

University of Essex

MSc in Artificial Intelligence

September 2024

Mitigating machine learning bias in criminal justice:
An ontological approach to predicting recidivism in England and Wales

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Word count: 13,918

Abstract

Recidivism is when someone who has previously been convicted of a crime reoffends. Reducing recidivism has benefits for society by reducing crime and its socioeconomic costs. Machine learning has been used to predict recidivism, but the impact of getting it wrong has significant implications. However, machine learning models in judicial use and academia have been found wanting, with racial biases caused by the underlying data and a paradoxical conflict between accuracy and fairness.

Ontology is proposed as a mitigation to reduce bias by classifying features according to their “safe use” based upon metaknowledge of the degree of correlation between the feature and a protected characteristic such as race. The ontology also allows the prediction results to be compared with the actual profiles for ethnicity and gender to ensure parity.

The ontology concept was initially tested using an anonymised recidivism dataset from the USA. Statistical analysis identified relationships between age, race, gender, and recidivism and calculated the correlations between all features and race and recidivism by gender. The results were used to classify the features in the ontology to guide data scientists creating machine learning algorithms to minimise the risk of bias. An ontology was then designed and built for England and Wales using publicly available metadata plus features from other studies to demonstrate the concept working with the complex data model of a real-world application.

There were challenges storing the feature correlations in the ontology because ontologies store knowledge, not metaknowledge. This was addressed by storing the metaknowledge as data properties, but it created separation between the knowledge and metaknowledge which would be prone to human error, so an enhancement to the semantic web is recommended.

The study shows that ontology is a practicable way of mitigating the risk of bias in machine learning models by identifying high-risk features to avoid (transparency of input) and then ensuring that results conform to expected distributions by comparing the ratios of positive and negative predictions with the training data across the protected classes (transparency of output). However, limitations with storing metaknowledge were discovered which meant the ontology was less robust than planned.

Future work is recommended to populate the ontology with actual data from England and Wales, to then train and test machine learning solutions and feed the results back into the ontology to fully prove the concept end-to-end. Modifications to the semantic web are also recommended to provide a means to store metaknowledge as knowledge within the ontology.

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Files are available at <https://github.com/feaviolp/msc-project/>

1 Introduction

A standard definition of recidivism is “whether a person returns to prison within three years of release” King & Elderbroom (2014: 2). This is an overly simplistic measure, however, and a more rounded definition would include “rearrest, reconviction, reincarceration for a new crime, or return to prison [for the same crime]” King & Elderbroom (2014: 2), who also note that observing for longer than three years would provide more data that could be used to analyse links between supervision and reoffending. For this study, the simple definition of “a prisoner returning to prison within three years of release” will be used unless otherwise stated.

Lowering recidivism is intuitively beneficial because it logically correlates to reducing crime, which is desirable in society. There are political and financial reasons too, including the justice reinvestment initiative in the United States of America (USA), whose goals include reducing the prison population, in part by lowering recidivism, to use the savings to invest in public safety (La Vigne et al., 2014). So, there is a socioeconomic case to reduce recidivism, which means that predicting who will recidivate is vital to providing interventions for targeted rehabilitation or for deciding who to release on parole.

There are machine learning models to predict recidivism. However, there are important questions about ethics and fairness, which are critical in this domain because getting it wrong can have serious implications; unnecessarily depriving someone of their liberty, or releasing someone who is a danger to the public. There are challenges with providing fair and ethical models due to the available features (Dressel & Farid, 2018), biases in the baseline data (Wadsworth et al., 2018; Biddle, 2022), and even the metrics chosen to assess the results (Caton & Haas, 2020). These challenges are analysed in a literature review with mitigation strategies suggested.

This project proposes the use of ontology to mitigate biases, focusing mainly on racial bias. A detailed statistical analysis is provided using publicly available anonymised American data to determine how the features correlate with recidivism and race. A proof of concept ontology is then built in Protégé using the same dataset. Having proven the concept, a more robust ontology is built in Protégé using metadata from England and Wales criminal justice, with additional features from the literature review.

Research question: “Can ontology mitigate bias when using machine learning to predict recidivism?”

Aim: Machine learning is used to predict recidivism, but previous studies have indicated ethical issues such as racial bias. This study will show if biases can be identified and mitigated with the use of ontology by creating an ontology of criminal justice in England and Wales. Features will be identified for safely predicting recidivism and features to be used with caution. Furthermore, the protected characteristic profiles can be compared with predicted profiles to check for parity.

Objectives:

- Identify features that predict recidivism.
- Identify features that potentially introduce biases when predicting recidivism.
- Assess if recidivism varies between characteristics such as ethnicity, gender and age.
- Create an ontology of criminal justice using available metadata and illustrate how the ontology can manage the features to reduce biases, as well as highlight potential biases in the output to further mitigate bias risks.

2 Ethical and Professional Considerations

This project did not include primary research, so considerations regarding participant safety including data storage and access were not relevant.

Ethical and professional considerations were assessed using the BCS code of conduct (BCS, 2022) (figure1).

	Code of conduct. You shall:	Compliance statement for this project
Public Interest	have due regard for public health, privacy, security and wellbeing of others and the environment.	N/A. No opportunity
	have due regard for the legitimate rights of Third Parties.	Compliant. No direct third-party interaction, but rights always considered
	conduct your professional activities without discrimination on the grounds of sex, sexual orientation, marital status, nationality, colour, race, ethnic origin, religion, age or disability, or of any other condition or requirement.	Compliant. This project aims to reduce discrimination
	promote equal access to the benefits of IT and seek to promote the inclusion of all sectors in society wherever opportunities arise.	N/A. The project does not discuss who would use the solution

Professional Competence and Integrity	only undertake to do work or provide a service that is within your professional competence.	Compliant. The project is an extension of learning undertaken on the MSc
	NOT claim any level of competence that you do not possess.	Compliant
	develop your professional knowledge, skills and competence on a continuing basis, maintaining awareness of technological developments, procedures, and standards that are relevant to your field.	Compliant. The project, including this report, are examples
	ensure that you have the knowledge and understanding of Legislation and that you comply with such Legislation, in carrying out your professional responsibilities.	Compliant. Legislation has been considered and discussed
	respect and value alternative viewpoints and, seek, accept and offer honest criticisms of work.	Compliant. Input from supervisors has shaped the scope
	avoid injuring others, their property, reputation, or employment by false or malicious or negligent action or inaction.	Compliant
	reject and will not make any offer of bribery or unethical inducement.	Compliant
Duty to Relevant Authority	carry out your professional responsibilities with due care and diligence in accordance with the Relevant Authority's requirements whilst exercising your professional judgement at all times.	Compliant
	seek to avoid any situation that may give rise to a conflict of interest between you and your Relevant Authority.	Compliant
	accept professional responsibility for your work and for the work of colleagues who are defined in a given context as working under your supervision.	Compliant
	NOT disclose or authorise to be disclosed, or use for personal gain, or to benefit a third party, confidential information except with the permission of your Relevant Authority, or as required by Legislation.	Compliant. No personal data used in the project. All data was public domain.
	NOT misrepresent or withhold information on the performance of products, systems or services (unless lawfully bound by a duty of confidentiality not to disclose such information), or take advantage of the lack of relevant knowledge or inexperience of others.	Compliant
Duty to the Profession	accept your personal duty to uphold the reputation of the profession and not take any action which could bring the profession into disrepute.	Compliant. All project activities were professional
	seek to improve professional standards through participation in their development, use and enforcement.	N/A. No opportunity
	uphold the reputation and good standing of BCS, the Chartered Institute for IT.	Compliant. The project addresses bias which is reputationally positive
	act with integrity and respect in your professional relationships with all members of BCS and with members of other professions with whom you work in a professional capacity.	Compliant. All research and supervisor discussions were respectful and professional
	encourage and support fellow members in their professional development.	N/A. No opportunity

Figure 1. Compliance with BCS code of conduct (BCS, 2022)

3 Literature Review

Reducing recidivism is the topic of many studies, as are the potentially biased results. This literature review examines how recidivism has been predicted and how machine learning has helped. It then examines the ethics and fairness of using machine learning to predict recidivism. It looks at how racial and other biases are inextricably intertwined in the results, with no meaningful way to completely untangle them. The importance of transparency is then explored as a mitigation to bias. Finally, the use of ontologies to improve ethics and fairness is briefly examined, although this is an area with little progress to date, hence the topic of this dissertation.

3.1 Why and How to Predict Recidivism?

Predicting recidivism for parole decisions has been used in America since the 1920s, using factors such as age, intelligence, nationality and criminal history (Borden, 1928), leading to the birth of actuarial measures (Burgess, 1928). Interestingly, Borden (1928) found higher intelligence had a positive correlation with higher recidivism, which is the opposite of more recent studies (Richter et al., 1996; Lotar Rihtarić et al., 2017), which could be due to demographic changes in the prison population over the past one hundred years, or other societal factors. This demonstrates that factors used to assess recidivism and how they are used must be adapted over time to remain relevant. This is an important point that will be discussed later.

Correctional Service of Canada (CSC) uses Statistical Information on Recidivism – Revised (SIR-R1) to assess the likelihood of reoffending within three years by scoring 15 items (Figure 2). The tool is considered effective because it gives results that are “17% better than chance” (Nafekh & Motiuk, 2002: ii). However, the results did not differentiate between false positives and false negatives, so it is unclear if the tool is skewed in either direction. Examining the outcome measures (Figure 3), the very good group (predicted to succeed) are significantly more accurate than the poor group (predicted to fail), which suggests a higher proportion of false positives overall. Additionally, comparing to chance is not as compelling as comparing to expert judgment without the tool, which is the natural alternative.

- | |
|---|
| 1. Current Offence |
| 2. Age at Admission |
| 3. Previous Incarceration |
| 4. Revocation or Forfeiture |
| 5. Act of Escape |
| 6. Security Classification |
| 7. Age at First Adult Conviction |
| 8. Previous Convictions for Assault |
| 9. Marital Status at Most Recent Admission |
| 10. Interval at Risk Since Last Offence |
| 11. Number of Dependents at Most Recent Admission |
| 12. Current Total Aggregate Sentence |
| 13. Previous Convictions for Sex Offences |
| 14. Previous Convictions for Break and Enter |
| 15. Employment Status at Arrest |

Figure 2. SIR-R1 scoring items (Nafekh & Motiuk, 2002: 26)

Outcome measures by SIR-RI groupings Male Non-Aboriginal Offenders (N=6,881)						
SIR-RI Group	General recidivism***		Violent***		Sexual	
	Successes %	Failures %	Successes %	Failures %	Successes %	Failures %
Very Good	94.4	5.6	99.2	0.8	99.6	0.4
Good	84.3	15.7	98.6	1.4	99.7	0.3
Fair	75.7	24.3	95.4	4.6	99.4	0.6
Fair / Poor	68.7	31.3	94.5	5.5	99.4	0.6
Poor	56.3	43.7	93.3	6.7	99.4	0.6
All Cases	78.5	21.5	96.6	3.4	99.5	0.5

Notes: ***p<.001

Figure 3. SIR-R1 outcome measures (Nafekh & Motiuk, 2002: 41)

Brown et al. (2009) compared the static SIR-R1 predictive score with a dynamic three-wave assessment, assessing pre-release, one month post-release and three months post-release. The dynamic variables significantly increased the accuracy of the predictions, with difficulties with employment, finances and substance abuse all correlating with a higher likelihood of reoffending. A word of caution: for ethical reasons, participants had to consent to be part of

the study, with a consent rate of 56.4% (Brown et al., 2009: 27), which potentially means an unrepresentative sample, although the findings were consistent with Lloyd et al. (2020) and Davies et al. (2022).

Dynamic factors have been proven to link to desistance (the opposite of recidivism). Getting married and having children (Farrington & West, 1995), obtaining employment (Farrington et al., 2017), and moving house to a lower crime area (Osborn, 1980) have all been shown to reduce patterns of offending. Andrews & Bonda (2024) posit that many biological and environmental factors cause a person to commit a crime, so it should follow that the factors to predict whether or not someone will recidivate are also complex. The unavoidable fact is that a person's propensity to reoffend is based upon dynamic and static factors, so monitoring and reassessing post-release provides a more accurate view. It could also facilitate interventions around the key indicators to allow probation officers to address issues and actively reduce recidivism rather than just predicting it.

Lloyd et al. (2020) found that regular reassessment significantly improved the accuracy of predicting recidivism. Using the Dynamic Risk Assessment for Offender Re-entry (DRAYOR; Serin, 2007), supervision officers working with ex-offenders on parole in New Zealand reassessed their scores every few weeks with improved accuracy compared with the original baseline scores. Davies et al. (2022) performed a similar study looking only at high-risk parolees with similar results. This is hardly surprising, demonstrating again that the factors that impact someone's propensity to recidivate are dynamic, changing over time according to the individual's circumstances. Furthermore, the simple passage of time itself changes the propensity to reoffend. The likelihood of reoffending reduces the longer a person remains in the community without offending, to the point where they eventually pose no greater threat than someone without a criminal conviction (Baumann et al., 2022).

Factors that increase the risk of recidivism from a Canadian study in 2010 were "young age, prior criminal history, negative peer associations, substance abuse, and antisocial personality disorder" (Hanson, 2010: 1); who also found that "Offenders of minority race were at increased risk for general and violent recidivism, but not sexual recidivism" (Hanson, 2010: 2). Tollenaar & van der Heijden (2013: 578) concurred that age is a significant factor stating "recidivism tends to decline with age; the odds lower by 3% for each extra year".

Bonta (1997) analysed 131 separate studies, producing 1,141 correlations. Characteristics that were the best recidivism predictors were criminal attitudes, criminal lifestyle, criminal

history, social achievement, age/gender/race, and family factors, concurring with Hanson (2010). However, actuarial measures using a variety of variables were found most effective, with Level of Service Inventory-Revised (LSI-R) performing best (Bonta, 1997), concluding that composite actuarial measures should be used, including the constituents in Figure 4.

Static Predictors
a) age
b) criminal history - both as an adult and juvenile
c) family factors - parental and family criminality, family rearing practices and structure
Dynamic Predictors
a) anti-social attitudes and values
b) anti-social personality (e.g., psychopathy)
c) companions
d) social achievement
e) substance abuse

Figure 4. Recommended constituents for recidivism assessment (Bonta, 1997: 2)

3.2 How is Recidivism Predicted in England and Wales?

The prison and probation service in England and Wales use various actuarial risk assessment tools, including “Risk of Serious Recidivism (RSR), OASys Sexual reoffending Predictor (OSP) and the Offender Group Reconviction Scale (OGRS)” (HM Prison & Probation Service, 2023: 6), who note that the tools need to be evidence-based, fair and without bias. The OGRS is the generic recidivism prediction tool that will be examined further.

OGRS was launched in 1996 as a manual “pen and paper” tool using six demographic and criminal history factors and updated with a computerised OGRS2 in 2000 with ten factors (Moore, 2015). In 2008, OGRS3 was introduced as an ordinal logistic regression model with fewer risk factors that can be scored more easily to be as simple as possible for probation and prison staff to use, being less prone to error while improving the predictive reliability, with Area Under Curve (AUC) of 80% compared with 78% for OGRS2 (Howard et al., 2009).

All versions used the same fundamental factors of age, gender, and offence history (Figure 5), but how they were used was adapted with each iteration. For example, OGRS3 used age when the offence was committed and age at release whereas previous versions excluded age at release (Moore, 2015), potentially skewing results for offenders with longer sentences.

An issue with OGRS is that it uses static characteristics (Stephens & Brown, 2001). The Home Office found evidence that social variables such as accommodation, employment, financial status and relationship with alcohol and drugs are “significantly related to reconviction” (May, 1999), albeit referring to reconviction following a community sentence rather than prison, but the factors should be similar. This supports the earlier view that dynamic variables impact recidivism (Davies et al., 2022; Farrington et al., 2017; Farrington & West, 1995; Hanson, 2010; Osborn, 1980). However, they state that criminal history factors such as those used in OGRS have a much stronger relationship (May, 1999), and Ministry of Justice (2024) describes how recidivism correlates with static factors such as age, gender, offence type and number of previous offences. Whilst criminal history factors might be more robust, they are static; the offender cannot influence them. Excluding dynamic factors that people can influence seems unfair, even if the impact is relatively small.

“Like most other actuarial measures, OGRS [...] is insensitive to changes in mental health-related risk and the effects on risk of therapeutic engagement which are important considerations in practice” (Hill et al., 2024).

The effort of including dynamic factors possibly outweighed the benefit when OGRS1 was a manual calculation in 1999, and Farrington & Davies (2007) note “the need for practitioners to have a simple method to use in practice”. However, even OGCR3 excludes dynamic factors, and with computerised solutions today, it would be much easier to include them.

	Version		
	1	2	3
Factors included in the model:			
Age and gender			
Gender	✓	✓	(AG)
Age at time of sentence	✓, (C)	✓, (C)	(C)
Age at release or start of order			(AG)
Combination of age and gender			✓
Age at first conviction	(C)	✓, (C)	(C)
Offence/offending history			
Type of offence (number of categories)	✓ (9)	✓ (27)	✓ (20)
Number of previous convictions	(C)	(C)	
Current or previous breach		✓	
Current or previous burglary		✓	
Number of previous youth custodial sentences	✓	✓	
Number of previous sanctions (convictions and cautions/reprimands/final warnings (CRFW))			(C)
Offending history status (first conviction; other conviction; first CRFW; second CRFW, or other CRFW)			✓
Is current sanction a conviction or another sanction?			(O)
'Copas rate' ¹⁰⁸	✓	✓	✓

Key: ✓ Included in its own right; (AG) Part of age/gender; (C) Part of 'Copas rate'; (O) Part of offending history status.

Figure 5. OGRS Factors (Moore, 2015: 154).

3.3 Machine Learning to Predict Recidivism

Machine learning solutions from industry and academia were reviewed next to discover the models and approaches tested, the features used, and how they compared with the key variables already discussed.

Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) (Equivant, 2019) is widely used in the USA's judicial system. It is a proprietary tool with many features, but the ones of interest here are the recidivism risk scales. COMPAS generates two scales: the General Recidivism Risk Scale (GRRS) and the Violent Recidivism Risk Scale (VRRS), with details about the differences between the scores in the practitioner's guide (Equivant, 2019). COMPAS is discussed at length in the ethics and fairness section. It was introduced at the beginning of this section because many machine learning solutions that have come since compare themselves to COMPAS.

When comparing Random Forest (RF) and XGBoost to predict recidivism, Curtis (2018) found that RF outperformed XGBoost, with AUC scores of 0.85 and 0.831 respectively, and similarly impressive accuracy and count of true positives and true negatives. However, there is a problem with measuring machine learning output: what do we wish to achieve? With 25.6% belonging to the target class of “reincarcerated” (Curtis, 2018), the dataset is imbalanced, and accuracy works best when the datasets are symmetric (Ghoneim, 2019). Area Under the Curve (AUC) is less problematic with imbalanced datasets. However, it treats the positive and negative classes equally, which might not always be desirable.

Considering the implications of false positives; offenders being wrongly predicted to reoffend and potentially losing their liberty as a result, or false negatives; offenders being wrongly predicted not to reoffend, care should be taken over which metrics to use. Indeed, “the choice of performance measure(s) itself may even harbor, disguise, or create new underlying ethical concerns” (Caton & Haas, 2020: 21). Some popular machine learning performance metrics are illustrated in Figure 6 alongside their respective implications for measuring models that predict recidivism. Curtis (2018) does not provide a confusion matrix with actual values. However, the sample size, percentage of offenders who reoffended, percentage of offenders who did not reoffend, and percentage of true positives and true negatives were provided, so the confusion matrix was reverse engineered from which precision, recall, F1-Scores and specificity were calculated (Figure 7). Here, it can be seen that both algorithms scored significantly higher on specificity than recall, meaning that true negatives were more accurately predicted than true positives. This is good news for offenders, but not for the public.

Performance measure	Summary	Implications	Favours
$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$	Overall accuracy. Treats false positive and false negatives equally.	Cannot determine if results are skewed towards over or under predicting recidivism.	Indeterminate
$Precision = \frac{TP}{TP + FP}$	How accurate the positive predictions were. Does not penalise false negatives.	Could score highly whilst still incorrectly predicting people not to recidivate who do.	Offenders
$Recall = \frac{TP}{TP + FN}$	How many of the total positive cases were predicted, without penalising for false positives.	Could score highly whilst incorrectly predicting people to recidivate who did not.	Public
$F1\ Score = \frac{2(Precision * Recall)}{Precision + Recall}$	Combination of precision and recall with a balanced score of positive predictions. However it excludes true negatives.	More balanced than accuracy, cannot determine if results are skewed towards over or under predicting recidivism.	Indeterminate
$Specificity = \frac{TN}{TN + FP}$	How many negative cases were predicted, without penalising for false negatives.	Could score highly whilst still incorrectly predicting people not to recidivate who do.	Offenders

Figure 6. Machine learning performance measures

	Random forest	XGBoost
AUC	0.85	0.831
Accuracy	76.53	76.87
True Positives %	79.52	72.99
True Negatives %	75.5	78.22
True Positives (TP)	52,571	48,254
False Positives (FP)	13,540	17,857
True Negatives (TN)	145,063	150,290
False Negatives (FN)	47,074	41,847
Precision	0.795	0.730
Recall (Sensitivity)	0.528	0.536
F1-Score	0.634	0.618
Specificity	0.915	0.894

Figure 7. Recidivism model comparison adapted from Curtis (2018)

Kovalchuk et al. (2023) compared various models using Ukrainian offender static data. They found that Decision Tree (DT) was the best for precision, recall and F-Measure (Figure 8), with the greatest computational efficiency and explainability due to its relative simplicity. The importance of explainability will be covered in more detail later when discussing ethics and fairness.

Model	Accuracy	Precision	Recall	F Measure	Sensitivity	Specificity	AUC
Naive Bayes	86.7%	78.9%	99.5%	88.0%	99.5%	74.4%	0.96
Generalized Linear Model	95.8%	92.8%	99.1%	95.8%	99.1%	92.6%	0.99
Logistic Regression	91.1%	85.0%	99.5%	91.7%	99.5%	83.1%	0.99
Fast Large Margin	80.5%	98.7%	61.3%	75.6%	61.3%	99.2%	0.99
Deep Learning	84.4%	76.1%	99.5%	86.3%	99.5%	69.6%	0.99
Decision Tree	98.3%	97.7%	98.8%	98.3%	98.8%	97.8%	0.99
Random Forest	98.3%	97.7%	98.8%	98.3%	98.8%	97.8%	0.99
Gradient Boosted Trees	98.3%	97.7%	98.8%	98.3%	98.8%	97.8%	0.99

Figure 8. Model Comparison (Kovalchuk et al., 2023: 8)

Wang et al. (2010) compared logistic regression, Artificial Neural Networks (ANN) and Support Vector Machine (SVM) using static variables. The performance varied between the models, and looking more closely at the results, specific instances of false positives and false negatives also varied more than expected between the models, so a hybrid solution combining all models was tested with improved results. The performance measures focused on sensitivity (the same as recall) and specificity, meaning they were concerned with true match rates. This is concerning because, in a real-world scenario, there would need to be consideration for the implications of false positives and false negatives, as already discussed. The hybrid solution was reported as good, with recall circa 0.4, specificity circa 0.85 and accuracy circa 0.7. However, a recall of 0.4 leaves many true positives undetected, which would not be in the public interest.

In another comparative study, Zeng et al. (2017) compared machine learning models, including various DT, RF, SVM and linear regression (LR) models using static variables commonly accessible to judicial officers. The prediction results, using AUC, were similar between the best RF and SVM models, LR and Supersparse Linear Integer Model (SLIM) (Ustun & Rudin, 2015), while DT fared worst. They recommend using SLIM because it is the simplest to use (Farrington & Davies, 2007; Tollenaar & van der Heijden, 2013) and the easiest to interpret. Zhang (2022) separately compared K Nearest Neighbour (KNN), RF, SVM and LR using static variables from the COMPAS dataset. The performance metrics focused on accuracy and AUC but with limited success.

Tollenaar & van der Heijden (2013) compared eleven models using static data and found no meaningful increase in accuracy with ML models over LR or Linear Discriminant Analysis (LDA). They found women recidivated significantly less than men, and conviction density (the number of convictions over time) was a significant predictor where “the number of previous

offences [...] show by far the largest effect on the probability of recidivism" (Tollenaar & van der Heijden, 2013: 579). They also considered real-world implementation challenges, preferring a small number of variables to make prediction models quick and easy, and "regardless of the complexity of the final model, the formulation of the model can always be translated into a set of equations in an Excel spreadsheet so it can readily be used by a probation worker" (Tollenaar & van der Heijden, 2013: 582).

Tollenaar & van der Heijden (2013) also make good use of the performance metrics to assess their models for real-world use. They preferred not to use accuracy alone for reasons similar to those already discussed, and they focused on sensitivity and specificity to predict positive and negative results. This way, the cost of a false positive or false negative can be altered according to the situation. However, they note that where the cost of false positives is the same as false negatives, the highest accuracy that they could achieve was 70%, which

"is too low to rely solely on [...] for decision making about individuals. We can use the predicted score for group-based predictions [...] but, when individual predictions are concerned, additional information concerning dynamic factors is required" (Tollenaar & van der Heijden, 2013: 583).

So even at 70% accuracy with static data, the results alone should not be used to make decisions about individuals, and yet that is a similar accuracy to COMPAS (Dieterich et al., 2016)!

Lin et al. (2020) tested logistic regression models using enhanced data with dynamic factors from LSI-R added to the static factors used in COMPAS. The model outperformed humans with almost 90% accuracy compared with less than 60% accuracy for humans (Miller, 2020), although that comparison is misleading because it is based upon human assessment without feedback. When the human participants were "trained" with feedback, their accuracy was over 80%, which was still lower than the LR model but significantly higher than using static data alone, which was around 70% accuracy. Adding dynamic data improves prediction accuracy (Brown et al., 2009; Davies et al., 2022; Farrington et al., 2017; Farrington & West, 1995; Hanson, 2010; Osborn, 1980); however, it also complicates the assessment.

Lin et al. (2020) tested with and without feedback for the human participants, but feedback is crucial for machine learning. Recidivism datasets show who reoffended once released, so by their nature; they are skewed because decisions have already been made about whom to release, which "makes it hard to evaluate counterfactual decision rules based on algorithmic

predictions” (Kleinberg et al., 2018). Dealing with this issue is outside the scope of this research.

3.4 Ethics and Fairness

This section discusses the ethical challenges of using machine learning to predict recidivism, starting with a detailed examination of challenges and rebuttals of COMPAS before moving on to more general considerations of ethics and fairness.

There are nine protected characteristics against which it is illegal to discriminate in England, Scotland and Wales: age, disability, gender reassignment, marriage and civil partnership, pregnancy and maternity, race, religion or belief, sex, and sexual orientation (Equality and Human Rights Commission, 2021). Similar legislation exists elsewhere. AI-based recidivism predictors would be considered high-risk AI systems under the proposed European Commission AI Act (European Commission, 2021). As such, potential biases need to be identified and addressed (Van Dijck, 2022).

3.5 Recidivism and Race

Angwin et al. (2016) challenged COMPAS’s fairness, claiming it was racially biased. They found that while the accuracy was similar for black and white people, the error types varied significantly. Black people were more likely to be predicted to reoffend who did not (false positives), and white people were more likely to be predicted not to reoffend who did (false negatives). This again illustrates the problem with using accuracy as the sole performance measure.

Dieterich et al. (2016) refuted the findings of Angwin et al. (2016), unsurprisingly considering the commercial nature of COMPAS. They claimed that COMPAS has predictive parity and that Angwin et al. (2016) were selective in what they measured and reported and “did not present any valid evidence that the risk scales are biased against blacks” (Dieterich et al., 2016: 22).

The updated practitioner’s guide shows a statistically significant correlation between COMPAS predictions and the widely used LSI-R (Farabee et al., 2010). However, a closer examination of the results reveals that while Pearson’s coefficient did indeed have highly

significant correlations, the actual correlations were moderate, with the highest (criminal involvement) being 0.64 (Figure 9). That does not prove that COMPAS is unreliable. However, it does illustrate that all papers need to be reviewed critically, especially when there is commercial interest in the outcome, as in this case. The conclusion is misleading even though the figures are accurate.

COMPAS	LSI-R	Correlation
Criminal Involvement	Criminal History	0.64 ($p < .0001$)
Criminal Associates/Peers	Companions	0.48 ($p < .0001$)
Substance Abuse	Alcohol/Drug Problem	0.53 ($p < .0001$)
Financial	Financial	0.49 ($p < .0001$)
Vocation/Education	Education/Employment	0.51 ($p < .0001$)
Family Criminality	Family/Marital	0.16 ($p > .10$)
Leisure	Leisure/Recreation	0.05 ($p > .10$)
Residential Instability	Accommodation	0.57 ($p < .0001$)
Criminal Attitudes	Attitudes/Orientation	0.20 ($p = .08$)

Figure 9. Correlations between COMPAS and LSI-R (Equivant, 2019: 25)

In a report commissioned by Broward Sheriff's Office, Blomberg et al. (2010) found that the predictive accuracy of COMPAS was slightly higher for black offenders, and "COMPAS is highly predictive of future recidivism" (Blomberg et al., 2010: 91). This is unsurprising when accuracy has already been found to be similar, but proven not to be a reliable measure on its own. This seems like a 98-page report to tell the Broward Sheriff's Office what they wanted to hear and what they already knew.

An LR model using seven features: age, sex, number of juvenile misdemeanours, number of juvenile felonies, number of prior (nonjuvenile) crimes, crime degree, and crime charge outperformed COMPAS, with 137 features, on accuracy and false positives (Dressel & Farid, 2018), although it still demonstrated a false positive bias towards black people. The use of 137 features has since been clarified by the company that makes COMPAS, stating "the vast number of these 137 are needs factors and are NOT used as predictors in the COMPAS risk assessment. The COMPAS risk assessment has six inputs only" (Equivant, 2018).

A simpler LR model using two features: age and total number of previous convictions, was comparable with COMPAS on accuracy and false positives, which supports the assertions that age and criminal history are the most important features for predicting recidivism (Rudin

et al., 2020). However, analysis of the data revealed that black offenders were disproportionately younger than white offenders (Rudin et al., 2018), which explains why modelling primarily on age still produced racially biased results.

Examining the data more closely, the rate of incarceration of black people was significantly higher than that of white people across the USA, within Florida (where COMPAS was validated), and within the dataset used by COMPAS (Dressel & Farid, 2021). That inescapable fact appears to drive the racial imbalance of the results. The same racial imbalance was even replicated when untrained humans were given a cut-down COMPAS dataset with seven features. Black people had more prior convictions because they were more likely to be arrested and imprisoned than white people (Fenton, 2016; Home Office, 2023; Mohdin & Garcia, 2023), so relying on prior convictions could contribute to racial bias (Wadsworth et al., 2018). Even though race was not a variable, it was encoded in the criminal history features because of the racial disparity in prisons, as eloquently described by Biddle (2022):

“In the case of penal systems that are populated disproportionately by historically marginalized groups, if researchers collect information about individuals who are already in these systems (as all of the developers of these tools do), then the baseline data will reflect the discriminatory practices that have led to these injustices.” (Biddle, 2022: 332)

However, predicting recidivism without knowing criminal history, as suggested by Wadsworth et al. (2018), would be significantly less accurate (Berk, 2012), so there is a dilemma.

Looking beyond race, socioeconomic features are predictors of recidivism (Eaglin, 2017); however, including them could imply that poorer people are at a higher risk of recidivism than wealthy people, which creates a feedback loop in sentencing that becomes self-fulfilling (Biddle, 2022), just like the apparent feedback loop for black offenders. “In the design of recidivism-prediction algorithms, the trade-offs that have been made have tended to disproportionately harm groups that are already unjustly disadvantaged” (Biddle, 2022: 399).

Delving into the abstract to illustrate the issue of an already biased dataset, Ensign et al. (2017) describe an apple-tasting example of partial monitoring, whereby tasting apples before selling ensures only apples that are good to sell are sold, but the already-tasted apple cannot be sold, which results in a loss. Not tasting them could result in bad apples being sold, resulting in a loss. Randomly sampling apples to determine the characteristics of good and

bad apples without tasting them all overcomes this problem. The relevance to recidivism prediction is that, to create a model that accurately predicts recidivism without bias, a random sample must be taken, which equates to releasing parolees or not at random to see who will recidivate. In reality, a judgement is made about whom to release and when, so there is already an inherent bias in the data. This is exacerbated by historic racial inequalities whereby a disproportionate number of black people have been convicted of crimes, which makes the criminal dataset racially imbalanced (Thomas, 2023).

Soares & Angelov (2019) developed a prototype-based algorithm that modelled black and white defendants separately using the COMPAS dataset. The accuracy of predictions for black defendants, white defendants, and overall was improved. Also, the number of false positives for black defendants and false negatives for white defendants was reduced. However, the number of false positives for white defendants and false negatives for black defendants increased, which was not widely acknowledged in the paper. The percentage of false positives for white defendants and false negatives for black defendants were both significantly higher than their corresponding black or white equivalent, suggesting that the model, in pursuit of fairness, has overcompensated. This suggests that assessing the ethnic classes separately might not be the optimal approach. Instead, ethnicity and all factors from which ethnicity can be derived could be removed from the model. Then, the results could be assessed separately for the ethnic groups to ensure a fair distribution. However, Rudin (2015) found that removing race did not materially impact accuracy, and removing anything that correlates with race would be troublesome because, as already discussed, predictive features such as age correlate with race (Rudin et al., 2018).

Skeem & Lowenkamp (2020) examined ways of debiasing algorithms and concluded that any debiasing method creates a trade-off between predictive accuracy, where the focus is crime prevention, and error rates, where the focus is individual fairness. When algorithms were debiased to remove any correlation with race, the error rates were higher, but disfavouring white defendants rather than black defendants, and so “providing algorithms with access to race (rather than omitting race or “blinding” its effects) can maximize calibration and minimize imbalanced error rates” (Skeem & Lowenkamp, 2020: 259). Furthermore, they found that COMPAS was not biased when assessed using fairness as a balance of accuracy rates for predictions; a measure of accuracy across classes, but it was racially biased when assessed using fairness as a balance in error rates for outcomes; a measure of the proportion of false positives across classes, in which black defendants were more likely to be classified as false

positive (predicted to reoffend but did not) than white defendants (Angwin et al., 2016; Biddle, 2022; Skeem & Lowenkamp, 2020). It seems that, concerning including race in the features for fairness to everyone, you are damned if you do and damned if you do not.

Squadrone et al. (2022) prototyped an “ethics by design” framework that essentially created rules for the impacts of different types of false positives and false negatives to address predicted (or known) biases. For example, they ruled that classifying a black defendant as not likely to reoffend was low risk, and classifying a black defendant as likely to reoffend was high risk. The results were reported as successfully reducing bias. However, the results show that accuracy decreased as “ethical compliance” increased. As false positives decreased (in both black and white defendants), false negatives increased. Once again, it is a trade-off.

Kleinberg et al. (2016: 4) defined three fairness measures: 1. Calibration within groups equates to the expected proportion of individuals in each group. 2. Balance for the negative class equates to individuals in the negative class having the same average predicted score between classes. 3. Balance for the positive class equates to individuals in the positive class having the same average predicted score between classes. Intuitively, they all seem appropriate; however, “except in highly constrained special cases, it is not possible to satisfy these three constraints simultaneously” (Kleinberg et al., 2016: 17). Yet again – trade-offs are needed.

3.6 Recidivism and Age

Age is a good predictor for recidivism (Bushway & Piehl, 2007; Kleiman et al., 2007; Stevenson & Slobogin, 2018), where “an early onset of offending typically predicts a long criminal career and the commission of many offences” Farrington & Davies (2007: 12). However, age is “really a proxy indicator of many time-related changes in life such as reduced physical and mental abilities, impulsivity, and improvement in maturity, judgment, education, and life skills” (Olver & Wong, 2015: 104). Therefore, age alone should not be used to assess recidivism likelihood because many of the features for which age is a proxy, such as “judgment, education, life skills, and even maturity together with antisocial tendencies and problematic lifestyles”, can be addressed without the need to wait for ageing (Olver & Wong, 2015: 104).

Age is a primary feature in every model assessed in this literature review. This is justified because of its strong correlation to recidivism. However, age correlates with race and cannot be influenced by the defendant, so over-indexing on age could be unfair.

3.7 Recidivism and Gender

A Supreme Court ruling about a capital punishment case ruled “It would be patently unconstitutional for a state to argue that a defendant is liable to be a future danger because of his race” Buck v Davis (2016). However, “in Wisconsin v. Loomis (2016), the court allowed for COMPAS risk estimates to differ by gender [because] failure to consider gender would make risk scores less accurate and overestimate the risk that women pose” (Skeem & Lowenkamp, 2020: 274).

Excluding gender as a factor results in overestimating the likelihood of women to recidivate (Skeem et al., 2015), and removing race, age and gender results in a substantial loss of performance (Berk, 2012), so while gender is a protected characteristic (Equality and Human Rights Commission, 2021), including it improves the accuracy and fairness of the model. However, is it fair to once again use a protected characteristic that cannot be influenced by the defendant to predict their future behaviour? Based upon the evidence, not doing so seems unfair (Skeem & Lowenkamp, 2020), however doing so also seems unfair.

Returning to the earlier discussion about performance metrics, overall accuracy equality is where the accuracy is the same between protected classes. However, this also does not differentiate between false positives and false negatives. Conditional use accuracy equality, or predictive parity (Chouldechova, 2017: 3-4) is where the precision and specificity of predictions are the same between different protected classes. This better balances the differing implications of false positives and false negatives between the protected classes.

“When base rates for protected group classes differ, one cannot have simultaneously conditional use accuracy equality and, across protected group classes, equal false positive and false rates.” (Berk et al., 2021: 20).

This is a necessary implication of this method of measuring fairness. It is known that females are less likely to recidivate than males (Skeem et al., 2015), so it is better to ensure the prediction profile matches reality than to ensure there is parity between the classes. There is, however, a risk that the actual results to which the predictions are being compared are

already unjustly skewed, and by fitting the results to the same profile those pre-existing biases are perpetuated, just like the earlier discussion about race profiles being skewed by historic racial injustices. This is a genuine concern, but not one that is addressed in this dissertation. In the words of Berk et al. (2021: 35) “One cannot expect any risk assessment tool to reverse centuries of racial injustice or gender inequality. That bar is far too high. But, one can hope to do better”.

3.8 The Importance of Explainability

Black box solutions are justified based on outcome-reasoning, which is where the performance of the model is assessed based on its output. This is much easier to discuss with non-technical stakeholders, however, it omits the detailed understanding of relationships between the parameters and the model outputs that are present with model-reasoning (Rodu & Baiocchi, 2023).

It is better to use an explainable ML model such as DT than to try to explain a black box model such as SVM or ANN, especially when the results are similar and there is marginal incremental performance from the black box model (Rudin, 2019). The explainable output is, by its nature transparent, and transparency is important for ethical machine learning models (Walmsley, 2021). Three forms of opacity, (the opposite of transparency), are “(1) opacity as intentional corporate or state secrecy, (2) opacity as technical illiteracy, and (3) an opacity that arises from the characteristics of machine learning algorithms and the scale required to apply them usefully” Burrell (2016: 1). So anything that increases opacity, intentionally or otherwise, reduces transparency and can therefore be considered to be less ethical, even if the results are balanced and accurate.

Curtis (2018) compared RF and XGBoost, both of which are black box and so difficult to explain, while Wang et al. (2023) found that interpretable machine learning models performed as well as black box models, and better than COMPAS. This is another trade-off, but one that is easier to reconcile. Firstly, when comparing machine learning models for recidivism, the candidate models should always include interpretable options such as DT and LR, and the performance measures should be considered alongside explainability. A slightly worse-performing explainable model is likely to be preferred to a slightly better-performing black box model, notwithstanding the challenges with reconciling the different performance measures already discussed.

Babad & Chun (2023) take explainability for fairness to an extreme level by reducing the number of parameters to a minimal number to make recidivism prediction models explainable. This appears to comply with the spirit of explainability and fairness, however, the final features are all static and therefore give the individuals no ability to influence their prediction. This appears to be unfair, so simply being transparent is not enough. In cases with societal impacts, a fair model must be simple enough to be explainable, but sophisticated enough to consider dynamic as well as static factors.

Butler et al. (2022) posit that even logistical regression models can be considered black box because there will still be unknown factors due to missing data, so the true nature of the input-output relationship will be unknown. This is missing the point. Even if somehow every possible data point were known the output is still only a prediction and therefore not 100% accurate. It is not the lack of accuracy but rather the lack of transparency that makes a machine learning model a black box. If input variables can be used to explain outputs, which is the case with logistical regression and DT, for example, then they are not black boxes.

Finally, Shaikh et al. (2017) proposed a system to interpret policies of fairness and bias from policy documents using natural language processing (NLP), to monitor the development of the ML systems and then test them to ensure compliance with those policies. This is a potential area for further study.

3.9 Ontology to Increase Fairness Through Transparency

This section examines how ontologies have been used to address ethical challenges with machine learning. It is relatively short because there is not much literature on the subject, hence this dissertation is new and innovative.

Kasirzadeh & Smart (2021) describe how counterfactuals can be used in ontology to test the fairness of machine learning algorithms by imagining a world where characteristics such as race are different. Examples given in the paper are trivial, where causal relationships are obvious. In the case of recidivism, the relationships between the parameters are complex, and there would be no way of saying with reasonable certainty if an individual either would or would not recidivate if their race were different. However, it would be relatively easy to check if the model would predict a different outcome if their race were different but everything else remained the same. This could be worth exploring further.

Franklin et al. (2023) created an ontology of fairness metrics, many of which have been discussed throughout this literature review. This helps to highlight and reason about different metrics and how they contribute, or not, to fairness. However, it does not address the fairness itself.

Lehnert (2021) discussed the need to be careful about the terms and relationships used in ontologies in order to reduce the risk of introducing bias. Again, this does not address the issue of bias already existing in the baseline dataset.

3.10 Summary

The factors that can cause recidivism predictions to be biased are complex and interdependent, including the very data from which the models are built and the metrics chosen to measure their performance. It appears to be impossible to balance everything and arrive at a completely fair and unbiased solution, so perhaps the best that can be done is to make the solution as fair as possible, which means including dynamic features alongside static features, and using explainable models so the reasons for predictions are clear and can potentially be challenged. The choice of performance metrics should also be justified, highlighting the risks; once again transparency is the key to fairness. Finally, how the models are used is important, and with scope for potential bias remaining, there should always be a human decision-maker at the end of the process to justify and explain the outcome. With decisions as important as this, the model should *guide* the answer, not *provide* the answer.

"An actuarial device may be able to tell you quite accurately that two-thirds of all cases in a particular risk category will fail, but it cannot tell which ones will fail. When a particular inmate comes up for parole, the decision-maker still will not know whether he will succeed or fail on parole" (Hoffman & Beck 1994: 203).

4 Methodology

Ontology is proposed to address the risks of bias in predicting recidivism in England and Wales by making correlations with race transparent, so features that present a higher risk of racial bias can be avoided, or at least used with caution with robust justification, and by allowing prediction results to be compared to training data to highlight racial biases.

Metadata from Crown Courts, Magistrate Courts, Prison Service and Probation Service in England and Wales was obtained from Ministry of Justice (2020), henceforth referred to as MoJ metadata. An ontology could be built from the metadata, but without data to populate the ontology the concept of identifying and monitoring the correlations with race before selecting features could not be fully tested. A recidivism dataset containing 25,835 anonymised records from Georgia, USA was obtained from National Institute of Justice (N.D.), henceforth referred to as the NIJ dataset, however, the features were different and the data model was significantly simpler because it had already been pre-processed and consolidated from two sources; the Georgia Department of Community Supervision and the Georgia Bureau of Investigation (Office of Justice Programs, N.D.). A multi-step approach was therefore adopted to prove the concept of maintaining the correlations within a complex ontology using the MoJ metadata after first proving the concept using the simpler NIJ dataset.

The methodology was divided into four steps:

1. Exploratory Data Analysis (EDA) using Python on the NIJ dataset to identify correlations on which to form hypotheses for detailed statistical analysis.
2. Detailed statistical analysis on the NIJ dataset using R to test the hypotheses.
3. Build an ontology in Protégé using the NIJ dataset as the domain scope and the results of the statistical analysis to highlight features with a higher risk of racial bias to prove and test the concept.
4. Build an ontology in Protégé using the MoJ metadata as the initial domain scope to further prove the concept using the MoJ taxonomy, with additional features informed by the literature review and the NIJ ontology, to extend the scope and illustrate how it could work in England and Wales. This did not include real data, however, some dummy records were created for illustration and testing.

5 Implementation

NIJ analysis files are at <https://github.com/feaviolp/msc-project/tree/main/NIJ%20Analysis>

NIJ ontology files are at <https://github.com/feaviolp/msc-project/tree/main/NIJ%20Ontology>

MoJ ontology files are at <https://github.com/feaviolp/msc-project/tree/main/MoJ%20Ontology>

5.1 NIJ Exploratory Data Analysis

Exploratory Data Analysis (EDA) was performed on the NIJ dataset using Python in a Jupyter Notebook (Appendix A).

First, the dataset was examined and pre-processed to deal with null values and some features were transformed into integers.

Next, the data were checked for correlations to identify features on which to form hypotheses to test with statistical analysis. It was clear, however, that while some features correlated more than others with recidivism, gender and race, there were no features with strong correlation so the statistical analysis should examine all features. This was still a useful outcome of the EDA to set the scope of the statistical analysis.

5.2 NIJ Statistical Analysis

Statistical analysis was performed on the NIJ dataset using R in a Jupyter Notebook (Appendix B).

Once again the data were pre-processed to deal with null values, and this time all ordinal and categorical features were converted to integers to enable significance testing.

The following hypotheses formed from the literature review were tested:

- There is a difference in recidivism by race, $\alpha=0.01$
- There is a difference in recidivism by gender, $\alpha=0.01$
- There is a difference in recidivism by age, $\alpha=0.01$
- There is a difference in offender age by race, $\alpha=0.01$

Chi-square was used to test if there was a difference in recidivism by race because both features are categorical. The results (Figure 10) show that, with $p < 0.00017$, the null hypothesis

is rejected. There is a difference in recidivism between black and white offenders, with black offenders being more likely to reoffend (Figure 11).

```
      BLACK  WHITE
false    6134   4797
true    8713   6191
Pearson's Chi-squared test with Yates' continuity correction

data: table(NIJ_orig$Recidivism_Within_3years, NIJ_orig$Race)
X-squared = 14.094, df = 1, p-value = 0.0001739
```

Figure 10. Chi-square test: difference in recidivism by race

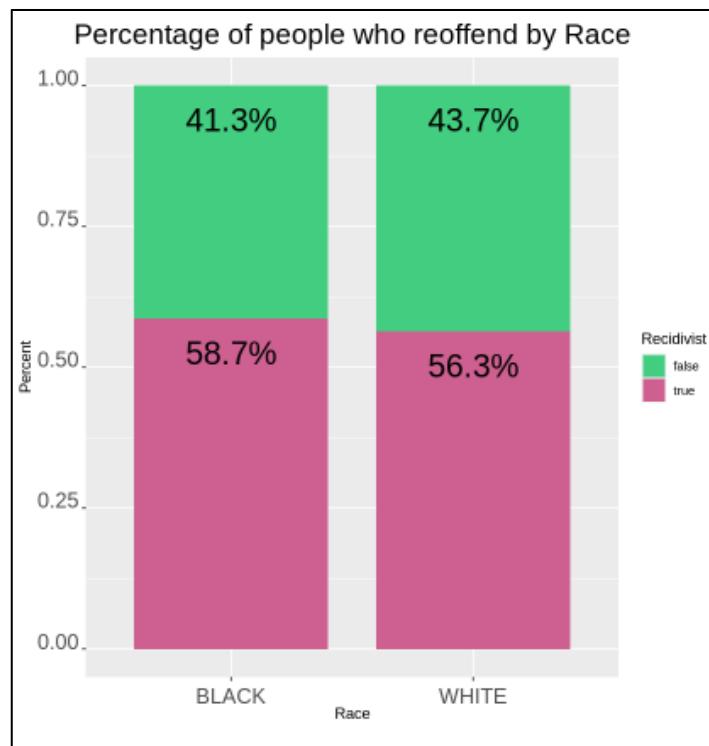


Figure 11. Percentage of people who reoffend by race

Recidivism and gender are both categorical so Chi-square was again used to test if there was a difference in recidivism by gender. The results (Figure 12) show, with $p < 2.2e^{-16}$, the null hypothesis is rejected. There is a difference in recidivism between male and female offenders, with male offenders being more likely to reoffend (Figure 13).

```

      Male Female
false  9206   1725
true  13462   1442
Pearson's Chi-squared test with Yates' continuity correction

data: table(NIJ_orig$Recidivism_Within_3years, NIJ_orig$Gender)
X-squared = 217.99, df = 1, p-value < 2.2e-16

```

Figure 12. Chi-square test: difference in recidivism by gender

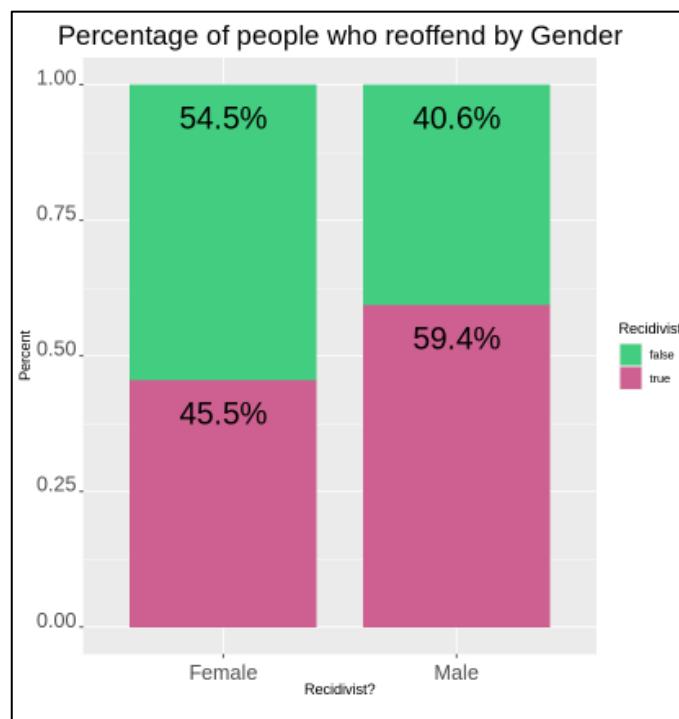


Figure 13. Percentage of people who reoffend by gender

The distribution of age was checked with a histogram and Q-Q plot and found to be not normal, which would typically mean using the non-parametric Mann-Whitney U test. However with a large sample size the central limit theorem allows the use of a t-test, so both were used to test if there was a difference in recidivism by age. The results show that with $p < 2.2e^{-16}$, the null hypothesis is rejected. There is a difference in age between reoffenders and non-reoffenders, with reoffenders being younger; mean age of 31.2 than non-reoffenders; mean age of 34.5 (Figure 14). This is further illustrated in the boxplot and bar chart in Figure 15.

```

Wilcoxon rank sum test with continuity correction

data: Age_at_Release by Recidivism_Within_3years
W = 98018098, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Welch Two Sample t-test

data: Age_at_Release by as_factor(Recidivism_Within_3years)
t = 28.822, df = 22988, p-value < 2.2e-16
alternative hypothesis: true difference in means between group false and group true is not equal to 0
95 percent confidence interval:
3.145913 3.605023
sample estimates:
mean in group false mean in group true
34.53737 31.16190

```

Figure 14. Mann-Whitney U test and t-test: difference in recidivism by age

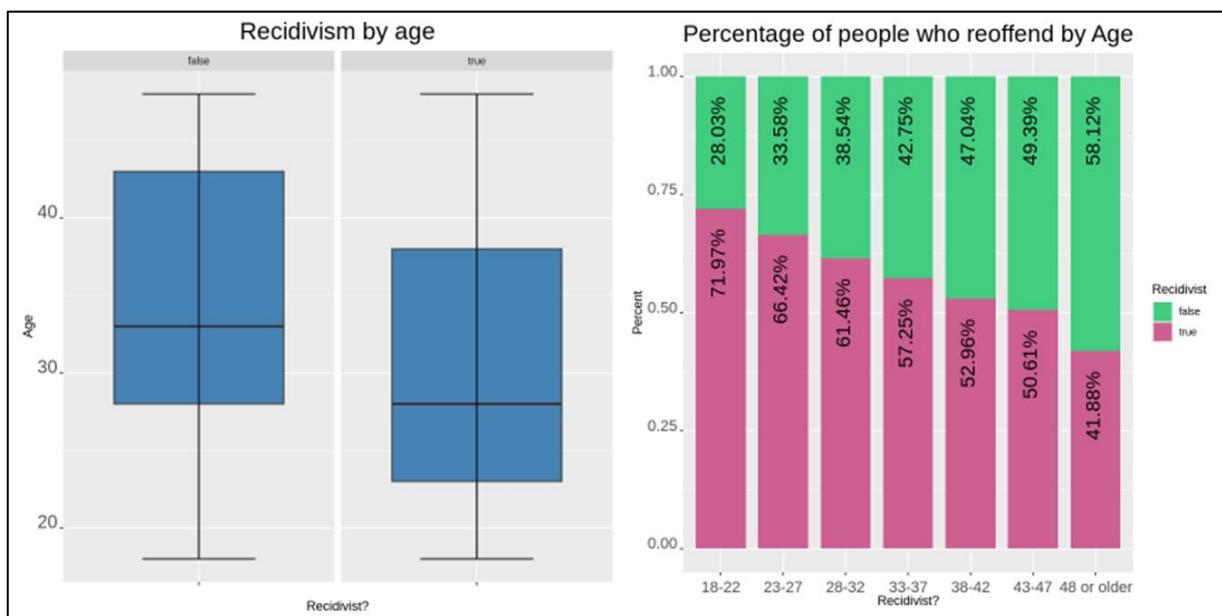


Figure 15. Recidivism by age

Mann-Whitney U test and t-test were used again to test if there was a difference in age by race, with the results showing that with $p < 2.2e^{-16}$, the null hypothesis is rejected. There is a difference in age between black offenders and white offenders, with black offenders younger; mean age of 31.6 than white offenders; mean age of 33.9 (Figure 16). This is further illustrated in the boxplot in Figure 17.

```

Wilcoxon rank sum test with continuity correction

data: Age_at_Release by Race
W = 69826119, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Welch Two Sample t-test

data: Age_at_Release by as_factor(Race)
t = -19.514, df = 24010, p-value < 2.2e-16
alternative hypothesis: true difference in means between group BLACK and group WHITE is not equal to 0
95 percent confidence interval:
-2.509302 -2.051234
sample estimates:
mean in group BLACK mean in group WHITE
31.62026      33.90053

```

Figure 16. Mann-Whitney U test and t-test: difference in age by race

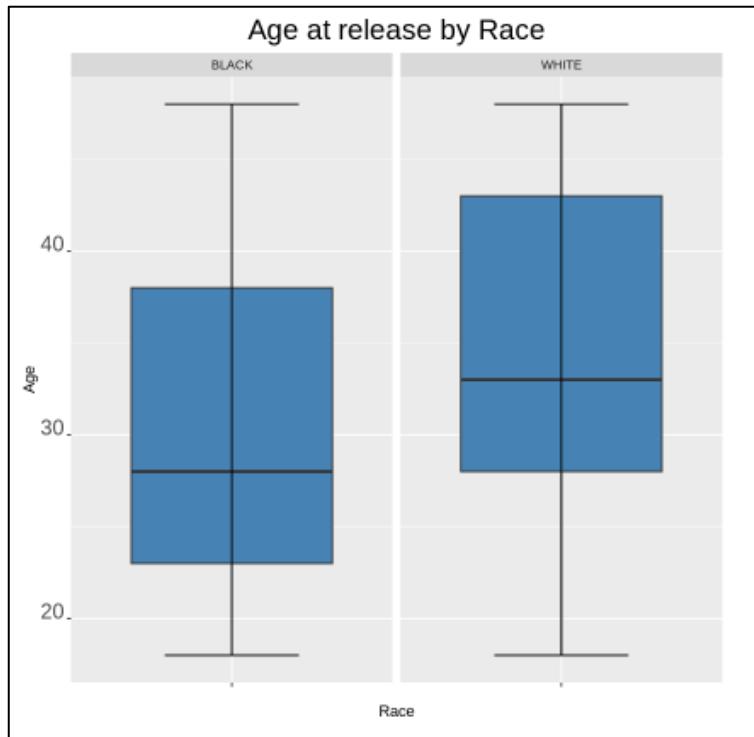


Figure 17. Age at release by race

The first three null hypotheses were all rejected, with statistically higher reoffending in black over white, male over female, and younger over older, all of which is consistent with the literature review. The fourth null hypothesis was also rejected, with black offenders being statistically younger than white offenders. This highlights one of the challenges identified in the literature review; age is a reliable predictor of recidivism, but age also correlates with race, so focusing too heavily on age risks racially biased results.

With the rejection of all four null hypotheses and the best practice from the literature review of modelling male and female recidivism separately, it was decided that the ontology will differentiate between genders when modelling correlations with recidivism and race.

Every feature was tested for correlation with recidivism and race for male and female offenders separately using Spearman's Rho, because the data are a mix of nominal and ordinal, with $\alpha=0.01$ due to the large sample size (Kim & Choi, 2021). Age had a correlation for male offenders of $r_s = -0.177$ with recidivism with $p = 2.2e^{-16}$ and $r_s = 0.121$ with race with $p = 2.2e^{-16}$. Those are not typically strong correlations, however, considering the previously discussed correlations between age and race with recidivism, it was decided to use $r_s \geq 0.1$ (weak correlation; Figure 18; Xiao et al., 2016) as the cut-off for feature risk and importance.

Value of r	Strength of relationship
-1.0 to -0.5 or 1.0 to 0.5	Strong
-0.5 to -0.3 or 0.3 to 0.5	Moderate
-0.3 to -0.1 or 0.1 to 0.3	Weak
-0.1 to 0.1	None or very weak

Figure 18. Strength of relationship (Xiao et al., 2016)

Figure 19 shows all r_s values, highlighted in green where $r_s \geq 0.1$ for recidivism, to represent features likely to be important to a recidivism prediction model, and highlighted in red where $r_s \geq 0.1$ for race, to highlight features that carry a higher risk of introducing racial bias. All negative values were converted to positive because the direction of correlation was unimportant for this analysis. Most values were statistically significant at $\alpha=0.01$, but some were not, which are highlighted in amber and set to $r_s = 0$.

The correlations between features in Figure 19 are metadata about the NIJ dataset. They were used in the design and build of the NIJ and MoJ ontologies to create ontologies with knowledge and metaknowledge stored alongside each other, in a novel use of ontology to address the increasing need for transparency in feature engineering.

Feature	Correlation with:				
	Everyone	Male		Female	
		Recidivism	Recidivism	Race	Recidivism
Age_at_Release	0.176	0.177	0.121	0.133	0.072
Residence_PUMA	0.025	0.026	0.139	0	0.187
Gang_Affiliated	0.185	0.185	0.086	N/A	N/A
Supervision_Risk_Score_First	0.180	0.185	0.053	0.146	0.046
Supervision_Level_First	0.061	0.053	0	0.069	0
Education_Level	0.088	0.088	0.057	0	0
Dependents	0.031	0.031	0.096	0	0.064
Prison_Offense	0.018	0.024	0.033	0	0.260
Prison_Years	0.130	0.134	0.066	0.186	0.109
Prior_Arrest_Episodes_Felony	0.199	0.187	0.025	0.262	0
Prior_Arrest_Episodes_Misd	0.178	0.161	0.094	0.279	0
Prior_Arrest_Episodes_Violent	0.065	0.055	0.111	0	0.213
Prior_Arrest_Episodes_Property	0.182	0.181	0.103	0.233	0
Prior_Arrest_Episodes_Drug	0.081	0.071	0	0.107	0.279
Prior_Arrest_Episodes_PPViolationCharges	0.229	0.218	0.063	0.303	0.067
Prior_Arrest_Episodes_DVCharges	0.066	0.062	0.052	0.052	0
Prior_Arrest_Episodes_GunCharges	0.044	0.036	0.104	0	0
Prior_Conviction_Episodes_Felony	0.105	0.094	0.032	0.169	0.047
Prior_Conviction_Episodes_Misd	0.175	0.160	0.070	0.247	0
Prior_Conviction_Episodes_Viol	0.047	0.043	0.088	0	0.161
Prior_Conviction_Episodes_Prop	0.161	0.157	0.104	0.232	0.073
Prior_Conviction_Episodes_Drug	0.065	0.059	0	0.077	0.235
Prior_Conviction_Episodes_PPViolationCharges	0.096	0.088	0.050	0.137	0
Prior_Conviction_Episodes_DomesticViolenceCharges	0.059	0.057	0.017	0	0
Prior_Conviction_Episodes_GunCharges	0.031	0.024	0.058	0	0
Prior_Revocations_Parole	0.058	0.051	0.037	0.060	0
Prior_Revocations_Probation	0.039	0.036	0.065	0.076	0.059
Condition_MH_SA	0.114	0.121	0.131	0.149	0.259
Condition_Cog_Ed	0.038	0.050	0.039	0	0
Condition_Other	0	0	0	0	0.065
Violations_ElectronicMonitoring	0.004	0	0.069	0	0.075
Violations_Instruction	0.064	0.058	0.046	0.087	0
Violations_FailToReport	0.030	0.024	0	0.069	0
Violations_MoveWithoutPermission	0.032	0.029	0	0.057	0
Delinquency_Reports	0.041	0.028	0	0.102	0.068
Program_Attendances	0.060	0.065	0.072	0	0.190
Program_UnexcusedAbsences	0.060	0.050	0.043	0.108	0
Residence_Changes	0.054	0.052	0.047	0.079	0
Avg_Days_per_DrugTest	0.011	0	0.078	0	0.135
DrugTests_THC_Positive	0.082	0.078	0.161	0	0.089
DrugTests_Cocaine_Positive	0.011	0	0.128	0	0.121
DrugTests_Meth_Positive	0.055	0.055	0.279	0.091	0.227
DrugTests_Other_Positive	0.004	0	0.121	0.053	0.126
Percent_Days_Employed	0.217	0.217	0.126	0.227	0.059
Jobs_Per_Year	0.074	0.074	0.120	0.088	0.060
Employment_Exempt	0.050	0.048	0.021	0	0
Legend					
		Recidivism correlation ≥ 0.1			
		Race correlation ≥ 0.1			
		No statistically significant correlation at $\alpha=0.01$			

Figure 19. Feature correlations with recidivism and race by gender

5.3 NIJ Ontology

The dataset and associated metadata from National Institute of Justice (N.D.) were used to derive knowledge to build an ontology. The Noy & McGuiness (2001) seven-step approach was superficially used with emphasis on the class hierarchy and properties of classes. It was superficial because the dataset was already presented in a simple flat structure with a single row per offender, so there was limited opportunity to address the overall scope. DeBellis (2021) was also used as a technical reference.

Initially, the class hierarchy was designed with every feature having its own class because a key requirement of the ontology was to highlight if there was a correlation between race and any other feature, so the features themselves were important, and it is preferred to have a separate class where the attribute is important to the domain (Noy & McGuiness, 2001). However, it became apparent that this approach was impracticable because the classes needed to contain the data properties about each offender as an instance, and also be members of inferred correlation classes to highlight if a feature was high or low risk or importance, which introduced circular references. The design was therefore changed so each feature was both an instance against which the race and recidivism correlations metaknowledge can be recorded via data properties (Figure 20) and an object property in the class hierarchy (Figure 21).

The screenshot shows the OWLviz interface with the following details:

- Active ontology:** The main tab bar includes Active ontology, Entities, Individuals by class, OWLViz, DL Query, and SPARQL Query.
- Data property hierarchy:** The left sidebar shows a tree structure under "Data property hierarchy":
 - owl:topDataProperty
 - hasFemaleRaceCorrelationValue
 - hasFemaleRecidivismCorrelationValue
 - hasMaleRaceCorrelationValue
 - hasMaleRecidivismCorrelationValue
- Selected Data Property:** "hasMaleRecidivismCorrelationValue" is selected, shown in green. Its details are displayed on the right:
 - Description:** hasMaleRecidivismCorrelationValue
 - Type:** Char
 - Functional:** Checked
 - Equivalent To:** (empty)
 - SubProperty Of:** (empty)
 - Domains (intersection):** Feature
 - Ranges:** xsd:float
 - Disjoint With:** (empty)
- Buttons:** On the right side of the main panel, there are four sets of buttons with question marks, at, cross, and circle symbols.

Figure 20. Data property hierarchy

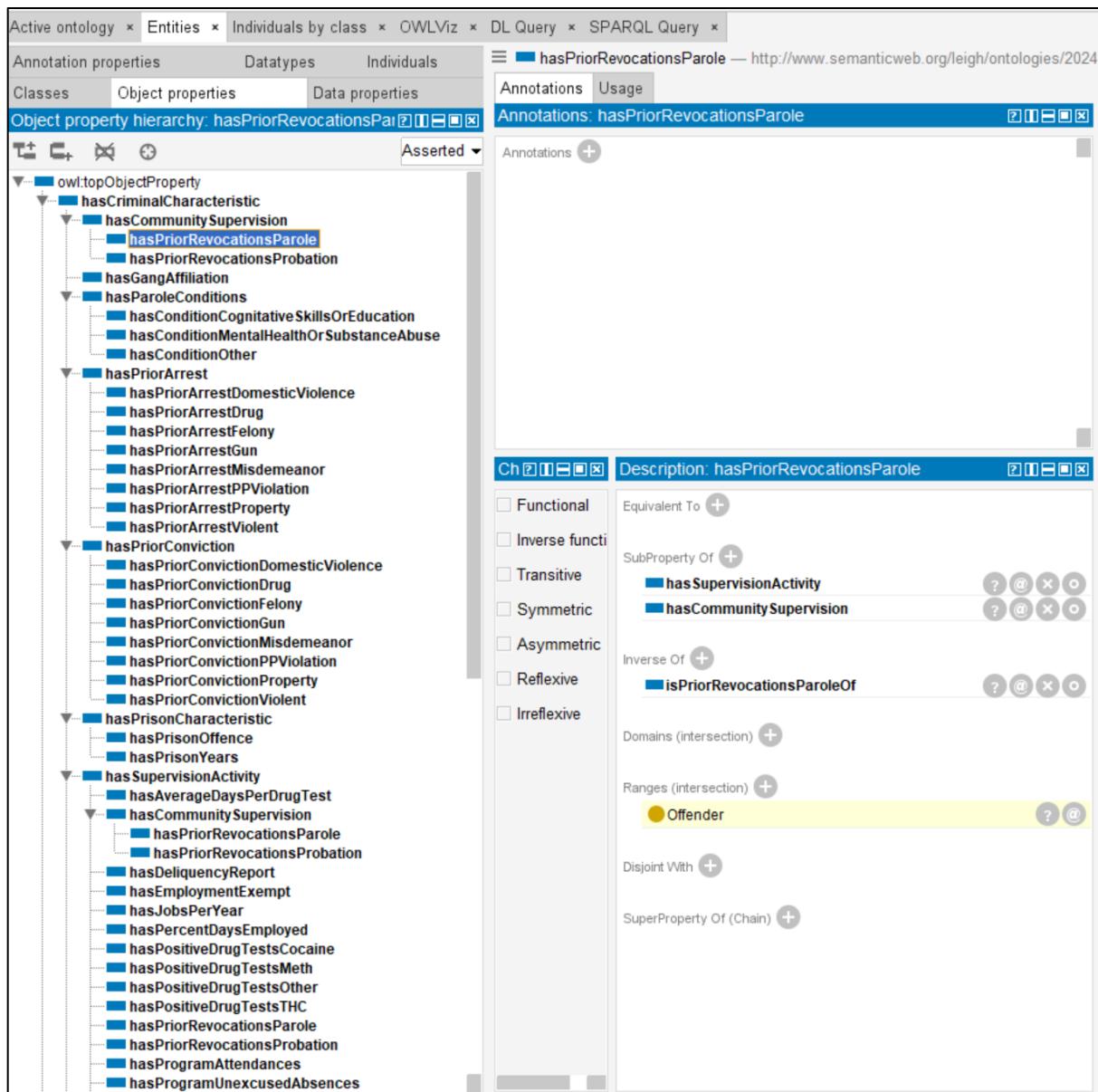


Figure 21. Object property hierarchy (truncated)

Defined classes were added to infer which features were high risk (race correlation ≥ 0.1 and < 1) and high importance (recidivism correlation ≥ 0.1) for male and female classes. Defined classes for low risk and low importance (with correlations < 0.1) and prohibited (with race correlation = 1, which is the race feature itself) were also added.

UML notation for ontologies (Bārzdiņš et al., 2010), adapted to include object properties, shows the final ontology design (Figure 22), while Figure 23 shows the inferred hierarchy from Protégé. The structure is relatively flat due to the simplicity of the dataset, with everything captured in one row per offender.

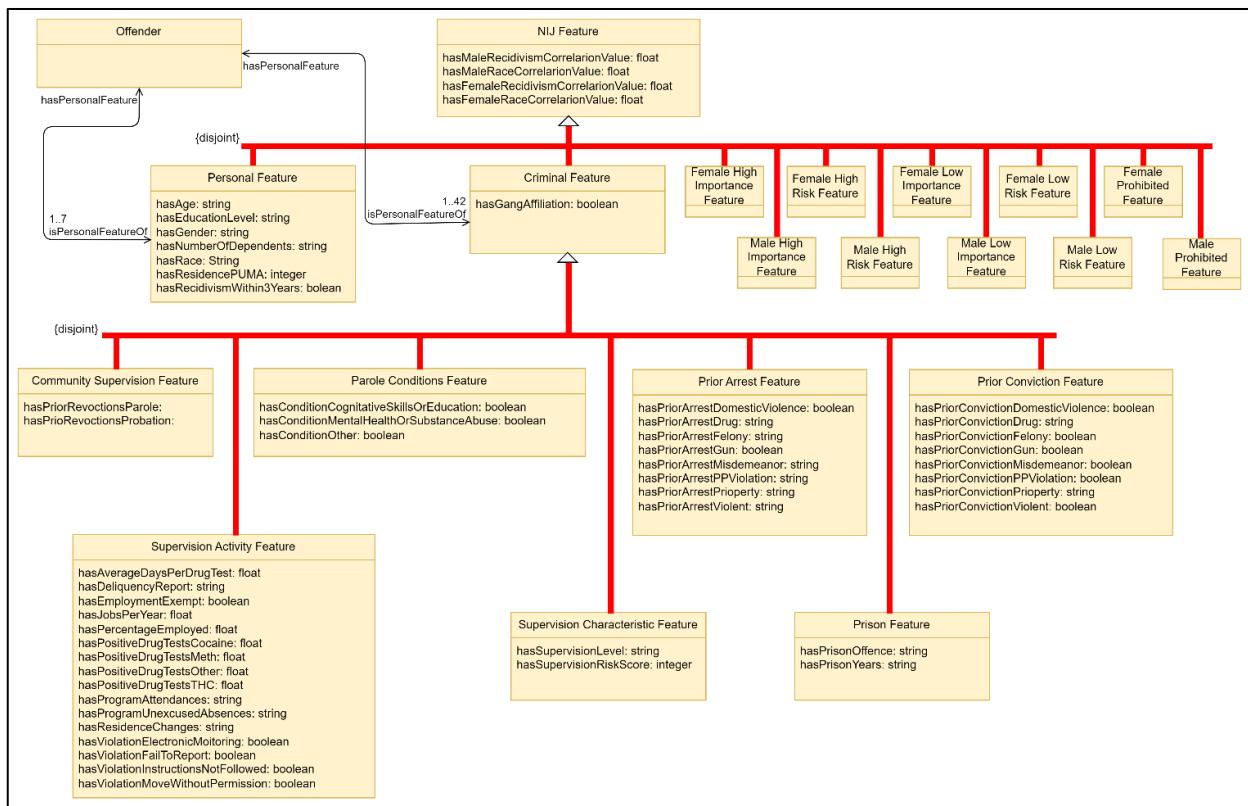


Figure 22. NIJ ontology design



Figure 23. Inferred hierarchy

The NIJ dataset was imported as offender instances using a Cellfie import script (Appendix C). Importing the instances in this way without first defining ranges of and dependencies between features is using the ontology more like a database, however, it was the most efficient way to prove the concept given the available data. The recidivism and race correlation values from Figure 19 were entered manually.

The ontology successfully stored all of the data from the NIJ dataset alongside the feature correlation metadata, assigning every feature to high/low risk/importance (Appendix D). Furthermore, simple DL Queries demonstrated, for example, how to find features that were both high importance and high risk for males (Figure 24) which are the features to be most cautious about.

The screenshot shows a user interface for a DL query. At the top, a yellow bar says "DL query:". Below it, a section titled "Query (class expression)" contains the text "MaleHighImportance and MaleHighRiskFeature". Underneath this are two buttons: "Execute" and "Add to ontology". The main area is titled "Query results" and shows "Instances (5 of 5)". A list of five features is displayed, each with a purple diamond icon and a question mark icon to its right:

- Age
- ConditionMentalHealthOrSubstanceAbuse
- PercentDaysEmployed
- PriorArrestProperty
- PriorConvictionProperty

Figure 24. DL Query for male high-risk and high-importance

SPARQL was used for additional filtering and showing the actual correlation values, for example, features where male correlation with race is higher than male correlation with recidivism (Figure 25).

Using that data, a data scientist would select features that correlate more highly with recidivism than race to build prediction models that are less racially biased.

Snap SPARQL Query:

```

PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX nij: <http://www.semanticweb.org/leigh/ontologies/2024/4/NIJ#>

#Show features where maleRaceCorrelationValue is greater than maleRecidivismCorrelationValue
SELECT ?feature ?maleRaceCorrelationValue ?maleRecidivismCorrelationValue
WHERE {
  ?feature nij:hasMaleRaceCorrelationValue ?maleRaceCorrelationValue ;
    nij:hasMaleRecidivismCorrelationValue ?maleRecidivismCorrelationValue .

  FILTER(?maleRaceCorrelationValue > ?maleRecidivismCorrelationValue)
}
ORDER BY DESC(?maleRaceCorrelationValue)


```

Execute

?feature	?maleRaceCorrelationValue	?maleRecidivismCorrelationValue
nij:PositiveDrugTestsMeth	0.279	0.055
nij:PositiveDrugTestsTHC	0.161	0.078
nij:ResidencePUMA	0.139	0.026
nij:ConditionMentalHealthOrSubstanceAbuse	0.131	0.121
nij:PositiveDrugTestsCocaine	0.128	0.0
nij:PositiveDrugTestsOther	0.121	0.0
nij:JobsPerYear	0.12	0.074
nij:PriorArrestViolent	0.111	0.055
nij:PriorArrestGun	0.104	0.036
nij:NumberOfDependents	0.096	0.031
nij:PriorConvictionViolent	0.088	0.043
nij:AverageDaysPerDrugTest	0.078	0.0
nij:ProgramAttendances	0.072	0.065
nij:ViolationElectronicMonitoring	0.069	0.0
nij:PriorRevocationsProbation	0.065	0.036
nij:PriorConvictionGun	0.058	0.024
nij:PrisonOffence	0.033	0.024

17 results

Figure 25. Features with male race correlation > male recidivism correlation

Having trained the model, the results would be loaded back into the ontology to check that the profiles are consistent. SPARQL would again be used to find the total number of people and the number who reoffended, by gender and race (Figure 26), which would then be re-run to ensure that the ratios remain consistent. The first order logic to build the query is:

Let $\text{Offender}(x)$ denote that x is an offender.

Let $\text{Gender}(x,g)$ denote that offender x has gender g .

Let $\text{Race}(x,r)$ denote that offender x has race r .

Let $\text{Reoffended}(x)$ denote that offender x has reoffended within three years.

$$\text{Total}(g,r,n) \equiv n = \#\{x | \text{Offender}(x) \wedge \text{Gender}(x,g) \wedge \text{Race}(x,r)\}$$
$$\text{ReoffendedCount}(g,r,m) \equiv m = \#\{x | \text{Offender}(x) \wedge \text{Gender}(x,g) \wedge \text{Race}(x,r) \wedge \text{Reoffended}(x)\}$$
$$\forall g,r \exists n,m (\text{Total}(g,r,n) \wedge \text{ReoffendedCount}(g,r,m))$$

Where:

- n is the total count of offenders with gender g and race r .
- m is the count of reoffended offenders with gender g and race r .

Snap SPARQL Query:

```
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX nij: <http://www.semanticweb.org/leigh/ontologies/2024/4/NIJ#>

#Total people and number who reoffended number gender and race
SELECT ?gender ?race (COUNT(?person) AS ?total) (COUNT(?reoffender) AS ?reoffended)
WHERE {
  ?person a nij:Offender ;
    nij:hasGender ?gender ;
    nij:hasRace ?race .

  OPTIONAL {
    ?person nij:hasRecidivismWithin3Years nij:true .
    BIND(IF(BOUND(?person), ?person, "") AS ?reoffender)
  }
}
GROUP BY ?gender ?race
ORDER BY ?gender ?race
```

Execute

?gender	?race	?total	?reoffended
nij:F	nij:BLACK	1082	474
nij:F	nij:WHITE	2085	968
nij:M	nij:BLACK	13765	8239
nij:M	nij:WHITE	8903	5223

Figure 26. Count of total people and people who reoffended by gender and race

The ontology now has everything needed to inform a data scientist about the features that are more likely to create an accurate model to predict recidivism and the features more likely

to introduce racial bias, and the data themselves, so they can create a model with transparency and report on the risk levels of the features selected.

Taking a worked example, a data scientist building a model to predict male recidivism might initially look for features with high importance and low risk (Figure 27). They know that age is a highly important feature so even though it is high-risk they decide to add that too. That leaves them with 8 features on which to train their model. Before proceeding further they would check the recidivism and race correlations of the 8 selected features (Figure 28). As expected, all have a correlation value ≥ 0.1 for recidivism, and only age has a correlation ≥ 0.1 with race, which is still lower than recidivism.

The screenshot shows a user interface for a DL query. At the top, there is a yellow header bar labeled "DL query". Below it, a section titled "Query (class expression)" contains the text "MaleHighImportance and MaleLowRiskFeature". Underneath this, there are two buttons: "Execute" (highlighted in orange) and "Add to ontology". The main area is titled "Query results" and contains a sub-section "Instances (7 of 7)". A list of seven items is shown, each preceded by a purple diamond icon:

- GangAffiliation
- PriorArrestFelony
- PriorArrestMisdemeanor
- PriorArrestPPViolation
- PriorConvictionMisdemeanor
- PrisonYears
- SupervisionRiskScore

Next to each item name is a small circular icon containing a question mark.

Figure 27. Features with high importance and low risk for males

Snap SPARQL Query:

```

PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX nij: <http://www.semanticweb.org/leigh/ontologies/2024/4/NIJ#>

#Show MaleImportantFeatures where maleRaceCorrelationValue is greater than maleRecidivismCorrelationValue
SELECT ?feature ?maleRecidivismCorrelationValue ?maleRaceCorrelationValue
WHERE {
  ?feature a nij:Feature ;
    nij:hasMaleRaceCorrelationValue ?maleRaceCorrelationValue ;
    nij:hasMaleRecidivismCorrelationValue ?maleRecidivismCorrelationValue .

  FILTER((?feature = nij:Age) || (?feature = nij:GangAffiliation) || (?feature = nij:PriorArrestFelony) || (?feature = nij:PriorArrestMisdemeanor) || (?feature = nij:PriorArrestPPViolation) || (?feature = nij:PriorConvictionMisdemeanor) || (?feature = nij:PrisonYears) || (?feature = nij:SupervisionRiskScore))
}
ORDER BY DESC(?maleRecidivismCorrelationValue)

```

Execute

?feature	?maleRecidivismCorrelationValue	?maleRaceCorrelationValue
nij:PriorArrestPPViolation	0.218	0.063
nij:PriorArrestFelony	0.187	0.025
nij:SupervisionRiskScore	0.185	0.053
nij:GangAffiliation	0.185	0.086
nij:Age	0.177	0.121
nij:PriorArrestMisdemeanor	0.161	0.094
nij:PriorConvictionMisdemeanor	0.16	0.07
nij:PrisonYears	0.134	0.066

8 results

Figure 28. Recidivism and race correlation for selected features

They consider the overall risk level acceptable so they export the male data for only those eight features from the ontology (Figure 29). Once the model has been trained and the data scientist is happy with the results, they will be imported back into the ontology to be checked for deviations from the existing racial ratios. The concept of creating an ontology that provides transparency about the risks of using specific features and the ability to check the prediction results against actual profiles has been proven using the NIJ dataset.

Snap SPARQL Query:

```

PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX nij: <http://www.semanticweb.org/leigh/ontologies/2024/4/NIJ#>

SELECT ?offender
(REPLACE(STR(?ageValue), STR(nij:), "") AS ?age)
(REPLACE(STR(?gangAffiliationValue), STR(nij:), "") AS ?gangAffiliation)
(REPLACE(STR(?priorArrestFelonyValue), STR(nij:), "") AS ?priorArrestFelony)
(REPLACE(STR(?priorArrestMisdemeanorValue), STR(nij:), "") AS ?priorArrestMisdemeanor)
(REPLACE(STR(?priorArrestPPViolationValue), STR(nij:), "") AS ?priorArrestPPViolation)
(REPLACE(STR(?priorConvictionMisdemeanorValue), STR(nij:), "") AS ?priorConvictionMisdemeanor)
(REPLACE(STR(?prisonYearsValue), STR(nij:), "") AS ?prisonYears)
(REPLACE(STR(?supervisionRiskScoreValue), STR(nij:), "") AS ?supervisionRiskScore)
WHERE {
?offender a nij:Offender .
?offender nij:hasGender nij:M .
?offender nij:hasAge ?ageValue .
OPTIONAL {?offender nij:hasGangAffiliation ?gangAffiliationValue .}
OPTIONAL {?offender nij:hasPriorArrestFelony ?priorArrestFelonyValue .}
OPTIONAL {?offender nij:hasPriorArrestMisdemeanor ?priorArrestMisdemeanorValue .}
OPTIONAL {?offender nij:hasPriorArrestPPViolation ?priorArrestPPViolationValue .}
OPTIONAL {?offender nij:hasPriorConvictionMisdemeanor ?priorConvictionMisdemeanorValue .}
OPTIONAL {?offender nij:hasPrisonYears ?prisonYearsValue .}
OPTIONAL {?offender nij:hasSupervisionRiskScore ?supervisionRiskScoreValue .}
}
ORDER BY ?offender

```

Execute

?offender	?age	?gangAffiliation	?priorArrestFel...	?priorArrestMis...	?priorArrestPP...	?priorConvictio...	?prisonYears	?supervisionRi...
nij:1	43-47	false	6	6OrMore	4	3	MoreThan3Years	3
nij:10	43-47	false	10OrMore	6OrMore	5OrMore	4OrMore	MoreThan3Years	5
nij:100	48OrOlder	false	10OrMore	6OrMore	5OrMore	4OrMore	MoreThan3Years	6
nij:1000	28-32	false	5	6OrMore	3	4OrMore	GreaterThan2To... 10	
nij:10000	43-47	false	5	1	2	0	LessThan1Year	3
nij:10002	38-42	false	10OrMore	6OrMore	2	4OrMore	MoreThan3Years	8
nij:10003	28-32	false	7	3	1	0	1-2Years	10
nij:10004	28-32	false	8	4	5OrMore	2	1-2Years	8
nij:10005	28-32	false	5	6OrMore	5OrMore	2	LessThan1Year	7
nij:10006	48OrOlder	false	5	3	1	2	GreaterThan2To... 4	
nij:10007	23-27	false	7	6OrMore	5OrMore	3	LessThan1Year	8
nij:10008	28-32	true	9	5	2	2	MoreThan3Years	9
nij:10009	23-27	true	3	0	1	1	GreaterThan2To... 5	
nij:1001	38-42	false	9	6OrMore	5OrMore	4OrMore	1-2Years	8

22668 results

Figure 29. Data export of selected features

5.4 MoJ Ontology

Having proven the concept with the NIJ dataset, the ontology for recidivism prediction in England and Wales was designed and built using metadata from Data First, a programme combining data from Crown Courts, Magistrate Courts, Prison Service and Probation Service (Ministry of Justice, 2020) using the Noy & McGuiness (2001) seven-step approach. The amalgamation of four datasets, each representing a sub-domain of criminal justice, created a significantly more complex design than the NIJ ontology.

First, the metadata for each dataset was examined to determine the scope and constructs of the data in the absence of a domain expert to interview as would be normal practice (Kendal & Green, 2019). The features covered a wide scope of criminal justice which could all have been built into a single ontology. Indeed, having everything in a single “Criminal Justice” ontology would enable additional use cases in the future. However, to prove the concept of using an ontology to manage the knowledge and the metaknowledge to enable ethical transparency for the specific use case of recidivism prediction, only the features that were considered useful were selected, excluding, for example, features about proceedings such as pleas and mode of trial. Verdict features were also omitted on the assumption that for this use case, all of the data pertains to guilty verdicts, with proceedings resulting in not-guilty outcomes omitted. As such, the domain “Recidivism in England and Wales” is a sub-domain of “Criminal Justice in England and Wales”.

There was a risk that, with no domain expert to interview, feature selection was not optimal. Since the exercise was to prove a concept and not to train machine learning models, the risk was acceptable. Domain expert input would be needed before taking the concept into production.

The features were grouped into classes according to their sub-domain and usage. Offender has one instance per offender with local data properties and data properties about the object properties of other classes such as gender and ethnicity. Each offender has 1-n cases. Each case has one offender (cases with multiple offenders would have separate case IDs in the ontology), one court, one principal offence (the offence which attracted the most severe sentence), one most serious offence (the offence that has the most severe potential sentence, which can be the same as the principal offence), and multiple sentence outcomes and probation requirements.

Properties were included for features that would be calculated externally from the ontology. For example, the number of previous offences would be calculated from the number of cases for each offender during data pre-processing outside the ontology before using the results in a machine learning model, so the results can then be stored in the ontology as another feature with its correlation values.

Additional properties were then added to capture information not in the Data First datasets that could potentially improve recidivism prediction according to the literature review and the statistical analysis of the NIJ dataset. The additional properties are denoted with a blue background in the ontology design, including a new class called “Prison Conduct” with features held in the prison system but not included in the Data First datasets (HM Prison and Probation Service, 2024; Ministry of Justice, 2023; Ministry of Justice, 2016; Prison Reform Trust, 2022). Once again UML notation for ontologies (Bārzdiņš et al., 2010) was adapted to include object properties (Figure 30). The inferred hierarchy, object property hierarchy and data property hierarchy are in Appendix E.

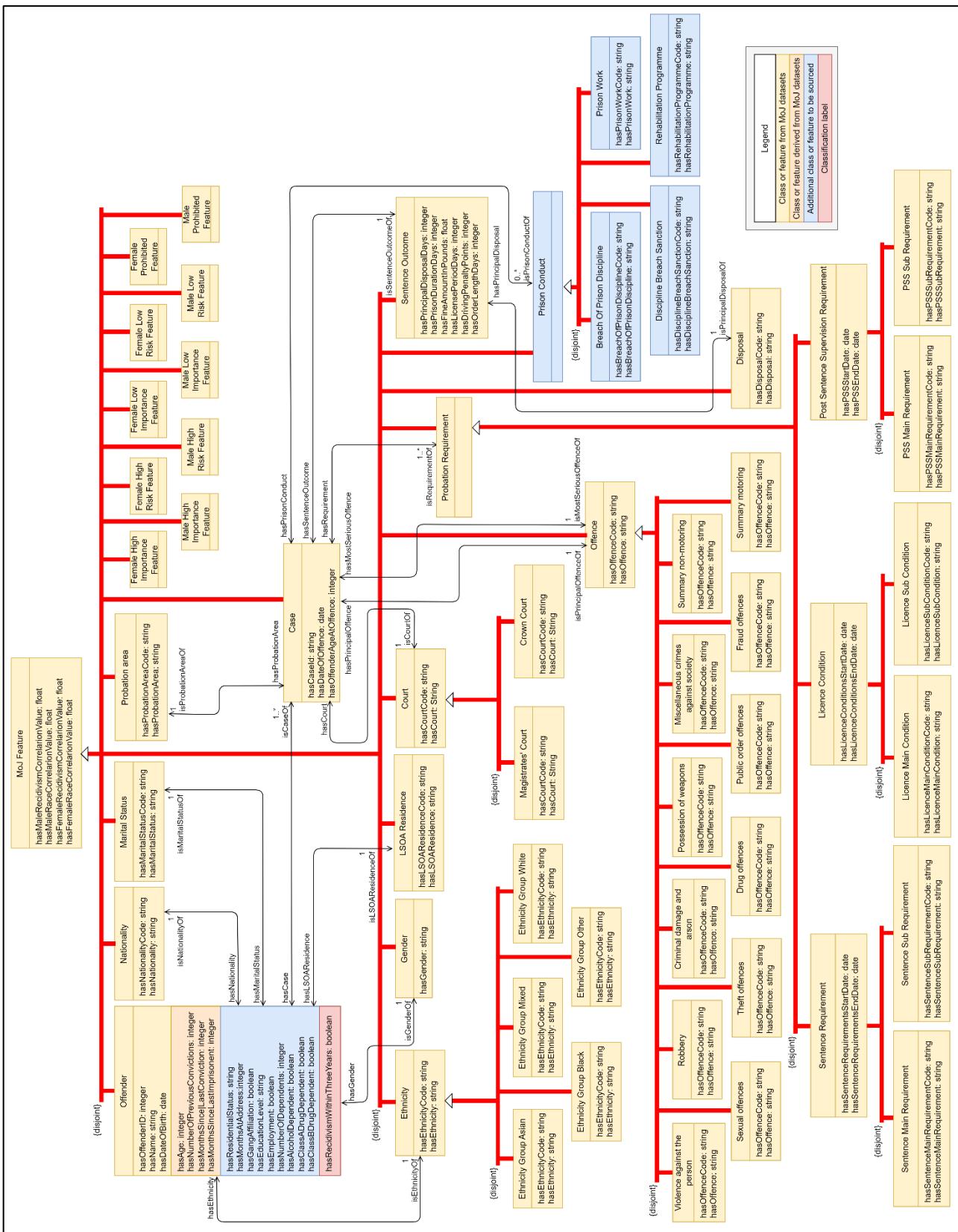


Figure 30. MoJ ontology design

Object and data instances were imported using Cellfie scripts (Appendix F) and an input spreadsheet (Appendix G) was created from lookup tables (HM Prison and Probation Service, 2024; Ministry of Justice, 2023; Ministry of Justice, 2016; Prison Reform Trust, 2022) plus Lower Super Output Areas (LSOAs) from Office for National Statistics (2023). Prefixes were added to instances of code objects to ensure uniqueness across classes. There were 35,672 LSOAs so only the first 100 were imported to prove the ontology without unnecessarily impacting performance during testing.

Horn clauses were added via Semantic Web Rule Language (SWRL) to infer descriptions from codes for code/description pairs so only code instances needed to be added to ensure data consistency (Figure 31).

Another spreadsheet (Appendix H) and Cellfie script (Appendix I) were created to import the recidivism and race correlation values to demonstrate how the metadata would be loaded (and re-loaded following regular re-reviews of the statistical analysis) in a real-world scenario. This time a statistical analysis was not possible because there was no real data, so dummy data were used to demonstrate the process. To make it look credible the dummy data were partially based upon the NIJ correlation values, but no statistical inference should be drawn. The process was to demonstrate the concept, not to provide actual results.

The race correlations in the MoJ ontology used Black and White as per the NIJ ontology, however, the MoJ ontology has a richer categorisation of ethnicity, with 19 instances across 6 classes. Without a domain expert to discuss how ethnicity could and should be classified, it was kept simple with White and Non-white as substitutes for White and Black, where White was considered to be the White class with its 4 instances of “British”, “Irish”, “Gypsy or Irish Traveler” and “Any other White background”. All other ethnicities were aligned with Non-white as the nearest equivalent to Black from the NIJ ontology. This was not intended to cause anyone any offence, it was simply a means of simplifying the MoJ ontology by aligning it to the NIJ ontology in the absence of a domain expert.

Horn clause (SWRL rule)
Offender(?o) ^ hasEthnicityCode(?o, ?code) ^ hasEthnicityCode(?e, ?code) ^ hasEthnicity(?e, ?ethnicity) -> hasEthnicity(?o, ?ethnicity)
Offender(?o) ^ hasLSOAResidenceCode(?o, ?code) ^ hasLSOAResidenceCode(?r, ?code) ^ hasLSOAResidence(?r, ?residence) -> hasLSOAResidence(?o, ?residence)
Offender(?o) ^ hasMaritalStatusCode(?o, ?code) ^ hasMaritalStatusCode(?m, ?code) ^ hasMaritalStatus (?m, ?status) -> hasMaritalStatus (?o, ?status)
Offender(?o) ^ hasNationalityCode(?o, ?code) ^ hasNationalityCode (?n, ?code) ^ hasNationality(?n, ?nationality) -> hasNationality(?o, ?nationality)
Case(?c) ^ hasCourtCode(?c, ?code) ^ hasCourtCode(?ct, ?code) ^ hasCourt(?ct, ?court) -> hasCourt(?c, ?court)
Case(?c) ^ hasPrincipleOffenceCode(?c, ?code) ^ hasOffenceCode(?o, ?code) ^ hasOffence(?o, ?offence) -> hasPrincipleOffence(?c, ?offence)
Case(?c) ^ hasMostSeriousOffenceCode(?c, ?code) ^ hasOffenceCode(?o, ?code) ^ hasOffence(?o, ?offence) -> hasMostSeriousOffenceCode(?c, ?offence)
Case(?c) ^ hasPrincipleDisposalCode(?c, ?code) ^ hasDisposalCode(?d, ?code) ^ hasDisposal(?d, ?disposal) -> hasPrincipleDisposal(?c, ?disposal)
Case(?c) ^ hasProbationAreaCode(?c, ?code) ^ hasProbationAreaCode(?p, ?code) ^ hasProbationArea(?p, ?area) -> hasProbationArea(?c, ?area)
Case(?c) ^ hasSentenceMainRequirementCode(?c, ?code) ^ hasSentenceMainRequirementCode(?r, ?code) ^ hasSentenceMainRequirement(?r, ?requirement) -> hasSentenceMainRequirement(?c, ?requirement)
Case(?c) ^ hasSentenceSubRequirementCode(?c, ?code) ^ hasSentenceSubRequirementCode(?r, ?code) ^ hasSentenceSubRequirement(?r, ?requirement) -> hasSentenceSubRequirement(?c, ?requirement)
Case(?c) ^ hasLicenceMainConditionCode(?c, ?code) ^ hasLicenceMainConditionCode(?cond, ?code) ^ hasLicenceMainCondition(?cond, ?condition) -> hasLicenceMainCondition(?c, ?condition)
Case(?c) ^ hasLicenceSubConditionCode(?c, ?code) ^ hasLicenceSubConditionCode(?cond, ?code) ^ hasLicenceSubCondition(?cond, ?condition) -> hasLicenceSubCondition(?c, ?condition)
Case(?c) ^ hasPSSMainRequirementCode(?c, ?code) ^ hasPSSMainRequirementCode(?r, ?code) ^ hasPSSMainRequirement(?r, ?requirement) -> hasPSSMainRequirement(?c, ?requirement)
Case(?c) ^ hasPSSSubRequirementCode(?c, ?code) ^ hasPSSSubRequirementCode(?r, ?code) ^ hasPSSSubRequirement(?r, ?requirement) -> hasPSSSubRequirement(?c, ?requirement)
Case(?c) ^ hasBreachOfPrisonDisciplineCode(?c, ?code) ^ hasBreachOfPrisonDisciplineCode(?b, ?code) ^ hasBreachOfPrisonDiscipline(?b, ?breach) -> hasBreachOfPrisonDiscipline(?c, ?breach)
Case(?c) ^ hasDisciplineBreachSanctionCode(?c, ?code) ^ hasDisciplineBreachSanctionCode(?s, ?code) ^ hasDisciplineBreachSanction(?s, ?sanction) -> hasDisciplineBreachSanction(?c, ?sanction)
Case(?c) ^ hasPrisonWorkCode(?c, ?code) ^ hasPrisonWorkCode(?w, ?code) ^ hasPrisonWork(?w, ?work) -> hasPrisonWork(?c, ?work)
Case(?c) ^ hasRehabilitationProgrammeCode(?c, ?code) ^ hasRehabilitationProgrammeCode(?p, ?code) ^ hasRehabilitationProgramme(?p, ?programme) -> hasRehabilitationProgramme(?c, ?programme)

Figure 31. Horn clauses to infer descriptions from codes

The initial ontology suffered from a performance issue, taking excessive time to reason running on a Microsoft Surface Laptop with Intel Core i7-1255U processor and 32GB DDR DRAM. By testing with and without different data loaded (Figure 32) and using different reasoners, which did not help and so not shown in the table, the issue was found to be caused by reasoning the high and low risk and importance defined classes with the correlation values. Having the correlation data properties set at the root class level meant that the reasoner was trying to reason all properties of all classes into one of the defined classes, even without correlation values. Ironically this is closer to the initial desired design which was not possible because data properties cannot be set against object properties or other data properties, hence why separate data properties for each feature were created against which to store the correlation values.

Design approach	Ontology memory pre-reasoning	Time to run reasoner	Ontology memory post-reasoning
Importance and risk defined classes alongside other classes and disjoint	235MB	2 hours 36 minutes	11GB
Importance and risk defined classes alongside other classes and not disjoint	235MB	29 minutes	10.2GB
Importance and risk defined classes deleted	235MB	0.5 seconds	380MB
MoJ Feature class containing importance and risk defined classes separated from other classes at ontology root	235MB	3 seconds	520MB

Figure 32. MoJ ontology performance tests

The design was modified to separate the “MoJ Feature” class holding the correlation data properties from the other classes (Figure 33) which had a significant positive impact, reducing the reasoner time from 29 minutes (without disjoint classes) to 3 seconds with only correlation instances loaded. The drawback of the updated design is further separation between the classes with the knowledge and the class with the metaknowledge, but there is separation in practical terms in both designs due to the construct of ontologies so the drawback was negligible.

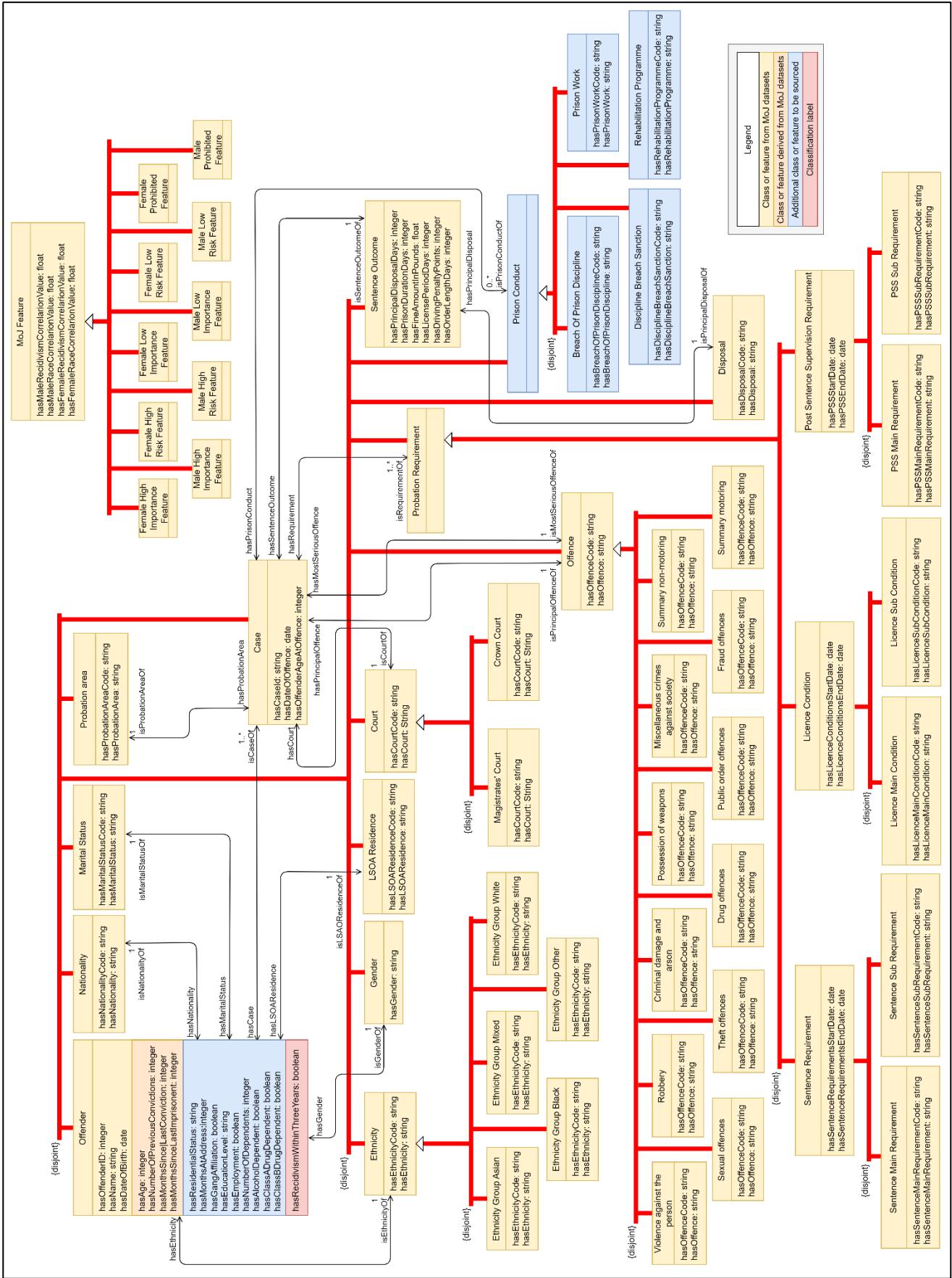


Figure 33. Updated MoJ ontology design

With the performance of the ontology improved; dummy data were created to represent sample offenders along with their cases and outcomes. Twelve offender instances and thirty-five case instances were created with credible data, including sentences aligned with Sentencing Council (N.D.), credible durations between dates of offence, sentence, licence etc., and court location aligned with probation area. The LSOA residence code was not aligned with the court or probation area due to only 100 instances being loaded, so in this case random instances were selected.

While it would have been easier to create a few offender and case instances manually, a spreadsheet was created (Appendix J) along with a Cellfie import script (Appendix K) to demonstrate how loading data from the external Data First dataset could work in practice.

The ontology was tested using manual data entry and import scripts to ensure data validation was working according to the object properties. Figure 34 shows, using manual entry, data that are not valid instances cannot be entered, and data that is valid for a different object property is rejected by the reasoner, so validation was successful.

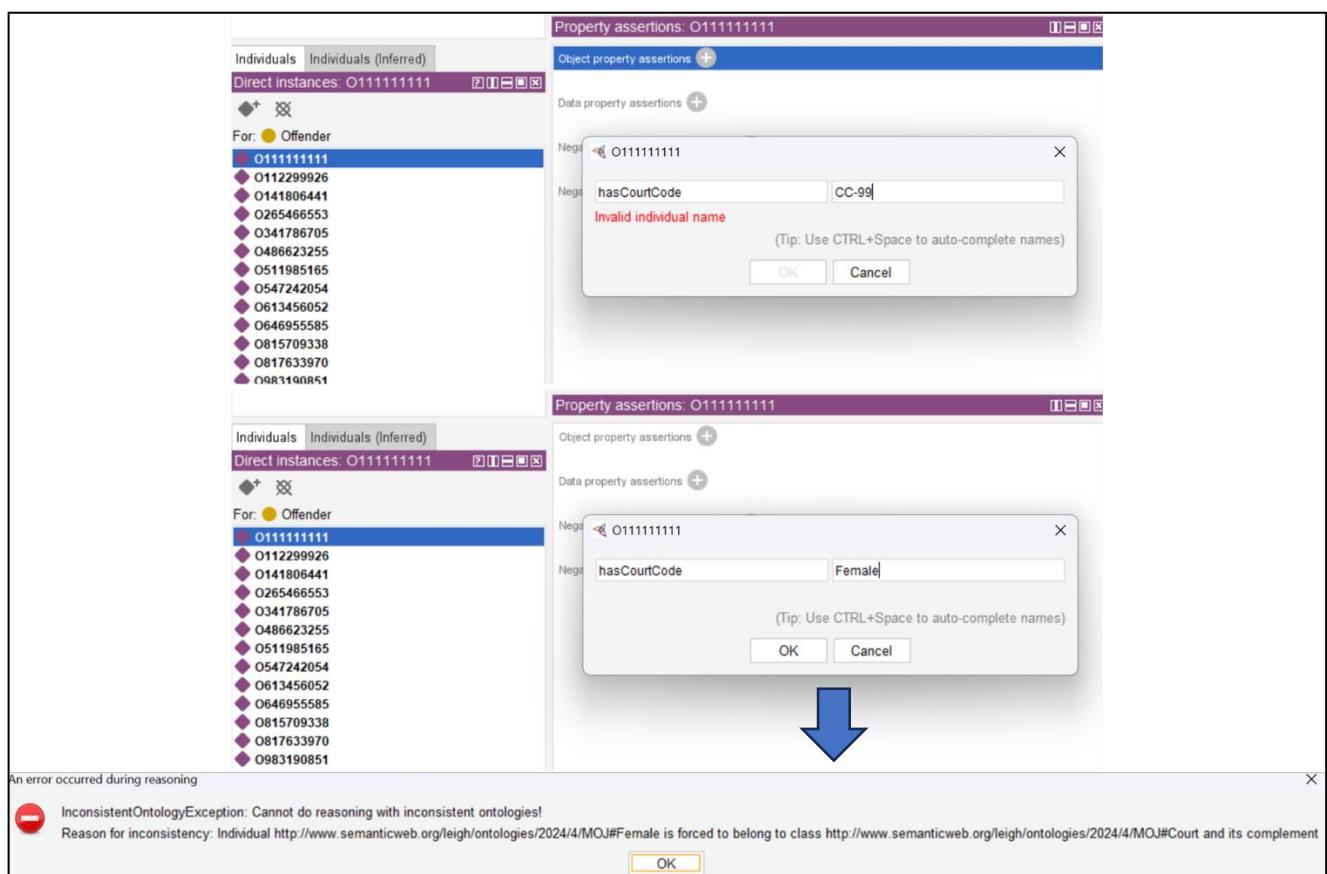


Figure 34. MoJ ontology data entry validation

Similar to the NIJ ontology, the MoJ ontology was tested using the defined classes to check which features were high or low risk or importance, and DL Queries and SPARQL queries were used for more detailed interrogation (examples in Appendix E). The SPARQL queries were more complicated than the NIJ ontology, as were the results, due to the more complex ontology with many-to-one mappings of numerous properties. Notwithstanding the additional complexity, the results were clear and accurate.

A similar worked example to the NIJ ontology follows, which first checked male high-risk and low-importance features (figure 35) to be excluded from all models.

The screenshot shows a user interface for a DL query. At the top, a yellow bar says "DL query:". Below it, a section titled "Query (class expression)" contains the text "MaleHighRiskFeature **and** MaleLowImportanceFeature". There are two buttons at the bottom of this section: "Execute" (highlighted with a yellow border) and "Add to ontology". Below this is a section titled "Query results" with a blue header bar that says "Instances (7 of 7)". The list of instances includes: BreachOfPrisonDisciplineCode, ClassADrugDependent, ClassBDrugDependent, MostSeriousOffenceCode, NationalityCode, SentenceMainRequirementCode, and SentenceSubRequirementCode. Each instance is preceded by a purple diamond icon and followed by a grey circular icon with a question mark.

Figure 35. DL Query for male high-risk and low-importance

Next the features with higher correlation to recidivism than race were examined (figure 36). Fifteen features were selected with recidivism correlation greater than 0.12. However, some of those features also had race correlations greater than 0.1. If the final machine learning model was shown to have racial biases when tested in the ontology, the model would be re-trained by systematically removing the features with the highest correlation with race.

Snap SPARQL Query:

```

PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX moj: <http://www.semanticweb.org/leigh/ontologies/2024/4/MOJ#>

#Show features where maleRecidivismCorrelationValue is greater than maleRaceCorrelationValue
SELECT ?feature ?maleRecidivismCorrelationValue ?maleRaceCorrelationValue
WHERE {
  ?feature moj:hasMaleRecidivismCorrelationValue ?maleRecidivismCorrelationValue ;
            moj:hasMaleRaceCorrelationValue ?maleRaceCorrelationValue .

  FILTER(?maleRecidivismCorrelationValue > ?maleRaceCorrelationValue)
}
ORDER BY DESC(?maleRecidivismCorrelationValue)

```

Execute

?feature	?maleRecidivismCorrelationValue	?maleRaceCorrelationValue
moj:MonthsSinceLastImprisonment	0.281	0.142
moj:MonthsSinceLastConviction	0.242	0.132
moj:Employment	0.217	0.126
moj:MonthsAtAddress	0.213	0.095
moj:GangAffiliation	0.185	0.086
moj:Age	0.177	0.121
moj:NumberOfPreviousConvictions	0.164	0.079
moj:OffenderAgeAtOffence	0.162	0.102
moj:PrisonDurationDays	0.162	0.092
moj:RehabilitationProgrammeCode	0.162	0.053
moj:PrincipalOffenceCode	0.161	0.092
moj:MaritalStatusCode	0.153	0.032
moj:PSSSubRequirementCode	0.152	0.056
moj:AlcoholDependent	0.132	0.098
moj:PrisonWorkCode	0.123	0.078
moj:OrderLengthDays	0.112	0.101
moj:LicenceSubConditionCode	0.099	0.045
moj:PSSMainRequirementCode	0.096	0.023
moj:LicenceMainConditionCode	0.092	0.076
moj:PrincipalDisposalDays	0.092	0.021
moj:EducationLevel	0.088	0.057
moj:PrincipalDisposalCode	0.075	0.021
moj:DrivingPenaltyPoints	0.052	0.024
moj:FineAmountPounds	0.043	0.012
moj:ProbationAreaCode	0.02	0.01

25 results

Figure 36. Features with male recidivism correlation > male race correlation

The descriptive instances of the fifteen features were examined using SPARQL (figure 37). They were exported using the code instances for training the machine learning model (Appendix E), which is beyond the scope of this project. The predictions would then be checked to ensure they matched the actual racial profiles (Appendix E) in the same way as the NIJ ontology.

Snap SPARQL Query

```

PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX moj: <http://www.semanticweb.org/leigh/ontologies/2024/4/MOJ#>

SELECT ?offender
  (REPLACE(STR(?monthsSinceImprisonmentValue), STR(moj:), "") AS ?monthsSinceImprisonment)
  (REPLACE(STR(?monthsSinceConvictionValue), STR(moj:), "") AS ?monthsSinceConviction)
  (REPLACE(STR(?employmentValue), STR(moj:), "") AS ?employment)
  (REPLACE(STR(?monthsAtAddressValue), STR(moj:), "") AS ?monthsAtAddress)
  (REPLACE(STR(?gangAffiliationValue), STR(moj:), "") AS ?gangAffiliation)
  (REPLACE(STR(?ageValue), STR(moj:), "") AS ?age)
  (REPLACE(STR(?previousConvictionsValue), STR(moj:), "") AS ?previousConvictions)
  (REPLACE(STR(?maritalStatusValue), STR(moj:), "") AS ?maritalStatus)
  (REPLACE(STR(?alcoholDependentValue), STR(moj:), "") AS ?alcoholDependent)
  (REPLACE(STR(?caseValue), STR(moj:), "") AS ?case)
  (REPLACE(STR(?rehabilitationProgrammeValue), STR(moj:), "") AS ?rehabilitationProgramme)
  (REPLACE(STR(?principalOffenceValue), STR(moj:), "") AS ?principalOffence)
  (REPLACE(STR(?PSSSubRequirementValue), STR(moj:), "") AS ?PSSSubRequirement)
  (REPLACE(STR(?prisonWorkValue), STR(moj:), "") AS ?prisonWork)
  (REPLACE(STR(?prisonDurationValue), STR(moj:), "") AS ?prisonDuration)
WHERE {
  ?offender a moj:Offender
  FILTER(REGEX(STR(?offender), CONCAT("^", STR(moj:), "O$")))
  OPTIONAL { ?offender moj:hasMonthsSinceLastImprisonment ?monthsSinceImprisonmentValue. }
  OPTIONAL { ?offender moj:hasMonthsSinceLastConviction ?monthsSinceConvictionValue. }
  OPTIONAL { ?offender moj:hasEmployment ?employmentValue. }
  OPTIONAL { ?offender moj:hasMonthsAtAddress ?monthsAtAddressValue. }
  OPTIONAL { ?offender moj:hasGangAffiliation ?gangAffiliationValue. }
  OPTIONAL { ?offender moj:hasAge ?ageValue. }
  OPTIONAL { ?offender moj:hasNumberOfPreviousConvictions ?previousConvictionsValue. }
  OPTIONAL { ?offender moj:hasMaritalStatus ?maritalStatusValue. }
  OPTIONAL { ?offender moj:hasAlcoholDependent ?alcoholDependentValue. }
  ?offender moj:hasCase ?case
  OPTIONAL { ?case moj:hasPrisonDurationDays ?prisonDurationValue. }
  OPTIONAL { ?case moj:hasPrisonDurationDays ?prisonDurationValue. }
  OPTIONAL { ?case moj:hasRehabilitationProgramme ?rehabilitationProgrammeValue. }
  OPTIONAL { ?case moj:hasPrincipalOffence ?principalOffenceValue. }
  OPTIONAL { ?case moj:hasPSSSubRequirement ?PSSSubRequirementValue. }
  OPTIONAL { ?case moj:hasPrisonWork ?prisonWorkValue. }
}
ORDER BY ?offender

```

Execute

?offender	?m...	?m...	?emp...	?m...	?gan...	?age	?p...	?maritalStatus	?alco...	?case	?rehabilitationPr...	?principalOffence	?PSSSubRequ...	?prisonWork	?pris...
moj:0112299926	11	false	13	false	63	4	Divorced or dissolu...	true	moj:C647325366	46 Theft from Shops					
moj:0112299926	11	false	13	false	63	4	Divorced or dissolu...	true	moj:C214350956	46 Theft from Shops					
moj:0112299926	11	false	13	false	63	4	Divorced or dissolu...	true	moj:C691205173	46 Theft from Shops					
moj:0112299926	11	false	13	false	63	4	Divorced or dissolu...	true	moj:C986467303	46 Theft from Shops					
moj:0112299926	11	false	13	false	63	4	Divorced or dissolu...	true	moj:C745987478	46 Theft from Shops					
moj:0141806441	2	false	52	false	59	0	Married or in civil ...	false	moj:C637473147	8.01 Assault occasioning actu...					
moj:0265466553	16	false	15	false	24	0	Married or in civil p...	true	moj:C196164791	46 Theft from Shops					
moj:0341786705	0	8	false	51	false	46	3	Married or in civil p...	true	moj:C527235880	92E.01 Possession of a contr...				730
moj:0341786705	0	8	false	51	false	46	3	Married or in civil p...	true	moj:C905424044	The Bridge Progr...	4.6 Causing Death by Careles...			
moj:0341786705	0	8	false	51	false	46	3	Married or in civil p...	true	moj:C794276181	92D.01 Possession of a contr...				
moj:0341786705	0	8	false	51	false	46	3	Married or in civil p...	true	moj:C830828088	92D.01 Possession of a contr...				
moj:0486623255	0	10	false	13	false	73	3	Widowed	false	moj:C478663808	46 Theft from Shops				
moj:0486623255	0	10	false	13	false	73	3	Widowed	false	moj:C338060576	Building Better R...	8.10 Breach of a restraining or...			730
moj:0486623255	0	10	false	13	false	73	3	Widowed	false	moj:C338060576	Becoming New M...	8.10 Breach of a restraining or...			730
moj:0486623255	0	10	false	13	false	73	3	Widowed	false	moj:C348844983	8.01 Assault occasioning actu...				
moj:0511985165	299	10	false	36	false	61	5	Single-not married/...	true	moj:C587659755	46 Theft from Shops				
moj:0511985165	299	10	false	36	false	61	5	Single-not married/...	true	moj:C618323430	Living as New Me	34 Robbery	Restorative Ju...	Workshop	365
moj:0511985165	299	10	false	36	false	61	5	Single-not married/...	true	moj:C535754077	45 Theft from Vehicle				
moj:0511985165	299	10	false	36	false	61	5	Single-not married/...	true	moj:C499266153	46 Theft from Shops				
moj:0511985165	299	10	false	36	false	61	5	Single-not married/...	true	moj:C113345537	46 Theft from Shops				
moj:0511985165	299	10	false	36	false	61	5	Single-not married/...	true	moj:C904791425	34 Robbery				
moj:0547242054	0	1	false	31	false	23	4	Single-not married/...	false	moj:C375098237	92D.01 Possession of a contr...				
moj:0547242054	0	1	false	31	false	23	4	Single-not married/...	false	moj:C851372657	46 Theft from Shops				
moj:0547242054	0	1	false	31	false	23	4	Single-not married/...	false	moj:C607333684	92D.01 Possession of a contr...				
moj:0547242054	0	1	false	31	false	23	4	Single-not married/...	false	moj:C569872265	Living as New Me	92A.09 Production supply and ...	Servery		1277
moj:0547242054	0	1	false	31	false	23	4	Single-not married/...	false	moj:C569872265	Living as New Me	92A.09 Production supply and ...	Cleaner		1277
moj:0547242054	0	1	false	31	false	23	4	Single-not married/...	false	moj:C254596091	92D.01 Possession of a contr...				
moj:0613456052	3	27	false	62	false	69	1	Married or in civil p...	true	moj:C808774974	Identity Matters	53D Fraud by false representa...	Servery		760
moj:0613456052	3	27	false	62	false	69	1	Married or in civil p...	true	moj:C808774974	Identity Matters	53D Fraud by false representa...	Cleaner		760
moj:0613456052	3	27	false	62	false	69	1	Married or in civil p...	true	moj:C723372549	46 Theft from Shops				
moj:0646955585	7	false	9	false	42	0	Single-not married/...	false	moj:C595710701	46 Theft from Shops					
moj:0815709338	4	false	58	false	20	0	Single-not married/...	false	moj:C755833865	46 Theft from Shops					
moj:0815709338	4	false	58	false	20	0	Single-not married/...	false	moj:C178906509	46 Theft from Shops					
moj:0815709338	4	false	58	false	20	0	Single-not married/...	false	moj:C881603678	46 Theft from Shops					
moj:0815709338	4	false	58	false	20	0	Single-not married/...	false	moj:C202280393	46 Theft from Shops					
moj:0815709338	4	false	58	false	20	0	Single-not married/...	false	moj:C112529789	46 Theft from Shops					
moj:0817633970	1	false	37	false	29	4	Single-not married/...	true	moj:C782821873	8.07 Racially or religiously ag...					
moj:0983190851	15	false	3	false	26	0	Married or in civil p...	false	moj:C281645560	8.07 Racially or religiously ag...					

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Figure 37. Examination of features

6 Evaluation

The four artefacts were evaluated in two groups; data analysis evaluation covering the EDA and statistical analysis, and ontology evaluation covering both the NIJ and MoJ ontologies.

6.1 Data Analysis Evaluation

The methods used in both the EDA and the statistical analysis reflected best practice techniques that have not fundamentally changed since their inception (Tukey, 1977), other than the availability of computational tools to aid the analysis, and the need to transform the data.

The initial EDA (Appendix A) replaced null values with appropriate values and transformed features that were almost discrete into discrete features, for example, a feature with a range “0, 1, 2, 3 or more” was changed to “0, 1, 2, 3”. This, alongside additional transformations detailed in the EDA, allowed numerical tests to be performed. Correlations were assessed between all of the numerical features and there were no strong correlations.

The dython library was used to further assess correlations between all features, including categorical features. Again, this produced no strong results.

Finally, the categorical features were one-hot encoded and correlation heatmaps were produced to determine which features correlated most closely with recidivism, race=black, race=white, gender=male, gender=female for everyone, and race=black and race=white for males, and race=black and race=white for females, and recidivism for black males, white males, black females and white females. The intention was to identify correlations on which to form hypotheses for a more detailed statistical analysis. However while some features correlated more highly and more consistently than others, the differences were too small to restrict the detailed analysis, so instead, the hypotheses were based upon the findings from the literature review. This was not a failing in the initial EDA because the lack of strong correlations was itself a meaningful finding.

The statistical analysis continued the EDA in R (Appendix B), testing four hypotheses:

- There is a difference in recidivism by race, $\alpha=0.01$
- There is a difference in recidivism by gender, $\alpha=0.01$
- There is a difference in recidivism by age, $\alpha=0.01$
- There is a difference in offender age by race, $\alpha=0.01$

Similar data pre-processing was performed to prepare the data, with the addition of converting all ordinal features to integers to allow statistical tests to be performed. Chi-square was used to test the hypotheses for categorical features. For numerical features, the distribution was first checked, as is standard practice, using histograms and q-q plots, which showed non-normal distributions in all cases. For smaller sample sizes this would require the use of the non-parametric Mann-Whitney U test, however, because the sample size was large, with 25,835 records, the central limit theorem meant that the t-test could still be used. R both were used, producing similar results. Following the rejection of all four null hypotheses, box plots and bar charts were produced to identify the direction and scale of the differences.

The results aligned with the literature review, with recidivism higher in black over white, male over female, and young over old, and black offenders being younger than white offenders. This created similar concerns to those identified in the literature review about how to deal with the different offending patterns. The same “least bad” method from the literature review was adopted; to differentiate between genders based on fairness, even though gender is a protected characteristic, and to protect against differentiating on race. On that basis, Spearman’s rank with $\alpha=0.01$ was used to calculate the Spearman’s Rho correlation between recidivism and race for males and females for every other feature to build a table of correlations for males and females separately since they will be treated separately.

The analysis stopped there because that gave enough information regarding the risks of the different features and potential racial biases to be used in the ontology. There was much more analysis that could have been performed. Indeed, if the objective was to create machine learning models to predict recidivism it would have gone further, but that was not the purpose of this study.

Overall, the evaluation of the data analysis is that it provided all of the information necessary to move to the ontology design and so fulfilled its purpose and was considered complete and successful.

6.2 Ontology Evaluation

The initial evaluation concerned how the ontologies stored the semantic knowledge. Methods to evaluate the ontologies were examined from Raad & Cruz (2015):

- Gold standard-based was not suitable because there was no similar ontology with which to compare.
- Corpus-based was discounted because without a corpus to use as a reference, or a domain expert to interrogate, it is impossible to determine if full coverage has been achieved. They could have been evaluated against the datasets used to design them, but that would be self-fulfilling and inappropriate.
- Task-based was considered suitable because likely tasks for the ontology can be suggested without a domain expert, although having one would still be preferable.
- Criteria-based was possible, but not desirable, because without domain expertise the appropriate criteria would be subjective and potentially just fitted to the solution to ensure a positive evaluation.

Task-based evaluation was selected, using tasks such as the ease of formulating queries to interrogate the ontology, the accuracy of the responses, and how explainable the system is (Obrst et al., 2007: 12). Performance was also considered in general terms, however, cognisant of the fact that the ontologies were developed on a laptop whereas production deployment would likely be on a cloud with significantly higher computational power, so specific performance criteria were not defined.

Both ontologies enabled offender and case data to be extracted using DL Queries and SPARQL queries as described in the implementation section, with results checked and confirmed to be accurate. Only the MoJ ontology provided data validation for offender and case instances, which was tested and proven to be accurate, because the NIJ data were loaded directly without defining the object properties first. The data structure and queries were simpler in the NIJ ontology, however, the MoJ ontology was more representative of a usable ontology taking data from various sources including courts, prisons and probation and linking offender and case data. This means that data taken from the MoJ ontology would require more pre-processing, but that is because the NIJ ontology was built using data that had already been pre-processed.

The class structure of the MoJ ontology is unambiguous with relationships clearly shown in the design, and inferences are logical and explainable. The clarity of the NIJ ontology was not assessed due to its simplicity.

Next, the ontologies were evaluated for their ability to increase the transparency of potential biases; the aim of this project.

The SPARQL queries to show the ratios of actual and predicted recidivists by gender and ethnicity demonstrated that models trained to predict recidivism can be objectively proven to predict, or not, according to actual profiles. This is a big step towards transparency of output.

The data properties capturing the correlations with race and recidivism by gender for every feature provided demonstrable transparency to expose potential risks of selecting certain features for training recidivism prediction models. This is an example of improving the transparency of input, which should improve the ethical quality of output, to be measured by the transparency of output.

However, there remains a challenge. The correlation features are separate from the object and data properties used to store the criminal justice data in the ontologies. The naming convention ensured a direct mapping, but it relies upon a robust process to ensure a) the correlation values are kept up-to-date, and b) that the correlations are checked and robustly justified before training a prediction model. There is nothing in the ontologies that forces compliance. Indeed, there is nothing in the ontologies that mandates that the correlation values exist at all because they exist as separate axioms. A robust and auditable process should address this, but it was still considered a weakness in the final designs.

Notwithstanding that challenge, the MoJ ontology was successful at providing a semantic knowledge base of criminal justice for England and Wales to store and retrieve knowledge about offenders and their cases as well as metaknowledge about the correlations of features with race and recidivism, thereby increasing transparency at both the input and output stages of creating machine learning models to predict recidivism. The objective of the ontology for this project has been met.

7 Learning

The project has generated significant learning and new skills.

The literature review uncovered ethical challenges with using machine learning within the recidivism prediction domain that apply across all domains. The need to be mindful of hidden biases within the data as well as the more obvious overt biases in feature selection were critical takeaways. Additionally, the need to be careful about which performance metrics to use when measuring the performance of machine learning algorithms was well noted because the choice can have a profound impact on hiding or exposing potential biases.

First-hand knowledge and skills in ontology, specifically Protégé, increased markedly as a result of this project. Limitations of Protégé, and the semantic web in general, that were previously unknown to this author were uncovered which required changes in design and approach to fulfil the aims of the project, all of which contributed to a rich learning experience.

First Order Logic was practiced and knowledge and skills improved during this project. Horn clauses were used in the production of rules to map object descriptions to code values using SWRL. First order logic was also used to describe a SPARQL query. First order logic was a challenging area when encountered in other modules of the MSc, so self-directed learning was necessary to improve the skills and knowledge to complete this project.

SPARQL was an area of significant self-directed learning too. Having not used it previously, a lot of research, along with trial and error, was required to produce working queries, first in the simple NIJ ontology, and then in the more complex MoJ ontology. Additional code was also included to remove prefixes for a more useful output. This took time and effort to complete, demonstrating continuous learning and application even after the core requirements had been achieved.

8 Conclusions and Recommendations

Features that predict recidivism in machine learning models and less sophisticated solutions have been identified in the literature review and by analysing a publicly available dataset. They were a mix of static and dynamic features. Static features were the easiest to measure, but dynamic features improved predictive accuracy and were fairer because they can be influenced by the offender.

Features that can introduce racial bias were also identified, and an overlap was found with recidivism prediction features, which created an ethical conundrum. Using features with the highest predictive accuracy would create an inherent racial bias. For example, age correlated with recidivism, and so was used in practically every recidivism prediction model. However, it also correlated with race, so predicting on age alone would create a racially biased solution.

In some cases, the data themselves were found to be biased because they were the results of historically biased decisions and actions.

Recidivism was found to vary by gender, but unlike race, gender was found to be a characteristic that should be differentiated on in the interest of fairness.

A key conclusion was that transparency is key to an ethical solution; being able to explain why a machine learning model made a prediction.

The choice of performance metrics to assess machine learning models was found to have a profound effect on exposing potential biases. For example, accuracy can score highly while producing biased results. The most appropriate metric should be chosen depending on the context, and ideally, multiple measures should be used to mitigate the risk of hidden bias.

Ontology was found to be a credible solution to mitigate, but not prevent, the risk of racial bias. This was achieved in two ways, termed transparency of input, and transparency of output:

1. **Transparency of input:** Clear exposure of feature correlations with recidivism and race to give data scientists information about the risk of bias they could be introducing for each feature.
2. **Transparency of output:** Comparing prediction results to racial profiles to ensure parity.

Transparency of output does not automatically equate to an unbiased solution, even if the prediction profile matches the training profile due to the issue with the data themselves often being biased. It does, however, allow for the right conversations and decisions to be made to improve the data over time.

It is recommended that the prototype MoJ ontology be industrialised in three ways:

1. The design should be reviewed with a subject matter expert to validate assumptions made from the metadata to ensure it is a true reflection of the knowledge.
2. The domain should be extended beyond recidivism prediction, with the help of the subject matter expert, to cover all of criminal justice in England and Wales.
3. The ontology should be populated with real data to validate if biases exist within existing tools such as OGRS3, and to provide guardrails to protect against bias with future machine learning models.

It is further recommended to include dynamic features in the next iteration of OGRS, or whatever tool comes next, to provide a fairer prediction that allows offenders to improve their scores through rehabilitative actions.

Additionally, the semantic web should be reviewed with the World Wide Web Consortium (W3C) to produce a means for storing metaknowledge as knowledge within the ontology. The requirement is to store metaknowledge as properties of classes and other object and data properties. If this were possible in Protégé it would have been possible to store the correlation values directly against the classes and properties rather than having to create separate data property instances to store the correlation values, which was effective but prone to human error. Thought would need to be given to reasoning capabilities and optimisation for this approach because it could result in very complicated relationships.

9 References

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Appendix A. NIJ Exploratory Data Analysis

Jupyter Notebook available at: <https://github.com/feaviolp/msc-project/blob/0a726abe16a82ed34d3f891361d0cca09d408edc/NIJ%20Analysis/NIJ%20EDA.ipynb>

Exploratory Data Analysis of the NIJ recidivism dataset

Data pre-processing

Import libraries

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import seaborn as sns
import scipy.stats as st
from sklearn import linear_model
from sklearn.preprocessing import LabelEncoder, StandardScaler
import warnings
# ignore future deprecation
warnings.filterwarnings('ignore')
```

Load the CSV file into a pandas dataframe

```
In [2]: url = "https://raw.githubusercontent.com/feaviolp/msc-project/main/NIJ%20Ontology/NIJ_s_Recidivism_Challenge_Full_Dataset.csv"
NIJ = pd.read_csv(url)
```

Look at the shape and features of the dataset

```
In [3]: NIJ.shape
```

```
Out[3]: (25835, 54)
```

```
In [4]: NIJ.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25835 entries, 0 to 25834
Data columns (total 54 columns):
 #   Column           Non-Null Count  Dtype  
 --- 
 0   ID               25835 non-null    int64  
 1   Gender            25835 non-null    object 
 2   Race              25835 non-null    object 
 3   Age_at_Release   25835 non-null    object 
 4   Residence_PUMA   25835 non-null    int64  
 5   Gang_Affiliated  22668 non-null    object 
 6   Supervision_Risk_Score_First  25368 non-null    float64 
 7   Supervision_Level_First   24115 non-null    object 
 8   Education_Level     25835 non-null    object 
 9   Dependents         25835 non-null    object 
 10  Prison_Offense    22558 non-null    object 
 11  Prison_Years      25835 non-null    object 
 12  Prior_Arrest_Episodes_Felony  25835 non-null    object 
 13  Prior_Arrest_Episodes_Misd   25835 non-null    object 
 14  Prior_Arrest_Episodes_Violent 25835 non-null    object 
 15  Prior_Arrest_Episodes_Property 25835 non-null    object 
 16  Prior_Arrest_Episodes_Drug   25835 non-null    object 
 17  Prior_Arrest_Episodes_PPViolationCharges 25835 non-null    object 
 18  Prior_Arrest_Episodes_DVCharges  25835 non-null    bool   
 19  Prior_Arrest_Episodes_GunCharges 25835 non-null    bool   
 20  Prior_Conviction_Episodes_Felony  25835 non-null    object 
 21  Prior_Conviction_Episodes_Misd   25835 non-null    object 
 22  Prior_Conviction_Episodes_Viol   25835 non-null    bool   
 23  Prior_Conviction_Episodes_Prop  25835 non-null    object 
 24  Prior_Conviction_Episodes_Drug  25835 non-null    object 
 25  Prior_Conviction_Episodes_PPViolationCharges 25835 non-null    bool   
 26  Prior_Conviction_Episodes_DomesticViolenceCharges 25835 non-null    bool   
 27  Prior_Conviction_Episodes_GunCharges 25835 non-null    bool   
 28  Prior_Revocations_Parole    25835 non-null    bool   
 29  Prior_Revocations_Probation  25835 non-null    bool   
 30  Condition_MH_SA          25835 non-null    bool   
 31  Condition_Cog_Ed         25835 non-null    bool   
 32  Condition_Other          25835 non-null    bool   
 33  Violations_ElectronicMonitoring 25835 non-null    bool
```

```

34 Violations_Instruction           25835 non-null bool
35 Violations_FailToReport        25835 non-null bool
36 Violations_MoveWithoutPermission 25835 non-null bool
37 Delinquency_Report             25835 non-null object
38 Program_Attendances           25835 non-null object
39 Program_UnexcusedAbsences      25835 non-null object
40 Residence_Changes              25835 non-null object
41 Avg_Days_per_DrugTest          19732 non-null float64
42 DrugTests_THC_Positive         20663 non-null float64
43 DrugTests_Cocaine_Positive     20663 non-null float64
44 DrugTests_Meth_Positive        20663 non-null float64
45 DrugTests_Other_Positive       20663 non-null float64
46 Percent_Days_Employed         25373 non-null float64
47 Jobs_Per_Year                  25027 non-null float64
48 Employment_Exempt              25835 non-null bool
49 Recidivism_Within_3years       25835 non-null bool
50 Recidivism_Arrest_Year1        25835 non-null bool
51 Recidivism_Arrest_Year2        25835 non-null bool
52 Recidivism_Arrest_Year3        25835 non-null bool
53 Training_Sample                 25835 non-null int64
dtypes: bool(20), float64(8), int64(3), object(23)
memory usage: 7.2+ MB

```

The dataset has 25,836 rows and 54 columns.

Some of the columns have missing values (less than 25,836 values).

Next describe the dataset, then look at the top and bottom 4 rows.

In [5]:	NIJ.describe()						
Out[5]:	ID	Residence_PUMA	Supervision_Risk_Score_First	Avg_Days_per_DrugTest	DrugTests_THC_Positive	DrugTests_Cocain	DrugTests_Meth
count	25835.000000	25835.000000	25360.000000	19732.000000	20663.000000	20663.000000	20663.000000
mean	13314.004838	12.361796	6.082216	93.890044	0.063350	0.063350	0.063350
std	7722.206327	7.133742	2.381442	117.169847	0.138453	0.138453	0.138453
min	1.000000	1.000000	1.000000	0.500000	0.000000	0.000000	0.000000
25%	6626.500000	6.000000	4.000000	28.837366	0.000000	0.000000	0.000000
50%	13270.000000	12.000000	6.000000	55.424812	0.000000	0.000000	0.000000
75%	20021.500000	18.000000	8.000000	110.333333	0.071429	0.071429	0.071429
max	26761.000000	25.000000	10.000000	1088.500000	1.000000	1.000000	1.000000

In [6]:	NIJ.head()								
Out[6]:	ID	Gender	Race	Age_at_Release	Residence_PUMA	Gang_Affiliated	Supervision_Risk_Score_First	Supervision_Level_First	Educat
0	1	M	BLACK	43-47	16	False	3.0	Standard	At I
1	2	M	BLACK	33-37	16	False	6.0	Specialized	Le
2	3	M	BLACK	48 or older	24	False	7.0	High	At I
3	4	M	WHITE	38-42	16	False	7.0	High	Le
4	5	M	WHITE	33-37	16	False	4.0	Specialized	Le

5 rows × 54 columns

In [7]:	NIJ.tail()								
Out[7]:	ID	Gender	Race	Age_at_Release	Residence_PUMA	Gang_Affiliated	Supervision_Risk_Score_First	Supervision_Level_First	
5	6	M	BLACK	48 or older	24	False	7.0	High	At I

25830	26756	M	BLACK	23-27	9	False	5.0	Standard
25831	26758	M	WHITE	38-42	25	False	5.0	Standard
25832	26759	M	BLACK	33-37	15	False	5.0	Standard
25833	26760	F	WHITE	33-37	15	NaN	5.0	Standard
25834	26761	M	WHITE	28-32	12	False	5.0	Standard

5 rows × 54 columns



Drop ID and Training_Sample because they will not be required for the EDA.

```
In [8]: NIJ.drop(columns=['ID', 'Training_Sample'], inplace=True)
```

Also drop Recidivism_Arrest_Year1, Recidivism_Arrest_Year2 and Recidivism_Arrest_Year3 because we're only interested in Recidivism_Within_3years

```
In [9]: NIJ.drop(columns=['Recidivism_Arrest_Year1', 'Recidivism_Arrest_Year2', 'Recidivism_Arrest_Year3'], inplace=True)
```

Now take a look at the rows with missing values.

```
In [10]: NIJ.isna().sum()
```

```
Out[10]: Gender                      0
Race                        0
Age_at_Release                0
Residence_PUMA                 0
Gang_Affiliated            3167
Supervision_Risk_Score_First    475
Supervision_Level_First        1720
Education_Level                  0
Dependents                     0
Prison_Offense                  3277
Prison_Years                     0
Prior_Arrest_Episodes_Felony      0
Prior_Arrest_Episodes_Misd       0
Prior_Arrest_Episodes_Violent     0
Prior_Arrest_Episodes_Property    0
Prior_Arrest_Episodes_Drug        0
Prior_Arrest_Episodes_PPViolationCharges 0
Prior_Arrest_Episodes_DVCharges    0
Prior_Arrest_Episodes_GunCharges   0
Prior_Conviction_Episodes_Felony    0
Prior_Conviction_Episodes_Misd      0
Prior_Conviction_Episodes_Viol     0
Prior_Conviction_Episodes_Prop     0
Prior_Conviction_Episodes_Drug      0
Prior_Conviction_Episodes_PPViolationCharges 0
Prior_Conviction_Episodes_DomesticViolenceCharges 0
Prior_Conviction_Episodes_GunCharges 0
Prior_Revolutions_Parole        0
Prior_Revolutions_Probation       0
Condition_MH_SA                  0
Condition_Cog_Ed                  0
Condition_Other                   0
Violations_ElectronicMonitoring    0
Violations_Instruction          0
Violations_FailToReport         0
Violations_MoveWithoutPermission   0
Delinquency_Reports                 0
Program_Attendances                0
Program_UnexcusedAbsences        0
Residence_Changes                  0
Avg_Days_per_DrugTest             6183
DrugTests_THC_Positive            5172
DrugTests_Cocaine_Positive        5172
```

```

DrugTests_Meth_Positive           5172
DrugTests_Other_Positive          5172
Percent_Days_Employed             462
Jobs_Per_Year                      888
Employment_Exempt                  0
Recidivism_Within_3years            0
dtype: int64

```

Replace null values with appropriate values:

- Gang_Affiliated is missing only for Female offenders so replace with NA
- Supervision_Risk_Score_First is INTEGER so replace with the most frequently occurring value
- Supervision_Level_First is CATEGORICAL so replace with the most frequently occurring value
- Prison_Offense is categorical and includes "Other" so replace with "Other"
- Avg_Days_per_DrugTest is FLOAT so replace with average value
- DrugTests_THC_Positive is FLOAT but replace with 0
- DrugTests_Cocaine_Positive is FLOAT but replace with 0
- DrugTests_Meth_Positive is FLOAT but replace with 0
- DrugTests_Other_Positive is FLOAT but replace with 0
- Percent_Days_Employed is FLOAT so replace with average value
- Jobs_Per_Year is FLOAT so replace with average value

```

In [11]: NIJ['Gang_Affiliated'].fillna('NA', inplace=True)
NIJ['Supervision_Risk_Score_First'].fillna(NIJ['Supervision_Risk_Score_First'].mode().iloc[0], inplace=True)
NIJ['Supervision_Level_First'].fillna(NIJ['Supervision_Level_First'].mode().iloc[0], inplace=True)
NIJ['Prison_Offense'].fillna('Other', inplace=True)
NIJ['Avg_Days_per_DrugTest'].fillna(NIJ['Avg_Days_per_DrugTest'].mean(), inplace=True)
NIJ['DrugTests_THC_Positive'].fillna('0', inplace=True)
NIJ['DrugTests_Cocaine_Positive'].fillna('0', inplace=True)
NIJ['DrugTests_Meth_Positive'].fillna('0', inplace=True)
NIJ['DrugTests_Other_Positive'].fillna('0', inplace=True)
NIJ['Percent_Days_Employed'].fillna(NIJ['Percent_Days_Employed'].mean(), inplace=True)
NIJ['Jobs_Per_Year'].fillna(NIJ['Jobs_Per_Year'].mean(), inplace=True)

```

Re-check to make sure there are no missing values

```
In [12]: NIJ.isna().sum()
```

```

Out[12]: Gender                   0
Race                      0
Age_at_Release              0
Residence_PUMA               0
Gang_Affiliated                0
Supervision_Risk_Score_First      0
Supervision_Level_First           0
Education_Level                  0
Dependents                     0
Prison_Offense                    0
Prison_Years                      0
Prior_Arrest_Episodes_Felony        0
Prior_Arrest_Episodes_Misd         0
Prior_Arrest_Episodes_Violent       0
Prior_Arrest_Episodes_Property       0
Prior_Arrest_Episodes_Drug          0
Prior_Arrest_Episodes_PPViolationCharges 0
Prior_Arrest_Episodes_DVCharges      0
Prior_Arrest_Episodes_GunCharges     0
Prior_Conviction_Episodes_Felony      0
Prior_Conviction_Episodes_Misd        0
Prior_Conviction_Episodes_Viol          0
Prior_Conviction_Episodes_Prop        0
Prior_Conviction_Episodes_Drug         0
Prior_Conviction_Episodes_PPViolationCharges 0
Prior_Conviction_Episodes_DomesticViolenceCharges 0
Prior_Conviction_Episodes_GunCharges    0
Prior_Revocations_Parole            0
Prior_Revocations_Probation          0
Condition_MM_SA                     0
Condition_Cog_Ed                     0
Condition_Other                      0
Violations_ElectronicMonitoring      0
Violations_Instruction                 0
Violations_FailToReport                 0
Violations_MoveWithoutPermission       0
Delinquency_Reports                   0
Program_Attendances                   0

```

```

Program_UnexcusedAbsences      0
Residence_Changes              0
Avg_Days_per_DrugTest          0
DrugTests_THC_Positive         0
DrugTests_Cocaine_Positive     0
DrugTests_Meth_Positive        0
DrugTests_Other_Positive       0
Percent_Days_Employed          0
Jobs_Per_Year                  0
Employment_Exempt              0
Recidivism_Within_3years       0
dtype: int64

```

Some features contain integers but max out with, "x or more". To enable numerical analysis the "or more" will be removed:

- Dependents: "3 or more" changed to "3"
- Prior_Arrest_Episodes_Felony: "10 more more" changed to "10"
- Prior_Arrest_Episodes_Misd: "6 or more" changed to "6"
- Prior_Arrest_Episodes_Violent: "3 or more" changed to "3"
- Prior_Arrest_Episodes_Property: "5 or more" changed to "5"
- Prior_Arrest_Episodes_Drug: "5 or more" changed to "5"
- Prior_Arrest_Episodes_PPViolationCharges: "5 or more" changed to "5"
- Prior_Conviction_Episodes_Felony.replace: "3 or more" changed to "3"
- Prior_Conviction_Episodes_Misd.replace: "4 or more" changed to "4"
- Prior_Conviction_Episodes_Prop.replace: "3 or more" changed to "3"
- Prior_Conviction_Episodes_Drug.replace: "2 or more" changed to "2"
- Delinquency_Reports: "4 or more" changed to "4"
- Program_Attendances: "10 more more" changed to "10"
- Program_UnexcusedAbsences: "3 or more" changed to "3"
- Residence_Changes: "3 or more" changed to "3"

```
In [13]: NIJ.Dependents.replace("3 or more","3", inplace=True)
NIJ.Prior_Arrest_Episodes_Felony.replace("10 or more","10", inplace=True)
NIJ.Prior_Arrest_Episodes_Misd.replace("6 or more","6", inplace=True)
NIJ.Prior_Arrest_Episodes_Violent.replace("3 or more","3", inplace=True)
NIJ.Prior_Arrest_Episodes_Property.replace("5 or more","5", inplace=True)
NIJ.Prior_Arrest_Episodes_Drug.replace("5 or more","5", inplace=True)
NIJ.Prior_Arrest_Episodes_PPViolationCharges.replace("5 or more","5", inplace=True)
NIJ.Prior_Conviction_Episodes_Felony.replace("3 or more","3", inplace=True)
NIJ.Prior_Conviction_Episodes_Misd.replace("4 or more","4", inplace=True)
NIJ.Prior_Conviction_Episodes_Prop.replace("3 or more","3", inplace=True)
NIJ.Prior_Conviction_Episodes_Drug.replace("2 or more","2", inplace=True)
NIJ.Delinquency_Reports.replace("4 or more","4", inplace=True)
NIJ.Program_Attendances.replace("10 or more","10", inplace=True)
NIJ.Program_UnexcusedAbsences.replace("3 or more","3", inplace=True)
NIJ.Residence_Changes.replace("3 or more","3", inplace=True)
```

Age_at_Release is populated with ranges which won't be assessed as numeric, so change each value to the first number in each range

```
In [14]: sorted(NIJ['Age_at_Release'].unique())
Out[14]: ['18-22', '23-27', '28-32', '33-37', '38-42', '43-47', '48 or older']
```

```
In [15]: NIJ.Age_at_Release.replace("18-22","18", inplace=True)
NIJ.Age_at_Release.replace("23-27","23", inplace=True)
NIJ.Age_at_Release.replace("28-32","28", inplace=True)
NIJ.Age_at_Release.replace("33-37","33", inplace=True)
NIJ.Age_at_Release.replace("38-42","38", inplace=True)
NIJ.Age_at_Release.replace("43-47","43", inplace=True)
NIJ.Age_at_Release.replace("48 or older","48", inplace=True)
```

```
In [16]: sorted(NIJ['Age_at_Release'].unique())
Out[16]: ['18', '23', '28', '33', '38', '43', '48']
```

Now replace M with Male and F with Female in Gender to make it easier to read later after the are one-hot encoded

```
In [17]: NIJ.Gender.replace("M","Male", inplace=True)
NIJ.Gender.replace("F","Female", inplace=True)
```

```
In [18]: NIJ
```

	Gender	Race	Age_at_Release	Residence_PUMA	Gang_Affiliated	Supervision_Risk_Score_First	Supervision_Level_First	Educa
0	Male	BLACK	43	16	False	3.0	Standard	At
1	Male	BLACK	33	16	False	6.0	Specialized	Le
2	Male	BLACK	48	24	False	7.0	High	At
3	Male	WHITE	38	16	False	7.0	High	Le
4	Male	WHITE	33	16	False	4.0	Specialized	Le
...
25830	Male	BLACK	23	9	False	5.0	Standard	At
25831	Male	WHITE	38	25	False	5.0	Standard	At
25832	Male	BLACK	33	15	False	5.0	Standard	At
25833	Female	WHITE	33	15	NA	5.0	Standard	At
25834	Male	WHITE	28	12	False	5.0	Standard	H

25835 rows × 49 columns

Now convert all of the modified columns to numeric.

```
In [19]: NIJ[["Dependents"]] = NIJ[["Dependents"]].apply(pd.to_numeric)
NIJ[["Prior_Arrest_Episodes_Felony", "Prior_Arrest_Episodes_Misd"]] = NIJ[["Prior_Arrest_Episodes_Felony", "Prior_Arrest_Episodes_Misd"]].apply(pd.to_numeric)
NIJ[["Prior_Arrest_Episodes_Violent", "Prior_Arrest_Episodes_Property"]] = NIJ[["Prior_Arrest_Episodes_Violent", "Prior_Arrest_Episodes_Property"]].apply(pd.to_numeric)
NIJ[["Prior_Arrest_Episodes_Drug", "Prior_Arrest_Episodes_PPViolationCharges"]] = NIJ[["Prior_Arrest_Episodes_Drug", "Prior_Arrest_Episodes_PPViolationCharges"]].apply(pd.to_numeric)
NIJ[["Prior_Conviction_Episodes_Felony", "Prior_Conviction_Episodes_Misd"]] = NIJ[["Prior_Conviction_Episodes_Felony", "Prior_Conviction_Episodes_Misd"]].apply(pd.to_numeric)
NIJ[["Prior_Conviction_Episodes_Prop", "Prior_Conviction_Episodes_Drug"]] = NIJ[["Prior_Conviction_Episodes_Prop", "Prior_Conviction_Episodes_Drug"]].apply(pd.to_numeric)
NIJ[["Delinquency_Reports", "Program_Attendances"]] = NIJ[["Delinquency_Reports", "Program_Attendances"]].apply(pd.to_numeric)
NIJ[["Program_UnexcusedAbsences", "Residence_Changes"]] = NIJ[["Program_UnexcusedAbsences", "Residence_Changes"]].apply(pd.to_numeric)
NIJ[["DrugTests_THC_Positive", "DrugTests_Cocaine_Positive"]] = NIJ[["DrugTests_THC_Positive", "DrugTests_Cocaine_Positive"]].apply(pd.to_numeric)
NIJ[["DrugTests_Meth_Positive", "DrugTests_Other_Positive"]] = NIJ[["DrugTests_Meth_Positive", "DrugTests_Other_Positive"]].apply(pd.to_numeric)
NIJ[["Age_at_Release"]] = NIJ[["Age_at_Release"]].apply(pd.to_numeric)
```

```
In [20]: NIJ['Prior_Arrest_Episodes_Misd'].unique()
```

```
Out[20]: array([6, 4, 0, 1, 3, 5, 2])
```

```
In [21]: NIJ['Gang_Affiliated'] = NIJ['Gang_Affiliated'].astype('bool')
```

Exploratory Data Analysis

Examine numerical and categorical features.

```
In [22]: numeric_features = NIJ.select_dtypes(include=[np.number])
numeric_features.columns
```

```
Out[22]: Index(['Age_at_Release', 'Residence_PUMA', 'Supervision_Risk_Score_First',
       'Dependents', 'Prior_Arrest_Episodes_Felony',
       'Prior_Arrest_Episodes_Misd', 'Prior_Arrest_Episodes_Violent',
```

```
'Prior_Arrest_Episodes_Property', 'Prior_Arrest_Episodes_Drug',
'Prior_Arrest_Episodes_PPViolationCharges',
'Prior_Conviction_Episodes_Felony', 'Prior_Conviction_Episodes_Misd',
'Prior_Conviction_Episodes_Prob', 'Prior_Conviction_Episodes_Drug',
'Delinquency_Reports', 'Program_Attendances',
'Program_UncexcusedAbsences', 'Residence_Changes',
'Avg_Days_per_DrugTest', 'DrugTests_THC_Positive',
'DrugTests_Cocaine_Positive', 'DrugTests_Meth_Positive',
'DrugTests_Other_Positive', 'Percent_Days_Employed', 'Jobs_Per_Year'],
dtype='object')
```

In [23]: categorical_features = NIJ.select_dtypes(include=[object])
categorical_features.columns

Out[23]: Index(['Gender', 'Race', 'Supervision_Level_First', 'Education_Level',
'Prison_Offense', 'Prison_Years'],
dtype='object')

Estimate Skewness and Kurtosis of numerical features

In [24]: numeric_features.skew()

Age_at_Release	0.262007
Residence_PUMA	0.098668
Supervision_Risk_Score_First	-0.136975
Dependents	0.050562
Prior_Arrest_Episodes_Felony	0.040836
Prior_Arrest_Episodes_Misd	-0.115781
Prior_Arrest_Episodes_Violent	0.688265
Prior_Arrest_Episodes_Property	0.321845
Prior_Arrest_Episodes_Drug	0.616521
Prior_Arrest_Episodes_PPViolationCharges	0.196785
Prior_Conviction_Episodes_Felony	0.160138
Prior_Conviction_Episodes_Misd	0.295852
Prior_Conviction_Episodes_Prob	0.546661
Prior_Conviction_Episodes_Drug	0.442748
Delinquency_Reports	1.162612
Program_Attendances	0.819652
Program_UncexcusedAbsences	2.093484
Residence_Changes	0.941644
Avg_Days_per_DrugTest	3.998832
DrugTests_THC_Positive	3.948409
DrugTests_Cocaine_Positive	8.049606
DrugTests_Meth_Positive	10.485032
DrugTests_Other_Positive	12.752432
Percent_Days_Employed	0.035112
Jobs_Per_Year	1.485389

Out[24]: numeric_features.kurt()

Age_at_Release	-1.092770
Residence_PUMA	-1.239448
Supervision_Risk_Score_First	-0.734744
Dependents	-1.560358
Prior_Arrest_Episodes_Felony	-1.362785
Prior_Arrest_Episodes_Misd	-1.515982
Prior_Arrest_Episodes_Violent	-0.857591
Prior_Arrest_Episodes_Property	-1.373212
Prior_Arrest_Episodes_Drug	-0.880327
Prior_Arrest_Episodes_PPViolationCharges	-1.488162
Prior_Conviction_Episodes_Felony	-1.446276
Prior_Conviction_Episodes_Misd	-1.415184
Prior_Conviction_Episodes_Prob	-1.237449
Prior_Conviction_Episodes_Drug	-1.427408
Delinquency_Reports	-0.425493
Program_Attendances	-0.877871
Program_UncexcusedAbsences	2.852693
Residence_Changes	-0.395310
Avg_Days_per_DrugTest	22.621673
DrugTests_THC_Positive	20.278025
DrugTests_Cocaine_Positive	88.639150
DrugTests_Meth_Positive	154.769982
DrugTests_Other_Positive	247.210002
Percent_Days_Employed	-1.720006
Jobs_Per_Year	3.325226

Correlations

```
In [26]: # NJJ.corr(method = 'pearson')  
numeric_features.corr()
```

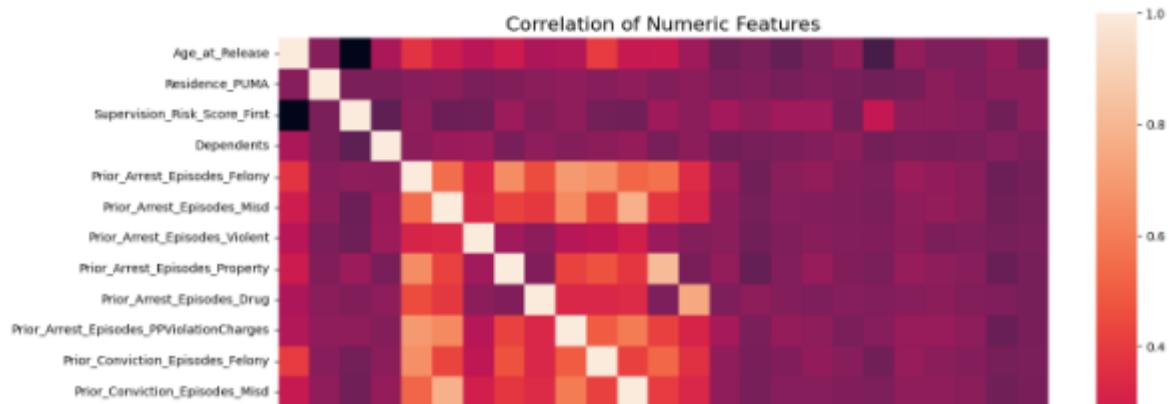
```
Out[26]:
```

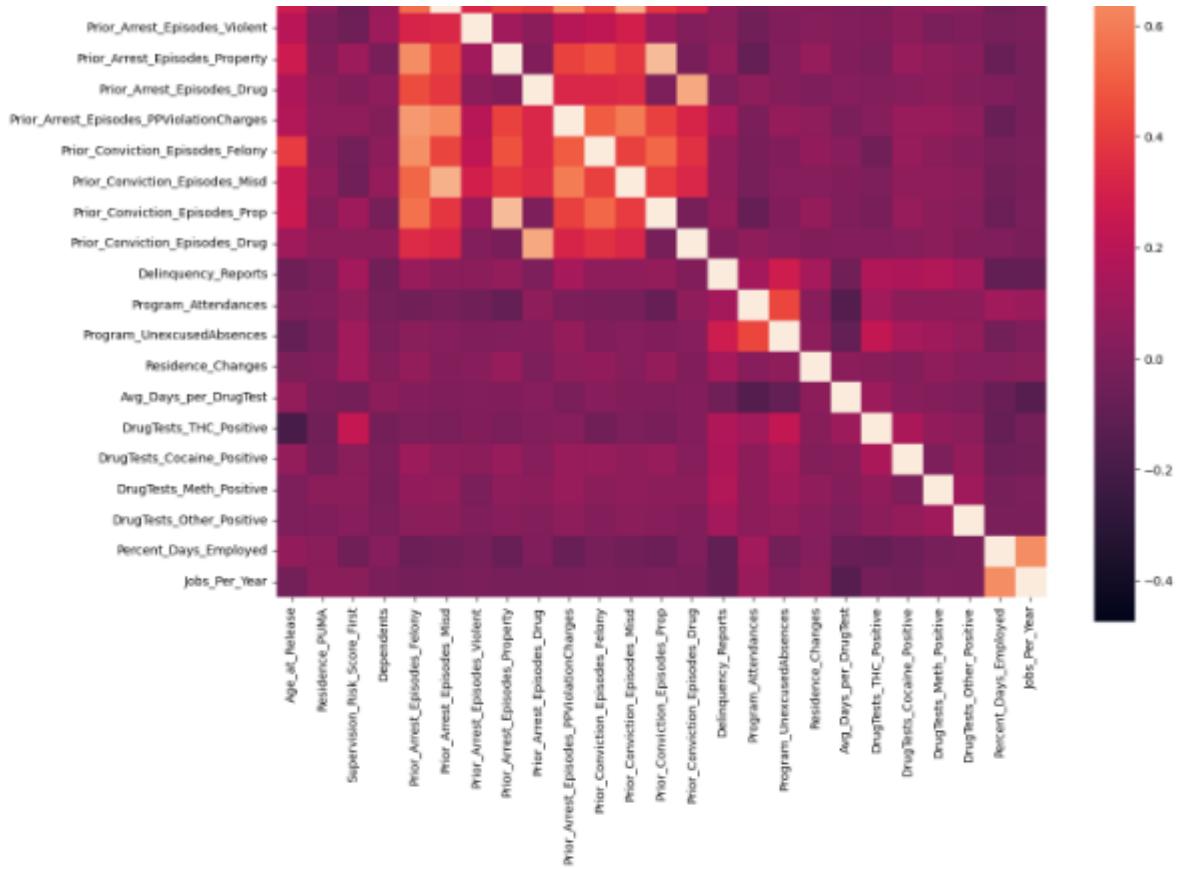
	Age_at_Release	Residence_PUMA	Supervision_Risk_Score_First	Dependents	Prior_Arrest_Epi
Age_at_Release	1.000000	0.022132	-0.474483	0.149536	
Residence_PUMA	0.022132	1.000000	-0.009568	-0.010828	
Supervision_Risk_Score_First	-0.474483	-0.009568	1.000000	-0.113169	
Dependents	0.149536	-0.010828	-0.113169	1.000000	
Prior_Arrest_Episodes_Felony	0.370477	0.028485	0.049855	0.046847	
Prior_Arrest_Episodes_Misd	0.272936	0.047212	-0.068378	0.092013	
Prior_Arrest_Episodes_Violent	0.193949	-0.013974	-0.062500	0.101109	
Prior_Arrest_Episodes_Property	0.263956	0.006619	0.097777	-0.020090	
Prior_Arrest_Episodes_Drug	0.155872	0.036650	0.006608	0.051614	
Prior_Arrest_Episodes_PPViolationCharges	0.173532	0.060351	0.060859	0.018629	
Prior_Conviction_Episodes_Felony	0.398924	0.027633	-0.041738	0.040165	
Prior_Conviction_Episodes_Misd	0.246866	0.058480	-0.051761	0.072735	
Prior_Conviction_Episodes_Prop	0.254130	0.009848	0.101852	-0.026460	
Prior_Conviction_Episodes_Drug	0.106459	0.046625	0.033248	0.040581	
Delinquency_Reports	-0.059886	-0.017291	0.126960	-0.049473	
Program_Attendances	-0.009654	-0.000652	0.061068	-0.025537	
Program_UnexcusedAbsences	-0.092027	-0.028561	0.117546	-0.017636	
Residence_Changes	-0.009472	-0.001424	0.118164	0.010702	
Avg_Days_per_DrugTest	0.067365	-0.024877	-0.036588	0.041916	
DrugTests_THC_Positive	-0.195092	-0.044197	0.240734	-0.034796	
DrugTests_Cocaine_Positive	0.067101	-0.031516	0.032673	-0.011982	
DrugTests_Meth_Positive	-0.002315	0.040276	0.047783	-0.024194	
DrugTests_Other_Positive	-0.002634	0.003403	0.029040	-0.015315	
Percent_Days_Employed	0.062651	0.034806	-0.045773	0.024515	
Jobs_Per_Year	-0.039791	0.044123	0.032629	-0.012196	

25 rows × 25 columns

```
In [27]: correlation = numeric_features.corr()  
f , ax = plt.subplots(figsize = (14,12))  
plt.title('Correlation of Numeric Features',y=1,size=16)  
sns.heatmap(correlation,square = True)
```

```
Out[27]: <Axes: title={'center': 'Correlation of Numeric Features'}>
```





In [28]:

```
pip install dython

Requirement already satisfied: dython in /usr/local/lib/python3.10/dist-packages (0.7.6)
Requirement already satisfied: numpy>=1.23.0 in /usr/local/lib/python3.10/dist-packages (from dython) (1.25.2)
Requirement already satisfied: pandas>=1.4.2 in /usr/local/lib/python3.10/dist-packages (from dython) (2.0.3)
Requirement already satisfied: seaborn>=0.12.0 in /usr/local/lib/python3.10/dist-packages (from dython) (0.13.1)
Requirement already satisfied: scipy>=1.7.1 in /usr/local/lib/python3.10/dist-packages (from dython) (1.11.4)
Requirement already satisfied: matplotlib>=3.6.0 in /usr/local/lib/python3.10/dist-packages (from dython) (3.7.1)
Requirement already satisfied: scikit-learn>=0.24.2 in /usr/local/lib/python3.10/dist-packages (from dython) (1.2.2)
Requirement already satisfied: psutil>=5.9.1 in /usr/local/lib/python3.10/dist-packages (from dython) (5.9.5)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.6.0->dython) (1.2.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.6.0->dython) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.6.0->dython) (4.53.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.6.0->dython) (1.4.5)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.6.0->dython) (24.1)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.6.0->dython) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.6.0->dython) (3.1.2)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.6.0->dython) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.4.2->dython) (2023.4)
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.4.2->dython) (2024.1)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.24.2->dython) (1.4.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.24.2->dython) (3.5.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib>=3.6.0->dython) (1.16.0)
```

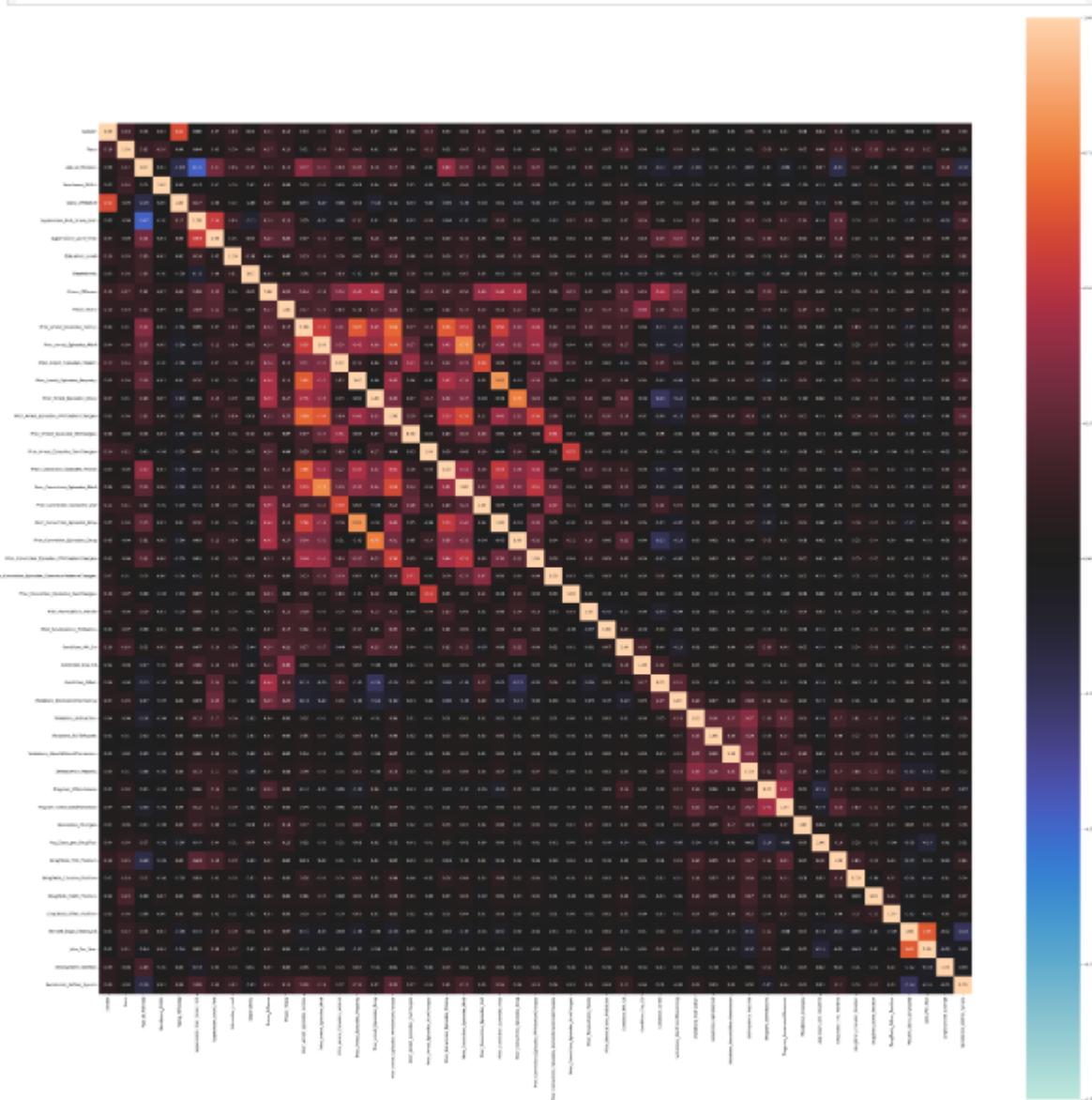
In [29]:

```
from dython.nominal import identify_nominal_columns
categorical_features=identify_nominal_columns(NIJ)
categorical_features
```

```
Out[29]: ['Gender',
 'Race',
 'Supervision_Level_First',
 'Education_Level',
 'Prison_Offense',
 'Prison_Years']
```

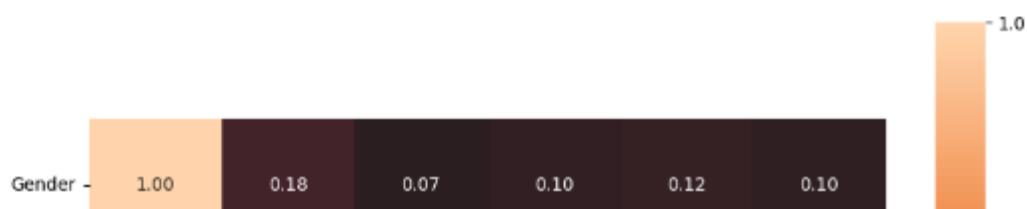
```
In [30]: from dython.nominal import associations
```

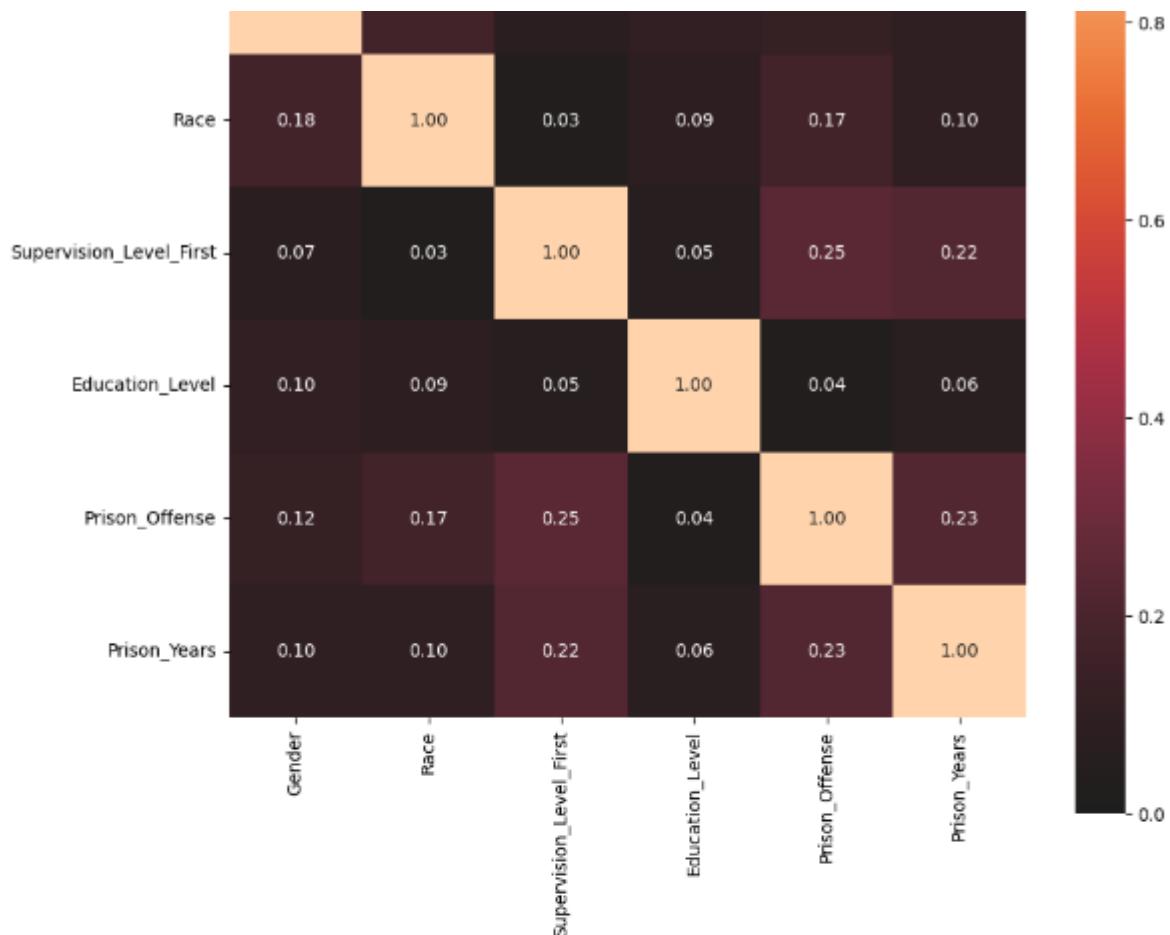
```
In [31]: complete_correlation=associations(NIJ, figsize=(50,50))
```



```
In [32]: selected_column= NIJ[categorical_features]
categorical_df = selected_column.copy()

categorical_correlation= associations(categorical_df, filename= 'categorical_correlation.png', figsize=(10,10))
```





Create a new dataframe for key features with that feature one hot encoded test correlations with that feature.

```
In [33]: one_hot = pd.get_dummies(NIJ.Gender)
NIJ = pd.concat([NIJ, one_hot], axis=1)

one_hot = pd.get_dummies(NIJ.Race)
NIJ = pd.concat([NIJ, one_hot], axis=1)

one_hot = pd.get_dummies(NIJ.Age_at_Release)
NIJ = pd.concat([NIJ, one_hot], axis=1)

one_hot = pd.get_dummies(NIJ.Supervision_Level_First)
NIJ = pd.concat([NIJ, one_hot], axis=1)

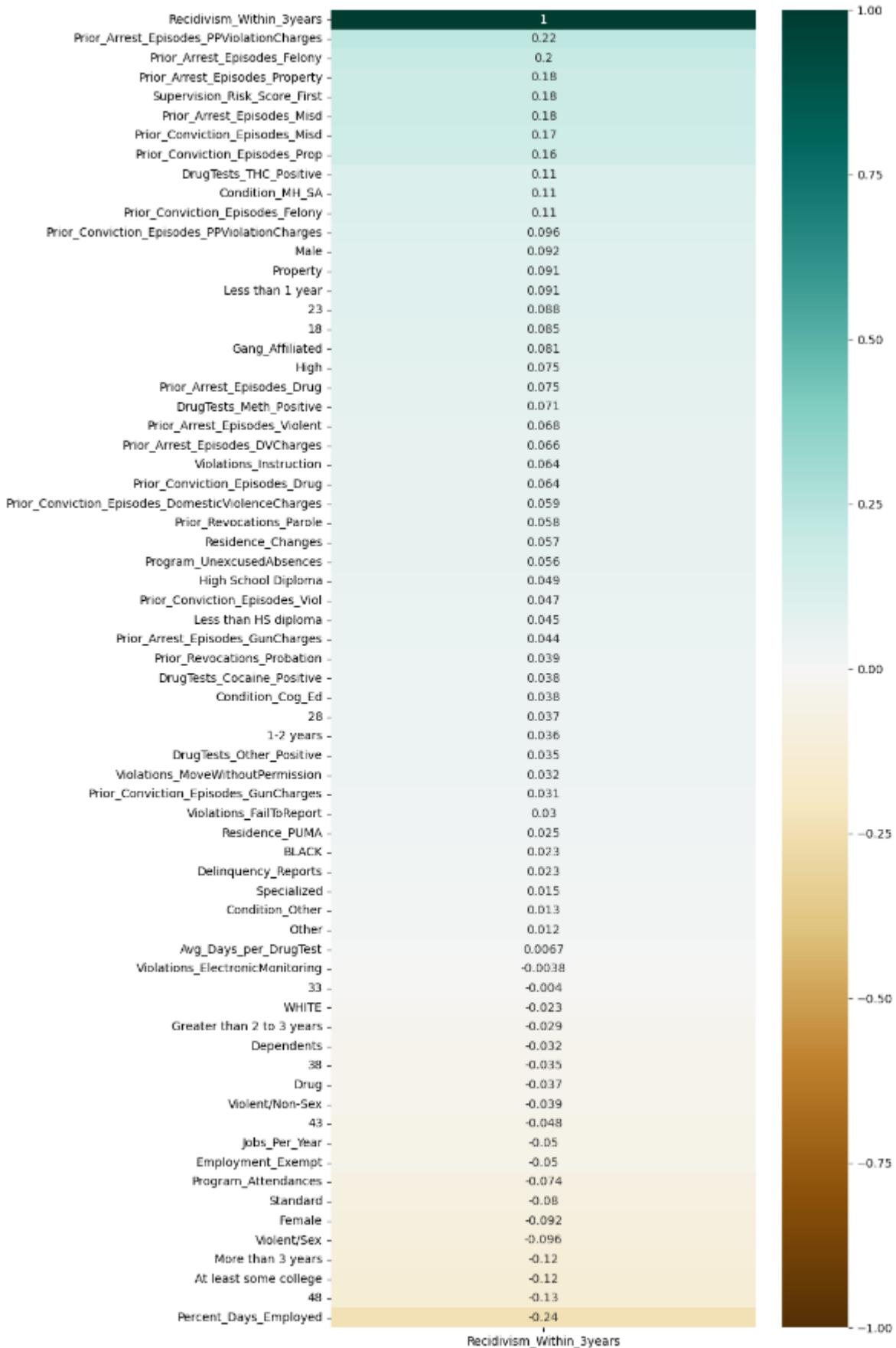
one_hot = pd.get_dummies(NIJ.Education_Level)
NIJ = pd.concat([NIJ, one_hot], axis=1)

one_hot = pd.get_dummies(NIJ.Prison_Offense)
NIJ = pd.concat([NIJ, one_hot], axis=1)

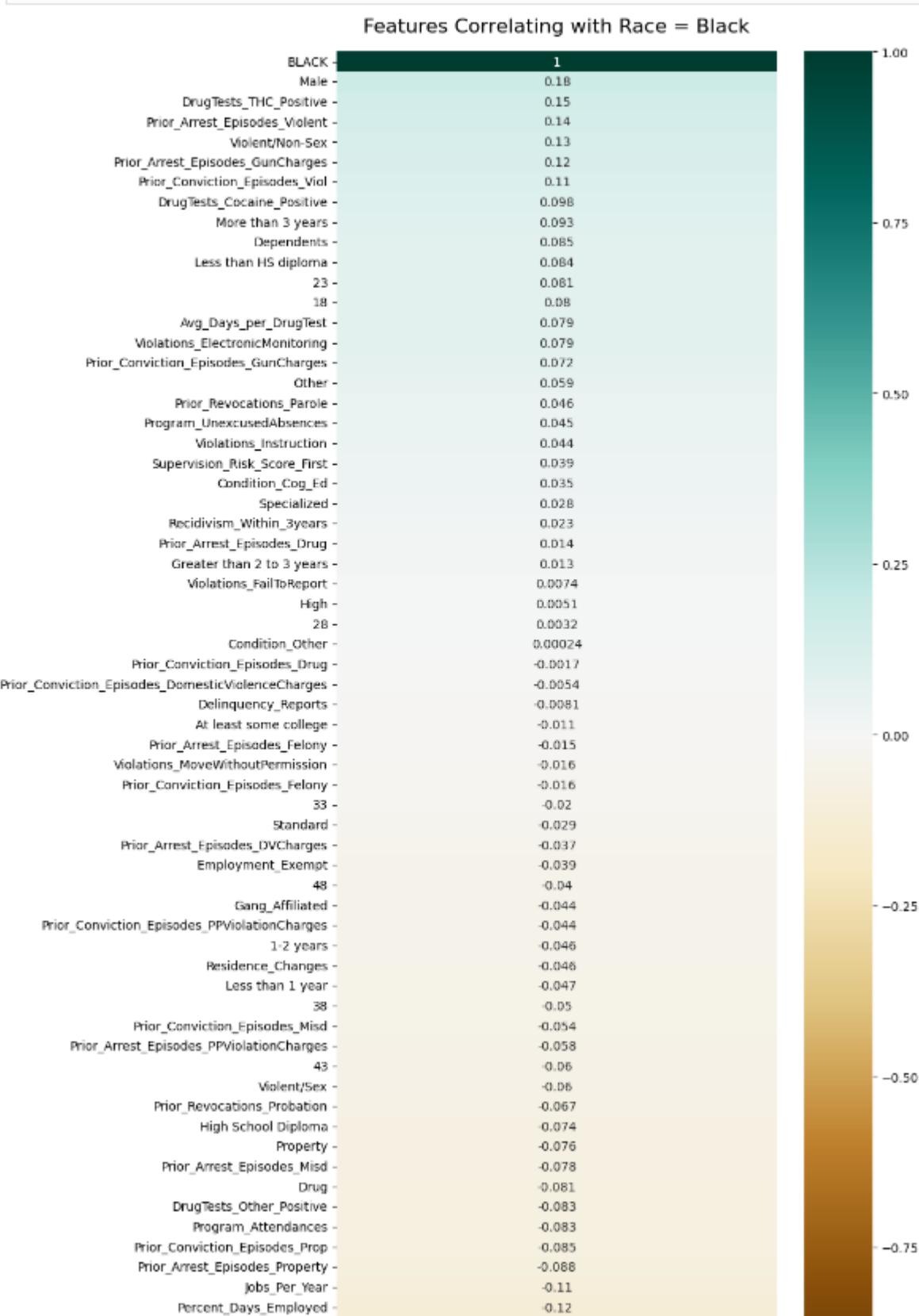
one_hot = pd.get_dummies(NIJ.Prison_Years)
NIJ = pd.concat([NIJ, one_hot], axis=1)
NIJ.drop(columns=['Gender', 'Race', 'Age_at_Release', 'Supervision_Level_First', 'Education_Level', 'Prison_Offense', 'Prison_Years'], axis=1)
```

```
In [34]: plt.figure(figsize=(8, 8))
heatmap = sns.heatmap(NIJ.corr(method ='pearson')[['Recidivism_Within_3years']].sort_values(by='Recidivism_Within_3years', ascending=False).set_title('Features Correlating with Recidivism', fontdict={'fontsize':16}, pad=16);
```

Features Correlating with Recidivism

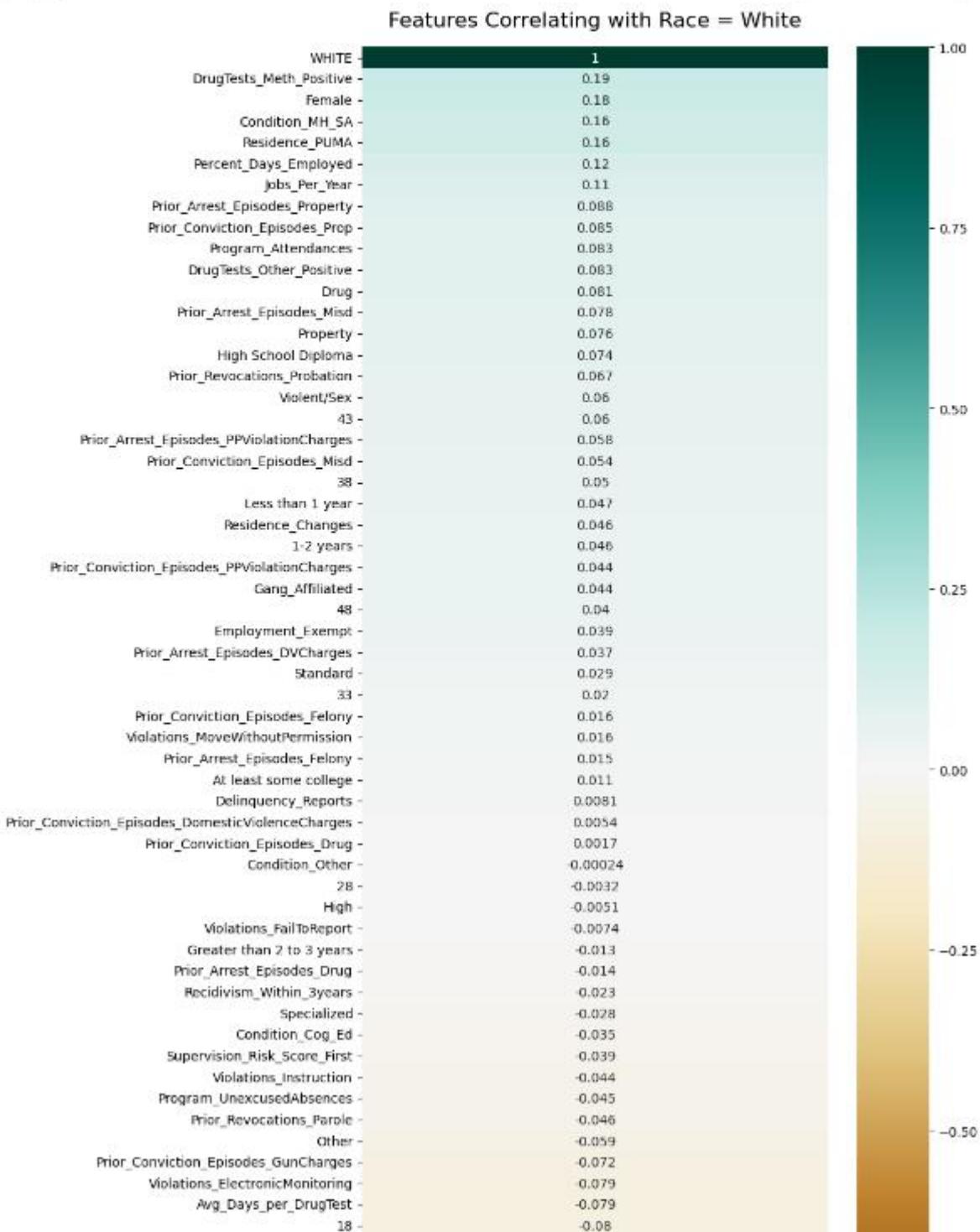


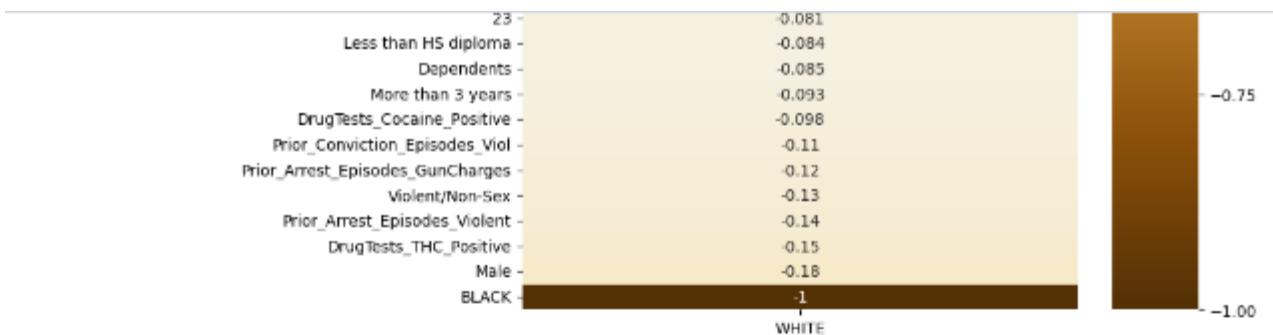
```
In [35]: plt.figure(figsize=(8, 20))
heatmap = sns.heatmap(NIJ.corr(method='pearson')[['BLACK']].sort_values(by='BLACK', ascending=False), vmin=-1, vmax=1,
                      heatmap.set_title('Features Correlating with Race = Black', fontdict={'fontsize':16}, pad=16);
```



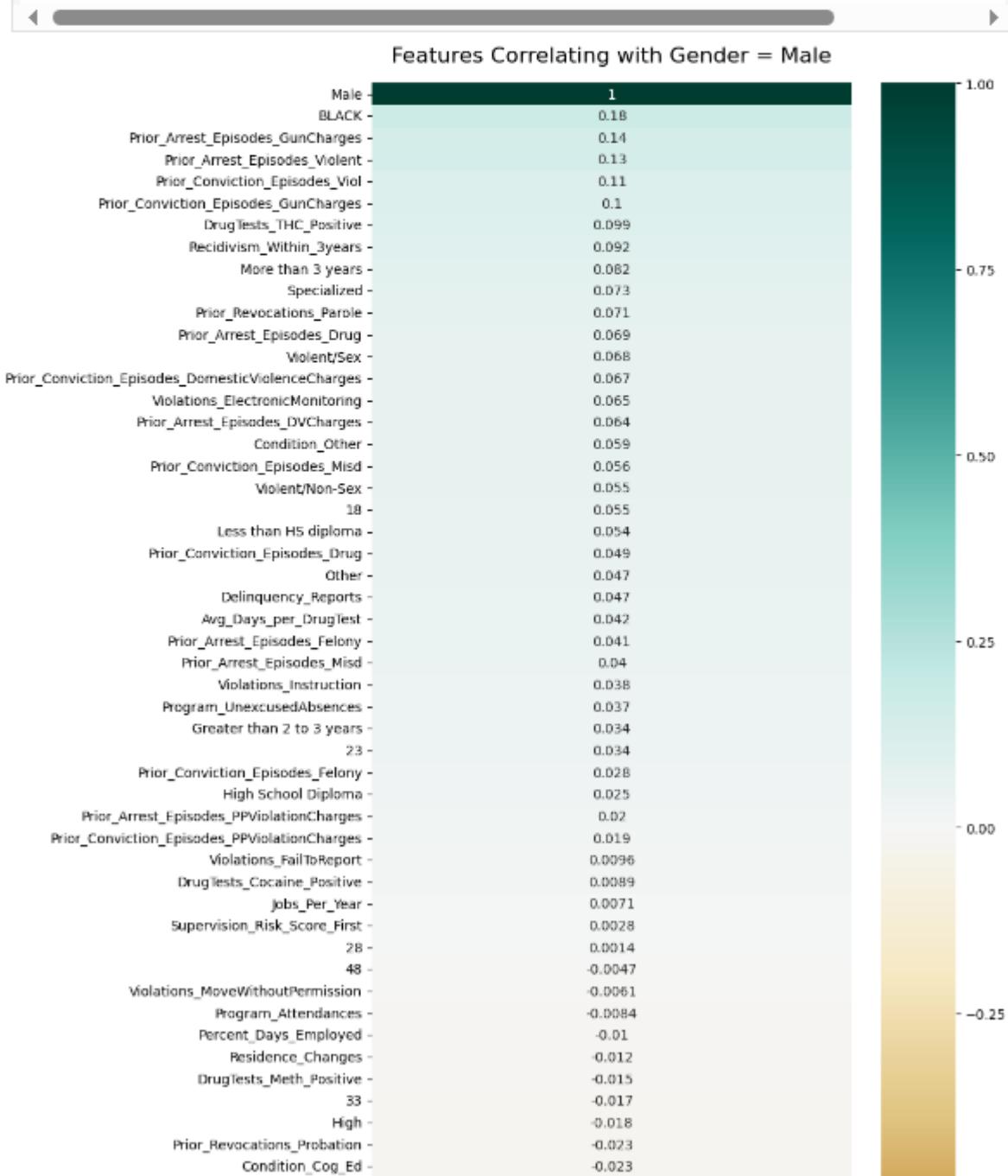


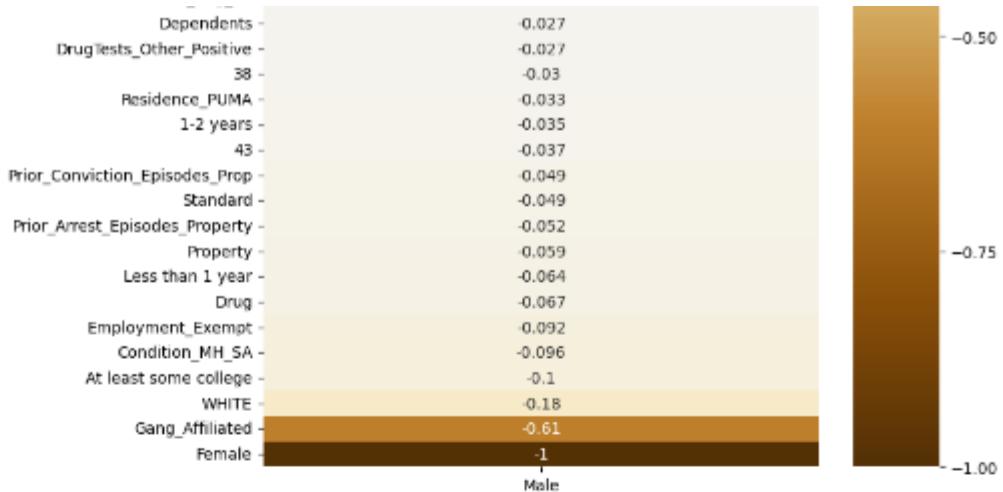
```
In [36]: plt.figure(figsize=(8, 20))
heatmap = sns.heatmap(NIJ corr(method = 'pearson')[['WHITE']].sort_values(by='WHITE', ascending=False), vmin=-1, vmax=1,
                      heatmap.set_title('Features Correlating with Race = White', fontdict={'fontsize':16}, pad=16);
```



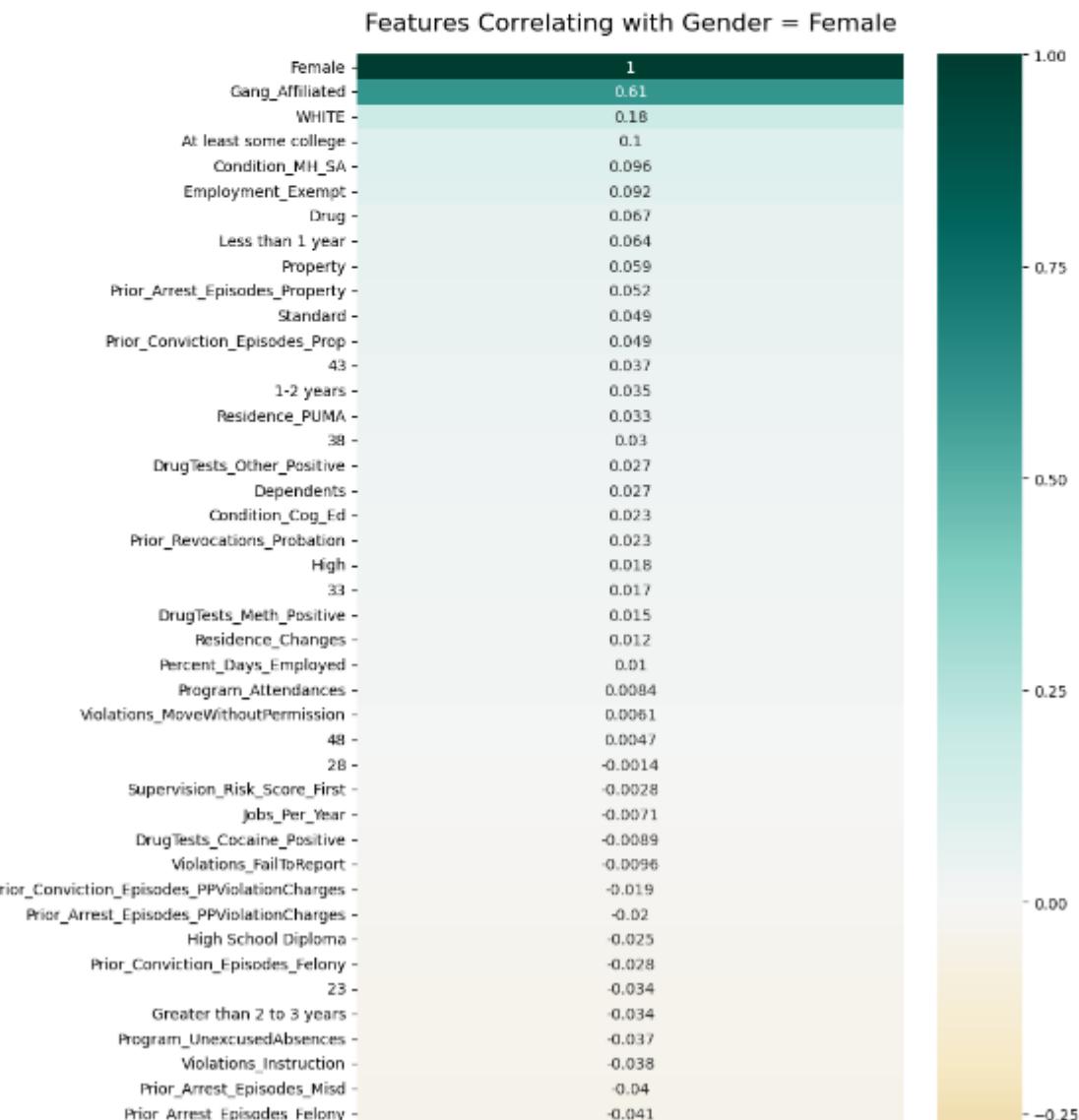


```
In [37]: plt.figure(figsize=(8, 20))
heatmap = sns.heatmap(NIJ.corr(method ='pearson')[['Male']].sort_values(by='Male', ascending=False), vmin=-1, vmax=1, annot=True, cmap='viridis', title='Features Correlating with Gender = Male', fontdict={'fontsize':16}, pad=16);
```





```
In [38]: plt.figure(figsize=(8, 20))
heatmap = sns.heatmap(NIJ.corr(method ='pearson')[['Female']].sort_values(by='Female', ascending=False), vmin=-1, vmax=1
heatmap.set_title('Features Correlating with Gender = Female', fontdict={'fontsize':16}, pad=16);
```





Check again with dataset with only male offenders and female offenders

```
In [39]: Male = NIJ.copy()
Male.drop(Male[Male.Male == False].index, inplace=True)
Male.drop(columns=['Male', 'Female'], inplace=True)
Male
```

```
Out[39]:
```

	Residence_PUMA	Gang_Affiliated	Supervision_Risk_Score_First	Dependents	Prior_Arrest_Episodes_Felony	Prior_Arrest_Episode
0	16	False	3.0	3	6	
1	16	False	6.0	1	7	
2	24	False	7.0	3	6	
3	16	False	7.0	1	8	
4	16	False	4.0	3	4	
...	
25829	5	False	5.0	3	1	
25830	9	False	5.0	1	2	
25831	25	False	5.0	3	0	
25832	15	False	5.0	3	0	
25834	12	False	5.0	3	6	

22668 rows × 66 columns

```
In [40]: Female = NIJ.copy()
Female.drop(Female[Female.Female == False].index, inplace=True)
Female.drop(columns=['Male', 'Female'], inplace=True)
Female
```

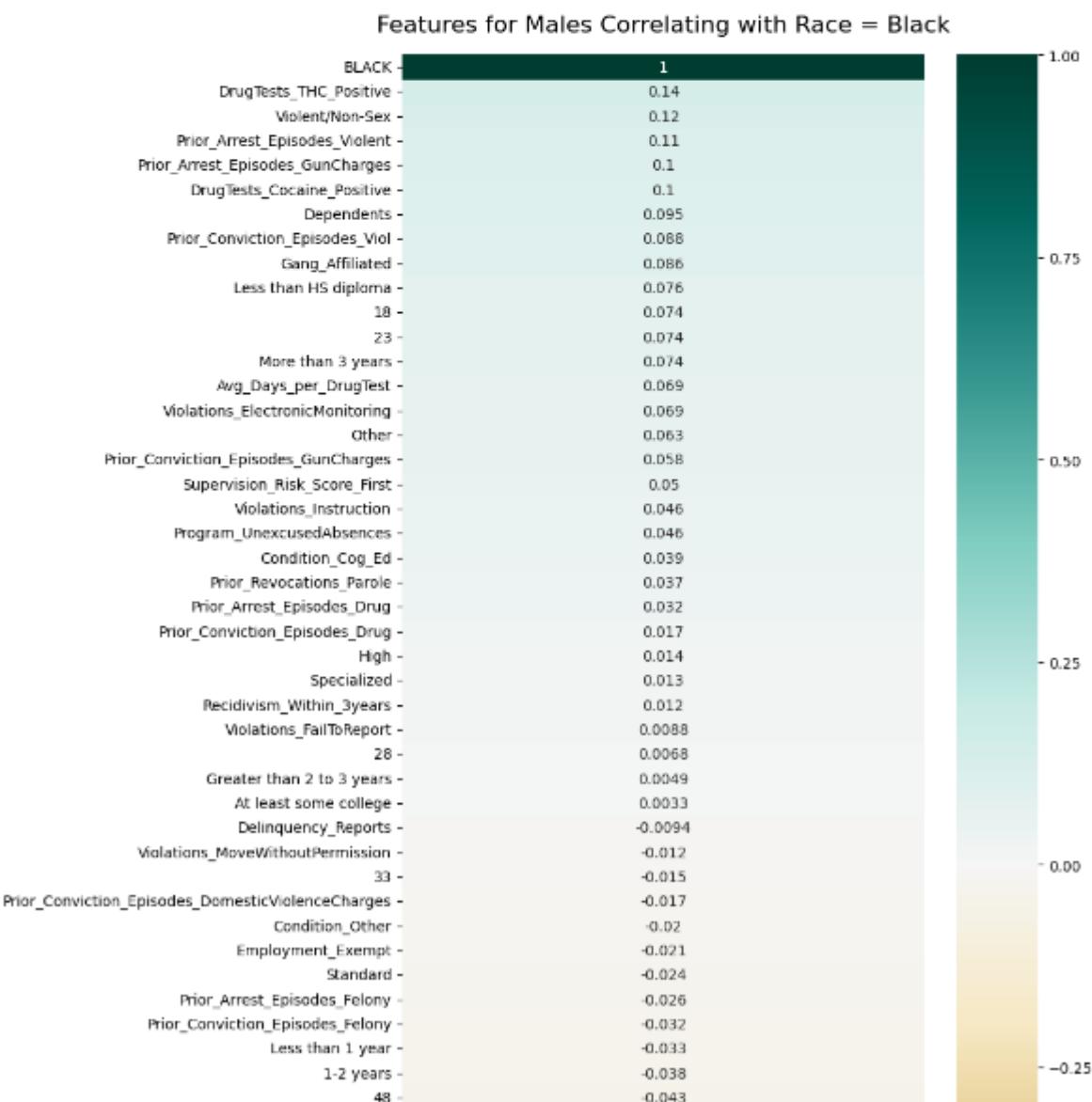
```
Out[40]:
```

	Residence_PUMA	Gang_Affiliated	Supervision_Risk_Score_First	Dependents	Prior_Arrest_Episodes_Felony	Prior_Arrest_Episode
8	5	True	7.0	0	10	

22	5	True	4.0	0	2
23	16	True	5.0	0	10
31	16	True	9.0	0	10
33	12	True	10.0	3	10
...
25779	22	True	8.0	3	1
25783	22	True	9.0	1	3
25790	20	True	7.0	3	1
25803	15	True	5.0	0	5
25833	15	True	5.0	3	0

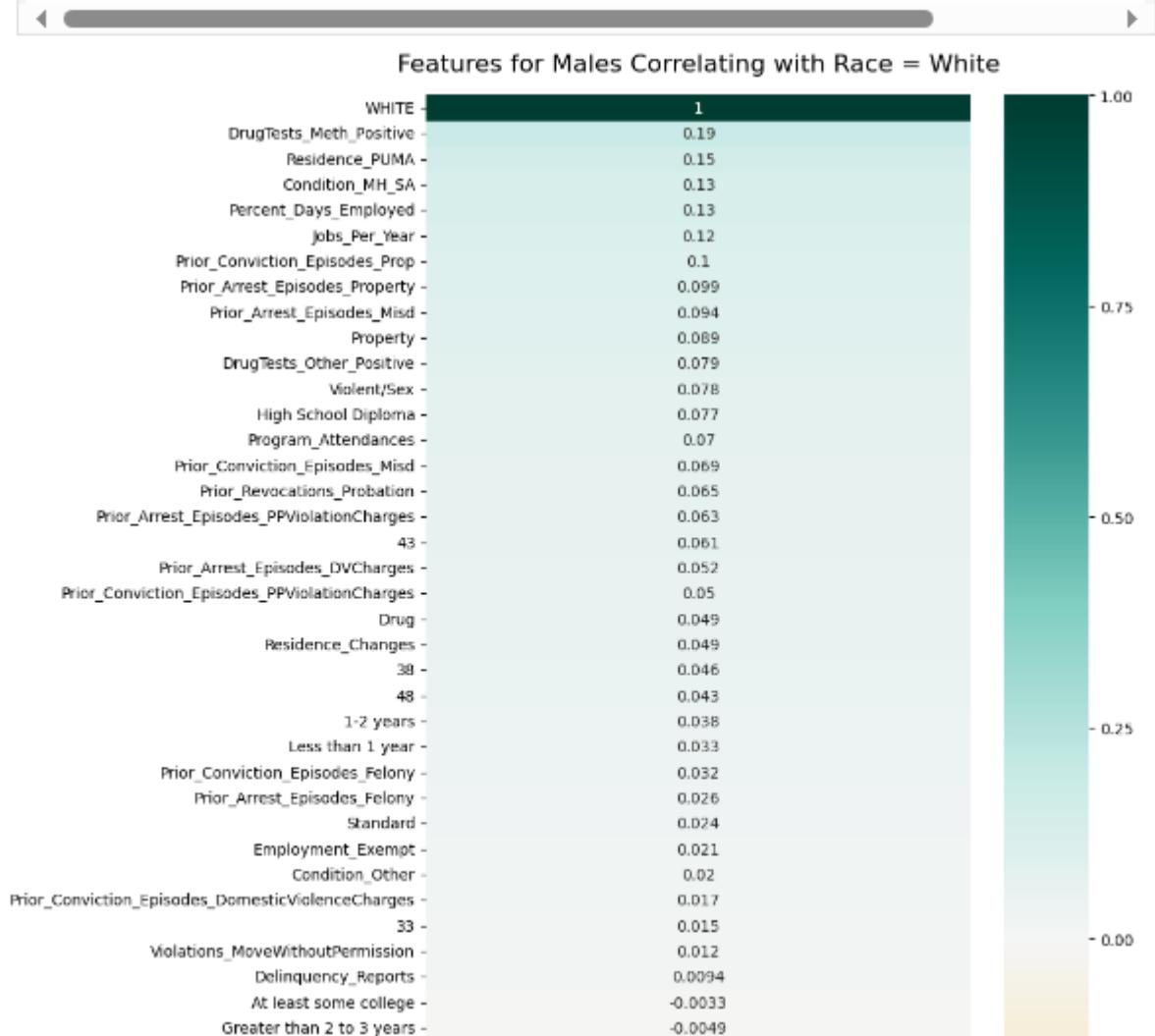
3167 rows × 66 columns

```
In [41]: plt.figure(figsize=(8, 20))
heatmap = sns.heatmap(Male.corr(method ='pearson')[['BLACK']].sort_values(by='BLACK', ascending=False), vmin=-1, vmax=1,
heatmap.set_title('Features for Males Correlating with Race = Black', fontdict={'fontsize':16}, pad=16);
```



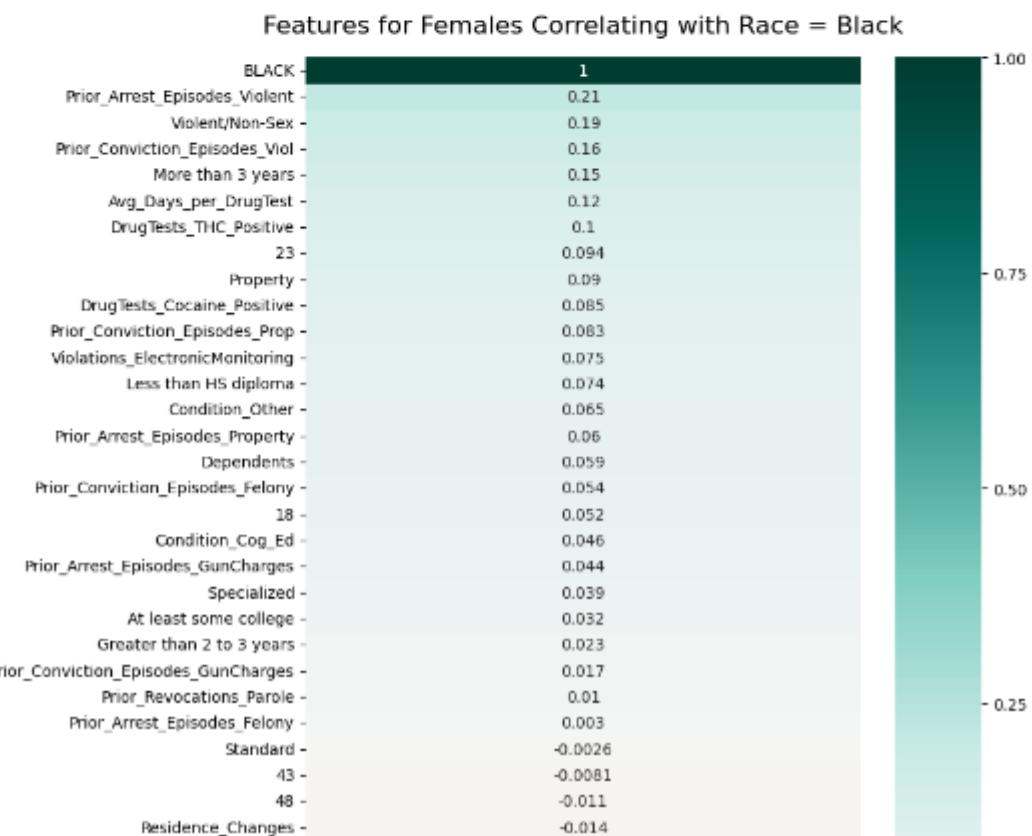


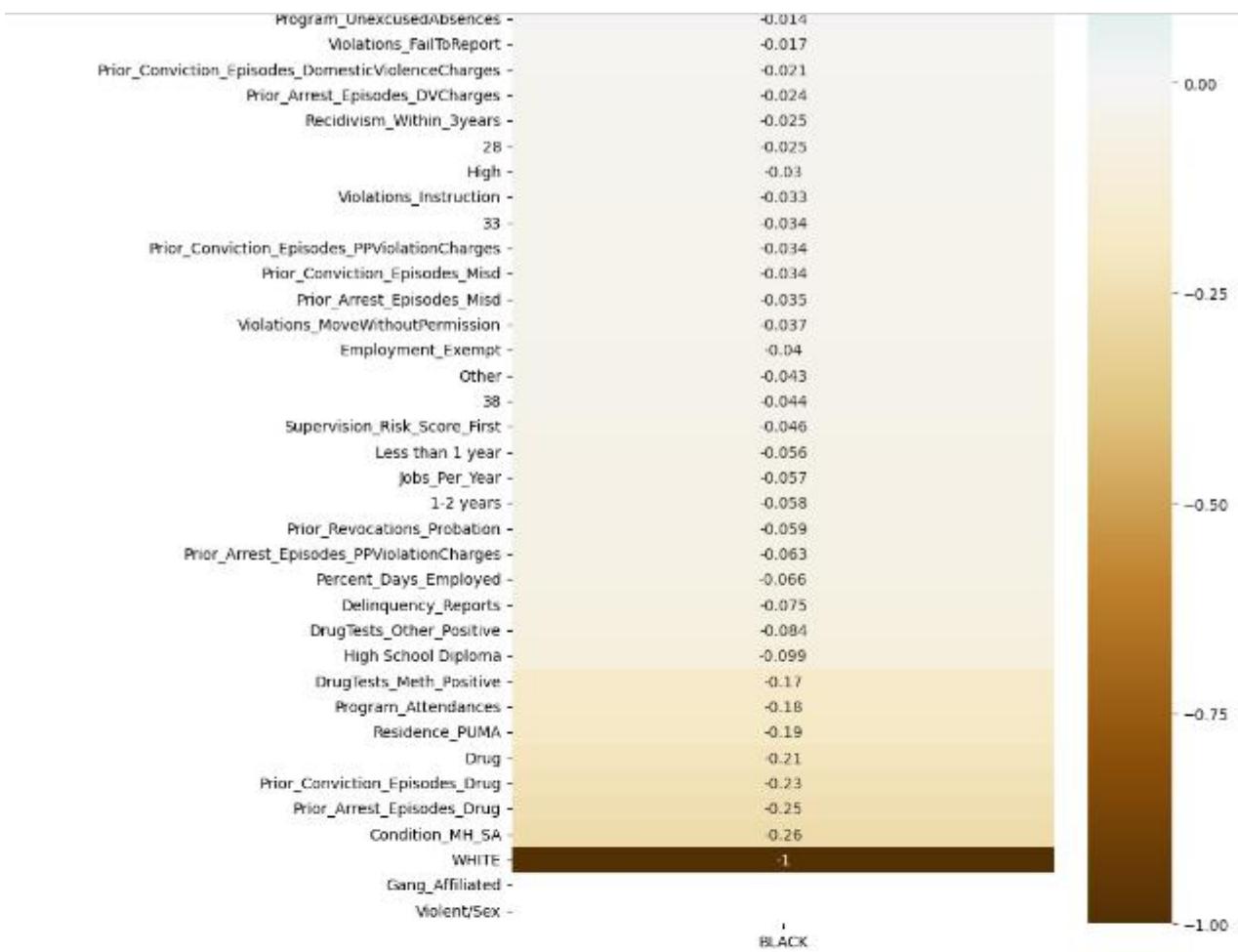
```
In [42]: plt.figure(figsize=(8, 20))
heatmap = sns.heatmap(Male.corr(method ='pearson')[['WHITE']].sort_values(by='WHITE', ascending=False), vmin=-1, vmax=1,
                      heatmap.set_title('Features for Males Correlating with Race = White', fontdict={'fontsize':16}, pad=16);
```



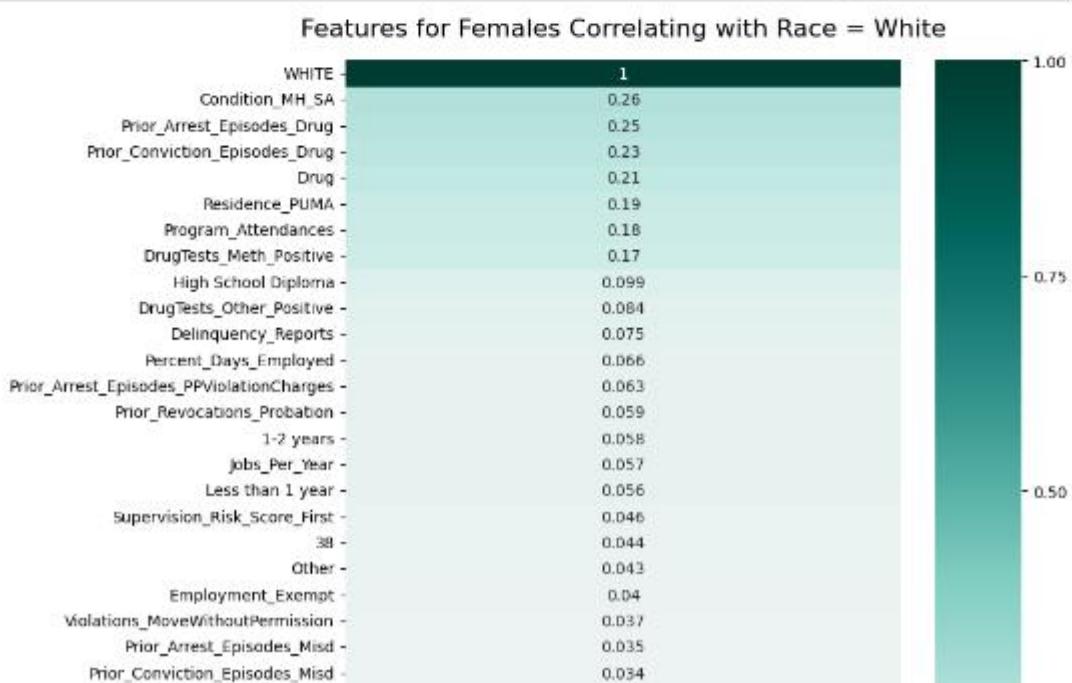


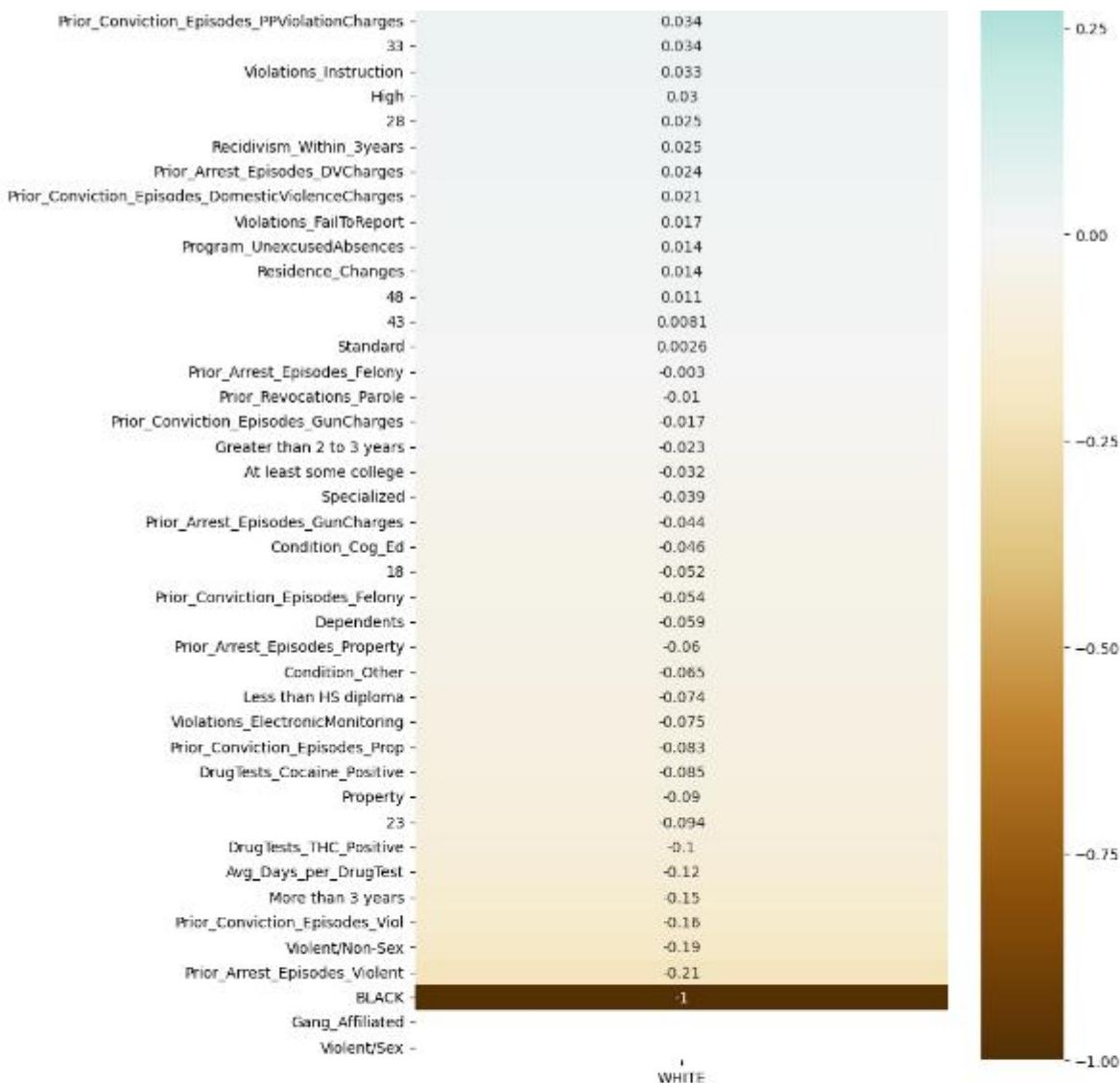
```
In [43]: plt.figure(figsize=(8, 20))
heatmap = sns.heatmap(Female.corr(method = 'pearson')[['BLACK']].sort_values(by='BLACK', ascending=False), vmin=-1, vmax=1, center=0, square=True, annot=True, fmt='.2f', cmap='RdYlGn', cbar_kws={'label': 'Correlation Value'})
heatmap.set_title('Features for Females Correlating with Race = Black', fontdict={'fontsize':16}, pad=16);
```





```
In [44]: plt.figure(figsize=(8, 20))
heatmap = sns.heatmap(Female.corr(method='pearson')[['WHITE']].sort_values(by='WHITE', ascending=False), vmin=-1, vmax=1)
heatmap.set_title('Features for Females Correlating with Race = White', fontdict={'fontsize':16}, pad=16);
```





```
In [45]: BlackMale = Male.copy()
BlackMale.drop(BlackMale[BlackMale.WHITE == True].index, inplace=True)
BlackMale.drop(columns=['BLACK', 'WHITE'], inplace=True)
BlackMale
```

Out[45]:

	Residence_PUMA	Gang_Affiliated	Supervision_Risk_Score_First	Dependents	Prior_Arrest_Episodes_Felony	Prior_Arrest_Episode
0	16	False	3.0	3	6	
1	16	False	6.0	1	7	
2	24	False	7.0	3	6	
6	18	False	2.0	2	10	
7	16	False	5.0	3	6	
...	...	—	—	—
25825	6	False	5.0	3	0	
25826	7	False	5.0	3	0	
25827	6	False	5.0	3	0	
25830	9	False	5.0	1	2	

```
25832      15    False      5.0      3      0
```

13765 rows × 64 columns

```
In [46]:  
WhiteMale = Male.copy()  
WhiteMale.drop(WhiteMale[WhiteMale.BLACK == True].index, inplace=True)  
WhiteMale.drop(columns=['BLACK', 'WHITE'], inplace=True)  
WhiteMale
```

Out[46]:

			Residence_PUMA		Gang_Affiliated	Supervision_Risk_Score_First	Dependents	Prior_Arrest_Episodes_Felony	Prior_Arrest_Episode
3	16	False			7.0	1		8	
4	16	False			4.0	3		4	
5	17	False			5.0	0		4	
10	5	False			3.0	1		3	
12	18	False			3.0	1		8	
...	
25824	18	False			5.0	3		0	
25828	14	False			5.0	3		0	
25829	5	False			5.0	3		1	
25831	25	False			5.0	3		0	
25834	12	False			5.0	3		6	

8903 rows × 64 columns

```
In [47]:  
BlackFemale = Female.copy()  
BlackFemale.drop(BlackFemale[BlackFemale.WHITE == True].index, inplace=True)  
BlackFemale.drop(columns=['BLACK', 'WHITE'], inplace=True)  
BlackFemale
```

Out[47]:

			Residence_PUMA		Gang_Affiliated	Supervision_Risk_Score_First	Dependents	Prior_Arrest_Episodes_Felony	Prior_Arrest_Episode
8	5	True			7.0	0		10	
39	2	True			2.0	1		2	
84	3	True			1.0	3		10	
87	3	True			7.0	2		10	
100	12	True			5.0	0		4	
...	
25684	3	True			4.0	3		1	
25698	1	True			1.0	3		1	
25710	4	True			3.0	3		10	
25734	10	True			7.0	0		1	
25790	20	True			7.0	3		1	

1082 rows × 64 columns

```
In [48]:  
WhiteFemale = Female.copy()  
WhiteFemale.drop(WhiteFemale[WhiteFemale.BLACK == True].index, inplace=True)  
WhiteFemale.drop(columns=['BLACK', 'WHITE'], inplace=True)
```

```
WhiteFemale
```

```
Out[48]:
```

	Residence_PUMA	Gang_Affiliated	Supervision_Risk_Score_First	Dependents	Prior_Arrest_Episodes_Felony	Prior_Arrest_Episode
22	5	True	4.0	0		2
23	16	True	5.0	0		10
31	16	True	9.0	0		10
33	12	True	10.0	3		10
42	16	True	2.0	0		10
...
25775	22	True	7.0	0		2
25779	22	True	8.0	3		1
25783	22	True	9.0	1		3
25803	15	True	5.0	0		5
25833	15	True	5.0	3		0

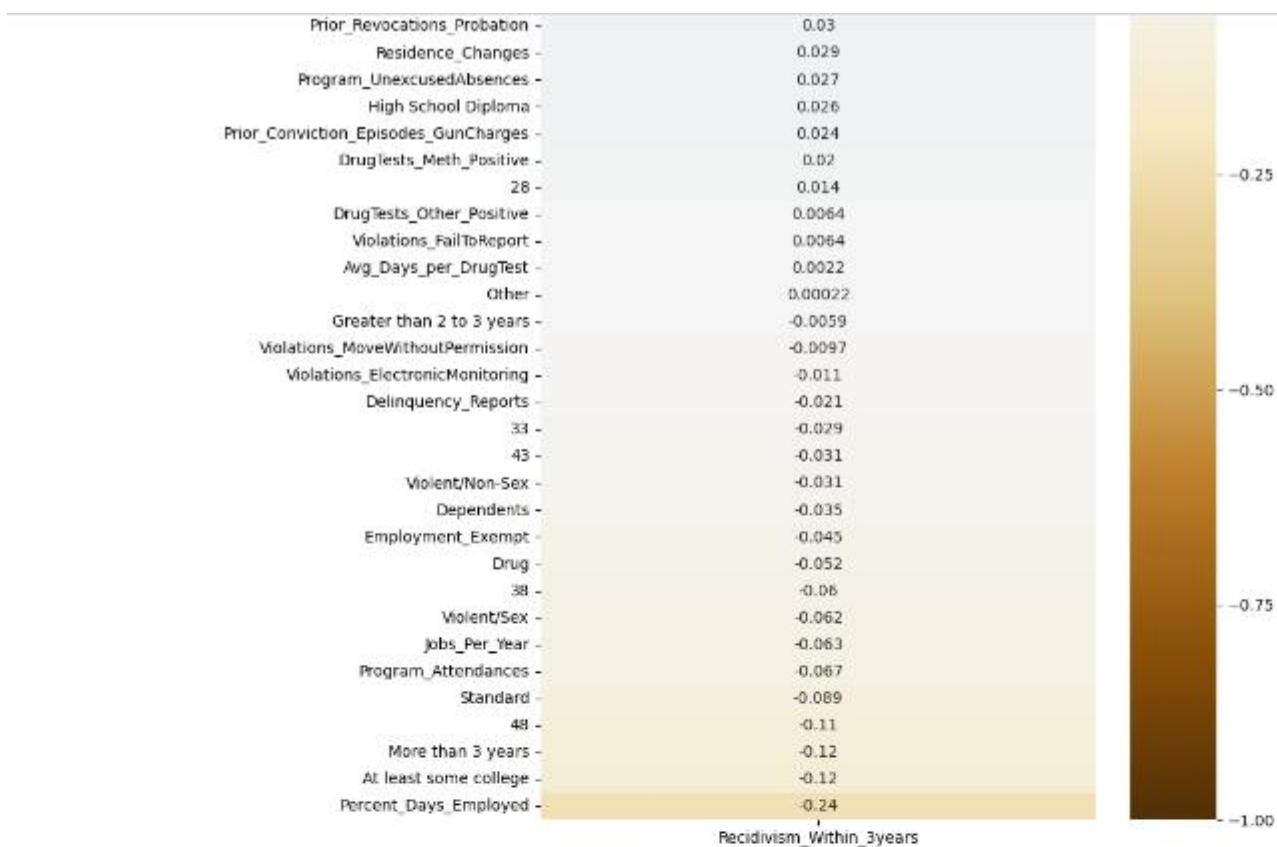
2085 rows × 64 columns

