

onnx_operator_cost

March 10, 2022

1 Infer operator computation cost

This notebook explores a way to predict the cost of operator Transpose based on some features.

```
[1]: from jyquickhelper import add_notebook_menu
      add_notebook_menu()
```

```
[1]: <IPython.core.display.HTML object>
```

```
[2]: %matplotlib inline
```

```
[3]: %load_ext mlproduct
```

1.1 ONNX graph and measures

```
[4]: import numpy
      from skl2onnx.common.data_types import FloatTensorType
      from skl2onnx.algebra.onnx_ops import OnnxTranspose

      def create_onnx_graph(perm=(0, 1, 2, 3), target_opset=14):
          tr = OnnxTranspose('X', perm=perm, output_names=['Y'], op_version=target_opset)
          return tr.to_onnx({'X': FloatTensorType([None] * len(perm))})

      onx = create_onnx_graph()

      %onnxview onx
```

```
[4]: <jyquickhelper.jspy.render_nb_js_dot.RenderJsDot at 0x258ef832760>
```

```
[5]: from mlproduct.onnxrt import OnnxInference

      onx = create_onnx_graph(perm=(1, 0, 3, 2))
      oinf = OnnxInference(onx)
      inputs = {'X': numpy.full((5, 6, 7, 8), 1, dtype=numpy.float32)}
      res = oinf.run(inputs)['Y']
      res.shape
```

```
[5]: (6, 5, 8, 7)
```

```
[6]: from onnxruntime import InferenceSession
sess = InferenceSession(onx.SerializeToString())
res = sess.run(None, inputs)[0]
res.shape
```

```
[6]: (6, 5, 8, 7)
```

```
[7]: from cpyquickhelper.numbers.speed_measure import measure_time

def measure_time_onnx(sess, X, number=50, repeat=30):
    inputs = {'X': X}
    return measure_time(lambda: sess.run(None, inputs), context=dict(sess=sess,
↪inputs=inputs),
                        div_by_number=True, number=number, repeat=repeat)

X = numpy.random.random((3, 224, 224, 4)).astype(numpy.float32)
measure_time_onnx(sess, X)
```

```
[7]: {'average': 0.00246777386666666646,
      'deviation': 0.00022911153911864325,
      'min_exec': 0.00222923800000000023,
      'max_exec': 0.00326508000000000005,
      'repeat': 30,
      'number': 50,
      'context_size': 232}
```

1.2 Simulation to build a database

1.2.1 Many dimensions, many permutations

```
[8]: from itertools import permutations
from tqdm import tqdm
from pandas import DataFrame

def process_shape(shape, rnd=False, number=50, repeat=30, bar=True):
    X = numpy.random.random(shape).astype(numpy.float32)
    obs = []
    perms = list(permutations(list(range(len(X.shape)))))
    baseline = None
    itergen = perms if (rnd or not bar) else tqdm(perms)
    for perm in itergen:
        if baseline is not None and rnd:
            if random.randint(0, 4) != 0:
                continue
        onx = create_onnx_graph(perm=perm)
        sess = InferenceSession(onx.SerializeToString())
        res = measure_time_onnx(sess, X, number=number, repeat=repeat)
        res['perm'] = perm
        res['shape'] = shape
        if baseline is None:
            baseline = res
        res["ratio"] = res["average"] / baseline["average"]
```

```

        res['dim'] = len(shape)
        obs.append(res)
    return DataFrame(obs).sort_values('average')

dfs = []
df = process_shape((12, 13, 15, 18))
dfs.append(df)
df

```

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```

[8]:
   average  deviation  min_exec  max_exec  repeat  number  context_size  \
3  0.000044  0.000006  0.000039  0.000057      30      50          232
1  0.000048  0.000003  0.000045  0.000058      30      50          232
18 0.000049  0.000003  0.000045  0.000062      30      50          232
9  0.000049  0.000001  0.000048  0.000053      30      50          232
12 0.000051  0.000004  0.000039  0.000062      30      50          232
4  0.000052  0.000005  0.000047  0.000073      30      50          232
8  0.000054  0.000006  0.000044  0.000067      30      50          232
2  0.000054  0.000007  0.000049  0.000081      30      50          232
14 0.000057  0.000006  0.000046  0.000064      30      50          232
0  0.000059  0.000019  0.000034  0.000093      30      50          232
6  0.000092  0.000019  0.000053  0.000139      30      50          232
11 0.000136  0.000020  0.000119  0.000186      30      50          232
13 0.000138  0.000023  0.000121  0.000181      30      50          232
10 0.000138  0.000018  0.000118  0.000176      30      50          232
16 0.000140  0.000015  0.000124  0.000193      30      50          232
15 0.000144  0.000019  0.000119  0.000196      30      50          232
17 0.000145  0.000022  0.000123  0.000199      30      50          232
23 0.000145  0.000017  0.000125  0.000196      30      50          232
20 0.000146  0.000015  0.000128  0.000184      30      50          232
22 0.000150  0.000017  0.000127  0.000170      30      50          232
19 0.000158  0.000021  0.000127  0.000192      30      50          232
21 0.000164  0.000045  0.000124  0.000231      30      50          232
7  0.000214  0.000060  0.000136  0.000295      30      50          232
5  0.000215  0.000071  0.000143  0.000340      30      50          232

```

	perm	shape	ratio	dim
3	(0, 2, 3, 1)	(12, 13, 15, 18)	0.750316	4
1	(0, 1, 3, 2)	(12, 13, 15, 18)	0.820821	4
18	(3, 0, 1, 2)	(12, 13, 15, 18)	0.823070	4
9	(1, 2, 3, 0)	(12, 13, 15, 18)	0.830604	4
12	(2, 0, 1, 3)	(12, 13, 15, 18)	0.861994	4
4	(0, 3, 1, 2)	(12, 13, 15, 18)	0.889753	4
8	(1, 2, 0, 3)	(12, 13, 15, 18)	0.909477	4
2	(0, 2, 1, 3)	(12, 13, 15, 18)	0.922354	4
14	(2, 1, 0, 3)	(12, 13, 15, 18)	0.972198	4
0	(0, 1, 2, 3)	(12, 13, 15, 18)	1.000000	4
6	(1, 0, 2, 3)	(12, 13, 15, 18)	1.557903	4
11	(1, 3, 2, 0)	(12, 13, 15, 18)	2.301556	4
13	(2, 0, 3, 1)	(12, 13, 15, 18)	2.336826	4
10	(1, 3, 0, 2)	(12, 13, 15, 18)	2.346118	4
16	(2, 3, 0, 1)	(12, 13, 15, 18)	2.379168	4

15	(2, 1, 3, 0)	(12, 13, 15, 18)	2.443392	4
17	(2, 3, 1, 0)	(12, 13, 15, 18)	2.455098	4
23	(3, 2, 1, 0)	(12, 13, 15, 18)	2.456431	4
20	(3, 1, 0, 2)	(12, 13, 15, 18)	2.473250	4
22	(3, 2, 0, 1)	(12, 13, 15, 18)	2.539817	4
19	(3, 0, 2, 1)	(12, 13, 15, 18)	2.684876	4
21	(3, 1, 2, 0)	(12, 13, 15, 18)	2.778193	4
7	(1, 0, 3, 2)	(12, 13, 15, 18)	3.627240	4
5	(0, 3, 2, 1)	(12, 13, 15, 18)	3.640132	4

```
[9]: df = process_shape((43, 44, 45))
      dfs.append(df)
      df
```

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```
[9]:
```

	average	deviation	min_exec	max_exec	repeat	number	context_size	\
3	0.000073	0.000009	0.000062	0.000094	30	50	232	
0	0.000074	0.000009	0.000065	0.000109	30	50	232	
1	0.000077	0.000008	0.000069	0.000101	30	50	232	
4	0.000097	0.000004	0.000083	0.000110	30	50	232	
2	0.000113	0.000029	0.000061	0.000141	30	50	232	
5	0.000375	0.000121	0.000292	0.000750	30	50	232	

	perm	shape	ratio	dim
3	(1, 2, 0)	(43, 44, 45)	0.985513	3
0	(0, 1, 2)	(43, 44, 45)	1.000000	3
1	(0, 2, 1)	(43, 44, 45)	1.032759	3
4	(2, 0, 1)	(43, 44, 45)	1.300915	3
2	(1, 0, 2)	(43, 44, 45)	1.515711	3
5	(2, 1, 0)	(43, 44, 45)	5.054301	3

```
[10]: df = process_shape((3, 244, 244))
       dfs.append(df)
       df
```

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```
[10]:
```

	average	deviation	min_exec	max_exec	repeat	number	context_size	\
2	0.000100	0.000009	0.000090	0.000125	30	50	232	
0	0.000105	0.000016	0.000078	0.000138	30	50	232	
1	0.000123	0.000013	0.000108	0.000161	30	50	232	
4	0.000124	0.000017	0.000108	0.000171	30	50	232	
3	0.000151	0.000016	0.000136	0.000197	30	50	232	
5	0.000672	0.000083	0.000626	0.001030	30	50	232	

	perm	shape	ratio	dim
2	(1, 0, 2)	(3, 244, 244)	0.955203	3
0	(0, 1, 2)	(3, 244, 244)	1.000000	3
1	(0, 2, 1)	(3, 244, 244)	1.178827	3
4	(2, 0, 1)	(3, 244, 244)	1.185666	3
3	(1, 2, 0)	(3, 244, 244)	1.438446	3

5 (2, 1, 0) (3, 244, 244) 6.418195 3

