## Annand DSE6003 Final

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## 1 DSE6003 Final Project Supplemental Code

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## $1.2 \quad 10/20/2023$

Import pandas and dataset. To ensure data quality, any NA values are removed from the dataset. A separate dataframe with only the five quasi-identifiers is created to focus on de-identification efforts.

A variety of functions were created in order to de-idnetify quasi-identifiers by converting values into ranges of values. This is done for Age, Household Income, Education Years, and Region.

```
[15]: def de_id_age(value):
          if value >= 18 and value < 26:
              return "18-25"
          elif value >= 26 and value < 35:
              return "26-34"
          elif value >= 35 and value < 45:
              return "35-44"
          elif value >= 45 and value < 55:
              return "45-54"
          elif value >= 55 and value < 65:
              return "55-64"
          elif value >= 65 and value < 75:
              return "65-74"
          elif value >= 75:
              return "75+"
      def de_id_income(value):
          if value <= 30:
```

```
return "0-30000"
    elif value > 30 and value <= 80:
        return "30001-80000"
    elif value > 80 and value <= 120:
        return "80001-120000"
    elif value > 120:
        return "120001+"
def de_id_education(value):
    if value < 11:
        return "0-11"
    elif value > 11 and value <= 15:
       return "12-15"
    elif value > 15 and value <= 19:
        return "16-19"
    elif value > 19:
        return "20-23"
def de_id_region(value):
    if value >= 1 and value <=3:
        return "1-3"
    elif value > 3:
        return "4-5"
```

New columns were created in the data frame to reflect the new generalized values for the quasiidentifiers that would be used in creating equivalence classes.

See the caveats in the documentation: https://pandas.pydata.org/pandas-

```
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  quasi_data['income_de_id'] = quasi_data['HouseholdIncome'].map(de_id_income)
C:\Users\janna\AppData\Local\Temp\ipykernel_28120\3279607735.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  quasi_data['edu_de_id'] = quasi_data['EducationYears'].map(de_id_education)
C:\Users\janna\AppData\Local\Temp\ipykernel_28120\3279607735.py:4:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  quasi_data['region_de_id'] = quasi_data['Region'].map(de_id_region)
```

Initialize variables that are equal to or used in calculating the probabilities of each re-identification action occurring.

```
# Probability of attempt based on Verizon DBIR - 83% are from external → adversaries

pr_attempt = 1 - 0.83

# Number of customers with Merrimac Communications before sale

merr_customers = 6000

# U.S. Adult Population

us_pop = 260836730

# Probability of an analyst knowing someone in the data set

pr_acquaintance = 1 - ((1-(merr_customers/us_pop))**150)

# Probability of a data breach is 60% for large companies

pr_breach = 0.60
```

A dataframe of all the equivalence classes is created. Each equivalence class has the same combination of all five quasi-identifiers.

The risk for each scenario is calculated for each equivalence class and added to the data frame.

```
[19]: # Calculate Pr(re-id) for all four scenarios
eq_classes['scenario_1'] = pr_attempt * eq_classes['pr_re_id']
eq_classes['scenario_2'] = pr_acquaintance * eq_classes['pr_re_id']
eq_classes['scenario_3'] = pr_breach * eq_classes['pr_re_id']
eq_classes['scenario_4'] = 1.00 * eq_classes['pr_re_id']
```

A function to assign each equivalence a range of re-identification risk it falls into.

```
[20]: def determine_risk_range(value):
    if value < 0.05:
        return "<5%"
    elif value >= 0.05 and value < 0.10:
        return "<10%"
    elif value >= 0.10 and value < 0.20:
        return "<20%"
    elif value >= 0.20 and value < 0.33:
        return "<33%"
    elif value >= 0.33 and value < 0.5:
        return "<50%"
    elif value >= 0.5:
        return ">50%"
```

We apply the function to determine thr risk range to the equivalence class data frame.

```
[21]: # Calculate risk for each equivalence class for each scenario
    eq_classes['s1.risk'] = eq_classes['scenario_1'].map(determine_risk_range)
    eq_classes['s2.risk'] = eq_classes['scenario_2'].map(determine_risk_range)
    eq_classes['s3.risk'] = eq_classes['scenario_3'].map(determine_risk_range)
    eq_classes['s4.risk'] = eq_classes['scenario_4'].map(determine_risk_range)
```

We determine the distrubtion of risk across each equivalence for each scenario.

```
[22]: s1_prob = eq_classes.groupby('s1.risk').size().reset_index()
    s1_prob.rename(columns ={0: "count"}, inplace=True)
    s1_prob['percentage'] = s1_prob['count'] / s1_prob['count'].sum()
    print(s1_prob)

s2_prob = eq_classes.groupby('s2.risk').size().reset_index()
    s2_prob.rename(columns ={0: "count"}, inplace=True)
    s2_prob['percentage'] = s2_prob['count'] / s2_prob['count'].sum()
    print(s2_prob)

s3_prob = eq_classes.groupby('s3.risk').size().reset_index()
    s3_prob.rename(columns ={0: "count"}, inplace=True)
    s3_prob['percentage'] = s3_prob['count'] / s3_prob['count'].sum()
    print(s3_prob)

s4_prob = eq_classes.groupby('s4.risk').size().reset_index()
    s4_prob.rename(columns ={0: "count"}, inplace=True)
```

```
s4_prob['percentage'] = s4_prob['count'] / s4_prob['count'].sum()
print(s4_prob)
```

```
s1.risk count percentage
0
     <10%
               66
                     0.176471
1
     <20%
              51
                     0.136364
             257
      <5%
                     0.687166
  s2.risk count percentage
      <5%
             374
                          1.0
0
  s3.risk
          count
                  percentage
0
     <10%
              82
                     0.219251
     <20%
              74
                     0.197861
1
2
     <33%
              36
                     0.096257
3
      <5%
             131
                     0.350267
     >50%
              51
                     0.136364
  s4.risk count
                  percentage
                     0.229947
0
     <10%
              86
     <20%
              68
                     0.181818
1
2
     <33%
              44
                     0.117647
3
      <5%
              59
                     0.157754
4
     <50%
              30
                     0.080214
5
     >50%
              87
                     0.232620
```

The maximum, average, and median risk was calculated for each scenario. Average risk is the same across all scenarios because all scenarios use the same number of equivalence classes and include the same total number of records.

```
[23]: # Scenario 1
      print("Scenario 1:")
      print(eq_classes['scenario_1'].max())
      print(eq_classes['scenario_1'].median())
      # Scenario 2
      print("Scenario 2:")
      print(eq_classes['scenario_2'].max())
      print(eq_classes['scenario_2'].median())
      # Scenario 3
      print("Scenario 3:")
      print(eq_classes['scenario_3'].max())
      print(eq_classes['scenario_3'].median())
      # Scenario 4
      print("Scenario 4:")
      print(eq_classes['scenario_4'].max())
      print(eq_classes['scenario_4'].median())
      #Average risk across scenarios
```

```
print("Average Risk")
     len(eq_classes) / len(data)
     Scenario 1:
     0.17000000000000004
     0.02428571428571429
     Scenario 2:
     0.0034445279415022956
     0.0004920754202146137
     Scenario 3:
     0.6
     0.0857142857142857
     Scenario 4:
     1.0
     0.14285714285714285
     Average Risk
[23]: 0.0748
```

[]: