



Predicting Loans with Machine Learning and Streamlit

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THE PROBLEM

Industry Overview



Most of the loan application process is laborious. **The outcome is a simple 'Yes' or 'No' without further explanation.**



Rejection is tough – don't let it make your business tougher. **There is communication gap to be bridged.**

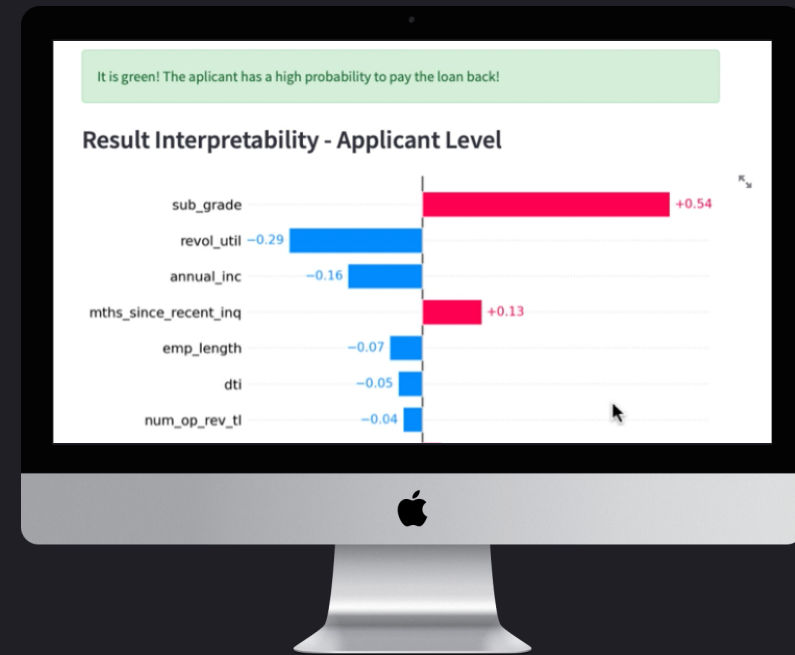
SOLUTION

Unlocking the Insights of Machine Learning

Despite its powerful capabilities, machine learning's charm was often hidden beneath technical jargon and the mystery of its "black box" operations.

The web application created with Streamlit used visual exploration to demonstrate the power of machine learning, showcasing the dynamic input feature and its **SHAP value** that drove the decision.

This improved the application's transparency and helped to close the communication gap.



What are SHAP Values?

- ☆ Calculation that represents the relative influence of each input features within the algorithm.
- ☆ It can be thought of as the 'weighting' that each feature had upon the final result of creditworthiness that the model predicted.

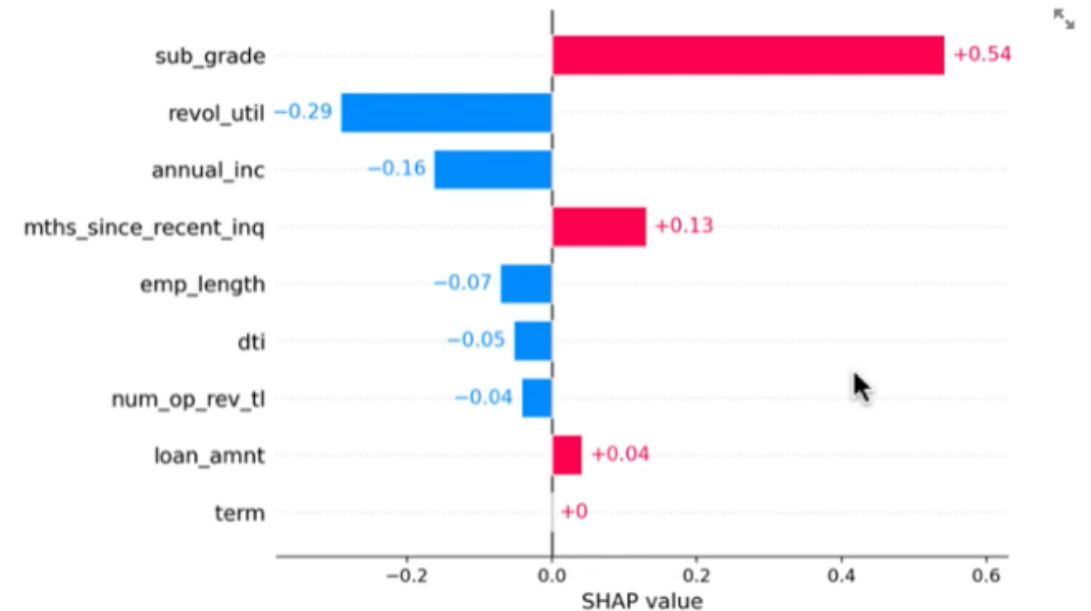
To predict default/ failure to pay back status, you need to follow the steps below:

1. Enter/choose the parameters that best describe your applicant on the left side bar;
2. Press the "Predict" button and wait for the result.

Below you could find prediction result:

It is green! The aplicant has a high probability to pay the loan back!

Result Interpretability - Applicant Level



Model Interpretability - Overall

Why Should I Care About SHAP Values?

Unveiling the Creditworthiness Prediction:



SHAP values provide an **intuitive** way to understand the impact of individual features on a model's predictions



SHAP values can be used to identify important features and **detect potential bias** in a model



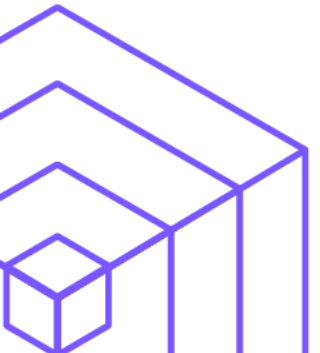
SHAP values can be used to improve model performance by **identifying redundant or irrelevant features**

Discover How Your Financial Profile Affects Your Risk with SHAP Values

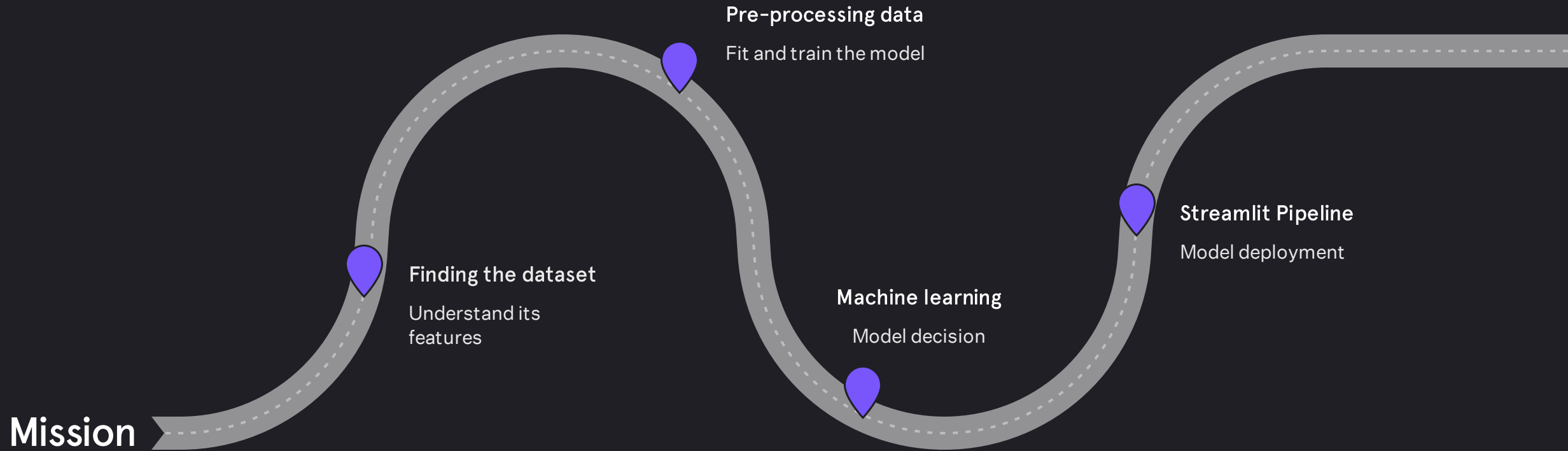


MISSION

Helping
customer to learn
from their data



How did we get here?





