



Classification of Medical Supply Shipments

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Statement and Project Goal

- Dataset provides information on shipments of antiretroviral drugs and HIV lab supplies to various countries
- Provides valuable insights into global spending on health commodities
- Proper categorization of key attributes can improve supply chain efficiency by reducing manual errors and optimizing logistics workflows

We are predicting the sub-classification of each shipment.



Dataset Description

Possible sub-classifications and incidence rate:

- HIV Test (1,567)
- HIV Test - Ancillary (161)
- Pediatric (1,955)
- Adult (6,595)
- ACT (16)
- Malaria (30)

10,325 shipments with 32 attributes (Not including class)

Majority of shipments - Adult, Pediatric, HIV Test

Heavily skewed



Pre-Processing Steps

1. WEKA Preparation
2. Missing Value Correction
3. Hidden Value Correction
4. Removing Redundant and Derived Columns
5. Normalization by Scaling
6. Stratified Sampling

Weka Preparation

Côte d'Ivoire

item description

HIV, Reveal G3 Rapi

```
import pandas as pd

df = pd.read_csv('Supply_Chain_Shipment_Pricing_Dataset_New.csv', quotechar="")

columns = ["country", "vendor", "item description", "molecule/test type", "manufacturing site"]

for column in columns:
    for val in df[column]:
        print(val)
        if "," in val:
            newVal = val.replace(",", "")
            df[column] = df[column].replace(val, newVal)

df.to_csv('Supply_Chain_Shipment_Pricing_Dataset_New_WithoutCommas.csv', index=False)
```

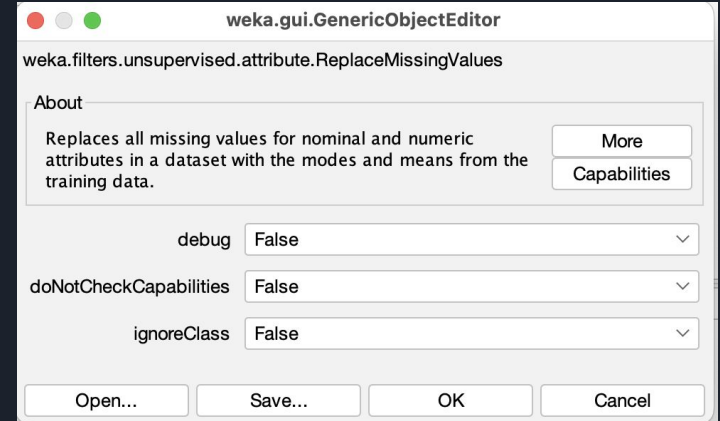


Missing Value Correction

‘shipment mode’ → 360 missing values

‘dosage’ → 1,736 missing values

‘line item insurance field (usd)’ → 287 missing values



Hidden Value Correction

Replaces “Date Not
Captured” with mode value
of columns

po sent to vendor da
Date Not Captured
Date Not Captured
Date Not Captured

See ASN-93 (ID#:1281)

```
import pandas as pd

df = pd.read_csv('Supply_Chain_Shipment_Pricing_Dataset_New_WithoutCommas_DateNotCapFixed.csv', quotechar="''")

columns = ["weight (kilograms)", "freight cost (usd)"]

for column in columns:
    for val in df[column]:
        if "See" in val:
            id_look_at = int(val.split("ID#:")[-1])
            result_value = df.loc[df.index[df['id'] == id_look_at].tolist()[0], column]
            df[column] = df[column].replace(val, result_value)

df.to_csv('Supply_Chain_Shipment_Pricing_Dataset_New_WithoutCommas_DateFixed_WeightFreightFixed.csv', index=False)
```

Replaces “Weight Captured
Separately” and “Freight
Included in Commodity Cost”
with the median value of
columns

Freight Included in Commodity Cost



Removing Redundant and Derived Columns

Unique values for every instance:

- 'Id'
- 'po / so #'
- 'asn/dn #'

Derived columns:

- 'vendor'
- 'item description'
- 'product group'



Normalization by Scaling and Stratified Sampling

Numeric Attributes in Dataset:

- 'unit of measure (per pack)'
- 'line item quantity'
- 'line item value'
- 'pack price'
- 'unit price'
- 'weight (kilograms)'
- 'freight cost (usd)'
- 'line item insurance (usd)'

Scaled on a range from 1 - 1000 (Large due to outliers)

40% Stratified Sample

10,325 instances (shipments) got converted into 4,197 instances

New sub-classification counts:

- Adult - 6,595 → 2,638
- Pediatric - 1,955 → 391
- 'HIV test' - 1,567 → 627
- 'HIV test - Ancillary' - 161 → 64
- 'ACT' - 16 → 6
- 'Malaria' - 30 → 12



Attribute Selection Methods

`ReliefFAttributeEval` → Assesses the importance of an attribute by repeatedly sampling instances and comparing the attribute's value with the nearest instance from both the same class and a different class

`CorrelationAttributeEval` → Assesses the importance of an attribute by calculating the Pearson correlation between the attribute and the class

`GainRatioAttributeEval` → Assesses the significance of an attribute by calculating the gain ratio about the class

`CfsSubsetEval` → Determines the value of a subset of attributes by considering both the individual predictive strength of each feature and the redundancy among them

ReliefFAttributeEval

Arbitrary cutoff value of ≤ 0.1

Ranked attributes:

0.79618	16	dosage form
0.62659	13	molecule/test type
0.62111	15	dosage
0.504	14	brand
0.46488	22	manufacturing site
0.2416	1	project code
0.22229	3	country
0.14606	2	pq #
0.14515	8	pq first sent to client date
0.08989	10	scheduled delivery date
0.08486	12	delivery recorded date
0.08381	11	delivered to client date
0.0654	9	po sent to vendor date
0.06196	6	vendor inco term
0.05561	17	unit of measure (per pack)
0.05353	7	shipment mode
0.02773	21	unit price
0.01723	20	pack price
0.00941	26	line item insurance (usd)
0.00941	5	fulfill via
0.00879	18	line item quantity
0.00757	19	line item value
0.00685	25	freight cost (usd)
0.00195	24	weight (kilograms)
0.00179	4	managed by
-0.0256	23	first line designation

Selected attributes: 16,13,15,14,22,1,3,2,8,10,12,11,9,6,17,7,21,20,26,5,18,19,25,24,4,23 : 26

CorrelationAttributeEval

Arbitrary cutoff value of ≤ 0.1

Ranked attributes:

0.3658	16	dosage form
0.3296	17	unit of measure (per pack)
0.3294	14	brand
0.2534	5	fulfill via
0.2526	20	pack price
0.2416	6	vendor inco term
0.2194	18	line item quantity
0.2006	21	unit price
0.1991	15	dosage
0.1755	7	shipment mode
0.1702	26	line item insurance (usd)
0.165	19	line item value
0.1481	9	po sent to vendor date
0.1403	24	weight (kilograms)
0.1349	22	manufacturing site
0.1133	23	first line designation
0.0934	13	molecule/test type
0.0643	25	freight cost (usd)
0.0596	3	country
0.0528	1	project code
0.0265	8	pq first sent to client date
0.0262	2	pq #
0.0168	10	scheduled delivery date
0.0164	4	managed by
0.0161	11	delivered to client date
0.016	12	delivery recorded date

Selected attributes: 16,17,14,5,20,6,18,21,15,7,26,19,9,24,22,23,13,25,3,1,8,2,10,4,11,12 : 26

GainRatioAttributeEval

Arbitrary cutoff value of ≤ 0.1

Ranked attributes:

0.4548	16 dosage form
0.3668	17 unit of measure (per pack)
0.3509	14 brand
0.2455	21 unit price
0.2317	15 dosage
0.216	22 manufacturing site
0.192	20 pack price
0.1848	13 molecule/test type
0.1585	6 vendor inco term
0.1375	9 po sent to vendor date
0.1338	5 fulfill via
0.1011	2 pq #
0.0861	8 pq first sent to client date
0.086	1 project code
0.083	10 scheduled delivery date
0.0818	11 delivered to client date
0.0811	12 delivery recorded date
0.0789	7 shipment mode
0.0781	18 line item quantity
0.0723	19 line item value
0.0651	26 line item insurance (usd)
0.061	24 weight (kilograms)
0.0564	3 country
0.0413	23 first line designation
0.0312	4 managed by
0.0296	25 freight cost (usd)

Selected attributes: 16,17,14,21,15,22,20,13,6,9,5,2,8,1,10,11,12,7,18,19,26,24,3,23,4,25 : 26



CfsSubsetEval

=== Attribute Selection on all input data ===

Search Method:

Best first.

