Project

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This project develops a machine learning model to predict the probabilities of whether people received the H1N1 vaccine based on the background, opinions, and health behaviors that respondents disclosed.

In [1]:
```
import numpy as np
import pylab as pl
import pandas as pd
import seaborn as sns
%matplotlib inline
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OrdinalEncoder, OneHotEncoder, MinMaxScaler, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_squared_error
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_validate
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import RocCurveDisplay
from sklearn.metrics import roc_auc_score, roc_curve, accuracy_score
from sklearn.model_selection import cross_val_score, StratifiedKFold

np.random.seed = 10
```

In [2]:
```
train_set = pd.read_csv('train.csv')
test_set = pd.read_csv('test.csv')
```

We will first browse the test set to see if there are any NaN and null values.

In [3]:
```
test_set.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2671 entries, 0 to 2670
Data columns (total 32 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   h1n1_concern                 2659 non-null   float64
 1   h1n1_knowledge               2659 non-null   float64
 2   behavioral_antiviral_meds    2659 non-null   float64
 3   behavioral_avoidance         2647 non-null   float64
 4   behavioral_face_mask         2668 non-null   float64
 5   behavioral_wash_hands        2669 non-null   float64
 6   behavioral_large_gatherings  2667 non-null   float64
 7   behavioral_outside_home      2661 non-null   float64
 8   behavioral_touch_face        2658 non-null   float64
 9   doctor_recc_h1n1             2470 non-null   float64
 10  doctor_recc_seasonal         2470 non-null   float64
 11  chronic_med_condition        2578 non-null   float64
 12  child_under_6_months         2598 non-null   float64
 13  health_worker                2602 non-null   float64
 14  health_insurance             1495 non-null   float64
 15  opinion_h1n1_vacc_effective  2634 non-null   float64
 16  opinion_h1n1_risk            2636 non-null   float64
 17  opinion_h1n1_sick_from_vacc  2632 non-null   float64
 18  opinion_seas_vacc_effective  2630 non-null   float64
 19  opinion_seas_risk            2626 non-null   float64
 20  opinion_seas_sick_from_vacc  2617 non-null   float64
 21  age_group                    2671 non-null   object 
 22  education                    2547 non-null   object 
 23  race                         2671 non-null   object 
 24  sex                          2671 non-null   object 
 25  income_poverty               2225 non-null   object 
 26  marital_status               2541 non-null   object 
 27  rent_or_own                  2482 non-null   object 
 28  employment_status            2541 non-null   object 
 29  household_adults             2646 non-null   float64
 30  household_children           2646 non-null   float64
 31  h1n1_vaccine                 2671 non-null   int64  
dtypes: float64(23), int64(1), object(8)
memory usage: 667.9+ KB
```

Almost all columns have null and NaN entries. We will deal with them while encoding.

Separate predictors and labels:

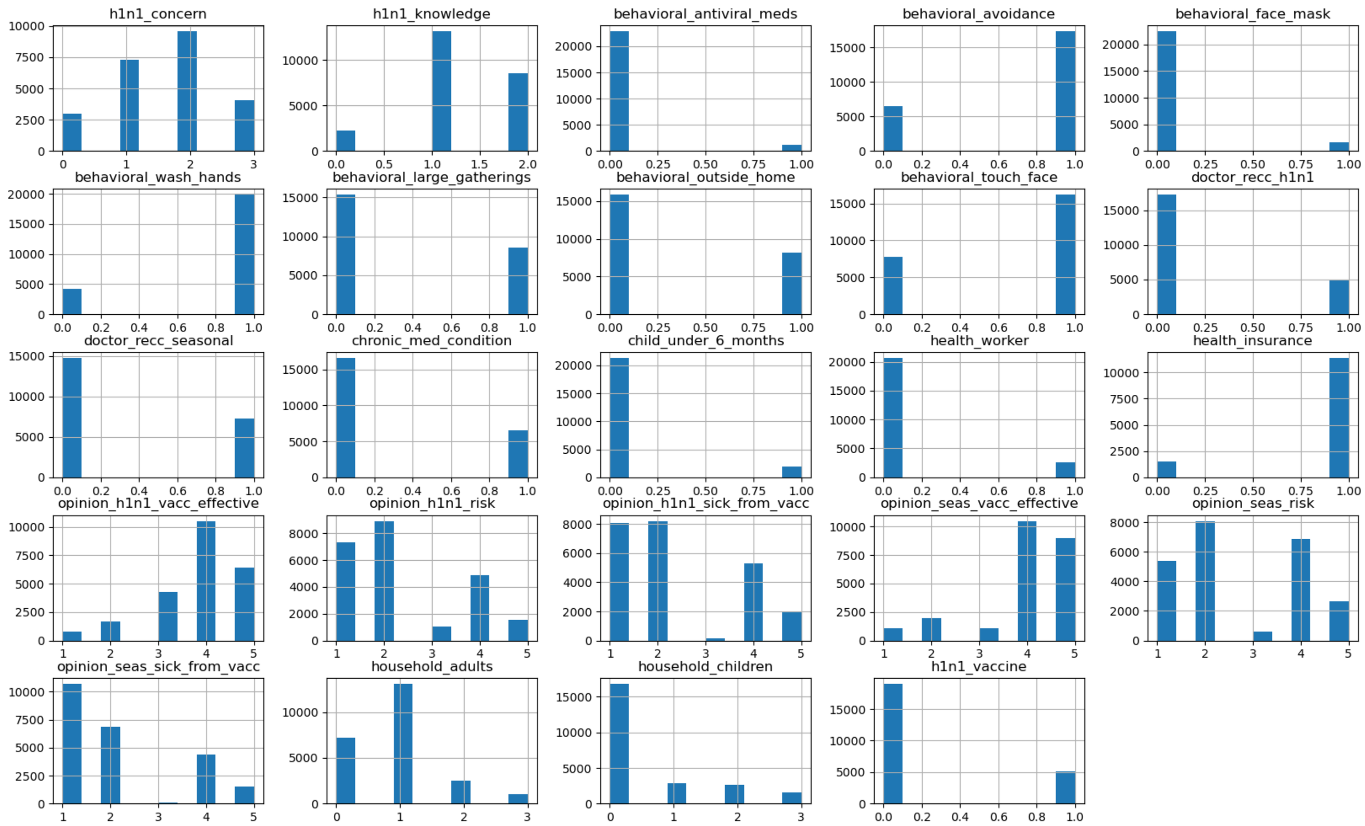
In [4]:
```
X_train = train_set.drop("h1n1_vaccine", axis=1)
y_train = train_set["h1n1_vaccine"].copy()
X_test = test_set.drop("h1n1_vaccine", axis=1)
y_test = test_set["h1n1_vaccine"].copy()
```

We will gain some insights into the training set.

