Food Inspections For the Ordinary

by FiFo Inc.

My Domain Knowledge

Inspection Grade

A

B

C

The Problem
& Proposed Solution

Restaurant health inspection records are public but often stored in difficult-to-navigate formats, making it hard for customers to access crucial information about prior violations. My goal with **FiFo** is to present this data in a clear, engaging way to help people make informed dining choices.

App

Visualise Inspection Information

Model

Predict Inspection Result

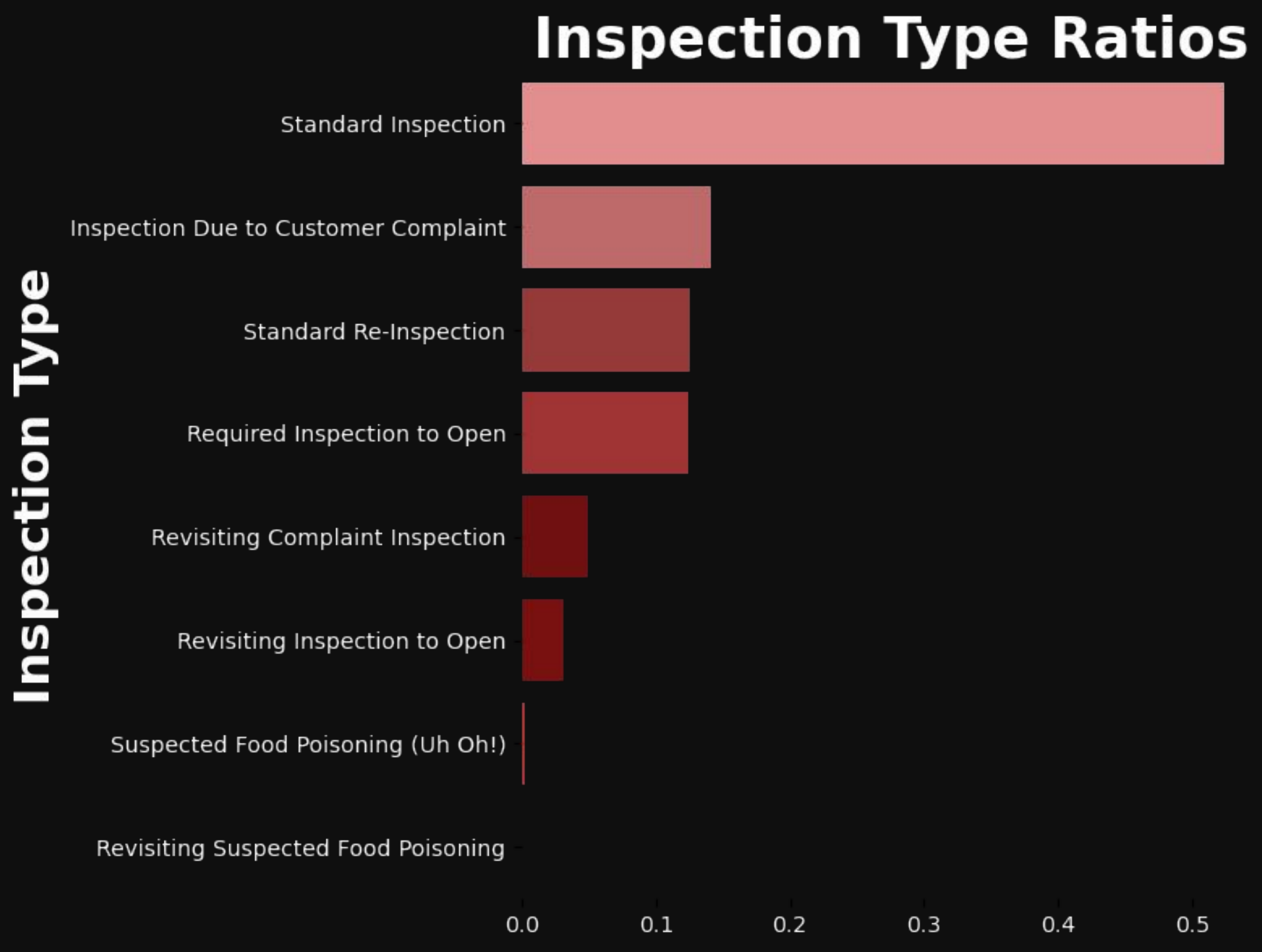
Goals

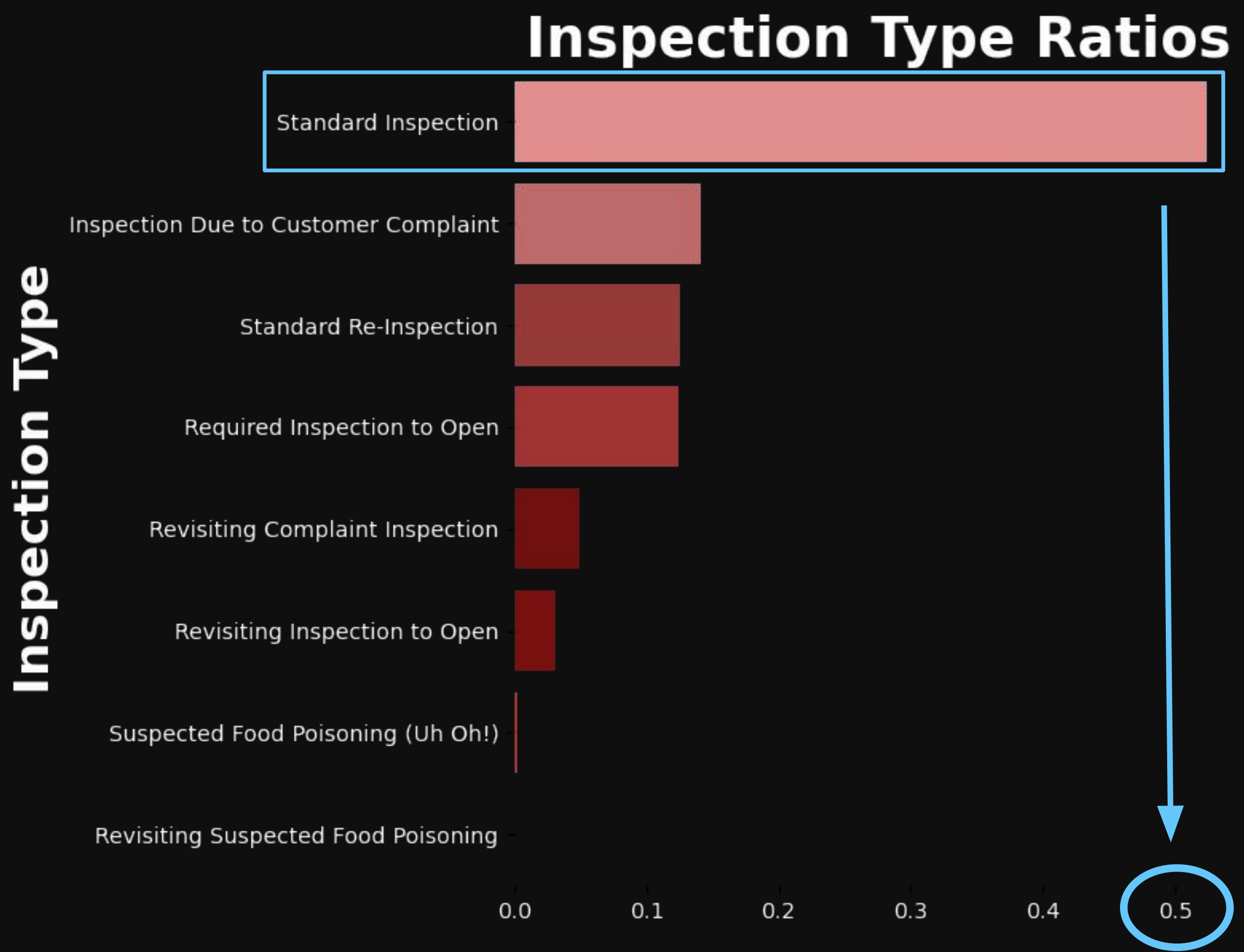
“Encourage people to make more educated & healthier choices on things which may impact their health and well-being greatly.”

Objective of FiFo Inc.

01
The Data

Exploring, cleaning, and visualising the **Chicago Food Inspections** dataset.


Inspection Type Ratios
Inspection Type
Standard Inspection
Inspection Due to Customer Complaint
Standard Re-Inspection
Required Inspection to Open
Revisiting Complaint Inspection
Revisiting Inspection to Open
Suspected Food Poisoning (Uh Oh!)
Revisiting Suspected Food Poisoning
0.0
0.1
0.2
0.3
0.4
0.5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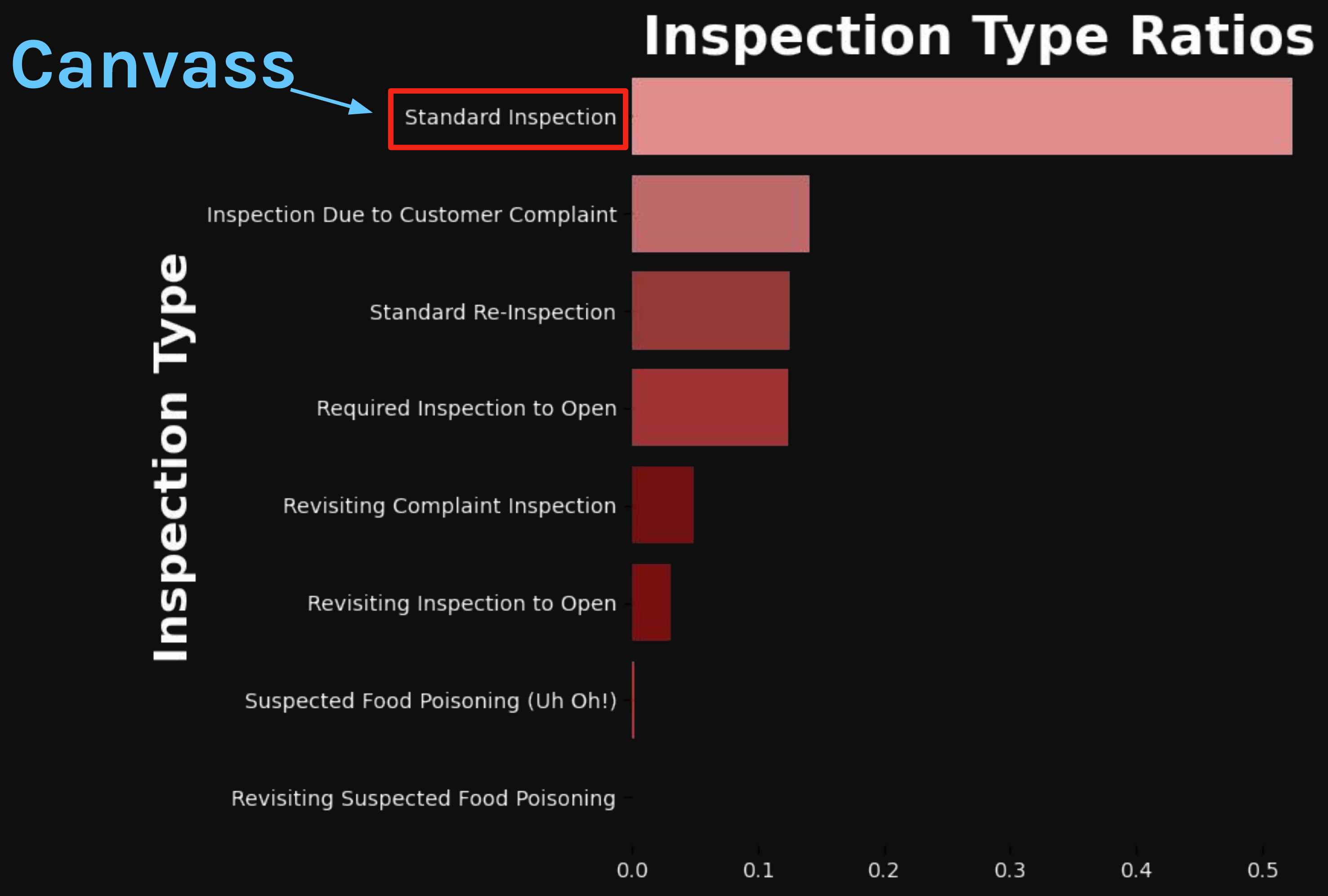
Canvass
Inspection Type Ratios
Inspection Type
Standard Inspection
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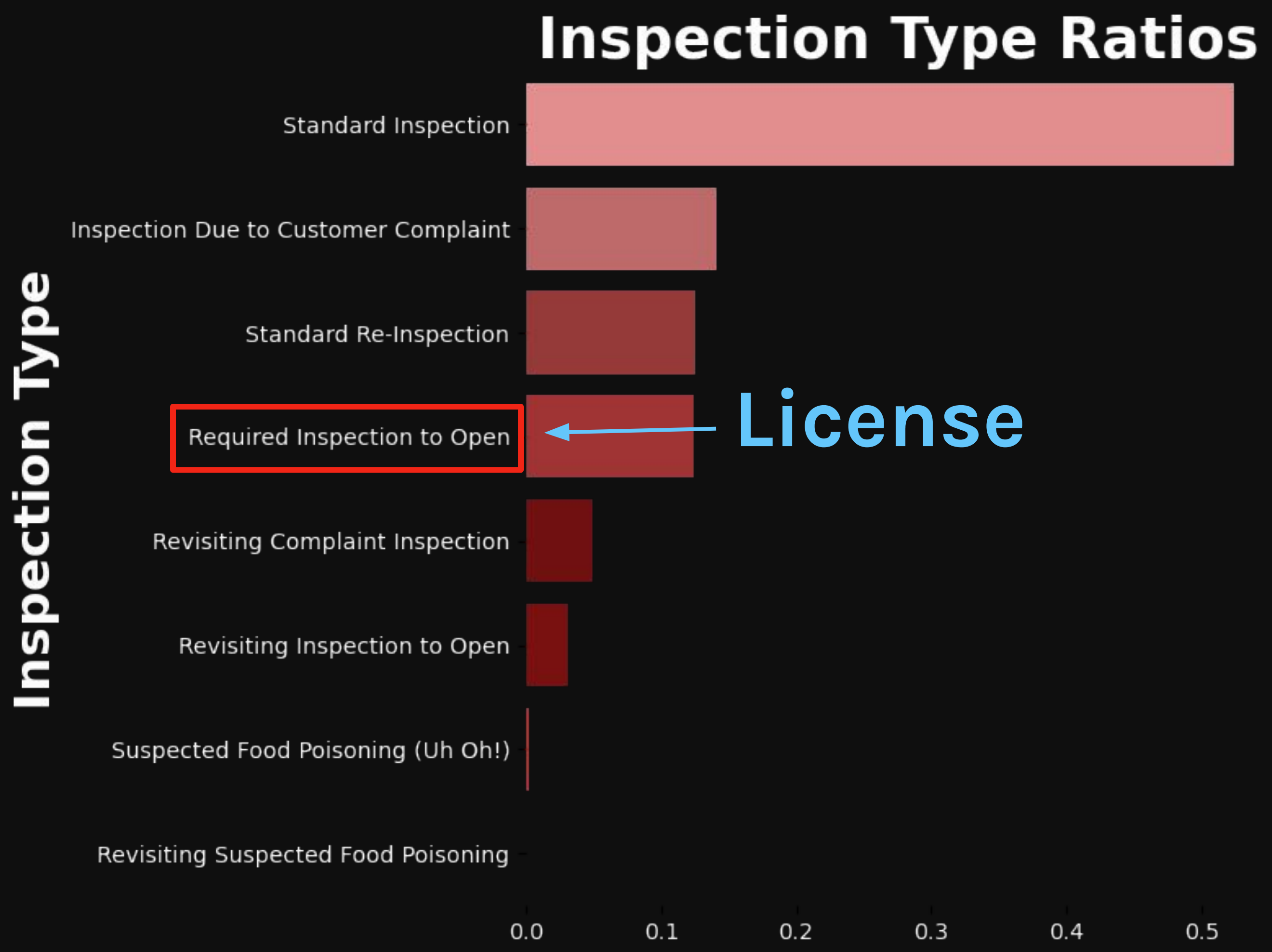

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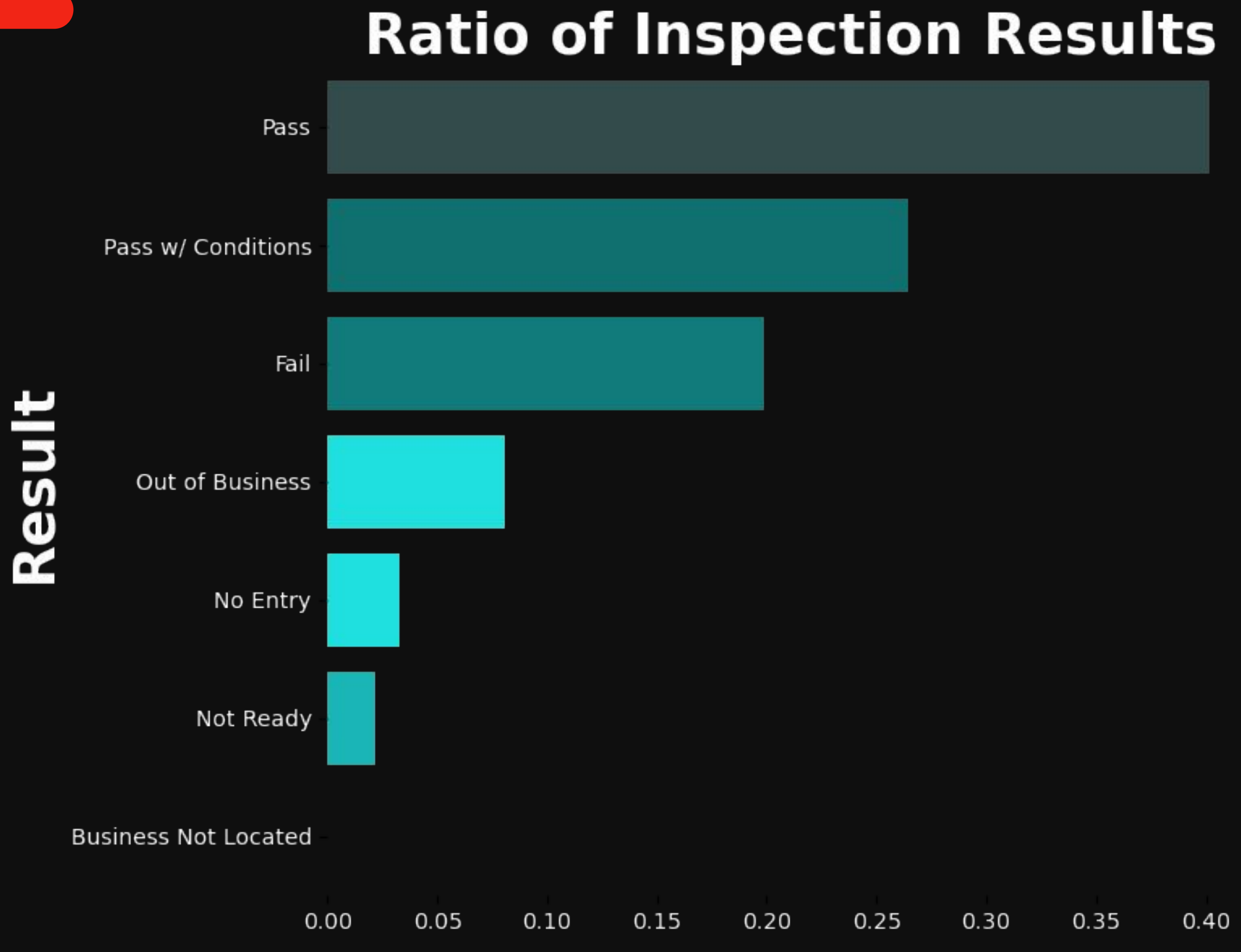
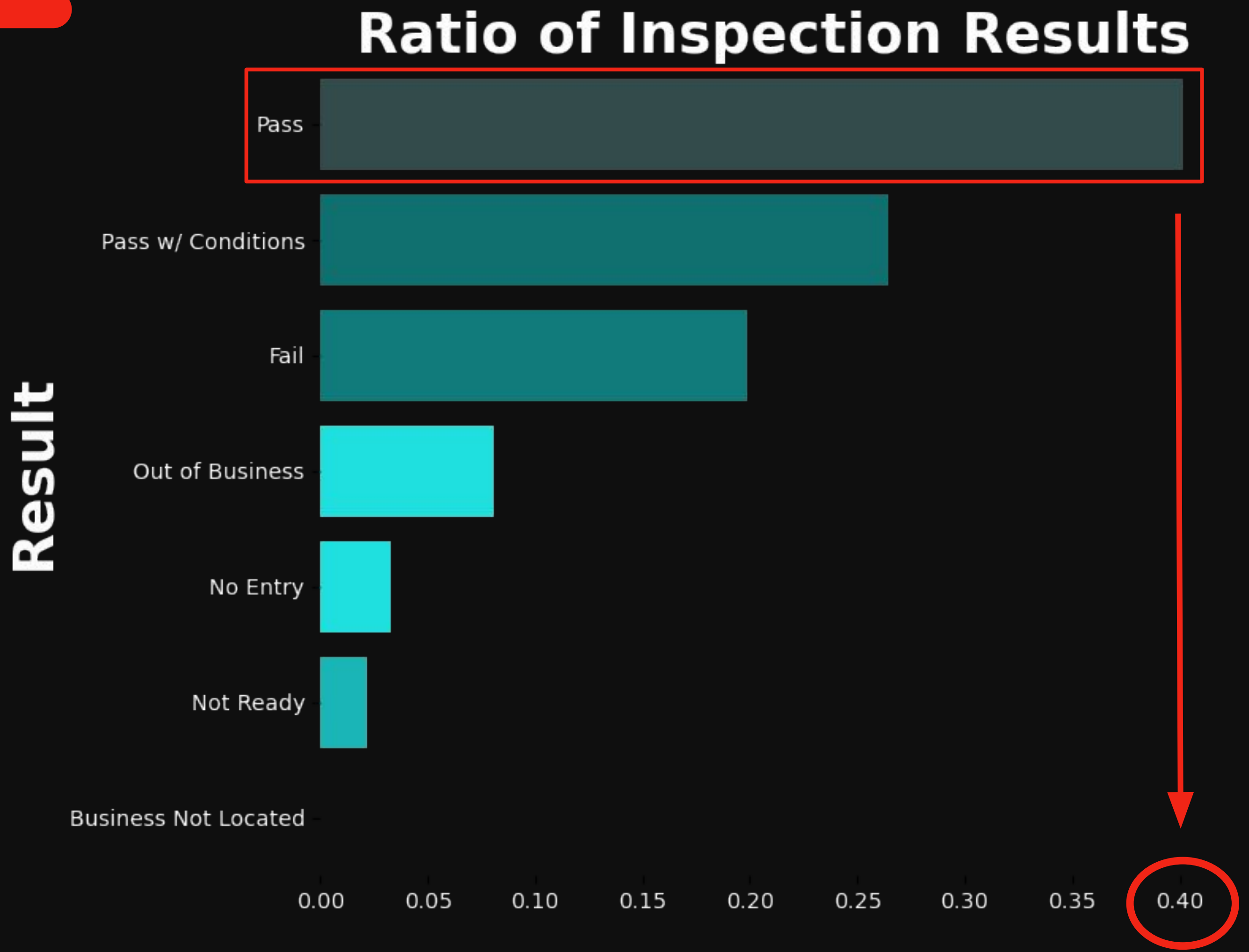
Revisiting Suspected Food Poisoning
License
0.0
0.1
0.2
0.3
0.4
0.5

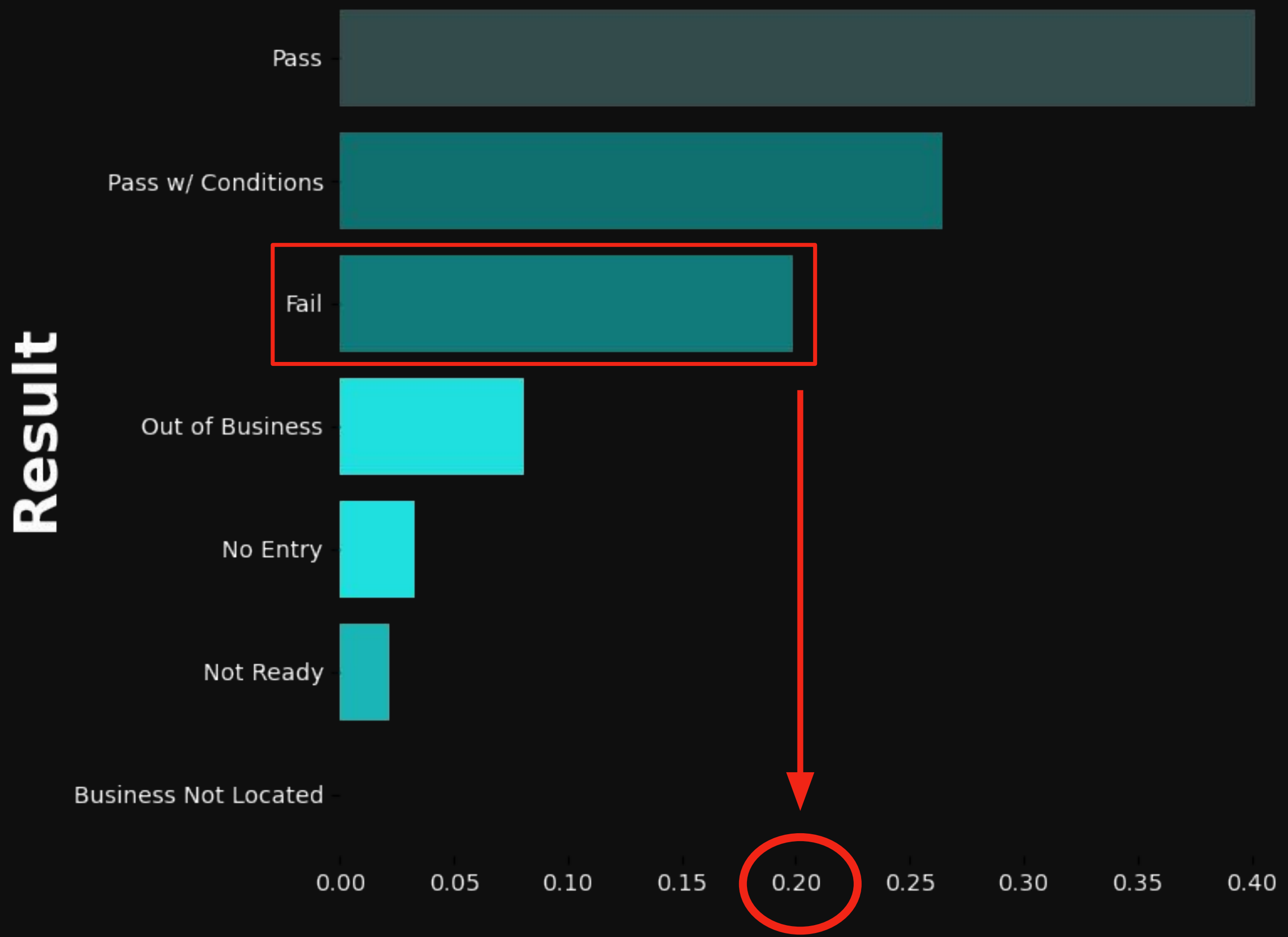


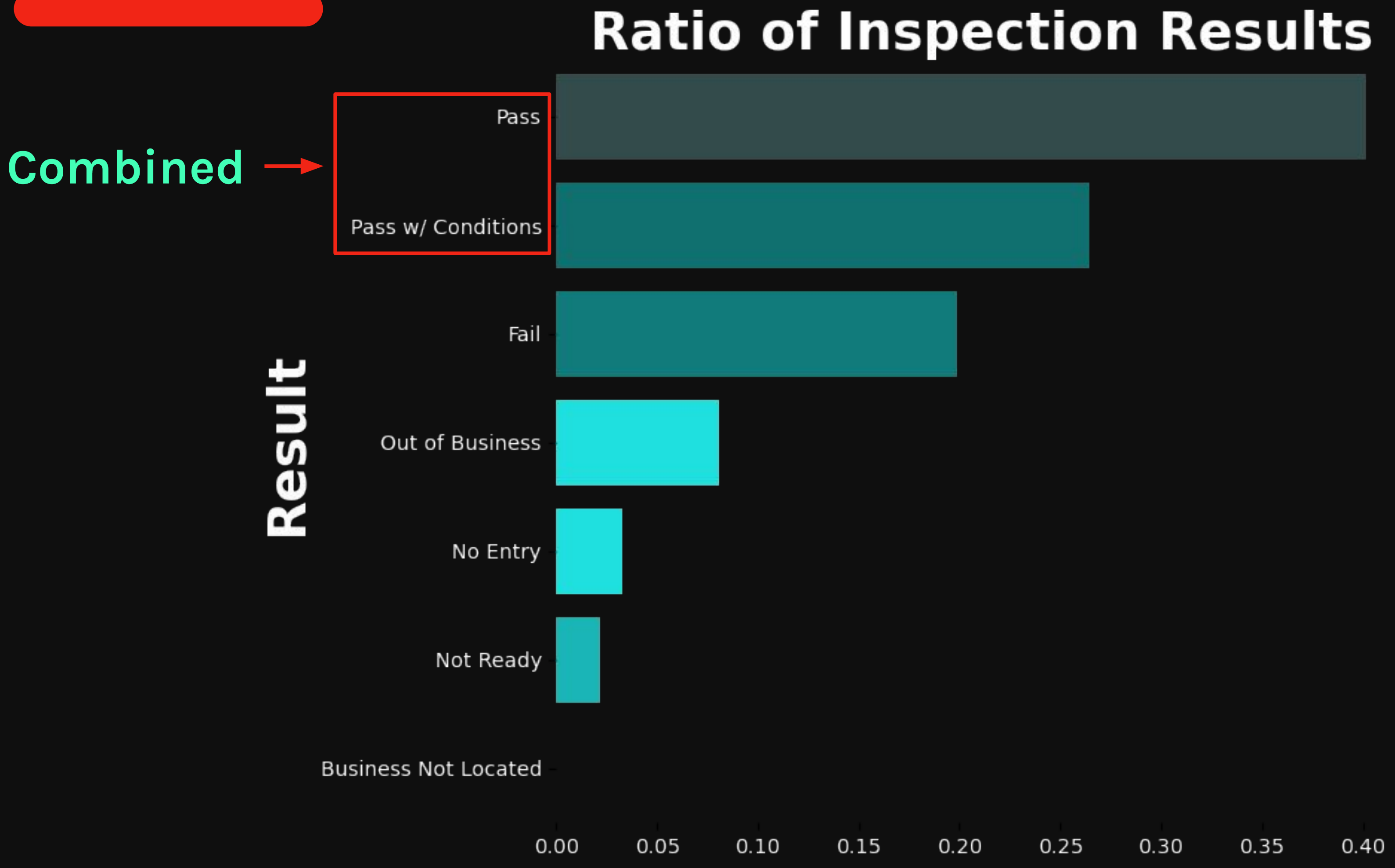
Ratio of Inspection Results
Result
Pass
Pass w/ Conditions
Fail
Out of Business
No Entry
Not Ready
Business Not Located
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40

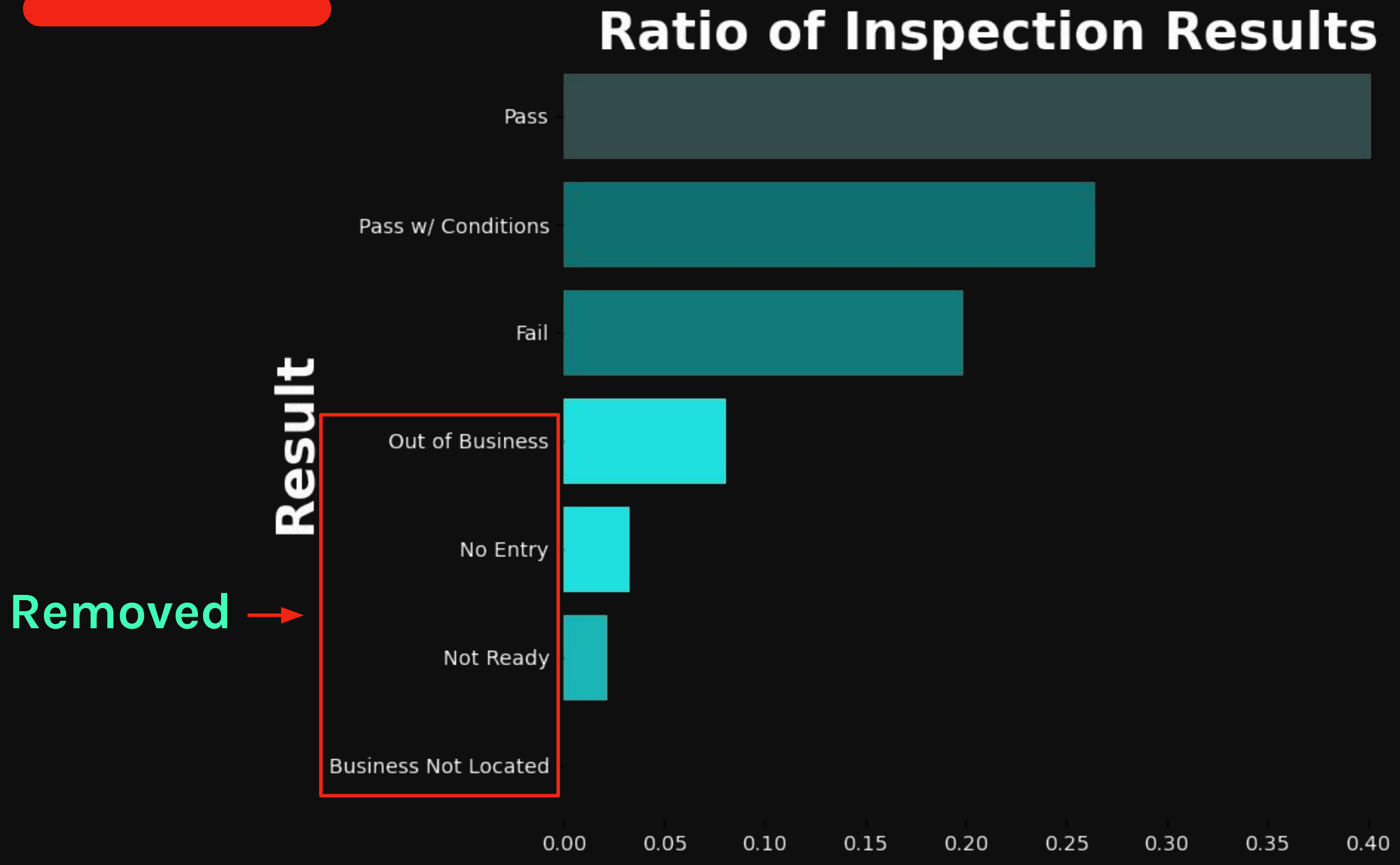


Ratio of Inspection Results
Result
Pass
Pass w/ Conditions
Fail
Out of Business
No Entry
Not Ready
Business Not Located
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40

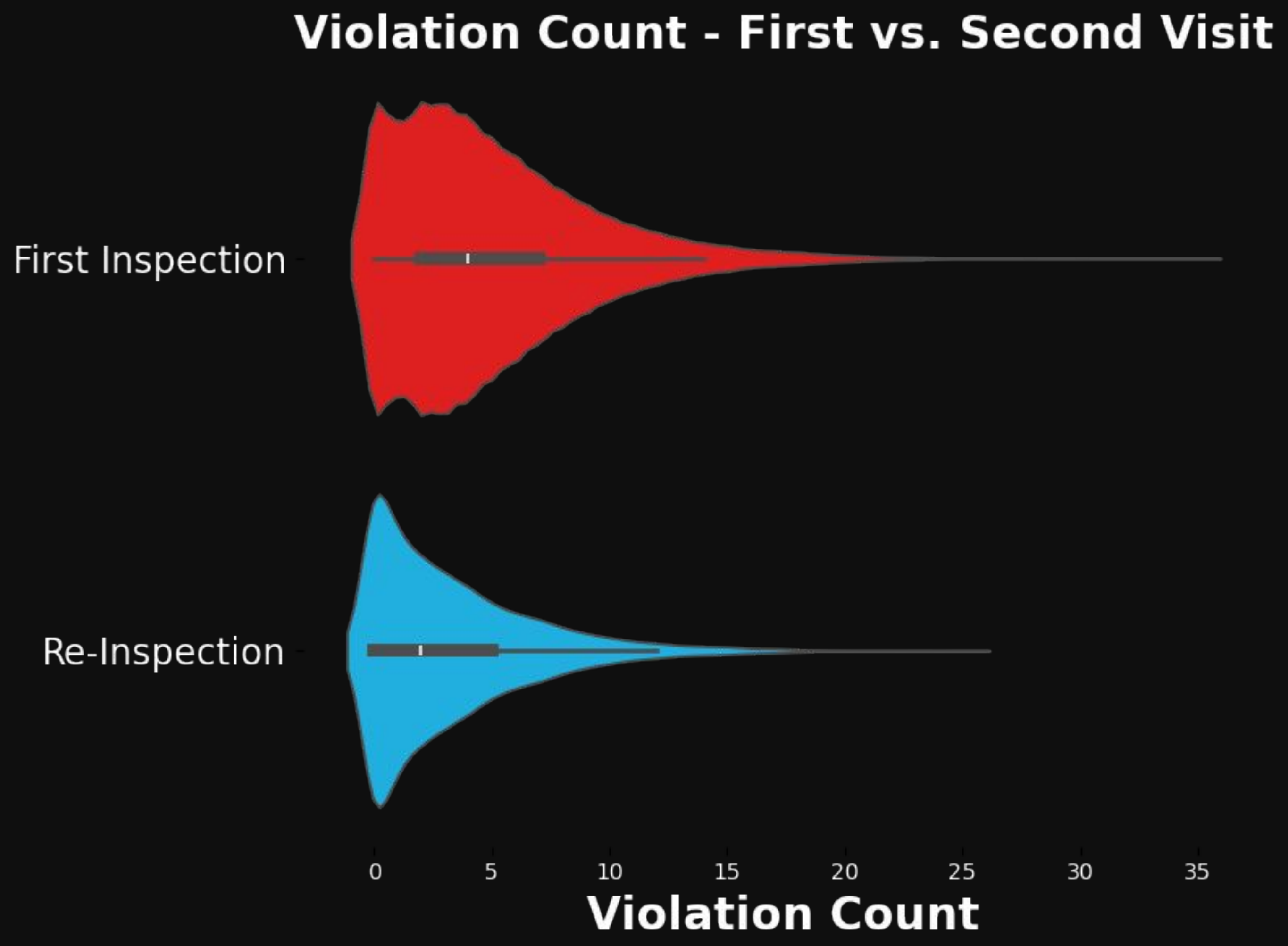
Ratio of Inspection Results

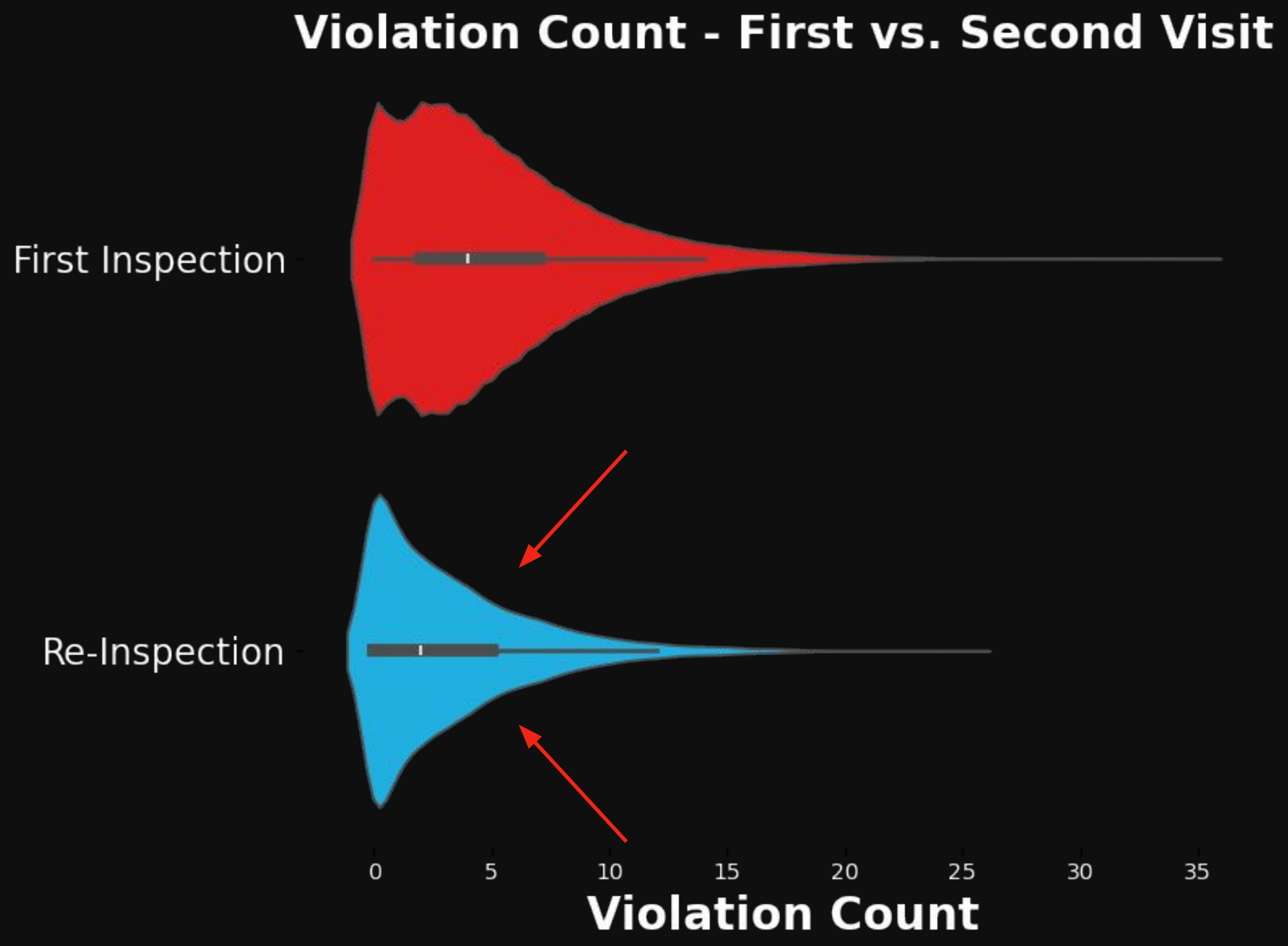



Combined
Ratio of Inspection Results
Result
Pass
Pass w/ Conditions
Fail
Out of Business
No Entry
Not Ready
Business Not Located
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40


Ratio of Inspection Results
Pass
Pass w/ Conditions
Fail
Out of Business
No Entry
Not Ready
Business Not Located
Result
Removed
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40

Designing New Features


Violation Count - First vs. Second Visit
First Inspection
Re-Inspection
0
5
10
15
20
25
30
35
Violation Count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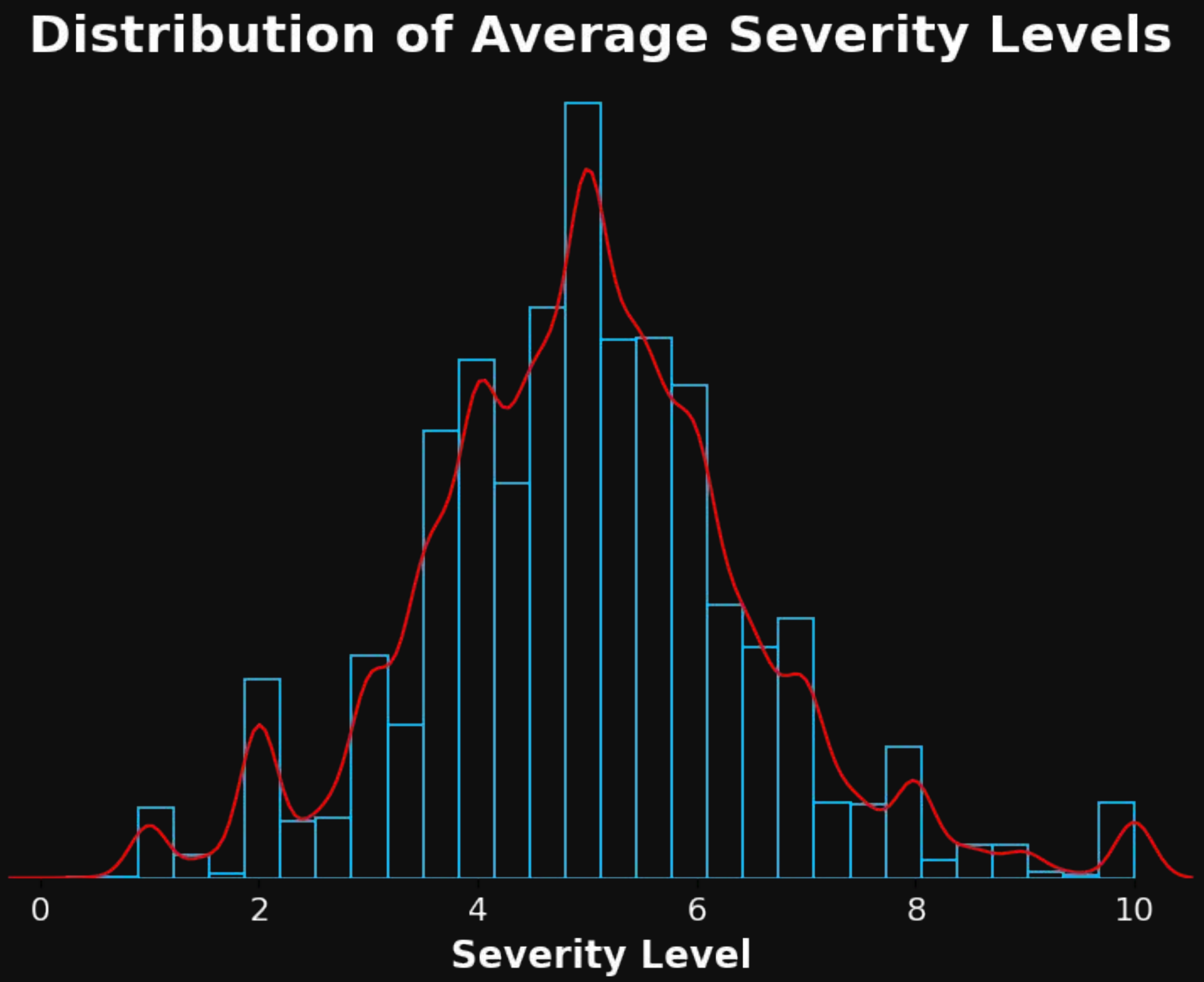
35
Violation Count



Distribution of Average Severity Levels
0
2
4
6
8
10
Severity Level

02

The Model

Predicting inspection results of
Chicago restaurants.

Logistic Regression

Binary Classification - Pass / Fail

Logistic Regression

Binary Classification - Pass / Fail

Interpretability

Allow restaurant owners to understand the factors influencing inspection outcomes

Logistic Regression

Binary Classification - Pass / Fail

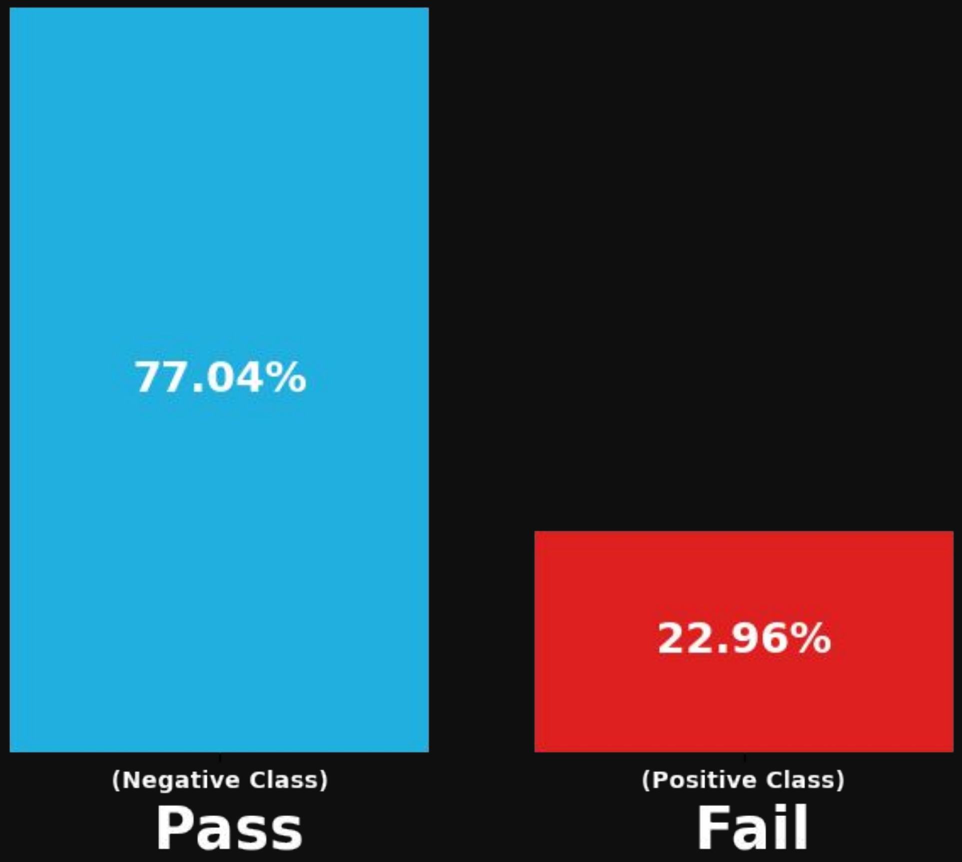
Interpretability

Allow restaurant owners to understand the factors influencing inspection outcomes

