HW3P2 Bootcamp

Utterance to Phoneme Mapping using Sequence Models

Fall 2022

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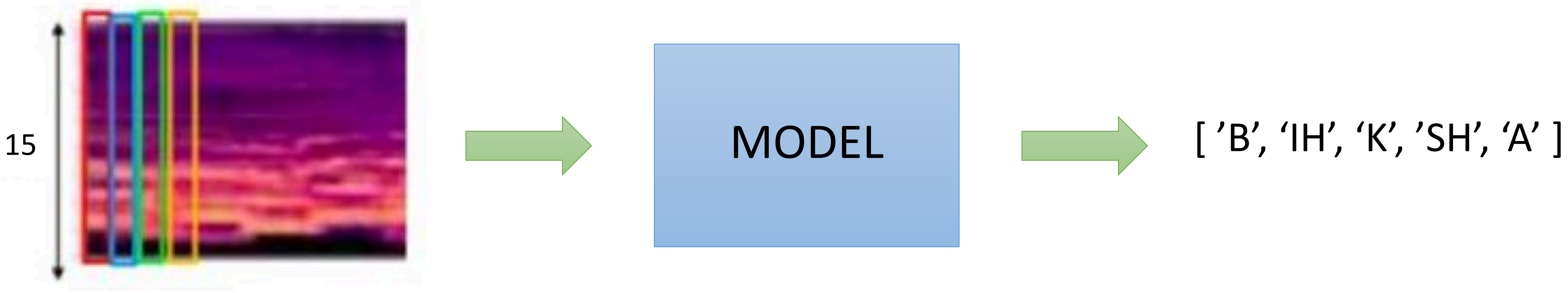
Thanks to Urvil Kenia for helping with the slides and ablation.

Logistics

- Early submission is due **Nov 3rd, 11:59PM ET**
  - Kaggle submission a with Lev. Dist <= 30
  - Canvas MCQ
- On time submission deadline: **Nov 17th, 11:59PM ET**
- This part may not take time as much as HW2P2 for training but the high cut-off will be significantly harder
- Constrains:
  - No attention

Problem at hand

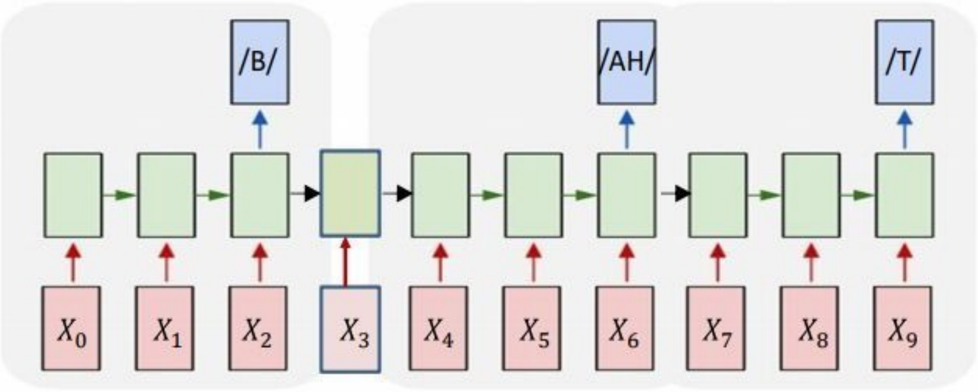


Input Utterance MFCC

Sequence of Phonemes

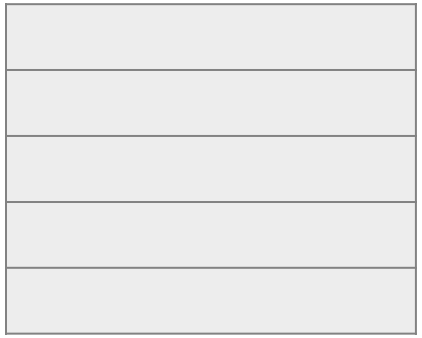
Data and Task

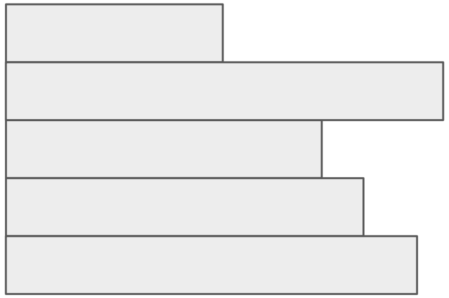
- Features: Same as HW1P2 (15D)
- Labels: Order synchronous but not time synchronous
- Should output sequence of phonemes
  - [‘B’, ‘IH’, ‘K’, ‘SH’, ‘A’] (precisely the indexes)
- Loss: CTCLoss
- Metric: mean Levenshtein distance
  - Can import (given in starter notebook)
  - Sequence of Phonemes -> String and then calculate distance (Use CMUdict and ARPABet)



Batch of Variable Length Inputs: Padding

- HW1, HW2: Equal length inputs
- HW3: Variable Length sequences
- Steps:
  - Padding
  - Packing

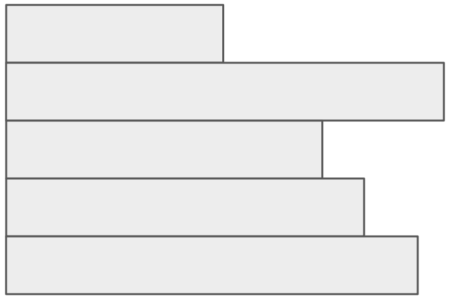




Ref: 11785 Fall 21 Bootcamp

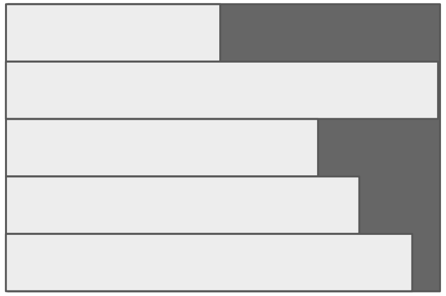
Batch of Variable Length Inputs: Padding

- Padding



Need to store unpadded lengths as well.
Have the variables *lengths_x, lengths_y* in the starter notebook

Padded to equal lengths



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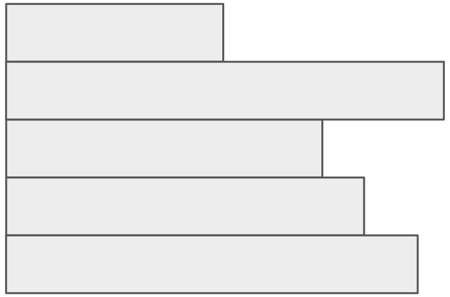

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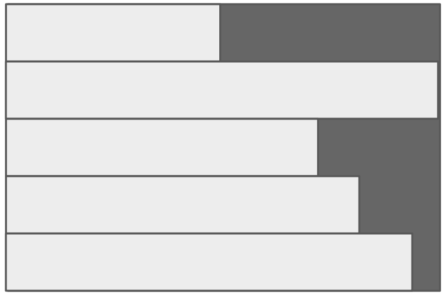

(B, *, 15) → (B, T, 15)

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Batch of Variable Length Inputs: Padding

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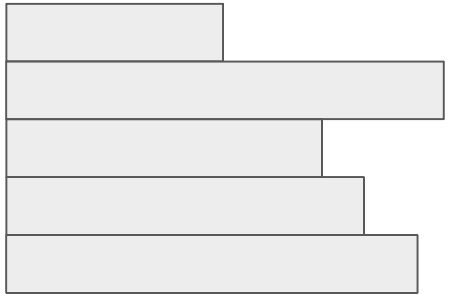

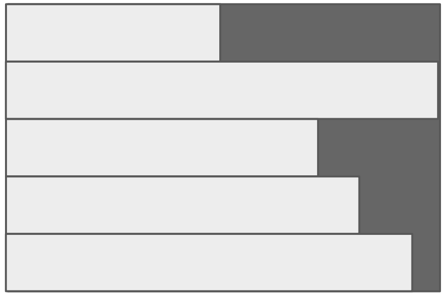

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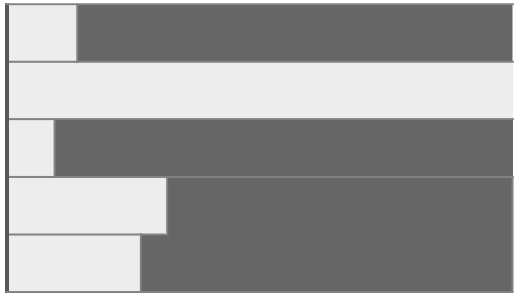
(B, *, 13) → (B, T, 13)



- Not for the whole dataset (instead we pack after padding)

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Batch of Variable Length Inputs: Packing

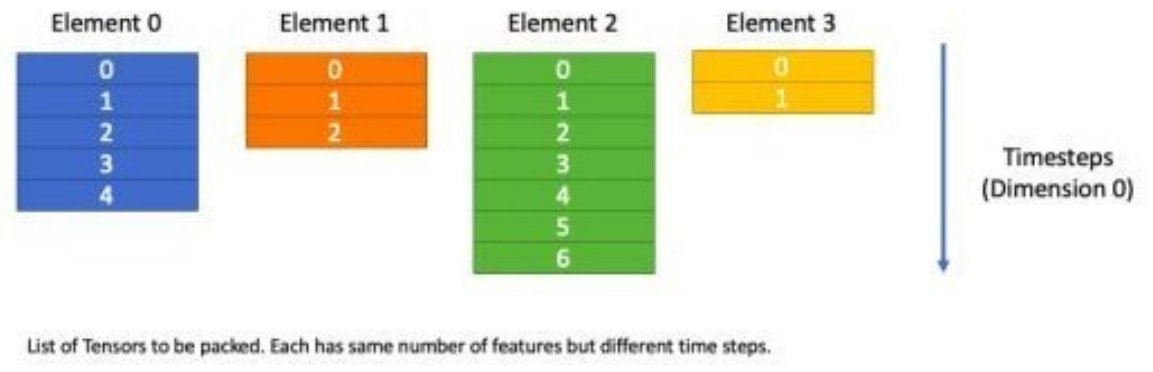

Figure 2: List of tensors we want to pack

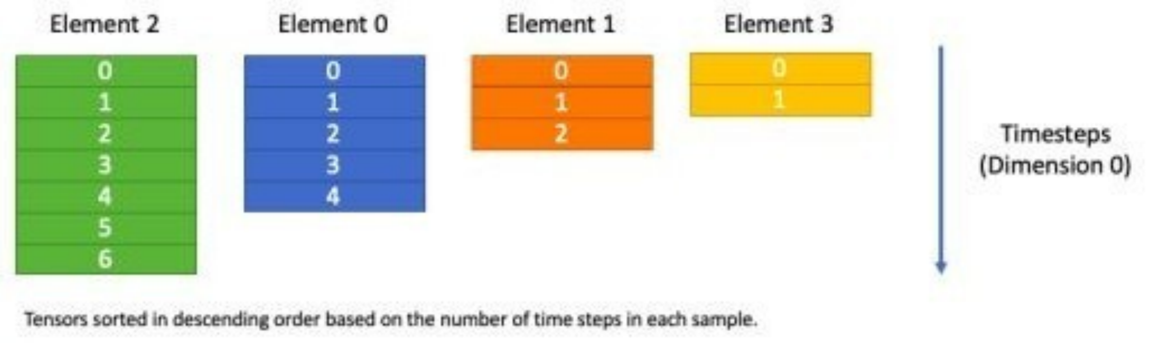

Figure 3: First we sort the list in a descending order based on number of timesteps in each

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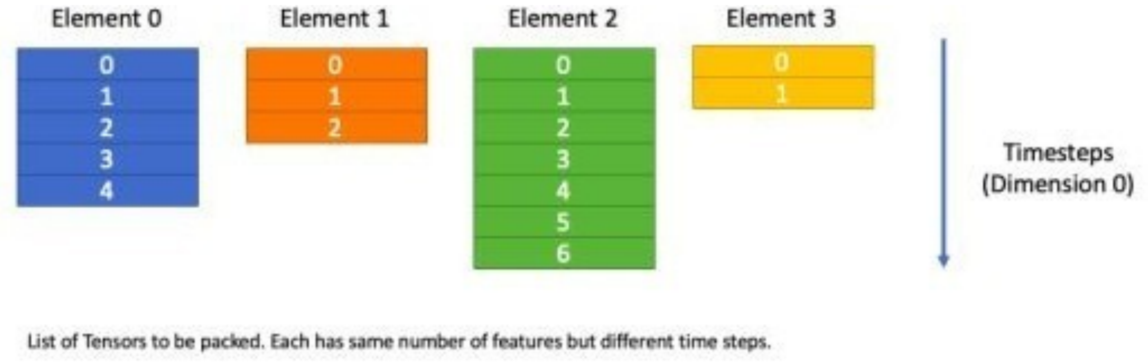

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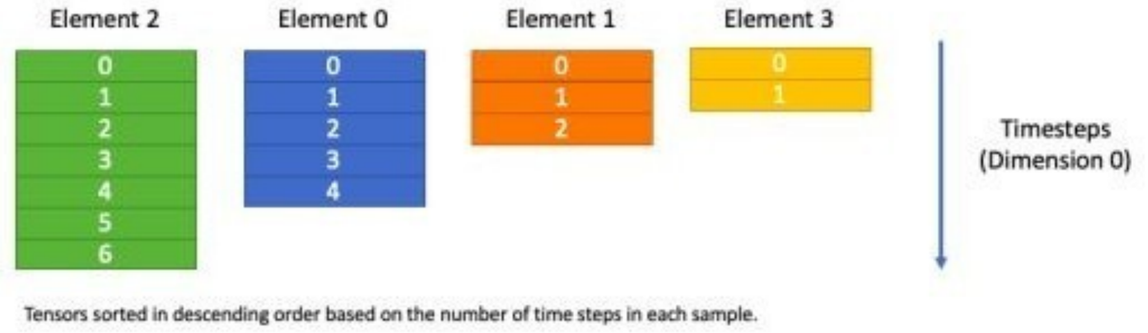

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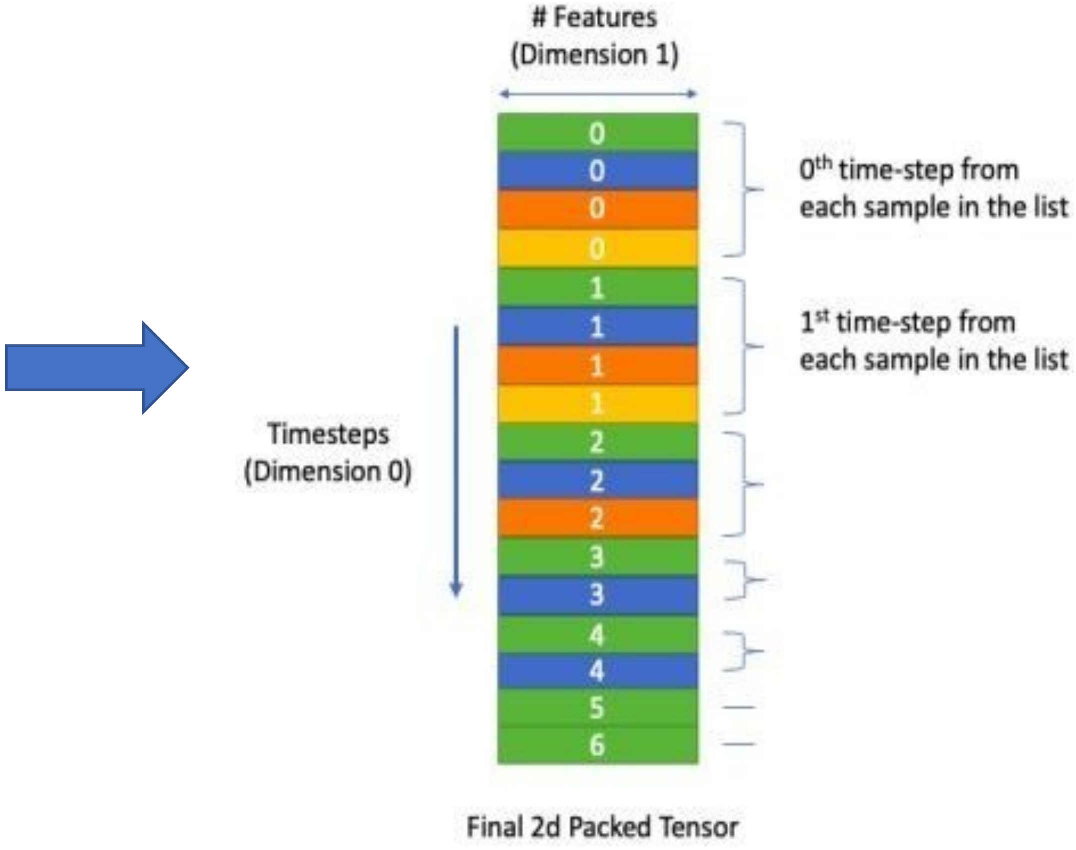

Figure 4: Final Packed 2d Tensor

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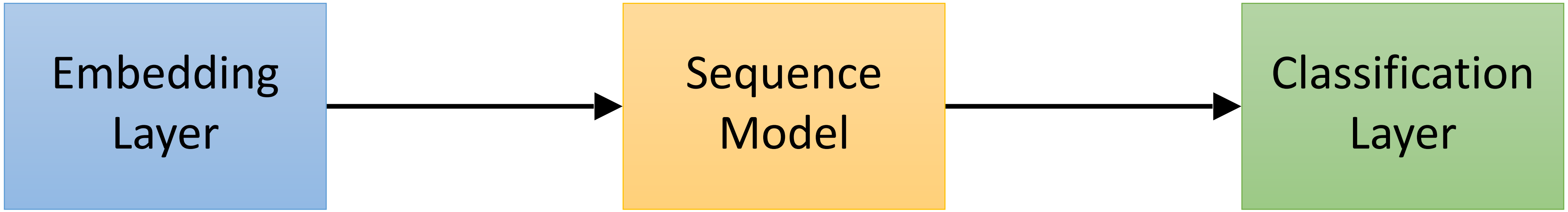
Parts of a Sequence Model



Embedding Layer

- Optional but recommended
- Used to increase/decrease the dimensionality of the input

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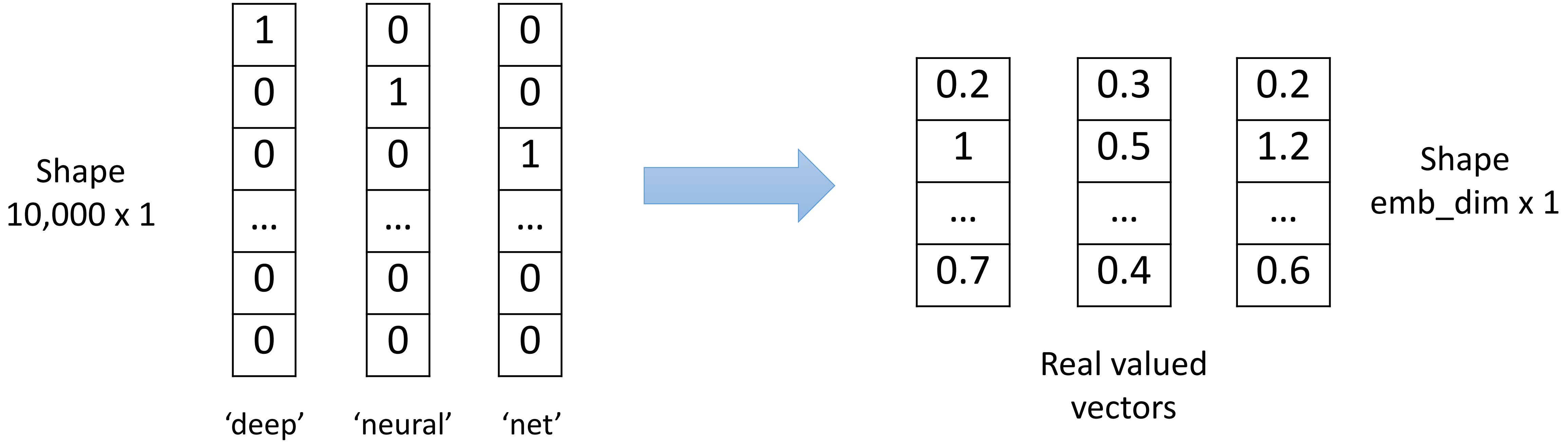
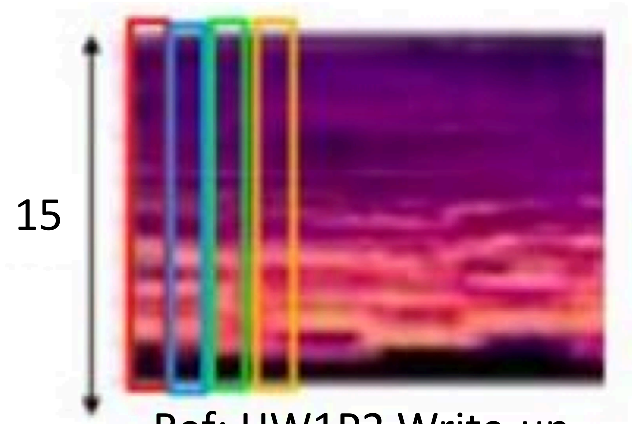
- Eg. In NLP, 10k vocabulary represented as 1 hot vectors with 10k dim



Embedding Layer

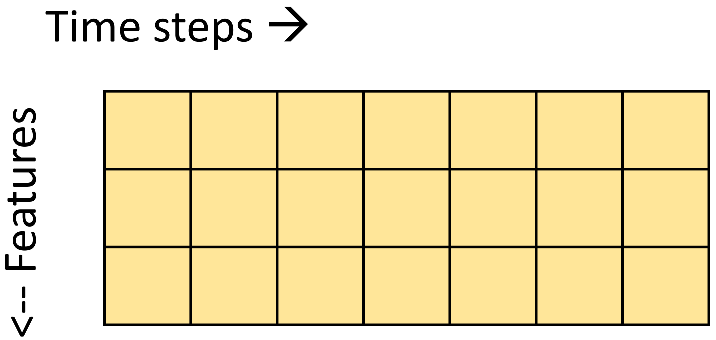
- Optional but recommended
- Used to increase/decrease the dimensionality of the input
- Our task:
  - Input dim = 15
  - Expand to emb_dim > 15 for feature extraction



Ref: HW1P2 Write-up

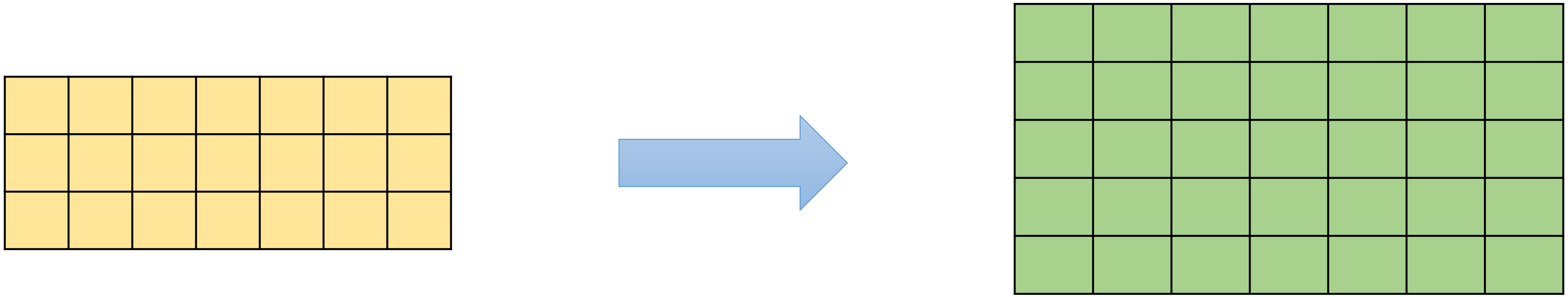
Embedding Layer: Conv1d Layers

- Consider the below as an input having 3 features at each time instant



Embedding Layer: Conv1d Layers

- We can use Convolution which increases the channels of the input as we go deeper.



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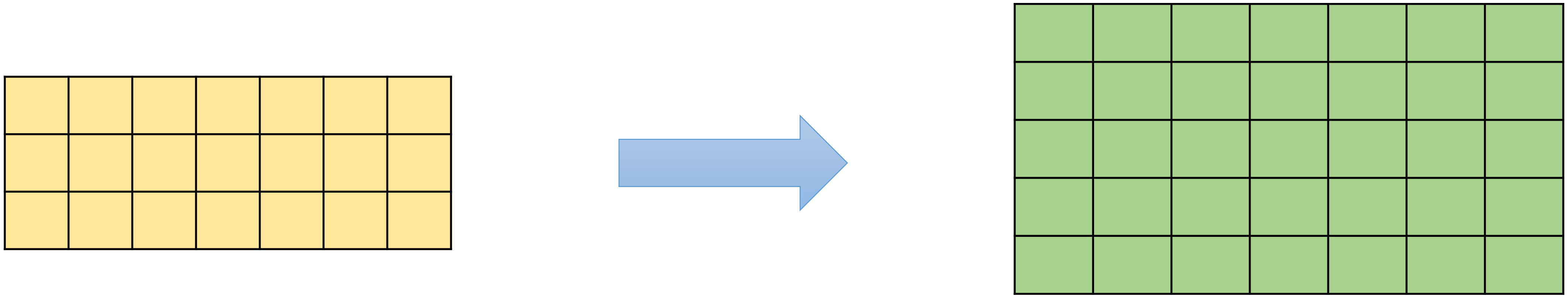

- No. Filters = 5
- Kernel= 3; Padding= 1; Stride= 1
- Kernel= 5; Padding= 2; Stride= 1

(Or anything similar)

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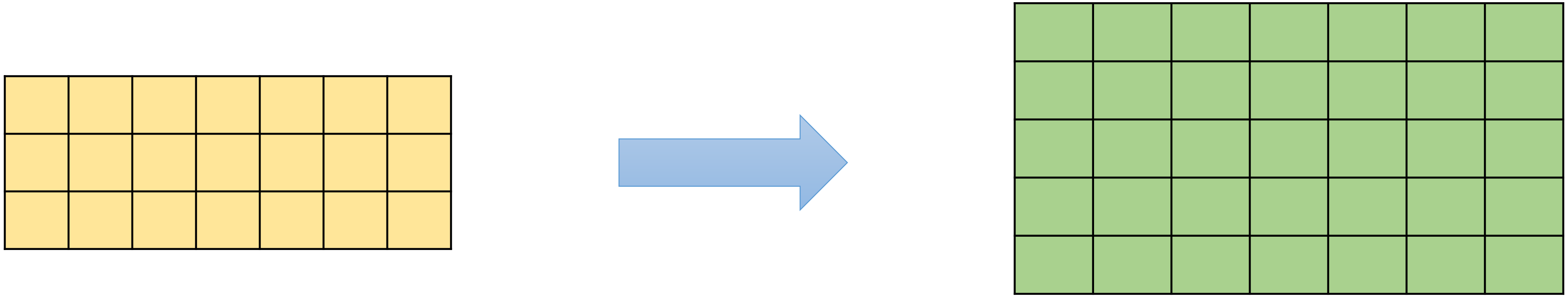

- No. Filters = 5
- Kernel= 3; Padding= 1; Stride= 1
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(Or anything similar)

3D →
5D

Embedding Layer: Conv1d Layers

- Our input is of shape (B, T, 15) (after padding). How can we change it to (B, T, 64) ?

Assuming *batch_first = True* (You may also have it as (T, B, 13)

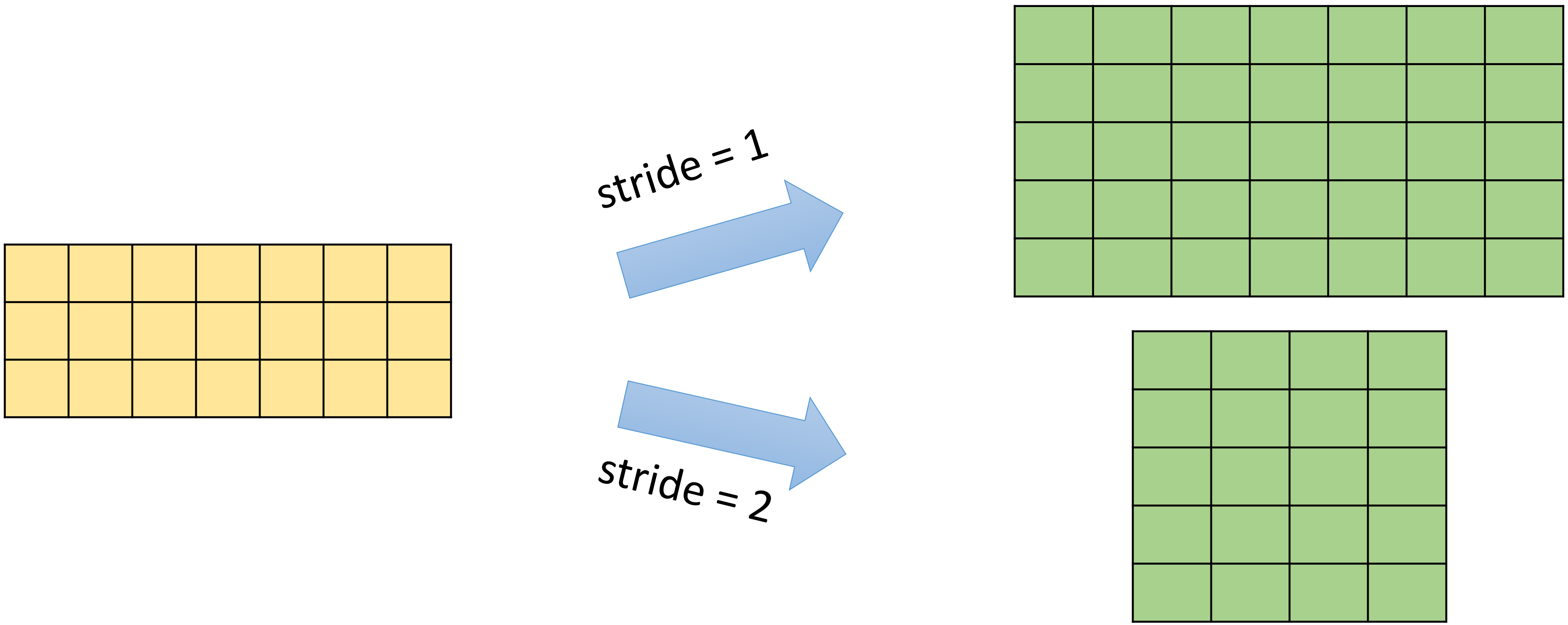
Embedding Layer: Conv1d Layers

- Our input is of shape (B, T, 15) (after padding). How can we change it to (B, T, 64) ?
- Transpose/Permute: (B, T, 15) → (B, 15, T) which makes #channels = 15 (Conv1d)
- Apply convolution (B, 15, T) → (B, 64, T)
- Transpose/Permute: (B, 64, T) → (B, T, 64) (pack and pass to LSTM/ GRU)
- Note: This is done in the forward function

Assuming *batch_first = True* (You may also have it as (T, B, 13)

Embedding Layer: Conv1d Layers

If stride > 1, we effectively reduce the time steps



Embedding Layer: Conv1d Layers

- Stride > 1 reduces computation for LSTM and training is faster.
- However, too much reduction in time steps will lead to loss of information (we don’t recommend downsampling more than 4x)

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- Stride > 1 reduces computation for LSTM and training is faster.
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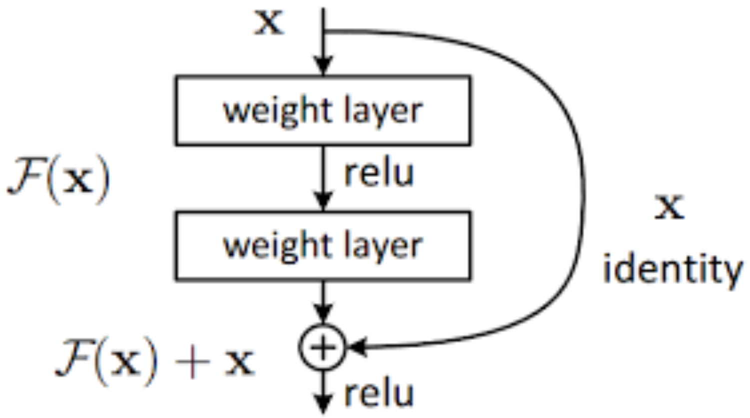
- **Note: Stride > 1 alters number of time steps. You need to change lengths_x accordingly**
  - Use convolution formula ***(X – K + 2*P)//S*** (or)
  - Clamp lengths to length of embedding (torch function)

Embedding Layer: Conv1d Layers

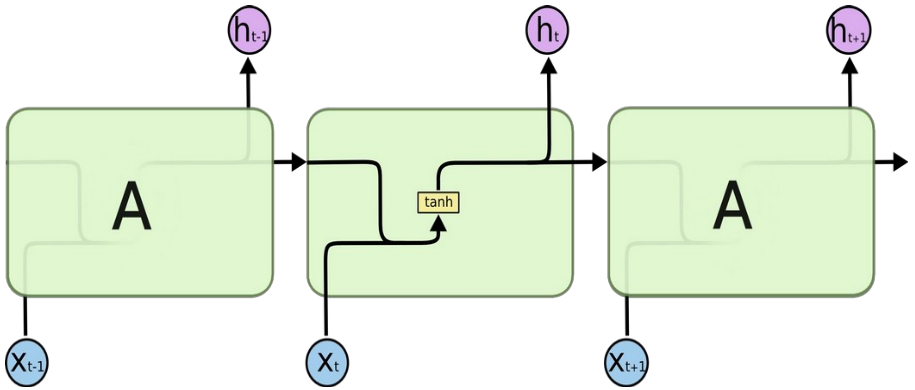
- You can try convolution layers based on residual blocks
- Hint: Remember HW2P2!

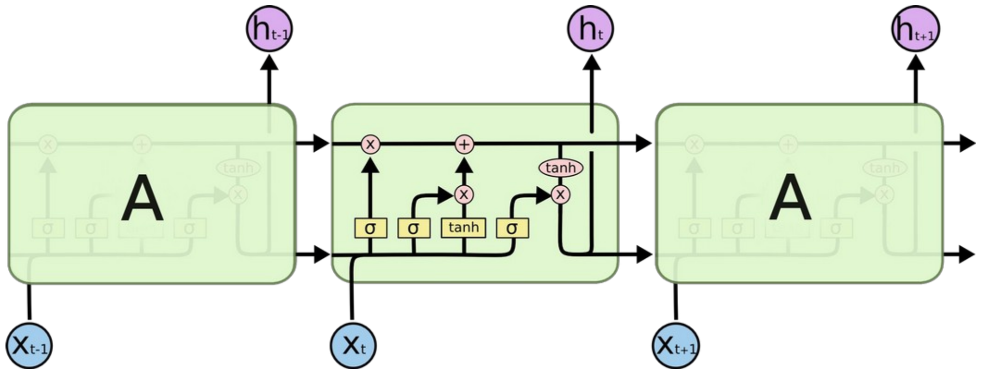


https://www.cv-foundation.org/openaccess/content_cvpr_2016/papers/He_Deep_Residual_Learning_CVPR_2016_paper.pdf

Sequence Model

- Can use RNN, GRU, LSTM (recommended) from *torch.nn*





http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Sequence Model

- Important parameters/hyper parameters in *nn.LSTM()*
  - *input_size (15 or emb_size)*
  - *hidden_dim*
  - *num_layers*
  - *dropout*
  - *bidirectional*
  - Note: when *bidirection = True*, LSTM outputs a shape of *hidden_dim* in the forward direction and *hidden_dim* in the backward direction (in total, *2*hidden_dim*)

Classification Layer

- Same as HW1P2
- Output from the sequence model goes to the classification layer
- Variations
  - Deeper
  - Wider
  - Different activations
  - Dropout

Hyperparameters and Regularization

- Cepstral Normalization:

$$X \rightarrow \quad (X - mean)/std$$

- Different weight initialization (for Conv and Linear layers)
- Weight decay with optimizer

Hyperparameters and Regularization

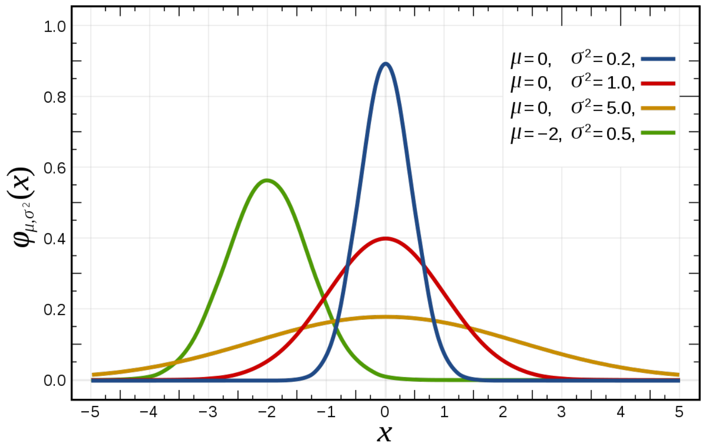
- Scheduler is very important
  - ReduceLRonPlateau (Most of our ablation)
    - Lev distance might start to oscillate at lower values
  - Cosine Annealing
    - Try with higher number of epochs

Hyperparameters and Regularization

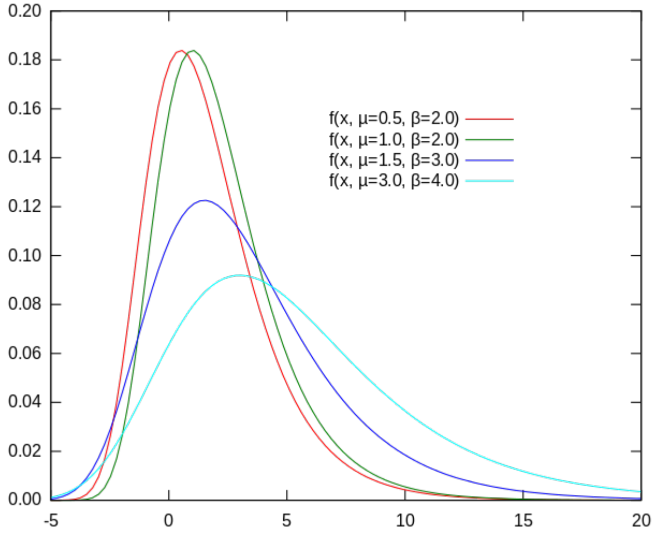
- Dropout is key
  - Can use dropout in all the 3 layers: Embedding, Sequence model and classification
  - You can also start with a small dropout rate and increase after the model gets trained
- Locked Dropout for LSTM layer

