Data 144 Final Presentation: Identifying Poisonous Mushrooms

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Introduction

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Research Question

Predicting Edibility of Mushrooms: A Machine Learning Approach

Project Description

We aim to predict whether simulated mushrooms are edible, poisonous, or classified as unsure (treated as poisonous).

What We’re Doing & Why It Matters

Mushroom poisoning is a significant issue, with approximately 704 major harms reported in the United States from 1999 to 2016.

Why it Matters:

- Unintentional ingestion of poisonous mushrooms is common.
- Prevention of mushroom poisoning is crucial.
- Key stakeholders may face risks in their activities.

Who Benefits

Biologists: Enhance their understanding of mushroom classification.

Hikers: Reduce the risk of accidental consumption during outdoor activities.

Foragers: Safeguard against unintentional poisoning while gathering mushrooms.

Why Machine Learning?

Simulated dataset: 20 features including one binary, 17 nominal, and 3 quantitative variables.

Ideal for feature engineering, Logistic Regression, and other ML methods.

Authentic dataset with real mushrooms available for testing models.

Dataset

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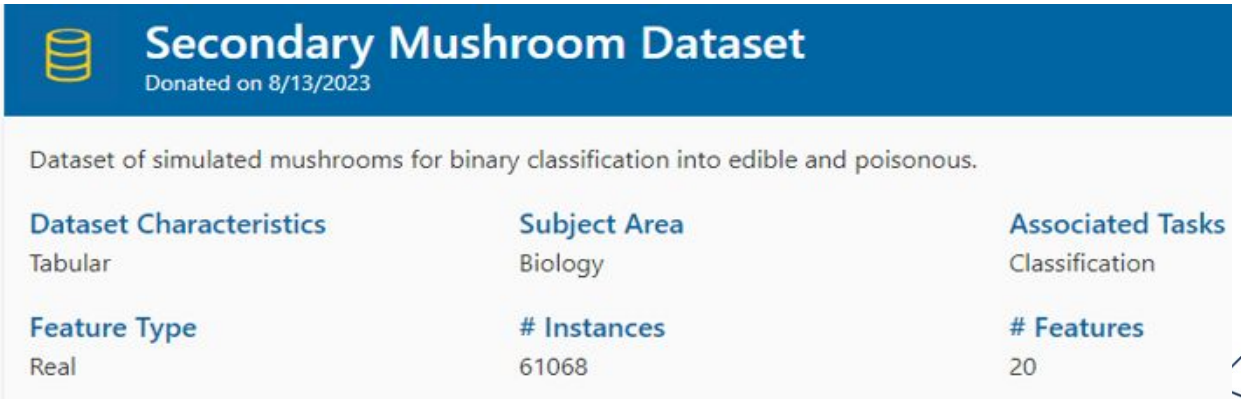
Dataset

UC Irvine Machine Learning Repository

“Mushroom data creation, curation, and simulation to support classification tasks”

By Dennis Wagner, D. Heider, Georges Hattab. 2021, Published in Scientific Reports



Details

- 61069 hypothetical mushrooms
- 3 continuous features -

  cap-diameter, stem-height, stem-width

- 17 categorical features -

  such as cap-color, veil-type, gill-spacing, habitat, and season

- each mushroom identified as edible or poisonous

Methods

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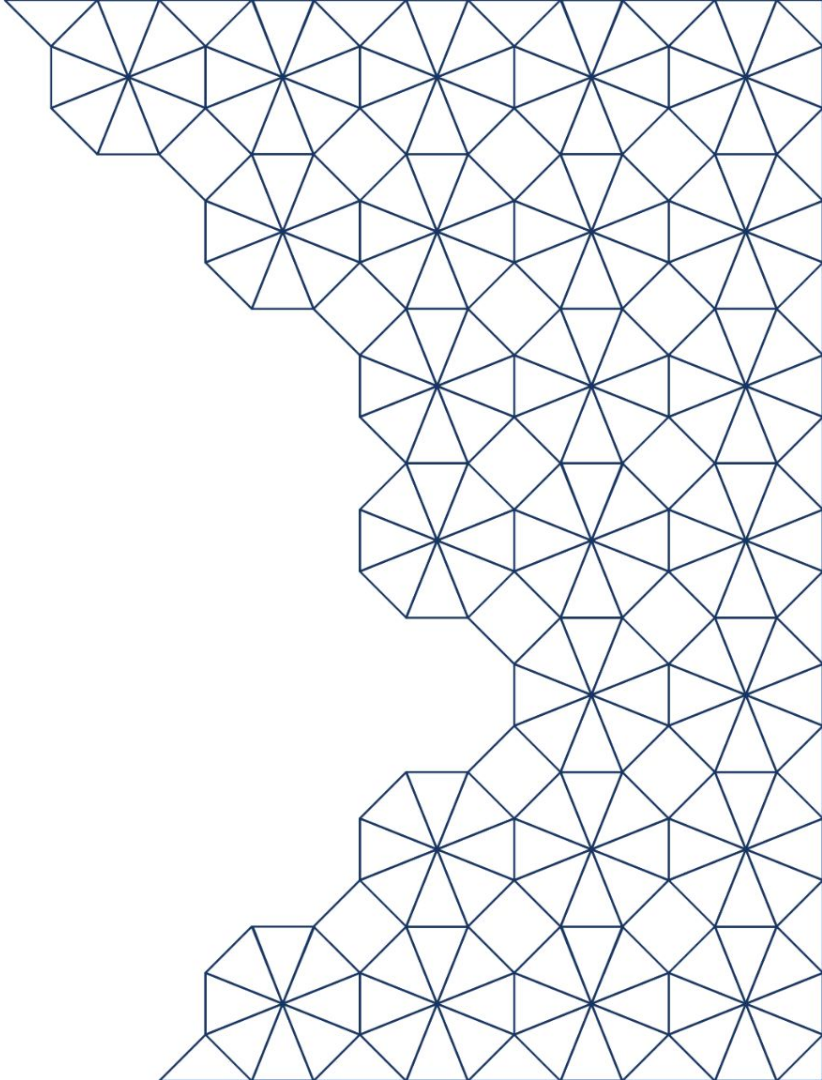
Methods

