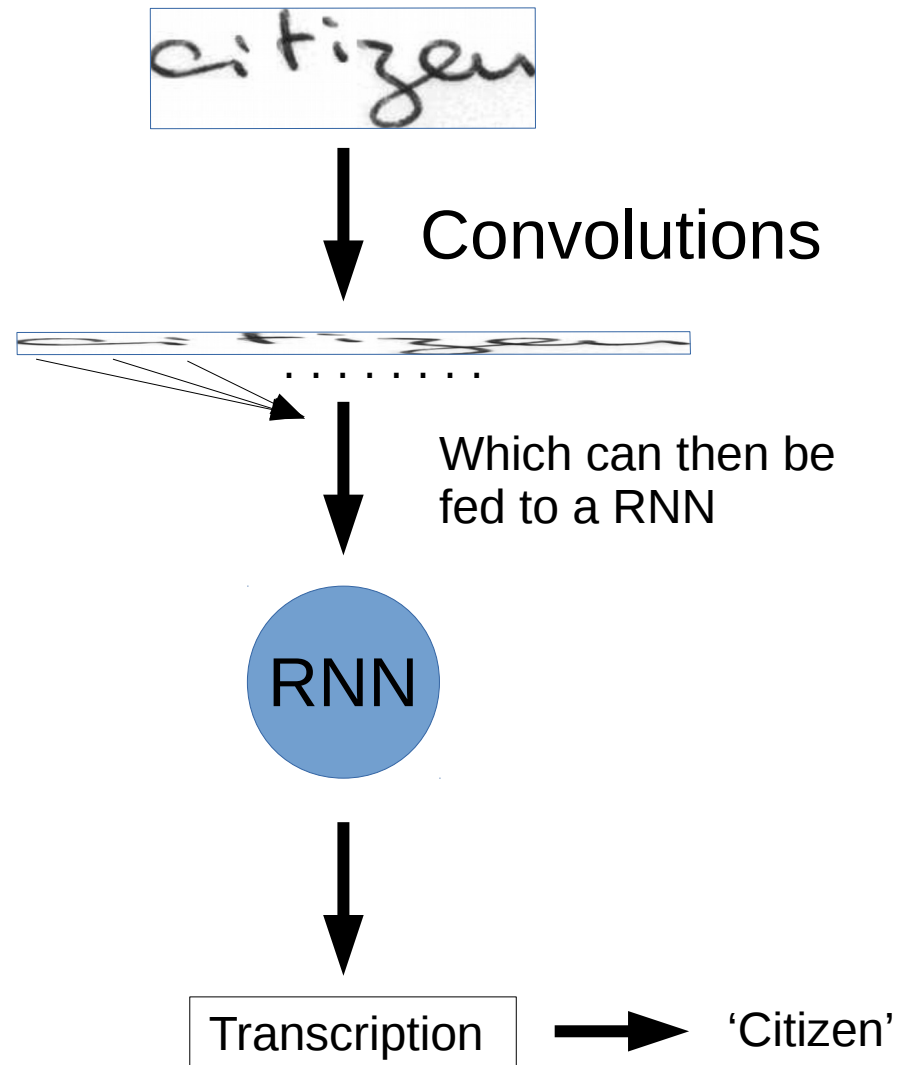
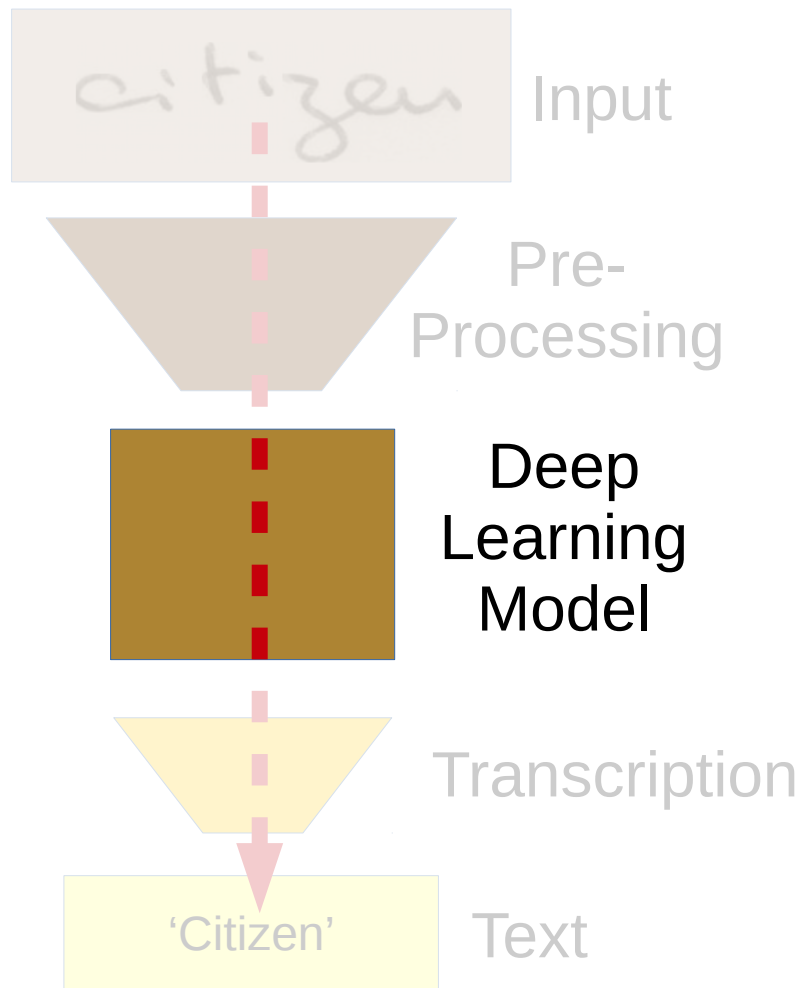


