Spark Essentials
Reviewing some functional programming concepts in Python

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Review of concepts

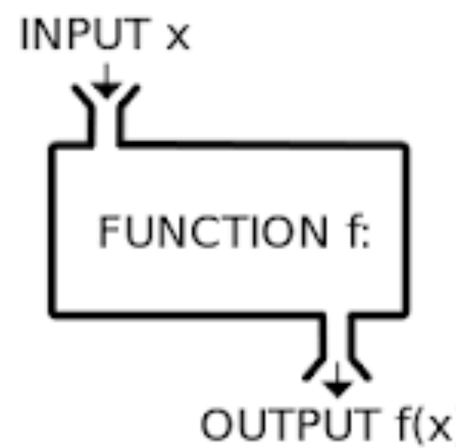
- What is Functional Programming - Python
  - Lambda
  - Map, Filter, Reduce
- List Comprehensions
- Sliced

Functional Programming

- Functional programming is a **style** whose underlying model of computation is the *function*.

- Functions take input and produce output, without any side effects.

- No state
- Immutable data
- Function as first-class citizen
- Recursion
- Purity …



https://marcobonzanini.com/2015/06/08/functional-programming-in-python/

Python Functional Programming

Python is a multi paradigm programming language. As a Python programmer why uses functional programming in Python?

Python is not a functional language but have a lot of features that enables us to applies functional principles in the development, turning our code more elegant, concise, maintanable, easier to understand and test.

Lambda function

- Syntax : **lambda argument_list: expression**
  - argument_list: comma separated list of arguments
  - expression is an arithmetic expression using these arguments.
- The function can be assigned to a variable

Example(1)

```
>> f = lambda x,y: x + y
>> f(1,2)
Out[1]: 3
```

- Only **one** expression in the lambda body
- Advantage of the lambda can be seen when it is used in combination with other functions (e.g. map, reduce, filter)

The map() function

- Syntax: **r = map(func, seq)**
  - *func* is the name of a function
  - Seq is a sequence (e.g. a list)
- *Map* applies the function *func* to all the elements of the sequence *seq* and returns a **new list** with the elements changed by *func*

Example(1):

```
>> nums = [1,2,3,4]
>> squares = map(lambda x: x * x, nums)
>>   print squares
Out[1]: [1, 4, 9, 16]
```

Example(2):

```
>> Celsius = [39.2, 36.5, 37.3, 37.8]
>> Fahrenheit = map(lambda x: (float(9) / 5) * x + 32, Celsius)
>> print Fahrenheit
Out[1]: [102.56, 97.70000000000003, 99.14000000000001, 100.03999999999999]
>> C = map(lambda x: (float(5) / 9) * (x - 32), Fahrenheit)
>> print C
Out[1]: [39.20000000000003, 36.5, 37.30000000000004, 37.79999999999997] >>>
```

The filter() function

- Syntax: f = filter(*function*, list)
  - *Function* that returns true or false – applied to every element of the list
  - *List to applied the function*

- *Filter* returns a **new list** with the "True" elements returned from applying the function to the list

Example:

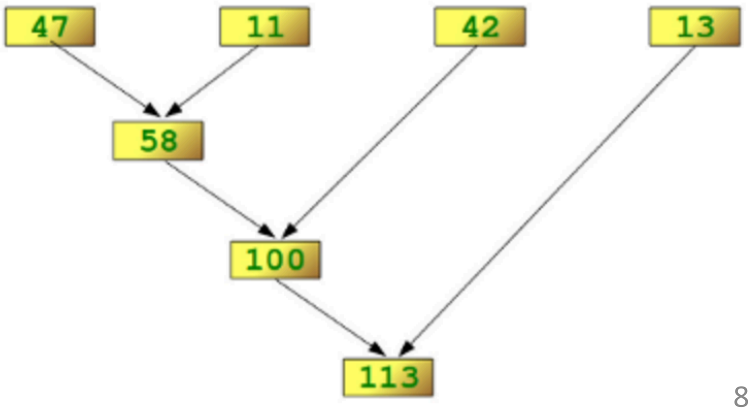
```
>> fib= [0, 1, 1, 2, 3, 5, 8, 13, 21, 34, 55]
>> result= filter(lambda x: x % 2, fib)
>> print result
Out[1]: [1, 1, 3, 5, 13, 21, 55]
```

The reduce() function

- Syntax: **r = reduce(func, seq)**
  - *func* is the name of a function
  - Seq is a sequence (e.g. a list)
- *Reduce* continually applies the function *func* to the sequence *seq*, and returns a single value.

Example:

```
>> result= reduce(lambda x,y: x + y, [47, 11, 42, 13])
Out[1]: 113
```



List Comprehensions

```
doubled_odds = []
for n in numbers:
    if n % 2 == 1:
        doubled_odds.append(n * 2)
```

```
doubled_odds = [n * 2 for n in numbers if n % 2 == 1]
```

We copy-paste from a `for` loop into a list comprehension by:

1. Copying the variable assignment for our new empty list
2. Copying the expression that we've been `append` -ing into this new list
3. Copying the `for` loop line, excluding the final `:`
4. Copying the `if` statement line, also without the `:`

List slicing

- Slicing: Extracting parts of list
- Syntax:

```
list[start:end]
list[start:]
list[end:]
list[:]
```

- `start` inclusive and excluding `end`
- Slicing returns a new list

```
>>> colors = ['yellow', 'red', 'blue', 'green', 'black']
>>> colors[0:]
['yellow', 'red', 'blue', 'green', 'black']

>>> colors[:4]
['yellow', 'red', 'blue', 'green']

>>> colors[1:3]
['red', 'blue']

>>> colors[:]
['yellow', 'red', 'blue', 'green', 'black']
```

Spark Essentials

- SparkContext
- RDDs
- Operations:
  - Basic transformations
  - Basic actions
- Persistence

SparkContext

- Main entry point to Spark functionality
- Created for you in Spark shells and notebooks as variable **sc**
- In standalone programs, you'd make your own
  – (Last slide)
  – Now we are assuming that we are working either in the shell or with notebooks

Creating RDDs

```
# Turn a local collection into an RDD
>> rdd_1 = sc.parallelize([1, 2, 3])

# Load text file from local FS, HDFS, or S3
>> rdd_2 = sc.textFile(“file.txt”)
>> rdd_3 = sc.textFile(“directory/*.txt”)
>> rdd_4 = sc.textFile(“hdfs://namenode:
9000/path/file”)

# Transforming an existing RDD
>> rdd_5 = rdd2.filter(function)
```

RDD operations

- *Transformations*
  - lazy operation to build RDDs from other RDDs
- *Actions*
  - Computes a result based on existing RDD or write it to storage

Transformations	Actions
map (func)	reduce(func)
flatMap(func)	collect()
filter(func)	count()
groupByKey()	first()
reduceByKey(func)	take(n)
mapValues(func)	saveAsTextFile(path)
sample(…)	countByKey()
union(other)	foreach(func)
distinct()	…
sortByKey()	
…	

 = easy  = medium

Essential Core & Intermediate Spark Operations

TRANSFORMATIONS

General

- map
- filter
- flatMap
- mapPartitions
- mapPartitionsWithIndex
- groupBy
- sortBy

Math / Statistical

- sample
- randomSplit

Set Theory / Relational

- union
- intersection
- subtract
- distinct
- cartesian
- zip

Data Structure / I/O

- keyBy
- zipWithIndex
- zipWithUniqueID
- zipPartitions
- coalesce
- repartition
- repartitionAndSortWithinPartitions
- pipe

ACTIONS

General

- reduce
- collect
- aggregate
- fold
- first
- take
- forEach
- top
- treeAggregate
- treeReduce
- forEachPartition
- collectAsMap

Math / Statistical

- count
- takeSample
- max
- min
- sum
- histogram
- mean
- variance
- stdev
- sampleVariance
- countApprox
- countApproxDistinct

Set Theory / Relational

- takeOrdered

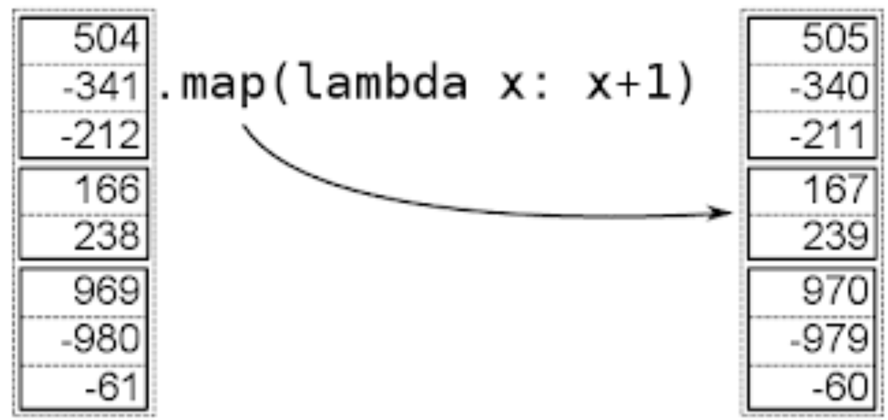
Data Structure / I/O

- saveAsTextFile
- saveAsSequenceFile
- saveAsObjectFile
- saveAsHadoopDataset
- saveAsHadoopFile
- saveAsNewAPIHadoopDataset
- saveAsNewAPIHadoopFile

pySpark map(), filter(), reduce()

Note: Different syntax than Python

- Map syntax:
  - rdd.map(function)
- Filter syntax:
  - rdd.filter(function)
- Reduce syntax:
  - rdd.reduce(function)



Passing functions to Spark

- With **lambda** syntax allows us to define “simple” functions inline. But we can pass defined functions.

```
def hasHadoop( line ):
    return “Hadoop” in line
```

```
>> lines = sc.textFile( “README.txt” )
>> hadoopLines = lines.filter( hasHadoop )
```

Basic Transformations

```
nums = sc.parallelize([1, 2, 3])

# Pass each element through a function
squares = nums.map(lambda x: x * x)   # => [1, 4, 9]

# Keep elements passing a predicate
even = squares.filter(lambda x: x % 2 == 0) # => [4]

# Map each element to zero or more others
nums.flatMap(lambda x: range(0, x))  # => [0, 0, 1,
0, 1, 2]

# Map each element to zero or more others
nums.map(lambda x: range(0, x))  # => [[0], [0, 1],
[0, 1, 2]]
```

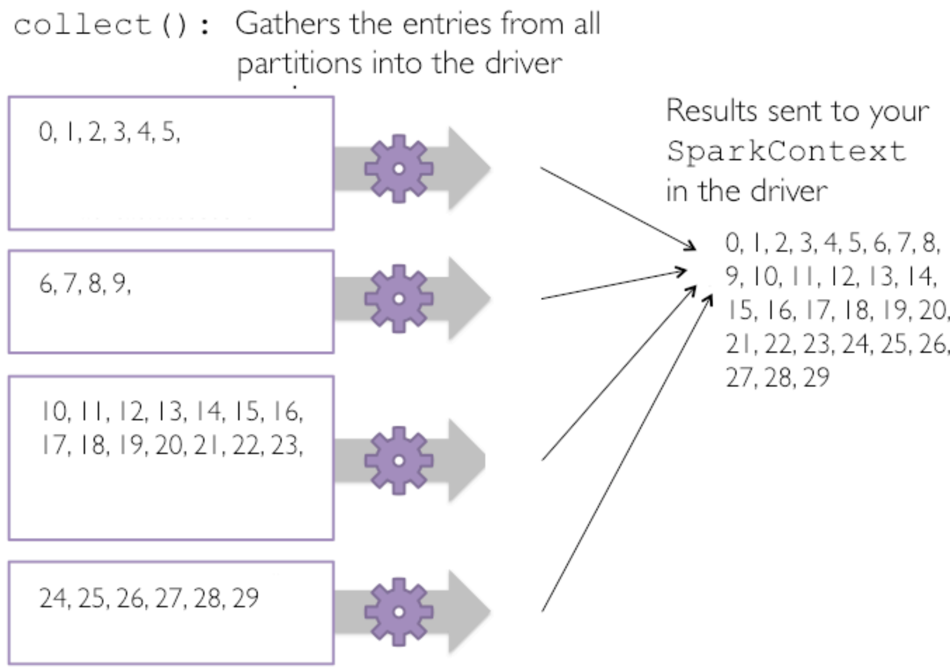
map() vs flatMap()

