BENCHMARKS: A Citizen's Scorecard on Judicial Accountability in Massachusetts

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Introduction

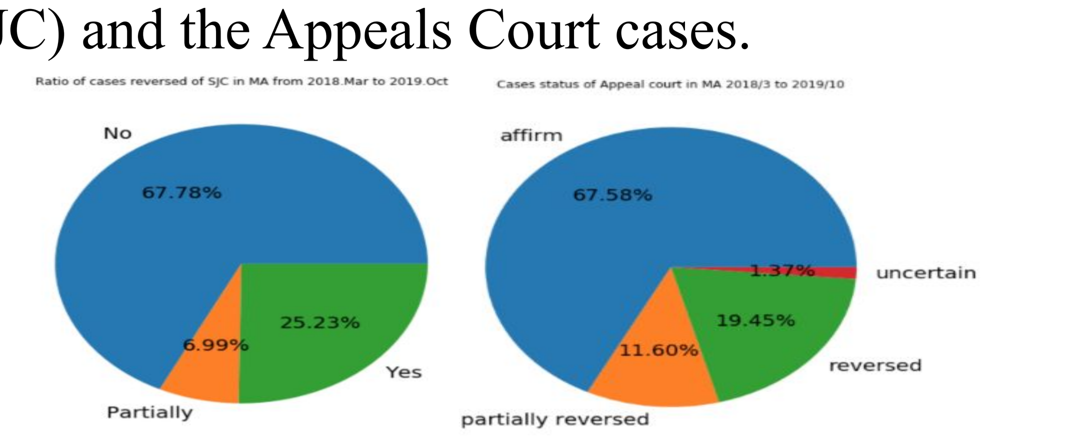
We worked with *BENCHMARKS: A Citizen's Scorecard on Judicial Accountability in Massachusetts* to determine the conditions under which judicial rulings are likely to be reversed. Focusing on cases appealed to the Massachusetts Supreme Judicial Court and Appellate Courts from 2008–2019, our goal was to use data science as a tool of investigative journalism to uncover never before-seen patterns of judicial behavior.

Questions we aim to answer

- What proportion of cases are reversed in Massachusetts?
- What are the similarities between cases that are reversed?
- Is it possible to predict when a case is going to be reversed ?

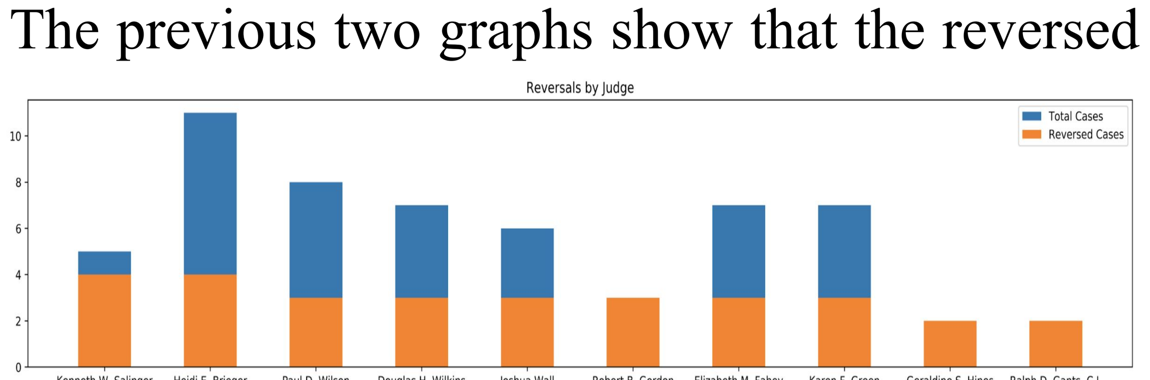
Data

The first main data source is **masscases**, a collection of reports, from the Massachusetts government website. Here we got public opinions text of the Supreme Judicial Court (SJC) and the Appeals Court cases.



Ratio of SJC and appealed cases reversed from 2018.3 - 2019.10

We cleaned the scraped data and determined how often each lower court judge is reversed. The previous two graphs show that the reversed



Judges with a reversal ratio of greater than 50%

Analysis

The graph above shows judges who presided over more than five cases and had more than 50% of cases they presided over reversed.

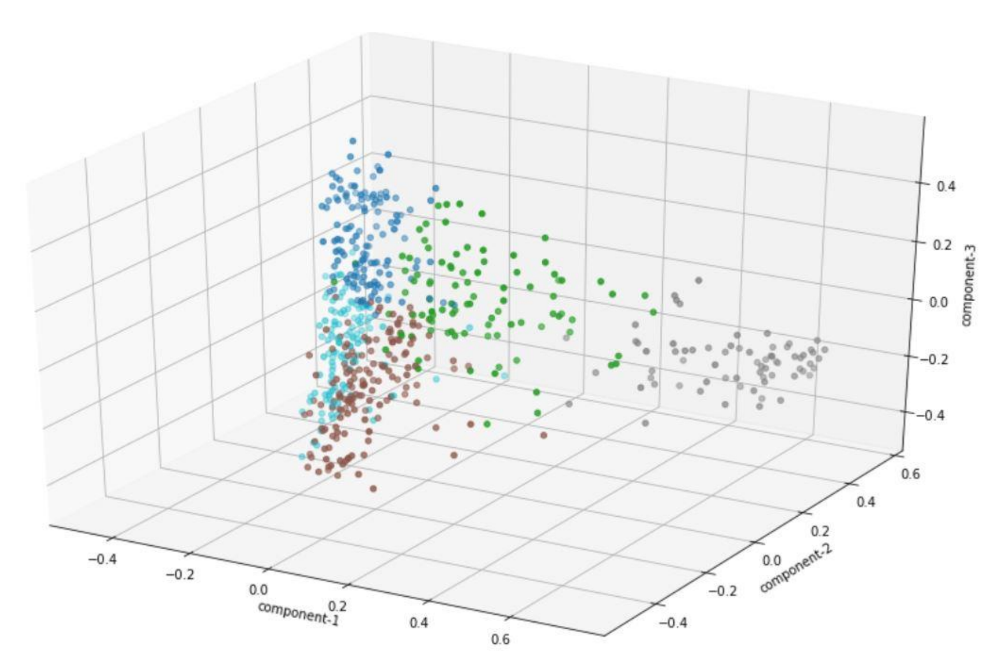
	all cases	all reversed cases	civil cases	reversed civil cases	reversed case rate	reversed civil case rate
Kenneth W. Salinger	5	4	2	1	0.800000	0.500000
Heidi E. Brieger	11	4	8	2	0.363636	0.250000
Paul D. Wilson	8	3	8	3	0.375000	0.375000
Douglas H. Wilkins	7	3	5	2	0.428571	0.400000
Joshua Wall	6	3	4	3	0.500000	0.750000
Robert B. Gordon	3	3	1	1	1.000000	1.000000
Elizabeth M. Fahey	7	3	2	1	0.428571	0.500000
Karen F. Green	7	3	6	2	0.428571	0.333333
Geraldine S. Hines	2	2	2	2	1.000000	1.000000
Ralph D. Gants, C.J.	2	2	1	1	1.000000	1.000000

Judges with most reversed cases recently

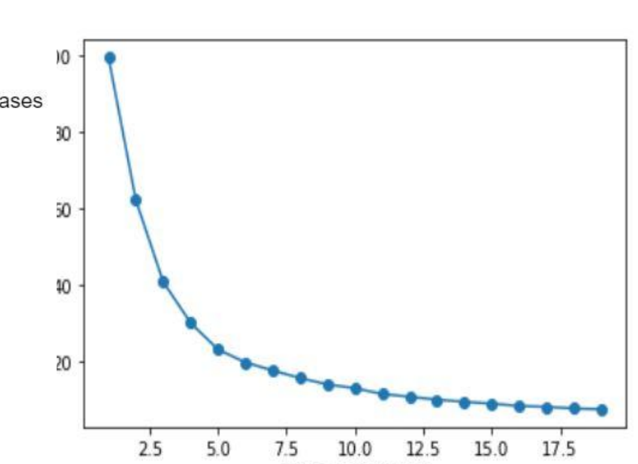
The graph above shows 10 top judges who mostly likely to reverse a case of both SJC and Appeal Court in MA. Kenneth W. Salinger, Robert B. Gordon, Geraldine S.Hines, and Ralph D. Gants have the highest reversed case rate where the latter 3 judges reversed all cases they processed, also these cases are all civil cases.

For this section of the analysis, we wanted to examine text data to possibly identify patterns between affirmed and reverse cases.We separated the affirmed and reversed cases into separate data frames. We found that that affirmed and reversed cases shared over half of their features

we wanted to see if clustering to use these features to group similar cases together. We utilized KMeans++, and here our the results.



- cluster 1: 153 opinions
  - 112 criminal cases and 39 civil cases
  - 101 affirmed cases and 52 reversed cases
- cluster 2: 96 opinions
  - 85 criminal cases and 11 civil cases
  - 75 affirmed and 21 reversed
- cluster 3: 131 opinions
  - 116 criminal cases and 15 civil cases
  - 90 affirmed and 41 reversed
- cluster 4: 69 opinions
  - 68 criminal and 1 civil
  - 56 affirm and 13 reverse
- cluster 5: 112 opinions
  - 103 criminal cases and 9 civil cases
  - 100 affirmed and 12 reversed.



