ML-Gold-Prospecting-Amador

August 19, 2025

0.0.1 Load and Subset the MRDS Dataset

Load the USGS MRDS dataset and filter records to include only sites in Amador County, California. This provides a focused dataset for analysis. Datasets can be downloaded from here: https://mrdata.usgs.gov/mrds/ Code can be found here: https://github.com/smorganstern/Quest-for-Golden-Treasures/releases

[1]:
```python
import pandas as pd
# Load MRDS dataset
df = pd.read_csv("mrds.csv", low_memory=False)
print('Total Rows in MRDS Dataset = ', df.shape[0])
# Filter for Amador County in California
df_amador = df[
    (df['state'] == 'California') &
    (df['county'].str.contains('Amador', case=False, na=False))
].copy()
```

```
Total Rows in MRDS Dataset =  304632
```

0.0.2 Define Binary Target `has_gold`

Creates a boolean label where `True` indicates the site contains gold, based on any mention of 'gold' in `commod1`, `commod2`, or `commod3`.

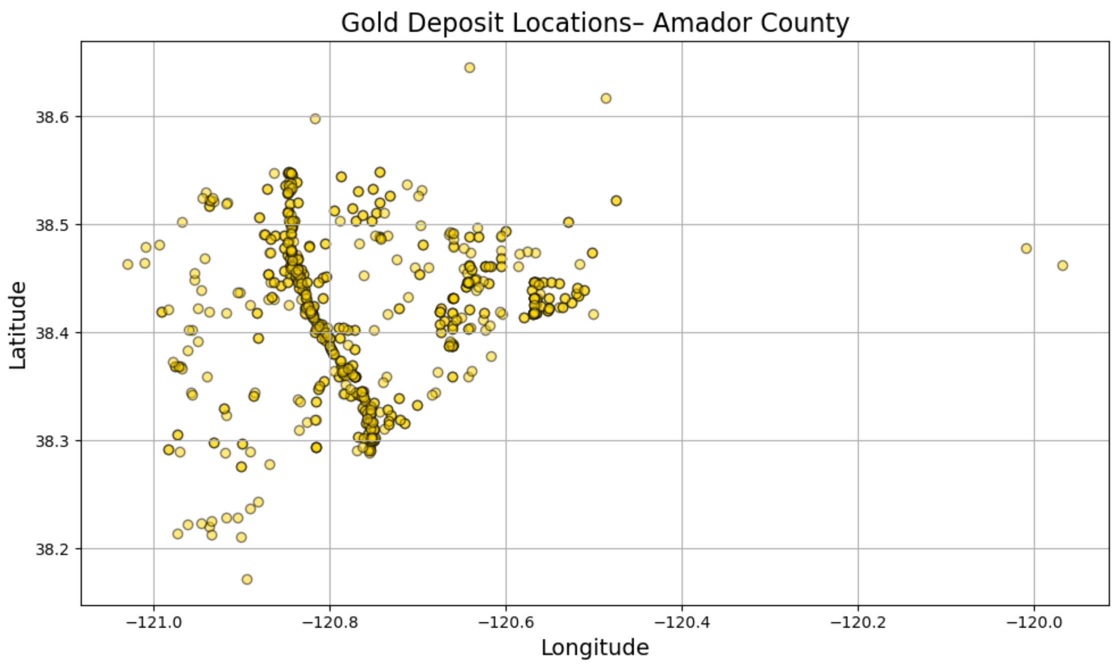
[2]:
```python
# Create binary target based on gold mentions
df_amador['has_gold'] = df_amador[['commod1', 'commod2', 'commod3']].apply(
    lambda row: any('gold' in str(x).lower() for x in row), axis=1
)
df_amador_gold = df_amador[df_amador['has_gold']].copy()
```

0.0.3 Gold Deposit Map – Amador County

Plots all gold-bearing sites in Amador County, providing a spatial view of known deposits.

[3]:
```python
import matplotlib.pyplot as plt
plt.figure(figsize=(10, 6))
plt.scatter(
    df_amador_gold['longitude'],
    df_amador_gold['latitude'],
    alpha=0.5,
```

```
    color='gold',
    edgecolors='black'
)
plt.title("Gold Deposit Locations- Amador County", fontsize=16)
plt.xlabel("Longitude", fontsize=14)
plt.ylabel("Latitude", fontsize=14)
plt.grid(True)
plt.tight_layout()
plt.show()
```



