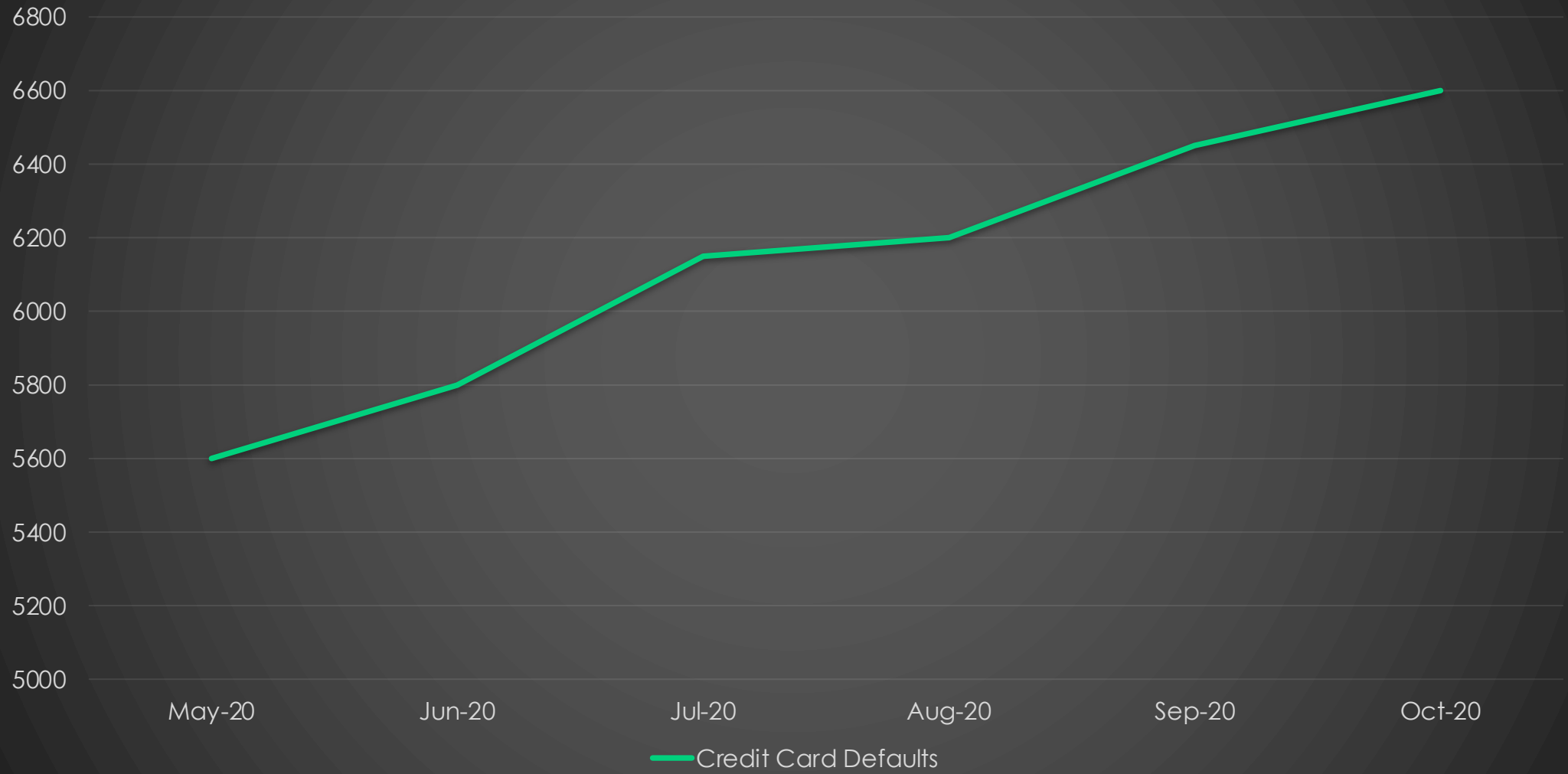


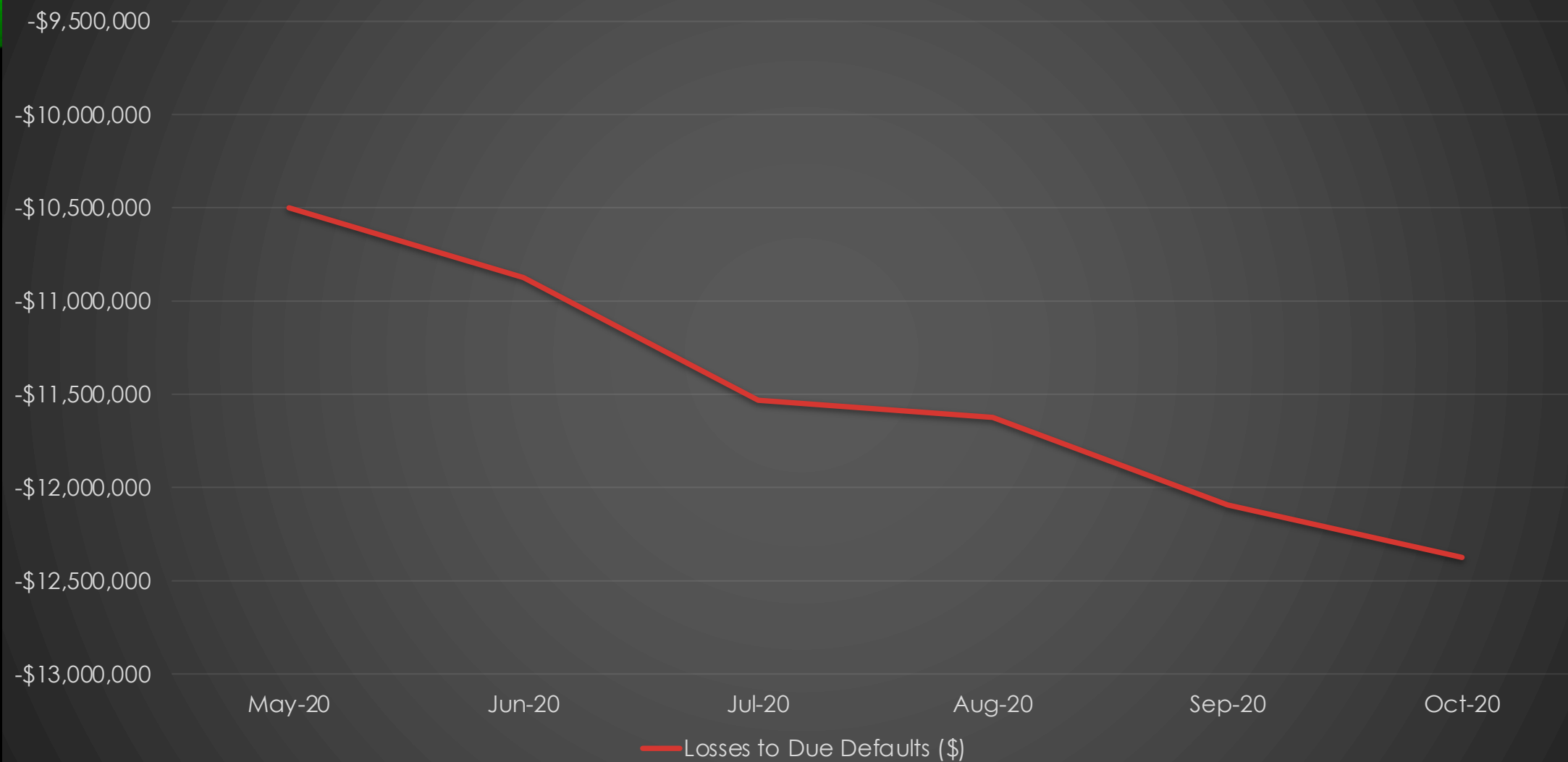
By Marcos Dominguez,
Data Scientist

CREDIT CARD DEFAULT: A DATA SCIENCE SOLUTION

Monthly Defaults (#)



