





Walkthrough:

Bianchi D., Delmonte R. (2002), Tecniche di apprendimento applicate al problema del tagging: una prima valutazione per l'Italiano, Convegno Nazionale Al*IA, Siena, pp.20-34.

Cimino A., Dell'Orletta F. (2016) "Building the state-of-the-art in POS tagging of Italian Tweets". In Proceedings of EVALITA '16, Evaluation of NLP and Speech Tools for Italian, 7 December, Napoli, Italy.

Tamburini F. (2016). (Better than) State-of-the-Art PoS-tagging for Italian Texts. In Proc. 3rd Italian Conference on Computational Linguistics - CLiC-IT 2016, Napoli, 5-6 December 2016, 280-284.

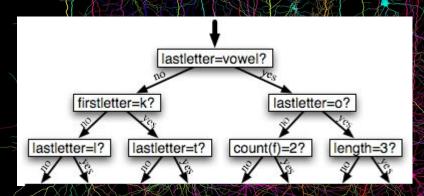
Center for





Decision Tree

- A decision tree is a **flowchart-like structure** in which each leaf node represents a class label
- The paths from root to leaf represent classification rules
- The decision tree is a set of <u>decision rules</u> in if-statement form.
 if condition 1 and condition 2 and condition 3 then outcome



$$H(X) = -\sum_{i=1}^{n} p(x_i) \log_b p(x_i)$$

Center for



Decision Tree an example of decision rules

```
if final-3 == 'a': return 'PRE'
 if final-3 == 'aar': return 'NOU'
 if final+3 == 'aba':
 if first-3 == 'ara': return 'ADJ'
 if first-3 == 'end': return 'ADJ'
 if first-3 == 'fia': return 'NOU'
 if first-3 == 'mon': return 'ADJ'
if first-3 == 'sil': return VER'
if final-3 == 'abe':
    if nVowels == 3: return 'NOU'
   if nVowels == 5: return 'ADJ'
    if nVowels == 6: return 'ADJ'
if final-3 == 'abi': return 'VER'
```

Center for





D. Bianchi, R. Delmonte, 2002

- Compared three different supervised learning techniques for (Italian) POS tagging classification:
- Decision trees, Neural Networks, Genetic Programming

Strength

- focus on ambiguity
- Drawbacks:
- uses only decision tree binary classifiers (e.g. VRB vs. PRN)
- separates straightforward and ambiguous cases in the training

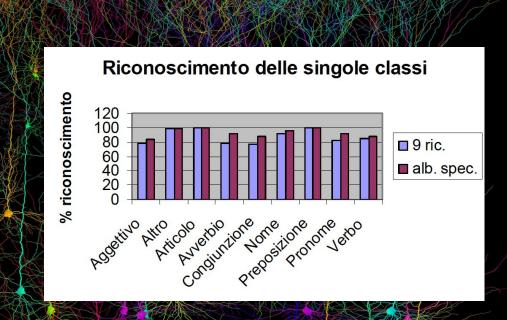
Center for





D. Bianchi, R. Delmonte, 2002

a state		
	accuracy	type
Dec.Tree	70.0%	unique
Dec.Tree	72.9%	binary
Dec.Tree	82.9%	special.
NN	79.2%	
Genetic p.	54.6%	binary
Genetic p.	81.2%	special.



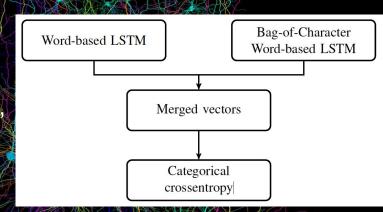
Center for



A. Cimino, F. Dell'Orletta, 2016

Developed a two-branch bidirectional Long Short Term Memory recurrent neural network.

- Word-based bi-LSTM: Word Embedding (i.e. word2vec, fastText), Morpho-syntactic category spell checker, word length, URL, uppercase, capitalized, end-of-sentence
- Bag-of-Character bi-LSTM: Characters, lowercase characters, numbers, alphanumeric, alphabetic



Center for



Configuration	Devel	Test	
Single bi-LSTM	96.39	93.67	
No handcrafted features	95.22	91.99	

Configuration	Devel	Test
Two-branch bi-LSTM	96.55	93.19
Word bi-LSTM	96.03	92.35
Bag-of-Char. Word bi-LSTM	84.47	80.77
No Morpho-syntactic lexicon	96.48	93.54
No spell checker	96.49	93.31
No word2vec lexicons	93.23	89.87
No fastText lexicon	95.85	92.43
No feature engineering	96.39	93.06

Table 1: Tagging accuracy (in percentage) of the different learning models on our development set and the official test set.

A. Cimino, F. Dell'Orletta, 2016

Based on model components testing:

- The Word-based bi-LSTM is clearly the best performer with respect to the Bag-of-Character one
- Morpho-syntactic lexicon information gives a negligible improvement on the training set and unexpectedly a slight drop on the test set.
- The spell checker do not contribute in increasing the tagging performances
- The results show that word2vec seems to be a better choice with respect to fastText (fastText was expected to be particularly useful for the analysis of non standard text such as social media ones)
- Handcrafted features yield an improvement of 1.34% and 1.68% on the training and the test sets respectively

Center for





F. Tamburini, 2016

Morphological features

Having a restricted list of possible tags for a single word-form enable the tagger to reduce the search space and force it to take reasonable decisions.

Powerful morphological analysers based on large lexica are invaluable resources to increase tagger accuracy.

In this paper, the word embeddings computed in a completely unsupervised way (i.e. word2vec) was extended by concatenating to them a vector containing the possible PoS-tags provided by the **Anlta analyser**.

Center for





F. Tamburini, 2016

SYSTEM	TA		Notes
	E07	E09	
MLP-256	96.45	95.57	Win=5
MLP-256	97.75	96.84	M,Win=5
2-BiLSTM-256	98.12	97.30	M,Win=5
2-BiLSTM-256	98.14	97.45	M,Seq
2-BiLSTM-256-CRF	98.18	97.48	M,Seq

Table 2: Tagging accuracies (TA) for different configurations for both datasets. ('M' marks the use of AnIta morphological information).

Two different ways of structuring the input features for processing were used:

- Win: based on a sliding window that starts from the beginning of each sentence and concatenates word feature vectors into one single vector.
- Seq: each sentence is managed as one single sequence

The information from AnIta proved to be crucial to reach such accuracy

values as well as stacked BiLSTM networks processing entire sentence sequences.

Center for





Bayes:

Bayes' theorem describes the probability of an event, based on prior knowledge of conditions that might be related to the event

Bayes' theorem then links the degree of belief in a proposition before and after accounting for evidence, and it measures a "degree of belief"

$$\Pr(A|X) = \frac{\Pr(X|A)\Pr(A)}{\Pr(X|A)\Pr(A) + \Pr(X|\text{not }A)\Pr(\text{not }A)}$$

Center for





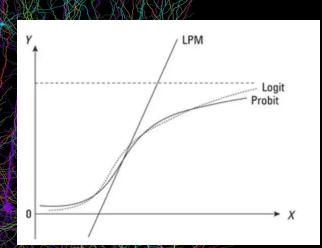
Logistic Regression

The logistic distribution function approaches 0 and 1 asymptotically, so Y values stay within the [0,1] range.

It is used to estimate the probability of a response based on one or more predictive variables (features).

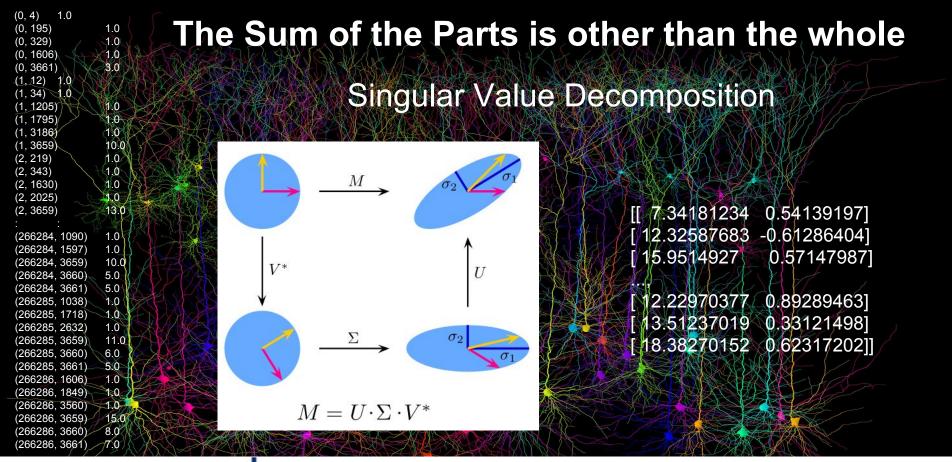
Such gradient ascent methods start with a zero weight vector and move in the direction of the gradient, LPM(w), the partial derivative of the objective function with respect to the weights.

Logit: $Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(Y=1|X)=[1+e-X'\beta]-1Pr(X=1|X)=[1+e-X'\beta]-1Pr(X=1|X)=[1+e-X'\beta]-1Pr(X=1|X)=[1+e-X'\beta]-1Pr(X=1|X)=[1+e-X'\beta]-1Pr(X=1|X)=[1+e-X'\beta]-1Pr(X=1|X)=[1+e-X'\beta]-1Pr(X=1|X)=[1+e-X'\beta]-1Pr(X=1|X)=[1+e-X'\beta]-1Pr(X=1|X)=[1+e-X'\beta]-1Pr(X=1|X)=[1+e-X'\beta]-1Pr(X=1|X)=[1+e-X'\beta]-1Pr(X=1|X)=[1+e-X'\beta]-1Pr(X=1|X)=[1+e-X'\beta]-1Pr(X=1|X)=[1+e-X'\beta]-1Pr(X=1|X)=[1+e-X'\beta]-1$



Center for









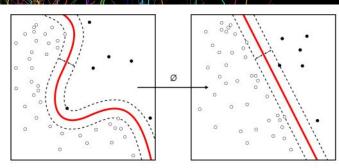
Support Vector Machine

A kernel is a similarity function

It takes inputs and returns how similar they are computing the kernel is easy, but computing the feature vector corresponding to the kernel is really really hard

Linear kernel $K(x, y) = \langle f(x), f(y) \rangle$

RBF kernel $(|\mathbf{k}(\mathbf{x},\mathbf{y})| = \exp(|\mathbf{x}||\mathbf{x}-\mathbf{y}||^2)$



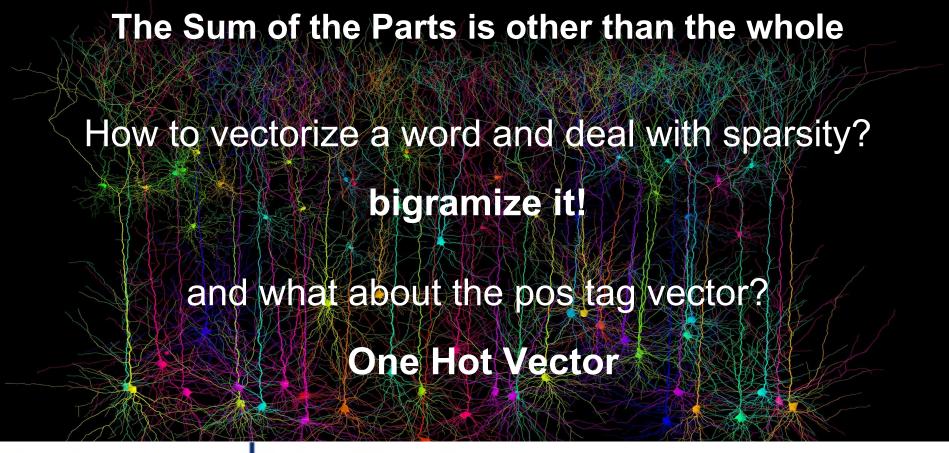
Center for



The Sum of the Parts is other than the whole Support Vector Machine rof linear

Center for







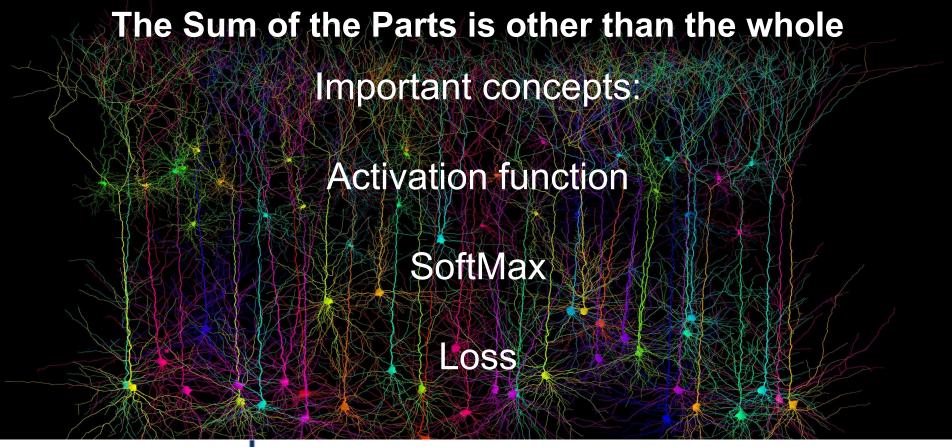


example of the vector of the word 'casa'

and its pos tag in 'one hot vector' form

Center for





Center for



The Sum of the Parts is other than the whole Rectified Linear Unit (ReLU) activation function

