Big Data Analysis Platforms

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Slides credited to Matei Zaharia, UC Berkeley

Outline

- Review of Virtual Machine (虛擬機器回顧)
- Hadoop Platform (運算分析系統架構)
- MapReduce
- Introduction to Python (Python入門簡介)
- Python Spark Platform (Python Spark運算分析架構)
- Parallel Programming With Spark

Why Spark?

- Fast, expressive cluster computing system compatible with Apache Hadoop
  - Works with any Hadoop-supported storage system (HDFS, S3, Avro, …)
- Improves **efficiency** through:
  - In-memory computing primitives
  - General computation graphs → Up to 100× faster
- Improves **usability** through:
  - Rich APIs in Java, Scala, Python
  - Interactive shell → Often 2-10× less code

How to Run It

- Local multicore: just a library in your program
- EC2: scripts for launching a Spark cluster
- Private cluster: Mesos, YARN, Standalone Mode

Languages

- APIs in Java, Scala and Python
- Interactive shells in Scala and Python

Key Idea

- **Work with distributed collections as you would with local ones**

- Concept: resilient distributed datasets (RDDs)
  - Immutable collections of objects spread across a cluster
  - Built through parallel transformations (map, filter, etc)
  - Automatically rebuilt on failure
  - Controllable persistence (e.g. caching in RAM)

Operations

- Transformations (e.g. map, filter, groupBy, join)
  - Lazy operations to build RDDs from other RDDs
- Actions (e.g. count, collect, save)
  - Return a result or write it to storage

Example: Mining Console Logs

- Load error messages from a log into memory, then interactively search for patterns

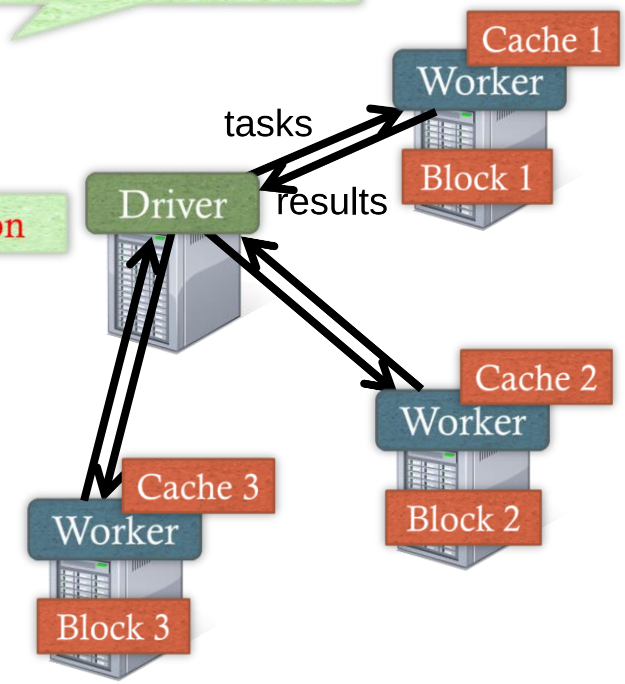
Base RDD

Transformed RDD

```
lines = spark.textFile("hdfs://...")
errors = lines.filter(lambda s: s.startswith("ERROR"))
messages = errors.map(lambda s: s.split('\t')[2])
messages.cache()
```

Action

```
messages.filter(lambda s: "foo" in s).count()
messages.filter(lambda s: "bar" in s).count()
. . .
```



Result: scaled to 1 TB data in 5-7 sec
(vs 170 sec for on-disk data)

