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Understanding Brand consistency from Web content

Soumyadeep Roy, Niloy Ganguly, Shamik Sural (IIT Kharagpur, India)
Niyati Chhaya, **Anandhavelu Natarajan** (Adobe Big Data Experience Lab, India)

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What is Brand Personality ?

- Organizations tend to maintain a personality or a set of human characteristics in their marketing campaigns
- One of the dimensions that form the brand image of an organization
  - Significantly contributes towards the understanding of consumer choice

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- Organizations tend to maintain a personality or a set of human characteristics in their marketing campaigns
- One of the dimensions that form the brand image of an organization
  - Significantly contributes towards the understanding of consumer choice
- Aaker(1997) formalizes the concept of brand personality into five dimensions

sincerity	excitement	competence	ruggedness	sophistication
Down-to-earth Honest Wholesome Cheerful	Daring Spirited Imaginative Up-to-date	Reliable Intelligent Successful	Outdoorsy Tough	Upper class Charming

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

Brand Consistency - Maintaining Brand personality over time and content

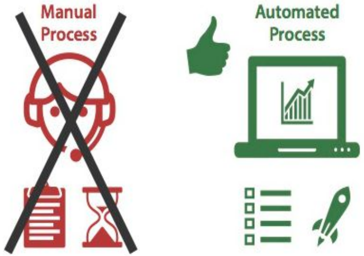
- In the era of digital marketing, organizations need to create a lot of online content to keep up the engagement with their audiences
  - Corporate blogs, advertisements (textual or multimedia) over different platforms (TV, mobile, Social networks and microblogging platforms like Twitter, Facebook, LinkedIn)
- Organizations tends to maintain a *consistent perception among the customers* (brand personality) over time and across content categories
  - Generate trust and retain more customers
  - Current strategies for maintaining brand image over time is of qualitative nature, but no quantitative measure exists

Problem Statement

- To develop independent binary classification models for the five brand personality dimensions
  - Given a web article from the official website of an organization, we predict whether a given brand personality trait is present or absent from it
  - The five brand personality dimensions : sincerity, excitement, competence, ruggedness, sophistication
- Formulate and analyze the notion of brand consistency on a large scale

Research challenges of Brand consistency

- 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 due to lack of an established metric
- Well tagged datasets for brand personality is not available
  - Crowdsourced annotation may suffer heavily from class-imbalance
- CLEF task called "RepLab"(Amigo et al. 2014) based on only Twitter, consider certain organizational aspects
  - Performance, products and services, leadership, citizenship, governance, workplace and innovation



Amigo et al., 2014, Overview of RepLab 2014: Author Profiling and Reputation Dimensions for Online Reputation Management, In Information Access, Evaluation, 307-322

Key takeaways and contributions

- Develop a supervised classification model with a high F1-score of 0.822 which score text articles from an organization's official websites in five brand personality dimensions
- We collect around **300K** web pages covering around **650 Fortune 1000** companies, posted between **January 2000** and **September 2017**

Key takeaways and contributions

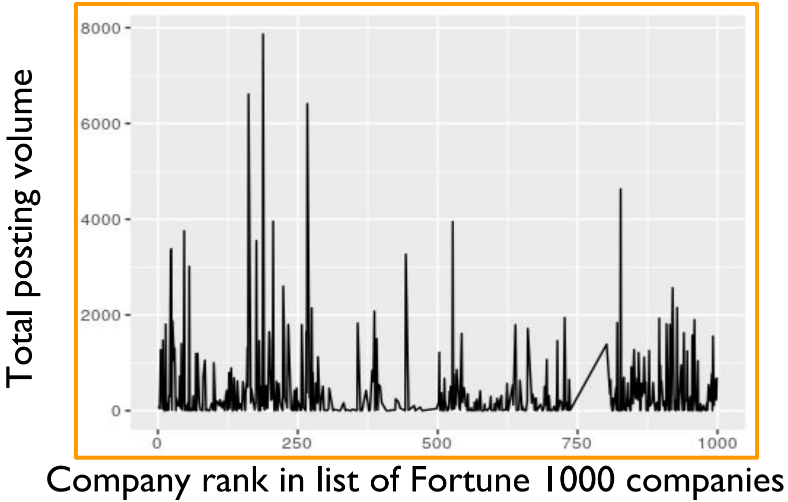
- Develop a supervised classification model with a high F1-score of 0.822 which score text articles from an organization's official websites in five brand personality dimensions
- We collect around 300K web pages covering around 650 Fortune 1000 companies, posted between January 2000 and September 2017
- Perform a characterization study to investigate how well a company maintains its brand personality across time and over different content categories.
    - Companies that post consistently and are higher ranked are better at maintaining brand consistency

Dataset

- We collected text content of the 2017 Fortune 1000 companies from their official websites through a large scale web crawling activity
  - Only consider company web pages that are directed towards the customers - about the company, media releases, blogs and communications
  - Use Scrapy framework (https://scrapy.org)
- Only consider postings between January, 2000 and September, 2017
- We extract timestamp data from page url and also from text content(around 50%)
  - 75% contain day level information while the remaining contain only year level information

Basic observations - I

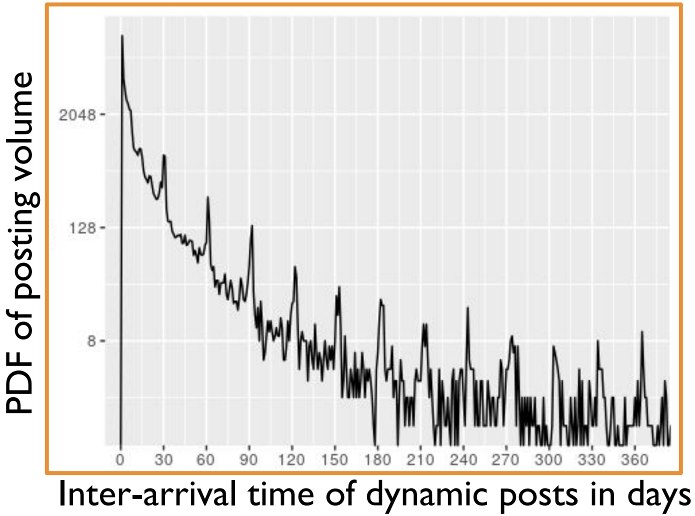
- Volume of posts is roughly similar in both top as well as bottom ranked companies



More number of spikes(indicates companies who post way more than average) occur among the top-ranked companies

Basic observations - 2

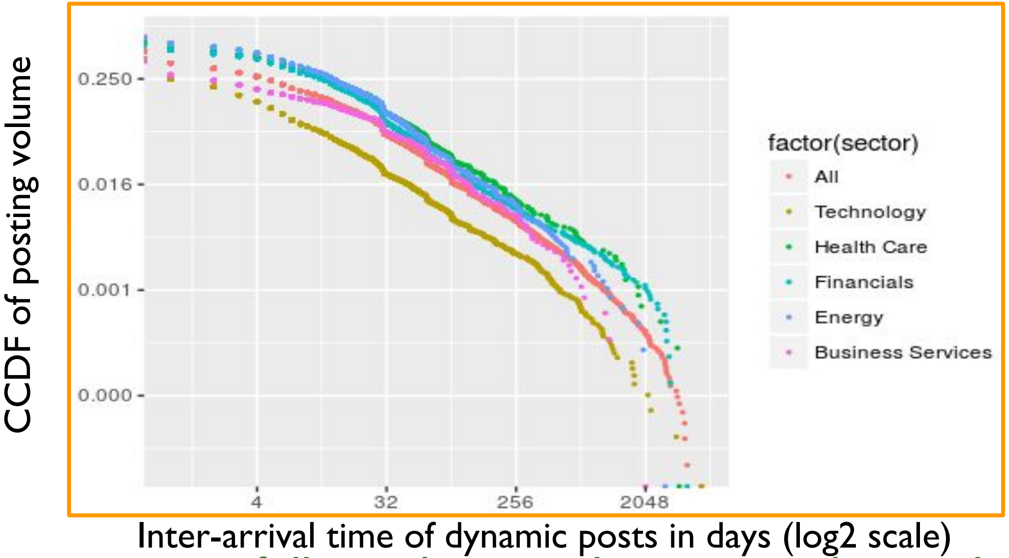
- We observe that these peaks are composed of around 78% web pages that are posted at the month end. The highest number belonged to post type ‘news’.
  - Dynamic posts - Content for continually engaging with the audience like blogs, news, media or press releases



Posting volume show peaks at an interval of 30-33 days in terms of inter-arrival time

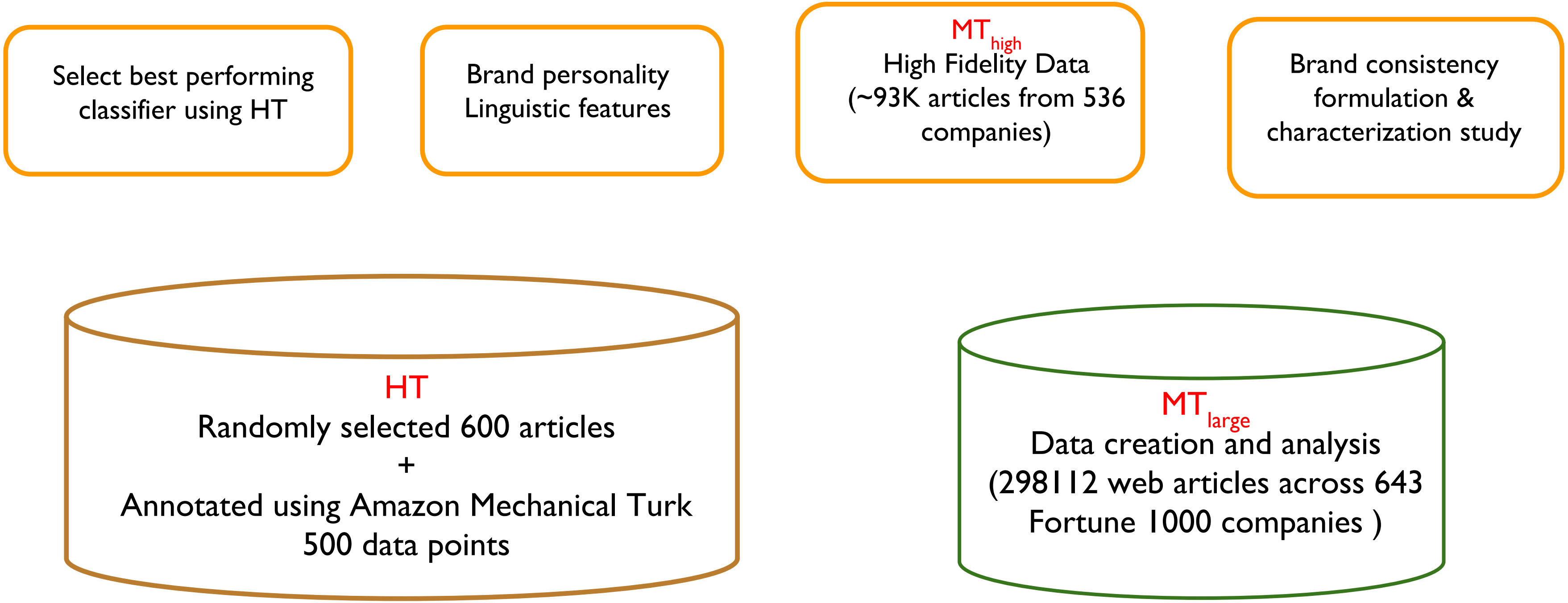
Basic observations - 3

- Top 5 sectors in terms of number of posts display heavy tail behavior
    - technology(48219), financials(11739), energy(4915), healthcare(4685), business services(3747)



Inter-arrival time postings follow a heavy-tail pattern and is similar across different sectors

Methodology workflow



Select best performing classifier using HT

Brand personality Linguistic features

MT_{high}
High Fidelity Data
(~93K articles from 536 companies)

Brand consistency formulation & characterization study

HT
Randomly selected 600 articles
+
Annotated using Amazon Mechanical Turk
500 data points

MT_{large}
Data creation and analysis
(298112 web articles across 643 Fortune 1000 companies)

Brand SVM Classifier (**BrSVM**; Feature : **LIWC**)

- Xu et al. (2016) used LIWC to model brand personality on social media
- Train over a suite of candidate supervised classification models and select the best classification model
  - Traditional classifiers : *Naive Bayes, Logistic Regression, Decision Tree, Random Forest, AdaBoost, Linear SVM*
  - Feature set used: *LIWC*
- **Feature Set selection :** We incrementally expand the feature set and add linguistic features on top of LIWC
  - LIWC > tfidf > contractions > collocations > chains of reference > flesch readability ease
  - Different feature sets are optimal for the different brand personality traits

Brand SVM Classifier (**BrSVM**; Feature : **LIWC++**)

Exisiting
LIWC(Xu et. al, 2016)

Proposed

- TF-IDF
- Contractions
- Collocations
- Chains of Reference
- Readability

- **Contractions -** Adds informality and conversational tone; Ex : isn't, we're
- **Collocations -** Frequently occurring word combinations from '*Pearson Academic Collocation List*'; Ex : very good, extremely good, big house
- **Readability -** Computed as Flesch's Readability Ease. Depends on word length, sentence length, # syllables per word
- **Chains of reference -** Use of reference to oneself and alike entities(noun phrases). Repetition, partial repetition, coreference, possessive inferrables

A. Xu, H. Liu, L. Gou, R. Akkiraju, J. Mahmud, V. Sinha, Y. Hu, and M. Qiao. Predicting perceived brand personality with social media. In Proceedings of the Tenth International Conference on Web and Social Media, Cologne, Germany, May 17-20, 2016., pages 436–445, 2016.

Experimental Setup - First Level Classifier

- Annotation : HT data, 500 web articles manually annotated and validated
    - Trait ranks also provided by annotators in terms of degree of presence
    - Company names blinded with the 'Sector' the company it belongs to.
    - Inter-annotator agreement : 67.25%
- Traditional classifiers : Naive Bayes, Logistic Regression, Decision Tree, Random Forest, AdaBoost, Linear SVM
- Feature set used : LIWC (Xu et al. 2016)
- 7-fold validation results (6/7th for training and 1/7th for testing on HT data)

BrSVM - Best classification model

Trait	sincerity	excitement	competence	ruggedness	sophistication
Naive bayes	0.371	0.268	0.721	0.319	0.239
Logistic Regression	0.659	0.798	0.853	0.654	0.725
Decision Tree	0.819	0.698	0.937	0.549	0.66
Random Forest	0.85	0.754	**0.946**	0.575	0.673
AdaBoost	0.859	0.753	0.936	0.589	0.672
SVM (Linear)	**0.885**	**0.815**	0.931	**0.655**	**0.725**

Our Linear SVM model(BrSVM) is able to achieve a F1-score of 0.822

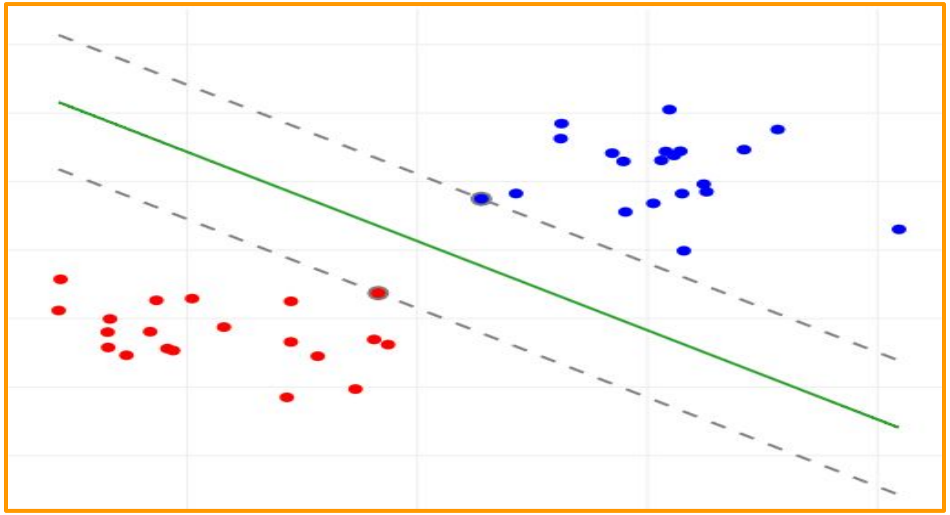
BrSVM Feature Set Selection

Feature sets	sincerity	excitement	competence	ruggedness	sophistication
LIWC (baseline)	0.885	0.815	0.931	**0.655**	**0.725**
tfidf*	0.923	**0.839**	**0.968**	0.545	0.707
contractions*	0.923	0.834	0.968	0.548	0.708
collocations*	0.923	0.837	0.968	0.545	0.709
chainref*	**0.925**	0.836	0.968	0.569	0.706
Best features	0.925	0.839	0.968	0.655	0.725

We observe that the optimal feature set is different for each brand personality trait

High fidelity data points

- We use FLCS to classify the MT_{large} data and only select those data points that are classified with **high confidence(>= 0.095)**, which forms MT_{high}
- We now empirically determine a threshold for each trait above which we tag the text with that particular trait to be present



Dataset overview

Dataset name	Total posts	Total companies	Collection strategy
MT_{large}	298112	643	Web scraping from official websites based on accept and deny keywords
HT	500	-	Randomly selected 600 points from MT_{large}, which satisfy strict annotation criteria
MT_{high}	93321	536	Subset of MT_{large} which is annotated with high confidence by FLCS
MT_{time}	49833	242	Subset of MT_{high} having timestamp data
MT_{notime}	43488	512	Subset of MT_{high} without having timestamp data

Type of company posts - static and dynamic

- Static pages explicitly defines the brand which a company stands for
  - mission, vision and core values
  - **Static keywords:** introduction, about, commitment, people, vision, strength, history, approach, benefits
- Dynamic web pages comprises of content that is for continually engaging with the audience
  - blogs, news, media or press releases

Brand consistency formulation

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

- **Representation of a post :**
  - **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
- **Similarity measure :** 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
- **Consistency levels :** From manual inspection, we observe that *binLabelSim* have a higher importance than *rankVectorSim*
  - Formulate four brand consistency levels, out of which the lowest level is '**not consistent**'

Top companies maintaining brand consistency

- Ranking based on the percentage of a company's posting being strongly consistent
- Ranking based on *ConScr mean value* for companies which have at least 20 strongly consistent temporal bins
- Observe that these companies have high mean and low standard deviation values of *binLabelSim* and *rankVectorSim*
- Top 5 companies in terms of highest percentage of consistent dynamic posts
  - FTI Consulting, Inc. (1.0)
  - Regis Corporation (0.54)
  - Engility Holdings, Inc. (0.84)
  - Caesars Entertainment Corporation (0.41)
  - Prudential Financial, Inc. (0.23)
- Uses $\mathbf{MT}_{\mathbf{notime}}$ **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 $\mathbf{MT}_{\mathbf{time}}$ **data**

Only few (5%) of companies are able to maintain high temporal consistency score

Product promotion posts

- 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.
- Competence is the primary trait with product promotion followed by sincerity

Trait	Companies in descending order
sincerity	Hospitality Properties Trust (159), Discover Financial Services (53), DaVita Inc. (41), Calpine Corporation (29), Darden Restaurants, Inc. (26)
excitement	Microsoft Corporation (164), Tribune Media Company (42), Tutor Perini Corporation (29)
competence	The Carlyle Group L.P. (67), CSX Corporation (51), Ally Financial Inc. (46), F5 Networks, Inc. (42), Vornado Realty Trust (37)
sophistication	Oceaneering International, Inc. (69), Tailored Brands, Inc. (62), Hawaiian Holdings, Inc. (45)

Top-ranked company vis-a-vis brand consistency

- Top-ranked companies : Within rank 1 - 150; Lead to 18 companies and Bottom-ranked companies : Within rank 850 - 1000; Lead to 20 companies

- Top ranked companies can maintain a higher company-level consistency score, on average, for the first 12 months than the bottom-ranked companies

Limitations

- Only consider textual content of a web page and do not cover any user-generated content regarding the companies
- Do not consider other aspects of a brand style guide like color, typography, positioning of headers and website sections

Future Work

- Jointly learning the five brand personality traits, instead of independent classifiers
  - One brand personality trait may weakly imply another trait (Ex. competence with excitement)
  - Further improve the classifier performance using deep learning techniques
- Investigate at a sentence-level instead of document-level brand consistency score
- Given a not consistent web article, develop a helper tool targeting brand managers and content writers, to identify the sentences that needs to be modified

Conclusion

- This is the first attempt to quantify brand personality from the text content of an organization's official website. Our proposed classification model, BrSVM achieves an **F1 score of 0.822**
- Collected around **300K** web page content covering around **650** Fortune 1000 companies and form an automatically annotated set, MT_{high} containing very highly confident points
- We study the brand characteristics of a company and observe that companies that post consistently and are higher ranked are better at maintaining brand consistency

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  - Email id: **soumyadeep.roy9@iitkgp.ac.in**
  - Github username: **roysoumya**
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Thank you for your attention