M3.3 Study - Effect of K-anonymity on Titanic unalive prediction

```python
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import anonypy
from random import random
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression

from sklearn.metrics import accuracy_score, precision_score, recall_score
```

Datasets (raw data & anonymized data)

Looking at the dataset

```python
#loading dataset
titanic = sns.load_dataset('titanic')

titanic.head()
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alone
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	NaN	Southampton	no	False
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	C	Cherbourg	yes	False
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False	NaN	Southampton	yes	True
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False	C	Southampton	yes	False
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True	NaN	Southampton	no	True

Columns were chosen and k-anonymized with the Anonypy library

looking at the head of the anonymized data

- Sex, age, sibsp (sibling & spouse), parch (parent & child), fare, survived was choosen as the "relevant features"
- added a "count" column
- added some interesting intervals

```python
titanicAnonymized = sns.load_dataset('titanic')

# print(titanicAnonymized.columns)

# print(titanicAnonymized['embarked'].value_counts())

#makes some columns categorical
catagorical = set(('sex', 'embarked'))

for name in catagorical:
    titanicAnonymized[name] = titanicAnonymized[name].astype("category")

featureColumns = ['sex', 'age', 'sibsp', 'parch', 'fare'] # Removes: pclass, deck, 'class', 'who', 'adult_male', 'embark_town', 'alive', 'alone', 'embarked'
sensitiveColumn = "survived"

# print(featureColumns + [sensitiveColumn])

#k-anonymity using anonypy library
p = anonypy.Preserver(titanicAnonymized, featureColumns, sensitiveColumn)
rows = p.anonymize_k_anonymity(k=4)

#new dataset with k-anonmity applied
titanicAnonymized = pd.DataFrame(rows)

titanicAnonymized.head()
```

	sex	age	sibsp	parch	fare	survived	count
0	[male]	[0.42-16.0]	[0-1]	[0-1]	[7.2292-9.5]	0	5
1	[male]	[0.42-16.0]	[0-1]	[0-1]	[7.2292-9.5]	1	2
2	[male]	[32.0]	[0]	[0]	[7.75-10.5]	0	6
3	[male]	[32.0]	[0]	[0]	[7.75-10.5]	1	3
4	[female]	[5.0-14.5]	[0-1]	[0]	[7.2292-14.4542]	0	2

Processing data for training

- every cell except survived has been generalized in order to fulfill k-anonomyziation
- this data in its current form is not yet ready for training
- How would a model handle the intervals?

```python
#based on count column repeat rows
titanicAnonymized = titanicAnonymized.loc[titanicAnonymized.index.repeat(titanicAnonymized['count'])].reset_index(drop=True)
titanicAnonymized = titanicAnonymized.drop(columns=['count'])

def transform_cell(cell):
    # If not a list, return as-is
    if not isinstance(cell, list):
        return cell

    # Flatten the comma-separated string inside the list
    if len(cell) == 1 and isinstance(cell[0], str) and ',' in cell[0]:
        parts = cell[0].split(',')
    else:
        parts = cell

    # Remove any "nan" strings
    cleaned = [v for v in parts if v != "nan"]

    if len(cleaned) == 1:
        item = cleaned[0]
        # Handle range like '15.0-16.0'
        if '-' in item and not item.startswith('-') and any(char.isdigit() for char in item):
            try:
                lower, upper = map(float, item.split('-'))
                return [lower, upper]
            except ValueError:
                return item
        return item  # categorical

    elif len(cleaned) > 1:
        return cleaned

    return None  # If all were "nan", return None (or np.nan if preferred)



# Apply transformation to all cells except the last two columns (which are int)
cols_to_transform = titanicAnonymized.columns.difference(['survived', 'count'])
titanicAnonymized[cols_to_transform] = titanicAnonymized[cols_to_transform].map(transform_cell)


titanicAnonymized.head(10)
```

	sex	age	sibsp	parch	fare	survived
0	male	[0.42, 16.0]	[0.0, 1.0]	[0.0, 1.0]	[7.2292, 9.5]	0
1	male	[0.42, 16.0]	[0.0, 1.0]	[0.0, 1.0]	[7.2292, 9.5]	0
2	male	[0.42, 16.0]	[0.0, 1.0]	[0.0, 1.0]	[7.2292, 9.5]	0
3	male	[0.42, 16.0]	[0.0, 1.0]	[0.0, 1.0]	[7.2292, 9.5]	0
4	male	[0.42, 16.0]	[0.0, 1.0]	[0.0, 1.0]	[7.2292, 9.5]	0
5	male	[0.42, 16.0]	[0.0, 1.0]	[0.0, 1.0]	[7.2292, 9.5]	1
6	male	[0.42, 16.0]	[0.0, 1.0]	[0.0, 1.0]	[7.2292, 9.5]	1
7	male	32.0	0	0	[7.75, 10.5]	0
8	male	32.0	0	0	[7.75, 10.5]	0
9	male	32.0	0	0	[7.75, 10.5]	0

Now some choices have to be made....

- how do we handle the ranges that the cells now are in?
  - took the average of upper and lower bound of the range
  - also tried random variable in the interval
  - accuracy and statistical information was traded for privacy

```python
X = titanicAnonymized.copy()

for col in X.columns:
    for i in range(len(X[col])):
        if not isinstance(X[col][i], list):
            continue
        X.loc[i, col] = (X[col][i][0]+X[col][i][1])/2

X.head()
```

	sex	age	sibsp	parch	fare	survived
0	male	8.21	0.5	0.5	8.3646	0
1	male	8.21	0.5	0.5	8.3646	0
2	male	8.21	0.5	0.5	8.3646	0
3	male	8.21	0.5	0.5	8.3646	0
4	male	8.21	0.5	0.5	8.3646	0

Evaluating logistic regression model on raw data

```python
# Step 1: Define X (features) and y (target)
# X = titanic.drop(columns=['survived'])  # 'survived' is the target column in the Seaborn Titanic dataset
X = titanic[['sex', 'age', 'sibsp', 'parch', 'fare']].copy()
y = titanic['survived']

# Step 2: Handle missing values and encode categorical variables
X['age'] = X['age'].fillna(X['age'].mean())  # Fill missing values in 'age' with the mean
X['fare'] = X['fare'].fillna(X['fare'].mean())  # Fill missing values in 'fare' with the mean

# Encode categorical variables
X = pd.get_dummies(X, columns=['sex'], drop_first=True)  # One-hot encode 'sex' and 'embarked'
# Step 3: Split the data into training and testing sets
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Step 4: Train a logistic regression model
model = LogisticRegression()
model.fit(x_train, y_train)

# Step 5: Evaluate the model
y_pred = model.predict(x_test)
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
print(f'Precision: {precision}')
print(f'Recall: {recall}')
print(f'Accuracy: {accuracy}')

raw_accuracy = accuracy
```

```
Precision: 0.8041237113402062
Recall: 0.7027027027027027
Accuracy: 0.8059701492537313
```

Evaluating logistic regression model on anonymized data

```python
# Step 1: Define X (features) and y (target)
# X = titanic.drop(columns=['survived'])  # 'survived' is the target column in the Seaborn Titanic dataset

X = titanicAnonymized.drop(columns=['survived']).copy()

for col in X.columns:
    for i in range(len(X[col])):
        if not isinstance(X[col][i], list):
            continue
        X.loc[i, col] = (X[col][i][0]+X[col][i][1])/2


y = titanicAnonymized['survived']

# Step 2: Handle missing values and encode categorical variables
# X['age'] = X['age'].fillna(X['age'].mean())  # Fill missing values in 'age' with the mean
# X['fare'] = X['fare'].fillna(X['fare'].mean())  # Fill missing values in 'fare' with the mean

# Encode categorical variables
X = pd.get_dummies(X, columns=['sex'], drop_first=True)  # One-hot encode 'sex' and 'embarked'
# Step 3: Split the data into training and testing sets
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Step 4: Train a logistic regression model
model = LogisticRegression()
model.fit(x_train, y_train)

# Step 5: Evaluate the model
y_pred = model.predict(x_test)
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
print(f'Precision: {precision}')
print(f'Recall: {recall}')
print(f'Accuracy: {accuracy}')
```

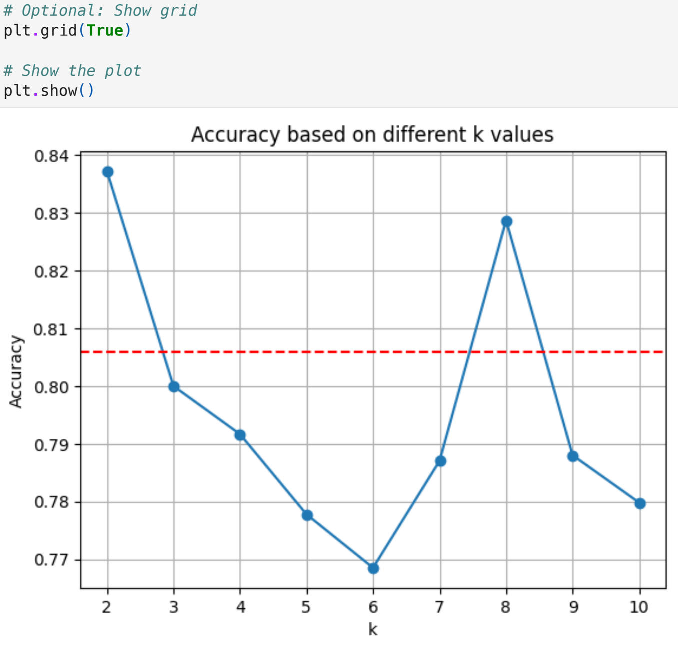
```
Precision: 0.7619047619047619
Recall: 0.7191011235955056
Accuracy: 0.7916666666666666
```

Plot of k effect on accuracy

