Sentiment Analysis on Yelp social network

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Abstract

In this paper, we propose a novel data model for Multimedia Social Networks, i.e. particular social media networks that combine information on users belonging to one or more social communities together with the content that is generated and used within the related environments. The proposed model relies on the hypergraph data structure to capture and represent in a simple way all the different kinds of relationships that are typical of social media networks, and in particular among users and multimedia content. We also introduce some user and multimedia ranking functions to enable different applications. Finally, some experiments concerning effectiveness of the approach for supporting relevant information retrieval activities are reported and discussed.

1 Introduction

Social media networks provide users an interactive platform to create and share multimedia content such as text, image, video, audio, and so on. Just as an example, each minute thousands of tweets are sent on Twitter, several hundreds of hours of videos are uploaded to YouTube, and a huge quantity of photos are shared on Instagram or uploaded to Flickr.

Within these "interest-based" networks, each user interacts with the others through a multimedia content and such interactions create "social links" that well characterize the behaviors of involved users in the networks. Here, multimedia data seems to play a "key-role" especially if we consider the *Social Network Analysis* (SNA) perspective: representing and understanding user-multimedia interaction mechanisms can be useful to predict user behavior, to model the evolution of multimedia content and social graphs, to design human-centric multimedia applications and services and so on. In particular, several research questions have to be addressed:

- It possible to exploit multimedia features and the notion of *similarity* to discover more useful links?
- Can all the different types of user annotations (e.g. tag, comment, review, etc.) and interactions with multimedia objects provide a further support for an advanced network analysis?
- Is it possible to integrate and efficiently manage in a unique network the information coming from different social media networks (for example, a Twitter user has usually an account also on Instagram or Flickr)?
- How can we deal with a very large volume of data?
- In this context, how is possible to model all the various relationships among users and multimedia objects[1]? Are the "graph-based" strategies still the most suitable solutions?

To capture the described issues, we adopt the term *Multimedia Social Networks* (MSNs) to indicate "*integrated social media networks that combine the information on users, belonging to one or more social communities, together with all the multimedia contents that can be generated and used within the related environments*".

Actually, the term MSN have been used over the last years in the literature together with *Social Multimedia Network* or *Social Media Network* to indicate information networks that leverage multimedia data in a social environment for several purposes: distributed resource allocation for multimedia content sharing in cloud-based systems [2], generation of personalized multimedia information recommendations in response to specific targets of interests [3],

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evaluation of the trust relationship among users [4], high dimensional video data distribution in social multimedia applications [5], characterization of user behavior and information propagation on the base of multimedia sharing activities [6], representation of a social collaboration network of archeologists for cultural heritage applications [7], just to cite some of the most recent proposals.

In this paper, inspired by hypergraph based approaches, we propose a novel data model[8, 9] for Multimedia Social Networks. Our model provides a solution for representing MSNs sufficiently general with respect to: i) a particular social information network, ii) the different kinds of entities, iii) the different types of relationships, iv) the different applications[10, 11]. Exploiting hypergraphs, the model allows us to represent in a simple way all the different kinds of relationships that are typical of a MSN (among multimedia contents, among users and multimedia content and among users themselves) and to enable several kinds of analytics and applications by means[12, 13] of the introduction of some user and multimedia (global and "topic sensitive") *ranking* functions.

We exploit functionalities of a well know framework for NLP processing, GATE [14] in order to extract relevant information from the famous online social network Yelp.

The paper is organized as in the following. Section 2 describes in details and using different examples our model with its properties and foundations. Section 3 shows the obtained experimental results using a standard Yelp dataset, while Section 4 reports conclusions and the future work.

2 The MSN data model

2.1 Basic Concepts

In our vision, a MSN is basically composed by three different entities:

- **Users** - the set of persons and organizations constituting the particular social community[15, 16]. Several information concerning their profile, interests, preferences, etc. can be exploited by our model.
- **Multimedia Objects** - the set of multimedia resources (i.e. images, video, audio, etc.) that can be shared within a MSN community. High level (*metadata*) and low level information (*features*) can be properly used in our model.
- **Annotation Assests** - the most significant terms or named entities - whose definition can be retrieved from dictionaries, ontologies and so on - of a given domain, or *topics*, exploited by users to annotate multimedia data and derived from the analysis of textual information such as keywords, labels, tags, comments etc.

