An Explainable AI Approach To Analysis Of General Elections In India (Working Title)

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Dedicated to my family and friends for their continued support and patience.

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Abstract

Machine learning has shown promising performance in high stakes applications such as in medical diagnosis, legal applications and financial risk management. In such applications, the consequences of analysis and predictions directly or indirectly impact human lives and society at large. Accuracy in predictions is not enough in such applications. Rather, *explaining why* an ML model has made certain prediction is equally or more important than mere prediction accuracy. *Explainable AI (XAI)* is the field of AI concerned with explaining the outcomes of models. It includes highly interpretable models such as decision tress, regression and Generalized Linear Models(GLM) and more complex models such as Deep Neural Networks(DNN) explained using *post hoc* explainability techniques. Secondly, in order to assess the reliability of ML models, decision makers also require confidence in the prediction. This confidence in prediction is expressed in terms of quantification of uncertainty using Bayesian probability theory.

In this research work, we apply both interpretable and explanatory XAI techniques to get insight into last four General Elections held in India. India is worlds largest democracy and elections have far reaching impact on the lives of more than 1.3 billion people. As part of the mandatory disclosures by law, all the candidates are required to file an affidavit detailing their wealth, eduction, and past criminal charges against them. We make use of this data to analyze how such demographic characteristics influence their likelihood of winning an election. Previous work on Indian election modeling hasn't taken full account of nested structure in data such as grouping by state or by a political alliance. As part of this research, we make use of the hierarchical and random effects models to account for nested structure in data. Lastly, we believe that insights gained from this analysis will help make data driven policy decisions for more robust and accountable electoral processes.

Keywords: Explainable AI (XAI), Interpretable Machine Learning, Social Data Science, Generalized Linear Models, Bayesian hierarchical modeling.

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Chapter 1

Introduction

1.1 Explainable Artificial Intelligence (XAI)

It's in human nature to be curious and inquire. However, for many of the day to day things we are fine with, without knowing how do they work. For example, lets consider a typical airplane flight. A layperson might understand basic laws of physics behind flight of an airplane but may not be able to explain in details its takeoff and maneuvering capabilities. However, we are perfectly fine to fly in an airplane without knowing or understanding all those details even when our life depends on it. This is mainly because we trust the expertise and skills of aerospace engineers, aviation experts and pilots who understand how these machines fly. However, in case of many complex machine learning (ML) models even experts can't explain why the model works the way they do. Additionally, explainability of models would also help in troubleshooting and debugging them for any issues or bugs.

Consider another example of a loan application decision by ML model. It might be mandated by law such as Article 22 of European GDPR, to explain, for example, why a loan application was rejected, called as "Right to Explanation" (Kaminski 2019). This issue is very closely related to *fairness* in machine learning. Without explainability fairness cannot be achieved. Explainable AI addresses this need.

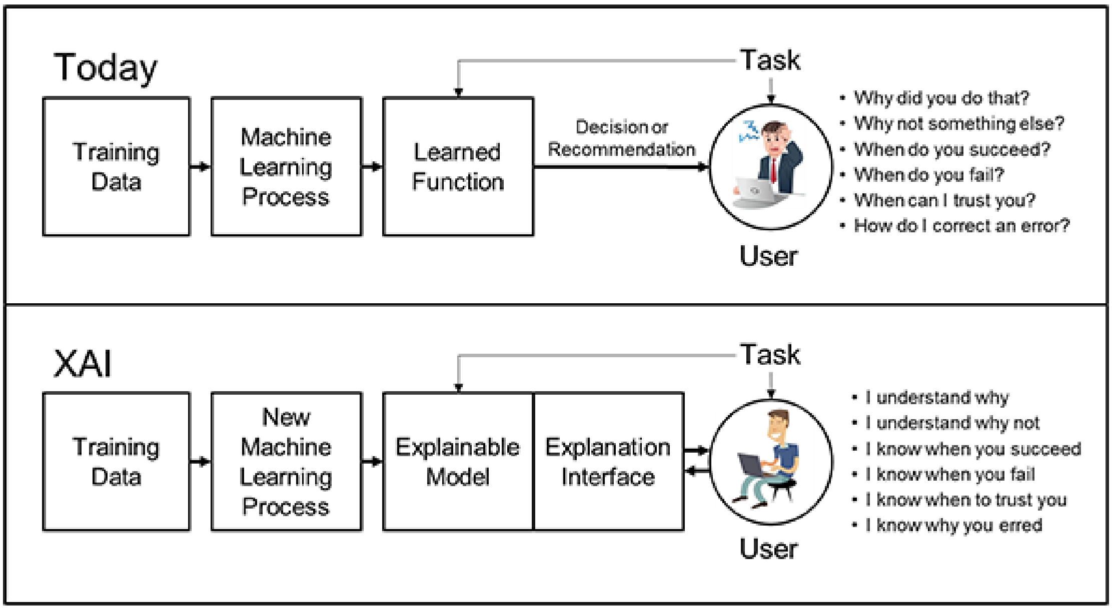


Figure 1.1: XAI

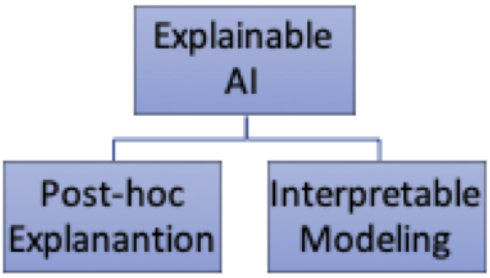


Figure 1.2: XAI Approaches

The field of an eXplainable AI (XAI) is concerned with making AI more explainable and interpretable to human beings. Dr. Matt Turek of DARPA captures the vision for XAI as shown in Figure 1.1 (Turek n.d.). Models built today lack the explainability for high stakes and critical applications.

XAI is a vast and very actively researched field of AI and ML. There are two high level ways in which explainability in AI is realized i.e. using either post-hoc explanation or through interpretable models as shown in Figure 1.2.

In *post-hoc explanation,* after building the model a surrogate model is built to get the explanation of model. For example, using a surrogate decision tree we might be able to explain why ANN predicts certain outcome.

