

## ▼ Лабораторная работа №4

Подготовка обучающей и тестовой выборки, кросс-валидация и подбор гиперпараметров на примере метода ближайших соседей.

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

Задание

1. Выберите набор данных (датасет) для решения задачи классификации или регрессии.
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.

## ► Установка окружения

↳ 12 cells hidden

## ▼ Работа с данными

```
1 import numpy as np
2 import pandas as pd
3 import matplotlib.pyplot as plt
4 from sklearn.model_selection import GridSearchCV
5 from sklearn.model_selection import learning_curve, validation_curve
6 from sklearn.model_selection import KFold, RepeatedKFold, LeaveOneOut, LeavePOut
7 from sklearn.model_selection import cross_val_score, cross_validate
8 from sklearn.metrics import roc_curve, confusion_matrix, roc_auc_score, accuracy
9 plt.style.use('ggplot').
```

```
1 #Load the dataset
2 df = pd.read_csv('diabetes.csv')
3
4 #Print the first 5 rows of the dataframe.
5 df.head()
```



Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	Diabetes
0	6	148	72	35	0	33.6
1	1	99	66	20	0	26.6

```
1 df.shape
```

→ (768, 9)

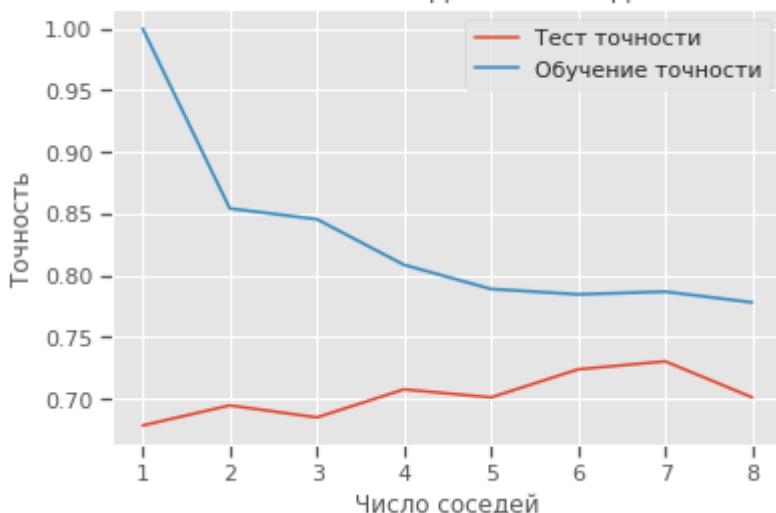
```
1 x = df.drop('Outcome', axis=1).values
2 y = df['Outcome'].values
```

```
1 from sklearn.neighbors import KNeighborsClassifier
2 from sklearn.model_selection import train_test_split
```

```
1 X_train,X_test,y_train,y_test = train_test_split(x,y,test_size=0.4,random_state
2
3 #Setup arrays to store training and test accuracies
4 neighbors = np.arange(1,9)
5 train_accuracy = np.empty(len(neighbors))
6 test_accuracy = np.empty(len(neighbors))
7
8 for i,k in enumerate(neighbors):
9     #Setup a knn classifier with k neighbors
10    knn = KNeighborsClassifier(n_neighbors=k)
11
12    #Fit the model
13    knn.fit(X_train, y_train)
14
15    #Compute accuracy on the training set
16    train_accuracy[i] = knn.score(X_train, y_train)
17
18    #Compute accuracy on the test set
19    test_accuracy[i] = knn.score(X_test, y_test).
```

```
1 #Generate plot
2 plt.title('k-NN Разновидность соседей')
3 plt.plot(neighbors, test_accuracy, label='Тест точности')
4 plt.plot(neighbors, train_accuracy, label='Обучение точности')
5 plt.legend()
6 plt.xlabel('Число соседей')
7 plt.ylabel('Точность')
8 plt.show()
```

→ **k-NN Разновидность соседей**



```

1 #Setup a knn classifier with k neighbors
2 knn = KNeighborsClassifier(n_neighbors=7).

1 #Fit the model
2 knn.fit(X_train,y_train).

→ KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                      metric_params=None, n_jobs=None, n_neighbors=7, p=2,
                      weights='uniform')

1 #Get accuracy. Note: In case of classification algorithms score method represen
2 knn.score(X_test,y_test).

→ 0.7305194805194806

1 #import classification_report
2 from sklearn.metrics import classification_report
3 y_pred = knn.predict(X_test)
4 print(classification_report(y_test,y_pred)).
```

	precision	recall	f1-score	support
0	0.78	0.82	0.80	201
1	0.62	0.56	0.59	107
micro avg	0.73	0.73	0.73	308
macro avg	0.70	0.69	0.70	308
weighted avg	0.73	0.73	0.73	308

## ▼ Точность

```

1 # 7 ближайших соседа
2 c11_1 = KNeighborsClassifier(n_neighbors=7)
3 c11_1.fit(X_train, y_train)
4 target1_1 = c11_1.predict(X_test)
5 accuracy_score(y_test, target1_1).
```