Several types of relationships can be established among the described entities: for example, a user can annotate an image with a particular tag, two friends can comment the same post, a user can tag another user in a photo, a user can share some videos within a group and so on.

Due to the variety and complexity of these relationships, we decided to leverage the *hypergraph* formalism to model a MSN. In particular, our model relies on several concepts, *Multimedia Social Network* (seen as particular a weighted *hypergraph*) and *social paths* (i.e. *hyperpaths*), which basic definitions are provided in the following.

Definition 2.1 (MSN) *A* Multimedia Social Network MSN *is a triple* $(V; H_e = \{e_i : i \in I\}; \omega)$*,* V *being a finite set of* vertices*,* H_e *a set of* hyperedges *with a finite set of indexes* I *and* $\omega : H_e \rightarrow [0,1]$ *a weight function. The set of vertices is defined as* $V = U \cup M \cup A$*,* U *being the set of MSN users,* M *the set of multimedia objects and* A *the set of annotation assets. Each hyperedge* $e_i \in H_e$ *is in turn defined by a ordered pair* $e_i = (e_i^+ = (V_{e_i}^+, i); e_i^- = (i, V_{e_i}^-))$*. The element* e_i^+ *is called the* tail *of the hyperarc* e_i *whereas* e_i^- *is its* head*,* $V_{e_i}^+ \subseteq V$ *being the set of vertices of* e_i^+*,* $V_{e_i}^- \subseteq V$ *the set of vertices of* e_i^- *and* $V_{e_i} = V_{e_i}^+ \cup V_{e_i}^-$ *the subset of vertices constituting the whole hyperedge.*

Actually, vertices and hyperedges are *abstract data types* with a set of properties (attributes and methods) that permit to support several applications. We use the "dot notation" to identify the attributes of a given vertex or hyperedge: as an example, e_i.id, e_i.name, e_i.time and e_i.type represent the id, name, timestamp and type of the hyperedge e_i, respectively.

In addition, the weight function can be used to define the confidence or uncertainty of a given relationship in terms of probability, fuzzy membership, etc.

Definition 2.2 (Social path) *A* social path *between vertices* v_{s_1} *and* v_{s_k} *of a MSN is a sequence of distinct vertices and hyperedges* $v_{s_1}, e_{s_1}, v_{s_2}, ..., e_{s_{k-1}}, v_{s_k}$ *such that* $\{v_{s_i}, v_{s_{i+1}}\} \subseteq V_{e_{s_i}}$ *for 1≤* $i \leq k-1$*. The* length *of the hyperpath is* $\alpha \cdot \sum_{i=1}^{k-1} \cdot \frac{1}{\omega(e_{s_i})}$*,* α *being a normalizing factor. We say that a social path* contains *a vertex* v_h *if* $\exists e_{s_i} : v_h \in e_{s_i}$*.*

Social paths between two nodes leverage the different kinds of relationships (see Section 3.2): a given path can "directly" connect two users because they are "friends" or members of the same group, or "indirectly", as they have shared the same picture or commented the same video.

2.2 Relationships

Analyzing the different types of relationships that can be established in the main social media networks, we have identified three categories:

- **User to User** relationships, describing user actions towards other users;
- **Similarity** relationships, describing a relatedness between two multimedia objects, users or annotation assets;
- **User to Multimedia** relationships, describing user actions on multimedia objects, eventually involving some annotation assets or other users.

Definition 2.3 (User to User relationship) *Let* $\widehat{U} \subseteq U$ *a subset of users in a MSN, we define* user to user relationship *a hyperedge* e_i *with the following properties:*

1. $V_{e_i}^{+} = u_k$ *such that* $u_k \in \widehat{U}$,
2. $V_{e_i}^{-} = \widehat{U} - u_k$.

The weight function for such relationship returns as value $\frac{\hat{H}_{kj}}{H_k}$, $\hat{H}_{kj}$ *being the average number of distinct user to user social paths between* u_k *and* u_j *for each* $u_j \in \widehat{U} - u_k$, *and* H_k *the number of user to user paths having as initial vertex* u_k[1].

Examples of "user to user" relationships are represented by *friendship*, *following* or *membership* in On-line Social Networks[17]. To better explain this type of relationships, we provide in Figure 1 an example of *friendship* relationship.

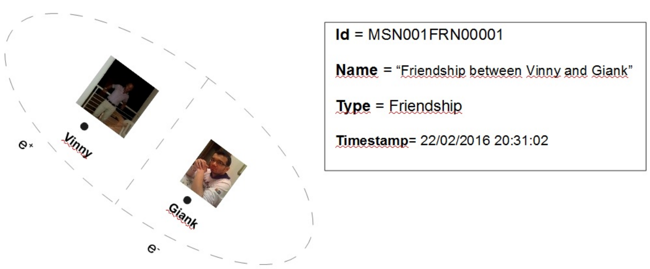

Figure 1. Friendship relationship

Definition 2.4 (Similarity relationship) *Let* $v_k, v_j \in V$ $(k \neq j)$ *two vertices of the same type of a MSN, we define* similarity relationship *a hyperedge* e_i *with the following properties:*

1. $V_{e_i}^{+} = v_k$,
2. $V_{e_i}^{-} = v_j$.

The weight function for this relationship returns similarity value between the two vertices.

[1]In this case ω represents the strengthness of the relationship between two users with respect to the other users.

The similarity relationships are defined on the top of a *similarity function* $f_{sim} : V \times V \rightarrow R$. It is possible to compute a similarity value:

- between two users by considering different types of features (interests, profile information, preferences, etc.);
- between two multimedia objects using the well-known (high and low level) features and metrics proposed in the literature;
- between two annotation assets exploiting the related topics and the well-known metrics on vocabularies or ontologies.

In our model, a similarity hyperedge is effectively generated if $\omega(\vec{e}_i) \geq \gamma$, γ being a given threshold. To better explain this type of relationships, we provide in Figure 2 an example of *multimedia similarity* relationship.

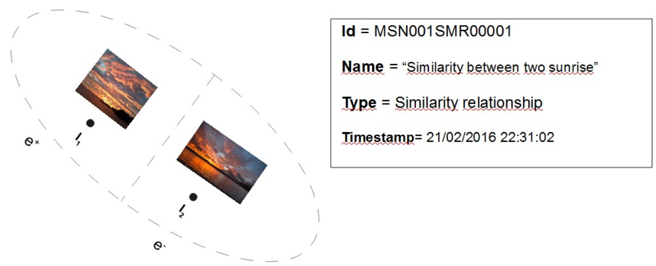

Figure 2. Multimedia similarity relationship

Definition 2.5 (User to Multimedia relationship) *Let* $\widehat{U} \subseteq U$ *a set of users in a MSN and* $\widehat{M} \subseteq M$ *a set of multimedia objects, we define* user to multimedia relationship *an hyperedge* e_i *with the following properties:*

1. $V_{e_i}^{+} = u_k$ *such that* $u_k \in \widehat{U}$,
2. $V_{e_i}^{-} \supseteq \widehat{M}$.

The weight function for such relationship reurns as value $\frac{\hat{H}_{kj}}{H_k}$, $\hat{H}_{kj}$ *being the average number of distinct user to multimedia social paths between* u_k *and* m_j *for each* $m_j \in \widehat{M}$, *and* H_k *the number of user to multimedia paths having as initial vertex* u_k[2].

Examples of "user to multimedia" relationships are represented, as an example, by *publishing*, *reaction*, *annotation* (in this case the set $V_{e_i}^{-}$ also contains one or more annotation assets) or *user tagging* (involving also one ore more users) activities. To better explain this type of relationships, we provide in Figure 3 an example of *multimedia tagging* relationship.

[2]In this case ω represents the strengthness of the relationship between a user and a given multimedia object with respect to the other objects.

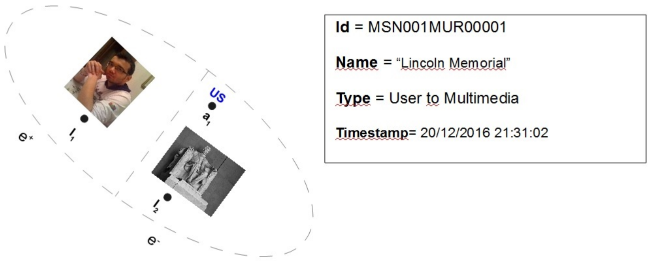

Figure 3. Multimedia tagging

2.3 Ranking functions

Ranking functions can be profitably used to "rank" users and multimedia objects in a MSN in an absolute way or with respect to a given topic of interest. Let us first introduce some preliminary definitions.

Definition 2.6 (Distances) *We define* minimum distance *($d_{min}(v_i, v_j)$),* maximum distance *($d_{max}(v_i, v_j)$) and* average distance *($d_{avg}(v_i, v_j)$) between two vertices of a MSN the length of the shortest hyperpath, the length of the longest hyperpath and the average length of the hyperpaths between v_i and v_j, respectively. In a similar manner, we define the* minimum distance *($d_{min}(v_i, v_j\,|v_k)$),* maximum distance *($d_{max}(v_i, v_j\,|v_k)$) and* average distance *($d_{avg}(v_i, v_j\,|v_k)$) between two vertices v_i and v_j, for which there exists a hyperpath containing v_k.*

In the computation of distances, we apply a *penalty* if the considered hyperpaths contain some users: all the distances can be computed as $\tilde{d}(v_i, v_j) = d(v_i, v_j) + \log(\beta \cdot N)$, N being the number of user vertices in the hyperpath between v_i and v_j and β a scaling factor[3].

Definition 2.7 (λ-Nearest Neighbors Set) *Given a vertex $v_i \in V$ of a MSN, we define the* λ-Nearest Neighbors Set *of v_i the subset of vertices NN_i^λ such that $\forall v_j \in NN_i^\lambda$ we have $\tilde{d}_{min}(v_i, v_j) \leq \lambda$ with $v_j \in U$. Considering only the constrained hyperpaths containing a vertex v_k, we denote with NN_{ik}^λ the set of nearest neighbors of v_i such that $\forall v_j \in NN_{ik}^\lambda$ we have $\tilde{d}_{min}(v_i, v_j\,|v_k) \leq \lambda$.*

If we consider as neighbors only vertices belonging to user type, the NN^λ set is called λ-*Nearest Users Set* and denoted as NNU^λ, similarly in case of multimedia objects we define the λ-*Nearest Objects Set* as NNO^λ . On the top of such definitions, we are able to introduce the *ranking functions*.

[3]Such strategy is necessary in the ranking to penalize *lurkers*, i.e.users of a MSN that are quite inactive and not directly interact with multimedia content but through user to user relationships.

Definition 2.8 (User Ranking function) *Given a user $u_i \in U$ and a subset of users $\widehat{U} \subseteq U (u_i \notin \widehat{U})$ of a MSN, a* user ranking function *is a particular function $\rho : U \rightarrow [0, 1]$ able to associate a specific* rank *to the user u_i with respect to the community $\widehat{U}$ that is computed as in the following:*

$$\rho_{u_i}\left(\widehat{U}\right) = \frac{\left|NNU_{u_i}^\lambda \cap \widehat{U}\right|}{\left|\widehat{U}\right|} \tag{1}$$

NNU_i^λ being the λ-Nearest Users Set of u_i.

Definition 2.9 (Multimedia Ranking function) *Given a multimedia object $m_i \in M$ and a subset of users $\widehat{U} \subseteq U$ of a MSN, a* multimedia ranking function *is a particular function $\rho : M \rightarrow [0, 1]$ able to associate a specific* rank *to the object m_i with respect to the community $\widehat{U}$ that is computed as in the following:*

$$\rho_{m_i}\left(\widehat{U}\right) = \frac{\left|NNU_{m_i}^\lambda \cap \widehat{U}\right|}{\left|\widehat{U}\right|} \tag{2}$$

$NNU_{m_i}^\lambda$ being the λ-Nearest Users Set of m_i.

In a similar manner, considering only hyperpaths containing a given topic a_j we can define the *topic sensitive* user ($\rho_{u_i}^{a_j}\left(\widehat{U}\right)$) and multimedia ($\rho_{m_i}^{a_j}\left(\widehat{U}\right)$) ranking functions.

Definition 2.10 (Topic User Ranking function) *Given a user $u_i \in U$ and a subset of users $\widehat{U} \subseteq U (u_i \notin \widehat{U})$ of a MSN, a* topic user ranking function *is a particular function $\rho_u^a : U \times A \rightarrow [0, 1]$ able to associate a specific* rank *to the user u_i with respect to the community $\widehat{U}$ given the topic a_j that is computed as in the following:*

$$\rho_{u_i}^{a_j}\left(\widehat{U}\right) = \frac{\left|NN_{ij}^\lambda \cap \widehat{U}\right|}{\left|\widehat{U}\right|} \tag{3}$$

NN_{uij}^λ being the λ-Nearest Users Set of u_i given a_j.

Definition 2.11 (Topic Multimedia Ranking function) *Given a multimedia object $m_i \in M$ and a subset of users $\widehat{U} \subseteq U$ of a MSN, a* multimedia ranking function *is a particular function $\rho_m^a : M \times A \rightarrow [0, 1]$ able to associate a specific* rank *to the object m_i with respect to the community $\widehat{U}$ given the topic a_j that is computed as in the following:*

$$\rho_{m_i}^{a_j}\left(\widehat{U}\right) = \frac{\left|NN_{kj}^\lambda \cap \widehat{U}\right|}{\left|\widehat{U}\right|} \tag{4}$$

NN_{mij}^λ being the λ-Nearest Users Set of m_i given a_j.