0.1 Engineer Quartz Proximity Feature

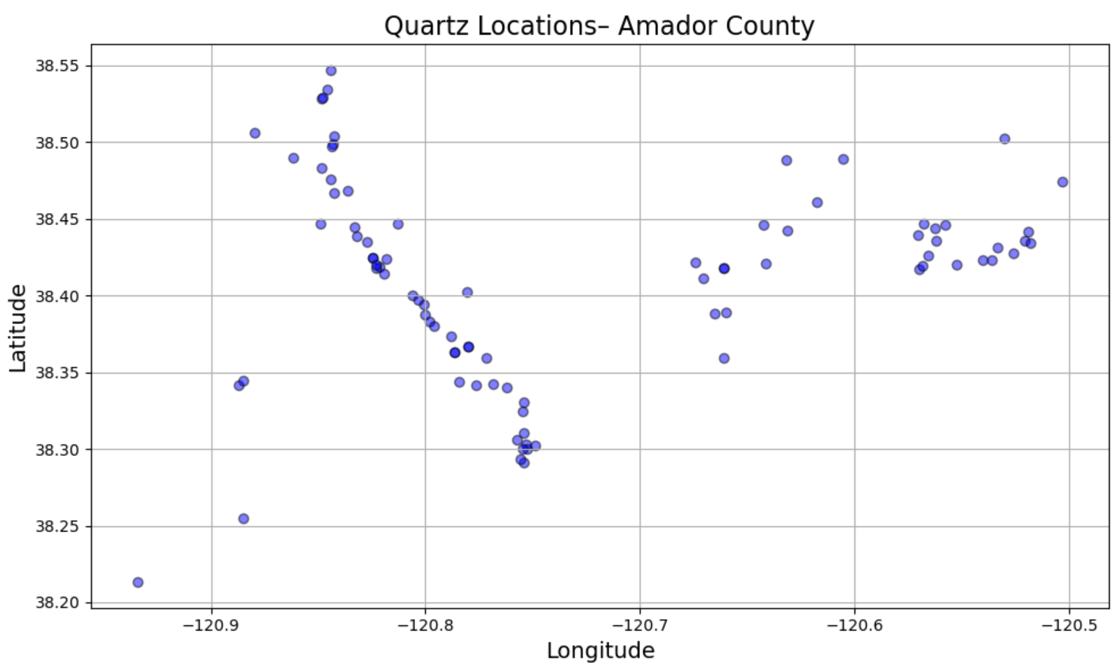
Create Quartz Indicator Adds a binary feature `has_quartz` if quartz is present in the `ore` or `gangue` fields, based on the geological association between quartz veins and gold deposits.

[4]:
```
# Flag quartz presence in ore or gangue
df_amador['has_quartz'] = df_amador[['ore', 'gangue']].apply(
    lambda row: any('quartz' in str(x).lower() for x in row), axis=1
)
df_amador_quartz = df_amador[df_amador['has_quartz']].copy()
```

Map Quartz Locations ### Quartz Deposit Map – Amador County Shows the spatial distribution of quartz occurrences to explore potential geological correlations.

[5]:
```
plt.figure(figsize=(10, 6))
plt.scatter(
```

```
    df_amador_quartz['longitude'],
    df_amador_quartz['latitude'],
    alpha=0.5,
    color='blue',
    edgecolors='black'
)
plt.title("Quartz Locations- Amador County", fontsize=16)
plt.xlabel("Longitude", fontsize=14)
plt.ylabel("Latitude", fontsize=14)
plt.grid(True)
plt.tight_layout()
plt.show()
```

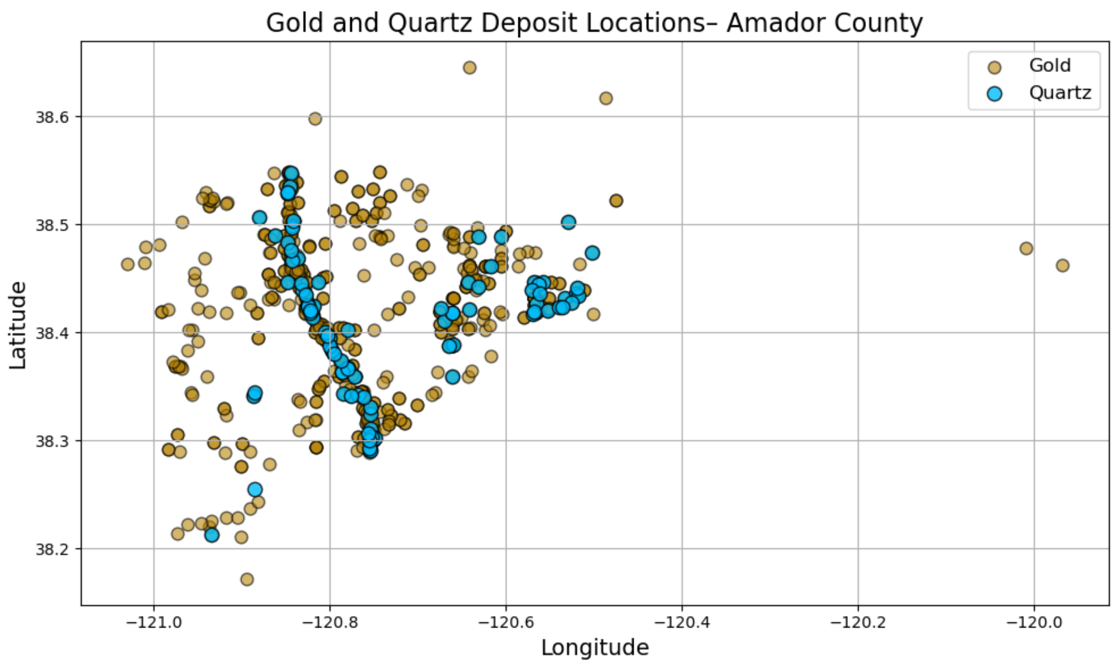


0.1.1 Combined Gold and Quartz Map

Overlays gold and quartz locations to illustrate spatial proximity and potential exploration targets.

[6]:
```
plt.figure(figsize=(10, 6))
# Gold deposits
plt.scatter(
    df_amador_gold['longitude'],
    df_amador_gold['latitude'],
    alpha=0.6,
    color='darkgoldenrod',
    edgecolors='black',
```

```
    s=60,
    label='Gold'
)
# Quartz deposits
plt.scatter(
    df_amador_quartz['longitude'],
    df_amador_quartz['latitude'],
    alpha=0.8,
    color='deepskyblue',
    edgecolors='black',
    s=80,
    label='Quartz'
)
plt.title("Gold and Quartz Deposit Locations- Amador County", fontsize=16)
plt.xlabel("Longitude", fontsize=14)
plt.ylabel("Latitude", fontsize=14)
plt.grid(True)
plt.legend(loc='upper right', fontsize=12)
plt.tight_layout()
plt.show()
```



0.1.2 Select Relevant Modeling Columns

Retains location, geological, and engineered features, along with the target variable `has_gold`. Commodity columns are excluded to avoid target leakage.

