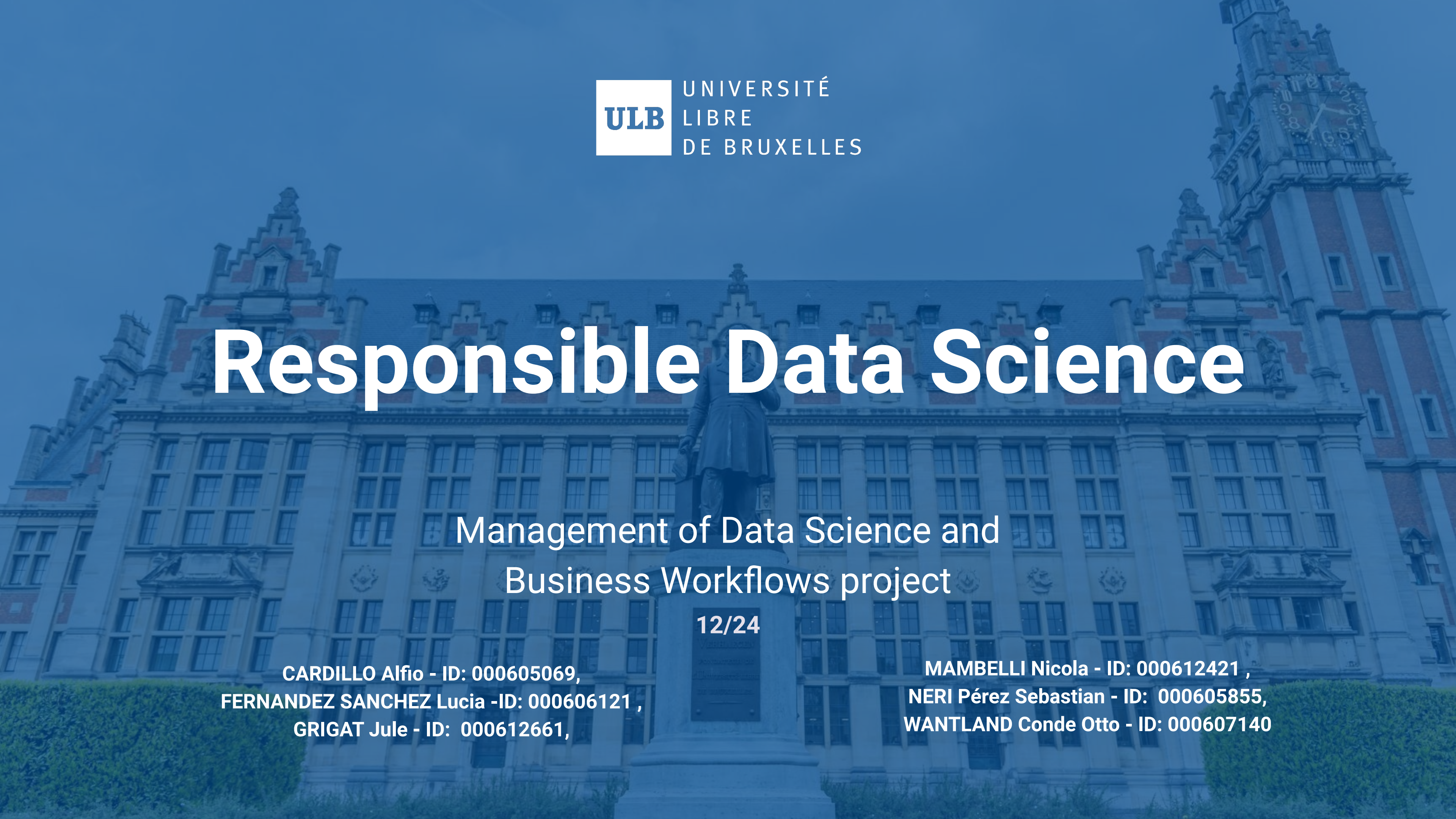

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Responsible Data Science

Management of Data Science and Business Workflows project

12/24

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1. Classification

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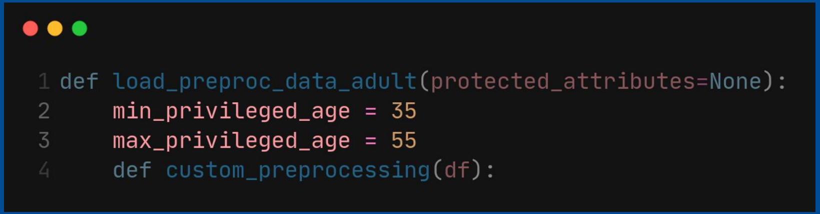
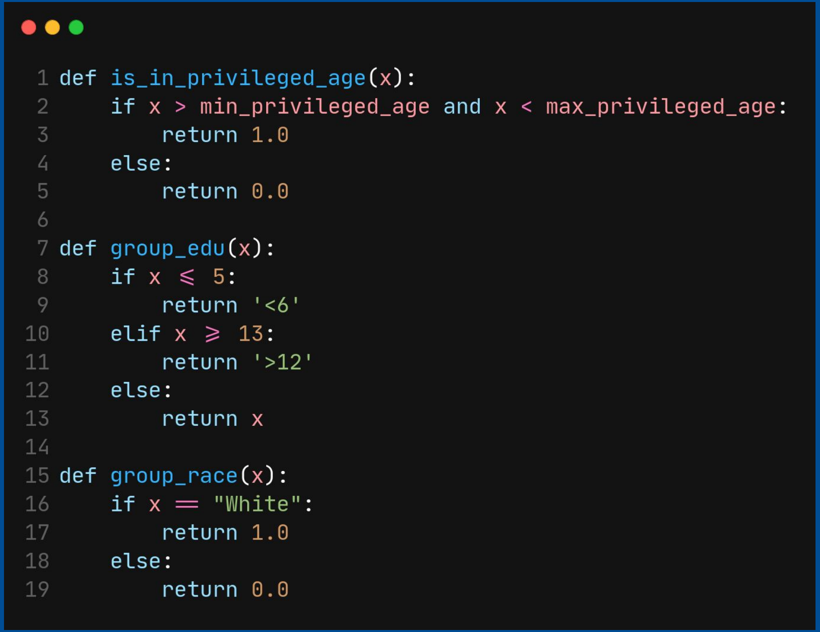
Preprocessing

