# Calculating Fraud Risk in Credit Card Data

Rhys Carter Metis, Spring 2021

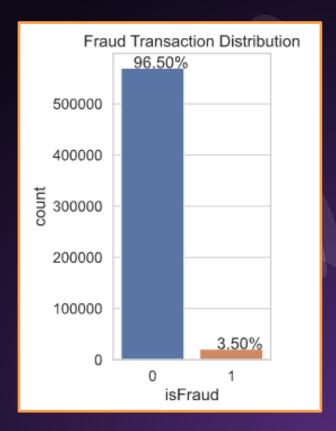
#### **Contents**

- 1. Project Background
- 2. Approach
- 3. Modeling Deep-Dive
- 4. Outcomes & Next Steps

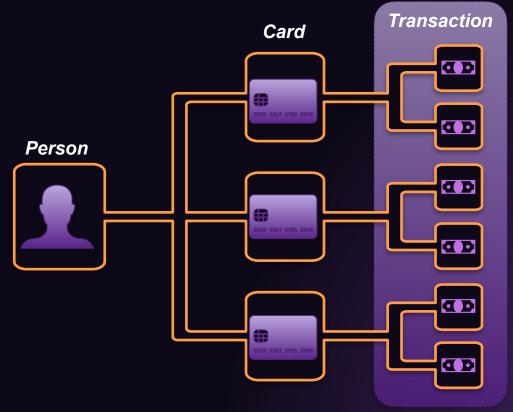


#### Fraud Detection & Classification

- Kaggle: <u>Predict Fraud vs.</u>
   Non-Fraud Transactions
  - E.g. Card owner not present
  - Sponsors: IEEE Computational
     Intelligence Society & Vesta Corporation
- Imbalanced Dataset
  - ~ 600k Transactions, 400+ Attributes
  - Mix of 'Identity' & 'Transaction' Data
  - Masked Personal Info

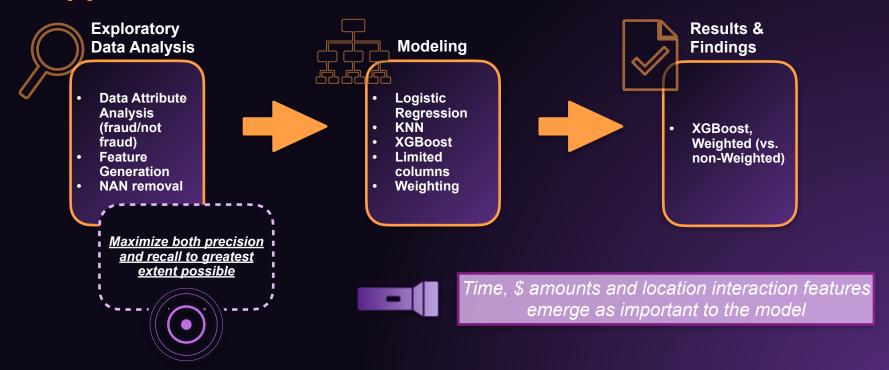


# Scope



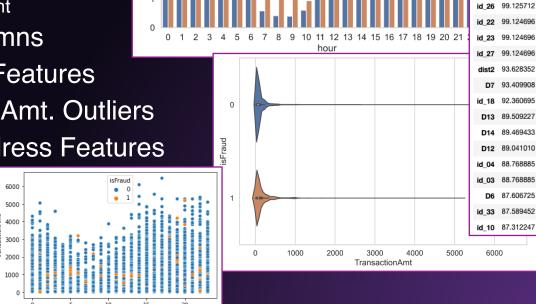
Initial analysis focused on the transaction level, with future analysis moving into grouping by card and person

#### . Approach



# **Data Deep-Dive**

- **Interpret Masked Info** 
  - e.g. 'card6' meaning card type, 'addr1' meaning zip or equivalent
- Trim Down Null Columns
- **Encode Categorical Features**
- Remove Transaction Amt. Outliers
- Add New Time & Address Features



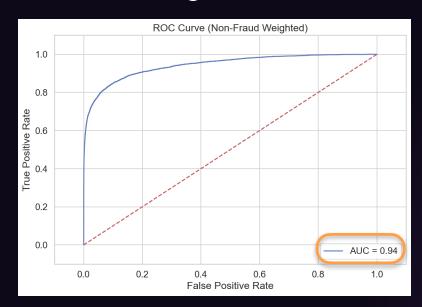
isFraud

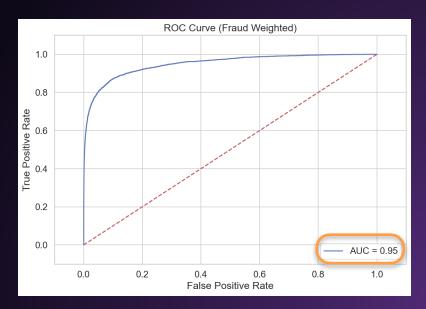
id 24 99.196157

id 21 99.126390

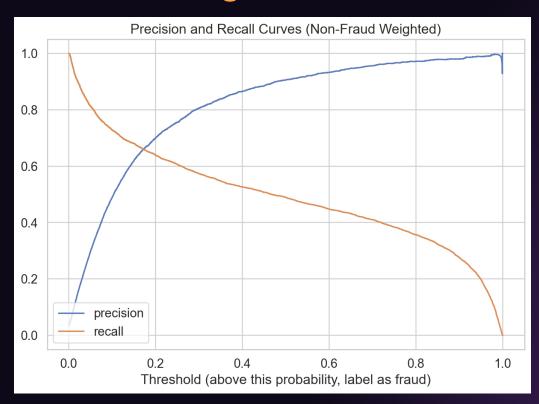
# . Analysis

- Larger model with ~200 features
- W/weighted fraud calculations, some AUC+, but minimal



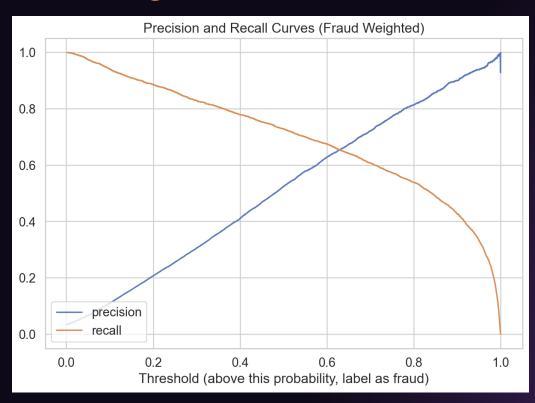


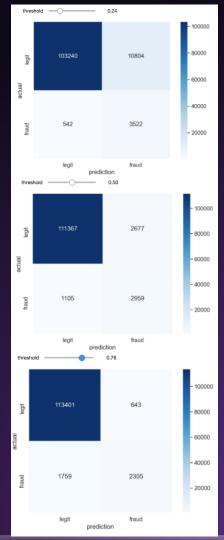
# **Non-Fraud Weighted**





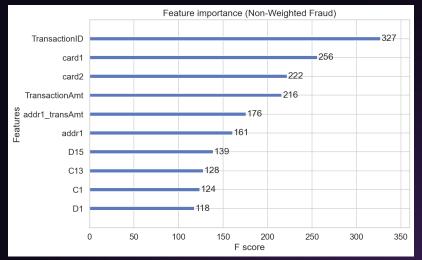
# **Fraud Weighted**

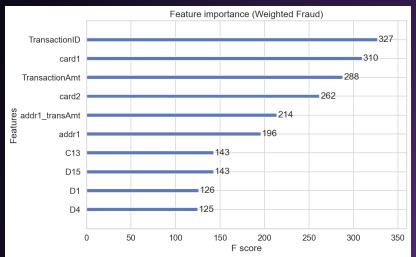




## **Feature Importance**

- C#: Counts (e.g. shared activity)
- Addr#: Location of the purchaser
- D#: Time Related
- V#: Vesta-designed

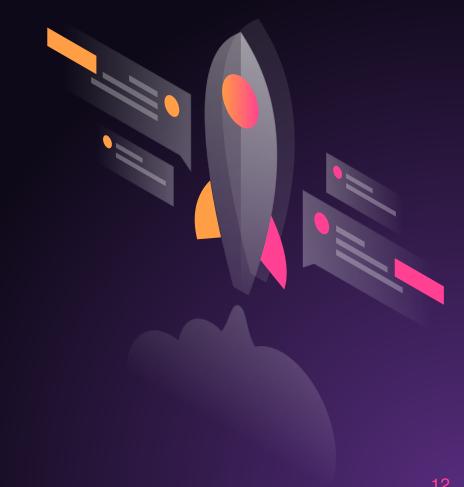




## **Key Takeaways & Next Steps**

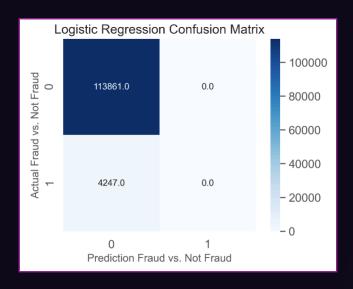
- Move forward w/weighted XGBoost Model to balance misses and customer impact
- Continue reviewing features for additional interactions
   (i.e. moving into information on the cardholder)
- Identify more duplicative features to further simplify
   (e.g. potentially a number of the created features from Vesta)

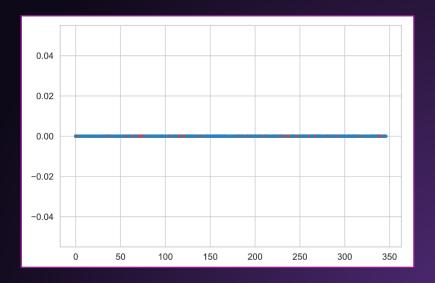
# - Backup



# **Logistic Regression**

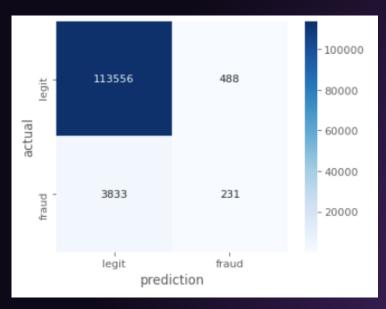
Poor predictor, based on limited (~20 columns) dataset





## K Nearest Neighbor (KNN)

 Improved, but still large False Negative and False Positive Rates



# **Feature Importance (Gain)**

