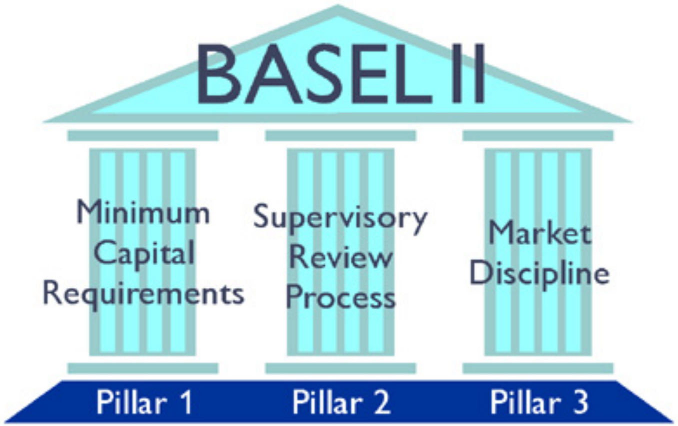
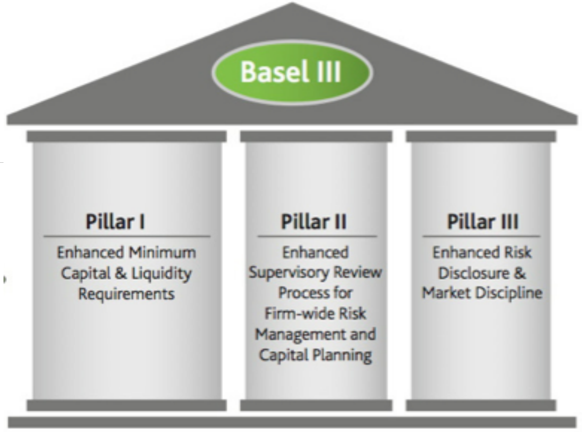
Estimating Financial Risk with Spark

Sandy Ryza | Senior Data Scientist

In reasonable circumstances, what's the most you can expect to lose?


BASEL II
Minimum Capital Requirements
Supervisory Review Process
Market Discipline
Pillar 1
Pillar 2
Pillar 3

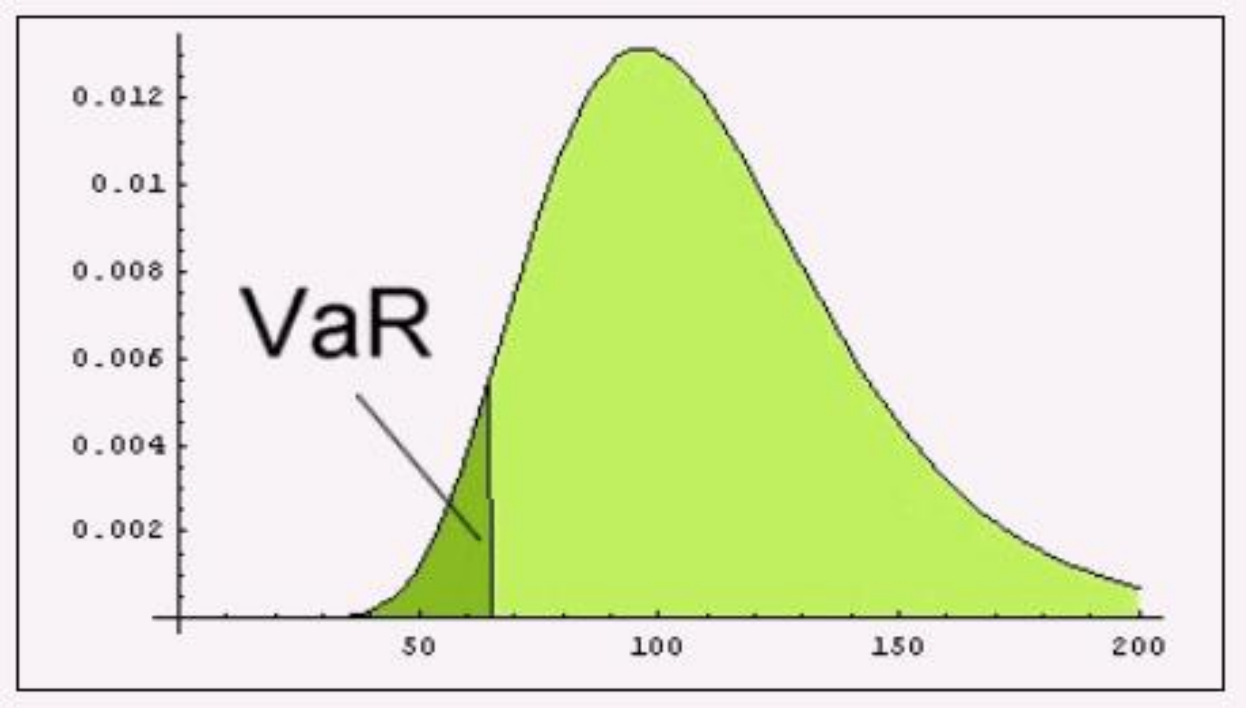

Risikodaten-aggregation
• Genauigkeit & Integrität
• Vollständigkeit
• Aktualität
• Anpassbarkeit
Risikobericht-erstattung
• Genauigkeit
• Umfang
• Verständlichkeit
• Frequenz
• Empfängerkreis
BCBS #239
Governance Und Infrastruktur
• Governance
• Daten- und IT-Struktur
Aufsichts-Prüfung
• Review
• Mängelbeseitigung
• Kooperationen


