Large scale non-linear learning on a single CPU

Andreas Mueller
NYU / scikit-learn

- Large Scale – “Out of core: Fits on a hard disk but in RAM”

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- Non-linear – because real-world problems are not.

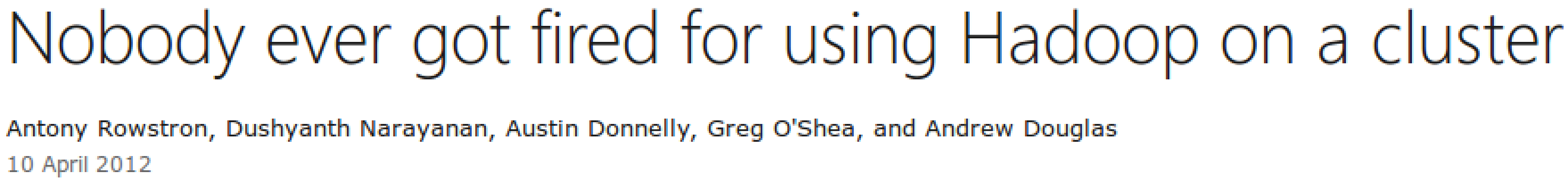
- Single CPU – Because parallelization is hard (and often unnecessary)

Three regimes of data

- Fits in RAM
- Fits on a Hard Drive
- Doesn't fit on a single PC

Three regimes of data

- Fits in RAM (up to 256 GB?)
- Fits on a Hard Drive (up to 6TB?)
- Doesn't fit on a single PC



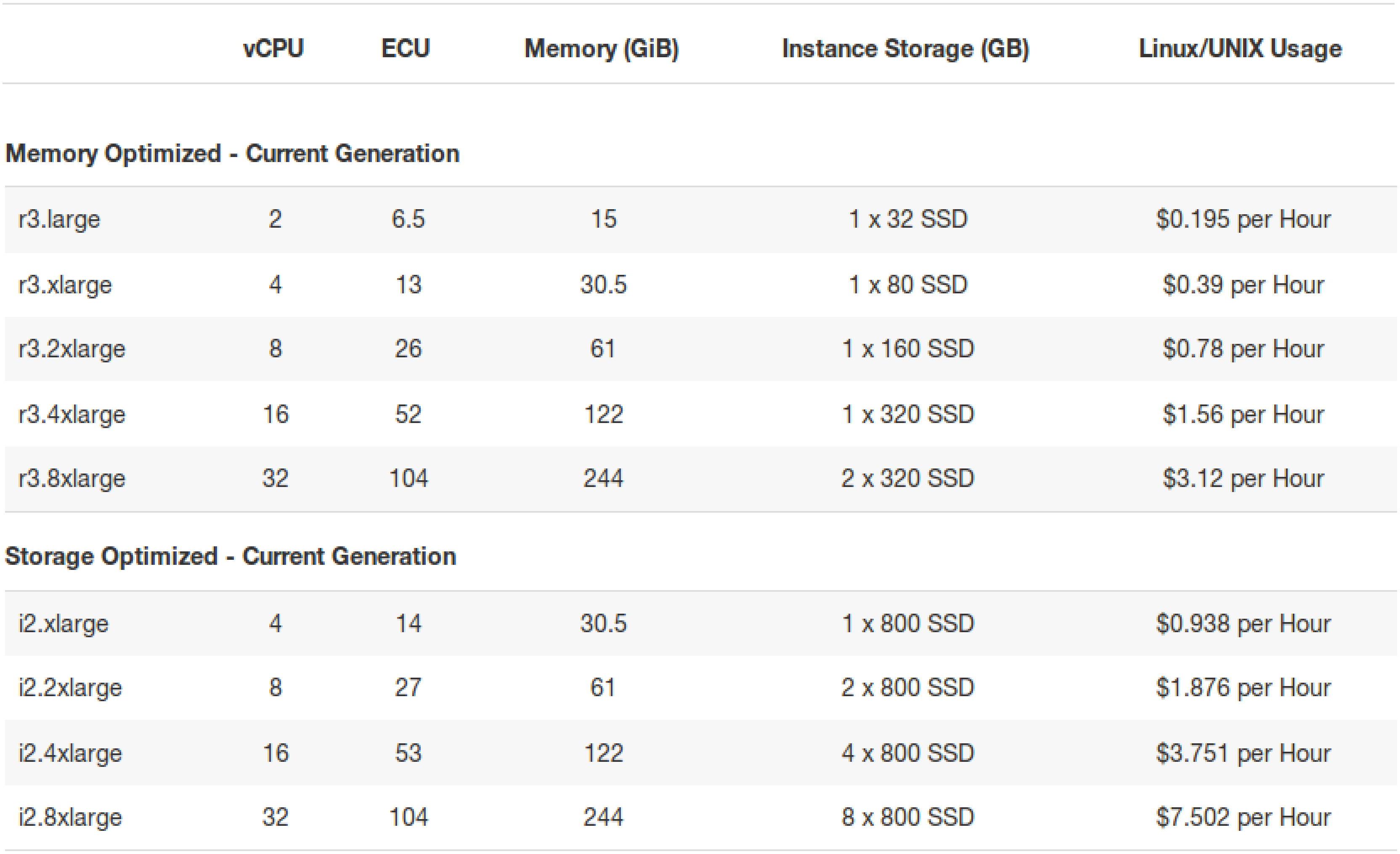
Nobody ever got fired for using Hadoop on a cluster

Antony Rowstron, Dushyanth Narayanan, Austin Donnelly, Greg O'Shea, and Andrew Douglas

10 April 2012

Why not do to out of core learning.

Your data is not that big!



	vCPU	ECU	Memory (GiB)	Instance Storage (GB)	Linux/UNIX Usage
Memory Optimized - Current Generation					
r3.large	2	6.5	15	1 x 32 SSD	$0.195 per Hour
r3.xlarge	4	13	30.5	1 x 80 SSD	$0.39 per Hour
r3.2xlarge	8	26	61	1 x 160 SSD	$0.78 per Hour
r3.4xlarge	16	52	122	1 x 320 SSD	$1.56 per Hour
r3.8xlarge	32	104	244	2 x 320 SSD	$3.12 per Hour
Storage Optimized - Current Generation					
i2.xlarge	4	14	30.5	1 x 800 SSD	$0.938 per Hour
i2.2xlarge	8	27	61	2 x 800 SSD	$1.876 per Hour
i2.4xlarge	16	53	122	4 x 800 SSD	$3.751 per Hour
i2.8xlarge	32	104	244	8 x 800 SSD	$7.502 per Hour

"256Gb ought to be enough for anybody."

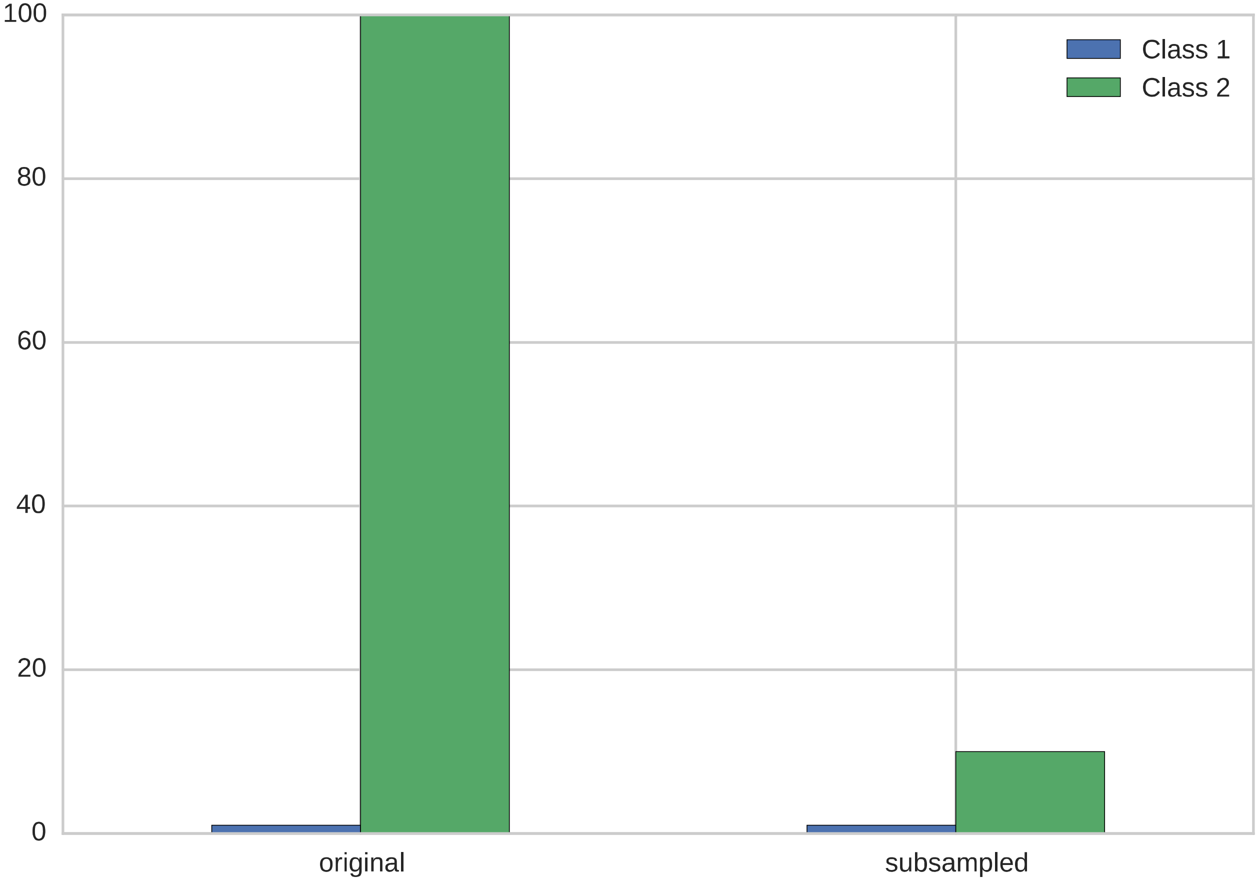
- me

"256Gb ought to be enough for anybody."
- me

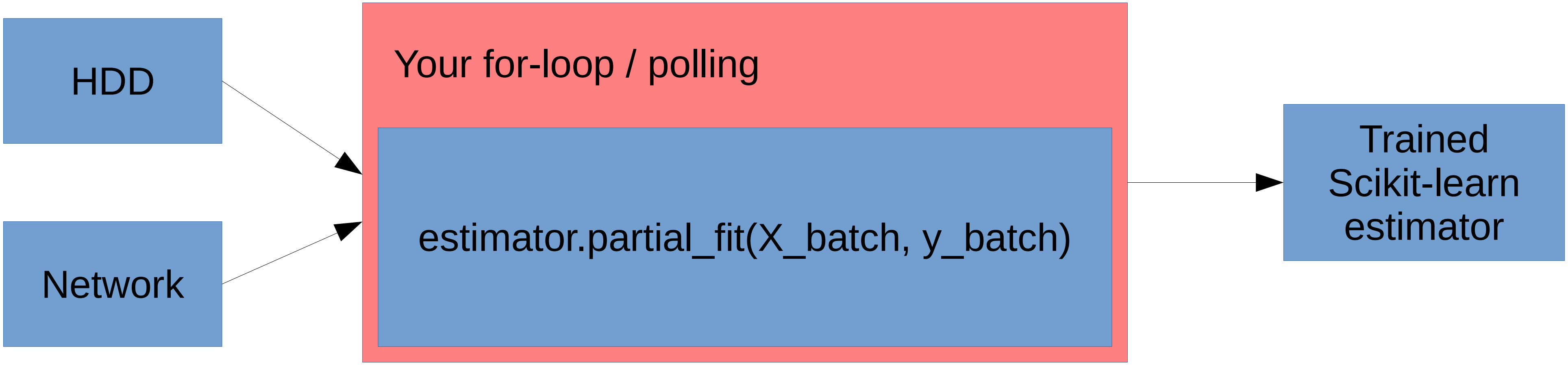
(for machine learning)

Subsample!

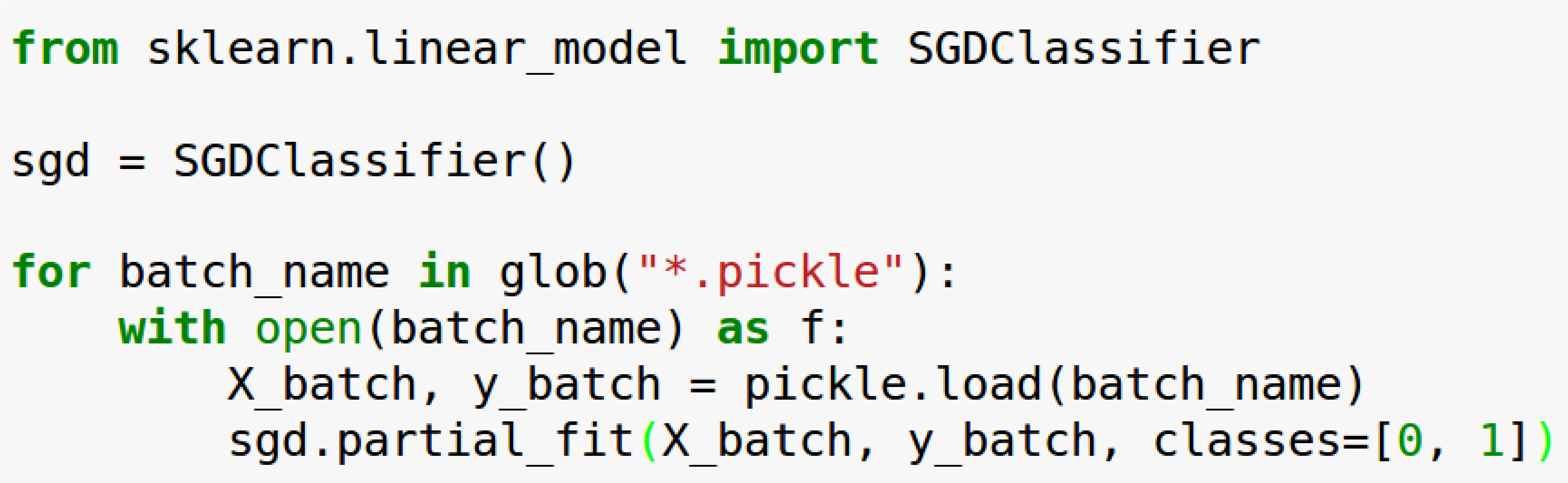
Subsample!



The scikit-learn way

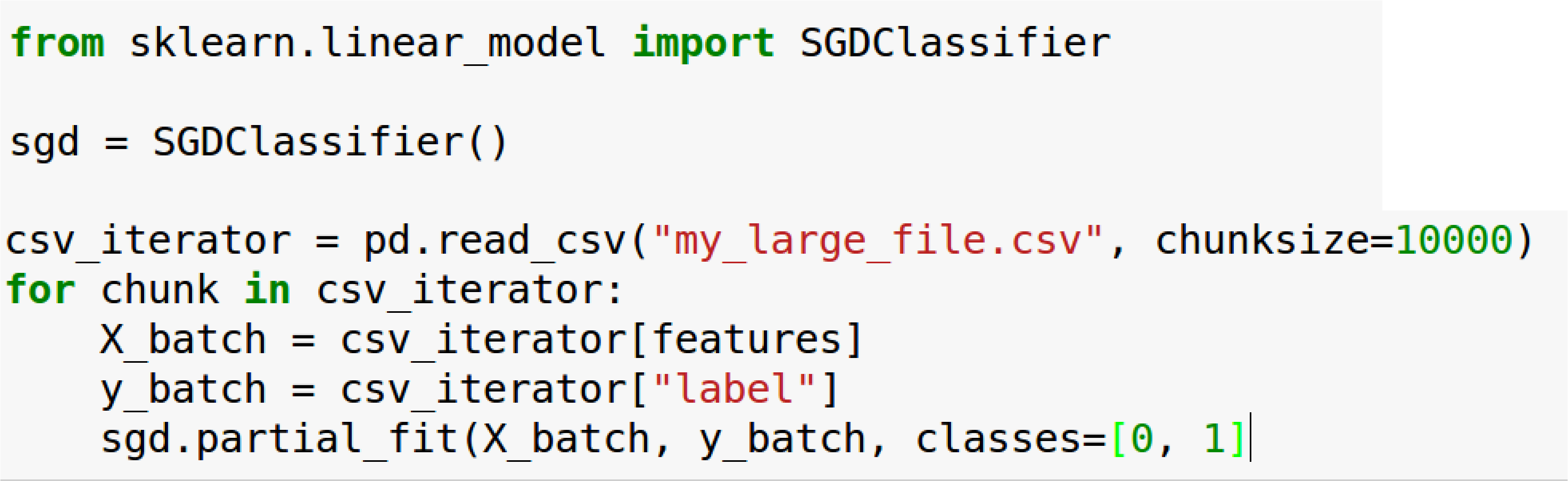

HDD
Network
Your for-loop / polling
estimator.partial_fit(X_batch, y_batch)
Trained Scikit-learn estimator

Linear Classification



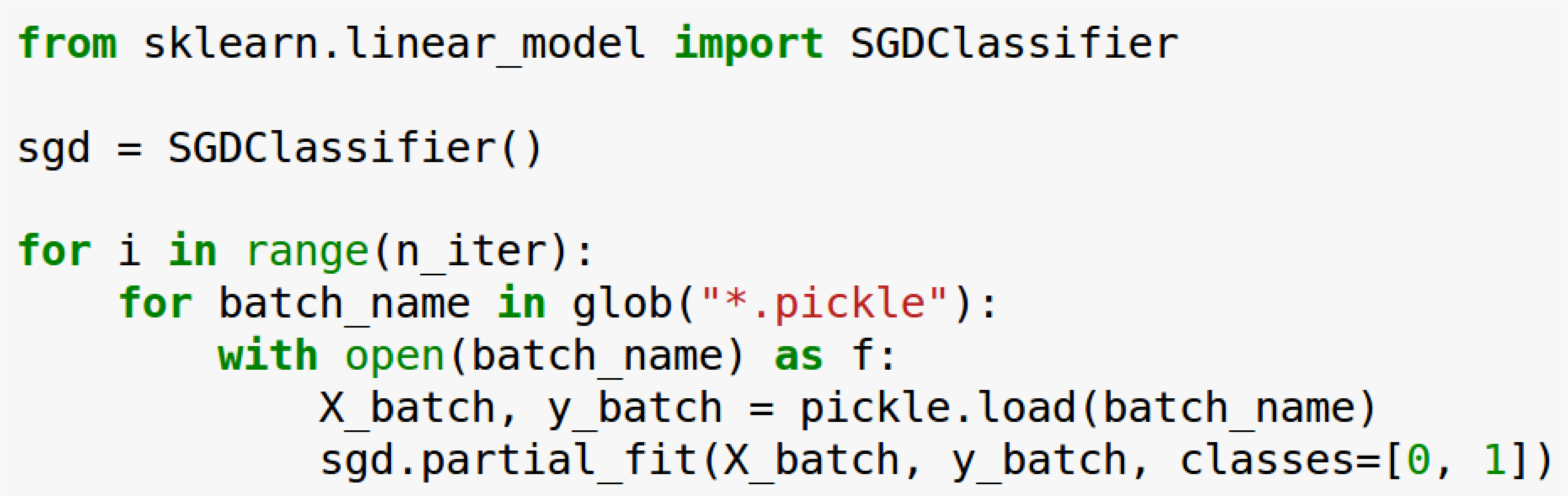
```python
from sklearn.linear_model import SGDClassifier

sgd = SGDClassifier()

for batch_name in glob("*.pickle"):
    with open(batch_name) as f:
        X_batch, y_batch = pickle.load(batch_name)
        sgd.partial_fit(X_batch, y_batch, classes=[0, 1])
```

Linear Classification



```
from sklearn.linear_model import SGDClassifier

sgd = SGDClassifier()

csv_iterator = pd.read_csv("my_large_file.csv", chunksize=10000)
for chunk in csv_iterator:
    X_batch = csv_iterator[features]
    y_batch = csv_iterator["label"]
    sgd.partial_fit(X_batch, y_batch, classes=[0, 1]
```

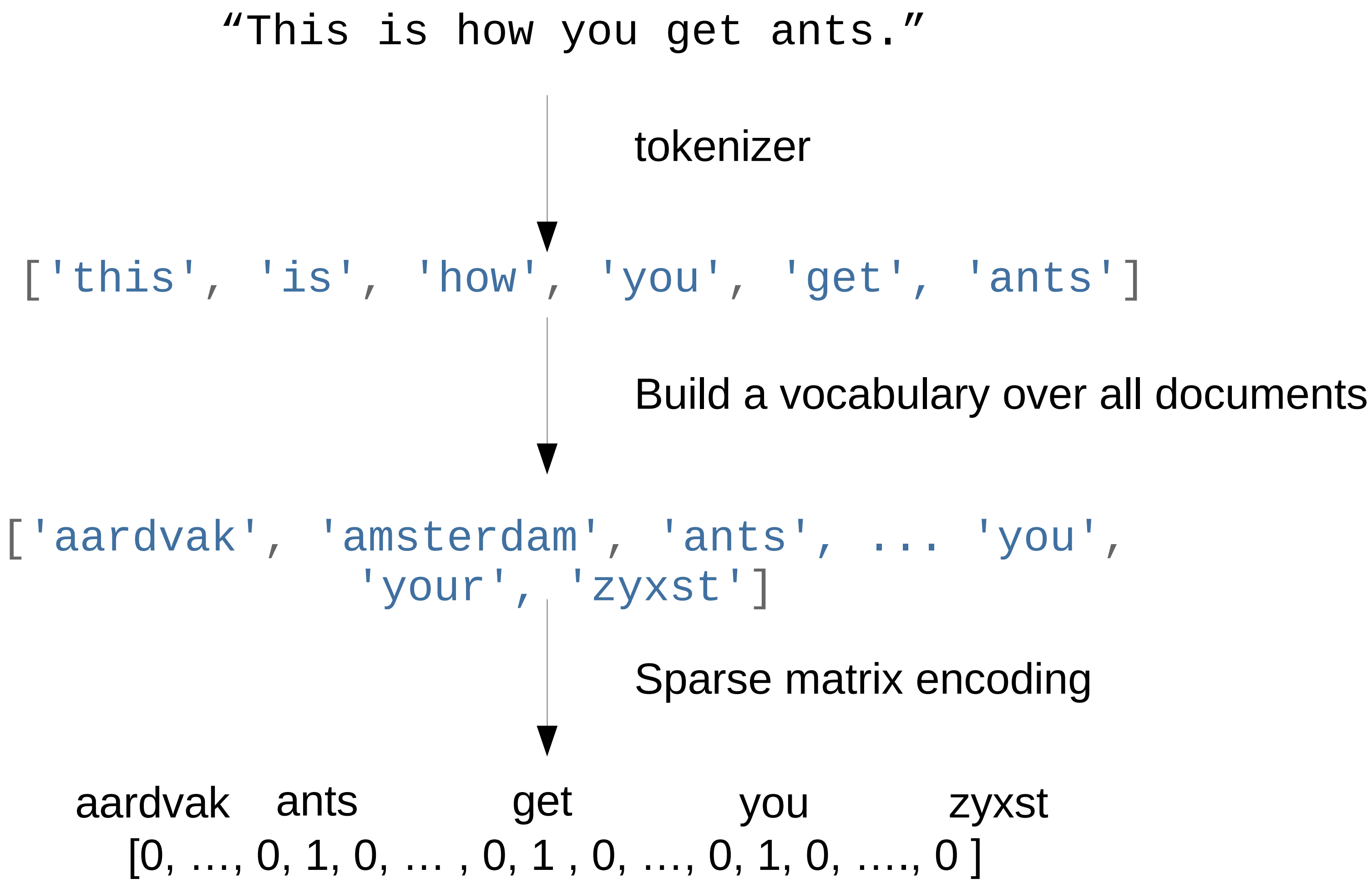
Linear Classification



```python
from sklearn.linear_model import SGDClassifier

sgd = SGDClassifier()

for i in range(n_iter):
    for batch_name in glob("*.pickle"):
        with open(batch_name) as f:
            X_batch, y_batch = pickle.load(batch_name)
            sgd.partial_fit(X_batch, y_batch, classes=[0, 1])
```

1st nonlinear option: Stateless Transformers

Text Classification: Bag Of Word



“This is how you get ants.”

tokenizer

['this', 'is', 'how', 'you', 'get', 'ants']

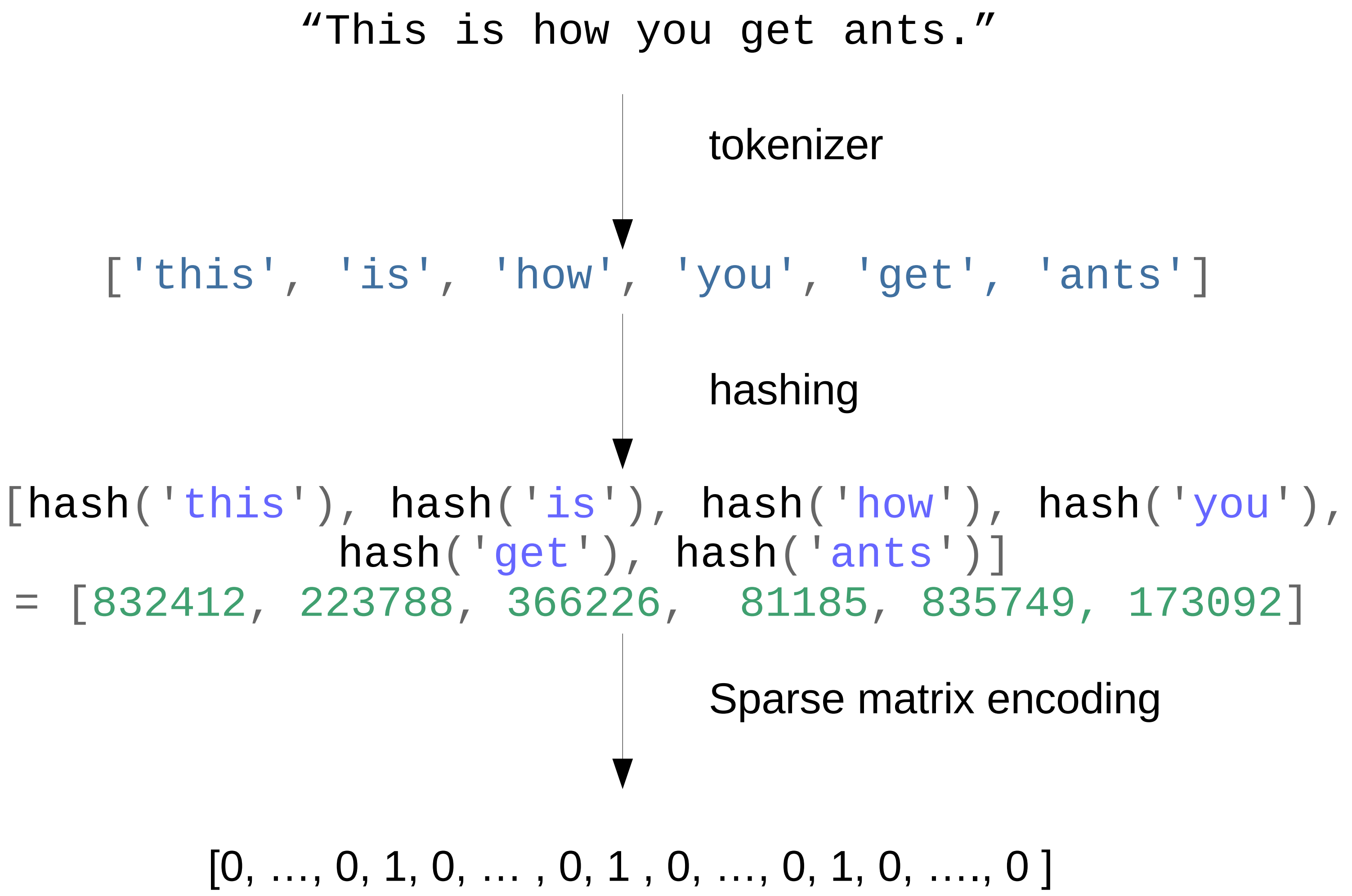
Build a vocabulary over all documents

['aardvak', 'amsterdam', 'ants', ... 'you', 'your', 'zyxst']

Sparse matrix encoding

```
aardvak   ants          get          you          zyxst
   [0, …, 0, 1, 0, … , 0, 1 , 0, …, 0, 1, 0, …., 0 ]
```

Text Classification: Hashing Trick



```
“This is how you get ants.”
```

tokenizer

```
['this', 'is', 'how', 'you', 'get', 'ants']
```

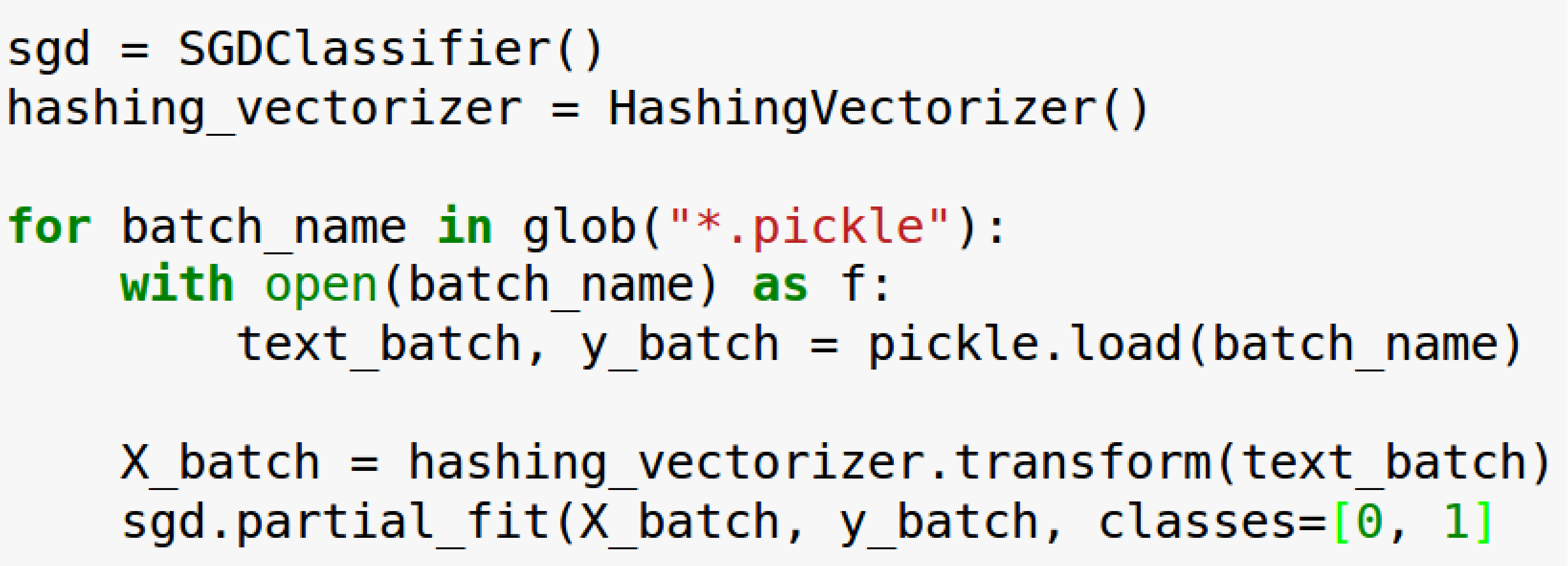
hashing

```
[hash('this'), hash('is'), hash('how'), hash('you'),
             hash('get'), hash('ants')]
= [832412, 223788, 366226,  81185, 835749, 173092]
```

Sparse matrix encoding

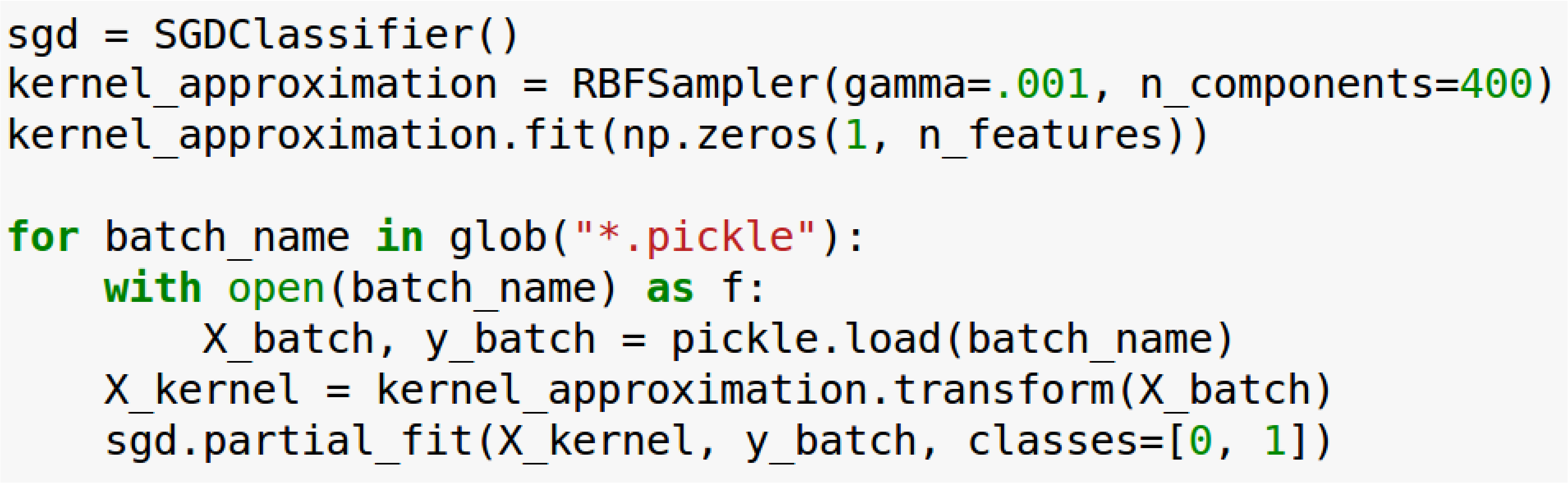
[0, …, 0, 1, 0, … , 0, 1 , 0, …, 0, 1, 0, …., 0]

Text Classification: Hashing Trick



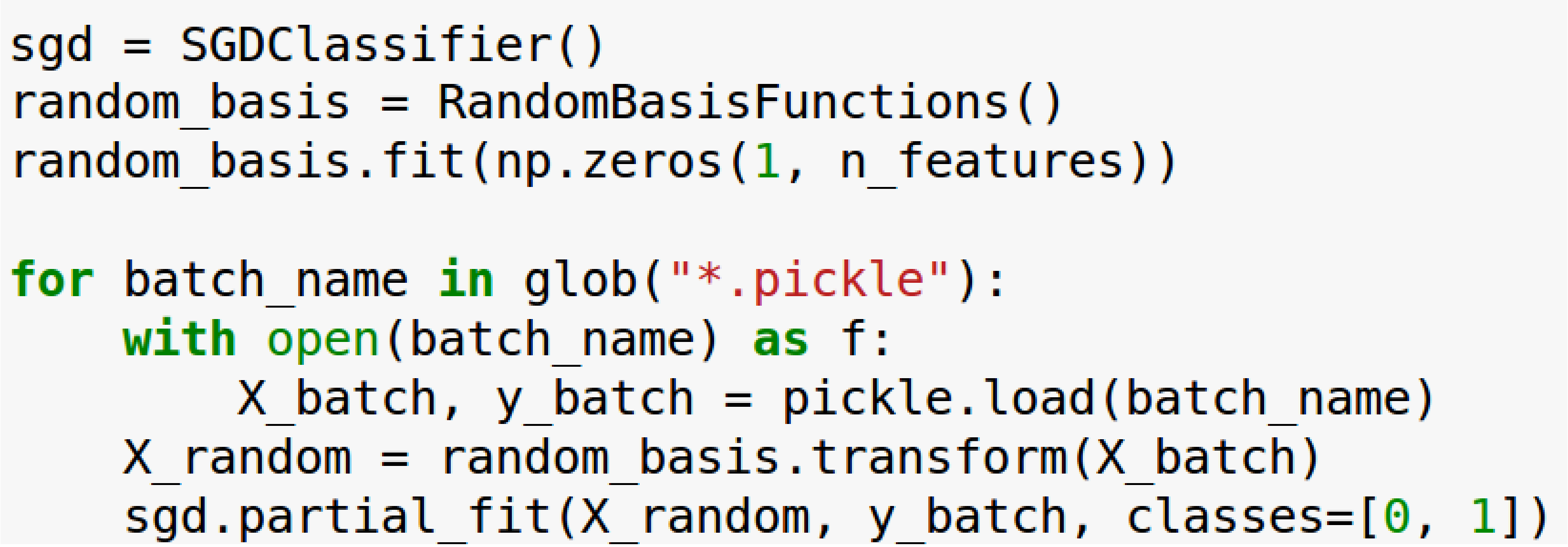
```python
sgd = SGDClassifier()
hashing_vectorizer = HashingVectorizer()

for batch_name in glob("*.pickle"):
    with open(batch_name) as f:
        text_batch, y_batch = pickle.load(batch_name)

    X_batch = hashing_vectorizer.transform(text_batch)
    sgd.partial_fit(X_batch, y_batch, classes=[0, 1])
```

Kernel Approximation



```
sgd = SGDClassifier()
kernel_approximation = RBFSampler(gamma=.001, n_components=400)
kernel_approximation.fit(np.zeros(1, n_features))

for batch_name in glob("*.pickle"):
    with open(batch_name) as f:
        X_batch, y_batch = pickle.load(batch_name)
    X_kernel = kernel_approximation.transform(X_batch)
    sgd.partial_fit(X_kernel, y_batch, classes=[0, 1])
```

Random Neural Nets

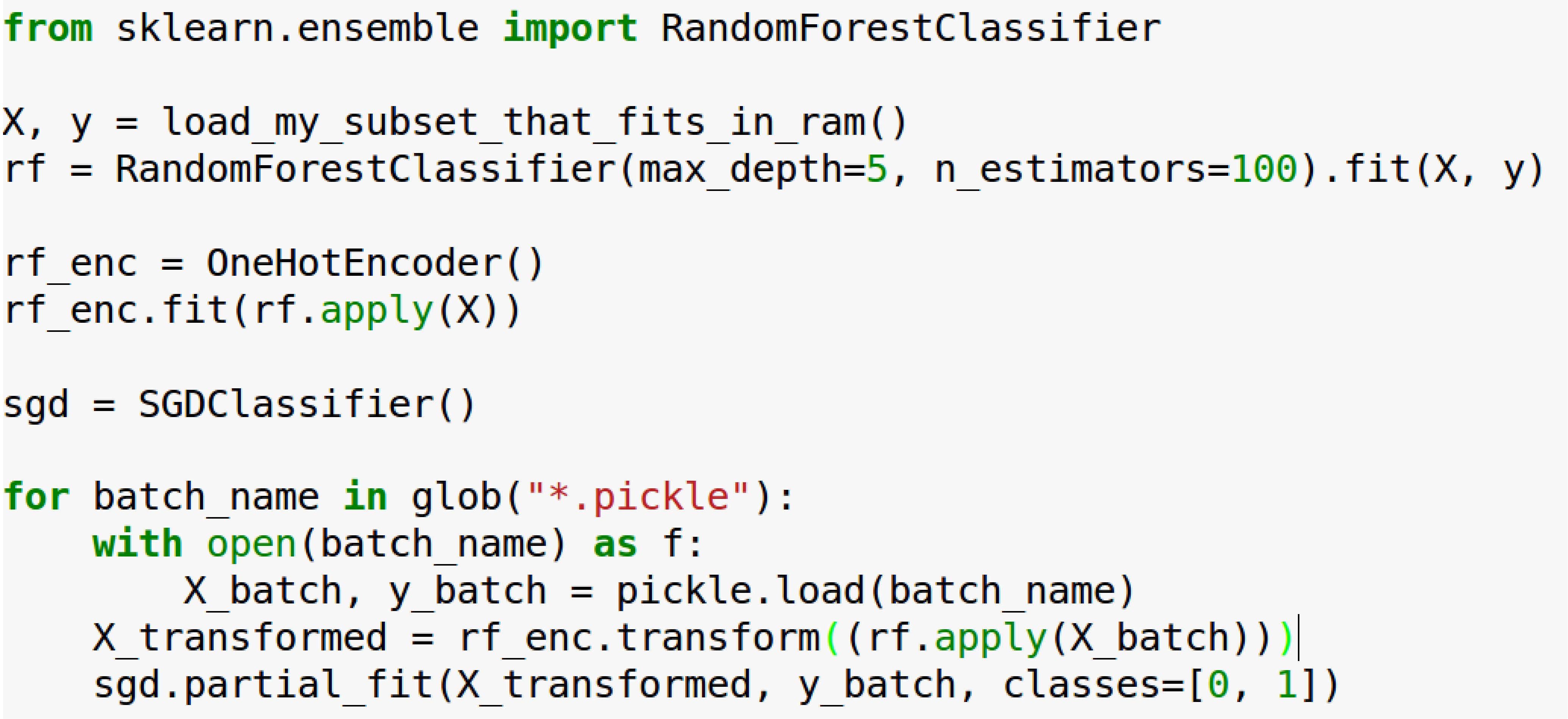


```
sgd = SGDClassifier()
random_basis = RandomBasisFunctions()
random_basis.fit(np.zeros(1, n_features))

for batch_name in glob("*.pickle"):
    with open(batch_name) as f:
        X_batch, y_batch = pickle.load(batch_name)
    X_random = random_basis.transform(X_batch)
    sgd.partial_fit(X_random, y_batch, classes=[0, 1])
```

(not merged yet)

2nd nonlinear option: Learn Transformations on Subsets

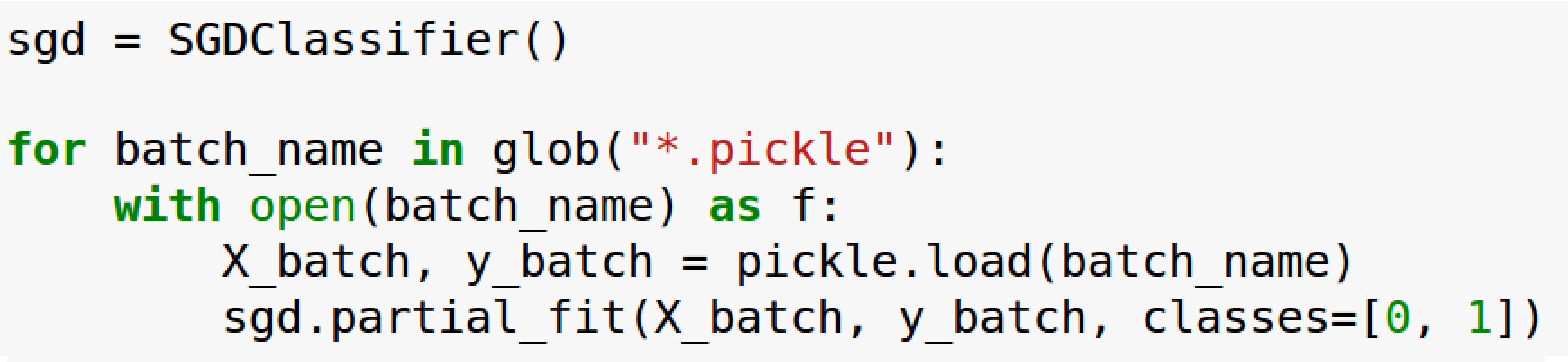
RandomForests



```python
from sklearn.ensemble import RandomForestClassifier

X, y = load_my_subset_that_fits_in_ram()
rf = RandomForestClassifier(max_depth=5, n_estimators=100).fit(X, y)

rf_enc = OneHotEncoder()
rf_enc.fit(rf.apply(X))

sgd = SGDClassifier()

for batch_name in glob("*.pickle"):
    with open(batch_name) as f:
        X_batch, y_batch = pickle.load(batch_name)
    X_transformed = rf_enc.transform((rf.apply(X_batch)))
    sgd.partial_fit(X_transformed, y_batch, classes=[0, 1])
```

3rd nonlinear option: Online Nonlinear Classification

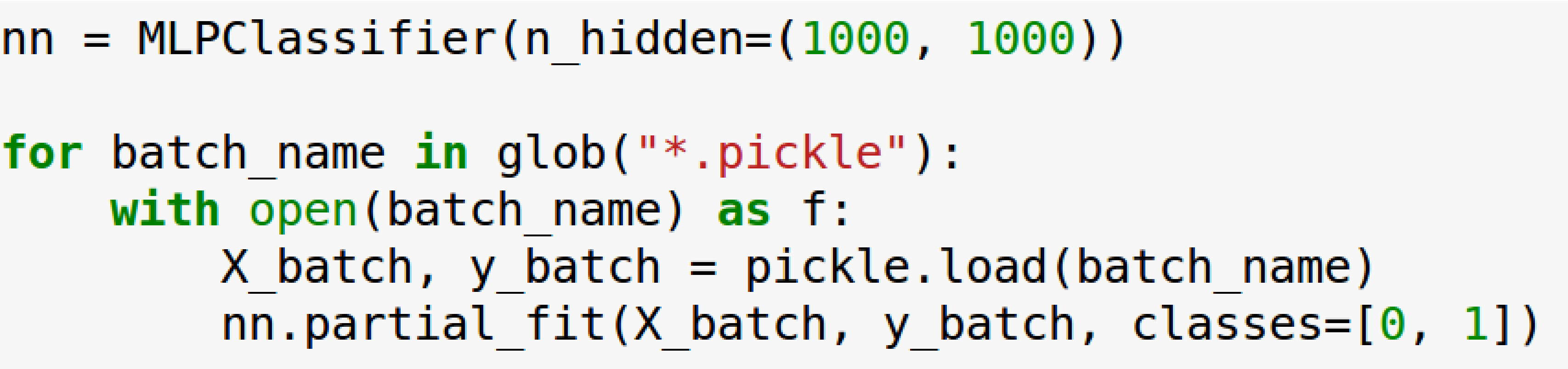
Neural Networks (MLPs)



```python
sgd = SGDClassifier()

for batch_name in glob("*.pickle"):
    with open(batch_name) as f:
        X_batch, y_batch = pickle.load(batch_name)
        sgd.partial_fit(X_batch, y_batch, classes=[0, 1])
```

(not merged yet)

Neural Networks (MLPs)



```
nn = MLPClassifier(n_hidden=(1000, 1000))

for batch_name in glob("*.pickle"):
    with open(batch_name) as f:
        X_batch, y_batch = pickle.load(batch_name)
        nn.partial_fit(X_batch, y_batch, classes=[0, 1])
```

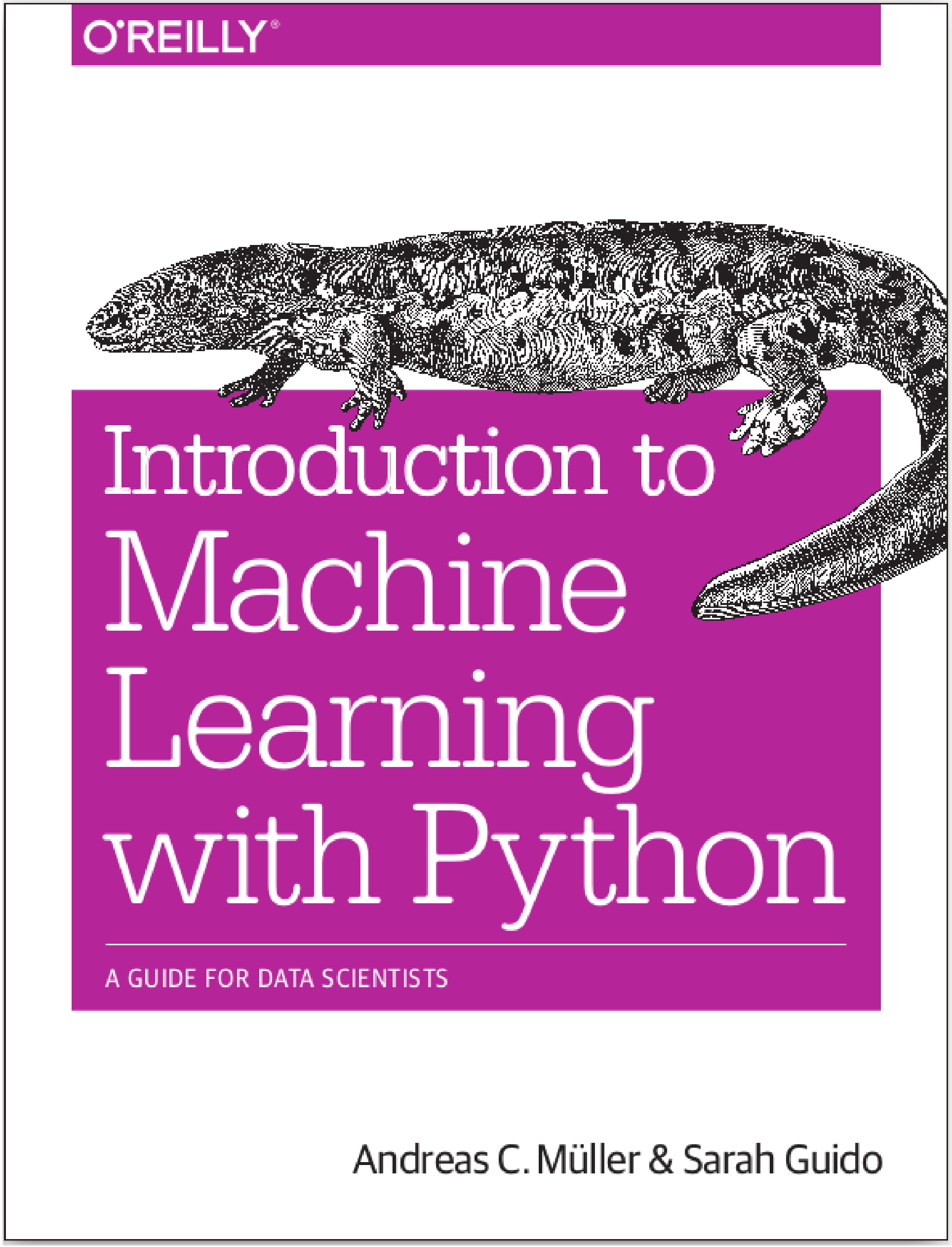
(not merged yet)

Other algorithms

- Naive Bayes
- `MinibatchKMeans`
- `Birch`
- `IncrementalPCA`
- `MiniBatchDictionaryLearning`
- `Scalers`
- `...`

What Else is Out There?

- Vowpal Wabbit (VW)
- More deep learning
- Hogwild!



O'REILLY®

Introduction to Machine Learning with Python

A GUIDE FOR DATA SCIENTISTS

Andreas C. Müller & Sarah Guido

Release June 2016

Thank you!

(and talk to me if you still think you need a cluster for ML)

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