- AIF360 preprocessing template
- Binarize age
- Add hours-per-week



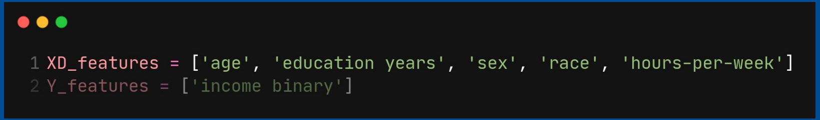
```python
def load_preproc_data_adult(protected_attributes=None):
    min_privileged_age = 35
    max_privileged_age = 55
    def custom_preprocessing(df):
```



```python
def is_in_privileged_age(x):
    if x > min_privileged_age and x < max_privileged_age:
        return 1.0
    else:
        return 0.0

def group_edu(x):
    if x <= 5:
        return '<6'
    elif x >= 13:
        return '>12'
    else:
        return x

def group_race(x):
    if x == "White":
        return 1.0
    else:
        return 0.0
```



```python
XD_features = ['age', 'education years', 'sex', 'race', 'hours-per-week']
Y_features = ['income binary']
```

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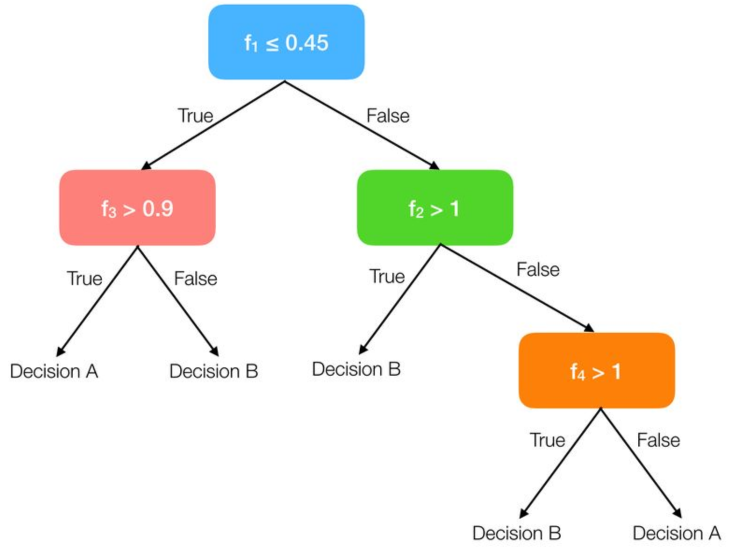
Decision Tree

- Classifier predicts probability, with the validation set we choose the best threshold.
- Balanced accuracy ~ 0.72
- Adding more features, increased the accuracy, but in some cases had some other impact.



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2. Fairness

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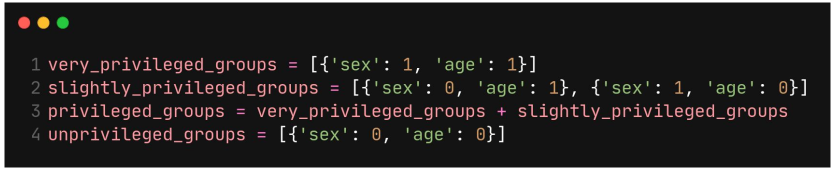
Privileged definition

- Very privileged
- Slightly privileged
- Privileged
- Unprivileged



```
very_privileged_groups = [{'sex': 1, 'age': 1}]
slightly_privileged_groups = [{'sex': 0, 'age': 1}, {'sex': 1, 'age': 0}]
privileged_groups = very_privileged_groups + slightly_privileged_groups
unprivileged_groups = [{'sex': 0, 'age': 0}]
```

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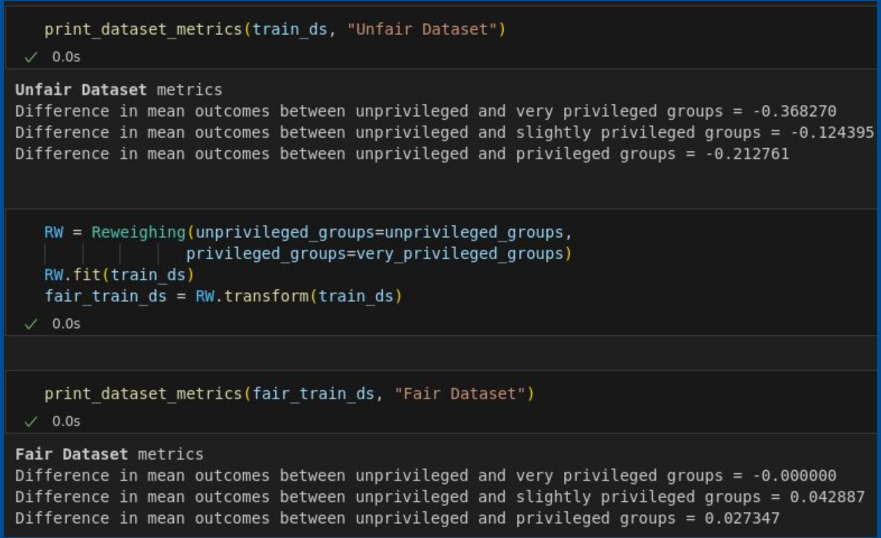
Reweighing

We actually end up penalizing the slightly and very privileged groups

$$Pr(Y = 1|D = \text{unprivileged}) - Pr(Y = 1|D = \text{privileged})$$



```
print_dataset_metrics(train_ds, "Unfair Dataset")
✓ 0.0s

Unfair Dataset metrics
Difference in mean outcomes between unprivileged and very privileged groups = -0.368270
Difference in mean outcomes between unprivileged and slightly privileged groups = -0.124395
Difference in mean outcomes between unprivileged and privileged groups = -0.212761

RW = Reweighing(unprivileged_groups=unprivileged_groups,
                privileged_groups=very_privileged_groups)
RW.fit(train_ds)
fair_train_ds = RW.transform(train_ds)
✓ 0.0s

print_dataset_metrics(fair_train_ds, "Fair Dataset")
✓ 0.0s

Fair Dataset metrics
Difference in mean outcomes between unprivileged and very privileged groups = -0.000000
Difference in mean outcomes between unprivileged and slightly privileged groups = 0.042887
Difference in mean outcomes between unprivileged and privileged groups = 0.027347
```

