Import the library with all predefine functions

In [1]:

```
import lazy_pipeline as lpipe
import matplotlib.pyplot as plt

import pandas as pd
import numpy as np
import time

# preprocessing of numeric features
from sklearn.preprocessing import KBinsDiscretizer

# used metrics
from sklearn.metrics import accuracy_score, f1_score
```

Make the notebook wider

In [2]:

```
from IPython.display import display, HTML
display(HTML("<style>.container { width:100% !important; }</style>"))
```

Check library versions

In [3]:

```
from platform import python_version
import sklearn

print(python_version())
print(lpipe.pd.__version__)
print(sklearn.__version__)
print(pd.__version__)
print(np.__version__)
```

```
3.7.6
1.0.1
0.22.1
1.0.1
1.18.1
```

Start of baseline

In [4]:

```
def process_data(df):

    # dataset preprocessing, replacing empty numeric values with column averages, categorical valu
    # I keep no more than 10 of the most popular values of each categorical attribute

    for col in df.select_dtypes(['number']).columns:
        df[col] = df[col].fillna(df[col].mean())

    for col in df.select_dtypes(['object']).columns:
        df[col] = df[col].fillna('unknown')
        use_values = df[col].value_counts().index.values[0:10]
        df[col] = df[col].apply(lambda x: x if x in use_values else 'other')

    return df


def discretize_data(df):

    # categorize the numerical features: divide into 5 intervals of equal length

    est = KBinsDiscretizer(n_bins=5, encode='ordinal', strategy='uniform')
    for col in df.select_dtypes(['number']).columns:
        df[col] = est.fit_transform(df[[col]])

    return df
```

```
def get_scores(y_preds, y_preds_fixedtrain):

    # let's turn the calculation of metrics from the initial notebook into a function
    # I decided to measure Accuracy and F1 score because they are ones of the most popular scores

    score_vals = {}
    for score_f in [accuracy_score, f1_score]:
        score_name = score_f.__name__
        preds = y_preds
        score_vals[score_name] = [score_f(y_test[:i], preds[:i]) for i in range(1, len(preds))]

        score_name = score_f.__name__ + '_fixedtrain'
        preds = y_preds_fixedtrain
        score_vals[score_name] = [score_f(y_test[:i], preds[:i]) for i in range(1, len(preds))]

    return score_vals


def get_scores_info (score_vals, t_preds, t_preds_fixedtrain):

    return {'accuracy_score' : np.mean(score_vals['accuracy_score']),
            'accuracy_score_fixedtrain' : np.mean(score_vals['accuracy_score_fixedtrain']),
            'f1_score' : np.mean(score_vals['f1_score']),
            'f1_score_fixedtrain' : np.mean(score_vals['f1_score_fixedtrain']),
            't_preds': np.mean(t_preds),
            't_preds_fixedtrain' : np.mean(t_preds_fixedtrain)}


def plot_metrics(score_vals, t_preds, t_preds_fixedtrain):

    # plotting metrics and calculation time

    plt.rcParams['figure.facecolor'] = (1,1,1,1)

    fig, axs = plt.subplots(2, 2, figsize=(12, 8))

    for ax, t in zip(axs[0],['accuracy_score', 'f1_score']):
        ax.set_ylim(0-0.05, 1+0.05)
        ax.plot(range(n_train+1, len(X)), score_vals[t], label='baseline clf.')
        ax.plot(range(n_train+1, len(X)), score_vals[t+'_fixedtrain'], label='baseline clf. (fixed

    axs[1,0].plot(range(n_train, len(X)), t_preds, label='baseline clf.')
    axs[1,0].plot(range(n_train, len(X)), t_preds_fixedtrain, label='baseline clf. (fixed train)')

    for (ax, t_verb, dim) in zip(axs.flatten(), ['Accuracy score', 'F1 score', 'Prediction time'],
        ax.set_title('\n'.join([f"{t_verb} progression", "w.r.t. the number of train examples"]),
        ax.set_xlabel('# of train examples', size=14)
        ax.set_ylabel(f"{t_verb} {dim}".strip(),  size=14)
        ax.legend()

    axs[1,1].set_axis_off()
    plt.tight_layout()
    plt.subplots_adjust()

    plt.show()
```