Monthly Loss (\$)

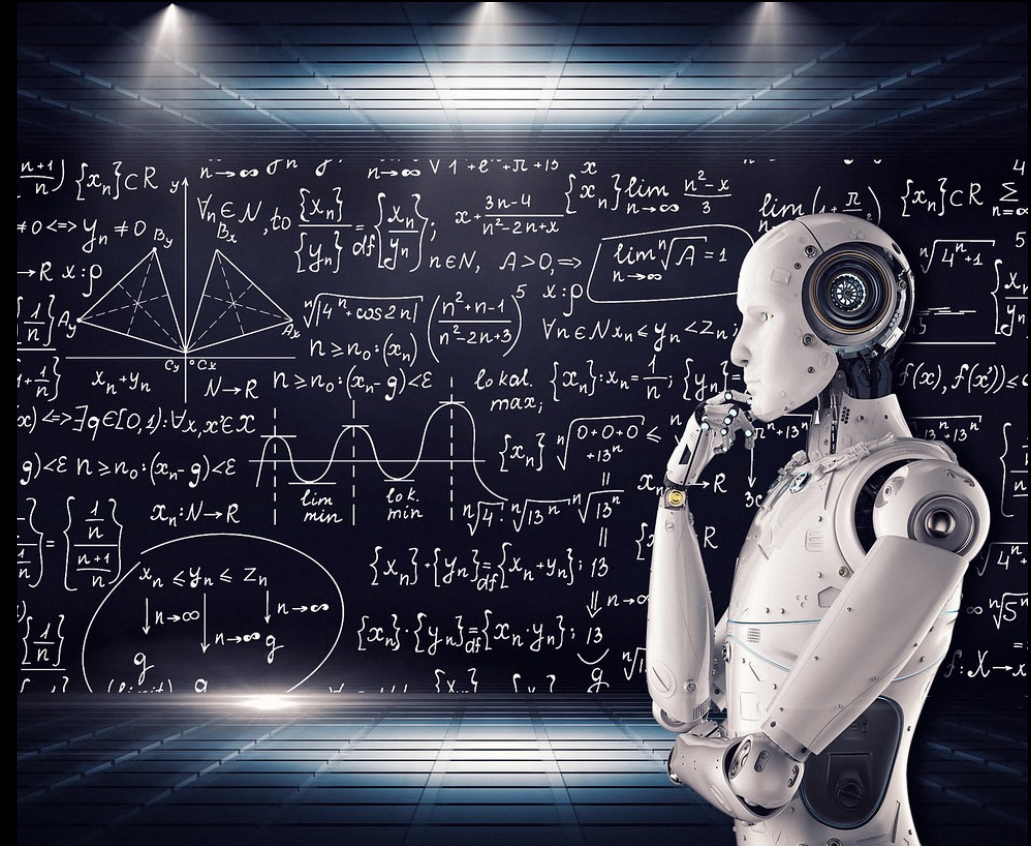


SOLUTION: MACHINE LEARNING MODEL



FINE TUNING

- Minimize overlooking “No” predictions
 - Recall
- Cost of overlooking a “No” > Cost of overlooking a “Yes”

