onnx_node_time

April 5, 2022

1 Time processing for every ONNX nodes in a graph

The following notebook show how long the runtime spends in each node of an ONNX graph.

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

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

[2]:
```
%load_ext mlprodict
```

[3]:
```
%matplotlib inline
```

1.1 LogisticRegression

[4]:
```
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
iris = load_iris()
X, y = iris.data, iris.target
X_train, X_test, y_train, y_test = train_test_split(X, y)
clr = LogisticRegression(solver='liblinear')
clr.fit(X_train, y_train)
```

[4]: LogisticRegression(solver='liblinear')

[5]:
```
import numpy
from mlprodict.onnx_conv import to_onnx
onx = to_onnx(clr, X_test.astype(numpy.float32))
with open("logreg_time.onnx", "wb") as f:
    f.write(onx.SerializeToString())
# add -l 1 if nothing shows up
%onnxview onx
```

[5]: <jyquickhelper.jspy.render_nb_js_dot.RenderJsDot at 0x23ea4d77fd0>

[6]:
```
from mlprodict.onnxrt import OnnxInference
import pandas
oinf = OnnxInference(onx)
res = oinf.run({'X': X_test}, node_time=True)
pandas.DataFrame(list(res[1]))
```

[6]:
```
   i               name            op_type      time
0  0  LinearClassifier  LinearClassifier  0.199603
1  1        Normalizer        Normalizer  0.000091
2  2              Cast              Cast  0.000014
3  3            ZipMap            ZipMap  0.000016
```

[7]:
```python
oinf.run({'X': X_test})['output_probability'][:5]
```

[7]:
```
{0: array([8.38235830e-01, 1.21554664e-03, 6.97352537e-04, 7.93823160e-01,
        9.24825077e-01]),
 1: array([0.16162989, 0.39692812, 0.25688601, 0.20607722, 0.07516498]),
 2: array([1.34279470e-04, 6.01856333e-01, 7.42416637e-01, 9.96200831e-05,
        9.94208860e-06])}
```

1.2 Measure time spent in each node

With parameter `node_time=True`, method *run* returns the output and time measurement.

[8]:
```python
exe = oinf.run({'X': X_test}, node_time=True)
exe[1]
```

[8]:
```
[{'i': 0,
  'name': 'LinearClassifier',
  'op_type': 'LinearClassifier',
  'time': 0.00015699999999974068},
 {'i': 1,
  'name': 'Normalizer',
  'op_type': 'Normalizer',
  'time': 5.43000000003957e-05},
 {'i': 2, 'name': 'Cast', 'op_type': 'Cast', 'time': 1.1699999999947863e-05},
 {'i': 3,
  'name': 'ZipMap',
  'op_type': 'ZipMap',
  'time': 1.940000000111297e-05}]
```

[9]:
```python
import pandas
pandas.DataFrame(exe[1])
```

[9]:
```
   i               name            op_type      time
0  0  LinearClassifier  LinearClassifier  0.000157
1  1        Normalizer        Normalizer  0.000054
2  2              Cast              Cast  0.000012
3  3            ZipMap            ZipMap  0.000019
```

1.3 Logistic regression: python runtime vs onnxruntime

Function enumerate_validated_operator_opsets implements automated tests for every model with artificial data. Option `node_time` automatically returns the time spent in each node and does it multiple time.

[10]:
```python
from mlprodict.onnxrt.validate import enumerate_validated_operator_opsets
res = list(enumerate_validated_operator_opsets(
            verbose=0, models={"LogisticRegression"}, opset_min=12,
            runtime='python', debug=False, node_time=True,
            filter_exp=lambda m, p: p == "b-cl"))
```

```
C:\xavierdupre\__home_\github_fork\scikit-
learn\sklearn\linear_model\_logistic.py:1356: UserWarning: 'n_jobs' > 1 does not
have any effect when 'solver' is set to 'liblinear'. Got 'n_jobs' = 4.
  " = {}.".format(effective_n_jobs(self.n_jobs)))
C:\xavierdupre\__home_\github_fork\scikit-
learn\sklearn\linear_model\_logistic.py:1356: UserWarning: 'n_jobs' > 1 does not
have any effect when 'solver' is set to 'liblinear'. Got 'n_jobs' = 4.
  " = {}.".format(effective_n_jobs(self.n_jobs)))
```

[11]:
```python
import pandas
df = pandas.DataFrame(res[0]['bench-batch'])
df['step'] = df.apply(lambda row: '{}-{}'.format(row['i'], row["name"]), axis=1)
df
```

[11]:

	i	name	op_type	time	N	max_time
0	0	LinearClassifier	LinearClassifier	0.000018	1	0.000033
1	1	Normalizer	Normalizer	0.000017	1	0.000069
2	2	Cast	Cast	0.000004	1	0.000009
3	3	ZipMap	ZipMap	0.000005	1	0.000007
4	0	LinearClassifier	LinearClassifier	0.000020	10	0.000052
5	1	Normalizer	Normalizer	0.000015	10	0.000035
6	2	Cast	Cast	0.000004	10	0.000013
7	3	ZipMap	ZipMap	0.000004	10	0.000008
8	0	LinearClassifier	LinearClassifier	0.000024	100	0.000036
9	1	Normalizer	Normalizer	0.000018	100	0.000023
10	2	Cast	Cast	0.000004	100	0.000006
11	3	ZipMap	ZipMap	0.000007	100	0.000005
12	0	LinearClassifier	LinearClassifier	0.000051	1000	0.000057
13	1	Normalizer	Normalizer	0.000041	1000	0.000045
14	2	Cast	Cast	0.000003	1000	0.000004
15	3	ZipMap	ZipMap	0.000004	1000	0.000004
16	0	LinearClassifier	LinearClassifier	0.000315	10000	0.000328
17	1	Normalizer	Normalizer	0.000272	10000	0.000284
18	2	Cast	Cast	0.000004	10000	0.000004
19	3	ZipMap	ZipMap	0.000004	10000	0.000004
20	0	LinearClassifier	LinearClassifier	0.005634	100000	0.005634
21	1	Normalizer	Normalizer	0.004671	100000	0.004671
22	2	Cast	Cast	0.000024	100000	0.000024
23	3	ZipMap	ZipMap	0.000013	100000	0.000013

