10 minutes to Koalas

This is a short introduction to Koalas, geared mainly for new users. This notebook shows you some key differences between pandas and Koalas. You can run this examples by yourself on a live notebook here (https://mybinder.org/v2/gh/databricks/koalas/master?filepath=docs%2Fsource%2Fgetting_started%2F10min.ipynb). For Databricks users, you can import the current .ipynb file (https://raw.githubusercontent.com/databricks/koalas/master/docs/source/getting_started/10min.ipynb) and run it after installing Koalas (https://github.com/databricks/koalas#how-do-i-use-this-on-databricks).

Customarily, we import Koalas as follows:

In [1]:

```
import pandas as pd
import numpy as np
import databricks.koalas as ks
from pyspark.sql import SparkSession
```

Object Creation

Creating a Koalas Series by passing a list of values, letting Koalas create a default integer index:

In [2]:

```
s = ks.Series([1, 3, 5, np.nan, 6, 8])
```

In [3]:

```
s
```

Out[3]:

```
0    1.0
1    3.0
2    5.0
3    NaN
4    6.0
5    8.0
Name: 0, dtype: float64
```

Creating a Koalas DataFrame by passing a dict of objects that can be converted to series-like.

In [4]:

```
kdf = ks.DataFrame(
    {'a': [1, 2, 3, 4, 5, 6],
     'b': [100, 200, 300, 400, 500, 600],
     'c': ["one", "two", "three", "four", "five", "six"]},
    index=[10, 20, 30, 40, 50, 60])
```

In [5]:

```
kdf
```

Out[5]:

	a	b	c
10	1	100	one
20	2	200	two
30	3	300	three
40	4	400	four
50	5	500	five
60	6	600	six

Creating a pandas DataFrame by passing a numpy array, with a datetime index and labeled columns:

In [6]:

```
dates = pd.date_range('20130101', periods=6)
```

In [7]:

```
dates
```

Out[7]:

```
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-0
4',
               '2013-01-05', '2013-01-06'],
              dtype='datetime64[ns]', freq='D')
```

In [8]:

```
pdf = pd.DataFrame(np.random.randn(6, 4), index=dates, columns=list('ABCD'))
```

In [9]:

```
pdf
```

Out[9]:

	A	B	C	D
2013-01-01	-0.407291	0.066551	-0.073149	0.648219
2013-01-02	-0.848735	0.437277	0.632657	0.312861
2013-01-03	-0.415537	-1.787072	0.242221	0.125543
2013-01-04	-1.637271	1.134810	0.282532	0.133995
2013-01-05	-1.230477	-1.925734	0.736288	-0.547677
2013-01-06	1.092894	-1.071281	0.318752	-0.477591

Now, this pandas DataFrame can be converted to a Koalas DataFrame

In [10]:

```
kdf = ks.from_pandas(pdf)
```

In [11]:

```
type(kdf)
```

Out[11]:

```
databricks.koalas.frame.DataFrame
```

It looks and behaves the same as a pandas DataFrame though

In [12]:

```
kdf
```

Out[12]:

	A	B	C	D
2013-01-01	-0.407291	0.066551	-0.073149	0.648219
2013-01-02	-0.848735	0.437277	0.632657	0.312861
2013-01-03	-0.415537	-1.787072	0.242221	0.125543
2013-01-04	-1.637271	1.134810	0.282532	0.133995
2013-01-05	-1.230477	-1.925734	0.736288	-0.547677
2013-01-06	1.092894	-1.071281	0.318752	-0.477591

Also, it is possible to create a Koalas DataFrame from Spark DataFrame.

Creating a Spark DataFrame from pandas DataFrame

In [13]:

```
spark = SparkSession.builder.getOrCreate()
```

In [14]:

```
sdf = spark.createDataFrame(pdf)
```

In [15]:

```
sdf.show()
```

```
+--------------------+-------------------+--------------------+-----
--------------+
|                   A|                  B|                   C|
D|
+--------------------+-------------------+--------------------+-----
--------------+
|-0.40729126067930577|0.06655086061836445|-0.07314878758440578| 0.64
82187447085683|
|  -0.848735274668907|0.43727685786558224|  0.6326566086816865|  0.3
12860815784838|
|-0.41553692955141575|-1.7870717259038067| 0.24222142308402184|  0.1
25543462922973|
|  -1.637270523583917| 1.1348099198020765|  0.2825324338895592|0.133
99483028402598|
| -1.2304766522352943|-1.9257342346663335|  0.7362879432261002|-0.54
76765308367703|
|  1.0928943198263723|-1.0712812856772376| 0.31875224896792975|-0.47
75906715060247|
+--------------------+-------------------+--------------------+-----
--------------+
```

Creating Koalas DataFrame from Spark DataFrame. `to_koalas()` is automatically attached to Spark DataFrame and available as an API when Koalas is imported.

In [16]:

```
kdf = sdf.to_koalas()
```

In [17]:

```
kdf
```

Out[17]:

	A	B	C	D
0	-0.407291	0.066551	-0.073149	0.648219
1	-0.848735	0.437277	0.632657	0.312861
2	-0.415537	-1.787072	0.242221	0.125543
3	-1.637271	1.134810	0.282532	0.133995
4	-1.230477	-1.925734	0.736288	-0.547677
5	1.092894	-1.071281	0.318752	-0.477591

Having specific [dtypes (http://pandas.pydata.org/pandas-docs/stable/basics.html#basics-dtypes)](http://pandas.pydata.org/pandas-docs/stable/basics.html#basics-dtypes) . Types that are common to both Spark and pandas are currently supported.

In [18]:

```
kdf.dtypes
```

Out[18]:

```
A    float64
B    float64
C    float64
D    float64
dtype: object
```

Viewing Data

See the [API Reference (https://koalas.readthedocs.io/en/latest/reference/index.html)](https://koalas.readthedocs.io/en/latest/reference/index.html).

See the top rows of the frame. The results may not be the same as pandas though: unlike pandas, the data in a Spark dataframe is not *ordered*, it has no intrinsic notion of index. When asked for the head of a dataframe, Spark will just take the requested number of rows from a partition. Do not rely on it to return specific rows, use `.loc` or `iloc` instead.

In [19]:

```
kdf.head()
```

Out[19]:

	A	B	C	D
0	-0.407291	0.066551	-0.073149	0.648219
1	-0.848735	0.437277	0.632657	0.312861
2	-0.415537	-1.787072	0.242221	0.125543
3	-1.637271	1.134810	0.282532	0.133995
4	-1.230477	-1.925734	0.736288	-0.547677

Display the index, columns, and the underlying numpy data.

You can also retrieve the index; the index column can be ascribed to a DataFrame, see later

In [20]:

```
kdf.index
```

Out[20]:

```
Int64Index([0, 1, 2, 3, 4, 5], dtype='int64')
```

In [21]:

```
kdf.columns
```

Out[21]:

```
Index(['A', 'B', 'C', 'D'], dtype='object')
```

In [22]:

```
kdf.to_numpy()
```

Out[22]:

```
array([[-0.40729126,  0.06655086, -0.07314879,  0.64821874],
       [-0.84873527,  0.43727686,  0.63265661,  0.31286082],
       [-0.41553693, -1.78707173,  0.24222142,  0.12554346],
       [-1.63727052,  1.13480992,  0.28253243,  0.13399483],
       [-1.23047665, -1.92573423,  0.73628794, -0.54767653],
       [ 1.09289432, -1.07128129,  0.31875225, -0.47759067]])
```

Describe shows a quick statistic summary of your data

In [23]:

```
kdf.describe()
```

Out[23]:

	A	B	C	D
count	6.000000	6.000000	6.000000	6.000000
mean	-0.574403	-0.524242	0.356550	0.032558
std	0.945349	1.255721	0.291566	0.463350
min	-1.637271	-1.925734	-0.073149	-0.547677
25%	-1.230477	-1.787072	0.242221	-0.477591
50%	-0.848735	-1.071281	0.282532	0.125543
75%	-0.407291	0.437277	0.632657	0.312861
max	1.092894	1.134810	0.736288	0.648219

Transposing your data

In [24]:

```
kdf.T
```

Out[24]:

	0	1	2	3	4	5
A	-0.407291	-0.848735	-0.415537	-1.637271	-1.230477	1.092894
B	0.066551	0.437277	-1.787072	1.134810	-1.925734	-1.071281
C	-0.073149	0.632657	0.242221	0.282532	0.736288	0.318752
D	0.648219	0.312861	0.125543	0.133995	-0.547677	-0.477591

Sorting by its index

In [25]:

```
kdf.sort_index(ascending=False)
```

Out[25]:

	A	B	C	D
5	1.092894	-1.071281	0.318752	-0.477591
4	-1.230477	-1.925734	0.736288	-0.547677
3	-1.637271	1.134810	0.282532	0.133995
2	-0.415537	-1.787072	0.242221	0.125543
1	-0.848735	0.437277	0.632657	0.312861
0	-0.407291	0.066551	-0.073149	0.648219

Sorting by value

In [26]:

```
kdf.sort_values(by='B')
```

Out[26]:

	A	B	C	D
4	-1.230477	-1.925734	0.736288	-0.547677
2	-0.415537	-1.787072	0.242221	0.125543
5	1.092894	-1.071281	0.318752	-0.477591
0	-0.407291	0.066551	-0.073149	0.648219
1	-0.848735	0.437277	0.632657	0.312861
3	-1.637271	1.134810	0.282532	0.133995

Missing Data

Koalas primarily uses the value `np.nan` to represent missing data. It is by default not included in computations.

In [27]:

```
pdf1 = pdf.reindex(index=dates[0:4], columns=list(pdf.columns) + ['E'])
```

In [28]:

```
pdf1.loc[dates[0]:dates[1], 'E'] = 1
```

In [29]:

```
kdf1 = ks.from_pandas(pdf1)
```

In [30]:

```
kdf1
```

Out[30]:

	A	B	C	D	E
2013-01-01	-0.407291	0.066551	-0.073149	0.648219	1.0
2013-01-02	-0.848735	0.437277	0.632657	0.312861	1.0
2013-01-03	-0.415537	-1.787072	0.242221	0.125543	NaN
2013-01-04	-1.637271	1.134810	0.282532	0.133995	NaN

To drop any rows that have missing data.

In [31]:

```
kdf1.dropna(how='any')
```

Out[31]:

	A	B	C	D	E
2013-01-01	-0.407291	0.066551	-0.073149	0.648219	1.0
2013-01-02	-0.848735	0.437277	0.632657	0.312861	1.0

Filling missing data.

In [32]:

```
kdf1.fillna(value=5)
```

Out[32]:

	A	B	C	D	E
2013-01-01	-0.407291	0.066551	-0.073149	0.648219	1.0
2013-01-02	-0.848735	0.437277	0.632657	0.312861	1.0
2013-01-03	-0.415537	-1.787072	0.242221	0.125543	5.0
2013-01-04	-1.637271	1.134810	0.282532	0.133995	5.0

Operations

Stats

Operations in general exclude missing data.

Performing a descriptive statistic:

In [33]:

```
kdf.mean()
```

Out[33]:

```
A   -0.574403
B   -0.524242
C    0.356550
D    0.032558
dtype: float64
```

Spark Configurations

Various configurations in PySpark could be applied internally in Koalas. For example, you can enable Arrow optimization to hugely speed up internal pandas conversion. See [PySpark Usage Guide for Pandas with Apache Arrow (https://spark.apache.org/docs/latest/sql-pyspark-pandas-with-arrow.html)](https://spark.apache.org/docs/latest/sql-pyspark-pandas-with-arrow.html).

In [34]:

```
prev = spark.conf.get("spark.sql.execution.arrow.enabled")  # Keep its default v
alue.
ks.set_option("compute.default_index_type", "distributed")  # Use default index
 prevent overhead.
import warnings
warnings.filterwarnings("ignore")  # Ignore warnings coming from Arrow optimizat
ions.
```

In [35]:

```
spark.conf.set("spark.sql.execution.arrow.enabled", True)
%timeit ks.range(300000).to_pandas()
```

```
493 ms ± 157 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

In [36]:

```
spark.conf.set("spark.sql.execution.arrow.enabled", False)
%timeit ks.range(300000).to_pandas()
```

```
1.39 s ± 109 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

In [37]:

```
ks.reset_option("compute.default_index_type")
spark.conf.set("spark.sql.execution.arrow.enabled", prev)  # Set its default val
ue back.
```

Grouping

By “group by” we are referring to a process involving one or more of the following steps:

- Splitting the data into groups based on some criteria
- Applying a function to each group independently
- Combining the results into a data structure

In [38]:

```
kdf = ks.DataFrame({'A': ['foo', 'bar', 'foo', 'bar',
                          'foo', 'bar', 'foo', 'foo'],
                    'B': ['one', 'one', 'two', 'three',
                          'two', 'two', 'one', 'three'],
                    'C': np.random.randn(8),
                    'D': np.random.randn(8)})
```

In [39]:

```
kdf
```

Out[39]:

	A	B	C	D
0	foo	one	1.028745	-0.804571
1	bar	one	0.593379	-1.592110
2	foo	two	0.051362	0.466273
3	bar	three	0.977622	-0.822670
4	foo	two	-1.105357	-0.027466
5	bar	two	-0.009076	0.977587
6	foo	one	0.643092	0.403405
7	foo	three	-1.451129	0.230347

Grouping and then applying the [sum() (https://koalas.readthedocs.io/en/latest/reference/api/databricks.koalas.groupby.GroupBy.sum.html#databrick](https://koalas.readthedocs.io/en/latest/reference/api/databricks.koalas.groupby.GroupBy.sum.html#databrick) function to the resulting groups.

In [40]:

```
kdf.groupby('A').sum()
```

Out[40]:

	C	D
A		
bar	1.561925	-1.437193
foo	-0.833286	0.267988

Grouping by multiple columns forms a hierarchical index, and again we can apply the sum function.

In [41]:

```
kdf.groupby(['A', 'B']).sum()
```

Out[41]:

A	B	C	D
bar	one	0.593379	-1.592110
	three	0.977622	-0.822670
	two	-0.009076	0.977587
foo	one	1.671837	-0.401166
	three	-1.451129	0.230347
	two	-1.053995	0.438807

Plotting

See the Plotting (https://koalas.readthedocs.io/en/latest/reference/frame.html#plotting) docs.

In [42]:

```
%matplotlib inline
from matplotlib import pyplot as plt
```

In [43]:

```
pser = pd.Series(np.random.randn(1000),
                 index=pd.date_range('1/1/2000', periods=1000))
```

In [44]:

```
kser = ks.Series(pser)
```

In [45]:

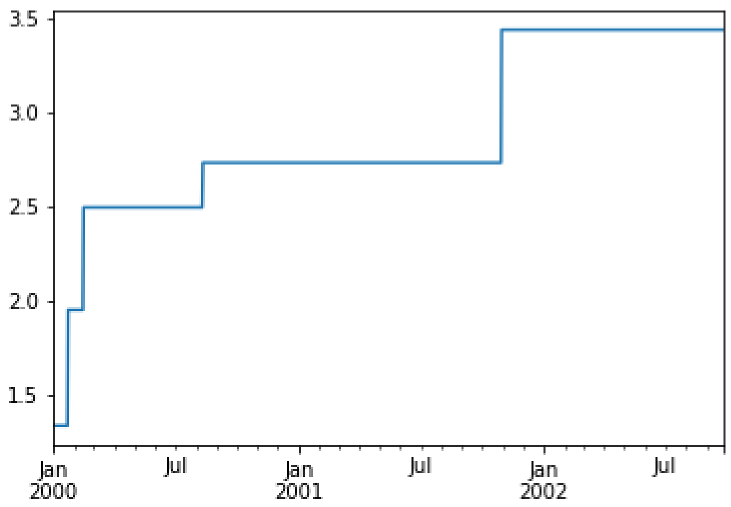
```
kser = kser.cummax()
```

In [46]:

```
kser.plot()
```

Out[46]:

<matplotlib.axes._subplots.AxesSubplot at 0x7feeb4b350b8>



On a DataFrame, the [plot() (https://koalas.readthedocs.io/en/latest/reference/api/databricks.koalas.frame.DataFrame.plot.html#databricks](https://koalas.readthedocs.io/en/latest/reference/api/databricks.koalas.frame.DataFrame.plot.html#databricks) method is a convenience to plot all of the columns with labels:

In [47]:

```
pdf = pd.DataFrame(np.random.randn(1000, 4), index=pser.index,
                   columns=['A', 'B', 'C', 'D'])
```

In [48]:

```
kdf = ks.from_pandas(pdf)
```

In [49]:

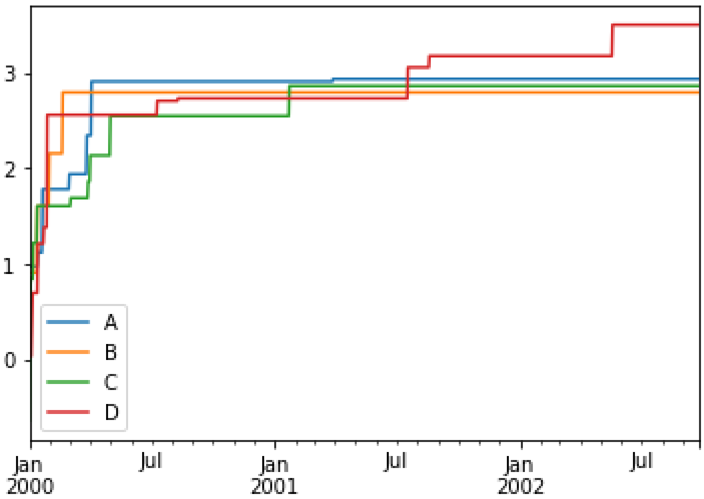
```
kdf = kdf.cummax()
```

In [50]:

```
kdf.plot()
```

Out[50]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7feebe266978>
```



Getting data in/out

See the [Input/Output (https://koalas.readthedocs.io/en/latest/reference/io.html)] docs.

CSV

CSV is straightforward and easy to use. See here (https://koalas.readthedocs.io/en/latest/reference/api/databricks.koalas.DataFrame.to_csv.html#databricks.ko to write a CSV file and here (https://koalas.readthedocs.io/en/latest/reference/api/databricks.koalas.read_csv.html#databricks.koalas.read to read a CSV file.

In [51]:

```
kdf.to_csv('foo.csv')
ks.read_csv('foo.csv').head(10)
```

Out[51]:

	A	B	C	D
0	0.976091	0.910572	-0.640756	0.034655
1	0.976091	0.910572	-0.150827	0.034655
2	0.976091	0.910572	0.796879	0.034655
3	0.976091	0.910572	0.849741	0.034655
4	0.976091	0.910572	0.849741	0.370709
5	0.976091	0.910572	0.849741	0.698402
6	0.976091	0.910572	1.217456	0.698402
7	0.976091	0.910572	1.217456	0.698402
8	0.976091	0.910572	1.217456	0.698402
9	0.976091	0.910572	1.217456	0.698402

Parquet

Parquet is an efficient and compact file format to read and write faster. See here (https://koalas.readthedocs.io/en/latest/reference/api/databricks.koalas.DataFrame.to_parquet.html#databrick to write a Parquet file and here (https://koalas.readthedocs.io/en/latest/reference/api/databricks.koalas.read_parquet.html#databricks.koalas. to read a Parquet file.

In [52]:

```
kdf.to_parquet('bar.parquet')
ks.read_parquet('bar.parquet').head(10)
```

Out[52]:

	A	B	C	D
0	0.976091	0.910572	-0.640756	0.034655
1	0.976091	0.910572	-0.150827	0.034655
2	0.976091	0.910572	0.796879	0.034655
3	0.976091	0.910572	0.849741	0.034655
4	0.976091	0.910572	0.849741	0.370709
5	0.976091	0.910572	0.849741	0.698402
6	0.976091	0.910572	1.217456	0.698402
7	0.976091	0.910572	1.217456	0.698402
8	0.976091	0.910572	1.217456	0.698402
9	0.976091	0.910572	1.217456	0.698402

Spark IO

In addition, Koalas fully support Spark's various datasources such as ORC and an external datasource. See here (https://koalas.readthedocs.io/en/latest/reference/api/databricks.koalas.DataFrame.to_spark_io.html#databric to write it to the specified datasource and here (https://koalas.readthedocs.io/en/latest/reference/api/databricks.koalas.read_spark_io.html#databricks.koalas to read it from the datasource.

In [53]:

```
kdf.to_spark_io('zoo.orc', format="orc")
ks.read_spark_io('zoo.orc', format="orc").head(10)
```

Out[53]:

	A	B	C	D
0	0.976091	0.910572	-0.640756	0.034655
1	0.976091	0.910572	-0.150827	0.034655
2	0.976091	0.910572	0.796879	0.034655
3	0.976091	0.910572	0.849741	0.034655
4	0.976091	0.910572	0.849741	0.370709
5	0.976091	0.910572	0.849741	0.698402
6	0.976091	0.910572	1.217456	0.698402
7	0.976091	0.910572	1.217456	0.698402
8	0.976091	0.910572	1.217456	0.698402
9	0.976091	0.910572	1.217456	0.698402