[7]:
```
import numpy as np
cols_to_keep = [
    'latitude', 'longitude', 'state', 'county',
    'ore', 'gangue', 'other_matl',
    'has_quartz', 'has_gold'
]
df_model = df_amador[cols_to_keep].copy()
```

0.1.3 Mask 'Gold' in Ore Column

Replaces exact matches of 'gold' in the `ore` column with NaN to prevent direct target leakage. This is because all the rows that contain Gold as the ore column also contain Gold in the commod(1-3).

[8]:
```
df_model['ore'] = df_model['ore'].str.strip().str.lower()
df_model.loc[df_model['ore'] == 'gold', 'ore'] = np.nan
```

0.1.4 Preprocessing – SimpleImputer Setup

Imports the imputer to handle missing categorical and numeric values.

[9]:
```
from sklearn.impute import SimpleImputer
SimpleImputer(fill_value='missing', strategy='constant')
```

[9]:
```
SimpleImputer(fill_value='missing', strategy='constant')
```

0.1.5 Preprocessing – OneHotEncoder Setup

Imports the encoder for categorical variables to prepare for model training.

[10]:
```
from sklearn.preprocessing import OneHotEncoder

OneHotEncoder(handle_unknown='ignore')
```

[10]:
```
OneHotEncoder(handle_unknown='ignore')
```

0.1.6 Preprocessing Configuration

Sets up transformers for numeric, categorical, and binary features in preparation for modeling.

[11]:
```
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split

X = df_model.drop(columns='has_gold')
y = df_model['has_gold']
```

```
numeric_features = ['latitude', 'longitude']
categorical_features = ['state', 'county', 'ore', 'gangue', 'other_matl']
binary_features = ['has_quartz']

preprocessor = ColumnTransformer(transformers=[
    ('num', Pipeline([
        ('imputer', SimpleImputer(strategy='mean')),
        ('scaler', StandardScaler())
    ]), numeric_features),
    ('cat', Pipeline([
        ('imputer', SimpleImputer(strategy='constant', fill_value='missing')),
        ('encoder', OneHotEncoder(handle_unknown='ignore'))
    ]), categorical_features),
    ('bin', 'passthrough', binary_features)
])
```

Model Training Combines preprocessing steps with a Random Forest classifier, then fits the model on the training data.

[12]:
```
clf = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', RandomForestClassifier(random_state=42))
])

X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y,
 ↪random_state=42)
clf.fit(X_train, y_train)
```

[12]:
```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('num',
                                                  Pipeline(steps=[('imputer',
SimpleImputer()),
                                                                  ('scaler',
StandardScaler())]),
                                                  ['latitude', 'longitude']),
                                                 ('cat',
                                                  Pipeline(steps=[('imputer',
SimpleImputer(fill_value='missing',
 strategy='constant')),
                                                                  ('encoder',
OneHotEncoder(handle_unknown='ignore'))]),
                                                  ['state', 'county', 'ore',
                                                   'gangue', 'other_matl']),
                                                 ('bin', 'passthrough',
                                                  ['has_quartz'])])),
                ('classifier', RandomForestClassifier(random_state=42))])
```

0.1.7 Feature Importance Extraction

Retrieves feature names from all preprocessing branches, aligns them with importance scores, and removes dummy _missing categories.

[13]:
```
cat_encoder = clf.named_steps['preprocessor'].named_transformers_['cat'].
  ↪named_steps['encoder']
num_features = clf.named_steps['preprocessor'].named_transformers_['num'].
  ↪named_steps['scaler'].get_feature_names_out()
cat_features = cat_encoder.get_feature_names_out()
bin_features = ['has_quartz']

all_features = np.concatenate([num_features, cat_features, bin_features])

important_features = pd.Series(clf.named_steps['classifier'].
  ↪feature_importances_, index=all_features)
important_features = important_features[~important_features.index.str.
  ↪contains('_missing')]
important_features.sort_values(ascending=False).head(15)
```

