

Towards Modularizing Machine Learning Jobs

Lance Co Ting Keh

Machine Learning @ Box

lance@box.com



About me

- Founding member of machine learning team at Box
- Designer and baby-sitter of the ML infrastructure
- MS and BS from Duke University specializing in ML and distributed systems

Machine Learning at

- 1.Security
- 2.Recommendations
- 3.Search Relevancy

Basic Anatomy of an ML job

1. **Read and parse:** enforce type system on input data
2. **Collate:** join and deduplicate datasets
3. **Feature massaging:** transform, augment, drop or append features
4. **Algorithm:** regression, classification, clustering, topic models, sampling, etc
5. **Metrics:** area-under-curve, binary and multi-class, ranking, etc
6. **Format and output results:** write to various data stores and end points

Sparkles

- Single logical unit of work
- Comprised of a series of Spark transformations and actions
- Enforces:
 - ☑ *type safety*
 - ☑ *modularity*
 - ☑ *testability*
 - ☑ *interpretable metrics and logging*
 - ☑ *best Spark-programming practices*

Usage

```
val finalSparkle =  
  for {  
    rddA <- ReadTextFile(textPath)  
    rddB <- ReadSequenceFile(sequencePath)  
    rddC <- JsonDecode[TypeA](rddA)  
    rddD <- DecodeKeyValue[TypeA](rddB)  
    rddE <- JoinByKey(List(rddC, rddD))  
    rddF <- Localize(rddE)  
    rddG <- LabelPropagation(rddF)  
    rddH <- AccuracyMetric(rddG)  
    rddI <- Globalize(rddH)  
    _ <- WriteMetadata(rddI)  
    _ <- WriteHDFS(rddJ)(_.asJson.nospaces)  
  } yield rddI
```

Design

- Want to compose modules of Spark computation

`flatMap: Sparkle[A] => (A => Sparkle[B]) => Sparkle[B]`

- Nice surface syntax

for-comprehensions

- Leverage type system to enforce input/output

It's just a function.. with some cleverness

Implementation

/ Spark job that will produce an A */*

trait Sparkle[A] {

}

Implementation

```
/* Spark job that will produce an A */  
trait Sparkle[A] {  
  /* Same as function SparkContext => A */  
  def run(sc: SparkContext): A  
}
```

Implementation

```
/* Spark job that will produce an A */
trait Sparkle[A] { parent =>
  /* Same as function SparkContext => A */
  def run(sc: SparkContext): A

  /* Compose with another Sparkle */
  def flatMap[B](f: A => Sparkle[B]): Sparkle[B] =
    new Sparkle[B] {
      def run(sc: SparkContext): B = {
        val parentResult: A = parent.run(sc)
        val nextSparkle: Sparkle[B] = f(parentResult)
        nextSparkle.run(sc)
      }
    }
}
```

Implementation

```
/* Spark job that will produce an A */
trait Sparkle[A] { parent =>
  /* Same as function SparkContext => A */
  def run(sc: SparkContext): A

  /* Compose with another Sparkle */
  def flatMap[B](f: A => Sparkle[B]): Sparkle[B] =
    new Sparkle[B] {
      def run(sc: SparkContext): B = {
        val parentResult: A = parent.run(sc)
        val nextSparkle: Sparkle[B] = f(parentResult)
        nextSparkle.run(sc)
      }
    }
}
```

Implementation

```
/* Spark job that will produce an A */
trait Sparkle[A] { parent =>
  /* Same as function SparkContext => A */
  def run(sc: SparkContext): A

  /* Compose with another Sparkle */
  def flatMap[B](f: A => Sparkle[B]): Sparkle[B]

  /* Transform output of Sparkle */
  def map[B](f: A => B): Sparkle[B] =
    new Sparkle[B] {
      def run(sc: SparkContext): B =
        f(parent.run(sc))
    }
}
```

Implementation

```
trait Sparkle[A] {  
  def run(sc: SparkContext): A  
  def flatMap[B](f: A => Sparkle[B]): Sparkle[B]  
  def map[B](f: A => B): Sparkle[B]  
}
```

- A Sparkle is just a function that requires a SparkContext and produces some value A
- We compose Sparkles using flatMap and map
 - This detail is often syntactically hidden via for-comprehensions

Implementation

```
trait Sparkle[A] {  
  def run(sc: SparkContext): A  
  def flatMap[B](f: A => Sparkle[B]): Sparkle[B]  
  def map[B](f: A => B): Sparkle[B]  
}
```

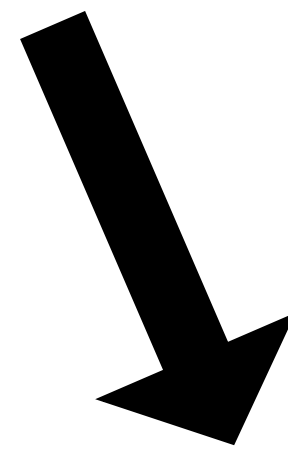
- How do Sparkle's take additional arguments?

```
case class JsonDecode[T](jsonRDD: RDD[String]) extends Sparkle[RDD[T]]  
{  
  /* Can reference `jsonRDD` in the function */  
  def run(sc: SparkContext): RDD[String] = . . .  
}
```

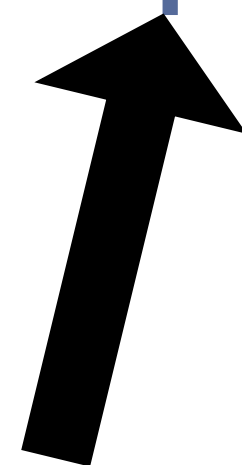
- This is how some languages support “closures”

Anatomy of a Sparkle

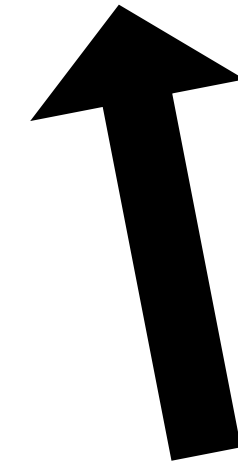
Function arguments



```
case class Foo(a: A, b: B, c: C) extends Sparkle[Z] {  
  def run(sc: SparkContext): Z  
}
```



Required arguments whose value
will be common across all
composed Sparkles. Mostly used by
Launchers, not Sparkles.



