Project Overview

This python notebook is part of my capstone project for the Data Science Nanodegree from Udacity. The provided data set contains simulated data that mimics customer behavior on the Starbucks rewards mobile app. Once in a while Starbucks sends offers to their customers through different channels, e.g. Email or Social Media. These offers vary for different users and range from simple advertisements up to discounts like "buy one get one free".

Problem Statement

The problem I chose to solve is to predict if a customer will respond to an offer. To achieve this, I will train a model with a combination of the transaction and profile data. Since the provided data set does not offer an easy access to the data needed I will create a new Dataframe with all viewed offers and their correspondig completion status and will merge that with the customer profile data and the data for the given offer.

Metrics

I will use accurancy and the F1-score to evaluate my model, altough accuracy does not work well for imbalanced data sets. The F1-score on the other hand is the harmonic mean of precision and recall. Precision measures how good the classifier prevents false negatives and recall measures how good the classifier finds all positive samples. Therefore I will focus on the F1-score.

Data Exploration & Cleanse

First View

The provided data set consists of three files:

- portfolio.json - containing offer ids and meta data about each offer (duration, type, etc.)
- profile.json - demographic data for each customer
- transcript.json - records for transactions, offers received, offers viewed, and offers completed

Imports & read files

In [1]:
```
import pandas as pd
import numpy as np
import math
import json
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import QuantileTransformer
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import learning_curve
from sklearn.ensemble import AdaBoostClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.neural_network import MLPClassifier
```

```
from sklearn.ensemble import RandomForestClassifier

%matplotlib inline
```

In [2]:
```
portfolio = pd.read_json('data/portfolio.json', orient='records', lines=True)
profile = pd.read_json('data/profile.json', orient='records', lines=True)
transcript = pd.read_json('data/transcript.json', orient='records', lines=True)
```

Portfolio

This file contains information about the offers, e.g. which channels were used and the offer type.

In [3]:
```
portfolio.shape[0]
```

Out[3]: 10

In [4]:
```
portfolio.head(10)
```

Out[4]:

	reward	channels	difficulty	duration	offer_type	id
0	10	[email, mobile, social]	10	7	bogo	ae264e3637204a6fb9bb56bc8210ddfd
1	10	[web, email, mobile, social]	10	5	bogo	4d5c57ea9a6940dd891ad53e9dbe8da0
2	0	[web, email, mobile]	0	4	informational	3f207df678b143eea3cee63160fa8bed
3	5	[web, email, mobile]	5	7	bogo	9b98b8c7a33c4b65b9aebfe6a799e6d9
4	5	[web, email]	20	10	discount	0b1e1539f2cc45b7b9fa7c272da2e1d7
5	3	[web, email, mobile, social]	7	7	discount	2298d6c36e964ae4a3e7e9706d1fb8c2
6	2	[web, email, mobile, social]	10	10	discount	fafdcd668e3743c1bb461111dcafc2a4
7	0	[email, mobile, social]	0	3	informational	5a8bc65990b245e5a138643cd4eb9837
8	5	[web, email, mobile, social]	5	5	bogo	f19421c1d4aa40978ebb69ca19b0e20d
9	2	[web, email, mobile]	10	7	discount	2906b810c7d4411798c6938adc9daaa5

- id (string) - offer id
- offer_type (string) - type of offer ie BOGO, discount, informational
- difficulty (int) - minimum required spend to complete an offer
- reward (int) - reward given for completing an offer
- duration (int) - time for offer to be open, in days
- channels (list of strings)

Profile

The profile contains information about the users, e.g. age, gender and a user id.

In [5]:
```
profile.shape[0]
```

Out[5]: 17000

In [6]:
```
profile.head(10)
```

Out[6]:

	gender	age	id	became_member_on	income
0	None	118	68be06ca386d4c31939f3a4f0e3dd783	20170212	NaN
1	F	55	0610b486422d4921ae7d2bf64640c50b	20170715	112000.0
2	None	118	38fe809add3b4fcf9315a9694bb96ff5	20180712	NaN
3	F	75	78afa995795e4d85b5d9ceeca43f5fef	20170509	100000.0
4	None	118	a03223e636434f42ac4c3df47e8bac43	20170804	NaN
5	M	68	e2127556f4f64592b11af22de27a7932	20180426	70000.0
6	None	118	8ec6ce2a7e7949b1bf142def7d0e0586	20170925	NaN
7	None	118	68617ca6246f4fbc85e91a2a49552598	20171002	NaN
8	M	65	389bc3fa690240e798340f5a15918d5c	20180209	53000.0
9	None	118	8974fc5686fe429db53ddde067b88302	20161122	NaN

- age (int) - age of the customer
- became_member_on (int) - date when customer created an app account
- gender (str) - gender of the customer (note some entries contain 'O' for other rather than M or F)
- id (str) - customer id
- income (float) - customer's income

Transcript

The transcript contains transaction data of all users. It has an event column, which describes the action that happend, a user id, a time stamp and a value, which has a different structure depending on the event.

In [7]:
```
transcript.shape[0]
```

Out[7]: 306534

In [8]:
```
transcript.head(10)
```

Out[8]:

	person	event	value	time
0	78afa995795e4d85b5d9ceeca43f5fef	offer received	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}	0
1	a03223e636434f42ac4c3df47e8bac43	offer received	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}	0
2	e2127556f4f64592b11af22de27a7932	offer received	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}	0
3	8ec6ce2a7e7949b1bf142def7d0e0586	offer received	{'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}	0
4	68617ca6246f4fbc85e91a2a49552598	offer received	{'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}	0

	person	event	value	time
5	389bc3fa690240e798340f5a15918d5c	offer received	{'offer id': 'f19421c1d4aa40978ebb69ca19b0e20d'}	0
6	c4863c7985cf408faee930f111475da3	offer received	{'offer id': '2298d6c36e964ae4a3e7e9706d1fb8c2'}	0
7	2eeac8d8feae4a8cad5a6af0499a211d	offer received	{'offer id': '3f207df678b143eea3cee63160fa8bed'}	0
8	aa4862eba776480b8bb9c68455b8c2e1	offer received	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}	0
9	31dda685af34476cad5bc968bdb01c53	offer received	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}	0

