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Aspect-Based Extraction and Analysis of Affective Knowledge from Social Media Streams

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ABSTRACT: This article introduces an approach to analyze emotional values associated with brands and companies.Online media coverage about products and services typically refers to awide range of aspects to which such emotional values apply. These aspects can include product features (such as a digital camera's maximum resolution), common applications (such as a smartphone used as a car navigation system), or perceptions in conjunction with a specific event (for example, as part of a sponsorship agreement). Our approach integrates affective and factual knowledge extraction to capture opinions related to specific aspects along multiple emotional dimensions. We use the automotive industry as a sample domain to demonstrate the proposed approach, given the large number of aspects that characterize its complex technical products. The aspect based extraction and analysis of affective knowledge from social media streams, is used to proposed the analysis the products and their moving details from the peoples through social media. The social media having many advertisements for theproducts depend on the products company they will make a contract with social media. Once the user search the related products. The social media will suggest the following details related to the products. Forthese facilities, the product owners will get the details about the products familiarities from the peoples. This will helps to extract the products that which is reach to the peoples, and which one is not reach so well to the peoples.so the social media is very help to reach the company products to the normal people through internet.

I.INTRODUCTION

In our world many companies develop his products for the society, like car companies develop new model cars, Cosmetics Company develop new cosmetics for the peoples, and many companies develop their products for sales. But some products only reach the moderate peoples, because of the cost of the products. The moderate peoples only purchase the products which is less than the others, that products only they can prefer, other products will face the loss, so that companies first know the moderate people's needs, advertisement in televisions and flex in main is not reach every people, because they don't get the specification of the products, so this is not a good decision to reach moderate peoples. DISADVANTAGES

1. High cost of the products
2. Product can't reach moderate peoples

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In proposed system the products based companies shared his advertisement in social media, every peoples will notices the advertisement of the company products, if the peoples want to know the details about products, they will view the advertisement and view the products, the peoples can give comments and rating for the products because of the products developing, the company owners have easy way to know that which of his products reached well from the people side. This is the way the company owners will extract the products through social media. Thecompany updates his new products specification and new offers in social media. The people will communicate through social media to company for purchasing. The social media will show the details that which products is reach more in the particular period to that related company. These are the main concept in this application.

ADVANTAGES

1.Easy to analyses the products details for the users. 2.Company owners can gathered which product is moving well.

3. Easy to reach customers

II. RELATED WORK

Better understanding of sentiment is crucial for building next-generation artificial intelligence sys- tems and increasing the value of business intelli- gence applications.1 This requires the integration of mul-tiple approaches into a unified system, including the three research areas outlined in the following.

Emotion Analysis

Emotion analysis draws upon psychology research. For instance, SenticNet2 is based on Plutchik's wheel of emotions.3 It contains 50,000 concepts and maps them to the four dimensions pro-posed in the Hourglass of Emotions4: "aptitude" (confident in interaction benefits), "attention" (interested in interaction con-tents), "pleasantness" (amused by interaction modalities), and "sensitivity" (comfortable with interaction dynamics). Word-Net- Affect5 has affective labels such as "emotion," "mood," and "cognitive state" to approximately 2,800 WordNet synsets. The General Inquirer provides emotional categories such as "vir-tual," "pleasure," and "pain."6 EmoLex contains approximately 10,000 terms,7 and Affective Norms for English Words knows the three categories "valence" (from unpleasant to pleasant), "arousal" (from calm to excited), and "dominance."8

Sentiment-Target Linking

This research field identifies the target of an opinionated statement. For instance, "VW Golf" is the target of "reliable" in the statement, "The VW Golf is reliable." Rule-based ap-proaches to sentiment-target linking use manually designed heuristics to find valid sentiment-target pairs—for example, sentiment-target proximity (distance-based approaches),9 semantic frames,10 or syntax-based approaches relying on a handful of patterns.11,12 Supervised machine learning meth-ods collect patterns from annotated corpora automatically. For example, Lei Zhuang and his colleagues13 and Liheng Xu14automatically extract dependency patterns between senti-ments and their targets.

Corpora such as J.D. Power and Associates (JDPA) support the evaluation of such tools.15 We used a similar approach to build our classifier and

further optimized its performance by evaluating and selecting features and including additional patterns learned from the multiperspective question answer- ing (MPQA) corpus.16

Aspect-Based Sentiment Analysis

Aspect-based sentiment analysis extends target- dependent sentiment analysis and identifies opinions on aspects of that entity. For example, given an entity "car," its design and en-gine characteristics are different aspects of the same entity. Most research focuses on product reviews and links men-tioned aspects to opinions.17 State-of-the-art approaches use term or n-gram frequencies18,19 and frequently employ machine learning—for example, conditional random fields (CRF),20 deep learning,21 and latent Dirichlet allocation (LDA).22 Other approaches combine syntactic rules and lexi-cal resources.23,24Our approach uses a knowledge base to identify as-pects.

This approach is similar to work by Caroline Brun and her colleagues, who bootstrap an aspect lexicon using a training corpus by combining WordNet and Wikipedia,25 or Basant Agarwal and his colleagues, who access Con-ceptNet and WordNet to create a product-review-specific ontology.26Proper opinion analysis is a combination of all these meth- ods. After identifying an emotion, it is necessary to connect it to its target to allow reasoning such as, "who thinks what about whom?" Finally, identifying additional aspects related to the target gives higher granularity and further insight into the true meaning of the expressed opinion.(that is, cars) to DBpedia. Afterward, it uses this information together with the context retrieved from DBpedia to query the knowledge acquisition component for aspects relevant to the targets from ConceptNet and to link

these aspects to the corresponding ConceptNet nodes (see Figure 4b).

The affective knowledge extrac-tion uses lexical lookups to identify tokens carrying affective knowledge and assigns them a value in the range [–1, 1]. The component supports mul-tiple emotional categories. Ground-ing emotion triggers is not limited to string matching; rather, it is also aware of parts-of-speech (POS) tags. In the case of "like," for example, it differentiates between the use as apositive verb and as a neutral com-parison term.

The system ignores product aliases unless the entity (obtained from DBpedia), its manufacturer, or the company's aliases occur in the text. This avoids problems with ge-neric names (such as numbers, fre- quent domain-agnostic terms, or short character sequences) and al-lows it to correctly identify "BMW" and "X5" (for example, in "Yesterday BMW showed its newest SUV for the first time. The new X5 has an updated design and comes with the latest and greatest engines") without creating links if "BMW" is not mentioned.The discovery of an aspect requires its subsequent linking to an entity(for example, "steering wheel" and "car"). A colocation heuristic helps find the closest candidate by scanning the current sentence first and, if unsuc-cessful, the entire document. The sen-timent-target linking classifier then links the common and commonsense knowledge to the affective knowledge targeted at it. Sentiment-target linking

Sentiment-target linking uses a set of sentiment

terms (that is, terms indicating a certain emotion or sentiment) Sm = {t si } and target terms (that is, sentiment targets or aspects) Tm = {t tj } extracted from sentence m, and returns a set of validsentiment- target pairs: {(t si , tt j)}, where y (t si , t t j) = True. Hereby, we formulate the sentiment-target link-

ing task as a binary classification problem. The classification function y reflects whether sentiment tsi and tar-get tokens tt j constitute a valid senti-ment- target pair.

The component starts by generat-ing all possible edges between the set of targets and the set of sentiments as candidates for valid sentiment-target pairs and further evaluates each of them independently. The component extracts features for every observation of a sentiment-target pair and uses them as input for the classification model previ-ously trained on a corpus annotated with correct sentiment- target pairs. To train the classifier, it uses obser- vations from a corpus annotated with words and phrases expressing senti-ments {t si }, targets {t t j }, and relation between them {(t sk , ttl)}. An observation.(tsi , tt j) is a set of features that cap-tures syntactic relations between the sentiment token tsi and the target token tt j . A recursive feature elimi-nation (RFE) procedure yields an optimal feature set to be extracted from the opinion graph for each ob- servation of a sentiment-target pair(ts , tt) , which comprises features suchi asj POS tags and dependencies between the sentiments and target nodes in the graph.

The sentiment-target linking uses a logistic regression classifier trained on the J.D. Power and Associates (JDPA, http://verbs.colorado.edu/ jdpacorpus) sentiment corpus and the Multiperspective Question An-swering (MPQA, http://mpqa.cs.pitt. edu/corpora/mpqa_corpus) opinion corpus, version 2.0 (also see the side-bar). An evaluation of the sentiment-target linking performance achieved an F-measure of 0.90 when evalu-ated on the gold-standard annota-tions for about 12,000 sentiment-tar- get pairs with stratified tenfold cross validation.

affective knowledge—for example, negation detection to invert the po-larity of a negated term. It uses nodes marked as triggers and stoppers to de- termine the start and end of the nega-tion scope within the opinion graph, and supports multiple negation.Aggregating the opinion triggers that have been linked to a particu-lar sentiment target yields the tar- get's value for the corresponding emotional category. By considering different sentiment aspects in this aggregation process, the system can analyze the emotions contributed by each aspect, yielding DATA ANALYTICS

An RDF triple store serves to store affective and factual knowledge. A proof-of-concept data analytics ap-plication queries the affective knowl-edge base to compare the emotions associated with four automobile brands having high media coverage (Audi, Daimler, Porsche, and Volks-wagen). It contrasts this analysis with an evaluation of two different aspects (drive and engine) relevant to prod- ucts of two of these brands (Audi and Porsche).