Data preparation

Airline Passenger Satisfaction dataset

https://www.kaggle.com/datasets/teejmahal20/airline-passenger-satisfaction

In [5]:
```
# Let's read the dataset, convert the target variable to a boolean type, and remove service colum

data = pd.read_csv('data/flight.csv')
y_name = 'satisfaction'
data[y_name] = (data[y_name]=='satisfied')
```

```
data = data.iloc[:,2:]

print(data.shape)
data.head(5)
```

(25976, 23)

Out[5]:

	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	Ease of Online booking	Gate location	...	Ir entertai
0	Female	Loyal Customer	52	Business travel	Eco	160	5	4	3	4	...	
1	Female	Loyal Customer	36	Business travel	Business	2863	1	1	3	1	...	
2	Male	disloyal Customer	20	Business travel	Eco	192	2	0	2	4	...	
3	Male	Loyal Customer	44	Business travel	Business	3377	0	0	0	2	...	
4	Female	Loyal Customer	49	Business travel	Eco	1182	2	3	4	3	...	

5 rows × 23 columns

Let's limit the sample to 500 objects and process the data

In [6]:
```
data = data.sample(500, random_state = 1)

data = process_data(data)
data = discretize_data(data)
```

Data binarization: one-hot encoding

In [7]:
```
y = data[y_name]
X = lpipe.binarize_X(data.drop(y_name, axis=1))
print(X.shape)
X.head(2)
```

(500, 99)

Out[7]:

	Gender: Female	Gender: Male	Customer Type: Loyal Customer	Customer Type: disloyal Customer	Age: 0.0	Age: 1.0	Age: 2.0	Age: 3.0	Age: 4.0	Type of Travel: Business travel	...	Departure Delay in Minutes: 0.0	Departure Delay in Minutes: 1.0
21362	True	False	True	False	False	False	False	False	True	False	...	True	False
11437	False	True	False	True	False	True	False	False	False	True	...	True	False

2 rows × 99 columns

Representation of a feature matrix as a list of sets:

In [8]:
```
X_bin = [set(X.columns[x]) for idx, x in X.iterrows()]
X_bin[0]
```

Out[8]:
```
{'Age: 4.0',
 'Arrival Delay in Minutes: 0.0',
 'Baggage handling: 3.0',
 'Checkin service: 4.0',
 'Class: Eco',
 'Cleanliness: 3.0',
 'Customer Type: Loyal Customer',
 'Departure Delay in Minutes: 0.0',
 'Departure/Arrival time convenient: 4.0',
 'Ease of Online booking: 3.0',
 'Flight Distance: 1.0',
 'Food and drink: 2.0',
 'Gate location: 0.0',
 'Gender: Female',
 'Inflight entertainment: 3.0',
 'Inflight service: 3.0',
 'Inflight wifi service: 3.0',
 'Leg room service: 3.0',
 'On-board service: 3.0',
 'Online boarding: 3.0',
 'Seat comfort: 3.0',
 'Type of Travel: Personal Travel'}
```

Converting a target variable to a list:

In [9]:
```
y = y.values.tolist()
```

We assume that at the initial stage we have only 10% of the total sample:

In [10]:
```
n_train = int(len(X)*0.1)
n_test = len(X) - n_train
y_test = y[n_train:]

n_train, n_test
```