In [5]:
```
data = train_set.copy()
```

In [6]:
```
data.hist(figsize=(20,12))
```

Out[6]:
```
array([[<AxesSubplot:title={'center':'h1n1_concern'}>,
        <AxesSubplot:title={'center':'h1n1_knowledge'}>,
        <AxesSubplot:title={'center':'behavioral_antiviral_meds'}>,
        <AxesSubplot:title={'center':'behavioral_avoidance'}>,
        <AxesSubplot:title={'center':'behavioral_face_mask'}>],
       [<AxesSubplot:title={'center':'behavioral_wash_hands'}>,
        <AxesSubplot:title={'center':'behavioral_large_gatherings'}>,
        <AxesSubplot:title={'center':'behavioral_outside_home'}>,
        <AxesSubplot:title={'center':'behavioral_touch_face'}>,
        <AxesSubplot:title={'center':'doctor_recc_h1n1'}>],
       [<AxesSubplot:title={'center':'doctor_recc_seasonal'}>,
        <AxesSubplot:title={'center':'chronic_med_condition'}>,
        <AxesSubplot:title={'center':'child_under_6_months'}>,
        <AxesSubplot:title={'center':'health_worker'}>,
        <AxesSubplot:title={'center':'health_insurance'}>],
       [<AxesSubplot:title={'center':'opinion_h1n1_vacc_effective'}>,
        <AxesSubplot:title={'center':'opinion_h1n1_risk'}>,
        <AxesSubplot:title={'center':'opinion_h1n1_sick_from_vacc'}>,
        <AxesSubplot:title={'center':'opinion_seas_vacc_effective'}>,
        <AxesSubplot:title={'center':'opinion_seas_risk'}>],
       [<AxesSubplot:title={'center':'opinion_seas_sick_from_vacc'}>,
        <AxesSubplot:title={'center':'household_adults'}>,
        <AxesSubplot:title={'center':'household_children'}>,
        <AxesSubplot:title={'center':'h1n1_vaccine'}>, <AxesSubplot:>]],
      dtype=object)
```



Most people seem to have an opinion on the h1n1 and the seasonal flu vaccine, with very few people having no opinion/not knowing. Doctors also tend to not recommend either vaccine to the respondents. Most respondents do not have any children in their household. A lot of respondents live alone or with one other partner.

Implement transformer preprocessor to the numerical and nominal columns.

In [7]:
```
#Sort by numerical and nominal
numerical_columns = ['household_adults', 'household_children',
                      'opinion_h1n1_vacc_effective', 'opinion_seas_vacc_effective',
                     'opinion_h1n1_risk', 'opinion_seas_risk',
                     'opinion_h1n1_sick_from_vacc', 'opinion_seas_sick_from_vacc', 'h1n1_conce
                     'h1n1_knowledge']
```

```
nominal_columns = ['age_group', 'behavioral_antiviral_meds', 'behavioral_avoidance',
                   'behavioral_face_mask', 'behavioral_wash_hands',
                   'behavioral_large_gatherings', 'behavioral_outside_home',
                  'behavioral_touch_face', 'doctor_recc_h1n1',
                  'chronic_med_condition', 'child_under_6_months',
                  'health_worker', 'health_insurance', 'education',
                  'race', 'sex', 'marital_status', 'rent_or_own',
                  'employment_status']

#Define estimators, transformers, and encoders. Handle unknowns by ignoring them
numerical_pipeline = Pipeline([('imputer', SimpleImputer(strategy='mean')),
                               ('scaler', StandardScaler())])
nominal_pipeline = Pipeline([('imputer', SimpleImputer(strategy='most_frequent')),
                             ('encoder', OneHotEncoder(handle_unknown='ignore'))])
```

We implement transformers for the ordinal column of `income_poverty`.

In [8]:
```
ordinal_columns= ['income_poverty']
order = [['Below Poverty', '<= $75,000, Above Poverty', '> $75,000']]

#Def estimators, transformers, and encoders. Handle unknowns by ignoring them

ordinal_pipeline = Pipeline([('imputer', SimpleImputer(strategy='most_frequent')),
                             ('encoder', OrdinalEncoder(categories=order,
                                                        handle_unknown='use_encoded_value',
                                                        unknown_value=-1,)),
                             ('scaler', StandardScaler())])
```

Now we implement the transformers.

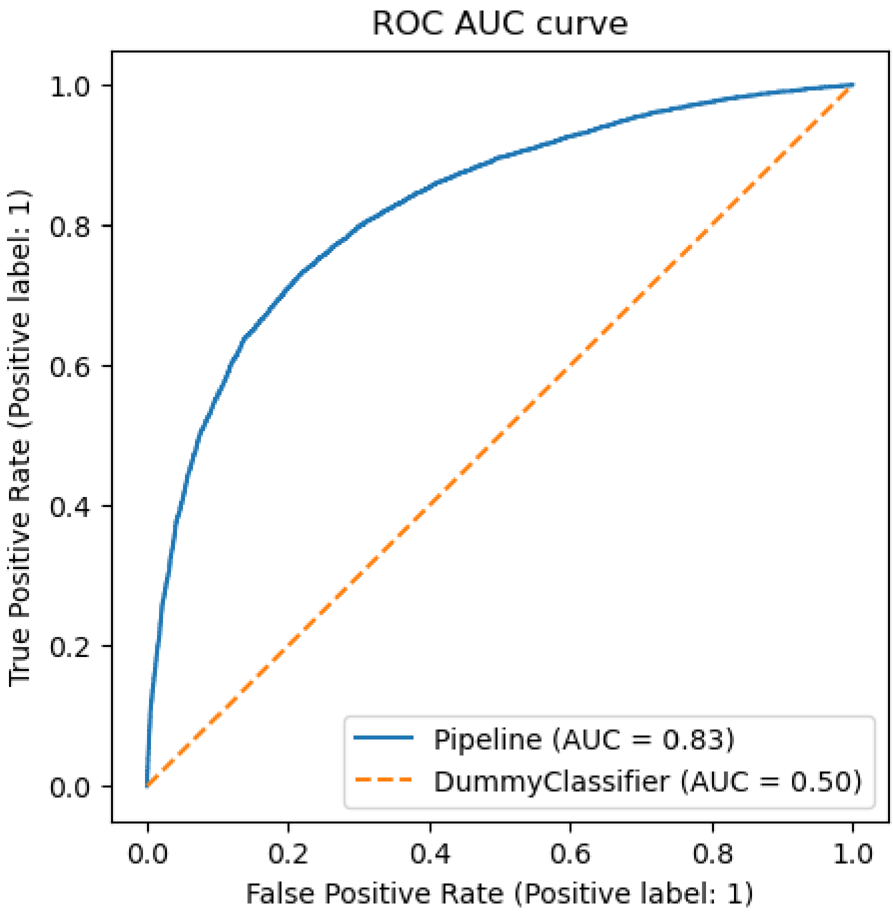
In [9]:
```
#Apply these transformers to the columns
preprocessor = ColumnTransformer([('numerical_transformer', numerical_pipeline, numerical_col
                                  ('nominal_transformer', nominal_pipeline, nominal_columns),
                                 ('ordinal_transformer', ordinal_pipeline, ordinal_columns)])
```

In [10]:
```
#dummy classifier
from sklearn.dummy import DummyClassifier

dummy_classifier = DummyClassifier(strategy="most_frequent")
dummy_classifier.fit(X_train, y_train)
```

Out[10]:
```
▾ DummyClassifier
DummyClassifier(strategy='most_frequent')
```

Now we evaluate the models. First we will choose the Logistic Regression model.

In [11]:
```
lr_model = Pipeline([('preprocessor', preprocessor), ('regressor', LogisticRegression())])

lr_model.fit(X_train, y_train);

y_train_predicted = lr_model.predict(X_train)

f = RocCurveDisplay.from_estimator(lr_model, X_train, y_train, pos_label=1,
ax=pl.figure(figsize=(5,5)).gca())
f = RocCurveDisplay.from_estimator(dummy_classifier, X_train, y_train, pos_label=1,
color="tab:orange", linestyle="--", ax=f.ax_)
f.ax_.set_title("ROC AUC curve");
```



In [12]:
```
roc_auc_score(y_train, lr_model.predict_proba(X_train)[:,1])
```

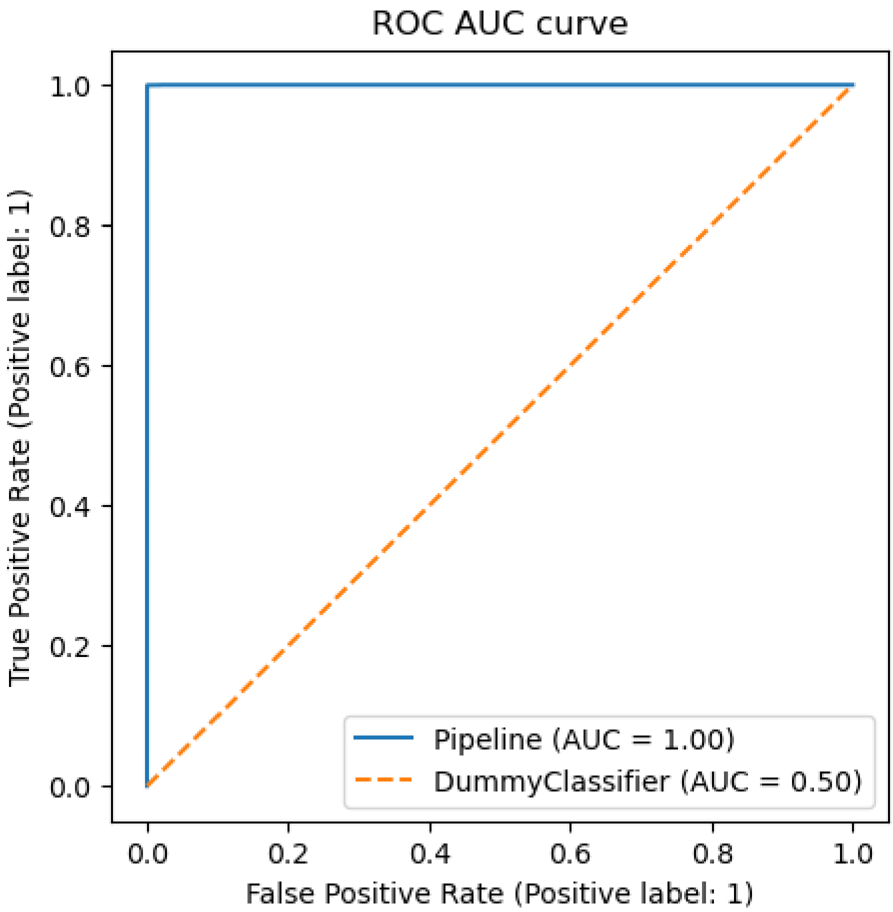
Out[12]: 0.8277246824212607

In [13]:
```
cv = StratifiedKFold(n_splits=5)
scores = cross_val_score(lr_model, X_train, y_train, cv=cv, scoring="accuracy")
print(f"Accuracy score: {scores.mean():.4f} +/- {scores.std():.4f}")
scores = cross_val_score(lr_model, X_train, y_train, cv=cv, scoring="balanced_accuracy")
print(f"Balanced accuracy score: {scores.mean():.4f} +/- {scores.std():.4f}")
```

```
Accuracy score: 0.8347 +/- 0.0036
Balanced accuracy score: 0.6786 +/- 0.0084
```

Now we will try the Random Forest model.

In [14]:
```
rf_model = Pipeline([('preprocessor', preprocessor),
                     ('classifier', RandomForestClassifier(random_state=0))
                    ])
rf_model.fit(X_train, y_train);
y_train_predicted = rf_model.predict(X_train);

f = RocCurveDisplay.from_estimator(rf_model, X_train, y_train, pos_label=1,
ax=pl.figure(figsize=(5,5)).gca())
f = RocCurveDisplay.from_estimator(dummy_classifier, X_train, y_train, pos_label=1,
color="tab:orange", linestyle="--", ax=f.ax_)
f.ax_.set_title("ROC AUC curve");
```



In [15]:
```
rf_model_roc_auc = roc_auc_score(y_train, rf_model.predict_proba(X_train)[:,1])
rf_model_roc_auc
```

Out[15]: 0.9999962189173712

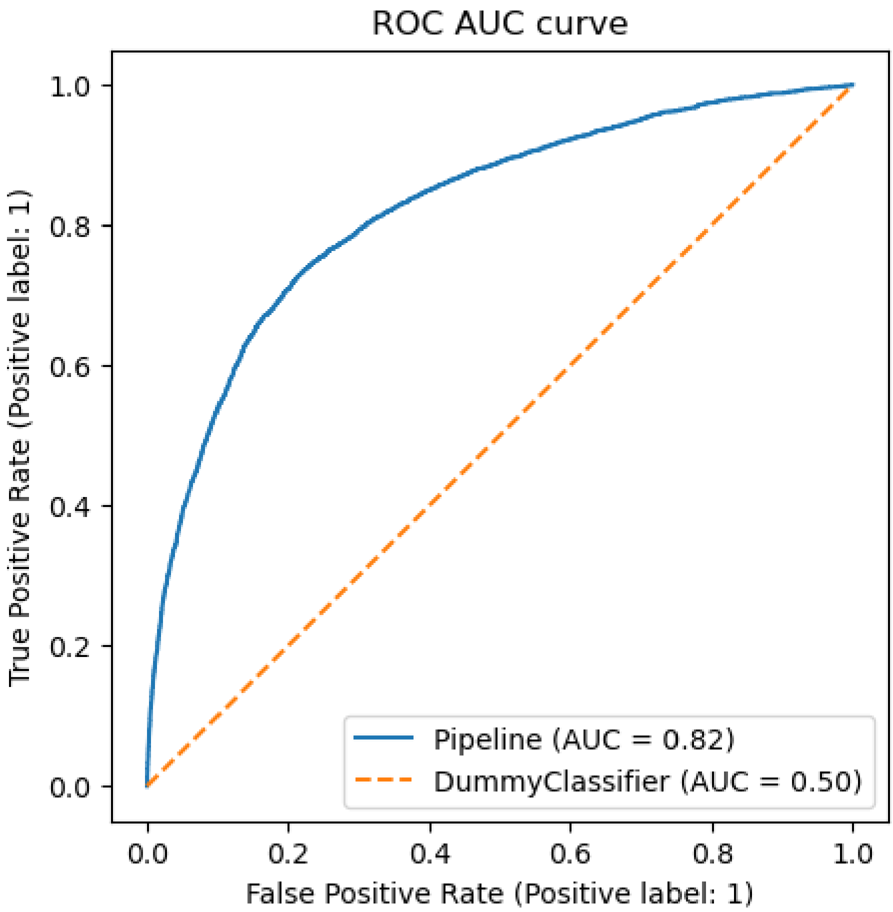
In [16]:
```
cv = StratifiedKFold(n_splits=5)
scores = cross_val_score(rf_model, X_train, y_train, cv=cv, scoring="accuracy")
print(f"Accuracy score: {scores.mean():.4f} +/- {scores.std():.4f}")
scores = cross_val_score(rf_model, X_train, y_train, cv=cv, scoring="balanced_accuracy")
print(f"Balanced accuracy score: {scores.mean():.4f} +/- {scores.std():.4f}")
```

```
Accuracy score: 0.8369 +/- 0.0049
Balanced accuracy score: 0.6819 +/- 0.0090
```

A lot better and slightly more accurate.