Basel III
Pillar I
Enhanced Minimum Capital & Liquidity Requirements
Pillar II
Enhanced Supervisory Review Process for Firm-wide Risk Management and Capital Planning
Pillar III
Enhanced Risk Disclosure & Market Discipline

```
def valueAtRisk(
  portfolio,
  timePeriod,
  pValue
): Double = { ... }
```

```
def valueAtRisk(
  portfolio,
  2 weeks,
  0.05
) = $1,000,000
```

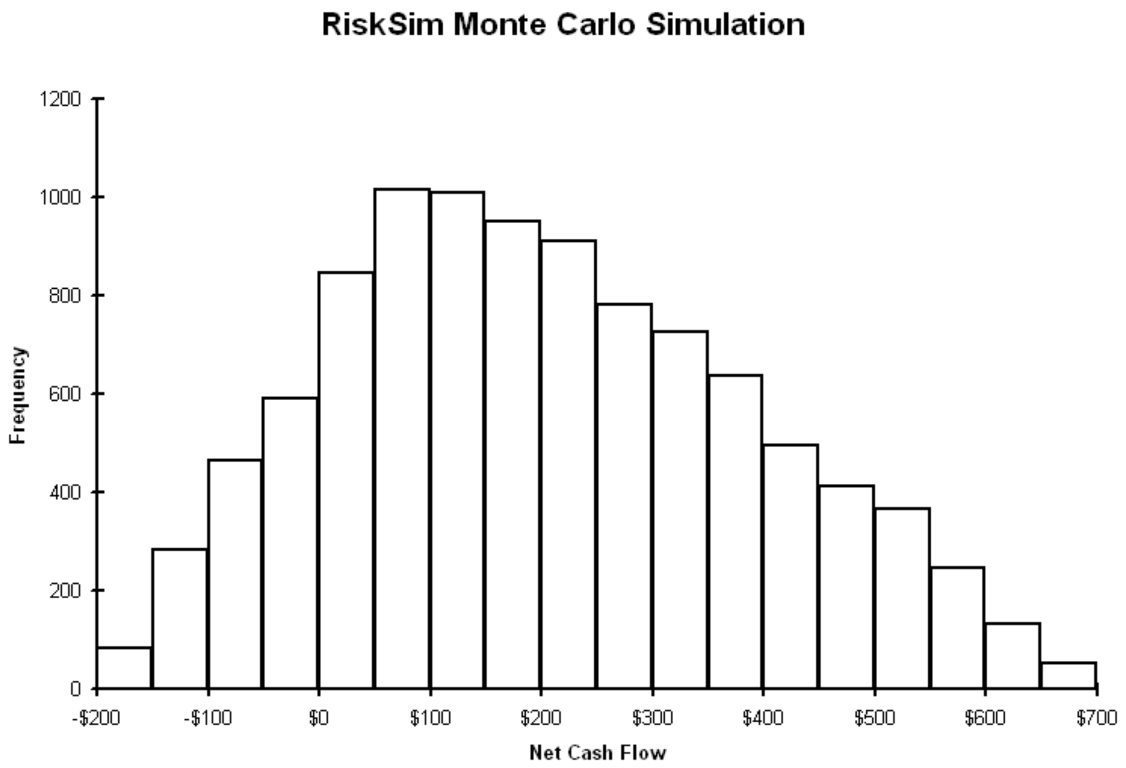
Probability density



Portfolio return ($) over the time period

VaR estimation approaches

- Variance-covariance
- Historical
- Monte Carlo


RiskSim Monte Carlo Simulation
1200
1000
800
600
400
200
0
Frequency
-$200
-$100
$0
$100
$200
$300
$400
$500
$600
$700
Net Cash Flow

Market Risk Factors

- Indexes (S&P 500, NASDAQ)
- Prices of commodities
- Currency exchange rates
- Treasury bonds