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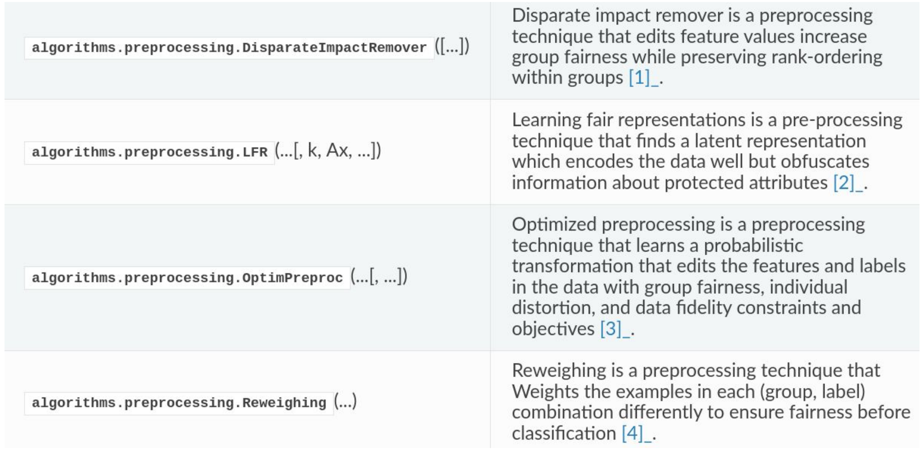
Other fairness algorithm

- Disparate Impact Remover: edit features
- LFR: obfuscates info about protected attributes
- OptimPreproc: edit features



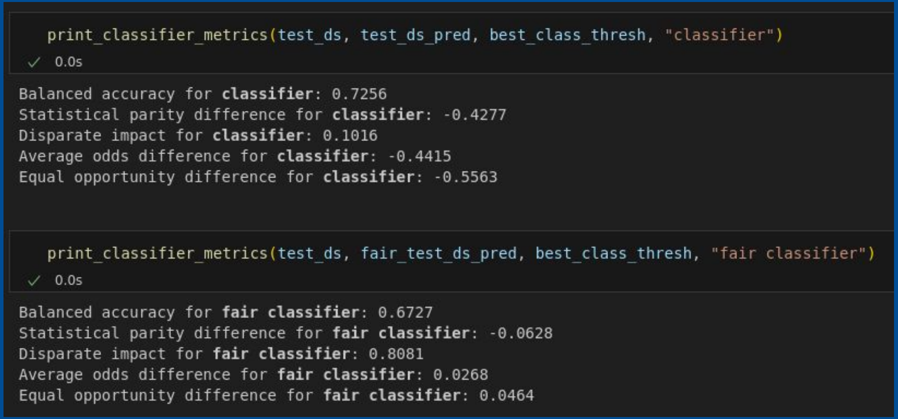
`algorithms.preprocessing.DisparateImpactRemover` ([...])	Disparate impact remover is a preprocessing technique that edits feature values increase group fairness while preserving rank-ordering within groups [1]_.
`algorithms.preprocessing.LFR` (...[, k, Ax, ...])	Learning fair representations is a pre-processing technique that finds a latent representation which encodes the data well but obfuscates information about protected attributes [2]_.
`algorithms.preprocessing.OptimPreproc` (...[, ...])	Optimized preprocessing is a preprocessing technique that learns a probabilistic transformation that edits the features and labels in the data with group fairness, individual distortion, and data fidelity constraints and objectives [3]_.
`algorithms.preprocessing.Reweighing` (...)	Reweighing is a preprocessing technique that Weights the examples in each (group, label) combination differently to ensure fairness before classification [4]_.

Fair classifier

- Lower accuracy
- Better fairness metrics

$$DI = \frac{Pr(Y = 1|D = \text{unprivileged})}{Pr(Y = 1|D = \text{privileged})}$$

$$EOR = TPR_{D=\text{unprivileged}} - TPR_{D=\text{privileged}}$$

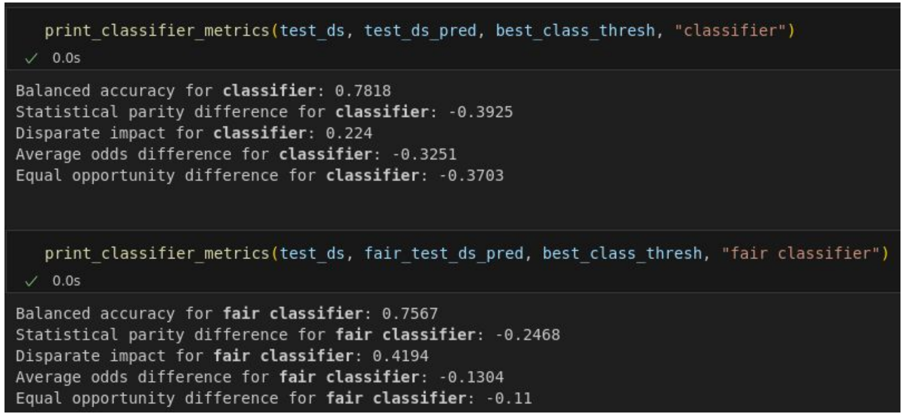


```
print_classifier_metrics(test_ds, test_ds_pred, best_class_thresh, "classifier")
✓ 0.0s

Balanced accuracy for classifier: 0.7256
Statistical parity difference for classifier: -0.4277
Disparate impact for classifier: 0.1016
Average odds difference for classifier: -0.4415
Equal opportunity difference for classifier: -0.5563
```

```
print_classifier_metrics(test_ds, fair_test_ds_pred, best_class_thresh, "fair classifier")
✓ 0.0s

Balanced accuracy for fair classifier: 0.6727
Statistical parity difference for fair classifier: -0.0628
Disparate impact for fair classifier: 0.8081
Average odds difference for fair classifier: 0.0268
Equal opportunity difference for fair classifier: 0.0464
```

What if we add marital status?

Possible connection with protected attribute age



```
print_classifier_metrics(test_ds, test_ds_pred, best_class_thresh, "classifier")
✓ 0.0s

Balanced accuracy for classifier: 0.7818
Statistical parity difference for classifier: -0.3925
Disparate impact for classifier: 0.224
Average odds difference for classifier: -0.3251
Equal opportunity difference for classifier: -0.3703
```

```
print_classifier_metrics(test_ds, fair_test_ds_pred, best_class_thresh, "fair classifier")
✓ 0.0s

Balanced accuracy for fair classifier: 0.7567
Statistical parity difference for fair classifier: -0.2468
Disparate impact for fair classifier: 0.4194
Average odds difference for fair classifier: -0.1304
Equal opportunity difference for fair classifier: -0.11
```

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3. Privacy

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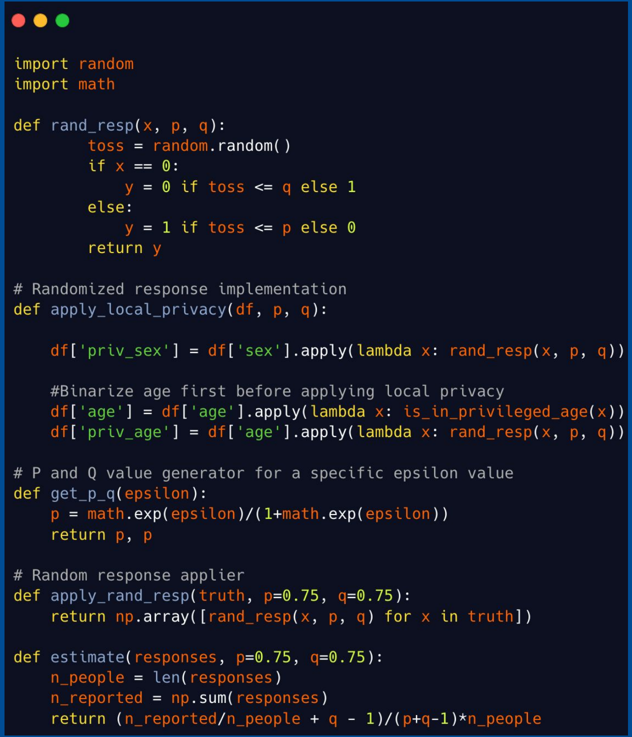
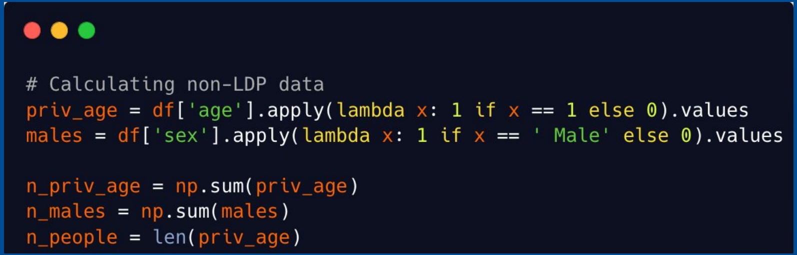
Implementing LDP

- Using Randomized Response

$$r = \frac{1}{p+q-1}\left(\frac{n_1^{rep}}{n} + q - 1\right).$$



```
import random
import math

def rand_resp(x, p, q):
        toss = random.random()
        if x == 0:
            y = 0 if toss <= q else 1
        else:
            y = 1 if toss <= p else 0
        return y

# Randomized response implementation
def apply_local_privacy(df, p, q):

    df['priv_sex'] = df['sex'].apply(lambda x: rand_resp(x, p, q))

    #Binarize age first before applying local privacy
    df['age'] = df['age'].apply(lambda x: is_in_privileged_age(x))
    df['priv_age'] = df['age'].apply(lambda x: rand_resp(x, p, q))

# P and Q value generator for a specific epsilon value
def get_p_q(epsilon):
    p = math.exp(epsilon)/(1+math.exp(epsilon))
    return p, p

# Random response applier
def apply_rand_resp(truth, p=0.75, q=0.75):
    return np.array([rand_resp(x, p, q) for x in truth])

def estimate(responses, p=0.75, q=0.75):
    n_people = len(responses)
    n_reported = np.sum(responses)
    return (n_reported/n_people + q - 1)/(p+q-1)*n_people
```



```
# Calculating non-LDP data
priv_age = df['age'].apply(lambda x: 1 if x == 1 else 0).values
males = df['sex'].apply(lambda x: 1 if x == ' Male' else 0).values

n_priv_age = np.sum(priv_age)
n_males = np.sum(males)
n_people = len(priv_age)
```

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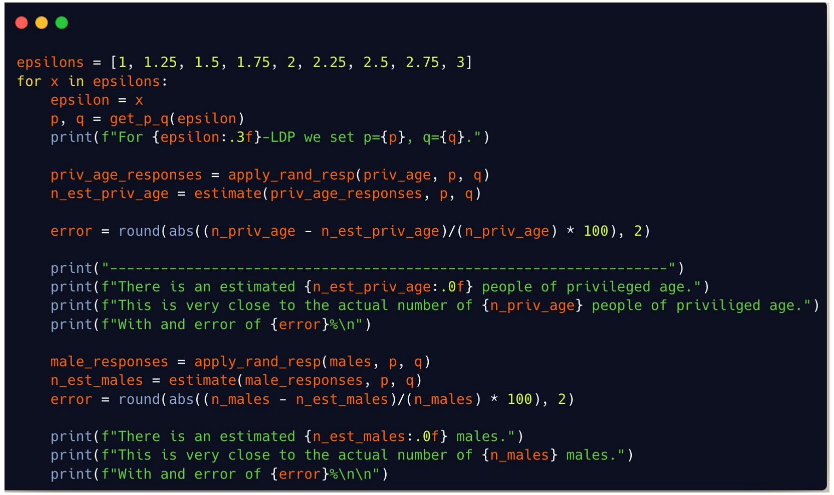
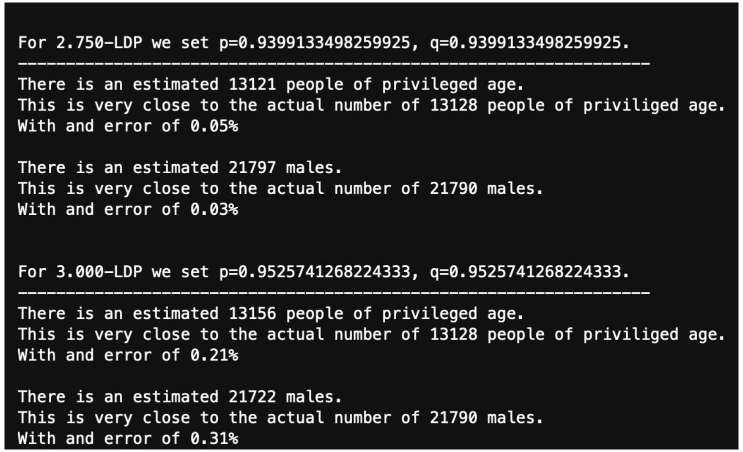
Results for Different Epsilon Values

Testing different values to find the best P and Q for our evaluation.



```
epsilons = [1, 1.25, 1.5, 1.75, 2, 2.25, 2.5, 2.75, 3]
for x in epsilons:
    epsilon = x
    p, q = get_p_q(epsilon)
    print(f"For {epsilon:.3f}-LDP we set p={p}, q={q}.")

    priv_age_responses = apply_rand_resp(priv_age, p, q)
    n_est_priv_age = estimate(priv_age_responses, p, q)

    error = round(abs((n_priv_age - n_est_priv_age)/(n_priv_age) * 100), 2)

    print("-------------------------------------------------------------------")
    print(f"There is an estimated {n_est_priv_age:.0f} people of privileged age.")
    print(f"This is very close to the actual number of {n_priv_age} people of priviliged age.")
    print(f"With and error of {error}%\n")

    male_responses = apply_rand_resp(males, p, q)
    n_est_males = estimate(male_responses, p, q)
    error = round(abs((n_males - n_est_males)/(n_males) * 100), 2)

    print(f"There is an estimated {n_est_males:.0f} males.")
    print(f"This is very close to the actual number of {n_males} males.")
    print(f"With and error of {error}%\n\n")
```



```
For 2.750-LDP we set p=0.9399133498259925, q=0.9399133498259925.
-------------------------------------------------------------------
There is an estimated 13121 people of privileged age.
This is very close to the actual number of 13128 people of priviliged age.
With and error of 0.05%

There is an estimated 21797 males.
This is very close to the actual number of 21790 males.
With and error of 0.03%


For 3.000-LDP we set p=0.9525741268224333, q=0.9525741268224333.
-------------------------------------------------------------------
There is an estimated 13156 people of privileged age.
This is very close to the actual number of 13128 people of priviliged age.
With and error of 0.21%

There is an estimated 21722 males.
This is very close to the actual number of 21790 males.
With and error of 0.31%
```

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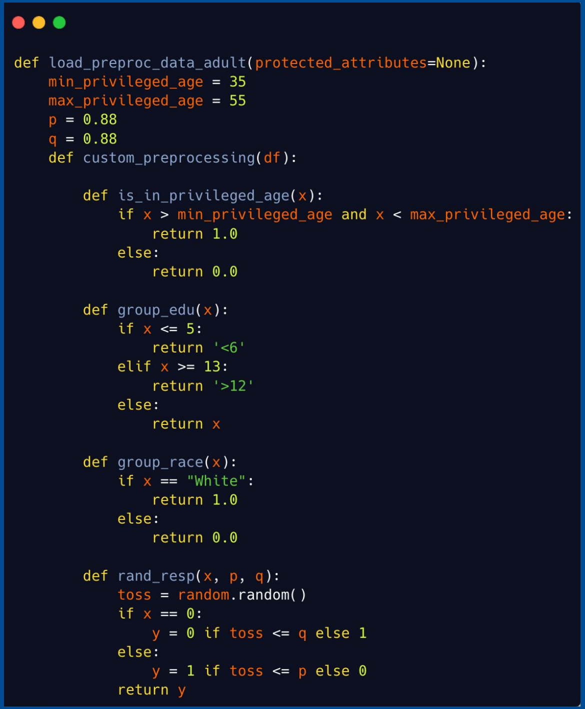
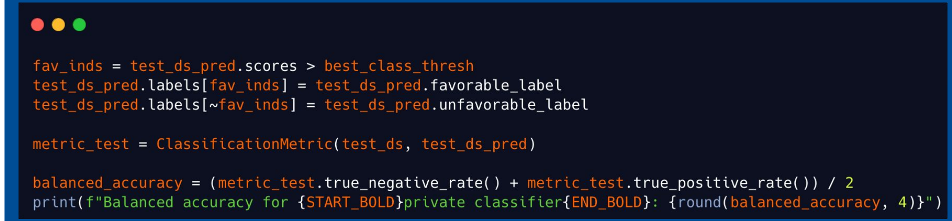
Implementation Into Classifier

- Balanced accuracy for private classifier: **71%**
- Implementing LDP lowers classifier accuracy slightly.



```python
def load_preproc_data_adult(protected_attributes=None):
    min_privileged_age = 35
    max_privileged_age = 55
    p = 0.88
    q = 0.88
    def custom_preprocessing(df):

        def is_in_privileged_age(x):
            if x > min_privileged_age and x < max_privileged_age:
                return 1.0
            else:
                return 0.0

        def group_edu(x):
            if x <= 5:
                return '<6'
            elif x >= 13:
                return '>12'
            else:
                return x

        def group_race(x):
            if x == "White":
                return 1.0
            else:
                return 0.0

        def rand_resp(x, p, q):
            toss = random.random()
            if x == 0:
                y = 0 if toss <= q else 1
            else:
                y = 1 if toss <= p else 0
            return y
```

