Will there be frogs v0.2

April 1, 2021

0.1 Will there be frogs?

0.2 Table of Contents

0.2.1 Introduction

In many countries, an environmental impact study (EIS) is required to assess the potential impact of actions that significantly affect the quality of the human environment. An EIS is very important but can be an expensive undertaking often involving the deployment of ecological experts to collect data. What if it was possible to do a pre-assessment of a project site? A pre-assessment could give an initial indication of areas to focus on and potentially shorten the the field time required.

0.2.2 Problem Definition

The impact of an infrastructure project on amphibian populations forms part of an EIS.

Can the presence of amphibians species near water reservoirs be predicted using features obtained from GS systems and satellite images?

0.2.3 Data

The data consists of 15 input variables and a multi-label target variable with 7 possible values indicating the presence of a certain type of frog.

Attribute Information

Inputs

- MV categorical
- SR numerical
- NR numerical
- TR categorical

- VR categorical
- SUR1 categorical
- SUR2 categorical
- SUR3 categorical
- UR categorical
- FR categorical
- OR categorical
- RR ordinal
- BR ordinal
- MR categorical
- CR categorical

Target

- Label 1: The presence of Green frogs
- Label 2: The presence of Brown frogs
- Label 3: The presence of Common toad
- Label 4: The presence of Fire-bellied toad
- Label 5: The presence of Tree frog
- Label 6: The presence of Common newt
- Label 7: The presence of Great Crested newt

Data Source The dataset was obtained from the UCI Machine Learning Repository: Amphibians

Marcin Blachnik, Marek SoÅ‚tysiak, Dominika DÄ…browska Predicting presence of amphibian species using features obtained from GIS and satellite images. ISPRS International Journal of Geo-Information 8 (3) pp. 123. MDPI. 2019

0.2.4 Problem Approach

This is a multi-label classification problem. This is not a multi-class classification problem as the classes are not mutually exclusive. Multiple species of amphibians can be found at a site.

Two classification algorithms will be evaluated on dataset and the quality of these models will be assessed. For each algorithm, several models will be developed and the best prediction model will be used to compare the algorithms.

0.2.5 Performance Metrics

The area under the receiver operating characteristic curve (AUC) will be used to evaluate the quality of the models. A perfect classifier will have a ROC AUC equal to 1, whereas a purely random classifier will have a ROC AUC equal to 0.5

0.2.6 Data Management

[180]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.model_selection import train_test_split
```

```
%matplotlib inline
```

The data for both road projects is contained in a single csv file. The repository claims that there are no missing values.

[181]:
```
amphibians = pd.read_csv('amphibians.csv', sep=';', header=1, index_col='ID')
amphibians.head()
```

[181]:
```
   Motorway   SR  NR  TR  VR  SUR1  SUR2  SUR3  UR  FR  …  BR  MR  CR  \
ID                                                      …
1        A1  600   1   1   4     6     2    10   0   0  …   0   0   1
2        A1  700   1   5   1    10     6    10   3   1  …   1   0   1
3        A1  200   1   5   1    10     6    10   3   4  …   1   0   1
4        A1  300   1   5   0     6    10     2   3   4  …   0   0   1
5        A1  600   2   1   4    10     2     6   0   0  …   5   0   1

    Green frogs  Brown frogs  Common toad  Fire-bellied toad  Tree frog  \
ID
1             0            0            0                  0          0
2             0            1            1                  0          0
3             0            1            1                  0          0
4             0            0            1                  0          0
5             0            1            1                  1          0

    Common newt  Great crested newt
ID
1             0                   0
2             1                   0
3             1                   0
4             0                   0
5             1                   1

[5 rows x 22 columns]
```

[182]:
```
amphibians.dtypes
```

[182]:
```
Motorway              object
SR                     int64
NR                     int64
TR                     int64
VR                     int64
SUR1                   int64
SUR2                   int64
SUR3                   int64
UR                     int64
FR                     int64
```

```
OR                    int64
RR                    int64
BR                    int64
MR                    int64
CR                    int64
Green frogs           int64
Brown frogs           int64
Common toad           int64
Fire-bellied toad     int64
Tree frog             int64
Common newt           int64
Great crested newt    int64
dtype: object
```

[183]:
```
# Check for missing values
amphibians.isna().sum()
```

[183]:
```
Motorway             0
SR                   0
NR                   0
TR                   0
VR                   0
SUR1                 0
SUR2                 0
SUR3                 0
UR                   0
FR                   0
OR                   0
RR                   0
BR                   0
MR                   0
CR                   0
Green frogs          0
Brown frogs          0
Common toad          0
Fire-bellied toad    0
Tree frog            0
Common newt          0
Great crested newt   0
dtype: int64
```

[184]:
```
# Determine the number of observations in the dataset
amphibians.shape
```

[184]:
```
(189, 22)
```

The dataset is quite small with only a 189 observations. A small dataset increases the risk of overfitting.

The dataset will be split into train and test set. The train set will be further split into a train and validation set.

[185]:
```
# View the number of frogs per species
species = ['Green frogs', 'Brown frogs', 'Common toad', 'Fire-bellied toad',␣
↪'Tree frog', 'Common newt', 'Great crested newt']
species_count = amphibians[species].sum().to_frame('count').reset_index()
# Group the values according to the motorway to determine if their are any␣
↪differences between the two motorways
species_count_motorway = amphibians.groupby('Motorway')[species].apply(lambda x␣
↪: x.astype(int).sum())
```

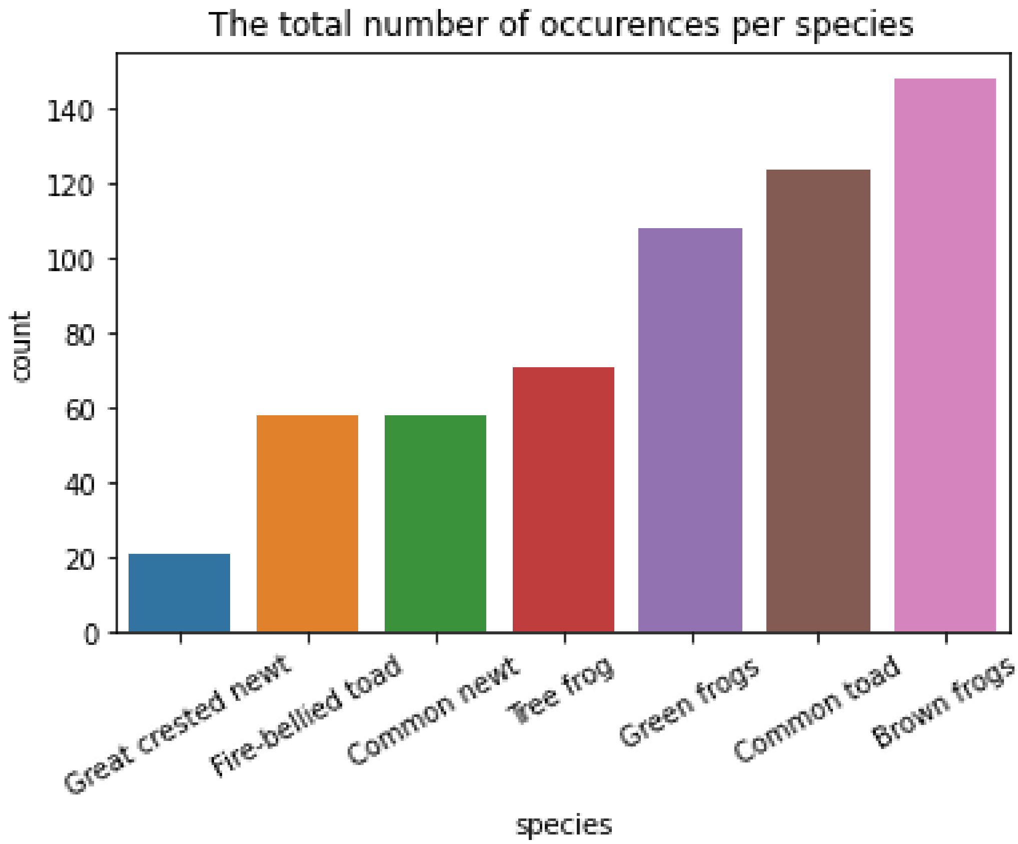
[186]:
```
species_count.columns = ['species', 'count']
species_count = species_count.sort_values('count')
species_count
```

[186]:

	species	count
6	Great crested newt	21
3	Fire-bellied toad	58
5	Common newt	58
4	Tree frog	71
0	Green frogs	108
2	Common toad	124
1	Brown frogs	148

[187]:
```
sns.barplot(data=species_count, x='species', y='count')
plt.xticks(rotation=30)
plt.title('The total number of occurences per species')
```

[187]: Text(0.5, 1.0, 'The total number of occurences per species')



This figure shows the total number of occurences per species. Brown frogs were present in 148 of the sites observed, followed by common toads and green frogs. The Great Crested Newt was present at only 21 of the 189 sites observed.

This a form of an unbalanced classification problem because some of the classes are underrepresented.

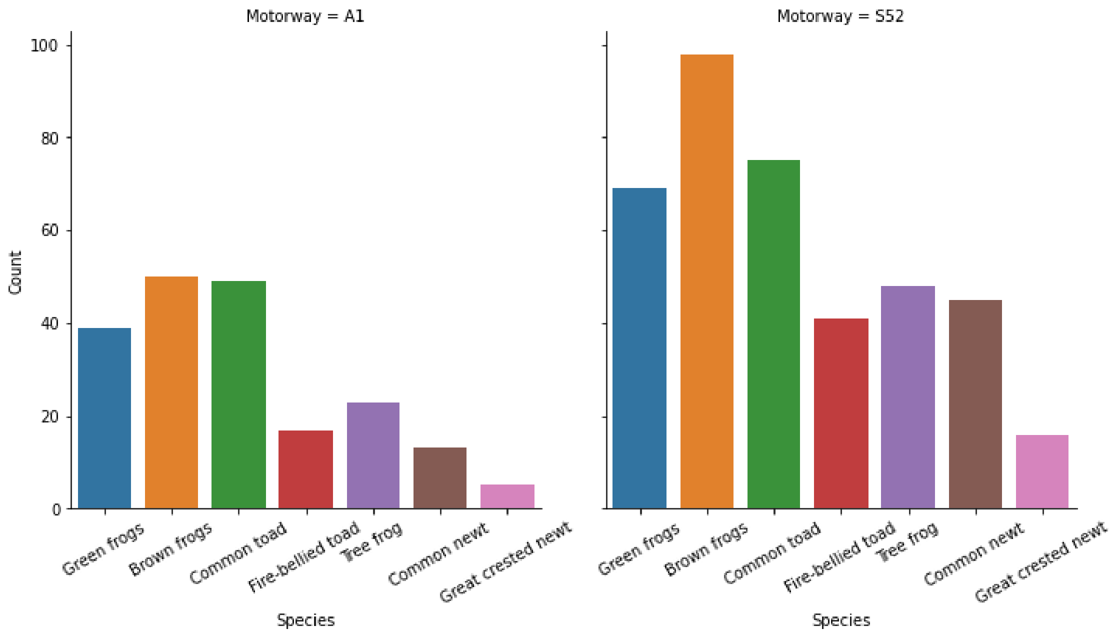
[188]:
```
species_count_motorway.reset_index(inplace=True)
species_count_motorway
```

[188]:
```
  Motorway  Green frogs  Brown frogs  Common toad  Fire-bellied toad  \
0       A1           39           50           49                 17
1      S52           69           98           75                 41

