Computational Linguistics

2A

CSC 485/2501
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2A. Dependency Grammar

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Based on slides by Roger Levy, Yuji Matsumoto, Dragomir Radev, Dan Roth, David Smith and Jason Eisner

Word Dependency Parsing

Raw sentence

He reckons the current account deficit will narrow to only 1.8 billion in September.

Part-of-speech tagging

POS-tagged sentence

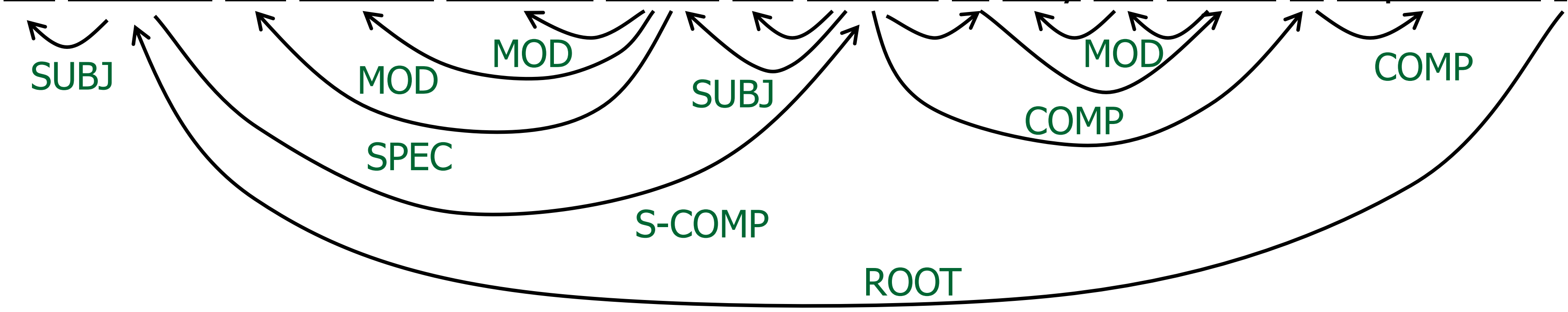
He reckons the current account deficit will narrow to only 1.8 billion in September.

He	reckons	the	current	account	deficit	will	narrow	to	only	1.8	billion	in	September	.
PRP	VBZ	DT	JJ	NN	NN	MD	VB	TO	RB	CD	CD	IN	NNP	.

Word dependency parsing

Word dependency parsed sentence

He reckons the current account deficit will narrow to only 1.8 billion in September .



Dependency Graphs

- A dependency structure can be defined as a directed graph G, consisting of
  - a set V of nodes,
  - a set E of arcs (edges),
  - a linear precedence order $<$ on V.
- Labeled graphs:
  - Nodes in V are labeled with word forms (and annotation).
  - Arcs in E are labeled with dependency types.
- Notational conventions ($i, j \in V$):
  - $i \rightarrow j \;\equiv\; (i, j) \in E$
  - $i \rightarrow^* j \;\equiv\; i = j \vee \exists k : i \rightarrow k,\ k \rightarrow^* j$

