

The Italian NLP Filter

Paolo Allegrini, Simone Marchi,
Simonetta Montemagni

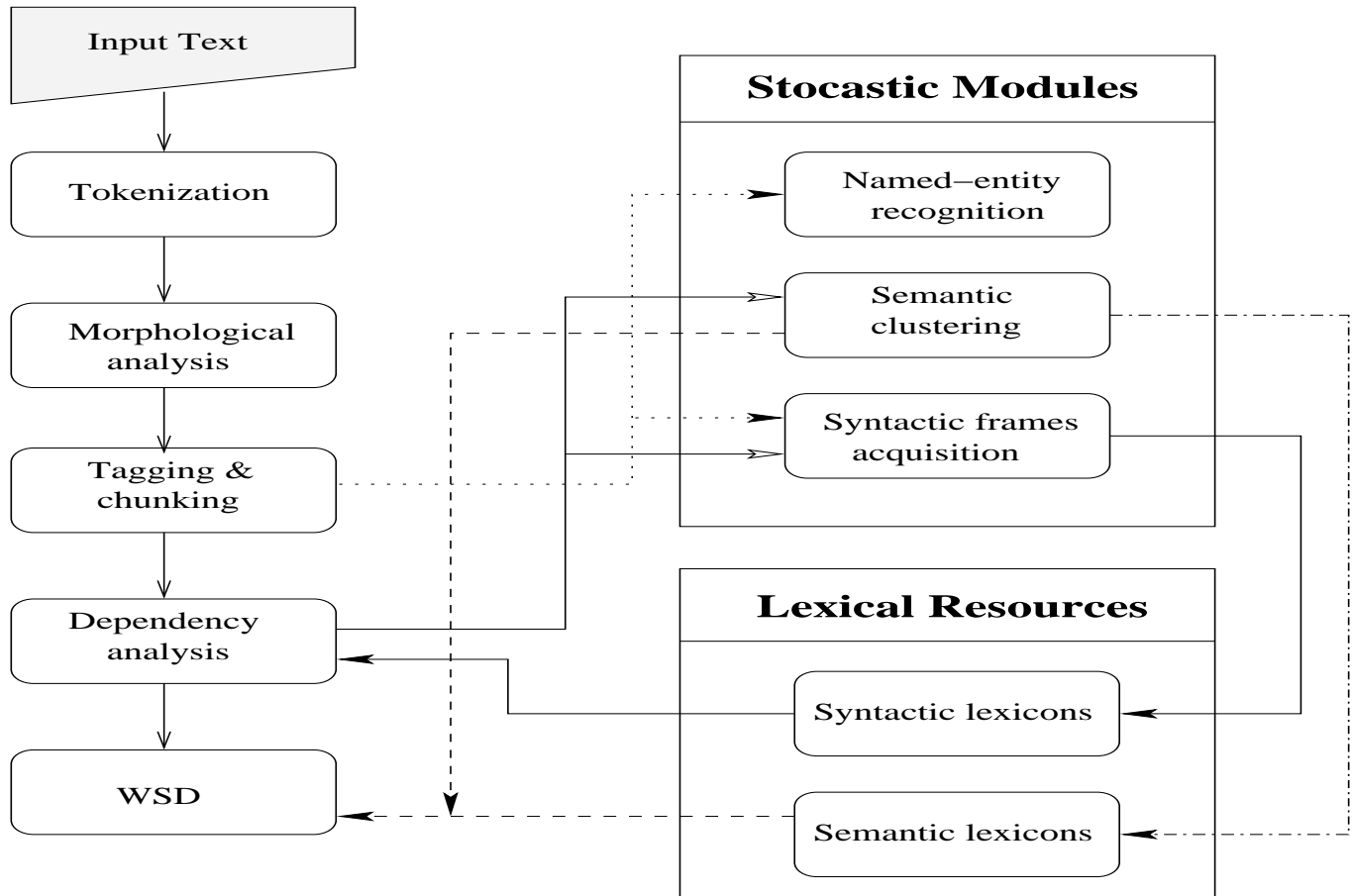
Istituto di Linguistica Computazionale del Consiglio
Nazionale delle Ricerche, Area della Ricerca di Pisa,
via Alfieri 1, S. Cataldo, 56124 Pisa, Italy

