Exploration of Judicial Facial Expression in Videos and Transcripts of Legal Proceedings

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by

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Contents

Chapter 1

Introduction

1.1 Statement of topic

Decisions by courtroom Justices have been discussed broadly in the legal literature. Gender, political views and religious background of both the Justices and counsel in the case potentially influence the decisions. This paper will explore the facial behaviour of the Justices during hearings with the objective of being to assess whether it can help to predict outcomes. Audio Visual(AV) recordings and case transcripts will be computationally processed and analysed to examine the decisions of each Justice.

1.2 Motivation

People have attempted to predict the decisions of the Justices in the past century using judge characteristics i.e. Gender, political views, religious background. More recently, scholars(Shullman, 2004; Chen et al., 2018) have been using on-court information (i.e. AV recording, transcript, language used by the Justices) to predict the decision of the Justices using the U.S. Supreme Court data. On-court information has also been used to study data from High Court of Australia. Tutton, Mack, and Roach Anleu (2018) has used an ethnographic approach to present a observational study of judicial behaviour based on watching the audio footage. Manually observing the AV recordings could lead to subjective evaluation of facial expression and this motivates us to build upon Tutton, Mack, and Roach Anleu (2018)'s work to employ facial recognition technology to study the facial expression of the justices, which will provide a more objective result than Tutton, Mack, and Roach Anleu (2018).

1.3 Literature review

The literature summary is divided into two parts: (1) current work in legal studies to understand the behaviour of the Justices and (2) existing facial recognition and emotion tagging technology.

1.3.1 Legal study from a behaviour perspective

There is a large law & economics and political science literature that attempts to predict how judges will vote in court cases. Much of this focuses on the characteristics of the judge i.e. gender, political views, religious background and characteristics of the parties in the case i.e. gender or race of the defendant in criminal cases (Nagel, 1962; Koppen and Kate, 1984; Aliotta, 1987-1988; Welch, Combs, and Gruhl, 1988; Steffensmeier and Britt, 2001; Kulik and Perry, 2003).

Moving from static information of the judge and parties involved, more studies start to incorporate the language used by the judge on the court to predict the decision of the Justices. Black et al. (2011) has study the use of pleasant and unpleasant language by the Justices and Shullman (2004) and Johnson et al. (2009) have studied the effect of frequency and content of Justices' questions. Epstein, Landes, and Posner (2010) use a regression analysis with the number of questions asked by the Justices used to infer the winning party in a case.

More recent legal study has focused on the usage of emotion and vocal characteristics of the Justices to predict the judge's vots. Although Chief Justices of Australia and Zealand (2017) present the following code of conduct:

> It is important for judges to maintain a standard of behaviour in court that is consistent with the status of judicial office and does not diminish the confidence

> of litigants in particular, and the public in general, in the ability, the integrity, the impartiality and the independence of the judge.

and this impartiality has been highlighted in judicial demeanour by Tutton, Mack, and Roach Anleu (2018) and Goffman (1956), Paul Ekman Ekman et al. (1991) suggests that from a behavioural perspective, some facial and vocal inflections are often unbeknown to the speakers themselves. Chen, Halberstam, and Alan (2016); Chen, Halberstam, Yu, et al. (2017) and Schubert et al. (1992) have studied the emotion of the Justices from vocal characteristics and suggest that these vocal characteristics, especially perceived masculinity is strongly correlated with the court outcomes. Dietrich, Enos, and Sen (2019) has used a multilevel logistic model with random effects to suggest that subconscious vocal inflections contain information that is not available from text.

Moreover, a more sizeable study by Chen et al. (2018) have incorporated both vocal and image information of the judge into a machine learning model to predict the court votes using the U.S. Supreme Court data from 1946-2014. He found that image features improved prediction of case outcomes from 64% to 69% and audio features improved prediction of case outcomes from 67% to 69%. This demonstrate the potential of incorporating facial information to understand the decision of the Justices.

The literature mentioned above is mostly conducted using the U.S. Supreme Court Database and less studies have been conducted using Australian High Court data. Tutton, Mack, and Roach Anleu (2018) has used an ethnographic approach to study the judicial demeanour in the High Court of Australia and it is the first of its kind to use transcript and AV recordings in Australia study. The study found that Justices present a detached facial demeanour during the court in most of the time while some human display of emotions i.e. laughter and humour have also been captured by the scholars. Tutton's work has confirmed the potential of using image information to understanding the Justices as in Chen's study, while the ethnographic approach could be biased and lead to subjective results when different people are observing the videos. Thus, building upon Tutton's study, my work fills the gap of producing objective result via utilising facial recognition technology.

1.3.2 Facial recognition

An anatomical study of the decomposition of facial muscles by (Ekman and Friesen, 1976) led to the devlopment of Facial Action Code (FAC) (Ekman and riesen, 1978) and identification of the six universal emotions on human faces. This work has been further revised as (*Facial Action Coding System* n.d.) and has laid a solid foundation for analysing facial expression and developing facial recognition softwares for researchers (Kobayashi and Hara, 1992; Huang and Huang, 1997; Lien et al., 2000; Kapoor, Qi, and Picard, 2003; Tong, Liao, and Ji, 2007; Cohn et al., 2009; Lucey et al., 2010).

To be able to analysis the facial expression, proper facial recognition technique is needed to first extract faces from images. Facial recognition softwares i.e. DeepFace (Taigman et al., 2014) from Facebook and FaceNet (Schroff, Kalenichenko, and Philbin, 2015) from Google have also been developed for face detection. OpenFace (Baltrusaitis et al., 2018) is the first open-sourced face recognition software that provides facial expression detection, including facial landmarking, head pose estimation, eye gaze tracking and facial action unit detection. The OpenFace toolkit has been used in different area in research including depression classification (Yang et al., 2016; Nasir et al., 2016b), emotion study (Pan and Hamilton, 2018; Nasir et al., 2016a; Huber et al., 2018) and even sports analytics (Kovalchik and Reid, 2018).

Chapter 2

Data Collection

2.1 Data Processing

The source data for this research project is the AV recordings publicly available from the High Court of Australia (Australia, 2019). Multiple procedures need to be performed to obtain the dataset.

The workflow for extracting numerical data from the videos can be found in Figure 2.1. Youtube-dl (Hsuan, Amine, and Sergey, 2019) has been used to download videos from the High Court of Australia(Australia, 2019) and the list of videos used in this research project is documented in the Appendix. Image frames are extracted from the videos for every minute via ffmpeg (Bellard, 2019), resulting in 1021 image frames (252 frames from `Nauru` videos and 769 frames from other five videos). Taipan (Kobakian and O'Hara-Wild, 2018) is then used to find the x-y coordinates of the location of the Justices in each image frame. ImageMagick (Cristy et al., 2019) is then used to crop the face of each Justice from each image frame that is taken from each video where three Justices present in `Nauru` videos and five Justices in other videos. The resulting 4601 cropped images (252 image frames from `Nauru` videos where three Justices are presented and 769 image frames from other videos where five justices are presented) are then sent to OpenFace (Baltrusaitis et al., 2018) to produce the variables for facial landmarking, head pose, eye gaze and facial action unit. This step is performed via the docker platform. The resulting outputs from

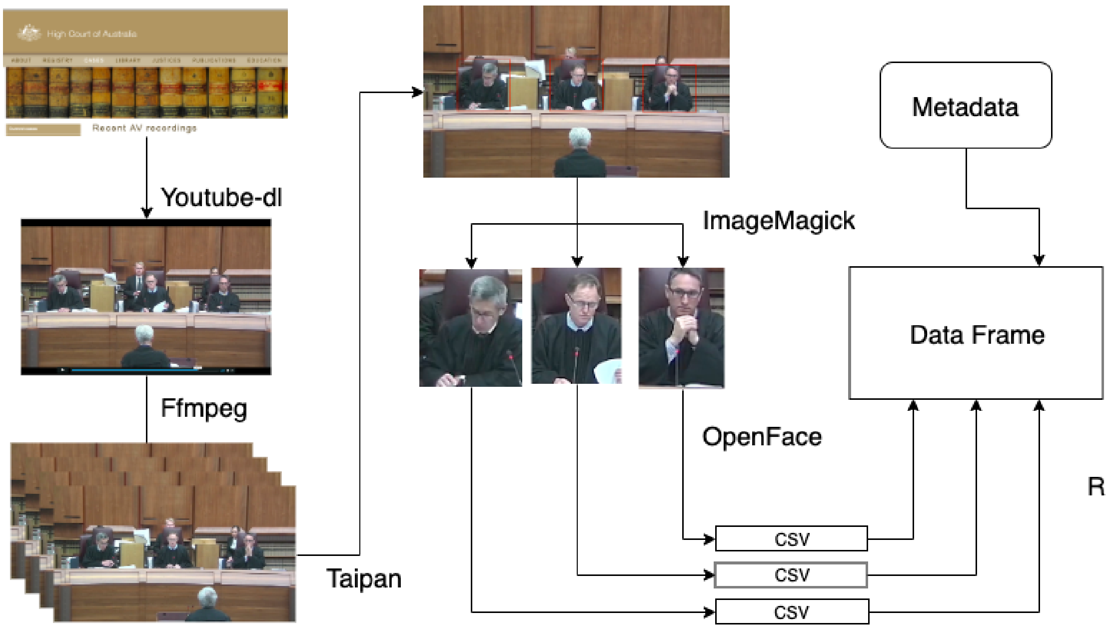


Figure 2.1: *data processing workflow*

OpenFace are individual comma-separated values (csv) files for each of the 4601 faces considered and processing is done in R to combine all the separate csv files into a final dataframe with appropriate index of `frame_id`, `judge_id` and `video_id`.

2.2 Variable description

OpenFace provides more than 711 variables measuring different aspect of a given face and a full description of the output variables can be found here. This outlines the difficulty of this project: no existing models will present accurate prediction and inference using 700+ variables - how can we incorporate these information to say about the facial expressions of the Justices during the hearings?

I conduct some exploratory data analysis on one video: `Nauru_a` and find the 700+ variables can be classified as follows with some insights

- **Confidence**: How confidence OpenFace is with the detection. Confidence is related to the angle that the Justice's face present in the images.
- **Gaze**: Gaze tracking: the vector from the pupil to corneal reflection. The dataset contains information on the gaze for both eyes while there is no distinct difference

between the eyes. Also I was trying to make animation to track the change of the gaze for judges but no good luck.

- **Pose**: the location of the head with respect to camera. Pose-related variables don't provide much useful information apart from gaze-related variables.

- **Landmarking**: landmarking variables for face and eyes. Landmarking variables allows me to plot the face of the judge in a particular frame. More work could be done to explore the usefulness of landmarking variables.

- **Action Unit**: Action units are used to describe facial expressions. this website provides a good animation on each action unit. The action unit has intensity measures ending with `_c` and presence measures ending with `_r`. These variables will be the focus of my project and a reference study of using action units to detect human emotion by Kovalchik can be found here.

2.3 Data format

In this project, we will make use of the action unit variables along with all the added indexes to analyse the face of the judge. In the wide format, apart from the first four index columns, each action unit has two columns with one for binary presence value and another for numeric intensity value. The Table 2.1 presents the first five rows of the dataset with columns for the first action unit only.

Table 2.1: *data in wide format*

judge	video	frame	AU01-r	AU02-r	AU04-r	AU05-r	AU06-r	AU07-r	AU09-r	AU10-
Bell	McKell	1	0	0	0.69	0.63	0	1.5	0	0
Bell	McKell	2	0	0	0.69	0.63	0	1.5	0	0

The data can also be expressed in the long format with action unit being another index and presence and intensity being two columns. The Table 2.2 presents the first five rows of the data in the long format.

