

**Task 1: Carefully read the background and collection plan again. What types of potential bias exist in your team lead's collection plan? Why was it biased?**

<b>Task 1a:</b>	<b>Task 1b:</b>
What types of potential bias exist in your team lead's collection plan?	Why was it biased?
<b>Exclusion</b>	Because there could be certain features or immeasurable factors that were excluded from the data set collected because it was thought to be irrelevant at the time the data was collected. That may not be the case now.
<b>Collection</b>	Because the collection process could have been flawed.
<b>Measurement</b>	Because there could have been a problem with the machine(s) or human(s) who did the collecting, measuring and/or observing.

**Task 2 How might these biases distort the results? What could you do to avoid these biases?**

<b>Bias</b>	<b>Possible Distortion</b>	<b>Explanation</b>	<b>Avoidant Strategies to minimize bias</b>
Exclusion	Narrow Geographic Scope	By only including transactions within 100 miles of the border, we are excluding any suspicious activity happening just outside that range or in other regions. It would underestimate or misrepresent the true scale of the money laundering as cartels may deliberately make deposits/withdrawals beyond the 100-mile radius to avoid detection	Broaden the inclusion criteria, by considering a broader radius of 100 miles from the border.
	Excluding other data types	Wire transfers or electronic transfers would be excluded entirely	Investigating known money laundering tactics, this could reveal gaps in data
	Relying upon only one source of data (team lead's)	It's several years old; we might miss patterns or signals	Use multiple data sources, currency exchange records, law

		that would be present in a broader data set. Just using the bank's data set excludes data from other agencies	enforcement data, maybe even bank regulatory data bases
<b>Bias</b>	<b>Possible Distortion</b>	<b>Explanation</b>	<b>Avoidant Strategies to minimize bias</b>
Collection	Outdated or unverified historical data	If money laundering tactics or banking regulations have changed, using old data could lead to inaccurate conclusions about current trends.	Validate and or update historical data by checking the older data against more recent transactions and new regulatory data. Perform an audit of the cleaning methods used.
	Assumed the proper cleaning of old data	If there were any errors in the cleaning process like removing outliers or misclassifying transactions, we may be working with skewed or incomplete data.	Establish clear data cleaning protocols by creating a data cleaning checklist that outlines things like how outliers are handled, how missing values are treated.
	Time frame Bias	The time frame is not specified in the old data collected by the team lead. This could result in not capturing any changes in cartel strategies over time, like during holidays, law enforcement raids or economic trends	Check for seasonal or periodic patterns by collecting data over multiple time periods (holidays, economic cycles, law enforcement raids). This would help capture temporal variation in money laundering behavior, prevent false generalizations.
<b>Bias</b>	<b>Possible Distortion</b>	<b>Explanation</b>	<b>Avoidant Strategies to minimize bias</b>
Measurement	Outdated cleaning/labeling methods	Because the cleaning and labeling methods are not named, we could misclassify money laundering tactics	If possible, review the older dataset's cleaning steps and re-clean or re-label transactions using current definitions

	Possible lack of standardized definitions from banks	Different banks may have varying definitions of “large deposit” or “suspicious deposit/withdrawal.” This could distort the true distribution of money laundering behavior.	Establish standardized data collection protocols like “large deposit is over \$xx.” This ensure consistency across different banks, regions.
	Observer/Coder Bias	Human error/bias: humans are deciding which transactions are suspicious based on subjective criteria, they might overlook or even over report certain patterns.	We could implement automated

**Task 3 If you know that there is bias in the collection method, what could you do to communicate your concerns to your team lead?**

Communication Method to Team Lead	Reason
Share my findings	I would put all the points that I’ve collected here on a spreadsheet. The way the information listed outlines each possible bias, how it will impact results and strategies to minimize the bias
Discuss issues	Arrange a briefing meeting that walks through my findings and answer any questions. This meeting would not include any stakeholders at this time, During the presentation of the final project, we can reference what was done to identify, control for and minimize bias.
Show examples	Use real-world examples of biases and their impact. Show examples of how best practices to identify and control for bias minimized bias in the results
Suggest incremental changes	Suggest expanding the geographic radius from 100 to 150 miles and adding another data source

**Task 4: Read through the details of testing. How might the lack of transparency around the experience and training of the investigators allow for bias?**

Human bias can corrupt the models for machine learning. Specifically, the lack of experience and training may cause the investigator(s) to interpret risk where there isn't any. We would need clear insight into each analyst's background, experience level, and how they've been trained to identify suspicious transactions. Standardized training and transparent guidelines for scoring transactions are essential to ensure that each analyst applies the same criteria, reducing the chance of personal bias creeping into the dataset.

**Task 5: Analyze the bar chart showing the scores of individual analysts and see where their scores fall on the distribution curve. If the mean of the scores was 307 and the standard deviation is 166, which score or scores might you eliminate to control for bias? Why?**

**Reviewing the charts:**

Each bar represents the number of "suspicious" labels assigned by an individual investigator. Immediately, Investigator #10 stands out visibly higher at 759.

The vertical red lines on the distribution curve indicate the standard deviation from the mean, 307

**Statistics:**

Mean (average) is 307

Stand Deviation is 166

**Calculating Standard Deviation Ranges**

One Standard Deviation Range 141 to 473

$$307 - 166 = 141$$

$$307 + 166 = 473$$

Two Standard Deviation Range -25 to 639

$$307 - (166 * 2) = 307 - 332 = -25$$

$$307 + (166 * 2) = 307 + 332 = 639$$

Three Standard Deviation Range -191 to 805

$$307 - (166 * 3) = 307 - 498 = -191$$

$$307 + (166 * 3) = 307 + 498 = 805$$

**Which score(s) might be an outlier(s)?**

Investigator #10: score of 759

The score is approximately 452 points above the mean ( $759 - 307 = 452$ )

759 is outside the 2 SD range:  $452 / 166 = 2.72$  (outside the 2 SD but still within 3 SD)

None of the other investigator's scores were more than 2 SD away from the mean (307); therefore, investigator #10 is the primary outlier.

**Why would the outlier(s) be eliminated?**

Generally, being 2 SD away from the mean often flags a potential outlier. If an investigator's labeling method is vastly different (i.e. perhaps they interpret "suspicious" much more often), then this can skew the overall model training. Removing or re-checking outliers can help control for potential bias.