Out[10]:
```
(50, 450)
```

Application of the model

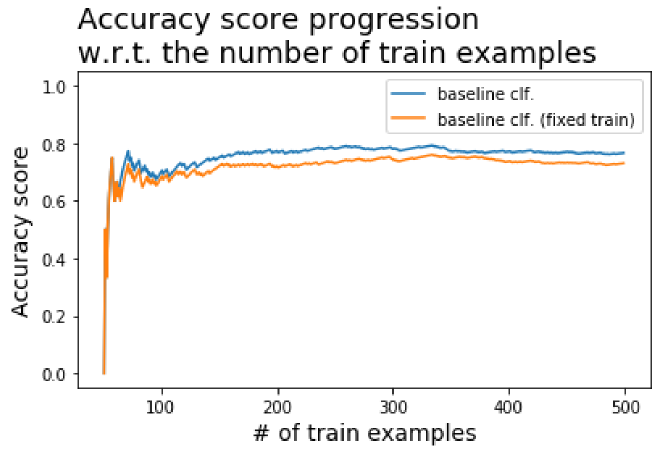
In [11]:
```
%%time
gen = lpipe.predict_array(X_bin, y, n_train, use_tqdm=True)
y_preds, t_preds = lpipe.apply_stopwatch(gen)

# updating the training sample
```

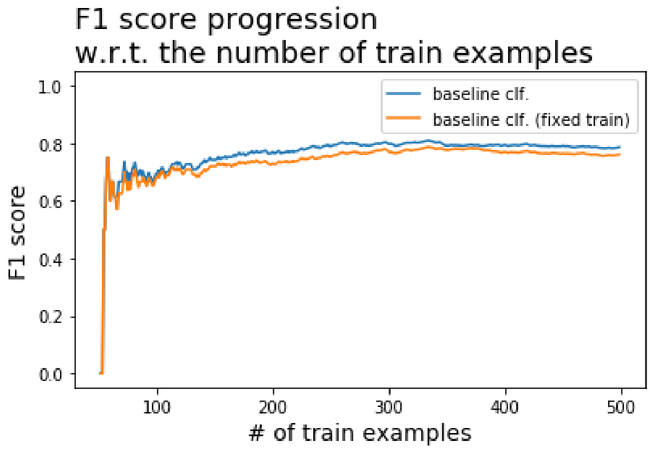
```
Predicting step by step: 100%|████████████████████████████████████████| 500/500 [0
0:07<00:00, 71.22it/s]
Wall time: 7.02 s
```

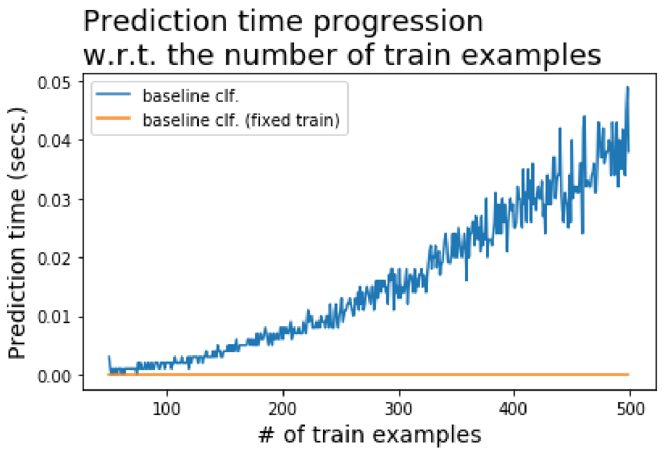
In [12]:
```
%%time
gen = list(lpipe.predict_array(X_bin, y, n_train, use_tqdm=True, update_train=False))
y_preds_fixedtrain, t_preds_fixedtrain = lpipe.apply_stopwatch(gen)

# without updating the training sample
```

```
Predicting step by step: 100%|████████████████████████████████████████| 500/500 [00:
00<00:00, 2110.59it/s]
Wall time: 241 ms
```

In [13]:
```
scores = get_scores(y_preds, y_preds_fixedtrain)

plot_metrics(scores, t_preds, t_preds_fixedtrain)
```







In conclusion, as we can see from the plots, orange curves are situated lower than blue ones, so we can make an assumption that when we update training sample, the accuracy score is raising.

In [14]:
```
get_scores_info(scores, t_preds, t_preds_fixedtrain)
```

Out[14]:
```
{'accuracy_score': 0.7562200315830624,
 'accuracy_score_fixedtrain': 0.7212799822789326,
 'f1_score': 0.7625785966832718,
 'f1_score_fixedtrain': 0.7376621185160739,
 't_preds': 0.015605789820353 19,
 't_preds_fixedtrain': 0.0}
```

Modification of the algorithm

In [16]:
```
# used algorithms

import lightgbm as lgb
from lazy_pipeline import predict_with_generators
from sklearn.tree import DecisionTreeClassifier
```

Instead of crossing sets, we use the matrix multiplication function in numpy. Let's add the ability to use algorithms (decision tree and gradient boosting) in lazy pipeline.

In [17]:
```
def predict_with_dot(x, X_train, Y_train):

    X_pos = np.array([x_train for x_train, y in zip(X_train, Y_train) if y])
    X_neg = np.array([x_train for x_train, y in zip(X_train, Y_train) if not y])

    pos_dot = np.dot(x,X_pos.T).sum()
    neg_dot = np.dot(x,X_neg.T).sum()

    return pos_dot > neg_dot


def predict_with_model(x, X_train, Y_train, use_model):

    model = use_model
```

```
    model.fit(X_train,Y_train)
    res = model.predict([x])

    return res[0]


# I used decision tree for testing, and gradient boosting (without any adjustment of model paramet

def predict_with_tree(x, X_train, Y_train):
    return predict_with_model(x, X_train, Y_train, DecisionTreeClassifier(max_depth = 6))


def predict_with_boosting(x, X_train, Y_train):
    return predict_with_model(x, X_train, Y_train, lgb.LGBMClassifier(max_depth =4, n_estimators =


def train_lpipe(X, y, n_train, predict_function, update_train):

    gen = lpipe.predict_array(X = X, Y = y, n_train = n_train, use_tqdm = False, predict_func = pr
    y_preds, t_preds = lpipe.apply_stopwatch(gen)

    return y_preds, t_preds


#It’s a high order function, which calls all the algorithms above and counts score

def get_results(predict_function, X, y, n_train):

    results = {}

    results['model_name'] = predict_function.__name__

    t_start = time.time()
    y_preds, t_preds = train_lpipe(X = X, y = y, n_train = n_train, predict_function = predict_fur
    t_stop = time.time()

    results['upd_time'] = t_stop - t_start

    t_start = time.time()
    y_preds_fixedtrain, t_preds_fixedtrain = train_lpipe(X = X, y = y, n_train = n_train, predict_
    t_stop = time.time()

    results['fixed_time'] = t_stop - t_start

    scores = get_scores(y_preds, y_preds_fixedtrain)

    scores_info = get_scores_info(scores, t_preds, t_preds_fixedtrain)
    for key in scores_info:
        results[key] = scores_info[key]

    return results
```

In [18]:
```
# convert all data to numeric format

X_int = X.astype(int).values
```

In [19]:
```
df_results = pd.DataFrame([get_results(predict_function, X_int, y, n_train) for predict_function i
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1515: UndefinedMetr
icWarning: F-score is ill-defined and being set to 0.0 due to no true nor predicted samples. Use
`zero_division` parameter to control this behavior.
  average, "true nor predicted", 'F-score is', len(true_sum)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1515: UndefinedMetr
icWarning: F-score is ill-defined and being set to 0.0 due to no true nor predicted samples. Use
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  average, "true nor predicted", 'F-score is', len(true_sum)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1515: UndefinedMetr
icWarning: F-score is ill-defined and being set to 0.0 due to no true nor predicted samples. Use
`zero_division` parameter to control this behavior.
  average, "true nor predicted", 'F-score is', len(true_sum)
```

In [20]:
```
# final table for comparison

df_results
```

Out[20]:

	model_name	upd_time	fixed_time	accuracy_score	accuracy_score_fixedtrain	f1_score	f1_score_fixedtrair
0	predict_with_dot	0.148907	0.037977	0.747410	0.817870	0.581582	0.74175€
1	predict_with_tree	0.727553	0.263840	0.836064	0.785045	0.803344	0.72863(
2	predict_with_boosting	10.372624	4.307353	0.862641	0.807403	0.823205	0.76203: