Jessica Gatta
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CLIMATE WINS

MACHINE LEARNING FOR WEATHER PREDICTION

OBJECTIVE, DATA, BIAS & ACCURACY

- Weather data from 18 mainland European stations
- Selection, interaction, and data quality bias
- Pleasant-weather data available for 15 stations
- Optimization via gradient descent on scaled data

BIAS AND ACCURACY CONSIDERATIONS

This project analyzes historical daily weather data from mainland Europe to evaluate **how machine learning can support ClimateWins' prediction goals**. While the main dataset is largely complete, l**imitations exist due to geographic concentration, human judgment in defining pleasant weather, and potential data collection errors. Pleasant-weather labels were only usable for 15 stations**, affecting comparability. ***Gradient descent optimization*** was applied to scaled data to minimize loss and improve model performance across all supervised learning models.

RESEARCH HYPOTESES

Based on ClimateWins’ objective, we propose several hypotheses that can be tested using supervised machine learning. These hypotheses explore whether historical temperature patterns can be used to predict pleasant weather conditions, whether machine learning models provide better predictive power than traditional methods, and whether preprocessing techniques such as feature scaling improve overall model performance and reliability.

01. TEMPERATURE

Temperature trends can predict future “pleasant weather” days

02. MACHINE LEARNING

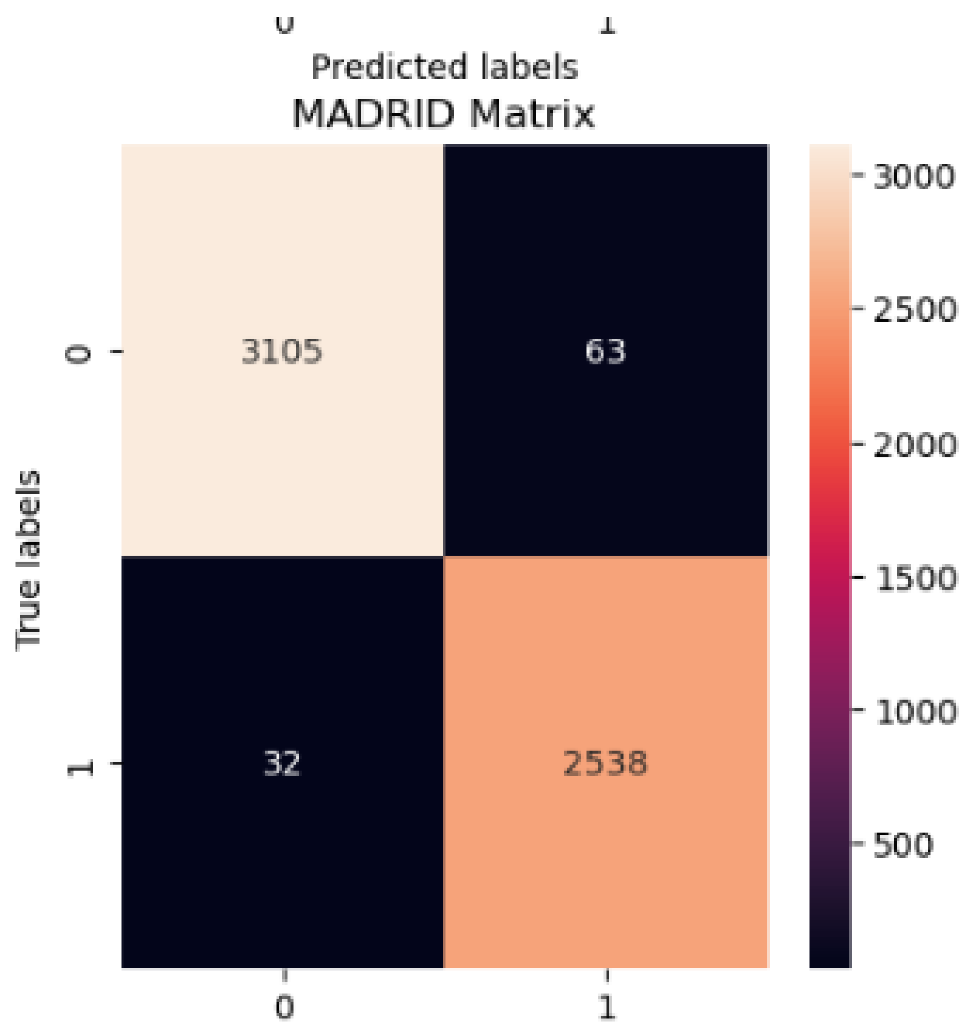
Machine learning models outperform rule-based approaches

03. PERFORMANCE

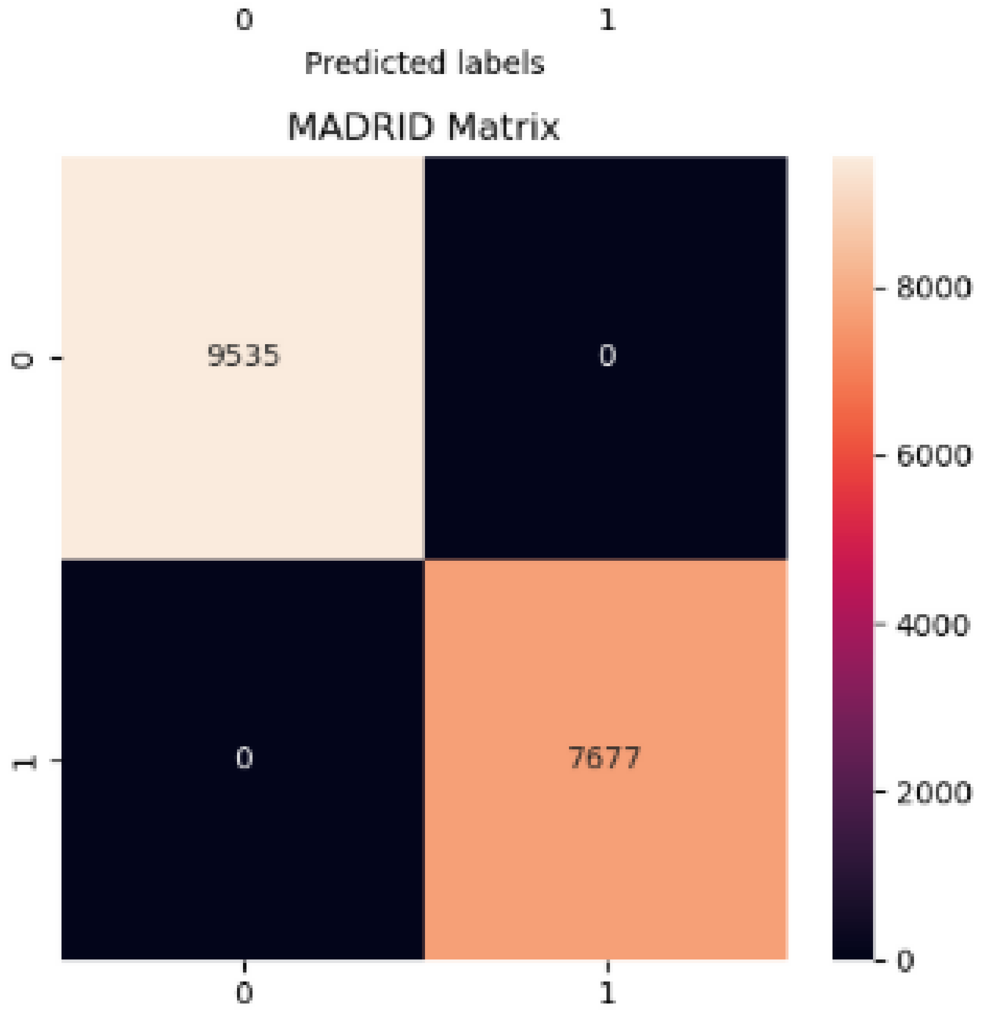
Feature scaling improves model accuracy and stability