Predicting Instrument Returns from Factor Returns

- Train a linear model on the factors for each instrument

$$r_{it} = c_i + \sum_{j=1}^{|w_i|} w_{ij} \cdot m_{tj}$$

Fancier

- Add features that are non-linear transformations of the market risk factors
- Decision trees
- For options, use Black-Scholes

cloudera

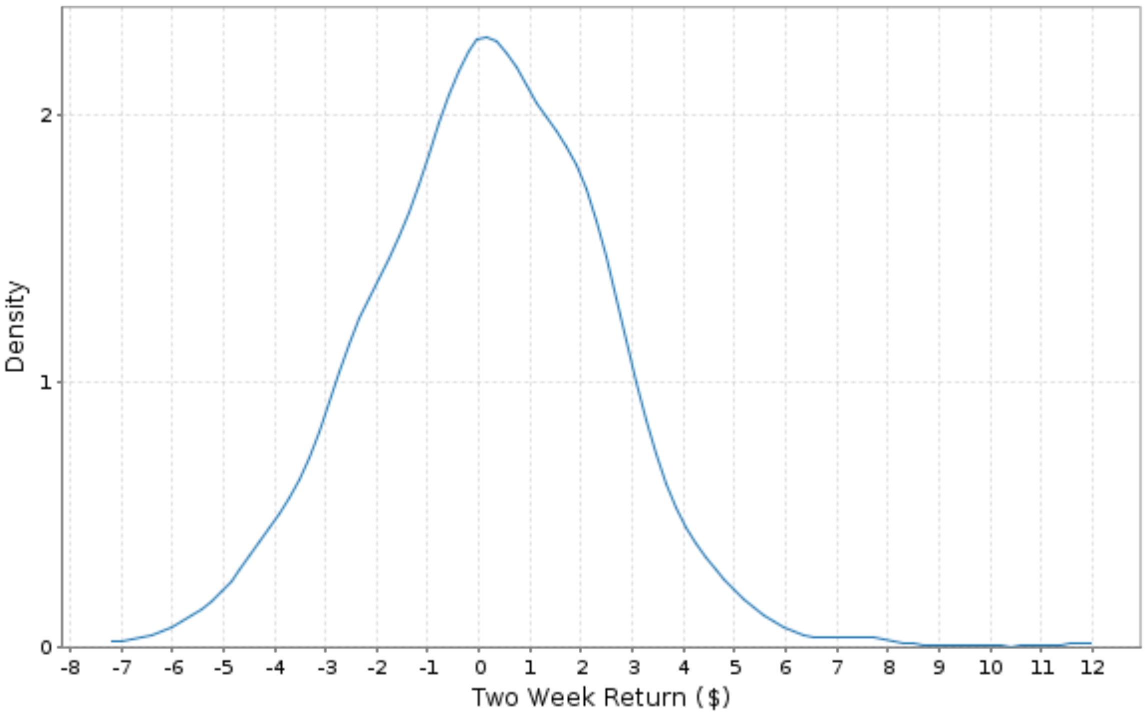
```scala
import org.apache.commons.math3.stat.regression.OLSMultipleLinearRegression

// Load the instruments and factors
val factorReturns: Array[Array[Double]] = ...
val instrumentReturns: RDD[Array[Double]] = ...

// Fit a model to each instrument
val models: Array[Array[Double]] =
  instrumentReturns.map { instrument =>
    val regression = new OLSMultipleLinearRegression()
    regression.newSampleData(instrument, factorReturns)
    regression.estimateRegressionParameters()
  }.collect()
```

cloudera

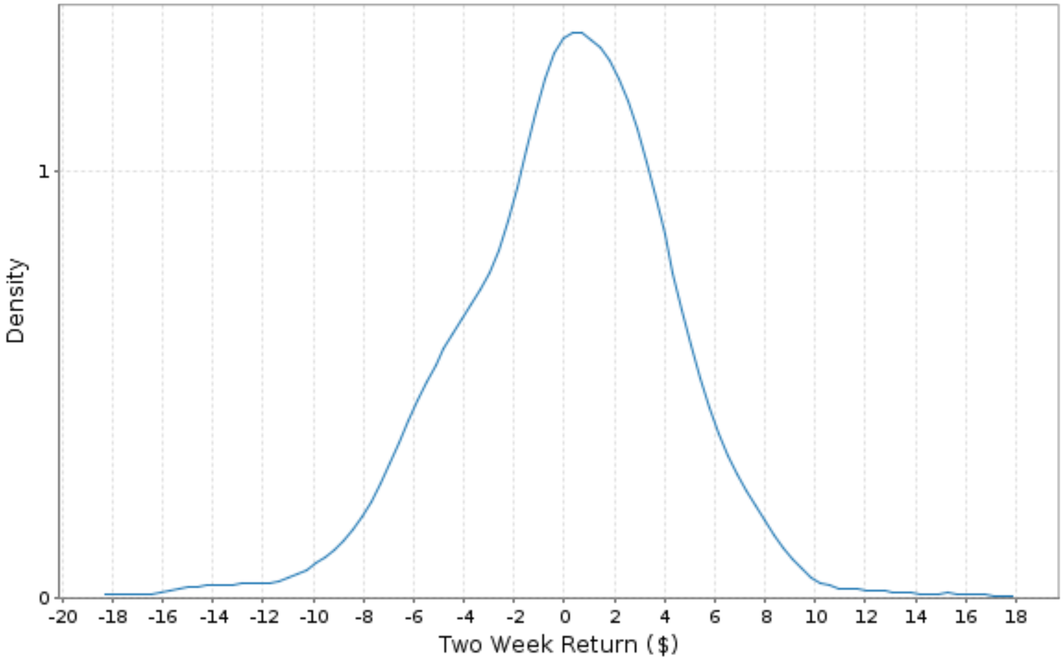
How to sample factor returns?

- Need to be able to generate sample vectors where each component is a factor return.
- Factors returns are usually correlated.

Distribution of US treasury bond two-week returns



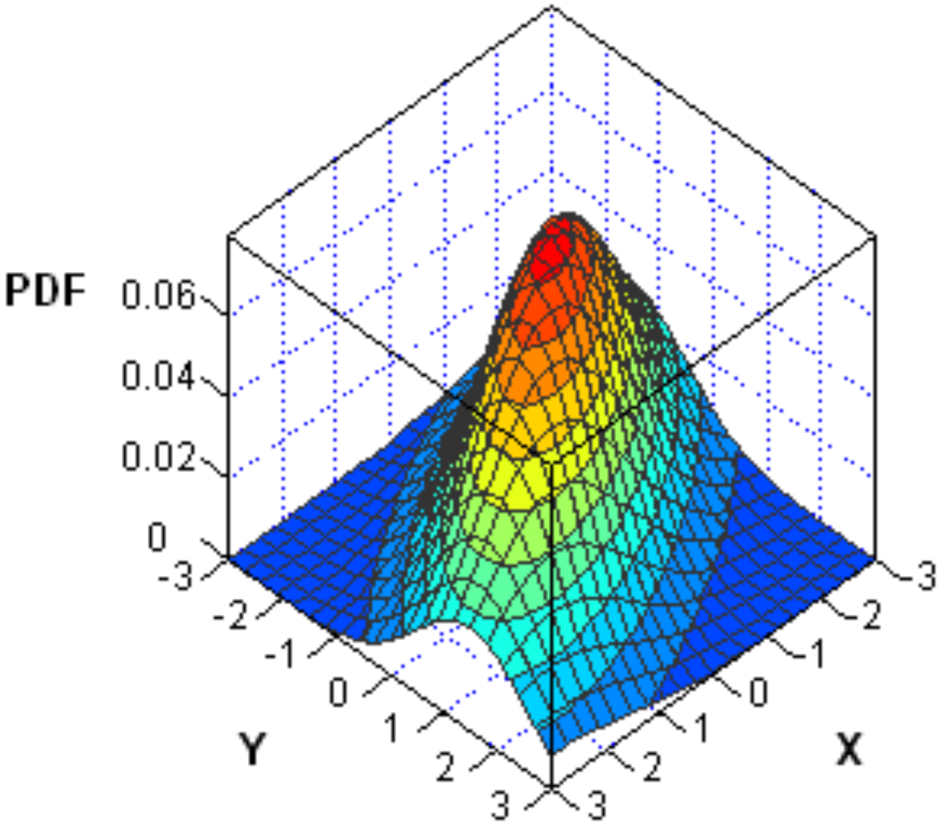
Distribution of crude oil two-week returns



The Multivariate Normal Distribution

$$m_t \sim \mathcal{N}(\mu, \Sigma)$$

- Probability distribution over vectors of length N
- Given all the variables but one, that variable is distributed according to a univariate normal distribution
- Models correlations between variables


PDF
0.06
0.04
0.02
0
-3
-2
-1
0
1
2
3
Y
3
2
1
0
-1
-2
-3
X

```scala
import org.apache.commons.math3.stat.correlation.Covariance

// Compute means
val factorMeans: Array[Double] = transpose(factorReturns)
  .map(factor => factor.sum / factor.size)

// Compute covariances
val factorCovs: Array[Array[Double]] = new Covariance(factorReturns)
  .getCovarianceMatrix().getData()
```

cloudera

Fancier

- Multivariate normal often a poor choice compared to more sophisticated options
- Fatter tails: Multivariate T Distribution
- Filtered historical simulation
  - ARMA
  - GARCH

Running the simulations

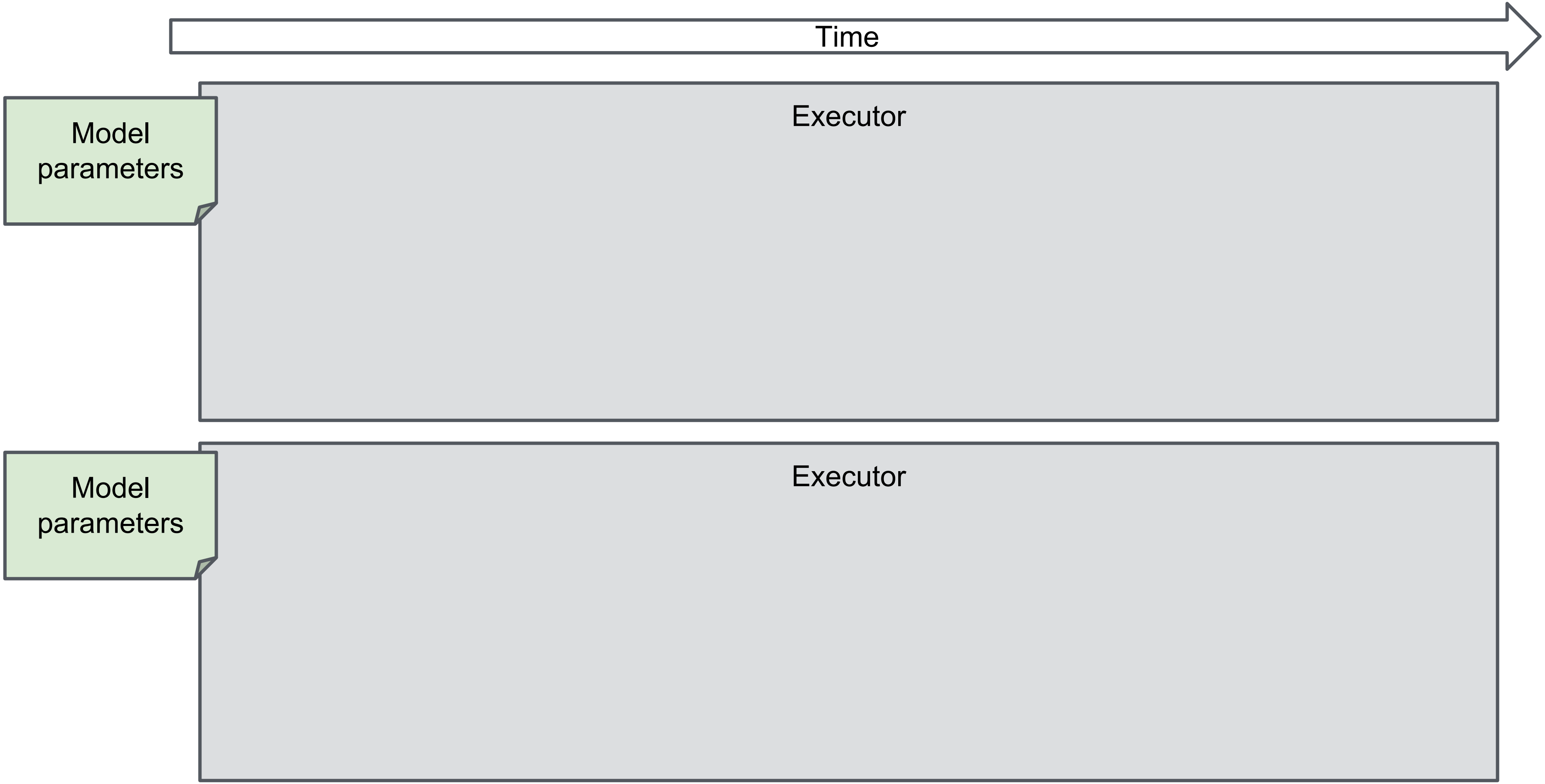
- Create an RDD of seeds
- Use each seed to generate a set of simulations
- Aggregate results

