Statistical Dialogue Systems

NPFL099 Statistické Dialogové systémy

2. Machine Learning Toolkit

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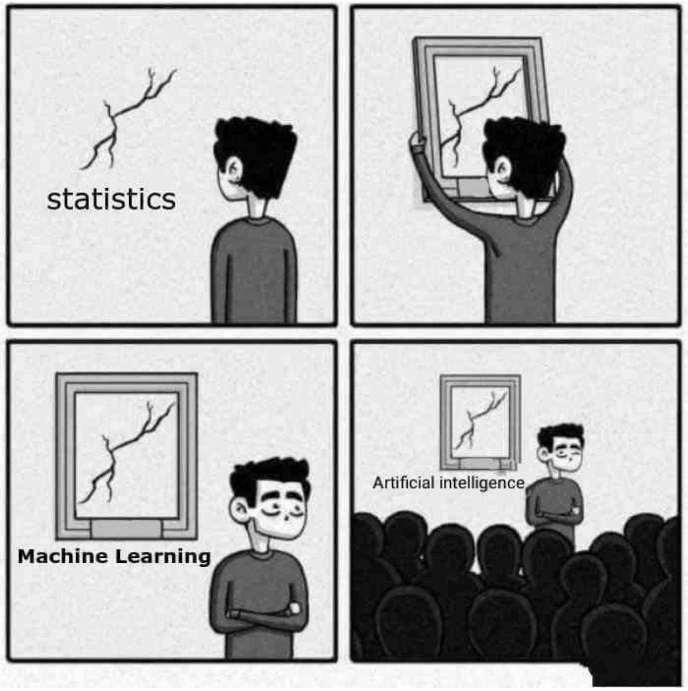
http://ufal.cz/npfl099

10. 10. 2019

Machine Learning

ML is basically function approximation

- function: data (**features**)→ **labels**
  - discrete labels = **classification**
  - continuous labels = **regression**
- function shape
  - this is where different algorithms differ
  - neural nets: complex functions, composed of simple building blocks (linear, sigmoid, tanh…)
- **training/learning** = adjusting function parameters to minimize error
  - **supervised** learning = based on data + labels given in advance
  - **reinforcement** learning = based on exploration & rewards given online



https://towardsdatascience.com/no-machine-learning-is-not-just-glorified-statistics-26d3952234e3

Neural networks

- Can be used for both classification & sequence models
- **Non-linear functions**, composed of basic building blocks
  - stacked into **layers**
- Layers are built of **activation functions**:
  - linear functions
  - nonlinearities – sigmoid, tanh, ReLU
  - softmax – probability estimates:

$$\text{softmax}(\mathbf{x})_i = \frac{\exp(x_i)}{\sum_{j=1}^{|\mathbf{x}|} \exp(x_j)}$$

- Fully differentiable – training by gradient descent
  - network output incurs loss/cost
  - gradients **backpropagated** from loss to all parameters (composite function differentiation)

Sigmoid

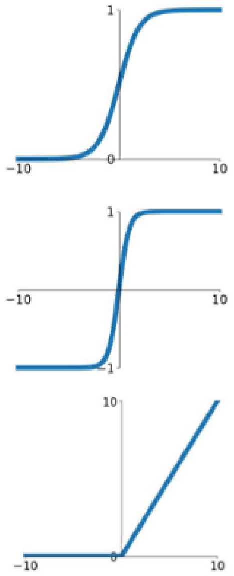
$\sigma(x) = \frac{1}{1+e^{-x}}$

tanh

$\tanh(x)$

ReLU

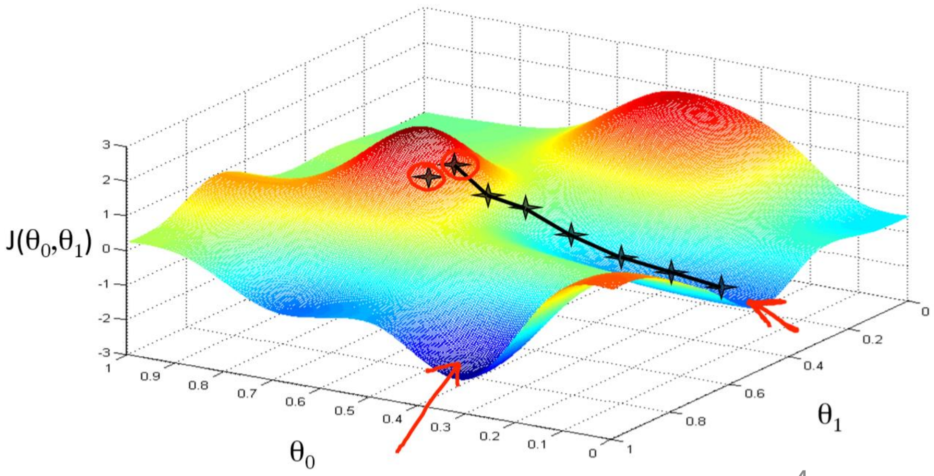
$\max(0, x)$



https://medium.com/@shrutijadon10104776/survey-on-activation-functions-for-deep-learning-9689331ba092

Gradient Descent

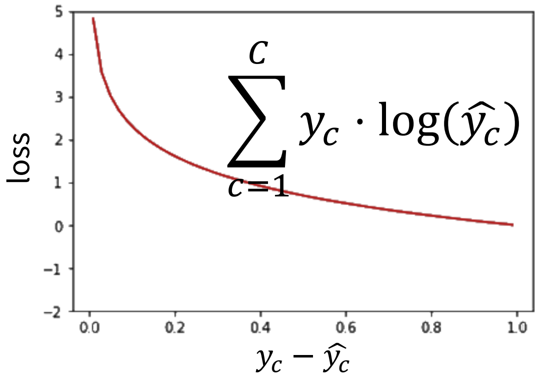
- supervised training– **gradient descent** methods
  - minimizing a **cost/loss function**
    (notion of error – given system output, how far off are we?)
  - calculus: derivative = steepness/slope
  - follow the slope to find the minimum – derivative gives the direction
  - **learning rate** = how fast do we go (needs to be tuned)
- gradient typically computed over **mini-batches**
  - random bunches of a few training instances
  - not as erratic as using just 1 instance,
    not so slow as computing over whole data
  - **stochastic gradient descent**

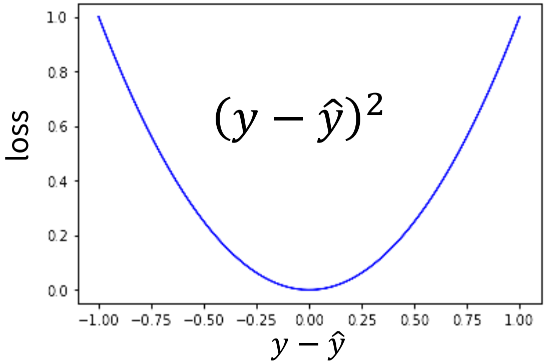


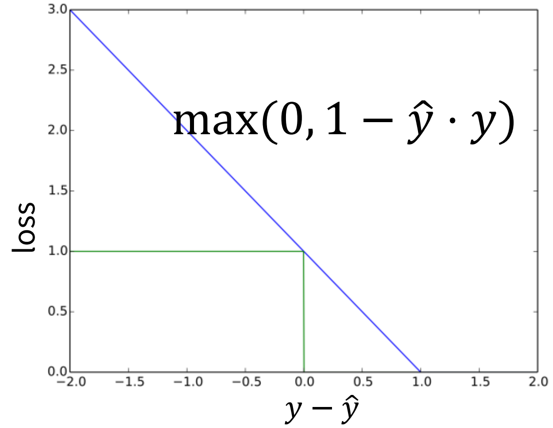
https://hackernoon.com/gradient-descent-aynk-7cbe95a778da

