Звіт

Виконала студентка групи ПП-41/1

Терещук Анна

Перед початком виконання основних завдань проводимо дослідницький аналіз даних:

	data_frame : display(data data_frame[a_frame)																
	symbolii	ng normal	ized- sses	make	fuel- type	aspiration	num- of- doors	body- style	drive- wheels	engine- location	wheel- base	6	engine- size	fuel- system	bore	stroke	compression- ratio	horsepo
	0	3	?	alfa- romero	gas	std	two	convertible	rwd	front	88.6		130	mpfi	3.47	2.68	9.0	
	1	3	?	alfa- romero	gas	std	two	convertible	rwd	front	88.6		130	mpfi	3.47	2.68	9.0	
	2	1	?	alfa- romero	gas	std	two	hatchback	rwd	front	94.5		152	mpfi	2.68	3.47	9.0	
	3	2	164	audi	gas	std	four	sedan	fwd	front	99.8		109	mpfi	3.19	3.4	10.0	
	4	2	164	audi	gas	std	four	sedan	4wd	front	99.4		136	mpfi	3.19	3.4	8.0	
		-1 -1	95 95	volvo	gas gas	std turbo	four	sedan sedan	rwd	front	109.1		141	mpfi mpfi		3.15	9.5 8.7	
		-1	95	volvo	gas	std	four	sedan	rwd	front	109.1		173	mpfi		2.87	8.8	
	203	-1	95	volvo	diesel	turbo	four	sedan	rwd	front	109.1		145	idi		3.4	23.0	
	204	-1	95	volvo	gas	turbo	four	sedan	rvvd	front	109.1		141	mpfi	3.78	3.15	9.5	
	205 rows × 26	columns																
1 norm. 2 make 3 fuel: 4 aspi: 5 num: 6 body: 7 driv; 8 engi: 10 leng: 11 widtl 12 heigi 13 curb: 14 engi: 15 num: 16 engi: 17 fuel: 18 bore 19 strol 20 compi	oling alized-losses -type ration of-doors -tyle e-wheels e-wheels h h h h t -weight e-type s-system e-size -system kee	205 non-nt	111 111 111 111 111 111 111 111 111 11	Dtype int64 object object object object object object float64 float64 float64 int64 object int64 object						as nu boo dr en wh he cu en nu en fu boo st co ho pe ci hi prr	el-type piration m-of-doo dy-style ive-whee gine-loc eel-base ngth dth ight ight gine-typ m-of-cyl gine-siz el-syste	rs ls ation t e inder e m n-rat	io	0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0				
25 price dtypes: f	loat64(5), int6 age: 41.8+ KB	205 non-nu 205 non-nu 54(5), obje	ll ct(16							[15]: da			icated	().sum()				
		t[17]:		ing normal	ized- sses ma	ke fuel- type asp	iration	im- of- ors style	drive- eng	gine- wheel-	engine- size	fue syster	l- bore :	stroke comp	pression- ratio	horsepow		
		0		3	NaN a	fa		two convertible		front 88.6			ifi 3.47	2.68	9.0	1		
				3		fa	std	two convertible	rwd	front 88.6	130	mp	ofi 3.47	2.68	9.0	1		
		1							rwd	front 94.5	152		e 2.00				1	
		1			NaN a	fa- ero gas	std	two hatchback	IWU		152	mp	fi 2.68	3.47	9.0	1		
		2			164 a	ero gas udi gas	std 1	'our sedan	fwd	front 99.8 front 99.4	109	mp	ifi 3.19	3.47	10.0	1 1		
		3 4		1 2 2 	164 a	ero gas udi gas udi gas	std f	our sedan	fwd 4wd 	front 99.8 front 99.4	109	mp mp	ofi 3.19	3.4	10.0 8.0	1 1		
		3 4		1 2	164 a	ero gas udi gas udi gas lvo gas	std f	'our sedan	fwd 4wd rwd	front 99.8	109 136 	mp mp	ifi 3.19	3.4	10.0	1 1 1 1 1		
		2 3 4 200		1 2 2 	164 a 164 a 95 vo 95 vo 95 vo	udi gas udi gas udi gas uvi gas uvi gas	std 1 std 1 std 1 turbo 1	our sedan our sedan our sedan our sedan	fwd 4wd rwd rwd	front 99.8 front 99.4 front 109.1	109 136 141 143 173	mp mp mp mp	ofi 3.19 ofi 3.19 ofi 3.78	3.4 3.4 3.15	10.0 8.0 9.5	1		

Використовуємо методи для оцінки значущості факторів.

```
In [23]:
    num_val = transformed_data.select_dtypes(exclude='object')
    obj_val = transformed_data.select_dtypes(exclude='int64')
    obj_val = transformed_data.select_dtypes(exclude='float64')
              varianceThreshold = VarianceThreshold(threshold=(0.5))
              varianceThreshold.fit(num_val)
              selected_data = varianceThreshold.transform(num_val)
              selected_data
  Out[23]: array([[1.6400e+02, 0.0000e+00, 3.0000e+00, ..., 2.4000e+01, 3.0000e+01,
                       [1.3950e+04],
[1.6400e+02, 0.0000e+00, 3.0000e+00, ..., 1.8000e+01, 2.2000e+01,
                        1.7450e+04],
                       [1.5800e+02, 0.0000e+00, 3.0000e+00, ..., 1.9000e+01, 2.5000e+01,
                        1.7710e+04],
                       [9.5000e+01, 1.7000e+01, 3.0000e+00, ..., 1.8000e+01, 2.3000e+01,
                       2.1485e+04],
[9.5000e+01, 1.7000e+01, 3.0000e+00, ..., 2.6000e+01, 2.7000e+01,
                        2.2470e+04],
                       [9.5000e+01, 1.7000e+01, 3.0000e+00, ..., 1.9000e+01, 2.5000e+01,
                        2.2625e+04]])
In [24]: num_val
Out[24]:
                                                                       99.8
                                                                                        4 3.19 3.40
                                                                                                                     102 55
                         164.0
                                                                                 109
                                                                                                                     115 5!
                         164.0
                                                                       99.4
                                                                                 136
                                                                                        4 3.19
                         158.0
                         158.0
                                                                       105.8
                                                                                        4 3.13
         10
                 0.8
                         192 0
                                                                       1012
                                                                                108
                                                                                        4 3 50 2 80
                                                                                                                     101 58
                                                                       109.1
        202
                0.2
                         95.0 17 1
                                                                    0 109.1
                                                                                173
                                                                                        4 3.58 2.87
                                                                                                           8.8
                                                                                                                     134 55
         203
                          95.0
                                                                       109.1
                                                                                        2 3.01
                                                                                        4 3.78
                         95.0
                                                                       109.1
        159 rows × 26 columns
        4
```

	3	0	1	0	0	3	1	0	2337	2	2	109	4	102	5500	24	30
	4	0	1	0	0	3	0	0	2824	2	1	136	4	115	5500	18	22
	6	0	1	0	0	3	1	0	2844	2	1	136	4	110	5500	19	25
	8	0	1	1	0	3	1	0	3086	2	1	131	4	140	5500	17	20
1	0	1	1	0	1	3	2	0	2395	2	2	108	4	101	5800	23	29
20	0 1	7	1	0	0	3	2	0	2952	2	2	141	4	114	5400	23	28
20	1 1	7	1	1	0	3	2	0	3049	2	2	141	4	160	5300	19	25
20	2 1	7	1	0	0	3	2	0	3012	4	3	173	4	134	5500	18	23
20	3 1	7	0	1	0	3	2	0	3217	2	3	145	2	106	4800	26	27
20	4 1	7	1	1	0	3	2	0	3062	2	2	141	4	114	5400	19	25

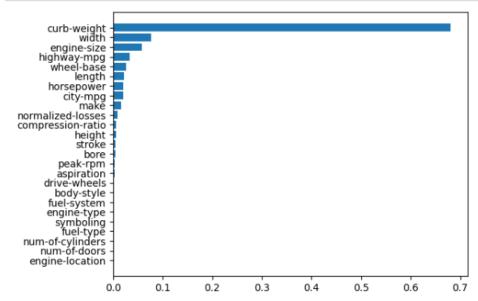
make tuel aspiration type aspiration doors style wheels location weight type cylinders size system horsepower pm mpg mpg

Наступний метод обирає к найвпливовіших факторів:

In [25]: obj_val

In [28]:	kbest trans	mns_array = trai t = sklearn.fea sformed_data_kb cted_features = sformed_data_kb sformed_data_kb	ture_select est = kbest kbest.get_ est = pd.Da	ion.Select .fit_trans _feature_na	:KBest(skle :form(num_v num_v :mes_out(co	al.drop(al["price lumns_arm
Out[28]:		normalized-losses	curb-weight	engine-size	horsepower	peak-rpm
	0	164.0	2337.0	109.0	102.0	5500.0
	1	164.0	2824.0	136.0	115.0	5500.0
	2	158.0	2844.0	136.0	110.0	5500.0
	3	158.0	3086.0	131.0	140.0	5500.0
	4	192.0	2395.0	108.0	101.0	5800.0
	154	95.0	2952.0	141.0	114.0	5400.0
	155	95.0	3049.0	141.0	160.0	5300.0
	156	95.0	3012.0	173.0	134.0	5500.0
	157	95.0	3217.0	145.0	106.0	4800.0
	158	95.0	3062.0	141.0	114.0	5400.0
	159 r	ows × 5 columns				

```
In [33]: feature_importances = tree_classifier.feature_importances_
    indices = np.argsort(feature_importances)
    plt.yticks(range(len(indices)), np.array(num_val.drop(["price"], axis=1).columns)[indices])
    plt.barh(range(len(indices)), feature_importances[indices])
    plt.show()
```



На наступному графіку можна побачити загальну кореляцію метрик, що відображає значення із найбільшою кореляцією:

