Analyzing Time Series Data with Spark

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1888
1889
1890
1891
1892

What’s time series data?

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What makes it unique?

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What do we do with it?

What’s time series data?

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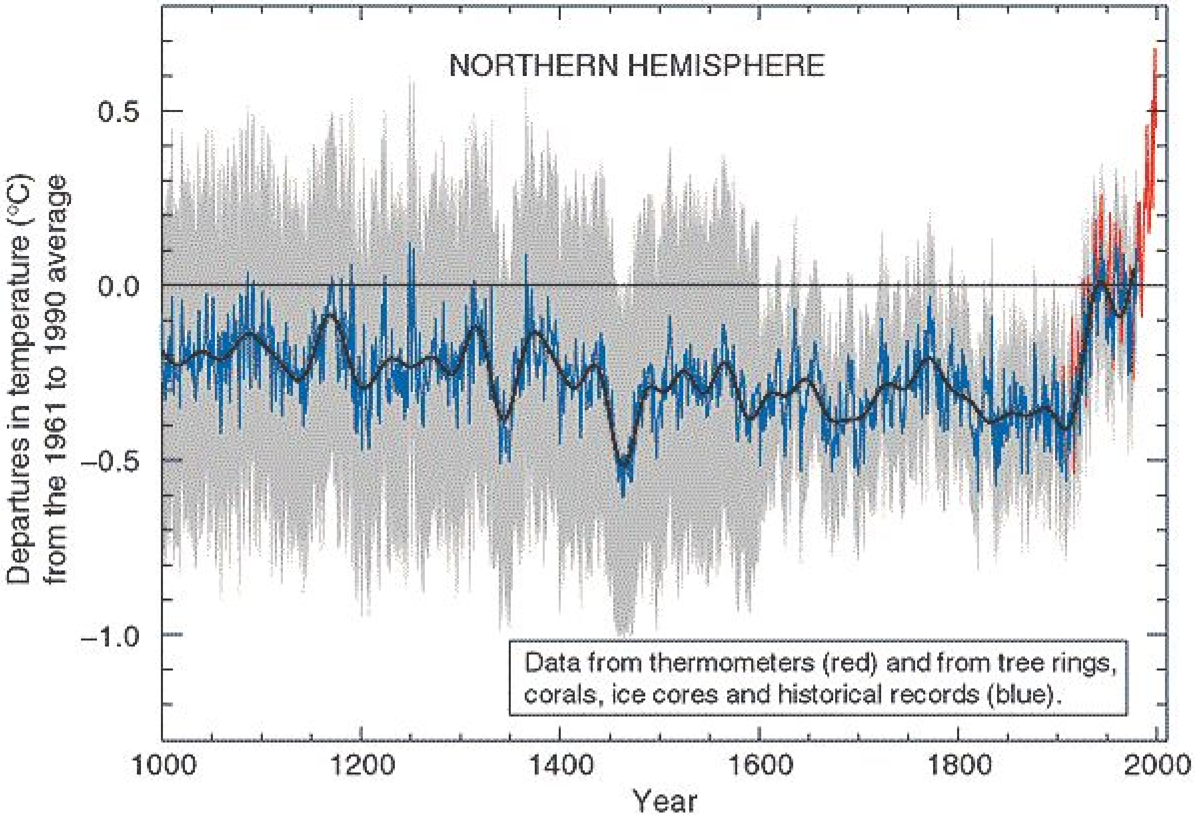
What do we do with it?

How do we deal with lots of it?


NORTHERN HEMISPHERE
Departures in temperature (°C) from the 1961 to 1990 average
0.5
0.0
−0.5
−1.0
1000
1200
1400
1600
1800
2000
Year
Data from thermometers (red) and from tree rings, corals, ice cores and historical records (blue).

Univariate

Time	**Observation**
4/10/1990 23:54:12	4.5
4/10/1990 23:54:13	5.5
4/10/1990 23:54:14	6.6
4/10/1990 23:54:15	7.8
4/10/1990 23:54:16	3.3

Multivariate

Time	Something	Something Else
4/10/1990 23:54:12	4.5	100.4
4/10/1990 23:54:13	5.5	101.3
4/10/1990 23:54:14	6.6	450.2
4/10/1990 23:54:15	7.8	600
4/10/1990 23:54:16	3.3	2000

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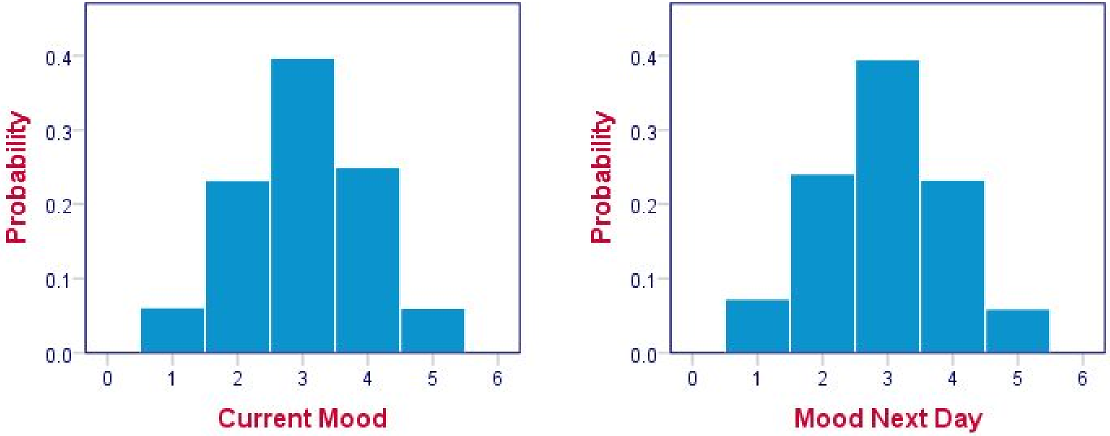
Basic Assumption of Most of Statistics

- Data is i.i.d (independent and identically distributed)



Time Series Dependencies

- What happens now depends on the past, but not the future
- What happens now depends on the recent past more than the distant past
- What happens now depends on the season
    - More traffic on weekdays
- What happens now depends on an absolute moment in time
    - Hurricane Sandy

Human time


HEY GIRL,
Time IS A SOCIAL CONSTRUCT, BUT EVERYONE LIKES TO CUDDLE.
memegenerator.net

Human time

```
vec = datestr(busdays('1/2/01','1/9/01','weekly'))
```

```
vec =

05-Jan-2001

12-Jan-2001
```

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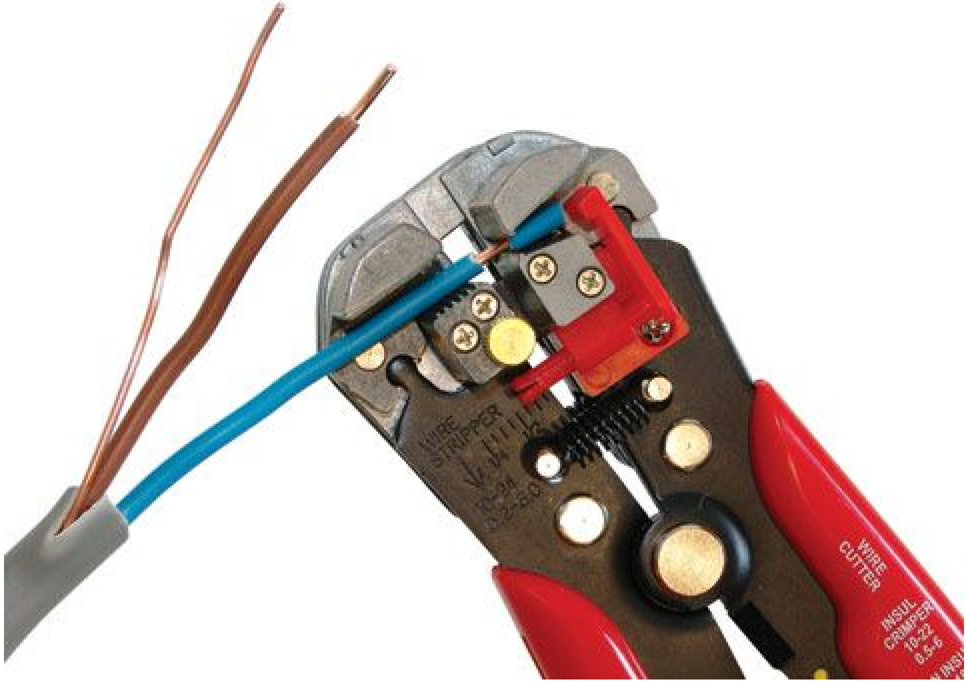
Forecasting

Das Orakel zu Delphi.

Stripping Out Time Dependencies



Detecting Anomalies

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Existing Packages

- Matlab
  - Econometrics toolbox
- Python
  - Pandas
- R
  - zoo, xts
- SAS
  - ETS

Window Functions

```
SELECT buyerid, saletime, qtysold,
LAG(qtysold,1) OVER (order by buyerid, saletime) AS prev_qtysold
FROM sales WHERE buyerid = 3 ORDER BY buyerid, saletime;
```

```
buyerid  |       saletime        | qtysold | prev_qtysold
---------+---------------------+---------+--------------
       3 | 2008-01-16 01:06:09 |       1 |
       3 | 2008-01-28 02:10:01 |       1 |            1
       3 | 2008-03-12 10:39:53 |       1 |            1
       3 | 2008-03-13 02:56:07 |       1 |            1
       3 | 2008-03-29 08:21:39 |       2 |            1
       3 | 2008-04-27 02:39:01 |       1 |            2
```

Window Functions

```
windowSpec = \
  Window
    .partitionBy(df['category']) \
    .orderBy(df['revenue'].desc()) \
    .rangeBetween(-sys.maxsize, sys.maxsize)

dataFrame = sqlContext.table("productRevenue")

revenue_difference = \
  (func.max(dataFrame['revenue']).over(windowSpec) - dataFrame['revenue'])

dataFrame.select(
  dataFrame['product'],
  dataFrame['category'],
  dataFrame['revenue'],
  revenue_difference.alias("revenue_difference"))
```

Window Functions

- Serial dependencies:
  - LAG
- Absolute position:
  - RANK

The “Time Series for Spark” Project

https://github.com/cloudera/spark-timeseries

Goal: Provide a natural API for manipulating large scale time series data.

Goal: Provide statistical routines for modeling large scale time series data.

Scala

Java

python

How do we lay it out?
* Within a machine
* Across machines

“Observations”

Timestamp	Key	Value
2015-04-10	A	2.0
2015-04-11	A	3.0
2015-04-10	B	4.5
2015-04-11	B	1.5
2015-04-10	C	6.0

“Instants”

Timestamp	A	B	C
2015-04-10	2.0	4.5	6.0
2015-04-11	3.0	1.5	NaN

“Time Series”

DateTimeIndex: [2015-04-10, 2015-04-11]	
Key	**Series**
A	[2.0, 3.0]
B	[4.5, 1.5]
C	[6.0, NaN]

Time series in real world applications

- Time series are not that big!

- But there might be lots of them
  - Payments for every mortgage in America
  - Metrics from every robot in a factory
  - Investment portfolio with hundreds of thousands of derivatives

TimeSeriesRDD

Stores a collection of univariate time series with a conformed time index

```
rdd: RDD[String, Vector[Double]]

index: DateTimeIndex
```

TimeSeriesRDD

	5:00 PM	6:00 PM	7:00 PM	8:00 PM	9:00 PM	10:00 PM
GOOG	$523		$524	$600	$574	$400
AAPL	$384	$384	$385	$385	$378	$345
YHOO	$40	$60			$70	$80
MSFT	$134	$138	$175	$178	$123	$184
ORCL	$23	$30	$35	$45	$38	

TimeSeriesRDD distributed partitioning

	5:00 PM	6:00 PM	7:00 PM	8:00 PM	9:00 PM	10:00 PM
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```scala
val tsRdd: TimeSeriesRDD = ...

// Find a sub-slice between two dates
val subslice = tsRdd.slice(
    ZonedDateTime.parse("2015-4-10", ISO_DATE),
    ZonedDateTime.parse("2015-4-14", ISO_DATE))

// Fill in missing values based on linear interpolation
val filled = subslice.fill("linear")

// Use an AR(1) model to remove serial correlations
val residuals = filled.mapSeries(series =>
    ar(series, 1).removeTimeDependentEffects(series))
```

DateTimeIndex

```
val dtIndex = DateTimeIndex.uniform(
  ZonedDateTime.parse("2015-4-10", ISO_DATE),
  ZonedDateTime.parse("2015-5-14", ISO_DATE),
  2 businessDays) // wowza that's some syntactic sugar

dtIndex.dateTimeAtLoc(5)
```

Time Series Models

ARIMA:

```scala
val modelsRdd = tsRdd.map { ts =>
  ARIMA.autoFit(ts)
}
```

GARCH:

```scala
val modelsRdd = tsRdd.map { ts =>
  GARCH.fitModel(ts)
}
```

Stats

```
val mostAutocorrelated = tsRdd.map { ts =>
  (TimeSeriesStatisticalTests.dwtest(ts), ts)
}.max
```

Roadmap: Core

- ~~RDDs~~ -> Datasets
- Full windowing
  - tumbling, sliding, sessions
- Full resampling
  - up and down
- Looong series
  - Across partitions

Roadmap: Stats

- Vector autoregression
- Regression ARIMA
- ARIMAX
- Full Holt-Winters
- Anomaly detection
    - Standard models