`flatMap`: Similar to map, it returns a new RDD by applying a function to each element of the RDD, but output is flattened.

```
>> rdd = sc.paralleliz([1, 2, 3])

>> rdd.map(lambada x: [x,  x * 2])
Out[1]:  [ [1, 2],  [2, 4],  [3, 6]]

>> rdd.flatMap(lambada x: [x, x * 2])
Out[1]:  [ 1, 2,  2, 4,  3, 6]
```

Basic Actions

```
nums = sc.parallelize([5, 1, 3, 2])

# Retrieve RDD contents as a local collection
 → Results must fit in memory on the local machine

nums.collect() # => [5, 1, 3, 2]

# Return first K elements
nums.take(2)   # => [5, 1]

# Return first K elements ordered

nums.takeOrdered(4) # => [1, 2, 3, 5]

# Return first K elements by applying

#a particular order

nums.takeOrdered(4, lamda n:-n)

# => [5, 3, 2, 1]

# Count number of elements
nums.count()   # => 4

# Merge elements with an associative function
nums.reduce(lambda x, y: x + y)  # => 12

# Write elements to a text file
nums.saveAsTextFile("hdfs://file.txt")
```



Persistence

- Spark **recomputes** the RDDs each time we call an action → expensive and can also cause data to be read from the disk again
- We can avoid this caching the data:
  - caching ()
  - persintace()
- Fault tolerant: In case of failure, Spark can rebuild the RDD
- Super Fast: will allow multiple operations on the same data set

Persistence

- RDDs can be **cached** using cache operation. They can also be **persisted** using persist operation.
- With cache(), you use only the default storage level MEMORY_ONLY.
- With persist(), you can specify which storage level you want,(rdd-persistence).
- Use persist() if you want to assign another storage level than MEMORY_ONLY to the RDD (which storage level to choose)

Persistence Example

```
>> lines = sc. textFile("README.md", 4)
>> lines.count()
Out[1]: 1024


>> pythonLines = lines.filter(lambda line:
"Python" in line)
>> pythonLines.count()
Out[1]: 50
```

Causes Spark to reload **lines** from disk used.

```
>> lines = sc. textFile("README.md", 4)
>> lines.persist()  # ~lines.cache()
>> lines.count()
Out[1]: 1024

>> pythonLines = lines.filter(lambda line:
"Python" in line)
>> pythonLines.count()
Out[1]: 50
```

Spark will avoid re-computing lines every time it is used

SparkContext - Cluster execution

```
import sys
from pyspark import SparkContext, SparkConf

if __name__ == "__main__":
    conf = SparkConf().setAppName("Spark Count")
    sc = SparkContext(conf=conf)
    logFile = "README.md"
    textFile = sc.textFile(logFile)
    wordCounts = textFile.flatMap(lambda line:
   line.split()).map(lambda word: (word,
   1)).reduceByKey(lambda a, b: a+b)
    wordCounts.collect()
```