Extending Spark ML

Super Happy New Pipeline Stage Time!

*Scala only - see developer for details.*
Who am I?

- My name is Holden Karau
- Preferred pronouns are she/her
- I’m a Principal Software Engineer at IBM’s Spark Technology Center
- Previously Alpine, Databricks, Google, Foursquare & Amazon
- Co-author of Learning Spark & Fast Data Processing with Spark
  - Co-author of a new book focused on Spark performance coming this year*
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What are we going to talk about?

- What Spark ML pipelines look like
- What Estimators and Transformers are
- How to implement a Transformer - and what else you will need to do to make an estimator
- I will of course try and sell you many copies of my new book if you have an expense account.
Spark ML pipelines

- In the batch setting, an estimator is trained on a dataset, and produces a static, immutable transformer.

EDIT: In the streaming setting, an estimator is trained on a dataset, and produces a static, immutable transformer.
So what does a pipeline stage look like?

Are either an:

- **Estimator** - no need to train can directly transform (e.g. HashingTF) (with transform)
- **Transformer** - has a method called “fit” which returns an estimator

Must provide:

- transformSchema (used to validate input schema is reasonable) & copy

Often have:

- Special params for configuration (so we can do meta-algorithms)
class HardCodedWordCountStage(override val uid: String) extends Transformer {
  def this() = this(Identifiable.randomUID("hardcodedwordcount"))

  def copy(extra: ParamMap): HardCodedWordCountStage = {
    defaultCopy(extra)
  }
}
Verify the input schema is reasonable:

```scala
override def transformSchema(schema: StructType): StructType = {
  // Check that the input type is a string
  val idx = schema.fieldIndex("happy_pandas")
  val field = schema.fields(idx)
  if (field.dataType != StringType) {
    throw new Exception(s"Input type ${field.dataType} did not match input type StringType")
  }
  // Add the return field
  schema.add(StructField("happy_panda_counts", IntegerType, false))
}
```
Do the “work” (e.g. predict labels or w/e):

```python
def transform(df: Dataset[_]): DataFrame = {
    val wordcount = udf { in: String => in.split(" ").size }
    df.select(col("*")),
        wordcount(df.col("happy_pandas")).as("happy_panda_counts")
}
```
What about configuring our stage?

class ConfigurableWordCount(override val uid: String) extends Transformer {
    final val inputCol = new Param[String](this, "inputCol", "The input column")
    final val outputCol = new Param[String](this, "outputCol", "The output column")

    def setInputCol(value: String): this.type = set(inputCol, value)

    def setOutputCol(value: String): this.type = set(outputCol, value)
So why do we configure it that way?

- Allow meta algorithms to work on it
- If you like inside of spark you’ll see “sharedParams” for common params (like input column)
- We can access those unless we pretend to be inside of org.apache.spark - so we have to make our own
So how to make an estimator?

- Very similar, instead of directly providing transform provide a `fit` which returns a “model” which implements the estimator interface as shown above.
- We could look at one - but I’m only supposed to talk for 10 minutes.
- So keep an eye out for my blog post in November :)
- Also take a look at the algorithms in Spark itself (helpful traits you can mixin to take care of many common things).
Resources to continue with:

- O’Reilly Radar (“Ideas”) Blog Post
  

- High Performance Spark Example Repo has some sample “custom” models
  
  - Of course buy several copies of the book - it is the gift of the season :p

- The models inside of Spark its self:
  
  (use some internal APIs but a good starting point)

- As always the Spark API documentation:

- My Slide share http://www.slideshare.net/hkarau
The next book.....

First seven chapters are available in “Early Release”*:  
● Extending ML is covered in Chapter 9 :)  

Get notified when updated & finished:  
● http://www.highperformancespark.com  
● https://twitter.com/highperfspark

* Early Release means extra mistakes, but also a chance to help us make a more awesome book.
If you care about Spark testing and don’t hate surveys:

Any PySpark Users: Have some simple UDFs you wish ran faster you are willing to share?:

Pssst: Have feedback on the presentation? Give me a shout (holden@pigscanfly.ca) if you feel comfortable doing so :)

Will tweet results “eventually” @holdenkarau

k thnx bye :)