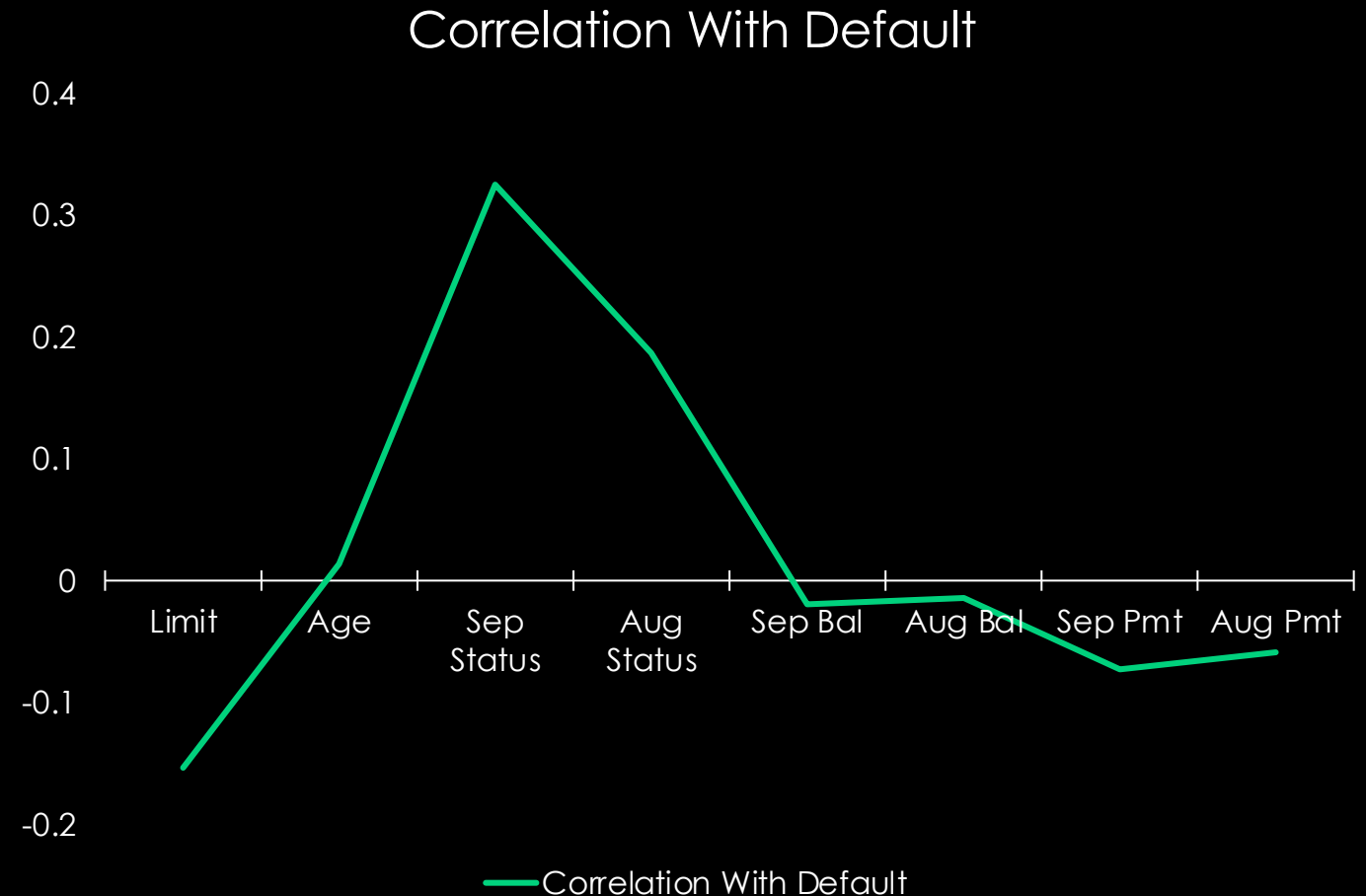


MODEL SELECTION: RANDOM FOREST

- Compared:
 - Multiple models
 - Multiple parameters
- Most accurate
- Least computationally complex

INPUT VARIABLES

- 26 variables total
 - Credit Limit
 - Payment Status
 - Monthly Payment
 - Monthly Balance
 - ...and many more
- Most important:
 - Payment Status



STRATEGY

1

Use ML model to identify customers likely to default

2

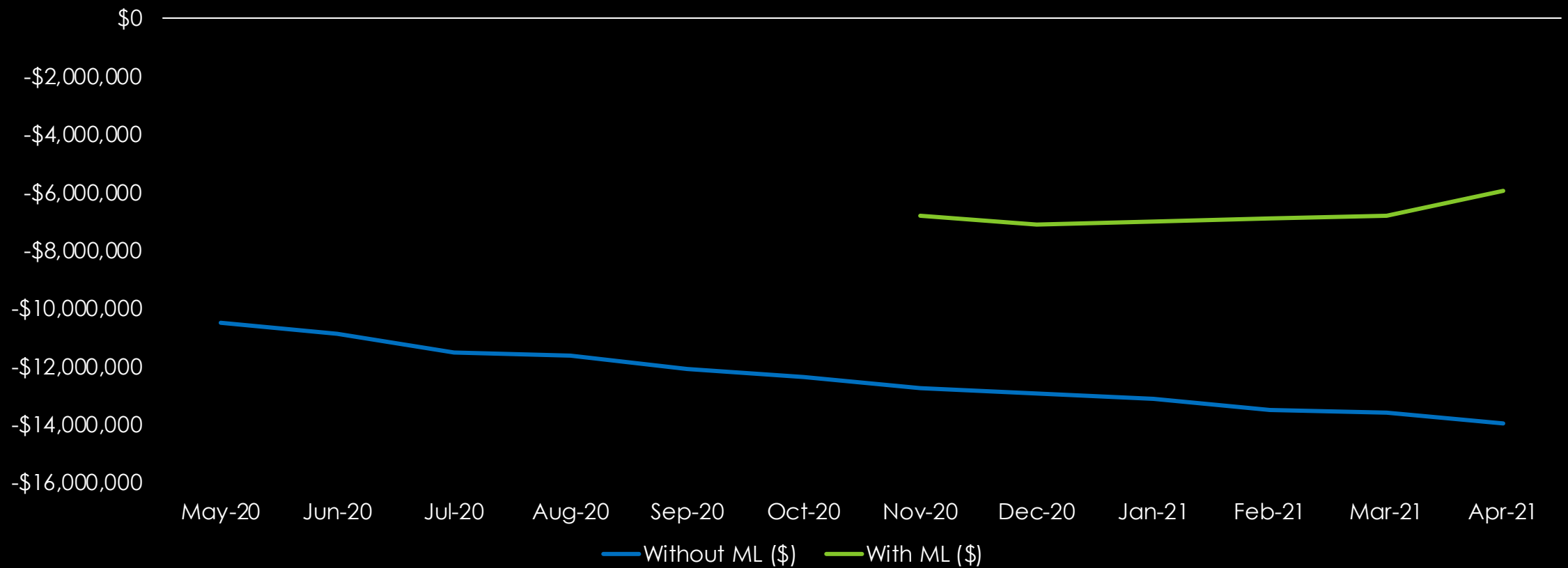
Notify relationship managers

3

Provide options:

- Forbearance
- Consolidate credit card debt

FORECAST



FORECAST NUMBERS

	Without ML (thousands)	With ML (thousands)
6 Month Forecast	\$(79,875)	\$(40,600)
Total Savings	\$0	\$39,275
Model Accuracy	0	55%
Defaults Prevented	0	21,950

DEMO

Credit Card Default: A Demonstration

By Marcos Dominguez, Data Scientist

Choose Monthly Status to Make a Prediction

June Status
On Time

On Time 4 Months Late

July Status
On Time

On Time 4 Months Late

August Status
On Time

On Time 4 Months Late

September Status
On Time

On Time 4 Months Late

Predict

ACKNOWLEDGEMENTS

- Dataset: UCI Machine Learning Repo, "default of credit card clients"
- Open-source tools used:
 - Scikit-learn
 - Pandas
 - Numpy
 - Matplotlib, seaborn
 - Streamlit
 - imblearn
 - ipywidgets