“Teaching
machine
to think”

Lucas - machine learning specialist



Lending Club dataset is used for model training

Available from Kaggle

Total observations

2.26m

Original features

150

Annual income:

65k

Loan amount

\$13k

Avg interest rate

13%

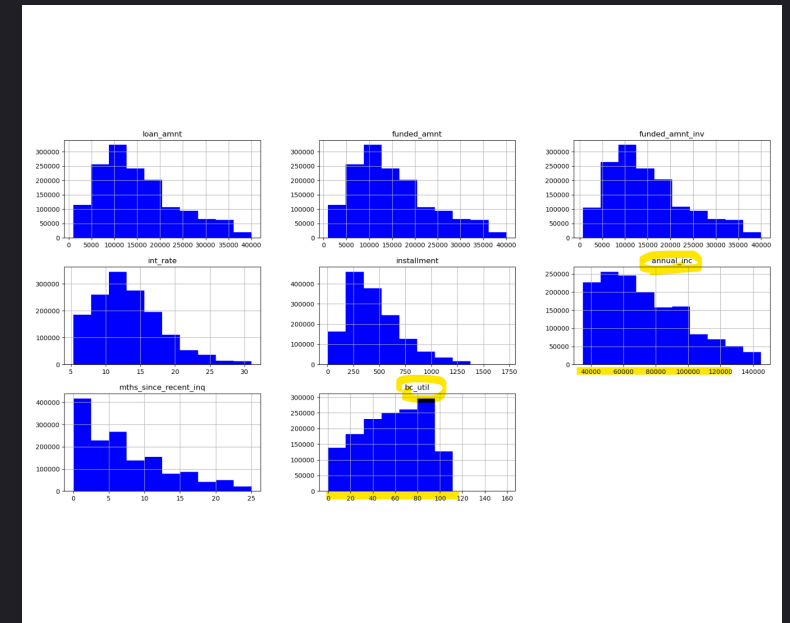
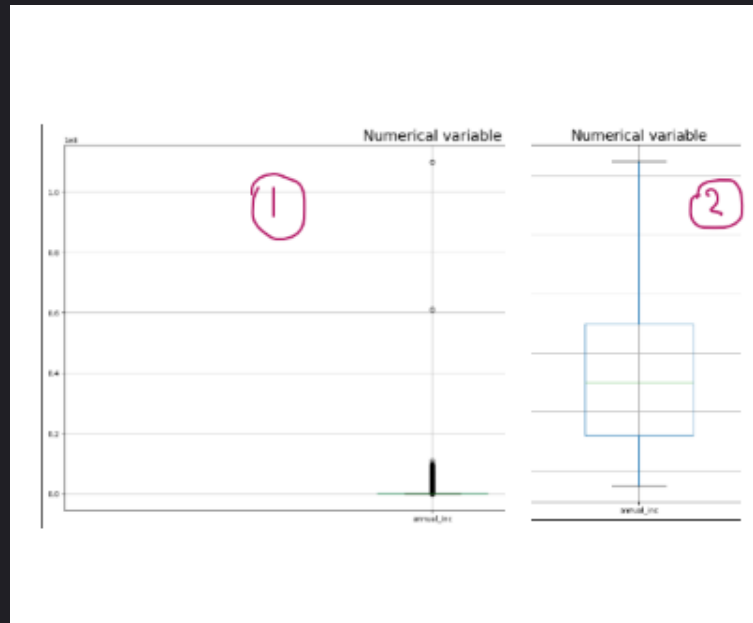
Selected features (aligned with pre-trained model)

17

Challenges

Pre-processing data

Dealing with outliers



Outlier

can significantly distort the feature distribution and ML algorithms such as: Linear Regression, Logistic Regression, Support Vector Machine

Remove outlier

```
# low_q = df.quantile(0.08)
# high_q = df.quantile(0.92)
# new_df = (df < q_hi) & (df > q_low)]
```

Distribution after dropping outliers

If you have a really good sense of what range the data should fall in, like people's ages, you can safely drop values that are outside of that range.

```
[24]: # Create new labels for ordinal data
ordinal_transformation = {'term': {'36 months': 1.0, '60 months': 2.0},
                           'grade': {"A": 1.0, "B": 2.0, "C": 3.0, "D": 4.0, "E": 5.0, "F": 6.0, "G": 7.0},
                           'sub_grade': {"A1": 1.0, "A2": 2.0, "A3": 3.0, "B1": 4.0, "B2": 5.0, "B3": 6.0, "C1": 7.0, "C2": 8.0, "C3": 9.0, "D1": 10.0, "D2": 11.0, "D3": 12.0, "E1": 13.0, "E2": 14.0, "E3": 15.0, "F1": 16.0, "F2": 17.0, "F3": 18.0, "G1": 19.0, "G2": 20.0, "G3": 21.0},
                           'emp_length': {"< 1 year": 0.0, '1 year': 1.0, '2 years': 2.0, '3 years': 3.0, '4 years': 4.0, '5 years': 5.0, '6 years': 6.0, '7 years': 7.0, '8 years': 8.0, '9 years': 9.0, '10+ years': 10.0}}

# Replace data
loans_df = loans_df.replace(ordinal_transformation)

# Preview data
loans_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1485538 entries, 0 to 2260698
Data columns (total 17 columns):
#   Column              Non-Null Count  Dtype
---  -
0   loan_amnt            1485538 non-null  float64
1   funded_amnt          1485538 non-null  float64
2   funded_amnt_inv      1485538 non-null  float64
3   term                 1485538 non-null  float64
4   int_rate             1485538 non-null  float64
5   installment          1485538 non-null  float64
6   grade                1485538 non-null  float64
7   sub_grade            1485538 non-null  float64
8   emp_title            1485538 non-null  object
9   emp_length           1485538 non-null  float64
10  home_ownership        1485538 non-null  object
11  annual_inc            1485538 non-null  float64
12  verification_status   1485538 non-null  object
13  loan_status           1485538 non-null  object
14  pymnt_plan            1485538 non-null  object
15  mths_since_recent_inq 1485538 non-null  float64
16  bc_util               1485538 non-null  float64
dtypes: float64(12), object(5)
memory usage: 204.0+ MB
```

'EMP_LENGTH: 2YR'

FEATURES

CATEGORICAL

'SUB_GRADE: A1'

'TERM: 6MOS'

'GRADE: A'

ORDINAL_ENCODING

Build and Train Machine Learning Models

Establish logistic regression model as baseline

```
# Set X and y variables for machine learning model
loans_df.drop('loan_status', axis=1)
loans_df['loan_status']

# Split data into test and training sets
train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=42, stratify=y)

# Import standard scaler
from sklearn.preprocessing import StandardScaler

# Create a scaler object
scaler = StandardScaler()

# Fit and transform the data
X_train_scaled = scaler.fit_transform(X_train)

# Use the scaled data for modeling
from sklearn.linear_model import LogisticRegression

model_scaled = LogisticRegression()
model_scaled.fit(X_train_scaled, y_train)

# Transform the test data using the same scaler
X_test_scaled = scaler.transform(X_test)

# Make predictions on the scaled test data
y_pred = model_scaled.predict(X_test_scaled)

# Print accuracy report
print('Accuracy of logistic regression classifier on test set: {:.2f}'.format(model_scaled.score(X_test_scaled, y_test)))
Accuracy of logistic regression classifier on test set: 0.80
```

Establish a random forest machine model

```
# Import random forest classifier
from sklearn.ensemble import RandomForestClassifier

# Import performance metrics
from sklearn.metrics import accuracy_score, classification_report

# Instantiate random forest classifier model instance
model_rf = RandomForestClassifier(random_state=1)

# Fit the model to the data using the training data
model_rf.fit(X_train_scaled, y_train)

# Use the testing data to make the model predictions
y_pred_rf = model_rf.predict(X_test_scaled)

# Review the model's predicted values
print(y_pred_rf[:10])
[1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]

# Print accuracy report
print('Accuracy of random forest model on test set: {:.2f}'.format(model_rf.score(X_test_scaled, y_test)))
Accuracy of random forest model on test set: 0.79
```

