20_ethics

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CPSC 330
Applied Machine Learning

1 Lecture 20: Ethics

UBC 2022 Summer

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1.1 Imports

[1]:
```
import os
import sys

import IPython
import matplotlib.pyplot as plt
import mglearn
import numpy as np
import pandas as pd
from IPython.display import HTML, display
from sklearn.dummy import DummyClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, f1_score, precision_score,␣
↪recall_score
from sklearn.model_selection import cross_val_score, cross_validate,␣
↪train_test_split
from sklearn.pipeline import Pipeline, make_pipeline
from sklearn.preprocessing import StandardScaler

%matplotlib inline
pd.set_option("display.max_colwidth", 200)

from IPython.display import Image
```

1.2 Lecture plan

- Guest lecture by Joel Ostblom (~40 mins to 1 hour)
  - The slides will be made available soon.
- ML fairness activity (~15 mins)

1.3 ML fairness activity

AI/ML systems can give the illusion of objectivity as they are derived from seemingly unbiased data & algorithm. However, human are inherently biased and AI/ML systems, if not carefully evaluated, can even further amplify the existing inequities and systemic bias in our society.

How do we make sure our AI/ML systems are *fair*? Which metrics can we use to quatify 'fairness' in AI/ML systems?

Let's examine this on the adult census data set.

[2]:
```
census_df = pd.read_csv("data/adult.csv")
census_df.shape
```

[2]:
```
(32561, 15)
```

[3]:
```
train_df, test_df = train_test_split(census_df, test_size=0.4, random_state=42)
```

[4]:
```
train_df
```

[4]:
```
        age    workclass  fnlwgt     education  education.num  \
25823    36      Private  245521       7th-8th              4
10274    26      Private  134287     Assoc-voc             11
27652    25    Local-gov  109526       HS-grad              9
13941    23      Private  131275       HS-grad              9
31384    27      Private  193122       HS-grad              9
…      …            …       …             …              …
29802    25      Private  410240       HS-grad              9
5390     51      Private  146767     Assoc-voc             11
860      55  Federal-gov  238192       HS-grad              9
15795    41      Private  154076  Some-college             10
23654    22      Private  162667       HS-grad              9

              marital.status         occupation relationship                race  \
25823  Married-civ-spouse    Farming-fishing      Husband               White
10274       Never-married              Sales    Own-child               White
27652  Married-civ-spouse       Craft-repair      Husband               White
13941       Never-married       Craft-repair    Own-child  Amer-Indian-Eskimo
31384  Married-civ-spouse  Machine-op-inspct      Husband               White
…                      …                  …            …                   …
29802       Never-married       Craft-repair    Own-child               White
5390   Married-civ-spouse     Prof-specialty      Husband               White
860    Married-civ-spouse       Tech-support      Husband               White
15795  Married-civ-spouse       Adm-clerical      Husband               White
```

```
23654       Never-married  Handlers-cleaners    Own-child              White

          sex  capital.gain  capital.loss  hours.per.week native.country  \
25823    Male             0             0              35         Mexico
10274  Female             0             0              35  United-States
27652    Male             0             0              38  United-States
13941    Male             0             0              40  United-States
31384    Male             0             0              40  United-States
…         …           …             …               …             …
29802    Male             0             0              40  United-States
5390     Male             0             0              40  United-States
860      Male             0          1887              40  United-States
15795    Male             0             0              50  United-States
23654    Male             0             0              50       Portugal

      income
25823  <=50K
10274  <=50K
27652  <=50K
13941  <=50K
31384  <=50K
…        …
29802  <=50K
5390    >50K
860     >50K
15795   >50K
23654  <=50K

[19536 rows x 15 columns]
```

[5]:
```python
train_df_nan = train_df.replace("?", np.nan)
test_df_nan = test_df.replace("?", np.nan)
train_df_nan.shape
```

[5]: (19536, 15)

[6]:
```python
# Let's identify numeric and categorical features

numeric_features = [
    "age",
    "fnlwgt",
    "capital.gain",
    "capital.loss",
    "hours.per.week",
]

categorical_features = [
```

```python
    "workclass",
    "marital.status",
    "occupation",
    "relationship",
    # "race",
    "native.country",
]

ordinal_features = ["education"]
binary_features = [
    "sex"
]  # Not binary in general but in this particular dataset it seems to have only␣
 ↪two possible values
drop_features = ["education.num"]
target = "income"
```

[7]:
```python
train_df["education"].unique()
```

[7]:
```
array(['7th-8th', 'Assoc-voc', 'HS-grad', 'Bachelors', 'Some-college',
       '10th', '11th', 'Prof-school', '12th', '5th-6th', 'Masters',
       'Assoc-acdm', '9th', 'Doctorate', '1st-4th', 'Preschool'],
      dtype=object)
```

