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Business Intelligence Improved by Data Mining Algorithms and Big Data Systems: An Overview of Different Tools Applied in Industrial Research

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Abstract The proposed paper shows different tools adopted in an industry project oriented on business intelligence (BI) improvement. The research outputs concern mainly data mining algorithms able to predict sales, logistic algorithms useful for the management of the products dislocation in the whole marketing network constituted by different stores, and web mining algorithms suitable for social trend analyses. For the predictive data mining and web mining algorithms have been applied Weka, Rapid Miner and KNIME tools, besides for the logistic ones have been adopted mainly Dijkstra's and Floyd-Warshall's algorithms. The proposed algorithms are suitable for an upgrade of the information infrastructure of an industry oriented on strategic marketing. All the facilities are enabled to transfer data into a Cassandra big data system behaving as a collector of massive data useful for BI. The goals of the BI outputs are the real time planning of the warehouse assortment and the formulation of strategic marketing actions. Finally is presented an innovative model oriented on E-commerce sales neural network forecasting based on multi-attribute processing. This model can process data of the other data mining outputs supporting logistic actions. This model proves how it is possible to embed many data mining algorithms into a unique prototypal information system connected to a big data, and how it can work on real business intelligence. The goal of the proposed paper is to show how different data mining tools can be adopted into a unique industry information system.

Keywords Artificial Intelligence, Data Mining, Business Intelligence, Embedded Information Platform, E-Commerce Sales Predictions, KNIME, Rapid Miner, Big Data Systems

1. Introduction: Main Project Architecture

The Business Intelligence (BI) is a tool to support decisions and control of company performance widely discussed in the scientific literature [1-4]. BI systems however, are suitable for Decision Support Systems (DSS), in Business Performance Measurement Systems (BPMS), and are able to integrate large database architectures [5]. The term "embedded system" derives mainly from the BI integrated into a specific communication system. This system integration can be improved by collecting different structured and unstructured data into a big data systems [6]. Furthermore, the alignment of Enterprise Resource Planning ERP platform with big data is a research issue [7] which requires an accurate database design.

Big data are used also for the application of data mining and artificial intelligence algorithms [8]-[9]. In this direction Apache Cassandra is a god scalable big data system [9], suitable for cloud computing and for predictive analytics.

1.1. Platform Data Flow Design

According to the preliminary state of the art has been formulated the main project architecture illustrated in Figure 1, where the physical stores, adopting their customer relationship management (CRM) and project management (PM), can be interconnected with a big data system collecting all BI data: big data can import data from different tools and database systems, by analyzing them in order to examine the "initial organizational status" of the company (indicated in the inset of Fig. 1 by the variables x_0,t_0), and to predict information useful for the BI. Business intelligence incudes:

- analysis of customer behavior (important element for the warehouse management): this analysis refers to the specific customer geolocation (nation, mountains, seaside, etc.) or to customer behaviors observing results of promotion activities;

- social networks (important for predictive analysis of consumption and sales): they represent consumer trends and can provide the customer satisfaction ratings;
- E-commerce data (analysis of sales of products available online useful for the comparison of store sales);
- statistical analysis;
- data mining processing (association rules, clustering and classification [10], etc.);
- other combined data analyses (correlations of attributes by using weather data, market data, open data, etc.);
- logistics (BI associated to logistic aspects and to product traceability).

Concerning the last point some methodologies are related to the minimum path to follow (Dijkstra's algorithm) [11-12], the loading and unloading of products in the same location (Savings algorithm) [13], the maximum flow problem (Ford-Fulkerson's algorithm) [14], the return to a starting point after the performing of a certain operation (Eulerian cycle algorithm) [15-16], the shortest route that crosses the transit nodes (2-opt algorithm) [17], the minimization of the total cost (Hungarian method) [18], the flexible transport solutions (Vogel 's approximation method) [19], the fewest kilometers allowing the greatest possible load and the maximum profit (Greedy algorithm) [20], the minimum cost of flows (Relabel-to-front-algorithm) [21], the minimum path "weighed" by appropriate conditions (Floyd-Warshall algorithm) [22], and the crossing of the nearest nodes starting from a random starting point (Nearest Neighbor algorithm) [23].

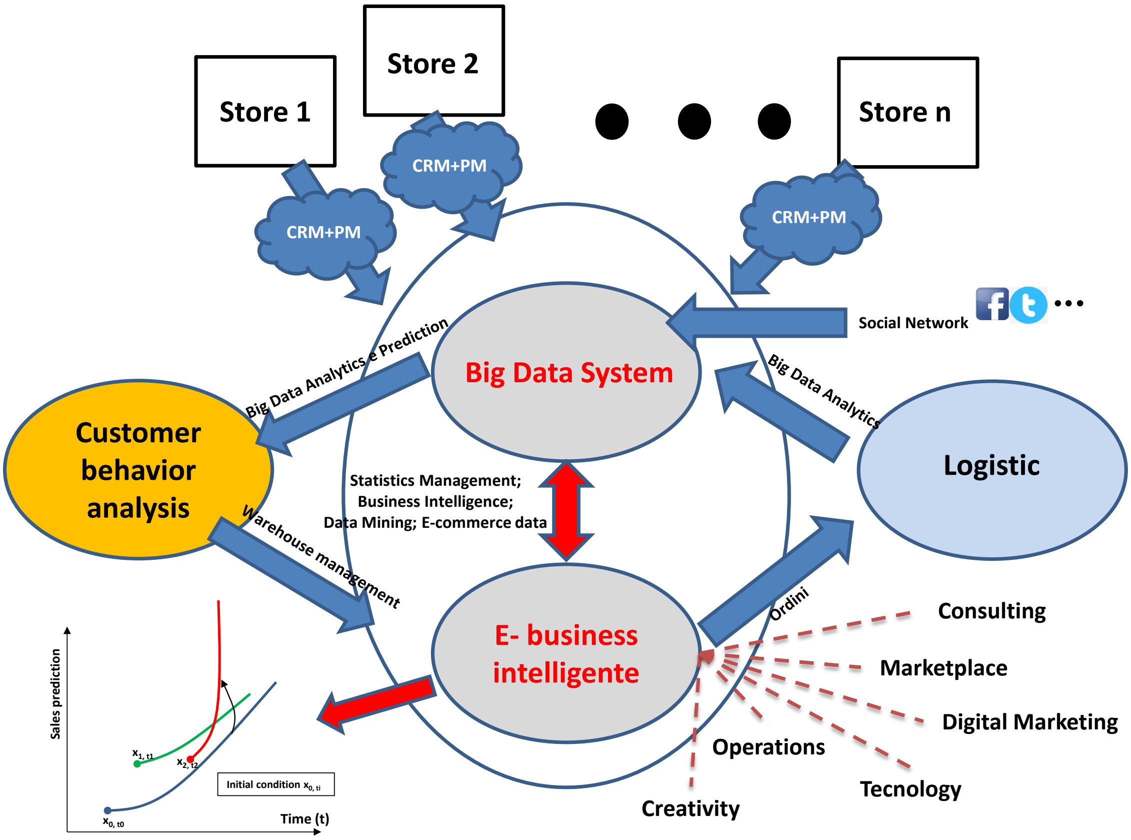


Figure 1. Main architecture of the project “Predishoes”.

Other recent papers highlighted the research topic of sales forecasting by sentiment analysis including big data analytics methodology [24]. Some researchers analyzed in details E-commerce customer experience and segmentation by predicting purchases [25]. Neural networks are good candidates for purchasing prediction [26]. Sales performance prediction in E-commerce has been performed in literature by sentiment mining [27], thus suggesting to consider sentiment analysis as an important input of the predictor. E-commerce customer preferences and browsing behavior data have been processed by algorithms in big data processing systems [28]. Sentiment analysis in E-commerce is suitable also for price prediction [29]. All the information associated with the features above described travel into the data flow of Fig. 2 illustrating the architecture of the case of study of the project. In this data flow all data sources are migrated into a Cassandra big data system by means of java and php scripts enabling timing (cron) of data migration and csv importing actions. Figure 2 indicates a way to manage data processed by using different BI tools.

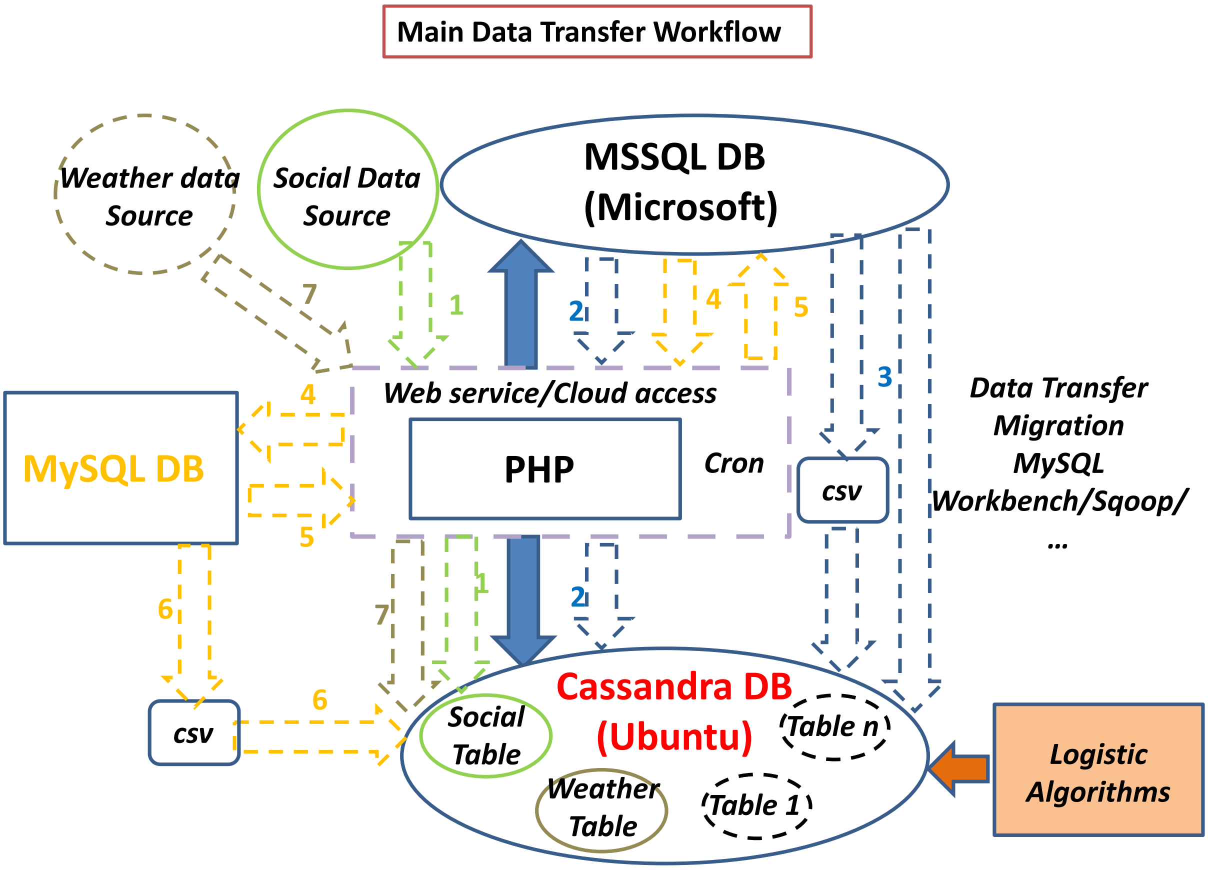


Figure 2. Functional workflow of the data transfer approach related to the case of study.

2. BI and Sales Prediction by Data Mining Algorithms

An important aspect related the BI is sales prediction. In this direction, using initially a simulation dataset, it has been adopted a Decision Tree algorithm in order understand how weather data influence the buying behavior in a single store: in Fig. 3 (a) is illustrated the simulation results of a RapidMiner workflow enhancing the best weather conditions for the sales of a store (major number of sales). Similarly also the Regression technique could be applied in order to predict sales of a store located in a defined geographical position [30] (see Fig. 3 (b)).

The used model for the prediction results of Fig. 3 (b) is represented by [30]:

$$\mathrm{Sales}_{ij}=-13{,}28-1{,}68x_1+0x_2+0.44x_3-0.11x_4+0.17x_5- \\ -0.03x_6+0.16x_7+1.67 \qquad (1)$$

being x_i the intercepts embedding weather information. Finally artificial neural networks (ANNs) provided the sales predictions by taking into account a training dataset made by monthly sales of a store (see Fig.4).