However, this may work in very simple models as more complex models even surrogate models would become complex with their own need of explainability. Secondly, such surrogate model has tendency to fit the training data and may not be able to explain new predictions correctly.

On the other hand, in *interpretable modeling* approach we try to build an interpretable model from ground up from the start. For example, linear regression or decision tree models are inherently interpretable without any needs for external aid for explanation. These models are relatively easier to interpret and explain their predictions. However, they may suffer from accuracy loss when compared to more complex models such as DNNs or Random Forests. There is tradeoff to be made here. However, for high stakes application where interpretability cannot be compromised such as in healthcare, financial risk management or legal applications, building interpretable model from ground up is the only viable option (Rudin 2019).

In this research work, we propose to analyze the electoral data from the General Elections from year 2004 to 2019 using *Explainable Social Data Science* approach. When data science models are applied to social science phenomenon, the nature of goals, methodologies and data used are different in many ways from other data science and machine learning applications (Wallach 2018). During 2004-2019, there were four general elections held in India viz. in the year 2004, 2009, 2014 and most recently in 2019. This is the research proposal for getting insights into the electoral performance of candidates with various backgrounds and belonging to different political parties using data science methodologies.

Insights gained from such analysis would help understand the implications of candidate's background on their electoral performance through scientific approach. Secondly, this research work could serve as in important data to help in future policy decision making related to electoral reforms.

1.2 Thesis Overview

This thesis is organized as follows.

Chapter 2

Modeling Indian General Elections

2.1 Introduction

As the political landscape of the word changed after the end of the World War II many colonies became independent nations. India was one of them. After independence India chose the parliamentary system of democracy with a federal structure. In this structure, Indian Parliament, called as Loksabha forms the lower house while Rajyasabha is an upper house. Elections are an integral part of a participative democracy. Members of Parliament (MPs) for Loksabha are elected from total of 543 parliamentary constituencies (PC) spread across 28 states and 8 union territories. Every five years Election Commission of India (ECI) conducts election in all the PCs through General Elections.Since its independence in 1947 India has been and remains to this day a vibrant democracy.

In order to continue to maintain its status as free and thriving democracy its electoral system needs to remain transparent and trustworthy. In order to achieve this goal there are various reforms and legislative acts are passed by parliament and rulings by various courts from time to time. One of such reforms was introduced by Supreme Court of India in the year 2003, making it mandatory for all the candidates contesting the elections to declare their educational qualification, profession, criminal background as well as financial information in the form of legal affidavit (Sen 2012). This is mainly done to bring more transparency to the electoral systems so that voters are made aware of the candidates.

Analyzing these candidate affidavits and comparing with electoral performance is an important application of data science.

2.2 Literature Survey

This section reviews the recent research covering the Indian elections and electorate(voters). Most of the focus has been focused on predicting the election outcome rather than analyzing and interpreting the causal nature in the models. We are mainly focusing on the models that provide intuitive explanations of the models built rather than forecasting election results.

Indian general election of 2019 are analyzed by Duraisamy, P et al. (Duraisamy and Jérôme 2017) to consider the effect of candidate's personal characteristics. In this work, impact of candidate's criminal background, wealth and whether the candidate was already a sitting MP i.e. incumbency was considered. The model was built using probit regression using maximum likelihood approach. After analyzing the model, authors concluded that the chances of winning for candidates with serious criminal charges are less. However, there are more chances of political parties fielding candidates with criminal charges when they are more uncertain about the outcome in a particular parliamentary constituency. Having movable wealth helped candidates in winning the elections. They found that incumbency had most positive effect on winning the elections in 2009. The extent to which indicted or "tainted" candidates are punished by voters is also extensively studied. An analysis using regression model using interaction terms between criminal background and wealth of the candidates developed by Dutta B. et al. (Dutta and P. Gupta 2014) In this study, they found that the extent to which voters punish the tainted candidates decreases as there are more candidates with similar backgrounds contesting in the same constituency. Also, using the wealth of the candidates, which is positively correlated with criminal backgrounds, these candidates are able to better fund their campaigns. As a result, they are able to overcome disadvantages from their criminal background using their wealth. This election fund campaign also explains why the political parties gave tickets to such candidates. Pehl M (Pehl 2015) reports that contrary to perception that giving tickets to tainted candidates tarnishes the image of the party, it has negligible effect on party's image. Secondly, non-national parties are more likely to field tainted and wealthy candidates than national parties.

Vaishnav M (Vaishnav 2011) argues that indicted candidates are given tickets by political parties when there are ethnic or religious division in the constituency that can be exploited. A multilevel logistic regression model was built to model the data and interpret the results. He compared the impact of the tainted candidates on the reserved constituencies for scheduled casts and scheduled tribes (SC, STs) as well as in non-direct elections and found no such advantage enjoyed by "bad politicians". This work also highlights the fact that data on the intra-part selection of candidates is unavailable. Therefore, it becomes challenging to determine from what pool of candidates the selection was made by the political party.

In an experimental study conducted by Banerjee, A et al. (Banerjee et al. 2014) in the state of Utter Pradesh during 2010, they found that irrespective of the educational or socio-economic status of the voters they have distaste for candidates with tainted backgrounds. They concluded that by educating and by providing the information on the backgrounds of candidates and their past performance has a better chance cleaning the electoral system. This theory was tested by George S et al. (George, S. Gupta, and Neggers 2018) in 2017 wherein they proactively provided candidate background information to voters through voice and text messages. They found that, constituencies where voters were informed, the vote share of the candidates with serious crimes dropped by 7.7% and also overall voter turnout increased by 1.6%.

2.3 Summary

Most of the research work we surveyed mentions the interlink between criminal background, wealth, incumbency, and ethnic background. However, no model was built specifically using interaction variables rather separate models are built and analyzed. Secondly, there is no provision in these model to include any state specific interplay. Voters from different states respond differently to candidates based on local and state level factors. Multilevel model that groups candidates according to the states or party would be more suitable for these datasets to capture group specific interplay. Most importantly, there is no provision for including the prior beliefs or information in the modeling process as well as no uncertainty in quantification of the results. All of these requirements can be met by multilevel Bayesian modeling approach.

Chapter 3

Research Questions

3.1 Introduction

In this chapter we analyze the last four general elections held in 2004, 2009, 2014 and 2019. Based on outcome of the analysis we formulate the research question and methodological expectations for the proposed dissertation work.

For analysis we have considered various demographical characteristics of candidates such as age, gender, education, profession, wealth, party, and criminal background. This information is a mandatory disclosure in from of affidavit from candidates contesting the elections. Election Commission of India (ECI) publishes these data on their website for public awareness. This data is summarized and made more easily consumable by Association of Democratic Reforms.(ADR) (*Association for Democratic Reforms | Improving and Strengthening Democracy in India* n.d.).

3.2 Demographic Characteristics

In this section we analyze various demographical factors one by one and provide graphical visualization of the same. The aim of this analysis and visualization is to detect patterns in the data and develop more insightful research questions.

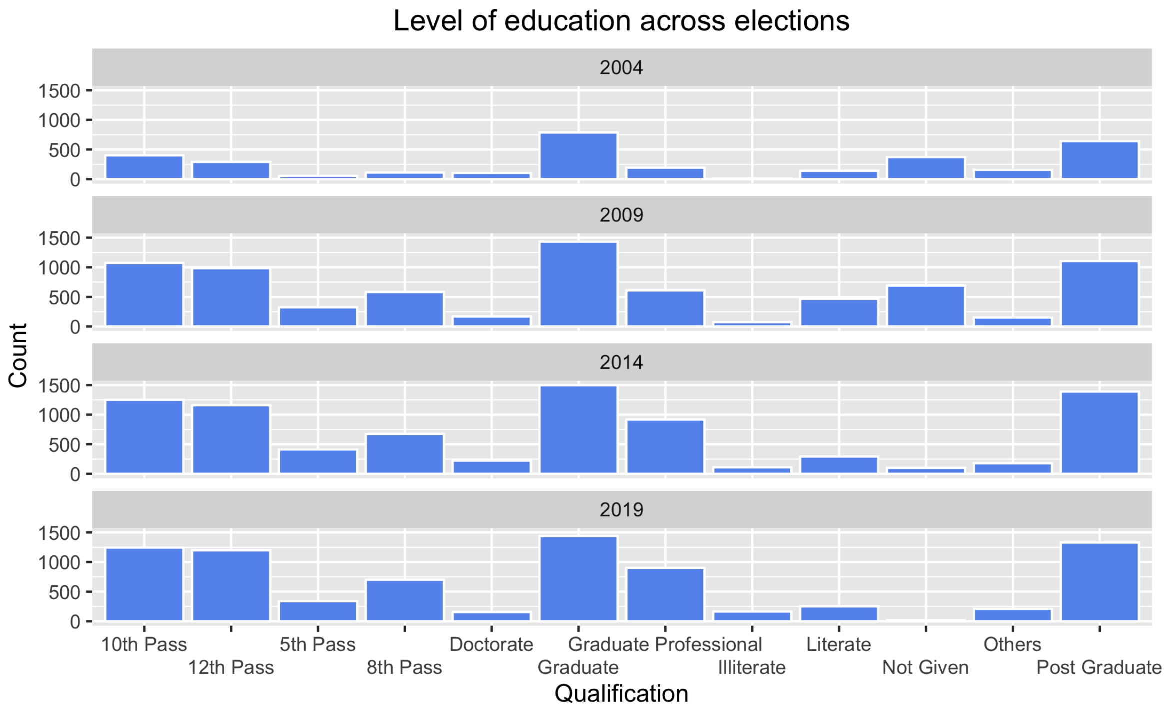


Figure 3.1: Educational Qualifications of candidates across elections

3.2.1 Educational Qualification

More and more candidates with higher educational qualification are contesting the election these days. From data analysis we see that there is constant rise of educationally qualified candidates who have graduate degrees and beyond in every election as shown in Figure 3.1.

From Figure 3.1 we note that many of these candidates hold professional qualifications such as in engineering, medicine and law. Secondly, number of candidates having such degrees is steadily rising. This is indeed a positive sign for democracy and society at large. As one would expect that, as number of professional candidates contesting elections increases there should be proportional increase in professional winners. However, as the plot in Figure 3.2 shows, this is not the case. There is an increase in professional graduate candidates of more than 300% from 192 in 2004 to almost 900 in 2019. However, the number of professionals winning the elections have

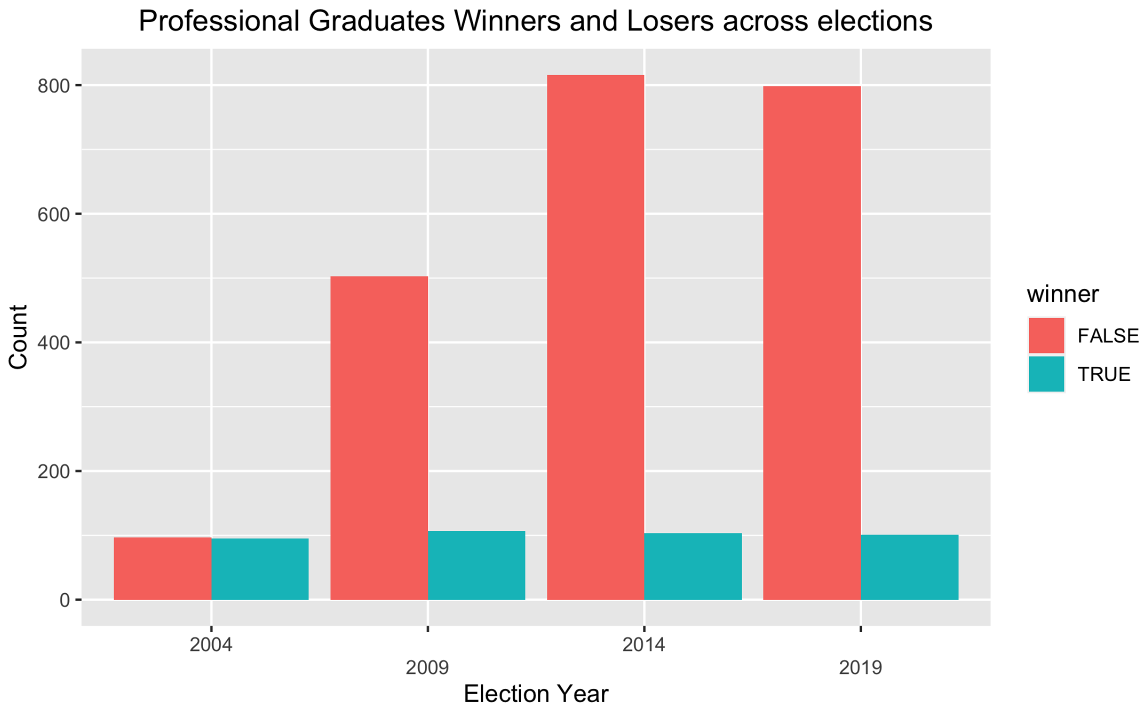


Figure 3.2: Professional Graduates : Winners and Losers

remained almost constant at around 100. Also, winning percentage was 49% in 2004 which dropped to 17% in 2009 and has been around 11% since last two elections.

Therefore, we pose following research questions(RQ),

RQ:*"Considering the clustering structure in the data, how does the educational qualification of candidates influence their likelihood of winning an election?"*

The research is expected to answer what factors are influencing the loss of professional graduates in these elections as well.

3.2.2 Age

Experience and age plays critical role in Indian politics. Considering the young demographics of India it seems obvious that more and more young people represented in election as shown in Figure 3.3.

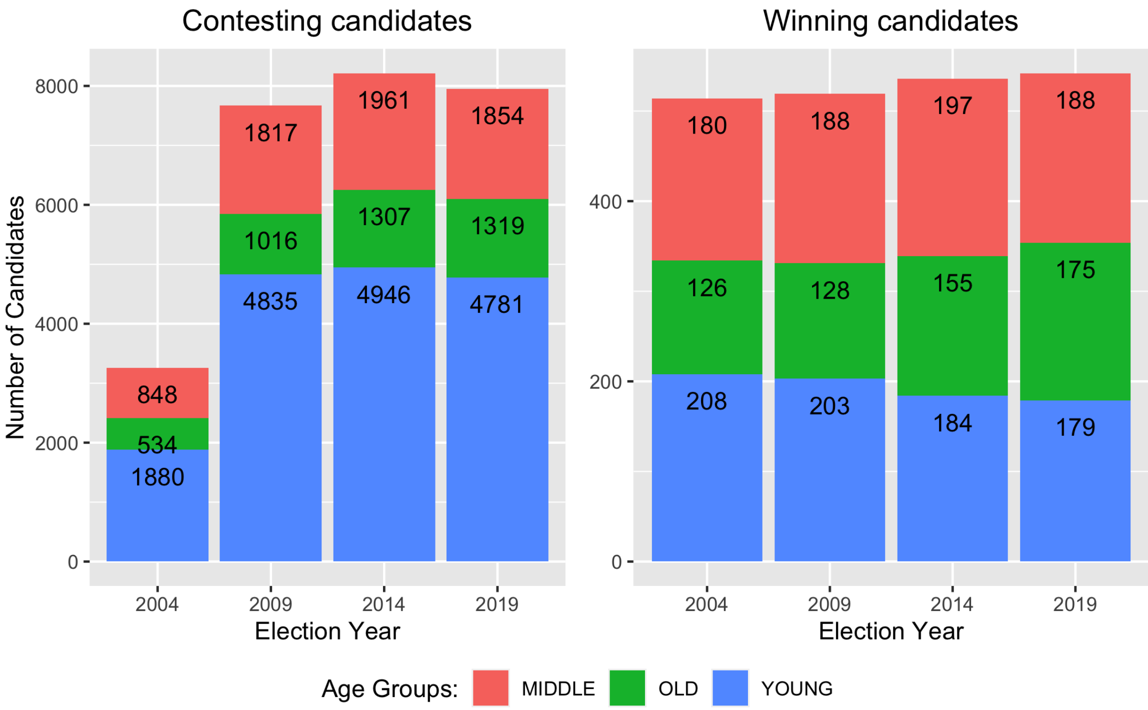


Figure 3.3: Age demography : $Young \leq 40, 40 < Middle \leq 60, 60 < Old$

While minimum age required by law to contest an election in India is 25 years, mean age has remained steady around 47 years as shown in Figure 3.4. Mean ages are shown with dashed vertical lines.

3.2.3 Gender

Figure 3.5 shows the gender distribution across last four elections. As shown in plot A, there is jump in the number of female contestants from year 2004 to 2009 from 227 to 519 i.e. almost 129% increase. However, as shown in plot B, winning percentage have dropped from 18% to 11% which has remained steady under 11% for next two elections.