	min_time	repeat	number	step
0	0.000015	20	30	0-LinearClassifier
1	0.000012	20	30	1-Normalizer
2	0.000003	20	30	2-Cast
3	0.000004	20	30	3-ZipMap
4	0.000017	20	20	0-LinearClassifier
5	0.000013	20	20	1-Normalizer
6	0.000003	20	20	2-Cast
7	0.000004	20	20	3-ZipMap
8	0.000019	10	8	0-LinearClassifier
9	0.000015	10	8	1-Normalizer
10	0.000003	10	8	2-Cast
11	0.000004	10	8	3-ZipMap
12	0.000047	5	5	0-LinearClassifier

```
13  0.000040       5       5        1-Normalizer
14  0.000003       5       5              2-Cast
15  0.000004       5       5            3-ZipMap
16  0.000315       3       3  0-LinearClassifier
17  0.000256       3       3        1-Normalizer
18  0.000004       3       3              2-Cast
19  0.000004       3       3            3-ZipMap
20  0.005634       1       2  0-LinearClassifier
21  0.004671       1       2        1-Normalizer
22  0.000024       1       2              2-Cast
23  0.000013       1       2            3-ZipMap
```

Following tables shows the time spent in each node, it is relative to the total time. For one observation, the runtime spends 10% of the time in ZipMap, it is only 1% or 2% with 10 observations. These proportions change due to the computing cost of each node.

[12]:
```
piv = df.pivot('step', 'N', 'time')
total = piv.sum(axis=0)
piv / total
```

[12]:
```
N                          1        10       100      1000     10000    100000
step
0-LinearClassifier  0.410138  0.459103  0.450882  0.512622  0.530490  0.544785
1-Normalizer        0.390060  0.353622  0.350126  0.414227  0.456671  0.451642
2-Cast              0.095729  0.089857  0.074343  0.034398  0.006092  0.002306
3-ZipMap            0.104073  0.097418  0.124649  0.038753  0.006747  0.001267
```

The python implementation of *ZipMap* does not change the data but wraps in into a frozen class ArrayZipMapDitionary which mocks a list of dictionaries *pandas* can ingest to create a DataFrame. The cost is a fixed cost and does not depend on the number of processed rows.

[13]:
```
from pyquickhelper.pycode.profiling import profile
bigX = numpy.random.randn(100000, X_test.shape[1]).astype(numpy.float32)
print(profile(lambda: oinf.run({'X': bigX}), pyinst_format="text")[1])
```

```
  _     ._   __/__   _ _  _  _ _/_   Recorded: 00:28:08  Samples:  4
 /_//_/// /_\ / //_// / //_'/ //     Duration: 0.009     CPU time: 0.031
/   _/                      v3.0.1

Program: c:\python372_x64\lib\site-packages\ipykernel_launcher.py -f C:\Users\xa
vie\AppData\Roaming\jupyter\runtime\kernel-287476aa-b8ba-4140-902a-b0aad833ffd0.
json

0.008 profile  pyquickhelper\pycode\profiling.py:49
`- 0.008 <lambda>  <ipython-input-13-ccd42692a7ed>:3
   `- 0.008 run  mlprodict\onnxrt\onnx_inference.py:475
      `- 0.008 _run_sequence_runtime  mlprodict\onnxrt\onnx_inference.py:558
         `- 0.008 run  mlprodict\onnxrt\onnx_inference_node.py:141
            |- 0.005 run  mlprodict\onnxrt\ops_cpu\_op.py:417
            |  `- 0.005 run  mlprodict\onnxrt\ops_cpu\_op.py:298
            |     `- 0.005 _run
mlprodict\onnxrt\ops_cpu\op_linear_classifier.py:40
            |        |- 0.003 [self]
            |        `- 0.002 argmax  <__array_function__ internals>:2
```

```
            |           `- 0.002 argmax  numpy\core\fromnumeric.py:1112
            |                 [3 frames hidden]  numpy
            |                    0.002 _wrapfunc  numpy\core\fromnumeric.py:55
            `- 0.003 run  mlprodict\onnxrt\ops_cpu\_op.py:383
               `- 0.003 run  mlprodict\onnxrt\ops_cpu\_op.py:298
                  `- 0.003 _run  mlprodict\onnxrt\ops_cpu\op_normalizer.py:66
                     `- 0.003 norm_l1
mlprodict\onnxrt\ops_cpu\op_normalizer.py:42
                        `- 0.003 _norm_L1_inplace
mlprodict\onnxrt\ops_cpu\op_normalizer.py:49
                           |- 0.002 [self]
                           `- 0.002 _sum  numpy\core\_methods.py:36
                                 [2 frames hidden]  numpy
```

The class *ArrayZipMapDictionary* is fast to build but has an overhead after that because it builds data when needed.

