```
In [9]: import numpy as np
          import pandas as pd
         from typing import Dict, Tuple
         from scipy import stats
         from sklearn.naive_bayes import GaussianNB, MultinomialNB, ComplementNB, BernoulliNB
         from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
         from sklearn.model_selection import train_test_split
         from sklearn.linear_model import LogisticRegression
         from sklearn.metrics import accuracy_score, balanced_accuracy_score
         from sklearn.metrics import precision_score, recall_score, f1_score, classification_report
         from sklearn.pipeline import Pipeline
         import seaborn as sns
         import matplotlib.pyplot as plt
          %matplotlib inline
         sns.set(style="ticks")
          import warnings
In [10]: warnings.filterwarnings('ignore') # Отключаем предупреждения
 In [3]: data = pd.read_csv('adult.data.csv')
          data.head()
 Out[3]:
                                                                                                                     hours-
                                             education-
                                                                                                     capital- capital-
                                                         marital-
                                                                                                                             native-
             age workclass fnlwgt education
                                                                 occupation relationship race
                                                                                                                                    salary
                                                                                                                           country
                                                  num
                                                          status
                                                                                                        gain
                                                                                                               loss
                                                                                                                      week
                                                       Never-
          0 39 | State-gov
                           77516 | Bachelors | 13
                                                                                                     2174
                                                                 Adm-clerical | Not-in-family | White | Male
                                                                                                                                     <=50K
                                                                                                                            States
                                                       married
                 Self-emp-
                                                       Married-
                                                                 Exec-
          1 50
                           83311
                                  Bachelors 13
                                                                                        White | Male
                                                                                                                                     <=50K
                                                                            Husband
                 not-inc
                                                                                                                            States
                                                       civ-spouse | managerial
                                                                                                                            United-
                                                                 Handlers-
                           215646 HS-grad
          2 38
                Private
                                                       Divorced
                                                                            Not-in-family | White | Male
                                                                                                                                     <=50K
                                                                                                                            States
                                                                 cleaners
                                                                                                                            United-
                                                       Married-
                                                                 Handlers-
          3 53 Private
                           234721 11th
                                                                                                                                    <=50K
                                                                            Husband
                                                                                        Black | Male
                                                                                                                            States
                                                                 cleaners
                                                       civ-spouse
                                                       Married-
                                                                 Prof-
          4 28 Private
                           338409 Bachelors | 13
                                                                            Wife
                                                                                        Black | Female | 0
                                                                                                                                    <=50K
                                                                                                                    40
                                                                                                                            Cuba
                                                       civ-spouse | specialty
In [42]: x_train, x_test, y_train, y_test = train_test_split(data['race'], data['sex'], test_size=0.5, random_state=1)
In [43]: def accuracy_score_for_classes(
              y_true: np.ndarray,
             y_pred: np.ndarray) -> Dict[int, float]:
              Вычисление метрики ассигасу для каждого класса
              y_true - истинные значения классов
              y_pred - предсказанные значения классов
              Возвращает словарь: ключ - метка класса,
              значение - Accuracy для данного класса
              # Для удобства фильтрации сформируем Pandas DataFrame
              d = {'t': y_true, 'p': y_pred}
              df = pd.DataFrame(data=d)
              # Метки классов
              classes = np.unique(y_true)
              # Результирующий словарь
              res = dict()
              # Перебор меток классов
              for c in classes:
                  # отфильтруем данные, которые соответствуют
                  # текущей метке класса в истинных значениях
                  temp_data_flt = df[df['t']==c]
                  # расчет ассигасу для заданной метки класса
                  temp_acc = accuracy_score(
                     temp_data_flt['t'].values,
                      temp_data_flt['p'].values)
                  # сохранение результата в словарь
                  res[c] = temp_acc
              return res
         def print_accuracy_score_for_classes(
              y_true: np.ndarray,
              y_pred: np.ndarray):
              Вывод метрики ассигасу для каждого класса
             accs = accuracy_score_for_classes(y_true, y_pred)
              if len(accs)>0:
                  print('Метка \t Accuracy')
              for i in accs:
                  print('{} \t {}'.format(i, accs[i]))
In [44]: def sentiment(v, c):
              model = Pipeline(
                 [("vectorizer", v),
                  ("classifier", c)])
              model.fit(x_train, y_train)
             y_pred = model.predict(x_test)
             print_accuracy_score_for_classes(y_test, y_pred)
         Классификация с использованием логистической регресии
In [45]: sentiment(TfidfVectorizer(), LogisticRegression(C=5.0, solver='lbfgs'))
          Метка
                  Accuracy
         Female 0.14269870609981516
         Male
                  0.9268696532057769
In [46]: sentiment(CountVectorizer(), MultinomialNB())
         Метка
                  Accuracy
         Female 0.14269870609981516
         Male
                  0.9268696532057769
In [47]: sentiment(TfidfVectorizer(), MultinomialNB())
         Метка
                  Accuracy
         Female 0.14269870609981516
                  0.9268696532057769
         Male
         sentiment(CountVectorizer(), ComplementNB())
         Метка
                  Accuracy
         Female 0.16506469500924215
                  0.9105878024100819
         Male
In [49]: sentiment(TfidfVectorizer(), ComplementNB())
          Метка
                  Accuracy
         Female 0.16506469500924215
                  0.9105878024100819
         Male
In [50]: sentiment(CountVectorizer(binary=True), BernoulliNB())
         Метка
                  Accuracy
         Female 0.15397412199630314
                  0.9184067703063196
         Male
```