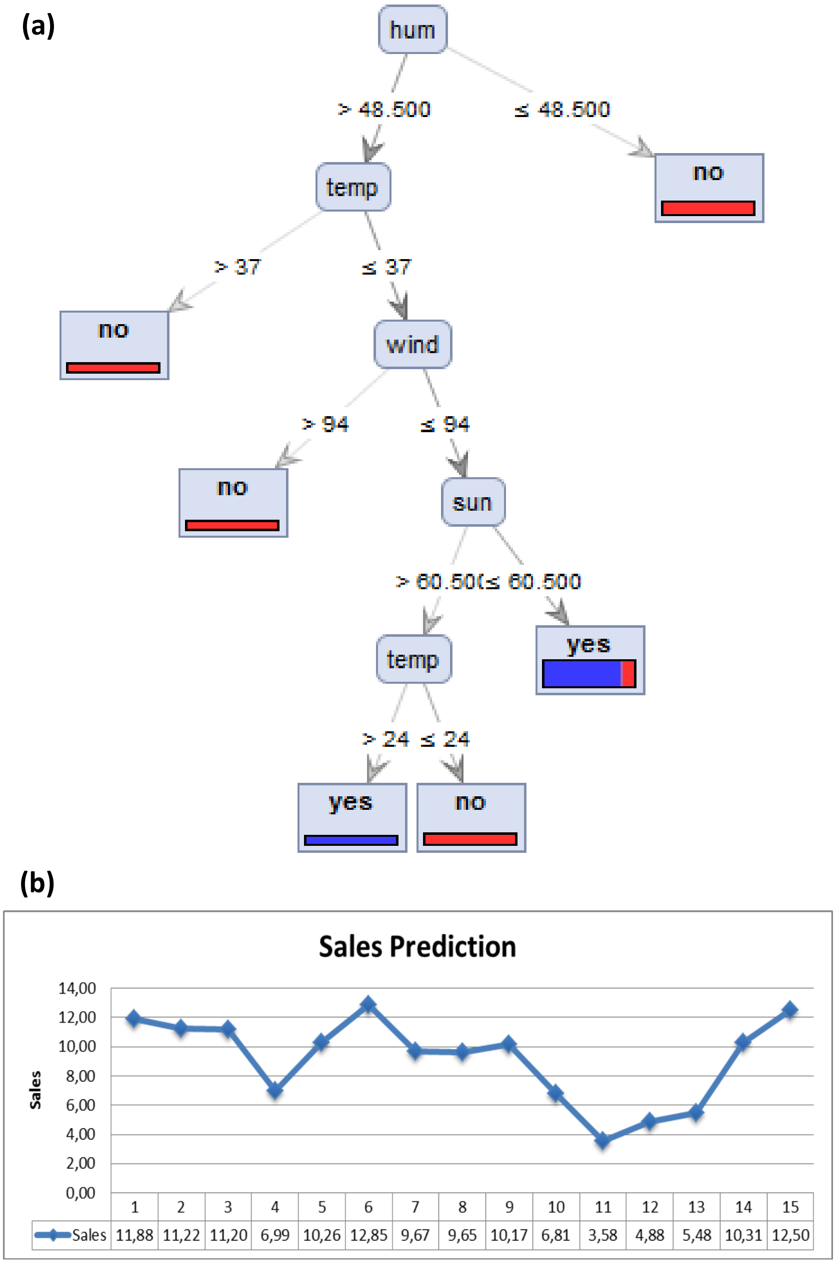
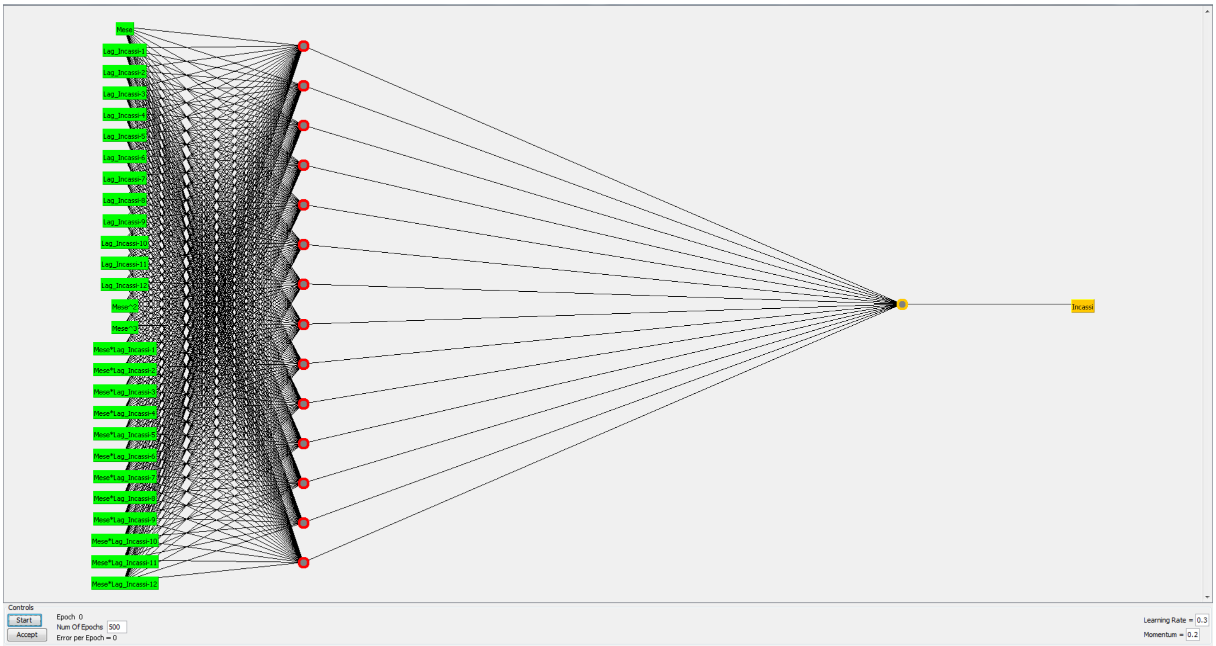
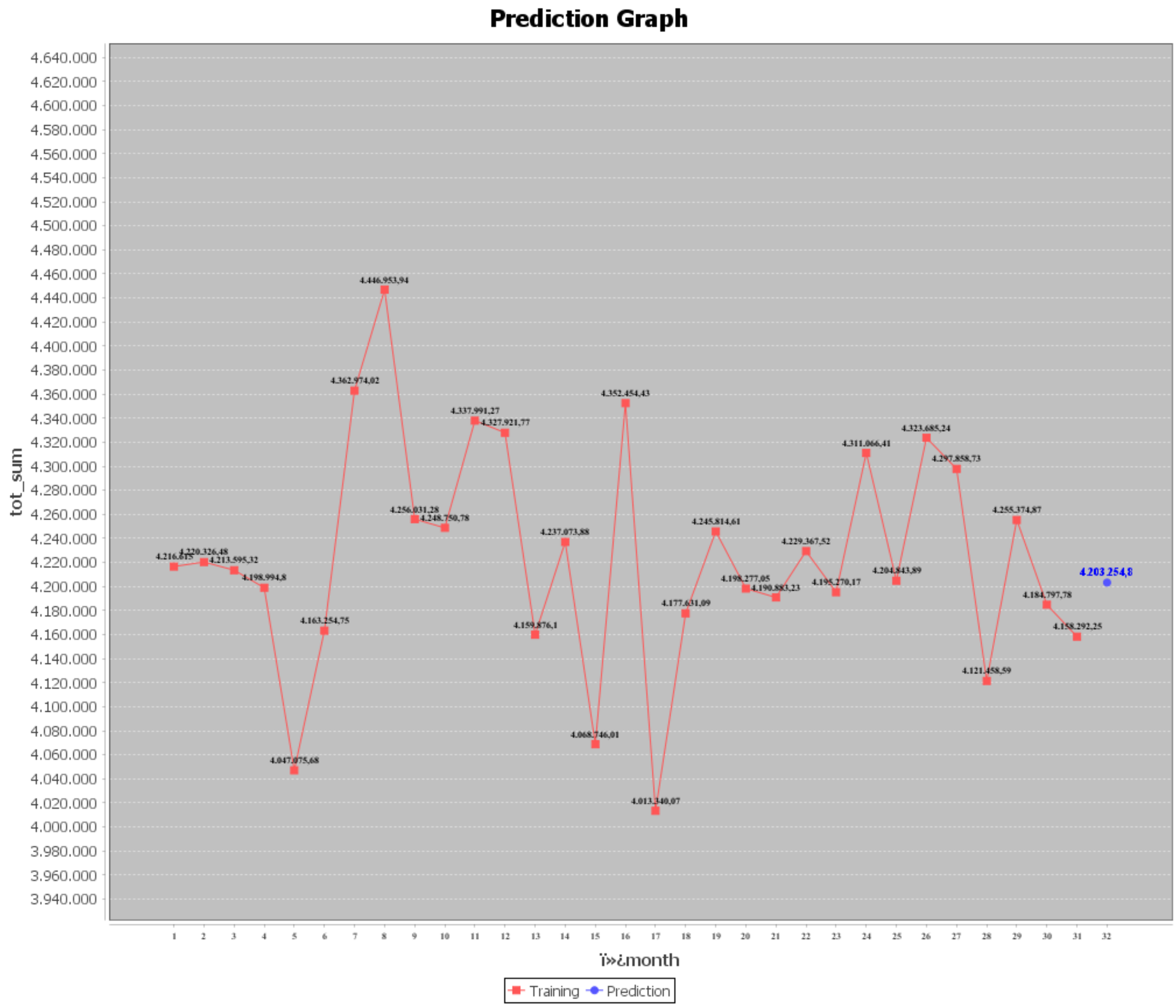
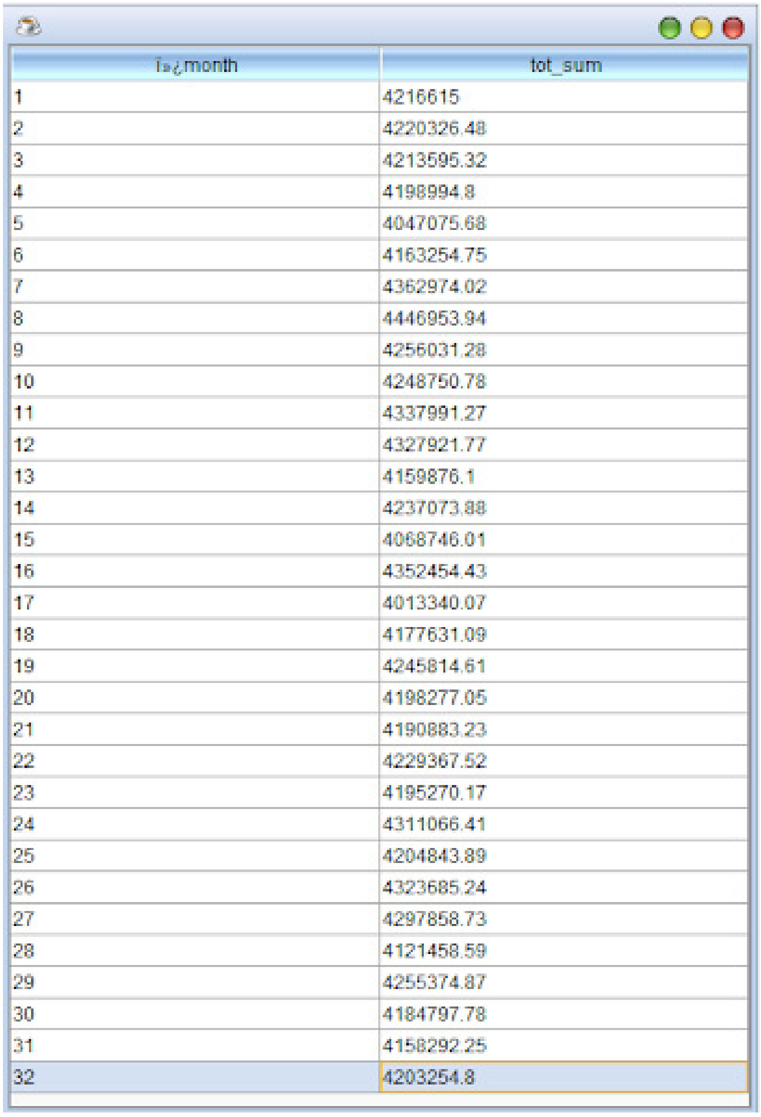


Figure 3. (a) RapidMiner Decision Tree output of (hum is humidity, temp is temperature, wind is the wind force, and sun is the sun condition). (b) Regression technique of sales prediction [30].



Epoch 0
Num Of Epochs 500
Error per Epoch = 0
Learning Rate = 0.3
Momentum = 0.2





ï»¿month	tot_sum
1	4216615
2	4220326.48
3	4213595.32
4	4198994.8
5	4047075.68
6	4163254.75
7	4362974.02
8	4446953.94
9	4256031.28
10	4248750.78
11	4337991.27
12	4327921.77
13	4159876.1
14	4237073.88
15	4068746.01
16	4352454.43
17	4013340.07
18	4177631.09
19	4245814.61
20	4198277.05
21	4190883.23
22	4229367.52
23	4195270.17
24	4311066.41
25	4204843.89
26	4323685.24
27	4297858.73
28	4121458.59
29	4255374.87
30	4184797.78
31	4158292.25
32	4203254.8

Figure 4. (Above) Artificial neural network for time forecasting of monthly sales of a single geolocated store (one hidden layer) and (below) simulation results.

For the ANN simulation has been adopted Weka libraries (Time Series Forecasting with Multilayer Perceptron -MLP- classifier [31]). Starting from an Excel file, artificial sales data have been created using the "RANDOM" function in Excel (the extracted CSV contains sales data relating to some months of the years 2016, 2017 and 2018). Figure 4 shows the graph of the predicted values (last blue points) calculated on synthetic data (training dataset indicated by the red points).

3. Logistic Algorithms Embedded in the Prototype Platform

The geolocation of a single store represent an important aspect for BI. As previously mentioned there are different which can be applied for logistic optimization, such as:

- Dijkstra's algorithm;
- Eulerian Cycle algorithm;
- Ford-Fulkerson algorithm;
- Greedy algorithm;
- Hungarian method;
- Nearest Neighbor;
- Savings algorithm;
- Floyd-Warshall algorithm;
- Vogel's Approximation Method;
- Lavesdk.

During the project has been primary applied the algorithm of the minimum paths (shortest paths of Dijkstra's algorithm equivalently to minor kilometers to travel) on an effective localization of some Apulian stores (see in Fig. 5 the associated graph model). The minimum path outputs are listed in Fig. 6 (paths 1B, 1A, 2A, 2B where the number indicates the patterns to arrive to the same destination point, the letter A indicates the time as weight, and the letter B represents the kilometer as weight).

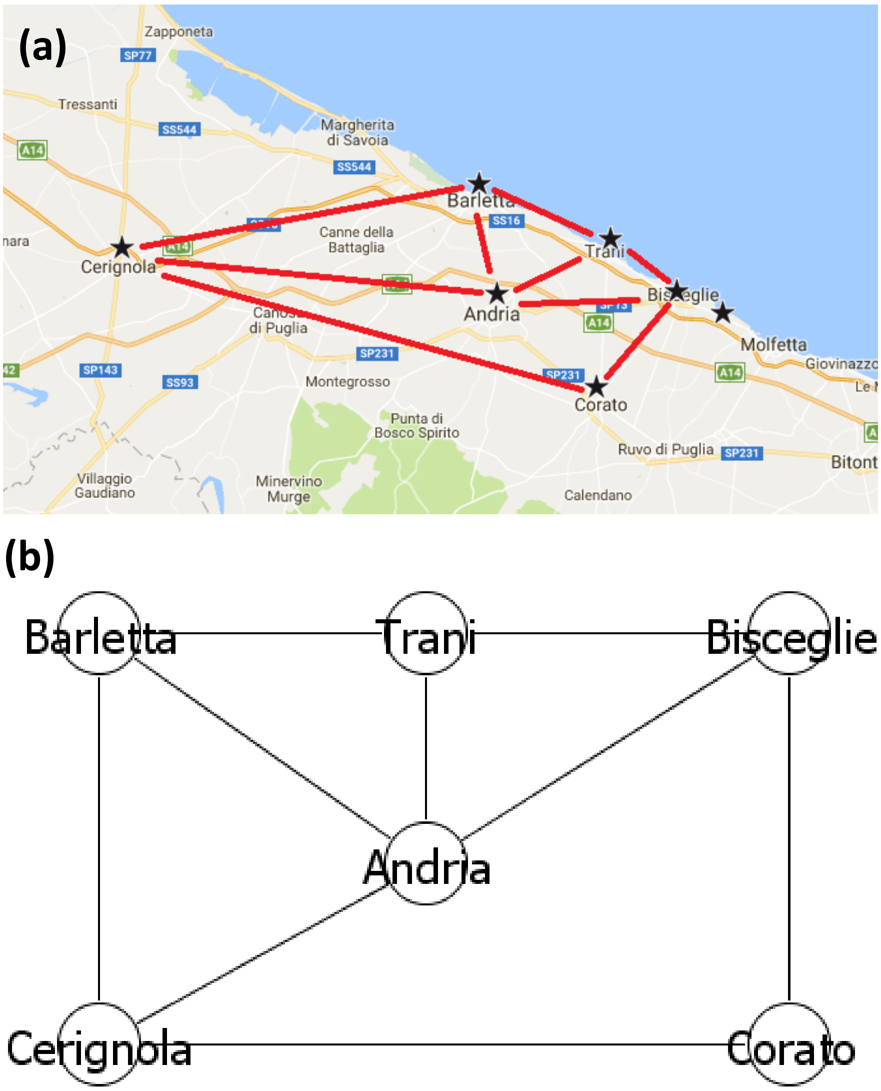
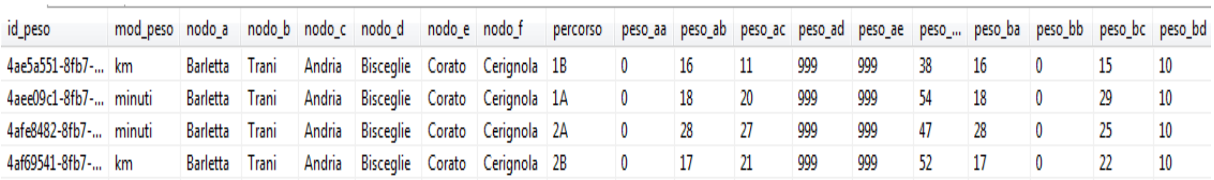


Figure 5. Graph of nodes constructed on a map containing different stores in the same region.



id_peso	mod_peso	nodo_a	nodo_b	nodo_c	nodo_d	nodo_e	nodo_f	percorso	peso_aa	peso_ab	peso_ac	peso_ad	peso_ae	peso_...	peso_ba	peso_bb	peso_bc	peso_bd
4ae5a551-8fb7-...	km	Barletta	Trani	Andria	Bisceglie	Corato	Cerignola	1B	0	16	11	999	999	38	16	0	15	10
4aee09c1-8fb7-...	minuti	Barletta	Trani	Andria	Bisceglie	Corato	Cerignola	1A	0	18	20	999	999	54	18	0	29	10
4afe8482-8fb7-...	minuti	Barletta	Trani	Andria	Bisceglie	Corato	Cerignola	2A	0	28	27	999	999	47	28	0	25	10
4af69541-8fb7-...	km	Barletta	Trani	Andria	Bisceglie	Corato	Cerignola	2B	0	17	21	999	999	52	17	0	22	10

Figure 6. Screenshot of the outputs of the Dijstra's algorithm stored into a Cassandra table.

Weights are calculated through a proportion based on different distances and travel time. Data are extracted by means of Google Maps tool and of the web site ViaMichelin.it determining routes, time and costs in function of traffic, road conditions and the type of road chosen (city, provincial, highway…). In particular, two different paths are chosen comparing the minimum path under defined conditions (in path 1, kilometers are less than in path 2, where provincial roads are not used). Table 1 and Table 2 show the two chosen paths.

The Dijstra's algorithm has been applied on the following stores represented by the cities where are located:

A. Barletta;
B. Trani;
C. Andria;
D. Bisceglie;
E. Corato;
F. Cerignola.

Table 1. Path 1 (SS16 indicates a state roads).

Path 1	A	B
A -> B	18 min. (7 min. SS16)	16 km (10 km SS16)
A -> C	20 min.	11 km
A -> F	54 min.	38 km
B -> C	29 min.	15 km
B -> D	10 min. (5 min. SS16)	10 km (8 km SS16)
F -> C	46 min. (24 min. SS16)	46 km (34 km SS16)
C -> D	28 min.	18 km
F -> E	56 min. (2 min. SS16)	51 km (4 km SS16)
E -> D	23 min.	15 km

Table 2. Path 2 (SS16 and A14 indicate a state roads and highway, respectively).

Path 2	A	B
A -> B	28 min. (1 min. SS16)	17 km (2 km SS16)
A -> C	27 min. (5 min. SS16)	21 km (7 km SS16)
A -> F	47 min. (21 min. A14)	52 km (35 km A14)
B -> C	25 min. (8 min. SS16)	22 km (11 km SS16)
B -> D	10 min. (5 min. SS16)	10 km (8 km SS16)
F -> C	44 min. (24 min. A14)	48 km (35 km A14)
C -> D	28 min. (8 min. SS16)	23 km (11 km SS16)
F -> E	52 min. (27 min. A14)	63 km (46 km A14)
E -> D	22 min.	15 km

By defining D location as the starting point, the Dijstra’s algorithm provides the following outputs of the minimum paths:

- In path 1A (where weights are equal to minutes), minimum paths to reach every destination from D (Bisceglie) are:
  - D -> C (28 min.) -> F (74 min.)
  - D -> B (10 min.) -> A (38 min.)
  - D -> B (10 min.)
  - D -> C (28 min.)
  - D -> E (23 min.)
- In path 1B (where weights are equal to kilometers), minimum paths to reach every destination from D (Bisceglie) are:
  - D -> C (18 km) -> F (64 km)
  - D -> B (10 km) -> A (26 km)
  - D -> B (10 km)
  - D -> C (18 km)
  - D -> E (15 km)
- In path 2A (where weights are equal to minutes), minimum paths to reach every destination from D (Bisceglie) are:
  - D -> C (28 min.) -> F (72 min.)
  - D -> B (10 min.) -> A (38 min.)
  - D -> B (10 min.)
  - D -> C (28 min.)
  - D -> E (22 min.)
- In path 2B (where weights are equal to kilometers), minimum paths to reach every destination from D (Bisceglie) are:
  - D -> C (23 km) -> F (71 km)
  - D -> B (10 km) -> A (27 km)
  - D -> B (10 km)
  - D -> C (23 km)
  - D -> E (15 km)

In Fig. 7 is illustrated the constructed shortest path tree related to all the examples: the shortest-path tree is the same for every chosen route (with minutes or kilometers). The calculated routes (D -> F) show that even if in route 2 there are 7 km more than in route 1, in terms of time it is possible to gain 2 minutes: this happens because, in the second route, 46 of the 71 km to travel are on state roads and highways.

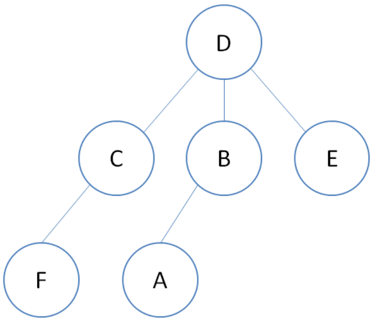


Figure 7. Constructed graph of minimum paths.

A control code has been implemented thus allowing the user to select the correct vertices of a path graph: this provides an optimization of the computational cost and the overcome of CPU loop problems. In fact, through the use of a while cycle, the code compares the vertices inserted with the standard ones. In particular the following three variables are created:

- variable *a* (it is the variable that allows to cycle all the possible vertices; it has been initialized to 0 and can reach a maximum number of 5; once it has passed 5, the system will exit the while loop);

- variable *flagstart* (it is the flag variable of the source node; it is initialized at 6 and decremented by 1 whenever the START variable is different from a; if the vertex is not valid, at the end of the cycle the flagstart variable will be equal to 0);
- variable *flagend* (it is the flag variable of the source node; it is initialized at 6 and decremented by 1 whenever the END variable is different from *a*; if the vertex is not valid, at the end of the cycle the *flagend* variable will be equal to 0).

Figure 8 shows the flowchart of the algorithm implemented for vertex control.

By applying the Floyd-Warshall algorithm have been compared the minimum paths with ones of the Dijstra's algorithm checking the same solution convergence (see Fig. 9 where E is the destination node and A is the source one).

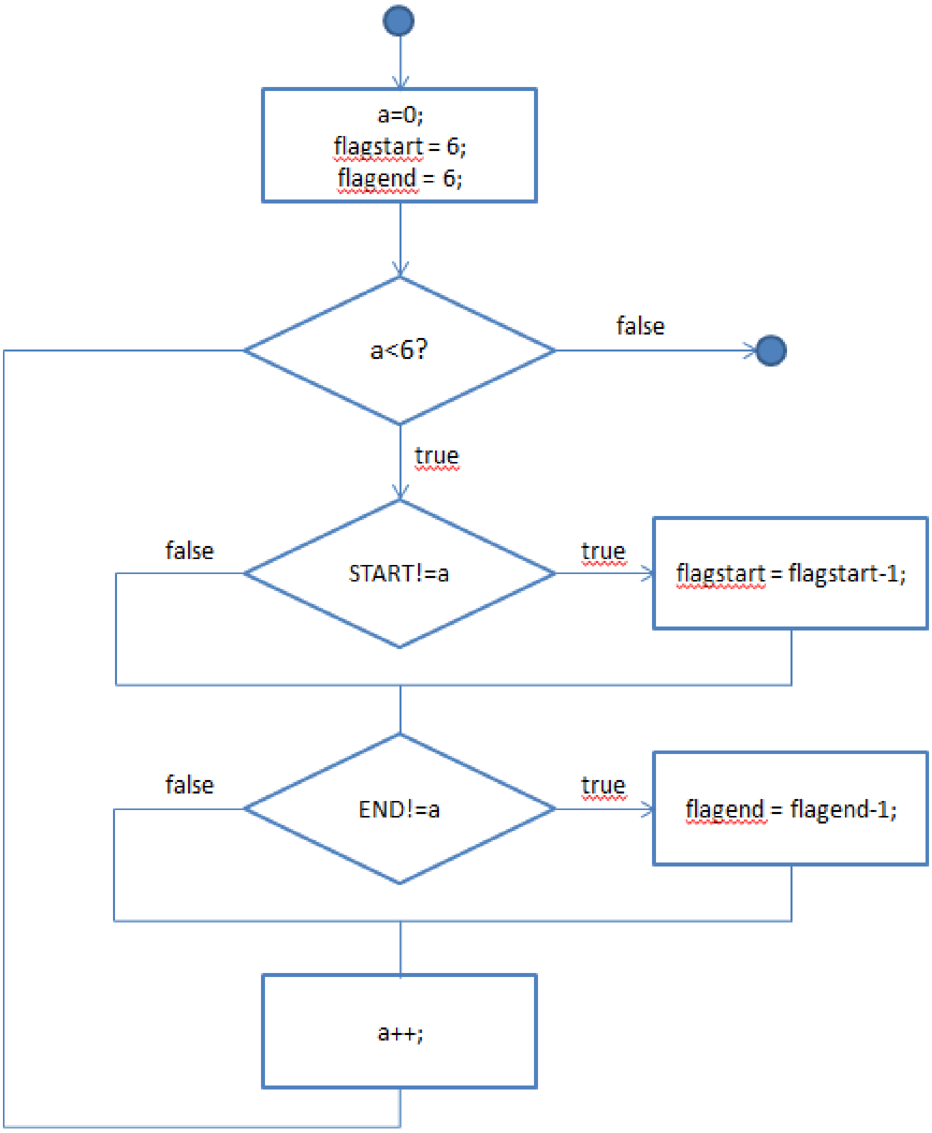
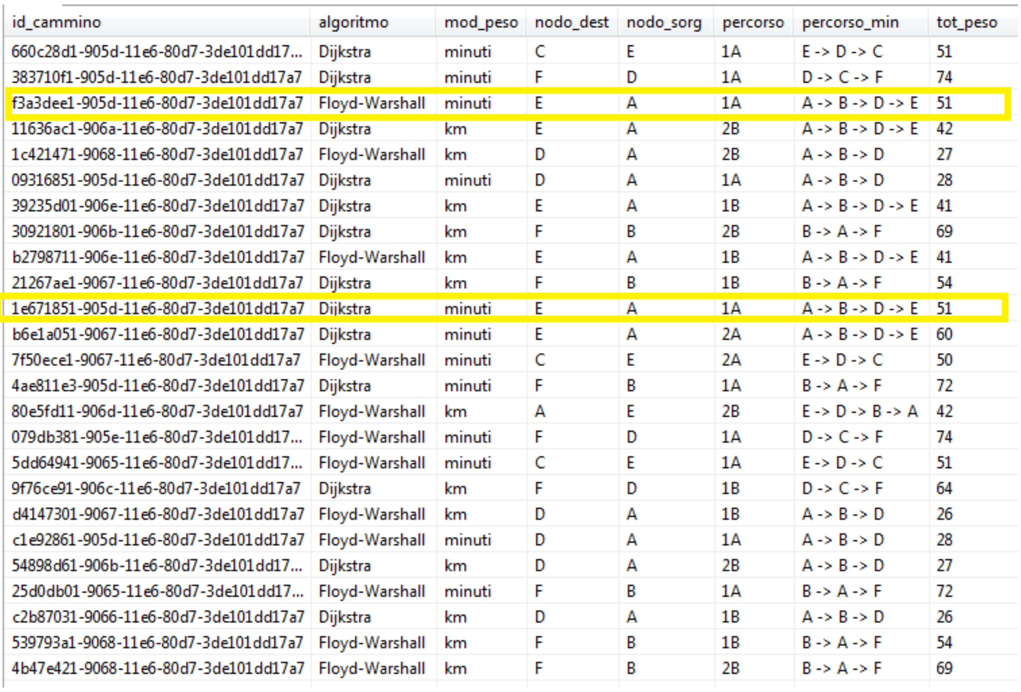


Figure 8. Flowchart of the algorithm implemented for vertex control.



id_cammino	algoritmo	mod_peso	nodo_dest	nodo_sorg	percorso	percorso_min	tot_peso
660c28d1-905d-11e6-80d7-3de101dd17...	Dijkstra	minuti	C	E	1A	E -> D -> C	51
383710f1-905d-11e6-80d7-3de101dd17a7	Dijkstra	minuti	F	D	1A	D -> C -> F	74
f3a3dee1-905d-11e6-80d7-3de101dd17a7	Floyd-Warshall	minuti	E	A	1A	A -> B -> D -> E	51
11636ac1-906a-11e6-80d7-3de101dd17a7	Dijkstra	km	E	A	2B	A -> B -> D -> E	42
1c421471-9068-11e6-80d7-3de101dd17a7	Floyd-Warshall	km	D	A	2B	A -> B -> D	27
09316851-905d-11e6-80d7-3de101dd17a7	Dijkstra	minuti	D	A	1A	A -> B -> D	28
39235d01-906e-11e6-80d7-3de101dd17a7	Dijkstra	km	E	A	1B	A -> B -> D -> E	41
30921801-906b-11e6-80d7-3de101dd17a7	Dijkstra	km	F	B	2B	B -> A -> F	69
b2798711-906e-11e6-80d7-3de101dd17a7	Floyd-Warshall	km	E	A	1B	A -> B -> D -> E	41
21267ae1-9067-11e6-80d7-3de101dd17a7	Dijkstra	km	F	B	1B	B -> A -> F	54
1e671851-905d-11e6-80d7-3de101dd17a7	Dijkstra	minuti	E	A	1A	A -> B -> D -> E	51
b6e1a051-9067-11e6-80d7-3de101dd17a7	Dijkstra	minuti	E	A	2A	A -> B -> D -> E	60
7f50ece1-9067-11e6-80d7-3de101dd17a7	Floyd-Warshall	minuti	C	E	2A	E -> D -> C	50
4ae811e3-905d-11e6-80d7-3de101dd17a7	Dijkstra	minuti	F	B	1A	B -> A -> F	72
80e5fd11-906d-11e6-80d7-3de101dd17a7	Floyd-Warshall	km	A	E	2B	E -> D -> B -> A	42
079db381-905e-11e6-80d7-3de101dd17...	Floyd-Warshall	minuti	F	D	1A	D -> C -> F	74
5dd64941-9065-11e6-80d7-3de101dd17...	Floyd-Warshall	minuti	C	E	1A	E -> D -> C	51
9f76ce91-906c-11e6-80d7-3de101dd17a7	Dijkstra	km	F	D	1B	D -> C -> F	64
d4147301-9067-11e6-80d7-3de101dd17a7	Floyd-Warshall	km	D	A	1B	A -> B -> D	26
c1e92861-905d-11e6-80d7-3de101dd17a7	Floyd-Warshall	minuti	D	A	1A	A -> B -> D	28
54898d61-906b-11e6-80d7-3de101dd17...	Dijkstra	km	D	A	2B	A -> B -> D	27
25d0db01-9065-11e6-80d7-3de101dd17...	Floyd-Warshall	minuti	F	B	1A	B -> A -> F	72
c2b87031-9066-11e6-80d7-3de101dd17a7	Dijkstra	km	D	A	1B	A -> B -> D	26
539793a1-9068-11e6-80d7-3de101dd17a7	Floyd-Warshall	km	F	B	1B	B -> A -> F	54
4b47e421-9068-11e6-80d7-3de101dd17a7	Floyd-Warshall	km	F	B	2B	B -> A -> F	69

Figure 9. Screenshot of the outputs of the Dijstra's and Floyd-Warshall algorithms.

Both the Dijstra's and the Floyd-Warshall algorithms have been implemented in java language adopting Eclipse platform. In Appendix A is listed the java script allowing the saving of the logistic algorithm into the Cassandra big data.

4. Web Mining: Analysis of Social Trends

Other important information to analyze for the BI can be obtained by web mining. In particular information found in social network could provide an interesting scenario about the social trends of particular classes of products. A critical aspect for web mining is to traduce the text into a sentiment score. In order to create a model of positive and negative words, it is important to apply before a tool able to extract this information from a phrase. A way is to adopt the tool "Tone Analyzer" [32]. In Fig 10 is illustrated the main data flow adopted for the sentiment extraction: (i) a keyword of a features of a product is found by a social network engine (Facebook, Twitter, etc.); (ii) the social network engine provides post and phrases containing the keyword; (iii) "Tone Analyzer" extracts the sentiment scores about the searched keywords embedded into a phrase; (iv) the sentiment data are stored into the big data system containing other historical sentiment scores. The analysis with historical data could provide the time evolution of the sentiment.

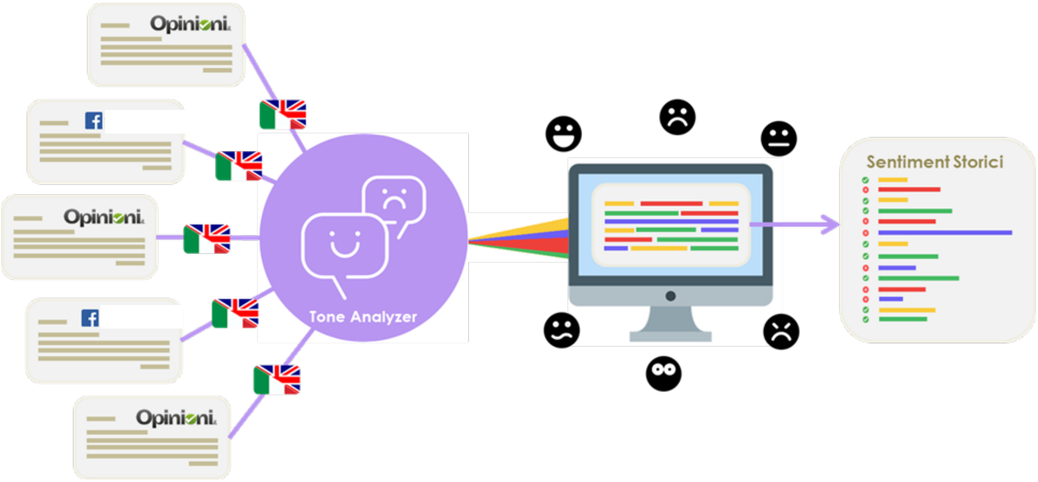
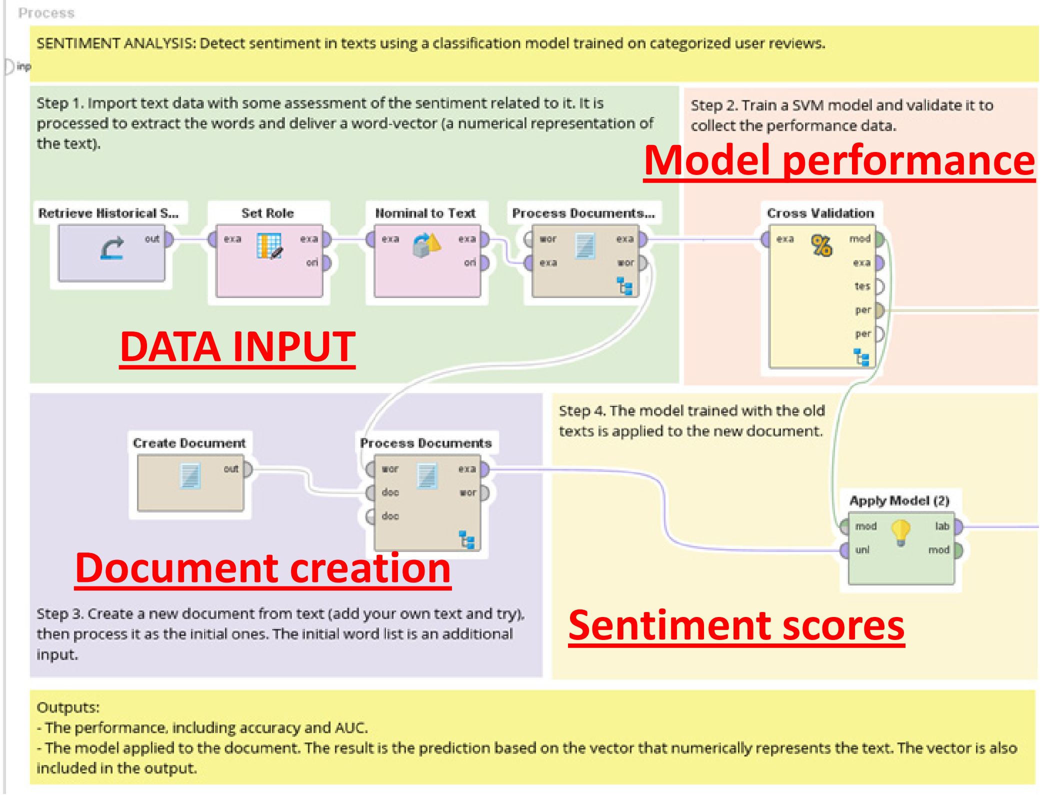


Figure 10. Post translations for the text processing of "Tone Analyzer".

A workflow suitable for text mining is illustrated in Fig. 11: the proposed Rapid Miner workflow implements a Support Vector Machine (SVM) algorithm [33]. The workflow of Fig. 11 is structured in the following four main step:

- step 1 (data input and data pre-processing able to provide a numerical representation of the text);
- step 2 (SVM model performance and model training);
- step 3 (document creation and testing);
- step 4 (sentiment outputs performed by the implemented model).

Another workflow adopted for the social sentiment analysis is the KNIME workflow of Fig. 12: this model executes the Decision Tree model and is structured in three stages such as: data pre-processing, data processing (training and testing), and model performance (model score and ROC curve).



SENTIMENT ANALYSIS: Detect sentiment in texts using a classification model trained on categorized user reviews.

Step 1. Import text data with some assessment of the sentiment related to it. It is processed to extract the words and deliver a word-vector (a numerical representation of the text).

Step 2. Train a SVM model and validate it to collect the performance data.

Step 4. The model trained with the old texts is applied to the new document.

Step 3. Create a new document from text (add your own text and try), then process it as the initial ones. The initial word list is an additional input.

Outputs:
- The performance, including accuracy and AUC.
- The model applied to the document. The result is the prediction based on the vector that numerically represents the text. The vector is also included in the output.

Figure 11. RapidMiner workflow: sentiment scores extracted from a text.

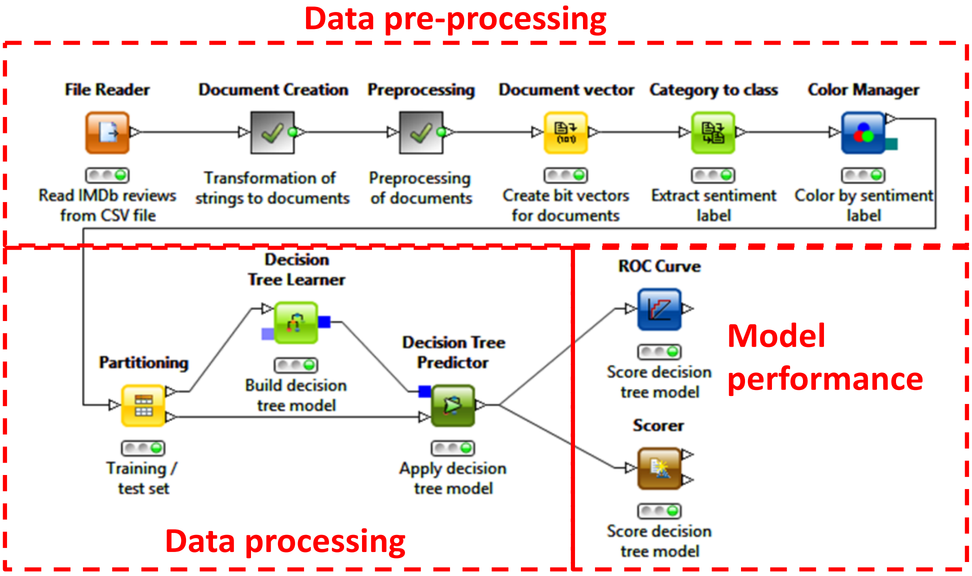
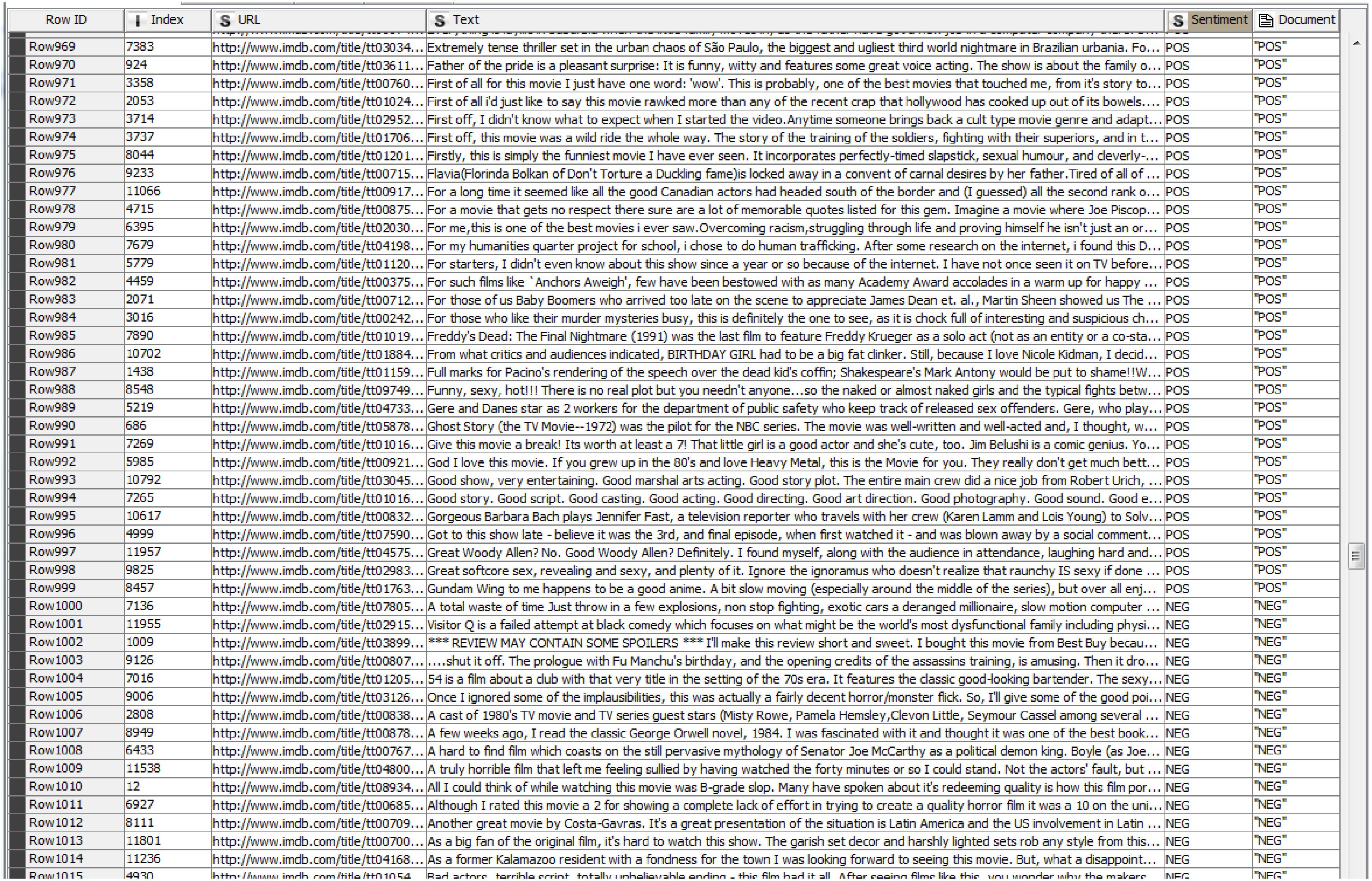


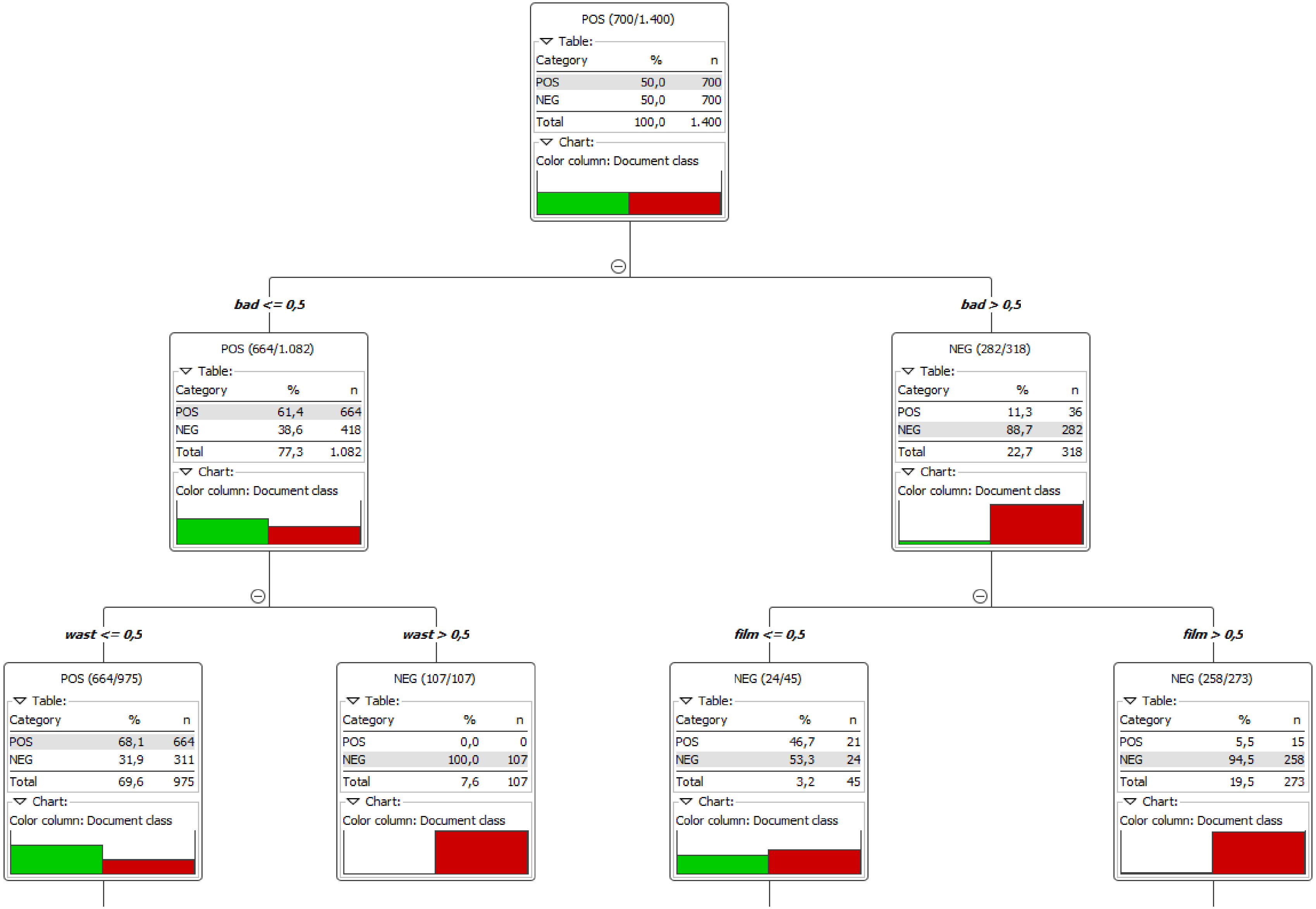
Figure 12. KNIME Sentiment analysis workflow [34].

An example of output of the sentiment analysis is illustrated in Fig. 13 reporting the scoring positive (POS) or negative (NEG) of different phrases.



Row ID	Index	URL	Text	Sentiment	Document
Row969	7383	http://www.imdb.com/title/tt03034...	Extremely tense thriller set in the urban chaos of São Paulo, the biggest and ugliest third world nightmare in Brazilian urbania. Fo...	POS	"POS"
Row970	924	http://www.imdb.com/title/tt03611...	Father of the pride is a pleasant surprise: It is funny, witty and features some great voice acting. The show is about the family o...	POS	"POS"
Row971	3358	http://www.imdb.com/title/tt00760...	First of all for this movie I just have one word: 'wow'. This is probably, one of the best movies that touched me, from it's story to...	POS	"POS"
Row972	2053	http://www.imdb.com/title/tt01024...	First of all i'd just like to say this movie rawked more than any of the recent crap that hollywood has cooked up out of its bowels....	POS	"POS"
Row973	3714	http://www.imdb.com/title/tt02952...	First off, I didn't know what to expect when I started the video.Anytime someone brings back a cult type movie genre and adapt...	POS	"POS"
Row974	3737	http://www.imdb.com/title/tt01706...	First off, this movie was a wild ride the whole way. The story of the training of the soldiers, fighting with their superiors, and in t...	POS	"POS"
Row975	8044	http://www.imdb.com/title/tt01201...	Firstly, this is simply the funniest movie I have ever seen. It incorporates perfectly-timed slapstick, sexual humour, and cleverly-...	POS	"POS"
Row976	9233	http://www.imdb.com/title/tt00715...	Flavia(Florinda Bolkan of Don't Torture a Duckling fame)is locked away in a convent of carnal desires by her father.Tired of all of ...	POS	"POS"
Row977	11066	http://www.imdb.com/title/tt00917...	For a long time it seemed like all the good Canadian actors had headed south of the border and (I guessed) all the second rank o...	POS	"POS"
Row978	4715	http://www.imdb.com/title/tt00875...	For a movie that gets no respect there sure are a lot of memorable quotes listed for this gem. Imagine a movie where Joe Piscop...	POS	"POS"
Row979	6395	http://www.imdb.com/title/tt02030...	For me,this is one of the best movies i ever saw.Overcoming racism,struggling through life and proving himself he isn't just an or...	POS	"POS"
Row980	7679	http://www.imdb.com/title/tt04198...	For my humanities quarter project for school, i chose to do human trafficking. After some research on the internet, i found this D...	POS	"POS"
Row981	5779	http://www.imdb.com/title/tt01120...	For starters, I didn't even know about this show since a year or so because of the internet. I have not once seen it on TV before...	POS	"POS"
Row982	4459	http://www.imdb.com/title/tt00375...	For such films like `Anchors Aweigh', few have been bestowed with as many Academy Award accolades in a warm up for happy ...	POS	"POS"
Row983	2071	http://www.imdb.com/title/tt00712...	For those of us Baby Boomers who arrived too late on the scene to appreciate James Dean et. al., Martin Sheen showed us The ...	POS	"POS"
Row984	3016	http://www.imdb.com/title/tt00242...	For those who like their murder mysteries busy, this is definitely the one to see, as it is chock full of interesting and suspicious ch...	POS	"POS"
Row985	7890	http://www.imdb.com/title/tt01019...	Freddy's Dead: The Final Nightmare (1991) was the last film to feature Freddy Krueger as a solo act (not as an entity or a co-sta...	POS	"POS"
Row986	10702	http://www.imdb.com/title/tt01884...	From what critics and audiences indicated, BIRTHDAY GIRL had to be a big fat clinker. Still, because I love Nicole Kidman, I decid...	POS	"POS"
Row987	1438	http://www.imdb.com/title/tt01159...	Full marks for Pacino's rendering of the speech over the dead kid's coffin; Shakespeare's Mark Antony would be put to shame!!W...	POS	"POS"
Row988	8548	http://www.imdb.com/title/tt09749...	Funny, sexy, hot!!! There is no real plot but you needn't anyone...so the naked or almost naked girls and the typical fights betw...	POS	"POS"
Row989	5219	http://www.imdb.com/title/tt04733...	Gere and Danes star as 2 workers for the department of public safety who keep track of released sex offenders. Gere, who play...	POS	"POS"
Row990	686	http://www.imdb.com/title/tt05878...	Ghost Story (the TV Movie--1972) was the pilot for the NBC series. The movie was well-written and well-acted and, I thought, w...	POS	"POS"
Row991	7269	http://www.imdb.com/title/tt01016...	Give this movie a break! Its worth at least a 7! That little girl is a good actor and she's cute, too. Jim Belushi is a comic genius. Yo...	POS	"POS"
Row992	5985	http://www.imdb.com/title/tt00921...	God I love this movie. If you grew up in the 80's and love Heavy Metal, this is the Movie for you. They really don't get much bett...	POS	"POS"
Row993	10792	http://www.imdb.com/title/tt03045...	Good show, very entertaining. Good marshal arts acting. Good story plot. The entire main crew did a nice job from Robert Urich, ...	POS	"POS"
Row994	7265	http://www.imdb.com/title/tt01016...	Good story. Good script. Good casting. Good acting. Good directing. Good art direction. Good photography. Good sound. Good e...	POS	"POS"
Row995	10617	http://www.imdb.com/title/tt00832...	Gorgeous Barbara Bach plays Jennifer Fast, a television reporter who travels with her crew (Karen Lamm and Lois Young) to Solv...	POS	"POS"
Row996	4999	http://www.imdb.com/title/tt07590...	Got to this show late - believe it was the 3rd, and final episode, when first watched it - and was blown away by a social comment...	POS	"POS"
Row997	11957	http://www.imdb.com/title/tt04575...	Great Woody Allen? No. Good Woody Allen? Definitely. I found myself, along with the audience in attendance, laughing hard and...	POS	"POS"
Row998	9825	http://www.imdb.com/title/tt02983...	Great softcore sex, revealing and sexy, and plenty of it. Ignore the ignoramus who doesn't realize that raunchy IS sexy if done ...	POS	"POS"
Row999	8457	http://www.imdb.com/title/tt01763...	Gundam Wing to me happens to be a good anime. A bit slow moving (especially around the middle of the series), but over all enj...	POS	"POS"
Row1000	7136	http://www.imdb.com/title/tt07805...	A total waste of time Just throw in a few explosions, non stop fighting, exotic cars a deranged millionaire, slow motion computer ...	NEG	"NEG"
Row1001	11955	http://www.imdb.com/title/tt02915...	Visitor Q is a failed attempt at black comedy which focuses on what might be the world's most dysfunctional family including physi...	NEG	"NEG"
Row1002	1009	http://www.imdb.com/title/tt03899...	*** REVIEW MAY CONTAIN SOME SPOILERS *** I'll make this review short and sweet. I bought this movie from Best Buy becau...	NEG	"NEG"
Row1003	9126	http://www.imdb.com/title/tt00807...	....shut it off. The prologue with Fu Manchu's birthday, and the opening credits of the assassins training, is amusing. Then it dro...	NEG	"NEG"
Row1004	7016	http://www.imdb.com/title/tt01205...	54 is a film about a club with that very title in the setting of the 70s era. It features the classic good-looking bartender. The sexy...	NEG	"NEG"
Row1005	9006	http://www.imdb.com/title/tt03126...	Once I ignored some of the implausibilities, this was actually a fairly decent horror/monster flick. So, I'll give some of the good poi...	NEG	"NEG"
Row1006	2808	http://www.imdb.com/title/tt00838...	A cast of 1980's TV movie and TV series guest stars (Misty Rowe, Pamela Hemsley,Clevon Little, Seymour Cassel among several ...	NEG	"NEG"
Row1007	8949	http://www.imdb.com/title/tt00878...	A few weeks ago, I read the classic George Orwell novel, 1984. I was fascinated with it and thought it was one of the best book...	NEG	"NEG"
Row1008	6433	http://www.imdb.com/title/tt00767...	A hard to find film which coasts on the still pervasive mythology of Senator Joe McCarthy as a political demon king. Boyle (as Joe...	NEG	"NEG"
Row1009	11538	http://www.imdb.com/title/tt04800...	A truly horrible film that left me feeling sullied by having watched the forty minutes or so I could stand. Not the actors' fault, but ...	NEG	"NEG"
Row1010	12	http://www.imdb.com/title/tt08934...	All I could think of while watching this movie was B-grade slop. Many have spoken about it's redeeming quality is how this film por...	NEG	"NEG"
Row1011	6927	http://www.imdb.com/title/tt00685...	Although I rated this movie a 2 for showing a complete lack of effort in trying to create a quality horror film it was a 10 on the uni...	NEG	"NEG"
Row1012	8111	http://www.imdb.com/title/tt00709...	Another great movie by Costa-Gavras. It's a great presentation of the situation is Latin America and the US involvement in Latin ...	NEG	"NEG"
Row1013	11801	http://www.imdb.com/title/tt00700...	As a big fan of the original film, it's hard to watch this show. The garish set decor and harshly lighted sets rob any style from this...	NEG	"NEG"
Row1014	11236	http://www.imdb.com/title/tt04168...	As a former Kalamazoo resident with a fondness for the town I was looking forward to seeing this movie. But, what a disappoint...	NEG	"NEG"
Row1015	4930	http://www.imdb.com/title/tt01054...	Bad actors, terrible script, totally unbelievable ending - this film had it all. After seeing films like this, you wonder why the makers	NEG	"NEG"

Figure 13. RapidMiner: Sentiment analysis of a text.



POS (700/1.400)

Table:

Category	%	n
POS	50,0	700
NEG	50,0	700
Total	100,0	1.400

Chart:

Color column: Document class

POS (664/1.082)

Table:

Category	%	n
POS	61,4	664
NEG	38,6	418
Total	77,3	1.082

Chart:

Color column: Document class

NEG (282/318)

Table:

Category	%	n
POS	11,3	36
NEG	88,7	282
Total	22,7	318

Chart:

Color column: Document class

POS (664/975)

Table:

Category	%	n
POS	68,1	664
NEG	31,9	311
Total	69,6	975

Chart:

Color column: Document class

NEG (107/107)

Table:

Category	%	n
POS	0,0	0
NEG	100,0	107
Total	7,6	107

Chart:

Color column: Document class

NEG (24/45)

Table:

Category	%	n
POS	46,7	21
NEG	53,3	24
Total	3,2	45

Chart:

Color column: Document class

NEG (258/273)

Table:

Category	%	n
POS	5,5	15
NEG	94,5	258
Total	19,5	273

Chart:

Color column: Document class

Figure 14. KNIME: Example of sentiment outputs of different keywords searched into a social text

A sentiment analysis output of KNIME workflow is shown in Fig. 14 where each keywords are allocated into a tree structure indicating also the occurrences into the analyzed text. The decision tree begins (first level) with the supposition that half of the 1400 classified reviews are positive. The decision to move from a "parent" leaf to a "child" leaf is based on the percentage of presence (<= 0.5 or > 0.5) of the chosen word. For example, at the second level of the tree, the word most often used was "bad". 61.4% of the 1082 reviews, in which the word "bad" is less present, that is “bad <= 0.5” (664 reviews), was classified as "positive". 88.7% of the 318 reviews in which the word "bad" is more present, that is “bad > 0.5” (282 reviews), was classified as "negative". At the third level, we find the other words which are subclasses of the weighted word “bad”.

The good performance of the Decision Tree algorithm is represented by the receiver operating characteristic curve (ROC) of Fig. 15. The ROC curve is a graphical plot illustrating the diagnostic ability of a binary classifier system as its discrimination threshold is varied. The sentiment results are saved into the Cassandra big data by means of the php script reported in Appendix B.

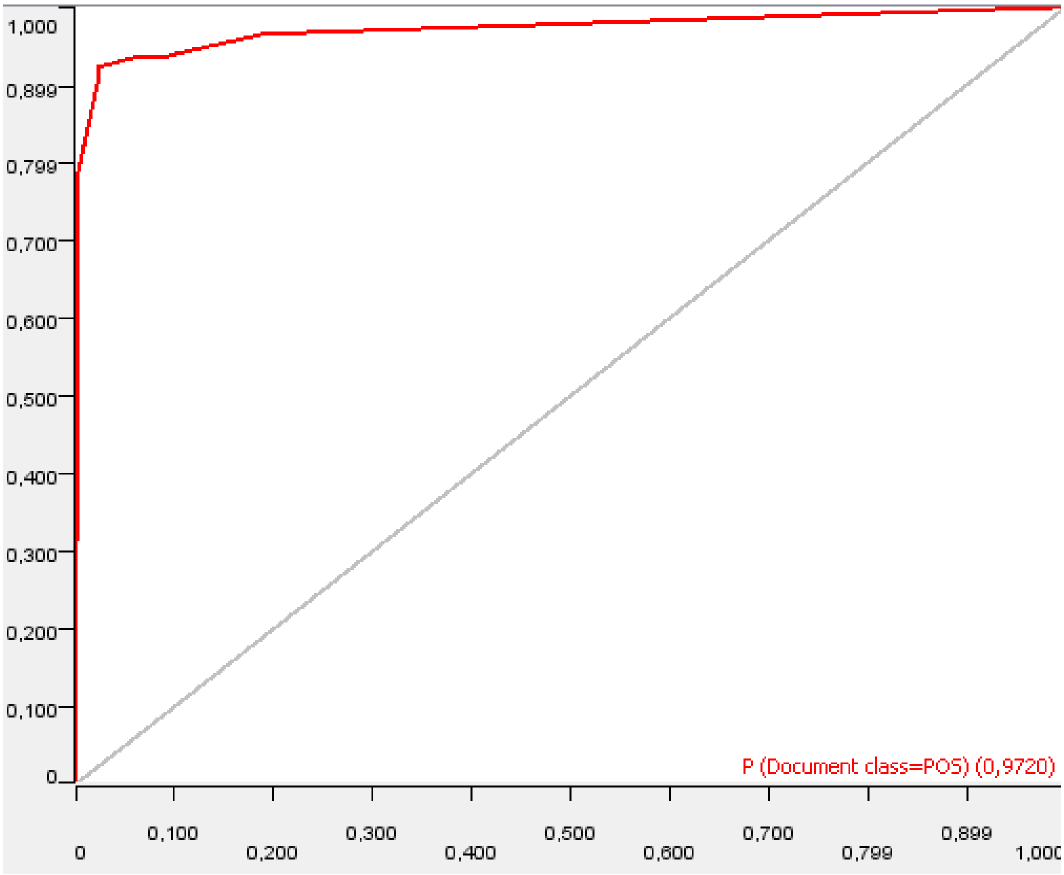


Figure 15. KNIME ROC curve related to the results of Fig. 14.

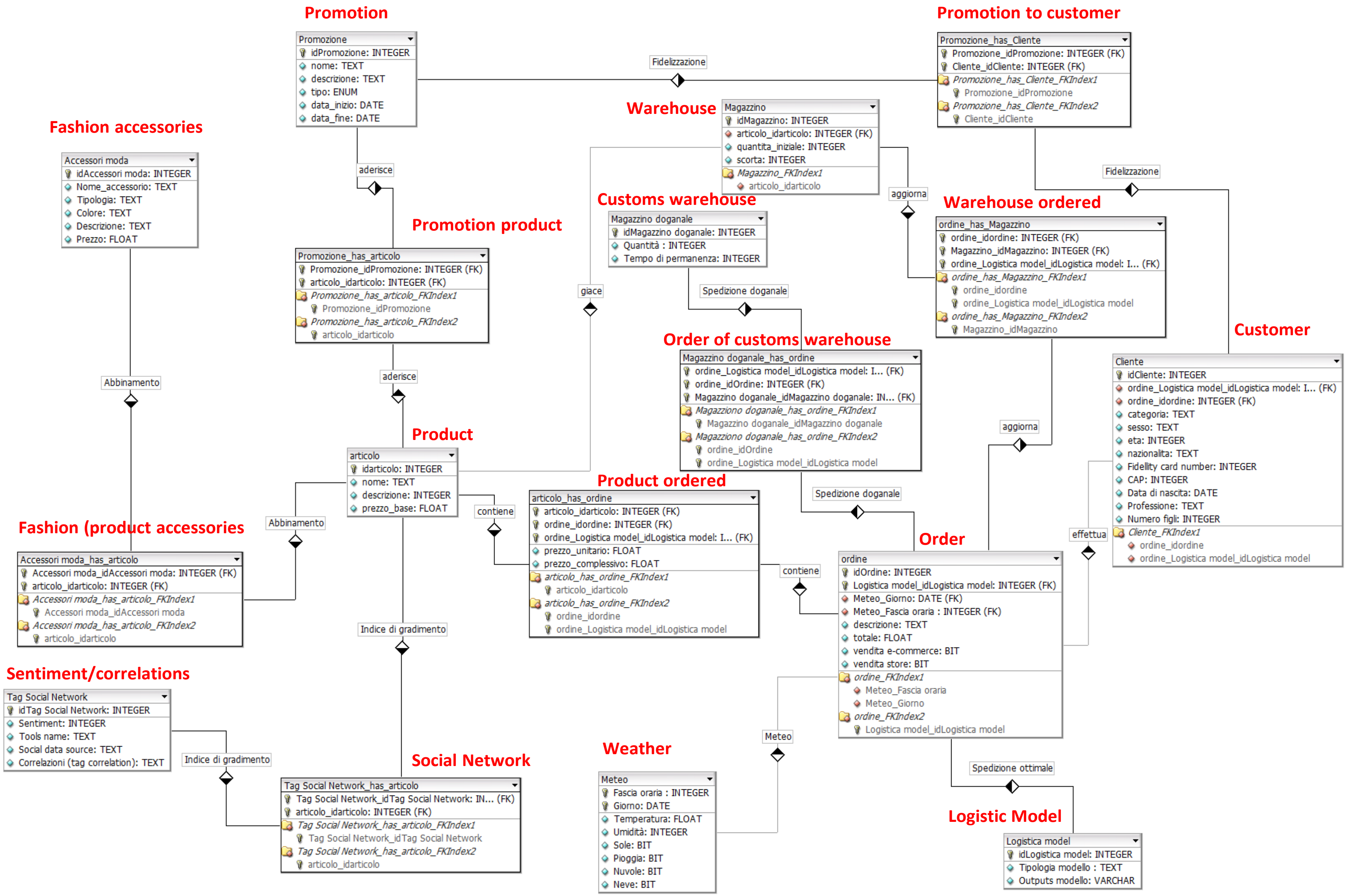

Promotion
Promozione
idPromozione: INTEGER
nome: TEXT
descrizione: TEXT
tipo: ENUM
data_inizio: DATE
data_fine: DATE
Fidelizzazione
Promotion to customer
Promozione_has_Cliente
Promozione_idPromozione: INTEGER (FK)
Cliente_idCliente: INTEGER (FK)
Promozione_has_Cliente_FKIndex1
Promozione_idPromozione
Promozione_has_Cliente_FKIndex2
Cliente_idCliente
Fashion accessories
Accessori moda
idAccessori moda: INTEGER
Nome_accessorio: TEXT
Tipologia: TEXT
Colore: TEXT
Descrizione: TEXT
Prezzo: FLOAT
Warehouse
Magazzino
idMagazzino: INTEGER
articolo_idarticolo: INTEGER (FK)
quantita_iniziale: INTEGER
scorta: INTEGER
Magazzino_FKIndex1
articolo_idarticolo
aderisce
aggiorna
Fidelizzazione
Customs warehouse
Magazzino doganale
idMagazzino doganale: INTEGER
Quantità : INTEGER
Tempo di permanenza: INTEGER
Promotion product
Promozione_has_articolo
Promozione_idPromozione: INTEGER (FK)
articolo_idarticolo: INTEGER (FK)
Promozione_has_articolo_FKIndex1
Promozione_idPromozione
Promozione_has_articolo_FKIndex2
articolo_idarticolo
Warehouse ordered
ordine_has_Magazzino
ordine_idordine: INTEGER (FK)
Magazzino_idMagazzino: INTEGER (FK)
ordine_Logistica model_idLogistica model: I... (FK)
ordine_has_Magazzino_FKIndex1
ordine_idordine
ordine_Logistica model_idLogistica model
ordine_has_Magazzino_FKIndex2
Magazzino_idMagazzino
giace
Spedizione doganale
Order of customs warehouse
Magazzino doganale_has_ordine
ordine_Logistica model_idLogistica model: I... (FK)
ordine_idOrdine: INTEGER (FK)
Magazzino doganale_idMagazzino doganale: IN... (FK)
Magazzino doganale_has_ordine_FKIndex1
Magazzino doganale_idMagazzino doganale
Magazzino doganale_has_ordine_FKIndex2
ordine_idOrdine
ordine_Logistica model_idLogistica model
Customer
Cliente
idCliente: INTEGER
ordine_Logistica model_idLogistica model: I... (FK)
ordine_idordine: INTEGER (FK)
categoria: TEXT
sesso: TEXT
eta: INTEGER
nazionalita: TEXT
Fidelity card number: INTEGER
CAP: INTEGER
Data di nascita: DATE
Professione: TEXT
Numero figli: INTEGER
Cliente_FKIndex1
ordine_idordine
ordine_Logistica model_idLogistica model
Abbinamento
aderisce
Product
articolo
idarticolo: INTEGER
nome: TEXT
descrizione: INTEGER
prezzo_base: FLOAT
aggiorna
Product ordered
articolo_has_ordine
articolo_idarticolo: INTEGER (FK)
ordine_idordine: INTEGER (FK)
ordine_Logistica model_idLogistica model: I... (FK)
prezzo_unitario: FLOAT
prezzo_complessivo: FLOAT
articolo_has_ordine_FKIndex1
articolo_idarticolo
articolo_has_ordine_FKIndex2
ordine_idordine
ordine_Logistica model_idLogistica model
Spedizione doganale
Fashion (product accessories
Abbinamento
contiene
Accessori moda_has_articolo
Accessori moda_idAccessori moda: INTEGER (FK)
articolo_idarticolo: INTEGER (FK)
Accessori moda_has_articolo_FKIndex1
Accessori moda_idAccessori moda
Accessori moda_has_articolo_FKIndex2
articolo_idarticolo
Order
effettua
contiene
ordine
idOrdine: INTEGER
Logistica model_idLogistica model: INTEGER (FK)
Meteo_Giorno: DATE (FK)
Meteo_Fascia oraria : INTEGER (FK)
descrizione: TEXT
totale: FLOAT
vendita e-commerce: BIT
vendita store: BIT
ordine_FKIndex1
Meteo_Fascia oraria
Meteo_Giorno
ordine_FKIndex2
Logistica model_idLogistica model
Indice di gradimento
Sentiment/correlations
Tag Social Network
idTag Social Network: INTEGER
Sentiment: INTEGER
Tools name: TEXT
Social data source: TEXT
Correlazioni (tag correlation): TEXT
Indice di gradimento
Meteo
Social Network
Weather
Tag Social Network_has_articolo
Tag Social Network_idTag Social Network: IN... (FK)
articolo_idarticolo: INTEGER (FK)
Tag Social Network_has_articolo_FKIndex1
Tag Social Network_idTag Social Network
Tag Social Network_has_articolo_FKIndex2
articolo_idarticolo
Meteo
Fascia oraria : INTEGER
Giorno: DATE
Temperatura: FLOAT
Umidità: INTEGER
Sole: BIT
Pioggia: BIT
Nuvole: BIT
Neve: BIT
Spedizione ottimale
Logistic Model
Logistica model
idLogistica model: INTEGER
Tipologia modello : TEXT
Outputs modello: VARCHAR

Figure 16. Big Data layout design.

5. Big Data Integration

All the data of the algorithms proposed in this paper are collected into a Cassandra big data system. In Fig. 16 is shown the big data layouts embedding different NoSQL tables such as warehouse products availability, promotions, customer data, logistic inputs and outputs, social sentiment results, catalog list of products and accessories. For the database design of the proposed case of study has been adopted the tool DB Designer 4 [35]. Figure 16 represents a possible implementation of data integration into a big data system.

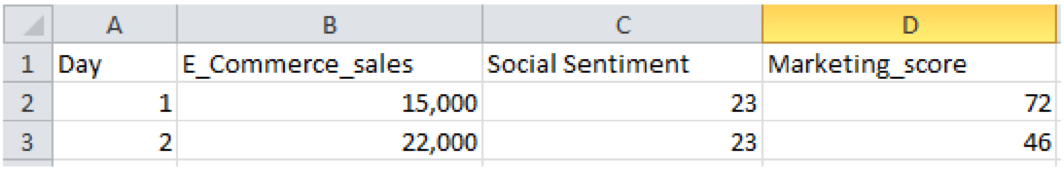
6. Data Mining Algorithm Improving Data Processing Innovation: E-Commerce Sales Prediction by Multi-attribute Processing

As proved by recent studies innovations in research involve multi-attribute analysis [36], and multi-dimensional analysis adopting Deep learning algorithms [37]. Furthermore it is developing the concept of data analysis from multi-dimensional big data multi-panel [38]. According with multi attribute analysis approach is proposed the model of Fig. 17 where are stored into a big data system (Cassandra or Vertica DB) the following attributes:

- historical E-commerce sales data;
- social sentiment scoring;
- marketing scoring (ratio between marketing trend score and product price);

In Fig. 17 is illustrated an example of the dataset layout adopted for the E-commerce sales prediction.

All data refers to the last 360 days of electronic commerce. For the first time is applied an innovative algorithm proposed in [39]. This KNIME workflow, based on ANN-MLP and RProp approaches [40]-[41], has been recently applied in medical applications for a single attribute input. For the first time this algorithm is applied for multi-inputs thus providing good performance.



	A	B	C	D
1	Day	E_Commerce_sales	Social Sentiment	Marketing_score
2	1	15,000	23	72
3	2	22,000	23	46

Figure 17. Layout of the experimental dataset

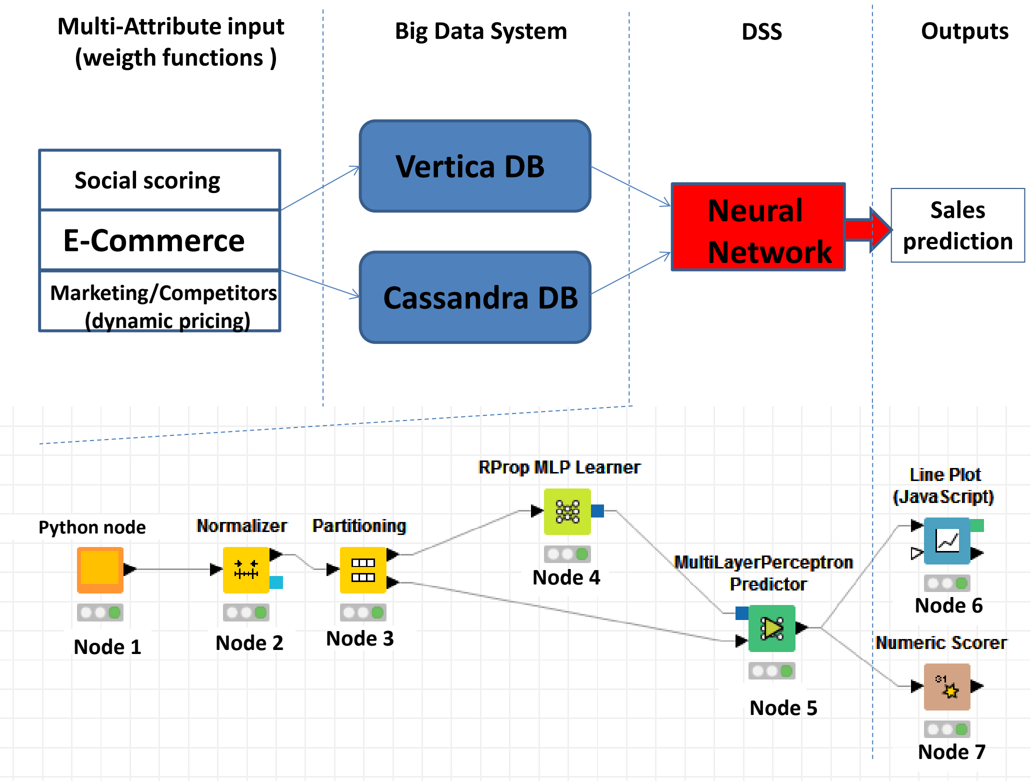


Figure 18. Innovative data mining multi-attribute model and related neural network KNIME workflow.