- Preprocessing
- Baseline *for comparison*
- MLP Classifier
- Boosted Tree
- Random Forest Classifier
- Logistic Regression
- Vanilla Bagging



Preprocessing

- **One-Hot Encoding**: 10+ features were categorical with 1-3 categories each
- **Test set**: For most models we used train-test split to have a validation set
  - Avoids overfitting
- **EDA w/ Pandas**: cast string columns to float, drop/rename columns,

Baseline

- **Simple Classifier**: Predict all mushrooms are edible
  - **Accuracy**: NOT useful here because 99% of dataset is labeled 'edible’
  - Use Recall Instead
- **Recall**: 56%

1. MLP Classifier

- Model specs:
  - Hidden Layer Size: (10,)
  - Activation: Logistic
  - Max Iterations: 200
  - Solver: lbfgs
- Used all numeric columns
  - Including one-hotted columns

1. MLP Classifier

- *Advantages*
  - Good for complex feature set (20 + features)
  - Good for large input size (60K + records)
- *Disadvantages*
  - Potential overfitting (but mitigated with train/test split)

2. Boosted Tree

```
model2 = GradientBoostingClassifier(random_state=42)
model2.fit(X_train, y_train)
y_test_pred = model2.predict(X_test)
```

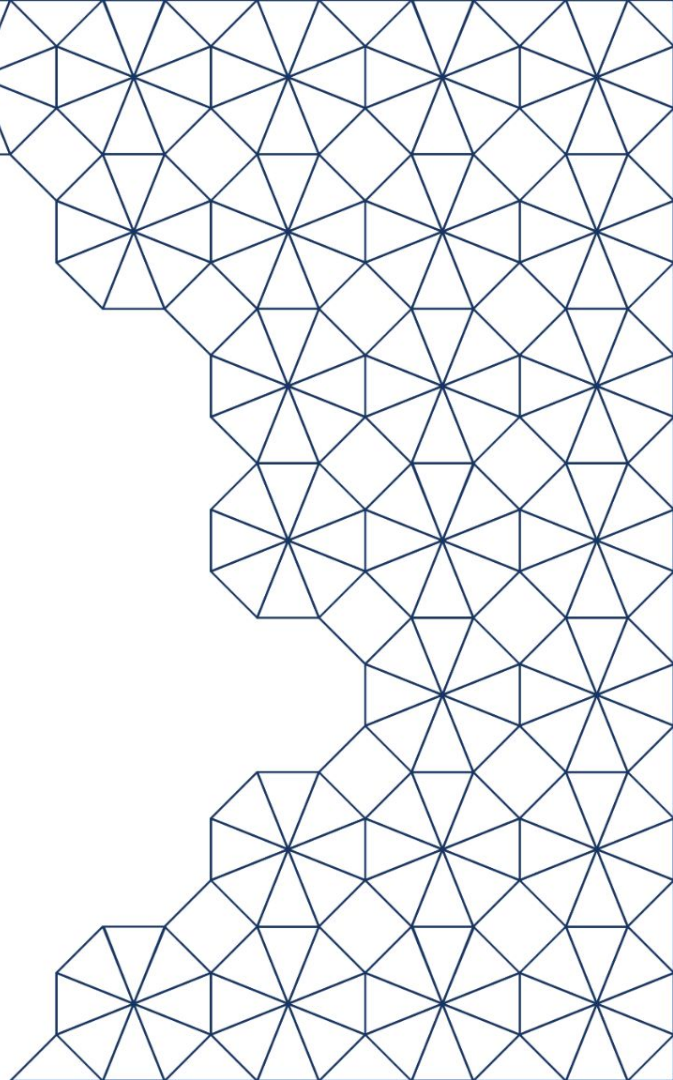
```
Model 2: Boosted Tree Performance on Test Set
Accuracy: 0.9320451940396267
Classification Report:
              precision    recall  f1-score   support

           e       0.92      0.92      0.92      5374
           p       0.94      0.94      0.94      6840

    accuracy                           0.93     12214
   macro avg       0.93      0.93      0.93     12214
weighted avg       0.93      0.93      0.93     12214
```