Table 2.2: *data in long format*

judge	video	frame	speaker	AU	presence	intensity
Bell	McKell	1	Appellent	AU01	1	0.00
Bell	McKell	1	Appellent	AU02	1	0.00
Bell	McKell	1	Appellent	AU04	0	0.69
Bell	McKell	1	Appellent	AU05	1	0.63
Bell	McKell	1	Appellent	AU06	0	0.00
Bell	McKell	1	Appellent	AU07	1	1.54
Bell	McKell	1	Appellent	AU09	1	0.00
Bell	McKell	1	Appellent	AU10	1	0.00
Bell	McKell	1	Appellent	AU12	0	0.00
Bell	McKell	1	Appellent	AU14	0	0.00
Bell	McKell	1	Appellent	AU15	1	0.00
Bell	McKell	1	Appellent	AU17	0	0.00
Bell	McKell	1	Appellent	AU20	1	0.05
Bell	McKell	1	Appellent	AU23	0	0.00
Bell	McKell	1	Appellent	AU25	1	0.00
Bell	McKell	1	Appellent	AU26	0	0.26
Bell	McKell	1	Appellent	AU28	NA	NA
Bell	McKell	1	Appellent	AU45	0	0.47
Bell	McKell	2	Appellent	AU01	0	0.00
Bell	McKell	2	Appellent	AU02	1	0.00
Bell	McKell	2	Appellent	AU04	1	0.69
Bell	McKell	2	Appellent	AU05	1	0.63
Bell	McKell	2	Appellent	AU06	0	0.00
Bell	McKell	2	Appellent	AU07	1	1.54
Bell	McKell	2	Appellent	AU09	1	0.00
Bell	McKell	2	Appellent	AU10	1	0.00
Bell	McKell	2	Appellent	AU12	0	0.00
Bell	McKell	2	Appellent	AU14	0	0.00
Bell	McKell	2	Appellent	AU15	1	0.00
Bell	McKell	2	Appellent	AU17	0	0.00
Bell	McKell	2	Appellent	AU20	1	0.05
Bell	McKell	2	Appellent	AU23	0	0.00
Bell	McKell	2	Appellent	AU25	1	0.00
Bell	McKell	2	Appellent	AU26	0	0.26
Bell	McKell	2	Appellent	AU28	NA	NA
Bell	McKell	2	Appellent	AU45	0	0.47

2.4 Missing value imputation

The missingness in the dataset could be due to the fact that a judge is reading the materials on the desk so the face is not captured for a particular frame or simply because some faces are not detectable for the given resolution of the video stream. However, since that data is in time series structure, simply drop the missing observation will cause the time interval to be irregular and complicate further analysis.

There are two different sets of variables that need imputation. `Presence` is a binary variable that takes value of one if an action unit is present in a particular frame for a judge in a video and `Intensity` measures how strong that action unit is. Linear interpolation from `forecast` package is suitable to impute `Intensity` and `Presence` is imputed through sampling from binomial distribution. The imputed action unit data is stored as `au_imputed` under the `raw_data` folder.

2.5 Data cleaning

There is a data quality issue coming from the data I get from OpenFace. For some observations, the intensity of the action unit could be high while the present variable has a zero value. This does not make sense since if an action unit has been detected as strong intensity for a judge in a particular frame, it should at least present on the judge's face. Therefore, I adjust for the presence value if the intensity is higher than one. One is being chosen as the threshold value since in Ekman's definition of the intensity of the action unit, a score of one means the action unit is at least slightly present in the judge's face. The adjusted data is stored as `au_tidy` under the `raw_data` folder.

Chapter 3

Methods

Here you need to write about the analytical methods that you are using

Chapter 4

Results

4.1 Notation

Let $\mathbf{X}$ be a matrix of predictors, and $\mathbf{Y}$ variable in our case is bivariate matrix of response variables, including a binary indicator of presence/absence and a numeric value measuring intensity, of facial action unit, where

- X_1 indicates `judge` with six categories $i = 1, 2, \cdots, 6$
- X_2 indicates `video` for each of the seven cases, $j = 1, 2, \cdots, 7$
- X_3 indicates action unit containing 18 possible facial expression.

- X_4 indicates `speaker`, either the appellant or respondent, $l = 1, 2$
- X_5 indicates `frame` corresponding to time, $t = 1, 2, \cdots, T_j$

Note that t could be considered a time variable, but because images are taken at 1 minute intervals, temporal dependence is unlikely to exist. Rather this should be considered an independent observation.

A full, main effects model for the data might be expressed as:

$$Y_{ijkl} = \mu + \alpha_i + \beta_j + \gamma_k + \delta_l + \varepsilon_{ijkl}$$

and we would be interested in interactions between judge, case, action unit and who is speaking. An alternative model structure, is to treat each action unit individually, and fit separate models.

Also, let P_{jitkl} represent the response variable presence, and I_{jitkl} represent the second response variable intensity. This notation will be helpful for defining the plots and models explained in this section.

4.2 Action unit: Presence

4.2.1 Mean presence

I first compute the average presence (P_{ik}) of each action unit for each judge as

$$P_{ik} = \frac{\sum_{jt} X_{ijtk}}{\sum_{j=1}^{J} T_j}$$

This is then plotted in Figure 4.1 to give an overview of the presence of all the action units across all the judge. The order of action unit on the y axis is ranked by the average presence of all the judge. The five most frequent action units are highlighted in blue for each judge and summarised in Table 4.1

It can be seen that some of the action units are common across almost all the judges, these includes

- AU02 (outer eyebrow raise),
- AU20 (lip stretcher),
- AU15 (Lip Corner Depressor)
- AU14 (Dimpler)

AU02 makes a contribution to surprise, which is a positive attitude showing that judges are interested in a particular moment (Ekman, Friesen, and Hager, 2002). According to (Ekman, Friesen, and Hager, 2002), AU14 indicates boredom and AU15 shows confusion. Along with other action units that presented with high frequency in a particular judge but not all (summarised in Table 4.3), the emotions judges displayed in the courtroom can be

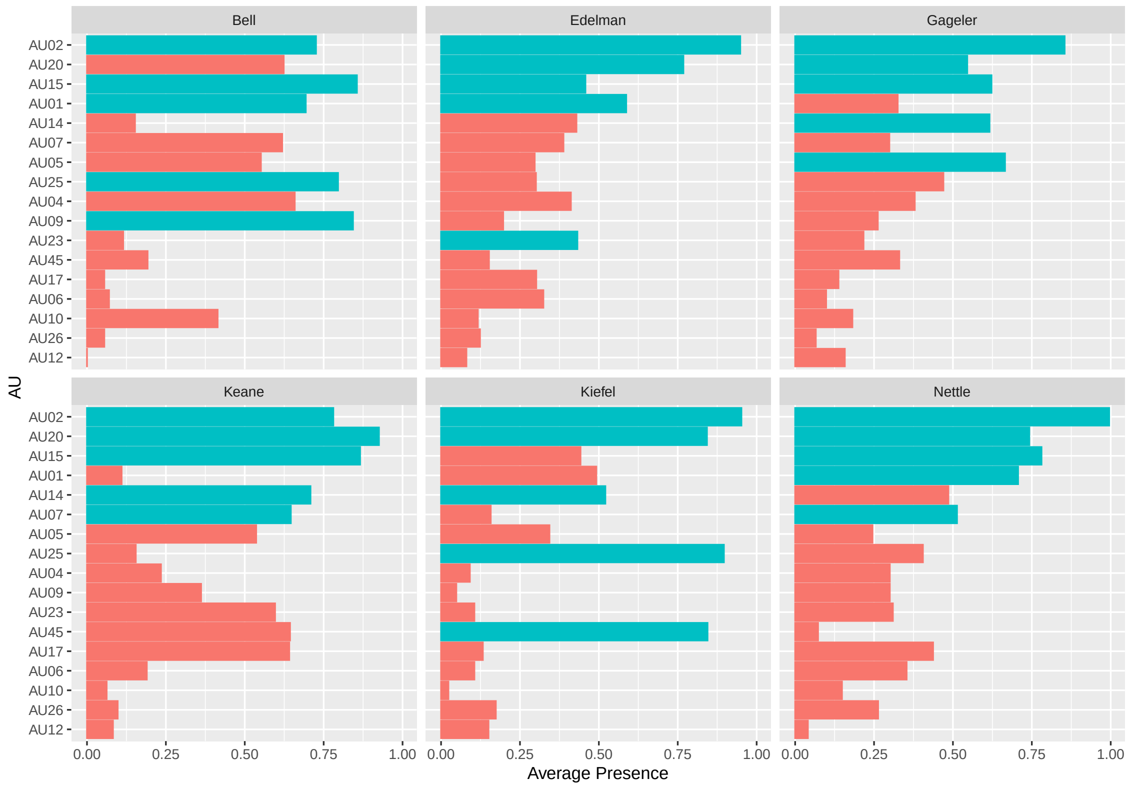


Figure 4.1: *The average presence score of each action unit for each judge, aggregating on video and time.*

Table 4.1: *The five most commonly presented action unit for each judge.*

index	Bell	Edelman	Gageler	Keane	Kiefel	Nettle
1	AU15	AU02	AU02	AU20	AU02	AU02
2	AU09	AU20	AU05	AU15	AU25	AU15
3	AU25	AU01	AU15	AU02	AU45	AU20
4	AU02	AU15	AU14	AU14	AU20	AU01
5	AU01	AU23	AU20	AU07	AU14	AU07

summarised into three categories, described in Table 4.2 along with the featured action units.

4.2.2 Model fit

The first model I use is a generalised linear model with binomial link to understand the presence of the action units. The variables used include the judge, action units and their interactions. The use of interaction terms allow for the effect of judge to be differed at different action unit level. The model can be written down as Equation 4.1.Judge Edelman and AU01 are selected as the base level.

Table 4.2: *Summarised emotions and featured action units*

emotion	Featured Action Unit
Surprise	AU01, AU02, AU05
Boredom	AU14, AU23
Confusion	AU07, AU15, AU23

Table 4.3: *Other high frequent action units*

judge	first	second	third
Bell	AU09: Nose wrinkler	AU25: Lips part	AU01: Inner brow raiser
Edelman	AU01: Inner brow raiser	AU23: Lip tightener	NA
Gageler	AU05: Upper lid raiser	NA	NA
Keane	AU07: Lid tightener	NA	NA
Kiefel	AU25: Lips part	AU45: Blink	NA
Nettle	AU01: Inner brow raiser	AU07: Lid tightener	NA

$$P_{ik} = \mu + \alpha_i + \gamma_k + (\alpha\gamma)_{ik} \tag{4.1}$$

I'm interested to know if the presence score for one pair of judge and action unit is signficiantly different from another pair. Aanalysis of Varaince (ANOVA) test result in Table 4.4 shows that there are significant variance for both judge, AU and their interactions. The next step after ANOVA is to test how each level of judge and AU different from another and I use multiple comparison to do this. (manually it will be 861 test to perform since 6 judges and 7 au - using multiple comparison, we can perform this take while control for a relatively low 5% false positive rate). The estimated coefficient for each judge and AU pair is reported in Table 4.5 along with the upper and lower confidence interval bond. The information in the group column is helpful to understand how one particular pair of judge and au is different from another pair. With compact letter display, the pair with the same letter/number are *NOT* significantly different from each other.