Start set: no attributes

Search direction: forward

Stale search after 5 node expansions

Total number of subsets evaluated: 162

Merit of best subset found: 0.618

Attribute Subset Evaluator (supervised, Class (nominal): 27 sub classification):

CFS Subset Evaluator

Including locally predictive attributes

Selected attributes: 5,16,17,23 : 4

fulfill via

dosage form

unit of measure (per pack)

first line designation



Personal Attribute Selection

Removed Attributes:

- 'project code'
- 'pq #'
- 'managed by'
- 'fulfill via'
- 'first line designation'
- 'pq first sent to client date'
- 'po sent to vendor date'
- 'scheduled delivery date'
- 'delivered to client date'
- 'delivery recorded date'



Train/Validation/Test Split

70/15/15 split

Training → 2,890 instances

Validation → 619 instances

Testing → 620 instances

```
import pandas as pd
from sklearn.model_selection import train_test_split

folders = ['ReliefFAAttributeEvalData', 'GainRatioAttributeEvalData',
           'CorrelationAttributeEvalData', 'CfsSubsetEvalData', 'PersonalAttributeData']
files = ['ReliefSampledDataset.csv', 'GainSampledDataset.csv',
         'CorrelationSampledDataset.csv', 'CfsSampledDataset.csv', 'PersonalSampledDataset.csv']

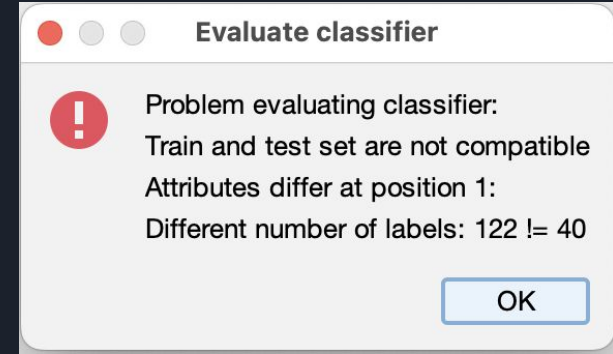
for idx, folder in enumerate(folders):
    df = pd.read_csv(f'{folder}/{files[idx]}')
    x = df.iloc[:, :-1]
    y = df.iloc[:, -1]
    X_train, X_temp, y_train, y_temp = train_test_split(x, y, test_size=0.30, stratify=y, random_state=42)
    X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.50, stratify=y_temp, random_state=42)
    train = pd.concat([X_train, y_train], axis=1)
    val = pd.concat([X_val, y_val], axis=1)
    test = pd.concat([X_test, y_test], axis=1)
    train.to_csv(f'{folder}/Train.csv', index=False)
    val.to_csv(f'{folder}/Val.csv', index=False)
    test.to_csv(f'{folder}/Test.csv', index=False)
```


Data Compatibility

Train and test datasets had different attribute labels, leading to errors

Solution Implemented:

- Converted each CSV file into an ARFF file
- Opened the FullSampledDataset ARFF file for each attribute selection method
- Copied data from the “@attribute” section down to the “@data” signature
- Pasted this data into the train and test ARFF files for the attribute selection



Top:

```
GainSampledDataset.arff
@relation GainSampledDataset

@attribute "pg #" {"Pre-PQ
Process",FPQ-4487,FPQ-15569,FPQ-8264,FPQ-6501,FPQ-7328,FPQ-14470,FPQ-13774,FPQ-12154,FPQ-6991,FP
Q-4167,FPQ-6252,FPQ-10606,FPQ-7858,FPQ-11043,FPQ-12623,FPQ-11539,FPQ-11623,FPQ-15006,FPQ-10537,FP
Q-13669,FPQ-9807,FPQ-9038,FPQ-10504,FPQ-10369,FPQ-10128,FPQ-14100,FPQ-12359,FPQ-15618,FPQ-13602
,FPQ-8527,FPQ-12456,FPQ-7521,FPQ-7553,FPQ-6936,FPQ-11295,FPQ-10396,FPQ-10249,FPQ-13790,FPQ-12273
,FPQ-10349,FPQ-12518,FPQ-14236,FPQ-14305,FPQ-8261,FPQ-4032,FPQ-3885,FPQ-6983,FPQ-10765,FPQ-15504
,FPQ-4587,FPQ-16474,FPQ-5613,FPQ-14253,FPQ-11919,FPQ-14694,FPQ-8929,FPQ-12252,FPQ-14995,FPQ-1004
6,FPQ-16001,FPQ-10785,FPQ-14713,FPQ-12443,FPQ-13125,FPQ-10907,FPQ-4891,FPQ-9275,FPQ-8053,FPQ-921
1,FPQ-14254,FPQ-5293,FPQ-11440,FPQ-10619,FPQ-15928,FPQ-4157,FPQ-15102,FPQ-4250,FPQ-10187,FPQ-126
86,FPQ-3096,FPQ-6263,FPQ-8135,FPQ-8209,FPQ-12134,FPQ-8116,FPQ-7438,FPQ-9894,FPQ-8611,FPQ-12570,FP
Q-12745,FPQ-14357,FPQ-9568,FPQ-5495,FPQ-12634,FPQ-4867,FPQ-11294,FPQ-15314,FPQ-7996,FPQ-8396,FP
Q-10104,FPQ-16302,FPQ-10018,FPQ-12197,FPQ-13998,FPQ-13874,FPQ-7987,FPQ-7909,FPQ-12041,FPQ-11881,
FPQ-9180,FPQ-15323,FPQ-10435,FPQ-9530,FPQ-14654,FPQ-9823,FPQ-11161,FPQ-9454,FPQ-3976,FPQ-6171,FP
Q-16329,FPQ-13548,FPQ-12845,FPQ-14628,FPQ-11304,FPQ-4207,FPQ-7908,FPQ-10314,FPQ-11783,FPQ-9231,FP
Q-3212,FPQ-7439,FPQ-16815,FPQ-4068,FPQ-10880,FPQ-12812,FPQ-5209,FPQ-5792,FPQ-4692,FPQ-15065,FPQ
-6037,FPQ-6119,FPQ-12073,FPQ-8263,FPQ-14930,FPQ-14294,FPQ-8315,FPQ-11390,FPQ-7807,FPQ-8071,FPQ-4
691,FPQ-14827,FPQ-12458,FPQ-9098,FPQ-7684,FPQ-11754,FPQ-13741,FPQ-15346,FPQ-8210,FPQ-16480,FPQ-1
3045,FPQ-12180,FPQ-4730,FPQ-5203,FPQ-12003,FPQ-12016,FPQ-5725,FPQ-4073,FPQ-8117,FPQ-3813,FPQ-010
```

Bottom:

```
USA',ABBSP,'Roche Madrid','MSD Midrand J burg SA','Guilin OSD site No 17 China','Micro Labs
Mosur India','MediTab (for Cipla) Daman IN','Micro Labs Ltd. (Brown & Burk) India','Weifa A.S.
Hausmannst. 6 P.O. Box 9113 Grønland 0133 Oslo Norway','ABBVIE Labs North Chicago US','GSK
Mississauga (Canada)','MSD Manati Puerto Rico (USA)','GSK Barnard Castle UK','BMS Evansville
US','GSK Crawley','Boehringer Ingelheim Roxane US'}
@attribute "sub classification" {"HIV test - Ancillary','HIV test',ACT,Adult,Malaria,Pediatric}

@data
'Pre-PQ Process','From RDC','N/A - From RDC','N/A - From RDC','HIV Lancet Safety for HIV Test
kits 100 Pcs',Generic,300mg,'Test kit - Ancillary',99.099099,0.007431,0,'Inverness Japan','HIV
test - Ancillary'
FPQ-4487,'Direct Drop',EXW,11/13/09,'HIV 1 Uni-Gold Recombigen HIV Control Vial 2 x 0.5 ml',Uni-
Gold,300mg,'Test kit - Ancillary',1.001001,23.037365,64.94867,'Trinity Biotech Plc','HIV test -
Ancillary'
FPQ-15569,'Direct Drop',EXW,2/20/15,'Chase Buffer Determine 100 Tests 2.5ml x 1
Vial',Determine,300mg,'Test kit - Ancillary',0,3.715704,20.951184,'Alere Medical Co. Ltd.','HIV
test - Ancillary'
```