2. Boosted Tree

- *Advantages*
  - Uses ensemble method of weak learners and averages
  - Assigning weight to incorrect predictions fixes errors
- *Disadvantages*
  - Expensive to train
  - Could be prone to overfitting



3. Random Forest Classifier

- **Model Parameters**:
  - n_estimators = 800
  - max_depth = 100
  - random_state = 42

```
model = RandomForestClassifier(max_features=1, n_estimators=800, max_depth=100, verbose=2, random_state=42)

model.fit(X_train, y_train)

pred = model.predict(X_test)
```

3. Random Forest Classifier

- *Advantages*
  - Can handle linear and non-linear relationships well.
  - Less prone to overfitting compared to normal decision tree
    - (Takes average)
- *Disadvantages*
  - Are not easily interpretable

4. Logistic Regression

- **Model Parameters**:
  - random_state = 42
  - max_iter = 10,000

```
from sklearn.linear_model import LogisticRegression

model_lr = LogisticRegression(max_iter=10000, random_state=42)

model_lr.fit(X_train, y_train)

pred = model_lr.predict(X_test)
```

4. Logistic Regression

- *Advantages*
  - Easy to implement and very efficient to train
  - Easy to interpret
- *Disadvantages*
  - Assumes the linear relationship between dependent and independent variables

5. Vanilla Bagging

- **Model Parameters**:
  - random_state = 42
  - Max_features = num_feature

```
#Vanilla Bagging
from sklearn.ensemble import RandomForestClassifier

#num_feature will be equal to the # of features in the train df
num_feature = len(X_train.columns)

model3 = RandomForestClassifier(random_state=42, max_features = num_feature)
model3.fit(X_train, y_train)
```

5. Vanilla Bagging

- *Advantages*
  - Lower the chance of overfitting by taking average
- *Disadvantages*
  - Extreme Case: If there is one strong predictive feature, it will always select this as first predictor
    - Have all same trees

Results & Conclusions

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Model Performance

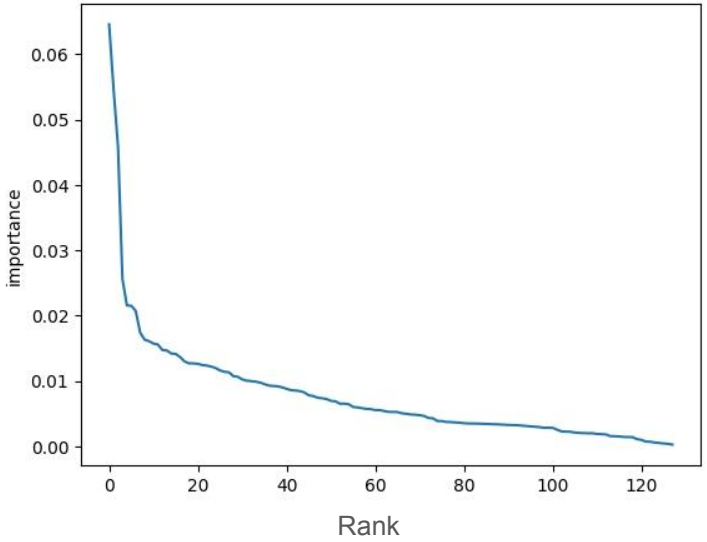
Goal: Minimize false negatives for poisonous mushrooms

- **MLP Classifier**
  - 98% accuracy, 98% recall
- **Gradient Boosting**
  - 93% accuracy, 94% recall
- **Random Forest Classifier**
  - 100% accuracy, 100% recall
- **Logistic Regression**
  - 86% accuracy, 87% recall
- **Vanilla Bagging**
  - 100% accuracy, 100% recall

Bagging Models like Random Forest perform well on the dataset

What's good about Random Forest?

Interpretability!



Feature	Importance
cap-diameter	0.054609
stem-height	0.045532
stem-color_w	0.025480
gill-spacing_c	0.021237
stem-surface_	0.021215
gill-spacing_	0.020742
gill-color_w	0.018048
cap-shape_x	0.016393
gill-spacing_d	0.016110

Top 10 feature importances

Limitation and Improvement

- Collinearity of Variables and PCA
- Cross Validation
- Technical Limitations
- Plant Species and the problem of sampling
    - Dilemma: What do we do when we encounter new mushrooms, will the models hold?

Implications

- Forest Like Data Models are good for finding species and classifying them as correctly poisonous or safe.

- However, with high cost of false negatives and unknown qualities of new species these models would not be great at predicting if a newly found species is poisonous or not.