   Tree frog  Common newt  Great crested newt
0         23           13                   5
1         48           45                  16
```

[189]:
```
g = sns.catplot(data=species_count_motorway, kind='bar', col='Motorway')
g.set_xticklabels(rotation=30)
g.set_axis_labels("Species", "Count")
```

[189]: <seaborn.axisgrid.FacetGrid at 0x7fe848087c10>



The figure above shows that is no real difference between the motorways where the data was collected. The relatively rarer species are Common toads, Fire-bellied toad, Tree frog, Common Newt and Great crested newts.

[190]:
```
# Are there any observations with no species present?
frogs_per_observation = amphibians[species].sum(axis=1).
 ↪to_frame('species_present')
frogs_per_observation[frogs_per_observation['species_present'] == 0]
```

[190]:

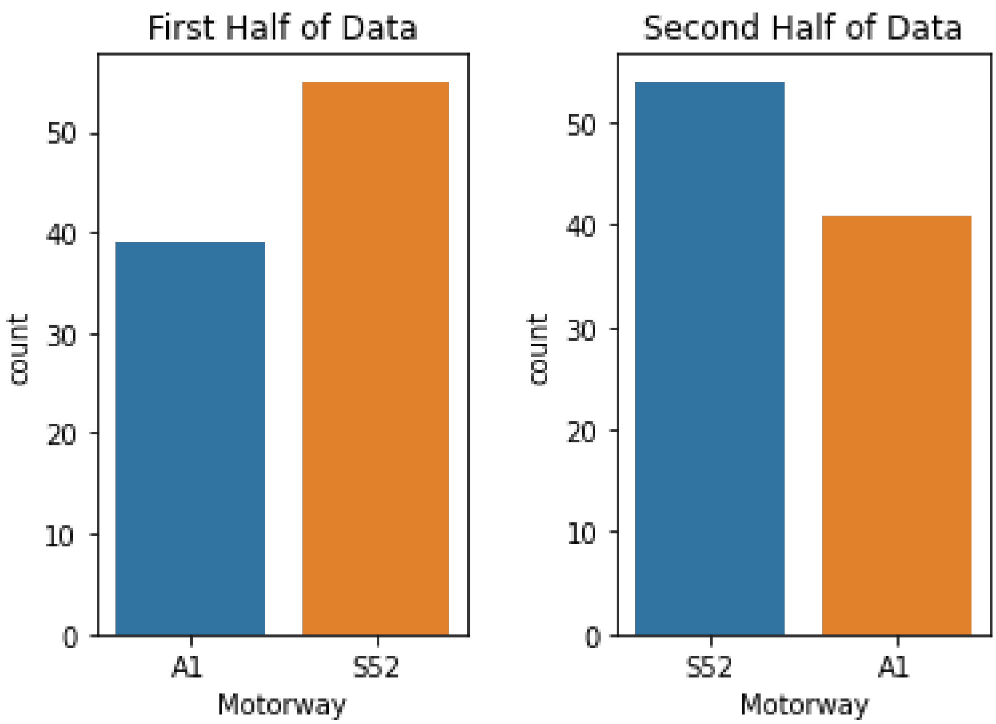
ID	species_present
1	0
6	0
125	0
129	0
132	0
179	0

There are 6 observations where there were no observations any species of amphibians

[191]:
```
# Check whether the data is ordered by splitting the data in half and comparing␣
 ↪the locations where the data came from
first_half, second_half = train_test_split(amphibians, test_size=0.5,␣
 ↪random_state=42)
```

[192]:
```
fig, ax = plt.subplots(1, 2)
fig.subplots_adjust(hspace=0.4, wspace=0.4)
sns.countplot(ax=ax[0],data=first_half, x='Motorway')
sns.countplot(ax=ax[1],data=second_half, x='Motorway')
ax[0].set_title('First Half of Data')
ax[1].set_title('Second Half of Data')
```

[192]:
```
Text(0.5, 1.0, 'Second Half of Data')
```



The observations are organized according to the location from where the data was collected (Motorway A1 or S52). We will need to shuffle the data before splitting it so that the model works well for any motorway.

Note: Need to revisit this split to check if the labels are equally distributed between sets

0.2.7 Exploration of the categorical variables

TR - Type of water reservoirs According to the dictionary, there 10 unique values for this variable

[193]:
```
amphibians['TR'].value_counts().sort_index()
```

[193]:
```
1     116
2       4
5      12
```

```
7       1
11      4
12     23
14     10
15     19
Name: TR, dtype: int64
```

[194]:
```
amphibians.groupby('Motorway')['TR'].value_counts().sort_index()
```

[194]:
```
Motorway  TR
A1        1     48
          2      3
          5      9
          11     4
          12    12
          14     3
          15     1
S52       1     68
          2      1
          5      3
          7      1
          12    11
          14     7
          15    18
Name: TR, dtype: int64
```

SUR1 - Surroundings 1 According to the dictionary, there 9 unique values for this variable

[195]:
```
amphibians['SUR1'].value_counts().sort_index()
```

[195]:
```
1     43
2     70
4      1
6     19
7     20
9      5
10    30
14     1
Name: SUR1, dtype: int64
```

There are levels of this category that are missing.

0.2.8 SUR2 - Surroundings 2¶

According to the dictionary, there 9 unique values for this variable

[196]:
```
amphibians['SUR2'].value_counts().sort_index()
```

[196]:
```
1     36
2     41
6     39
7     18
9     10
10    44
11     1
Name: SUR2, dtype: int64
```

There are levels of this category that are missing.

0.2.9 SUR3 - Surroundings 3¶

According to the dictionary, there 9 unique values for this variable

[197]:
```python
amphibians['SUR3'].value_counts().sort_index()
```

[197]:
```
1     29
2     29
5      2
6     55
7     18
9     10
10    45
11     1
Name: SUR3, dtype: int64
```

0.2.10 CR - Type of shore

[198]:
```python
amphibians['CR'].value_counts().sort_index()
```

[198]:
```
1    186
2      3
Name: CR, dtype: int64
```

There are only 3 observations where the shore is concrete. Could it be strong feature for there won't be any amphibians? Or not informative at all?

0.2.11 VR - Intensity of vegetation development

According to the dictionary, there should be 5 unique values for this variable

[199]:
```python
amphibians['VR'].value_counts().sort_index()
```

[199]:
```
0    30
1    55
2    35
3    41
```

```
4    28
Name: VR, dtype: int64
```

All the levels of the variable appear in the dataset

0.2.12 MR - Maintenance status of the reservoir

According to the dictionary, there should be 3 unique values for this variable

Comment: Trash caused devastation of the reservoir ecosystem. Backfiling and leveling of water reservoirs with ground and debris should also be considered

[200]:
```
amphibians['MR'].value_counts().sort_index()
```

[200]:
```
0    184
1      1
2      4
Name: MR, dtype: int64
```

My gut says this feature won't be informative.

0.2.13 FR - The presence of fishing

According to the dictionary, there should be 3 unique values for this variable

[201]:
```
amphibians['FR'].value_counts().sort_index()
```

[201]:
```
0    125
1     16
2     15
3     18
4     15
Name: FR, dtype: int64
```

There 5 levels of this variable in the dictionary. Check if data was collected differently for the two roads?

[202]:
```
amphibians['BR'].value_counts().sort_index()
```

[202]:
```
0     39
1     62
2     29
5     46
9      7
10     6
Name: BR, dtype: int64
```

The BR or Building development variable indicated the minimum distance from a water reservoir to roads. The options according to the data dictionary are:

less than 50 m

50-100 m

100-200 m

200-500 m

500-1000 m

1000 m

[203]:
```
amphibians['RR'].value_counts().sort_index()
```

[203]:
```
0     47
1     50
2     39
5     42
9      7
10     4
Name: RR, dtype: int64
```

The RR or Road variable indicated the minimum distance from a water reservoir to roads. The options according to the data dictionary are:

less than 50 m

50-100 m

100-200 m

200-500 m

500-1000 m

1000 m

The values of the two ordinal variables does not correspond to the descriptions of the variables but there are also 6 unique values.

0.2.14 OR - Access from water table to land habitats

According to the dictionary, there should be 4 unique values for this variable

[204]:
```
amphibians['OR'].value_counts().sort_index()
```

[204]:
```
25       7
50      16
75      22
80       1
99       2
100    141
Name: OR, dtype: int64
```

[205]:
```
# Drop the Motorway column from the dataset as this is not used
amphibians = amphibians.drop(columns='Motorway')
```

[206]:
```
# Split the data into features and target
amphibians_feat = amphibians.drop(species, axis=1)
```

[207]:
```
cat_feat_list = ['TR', 'SUR1', 'SUR2', 'SUR3', 'CR', 'VR', 'MR', 'UR', 'FR',␣
↪'BR', 'RR', 'OR']
```

[208]:
```
amphibians_feat[cat_feat_list] = amphibians_feat[cat_feat_list].
↪astype('category')
```

[209]:
```
amphibians_feat.dtypes
```

[209]:
```
SR         int64
NR         int64
TR      category
VR      category
SUR1    category
SUR2    category
SUR3    category
UR      category
FR      category
OR      category
RR      category
BR      category
MR      category
CR      category
dtype: object
```

0.3 Model Development

[210]:
```
from sklearn.preprocessing import OneHotEncoder
from sklearn.pipeline import make_pipeline
from sklearn.pipeline import Pipeline
from sklearn.compose import make_column_transformer
from sklearn.compose import make_column_selector
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import roc_auc_score, roc_curve
```

0.3.1 Overfitting strategy

The original dataset is split into a train and test set.

[211]:
```
# Shuffle and split the data into train, test and validations sets
X_train, X_test, y_train, y_test = train_test_split(amphibians_feat,␣
↪amphibians[species], test_size=0.20, random_state=42, shuffle=True)
```

0.3.2 Preprocessing

The categorical columns are converted using one hot encoding

[212]:
```
one_hot_encoder = make_column_transformer((OneHotEncoder(sparse=False,␣
↪handle_unknown='ignore'),
     make_column_selector(dtype_include='category')),
    remainder='passthrough')
```

0.3.3 Ramdom Forest (RF) Classifier

[213]:
```
rf = Pipeline(steps=[('one_hot_encoder', one_hot_encoder), ('classifier',␣
↪RandomForestClassifier(random_state=42))])
```

RF Hyperparamerter Tuning

[214]:
```
param_grid = {'classifier__n_estimators': [5, 10, 15, 20, 30, 40],
              'classifier__max_features': ['auto', 'sqrt', 'log2'],
              'classifier__max_depth' : [4,5,6,7,8],
              'classifier__criterion' :['gini', 'entropy']}
```

[215]:
```
gridsearch_rf = GridSearchCV(rf, param_grid, cv=5, scoring='roc_auc',␣
↪return_train_score=True)
```

[216]:
```
gridsearch_rf.fit(X_train, y_train)
```

[216]:
```
GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('one_hot_encoder',
ColumnTransformer(remainder='passthrough',
transformers=[('onehotencoder',
OneHotEncoder(handle_unknown='ignore',
       sparse=False),
<sklearn.compose._column_transformer.make_column_selector object at
0x7fe888681ca0>)])),
                                       ('classifier',
RandomForestClassifier(random_state=42))]),
             param_grid={'classifier__criterion': ['gini', 'entropy'],
                         'classifier__max_depth': [4, 5, 6, 7, 8],
                         'classifier__max_features': ['auto', 'sqrt', 'log2'],
                         'classifier__n_estimators': [5, 10, 15, 20, 30, 40]},
             return_train_score=True, scoring='roc_auc')
```

[217]:
```
gridsearch_rf.best_params_
```

[217]:
```
{'classifier__criterion': 'entropy',
 'classifier__max_depth': 5,
 'classifier__max_features': 'log2',
 'classifier__n_estimators': 40}
```

[218]:
```
gridsearch_rf.best_score_
```

[218]:
```
0.667467282741627
```

[219]:
```
y_pred_rf = gridsearch.predict_proba(X_test)
```

[220]:
```
y_pred_rf = np.transpose([pred[:, 1] for pred in y_pred_rf])
```

[221]:
```
# AUC scores for the classes

auc_scores_classes_rf = roc_auc_score(y_test, y_pred_rf, average=None)
auc_scores_classes_rf
```

[221]:
```
array([0.78991597, 0.55833333, 0.54492754, 0.68199234, 0.69318182,
       0.68484848, 0.72972973])
```

[238]:
```
# Unweighted mean AUC

auc_scores_macro_rf = roc_auc_score(y_test, y_pred_rf, average='macro')
auc_scores_macro_rf
```

[238]:
```
0.6689898865537938
```

The RF classifier achieves an unweighted average AUC of 0.669 on the test data.

0.3.4 Gradient Boosting Tree (GBT) Classifier

A GBT classifier will be trained for each class or label. The outputs from individual GBT classifiers are combined to produce a multi-label output.

[223]:
```
# Define a pipeline to convert the categorical variables using one hot encoding
gbt = Pipeline(steps=[('one_hot_encoder', one_hot_encoder), ('classifier',␣
↪MultiOutputClassifier(GradientBoostingClassifier(random_state=42)))])
```

GBT Hyperparamerter Tuning

[224]:
```
param_grid_gbt = {'classifier__estimator__n_estimators': [5, 10, 15, 20, 30,␣
↪40]}
```

[225]:
```
gridsearch_gbt = GridSearchCV(gbt, param_grid_gbt, cv=5, scoring='roc_auc',␣
↪return_train_score=True)
```

[226]:
```
gridsearch_gbt.fit(X_train, y_train)
```

[226]:
```
GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('one_hot_encoder',
ColumnTransformer(remainder='passthrough',
transformers=[('onehotencoder',
OneHotEncoder(handle_unknown='ignore',
       sparse=False),
<sklearn.compose._column_transformer.make_column_selector object at
0x7fe888681ca0>)])),
                                       ('classifier',
MultiOutputClassifier(estimator=GradientBoostingClassifier(random_state=42)))]),
             param_grid={'classifier__estimator__n_estimators': [5, 10, 15, 20,
                                                                  30, 40]},
             return_train_score=True, scoring='roc_auc')
```

[227]:
```
gridsearch_gbt.best_params_
```

[227]:
```
{'classifier__estimator__n_estimators': 40}
```

[228]:
```
gridsearch_gbt.best_score_
```

[228]:
```
0.6215602305803406
```

[229]:
```
y_pred_gbt = gbt_gridsearch.predict_proba(X_test)
```

[230]:
```
y_pred_gbt = np.transpose([pred[:, 1] for pred in y_pred_gbt])
```

[231]:
```
# AUC scores for the classes

auc_scores_classes_gbt = roc_auc_score(y_test, y_pred_gbt, average=None)
auc_scores_classes_gbt
```

[231]:
```
array([0.72268908, 0.43333333, 0.61304348, 0.61685824, 0.67613636,
       0.70909091, 0.83783784])
```

[232]:
```
# Unweighted mean AUC

auc_scores_macro_gbt = roc_auc_score(y_test, y_pred_gbt, average='macro')
auc_scores_macro_gbt
```

[232]:
```
0.6584270336196368
```

The GBT classifier achieves an unweighted average AUC of 0.658 on the test data.

0.3.5 Comparison of Results

[235]:
```
auc_results = pd.DataFrame({'species': species, 'rf': auc_scores_classes_rf,␣
↪'gbt': auc_scores_classes_gbt})
```

[236]:
```
auc_results
```

[236]:
```
              species        rf       gbt
0         Green frogs  0.789916  0.722689
1         Brown frogs  0.558333  0.433333
2         Common toad  0.544928  0.613043
3   Fire-bellied toad  0.681992  0.616858
4           Tree frog  0.693182  0.676136
5         Common newt  0.684848  0.709091
6  Great crested newt  0.729730  0.837838
```

The table above shows a comparison of the AUC scores achieved by each algorithm per class. A perfect classifier would have a ROC AUC equal to 1 and a purely random classifier will have a ROC AUC equal to 0.5. The RF and GBT both perform poorly for Brown Frogs.

[242]:
```
print('Unweighted average AUC for RF:', auc_scores_macro_rf)
print('Unweighted average AUC for GBT:', auc_scores_macro_gbt)
```

```
Unweighted average AUC for RF: 0.6689898865537938
Unweighted average AUC for GBT: 0.6584270336196368
```

0.3.6 Conclusion and Recommendations

The study shows that there is potential to develop a prediction model that makes use features extracted from publicly available GIS data and satellite images. The dataset is small and the predictive model would benefit from more training data.

The values of the categorical variables did not always match the data dictionary and should be followed up on with the data collection team. For example, the categorical variable for the presence of fishing should have 3 levels according to the data dictionary but the variable has 5 levels in the dataset.

0.3.7 References

-Multilabel_classification