Now we try the SVM model.

In [17]:
```
from sklearn.svm import SVC
svm_classifier = Pipeline(steps=[('preprocessor', preprocessor),
                                ('classifier', SVC(kernel='linear', probability=True, C=1.0,
                                ])
svm_classifier.fit(X_train, y_train)

f = RocCurveDisplay.from_estimator(svm_classifier, X_train, y_train, pos_label=1,
ax=pl.figure(figsize=(5,5)).gca())
f = RocCurveDisplay.from_estimator(dummy_classifier, X_train, y_train, pos_label=1,
color="tab:orange", linestyle="--", ax=f.ax_)
f.ax_.set_title("ROC AUC curve");
```



In [18]:
```
roc_auc_score(y_train, svm_classifier.predict_proba(X_train)[:,1])
```

Out[18]: 0.8230312370194083

In [19]:
```
cv = StratifiedKFold(n_splits=5)
scores = cross_val_score(svm_classifier, X_train, y_train, cv=cv, scoring="accuracy")
print(f"Accuracy score: {scores.mean():.4f} +/- {scores.std():.4f}")
scores = cross_val_score(svm_classifier, X_train, y_train, cv=cv, scoring="balanced_accuracy"
print(f"Balanced accuracy score: {scores.mean():.4f} +/- {scores.std():.4f}")
```

```
Accuracy score: 0.8293 +/- 0.0015
Balanced accuracy score: 0.6839 +/- 0.0044
```

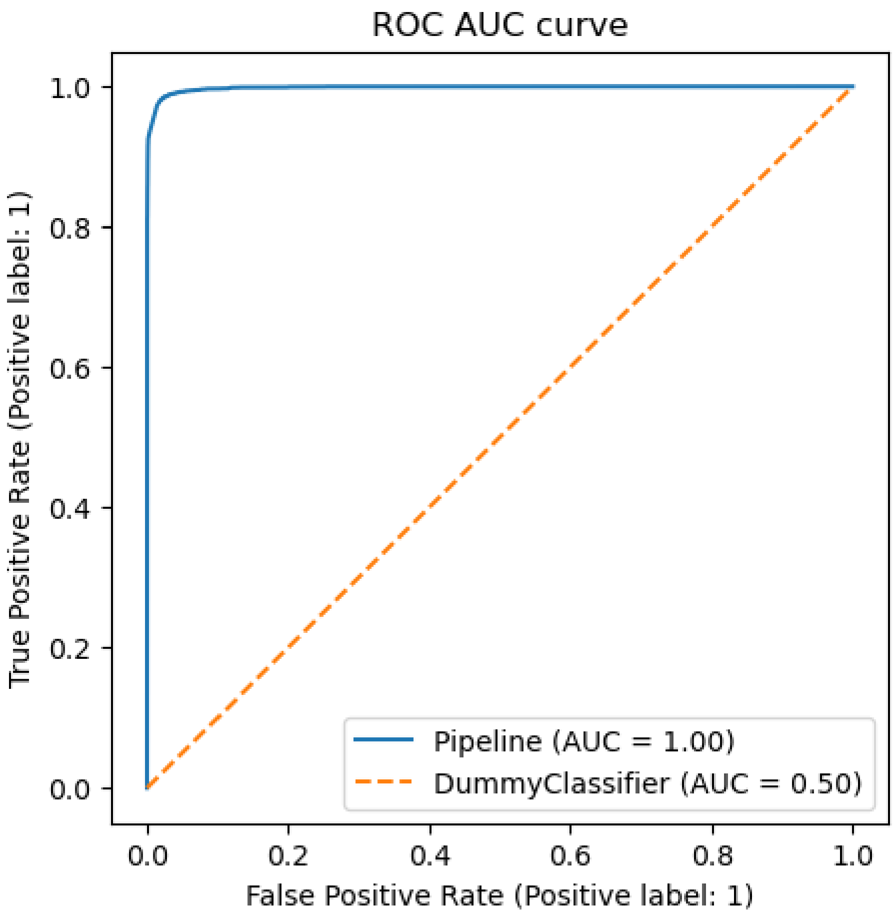
It seems like the Random Forest model is the best, so we will use this on the test set, and it will be our model A.

I would like to see if the removal of the opinions columns from the dataset will make a difference to the AUC-ROC score.

In [20]:
```
X_train_A = X_train.drop(['opinion_h1n1_vacc_effective','opinion_seas_vacc_effective',
                    'opinion_h1n1_risk', 'opinion_seas_risk',
                    'opinion_h1n1_sick_from_vacc', 'opinion_seas_sick_from_vacc'], axis=1)
numerical_columns_2 = ['household_adults', 'household_children','h1n1_concern',
                    'h1n1_knowledge']

numerical_pipeline_2 = Pipeline([('imputer', SimpleImputer(strategy='mean')),
                               ('scaler', StandardScaler())])
preprocessor_2 = ColumnTransformer([('numerical_transformer', numerical_pipeline_2, numerical
                                  ('nominal_transformer', nominal_pipeline, nominal_columns),
                                 ('ordinal_transformer', ordinal_pipeline, ordinal_columns)])
```

In [21]:
```
rf_model_A = Pipeline([('preprocessor', preprocessor_2),
                     ('classifier', RandomForestClassifier(random_state=0))
                    ])
rf_model_A.fit(X_train_A, y_train);
```

```
y_train_predicted = rf_model_A.predict(X_train_A);

f = RocCurveDisplay.from_estimator(rf_model_A, X_train_A, y_train, pos_label=1,
ax=pl.figure(figsize=(5,5)).gca())
f = RocCurveDisplay.from_estimator(dummy_classifier, X_train_A, y_train, pos_label=1,
color="tab:orange", linestyle="--", ax=f.ax_)
f.ax_.set_title("ROC AUC curve");
```



In [22]:
```
roc_auc_score(y_train, rf_model_A.predict_proba(X_train_A)[:,1])
```

Out[22]: 0.9982537682747307

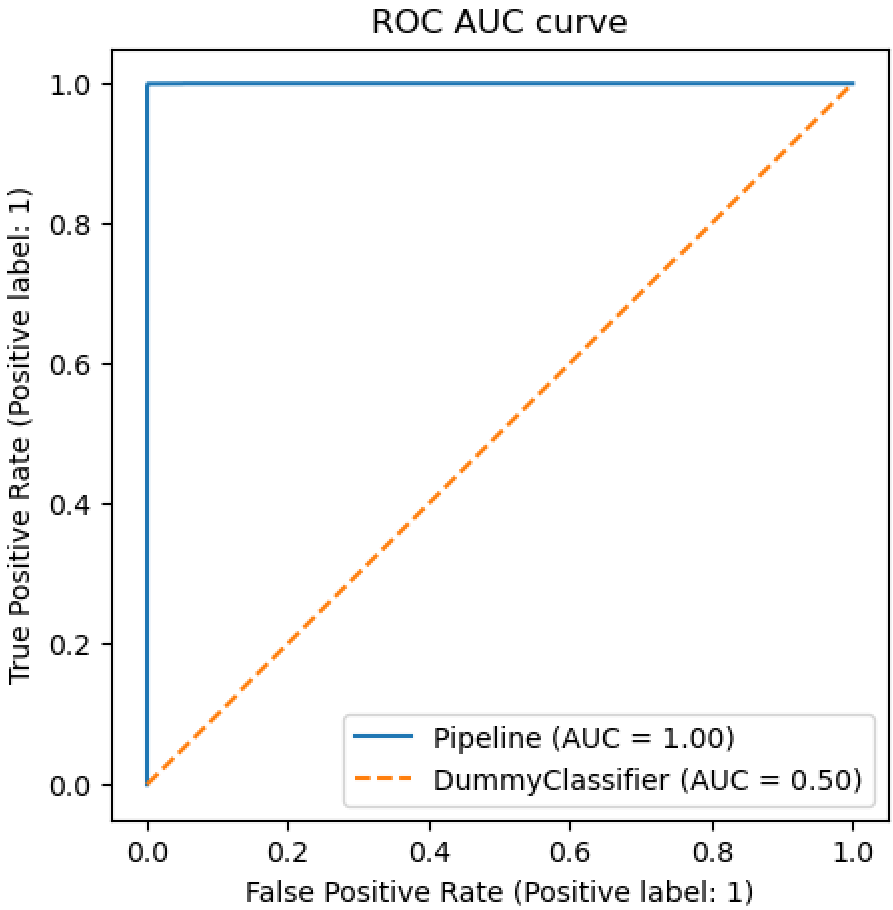
This performs worse.

