Prediction of Forest Cover Type in Roosevelt National Forest Colorado, US

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February 2021

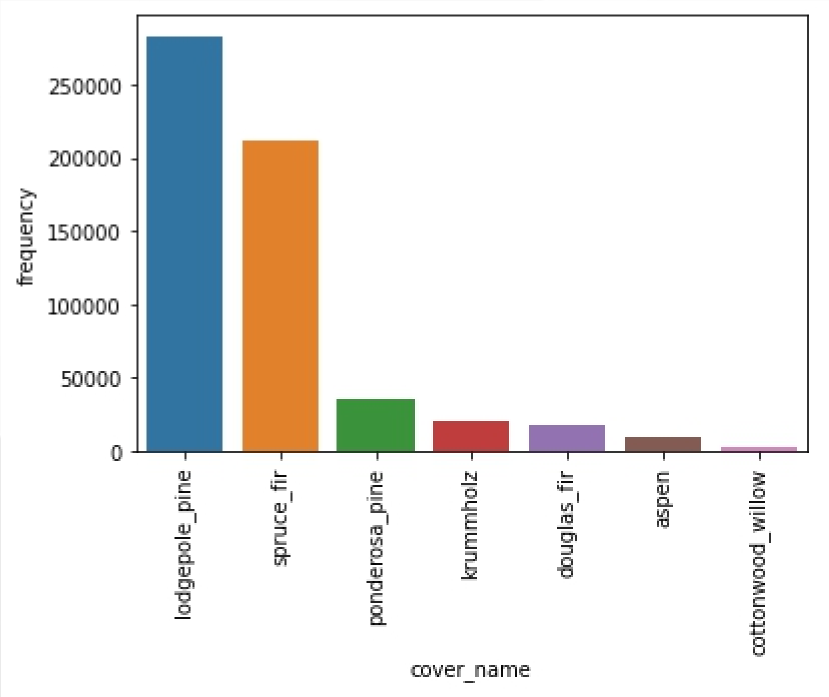
Outline

- project description
- data overview and exploration
- initial model investigation (`sklearn` and trees)
- model development process
- modeling results
- model tuning and finalization
- model deployment and serving (work in progress)

Project Description

- classification problem in environmental science
- dataset is for Roosevelt National Forest, Colorado, USA
- http://archive.ics.uci.edu/ml/datasets/Covertype
- Blackard, Jock A., Dean, Denis J., Anderson, Charles W. (1998). Covertype Data Set : University of California--Irvine Machine Learning Repository.

Cover Type (Target Values)



	count	fraction
cover_name		
lodgepole_pine	283301	0.487599
spruce_fir	211840	0.364605
ponderosa_pine	35754	0.061537
krummholz	20510	0.035300
douglas_fir	17367	0.029891
aspen	9493	0.016339
cottonwood_willow	2747	0.004728

- 7 values for cover type
- significant class imbalance
- 85% of observations in 2 largest classes
- 5 smallest classes present at 0.5 to 6% each

Features

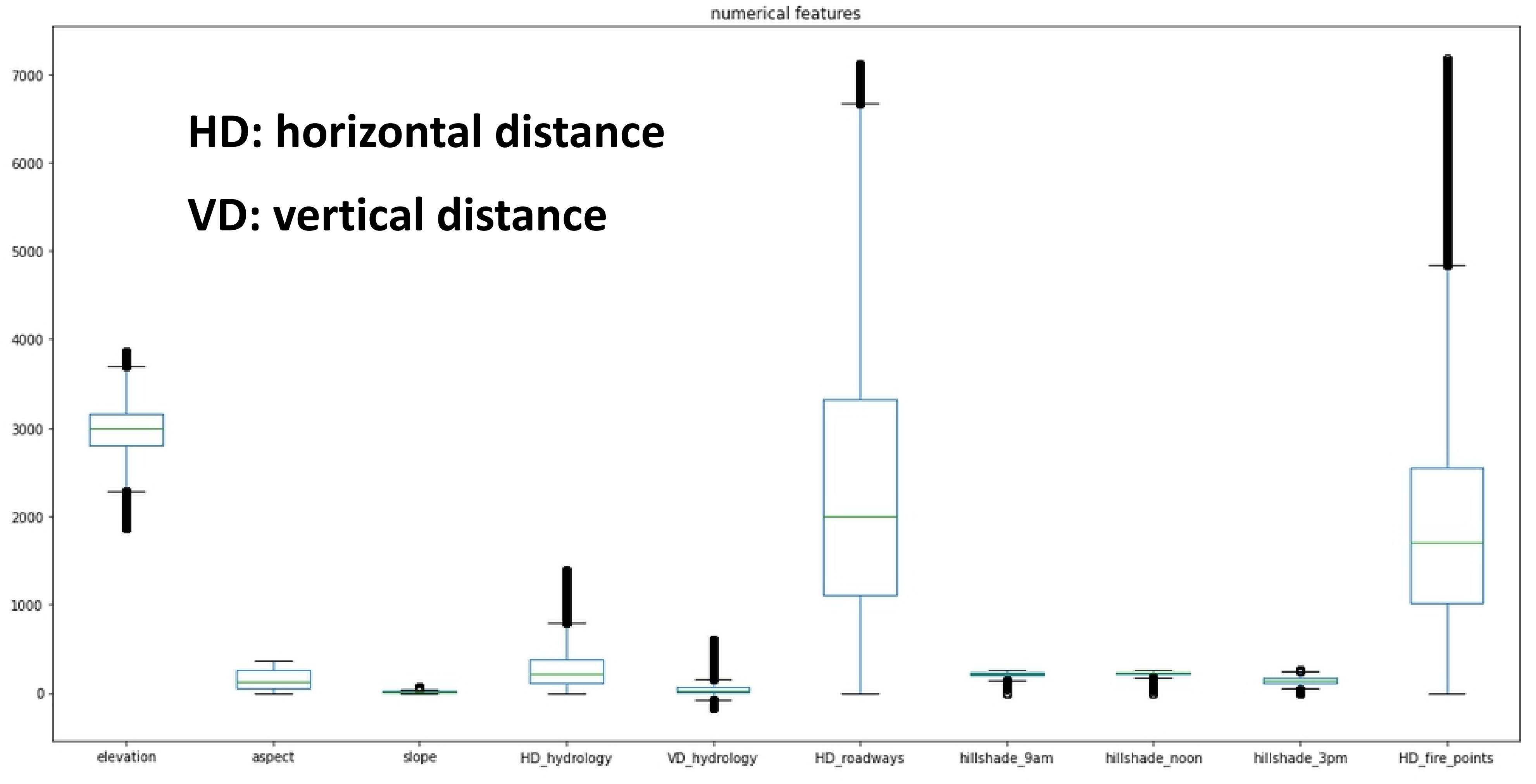
12 features

- 10 numerical
- 1st categorical feature (non-ordinal): 4 categories
- 2nd categorical feature (non-ordinal): 40 categories

original data

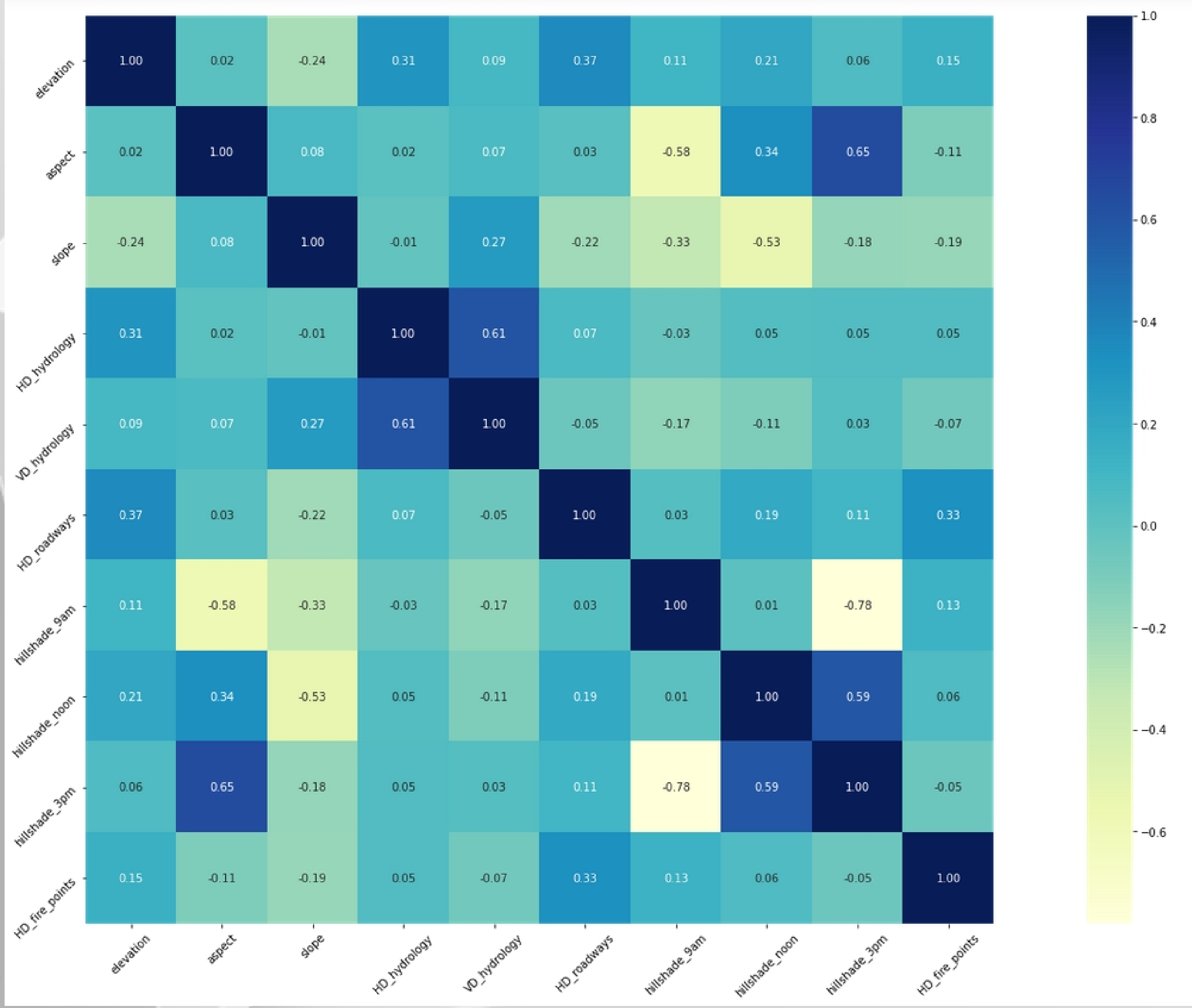
- csv file
- 581,012 observations
- clean, no missing values
- both categorical features only given as 1-hot encoded columns
- additional information provided on meaning of each encoded value
- pre-processing reversed 1-hot encoding to make columns with category value

Data Exploration: Numerical Features (Box)



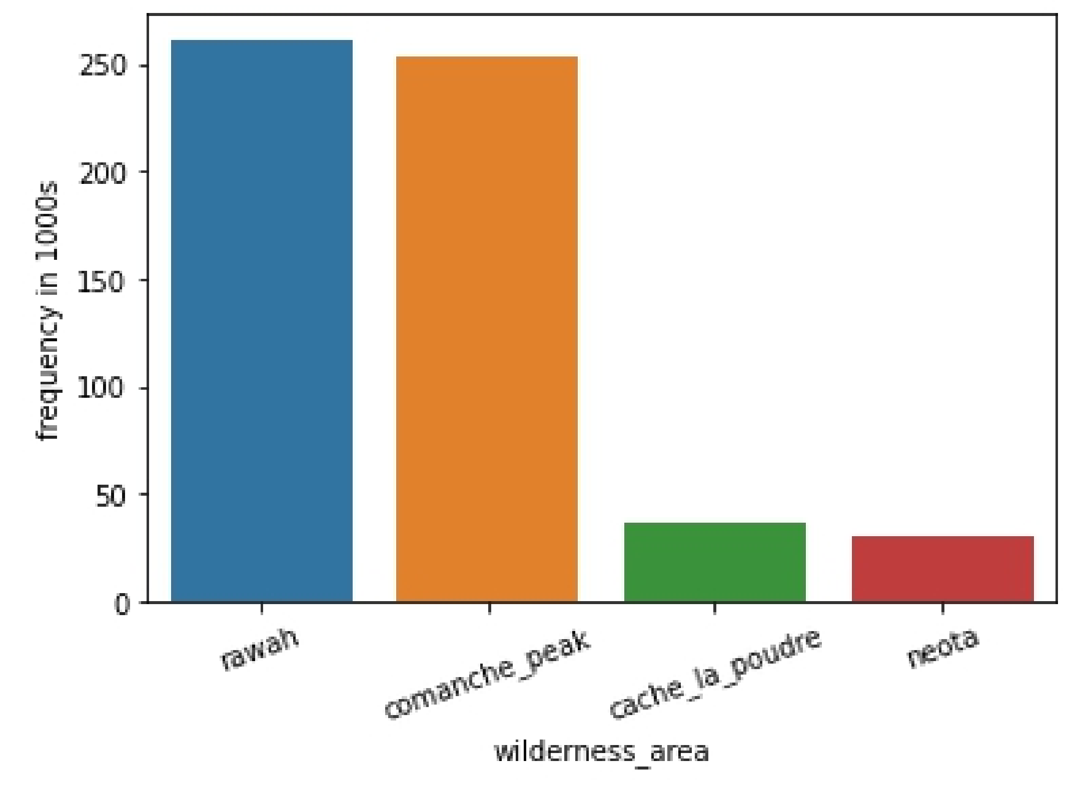
- different magnitudes
- not normally distributed

Data Exploration: Numerical Features (Correlation)



- **no strong correlations**

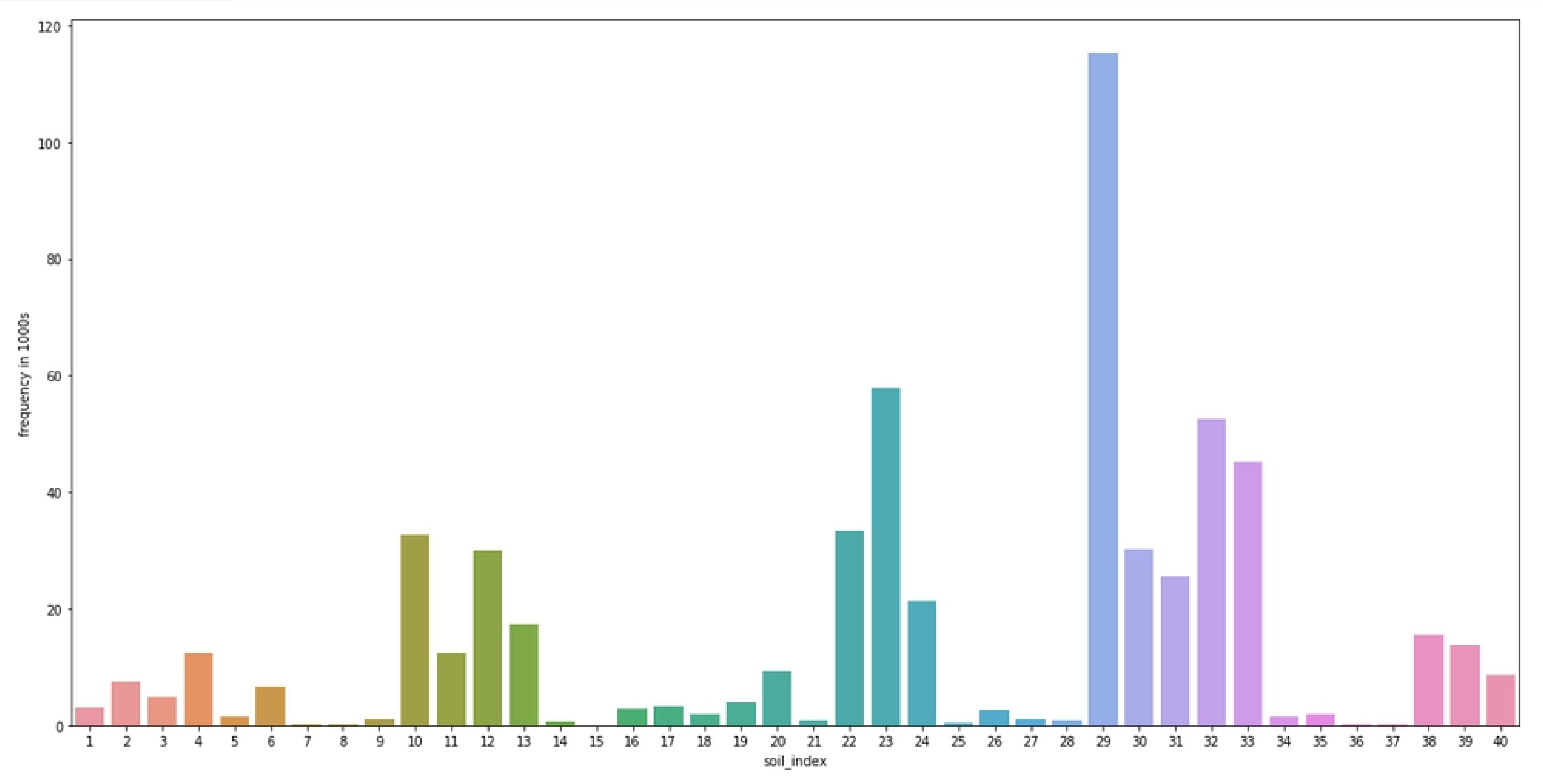
Data Exploration: Categorical Feature Wilderness Area



4 wilderness areas within

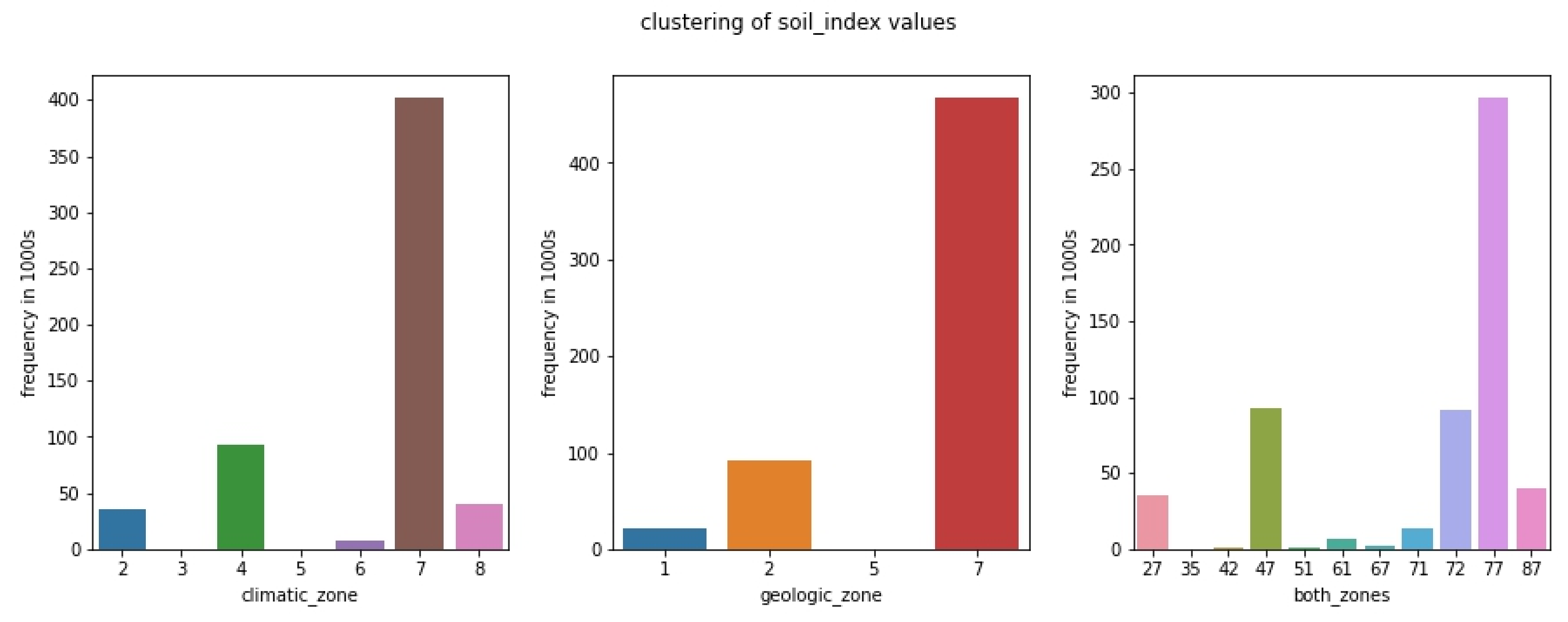
Roosevelt National Forest

Data Exploration: Categorical Feature Soil Type



- each category represents a US Forestry Service Ecological Landtype Unit (ELU)
- ELU code contains a digit for climatic zone and a digit for geologic zone

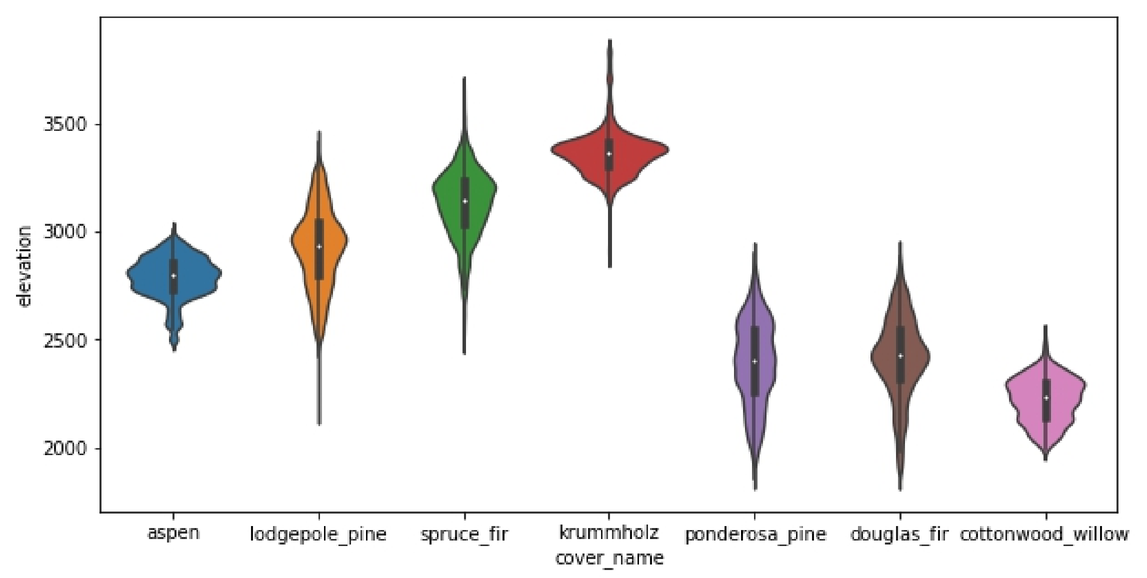
Data Exploration: Soil Type Clusters



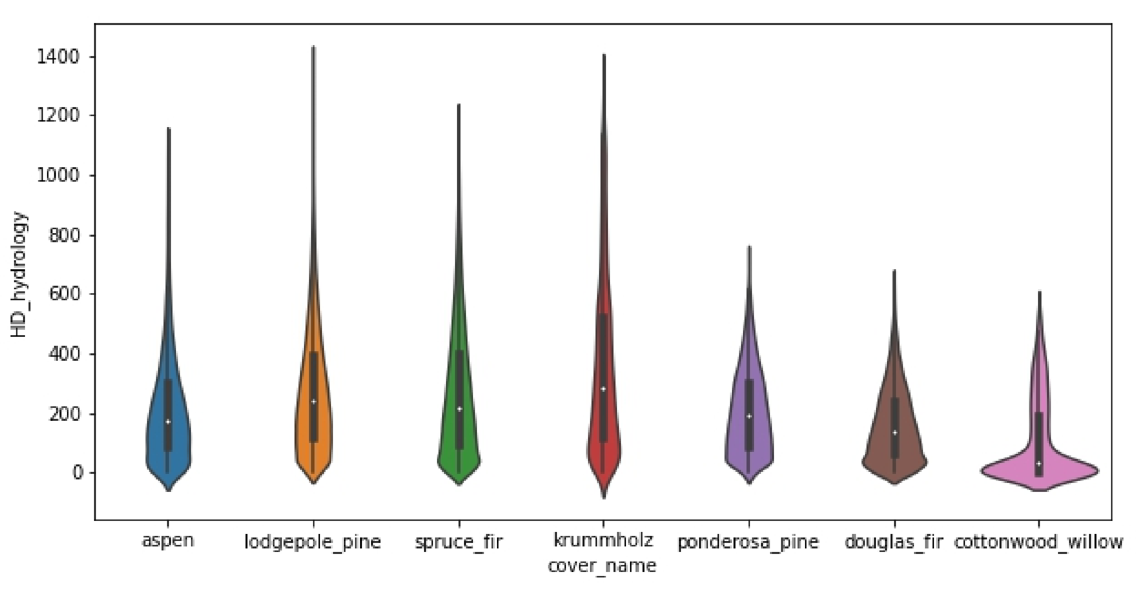
- each zone value on horizontal axis IS IN dataset
- bar may be too small to see

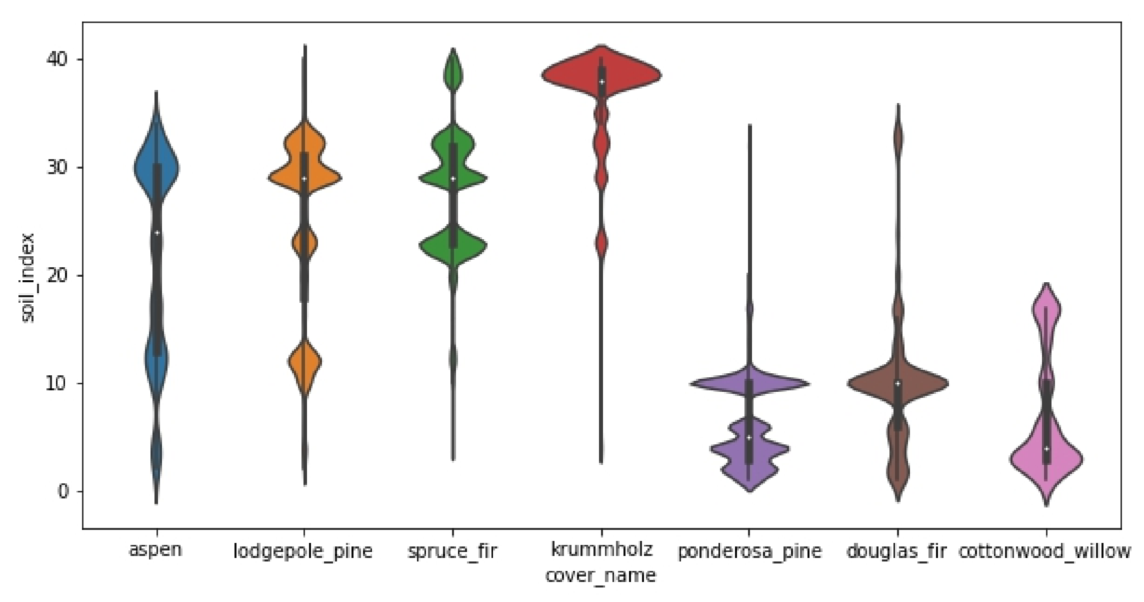
- soil type, climatic zone, and geologic zone descriptive information is included with dataset
- pre-process soil type for 3 clustering techniques
    - climatic zone (7 values)
    - geologic zone (4 values)
    - unique combinations of climatic and geologic (11 values)

Data Exploration: Feature Distribution by Target



- distribution of elevation and soil index varies by target class
- distribution of HD_hydrology does not





Initial Model Investigation

- `fit` model, no cross-validation, default hyper-parameter values
- data pre-processing
  - ✓ min-max scaling of numerical values
  - ✓ one-hot encoding of soil type (40 values)
  - ✓ one-hot encoding of wilderness area
- `sklearn` models
  - ✓ logistic regression
  - ✓ SVM
  - ✓ gaussian naive bayes
  - ✓ multinomial naive bayes
  - ✓ complement naive bayes

Initial Model Investigation (cont)

- tree models
  - ✓ decision tree
  - ✓ random forest
  - ✓ gradient boosting (GB)
  - ✓ XGBoost
  - ✓ Light GBM
  - ✓ CatBoost
- model metrics
  - ✓ accuracy
  - ✓ average and weighted average of class precision, recall, f1-score
- metrics by class
  - ✓ accuracy, precision, recall, f1-score

Initial Model Investigation: `sklearn` Results

- SVM ran for 2.5 hr but did not complete
  - ✓ others finished in < 10 min; did not try to resolve
- decision Gaussian NB: very large confusion among several classes
- model comparison
  - ✓ similar performance on train and test data
  - ✓ gaussian NB has worse performance
  - ✓ multinomial and complement NB: almost identical performance
  - ✓ logistic regression has slightly better performance than NB
  - ✓ weighted averages of precision, recall, f1 larger than macro averages due to decreased emphasis on poor performing small classes

Initial Model Investigation: `sklearn` Results (cont)

- performance by class
  - ✓ similar performance on train and test data
  - ✓ all models have difficulty with 3 smallest classes
  - ✓ complement NB has no predictions for 2 small classes
  - ✓ gaussian NB has high recall for 3 smallest classes but poor precision for them

Initial Model Investigation: Tree Results

- model comparison
  - ✓ GB, XGBoost, LightGBM, CatBoost almost identical performance
  - ✓ they are better than decision tree and random forest
- performance by class
  - ✓ random forest does not predict any instances of 4 smallest classes
  - ✓ decision tree performance on 4 smallest classes poorer than on 3 largest classes
- GB, XGBoost, LightGBM, CatBoost on 4 smallest classes
  - ✓ generally better precision than recall
  - ✓ XGBoost slightly better precision and recall than others; CatBoost generally performs worse
- LightGBM, CatBoost (use categorical features directly)
  - ✓ very similar performance
  - ✓ LightGBM slightly better for precision, CatBoost slightly better for recall

Model Development Process

- use `pycaret`
  - ✓ feature pre-processing
  - ✓ fit and compare several models (default hyper-parameters)
  - ✓ hyper-parameter tuning of a few selected models
  - ✓ finalize model and save to pickle file
- work with subset of data on local machine
  - ✓ develop and debug Jupyter notebooks
  - ✓ techniques for encoding high cardinality feature (soil type)
  - ✓ oversampling of target minority classes
  - ✓ how to access train and test datasets
  - ✓ make predictions
  - ✓ prepare result dataframes used for plotting
  - ✓ prepare plots (from pickled result dataframes)

Model Development Process (cont)

- work with full dataset on Paperspace (cloud provider)
  - ✓ initial investigations with free machine (8 vCPU, 30 GB memory, 6 hr time limit)
  - ✓ tuning with paid machine (12 vCPU, 30 GB memory, no time limit)
- model metrics from 3-fold cross-validation
  - ✓ accuracy
  - ✓ average and weighted average of precision, recall, f1-score
- metrics by class (predict training data with fitted model)
  - ✓ accuracy, precision, recall, f1-score

Data Pre-Processing

- soil index: non-ordinal, high cardinality (40 values)
  - ✓ manual clustering using domain knowledge
  - ✓ 3 clustering techniques (climatic zone, geologic zone, both zones)
- min-max scaling of numerical features
- over sampling of minority classes using `imblearn`

Model Development: Soil Type

- non-ordinal, high categorical feature (40 values)
- investigated these techniques for handling
  - ✓ one-hot encoding
  - ✓ frequency encoding
  - ✓ climatic zone clustering (7 values)
  - ✓ geologic zone clustering (4 values)
  - ✓ climatic + geologic zone clustering (11 combinations present)
- investigate these models (default hyper-parameters)
  - ✓ logistic regression
  - ✓ decision tree
  - ✓ XGBoost
  - ✓ LightGBM (uses categorical features directly, not one-hot encoded)
  - ✓ CatBoost (uses categorical features directly, not one-hot encoded)

