

# Model Persistence scikit-learn and ONNX

Xavier Dupré

Senior Data Scientist at Microsoft

Professor at ENSAE

# Open Source

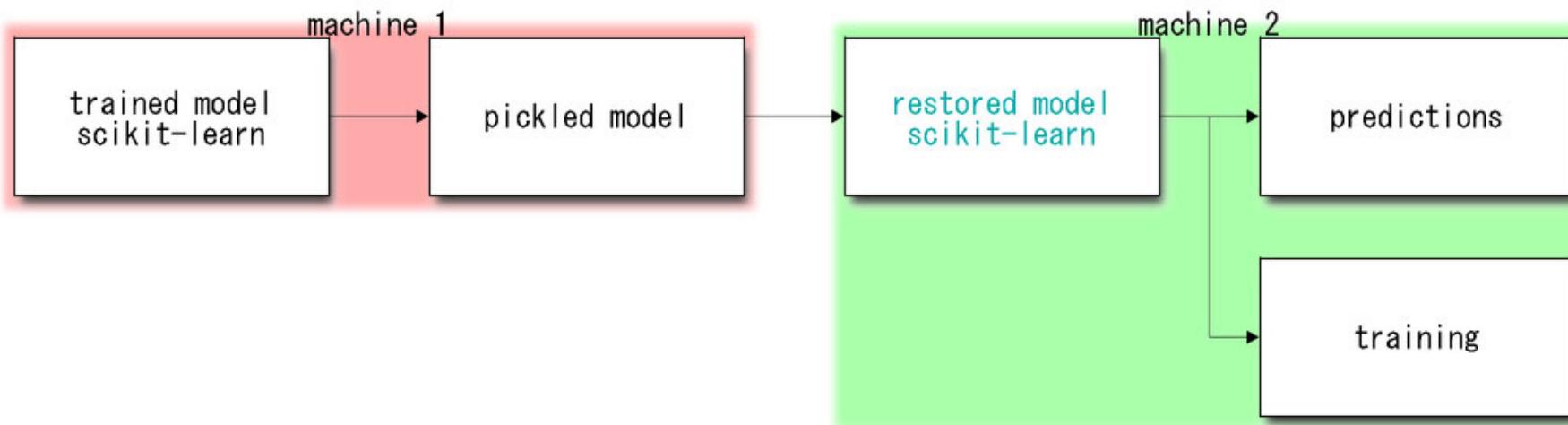
Everything in this presentation  
is **open source (MIT license)**  
and hosted on **github**.

# Plan

- Persistence and predictions
- ONNX specifications
- Conversion to ONNX
- Runtime / Benchmark
- Future Plans

# Persistence and Prediction

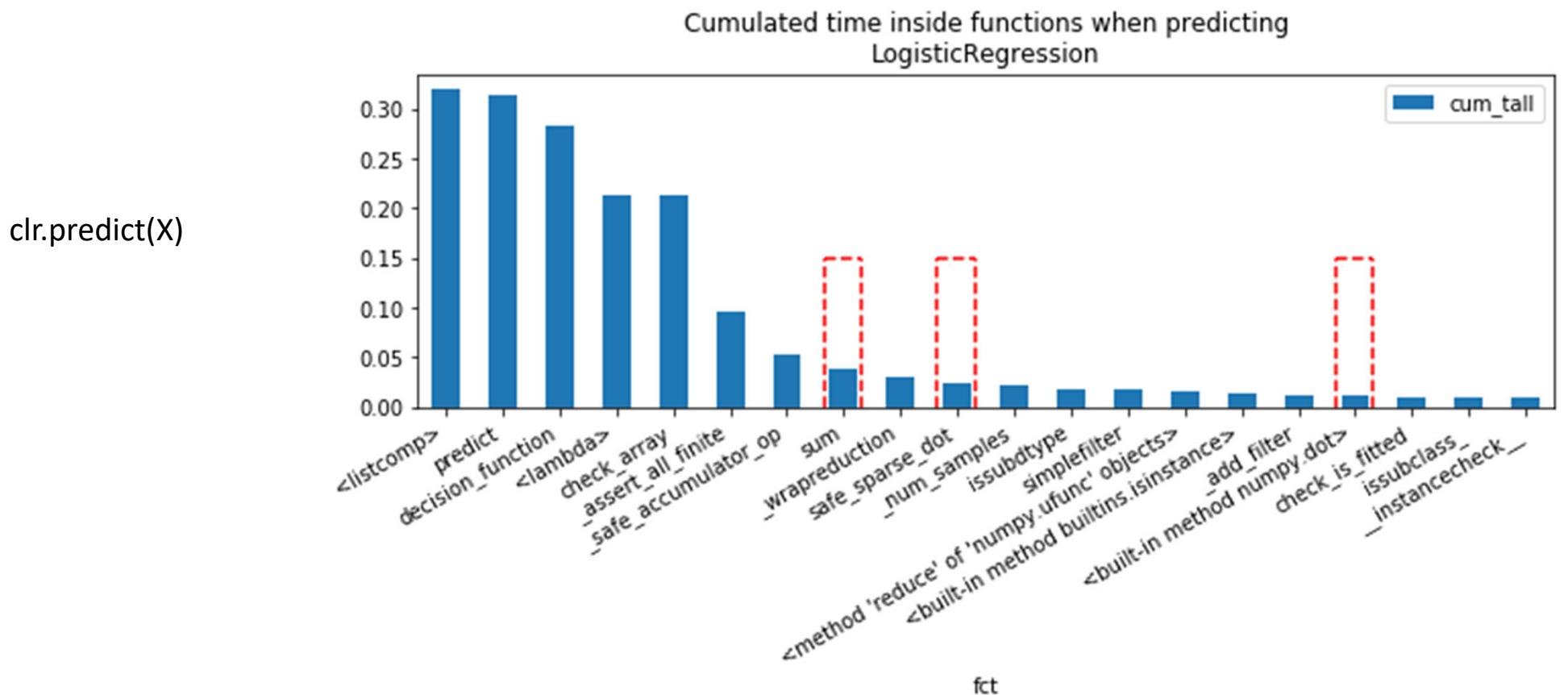
# Persistence with pickle



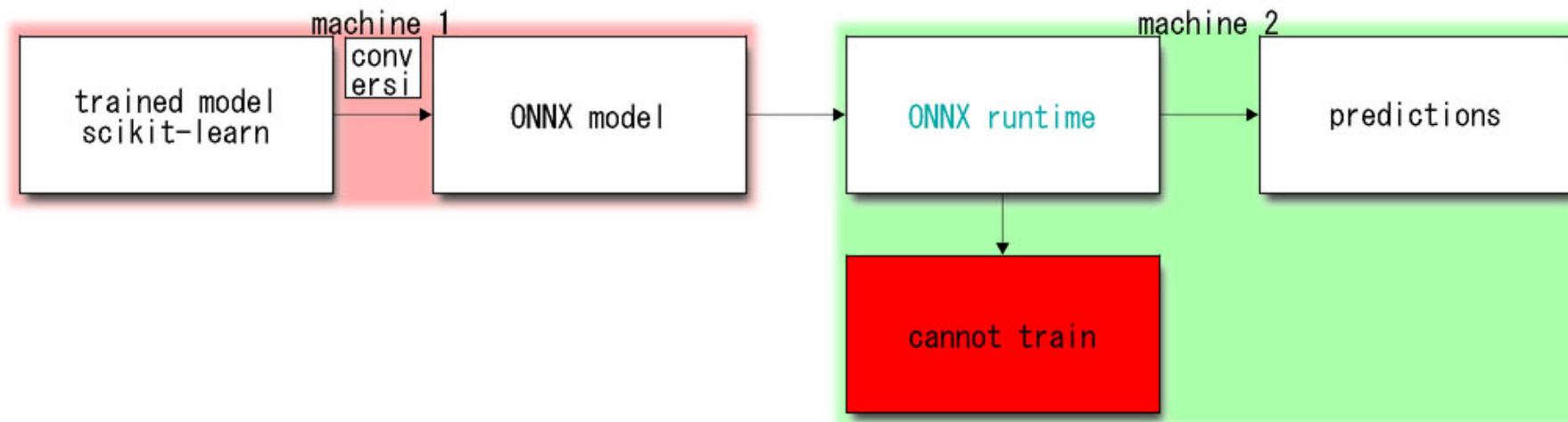
## Issues:

- Unpickle is unstable (python version...)
- Predictions are not fast (scikit-learn is optimized for batch predictions)

# With Iris: python >> cython



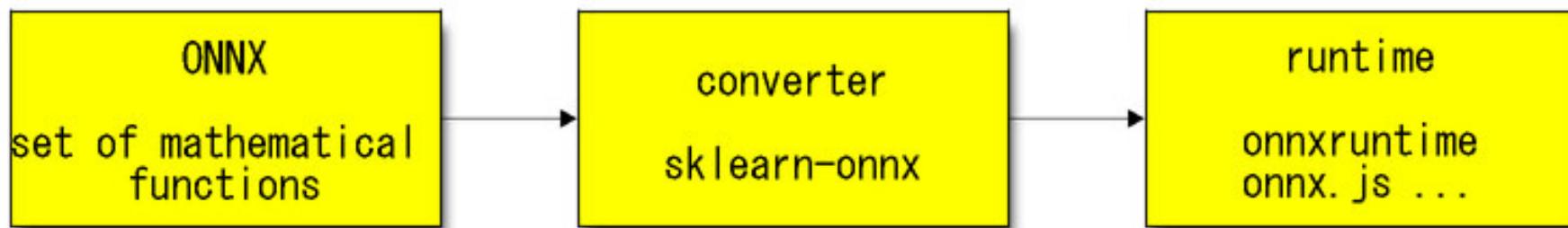
# Persistence with ONNX



ONNX...

- Is a serialization format based on protobuf
- Aims at describing any prediction function from machine learned models

# Three components for ONNX



# ONNX

- ONNX = **Set of mathematical operations** assembled into a **graph**.
- It is **versioned** and **stable**: backward compatibility.
- It is optimized for deep learning, it works with **single float**

# Simple function in ONNX

```
[1]: beta = np.random.randn(4, 3)
M = (X @ beta)
expM = np.exp(M)
pred = expM / (expM + 1)
pred[:5]
```

```
[1]: array([[0.0022439 , 0.60292776, 0.11036919],
       [0.00474268, 0.46085765, 0.15304197],
       [0.00367439, 0.5859233 , 0.13088156],
       [0.00469139, 0.54574802, 0.15141273],
       [0.00201307, 0.65597864, 0.10384264]])
```

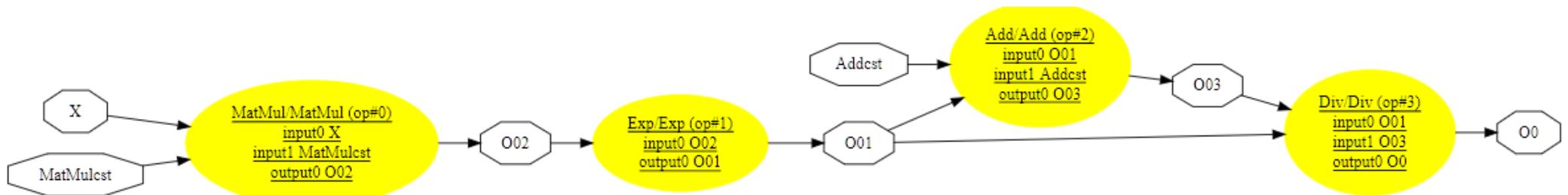
$f(X) = \dots$

```
: X32 = X.astype(np.float32)
beta32 = beta.astype(np.float32)

onnxExpM = OnnxExp(OnnxMatMul('X', beta32))

cst = np.ones((1, 3), dtype=np.float32)
onnxExpM1 = OnnxAdd(onnxExpM, cst)           # use of broadcasting

onnxPred = OnnxDiv(onnxExpM, onnxExpM1)
```



# Serialization, metadata

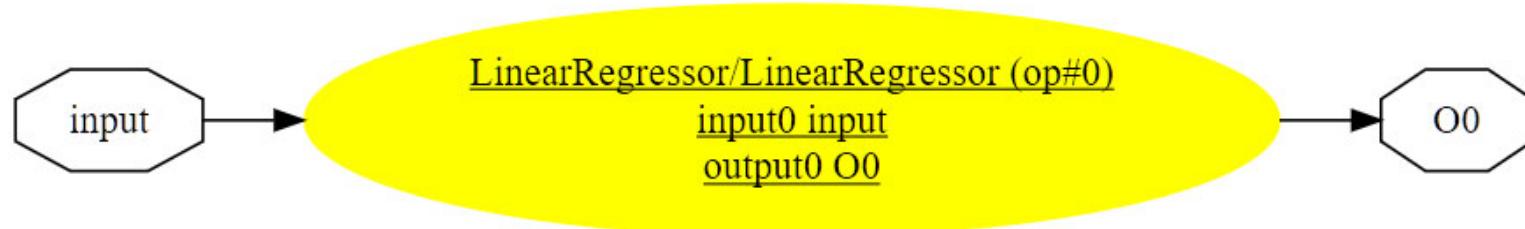
```
In [92]: with open("model-1.onnx", "wb") as f:  
    f.write(model_onnx.SerializeToString())
```

```
In [94]: import onnx  
model2 = onnx.load("model-1.onnx")
```

```
ir_version: 5  
producer_name: "skl2onnx"  
producer_version: "1.4.9999"  
domain: "ai.onnx"  
model_version: 0  
graph {  
    node {  
        input: "X"  
        input: "MatMulcst"  
        output: "O02"  
        name: "MatMul"  
        op_type: "MatMul"  
        domain: ""  
    }  
    node {  
        ...  
    }  
}
```

# Machine learning functions

```
lin_reg = OnnxLinearRegressor('input',  
                             coefficients=beta, targets=2)
```



# Conversion to ONNX

- Each library gets its converter libraries
- **sklearn-onnx for scikit-learn**

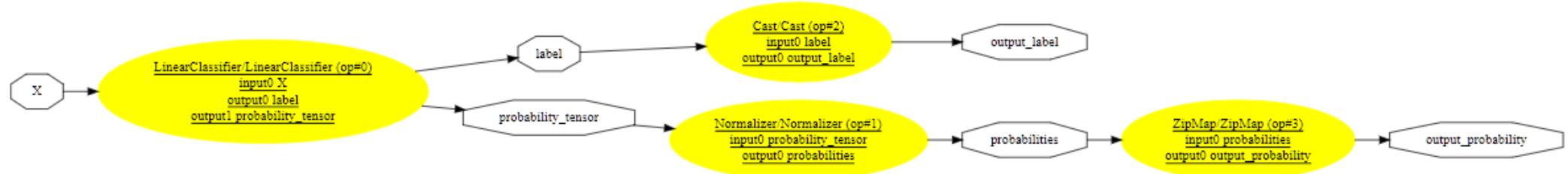
# Logistic Regression to ONNX

```
In [19]: clr = LogisticRegression(multi_class="auto", solver="liblinear").fit(X, y)
clr
```

```
Out[19]: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                           intercept_scaling=1, l1_ratio=None, max_iter=100,
                           multi_class='auto', n_jobs=None, penalty='l2',
                           random_state=None, solver='liblinear', tol=0.0001, verbose=0,
                           warm_start=False)
```

```
In [20]: from skl2onnx import to_onnx

model_onnx = to_onnx(clr, X.astype(np.float32))
```

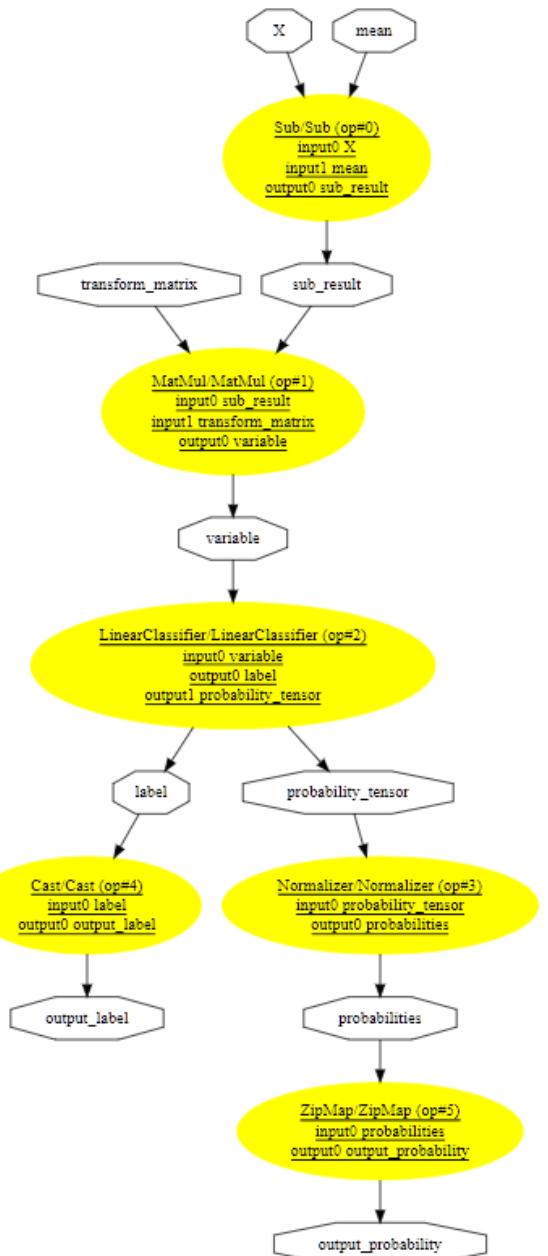


# Pipeline to ONNX

```
pipe = Pipeline([('pca', PCA(n_components=2)),
                 ('lr', LogisticRegression(multi_class="auto"))])
pipe.fit(X, y)
```

```
Pipeline(memory=None,
         steps=[('pca',
                 PCA(copy=True, iterated_power='auto', n_components=2,
                     random_state=None, svd_solver='auto', tol=0.0,
                     whiten=False))]
```

```
In [22]: model_onnx = to_onnx(pipe, X.astype(np.float32))
```



# Runtime

- Predict anywhere (CPU, GPU, ARM, js, ...)
- No dependency on the training framework
- A runtime implements a subset of the mathematical functions defined in ONNX.

# onnxruntime (by Microsoft)

- Runtime written in C++
- Available for CPU, GPU, ARM
- Binding for C, C++, C#, Python
- Use openmp, mkldnn, tensorrt, tvm, ngraph...

```
In [23]: from onnxruntime import InferenceSession
          sess = InferenceSession(model_onnx.SerializeToString())
          label, proba = sess.run(None, {'X': X32})
          label[:3]
Out[23]: array([0, 0, 0], dtype=int64)
```

# Benchmark: one-off prediction LR

```
In [75]: clr = LogisticRegression(multi_class="auto", solver="liblinear").fit(X, y)
```

```
In [76]: %timeit clr.predict_proba(X[:1])
```

```
59.7 µs ± 4.22 µs per loop (mean ± std. dev. of 7 runs, 10000 loops each)
```

```
In [77]: sess = InferenceSession(model_onnx.SerializeToString())
X32 = X.astype(np.float32)
%timeit sess.run(None, {'X': X32[:1]})
```

```
17.5 µs ± 521 ns per loop (mean ± std. dev. of 7 runs, 100000 loops each)
```

# Benchmark: one-off prediction RF

```
In [78]: clr = RandomForestClassifier(n_estimators=10).fit(X, y)
```

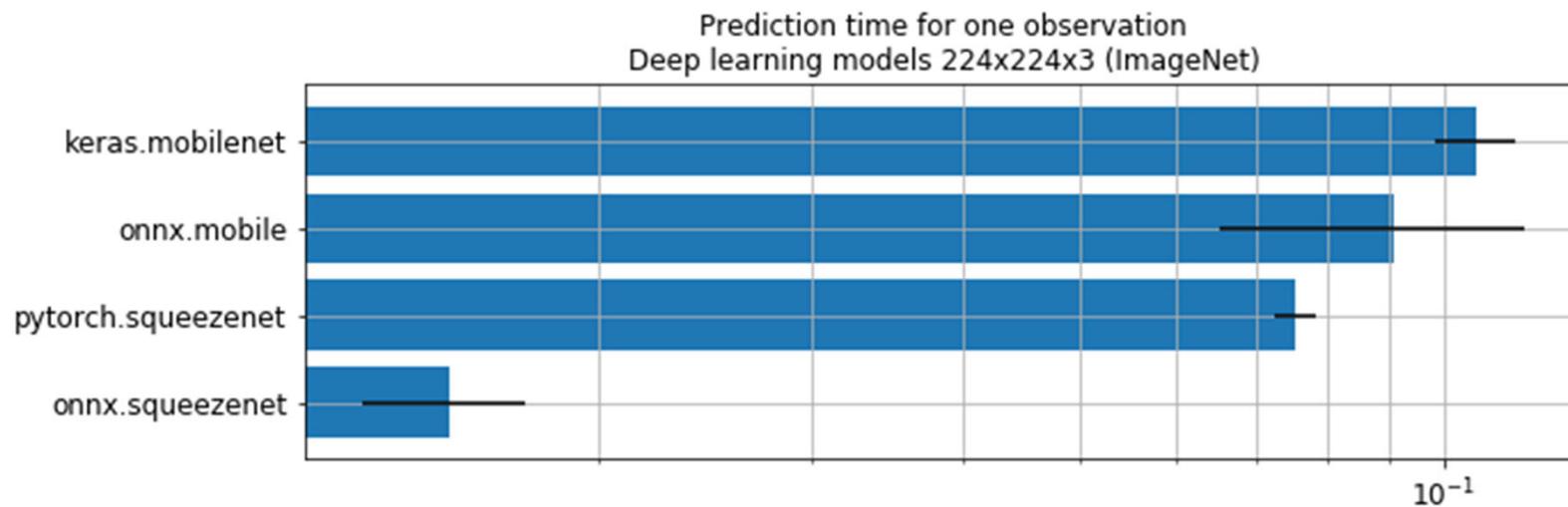
```
In [79]: %timeit clr.predict_proba(X[:1])
```

770 µs ± 85.3 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)

```
In [80]: sess = InferenceSession(model_onnx.SerializeToString())
X32 = X.astype(np.float32)
%timeit sess.run(None, {'X': X32[:1]})
```

18.4 µs ± 2.79 µs per loop (mean ± std. dev. of 7 runs, 100000 loops each)

# Benchmark: deep learning (CPU)



# Future plans

# Today

- Converters for main machine learned models in scikit-learn
- Possibility to add custom converters

# Next

- Support for sparse tensors
- Speed improvements
- Better documentation

---

[OnnxSklearnAdaBoostClassifier](#)

[OnnxSklearnLabelEncoder](#)

[OnnxSklearnRandomForestCl](#)

---

[OnnxSklearnAdaBoostRegressor](#)

[OnnxSklearnLasso](#)

[OnnxSklearnRandomForestRe](#)

---

[OnnxSklearnBernoulliNB](#)

[OnnxSklearnLassoLars](#)

[OnnxSklearnRidge](#)

---

[OnnxSklearnBinarizer](#)

[OnnxSklearnLinearRegression](#)

[OnnxSklearnRobustScaler](#)

---

[OnnxSklearnCalibratedClassifierCV](#)

[OnnxSklearnLinearSVC](#)

[OnnxSklearnSGDClassifier](#)

Thank you.

Any question: [xadupre@microsoft.com](mailto:xadupre@microsoft.com)