allegrip@ilc.cnr.it simone.marchi@ilc.cnr.it
simo@ilc.cnr.it

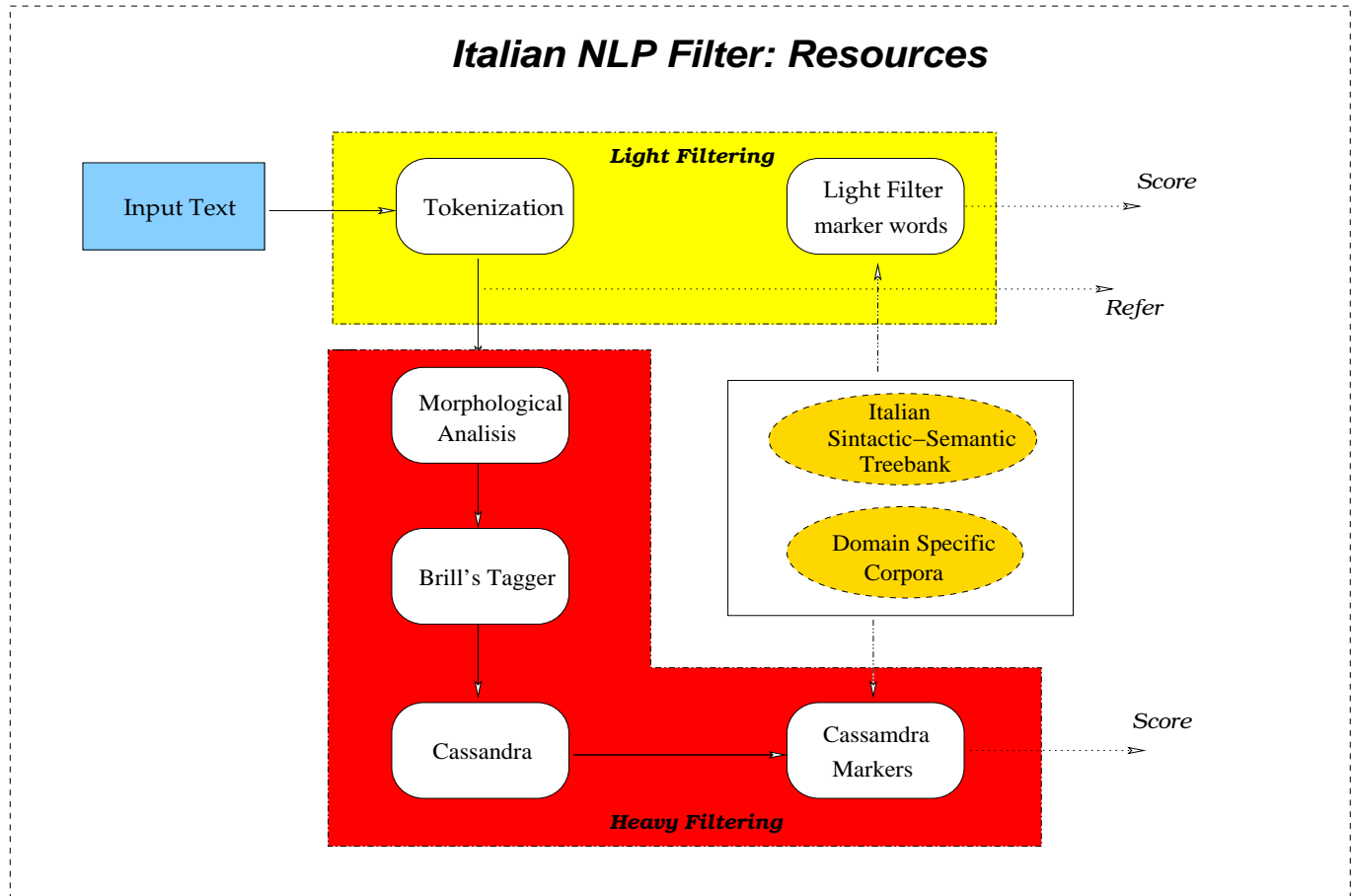
Summary

- Resources available (online and offline)
- Architecture
- Light filter: Off-line NLP processing and regular expressions
- Heavy filter: Online NLP processing and CASSANDRA
- Evaluation (in house and at Telefonica)
- Conclusions

ILC NLP resources for content filtering



ILC NLP filter architecture



The Light Filter

- Saliency score acquired from a morpho-syntactically annotated and lemmatised training corpus of 300.000 word tokens
- List of "marker"-words (30 lemmata) → *indirect lemmatisation strategy*
- Tokenised text, segmented into text windows of 100 words
- Score = maximum local frequency relevant words in text windows

Recognizing salient words needs pos-tagging and lemmatisation.

