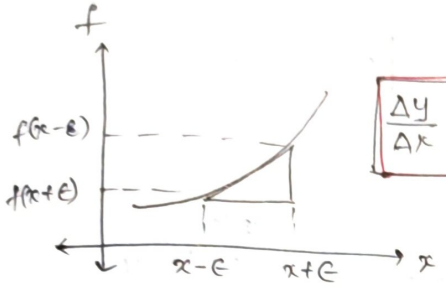
Index

ResNets — Residual Networks

Gradient Checking

* Numerical approximation of derivative of f :- $\lim_{\epsilon \to 0} \frac{f(x+\epsilon) - f(x-\epsilon)}{2\epsilon}$

* Actual der → calculated by formula or backprop.



$\frac{\Delta y}{\Delta x} \approx \frac{f(x+\epsilon) - f(x-\epsilon)}{2\epsilon}$

because ϵ is small, difference also is small

$$\text{Grad-check} = \frac{\|dw - dw_{approx}\|_2}{\|dw\|_2 + \|dw_{approx}\|_2}$$ → Euclidean distance

→ vvsmall $< 10e^{-7}$ → correct

$> 10e^{-3}$ → false / not correct

Ex:- $W = w_1, w_2$, $X = x_1, x_2$ $\quad f(w_1, w_2, x_1, x_2) = w_1^2 x_1 + w_2^2 x_2$

$\frac{df}{dw_1} = 2 \cdot w_1 x_1 \rightarrow (1)$ $\quad \frac{df}{dw_2} = 2 \cdot w_2 x_2$; $\left(\frac{df}{dw_1}\right)_{approx} = \frac{f(w_1+\epsilon_1, w_2 \cdots) - f(w_1-\epsilon_1, \cdots)}{2\epsilon}$

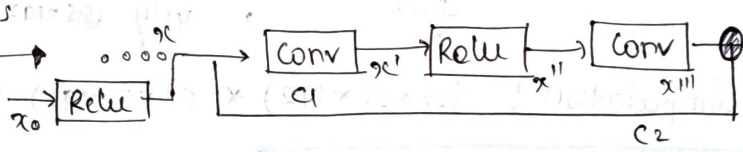
$(dw) = 2 w_1 x_1 = 6 \rightarrow (1)$ $\quad (dw_1)_{approx} = 5.9999999 \rightarrow (2)$

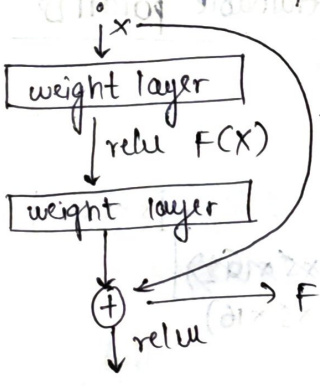
$$\text{Grad-check} = \left(\frac{6 - 5.9999\cdots}{6 + 5.9999}\right) = 4.251268e^{-13}$$

∴ as $< e^{-13}$ → backprop is correct

ResNets :- motivation ⇒ when no of layers were increased, the loss was higher than lesser layers even with huge no of iterations

Residual / skip block / identity → if C_1, C_2 useless $x \rightarrow x$





skip conn

why it works?

$Relu(x_0) = x$, $Relu(x) = Relu(Relu(x_0)) = x_0$

$= Relu(x_0) = x$

L_1, L_2, dropout

Now consider due to strong regularization C_1 and C_2 become useless, ie w or $l = 0$;

so previously, → now, o/p $= x''' + x = x$ ← so called skip connection

this cont propagate further ← o/p $= x''' = 0$

∴ C_1 and C_2 dont matter ie skip

$Relu(Relu(x)) = Relu(x)$

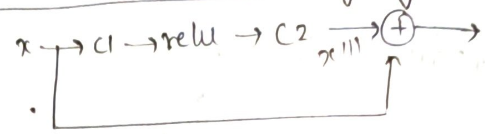
if +ve, $Relu(x) = Relu(x) = x$

−ve $= 0$

(22) Key takeaway → gauranted no decrease in perfomance, small increase

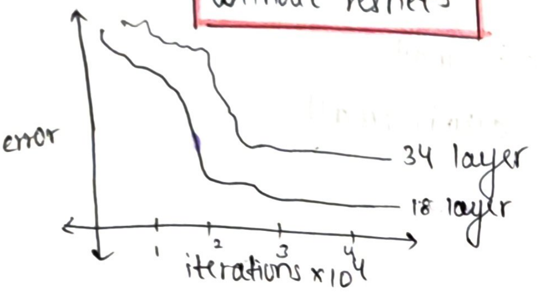
* adding additional layers would not hurt performance as they get skipped if they are found useless.
* if new layers are useful
  regt weights are non-zero.

Note :



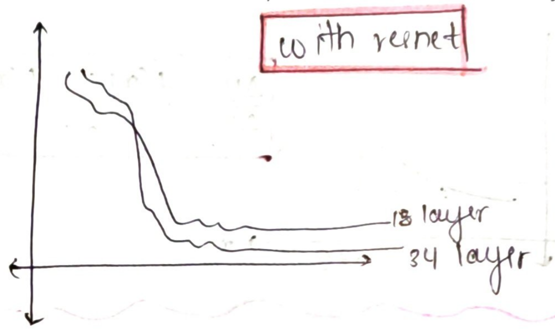
make sure (x) and (x''') have same shape - use padding

without resnets



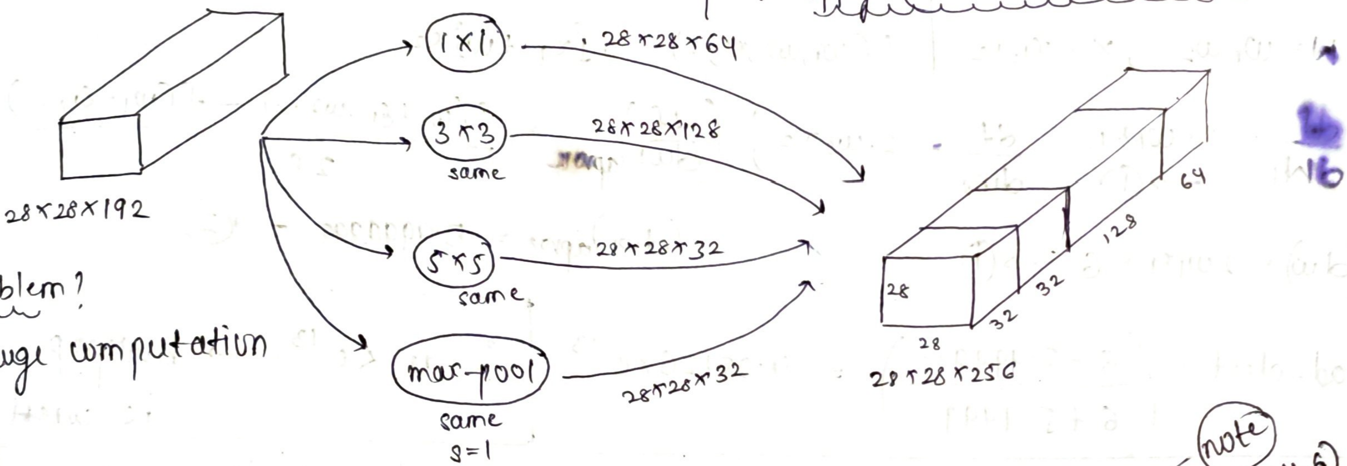
with → res-nets

with resnet



Inception Network

→ apply more than 1 type of kernels at once
→ apply (1x1x192) kernels 64 times



problem?
huge computation
↳ Ex:

28x28x192 → CONV 5x5, same, 32 → 28x28x32

→ apply (5x5x192) kernel 32 times

note: $K = (4,6)$ ||| $(4,6,\text{prev layer d})$

computation :- (28x28x192) * (5x5x192) = 120 million.

no of trainable params

using 1x1 conv as bottleneck layer

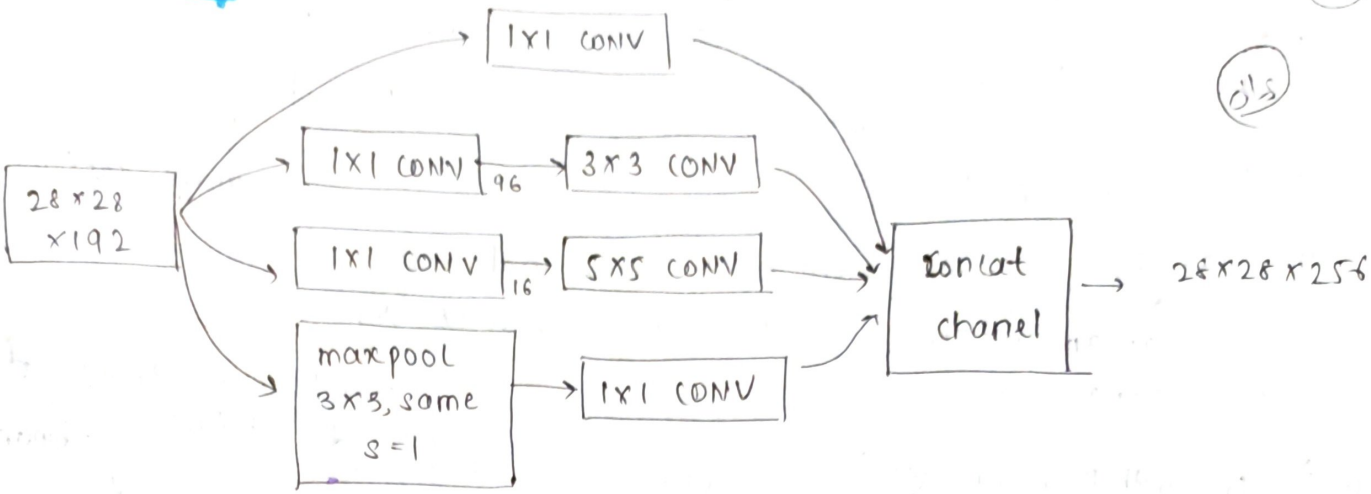
28x28x192 → CONV 1x1,16 → 28x28x16 → CONV 5x5,32 → 28x28x32

computations : [(28x28x192) * (1x1x192)] + [(28x28x16) * ~~(5x5x(64))~~ (5x5x16)] 5x5x16

= 12.4 million <<<< 120 milion.

∴ (i/p → CONV 1x1 → CONV 5x5) is better than (i/p → CONV 5x5) computationaly

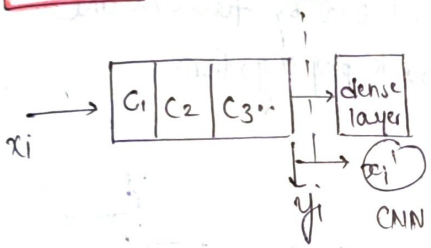
Inception module



Transfer Learning → using pretrained models

Ex:- VGG16 trained with imagenet dataset ; New dataset = $D = \{x, y\}_i^n$

Case 1 CNN Codes



For x_i in D,

get x_i' → vector obtained from last conv layer

$\therefore D' = \{x_i', y\}$

↳ train any ML model

Case 2 fine tune last layers

they identify basics

→ Freeze most layers ⟹ Initial layers are helpful

→ fine tune only last few layers ⟹ use your dataset to train last layers.

Case 3 tune all layers

→ use VGG + ImageNet model as a initialization

→ train the model using ur dataset

Use cases → where to use?

↳ factors → similarity with Imagenet and size of dataset

Case 1 D ≈ ImageNet, |D| small

→ CNN codes

Case 3 D ≈ ImgNet, |D| medium sized

→ fine tune last few layers

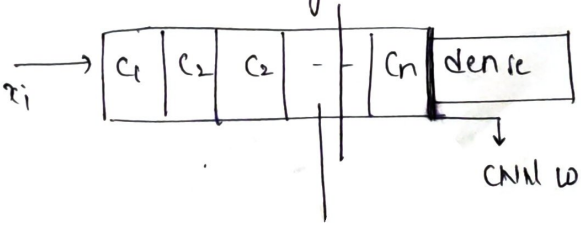
Case 5 |D| large (size of D), D ≠ ImgNet (similarity to ImgNet)

→ use pretrained model as init and train/tune whole model

Case 2 D ≈ ImgNet, |D| large

→ tune full n/w

Case 4 |D| is small, D ≠ ImgNet



more generalized as Cn will be useful if similar

→ pick from later CONV layers but not last

(24)

Recurrent Neural Networks

↳ retains and leverages sequence info

core idea : sequence of inputs

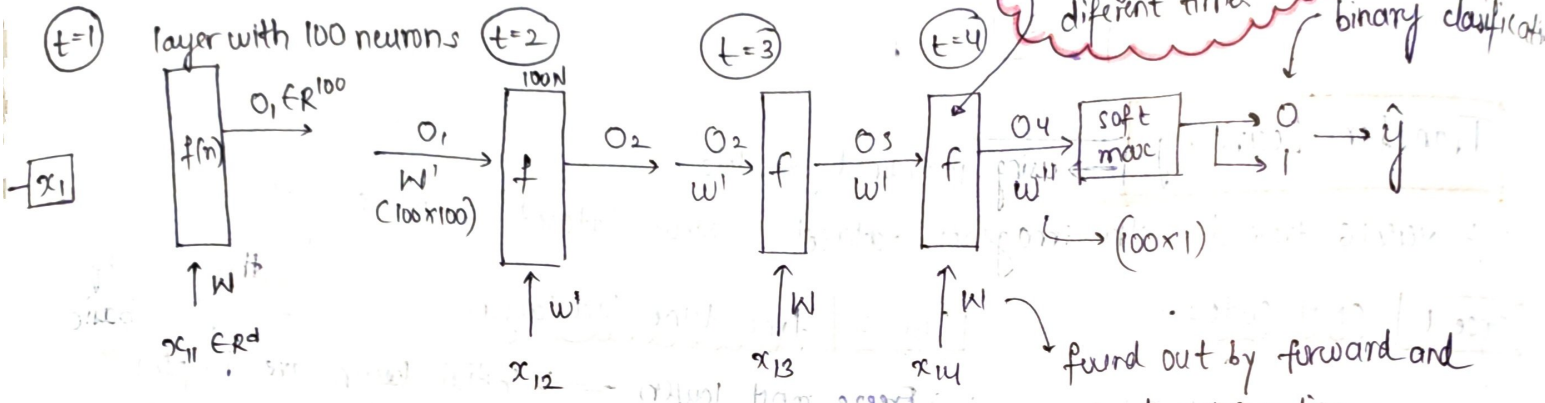
↳ app^n → machine translation, time series, speech recognition, image captioning

Ex: Amazon fine food reviews

$D = \{x_i, y_i\}$ → Each word is 'd' dimensional vector where d = size of vocabulary

$x_1 = \langle x_{11}, x_{12}, x_{13}, x_{14} \rangle$

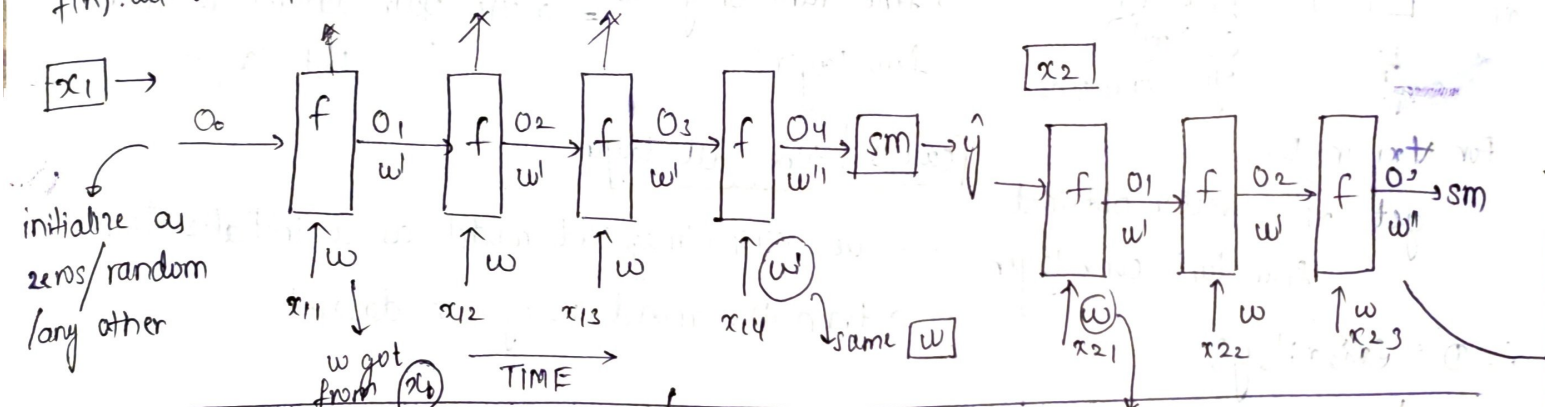
$x_2 = \langle x_{21}, x_{22}, x_{23} \rangle$



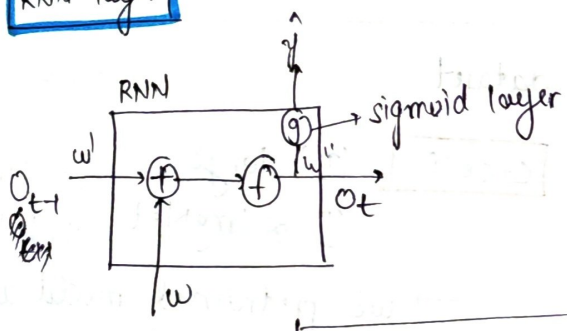
W: d×100

$f(n)$: activation fn

$O_2 : f(w'O_1 + wx_{12})$



RNN layer

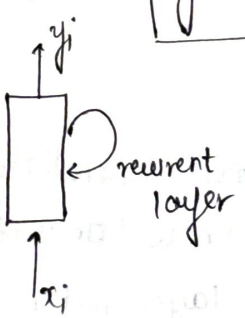


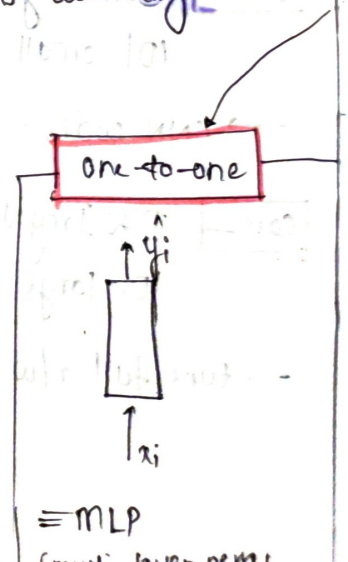
$$O_t = f(wx_{it} + O_{t-1}w')$$

$$\hat{y} = g(O_t w'')$$

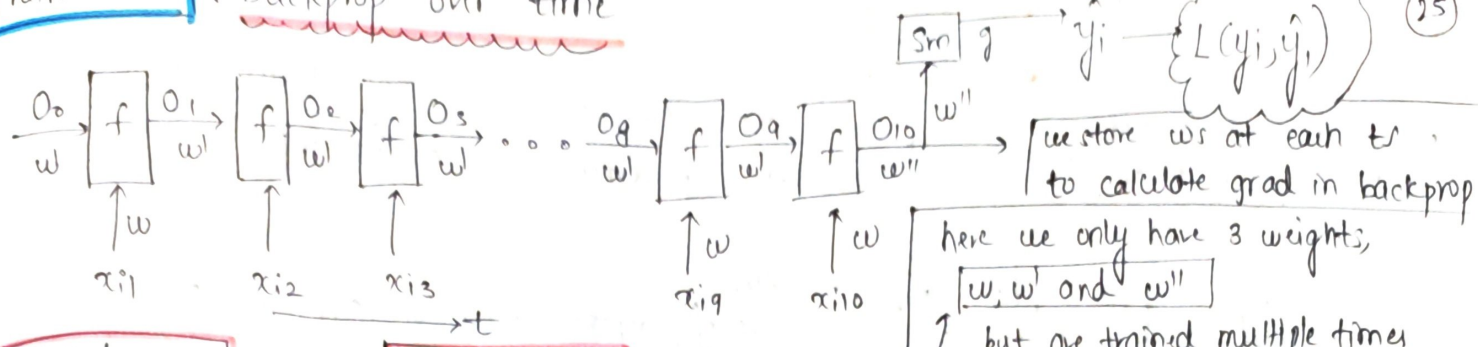
→ In the whole process we have only 3 matrices, w, w' and w''

→ they are given different inputs according to time t





Train RNN : Backprop over time



Forward prop

$$O_1 = f(O_0 w' + x_{i1} w)$$
$$O_2 = f(O_1 w' + x_{i2} w)$$
$$\vdots$$
$$O_{10} = f(O_9 w' + x_{i10} w)$$
$$\hat{y}_i = g(w'' \cdot O_{10})$$

Backward prop

reverse arrows

① $\frac{\partial L}{\partial \hat{y}_i}$ → ② $\frac{\partial L}{\partial w''_{10}} = \frac{\partial L}{\partial \hat{y}_i} \cdot \frac{\partial \hat{y}_i}{\partial O_{10}}$ → ③ $\frac{\partial L}{\partial w_{11}} = \frac{\partial L}{\partial \hat{y}_i} \frac{\partial \hat{y}_i}{\partial O_{10}} \frac{\partial O_{10}}{\partial w_{11}}$

$$w_{t=10} = \frac{\partial L_{10}}{\partial w} = \frac{\partial L}{\partial \hat{y}_i} \frac{\partial \hat{y}_i}{\partial O_{10}} \cdot \frac{\partial O_{10}}{\partial w} \longrightarrow \left(\frac{\partial L}{\partial w}\right)_{t=1}$$

$$w'_{t=10} \approx \frac{\partial L}{\partial w'} = \frac{\partial L}{\partial \hat{y}_i} \frac{\partial \hat{y}_i}{\partial O_{10}} \frac{\partial O_{10}}{\partial w'} \qquad \left(\frac{\partial L}{\partial w'}\right)_{t=1}$$

Problems with backprop over time

$\left(\frac{\partial L}{\partial w}\right)_{t=1}$ = multiplication and addition of multiple values → vanishing gradient, exploding gradient (not bcoz of deep layers but bcoz of backprop over time ∝ depends on t's)

→ LSTM and GRU used

↳ $w_{t=9} = \frac{\partial L}{\partial w_{10}}$

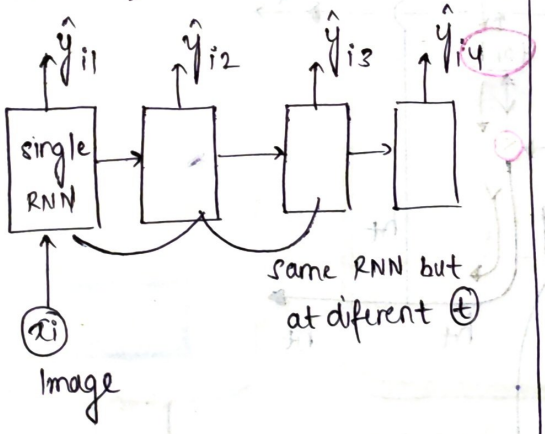
Types of RNN architectures

① Many-to-one RNN

uses: sentiment analysis, movie review rating

② One-to-many RNN

i/p : single
o/p : sequence



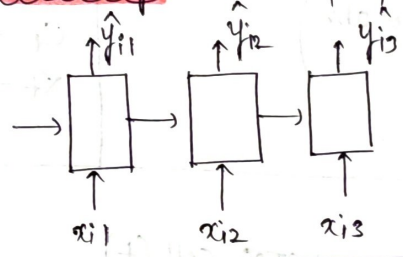
Ex: Image captioning

Many-to-many

len(i/p) = len(o/p) (seq2seq)

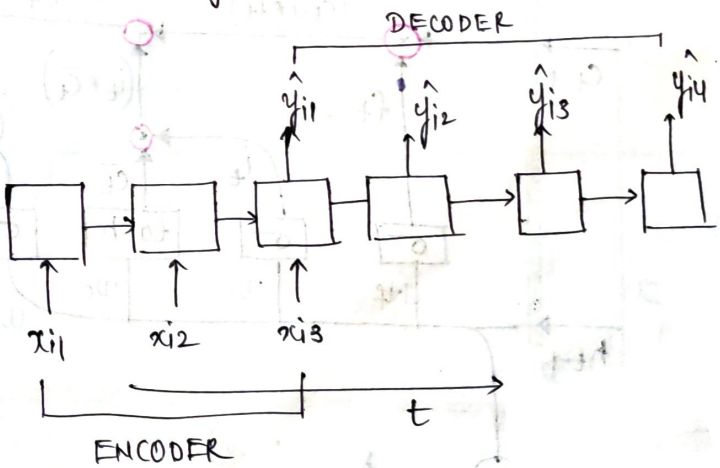
→ # word → which part of speech

① same length :- parts of speech



[parallel execution] can be done

② different length — Encoder-Decoder



use :- language translation = Eng → Spanish

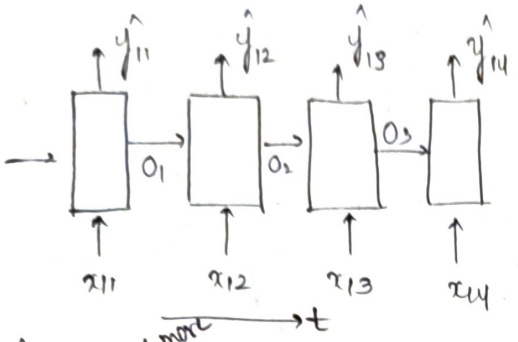
a sentence in Eng with 10 words → may have only 8 words when translated into Spanish

1997 LONG SHORT TERM MEMORY RNN

LSTM

why we need LSTM when RNN exists?

- RNN cant take care of long term dependency ie later o/p depends on earlier input



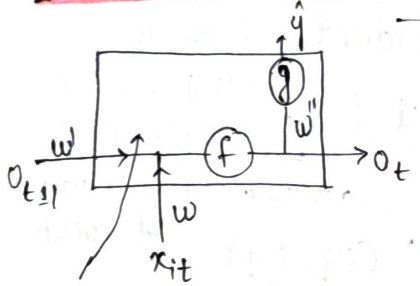
→ here,
* $\hat{y}_{14}$ depends more on x_{14} and O_3 and depends very less on O_1 and x_{11}
* lets say we want $\hat{y}_{14}$ to be more dependent on x_{11} which cant be accomplished

Ex:- In some languages starting words might be of more importance when translating

why $\hat{y}_{14}$ depends more on x_{11}?
→ there is lot of propagation & time b/w x_{11} and $\hat{y}_{14}$

LSTM

Improved simple RNN



concatenation

$O_t = f([w,w'] \cdot [x_{it}, O_{t-1}])$

$\hat{y} = g(O_t w'')$

merge vectors → [w' w]

concatenate: $[x_{it}\ O_t]$ (stack one abv other)

similarity

$C_t \equiv O_t$

$X_t \equiv X_{it}$

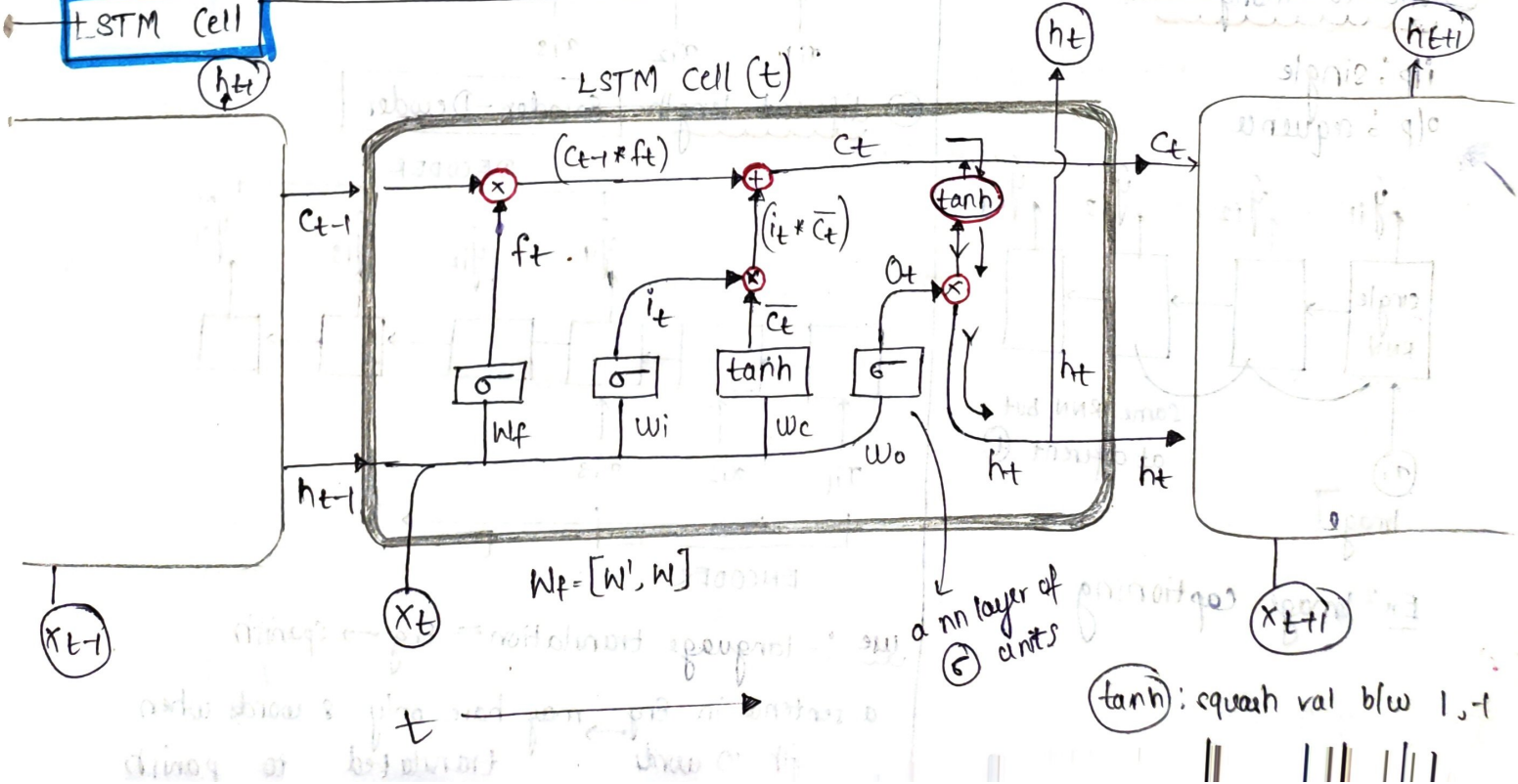
$h_t \equiv \hat{y}_{it}$

Notations

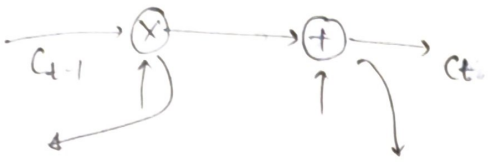
- ○ → point operation (apply 2 each)
- □ → Neural network layer
- C_t → cell state
- X_t → i/p point
- → concatenate
- → copy

Ex: [1 2 3] [1 1 1] ⊗ [1·1 2·1 3·1]

LSTM Cell



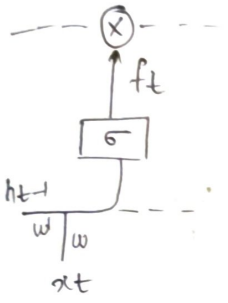
skip / identity layer → if your op needs long term memory just skip



if i/p to ⊗ = [1,1, ...] and i/p to ⊕ = [0,0,0 ...] → $[C_{t-1} \longrightarrow C_t]$

cell / layer is skipped

Forget part



concat

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

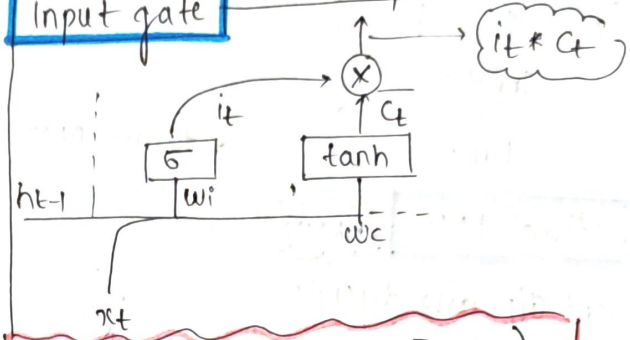
W_f : forget weights $[w, w_i]$

b_f : bias factor

f_t → how much data to forget

Input gate

add new info



$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\bar{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

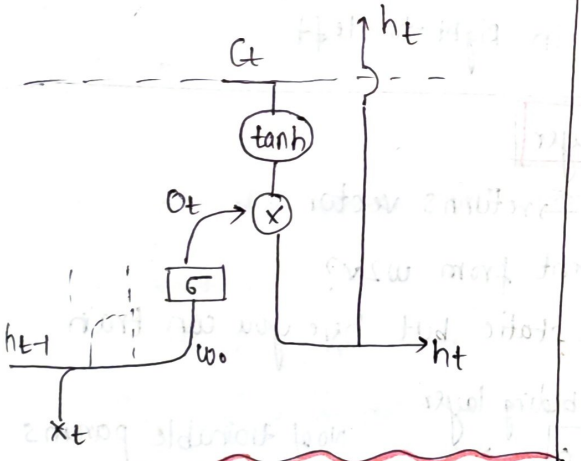
identity + forget + input gate ⟹

$$C_t = (f_t * C_{t-1}) + (i_t * \bar{C}_t)$$

GRU
* two param → better with less data
* not good for long sequence

Output gate

how much op to send?

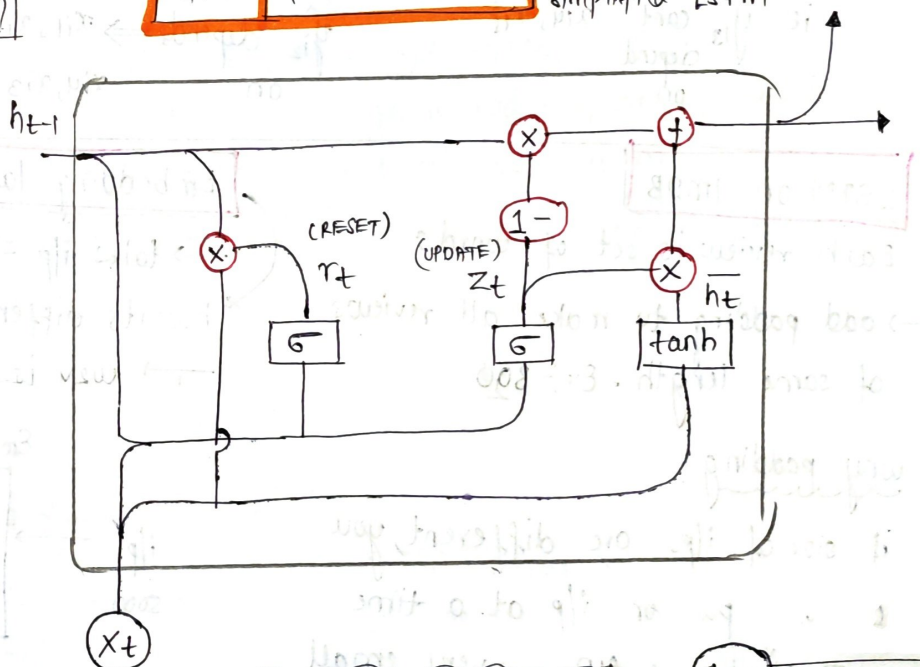


$$O_t = \sigma(W_o [h_{t-1}, x_t] + b_o)$$

$$h_t = \tanh(C_t) * O_t$$

GRU | Gated RNN unit

simplified LSTM



GRU vs LSTM

→ LSTM have 3 gates
GRU have 2 gates – reset, update

∴ As lesser gates → lesser eqn → faster to train

o/p, forget, ip

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t])$$

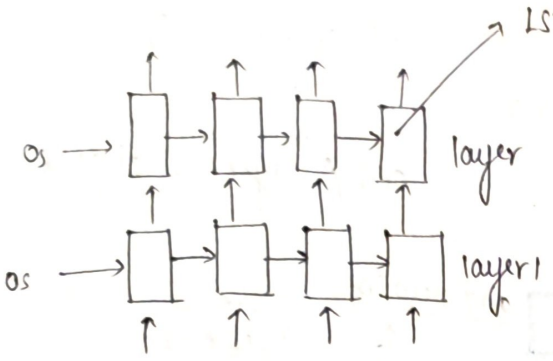
$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t])$$

$$\bar{h}_t = \tanh(W \cdot [r_t * h_{t-1}, x_t])$$

$$h_t = (1 - z_t) * h_{t-1} + (z_t * \bar{h}_t)$$

1 − [1,1, ...] − [ip vector]

Deep RNN



→ Becomes same as MLP, we can use,
- → dropouts
- → Batch Normalization

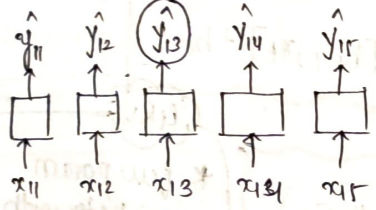
→ cant be used for live audio stream

→ to use BRNN whole i/p must be present

Bi-Directional RNN — BRNN

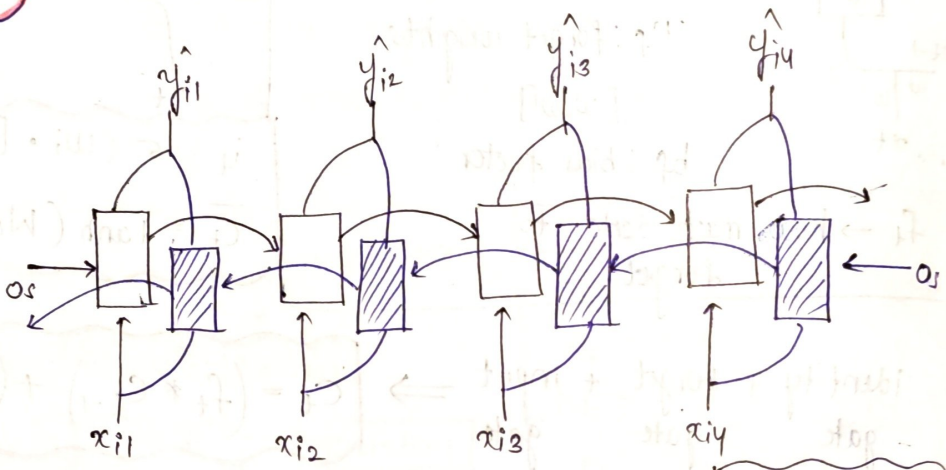
what if current O/p also depends on future i/p ?

Ex:



$\hat{y}_{13}$ depends upon x_{11}, x_{12}, x_{13}

but cant depend on future i/p ie $\hat{y}_{13}$ cant depend on x_{14}, x_{15}



Here in BRNN,

$\hat{y}_{i2}$ depends on ⟹ x_{i1}, x_{i2} in Forward
x_{i4}, x_{i3} in Right-to-left

Blue – R→L
black – L→R

LSTM on IMDB

Each review is set of words

→ add padding to make all reviews of same length. Ex:- 3900

why padding ?

→ if size of i/ps are different, you can only pass one i/p at a time
≡ Stochastic GD → very small

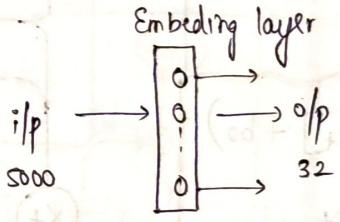
→ if i/p size is same, you can parallelly process inputs like in batch GD → faster

Embedding layer

→ takes i/p → returns vector

how its different from w2v?

→ w2v is static but here you can train



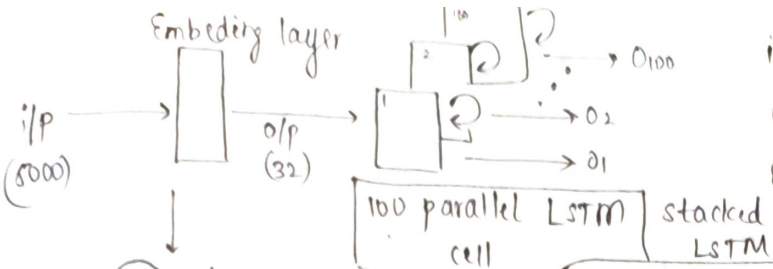
No of trainable params
= 5000 × 32
= 160K params

No of train params in LSTM

m = no of inputs = 32
n = no of o/ps = 100

Biases

$$\#params = 4(nm^2 + n^2 + n)$$



input : (25000 × 600)
output : (100) → (1)
Embeding layer → (600 × 32)

(i/p) indices : (1 - 5000)
(o/p) vector of size 32
#params = 5K × 32

Generative :- step 1 : generate samples
adversarial :- step 3 : (enemy) chuck dissimilars

core idea : generate dataset similar to D but not same/copy

Generative Adversarial Networks

simpler task : 1D scalar → (step3) check how similar D and D'

D = {set of heights}

Generate D' similar to D

(prob model)

→ (s1) generate PDF of D, P(H)

* find which distr it is

Ex :- it is normal distr

$P_\theta(H)$ → vector which is distr params μ, σ

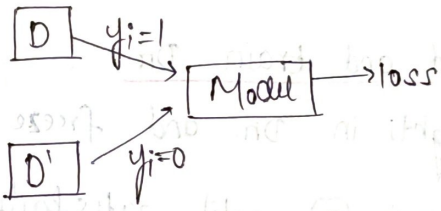
$P_\theta(H) = N(\theta = [\mu, \sigma])$

→ (s2) generate samples randomly from $P_\theta(H) = D'$

① use statistical tests
JS-dist
KL-div

problem : it works only with small dimension

② model aproach

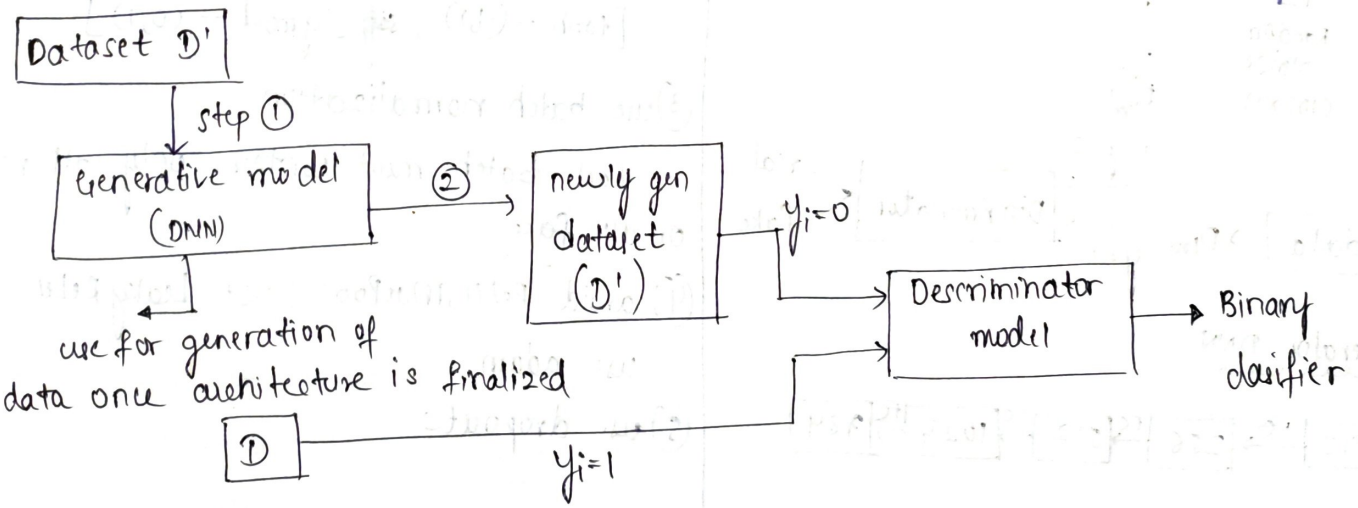


as loss ↑ → similarity ↑

→ if loss is less, then D and D' are seperable
∵ D and D' are not similar

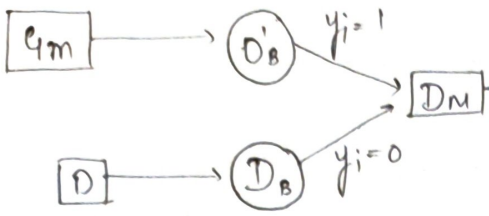
→ if loss is large ie bad performing model
→ D and D' are similar

Note :- probabilistic models dont work for multivariate analysis. so use ML/DNN



(30) **Train GAN**

D'_B = batch of dataset say of 100 datapoints



(maximize loss)
↳ use **gradient ascend** to maximize loss

working : **Alternate train opt=**

step 1 Keep Dm fixed and train Gm

⟶ for Dm initialize we a random sample as train data Ex:- normal dist? vector
~~Ex:~~ train the model for it

* Here Gm does up-sampling ; i/p (100 d ⟶ op 784 d) MNSIT

(*) Initially D'_B generated would be very-very random and thus different from D. So loss will be very less which is bad for us

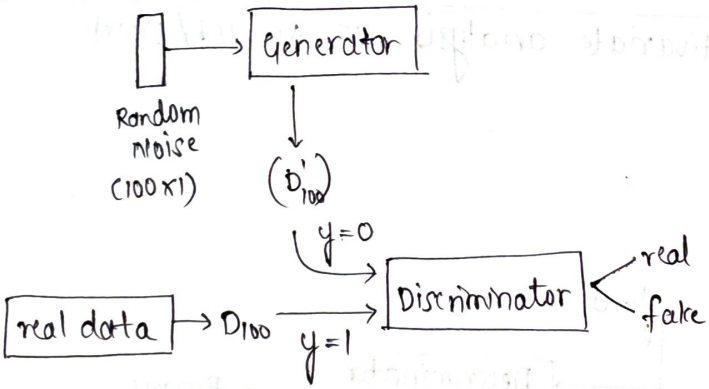
* we need to find and maximize loss using gradient ascend

step 2 Keep Gm fixed and train Dm

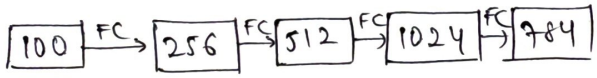
* only update weights in Dm and freeze weights in Gm

→ Alternatively do ① and ② until satisfactory loss is obtained

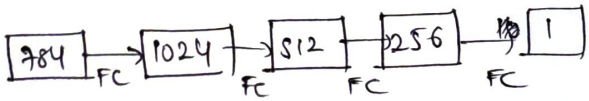
GAN for MNSIT



Generator DNN



discriminator DNN



Tips

① use normal distribution for sampling

② Normalize images b/w 1 and -1
→ use tanh as last layer of generator
[tanh - (-1,1) , ~~sig~~ sigmoid - (0,1)]

③ use batch normalization
Each batch must contain only all real or all fake

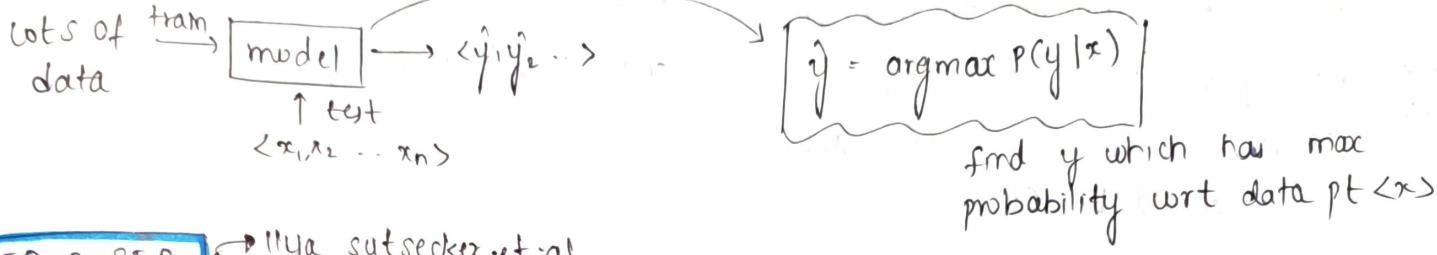
④ avoid ReLU, MaxPool ; use LeakyReLU
use adam

⑤ use dropouts

Encoder - Decoder

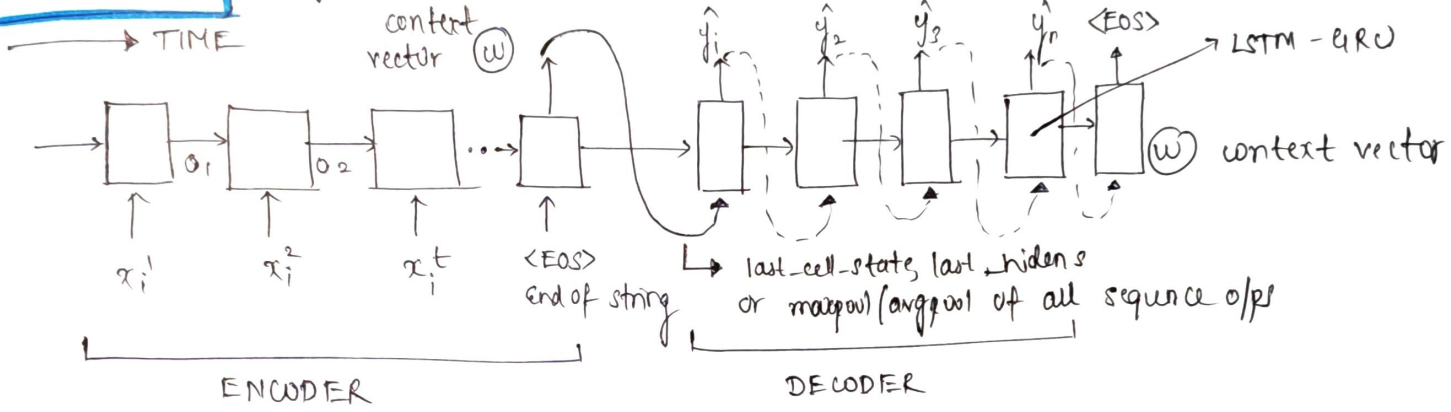
$\text{argmax}\ P(\langle y_1, y_2 \cdots y_n \rangle \mid \langle x \rangle)$

Probabilistic repr of model



SEQ-2-SEQ

Ilya sutskever et al



what is output sentence is long? [cho et al]

→ context vector is fed to all decoder cells, rather than only first decoder cell

→ but LSTM can't take 2 i/p at time stamp

↓

used modified LSTM

Image-2-caption

Karpathy et al

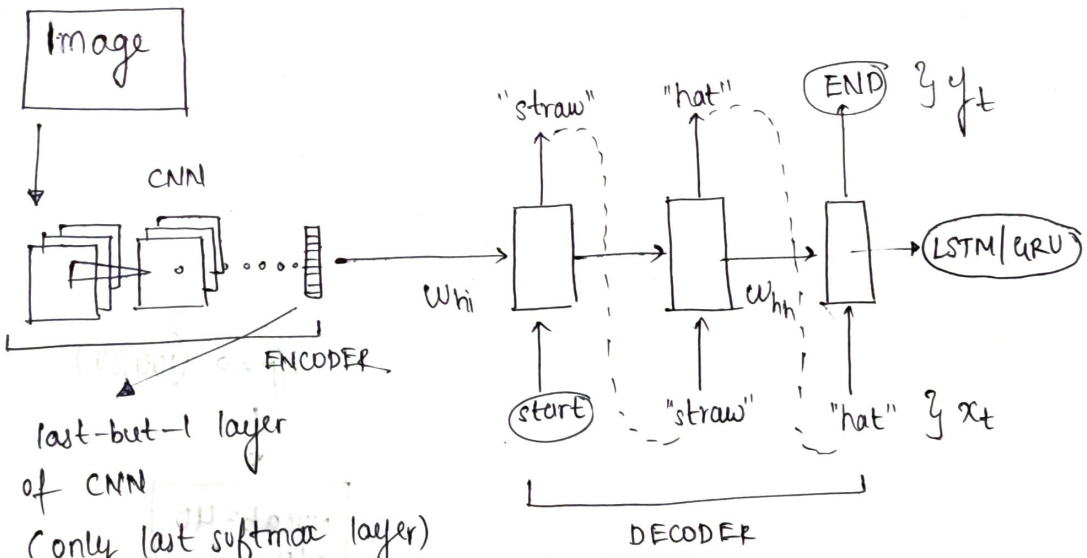


Image context vector

Applications

1. translation of text
2. Email auto complete and smart replies
3. Image captions and descriptions
4. statically finding code errors

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Char RNN

* many-to-many RNN → given large corpus of sequence of data predict which char follows given char most probably
* one o/p corresponding to each i/p

(train i/p) let sequence be $c_1, c_2, c_3 .. c_n$
if i/p is c_2 } learn this
o/p should be c_3 }

i/p ⇒ (100, 50)

↓

vocab=40
o/p = 8

~~Embed (8,~~

Embed (40, 8, input_len = 20)

↓

op → (None, 100, 8)

param s = vocab size * 8

Word Embedding Layer

DL + NLP

word embedding ?

→ represent word with vector → TF-IDF, BOW, Word2Vec et

word_embedding_layer → let nlw learn embeddings by itself

Process

sentence (seq of words) → Integer representation → Embeding layer (learn) → word embedings

Glove + Embedding matrix (pre-trained)

Ex :-

docs = ["sentence is one . . . ",
"sentence - 2 . . . "..]

① **Tokenizer** (word → int)

{"word": index}

→ t = Tokenizer().fit_on_texts(docs)

~~X_tr = t.fit~~

→ X_tr = t.texts_to_sequences(docs)

→ X_tr is vector of integers.
Each word is represented by value indicating its index in dictionary of vocabulary.

t.word_index

let len(t.word_index) = 300 (300 words)

padding make all sentences have same len

→ maxLen = for $\vec{v}$ in X_tr find largest $\vec{v}$

→ X_tr = pad_sequence(X_tr, padding='post', dtype='int' (float) maxlen=maxLen)

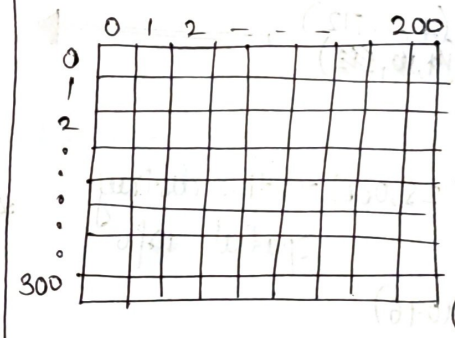
∴ we have each sentence/data point with len = maxLen

Ex → [1, 0 14 0 0 0 0 . . .]

use glove-vector / pretrained model

→ asume ur glove vector has 200 dim-vector for each weight.

Create Embeding matrix



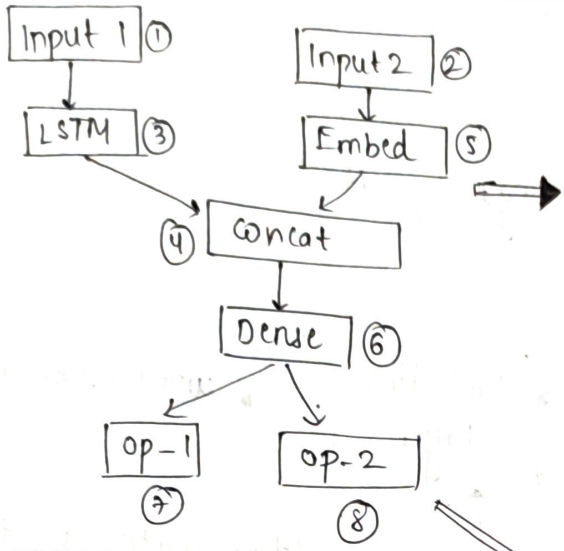
∀ each word in vocab, have a v-dim vector

```
for word,idx in t.word_index:
    embed[idx] = glove.get(word)
```

Embedding Layer

```
e = Embedding(input_dim = len(vocab),      → total no of words in vocab/len(em)
              output_dim = 200,            → output dimension of each word (200 in our case)
              input_length = maxLen,       → length of each training data.
              trainable = false,
              weights = [Embed_matrix] )   } for pretrained glove vector
```

Functional API Keras



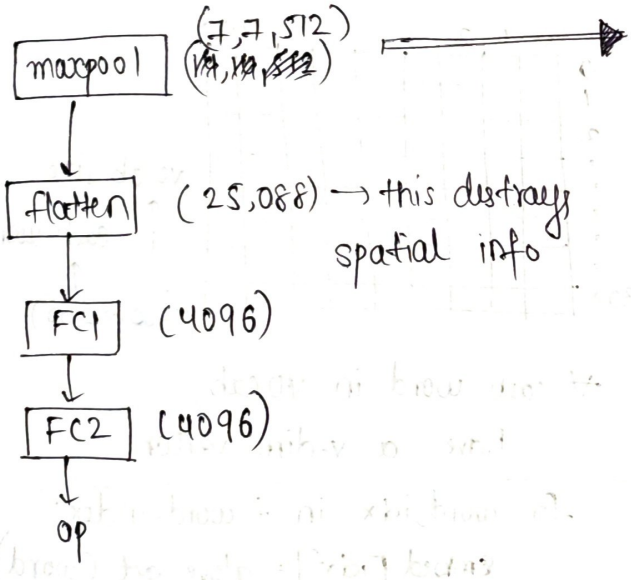
① Inp-1 = Input ((128,))
③ LSTM = LSTM( ) (Inp-1)
② Inp2 = Input ((10,))
⑤ Embed-L = Embedding( ) (Inp2)
④ concat = concatenate( )([LSTM, Embed-L])
⑥ Dense = Dense( ) (concat)
⑦ op-1 = Dense (10, softmax) (Dense)
⑧ op-2 = Dense (2, softmax) (Dense)

Train

model.fit (~~epochs=10~~,
train ⟶ [xtrain-1, xtrain-2],
ytrain ⟶ [ytrain-1, y-train-2],
epochs=10);

model = Keras.Model(
ip ⟶ [inp-1, inp2],
op ⟶ [op-1, op-2]);

Replace FC layer by Conv 2D



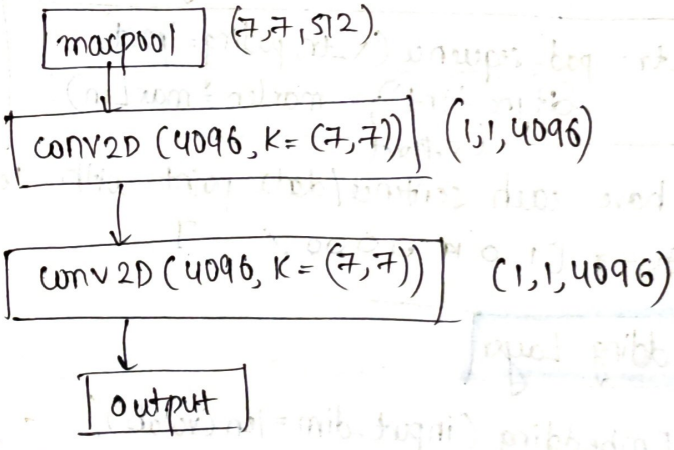
replace FC by CONV 2D

for FC1 we need 4096 ≡ (1,1,4096)

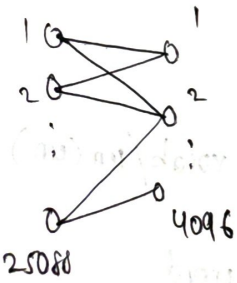
$*(7,7,512) \xrightarrow[s=1,\ fn=4096]{K=(7\times7)} (1,1,4096)$

$\left(\frac{(7-7+1)}{1}, \frac{(7-7+1)}{1}, 4096\right)$

$= 1,1,4096$

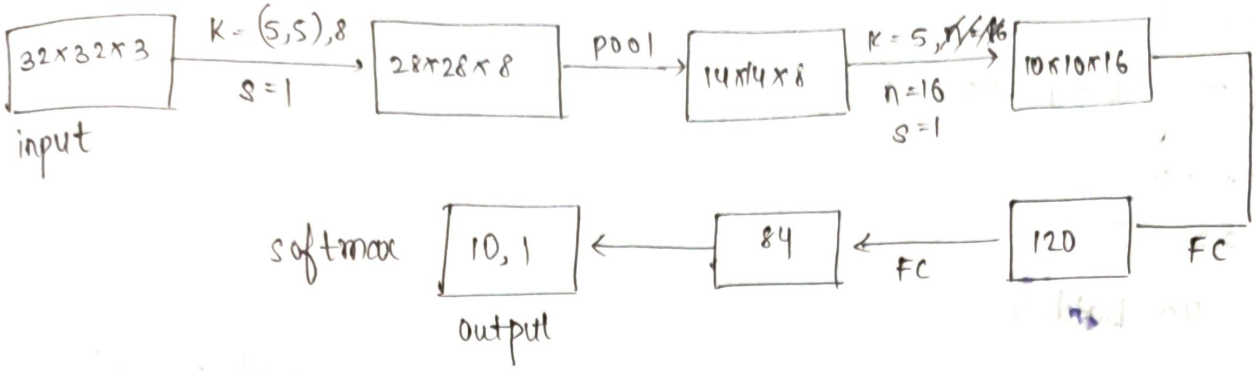


FC1



∴ 4096 * 25088 com

Calculate CNN params



* conv layers

$$(n,n) \longrightarrow \left(\frac{n-k+2p}{s}+1, \frac{n-k+2p}{s}+1, \text{no filters}\right)$$

$$\#\text{params in conv layer} = \left[\left(k \times k \times \text{no of filter in previous layer}\right) + 1\right] * \text{no of filters in current layer}$$

(+1 → Bias term for each filter)

$$\#\text{params in FC} = FC(Fcn) = \#\text{neurons in last layer} * \#\text{neurons in crent FC} + Fcn$$

(Fcn → Bias term)

count

layer	shape	# params	activation size
Input	(32×32×3)	0	32×32×3 = 3072
CONV1 K=5, n=8	(28×28×8)	$\left(\left(5 \times 5 \times 3\right)+1\right) 8$ = 608	6272
POOL1	(14×14×8)	0	1568
CONV2 K=5, n=16	(10×10×16)	$\left(\left(5 \times 5 \times 8\right)+1\right) 16$ $[(5\times5\times8)+1]*16$ = 3216	1600
FC1 (120)	(120,1)	(10×10×16 ×120) +120 = 192120	120

prev-kernel

$[(5\times5\times3)+1] * 8$

bias, cur kernel

* Embeding layer (vocab size, output_dim)

o/p → (None, i/p-size, output)

→ (vocab-size * output_dim)

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Batch size

→ model.fit(x, y, batch_size = b);

let len(x) = 200

batch_size = 5

∴ we get 40 batches

training ⟶ Epoch 1 ⟶ divide data into 40 batches ⟶ pass batch 1 & update weight
pass batch 2 & update weight.

∴ In one epoch, weights are update $\left(\frac{\text{size of dataset}}{\text{batch\_size}}\right)$ no of time ie 40 in our case

Image Segmentation

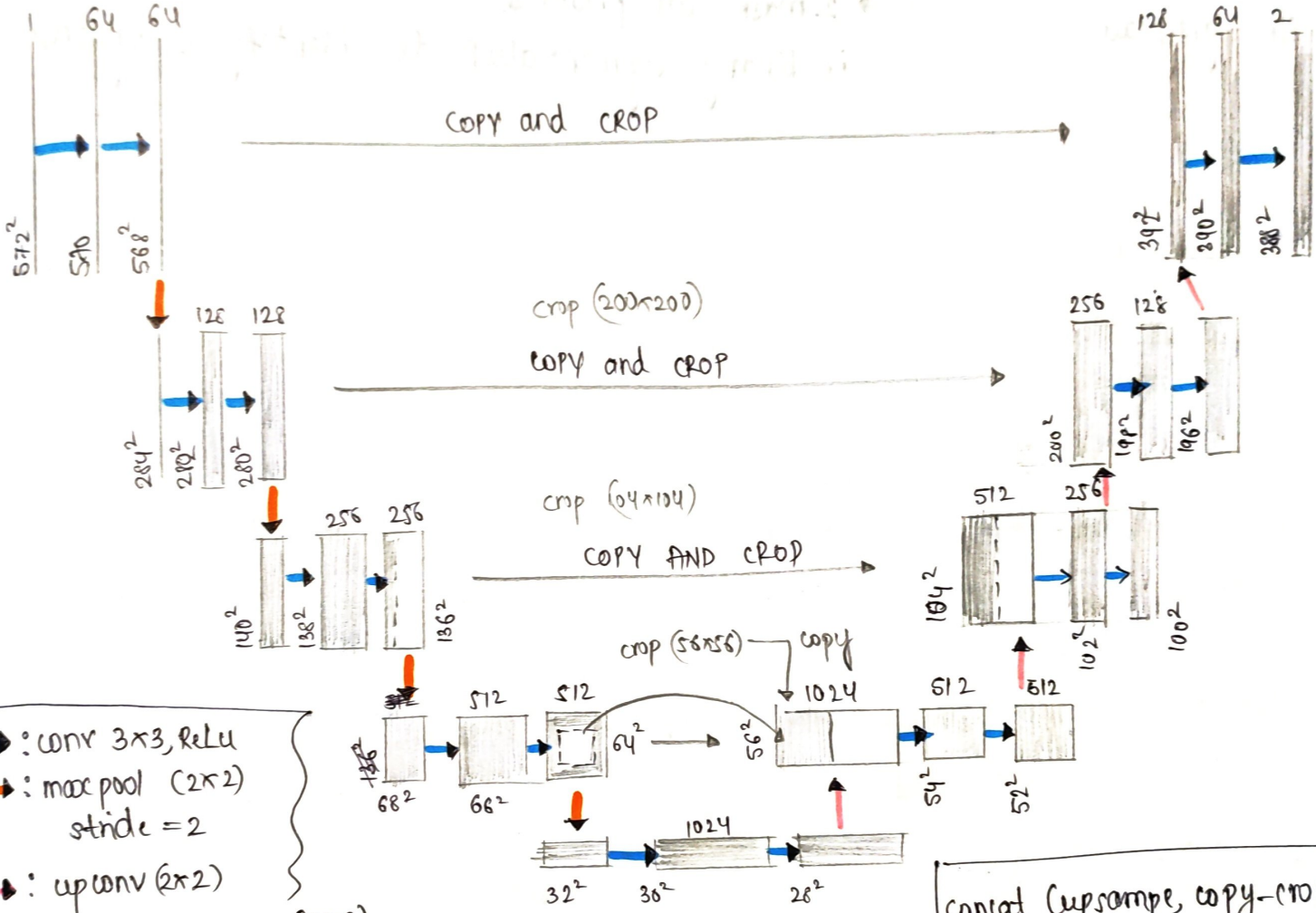
→ divide into areas / segments

→ measures :-

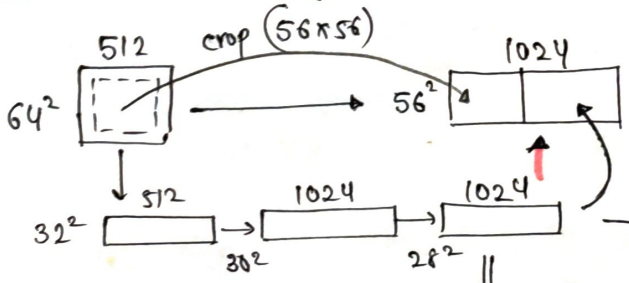
① jacards similarity = $\frac{R \cap R'}{R \cup R'}$ (IOU)

② cross entrophy = per pixel comparision

Unet



upsample base layer



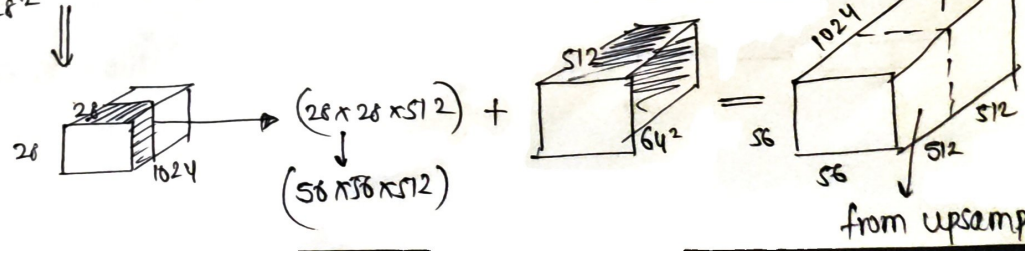
upsample

① upsample : duplicate rows and colums

28×28×1024 → 56×56×1024

② conv2D (f = 512, (2×2))

(56×56×512)



(38) General idea

* as we go down, image size halves and no of filters doubles
  ie we go into pixel level as we go down
* (upsampling + copy-N-crop) acts like a residual unit ie get information from lower level as well as from copy-crop unit
* Here o/p = (388×388×2)
  - 2 masks are predicted
    ie binary segmentation to identify 2 regions

i/p - grayscale

moving window average

consider you have data for (t) days
future data (t+1) depends on average of previous (K) days

other ways
- mean avg
- median
- exponentially weighted

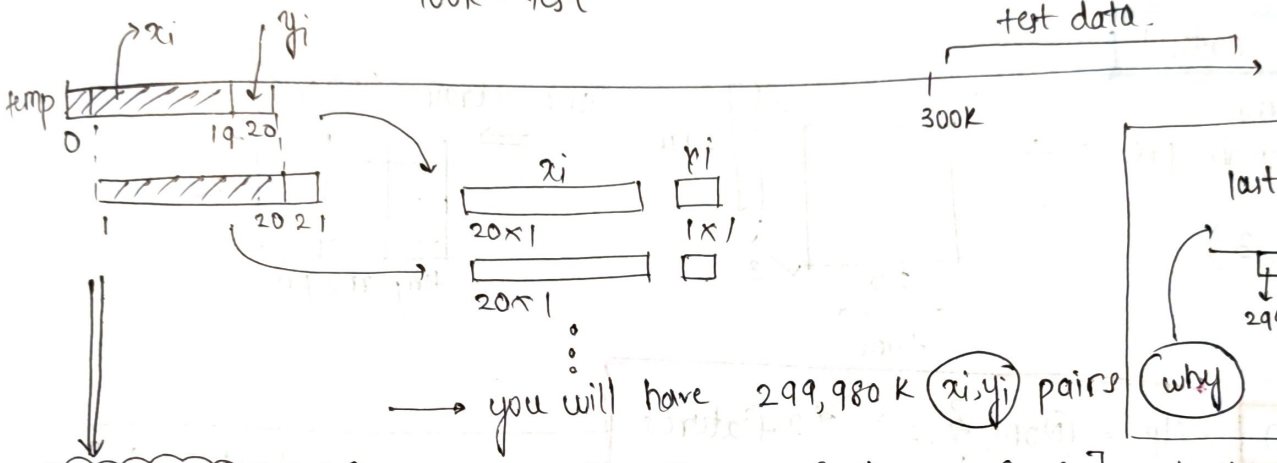
Dataset :- weather temp each 10 minutes given

Univariate prediction

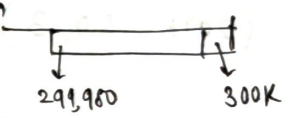
asume (K=20) we take window size = 20

* Normalize all data
  → only train data

dataset creation :- 300K - train
100K - test



last sample is



why

→ you will have 299,980 K (xi, yi) pairs

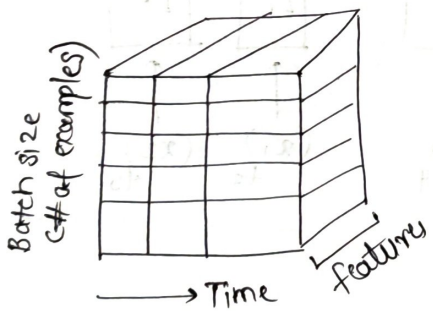
new dataset → (299,980, 20, 1) [reshape (20,) into (20,1)] → better for training model

we have data of 299,980K windows/time series

LSTM training diagram

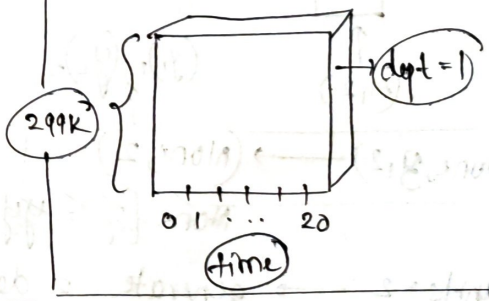
* LSTM expects data in this format → [batch, time, features]

height (y) → samples
x → time series
depth → features (univariate 1)



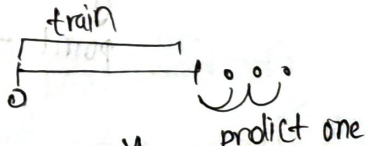
loss = mae
mean absolute error

Our data

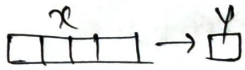


multivariate - single step

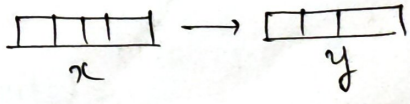
→ given a windows predict only one data at $t_1 - - t_n$



* single step → predict only one pnt at future

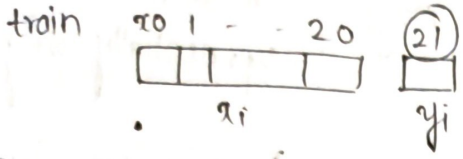


* multi step → predict over multiple points

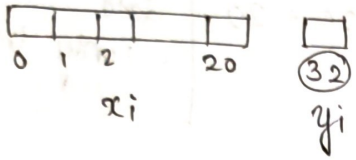


Dataset generation hacks

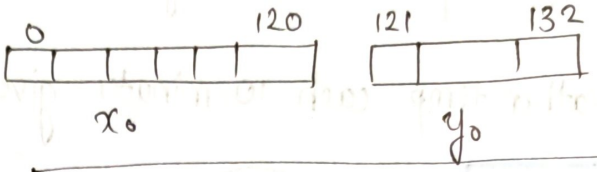
① predict next hour itself



② predict next 12 hrs



② predict next 12 hours data using past 120 hours → multi step

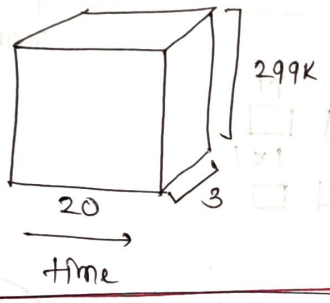


∴ xtrain = (299K, 20, 1)
ytest = (299K, 12, 1) or (299K, 12)

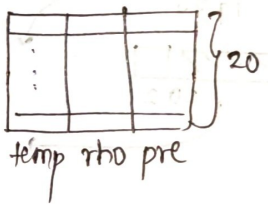
multivariate dataset

predict — temp
data — temp, rho, pre ⟹

(299K, 20, 3)



one xtrain (20×3) ⟹



Keras LSTM

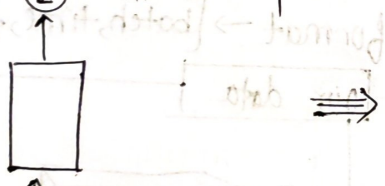
ip = (None, 4, 2) — 2 features; 4 time-steps

output → ①

LSTM (units = 2)

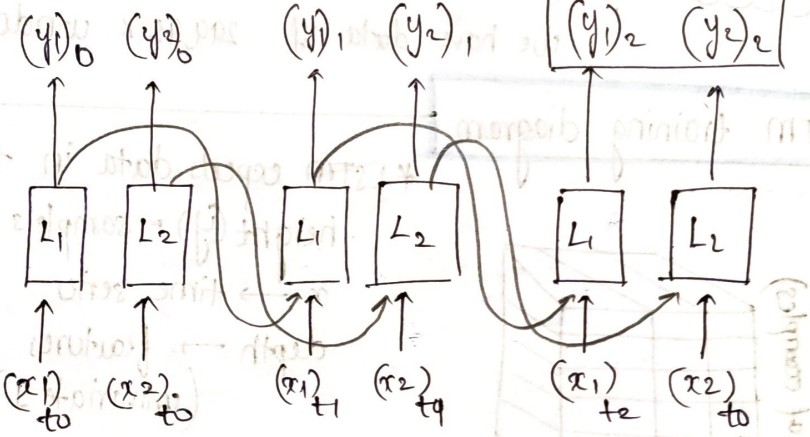
ip → (x0 x1 x2)

② → dim = no of units

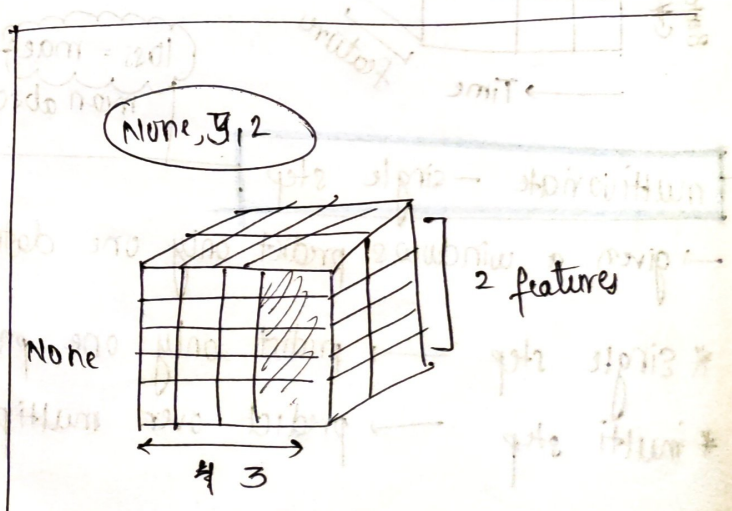


(None, 3, 2) → (None, 2)

~~None, [illegible]~~



units = 2 → generate 2 data for each point → one o/p from last unit



return_sequences = true

* dont only return last_state o/p → $[[y_{10}, y_{20}], [y_{11}, y_{21}], [y_{12}, y_{22}]]$ but o/p for each state and time step

21/3

(None, 3, 2) → LSTM (units=5, ret_sequences) → (None, 5) → (None, 3, 5)

(None, time_steps, units)

no of units

NO of time steps

return_states = true

shape = (3,1)

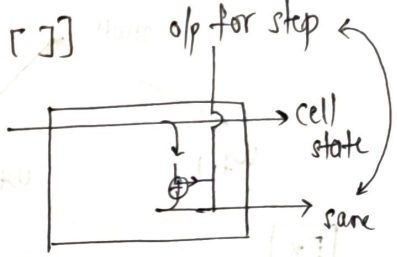
LSTM (1, ret_states) ⟹ lstm1, state_h, state_c → [[ ], [ ], [ ]] (3×5)

lstm_1 → LSTM → state_c, state_h

both

hidden state o/p for last time step

cell state for last time step



* LSTM (1, ret_states = true, ret_seq = true) → [lstm1, state_h, state_c] → [[O_1, O_2, O_3], [ ], [ ],]

i/p = (3,1)

o/p of all layers/time steps

o/p at last

o/p cell state of last cell

Standard

i/p → (None, time_steps, feat)

- LSTM (units) → (None, units)
- LSTM (units, ret_sequences) → (None, time_steps, units)
- LSTM (units, ret_states) → ([None, 16], [None, 16], [None, 16])
- LSTM (units, ret_states + ret_sequences) → ([None, time_steps, units], [None, units], [None, units])

return hidden state o/p for each time step → one timestep will have (units) outputs ∴ ts × units

unit.

unit

* only ret_states → ret_states with ret_sequences

lstm_1 and state_h are same (None, units) (None, units)

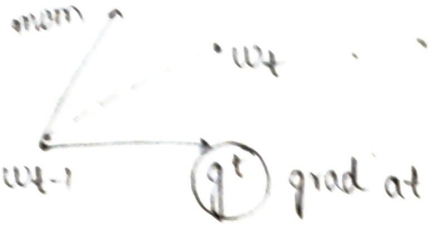
lstm_1 = (None, ts, units)

state_h = (None, units)

Nesterov Accelerated gradient

momentum = ewa of previous steps

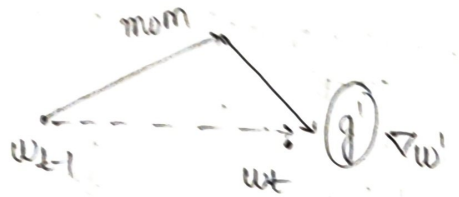
→ SGD + momentum = $w_t = w_{t-1} - [\gamma V_{t-1} + \eta g_t]$ ← gradient



NAG → it says ① calculate momentum

② calculate gradient at momentum pt $(w_{t-1} - \gamma V_{t-1})$

③ move in direction of grad



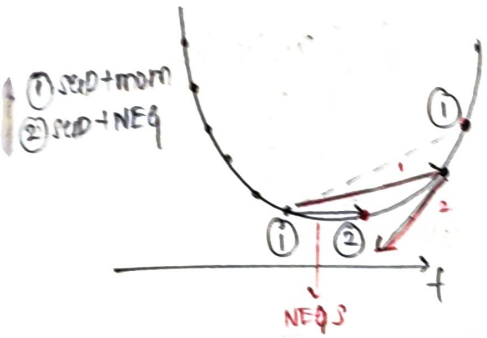
$(w_t)' = w_t - \gamma \cdot V_{t-1}$ → step1 : momentum

$V_t = \gamma V_{t-1} + \eta \cdot g'$

where,

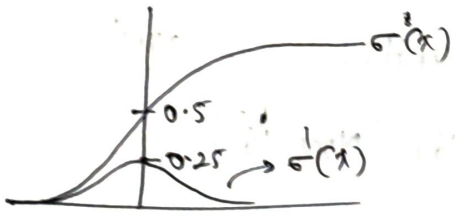
***** $g' = \nabla w_t'$ (grad at w_{t-1} + momentum

Ex



* at point ①, we previously had many +ve update ∴ velocity / momentum will be high and it may overshoot minima
* NEG :- it move first to momentum point which is on other side, and then gradient is calculated which is (-ve) as slope is -ve ∴ it overshoots less than SGD + momentum

derivative of sigmoid



wkt $\sigma'(x) = \sigma(x)(1-\sigma(x))$

max = 0.25 at (x=0)

min = 0

differentiation rules

① Reciprocal rule

$\left[\frac{1}{g(x)}\right]'$ or $\left[g(x)^{-1}\right]' \xrightarrow{d/dx} \frac{-g'(x)}{g(x)^2}$

$\frac{d}{dx}\left(\frac{1}{g(x)}\right) = \frac{-\frac{d}{dx}(g(x))}{(g(x))^2}$

② Exponential rule

$\frac{d}{dx}\left(e^{f(x)}\right) = e^{f(x)} \cdot f'(x)$

$\Rightarrow \sigma'(x) = \frac{d}{dx}\left[\frac{1}{1+e^{-x}}\right] = \boxed{\frac{-\frac{d}{dx}(1+e^{-x})}{(1+e^{-x})^2}} \rightarrow (1)$ using reciprocal rule

→ solving Numerator of (1)

$$-\frac{d}{dx}(1+e^{-x}) = -\left[\frac{d}{dx}(1) + e^{-x}\cdot\frac{d}{dx}(-x)\right] = -\left[0 + (e^{-x})(-1)\right]$$

$$= e^{-x}$$

$\therefore$ (1) becomes $\Rightarrow \boxed{\frac{e^{-x}}{(1+e^{-x})^2}} \Rightarrow (2)$ $\therefore \sigma'(x) = \frac{e^{-x}}{(1+e^{-x})^2}$

Simplifying (2) further

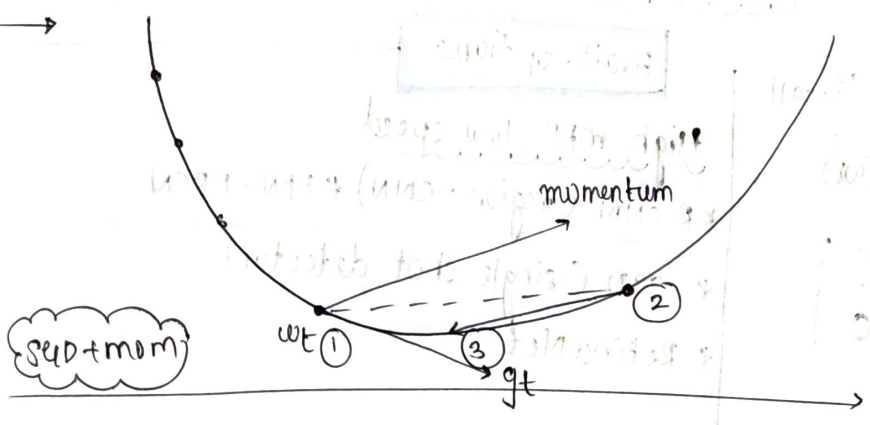
$$\frac{e^{-x}\cdot 1}{(1+e^{-x})(1+e^{-x})} \rightarrow \frac{(e^{-x}+1-1)\cdot 1}{(1+e^{-x})(1+e^{-x})} \rightarrow \left[\frac{1}{(1+e^{-x})}\right]\left[\frac{e^{-x}+1-1}{1+e^{-x}}\right]$$

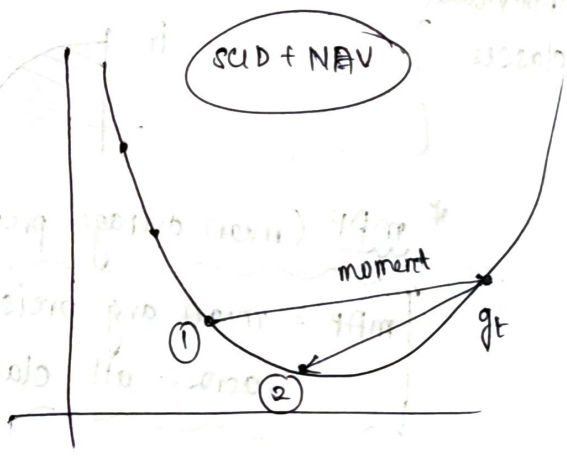
$\sigma(x)$

$$\rightarrow \sigma(x)\left[\frac{e^{-x}+1-1}{(1+e^{-x})}\right] \rightarrow \sigma\cdot\left[\frac{e^{-x}+1}{1+e^{-x}} - \frac{1}{1+e^{-x}}\right] \quad \{\text{split into fractions}\}$$

$$= \sigma(x)\left[1-\sigma(x)\right] \qquad \boxed{\therefore \sigma'(x) = \sigma(x)\cdot(1-\sigma(x))}$$

→





* at pnt w_t, v_t/momentum ↑ as we made lot of +ve increments previously

∴ due to this point overshoots to right side

↳ in case of NAG, we calculate ∇grad at momentum which is on right side ∴ it will be closer to minima and in negative direction

YOLO Algorithm

object detection

Object Detection

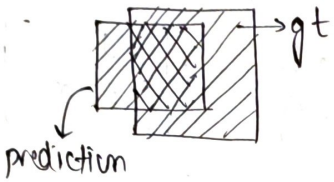
→ <x, y, w, h> → (x, y) — center, (w, h) — box width, h

* Focus on bounding boxes and not on pixels → use image segmentation (slower and not suitable for real-time apps)
* ip → algo → o/p image with bounding boxes with confidence level (0→1)

Performance Metrics

IoU = overlap area / union area

GT (ground truth) — human labelled data



* prediction is correct if IoU ≥ 0.5

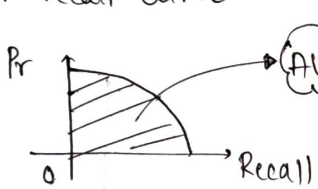
steps

① convert o/p to binary ie True or false using IoU & bounding boxes

② Image may have multiple bounding boxes,

So,

* for each class (chair, person ...)
  * individual classes → calculate avg-precision ≡ area under pre-recall curve
  * individual classes → plot Pr-recall curve



* mAP (mean average precision)

mAP = mean avg precision across all classes

Trade off

→ speed vs mAP

- speed → video based (self-dr cars, real time face)
- mAP → medical diagnosis (precision is imp) or OCR

Avail-options

High mAP, low speed

* R-CNN (region-CNN)
* FPN-FRCN
* SSD (single shot detector)
* RetinaNet

YOLO → faster and good mAP

- YOLOV3-320 → input image size
- YOLOV3-416
- YOLOV3-608

Note: as image size ↑ time ↑

YOLO V3

Architecture → only used fr initialize

YOLOV2	DarkNet-19
V3	DarkNet-53

1) Feature Extractor / Backbone (Pre-Training)

DarkNet-53 53 conv-layer (fully convolution n/w)

padding = same

	Layer	Filters	Size	O/p
	conv	32	(3×3)	256×256
	conv	64	(3×3) stride=2	128×128
1×	conv	32	(1×1)	
	conv	64	(3×3)	
	residual			128×128
	conv	128	3×3/2	64×64
2×	conv	64	(1×1)	
	conv	128	(3×3)	
	residual			64×64
	conv	256	3×3/2	32×32
8×	conv	128	1×1	
	conv	256	3×3	
	residual			32×32
	conv	512	3×3/2	16×16
8×	conv	256	1×1	
	conv	512	3×3	
	residual			16×16
	conv	1024	3×3/2	8×8
4×	conv	512	1×1	
	conv	1024	3×3	
	residual			8×8
	Avgpool	global		
	connected	1000		
	Softmax			

416×416×3 → 13×13×1024

(416/32) — last filter size

Characteristics

1. 53 conv layers
2. fully conv neural n/w
3. Each conv ≡ CONV → Batch Norm → Leaky ReLu
4. conv with stride-2 → acts as max-pool
5. no maxpooling

*whole model is trained on ImageNet and save weights

→ this only detects image objects but not bounding boxes

stride=2

why we DarkNet when we had Resnets?

Backbone	Top-5	Bops	BFlops/s	FPS
Res-152	77	2930	1090	37
Dark Net	77.2	18.7	1457	78

→ darknet almost gives same or little less accuracy comp to resNet

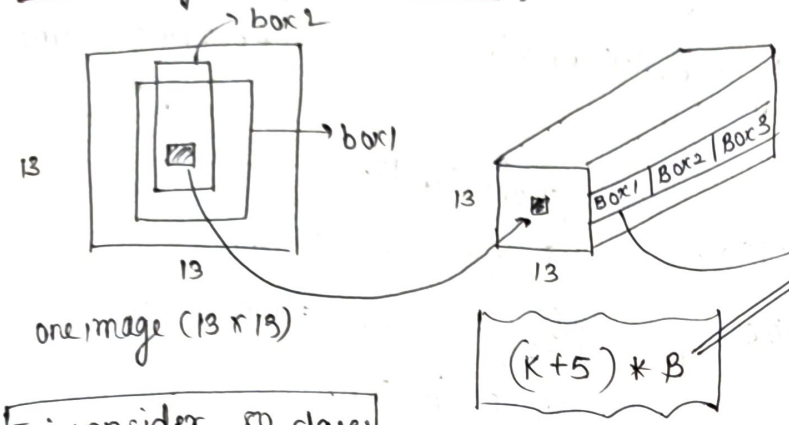
* BN ops is less (Billions of ops needed)
* BFLops/s is high (Bil of float op/sec).
* and FPS is high

② bounding boxes and output

(i/p) $416 \times 416 \times 3 \xrightarrow{\text{DNet}} 13 \times 13 \times 1024 \xrightarrow{\text{Box}} 13 \times 13 \times 425$ (o/p)

assume K = 80 and B = 5

How do you represent boxes?



one image (13 × 13)

(K+5) * B

(Each cell may belong to many boxes)

#no of boxes

Each bounding box

t_x	t_y	t_w	t_h	P_o	C_o	...	C_K	* B

(x, y) → centre of box with dimensions w.r.t

P_o → objective score – (0/1) whether it contains an obj / not

$C_o \rightarrow C_K$: class scores for K no of

Ex: consider 80 classes

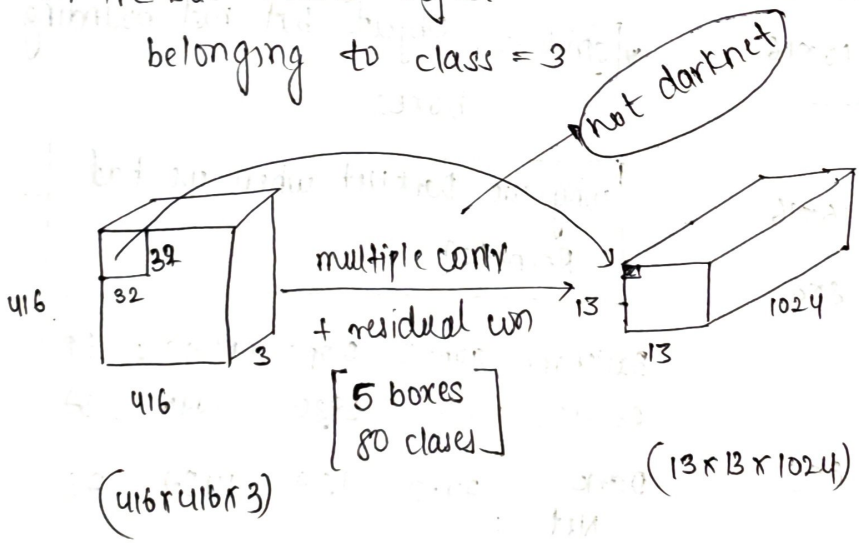
* box1 = $(P_o, x, y, w, h, C_1, \ldots C_{80})$

* score = $P_o * C = \begin{bmatrix} P_o C_1 \\ P_o C_2 \\ P_o C_3 \\ \vdots \\ P_o C_{80} \end{bmatrix} = \begin{bmatrix} 0.12 \\ 0.21 \\ 0.80 \\ \vdots \\ 0.10 \end{bmatrix}$ → probability that object bounded ∈ class 2

$P(C=K) = P_o * P_K$ or $P_o * C_K$

* assume we get $P_o C_3 = 0.80$ as max

∴ the box bounds object belonging to class = 3



(416 × 416 × 3)

[5 boxes, 80 classes]

(13 × 13 × 1024)

$\frac{416}{13} = 32$

∴ Each pixel in o/p is of size (1 × 1 × 1024) is captured from (32 × 32 × 3) grid input.

Effective Receptive Field

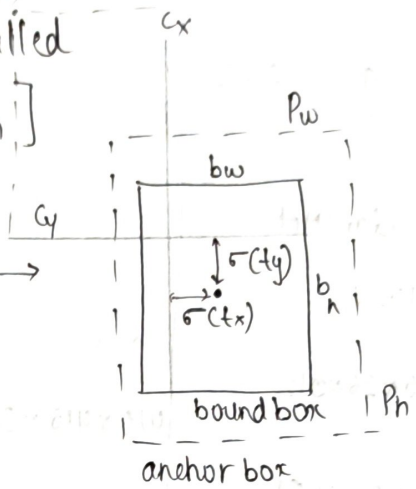
Anchor Boxes → prior boxes where you highly probable to find

* Tried to predict (t_x, t_y, t_w, t_h) directly but couldn't get good results

So,

① Fix some predefined boxes called anchor-boxes : $[C_x, C_y, P_w, P_h]$

② define bounding boxes in terms of anchor boxes →



$C_x, C_y \equiv$ priors

$b_x = \sigma(t_x) + C_x$

$b_y = \sigma(t_y) + C_y$

$b_w = P_w \cdot e^{t_w}$

$b_h = P_h \cdot e^{t_h}$

$\sigma = 0-1$

(b_x, b_y) should be atmax 1 pixel away from (C_x, C_y)

∴ given box cordinates and anchor boxes you can find $[b_x, b_y, b_w, b_h]$

learned box + anchor box → actual bounding box

How to find how many anchor boxes and location?

→ apply kmeans clustering on coco dataset which is set of all bounding boxes

→ $(k=5)$ was found to be best which indicates that these 5 anchor boxes have high probability region

Objectness score — (P_o)

Is there any object or not? 0/1

↳ have a log-regresion for each box

* $[C_0 - - C_k]$

↳ tried softmax — didn't work Because of heirarchy present

⇒ Soln

Build one logistic regresion for each class ie u need $P_o + (C_0 \cdots C_k)$ log-regresions

if for any Bbox, if P_o is v.v.small → it has very less chance of enclosing any object ∴ can be ignored

$\lambda_{co\text{-}ord} = 5$ — $t_x, t_y \to 0 - \infty$

$\lambda_{noobj} = 0.5$ → $P_o = (0 \text{ to } 1)$

Loss

$$\sum_{\text{all bounding boxes containing object in train data } y_{train}} \Big[\text{log-loss for } P_o + \text{log-loss for } (C_0 \cdots C_k) + \lambda_{co\text{-}ord} * \text{sq. loss for } t_x, t_y, \sqrt{t_w}, \sqrt{t_h} \Big] + \sum_{\text{all boxes in predicted which dont have obj (predicted boxes not present in } y_{train})} \lambda_{no\text{-}obj} * \text{log-loss for } (P_o)$$

4 Multiscale prediction

* 13×13 image feature can only detect large objects

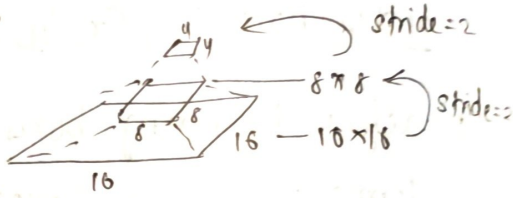
Idea

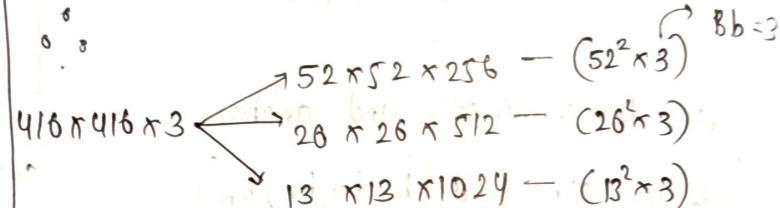
* predict with different grid sizes
  - How to get?

Extract from layers in darkNet

1. last layer → 13×13×1024
2. last but-1 → 26×26×512
   conv layer with s=2
3. 2nd last → 52×52×256
   conv layer s=2

Image pyramid



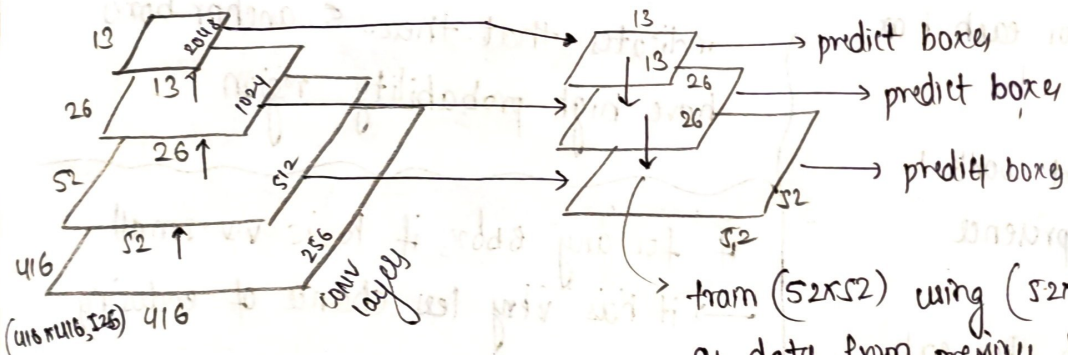


↓

10,647 Bboxes of different scales

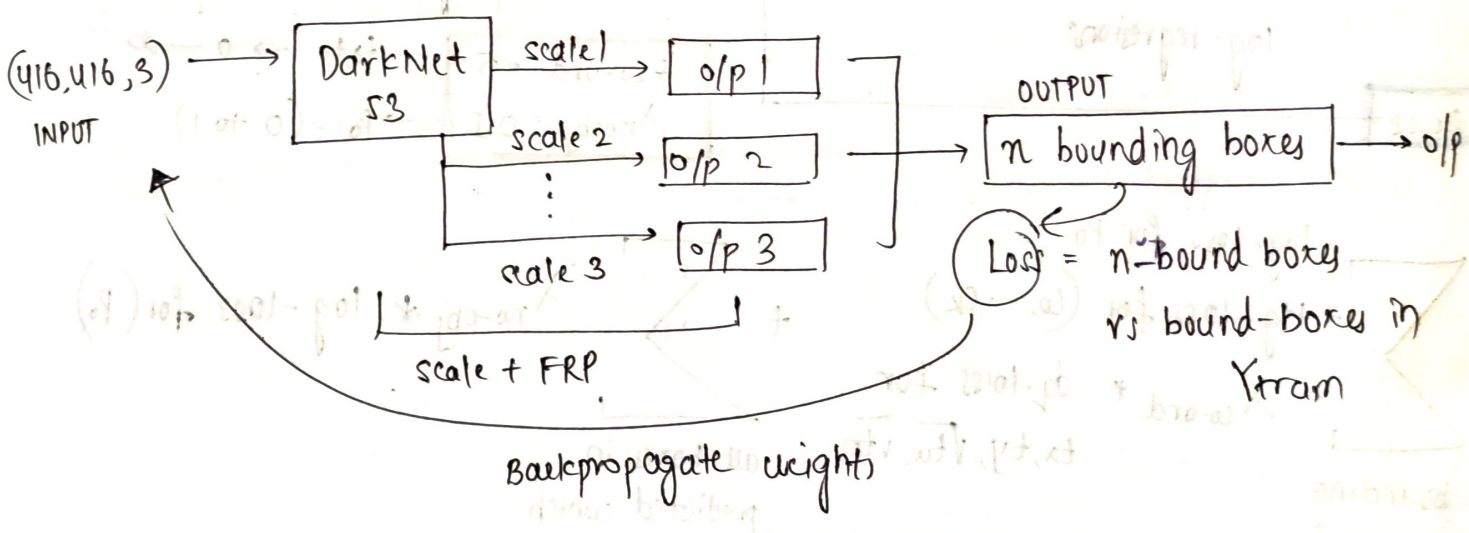
FPN — Feature pyramid networks

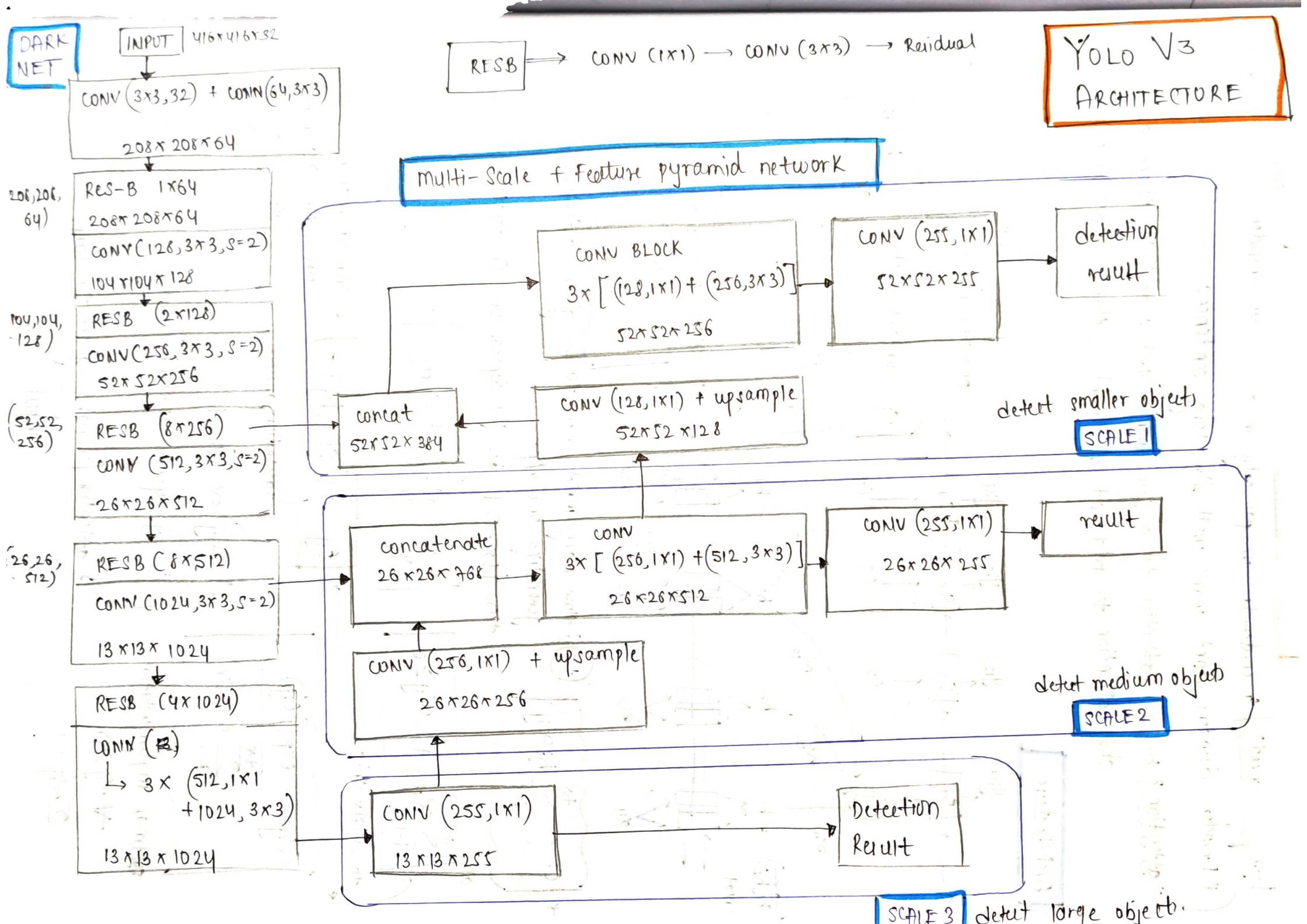
→ not only use different grid sizes to predict but also cross-grid information to use

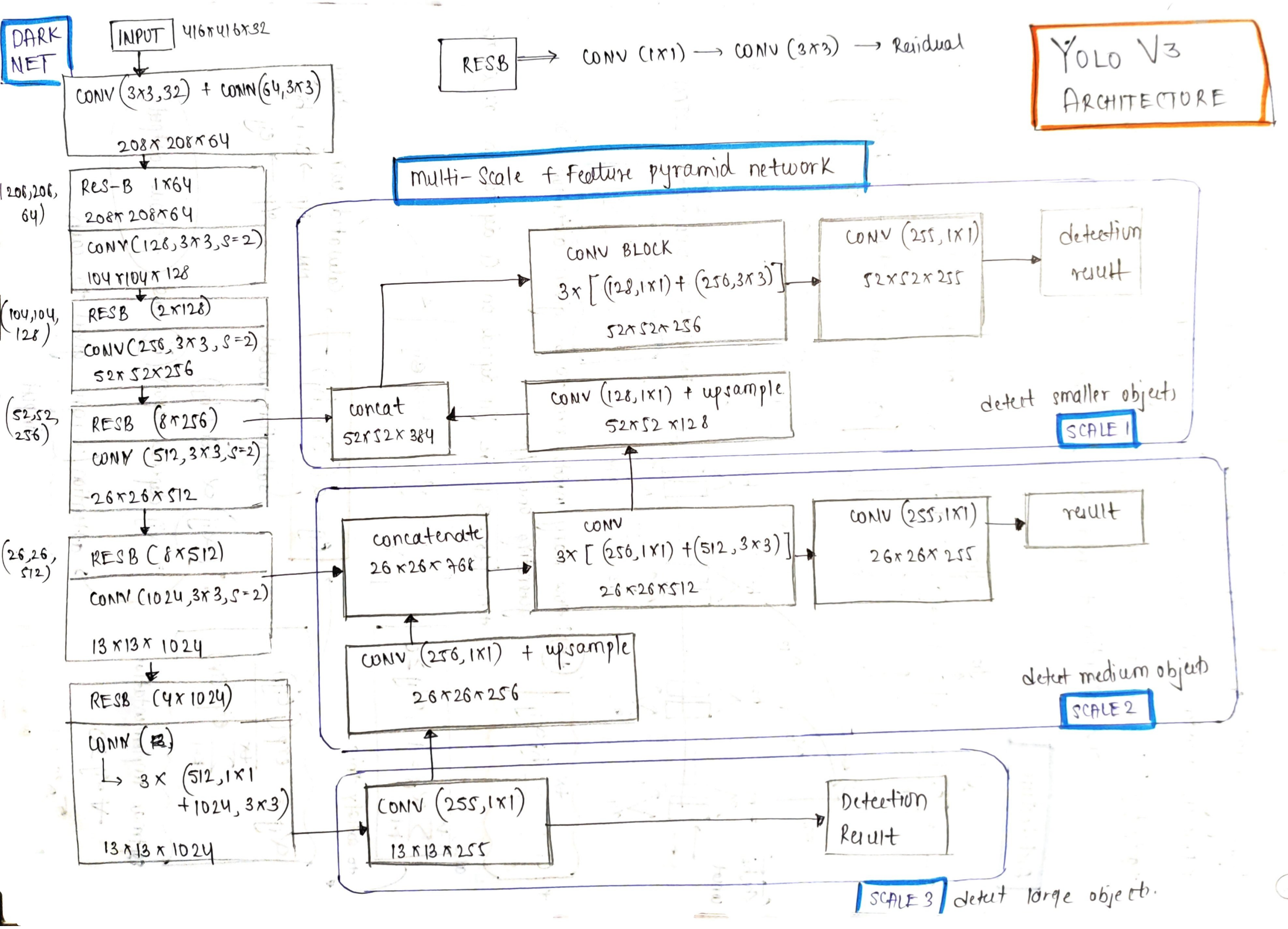


FPN + lateral connections

Workflow




DARK NET
INPUT 416x416x3
CONV (3x3, 32) + CONV (64, 3x3)
208 x 208 x 64
RESB → CONV (1x1) → CONV (3x3) → Residual
YOLO V3 ARCHITECTURE
Multi-Scale + Feature pyramid network
RES-B 1x64
208x208x64
CONV (128, 3x3, S=2)
104x104x128
(208, 208, 64)
RESB (2x128)
CONV (256, 3x3, S=2)
52x52x256
(104, 104, 128)
RESB (8x256)
CONV (512, 3x3, S=2)
26x26x512
(52, 52, 256)
RESB (8x512)
CONV (1024, 3x3, S=2)
13x13x1024
(26, 26, 512)
RESB (4x1024)
CONV (B)
3x (512, 1x1 + 1024, 3x3)
13x13x1024
CONV BLOCK
3x [(128, 1x1) + (256, 3x3)]
52x52x256
CONV (255, 1x1)
52x52x255
detection result
concat
52x52x384
CONV (128, 1x1) + upsample
52x52x128
detect smaller objects
SCALE 1
concatenate
26x26x768
CONV
3x [(256, 1x1) + (512, 3x3)]
26x26x512
CONV (255, 1x1)
26x26x255
result
CONV (256, 1x1) + upsample
26x26x256
detect medium objects
SCALE 2
CONV (255, 1x1)
13x13x255
Detection Result
SCALE 3
detect large objects.


DARK NET
INPUT
416x416x32
CONV (3x3,32) + CONV (64,3x3)
208x208x64
RESB
CONV (1x1) → CONV (3x3) → Residual
YOLO V3 ARCHITECTURE
Multi-Scale + Feature pyramid network
(208,208, 64)
Res-B 1x64
208x208x64
CONV(128,3x3,S=2)
104x104x128
(104,104, 128)
RESB (2x128)
CONV(256,3x3,S=2)
52x52x256
(52,52, 256)
RESB (8x256)
CONV (512,3x3,S=2)
26x26x512
(26,26, 512)
RESB (8x512)
CONV (1024,3x3,S=2)
13x13x1024
RESB (4x1024)
CONV (B)
↳ 3x (512,1x1 +1024,3x3)
13x13x1024
CONV (255,1x1)
13x13x255
Detection Result
SCALE 3 detect large objects.
CONV (256,1x1) + upsample
26x26x256
concatenate
26x26x768
CONV
3x [(256,1x1) + (512,3x3)]
26x26x512
CONV (255,1x1)
26x26x255
result
detect medium objects
SCALE 2
CONV (128,1x1) + upsample
52x52x128
concat
52x52x384
CONV BLOCK
3x [(128,1x1) + (256,3x3)]
52x52x256
CONV (255,1x1)
52x52x255
detection result
detect smaller objects
SCALE 1

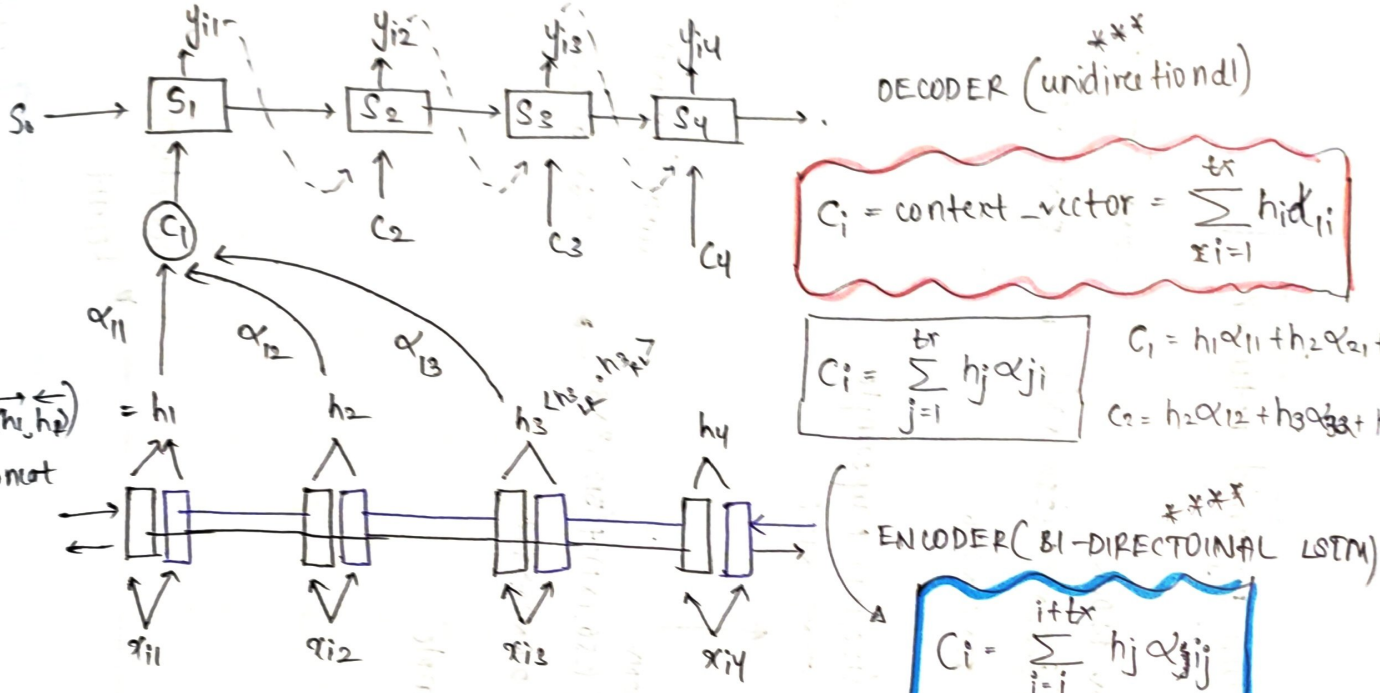
Attention Models

why you need? In en-decoders we pass only one c_i from encoder — this may not capture the essence of whole sentence

* Encoders decoders dont work well for long sentences

→ attention? We give attention to a few words (tx) translate them and shift attention to next set of words (Human characteristic)

Architecture



$$c_i = \text{context\_vector} = \sum_{xi=1}^{tx} h_i \alpha_{ji}$$

$$c_i = \sum_{j=1}^{tx} h_j \alpha_{ji}$$

$c_1 = h_1\alpha_{11} + h_2\alpha_{21} + h_3\alpha_{31}$

$c_2 = h_2\alpha_{12} + h_3\alpha_{32} + h_4\alpha_{42}$

$$c_i = \sum_{j=i}^{i+tx} h_j \alpha_{ij}$$

* $$c_i = \sum_{j=1}^{tx} h_j \alpha_{ij}$$

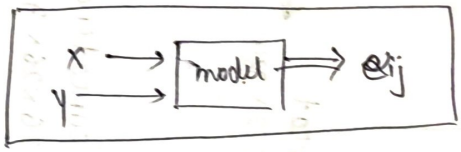
tx : how many inputs need to be given attention for generating one o/p.

Here $tx = 3$ ie y_{i1} depends on c_1 depends on x_{i1}, x_{i2}, x_{i3}

also,

$$\sum_{i=1}^{tx} \alpha_{1i} = 1 \;,\; \alpha_{ij} \geq 0$$

to satisfy this



$$e_{ij} = a(s_{i-1}, h_j)$$

attention-model

Calculated using 2-layer NN i/p → s_{i-1}, h_j o/p → e_{ij}

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{K=1}^{tx} \exp(e_{iK})}$$

softmax implementation

$\forall \alpha_{ij} \geq 0$

$\sum \alpha_{ij} = 1$

$\sum \alpha_{iK} = 1$ all α corresponding to K

$\therefore \alpha_{ij} \propto (s_{i-1}, h_j)$

= α_{ij} depends upon h_j and previous output so

→ attention/weight given to each input

Time complexity

K_1 = len(input)

K_2 = len(output)

$TC = O(K_1 \cdot K_2)$

if $tx = K_2$,

then $TC = O(K_1, K_2)$

ie consider whole sentence as attention to generate o/p.

α_{ij} importance

Ex: for calculating y_{i2} you use $\alpha_1, \alpha_2, \alpha_3$

in this case if α_1 is large than that particular word had more impact on prediction

Ex: french → english

	you	and	call → o/p
ti	0.9	0	1
ami	0.1	2	0
me	0	2	10

i/p

to predict w_3 = call me was most useful.

Image Captioning

i/p image → feature extraction using CNN → encoder

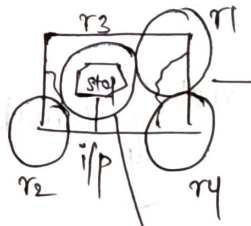
RNN with attention over image regions → decoder → LSTM → op

generate K d-dim vectors

each vector representing one region of image

(treat each vector as word i/p)

Visualize α_{ij}



A mountain road with stop sign

see highest α_{ij}

say highest is α_{23}

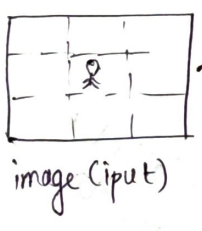
region (3) contributed most

tf.keras.Attention layer

→ inbuilt into keras

other blogs

Visualize



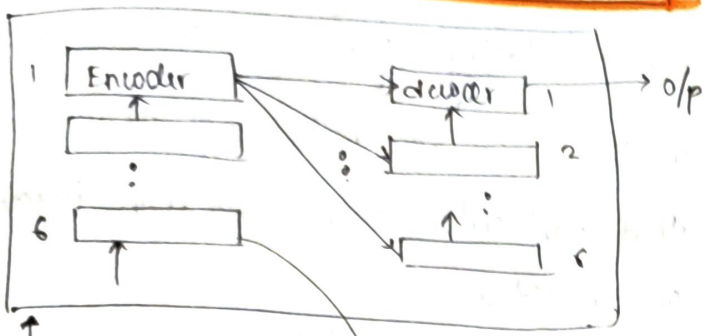
divide into 9 region vectors

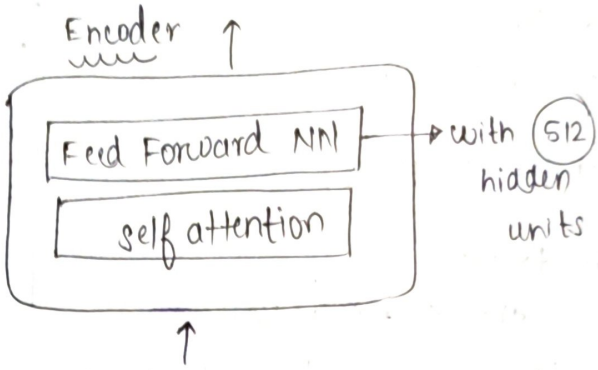
decoder with attentions → output word (man)

visualize α_{ij}s as feature importance

(region with face will have high α_{ij})

Transformers → Not RNN (! time based)





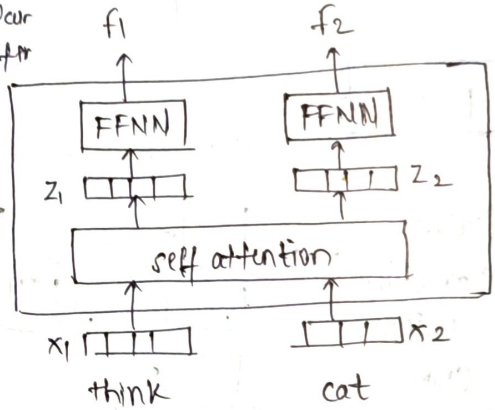
ENCODER

depends on all words

Self attention → attention :- what words determine Wcur
self-att :- what does Wcur connect/refer

the boy crossed the road as it was empty

what does it refer/connect to

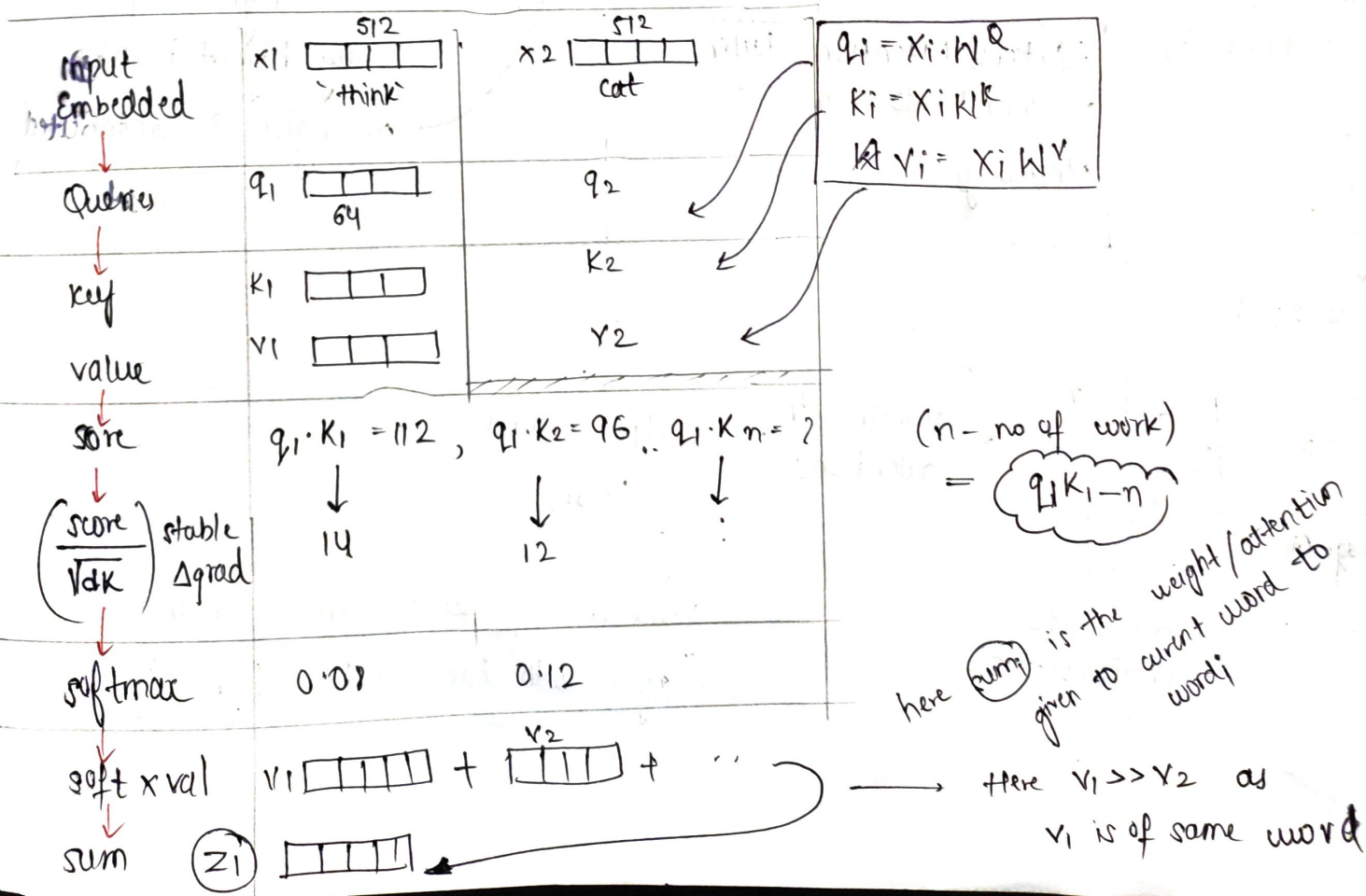


*inputs sent at once,
No time-based sending →

steps

hyper-params :

$d_k = 64$, W^Q – Query mat, W^K – keys, W^V – value } learnable



matrix computation

$X \times W^Q = Q$

$X \times W^K = K$

$X \times W^V = V$

$$\text{softmax}\left(\frac{Q \times K^T}{\sqrt{d_k}}\right) V = Z$$

$\therefore$ self-attention focuses on some words which matter more in its neighborhood (ie same sentence)

One-headed :- only 1 set of matrices

multi-headed (8 pairs of W^Q, W^K, W^V)

same steps but with (W_0^Q, W_0^K, W_0^V) to (W_7^Q, W_7^K, W_7^V) = 8 (zis)

$\therefore$ for X we get $(Z_0, Z_1, Z_2 \cdots Z_7)$

concat $(Z_0, Z_1 \cdots Z_7) \times W_0 = Z$

weight matrix = the dim is same as Z for one head (using W)

positional Embedding

we pass all words at once, how to maintain time/position

input je seri would o/p

embedings + positional encoding

positional encoding: indicates position as well as distance b/w words

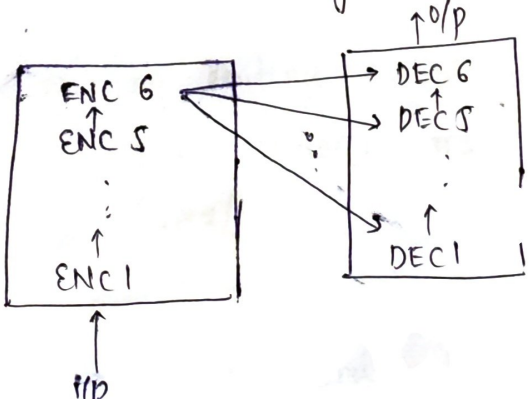
* pos vectors are static ie P_1, P_2, P_3 are precalculated

st. $P_1 > P_2 > P_3$ position

$(P_1 - P_2) < (P_1 - P_3)$ distance

* original research paper

(Attention is all you need)

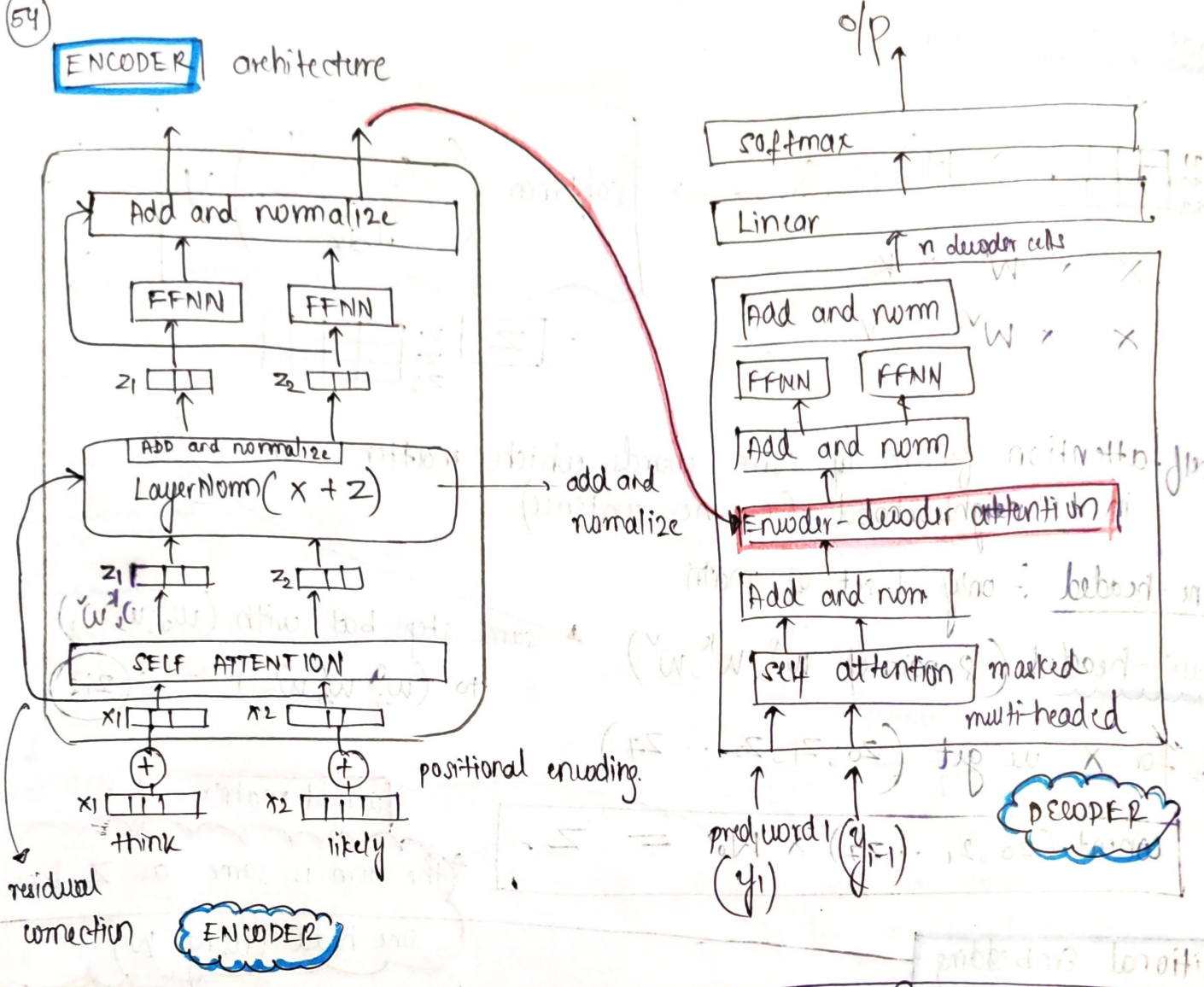


learnable matrices

① W_Q^{1-8} ② W_K^{1-8} ③ W_V^{1-8}

④ W

ENCODER architecture



Train phase

① pass whole sentence to encoders, you get a output

② pass it to decoder and predict first word

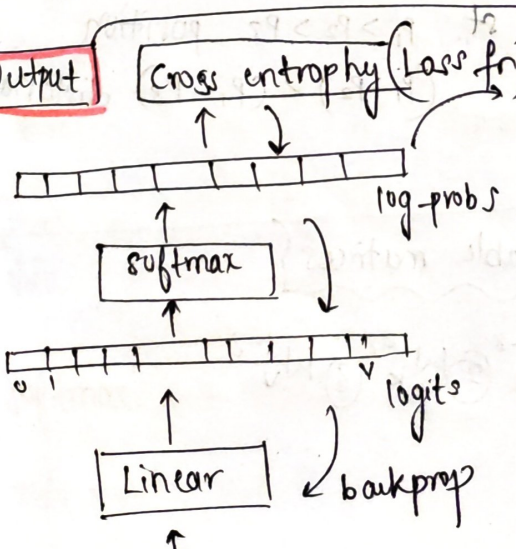
encoder → pass once
decoder → time based

second word :- don't touch encoder

→ pass first word to encoder → o/p second word

third word :- pass 1st and 2nd o/p word ⟹ third o/p word

Output



size - vocab-size

output word = vocab [argmax (op)]

Advantages of Transformers

* Faster than RNN models as all data is ingested once
* state-of-the-art (2018)
* Inspired from CNN (self-attention / neighborhood ≈ convolutions in CNN)

BERT

Bidirectional encoder representation from transformer

sentence 2 vector

* BERT only has Encoder block called Transformer block.

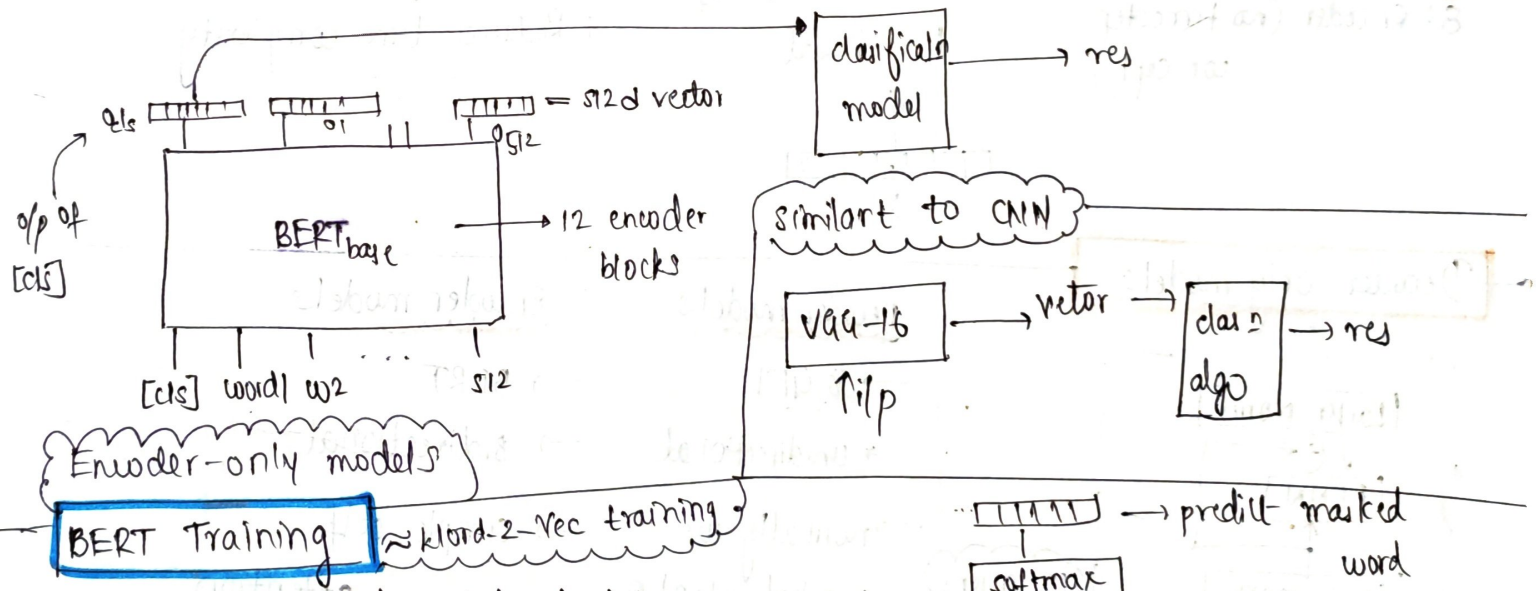
→ most useful as **Transfer Learning**

Base — FFN (768 units) + 12 attention heads

Large — FFN (1024 units) + 16 attention heads

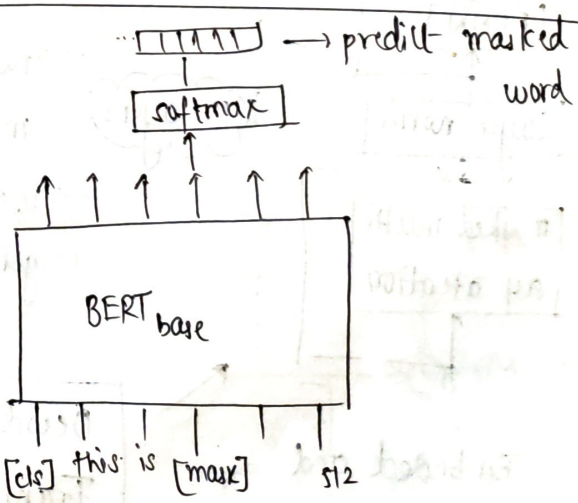
Transfer learning (spam or not)

Base Bert :- can take upto 512 worded sentency and produces 512 o/p each of dimension (768)



Encoder-only models

BERT Training ≈ Word-2-Vec training

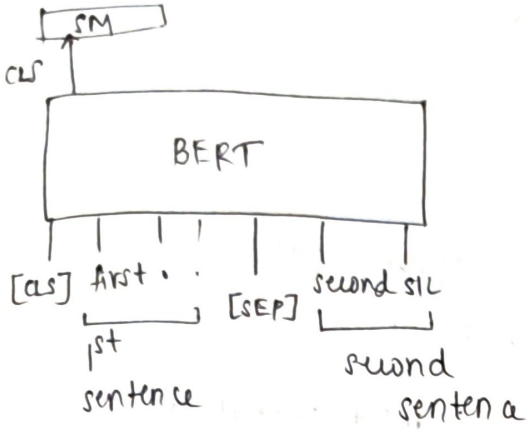


* Bidirectional models, while training look @ words before and after.

steps

* provide any sentence as i/p and while doing so randomly mask 15% of words/token
* try to predict masked tokens given other words and optimize

BERT with 2 sentences

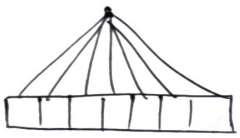


BERT training

NWP = next word prediction

Attention types

① Self attention

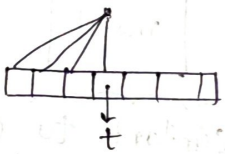


* depends on all words

Ex:- Encoder (no timestep concept)

② Masked attention

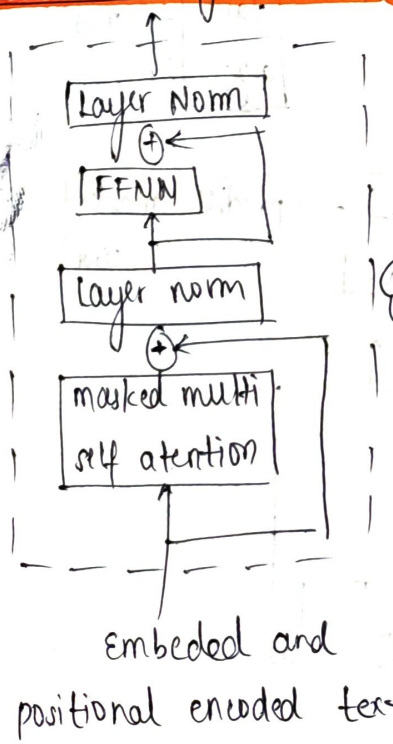
* at timestep (ti), self attention calculated on $t_0 \cdots t_{i-1}$
* used in decoders as time based



③ Sparse self attention

* if len(sentence) = N
  choose only $\sqrt{N}$ words for calculating self attention
* Reduces time complexity.

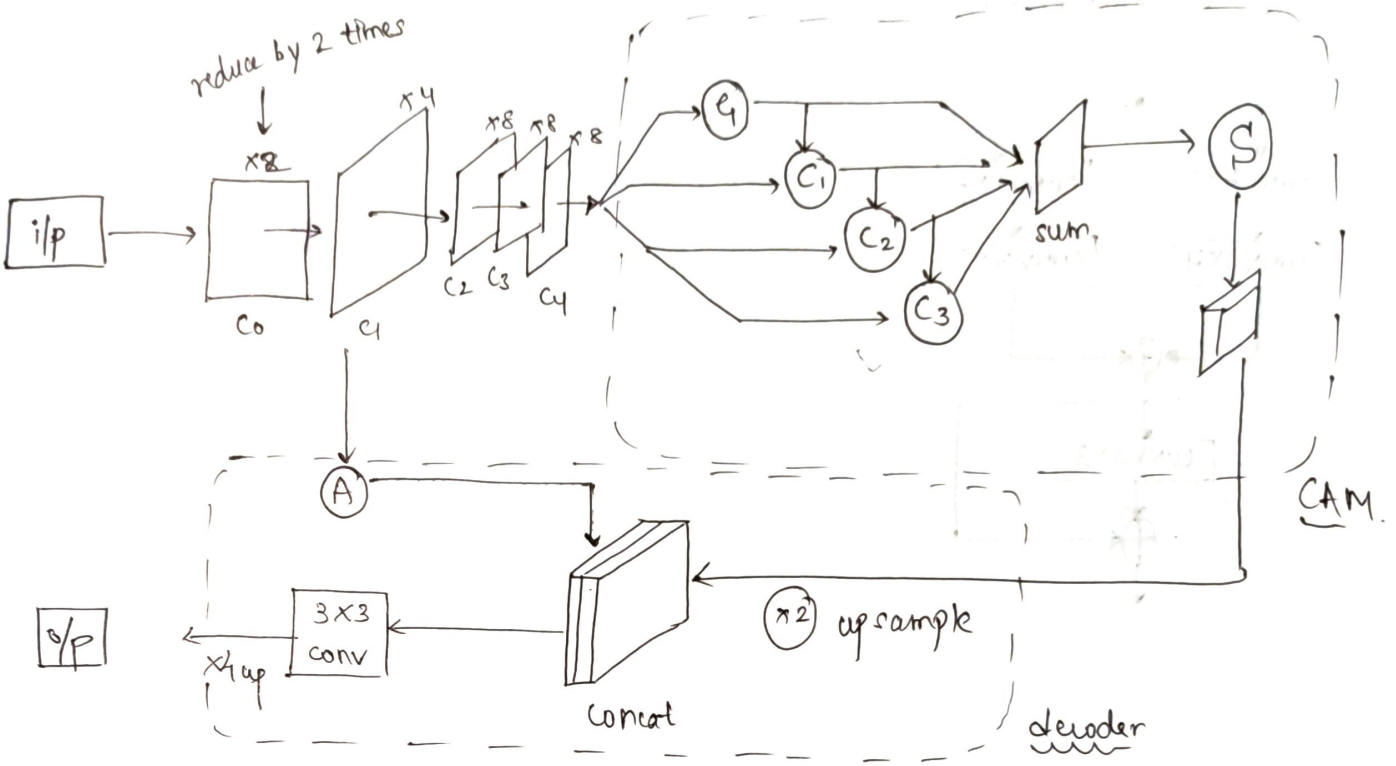
Decoder only models



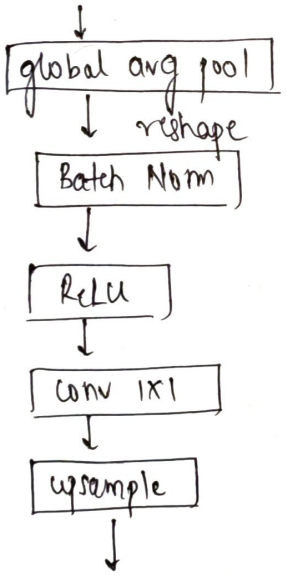
Decoder models	Encoder models
→ GPT	→ BERT
→ unidirectional	→ Bidirectional
→ normally use masked atent n	→ simple self attention
→ used more in generative tasks	→ used mostly for text representation / embedding tasks

Decoder only Transformers ≡ GPT-1

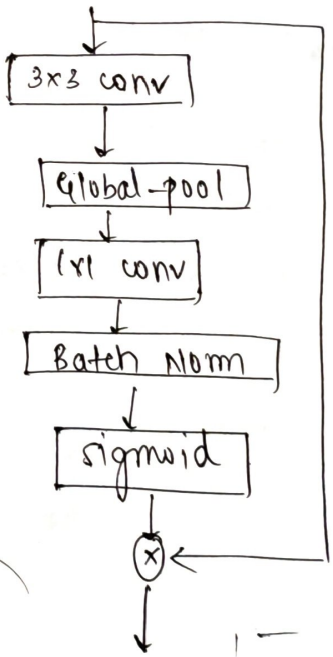
CANET — Image segmentation



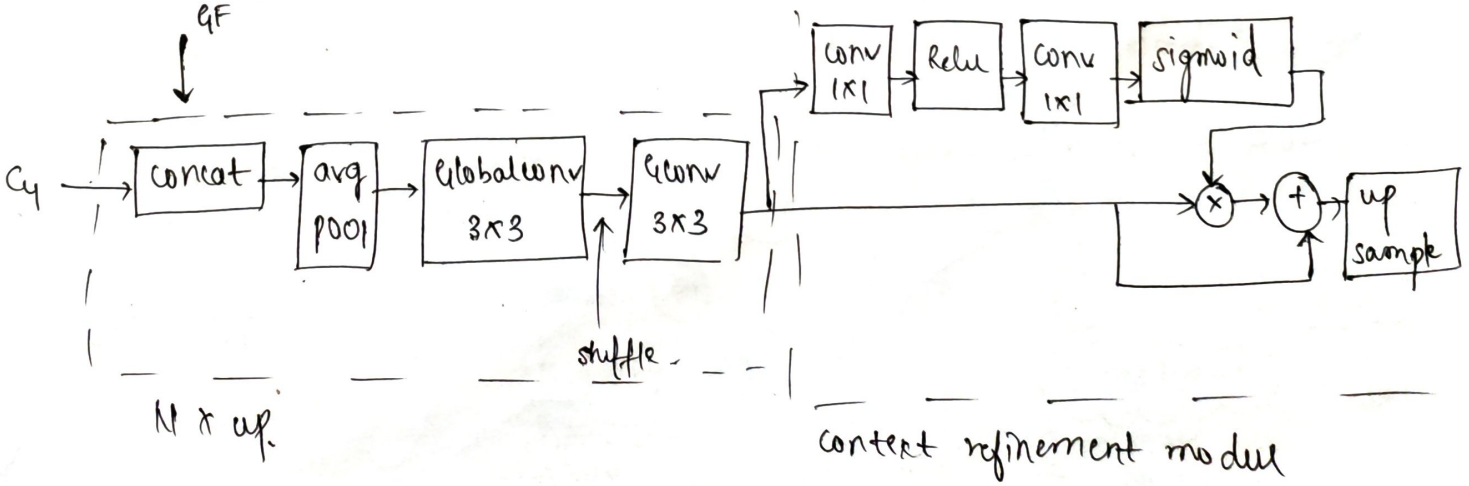
① (G) Global flow



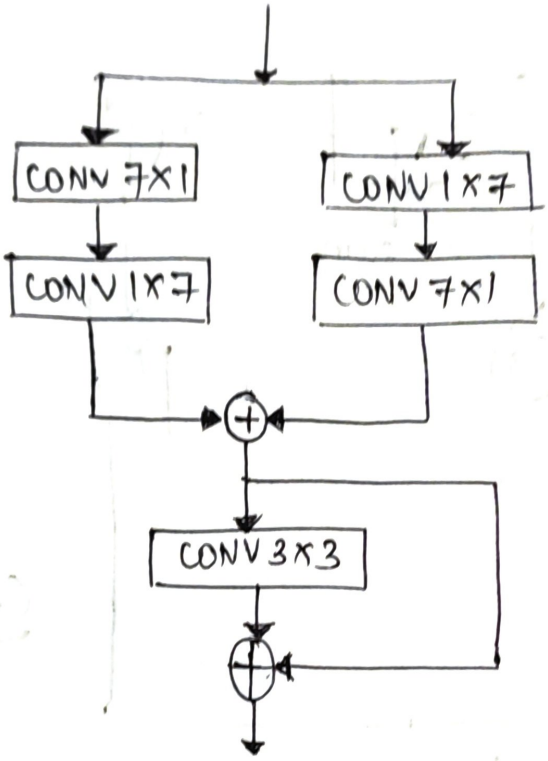
③ (S) Feature selection module



② (C) Context fusion module



AGCN Adapted global convolution n/w

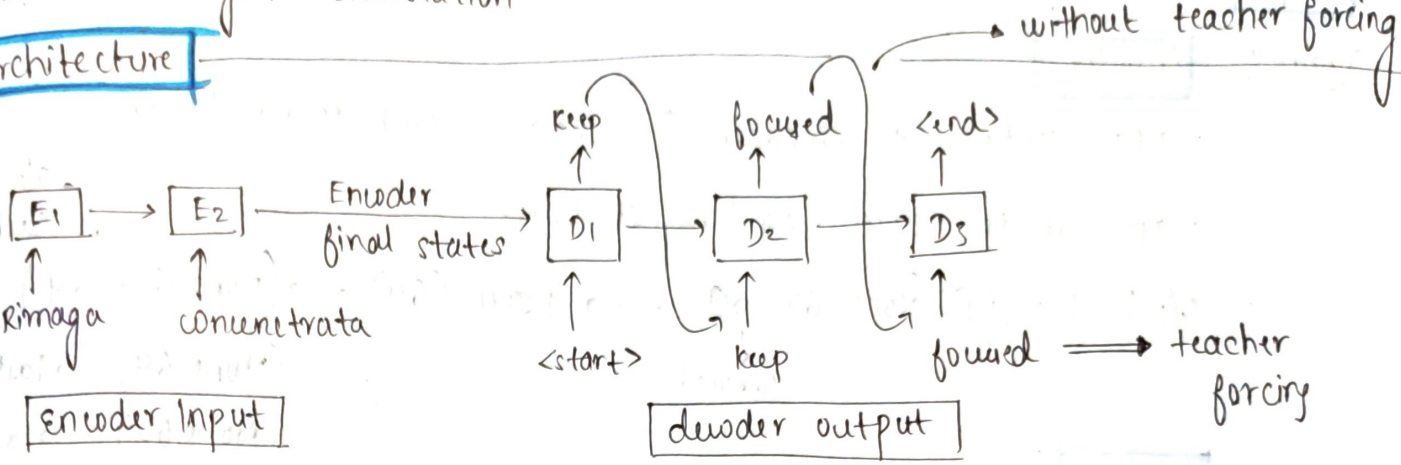


Sequence - 2 - Sequence

Use case

→ Italian to English translation

Architecture



Data

(X): rimag concentro ⟶ Encoder iput

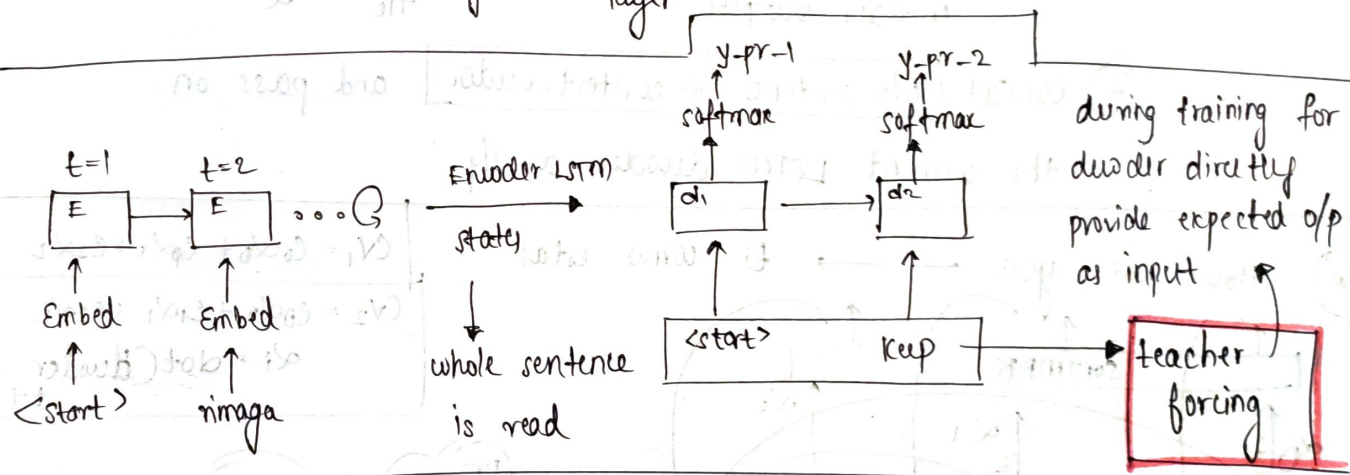
(y) keep focused ⟶ decoder i/p : <start> keep focused

decoder o/p : keep focused <end>

↳ apply tokenizer to convert text into integers.

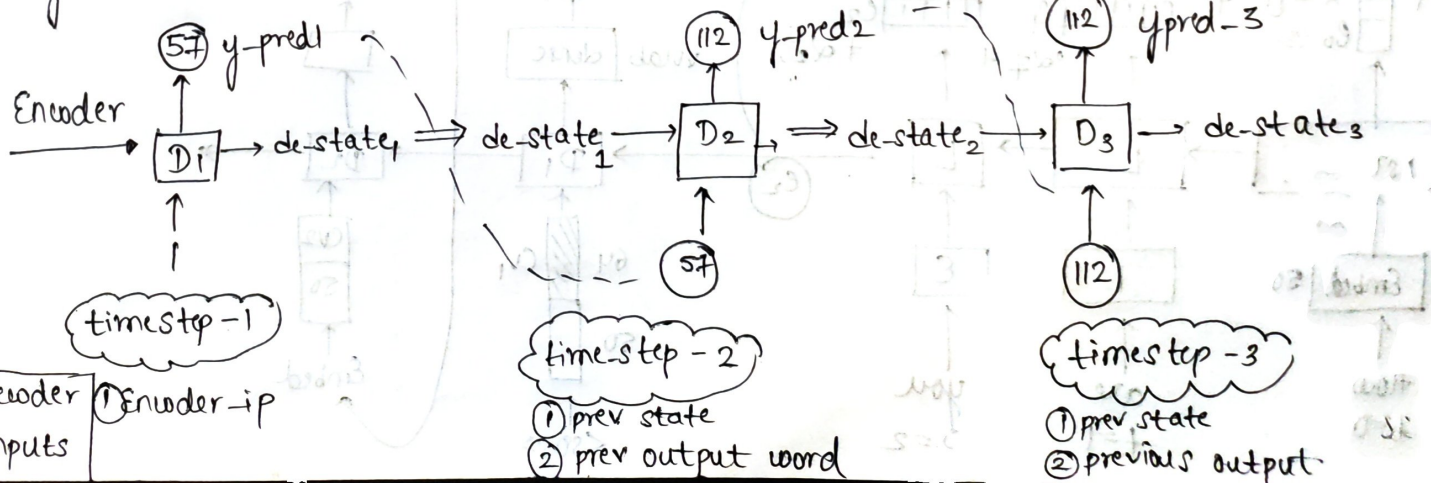
↳ (batch size, sentence_length) —Embeding layer→ (batch_size, sentence_len, output_dim)

Ex



Inference

↳ you dont have teacher forcing sentences



Seq-2-Seq Attention

Steps

Train :- **Encoder**

→ pass sentence to encoder : words → embedding layer

↳ pass it to LSTM (seq=True, st=True)

o/p: Ex (i/p) (None, 600, 69) → LSTM (64) → (None, 600, 64)

o/p of each ts

embeded

(None, 64) → last h_s

(None, 64) → last c_s

Decoder

→ pass desired o/p sentence (teacher forcing)

at ts (t)

① using h_{t-1} and (He) find context vector

Here tx = input_length (all sentence)

h_{t-1} : decoder hiden_state at prev ts

He : $(h_1, h_2 \dots h_n)$ encoder outputs

$$\begin{bmatrix} h_1 \\ h_2 \\ h_3 \end{bmatrix} \cdot \begin{bmatrix} \alpha_{t1} \\ \alpha_{t2} \\ \alpha_{t3} \end{bmatrix} = h_1\alpha_{1t} + h_2\alpha_{2t} + \dots$$

He α

② concat [o/p sentence + context_vector] and pass on the current LSTM decoder as i/p

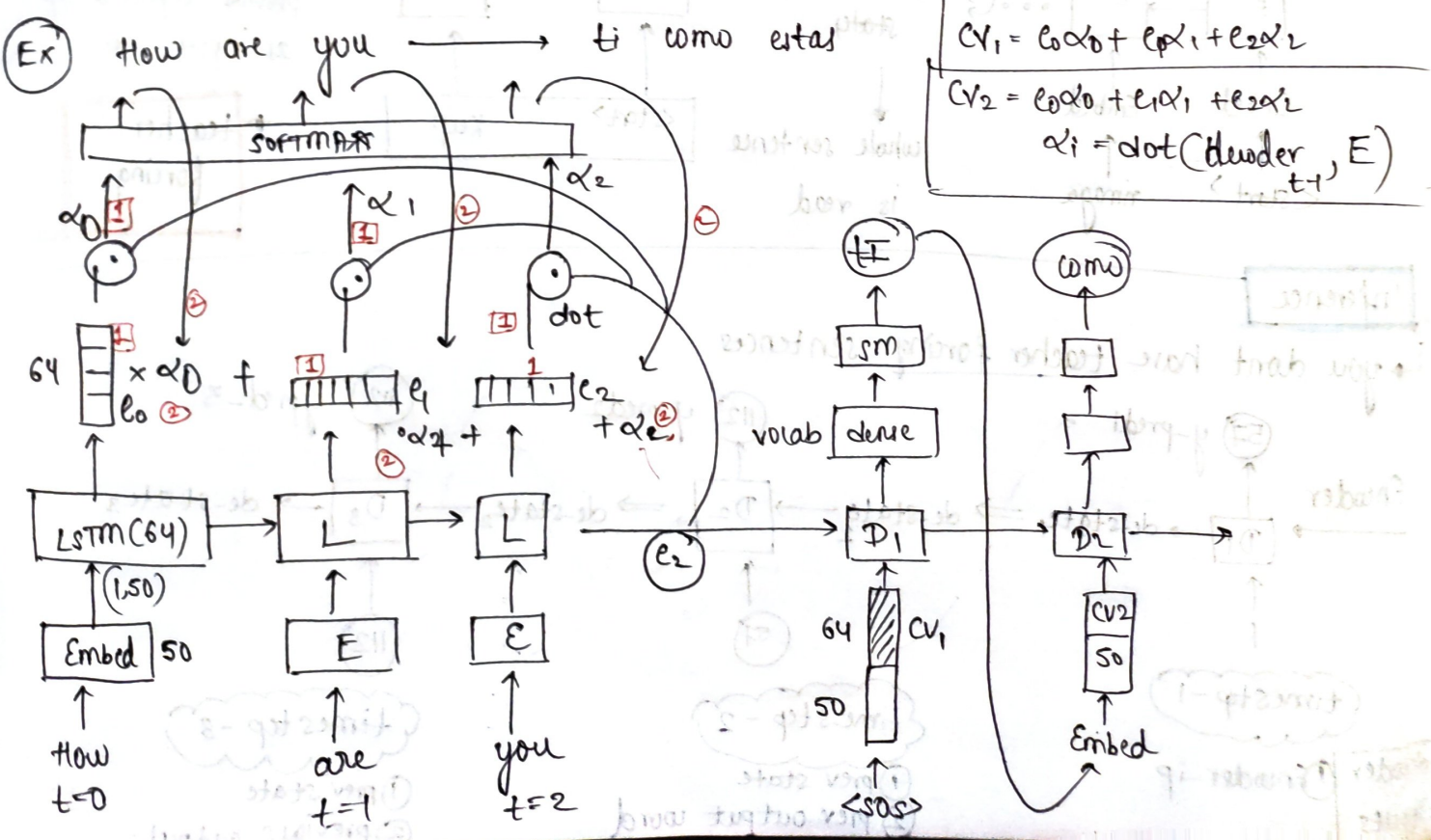
---

Ex How are you → ti como estas

$CV_1 = e_0\alpha_0 + e_1\alpha_1 + e_2\alpha_2$

$CV_2 = e_0\alpha_0 + e_1\alpha_1 + e_2\alpha_2$

$\alpha_i = dot(decoder_{t-1}, E)$



How to find α_{ij}s

Encoder

i/p → (None, 600, 50) → (None, 600, 64)

(600, 64) → all hidden states → He
(64, 1) → last h-s
(64, 1) → last c-s

decoder

LSTM = 64

at time = 1

① o/p from prev decoder step = $(h_{t-1})_d$ (64, 1) → what if decoder LSTM (128)?

Now for first we last h-s of encoder

He (h_{t-1}) = (600, 64) · (64, 1)
= (600, 1)

∴ you get 600 (α) = $\alpha_0 - \alpha_{600}$

→ pass it to softmax so that $\sum \alpha_i = 1$

* use a matrix W of shape (enc_units × decoder_units)

He (W) · h_{t-1}
= (600, 64)(64, 128)(128, 1)
= (600, 1)

→ learned by backprop

overal

inp → encoder → (calculate α_{ij}s) → decoder → output

attention weight of each word

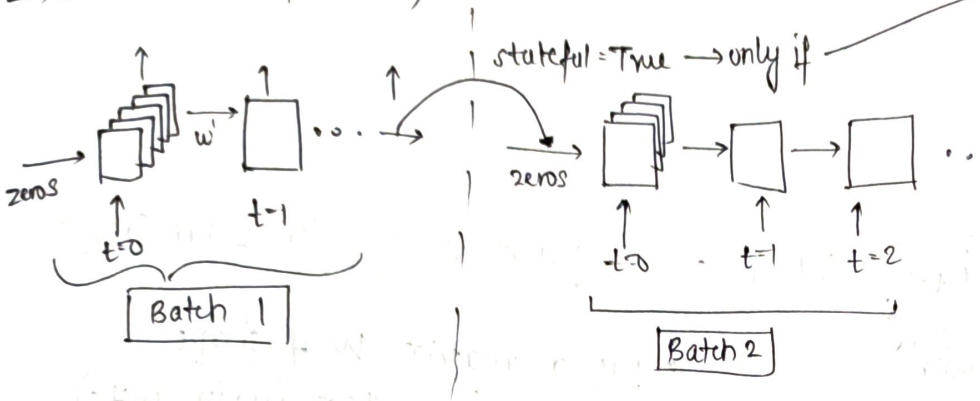
char-RNN concepts

Stateful LSTM → used when batches are sequential

row-wise or continuity

Batches must be sequential

→ LSTM(5, stateful=True)



0 1 2 3 4	5 6 7 8
9,10,11,12,13	14,15,16,17
.	.
.	.
Batch 1	Batch 2

Here stateful can be used

* while training batch 1, initialy weights are zeros and are gradually updated They are discarded at last step
* when batch 2 is trained again initial weights are zeros
  - ↳ Instead we can use the weights which are obtained from last unit of batch 1 ← stateful

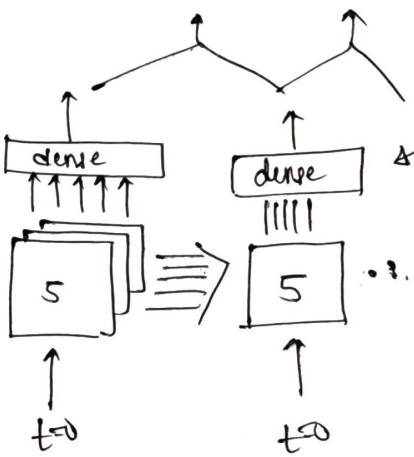
imp

use if dataset is proper, we can learn longer RNN sequences

Ex: given ex dataset
we would learn sentences/sequences of len=4 (0-4, 5-8)
→ (*) with stateful we can learn longer ie (0,8) (9,17)

TimeDistributed Layer → apply a dense layer on top of output of each LSTM timestep

* LSTM(5, ret_sequence = True)



Code → TimeDistributed(Dense(vocab-size))

Ex: LSTM(64, ret_seq = True)

(Batch, 18) → (batch, time_steps, 64)

(Batch, 18) —LSTM→ (bat, ts, 64) —TimeDist(Dense(16))→ (batch, ts, 16)

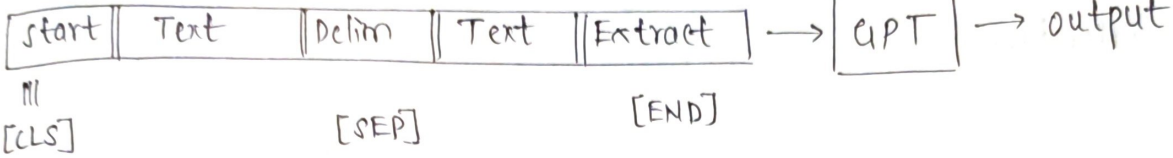
Generative Pre Training

GPT - 1

Architecture : ~~tro~~ Decoder only transfomer
↳ 12 decoder calls (pg 56)

Training : Next word prediction
→ give word (w_i) predict (w_{i+1})

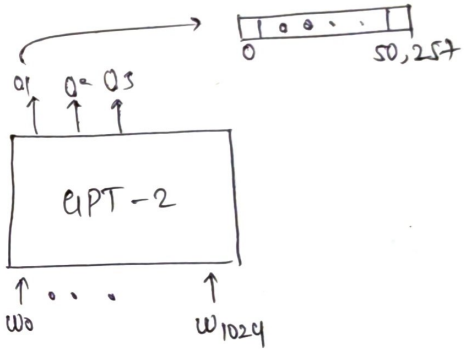
Tokens



GPT-2

Improvements on GPT-1

* max input length = 1024 (GPT1 - 512)
* vocab size = 50,257 (GPT1 - 40K)
* Layer Norm is used @ input of each sub block
* larger batch size : 512 (GPT1 - 64)
* token embeding size = $d_{model} = 768$
* used 10x more data to train
  +
  Had 10x more parameters



Params	layers	d_{model}	
117M	12	768	→ GPT2 small
345M	24	1024	
762M	36	1280	
1.542B	48	1600	→ GPT2 large

* Zero-shot learning
  ① Pretrain modul (NWP)
  ② Fine tune model by giving your dataset
  ③ make predictions

  NO fine tune (Pretrain and directly predict)

→ few-shot learning
① → ② → ③

disadvantages

performs poorly on rare or specialized content

GPT-3

→ 100x more params (175B)

→ trained on

[300B text tokens + common crawl data (2016–2019)]

→ uses sparse attention

disadvantages

→ Cost and compute power

→ Interpretability

→ Biases in predictions

LIME

Local Interpretable model Agnostic Explainations

Intuition

* Data = {x, y}
* classifier (model) = f(x)

∴ x → f(x) → y

↓ may not be interpretable (BERT 512)

local interpretable

→ considers only a local region to give interpretability
→ not global (only focus on locality)

Algorithm

Step 1:- given x, calculate x'

$x \in R^d \rightarrow f(x) \rightarrow y$

↓

$x' \in \{0,1\}^d$

* x' is interpretable
* x' is a binary vetor (each ele is 0/1 indicating presence or absence).
* dimensions of x and x' may vary

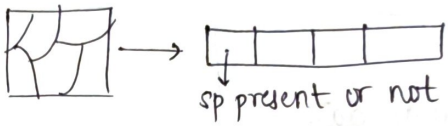
$x \rightarrow x'$

Text :- use BOW

sentence → BERT → x (512 dim)

→ BOW → x'

Images :- divide image into super pixels



Tabular data :
→ ① Categories ← OHE
② continous → binning values.

Step 2:- Surrogate model (g)

g ∈ G (models which are easily interpretable Ex:- LR, DT)

→ Ω(g) = complexity of g (depth, # non-zero weights)

(g) is trained on (x') and not x

g(x') not g(x)

Proximity

$\pi_x(z)$ → proximity b/w (x) and (z)

π_x → locality of x

local fidelity

$L(f, g, \pi_x)$ → how best g(x') approximates f(x) in locality given by π_x

↓ better, f and g are similar
↑ bad

optimization f:

$$\xi(x) = \min_{g \in G} L(f, g, \pi_x) + \Omega(g)$$

G: Linear models / DT

L: squared Loss

$$\pi_x = \exp\left(\frac{-D(x,z)^2}{\sigma^2}\right)$$ ← Exponential kernel

z | $L(f, g, \pi_x) = \sum_{z,z'} \pi_x(z)\,(f(z) - g(z'))^2$ | $z, z' \in Z$

* weighted according to proximity

1 → ∀ each p^1, z find z'

↓

find locality of x_q → (π_x)

optimisation :- $\xi(x) = \min \{ L(f, g, \pi_x) + \Omega(g) \}$ → K-Lasso

K-lasso :- L1 regularized linear regression with only top-K features

Ex: S-lasso :- L1 regularisation keeps only (3) features and makes others 0.
thus we get only 3 features used for interpretability.

Advantages

* works on image, text, tabular data
* x may not be same as x'

Drawbacks

* deciding neighborhood $-\pi_x(z)$
  Hyper param = σ
  $D(x,z)$ may be issue with high-dim data
* finding (x') from (x) may not be straight forward.
* unstable
  Similar/closer points may give different interpretability
* Lack of robustness

Research paper algo

Algo: Sparse linear explanations using LIME
Ip : $f(x)$, N, $x \rightarrow x'$, π_x (similarity kernel)
K (length of explanations)

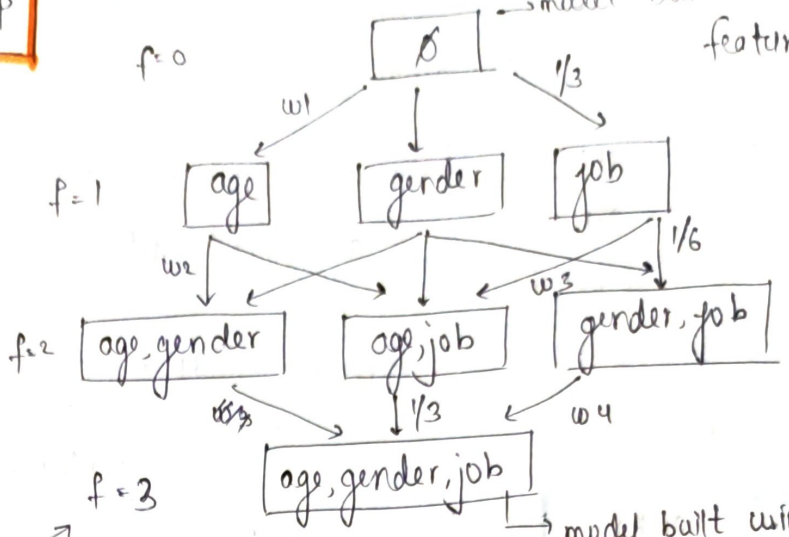
algo :- $Z \leftarrow \{\}$
for $i \in \{1, 2 \ldots N\}$ do
$z_i' \leftarrow$ sample-around (x')
$Z \leftarrow Z \cup \langle z_i', f(z_i), \pi_x(z_i) \rangle$
end for
$w \leftarrow$ K-lasso (Z, K) with z' features
$f(z)$ as target.
return w

SHAP

Shapely Additive explanations

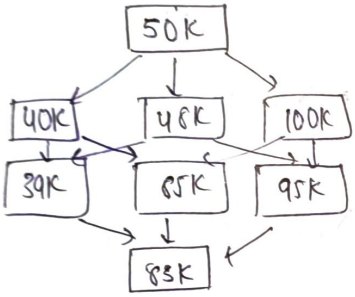
* Model : Predict salary
features : age, gender, job
output : y_i

x_0 : query point, $\bar{y} = \Sigma y_i$
$\hat{y}_0$ pred value



① for (d) feature, train 2^d models

② pass (x_0) and find predictions for each model



$\hat{y}_0 = 83K$, $\bar{y} = 50K$

Marginal Contribution

$MC_{Age\{Age\}}(x_0) = -10k$ → contribution of age when we have only age feature compared to model with {age, gender} feature

$MC_{Age\{Age,gender\}}(x_0) = -9k$ → output(age, gender) − output(age)

39 − 48 = −9K

③ Shapely values of each feature

$$SHAP(age)_{(x_0)} = w_1 \cdot MC_{age,\{age\}} + w_2 \cdot MC_{age,\{age,gender\}} + w_3 \cdot MC_{"\{age,job\}} + w_4 \cdot MC_{\{age,gender,job\}}$$

→ No nodes at level = FC_f [$F = \{f_1 \cdots f_n\}$]
No of edges = $f : FC_f$
↳ no of features selected

$$SHAP(feature)_{x_0} = \sum_{set | feature \in set} [edge\text{-}weight(pred(x)_{set} - pred(x)_{set/feat})]$$

$$edge\text{-}wt = \left(|set| \; FC_{|set|}\right)^{-1}$$

$pred(x)_{set/feature}$ ⟹ model trained using features = |set| − feature (f_i)

property

$w_1 = w_2 + w_3 = w_4$

① at a level all (w_is) are same

② all weights at level are same

→ $SHAP(age)[x_0] = -11.33K\$$

∴ In finding $x_0 \rightarrow y_0$, contribution of age is −11.33K.

Understanding

$x_0 \longrightarrow \hat{y}_0$

ϕ = 50K$

$[age, gender, job] = 83K$

SHAP(age) = S_1 = -11.33K

job = S_2 = -2.33K

gender = S_3 = 46.60K

↳ our model predicted $\hat{y}_0$ which was 33K away/different from $\phi / \bar{y}$

⇓

difference = 33K = (-11.33K) + (-2.33K) + (46.60K)

↓

contrib of age

Paper — actual SHAP

* convert x to interpretable repr

$x \longrightarrow x' \in \{0,1\}^M$ (BoW)

* train surrogate model

$g(x') \approx f(hm(x))$

① sum of shapely values

$= \hat{y}_F - \hat{y}_\phi$

$\hat{y}_F$ ↓ all feature; $\hat{y}_\phi$ ↘ no features

Additive feature attribution

$$g(z') = \phi_0 + \sum_{i=1}^{M} \phi_i z_i'$$

M = # features

$g(z)$ = surrogate fn

ϕ_i = shapely value for feature i

$z_i' \rightarrow$ feature ① is present or not

Expectations or average value of RV

$$E(X) = \sum_{x \in X} x P(X=x) \quad \text{(PMF)} \qquad \text{or} \qquad \int_x x P(x)\,dx \quad \text{(PDF)}$$

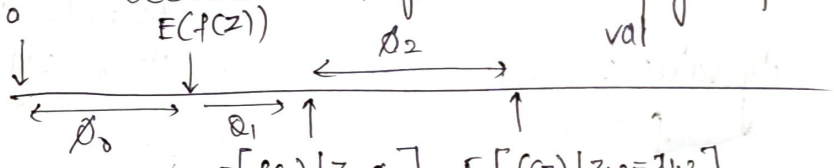
$$E(f(x)) = \sum_x f(x) \cdot P(X=x)$$

$$E(x \mid y=y_i) = \sum_x x P(x \mid y=y_i)$$

$$= \sum_{x \in X} x \cdot P(X=x \mid y=y_i)$$

rel^n with shapely values

shapely ≡ expectation val



↳ average/expectation given feature 1 is fixed

KERNEL SHAP

Kernel shap = LIME + shapely val + Shapely Kernel → and use FI

(In LIME we fit interpretable model at last, here instead we find shapely values)

$$\pi_x(z') = \frac{M-1}{{}^{M}C_{|z'|} \, |z'| \, (M - |z'|)}$$

SHAPELY KERNEL

M = # dim in x

$|z'|$ = len (z_0)

problems

computationally NP-hard

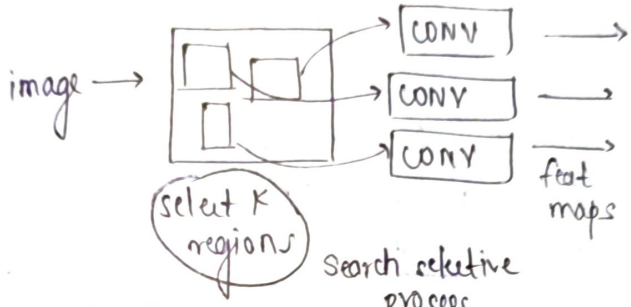
∴ use approximations

OBJECT DETECTIONS

Rigional CNN → detect regions in Imag

R-CNN

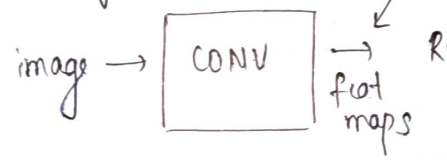
↳ slower and low FPS → CONV layer for each region



RCNN
Search selective regions → CONV on each

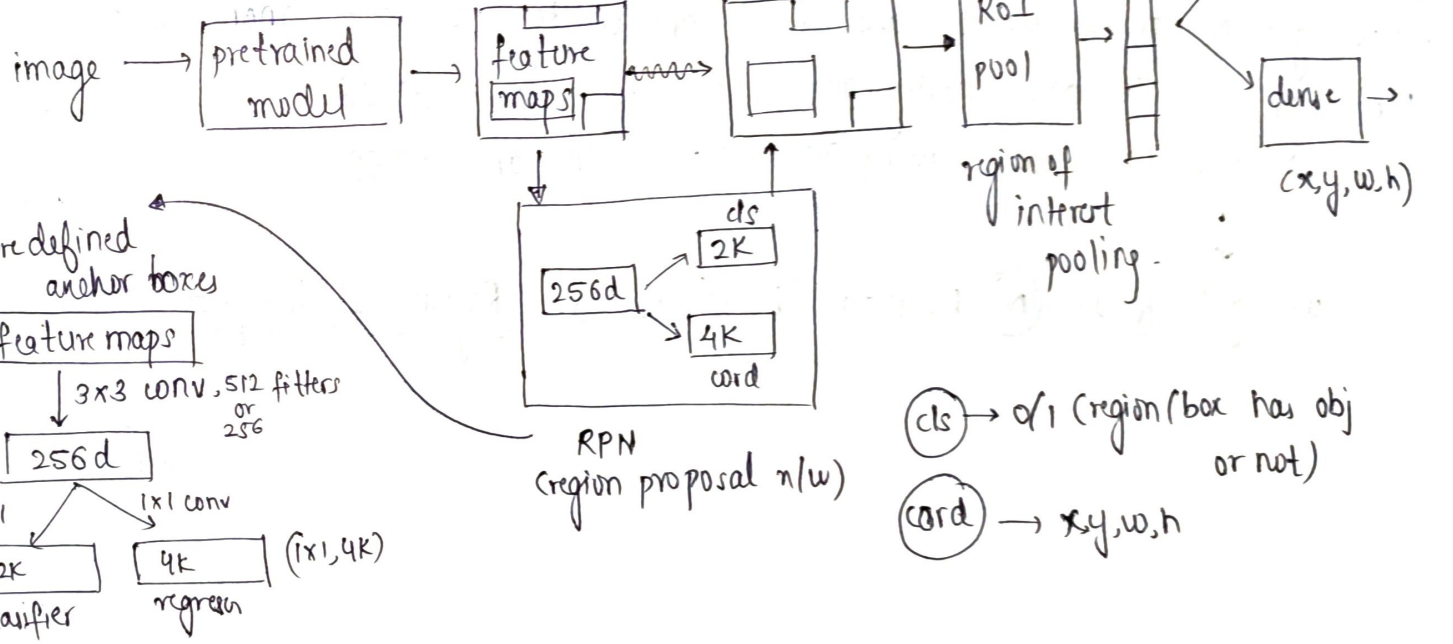
Fast-RCNN

↳ apply CONV once and then choose feature maps



Fast-RCNN
conv once → search selective regions
(returns multiple RoI's)
use maxpool to give us fixed sized regions (7×7 paper)

Faster RCNN



cls → 0/1 (region/box has obj or not)

cord → x,y,w,h

workflow

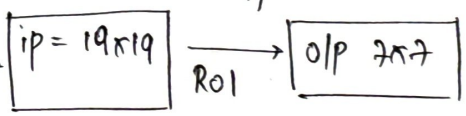
Read img + boxes → get feature maps from a CNN → RPN → ∀ each RoI do RoI pool → train for classifier / regressor models

RoI pool vs RoI algin → can deal with fractional stride by breaking each pixel into further subpixels

RoI = maxpool

↳ causes stride to be quantized

say RoIPool (7×7)



stride = $\frac{19}{7}$ = 2 ... → stride = 2

we are ignoring decimal and hence some part of image

RPN training

→ if feature map size is M×N (K: no of anchor boxes)

then clasifier wghts = M×N×(K*2) ⟶ P(forground), P(background) (object)

regresor weights = M×N×(K*4) ⟶ $t_i = \langle t_x, t_y, t_w, t_h \rangle$

RPN Loss = log loss on clasifier + distance loss fr regresor (dist b/w true and pred t_i ground t_i given by ground truth)

$$L(\{p_i\}, \{t_i\}) = \frac{1}{N_{cls}} \sum_i L_{CLS}(p_i, p_i^*) + \lambda \frac{1}{N_{reg}} p_i^* (L_{reg}(t_i, t_i^*)$$

N_{cls} = no of anchors

N_{reg} = no of anchor locations

p_i^* – actual object present/not

t_i^* – actual t_i of ground truth boxes

L_{cls} – log loss

Non-max supresion

→ we get N anchor boxes and asign probability to each anchor box

We asign +ve to areas having IOU > 0.7 with any GTBB

-ve to areas having IOU < 0.3 with any GTBB

↓

we get final (N) bounding boxes called Regions of Interest

OLS for Linear Regression

$\hat{y}_i = \beta_0 + \beta_1 x_i$

Loss function $= \frac{1}{N}\sum (y_i - \hat{y}_i)^2 = \sum (y_i - (\beta_0 + \beta_1 x_i))^2$

$\beta_0 = \bar{y} - \beta_1 \bar{x}$

$\beta_1 = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$

$\beta_0 = c$

$\beta_1 = m$

diff wrt β_0

$\frac{\partial L}{\partial \beta_0} = 2\sum (y_i - (\beta_0 + \beta_1 x_i))^{-1} = -2\sum (y_i - \hat{y}) = 0$

$\sum_{i=1}^{n} (y_i - \beta_0 - \beta_1 x_i) = 0$

$\sum y_i - \sum \beta_0 - \sum \beta_1 x_i = n\bar{y} - n\beta_0 - \beta_1 \sum x_i$

$\rightarrow n\bar{y} - n\beta_0 - \beta_1 n\bar{x} = 0$

$n\beta_0 = n\bar{y} - \beta_1 n\bar{x}$ (divide by n)

$\beta_0 = \bar{Y} - \beta_1 \bar{x}$

$\frac{\sum y_i}{n} = \bar{y}$ $\quad \frac{\sum x_i}{n} = \bar{x}$

$\sum y_i = n\bar{y}$ $\quad \sum x_i = n\bar{x}$

diff wrt β_1

$\frac{\partial L}{\partial \beta_1} = -2\sum (y_i - \hat{y}_i) x_i = 0$

$\sum (y_i - \beta_0 - \beta_1 x_i) x_i = 0$

$\sum (y_i - \bar{y} - \beta_1 \bar{x} - \beta_1 x_i) x_i = 0$

$\sum (y_i - \bar{y} - \beta_1 (x_i - \bar{x})) x_i = 0$

$\sum x_i (y_i - \bar{y}) - \beta_1 \sum x_i (x_i - \bar{x}_i)$

$\sum x_i (y_i - \bar{y}) = \beta_1 \sum x_i (x_i - \bar{x})$

$\beta_1 = \frac{\sum (y_i - \bar{y})}{\sum (x_i - \bar{x})}$

multiply and divide by $(x_i - \bar{x})$ Nr and Dr

$\beta_1 = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$

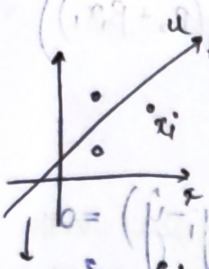
grad descent

$\frac{\partial L}{\partial \beta_0} = -\frac{2}{N}\sum (y_i - \hat{y})$

$\frac{\partial L}{\partial \beta_1} = -\frac{2}{N}\sum x_i (y_i - \hat{y})$

PCA

mathematical way



it can be proved that

$\max(x_i u^T) \equiv$ largest eigen vector

minimize fit and maximize variance

$\Rightarrow$ **steps**

↳ standardize data → covariance mat → find eigen values $\lambda_1, \lambda_2 \dots \lambda_n$ & eigen vectors $v_1, v_2 \dots v_n$

$$X_{std} = \frac{X^T X}{n-1} = S$$

$$\text{var}(x_i) = \frac{1}{n-1} \sum (x_i \cdot u^T - u^T \bar{x}_i)^2$$

$x_i \cdot u^T$ → **projection**

$u^T \bar{x}_i$ → 0 (if std)

also,

$$v_1 \perp v_2 \perp v_3$$
$$v_1 \cdot v_2 = 0$$
$$v_2 \cdot v_3 = 0$$

↳

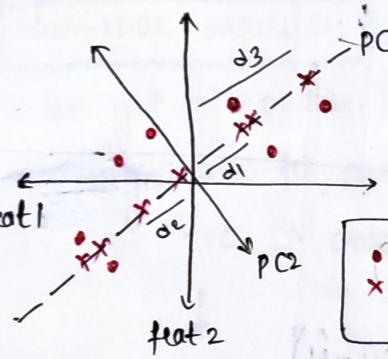
$$S v_1 = \lambda_1 v_1$$
$$S v_2 = \lambda_2 v_2$$

Loading score

- % variance explained by eigen vector v_i

$$\%\text{var} = \frac{\lambda_i}{\sum \lambda_i}$$

Graphically



standardize data ($\mu = 0$, centered at (0,0))

PC1 → **aim** minimize fit residuals ← similar to L or R

→ maximize variance of projected points

↳ in this case line and (u) on origin

∴ calculate distance of each projected point from mean ≡ origin

↳ $d_1^2 + d_2^2 \dots d_n^2 = SS(\text{distance})$ ≡ Eigen value for PC1

$\sqrt{\text{Eigval}} = \text{singular val}$

→ unit vector along PC1 = eigen vector for PC1

∴ **PC1 is a linear combination of f1 and f2**

once PC1 is set,

fit another line $\perp^r$ to PC1 $\Rightarrow$ PC2

NOW we can't fit another line $\perp^r$ to PC1, PC2 ← you can pick one line along z axis

so for 2d we have **2 PC**

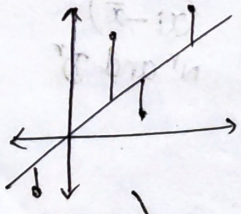
→ but if you project 2d points on it variance = 0

we can use % var / loading score to pick best one

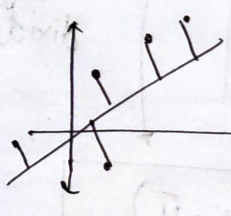
Linear reg vs PCA

Linear reg → minimize vertical dist b/w point and line

PCA → minimize orthogonal (shortest) distance

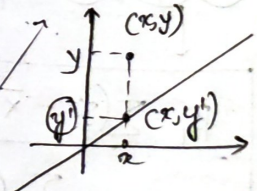


Linear reg



PCA

in LR, we have to predict y given x



∴ (y'-y) is error

XGBoost

REGRESSION

dosage	age		efectiveness	res0
5	20		13	~~0~~ 1
10	21		14	-5
12	29		12	+10
8	30		1	-8

x → y

Base model → not accurate

$\bar{y} = \frac{13+14+12+1}{4} = 20.5$ (assume)

assume $\bar{y} = 12$

$\left[\sum res_i\right]^2$ → (add)^2

Similarity score (SS) $= \frac{(\sum res_i)^2}{\#res + \lambda}$

Ig at node $= (SS_{left} + SS_{right}) - SS_{cur}$

(left, right: child nodes)

Prediction

→ you start at root until leaf node is reached

result $= \frac{(\sum res)}{\#res + \lambda}$ — No square

res_i in root node

Ex: [1, -5] is leaf → res $= \frac{-4}{2+\lambda}$

→ model 1 (BASE model)

res = [1, -5, 10, -8] SS = 10

gain $= (30+20-10) = 40$

dosage <10 / >10

you can check diff feat/value beter gain

<10: res = [1, -5] SS = 30

>10: res = [10, 8] SS = 20

gain $= 15+12-20 = 2$

d<12 / d>12

10 (SS = 15) | -8 (SS = 12)

stop = only 1 node

One model is built

prune tree using (γ) gamma

if (Ig at node) $- \gamma \geq 0$ (don't prune)

∴ if gain $- \gamma > 0$ → no prune

gain $- \gamma < 0$ → prune

gain > γ → keep

else prune

* while pruning, always start from leaf node. if you can't prune a leaf then you can't prune its parent

Ex: $\gamma = 5$

→ [10, 8] branch gets removed

d>12

model$_1$ ✓

built model 2 which fits residuals of (model$_1$)

pred res_1

$res_1 = res_1 - pred$

Regularizations

① (λ) as $\lambda\uparrow$, SS ↓

as SS ↓, gain ↓

as gain ↓, chances of pruning are here

∴ as $\lambda\uparrow$ prevents overfit

gamma (γ)

if $\gamma\uparrow$ → more branches will get pruned

as $\lambda\uparrow$ → more pruning

→ smaller output value

Classification

Base model ($p = 0.5$)

$$SS = \frac{(\sum res)^2}{\lambda + \sum (prev\_prob\,(1 - prev\_prob))}$$

probability of previous fit model (Base = 0.5)

$-\lambda$

* XGBoost has threshold for min no of leaves in tree →

$$cover = \left(\sum prev\_prob\,(1 - prev\_prob)\right)$$

if at any node if #res ≤ cover stop growth

$$cover = dr \text{ of root} - \lambda$$

min_child_split

∴ at a node, if $cover_{node} >$ min_cover

→ you can use (node) as leaf

if $cover_{node} \leq$ min_cover

→ you can't use as leaf

Ex: min_cover = 1

∀ all leaf nodes, cover (node) > 1

∴ build tree_model ① → leaf node must ② > min_cover → prune if gain < γ ③

Output

$$res(node) = \frac{\sum res}{\left(\sum pp(1-pp)\right) + \lambda}$$

→ we need probabilities ⟹ $\log\left(\frac{p}{1-p}\right)$ log (odds)

p = res

Overal

$\lambda > 0$, reduces sensitivity of tree to (outliers)

↓

prevent overfit

Pick random subset of data to (HIMT) train models

→ just like bagging xgboost also uses random rows of data

↳ increases speed & faster on large datasets

$-0.5, 0.5, 0.5, -0.5$ SS = 0

dosage > 10

-0.5 | $0.5, 0.5, -0.5$

$SS = \frac{(-0.5)^2}{0.5(1-0.5) + \lambda}$

XGBoost optimizations

Loss function

λO_{val}^2 → regularization term prevent O_{val} becoming too large

model-1

$$L = \left[\sum_{i=1}^{n} L(y_i, \hat{y}_i)\right] + \gamma T + \frac{1}{2}\lambda O_{val}^2$$

$\hat{y}_i$ → current out-put

$$= \text{Base model score} + \sum \text{residuals up to } n-1 + O_{val}$$

O_{val} = output from current model/tree for point y_i

T - no of terminal nodes (used for post pruning)

$$L = \sum_{i=1}^{n} L(y_i, (\hat{y}_i)_0 + O_{val}) + \gamma T + \frac{1}{2}\lambda O_{val}^2$$

Approximate greedy

→ we decide node split based on gain and then just pick one with best gain and split. once split we dont revisit node again which saves time.

Parallel + weighted quantile sketch

→ if feature is continous, calculating all thresholds and checking is slow

→ Instead, we pick quantiles among data and then we these quantiles

Generally, XGBoost uses around 33 Quantile (test spit 33 times)

→ **sketch algos** → they split data to various pcs and later combine to find approximate quantiles (histograms)

+ weighting (use cover and prob) ⟹ weighted Quantile sketches

└→ in this each histogram region of quantile will have same no of observations

Cache-aware access

→ try to store gradients and deri in cache as they are frequently accessed

XGBoost pros

- Improved Grad Boost
- Regularization
- aprox greedy algo
- parallel learing
- weighted quantile sketch
- *sparsity aware split find
- * Cache awareness
- * pick random rows like bagging.
- *Block out-of-core computation

→ if data is too large and cant fit in RAM compress it into chunks and save in HDD

→ when needed CPU reads this chunks parallely → uncompress and use (although zip/unzip takes time but better than slow disk read)

Sparsity aware split

assume missing features
↳ initial residue can be found (y_i - average(vals))

dosage	effe	resi
10	9	3
21	2	4
19	7	-2
?	1	-6
?	8	-1

split (?) in new table

?	1	-6
?	8	-1

10	9	3
21	2	4
19	7	-2

as data is small we use avg of 2 each non-? rows
else for large dataset, we use quantiles

initial node with non-missing residues + missing residuals

step 1 → 3, 4, -2, -6, -1

dos > 15

3 | 4, -2

mean of 2 each non-?

(don't include residuals of ? in leaves)

step 2

now add residues of (??) rows to left leaf and then right leaf and calculate gains

g_{left} = dos > 15 → 3, -6, -1 | 4, -2

g_{right} = dos > 15 → 3 | 4, -2, -1

→ pick best gain and add those leafs

step 3 pick average of next 2 non-? closes and check again (21, 19)

TSNE

t-distributed stochastic neighborhood embedding

Core idea Instead of focusing to preserve distances, focus on preserving neighbors.

① Stochastic nbrhood embedding

$$L = \sum_{ij} P_{ij} \log \frac{P_{ij}}{q_{ij}}$$ KL divergence blw similarities

P_{ij} := pairwise affinity b/w p_i and p_j in high-dim space

q_{ij} := pairwise affinities in low-dim space

* affinities tends → 1 ; if points are closer
  → 0 ; if far away
* sum of all similarities / affinities = 1
* if 2 points close in high-d are projected far away in low-dim, loss is greater

High-dim similarities =

$$p_{j|i} = \frac{\exp(-\|x_i - x_j\|^2 / 2\sigma_i^2)}{\sum_{k \neq i} \exp(-\|x_i - x_j\|^2 / 2\sigma_i^2)}$$ → used such that $\sum p_{ij} = 1$

Perplexity — how many neighbors to preserve (around 30)

$P = 2^H$; $H = -\sum_{j \neq i} P_{j|i} \log_2 P_i$

$w_{ij} = K(\|y_i - y_j\|^2)$

$$P_{ij} = \frac{P_{i|j} + P_{j|i}}{2n}$$

$$\text{loss fn} = \sum_{ij} P_{ij} \log q_{ij} + \sum P_{ij} \log \frac{w_{ij}}{Z}$$

→ low-dim similarities

$$q_{ij} = \frac{K(\|y_i - y_j\|^2)}{Z} \quad \text{where, } K = K(d) = 1/(1+d^2)$$

[t-distributed kernel for calculating similarities]

$$Z = \sum_{k \neq l} K(\|y_k - y_l\|^2)$$

decision tree with 1 root, 2 leaf

ADABoost → KEY POINTS — ① Base learners are weak (stumps)

② Each BL is dependent on information frm prev

③ Each BL may have diff weight in final voting

Steps

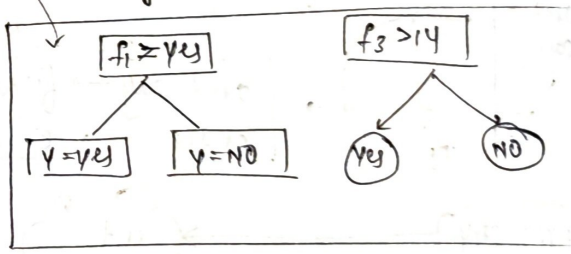
① Initially give same weight to all samples

	f_1	f_2	f_3	Y	wt
1	Yes	0		Y	1/5
2	No	1		Y	1/5
3	Yes	0		N	1/5
4	Yes	2		N	1/5
5	No	2		N	1/5

→ fit a BL (stump)

→ create stump for f_1 f_2 f_3 & check which gives more gini index

→ that stump is BL1



② update wt

→ predict (4) using BL1 — ex say (4) (5) were incorrectly ⇒ TE = $\frac{1}{8} + \frac{1}{8} = \frac{1}{4}$ classified by BL1

Total Error = ∑ weights of incorrectly classified sample

$$\text{amt\_say} = \frac{1}{2} \log\left(\frac{1 - TE}{TE}\right)$$

③ new weights (wt1)

penalize incorrect more

∀ sample,

- if sample incorrectly classified → $wt = wt \times e^{-\text{amt\_say}}$
- correctly classified → $w^t = wt \times e^{\text{amt\_say}}$

Normalize aftr calculating wt1 so that $\sum wt = 1$

Normalize entire col → $\sum x_i \rightarrow x_i = \frac{x_i}{\text{sum}(x)}$

Next BL →

→ create new dataset with same size

→ say len(dataset) = 5

* pick 5 rows from dataset randomly, such that prob of each row getting picked is proportional to wt value (proportional sampling)

* some rows may get repeated

↳ fit stumps (BL1) → TE → amt_say → wt2 → new data for BL2

majority vote

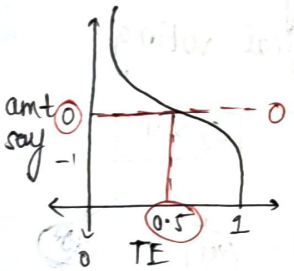
say 3 BL → yes, 3 B → No → find Σamt_say(BL1), Σamt_say(BL2) → which gives more → pick that result

amt = 3·2, 4·2 → NO ✓

Observations

$AmTE = \frac{1}{2}\log\left(\frac{1-x}{x}\right)$

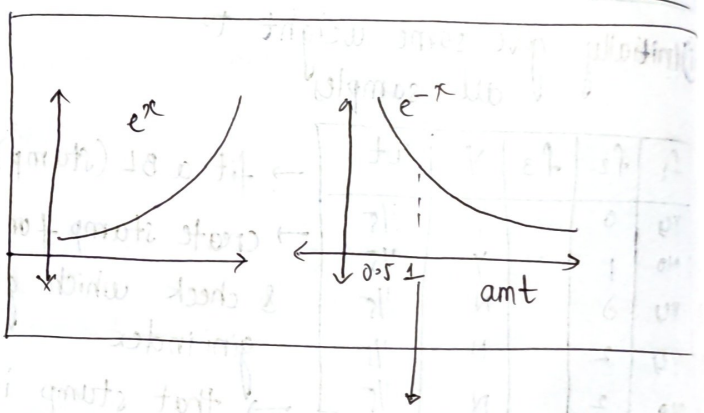
$amt\_say = \frac{1}{2}\log\left(\frac{1-TE}{TE}\right)$



error ↑ → amt_say ↓

amt_say → fixed for BL

change → e^{-x} or e^{+x}



AMT_SAY → wt updates

* If TE = 1, (worst)
  amt_say < 0
  (more error, less amt_say)

* If TE = 0 (best)
  amt_say > 0

* if TE = 0.5 (random model)
  amt_say = 0

wt updates → +ve classified (correct) → more amt say, lesser is e^{-x}

(wt, e^{-amt_say}) ∴ if amt_say >> wt update very little (it may be < wt_{i-1})

-ve classified incorrect → more amt_say, more is e^x ∴ wt update is more

wt · e^{amt_say}

Idea

TE is small (better BL)
↳ update INC ~~more~~ less
↳ reduce correct mark

* say TE is large,
  ↳ then incorrect pts wt will be increased more as we want to predict them in next stump
  ↳ correct pts wt will reduce because they have already been correctly clf by BL