

Independent Component Analysis

– in Clojure

AIM Lab group meeting, May 19, 2010

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Outline

- Independent Component Analysis
 - A quick intro
- Clojure
 - Another quick intro
- Results
- Future work and conclusion

Motivation

- I wanted:
 - To learn a new programming language
 - Clojure
 - Apply the language to a specific problem
- Solution:
 - Build upon last year's ICA research
 - Implement an ICA algorithm in Clojure

What is ICA?

- Separates data into maximally independent components
- We assume that the original signals are *independent*
 - $P(A \cap B) = P(A) * P(B)$
- We assume that the original signals are *linearly mixed*
 - $x_1 = a * s_1 + b * s_2$

ICA – an intuitive example

- The *cocktail party problem*
 - n persons in a room
 - All speaking at the same time
 - n mixed signals
 - E.g. n microphones in different locations
 - Our brain can easily distinguish the n signals
 - A computer needs help, e.g. ICA

Definition of ICA

- Given an m by n data matrix x
 - m is the (assumed) number of original signals
 - n is the number of data points
- Assume that x is a linear mix of original signals s , according to:

$$x = As$$

- A is thus an m by m mixing matrix

Definition of ICA – cont.

- Goal is to find an unmixing matrix W such that:

$$s' = Wx$$

- s' is an approximation to the original signals s
- W is the inverse of A

- $W = A^{-1}$

ICA caveats

- We cannot determine the original *sign* (+/-) of the found components
- We cannot determine the *order* of the found components.
- The distributions of the original signals must be *nongaussian*
 - gaussian distribution = normal distribution

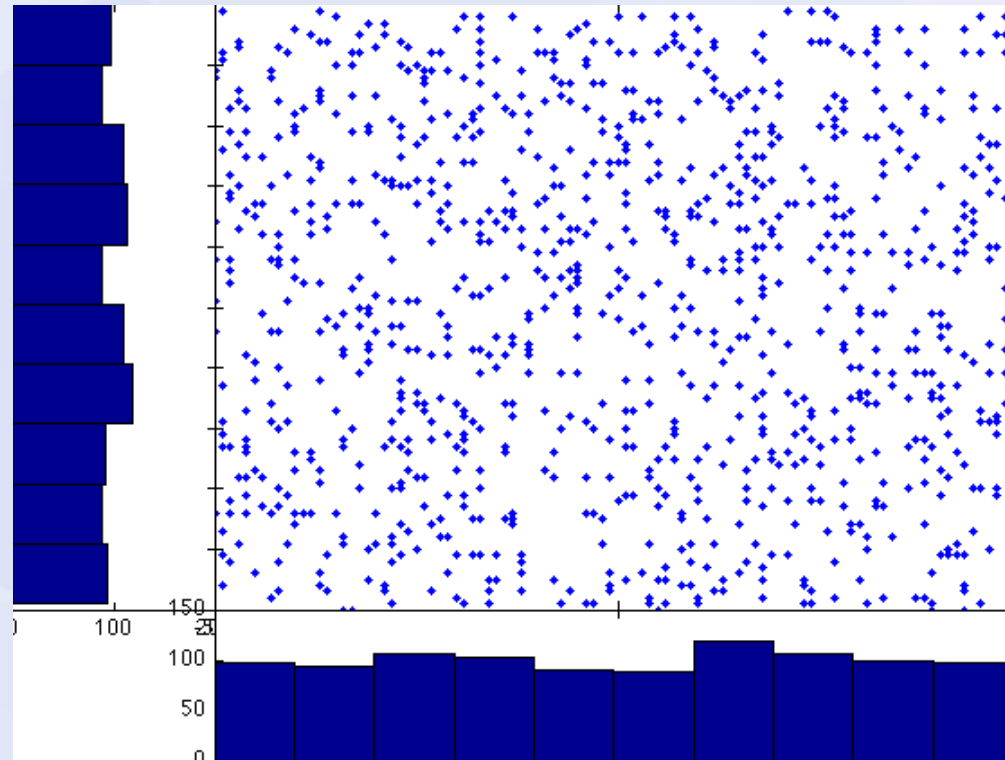
How does ICA work?

- Central Limit Theorem
 - The distribution of the sum of independent variables is more gaussian than the distribution of the variables themselves
- For an unmixing vector w , ICA maximizes the nongaussianity of

$$w^T x$$

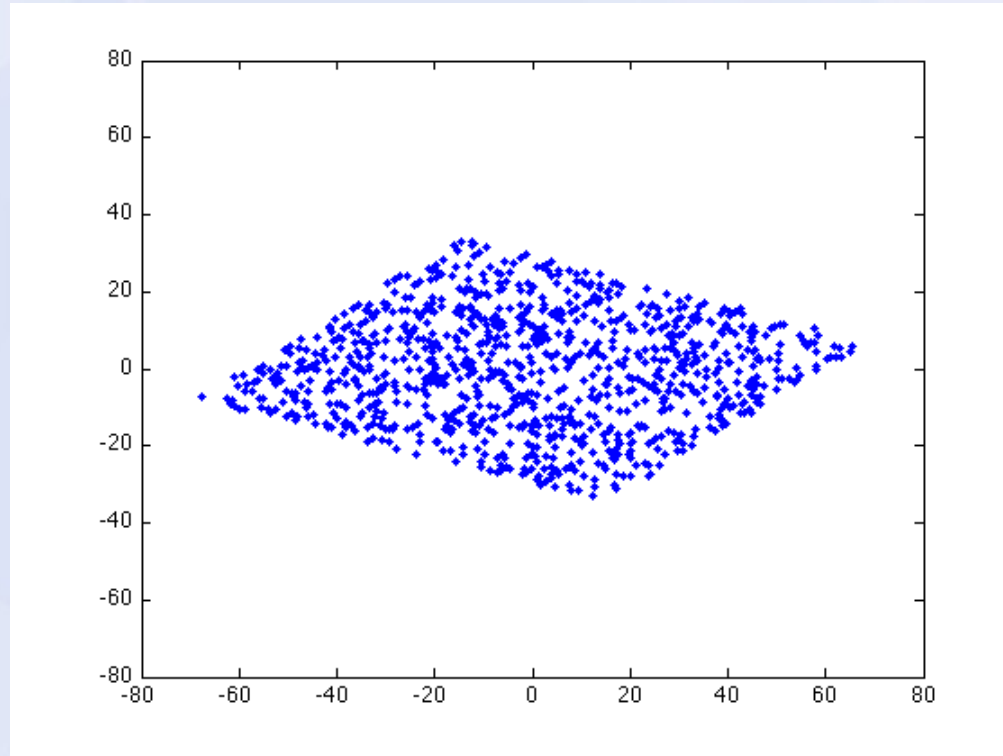
Let's look at an example

ICA example – random signals



Scatter-plot of two random signals, along with their distributions which are uniform

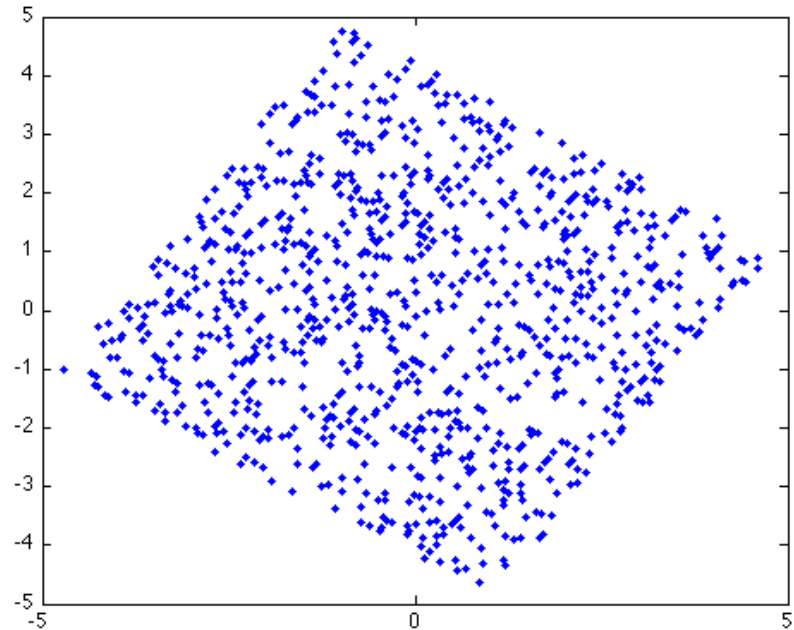
ICA example – mixed signals



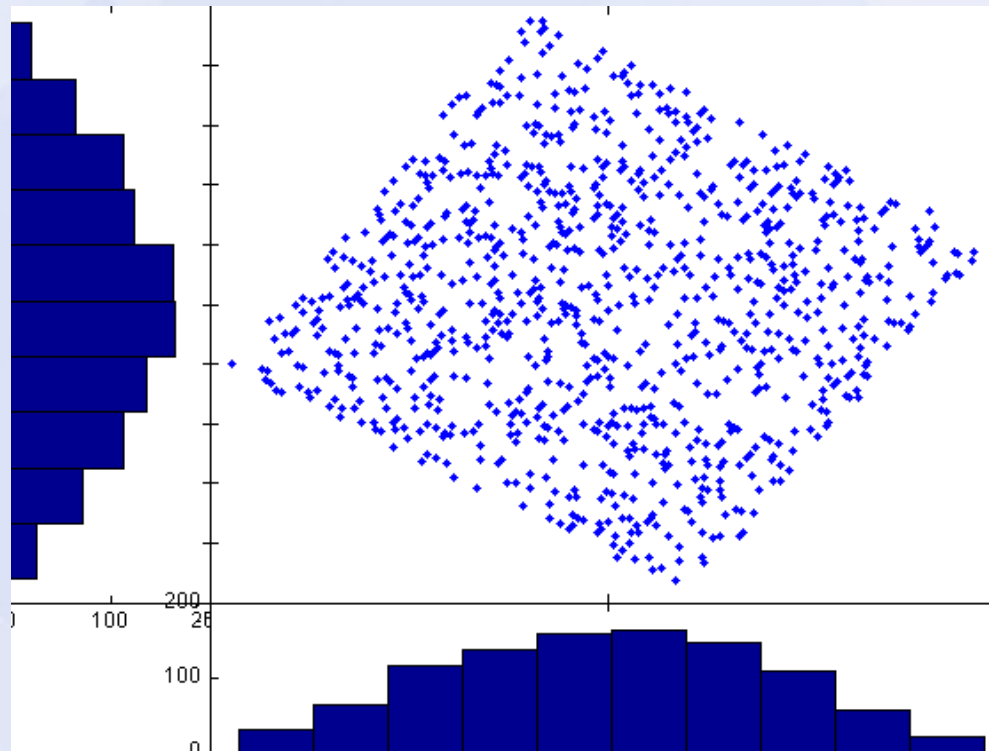
Scatter-plot of the mixed signals

ICA example – preprocessing

- *Whitening* of data components:
- Uncorrelation
- Variances equal unity



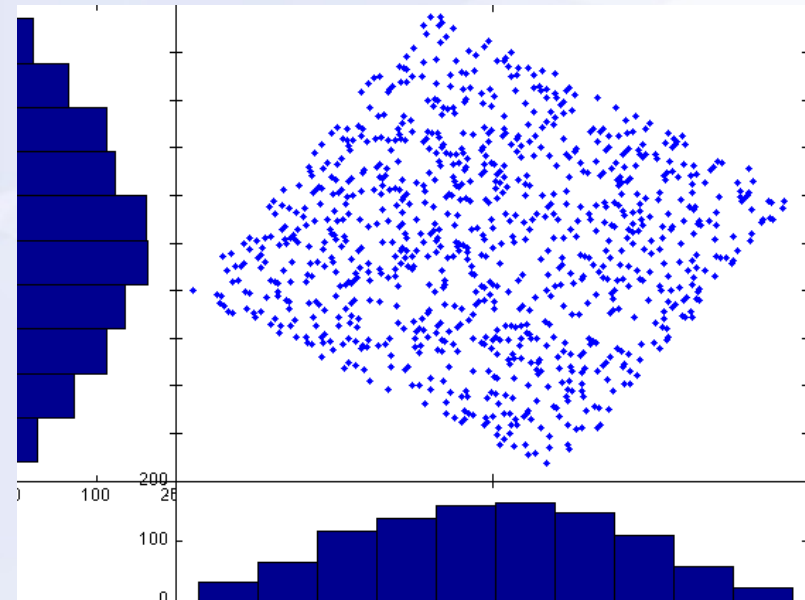
ICA example – whitened data



Scatter-plot of whitened mixed signals, along with their distributions which are more gaussian than the original signals

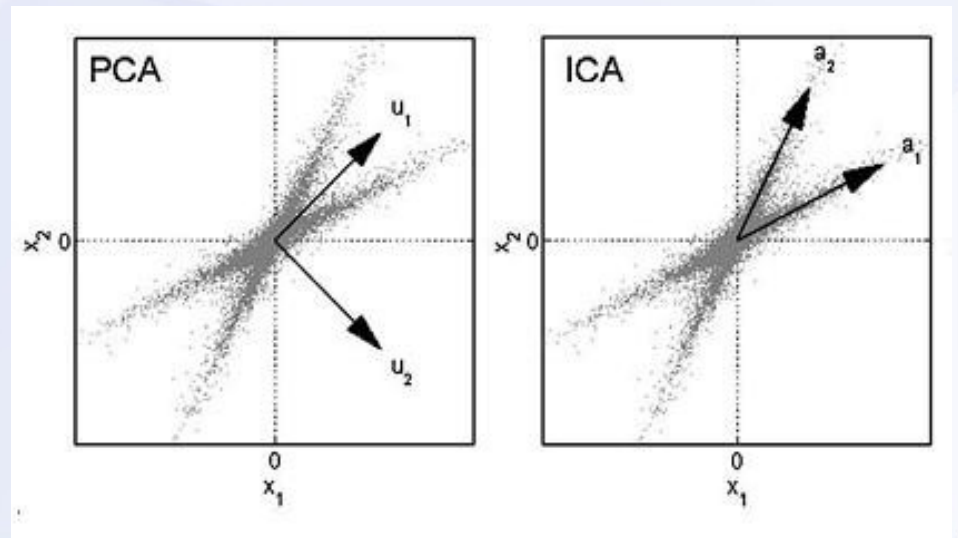
ICA example – finding components intuitively

- Find weight vectors w_1 , w_2 that “rotate” the mixed signals
- w_1 and w_2 maximize non-gaussianity of the components of x



Principal Components Analysis versus ICA

- PCA finds components with decreasing “importance”
- ICA finds maximally independent components
- PCA is sometimes used as a pre-processing step for ICA



Clojure overview

- Dynamic
 - Direct interaction through the REPL
 - REPL = Read Eval Print Loop
 - Compiles on-the-fly
- LISP dialect
- Functional programming language
 - Functions are first-class objects

Clojure overview

- Designed for concurrency
 - Software transactional memory (STM)
 - Immutable and persistent data structures
- Runs on the Java Virtual Machine (JVM)
 - Compiles into bytecode
 - Access to the entire Java library
 - But discourages use of Java data structures since they are not immutable

Clojure syntax

()

Clojure syntax

- But seriously, it is very sparse
- Clojure uses the code-as-data principle as other LISPs
 - S-expressions “()” are parsed into data structures and then compiled
 - In other words, everything is basically a data structure
 - Prefix notation

Is Clojure cool?

- Potentially
 - It is gaining a lot of attention
 - A lot of people are overly excited about it
 - Makes concurrency easier
 - No locking
- It requires a *totally* different mindset than normal OO/imperative programming
 - I haven't gotten it yet

ICA and Clojure – challenges

- Going from mathematical definition to code
- Understanding Clojure
 - Working with immutable data structures
 - Data cannot “change”
 - Recursion versus looping

FastICA

- Assumes data to be centered and whitened
- Uses *negentropy* to measure nongaussianity
 - Negentropy is maximal for a distribution that is nongaussian

FastICA

- General update rule (from literature):

$$\mathbf{w}' = E\{\mathbf{x}g(\mathbf{w}^T\mathbf{x})\} - E\{g'(\mathbf{w}^T\mathbf{x})\}\mathbf{w}$$

$$\mathbf{w} = \mathbf{w}' / \|\mathbf{w}'\|$$

repeat until converged (i.e. old and new \mathbf{w} point in same direction)

- In practice (from Matlab implementation)

$$\mathbf{w}' = E\{\mathbf{x}(\mathbf{x}^T\mathbf{w})^3\} - 3\mathbf{w}$$

$$\mathbf{w} = \mathbf{w}' / \|\mathbf{w}'\|$$

Current progress

- FastICA implemented in Clojure
 - Based largely on the Matlab version
 - Uses the Clojure library *Incanter*
 - Goal of Incanter is to supply R-like functionality in Clojure
 - Simple “deflation” approach for decorrelating found basis vectors

Current progress

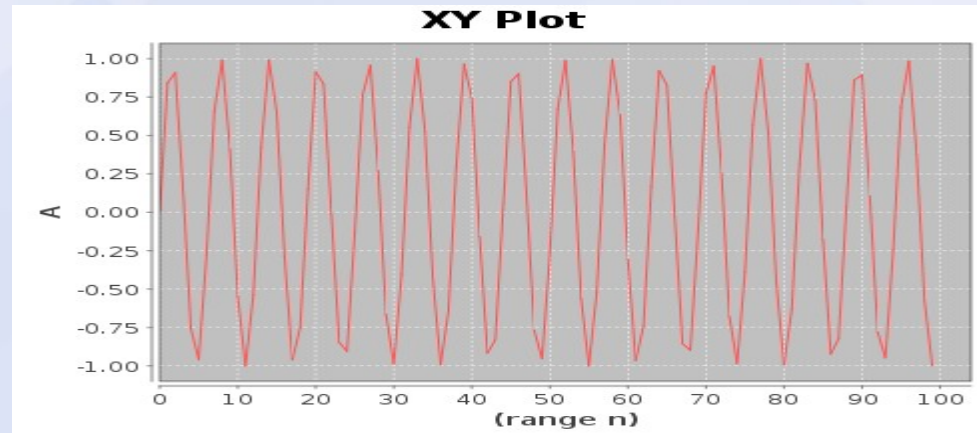
- Comparison with Matlab implementation
 - Looking at found independent components (very subjective)
 - Measuring running time
 - Requires very large data sets
 - Current experiments run in ms
 - I haven't done this yet.

Test 1

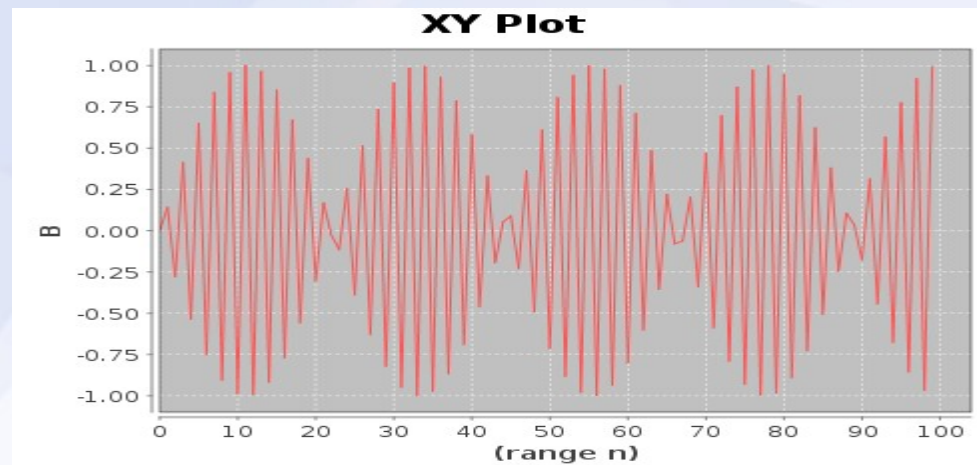
- Two sources
 - $s_1 = \sin(x)$, $x = 0, \dots, 99$
 - $s_2 = \sin(3x)$, $x = 0, \dots, 99$
- Two mixed signals (linear combinations)
 - $x_1 = s_1 - 2*s_2$
 - $x_2 = 1.73*s_1 + 3.41*s_2$

Test 1 – original sources

s1

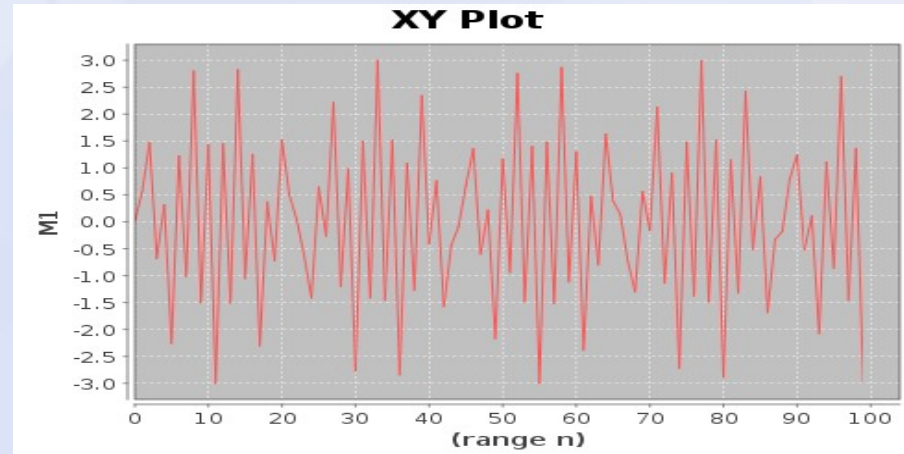


s2



Test 1 – mixed signals

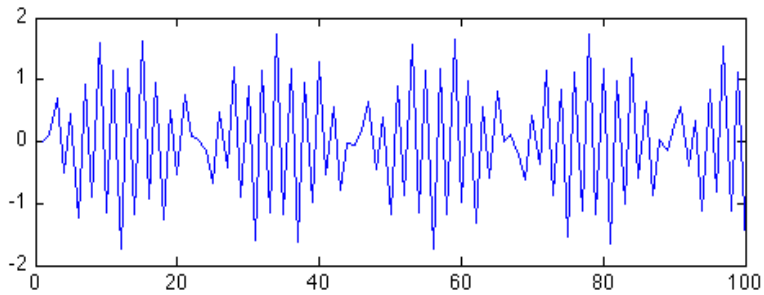
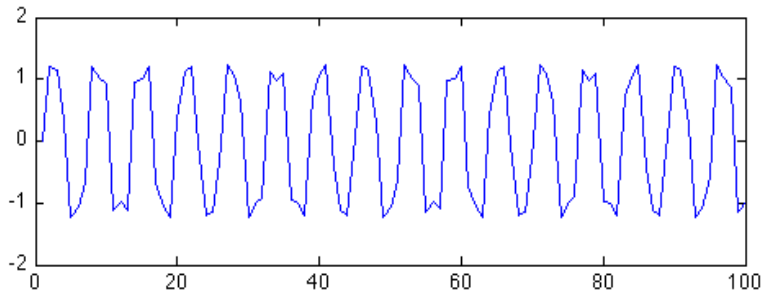
x1



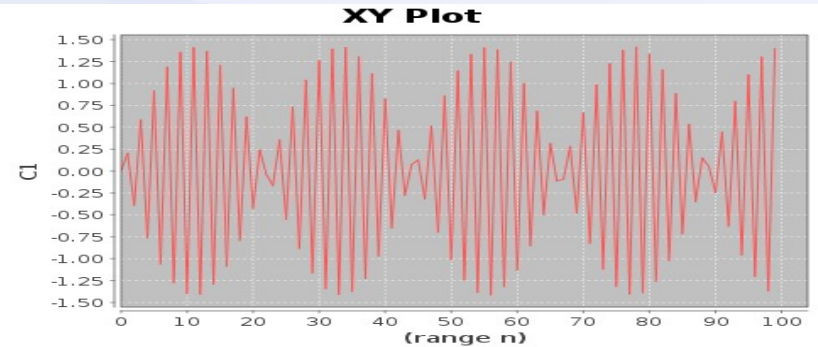
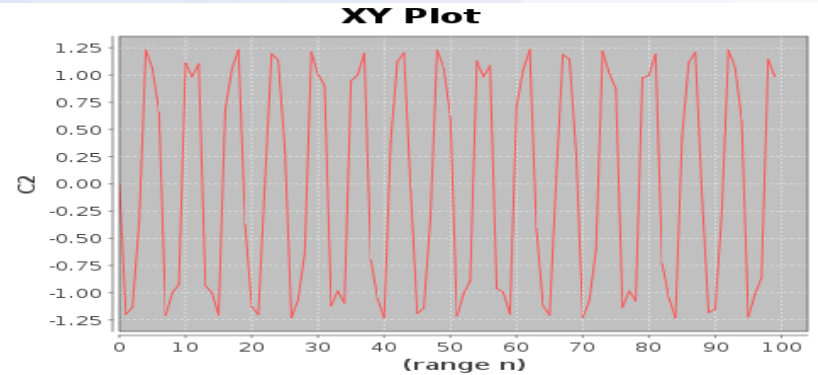
x2



Test 1 – found components



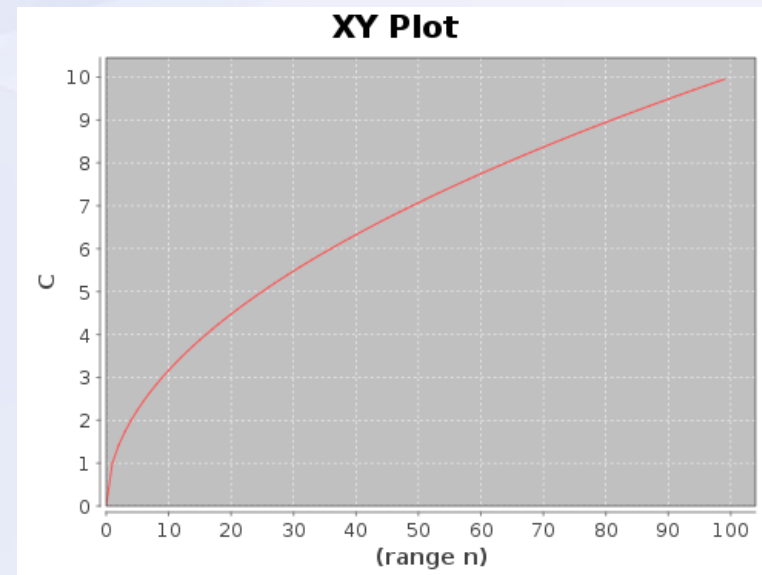
Matlab implementation



Clojure implementation

Test 2

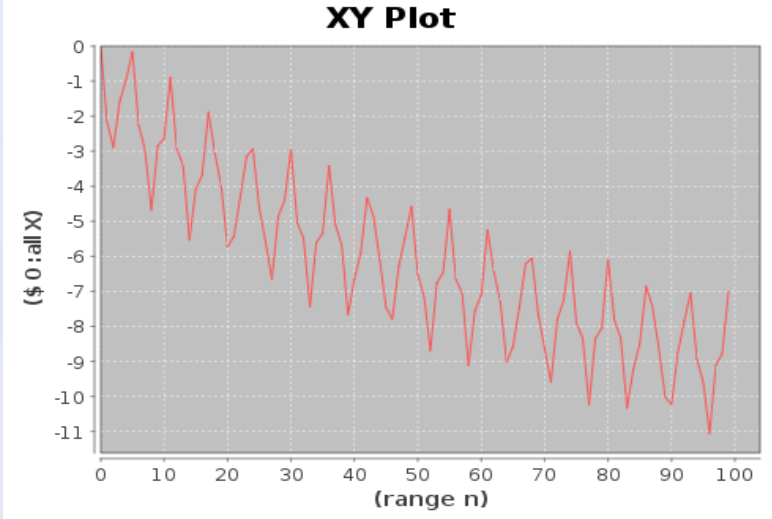
- Add a third component
 - $s3 = \sqrt{x}$, $x = 0, \dots, 99$
- $x1$, $x2$ and $x3$ are mixed by a *random* mixing matrix A with values between -3 and 3



