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Measuring Corporate Reputation
with BERT-based Transformers

C. Scalia,[1] A. Filetti[1]

[1]Eni S.p.A., Piazza Ezio Vanoni, 1, 20097 San Donato Milanese, Italy

cesare.scalia@eni.com

Abstract

This poster presents a novel approach to measuring corporate reputation using a fine-tuned BERT transformer (Bidirectional Encoder Representations from Transformers).

After a first introduction of the "seven drivers" reputational framework, we demonstrated that by leveraging BERT's contextual language representations and fine-tuning techniques, it is possible to develop an algorithm capable of effectively capturing the contexts of reputational categories.

The proposed approach outperforms other text classifiers with a single model, enabling real-time tracking and measurement of corporate reputation, providing valuable insights into communication opportunities and stakeholders' perception of a brand.

This research contributes to the field of corporate reputation management and has implications for understanding and enhancing organizational image in today's dynamic business environment.

Introduction

Reputation has become a critical asset for companies, necessitating the inclusion of reputational risks in risk management models.

The advent of the Internet presents a dual-faced scenario in this regard. On one hand, it offers immense opportunities due to the vast amount of data available from diverse sources like social media, online newspapers, print media, and blogs. On the other hand, effectively harnessing and deriving insights from this wealth of information to identify communication opportunities, comprehend stakeholders' perceptions of the brand and monitor and swiftly detect reputational crises in near real-time, and with a high level of granularity, poses significant challenges.

Hence, the development of appropriate methodologies to monitor and measure corporate reputation becomes imperative. Consequently, an increasing number of companies are acknowledging the necessity of developing and training tailored machine learning models in order to analyze and interpret this expansive information landscape enhancing their analytical capabilities and fortify their monitoring systems.

Seven reputational drivers model

The theoretical framework for modeling corporate reputation as an intangible asset is provided by the seven reputational drivers model, initially introduced by Van Riel (2007). This model defines reputation as an emotional connection between the company and its stakeholders, with 7 rational dimensions underpinning it. Consistently with the model, media conversations can be categorized into these seven macro categories that represent distinct ways of connecting the brand with its stakeholders. These categories include:

- **Products and Services**: Discussions and comments related to the company's produced and/or provided products and services
- **Innovation**: discussions about technologies, digitization, and innovative approaches
- **Workplace**: contents focusing on employment within the company, its culture, and anything related to its employees
- **Integrity and Transparency**: discussions related to the company's ethical behavior, transparency, and fairness
- **Citizenship**: contents discussing the impact of the company's activities on the communities it operates in.
- **Leadership**: discussions revolving around leadership qualities and the company's vision
- **Performance**: contents related to the company's financial performance .

Fine-tuning

The creation of a single multilabel text classifier for the seven driver categories involves the process of fine-tuning a pre-trained model, specifically the DistilRoBERTa model. Fine-tuning allows us to adapt the model to the task at hand and improve its performance in the specific domain of corporate reputation classification.

DistilRoBERTa is a distilled version of the renowned RoBERTa-base model, which has undergone extensive training through unsupervised Masked Language Modeling (MLM) tasks. With six transformer layers, 768 dimensions, and 12 attention heads, DistilRoBERTa offers a total of 82 million parameters. Notably, this version is twice as fast and has 40% fewer parameters compared to the original model, making it an efficient choice for our purposes.

The training dataset for the corporate reputation machine learning model comprises approximately 7,700 text samples collected from Twitter. These texts were previously annotated by analysts and industry experts within the company to establish key performance indicators (KPIs) for monitoring corporate reputation. It is important to note that the dataset exhibits class imbalance, with certain categories like Products and Performance having more samples than Workplace (as illustrated in Fig 1).

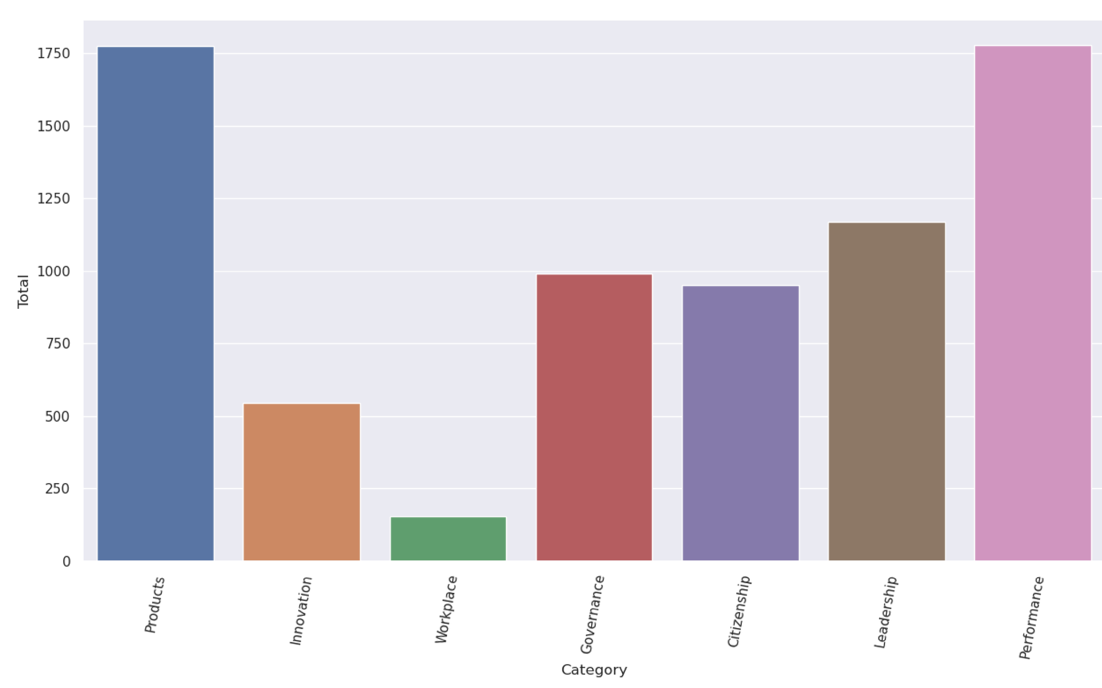

Figure 1

To address this class imbalance, we performed downsampling, limiting the model to a maximum of 500 examples per class while considering the multilabel nature of the model. This downsampling approach helped to ensure a more balanced representation of categories in the dataset. Consequently, approximately 65% of the dataset was utilized for training, 33% for testing, and the remaining 2% for validation purposes.

The preprocessing of input texts involved cleaning them by removing hashtags, URLs, and non-ASCII characters. Additionally, the texts were converted into tuples to leverage the capabilities of the Hugging Face datasets library, optimizing data encoding and tokenization processes.

For the adaptation phase of model weight adjustment, we utilized PyTorch and Hugging Face's Transformers library. Through backpropagation, we iterated the process for five epochs obtaining achieving an F1 score of 0.8, demonstrated the effectiveness of the fine-tuned BERT-based multilabel text classifier in accurately categorizing texts within the seven driver categories.

In comparison, we also developed a classifier based on seven binary Random Forest classifiers (one for each category). However, these approach only achieved an F1 score of 0.5 , indicating a significant contrast in performance compared to the fine-tuned BERT model demonstrated the superiority of transformers over traditional machine learning models for this specific task.

Results

We present a table showcasing sample results obtained from our fine-tuned BERT algorithm, demonstrating its capability to accurately assign reputational drivers to diverse textual samples:

Tweet	Reputational Drivers
Director at @eni, said: "The MoU we are signing today, with RDB, is focused on long-term value opportunities for all stakeholders	Leadership
Eni-Total discovers large gas deposits in block six, reports say	Products and Services
Eniverse (EniverseVentures), the corporate Venture Builder of the "@eni," dedicated to innovation	Innovation
@eni CEO at @Europarl: @eni approach in Africa as model to foster local and social development	Citizenship & Leadership

Typical output of our algorithm in production is a reputational scorecard (Fig. 2) which offers valuable insights into the perception of various dimensions of corporate reputation and allows for a quantitative evaluation of the company's performance across these categories

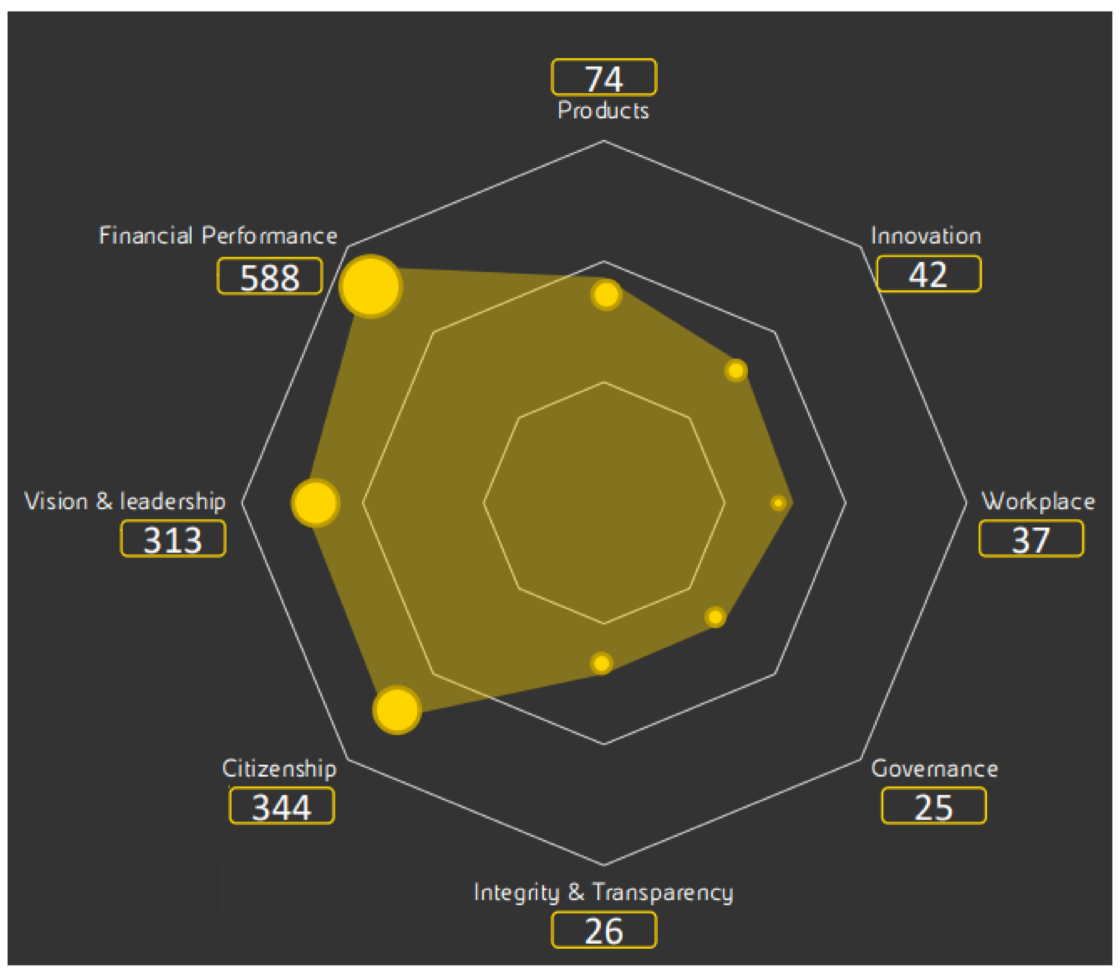

Figure 2

Conclusions

In conclusion, our study demonstrates the effectiveness of fine-tuning a BERT transformer for classifying reputational drivers. This algorithm can provides organizations with a powerful tool to measure and manage their corporate reputation effectively, leading to informed decision-making and improved stakeholder perception.

References

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