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Факультет «Информатика и системы управления»

Кафедра «Автоматизированные системы обработки информации и управления»

“Методы машинного обучения”

Отчет по лабораторной работе №4

“Изучение библиотек обработки данных”

Выполнил:

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Группа ИУ5-21м

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Лабораторная работа №4

Цель: изучение сложных способов подготовки выборки и подбора гиперпараметров на примере метода ближайших соседей.

Задание

1. Выберите набор данных (датасет) для решения задачи классификации или регресии.
2. В случае необходимости проведите удаление или заполнение пропусков и кодирование категориальных признаков.
3. С использованием метода train_test_split разделите выборку на обучающую и тестовую.
4. Обучите модель ближайших соседей для произвольно заданного гиперпараметра K. Оцените качество модели с помощью трех подходящих для задачи метрик.
5. Постройте модель и оцените качество модели с использованием кросс-валидации. Проведите эксперименты с тремя различными стратегиями кросс-валидации.
6. Произведите подбор гиперпараметра K с использованием GridSearchCV и кросс-валидации.
7. Повторите пункт 4 для найденного оптимального значения гиперпараметра K. Сравните качество полученной модели с качеством модели, полученной в пункте 4.
8. Постройте кривые обучения и валидации.

Ход выполнения лабораторной работы

Выбор датасета

В качестве исходных данных выбираем датасет Heart Disease UCI (https://www.kaggle.com/ronitf/heart-disease-uci (https://www.kaggle.com/ronitf/heart-disease-uci)). 303 записи, 14 признаков, целевой признак относится к наличию болезни сердца у пациента: 0 - нет болезни сердца, 1 - есть.

In [0]:

```
from google.colab import drive, files
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/con
tent/drive", force_remount=True).
```

In [0]:

```
from google.colab import files
import os
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
os.listdir()
data = pd.read_csv('drive/My Drive/mmo_datasets/heart.csv',
                   sep=",", encoding="iso-8859-1")
```

In [0]:

```
total_count = data.shape[0]
num_cols = []
for col in data.columns:
    # Количество пустых значений
    temp_null_count = data[data[col].isnull()].shape[0]
    dt = str(data[col].dtype)
    if temp_null_count>0:
        num_cols.append(col)
        temp_perc = round((temp_null_count / total_count) * 100.0, 2)
        print('Колонка {}. Тип данных {}. Количество пустых значений {}, {}%.'
              .format(col, dt, temp_null_count, temp_perc))

data_cleared = data
```

In [0]:

```
uniquevalues = np.unique(data_cleared['target'].values)
uniquevalues
```

Out[0]:

```
array([0, 1])
```

In [0]:

```
data_cleared.head(10)
```

Out[0]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1
5	57	1	0	140	192	0	1	148	0	0.4	1	0	1	1
6	56	0	1	140	294	0	0	153	0	1.3	1	0	2	1
7	44	1	1	120	263	0	1	173	0	0.0	2	0	3	1
8	52	1	2	172	199	1	1	162	0	0.5	2	0	3	1
9	57	1	2	150	168	0	1	174	0	1.6	2	0	2	1

train_test_split

In [0]:

```
target = data_cleared['target']
data_cleared = data_cleared.drop('target', axis=1)
```

In [0]:

```
data_cleared.head(10)
```

Out[0]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2
5	57	1	0	140	192	0	1	148	0	0.4	1	0	1
6	56	0	1	140	294	0	0	153	0	1.3	1	0	2
7	44	1	1	120	263	0	1	173	0	0.0	2	0	3
8	52	1	2	172	199	1	1	162	0	0.5	2	0	3
9	57	1	2	150	168	0	1	174	0	1.6	2	0	2

In [0]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(
    data_cleared,
    target,
    test_size=0.2,
    random_state=1
)
```

In [0]:

```
X_train.shape, Y_train.shape
```

Out[0]:

((242, 13), (242,))

In [0]:

```
X_test.shape, Y_test.shape
```

Out[0]:

((61, 13), (61,))

Обучение для произвольного параметра K

In [0]:

```
from sklearn.neighbors import KNeighborsRegressor, KNeighborsClassifier
```

In [0]:

```
knn_model = KNeighborsClassifier(n_neighbors=5)
knn_model.fit(X_train, Y_train)
predicted = knn_model.predict(X_test)
predicted
```

Out[0]:

```
array([0, 1, 1, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0,
       0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0,
       1, 1, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0])
```

In [0]:

