## Chapter Goals

- Dealing with missing values in learning.
- Modeling, while avoiding over-fitting, by pruning (tree and rules)
- Industrial algorithms

# General Lab Guidlines

- Visualization.
- Modifiable code snippets.

## Further

• How is *cost complexity pruning* a post-pruning method, while a tree is built from scratch? Any library implementing the subtree raise method?

```
# Loading a dataset
# dataset names: "airline", "breast-cancer", "contact-lenses", "cpu",
"cpu.with.vendor", "credit-g", "diabetes", "glass", "hypothyroid",
"ionosphere", "iris.2D", "iris", "labor", "segment-challenge",
"segment-test", "soybean", "supermarket", "unbalanced", "vote",
"weather.nominal", "weather.numeric"
# df = pd.read_csv("data/weather.numeric.csv")
# instances = loader.load_file("data/weather.numeric.arff")
```

## Modules & Datasets Setup

#### # @title

!apt-get install default-jdk
!apt install libgraphviz-dev

Reading package lists... Done Building dependency tree... Done Reading state information... Done default-jdk is already the newest version (2:1.11-72build2). 0 upgraded, 0 newly installed, 0 to remove and 19 not upgraded. Reading package lists... Done Building dependency tree... Done Reading state information... Done libgraphviz-dev is already the newest version (2.42.2-6). 0 upgraded, 0 newly installed, 0 to remove and 19 not upgraded. # @title !pip install pygraphviz !pip install python-javabridge !pip install python-weka-wrapper3 !pip install sklearn-weka-plugin Requirement already satisfied: pygraphviz in /usr/local/lib/python3.10/dist-packages (1.11) Requirement already satisfied: python-javabridge in /usr/local/lib/python3.10/dist-packages (4.0.3) Requirement already satisfied: numpy>=1.20.1 in /usr/local/lib/python3.10/dist-packages (from python-javabridge) (1.23.5)Requirement already satisfied: python-weka-wrapper3 in /usr/local/lib/python3.10/dist-packages (0.2.14) Requirement already satisfied: python-javabridge>=4.0.0 in /usr/local/lib/python3.10/dist-packages (from python-weka-wrapper3) (4.0.3)Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from python-weka-wrapper3) (1.23.5)Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from python-weka-wrapper3) (23.2)Requirement already satisfied: configurable-objects in /usr/local/lib/python3.10/dist-packages (from python-weka-wrapper3) (0.0.1)Requirement already satisfied: simple-data-flow in /usr/local/lib/python3.10/dist-packages (from python-weka-wrapper3) (0.0.1)Requirement already satisfied: sklearn-weka-plugin in /usr/local/lib/python3.10/dist-packages (0.0.7) Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from sklearn-weka-plugin) (1.23.5)Requirement already satisfied: python-weka-wrapper3>=0.2.5 in /usr/local/lib/python3.10/dist-packages (from sklearn-weka-plugin) (0.2.14)Requirement already satisfied: sklearn in /usr/local/lib/python3.10/dist-packages (from sklearn-weka-plugin) (0.0.post10) Requirement already satisfied: python-javabridge>=4.0.0 in /usr/local/lib/python3.10/dist-packages (from python-wekawrapper3>=0.2.5->sklearn-weka-plugin) (4.0.3) Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from python-wekawrapper3>=0.2.5->sklearn-weka-plugin) (23.2) Requirement already satisfied: configurable-objects in /usr/local/lib/python3.10/dist-packages (from python-wekawrapper3>=0.2.5->sklearn-weka-plugin) (0.0.1)

```
Requirement already satisfied: simple-data-flow in
/usr/local/lib/python3.10/dist-packages (from python-weka-
wrapper3>=0.2.5->sklearn-weka-plugin) (0.0.1)
# @title
#Restart runtime after installing the dependencies
# @title
import os
import glob
import numpy as np
import pandas as pd
import weka.core.jvm as jvm
from weka.core import converters
import matplotlib.pyplot as plt
# @title
data dir = 'data'
# @title
#!rm -r weka
#!rm -r data
# @title
#ivm.stop()
jvm.start(packages=True)
DEBUG:weka.core.jvm:Adding bundled jars
DEBUG:weka.core.jvm:Classpath=['/usr/local/lib/python3.10/dist-
packages/javabridge/jars/rhino-1.7R4.jar',
'/usr/local/lib/python3.10/dist-packages/javabridge/jars/runnablegueue
.jar',
'/usr/local/lib/python3.10/dist-packages/javabridge/jars/cpython.jar'
'/usr/local/lib/python3.10/dist-packages/weka/lib/arpack_combined.jar'
, '/usr/local/lib/python3.10/dist-packages/weka/lib/mtj.jar',
'/usr/local/lib/python3.10/dist-packages/weka/lib/core.jar',
'/usr/local/lib/python3.10/dist-packages/weka/lib/weka.jar'
'/usr/local/lib/python3.10/dist-packages/weka/lib/python-weka-
wrapper.jar']
DEBUG:weka.core.jvm:MaxHeapSize=default
DEBUG:weka.core.jvm:Package support enabled
# @title
# Preparing Datasets
if not os.path.exists(data dir):
    !mkdir $data dir
    for file in ['airline.arff', 'breast-cancer.arff', 'contact-
lenses.arff', 'cpu.arff', 'cpu.with.vendor.arff', 'credit-g.arff'
'diabetes.arff', 'glass.arff', 'hypothyroid.arff', 'ionosphere.arff',
'iris.2D.arff', 'iris.arff', 'labor.arff', 'segment-challenge.arff',
'segment-test.arff', 'soybean.arff', 'supermarket.arff',
```

```
'unbalanced.arff', 'vote.arff', 'weather.nominal.arff',
'weather.numeric.arff',]:
        url =
'https://git.cms.waikato.ac.nz/weka/weka/-/raw/main/trunk/wekadocs/
data/' + file
        !wget -P $data dir $url
    loader =
converters.Loader(classname="weka.core.converters.ArffLoader")
    saver =
converters.Saver(classname="weka.core.converters.CSVSaver")
    for file in glob.glob(os.path.join(data dir, '*.arff')):
        dataset = loader.load file(file)
        filename, file extension = os.path.splitext(file)
        saver.save file(dataset, filename + '.csv')
    !wget -P $data dir https://raw.githubusercontent.com/Rytuo/ITMO-
CT/master/Others/AdvancedML/data/OpenML/data/1438.arff
    !rm -r weka
import weka.core.packages as packages
packages.install package("simpleEducationalLearningSchemes")
packages.install package("generalizedSequentialPatterns")
packages.install package("classAssociationRules")
from weka.core.converters import Loader
loader = Loader(classname="weka.core.converters.ArffLoader")
```

## 6.1 Decision Trees

### Numeric Attributes

```
# Discretization: Converting numeric to categorical.
import pandas as pd
sr = pd.Series([10, 20, 15, 5, 30, 25, 7, 12, 17, 22])
binEdges = [0, 10, 20, 30]
binLabels = ['Low', 'Medium', 'High']
categorized sr = pd.cut(sr, bins=binEdges, labels=binLabels)
categorized sr
0
        Low
1
     Medium
2
     Medium
3
        Low
4
       High
```

```
5 High
6 Low
7 Medium
8 Medium
9 High
dtype: category
Categories (3, object): ['Low' < 'Medium' < 'High']</pre>
```

**Task 1.1** Experiment with some dataset, and intuitively decide the number of labels.

**Task 1.2** Think of a general heuristic/strategy to optimize the number of labels.

### **Missing Values**

```
# Use these probabilities to classify the row with missing value
# Assume the row has some label, then multiply the classification
result by the corresponding probability
# Aggregate all classification answers
import pandas as pd
import random
# Create a sample DataFrame with missing values
df = pd.DataFrame({
    "F1": [random.choice([1, 2, 3, None]) for _ in range(30)],
    "F2": [random.choice(['A', 'B', 'C', None]) for _ in range(30)]
  }
)
# Function to compute sums and probabilities
def probabilitiesOfMissing(df, featureStr):
    # Drop rows with missing values in the feature
    df no missing = df.dropna(subset=[featureStr])
    # Calculate the sum of distinct values for the feature
    sums = df no missing[featureStr].value counts()
    # Calculate the total sum
    total sum = sums.sum()
    # Calculate the probability for each distinct value
    probabilities = sums / total sum
    return sums, probabilities
# Compute sums and probabilities for Feature 2
sums2, probabilities2 = probabilitiesOfMissing(df, "F2")
print("Probabilities for F2:")
print(probabilities2)
```

```
Probabilities for F2:
A 0.476190
C 0.380952
B 0.142857
Name: F2, dtype: float64
```

**Task 1.3** Contrast this heuristic with dropping null values and with substituting missings by the average. Try to quantify your conclusions on some dataset.

### Pruning

```
# cost complexity pruning
# reference:
https://scikit-learn.org/stable/auto examples/tree/plot cost complexit
y pruning.html
from sklearn.tree import DecisionTreeClassifier
from sklearn.datasets import load iris
from sklearn.model selection import train test split
# Load the Iris dataset and split it into training and testing sets
iris = load iris(); X = iris.data; y = iris.target
X train, X test, y train, y test = train test split(X, y,
test_size=0.3, random_state=42)
# Train a decision tree classifier
clf = DecisionTreeClassifier(random state=42)
clf.fit(X train, y train)
# Prune the existing decision tree using the prune path method
path = clf.cost complexity pruning path(X train, y train)
ccp alphas, impurities = path.ccp alphas, path.impurities
# Choose the alpha value for pruning
alpha toPrune = 0.03 # You can adjust this value based on your data
# Prune the tree using the chosen alpha value
prunedTree = DecisionTreeClassifier(ccp_alpha=alpha_toPrune,
random state=42)
prunedTree.fit(X train, y train)
Original Decision Tree Accuracy: 1.00
Pruned Decision Tree Accuracy: 0.98
# Original Tree
import matplotlib.pyplot as plt
from sklearn.tree import plot tree
plt.figure(figsize=(15, 10))
```

```
plot_tree(clf, filled=True, feature_names=iris.feature_names,
class_names=iris.target_names)
plt.show()
```



#### # Pruned Tree

```
import matplotlib.pyplot as plt
from sklearn.tree import plot_tree
```

```
# Plot the decision tree
plot_tree(prunedTree, filled=True, feature_names=iris.feature_names,
class_names=iris.target_names)
plt.show()
```



**Task 1.4** Construct couple of decision trees, and compare accuracies vs depth or nodes number. Through a visualization of these two measures, Guess the optimal tree.

# 6.2 Classification Rules

## Criteria for Choosing Tests

**Task 2.1** Refer back to Lab 04, Pick-up a rule-based algorithm, and assess error rate of a rule of your choice. Alternatively, You can use the code snippet of *Generating Good Rules* section.

## Missing Values, Numeric Attributes

**Task 2.2** Refer back to Lab 04, Pick-up a rule-based algorithm, and some instance of your choice. Remove a feature from the instance, then re-classify it. You can use the code snippet of *Generating Good Rules* to aid you in analysis.

## Generating Good Rules

```
# Create a dummy DataFrame with random data
import pandas as pd
import random
df = pd.DataFrame({
    "F1": [random.choice(['A', 'B', 'C']) for _ in range(10)],
```

```
"F2": [random.choice(['X', 'Y', 'Z']) for _ in range(10)],
    "class": [random.choice([0, 1]) for _ in range(10)]
})
Coverage of the rule for F1 = A: 5 rows
Accuracy of the rule: 40.00%
# Coverate and Accuracy of a hand-crafted rule
import numpy as np
# Define a rule. If F1 = A, return 0
def myRule1(row):
  if row["F1"] == "A":
    return 0
  return np.NaN
# instances the rule is applicable on
# apply predicted class by our rule
instancesCovered = df.apply(myRule1,
axis=1).dropna().to frame(name="predictedClass")
# join data's class (ground truth)
instancesCovered = instancesCovered.join(df["class"])
# Coverage: Number of instances the rule is applicable on
ruleCoverage = len( instancesCovered )
# Number of correctly classified instances
count CorrectlyClassified = (instancesCovered["predictedClass"] ==
instancesCovered["class"]).value counts()[True]
# Accuracy: Number of correctly classified instances, out of covered
instances
ruleAccuracy = count_CorrectlyClassified / ruleCoverage
print(f"Coverage: {ruleCoverage}")
print(f"Accuracy: {ruleAccuracy:.2%}")
Coverage: 5
Accuracy: 60.00%
```

Task 2.3 Modify myRule1 function to increase coverage and accuracy.

**Task 2.4** Partition the dataset into *training* and *testing*. Apply *task 2.4* on *training* data without seeing *testing*. Compute accuracy and measures on *testing*. Note since data were randomly generated, You shouldn't expect rules well-generalizing

## Using Global Optimization

```
# train model
# from weka.classifiers import Classifier
# cls = Classifier(classname="weka.classifiers.rules.JRip")
# cls.build_classifier(instances)
```

Task 2.5 Refer back to Lab 04, Use the above code snipper on the same template of the lab.

### **Rules with Exceptions**

**Task 2.6** Refer back to Lab 04, on XOR classifier. Modify the code so that it has a default output with exceptions. Outputs must be equivalent to the original code.

# 6.3 Association Rules

Sources

- FP-Growth by Weka
- Generalized Sequential Petterns by Weka
- CBA by weka

## **Generalized Sequential Petterns**

```
# weather nominal dataset
instances = loader.load file("data/weather.nominal.arff")
instances
@relation weather.symbolic
@attribute outlook {sunny,overcast,rainy}
@attribute temperature {hot,mild,cool}
@attribute humidity {high,normal}
@attribute windy {TRUE,FALSE}
@attribute play {yes,no}
@data
sunny,hot,high,FALSE,no
sunny,hot,high,TRUE,no
overcast, hot, high, FALSE, yes
rainy,mild,high,FALSE,yes
rainy,cool,normal,FALSE,yes
rainy,cool,normal,TRUE,no
overcast, cool, normal, TRUE, yes
sunny,mild,high,FALSE,no
sunny,cool,normal,FALSE,yes
rainy,mild,normal,FALSE,yes
sunny,mild,normal,TRUE,yes
```

```
overcast, mild, high, TRUE, yes
overcast, hot, normal, FALSE, yes
rainy,mild,high,TRUE,no
# train model
from weka.associations import Associator
associator =
Associator(classname="weka.associations.GeneralizedSequentialPatterns"
)
associator.build associations(instances)
# model inspection
associator.description
<bound method OptionHandler.description of
Apriori
_____
Minimum support: 0.15 (2 instances)
Minimum metric <confidence>: 0.9
Number of cycles performed: 17
Generated sets of large itemsets:
Size of set of large itemsets L(1): 12
Size of set of large itemsets L(2): 47
Size of set of large itemsets L(3): 39
Size of set of large itemsets L(4): 6
Best rules found:
1. outlook=overcast 4 ==> play=yes 4 <conf:(1)> lift:(1.56) lev:
(0.1) [1] conv:(1.43)
2. temperature=cool 4 ==> humidity=normal 4 <conf:(1)> lift:(2)
lev:(0.14) [2] conv:(2)
3. humidity=normal windy=FALSE 4 ==> play=yes 4 <conf:(1)> lift:
(1.56) lev:(0.1) [1] conv:(1.43)
4. outlook=sunny play=no 3 ==> humidity=high 3 <conf:(1)> lift:(2)
lev:(0.11) [1] conv:(1.5)
5. outlook=sunny humidity=high 3 ==> play=no 3 <conf:(1)> lift:
(2.8) lev:(0.14) [1] conv:(1.93)
6. outlook=rainy play=yes 3 ==> windy=FALSE 3 <conf:(1)> lift:
(1.75) lev:(0.09) [1] conv:(1.29)
7. outlook=rainy windy=FALSE 3 ==> play=yes 3 <conf:(1)> lift:
(1.56) lev:(0.08) [1] conv:(1.07)
8. temperature=cool play=yes 3 ==> humidity=normal 3 <conf:(1)>
lift:(2) lev:(0.11) [1] conv:(1.5)
 9. outlook=sunny temperature=hot 2 ==> humidity=high 2 <conf:(1)>
```

```
lift:(2) lev:(0.07) [1] conv:(1)
10. temperature=hot play=no 2 ==> outlook=sunny 2 <conf:(1)> lift:
(2.8) lev:(0.09) [1] conv:(1.29)
>
```