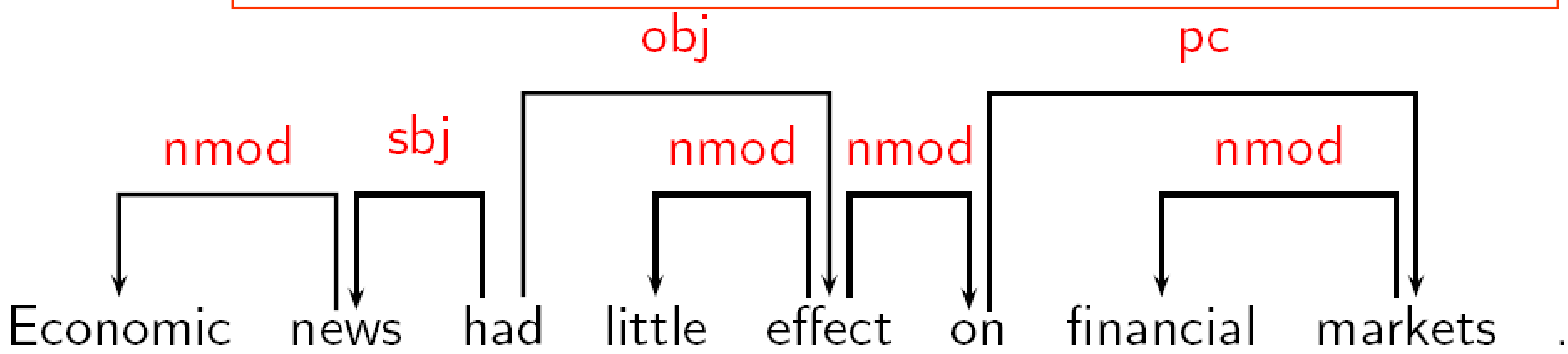
Formal Conditions on Dependency Graphs

- G is (weakly) connected:
  - For every node i there is a node j such that $i \to j$ or $j \to i$.
- G is acyclic:
  - If $i \to j$ then not $j \to^* i$.
- G obeys the single-head constraint:
  - If $i \to j$, then not $k \to j$, for any $k \neq i$.
- G is projective:
  - If $i \to j$ then $i \to^* k$, for any k such that $i < k < j$ or $j < k < i$.

Connectedness, Acyclicity and Single-Head

- Intuitions:
  - Syntactic structure is complete (Connectedness).
  - Syntactic structure is hierarchical (Acyclicity).
  - Every word has at most one syntactic head (Single-Head).
- Connectedness can be enforced by adding a special root node.

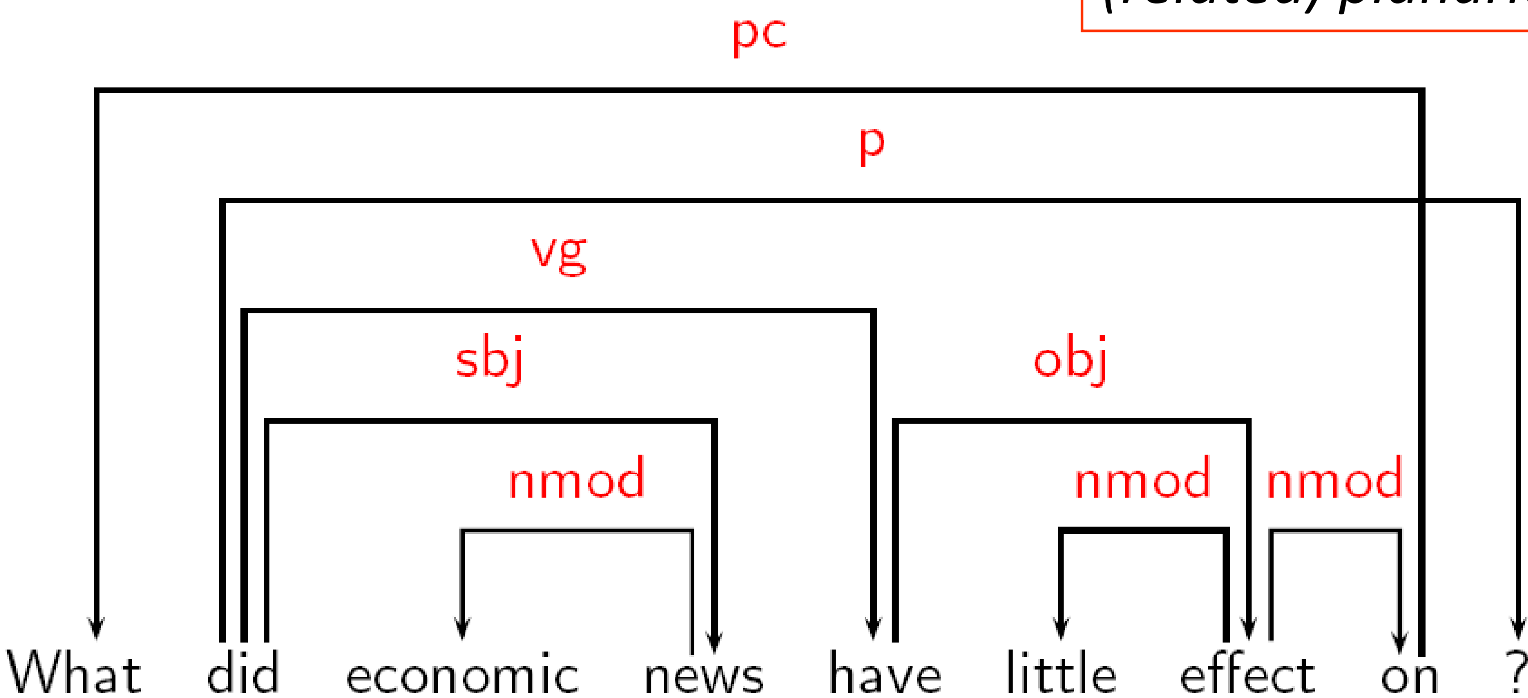
All these conditions will be violated for semantic dependency graphs we will consider later



Projectivity

- Most theoretical frameworks do not assume projectivity.
- Non-projective structures are needed to account for
  - long-distance dependencies,
  - free word order.

You can think of it as (related) planarity



Underspecifications of simple typed dependencies

- Flat bracketings
- Non-projective dependency

  A woman arrived who was wearing a hat

- Complex word-word dependency constructions:
  - Predicative adjectives

    I ate the fish naked/raw

  - Coordination

    Pat and Terry sat and laughed

- More generally, semantic roles:

  The door opened
  Erin opened the door
  The door opened a crack

- Quantifier scoping, temporal interpretation and so forth

Shift-Reduce Type Algorithms

- Data structures:
  - Stack $[\ldots, w_i]_S$ of partially processed tokens
  - Queue $[w_j, \ldots]_Q$ of remaining input tokens
- Parsing actions built from atomic actions:
  - Adding arcs ($w_i \rightarrow w_j$, $w_i \leftarrow w_j$)
  - Stack and queue operations
- Left-to-right parsing in $O(n)$ time
- Restricted to projective dependency graphs

Yamada's Algorithm

- Three parsing actions:

$$\text{Shift} \quad \frac{[\ldots]_S \quad [w_i, \ldots]_Q}{[\ldots, w_i]_S \quad [\ldots]_Q}$$

$$\text{Left} \quad \frac{[\ldots, w_i, w_j]_S \quad [\ldots]_Q}{[\ldots, w_i]_S \quad [\ldots]_Q \quad w_i \rightarrow w_j}$$

$$\text{Right} \quad \frac{[\ldots, w_i, w_j]_S \quad [\ldots]_Q}{[\ldots, w_j]_S \quad [\ldots]_Q \quad w_i \leftarrow w_j}$$

- Algorithm variants:
  - Originally developed for Japanese (strictly head-final) with only the Shift and Right actions [Kudo and Matsumoto 2002]
  - Adapted for English (with mixed headedness) by adding the Left action [Yamada and Matsumoto 2003]
  - Multiple passes over the input give time complexity $O(n^2)$

Nivre's Algorithm

- Four parsing actions:

$$\text{Shift} \quad \frac{[\ldots]_S \quad [w_i, \ldots]_Q}{[\ldots, w_i]_S \quad [\ldots]_Q}$$

$$\text{Reduce} \quad \frac{[\ldots, w_i]_S \quad [\ldots]_Q \quad \exists w_k : w_k \rightarrow w_i}{[\ldots]_S \quad [\ldots]_Q}$$

$$\text{Left-Arc}_r \quad \frac{[\ldots, w_i]_S \quad [w_j, \ldots]_Q \quad \neg\exists w_k : w_k \rightarrow w_i}{[\ldots]_S \quad [w_j, \ldots]_Q \quad w_i \xleftarrow{r} w_j}$$

$$\text{Right-Arc}_r \quad \frac{[\ldots, w_i]_S \quad [w_j, \ldots]_Q \quad \neg\exists w_k : w_k \rightarrow w_j}{[\ldots, w_i, w_j]_S \quad [\ldots]_Q \quad w_i \xrightarrow{r} w_j}$$

- Characteristics:
  - Integrated labeled dependency parsing
  - Arc-eager processing of right-dependents
  - Two passes over the input gives time complexity $O(n)$

Example

$[\text{root}]_S$ $[\text{Economic news had little effect on financial markets .}]_Q$