```
from sklearn.metrics import accuracy_score
accuracy_score(Y_test, predicted)
```

Out[0]:

```
0.5737704918032787
```

In [0]:

```
from sklearn.metrics import balanced_accuracy_score
balanced_accuracy_score(Y_test, predicted)
```

Out[0]:

```
0.5720430107526882
```

In [0]:

```
# https://scikit-learn.org/stable/auto_examples/model_selection/plot_confusion_matrix.html#sphx-glr-auto-exa
mples-model-selection-plot-confusion-matrix-py
from sklearn.utils.multiclass import unique_labels
def plot_confusion_matrix(y_true, y_pred, classes,
                          normalize=False,
                          title=None,
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if not title:
        if normalize:
            title = 'Normalized confusion matrix'
        else:
            title = 'Confusion matrix, without normalization'

    # Compute confusion matrix
    cm = confusion_matrix(y_true, y_pred)
    # Only use the labels that appear in the data
    classes = classes[unique_labels(y_true, y_pred)]
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    fig, ax = plt.subplots()
    im = ax.imshow(cm, interpolation='nearest', cmap=cmap)
    ax.figure.colorbar(im, ax=ax)
    # We want to show all ticks...
    ax.set(xticks=np.arange(cm.shape[1]),
           yticks=np.arange(cm.shape[0]),
           # ... and label them with the respective list entries
           xticklabels=classes, yticklabels=classes,
           title=title,
           ylabel='True label',
           xlabel='Predicted label')

    # Rotate the tick labels and set their alignment.
    plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
             rotation_mode="anchor")

    # Loop over data dimensions and create text annotations.
    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i in range(cm.shape[0]):
        for j in range(cm.shape[1]):
            ax.text(j, i, format(cm[i, j], fmt),
                    ha="center", va="center",
                    color="white" if cm[i, j] > thresh else "black")
    fig.tight_layout()
    return ax
```

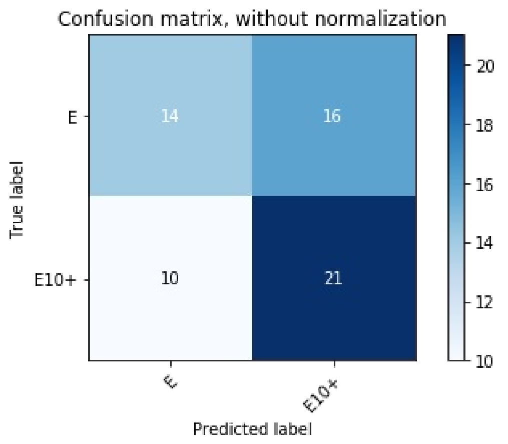
In [0]:

```
plot_confusion_matrix(Y_test, predicted,
                      classes=np.array(['E', 'E10+', 'M', 'T']),
                      title='Confusion matrix, without normalization')
```

Confusion matrix, without normalization

Out[0]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f13d7451240>



In [0]:

```
from sklearn.metrics import precision_score, recall_score, f1_score
(precision_score(Y_test, predicted, average='weighted'),
 recall_score(Y_test, predicted, average='weighted'))
```

Out[0]:

(0.5753212228622065, 0.5737704918032787)

In [0]:

```
f1_score(Y_test, predicted, average='weighted')
```

Out[0]:

0.5688953176899175

Построение модели и оценка с помощью кросс-валидации

In [0]:

```
from sklearn.model_selection import KFold, ShuffleSplit, StratifiedShuffleSplit
from sklearn.model_selection import cross_val_score, cross_validate

scoring = {'precision': 'precision_weighted',
           'recall': 'recall_weighted',
           'f1': 'f1_weighted'}
```

In [0]:

```
scores1 = cross_validate(KNeighborsClassifier(n_neighbors=2),
                         data_cleared,
                         target,
                         scoring=scoring,
                         cv=KFold(n_splits=3),
                         return_train_score=True
                        )
scores1
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1145: UndefinedMetricW
arning: Recall is ill-defined and being set to 0.0 in labels with no true samples.
  'recall', 'true', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1145: UndefinedMetricW
arning: F-score is ill-defined and being set to 0.0 in labels with no true samples.
  'recall', 'true', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1145: UndefinedMetricW
arning: Recall is ill-defined and being set to 0.0 in labels with no true samples.
  'recall', 'true', average, warn_for)
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/classification.py:1145: UndefinedMetricW
arning: F-score is ill-defined and being set to 0.0 in labels with no true samples.
  'recall', 'true', average, warn_for)
```

Out[0]:

```
{'fit_time': array([0.0035882 , 0.00298381, 0.00277495]),
 'score_time': array([0.01822829, 0.01480269, 0.0153482 ]),
 'test_f1': array([0.28813559, 0.55414336, 0.62585034]),
 'test_precision': array([1.        , 0.69316227, 1.        ]),
 'test_recall': array([0.16831683, 0.56435644, 0.45544554]),
 'train_f1': array([0.80387838, 0.79945524, 0.89967881]),
 'train_precision': array([0.86178676, 0.86071429, 0.93169995]),
 'train_recall': array([0.82673267, 0.80693069, 0.89108911])}
```

In [0]:

```
scores2 = cross_validate(KNeighborsClassifier(n_neighbors=2),
                         data_cleared,
                         target,
                         scoring=scoring,
                         cv=ShuffleSplit(n_splits=5, test_size=0.25),
                         return_train_score=True
                        )
scores2
```

Out[0]:

```
{'fit_time': array([0.00568986, 0.00283527, 0.00285411, 0.00288081, 0.0028367 ]),
 'score_time': array([0.01616049, 0.01285553, 0.01286197, 0.01299715, 0.0131793 ]),
 'test_f1': array([0.59090453, 0.43465982, 0.54309958, 0.49336384, 0.54641813]),
 'test_precision': array([0.65233425, 0.50489204, 0.55322831, 0.58439201, 0.62388664]),
 'test_recall': array([0.59210526, 0.44736842, 0.55263158, 0.52631579, 0.55263158]),
 'train_f1': array([0.77611602, 0.82921815, 0.78953072, 0.80197881, 0.77611602]),
 'train_precision': array([0.85151099, 0.87616921, 0.85960413, 0.86379331, 0.85151099]),
 'train_recall': array([0.78414097, 0.83259912, 0.79295154, 0.8061674 , 0.78414097])}
```

In [0]:

```
scores3 = cross_validate(KNeighborsClassifier(n_neighbors=2),
                         data_cleared,
                         target,
                         scoring=scoring,
                         cv=StratifiedShuffleSplit(n_splits=5, test_size=0.2),
                         return_train_score=True
                        )
scores3
```

Out[0]:

```
{'fit_time': array([0.00362515, 0.00277042, 0.00277781, 0.00282669, 0.00318956]),
 'score_time': array([0.01695871, 0.01117134, 0.01135397, 0.01128387, 0.01146054]),
 'test_f1': array([0.61222806, 0.60401357, 0.61928718, 0.5710147 , 0.53801583]),
 'test_precision': array([0.66323471, 0.62287796, 0.64371954, 0.58848816, 0.55409836]),
 'test_recall': array([0.62295082, 0.60655738, 0.62295082, 0.57377049, 0.54098361]),
 'train_f1': array([0.81073333, 0.78385644, 0.79288886, 0.77931087, 0.80184646]),
 'train_precision': array([0.86803519, 0.85601355, 0.85991995, 0.85409652, 0.86392588]),
 'train_recall': array([0.81404959, 0.7892562 , 0.79752066, 0.78512397, 0.80578512])}
```

In [0]:

```
print("%s, %s, %s" % (np.mean(scores1["test_precision"]),
                      np.mean(scores2["test_precision"]),
                      np.mean(scores3["test_precision"])))
```

```
0.8977207579912921, 0.5837466496118905, 0.6144837452406424
```

Лучшую точность модели получилось достичь с использованием стратегии кросс-валидации KFold.

Подбор гиперпараметра K с использованием GridSearchCV и кросс-валидации

In [0]:

```
n_range = np.array(range(2,32,2))
tuned_parameters = [{'n_neighbors': n_range}]
tuned_parameters
```

Out[0]:

```
[{'n_neighbors': array([ 2,  4,  6,  8, 10, 12, 14, 16, 18, 20, 22, 24, 26, 28, 30])}]
```

In [0]:

```
from sklearn.model_selection import GridSearchCV

clf_gs = GridSearchCV(KNeighborsClassifier(),
                      tuned_parameters,
                      cv=ShuffleSplit(n_splits=5, test_size=0.25),
                      scoring='accuracy')
clf_gs.fit(X_train, Y_train)
```

Out[0]:

```
GridSearchCV(cv=ShuffleSplit(n_splits=5, random_state=None, test_size=0.25, train_size=None),
       error_score='raise-deprecating',
       estimator=KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=None, n_neighbors=5, p=2,
           weights='uniform'),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid=[{'n_neighbors': array([ 2,  4,  6,  8, 10, 12, 14, 16, 18, 20, 22, 24, 26, 2
8, 30])}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='accuracy', verbose=0)
```

In [0]:

```
clf_gs.best_params_
```

Out[0]:

```
{'n_neighbors': 8}
```

In [0]:

```
clf_gs.best_estimator_
```

Out[0]:

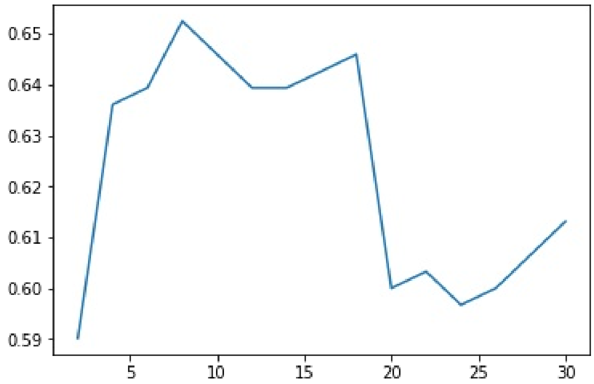
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=None, n_neighbors=8, p=2,
           weights='uniform')
```

In [0]:

```
plt.plot(n_range, clf_gs.cv_results_['mean_test_score'])
```

Out[0]:

```
[<matplotlib.lines.Line2D at 0x7f13d6f41940>]
```



Сравнение качества обучения моделей

In [0]:

```
knn_best_model = KNeighborsClassifier(n_neighbors=24)
knn_best_model.fit(X_train, Y_train)
predicted_best = knn_best_model.predict(X_test)
predicted_best
```

Out[0]:

```
array([1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0,
       0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 0,
       1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0])
```

In [0]:

```
(accuracy_score(Y_test, predicted),
 accuracy_score(Y_test, predicted_best))
```

Out[0]:

```
(0.5737704918032787, 0.6557377049180327)
```

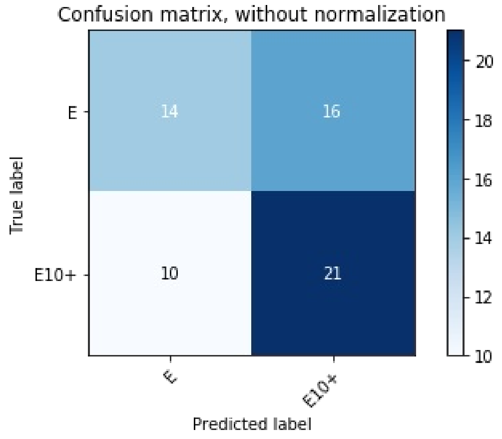
In [0]:

```
plot_confusion_matrix(Y_test, predicted,
                      classes=np.array(['E', 'E10+', 'M', 'T']),
                      title='Confusion matrix, without normalization')
```

Confusion matrix, without normalization

Out[0]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f13d6f4a320>



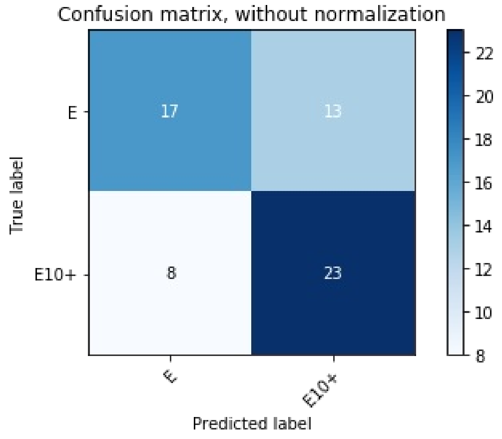
In [0]:

```
plot_confusion_matrix(Y_test, predicted_best,
                      classes=np.array(['E', 'E10+', 'M', 'T']),
                      title='Confusion matrix, without normalization')
```

Confusion matrix, without normalization

Out[0]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f13d6eeacf8>



In [0]:

```
(precision_score(Y_test, predicted, average='weighted'),
precision_score(Y_test, predicted_best, average='weighted'))
```

Out[0]:

(0.5753212228622065, 0.6591074681238616)

In [0]:

```
(recall_score(Y_test, predicted, average='weighted'),
recall_score(Y_test, predicted_best, average='weighted'))
```

Out[0]:

(0.5737704918032787, 0.6557377049180327)

In [0]:

```
(f1_score(Y_test, predicted, average='weighted'),
f1_score(Y_test, predicted_best, average='weighted'))
```

Out[0]:

```
(0.5688953176899175, 0.65293502680339)
```

Таким образом, подбор гиперпараметра позволил улучшить результаты оценки модели посредством всех представленных метрик.