I will put these columns back and remove the education, marital status and housing situation columns.

In [23]:
```
X_train_A_2 = X_train.drop(['education', 'marital_status', 'rent_or_own'], axis=1)

nominal_columns_2 = ['age_group', 'behavioral_antiviral_meds', 'behavioral_avoidance',
                    'behavioral_face_mask', 'behavioral_wash_hands',
                    'behavioral_large_gatherings', 'behavioral_outside_home',
                   'behavioral_touch_face', 'doctor_recc_h1n1',
                   'chronic_med_condition', 'child_under_6_months',
                   'health_worker', 'health_insurance', 'race', 'sex',
                   'employment_status']
nominal_pipeline_2 = Pipeline([('imputer', SimpleImputer(strategy='most_frequent')),
                             ('encoder', OneHotEncoder(handle_unknown='ignore'))])

preprocessor_3 = ColumnTransformer([('numerical_transformer', numerical_pipeline, numerical_c
                                  ('nominal_transformer', nominal_pipeline_2, nominal_columns
                                 ('ordinal_transformer', ordinal_pipeline, ordinal_columns)])
```

In [24]:
```
rf_model_A_2 = Pipeline([('preprocessor', preprocessor_3),
                     ('classifier', RandomForestClassifier(random_state=0))
                    ])
rf_model_A_2.fit(X_train_A_2, y_train);
```

```
y_train_predicted = rf_model_A_2.predict(X_train_A_2);

f = RocCurveDisplay.from_estimator(rf_model_A_2, X_train_A_2, y_train, pos_label=1,
ax=pl.figure(figsize=(5,5)).gca())
f = RocCurveDisplay.from_estimator(dummy_classifier, X_train_A_2, y_train, pos_label=1,
color="tab:orange", linestyle="--", ax=f.ax_)
f.ax_.set_title("ROC AUC curve");
```

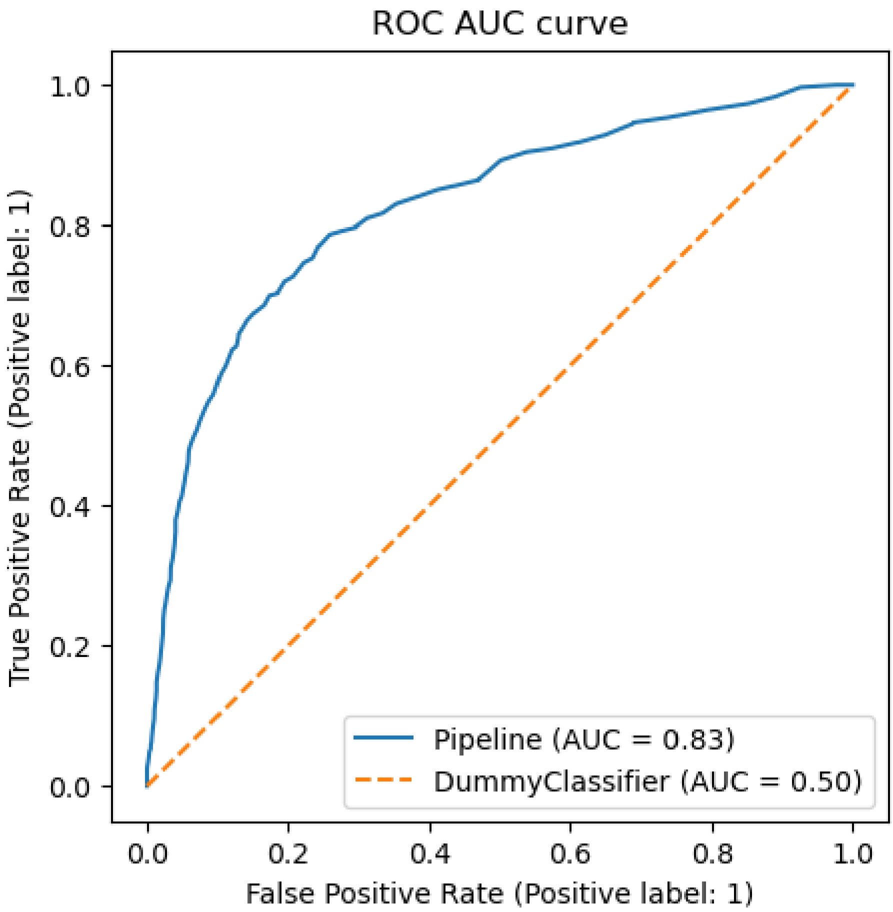


In [25]:
```
roc_auc_score(y_train, rf_model_A_2.predict_proba(X_train_A_2)[:,1])
```

Out[25]: `0.9999879140394549`

Recompare with our original model trained: `0.99999621891737 12`. The above model performs slightly worse. So we will keep our original model trained.

In [26]:
```
y_test_predicted = rf_model.predict(X_test)
f = RocCurveDisplay.from_estimator(rf_model, X_test, y_test, pos_label=1,
ax=pl.figure(figsize=(5,5)).gca())
f = RocCurveDisplay.from_estimator(dummy_classifier, X_test, y_test, pos_label=1,
color="tab:orange", linestyle="--", ax=f.ax_)
f.ax_.set_title("ROC AUC curve");
```