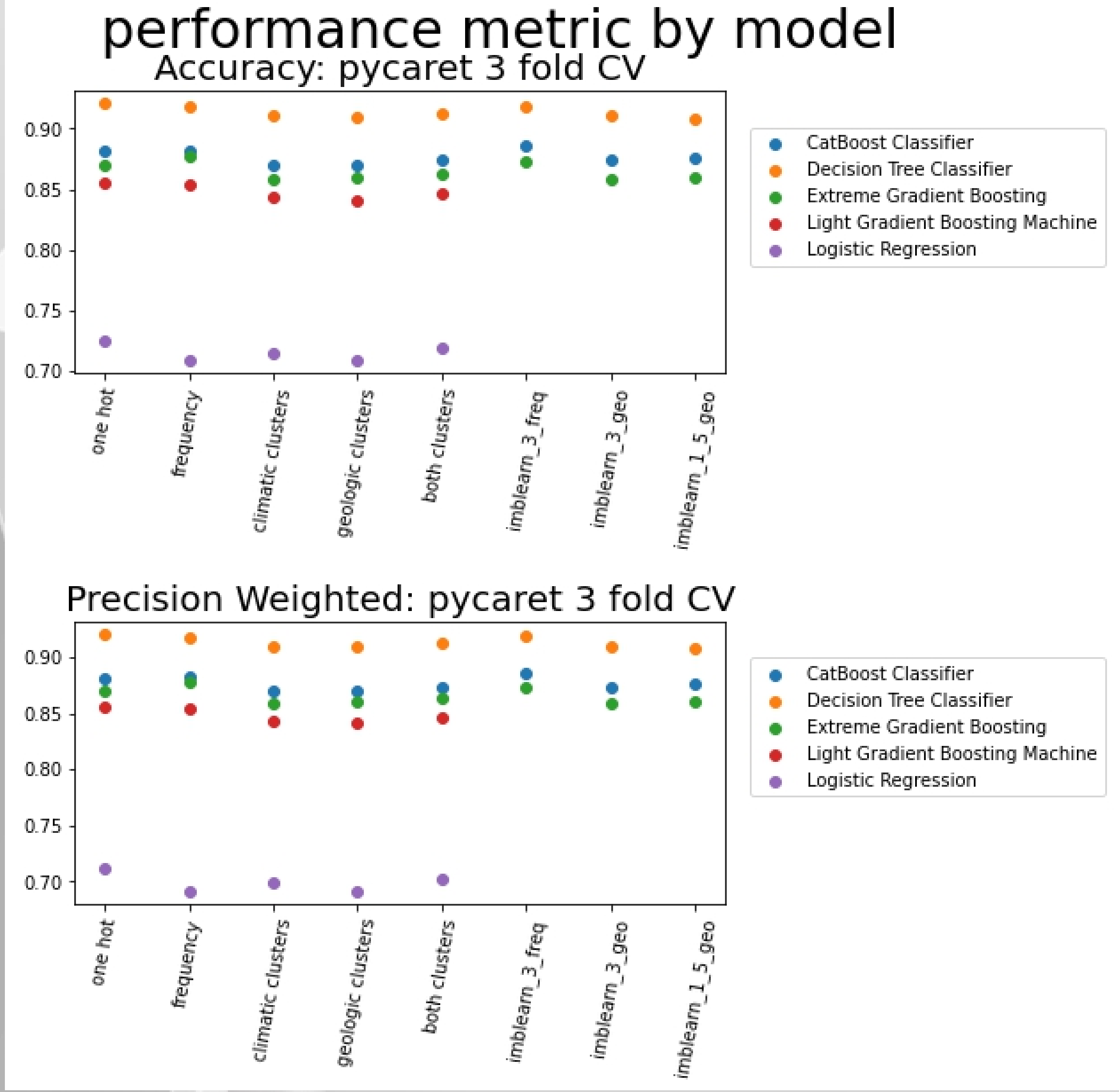
Model Development: Soil Type Results

- for each model
  - ✓ accuracy, weighted metrics, and average metrics slightly better for one-hot and frequency encoding
- decision tree
  - ✓ significantly better accuracy than other models
  - ✓ other metrics (except average precision) also better
- logistic regression significantly worse than other models
- 3 remaining models have similar performance
  - ✓ ordering best to worse: CatBoost, XGBoost, LightGBM
- for models that do not directly use categorical features
  - ✓ one-hot takes 20-40% more CPU time to train than frequency

Model Development: Soil Type Results (cont)

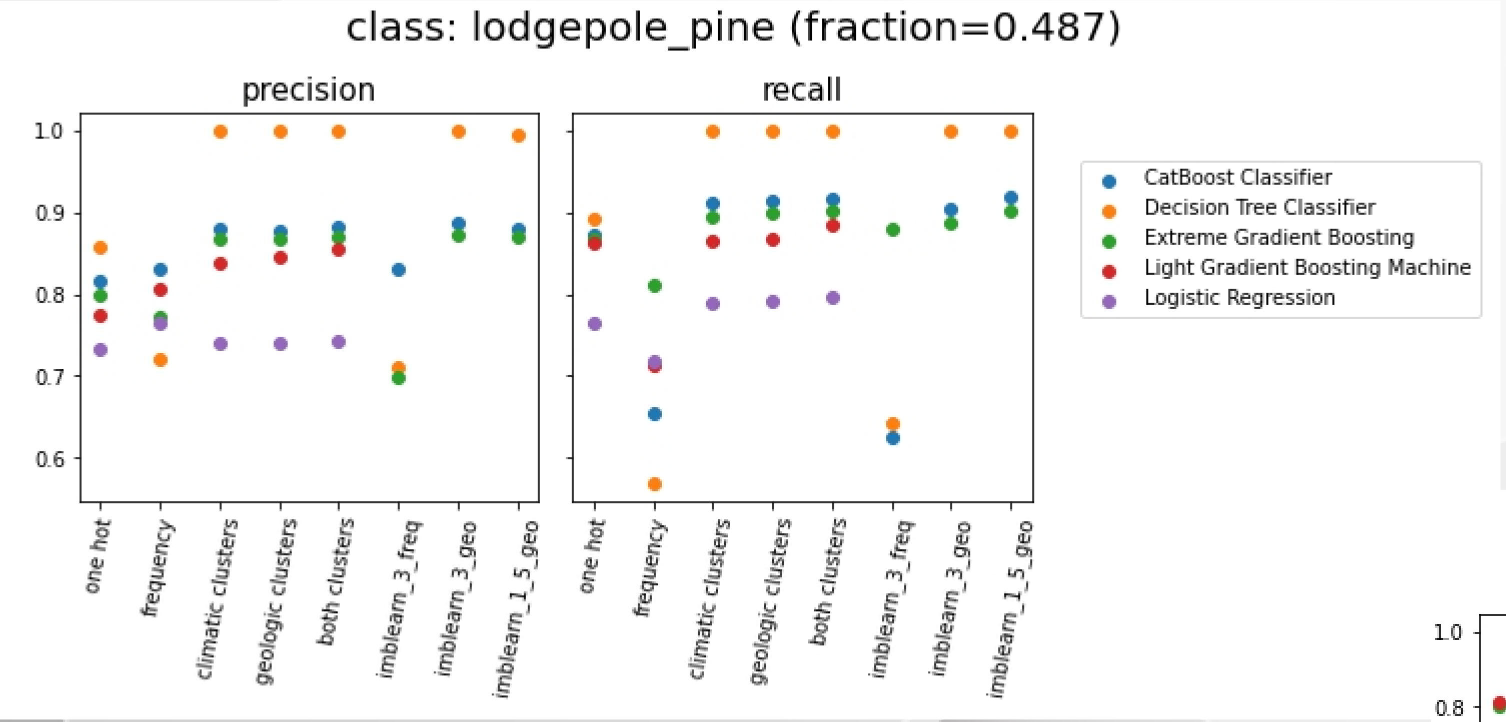
- metrics by class (predict entire training set)
  - ✓ generally, 3 clustering techniques perform better for each model
  - ✓ exception is logistic regression, which has significantly poorer performance than other models
  - ✓ little difference in performance among clustering techniques

Model Metrics: Screening Plots

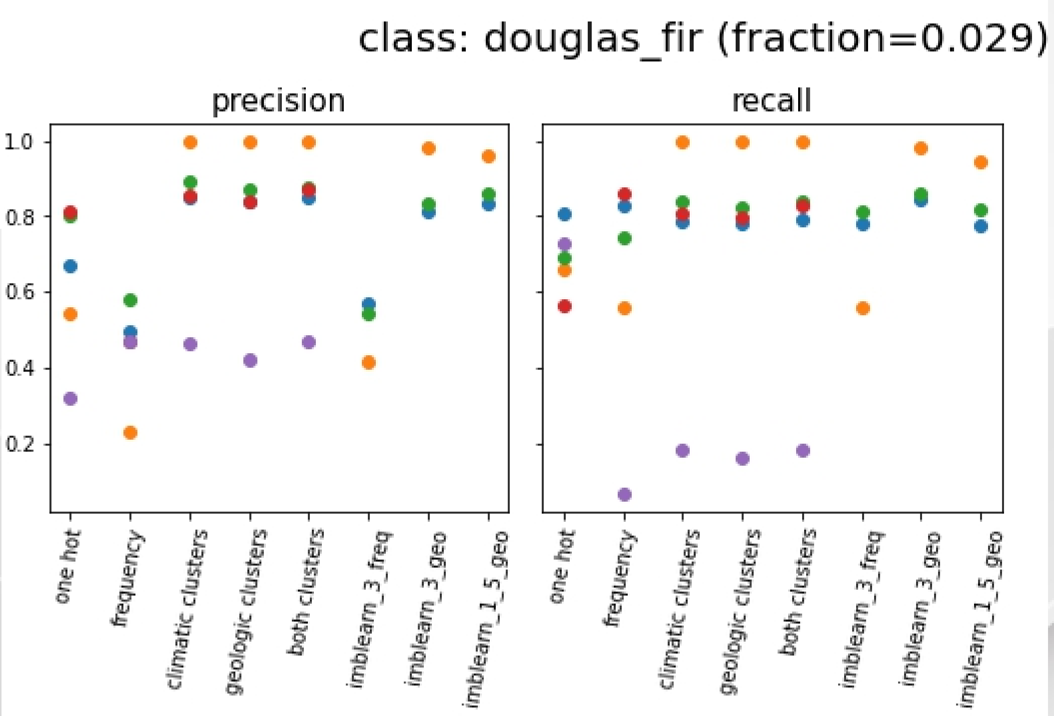


- **metrics investigated**
  - ✓ **accuracy**
  - ✓ **average and weighted average of precision, recall, f1**
  - ✓ **2 metrics shown; conclusions apply to all metrics**
- **one-hot and frequency encoding have slightly better performance for all models**
- **over-sampling of 5 smallest classes has only slight impact on performance**

Class Metrics: Screening Plots



- lodgepole_pine: majority class
- douglas_fir: 3rd smallest class
- conclusions same for all classes



- 3 cluster techniques
  - ✓ similar performance for all models
  - ✓ significantly better than one-hot and frequency
- over-sample factor = 3
  - ✓ geologic cluster significantly better than frequency

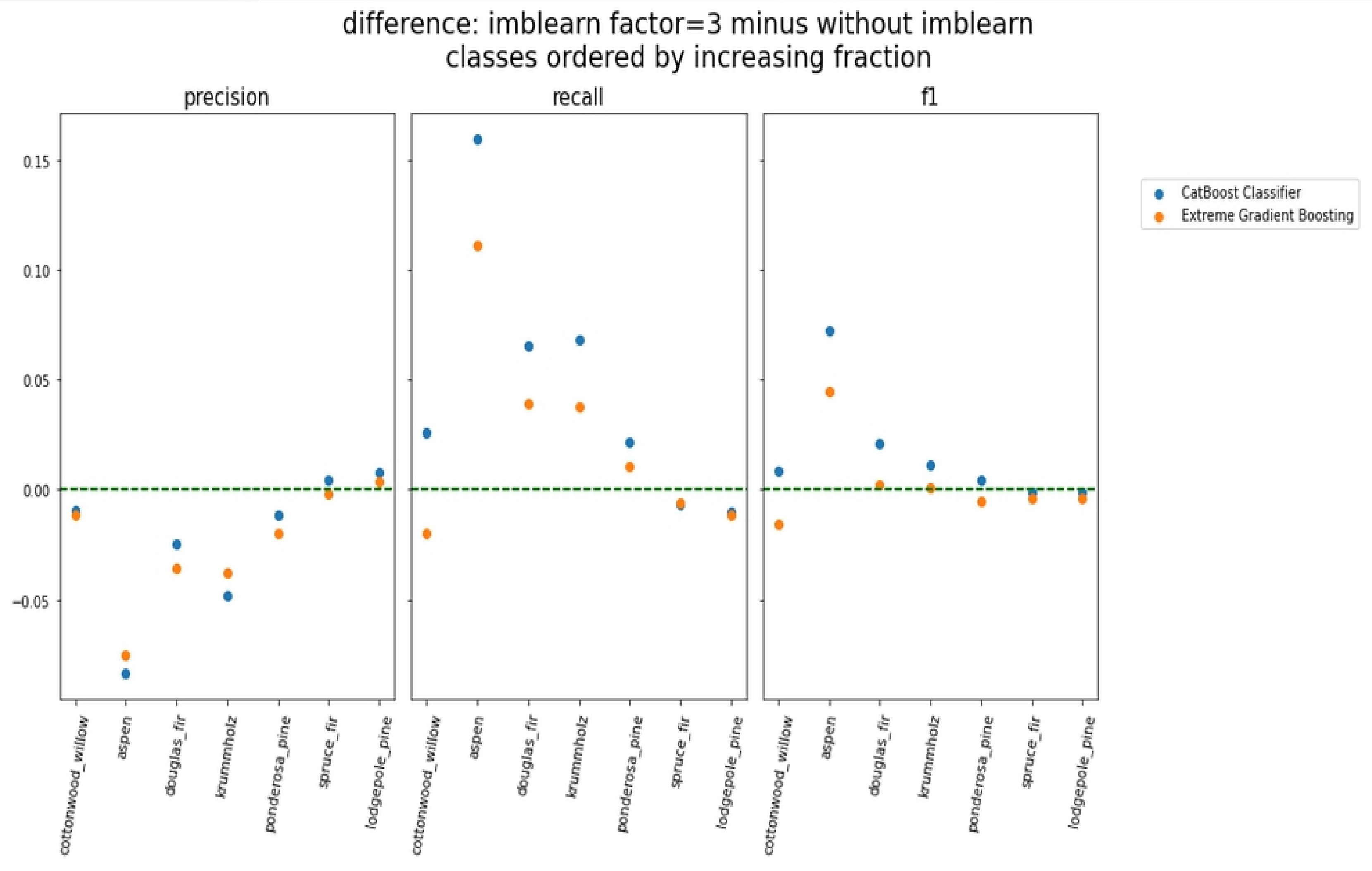
Model Development: Class Imbalance

- used `pycaret` functionality for including `imbalanced_learn`
  - ✓ over-sample and clean
- 5 smallest classes over-sampled to increase total count of each by factor of 3 in train data
- based on 3-fold CV results: use decision tree, XGBoost, CatBoost
- round 1: based on 3-fold CV results
  - ✓ use frequency encoding of soil type
- round 2: based on performance metrics by class
  - ✓ use geologic zone encoding (fewest clusters, 4 verses 7 or 11)
- round 3: over-sample by factor of 1.5
  - ✓ geologic zone encoding

Model Development: Class Imbalance Results

- over-sample with factor = 3: model metrics
  - ✓ little difference between with and without over-sampling
- over-sample with factor = 3: metrics for 5 smallest classes
  - ✓ with over-sampling, precision slightly lower and recall slightly higher
- over-sample with factor = 1.5: metrics for 5 smallest classes
  - ✓ only slight differences with and without over-sampling
  - ✓ differences smaller than factor = 3
  - ✓ no clear pattern to differences

Class Metrics: Over-Sampling



- over-sample 5 smallest classes
  - ✓ precision reduced
  - ✓ recall increased

Model Tuning: Parameters

- geologic clustering for soil type
- over-sample factor = 3
- 3-fold cross-validation, 15 iterations

Decision Tree

- parameter grid

```
tune_grid = {'max_depth': [5, 10, 15, 20, 25],
             'min_samples_leaf': [2, 4, 6, 8, 10],
             'min_samples_split': [6, 8, 10],
             'criterion': ['gini', 'entropy'],
             'max_features': [1.0, 'sqrt', 'log2']
            }
```

- best model

```
{'actual_estimator__min_samples_split': 6,
 'actual_estimator__min_samples_leaf': 4,
 'actual_estimator__max_features': 1.0,
 'actual_estimator__max_depth': 20,
 'actual_estimator__criterion': 'entropy'}
```

CatBoost

- parameter grid 1

```
tune_grid_cb = {'n_estimators': [50, 100, 150, 200, 300],
                'random_strength': [0.0, 0.2, 0.4, 0.6, 0.8],
                'l2_leaf_reg': [0.1, 1, 10, 100],
                'depth': [2, 4, 6, 8, 10]
               }
```

- best model 1
  - ✓ significantly worse than best decision tree

```
{'actual_estimator__random_strength': 0.0,
 'actual_estimator__n_estimators': 300,
 'actual_estimator__l2_leaf_reg': 0.1,
 'actual_estimator__depth': 8}
```

- parameter grid 2, same as above except

```
tune_grid_cb['n_estimators'] = [200, 300, 400, 500]
```

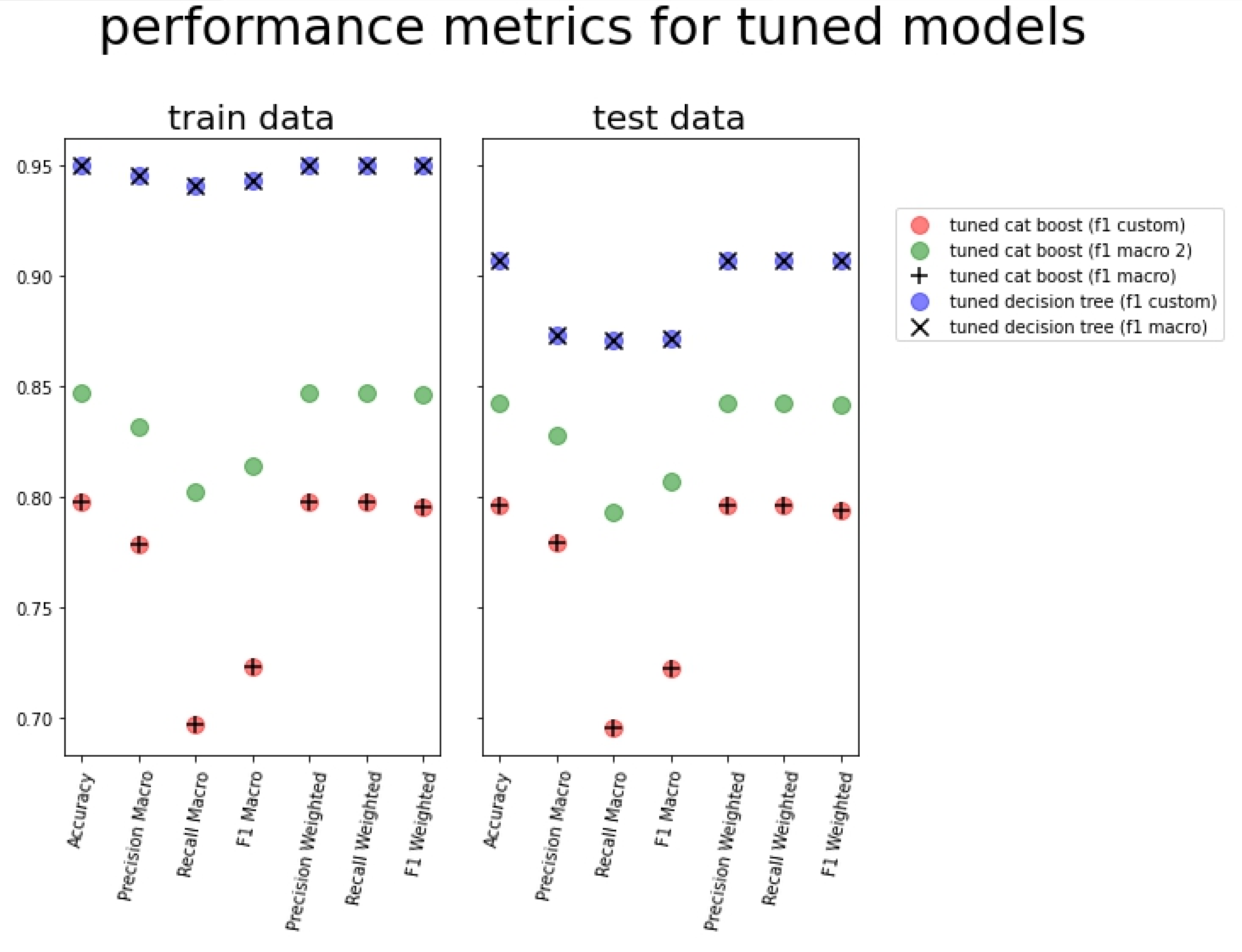
- best model 2

```
{'actual_estimator__random_strength': 0.2,
 'actual_estimator__n_estimators': 400,
 'actual_estimator__l2_leaf_reg': 1,
 'actual_estimator__depth': 10}
```

Model Tuning: Metrics

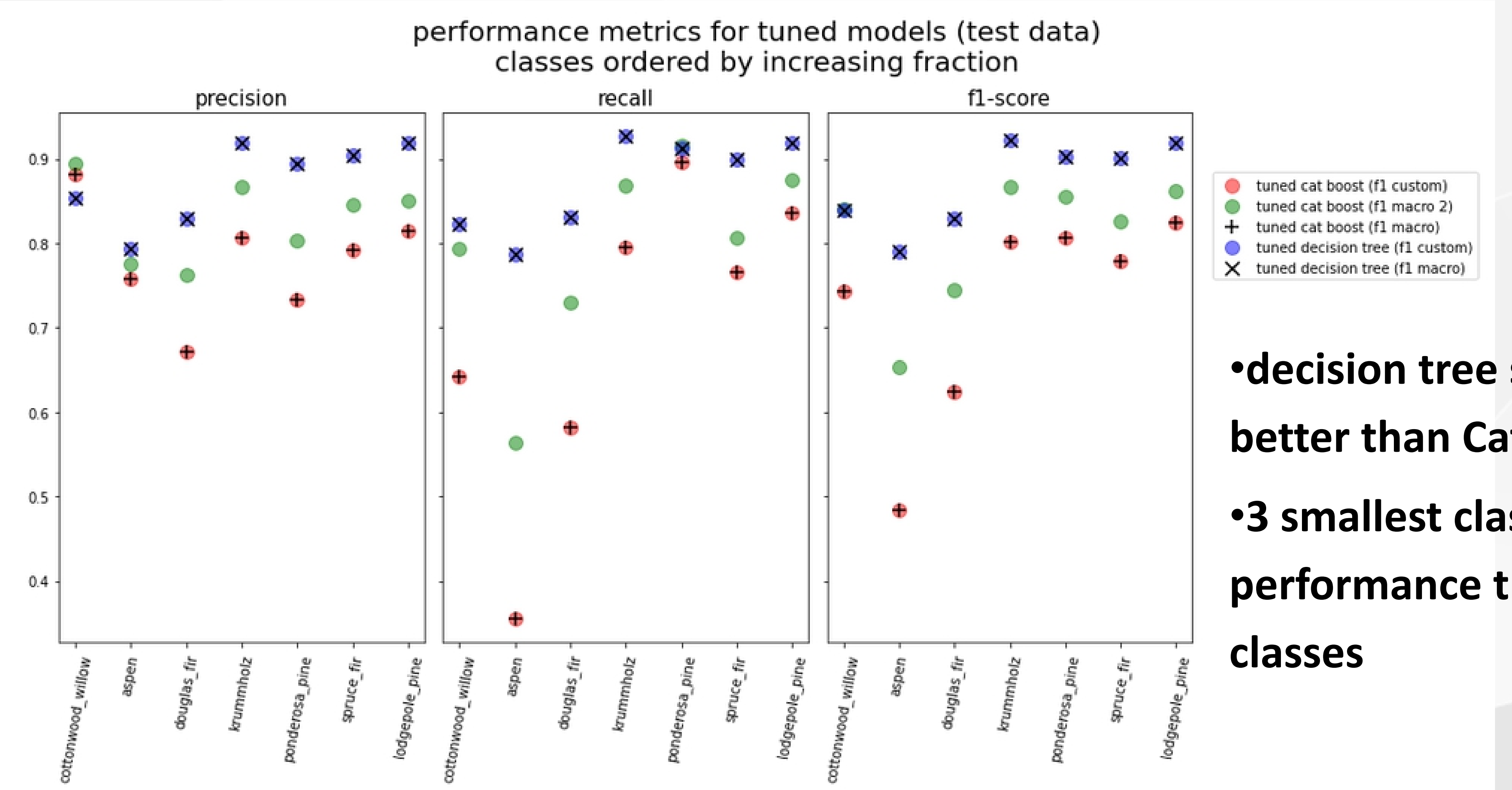
- f1 macro
  - ✓ average f1-score for all 7 classes, each class weight = 1
- f1 custom
  - ✓ average f1-score, 5 smallest classes weight = 3, 2 largest weight = 1