Center for

Mind/Brain Sciences



UNIVERSITY OF TRENTO - Italy

SoftMax

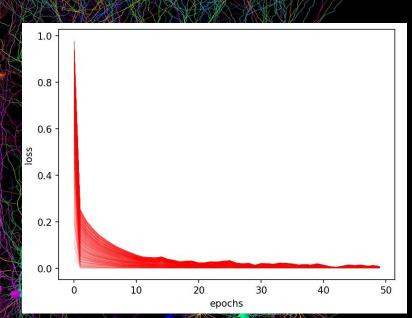
- Classification problems have the advantage that the classes are mutually exclusive
- Used in the *final layer* of a neural network-based classifier, they give a non-linear variant of multinomial logistic regression
- Used to predict the probabilities of the different possible outcomes of a categorically distributed dependent variable, given a set of independent variables

Center for



Loss

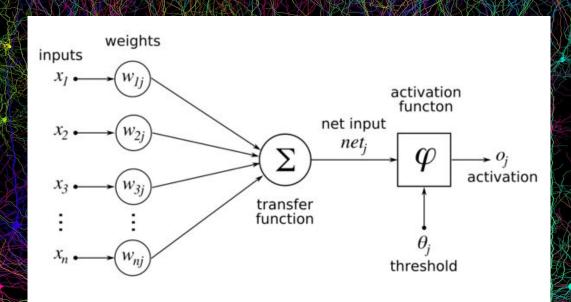
The "loss" (or cost) is the cost associated with the difference between the prediction in the actual state of the neural network and the correct values



Center for



Artificial Neural Network



Center for



The Sum of the Parts is other than the whole ours Results - Mathematical Models Accuracy 0.888 Bayes 0.9004 Decision Tree Logistic Regression (regul.=1) 0.9146 Logistic Regression (regul.=10) 0.9074 0.9036 Logistic Regression (regul.=100) Logistic Regression (regul.=1000) 0.9004

Center for





ours Results - Support Vector Machine

	Linear Kernel	rbf Kernel	
regul = 1 Gamma = 1	0.83220	0.845949	
regul = 1 Gamma = 10	0.83220	0.846673	R
regul = 1 Gamma = 100	0.83220	0.847878	
regul = 10 Gamma = 1	0.83220	0.846190	
regul = 10 Gamma = 10	0.83220	0.848360	
regul = 10 Gamma = 100	0.83220	0.849083	

	Linear Kernel	rbf Kernel	
regul = 100 Gamma = 1	0.83220	0.8457087	
regul = 100 Gamma = 10	0.83220	0.8488428	
regul = 100 Gamma = 100	0.83220	0.8488428	
regul = 1000 Gamma = 1	0.83220	0.8478784	
regul = 1000 Gamma = 10	0.83220	0,8481195	
regul = 1000 Gamma = 100	0.83220	0.8459498	
	SOM KIND OF WALL		

Center for

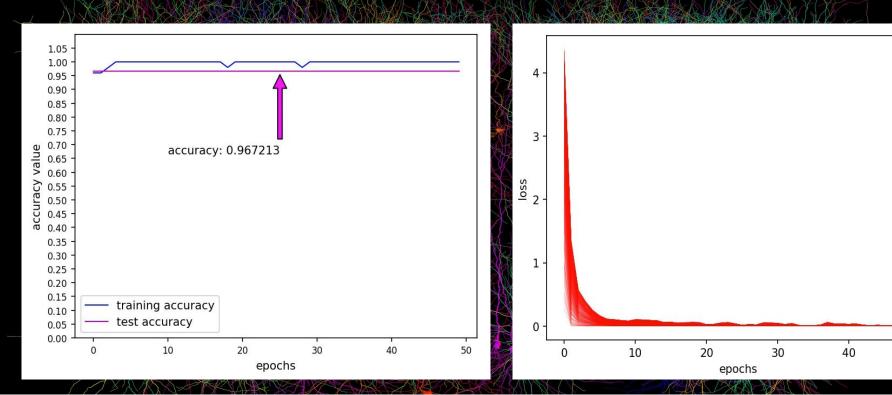


ours Results - Artificial Neural Network

	1 hidden layer	2 hidden layer	3 hidden layer
Accuracy	0.967213	0.951543	0.844021
Neurons first layer	500	250	250
Neurons second layer	0	125	125
Neurons third layer	0	0	25
starting learning rate	1e-02	e-02	e-02

Center for





Center for



The Sum of the Parts is other than the whole **Future directions** create a convolutional artificial neural network which predicts the Part of Speech feeded within a context window