- event (str) - record description (ie transaction, offer received, offer viewed, etc.)
- person (str) - customer id
- time (int) - time in hours since start of test. The data begins at time t=0
- value - (dict of strings) - either an offer id or transaction amount depending on the record

Transcript of a single person

When filtered to a specific user id you get the transaction history of a single user:

In [9]:
```
transcript[transcript["person"] == '78afa995795e4d85b5d9ceeca43f5fef']
```

Out[9]:

	person	event	value	time
0	78afa995795e4d85b5d9ceeca43f5fef	offer received	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}	0
15561	78afa995795e4d85b5d9ceeca43f5fef	offer viewed	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}	6
47582	78afa995795e4d85b5d9ceeca43f5fef	transaction	{'amount': 19.89}	132
47583	78afa995795e4d85b5d9ceeca43f5fef	offer completed	{'offer_id': '9b98b8c7a33c4b65b9aebfe6a799e6d9...	132
49502	78afa995795e4d85b5d9ceeca43f5fef	transaction	{'amount': 17.78}	144
53176	78afa995795e4d85b5d9ceeca43f5fef	offer received	{'offer id': '5a8bc65990b245e5a138643cd4eb9837'}	168
85291	78afa995795e4d85b5d9ceeca43f5fef	offer viewed	{'offer id': '5a8bc65990b245e5a138643cd4eb9837'}	216
87134	78afa995795e4d85b5d9ceeca43f5fef	transaction	{'amount': 19.67}	222
92104	78afa995795e4d85b5d9ceeca43f5fef	transaction	{'amount': 29.72}	240
141566	78afa995795e4d85b5d9ceeca43f5fef	transaction	{'amount': 23.93}	378
150598	78afa995795e4d85b5d9ceeca43f5fef	offer received	{'offer id': 'ae264e3637204a6fb9bb56bc8210ddfd'}	408
163375	78afa995795e4d85b5d9ceeca43f5fef	offer viewed	{'offer id': 'ae264e3637204a6fb9bb56bc8210ddfd'}	408
201572	78afa995795e4d85b5d9ceeca43f5fef	offer received	{'offer id': 'f19421c1d4aa40978ebb69ca19b0e20d'}	504
218393	78afa995795e4d85b5d9ceeca43f5fef	transaction	{'amount': 21.72}	510

	person	event	value	time
218394	78afa995795e4d85b5d9ceeca43f5fef	offer completed	{'offer_id': 'ae264e3637204a6fb9bb56bc8210ddfd...	510
218395	78afa995795e4d85b5d9ceeca43f5fef	offer completed	{'offer_id': 'f19421c1d4aa40978ebb69ca19b0e20d...	510
230412	78afa995795e4d85b5d9ceeca43f5fef	transaction	{'amount': 26.56}	534
262138	78afa995795e4d85b5d9ceeca43f5fef	offer viewed	{'offer id': 'f19421c1d4aa40978ebb69ca19b0e20d'}	582

Corresponding profile entry

Using the same user id on the profile dataframe returns the information about the user:

In [10]:
```
profile[profile["id"] == '78afa995795e4d85b5d9ceeca43f5fef']
```

Out[10]:

	gender	age	id	became_member_on	income
3	F	75	78afa995795e4d85b5d9ceeca43f5fef	20170509	100000.0

Clean portfolio data

Since the portfolio data set is already in a good shape, I will only rename the "id" column to "offer_id" to make the name more specific and create dummies for the offer type and channels:

In [11]:
```
cleaned_portfolio = portfolio.copy(deep=True)
```

In [12]:
```
cleaned_portfolio = cleaned_portfolio.rename(columns={'id': 'offer_id'})
```

In [13]:
```
cleaned_portfolio = pd.get_dummies(cleaned_portfolio, columns=['offer_type'])
```

In [14]:
```
cleaned_portfolio = pd.concat([cleaned_portfolio,pd.get_dummies(cleaned_portfolio['c
```

In [15]:
```
cleaned_portfolio.head(10)
```

Out[15]:

	reward	difficulty	duration	offer_id	offer_type_bogo	offer_type_dis
0	10	10	7	ae264e3637204a6fb9bb56bc8210ddfd	1	
1	10	10	5	4d5c57ea9a6940dd891ad53e9dbe8da0	1	
2	0	0	4	3f207df678b143eea3cee63160fa8bed	0	
3	5	5	7	9b98b8c7a33c4b65b9aebfe6a799e6d9	1	
4	5	20	10	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	
5	3	7	7	2298d6c36e964ae4a3e7e9706d1fb8c2	0	
6	2	10	10	fafdcd668e3743c1bb461111dcafc2a4	0	
7	0	0	3	5a8bc65990b245e5a138643cd4eb9837	0	
8	5	5	5	f19421c1d4aa40978ebb69ca19b0e20d	1	
9	2	10	7	2906b810c7d4411798c6938adc9daaa5	0	

Clean profile data

The profile data contains 17000 user profiles. The .head method already showed, that there is a lot of missing data. I will drop these rows since we need a full profile to train the model. I will also rename the "id" column to "user_id" to make it more specific and will create dummies for "gender" and "became_member_on". To reduce the variance in "became_member_on" I will only use the year and cut the month and day part:

In [16]:
```
cleaned_profile = profile.copy(deep=True)
```

In [17]:
```
cleaned_profile = cleaned_profile.rename(columns={'id': 'user_id'})
```

In [18]:
```
cleaned_profile = cleaned_profile.dropna()
```

In [19]:
```
cleaned_profile['became_member_on'] = cleaned_profile['became_member_on'].astype(str
```

In [20]:
```
cleaned_profile = pd.get_dummies(cleaned_profile, columns=['gender','became_member_o
```

In [21]:
```
cleaned_profile.head(10)
```

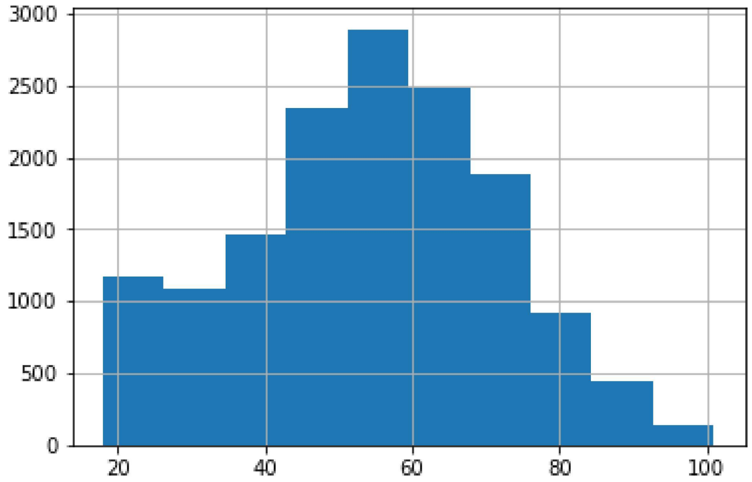
Out[21]:

	age	user_id	income	gender_F	gender_M	gender_O	became_me
1	55	0610b486422d4921ae7d2bf64640c50b	112000.0	1	0	0	
3	75	78afa995795e4d85b5d9ceeca43f5fef	100000.0	1	0	0	
5	68	e2127556f4f64592b11af22de27a7932	70000.0	0	1	0	
8	65	389bc3fa690240e798340f5a15918d5c	53000.0	0	1	0	
12	58	2eeac8d8feae4a8cad5a6af0499a211d	51000.0	0	1	0	
13	61	aa4862eba776480b8bb9c68455b8c2e1	57000.0	1	0	0	
14	26	e12aeaf2d47d42479ea1c4ac3d8286c6	46000.0	0	1	0	
15	62	31dda685af34476cad5bc968bdb01c53	71000.0	1	0	0	
16	49	62cf5e10845442329191fc246e7bcea3	52000.0	0	1	0	
18	57	6445de3b47274c759400cd68131d91b4	42000.0	0	1	0	

Profile data is always interesting to analyze and gives insight into the user base, so I will plot histograms for the most interesting values:

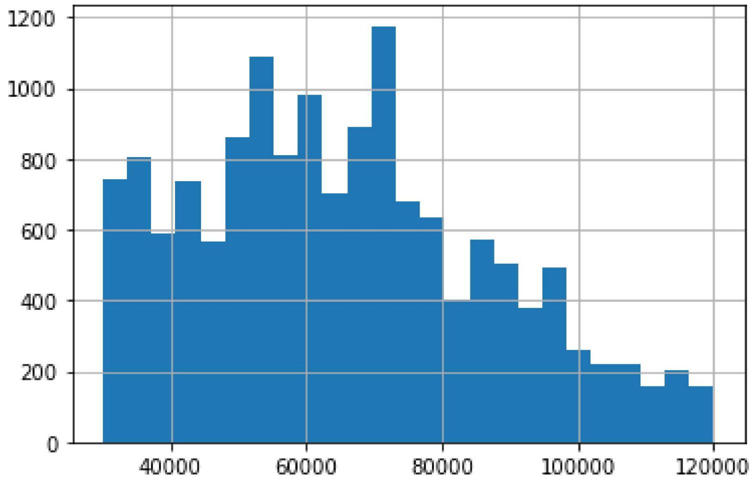
In [22]:
```
cleaned_profile['age'].hist(bins=10)
```

Out[22]: <AxesSubplot:>



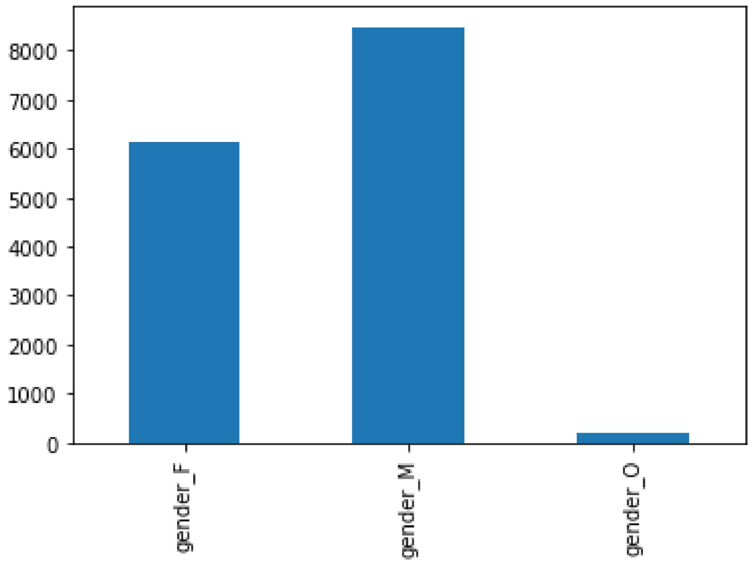
In [23]:
```
cleaned_profile['income'].hist(bins=25)
```

Out[23]: <AxesSubplot:>



In [24]:
```
cleaned_profile[['gender_F','gender_M','gender_O']].sum(axis=0).plot.bar()
```

Out[24]: <AxesSubplot:>



The age peaks around 50 to 60 years, the majority earns less than 80000$ and there are more men than woman among the users.

Clean transcript data

The transript is the most challanging data set because "value" has a different structure depending the the event type. If the event is "transaction" the value is stores an amount ("{'amount': 23.93}") and otherwise the value stores an offer id ("{'offer id': 'f19421c1d4aa40978ebb69ca19b0e20d'}"). I will create a new column to store the amount seperatly from the offer id and remove the json structure:

In [25]:
```
cleaned_transcript = transcript.copy(deep=True)
```

In [26]:
```
cleaned_transcript["amount"] = cleaned_transcript["value"]
```

In [27]:
```
cleaned_transcript.loc[cleaned_transcript["event"] != "transaction", "amount"] = Non
cleaned_transcript['amount'] = cleaned_transcript['amount'].astype(str).str[11:-1]
cleaned_transcript.loc[cleaned_transcript["event"] != "transaction", "amount"] = Non
cleaned_transcript['amount'] = cleaned_transcript['amount'].astype(float)
```

In [28]:
```
cleaned_transcript.loc[cleaned_transcript["event"] == "transaction", "value"] = None
cleaned_transcript.loc[cleaned_transcript["event"] == "offer completed", "value"] =
cleaned_transcript.loc[cleaned_transcript["event"] != "offer completed", "value"] =
```