Кривые обучения и валидации

In [0]:

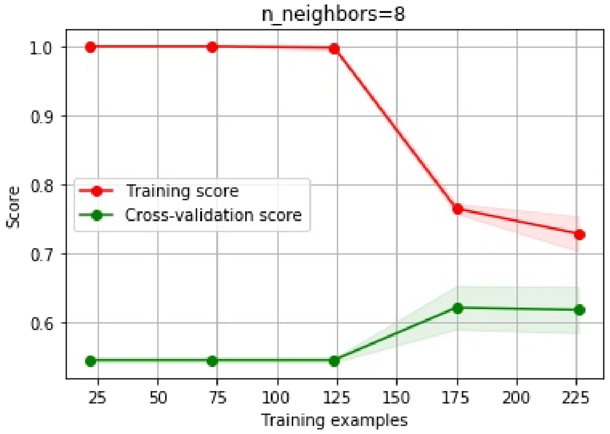
```
from sklearn.model_selection import learning_curve, validation_curve

def plot_learning_curve(estimator, title, X, y, ylim=None, cv=None,
                        n_jobs=None, train_sizes=np.linspace(.1, 1.0, 5)):
    plt.figure()
    plt.title(title)
    if ylim is not None:
        plt.ylim(*ylim)
    plt.xlabel("Training examples")
    plt.ylabel("Score")
    train_sizes, train_scores, test_scores = learning_curve(
        estimator, X, y, cv=cv, n_jobs=n_jobs, train_sizes=train_sizes)
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)
    plt.grid()

    plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                     train_scores_mean + train_scores_std, alpha=0.1,
                     color="r")
    plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                     test_scores_mean + test_scores_std, alpha=0.1, color="g")
    plt.plot(train_sizes, train_scores_mean, 'o-', color="r",
             label="Training score")
    plt.plot(train_sizes, test_scores_mean, 'o-', color="g",
             label="Cross-validation score")

    plt.legend(loc="best")
    return plt

def plot_validation_curve(estimator, title, X, y,
                          param_name, param_range, cv,
                          scoring="accuracy"):
    train_scores, test_scores = validation_curve(
        estimator, X, y, param_name=param_name, param_range=param_range,
        cv=cv, scoring=scoring, n_jobs=1)
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)

    plt.title(title)
    plt.xlabel(param_name)
    plt.ylabel("Score")
    plt.ylim(0.0, 1.1)
    lw = 2
    plt.plot(param_range, train_scores_mean, label="Training score",
             color="darkorange", lw=lw)
    plt.fill_between(param_range, train_scores_mean - train_scores_std,
                     train_scores_mean + train_scores_std, alpha=0.2,
                     color="darkorange", lw=lw)
    plt.plot(param_range, test_scores_mean, label="Cross-validation score",
             color="navy", lw=lw)
    plt.fill_between(param_range, test_scores_mean - test_scores_std,
                     test_scores_mean + test_scores_std, alpha=0.2,
                     color="navy", lw=lw)
    plt.legend(loc="best")
    return plt
```

In [0]:

```
plot_learning_curve(KNeighborsClassifier(n_neighbors=8),
                    'n_neighbors=8',
                    data_cleared,
                    target,
                    cv=4
                   )
```

Out[0]:

<module 'matplotlib.pyplot' from '/usr/local/lib/python3.6/dist-packages/matplotlib/pyplot.py'>



In [0]:

```
n_range2 = np.array(range(2,24,2))

plot_validation_curve(KNeighborsClassifier(), 'knn',
                      data_cleared,
                      target,
                      param_name='n_neighbors',
                      param_range=n_range2,
                      cv=4,
                      scoring="accuracy"
                     )
```

Out[0]:

<module 'matplotlib.pyplot' from '/usr/local/lib/python3.6/dist-packages/matplotlib/pyplot.py'>