[8]:
```python
education_levels = [
    "Preschool",
    "1st-4th",
    "5th-6th",
    "7th-8th",
    "9th",
    "10th",
    "11th",
    "12th",
    "HS-grad",
    "Prof-school",
    "Assoc-voc",
    "Assoc-acdm",
    "Some-college",
    "Bachelors",
    "Masters",
    "Doctorate",
]
```

[9]:
```python
assert set(education_levels) == set(train_df["education"].unique())
```

[10]:
```python
X_train = train_df_nan.drop(columns=[target])
y_train = train_df_nan[target]
```

```python
X_test = test_df_nan.drop(columns=[target])
y_test = test_df_nan[target]
```

[11]:
```python
from sklearn.compose import ColumnTransformer, make_column_transformer
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder, OrdinalEncoder, StandardScaler

numeric_transformer = make_pipeline(StandardScaler())

ordinal_transformer = OrdinalEncoder(categories=[education_levels], dtype=int)

categorical_transformer = make_pipeline(
    SimpleImputer(strategy="constant", fill_value="missing"),
    OneHotEncoder(handle_unknown="ignore", sparse=False),
)

binary_transformer = make_pipeline(
    SimpleImputer(strategy="constant", fill_value="missing"),
    OneHotEncoder(drop="if_binary", dtype=int),
)

preprocessor = make_column_transformer(
    (numeric_transformer, numeric_features),
    (ordinal_transformer, ordinal_features),
    (binary_transformer, binary_features),
    (categorical_transformer, categorical_features),
    ("drop", drop_features),
)
```

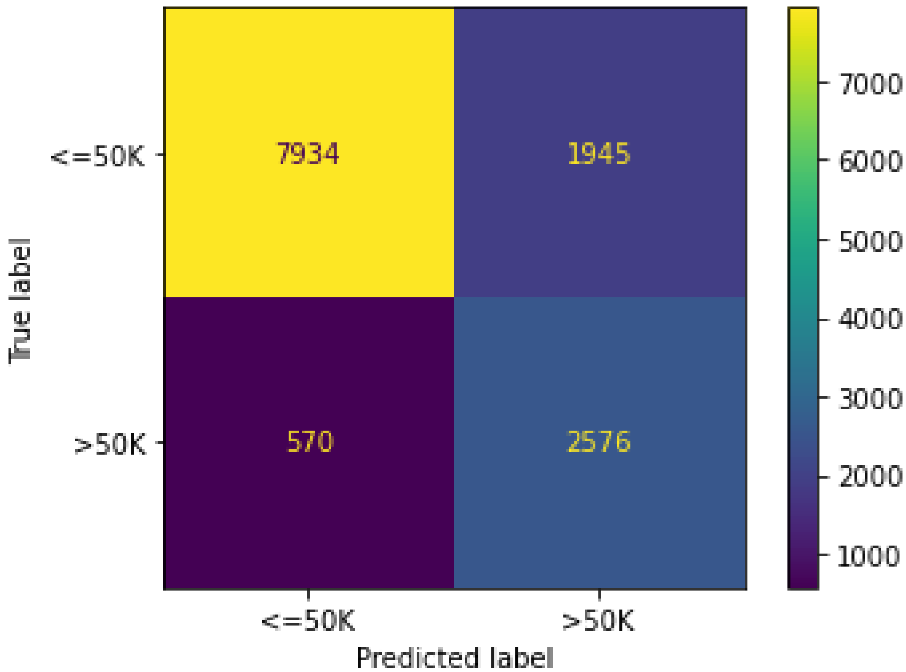
[12]:
```python
y_train.value_counts()
```

[12]:
```
<=50K    14841
>50K      4695
Name: income, dtype: int64
```

[13]:
```python
pipe_lr = make_pipeline(
    preprocessor, LogisticRegression(class_weight="balanced", max_iter=1000)
)
```

[14]:
```python
pipe_lr.fit(X_train, y_train);
```

[15]:
```python
from sklearn.metrics import ConfusionMatrixDisplay  # Recommended method in␣
↪sklearn 1.0

ConfusionMatrixDisplay.from_estimator(pipe_lr, X_test, y_test);
```



Let's examine confusion matrix separately for the two genders we have in the data.