MODELS EVALUATED

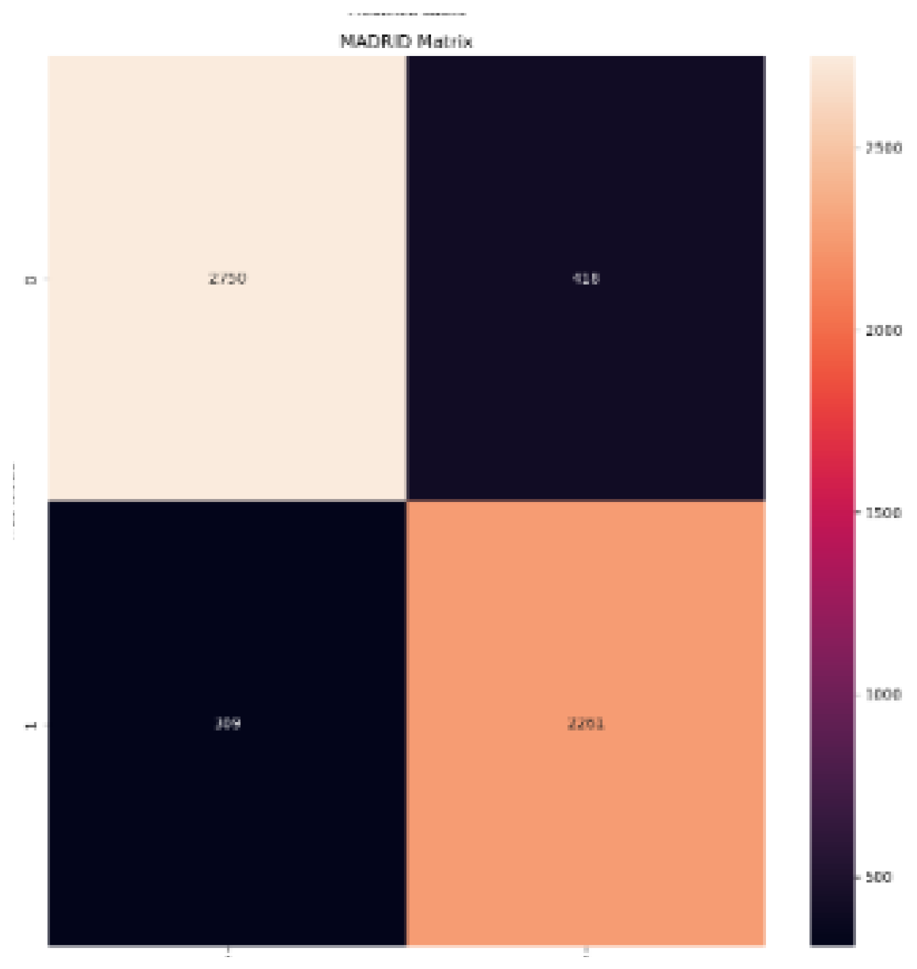
K-NEAREST NEIGHBORS (KNN), DECISION TREE, AND ARTIFICIAL NEURAL NETWORK (ANN)



ANN SCENARIO 3



DECISION TREE



KNN

Multi-output approach predicts all stations simultaneously, ensuring consistent evaluation.

Model choice reflects increasing flexibility and capability to generalize across varying weather conditions.

Each model was selected to test different levels of complexity and prediction capability.

- The **KNN** provides a simple comparison baseline
- The **Decision Tree** offers interpretability
- The **ANN** introduces advanced pattern recognition and generalization ability to ensure robust performance across Europe.

KNN & DECISION TREE RESULTS

K-NEAREST NEIGHBORS (KNN)

- Performs well in stations with stable historical patterns.
- Less reliable in regions with variable climates, limiting operational use.

DECISION TREE

- Perfect training accuracy indicates strong pattern capture.
- Lower testing accuracy reveals overfitting; pruning recommended for reliability.

KNN is effective in predictable climates but can fail where weather patterns fluctuate, which could affect operational planning. Decision Trees memorize training data perfectly but show reduced accuracy when predicting new days, highlighting the need for pruning to ensure actionable insights.

Weather Station	Accuracy Rate KNN	Accuracy Rate Decision Tree
BASEL	85%	94%
BELGRADE	84%	96%
BUDAPEST	85%	95%
DEBILT	88%	93%
DUSSELDORF	87%	99%
HEATHROW	85%	90%
KASSEL	90%	95%
LJUBLJANA	86%	98%
MAASTRICHT	88%	93%
MADRID	87%	95%
MUNCHENB	88%	95%
OSLO	90%	95%
SONNBLICK	100%	100%
STOCKHOLM	89%	91%
VALENTIA	95%	94%