Predicting Case Reversal

- Can we predict when a case is going to be reversed ?
- With the current data not yet, not with a high accuracy.
- A more descriptive dataset is required along with an in depth legal knowledge to process them.
- Features like case text and headnotes would be helpful which currently could not be scrapped due to high website security.
- Also given any dataset the technique of handling missing values is important. This is more so in the case of case of variables representing legal features. Hence good legal knowledge or working in collaboration with people with judicial is recommended.
- Here are our learnings on the current dataset.

Category of case	Integer Class representation	Count	Count % (rounded to one decimal)
Affirmed	0	10014	85.9 %
Reversed	1	1104	9.5 %
Partially Reversed	2	534	4.6 %

Table 1 : Class wise distribution of data samples

- To correct skewed nature of the data different sampling techniques (oversampling and undersampling) were tried. ADASYN oversampling was observed to be best.
- Here are the final results using only numerical data

Model	Confusion Matrix	Class Wise accuracy
Decision Tree (DT)	[[1642, 214, 154], [161, 45, 14], [77, 13, 11]]	Class 0: 0.817 Class 1: 0.205 Class 2: 0.109
Gradient Boosted Decision Tree (GBDT)	[[1725, 196, 89], [148, 66, 6], [81, 12, 8]]	Class 0: 0.858 Class 1: 0.3 Class 2: 0.079

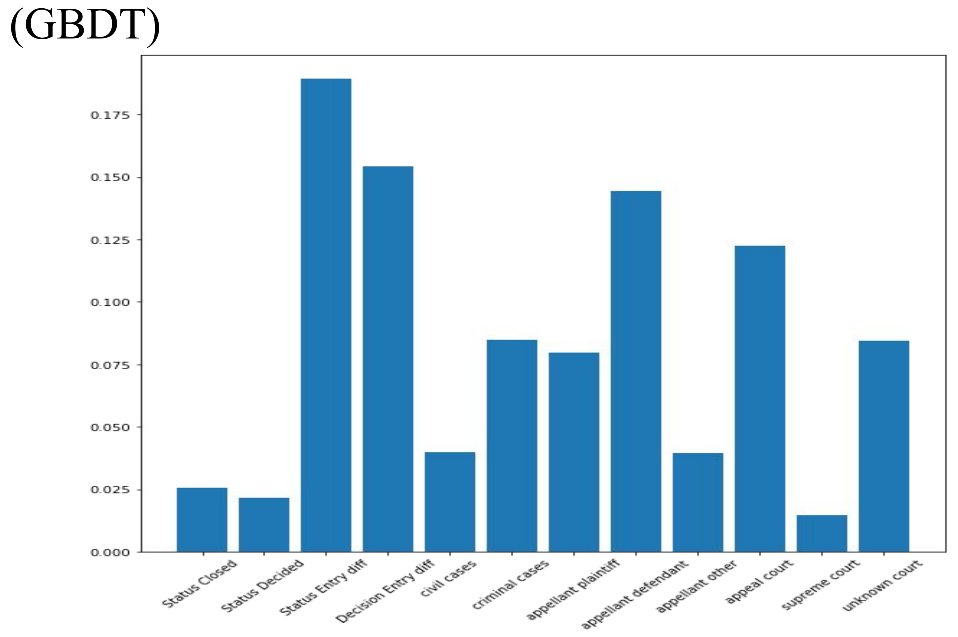
Table 6 :Model Comparison

- Results by including features about the nature of the case

Model	Confusion Matrix	Class Wise accuracy
Decision Tree (DT)	[[733, 34, 22], [49, 5, 0], [30, 0, 1]]	Class 0: 0.929 Class 1: 0.0926 Class 2: 0.0323

Table 7 : Results of DT using text features

- Thus the nature of the case doesn't effect case reversal.
- Feature importances using Gradient Boosted Decision Tree (GBDT)



- Top five features are difference between status date and entry date, decision date and entry date and Appellant Defendent. court type and type of case.
- The fact that Appellant defendant matters is worth investigating. Also on a whole criminal cases seem to have higher reversals than civil cases

Conclusions

- For our new data, we were able to identify judges who have a reversal rate of over 50 percent:Where Kenneth W. Salinger, Robert B. Gordon, Geraldine S.Hines, and Ralph D. Gants
- From analyzing the opinions text, there were no clear patterns for clustering opinions of affirmed or reversed cases.
- The current dataset is not descriptive enough for breakthrough pattern analysis using machine learning.
- Beyond that for predicting reversals while the type of the case matters the specific nature of the case doesn't seem to matter.
- Appellant Defendant and the type of court involved seem to have a correlation with case reversals that is worth examining.

Future Steps

- More descriptive data including which includes case text and other features need to be scraped.
- Given the difficulty in scraping government website, future teams need to discover other methods; while data obtained by our team is a good foundation, it has limited potential for pattern recognition with machine learning.
- Extensive feature engineering in collaboration with legal experts will be key to make any any scraped data useful for this task.
- Finally, given that sufficient "good" data is collected, the next group can attempt to use anomaly detection algorithms to detect outliers as potential reversals

Acknowledgements

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