Hyperparameters and Regularization

- Addition of Noise *(only during training)*
  - Gaussian Noise
  - Gumbel Noise
- Need not add to all samples. Implement your module *AddNoise(nn.module)* in such a way that it adds noise to random inputs



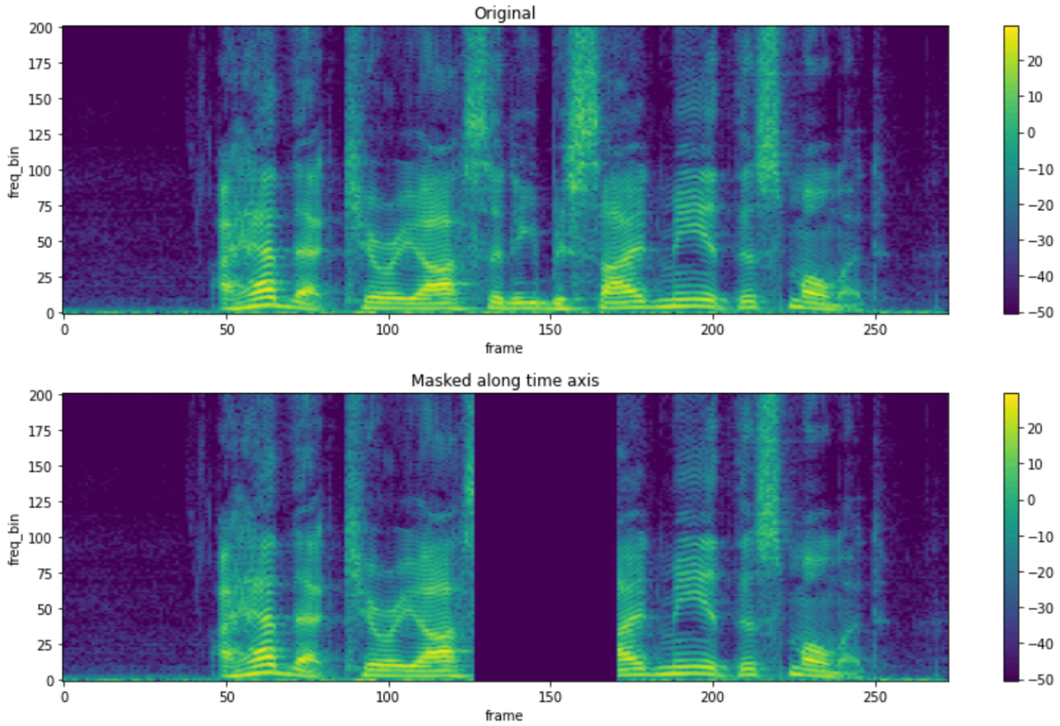
https://en.wikipedia.org/wiki/Normal_distribution

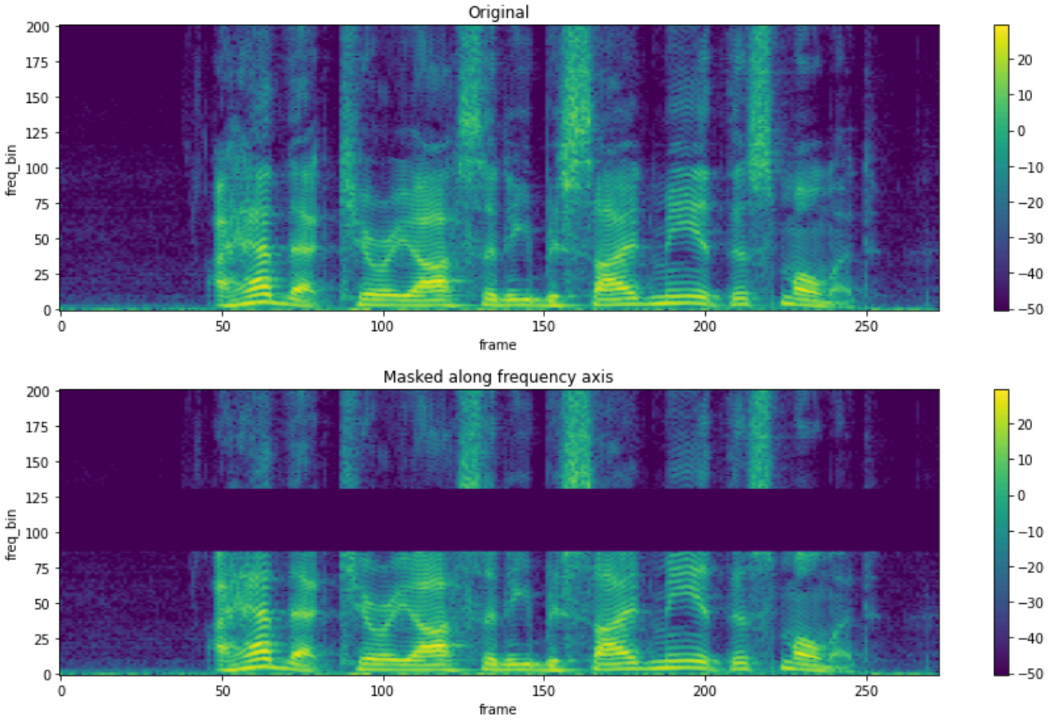


https://en.wikipedia.org/wiki/Gumbel_distribution

Hyperparameters and Regularization

- Torch Audio Transforms [docs]
  - Time Masking
  - Frequency Masking





Hyperparameters and Regularization

- Beam width
  - Higher beam width may give better results (advisable to keep test beam width below 50 for computation purposes)
  - Sometimes bw = 1 (greedy search) also gives good results
  - Tip: Don’t use a high beam width while validating in each epoch (time per epoch will be higher)

Final Tips

- Make sure to split work within your study groups

All the best!