Computational Approaches for Online Reputation Monitoring

- Modeling, Analysis and Recommendation

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Outline of the talk

- Introduction
  - What is Online Reputation Monitoring (ORM)
  - Objectives of the Thesis
- Chapter 1: Predicting Brand Personality from Web Content
  - Novel deep learning and transfer learning based classification model to deal with limited labeled data
  - Large-scale data collection and formation of high fidelity data points
- Chapter 2: Understanding Brand Consistency from Web Content
  - Formulation and Characterization study
  - Developing a helper tool to identify the sentences that needs to be modified
- Conclusion
- Limitations and Future directions
- Reviewer comments

Online Reputation Monitoring - Overview

- Modes of reputations are different across different sectors
  - **Products** : Automobiles and Manufacturing
  - **Transparency and Ethical aspect** : Banking, Financial Services

E. Amigó, A. Corujo, J. Gonzalo, E. Meij, M. de Rijke, et al., "Overview of RepLab 2012: Evaluating online reputation management systems.," in CLEF (Online Working Notes/Labs/Workshop), 2012.

Online Reputation Monitoring - Overview

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  - **Products** : Automobiles and Manufacturing
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- In the era of digital marketing, brands need to create a lot of online content to keep up the engagement with their audiences
  - Corporate blogs, advertisements (textual or multimedia) over different platforms (TV, mobile, Social networks/Microblogging platforms like Twitter, LinkedIn, Facebook)
- Organizations tends to maintain a *consistent perception among the customers* (brand personality) over time and across content categories
  - Generate trust and retain more customers

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What is Brand Personality ?

- User perception regarding the brand of the company
- Brands tend to maintain a personality or a set of human characteristics in their marketing campaigns
- Customers wants to make a brand more self-relevant

Aaker, J. L. 1997. Dimensions of brand personality. Journal of marketing research 347–356.

Objectives of thesis

- Develop an online monitoring system to predict the brand personality based on the corporate website content
  - Corporate websites : Official websites for organizations in the Fortune 1000 list for year 2017
  - Five brand personality dimensions : sincerity, excitement, competence, ruggedness, sophistication
- Develop a helper tool that recommends sentence-level changes to make the textual content more consistent with the organization's target brand personality

Understanding Brand Consistency from Web Content

Brand consistency - Maintaining brand personality over time and content

- Develop a mechanism to filter out posts that are not consistent with the target brand personality of an organization and provide an explanation on possible contributing factors
- Develop a helper tool that identifies the sentences within a given highly inconsistent document that needs to be addressed

Research challenges of Brand consistency

- Personality and character of an individual content creator may often outshine that of the company
    - For larger companies, may lead to unbalanced feel to the portfolio of marketing material
- Monitoring and maintaining brand consistency on a large scale is difficult and require costly human experts
    - Currently, done manually by brand manager, content writers with the help of a brand style guide
- Brand consistency is tough to measure
    - No established metric or measure
    - Given its subjective nature, cost due to brand inconsistency is difficult to capture

Key takeaways and contributions

- Formulation of brand consistency score(consScr) for a post as well as for a company
  - Based on similarity between 5-dimensional binary label vectors and rank vectors
  - A temporal as well as a non-temporal evaluation metric
  - Four consistency levels : strongly consistent, partially consistent, somewhat consistent, not consistent
- We observe that companies that post consistently and are higher ranked are better at maintaining brand consistency
- We study the effect of company level events on brand consistency
- Our proposed sentence recommendation model for identifying sentences shows comparable performance with the baselines

Brand consistency formulation

- <u>Representation of a post</u>
  - **Label vector -** Stores the binary label of whether a trait is present or absent in the text
  - **Rank vector -** Stores an order of precedence of traits based on confidence score
- <u>Similarity measure</u> : We calculate the similarity between a dynamic post and the representative vectors(static post) of the company
  - **binLabelSim -** Levenshtein distance
  - **rankVectorSim -** Mean of Pearson, Kendall tau and Spearman rank correlation coefficient

sinc	exc	com	rug	sop
1	1	0	0	0
2	1	3	4	5

Static keywords	introduction, about, commitment, people, vision, strength, history, approach, benefits
Dynamic keywords	media, blog, news, press, investors

Brand consistency formulation

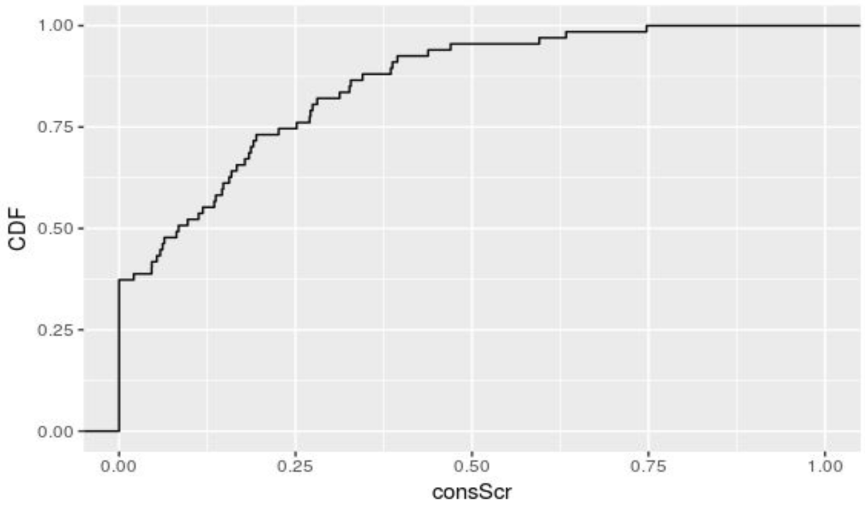
- **Consistency levels :** From manual inspection, we observe that *binLabelSim* have a higher importance than *rankVectorSim*
- **Consistency score (ConsScr) :** Ratio of number of consistent posts(the first 3 levels) and the total number of posts within that time frame
    - A ConsScr closer to 1.0 indicates higher degree of consistency
    - We consider a given temporal bin(12 weeks) to be consistent if ConsScr >= 0.5

Consistency levels	binLabelSim	rankVectorSim
Level 3	>= 0.8	>= 0.6
Level 2	>= 0.8	>= 0.2
Level 1	>= 0.5	>= 0.6
Level 0	otherwise	otherwise

This is how we identify the inconsistent posts, as posts belonging to the "not consistent" category

Experimental setup

Only a few companies is able to maintain high temporal consistency score



Sector-wide analysis

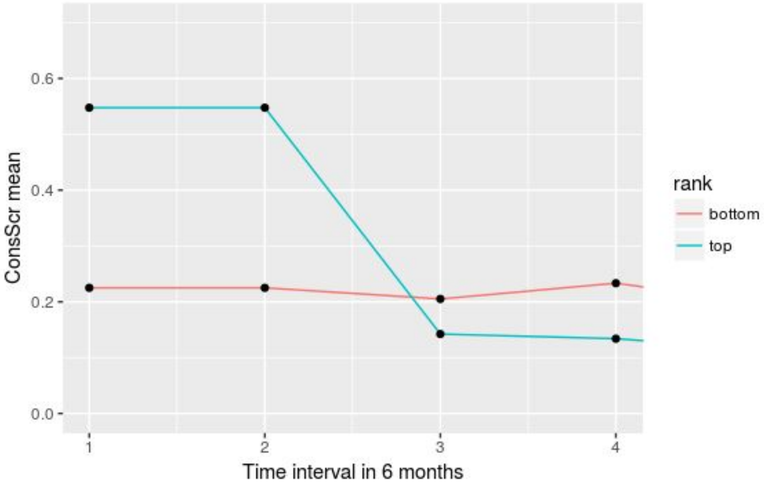
- We compare the percentage of posts across the different consistency levels for the different sectors.
- We now provide the sectors ordered in increasing value of sector–wise average inconsistent ratio
    - Business Services (0.58)
    - Healthcare (0.64)
    - Energy (0.76)
    - Financials (0.83)
    - Technology (0.86)
    - Media (0.9)
- We observe that Healthcare and Business Services sector are relatively more consistent while Media sector is not much consistent
- Use MT_{high} data

Top companies maintaining temporal brand consistency

- Notion at a company-level rather than as a post attribute
- Follow a temporal binning strategy where posts of 12 weeks are binned together
- Rank the companies in terms of highest temporal consistency score (*Equal to average ConsScr value across all the temporal bins having at least 3 posts*)
  - Engility Holdings (0.747)
  - Regis Corporation (0.633)
  - Principal Financial Group, Inc. (0.595)
  - Westlake Chemical Corporation (0.47)
  - Capital One Financial Corporation (0.438)
- Use MT_{time} data

Top-ranked company vis-a-vis brand consistency

- Consider top and bottom ranked companies having at least 25 dynamic posts
  - Top-ranked companies : Within rank 1 - 150; Lead to 18 companies
  - Bottom-ranked companies : Within rank 850 - 1000; Lead to 20 companies
- We observe that top ranked companies can maintain a higher *ConsScr mean* for the first 12 months than the bottom-ranked companies



Effect of product promotion posts on brand consistency

- Corresponds to "products and services" category of the RepTrack framework
- We construct a data subset of **3255 articles** by performing a lexicon based search
    - Check whether the following keywords - event, promotions, promot, products, product-launch, announce, launch, are present in web page URL.
- We observe competence is the primary trait with product promotion followed by sincerity.

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- We observe competence is the primary trait with product promotion followed by sincerity.
- Companies with "competence" as their primary trait is boosted more often by such promotion posts as compared to the other traits.
- Higher is the product promotion posts, higher is the drop of company-level score.
- presence of product promotion posts affect the company consistency score and may also affect the ranking of companies

Effect of brand extensions on brand consistency

- Brand extensions, in terms of product lines different from the sector of the respective company
  - **Tata :** Tata Advanced Systems Ltd., Tata Consultancy Services, Tata Motors, Tata Steel
  - **Orange :** Cyber Defense, Health care
  - We extract the "ORG"(organizations) mentions from the textual content of the website, using Stanford NER tagger

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  - We extract the "ORG" (organizations) mentions from the textual content of the website, using Stanford NER tagger
- Manually check and obtain 10 Fortune 1000 companies, having brand extensions
  - The conScrComp of such companies is lower than the average consScrComp values across all
  - Mentions as brand extension variants (1) assets and subsidiary company (CVS Health); (2) various company branches in different countries (Fujitsu); (3) research division (Gartner Research)
- Brand extension related posts negatively affects consScrComp
  - Since, median consistency score of these 10 companies improved by 4.31% (mean improved by 0.6%)

Effect of topical consistency of static posts on brand consistency

- Formation of MTauth : Brand extensions and promotion posts are deliberate and intentional and should not be considered for computing consScrComp for a company.
  - We thus remove them a total of 4152) posts from MThigh
- Train a LDA model over randomly select 50K web articles of MThigh for 100 topics
  - For each company, we compute a topical consistency score (topicConsVal) as the mean pair-wise cosine similarity scores among each static pos
  - Represented by a 100 dimensional vector, where the i-th element stands for the probability of topic 'i' for the document.
  - Company with at least 2 static posts, which leads to 79 companies.
- It is more difficult to maintain brand consistency for companies with low topicConsVal
-

Recommendation tool

- Sentence-level Qualitative Study
- Methodology
    - Informativeness of sentence - Text summarization algorithms
    - Brand Consistency Score - Use FLCS to give brand personality tags
    - Polarity - Negative sentiment words may decrease reputation in most cases
    - Centrality - Target entity (company, its employees, its products, products and personalities in similar domain, or miscellaneous
- Experiments and results
    - Dataset and Annotation setup
    - Evaluation metric and Baselines

Problem definition

- We develop a sentence-level recommender system which will act as a helper tool to make it more consistent to the target perception of the company
- Develop a sentence ranking scheme and selecting the top K sentences to remove in order to improve consistency, but maintaining informational content

Research challenges faced

- Manual annotation for the recommendation task is difficult
    - No previously annotated dataset is available
    - Subjective nature of brand personality
- Some sentences contain both positive and negative sentiment
    - Not all negative sentiment words reduce the reputation of a brand
    - Reputation polarity is different from sentiment analysis
- DL final trained on whole documents, and thus its document level representation needs to be padded to a vector of dimension 3000. However, this does not work for sentences, which is on average consists of 10 words.

Methodology

- Brand consistency score: computed based on cosine similarity, earlier computed as "binLabelSim" score. Instead of the whole document, prediction done for each sentence of the document. DL_{final} fails to work on sma
- Negative polarity : More weightage to negative sentiment words in a sentence
- Centrality : More relatedness with the company (employees and products)
- Propose ALL-3 that combines the three aspects
  - Develop a more fine-grained, task-specific scoring function (task-relevance) **7 levels**
  - Priority of aspects (highest to lowest) : centrality, negative polarity, brand consistency

Dataset and Annotation Setup

- Article selection : From MThigh, select sentences belonging to "not consistent" consistency level
  - Flesch readability ease >= 20
  - Remove posts belonging to Nordstrom(1137 posts) and Microsoft(654 posts), Lead to 743 posts, called MTstudy
  - Select only those web articles that have word count between 300 and 500 which amounts to 202 articles
- Sentence selection for annotation - in terms of informative content
  - We only select the sentences that are among the top 3 sentences in at least one of the six text summarization algorithms
  - Text summarization algorithms : TextRank, Feature Base (2), Topic base (3)
  - Ranking : use MMR, ILP (with constraints like sentence length and length of summary
- Annotate 36 such sentences

Performance comparison

- ROUGE-N F1 score is used as an evaluation metric
- Our model based on brand consistency, negative polarity and centrality, significantly outperforms the baselines
  - ROUGE-1 (0.571 VS. 0.54)
  - ROUGE-2 (0.472 VS. 0.435)
  - ROUGE-LCS (0.823 VS. 0.821)
- Centrality performs the best among all the single-aspect baselines

Models	ROUGE-1	ROUGE-2	ROUGE-L
FEA_LEXI3	0.544	0.438	0.779
TOPIC3	0.512	0.403	0.815
RAND3	0.381	0.233	0.757
LEAD3	0.415	0.277	0.758
CTR3	**0.54**	**0.435**	**0.821**
POL3	0.492	0.372	0.789
CONST3	0.494	0.382	0.805
CONST-POL3	0.502	0.392	0.807
ALL3	**0.571**	**0.472**	**0.823**

Conclusion

- Develop optimal classification models based on deep transfer learning for brand personality detection from text
- Developed a large-scale set of high fidelity data points (330K web pages from 650 companies)
- Formulated the brand consistency notion for each post, for a company, and studied company-level contributing factors
- Developed a novel sentence ranking scheme for the helper tool

Scope of Thesis

- Only consider 'Tone and Voice' aspect of brand style guide
  - Other text categories available : typography, color, position of headers and content boxes
- Do not consider any form of non-textual data like images, in our classification model
- Do not consider user-generated content (comments, posts) targeting organizations
- Do not study the impact of large-scale company events and decisions like mergers and acquisitions, re-branding and for brand divestments

Future Work

- Extending our helper tool for longer web articles
  - Currently, it is limited to maximum of 500 words. We may use text or topic segmentation algorithms
  - Instead of recommending sentences, we recommend text segments which is more practical
- Developing a brand personality-based style transfer in terms of reputation polarity
  - Target attribute that needs to be altered like sentiment or reputation polarity (+ve to -ve)
- Building Affective Lexicons for Brand Personality traits
  - We observe LIWC to be a significant factor for a given brand personality trait
  - These lexicons will be very useful for distant supervision and semi-supervised tasks
- Develop a multimodal classifier for brand personal prediction task
  - Use website images along with the text
- Evaluate the proposed brand consistency quantification to user-generated content
  - Use benchmark datasets of CLEF Shared Tasks of RepLab 2013 and 2014 (Twitter data) and product reviews

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Thank you for your attention