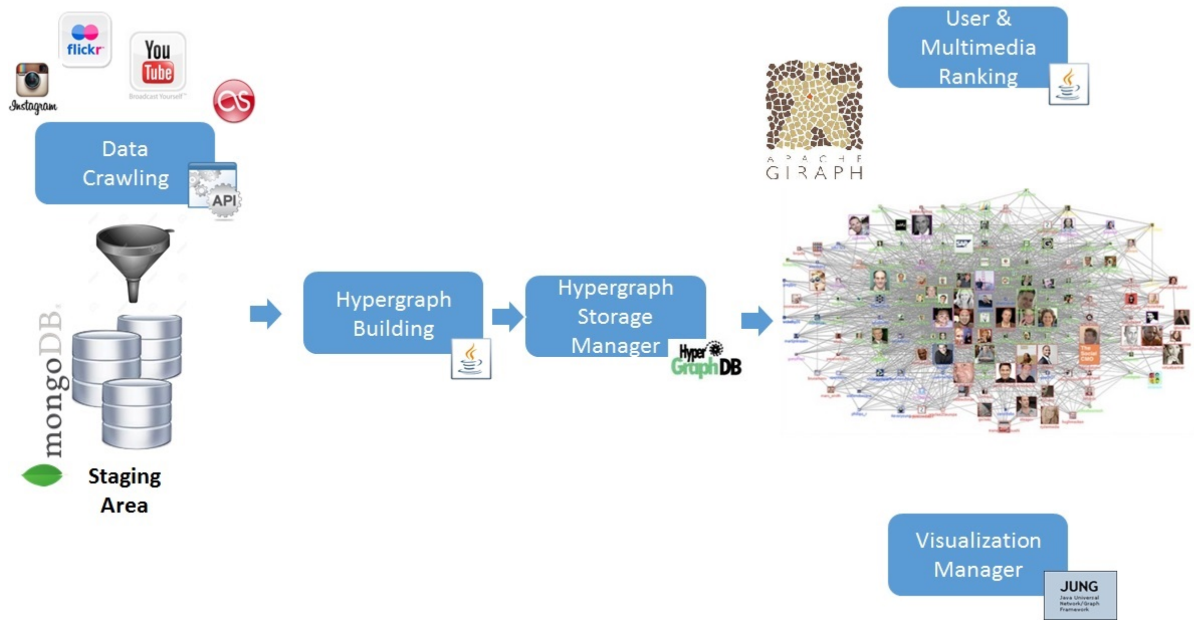

Figure 4. Proposed prototype

In our model the concept of *rank* of a given node is related to the concept of *influence*, and in our vision it can be measured by the number of user nodes that are "reachable" within a certain number of steps using social paths.

By similarity relationships paths can be "implicitly" instantiated: two users (that are not friend, do not belong to any group and do not share any multimedia object) have annotated two images that are very similar, or they have commented two different posts which concern similar topics.

3 Methodology to extract information by Social Network

In order to apply our ranking evaluation we have to extract information about the posts of the customers of an Online Social Network. In this section, we describe our analyses performed on Yelp social network.
The Dataset used for the experimentation is given by Yelp website, it is is composed by: 4.1 millions of reviews, 947 thousands of tips posted by 1 million users for 144 thousands of businesses.

In order to obtain information about each review, we used Gate NLP Tool developed by University of Sheffield (https://gate.ac.uk).

Gate is an open source software able to solve many text-processing problems. This tool is plugin-based so is possible to customize the processing steps adding or removing modules, in order to obtain different results.
Gate components are specialized types of Java Bean and are of three type:

- Language resources (LRs): entities such as lexicons, corpora or ontologies.
- Processing resources (PRs): entities such as parsers, generators or ngram modellers.
- Visual resources (VRs): visualization and editing components

Gate's CORE, for its structure, is named CREOLE: Collection of Reusable Objects for Language Engineering.

Because Yelp reviews are encoded as a set of JSON tuples, a semi-structured data type, we needed to store this dataset into a NoSQL Database. We chose CouchDB, a Document-Oriented Database by Apache Foundation.

CouchDB is a schemaless database with an intuitive HTTP/JSON API. It speaks JSON natively so it is what we needed. To perform analysis on each review, we used an Official plugin of the GATE framework, developed for Twitter.

The pipeline used in this plug-in is composed by:

- Document reset:for resetting the default annotation set;
- TwitIE: a pipeline specialized to analyze tweets.
- Gate Morphological Analyzer: taking as input a tokenized GATE document. Considering one token and its part of speech tag, one at a time, it identifies its lemma. LanguageProcessingGaz: an ANNIE Gazetteer. The role of the gazetteer is to identify entity names in the text based on lists.