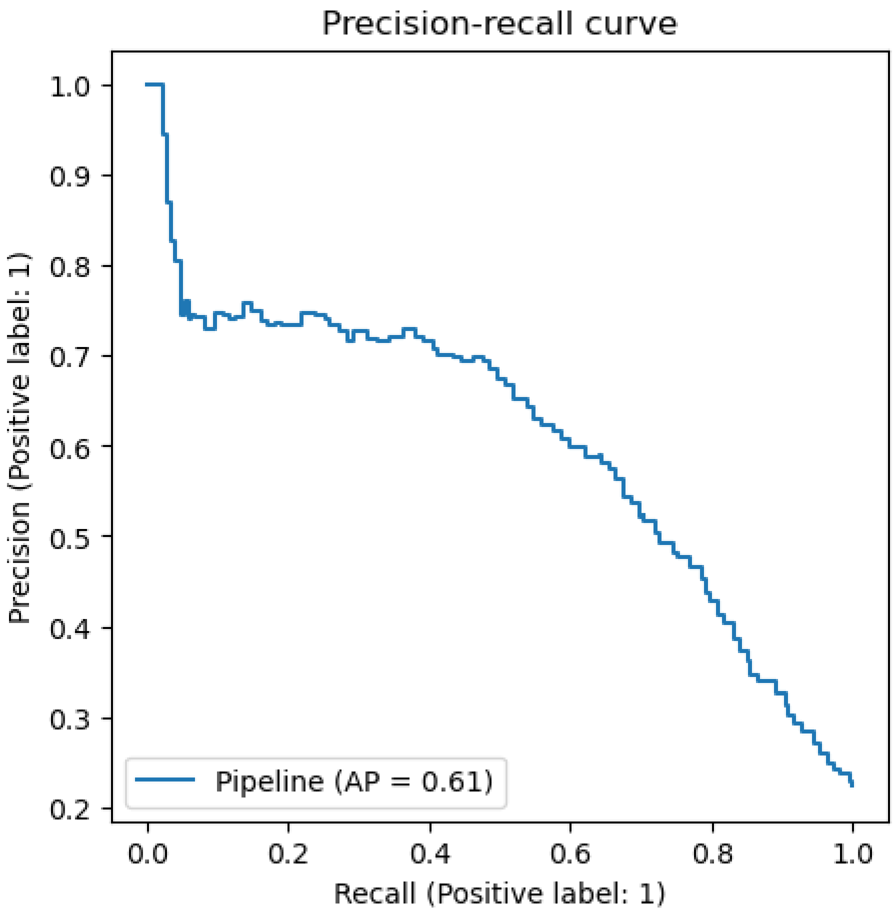


In [27]:
```
roc_auc_score(y_test, rf_model.predict_proba(X_test)[:,1])
```

Out[27]: 0.8257770680035579

We will also report on the AUC-PR, the accuracy, the sensitivity, and the specificity.

In [28]:
```
from sklearn.metrics import PrecisionRecallDisplay

f = PrecisionRecallDisplay.from_estimator(rf_model, X_test, y_test, pos_label=1,
ax=pl.figure(figsize=(5,5)).gca())
f.ax_.set_title("Precision-recall curve");
```



In [29]:
```
from sklearn.metrics import average_precision_score

average_precision_score(y_test, rf_model.predict_proba(X_test)[:,1], pos_label=1)
```

Out[29]: 0.6063589426505896

In [30]:
```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import auc
M = confusion_matrix(y_test, y_test_predicted)
tn, fp, fn, tp = M.ravel()
acc = (tp + tn) / (tn + tp + fn + fp)
sen = tp / (tp + fn)
spe = tn / (tn + fp)
print(f'Accuracy: {acc}\nSensitivity: {sen}\nSpecificity: {spe}')
```

```
Accuracy: 0.8307749906402097
Sensitivity: 0.412751677852349
Specificity: 0.9508433734939759
```

Model B

To select the five-six features we use LASSO regression.

In [31]:
```
from sklearn.linear_model import Lasso
#LASSO regression required an alpha value of 0.019 to get 6 features.
lasso_pipe = Pipeline([('preprocessor', preprocessor),
                       ('lasso', Lasso(alpha=0.019, max_iter=50000))])
lasso_pipe.fit(X_train, y_train)
print("Number of features used: {}".format(np.sum(lasso_pipe['lasso'].coef_ != 0)))
```

```
Number of features used: 6
```

In [32]:
```
#Extracting the features that the LASSO regression used.
lasso_model = lasso_pipe['lasso']
coefficients = lasso_model.coef_
selected_feature_indices = [i for i, coef in enumerate(coefficients) if coef != 0]
```

```
selected_feature_names = X_train.columns[selected_feature_indices]
selected_feature_names
```

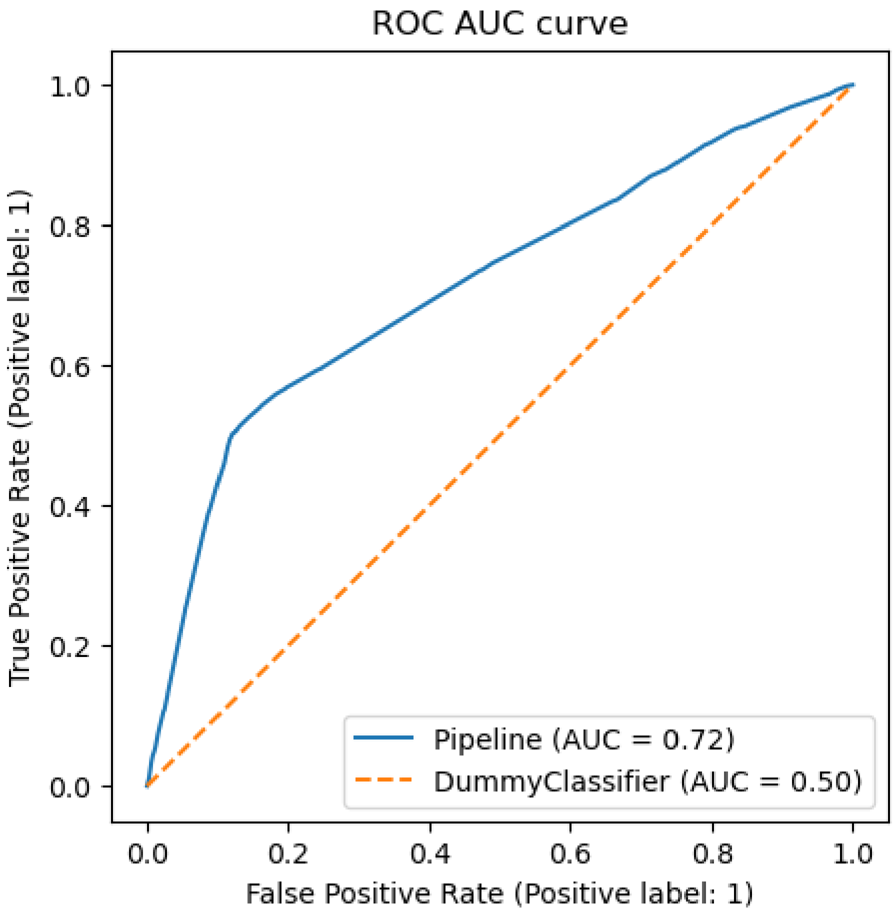
Out[32]:
```
Index(['behavioral_antiviral_meds', 'behavioral_face_mask',
       'behavioral_wash_hands', 'doctor_recc_h1n1', 'household_adults',
       'household_children'],
      dtype='object')
```

In [33]:
```
X_train_B = X_train[['behavioral_antiviral_meds', 'behavioral_face_mask',
       'behavioral_wash_hands', 'doctor_recc_h1n1', 'household_adults',
       'household_children']].copy()
```

We will use a logistic regression model as our model B.