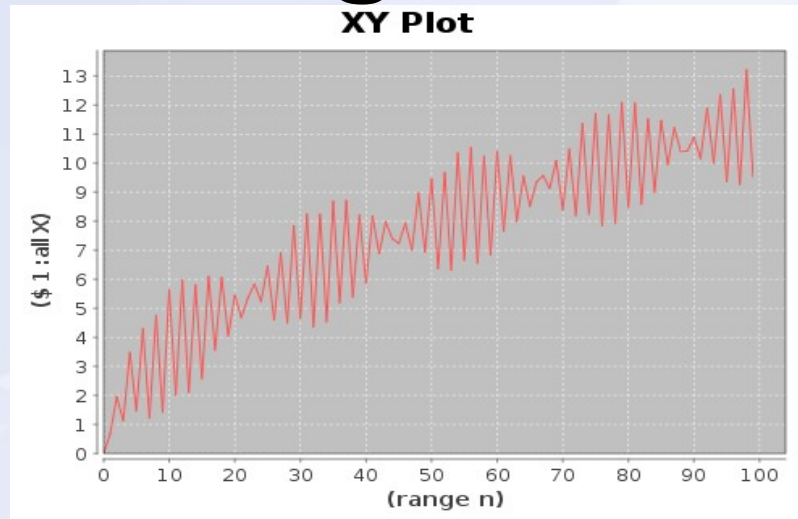
s3

Test 2 – mixed signals

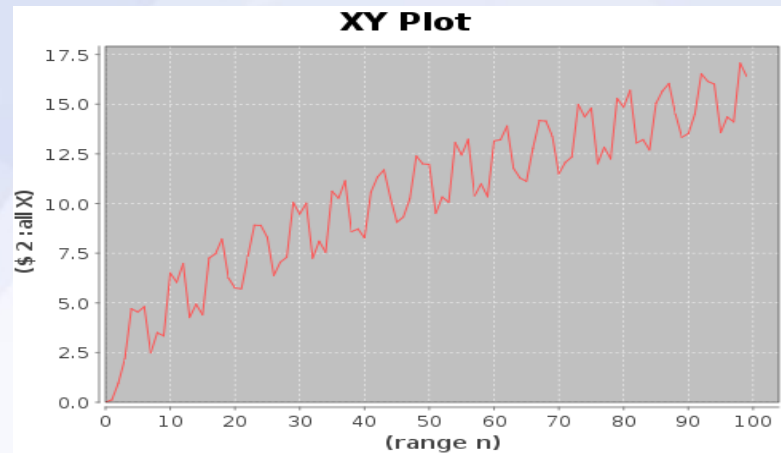
x1



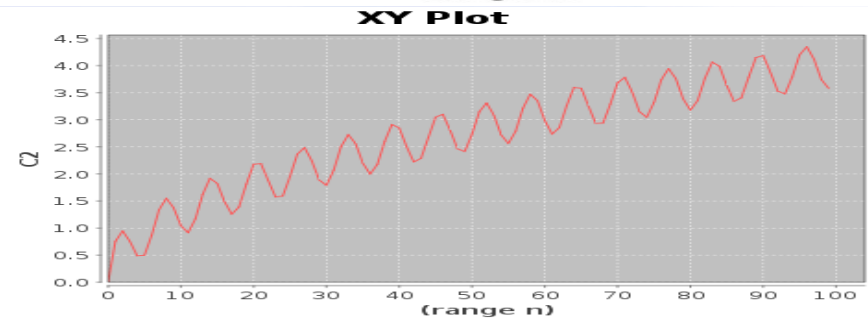
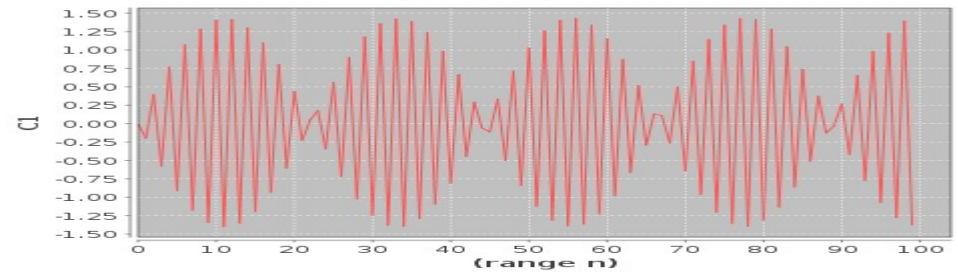
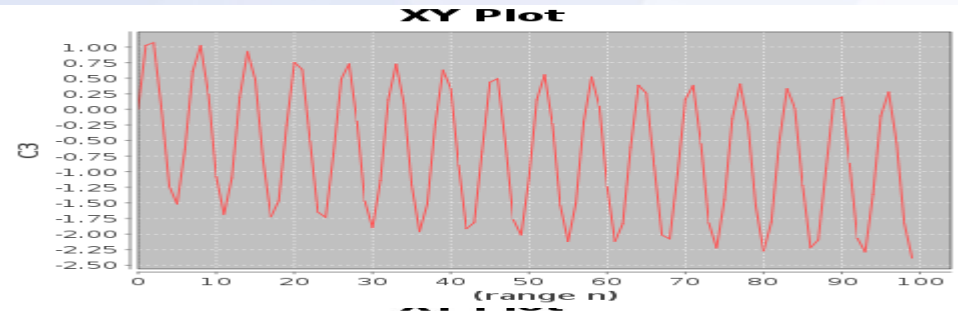
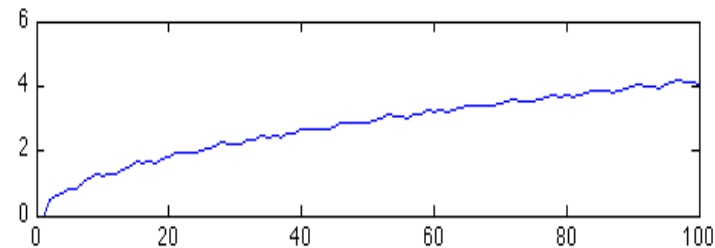
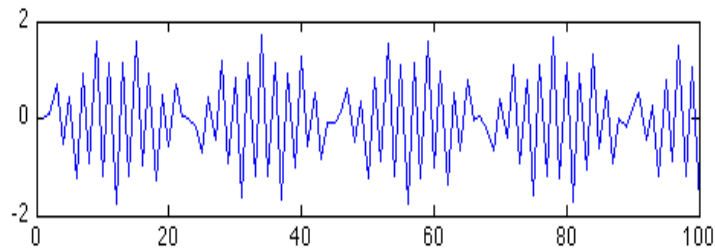
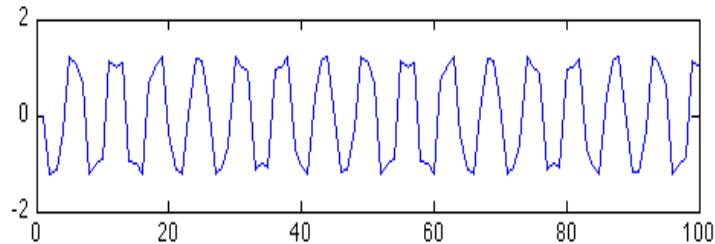
x2



