Predictive Modelling to Estimate Number of Women Help Centres in India

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Abstract

This Paper uses Machine Learning Algorithms namely, Principal Component Analysis, Random Forest and Clustering to analyse crime committed against women in India. We look at multiple categories of crime against women(rape, murder, domestic violence etc) and estimate the magnitude of crime. We extend this prediction to translate to number of help centres required which are called One Stop Centres. The Ministry of Women and Children has already finalised the number of centres to be constructed at State level (some are under construction and some have been completed). We then juxtapose the predicted numbers on planned Numbers to arrive at deficit and surplus numbers and actual number of centres planned and the predictions based on actuals are not in tandem.

Contents

1 Overview

Crime against women in India currently amounts to 60,96,310 cases reported by the latest 2021 report of National Crime Records Bureau. India ranks as one of the most unsafe countries for in terms of women safety. According to NCRB National Crime Records Bureau (NCRB) crime is committed against women every 3 minutes. Crime is committed in different forms such as domestic violence, rape, dowry, modesty defamation and more. Alarmingly 65% of the men believe that women "deserve to be beaten up". Recipients of the crime range from infants to elderly. Naturally, over the years this issue has provoked research to recognize what led to the concerning status of women safety in India globally. This has attracted academic research from behavioural scientist, psychologists, women organization and think tanks. Several speculated factors have been highlighted as to contributing to this issue. Male dominance coupled with female submission is known to aggravate the problem. Multiple studies suggest that women feel more powerless than men given the same circumstances. Imposition by men who think they are entitled to supremacy makes the situation worse.

Moreover, law enforcement institutions by executive (Police) and judiciary have not been efficient enough either. Huge number of women abuse cases are being reported as false, large number of cases are pending at court, the laws are not well defined, juvenile criminals are being excused and many more such gaps.

Cases of victim blaming have been particularly intense. This has a cascading effect. Most of these crimes are more mentally challenging than other kinds. A further implication is that the victim has an inherent fear while reporting these cases. Moreover, in legal battles the revisiting of the traumatic experience is daunting that further attenuates this phenomena of not reporting the crime.

The clients are better off avoiding the whole episode altogether. Societal stigmas might explain how there is under-reporting.

The problem also has a demographic angle. Some states have a more severe issue than the others and this throws light on lack of appropriate policy environment to rectify the situation. Furthermore, the policy funding, implementation and similar dependencies are determined at state level.

10 years ago, the famous "Nirbhaya" case led to an uproar across the nation leading to country-wide protest and condemnation from international organizations. This heat continued for next 5 years and in response to that current Modi-led government began a one stop centre (OSC) scheme wherein institutions are to be setup across the country to address all relevant challenges women face while tacking abuse and violence. The centre aims to to support with filing complaints, counselling, emergency services, medical assistance, legal aid, shelter, helpline and video conferencing facilities etc. The government currently has 150 OSCs across the country. Their methodology of arriving at these numbers was based on just three factors (weighted) – no of crime cases (40%), child sex ratio (30%) and female population (30%). Not only is the process not holistic but it relies on archaic data (2014).

We use some machine learning techniques to understand the dynamics of crime against women in India more specifically to evaluate the speculated factors responsible. 37 categories of crime are captured by NCRB. We use Principal Component Analysis (PCA) to condense the categories into fewer more relevant features. We also perform hierarchical clustering on all of these numbers in an attempt to club similar states together and look for similarities between these states in terms of policy and governance. Lastly, we use a random forest predictive modelling to predict the number of cases and in turn no of OSCs at state level. We then compare the prediction with number of centres that are planned to be in effect.

The below plot depicts a view of how crime rate has changed across states and union territories (UT) over the last 10 years.

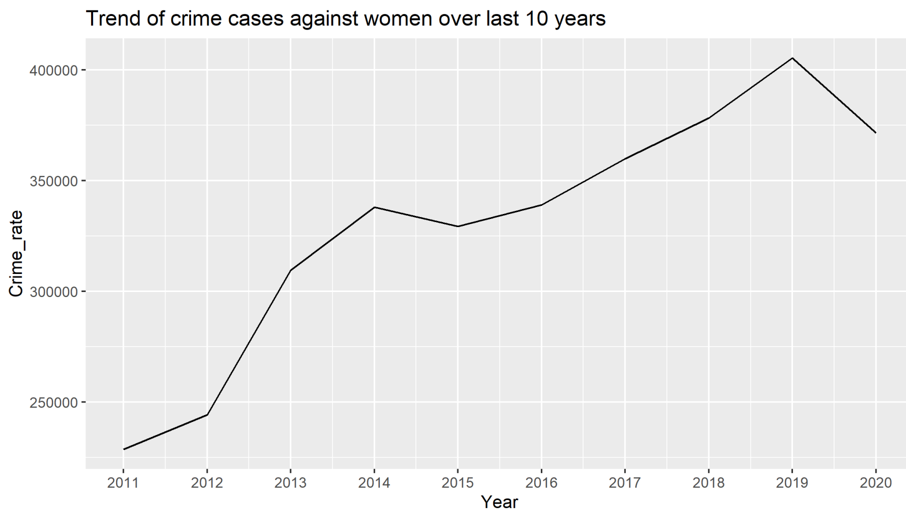

Figure 1: Crime against women over the years

2 Data

2.1 Crime data from NCRB

NCRB produces annual report capturing the crime cases under various category. We pulled information on number of cases over 37 categories. These were primarily rape (attempt to, gang, child), murder, suicide, acid attack, domestic violence, kidnapping, trafficking, importation/selling, dowry, attack on modesty, cybercrime, sexual harassment, indecent representation of women and publishing sexually explicit materials. These numbers are published at district level and we focused on 509 districts across all states of India. Figure 2 lists the crime categories that are captured and recorded by NCRB.

murder with rape	kidnap	trafficking	dowry	publish obscene
dowry deaths	kidnap murder	sell minor	prostitution	cybercrime
suicide	kidnap ransom	buy minor	detain prostitution	child rape
miscarriage	kidnap miscarriage	rape	vicinity prostitution	child assault
acid attack	procuring minor	attmpt rape	soliciting prostitution	sexual harassment
attempt acid attack	procuring foreign girls	modesty attack	prostitution other	child porn
cruelty by husband family	kidnap others	insult modesty	domestic violence	indecency
Protection of Children from Sexual Offenses Act				

Figure 2: Crime against women over the years

2.2 Police crime data

In order to discern the impact of law enforcement across states we pulled information from Indian Police crime data on number of cases pending by court, pending by police, conviction by police, conviction by court, police officers' density, women police officers' density and number of women police stations. Numerous surveys suggest that women find it easier to report crime when they face a women officer on the other side of the table. This data is not available at district level. In the whole nation there are 416 women police stations. On an average only 10% of the police force is women in India.

2.3 National Health Family Survey of India

An interesting part of census data is where they survey both men and women about the general perception of women empowerment. We have numbers on women employment, percentage of women who are heads of the family, female literacy rate and women earnings relative to their husbands. We also capture some statistics around how many women feel they independently or jointly discuss how their income spent and how their husband's income is spent. In order to evaluate decision-making responsibilities of women, we see what percentage of women feel they have decision-making powers either independently or jointly. For example, in India 71% of women say that they take major decisions jointly with men and 56% men think that women should be allowed to make decisions jointly. The survey also covers a statement on earning parity. India only 40% of women earn nearly as much as their partners.

Number of women police stations and female heads was although not available at district level, this information seemed important for predictive modelling and therefore we collected it by contacting individuals' stations and visiting their official website (509 district stations).

3 The Model

3.1 Clustering

Given the smaller size of the dataset we observed better results from hierarchical clustering over kmeans. We chose complete linkage method because the dendogram as a result, was more balanced compared to average and single (minimum) both of which are skewed to one side. A balanced dendogram is more useful interpretation as it does a relatively more scattered clustering especially when we have fewer observations

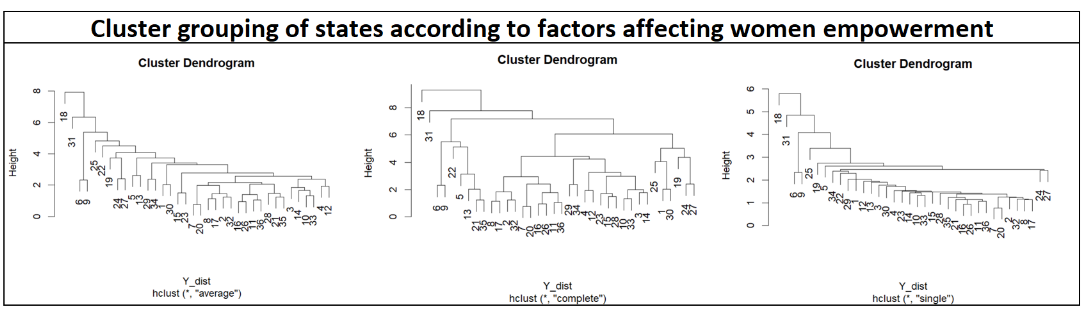

Figure 3: Dendogram comparison of single, complete and average linkage methods for women empowerment cluster

We perform 2 different clustering. The first is one based on law enforcement factors. This provides an insight into how tight are the states in curbing crime. The second one is to analyse how empowering do women feel in these states.

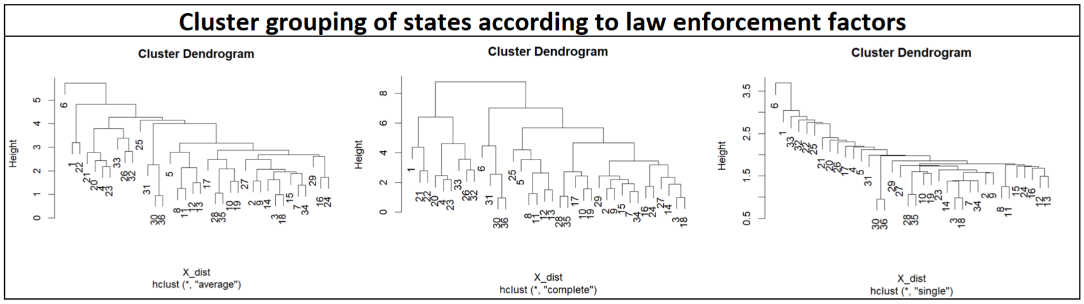

Figure 4: Dendogram comparison of single, complete and average linkage methods for law enforcement cluster

We accordingly choose number of clusters to be able to effectively analyse the similarities within a cluster and dissimilarities among clusters from policy point of view. For this paper we choose 5 clusters.

3.1.1 Results

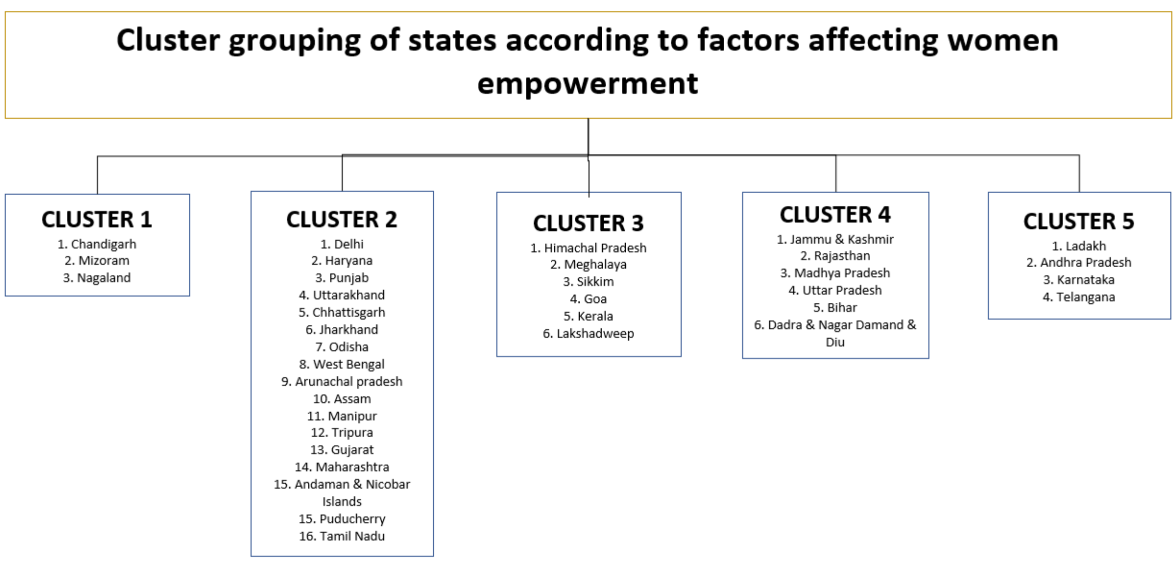

Figure 5: Clustering based on women empowerment factors

Cluster 2 is the largest and likely a combination of multiple factors and therefore it is harder to find a patter here. Something that is interesting here is cluster 3 which enlists states with high female literacy rates. Interestingly these are also the where in general literacy rates are higher for all sexes. These states have a lot of professions that are driven by women for example, bars, travel agencies, hotels etc. Cluster 1 has states where women literacy rates are low and they don't often recognize themselves as head of the family. A noteworthy takeaway from here is that states where women see themselves as heads and equal earners, don't necessarily come from high literacy states. Perhaps there is no reason to believe the two flow in tandem.

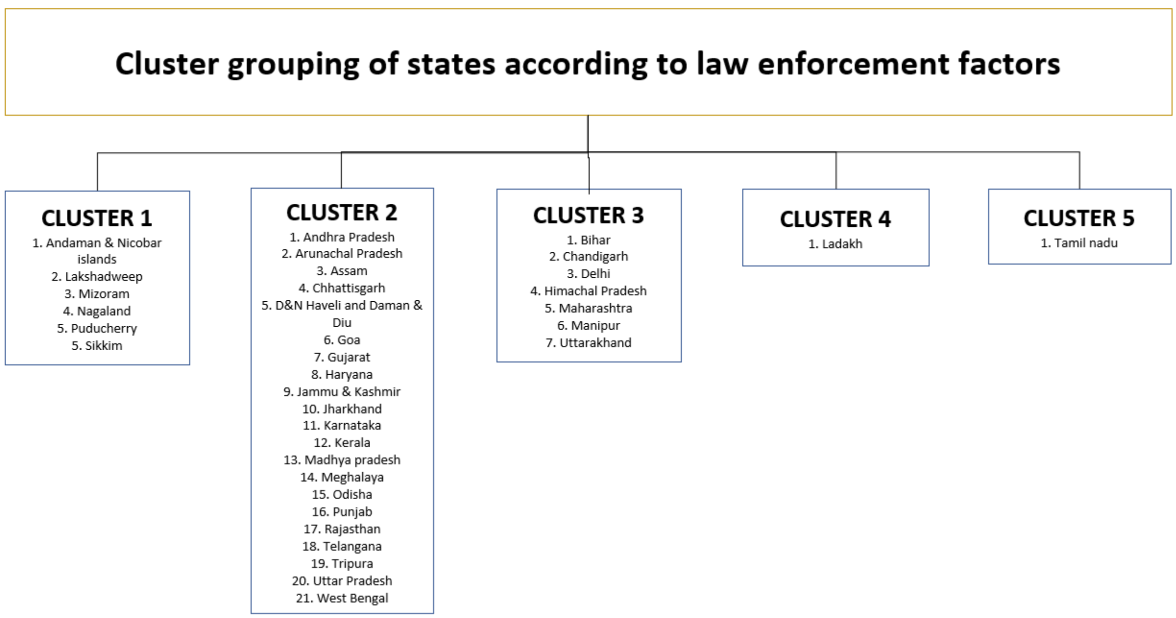

Figure 6: Clustering based on law enforcement factors

Cluster 3 interestingly groups states with larger size of police force but fewer police station runs by women officer. Cluster 1 on the other hands groups states with smaller force. Note this information is not present in the raw data. The fact that clustering can highlight commonalities that are not present in data is where we can use them in policy design. For example, here the further research would be to see if larger police force will help reduce the crime or have no effect or should the focus be on women police stations.

3.2 Principal Component Analysis

Since NCRB captures 37 categories of crime we use PCA to reduce 18 categories. The way we decide the number of components is by looking at the scree plot (figure 7). It explains what percentage of variance is explained by all the components together and individually. The point where the curve elbows out is 10 but with 10 components only 54% of the variation is explained. Therefore, we went a little further somewhere around 20 components. Beyond this point the incremental variance explanation is insignificant. Note that as we add more components the cumulative proportion is always going to increase (and eventually reach 100% when we add all 37 components).

The reason we are compressing the dataset is because we want to run regressions and predict the number of cases. Therefore, the way we pick the right number of categories is to calculate the RMSE of random forest predictive model and pick the most accurate model. Since random forest model accuracy depends on train and test splits, we perform the measure on same set of train and test splits. Finally with these two steps we arrive at 18 components. With 18 components we can explain nearly 75% of the data. This is decent enough.

3.2.1 Results

The first PCA component seems to be more or less an average (except for 2 categories which are lower in number). Later on, when we perform random forest we will notice that this is the most important variable in the predictive modelling. The second PCA component is interesting in that it has contrasted the crime categories that are more prevalent versus less frequent. For example, rape, cru-

Importance of first k=18 (out of 37) components		
Components	**Proportion of Variance**	**Cumulative Proportion**
PC1	13.05%	13.05%
PC2	7.21%	20.26%
PC3	5.70%	25.97%
PC4	5.60%	31.57%
PC5	4.90%	36.47%
PC6	4.17%	40.64%
PC7	3.81%	44.46%
PC8	3.32%	47.78%
PC9	3.14%	50.92%
PC10	3.13%	54.05%
PC11	2.98%	57.02%
PC12	2.90%	59.93%
PC13	2.86%	62.79%
PC14	2.77%	65.55%
PC15	2.70%	68.25%
PC16	2.53%	70.78%
PC17	2.45%	73.23%
PC18	2.43%	**75.66%**

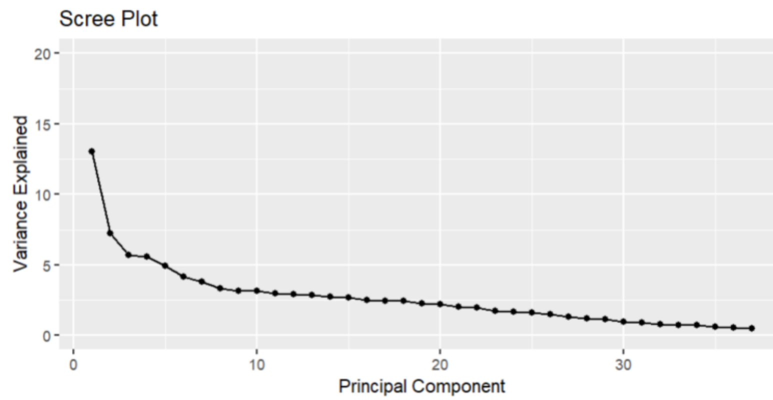

Figure 7: Scree Plot of 18 components

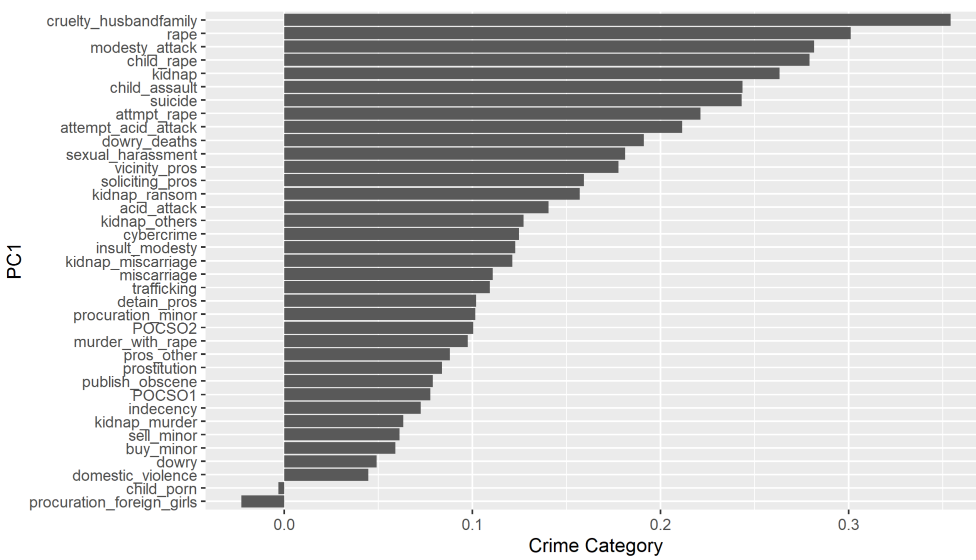

Figure 8: PC1

elty by family members of husband, dowry, coerced prostitution, child assault, acid attack etc occur more frequently (or at least reported) than kidnapping for ransom, insulting modesty etc. This is a good indication to policymakers that which area of crime and justice requires foremost focus. India is a huge country with million problems and therefore funnelling approach becomes very

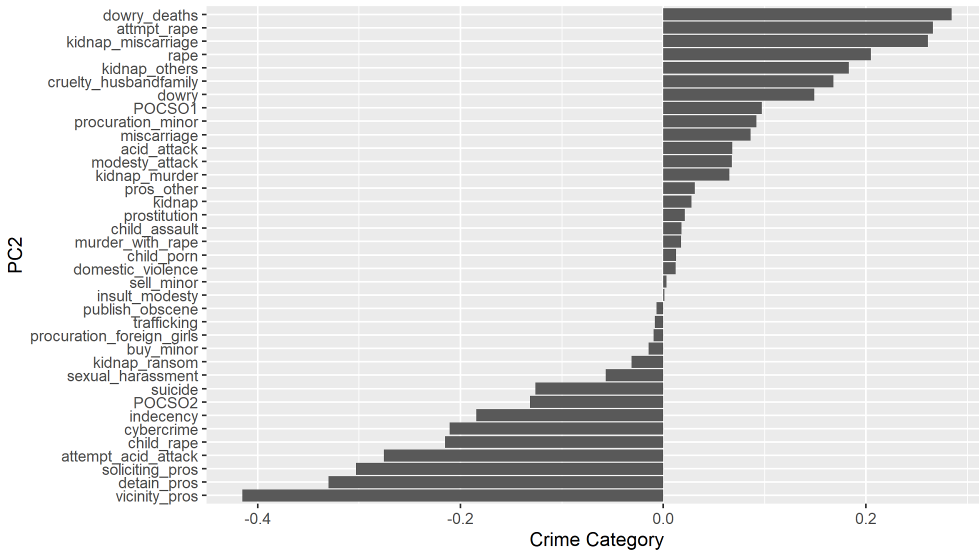

Figure 9: PC2

crucial. Such statistics can prove useful in those cases. The coefficients of all components is given in the Appendix.

3.3 Predictive Modelling

We used gradient boosting method and random forest which gave a lower RMSE (116) when compared to boosting (160) . Therefore, we used random forest to predict crime rate at district level and then compare this to existing number of functional OSCs and analyse where we may need to augment efforts. The reason we don't directly predict the number of OSCs is because currently the structure of OSC is unknown to me – i.e number of employees dedicated to each wing of the centre, expected volume of requests, hiring plan etc.

3.3.1 Results

Variable importance plot explains the contribution of all the features in reducing the prediction error. For instance, if I eliminated PC1 from the predictive model, then the model accuracy will reduce the most and if I dropped PC18 from the model, then the accuracy would be least affected. This makes PC1 most important in modelling and PC18 least important. They are arranged in the order of their importance with respect to the accuracy error. As expected PC1 is most important when it comes to modelling. Surprisingly number of women police stations is least important. Now this can mean either of two things: a) in fact women police stations don't make women safer which is highly unlikely or b) there aren't enough women police stations built to analyse the data which makes much more sense here. Most places don't have women police station or have just 1 as a result of which there is not much variation in this data for the algorithm to learn from. This is an interesting insight into how to interpret the variable importance graph.

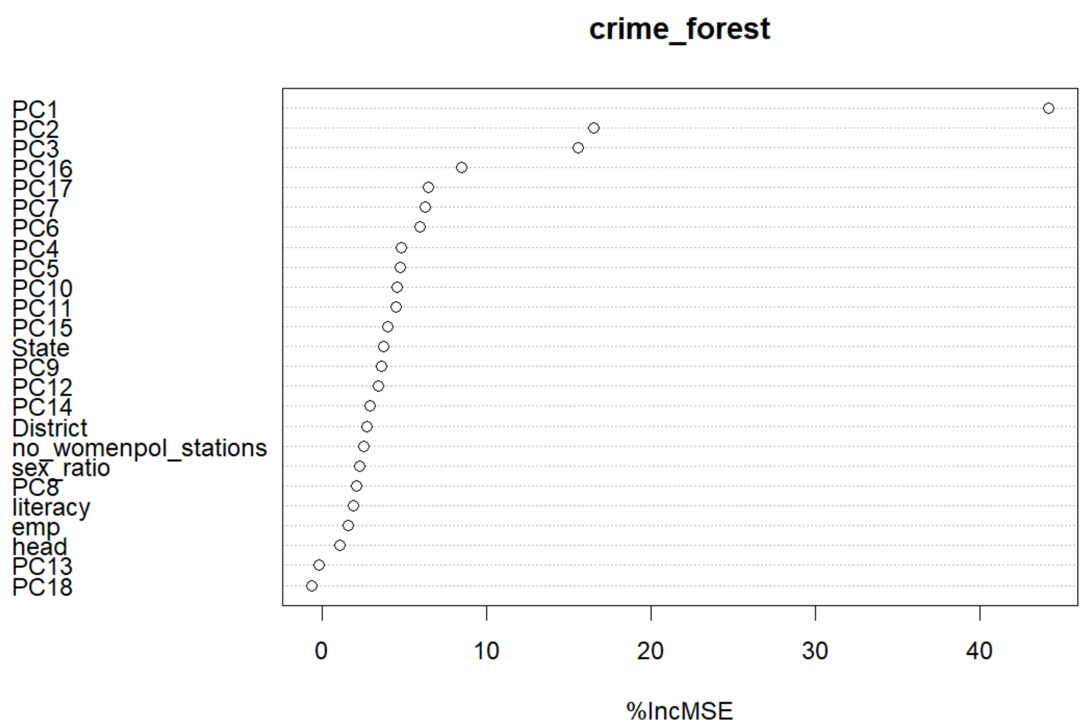

Figure 10: Variable Importance Plot

Something to explicitly point out is the fact that factors like sex ratio which the ministry considers while deciding the number of OSCs to build, is way below on the importance chart.

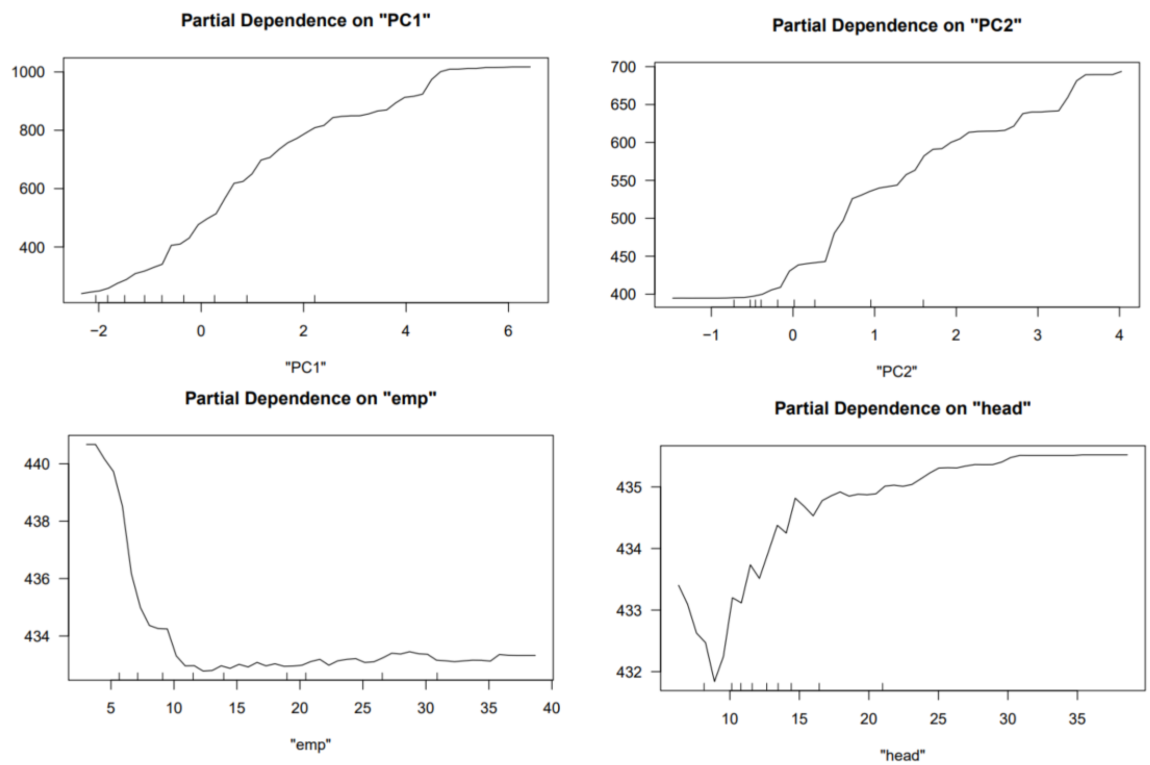

Figure 11: Partial Dependence Plots

Partial dependence plots of PC1 and PC2 are quite reasonable as they represent crime rate, increasing those factors would increase likelihood of crime. Head graph depicts how crime rate changes as proportion of females heading household increases which is puzzling as heading household is empowering and yet shows that crime increases with this feature. But this is in coherence with variable importance plot where the head feature is 3rd least important.

What is remarkable is the how crime rate changes with female employment. Initially as female employment is low crime rate is very high (expected). Beyond a certain point as employment gets higher the crime rate is infinitesimally small and then it saturates at that level. This suggest how effective employment is in obstructing crime against women.

4 Conclusion

Number of cases to be handled by each OSC as per predictions

State	#crime predicted	#actual OSCs	cases_per_osc
Andhra Pradesh	3648	13	281
Arunachal Pradesh	8	24	0
Assam	2880	33	87
Bihar	2371	38	62
Chhattisgarh	610	27	23
Delhi	1606	11	145.96
Goa	169	2	84
Haryana	5604	22	255
Himachal Pradesh	376	12	31
Jammu & Kashmir	184	20	9
Jharkhand	1756	24	73
Karnataka	1618	30	54
Kerala	1865	14	133
Madhya Pradesh	4021	52	77
Maharashtra	3712	37	100
Manipur	290	16	18
Meghalaya	97	11	9
Mizoram	33	8	4
Nagaland	10	11	1
Odisha	2012	30	67
Punjab	736	22	33
Rajasthan	5145	33	156
Sikkim	47	4	12
Tamil Nadu	1394	34	41
Uttar Pradesh	5702	75	76
Uttarakhand	119	13	9
West Bengal	3133	0	0

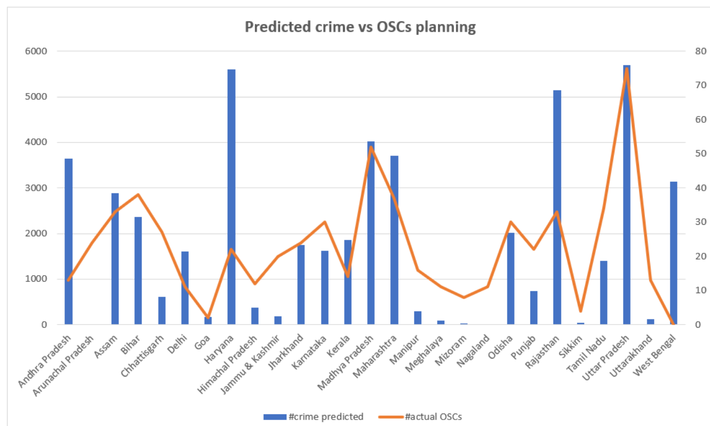

Figure 12: Comparison of predicted number of crime against women cases and actual number of OSCs

It is evident from the list above that states with high crime rate (Rajasthan, Andhra Pradesh, Haryana) have to manage extremely high number of cases. The comparison between predicted crime rate and actual functional OSCs suggests gross mismatch. Most states with high crime rate need more centres. West Bengal has some districts topping the list in crime rate consistently and there is no functional centre yet (which might be an operational issue and not a planning error). Whereas Arunachal Pradesh has excess centres. Delhi and Rajasthan which have been infamous for rape cases but as per their planning they are expected to handle over 100 cases. This explains that machine learning models are definitely superior to mere weighted average approach. The adverse consequences of this planning are severe since funds and contracts are sanctioned to states based on the weighted average approach. Currently one of the major blockers this scheme faces is insufficient funds. Therefore, judicious spending warrants a more sophisticated methodology of planning how many centres are needed at state level.

Clustering has some very useful insights for policy design. Discerning similarities between states can help replicate policies that have worked for one some of the states. Implementing policy without having to reinvent the wheel cannot be done naively but certainly is a low-hanging fruit. For example, cluster 3 in women empowerment clustering bunched states like Sikkim, Meghalaya, Goa, Kerala and Himachal Pradesh. These states are similar in terms of having the least gender gap in work environment as well as per the societal norms, highest labor force participation among women and sense of security. It is interesting that these factors were not incorporated but are similar trends across the states in cluster 3 and therefore, might be an indication towards what is working well for them. For example, the states with high crime rate and low labor force participation should implement policies to encourage women employment.

5 Future Development

5.1 Victim Blaming - Sentiment analysis

A future development of this project would be to factor in victim blaming sentiment in the realm of violence. India is plagued by victim targeting as is suggested by numerous surveys and anecdotes however there is no official public data available on this. Such factors influence whether women/girls are willing to report these cases. Even today thousands of females don't report sexual abuse because of the fear of it being backfired. By using sentiment analysis techniques we can study text around perception of survivors, attackers, general public, authority etc.

5.2 Data collection

A further improvement would be to gather data for all of these features at district level in order to obtain bigger samples. Law enforcement and some of women empowerment clustering was done on states/union territories of India due to lack of publicly available data at district level. That amounts to too few entries to be able to do random forest forecasting and therefore we restricted features to attributes available for all districts we could gather through online resources and telephonic inputs. Having the rest of the information at district will better inform he model. Perhaps clustering would also give a more thought-provoking conclusion if the sample comprised of all districts instead of just states.

5.3 OSC Functionality

Knowledge of responsibilities of OSCs, hiring structure and funding amount can be useful features to the model. This information will aid in extending to the prediction to number of OSCs from number of cases therefore making it easier to compare predicted OSCs vs actuals.

References

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A Appendix

Principal Components of crime categories

Category	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13	PC14	PC15	PC16	PC17	PC18
murder_with_rape	0.1	0.02	-0.03	0.05	-0.22	0.05	-0.22	0.11	-0.09	-0.36	0.23	0.36	0.11	-0.33	-0.15	-0.01	-0.12	-0.05
dowry_deaths	0.19	0.28	-0.2	-0.3	-0.2	0.08	0.14	-0.05	-0.08	-0.06	-0.14	-0.03	0	-0.08	-0.02	0.03	0.13	-0.07
suicide	0.24	-0.13	0.27	-0.15	0.13	0.01	-0.05	-0.16	0.08	-0.03	0.03	0.15	-0.11	-0.15	-0.05	0.1	0.13	0.14
miscarriage	0.11	0.09	-0.05	-0.1	-0.12	0	-0.53	-0.23	0.09	0.17	-0.09	-0.1	0.03	0.15	0.01	-0.09	-0.08	-0.1
acid_attack	0.14	0.07	0.06	-0.13	0.04	-0.11	-0.15	0.13	-0.3	0.4	-0.23	0.22	0	-0.02	-0.04	-0.03	-0.28	-0.3
attempt_acid_attack	0.21	-0.28	-0.09	-0.15	0.21	0.08	-0.16	0.03	-0.18	0.02	0.12	-0.21	0.01	-0.02	-0.02	-0.11	-0.05	-0.03
cruelty_husbandfamily	0.35	0.17	0.06	0.11	0.15	-0.04	-0.01	0.04	-0.03	-0.03	0	-0.03	-0.09	0.07	0.01	0.11	-0.08	-0.07
kidnap	0.26	0.03	0.32	0.04	-0.15	0.14	-0.01	-0.02	-0.07	0.12	0.03	0.03	0.12	0.09	-0.03	0.04	-0.17	-0.03
kidnap_murder	0.06	0.07	-0.15	-0.09	-0.09	0.06	0.1	-0.07	0.25	0.31	0.39	0.1	-0.25	0.01	-0.01	0.35	0.03	0.05
kidnap_ransom	0.16	-0.03	-0.32	0.22	-0.01	0.05	-0.27	0.01	0.2	0.15	0.04	-0.07	-0.06	0.01	0.05	-0.01	0.2	0.19
kidnap_miscarriage	0.12	0.26	-0.33	-0.27	-0.1	-0.02	0.12	0.12	0.01	-0.2	-0.09	-0.06	0.02	0.08	0.04	0.1	0.07	-0.05
procuration_minor	0.1	0.09	-0.12	0.12	0.16	-0.12	0.08	0.3	0.4	0	-0.04	0	-0.21	0.16	0.01	0.07	-0.14	0.04
procuration_foreign_girls	-0.02	-0.01	-0.01	0.02	0.02	0	0	0.03	0.05	0.01	-0.02	-0.07	-0.06	0.25	-0.95	-0.05	0.09	-0.03
kidnap_others	0.13	0.18	-0.2	0.2	0.17	-0.03	0.08	0.11	-0.07	-0.2	0.14	0.26	0.06	-0.18	-0.08	-0.2	-0.18	0.12
trafficking	0.11	-0.01	0.12	0.16	-0.02	-0.07	0.1	0.28	0.25	0.06	0.04	-0.29	0.26	-0.04	0.08	-0.07	0.17	-0.54
sell_minor	0.06	0	-0.04	0	0.15	-0.03	-0.09	0.5	-0.15	0.34	0	0.16	-0.09	-0.1	0.04	-0.32	0.36	0.26
buy_minor	0.06	-0.01	0.09	-0.03	-0.02	0.14	0.03	0.06	-0.03	-0.08	-0.01	-0.58	-0.43	-0.37	-0.05	-0.25	-0.32	0.12
rape	0.3	0.2	0.05	0.19	0.04	0.15	0.11	-0.06	-0.06	-0.13	0.08	-0.09	0	0.05	0	-0.05	-0.01	0.03
attmpt_rape	0.22	0.27	-0.08	0.29	0.17	0.08	0.02	-0.12	-0.15	0.14	-0.04	-0.07	0.07	0.11	0.01	0.12	-0.09	-0.05
modesty_attack	0.28	0.07	0.21	0.15	-0.2	-0.08	0.02	0.1	0.01	-0.12	0.14	-0.02	-0.04	-0.02	0.01	0.01	0.27	-0.08
insult_modesty	0.12	0	0.2	0.03	0.02	-0.57	-0.02	-0.21	-0.03	0	0.01	-0.04	0.01	-0.12	-0.05	-0.02	0.13	0.05
dowry	0.05	0.15	-0.21	-0.27	-0.14	-0.26	0.09	-0.08	-0.13	0.08	0.1	-0.17	0.17	-0.08	-0.04	-0.3	0.19	0.01
prostitution	0.08	0.02	0.11	-0.09	0.01	0.17	0.11	-0.12	0.03	-0.18	0.12	0.12	-0.02	0.59	0.16	-0.53	-0.01	0.09
detain_pros	0.1	-0.33	-0.29	0.07	-0.15	-0.05	0.15	-0.12	0.05	0.08	-0.19	0.06	-0.04	0.03	0.01	-0.11	-0.14	0.01
vicinity_pros	0.18	-0.42	-0.23	-0.02	0.14	-0.02	0.05	-0.06	-0.02	-0.11	0.05	-0.08	0.09	0.04	0	0.06	-0.01	-0.12
soliciting_pros	0.16	-0.3	-0.04	-0.13	0.23	0.08	-0.04	0	-0.11	-0.16	0.2	-0.03	0.11	0.03	0	0.12	0.25	-0.15
pros_other	0.09	0.03	0.13	0.03	0.08	-0.48	0.05	-0.24	0.17	-0.04	-0.03	0.02	-0.09	0	0.03	-0.1	-0.01	0.16
domestic_violence	0.04	0.01	0.1	-0.03	-0.04	0.13	0.14	0.05	0.26	0.16	-0.05	-0.15	0.67	-0.14	-0.09	0	-0.14	0.4
publish_obscene	0.08	-0.01	-0.12	0.07	-0.27	-0.06	-0.53	0.03	0.21	-0.16	0.02	-0.06	0.07	0.04	0.04	-0.04	-0.06	0.06
cybercrime	0.12	-0.21	0	0.23	-0.43	-0.08	0.14	0.1	-0.2	0.02	-0.08	-0.06	-0.09	0.1	0.02	0.06	0.06	0.08
child_rape	0.28	-0.22	0.13	-0.16	0.01	0.09	0	0.11	0.13	0.1	-0.05	0.1	0.03	0.01	0.01	0	-0.07	0.17
child_assault	0.24	0.02	0.11	-0.35	-0.15	0.2	0.1	-0.05	0.16	0.03	-0.18	0.1	-0.14	-0.11	-0.02	0.05	0.12	0.03
sexual_harassment	0.18	-0.06	-0.19	-0.18	0.17	-0.31	0.06	0.12	-0.07	-0.1	-0.09	-0.02	0.12	0.12	0.01	0.18	-0.3	0.14
child_porn	0	0.01	-0.08	-0.07	-0.12	-0.07	0.13	-0.11	-0.03	0.32	0.65	0	0.02	-0.02	-0.02	-0.13	-0.23	-0.09
POCSO1	0.08	0.1	-0.15	0.25	0.18	0.18	0	-0.4	-0.19	0.12	-0.1	-0.07	0.07	-0.14	-0.02	0.03	0.23	0.12
POCSO2	0.1	-0.13	-0.14	0.14	0	0.05	0.19	-0.21	0.32	0.07	-0.21	0.28	-0.04	-0.27	-0.05	-0.33	-0.03	-0.31
indecency	0.07	-0.18	-0.06	0.21	-0.37	-0.05	0.16	0.05	-0.25	0.06	-0.06	0.02	-0.02	0.11	-0.01	0.09	-0.03	0.14

Figure 13: Coefficients of all 18 components