[16]:
```
X_train_enc = preprocessor.fit_transform(X_train)
preprocessor.named_transformers_["pipeline-2"]["onehotencoder"].
 ↪get_feature_names_out()
```

[16]:
```
array(['x0_Male'], dtype=object)
```

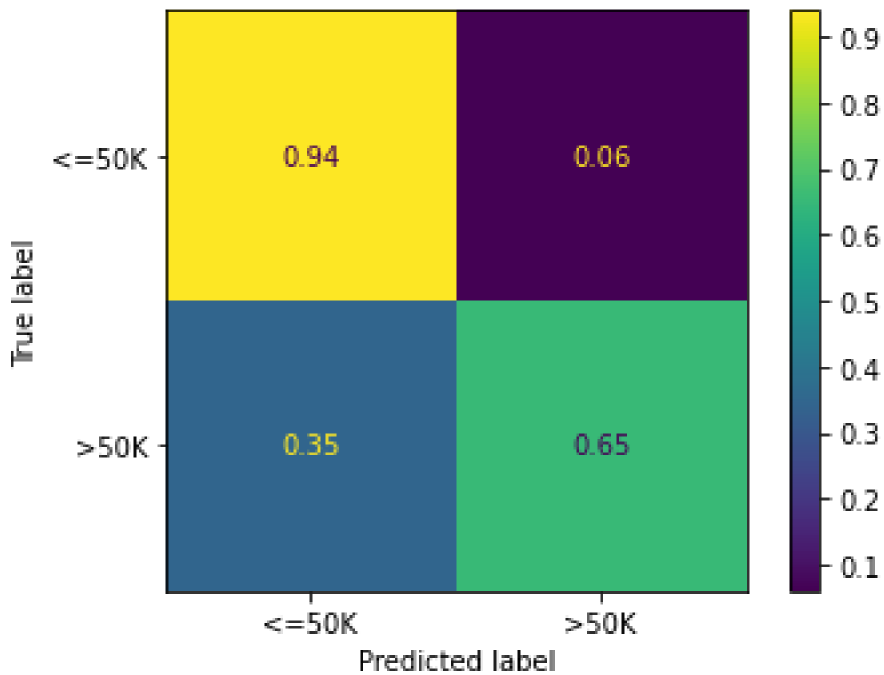
[17]:
```
X_test.head()
```

[17]:
```
       age workclass  fnlwgt     education  education.num      marital.status  \
14160   29   Private  280618  Some-college             10  Married-civ-spouse
27048   19   Private  439779  Some-college             10       Never-married
28868   28   Private  204734  Some-college             10  Married-civ-spouse
5667    35   Private  107991          11th              7       Never-married
7827    20   Private   54152  Some-college             10       Never-married

              occupation   relationship   race     sex  capital.gain  \
14160  Handlers-cleaners        Husband  White    Male             0
27048              Sales      Own-child  White    Male             0
28868       Tech-support           Wife  White  Female             0
5667               Sales  Not-in-family  White    Male             0
7827        Adm-clerical      Own-child  White  Female             0

       capital.loss  hours.per.week native.country
```

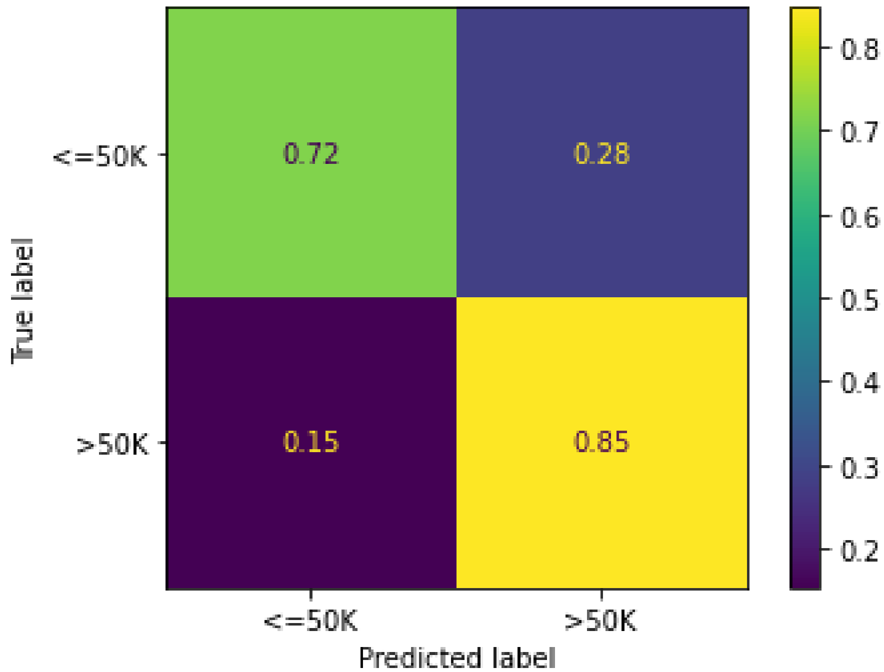
```
14160              0              40  United-States
27048              0              15  United-States
28868              0              40  United-States
5667               0              45  United-States
7827               0              30            NaN
```

[18]:
```python
X_female = X_test.query("sex=='Female'")
X_male = X_test.query("sex=='Male'")

y_female = y_test[X_female.index]
y_male = y_test[X_male.index]
female_preds = pipe_lr.predict(X_female)
male_preds = pipe_lr.predict(X_male)
```

[19]:
```python
ConfusionMatrixDisplay.from_estimator(pipe_lr, X_female, y_female,␣
↪normalize="true");
```



[20]:
```python
ConfusionMatrixDisplay.from_estimator(pipe_lr, X_male, y_male,␣
↪normalize="true");
```



What's the accuracy of this model?

[21]:
```python
from sklearn.metrics import confusion_matrix

data = {"male": [], "female": []}
f_TN, f_FP, f_FN, f_TP = confusion_matrix(y_female, female_preds).ravel()
m_TN, m_FP, m_FN, m_TP = confusion_matrix(y_male, male_preds).ravel()
```

[22]:
```python
accuracy_male = accuracy_score(y_male, male_preds)
accuracy_female = accuracy_score(y_female, female_preds)
data["male"].append(accuracy_male)
data["female"].append(accuracy_female)

print("Accuracy male: {:.3f}".format(accuracy_male))
print("Accuracy female: {:.3f}".format(accuracy_female))
```

```
Accuracy male: 0.756
Accuracy female: 0.909
```

[ ]:
```python

```

[23]:
```python
y_female.value_counts(normalize=True)
```

[23]:
```
<=50K    0.892675
>50K     0.107325
Name: income, dtype: float64
```

[24]:
```
y_male.value_counts(normalize=True)
```

[24]:
```
<=50K    0.691999
>50K     0.308001
Name: income, dtype: float64
```

There is more class imbalance for female!

Let's assume that a company is using this classifier for loan approval with a simple rule that if the income is >=50K, approve the loan else reject the loan.

Statistical parity suggests that the proportion of each segment of a protected class (e.g. sex) should receive the positive outcome at equal rates. For example, the number of loans approved for female should be equal to male.

Calculate the precision for male and female. Based on your results, do you think this income classifier is fair?

[25]:
```
precision_male = precision_score(y_male, male_preds, pos_label=">50K")
precision_female = precision_score(y_female, female_preds, pos_label=">50K")
data["male"].append(precision_male)
data["female"].append(precision_female)

print("Precision male: {:.3f}".format(precision_male))
print("Precision female: {:.3f}".format(precision_female))
```

```
Precision male: 0.570
Precision female: 0.566
```

Equal opportunity suggests that each group should get the positive outcome at equal rates, assuming that people in this group qualify for it. For example, if a man and a woman have both a certain level of income, we want them to have the same chance of getting the loan. In other words, the true positive rate (TPR or recall) of both groups should be equal.

[26]:
```
recall_male = recall_score(y_male, male_preds, pos_label=">50K")
recall_female = recall_score(y_female, female_preds, pos_label=">50K")

data["male"].append(recall_male)
data["female"].append(recall_female)

print("Recall male: {:.3f}".format(recall_male))
print("Recall female: {:.3f}".format(recall_female))
```

```
Recall male: 0.847
Recall female: 0.654
```

There is usually a tradeoff between rationality (adopting effective means to achieve your desired outcome) and bias. The desired outcome of banks, for example, is to maximize their profit. So in many circumstances, they not only care about approving as many qualified applications as possible (true positive), but also to avoid approving unqualified applications (false postive) because default loan could have detrimental effects for them.

Let's examine false positive rate (FPR) of both groups.

[27]:
```
fpr_male = m_FP / (m_FP + m_TN)
fpr_female = f_FP / (f_FP + f_TN)

data["male"].append(fpr_male)
data["female"].append(fpr_female)

print("FPR male: {:.3f}".format(fpr_male))
print("FPR female: {:.3f}".format(fpr_female))
```

```
FPR male: 0.284
FPR female: 0.060
```

[28]:
```
pd.DataFrame(data, index=["accuracy", "precision", "recall", "FPR"])
```

[28]:

	male	female
accuracy	0.756285	0.909133
precision	0.570246	0.566355
recall	0.847186	0.654428
FPR	0.284174	0.060244

- Discuss these results with your neighbours.
- Does the effect still exist if the sex feature is removed from the model (but you still have it available separately to do the two confusion matrices)?