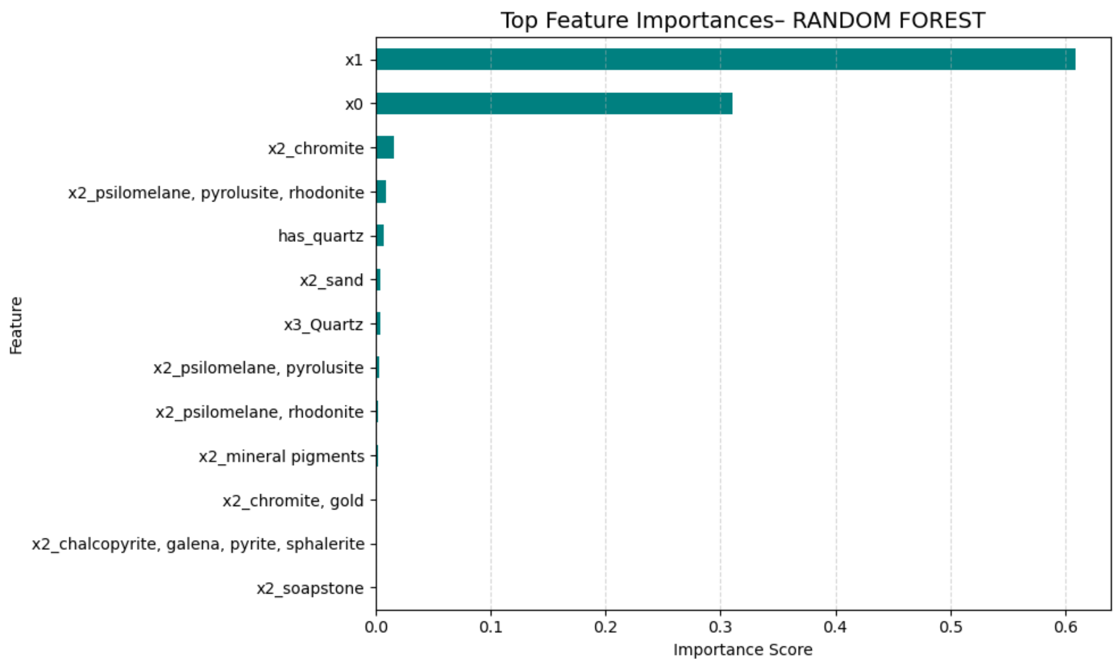
[13]:
```
x1                                              0.609180
x0                                              0.310060
x2_chromite                                     0.016520
x2_psilomelane, pyrolusite, rhodonite           0.009203
has_quartz                                      0.007199
x2_sand                                         0.004485
x3_Quartz                                       0.003718
x2_psilomelane, pyrolusite                      0.002946
x2_psilomelane, rhodonite                       0.002531
x2_mineral pigments                             0.002117
x2_chromite, gold                               0.001693
x2_chalcopyrite, galena, pyrite, sphalerite     0.001659
x2_soapstone                                    0.001622
x1_Amador                                       0.001583
x4_Chromite, Serpentine                         0.001151
dtype: float64
```

0.1.8 Top Feature Importances – Random Forest

Displays the top predictors as a horizontal bar chart for interpretability.

[14]:
```
top_n = 13
top_features = important_features.sort_values(ascending=True).tail(top_n)

plt.figure(figsize=(10, 6))
top_features.plot(kind='barh', color='teal')
plt.title('Top Feature Importances- RANDOM FOREST', fontsize=14)
plt.xlabel('Importance Score')
```

```
plt.ylabel('Feature')
plt.tight_layout()
plt.grid(axis='x', linestyle='--', alpha=0.5)
plt.show()
```



0.1.9 Model Evaluation

Generates a confusion matrix, classification report, and ROC–AUC score on the test set to assess predictive performance.

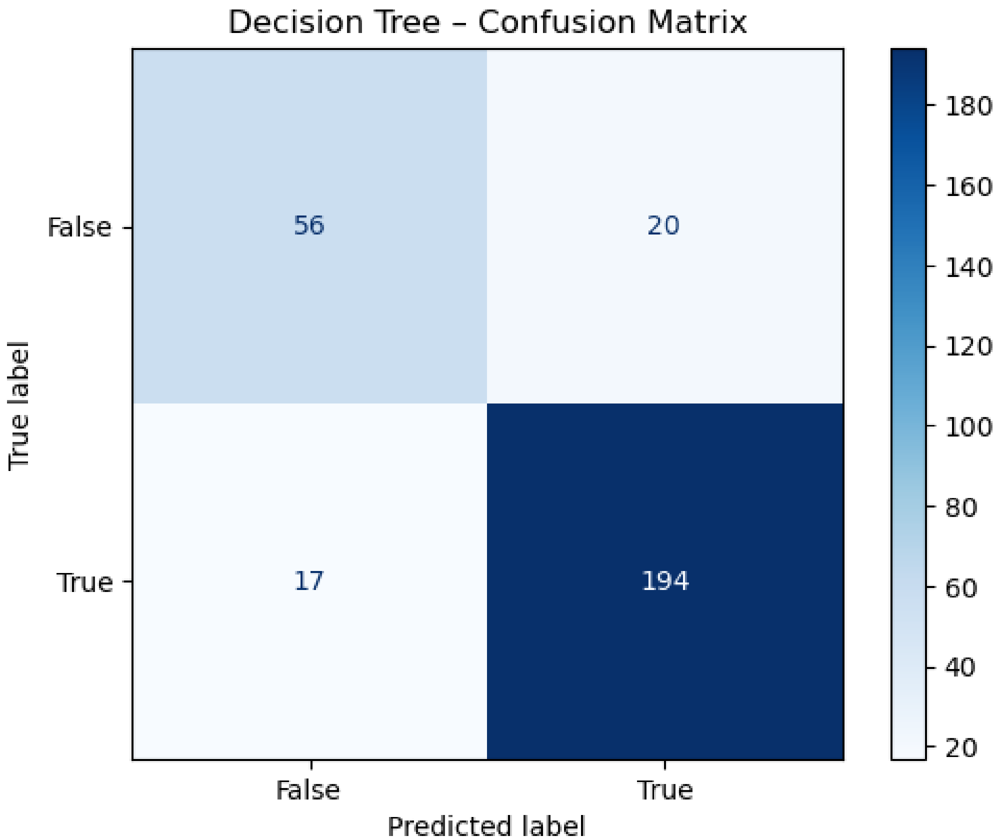
0.2 Decision Tree

I apply a **Decision Tree Classifier** using the Gini impurity criterion to split nodes.
This model is simple, interpretable, and can reveal the structure of decision boundaries in the dataset.
I evaluate its performance with precision, recall, F1-score, and ROC–AUC, and then plot a confusion matrix to examine class-level predictions.

[15]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, roc_auc_score, confusion_matrix, ConfusionMatrixDisplay

dt_pipe = Pipeline([
    ('preprocessor', preprocessor),                # use your existing ColumnTransformer
    ('classifier', DecisionTreeClassifier(random_state=42))
```

```
])

dt_pipe.fit(X_train, y_train)
y_pred_dt = dt_pipe.predict(X_test)
y_proba_dt = dt_pipe.predict_proba(X_test)[:, 1]

print("Decision Tree Results:")
print(classification_report(y_test, y_pred_dt))
print("ROC-AUC:", roc_auc_score(y_test, y_proba_dt))

cm_dt = confusion_matrix(y_test, y_pred_dt)
ConfusionMatrixDisplay(confusion_matrix=cm_dt, display_labels=dt_pipe.
 ↪named_steps['classifier'].classes_)\
    .plot(cmap='Blues', values_format='d')
plt.title("Decision Tree - Confusion Matrix")
plt.show()
```

```
Decision Tree Results:
              precision    recall  f1-score   support

       False       0.77      0.74      0.75        76
        True       0.91      0.92      0.91       211

    accuracy                           0.87       287
   macro avg       0.84      0.83      0.83       287
weighted avg       0.87      0.87      0.87       287

ROC-AUC: 0.8341855824395112
```

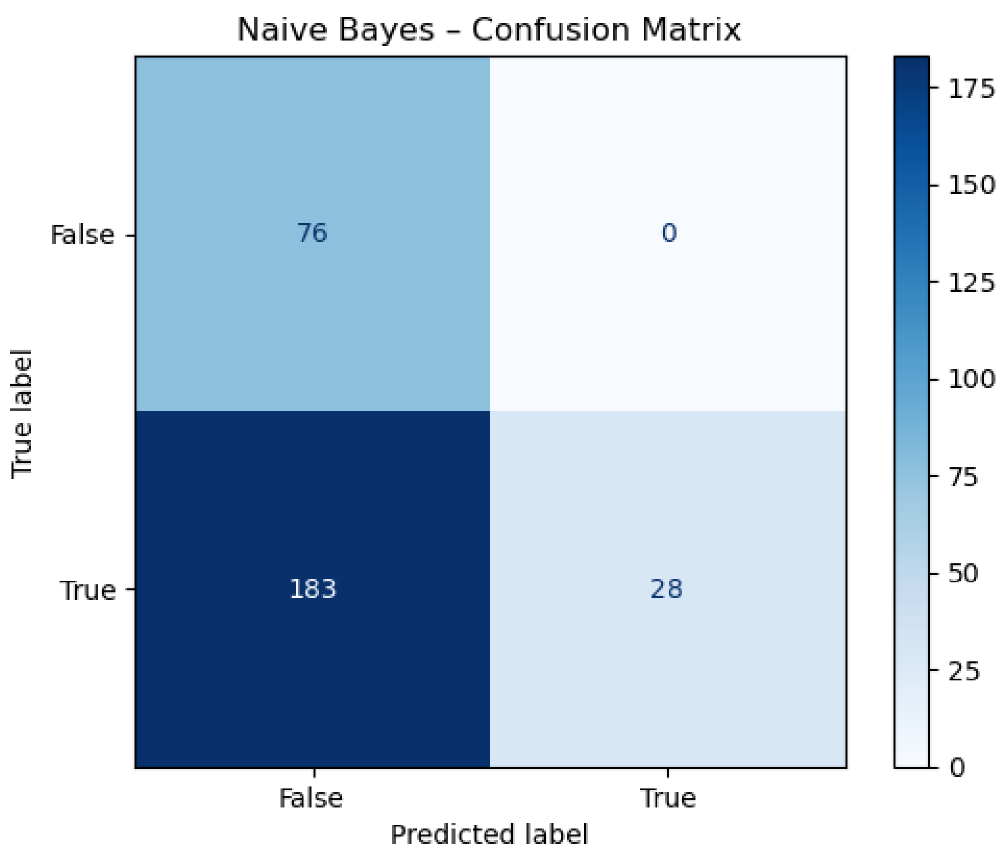


0.2.1 Naïve Bayes with densifier

[16]:
```
from sklearn.naive_bayes import GaussianNB
from sklearn.preprocessing import FunctionTransformer

nb_pipe = Pipeline([
    ('preprocessor', preprocessor),
    ('to_dense', FunctionTransformer(lambda X: X.toarray(),
 ↪accept_sparse=True)),
    ('classifier', GaussianNB())
])

nb_pipe.fit(X_train, y_train)
y_pred_nb = nb_pipe.predict(X_test)
y_proba_nb = nb_pipe.predict_proba(X_test)[:, 1]

print("Naive Bayes Results:")
print(classification_report(y_test, y_pred_nb))
print("ROC-AUC:", roc_auc_score(y_test, y_proba_nb))
```

```python
cm_nb = confusion_matrix(y_test, y_pred_nb)
ConfusionMatrixDisplay(confusion_matrix=cm_nb, display_labels=nb_pipe.
 ↪named_steps['classifier'].classes_)\
    .plot(cmap='Blues', values_format='d')
plt.title("Naive Bayes - Confusion Matrix")
plt.show()
```

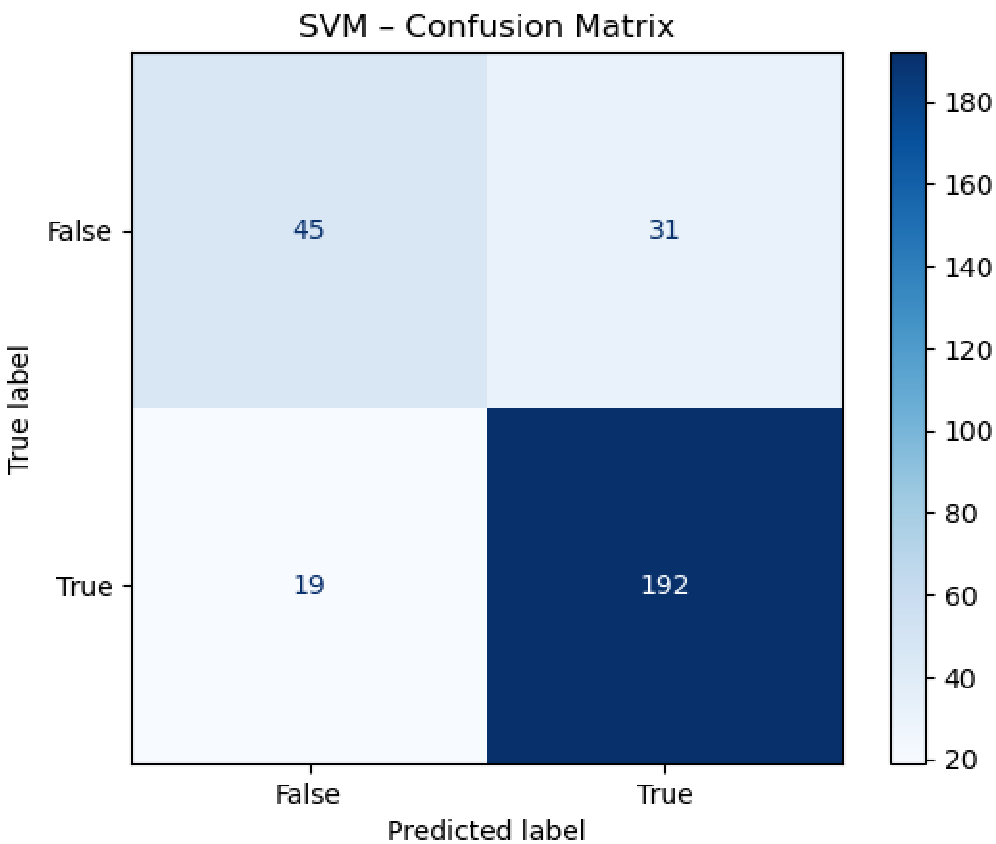
```
Naive Bayes Results:
              precision    recall  f1-score   support

       False       0.29      1.00      0.45        76
        True       1.00      0.13      0.23       211

    accuracy                           0.36       287
   macro avg       0.65      0.57      0.34       287
weighted avg       0.81      0.36      0.29       287

ROC-AUC: 0.7608194063357445
```



0.2.2 SVC with densifier

[17]:
```
from sklearn.svm import SVC

svm_pipe = Pipeline([
    ('preprocessor', preprocessor),
    ('to_dense', FunctionTransformer(lambda X: X.toarray(),␣
 ↪accept_sparse=True)),
    ('classifier', SVC(kernel='linear', probability=True, random_state=42))
])

svm_pipe.fit(X_train, y_train)
y_pred_svm = svm_pipe.predict(X_test)
y_proba_svm = svm_pipe.predict_proba(X_test)[:, 1]

print("SVM Results:")
print(classification_report(y_test, y_pred_svm))
print("ROC-AUC:", roc_auc_score(y_test, y_proba_svm))

cm_svm = confusion_matrix(y_test, y_pred_svm)
ConfusionMatrixDisplay(confusion_matrix=cm_svm, display_labels=svm_pipe.
 ↪named_steps['classifier'].classes_)\
    .plot(cmap='Blues', values_format='d')
plt.title("SVM - Confusion Matrix")
plt.show()
```

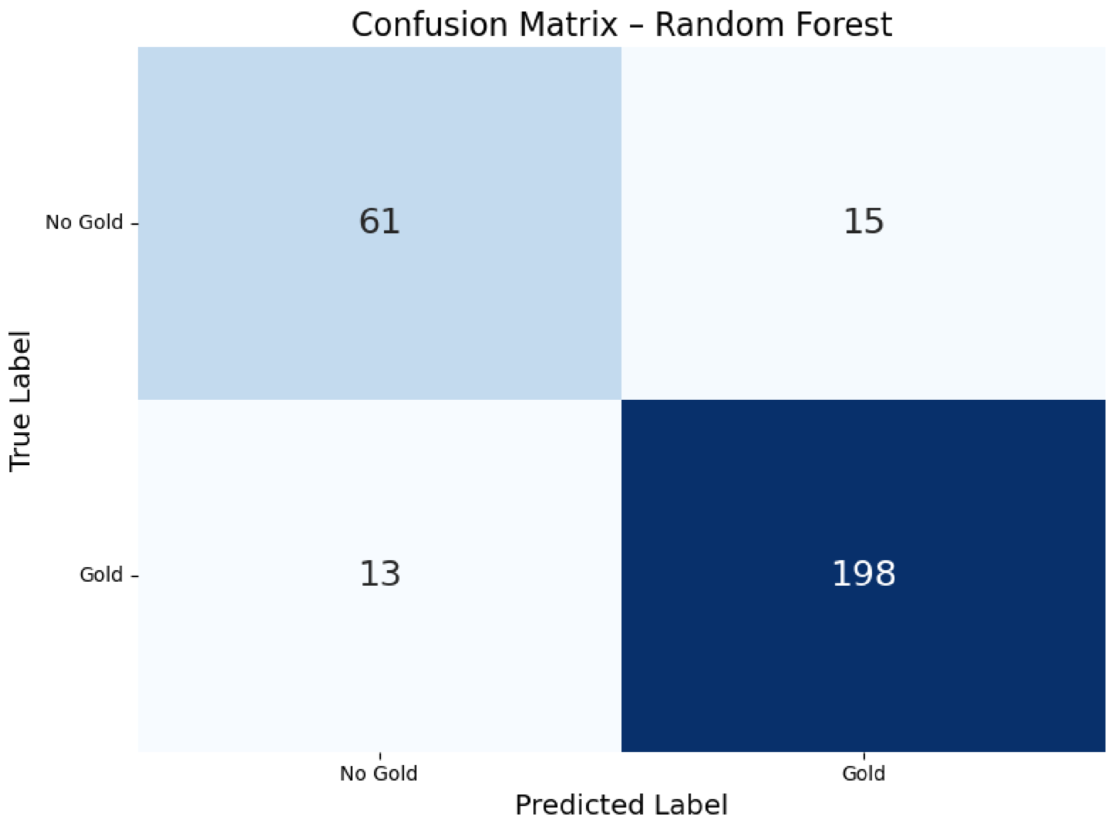
```
SVM Results:
              precision    recall  f1-score   support

       False       0.70      0.59      0.64        76
        True       0.86      0.91      0.88       211

    accuracy                           0.83       287
   macro avg       0.78      0.75      0.76       287
weighted avg       0.82      0.83      0.82       287

ROC-AUC: 0.7234035919181842
```



0.2.3 Confusion Matrix - Random Forest

[18]:
```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay,␣
↪classification_report, roc_auc_score

# Predictions
y_pred = clf.predict(X_test)
y_proba = clf.predict_proba(X_test)[:, 1]

# Compute confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Class labels for display
labels = ['No Gold', 'Gold']

# Plot as a large heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
```

```
            xticklabels=labels, yticklabels=labels,
            cbar=False, annot_kws={"size": 18})
plt.xlabel('Predicted Label', fontsize=14)
plt.ylabel('True Label', fontsize=14)
plt.title('Confusion Matrix - Random Forest', fontsize=16)
plt.yticks(rotation=0)
plt.xticks(rotation=0)
plt.tight_layout()
plt.show()

# Print detailed metrics
print(classification_report(y_test, y_pred, target_names=labels))
print("ROC-AUC Score:", roc_auc_score(y_test, y_proba))
```




```
              precision    recall  f1-score   support

     No Gold       0.82      0.80      0.81        76
        Gold       0.93      0.94      0.93       211

    accuracy                           0.90       287
   macro avg       0.88      0.87      0.87       287
```

```
weighted avg       0.90      0.90      0.90       287

ROC-AUC Score: 0.9387627837365927
```

0.2.4 Random Forest Hyperparameter Optimization

Compares GridSearchCV and RandomizedSearchCV to identify improved hyperparameters for the Random Forest classifier.
Uses stratified folds, recall scoring, and measures fit times for each approach.

[19]:
```
import time
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV,␣
↪StratifiedKFold, train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, roc_auc_score

# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y,␣
↪random_state=42)

# Common pipeline
base_pipe = Pipeline([
    ('preprocessor', preprocessor),
    ('model', RandomForestClassifier(random_state=42, class_weight='balanced'))
])

# GridSearchCV
grid_params = {
    'model__n_estimators': [100, 200],
    'model__max_depth': [None, 10],
    'model__min_samples_split': [2, 3]
}
grid_cv = StratifiedKFold(n_splits=2, shuffle=True, random_state=42)
grid_search = GridSearchCV(
    estimator=base_pipe,
    param_grid=grid_params,
    cv=grid_cv,
    scoring='recall',
    n_jobs=-1,
    verbose=2
)
start_grid = time.time()
grid_search.fit(X_train, y_train)
end_grid = time.time()
grid_best = grid_search.best_estimator_
grid_pred = grid_best.predict(X_test)
grid_auc = roc_auc_score(y_test, grid_best.predict_proba(X_test)[:, 1])
```

```python
# RandomizedSearchCV
random_params = {
    'model__n_estimators': [50, 100, 150, 200],
    'model__max_depth': [None, 5, 10, 15],
    'model__min_samples_split': [2, 3, 4, 5]
}
random_search = RandomizedSearchCV(
    estimator=base_pipe,
    param_distributions=random_params,
    n_iter=10,
    cv=grid_cv,
    scoring='recall',
    n_jobs=-1,
    random_state=42,
    verbose=2
)
start_rand = time.time()
random_search.fit(X_train, y_train)
end_rand = time.time()
rand_best = random_search.best_estimator_
rand_pred = rand_best.predict(X_test)
rand_auc = roc_auc_score(y_test, rand_best.predict_proba(X_test)[:, 1])

# Results
print("\nGridSearchCV Results:")
print("Best Params:", grid_search.best_params_)
print(classification_report(y_test, grid_pred))
print("ROC-AUC:", grid_auc)
print(f"Time taken: {(end_grid - start_grid):.2f} seconds")

print("\nRandomizedSearchCV Results:")
print("Best Params:", random_search.best_params_)
print(classification_report(y_test, rand_pred))
print("ROC-AUC:", rand_auc)
print(f"Time taken: {(end_rand - start_rand):.2f} seconds")
```

```
Fitting 2 folds for each of 8 candidates, totalling 16 fits
Fitting 2 folds for each of 10 candidates, totalling 20 fits