x3

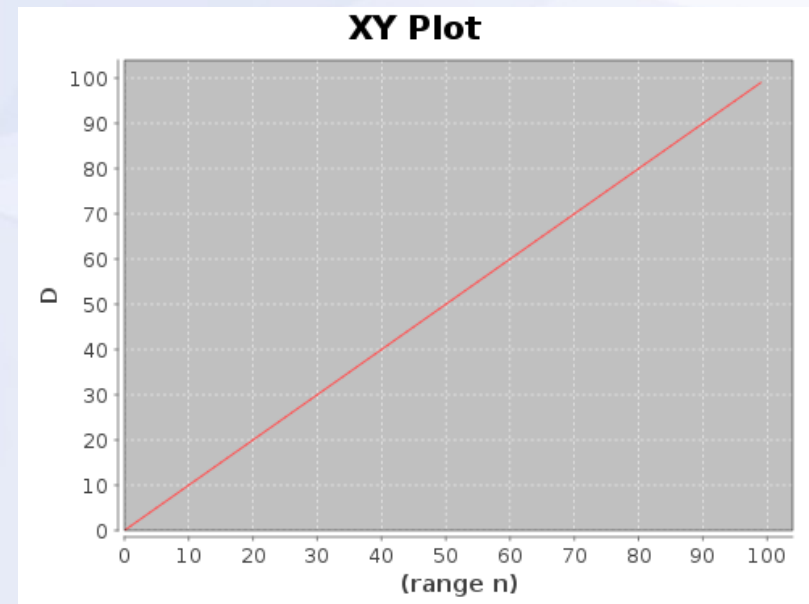


Test 2 – found components



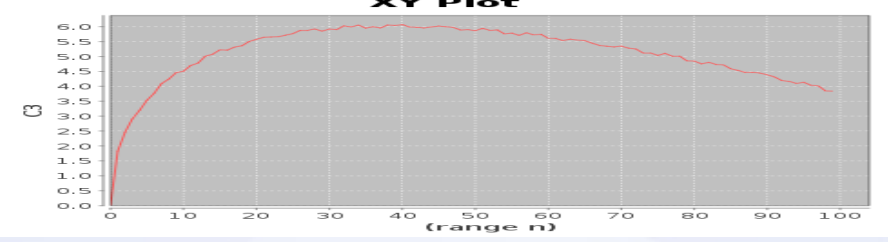
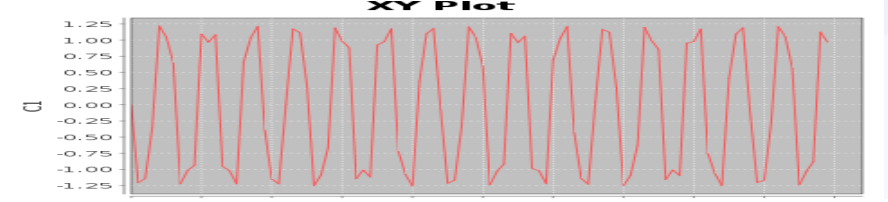
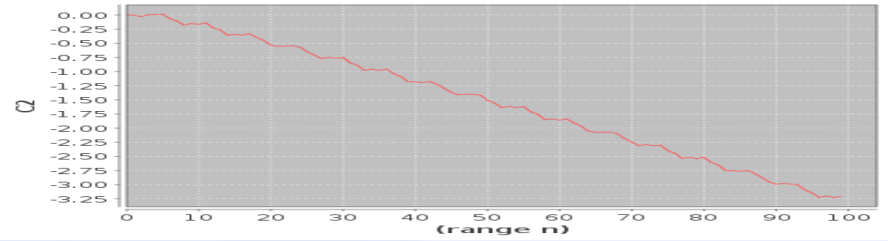
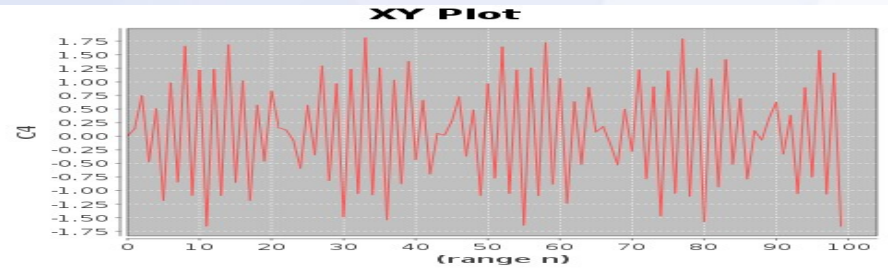
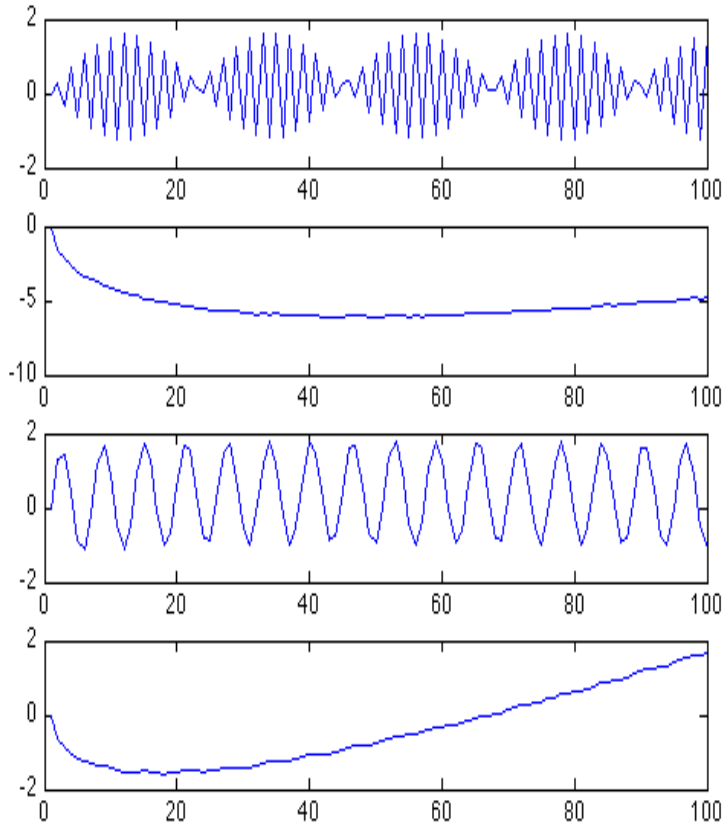
Test 3