```
In [49]:
```

```
plt.figure(figsize=(8, 20))
heatmap = sns.heatmap(BlackMale.corr(method ='pearson')[['Recidivism_Within_3years']].sort_values(by='Recidivism_Within_3years', ascending=False).head(20), annot=True, cmap='viridis', square=True, cbar_kws={'label': 'Correlation Coefficient'})
heatmap.set_title('Features for Black Males Correlating with Recidivism', fontdict={'fontsize':16}, pad=16);
```

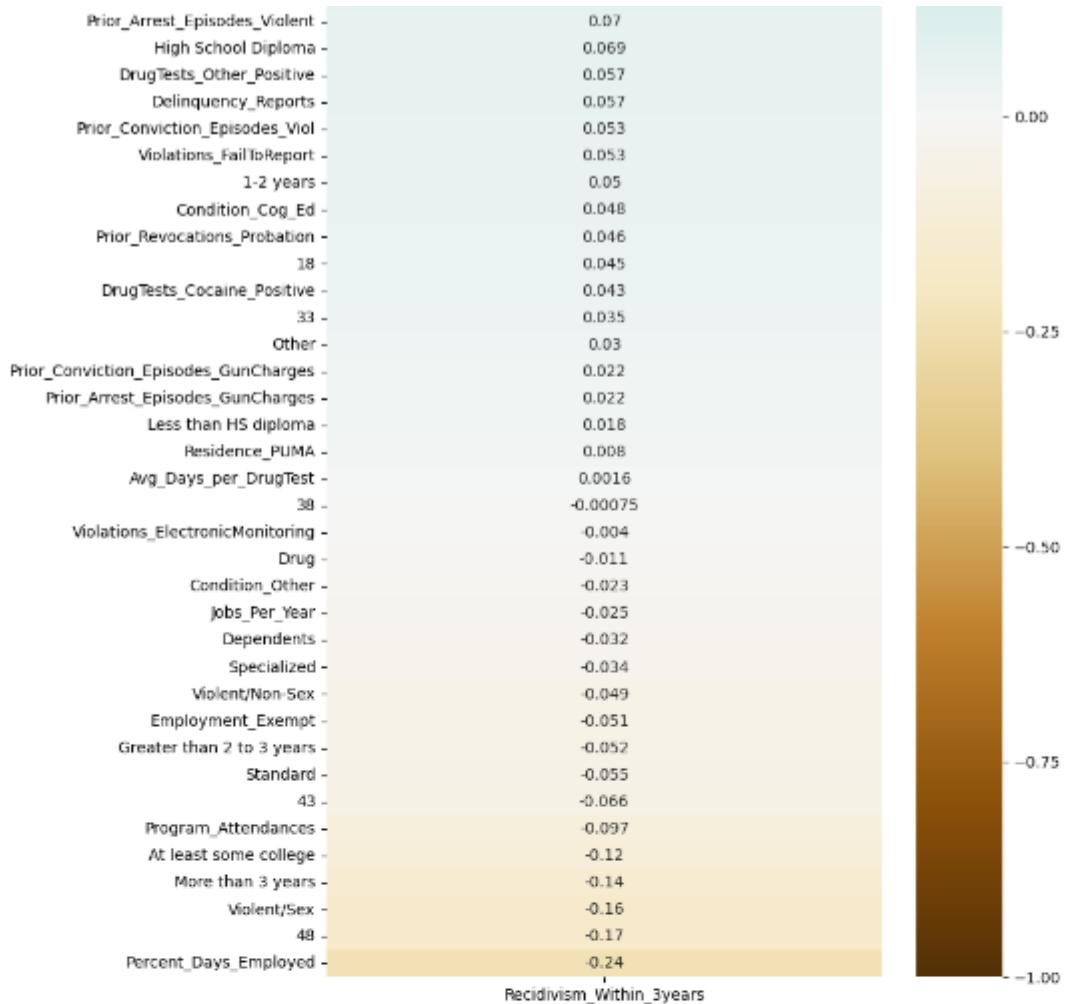
Features for Black Males Correlating with Recidivism



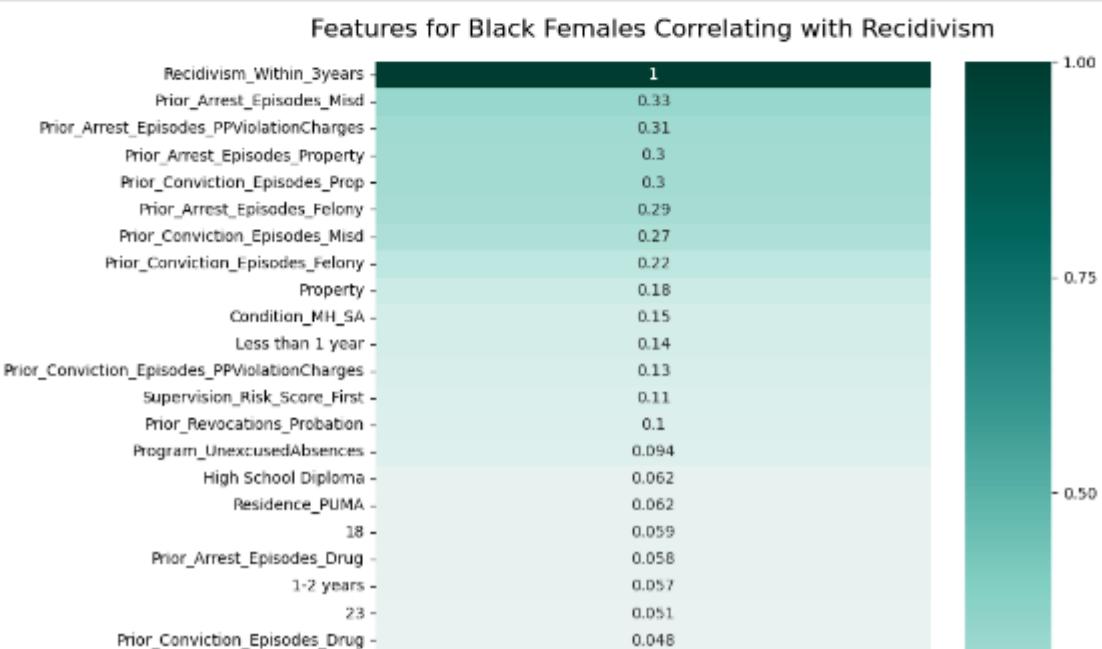


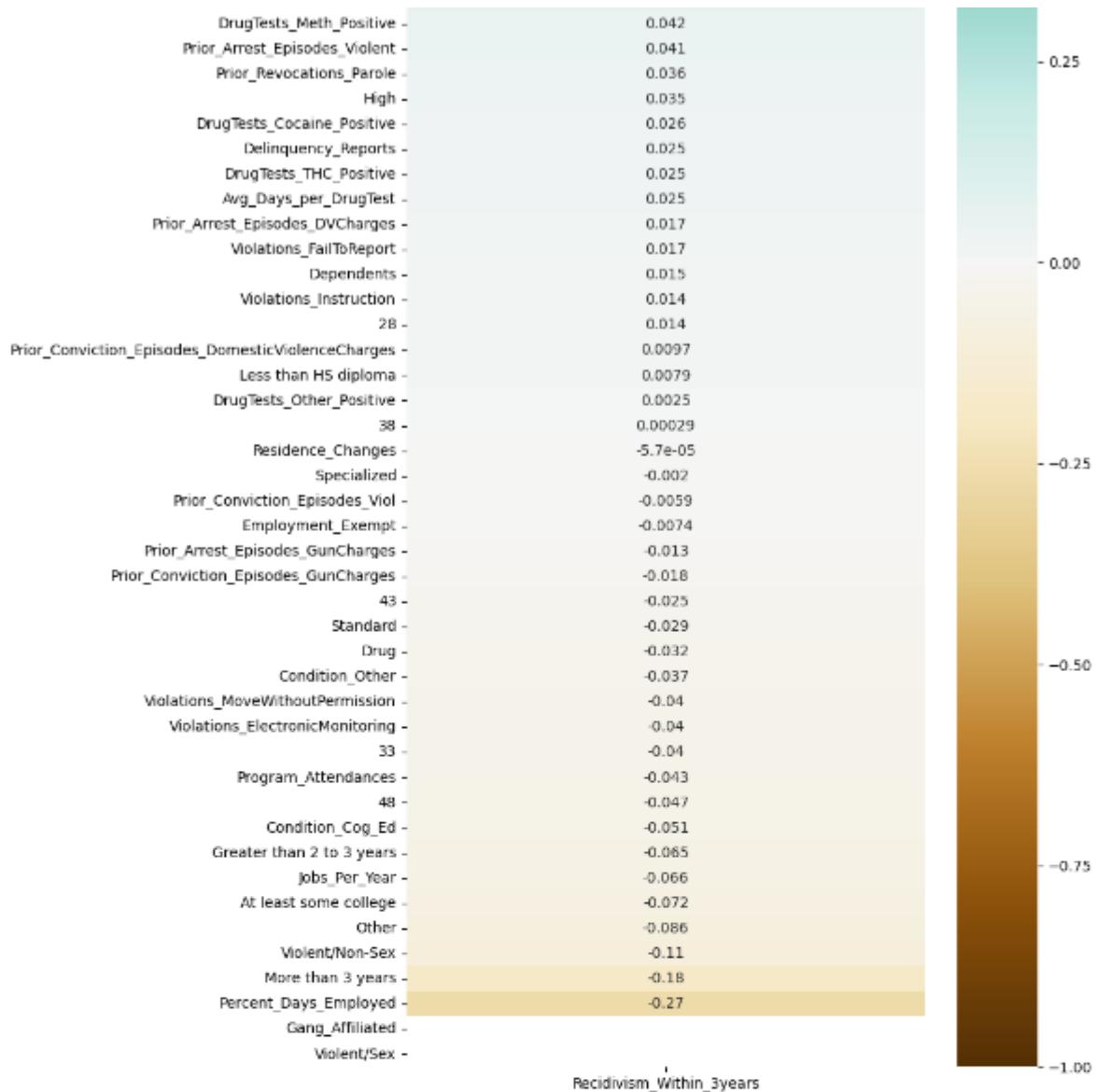
```
In [50]: plt.figure(figsize=(8, 20))
heatmap = sns.heatmap(WhiteMale.corr(method ='pearson')[['Recidivism_Within_3years']].sort_values(by='Recidivism_Within_3years', ascending=False), annot=True, cmap='viridis', center=0, square=True, cbar_kws={'label': 'Correlation Coefficient'})
heatmap.set_title('Features for White Males Correlating with Recidivism', fontdict={'fontsize':16}, pad=16);
```





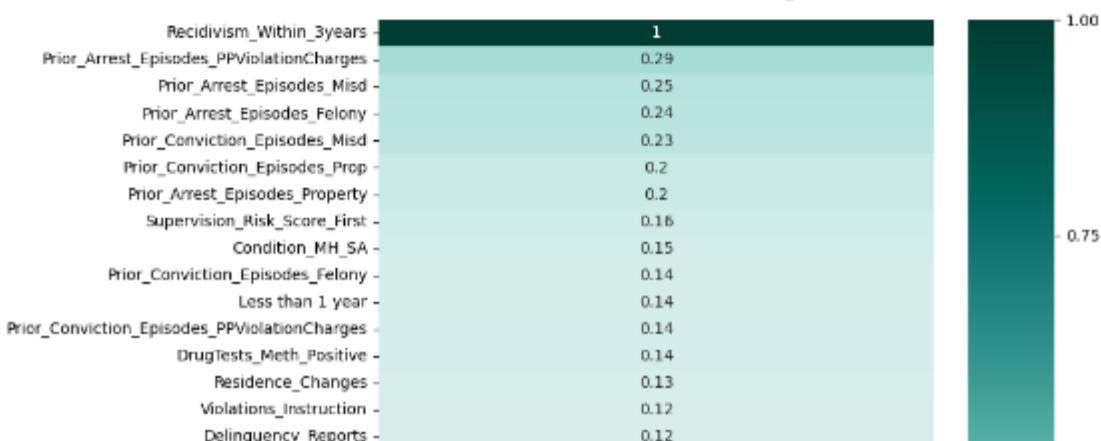
```
In [51]: plt.figure(figsize=(8, 20))
heatmap = sns.heatmap(BlackFemale.corr(method ='pearson')[['Recidivism_Within_3years']].sort_values(by='Recidivism_Within_3years', ascending=False).head(10).corr(), annot=True, cmap='viridis')
heatmap.set_title('Features for Black Females Correlating with Recidivism', fontdict={'fontsize':16}, pad=16);
```

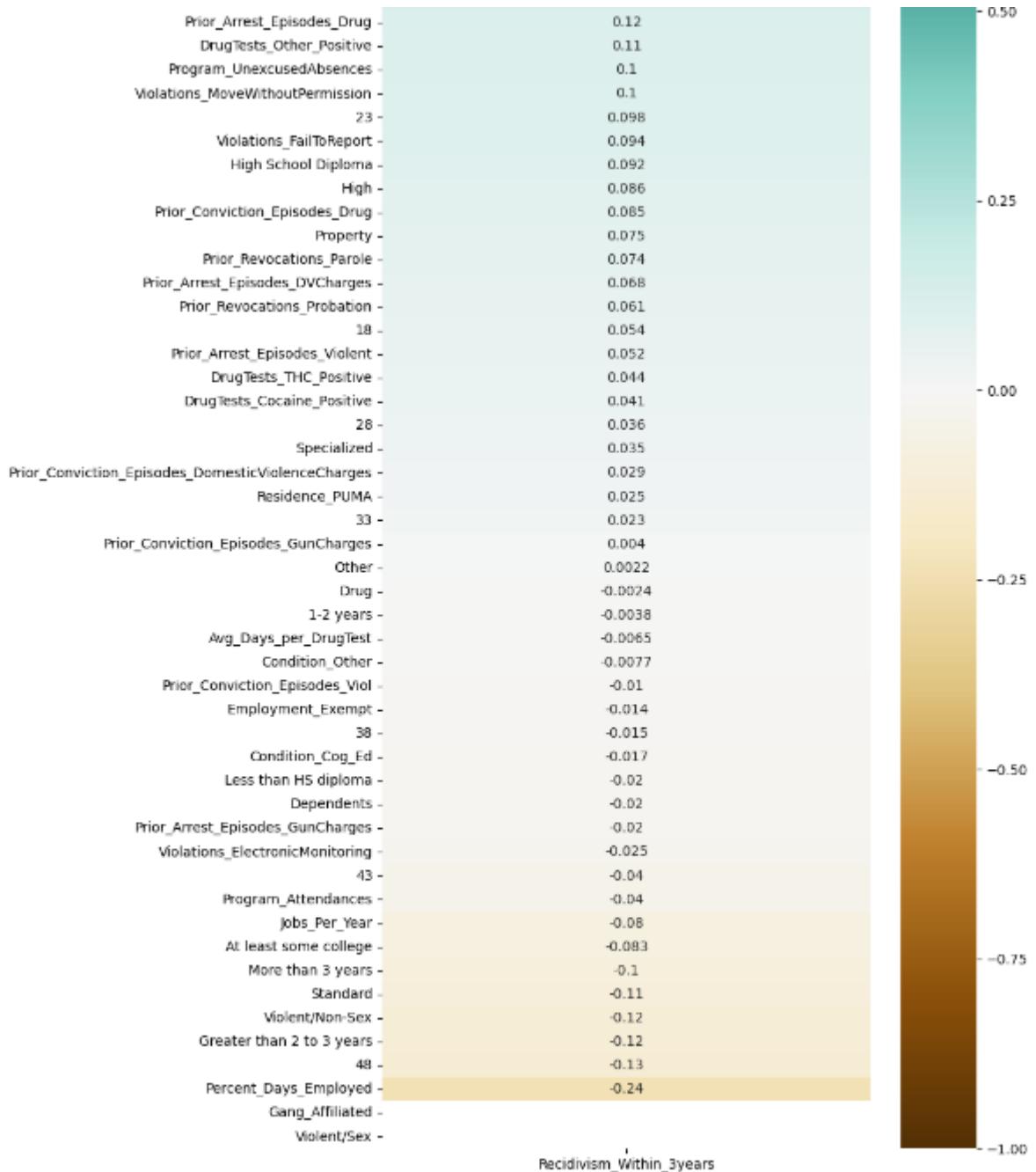




```
In [52]: plt.figure(figsize=(8, 20))
heatmap = sns.heatmap(WhiteFemale.corr(method ='pearson')[['Recidivism_Within_3years']].sort_values(by='Recidivism_Within_3years', ascending=False).head(10), title='Features for White Females Correlating with Recidivism', fontdict={'fontsize':16}, pad=16);
```

Features for White Females Correlating with Recidivism





Appendix B. NIJ Statistical Analysis

Jupyter Notebook available at: <https://github.com/feaviolp/msc-project/blob/0a726abe16a82ed34d3f891361d0cca09d408edc/NIJ%20Analysis/NIJ%20statistics.ipynb>

Statistical analysis of the NIJ recidivism dataset

Data pre-processing

```
Import libraries
```

```
In [1]: library(haven)
library(dplyr)
library(ggplot2)
```

```
Attaching package: 'dplyr'
```

```
The following objects are masked from 'package:stats':
```

```
filter, lag
```

```
The following objects are masked from 'package:base':
```

```
intersect, setdiff, setequal, union
```

```
In [2]: NIJ <- read.csv("https://raw.githubusercontent.com/feaviolp/msc-project/main/NIJ%20ontology/NIJ_s_Rcidivism_Challenge_Full_View(NIJ)
```

ID	Gender	Race	Age_at_Release	Residence_PUMA	Gang_Affiliated	Supervision_Risk_Score_First	Supervision_Level_First	Education
<int>	<chr>	<chr>	<chr>	<int>	<chr>	<int>	<chr>	<chr>
A								
data.frame:								
25835	*	54						
1	M	BLACK	43-47	16	false	3	Standard	At least
2	M	BLACK	33-37	16	false	6	Specialized	Less t
3	M	BLACK	48 or older	24	false	7	High	At leas
4	M	WHITE	38-42	16	false	7	High	Less t
5	M	WHITE	33-37	16	false	4	Specialized	Less t
6	M	WHITE	38-42	17	false	5	Standard	High
7	M	BLACK	48 or older	18	false	2	Standard	Less t
8	M	BLACK	38-42	16	false	5	High	High
9	F	BLACK	43-47	5		7	High	High
10	M	BLACK	43-47	16	false	5	Standard	High
11	M	WHITE	43-47	5	false	3	Specialized	Less t
12	M	BLACK	33-37	16	false	5	Specialized	High
13	M	WHITE	48 or older	18	false	3	Standard	Less t

14	M	BLACK	33-37	3	true	7		High	D	
15	M	WHITE	33-37	5	false	7	Standard	Less than	d	
16	M	BLACK	33-37	3	false	4	Standard	Less than	d	
17	M	BLACK	38-42	16	false	6		High	Less than	d
18	M	WHITE	43-47	24	false	1	Standard	High	D	
19	M	BLACK	48 or older	12	false	7		High	At least	1
20	M	WHITE	48 or older	16	false	3	Standard	Less than	d	
21	M	BLACK	38-42	5	false	3	Standard	High	D	
22	M	BLACK	33-37	16	false	5	Standard	Less than	d	
23	F	WHITE	48 or older	5		4		High	D	
24	F	WHITE	43-47	16		5	Standard	Less than	d	
25	M	BLACK	38-42	18	false	5	Standard	Less than	d	
26	M	WHITE	48 or older	17	false	2		Less than	d	
27	M	WHITE	48 or older	14	false	2	Specialized	Less than	d	
28	M	WHITE	48 or older	23	false	3	Standard	Less than	d	
29	M	BLACK	43-47	6	false	6		High	D	
30	M	BLACK	18-22	2	false	10	Specialized	Less than	d	
:	:	:	:	:	:	:		:	:	
26731	M	WHITE	43-47	7	false	3	Standard	High	D	
26732	M	BLACK	38-42	5	false	5	Standard	High	D	
26733	M	WHITE	23-27	17	false	5	Standard	High	D	
26734	M	BLACK	28-32	12	false	4	Standard	High	D	
26735	M	BLACK	23-27	19	false	7		High	At least	1
26736	M	WHITE	38-42	12	true	5	Standard	At least	1	
26737	M	BLACK	28-32	8	false	5	Standard	At least	1	
26738	M	BLACK	33-37	11	false	5	Specialized	High	D	
26739	M	WHITE	43-47	2	false	5	Standard	At least	1	
26740	M	WHITE	48 or older	12	false	5	Standard	At least	1	
26741	M	WHITE	28-32	3	false	5	Standard	At least	1	
26742	M	WHITE	23-27	9	false	5	Standard	At least	1	

26743	M	WHITE	43-47	8	false	3	Standard	At least
26744	M	BLACK	48 or older	21	false	7	Standard	Less than
26745	M	WHITE	48 or older	24	false	5	Standard	At least
26746	M	BLACK	43-47	6	false	5	Standard	At least
26747	M	WHITE	33-37	8	false	5	Standard	At least
26748	M	WHITE	48 or older	7	false	5	Standard	At least
26749	M	BLACK	28-32	2	false	5	Standard	High D
26750	M	WHITE	23-27	18	false	5	Standard	High D
26751	M	BLACK	38-42	6	false	5	Standard	At least
26752	M	BLACK	28-32	7	false	5	Standard	At least
26753	M	BLACK	23-27	6	false	5	Standard	At least
26754	M	WHITE	43-47	14	false	5	Standard	At least
26755	M	WHITE	33-37	5	false	5	Standard	At least
26756	M	BLACK	23-27	9	false	5	Standard	At least
26758	M	WHITE	38-42	25	false	5	Standard	At least
26759	M	BLACK	33-37	15	false	5	Standard	At least
26760	F	WHITE	33-37	15		5	Standard	At least
26761	M	WHITE	28-32	12	false	5	Standard	High D

Remove redundant columns from the dataframe

```
In [3]: NIJ = subset(NIJ, select = -c(Recidivism_Arrest_Year1, Recidivism_Arrest_Year2, Recidivism_Arrest_Year3, Training_Sample))
```

Replace null values with appropriate values:

- Gang_Affiliated is missing only for Female offenders so replace with FALSE
- Supervision_Risk_Score_First is INTEGER so replace with the most frequently occurring value
- Supervision_Level_First is CATEGORICAL so replace with the most frequently occurring value
- Prison_Offense is categorical and includes "Other" so replace with "Other"
- Avg_Days_per_DrugTest is FLOAT so replace with average value
- DrugTests_THC_Positive is FLOAT but replace with 0
- DrugTests_Cocaine_Positive is FLOAT but replace with 0
- DrugTests_Meth_Positive is FLOAT but replace with 0
- DrugTests_Other_Positive is FLOAT but replace with 0
- Percent_Days_Employed is FLOAT so replace with average value
- Jobs_Per_Year is FLOAT so replace with average value

```
In [4]: NIJ$Gang_Affiliated <- replace(NIJ$Gang_Affiliated, NIJ$Gang_Affiliated == '', 'false')
NIJ$Supervision_Risk_Score_First[is.na(NIJ$Supervision_Risk_Score_First)]<- names(which.max(table(NIJ$Supervision_Risk_Score))
NIJ$Supervision_Level_First <- replace(NIJ$Supervision_Level_First, NIJ$Supervision_Level_First == '', names(which.max(table(NIJ$Supervision_Level_First)))
NIJ$Prison_Offense <- replace(NIJ$Prison_Offense, NIJ$Prison_Offense == '', 'Other')
NIJ$Avg_Days_per_DrugTest[is.na(NIJ$Avg_Days_per_DrugTest)]<-mean(NIJ$Avg_Days_per_DrugTest ,na.rm=TRUE)
```

```

NIJ$DrugTests_THC_Positive[is.na(NIJ$DrugTests_THC_Positive)]<-0
NIJ$DrugTests_Cocaine_Positive[is.na(NIJ$DrugTests_Cocaine_Positive)]<-0
NIJ$DrugTests_Meth_Positive[is.na(NIJ$DrugTests_Meth_Positive)]<-0
NIJ$DrugTests_Other_Positive[is.na(NIJ$DrugTests_Other_Positive)]<-0
NIJ$Percent_Days_Employed[is.na(NIJ$Percent_Days_Employed)]<-mean(NIJ$Percent_Days_Employed ,na.rm=TRUE)
NIJ$Jobs_Per_Year[is.na(NIJ$Jobs_Per_Year)]<-mean(NIJ$Jobs_Per_Year ,na.rm=TRUE)

```

Copy the dataframe to use for descriptive analysis later and replace M and F with Male and Female.

In [5]:

```

NIJ_orig <- NIJ
NIJ_orig$Gender <- replace(NIJ_orig$Gender, NIJ_orig$Gender == 'M', 'Male')
NIJ_orig$Gender <- replace(NIJ_orig$Gender, NIJ_orig$Gender == 'F', 'Female')

```

Some features contain integers but max out with, "x or more". To enable numerical analysis the "or more" will be removed and the column changed to integer:

- Dependants: "3 or more" changed to "3"
- Prior_Arrest_Episodes_Felony: "10 more more" changed to "10"
- Prior_Arrest_Episodes_Misd: "6 or more" changed to "6"
- Prior_Arrest_Episodes_Violent: "3 or more" changed to "3"
- Prior_Arrest_Episodes_Property: "5 or more" changed to "5"
- Prior_Arrest_Episodes_Drug: "5 or more" changed to "5"
- Prior_Arrest_Episodes_PPViolationCharges: "5 or more" changed to "5"
- Prior_Conviction_Episodes_Felony.replace: "3 or more" changed to "3"
- Prior_Conviction_Episodes_Misd.replace: "4 or more" changed to "4"
- Prior_Conviction_Episodes_Prop.replace: "3 or more" changed to "3"
- Prior_Conviction_Episodes_Drug.replace: "2 or more" changed to "2"
- Delinquency_Reports: "4 or more" changed to "4"
- Program_Attendances: "10 more more" changed to "10"
- Program_UnexcusedAbsences: "3 or more" changed to "3"
- Residence_Changes: "3 or more" changed to "3"

In [6]:

```

NIJ$Dependants <- replace(NIJ$Dependants, NIJ$Dependants == '3 or more', '3')
NIJ$Dependants <- as.integer(NIJ$Dependants)

NIJ$Prior_Arrest_Episodes_Felony <- replace(NIJ$Prior_Arrest_Episodes_Felony, NIJ$Prior_Arrest_Episodes_Felony == '10 or more', '10')
NIJ$Prior_Arrest_Episodes_Felony <- as.integer(NIJ$Prior_Arrest_Episodes_Felony)

NIJ$Prior_Arrest_Episodes_Misd <- replace(NIJ$Prior_Arrest_Episodes_Misd, NIJ$Prior_Arrest_Episodes_Misd == '6 or more', '6')
NIJ$Prior_Arrest_Episodes_Misd <- as.integer(NIJ$Prior_Arrest_Episodes_Misd)

NIJ$Prior_Arrest_Episodes_Violent <- replace(NIJ$Prior_Arrest_Episodes_Violent, NIJ$Prior_Arrest_Episodes_Violent == '3 or more', '3')
NIJ$Prior_Arrest_Episodes_Violent <- as.integer(NIJ$Prior_Arrest_Episodes_Violent)

NIJ$Prior_Arrest_Episodes_Property <- replace(NIJ$Prior_Arrest_Episodes_Property, NIJ$Prior_Arrest_Episodes_Property == '5 or more', '5')
NIJ$Prior_Arrest_Episodes_Property <- as.integer(NIJ$Prior_Arrest_Episodes_Property)

NIJ$Prior_Arrest_Episodes_Drug <- replace(NIJ$Prior_Arrest_Episodes_Drug, NIJ$Prior_Arrest_Episodes_Drug == '5 or more', '5')
NIJ$Prior_Arrest_Episodes_Drug <- as.integer(NIJ$Prior_Arrest_Episodes_Drug)

NIJ$Prior_Arrest_Episodes_PPViolationCharges <- replace(NIJ$Prior_Arrest_Episodes_PPViolationCharges, NIJ$Prior_Arrest_Episodes_PPViolationCharges == '5 or more', '5')
NIJ$Prior_Arrest_Episodes_PPViolationCharges <- as.integer(NIJ$Prior_Arrest_Episodes_PPViolationCharges)

NIJ$Prior_Conviction_Episodes_Felony <- replace(NIJ$Prior_Conviction_Episodes_Felony, NIJ$Prior_Conviction_Episodes_Felony == '4 or more', '4')
NIJ$Prior_Conviction_Episodes_Felony <- as.integer(NIJ$Prior_Conviction_Episodes_Felony)

NIJ$Prior_Conviction_Episodes_Misd <- replace(NIJ$Prior_Conviction_Episodes_Misd, NIJ$Prior_Conviction_Episodes_Misd == '4 or more', '4')
NIJ$Prior_Conviction_Episodes_Misd <- as.integer(NIJ$Prior_Conviction_Episodes_Misd)

NIJ$Prior_Conviction_Episodes_Prop <- replace(NIJ$Prior_Conviction_Episodes_Prop, NIJ$Prior_Conviction_Episodes_Prop == '3 or more', '3')
NIJ$Prior_Conviction_Episodes_Prop <- as.integer(NIJ$Prior_Conviction_Episodes_Prop)

NIJ$Prior_Conviction_Episodes_Drug <- replace(NIJ$Prior_Conviction_Episodes_Drug, NIJ$Prior_Conviction_Episodes_Drug == '2 or more', '2')
NIJ$Prior_Conviction_Episodes_Drug <- as.integer(NIJ$Prior_Conviction_Episodes_Drug)

NIJ$Delinquency_Reports <- replace(NIJ$Delinquency_Reports, NIJ$Delinquency_Reports == '4 or more', '4')
NIJ$Delinquency_Reports <- as.integer(NIJ$Delinquency_Reports)

NIJ$Program_Attendances <- replace(NIJ$Program_Attendances, NIJ$Program_Attendances == '10 or more', '10')
NIJ$Program_Attendances <- as.integer(NIJ$Program_Attendances)

NIJ$Program_UnexcusedAbsences <- replace(NIJ$Program_UnexcusedAbsences, NIJ$Program_UnexcusedAbsences == '3 or more', '3')

```

```

NIJ$Program_UnexcusedAbsences <- as.integer(NIJ$Program_UnexcusedAbsences)
NIJ$Residence_Changes <- replace(NIJ$Residence_Changes, NIJ$Residence_Changes == '3 or more', '3')
NIJ$Residence_Changes <- as.integer(NIJ$Residence_Changes)

```

Age_at_Release is populated with ranges which won't be assessed as numeric, so change each value to the first number in each range and convert to integer:

```

In [7]: NIJ$Age_at_Release <- replace(NIJ$Age_at_Release, NIJ$Age_at_Release == '18-22', '18')
NIJ$Age_at_Release <- replace(NIJ$Age_at_Release, NIJ$Age_at_Release == '23-27', '23')
NIJ$Age_at_Release <- replace(NIJ$Age_at_Release, NIJ$Age_at_Release == '28-32', '28')
NIJ$Age_at_Release <- replace(NIJ$Age_at_Release, NIJ$Age_at_Release == '33-37', '33')
NIJ$Age_at_Release <- replace(NIJ$Age_at_Release, NIJ$Age_at_Release == '38-42', '38')
NIJ$Age_at_Release <- replace(NIJ$Age_at_Release, NIJ$Age_at_Release == '43-47', '43')
NIJ$Age_at_Release <- replace(NIJ$Age_at_Release, NIJ$Age_at_Release == '48 or older', '48')

NIJ$Age_at_Release <- as.integer(NIJ$Age_at_Release)

```

Prison_Years is populated with range descriptions so change to integer:

```

In [8]: NIJ$Prison_Years <- replace(NIJ$Prison_Years, NIJ$Prison_Years == 'Less than 1 year', '0')
NIJ$Prison_Years <- replace(NIJ$Prison_Years, NIJ$Prison_Years == '1-2 years', '1')
NIJ$Prison_Years <- replace(NIJ$Prison_Years, NIJ$Prison_Years == 'Greater than 2 to 3 years', '2')
NIJ$Prison_Years <- replace(NIJ$Prison_Years, NIJ$Prison_Years == 'More than 3 years', '3')

NIJ$Prison_Years <- as.integer(NIJ$Prison_Years)

```

Convert ordinal values to integers:

Supervision_Level_First

- Standard = 1
- High = 2
- Specialized = 3

Education_Level

- Less than HS diploma = 1
- High School Diploma = 2
- At least some college = 3

```

In [9]: NIJ$Supervision_Level_First <- replace(NIJ$Supervision_Level_First, NIJ$Supervision_Level_First == 'Standard', '1')
NIJ$Supervision_Level_First <- replace(NIJ$Supervision_Level_First, NIJ$Supervision_Level_First == 'High', '2')
NIJ$Supervision_Level_First <- replace(NIJ$Supervision_Level_First, NIJ$Supervision_Level_First == 'Specialized', '3')

NIJ$Supervision_Level_First <- as.integer(NIJ$Supervision_Level_First)

NIJ$Education_Level <- replace(NIJ$Education_Level, NIJ$Education_Level == 'Less than HS diploma', '1')
NIJ$Education_Level <- replace(NIJ$Education_Level, NIJ$Education_Level == 'High School Diploma', '2')
NIJ$Education_Level <- replace(NIJ$Education_Level, NIJ$Education_Level == 'At least some college', '3')

NIJ$Education_Level <- as.integer(NIJ$Education_Level)

```

Convert boolean and character features to integer

In [10]: glimpse(NIJ)

```

Rows: 25,835
Columns: 50
$ ID                               <int> 1, 2, 3, 4, 5, 6, 7, ...
$ Gender                            <chr> "M", "M", "M", ...
$ Race                             <chr> "BLACK", "BLACK", "B...
$ Age_at_Release                    <int> 43, 33, 48, 38, 33, ...
$ Residence_PUMA                   <int> 16, 16, 24, 16, 16, ...
$ Gang_Affiliated                  <chr> "false", "false", "f...
$ Supervision_Risk_Score_First    <chr> "3", "6", "7", "7", ...
$ Supervision_Level_First           <int> 1, 3, 2, 2, 3, 1, 1, ...
$ Education_Level                  <int> 3, 1, 3, 1, 1, 2, 1, ...
$ Dependents                        <int> 3, 1, 3, 1, 3, 0, 2, ...
$ Prison_Offense                   <chr> "Drug", "Violent/Non...
$ Prison_Years                      <int> 3, 3, 1, 1, 1, 3, 0, ...
$ Prior_Arrest_Episodes_Felony     <int> 6, 7, 6, 8, 4, 4, 10, ...

```

```

$ Prior_Arrest_Episodes_Misd      <int> 6, 6, 6, 6, 4, 0, 6,-
$ Prior_Arrest_Episodes_Violent   <int> 1, 3, 3, 0, 3, 1, 1,-
$ Prior_Arrest_Episodes_Property <int> 3, 0, 2, 3, 2, 3, 5,-
$ Prior_Arrest_Episodes_Drug     <int> 3, 3, 2, 3, 1, 0, 1,-
$ Prior_Arrest_Episodes_PPViolationCharges <int> 4, 5, 5, 3, 3, 0, 5,-
$ Prior_Arrest_Episodes_DVCharges <chr> "false", "true", "tr...
$ Prior_Arrest_Episodes_GunCharges <chr> "false", "false", "f...
$ Prior_Conviction_Episodes_Felony <int> 3, 3, 3, 3, 1, 1, 3,-
$ Prior_Conviction_Episodes_Misd   <int> 3, 4, 2, 4, 0, 0, 1,-
$ Prior_Conviction_Episodes_Viol  <chr> "false", "true", "tr...
$ Prior_Conviction_Episodes_Prop  <int> 2, 0, 1, 3, 0, 2, 3,-
$ Prior_Conviction_Episodes_Drug  <int> 2, 2, 2, 2, 1, 0, 0,-
$ Prior_Conviction_Episodes_PPViolationCharges <chr> "false", "true", "fa...
$ Prior_Conviction_Episodes_DomesticViolenceCharges <chr> "false", "true", "tr...
$ Prior_Conviction_Episodes_GunCharges <chr> "false", "true", "fa...
$ Prior_Revocations_Parole       <chr> "false", "false", "f...
$ Prior_Revocations_Probation   <chr> "true", "false", "tr...
$ Condition_MH_SA               <chr> "true", "false", "tr...
$ Condition_Cog_Ed              <chr> "true", "false", "tr...
$ Condition_Other                <chr> "false", "false", "f...
$ Violations_ElectronicMonitoring <chr> "false", "false", "f...
$ Violations_Instruction        <chr> "false", "true", "tr...
$ Violations_FailToReport       <chr> "false", "false", "f...
$ Violations_MoveWithoutPermission <chr> "false", "false", "f...
$ Delinquency_Report             <int> 0, 4, 4, 0, 0, 0, 0,-
$ Program_Attendances           <int> 6, 0, 6, 6, 7, 0, 0,-
$ Program_UnexcusedAbsences    <int> 0, 0, 0, 0, 0, 0, 0,-
$ Residence_Changes              <int> 2, 2, 0, 3, 0, 3, 1,-
$ Avg_Days_per_DrugTest          <dbl> 612.00000, 35.66667,-
$ DrugTests_THC_Positive         <dbl> 0.0000000, 0.0000000...
$ DrugTests_Cocaine_Positive    <dbl> 0, 0, 0, 0, 0, 0,-
$ DrugTests_Meth_Positive        <dbl> 0.0000000, 0.000000...
$ DrugTests_Other_Positive       <dbl> 0.0000000, 0.00000...
$ Percent_Days_Employed          <dbl> 0.4885621, 0.4252336...
$ Jobs_Per_Year                  <dbl> 0.4476103, 2.000000...
$ Employment_Exempt              <chr> "false", "false", "f...
$ Recidivism_Within_3years       <chr> "false", "true", "tr...

```

```

In [11]: NIJ$Gender <- as.integer(factor(NIJ$Gender))
NIJ$Race <- as.integer(factor(NIJ$Race))
NIJ$Gang_Affiliated <- as.integer(factor(NIJ$Gang_Affiliated))
NIJ$Supervision_Risk_Score_First <- as.integer(NIJ$Supervision_Risk_Score_First)
NIJ$Prison_Offense <- as.integer(factor(NIJ$Prison_Offense))
NIJ$Prior_Arrest_Episodes_DVCharges <- as.integer(factor(NIJ$Prior_Arrest_Episodes_DVCharges))
NIJ$Prior_Arrest_Episodes_GunCharges <- as.integer(factor(NIJ$Prior_Arrest_Episodes_GunCharges))
NIJ$Prior_Conviction_Episodes_Viol <- as.integer(factor(NIJ$Prior_Conviction_Episodes_Viol))
NIJ$Prior_Conviction_Episodes_PPViolationCharges <- as.integer(factor(NIJ$Prior_Conviction_Episodes_PPViolationCharges))
NIJ$Prior_Conviction_Episodes_DomesticViolenceCharges <- as.integer(factor(NIJ$Prior_Conviction_Episodes_DomesticViolenceCh...
NIJ$Prior_Conviction_Episodes_GunCharges <- as.integer(factor(NIJ$Prior_Conviction_Episodes_GunCharges))
NIJ$Prior_Revocations_Parole <- as.integer(factor(NIJ$Prior_Revocations_Parole ))
NIJ$Prior_Revocations_Probation <- as.integer(factor(NIJ$Prior_Revocations_Probation))
NIJ$Condition_MH_SA <- as.integer(factor(NIJ$Condition_MH_SA))
NIJ$Condition_Cog_Ed <- as.integer(factor(NIJ$Condition_Cog_Ed))
NIJ$Condition_Other <- as.integer(factor(NIJ$Condition_Other))
NIJ$Violations_ElectronicMonitoring <- as.integer(factor(NIJ$Violations_ElectronicMonitoring))
NIJ$Violations_Instruction <- as.integer(factor(NIJ$Violations_Instruction))
NIJ$Violations_FailToReport <- as.integer(factor(NIJ$Violations_FailToReport))
NIJ$Violations_MoveWithoutPermission <- as.integer(factor(NIJ$Violations_MoveWithoutPermission))
NIJ$Employment_Exempt <- as.integer(factor(NIJ$Employment_Exempt))
NIJ$Recidivism_Within_3years <- as.integer(factor(NIJ$Recidivism_Within_3years))

◀ ▶

```

```

In [12]: glimpse(NIJ)

```

	Rows: 25,835	Columns: 50
\$ ID	<int> 1, 2, 3, 4, 5, 6, 7,-	
\$ Gender	<int> 2, 2, 2, 2, 2, 2,-	
\$ Race	<int> 1, 1, 1, 2, 2, 1,-	
\$ Age_at_Release	<int> 43, 33, 48, 38, 33, -	
\$ Residence_PUMA	<int> 16, 16, 24, 16, 16, -	
\$ Gang_Affiliated	<int> 1, 1, 1, 1, 1, 1,-	
\$ Supervision_Risk_Score_First	<int> 3, 6, 7, 7, 4, 5, 2,-	
\$ Supervision_Level_First	<int> 1, 3, 2, 2, 3, 1, 1,-	
\$ Education_Level	<int> 3, 1, 3, 1, 1, 2, 1,-	
\$ Dependents	<int> 3, 1, 3, 1, 3, 0, 2,-	
\$ Prison_Offense	<int> 1, 4, 1, 3, 4, 3, 2,-	
\$ Prison_Years	<int> 3, 3, 1, 1, 1, 3, 0,-	
\$ Prior_Arrest_Episodes_Felony	<int> 6, 7, 6, 8, 4, 4, 10,-	
\$ Prior_Arrest_Episodes_Misd	<int> 6, 6, 6, 6, 4, 0, 6,-	

```

$ Prior_Arrest_Episodes_Violent          <int> 1, 3, 3, 0, 3, 1, 1,..
$ Prior_Arrest_Episodes_Property         <int> 3, 0, 2, 3, 2, 3, 5,..
$ Prior_Arrest_Episodes_Drug             <int> 3, 3, 2, 3, 1, 0, 1,..
$ Prior_Arrest_Episodes_PPViolationCharges <int> 4, 5, 5, 3, 3, 0, 5,..
$ Prior_Arrest_Episodes_DVCharges        <int> 1, 2, 2, 1, 2, 1, 1,..
$ Prior_Arrest_Episodes_GunCharges       <int> 1, 1, 1, 1, 1, 1, 2,..
$ Prior_Conviction_Episodes_Felony      <int> 3, 3, 3, 3, 1, 1, 3,..
$ Prior_Conviction_Episodes_Misd         <int> 3, 4, 2, 4, 0, 0, 1,..
$ Prior_Conviction_Episodes_Viol          <int> 1, 2, 2, 1, 2, 1, 1,..
$ Prior_Conviction_Episodes_Prop         <int> 2, 0, 1, 3, 0, 2, 3,..
$ Prior_Conviction_Episodes_Drug          <int> 2, 2, 2, 2, 1, 0, 0,..
$ Prior_Conviction_Episodes_PPViolationCharges <int> 1, 2, 1, 1, 1, 1, 2,..
$ Prior_Conviction_Episodes_DomesticViolenceCharges <int> 1, 2, 2, 1, 1, 1, 1,..
$ Prior_Conviction_Episodes_GunCharges    <int> 1, 2, 1, 1, 1, 1, 2,..
$ Prior_Revocations_Parole              <int> 1, 1, 1, 1, 1, 1, 1,..
$ Prior_Revocations_Probation           <int> 2, 1, 2, 2, 2, 1, 1,..
$ Condition_MH_SA                      <int> 2, 1, 2, 2, 2, 1, 1,..
$ Condition_Cog_Ed                     <int> 2, 1, 2, 2, 2, 1, 1,..
$ Condition_Other                       <int> 1, 1, 1, 1, 2, 2, 1,..
$ Violations_ElectronicMonitoring      <int> 1, 1, 1, 1, 1, 1, 1,..
$ Violations_Instruction                <int> 1, 2, 2, 1, 1, 1, 1,..
$ Violations_FailToReport              <int> 1, 1, 1, 1, 1, 1, 1,..
$ Violations_MoveWithoutPermission     <int> 1, 1, 2, 1, 1, 2, 1,..
$ Delinquency_Reports                  <int> 0, 4, 4, 0, 0, 0, 0,..
$ Program_Attendances                 <dbl> 6, 0, 6, 6, 7, 0, 0,..
$ Program_UnexcusedAbsences           <int> 0, 0, 0, 0, 0, 0, 0,..
$ Residence_Changes                   <int> 2, 2, 0, 3, 0, 3, 1,..
$ Avg_Days_per_DrugTest               <dbl> 612.00000, 35.66667,..
$ DrugTests_THC_Positive              <dbl> 0.0000000, 0.0000000,..
$ DrugTests_Cocaine_Positive          <dbl> 0, 0, 0, 0, 0, 0, 0,..
$ DrugTests_Meth_Positive             <dbl> 0.0000000, 0.0000000,..
$ DrugTests_Other_Positive            <dbl> 0.0000000, 0.0000000,..
$ Percent_Days_Employed              <dbl> 0.4885621, 0.4252336,..
$ Jobs_Per_Year                      <dbl> 0.4476103, 2.0000000,..
$ Employment_Exempt                  <int> 1, 1, 1, 1, 1, 1, 1,..
$ Recidivism_Within_3years            <int> 1, 2, 2, 1, 2, 1, 2,..

```

In [13]:

View(NIJ)

	ID	Gender	Race	Age_at_Release	Residence_PUMA	Gang_Affiliated	Supervision_Risk_Score_First	Supervision_Level_First	Ec
	<int>	<int>	<int>	<int>	<int>	<int>	<int>	<int>	<int>
A									
data.frame:									
25835 × 10									
1	1	2	1	43	16	1	3	1	
2	2	2	1	33	16	1	6	3	
3	3	2	1	48	24	1	7	2	
4	4	2	2	38	16	1	7	2	
5	5	2	2	33	16	1	4	3	
6	6	2	2	38	17	1	5	1	
7	7	2	1	48	18	1	2	1	
8	8	2	1	38	16	1	5	2	
9	9	1	1	43	5	1	7	2	
10	10	2	1	43	16	1	5	1	
11	11	2	2	43	5	1	3	3	
12	12	2	1	33	16	1	5	3	
13	13	2	2	48	18	1	3	1	
14	14	2	1	33	3	2	7	1	
15	15	2	2	33	5	1	7	1	
16	16	2	1	33	3	1	4	1	
17	17	2	1	38	16	1	6	2	
18	18	2	2	43	24	1	1	1	
19	19	2	1	48	12	1	7	2	

20	20	2	2	48	16	1	3	1
21	21	2	1	38	5	1	3	1
22	22	2	1	33	16	1	5	1
23	23	1	2	48	5	1	4	1
24	24	1	2	43	16	1	5	1
25	25	2	1	38	18	1	5	1
26	26	2	2	48	17	1	2	1
27	27	2	2	48	14	1	2	3
28	28	2	2	48	23	1	3	1
29	29	2	1	43	6	1	6	2
30	30	2	1	18	2	1	10	3
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
25806	26731	2	2	43	7	1	3	1
25807	26732	2	1	38	5	1	5	1
25808	26733	2	2	23	17	1	5	1
25809	26734	2	1	28	12	1	4	1
25810	26735	2	1	23	19	1	7	2
25811	26736	2	2	38	12	2	5	1
25812	26737	2	1	28	8	1	5	1
25813	26738	2	1	33	11	1	5	3
25814	26739	2	2	43	2	1	5	1
25815	26740	2	2	48	12	1	5	1
25816	26741	2	2	28	3	1	5	1
25817	26742	2	2	23	9	1	5	1
25818	26743	2	2	43	8	1	3	1
25819	26744	2	1	48	21	1	7	1
25820	26745	2	2	48	24	1	5	1
25821	26746	2	1	43	6	1	5	1
25822	26747	2	2	33	8	1	5	1
25823	26748	2	2	48	7	1	5	1
25824	26749	2	1	28	2	1	5	1
25825	26750	2	2	23	18	1	5	1
25826	26751	2	1	38	6	1	5	1
25827	26752	2	1	28	7	1	5	1
25828	26753	2	1	23	6	1	5	1
25829	26754	2	2	43	14	1	5	1
25830	26755	2	2	33	5	1	5	1
25831	26756	2	1	23	9	1	5	1
25832	26758	2	2	38	25	1	5	1
25833	26759	2	1	33	15	1	5	1
25834	26760	1	2	33	15	1	5	1
25835	26761	2	2	28	12	1	5	1

< ➞ > In order to present age plots based on Race and Gender, a new datafram is created based upon the original NIU datafame with categorical values and the Age ranges converted to integers from the transformed datafame.

```
In [14]:  
RaceGenderAge <- NIJ_orig  
RaceGenderAge$Age_at_Release <- NIJ$Age_at_Release
```

Separate the dataset into Male and Female for more detailed comparisons later.

```
In [15]:  
Male <- subset(NIJ, Gender == 2)  
Female <- subset(NIJ, Gender == 1)
```

Statistical analysis

Examine statistical differences in the data between the protected characteristics

Is there a difference in recidivism by race?

Both Race and Recidivism_Within_3years are categorical so Chi-square test used to see if there is a difference in the level of recidivism between Black and White offenders.

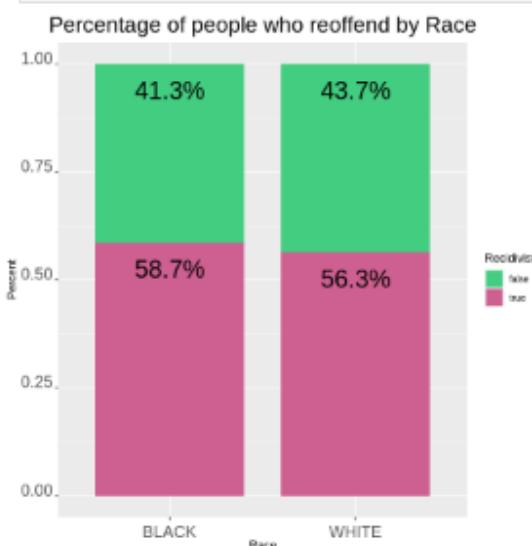
```
In [16]:  
table(as_factor(NIJ_orig$Recidivism_Within_3years), as_factor(NIJ_orig$Race))  
chisq.test(table(NIJ_orig$Recidivism_Within_3years, NIJ_orig$Race))
```

	BLACK	WHITE
false	6134	4797
true	8713	6191

Pearson's Chi-squared test with Yates' continuity correction

data: table(NIJ_orig\$Recidivism_Within_3years, NIJ_orig\$Race)
X-squared = 14.094, df = 1, p-value = 0.0001739

```
In [17]:  
ggplot(NIJ_orig, aes(fill=Recidivism_Within_3years, x=Race)) +  
  geom_bar(position = "fill", width=0.8) +  
  labs(title='Percentage of people who reoffend by Race', x='Race', y='Percent') +  
  geom_text(  
    aes(label = after_stat(  
      scales::percent(  
        ave(count, x, FUN = function(x) x / sum(x))  
      ))  
    ),  
    stat = "count", position = "fill"  
    , vjust=2, hjust=0.5, size = 8) +  
  guides(fill = guide_legend(title = "Recidivist")) +  
  scale_fill_manual(values = c('seagreen3', 'hotpink3')) +  
  theme_grey() +  
  theme(plot.title = element_text(hjust = 0.5, size = 20)) +  
  theme(axis.text.x=element_text(angle=0,hjust=0.5,vjust=0, size=15)) +  
  theme(axis.text.y=element_text(angle=0,hjust=0.5,vjust=0, size=15))
```

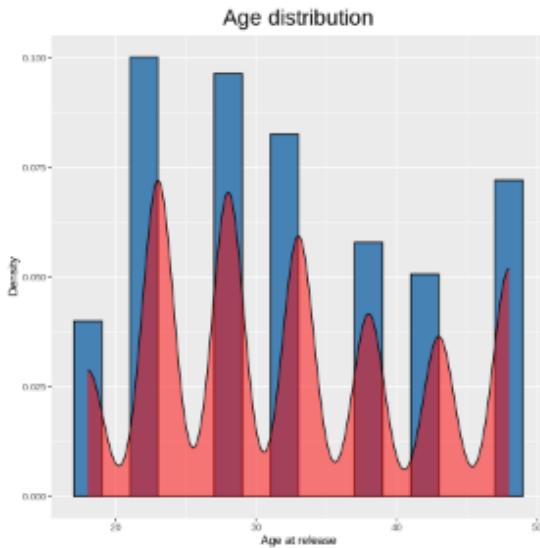


Is there a difference in recidivism by Age?

First check if Age is normally distributed in total, by race, and by gender.

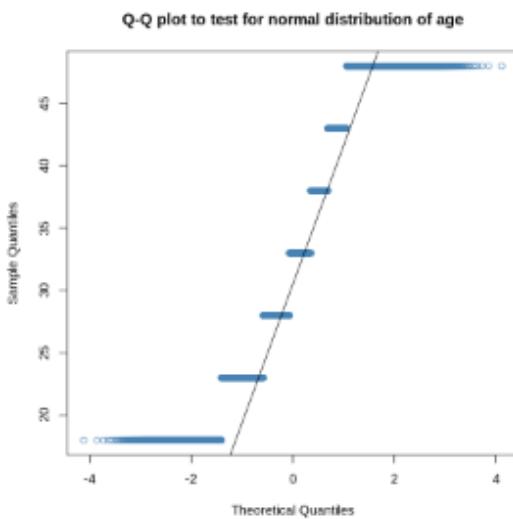
In [18]:

```
ggplot(RaceGenderAge, aes(x=Age_at_Release)) +  
  geom_histogram(aes(y=after_stat(density)), binwidth=2,  
                 colour='black', fill='steel blue') +  
  geom_density(alpha=0.5, fill='red') +  
  labs(title = "Age distribution", y = 'Density', x='Age at release') +  
  theme_grey() +  
  theme(plot.title = element_text(hjust = 0.5, size = 20))
```



In [19]:

```
qqnorm(RaceGenderAge$Age_at_Release,  
       col='steelblue',  
       main='Q-Q plot to test for normal distribution of age')  
qqline(RaceGenderAge$Age_at_Release)
```

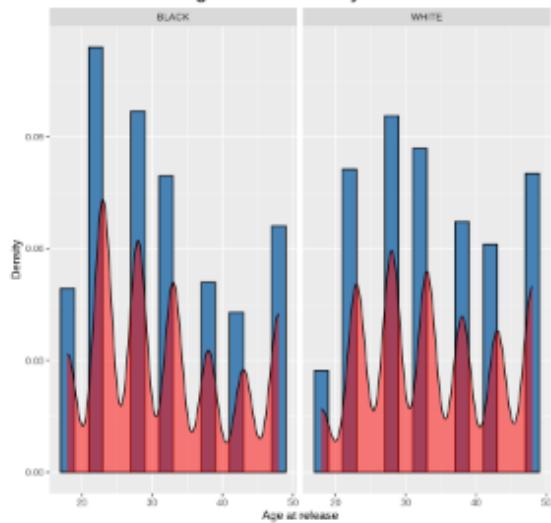


In [20]:

```
ggplot(RaceGenderAge, aes(x=Age_at_Release)) +  
  geom_histogram(aes(y=after_stat(density)), binwidth=2,  
                 colour='black', fill='steel blue') +  
  geom_density(alpha=0.5, fill='red') +  
  facet_grid(~as.factor(Race)) +  
  labs(title = "Age distribution by Race", y = 'Density', x='Age at release') +  
  theme_grey() +
```

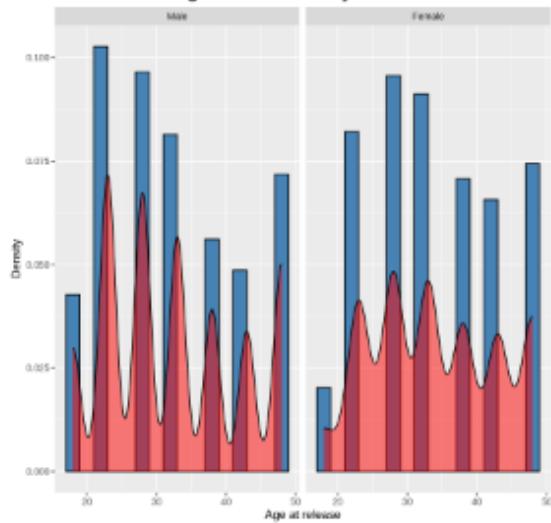
```
theme(plot.title = element_text(hjust = 0.5, size = 20))
```

Age distribution by Race



```
In [21]: ggplot(RaceGenderAge, aes(x=Age_at_Release)) +  
  geom_histogram(aes(y=after_stat(density)), binwidth=2,  
    colour='black', fill='steel blue') +  
  geom_density(alpha=0.5, fill='red') +  
  facet_grid(~as_factor(Gender)) +  
  labs(title = "Age distribution by Gender", y = 'Density', x='Age at release') +  
  theme_grey() +  
  theme(plot.title = element_text(hjust = 0.5, size = 20))
```

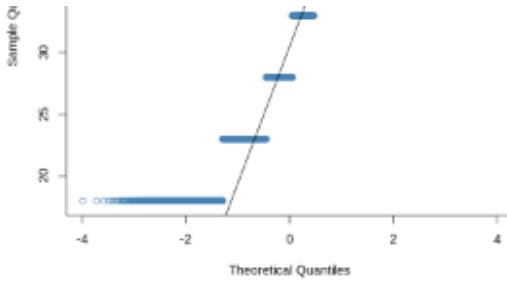
Age distribution by Gender



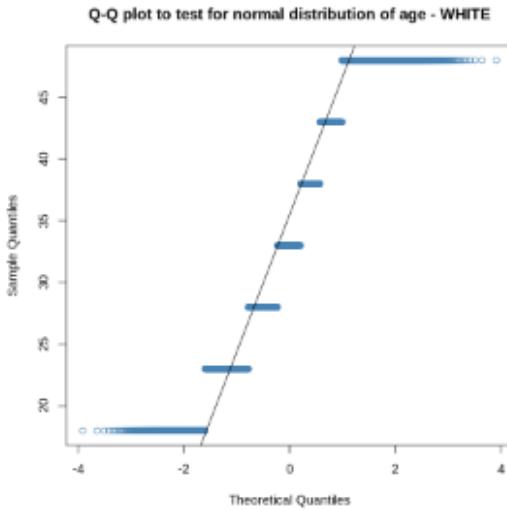
```
In [22]: qqnorm(RaceGenderAge$Age_at_Release[as_factor(RaceGenderAge$Race)=='BLACK'],  
  col='steelblue',  
  main='Q-Q plot to test for normal distribution of age - Black')  
qqline(RaceGenderAge$Age_at_Release[as_factor(RaceGenderAge$Race)=='BLACK'])
```

Q-Q plot to test for normal distribution of age - Black





```
In [23]: qqnorm(RaceGenderAge$Age_at_Release[as_factor(RaceGenderAge$Race)=='WHITE'],
            col='steelblue',
            main='Q-Q plot to test for normal distribution of age - WHITE')
qqline(RaceGenderAge$Age_at_Release[as_factor(RaceGenderAge$Race)=='WHITE'])
```



The distribution of Age is not normal so the non-parametric Mann-Whitney U test can be used. However, with a large sample size the central limit theorem allows the use of a t-test, so both will be checked.

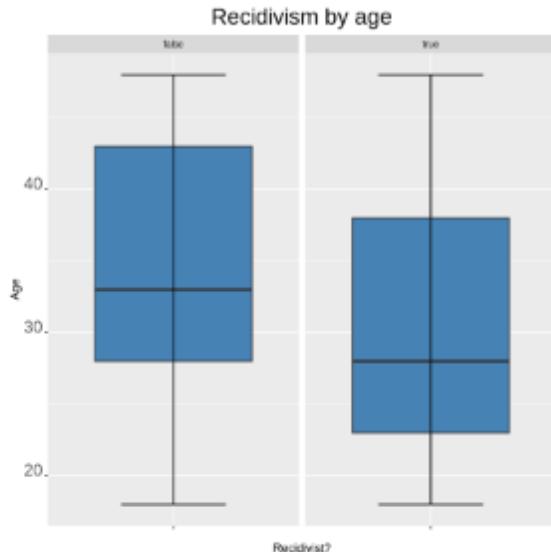
```
In [24]: wilcox.test(Age_at_Release ~ Recidivism_Within_3years, data=RaceGenderAge)
t.test(Age_at_Release ~ as_factor(Recidivism_Within_3years), data=RaceGenderAge)
```

```
Wilcoxon rank sum test with continuity correction

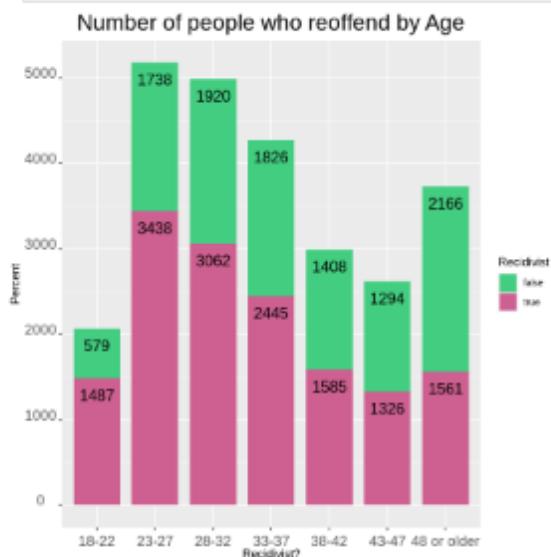
data: Age_at_Release by Recidivism_Within_3years
W = 98818898, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Welch Two Sample t-test

data: Age_at_Release by as_factor(Recidivism_Within_3years)
t = 28.822, df = 22988, p-value < 2.2e-16
alternative hypothesis: true difference in means between group false and group true is not equal to 0
95 percent confidence interval:
 3.145913 3.605823
sample estimates:
mean in group false mean in group true
 34.53737    31.16190
```

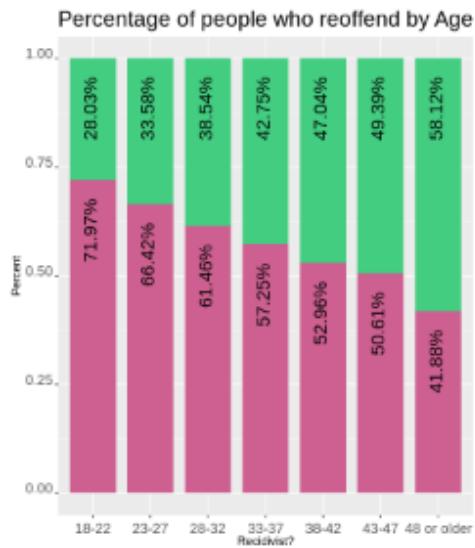
```
In [25]: ggplot(RaceGenderAge, aes(x='', y=Age_at_Release)) +
  geom_boxplot(fill='steel blue') +
  stat_boxplot(geom ='errorbar', width=0.5) +
  labs(title = "Recidivism by age", y = 'Age', x='Recidivist?') +
  facet_grid(~as_factor(Recidivism_Within_3years)) +
  theme_grey() +
  theme(plot.title = element_text(hjust = 0.5, size = 20)) +
  theme(axis.text.y=element_text(angle=0,hjust=0.5,vjust=0, size=15))
```



```
In [26]: ggplot(NIJ_orig, aes(fill=Recidivism_Within_3years, x=Age_at_Release)) +
  geom_bar(position='stack', stat='count', width=0.8) +
  labs(title='Number of people who reoffend by Age', x='Recidivist?', y='Percent') +
  geom_text(aes(label = after_stat(count)), stat = "count", position = "stack", vjust=2, size = 5) +
  guides(fill = guide_legend(title = "Recidivist")) +
  scale_fill_manual(values = c('seagreen3', 'hotpink3')) +
  theme_grey() +
  theme(plot.title = element_text(hjust = 0.5, size = 20)) +
  theme(axis.text.x=element_text(angle=0,hjust=0.5,vjust=0, size=13)) +
  theme(axis.text.y=element_text(angle=0,hjust=0.5,vjust=0, size=13))
```



```
In [27]: ggplot(NIJ_orig, aes(fill=Recidivism_Within_3years, x=Age_at_Release)) +
  geom_bar(position = "fill", width=0.8) +
  labs(title='Percentage of people who reoffend by Age', x='Recidivist?', y='Percent') +
  geom_text(
    aes(label = after_stat(
      scales::percent(
        ave(count, x, FUN = function(x) x / sum(x))
      )
    )),
    stat = "count", position = "fill"
  , vjust=0.3, hjust=1.3, angle=90, size = 6) +
  guides(fill = guide_legend(title = "Recidivist")) +
  scale_fill_manual(values = c('seagreen3', 'hotpink3')) +
  theme_grey() +
  theme(plot.title = element_text(hjust = 0.5, size = 20)) +
  theme(axis.text.x=element_text(angle=0,hjust=0.5,vjust=0, size=13)) +
  theme(axis.text.y=element_text(angle=0,hjust=0.5,vjust=0, size=13))
```



Is there a difference in Age by Race?

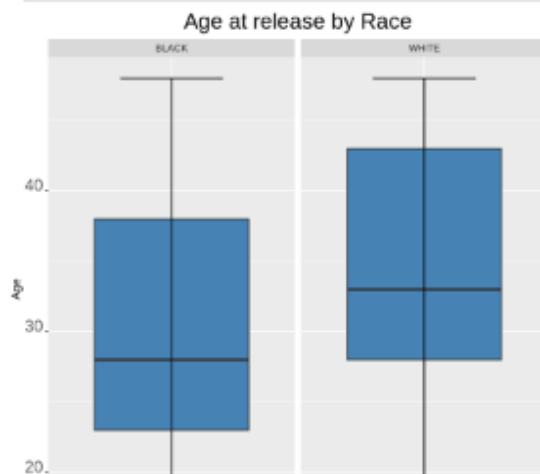
```
In [28]: wilcox.test(Age_at_Release ~ Race, data=RaceGenderAge)
t.test(Age_at_Release ~ as_factor(Race), data=RaceGenderAge)

Wilcoxon rank sum test with continuity correction

data: Age_at_Release by Race
W = 69826119, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Welch Two Sample t-test

data: Age_at_Release by as_factor(Race)
t = -19.514, df = 24010, p-value < 2.2e-16
alternative hypothesis: true difference in means between group BLACK and group WHITE is not equal to 0
95 percent confidence interval:
-2.509302 -2.051234
sample estimates:
mean in group BLACK mean in group WHITE
31.62826      33.90053
```

```
In [29]: ggplot(RaceGenderAge, aes(x='', y=Age_at_Release)) +
  geom_boxplot(fill='steel blue') +
  stat_boxplot(geom = 'errorbar', width=0.5) +
  labs(title = "Age at release by Race", y = 'Age', x='Race') +
  facet_grid(~as_factor(Race)) +
  theme_grey() +
  theme(plot.title = element_text(hjust = 0.5, size = 20)) +
  theme(axis.text.y=element_text(angle=0,hjust=0.5,vjust=0, size=15))
```





Is there a difference in recidivism by gender?

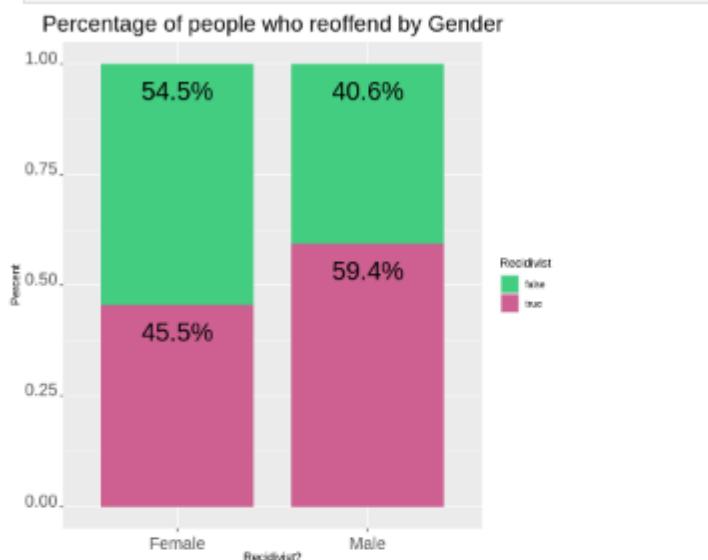
Both Gender and Recidivism_Within_3years are categorical so Chi-Square is used.

```
In [30]: table(as_factor(NIJ_orig$Recidivism_Within_3years), as_factor(NIJ_orig$Gender))
chisq.test(table(NIJ_orig$Recidivism_Within_3years, NIJ_orig$Gender))
```

```
Male Female
false  9206   1725
true   13462   1442
Pearson's Chi-squared test with Yates' continuity correction

data: table(NIJ_orig$Recidivism_Within_3years, NIJ_orig$Gender)
X-squared = 217.99, df = 1, p-value < 2.2e-16
```

```
In [31]: ggplot(NIJ_orig, aes(fill=Recidivism_Within_3years, x=Gender)) +
  geom_bar(position = "fill", width=0.8) +
  labs(title='Percentage of people who reoffend by Gender', x='Recidivist?', y='Percent') +
  geom_text(
    aes(label = after_stat(
      scales::percent(
        ave(count, x, FUN = function(x) x / sum(x))
      )
    )),
    stat = "count", position = "fill"
  , vjust=2, hjust=0.5, size = 8) +
  guides(fill = guide_legend(title = "Recidivist")) +
  scale_fill_manual(values = c('seagreen3', 'hotpink3')) +
  theme_grey() +
  theme(plot.title = element_text(hjust = 0.5, size = 20)) +
  theme(axis.text.x=element_text(angle=0,hjust=0.5,vjust=0, size=15)) +
  theme(axis.text.y=element_text(angle=0,hjust=0.5,vjust=0, size=15))
```



Correlations with recidivism and race

Is there a correlation between Age_at_Release and recidivism and/or race for everyone, or just males, or just females?

```
In [32]: wilcox.test(Age_at_Release ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Age_at_Release, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction

data: Age_at_Release by Recidivism_Within_3years
W = 98018098, p-value < 2.2e-16
```

```

alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Age_at_Release and NIJ$Recidivism_Within_3years
S = 3.3805e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.1762601

```

```
In [33]: wilcox.test(Age_at_Release ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Age_at_Release, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```

Wilcoxon rank sum test with continuity correction

data: Age_at_Release by Recidivism_Within_3years
W = 74667771, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Age_at_Release and Male$Recidivism_Within_3years
S = 2.2843e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.1766892

```

```
In [34]: wilcox.test(Age_at_Release ~ Race, data=Male)
cor.test(Male$Age_at_Release, Male$Race, method='spearman', use='complete.obs', exact=FALSE)
```

```

Wilcoxon rank sum test with continuity correction

data: Age_at_Release by Race
W = 52688014, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Age_at_Release and Male$Race
S = 1.7059e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1212351

```

```
In [35]: wilcox.test(Age_at_Release ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Age_at_Release, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```

Wilcoxon rank sum test with continuity correction

data: Age_at_Release by Recidivism_Within_3years
W = 1432521, p-value = 8.335e-14
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Age_at_Release and Female$Recidivism_Within_3years
S = 5996475425, p-value = 6.563e-14
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.1326694

```

```
In [36]: wilcox.test(Age_at_Release ~ Race, data=Female)
cor.test(Female$Age_at_Release, Female$Race, method='spearman', use='complete.obs', exact=FALSE)
```

```

Wilcoxon rank sum test with continuity correction

data: Age_at_Release by Race
W = 1029906, p-value = 4.66e-05
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Age_at_Release and Female$Race
S = 4.911e-09, p-value = 4.572e-05
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.07237061

```

Is there a correlation between Residence_PUMA and recidivism and/or race for everyone, or just males, or just females?

```
In [37]: wilcox.test(Residence_PUMA ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Residence_PUMA, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Residence_PUMA by Recidivism_Within_3years
W = 79878281, p-value = 5.764e-05
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Residence_PUMA and NIJ$Recidivism_Within_3years
S = 2.882e+12, p-value = 5.751e-05
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.02502519

In [38]: wilcox.test(Residence_PUMA ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Residence_PUMA, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Residence_PUMA by Recidivism_Within_3years
W = 60068431, p-value = 8.666e-05
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Residence_PUMA and Male$Recidivism_Within_3years
S = 1.8907e+12, p-value = 8.647e-05
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.02607135

In [39]: wilcox.test(Residence_PUMA ~ Race, data=Male)
cor.test(Male$Residence_PUMA, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Residence_PUMA by Race
W = 51225560, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Residence_PUMA and Male$Race
S = 1.6717e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1388776

In [40]: wilcox.test(Residence_PUMA ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Residence_PUMA, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Residence_PUMA by Recidivism_Within_3years
W = 1183842, p-value = 0.01928
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Residence_PUMA and Female$Recidivism_Within_3years
S = 5073939404, p-value = 0.01926
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.0415877

In [41]: wilcox.test(Residence_PUMA ~ Race, data=Female)
cor.test(Female$Residence_PUMA, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Residence_PUMA by Race
W = 878884, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Residence_PUMA and Female$Race
S = 4301514099, p-value < 2.2e-16
```

```

alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1874905

Is there a correlation between Gang_Affiliated and recidivism and/or race for everyone, or just males?

(Females do not have Gang_Affiliated recorded)

In [42]: wilcox.test(Gang_Affiliated ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Gang_Affiliated, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Gang_Affiliated by Recidivism_Within_3years
W = 70514106, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Gang_Affiliated and NIJ$Recidivism_Within_3years
S = 2.3432e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1846643

In [43]: wilcox.test(Gang_Affiliated ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Gang_Affiliated, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Gang_Affiliated by Recidivism_Within_3years
W = 53121518, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Gang_Affiliated and Male$Recidivism_Within_3years
S = 1.5821e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1850057

In [44]: wilcox.test(Gang_Affiliated ~ Race, data=Male)
cor.test(Male$Gang_Affiliated, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Gang_Affiliated by Race
W = 65362700, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Gang_Affiliated and Male$Race
S = 2.1082e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.08599346

Is there a correlation between Supervision_Risk_Score_First and recidivism and/or race for everyone, or just males, or just females?

In [45]: wilcox.test(Supervision_Risk_Score_First ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Supervision_Risk_Score_First, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Supervision_Risk_Score_First by Recidivism_Within_3years
W = 64434499, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Supervision_Risk_Score_First and NIJ$Recidivism_Within_3years
S = 2.3561e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1801646

```

```
In [46]: wilcox.test(Supervision_Risk_Score_First ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Supervision_Risk_Score_First, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Supervision_Risk_Score_First by Recidivism_Within_3years
W = 48568409, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Supervision_Risk_Score_First and Male$Recidivism_Within_3years
S = 1.5816e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1852754

In [47]: wilcox.test(Supervision_Risk_Score_First ~ Race, data=Male)
cor.test(Male$Supervision_Risk_Score_First, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Supervision_Risk_Score_First by Race
W = 65061744, p-value = 2.211e-15
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Supervision_Risk_Score_First and Male$Race
S = 2.0435e+12, p-value = 2.119e-15
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.05266429

In [48]: wilcox.test(Supervision_Risk_Score_First ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Supervision_Risk_Score_First, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Supervision_Risk_Score_First by Recidivism_Within_3years
W = 1034138, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Supervision_Risk_Score_First and Female$Recidivism_Within_3years
S = 4518704309, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1464656

In [49]: wilcox.test(Supervision_Risk_Score_First ~ Race, data=Female)
cor.test(Female$Supervision_Risk_Score_First, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Supervision_Risk_Score_First by Race
W = 1064797, p-value = 0.009081
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Supervision_Risk_Score_First and Female$Race
S = 5048632463, p-value = 0.00906
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.0463679

Is there a correlation between Supervision_Level_First and recidivism and/or race for everyone, or just males, or just females?

In [50]: wilcox.test(Supervision_Level_First ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Supervision_Level_First, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction
```

```

data: Supervision_Level_First by Recidivism_Within_3years
W = 76067222, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Supervision_Level_First and NIJ$Recidivism_Within_3years
S = 2.699e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.06084827

In [51]: wilcox.test(Supervision_Level_First ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Supervision_Level_First, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Supervision_Level_First by Recidivism_Within_3years
W = 58355268, p-value = 1.22e-15
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Supervision_Level_First and Male$Recidivism_Within_3years
S = 1.8381e+12, p-value = 1.168e-15
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.05315242

In [52]: wilcox.test(Supervision_Level_First ~ Race, data=Male)
cor.test(Male$Supervision_Level_First, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Supervision_Level_First by Race
W = 62723586, p-value = 0.001243
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Supervision_Level_First and Male$Race
S = 1.9829e+12, p-value = 0.001241
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.02144681

In [53]: wilcox.test(Supervision_Level_First ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Supervision_Level_First, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Supervision_Level_First by Recidivism_Within_3years
W = 1153571, p-value = 0.0001114
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Supervision_Level_First and Female$Recidivism_Within_3years
S = 4938517683, p-value = 0.0001097
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.06867851

In [54]: wilcox.test(Supervision_Level_First ~ Race, data=Female)
cor.test(Female$Supervision_Level_First, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Supervision_Level_First by Race
W = 1147841, p-value = 0.3715
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Supervision_Level_First and Female$Race
S = 5378196639, p-value = 0.3716
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.01588321

```

Is there a correlation between Education_Level and recidivism and/or race for everyone, or just males, or just females?

In [55]:

```
wilcox.test(Education_Level ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Education_Level, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Education_Level by Recidivism_Within_3years
W = 89183922, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Education_Level and NIJ$Recidivism_Within_3years
S = 3.1264e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.08785932
```

In [56]:

```
wilcox.test(Education_Level ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Education_Level, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Education_Level by Recidivism_Within_3years
W = 67810954, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Education_Level and Male$Recidivism_Within_3years
S = 2.1105e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.08715922
```

In [57]:

```
wilcox.test(Education_Level ~ Race, data=Male)
cor.test(Male$Education_Level, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Education_Level by Race
W = 57504234, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Education_Level and Male$Race
S = 1.8315e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.05653968
```

In [58]:

```
wilcox.test(Education_Level ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Education_Level, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Education_Level by Recidivism_Within_3years
W = 1295912, p-value = 0.02993
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Education_Level and Female$Recidivism_Within_3years
S = 5498378072, p-value = 0.02991
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.03858418
```

In [59]:

```
wilcox.test(Education_Level ~ Race, data=Female)
cor.test(Female$Education_Level, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Education_Level by Race
W = 1092961, p-value = 0.126
alternative hypothesis: true location shift is not equal to 0
```

```
Spearman's rank correlation rho

data: Female$Education_Level and Female$Race
S = 5158157751, p-value = 0.126
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.02719088

Is there a correlation between Dependents and recidivism and/or race for everyone, or just males, or just females?
```

```
In [60]: wilcox.test(Dependents ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Dependents, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction

data: Dependents by Recidivism_Within_3years
W = 84298694, p-value = 6.358e-07
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Dependents and NIJ$Recidivism_Within_3years
S = 2.963e+12, p-value = 6.324e-07
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.03098377
```

```
In [61]: wilcox.test(Dependents ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Dependents, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction

data: Dependents by Recidivism_Within_3years
W = 64158533, p-value = 2.519e-06
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Dependents and Male$Recidivism_Within_3years
S = 2.002e+12, p-value = 2.506e-06
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.03126164
```

```
In [62]: wilcox.test(Dependents ~ Race, data=Male)
cor.test(Male$Dependents, Male$Race, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction

data: Dependents by Race
W = 67958992, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Dependents and Male$Race
S = 2.1273e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.09582089
```

```
In [63]: wilcox.test(Dependents ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Dependents, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction

data: Dependents by Recidivism_Within_3years
W = 1253358, p-value = 0.6966
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Dependents and Female$Recidivism_Within_3years
S = 5330799694, p-value = 0.6966
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.006930435
```

```
In [64]: wilcox.test(Dependents ~ Race, data=Female)
```

```
cor.test(Female$Dependents, Female$Race, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction

data: Dependents by Race
W = 1212521, p-value = 0.0003262
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Dependents and Female$Race
S = 5632225875, p-value = 0.0003226
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.06386658
```

Is there a correlation between Prison_Offense and recidivism and/or race for everyone, or just males, or just females?

In [65]:

```
wilcox.test(Prison_Offense ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Prison_Offense, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction

data: Prison_Offense by Recidivism_Within_3years
W = 83076946, p-value = 0.004727
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Prison_Offense and NIJ$Recidivism_Within_3years
S = 2.9244e+12, p-value = 0.004725
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.01757645
```

In [66]:

```
wilcox.test(Prison_Offense ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Prison_Offense, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction

data: Prison_Offense by Recidivism_Within_3years
W = 63649651, p-value = 0.0003267
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prison_Offense and Male$Recidivism_Within_3years
S = 1.9876e+12, p-value = 0.0003262
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.02386608
```

In [67]:

```
wilcox.test(Prison_Offense ~ Race, data=Male)
cor.test(Male$Prison_Offense, Male$Race, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction

data: Prison_Offense by Race
W = 63609402, p-value = 5.472e-07
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prison_Offense and Male$Race
S = 2.0059e+12, p-value = 5.438e-07
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.03326985
```

In [68]:

```
wilcox.test(Prison_Offense ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Prison_Offense, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction

data: Prison_Offense by Recidivism_Within_3years
W = 1280385, p-value = 0.1343
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho
```

```

data: Female$Prison_Offense and Female$Recidivism_Within_3years
S = 5.435e+09, p-value = 0.1343
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.0266105

In [69]: wilcox.test(Prison_Offense ~ Race, data=Female)
cor.test(Female$Prison_Offense, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prison_Offense by Race
W = 1468656, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prison_Offense and Female$Race
S = 6671785940, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.2602282

Is there a correlation between Prison_Years episodes and recidivism and/or race for everyone, or just males, or just females?

In [70]: wilcox.test(Prison_Years ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Prison_Years, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prison_Years by Recidivism_Within_3years
W = 93350168, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Prison_Years and NIJ$Recidivism_Within_3years
S = 3.2472e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.1298835

In [71]: wilcox.test(Prison_Years ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Prison_Years, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prison_Years by Recidivism_Within_3years
W = 71377101, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prison_Years and Male$Recidivism_Within_3years
S = 2.2016e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.1341215

In [72]: wilcox.test(Prison_Years ~ Race, data=Male)
cor.test(Male$Prison_Years, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prison_Years by Race
W = 65906564, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prison_Years and Male$Race
S = 2.0781e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.06637585

In [73]: wilcox.test(Prison_Years ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Prison_Years, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

```

```

Wilcoxon rank sum test with continuity correction

data: Prison_Years by Recidivism_Within_3years
W = 1496864, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prison_Years and Female$Recidivism_Within_3years
S = 6278922029, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.1860285

In [74]: wilcox.test(Prison_Years ~ Race, data=Female)
cor.test(Female$Prison_Years, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prison_Years by Race
W = 1269646, p-value = 7.72e-10
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prison_Years and Female$Race
S = 5872811843, p-value = 6.932e-10
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.1093187

Is there a correlation between Prior_Arrest_Episodes_Felony and recidivism and/or race for everyone, or just males, or just females?

In [75]: wilcox.test(Prior_Arrest_Episodes_Felony ~ Recidivism_Within_3years, data=NJ)
cor.test(NJ$Prior_Arrest_Episodes_Felony, NJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_Felony by Recidivism_Within_3years
W = 62707353, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NJ$Prior_Arrest_Episodes_Felony and NJ$Recidivism_Within_3years
S = 2.3022e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1989344

In [76]: wilcox.test(Prior_Arrest_Episodes_Felony ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Prior_Arrest_Episodes_Felony, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_Felony by Recidivism_Within_3years
W = 48507358, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Arrest_Episodes_Felony and Male$Recidivism_Within_3years
S = 1.579e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1866431

In [77]: wilcox.test(Prior_Arrest_Episodes_Felony ~ Race, data=Male)
cor.test(Male$Prior_Arrest_Episodes_Felony, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_Felony by Race
W = 59468355, p-value = 0.0001487
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

```

```

data: Male$Prior_Arrest_Episodes_Felony and Male$Race
S = 1.8924e+12, p-value = 0.0001484
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.02519452

In [78]: wilcox.test(Prior_Arrest_Episodes_Felony ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Prior_Arrest_Episodes_Felony, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_Felony by Recidivism_Within_3years
W = 869366, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Arrest_Episodes_Felony and Female$Recidivism_Within_3years
S = 3908319286, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.2617607

In [79]: wilcox.test(Prior_Arrest_Episodes_Felony ~ Race, data=Female)
cor.test(Female$Prior_Arrest_Episodes_Felony, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_Felony by Race
W = 1117985, p-value = 0.6771
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Arrest_Episodes_Felony and Female$Race
S = 5254927796, p-value = 0.6772
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.007400947

Is there a correlation between Prior_Arrest_Episodes_Misd and recidivism and/or race for everyone, or just males, or just females?

In [80]: wilcox.test(Prior_Arrest_Episodes_Misd ~ Recidivism_Within_3years, data=NII)
cor.test(NII$Prior_Arrest_Episodes_Misd, NII$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_Misd by Recidivism_Within_3years
W = 64852604, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NII$Prior_Arrest_Episodes_Misd and NII$Recidivism_Within_3years
S = 2.3616e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1782683

In [81]: wilcox.test(Prior_Arrest_Episodes_Misd ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Prior_Arrest_Episodes_Misd, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_Misd by Recidivism_Within_3years
W = 50501961, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Arrest_Episodes_Misd and Male$Recidivism_Within_3years
S = 1.6288e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1609577

```

```
In [82]: wilcox.test(Prior_Arrest_Episodes_Misd ~ Race, data=Male)
cor.test(Male$Prior_Arrest_Episodes_Misd, Male$Race, method='spearman', use='complete.obs', exact=FALSE)
```

Wilcoxon rank sum test with continuity correction

```
data: Prior_Arrest_Episodes_Misd by Race
W = 54645267, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Arrest_Episodes_Misd and Male$Race
S = 1.7596e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.09360806
```

```
In [83]: wilcox.test(Prior_Arrest_Episodes_Misd ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Prior_Arrest_Episodes_Misd, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

Wilcoxon rank sum test with continuity correction

```
data: Prior_Arrest_Episodes_Misd by Recidivism_Within_3years
W = 848096, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Arrest_Episodes_Misd and Female$Recidivism_Within_3years
S = 3816603155, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.2790849
```

```
In [84]: wilcox.test(Prior_Arrest_Episodes_Misd ~ Race, data=Female)
cor.test(Female$Prior_Arrest_Episodes_Misd, Female$Race, method='spearman', use='complete.obs', exact=FALSE)
```

Wilcoxon rank sum test with continuity correction

```
data: Prior_Arrest_Episodes_Misd by Race
W = 1079116, p-value = 0.04167
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Arrest_Episodes_Misd and Female$Race
S = 5102467471, p-value = 0.04165
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.03619905
```

Is there a correlation between Prior_Arrest_Episodes_Violent and recidivism and/or race for everyone, or just males, or just females?

```
In [85]: wilcox.test(Prior_Arrest_Episodes_Violent ~ Recidivism_Within_3years, data=NII)
cor.test(NII$Prior_Arrest_Episodes_Violent, NII$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

Wilcoxon rank sum test with continuity correction

```
data: Prior_Arrest_Episodes_Violent by Recidivism_Within_3years
W = 75588886, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NII$Prior_Arrest_Episodes_Violent and NII$Recidivism_Within_3years
S = 2.6864e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.06523665
```

```
In [86]: wilcox.test(Prior_Arrest_Episodes_Violent ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Prior_Arrest_Episodes_Violent, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

Wilcoxon rank sum test with continuity correction

```

data: Prior_Arrest_Episodes_Violent by Recidivism_Within_3years
W = 58131862, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Arrest_Episodes_Violent and Male$Recidivism_Within_3years
S = 1.8338e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.05537433

```

In [87]:

```
wilcox.test(Prior_Arrest_Episodes_Violent ~ Race, data=Male)
cor.test(Male$Prior_Arrest_Episodes_Violent, Male$Race, method='spearman', use='complete.obs', exact=FALSE)
```

Wilcoxon rank sum test with continuity correction

```

data: Prior_Arrest_Episodes_Violent by Race
W = 68928160, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Arrest_Episodes_Violent and Male$Race
S = 2.1569e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.1118488

```

In [88]:

```
wilcox.test(Prior_Arrest_Episodes_Violent ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Prior_Arrest_Episodes_Violent, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

Wilcoxon rank sum test with continuity correction

```

data: Prior_Arrest_Episodes_Violent by Recidivism_Within_3years
W = 1198582, p-value = 0.04395
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Arrest_Episodes_Violent and Female$Recidivism_Within_3years
S = 5104568413, p-value = 0.04395
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.03580372

```

In [89]:

```
wilcox.test(Prior_Arrest_Episodes_Violent ~ Race, data=Female)
cor.test(Female$Prior_Arrest_Episodes_Violent, Female$Race, method='spearman', use='complete.obs', exact=FALSE)
```

Wilcoxon rank sum test with continuity correction

```

data: Prior_Arrest_Episodes_Violent by Race
W = 1383962, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Arrest_Episodes_Violent and Female$Race
S = 6422727039, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.2131837

```

Is there a correlation between Prior_Arrest_Episodes_Property and recidivism and/or race for everyone, or just males, or just females?

In [90]:

```
wilcox.test(Prior_Arrest_Episodes_Property ~ Recidivism_Within_3years, data=N1J)
cor.test(N1J$Prior_Arrest_Episodes_Property, N1J$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

Wilcoxon rank sum test with continuity correction

```

data: Prior_Arrest_Episodes_Property by Recidivism_Within_3years
W = 64485580, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: N1J$Prior_Arrest_Episodes_Property and N1J$Recidivism_Within_3years
S = 2.351e+12, p-value < 2.2e-16

```

```

alternative hypothesis: true rho is not equal to 0
sample estimates:
      rho
0.1819637

In [91]: wilcox.test(Prior_Arrest_Episodes_Property ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Prior_Arrest_Episodes_Property, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_Property by Recidivism_Within_3years
W = 49017653, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Arrest_Episodes_Property and Male$Recidivism_Within_3years
S = 1.5891e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
      rho
0.1814225

In [92]: wilcox.test(Prior_Arrest_Episodes_Property ~ Race, data=Male)
cor.test(Male$Prior_Arrest_Episodes_Property, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_Property by Race
W = 53947021, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Arrest_Episodes_Property and Male$Race
S = 1.7488e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
      rho
0.183253

In [93]: wilcox.test(Prior_Arrest_Episodes_Property ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Prior_Arrest_Episodes_Property, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_Property by Recidivism_Within_3years
W = 915387, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Arrest_Episodes_Property and Female$Recidivism_Within_3years
S = 4062578159, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
      rho
0.2326229

In [94]: wilcox.test(Prior_Arrest_Episodes_Property ~ Race, data=Female)
cor.test(Female$Prior_Arrest_Episodes_Property, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_Property by Race
W = 1206106, p-value = 0.001075
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Arrest_Episodes_Property and Female$Race
S = 5601793500, p-value = 0.001067
alternative hypothesis: true rho is not equal to 0
sample estimates:
      rho
-0.05811824

Is there a correlation between Prior_Arrest_Episodes_Drug and recidivism and/or race for everyone, or just males, or just females?

In [95]: wilcox.test(Prior_Arrest_Episodes_Drug ~ Recidivism_Within_3years, data=NII)

```

```

cor.test(NIJ$Prior_Arrest_Episodes_Drug, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_Drug by Recidivism_Within_3years
W = 73955160, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Prior_Arrest_Episodes_Drug and NIJ$Recidivism_Within_3years
S = 2.6418e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.00076391

In [96]: wilcox.test(Prior_Arrest_Episodes_Drug ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Prior_Arrest_Episodes_Drug, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_Drug by Recidivism_Within_3years
W = 56888106, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Arrest_Episodes_Drug and Male$Recidivism_Within_3years
S = 1.8028e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.07135533

In [97]: wilcox.test(Prior_Arrest_Episodes_Drug ~ Race, data=Male)
cor.test(Male$Prior_Arrest_Episodes_Drug, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_Drug by Race
W = 62377282, p-value = 0.01901
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Arrest_Episodes_Drug and Male$Race
S = 1.9715e+12, p-value = 0.01901
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.01557807

In [98]: wilcox.test(Prior_Arrest_Episodes_Drug ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Prior_Arrest_Episodes_Drug, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_Drug by Recidivism_Within_3years
W = 1094805, p-value = 1.877e-09
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Arrest_Episodes_Drug and Female$Recidivism_Within_3years
S = 4728813189, p-value = 1.702e-09
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1067783

In [99]: wilcox.test(Prior_Arrest_Episodes_Drug ~ Race, data=Female)
cor.test(Female$Prior_Arrest_Episodes_Drug, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_Drug by Race
W = 756876, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Arrest_Episodes_Drug and Female$Race

```

```
S = 3814879926, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.2794184

Is there a correlation between Prior_Arrest_Episodes_PPViolationCharges and recidivism and/or race for everyone, or just males, or just females?
```

```
In [100... wilcox.test(Prior_Arrest_Episodes_PPViolationCharges ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Prior_Arrest_Episodes_PPViolationCharges, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs',
      Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_PPViolationCharges by Recidivism_Within_3years
W = 60091696, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Prior_Arrest_Episodes_PPViolationCharges and NIJ$Recidivism_Within_3years
S = 2.2152e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.2292122

In [101... wilcox.test(Prior_Arrest_Episodes_PPViolationCharges ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Prior_Arrest_Episodes_PPViolationCharges, Male$Recidivism_Within_3years, method='spearman', use='complete.obs',
      Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_PPViolationCharges by Recidivism_Within_3years
W = 46411974, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Arrest_Episodes_PPViolationCharges and Male$Recidivism_Within_3years
S = 1.5179e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.2180697

In [102... wilcox.test(Prior_Arrest_Episodes_PPViolationCharges ~ Race, data=Male)
cor.test(Male$Prior_Arrest_Episodes_PPViolationCharges, Male$Race, method='spearman', use='complete.obs', exact=FALSE,
      Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_PPViolationCharges by Race
W = 56798607, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Arrest_Episodes_PPViolationCharges and Male$Race
S = 1.8188e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.06311263

In [103... wilcox.test(Prior_Arrest_Episodes_PPViolationCharges ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Prior_Arrest_Episodes_PPViolationCharges, Female$Recidivism_Within_3years, method='spearman', use='complete
      Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_PPViolationCharges by Recidivism_Within_3years
W = 815493, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Arrest_Episodes_PPViolationCharges and Female$Recidivism_Within_3years
S = 3689494796, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
```

```
0.3830943
```

```
In [104..
```

```
wilcox.test(Prior_Arrest_Episodes_PPViolationCharges ~ Race, data=Female)
cor.test(Female$Prior_Arrest_Episodes_PPViolationCharges, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_PPViolationCharges by Race
W = 1038286, p-value = 0.0001738
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Arrest_Episodes_PPViolationCharges and Female$Race
S = 4940861570, p-value = 0.0001715
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.06672466
```

Is there a correlation between Prior_Arrest_Episodes_DVCharges and recidivism and/or race for everyone, or just males, or just females?

```
In [105..
```

```
wilcox.test(Prior_Arrest_Episodes_DVCharges ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Prior_Arrest_Episodes_DVCharges, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_DVCharges by Recidivism_Within_3years
W = 77416886, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Prior_Arrest_Episodes_DVCharges and NIJ$Recidivism_Within_3years
S = 2.6842e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.06599674
```

```
In [106..
```

```
wilcox.test(Prior_Arrest_Episodes_DVCharges ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Prior_Arrest_Episodes_DVCharges, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_DVCharges by Recidivism_Within_3years
W = 59019107, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Arrest_Episodes_DVCharges and Male$Recidivism_Within_3years
S = 1.8217e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.06158075
```

```
In [107..
```

```
wilcox.test(Prior_Arrest_Episodes_DVCharges ~ Race, data=Male)
cor.test(Male$Prior_Arrest_Episodes_DVCharges, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_DVCharges by Race
W = 58806456, p-value = 5.683e-15
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Arrest_Episodes_DVCharges and Male$Race
S = 1.8406e+12, p-value = 5.461e-15
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.05187982
```

```
In [108..
```

```
wilcox.test(Prior_Arrest_Episodes_DVCharges ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Prior_Arrest_Episodes_DVCharges, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_DVCharges by Recidivism_Within_3years
W = 1204388, p-value = 0.003319
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Arrest_Episodes_DVCharges and Female$Recidivism_Within_3years
S = 5017888186, p-value = 0.003304
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.05219028

In [109]: wilcox.test(Prior_Arrest_Episodes_DVCharges ~ Race, data=Female)
cor.test(Female$Prior_Arrest_Episodes_DVCharges, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_DVCharges by Race
W = 1111890, p-value = 0.1854
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Arrest_Episodes_DVCharges and Female$Race
S = 5169505323, p-value = 0.1854
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.02353633

Is there a correlation between Prior_Arrest_Episodes_GunCharges and recidivism and/or race for everyone, or just males, or just females?

In [110]: wilcox.test(Prior_Arrest_Episodes_GunCharges ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Prior_Arrest_Episodes_GunCharges, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_GunCharges by Recidivism_Within_3years
W = 78283818, p-value = 2.252e-12
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Prior_Arrest_Episodes_GunCharges and NIJ$Recidivism_Within_3years
S = 2.7484e+12, p-value = 2.202e-12
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.04366299

In [111]: wilcox.test(Prior_Arrest_Episodes_GunCharges ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Prior_Arrest_Episodes_GunCharges, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_GunCharges by Recidivism_Within_3years
W = 59908620, p-value = 5.836e-08
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Arrest_Episodes_GunCharges and Male$Recidivism_Within_3years
S = 1.8713e+12, p-value = 5.785e-08
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.03602491

In [112]: wilcox.test(Prior_Arrest_Episodes_GunCharges ~ Race, data=Male)
cor.test(Male$Prior_Arrest_Episodes_GunCharges, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_GunCharges by Race
W = 67184610, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

```

```

data: Male$Prior_Arrest_Episodes_GunCharges and Male$Race
S = 2.1433e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.1040821

In [113]: wilcox.test(Prior_Arrest_Episodes_GunCharges ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Prior_Arrest_Episodes_GunCharges, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_GunCharges by Recidivism_Within_3years
W = 1257350, p-value = 0.3023
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Arrest_Episodes_GunCharges and Female$Recidivism_Within_3years
S = 5391168898, p-value = 0.3023
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.01833352

In [114]: wilcox.test(Prior_Arrest_Episodes_GunCharges ~ Race, data=Female)
cor.test(Female$Prior_Arrest_Episodes_GunCharges, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Arrest_Episodes_GunCharges by Race
W = 1159255, p-value = 0.01292
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Arrest_Episodes_GunCharges and Female$Race
S = 5.528e+09, p-value = 0.0129
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.04418063

Is there a correlation between Prior_Conviction_Episodes_Felony and recidivism and/or race for everyone, or just males, or just females?

In [115]: wilcox.test(Prior_Conviction_Episodes_Felony ~ Recidivism_Within_3years, data=NII)
cor.test(NII$Prior_Conviction_Episodes_Felony, NII$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Felony by Recidivism_Within_3years
W = 71820576, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NII$Prior_Conviction_Episodes_Felony and NII$Recidivism_Within_3years
S = 2.5724e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.104915

In [116]: wilcox.test(Prior_Conviction_Episodes_Felony ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Prior_Conviction_Episodes_Felony, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Felony by Recidivism_Within_3years
W = 55387404, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Conviction_Episodes_Felony and Male$Recidivism_Within_3years
S = 1.7596e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.09356382

```

```
In [117]: wilcox.test(Prior_Conviction_Episodes_Felony ~ Race, data=Male)
cor.test(Male$Prior_Conviction_Episodes_Felony, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Felony by Race
W = 59036107, p-value = 1.428e-06
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Conviction_Episodes_Felony and Male$Race
S = 1.8791e+12, p-value = 1.42e-06
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.03202288

In [118]: wilcox.test(Prior_Conviction_Episodes_Felony ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Prior_Conviction_Episodes_Felony, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Felony by Recidivism_Within_3years
W = 1009364, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Conviction_Episodes_Felony and Female$Recidivism_Within_3years
S = 4400670768, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1687609

In [119]: wilcox.test(Prior_Conviction_Episodes_Felony ~ Race, data=Female)
cor.test(Female$Prior_Conviction_Episodes_Felony, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Felony by Race
W = 1189712, p-value = 0.008634
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Conviction_Episodes_Felony and Female$Race
S = 5541207330, p-value = 0.008613
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.04667416

Is there a correlation between Prior_Conviction_Episodes_Misd and recidivism and/or race for everyone, or just males, or just females?

In [120]: wilcox.test(Prior_Conviction_Episodes_Misd ~ Recidivism_Within_3years, data=NJ)
cor.test(NJ$Prior_Conviction_Episodes_Misd, NJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Misd by Recidivism_Within_3years
W = 65279298, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NJ$Prior_Conviction_Episodes_Misd and NJ$Recidivism_Within_3years
S = 2.3718e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1747248

In [121]: wilcox.test(Prior_Conviction_Episodes_Misd ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Prior_Conviction_Episodes_Misd, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction
```

```

data: Prior_Conviction_Episodes_Misd by Recidivism_Within_3years
W = 50631872, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Conviction_Episodes_Misd and Male$Recidivism_Within_3years
S = 1.6309e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.159869

In [122... wilcox.test(Prior_Conviction_Episodes_Misd ~ Race, data=Male)
cor.test(Male$Prior_Conviction_Episodes_Misd, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Misd by Race
W = 56344087, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Conviction_Episodes_Misd and Male$Race
S = 1.8055e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.06994302

In [123... wilcox.test(Prior_Conviction_Episodes_Misd ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Prior_Conviction_Episodes_Misd, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Misd by Recidivism_Within_3years
W = 898976, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Conviction_Episodes_Misd and Female$Recidivism_Within_3years
S = 3984628403, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.2473468

In [124... wilcox.test(Prior_Conviction_Episodes_Misd ~ Race, data=Female)
cor.test(Female$Prior_Conviction_Episodes_Misd, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Misd by Race
W = 1074738, p-value = 0.024
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Conviction_Episodes_Misd and Female$Race
S = 5081735000, p-value = 0.02397
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.04811519

Is there a correlation between Prior_Conviction_Episodes_Viol and recidivism and/or race for everyone, or just males, or just females?

In [125... wilcox.test(Prior_Conviction_Episodes_Viol ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Prior_Conviction_Episodes_Viol, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Viol by Recidivism_Within_3years
W = 77853423, p-value = 6.195e-14
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Prior_Conviction_Episodes_Viol and NIJ$Recidivism_Within_3years

```

```
S = 2.7397e+12, p-value = 6.014e-14
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.04668643
```

```
In [126]: wilcox.test(Prior_Conviction_Episodes_Viol ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Prior_Conviction_Episodes_Viol, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Viol by Recidivism_Within_3years
W = 59387315, p-value = 9.273e-11
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Conviction_Episodes_Viol and Male$Recidivism_Within_3years
S = 1.8577e+12, p-value = 9.104e-11
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.04302958
```

```
In [127]: wilcox.test(Prior_Conviction_Episodes_Viol ~ Race, data=Male)
cor.test(Male$Prior_Conviction_Episodes_Viol, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Viol by Race
W = 66492996, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Conviction_Episodes_Viol and Male$Race
S = 2.1113e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.08757594
```

```
In [128]: wilcox.test(Prior_Conviction_Episodes_Viol ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Prior_Conviction_Episodes_Viol, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Viol by Recidivism_Within_3years
W = 1255835, p-value = 0.4866
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Conviction_Episodes_Viol and Female$Recidivism_Within_3years
S = 5359576495, p-value = 0.4866
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.01236606
```

```
In [129]: wilcox.test(Prior_Conviction_Episodes_Viol ~ Race, data=Female)
cor.test(Female$Prior_Conviction_Episodes_Viol, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Viol by Race
W = 1277894, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Conviction_Episodes_Viol and Female$Race
S = 6145087303, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.1607406
```

Is there a correlation between Prior_Conviction_Episodes_Prop and recidivism and/or race for everyone, or just males, or just females?

```
In [130]: wilcox.test(Prior_Conviction_Episodes_Prop ~ Recidivism_Within_3years, data=NII)
```

```

cor.test(NIJ$Prior_Conviction_Episodes_Prop, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Prop by Recidivism_Within_3years
W = 66961644, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Prior_Conviction_Episodes_Prop and NIJ$Recidivism_Within_3years
S = 2.4114e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1609443

In [131... wilcox.test(Prior_Conviction_Episodes_Prop ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Prior_Conviction_Episodes_Prop, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Prop by Recidivism_Within_3years
W = 51172761, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Conviction_Episodes_Prop and Male$Recidivism_Within_3years
S = 1.6367e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1568742

In [132... wilcox.test(Prior_Conviction_Episodes_Prop ~ Race, data=Male)
cor.test(Male$Prior_Conviction_Episodes_Prop, Male$Race, method='spearman', use='complete.obs', exact=FALSE)
Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Prop by Race
W = 54186755, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Conviction_Episodes_Prop and Male$Race
S = 1.7402e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1036055

In [133... wilcox.test(Prior_Conviction_Episodes_Prop ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Prior_Conviction_Episodes_Prop, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Prop by Recidivism_Within_3years
W = 923958, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Conviction_Episodes_Prop and Female$Recidivism_Within_3years
S = 4065717970, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.2320298

In [134... wilcox.test(Prior_Conviction_Episodes_Prop ~ Race, data=Female)
cor.test(Female$Prior_Conviction_Episodes_Prop, Female$Race, method='spearman', use='complete.obs', exact=FALSE)
Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Prop by Race
W = 1224242, p-value = 3.679e-05
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

```

```
data: Female$Prior_Conviction_Episodes_Proportion and Female$Race
S = 5682390620, p-value = 3.606e-05
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.07334216

Is there a correlation between Prior_Conviction_Episodes_Drug and recidivism and/or race for everyone, or just males, or just females?
```

```
In [135]: wilcox.test(Prior_Conviction_Episodes_Drug ~ Recidivism_Within_3years, data=NIIJ)
cor.test(NIIJ$Prior_Conviction_Episodes_Drug, NIIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Drug by Recidivism_Within_3years
W = 75714134, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIIJ$Prior_Conviction_Episodes_Drug and NIIJ$Recidivism_Within_3years
S = 2.6859e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.06542195

In [136]: wilcox.test(Prior_Conviction_Episodes_Drug ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Prior_Conviction_Episodes_Drug, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Drug by Recidivism_Within_3years
W = 57978966, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Conviction_Episodes_Drug and Male$Recidivism_Within_3years
S = 1.8263e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.05922146

In [137]: wilcox.test(Prior_Conviction_Episodes_Drug ~ Race, data=Male)
cor.test(Male$Prior_Conviction_Episodes_Drug, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Drug by Race
W = 62162486, p-value = 0.04593
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Conviction_Episodes_Drug and Male$Race
S = 1.967e+12, p-value = 0.04592
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.01325808

In [138]: wilcox.test(Prior_Conviction_Episodes_Drug ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Prior_Conviction_Episodes_Drug, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Drug by Recidivism_Within_3years
W = 1142982, p-value = 1.411e-05
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Conviction_Episodes_Drug and Female$Recidivism_Within_3years
S = 4885557823, p-value = 1.376e-05
alternative hypothesis: true rho is not equal to 0
sample estimates:
```

```

rho
0.07717094

In [139]: wilcox.test(Prior_Conviction_Episodes_Drug ~ Race, data=Female)
cor.test(Female$Prior_Conviction_Episodes_Drug, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_Drug by Race
W = 835706, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Conviction_Episodes_Drug and Female$Race
S = 4049473944, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.2350981

Is there a correlation between Prior_Conviction_Episodes_PPViolationCharges and recidivism and/or race for everyone, or just males, or just females?

In [140]: wilcox.test(Prior_Conviction_Episodes_PPViolationCharges ~ Recidivism_Within_3years, data=NJ)
cor.test(NJ$Prior_Conviction_Episodes_PPViolationCharges, NJ$Recidivism_Within_3years, method='spearman', use='complete.o

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_PPViolationCharges by Recidivism_Within_3years
W = 74057633, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NJ$Prior_Conviction_Episodes_PPViolationCharges and NJ$Recidivism_Within_3years
S = 2.5991e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.09561764

In [141]: wilcox.test(Prior_Conviction_Episodes_PPViolationCharges ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Prior_Conviction_Episodes_PPViolationCharges, Male$Recidivism_Within_3years, method='spearman', use='complete

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_PPViolationCharges by Recidivism_Within_3years
W = 56720589, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Conviction_Episodes_PPViolationCharges and Male$Recidivism_Within_3years
S = 1.7698e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.08832585

In [142]: wilcox.test(Prior_Conviction_Episodes_PPViolationCharges ~ Race, data=Male)
cor.test(Male$Prior_Conviction_Episodes_PPViolationCharges, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_PPViolationCharges by Race
W = 58298834, p-value = 3.254e-14
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Conviction_Episodes_PPViolationCharges and Male$Race
S = 1.8434e+12, p-value = 3.141e-14
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.05039863

In [143]: wilcox.test(Prior_Conviction_Episodes_PPViolationCharges ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Prior_Conviction_Episodes_PPViolationCharges, Female$Recidivism_Within_3years, method='spearman', use='comp

```

```

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_PPViolationCharges by Recidivism_Within_3years
W = 1086266, p-value = 1.198e-14
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Conviction_Episodes_PPViolationCharges and Female$Recidivism_Within_3years
S = 4568091239, p-value = 9.108e-15
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1371369

In [144]: wilcox.test(Prior_Conviction_Episodes_PPViolationCharges ~ Race, data=Female)
cor.test(Female$Prior_Conviction_Episodes_PPViolationCharges, Female$Race, method='spearman', use='complete.obs', exact=False)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_PPViolationCharges by Race
W = 1091052, p-value = 0.05737
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Conviction_Episodes_PPViolationCharges and Female$Race
S = 5115290797, p-value = 0.05735
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.03377687

Is there a correlation between Prior_Conviction_Episodes_DomesticViolenceCharges and recidivism and/or race for everyone, or just males, or just females?

In [145]: wilcox.test(Prior_Conviction_Episodes_DomesticViolenceCharges ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Prior_Conviction_Episodes_DomesticViolenceCharges, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs')

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_DomesticViolenceCharges by Recidivism_Within_3years
W = 78779560, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Prior_Conviction_Episodes_DomesticViolenceCharges and NIJ$Recidivism_Within_3years
S = 2.7834e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.05932661

In [146]: wilcox.test(Prior_Conviction_Episodes_DomesticViolenceCharges ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Prior_Conviction_Episodes_DomesticViolenceCharges, Male$Recidivism_Within_3years, method='spearman', use='complete.obs')

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_DomesticViolenceCharges by Recidivism_Within_3years
W = 59933661, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Conviction_Episodes_DomesticViolenceCharges and Male$Recidivism_Within_3years
S = 1.8312e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.05671442

In [147]: wilcox.test(Prior_Conviction_Episodes_DomesticViolenceCharges ~ Race, data=Male)
cor.test(Male$Prior_Conviction_Episodes_DomesticViolenceCharges, Male$Race, method='spearman', use='complete.obs', exact=False)

Wilcoxon rank sum test with continuity correction

```

```

data: Prior_Conviction_Episodes_DomesticViolenceCharges by Race
W = 60656927, p-value = 0.009016
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Conviction_Episodes_DomesticViolenceCharges and Male$Race
S = 1.9876e+12, p-value = 0.009013
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.01734553

In [148]:
wilcox.test(Prior_Conviction_Episodes_DomesticViolenceCharges ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Prior_Conviction_Episodes_DomesticViolenceCharges, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=F)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_DomesticViolenceCharges by Recidivism_Within_3years
W = 12332808, p-value = 0.1833
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Conviction_Episodes_DomesticViolenceCharges and Female$Recidivism_Within_3years
S = 5168916907, p-value = 0.1834
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.02364747

In [149]:
wilcox.test(Prior_Conviction_Episodes_DomesticViolenceCharges ~ Race, data=Female)
cor.test(Female$Prior_Conviction_Episodes_DomesticViolenceCharges, Female$Race, method='spearman', use='complete.obs', exact=F)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_DomesticViolenceCharges by Race
W = 1119226, p-value = 0.245
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Conviction_Episodes_DomesticViolenceCharges and Female$Race
S = 5184708393, p-value = 0.245
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.02066463

Is there a correlation between Prior_Conviction_Episodes_GunCharges and recidivism and/or race for everyone, or just males, or just females?

In [150]:
wilcox.test(Prior_Conviction_Episodes_GunCharges ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Prior_Conviction_Episodes_GunCharges, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=F)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_GunCharges by Recidivism_Within_3years
W = 79728950, p-value = 7.358e-07
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Prior_Conviction_Episodes_GunCharges and NIJ$Recidivism_Within_3years
S = 2.7854e+12, p-value = 7.319e-07
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.0308074

In [151]:
wilcox.test(Prior_Conviction_Episodes_GunCharges ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Prior_Conviction_Episodes_GunCharges, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=F)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_GunCharges by Recidivism_Within_3years
W = 60900371, p-value = 0.0003296
alternative hypothesis: true location shift is not equal to 0

```

```

Spearman's rank correlation rho

data: Male$Prior_Conviction_Episodes_GunCharges and Male$Recidivism_Within_3years
S = 1.895e+12, p-value = 0.0003291
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.02385081

In [152]: wilcox.test(Prior_Conviction_Episodes_GunCharges ~ Race, data=Male)
cor.test(Male$Prior_Conviction_Episodes_GunCharges, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_GunCharges by Race
W = 63864555, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Conviction_Episodes_GunCharges and Male$Race
S = 2.0545e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.05830988

In [153]: wilcox.test(Prior_Conviction_Episodes_GunCharges ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Prior_Conviction_Episodes_GunCharges, Female$Recidivism_Within_3years, method='spearman', use='complete.obs')

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_GunCharges by Recidivism_Within_3years
W = 1245895, p-value = 0.8825
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Conviction_Episodes_GunCharges and Female$Recidivism_Within_3years
S = 5317644095, p-value = 0.8825
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.004445484

In [154]: wilcox.test(Prior_Conviction_Episodes_GunCharges ~ Race, data=Female)
cor.test(Female$Prior_Conviction_Episodes_GunCharges, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Conviction_Episodes_GunCharges by Race
W = 1135827, p-value = 0.3426
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Conviction_Episodes_GunCharges and Female$Race
S = 5383417056, p-value = 0.3426
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.01686929

Is there a correlation between Prior_Revocations_Parole and recidivism and/or race for everyone, or just males, or just females?

In [155]: wilcox.test(Prior_Revocations_Parole ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Prior_Revocations_Parole, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Revocations_Parole by Recidivism_Within_3years
W = 78663156, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Prior_Revocations_Parole and NIJ$Recidivism_Within_3years
S = 2.7083e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.05761161

```

```
In [156... wilcox.test(Prior_Revocations_Parole ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Prior_Revocations_Parole, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Revocations_Parole by Recidivism_Within_3years
W = 60002865, p-value = 1.504e-14
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Revocations_Parole and Male$Recidivism_Within_3years
S = 1.8422e+12, p-value = 1.449e-14
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.05105864
```

```
In [157... wilcox.test(Prior_Revocations_Parole ~ Race, data=Male)
cor.test(Male$Prior_Revocations_Parole, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Revocations_Parole by Race
W = 62678036, p-value = 3.269e-08
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Revocations_Parole and Male$Race
S = 2.0125e+12, p-value = 3.238e-08
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.03670668
```

```
In [158... wilcox.test(Prior_Revocations_Parole ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Prior_Revocations_Parole, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Revocations_Parole by Recidivism_Within_3years
W = 1214225, p-value = 0.0006729
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Revocations_Parole and Female$Recidivism_Within_3years
S = 4974165813, p-value = 0.0006671
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.0608434
```

```
In [159... wilcox.test(Prior_Revocations_Parole ~ Race, data=Female)
cor.test(Female$Prior_Revocations_Parole, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Revocations_Parole by Race
W = 1132668, p-value = 0.5715
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Revocations_Parole and Female$Race
S = 5347349991, p-value = 0.5716
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.01005661

Is there a correlation between Prior_Revocations_Probation and recidivism and/or race for everyone, or just males, or just females?
```

```
In [160... wilcox.test(Prior_Revocations_Probation ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Prior_Revocations_Probation, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Revocations_Probation by Recidivism_Within_3years
W = 79186288, p-value = 3.587e-10
```

```

alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Prior_Revocations_Probation and NIJ$Recidivism_Within_3years
S = 2.7617e+12, p-value = 3.457e-10
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.03903791

In [161]:
wilcox.test(Prior_Revocations_Probation ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Prior_Revocations_Probation, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Revocations_Probation by Recidivism_Within_3years
W = 60371791, p-value = 5.46e-08
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Revocations_Probation and Male$Recidivism_Within_3years
S = 1.8712e+12, p-value = 5.412e-08
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.03610383

In [162]:
wilcox.test(Prior_Revocations_Probation ~ Race, data=Male)
cor.test(Male$Prior_Revocations_Probation, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Revocations_Probation by Race
W = 58411387, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Prior_Revocations_Probation and Male$Race
S = 1.8146e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.06523093

In [163]:
wilcox.test(Prior_Revocations_Probation ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Prior_Revocations_Probation, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Revocations_Probation by Recidivism_Within_3years
W = 1172974, p-value = 1.953e-05
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Revocations_Probation and Female$Recidivism_Within_3years
S = 4892332009, p-value = 1.988e-05
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.07589137

In [164]:
wilcox.test(Prior_Revocations_Probation ~ Race, data=Female)
cor.test(Female$Prior_Revocations_Probation, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Prior_Revocations_Probation by Race
W = 1075613, p-value = 0.0009031
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Prior_Revocations_Probation and Female$Race
S = 4981816114, p-value = 0.0008962
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.05898879

```

Is there a correlation between Condition_MH_SA and recidivism and/or race for everyone, or just males, or just females?

```
In [165.. wilcox.test(Condition_MH_SA ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Condition_MH_SA, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

Wilcoxon rank sum test with continuity correction

```
data: Condition_MH_SA by Recidivism_Within_3years
W = 72554760, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
    Spearman's rank correlation rho

data: NIJ$Condition_MH_SA and NIJ$Recidivism_Within_3years
S = 2.5467e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1138556
```

```
In [166.. wilcox.test(Condition_MH_SA ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Condition_MH_SA, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

Wilcoxon rank sum test with continuity correction

```
data: Condition_MH_SA by Recidivism_Within_3years
W = 54645947, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
    Spearman's rank correlation rho

data: Male$Condition_MH_SA and Male$Recidivism_Within_3years
S = 1.7065e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1209539
```

```
In [167.. wilcox.test(Condition_MH_SA ~ Race, data=Male)
cor.test(Male$Condition_MH_SA, Male$Race, method='spearman', use='complete.obs', exact=FALSE)
```

Wilcoxon rank sum test with continuity correction

```
data: Condition_MH_SA by Race
W = 53392083, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
    Spearman's rank correlation rho

data: Male$Condition_MH_SA and Male$Race
S = 1.687e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1309923
```

```
In [168.. wilcox.test(Condition_MH_SA ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Condition_MH_SA, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

Wilcoxon rank sum test with continuity correction

```
data: Condition_MH_SA by Recidivism_Within_3years
W = 10900279, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
    Spearman's rank correlation rho

data: Female$Condition_MH_SA and Female$Recidivism_Within_3years
S = 4508583709, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1483773
```

```
In [169.. wilcox.test(Condition_MH_SA ~ Race, data=Female)
cor.test(Female$Condition_MH_SA, Female$Race, method='spearman', use='complete.obs', exact=FALSE)
```

Wilcoxon rank sum test with continuity correction

```
data: Condition_MH_SA by Race
W = 872784, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
    Spearman's rank correlation rho
```

```
data: Female$Condition_MH_SA and Female$Race
S = 3921860347, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.259203
```

Is there a correlation between Condition_Cog_Ed and recidivism and/or race for everyone, or just males, or just females?

In [170]:

```
wilcox.test(Condition_Cog_Ed ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Condition_Cog_Ed, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Condition_Cog_Ed by Recidivism_Within_3years
W = 78386279, p-value = 1.659e-09
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Condition_Cog_Ed and NIJ$Recidivism_Within_3years
S = 2.7661e+12, p-value = 1.64e-09
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.0375043
```

In [171]:

```
wilcox.test(Condition_Cog_Ed ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Condition_Cog_Ed, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Condition_Cog_Ed by Recidivism_Within_3years
W = 58850274, p-value = 6.813e-14
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Condition_Cog_Ed and Male$Recidivism_Within_3years
S = 1.8447e+12, p-value = 6.588e-14
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.04975858
```

In [172]:

```
wilcox.test(Condition_Cog_Ed ~ Race, data=Male)
cor.test(Male$Condition_Cog_Ed, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Condition_Cog_Ed by Race
W = 63723816, p-value = 3.217e-09
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Condition_Cog_Ed and Male$Race
S = 2.0176e+12, p-value = 3.177e-09
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.03932174
```

In [173]:

```
wilcox.test(Condition_Cog_Ed ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Condition_Cog_Ed, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Condition_Cog_Ed by Recidivism_Within_3years
W = 1280036, p-value = 0.09484
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Condition_Cog_Ed and Female$Recidivism_Within_3years
S = 5451659984, p-value = 0.09484
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.02975964
```

In [174]:

```
wilcox.test(Condition_Cog_Ed ~ Race, data=Female)
cor.test(Female$Condition_Cog_Ed, Female$Race, method='spearman', use='complete.obs', exact=FALSE)
```

```

Wilcoxon rank sum test with continuity correction

data: Condition_Cog_Ed by Race
W = 1182118, p-value = 0.01032
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Condition_Cog_Ed and Female$Race
S = 5535429871, p-value = 0.0103
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.04558286

Is there a correlation between Condition_Other and recidivism and/or race for everyone, or just males, or just females?

In [175]: wilcox.test(Condition_Other ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Condition_Other, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Condition_Other by Recidivism_Within_3years
W = 80463756, p-value = 0.03843
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Condition_Other and NIJ$Recidivism_Within_3years
S = 2.8369e+12, p-value = 0.03842
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.01288046

In [176]: wilcox.test(Condition_Other ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Condition_Other, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Condition_Other by Recidivism_Within_3years
W = 61307782, p-value = 0.09621
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Condition_Other and Male$Recidivism_Within_3years
S = 1.9198e+12, p-value = 0.09621
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.01104915

In [177]: wilcox.test(Condition_Other ~ Race, data=Male)
cor.test(Male$Condition_Other, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Condition_Other by Race
W = 60103686, p-value = 0.002897
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Condition_Other and Male$Race
S = 1.9029e+12, p-value = 0.002895
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.01978344

In [178]: wilcox.test(Condition_Other ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Condition_Other, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Condition_Other by Recidivism_Within_3years
W = 1265282, p-value = 0.2621
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Condition_Other and Female$Recidivism_Within_3years

```

```

S = 5399632843, p-value = 0.2621
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.01993227

In [179]: wilcox.test(Condition_Other ~ Race, data=Female)
cor.test(Female$Condition_Other, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Condition_Other by Race
W = 1195148, p-value = 0.0002434
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Condition_Other and Female$Race
S = 5639328585, p-value = 0.0002405
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.06520821

Is there a correlation between Violations_ElectronicMonitoring and recidivism and/or race for everyone, or just males, or just females?

In [180]: wilcox.test(Violations_ElectronicMonitoring ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Violations_ElectronicMonitoring, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Violations_ElectronicMonitoring by Recidivism_Within_3years
W = 81621988, p-value = 0.5406
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Violations_ElectronicMonitoring and NIJ$Recidivism_Within_3years
S = 2.8849e+12, p-value = 0.5406
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.003807369

In [181]: wilcox.test(Violations_ElectronicMonitoring ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Violations_ElectronicMonitoring, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Violations_ElectronicMonitoring by Recidivism_Within_3years
W = 62240571, p-value = 0.2271
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Violations_ElectronicMonitoring and Male$Recidivism_Within_3years
S = 1.9569e+12, p-value = 0.2271
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.000022131

In [182]: wilcox.test(Violations_ElectronicMonitoring ~ Race, data=Male)
cor.test(Male$Violations_ElectronicMonitoring, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Violations_ElectronicMonitoring by Race
W = 63614584, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Violations_ElectronicMonitoring and Male$Race
S = 2.0745e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.06863688

In [183]: wilcox.test(Violations_ElectronicMonitoring ~ Recidivism_Within_3years, data=Female)

```

```

cor.test(Female$Violations_ElectronicMonitoring, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
Wilcoxon rank sum test with continuity correction

data: Violations_ElectronicMonitoring by Recidivism_Within_3years
W = 1257222, p-value = 0.06578
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Violations_ElectronicMonitoring and Female$Recidivism_Within_3years
S = 5467231769, p-value = 0.06576
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.03270098

In [184... wilcox.test(Violations_ElectronicMonitoring ~ Race, data=Female)
cor.test(Female$Violations_ElectronicMonitoring, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Violations_ElectronicMonitoring by Race
W = 1157428, p-value = 2.502e-05
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Violations_ElectronicMonitoring and Female$Race
S = 5690662549, p-value = 2.447e-05
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.07498464

Is there a correlation between Violations_Instruction and recidivism and/or race for everyone, or just males, or just females?

In [185... wilcox.test(Violations_Instruction ~ Recidivism_Within_3years, data=NIIJ)
cor.test(NIIJ$Violations_Instruction, NIIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Violations_Instruction by Recidivism_Within_3years
W = 77444129, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIIJ$Violations_Instruction and NIIJ$Recidivism_Within_3years
S = 2.689e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.06434993

In [186... wilcox.test(Violations_Instruction ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Violations_Instruction, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Violations_Instruction by Recidivism_Within_3years
W = 59161984, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Violations_Instruction and Male$Recidivism_Within_3years
S = 1.8286e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.05803821

In [187... wilcox.test(Violations_Instruction ~ Race, data=Male)
cor.test(Male$Violations_Instruction, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Violations_Instruction by Race
W = 63499836, p-value = 3.093e-12
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

```

```

data: Male$Violations_Instruction and Male$Race
S = 2.0312e+12, p-value = 3.017e-12
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.04631797

In [188... wilcox.test(Violations_Instruction ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Violations_Instruction, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Violations_Instruction by Recidivism_Within_3years
W = 1169968, p-value = 1.142e-06
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Violations_Instruction and Female$Recidivism_Within_3years
S = 4836329239, p-value = 1.097e-06
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.08646969

In [189... wilcox.test(Violations_Instruction ~ Race, data=Female)
cor.test(Female$Violations_Instruction, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Violations_Instruction by Race
W = 1101250, p-value = 0.06404
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Violations_Instruction and Female$Race
S = 5119866222, p-value = 0.06403
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.03291262

Is there a correlation between Violations_FailToReport and recidivism and/or race for everyone, or just males, or just females?

In [190... wilcox.test(Violations_FailToReport ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Violations_FailToReport, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Violations_FailToReport by Recidivism_Within_3years
W = 80138495, p-value = 9.9e-07
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Violations_FailToReport and NIJ$Recidivism_Within_3years
S = 2.7864e+12, p-value = 9.85e-07
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.03044632

In [191... wilcox.test(Violations_FailToReport ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Violations_FailToReport, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Violations_FailToReport by Recidivism_Within_3years
W = 61149200, p-value = 0.0002492
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Violations_FailToReport and Male$Recidivism_Within_3years
S = 1.894e+12, p-value = 0.0002487
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.02433072

```

```
In [192]: wilcox.test(Violations_FailToReport ~ Race, data=Male)
cor.test(Male$Violations_FailToReport, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Violations_FailToReport by Race
W = 61567598, p-value = 0.1866
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Violations_FailToReport and Male$Race
S = 1.9583e+12, p-value = 0.1866
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.008772355

In [193]: wilcox.test(Violations_FailToReport ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Violations_FailToReport, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Violations_FailToReport by Recidivism_Within_3years
W = 1199798, p-value = 9.268e-05
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Violations_FailToReport and Female$Recidivism_Within_3years
S = 4926313489, p-value = 9.122e-05
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.06947264

In [194]: wilcox.test(Violations_FailToReport ~ Race, data=Female)
cor.test(Female$Violations_FailToReport, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Violations_FailToReport by Race
W = 1117725, p-value = 0.3377
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Violations_FailToReport and Female$Race
S = 5203902690, p-value = 0.3378
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.01703904

Is there a correlation between Violations_MoveWithoutPermission and recidivism and/or race for everyone, or just males, or just females?

In [195]: wilcox.test(Violations_MoveWithoutPermission ~ Recidivism_Within_3years, data=NJ)
cor.test(NJ$Violations_MoveWithoutPermission, NJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Violations_MoveWithoutPermission by Recidivism_Within_3years
W = 79785276, p-value = 3.566e-07
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NJ$Violations_MoveWithoutPermission and NJ$Recidivism_Within_3years
S = 2.7829e+12, p-value = 3.545e-07
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.03167298

In [196]: wilcox.test(Violations_MoveWithoutPermission ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Violations_MoveWithoutPermission, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Violations_MoveWithoutPermission by Recidivism_Within_3years
```

```
W = 60802650, p-value = 1.396e-05
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Violations_MoveWithoutPermission and Male$Recidivism_Within_3years
S = 1.8853e+12, p-value = 1.391e-05
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.02885641
```

```
In [197]: wilcox.test(Violations_MoveWithoutPermission ~ Race, data=Male)
cor.test(Male$Violations_MoveWithoutPermission, Male$Race, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction

data: Violations_MoveWithoutPermission by Race
W = 60795072, p-value = 0.07145
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Violations_MoveWithoutPermission and Male$Race
S = 1.918e+12, p-value = 0.07145
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.01197301
```

```
In [198]: wilcox.test(Violations_MoveWithoutPermission ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Violations_MoveWithoutPermission, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction

data: Violations_MoveWithoutPermission by Recidivism_Within_3years
W = 1197555, p-value = 0.001439
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Violations_MoveWithoutPermission and Female$Recidivism_Within_3years
S = 4994273495, p-value = 0.00143
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.05663573
```

```
In [199]: wilcox.test(Violations_MoveWithoutPermission ~ Race, data=Female)
cor.test(Female$Violations_MoveWithoutPermission, Female$Race, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction

data: Violations_MoveWithoutPermission by Race
W = 1899176, p-value = 0.03681
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Violations_MoveWithoutPermission and Female$Race
S = 5097658027, p-value = 0.03678
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.03710751
```

Is there a correlation between Delinquency_Reports and recidivism and/or race for everyone, or just males, or just females?

```
In [200]: wilcox.test(Delinquency_Reports ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Delinquency_Reports, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction

data: Delinquency_Reports by Recidivism_Within_3years
W = 78229373, p-value = 3.869e-11
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Delinquency_Reports and NIJ$Recidivism_Within_3years
S = 2.7557e+12, p-value = 3.882e-11
alternative hypothesis: true rho is not equal to 0
sample estimates:
```

```
rho  
0.04111878
```

```
In [201]:  
wilcox.test(Delinquency_Reports ~ Recidivism_Within_3years, data=Male)  
cor.test(Male$Delinquency_Reports, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction  
  
data: Delinquency_Reports by Recidivism_Within_3years  
W = 68286503, p-value = 3.061e-05  
alternative hypothesis: true location shift is not equal to 0  
Spearman's rank correlation rho  
  
data: Male$Delinquency_Reports and Male$Recidivism_Within_3years  
S = 1.8875e+12, p-value = 3.052e-05  
alternative hypothesis: true rho is not equal to 0  
sample estimates:  
rho  
0.02769022
```

```
In [202]:  
wilcox.test(Delinquency_Reports ~ Race, data=Male)  
cor.test(Male$Delinquency_Reports, Male$Race, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction  
  
data: Delinquency_Reports by Race  
W = 60951532, p-value = 0.4194  
alternative hypothesis: true location shift is not equal to 0  
Spearman's rank correlation rho  
  
data: Male$Delinquency_Reports and Male$Race  
S = 1.9309e+12, p-value = 0.4195  
alternative hypothesis: true rho is not equal to 0  
sample estimates:  
rho  
0.005362688
```

```
In [203]:  
wilcox.test(Delinquency_Reports ~ Recidivism_Within_3years, data=Female)  
cor.test(Female$Delinquency_Reports, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction  
  
data: Delinquency_Reports by Recidivism_Within_3years  
W = 1131918, p-value = 9.61e-08  
alternative hypothesis: true location shift is not equal to 0  
Spearman's rank correlation rho  
  
data: Female$Delinquency_Reports and Female$Recidivism_Within_3years  
S = 4754276078, p-value = 8.865e-09  
alternative hypothesis: true rho is not equal to 0  
sample estimates:  
rho  
0.1019686
```

```
In [204]:  
wilcox.test(Delinquency_Reports ~ Race, data=Female)  
cor.test(Female$Delinquency_Reports, Female$Race, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction  
  
data: Delinquency_Reports by Race  
W = 1056483, p-value = 0.0001168  
alternative hypothesis: true location shift is not equal to 0  
Spearman's rank correlation rho  
  
data: Female$Delinquency_Reports and Female$Race  
S = 4931598209, p-value = 0.000115  
alternative hypothesis: true rho is not equal to 0  
sample estimates:  
rho  
0.06847441
```

Is there a correlation between Program_Attendances and recidivism and/or race for everyone, or just males, or just females?

```
In [205]:  
wilcox.test(Program_Attendances ~ Recidivism_Within_3years, data=NIJ)  
cor.test(NIJ$Program_Attendances, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction  
  
data: Program_Attendances by Recidivism_Within_3years
```

```

W = 86704988, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Program_Attendances and NIJ$Recidivism_Within_3years
S = 3.046e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.05986484

In [206]: wilcox.test(Program_Attendances ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Program_Attendances, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Program_Attendances by Recidivism_Within_3years
W = 66285810, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Program_Attendances and Male$Recidivism_Within_3years
S = 2.0665e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.06450459

In [207]: wilcox.test(Program_Attendances ~ Race, data=Male)
cor.test(Male$Program_Attendances, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Program_Attendances by Race
W = 56476294, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Program_Attendances and Male$Race
S = 1.8014e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.0720632

In [208]: wilcox.test(Program_Attendances ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Program_Attendances, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Program_Attendances by Recidivism_Within_3years
W = 1270157, p-value = 0.268
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Program_Attendances and Female$Recidivism_Within_3years
S = 5398324963, p-value = 0.2681
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.01968523

In [209]: wilcox.test(Program_Attendances ~ Race, data=Female)
cor.test(Female$Program_Attendances, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Program_Attendances by Race
W = 884718, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Program_Attendances and Female$Race
S = 4.287e+09, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.190241

```

Is there a correlation between Program_UnexcusedAbsences and recidivism and/or race for everyone, or just males, or just females?

```
In [210]: wilcox.test(Program_UnexcusedAbsences ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Program_UnexcusedAbsences, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Program_UnexcusedAbsences by Recidivism_Within_3years
W = 77510396, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Program_UnexcusedAbsences and NIJ$Recidivism_Within_3years
S = 2.7014e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.06004243

In [211]: wilcox.test(Program_UnexcusedAbsences ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Program_UnexcusedAbsences, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Program_UnexcusedAbsences by Recidivism_Within_3years
W = 59407433, p-value = 3.851e-14
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Program_UnexcusedAbsences and Male$Recidivism_Within_3years
S = 1.8437e+12, p-value = 3.719e-14
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.05025331

In [212]: wilcox.test(Program_UnexcusedAbsences ~ Race, data=Male)
cor.test(Male$Program_UnexcusedAbsences, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Program_UnexcusedAbsences by Race
W = 63432572, p-value = 1.387e-18
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Program_UnexcusedAbsences and Male$Race
S = 2.024e+12, p-value = 1.362e-10
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.04262437

In [213]: wilcox.test(Program_UnexcusedAbsences ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Program_UnexcusedAbsences, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Program_UnexcusedAbsences by Recidivism_Within_3years
W = 1146698, p-value = 1.391e-09
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Program_UnexcusedAbsences and Female$Recidivism_Within_3years
S = 4724258046, p-value = 1.257e-09
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1076387

In [214]: wilcox.test(Program_UnexcusedAbsences ~ Race, data=Female)
cor.test(Female$Program_UnexcusedAbsences, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Program_UnexcusedAbsences by Race
W = 1113867, p-value = 0.3548
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho
```

```
data: Female$Program_UnexcusedAbsences and Female$Race
S = 5.207e+09, p-value = 0.3549
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.01644606
```

Is there a correlation between Residence_Changes and recidivism and/or race for everyone, or just males, or just females?

```
In [215]: wilcox.test(Residence_Changes ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Residence_Changes, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Residence_Changes by Recidivism_Within_3years
W = 76768688, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Residence_Changes and NIJ$Recidivism_Within_3years
S = 2.72e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.05355539
```

```
In [216]: wilcox.test(Residence_Changes ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Residence_Changes, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Residence_Changes by Recidivism_Within_3years
W = 58515399, p-value = 8.532e-15
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Residence_Changes and Male$Recidivism_Within_3years
S = 1.8412e+12, p-value = 8.208e-15
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.05153858
```

```
In [217]: wilcox.test(Residence_Changes ~ Race, data=Male)
cor.test(Male$Residence_Changes, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Residence_Changes by Race
W = 58114846, p-value = 8.763e-13
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Residence_Changes and Male$Race
S = 1.8491e+12, p-value = 8.523e-13
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.04748188
```

```
In [218]: wilcox.test(Residence_Changes ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Residence_Changes, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Residence_Changes by Recidivism_Within_3years
W = 11380082, p-value = 8.412e-06
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Residence_Changes and Female$Recidivism_Within_3years
S = 4.875e+09, p-value = 8.181e-06
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.07916598
```

```
In [219]: wilcox.test(Residence_Changes ~ Race, data=Female)
cor.test(Female$Residence_Changes, Female$Race, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction

data: Residence_Changes by Race
W = 1118681, p-value = 0.4436
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Residence_Changes and Female$Race
S = 5.222e+09, p-value = 0.4437
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.01361617
```

Is there a correlation between Avg_Days_per_DrugTest and recidivism and/or race for everyone, or just males, or just females?

```
In [220]: wilcox.test(Avg_Days_per_DrugTest ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Avg_Days_per_DrugTest, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction

data: Avg_Days_per_DrugTest by Recidivism_Within_3years
W = 82501010, p-value = 0.0762
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Avg_Days_per_DrugTest and NIJ$Recidivism_Within_3years
S = 2.9956e+12, p-value = 0.0762
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.01103187
```

```
In [221]: wilcox.test(Avg_Days_per_DrugTest ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Avg_Days_per_DrugTest, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction

data: Avg_Days_per_DrugTest by Recidivism_Within_3years
W = 63152875, p-value = 0.0135
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Avg_Days_per_DrugTest and Male$Recidivism_Within_3years
S = 1.9731e+12, p-value = 0.0135
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.0164876
```

```
In [222]: wilcox.test(Avg_Days_per_DrugTest ~ Race, data=Male)
cor.test(Male$Avg_Days_per_DrugTest, Male$Race, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction

data: Avg_Days_per_DrugTest by Race
W = 66885995, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Avg_Days_per_DrugTest and Male$Race
S = 2.0927e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.07797769
```

```
In [223]: wilcox.test(Avg_Days_per_DrugTest ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Avg_Days_per_DrugTest, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction

data: Avg_Days_per_DrugTest by Recidivism_Within_3years
W = 1239768, p-value = 0.8765
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Avg_Days_per_DrugTest and Female$Recidivism_Within_3years
```

```
S = 5279486704, p-value = 0.8765
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.002762034
```

```
In [224... wilcox.test(Avg_Days_per_DrugTest ~ Race, data=Female)
cor.test(Female$Avg_Days_per_DrugTest, Female$Race, method='spearman', use='complete.obs', exact=FALSE)
```

Wilcoxon rank sum test with continuity correction

```
data: Avg_Days_per_DrugTest by Race
W = 1311614, p-value = 3.673e-14
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Avg_Days_per_DrugTest and Female$Race
S = 6006556687, p-value = 2.851e-14
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.1345736
```

Is there a correlation between DrugTests_THC_Positive and recidivism and/or race for everyone, or just males, or just females?

```
In [225... wilcox.test(DrugTests_THC_Positive ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$DrugTests_THC_Positive, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

Wilcoxon rank sum test with continuity correction

```
data: DrugTests_THC_Positive by Recidivism_Within_3years
W = 75487226, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$DrugTests_THC_Positive and NIJ$Recidivism_Within_3years
S = 2.6378e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.08214599
```

```
In [226... wilcox.test(DrugTests_THC_Positive ~ Recidivism_Within_3years, data=Male)
cor.test(Male$DrugTests_THC_Positive, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

Wilcoxon rank sum test with continuity correction

```
data: DrugTests_THC_Positive by Recidivism_Within_3years
W = 57489348, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$DrugTests_THC_Positive and Male$Recidivism_Within_3years
S = 1.7889e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.07847997
```

```
In [227... wilcox.test(DrugTests_THC_Positive ~ Race, data=Male)
cor.test(Male$DrugTests_THC_Positive, Male$Race, method='spearman', use='complete.obs', exact=FALSE)
```

Wilcoxon rank sum test with continuity correction

```
data: DrugTests_THC_Positive by Race
W = 70385384, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$DrugTests_THC_Positive and Male$Race
S = 2.2531e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.166628
```

```
In [228... wilcox.test(DrugTests_THC_Positive ~ Recidivism_Within_3years, data=Female)
cor.test(Female$DrugTests_THC_Positive, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```

Wilcoxon rank sum test with continuity correction

data: DrugTests_THC_Positive by Recidivism_Within_3years
W = 1226076, p-value = 0.2244
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$DrugTests_THC_Positive and Female$Recidivism_Within_3years
S = 5179888393, p-value = 0.2245
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.02159819

In [229... wilcox.test(DrugTests_THC_Positive ~ Race, data=Female)
cor.test(Female$DrugTests_THC_Positive, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: DrugTests_THC_Positive by Race
W = 1197473, p-value = 5.107e-07
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$DrugTests_THC_Positive and Female$Race
S = 5766647806, p-value = 4.876e-07
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.08925743

Is there a correlation between DrugTests_Cocaine_Positive and recidivism and/or race for everyone, or just males, or just females?

In [230... wilcox.test(DrugTests_Cocaine_Positive ~ Recidivism_Within_3years, data=NJ)
cor.test(NJ$DrugTests_Cocaine_Positive, NJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: DrugTests_Cocaine_Positive by Recidivism_Within_3years
W = 80963668, p-value = 0.06556
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NJ$DrugTests_Cocaine_Positive and NJ$Recidivism_Within_3years
S = 2.841e+12, p-value = 0.06556
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.01145671

In [231... wilcox.test(DrugTests_Cocaine_Positive ~ Recidivism_Within_3years, data=Male)
cor.test(Male$DrugTests_Cocaine_Positive, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: DrugTests_Cocaine_Positive by Recidivism_Within_3years
W = 61613674, p-value = 0.1112
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$DrugTests_Cocaine_Positive and Male$Recidivism_Within_3years
S = 1.9208e+12, p-value = 0.1112
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.01055009

In [232... wilcox.test(DrugTests_Cocaine_Positive ~ Race, data=Male)
cor.test(Male$DrugTests_Cocaine_Positive, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: DrugTests_Cocaine_Positive by Race
W = 655308892, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$DrugTests_Cocaine_Positive and Male$Race

```

```

S = 2.1984e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.1283088

In [233.. wilcox.test(DrugTests_Cocaine_Positive ~ Recidivism_Within_3years, data=Female)
cor.test(Female$DrugTests_Cocaine_Positive, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: DrugTests_Cocaine_Positive by Recidivism_Within_3years
W = 1240552, p-value = 0.7663
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$DrugTests_Cocaine_Positive and Female$Recidivism_Within_3years
S = 5266141893, p-value = 0.7663
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.005282725

In [234.. wilcox.test(DrugTests_Cocaine_Positive ~ Race, data=Female)
cor.test(Female$DrugTests_Cocaine_Positive, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: DrugTests_Cocaine_Positive by Race
W = 1197177, p-value = 1.009e-11
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$DrugTests_Cocaine_Positive and Female$Race
S = 5934402294, p-value = 8.57e-12
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.1209444

Is there a correlation between DrugTests_Meth_Positive and recidivism and/or race for everyone, or just males, or just females?

In [235.. wilcox.test(DrugTests_Meth_Positive ~ Recidivism_Within_3years, data=NJ)
cor.test(NJ$DrugTests_Meth_Positive, NJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: DrugTests_Meth_Positive by Recidivism_Within_3years
W = 79020430, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NJ$DrugTests_Meth_Positive and NJ$Recidivism_Within_3years
S = 2.7164e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.05479223

In [236.. wilcox.test(DrugTests_Meth_Positive ~ Recidivism_Within_3years, data=Male)
cor.test(Male$DrugTests_Meth_Positive, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: DrugTests_Meth_Positive by Recidivism_Within_3years
W = 60155968, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$DrugTests_Meth_Positive and Male$Recidivism_Within_3years
S = 1.8346e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.05496933

In [237.. wilcox.test(DrugTests_Meth_Positive ~ Race, data=Male)
cor.test(Male$DrugTests_Meth_Positive, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

```

```

Wilcoxon rank sum test with continuity correction

data: DrugTests_Meth_Positive by Race
W = 52129654, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$DrugTests_Meth_Positive and Male$Race
S = 1.399e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.279359

In [238]: wilcox.test(DrugTests_Meth_Positive ~ Recidivism_Within_3years, data=Female)
cor.test(Female$DrugTests_Meth_Positive, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: DrugTests_Meth_Positive by Recidivism_Within_3years
W = 1170252, p-value = 3.223e-07
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$DrugTests_Meth_Positive and Female$Recidivism_Within_3years
S = 4813322239, p-value = 3.067e-07
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.09081546

In [239]: wilcox.test(DrugTests_Meth_Positive ~ Race, data=Female)
cor.test(Female$DrugTests_Meth_Positive, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: DrugTests_Meth_Positive by Race
W = 952752, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$DrugTests_Meth_Positive and Female$Race
S = 4.09e+09, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.2274356

Is there a correlation between DrugTests_Other_Positive and recidivism and/or race for everyone, or just males, or just females?

In [240]: wilcox.test(DrugTests_Other_Positive ~ Recidivism_Within_3years, data=NII)
cor.test(NII$DrugTests_Other_Positive, NII$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: DrugTests_Other_Positive by Recidivism_Within_3years
W = 81321518, p-value = 0.5721
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NII$DrugTests_Other_Positive and NII$Recidivism_Within_3years
S = 2.8638e+12, p-value = 0.5721
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.003515093

In [241]: wilcox.test(DrugTests_Other_Positive ~ Recidivism_Within_3years, data=Male)
cor.test(Male$DrugTests_Other_Positive, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: DrugTests_Other_Positive by Recidivism_Within_3years
W = 61980588, p-value = 0.9374
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

```

```
data: Male$DrugTests_Other_Positive and Male$Recidivism_Within_3years
S = 1.9423e+12, p-value = 0.9374
alternative hypothesis: true rho is not equal to 0
sample estimates:
      rho
-0.0005213972
```

In [242]

```
wilcox.test(DrugTests_Other_Positive ~ Race, data=Male)
cor.test(Male$DrugTests_Other_Positive, Male$Race, method='spearman', use='complete.obs', exact=FALSE)
```

Wilcoxon rank sum test with continuity correction

```
data: DrugTests_Other_Positive by Race
W = 57820564, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$DrugTests_Other_Positive and Male$Race
S = 1.7069e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
      rho
0.1207307
```

In [243]

```
wilcox.test(DrugTests_Other_Positive ~ Recidivism_Within_3years, data=Female)
cor.test(Female$DrugTests_Other_Positive, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

Wilcoxon rank sum test with continuity correction

```
data: DrugTests_Other_Positive by Recidivism_Within_3years
W = 1206134, p-value = 0.002456
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$DrugTests_Other_Positive and Female$Recidivism_Within_3years
S = 5009135222, p-value = 0.002443
alternative hypothesis: true rho is not equal to 0
sample estimates:
      rho
0.05382851
```

In [244]

```
wilcox.test(DrugTests_Other_Positive ~ Race, data=Female)
cor.test(Female$DrugTests_Other_Positive, Female$Race, method='spearman', use='complete.obs', exact=FALSE)
```

Wilcoxon rank sum test with continuity correction

```
data: DrugTests_Other_Positive by Race
W = 1043939, p-value = 1.156e-12
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$DrugTests_Other_Positive and Female$Race
S = 4625082991, p-value = 9.502e-13
alternative hypothesis: true rho is not equal to 0
sample estimates:
      rho
0.1263718
```

Is there a correlation between Percent_Days_Employed and recidivism and/or race for everyone, or just males, or just females?

In [245]

```
wilcox.test(Percent_Days_Employed ~ Recidivism_Within_3years, data=NIJ)
cor.test(NIJ$Percent_Days_Employed, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

Wilcoxon rank sum test with continuity correction

```
data: Percent_Days_Employed by Recidivism_Within_3years
W = 101742703, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Percent_Days_Employed and NIJ$Recidivism_Within_3years
S = 3.4989e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
      rho
-0.2174536
```

In [246]

```
wilcox.test(Percent_Days_Employed ~ Recidivism_Within_3years, data=Male)
```

```
cor.test(Male$Percent_Days_Employed, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction
```

```
data: Percent_Days_Employed by Recidivism_Within_3years  
W = 77420973, p-value < 2.2e-16  
alternative hypothesis: true location shift is not equal to 0  
Spearman's rank correlation rho  
  
data: Male$Percent_Days_Employed and Male$Recidivism_Within_3years  
S = 2.3616e+12, p-value < 2.2e-16  
alternative hypothesis: true rho is not equal to 0  
sample estimates:  
rho  
-0.2165066
```

In [247]:

```
wilcox.test(Percent_Days_Employed ~ Race, data=Male)  
cor.test(Male$Percent_Days_Employed, Male$Race, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction
```

```
data: Percent_Days_Employed by Race  
W = 52345212, p-value < 2.2e-16  
alternative hypothesis: true location shift is not equal to 0  
Spearman's rank correlation rho  
  
data: Male$Percent_Days_Employed and Male$Race  
S = 1.6971e+12, p-value < 2.2e-16  
alternative hypothesis: true rho is not equal to 0  
sample estimates:  
rho  
0.1257944
```

In [248]:

```
wilcox.test(Percent_Days_Employed ~ Recidivism_Within_3years, data=Female)  
cor.test(Female$Percent_Days_Employed, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction
```

```
data: Percent_Days_Employed by Recidivism_Within_3years  
W = 1564024, p-value < 2.2e-16  
alternative hypothesis: true location shift is not equal to 0  
Spearman's rank correlation rho  
  
data: Female$Percent_Days_Employed and Female$Recidivism_Within_3years  
S = 6.494e+09, p-value < 2.2e-16  
alternative hypothesis: true rho is not equal to 0  
sample estimates:  
rho  
-0.2266397
```

In [249]:

```
wilcox.test(Percent_Days_Employed ~ Race, data=Female)  
cor.test(Female$Percent_Days_Employed, Female$Race, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction
```

```
data: Percent_Days_Employed by Race  
W = 1048062, p-value = 0.0008339  
alternative hypothesis: true location shift is not equal to 0  
Spearman's rank correlation rho  
  
data: Female$Percent_Days_Employed and Female$Race  
S = 4979729207, p-value = 0.0008274  
alternative hypothesis: true rho is not equal to 0  
sample estimates:  
rho  
0.05938299
```

Is there a correlation between Jobs_Per_Year and recidivism and/or race for everyone, or just males, or just females?

In [250]:

```
wilcox.test(Jobs_Per_Year ~ Recidivism_Within_3years, data=NIJ)  
cor.test(NIJ$Jobs_Per_Year, NIJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction
```

```
data: Jobs_Per_Year by Recidivism_Within_3years  
W = 88435116, p-value < 2.2e-16  
alternative hypothesis: true location shift is not equal to 0  
Spearman's rank correlation rho  
  
data: NIJ$Jobs_Per_Year and NIJ$Recidivism_Within_3years
```

```
S = 3.08//e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.07439718
```

```
In [251]: wilcox.test(Jobs_Per_Year ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Jobs_Per_Year, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction

data: Jobs_Per_Year by Recidivism_Within_3years
W = 67242287, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Jobs_Per_Year and Male$Recidivism_Within_3years
S = 2.084e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.07351884
```

```
In [252]: wilcox.test(Jobs_Per_Year ~ Race, data=Male)
cor.test(Male$Jobs_Per_Year, Male$Race, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction

data: Jobs_Per_Year by Race
W = 52689576, p-value < 2.2e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Jobs_Per_Year and Male$Race
S = 1.7078e+12, p-value < 2.2e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.1202892
```

```
In [253]: wilcox.test(Jobs_Per_Year ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Jobs_Per_Year, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction

data: Jobs_Per_Year by Recidivism_Within_3years
W = 1368512, p-value = 7.639e-07
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Jobs_Per_Year and Female$Recidivism_Within_3years
S = 5759319738, p-value = 7.316e-07
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.08787324
```

```
In [254]: wilcox.test(Jobs_Per_Year ~ Race, data=Female)
cor.test(Female$Jobs_Per_Year, Female$Race, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction

data: Jobs_Per_Year by Race
W = 1047517, p-value = 0.0000142
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Jobs_Per_Year and Female$Race
S = 4979106780, p-value = 0.0000078
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.05950055
```

Is there a correlation between Employment_Exempt and recidivism and/or race for everyone, or just males, or just females?

```
In [255]: wilcox.test(Employment_Exempt ~ Recidivism_Within_3years, data=NJ)
cor.test(NJ$Employment_Exempt, NJ$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)
```

```
Wilcoxon rank sum test with continuity correction
```

```

data: Employment_Exempt by Recidivism_Within_3years
W = 84276414, p-value = 5.886e-16
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: NIJ$Employment_Exempt and NIJ$Recidivism_Within_3years
S = 3.8186e+12, p-value = 5.654e-16
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.05034328

In [256]: wilcox.test(Employment_Exempt ~ Recidivism_Within_3years, data=Male)
cor.test(Male$Employment_Exempt, Male$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Employment_Exempt by Recidivism_Within_3years
W = 63946261, p-value = 4.568e-13
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Employment_Exempt and Male$Recidivism_Within_3years
S = 2.0346e+12, p-value = 4.437e-13
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.04087239

In [257]: wilcox.test(Employment_Exempt ~ Race, data=Male)
cor.test(Male$Employment_Exempt, Male$Race, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Employment_Exempt by Race
W = 60430204, p-value = 0.00191
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Male$Employment_Exempt and Male$Race
S = 1.9013e+12, p-value = 0.001908
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.02061653

In [258]: wilcox.test(Employment_Exempt ~ Recidivism_Within_3years, data=Female)
cor.test(Female$Employment_Exempt, Female$Recidivism_Within_3years, method='spearman', use='complete.obs', exact=FALSE)

Wilcoxon rank sum test with continuity correction

data: Employment_Exempt by Recidivism_Within_3years
W = 1254642, p-value = 0.5502
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

data: Female$Employment_Exempt and Female$Recidivism_Within_3years
S = 5350320401, p-value = 0.5503
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.01061769

In [259]: wilcox.test(Employment_Exempt ~ Race, data=Female)
cor.test(Female$Employment_Exempt, Female$Race, method='spearman', use='complete.obs', exact=FALSE)

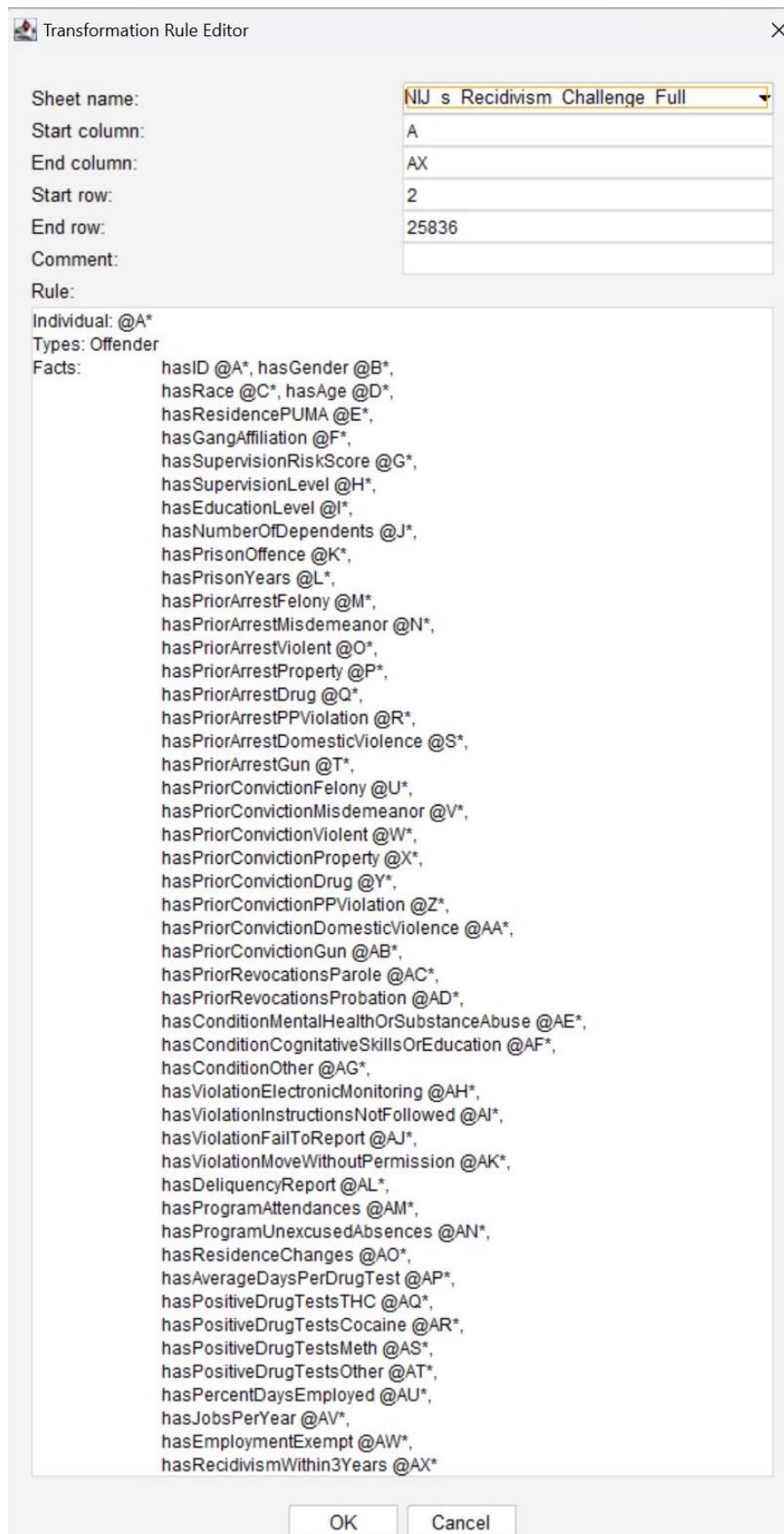
Wilcoxon rank sum test with continuity correction

data: Employment_Exempt by Race
W = 1088352, p-value = 0.02277
alternative hypothesis: true location shift is not equal to 0
Spearman's rank correlation rho