The column "value" now holds the offer ids. Unfortunatly some of the values are using double quotes instead of single quotes. I will replace the double quotes with single quotes:

In [29]:
```
print(cleaned_transcript['value'].unique())
```

```
['9b98b8c7a33c4b65b9aebfe6a799e6d9' '0b1e1539f2cc45b7b9fa7c272da2e1d7'
 '2906b810c7d4411798c6938adc9daaa5' 'fafdcd668e3743c1bb461111dcafc2a4'
 '4d5c57ea9a6940dd891ad53e9dbe8da0' 'f19421c1d4aa40978ebb69ca19b0e20d'
 '2298d6c36e964ae4a3e7e9706d1fb8c2' '3f207df678b143eea3cee63160fa8bed'
 'ae264e3637204a6fb9bb56bc8210ddfd' '5a8bc65990b245e5a138643cd4eb9837' ''
 "ae264e3637204a6fb9bb56bc8210ddfd'" "4d5c57ea9a6940dd891ad53e9dbe8da0'"]
```

In [30]:
```
cleaned_transcript["value"] = cleaned_transcript["value"].str.replace('\'','')
```

In [31]:
```
print(cleaned_transcript['value'].unique())
```

```
['9b98b8c7a33c4b65b9aebfe6a799e6d9' '0b1e1539f2cc45b7b9fa7c272da2e1d7'
 '2906b810c7d4411798c6938adc9daaa5' 'fafdcd668e3743c1bb461111dcafc2a4'
 '4d5c57ea9a6940dd891ad53e9dbe8da0' 'f19421c1d4aa40978ebb69ca19b0e20d'
 '2298d6c36e964ae4a3e7e9706d1fb8c2' '3f207df678b143eea3cee63160fa8bed'
 'ae264e3637204a6fb9bb56bc8210ddfd' '5a8bc65990b245e5a138643cd4eb9837' '']
```

I will also rename the column "person" to "user_id" and "value" to "offer_id":

In [32]:
```
cleaned_transcript = cleaned_transcript.rename(columns={'person': 'user_id', 'value'
```

Since I'm only interested in transactions from users with a full profile I will match the user ids to the user ids left in the cleaned profile data:

In [33]:
```
print(cleaned_profile['user_id'].unique().shape)
print(cleaned_transcript['user_id'].unique().shape)

#remove all rows with dropped user ids
cleaned_transcript = cleaned_transcript[cleaned_transcript['user_id'].isin(cleaned_p

print(cleaned_transcript['user_id'].unique().shape)
```

```
(14825,)
(17000,)
(14825,)
```

In [34]:
```
cleaned_transcript.head(10)
```

Out[34]:

	user_id	event	offer_id	time	amount
0	78afa995795e4d85b5d9ceeca43f5fef	offer received	9b98b8c7a33c4b65b9aebfe6a799e6d9	0	NaN
2	e2127556f4f64592b11af22de27a7932	offer received	2906b810c7d4411798c6938adc9daaa5	0	NaN
5	389bc3fa690240e798340f5a15918d5c	offer received	f19421c1d4aa40978ebb69ca19b0e20d	0	NaN
7	2eeac8d8feae4a8cad5a6af0499a211d	offer received	3f207df678b143eea3cee63160fa8bed	0	NaN
8	aa4862eba776480b8bb9c68455b8c2e1	offer received	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	NaN
9	31dda685af34476cad5bc968bdb01c53	offer received	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	NaN
12	4b0da7e80e5945209a1fdddfe813dbe0	offer received	ae264e3637204a6fb9bb56bc8210ddfd	0	NaN
13	c27e0d6ab72c455a8bb66d980963de60	offer received	3f207df678b143eea3cee63160fa8bed	0	NaN
14	d53717f5400c4e84affdaeda9dd926b3	offer received	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	NaN
15	f806632c011441378d4646567f357a21	offer received	fafdcd668e3743c1bb461111dcafc2a4	0	NaN

In [35]:

```
cleaned_transcript[cleaned_transcript["user_id"] == '78afa995795e4d85b5d9ceeca43f5fe
```

Out[35]:

	user_id	event	offer_id	time	am
0	78afa995795e4d85b5d9ceeca43f5fef	offer received	9b98b8c7a33c4b65b9aebfe6a799e6d9	0	
15561	78afa995795e4d85b5d9ceeca43f5fef	offer viewed	9b98b8c7a33c4b65b9aebfe6a799e6d9	6	
47582	78afa995795e4d85b5d9ceeca43f5fef	transaction		132	
47583	78afa995795e4d85b5d9ceeca43f5fef	offer completed	9b98b8c7a33c4b65b9aebfe6a799e6d9	132	
49502	78afa995795e4d85b5d9ceeca43f5fef	transaction		144	
53176	78afa995795e4d85b5d9ceeca43f5fef	offer received	5a8bc65990b245e5a138643cd4eb9837	168	
85291	78afa995795e4d85b5d9ceeca43f5fef	offer viewed	5a8bc65990b245e5a138643cd4eb9837	216	
87134	78afa995795e4d85b5d9ceeca43f5fef	transaction		222	
92104	78afa995795e4d85b5d9ceeca43f5fef	transaction		240	
141566	78afa995795e4d85b5d9ceeca43f5fef	transaction		378	
150598	78afa995795e4d85b5d9ceeca43f5fef	offer received	ae264e3637204a6fb9bb56bc8210ddfd	408	
163375	78afa995795e4d85b5d9ceeca43f5fef	offer viewed	ae264e3637204a6fb9bb56bc8210ddfd	408	

	user_id	event	offer_id	time	am
201572	78afa995795e4d85b5d9ceeca43f5fef	offer received	f19421c1d4aa40978ebb69ca19b0e20d	504	
218393	78afa995795e4d85b5d9ceeca43f5fef	transaction		510	
218394	78afa995795e4d85b5d9ceeca43f5fef	offer completed	ae264e3637204a6fb9bb56bc8210ddfd	510	
218395	78afa995795e4d85b5d9ceeca43f5fef	offer completed	f19421c1d4aa40978ebb69ca19b0e20d	510	
230412	78afa995795e4d85b5d9ceeca43f5fef	transaction		534	
262138	78afa995795e4d85b5d9ceeca43f5fef	offer viewed	f19421c1d4aa40978ebb69ca19b0e20d	582	

Preprocess and merge data

Create offer based transcript dataframe

To prepare the data to be used for training a model I will create a new data frame that stores a user id, an offer id and a bool value that indicates whether an offer was completed. I will also take into account if the offer was viewed before completion. This can happen when a user buys something and an offer was sent but not read. I will count those as not completed since I want to know if an offer had an impact on the customer:

In [36]:
```
offers = pd.DataFrame(columns=['user_id', 'offer_id', 'completed_after_viewed'])

for user_id in cleaned_transcript['user_id'].unique():
    transcript_user = cleaned_transcript[cleaned_transcript["user_id"] == user_id]
    received_offers = list(filter(None, transcript_user['offer_id'].unique()))

    for received_offer in received_offers:
        time_viewed = transcript_user.loc[(transcript_user["event"] == "offer viewed
        time_completed = transcript_user.loc[(transcript_user["event"] == "offer com

        completed_after_viewed = 0
        if (len(time_viewed) > 0 and len(time_completed) > 0 and time_viewed[0] < ti
            completed_after_viewed = 1

        offers = offers.append(pd.Series(data={'user_id':user_id, 'offer_id':receive
```

In [37]:
```
offers.head(10)
```

Out[37]:

	user_id	offer_id	completed_after_viewed
0	78afa995795e4d85b5d9ceeca43f5fef	9b98b8c7a33c4b65b9aebfe6a799e6d9	1
1	78afa995795e4d85b5d9ceeca43f5fef	5a8bc65990b245e5a138643cd4eb9837	0
2	78afa995795e4d85b5d9ceeca43f5fef	ae264e3637204a6fb9bb56bc8210ddfd	1
3	78afa995795e4d85b5d9ceeca43f5fef	f19421c1d4aa40978ebb69ca19b0e20d	0
4	e2127556f4f64592b11af22de27a7932	2906b810c7d4411798c6938adc9daaa5	0
5	e2127556f4f64592b11af22de27a7932	3f207df678b143eea3cee63160fa8bed	0

	user_id	offer_id	completed_after_viewed
6	e2127556f4f64592b11af22de27a7932	9b98b8c7a33c4b65b9aebfe6a799e6d9	1
7	e2127556f4f64592b11af22de27a7932	fafdcd668e3743c1bb461111dcafc2a4	0
8	389bc3fa690240e798340f5a15918d5c	f19421c1d4aa40978ebb69ca19b0e20d	1
9	389bc3fa690240e798340f5a15918d5c	9b98b8c7a33c4b65b9aebfe6a799e6d9	1

Merge data

After creating the data frame above I will now merge the user and offer data into the newly created data frame:

In [38]:
```
merged_data = pd.merge(offers, cleaned_portfolio, on="offer_id")
```

In [39]:
```
merged_data = pd.merge(merged_data, cleaned_profile, on="user_id")
```

In [40]:
```
merged_data[merged_data["user_id"] == '78afa995795e4d85b5d9ceeca43f5fef']
```

Out[40]:

	user_id	offer_id	completed_after_viewed	re
0	78afa995795e4d85b5d9ceeca43f5fef	9b98b8c7a33c4b65b9aebfe6a799e6d9	1	
1	78afa995795e4d85b5d9ceeca43f5fef	5a8bc65990b245e5a138643cd4eb9837	0	
2	78afa995795e4d85b5d9ceeca43f5fef	ae264e3637204a6fb9bb56bc8210ddfd	1	
3	78afa995795e4d85b5d9ceeca43f5fef	f19421c1d4aa40978ebb69ca19b0e20d	0	

4 rows × 24 columns

I will now remove the user and offer id column since those values doesn't hold any valueable information for training a model:

In [41]:
```
merged_data = merged_data.drop(columns=['user_id', 'offer_id'])
```

In [42]:
```
merged_data.head(10)
```

Out[42]:

	completed_after_viewed	reward	difficulty	duration	offer_type_bogo	offer_type_discount	offer_
0	1	5	5	7	1	0	
1	0	0	0	3	0	0	
2	1	10	10	7	1	0	
3	0	5	5	5	1	0	
4	1	5	5	7	1	0	
5	0	2	10	7	0	1	
6	0	0	0	4	0	0	
7	0	2	10	10	0	1	
8	1	5	5	7	1	0	
9	1	5	5	5	1	0	

10 rows × 22 columns

To make sure that the "completed_after_viewed" column is a valid y-value I will set the type to int:

In [43]:
```
merged_data['completed_after_viewed'] = merged_data['completed_after_viewed'].astype
```

Scale data

In this last preprocessing step I will scale numerical values. For reward, difficulty and duration i chose the MinMaxScaler, which scales the data from 0 to 1 where 0 is the minimum found in the data and 1 the maximum. For age and income I will use the QuantileTransformer that will map the data to a uniform distribution with the range of 0 to 1. That means that outliers will have less impact on the model training:

In [44]:
```
merged_data[['reward', 'difficulty', 'duration']] = MinMaxScaler().fit_transform(mer
```

In [45]:
```
merged_data[['age','income']] = QuantileTransformer().fit_transform(merged_data[['ag
```

In [46]:
```
merged_data.head(10)
```

Out[46]:

	completed_after_viewed	reward	difficulty	duration	offer_type_bogo	offer_type_discount	offer_
0	1	0.5	0.25	0.571429	1	0	
1	0	0.0	0.00	0.000000	0	0	
2	1	1.0	0.50	0.571429	1	0	
3	0	0.5	0.25	0.285714	1	0	
4	1	0.5	0.25	0.571429	1	0	
5	0	0.2	0.50	0.571429	0	1	
6	0	0.0	0.00	0.142857	0	0	
7	0	0.2	0.50	1.000000	0	1	
8	1	0.5	0.25	0.571429	1	0	
9	1	0.5	0.25	0.285714	1	0	

10 rows × 22 columns

Create train and test data

I will split the data in a training and a test set. The training set will have 80% of the data and the test set will use the remaining 20%:

In [47]:
```
x = merged_data.drop(columns=['completed_after_viewed'])
y = merged_data['completed_after_viewed']
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.2)
```

Train and evaluate models

In [48]:
```
def train_and_evaluate_model(x_train, y_train, x_test, y_test, model, parameters):
    '''
    Performs a grid search on the given model with given parameters and prints out a
    :param model: model to be tested
    :param X_test: X test values
    :param Y_test: Y test values
    :param category_names: category labels for Y
    :returns: trained model
    '''
    model = GridSearchCV(model, param_grid=parameters, verbose=0, cv=3)
    model.fit(x_train, y_train)
    print(classification_report(y_test, y_pred = model.best_estimator_.predict(x_tes

    return model
```

In [70]:
```
def plot_learning_curve(x, y, estimator):
    '''
    Plots the learning curve for given estimator
    :param estimator: estimator to be used
    :param X_test: X test values
    :param Y_test: Y test values
    '''
    train_sizes, train_scores, test_scores = learning_curve(estimator, x, y, cv=None
    plt.xlabel("Training examples")
    plt.ylabel("Score")
    plt.xlim([-0.5, 9.5])
    plt.ylim([0, 1])
    plt.grid()
    plt.plot(np.mean(train_scores, axis=1), 'o-', color="r", label="Train")
    plt.plot(np.mean(test_scores, axis=1), 'o-', color="b", label="Test")
    plt.legend(loc="best")
    plt.show()
```

To get a baseline for the model evaluation I will print a classification report with all predictions set to 0:

In [50]:
```
print(classification_report(y_test, y_pred = np.full(11045, 0, dtype=int), zero_divi
```

```
              precision    recall  f1-score   support

           0       0.67      1.00      0.81      7442
           1       0.00      0.00      0.00      3603

    accuracy                           0.67     11045
   macro avg       0.34      0.50      0.40     11045
weighted avg       0.45      0.67      0.54     11045
```

As expected the accuracy is not that bad with 0.68 and the F1-score is substantially worse with 0.55.

Now I will test five different classifiers to find out which one gives the best results. I will use the classifiers in combination with a grid search and a few parameter combinations to get better results from each of them. Grid search also uses cross validation to prevent overfitting:

AdaBoost

The first model I will use is an AdaBoost classifier. AdaBoost is a good out of the box classifier with a relatively fast training time. While other classifier might give a better performance, it's a good choice to start with:

In [51]:
```
ada = train_and_evaluate_model(x_train,
```

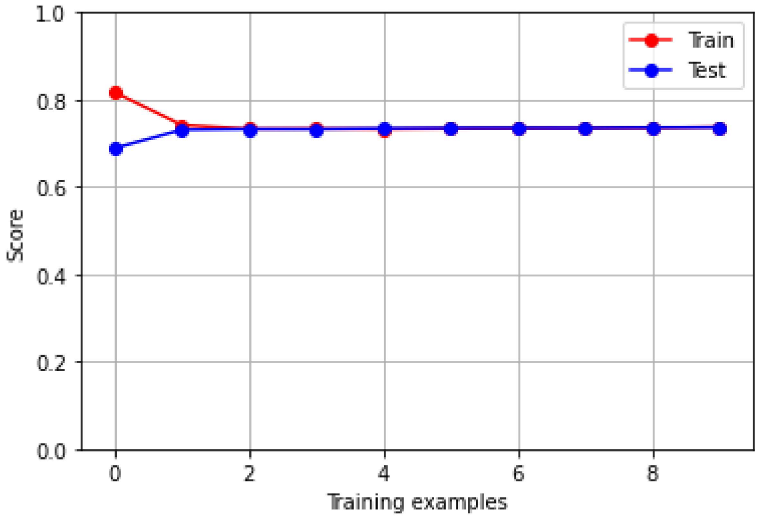
```
                        y_train,
                        x_test,
                        y_test,
                        AdaBoostClassifier(random_state=42),
                        {'learning_rate': [0.66, 1, 1.25], 'n_estimators': [100, 50
```

```
              precision    recall  f1-score   support

           0       0.77      0.88      0.82      7442
           1       0.64      0.45      0.52      3603

    accuracy                           0.74     11045
   macro avg       0.70      0.66      0.67     11045
weighted avg       0.72      0.74      0.72     11045
```

In [72]:
```
plot_learning_curve(x_train, y_train, ada.best_estimator_)
```



In [53]:
```
ada.best_estimator_
```

Out[53]:
```
AdaBoostClassifier(learning_rate=0.66, n_estimators=100, random_state=42)
```

AdaBoost has an accuracy of 0.74 and a F1-score of 0.73. While the accuracy is only slightly better than the baseline from above the F1-score is much better. The learning curve indicates that there is no over- or underfitting.

K-Nearest Neighbors

The next classifier I will test is the K-Nearest Neighbors:

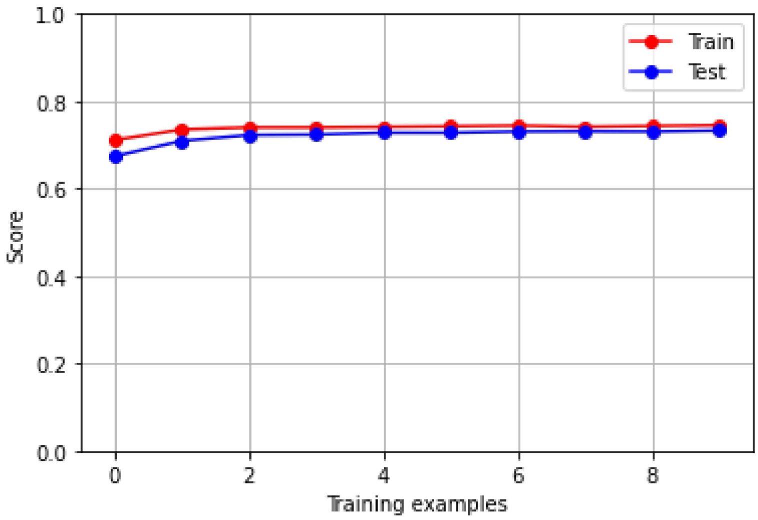
In [54]:
```
knc = train_and_evaluate_model(x_train,
                        y_train,
                        x_test,
                        y_test,
                        KNeighborsClassifier(),
                        {'n_neighbors': [10,20,50], 'leaf_size': [1, 2, 5]})
```

```
              precision    recall  f1-score   support

           0       0.77      0.87      0.82      7442
           1       0.63      0.47      0.54      3603

    accuracy                           0.74     11045
   macro avg       0.70      0.67      0.68     11045
weighted avg       0.72      0.74      0.72     11045
```

In [55]:
```
plot_learning_curve(x_train, y_train, knc.best_estimator_)
```



In [56]:
```
knc.best_estimator_
```

Out[56]:
```
KNeighborsClassifier(leaf_size=1, n_neighbors=50)
```

K-Nearest Neighbors has the same accuracy and F1-score (accuracy: 0.74, F1-score: 0.73) as AdaBoost. The learing curve indicates that there is again under- or overfitting.