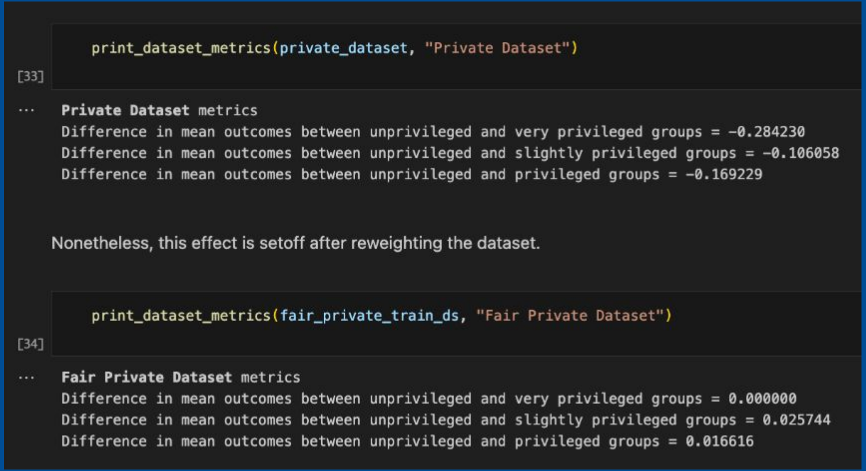


```python
fav_inds = test_ds_pred.scores > best_class_thresh
test_ds_pred.labels[fav_inds] = test_ds_pred.favorable_label
test_ds_pred.labels[~fav_inds] = test_ds_pred.unfavorable_label

metric_test = ClassificationMetric(test_ds, test_ds_pred)

balanced_accuracy = (metric_test.true_negative_rate() + metric_test.true_positive_rate()) / 2
print(f"Balanced accuracy for {START_BOLD}private classifier{END_BOLD}: {round(balanced_accuracy, 4)}")
```

4. Privacy + Fairness

Re-weighing of the Private Dataset

- Largest gap (-0.284) in private dataset: unprivileged vs. very privileged.
- Moderate gap (-0.169) in private dataset: unprivileged vs. privileged.
- Fair dataset: no gap (0.000) for unprivileged vs. very privileged.
- Small gap (0.026) in fair dataset: unprivileged vs. slightly privileged.
- Fair dataset reduces disparities significantly.



```
[33]  print_dataset_metrics(private_dataset, "Private Dataset")
```

```
Private Dataset metrics
Difference in mean outcomes between unprivileged and very privileged groups = -0.284230
Difference in mean outcomes between unprivileged and slightly privileged groups = -0.106058
Difference in mean outcomes between unprivileged and privileged groups = -0.169229
```

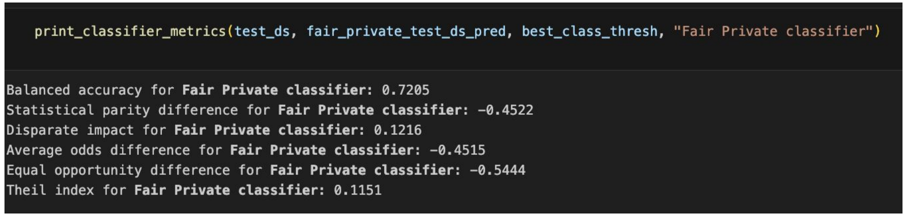
Nonetheless, this effect is setoff after reweighting the dataset.

```
[34]  print_dataset_metrics(fair_private_train_ds, "Fair Private Dataset")
```

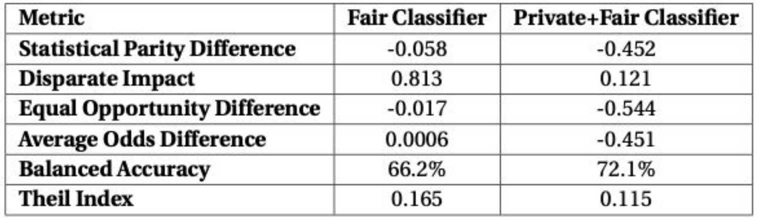
```
Fair Private Dataset metrics
Difference in mean outcomes between unprivileged and very privileged groups = 0.000000
Difference in mean outcomes between unprivileged and slightly privileged groups = 0.025744
Difference in mean outcomes between unprivileged and privileged groups = 0.016616
```

Results

- Private+Fair favors privileged groups more than Fair Classifier.
- Larger biases in Equal Opportunity show unequal treatment.
- Private+Fair has higher balanced accuracy (72.1%).
- Improved Theil Index (0.115) indicates better info distribution.
- Trade-off: fairness sacrificed for performance, raising ethical concerns.



```
print_classifier_metrics(test_ds, fair_private_test_ds_pred, best_class_thresh, "Fair Private classifier")

Balanced accuracy for Fair Private classifier: 0.7205
Statistical parity difference for Fair Private classifier: -0.4522
Disparate impact for Fair Private classifier: 0.1216
Average odds difference for Fair Private classifier: -0.4515
Equal opportunity difference for Fair Private classifier: -0.5444
Theil index for Fair Private classifier: 0.1151
```



Metric	Fair Classifier	Private+Fair Classifier
Statistical Parity Difference	-0.058	-0.452
Disparate Impact	0.813	0.121
Equal Opportunity Difference	-0.017	-0.544
Average Odds Difference	0.0006	-0.451
Balanced Accuracy	66.2%	72.1%
Theil Index	0.165	0.115

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5.Explainability

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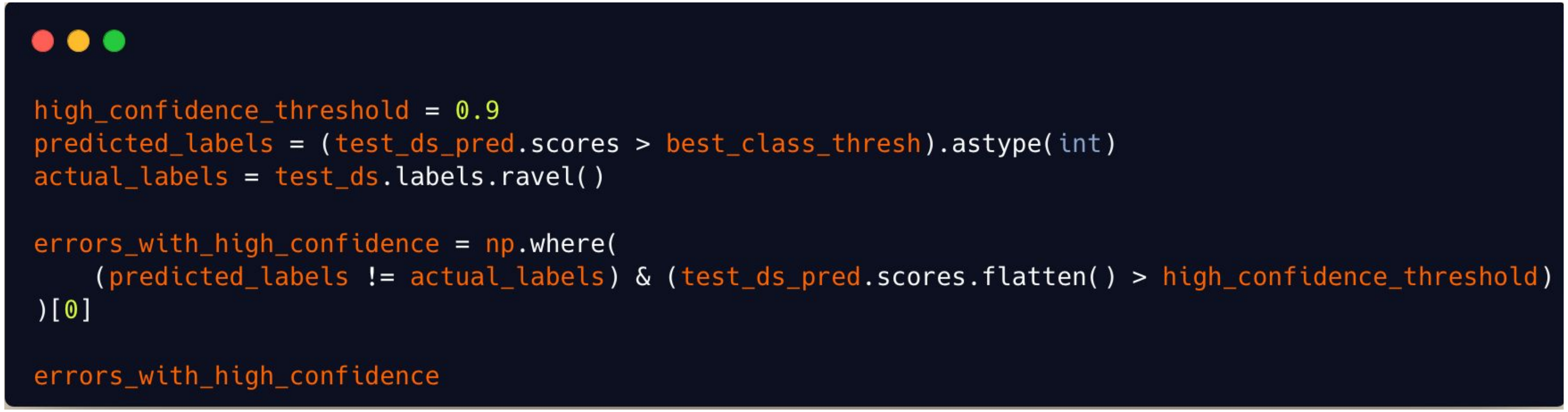
Methodology

Study the explainability of the private classifier.



```
high_confidence_threshold = 0.9
predicted_labels = (test_ds_pred.scores > best_class_thresh).astype(int)
actual_labels = test_ds.labels.ravel()

errors_with_high_confidence = np.where(
    (predicted_labels != actual_labels) & (test_ds_pred.scores.flatten() > high_confidence_threshold)
)[0]

errors_with_high_confidence
```

array([0, 0, 0, ..., 7326, 7326, 7326])

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1. **Errors concentrated in certain characteristics:**

- This suggests that the errors occur primarily in specific subgroups, such as young males of nonprivileged age.