Strategy: On-line Augmented Tokenization and off-line morphological generation.

The Heavy Filter

Operates on *morpho-syntactically annotated and lemmatised text*

Background resources:

*longer list of "marker"-words (including ambiguous ones)
a corpus of typical word co-occurrence patterns
clusters of domain-specific semantically similar words*

Background info automatically extracted from a training corpus of 1.660.000 word tokens through use of advanced NLP techniques (dependency analysis)

Implementation of a new entropy-based classification technique, called CASSANDRA (Complex Analysis of Sequences via Scaling AND Randomness Assessment)

Good results also on a corpus of erotic stories

Why an NLP-based Approach? -I-

$$\text{Salience } s \equiv \frac{f_{ES} - f_{TB}}{f_{ES} + f_{TB}}$$

we have for forms the following list:
(increasing s for words $\in TB \cap ES$)

...

vedevo	0.9375	ginocchia	0.939394	saliva	0.939394
secchio	0.939394	tu	0.939394	spinse	0.941176
bocca	0.941691	lascio'	0.944444	reggiseno	0.944444
rispose	0.947368	stai	0.948718	uccello	0.95
fianchi	0.95122	riusciva	0.95122	jeans	0.953488
mie	0.956522	inizio'	0.960784	clitoride	0.961538
slip	0.961538	cosce	0.962617	vagina	0.962963
farmi	0.964286	stavo	0.964286	fino	0.965957
capezzoli	0.966667	Roberta	0.969349	Laura	0.971831
schiena	0.975	cosi	0.977273	seni	0.978022
Elena	0.984674	labbra	0.98895		

Why an NLP-based Approach? -II-

... MORBIDO#A 0.857143 SUDATO#A 0.857143 COPERTO#A 0.866667
DUBBIO#A 0.866667 SORPRESO#A 0.894737 SODO#A 0.916667 UMIDO#A
0.923077 LEGATO#A 0.948718 ECCITATO#A 0.978947 TUTTO#A 0.994723

... DENTRO#B 0.851852 A_FATICA#B 0.857143 ATTENTAMENTE#B 0.875
LENTAMENTE#B 0.877301 VELOCEMENTE#B 0.911111

... PUTTANA#S 0.875 REGGISENO#S 0.891892
PORCO#S 0.904762 VAGINA#S 0.927273 CUSCINO#S 0.928571
PENETRAZIONE#S 0.935484 BOCCA#S 0.937143 CAPEZZOLO#S 0.952941
CALZA#S 0.954545 JEANS#S 0.954545 CLITORIDE#S 0.961538 SLIP#S
0.961538 SCHIENA#S 0.975309 LABBRO#S 0.989247

SOPRA#E 0.842105 DENTRO#E 0.901786

... ALZARE#V 0.884393 ASSAPORARE#V 0.888889 INFILARE#V 0.893805
SPORGERE#V 0.894737 VERGOGNARE#V 0.894737 ABBASSARE#V 0.897436
COLARE#V 0.913043 DIVARICARE#V 0.928571 DISTENDERE#V 0.945946
INGOIARE#V 0.955556 PENETRARE#V 0.965517 GEMERE#V 0.966667
ACCAREZZARE#V 0.972414 BACIARE#V 0.972789 ECCITARE#V 0.987654

salient words in $ES \cap TB$ can still be used for filtering

crude dimension-reduction: projection into one dimension

Mathematical Foundation of Heavy filter -I-

$P(x, t)$ is the prob. of finding x events in a segment of t words, chosen randomly. In other words, we put a 1 if a "marker" word is met, a 0 otherwise. \rightarrow sequence $\{\xi_i\}$ as, e.g.
1 0 0 0 0 0 0 1 0 0 0 0 1 0 0 1 0 1 1 0 1 1 0

Then x is defined as
$$x_n(l) = \sum_{i=l}^{l+n} \xi_i$$

Considering $n \rightarrow t$, $x_n - \langle x_n \rangle \rightarrow x$, ergodicity implies scaling, namely

$$P(x, t) = \frac{1}{t^\delta} F\left(\frac{x}{t^\delta}\right) \quad (1)$$

$$S(t) = - \int_{-\infty}^{\infty} P(x, t) \ln [P(x, t)] dx \quad (2)$$

$$S(t) = A + \delta \ln(t) \quad (3)$$

$$\langle x^2 \rangle \propto t^{2\delta}, \quad \langle (\xi - \bar{\xi})(\xi(t) - \bar{\xi}) \rangle \propto t^{2\delta-2} \quad (4)$$

Mathematical Foundation of Heavy filter -II- truncated Lévy diffusion process

Events time distance t distributed as

$$\psi(t) = (\mu - 1) \frac{T^{\mu-1}}{(t + T)^\mu}. \quad (5)$$

The theory based on CTRW and GCLT yields a (truncated) Levy PDF. DE detects the approximate scaling of the central part.

$$\delta = \frac{1}{\mu - 1} \text{ if } 2 < \mu < 3, \delta = 0.5 \text{ if } \mu > 3 \quad (6)$$

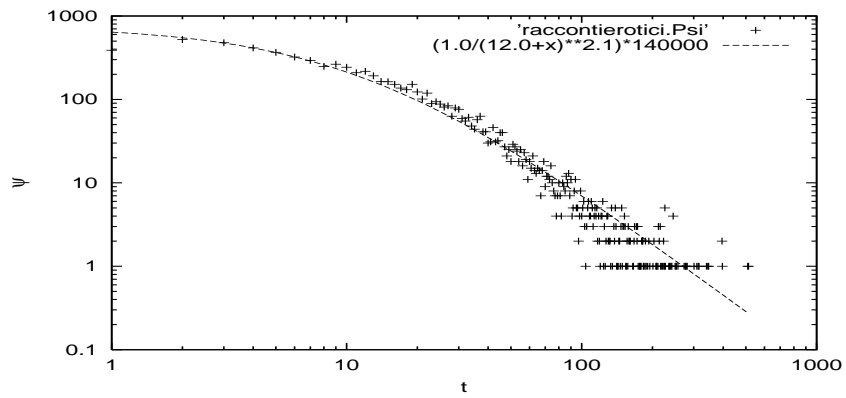
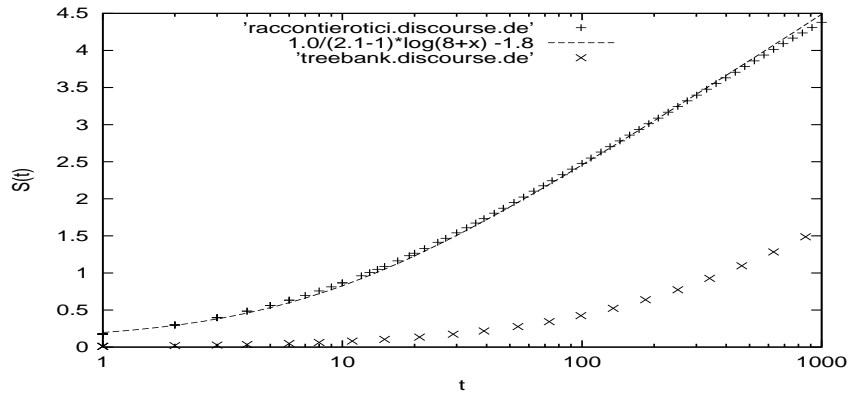
The theory rests on the dichotomous assumption.

It rests on uncorrelated waiting times between events.

Under these conditions each event carries a unit of information.

If in a corpus we find a marker (e.g. a list of words) such that $\delta \approx 1/(\mu - 1)$ then this marker is informative in that corpus.

Testing the Hypothesis



salient words seem to fit the information test.

Complex Analysis of Sequences via Scaling AND Randomness Assessment (CASSANDRA)

- We define a local entropy as a function of the position along the sequence of a "large" window
- We use a local complexity indicator:

$$\delta(T) = \frac{1}{N} \sum_{t=2}^N [S(t) - 1/2 \ln(t) - S(1)] \quad (7)$$

if $\delta(x) = 0 \rightarrow$ no correlation

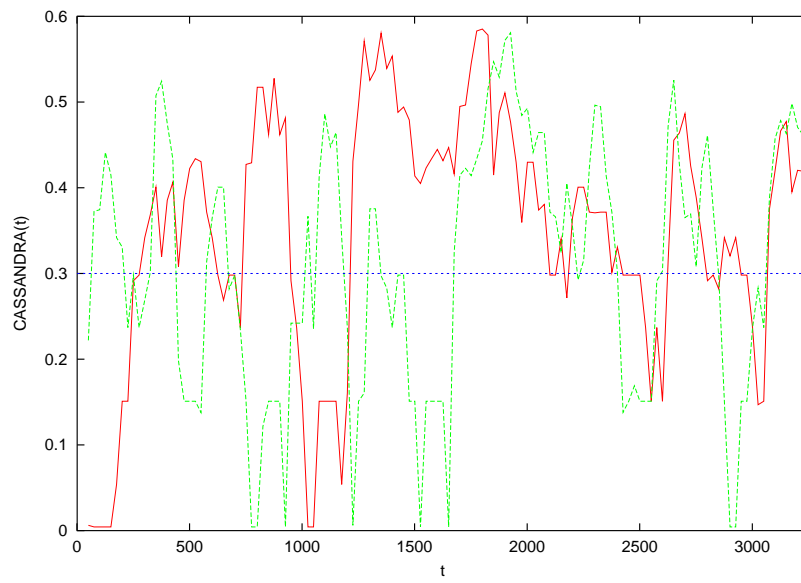
if $\delta(x) > 0 \rightarrow$ correlation (persistence)

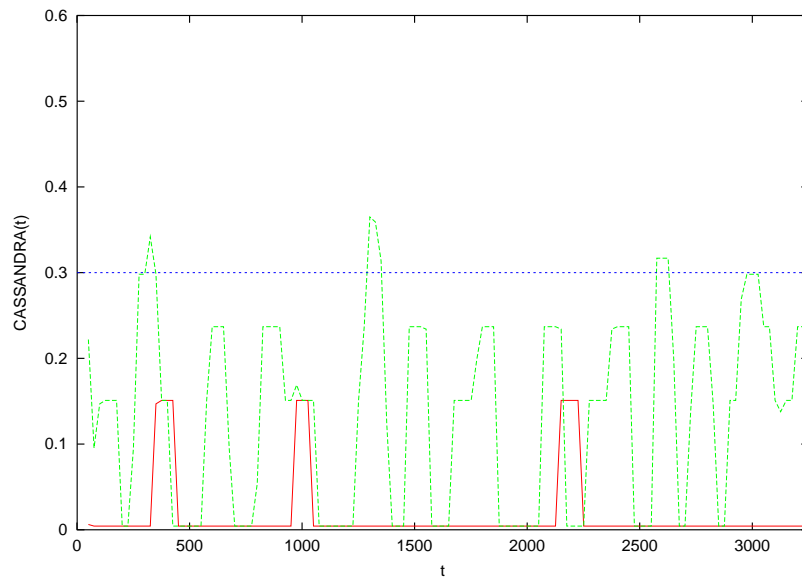
if $\delta(x) < 0 \rightarrow$ correlation (anti-persistence)

This method combines local frequency properties and correlational ones. In a sense it is similar to the wavelet transform.

we perform the analysis on training, control and test corpora, with a window-size of 100 words.

CASSANDRA at work





Italian NLP Filter Results

ILC evaluation for light filter

Predicted	Actual	Harmful	Harmless	Unknown	Total
Harmful		3143	131	228	3502
Harmless		6	4010	179	4195
Total		3149	4141	407	7697
Precision		0.998	0.968		
Recall		0.897	0.956		
F-Measure		0.948	0.962		

ILC evaluation for light and heavy filter

Predicted	Actual	Harmful	Harmless	Unknown	Total
Harmful		3181	165	156	3502
Harmless		15	4111	69	4195
Total		3196	4276	225	7697
Precision		0.995	0.961		
Recall		0.908	0.980		
F-Measure		0.952	0.970		

Telefónica evaluation (Image + NLP)

Predicted	Actual	Harmful	Harmless	Unknown	Total
Harmful		7053	258	189	7500
Harmless		156	7126	218	7500
Total		7209	7384	407	15000
Precision		0.978	0.965		
Recall		0.940	0.950		
F-Measure		0.959	0.958		