Model decision

Accuracy score

80%

Logistic Regression

79%

Random Forest

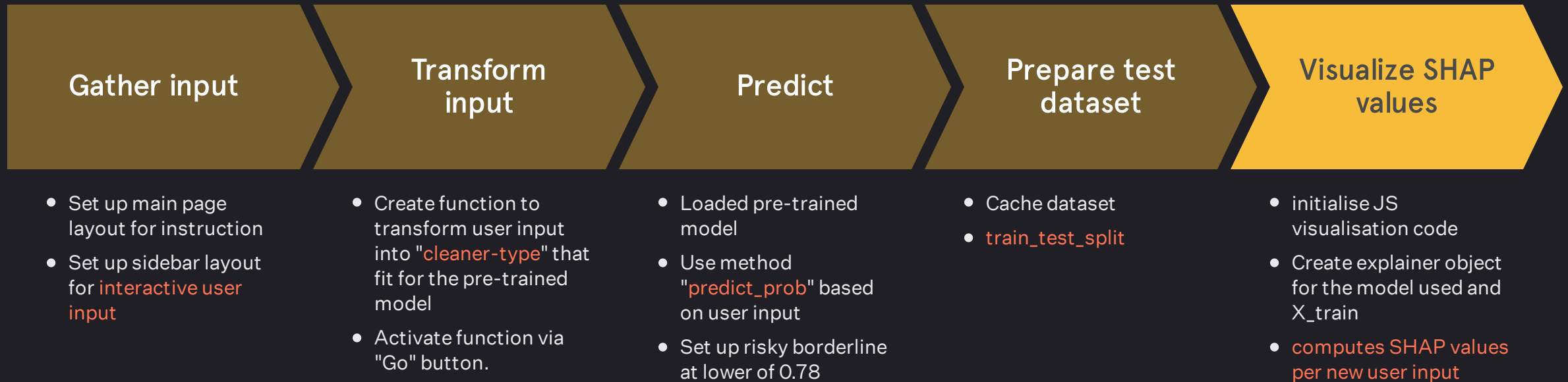


“A great user experience starts with great front-end code”

Nat - front end engineer

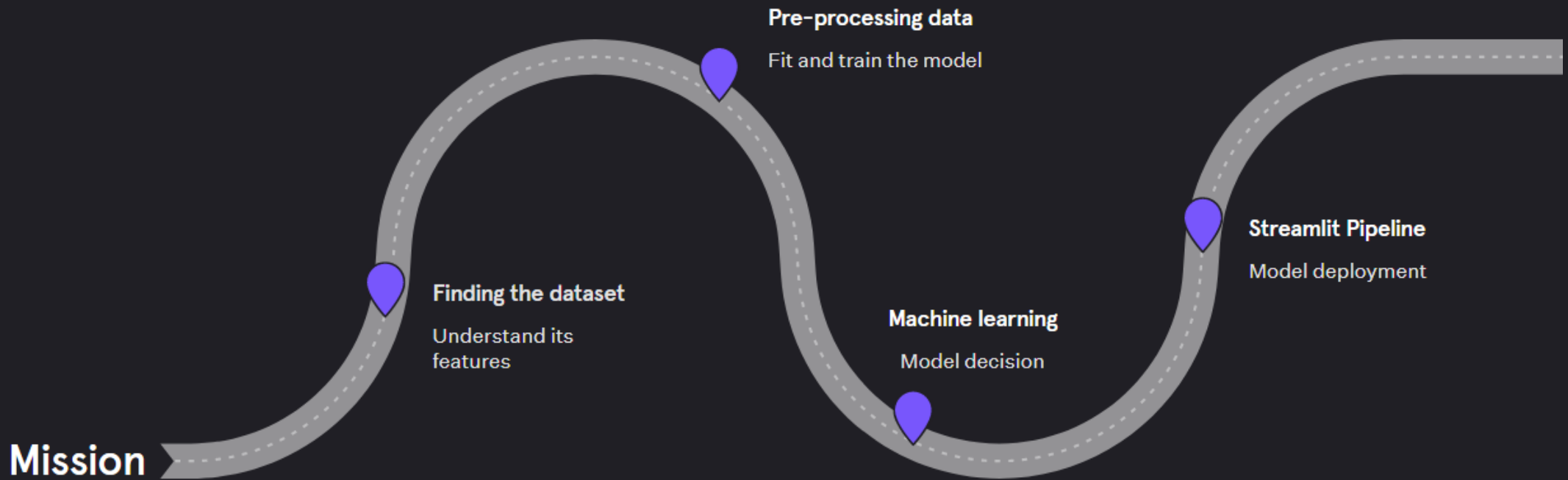
 Streamlit

Streamlit Pipeline



Demos





Summary & Upgrade potential



Feature engineering



Hyperparameter tuning