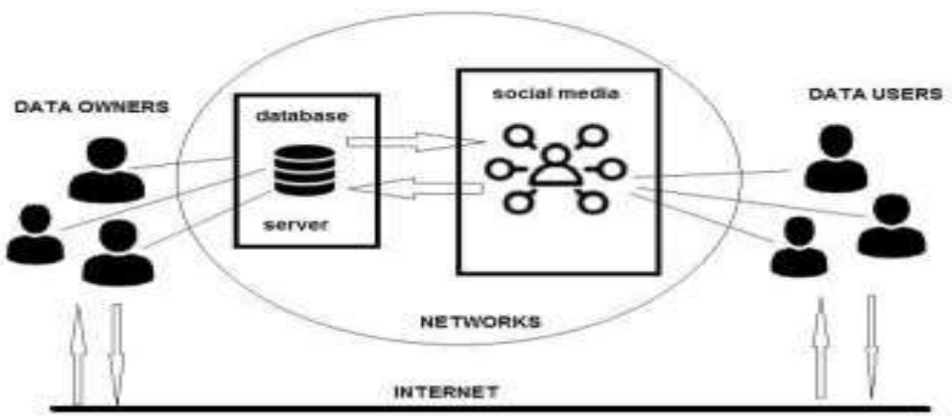
The affective knowledge repository facilitates polarity classification and emotional analysis aligned with the "Hourglass of Emotions" (see the sidebar). For instance, the "engine" of "VW" receives a sensitivity of −0.07, whereas "Golf" has a sensi-tivity of 0.014. After determining the emotional strength associated with each company and aspect, we ag- gregate over all aspects and calcu-late a total value using the following formula:

$Strekgth = k/k$

Experiments

Using a subset of the archive of the Media Watch on Climate Change (social media messages published between 28 September and 28 November 2015), the evaluation corpus consists of 1,000 Twitter and Google+ postings containing the word "car," and4,000 referring to one of the car brands Audi, Daimler, Porsche, and Volks-wagen. The former helped extract sentiment aspects and targets con- tained in the knowledge base, the latter supported the evaluation of aspect-based emotion analysis.

ARCHITECTURE DIAGRAM



III. **Client Server Over view:**

With the varied topic in existence in the fields of computers, Client Server is one, which has generated more heat than light, and also more hype than reality. This technology has

acquired a certain critical mass attention with its dedication conferences and magazines. Major computer vendors such as IBM and DEC, have declared that Client Servers is their main future market. A survey of DBMS magazine reveled that 76% of its readers were actively looking at the client server solution. The growth in the client server development tools from $200 million in 1992 to more than $1.2 billion in 1996.Client server implementations are complex but the underlying concept is simple and powerful. A client is an application running with local resources but able to request the database and relate the services from separate remote server. The software mediating this
client server interaction is often referred to as MIDDLEWARE.The typical client either a PC or a Work Station connected through a network to a more powerful PC, Workstation, Midrange or Main Frames server usually capable of handling request from more than one client. However, with some configuration server may also act as client. A server may need to access other server in order to process the original client request.The key client server idea is that client as user is essentially insulated from the physical location and formats of the data needs for their application. With the proper middleware, a client input from or report can transparently access and manipulate both local database on the client machine and remote databases on one or more servers. An added bonus is the client server opens the door to multi-vendor database access indulging heterogeneous table joins.Two prominent systems in existence are client server and file server systems. It is essential to distinguish between client servers and file server systems. Both provide shared network access to data but the comparison dens there! The file server simply provides a remote disk drive that can be accessed by LAN applications on a file by file basis. The client server offers full relational database services such as SQL-Access, Record modifying, Insert, Delete with full relational integrity backup/ restore performance for high volume of transactions, etc. the client server middleware provides a flexible interface between client and server, who does what, when and to whom.

Client server has evolved to solve a problem
that has been around since the earliest days of computing: how best to distribute your computing, data generation and data storage resources in order to obtain efficient, cost effective departmental an enterprise wide data processing.

During mainframe era choices were quite limited. A central machine housed both the CPU and DATA (cards, tapes, drums and later disks). Access to these resources was initially confined to batched runs that produced departmental reports at the appropriate intervals. A strong central information service department ruled the corporation. The role of the rest of the corporation limited to requesting new or more frequent reports and to provide hand written forms from which the central data banks were created and updated.
The earliest client server solutions therefore could best be characterized as “SLAVE-MASTER”.Time-sharing changed the picture. Remote terminal could view and even change the central data, subject to access permissions. And, as the central data banks evolved in to sophisticated relational database with non-programmer query languages, online users could formulate adhoc queries and produce local reports without adding to the MIS applications software backlog. However remote access was through dumb terminals, and the client server remained subordinate to the Slave\Master.

ALGORITHM:

Affective knowledge includes sentiment and other emotions expressed in a document, which are captured and evaluated by opinion-mining algorithms. Typically, such algorithms are based on machine learning, lexical methods, or a combination of both.1 to identify entities and aspects; the presented system also extracts factual knowledge using a knowledge base built on data from linked Data sources such as DB media and Concept Net. This knowledge base holds information about products, including not only product characteristics but also Corporate.

MINING ALGORITHM

Require: sets of target industries, target predicates and product predicates

1: // Lists for storing the results of the graph mining process

2: companies {}, products {}, entity_graph {},

3: // graph mining

4: for all triple from query (?s <rdf:type><dbo:Company>) do

5: if (?s <dbp:industry> ?o) and ?o in target_industries then

6: companies.add(triple.s)

7: entity_graph.add_triple(triple)

8: end if

9: end for

10: for all triple from (query (?s ?p ?o companies) query(?s companies ?p ?o) query(?s ?p target_predicates ?o)) do

11: if triple.p product_predicates then 12: products.add(triple.o)

13: end if

14: entity_graph.add_triple(triple)

15: end for

16: for all triple from query (?s <dbp:aka> ?o) do 17: entity_graph.add_triple(triple)

18: end for

19: return companies

MODULES

1. Social media
2. Add and view new products 3.Existing products handling 4.User accessing

1. **SOCIAL MEDIA:**

The social media is the main concept in this project, the data owner updates his product advertisements in the social media, eachcompany maintain one database server for their products.After updating his products advertisements the social media will show that company advertisement.The users will see the advertisements in social media, if the user wishes to analyze some products they will search the company and that related products, the social media server will search the products in the database and show this to user.After getting the user needs they will see the specifications and further details, if they want that product they will give a request to that product company.The data owner receives the request and they will direct contact through mail.

2. **Add and view new products**

The data owner develop the new products for their company they will upload the advertisement in social media; the media server will stored the data to the company related database.If the data owner wants to make any updates in those products details they will login into the account and make some updates and restoring it in server.Any user can view the company's products details and contact them through mail.

3. **Existing products handling**

The social media server having the users rating, comments and new modification for particular company products. Those details are maintained in database by the company server.The data owner can view that products details from the users and concentrate on that products, they can demolish the existing products and make changes in that products to make new products depends on the user needs.The graphical representation is made for the existing products depend on the user ratings and comments.

4. **User accessing**

In user accessing module the user can give ratings and comments for the products, which is send to the related company.The data owner will analyze the products sales and how much that product will reach the user; the data owner will show it in graphical representation. The other users can easily analyzing which product is the best one for purchasing. The user purchasing also view by the graphical representation. That graphical representation is useful for the data owner to give the other best product.

IV. **PERFORMANCEEVALUATION**

The following evaluation draws upon the 50 most frequently occurring sentiment aspects and targets in the evaluation corpus to assess the usefulness and impact of the knowledge extracted by the graph mining. Five in-dependent domain experts classified the usefulness of each extracted concept for describing aspects relevant to the perception (polarity, emotions) of car companies, brands, and products in one of three categories: useful (the aspect is related to the domain), not useful (the aspect has no connection to the domain), and neutral (the term is too generic to be clearly associated with the domain). On average, 81.2percent of the extracted concepts have been considered useful. The Krippend or ff alpha for inter-ratera Agreement between experts is 0.504,reflecting only a moderate agreement among domain experts. The evaluation illustrates two short- comings of the current approach.

First, the assumption that automotive companies only manufacture cars does not hold true. Among the 50 most frequent entities/aspects in the “car” corpus, the system identified “ knife” because the company American Expedition Vehicles also produces knives. We investigated narrowing the prod-ucts based on their rdfs: class property but encountered a diverse set of assigned classes that have no singlecommon super class or shared property.

V. CONCLUSION

In this paper, we presented a framework for detecting users’ psychological stress states from users’ weekly social media data, leveraging tweets’ content as well as users’ social interactions. Employing real-world social media data as the basis, we studied the correlation between user’ psychological stress states and their social interaction behaviors. To fully leverage both content and social interaction information of users’ tweets, we proposed a hybrid model which combines the factor graph model (FGM) with a convolution neural network (CNN). In this work, we also discovered several intriguing phenomena of stress. We found that the number of social structures of sparse connection (i.e. with no delta connections) of stressed users is around 14% higher than that of non stressed users, indicating that the social structure of stressed users’ friends tend to be less connected and less complicated than that of non-stressed users. These phenomena could be useful references for future related studies.

VI. FEATURE SCOPE

The scope of the project is in detecting users’ psychological stress states from users’ weekly social media data, leveraging tweets’ content as well as users’ social interactions and also in user-level emotion detection in social networks.

VII. REFERENCES

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