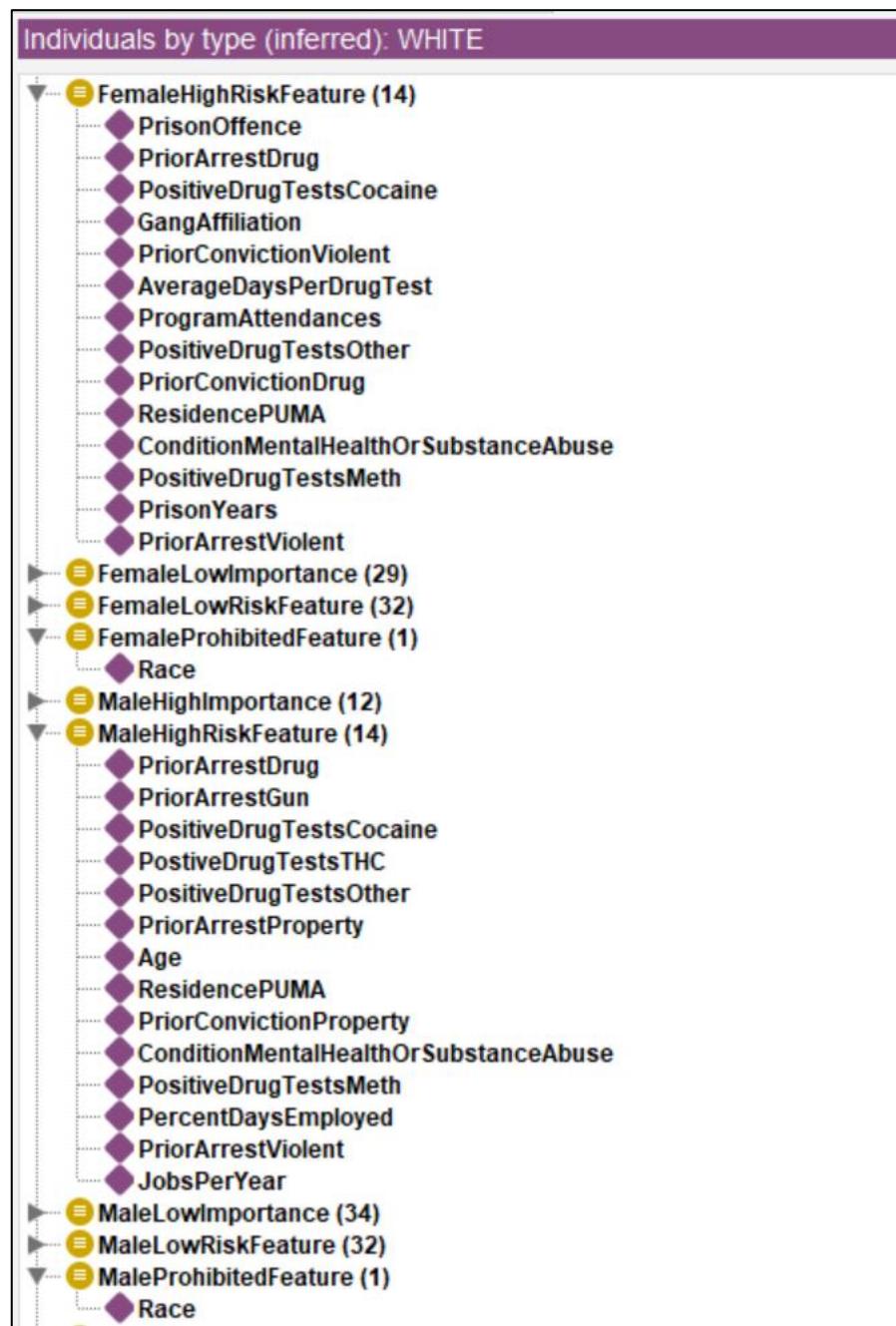
data: Female$Employment_Exempt and Female$Race
S = 5079833732, p-value = 0.02274
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
0.04047432

```

Appendix C. NIJ Ontology Cellfie Import Script

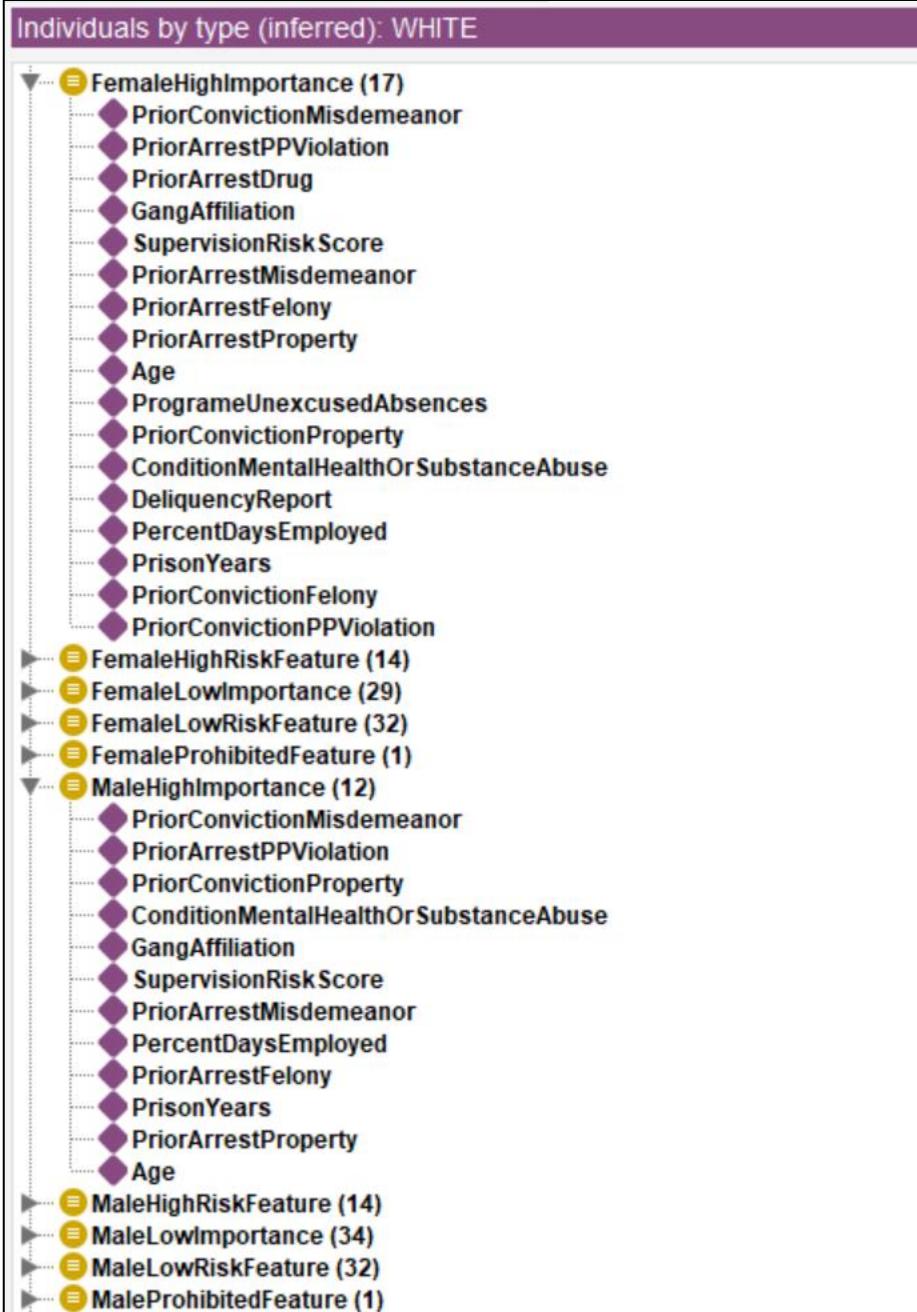


Appendix D. NIJ Ontology High/low Risk/importance Features



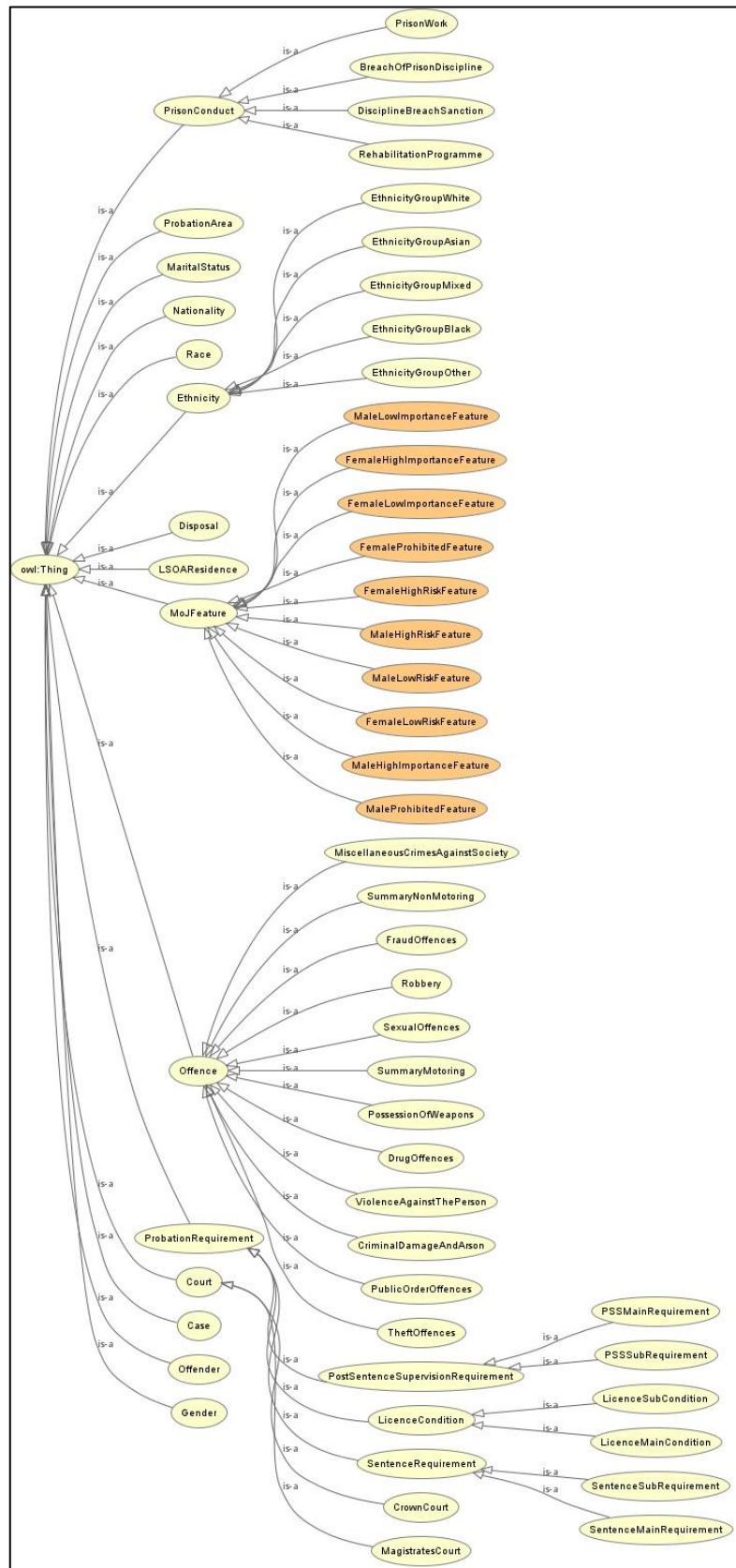
Individuals by type (inferred): WHITE

- FemaleLowRiskFeature (32)
 - ◆ PriorArrestGun
 - ◆ ViolationMoveWithoutPermission
 - ◆ PositiveDrugTestsTHC
 - ◆ PriorArrestMisdemeanor
 - ◆ SupervisionRiskScore
 - ◆ EmploymentExempt
 - ◆ PriorRevocationsParole
 - ◆ PriorConvictionDomesticViolence
 - ◆ PriorArrestProperty
 - ◆ ViolationElectronicMonitoring
 - ◆ PercentDaysEmployed
 - ◆ PriorConvictionGun
 - ◆ NumberOfDependents
 - ◆ EducationLevel
 - ◆ ConditionCognititativeSkillsOrEducation
 - ◆ PriorConvictionMisdemeanor
 - ◆ PriorArrestPPViolation
 - ◆ PriorArrestFelony
 - ◆ Age
 - ◆ PriorRevocationsProbation
 - ◆ SupervisionLevel
 - ◆ ProgramUnexcusedAbsences
 - ◆ PriorConvictionProperty
 - ◆ DelinquencyReport
 - ◆ ResidenceChanges
 - ◆ PriorArrestDomesticViolence
 - ◆ ConditionOther
 - ◆ JobsPerYear
 - ◆ ViolationInstructionsNotFollowed
 - ◆ ViolationFailToReport
 - ◆ PriorConvictionFelony
 - ◆ PriorConvictionPPViolation
- FemaleProhibitedFeature (1)
- MaleHighImportance (12)
- MaleHighRiskFeature (14)
- MaleLowImportance (34)
- MaleLowRiskFeature (32)
 - ◆ ViolationMoveWithoutPermission
 - ◆ GangAffiliation
 - ◆ PriorConvictionViolent
 - ◆ PriorArrestMisdemeanor
 - ◆ SupervisionRiskScore
 - ◆ EmploymentExempt
 - ◆ ProgramAttendances
 - ◆ PriorRevocationsParole
 - ◆ PriorConvictionDomesticViolence
 - ◆ ViolationElectronicMonitoring
 - ◆ PriorConvictionGun
 - ◆ NumberOfDependents
 - ◆ EducationLevel
 - ◆ ConditionCognititativeSkillsOrEducation
 - ◆ PriorConvictionMisdemeanor



Individuals by type (inferred): WHITE	
↳	FemaleHighRiskFeature (14)
↳	FemaleLowImportance (29)
↳	PriorArrestGun
↳	ViolationMoveWithoutPermission
↳	PositiveDrugTestsTHC
↳	PriorConvictionViolent
↳	EmploymentExempt
↳	ProgramAttendances
↳	PriorRevocationsParole
↳	PositiveDrugTestsOther
↳	PriorConvictionDomesticViolence
↳	ResidencePUMA
↳	PositiveDrugTestsMeth
↳	ViolationElectronicMonitoring
↳	PriorConvictionGun
↳	NumberOfDependents
↳	PriorArrestViolent
↳	EducationLevel
↳	ConditionCognititative SkillsOrEducation
↳	PrisonOffence
↳	PositiveDrugTestsCocaine
↳	AverageDaysPerDrugTest
↳	PriorConvictionDrug
↳	PriorRevocationsProbation
↳	SupervisionLevel
↳	ResidenceChanges
↳	PriorArrestDomesticViolence
↳	ConditionOther
↳	JobsPerYear
↳	ViolationInstructionsNotFollowed
↳	ViolationFailToReport
↳	FemaleLowRiskFeature (32)
↳	FemaleProhibitedFeature (1)
↳	MaleHighImportance (12)
↳	MaleHighRiskFeature (14)
↳	MaleLowImportance (34)
↳	PriorArrestGun
↳	ViolationMoveWithoutPermission
↳	PositiveDrugTestsTHC
↳	PriorConvictionViolent
↳	EmploymentExempt
↳	ProgramAttendances
↳	PriorRevocationsParole
↳	PositiveDrugTestsOther
↳	PriorConvictionDomesticViolence
↳	ResidencePUMA
↳	PositiveDrugTestsMeth
↳	ViolationElectronicMonitoring
↳	PriorConvictionGun
↳	NumberOfDependents
↳	PriorArrestViolent
↳	EducationLevel
↳	ConditionCognititative SkillsOrEducation

Appendix E. MoJ Ontology Protégé Screenshots



Inferred hierarchy



Object properties and data properties

Active ontology	Entities	Individuals by class	OWLviz	DL Query	SPARQL Query	SWRL Tab	SPARQL Query	Rule
Name								
Breach of prison discipline mapping	<input checked="" type="checkbox"/>	Moj:Case(c) ^ Moj:hasBreachOrPisitionDisciplineCode(?c, ?code) ^ Moj:hasBreachOrPisitionDisciplineCode(?b, ?breach) ^ Moj:hasBreachOrPisitionDiscipline(?b, ?breach) ^ Moj:hasBreachOrPisitionDiscipline(?b, ?breach) ^ Moj:hasBreachOrPisitionDiscipline(?b, ?breach)						
Court mapping	<input checked="" type="checkbox"/>	Moj:Case(c) ^ Moj:hasCourtCode(?c, ?code) ^ Moj:hasCourt(?ct, ?court)						
Discipline breach sanction mapping	<input checked="" type="checkbox"/>	Moj:Case(c) ^ Moj:hasDisciplineBreachSanctionCode(?c, ?code) ^ Moj:hasDisciplineBreachSanctionCode(?s, ?sanction) ^ Moj:hasDisciplineBreachSanction(?s, ?sanction) ^ Moj:hasDisciplineBreachSanction(?s, ?sanction)						
Ethnicity mapping	<input checked="" type="checkbox"/>	Moj:Offender(?o) ^ Moj:hasEthnicityCode(?e, ?code)						
LSOA Residence mapping	<input checked="" type="checkbox"/>	Moj:Offender(?o) ^ Moj:hasLSOAResidenceCode(?o, ?code)						
Licence main condition mapping	<input checked="" type="checkbox"/>	Moj:Case(c) ^ Moj:hasLicenceMainConditionCode(?c, ?code)						
Licence sub condition mapping	<input checked="" type="checkbox"/>	Moj:Offender(?o) ^ Moj:hasLicenceSubConditionCode(?o, ?code)						
Marital status mapping	<input checked="" type="checkbox"/>	Moj:Case(c) ^ Moj:hasMaritalStatusCode(?o, ?code)						
Most serious offence mapping	<input checked="" type="checkbox"/>	Moj:Offender(?o) ^ Moj:hasMostSeriousOffenceCode(?o, ?code) ^ Moj:hasOffenceCode(?o, ?code)						
Nationality mapping	<input checked="" type="checkbox"/>	Moj:Case(c) ^ Moj:hasNationalityCode(?o, ?code)						
PSS main requirement mapping	<input checked="" type="checkbox"/>	Moj:Case(c) ^ Moj:hasPSSMainRequirementCode(?c, ?code)						
PSS sub requirement mapping	<input checked="" type="checkbox"/>	Moj:Case(c) ^ Moj:hasPSSSubRequirementCode(?c, ?code)						
Principle disposal mapping	<input checked="" type="checkbox"/>	Moj:Case(c) ^ Moj:hasDisposalCode(?d, ?code)						
Principle offence mapping	<input checked="" type="checkbox"/>	Moj:Case(c) ^ Moj:hasOffenceCode(?o, ?code)						
Prison work mapping	<input checked="" type="checkbox"/>	Moj:Case(c) ^ Moj:hasPrisonWorkCode(?c, ?code)						
Probation area mapping	<input checked="" type="checkbox"/>	Moj:Case(c) ^ Moj:hasProbationAreaCode(?p, ?code)						
Race mapping	<input checked="" type="checkbox"/>	Moj:Offender(?o) ^ Moj:hasEthnicityCode(?e, ?code)						
Rehabilitation programme mapping	<input checked="" type="checkbox"/>	Moj:Case(c) ^ Moj:hasRehabilitationProgrammeCode(?c, ?code) ^ Moj:hasRehabilitationProgrammeCode(?p, ?code)						
Sentence main requirement mapping	<input checked="" type="checkbox"/>	Moj:Case(c) ^ Moj:hasSentenceMainRequirementCode(?r, ?code)						
Sentence sub requirement mapping	<input checked="" type="checkbox"/>	Moj:Case(c) ^ Moj:hasSentenceSubRequirementCode(?r, ?code)						

SWRL rules

Property assertions: O511985165	
Object property assertions	+
hasLSOAResidenceCode LSOA-E01000012	?
hasEthnicityCode Eth-W1	@
hasNationalityCode Nat-BRIT	×
hasMaritalStatusCode MS-S	○
hasGender Male	?
hasCase C587659755	@
hasCase C618323430	?
hasCase C535754077	@
hasCase C499266153	?
hasCase C113345537	@
hasCase C904791425	?
hasPersonalCharacteristic Eth-W1	@
hasPersonalCharacteristic MS-S	?
hasPersonalCharacteristic Male	?
hasPersonalCharacteristic LSOA-E01000012	@
hasPersonalCharacteristic Nat-BRIT	?
Data property assertions	+
hasEducationLevel "High School"	?
hasRecidivismWithinThreeYears false	@
hasAlcoholDependent true	×
hasGangAffiliation false	?
hasAge 61	@
hasMonthsSinceLastConviction 10	?
hasEmployment false	@
hasClassBDrugDependent false	×
hasMonthsAtAddress 36	?
hasNumberOfPreviousConvictions 5	@
hasMonthsSinceLastImprisonment 299	?
hasNumberOfDependents 0	@
hasResidentialStatus "Homeless"	?
hasName "John Smith"	@
hasDateOfBirth "1962-12-03T00:00:00"^^xsd:dateTime	?
hasClassADrugDependent false	@
hasOffenderID "O511985165"	?
OffenderProperty 0	@
OffenderProperty "British"	?
OffenderProperty "Single-not married/in civil partnership"	@
OffenderProperty "White"	?
OffenderProperty 5	@
OffenderProperty 36	?
OffenderProperty true	@
OffenderProperty 10	?
OffenderProperty false	@
OffenderProperty "White British"	?
OffenderProperty "Barking and Dagenham 015D"	@
OffenderProperty "John Smith"	?
OffenderProperty 299	@
OffenderProperty "High School"	?
OffenderProperty "Homeless"	@
OffenderProperty "1962-12-03T00:00:00"^^xsd:dateTime	?
OffenderProperty 61	@
OffenderProperty "O511985165"	?
hasEthnicity "White British"	@
hasLSOAResidence "Barking and Dagenham 015D"	?
hasMaritalStatus "Single-not married/in civil partnership"	@
hasNationality "British"	?
hasRace "White"	@
Negative object property assertions	+
Negative data property assertions	+

Sample offender property assertions

Property assertions: C338060576	
Object property assertions +	<ul style="list-style-type: none"> hasPrincipalDisposalCode Dis-IMP hasPrincipalOffenceCode Off-831 hasLicenceMainConditionCode LCM-LCF hasDisciplineBreachSanctionCode DBS-3 hasDisciplineBreachSanctionCode DBS-2 hasLicenceSubConditionCode LCS-D03 hasCourtCode CC-77 isCaseOf O486623255 hasRehabilitationProgrammeCode RP-BNM+ hasMostSeriousOffenceCode Off-831 hasBreachOfPrisonDisciplineCode BOD-1B hasRehabilitationProgrammeCode RP-BBR hasDisciplineBreachSanctionCode DBS-4 hasBreachOfPrisonDisciplineCode BOD-17A hasProbationAreaCode PA-N59 hasLicenceSubConditionCode LCS-LC147 hasCase Off-831 hasLicenceCondition LCS-D03 hasLicenceCondition LCM-LCF hasLicenceCondition LCS-LC147 hasPrisonConduct RP-BBR hasPrisonConduct BOD-1B hasPrisonConduct BOD-17A hasPrisonConduct RP-BNM+ hasPrisonConduct DBS-3 hasPrisonConduct DBS-2 hasPrisonConduct DBS-4 hasProbationRequirement LCS-D03 hasProbationRequirement LCM-LCF hasProbationRequirement LCS-LC147
Data property assertions +	<ul style="list-style-type: none"> hasOffenderAgeAtOffence 72 hasOrderLengthDays 730 hasLicenceConditionsEndDate "2025-07-14T00:00:00"^^xsd:dateTime hasLicencePeriodDays 365 hasCaseID "C338060576" hasLicenceConditionsStartDate "2024-07-15T00:00:00"^^xsd:dateTime hasPrisonDurationDays 730 hasDateOfOffence "2023-02-16T00:00:00"^^xsd:dateTime hasPrincipleDisposalDays 730 CaseProperty "Stopped work" CaseProperty "8.10 Breach of a restraining order" CaseProperty "Assault on staff" CaseProperty "Alcohol consumption" CaseProperty "Destruction intentionally" CaseProperty "Extra days" CaseProperty "Stopped money" CaseProperty "Imprisonment" CaseProperty 72 CaseProperty "Caution" CaseProperty "Theft from another prisoner" CaseProperty 365 CaseProperty "Possession of unauthorised article" CaseProperty "Assault on prisoner" CaseProperty "2023-02-16T00:00:00"^^xsd:dateTime CaseProperty "Sale of unauthorised article" CaseProperty "Set fire intentionally" CaseProperty "Building Better Relationships" CaseProperty "Segregation" CaseProperty 730 CaseProperty "C338060576" CaseProperty "Becoming New Me +" CaseProperty "Lost privileges" LicenceCondition "NHS - Market Garden Project" LicenceCondition "Not contact serving/remand prisoner" LicenceCondition "Licence - Curfew" LicenceCondition "2024-07-15T00:00:00"^^xsd:dateTime LicenceCondition "2025-07-14T00:00:00"^^xsd:dateTime PrisonConductProperty "Stopped work" PrisonConductProperty "Assault on staff" PrisonConductProperty "Alcohol consumption" PrisonConductProperty "Destruction intentionally" PrisonConductProperty "Extra days" PrisonConductProperty "Stopped money" PrisonConductProperty "Caution" PrisonConductProperty "Theft from another prisoner" PrisonConductProperty "Possession of unauthorised article" PrisonConductProperty "Assault on prisoner" PrisonConductProperty "Sale of unauthorised article" PrisonConductProperty "Set fire intentionally" PrisonConductProperty "Building Better Relationships"
Negative object property assertions +	<ul style="list-style-type: none"> PrisonConductProperty "Segregation" PrisonConductProperty "Becoming New Me +" PrisonConductProperty "Lost privileges" ProbationRequirementProperty "South Central" ProbationRequirementProperty "NHS - Market Garden Project" ProbationRequirementProperty "Not contact serving/remand prisoner" ProbationRequirementProperty "Licence - Curfew" ProbationRequirementProperty "2024-07-15T00:00:00"^^xsd:dateTime ProbationRequirementProperty "2025-07-14T00:00:00"^^xsd:dateTime SentenceOutcomeProperty 730 SentenceOutcomeProperty "Imprisonment" SentenceOutcomeProperty 365 hasBreachOfPrisonDiscipline "Sale of unauthorised article" hasBreachOfPrisonDiscipline "Assault on staff" hasBreachOfPrisonDiscipline "Alcohol consumption" hasBreachOfPrisonDiscipline "Set fire intentionally" hasBreachOfPrisonDiscipline "Destruction intentionally" hasBreachOfPrisonDiscipline "Theft from another prisoner" hasBreachOfPrisonDiscipline "Possession of unauthorised article" hasBreachOfPrisonDiscipline "Assault on prisoner" hasCourt "Oxford Crown Court" hasDisciplineBreachSanction "Stopped work" hasDisciplineBreachSanction "Extra days" hasDisciplineBreachSanction "Segregation" hasDisciplineBreachSanction "Stopped money" hasDisciplineBreachSanction "Caution" hasDisciplineBreachSanction "Lost privileges" hasLicenceMainCondition "Licence - Curfew" hasLicenceSubCondition "NHS - Market Garden Project" hasLicenceSubCondition "Not contact serving/remand prisoner" hasPrincipalOffence "8.10 Breach of a restraining order" hasPrincipleDisposal "Imprisonment" hasProbationArea "South Central" hasRehabilitationProgramme "Building Better Relationships" hasRehabilitationProgramme "Becoming New Me +"
Negative data property assertions +	

Sample case property assertions

Description: MaleHighImportanceFeature

Equivalent To +

- MoJFeature
and (hasMaleRecidivismCorrelationValue only xsd:float[>= 0.1f])

SubClass Of +

- MoJFeature

General class axioms +

SubClass Of (Anonymous Ancestor)

- hasFemaleRecidivismCorrelationValue some xsd:float
- hasMaleRaceCorrelationValue some xsd:float
- hasFemaleRaceCorrelationValue some xsd:float
- hasMaleRecidivismCorrelationValue some xsd:float

Instances +

- Age
- AlcoholDependent
- Employment
- GangAffiliation
- LSOAResidenceCode
- MaritalStatusCode
- MonthsAtAddress
- MonthsSinceLastConviction
- MonthsSinceLastImprisonment
- NumberOfPreviousConvictions
- OffenderAgeAtOffence
- OrderLengthDays
- PrincipalOffenceCode
- PrisonDurationDays
- PrisonWorkCode
- PSSSubRequirementCode
- RehabilitationProgrammeCode

Target for Key +

Disjoint With +

- MaleLowImportanceFeature

Disjoint Union Of +

Description: MaleLowImportanceFeature

Equivalent To +

- MoJFeature
and (hasMaleRecidivismCorrelationValue only xsd:float[< 0.1f])

SubClass Of +

- MoJFeature

General class axioms +

SubClass Of (Anonymous Ancestor)

- hasFemaleRecidivismCorrelationValue some xsd:float
- hasMaleRaceCorrelationValue some xsd:float
- hasFemaleRaceCorrelationValue some xsd:float
- hasMaleRecidivismCorrelationValue some xsd:float

Instances +

- BreachOfPrisonDisciplineCode
- ClassDrugDependent
- ClassBDrugDependent
- CourtCode
- DateOfBirth
- DisciplineBreachSanctionCode
- DrivingPenaltyPoints
- EducationLevel
- FineAmountPounds
- LicenceMainConditionCode
- LicencePeriodDays
- LicenceSubConditionCode
- MostSeriousOffenceCode
- NationalityCode
- NumberOfDependents
- PrincipalDisposalCode
- PrincipalDisposalDays
- ProbationAreaCode
- PSSMainRequirementCode
- ResidentialStatus
- SentenceMainRequirementCode
- SentenceSubRequirementCode

Target for Key +

Disjoint With +

- MaleHighImportanceFeature

High and low importance features

Description: MaleHighRiskFeature

Equivalent To +

- MoJFeature
and ((hasMaleRaceCorrelationValue only xsd:float[>= 0.1f])
and (hasMaleRaceCorrelationValue only xsd:float[< 1.0f]))

SubClass Of +

- MoJFeature

General class axioms +

SubClass Of (Anonymous Ancestor)

- hasFemaleRecidivismCorrelationValue some xsd:float
- hasMaleRaceCorrelationValue some xsd:float
- hasFemaleRaceCorrelationValue some xsd:float
- hasMaleRecidivismCorrelationValue some xsd:float

Instances +

- Age
- BreachOfPrisonDisciplineCode
- ClassADrugDependent
- ClassBDrugDependent
- Employment
- LSOAResidenceCode
- MonthsSinceLastConviction
- MonthsSinceLastImprisonment
- MostSeriousOffenceCode
- NationalityCode
- OffenderAgeAtOffence
- OrderLengthDays
- SentenceMainRequirementCode
- SentenceSubRequirementCode

Target for Key +

Disjoint With +

- MaleLowRiskFeature
- MaleProhibitedFeature

Disjoint Union Of +

Description: MaleLowRiskFeature

Equivalent To +

- MoJFeature
and ((hasMaleRaceCorrelationValue only xsd:float[< 0.1f]))

SubClass Of +

- MoJFeature

General class axioms +

SubClass Of (Anonymous Ancestor)

- hasFemaleRecidivismCorrelationValue some xsd:float
- hasMaleRaceCorrelationValue some xsd:float
- hasFemaleRaceCorrelationValue some xsd:float
- hasMaleRecidivismCorrelationValue some xsd:float

Instances +

- AlcoholDependent
- CourtCode
- DateOfBirth
- DisciplineBreachSanctionCode
- DrivingPenaltyPoints
- EducationLevel
- FineAmountPounds
- GangAffiliation
- LicenceMainConditionCode
- LicencePeriodDays
- LicenceSubConditionCode
- MaritalStatusCode
- MonthsAtAddress
- NumberOfDependents
- NumberOfPreviousConvictions
- PrincipalDisposalCode
- PrincipalDisposalDays
- PrincipalOffenceCode
- PrisonDurationDays
- PrisonWorkCode
- ProbationAreaCode
- PSSMainRequirementCode
- PSSSubRequirementCode
- RehabilitationProgrammeCode
- ResidentialStatus

Target for Key +

Description: MaleProhibitedFeature

Equivalent To +

- MoJFeature
and (hasMaleRaceCorrelationValue only xsd:float[>= 1.0f])

SubClass Of +

- MoJFeature

General class axioms +

SubClass Of (Anonymous Ancestor)

- hasFemaleRecidivismCorrelationValue some xsd:float
- hasMaleRaceCorrelationValue some xsd:float
- hasFemaleRaceCorrelationValue some xsd:float
- hasMaleRecidivismCorrelationValue some xsd:float

Instances +

- EthnicityCode

Target for Key +

Disjoint With +

- MaleLowRiskFeature
- MaleHighRiskFeature

Disjoint Union Of +

High risk, low risk, and prohibited features

Snap SPARQL Query:															
PREFIX owl: <http://www.w3.org/2002/07/owl#> PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#> PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#> PREFIX moj: <http://www.semanticweb.org/leigh/ontologies/2024/4/MOJ#>															
SELECT ?offender (REPLACE(STR(?monthsSinceImprisonmentValue), STR(moj:), "") AS ?monthsSinceImprisonment) (REPLACE(STR(?monthsSinceConvictionValue), STR(moj:), "") AS ?monthsSinceConviction) (REPLACE(STR(?employmentValue), STR(moj:), "") AS ?employment) (REPLACE(STR(?monthsAtAddressValue), STR(moj:), "") AS ?monthsAtAddress) (REPLACE(STR(?gangAffiliationValue), STR(moj:), "") AS ?gangAffiliation) (REPLACE(STR(?ageValue), STR(moj:), "") AS ?age) (REPLACE(STR(?previousConvictionsValue), STR(moj:), "") AS ?previousConvictions) (REPLACE(STR(?maritalStatusValue), STR(moj:), "") AS ?maritalStatus) (REPLACE(STR(?alcoholDependentValue), STR(moj:), "") AS ?alcoholDependent) (REPLACE(STR(?caseValue), STR(moj:), "") AS ?case) (REPLACE(STR(?rehabilitationProgrammeValue), STR(moj:), "") AS ?rehabilitationProgramme) (REPLACE(STR(?principalOffenceValue), STR(moj:), "") AS ?principalOffence) (REPLACE(STR(?PSSSubRequirementValue), STR(moj:), "") AS ?PSSSubRequirement) (REPLACE(STR(?prisonWorkValue), STR(moj:), "") AS ?prisonWork) (REPLACE(STR(?prisonDurationValue), STR(moj:), "") AS ?prisonDuration) WHERE { ?offender a moj:Offender FILTER(REGEX(STR(?offender), CONCAT("^", STR(moj:), "O"))) OPTIONAL { ?offender moj:hasMonthsSinceLastImprisonment ?monthsSinceImprisonmentValue. } OPTIONAL { ?offender moj:hasMonthsSinceLastConviction ?monthsSinceConvictionValue. } OPTIONAL { ?offender moj:hasEmployment ?employmentValue. } OPTIONAL { ?offender moj:hasMonthsAtAddress ?monthsAtAddressValue. } OPTIONAL { ?offender moj:hasGangAffiliation ?gangAffiliationValue. } OPTIONAL { ?offender moj:hasAge ?ageValue. } OPTIONAL { ?offender moj:hasNumberOfPreviousConvictions ?previousConvictionsValue. } OPTIONAL { ?offender moj:hasMaritalStatusCode ?maritalStatusValue. } OPTIONAL { ?offender moj:hasAlcoholDependent ?alcoholDependentValue. } ?offender moj:hasCase ?case OPTIONAL { ?case moj:hasPrisonDurationDays ?prisonDurationValue. } OPTIONAL { ?case moj:hasPrisonDurationDays ?prisonDurationValue. } OPTIONAL { ?case moj:hasRehabilitationProgrammeCode ?rehabilitationProgrammeValue. } OPTIONAL { ?case moj:hasPrincipalOffenceCode ?principalOffenceValue. } OPTIONAL { ?case moj:hasPSSSubRequirementCode ?PSSSubRequirementValue. } OPTIONAL { ?case moj:hasPrisonWorkCode ?prisonWorkValue. } } ORDER BY ?offender															
Execute															
?offender	?mo... 11	?mo... false	?emp... 13	?m... false	?gan... 63	?a... 4	?p... MS-D	?marit... true	?alco... moj:C647325366	?case	?rehabili... Off-4600	?princip... Off-4600	?PSSSubR... Off-4600	?prison... Off-4600	?pris...
moj:O112299926	11	false	13	false	63	4	MS-D	true	moj:C214350956		Off-4600				
moj:O112299926	11	false	13	false	63	4	MS-D	true	moj:C691205173		Off-4600				
moj:O112299926	11	false	13	false	63	4	MS-D	true	moj:C986467303		Off-4600				
moj:O112299926	11	false	13	false	63	4	MS-D	true	moj:C745987478		Off-4600				
moj:O141806441	2	false	52	false	59	0	MS-M	false	moj:C637473147		Off-806				
moj:O265466553	16	false	15	false	24	0	MS-M	true	moj:C196164791		Off-4600				
moj:O341786705 0	8	false	51	false	46	3	MS-M	true	moj:C527235880		Off-9261				
moj:O341786705 0	8	false	51	false	46	3	MS-M	true	moj:C905424044	RP-TBP	Off-406	730			
moj:O341786705 0	8	false	51	false	46	3	MS-M	true	moj:C794276181		Off-9250				
moj:O341786705 0	8	false	51	false	46	3	MS-M	true	moj:C830828808		Off-9250				
moj:O486623255 0	10	false	13	false	73	3	MS-W	false	moj:C478663808		Off-4600				
moj:O486623255 0	10	false	13	false	73	3	MS-W	false	moj:C338060576	RP-BBR	Off-831	730			
moj:O486623255 0	10	false	13	false	73	3	MS-W	false	moj:C338060576	RP-BNM+	Off-831	730			
moj:O486623255 0	10	false	13	false	73	3	MS-W	false	moj:C348844983		Off-806				
moj:O511985165 299	10	false	36	false	61	5	MS-S	true	moj:C587659755		Off-4600				
moj:O511985165 299	10	false	36	false	61	5	MS-S	true	moj:C618323430	RP-LNM	Off-3400	PSSS-SA20	PW-6	365	
moj:O511985165 299	10	false	36	false	61	5	MS-S	true	moj:C535754077		Off-4510				
moj:O511985165 299	10	false	36	false	61	5	MS-S	true	moj:C499266153		Off-4600				
moj:O511985165 299	10	false	36	false	61	5	MS-S	true	moj:C113345537		Off-4600				
moj:O511985165 299	10	false	36	false	61	5	MS-S	true	moj:C904791425		Off-3400				
moj:O547242054 0	1	false	31	false	23	4	MS-S	false	moj:C375098237		Off-9250				
moj:O547242054 0	1	false	31	false	23	4	MS-S	false	moj:C851372657		Off-4600				
moj:O547242054 0	1	false	31	false	23	4	MS-S	false	moj:C607333684		Off-9250				
moj:O547242054 0	1	false	31	false	23	4	MS-S	false	moj:C569872265	RP-LNM	Off-9210	PW-1	1277		
moj:O547242054 0	1	false	31	false	23	4	MS-S	false	moj:C254596091		Off-9250				
moj:O613456052 3	27	false	62	false	69	1	MS-M	true	moj:C808774974	RP-IM	Off-5301	PW-1	760		
moj:O613456052 3	27	false	62	false	69	1	MS-M	true	moj:C808774974	RP-IM	Off-5301	PW-2	760		
moj:O613456052 3	27	false	62	false	69	1	MS-M	true	moj:C723372549		Off-4600				
moj:O646955585	7	false	9	false	42	0	MS-S	false	moj:C595710701		Off-4600				
moj:O815709338	4	false	58	false	20	0	MS-S	false	moj:C755833865		Off-4600				
moj:O815709338	4	false	58	false	20	0	MS-S	false	moj:C178906509		Off-4600				
moj:O815709338	4	false	58	false	20	0	MS-S	false	moj:C881603678		Off-4600				
moj:O815709338	4	false	58	false	20	0	MS-S	false	moj:C202280393		Off-4600				
moj:O815709338	4	false	58	false	20	0	MS-S	false	moj:C112529789		Off-4600				
moj:O817633970	1	false	37	false	29	4	MS-S	true	moj:C782821873		Off-835				
moj:O983190851	15	false	3	false	26	0	MS-M	false	moj:C281645560		Off-835				

SPARQL query to export code instances

Snap SPARQL Query:



```
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX moj: <http://www.semanticweb.org/leigh/ontologies/2024/4/MOJ#>

#Total people and number who reoffended by gender and race
SELECT ?gender ?race (COUNT(?person) AS ?total) (COUNT(?reoffender) AS ?reoffended)
WHERE {
  ?person a moj:Offender ;
    moj:hasGender ?gender ;
    moj:hasRace ?race .

  OPTIONAL {
    ?person moj:hasRecidivismWithinThreeYears true .
    BIND(IF(BOUND(?person), ?person, "") AS ?reoffender)
  }
}
GROUP BY ?gender ?race
ORDER BY ?gender ?race
```

Execute

?gender	?race	?total	?reoffended
moj:Female	Non-White^^xsd:string	3	1
moj:Female	White^^xsd:string	2	1
moj:Male	Non-White^^xsd:string	4	2
moj:Male	White^^xsd:string	3	2

4 results

SPARQL query to examine racial profile of recidivism

Appendix F. MoJ Object Instances (Truncated)

Ethnicity Code	Ethnicity Description	Marital status code	Marital status	Nationality code	Nationality	Magistrates' Court Code	Magistrates' Court Name	Crown Court Code	Crown Court Name	Offence code	Offence description
A1	Indian	C	Co-habiting (living with partner)	AB	Aruban	1013	Bristol Magistrates' Court	78	Aylesbury Crown Court	101	1 Murder
A2	Pakistani	D	Divorced or dissolved	AFGA	Afghan	1021	North Avon Magistrates' Court	30	Bradford Crown Court	102	1 Murder
A3	Bangladeshi	M	Married or in civil partnership	AG	Anguillan	1022	Bath and Wansdyke Magistrates' Court	66	Kingston-upon-Hull Crown Court	200	2 Attempted Murder
A9	Any other Asian background	N	Prefer not to say	ALBA	Albanian	1023	North Somerset Magistrates' Court	58	Birmingham Crown Court	301	3B Threats to kill
B1	Caribbean	P	Separated-not living with legal	ALGE	Algerian	1030	Somerset Magistrates' Court	63	Bournemouth Crown Court	302	3A Conspiracy to murder
B2	African	S	Single-not married/in civil partnership	AMER	American	1051	Bedford and Mid Bedfordshire Magistrates' Court	68	Dorchester Crown Court	303	3A Conspiracy to murder
B9	Any other Black background	W	Widowed	AN	Dutch Antillean	1055	Luton and South Bedfordshire Magistrates' Court	12	Bristol Crown Court	304	3A Conspiracy to murder
M1	White and Black Caribbean			ANGOL	Angolan	1072	East Berkshire Magistrates' Court	16	Burnley Crown Court	305	3A Conspiracy to murder
M2	White and Black African			ANTIG	Antiguan, Barbudan	1075	West Berkshire Magistrates' Court	17	Cambridge Crown Court	306	3A Conspiracy to murder
M3	White and Asian			ARGEN	Argentine	1076	Reading Magistrates' Court	55	Cardiff Crown Court	401	4.1 Manslaughter
M9	Any other mixed			ARME	Armenian	1080	Bedfordshire Magistrates' Court	62	Carlisle Crown Court	402	4.2 Infanticide
O1	Chinese			ASM	American Samoan	1124	Milton Keynes Magistrates' Court	41	Central Criminal Court	403	4.3 Child Destruction
O2	Arab			AUSI	Australian	1129	Central Buckinghamshire Magistrates' Court	11	Chelmsford Crown Court	404	4.4 Causing Death by Dangerous Driving (MOT)
O9	Any other ethnic group			AUST	Austrian	1130	Wycombe and Beaconsfield Magistrates' Court	69	Chester Crown Court	405	4.5 Manslaughter Due to Diminished Responsibility
W1	British			AZERB	Azerbaijani	1162	Peterborough Magistrates' Court	65	Chichester Crown Court	406	4.6 Causing Death by Careless Driving when under the influence of Drink or Drugs (MOT)
W2	Irish			BAHA	Bahamian	1165	Cambridge Magistrates' Court	60	Coventry Crown Court	407	4.7 Causing Death of a child or vulnerable person
W3	Gypsy or Irish Traveller			BAHR	Bahraini	1166	East Cambridgeshire Magistrates' Court	47	Croydon Crown Court	408	4.8 Causing Death by careless or inconsiderate driving (MOT)
W9	Any other White background			BANGL	Bangladeshi	1167	Fenland Magistrates' Court	26	Derby Crown Court	409	4.9 Causing death by driving unlicensed disqualified or uninsured drivers (MOT)
NS	Not stated			BARB	Barbadian or Bajuns	1168	Huntingdonshire Magistrates' Court	23	Doncaster Crown Court	410	4.10 Applicable organisation causing death by gross breach of duty of care
				BELA	Belarusian	1177	Halton Magistrates' Court	59	Wolverhampton Crown Court	411	4.11 Causing or allowing child or vulnerable adult to suffer serious physical harm
				BELG	Belgian	1178	Macclesfield Magistrates' Court	5	Durham Crown Court	412	4.12 Causing serious injury by dangerous driving (MOT)

Offence group code	Offence group description	Disposal Code	Disposal name	Probation area code	Probation area name	Requirement type main category code	Requirement type main category	Requirement type sub category code
1	Violence against the person	ABDIS	Absolute Discharge	ACI	Altcourse (HMP)	3	Residential	701
1	Violence against the person	ADISQU	Disqualification Order (from working with children) - ADULTS	AGI	Askham Grange (HMP & YOI)	7	Court - Accredited Programme	702
1	Violence against the person	ALTCT	Alternative Court: Jury Discharged from Verdict	ALL	No Trust or Trust Unknown	7A	Accredited Programme - Not specified at Court	703
1	Violence against the person	ALTRTCS	Alcohol Treatment	ASI	Ashfield (HMYOI)	A1	Local - CRAMS Activity	704
1	Violence against the person	ALTRTSS	Alcohol Treatment	ASP	Avon & Somerset	A2	Local - Guided Skills Learning	705
1	Violence against the person	ASBOSEN	Order re anti-social behaviour additional to sentence	AYI	Aylesbury (HMYOI)	A3	Local - Basic Skills	706
1	Violence against the person	ATCRQCS	Attendance Centre Requirements	BAI	Belmarsh (HMP)	A4	Local - ETE	707
1	Violence against the person	ATCRQSS	Attendance Centre Requirements	BCI	Buckley Hall (HMP)	A5	Local - Skills for Life - Literacy	708
1	Violence against the person	ATCRQYR	Attendance Centre Requirement	BED	Bedfordshire	A6	Local - Skills for Life - Numeracy	709
1	Violence against the person	ATTcen	Attendance Centre Order	BFI	Bedford (HMP)	A7	Local - Skills for Life - ESOL	710
1	Violence against the person	BARR	May be placed on Barring List	BLI	Bristol (HMP)	A8	Local - Skills for Life - Other	711
1	Violence against the person	BOCOND	Bind Over with Conditions	BMI	Birmingham (HMP)	B	Education (YRO)	712
1	Violence against the person	BOGB	Bind Over	BNI	Bullingdon (HMP)	B4	Local - Non Accr Prog	713
1	Violence against the person	BOJDG	Bind Over to Appear for Judgment	BRI	Bure (HMP)	C	Intensive Supervision and Surveillance (YRO)	714
1	Violence against the person	BOJDGD	Bind Over to Appear for Judgment on Date given	BSI	Brinsford (HMYOI)	CSPE	Court Stated Punitive Element	715
1	Violence against the person	BWBAILB	Backed for Bail: Failed to answer bail	BT1	BVT CRC	E	Drug Testing (YRO)	716
1	Violence against the person	BWBAILN	Not Backed for Bail: Failed to answer bail	BVT	BVT NPS Division	ESXRM	Local - ESX Interventions	718
1	Violence against the person	BWSUMB	Backed for Bail: Failed to answer summons	BWI	Berwyn (HMP)	F	Rehabilitation Activity Requirement (RAR)	719
1	Violence against the person	BWSUMN	Not Backed for Bail: Failed to answer summons	BXI	Brixton (HMP)	G	Drug Rehabilitation	720
1	Violence against the person	CD	Conditional Discharge Order	BZI	Bronzefield (HMP)	GMPRM1	Local - GMPT Activities	721
1	Violence against the person	CJCO	Confiscation Order under S71 CJA 1988	CO1	CPA Northumbria	H	Alcohol Treatment	722

Requirement type sub category	License condition main category code	License condition main category	License condition sub category code	License condition sub category	Post sentence supervision main category code	Post sentence supervision main category	Post sentence supervision sub category code
Think First	EM01	Licence - Location Monitoring (GPS Tagging)	701	Comply with any requirements for the purpose of addressing alcohol/ drug/ sexual/ gambling/ solvent abuse/ anger/ debt/ prolific offending behaviour problems	S08	Specified Activity	SA01
Enhanced Thinking Skills	ESXLC	Local - ESX Interventions	702	Participate in a prolific or other priority offender (PPO) project	S09	Drug Testing	SA02
One to One	GMPLC1	Local - GMPT Activities	799	Other (see notes) (799) Attend medical/psychiatric appointments and co-operate with	S10	Drug Appointments Standard 7 Conditions	SA03 SA04
Cognitive Skills Booster	GPT002	Local - GPT ETE With Award	A01	Receive home visits from mental health worker			SA05
CALM	LA4	Local - ETE	A02				
Aggression Replacement Training	LA5	Local - Skills for Life - Literacy	A202	Entry Level 1			SA06
Integrated Domestic Abuse	LA6	Local - Skills for Life - Numeracy	A203	Entry Level 2			SA07
CDVP - Domestic Violence	LA8	Local - Skills for Life - Other	A204	Entry Level 3			SA08
TV-SOGP	LAP	Licence - Accredited Programme	A205	Level Unknown			SA09
NBR Sex Offender Rolling Prog	LC100	WTS ETE External Signposting	A206	Level 1			SA10
C-SOGP	LC101	WTS ETE Internal Management	A207	Level 2			SA11
ASRO	LC102	WTS Role	A99	Other (see notes)			SA12
Offender Substance Abuse Prog	LC103	WTS SARC	C01	Not to seek to approach or communicate with victim/family member			SA13
PRISM	LC16	Local - Health Trainer	C02	Not to have unsupervised contact with children			SA14
Drink Impaired Drivers Womens Acquisitive Crime	LC17	Local - Victim Liaison	C99	Other (see notes)			SA15
	LC18	Local - Restorative Justice	CE1	Not to contact person with terrorist related offence			SA16
Cognitive Self Change Block 6	LC27	Local - LCS ETE	D01	Not to contact/associate with named individual			SA17
Internet Sex Offender Treatment	LC28	Local - HBS Activities	D02	Not to contact known sex offender			SA18
COVAID (Control - Angry Impulsive Drinkers)	LC29	Local - Notts Activities	D03	Not contact serving/remand prisoner			SA19
LIAP (Low Intensity Alcohol Programme)	LC30	Licence - Programme	D04	Not to associate with any person linked with specific group/organisation			SA20
TSP (Thinking Skills)	LC32	Local - WY ETE	D99	Other (see notes)			SA21

Post sentence supervision sub category	LSOA Residence Code	LSOA Residence Name	Prison discipline breach code	Prison discipline breach	Prison sanction code	Prison sanction	Prison work code	Prison work	Rehabilitation programme code	Rehabilitation programme name
										Alcohol Dependence Treatment Programme
Anger Management - High Intensity	E01000001	City of London 001A	1A	Assault on staff	1	Caution	1	Cleaner	ADTP	
Anger Management - Medium Intensity	E01000002	City of London 001B	1B	Assault on prisoner	2	Lost privileges	2	Servery	BNM+	Becoming New Me + Breaking Free: Health and Justice Package
Anger Management - Low Intensity	E01000003	City of London 001C	2	Detain person against their will	3	Stopped money	3	Prisoner representative	BF	Building Better Relationships
Compliance Breach - High Intensity	E01000005	City of London 001E	3	Deny access	4	Segregation	4	Laundry	BBR	Challenge to Change
Compliance Breach - Medium Intensity	E01000006	Barking and Dagenham 016A	4A	Fight, multiple participants	5	Stopped work	5	Education	C2C	Control of Violence for Angry Impulsive Drinkers – Group Secure
Compliance Breach - Low Intensity	E01000007	Barking and Dagenham 015A	4B	Fight, sustained attack	6	Extra days	6	Workshop	COVAID-GS	Control of Violence for Angry Impulsive Drinkers – Group Secure Women
Domestic Violence - High Intensity	E01000008	Barking and Dagenham 015B	5A	Intentional endangerment			7	Orderly, librarian	COVAID-GSW	Democratic Therapeutic Community Mode
Domestic Violence - Medium Intensity	E01000009	Barking and Dagenham 016B	5B	Reckless endangerment			8	Orderly, reception	DTC	Therapeutic Communities Plus
Domestic Violence - Low Intensity	E01000011	Barking and Dagenham 016C	6	Intentional obstruction			9	Orderly, healthcare	TC+	Healthy Identity Intervention
ETE - High Intensity	E01000012	Barking and Dagenham 015D	7A	Escape					HII	Healthy Sex Programme
ETE - Medium Intensity	E01000013	Barking and Dagenham 013A	7B	Abscond					HSP	
ETE - Low Intensity	E01000014	Barking and Dagenham 013B	8	Fail to comply with conditions					H	Horizon
Hate Crime - High Intensity	E01000015	Barking and Dagenham 009A	9A	Substance abuse, class A					IM	Identity Matters
Hate Crime - Medium Intensity	E01000016	Barking and Dagenham 009B	9B	Substance abuse, class B or C					K	Kaizen
Hate Crime - Low Intensity	E01000017	Barking and Dagenham 009C	9C	Substance abuse, non-prescribed medication					LNM	Living as New Me
Mental Health - High Intensity	E01000018	Barking and Dagenham 009D	10	Intoxicated					NMS	New Me Strengths
Mental Health - Medium Intensity	E01000019	Barking and Dagenham 023A	11	Alcohol consumption					TBP	The Bridge Programme
Mental Health - Low Intensity	E01000020	Barking and Dagenham 023B	12	Possession of unauthorised article					TSP	Thinking Skills Programme
Restorative Justice - High Intensity	E01000021	Barking and Dagenham 008A	13	Sale of unauthorised article						
Restorative Justice - Medium Intensity	E01000022	Barking and Dagenham 008B	14	Sale of article for personal use						
Restorative Justice - Low Intensity	E01000024	Barking and Dagenham 008D	15	Theft from another prisoner						

Appendix G. MoJ Ontology Cellfie Import Scripts

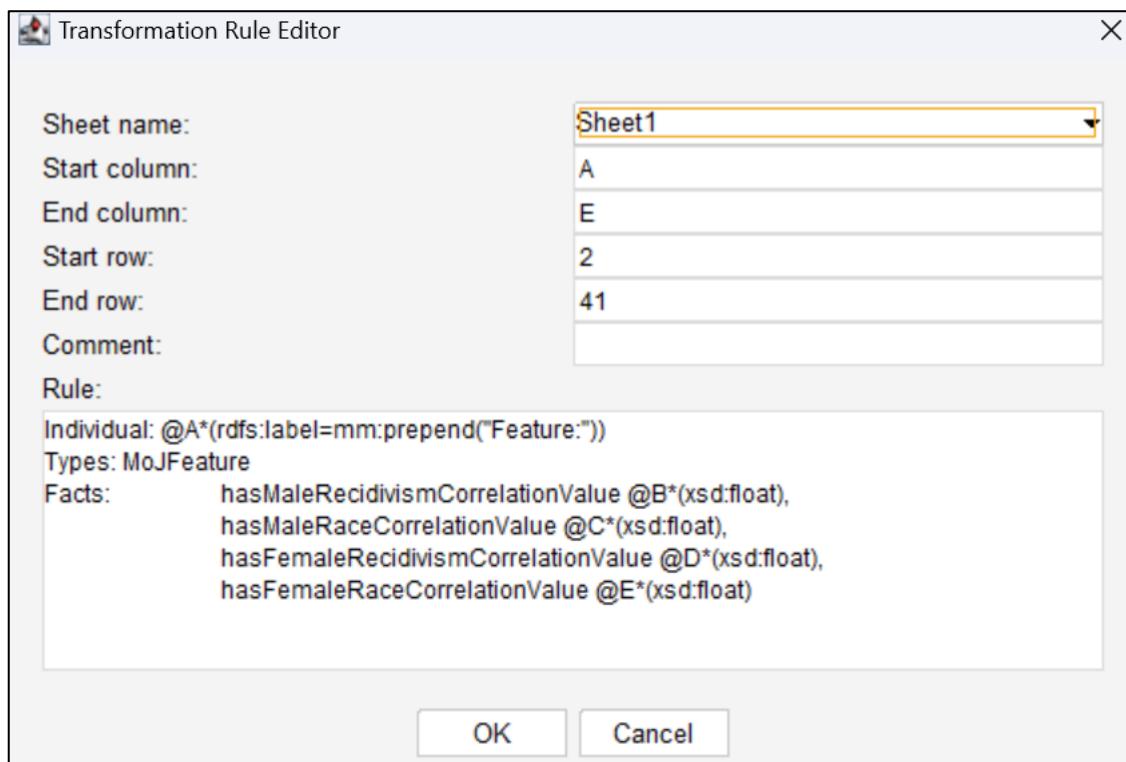
<p>Sheet name: Sheet1</p> <p>Start column: P</p> <p>End column: Q</p> <p>Start row: 2</p> <p>End row: 208</p> <p>Comment:</p> <p>Rule:</p> <pre>Individual: @P*(rdfs:label=mm:prepend("Dis-")) Types: Disposal Facts: hasDisposalCode @P*(rdfs:label=mm:prepend("Dis-")), hasDisposal @Q*</pre>	<p>Sheet name: Sheet1</p> <p>Start column: A</p> <p>End column: C</p> <p>Start row: 2</p> <p>End row: 20</p> <p>Comment:</p> <p>Rule:</p> <pre>Individual: @A*(rdfs:label=mm:prepend("Eth-")) Types: @C* Facts: hasEthnicityCode @A*(rdfs:label=mm:prepend("Eth-")), hasEthnicity @B*</pre>
<p>Sheet name: Sheet1</p> <p>Start column: Z</p> <p>End column: AA</p> <p>Start row: 2</p> <p>End row: 209</p> <p>Comment:</p> <p>Rule:</p> <pre>Individual: @Z*(rdfs:label=mm:prepend("LCS-")) Types: LicenceSubCondition Facts: hasLicenceSubConditionCode @Z*(rdfs:label=mm:prepend("LCS-")), hasLicenceSubCondition @AA*</pre>	<p>Sheet name: Sheet1</p> <p>Start column: X</p> <p>End column: Y</p> <p>Start row: 2</p> <p>End row: 55</p> <p>Comment:</p> <p>Rule:</p> <pre>Individual: @X*(rdfs:label=mm:prepend("LCM-")) Types: LicenceMainCondition Facts: hasLicenceMainConditionCode @X*(rdfs:label=mm:prepend("LCM-")), hasLicenceMainCondition @Y*</pre>
<p>Sheet name: Sheet1</p> <p>Start column: AF</p> <p>End column: AG</p> <p>Start row: 2</p> <p>End row: 35673</p> <p>Comment:</p> <p>Rule:</p> <pre>Individual: @AF*(rdfs:label=mm:prepend("LSOA-")) Types: LSOAResidence Facts: hasLSOAResidenceCode @AF*(rdfs:label=mm:prepend("LSOA-")), hasLSOAResidence @AG*</pre>	<p>Sheet name: Sheet1</p> <p>Start column: H</p> <p>End column: I</p> <p>Start row: 2</p> <p>End row: 345</p> <p>Comment:</p> <p>Rule:</p> <pre>Individual: @H*(rdfs:label=mm:prepend("MC-")) Types: MagistratesCourt Facts: hasCourtCode @H*(rdfs:label=mm:prepend("MC-")), hasCourt @I*</pre>
<p>Sheet name: Sheet1</p> <p>Start column: D</p> <p>End column: E</p> <p>Start row: 2</p> <p>End row: 8</p> <p>Comment:</p> <p>Rule:</p> <pre>Individual: @D*(rdfs:label=mm:prepend("MS-")) Types: MaritalStatus Facts: hasMaritalStatusCode @D*(rdfs:label=mm:prepend("MS-")), hasMaritalStatus @E*</pre>	<p>Sheet name: Sheet1</p> <p>Start column: F</p> <p>End column: G</p> <p>Start row: 2</p> <p>End row: 218</p> <p>Comment:</p> <p>Rule:</p> <pre>Individual: @F*(rdfs:label=mm:prepend("Nat-")) Types: Nationality Facts: hasNationalityCode @F*(rdfs:label=mm:prepend("Nat-")), hasNationality @G*</pre>
<p>Sheet name: Sheet1</p> <p>Start column: L</p> <p>End column: O</p> <p>Start row: 2</p> <p>End row: 407</p> <p>Comment:</p> <p>Rule:</p> <pre>Individual: @L*(rdfs:label=mm:prepend("Off-")) Types: @O* Facts: hasOffenceCode @L*(rdfs:label=mm:prepend("Off-")), hasOffence @M*(rdfs:label=mm:prepend("))</pre>	<p>Sheet name: Sheet1</p> <p>Start column: AH</p> <p>End column: AI</p> <p>Start row: 2</p> <p>End row: 38</p> <p>Comment:</p> <p>Rule:</p> <pre>Individual: @AH*(rdfs:label=mm:prepend("BOD-")) Types: BreachOfPrisonDiscipline Facts: hasBreachOfPrisonDisciplineCode @AH*(rdfs:label=mm:prepend("BOD-")), hasBreachOfPrisonDiscipline @AI*</pre>

<p>Sheet name: Sheet1</p> <p>Start column: AL</p> <p>End column: AM</p> <p>Start row: 2</p> <p>End row: 10</p> <p>Comment:</p> <p>Rule:</p> <p>Individual: @AL*(rdfs:label=mm:prepend("PW-"))</p> <p>Types: PrisonWork</p> <p>Facts: hasPrisonWorkCode @AL*(rdfs:label=mm:prepend("PW-")), hasPrisonWork @AM*</p>	<p>Sheet name: Sheet1</p> <p>Start column: R</p> <p>End column: S</p> <p>Start row: 2</p> <p>End row: 209</p> <p>Comment:</p> <p>Rule:</p> <p>Individual: @R*(rdfs:label=mm:prepend("PA-"))</p> <p>Types: ProbationArea</p> <p>Facts: hasProbationAreaCode @R*(rdfs:label=mm:prepend("PA-")), hasProbationArea @S*</p>
<p>Sheet name: Sheet1</p> <p>Start column: AB</p> <p>End column: AC</p> <p>Start row: 2</p> <p>End row: 5</p> <p>Comment:</p> <p>Rule:</p> <p>Individual: @AB*(rdfs:label=mm:prepend("PSSM-"))</p> <p>Types: PSSMainRequirement</p> <p>Facts: hasPSSMainRequirementCode @AB*(rdfs:label=mm:prepend("PSSM-")), hasPSSMainRequirement @AC*</p>	<p>Sheet name: Sheet1</p> <p>Start column: AD</p> <p>End column: AE</p> <p>Start row: 2</p> <p>End row: 47</p> <p>Comment:</p> <p>Rule:</p> <p>Individual: @AD*(rdfs:label=mm:prepend("PSSS-"))</p> <p>Types: PSSSubRequirement</p> <p>Facts: hasPSSSubRequirementCode @AD*(rdfs:label=mm:prepend("PSSS-")), hasPSSSubRequirement @AE*</p>
<p>Sheet name: Sheet1</p> <p>Start column: AN</p> <p>End column: AO</p> <p>Start row: 2</p> <p>End row: 18</p> <p>Comment:</p> <p>Rule:</p> <p>Individual: @AN*(rdfs:label=mm:prepend("RP-"))</p> <p>Types: RehabilitationProgramme</p> <p>Facts: hasRehabilitationProgrammeCode @AN*(rdfs:label=mm:prepend("RP-")), hasRehabilitationProgramme @AO*</p>	<p>Sheet name: Sheet1</p> <p>Start column: T</p> <p>End column: U</p> <p>Start row: 2</p> <p>End row: 71</p> <p>Comment:</p> <p>Rule:</p> <p>Individual: @T*(rdfs:label=mm:prepend("SRM-"))</p> <p>Types: SentenceMainRequirement</p> <p>Facts: hasSentenceMainRequirementCode @T*(rdfs:label=mm:prepend("SRM-")), hasSentenceMainRequirement @U*</p>
<p>Sheet name: Sheet1</p> <p>Start column: V</p> <p>End column: W</p> <p>Start row: 2</p> <p>End row: 328</p> <p>Comment:</p> <p>Rule:</p> <p>Individual: @V*(rdfs:label=mm:prepend("SRS-"))</p> <p>Types: SentenceSubRequirement</p> <p>Facts: hasSentenceSubRequirementCode @V*(rdfs:label=mm:prepend("SRS-")), hasSentenceSubRequirement @W*</p>	<p>Sheet name: Sheet1</p> <p>Start column: AJ</p> <p>End column: AK</p> <p>Start row: 2</p> <p>End row: 7</p> <p>Comment:</p> <p>Rule:</p> <p>Individual: @AJ*(rdfs:label=mm:prepend("DBS-"))</p> <p>Types: DisciplineBreachSanction</p> <p>Facts: hasDisciplineBreachSanctionCode @AJ*(rdfs:label=mm:prepend("DBS-")), hasDisciplineBreachSanction @AK*</p>
<p>Sheet name: Sheet1</p> <p>Start column: A</p> <p>End column: E</p> <p>Start row: 2</p> <p>End row: 41</p> <p>Comment:</p> <p>Rule:</p> <p>Individual: @A*(rdfs:label=mm:prepend("Feature:"))</p> <p>Types: MoJFeature</p> <p>Facts: hasMaleRecidivismCorrelationValue @B*(xsd:float), hasMaleRaceCorrelationValue @C*(xsd:float), hasFemaleRecidivismCorrelationValue @D*(xsd:float), hasFemaleRaceCorrelationValue @E*(xsd:float)</p>	<p>Sheet name: Sheet1</p> <p>Start column: J</p> <p>End column: K</p> <p>Start row: 2</p> <p>End row: 78</p> <p>Comment:</p> <p>Rule:</p> <p>Individual: @J*(rdfs:label=mm:prepend("CC-"))</p> <p>Types: CrownCourt</p> <p>Facts: hasCourtCode @J*(rdfs:label=mm:prepend("CC-")), hasCourt @K*</p>

Appendix H. MoJ Feature Correlation Instances

Feature	MaleRecidivismCorrelationValue	MaleRaceCorrelationValue	FemaleRecidivismCorrelationValue	FemaleRaceCorrelationValue
DateOfBirth	0.01	0.03	0.04	0.05
Age	0.177	0.121	0.133	0.072
NumberOfPreviousConvictions	0.164	0.079	0.247	0.04
MonthsSinceLastConviction	0.242	0.132	0.298	0.163
MonthsSinceLastImprisonment	0.281	0.142	0.312	0.172
ResidentialStatus	0.01	0.03	0.04	0.05
MonthsAtAddress	0.213	0.095	0.194	0.071
GangAffiliation	0.185	0.086	0.093	0.043
EducationLevel	0.088	0.057	0.039	0
Employment	0.217	0.126	0.227	0.059
NumberOfDependents	0.031	0.096	0.007	0.064
AlcoholDependent	0.132	0.098	0.103	0.084
ClassADrugDependent	0	0.121	0.053	0.126
ClassBDrugDependent	0	0.128	0	0.121
EthnicityCode		1		1
NationalityCode	0.042	0.132	0.016	0.187
MaritalStatusCode	0.153	0.032	0.198	0.021
LSOAResidenceCode	0.123	0.143	0.123	0.143
OffenderAgeAtOffence	0.162	0.102	0.12	0.043
PrincipleOffenceCode	0.161	0.092	0.141	0.089
MostSeriousOffenceCode	0.082	0.162	0.052	0.172
CourtCode	0.02	0.02	0.02	0.02
ProbationAreaCode	0.02	0.01	0.02	0.01
PrincipleDisposalCode	0.075	0.021	0.012	0.043
PrincipleDisposalDays	0.092	0.021	0.083	0.032
PrisonDurationDays	0.162	0.092	0.159	0.089
FineAmountPounds	0.043	0.012	0.032	0.011
LicencePeriodDays	0.01	0.03	0.04	0.05
DrivingPenaltyPoints	0.052	0.024	0.063	0.012
OrderLengthDays	0.112	0.101	0.111	0.092
BreachOfPrisonDisciplineCode	0.096	0.123	0.076	0.072
DisciplineBreachSanctionCode	0.072	0.087	0.043	0.023
PrisonWorkCode	0.123	0.078	0.111	0.062
RehabilitationProgrammeCode	0.162	0.053	0.151	0.042
SentenceMainRequirementCode	0.092	0.121	0.078	0.101
SentenceSubRequirementCode	0.098	0.143	0.087	0.098
LicenceMainConditionCode	0.092	0.076	0.087	0.054
LicenceSubConditionCode	0.099	0.045	0.084	0.034
PSSMainRequirementCode	0.096	0.023	0.04	0.05
PSSSubRequirementCode	0.152	0.056	0.123	0.023

Appendix I. MoJ Feature Correlation Cellfile Import Script



Appendix J. MoJ Offender and Case Dummy Instances

Offender ID	Name	Date of Birth	Age	Number of previous convictions	Months since last conviction	Months since last imprisonment	Residential status	Months at address	Gang affiliation
511985165	John Smith	1962-12-03	61	5	10	299	Homeless	36	false
141806441	Lillian Harpole	1965-03-05	59	0	2		Homeowner	52	false
486623255	Zachary Nixon	1951-02-06	73	3	10	0	Rented	13	false
613456052	George Chadwick	1954-12-16	69	1	27	3	Homeowner	62	false
112299926	Scarlett Morgan	1961-04-05	63	4	11		Homeless	13	false
646955585	Muhammad King	1982-05-17	42	0	7		Rented	9	false
341786705	Grace Fitzgerald	1978-03-22	46	3	8	0	Homeowner	51	false
983190851	Jack Harrison	1998-02-21	26	0	15		Rented	3	false
815709338	Natasha Murphy	2003-10-03	20	0	4		Living with parents	58	false
817633970	Christopher Robson	1994-10-28	29	4	1		Homeowner	37	false
265466553	Aaliyah Martin	2000-04-16	24	0	16		Rented	15	false
547242054	Stephen Johnson	2001-06-12	23	4	1	0	Living with parents	31	false

Education level	Employment	Number of dependents	Alcohol dependent	Clas A drug dependent	Class B drug dependent	Gender	Ethnicity code	Nationality code	Marital status code	LSOA residence code
High School	false	0	true	false	false	Male	W1	BRIT	S	E01000012
None	false	2	false	false	false	Female	W1	BRIT	M	E01000031
High School	false	1	false	true	false	Male	O2	BRIT	W	E01000249
High School	false	3	true	true	false	Male	B2	BRIT	M	E01000250
High School	false	4	true	true	true	Female	W1	BRIT	D	E01000251
Graduate	false	0	false	false	false	Male	A9	IRAN	S	E01000252
High School	false	2	true	true	false	Female	M3	BRIT	M	E01000253
High School	false	1	false	false	false	Male	B2	BRIT	M	E01000254
High School	false	0	false	false	false	Female	B2	BRIT	S	E01000255
Post Graduate	false	2	true	false	false	Male	W1	BRIT	S	E01000256
High School	false	0	true	false	false	Female	O2	BRIT	M	E01000257
High School	false	0	false	true	true	Male	W1	BRIT	S	E01000258

Case ID	Offender ID	Date of offence	Offender age at offence	Principle offence code	Most serious offence code	Court code	Probation area code	Principle disposal code	Principle disposal days	Prison duration days	Fine amount pounds	Licence period days	Driving penalty points	Order length days	Breach of prison discipline code				
904791425	511985165	1993-05-12	30	3400	3400	CC-36	WTS	SS	730	525	183	730	365	11	16A	12	1A	13	
618323430	511985165	1998-01-21	35	3400	3400	CC-36	WTS	IMP	365	365									
878659755	511985165	2002-06-02	39	4600	4600	MC-1894	WTS	FINE		200									
113345537	511985165	2016-03-13	53	4600	4600	MC-1894	WTS	FINE		125									
535754077	511985165	2018-08-05	55	4510	4510	MC-1894	WTS	FINE		290									
499266153	511985165	2023-02-16	60	4600	4600	CC-36	WTS	SS	365										
637473147	141806441	2023-10-13	58	806	806	MC-2870	C14	CPO	365										
478663808	486623255	1992-12-03	41	4600	4600	MC-1922	N59	FINE		150									
34884983	486623255	2022-09-22	71	806	806	CC-77	N59	CPO	730										
338060576	486623255	2023-02-16	72	831	831	CC-77	N59	IMP	730	730		365	730	17A	1B				
723372549	613456052	2003-02-02	48	4600	4600	MC-1922	N59	FINE		255									
808774974	613456052	2021-09-04	66	5301	5301	CC-77	N59	IMP	760	760	565	760	760	16B					
691205173	112299926	2020-06-12	59	4600	4600	MC-2330	NTS	FINE		150									
214350956	112299926	2021-05-04	60	4600	4600	MC-2330	NTS	FINE		240									
647325366	112299926	2021-12-03	60	4600	4600	MC-2330	NTS	FINE		110									
745987478	112299926	2022-09-03	61	4600	4600	MC-2330	NTS	FINE		255									
986467303	112299926	2023-01-12	61	4600	4600	MC-2330	NTS	FINE		120									
955710701	646955585	2023-05-12	40	4600	4600	MC-1943	HU	FINE		215									
527235880	341786705	2020-01-01	41	9261	4600	MC-2978	N55	FINE		100									
794276181	341786705	2021-03-12	42	9250	9250	MC-2978	N55	CPO	365										
830828808	341786705	2022-09-20	44	9250	9250	MC-2978	N55	SS	365										
905424044	341786705	2023-04-23	45	406	406	CC-30	N55	IMP	730	730	365	6	730	22					
281645560	983190851	2022-12-05	24	835	835	CC-30	N55	CPO	730										
782821873	817633970	2023-08-29	19	835	835	MC-1613	ESX	FINE		210									
112529789	815709338	2022-06-09	27	4600	4600	MC-1051	BED	FINE		175									
861603678	815709338	2022-12-21	28	4600	4600	MC-1051	BED	FINE		205									
202280393	815709338	2023-02-01	28	4600	4600	MC-1051	BED	FINE		180									
755833865	815709338	2023-10-10	28	4600	4600	MC-1051	BED	CPO	365	50									
178906509	815709338	2024-03-23	29	4600	4600	CC-79	BED	SS	548										
196164791	265466553	2022-11-24	22	4600	4600	MC-1051	BED	FINE		130									
851372657	547242054	2022-08-10	21	4600	9250	MC-1051	BED	FINE		210									
254596091	547242054	2022-11-27	21	9250	9250	CC-79	BED	CPO	365										
375096237	547242054	2023-03-01	21	9250	9250	CC-79	BED	CPO	365										
607333684	547242054	2023-09-26	22	9250	9250	CC-79	BED	SS	548										
569872265	547242054	2023-12-12	22	9210	9210	CC-79	BED	IMP	1277	1277	365	1277	13	15	1B	1A			

Discipline breach sanction code	Prison work code	Rehabilitation programme code	Rehabilitation programme code	Rehabilitation programme code	Rehabilitation programme code								
1	3	2	4	5	6					LNM			
4	2	3								BBR	BNM+		
1				1	2					IM			
2										TBP			
2	5	3	4	6	1					LNM			

Sentence requirements start date	Sentence requirements end date	Sentence main requirement code	Sentence sub requirement code	Licence conditions start date	Licence condition code	Licence sub condition code	PSS main requirement code	PSS sub requirement code										
1993-12-02	1995-12-01	3	703	RS111				1999-05-26	1999-11-25	EM01	701			1999-11-26	2000-05-25	3	SA20	
2023-05-11	2024-05-10	T	702	ALCMON														
2023-10-17	2024-10-16	W	703	706														
2023-01-18	2024-01-17	W	ALCMON	GMP007	706			2024-07-15	2025-07-14	LCF	D03	LC147						
								2023-02-05	2024-02-04	EM01	701	LC139						
2021-08-02	2022-08-01	W	724															
2023-01-19	2024-01-18	X	ESX011	RS156				1999-05-26	1999-11-26	IAS	LC180	LC238	LC260	LC76				
2023-04-10	2025-04-09	5																
2024-02-02	2025-02-01	W	731															
2024-05-05	2025-05-04																	
2023-03-03	2024-03-02	W																
2023-07-17	2024-07-16	W																
2023-12-12	2025-06-11	X	731					2026-02-16	2027-10-12	EM01	Y01	LC262						

Appendix K. MoJ Offender and Case Cellfile Import Scripts