Models

`bayes.NaiveBayes` → Calculates the probability of a class based on feature independence assumptions and determines numeric estimator precision values from the training data

`trees.J48` → Implements the C4.5 decision tree algorithm, which can generate pruned or unpruned decision trees

`rules.OneR` → Creates a classifier using the One Rule (1R) algorithm, which selects a single attribute that best predicts the target variable

`rules.RandomForest` → Builds a Random Forest, an ensemble of decision trees where each tree is trained on a random subset of the data and features

Results - Accuracy Percentage

		Attribute Selection Methods				
		ReliefF	Correlation	GainRatio	CfsSubset	Personal Selection
Models	NaiveBayes	96.61	85	94.19	92.74	81.94
	J48	99.68	99.19	99.35	97.26	99.35
	OneR	93.23	93.23	93.23	93.23	93.23
	RandomForest	99.19	99.68	99.68	97.58	99.68

Results - Best Model Error Comparison

	Attribute Selection Method & Model			
	ReliefF & J48	Correlation & Random Forest	Gain Ratio & Random Forest	Personal Selection & Random Forest
Mean Absolute Error	0.0018	0.01	0.0128	0.0053
Root Mean Squared Error	0.0328	0.0429	0.0486	0.0372
Relative Absolute Error (%)	1.0035	5.6323	7.187	2.9657
Root Relative Squared Error (%)	11.0072	14.4085	16.2953	12.4942



Analysis

- All of best models misclassified same two instances
 - Singular 'ACT' point
 - One out of two 'Malaria' points misclassified
- Attribute found in all 5 selection methods → 'dosage form'
 - Good indicator of which type of shipment it is
 - Certain types of dosage are indicative of pediatric or adult shipments



Conclusion

Best Performance: ReliefFAttributeEval selection method, combined with the J48 algorithm

Outperformed other models regarding:

- Root Mean Squared Error
- Relative Absolute Error
- Root Relative Squared Error
- Mean Absolute Error

Good balance of performance considering underrepresented sub-classifications



How to Reproduce Our Best Model

1. Preprocessing
 - a. Weka Preparation
 - b. Missing and Hidden Value Correction
 - c. Removing Redundant and Derived Columns
 - d. Normalization by Scaling
 - e. Stratified Sampling
 - f. Train/Val/Test Split
2. Attribute Selection
 - a. Conduct ReliefFAttributeEval
3. Classification
 - a. J48



Next Steps and Future Studies

Building dataset with more “ACT” and “Malaria”

Further research regarding more advanced ML techniques for highly imbalanced datasets



References

Dataset:

- [1] Palacios, M. (2021). Supply Chain Shipment Pricing Dataset [Dataset]. In Data.gov. Doby.
<https://catalog.data.gov/dataset/supply-chain-shipment-pricing-data-07d29>

Model Information Links:

- [2] <https://weka.sourceforge.io/doc.stable/weka/classifiers/bayes/NaiveBayes.html>
[3] <https://weka.sourceforge.io/doc.stable/weka/classifiers/trees/J48.html>
[4] <https://weka.sourceforge.io/doc.dev/weka/classifiers/rules/OneR.html>
[5] <https://weka.sourceforge.io/doc.dev/weka/classifiers/trees/RandomForest.html>