```
[11]: df = process_shape((3, 244, 244, 1))
      dfs.append(df)
      df
```

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```
[11]:
```

	average	deviation	min_exec	max_exec	repeat	number	context_size \
4	0.000092	0.000008	0.000078	0.000107	30	50	232
0	0.000107	0.000018	0.000084	0.000157	30	50	232
6	0.000124	0.000068	0.000088	0.000323	30	50	232
12	0.000126	0.000017	0.000107	0.000185	30	50	232
3	0.000130	0.000009	0.000120	0.000163	30	50	232
18	0.000137	0.000047	0.000090	0.000250	30	50	232
1	0.000147	0.000017	0.000106	0.000175	30	50	232
8	0.000185	0.000017	0.000164	0.000246	30	50	232
9	0.000189	0.000044	0.000142	0.000265	30	50	232
2	0.000201	0.000054	0.000121	0.000289	30	50	232
7	0.000522	0.000061	0.000457	0.000733	30	50	232
10	0.000533	0.000157	0.000456	0.001128	30	50	232
13	0.000640	0.000189	0.000477	0.001289	30	50	232
16	0.000660	0.000106	0.000503	0.000860	30	50	232
5	0.000692	0.000136	0.000529	0.001021	30	50	232
19	0.000749	0.000206	0.000508	0.001324	30	50	232
14	0.000754	0.000105	0.000633	0.000994	30	50	232
11	0.000791	0.000264	0.000561	0.001386	30	50	232
15	0.000818	0.000278	0.000625	0.001522	30	50	232
17	0.000893	0.000212	0.000646	0.001477	30	50	232
21	0.000944	0.000293	0.000581	0.001626	30	50	232
20	0.000976	0.000347	0.000584	0.001742	30	50	232
22	0.001011	0.000337	0.000544	0.001810	30	50	232
23	0.001128	0.000322	0.000629	0.001737	30	50	232

	perm	shape	ratio	dim
4	(0, 3, 1, 2)	(3, 244, 244, 1)	0.859903	4
0	(0, 1, 2, 3)	(3, 244, 244, 1)	1.000000	4
6	(1, 0, 2, 3)	(3, 244, 244, 1)	1.162456	4
12	(2, 0, 1, 3)	(3, 244, 244, 1)	1.180996	4
3	(0, 2, 3, 1)	(3, 244, 244, 1)	1.210077	4
18	(3, 0, 1, 2)	(3, 244, 244, 1)	1.276642	4
1	(0, 1, 3, 2)	(3, 244, 244, 1)	1.369978	4
8	(1, 2, 0, 3)	(3, 244, 244, 1)	1.725391	4
9	(1, 2, 3, 0)	(3, 244, 244, 1)	1.766905	4
2	(0, 2, 1, 3)	(3, 244, 244, 1)	1.878802	4
7	(1, 0, 3, 2)	(3, 244, 244, 1)	4.874009	4
10	(1, 3, 0, 2)	(3, 244, 244, 1)	4.973916	4
13	(2, 0, 3, 1)	(3, 244, 244, 1)	5.980796	4
16	(2, 3, 0, 1)	(3, 244, 244, 1)	6.167703	4
5	(0, 3, 2, 1)	(3, 244, 244, 1)	6.460759	4
19	(3, 0, 2, 1)	(3, 244, 244, 1)	6.996362	4
14	(2, 1, 0, 3)	(3, 244, 244, 1)	7.041007	4
11	(1, 3, 2, 0)	(3, 244, 244, 1)	7.389431	4

15	(2, 1, 3, 0)	(3, 244, 244, 1)	7.634646	4
17	(2, 3, 1, 0)	(3, 244, 244, 1)	8.339926	4
21	(3, 1, 2, 0)	(3, 244, 244, 1)	8.814785	4
20	(3, 1, 0, 2)	(3, 244, 244, 1)	9.112243	4
22	(3, 2, 0, 1)	(3, 244, 244, 1)	9.437403	4
23	(3, 2, 1, 0)	(3, 244, 244, 1)	10.530182	4

```
[12]: df = process_shape((1, 244, 244, 3))
      dfs.append(df)
      df
```

```
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```

[12]:	average	deviation	min_exec	max_exec	repeat	number	context_size	\
8	0.000092	0.000014	0.000078	0.000132	30	50	232	
6	0.000098	0.000013	0.000083	0.000142	30	50	232	
9	0.000107	0.000018	0.000075	0.000137	30	50	232	
3	0.000115	0.000015	0.000092	0.000147	30	50	232	
0	0.000122	0.000028	0.000094	0.000201	30	50	232	
1	0.000194	0.000036	0.000160	0.000311	30	50	232	
4	0.000195	0.000019	0.000163	0.000258	30	50	232	
18	0.000235	0.000058	0.000172	0.000345	30	50	232	
2	0.000408	0.000156	0.000229	0.000718	30	50	232	
12	0.000513	0.000215	0.000300	0.001430	30	50	232	
10	0.000558	0.000131	0.000458	0.001023	30	50	232	
7	0.000604	0.000188	0.000471	0.001065	30	50	232	
14	0.000620	0.000142	0.000410	0.001121	30	50	232	
23	0.000679	0.000097	0.000590	0.000928	30	50	232	
22	0.000710	0.000161	0.000620	0.001390	30	50	232	
17	0.000737	0.000240	0.000493	0.001174	30	50	232	
11	0.000824	0.000288	0.000515	0.001879	30	50	232	
21	0.000913	0.000216	0.000613	0.001410	30	50	232	
20	0.000918	0.000328	0.000572	0.002079	30	50	232	
16	0.001057	0.000609	0.000502	0.002702	30	50	232	
5	0.001061	0.000612	0.000539	0.003790	30	50	232	
19	0.001212	0.000417	0.000719	0.002561	30	50	232	
15	0.001311	0.000505	0.000856	0.003377	30	50	232	
13	0.001433	0.000505	0.000721	0.002335	30	50	232	

	perm	shape	ratio	dim
8	(1, 2, 0, 3)	(1, 244, 244, 3)	0.753009	4
6	(1, 0, 2, 3)	(1, 244, 244, 3)	0.802808	4
9	(1, 2, 3, 0)	(1, 244, 244, 3)	0.873932	4
3	(0, 2, 3, 1)	(1, 244, 244, 3)	0.940606	4
0	(0, 1, 2, 3)	(1, 244, 244, 3)	1.000000	4
1	(0, 1, 3, 2)	(1, 244, 244, 3)	1.585479	4
4	(0, 3, 1, 2)	(1, 244, 244, 3)	1.598770	4
18	(3, 0, 1, 2)	(1, 244, 244, 3)	1.923654	4
2	(0, 2, 1, 3)	(1, 244, 244, 3)	3.345406	4
12	(2, 0, 1, 3)	(1, 244, 244, 3)	4.205477	4
10	(1, 3, 0, 2)	(1, 244, 244, 3)	4.572658	4
7	(1, 0, 3, 2)	(1, 244, 244, 3)	4.947937	4
14	(2, 1, 0, 3)	(1, 244, 244, 3)	5.078387	4

23	(3, 2, 1, 0)	(1, 244, 244, 3)	5.561888	4
22	(3, 2, 0, 1)	(1, 244, 244, 3)	5.818089	4
17	(2, 3, 1, 0)	(1, 244, 244, 3)	6.040189	4
11	(1, 3, 2, 0)	(1, 244, 244, 3)	6.752663	4
21	(3, 1, 2, 0)	(1, 244, 244, 3)	7.476378	4
20	(3, 1, 0, 2)	(1, 244, 244, 3)	7.521481	4
16	(2, 3, 0, 1)	(1, 244, 244, 3)	8.657076	4
5	(0, 3, 2, 1)	(1, 244, 244, 3)	8.693870	4
19	(3, 0, 2, 1)	(1, 244, 244, 3)	9.929308	4
15	(2, 1, 3, 0)	(1, 244, 244, 3)	10.739398	4
13	(2, 0, 3, 1)	(1, 244, 244, 3)	11.740772	4

```
[13]: df = process_shape((3, 244, 244, 3), number=15, repeat=15)
      dfs.append(df)
      df
```

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```
[13]:
```

	average	deviation	min_exec	max_exec	repeat	number	context_size	\
0	0.001088	0.000085	0.000986	0.001291	15	15	232	
4	0.001227	0.000088	0.001152	0.001474	15	15	232	
18	0.001277	0.000118	0.001079	0.001490	15	15	232	
6	0.001311	0.000320	0.001007	0.001925	15	15	232	
1	0.001415	0.000307	0.001200	0.002498	15	15	232	
3	0.001426	0.000221	0.001191	0.001863	15	15	232	
9	0.001510	0.000432	0.001132	0.002417	15	15	232	
8	0.001552	0.000030	0.001500	0.001602	15	15	232	
12	0.001724	0.000193	0.001470	0.002142	15	15	232	
2	0.001790	0.000191	0.001566	0.002238	15	15	232	
7	0.002528	0.000154	0.002327	0.002983	15	15	232	
19	0.002571	0.000186	0.002383	0.002922	15	15	232	
21	0.002591	0.000253	0.002431	0.003403	15	15	232	
22	0.002698	0.000412	0.002346	0.003689	15	15	232	
20	0.002806	0.000783	0.002147	0.004296	15	15	232	
16	0.003212	0.000304	0.002773	0.003851	15	15	232	
14	0.003228	0.000796	0.002071	0.004791	15	15	232	
11	0.003257	0.000287	0.002912	0.003739	15	15	232	
17	0.003574	0.000479	0.003028	0.005042	15	15	232	
10	0.003942	0.001860	0.002446	0.008241	15	15	232	
15	0.004249	0.001217	0.003175	0.008041	15	15	232	
5	0.004685	0.001343	0.002827	0.006868	15	15	232	
13	0.005539	0.002180	0.002991	0.009602	15	15	232	
23	0.005575	0.001930	0.002876	0.008157	15	15	232	

	perm	shape	ratio	dim
0	(0, 1, 2, 3)	(3, 244, 244, 3)	1.000000	4
4	(0, 3, 1, 2)	(3, 244, 244, 3)	1.128126	4
18	(3, 0, 1, 2)	(3, 244, 244, 3)	1.173721	4
6	(1, 0, 2, 3)	(3, 244, 244, 3)	1.205182	4
1	(0, 1, 3, 2)	(3, 244, 244, 3)	1.300901	4
3	(0, 2, 3, 1)	(3, 244, 244, 3)	1.311361	4
9	(1, 2, 3, 0)	(3, 244, 244, 3)	1.388068	4
8	(1, 2, 0, 3)	(3, 244, 244, 3)	1.427105	4

12	(2, 0, 1, 3)	(3, 244, 244, 3)	1.585155	4
2	(0, 2, 1, 3)	(3, 244, 244, 3)	1.645717	4
7	(1, 0, 3, 2)	(3, 244, 244, 3)	2.324384	4
19	(3, 0, 2, 1)	(3, 244, 244, 3)	2.363443	4
21	(3, 1, 2, 0)	(3, 244, 244, 3)	2.381860	4
22	(3, 2, 0, 1)	(3, 244, 244, 3)	2.480308	4
20	(3, 1, 0, 2)	(3, 244, 244, 3)	2.579517	4
16	(2, 3, 0, 1)	(3, 244, 244, 3)	2.953032	4
14	(2, 1, 0, 3)	(3, 244, 244, 3)	2.967523	4
11	(1, 3, 2, 0)	(3, 244, 244, 3)	2.994043	4
17	(2, 3, 1, 0)	(3, 244, 244, 3)	3.285842	4
10	(1, 3, 0, 2)	(3, 244, 244, 3)	3.624145	4
15	(2, 1, 3, 0)	(3, 244, 244, 3)	3.906361	4
5	(0, 3, 2, 1)	(3, 244, 244, 3)	4.307072	4
13	(2, 0, 3, 1)	(3, 244, 244, 3)	5.092422	4
23	(3, 2, 1, 0)	(3, 244, 244, 3)	5.125597	4

```
[14]: df = process_shape((3, 244, 244, 6), number=15, repeat=15)
      dfs.append(df)
      df
```

```
100%|_ _ _ _ _ _ _ _ _ _ | 24/24 [00:34<00:00, 1.43s/it]
```

[14]:	average	deviation	min_exec	max_exec	repeat	number	context_size	\
1	0.002249	0.000144	0.002067	0.002627	15	15	232	
3	0.002711	0.000171	0.002458	0.002995	15	15	232	
12	0.002773	0.000683	0.002260	0.004103	15	15	232	
4	0.002953	0.000677	0.002187	0.004132	15	15	232	
2	0.003232	0.000963	0.002303	0.005088	15	15	232	
6	0.003363	0.000372	0.002883	0.004025	15	15	232	
8	0.003397	0.000237	0.002886	0.003846	15	15	232	
9	0.003653	0.000874	0.002567	0.005244	15	15	232	
14	0.003697	0.000186	0.003495	0.004150	15	15	232	
0	0.003705	0.000797	0.002111	0.005164	15	15	232	
18	0.003780	0.000882	0.002701	0.005402	15	15	232	
10	0.004938	0.000367	0.004532	0.005844	15	15	232	
7	0.005918	0.001085	0.004598	0.008312	15	15	232	
13	0.006106	0.000556	0.005619	0.007305	15	15	232	
11	0.006722	0.001807	0.005067	0.011245	15	15	232	
20	0.007071	0.000982	0.005454	0.008559	15	15	232	
21	0.007441	0.001732	0.006199	0.012169	15	15	232	
15	0.007815	0.001757	0.005932	0.010779	15	15	232	
16	0.008546	0.001384	0.005878	0.010614	15	15	232	
5	0.010339	0.002789	0.005878	0.018301	15	15	232	
17	0.010677	0.001457	0.008504	0.014070	15	15	232	
23	0.012421	0.003052	0.007818	0.018106	15	15	232	
22	0.013432	0.004496	0.006536	0.021250	15	15	232	
19	0.014579	0.004026	0.007144	0.020739	15	15	232	
	perm	shape	ratio	dim				
1	(0, 1, 3, 2)	(3, 244, 244, 6)	0.606961	4				
3	(0, 2, 3, 1)	(3, 244, 244, 6)	0.731795	4				
12	(2, 0, 1, 3)	(3, 244, 244, 6)	0.748578	4				

4	(0, 3, 1, 2)	(3, 244, 244, 6)	0.797062	4
2	(0, 2, 1, 3)	(3, 244, 244, 6)	0.872427	4
6	(1, 0, 2, 3)	(3, 244, 244, 6)	0.907834	4
8	(1, 2, 0, 3)	(3, 244, 244, 6)	0.917011	4
9	(1, 2, 3, 0)	(3, 244, 244, 6)	0.986071	4
14	(2, 1, 0, 3)	(3, 244, 244, 6)	0.997901	4
0	(0, 1, 2, 3)	(3, 244, 244, 6)	1.000000	4
18	(3, 0, 1, 2)	(3, 244, 244, 6)	1.020432	4
10	(1, 3, 0, 2)	(3, 244, 244, 6)	1.333061	4
7	(1, 0, 3, 2)	(3, 244, 244, 6)	1.597357	4
13	(2, 0, 3, 1)	(3, 244, 244, 6)	1.648325	4
11	(1, 3, 2, 0)	(3, 244, 244, 6)	1.814552	4
20	(3, 1, 0, 2)	(3, 244, 244, 6)	1.908667	4
21	(3, 1, 2, 0)	(3, 244, 244, 6)	2.008635	4
15	(2, 1, 3, 0)	(3, 244, 244, 6)	2.109489	4
16	(2, 3, 0, 1)	(3, 244, 244, 6)	2.306951	4
5	(0, 3, 2, 1)	(3, 244, 244, 6)	2.790823	4
17	(2, 3, 1, 0)	(3, 244, 244, 6)	2.882191	4
23	(3, 2, 1, 0)	(3, 244, 244, 6)	3.352770	4
22	(3, 2, 0, 1)	(3, 244, 244, 6)	3.625680	4
19	(3, 0, 2, 1)	(3, 244, 244, 6)	3.935483	4

1.2.2 Random cases

```
[15]: import random

if False: # comment out for more training data
    for i in tqdm(range(0, 30)):
        dim = random.randint(3, 5)
        total = 1e8
        while total > 1e6 or total < 0:
            if dim == 3:
                shape = [random.randint(3, 64), random.randint(3, 224), random.
randint(3, 64)]
            elif dim == 4:
                shape = (
                    [random.randint(3, 8)] +
                    [random.randint(16, 224) for d in range(2)] +
                    [random.randint(16, 64)])
            elif dim == 5:
                shape = (
                    [random.randint(3, 8)] +
                    [random.randint(16, 32) for d in range(3)] +
                    [random.randint(16, 64)])
            else:
                raise NotImplementedError()
            ashape = numpy.array(shape, dtype=numpy.float64)
            total = numpy.prod(ashape)

        if total > 1000000:
            number, repeat = 2, 2
        elif total > 800000:
            number, repeat = 3, 3
```

```

elif total > 500000:
    number, repeat = 5, 5
elif total > 200000:
    number, repeat = 7, 7
else:
    number, repeat = 10, 10

df = process_shape(tuple(shape), number=number, repeat=repeat, bar=False)
dfs.append(df)

for i in range(len(shape)):
    shape2 = shape.copy()
    shape2[i] = 1
    df = process_shape(tuple(shape), number=number, repeat=repeat, bar=False)
    dfs.append(df)

len(dfs)

```

[15]: 7

```

[16]: import pandas

data = pandas.concat(dfs, axis=0).reset_index(drop=True)
data.tail()

```

```

[16]:      average  deviation  min_exec  max_exec  repeat  number  context_size \
127  0.010339   0.002789   0.005878  0.018301     15     15         232
128  0.010677   0.001457   0.008504  0.014070     15     15         232
129  0.012421   0.003052   0.007818  0.018106     15     15         232
130  0.013432   0.004496   0.006536  0.021250     15     15         232
131  0.014579   0.004026   0.007144  0.020739     15     15         232

      perm      shape      ratio  dim
127  (0, 3, 2, 1)  (3, 244, 244, 6)  2.790823  4
128  (2, 3, 1, 0)  (3, 244, 244, 6)  2.882191  4
129  (3, 2, 1, 0)  (3, 244, 244, 6)  3.352770  4
130  (3, 2, 0, 1)  (3, 244, 244, 6)  3.625680  4
131  (3, 0, 2, 1)  (3, 244, 244, 6)  3.935483  4

```

```

[17]: data.shape

```

[17]: (132, 11)

```

[18]: data[['dim', 'shape', 'ratio']].groupby(['dim', 'shape']).agg({'ratio': [min, max,
→ numpy.mean, numpy.median]})

```

```

[18]:      ratio
      min      max      mean      median
dim shape
3  (3, 244, 244)  0.955203  6.418195  2.029389  1.182247
   (43, 44, 45)   0.985513  5.054301  1.814867  1.166837
4  (1, 244, 244, 3) 0.753009 11.740772  5.023301  5.013162
   (3, 244, 244, 1) 0.859903 10.530182  4.882680  5.477356
   (3, 244, 244, 3) 1.000000  5.125597  2.481287  2.372651

```

(3, 244, 244, 6)	0.606961	3.935483	1.704169	1.465209
(12, 13, 15, 18)	0.750316	3.640132	1.866691	2.319191

1.3 features

1.3.1 Computing the features

```
[19]: def _edit_distance(mot1, mot2):
    dist = {(-1, -1): 0}
    pred = {(-1, -1): None}
    if len(mot1) == 0:
        for j, d in enumerate(mot2):
            dist[-1, j] = dist[-1, j - 1] + 1
            pred[-1, j] = (-1, j - 1)
            dist[j, -1] = dist[j - 1, -1] + 1
            pred[j, -1] = (j - 1, -1)
    for i, c in enumerate(mot1):
        dist[i, -1] = dist[i - 1, -1] + 1
        pred[i, -1] = (i - 1, -1)
        dist[-1, i] = dist[-1, i - 1] + 1
        pred[-1, i] = (-1, i - 1)
        for j, d in enumerate(mot2):
            opt = []
            if (i - 1, j) in dist:
                x = dist[i - 1, j] + 1
                opt.append((x, (i - 1, j)))
            if (i, j - 1) in dist:
                x = dist[i, j - 1] + 1
                opt.append((x, (i, j - 1)))
            if (i - 1, j - 1) in dist:
                x = dist[i - 1, j - 1] + (1 if c != d else 0)
                opt.append((x, (i - 1, j - 1)))
            mi = min(opt)
            dist[i, j] = mi[0]
            pred[i, j] = mi[1]

    return dist[len(mot1) - 1, len(mot2) - 1]

_edit_distance("abdc", "cbda")
```

[19]: 2

```
[20]: _edit_distance((0, 1, 2, 3), (0, 2, 1, 3))
```

[20]: 2

```
[21]: from math import log

def _is_rotation(perm):
    t = tuple(perm)
    c = list(range(len(perm)))
    for i in range(len(c)):
```

```

        for k in range(len(c)):
            c[k] = (k + i) % len(c)
        if t == tuple(c):
            return True
    return False

def _relu(x, origin=0):
    return origin if x < origin else x

def compute_features(shape, perm):
    total = numpy.prod(numpy.array(shape, dtype=numpy.int64))

    begin = 1
    dbegin = 0
    for i, p in enumerate(perm):
        if p != i:
            break
        dbegin += 1
        begin *= shape[i]

    end = 1
    dend = 0
    for i in range(len(perm)-1, -1, -1):
        if perm[i] != i:
            break
        dend += 1
        end *= shape[i]

    dis_cont = 0
    for i in range(1, len(shape)):
        if perm[i] != perm[i-1] + 1:
            dis_cont += 1

    middle = max(1, int(total / (end * begin)))
    feat = dict(size=total, begin=begin, end=end, middle=middle,
                dim=len(shape), discont=dis_cont)

    for c in [16, 32]:
        feat["end%d" % c] = _relu(end, c)

    keys = list(feat)
    for k in keys:
        if k in {'dim', 'cpu', 'size'}:
            continue
        feat["r%s" % k] = float(feat[k] / total)

    for c in [2, 4, 8, 16, 32, 64]:
        feat["iend%d" % c] = float(end >= c)
        feat["ibegin%d" % c] = float(begin >= c)

    # feat['CST'] = 1

```

```

feat['CST_'] = -1
feat['dbegin'] = - dbegin
feat['dend'] = - dend

keys = list(feats)
for k in keys:
    if k.startswith('end') or k.startswith('begin'):
        feat[k] = - feat[k]
    elif k.startswith('rend') or k.startswith('rbegin'):
        feat[k] = - feat[k]
    elif k.startswith('iend') or k.startswith('ibegin'):
        feat[k] = - feat[k]
    elif k == "rdiscont":
        feat[k] = - feat[k]

idp = list(range(len(perm)))
feat["rot"] = -1 if _is_rotation(perm) else 0
feat["rev"] = 1 if perm == tuple(idp[::-1]) else 0
feat["edit"] = _edit_distance(idp, perm)
feat["redit"] = feat["edit"] / len(idp)
return feat

```

```
compute_features((3, 5, 7), (0, 1, 2))
```

```

[21]: {'size': 105,
      'begin': -105,
      'end': -105,
      'middle': 1,
      'dim': 3,
      'discont': 0,
      'end16': -105,
      'end32': -105,
      'rbegin': -1.0,
      'rend': -1.0,
      'rmiddle': 0.009523809523809525,
      'rdiscont': -0.0,
      'rend16': -1.0,
      'rend32': -1.0,
      'iend2': -1.0,
      'ibegin2': -1.0,
      'iend4': -1.0,
      'ibegin4': -1.0,
      'iend8': -1.0,
      'ibegin8': -1.0,
      'iend16': -1.0,
      'ibegin16': -1.0,
      'iend32': -1.0,
      'ibegin32': -1.0,
      'iend64': -1.0,
      'ibegin64': -1.0,
      'CST_': -1,
      'dbegin': -3,

```

```
'dend': -3,  
'rot': -1,  
'rev': 0,  
'edit': 0,  
'redit': 0.0}
```

```
[22]: compute_features((3, 5, 7), (2, 1, 0))
```

```
[22]: {'size': 105,  
      'begin': -1,  
      'end': -1,  
      'middle': 105,  
      'dim': 3,  
      'discont': 2,  
      'end16': -16,  
      'end32': -32,  
      'rbegin': -0.009523809523809525,  
      'rend': -0.009523809523809525,  
      'rmiddle': 1.0,  
      'rdiscont': -0.01904761904761905,  
      'rend16': -0.1523809523809524,  
      'rend32': -0.3047619047619048,  
      'iend2': -0.0,  
      'ibegin2': -0.0,  
      'iend4': -0.0,  
      'ibegin4': -0.0,  
      'iend8': -0.0,  
      'ibegin8': -0.0,  
      'iend16': -0.0,  
      'ibegin16': -0.0,  
      'iend32': -0.0,  
      'ibegin32': -0.0,  
      'iend64': -0.0,  
      'ibegin64': -0.0,  
      'CST_': -1,  
      'dbegin': 0,  
      'dend': 0,  
      'rot': 0,  
      'rev': 1,  
      'edit': 2,  
      'redit': 0.6666666666666666}
```

```
[23]: compute_features((3, 5, 7), (1, 2, 0))
```

```
[23]: {'size': 105,  
      'begin': -1,  
      'end': -1,  
      'middle': 105,  
      'dim': 3,  
      'discont': 1,  
      'end16': -16,  
      'end32': -32,  
      'rbegin': -0.009523809523809525,  
      'rend': -0.009523809523809525,
```

```
rmiddle': 1.0,  
'rdiscont': -0.009523809523809525,  
'rend16': -0.1523809523809524,  
'rend32': -0.3047619047619048,  
'iend2': -0.0,  
'ibegin2': -0.0,  
'iend4': -0.0,  
'ibegin4': -0.0,  
'iend8': -0.0,  
'ibegin8': -0.0,  
'iend16': -0.0,  
'ibegin16': -0.0,  
'iend32': -0.0,  
'ibegin32': -0.0,  
'iend64': -0.0,  
'ibegin64': -0.0,  
'CST_': -1,  
'dbegin': 0,  
'dend': 0,  
'rot': -1,  
'rev': 0,  
'edit': 2,  
'redit': 0.6666666666666666}
```

1.3.2 Computing the features for all simulations

```
[24]: def compute_features_dataframe(df):

    def merge(row):
        feat = compute_features(row['shape'], row['perm'])
        feat['yt'] = row['average']
        feat['yr'] = row['ratio']
        return feat

    rows = []
    for i in tqdm(range(df.shape[0])):
        rows.append(dict(shape=df.loc[i, "shape"], perm=df.loc[i, "perm"],
                        average=df.loc[i, "average"], ratio=df.loc[i, "ratio"]))

    obs = []
    for row in tqdm(rows):
        obs.append(merge(row))
    return DataFrame(obs)

fdata = compute_features_dataframe(data)
col_sort = list(sorted(fdata.columns))
fdata = fdata[col_sort]
fdata.tail()
```

```
100%|_ _ _ _ _ _ _ _ _ _ | 132/132 [00:00<00:00, 9459.22it/s]
100%|_ _ _ _ _ _ _ _ _ _ | 132/132 [00:00<00:00, 3601.95it/s]
```

```
[24]:
```

	CST_	begin	dbegin	dend	dim	discont	edit	end	end16	end32	...	\
127	-1	-3	-1	0	4	3	2	-1	-16	-32	...	
128	-1	-1	0	0	4	2	4	-1	-16	-32	...	
129	-1	-1	0	0	4	3	4	-1	-16	-32	...	
130	-1	-1	0	0	4	2	4	-1	-16	-32	...	
131	-1	-1	0	0	4	3	3	-1	-16	-32	...	

	redit	rend	rend16	rend32	rev	rmiddle	rot	size	\
127	0.50	-9.331422e-07	-0.000015	-0.00003	0	0.333333	0	1071648	
128	1.00	-9.331422e-07	-0.000015	-0.00003	0	1.000000	0	1071648	
129	1.00	-9.331422e-07	-0.000015	-0.00003	1	1.000000	0	1071648	
130	1.00	-9.331422e-07	-0.000015	-0.00003	0	1.000000	0	1071648	
131	0.75	-9.331422e-07	-0.000015	-0.00003	0	1.000000	0	1071648	

	yr	yt
127	2.790823	0.010339
128	2.882191	0.010677
129	3.352770	0.012421
130	3.625680	0.013432
131	3.935483	0.014579

[5 rows x 35 columns]

1.3.3 correlations

```
[25]: fdata.corr()
```

```
[25]:
```

	CST_	begin	dbegin	dend	dim	discont	edit	\
CST_	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
begin	NaN	1.000000	0.596816	0.596414	0.014118	0.404952	0.405175	
dbegin	NaN	0.596816	1.000000	0.676899	0.077162	0.486887	0.669598	
dend	NaN	0.596414	0.676899	1.000000	0.077162	0.486887	0.669598	
dim	NaN	0.014118	0.077162	0.077162	1.000000	0.305320	0.272614	
discont	NaN	0.404952	0.486887	0.486887	0.305320	1.000000	0.531254	
edit	NaN	0.405175	0.669598	0.669598	0.272614	0.531254	1.000000	
end	NaN	0.999998	0.596384	0.596936	0.014153	0.404971	0.405223	
end16	NaN	0.999998	0.596374	0.596907	0.014145	0.404961	0.405204	
end32	NaN	0.999998	0.596363	0.596881	0.014135	0.404948	0.405189	
ibegin16	NaN	0.488586	0.854056	0.553792	0.160800	0.476225	0.528132	
ibegin2	NaN	0.297779	0.792225	0.326418	0.080033	0.230393	0.539082	
ibegin32	NaN	0.488586	0.854056	0.553792	0.160800	0.476225	0.528132	
ibegin4	NaN	0.420023	0.814178	0.474232	0.114432	0.388689	0.517951	
ibegin64	NaN	0.510659	0.869357	0.586430	0.083333	0.488512	0.533376	
ibegin8	NaN	0.420023	0.814178	0.474232	0.114432	0.388689	0.517951	
iend16	NaN	0.405858	0.452474	0.807989	0.181503	0.383654	0.517311	
iend2	NaN	0.297323	0.326418	0.792225	0.080033	0.230393	0.539082	
iend32	NaN	0.468224	0.524298	0.841277	0.233408	0.465593	0.524167	
iend4	NaN	0.360597	0.400119	0.792963	0.141421	0.321878	0.519634	
iend64	NaN	0.487959	0.553792	0.854056	0.160800	0.476225	0.528132	
iend8	NaN	0.405858	0.452474	0.807989	0.181503	0.383654	0.517311	
middle	NaN	0.126896	0.303868	0.319057	0.178317	0.152095	0.377874	
rbegin	NaN	0.681576	0.832794	0.831933	0.160296	0.594171	0.594568	
rdiscont	NaN	-0.132163	-0.158903	-0.158903	-0.077379	-0.320270	-0.168278	

redit	NaN	0.418022	0.690333	0.690333	0.115902	0.504206	0.984655
rend	NaN	0.681573	0.831887	0.833059	0.160407	0.594219	0.594688
rend16	NaN	0.681573	0.831895	0.832975	0.160417	0.594226	0.594639
rend32	NaN	0.681573	0.831903	0.832924	0.160414	0.594223	0.594619
rev	NaN	0.038216	0.111636	0.111636	-0.160357	0.150144	0.208568
rmiddle	NaN	0.256349	0.605990	0.623582	0.106693	0.225854	0.652532
rot	NaN	0.325594	0.298090	0.298090	0.240946	0.823937	0.338994
size	NaN	-0.133581	0.016411	0.016411	0.212685	0.064937	0.057981
yr	NaN	0.127658	0.291318	0.305489	0.138961	0.388140	0.464225
yt	NaN	-0.008816	0.139951	0.155098	0.192305	0.203342	0.283262

	end	end16	end32	...	redit	rend	rend16	\
CST_	NaN	NaN	NaN	...	NaN	NaN	NaN	
begin	0.999998	0.999998	0.999998	...	0.418022	0.681573	0.681573	
dbegin	0.596384	0.596374	0.596363	...	0.690333	0.831887	0.831895	
dend	0.596936	0.596907	0.596881	...	0.690333	0.833059	0.832975	
dim	0.014153	0.014145	0.014135	...	0.115902	0.160407	0.160417	
discont	0.404971	0.404961	0.404948	...	0.504206	0.594219	0.594226	
edit	0.405223	0.405204	0.405189	...	0.984655	0.594688	0.594639	
end	1.000000	1.000000	1.000000	...	0.418062	0.681565	0.681565	
end16	1.000000	1.000000	1.000000	...	0.418044	0.681550	0.681550	
end32	1.000000	1.000000	1.000000	...	0.418029	0.681533	0.681533	
ibegin16	0.487938	0.487930	0.487919	...	0.533981	0.715870	0.715889	
ibegin2	0.297285	0.297281	0.297277	...	0.548605	0.436111	0.436126	
ibegin32	0.487938	0.487930	0.487919	...	0.533981	0.715870	0.715889	
ibegin4	0.419433	0.419424	0.419415	...	0.528284	0.615385	0.615471	
ibegin64	0.509999	0.509990	0.509979	...	0.555529	0.748243	0.748253	
ibegin8	0.419433	0.419424	0.419415	...	0.528284	0.615385	0.615471	
iend16	0.406614	0.406575	0.406542	...	0.513917	0.597165	0.597061	
iend2	0.297930	0.297895	0.297872	...	0.548605	0.437541	0.437398	
iend32	0.469061	0.469029	0.468993	...	0.514805	0.688714	0.688640	
iend4	0.361290	0.361251	0.361222	...	0.521120	0.530594	0.530467	
iend64	0.488816	0.488786	0.488752	...	0.533981	0.717677	0.717612	
iend8	0.406614	0.406575	0.406542	...	0.513917	0.597165	0.597061	
middle	0.126960	0.126947	0.126937	...	0.355980	0.186472	0.186669	
rbegin	0.681564	0.681549	0.681532	...	0.613417	0.999992	0.999993	
rdiscont	-0.132191	-0.132195	-0.132192	...	-0.163660	-0.193464	-0.193106	
redit	0.418062	0.418044	0.418029	...	1.000000	0.613517	0.613466	
rend	0.681565	0.681550	0.681533	...	0.613517	1.000000	1.000000	
rend16	0.681565	0.681550	0.681533	...	0.613466	1.000000	1.000000	
rend32	0.681565	0.681550	0.681533	...	0.613446	0.999999	1.000000	
rev	0.038236	0.038231	0.038228	...	0.244134	0.056153	0.056129	
rmiddle	0.256479	0.256451	0.256430	...	0.655658	0.376658	0.376574	
rot	0.325559	0.325557	0.325552	...	0.317106	0.477579	0.477613	
size	-0.133665	-0.133671	-0.133677	...	0.024651	0.034412	0.034679	
yr	0.127730	0.127716	0.127707	...	0.450928	0.187551	0.187559	
yt	-0.008844	-0.008852	-0.008859	...	0.256097	0.095557	0.095755	

	rend32	rev	rmiddle	rot	size	yr	yt
CST_	NaN	NaN	NaN	NaN	NaN	NaN	NaN
begin	0.681573	0.038216	0.256349	0.325594	-0.133581	0.127658	-0.008816
dbegin	0.831903	0.111636	0.605990	0.298090	0.016411	0.291318	0.139951
dend	0.832924	0.111636	0.623582	0.298090	0.016411	0.305489	0.155098

dim	0.160414	-0.160357	0.106693	0.240946	0.212685	0.138961	0.192305
discont	0.594223	0.150144	0.225854	0.823937	0.064937	0.388140	0.203342
edit	0.594619	0.208568	0.652532	0.338994	0.057981	0.464225	0.283262
end	0.681565	0.038236	0.256479	0.325559	-0.133665	0.127730	-0.008844
end16	0.681550	0.038231	0.256451	0.325557	-0.133671	0.127716	-0.008852
end32	0.681533	0.038228	0.256430	0.325552	-0.133677	0.127707	-0.008859
ibegin16	0.715901	0.078215	0.522399	0.283800	0.037462	0.254352	0.136416
ibegin2	0.436148	0.128338	0.685605	0.049586	-0.027198	0.324851	0.109929
ibegin32	0.715901	0.078215	0.522399	0.283800	0.037462	0.254352	0.136416
ibegin4	0.615584	0.090985	0.594774	0.207651	0.116460	0.278810	0.179014
ibegin64	0.748257	0.074833	0.501069	0.307207	0.017724	0.243128	0.124459
ibegin8	0.615584	0.090985	0.594774	0.207651	0.116460	0.278810	0.179014
iend16	0.597069	0.094032	0.619928	0.191751	0.125689	0.307633	0.182267
iend2	0.437338	0.128338	0.724562	0.049586	-0.027198	0.337071	0.146321
iend32	0.688553	0.081511	0.544599	0.262448	0.049643	0.261930	0.139099
iend4	0.530439	0.105830	0.673384	0.136300	-0.039355	0.351151	0.127468
iend64	0.717534	0.078215	0.523746	0.283800	0.030938	0.255567	0.127728
iend8	0.597069	0.094032	0.619928	0.191751	0.125689	0.307633	0.182267
middle	0.186918	0.052991	0.467981	0.000903	0.728990	-0.008120	0.821357
rbegin	0.999993	0.056108	0.376357	0.477649	0.034328	0.187411	0.095471
rdiscont	-0.192632	-0.054527	-0.001602	-0.265672	0.551880	0.004517	0.386893
redit	0.613446	0.244134	0.655658	0.317106	0.024651	0.450928	0.256097
rend	0.999999	0.056153	0.376658	0.477579	0.034412	0.187551	0.095557
rend16	1.000000	0.056129	0.376574	0.477613	0.034679	0.187559	0.095755
rend32	1.000000	0.056116	0.376557	0.477630	0.035005	0.187607	0.095996
rev	0.056116	1.000000	0.180470	0.117200	-0.034106	0.218387	0.094260
rmiddle	0.376557	0.180470	1.000000	-0.064351	-0.013771	0.468925	0.195497
rot	0.477630	0.117200	-0.064351	1.000000	0.051246	0.243294	0.126195
size	0.035005	-0.034106	-0.013771	0.051246	1.000000	-0.236289	0.805926
yr	0.187607	0.218387	0.468925	0.243294	-0.236289	1.000000	-0.013907
yt	0.095996	0.094260	0.195497	0.126195	0.805926	-0.013907	1.000000

[35 rows x 35 columns]

```
[26]: fdata.corr()['yt']
```

```
[26]: CST_      NaN
begin      -0.008816
dbegin      0.139951
dend        0.155098
dim          0.192305
discont      0.203342
edit         0.283262
end         -0.008844
end16       -0.008852
end32       -0.008859
ibegin16     0.136416
ibegin2      0.109929
ibegin32     0.136416
ibegin4      0.179014
ibegin64     0.124459
ibegin8      0.179014
iend16       0.182267
```

```

iend2      0.146321
iend32     0.139099
iend4      0.127468
iend64     0.127728
iend8      0.182267
middle     0.821357
rbegin     0.095471
rdiscont   0.386893
redit      0.256097
rend       0.095557
rend16     0.095755
rend32     0.095996
rev        0.094260
rmiddle    0.195497
rot        0.126195
size       0.805926
yr         -0.013907
yt         1.000000
Name: yt, dtype: float64

```

We check the sign of the correlations of all features with *yt*. If it is positive, increasing the feature increases the processing time. We try to get only positive correlations. *end* is the flattened last dimensions left unchanged by the permutation. The bigger it is, the faster the transposition is. That's why the function computing all features multiplies this number by -1 to get a feature positively correlated to the processing time. *end16* is equal to *end* when $\text{end} < -16$ and -16 when $\text{end} \geq -16$. This is a simplification of the cost of moving data from memory to cache L1. This cost is linear when the data to move is big enough, but almost constant for small chunks.

1.4 Linear regression

We choose a linear regression because the prediction are not limited. The training set does not include all configuration and surely does not include all possible high value the model may have to predict.

The goal is not necessarily to predict the fastest permutation but to predict the processing time as the goal is to find the best combination of transpositions in a ONNX graph (einsum). The final goal is to predict which graphs optimizes a series of transpositions.

The target could be the processing time or the logarithm of this time. However, making mistakes on small times is not an issue but errors on high processing time is not a good thing.

We could also try to predict a ratio *transposition time / copy time* but it still gives more important to small matrix size.

Many variables are correlated. Variables should be selected.

1.4.1 Dataset

```
[27]: X = fdata.drop(["yt", "yr"], axis=1)
      x_names = list(X.columns)
      yt = fdata['yt'] * 1000
```

```
[28]: numpy.mean(yt)
```

```
[28]: 1.8809171132996723
```

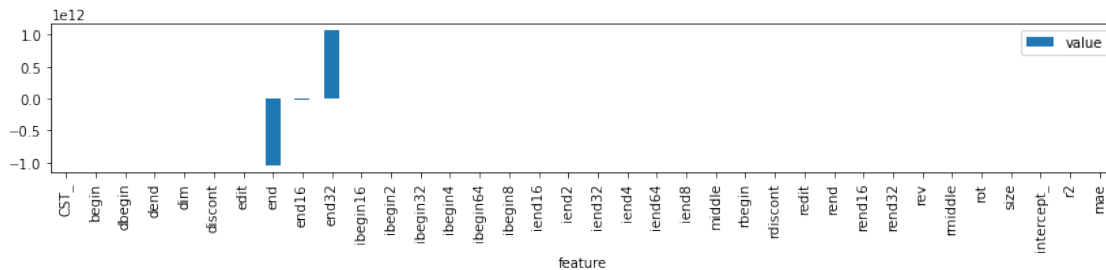
1.4.2 Simple model

```
[29]: from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline
from sklearn.metrics import r2_score, mean_absolute_error

pipe = make_pipeline(StandardScaler(with_mean=False),
    LinearRegression(fit_intercept=False))
pipe.fit(X, yt)
model = pipe.steps[1][1]
coef = {k: v for k, v in zip(X.columns, model.coef_)}
coef['name'] = 'reg'
coef['intercept_'] = model.intercept_
pred = numpy.maximum(pipe.predict(X), 0)
coef['r2'] = r2_score(yt, pred)
coef['mae'] = mean_absolute_error(yt, pred)
coef['model'] = pipe
coefs = [coef]
coef["r2"], coef['mae']
```

```
[29]: (0.8157414076410756, 0.6368865305095469)
```

```
[30]: df = DataFrame([(k, v) for k, v in coef.items() if k not in {'name', 'model'}],
                    columns=["feature", "value"]).set_index("feature")
df.plot(kind="bar", figsize=(14, 2));
```



```
[31]: df
```

```
[31]:          value
feature
CST_      -3.076618e+08
begin     -2.941725e+01
dbegin    -1.854147e-01
dend      -9.638954e-02
dim        -1.037599e-01
discont    5.204404e-01
edit       3.582481e-01
end       -1.046584e+12
end16     -2.278042e+10
end32      1.069321e+12
ibegin16  -3.713466e+00
```

```

ibegin2      1.439716e-02
ibegin32     3.784367e+00
ibegin4     -6.813416e+00
ibegin64    -7.576102e-02
ibegin8      6.927856e+00
iend16      2.028144e+07
iend2       8.225773e+06
iend32      4.322857e+07
iend4       1.097274e+07
iend64      1.996315e-01
iend8       2.028143e+07
middle      1.541218e+00
rbegin      4.940619e+01
rdiscont    7.614642e-01
redit       8.622710e-02
rend       6.615750e+02
rend16     3.459172e+02
rend32    -1.057057e+03
rev        1.537206e-01
rmiddle    -4.563712e-01
rot        7.771901e-02
size       1.295707e+00
intercept_  0.000000e+00
r2         8.157414e-01
mae        6.368865e-01

```

Coefficients associated to features *end*, *end16* are almost opposed and it would better to get a model which keeps only one.

1.4.3 Quantile Regression

```

[32]: from mlinsights.mlmodel import QuantileLinearRegression
pipe = make_pipeline(StandardScaler(with_mean=False),
    QuantileLinearRegression(fit_intercept=False))
pipe.fit(X, yt)
model = pipe.steps[1][1]
coef = {k: v for k, v in zip(X.columns, model.coef_)}
coef['name'] = 'med'
coef['intercept_'] = model.intercept_
pred = numpy.maximum(pipe.predict(X), 0)
coef['r2'] = r2_score(yt, pred)
coef['mae'] = mean_absolute_error(yt, pred)
coef['model'] = pipe
coefs.append(coef)
coef["r2"], coef['mae']

```

```

[32]: (0.7924498414927943, 0.5679387557069854)

```

```

[33]: DataFrame(coef.items(), columns=["feature", "value"]).set_index("feature")

```

```

[33]:
feature
CST_      1433409.249051
begin      27.13405

```

dbegin	0.07931
dend	0.087576
dim	0.006919
discont	0.413378
edit	0.186032
end	4876069525.422424
end16	106134745.367844
end32	-4982003112.711292
ibegin16	0.129918
ibegin2	-0.069604
ibegin32	-0.221099
ibegin4	-0.045585
ibegin64	-0.1085
ibegin8	0.073031
iend16	-94492.918693
iend2	-38324.37475
iend32	-201401.795017
iend4	-51122.392443
iend64	0.15928
iend8	-94492.881923
middle	1.588707
rbegin	36.958438
rdiscont	0.375421
redit	0.071189
rend	4424.263222
rend16	-7664.018684
rend32	3202.681647
rev	0.08288
rmiddle	-0.207068
rot	-0.095643
size	0.938597
name	med
intercept_	0
r2	0.79245
mae	0.567939
model	(StandardScaler(with_mean=False), QuantileLine...

1.4.4 Lasso

To select features.

```
[34]: from sklearn.linear_model import Lasso

scores = []
models = []
for a in tqdm([0.001, 0.01, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1., 2.]):
    alpha = a * 1.
    pipe = make_pipeline(
        StandardScaler(with_mean=False),
        Lasso(alpha=alpha, fit_intercept=False, max_iter=5000))
    pipe.fit(X, yt)
    pred = numpy.maximum(pipe.predict(X), 0)
    model = pipe.steps[1][1]
    scores.append(dict(r2=r2_score(yt, pred), mae=mean_absolute_error(yt, pred),
```

```

        alpha=alpha, null=(numpy.abs(model.coef_) < 1e-6).sum(),
        n=len(model.coef_)))
models.append(pipe)
if alpha >= 0.01 and alpha <= 0.2:
    coef = {k: v for k, v in zip(X.columns, pipe.steps[1][1].coef_)}
    coef['name'] = "Lasso-%f" % alpha
    coef['model'] = pipe
    coef['r2'] = r2_score(yt, pred)
    coef['mae'] = mean_absolute_error(yt, pred)
    coefs.append(coef)

DataFrame(scores)

```

100%|██████████| 13/13 [00:00<00:00, 69.97it/s]

```

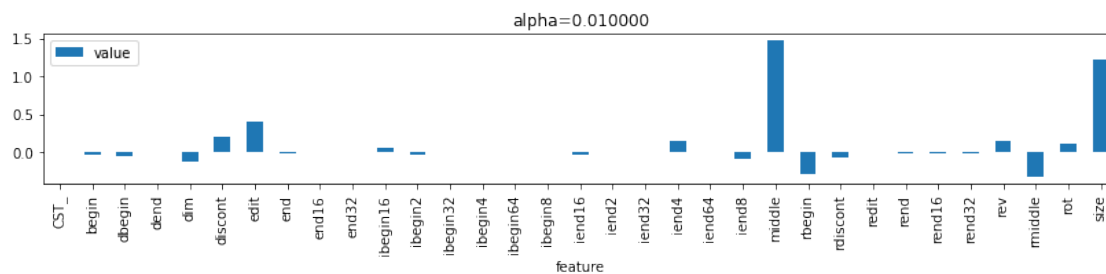
[34]:
      r2      mae  alpha  null   n
0  0.809704  0.629480  0.001     4  33
1  0.807546  0.629886  0.010    10  33
2  0.782541  0.676499  0.100    23  33
3  0.766911  0.680344  0.200    28  33
4  0.751546  0.703684  0.300    29  33
5  0.738223  0.742962  0.400    30  33
6  0.730937  0.735958  0.500    31  33
7  0.718437  0.758143  0.600    30  33
8  0.701329  0.800503  0.700    30  33
9  0.681590  0.848549  0.800    30  33
10 0.659218  0.898770  0.900    30  33
11 0.634218  0.949493  1.000    30  33
12 0.239413  1.600542  2.000    30  33

```

```

[35]: coef = {k: v for k, v in zip(X.columns, models[1].steps[1][1].coef_)}
df = DataFrame(coef.items(), columns=["feature", "value"]).set_index("feature")
df.plot(kind="bar", figsize=(14, 2), title="alpha=%f" % scores[1]["alpha"]);

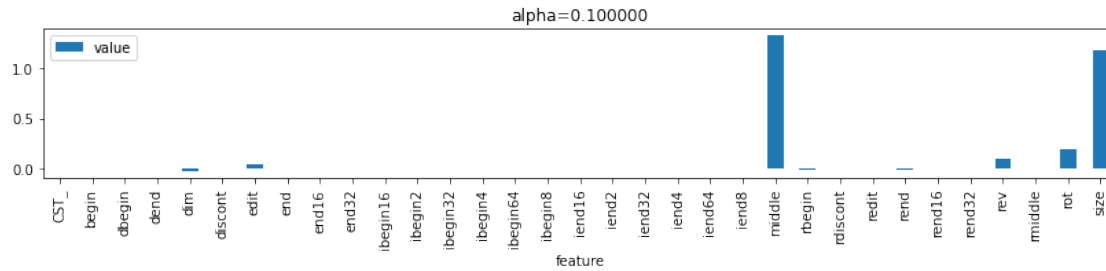
```



```

[36]: coef = {k: v for k, v in zip(X.columns, models[2].steps[1][1].coef_)}
df = DataFrame(coef.items(), columns=["feature", "value"]).set_index("feature")
df.plot(kind="bar", figsize=(14, 2), title="alpha=%f" % scores[2]["alpha"]);

```

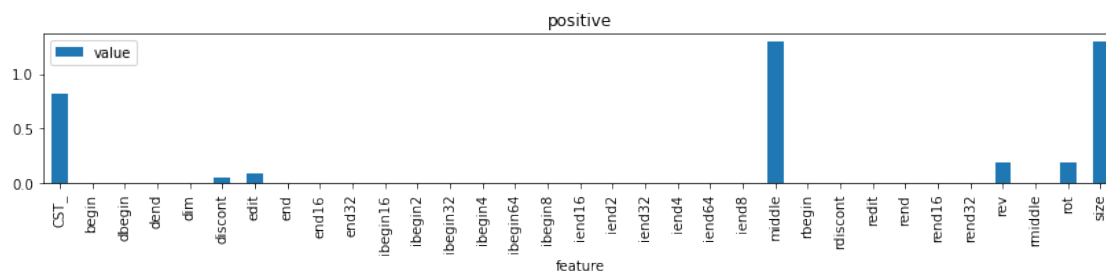


1.4.5 Linear regression with positive weights

```
[37]: pipe = make_pipeline(StandardScaler(with_mean=False), LinearRegression(positive=True,
    fit_intercept=False))
pipe.fit(X, yt)
model = pipe.steps[1][1]
coef = {k: v for k, v in zip(X.columns, model.coef_)}
coef['name'] = 'pos'
coef['intercept_'] = model.intercept_
pred = numpy.maximum(pipe.predict(X), 0)
coef['r2'] = r2_score(yt, pred)
coef['mae'] = mean_absolute_error(yt, pred)
coef['model'] = pipe
coefs.append(coef)
coef["r2"], coef['mae']
```

[37]: (0.7905447080626958, 0.6768663007518693)

```
[38]: coef = {k: v for k, v in zip(X.columns, pipe.steps[1][1].coef_)}
df = DataFrame(coef.items(), columns=["feature", "value"]).set_index("feature")
df.plot(kind="bar", figsize=(14, 2), title="positive");
```



1.4.6 Quantile regression with positive weights

```
[39]: pipe = make_pipeline(StandardScaler(with_mean=False),
    QuantileLinearRegression(positive=True, fit_intercept=False))
pipe.fit(X, yt)
model = pipe.steps[1][1]
```



```

coef = {k: v for k, v in zip(X.columns, model.coef_)}
coef['name'] = 'medpos'
coef['intercept_'] = model.intercept_
pred = numpy.maximum(pipe.predict(X), 0)
coef['r2'] = r2_score(yt, pred)
coef['mae'] = mean_absolute_error(yt, pred)
coef['model'] = pipe
coefs.append(coef)
coef["r2"], coef['mae']

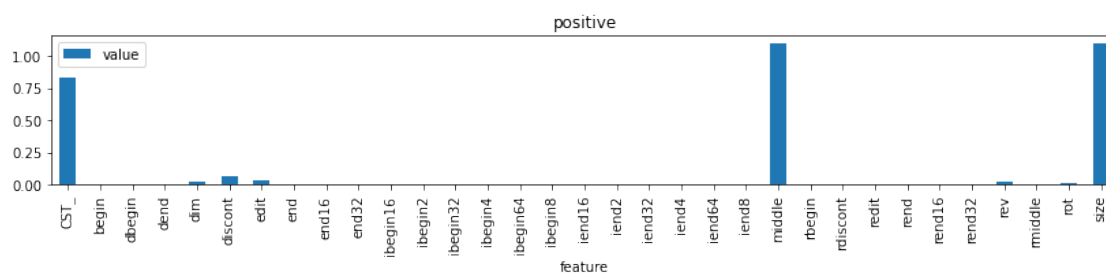
```

[39]: (0.752689515971656, 0.6468340444504788)

```

[40]: coef = {k: v for k, v in zip(X.columns, pipe.steps[1][1].coef_)}
df = DataFrame(coef.items(), columns=["feature", "value"]).set_index("feature")
df.plot(kind="bar", figsize=(14, 2), title="positive");

```



1.4.7 Summary

```

[41]: dfcoef = DataFrame(coefs)
dfcoef[:::-1].T

```

```

[41]:
CST_          0.829482
begin          0.0
dbegin         0.0
dend           0.0
dim            0.023846
discont        0.060636
edit           0.03823
end            0.0
end16          0.0
end32          0.0
ibegin16       0.0
ibegin2        0.0
ibegin32       0.0
ibegin4        0.0
ibegin64       0.0
ibegin8        0.0
iend16         0.0
iend2          0.0
iend32        0.0

```

iend4	0.0
iend64	0.0
iend8	0.0
middle	1.101543
rbegin	0.0
rdiscont	0.0
redit	0.0
rend	0.0
rend16	0.0
rend32	0.0
rev	0.026757
rmiddle	0.0
rot	0.009222
size	1.100532
name	medpos
intercept_	0.0
r2	0.75269
mae	0.646834
model	(StandardScaler(with_mean=False), QuantileLine...

	5 \
CST_	0.821048
begin	0.0
dbegin	0.0
dend	0.0
dim	0.0
discont	0.056297
edit	0.094856
end	0.0
end16	0.0
end32	0.0
ibegin16	0.0
ibegin2	0.0
ibegin32	0.0
ibegin4	0.0
ibegin64	0.0
ibegin8	0.0
iend16	0.0
iend2	0.0
iend32	0.0
iend4	0.0
iend64	0.0
iend8	0.0
middle	1.30347
rbegin	0.0
rdiscont	0.0
redit	0.0
rend	0.0
rend16	0.0
rend32	0.0
rev	0.189909
rmiddle	0.0
rot	0.185687

size	1.300222
name	pos
intercept_	0.0
r2	0.790545
mae	0.676866
model	(StandardScaler(with_mean=False), LinearRegres...

	4 \
CST_	0.0
begin	-0.0
dbegin	-0.0
dend	-0.0
dim	-0.014763
discont	0.0
edit	0.0
end	-0.0
end16	-0.0
end32	-0.0
ibegin16	-0.0
ibegin2	-0.0
ibegin32	-0.0
ibegin4	-0.0
ibegin64	-0.0
ibegin8	-0.0
iend16	-0.0
iend2	0.0
iend32	-0.0
iend4	-0.0
iend64	-0.0
iend8	-0.0
middle	1.290699
rbegin	-0.0
rdiscont	0.0
redit	0.0
rend	-0.0
rend16	-0.0
rend32	-0.0
rev	0.013992
rmiddle	-0.0
rot	0.108468
size	1.099463
name	Lasso-0.200000
intercept_	NaN
r2	0.766911
mae	0.680344
model	(StandardScaler(with_mean=False), Lasso(alpha=...

	3 \
CST_	0.0
begin	-0.0
dbegin	-0.0
dend	-0.0
dim	-0.030446

discont	0.0
edit	0.0418
end	-0.0
end16	-0.0
end32	-0.0
ibegin16	-0.0
ibegin2	-0.0
ibegin32	-0.0
ibegin4	-0.0
ibegin64	-0.0
ibegin8	-0.0
iend16	-0.0
iend2	-0.0
iend32	-0.0
iend4	-0.0
iend64	-0.0
iend8	-0.0
middle	1.325916
rbegin	-0.020369
rdiscont	-0.0
redit	0.0
rend	-0.007655
rend16	-0.003393
rend32	-0.005349
rev	0.097585
rmiddle	-0.0
rot	0.197021
size	1.183553
name	Lasso-0.100000
intercept_	NaN
r2	0.782541
mae	0.676499
model	(StandardScaler(with_mean=False), Lasso(alpha=...

	2 \
CST_	0.0
begin	-0.03443
dbegin	-0.044705
dend	-0.0
dim	-0.120949
discont	0.210421
edit	0.396052
end	-0.007053
end16	-0.000036
end32	-0.00004
ibegin16	0.066669
ibegin2	-0.02181
ibegin32	0.0
ibegin4	0.0
ibegin64	0.0
ibegin8	0.0
iend16	-0.022416
iend2	0.0

iend32	-0.0
iend4	0.151081
iend64	-0.0
iend8	-0.08907
middle	1.466733
rbegin	-0.28295
rdiscont	-0.066385
redit	0.0
rend	-0.007593
rend16	-0.010514
rend32	-0.013172
rev	0.142791
rmiddle	-0.324716
rot	0.108146
size	1.22329
name	Lasso-0.010000
intercept_	NaN
r2	0.807546
mae	0.629886
model	(StandardScaler(with_mean=False), Lasso(alpha=...

	1 \
CST_	1433409.249051
begin	27.13405
dbegin	0.07931
dend	0.087576
dim	0.006919
discont	0.413378
edit	0.186032
end	4876069525.422424
end16	106134745.367844
end32	-4982003112.711292
ibegin16	0.129918
ibegin2	-0.069604
ibegin32	-0.221099
ibegin4	-0.045585
ibegin64	-0.1085
ibegin8	0.073031
iend16	-94492.918693
iend2	-38324.37475
iend32	-201401.795017
iend4	-51122.392443
iend64	0.15928
iend8	-94492.881923
middle	1.588707
rbegin	36.958438
rdiscont	0.375421
redit	0.071189
rend	4424.263222
rend16	-7664.018684
rend32	3202.681647
rev	0.08288
rmiddle	-0.207068

rot	-0.095643
size	0.938597
name	med
intercept_	0.0
r2	0.79245
mae	0.567939
model	(StandardScaler(with_mean=False), QuantileLine...
	0
CST_	-307661768.128088
begin	-29.417247
dbegin	-0.185415
dend	-0.09639
dim	-0.10376
discont	0.52044
edit	0.358248
end	-1046583604803.358887
end16	-22780416305.902706
end32	1069320839370.567505
ibegin16	-3.713466
ibegin2	0.014397
ibegin32	3.784367
ibegin4	-6.813416
ibegin64	-0.075761
ibegin8	6.927856
iend16	20281439.108194
iend2	8225773.255917
iend32	43228573.054944
iend4	10972737.091606
iend64	0.199631
iend8	20281426.580972
middle	1.541218
rbegin	49.406192
rdiscont	0.761464
redit	0.086227
rend	661.575013
rend16	345.917179
rend32	-1057.05651
rev	0.153721
rmiddle	-0.456371
rot	0.077719
size	1.295707
name	reg
intercept_	0.0
r2	0.815741
mae	0.636887
model	(StandardScaler(with_mean=False), LinearRegres...

```
[42]: dfcoef[["name", "r2", "mae"]].set_index('name').plot(kind="bar", title="performance_
      ↪ across models");
```


1.5 Investigation

```
[44]: data_err = data.drop(["context_size", "repeat"], axis=1).copy()
data_err['predict'] = numpy.maximum(coefs[0]['model'].predict(X), 0) / 1000
data_err['err'] = (data_err['predict'] - data_err['average'])
data_err['abserr'] = numpy.abs(data_err['predict'] - data_err['average'])
data_err['rel'] = (data_err['predict'] - data_err['average']) / data_err['average']
s = data_err.sort_values('abserr')
pandas.concat([s.head(n=10), s.tail(n=10)])
```

```
[44]:
```

	average	deviation	min_exec	max_exec	number	perm \
28	0.000113	0.000029	0.000061	0.000141	50	(1, 0, 2)
55	0.000893	0.000212	0.000646	0.001477	50	(2, 3, 1, 0)
26	0.000077	0.000008	0.000069	0.000101	50	(0, 2, 1)
39	0.000126	0.000017	0.000107	0.000185	50	(2, 0, 1, 3)
66	0.000195	0.000019	0.000163	0.000258	50	(0, 3, 1, 2)
50	0.000692	0.000136	0.000529	0.001021	50	(0, 3, 2, 1)
76	0.000824	0.000288	0.000515	0.001879	50	(1, 3, 2, 0)
54	0.000818	0.000278	0.000625	0.001522	50	(2, 1, 3, 0)
1	0.000048	0.000003	0.000045	0.000058	50	(0, 1, 3, 2)
2	0.000049	0.000003	0.000045	0.000062	50	(3, 0, 1, 2)
120	0.005918	0.001085	0.004598	0.008312	15	(1, 0, 3, 2)
128	0.010677	0.001457	0.008504	0.014070	15	(2, 3, 1, 0)
121	0.006106	0.000556	0.005619	0.007305	15	(2, 0, 3, 1)
118	0.003780	0.000882	0.002701	0.005402	15	(3, 0, 1, 2)
115	0.003653	0.000874	0.002567	0.005244	15	(1, 2, 3, 0)
129	0.012421	0.003052	0.007818	0.018106	15	(3, 2, 1, 0)
119	0.004938	0.000367	0.004532	0.005844	15	(1, 3, 0, 2)
127	0.010339	0.002789	0.005878	0.018301	15	(0, 3, 2, 1)
130	0.013432	0.004496	0.006536	0.021250	15	(3, 2, 0, 1)
131	0.014579	0.004026	0.007144	0.020739	15	(3, 0, 2, 1)

	shape	ratio	dim	predict	err	abserr \
28	(43, 44, 45)	1.515711	3	0.000113	1.251063e-07	1.251063e-07
55	(3, 244, 244, 1)	8.339926	4	0.000893	-2.410649e-07	2.410649e-07
26	(43, 44, 45)	1.032759	3	0.000077	4.172780e-07	4.172780e-07
39	(3, 244, 244, 1)	1.180996	4	0.000115	-1.179187e-05	1.179187e-05
66	(1, 244, 244, 3)	1.598770	4	0.000210	1.510728e-05	1.510728e-05
50	(3, 244, 244, 1)	6.460759	4	0.000709	1.714180e-05	1.714180e-05
76	(1, 244, 244, 3)	6.752663	4	0.000843	1.902846e-05	1.902846e-05
54	(3, 244, 244, 1)	7.634646	4	0.000843	2.572773e-05	2.572773e-05
1	(12, 13, 15, 18)	0.820821	4	0.000000	-4.837787e-05	4.837787e-05
2	(12, 13, 15, 18)	0.823070	4	0.000000	-4.851040e-05	4.851040e-05
120	(3, 244, 244, 6)	1.597357	4	0.008259	2.341673e-03	2.341673e-03
128	(3, 244, 244, 6)	2.882191	4	0.008132	-2.545011e-03	2.545011e-03
121	(3, 244, 244, 6)	1.648325	4	0.008700	2.593662e-03	2.593662e-03
118	(3, 244, 244, 6)	1.020432	4	0.006488	2.707333e-03	2.707333e-03
115	(3, 244, 244, 6)	0.986071	4	0.006488	2.834624e-03	2.834624e-03
129	(3, 244, 244, 6)	3.352770	4	0.009386	-3.034652e-03	3.034652e-03
119	(3, 244, 244, 6)	1.333061	4	0.008700	3.761588e-03	3.761588e-03


```

127 (3, 244, 244, 6) 2.790823 4 0.005271 -5.068171e-03 5.068171e-03
130 (3, 244, 244, 6) 3.625680 4 0.008132 -5.299336e-03 5.299336e-03
131 (3, 244, 244, 6) 3.935483 4 0.008259 -6.320138e-03 6.320138e-03

```

```

      rel
28  0.001111
55 -0.000270
26  0.005440
39 -0.093246
66  0.077417
50  0.024778
76  0.023087
54  0.031471
1  -1.000000
2  -1.000000
120 0.395716
128 -0.238356
121 0.424746
118 0.716171
115 0.775972
129 -0.244323
119 0.761694
127 -0.490205
130 -0.394540
131 -0.433499

```

All big errors are negative. The model seems to give a lower value for all big errors. These errors may be outliers, the processor was busy doing something else at that time.

```
[45]: s = data_err.sort_values('predict')
      pandas.concat([s.head(n=10), s.tail(n=10)])
```

```
[45]:
```

	average	deviation	min_exec	max_exec	number	perm \
20	0.000158	0.000021	0.000127	0.000192	50	(3, 0, 2, 1)
42	0.000147	0.000017	0.000106	0.000175	50	(0, 1, 3, 2)
34	0.000151	0.000016	0.000136	0.000197	50	(1, 2, 0)
33	0.000124	0.000017	0.000108	0.000171	50	(2, 0, 1)
44	0.000189	0.000044	0.000142	0.000265	50	(1, 2, 3, 0)
27	0.000097	0.000004	0.000083	0.000110	50	(2, 0, 1)
25	0.000074	0.000009	0.000065	0.000109	50	(0, 1, 2)
24	0.000073	0.000009	0.000062	0.000094	50	(1, 2, 0)
22	0.000214	0.000060	0.000136	0.000295	50	(1, 0, 3, 2)
21	0.000164	0.000045	0.000124	0.000231	50	(3, 1, 2, 0)
128	0.010677	0.001457	0.008504	0.014070	15	(2, 3, 1, 0)
130	0.013432	0.004496	0.006536	0.021250	15	(3, 2, 0, 1)
122	0.006722	0.001807	0.005067	0.011245	15	(1, 3, 2, 0)
125	0.007815	0.001757	0.005932	0.010779	15	(2, 1, 3, 0)
120	0.005918	0.001085	0.004598	0.008312	15	(1, 0, 3, 2)
123	0.007071	0.000982	0.005454	0.008559	15	(3, 1, 0, 2)
131	0.014579	0.004026	0.007144	0.020739	15	(3, 0, 2, 1)
121	0.006106	0.000556	0.005619	0.007305	15	(2, 0, 3, 1)
119	0.004938	0.000367	0.004532	0.005844	15	(1, 3, 0, 2)
129	0.012421	0.003052	0.007818	0.018106	15	(3, 2, 1, 0)

	shape	ratio	dim	predict	err	abserr	rel
20	(12, 13, 15, 18)	2.684876	4	0.000000	-0.000158	0.000158	-1.000000
42	(3, 244, 244, 1)	1.369978	4	0.000000	-0.000147	0.000147	-1.000000
34	(3, 244, 244)	1.438446	3	0.000000	-0.000151	0.000151	-1.000000
33	(3, 244, 244)	1.185666	3	0.000000	-0.000124	0.000124	-1.000000
44	(3, 244, 244, 1)	1.766905	4	0.000000	-0.000189	0.000189	-1.000000
27	(43, 44, 45)	1.300915	3	0.000000	-0.000097	0.000097	-1.000000
25	(43, 44, 45)	1.000000	3	0.000000	-0.000074	0.000074	-1.000000
24	(43, 44, 45)	0.985513	3	0.000000	-0.000073	0.000073	-1.000000
22	(12, 13, 15, 18)	3.627240	4	0.000000	-0.000214	0.000214	-1.000000
21	(12, 13, 15, 18)	2.778193	4	0.000000	-0.000164	0.000164	-1.000000
128	(3, 244, 244, 6)	2.882191	4	0.008132	-0.002545	0.002545	-0.238356
130	(3, 244, 244, 6)	3.625680	4	0.008132	-0.005299	0.005299	-0.394540
122	(3, 244, 244, 6)	1.814552	4	0.008259	0.001537	0.001537	0.228654
125	(3, 244, 244, 6)	2.109489	4	0.008259	0.000444	0.000444	0.056871
120	(3, 244, 244, 6)	1.597357	4	0.008259	0.002342	0.002342	0.395716
123	(3, 244, 244, 6)	1.908667	4	0.008259	0.001188	0.001188	0.168070
131	(3, 244, 244, 6)	3.935483	4	0.008259	-0.006320	0.006320	-0.433499
121	(3, 244, 244, 6)	1.648325	4	0.008700	0.002594	0.002594	0.424746
119	(3, 244, 244, 6)	1.333061	4	0.008700	0.003762	0.003762	0.761694
129	(3, 244, 244, 6)	3.352770	4	0.009386	-0.003035	0.003035	-0.244323

1.5.1 Correlation between predictors

```
[46]: cc = DataFrame(dict([(c['name'], numpy.maximum(c['model'].predict(X), 0)) for c in
    ↪coefs]))
cc['yt'] = yt
cc
```

```
[46]:
```

	reg	med	Lasso-0.010000	Lasso-0.100000	Lasso-0.200000	\
0	0.298789	0.052436	0.000000	0.000000	0.000000	
1	0.000000	0.071575	0.000000	0.000000	0.000000	
2	0.000000	0.048393	0.000000	0.000000	0.000000	
3	0.000000	0.048393	0.000000	0.000000	0.000000	
4	0.248089	0.050781	0.000000	0.000000	0.000000	
..	
127	5.270700	4.177012	4.917105	4.615490		4.464429
128	8.132342	7.354799	8.107191	7.646966		7.334861
129	9.386005	8.186190	8.991256	8.082431		7.397300
130	8.132342	7.354799	8.107191	7.646966		7.334861
131	8.259236	7.561004	7.962160	7.605605		7.334861

	pos	medpos	yt
0	0.000000	0.000000	0.044222
1	0.000000	0.000000	0.048378
2	0.000000	0.000000	0.048510
3	0.000000	0.000000	0.048954
4	0.000000	0.000000	0.050805
..
127	4.837032	4.251381	10.338870
128	7.858363	6.706548	10.677354
129	8.771040	6.896204	12.420657
130	7.858363	6.706548	13.431679

```
131  7.829728  6.738972  14.579374
```

```
[132 rows x 8 columns]
```

```
[47]: cc.corr()
```

```
[47]:
```

	reg	med	Lasso-0.010000	Lasso-0.100000	\
reg	1.000000	0.994124	0.996922	0.985715	
med	0.994124	1.000000	0.995863	0.989990	
Lasso-0.010000	0.996922	0.995863	1.000000	0.992689	
Lasso-0.100000	0.985715	0.989990	0.992689	1.000000	
Lasso-0.200000	0.979826	0.987374	0.987930	0.998564	
pos	0.988323	0.990341	0.994420	0.998756	
medpos	0.980433	0.988401	0.988358	0.997985	
yt	0.903528	0.894833	0.899384	0.886902	

	Lasso-0.200000	pos	medpos	yt
reg	0.979826	0.988323	0.980433	0.903528
med	0.987374	0.990341	0.988401	0.894833
Lasso-0.010000	0.987930	0.994420	0.988358	0.899384
Lasso-0.100000	0.998564	0.998756	0.997985	0.886902
Lasso-0.200000	1.000000	0.995092	0.999385	0.880614
pos	0.995092	1.000000	0.995169	0.890093
medpos	0.999385	0.995169	1.000000	0.881208
yt	0.880614	0.890093	0.881208	1.000000

1.6 Standalone predictions

```
[48]: def get_coef(pipe, names):
      c1 = pipe.steps[0][-1].scale_
      c2 = pipe.steps[1][-1].coef_
      return dict(zip(names, c2 / c1))

get_coef(coefs[-1]["model"], X.columns)
```

```
[48]: {'CST_': 0.829481835464256,
      'begin': 0.0,
      'dbegin': 0.0,
      'dend': 0.0,
      'dim': 0.08294721851224843,
      'discont': 0.07025394222472751,
      'edit': 0.03782977428195987,
      'end': 0.0,
      'end16': 0.0,
      'end32': 0.0,
      'ibegin16': 0.0,
      'ibegin2': 0.0,
      'ibegin32': 0.0,
      'ibegin4': 0.0,
      'ibegin64': 0.0,
      'ibegin8': 0.0,
      'iend16': 0.0,
```

```

'iend2': 0.0,
'iend32': 0.0,
'iend4': 0.0,
'iend64': 0.0,
'iend8': 0.0,
'middle': 3.42896339670081e-06,
'rbegin': 0.0,
'rdiscont': 0.0,
'redit': 0.0,
'rend': 0.0,
'rend16': 0.0,
'rend32': 0.0,
'rev': 0.11940214295823245,
'rmiddle': 0.0,
'rot': 0.023189032947793925,
'size': 3.021302183272755e-06}

```

```

[49]: def predict(coefs, shape, perm):
        feat = compute_features(shape, perm)
        res = 0
        for k, v in feat.items():
            res += v * coefs[k]
        return res / 1000

def predict_model(model, shape, perm, names):
    feat = compute_features(shape, perm)
    a = numpy.zeros((1, len(names)), dtype=numpy.float64)
    for i, n in enumerate(names):
        a[0, i] = feat[n]
    return model.predict(a) / 1000

coef = get_coef(coefs[-1]["model"], X.columns)
(predict(coef, (3, 224, 224, 6), (3, 0, 1, 2)),
 predict_model(coefs[-1]["model"], (3, 224, 224, 6), (3, 0, 1, 2), X.columns))

```

```

[49]: (0.005450704959759156, array([0.0054507]))

```

```

[50]:

```