Only 70 of 100 buckets were used, since 30 did not contain enough data for validation. Larger diversity of data and fewer epochs combat overfitting.

# QUESTIONS ?

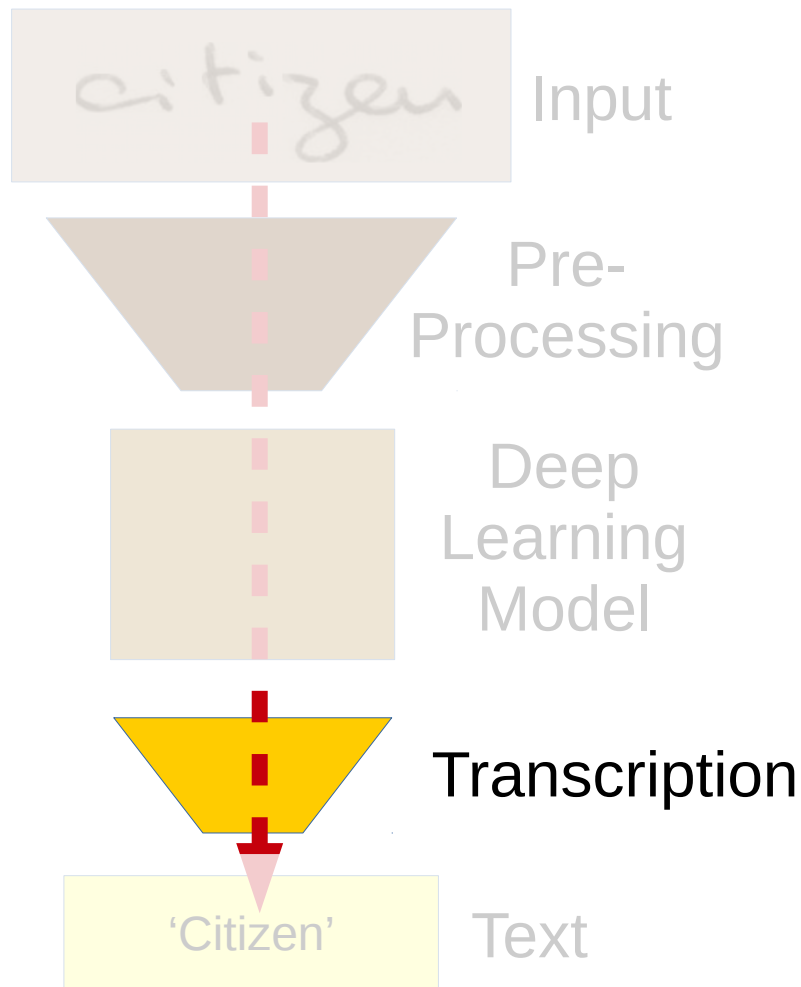


# QUESTIONS ?





# QUESTIONS ?



## Beam Search