2. High but incorrect confidence

- Instances show predictions with high confidence (>= 0.6).

- The model might be overestimating its confidence in certain scenarios where key features, such as age and sex, are noisy or not well represented.

Recommendation

- The noise added for privacy may be disproportionately affecting certain groups, causing systematic errors in these categories.
- It is recommended to evaluate noise reduction in age and sex or adjust hyper parameters to improve the balance between privacy and accuracy.

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6. Explainability and LLM

Using the Explainability Method LIME

LIME is an explainability Method which generates feature-importance pairs showing how each attribute contributes to a prediction.

Steps taken for this part:

1. Choose an explainability method - LIME
2. Construct and configure the Model
3. Execute the model to explain the “errors with high confidence” from the previous part of the project
4. Print the results to a .json file
5. Let an LLM explain the results - Llama 3.2

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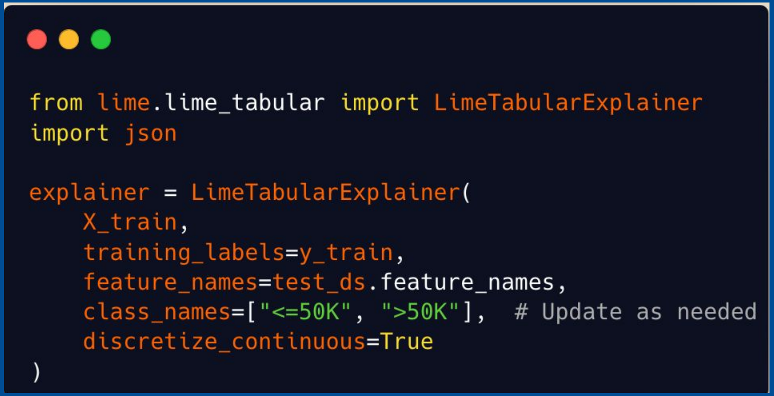
Constructing the LIME Model

- Set Train data and Train Labels, and include attributes
- Set the classification attribute to <=50K and >50K

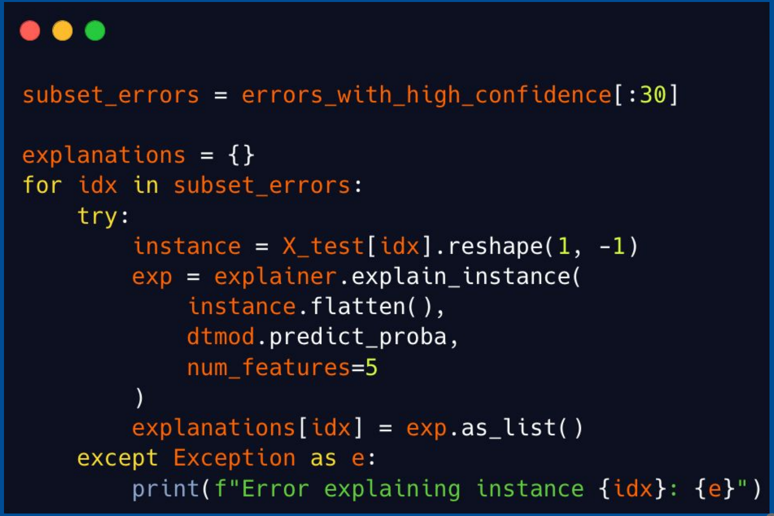
Running the Model

- Using the model to explore the subset of errors with high confidence.



```python
from lime.lime_tabular import LimeTabularExplainer
import json

explainer = LimeTabularExplainer(
    X_train,
    training_labels=y_train,
    feature_names=test_ds.feature_names,
    class_names=["<=50K", ">50K"],  # Update as needed
    discretize_continuous=True
)
```



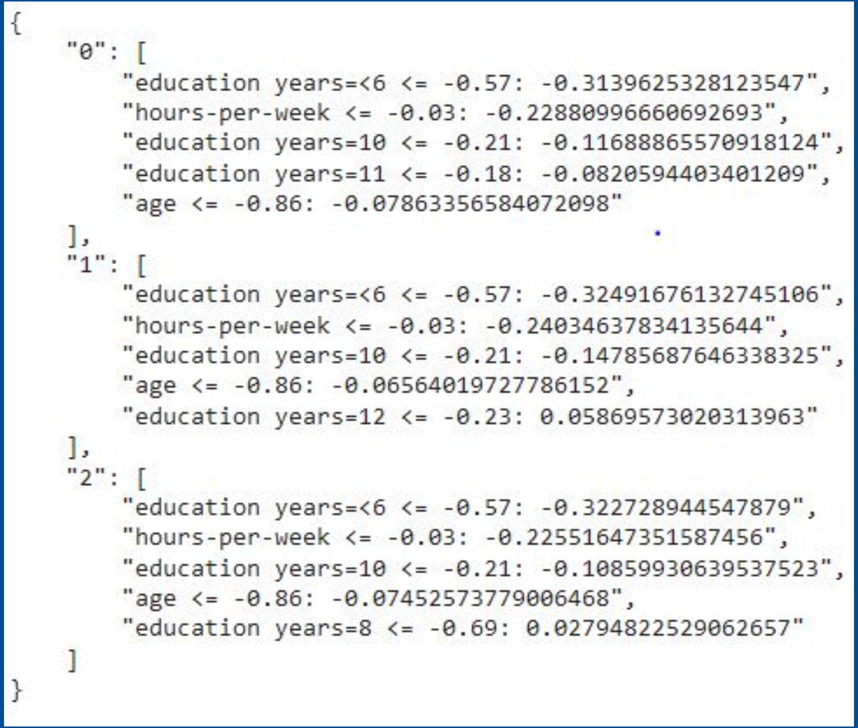
```python
subset_errors = errors_with_high_confidence[:30]

explanations = {}
for idx in subset_errors:
    try:
        instance = X_test[idx].reshape(1, -1)
        exp = explainer.explain_instance(
            instance.flatten(),
            dtmod.predict_proba,
            num_features=5
        )
        explanations[idx] = exp.as_list()
    except Exception as e:
        print(f"Error explaining instance {idx}: {e}")
```