GridSearchCV Results:
Best Params: {'model__max_depth': None, 'model__min_samples_split': 2,
'model__n_estimators': 100}
              precision    recall  f1-score   support

       False       0.83      0.78      0.80        76
        True       0.92      0.94      0.93       211
```

```
    accuracy                           0.90       287
   macro avg       0.88      0.86      0.87       287
weighted avg       0.90      0.90      0.90       287

ROC-AUC: 0.9358006984285357
Time taken: 10.69 seconds

RandomizedSearchCV Results:
Best Params: {'model__n_estimators': 100, 'model__min_samples_split': 3,
'model__max_depth': None}
              precision    recall  f1-score   support

       False       0.82      0.80      0.81        76
        True       0.93      0.94      0.93       211

    accuracy                           0.90       287
   macro avg       0.88      0.87      0.87       287
weighted avg       0.90      0.90      0.90       287

ROC-AUC: 0.9394799201795958
Time taken: 1.38 seconds
```

0.2.5 Attach Predictions to Coordinates

Adds model predictions to the corresponding latitude and longitude coordinates from the test set in preparation for spatial plotting.

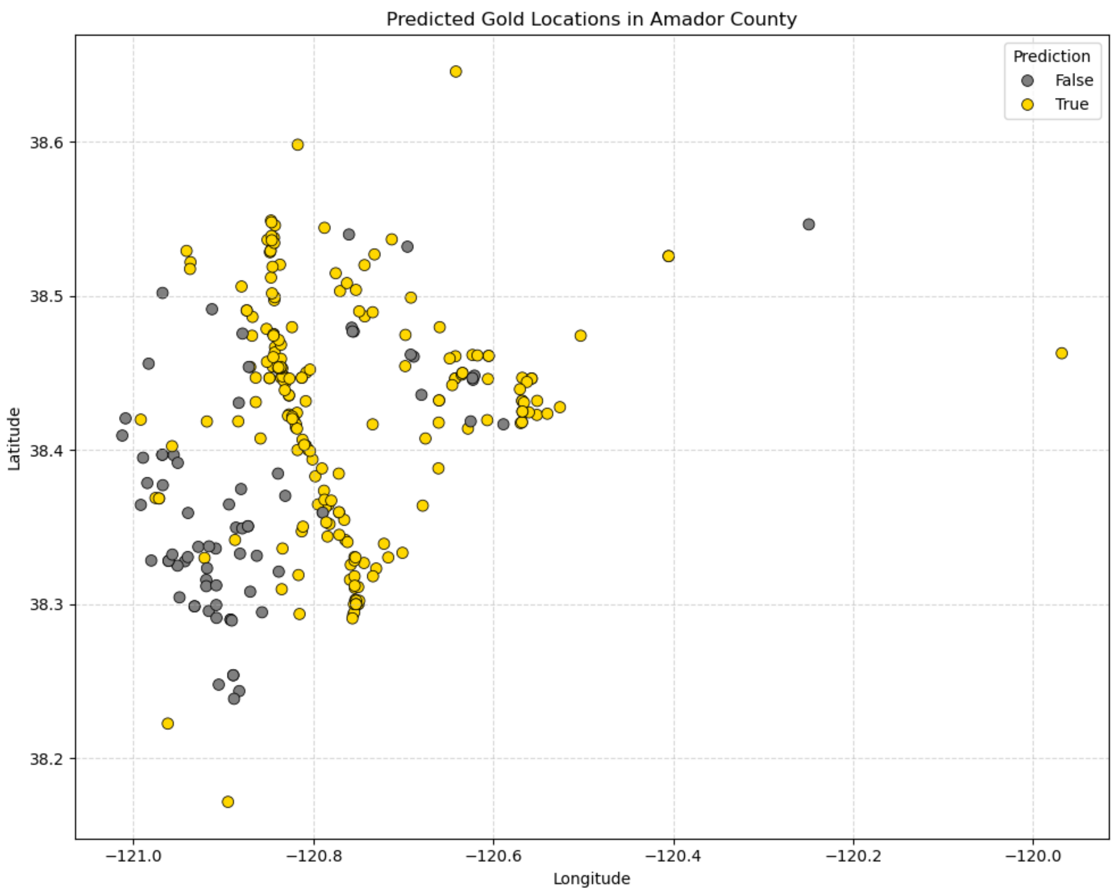
[20]:
```python
# Get predictions
y_pred = clf.predict(X_test)

# Reattach coordinates for mapping
coords = X_test[['latitude', 'longitude']].copy()
coords['prediction'] = y_pred
```

0.2.6 Predicted Gold Locations Map – Amador County

Plots predicted gold sites in gold and non-gold sites in gray, providing a spatial interpretation of model outputs.

[21]:
```python
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(10, 8))
sns.scatterplot(
    data=coords,
    x='longitude',
    y='latitude',
    hue='prediction',
```

```
    palette={True: 'gold', False: 'gray'},
    s=50,
    edgecolor='black'
)
plt.title('Predicted Gold Locations in Amador County')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.legend(title='Prediction')
plt.grid(True, linestyle='--', alpha=0.5)
plt.tight_layout()
plt.show()
```



0.3 Summary

0.4 Most accurate / best overall: Random Forest - consistently delivered the best combination of accuracy 90%, high precision 0.92, high recall 0.94, and highest ROC-AUC 0.939.

0.4.1 High recall means the model finds most of the sites that truly contain gold, missing very few.

0.4.2 High precision means that most of the sites flagged as gold-positive actually contain gold.