Text classification.
Basic Neural Networks at NLP

MIPT
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Topic

Task description

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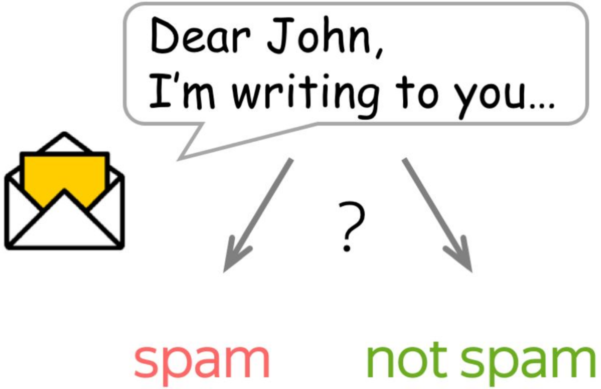
- **Input:**

$$x \in X - documents$$
$$y \in Y - classes/labels$$



- **Output:**

Assign an unknown document to one of the classes - *binary classification*.

$$Select\ f(x) = y, y \in Y, Y = \{0, 1\}$$

Task description

- **Input:**

$$x \in X - documents$$
$$y \in Y - classes/labels$$

- **Output:**

Assign an unknown document to one of the classes - *multiclass classification*.

$$Select\ f(x) = y, y \in Y, Y = \{0, 1, \ldots, K-1\}$$

Task description

- **Input:**

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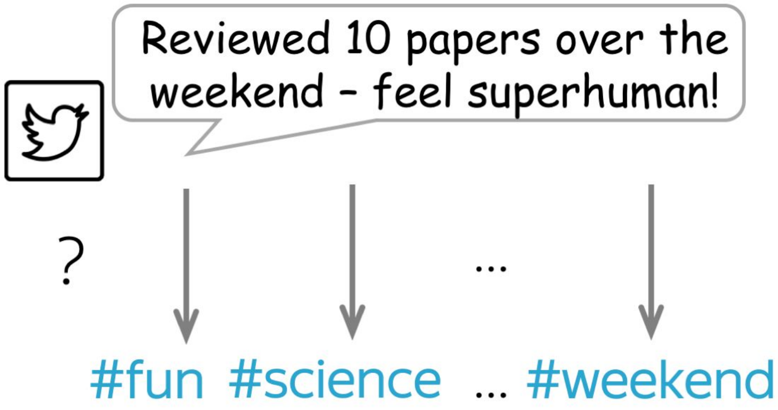
$$y \in Y - classes/labels$$



- **Output:**

Assign an unknown document to multiple classes - *multi-label classification*.

$$Select\ f(x) = \{y_0, \dots y_i, \dots\}, i < K, y \in Y, Y = \{0, 1, \dots, K-1\}$$

Task description

- We assume that we have a collection of documents with ground-truth labels. The input of a classifier is a document *x*

$$x = (x_0, x_1, \ldots, x_n)$$

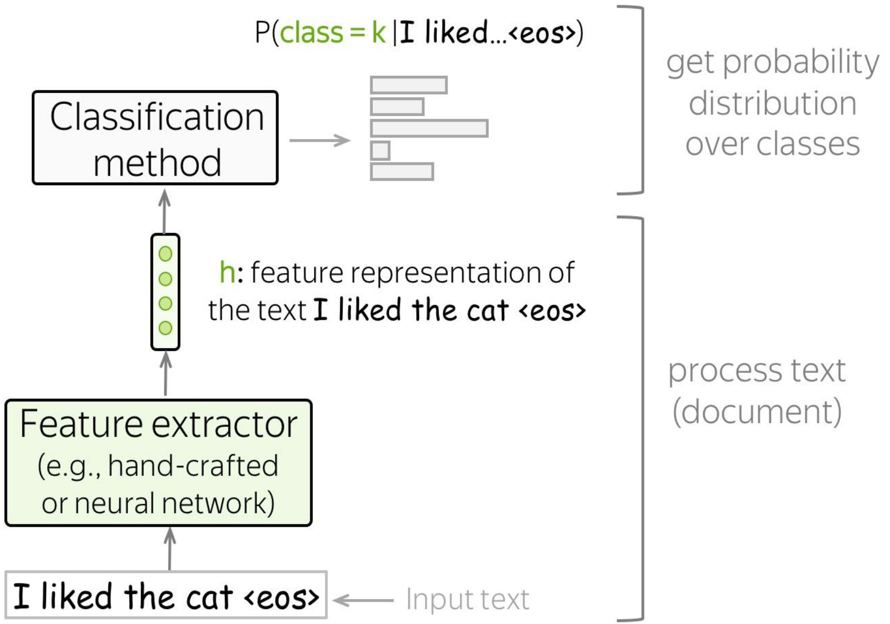
the output is a label:

$$y \in Y, Y = \{0, 1, \ldots, K-1\}$$

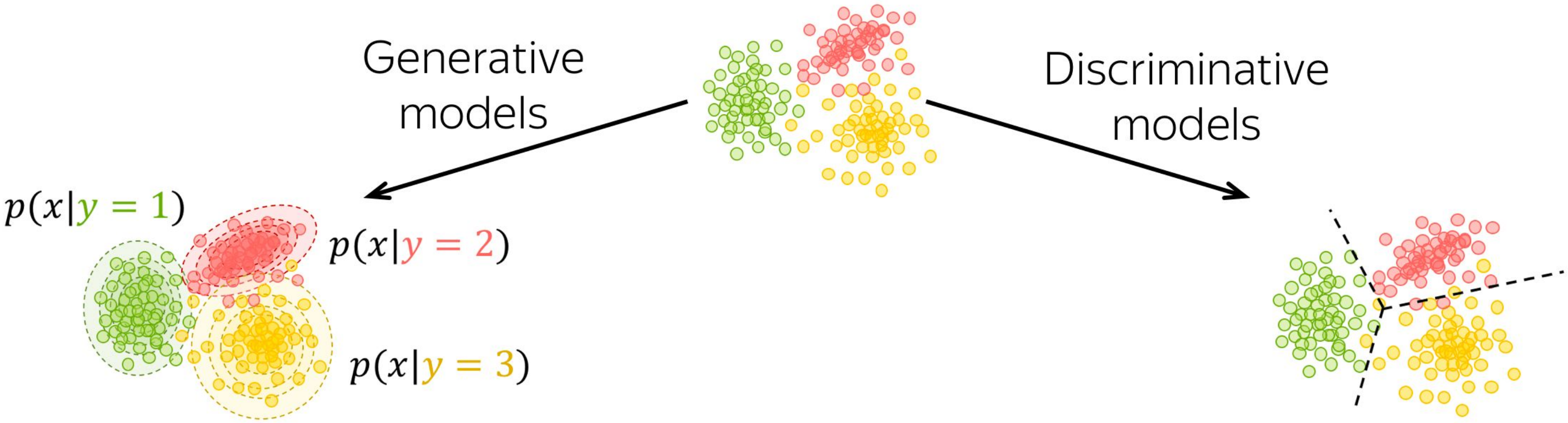
- We should select *f(x)=y*. *f* - our ML algorithm.

General classification framework

- Text classifiers have the following structure:
  - A **feature extractor** can be either manually defined (as in classical approaches) or learned (e.g., with neural networks).
  - A **classifier** has to assign class probabilities given feature representation of a text. The most common way to do this is using logistic regression, but other variants are also possible (e.g., Naive Bayes classifier or SVM).



Generative and Discriminative models



Learn: data distribution $p(x,y) = p(x|y) \cdot p(y)$

How predict: $y = \arg\max_k P(x, y=k) =$

$= \arg\max_k P(x|y=k) \cdot P(y=k)$

Learn: boundary between classes $p(y|x)$

How predict: $y = \arg\max_k P(y=k|x)$

Generative and Discriminative models

- **Generative** models learn joint probability distribution of data $p(x,y)=p(x|y) \cdot p(y)$. To make a prediction given an input *x*, these models pick a class with the highest joint probability:

$$y = \arg\max_k p(x|y=k) \cdot p(y=k)$$

- **Discriminative** models are interested only in the conditional probability $p(y|x)$, i.e. they learn only the border between classes. To make a prediction given an input *x*, these models pick a class with the highest conditional probability:

$$y = \arg\max_k p(y=k|x)$$

Some methods for text classification

- Naive Bayes Classifier
- SVM
- Maximum Entropy Classifier (aka Logistic Regression)
- Neural Networks 🤗

General classification framework

- **Feature representation** of the input text:

$$h = (1, f_1, f_2, \ldots, f_n)$$

- Vectors with **feature weights** for each of the classes

$$w^{(k)} = (w_0^{(k)}, \ldots, w_n^{(k)}), k = 0, \ldots, K-1$$

- For each class, weigh features, i.e. take the **dot product** of feature representation *h* with feature weights:

$$w^{(k)}h = w_0^{(k)} + w_1^{(k)} \cdot f_1 + \cdots + w_n^{(k)} \cdot f_n, k = 0, \ldots, K-1.$$

- Get **class probabilities** using softmax:

$$P(y = k|h) = \frac{\exp(w^{(k)}h)}{\sum_{i=1}^{K} \exp(w^{(i)}h)}.$$

General classification framework

- Define *h* as **function** of *x*, where *x* is the document from collection *X*:

$$y = \arg\max_k P(y = k|h) = \arg\max_k P(y = k|logits_k),$$

$$logits_k = w^{(k)} h(x)$$

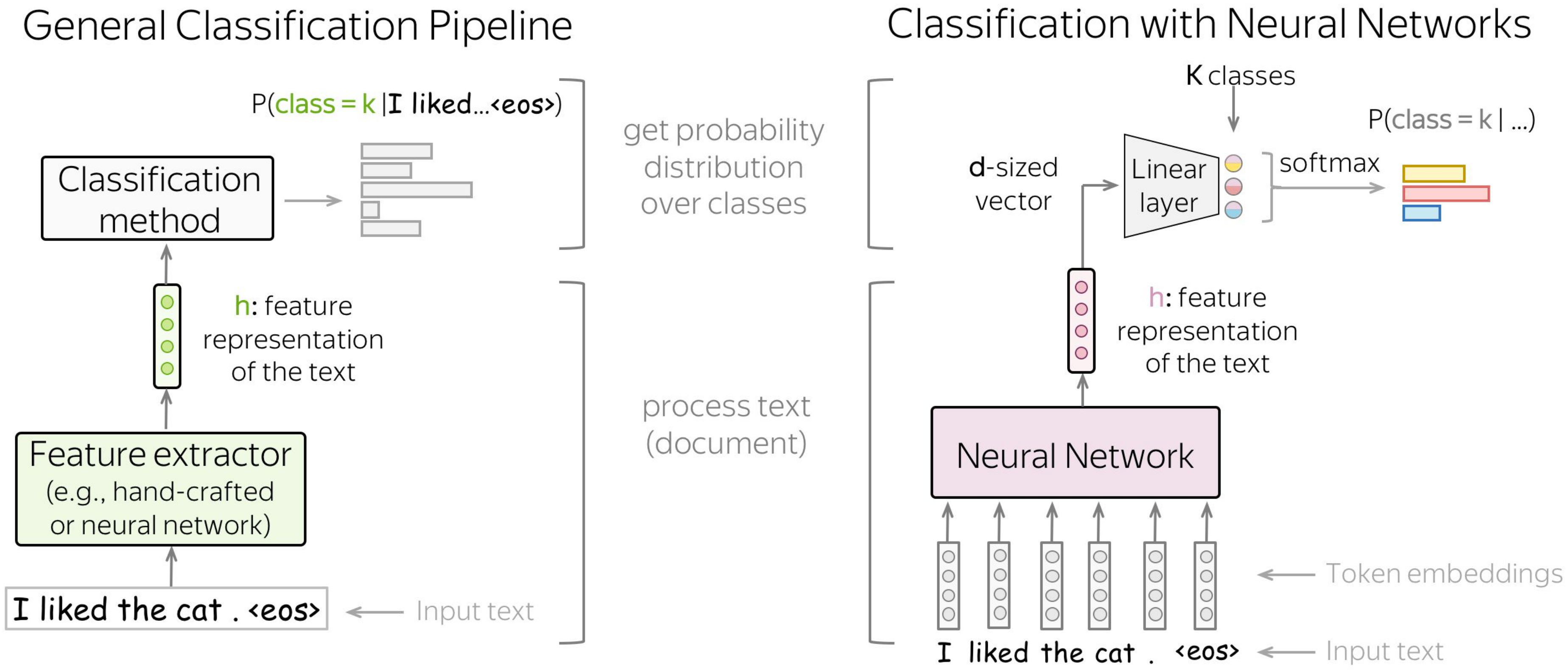
- Or at matrix form:

$$logits = Wh(x)$$

$$y = argmax(logits, dim = -1)$$

- Here *h(x)* is your **favorite** algorithm of ML (include neural nets)!
- Function *h(x)* is **feature extractor**.
- Also *h(x) generates* **representation** of text *x.*

General classification framework



Training

- Neural classifiers are trained to predict probability distributions over classes. Intuitively, at each step we maximize the probability a model assigns to the correct class. The standard loss function is the cross-entropy loss.
- Cross-entropy loss for the target probability distribution:

$$p^* = (0, \ldots, 0, 1, 0, \ldots)$$

(1 for the target label, 0 for the rest) and the predicted by the model distribution:

$$p = (p_1, \ldots, p_K), p_i = p(i|x)$$

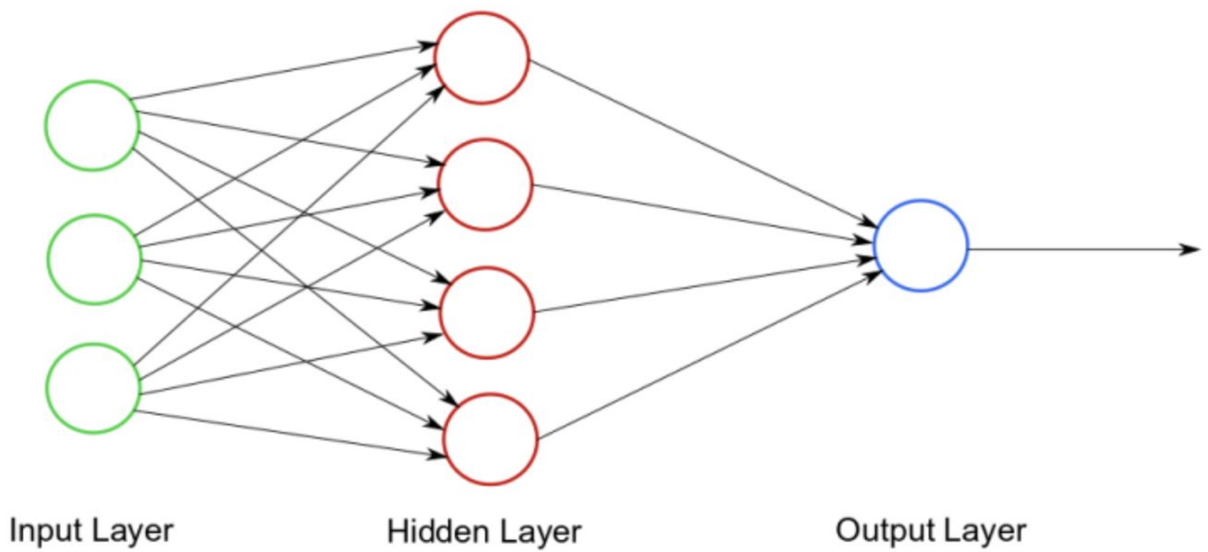
- And loss:

$$Loss(p^*, p) = -p^* \log(p) = -\sum_{i=1}^{K} p_i^* \log(p_i).$$

Basic Neural networks for classification

Networks with one hidden layer

- **Theorem (universal approximator)** Any continuous function on a compact can be uniformly approximated by a neural network with one hidden layer.

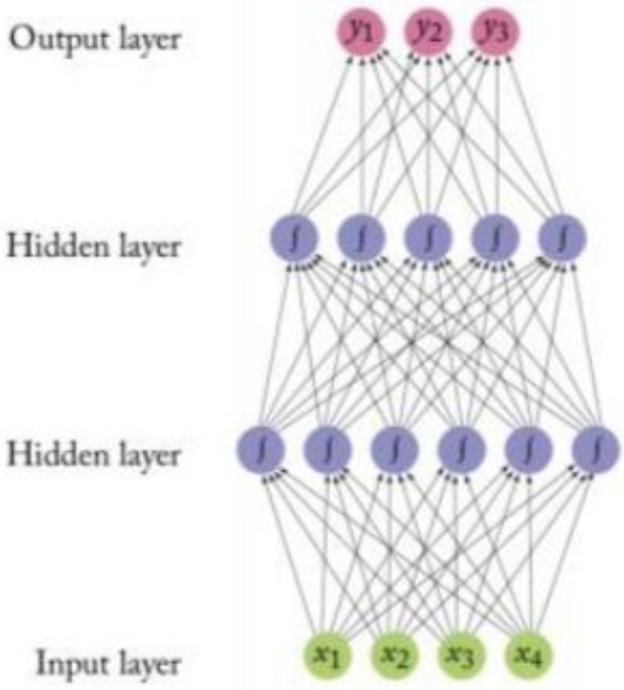


Multilayer feedforward networks

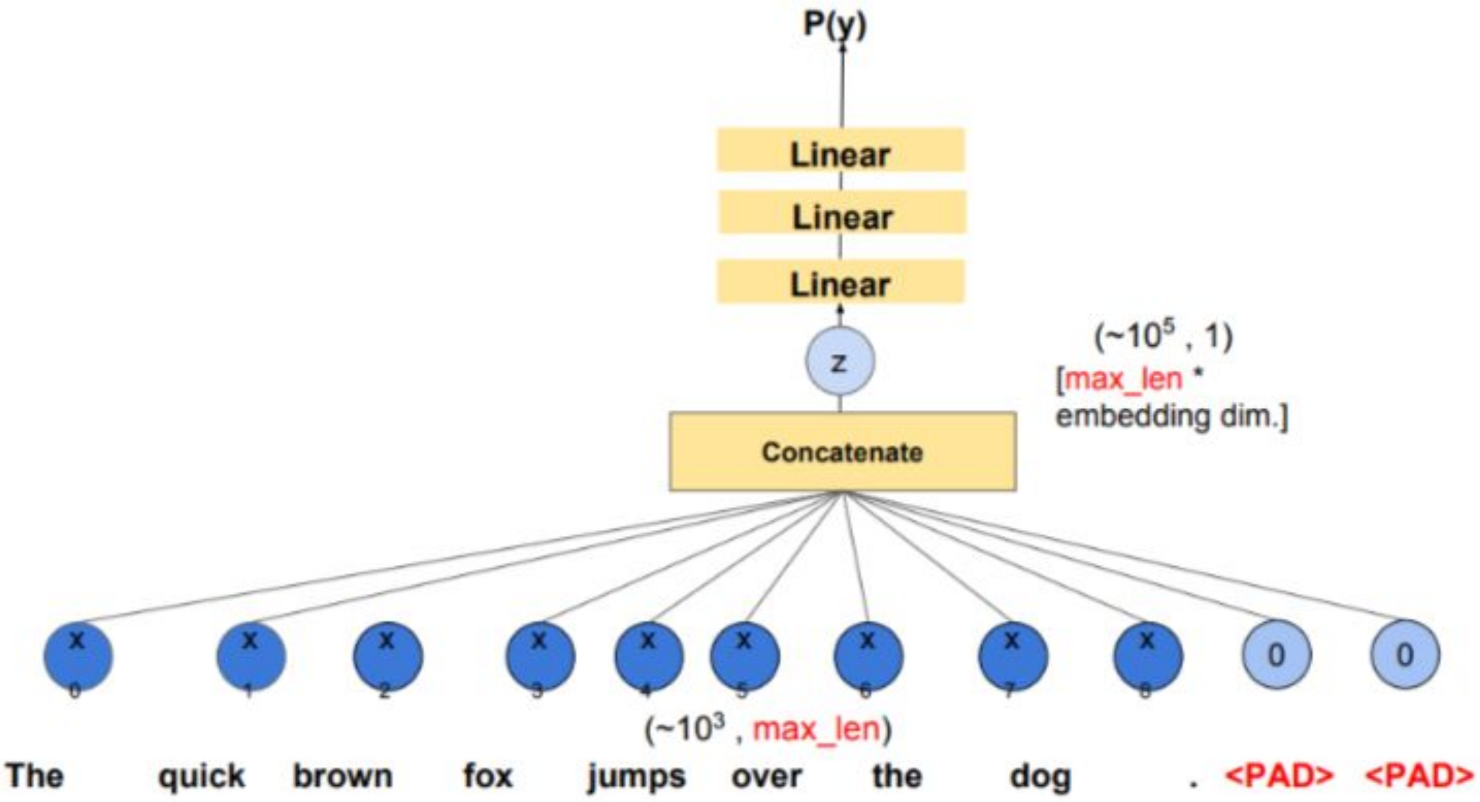
$$\mathrm{NN}_{\mathrm{MLP2}}(x) = y$$

$$h_1 = g^1(xW^1 + b^1)$$
$$h_2 = g^2(h^1 W^2 + b^2)$$
$$y = h^2 W^3$$

$$x \in \mathbb{R}^{d_{in}}, y \in \mathbb{R}^{d_{out}}$$
$$W^1 \in \mathbb{R}^{d_{in} \times d_1}, b^1 \in \mathbb{R}^{d_1}$$
$$W^2 \in \mathbb{R}^{d_1 \times d_2}, b^2 \in \mathbb{R}^{d_2}$$
$$W^3 \in \mathbb{R}^{d_2 \times d_{out}}$$



Multilayer perceptron



Problems of Fully Connected Neural Networks

- **Problems:**
  - Vanishing/Exploding gradients

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  - Lack of translational invariance (weights are specific to the absolute coordinate of a word).

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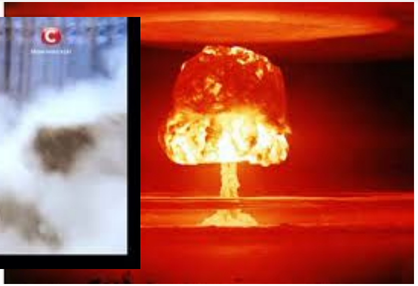

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  - Requires a huge number of neurons
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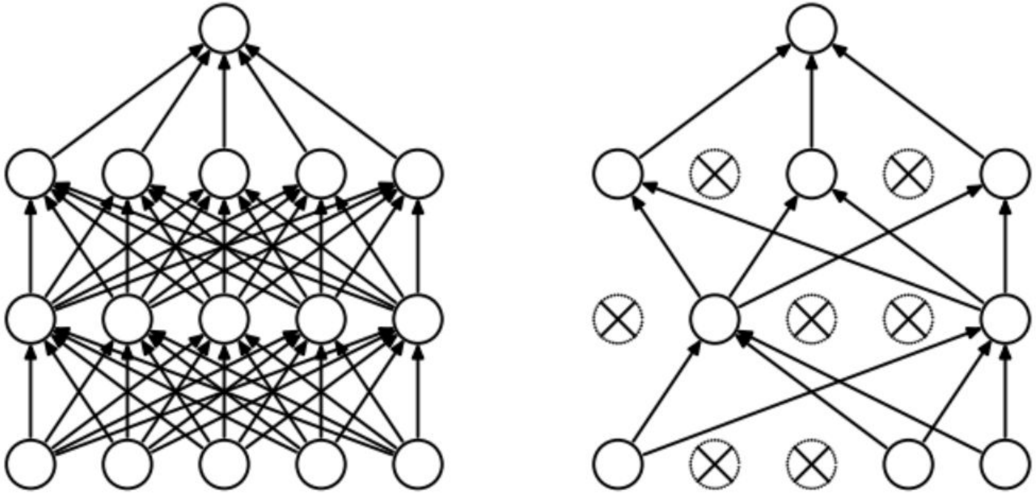
- Possible **solution -** data preprocessing

Problems of Fully Connected Neural Networks

- **Problems:**
  - Vanishing/Exploding gradients
  - Requires a huge number of neurons
  - Overfitting
  - Lack of translational invariance (weights are specific to the absolute coordinate of a word).
- Possible **solution -** data preprocessing
- Possible **solution -** introduction of new types of layers:
  - CNN
  - Dropout
  - Pooling
  - Normalization

Dropout regularization

- **Training Phase:** for each hidden layer, for each training sample, for each iteration, ignore (zero out) a random fraction, p, of nodes (and corresponding activations).
- **Testing Phase**: use all activations, but reduce them by a factor p (to account for the missing activations during training).



(a) Standard Neural Net (b) After applying dropout.

Dropout regularization

- **Some Observations:**
  - Dropout forces a neural network to learn more robust features that are useful in conjunction with many different random subsets of the other neurons.
  - Dropout roughly doubles the number of iterations required to converge. However, training time for each epoch is less.
  - With H hidden units, each of which can be dropped, we have 2^H possible models. In testing phase, the entire network is considered and each activation is reduced by a factor p.

Convolution Neural Networks (CNN)

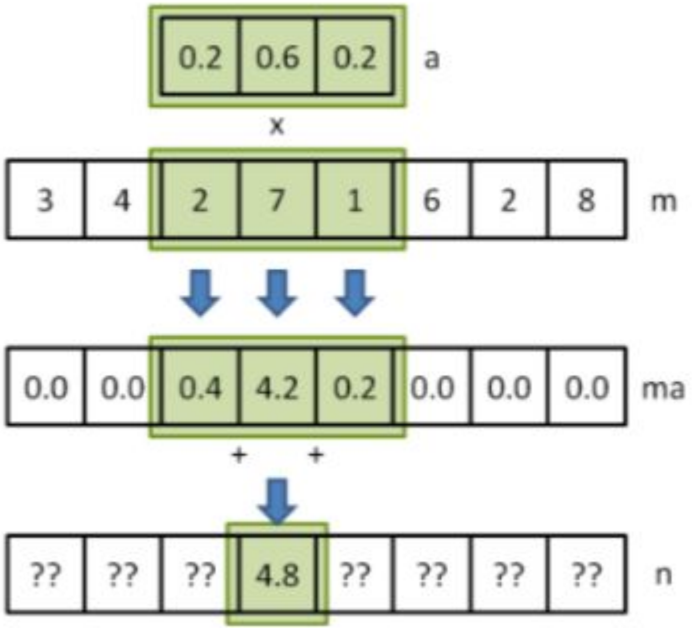
Convolutional neural networks

- **Convolutional neural networks**:
  - Borrowed from the field of computer vision.
  - The peak of popularity was in 2014 (up to + 10% accuracy in classification problems), over time they were supplanted by recurrent neural networks.
- **Help solve problems**:
  - Often, inputs are of variable length (texts, paragraphs, offers)
  - Translational invariance

Convolution

- **Definition**: The result of the operation of **convolution** of an array m with a kernel a is a signal n. Notation: *n=m*a*

$$n[k] = \sum_{i=-w/2}^{i=w/2} m[k+i] \cdot a[-i][k+i]$$



Padding

- Zero padding

0	0	**A**	**B**	**C**	0	0

- Copy of boundary

A	A	**A**	**B**	**C**	C	C

- Mirror padding

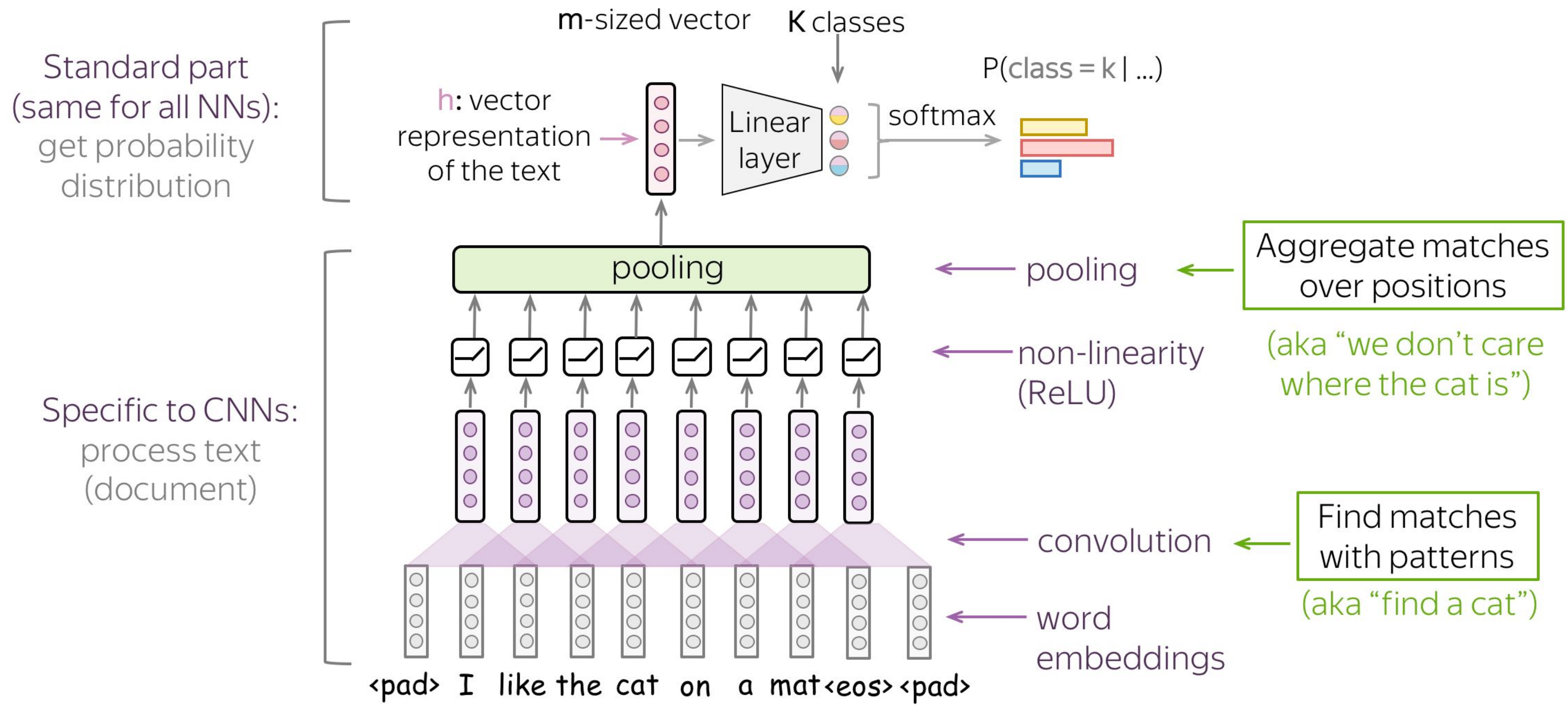
B	A	**A**	**B**	**C**	C	B

C	B	**A**	**B**	**C**	B	A

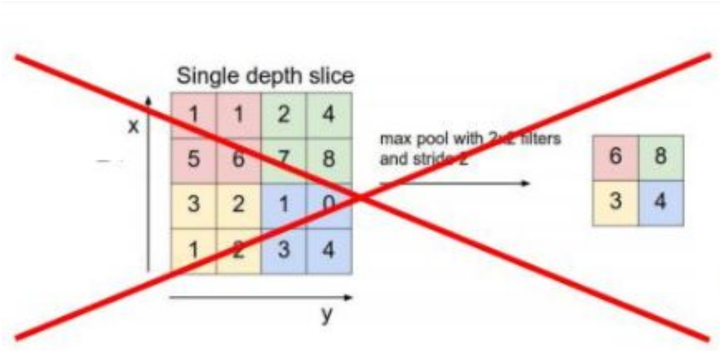
- Cycle padding

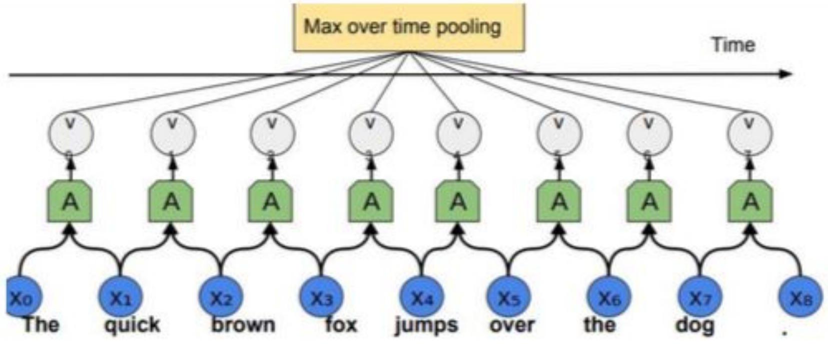
B	C	**A**	**B**	**C**	A	B

A Typical Model: Convolution + Pooling Blocks



Task description





- **Voting**: the most active neurons wins.
- Developed **invariance** to small shifts (within window).
- **Reduced computational** costs.
- There is avg pooling, but **max pooling** over time works better in text classification tasks.

Yoon Kim. Convolutional Neural Networks for Sentence Classification. 2014

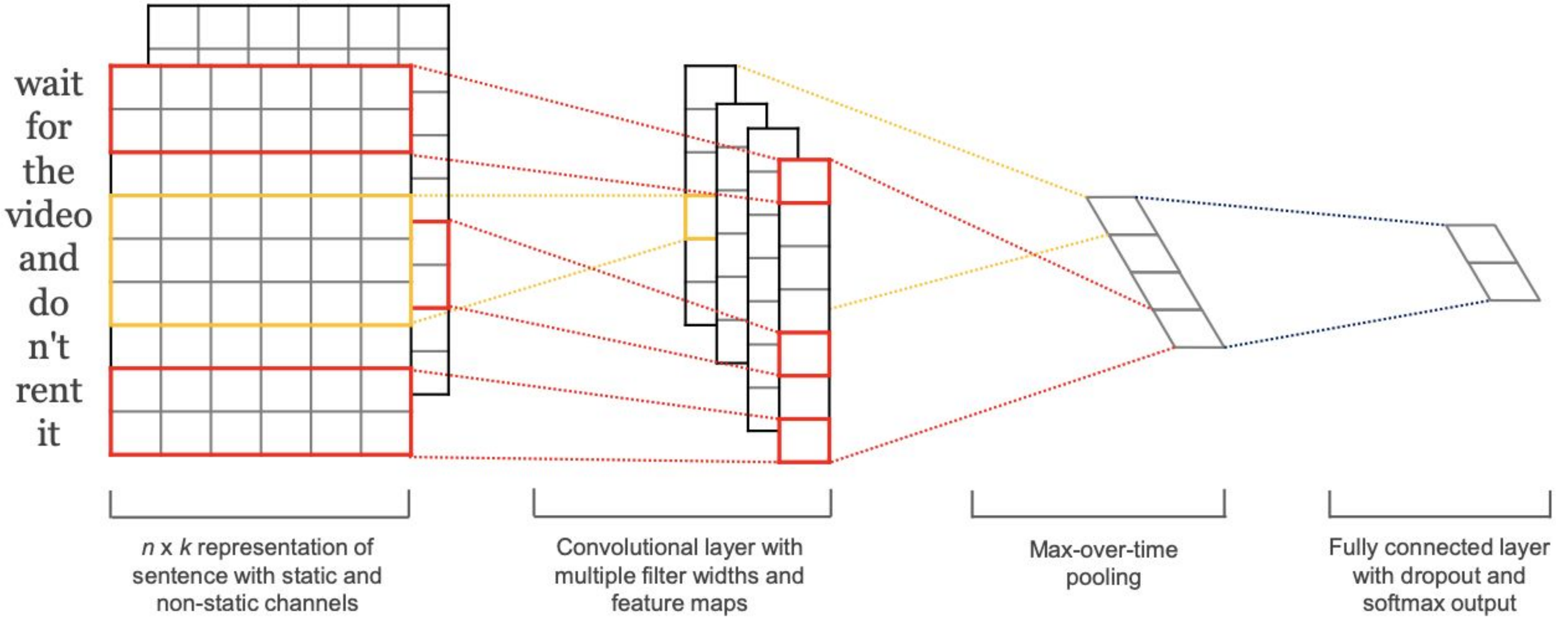


Figure 1: Model architecture with two channels for an example sentence.

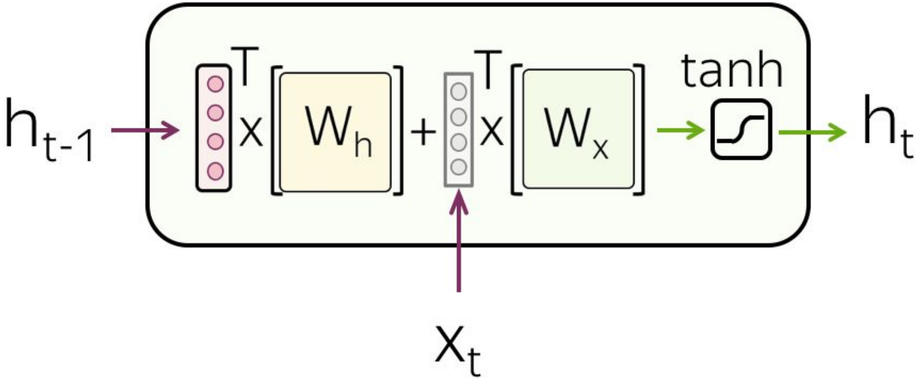
[Convolutional Neural Networks for Sentence Classification]()

Recurrent Neural Networks (RNNs)

Vanilla RNN

- **RNN** reads a text token by token, at each step using a new token embedding and the previous state.
- **Note** that the RNN cell is the same at each step!
- **Vanilla RNN**, transforms *h(t-1) and x(t)* linearly, then applies a non-linearity (most often, the *tanh* function)

$$h_t = \tanh(h_{t-1} W_h + x_t W_t).$$



How to learn RNN?

- **Backpropogation Through Time:**

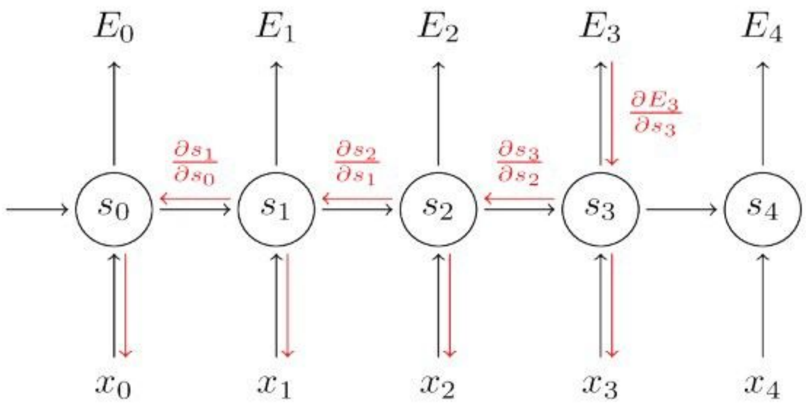
$$\frac{\partial E}{\partial \mathbf{W}} = \sum_t \frac{\partial E_t}{\partial \mathbf{W}}$$

$$\frac{\partial E_3}{\partial \mathbf{W}} = \frac{\partial E_3}{\partial \hat{y}_3} \frac{\partial \hat{y}_3}{\partial s_3} \frac{\partial s_3}{\partial \mathbf{W}}$$

But $s_3 = \tanh(Ux_t + Ws_2)$

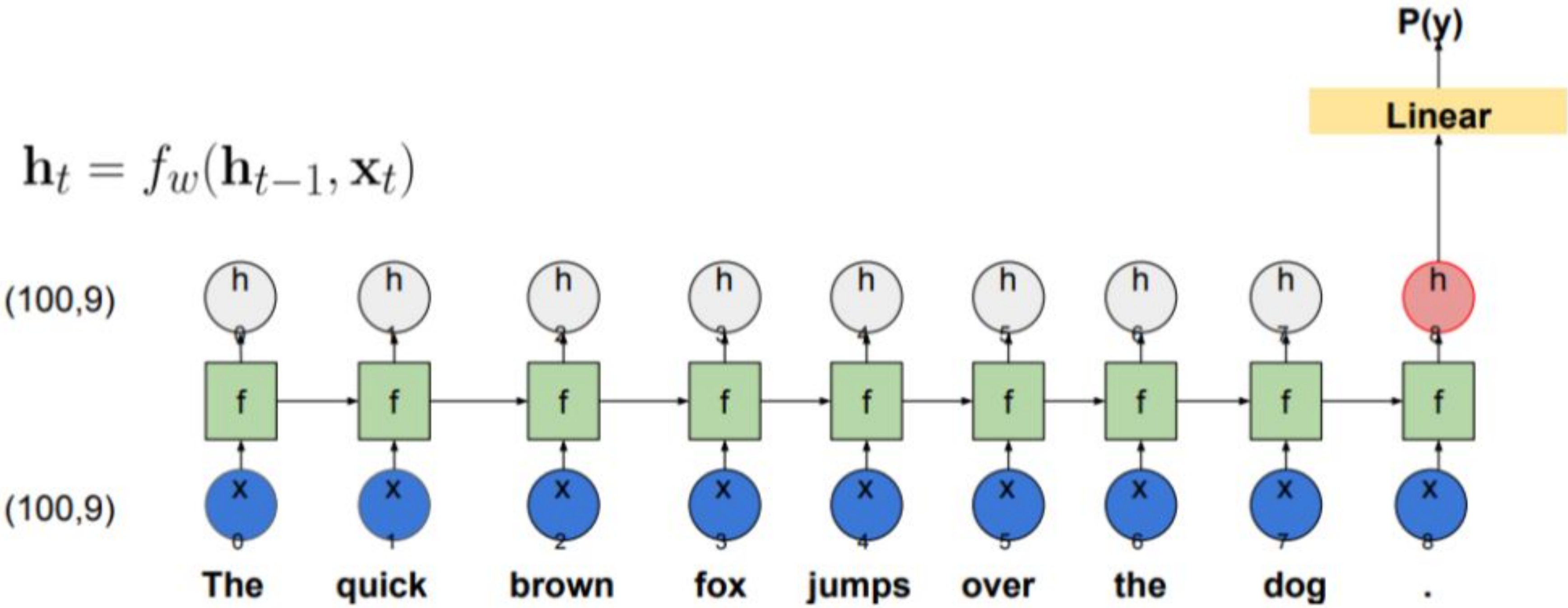
S_3 depends on s_2, which depends on W and s_1, and so on.

$$\frac{\partial E_3}{\partial \mathbf{W}} = \sum_{k=0}^{3} \frac{\partial E_3}{\partial \hat{y}_3} \frac{\partial \hat{y}_3}{\partial s_3} \frac{\partial s_3}{\partial s_k} \frac{\partial s_k}{\partial \mathbf{W}}$$



RNN for classification

$$\mathbf{h}_t = f_w(\mathbf{h}_{t-1}, \mathbf{x}_t)$$



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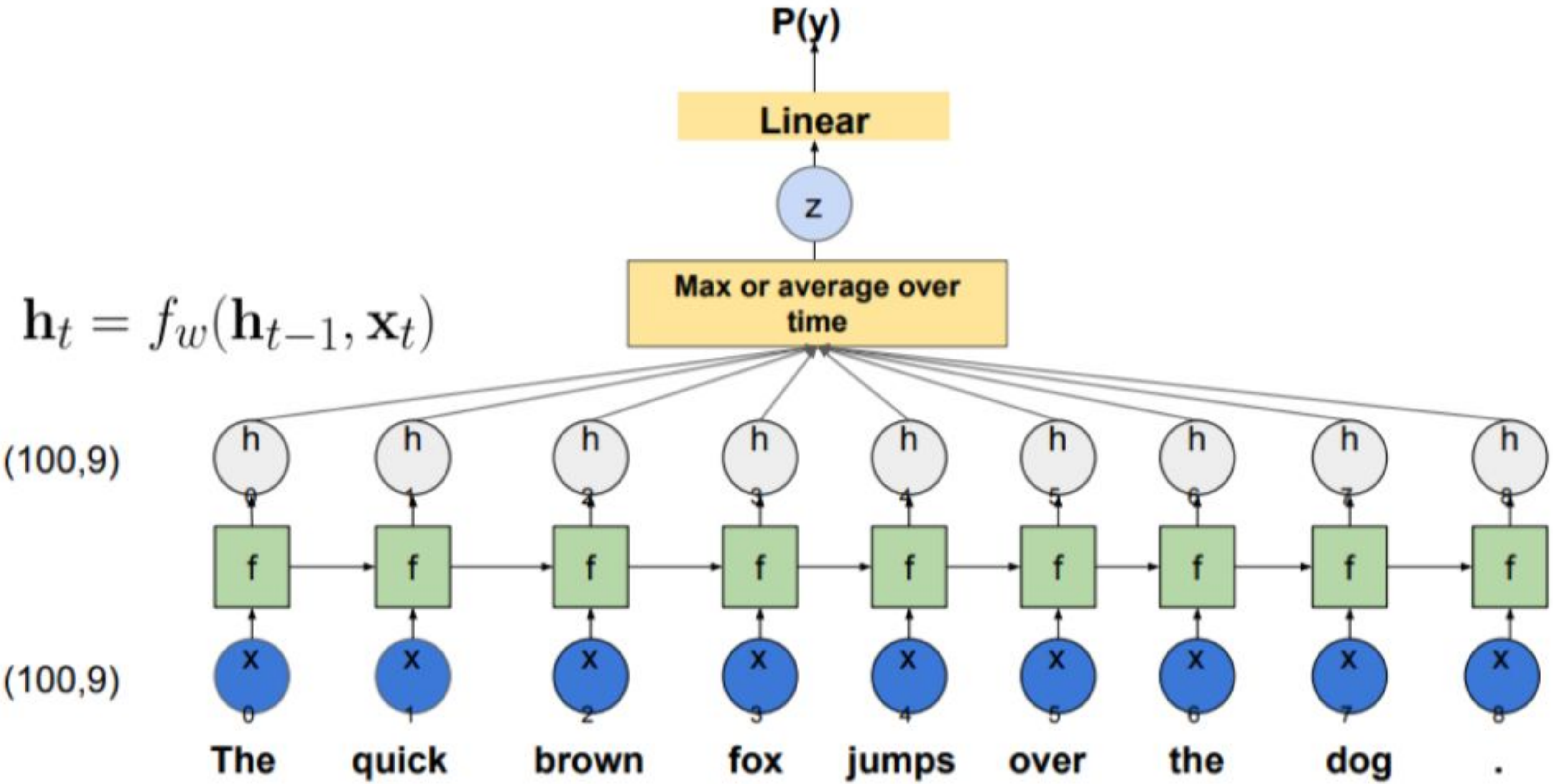
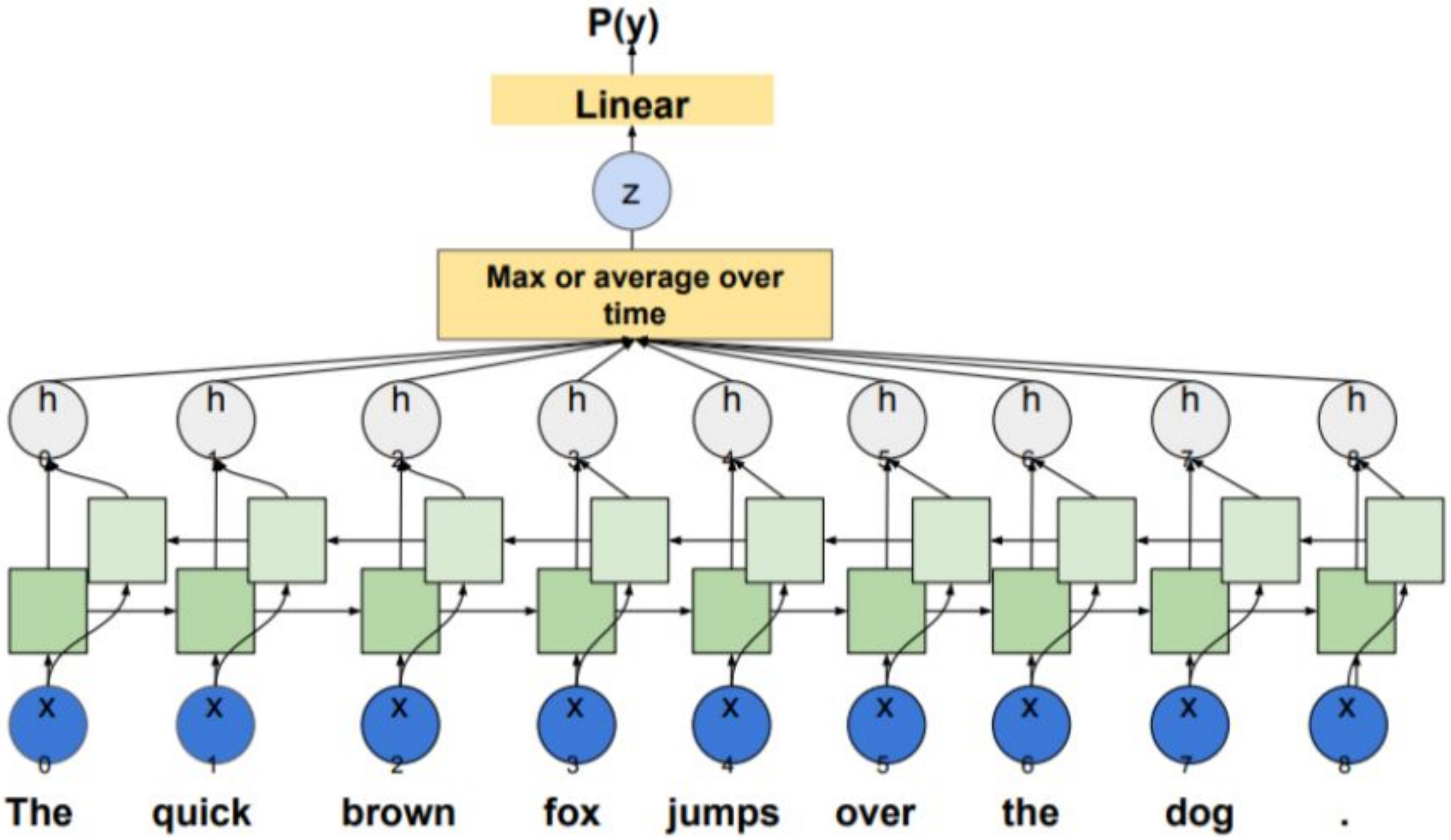


Task description

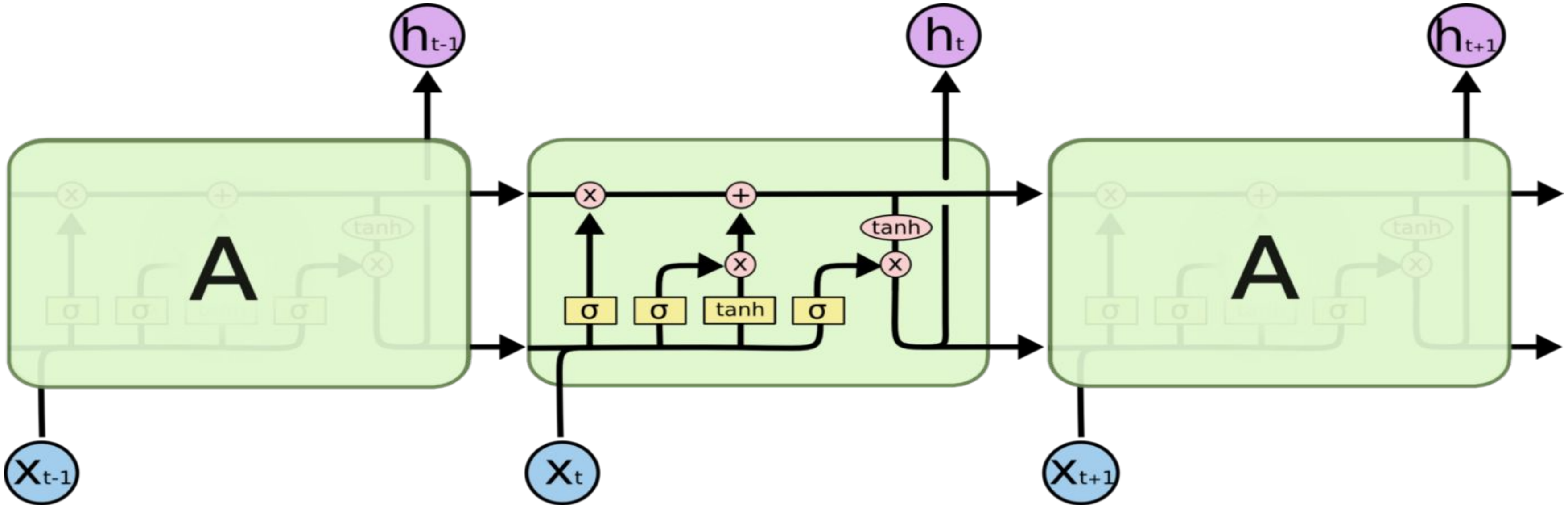


RNN overview

- RNN is difficult to train:
  - vanishing gradient problem
  - the problem of fast forgetting
- Solution: guided neurons of a special type: LSTM and GRU.
- Other modifications: peephole lstm (2014), QRNN (2016), AWD LSTM (2017), Mogrifier LSTM (2019-2020).

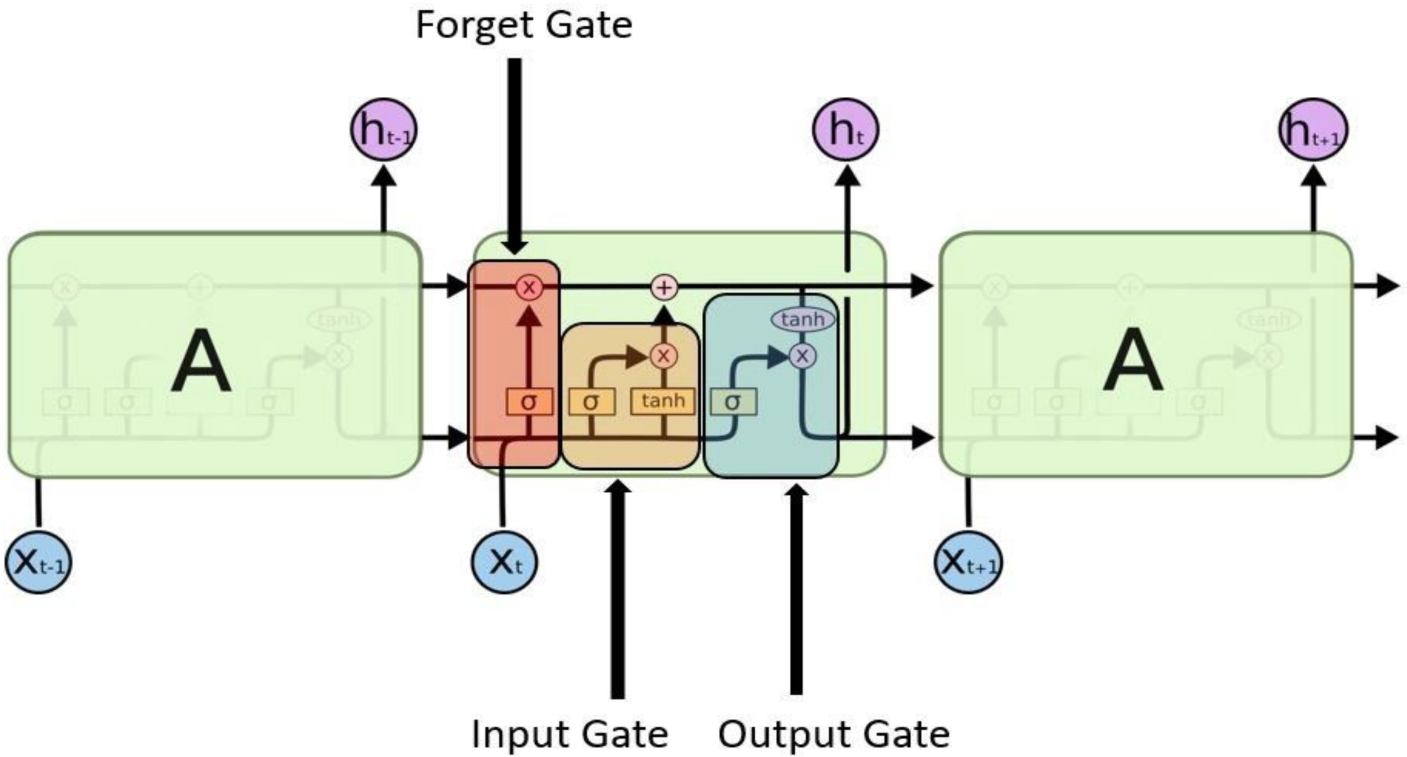
Long Short Term Memory (LSTM)

- A special kind of RNN's, capable of **Learning Long-term dependencies**.
- **LSTM's** have a Nature of Remembering information for a long periods of time is their Default behaviour.



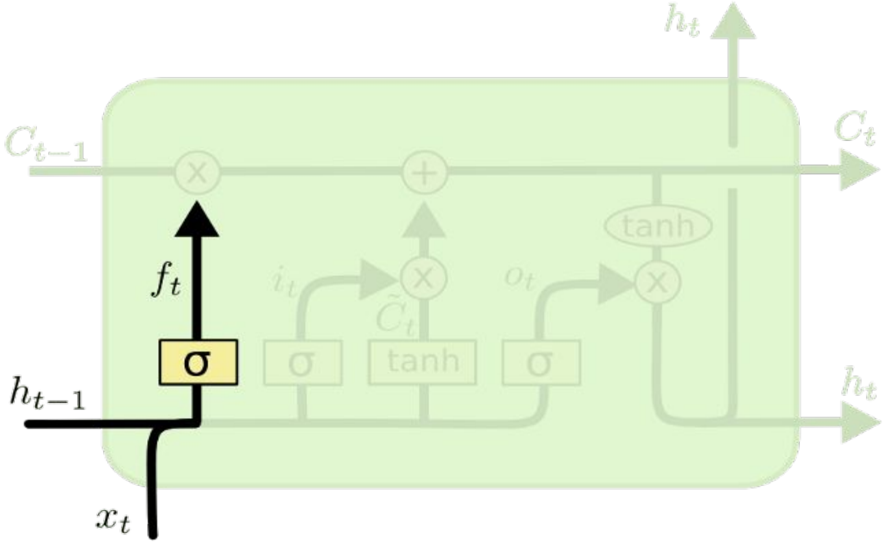
LSTM

- LSTM had a **three step** Process: **Every LSTM** module will have 3 gates named as **Forget gate**, **Input gate**, **Output gate**.



LSTM

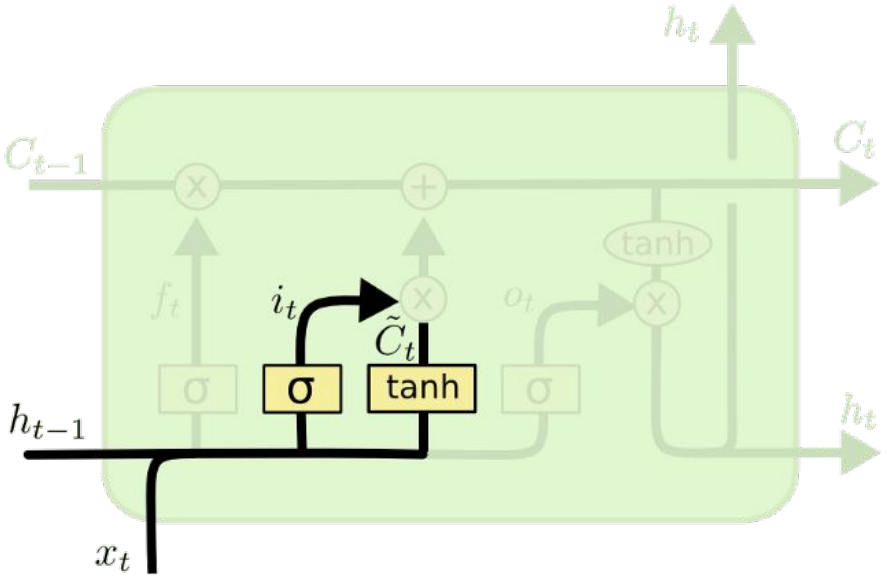
- **Forget Gate**
  - *Decides how much of the past you should remember.*
  - This gate Decides which information to be omitted in from the cell in that particular time stamp. It is decided by the **sigmoid function.** it looks at the previous state(**ht-1**) and the content input(**Xt**) and outputs a number between **0(***omit this*)and **1(***keep this***)**for each number in the cell state **Ct−1**.



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

LSTM

- Update Gate/input gate:
  - Decides How much of this unit is added to the current state
  - Sigmoid function decides which values to let through **0,1**. and **tanh** function gives weightage to the values which are passed deciding their level of importance ranging from**-1** to **1**.

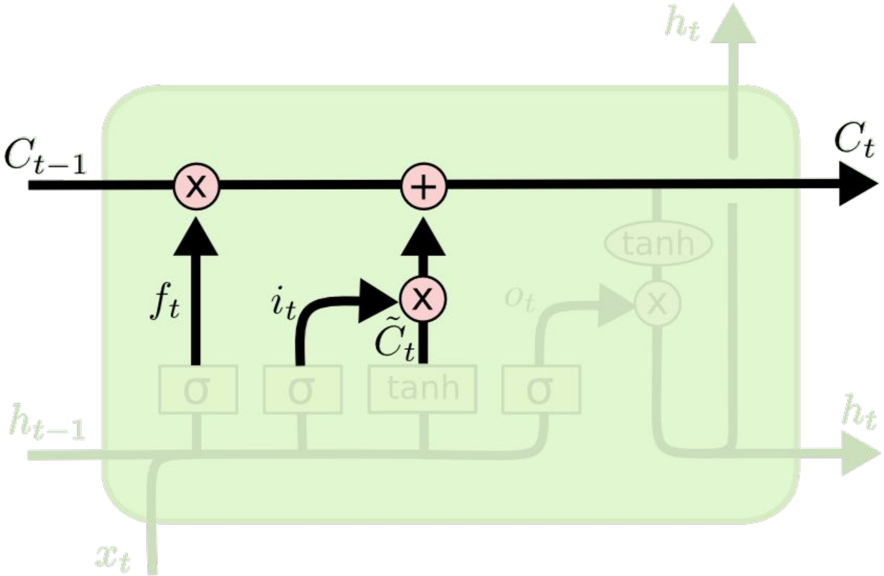


$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_C)$$

LSTM

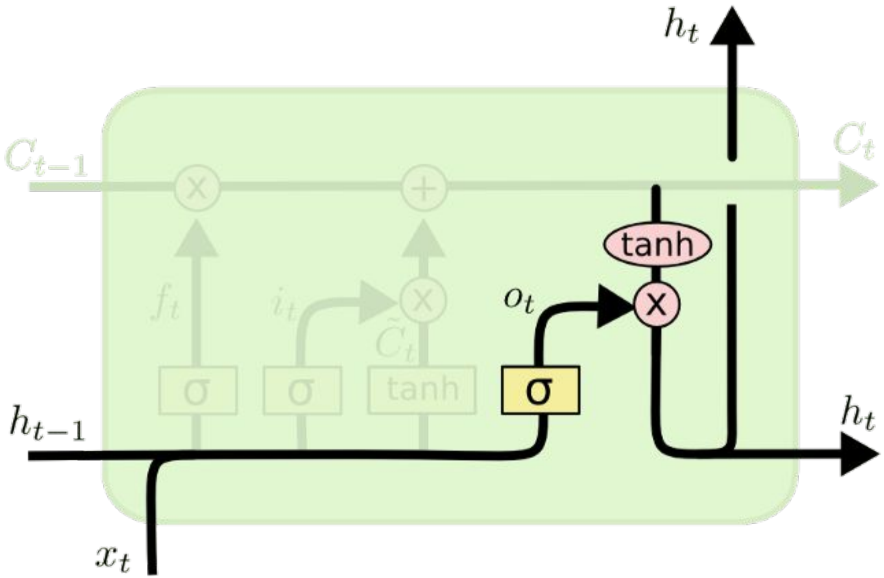
- We multiply the old state by *f(t)*, forgetting the things we decided to **forget** earlier. Then we add *i(t)∗C̃(t)*. This is the new candidate values, scaled by how much we decided to **update** each state value.



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

LSTM

- **Output Gate:**
  - Decides which part of the current cell makes it to the output.
  - Sigmoid function decides which values to let through **0,1**. and **tanh** function gives weightage to the values which are passed deciding their level of importance ranging from**-1** to 1 and multiplied with output of **Sigmoid**.

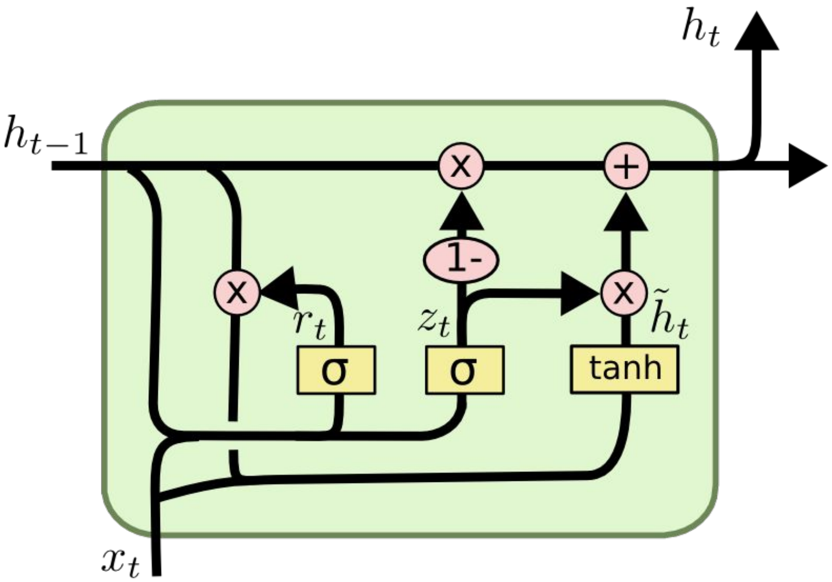


$$o_t = \sigma\left(W_o \left[h_{t-1}, x_t\right] + b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

Gated Recurrent Unit (GRU)

- GRU **combines** the **forget** and **input** gates into a single “**update gate**.” It also merges the cell state and hidden state, and makes some other changes. The resulting model is simpler than standard LSTM models, and has been growing increasingly popular.



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

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

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

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

CNNs vs RNNs

- With a lot of reservations RNNs demonstrates slightly better results on the benchmark classification tasks.
- CNNs work well on the tasks that can be reduced to keyword search. Keyword mean NEs and so on.
- Also, RNNs have slower inference than CNNs. CNNs are easier to train.
- For RNN you need more data.

Comparative Study of CNN and RNN for Natural Language Processing [Yin et al 2017] - https://arxiv.org/abs/1702.01923.

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It's seems to be very task-dependent thing.
So you should try both options.

Comparative Study of CNN and RNN for Natural Language Processing [Yin et al 2017] - https://arxiv.org/abs/1702.01923.

Learning pytorch

- Very good examples (**for google colab!**):
  - https://github.com/param087/Pytorch-tutorial-on-Google-colab
- And official https://pytorch.org/tutorials/

Questions

Reference

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  - Convolutional Neural Network for Paraphrase Identification
  - Relation Classification via Convolutional Deep Neural Network
  - Character-level Convolutional Networks for Text Classification

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