In [34]:
```
#Sort by numerical and nominal
numerical_columns_3 = ['household_adults', 'household_children']
nominal_columns_3 = ['behavioral_antiviral_meds', 'behavioral_face_mask',
                     'behavioral_wash_hands', 'doctor_recc_h1n1',]

#Define estimators, transformers, and encoders. Handle unknowns by ignoring them
numerical_pipeline_3 = Pipeline([('imputer', SimpleImputer(strategy='mean')),
                                 ('scaler', StandardScaler())])
nominal_pipeline_3 = Pipeline([('imputer', SimpleImputer(strategy='most_frequent')),
                               ('encoder', OneHotEncoder(handle_unknown='ignore'))])

preprocessor_4 = ColumnTransformer([('numerical_transformer', numerical_pipeline_3, numerical_
                                    ('nominal_transformer', nominal_pipeline_3, nominal_columns_
```

In [35]:
```
lr_model_B = Pipeline([('preprocessor', preprocessor_4), ('regressor', LogisticRegression())]

lr_model_B.fit(X_train_B, y_train);

y_train_predicted = lr_model_B.predict(X_train_B)

f = RocCurveDisplay.from_estimator(lr_model_B, X_train_B, y_train, pos_label=1,
ax=pl.figure(figsize=(5,5)).gca())
f = RocCurveDisplay.from_estimator(dummy_classifier, X_train_B, y_train, pos_label=1,
color="tab:orange", linestyle="--", ax=f.ax_)
f.ax_.set_title("ROC AUC curve");
```



In [36]:

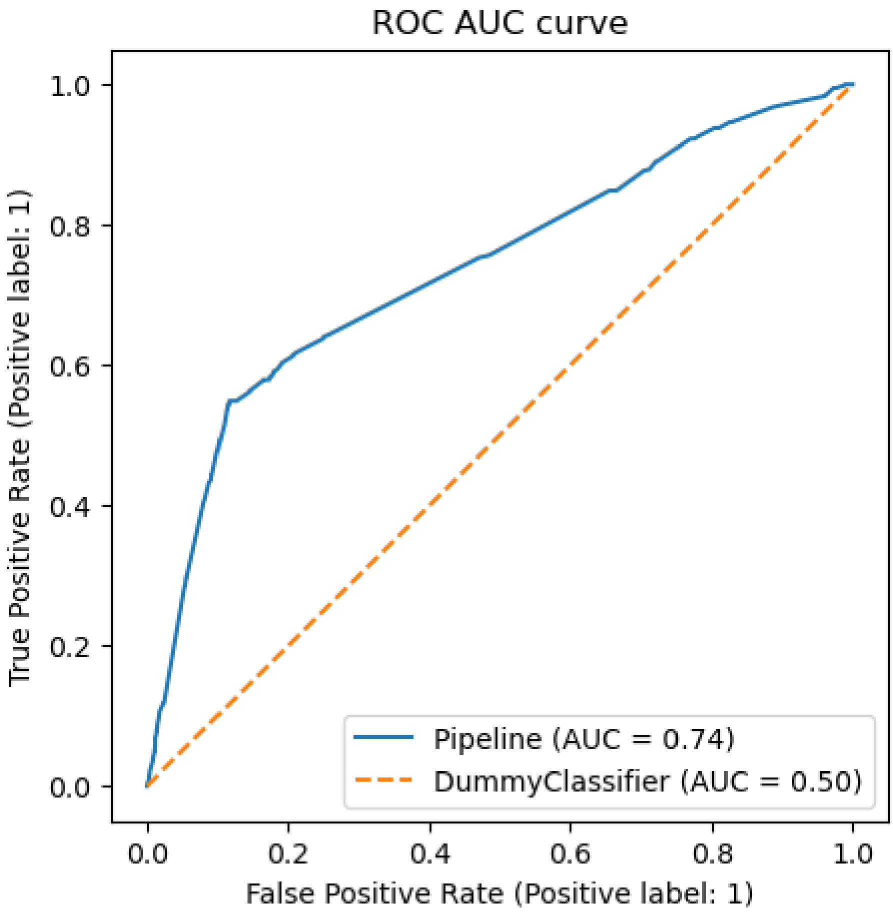
```
roc_auc_score(y_train, lr_model_B.predict_proba(X_train)[:,1])
```

Out[36]: 0.7151562640427228

Now we will use it on the test set.

In [37]:

```
y_test_predicted = lr_model_B.predict(X_test)
f = RocCurveDisplay.from_estimator(lr_model_B, X_test, y_test, pos_label=1,
ax=pl.figure(figsize=(5,5)).gca())
f = RocCurveDisplay.from_estimator(dummy_classifier, X_test, y_test, pos_label=1,
color="tab:orange", linestyle="--", ax=f.ax_)
f.ax_.set_title("ROC AUC curve");
```

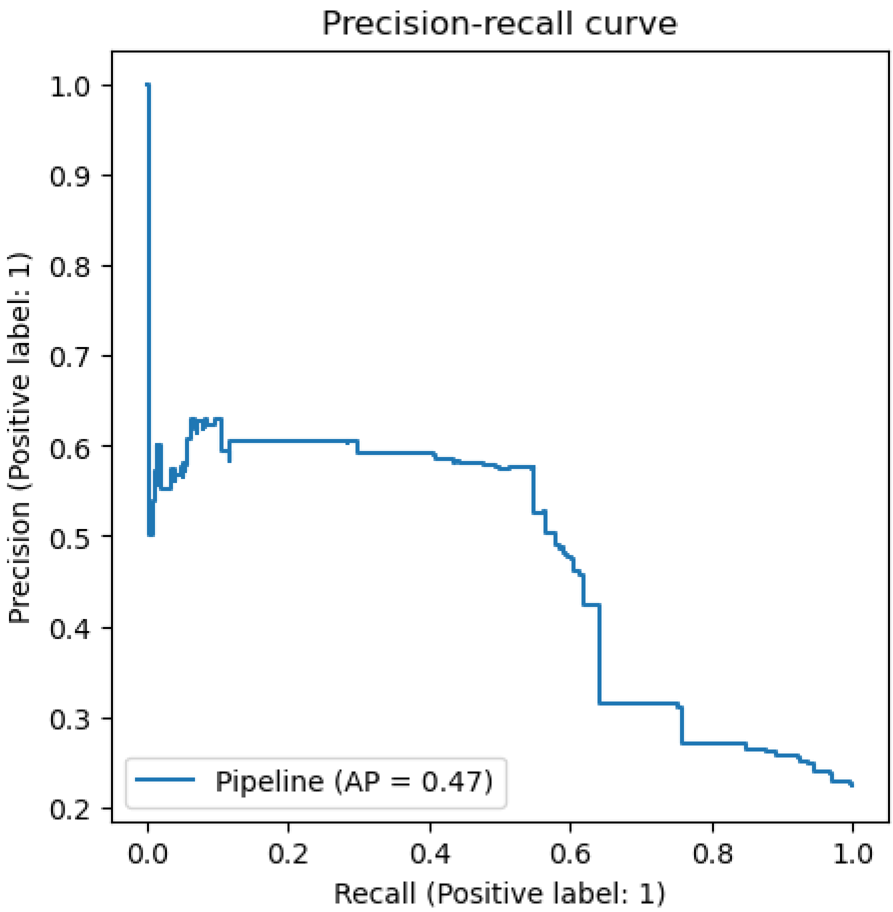


In [38]:
```
roc_auc_score(y_test, lr_model_B.predict_proba(X_test)[:,1])
```

Out[38]: 0.7372018274440042

We will also report on the AUC-PR, the accuracy, the sensitivity, and the specificity.