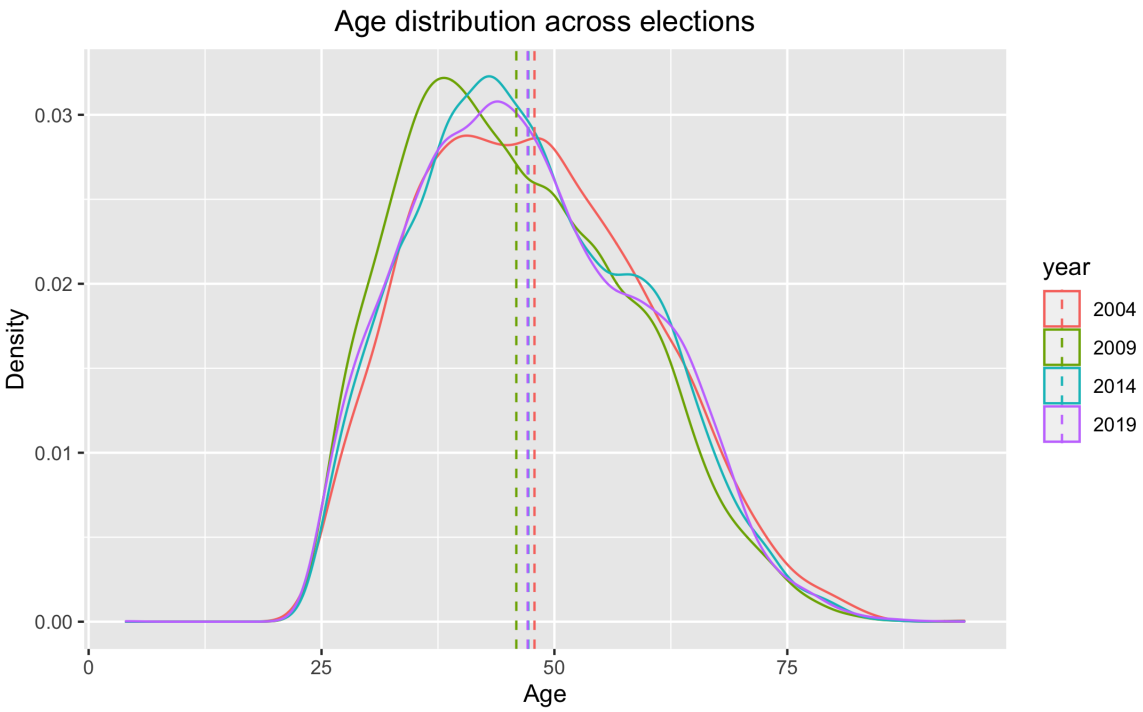


Figure 3.4: Age distribution.Mean age is shown with dashed vertical lines.

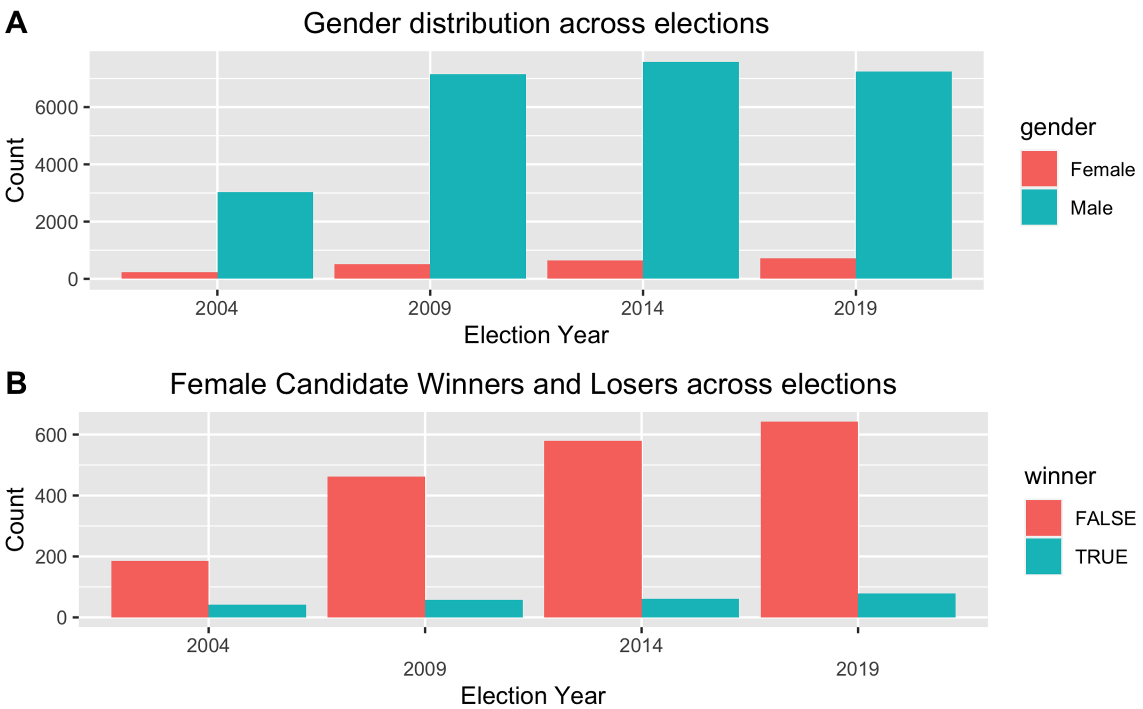


Figure 3.5: Gender distribution across elections

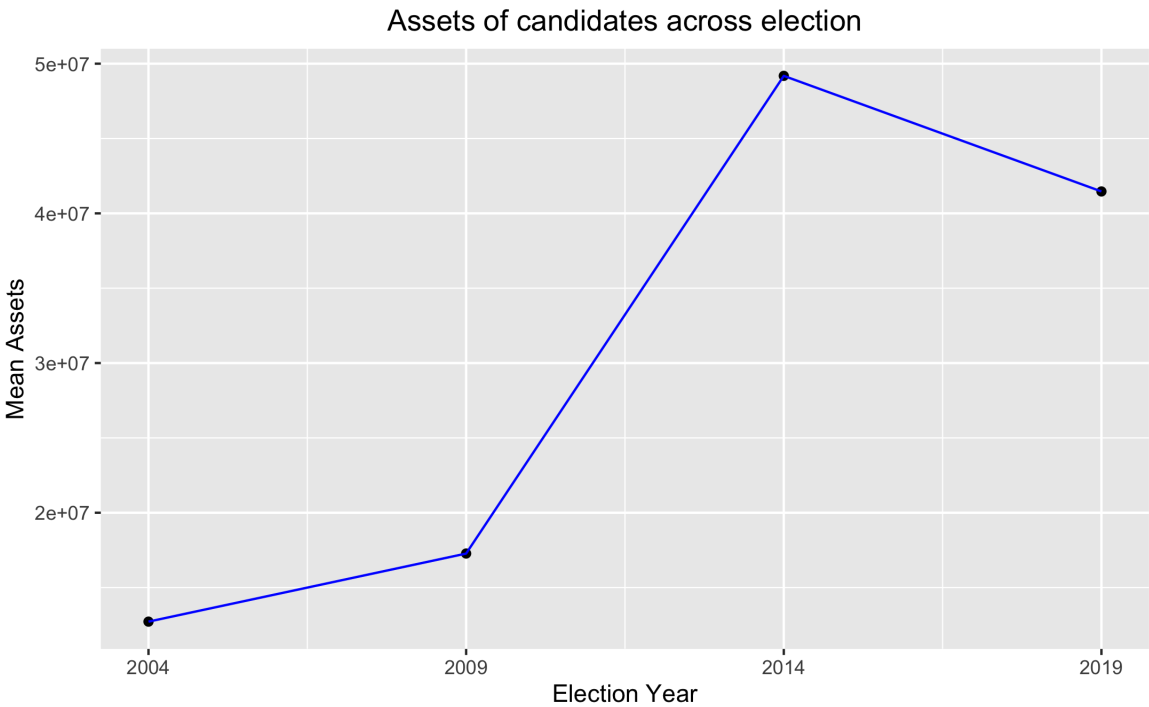


Figure 3.6: Mean assets of candidates(in Indian Rupees)

3.2.4 Assets

Increased election spending is making it difficult for good candidates who lack financial resources to contest elections in India. Mean assets of candidates in 2004 general election were Rs. 1.1 Crore (Rs. 11 Million, approx. US$ 280,000), By 2014 election it reached to over Rs. 4.9 Crore (Rs. 49 Million, approx. US$ 806, 000) [1] as shown in Figure 3.6.