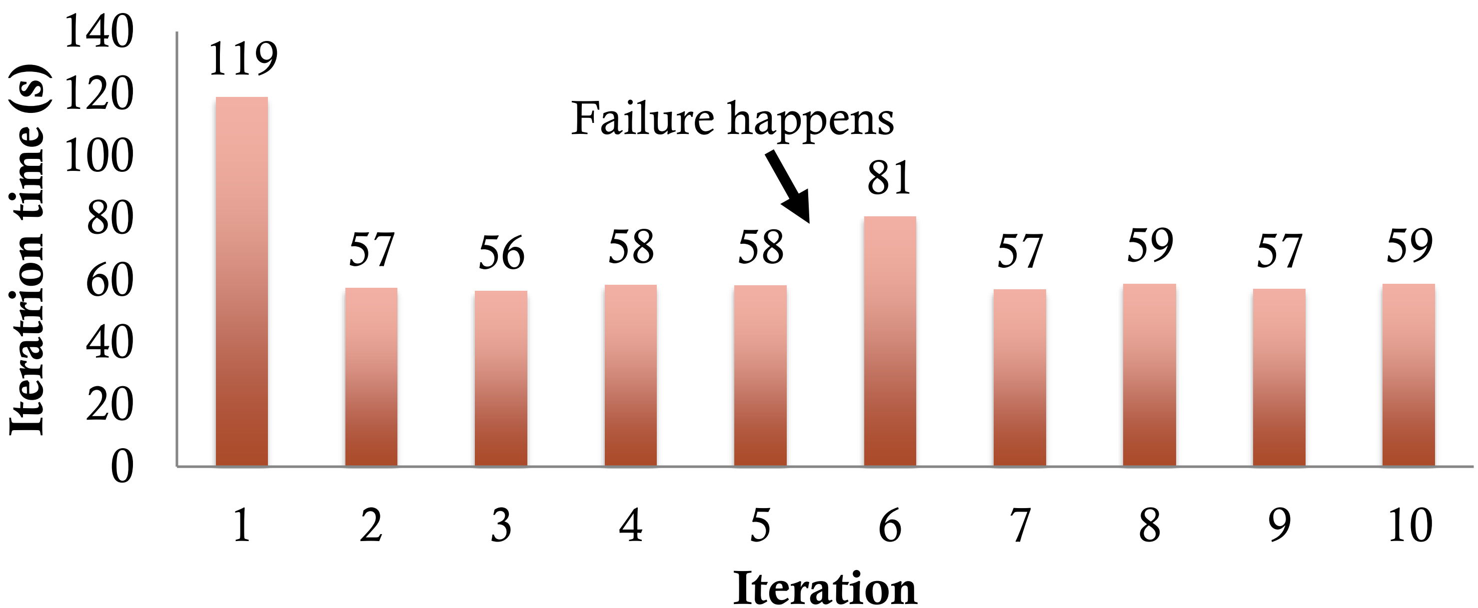
RDD Fault Tolerance

RDDs track the transformations used to build them (their *lineage*) to recompute lost data

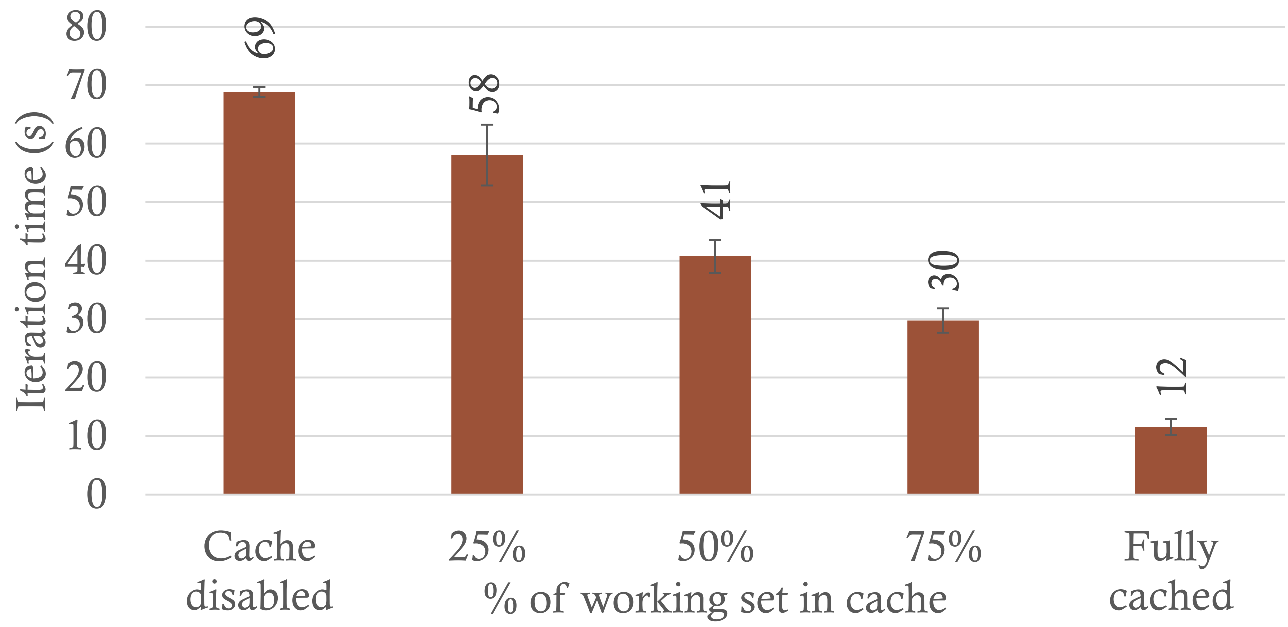
E.g:

```
messages = textFile(...).filter(lambda s: s.contains(“ERROR”))
                        .map(lambda s: s.split(‘\t’)[2])
```

Fault Recovery Test



Behavior with Less RAM



Spark in Java and Scala

Java API:

```
JavaRDD<String> lines =
spark.textFile(…);

errors = lines.filter(
  new Function<String,
Boolean>() {
    public Boolean
call(String s) {
      return
s.contains("ERROR");
    }
});

errors.count()
```

Scala API:

```
val lines =
spark.textFile(…)

errors = lines.filter(s =>
s.contains("ERROR"))
// can also write
filter(_.contains("ERROR"))

errors.count
```

Which Language Should I Use?

- Standalone programs can be written in any, but console is only Python & Scala
- **Python developers:** can stay with Python for both
- **Java developers:** consider using Scala for console (to learn the API)
- Performance: Java / Scala will be faster (statically typed), but Python can do well for numerical work with NumPy

Scala Cheat Sheet

More details:
scala-lang.org

Variables:

```
var x: Int = 7
var x = 7      // type inferred
```

```
val y = “hi”   // read-only
```

Functions:

```
def square(x: Int): Int = x*x
```

```
def square(x: Int): Int = {
  x*x   // last line returned
}
```

Collections and closures:

```
val nums = Array(1, 2, 3)
```

```
nums.map((x: Int) => x + 2) // => Array(3, 4, 5)
```

```
nums.map(x => x + 2)  // => same
nums.map(_ + 2)       // => same
```

```
nums.reduce((x, y) => x + y) // => 6
nums.reduce(_ + _)           // => 6
```

Java interop:

```
import java.net.URL
```

```
new URL(“http://cnn.com”).openStream()
```

Learning Spark

- Easiest way: Spark interpreter (`spark-shell` or `pyspark`)
    - Special Scala and Python consoles for cluster use
- Runs in local mode on 1 thread by default, but can control with `MASTER` environment var:

```
MASTER=local      ./spark-shell              # local, 1 thread
MASTER=local[2]   ./spark-shell              # local, 2
threads
MASTER=spark://host:port ./spark-shell  # Spark
standalone cluster
```

First Stop: SparkContext

- Main entry point to Spark functionality
- Created for you in Spark shells as variable `sc`
- In standalone programs, you'd make your own (see later for details)

Creating RDDs

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

# Load text file from local FS, HDFS, or S3
sc.textFile("file.txt")
sc.textFile("directory/*.txt")
sc.textFile("hdfs://namenode:9000/path/file")

# Use any existing Hadoop InputFormat
sc.hadoopFile(keyClass, valClass, inputFmt, conf)
```

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}
```

Range object (sequence of numbers 0, 1, …, x-1)

Basic Actions

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

# Retrieve RDD contents as a local collection
nums.collect() # => [1, 2, 3]

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

# Count number of elements
nums.count()   # => 3

# Merge elements with an associative function
nums.reduce(lambda x, y: x + y)  # => 6

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

Working with Key-Value Pairs

- Spark's "distributed reduce" transformations act on RDDs of *key-value pairs*
- Python:

```python
pair = (a, b)
pair[0] # => a
pair[1] # => b
```

- Scala:

```scala
val pair = (a, b)
pair._1 // => a
pair._2 // => b
```

- Java:

```java
Tuple2 pair = new Tuple2(a, b);  // class scala.Tuple2
pair._1 // => a
pair._2 // => b
```

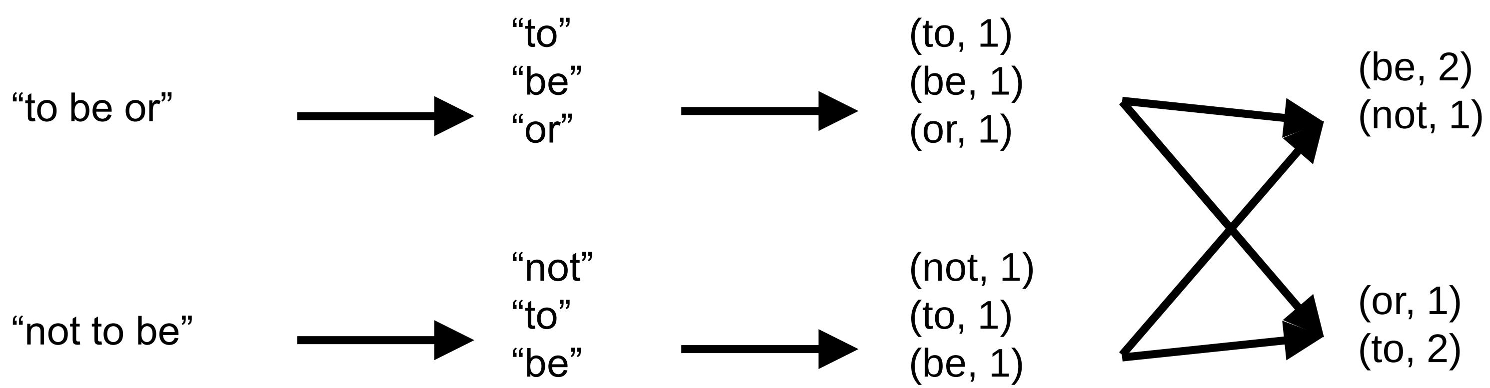
Some Key-Value Operations

```
pets = sc.parallelize([(“cat”, 1), (“dog”, 1), (“cat”, 2)])

pets.reduceByKey(lambda x, y: x + y)
# => {(cat, 3), (dog, 1)}

pets.groupByKey()
# => {(cat, Seq(1, 2)), (dog, Seq(1)}

pets.sortByKey()
# => {(cat, 1), (cat, 2), (dog, 1)}
```

`reduceByKey` also automatically implements combiners on the map side

Example: Word Count

```
lines = sc.textFile(“hamlet.txt”)

counts = lines.flatMap(lambda line: line.split(“ ”)) \
              .map(lambda word: (word, 1)) \
              .reduceByKey(lambda x, y: x + y)
```



Multiple Datasets

```
visits = sc.parallelize([(“index.html”, “1.2.3.4”),
                         (“about.html”, “3.4.5.6”),
                         (“index.html”, “1.3.3.1”)])

pageNames = sc.parallelize([(“index.html”, “Home”),
(“about.html”, “About”)])

visits.join(pageNames)
# (“index.html”, (“1.2.3.4”, “Home”))
# (“index.html”, (“1.3.3.1”, “Home”))
# (“about.html”, (“3.4.5.6”, “About”))

visits.cogroup(pageNames)
# (“index.html”, (Seq(“1.2.3.4”, “1.3.3.1”), Seq(“Home”)))
# (“about.html”, (Seq(“3.4.5.6”), Seq(“About”)))
```

Controlling the Level of Parallelism

- All the pair RDD operations take an optional second parameter for number of tasks

```
words.reduceByKey(lambda x, y: x + y,
5)
words.groupByKey(5)
visits.join(pageViews, 5)
```

Using Local Variables

- External variables you use in a closure will automatically be shipped to the cluster:

```
query = raw_input("Enter a query:")
pages.filter(lambda x:
x.startswith(query)).count()
```

- Some caveats:
  - Each task gets a new copy (updates aren't sent back)
  - Variable must be Serializable (Java/Scala) or Pickle-able (Python)
  - Don't use fields of an outer object (ships all of it!)

Closure Mishap Example

```
class MyCoolRddApp {
  val param = 3.14
  val log = new Log(...)
  ...

  def work(rdd: RDD[Int]) {
    rdd.map(x => x + param)
       .reduce(...)
  }
}
```

NotSerializableException: MyCoolRddApp (or Log)

How to get around it:

```
class MyCoolRddApp {
  ...

  def work(rdd: RDD[Int]) {
    val param_ = param
    rdd.map(x => x + param_)
       .reduce(...)
  }
}
```

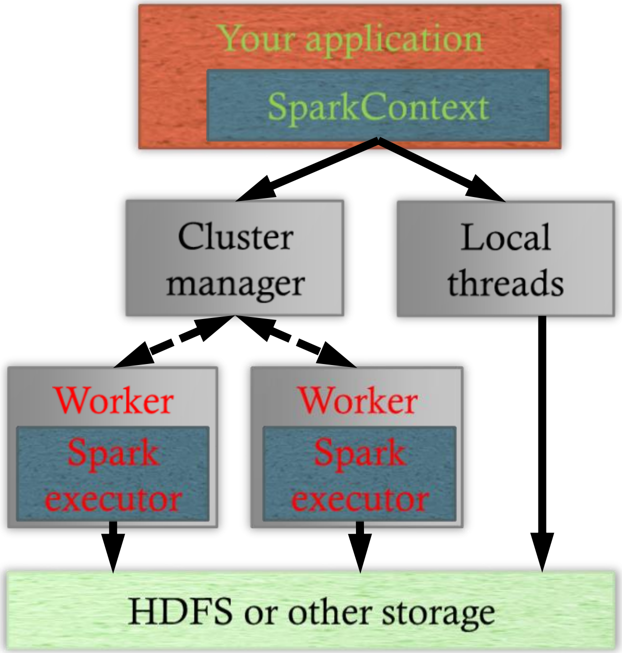
References only local variable instead of `this.param`

More Details

- Spark supports lots of other operations!
- Full programming guide: spark-project.org/documentation

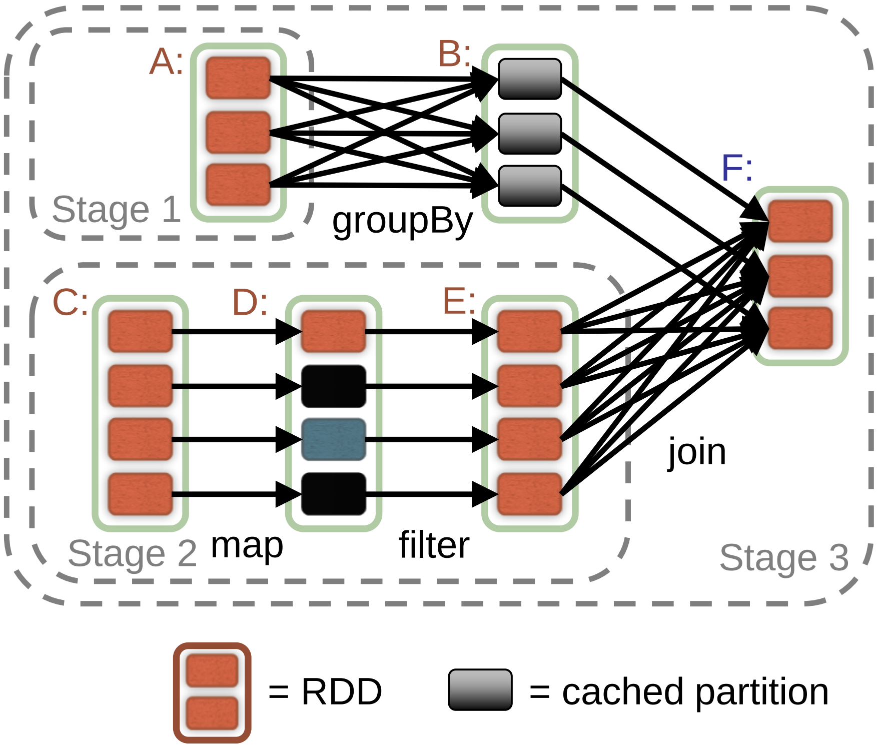
Software Components

- Spark runs as a library in your program
  (one instance per app)
- Runs tasks locally or on a cluster
  - Standalone deploy cluster, Mesos or YARN
- Accesses storage via Hadoop InputFormat API
  - Can use HBase, HDFS, S3, …



Task Scheduler

- Supports general task graphs
- Pipelines functions where possible
- Cache-aware data reuse & locality
- Partitioning-aware to avoid shuffles



Hadoop Compatibility

- Spark can read/write to any storage system / format that has a plugin for Hadoop!
  - Examples: HDFS, S3, HBase, Cassandra, Avro, SequenceFile
  - Reuses Hadoop's InputFormat and OutputFormat APIs
- APIs like `SparkContext.textFile` support filesystems, while `SparkContext.hadoopRDD` allows passing any Hadoop JobConf to configure an input source

Build Spark

- Requires Java 6+, Scala 2.9.2

```
git clone git://github.com/mesos/spark
cd spark
sbt/sbt package

# Optional: publish to local Maven cache
sbt/sbt publish-local
```

Add Spark to Your Project

- Scala and Java: add a Maven dependency on

```
groupId:    org.spark-project
artifactId: spark-core_2.9.1
version:    0.7.0-SNAPSHOT
```

- Python: run program with our `pyspark` script

Create a SparkContext

Scala

```
import spark.SparkContext
import spark.SparkContext._

val sc = new SparkContext(“masterUrl”,“name”,“sparkHome”,Seq(“app.jar”))
```

Cluster URL, or local / local[N]

App name

Spark install path on cluster

List of JARs with app code (to ship)

Java

```
import spark.api.java.JavaSparkContext;

JavaSparkContext sc = new JavaSparkContext(
    “masterUrl”, “name”, “sparkHome”, new String[] {“app.jar”}));
```

Python

```
from pyspark import SparkContext

sc = SparkContext(“masterUrl”, “name”, “sparkHome”, [“library.py”]))
```

Complete App: Scala

```
import spark.SparkContext
import spark.SparkContext._

object WordCount {
  def main(args: Array[String]) {
    val sc = new SparkContext("local", "WordCount", args(0),
Seq(args(1)))
    val lines = sc.textFile(args(2))
    lines.flatMap(_.split(" "))
         .map(word => (word, 1))
         .reduceByKey(_ + _)
         .saveAsTextFile(args(3))
  }
}
```

Complete App: Python

```
import sys
from pyspark import SparkContext

if __name__ == "__main__":
    sc = SparkContext( “local”, “WordCount”, sys.argv[0], None)
    lines = sc.textFile(sys.argv[1])

    lines.flatMap(lambda s: s.split(“ ”)) \
         .map(lambda word: (word, 1)) \
         .reduceByKey(lambda x, y: x + y) \
         .saveAsTextFile(sys.argv[2])
```

Local Mode

- Just pass `local` or `local[k]` as master URL
- Still serializes tasks to catch marshaling errors
- Debug using local debuggers
  - For Java and Scala, just run your main program in a debugger
  - For Python, use an attachable debugger (e.g. PyDev, winpdb)
- Great for unit testing

Private Cluster

- Can run with one of:
  - Standalone deploy mode (similar to Hadoop cluster scripts)
  - Apache Mesos: spark-project.org/docs/latest/running-on-mesos.html
  - Hadoop YARN: spark-project.org/docs/0.6.0/running-on-yarn.html
- Basically requires configuring a list of workers, running launch scripts, and passing a special cluster URL to SparkContext

Amazon EC2

- Easiest way to launch a Spark cluster

```
git clone git://github.com/mesos/spark.git
cd spark/ec2
./spark-ec2 -k keypair –i id_rsa.pem –s slaves \
      [launch|stop|start|destroy] clusterName
```

- Details: spark-project.org/docs/latest/ec2-scripts.html

- **New: run Spark on Elastic MapReduce – tinyurl.com/spark-emr**

Viewing Logs

- Click through the web UI at `master:8080`
- Or, look at `stdout` and `stdout` files in the Spark or Mesos "work" directory for your app:

  `work/<ApplicationID>/<ExecutorID>/stdout`
- Application ID (Framework ID in Mesos) is printed when Spark connects

Homework5: Work Count in Python Spark

- 下載安裝eclipse Scala IDE
- 安裝pyDev，並設定環境變數
- 新增pyDev專案，使用Python Spark重新製作 Word Count的例子
- 紀錄執行結果
- 報告撰寫及繳交

Any Questions?