Example

$[$root Economic$]_S$ $[$news had little effect on financial markets .$]_Q$

Shift

Example

nmod

[root]$_S$ Economic [news had little effect on financial markets .]$_Q$

Left-Arc$_{nmod}$

Example

nmod

[root Economic news]$_S$ [had little effect on financial markets .]$_Q$

Shift

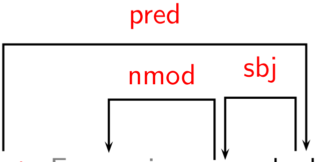
Example

nmod sbj

[root]$_S$ Economic news [had little effect on financial markets .]$_Q$

Left-Arc$_{sbj}$

Example



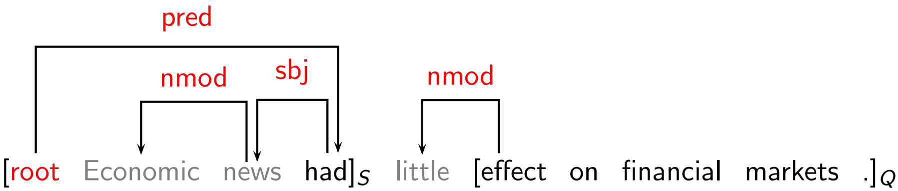
[root Economic news had]$_S$ [little effect on financial markets .]$_Q$

Right-Arc$_{pred}$

Example

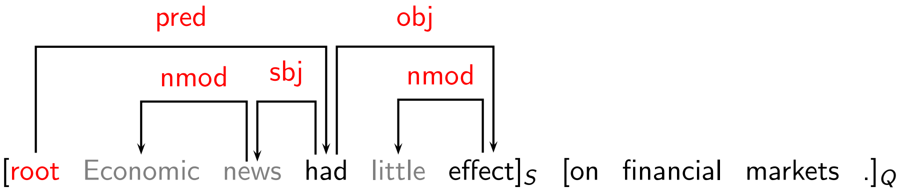
Shift

Example



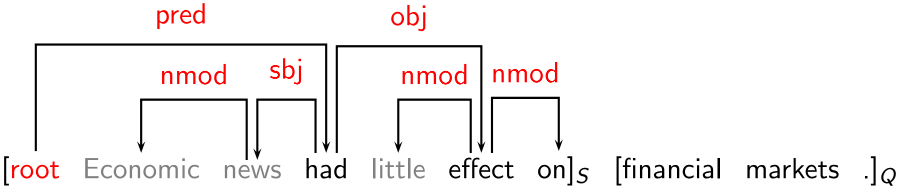
Left-Arc$_{nmod}$

Example



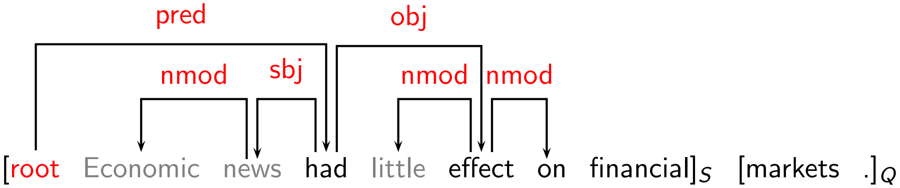
Right-Arc$_{obj}$

Example



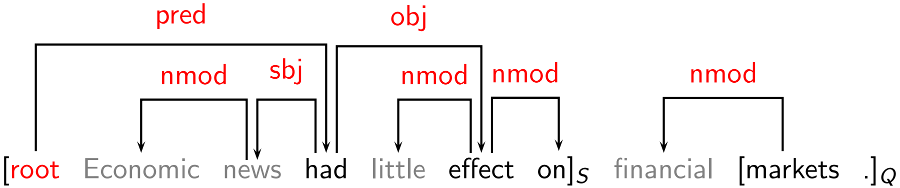
Right-Arc$_{nmod}$

Example



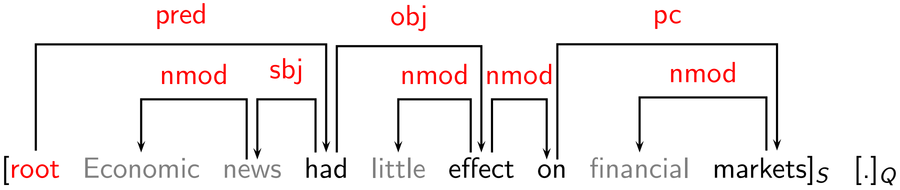
Shift

Example



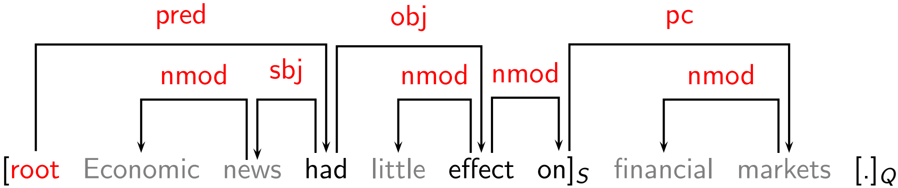
Left-Arc$_{nmod}$

Example



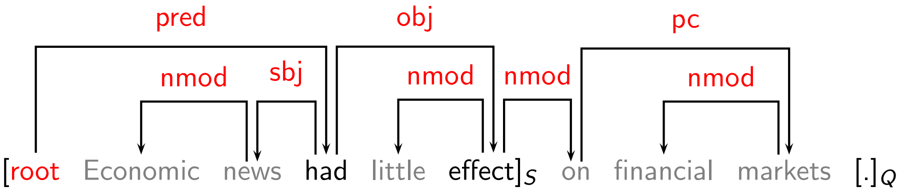
Right-Arc$_{pc}$

Example



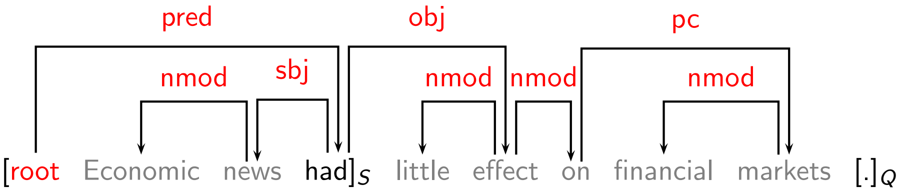
Reduce

Example



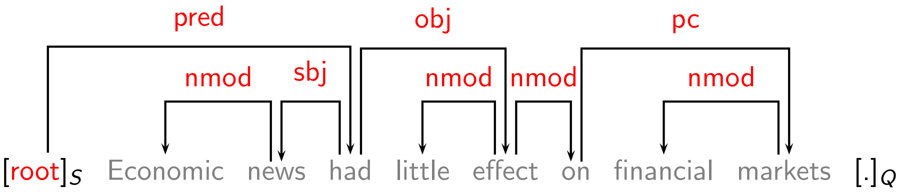
Reduce

Example



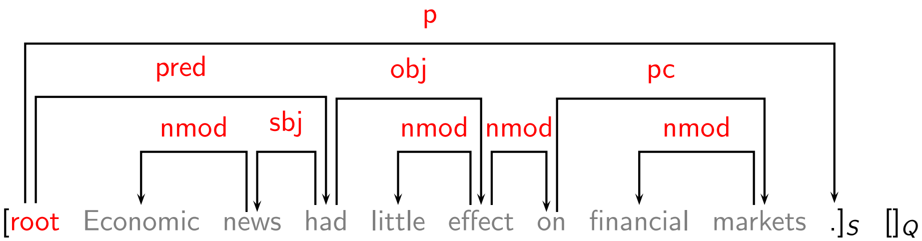
Reduce

Example



Reduce

Example



Right-Arc$_p$

Classifier-Based Parsing

- Data-driven deterministic parsing:
  - Deterministic parsing requires an oracle.
  - An oracle can be approximated by a classifier.
  - A classifier can be trained using treebank data.
- Learning methods:
  - Support vector machines (SVM)
    [Kudo and Matsumoto 2002, Yamada and Matsumoto 2003, Isozaki et al. 2004, Cheng et al. 2004, Nivre et al. 2006]
  - Memory-based learning (MBL)
    [Nivre et al. 2004, Nivre and Scholz 2004]
  - Maximum entropy modeling (MaxEnt)
    [Cheng et al. 2005]
  - Neural networks
    [you!]

Feature Models

- Learning problem:
  - Approximate a function from parser states, represented by feature vectors to parser actions, given a training set of gold standard derivations.
- Typical features:
  - Tokens:
    - Target tokens
    - Linear context (neighbors in S and Q)
    - Structural context (parents, children, siblings in G)
  - Attributes:
    - Word form (and lemma)
    - Part-of-speech (and morpho-syntactic features)
    - Dependency type (if labeled)
    - Distance (between target tokens)

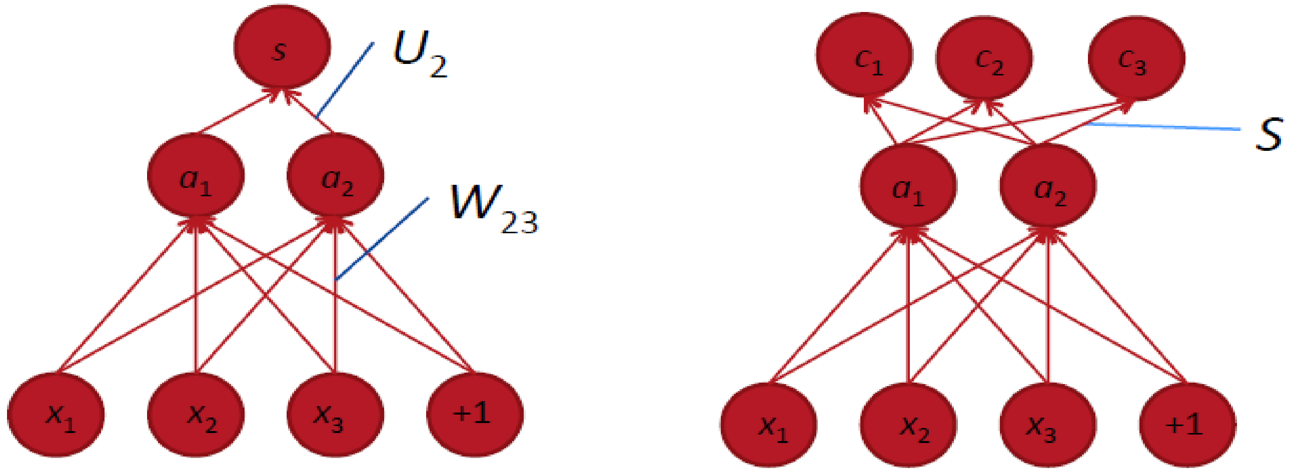
Neural Networks

(Fig: courtesy R Socher)

Neural Networks can be built for different input, output types.

- Outputs can be:
  - Linear, single output (Linear)
  - Linear, multiple outputs (Linear)
  - Single output binary (Logistic)
  - Multi output binary (Logistic)
  - 1 of k ~~Multinomial~~ output (Softmax)
    categorical

- Inputs can be:
  - A scalar number
  - Vector of Real numbers
  - Vector of Binary



Goal of training: Given the training data (inputs, targets) and the architecture, determine the model parameters.

Model Parameters for a 3 layer network:

- Weight matrix from input layer to the hidden (W_{jk})
- Weight matrix from hidden layer to the output (W_{kj})
- Bias terms for hidden layer
- Bias terms for output layer

Our strategy will be:

- Compute the error at the output
- Determine the contribution of each parameter to the error by taking the differential of error wrt the parameter
- Update the parameter commensurate with the error it contributed.

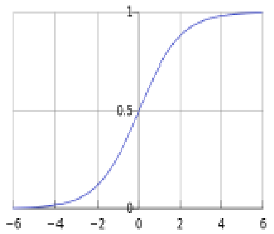
Design Choices

- When building a neural network, the designer would choose the following hyper parameters and non linearities based on the application characteristics:
  - Number of hidden layers
  - Number of hidden units in each layer
  - Learning rate
  - Regularization coefft
  - Number of outputs
  - Type of output (linear, logistic, softmax)
  - Choice of Non linearity at the output layer and hidden layer (See next slide)
  - Input representation and dimensionality

Commonly used non linearities (fig: courtesy Socher)

logistic ("sigmoid")

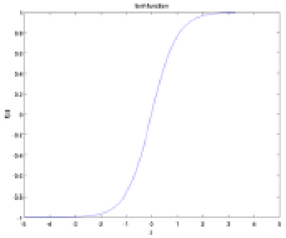
$$f(z) = \frac{1}{1+\exp(-z)}.$$



$$f'(z) = f(z)(1-f(z))$$

tanh

$$f(z) = \tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}},$$

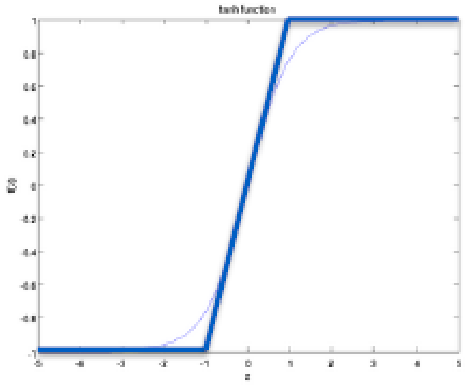


$$f'(z) = 1 - f(z)^2$$

$$\tanh(z) = 2\text{logistic}(2z) - 1$$

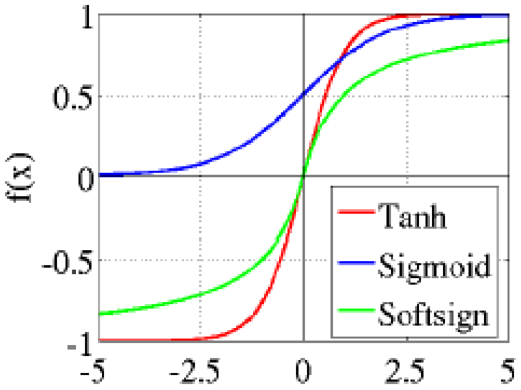
hard tanh

$$\text{HardTanh}(x) = \begin{cases} -1 & \text{if } x < -1 \\ x & \text{if } -1 <= x <= 1 \\ 1 & \text{if } x > 1 \end{cases}$$



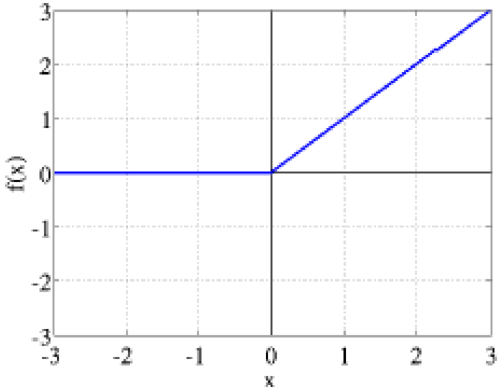
soft sign

$$\text{softsign}(z) = \frac{a}{1+|a|}$$



rectified linear (ReLu)

$$\text{rect}(z) = \max(z, 0)$$



Objective Functions and gradients

- Linear – Mean squared error
  - $E(w) = \frac{1}{2N}\sum_{1}^{N}(t_n - y_n)^2$
- Logistic with binary classifications: Cross Entropy Error
- Logistic with k outputs: k > 2: Cross Entropy Error
- Softmax: 1 of K "multinomial" classification: Cross Entropy Error, minimize NLL
- In all the above cases we can show that the gradient is: (y_k - t_k) where y_k is the predicted output for the output unit k and t_k is the corresponding target

High Level Backpropagation Algorithm

- Apply the input vector to the network and forward propagate. This will yield the activations for hidden layer(s) and the output layer
  - $net_j = \sum_i w_{ji} z_i,$
  - $z_j = h(net_j)$ where h is your choice of non linearity. Usually it is sigmoid or tanh. Rectified Linear Unit (RelU) is also used.
- Evaluate the error δ_k for all the output units

  $\delta_k = o_k - t_k$ where o_k is the output produced by the model and t_k is the target provided in the training dataset

- Backpropagate the δ's to obtain δ_j for each hidden unit j

$$\delta_j = h'(z_j) \sum_k w_{kj} \delta_k$$

- Evaluate the required derivatives

$$\frac{\partial E}{\partial W_{ji}} = \delta_j z_i$$