To get the sense of enormity of these jump in figures we need to note the fact that India's GDP per capita was US$ 627.77 and US$ 1573.88 in the year 2004 and 2014 respectively[2], that is a rise of two and half times in GDP per capita while average assets of candidates rose by more than four times.

Candidate's ability to spend on the campaigns plays a critical role in influencing

[1]By then exchange rates between Indian Rupees and US$
[2]Source: World Bank

Listing 3.1: Singficance: assets ~ winner

```
> anova(lm(assets ~ winner, data = loksabha_all_df))
Analysis of Variance Table
Response: assets
                 Df  Sum Sq Mean Sq F value    Pr(>F)
winner            1    42.9  42.924  42.991 5.599e-11 ***
Residuals     27096 27054.1   0.998 '
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

the decisions by party high commands in deciding who gets the "tickets" to contest elections. There is dependency between likelihood of winning and assets of the candidates as shown by Analysis Variance(ANOVA) test as shown in Listing 3.1.

3.2.5 Criminal Background

Since its been made mandatory by Supreme Court ruling in 2002, all the candidates fighting the elections needs to declare if there are any criminal charges filed against them. This may include charges as a result of agitations and political protest which is a part of participating democracy. However, it also includes information whether candidate has criminal charges of serious nature or not. This is shown in Figure 3.7 .

As seen in Figure 3.7 there is a constant rise in the candidates with criminal charges contesting election and many of them have serious charges against them. There is more than three fold rise in candidates with criminal cases against them during the period 2004 and 2009 from 462 in 2004 to 1506 in 2014. Amongst this, there were 266 serious criminal charges in 2004 and 1074 in 2019, staggering increase of four fold. MPs with serious cases against them have risen at steady average of about 40% per elections as shown in Figure 3.8.

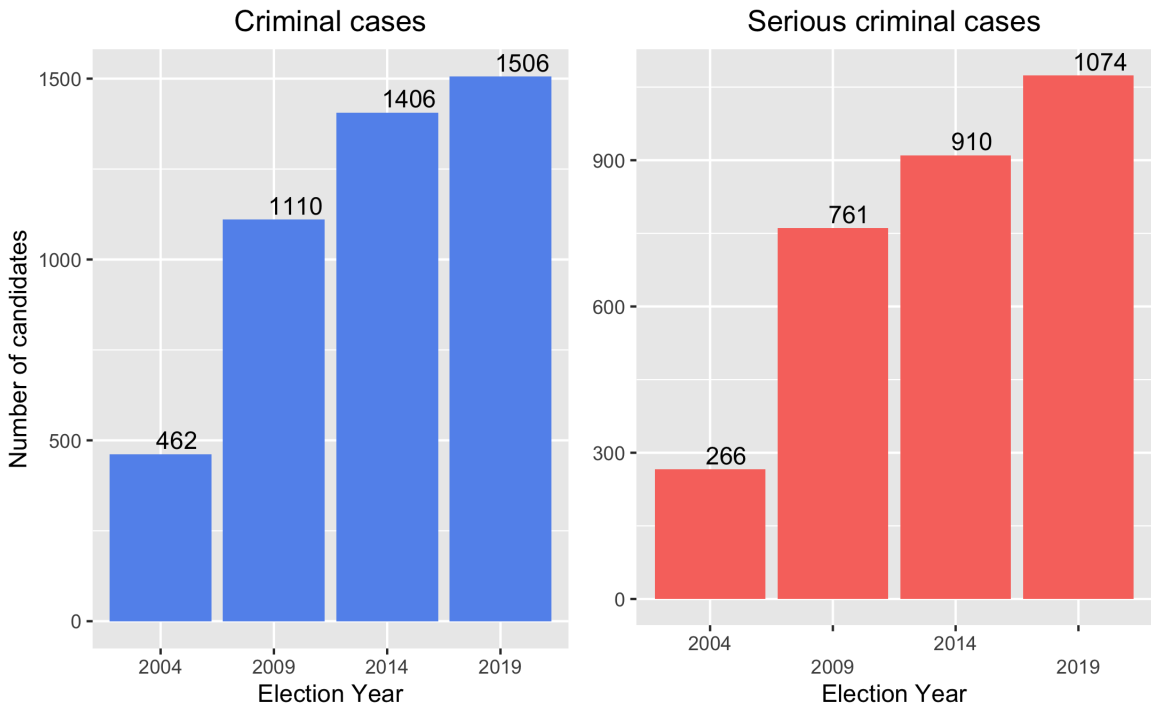


Figure 3.7: Increase in number of candidates with criminal cases

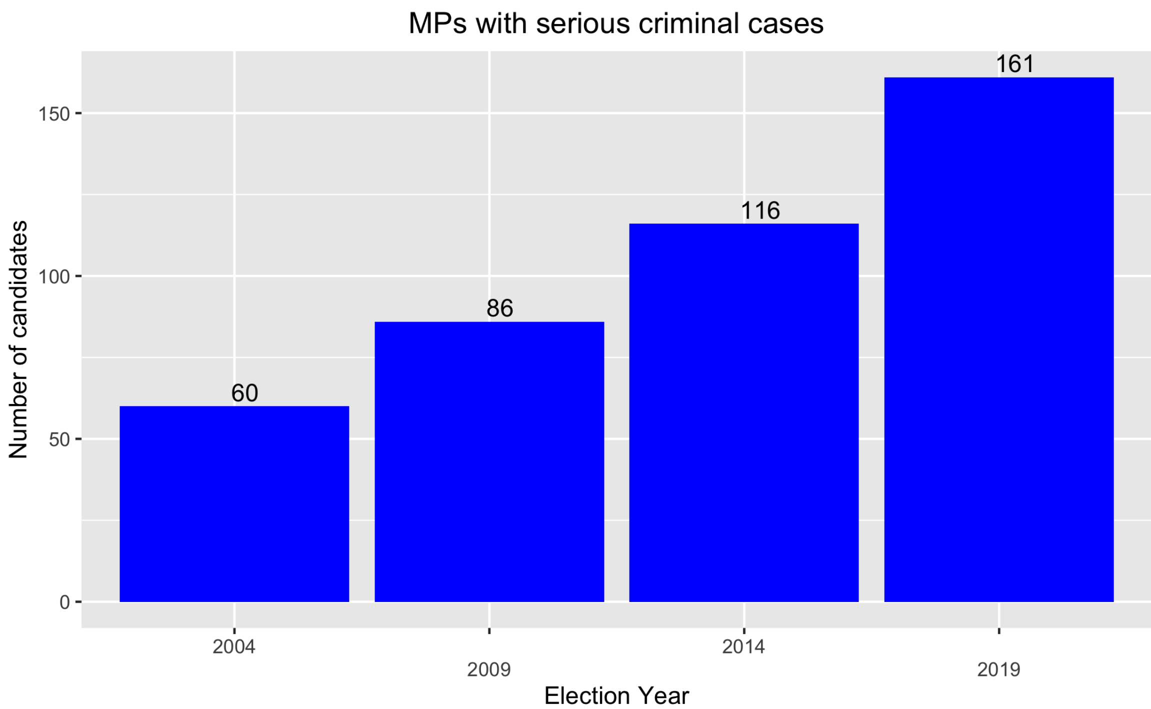


Figure 3.8: MPs with serious criminal cases

Secondly, it would be insightful to know how this interacts with assets of the candidates.

Therefore we intend to answer following question,

RQ: "What is the effect of interaction among serious criminal charges and assets on the outcome of the elections."

Also,

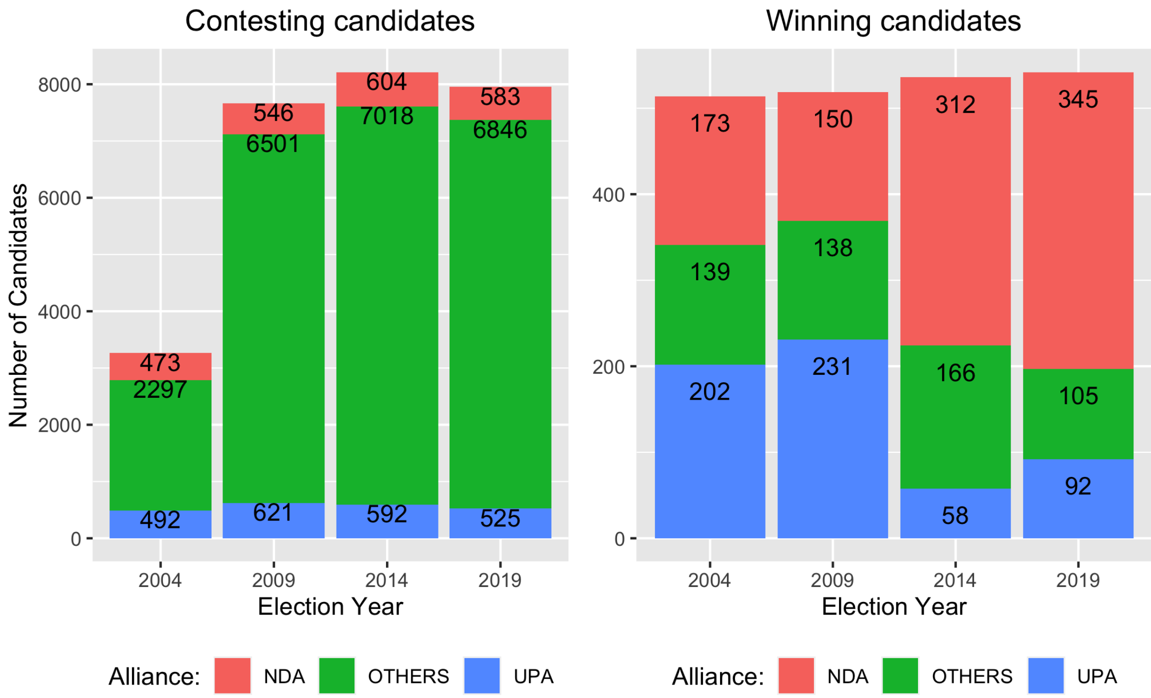
RQ: "Considering the grouping structure in the data, what is interaction effect of criminal charges and candidates assets on election outcome".

3.2.6 Alliance

There are two main national parties in Indian politics since last three decades viz. Bharatiya Janata Party(BJP) and Indian National Congress (INC). However, since 1990s multi-party alliances have played a critical role in Indian politics. BJP lead National Democratic Alliance(NDA) has won last two elections in 2014 and 2019 while INC lead United Progressive Alliance(UPA) has won earlier two elections in 2004 and 2009. Number of candidates contesting these elections from each alliance and their winning performance is shown in Figure 3.9. It is worthwhile to note that these alliances are not constant over time and parties come and go. Secondly, regional parties who may not be the part of any alliance such as All India Trinmool Congress(AITMC) from the state of West Bengal, won over 22 seats in 2019 elections.

With regard to alliances, we aim to answer following question,