[14]:
```python
res = oinf.run({'X': bigX})
prob = res['output_probability']
type(prob)
```

[14]:
```
mlprodict.onnxrt.ops_cpu.op_zipmap.ArrayZipMapDictionary
```

[15]:
```python
%timeit pandas.DataFrame(prob)
```

```
721 ms ± 54.5 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

[16]:
```python
list_of_dict = [v.asdict() for v in prob]
%timeit pandas.DataFrame(list_of_dict)
```

```
108 ms ± 2.01 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)
```

But if you just need to do the following:

[17]:
```python
%timeit pandas.DataFrame(prob).values
```

```
713 ms ± 56.6 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

Then, you can just do that:

[18]:
```python
print(prob.columns)
%timeit prob.values
```

```
[0, 1, 2]
390 ns ± 51.2 ns per loop (mean ± std. dev. of 7 runs, 1000000 loops each)
```

And then:

[19]:
```python
%timeit -n 100 pandas.DataFrame(prob.values, columns=prob.columns)
```

```
215 µs ± 82.6 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)
```

We can then compare to what *onnxruntime* would do when the runtime is called indenpently for each node. We use the runtime named onnxruntime2. Class *OnnxInference* splits the ONNX graph into multiple ONNX graphs, one for each node, and then calls *onnxruntime* for each of them indenpently. *Python* handles the graph logic.

[20]:
```
res = list(enumerate_validated_operator_opsets(
            verbose=0, models={"LogisticRegression"}, opset_min=12,
            runtime='onnxruntime2', debug=False, node_time=True))
```

```
C:\xavierdupre\__home_\github_fork\scikit-
learn\sklearn\linear_model\_logistic.py:1356: UserWarning: 'n_jobs' > 1 does not
have any effect when 'solver' is set to 'liblinear'. Got 'n_jobs' = 4.
  " = {}.".format(effective_n_jobs(self.n_jobs)))
C:\xavierdupre\__home_\github_fork\scikit-
learn\sklearn\linear_model\_logistic.py:1356: UserWarning: 'n_jobs' > 1 does not
have any effect when 'solver' is set to 'liblinear'. Got 'n_jobs' = 4.
  " = {}.".format(effective_n_jobs(self.n_jobs)))
C:\xavierdupre\__home_\github_fork\scikit-
learn\sklearn\linear_model\_logistic.py:1356: UserWarning: 'n_jobs' > 1 does not
have any effect when 'solver' is set to 'liblinear'. Got 'n_jobs' = 4.
  " = {}.".format(effective_n_jobs(self.n_jobs)))
C:\xavierdupre\__home_\github_fork\scikit-
learn\sklearn\linear_model\_logistic.py:1356: UserWarning: 'n_jobs' > 1 does not
have any effect when 'solver' is set to 'liblinear'. Got 'n_jobs' = 4.
  " = {}.".format(effective_n_jobs(self.n_jobs)))
C:\xavierdupre\__home_\github_fork\scikit-
learn\sklearn\linear_model\_logistic.py:1356: UserWarning: 'n_jobs' > 1 does not
have any effect when 'solver' is set to 'liblinear'. Got 'n_jobs' = 4.
  " = {}.".format(effective_n_jobs(self.n_jobs)))
C:\xavierdupre\__home_\github_fork\scikit-
learn\sklearn\linear_model\_logistic.py:1356: UserWarning: 'n_jobs' > 1 does not
have any effect when 'solver' is set to 'liblinear'. Got 'n_jobs' = 4.
  " = {}.".format(effective_n_jobs(self.n_jobs)))
C:\xavierdupre\__home_\github_fork\scikit-
learn\sklearn\linear_model\_logistic.py:1356: UserWarning: 'n_jobs' > 1 does not
have any effect when 'solver' is set to 'liblinear'. Got 'n_jobs' = 4.
  " = {}.".format(effective_n_jobs(self.n_jobs)))
C:\xavierdupre\__home_\github_fork\scikit-
learn\sklearn\linear_model\_logistic.py:1356: UserWarning: 'n_jobs' > 1 does not
have any effect when 'solver' is set to 'liblinear'. Got 'n_jobs' = 4.
  " = {}.".format(effective_n_jobs(self.n_jobs)))
C:\xavierdupre\__home_\github_fork\scikit-
learn\sklearn\linear_model\_logistic.py:1356: UserWarning: 'n_jobs' > 1 does not
have any effect when 'solver' is set to 'liblinear'. Got 'n_jobs' = 4.
  " = {}.".format(effective_n_jobs(self.n_jobs)))
C:\xavierdupre\__home_\github_fork\scikit-
learn\sklearn\linear_model\_logistic.py:1356: UserWarning: 'n_jobs' > 1 does not
have any effect when 'solver' is set to 'liblinear'. Got 'n_jobs' = 4.
  " = {}.".format(effective_n_jobs(self.n_jobs)))
```

[21]:
```
res0 = None
for i, r in enumerate(res):
    if "available-ERROR" in r:
        print(i, str(r['available-ERROR']).split("\n")[0])
    elif res0 is None:
        res0 = r
```

```
0 Unable to load node 'ZipMap' (output type was inferred)
```

```
1 Unable to load node 'ZipMap' (output type was inferred)
4 Unable to load node 'LinearClassifier' (output type was guessed)
5 Unable to load node 'LinearClassifier' (output type was guessed)
6 Unable to load node 'LinearClassifier' (output type was guessed)
7 Unable to load node 'LinearClassifier' (output type was guessed)
8 Unable to load node 'ZipMap' (output type was inferred)
9 Unable to load node 'ZipMap' (output type was inferred)
```

[22]:
```python
if '_6ort_run_batch_exc' in res[0]:
    m = "Something went wrong.", res[0]['_6ort_run_batch_exc']
else:
    df = pandas.DataFrame(res0['bench-batch'])
    print(df)
    df['step'] = df.apply(lambda row: '{}-{}'.format(row['i'], row["name"]), axis=1)
    piv = df.pivot('step', 'N', 'time')
    total = piv.sum(axis=0)
    m = piv / total
m
```

```
   i              name           op_type      time       N  max_time  \
0  0  LinearClassifier  LinearClassifier  0.000052       1  0.000190
1  0  LinearClassifier  LinearClassifier  0.000044      10  0.000070
2  0  LinearClassifier  LinearClassifier  0.000071     100  0.000133
3  0  LinearClassifier  LinearClassifier  0.000066    1000  0.000079
4  0  LinearClassifier  LinearClassifier  0.000409   10000  0.000408
5  0  LinearClassifier  LinearClassifier  0.003275  100000  0.003275

   min_time  repeat  number
0  0.000028      20      30
1  0.000031      20      20
2  0.000046      10       8
3  0.000057       5       5
4  0.000365       3       3
5  0.003275       1       2
```

[22]:
```
N                     1       10      100     1000    10000   100000
step
0-LinearClassifier     1.0     1.0     1.0     1.0     1.0     1.0
```

onnxruntime creates a new container each time a ZipMap is executed. That's whay it takes that much time and the ratio increases when the number of observations increases.

1.4 GaussianProcessRegressor

This operator is slow for small batches compare to scikit-learn but closes the gap as the batch size increases. Let's see where the time goes.

[23]:
```python
from onnx.defs import onnx_opset_version
from mlprodict.tools.asv_options_helper import get_opset_number_from_onnx
onnx_opset_version(), get_opset_number_from_onnx()
```

[23]:
```
(12, 12)
```

[24]:
```python
res = list(enumerate_validated_operator_opsets(
            verbose=1, models={"GaussianProcessRegressor"},
            opset_min=get_opset_number_from_onnx(),
            opset_max=get_opset_number_from_onnx(),
            runtime='python', debug=False, node_time=True,
            filter_exp=lambda m, p: p == "b-reg"))
```

```
[enumerate_validated_operator_opsets] opset in [12, 12].

GaussianProcessRegressor    :   0%|          | 0/1 [00:00<?, ?it/s]

[enumerate_compatible_opset] opset in [12, 12].

GaussianProcessRegressor    : 100%|¿ ¿ ¿ ¿ ¿ ¿ ¿ ¿ ¿ ¿ | 1/1 [00:05<00:00,  5.66s/it]
```

[25]:
```python
res0 = None
for i, r in enumerate(res):
    if "available-ERROR" in r:
        print(i, str(r['available-ERROR']).split("\n")[0])
    elif res0 is None:
        res0 = r
```

[26]:
```python
df = pandas.DataFrame(res0['bench-batch'])
df['step'] = df.apply(lambda row: '{0:02d}-{1}'.format(row['i'], row["name"]), axis=1)
df.head()
```

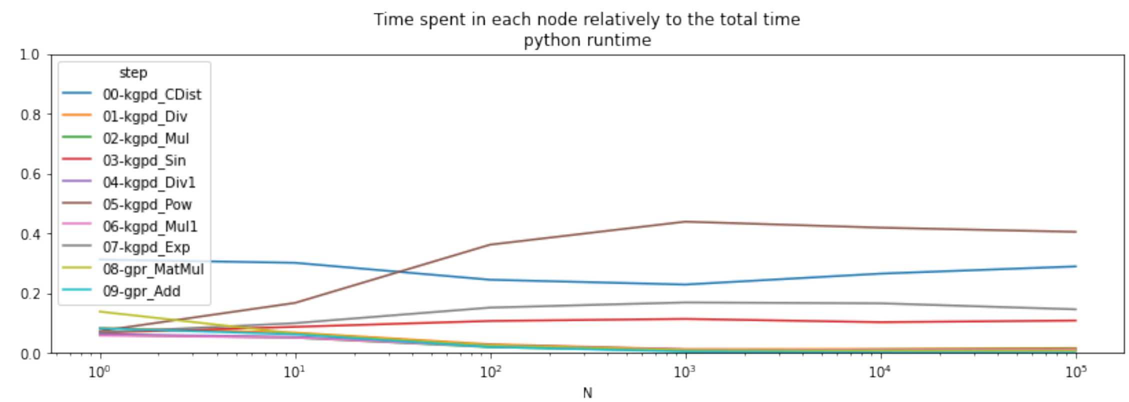
[26]:
```
   i        name op_type      time  N  max_time  min_time  repeat  number  \
0  0  kgpd_CDist   CDist  0.000033  1  0.000045  0.000027      20      30
1  1    kgpd_Div     Div  0.000009  1  0.000016  0.000007      20      30
2  2    kgpd_Mul     Mul  0.000006  1  0.000007  0.000005      20      30
3  3    kgpd_Sin     Sin  0.000007  1  0.000009  0.000006      20      30
4  4   kgpd_Div1     Div  0.000007  1  0.000008  0.000005      20      30

            step
0  00-kgpd_CDist
1    01-kgpd_Div
2    02-kgpd_Mul
3    03-kgpd_Sin
4   04-kgpd_Div1
```

[27]:
```python
pivpy = df.pivot('step', 'N', 'time')
total = pivpy.sum(axis=0)
pivpy / total
```

[27]:
```
N                   1         10        100       1000      10000     100000
step
00-kgpd_CDist  0.311496  0.300665  0.244035  0.227984  0.264447  0.288546
01-kgpd_Div    0.082535  0.067193  0.028348  0.011667  0.012230  0.015447
02-kgpd_Mul    0.059840  0.050664  0.018670  0.006959  0.010950  0.012468
03-kgpd_Sin    0.067037  0.086529  0.106165  0.113068  0.102102  0.107563
04-kgpd_Div1   0.061852  0.053088  0.025749  0.010935  0.009810  0.009875
05-kgpd_Pow    0.072520  0.166539  0.361318  0.438253  0.418169  0.404182
06-kgpd_Mul1   0.057508  0.050477  0.020386  0.010334  0.009079  0.010466
```

```
07-kgpd_Exp     0.067885  0.098850  0.150876  0.168079  0.165177  0.145106
08-gpr_MatMul   0.137546  0.064570  0.025069  0.009029  0.007134  0.006159
09-gpr_Add      0.081782  0.061424  0.019383  0.003692  0.000903  0.000190
```

[28]:
```python
ax = (pivpy / total).T.plot(logx=True, figsize=(14, 4))
ax.set_ylim([0,1])
ax.set_title("Time spent in each node relatively to the total time\npython runtime");
```



The operator *Scan* is clearly time consuming when the batch size is small. *onnxruntime* is more efficient for this one.

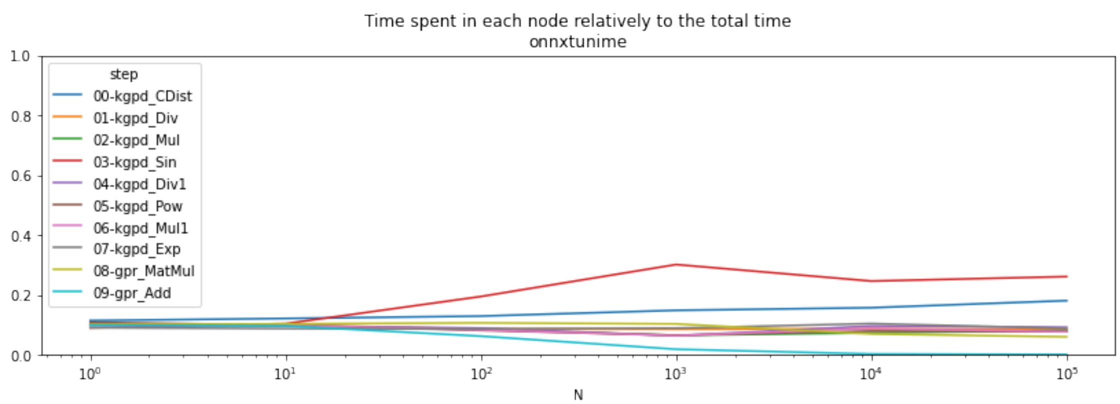
[29]:
```python
res = list(enumerate_validated_operator_opsets(
            verbose=1, models={"GaussianProcessRegressor"},
            opset_min=get_opset_number_from_onnx(),
            opset_max=get_opset_number_from_onnx(),
            runtime='onnxruntime2', debug=False, node_time=True,
            filter_exp=lambda m, p: p == "b-reg"))
```

```
[enumerate_validated_operator_opsets] opset in [12, 12].

GaussianProcessRegressor    :   0%|          | 0/1 [00:00<?, ?it/s]

[enumerate_compatible_opset] opset in [12, 12].

GaussianProcessRegressor    : 100%|¿ ¿ ¿ ¿ ¿ ¿ ¿ ¿ ¿ ¿ | 1/1 [00:06<00:00,  6.84s/it]
```

[30]:
```python
try:
    df = pandas.DataFrame(res[0]['bench-batch'])
except KeyError as e:
    print("No model available.")
    r, df = None, None
if df is not None:
    df['step'] = df.apply(lambda row: '{0:02d}-{1}'.format(row['i'], row["name"]),␣
 ↪axis=1)
    pivort = df.pivot('step', 'N', 'time')
    total = pivort.sum(axis=0)
    r = pivort / total
r
```

```
[30]: N                   1         10        100       1000      10000     100000
step
00-kgpd_CDist  0.114001  0.120884  0.128845  0.148042  0.156776  0.180377
01-kgpd_Div    0.101792  0.098622  0.085983  0.085108  0.086603  0.084520
02-kgpd_Mul    0.099980  0.097547  0.084001  0.064706  0.072849  0.081023
03-kgpd_Sin    0.089632  0.103505  0.194194  0.301002  0.245769  0.260717
04-kgpd_Div1   0.099119  0.096737  0.088709  0.063237  0.095840  0.091635
05-kgpd_Pow    0.108045  0.098307  0.081161  0.064898  0.079015  0.076962
06-kgpd_Mul1   0.098561  0.098475  0.082770  0.063557  0.087732  0.076762
07-kgpd_Exp    0.090019  0.087015  0.086282  0.088542  0.103798  0.087690
08-gpr_MatMul  0.100426  0.102766  0.106220  0.102751  0.069157  0.059617
09-gpr_Add     0.098425  0.096143  0.061836  0.018155  0.002462  0.000696
```

```
[31]: if r is not None:
          ax = (pivort / total).T.plot(logx=True, figsize=(14, 4))
          ax.set_ylim([0,1])
          ax.set_title("Time spent in each node relatively to the total time\nonnxtunime");
```



The results are relative. Let's see which runtime is best node by node.

```
[32]: if r is not None:
          r = (pivort - pivpy) / pivpy
      r
```

```
[32]: N                   1         10        100       1000      10000     100000
step
00-kgpd_CDist -0.239113 -0.367743 -0.630420 -0.703226 -0.677041 -0.631775
01-kgpd_Div    1.564119  1.308106  1.123155  2.333824  2.857590  2.223117
02-kgpd_Mul    2.473648  2.027773  2.149388  3.249448  2.624165  2.828025
03-kgpd_Sin    1.779780  0.881090  0.280401  0.216680  0.311288  0.427768
04-kgpd_Div1   2.331710  1.865534  1.411570  1.642922  4.321977  4.466249
05-kgpd_Pow    2.097502 -0.071724 -0.842765 -0.932321 -0.897065 -0.887837
06-kgpd_Mul1   2.563218  2.067909  1.842112  1.811019  4.263897  3.320524
07-kgpd_Exp    1.756911  0.384288 -0.599693 -0.759241 -0.657668 -0.644029
08-gpr_MatMul  0.517953  1.502798  1.965953  4.201281  4.281286  4.701255
09-gpr_Add     1.502111  1.461452  1.233097  1.247736  0.486358  1.160395
```

Based on this, *onnxruntime* is faster for operators *Scan*, *Pow*, *Exp* and slower for all the others.

1.5 Measuring the time with a custom dataset

We use the example Comparison of kernel ridge and Gaussian process regression.

[33]:
```
import numpy
import pandas
import matplotlib.pyplot as plt
from sklearn.kernel_ridge import KernelRidge
from sklearn.model_selection import GridSearchCV
from sklearn.gaussian_process import GaussianProcessRegressor
from sklearn.gaussian_process.kernels import WhiteKernel, ExpSineSquared

rng = numpy.random.RandomState(0)

# Generate sample data
X = 15 * rng.rand(100, 1)
y = numpy.sin(X).ravel()
y += 3 * (0.5 - rng.rand(X.shape[0]))  # add noise

gp_kernel = ExpSineSquared(1.0, 5.0, periodicity_bounds=(1e-2, 1e1))
gpr = GaussianProcessRegressor(kernel=gp_kernel)
gpr.fit(X, y)
```

```
C:\xavierdupre\__home_\github_fork\scikit-
learn\sklearn\gaussian_process\kernels.py:409: ConvergenceWarning: The optimal
value found for dimension 0 of parameter length_scale is close to the specified
lower bound 1e-05. Decreasing the bound and calling fit again may find a better
value.
  ConvergenceWarning)
C:\xavierdupre\__home_\github_fork\scikit-
learn\sklearn\gaussian_process\kernels.py:418: ConvergenceWarning: The optimal
value found for dimension 0 of parameter periodicity is close to the specified
upper bound 10.0. Increasing the bound and calling fit again may find a better
value.
  ConvergenceWarning)
```

[33]:
```
GaussianProcessRegressor(kernel=ExpSineSquared(length_scale=1, periodicity=5))
```

[34]:
```
onx = to_onnx(gpr, X_test.astype(numpy.float64))
with open("gpr_time.onnx", "wb") as f:
    f.write(onx.SerializeToString())
%onnxview onx -r 1
```

[34]:
```
<jyquickhelper.jspy.render_nb_js_dot.RenderJsDot at 0x23eb2856cc0>
```

[35]:
```
from mlprodict.tools import get_ir_version_from_onnx
onx.ir_version = get_ir_version_from_onnx()
```

[36]:
```
oinfpy = OnnxInference(onx, runtime="python")
oinfort = OnnxInference(onx, runtime="onnxruntime2")
```

`runtime==onnxruntime2` tells the class `OnnxInference` to use *onnxruntime* for every node independently, there are as many calls as there are nodes in the graph.

[37]:
```
respy = oinfpy.run({'X': X_test}, node_time=True)
try:
    resort = oinfort.run({'X': X_test}, node_time=True)
except Exception as e:
    print(e)
    resort = None
```

[38]:
```
if resort is not None:
    df = pandas.DataFrame(respy[1]).merge(pandas.DataFrame(resort[1]), on=["i",␣
 ↪"name", "op_type"],
                                          suffixes=("_py", "_ort"))
    df['delta'] = df.time_ort - df.time_py
else:
    df = None
df
```

[38]:

	i	name	op_type	time_py	time_ort	delta
0	0	Sc_Scan	Scan	0.007998	0.005970	-0.002028
1	1	kgpd_Transpose	Transpose	0.000032	0.000599	0.000567
2	2	kgpd_Sqrt	Sqrt	0.000063	0.000112	0.000049
3	3	kgpd_Div	Div	0.000143	0.000097	-0.000045
4	4	kgpd_Mul	Mul	0.000038	0.000321	0.000283
5	5	kgpd_Sin	Sin	0.000095	0.000146	0.000051
6	6	kgpd_Div1	Div	0.000027	0.000096	0.000069
7	7	kgpd_Pow	Pow	0.000299	0.000104	-0.000196
8	8	kgpd_Mul1	Mul	0.000032	0.000097	0.000065
9	9	kgpd_Exp	Exp	0.000383	0.000111	-0.000271
10	10	gpr_MatMul	MatMul	0.000080	0.004359	0.004279
11	11	gpr_Add	Add	0.000034	0.000165	0.000131

The following function runs multiple the same inference and aggregates the results node by node.

[39]:
```
from mlprodict.onnxrt.validate.validate import benchmark_fct
res = benchmark_fct(lambda X: oinfpy.run({'X': X_test}, node_time=True),
                    X_test, node_time=True)
```

[40]:
```
df = pandas.DataFrame(res)
df[df.N == 100]
```

[40]:

	i	name	op_type	time	N	max_time	min_time	repeat	\
24	0	Sc_Scan	Scan	0.004154	100	0.004330	0.003843	10	
25	1	kgpd_Transpose	Transpose	0.000013	100	0.000019	0.000010	10	
26	2	kgpd_Sqrt	Sqrt	0.000018	100	0.000022	0.000015	10	
27	3	kgpd_Div	Div	0.000025	100	0.000092	0.000015	10	
28	4	kgpd_Mul	Mul	0.000012	100	0.000019	0.000009	10	
29	5	kgpd_Sin	Sin	0.000057	100	0.000070	0.000050	10	
30	6	kgpd_Div1	Div	0.000014	100	0.000017	0.000011	10	
31	7	kgpd_Pow	Pow	0.000172	100	0.000198	0.000155	10	
32	8	kgpd_Mul1	Mul	0.000020	100	0.000101	0.000009	10	
33	9	kgpd_Exp	Exp	0.000213	100	0.000249	0.000193	10	
34	10	gpr_MatMul	MatMul	0.000034	100	0.000047	0.000026	10	
35	11	gpr_Add	Add	0.000013	100	0.000019	0.000011	10	

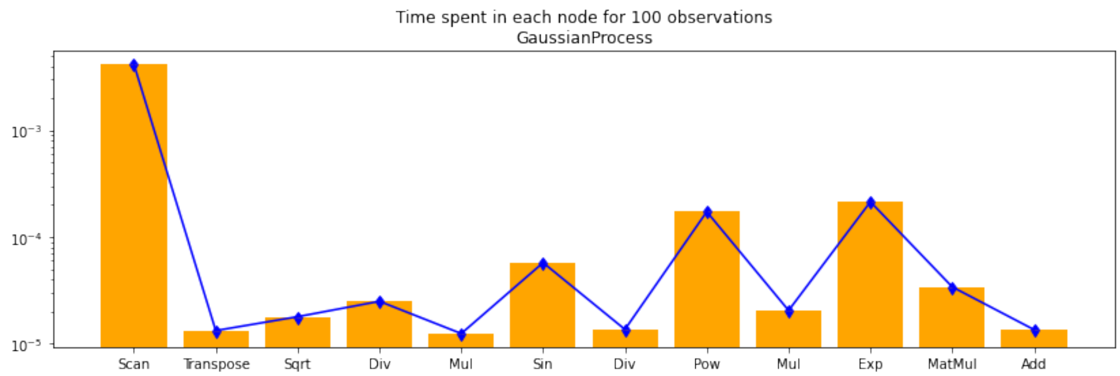
number

```
24          8
25          8
26          8
27          8
28          8
29          8
30          8
31          8
32          8
33          8
34          8
35          8
```

[41]:
```
df100 = df[df.N == 100]
```

[42]:
```
%matplotlib inline
```

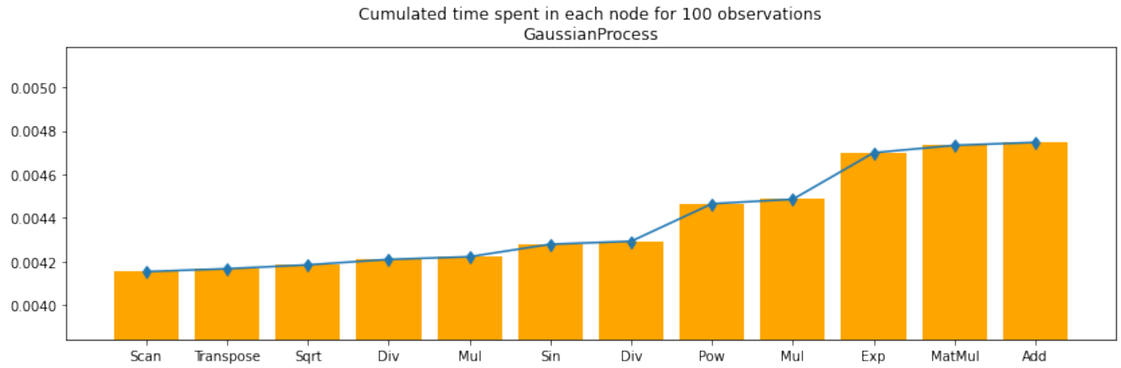
[43]:
```
fig, ax = plt.subplots(1, 1, figsize=(14, 4))
ax.bar(df100.i, df100.time, align='center', color='orange')
ax.set_xticks(df100.i)
ax.set_yscale('log')
ax.set_xticklabels(df100.op_type)
ax.errorbar(df100.i, df100.time,
            numpy.abs(df100[["min_time", "max_time"]].T.values - df100.time.values.
 ↪ravel()),
            uplims=True, lolims=True, color='blue')
ax.set_title("Time spent in each node for 100 observations\nGaussianProcess");
```



[44]:
```
df100c = df100.cumsum()
```

[45]:
```
fig, ax = plt.subplots(1, 1, figsize=(14, 4))
ax.bar(df100.i, df100c.time, align='center', color='orange')
ax.set_xticks(df100.i)
#ax.set_yscale('log')
ax.set_ylim([df100c.min_time.min(), df100c.max_time.max()])
ax.set_xticklabels(df100.op_type)
ax.errorbar(df100.i, df100c.time,
```

```
            numpy.abs((df100c[["min_time", "max_time"]].T.values - df100c.time.values.
 ↪ravel())),
            uplims=True, lolims=True)
ax.set_title("Cumulated time spent in each node for 100␣
 ↪observations\nGaussianProcess");
```



1.6 onnxruntime2 / onnxruntime1

The runtime `onnxruntime1` uses *onnxruntime* for the whole ONNX graph. There is no way to get the computation time for each node except if we create a ONNX graph for each intermediate node.

[46]:
```
oinfort1 = OnnxInference(onx, runtime='onnxruntime1')
```

[47]:
```
split = oinfort1.build_intermediate()
split
```

[47]:
```
OrderedDict([('scan0', OnnxInference(...)),
             ('scan1', OnnxInference(...)),
             ('kgpd_transposed0', OnnxInference(...)),
             ('kgpd_Y0', OnnxInference(...)),
             ('kgpd_C03', OnnxInference(...)),
             ('kgpd_C02', OnnxInference(...)),
             ('kgpd_output02', OnnxInference(...)),
             ('kgpd_C01', OnnxInference(...)),
             ('kgpd_Z0', OnnxInference(...)),
             ('kgpd_C0', OnnxInference(...)),
             ('kgpd_output01', OnnxInference(...)),
             ('gpr_Y0', OnnxInference(...)),
             ('GPmean', OnnxInference(...))])
```

[48]:
```
dfs = []
for k, v in split.items():
    print("node", k)
    res = benchmark_fct(lambda x: v.run({'X': x}), X_test)
    df = pandas.DataFrame(res)
    df['name'] = k
    dfs.append(df.reset_index(drop=False))
```

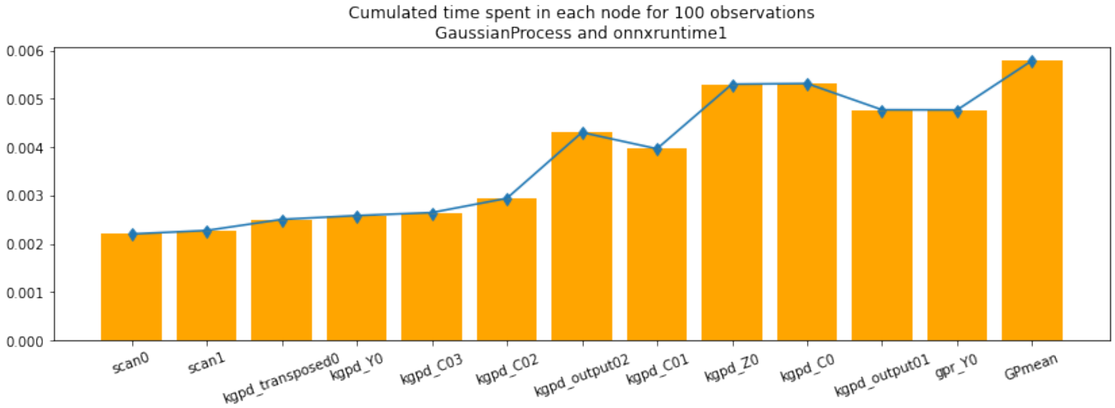
```
node scan0
node scan1
node kgpd_transposed0
node kgpd_Y0
node kgpd_C03
node kgpd_C02
node kgpd_output02
node kgpd_C01
node kgpd_Z0
node kgpd_C0
node kgpd_output01
node gpr_Y0
node GPmean
```

[49]:
```
df = pandas.concat(dfs)
df.head()
```

[49]:
```
       index          1         10        100      1000     10000    100000  \
0    average   0.000623   0.000592   0.000754  0.002202  0.017529  0.201192
1  deviation   0.000115   0.000030   0.000034  0.000026  0.000976  0.000000
2   min_exec   0.000541   0.000537   0.000657  0.002169  0.016677  0.201192
3   max_exec   0.000980   0.000639   0.000780  0.002239  0.018896  0.201192
4     repeat  20.000000  20.000000  10.000000  5.000000  3.000000  1.000000

    name
0  scan0
1  scan0
2  scan0
3  scan0
4  scan0
```

[50]:
```
df100c = df[df['index'] == "average"]
df100c_min = df[df['index'] == "min_exec"]
df100c_max = df[df['index'] == "max_exec"]
ave = df100c.iloc[:, 4]
ave_min = df100c_min.iloc[:, 4]
ave_max = df100c_max.iloc[:, 4]
ave.shape, ave_min.shape, ave_max.shape
index = numpy.arange(ave.shape[0])
```

[51]:
```
fig, ax = plt.subplots(1, 1, figsize=(14, 4))
ax.bar(index, ave, align='center', color='orange')
ax.set_xticks(index)
ax.set_xticklabels(df100c.name)
for tick in ax.get_xticklabels():
    tick.set_rotation(20)
ax.errorbar(index, ave,
            numpy.abs((numpy.vstack([ave_min.values, ave_max.values]) - ave.values.
↪ravel())),
            uplims=True, lolims=True)
ax.set_title("Cumulated time spent in each node for 100 "
             "observations\nGaussianProcess and onnxruntime1");
```



The visual graph helps matching the output names with the operator type. The curve is not monotononic because each experiment computes every output from the start. The number of repetitions should be increased. Documentation of function benchmark_fct tells how to do it.

[52]:

```

```