Exemplary Model Output

- To be translated into understandable text by the LLM concluding:

  “The minimum education requirements for various jobs across different age groups and weekly working hours”



```
{
    "0": [
        "education years=<6 <= -0.57: -0.3139625328123547",
        "hours-per-week <= -0.03: -0.2288099660692693",
        "education years=10 <= -0.21: -0.1168886570918124",
        "education years=11 <= -0.18: -0.0820594403401209",
        "age <= -0.86: -0.0786335658407209"
    ],
    "1": [
        "education years=<6 <= -0.57: -0.3249167613274510",
        "hours-per-week <= -0.03: -0.2403463783413564",
        "education years=10 <= -0.21: -0.1478568764633832",
        "age <= -0.86: -0.0656401972778615",
        "education years=12 <= -0.23: 0.0586957302031396"
    ],
    "2": [
        "education years=<6 <= -0.57: -0.322728944547879",
        "hours-per-week <= -0.03: -0.2255164735158745",
        "education years=10 <= -0.21: -0.1085993063953752",
        "age <= -0.86: -0.0745257377900646",
        "education years=8 <= -0.69: 0.0279482252906265"
    ]
}
```

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7. Free Exploration

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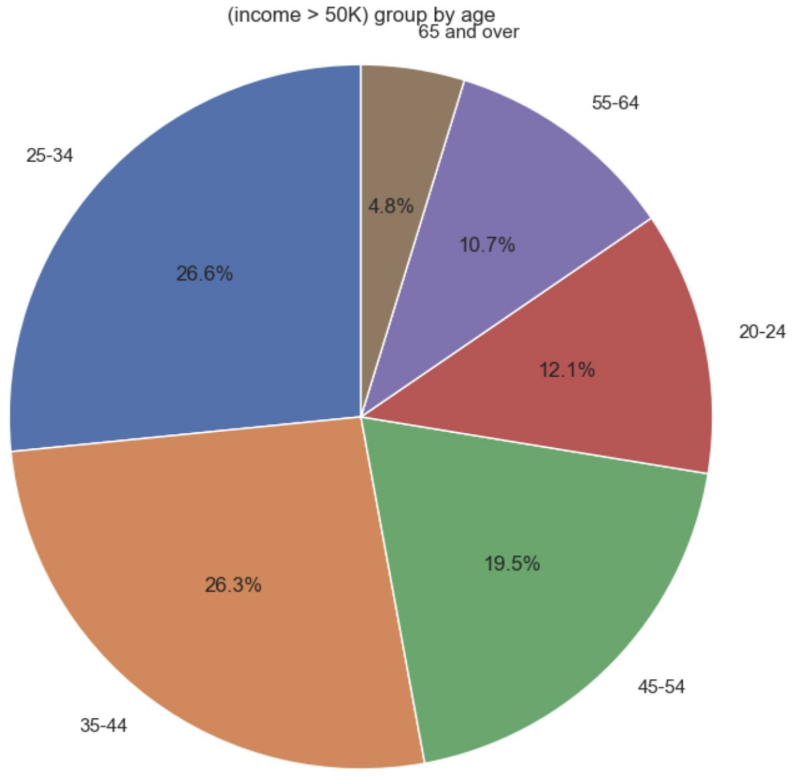
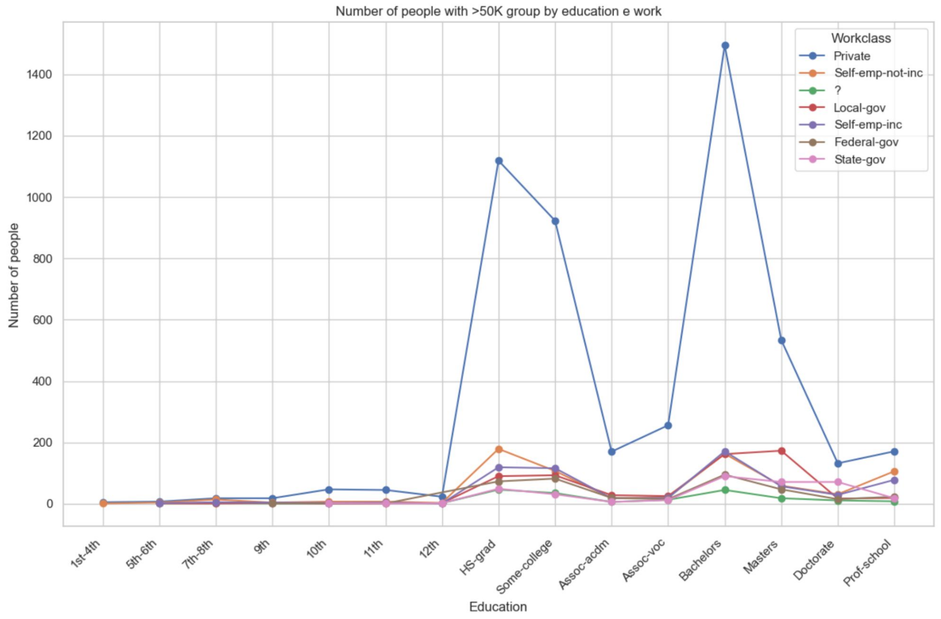
Income by age

The age group that represents the largest slice of the pie chart is the one that corresponds to people aged 25 to 34, making up 26.6% of the whole group





Income by Education and Work

This leads to the intuitive observation that, currently, for all jobs, the majority of people prefer to obtain a bachelor's degree.

Thank you for your attention!

Learn more at:
https://github.com/Carda01/responsibleDS_adult