Random Forest

The third classifier I will test is the Random Forest Classifier.

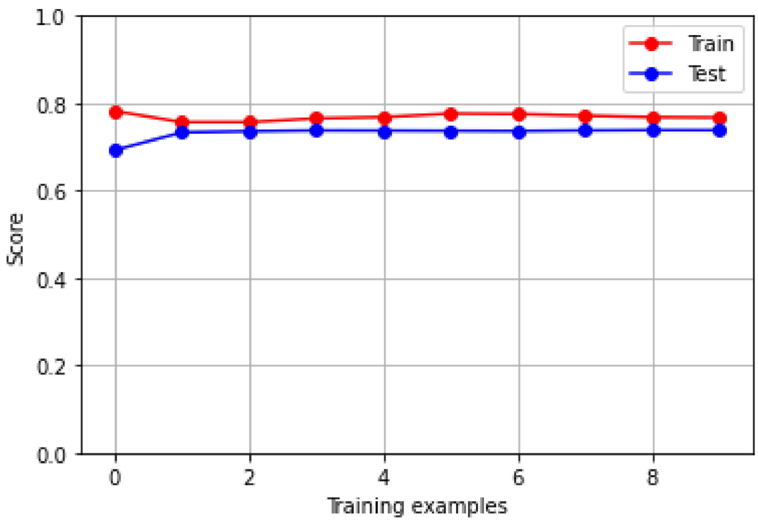
In [57]:
```
rfc = train_and_evaluate_model(x_train,
                               y_train,
                               x_test,
                               y_test,
                               RandomForestClassifier(random_state=42),
                               {'n_estimators': [1500, 2000], 'min_samples_leaf': [10,15,2
```

```
              precision    recall  f1-score   support

           0       0.77      0.87      0.82      7442
           1       0.63      0.48      0.55      3603

    accuracy                           0.74     11045
   macro avg       0.70      0.67      0.68     11045
weighted avg       0.73      0.74      0.73     11045
```

In [58]:
```
plot_learning_curve(x_train, y_train, rfc.best_estimator_)
```



In [59]:
```
rfc.best_estimator_
```

Out[59]:
```
RandomForestClassifier(min_samples_leaf=15, n_estimators=1500, random_state=42)
```

The accuracy and F1-score is 0.74 respectively 0.73 again while the learning curves of the train and test data are close together and don't indicate any over- or underfitting.

Multi-layer Perceptron

The fourth estimator is a MLPClassifier which uses a stochastic gradient descent algorithm:

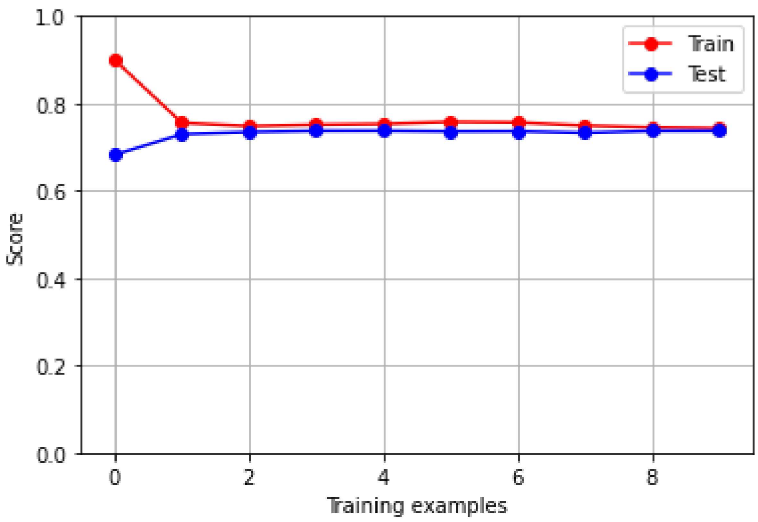
In [60]:
```
mlp = train_and_evaluate_model(x_train,
                               y_train,
                               x_test,
                               y_test,
                               MLPClassifier(random_state=42, max_iter=10000),
                               {'alpha': [0.01, 0.001, 0.0001]})
```

```
              precision    recall  f1-score   support

           0       0.80      0.83      0.81      7442
           1       0.61      0.56      0.58      3603

    accuracy                           0.74     11045
   macro avg       0.70      0.69      0.70     11045
weighted avg       0.73      0.74      0.74     11045
```

In [61]:
```
plot_learning_curve(x_train, y_train, mlp.best_estimator_)
```



In [66]:
```
mlp.best_estimator_
```

Out[66]:
```
MLPClassifier(max_iter=10000, random_state=42)
```

The MLPClassifier has again an accuracy of 0.74 but a slightly better F1-score with 0.74 then the previous tested classifiers. The learning curve looks similar to the previous tested classifiers.

C-Support Vector

The last classifier I will use is a C-Support Vector Classification:

In [62]:
```
svc = train_and_evaluate_model(x_train,
                               y_train,
                               x_test,
                               y_test,
```

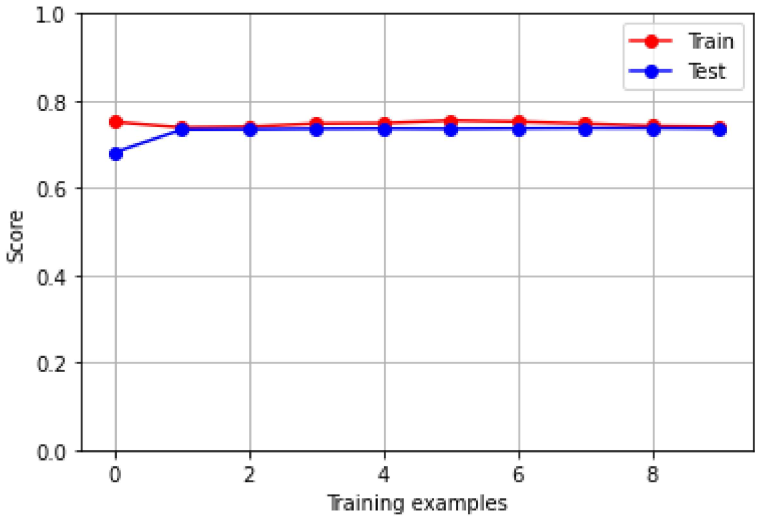
```
                    SVC(random_state=42),
                    {'gamma': [0.25,0.5], 'C': [0.125,0.25]})
```

```
              precision    recall  f1-score   support

           0       0.77      0.87      0.82      7442
           1       0.63      0.47      0.54      3603

    accuracy                           0.74     11045
   macro avg       0.70      0.67      0.68     11045
weighted avg       0.73      0.74      0.73     11045
```

In [63]:
```
plot_learning_curve(x_train, y_train, svc.best_estimator_)
```



In [67]:
```
svc.best_estimator_
```

Out[67]:
```
SVC(C=0.25, gamma=0.5, random_state=42)
```

The SVC classifier has again an accuracy of 0.74 and a F1-score of 0.73. The learning curve does not show any under- or overfitting.

Feature importances

In this last part I will analyze what the most important features are:

In [64]:
```
feature_importances=pd.DataFrame({'features':x_train.columns,'feature_importance':rf
feature_importances.sort_values('feature_importance',ascending=False)
```

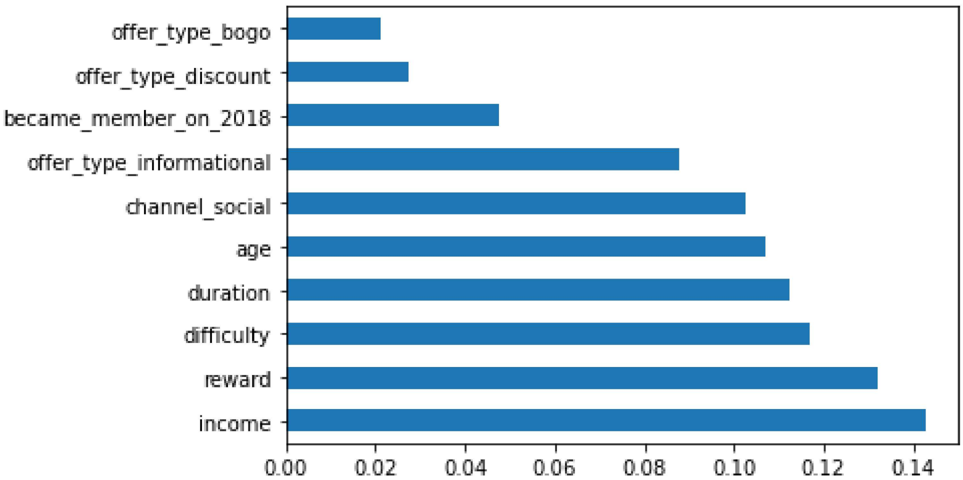
Out[64]:

	features	feature_importance
11	income	0.142657
0	reward	0.132045
1	difficulty	0.116725
2	duration	0.112348
10	age	0.107113
8	channel_social	0.102432
5	offer_type_informational	0.087648
20	became_member_on_2018	0.047585
4	offer_type_discount	0.027214

	features	feature_importance
3	offer_type_bogo	0.021066
18	became_member_on_2016	0.020972
7	channel_mobile	0.017246
9	channel_web	0.012971
19	became_member_on_2017	0.012869
13	gender_M	0.012157
12	gender_F	0.010013
17	became_member_on_2015	0.008486
16	became_member_on_2014	0.005046
15	became_member_on_2013	0.002103
14	gender_O	0.001304
6	channel_email	0.000000

In [65]:
```
(pd.Series(rfc.best_estimator_.feature_importances_, index=x.columns)
   .nlargest(10)
   .plot(kind='barh'))
```

Out[65]: <AxesSubplot:>



Apparently, the most important features referring to a user are income, age and if they became member on 2018 (the most recent date of the data given). The most important features of an offer are reward, difficulty, duration, channel social and the different offer types, although the offer type informational seems to have a much greater impact than the other ones.

Conclusion

Reflection

I chose to predict whether a customer will respond to an offer or not. To achieve this, I had to clean up and prepare the data to be used in a machine learning algorithm. While cleaning up the portfolio and profile data was easy the transaction data was a challange. Although the data I was interested in was there I had to put a lot of work to bring this data into a structure that allowed me work with it. Based on the transaction data I created a new data frame that holds an entry per user per offer and indicates if the offer was completed or not. Since I was interested in whether the offer had an influence on the user or not I chose to assess an offer as completed only if it was viewed first. Then I merged the portfolio and profile data into the new dataframe and scaled all non boolean values.

After the data preprocessing I chose five different classifiers to test. Interestingly, all five classifiers had roughly the same performance. This part was unexpected, although I used grid search to optimize each of the classifiers. Nevertheless I was expecting at least some variation of accuracy and F1-score. The unexeptional scores of accuracy with 0.74 and a F1-score with 0.73 (0.74 for MLP) was not unexpected though. The randomness of the data is tricky to deal with: even the same person may respond to the same offer differently on a different day. You just never know when someone wants a up of coffee.

The analysis of the feature importances showed that both customer and offer features are important whether an offer is successful or not. For the customer features income and age are most important and reward, difficulty and duration for the offer features.

Improvement

One thing that could be improved is the use of the data given by the event type "transaction". This event is used when a customer buys something and the amount spent is stored. With that data you could either calculate the total amount spent or, in combination with "became_member_on" from the profile data, calculate the average amount spent per month. This might also help the classifier to get better results (no guarantee though) or you could exclude customers who already spend much from offers which makes sense from a business perspective.