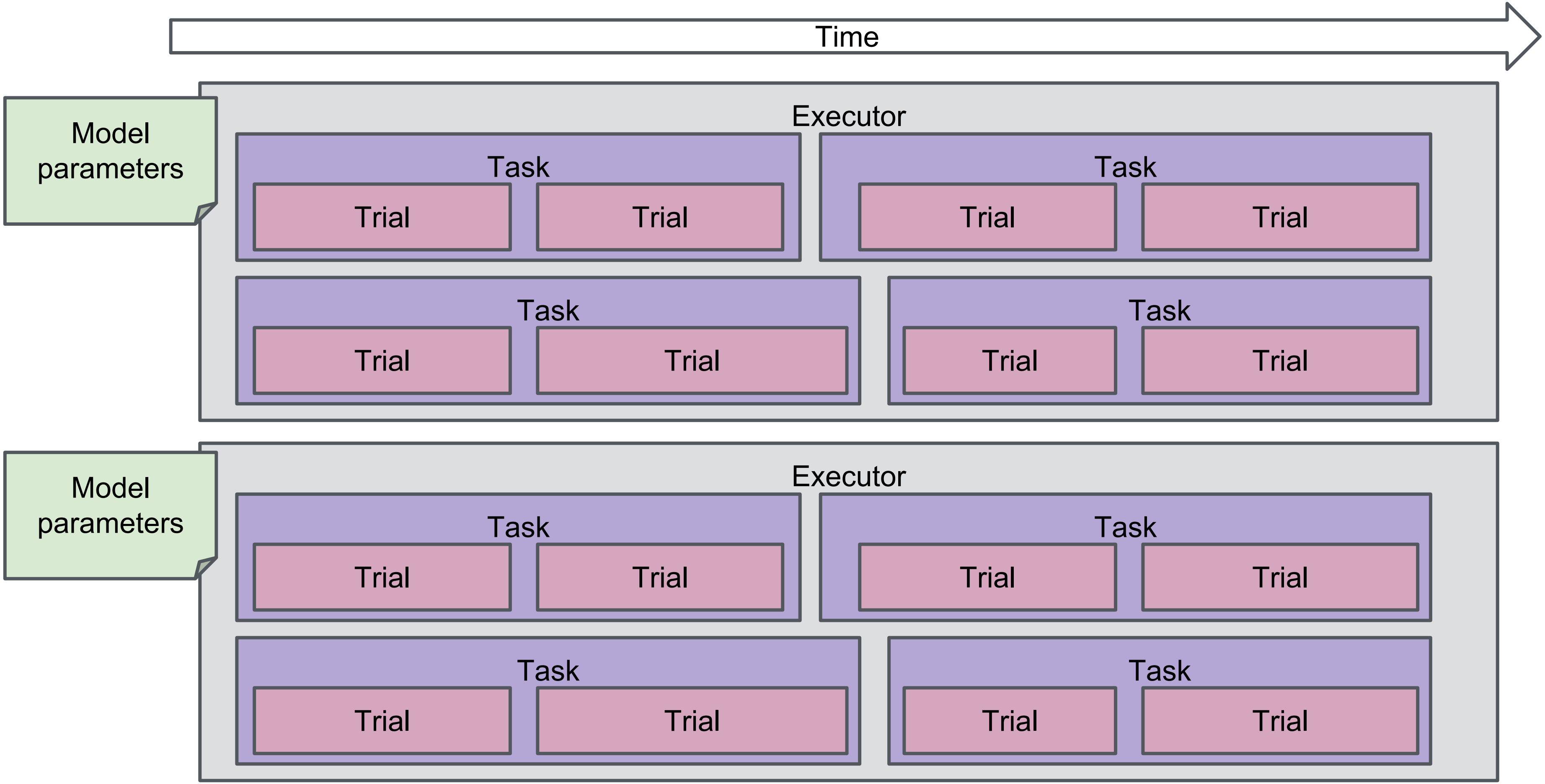
cloudera

```scala
// Broadcast the factor return -> instrument return models
val bModels = sc.broadcast(models)

// Generate a seed for each task
val seeds = (baseSeed until baseSeed + parallelism)
val seedRdd = sc.parallelize(seeds, parallelism)

// Create an RDD of trials
val trialReturns: RDD[Double] = seedRdd.flatMap { seed =>
  trialReturns(seed, trialsPerTask, bModels.value, factorMeans, factorCovs)
}
```

```scala
def trialReturn(factorDist: MultivariateNormalDistribution, models: Seq[Array[Double]]): Double = {
  val trialFactorReturns = factorDist.sample()
  var totalReturn = 0.0

  for (model <- models) {
    // Add the returns from the instrument to the total trial return
    for (i <- until trialFactorsReturns.length) {
      totalReturn += trialFactorReturns(i) * model(i)
    }
  }
  totalReturn
}
```

cloudera

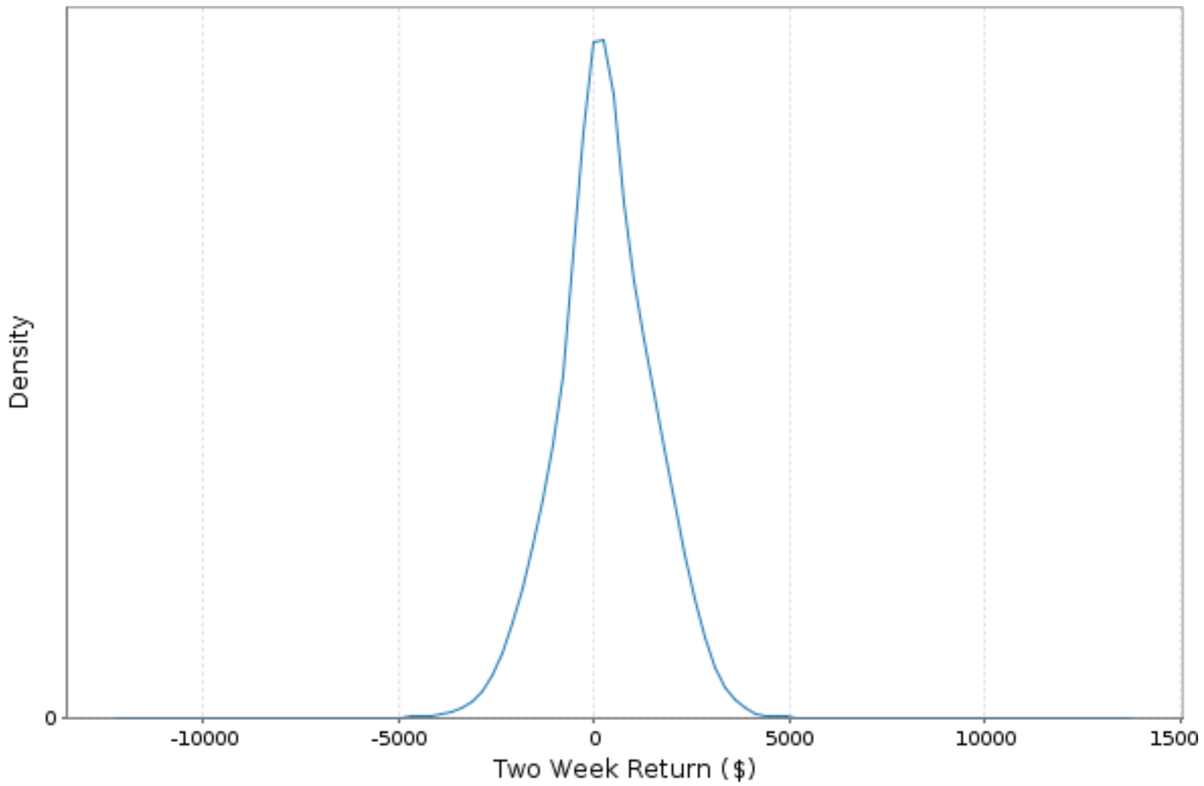

Time
Model parameters
Executor
Model parameters
Executor


Time
Model parameters
Executor
Task
Trial
Trial
Task
Trial
Trial
Task
Trial
Trial
Task
Trial
Trial
Model parameters
Executor
Task
Trial
Trial
Task
Trial
Trial
Task
Trial
Trial
Task
Trial
Trial

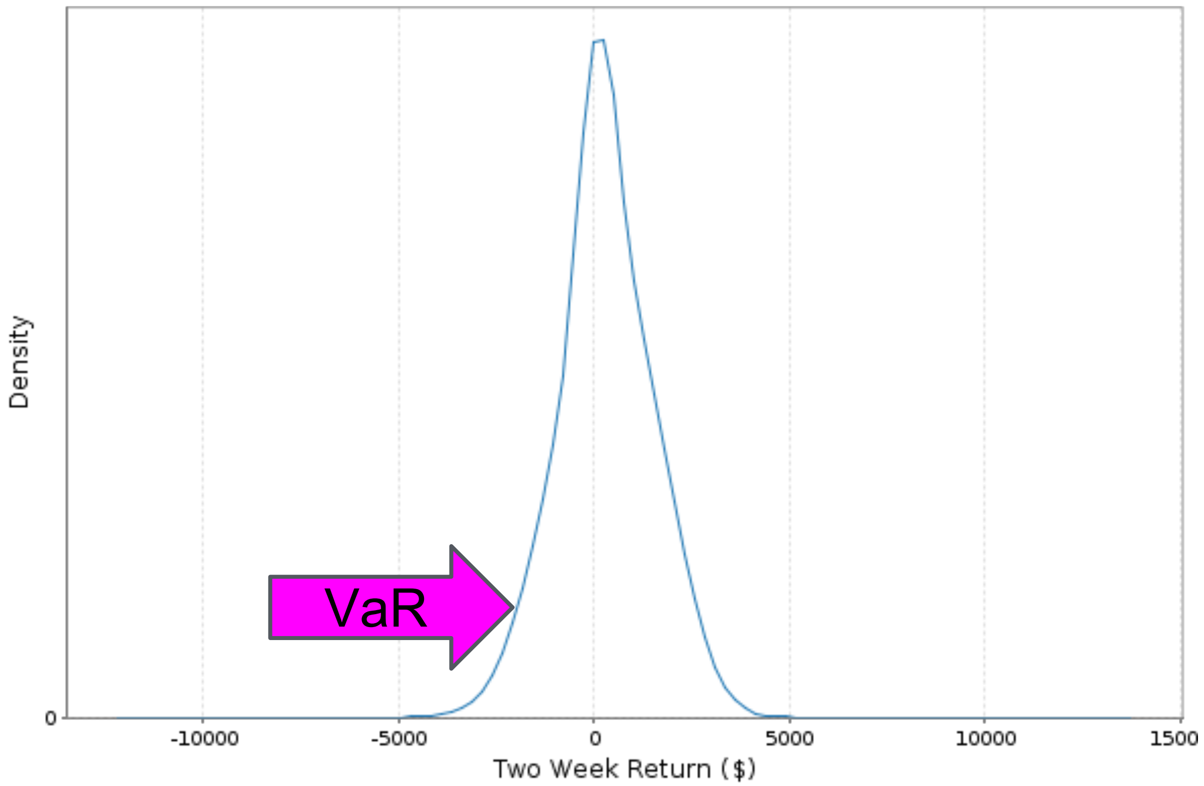
cloudera

```scala
// Cache for reuse
trialReturns.cache()

val numTrialReturns = trialReturns.count().toInt

// Compute value at risk
val valueAtRisk = trials.takeOrdered(numTrialReturns / 20).last

// Compute expected shortfall
val expectedShortfall =
  trials.takeOrdered(numTrialReturns / 20).sum / (numTrialReturns / 20)
```

cloudera



cloudera


VaR
Density
0
-10000
-5000
0
5000
10000
1500
Two Week Return ($)

So why Spark?