Function output type

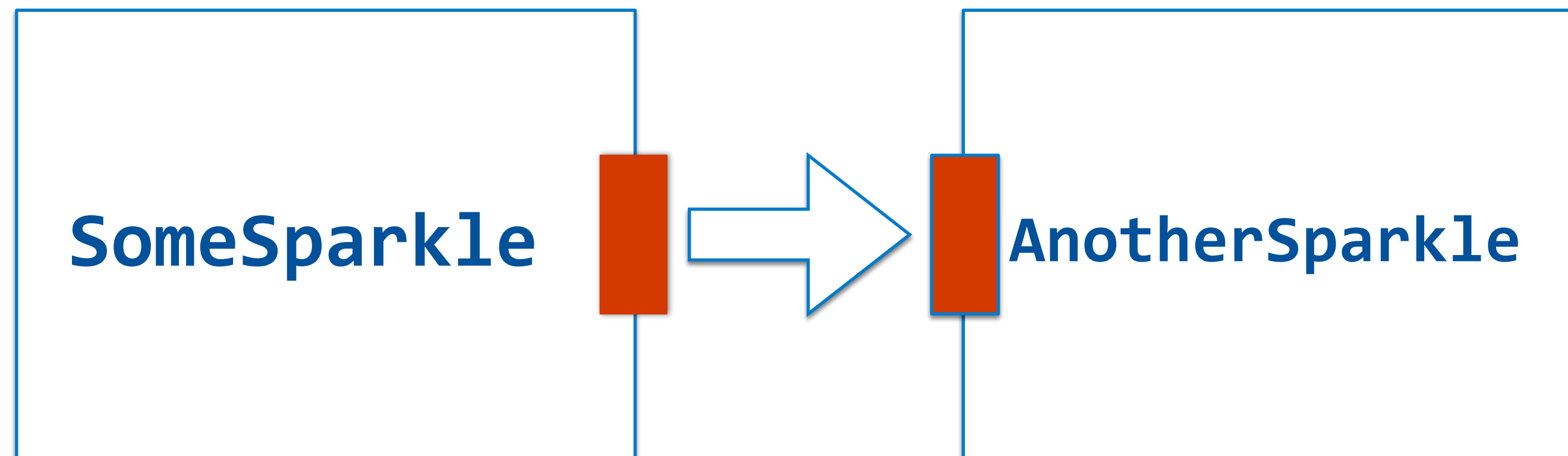


Type Safety with Sparkles

```
val finalSparkle =  
  for {  
    rddA <- SomeSparkle(param)  
    rddB <- AnotherSparkle(rddA)  
    rddC <- YetAnotherSparkle(rddB)  
    ...  
  } yield res
```

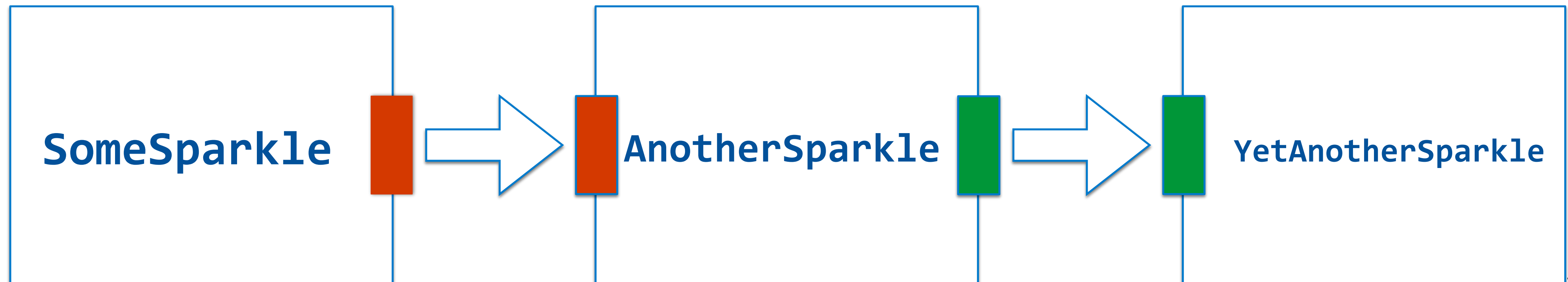
Type Safety with Sparkles

```
val finalSparkle =  
  for {  
    rddA <- SomeSparkle(param)  
    rddB <- AnotherSparkle(rddA)  
    rddC <- YetAnotherSparkle(rddB)  
    ...  
  } yield res
```



Type Safety with Sparkles

```
val finalSparkle =  
  for {  
    rddA <- SomeSparkle(param)  
    rddB <- AnotherSparkle(rddA)  
    rddC <- YetAnotherSparkle(rddB)  
    ...  
  } yield res
```



Modularity with Sparkles



Testing Sparkles

```
mock[RDD]
  ↙   ↘
case class Foo(a: A, b: B, c: C) extends
Sparkle[Z] {

  def run(sc: SparkContext): Z = {
    ...
  }
} mock[SparkContext]
```

Metrics and Logging with Sparkles

```
case class Foo(a: A, b: B, c: C) extends Sparkle[Z] {  
  
  def run(sc: SparkContext): Z  
  
  def runVerbose(sc: SparkContext): Z = {  
    logUsefulThings()  
    collectUsefulMetrics()  
  
    run(sc)  
  
    collectUsefulMetrics()  
    logUsefulThings()  
  }  
}
```

Good Code with Sparkles



Summary

- Sparkles provide a **natural way** of thinking of Spark work
- **Increase velocity** with modularity and DRY-ness
- **Reduce programmatic** errors with type safety and testability
- Helps enforce best Spark **programming practices**
- **Standardize** metrics and logging