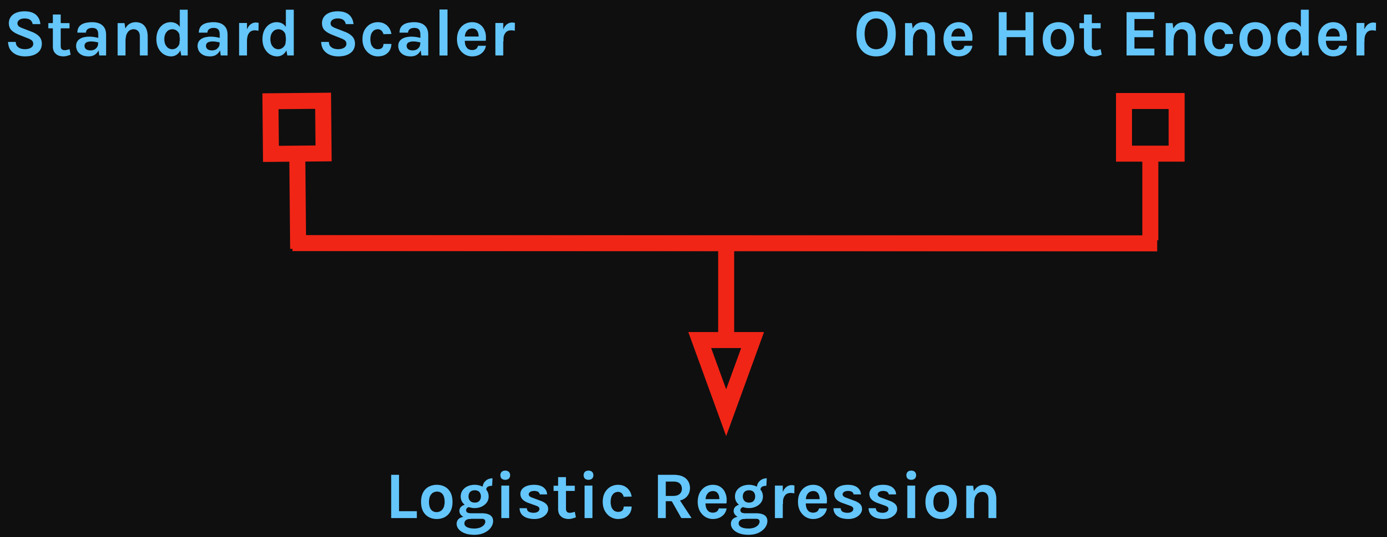
Recall

Minimize the risk of missing critical inspection failures

Class Balance



Pipeline



Model Results

Iterations	Accuracy	Precision	Recall	F1
First	87%	76%	60%	67%

Model Results

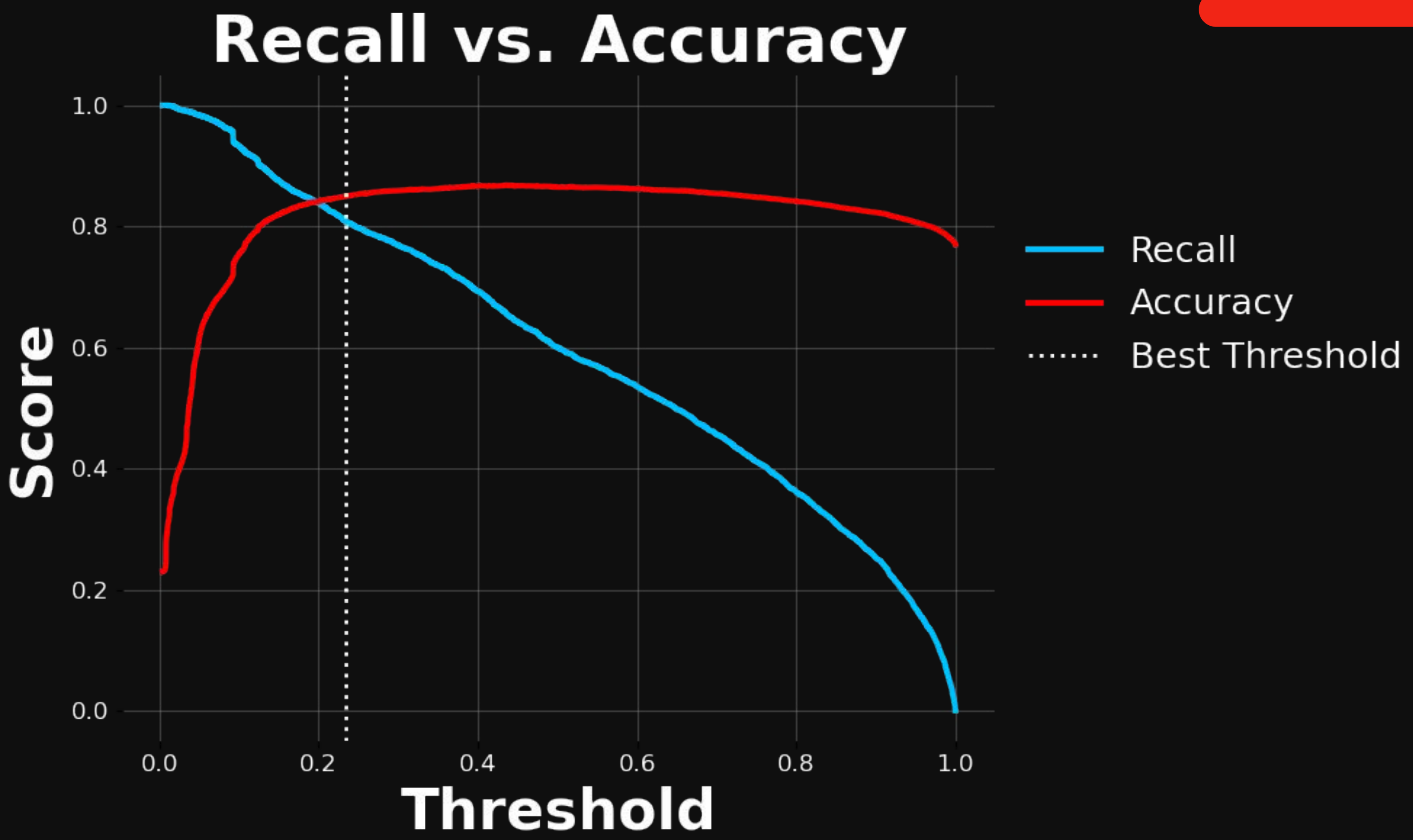
Iterations	Accuracy	Precision	Recall	F1
First	87%	76%	60%	67%
Second	86%	67%	77%	71%

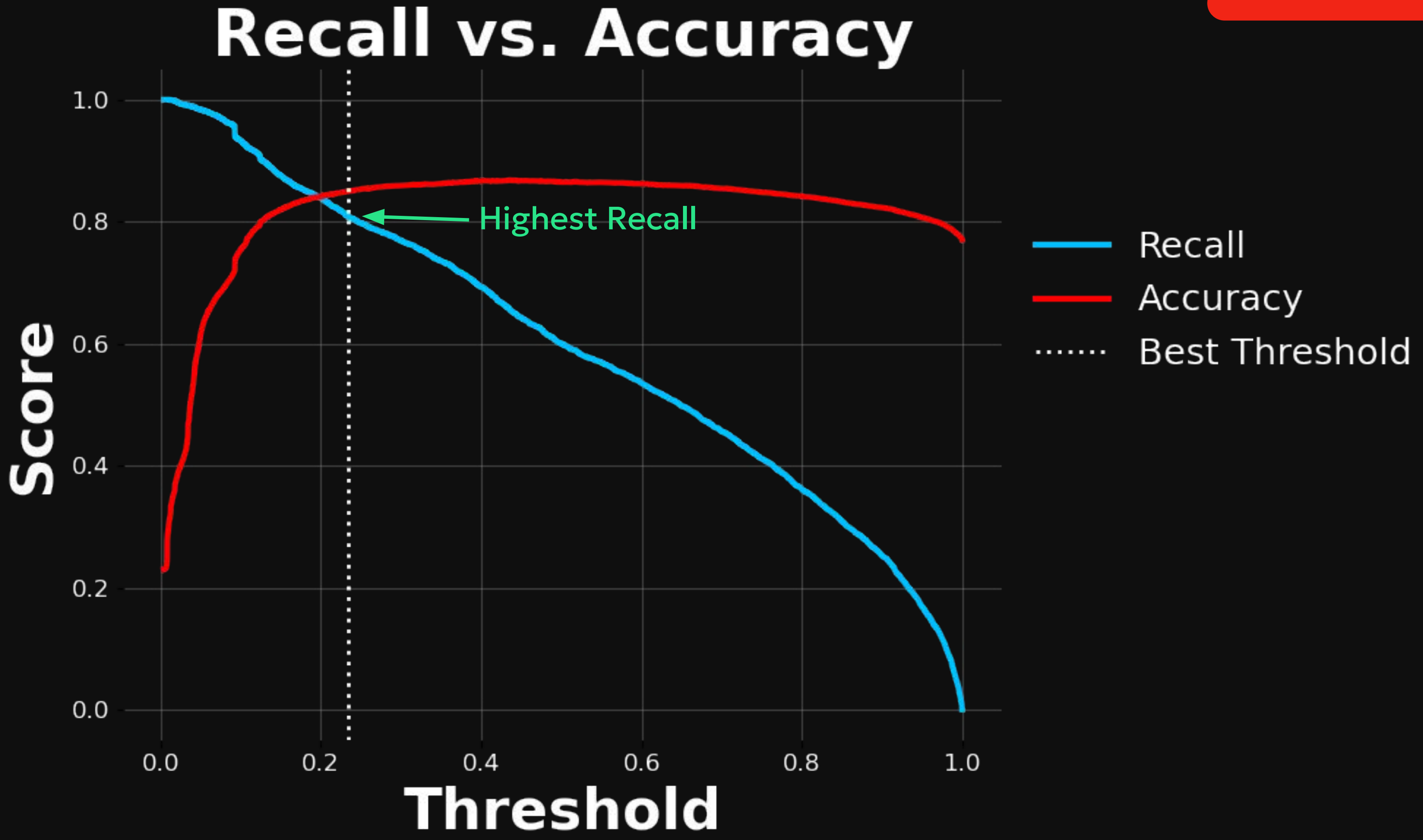
Model Results

Iterations	Accuracy	Precision	Recall	F1
First	87%	76%	60%	67%
Second	86%	67%	77%	71%
Third	85%	64%	81%	71%

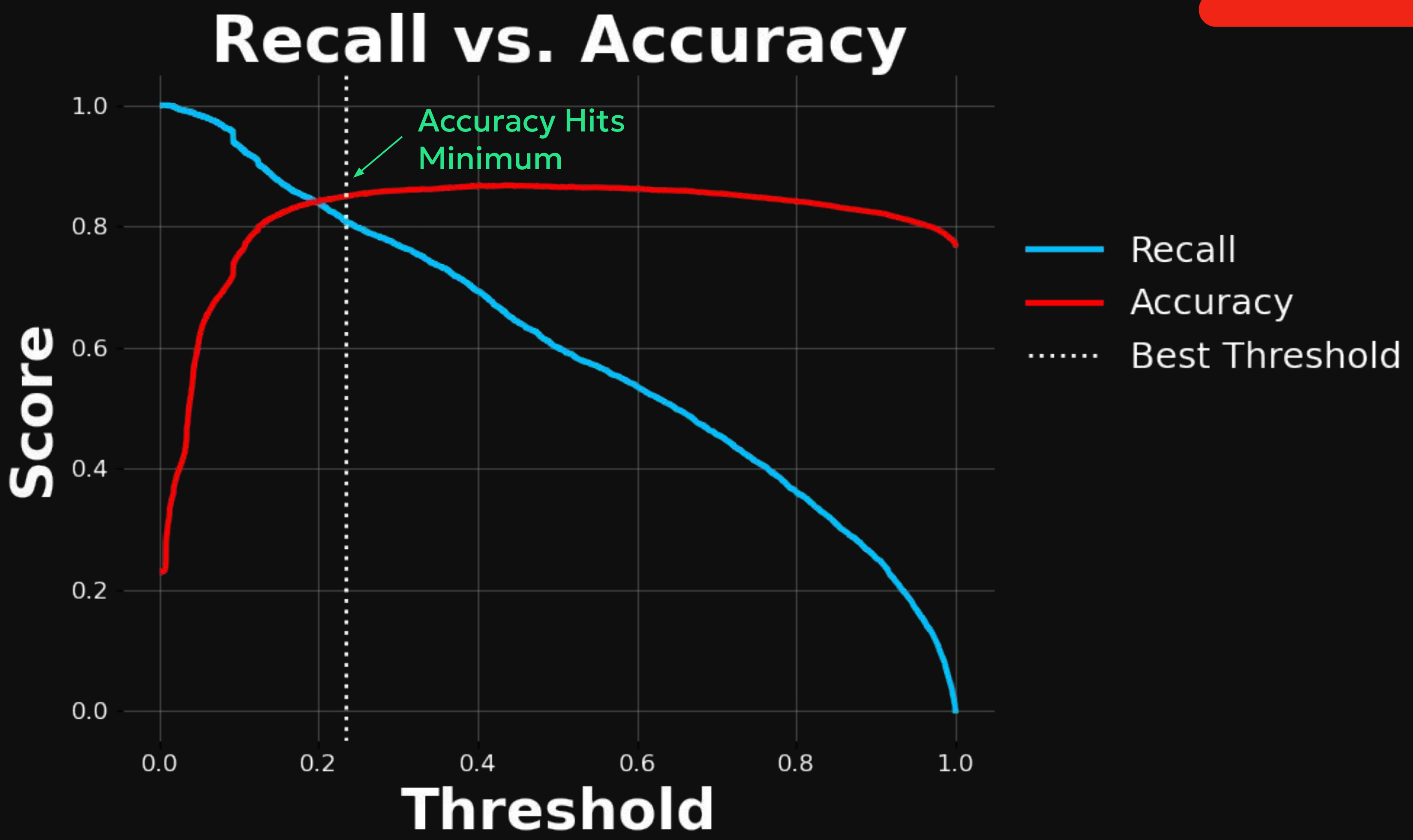
Model Results

Iterations	Accuracy	Precision	Recall	F1
First	87%	76%	60%	67%
Second	86%	67%	77%	71%
Third	85%	64%	81%	71%


Recall vs. Accuracy
1.0
0.8
0.6
0.4
0.2
0.0
Score
0.0
0.2
0.4
0.6
0.8
1.0
Threshold
Recall
Accuracy
Best Threshold



Recall vs. Accuracy
Score
Threshold
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Highest Recall
Recall
Accuracy
Best Threshold



Recall vs. Accuracy
Accuracy Hits Minimum
1.0
0.8
0.6
0.4
0.2
0.0
Score
0.0
0.2
0.4
0.6
0.8
1.0
Threshold
Recall
Accuracy
Best Threshold

Model Conclusion

Model Conclusion

Potential Issues

- Broken Assumptions
- Need Better Features

03

App

Running a demo in Streamlit

Future of FiFo Inc.

App Development

Many design features and graphs still needed but the demo was really fun to build.

Model

Explore different classifiers apart from **Logistic Regression.**

Next Steps

- Explore more in depth each violation and its nuances.
- Scaling my work to apply for multiple cities and different types of establishments.

Thank you!