DL4NLP: Summary

Chapter 1: Intro

Humas are good at understanding the nuances of language but poor at formally describing the rules that govern it.

So far, supervised machine learning algorithms came up with usage patterns and regularities for word usage => finding the decisive words to classify an example into a specific category.

ML methods excel when a **good set of rules is very hard to define/obtain** (discovering the function) but **classifying an example into a category is easy** (assiging the label).

characteristics and problems of natural language:

- **discrete and symbolic**: characters => words => objects, concepts, sentences, actions
    - words cannot compared like colors. e.g., sandwhich and pizza don't have an inherent relation that can be inferred from the symbols/chars apart from that both contain the chars 'a' and 'i'.
- **compositional: characters** => words => objects, concepts, sentences, actions. the meaning of a sentence can be larger than the meaning of a word.
- **data sparsity**: the number of correct word combinations and valid sentences is almost unlimited

Chapter 2: Machine Learning Pipeline

1. Feature Selection: Extraction, Encoding, Transformation (e.g., normalization, standardization)

    > Standardization and Normalization are important in NN-models as these are sensitive to different scales.

2. Performance Metric Selection: Internval (directly optimized during trainig) vs. External (application specific)
3. Selection of Classifier/Regression Model, Optimization Algo, Loss Function, Regularization, Parameter Turning
4. Evaluation of Models: Cross Validation

"No Free Lunch Theorem": Any two algorithms are equivalent whent heir performance is averaged across all possible problems => careful selection of algorithm for dataset/problem is necessary.

Chapter 3: Learning Basics and Linear Models

hypothesis class: family of functions (e.g., linear functions, decision trees, etc.) => creates an **inductive bias** (bias-variance tradeoff) - limits the best possible result to the best possible result given the chosen functions

main goal: learned functions need to generalize well to previously unseen examples

Train, Validation and Test Set

leave-one-out cross validation: good approximation of accuracy, costly - computation time!

> **random splitting / leave-one-out** is problematic with natural language since it's sequence data. old language data should be used to predict new data points. new data points should not be used during training.

held-out set / k-fold cross validation: split data into 5-10 folds, use 1 fold as validation set (~10-20% of data is used for validation) and train on k-1 folds, each time the same model is trained => a different folds is used for validation.

balancing, shuffling, stratifying: shuffle the data before splitting, classes of examples should be balanced and if possible the splits should be stratified => contain the same number of examples of each class per split

three-way split: need a third split if multiple models shall be trained, tweak and compared according to their quality. If only two splits (train/validation) are used => result on validation set is overly optimistic.

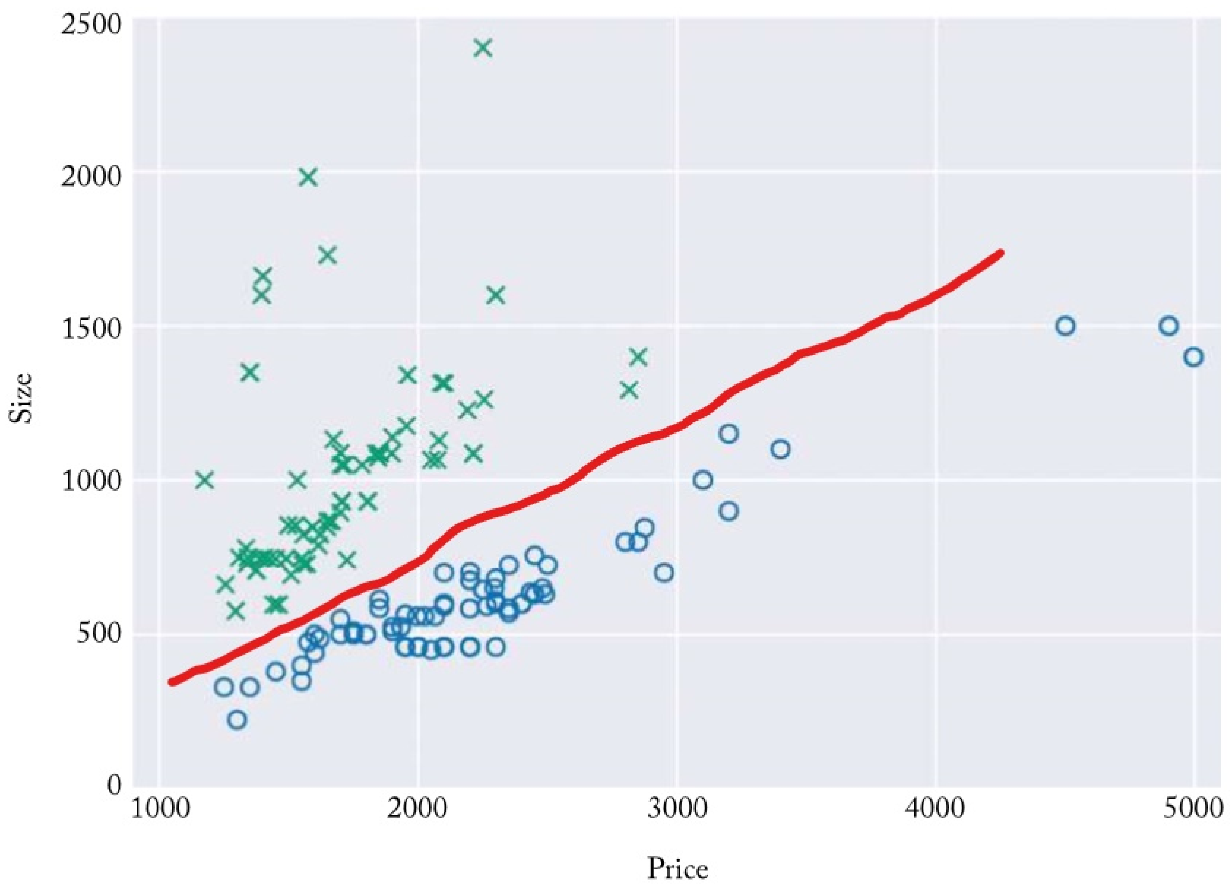
> All experiments, tweaks, error analysis and model selection are performed on the **validation set**.
>
> The final/selected model is run once against the **test set** => good estimate of the expected quality of the model on unseen data i.e. its ability to generalize.

Linear Models

$f(x) = xW + b$ or $f(x; W, b) = xW + b$

+: easy, efficient to train, strictly convex optimization => always converges to the global minima

-: restricted to linear relations



binary classification: $f(x) = sign(xW + b)$

If $x = [x_1, x_2]$ then $sign(x_1 W_1 + x_2 W_2 + b) = sign(prize * W_1 + size * W_2 + b)$ => can be interpreted as weighting the factors relative to each other.

log-linear classification / "sigmoid" function: $\sigma(x) = \frac{1}{1+\exp(-x)}$

send result of $f(x)$ through sigmoid function $\sigma(f(x))$ => produces confidence levels between [0,1]

> can be seen as a MLP with a single neuron and sigmoid activation function.

multi-class classification: 2+ classes

find the argmax of the vector of scores $\hat{y} = argmax_i\, \hat{\mathbf{y}}$

log-linear multi-class classification - softmax function

$$\hat{\mathbf{y}}_i = softmax(xW + b) = \frac{\exp(xW + b)_i}{\sum_j \exp(xW + b)_j}$$

Forces all values of $\hat{\mathbf{y}}$ to be positive and sum to 1 => produces an interpretable probability distribution.

Linear Separability

A dataset is **linearly separable** if a straight line can separate the classes. => solutions if not separable:

1. move to **higher dim** (add more features => e.g., polynomial regression / classification)
2. use **richer hypothesis class** (e.g., non-linear models such as NN or kernelized-methods which operate in higher dimensions).

   A **kernel method** defines a generic mapping (e.g., polynomial $\phi(x) = x^d$). **Kernel trick:** Compute inner-product => implicit computation in higher dimensional space. This allows to work in higher dim space without ever computing the transformed representations. But high-dim space has increased risk over overfitting.

   > Computational complexity of kernel methods scales linearly with dataset size => unpractical! Compared to NN which scales linearly with size of the network independent of dataset size.

3. allow some examples to be miss/wrongly-classified

Loss Functions

Loss function: $L(\hat{y}, y)$ quantifies the error that occurred when predicting $\hat{y}$ while the true label is y. Formally, it assigns a numerical value to the predicted output $\hat{y}$ given the true output y. The difference Δ is 0, only if $\hat{y} = y$.

Example below shows: "per-instances Loss L" & corpus-wide average loss over all training examples

$$\text{Loss Function: } \hat{\theta} = argmin_\theta \frac{1}{n} \sum_{i=1}^{n} L(f(x_i; \theta), y_i)$$

$$\text{Loss Function with Regularization: } \hat{\theta} = argmin_\theta \frac{1}{n} \sum_{i=1}^{n} L(f(x_i; \theta), y_i) + \lambda R(\theta))$$

Examples of Different Loss Functions

Hinge Loss (Binary): $L_{hinge}(\hat{y}, y) = \max 0, 1 - y * \hat{y} \text{ where: } \hat{y} = sign(xW + b)$

Hinge Loss (Multi-Class): let $\hat{\mathbf{y}} = \hat{y}_1, ..., \hat{y}_n$ and $t = argmax_i\, \mathbf{y}_i$ (the highest scoring class k) and second highest t such that $k \neq t$ => the loss is defined as follows: $L_{hinge}(\hat{y}, y) = \max\{0, 1 - (\hat{y}_t - \hat{y}_k)\}$

> Both loss functions attempt to score the correct class above all other classes with a margin of at least 1.

Binary Cross Entropy Loss / Logistic Loss: binary classification with conditional probability outputs. the classifier's output $\tilde{y}$ is transformed using the sigmoid function $\hat{y} = \sigma(\tilde{y})$.

$$\text{prediction} = \frac{0 \text{ if } \hat{y} < 0.5}{1 \text{ if } \hat{y} \geq 0.5}$$

The model is trained to maximize the log conditional probability $\log P(y = 1|x)$ for each training example $(\mathbf{x}, y)$: $L_{logistic}(\hat{y}, y) = -y \log \hat{y} - (1 - y) \log(1 - \hat{y})$.

Categorical Cross Entroy Loss / Negative Log Likelihood: let $\mathbf{y} = y_1, ..., y_n$ be a vector representing the true labels (1,...,n) and $\hat{\mathbf{y}} = \hat{y}_1, ..., \hat{y}_n$ the output of the classifer, which was transformed by the softmax function and represents the class membership conditional distribution let $\hat{y}_i = P(y = i|\mathbf{x})$. The categorical cross entropy loss is a measure of **dissimilarity** between the true label distribution $\mathbf{y}$ and the predicted label $\hat{\mathbf{y}}$.

$$L_{\text{Cross-Entropy}}(\hat{y}, y) = -\sum_i y_i \log \hat{y}_i$$

Regularization

If a model is forced to predict all labels correctly, it is very likely to **over-fit** as it will assigned very large weights to certain seemlingly decisive features. Regularization is a way to force the model to keep the weights small i.e. keep the complexity of the model low. Regularization penalizes large weights i.e. it increases the loss score (e.g., l2 norm reg - quadratic penalty for weights).

Common choices are: $\lambda R(\theta))$ as **L2**-norm (also called Gaussian Prior/Weight Decay), **L1**-norm (also called Laplace Prior) or **elastic-net** (combination of L2 & L1). Example for L2: $R_{L_2}(W) = ||W||^2 = \sum_{i,j}(W_{i,j})^2$

> Note: The bias term θ_0 is not regularized.

Another form of regularization is **Dropout** (very effective in NN) which prevents the network from learning to rely on specific weights (e.g., $w_{1,1} = 0.8$) by randomly setting ($p = 0.5$ - 50%) of all neurons in the network to 0.

> Note: This is only done during training - not during prediction.

Gradient-based Optimization

> We're only looking at gradient-based optimization since it works in many cases unlike closed-form solutions which only exist for a limited number of models. Also, closed-form solutions require inverting the matrix X which makes them very inefficient with increasing dataset size n.

Setting the parameters **W** such that the loss over the training examples is minimized. Done by 1. computing an estimate of the loss L over the training set, 2. computing the gradients of the parameters θ (the gradient is the collection of all partial derivatives) and 3. moving the parameters in the opposite direction of the gradient.

Stochastic Gradient Descent (SGD): sample a training point (x, y) and compute the gradient of the error.

```
while stopping_criteria_not_met:
    x, y = sample_traing_point(X)
    loss = compute_loss(L(f(x,W),y))
    grad = compute_gradient(L(f(x,W),y)) w.r.t. W
    w = w - lr*grad
return w
```

Error estimate based on a single training data point is inaccurate => noise! To reduce this noise, a sample of **m** examples can be used => **Mini-Batch SGD**.

> **Larger m** provides more accurate estimate, **Smaller m** allows for faster updates => faster convergence

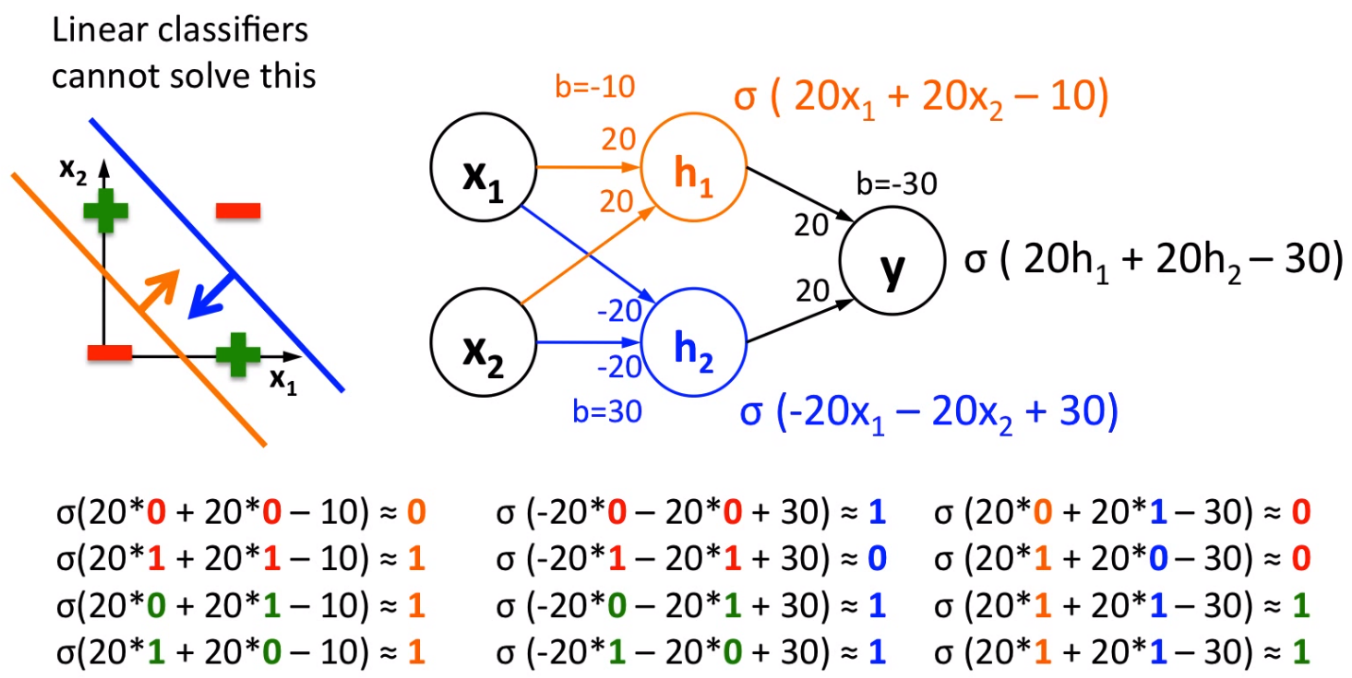
Momentum:

Adaptive Learning Rate:

Early-Stopping: Stop training once the validation error has stopped decreasing for a fixed number of iterations

Chapter 4: Neural Networks

XOR-Problem: Not linearly separable dataset => what is the solution?



Neural Networks: learning parameterizable ('learning features') differentiable mathematical functions instead of learning the weight combinations for fixed feature functions

- network is provided with a set of basic / "core" features
- combination into higher-level / more meaningful features is learned automatically by the network

Multi-Layer Perceptron (MLP): defining a trainable non-linear mapping function and training it together with the lienar classifier => finding a suitable representation is the responsibility of the algorithm.

$$\hat{y} = \phi(x)W + b$$
$$\phi(x) = g(xW' + b')$$
$$\text{where g(x) can be any non-linear activation function e.g., relu } g(x) = \max(0, x)$$

$$\text{MLP}_1(x) = (xW' + b')W + b = (xW^1 + b^1)W^2 + b^2$$

+: successfully solve XOR-Problem, differentiable => gradient-based optimization still works

-: function is no longer strictly convex

Fully-Connected Layer: Each neuron on layer n is connected to each neuron on layer n+1

Deep Learning: More than 1 hidden layer chained together

- successive transformations of the input data => final transformation predicts the output

Universal Approximation Theorem states that with MLP_1 theoretically any measureable function from one finite space to another can be approximated. **But** this is unrealistic in practice since it will be very hard to find the correct weights for this function + the function might have an exponential amount of neurons.

Activation Functions

Sigmoid, Hyperbolic Tangent: $\tanh(x) = \frac{\exp(2x)-1}{\exp(2x)+1}, \text{transforms x to: } x \in [-1, 1]$ since values are capped at 1 + gradients at x=1,-1 are ~ 0 => entire gradient becomes ~ 0 => "vanishing gradients problem"

ReLu (Rectified Linear Units): $\text{ReLu}(x) = \max(0, x)$ => not expensive to compute, gradients don't saturate!

Different Types of NN-Models

FF-NN: fixed or variable sized input, disregard the order of elements, learns the combination of input components, can be used whenever a linear model could be used, non-linearity often leads to superior classification results

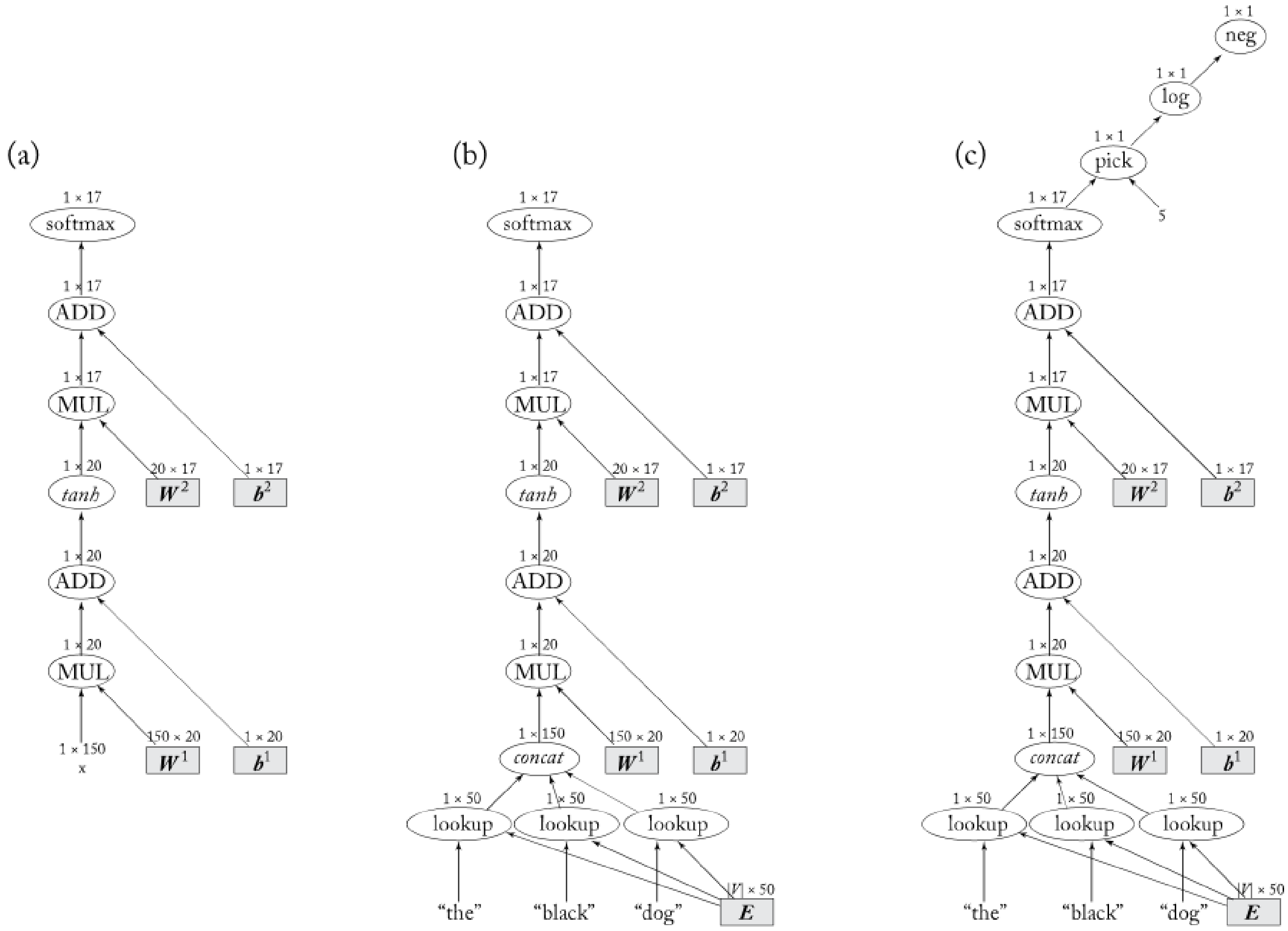
CNN: specialized to extract local patterns e.g., n-grams from arbitrarily sized inputs, sensitive to word order

RNN: specialized for sequential data, input: sequence of items, output: fixed-size vector like a 'summary', rarely used as standalone component => output of RNN used as input for FF-NN

- no more *k-markov assumption*, condition on entire sentence, take word order into account

Training NNs

Computation Graph Abstraction (DAG)



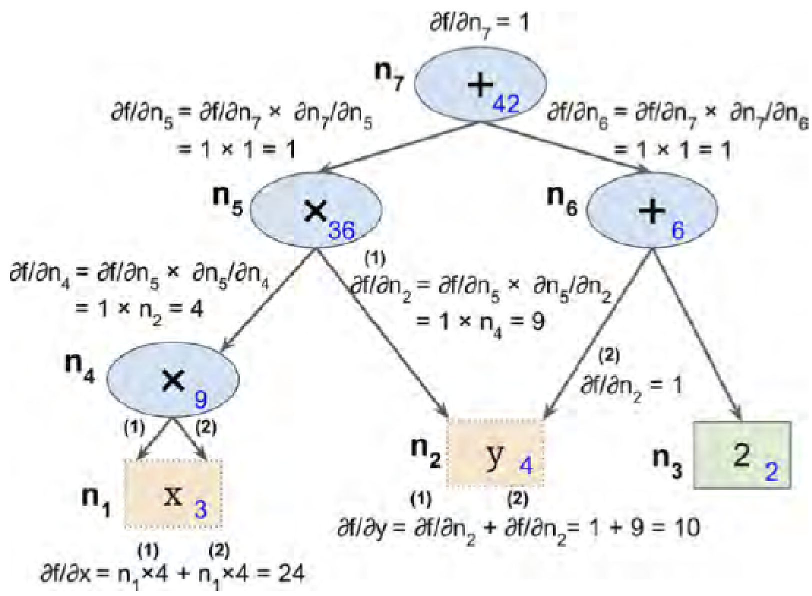
> Note: b) can be used to predict, c) can be used for training

Nodes: can be operations, inputs, or other computation graphs with in-/outputs

Forward Pass: Evaluating the predictions for given inputs and weights

Backward Pass: Computing the gradients for the given parameters w.r.t. a scalar loss. Requires a forward pass up to a designated node i.e. the loss-node ~ mostly the output node. Then, the backward computation computes the gradients starting from the loss-node backwards => applies the chain-rule of differentiation.

Backpropagation



http://colah.github.io/posts/2015-08-Backprop/ => tutorial explaining Backpropagation step-by-step

Backpropagation is a special case of the alogrithm: *reverse mode auto differentiation* => tracks how "one output affects every input".

Tips & Tricks When Training NN

Initialization: Since the objective function is not strictly convex => the optimization might get stuck in a local minimum or saddle point => starting from different initial points i.e. random values may result in different results.

> Note: Depending on the type of activation function different random initialization strategies provide the best results.

Restarts: If the computational resources allow, it is advisable to run the training process multiple times each with different random initialization => choose the best model based on the result on the validation set.

Ensembles: The different models produced by the multiple restarts can be used together to predict the result (e.g., using majority vote, etc.)

Vanishing Gradients: use **different activation function** (e.g., ReLU instead of Tanh), make network **shallower** (i.e., less layers), **step-wise training** - train the first layer + fix weights then train the next layers..., **batch-normalization** (i.e., activation at each layer are normalized to have 0 mean and 1 variance across the mini-batch), use **special architectures** such as LSTMs or GRUs for recurrent NN

Exploding Gradients: Clip the gradient at a specific max. threshold

Saturated Neurons (Tanh, Sigmoid): Output values for a layer are all close to 1 => small gradients. **Cause:** too large values entering the layer => **Solution:** change initialization, scale the range of input values, change the learning rate.

"Dead" Neurons (ReLu): All signals entering a layer are negative => **Cause:** Large gradient update => **Solution:** reduce learning rate.

Learning Rate Scheduling: If learning rate is too small => takes too long to converge, If... too large => doesn't converge / oscillates => **Solution:** montior loss over time => decrease learning rate once the loss does no longer decrease on validation set.

Representations (Chapters 6,8,9)

Feature Extraction: Mapping from textual data to real valued vectors.

Types of Features

Binary Features: 0/1 (absent/present), **Count Features:** Occurences of token/event

Lemmas: A lemma is the dictionary entry of a word (e.g., *booking, booked, books* all refer to *book*)

Stems: coarser process than lemmatizing => map a sequence of words to a shorter sequences (e.g., *picture, pictures, picutred* can be represented as *pictur*)

Sparse Vector Representations

Bag of Words: A bag of words representations (a matrix) contains a row per document D and all unique words of the corpus as columns. The frequency of each word that occurs in a document D is stored in the respective cell (e.g., corpus = ['hi', 'is', 'make',..., 'are', 'you'], doc $D_A = [5, 10, 2, 0, ...]$, $D_B = [3, 5, 1, ...]$).

+: fast and easy to create and use

-: doesn't consider the order of words, matrix is high-dimensional and sparse

- **Weighting** (e.g., TF-IDF + Doc Length Normalization) can be integrated.
- Instead of words, consecutive words **(n-grams)** can be considered (e.g., bigram => n=2: 'how are', 'are you')

  > Note: Bag-of-Bigrams/Trigrams is a lot more powerful than Bag-of-Words.
  >
  > Also, a linear classifier trained on a Bag-of-Bigrams is often very hard to beat for a NN model trained only given the core features and tasked to infer all other relevant features.
  >
  > Vanilla MLPs cannot infer from a doc on its own => use CNNs or RNNs.

Using a **window over the target word** allows to take the local context into account (e.g., target word = *jumped*, sentence = "*The brown fox jumped over the fence*", window = 2, context words = [*brown, fox, over, the*]).

=> can take the relative order of the words into account (e.g., word-2=*brown*, word-1=*fox*, word+1=*over*, etc.)

Linguistic Properties: Part-of-Speech tag, Syntatic or Semantic role of a word

> Note: It's not yet clear whether it's necessary to add manually designed linguistic properties when working with deep learning algorithms. In general, they can be inferred given sufficient training data which is also currently the main issue of most datasets... Additionally, it can help to let the network focus on a specific aspect.

Encoding Categorical Features

Sparse Encoding: Assigning a unique dimension i.e. column of a matrix for each unqiue feature. Example: a bag of words representation with 20'000 unqiue words will have a 20'000 dimensional (dim) vector. A doc D containing 10 words can be encoded by setting a 1 in the vector for each word that occurs in D (e.g., D = [1, 0, 1, 0, 0, 1, 0, 1,....]). The resulting feature vector will be **very sparse** (at most 10 non-zero values, 19'990 zeros).

One-Hot Encoding: A single dim has a value of 1 and all others have a value of zero (e.g., [[1,0,0], [0,1,0], [0,0,1]])

Distributional Features: Learning the meaning of a word from the context it's used in. Requires large amounts of text => methods: cluster words or assigning similiar vectors to similar words.