This result is also plotted in Figure 4.2. Insights:

- Individual difference:
  - Kean and Bell has relatively less AU02: Outer brow raiser presenting
  -

Table 4.4: *ANOVA result*

	Df	Deviance	Resid. Df	Resid. Dev
NULL	NA	NA	15183	18900.38
judge	5	298.5383	15178	18601.84
AU	3	1682.9621	15175	16918.88
judge:AU	15	1113.8722	15160	15805.01

Table 4.5: *model result*

judge	AU	prob	SE	df	asymp.LCL	asymp.UCL
Edelman	AU02	0.95	0.0069	Inf	0.93	0.96
Bell	AU02	0.73	0.0223	Inf	0.68	0.77
Gageler	AU02	0.85	0.0125	Inf	0.83	0.88
Keane	AU02	0.78	0.0207	Inf	0.74	0.82
Kiefel	AU02	0.95	0.0091	Inf	0.93	0.97
Nettle	AU02	1.00	0.0028	Inf	0.99	1.00
Edelman	AU14	0.43	0.0155	Inf	0.40	0.46
Bell	AU14	0.15	0.0179	Inf	0.12	0.19
Gageler	AU14	0.62	0.0173	Inf	0.58	0.65
Keane	AU14	0.71	0.0227	Inf	0.66	0.75
Kiefel	AU14	0.52	0.0211	Inf	0.48	0.56
Nettle	AU14	0.49	0.0201	Inf	0.45	0.52
Edelman	AU15	0.46	0.0156	Inf	0.43	0.49
Bell	AU15	0.86	0.0176	Inf	0.82	0.89
Gageler	AU15	0.62	0.0172	Inf	0.59	0.66
Keane	AU15	0.87	0.0170	Inf	0.83	0.90
Kiefel	AU15	0.44	0.0210	Inf	0.40	0.48
Nettle	AU15	0.78	0.0166	Inf	0.75	0.81
Edelman	AU20	0.77	0.0132	Inf	0.74	0.79
Bell	AU20	0.62	0.0242	Inf	0.57	0.67
Gageler	AU20	0.55	0.0177	Inf	0.51	0.58
Keane	AU20	0.93	0.0131	Inf	0.90	0.95
Kiefel	AU20	0.84	0.0154	Inf	0.81	0.87
Nettle	AU20	0.74	0.0176	Inf	0.71	0.77

4.2.3 Presence by videos

Apart from visualising the general presence score for all the action units, I'm also interested in the break down statistics by video (P_{ijk}). This is computed as

$$P_{ijk} = \frac{\sum_t X_{ijtk}}{T_j}$$

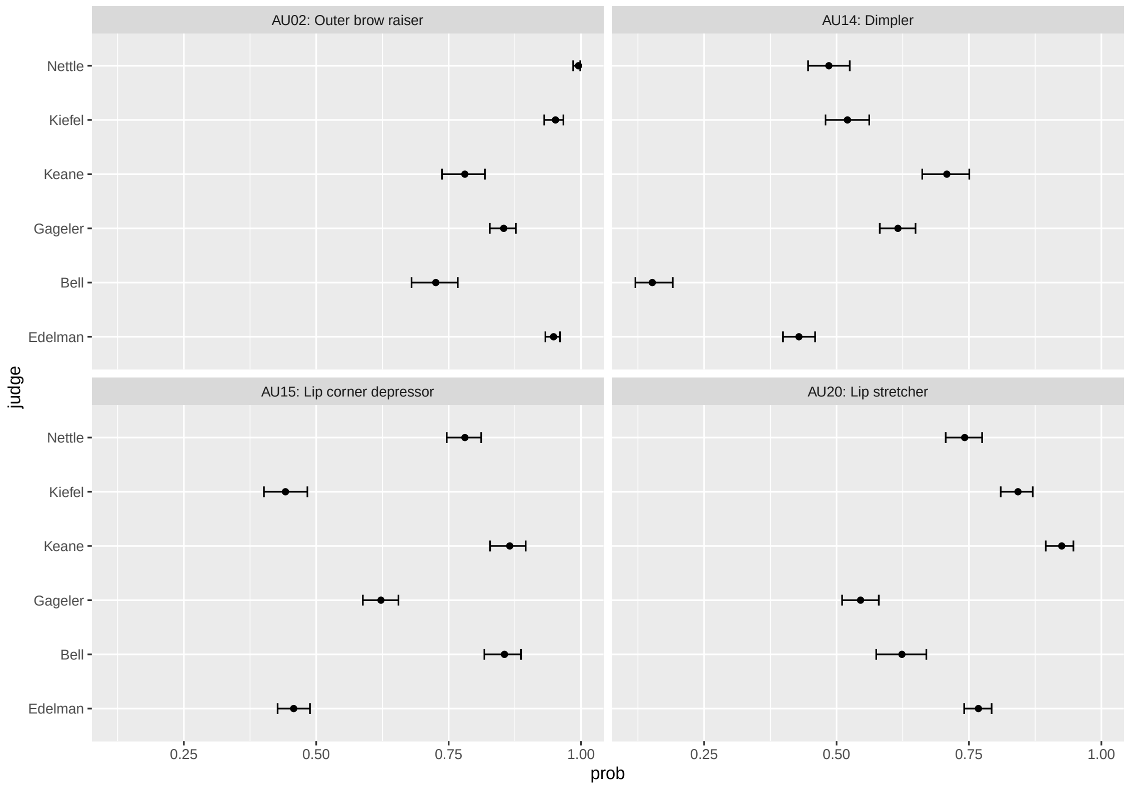


Figure 4.2: *THis is the graphical representation of model1*

for the four most common action units: AU02, AU14, AU15, AU20 and plotted in Figure 4.3. From this plot, we can observe that

- some of the judge are have relatively stable display of action unit throughout different videos (i.e. Edelman and Nettle),
- while Gagaler seems to be highly reactive to some cases (i.e. OKS, Nauru_a, Nauru_b).

4.2.4 Model fit

The second model as shown in Equation 4.2 is estimated to understand the interaction effect between judge and video while taking into account the main effect of judge, video and action unit and other pair wise interactions.

$$P_{ijk} = \mu + \alpha_i + \beta_j + \gamma_k + (\alpha\beta)_{ij} + (\alpha\gamma)_{ik} + (\beta\gamma) + jk \tag{4.2}$$

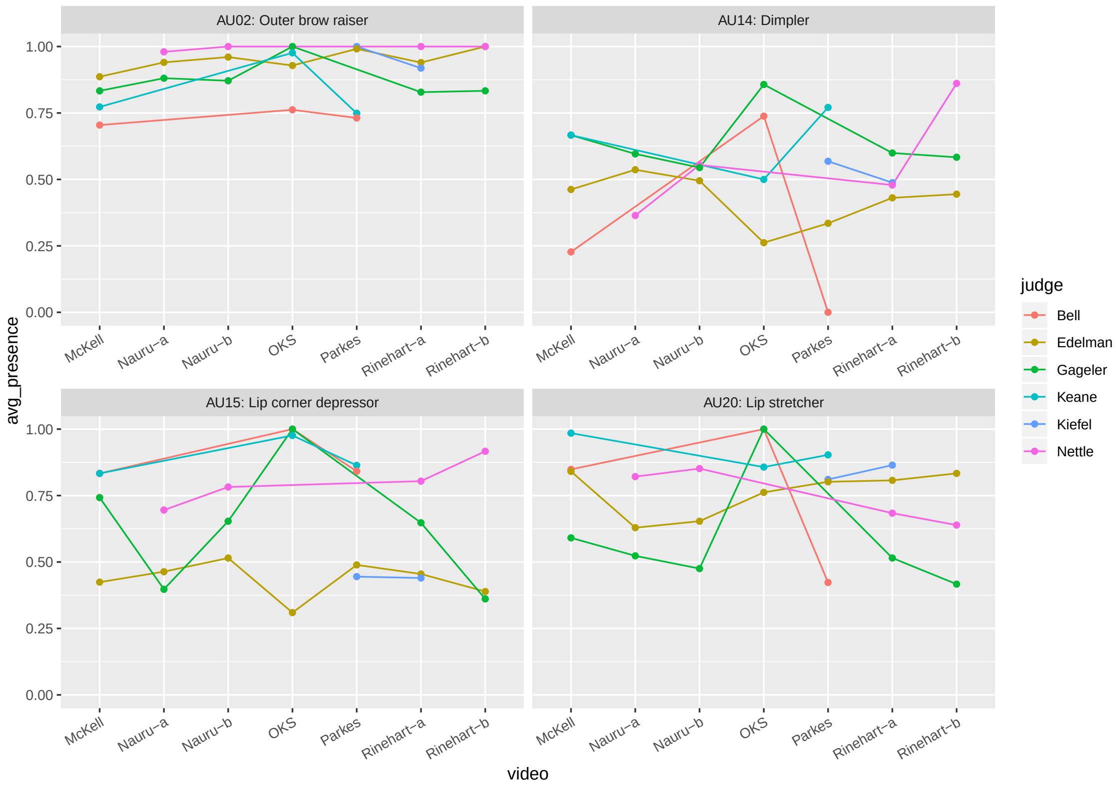


Figure 4.3: *Average presence of the four most common action units for each judge by video*

Building upon the previous model, we incorporate the effect of videos in this model. There are three main effects of judge, video and action unit in the model. We also incorporate the interaction term between judge and video, which allows the effect of judge to change at each video level. The interaciton term for video and action unit is also added because this allows different videos to have different present score for each different action unit.

The estimated coefficients are presented in Table A.3

What we could find from Figure 4.4

- Judge Edelman, Keane and Kiefel behave relatively consistent throughout all the videos. Judge Gageler is also consistent throughout the trails except for video OKS.
- The interval band for Gageler in case OKS is very different from those in other videos - consistent with exploratory data analysis
- Judge Bell behaves quite differently in the three videos she participates - consistent with EDA

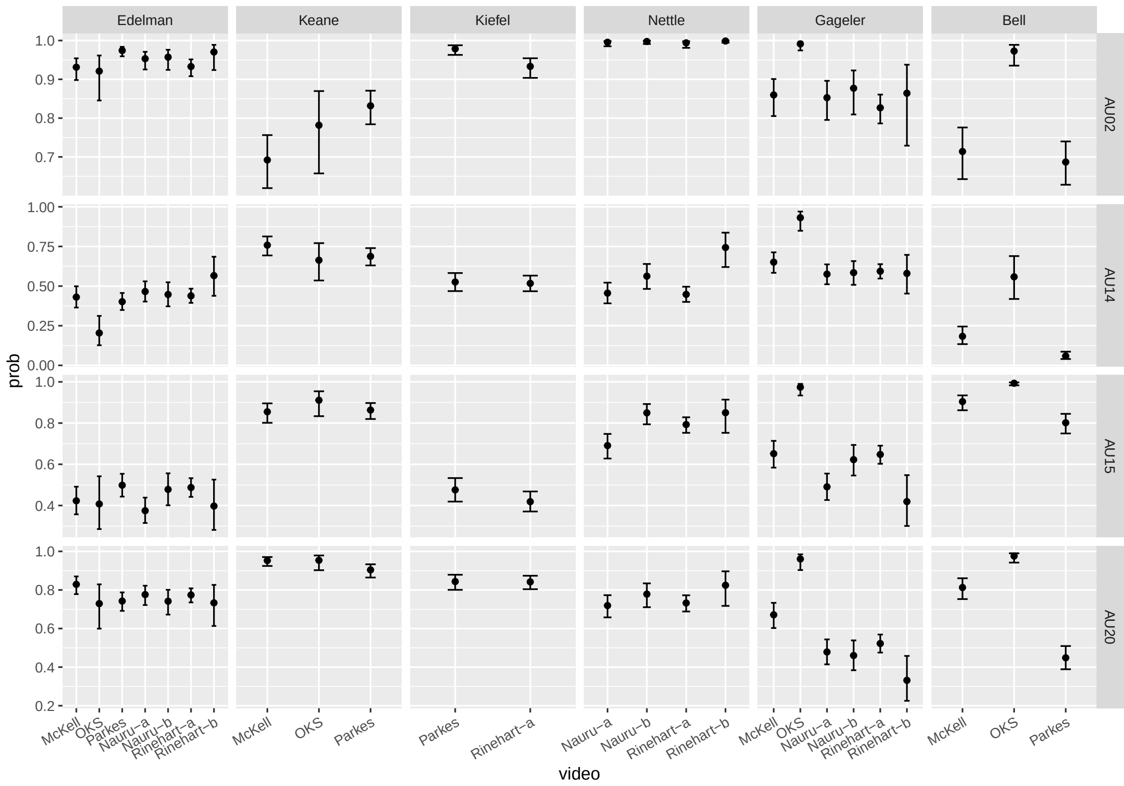


Figure 4.4: *This is the graphical representaion for model 2*

- Judge Edelman has one in OKS for AU14 being pretty different -> consistent with EDA

4.2.5 Appellant vs. Respondent

The third model as shown in Equation 4.3 is estimated to understand the interaction effect between judge and speaking party.

$$P_{ijk} = \mu + \alpha_i + \beta_j + \gamma_k + \delta_l + (\alpha\delta)_{il} \tag{4.3}$$

The estimated coefficients are presented in Table A.4

What we could find from Figure 4.5

- Judges are behaving pretty similar when different parties are talking

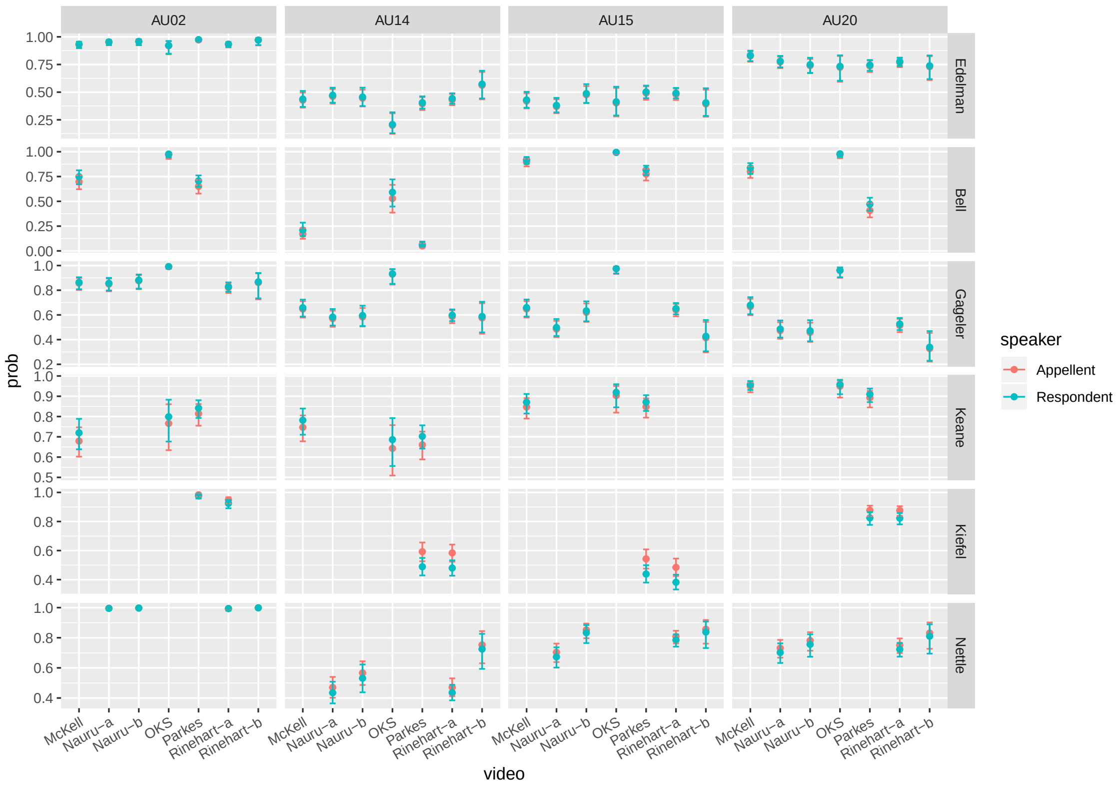


Figure 4.5: *THis is the graphical representation of model3*

4.3 Action unit: Intensity

4.3.1 General Intensity plot

In Ekman's 20002 FACS manual, the intensity of an action unit is defined based on five classes: Trace: 0-1, Slight: 1-2, Marked or pronounced: 2-3, Severe or extreme: 3-4 and Maximum: 4-5.

The boxplot of the intensity for all the judges across all the videos is presented in Figure 4.6. Each bar-and-whisker represents the intensity (I_{ijtk}) of all the action units aggregated on time for a particular judge i in a specific case j. For example, the first bar-and-whisker in case Nauru_a is created using all the 17 action units of Edelman through out the elapsed time in Nauru_a case.

From the plot, we can see that most of the action units have low intensity score and this is expected because usually judges are expected to behave neutral in the court room. Thus a square root transformation is taken on the y axis for better visualisation effect. We

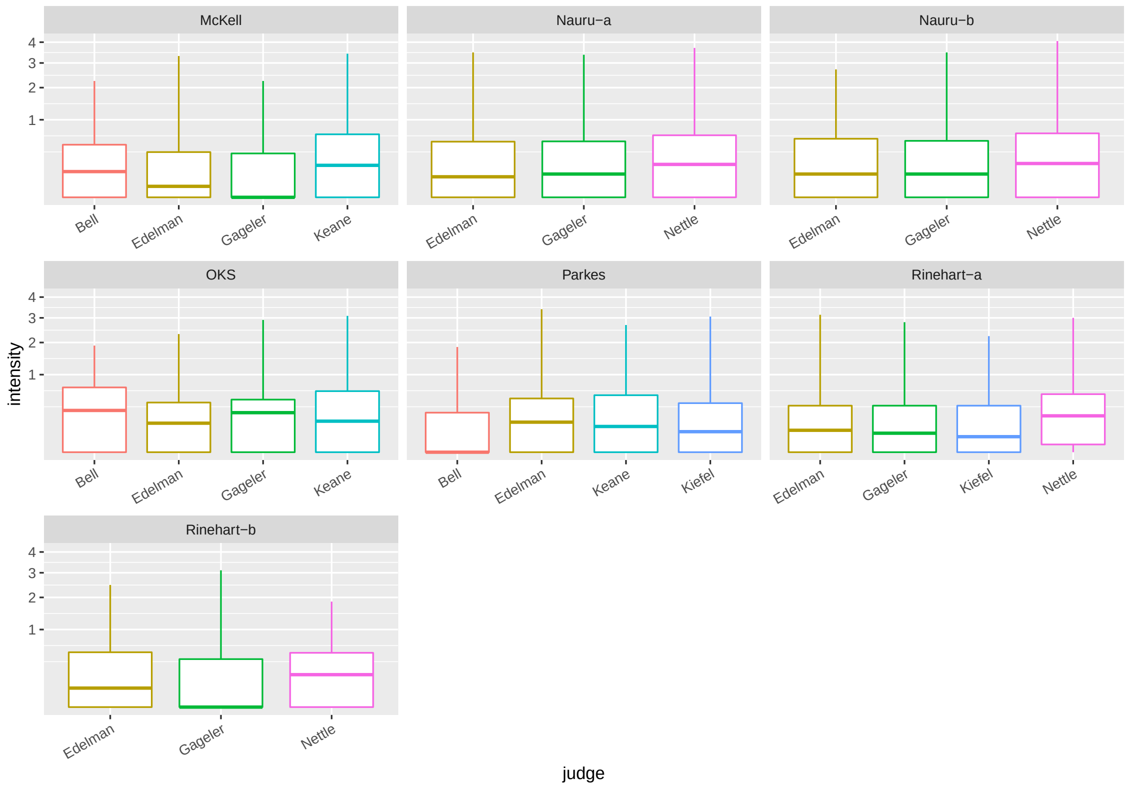


Figure 4.6: *General intensity score by judge and video*

can find that Judge Nettle seems to have higher average in all the four cases he appears: Nauru_a&b, Rinehart_a &b.

4.3.2 Mean intensity

Mean intensity score (I_{ik}) of each action unit for each of the judge is computed as

$$I_{ik} = \frac{\sum_{jt} X_{ijtk}}{\sum_{j=1}^{J} T_j}$$

and plotted in Figure 4.7. The five most intense action units for each judge are presented in Table 4.6. We can find that the common high intense action units includes

- AU20 (Lip Stretcher)
- AU07 (Lid Tightener)
- AU04 (Brow Lowerer)

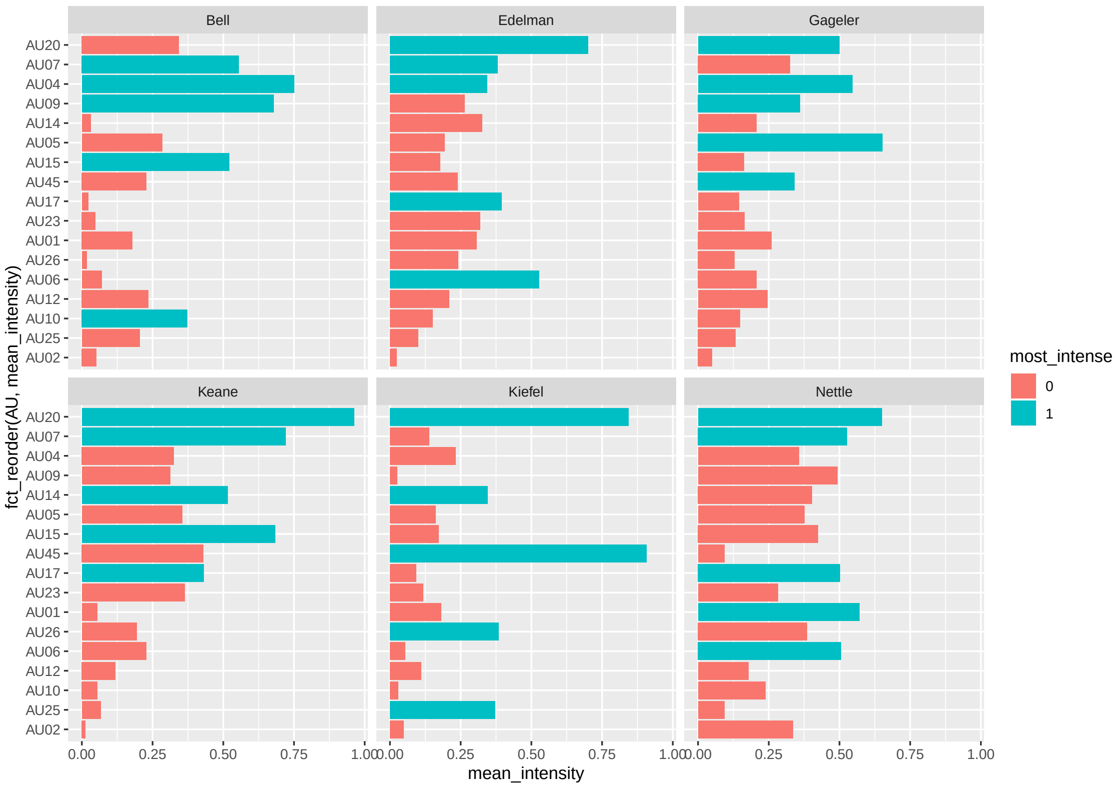


Figure 4.7: *Mean intensity score for each judge and action unit aggregating on videos.*

Table 4.6: *The five most intense action unit for each judge.*

index	Bell	Edelman	Gageler	Keane	Kiefel	Nettle
1	AU04	AU20	AU05	AU20	AU45	AU20
2	AU09	AU06	AU04	AU07	AU20	AU01
3	AU07	AU17	AU20	AU15	AU26	AU07
4	AU15	AU07	AU09	AU14	AU25	AU06
5	AU10	AU04	AU45	AU17	AU14	AU17

AU04 also belongs to the confusion category as AU07. This could help to understand that judges are more likely to express a stronger confusing expression than other emotions.