ANN MODEL COMPARISON

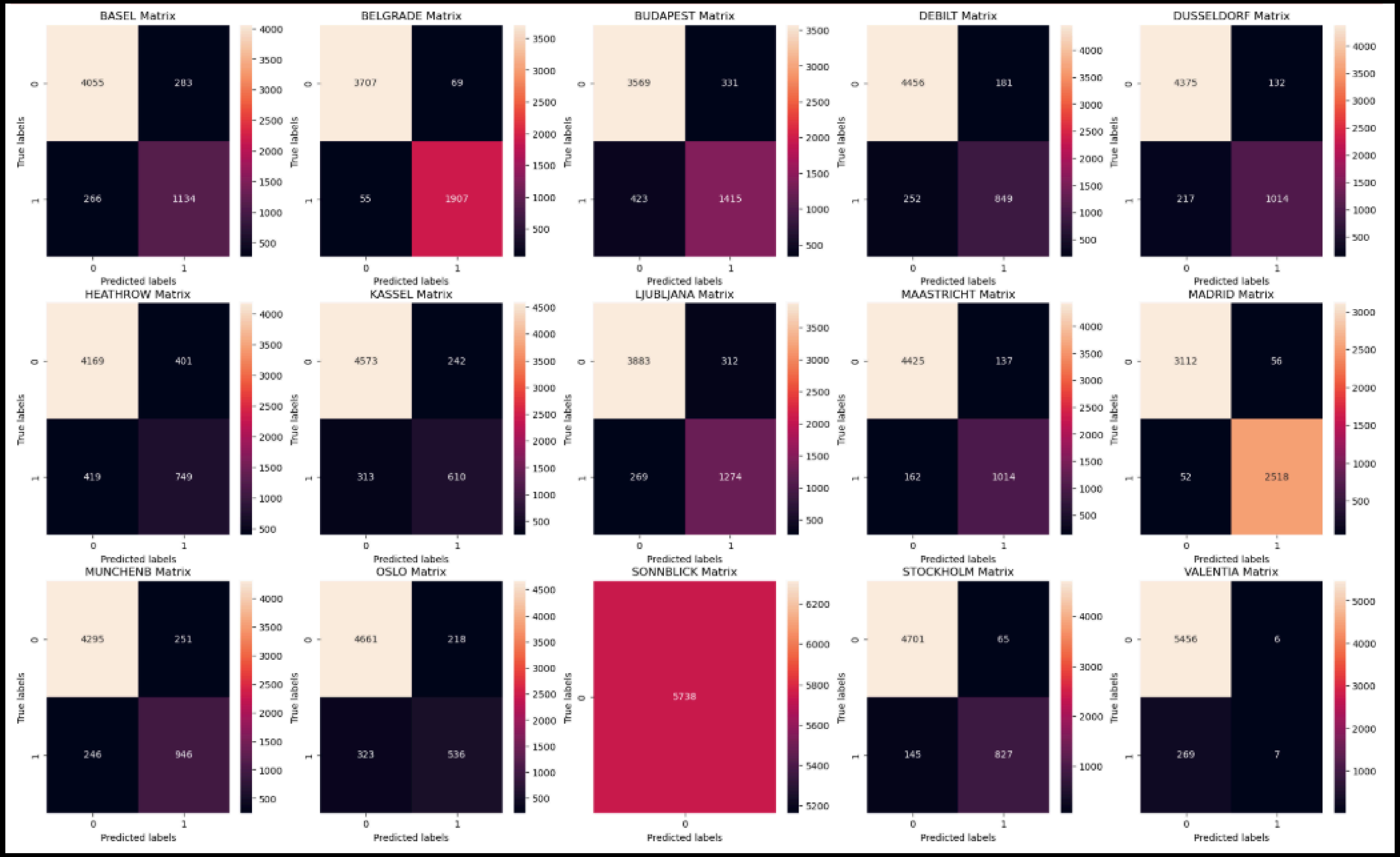
EVALUATING NETWORK COMPLEXITY FOR
BETTER GENERALIZATION

Scenario	AVG Testing Accuracy	Accuracy Range
1	91%	84-100%
2	93%	86-100%
3	96%	92-100%

- Three ANN configurations tested: Scenario 1 (5,5), Scenario 2 (20,10,5), Scenario 3 (50,20,10).
- Scenario 3 consistently achieves the highest testing accuracy.
- Scenario 1 and 2 included for comparison.

The ANN models differ in hidden layer configuration and complexity. Scenario 3 consistently demonstrates the highest and most reliable testing accuracy across all stations, making it the preferred choice for ClimateWins' operational needs. Scenarios 1 and 2 are included to show the effect of lower complexity on predictive performance.

WHY SCENARIO 3 WAS SELECTED



Scenario 3 captures complex relationships in the weather data without overfitting to historical patterns. This ensures ClimateWins can rely on its predictions for operational decisions across diverse climates. The consistent performance across stations demonstrates its suitability as the recommended model.

- High testing accuracy across all stations.
- Minimal gap between training and testing performance.
- Reduces risk of overfitting while maintaining predictive strength.

CONCLUSIONS & RECCOMENDATIONS

ANN Scenario 3 provides the most robust predictions for pleasant days, balancing accuracy and generalization. To further enhance operational effectiveness, we recommend expanding data coverage, improving historical data quality, refining models with hybrid and feature-enhanced approaches, and updating models as new observations become available.

- ANN Scenario 3 recommended for operational prediction
- Expand data coverage: more stations & regions
- Improve data quality: address historical errors & standardize measurements
- Refine models: hybrid approaches, additional climate features
- Continuously update models with new data

Q&A

THANK YOU!

Any questions regarding models, results, or recommendations is welcome.
This slide closes the presentation while providing an opportunity for discussion and clarification.

CONTACTS

jessigatta91@icloud.com

+1 (757)352-0640