Dense Encodings: No unqiue dim per feature => all core features are *embedded* into a d-dim vector (d ~ 100-200). The embeddings can now be treated as parameters of the model.

+: computationally more efficient, generalization power => caputring the similiarities between the words, relate/compare words (e.g., distance between the word vectors)

Embedding Layer: mapping of discrete symbols (e.g., chars, words) to continuous vectors in low dim space. Mapping or lookup function. Mapping is done with a hash function.

Combining Dense Vectors

Window-Based Features: If relative position is relevant, **concatenated** the context to the target word [word-2, word-1, target_word, word+1, word+2] otherwise use **sum/weighted-sum** (to discount for words further away).

Variable Number of Features (Continuous Bag-Of-Words): A way to represent an unbounded number of words (e.g., the number of words in a sentence) as a fixed size input vector. It works by either summing or averaging the embedding vectors of the corresponding features. Can also incorporate TF-IDF weights.

Embeddings (Chapters 10,11)

Tips & Tricks regarding Embeddings

Padding: using a zero-vector (concatenation) when a feature doesn't exist might be sup-optimal. Instead a special PAD-symbol can be added and the associated padding vector can be used. It's recommended to use different padding vectors for different use cases (e.g., no-left-word, no-right-word, etc.)

Unknown Words: embedding vector is not available because the feature doesn't exist in the vocabulary (OOV) since it wasn't part of the training vocabulary. Reserve special 'Unknown' symbols (e.g., *__ing* for an unkown word ending with *-ing*).

> Alternative: Training char-level embeddings => new words can be composed from char embeddings.

To be able to use these unkown symbols during inference, they must also occur during training => otherwise the vectors are not updated and as useful as randomly initialized vectors. This can be done by **replacing** all (or some) of the **features with a low frequency** in the training with the **unkown symbol**. A better solution is to use **word-dropout**: randomly replace words with the unknown symbol based on the frequency of the word.

> Additional benefit of word-dropout! It can help preventing overfitting and improving robustness => stopping the model from relying too much on a single word.
>
> In this case, words should be dropped independent of their frequency and not be replaced with an unkown symbol. Reason: During inference, there will not be such a large concentration of unkown words.

Vector Sharing: embeddings can be shared if the behaviour/meaning of a word in different positions is the same, otherwise use separate embeddings.

Pre-Trained Word Embeddings

With sufficient training data, embeddings can be **randomly initialized** and **trained/"learned" as parameters** of NN. In practice, randomly initialize common words + use pre-trained embeddings for rare words. Additional Info: [When to use pre-trained embeddings?]

Supervised task-specific pre-training: pre-train word embeddings on a separate task for which there is a lot of labeled data and then using the embeddings to train the task with only little labeled data.

"Unsupervised" pre-training: commonly there isn't an auxiliary task with large enough amounts of labeled data => use "*unsupervised*" auxiliary task. Not a real unsupervised task!

Distributional Hypothesis

Word representations using the **distributional hypothesis**; "*words are similiar if they appear in similar contexts.*"

> Also, considered count-based methods.

- Word-context matrices (sparse, high-dim) => needs Dim-Reduction (e.g., SVD), Word-context Weighting
- **Point-Wise-Mutual Information (PMI)**: favors contexts that co-occur more with the given word than with other words => reduces the impact of common contexts on words (e.g., 'cute cat' and 'small cat' will be treated more informative than 'a cat' or 'the cat')

$$\mathrm{PMI}(x, y) = \log \frac{P(x, y)}{P(x)P(y)} = \log \frac{\#(w, c)|D|}{\#(w)\#(c)}$$

- Cosine similarity can be used to compare vectors.

> **Note:** Vector dimensions can be interpretable since each dim refers to a lingustic context. But only if no dim-reduction has been applied.

Window-Based Cooccurrence Matrix

Example corpus:

- I like deep learning.
- I like NLP.
- I enjoy flying.

counts	I	like	enjoy	deep	learning	NLP	flying	.
I	0	2	1	0	0	0	0	0
like	2	0	0	1	0	1	0	0
enjoy	1	0	0	0	0	0	1	0
deep	0	1	0	0	1	0	0	0
learning	0	0	0	1	0	0	0	1
NLP	0	1	0	0	0	0	0	1
flying	0	0	1	0	0	0	0	1
.	0	0	0	0	1	1	1	0

Distributed Representations

Word representations using **distributed representations;** "*the meaning of a word is caputered by its vector and the relations with other vectors i.e. other words.*" **Note:** Vector dimensions are not interpretable.

word2vec, an example of a distributed representation algorithm

CBOW: predict a word based on the k surrounding context words. Probabilistic objective and a simple score function: $s(w, c) = \sum \text{embedding vectors of context components}$ => produces one vector per context as context-word to compare to the target word (but averaging => loses word order information)

Skip-Gram: predict the context from its word. Independence assumption among the context words => a word-context pair $(w, c_{1:k})$ is represented as k different contexts $(w, c_1), \ldots, (w, c_k)$. Each context has its own embedding vector.

Strategies and Techniques

Negative-Sampling: a set D with correct word-context pairs from the corpus + a set $\bar{D}$ with incorrect word-context pairs; per positive word-context pair k-negative examples are sampled. The **goal** is to estimate the probability that the word-context pair came from D. Maximizes the negative log-likelihood of the data $D \cup \bar{D}$.

> Negative Sampling transforms the problem ("Computing the probability of the target-word given the current context-word") into a binary classification problem ("Does this context- and target-word combination exist in the corpus or not?") => more efficient, no longer requires softmax but can use sigmoid.
>
> Additionally, sigmoid is only computed for correct word-context pair + negative samples.

$$\text{Softmax: } p(w_i|w_c) = y_{pred_i} = \frac{e^{u_i}}{\sum_{k=1}^{V} e^{u_k}} \text{ is transformed to a } \textbf{binary classification:}$$

$$P(y=1|w_{context}, w_{target}) = \frac{1}{1 + exp(-score(w_{context}, w_{target}))} = \sigma({\mathbf{v}'}^{\mathrm{T}}_{w_{context}} \mathbf{v}_{w_{target}})$$

Sliding-Window Size: larger windows => topical similarities (e.g., 'dog', 'bark', 'leash' or 'walked', 'run'), smaller windows => functional/syntactic similarities (e.g., 'walking', 'running', 'approaching' or 'Pitbull', 'Rotweiler', 'Poodle')

> Note: The type of context & size of context-window have a strong impact on the word embeddings!

Subsampling of Frequent Words: Frequent words occur too often during training (**cons:** no real impact on other words, longer training times). Therefore, each word in the training coprus shall be disregarded depending on its frequency (higher => more likely) => **goal:** equally distribute the frequency of all words.

Hierarchical Softmax: storing the results of the softmax function in a tree-structure instead of a flat-layer => **goal:** $\mathrm{O}(V) \rightarrow \mathrm{O}(\log(V))$.

Other well-known algorithms

GloVe: Global Vectors for Word Representations

Constructs an explicit word-context matrix ('*distributional count-based method*') => dimensionality reduction to produce (word x features) matrix.

Trained on aggregated global word-word co-occurrence statistics from corpus. Parameters in GloVe are like those of PMI matrix but learned not fixed.

fastText

n-gram of chars to train embeddings => **pro:** better word embeddings for rare words

Char-based and Sub-Word Embeddings

very small model size (one vector per char => max. +/- 1000 chars)

Out-Of-Vocabulary (OOV) solution => every word can be composed using multiple char-, subword-embeddings

char-level is a hard constraint (not necessary) => use sub-words (e.g., suffixes, prefixes, char-trigrams, etc.) => In practice, use word vector if it exists + char-trigrams.

Dealing with **multi-token words** (e.g., Boston University, New York, ice cream) => preprocess and substitute whitespace for a special token (e.g., Boston_University)

Convolutional Neural Networks (CNNs/ConvNets) (Chapter 13)

"*... making predictions based on ordered sets*" => possibility: CBOW + fully-connected NN => downfall: no word order (e.g., '*it was not good, it was bad*' has the same representation as '*it was not bad, it was good*') **BUT** global ordering of '*not good*' and '*not bad*' doesn't matter => **local ordering matters!**

> Looking at n-grams is more informative than looking at bag-of-words. **BUT** embedding n-grams + building CBOW results in **huge embedding matrices (high dim, sparse)** + if '*very good*' has been seen during training but '*quite good*' not, the model cannot deduce anything from the shared components => Alternative: **CNN!**

CNN Architecture

CNNs are designed to **identify indicative local predictors** + **combine** them to **produce fixed size vectors**.

Convolution Step

Filter applies a non-linear (learned) function over a k-word sliding window (receptive filed) => transforms k-words into a scalar value. Different types of filters (#f) can be applied => f-dim vector, where each dim is a filter.

Pooling Step

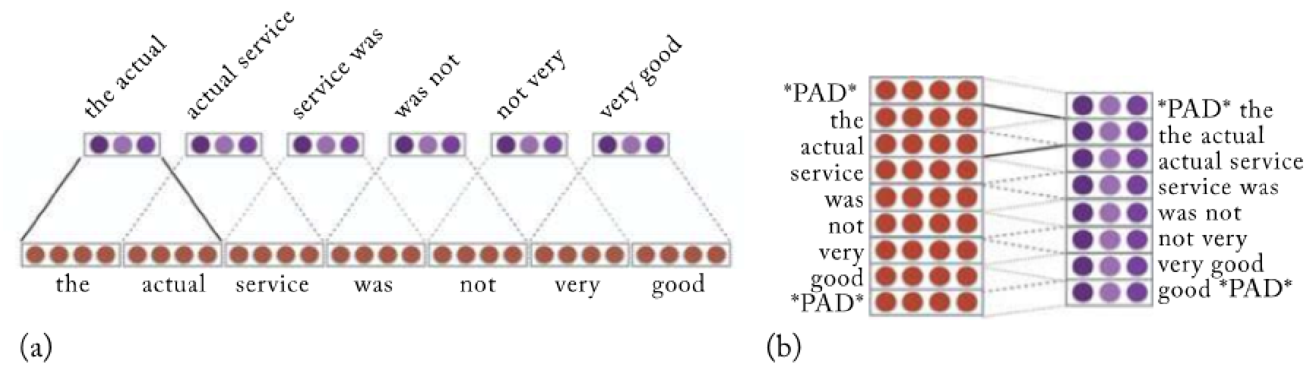
A **pooling operation** combines the vectors from the different windows into a single f-dim vector by **taking the max or average value** in each of the f-dimensions over the different windows.

> Each filter extracts a different indicator from the window. Pooling focuses on important indicators.
>
> Parameters of filters are tuned during training.

1D Convolution over Text

Filter = applying dot-product with weight vector $\mathbf{u} \in R^{k*d_{emb}}$ ("the filter") + non-linear activation => scalar value!

$$\text{Concatenate Word-Vectors:} \quad \mathbf{x_i} = \oplus(\mathbf{w_{i:i+k-1}})$$
$$\text{Filter:} \quad p_i = g(\mathbf{x_i} \cdot \mathbf{u}) \quad p_i \in \mathbb{R}, \mathbf{u} \in \mathbb{R}^{k \cdot d_{emb}}, \text{g: non-linear activation}$$
$$\text{Multiple Filters:} \quad \mathbf{p_i} = g(\mathbf{x_i} \cdot \mathbf{U} + b) \quad \mathbf{p_i} \in \mathbb{R}^f, \mathbf{U} \in \mathbb{R}^{k \cdot d_{emb} \times f}, \text{f=\#filters}$$



> window size k = 2, # filters f = 3

Narrow Convolution (No padding): $n - k + 1$ positions to start => $n - k + 1$ vectors

Wide Convolution (pad with $k - 1$ padding-words to each side): $n + k - 1$ vectors

> Hierarchical convolution with smaller window size is mostly preferred over wide convolution with large window

Multi-Channel (Analogy from vision: multiple color channels e.g., RGB): 1. channel: words, 2. channel: POS tags

Pooling

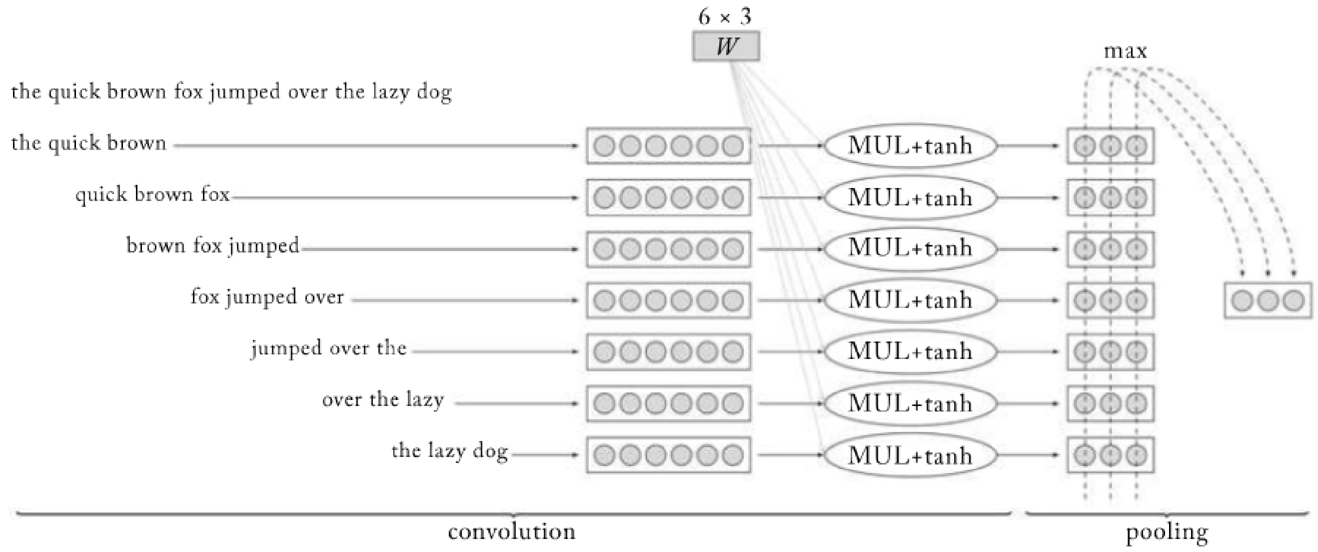
Max-Pooling = taking the max-value across each dimension. K-Max Pooling retains the k-top values.

Average-Pooling = averaging the values across each dimension.

$$\text{Max-Pooling:} \quad \mathbf{c}_{[j]} = \max_{1<i\leq m} \mathbf{p_i}_{[j]} \quad \forall j \in [1, f\ (\#\text{filters})]$$

$$\text{Average-Pooling:} \quad \mathbf{c} = \frac{1}{m} \sum_{i=1}^{m} \mathbf{p_i}$$

Dynamic Pooling: Not a single pooling operation => retains some positional information! Done by splitting the vectors $\mathbf{p_i}$ into r distinct groups. Apply pooling separately + concatenate the r resulting f-dim vectors $\mathbf{c_1, \ldots, c_r}$.



> narrow convolution (n-k+1): sentence length n = 9, window size k = 3, each word has 2-dim embedding vector => concatenate words => 6-dim representation, # of filters (f) = 3, max-pooling (max per dim) => 3-dim output

Multiple convolution layers can be applied in parallel with different window sizes => caputring different k-grams.

Alternative: Feature-Hashing

CNNs can be computationally expensive (matrix multiplications)! Instead **use k-gram embeddings** directly + pool k-grams using **average pooling** => continuous bag-of-n-grams! BUT embedding k-grams => bad (high dim, sparse)

Alternative: Don't pre-compute vocabulary-2-index mappings. Instead hash every k-gram into embedding matrix at training time.

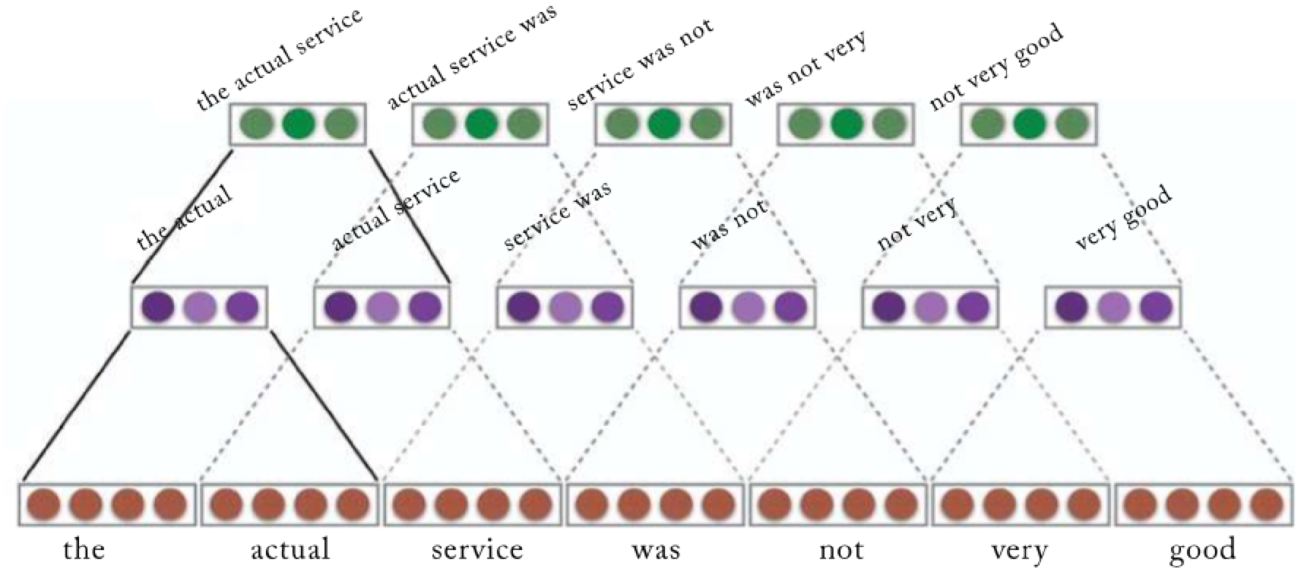
Hierarchical Convolutions

The output of one convolution layer can be fed into another convolution layer => increases the effective windows.

Strides: Sliding window step size i.e. the start position of next sliding window (e.g., stide size = 1, sliding window start @ 1,2,3,...; stride size = 2, sliding window starts @ 1,3,5,...). Larger stride sizes => shorter output sequences.

Dilated Convolution Architecture: stride size (window size k - 1) => one overlapping! Alternative with stride size = 1 => shortening the sequence length with local pooling (e.g., pool every two neighbouring vectors)

Parameter-Tying: use same set of parameters $\mathbf{U}, \mathbf{b}$ across all layers => allows to use unlimited # of conv layers b.c. allows to reduce arbitrarily length sequences into a single vector by sequence of narrow convolutions.



> 2 convolution layers, window size = 2, stride size = 1

Issues with Deep CNNs

Training problems due to **vanishing gradients**.

Skip connections can bypass certain layers and can be integrated again on higher level layers. Done by feeding into the *i-th layer* not only the vectors of *(i-1)th layer* but also from previous layers (concatenated, summed, averaged).

Recurrent Neural Networks (RNNs) (Chapters 14,15,16)

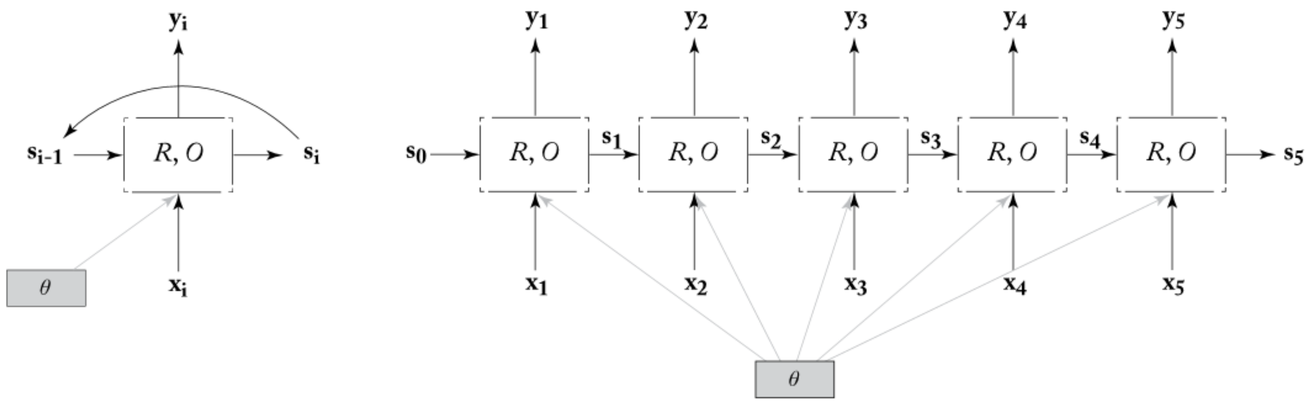
When dealing with language data => sequences of letters (words), words (sentences) or sentences (documents) => **long-range dependencies** => RNNs allow modelling arbitrarily sized sequential inputs in a fixed-size vectors while keeping structur properties (e.g., order, etc.) of inputs.

Markov Assumption RNNs allow for models **without Markov assumption** ("*A **k-th** order markov assumption assumes that the next word in a sequence depends only on the last **k** words.*") => next word can be **conditioned on the entire history**.

The RNN Abstraction

The RNN is defined recursively, taking as input a state vector $\mathbf{s_{i-1}}$ and an input vector $\mathbf{x_i}$, returning a new state vector $\mathbf{s_i}$ + outputing $\mathbf{y_i}$.

$$\mathrm{RNN}(\mathbf{x_{1:n}}, \mathbf{s_0}) = \mathbf{y_{1:n}}, \quad \mathbf{y_i} = \mathrm{O}(\mathbf{s_i}), \quad \mathbf{s_i} = R(\mathbf{s_{i-1}}, \mathbf{x_i})$$
$$\mathbf{x_i} \in \mathbb{R}^{d_{in}}, \mathbf{y_n} \in \mathbb{R}^{d_{out}}, \mathbf{s_i} \in \mathbb{R}^{f(d_{out})}$$



> Left: Recursive Representation, Right: Unrolled over 5 states (parameters shared across all time steps)

RNN Training

Unrolled RNN can be seen as very deep NN with shared parameters => to train: unroll the RNN, add loss node + use backpropagation through time (BPTT).

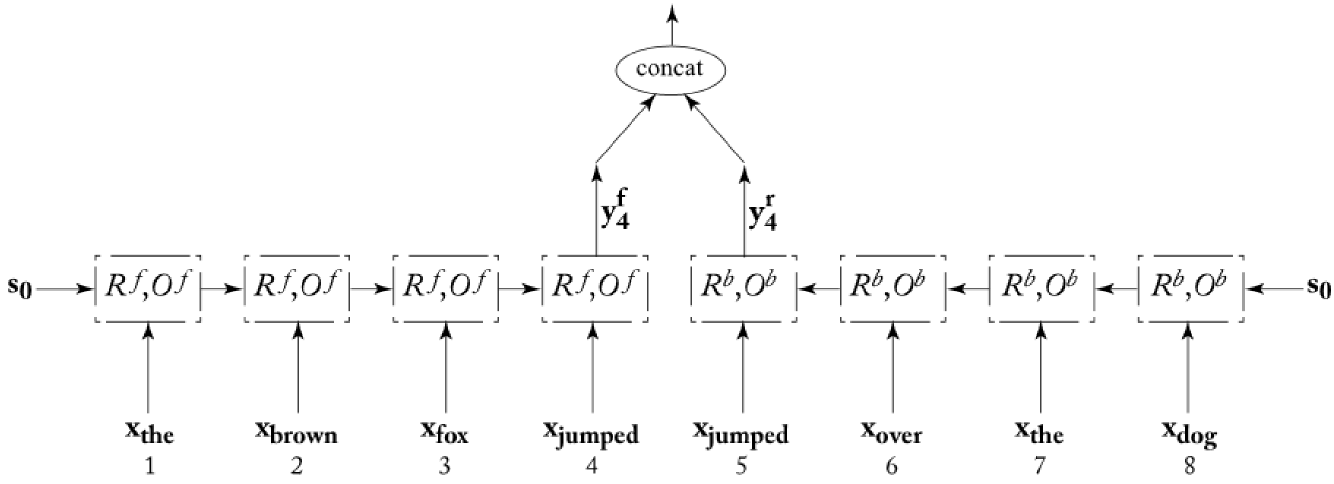
RNN is never used on its own => trainable component of a larger NN. This way RNN **encodes properties** which are **useful for downstream prediction task**.

Bi-Directional RNN

Relaxes the fixed window size assumption => look arbitrarily into the future (consider $\mathbf{w_{i+1:n}}$, not just $\mathbf{w_{1:i}}$). Can also be considered a general purpose feature extractor with arbitrarily sized window.

Maintains **two states** (by separate RNNs) per input position: $s_i^{\text{forward}}, s_i^{\text{backward}}$ => **normal** + **reversed** sequence

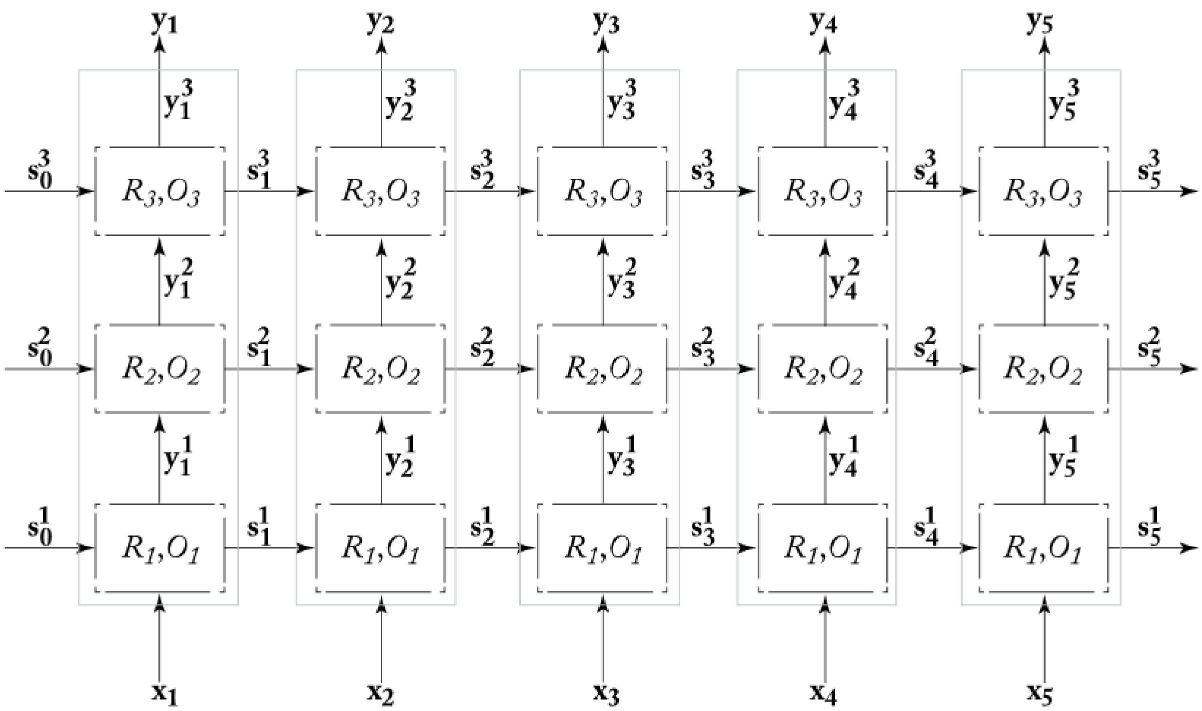
> **Output:** concatenate the two states + mostly linear transform (reduce dimensions) back to single RNN input



> biRNN at word: *jumped*

Multi-Layer (Stacked) RNNs / *deep RNNs*

RNNs can be stacked in layers to form a grid: $\mathrm{RNN}_1, ..., \mathrm{RNN}_k$ - input for RNN_1 is $\mathbf{x_{i:n}}$ whereas for the following RNNs the input is the output of the previous RNN.



RNN Applications / Usages

Acceptor (N:1): input sequence => use final state to predict outcome (e.g., sentiment classification, part-of-speech)

Encoder (N:1): Input sequence => use final state as encoding of info + other signals to predict (e.g., summary)

Transducer (N:N): One output for every input (every step) => sum/average result (e.g., language modeling - predicting the distribution over *(i+1)th* word using words $\mathbf{w_{1:n}}$ as input.

Gated Architectures

LSTM

GRU