4.3.3 Model fit

4.3.4 Intensity plot for the most frequent action units

Apart from visualising the general intensity score for all the action units, I'm also interested in the intensity score of the most frequent action units. Figure 4.8 presents this. The statistics being plotted is I_{ijtk} with k including AU02, AU14, AU15 and AU20 as the

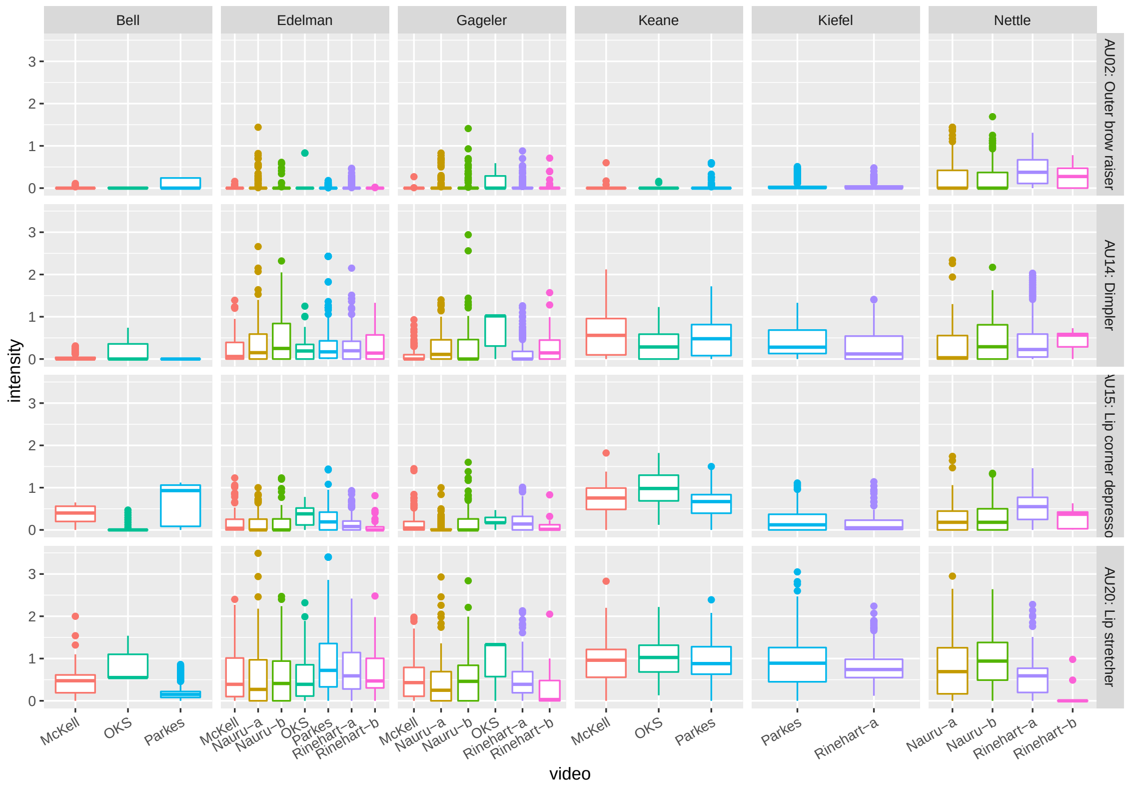
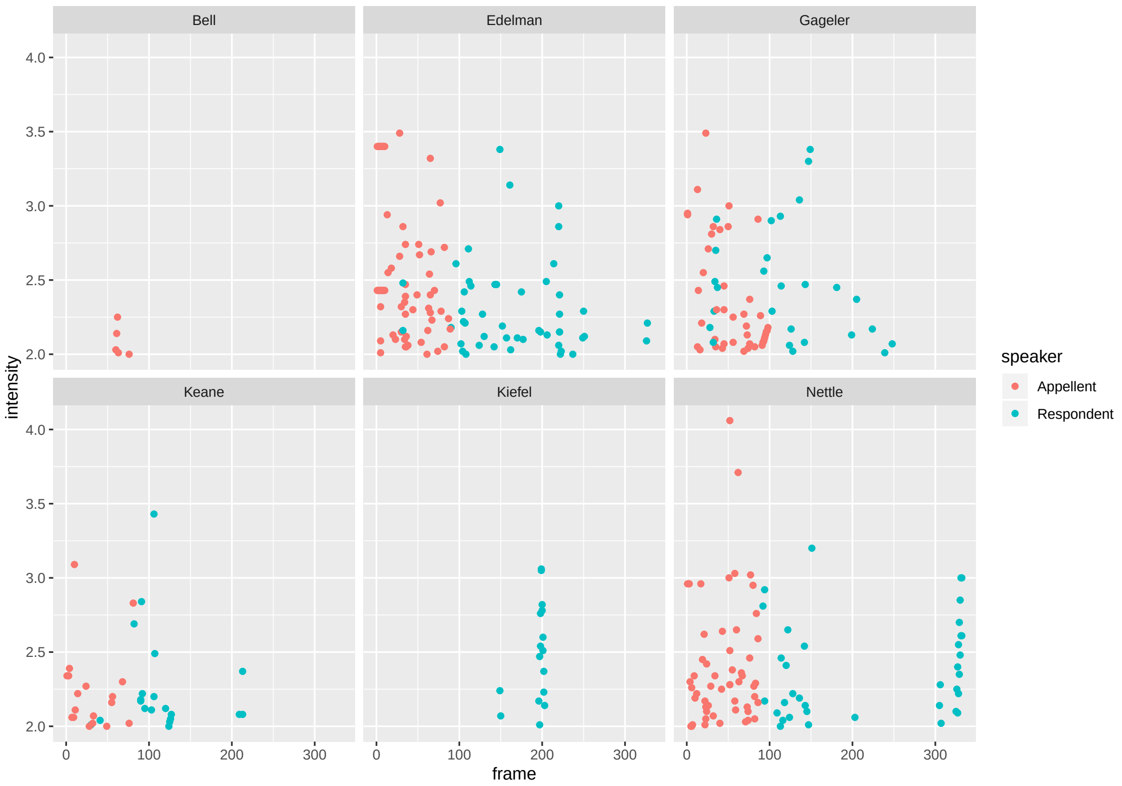


Figure 4.8: *Intensity score of the most frequent action units, seperating by judge and video ID.*

most common four action units. From this plot, we can learn that AU02, although being commonly detected for all the judges, has low intensity score.

4.3.5 High intensity points

We filter out the points have intensity greater than 2 (at least "slight" as per Ekman) in the previous plot and plot it against time and color by the speaker. It tells us that Edelman, Gageler and Nettle are the judges have stronger emotion that can be detected (since they have more points with intensity greater than 2). Different judges also have different time where they display stronger emotions. For example, Justice Nettle are more likely to have stronger emotion throughout the time when the appellant is speaking but only at the beginning and ending period when the respondent is speaking.


Bell
Edelman
Gageler
Keane
Kiefel
Nettle
intensity
frame
4.0
3.5
3.0
2.5
2.0
0
100
200
300
speaker
Appellent
Respondent

Appendix A

Additional stuff

Table A.1: *Details of videos processed.*

Case	Name	AV recording link
Republic of Nauru v. WET040	Nauru_a	http://www.hcourt.gov.au/cases/cases-av/av-2018-11-07a
TTY167 v. Republic of Nauru	Nauru_b	http://www.hcourt.gov.au/cases/cases-av/av-2018-11-07b
Rinehart & Anor v. Hancock Prospecting Pty Ltd & Ors on 13 Nov 18	Rinehart_a	http://www.hcourt.gov.au/cases/cases-av/av-2018-11-13
Rinehart & Anor v. Hancock Prospecting Pty Ltd & Ors on 14 Nov 18	Rinehart_b	http://www.hcourt.gov.au/cases/cases-av/av-2018-11-14a
Parkes Shire Council v. South West Helicopters Pty Limited	Parkes	http://www.hcourt.gov.au/cases/cases-av/av-2018-11-14b

Case	Name	AV recording link
McKell v. The Queen	`McKell`	http://www.hcourt.gov.au/cases/cases-av/av-2018-12-07
OKS v. The State of Western Australia	`OKS`	http://www.hcourt.gov.au/cases/cases-av/av-2019-02-14

A.1 List of the name of ction units

Table A.2: *The meaning of all the action unit estimated*

AU-meaning
AU01: Inner brow raiser
AU02: Outer brow raiser
AU04: Brow lowerer
AU05: Upper lid raiser
AU06: Cheek raiser
AU07: Lid tightener
AU09: Nose wrinkler
AU10: Upper lip raiser
AU12: Lip corner puller
AU14: Dimpler
AU15: Lip corner depressor
AU17: Chin raiser
AU20: Lip stretcher
AU23: Lip tightener
AU25: Lips part
AU26: Jaw drop
AU28: Lip suck
AU45: Blink

A.2 Model estimation result

Table A.3: *model result 2*

judge	video	AU	prob	SE	asymp.LCL	asymp.UCL
Edelman	McKell	AU02	0.931	0.01401	0.90	0.954
Bell	McKell	AU02	0.714	0.03411	0.64	0.776
Gageler	McKell	AU02	0.860	0.02419	0.81	0.901
Keane	McKell	AU02	0.692	0.03503	0.62	0.756
Edelman	Nauru-a	AU02	0.953	0.01127	0.93	0.971
Gageler	Nauru-a	AU02	0.853	0.02556	0.80	0.896
Nettle	Nauru-a	AU02	0.995	0.00275	0.99	0.999
Edelman	Nauru-b	AU02	0.957	0.01263	0.92	0.976
Gageler	Nauru-b	AU02	0.877	0.02850	0.81	0.923
Nettle	Nauru-b	AU02	0.998	0.00161	0.99	0.999
Edelman	OKS	AU02	0.921	0.02810	0.85	0.961
Bell	OKS	AU02	0.973	0.01224	0.94	0.989
Gageler	OKS	AU02	0.991	0.00482	0.97	0.997
Keane	OKS	AU02	0.782	0.05426	0.66	0.870
Edelman	Parkes	AU02	0.974	0.00603	0.96	0.984
Bell	Parkes	AU02	0.687	0.02858	0.63	0.740
Keane	Parkes	AU02	0.832	0.02202	0.78	0.871
Kiefel	Parkes	AU02	0.979	0.00604	0.96	0.988
Edelman	Rinehart-a	AU02	0.933	0.01095	0.91	0.951
Gageler	Rinehart-a	AU02	0.827	0.01894	0.79	0.861
Kiefel	Rinehart-a	AU02	0.933	0.01271	0.90	0.954
Nettle	Rinehart-a	AU02	0.994	0.00353	0.98	0.998
Edelman	Rinehart-b	AU02	0.970	0.01455	0.92	0.989
Gageler	Rinehart-b	AU02	0.864	0.05155	0.73	0.938
Nettle	Rinehart-b	AU02	0.999	0.00095	0.99	1.000
Edelman	McKell	AU14	0.431	0.03440	0.36	0.499
Bell	McKell	AU14	0.183	0.02830	0.13	0.245

Table A.3: *model result 2*

judge	video	AU	prob	SE	asymp.LCL	asymp.UCL
Gageler	McKell	AU14	0.651	0.03312	0.58	0.713
Keane	McKell	AU14	0.758	0.03063	0.69	0.813
Edelman	Nauru-a	AU14	0.466	0.03275	0.40	0.530
Gageler	Nauru-a	AU14	0.575	0.03218	0.51	0.637
Nettle	Nauru-a	AU14	0.456	0.03350	0.39	0.522
Edelman	Nauru-b	AU14	0.447	0.03911	0.37	0.524
Gageler	Nauru-b	AU14	0.585	0.03848	0.51	0.658
Nettle	Nauru-b	AU14	0.562	0.04047	0.48	0.640
Edelman	OKS	AU14	0.204	0.04718	0.13	0.312
Bell	OKS	AU14	0.558	0.07074	0.42	0.689
Gageler	OKS	AU14	0.931	0.02873	0.85	0.970
Keane	OKS	AU14	0.663	0.06109	0.54	0.771
Edelman	Parkes	AU14	0.402	0.02753	0.35	0.457
Bell	Parkes	AU14	0.059	0.01160	0.04	0.086
Keane	Parkes	AU14	0.687	0.02796	0.63	0.740
Kiefel	Parkes	AU14	0.526	0.02919	0.47	0.582
Edelman	Rinehart-a	AU14	0.438	0.02287	0.39	0.484
Gageler	Rinehart-a	AU14	0.594	0.02316	0.55	0.638
Kiefel	Rinehart-a	AU14	0.517	0.02524	0.47	0.566
Nettle	Rinehart-a	AU14	0.448	0.02456	0.40	0.496
Edelman	Rinehart-b	AU14	0.566	0.06411	0.44	0.685
Gageler	Rinehart-b	AU14	0.580	0.06352	0.45	0.697
Nettle	Rinehart-b	AU14	0.743	0.05574	0.62	0.837
Edelman	McKell	AU15	0.423	0.03445	0.36	0.491
Bell	McKell	AU15	0.904	0.01816	0.86	0.934
Gageler	McKell	AU15	0.652	0.03329	0.58	0.714
Keane	McKell	AU15	0.855	0.02392	0.80	0.896

Table A.3: *model result 2*

judge	video	AU	prob	SE	asymp.LCL	asymp.UCL
Edelman	Nauru-a	AU15	0.375	0.03152	0.32	0.438
Gageler	Nauru-a	AU15	0.491	0.03294	0.43	0.555
Nettle	Nauru-a	AU15	0.691	0.03057	0.63	0.747
Edelman	Nauru-b	AU15	0.478	0.03990	0.40	0.556
Gageler	Nauru-b	AU15	0.623	0.03813	0.55	0.694
Nettle	Nauru-b	AU15	0.850	0.02498	0.79	0.892
Edelman	OKS	AU15	0.407	0.06677	0.29	0.542
Bell	OKS	AU15	0.993	0.00319	0.98	0.997
Gageler	OKS	AU15	0.974	0.01259	0.93	0.990
Keane	OKS	AU15	0.911	0.02957	0.83	0.954
Edelman	Parkes	AU15	0.498	0.02836	0.44	0.554
Bell	Parkes	AU15	0.801	0.02427	0.75	0.845
Keane	Parkes	AU15	0.863	0.01969	0.82	0.897
Kiefel	Parkes	AU15	0.476	0.02923	0.42	0.533
Edelman	Rinehart-a	AU15	0.487	0.02319	0.44	0.533
Gageler	Rinehart-a	AU15	0.648	0.02246	0.60	0.690
Kiefel	Rinehart-a	AU15	0.419	0.02488	0.37	0.468
Nettle	Rinehart-a	AU15	0.793	0.01925	0.75	0.828
Edelman	Rinehart-b	AU15	0.397	0.06348	0.28	0.526
Gageler	Rinehart-b	AU15	0.419	0.06417	0.30	0.547
Nettle	Rinehart-b	AU15	0.850	0.04053	0.75	0.914
Edelman	McKell	AU20	0.829	0.02334	0.78	0.870
Bell	McKell	AU20	0.813	0.02751	0.75	0.861
Gageler	McKell	AU20	0.671	0.03347	0.60	0.733
Keane	McKell	AU20	0.953	0.01143	0.92	0.971
Edelman	Nauru-a	AU20	0.776	0.02562	0.72	0.822
Gageler	Nauru-a	AU20	0.479	0.03319	0.41	0.544

Table A.3: *model result 2*

judge	video	AU	prob	SE	asymp.LCL	asymp.UCL
Nettle	Nauru-a	AU20	0.719	0.02943	0.66	0.773
Edelman	Nauru-b	AU20	0.742	0.03287	0.67	0.801
Gageler	Nauru-b	AU20	0.460	0.03976	0.38	0.538
Nettle	Nauru-b	AU20	0.778	0.03157	0.71	0.834
Edelman	OKS	AU20	0.729	0.05918	0.60	0.829
Bell	OKS	AU20	0.976	0.01098	0.94	0.990
Gageler	OKS	AU20	0.960	0.01853	0.90	0.984
Keane	OKS	AU20	0.954	0.01806	0.90	0.979
Edelman	Parkes	AU20	0.742	0.02448	0.69	0.787
Bell	Parkes	AU20	0.448	0.03085	0.39	0.509
Keane	Parkes	AU20	0.904	0.01730	0.86	0.933
Kiefel	Parkes	AU20	0.844	0.01992	0.80	0.879
Edelman	Rinehart-a	AU20	0.774	0.01857	0.74	0.808
Gageler	Rinehart-a	AU20	0.522	0.02394	0.48	0.569
Kiefel	Rinehart-a	AU20	0.842	0.01775	0.80	0.874
Nettle	Rinehart-a	AU20	0.732	0.02151	0.69	0.772
Edelman	Rinehart-b	AU20	0.733	0.05482	0.61	0.826
Gageler	Rinehart-b	AU20	0.331	0.06028	0.23	0.458
Nettle	Rinehart-b	AU20	0.824	0.04538	0.72	0.897

Table A.4: *model result 3*

judge	video	AU	speaker	prob	SE	asymp.LCL	asymp.UCL
Edelman	McKell	AU02	Appellent	0.930	0.0143	0.897	0.954
Bell	McKell	AU02	Appellent	0.697	0.0363	0.622	0.763
Gageler	McKell	AU02	Appellent	0.858	0.0247	0.802	0.900

Table A.4: *model result 3*

judge	video	AU	speaker	prob	SE	asymp.LCL	asymp.UCL
Keane	McKell	AU02	Appellent	0.679	0.0371	0.602	0.747
Edelman	Nauru-a	AU02	Appellent	0.952	0.0115	0.924	0.970
Gageler	Nauru-a	AU02	Appellent	0.850	0.0263	0.791	0.895
Nettle	Nauru-a	AU02	Appellent	0.996	0.0026	0.986	0.999
Edelman	Nauru-b	AU02	Appellent	0.957	0.0127	0.924	0.976
Gageler	Nauru-b	AU02	Appellent	0.876	0.0286	0.809	0.923
Nettle	Nauru-b	AU02	Appellent	0.998	0.0016	0.991	0.999
Edelman	OKS	AU02	Appellent	0.920	0.0287	0.842	0.961
Bell	OKS	AU02	Appellent	0.970	0.0137	0.928	0.988
Gageler	OKS	AU02	Appellent	0.991	0.0049	0.974	0.997
Keane	OKS	AU02	Appellent	0.766	0.0581	0.634	0.861
Edelman	Parkes	AU02	Appellent	0.974	0.0063	0.958	0.983
Bell	Parkes	AU02	Appellent	0.651	0.0358	0.578	0.717
Keane	Parkes	AU02	Appellent	0.814	0.0272	0.755	0.862
Kiefel	Parkes	AU02	Appellent	0.984	0.0048	0.971	0.991
Edelman	Rinehart-a	AU02	Appellent	0.931	0.0117	0.904	0.951
Gageler	Rinehart-a	AU02	Appellent	0.822	0.0209	0.777	0.859
Kiefel	Rinehart-a	AU02	Appellent	0.949	0.0106	0.924	0.966
Nettle	Rinehart-a	AU02	Appellent	0.994	0.0032	0.983	0.998
Edelman	Rinehart-b	AU02	Appellent	0.970	0.0148	0.923	0.989
Gageler	Rinehart-b	AU02	Appellent	0.862	0.0523	0.725	0.937
Nettle	Rinehart-b	AU02	Appellent	0.999	0.0009	0.995	1.000
Edelman	McKell	AU14	Appellent	0.427	0.0349	0.360	0.496
Bell	McKell	AU14	Appellent	0.170	0.0276	0.123	0.231
Gageler	McKell	AU14	Appellent	0.647	0.0339	0.579	0.711
Keane	McKell	AU14	Appellent	0.747	0.0326	0.678	0.805
Edelman	Nauru-a	AU14	Appellent	0.461	0.0337	0.396	0.528

Table A.4: *model result 3*

judge	video	AU	speaker	prob	SE	asymp.LCL	asymp.UCL
Gageler	Nauru-a	AU14	Appellent	0.570	0.0334	0.504	0.634
Nettle	Nauru-a	AU14	Appellent	0.470	0.0355	0.402	0.540
Edelman	Nauru-b	AU14	Appellent	0.446	0.0392	0.371	0.523
Gageler	Nauru-b	AU14	Appellent	0.583	0.0386	0.506	0.656
Nettle	Nauru-b	AU14	Appellent	0.567	0.0405	0.486	0.644
Edelman	OKS	AU14	Appellent	0.201	0.0470	0.124	0.309
Bell	OKS	AU14	Appellent	0.528	0.0733	0.386	0.666
Gageler	OKS	AU14	Appellent	0.930	0.0294	0.846	0.970
Keane	OKS	AU14	Appellent	0.643	0.0646	0.509	0.757
Edelman	Parkes	AU14	Appellent	0.395	0.0300	0.338	0.455
Bell	Parkes	AU14	Appellent	0.050	0.0109	0.033	0.076
Keane	Parkes	AU14	Appellent	0.660	0.0352	0.588	0.726
Kiefel	Parkes	AU14	Appellent	0.593	0.0332	0.526	0.656
Edelman	Rinehart-a	AU14	Appellent	0.432	0.0260	0.382	0.483
Gageler	Rinehart-a	AU14	Appellent	0.586	0.0268	0.533	0.637
Kiefel	Rinehart-a	AU14	Appellent	0.584	0.0301	0.524	0.641
Nettle	Rinehart-a	AU14	Appellent	0.471	0.0305	0.412	0.530
Edelman	Rinehart-b	AU14	Appellent	0.562	0.0646	0.435	0.682
Gageler	Rinehart-b	AU14	Appellent	0.576	0.0641	0.448	0.694
Nettle	Rinehart-b	AU14	Appellent	0.752	0.0549	0.630	0.844
Edelman	McKell	AU15	Appellent	0.419	0.0349	0.353	0.489
Bell	McKell	AU15	Appellent	0.897	0.0196	0.852	0.930
Gageler	McKell	AU15	Appellent	0.648	0.0340	0.579	0.711
Keane	McKell	AU15	Appellent	0.847	0.0255	0.790	0.891
Edelman	Nauru-a	AU15	Appellent	0.371	0.0323	0.310	0.436
Gageler	Nauru-a	AU15	Appellent	0.486	0.0341	0.419	0.552
Nettle	Nauru-a	AU15	Appellent	0.704	0.0315	0.638	0.761