Cost/Loss Functions

- differ based on what we're trying to predict
- **logistic / log loss** ("cross entropy")
  - for classification / softmax – including **word prediction**
    - classes from the whole dictionary
  - pretty stupid for sequences, but works
    - sequence shifted by 1 ⇒ everything wrong
- **squared error loss** – for regression
  - forcing the predicted float value to be close to actual
- **hinge loss** – for binary classification (SVMs), ranking
  - forcing correct sign
- many others, variants



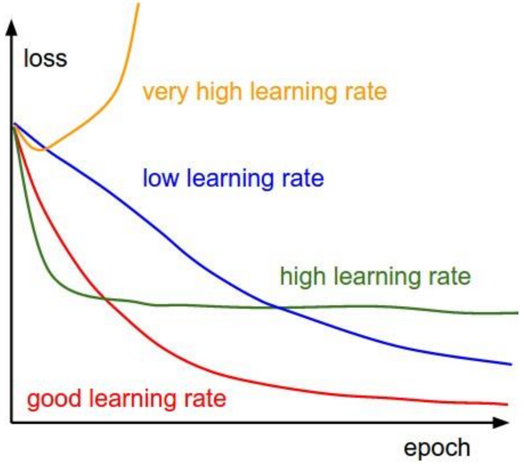




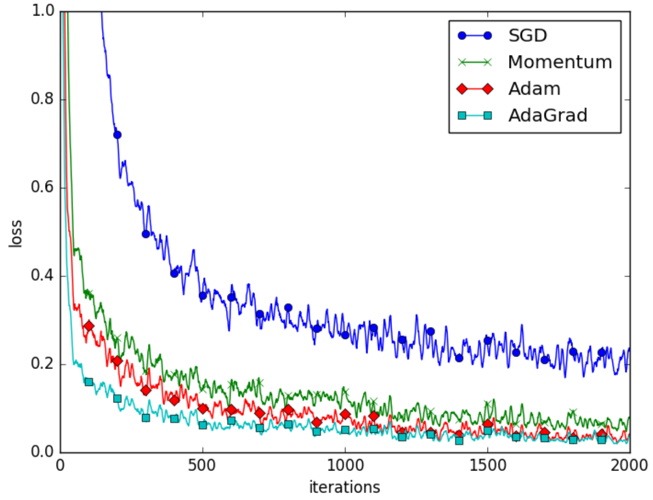
https://machinelearningmastery.com/loss-and-loss-functions-for-training-deep-learning-neural-networks/
https://medium.com/@risingdeveloper/visualization-of-some-loss-functions-for-deep-learning-with-tensorflow-9f60be9d09f9
https://en.wikipedia.org/wiki/Hinge_loss

Gradient Descent: Learning Rate

- Learning rate (α) is tricky
  - too high α = may not find optimum
  - too low α = may take forever
- **Learning rate decay**: start high, lower α gradually
- **Momentum**: moving average
  - $m = \beta \cdot m - \alpha \cdot \Delta$, update by m
- Better options – per-parameter
  - look at how often each single weight gets updated
  - **AdaGrad** – all history
    - remember sum of total gradients squared: $\sum_t \Delta_t^2$
    - divide learning rate by $\sqrt{(\sum \Delta_t^2)}$
  - **Adam** – per-parameter momentum
    - moving averages for Δ & Δ^2: $m = \beta_1 \cdot m + (1 - \beta_1)\Delta$, $v = \beta_2 \cdot v + (1 - \beta_2)\Delta^2$
    - use m instead of Δ, divide learning rate by $\sqrt{(v)}$



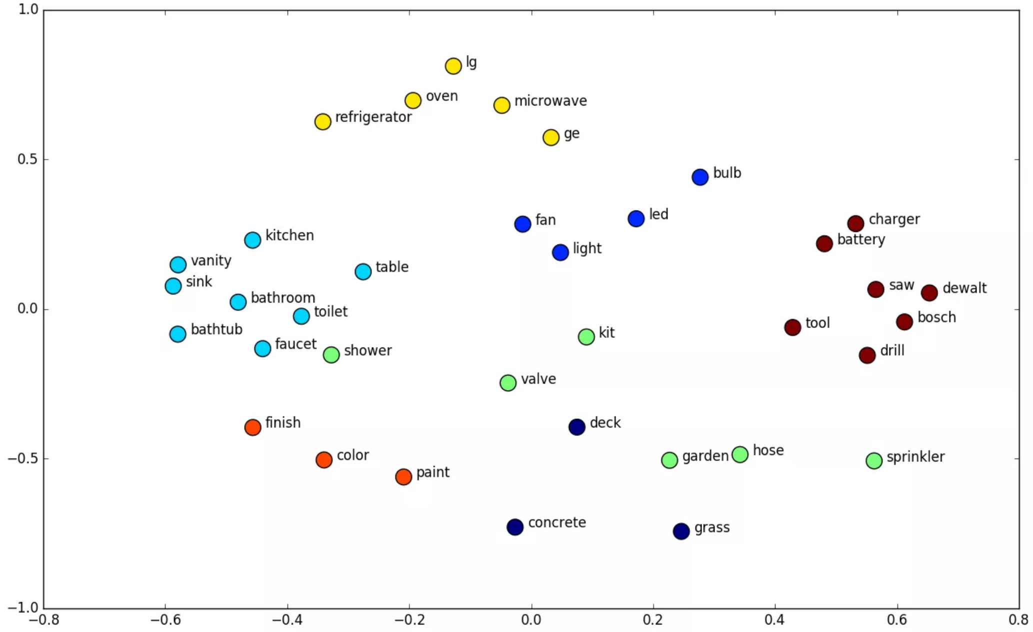
http://cs231n.github.io/neural-networks-3/



http://kaeken.hatenablog.com/entry/2016/11/10/203151

Word Embeddings

- let the network learn features by itself
  - input is just words
    (vocabulary is numbered)
- distributed word representation
  - each word = **vectors of floats**
- part of network parameters – trained
  a) random initialization
  b) pretraining



http://blog.kaggle.com/2016/05/18/home-depot-product-search-relevance-winners-interview-1st-place-alex-andreas-nurlan/

- network learns which words are used similarly
  - they end up having
    close embedding values
  - different embeddings
    for different tasks

http://ruder.io/word-embeddings-2017/

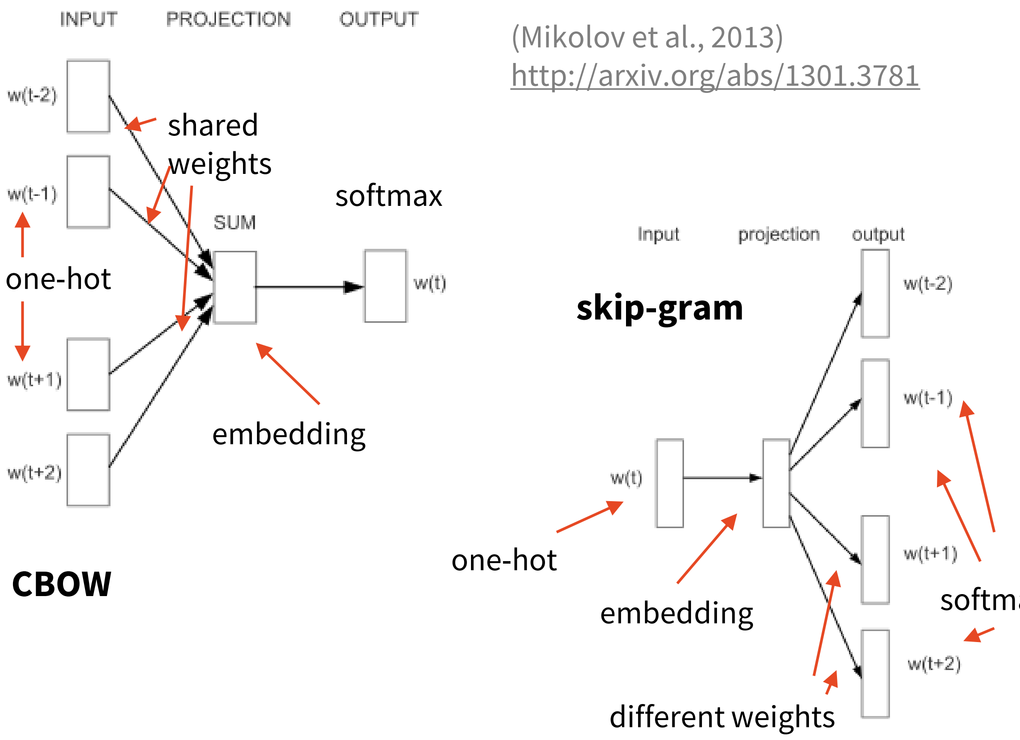
Word Embeddings

- Vocabulary is unlimited, embedding matrix isn't
  - + the bigger the embedding matrix, the slower your models
- Special **out-of-vocabulary token** <unk>
  - "default" / older option
  - all words not found assigned this entry
  - can be trained using some rare words in the data
  - problem for generation – you don't want these on the output
- Using limited sets
  - **characters** – very small set
    - works, but makes for very long sequences
  - **subwords** – decided e.g. by byte-pair encoding
    - start from individual characters
    - iteratively merge most frequent bigram, until you get desired # of subwords
    - *sub@@ word* – the @@ marks "no space after"

(Sennrich et al., 2016)
https://www.aclweb.org/anthology/P16-1162/

Pretrained Word Embeddings

- **Word2Vec**
  - Continuous Bag-of-Words
    - predict a word, given $\pm k$ words window
    - disregarding word order within the window
  - Skip-gram: reverse
    - given a word, predict its $\pm k$ word window
    - now word order matters (closer words = higher weight)



(Mikolov et al., 2013)
http://arxiv.org/abs/1301.3781

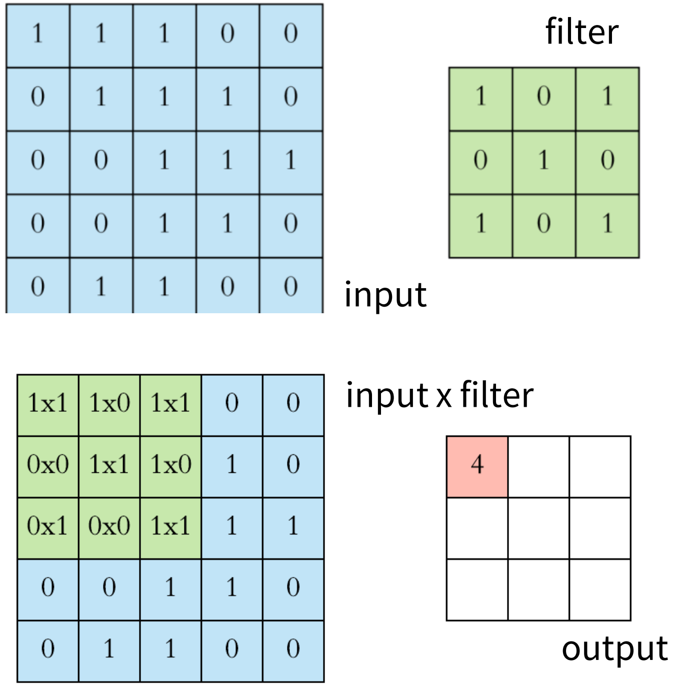
- **GloVe**
  - optimized directly from corpus co-occurrences (= w_1 close to w_2)
  - target: $e_1 \cdot e_2 = \log(\#\text{co-occurrences})$
    - number weighted by distance, weighted down for low totals
  - trained by minimizing reconstruction loss on a co-occurrence matrix

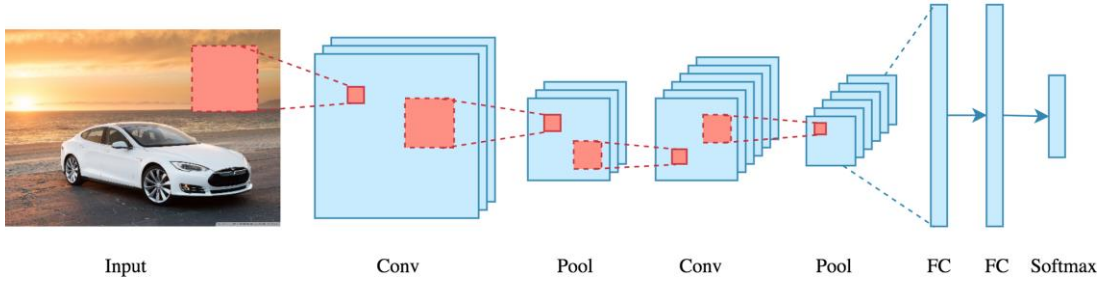
(Pennington et al., 2014)
http://aclweb.org/anthology/D14-1162

https://geekyisawesome.blogspot.com/2017/03/word-embeddings-how-word2vec-and-glove.html
https://machinelearninginterview.com/topics/natural-language-processing/what-is-the-difference-between-word2vec-and-glove/

Convolutional Networks

- Designed for computer vision – inspired by human vision
  - works for language in 1D, too!
- Use less parameters than fully connected – **filter/kernel**
- Apply filter repeatedly over the input
  - element-wise multiply window of input x filter
  - sum + apply non-linearity (ReLU) to result
  - => produce 1 element of output
- **Stride** – how many steps to skip
  - less overlap, reducing output dimension
- **Pooling** – no filter, pre-set operation
  - **maximum**/average on each window
  - typical CNN architecture alternates convolution & pooling



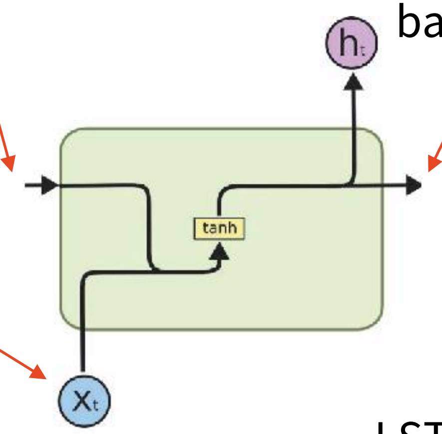


https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

Recurrent Neural Networks

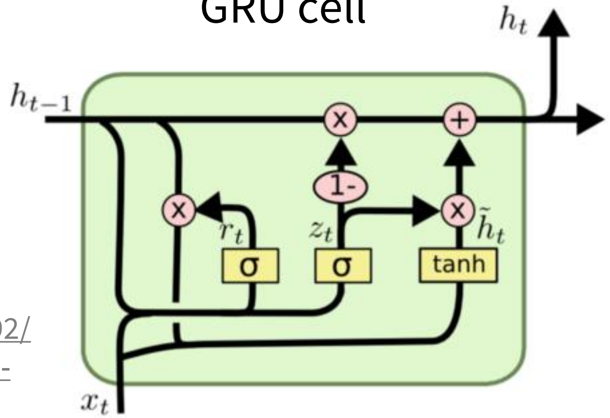
- Many identical layers with shared parameters (**cells**)
  - ~ the same layer is applied multiple times, taking its own outputs as input
    - ~ same number of layers as there are tokens
    - output = **hidden state** – fed to the next step
  - additional input – next token features

basic RNN cell

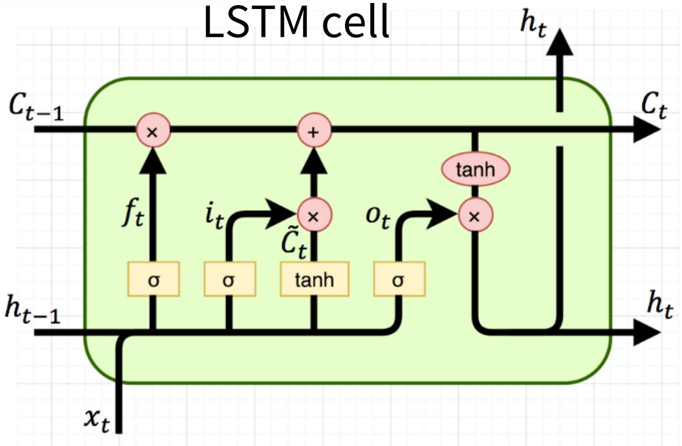


- Cell types
  - **basic RNN**: linear + tanh
    - problem: vanishing gradients
    - can't hold long recurrences
  - **GRU, LSTM**: more complex, to make backpropagation work better
    - "gates" to keep old values