Model Tuning: Overall Results



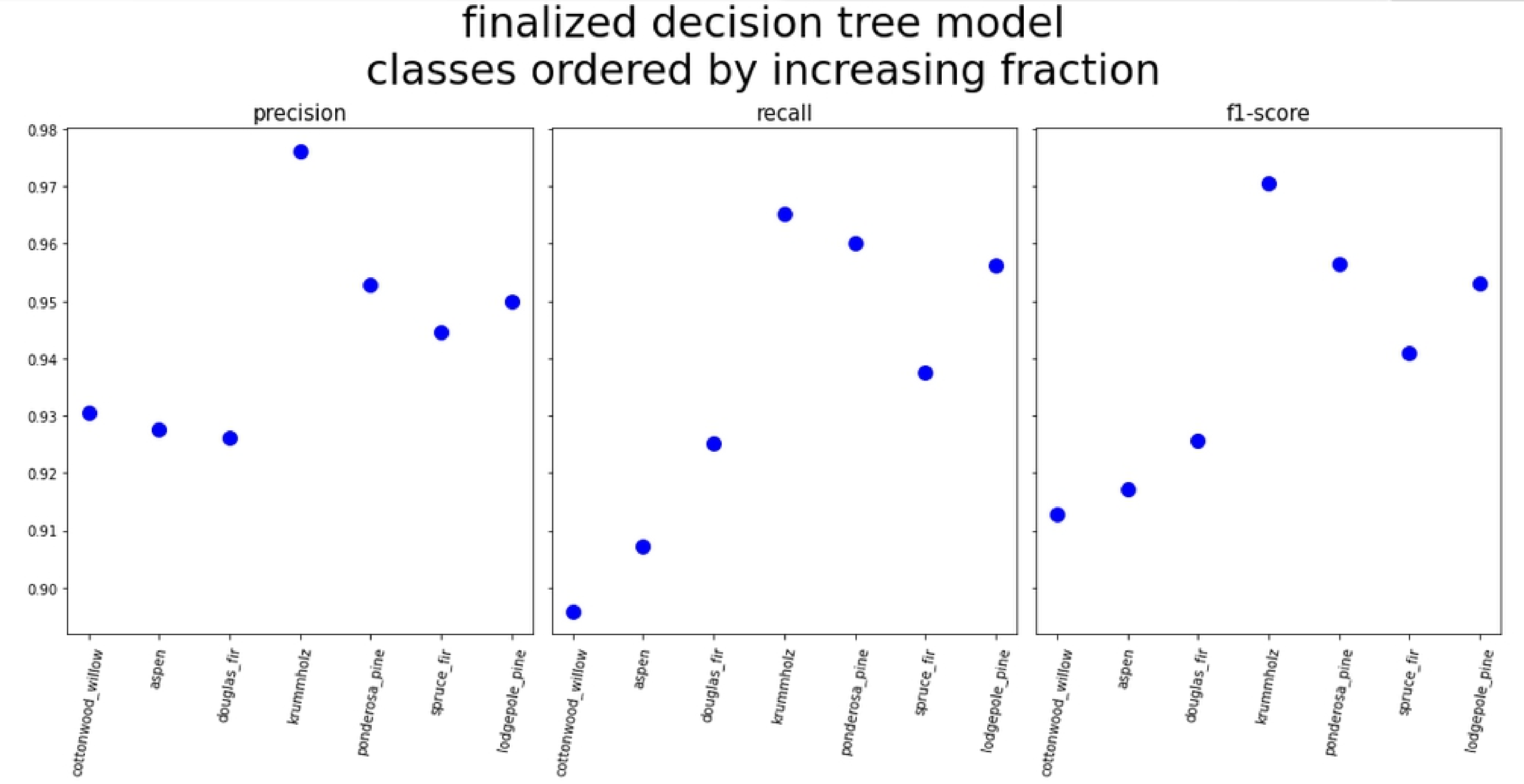
- optimization metric has no impact on results
- decision tree significantly better than CatBoost
- weighted metrics larger than macro metrics due to decreased emphasis on poorer performing small classes

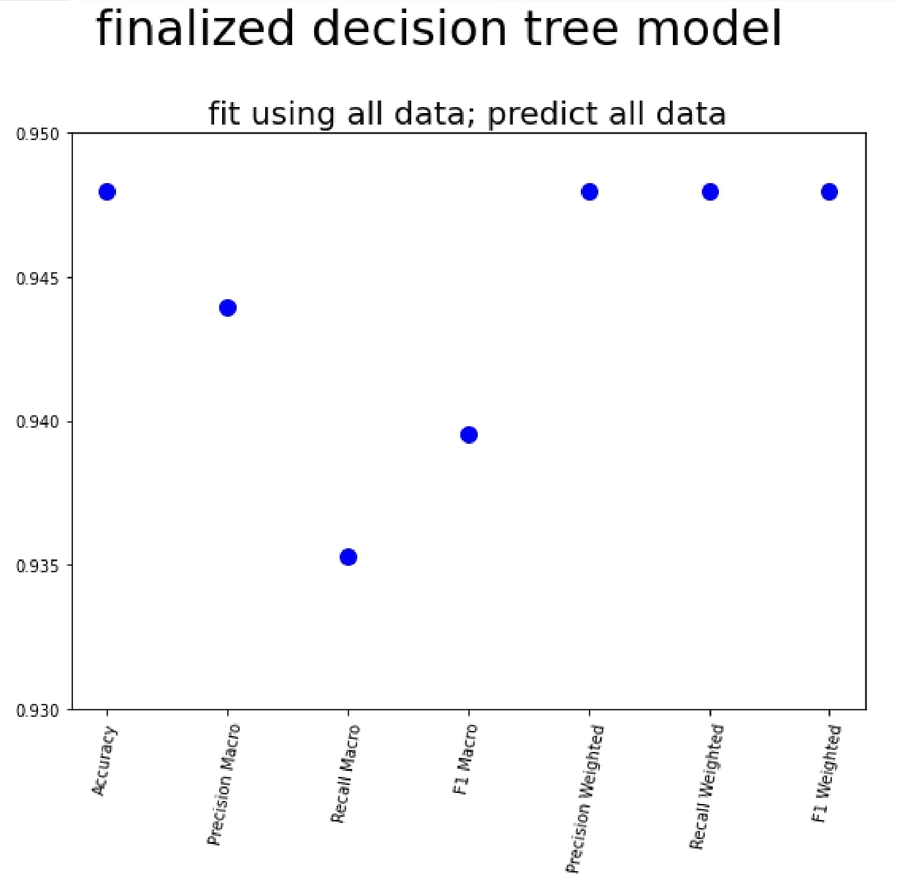
Model Tuning: Results by Class



- decision tree significantly better than CatBoost
- 3 smallest classes worse performance than other classes

Finalize Model





- **decision tree selected for finalization**
- **fit using all data**

Model Deployment

- work is in progress