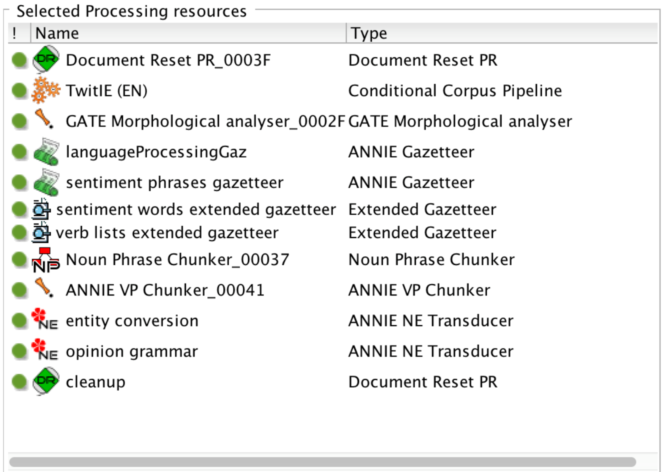

Figure 5. Review Analysis Pipeline

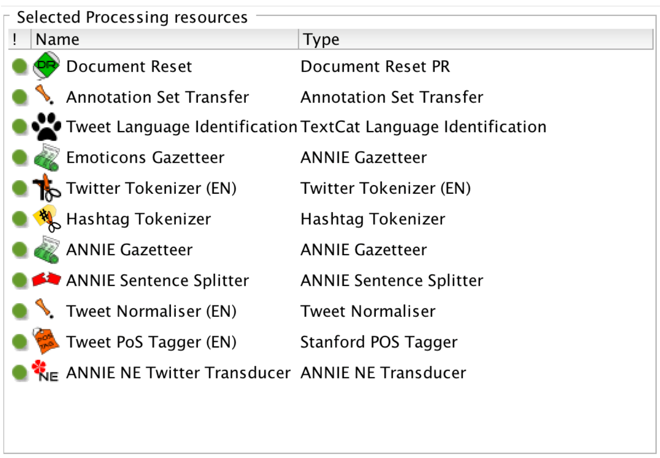

Figure 6. TwitIE Pipeline

- Verb Lists Extended Gazetteer: an extended version of the Gate Default List Gazetteer.
- Noun Phrase Chunker: The NP Chunker application is a Java implementation of the Ramshaw and Marcus BaseNP chunker which attempts to insert brackets marking noun phrases in text which have been marked with POS tags
- ANNIE VP Chunker: The rule-based verb chunker, based on a number of English grammars.
- Entity Conversion, ANNIE NE Transducer: a semantic tagger. It contains rules, which act on annotations assigned in earlier phases, in order to produce outputs of annotated entities.
- Opinion Grammar, ANNIE NE Transducer.
- TwitIE is a specialized pipeline that is composed by many components.

The core of this application is TextCat Language Identification and a huge set of gazetteers customized to recognize hashtags and emojis.
TextCat Language Identification is necessary because our dataset is composed by reviews written in English, French and Deutsch natural language. TwitIE is the lexical and semantic analyzer in our pipeline and its results allow to perform deeper text analysis.

We use the described GATE functionalities in order to analyze the set of reviews. We have to set the documents parameters.

We create a Corpus from the input Documents.

We launch the system functionalities by selecting the Application English-OM and set the corpus to analyze.
After the computation ended, we to check the results Double-click on Document, click on Annotation Sets and Annotation List to view tags.
Each sentence that have a sentiment[18], will be tagged as SentenceSentiment with a set of Features[19], that are customizable using a JAPE Grammar: a set of phases, each of which consists of a set of pattern/action rules. The phases run sequentially and constitute a cascade of finite state transducers over annotations. The left-hand-side (LHS) of the rules consist of an annotation pattern description. The right-hand-side (RHS) consists of annotation manipulation statements.

In order to manage the 4.1 millions of reviews composing the dataset, we created a batch java program that uploaded the reviews as Document on CouchDB. After that, our program perform a HTTP GET request to database to obtain, for each single file, the text of the review, executing Gate on it, load Sentiment parameters and perform the Sentiment Analysis. The last step is to update the Document on CouchDB, performing an HTTP PUT request. The obtained

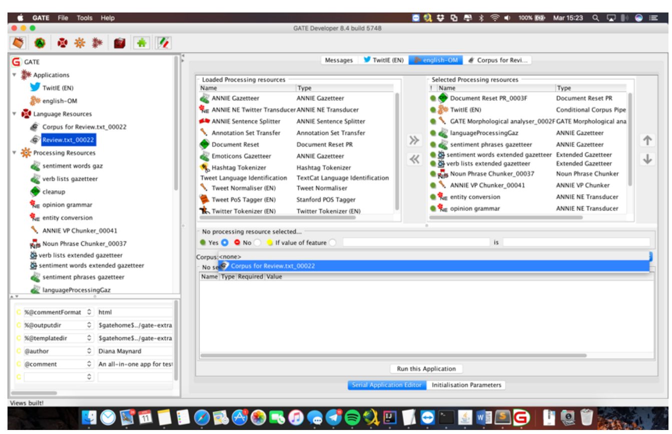

Figure 7. Corpus Selection

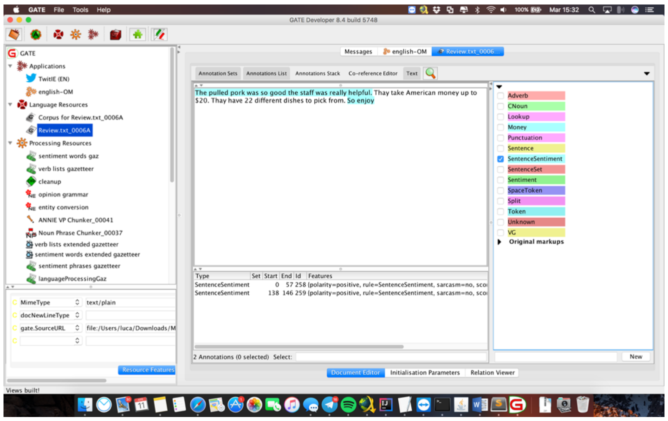

Figure 8. Document Annotations View

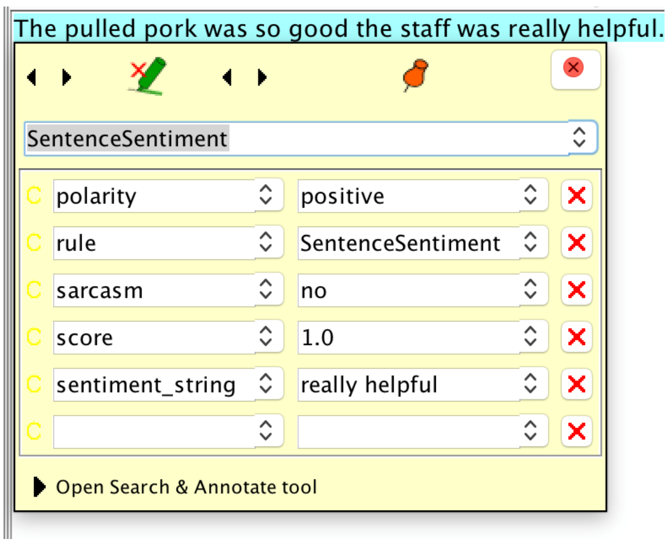

Figure 9. Information about reviews

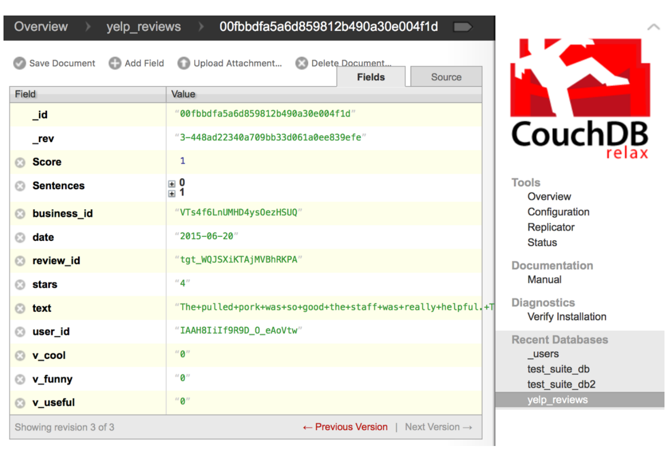

Figure 10. Obtained Output

information are structured in two fields:

Score, representing the sentiment of the entire review. It is the mean value of the single sentences score. Sentences, which is an array of sentences that generated Score.

4 Conclusions and Future Work

In this paper we described a data model for *Multimedia Social Networks*, extracting and modelling information about users. Inspired by hypergraph based approaches, our model provides a solution for representing MSNs sufficiently general with respect to: i) a particular social information network, ii) the different kinds of entities, iii) the different types of relationships, iv) the different applications.

We developed a methodology using a combination of modules applications provided by GATE NLP toolkit, that allows the extraction of relevant information from post related to the online social network Yelp.

As future work, we are planning to exploit the introduced ranking functions to support multimedia recommendation and influence analysis applications, in order to perform an experimental evaluation of the proposed model.

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