RQ "Considering the clustering structure in the dataset, how alliances impact the outcome of the elections".



3.9

Figure 3.9: Alliance Performance

3.2.7 Data Analysis Summary

We present an exploratory data analysis results and visualization of the four general elections data from year 2004 to 2019. Following are some of the salient observations,

- Overall education qualification has shown upward rise with more professionally qualified candidates such as doctors and engineers contesting the elections.
- Young and middle age candidates dominates both contesting and winning populations as expected from Indian demographics.
- There is sharp rise in number of female participants from 2004 to 2009 elections of about 129% , however winning proportions remained steady around 11% in last three elections.
- Similarly, there was sharp four fold rise in average assets of the candidates from 2004 to 2009. As of last, 2019 election average assets were around Rs. 4.1 Crore(Rs. 41 Million).

- Candidates with criminal cases have risen steadily with an average increase in number of MPs with serious criminal cases against them at a rate of about 40% per election in 2004.
- In last four elections, two were won by each NDA and UPA, with later two elections giving BJP clear majority.

3.3 Research Questions

After analyzing the data, we formulated following research questions,

1. *Considering the clustering structure in the data, how does the educational qualifications of candidates influence the voters in India?*
2. *What is the effect of interaction among serious criminal charges and assets on the outcome of the elections?*
3. *Considering the grouping structure in the data, what is interaction effect of criminal charges and candidates assets on election outcome?*
4. *Considering the clustering structure in the dataset, how alliances impact the outcome of the elections?*

3.4 Methodological Aims

We aim to answer these research questions using statistical modeling and machine learning techniques. Given that this is a social data science problem, from the methodological perspective we have set following goals,

1. Models build should not only fit the data and provide predictions with higher accuracy but should also be interpretable, explainable and intuitive.
2. Uncertainties in the inference should be quantifiable in terms of probabilities.

3. Model should be able to incorporate any prior knowledge and expert judgement.

Part I

Multilevel Modeling

Chapter 4

Bayesian Hierarchical Modeling

4.1 Introduction

Application of data science to social science need to go beyond accuracy of prediction of models. Model needs to explain influence of features on the outcome as well the interrelationship between them in a transparent and intuitive manner. Bayesian inferential methods are natural fit in order to meet this requirement.

Part II

Post Hoc Explanations

Chapter 5

Post Hoc Explanations

5.1 Introduction

Certain class of models such as regression and it's variants, decision trees are inherently interpretable. These model on their own can explain the feature outcome. However, complex models such as XGBOOT, Random Forest and Deep Neural Networks need an external help for explaining their results. These explanations are typically done post the predictions and hence are called *post-hoc explanations*.

5.2 Types of Post Hoc Explanations

There are broadly two types of explanations provided by XAI viz. feature based and sample based explanations. Both of these methods are model agnostic.

5.2.1 Feature Based Explanations

This method relies on the explanation by discovering important features that influenced directly the decision of the model for a prediction. In case of interpretable model, for example in linear regression models, we can explain the importance of attributes by the slope parameters associated with the feature. No external method

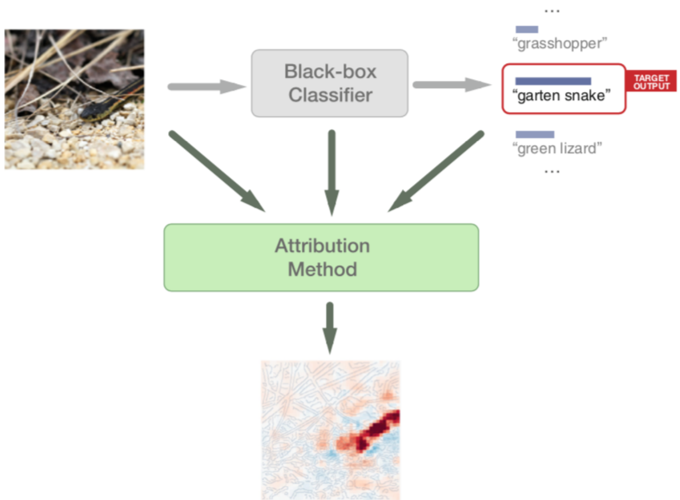


Figure 5.1: Gradient Based Explanations (Ancona et al. 2019)

is need for explaining the prediction made by the model for a test dataset. These are also called as attribution methods in literature. However, for other non-linear and complex models such as eXtreme Gradient Boosting (XGB) machine or Convolutional Neural Network(CNN) based models post-hoc explanation are more widely researched and practiced.

In post-hoc explanation the method could use gradient based methods (Ancona et al. 2019) i.e. changing the value of the feature the impact it causes on the model output is measured. Larger the impact more important the feature. Figure 5.1 shows the general setup of the gradient based explanations. Attribution method, as in this example, identifies most the important part of the image that is causes the image to be identified garden snake.

Another class of post-hoc explanation methods widely used are *removal based* methods. In these methods a permutations of models are built by removing subset of features and measuring the impact on prediction accuracy. In the next section we review two of the most important feature based explanation method viz. Shapley values and Local interpretable model-agnostic explanations (LIME).

5.2.1.1 Shapley Values

5.2.1.2 LIME

Local interpretable model-agnostic explanations (LIME)

For an in-depth comparison of such and other explanations by removing variables please refer to the framework developed by (Covert, Lundberg, and Lee 2020).

5.2.2 Sample Based Explanations

In this type of explanations the most influencing samples responsible for prediction are identified. Naive way to achieve this is by removing a training sample and then training the model to get the influence of the sample on training or test loss. However, there more computationally efficient methods are developed. One such methods was suggested by Koh et al. (Koh and Liang 2017) In this method, samples are up-weighted by infinitesimal small weight ϵ. Without retraining the model we can get the influence of the reweighed sample. The influence of up-weighting feature i on the parameter $\hat{\theta}$ is given by (Cook and Weisberg 1982),

$$Influence_{up=i,params} = \tfrac{d\hat{\theta}}{d\epsilon}|_{\epsilon=0} = -H^{-1}\nabla_{\theta}L(i,\hat{\theta})$$

Here,H is the Hessian matrix and $L(i,\hat{\theta})$ is the loss function when feature i is included in the model.Using this property, with weight $\epsilon = -1/n$ which is equivalent to removing the feature, authors empirically show that we can get the influence of the sample without actually retraining the model.

Another variant of the similar method where a positive and negative representer points are derived for a test point using kernel methods for DNN is proposed by Yeh et al. (Yeh et al. 2018).

Most of these methods try to explain the predictions by DNN based models for image recognition and natural language processing(NLP) tasks. Detailed review and taxonomy of these methods is provided by Vilone et al. (Vilone and Longo 2020).

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Appendix A

Appendix Name

Colourless green ideas sleep furiously.