In [39]:
```
f = PrecisionRecallDisplay.from_estimator(lr_model_B, X_test, y_test, pos_label=1,
ax=pl.figure(figsize=(5,5)).gca())
f.ax_.set_title("Precision-recall curve");
```



In [40]:
```
average_precision_score(y_test, lr_model_B.predict_proba(X_test)[:,1], pos_label=1)
```

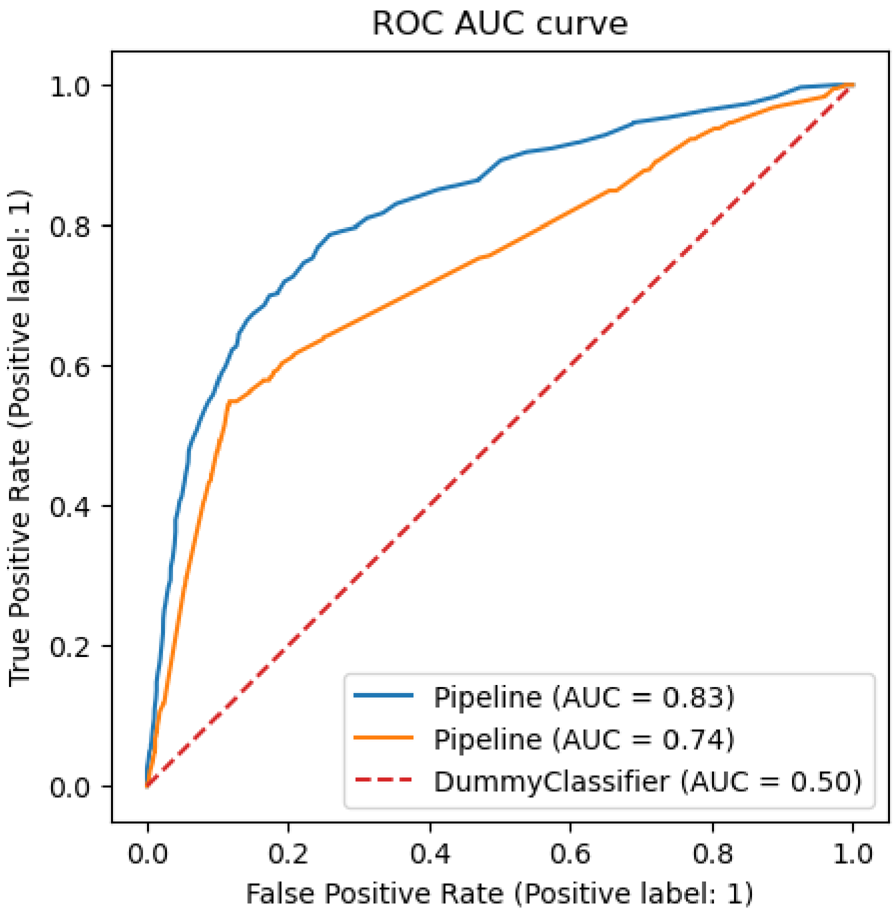
Out[40]:
```
0.46912406187921696
```

In [41]:
```
M = confusion_matrix(y_test, y_test_predicted)
tn, fp, fn, tp = M.ravel()
acc = (tp + tn) / (tn + tp + fn + fp)
sen = tp / (tp + fn)
spe = tn / (tn + fp)
print(f'Accuracy: {acc}\nSensitivity: {sen}\nSpecificity: {spe}')
```

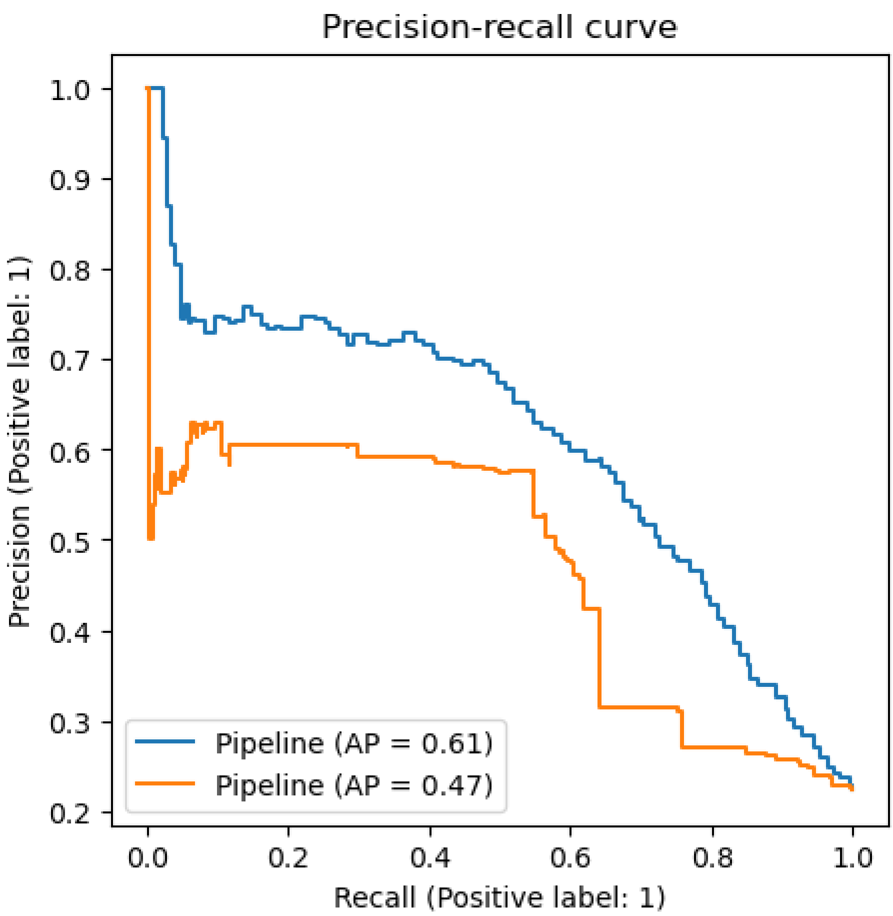
```
Accuracy: 0.8064395357543991
Sensitivity: 0.4748322147651007
Specificity: 0.9016867469879518
```

We will plot the ROC and PR curves of model A and B on the same plot.

In [42]:
```
f = RocCurveDisplay.from_estimator(rf_model, X_test, y_test, pos_label=1,
ax=pl.figure(figsize=(5,5)).gca())
f = RocCurveDisplay.from_estimator(lr_model_B, X_test, y_test, pos_label=1,
ax=f.ax_)
f = RocCurveDisplay.from_estimator(dummy_classifier, X_test, y_test, pos_label=1,
color="tab:red", linestyle="--", ax=f.ax_)
f.ax_.set_title("ROC AUC curve");
```



In [43]:
```
f = PrecisionRecallDisplay.from_estimator(rf_model, X_test, y_test, pos_label=1,
ax=pl.figure(figsize=(5,5)).gca())
f = PrecisionRecallDisplay.from_estimator(lr_model_B, X_test, y_test, pos_label=1,
ax=f.ax_)
f.ax_.set_title("Precision-recall curve");
```



That concludes the project.

Discussion

Some difficulties I had were:

- attempting to optimize model A to a point that was even better than the current model. My attempts made marginal difference. Despite this, the model performed worse on the test set than in training.
- The SVM model also takes a very large amount of time to process - roughly 12 minutes for the cross-fold validation to take place, so this slowed my progress a ltitle.
- I was a bit confused encoding the ordinal variables; I assumed that we also needed to one-hot encode the "opinion" columns despite them already being numerically encoded.
- I had difficulties with the feature selection process too; it isn't made terribly clear that LASSO regression is used for feature selection, and then it isn't clear how to change the Lasso() function to get the desired number of features.

Solving the above difficulties was a learning process for me. I have also learned that predicting continuous variables and predicting binary variables require different approaches. In the future I would like to learn more ways of classifying binary variables and other ways to optimize to the best of our ability.