Ease of use

- Parallel computing for 5-year olds
- Scala, Python, and R REPLs

Single platform for

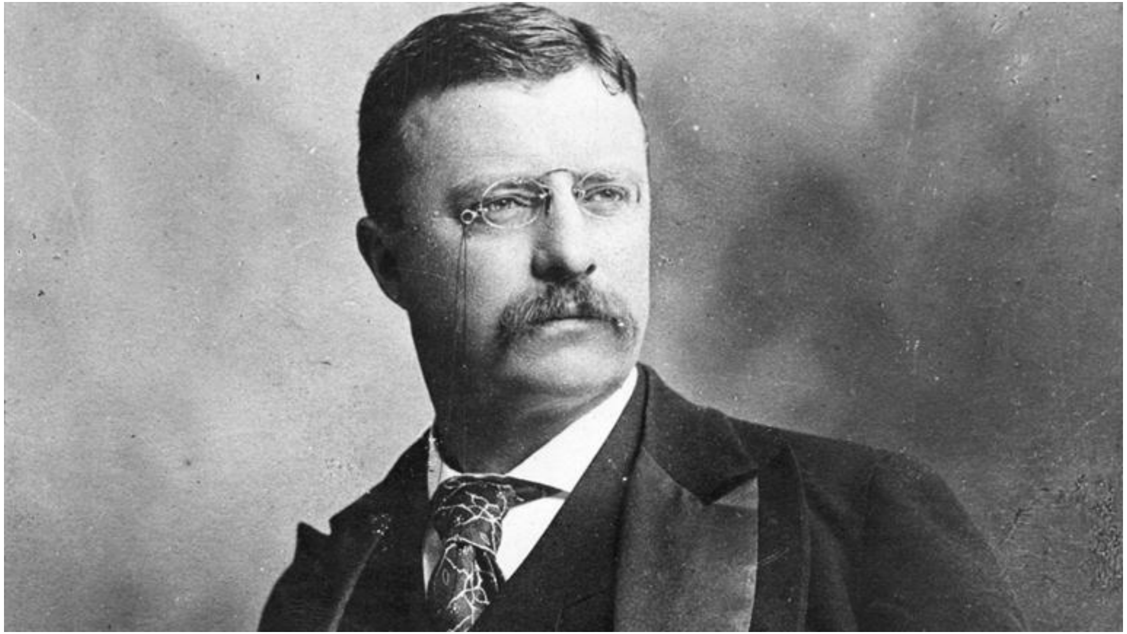
- Cleaning data
- Fitting models
- Running simulations
- Storing results
- Analyzing results

But it’s CPU-bound and we’re using Java?

- Computational bottlenecks are normally in matrix operations, which can be BLAS-ified
- Can call out to GPUs just like in C++
- Memory access patterns aren’t high-GC inducing

cloudera

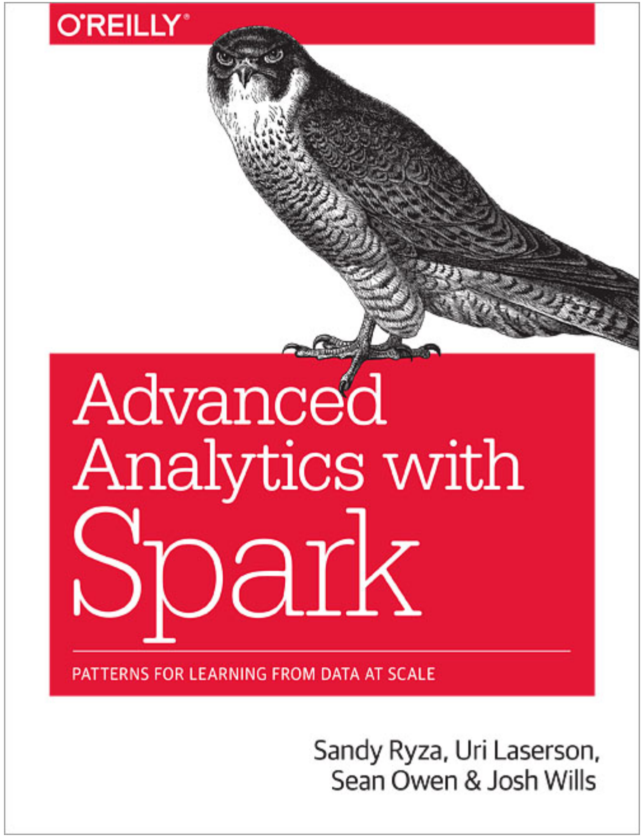
Want to do this yourself?



cloudera

spark-timeseries

- https://github.com/cloudera/spark-timeseries
- Everything here + some fancier stuff
- Patches welcome!


O'REILLY
Advanced Analytics with Spark
PATTERNS FOR LEARNING FROM DATA AT SCALE
Sandy Ryza, Uri Laserson, Sean Owen & Josh Wills

cloudera