GRU cell



LSTM cell



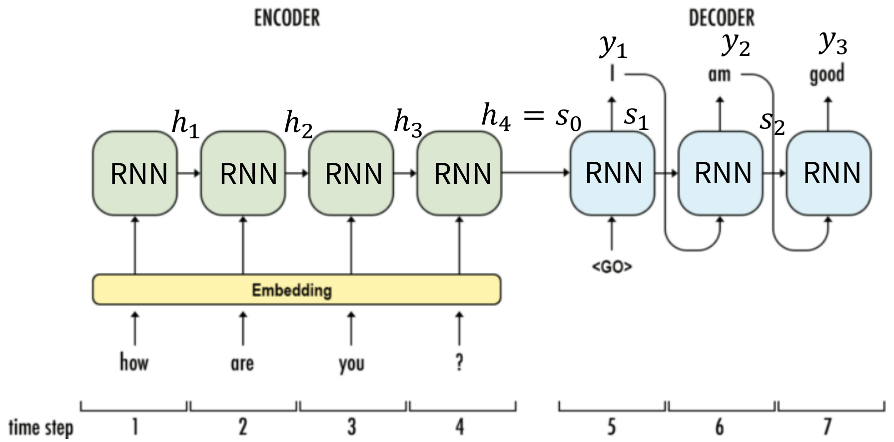
https://medium.com/@saurabh.rathor092/simple-rnn-vs-gru-vs-lstm-difference-lies-in-more-flexible-control-5f33e07b1e57

Encoder-Decoder Networks
(Sequence-to-sequence)

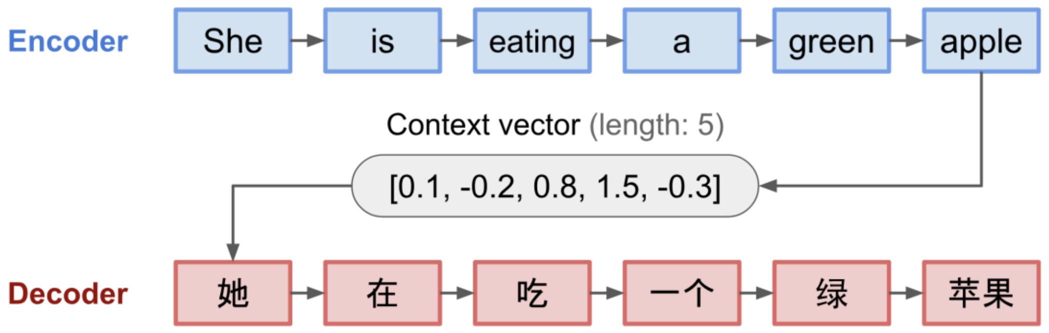
- Default RNN paradigm for sequences/structure prediction
  - **encoder** RNN: encodes the input token-by-token into **hidden states** h_t
    - next step: last hidden state + next token as input
  - **decoder** RNN: constructs the output token-by-token
    - initialized by last encoder hidden state
    - output: hidden state & softmax over output vocabulary + argmax
    - next step: last hidden state + last generated token as input
  - LSTM/GRU cells over vectors of ~ embedding size
  - used in MT, dialogue, parsing…
    - more complex structures linearized to sequences

$$\boldsymbol{h}_0 = \mathbf{0}$$
$$\boldsymbol{h}_t = \text{cell}(\boldsymbol{x}_t, \boldsymbol{h}_{t-1})$$

$$\boldsymbol{s}_0 = \boldsymbol{h}_T$$
$$p(y_t | y_1, \dots y_{t-1}, \mathbf{x}) = \text{softmax}(\boldsymbol{s}_t)$$
$$\boldsymbol{s}_t = \text{cell}(\boldsymbol{y}_{t-1}, \boldsymbol{s}_{t-1})$$



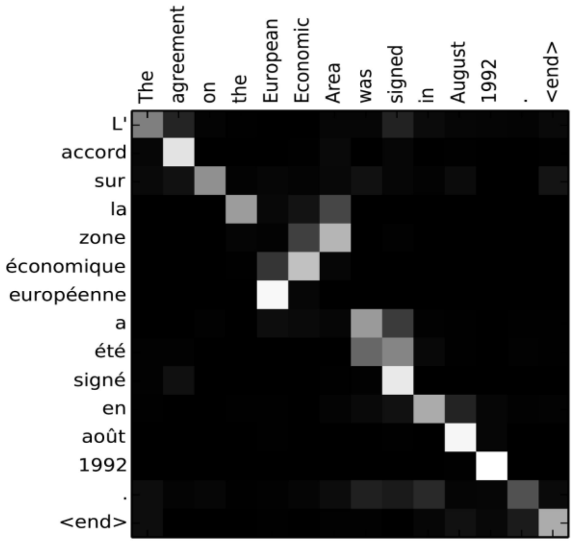
https://medium.com/syncedreview/a-brief-overview-of-attention-mechanism-13c578ba9129

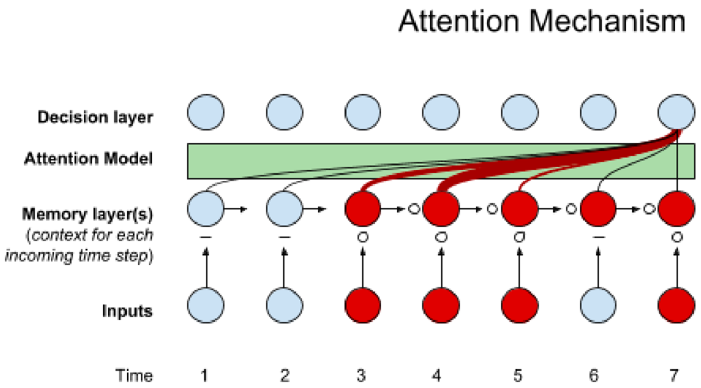


https://lilianweng.github.io/lil-log/2018/06/24/attention-attention.html

Attention

- Encoder-decoder is too crude for complex sequences
  - the whole input is crammed into a fixed-size vector (last hidden state)
- **Attention** = “memory” of **all** encoder hidden states
  - weighted combination, re-weighted for every decoder step
    → can focus on currently important part of input
  - fed into decoder inputs + decoder softmax layer
- **Self-attention** – over previous decoder steps
  - increases consistency when generating long sequences



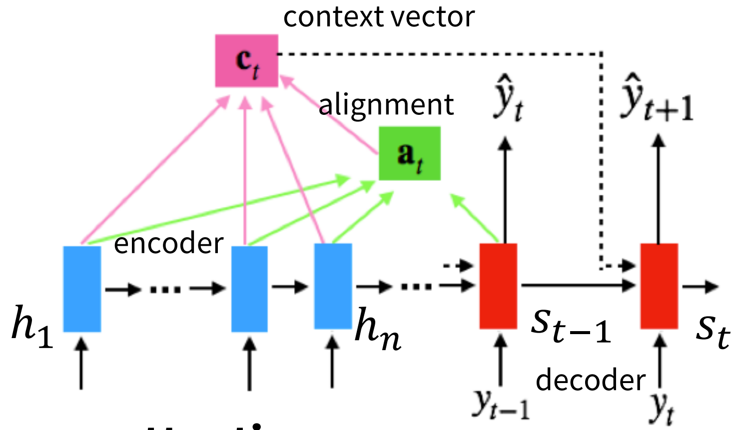


https://skymind.ai/wiki/attention-mechanism-memory-network

Bahdanau & Luong **Attention**

(Bahdanau et al., 2015)
http://arxiv.org/abs/1409.0473
(Luong et al., 2015)
http://arxiv.org/abs/1508.04025

- different combination with decoder state
  - Bahdanau: use on input to decoder cell
  - Luong: modify final decoder state
- different weights computation



Bahdanau attention

attention weights = alignment model

decoder state

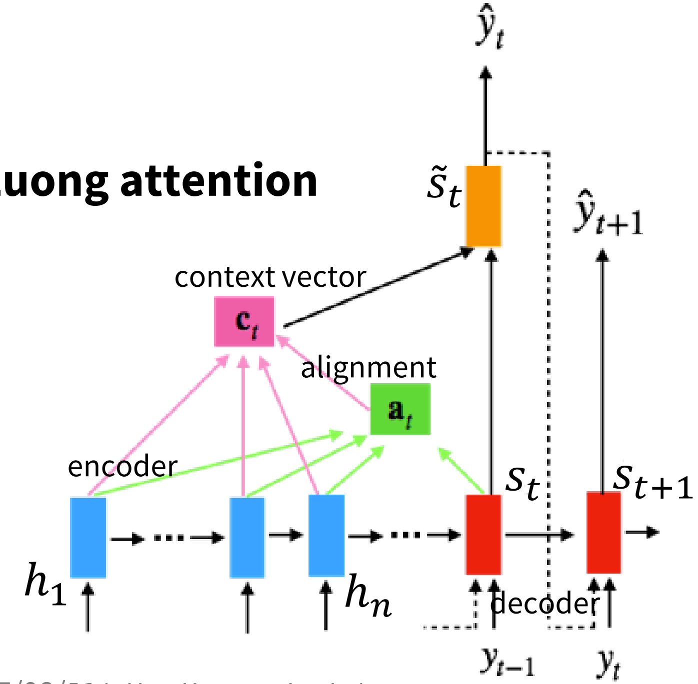
trained parameters

Bahdanau:

$$\alpha_{ti} = \mathrm{softmax}(\boldsymbol{v}_\alpha \cdot \tanh(\mathbf{W}_\alpha \cdot \boldsymbol{s}_{t-1} + \mathbf{U}_\alpha \cdot \boldsymbol{h}_i))$$

encoder hidden state

Luong attention



Luong:

$$\alpha_{ti} = \mathrm{softmax}(\boldsymbol{h}_i^\top \cdot \boldsymbol{s}_t)$$

decoder state

encoder hidden state

attention value = context vector

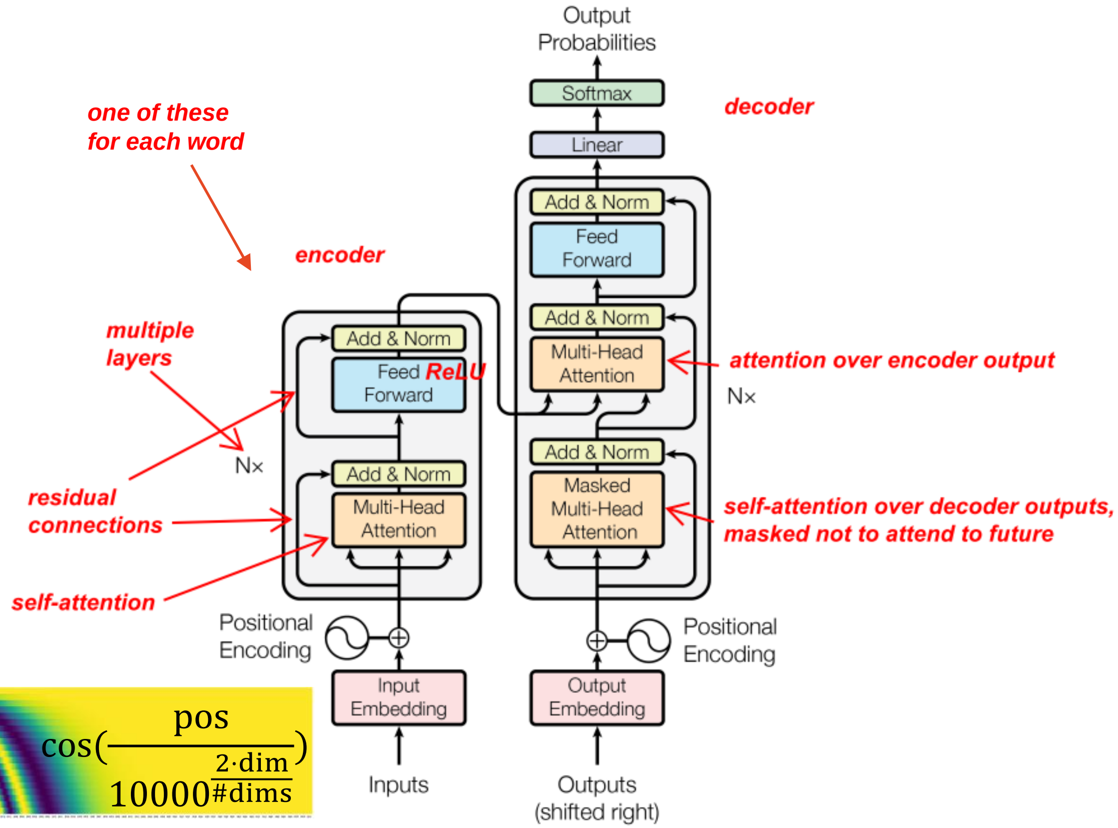
same for both – sum encoder hidden states weighted by α_{ti}

$$\boldsymbol{c}_t = \sum_{i=1}^{n} \alpha_{ti} \boldsymbol{h}_i$$

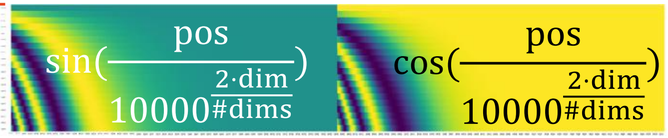
http://cnyah.com/2017/08/01/attention-variants/

Transformer

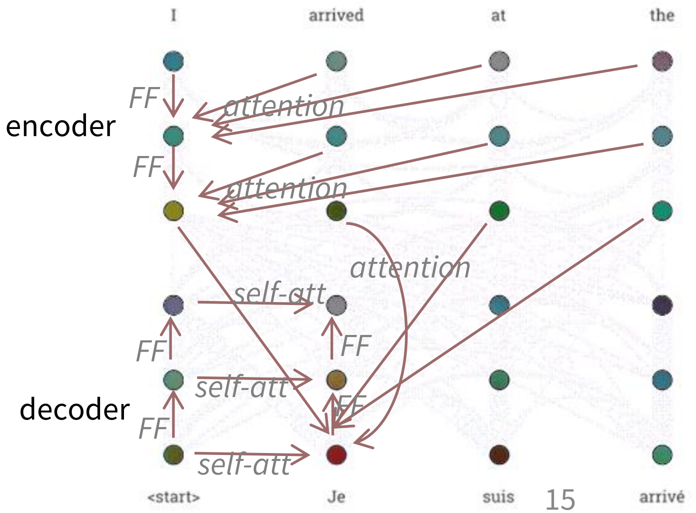
(Waswani et al., 2017)
https://arxiv.org/abs/1706.03762



- getting rid of (encoder) recurrences
  - replace everything with attention + feed-forward networks
  - ⇒ needs more layers
  - ⇒ needs to encode positions
- positional encoding
  - adding position-dependent patterns to the input



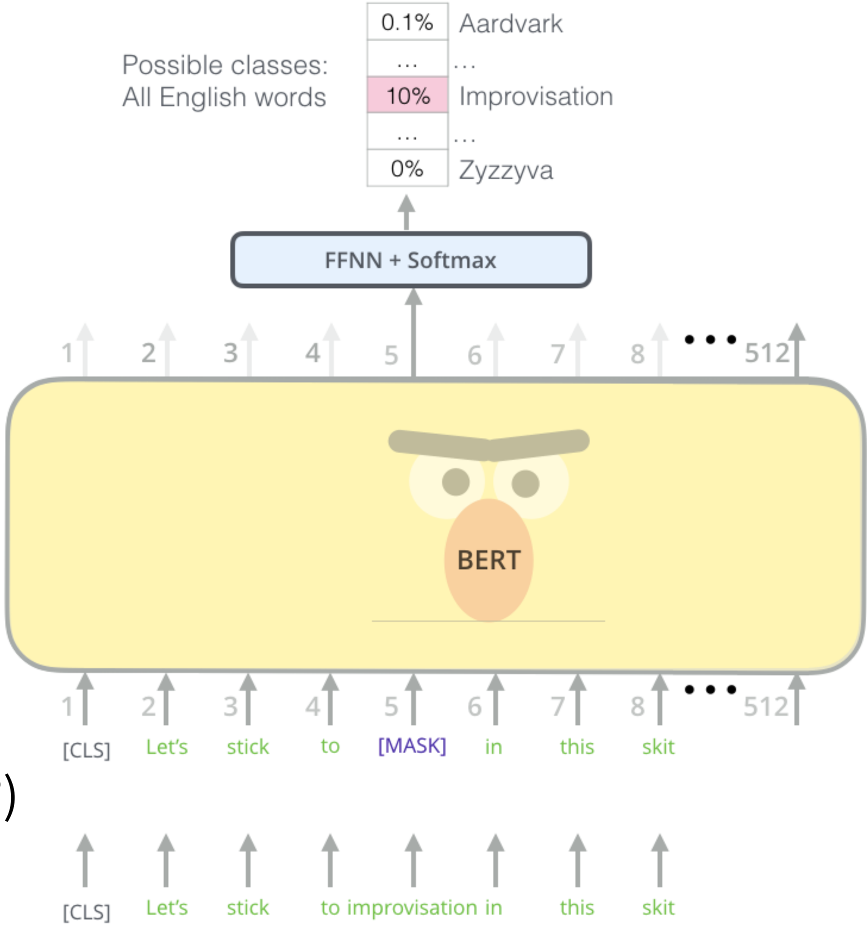
- attention – dot-product (Luong style)
  - scaled by $\frac{1}{\sqrt{\#dims}}$ (so values don't get too big)
  - **more heads** (attentions in parallel) – focus on multiple inputs
- faster to train, better results (sometimes)



http://jalammar.github.io/illustrated-transformer/ https://ai.googleblog.com/2017/08/transformer-novel-neural-network.html

Contextual Word Embeddings

- Beyond pretrained word embeddings
  - words have different meanings based on context
  - static word embeddings (word2vec/GloVe) don't reflect that
- **ELMo**
  - 2-layer bidirectional LSTMs
    trained for language modelling
  - ELMo embeddings = weighted sum of
    input static embeddings & both layers & directions
    - the weights are trained for a specific downstream task
- **BERT**
  - huge Transformer encoder trained for:
    - masked word prediction
    - adjacent sentences detection (does B come right after A?)
  - BERT = any combination of the Transformer layers

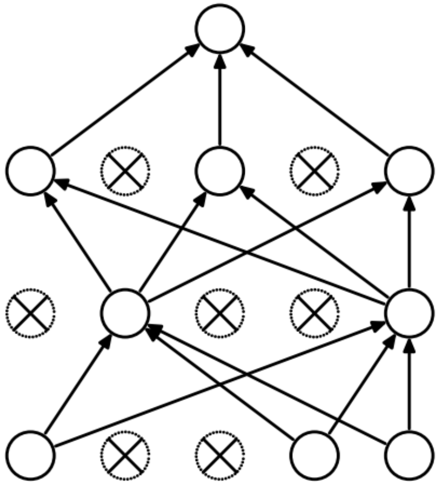


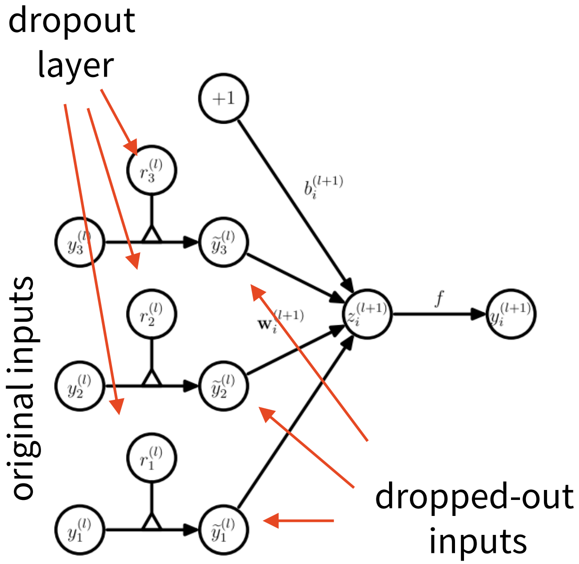
http://jalammar.github.io/illustrated-bert/

Dropout

(Srivastava et al., 2014)
http://jmlr.org/papers/v15/srivastava14a.html

- overfitting to training data is a problem for NNs
  - too many parameters
- **Dropout** – simple regularization technique
  - more effective than e.g. weight decay (L2)
  - **zero out some neurons/connections** in the network at random
  - technically: multiply by dropout layer
    - 0/1 with some probability (typically 0.5–0.8)
  - at training time only – full network for prediction
  - weights scaled down after training
    - they end up larger than normal because there’s fewer nodes
    - done by libraries automatically
  - may still need larger networks to compensate



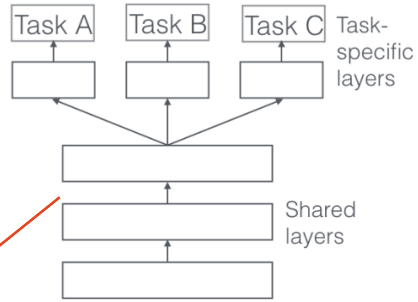


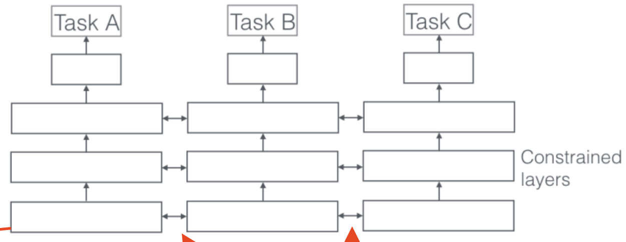
(b) Dropout network

Multi-task Learning

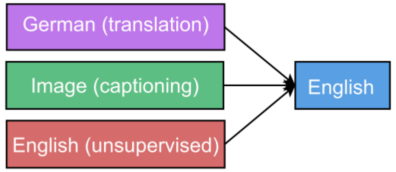
(Ruder, 2017)
http://arxiv.org/abs/1706.05098
(Fan et al., 2017)
http://arxiv.org/abs/1706.04326
(Luong et al., 2016)
http://arxiv.org/abs/1511.06114

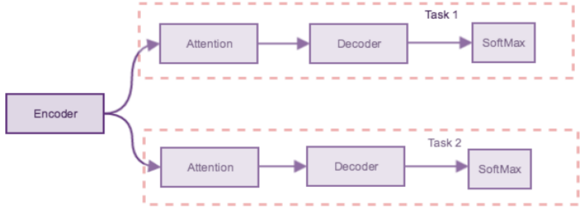
- achieve better generalization by learning more things at once
  - a form of regularization
  - implicit data augmentation
  - biasing/focusing the model
    - e.g. by explicitly training for an important subtask
- parts of network shared, parts task-specific
  - hard sharing = parameters truly shared (most common)
  - soft sharing = regularization by parameter distance
  - different approaches w. r. t. what to share
- training – alternating between tasks
  - so the network doesn't "forget"

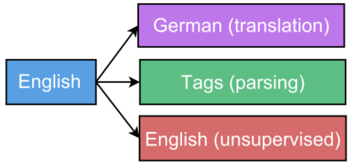


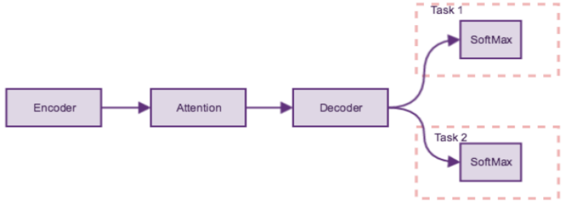


e.g. L2 on distance





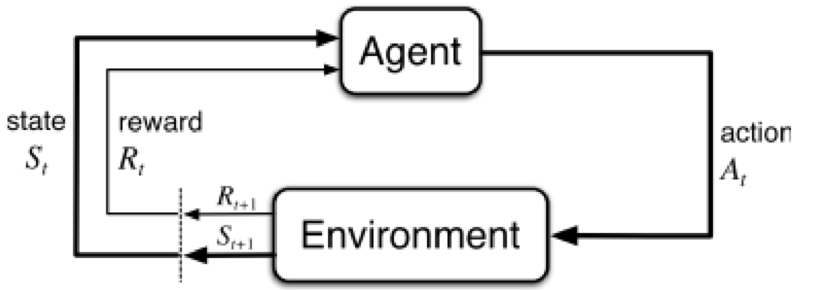




Reinforcement Learning

- Learning from **weaker supervision**
  - only get feedback once in a while, not for every output
  - good for globally optimizing sequence generation
    - you know if the whole sequence is good
    - you don't know if step X is good
  - sequence = e.g. sentence, dialogue
- Framing the problem as **states** & **actions** & **rewards**
  - "robot moving in space", but works for dialogue too
  - state = generation so far (sentence, dialogue state)
  - action = one generation output (word, system dialogue act)
  - defining rewards might be an issue
- Training: **maximizing long-term reward**
  - via state/action values (Q function)
  - directly – optimizing policy

your model

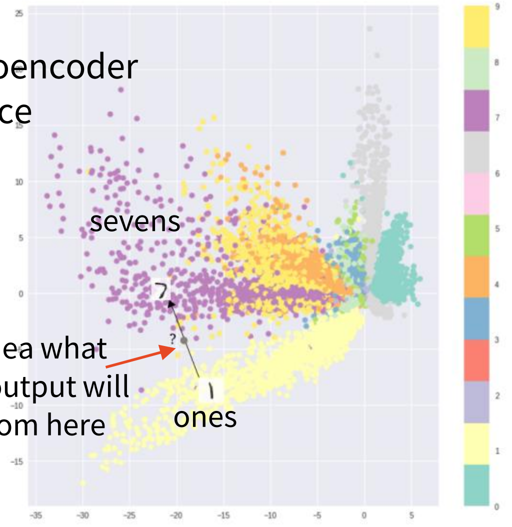


(Sutton & Barto, 2018)

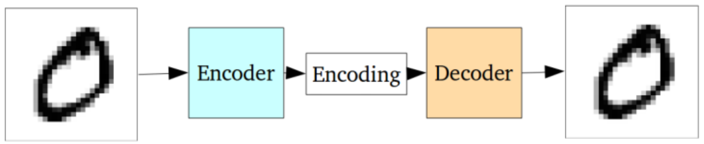
some definition
of rewards

https://towardsdatascience.com/intuitively-understanding-variational-autoencoders-1bfe67eb5daf

Autoencoders

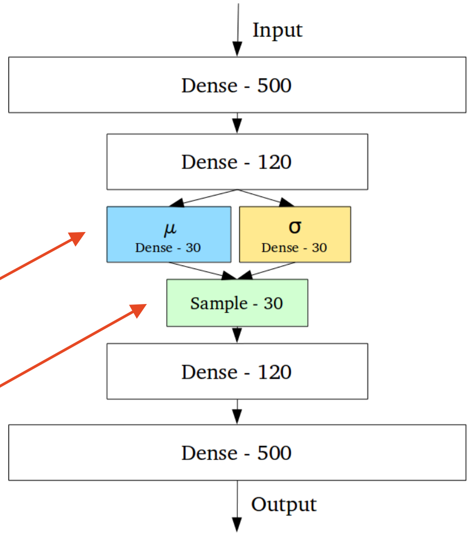


- Using NNs as **generative models**
  - more than classification – modelling the whole distribution
    - (of e.g. possible texts, images)
  - **generate new instances** that look similar to training data
  - **unsupervised learning**
- **Autoencoder**: input → encoding → input

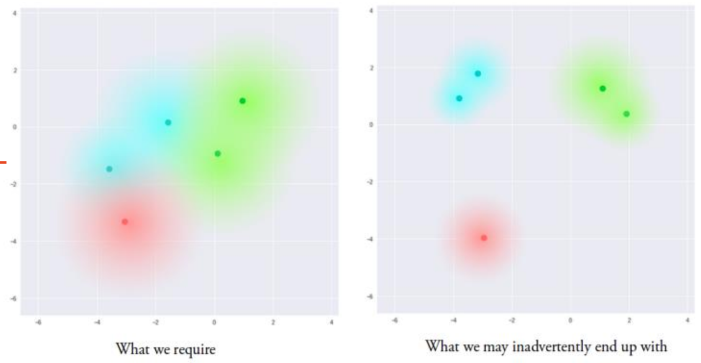


  - encoding ~ “embedding” in latent space (i.e. some vector)
  - trained by reconstruction loss
  - problem: can’t easily get valid embeddings for generating new outputs
    - parts of embedding space might be unused – will generate weird stuff
    - no easy interpretation of embeddings – no idea what the model will generate
  - still has uses:
    - **denoising autoencoder**: add noise to inputs, train to generate clean outputs
    - multi-task learning, representations for use in downstream tasks

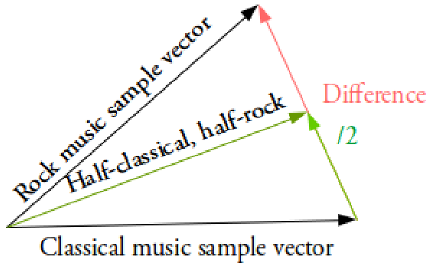
Variational Autoencoders



- Making the encoding latent space more useful
  - using **Gaussians** – continuous space by design
  1) encoding input into vectors of means μ & std. deviations σ
  2) sampling encodings from $N(\mu, \sigma)$ for generation
     - samples vary a bit even for the same input
     - decoder learns to be more robust
  - model can degenerate into normal AE ($\sigma \rightarrow 0$)
     - we need to encourage some σ, smoothness, overlap ($\mu \sim 0$)
     - add 2nd loss: KL divergence from $N(0,1)$
     - VAE learns a trade-off between using unit Gaussians & reconstructing inputs



- Problem: still not too much control of the embeddings
  - we can only guess what kind of output the model will generate



https://towardsdatascience.com/intuitively-understanding-variational-autoencoders-1bfe67eb5daf
http://kvfrans.com/variational-autoencoders-explained/

VAE details

- VAE objective:
  - **reconstruction loss** (maximizing $p(x|z)$ in the decoder), MLE as per usual
  - **latent loss** (KL-divergence from ideal $p(z) \sim \mathcal{N}(0,1)$ in the encoder)

$$\mathcal{L} = -\mathbb{E}_q[\log p(x|z)] + KL[q(z|x)||p(z)]$$

- This is equivalent to maximizing true $\log p(x)$ with some error
  - i.e. maximizing **evidence lower bound** (ELBO) / variational lower bound:

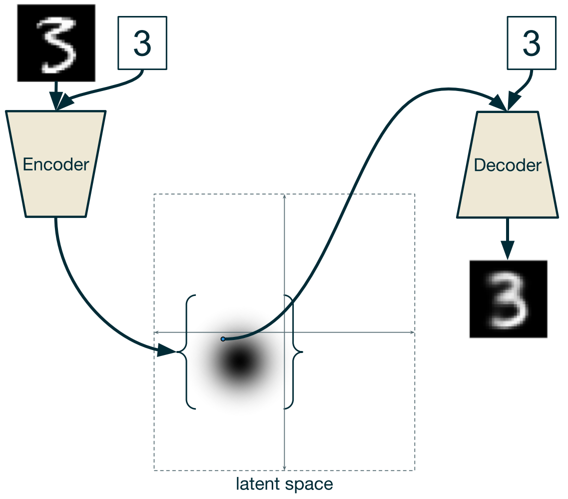
$$\mathbb{E}_q[\log p(x|z)] - KL[q(z|x)||p(z)] = \underbrace{\underset{\text{“evidence” (i.e. data)}}{\log p(x)} - \overset{\text{error incurred by using } q \text{ instead of true distribution } p}{KL[q(z|x)||p(z|x)]}}_{\text{ELBO}}$$

- Sidestepping sampling – **reparameterization trick**
  - $z \sim \mu + \sigma \cdot \mathcal{N}(0,1)$, then differentiate w. r. t. μ and σ

https://wiseodd.github.io/techblog/2016/12/10/variational-autoencoder/

Conditional Variational Autoencoders

- Direct control over types of things to generate
- Additional conditioning on a given label/type/class c
  - c can be anything (discrete, continuous…)
    - image class: MNIST digit
    - sentiment
    - “is this a good reply?”
    - coherence level
  - just concatenate to input
  - given to both encoder & decoder at training time
- Generation – need to provide c
  - CVAE will generate a sample of type c
  - Latent space is partitioned by c
    - same latent input with different c will give different results

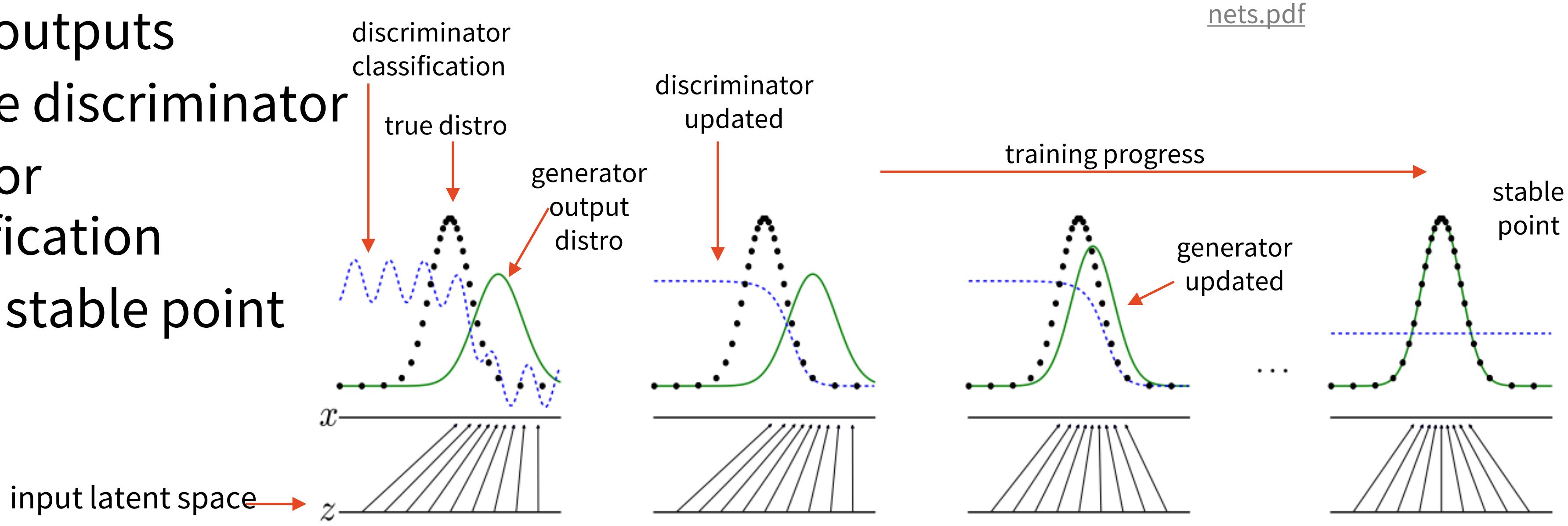


https://ijdykeman.github.io/ml/2016/12/21/cvae.html

Generative Adversarial Nets

- Training generative models to generate **believable** outputs
  - to do so, they necessarily get a better grasp on the distribution
- Getting loss from a 2nd model:
  - **discriminator D** – “adversary” classifying real vs. generated samples
  - **generator G** – trained to fool the discriminator
    - the best chance to fool the discriminator is to generate likely outputs
- Training iteratively (EM style)
  - generate some outputs
  - classify + update discriminator
  - update generator based on classification
  - this will reach a stable point

(Goodfellow et al, 2014)
http://papers.nips.cc/paper/5423-generative-adversarial-nets.pdf

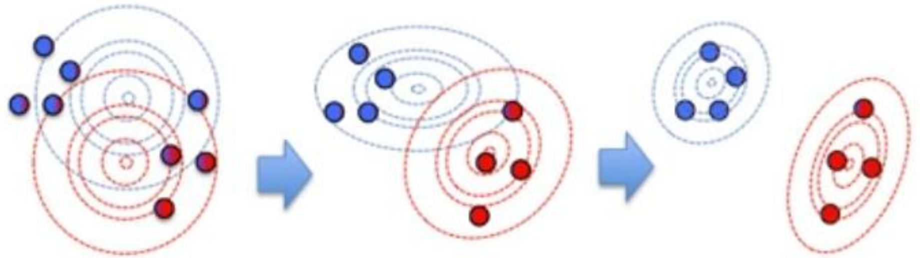


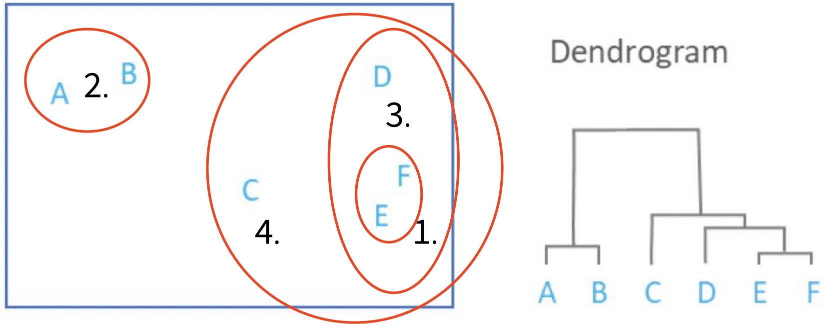
Clustering

https://en.wikipedia.org/wiki/K-means_clustering
https://www.displayr.com/what-is-hierarchical-clustering/
https://towardsdatascience.com/gaussian-mixture-models-d13a5e915c8e

- Unsupervised, finding similarities in data
- basic algorithms
  - **k-means**: assign into k clusters randomly, iterate:
    - compute means (centroids)
    - reassign to nearest centroid
  - **Gaussian mixture**: similar, but soft & variance
    - clusters = multivariate Gaussian distributions
    - estimating probabilities of belonging to each cluster
    - cluster mean/variance based on data weighted by probabilities
  - **hierarchical** (bottom up):
    start with one cluster per instance, iterate:
    - merge 2 closest clusters
    - end when you have k clusters / distance is too big
  - hierarchical top-down (reversed ↩)
- distance metrics & features decide what ends up together

https://www.youtube.com/watch?v=9YA2t78Ha68





Summary

- ML as a function mapping in → out
- Neural networks (function shapes)
  - CNNs, RNNs, encoder-decoder (seq2seq), attention, Transformer
  - input representation: embeddings (+ pretrained, + contextual)
- Supervised training
  - cost function
  - gradient descent + learning rate tricks
  - dropout
- Unsupervised learning
  - autoencoders
  - variational autoencoders
  - generative adversarial nets
  - clustering

Thanks

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room 424 (but email me first)

No labs today!
See you next week

Get the slides here:

http://ufal.cz/npfl099

References/Further:

Goodfellow et al. (2016): Deep Learning, MIT Press (http://www.deeplearningbook.org)
Kim et al. (2018): Tutorial on Deep Latent Variable Models of Natural Language (http://arxiv.org/abs/1812.06834)
Milan Straka's Deep Learning slides: http://ufal.mff.cuni.cz/courses/npfl114/1819-summer