Below are described the nodes of Fig. 18:

- Node 1 (Python node): this node enables the connectivity with big data systems such as Cassandra or HP Vertica;
- Node 2 (Normalizer): this operator normalizes all values in a scale between 0 and 1 (0 corresponds to the minimum sales number, and 1 is the maximum one) thus allowing to reduce the data processing error;
- Node 3 (Partitioning): this block allows to provide the training dataset (first partitioning) and the testing dataset (second partitioning) ;
- Node 4 (RProp MLP Learner): module able to learn the MLP model processing the training dataset;
- Node 5 (MultiLayerPerceptron Predictor): MLP algorithm testing the neural network model;
- Node 6 (Line Plot): module able to plot sales prediction results;
- Node 7 (Numeric Scorer): block providing model performances.

In Fig. 19 is shown the E-commerce sales prediction trend for the next 17 days.

The parameters of the adopted for the neural network model are the following ones: 95% is the relative size of the first partition, the maximum number of iterations is 300, the hidden layers number is 2, the hidden neurons number per layer is 10. The performed means absolute error is 0.1, this means that the predicted sales of the next could oscillate around ± 0.05. In Fig. 20 is illustrated the error plot trend validating the algorithm performance.

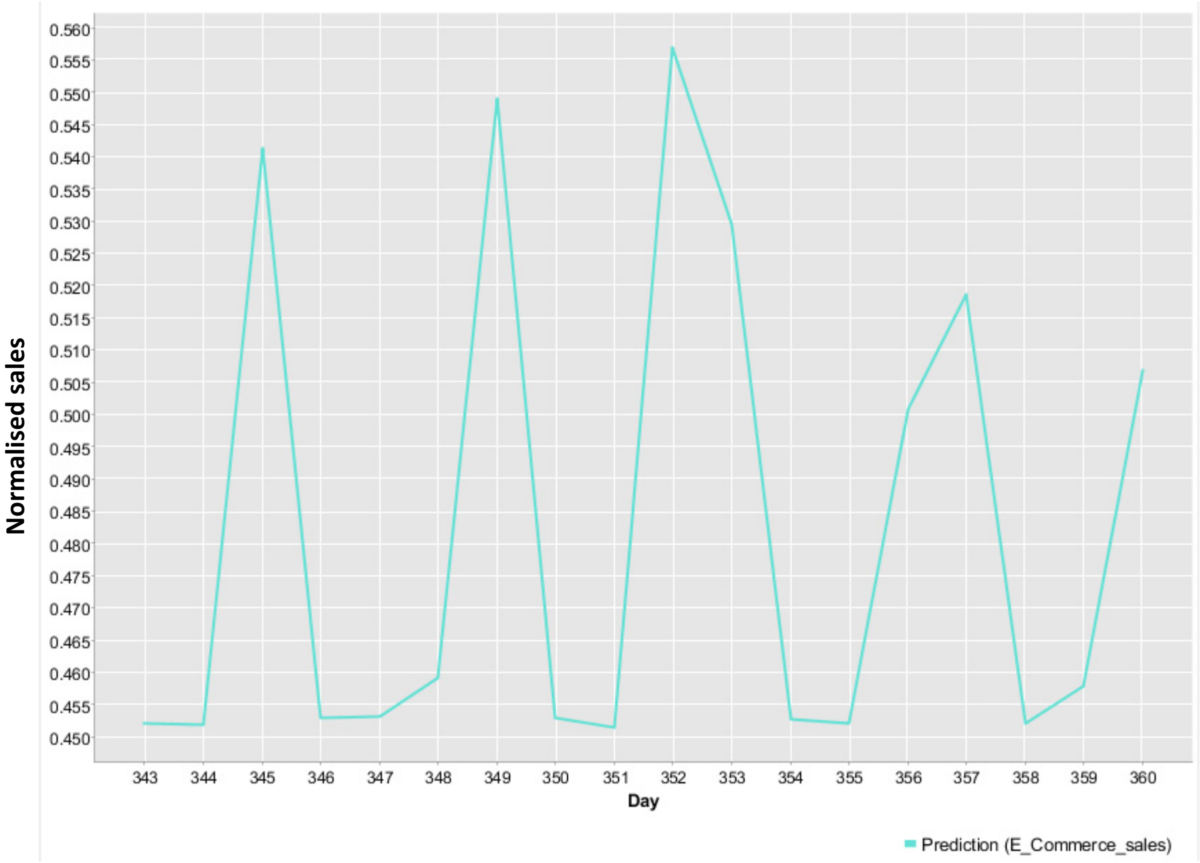


Figure 19. Innovative data mining multi-attribute model and related neural network (plot provided by the execution of the node 6 of Fig. 18).

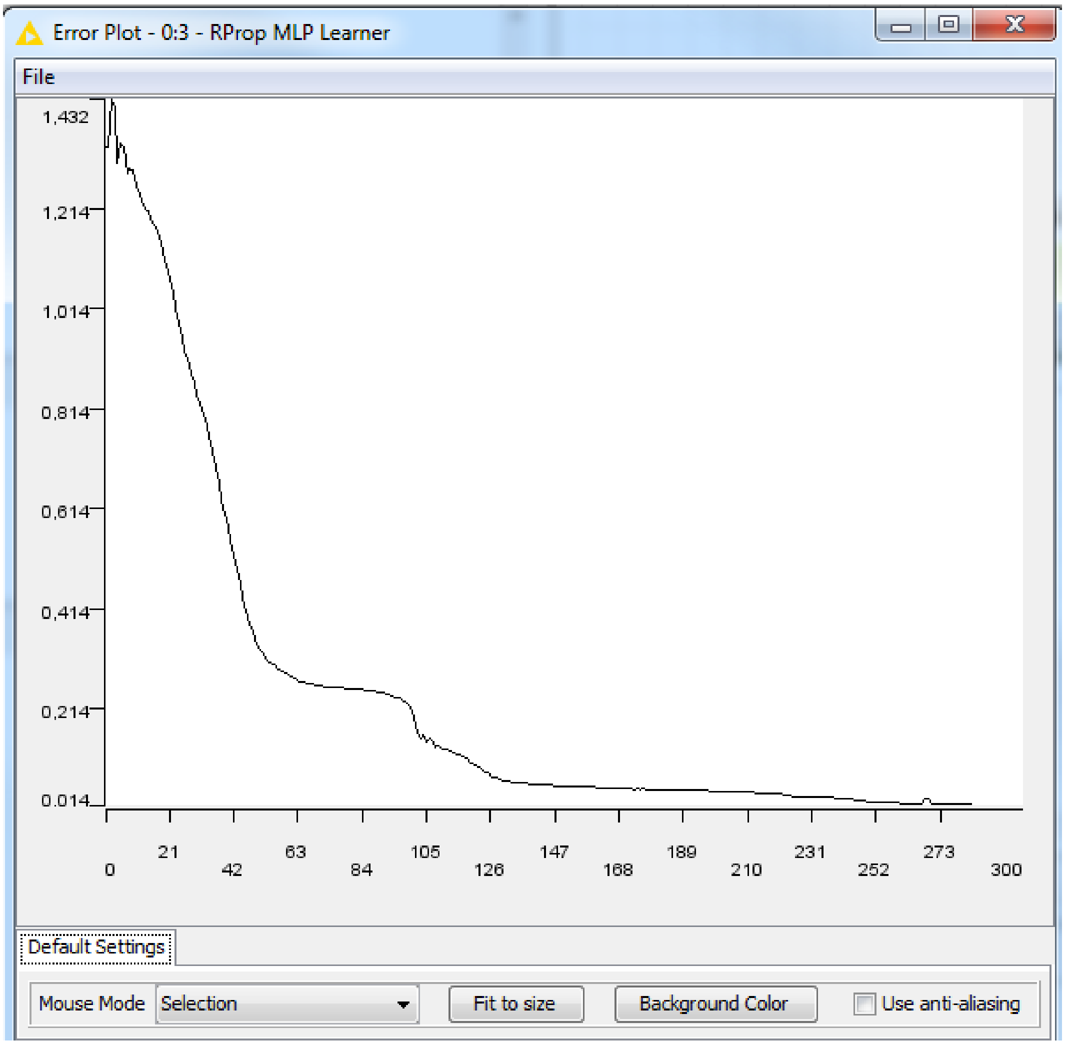


Figure 20. Error plot trend.

7. Conclusions

The proposed paper analyzes some important tools implemented in an industry research project oriented on business intelligence. These tools are related to logistic algorithms, sales prediction, and social analysis. Data mining has been applied for the last two tools by means of WEKA libraries, and Rapid Miner and KNIME workflows. A good performance is checked for all the algorithms outputs, finding a good matching between Dijkstra Floyd-Warshall results, and a good ROC curve for the sentiment analysis. Furthermore the proposed study enhances the integration of these tools into a structured communication systems embedding big data. In order to provide a feasibility study about data flow implementation, have been provided the data management scheme and the database layout able to collect all the input and data outputs of the proposed algorithms. Cassandra big data has been designed and implemented for the integration of different data sources suitable for the data processing of business intelligence outputs and marketing strategies. The paper illustrates a review of different tools which can be adopted for business intelligence, by providing information about how they can be applied by showing some examples. The proposed work could be help to understand how algorithms could be integrated into an industrial information system. As final results is proposed an innovative model based on multi-attribute analysis, big data connection and neural network workflow able to predict E-commerce sales with a good performance score. Some of inputs of this model are the outputs of other data mining tools such as social sentiment analysis.

Appendix A

A java code has been implemented to connect the Cassandra database and to save in it the shortest paths results obtained by the logistic algorithm. The implementation has been performed embedding the Cassandra JDBCs into the algorithm. The implemented code is shown below:

```
import com.datastax.driver.core.Cluster;
import com.datastax.driver.core.Host;
import com.datastax.driver.core.Metadata;
import com.datastax.driver.core.Session;
import static java.lang.System.out;
public class CassandraConnector
{
private Cluster cluster;
private Session session;
public void connect(final String node, final int port)
{
this.cluster = Cluster.builder().addContactPoint(node).withPort(port).build();
final Metadata metadata = cluster.getMetadata();
out.printf("Connected to cluster: %s\n", metadata.getClusterName());
for (final Host host : metadata.getAllHosts())
{
out.printf("Datacenter: %s; Host: %s; Rack: %s\n",
host.getDatacenter(), host.getAddress(), host.getRack());
}
session = cluster.connect("test_primadonna");
}
public Session getSession()
{
return this.session;
}
public void close()
{
cluster.close();
}
}
```

The implemented code follows a precise structure:

1). Connection to the Cassandra server;
2). Path displaying (1A, 1B, 2A, 2B);
3). Path selection;
4). Displaying of weight matrix that refers to the selected path;
5). Initial and destination vertex selection;
6). Algorithm selection;
7). If Dijkstra, shortest path and weight visualization;
8). If Floyd-Warshall, final matrices (weights and predecessors) displaying and path and weight visualization;
9). Insertion in the DB (if it is not already present).

Appendix B

In order to save the sentiment results to the Cassandra database it is necessary to set some connection parameters through the following php code (it save the .csv data into the Cassandra database):

```
<?php
...
$cassandra = new Cassandra();
 $server_host    = '[nome_server]';
 $server_port    = [porta_server];
 $server_username = '[nome_user]';
 $server_password = '[password]';
 $server_keyspace = '[nome_keyspace]';

 $cassandra->connect($server_host, $server_username, $server_password, $server_keyspace, $server_port);

...
 $cassandra -> close();
...
?>
```

Where:

- • The $server_host variable contains the name of the host to which the user must connect;
- The $server_port variable contains the connection port number;
- The variable $server_username contains the connection username;
- The $server_password variable contains the connection password;
- The $server_keyspace variable contains the name of the keyspace to which the script must connect;
- The code $cassandra-> connect (...) with all the above parameters as input variables allows the script to open the connection;
- The code $ cassandra -> close () corresponds to the command to close the previously opened connection.

Acknowledgements

The work has been developed within the framework of the project titled: Sistema di Business Intelligence di tipo “embedded” basato su prediction real time in sistemi Big Data orientate al settore di calzature e accessori moda “Predishoes” (Business Intelligence Embedded System based on real time prediction in Big Data systems oriented on fashion “Predishoes”).We are very grateful to the following Dyrecta Lab researchers: G. Birardi, V. Custodero, L. D’Alessandro, F. De Carlo, G. Fanelli, M. Legrottaglie, A. Leogrande, G. Lofano, V. Maritati, L. Pellicani, D. D. Romagno, N. Savino, P. Scagliusi, A. Semeraro, M. Solazzo, D. Suma, and E. Valenzano.

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