Table A.4: *model result 3*

judge	video	AU	speaker	prob	SE	asymp.LCL	asymp.UCL
Edelman	Nauru-b	AU15	Appellent	0.477	0.0400	0.400	0.555
Gageler	Nauru-b	AU15	Appellent	0.621	0.0383	0.544	0.693
Nettle	Nauru-b	AU15	Appellent	0.852	0.0247	0.797	0.894
Edelman	OKS	AU15	Appellent	0.403	0.0671	0.281	0.538
Bell	OKS	AU15	Appellent	0.992	0.0036	0.981	0.997
Gageler	OKS	AU15	Appellent	0.974	0.0129	0.932	0.990
Keane	OKS	AU15	Appellent	0.903	0.0323	0.819	0.951
Edelman	Parkes	AU15	Appellent	0.492	0.0311	0.431	0.552
Bell	Parkes	AU15	Appellent	0.775	0.0303	0.710	0.828
Keane	Parkes	AU15	Appellent	0.848	0.0241	0.794	0.890
Kiefel	Parkes	AU15	Appellent	0.543	0.0340	0.476	0.608
Edelman	Rinehart-a	AU15	Appellent	0.480	0.0264	0.429	0.532
Gageler	Rinehart-a	AU15	Appellent	0.640	0.0259	0.588	0.690
Kiefel	Rinehart-a	AU15	Appellent	0.484	0.0309	0.424	0.545
Nettle	Rinehart-a	AU15	Appellent	0.808	0.0215	0.762	0.846
Edelman	Rinehart-b	AU15	Appellent	0.394	0.0636	0.278	0.523
Gageler	Rinehart-b	AU15	Appellent	0.415	0.0644	0.297	0.544
Nettle	Rinehart-b	AU15	Appellent	0.857	0.0395	0.761	0.918
Edelman	McKell	AU20	Appellent	0.827	0.0238	0.775	0.869
Bell	McKell	AU20	Appellent	0.800	0.0296	0.736	0.852
Gageler	McKell	AU20	Appellent	0.668	0.0342	0.598	0.731
Keane	McKell	AU20	Appellent	0.950	0.0122	0.920	0.969
Edelman	Nauru-a	AU20	Appellent	0.773	0.0265	0.717	0.821
Gageler	Nauru-a	AU20	Appellent	0.474	0.0343	0.407	0.541
Nettle	Nauru-a	AU20	Appellent	0.731	0.0301	0.668	0.786
Edelman	Nauru-b	AU20	Appellent	0.741	0.0330	0.671	0.800
Gageler	Nauru-b	AU20	Appellent	0.459	0.0398	0.382	0.537

Table A.4: *model result 3*

judge	video	AU	speaker	prob	SE	asymp.LCL	asymp.UCL
Nettle	Nauru-b	AU20	Appellent	0.781	0.0314	0.714	0.837
Edelman	OKS	AU20	Appellent	0.725	0.0602	0.593	0.827
Bell	OKS	AU20	Appellent	0.973	0.0123	0.935	0.989
Gageler	OKS	AU20	Appellent	0.960	0.0190	0.901	0.984
Keane	OKS	AU20	Appellent	0.950	0.0198	0.893	0.977
Edelman	Parkes	AU20	Appellent	0.737	0.0267	0.681	0.786
Bell	Parkes	AU20	Appellent	0.408	0.0368	0.338	0.481
Keane	Parkes	AU20	Appellent	0.893	0.0207	0.845	0.927
Kiefel	Parkes	AU20	Appellent	0.877	0.0183	0.837	0.909
Edelman	Rinehart-a	AU20	Appellent	0.769	0.0209	0.726	0.808
Gageler	Rinehart-a	AU20	Appellent	0.514	0.0276	0.460	0.568
Kiefel	Rinehart-a	AU20	Appellent	0.876	0.0168	0.839	0.905
Nettle	Rinehart-a	AU20	Appellent	0.750	0.0247	0.699	0.795
Edelman	Rinehart-b	AU20	Appellent	0.730	0.0554	0.609	0.825
Gageler	Rinehart-b	AU20	Appellent	0.328	0.0603	0.222	0.455
Nettle	Rinehart-b	AU20	Appellent	0.831	0.0443	0.726	0.902
Edelman	McKell	AU02	Respondent	0.933	0.0141	0.900	0.956
Bell	McKell	AU02	Respondent	0.749	0.0362	0.671	0.813
Gageler	McKell	AU02	Respondent	0.864	0.0246	0.808	0.905
Keane	McKell	AU02	Respondent	0.720	0.0386	0.638	0.789
Edelman	Nauru-a	AU02	Respondent	0.954	0.0112	0.927	0.972
Gageler	Nauru-a	AU02	Respondent	0.856	0.0258	0.798	0.900
Nettle	Nauru-a	AU02	Respondent	0.995	0.0030	0.984	0.999
Edelman	Nauru-b	AU02	Respondent	0.959	0.0125	0.926	0.977
Gageler	Nauru-b	AU02	Respondent	0.882	0.0287	0.813	0.927
Nettle	Nauru-b	AU02	Respondent	0.997	0.0018	0.990	0.999
Edelman	OKS	AU02	Respondent	0.923	0.0277	0.848	0.962

Table A.4: *model result 3*

judge	video	AU	speaker	prob	SE	asymp.LCL	asymp.UCL
Bell	OKS	AU02	Respondent	0.976	0.0108	0.943	0.990
Gageler	OKS	AU02	Respondent	0.991	0.0047	0.975	0.997
Keane	OKS	AU02	Respondent	0.799	0.0526	0.677	0.883
Edelman	Parkes	AU02	Respondent	0.975	0.0060	0.960	0.984
Bell	Parkes	AU02	Respondent	0.707	0.0295	0.646	0.761
Keane	Parkes	AU02	Respondent	0.842	0.0222	0.793	0.880
Kiefel	Parkes	AU02	Respondent	0.976	0.0069	0.958	0.986
Edelman	Rinehart-a	AU02	Respondent	0.934	0.0110	0.909	0.952
Gageler	Rinehart-a	AU02	Respondent	0.829	0.0192	0.788	0.864
Kiefel	Rinehart-a	AU02	Respondent	0.925	0.0144	0.891	0.948
Nettle	Rinehart-a	AU02	Respondent	0.994	0.0037	0.980	0.998
Edelman	Rinehart-b	AU02	Respondent	0.971	0.0142	0.926	0.989
Gageler	Rinehart-b	AU02	Respondent	0.868	0.0507	0.734	0.940
Nettle	Rinehart-b	AU02	Respondent	0.999	0.0010	0.994	1.000
Edelman	McKell	AU14	Respondent	0.438	0.0369	0.367	0.511
Bell	McKell	AU14	Respondent	0.210	0.0345	0.150	0.285
Gageler	McKell	AU14	Respondent	0.659	0.0353	0.586	0.724
Keane	McKell	AU14	Respondent	0.782	0.0330	0.710	0.840
Edelman	Nauru-a	AU14	Respondent	0.472	0.0348	0.405	0.540
Gageler	Nauru-a	AU14	Respondent	0.582	0.0343	0.514	0.648
Nettle	Nauru-a	AU14	Respondent	0.435	0.0370	0.364	0.508
Edelman	Nauru-b	AU14	Respondent	0.456	0.0429	0.374	0.541
Gageler	Nauru-b	AU14	Respondent	0.595	0.0423	0.510	0.675
Nettle	Nauru-b	AU14	Respondent	0.531	0.0477	0.438	0.622
Edelman	OKS	AU14	Respondent	0.208	0.0483	0.129	0.318
Bell	OKS	AU14	Respondent	0.591	0.0715	0.448	0.721
Gageler	OKS	AU14	Respondent	0.933	0.0282	0.852	0.971

Table A.4: *model result 3*

judge	video	AU	speaker	prob	SE	asymp.LCL	asymp.UCL
Keane	OKS	AU14	Respondent	0.686	0.0612	0.556	0.792
Edelman	Parkes	AU14	Respondent	0.405	0.0284	0.351	0.462
Bell	Parkes	AU14	Respondent	0.064	0.0127	0.043	0.094
Keane	Parkes	AU14	Respondent	0.703	0.0293	0.642	0.757
Kiefel	Parkes	AU14	Respondent	0.489	0.0309	0.429	0.549
Edelman	Rinehart-a	AU14	Respondent	0.442	0.0240	0.396	0.490
Gageler	Rinehart-a	AU14	Respondent	0.598	0.0242	0.550	0.645
Kiefel	Rinehart-a	AU14	Respondent	0.480	0.0271	0.427	0.533
Nettle	Rinehart-a	AU14	Respondent	0.435	0.0263	0.384	0.487
Edelman	Rinehart-b	AU14	Respondent	0.573	0.0652	0.443	0.693
Gageler	Rinehart-b	AU14	Respondent	0.588	0.0647	0.458	0.706
Nettle	Rinehart-b	AU14	Respondent	0.725	0.0601	0.593	0.826
Edelman	McKell	AU15	Respondent	0.430	0.0370	0.359	0.503
Bell	McKell	AU15	Respondent	0.919	0.0173	0.878	0.947
Gageler	McKell	AU15	Respondent	0.659	0.0354	0.587	0.725
Keane	McKell	AU15	Respondent	0.871	0.0244	0.815	0.911
Edelman	Nauru-a	AU15	Respondent	0.381	0.0336	0.317	0.448
Gageler	Nauru-a	AU15	Respondent	0.498	0.0353	0.429	0.567
Nettle	Nauru-a	AU15	Respondent	0.673	0.0345	0.602	0.737
Edelman	Nauru-b	AU15	Respondent	0.487	0.0436	0.403	0.572
Gageler	Nauru-b	AU15	Respondent	0.633	0.0416	0.548	0.710
Nettle	Nauru-b	AU15	Respondent	0.833	0.0304	0.765	0.884
Edelman	OKS	AU15	Respondent	0.413	0.0678	0.289	0.549
Bell	OKS	AU15	Respondent	0.994	0.0028	0.985	0.998
Gageler	OKS	AU15	Respondent	0.975	0.0123	0.935	0.990
Keane	OKS	AU15	Respondent	0.919	0.0277	0.845	0.959
Edelman	Parkes	AU15	Respondent	0.502	0.0292	0.445	0.559

Table A.4: *model result 3*

judge	video	AU	speaker	prob	SE	asymp.LCL	asymp.UCL
Bell	Parkes	AU15	Respondent	0.816	0.0242	0.764	0.859
Keane	Parkes	AU15	Respondent	0.871	0.0197	0.828	0.905
Kiefel	Parkes	AU15	Respondent	0.438	0.0306	0.380	0.499
Edelman	Rinehart-a	AU15	Respondent	0.491	0.0243	0.444	0.538
Gageler	Rinehart-a	AU15	Respondent	0.652	0.0234	0.605	0.696
Kiefel	Rinehart-a	AU15	Respondent	0.382	0.0261	0.332	0.434
Nettle	Rinehart-a	AU15	Respondent	0.785	0.0208	0.741	0.823
Edelman	Rinehart-b	AU15	Respondent	0.404	0.0651	0.285	0.535
Gageler	Rinehart-b	AU15	Respondent	0.427	0.0660	0.305	0.558
Nettle	Rinehart-b	AU15	Respondent	0.838	0.0443	0.732	0.907
Edelman	McKell	AU20	Respondent	0.833	0.0241	0.780	0.875
Bell	McKell	AU20	Respondent	0.838	0.0277	0.776	0.885
Gageler	McKell	AU20	Respondent	0.678	0.0354	0.606	0.744
Keane	McKell	AU20	Respondent	0.958	0.0109	0.931	0.975
Edelman	Nauru-a	AU20	Respondent	0.780	0.0265	0.724	0.828
Gageler	Nauru-a	AU20	Respondent	0.486	0.0355	0.417	0.555
Nettle	Nauru-a	AU20	Respondent	0.702	0.0333	0.633	0.763
Edelman	Nauru-b	AU20	Respondent	0.749	0.0349	0.675	0.811
Gageler	Nauru-b	AU20	Respondent	0.471	0.0441	0.386	0.557
Nettle	Nauru-b	AU20	Respondent	0.756	0.0382	0.674	0.823
Edelman	OKS	AU20	Respondent	0.734	0.0591	0.603	0.833
Bell	OKS	AU20	Respondent	0.979	0.0097	0.949	0.991
Gageler	OKS	AU20	Respondent	0.961	0.0182	0.905	0.985
Keane	OKS	AU20	Respondent	0.958	0.0167	0.910	0.981
Edelman	Parkes	AU20	Respondent	0.745	0.0249	0.693	0.791
Bell	Parkes	AU20	Respondent	0.471	0.0333	0.407	0.536
Keane	Parkes	AU20	Respondent	0.910	0.0169	0.871	0.938

Table A.4: *model result 3*

judge	video	AU	speaker	prob	SE	asymp.LCL	asymp.UCL
Kiefel	Parkes	AU20	Respondent	0.825	0.0223	0.777	0.864
Edelman	Rinehart-a	AU20	Respondent	0.777	0.0191	0.737	0.812
Gageler	Rinehart-a	AU20	Respondent	0.527	0.0251	0.477	0.575
Kiefel	Rinehart-a	AU20	Respondent	0.823	0.0200	0.780	0.859
Nettle	Rinehart-a	AU20	Respondent	0.722	0.0233	0.674	0.766
Edelman	Rinehart-b	AU20	Respondent	0.739	0.0551	0.618	0.832
Gageler	Rinehart-b	AU20	Respondent	0.339	0.0622	0.229	0.469
Nettle	Rinehart-b	AU20	Respondent	0.810	0.0494	0.695	0.889

Bibliography

Aliotta, JM (1987-1988). Combining Judges' Attributes and Case Characteristics: An Alternative Approach to Explaining Supreme Court Decisionmaking. *Judicature* **71**, 277.

Australia, HC of (2019). *Recent AV recordings*. Accessed: 2019-05-03. http://www.hcourt.gov.au/cases/recent-av-recordings.

Baltrusaitis, T, A Zadeh, YC Lim, and LP Morency (2018). Openface 2.0: Facial behavior analysis toolkit. In: *2018 13th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2018)*. IEEE, pp.59–66.

Bellard, F (2019). *ffmpeg*. https://ffmpeg.org/.

Black, RC, SA Treul, TR Johnson, and J Goldman (2011). Emotions, oral arguments, and Supreme Court decision making. *The Journal of Politics* **73**(2), 572–581.

Chen, DL, M Kumar, V Motwani, and P Yeres (2018). *Is Justice Really Blind? And Is It Also Deaf*. Tech. rep. Technical report.

Chen, D, Y Halberstam, and C Alan (2016). Perceived masculinity predicts us supreme court outcomes. *PloS one* **11**(10), e0164324.

Chen, D, Y Halberstam, A Yu, et al. (2017). Covering: Mutable characteristics and perceptions of voice in the US Supreme Court. *Review of Economic Studies invited to resubmit, TSE Working Paper* (16-680).

Chief Justices of Australia, TC of and N Zealand (2017). *Guide to Judicial Conduct*. 3rd. Melbourne: Austral-asian Institute of Judicial Administration.

Cohn, JF, TS Kruez, I Matthews, Y Yang, MH Nguyen, MT Padilla, F Zhou, and F De la Torre (2009). Detecting depression from facial actions and vocal prosody. In: *2009 3rd International Conference on Affective Computing and Intelligent Interaction and Workshops*, pp.1–7.

Cristy, J, D Lemstra, G Randers-Pehrson, and B Roucries (2019). *ImageMagick-dl*. https://github.com/ImageMagick.

Dietrich, BJ, RD Enos, and M Sen (2019). Emotional arousal predicts voting on the US supreme court. *Political Analysis* **27**(2), 237–243.

Ekman, P and WV Friesen (1976). Measuring facial movement. *Environmental psychology and nonverbal behavior* **1**(1), 56–75.

Ekman, P, WV Friesen, and JC Hager (2002). Facial action coding system: The manual on CD ROM. *A Human Face, Salt Lake City*, 77–254.

Ekman, P, M O'Sullivan, WV Friesen, and KR Scherer (1991). Invited article: Face, voice, and body in detecting deceit. *Journal of nonverbal behavior* **15**(2), 125–135.

Ekman, P and WV riesen (1978). *Facial action coding system*. Palo Alto: CA: Consulting Psychologists Press.

Epstein, L, WM Landes, and RA Posner (2010). Inferring the winning party in the Supreme Court from the pattern of questioning at oral argument. *The Journal of Legal Studies* **39**(2), 433–467.

Facial Action Coding System (n.d.). https://www.paulekman.com/facial-action-coding-system/.

Goffman, E (1956). The nature of deference and demeanor. *American Anthropologist* **58**(3), 473–502.

Hsuan, YC, R Amine, and M Sergey (2019). *youtube-dl*. https://github.com/ytdl-org/youtube-dl/.

Huang, CL and YM Huang (1997). Facial Expression Recognition Using Model-Based Feature Extraction and Action Parameters Classification. *Journal of Visual Communication and Image Representation* **8**(3), 278–290.

Huber, B, D McDuff, C Brockett, M Galley, and B Dolan (2018). Emotional Dialogue Generation Using Image-Grounded Language Models. In: *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. CHI '18. Montreal QC, Canada: ACM, pp.277:1–277:12. http://doi.acm.org/10.1145/3173574.3173851.

Johnson, TR, RC Black, J Goldman, and SA Treul (2009). Inquiring minds want to know: Do justices tip their hands with questions at oral argument in the US supreme court. *Washington University Journal of Law and Policy* **29**, 241.

Kapoor, A, Y Qi, and RW Picard (2003). Fully automatic upper facial action recognition. In: *IEEE International SOI Conference. Proceedings (Cat. No.03CH37443)*, pp.195–202.

Kobakian, S and M O'Hara-Wild (2018). *taipan: Tool for Annotating Images in Preparation for Analysis*. R package version 0.1.2. https://CRAN.R-project.org/package=taipan.

Kobayashi, H and F Hara (1992). Recognition of Six basic facial expression and their strength by neural network. In: *Proceedings IEEE International Workshop on Robot and Human Communication*, pp.381–386.

Koppen, PJ van and JT Kate (1984). Individual Differences in Judicial Behavior: Personal Characteristics and Private Law Decision-Making. *Law and Society Review* **18**(2), 225–247.

Kovalchik, S and M Reid (2018). Going inside the inner game: Predicting the emotions of professional tennis players from match broadcasts. In: MIT Sloan Sports Analytics Conference.

Kulik, CT and MB Perry Elissa L.and Pepper (2003). Here Comes the Judge: The Influence of Judge Personal Characteristics on Federal Sexual Harassment Case Outcomes. *Law and Human Behavior* **27**(1), 69–86.

Lien, JJJ, T Kanade, JF Cohn, and CC Li (2000). Detection, tracking, and classification of action units in facial expression. *Robotics and Autonomous Systems* **31**(3), 131–146.

Lucey, P, JF Cohn, T Kanade, J Saragih, Z Ambadar, and I Matthews (2010). The Extended Cohn-Kanade Dataset (CK+): A complete dataset for action unit and emotion-specified expression. In: *IEEE Computer Society Conference on Computer Vision and Pattern Recognition - Workshops*, pp.94–101.

Nagel, SS (1962). Testing Relations Between Judicial Characteristics and Judicial Decision-Making. *Western Political Quarterly* **15**(3), 425–437. eprint: https://doi.org/10.1177/106591296201500301.

Nasir, M, A Jati, PG Shivakumar, S Nallan Chakravarthula, and P Georgiou (2016a). Multimodal and Multiresolution Depression Detection from Speech and Facial Landmark Features. In: *Proceedings of the 6th International Workshop on Audio/Visual Emotion Challenge*. AVEC '16. Amsterdam, The Netherlands: ACM, pp.43–50. http://doi.acm.org/10.1145/2988257.2988261.

Nasir, M, A Jati, PG Shivakumar, S Nallan Chakravarthula, and P Georgiou (2016b). Multimodal and multiresolution depression detection from speech and facial landmark features. In: *Proceedings of the 6th International Workshop on Audio/Visual Emotion Challenge*. ACM, pp.43–50.

Pan, X and AFdC Hamilton (2018). Why and how to use virtual reality to study human social interaction: The challenges of exploring a new research landscape. *British Journal of Psychology* **109**(3), 395–417. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/bjop.12290.

Schroff, F, D Kalenichenko, and J Philbin (2015). Facenet: A unified embedding for face recognition and clustering. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp.815–823.

Schubert, JN, SA Peterson, G Schubert, and S Wasby (1992). Observing Supreme Court oral argument: A biosocial approach. *Politics and the Life Sciences* **11**(1), 35–52.

Shullman, SL (2004). The illusion of devil's advocacy: How the justices of the supreme court foreshadow their decisions during oral argument. *Journal of Appellate Practice and Process 2* **271**(6).

Steffensmeier, D and CL Britt (2001). Judges' Race and Judicial Decision Making: Do Black Judges Sentence Differently? *Social Science Quarterly* **82**(4), 749–764. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/0038-4941.00057.

Taigman, Y, M Yang, M Ranzato, and L Wolf (2014). Deepface: Closing the gap to human-level performance in face verification. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp.1701–1708.

Tong, Y, W Liao, and Q Ji (2007). Facial Action Unit Recognition by Exploiting Their Dynamic and Semantic Relationships. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **29**(10), 1683–1699.

Tutton, J, K Mack, and S Roach Anleu (2018). Judicial Demeanor: Oral Argument in the High Court of Australia. *Justice System Journal* **39**(3), 273–299.

Welch, S, M Combs, and J Gruhl (1988). Do Black Judges Make a Difference? *American Journal of Political Science* **32**(1), 126–136.

Yang, L, D Jiang, L He, E Pei, MC Oveneke, and H Sahli (2016). Decision tree based depression classification from audio video and language information. In: *Proceedings of the 6th International Workshop on Audio/Visual Emotion Challenge*. ACM, pp.89–96.