```python
titanicAnonymized = sns.load_dataset('titanic')

featureColumns = ['sex', 'age', 'sibsp', 'parch', 'fare'] # Removes: pclass, deck, 'class', 'who', 'adult_male', 'embark_town', 'alive', 'alone', 'embarked'
sensitiveColumn = "survived"
catagorical = set(('sex', 'embarked'))

for name in catagorical:
    titanicAnonymized[name] = titanicAnonymized[name].astype("category")

anonymizedDataSets = []
k_values = range(2, 11)

for i in k_values:
    p = anonypy.Preserver(titanicAnonymized, featureColumns, sensitiveColumn)
    rows = p.anonymize_k_anonymity(k=i)
    k_anom_data = pd.DataFrame(rows)
    k_anom_data = k_anom_data.loc[k_anom_data.index.repeat(k_anom_data['count'])].reset_index(drop=True)
    k_anom_data = k_anom_data.drop(columns=['count'])
    cols_to_transform = k_anom_data.columns.difference(['survived', 'count'])
    k_anom_data[cols_to_transform] = k_anom_data[cols_to_transform].map(transform_cell)

    anonymizedDataSets.append(k_anom_data)
```

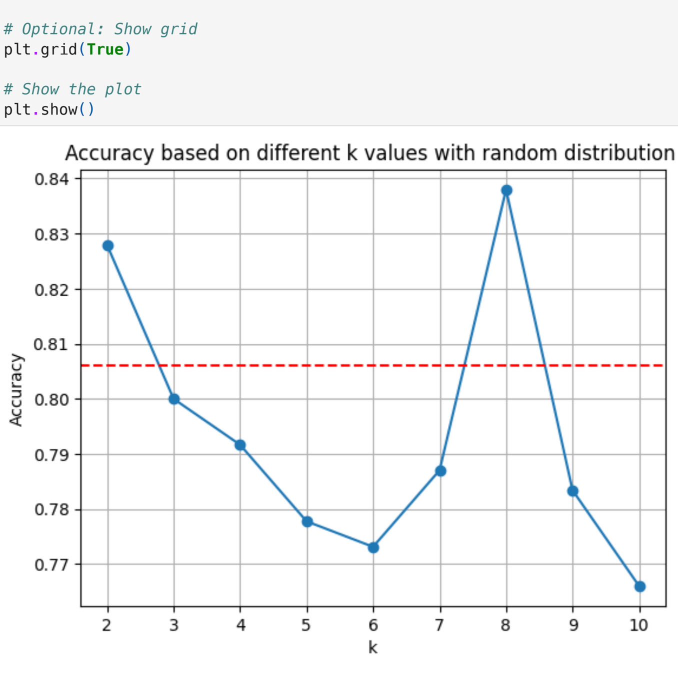
```python
accuracy_list = []

for i in range(len(anonymizedDataSets)):
    dataSet = anonymizedDataSets[i]
    X = dataSet.drop(columns=['survived']).copy()
    y = dataSet['survived']

    for col in X.columns:
        for i in range(len(X[col])):
            if not isinstance(X[col][i], list):
                continue
            X.loc[i, col] = (X[col][i][0]+X[col][i][1])/2


    X = pd.get_dummies(X, columns=['sex'], drop_first=True)  # One-hot encode 'sex' and 'embarked'
    x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

    model = LogisticRegression()
    model.fit(x_train, y_train)

    y_pred = model.predict(x_test)
    accuracy = accuracy_score(y_test, y_pred)
    accuracy_list.append(accuracy)

# print(k_values)
# print(accuracy_list)
```

```python
import matplotlib.pyplot as plt

y = k_values
x = accuracy_list

# Create the plot
plt.plot(y, x, marker='o')  # y on x-axis, x on y-axis (could reverse if needed)
plt.axhline(y=raw_accuracy, color='red', linestyle='--', label='Reference Accuracy')

# Add labels and title
plt.xlabel('k')       # Replace with your actual label
plt.ylabel('Accuracy')       # Replace with your actual label
plt.title('Accuracy based on different k values')     # Replace with your plot's title

# Optional: Show grid
plt.grid(True)

# Show the plot
plt.show()
```



Plot of k effect on accuracy using random distribution

```python
titanicAnonymized = sns.load_dataset('titanic')

featureColumns = ['sex', 'age', 'sibsp', 'parch', 'fare'] # Removes: pclass, deck, 'class', 'who', 'adult_male', 'embark_town', 'alive', 'alone', 'embarked'
sensitiveColumn = "survived"
catagorical = set(('sex', 'embarked'))

for name in catagorical:
    titanicAnonymized[name] = titanicAnonymized[name].astype("category")

anonymizedDataSets = []
k_values = range(2, 11)

for i in k_values:
    p = anonypy.Preserver(titanicAnonymized, featureColumns, sensitiveColumn)
    rows = p.anonymize_k_anonymity(k=i)
    k_anom_data = pd.DataFrame(rows)
    k_anom_data = k_anom_data.loc[k_anom_data.index.repeat(k_anom_data['count'])].reset_index(drop=True)
    k_anom_data = k_anom_data.drop(columns=['count'])
    cols_to_transform = k_anom_data.columns.difference(['survived', 'count'])
    k_anom_data[cols_to_transform] = k_anom_data[cols_to_transform].map(transform_cell)

    anonymizedDataSets.append(k_anom_data)

accuracy_list = []

for i in range(len(anonymizedDataSets)):
    dataSet = anonymizedDataSets[i]
    X = dataSet.drop(columns=['survived']).copy()
    y = dataSet['survived']

    for col in X.columns:
        for i in range(len(X[col])):
            if not isinstance(X[col][i], list):
                continue
            X.loc[i, col] = random() * (X[col][i][1] - X[col][i][0]) + X[col][i][0]


    X = pd.get_dummies(X, columns=['sex'], drop_first=True)  # One-hot encode 'sex' and 'embarked'
    x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

    model = LogisticRegression()
    model.fit(x_train, y_train)

    y_pred = model.predict(x_test)
    accuracy = accuracy_score(y_test, y_pred)
    accuracy_list.append(accuracy)

# print(k_values)
# print(accuracy_list

import matplotlib.pyplot as plt

y = k_values
x = accuracy_list

# Create the plot
plt.plot(y, x, marker='o')  # y on x-axis, x on y-axis (could reverse if needed)
plt.axhline(y=raw_accuracy, color='red', linestyle='--', label='Reference Accuracy')
# Add labels and title
plt.xlabel('k')       # Replace with your actual label
plt.ylabel('Accuracy')       # Replace with your actual label
plt.title('Accuracy based on different k values with random distribution ')     # Replace with your plot's title

# Optional: Show grid
plt.grid(True)

# Show the plot
plt.show()
```



Plot of k effect on accuracy using only the 'fare' column

```python
titanicAnonymized = sns.load_dataset('titanic')

featureColumns = ['fare'] # Removes: pclass, deck, 'class', 'who', 'adult_male', 'embark_town', 'alive', 'alone', 'embarked'
sensitiveColumn = "survived"

anonymizedDataSets = []
k_values = range(2, 11)

for i in k_values:
    p = anonypy.Preserver(titanicAnonymized, featureColumns, sensitiveColumn)
    rows = p.anonymize_k_anonymity(k=i)
    k_anom_data = pd.DataFrame(rows)
    k_anom_data = k_anom_data.loc[k_anom_data.index.repeat(k_anom_data['count'])].reset_index(drop=True)
    k_anom_data = k_anom_data.drop(columns=['count'])
    cols_to_transform = k_anom_data.columns.difference(['survived', 'count'])
    k_anom_data[cols_to_transform] = k_anom_data[cols_to_transform].map(transform_cell)

    anonymizedDataSets.append(k_anom_data)

accuracy_list = []

for i in range(len(anonymizedDataSets)):
    dataSet = anonymizedDataSets[i]
    X = dataSet.drop(columns=['survived']).copy()
    y = dataSet['survived']

    for col in X.columns:
        for i in range(len(X[col])):
            if not isinstance(X[col][i], list):
                continue
            X.loc[i, col] = (X[col][i][0]+X[col][i][1])/2

    x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

    model = LogisticRegression()
    model.fit(x_train, y_train)

    y_pred = model.predict(x_test)
    accuracy = accuracy_score(y_test, y_pred)
    accuracy_list.append(accuracy)

# print(k_values)
# print(accuracy_list)
```

```python
import matplotlib.pyplot as plt

y = k_values
x = accuracy_list

# Create the plot
plt.plot(y, x, marker='o')  # y on x-axis, x on y-axis (could reverse if needed)
plt.axhline(y=raw_accuracy, color='red', linestyle='--', label='Reference Accuracy')

# Add labels and title
plt.xlabel('k')       # Replace with your actual label
plt.ylabel('Accuracy')       # Replace with your actual label
plt.title('Accuracy based on different k values (only \'fare\')')     # Replace with your plot's title

# Optional: Show grid
plt.grid(True)

# Show the plot
plt.show()
```