→ 0.7305194805194806

## ▼ Конфигурационная матрица

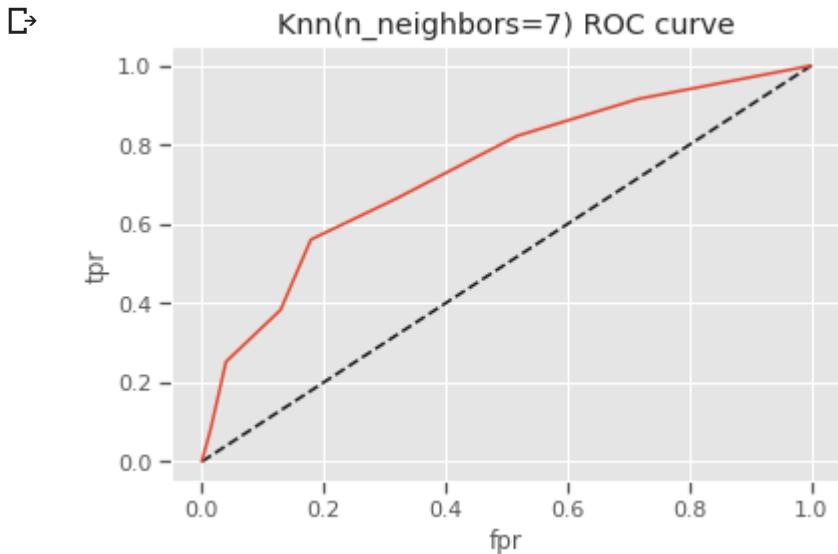
```

1 y_pred = knn.predict(X_test)
2 confusion_matrix(y_test,y_pred)
3 pd.crosstab(y_test, y_pred, rownames=[ 'True' ], colnames=[ 'Predicted' ], margins=
```

		Predicted		All
		True		
		0	1	All
True		165	36	201
0		47	60	107
1		212	96	308
All				

## ▼ ROC (рабочая характеристика приемника ) кривая

```
1 y_pred_proba = knn.predict_proba(X_test)[:,1]
2 fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
3 plt.plot([0,1],[0,1],'k--')
4 plt.plot(fpr,tpr, label='Knn')
5 plt.xlabel('fpr')
6 plt.ylabel('tpr')
7 plt.title('Knn(n_neighbors=7) ROC curve')
8 plt.show()
```



```
1 roc_auc_score(y_test,y_pred_proba).
```

→ 0.7345050448691124

## ▼ Перекрестная Проверка

```
1 param_grid = {'n_neighbors':np.arange(1,50)}
2 knn = KNeighborsClassifier()
3 knn_cv= GridSearchCV(knn,param_grid,cv=5)
4 knn_cv.fit(X,y).
```

→ GridSearchCV(cv=5, error\_score='raise-deprecating',
estimator=KNeighborsClassifier(algorithm='auto', leaf\_size=30, metric=
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([ 1, 2, 3, 4, 5, 6, 7, 8, 9,
18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34,
35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49])},
pre\_dispatch='2\*n\_jobs', refit=True, return\_train\_score='warn',
scoring=None, verbose=0)

```
1 knn_cv.best_score_
```

→ 0.7578125

```
1 knn_cv.best_params_
```

```
↳ {'n_neighbors': 14}
```

## ▼ К-раз

```
1 scores = cross_val_score(KNeighborsClassifier(n_neighbors=2),  
2                           X, y,  
3                           cv=KFold(n_splits=3))  
4 scores
```

```
↳ array([0.671875 , 0.72265625, 0.73046875])
```

## ▼ Оставить один (LOO)

```
1 # Эквивалент KFold(n_splits=n)  
2 loo = LeaveOneOut()  
3 loo.get_n_splits(X)  
4  
5 for train_index, test_index in loo.split(X):  
6     print("TRAIN:", train_index, "TEST:", test_index)  
7     X_train, X_test = X[train_index], X[test_index]  
8     y_train, y_test = y[train_index], y[test_index]  
9     print(X_train, X_test, y_train, y_test)
```

```
↳
```



523	524	525	526	527	528	529	530	531	532	533	534	535	536	537	538	539	540
541	542	543	544	545	546	547	548	549	550	551	552	553	554	555	556	557	558
559	560	561	562	563	564	565	566	567	568	569	570	571	572	573	574	575	576
577	578	579	580	581	582	583	584	585	586	587	588	589	590	591	592	593	594
595	596	597	598	599	600	601	602	603	604	605	606	607	608	609	610	611	612
613	614	615	616	617	618	619	620	621	622	623	624	625	626	627	628	629	630
631	632	633	634	635	636	637	638	639	640	641	642	643	644	645	646	647	648
649	650	651	652	653	654	655	656	657	658	659	660	661	662	663	664	665	666
667	668	669	670	671	672	673	674	675	676	677	678	679	680	681	682	683	684
685	686	687	688	689	690	691	692	693	694	695	696	697	698	699	700	701	702
703	704	705	706	707	708	709	710	711	712	713	714	715	716	717	718	719	720
721	722	723	724	725	726	727	728	729	730	731	732	733	734	735	736	737	738
739	740	741	742	743	744	745	746	747	748	749	750	751	752	753	754	755	756
757	758	759	760	761	762	763	764	765	766	767]	TEST:	[1]					
[[6.00e+00 1.48e+02 7.20e+01 ... 3.36e+01 6.27e-01 5.00e+01]																	
[8.00e+00 1.83e+02 6.40e+01 ... 2.33e+01 6.72e-01 3.20e+01]																	
[1.00e+00 8.90e+01 6.60e+01 ... 2.81e+01 1.67e-01 2.10e+01]																	
...																	
[5.00e+00 1.21e+02 7.20e+01 ... 2.62e+01 2.45e-01 3.00e+01]																	
[1.00e+00 1.26e+02 6.00e+01 ... 3.01e+01 3.49e-01 4.70e+01]																	
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