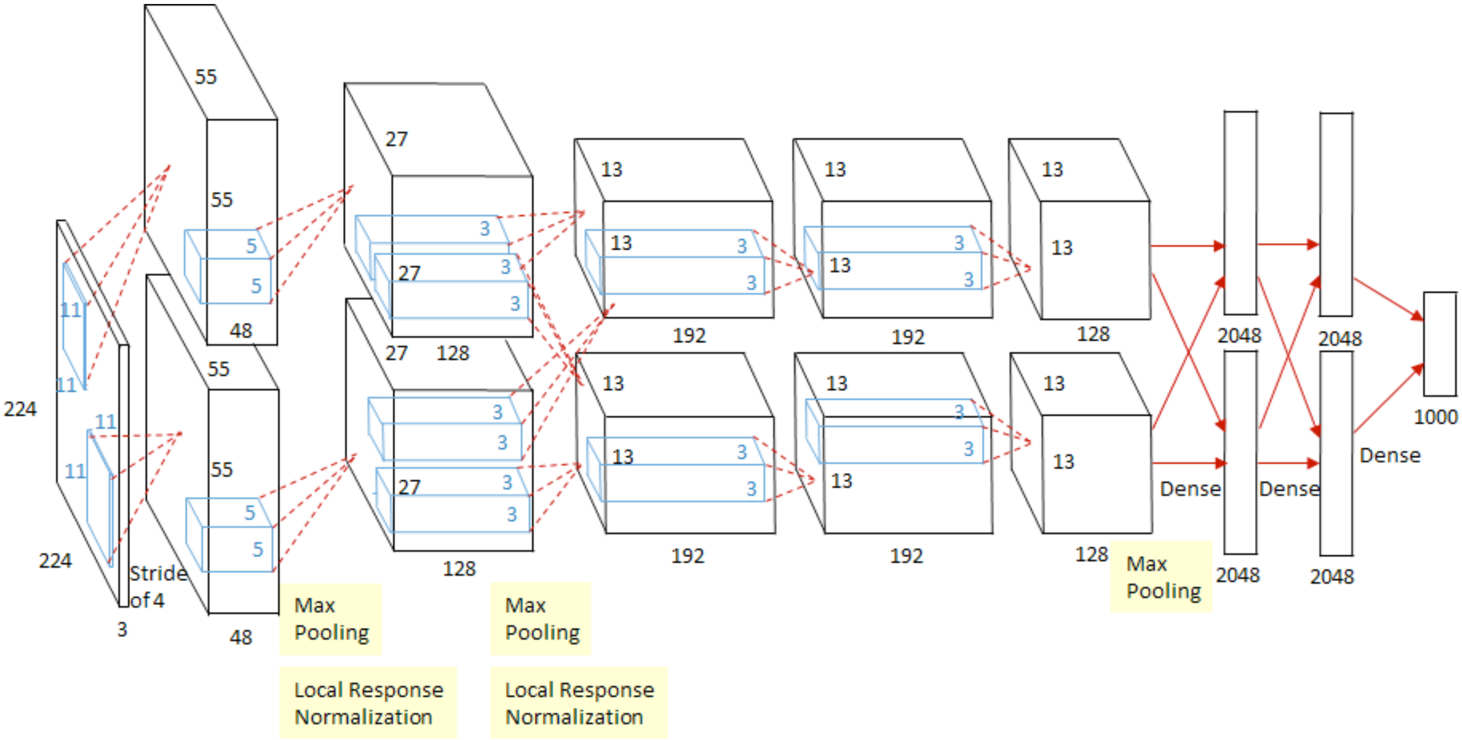
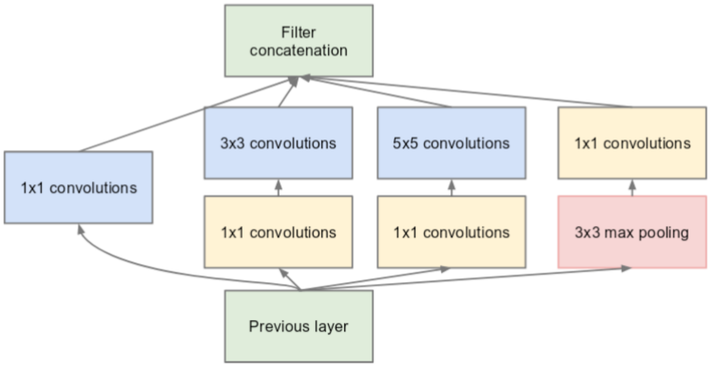
Whirlwind tour of modern deep learning

Vision Model

Alexnet (2012) - Conv. +GPU

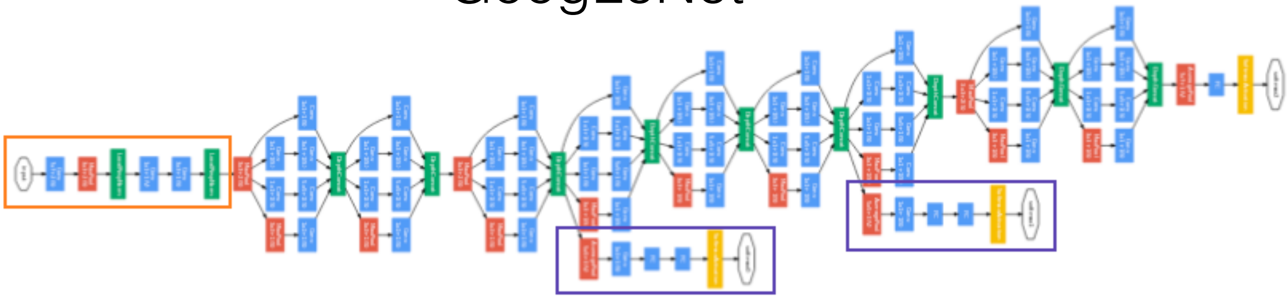


Inception 2014-2016

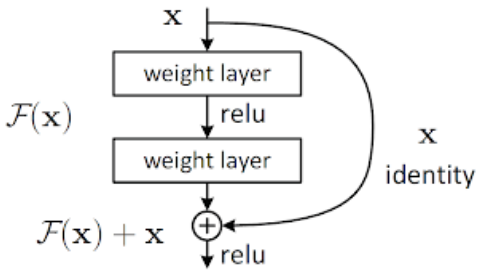


(b) Inception module with dimension reductions

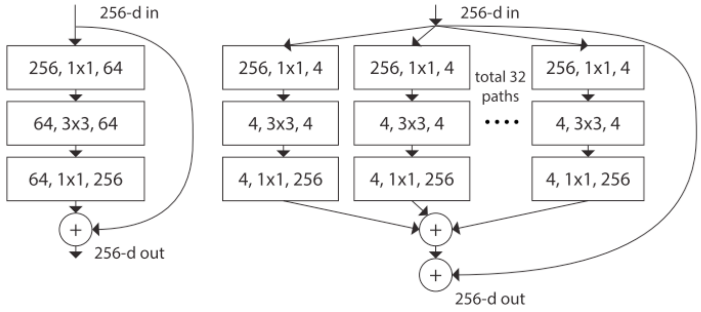
GoogLeNet

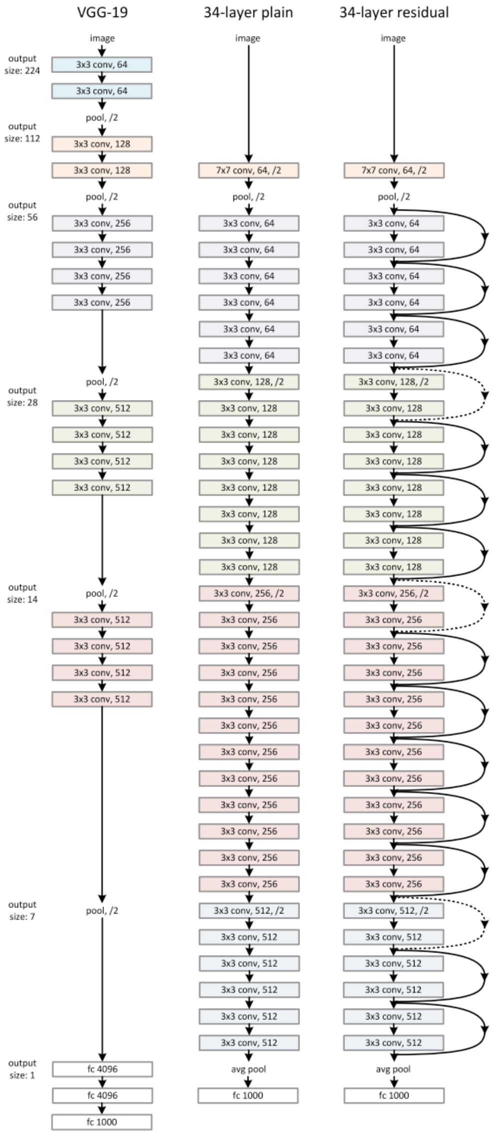


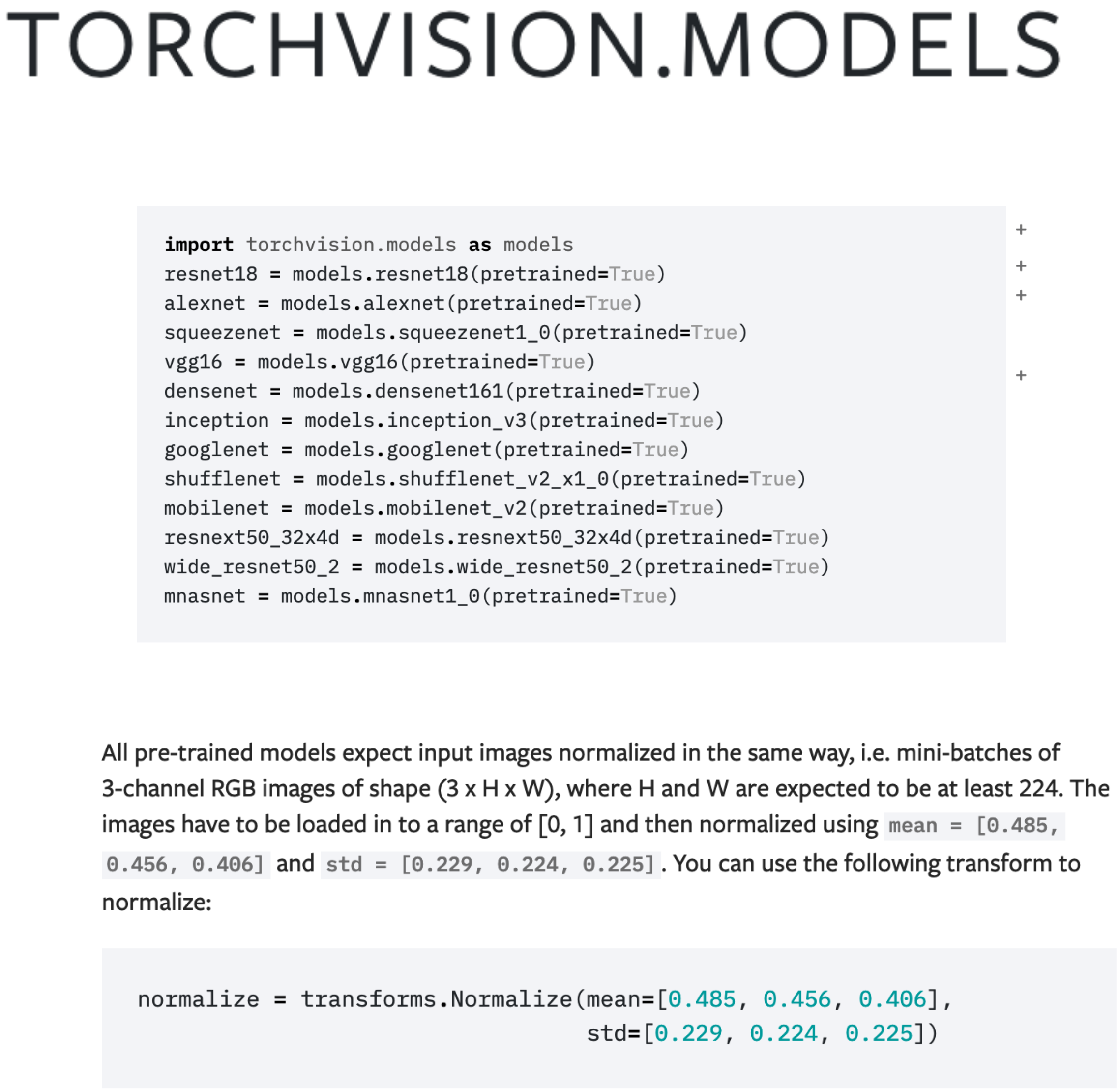
Resnet 2016


x
weight layer
$\mathcal{F}(\mathbf{x})$
relu
weight layer
x
identity
$\mathcal{F}(\mathbf{x}) + \mathbf{x}$
relu

ResXnet 2016







TORCHVISION.MODELS

```
import torchvision.models as models
resnet18 = models.resnet18(pretrained=True)
alexnet = models.alexnet(pretrained=True)
squeezenet = models.squeezenet1_0(pretrained=True)
vgg16 = models.vgg16(pretrained=True)
densenet = models.densenet161(pretrained=True)
inception = models.inception_v3(pretrained=True)
googlenet = models.googlenet(pretrained=True)
shufflenet = models.shufflenet_v2_x1_0(pretrained=True)
mobilenet = models.mobilenet_v2(pretrained=True)
resnext50_32x4d = models.resnext50_32x4d(pretrained=True)
wide_resnet50_2 = models.wide_resnet50_2(pretrained=True)
mnasnet = models.mnasnet1_0(pretrained=True)
```

All pre-trained models expect input images normalized in the same way, i.e. mini-batches of 3-channel RGB images of shape (3 x H x W), where H and W are expected to be at least 224. The images have to be loaded in to a range of [0, 1] and then normalized using `mean = [0.485, 0.456, 0.406]` and `std = [0.229, 0.224, 0.225]`. You can use the following transform to normalize:

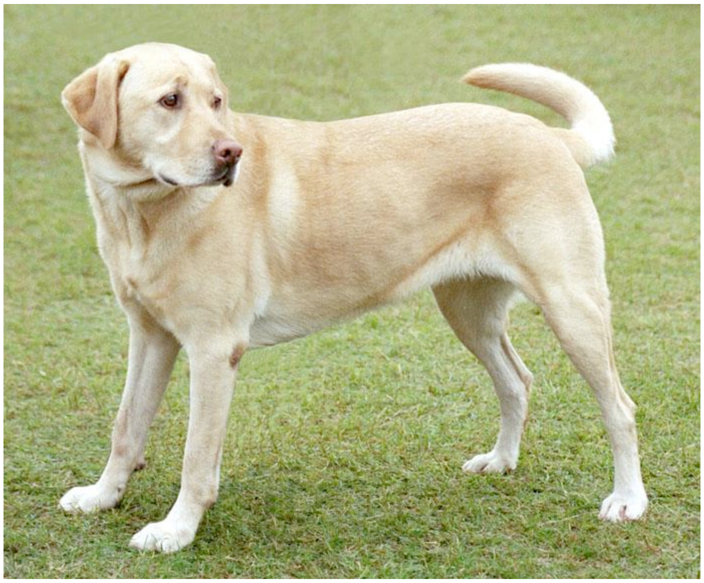
```
normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                 std=[0.229, 0.224, 0.225])
```

Neural style transfer

https://www.tensorflow.org/tutorials/generative/style_transfer

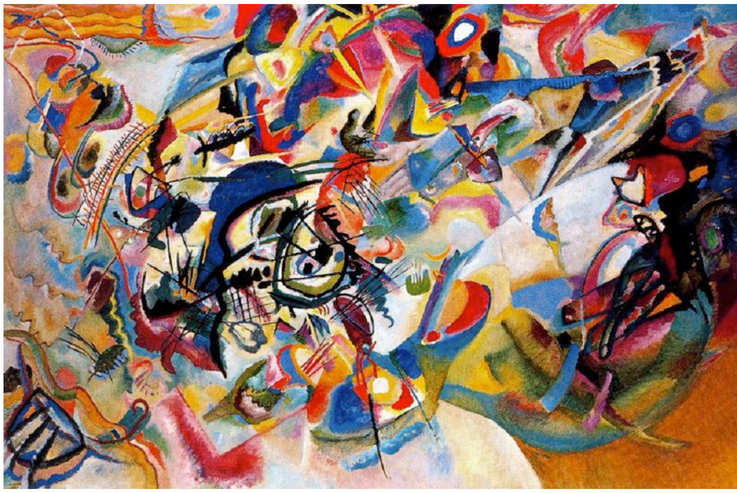
https://medium.com/tensorflow/neural-style-transfer-creating-art-with-deep-learning-using-tf-keras-and-eager-execution-7d541ac31398

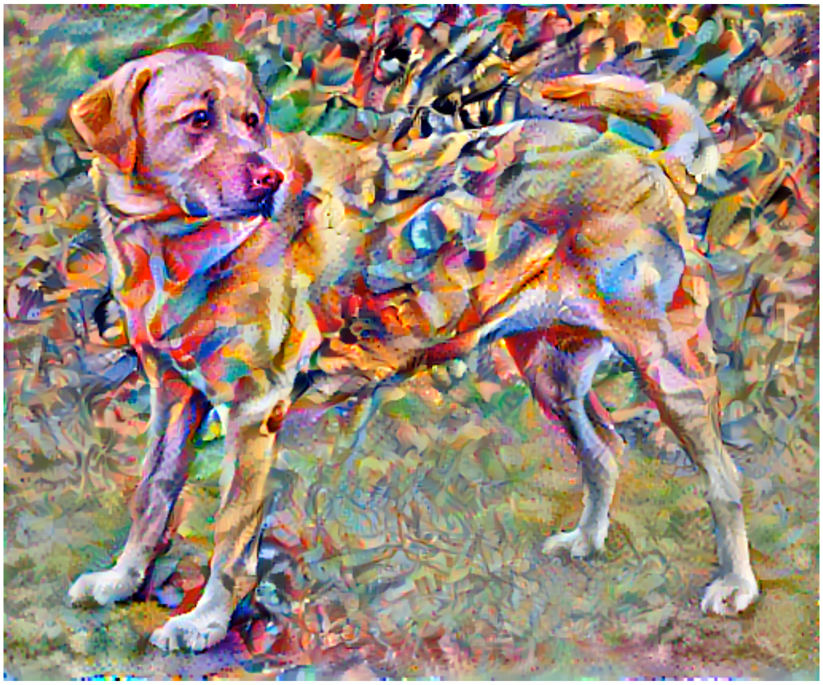
Content

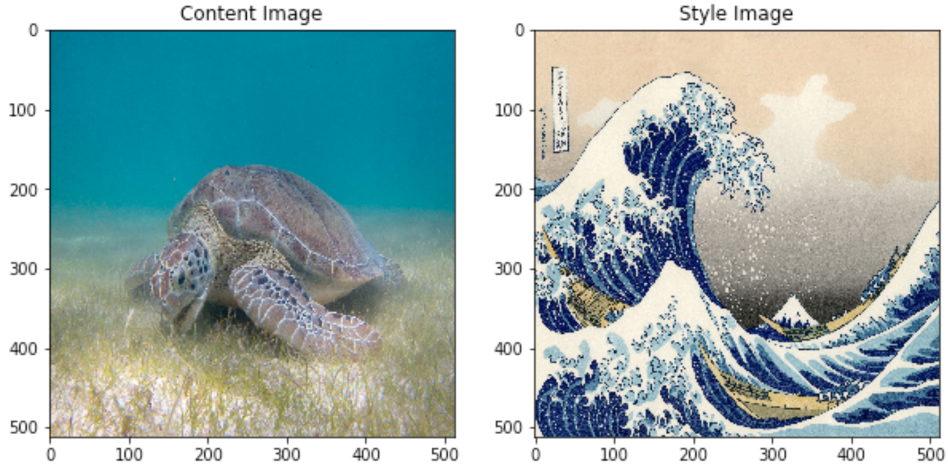


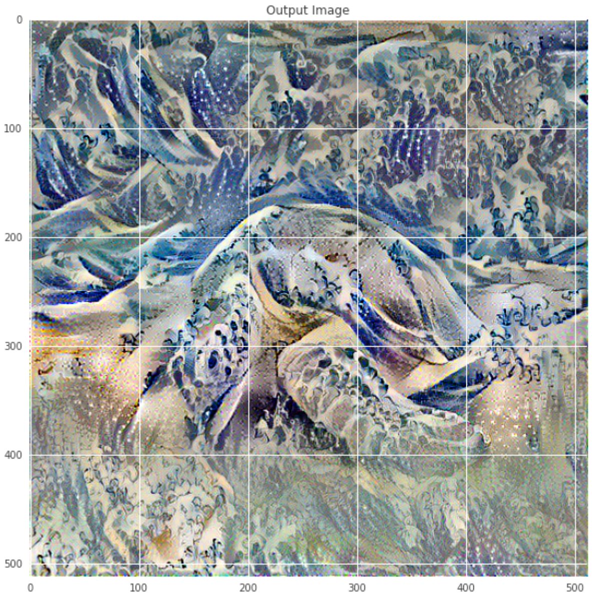
+

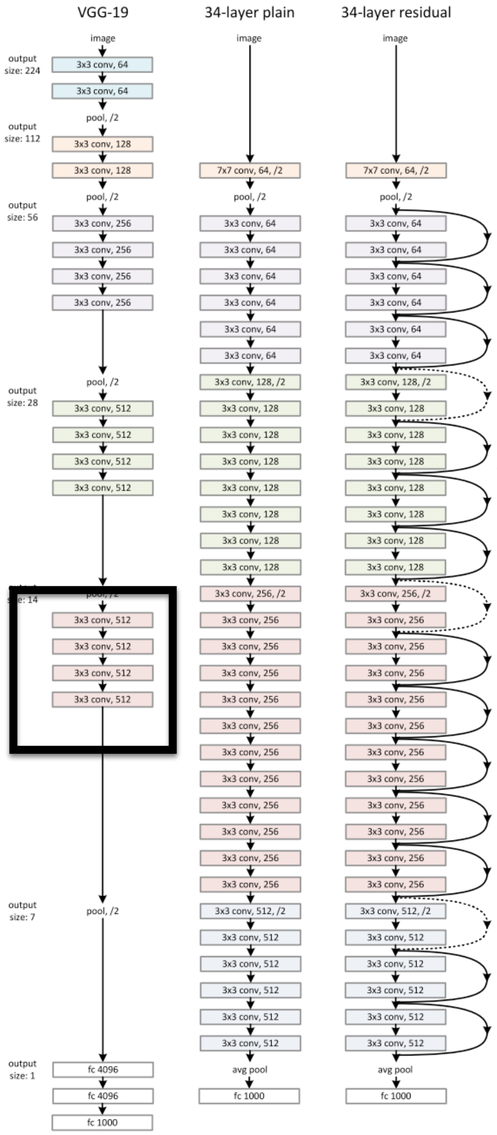
Style






Content Image
Style Image
0
100
200
300
400
500
0
100
200
300
400
500


Output Image
0
100
200
300
400
500
0
100
200
300
400
500



Content: means
Style: Correlations between filter

$$L^l_{content}(p,x)=\sum_{i,j}(F^l_{ij}(x)-P^l_{ij}(p))^2$$

$$E_l=\frac{1}{4N_l^2M_l^2}\sum_{i,j}(G^l_{ij}-A^l_{ij})^2$$

$$L_{style}(a,x)=\sum_{l\in L}w_lE_l$$

Natural Language Processing

Word2Vec: Map words to vector space

https://www.tensorflow.org/tutorials/text/word2vec

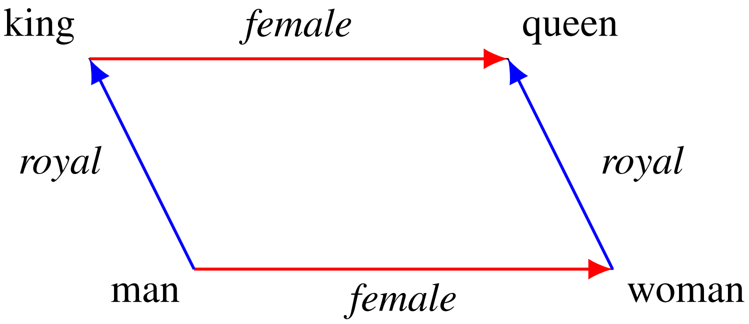
Window Size	Text	Skip-grams
2	[The **wide** road shimmered] in the hot sun.	wide, the wide, road wide, shimmered
	The [wide road **shimmered** in the] hot sun.	shimmered, wide shimmered, road shimmered, in shimmered, the
	The wide road shimmered in [the hot **sun**].	sun, the sun, hot
3	[The **wide** road shimmered in] the hot sun.	wide, the wide, road wide, shimmered wide, in
	[The wide road **shimmered** in the hot] sun.	shimmered, the shimmered, wide shimmered, road shimmered, in shimmered, the shimmered, hot
	The wide road shimmered [in the hot **sun**].	sun, in sun, the sun, hot

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c,j\neq 0}\log p(w_{t+j}|w_t)$$

$$p(w_O|w_I)=\frac{\exp\left({v'_{w_O}}^{\top}v_{w_I}\right)}{\sum_{w=1}^{W}\exp\left({v'_w}^{\top}v_{w_I}\right)}$$

Talk about negative sampling

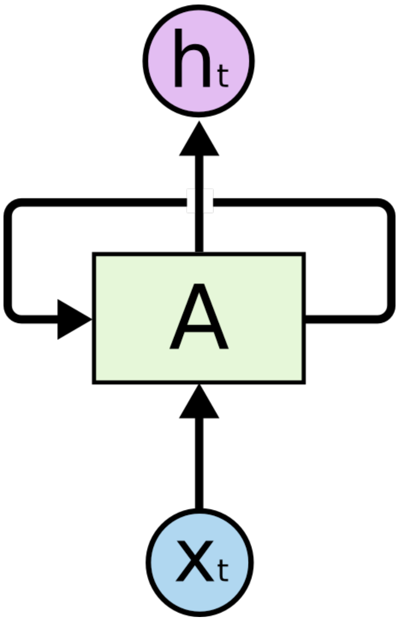
Word analogies

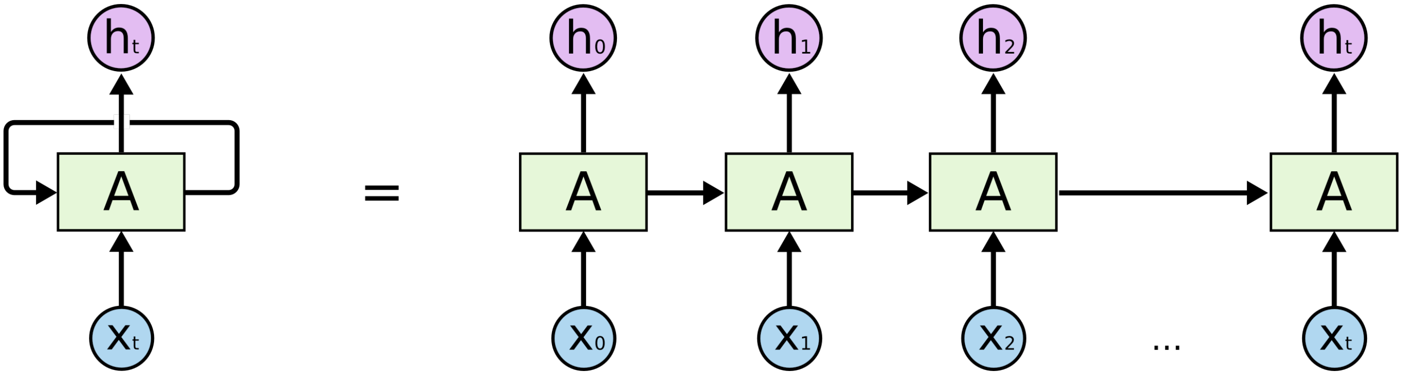


https://p.migdal.pl/2017/01/06/king-man-woman-queen-why.html https://pytorch.org/tutorials/beginner/nlp/sequence_models_tutorial.html

Recurrent Neural Networks

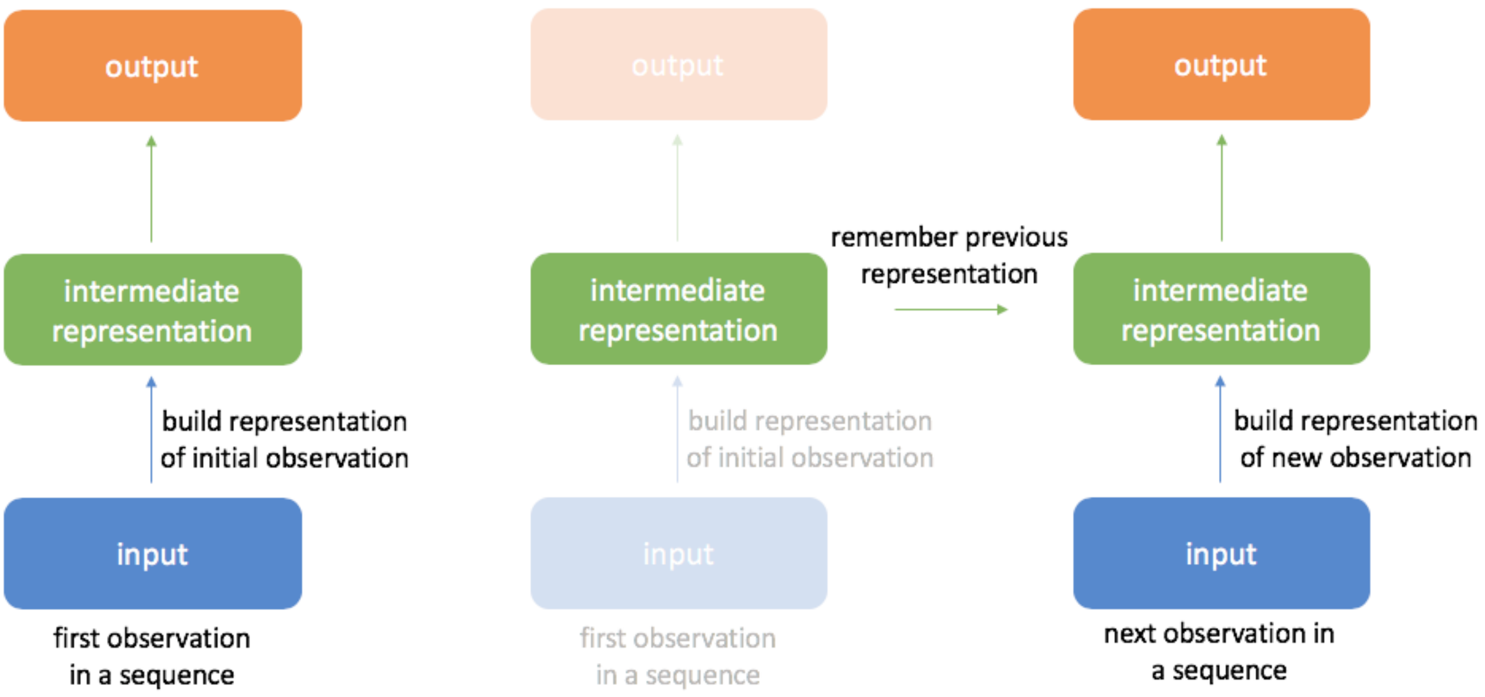
https://www.jeremyjordan.me/introduction-to-recurrent-neural-networks/


h_t
A
x_t


h_t
A
x_t
=
h_0
h_1
h_2
h_t
A
A
A
A
x_0
x_1
x_2
...
x_t

Non-sequential

Sequential



output

intermediate representation

build representation of initial observation

input

first observation in a sequence

output

intermediate representation

build representation of initial observation

input

first observation in a sequence

remember previous representation

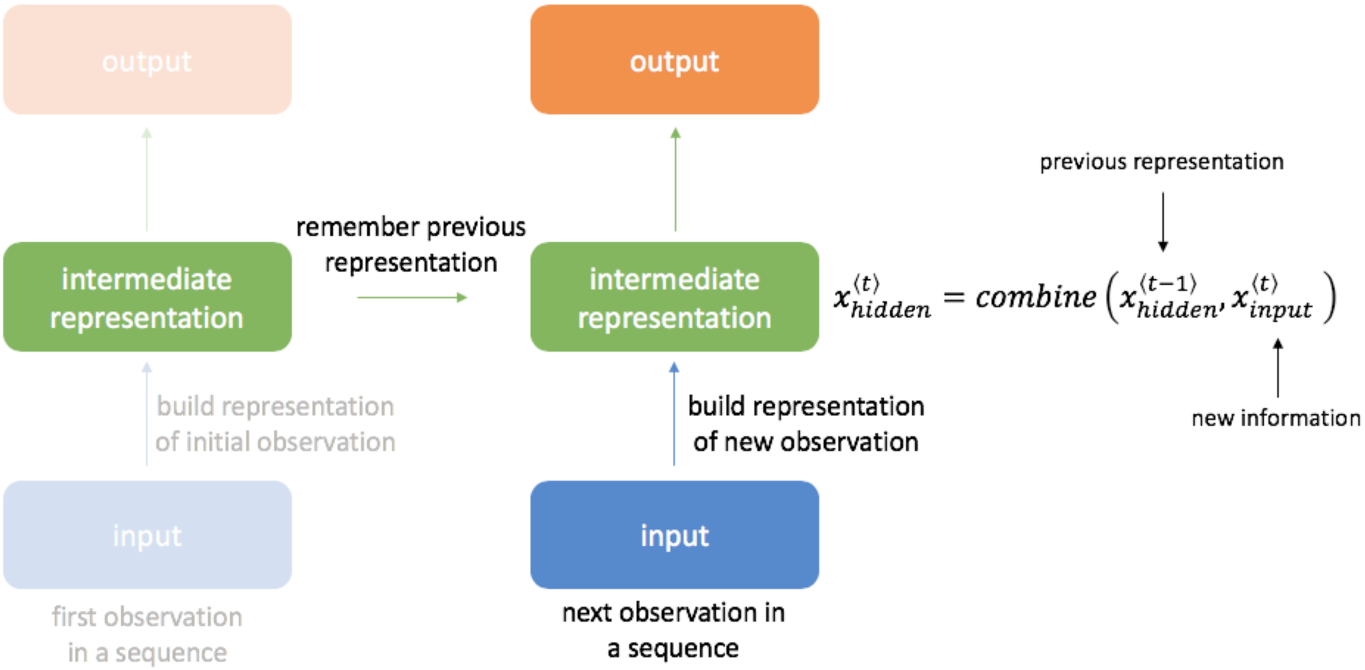
output

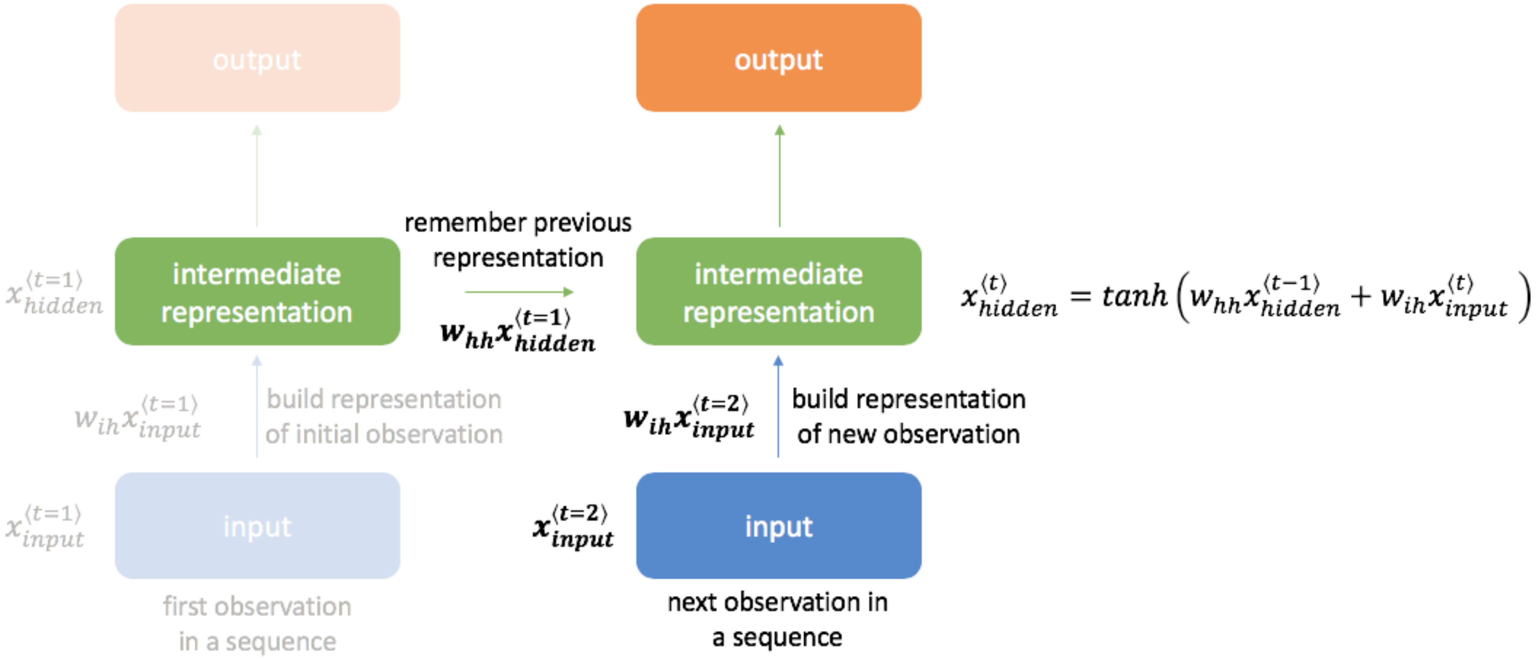
intermediate representation

build representation of new observation

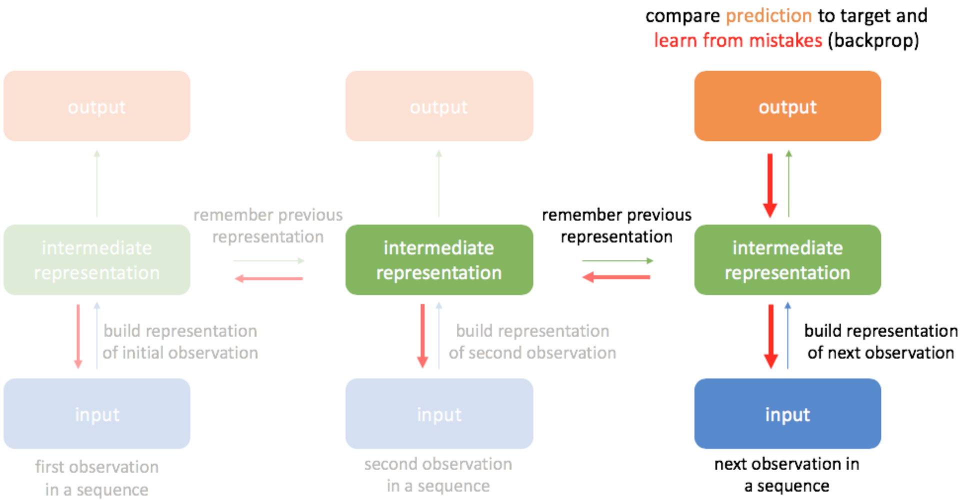
input

next observation in a sequence


output
output
previous representation
remember previous representation
intermediate representation
intermediate representation
$x_{hidden}^{\langle t\rangle} = combine\left(x_{hidden}^{\langle t-1\rangle}, x_{input}^{\langle t\rangle}\right)$
build representation of initial observation
build representation of new observation
new information
input
input
first observation in a sequence
next observation in a sequence


output
output
$x_{hidden}^{\langle t=1\rangle}$
intermediate representation
remember previous representation
$w_{hh}x_{hidden}^{\langle t=1\rangle}$
intermediate representation
$x_{hidden}^{\langle t\rangle} = tanh\left(w_{hh}x_{hidden}^{\langle t-1\rangle} + w_{ih}x_{input}^{\langle t\rangle}\right)$
$w_{ih}x_{input}^{\langle t=1\rangle}$
build representation of initial observation
$w_{ih}x_{input}^{\langle t=2\rangle}$
build representation of new observation
$x_{input}^{\langle t=1\rangle}$
input
$x_{input}^{\langle t=2\rangle}$
input
first observation in a sequence
next observation in a sequence

Backprop



compare prediction to target and
learn from mistakes (backprop)

output

output

output

remember previous
representation

remember previous
representation

intermediate
representation

intermediate
representation

intermediate
representation

build representation
of initial observation

build representation
of second observation

build representation
of next observation

input

input

input

first observation
in a sequence

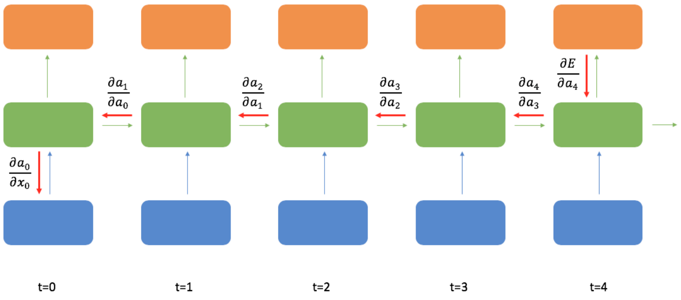
second observation
in a sequence

next observation in
a sequence

Notation:

$a_t = x_{hidden}^{\langle t=t \rangle}$ (the output of a recurrent layer)

$x_t = x_{input}^{\langle t=t \rangle}$ (the input to a recurrent layer)

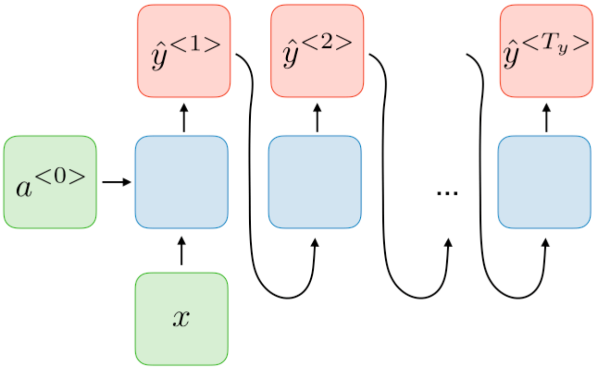


$\frac{\partial a_1}{\partial a_0}$ $\frac{\partial a_2}{\partial a_1}$ $\frac{\partial a_3}{\partial a_2}$ $\frac{\partial a_4}{\partial a_3}$ $\frac{\partial E}{\partial a_4}$

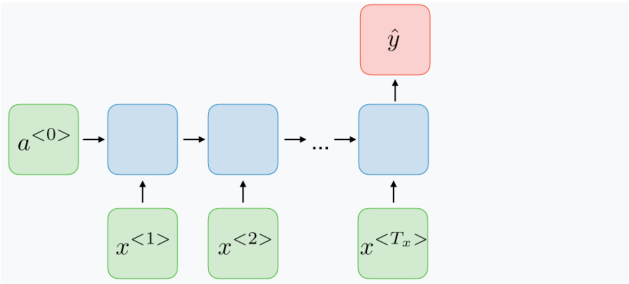
$\frac{\partial a_0}{\partial x_0}$

t=0 t=1 t=2 t=3 t=4

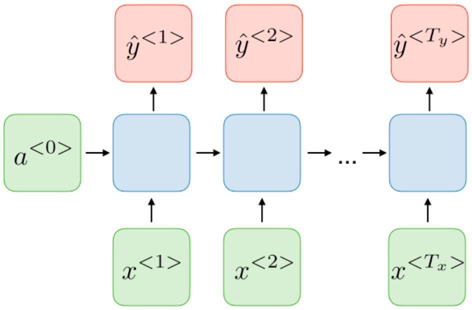
One-to-many



Many-to-one



Many-to-Many

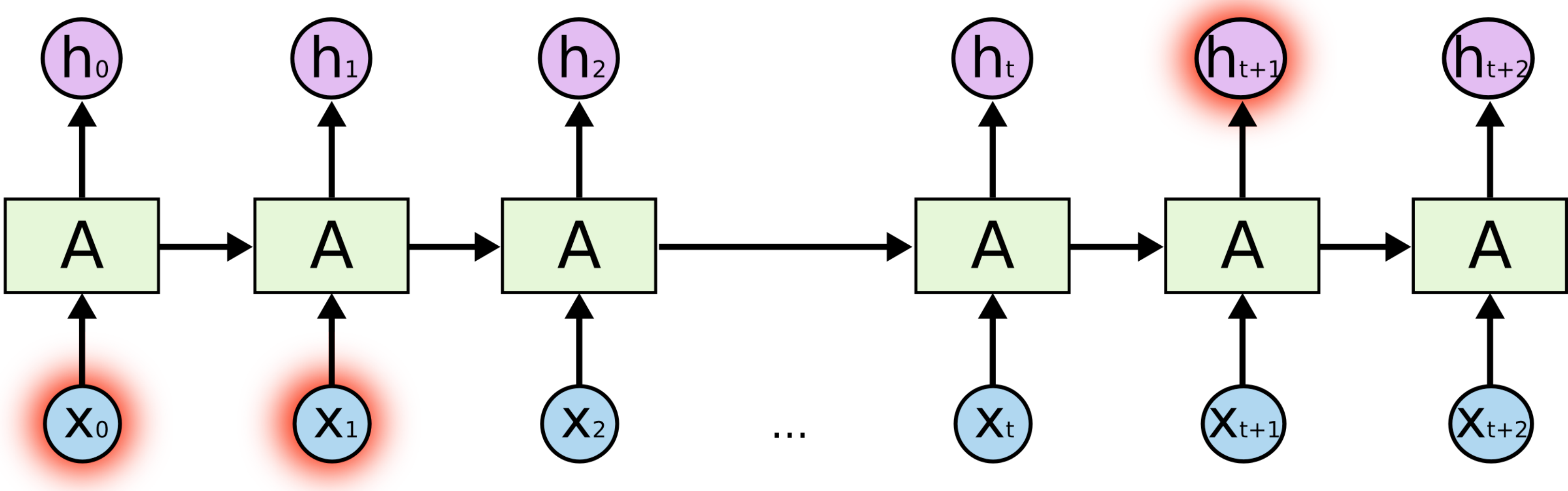


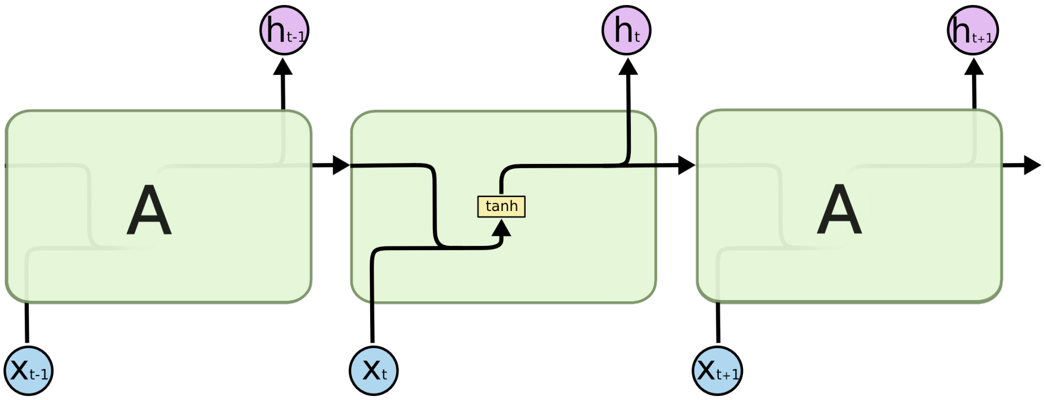
LTSM- Networks

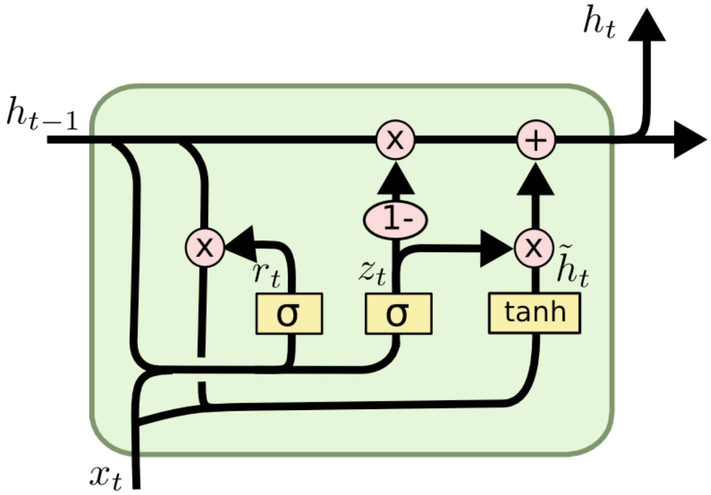
https://pytorch.org/tutorials/beginner/nlp/sequence_models_tutorial.html

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

How do you remember things for long times?
Many layers….







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

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

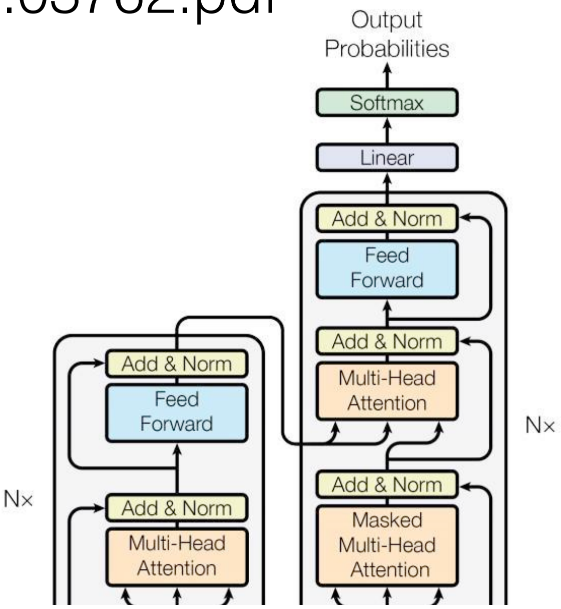
$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

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

Transformers

https://pytorch.org/tutorials/beginner/transformer_tutorial.html

https://arxiv.org/pdf/1706.03762.pdf



Tranformers: Language Translation