- Add a fourth component
 - $s4 = x, x = 0, \dots, 99$
- $x1, x2, x3$ and $x4$ are mixed by a *random* mixing matrix A with values between -3 and 3



s3

Test 3 – found components



Test results

- Same algorithm, different outcome, why?
 - Different mixing matrices
 - But for test 1, they were identical
 - Different start vectors
 - Converges differently?

ICA on real world data

- Demixing sound signals
- Face recognition
 - Facial “components”
- Stock market prices
 - Underlying hidden factors
 - I tried this

ICA on stock market

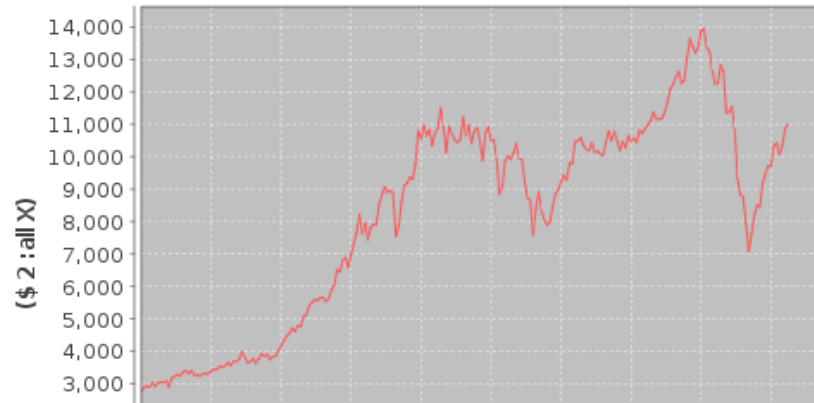
- Three large stock market indexes
 - Dow Jones (USA)
 - Nikkei (Japan)
 - FTSE (Europe)
- Monthly data from 1991-2010
- Each stock index is an observed variable
- Each time point is an observation

ICA on stock market

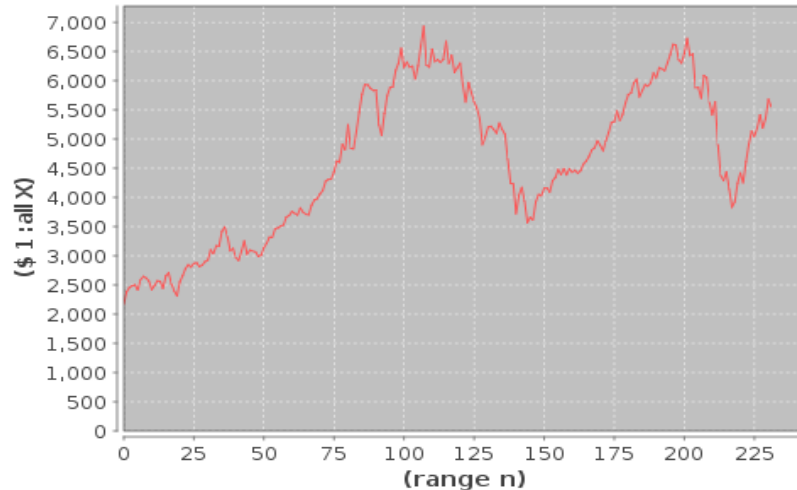
- Hypothesis:
 - The three indexes have some underlying hidden factors that affect all three stock markets
 - Can this be true?

Stock market indexes

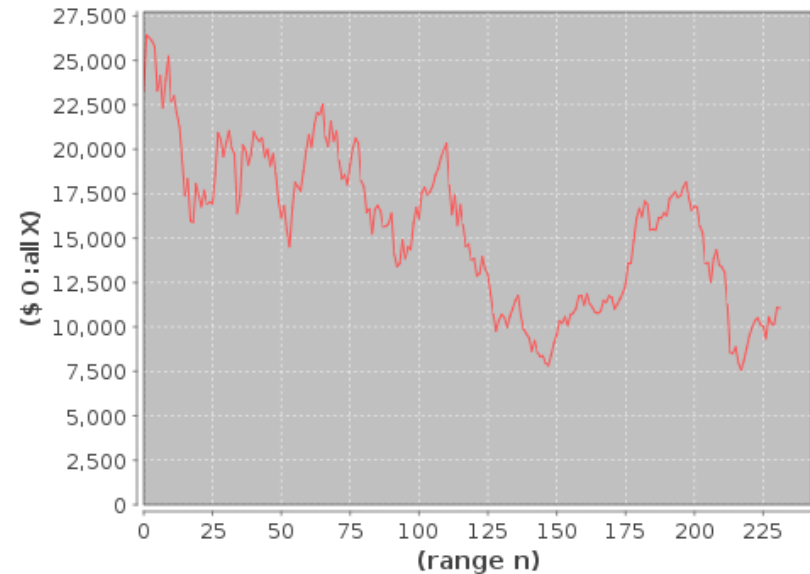
dow-adjclose-2010-1991.csv



ftse-adjclose-2010-1991.csv

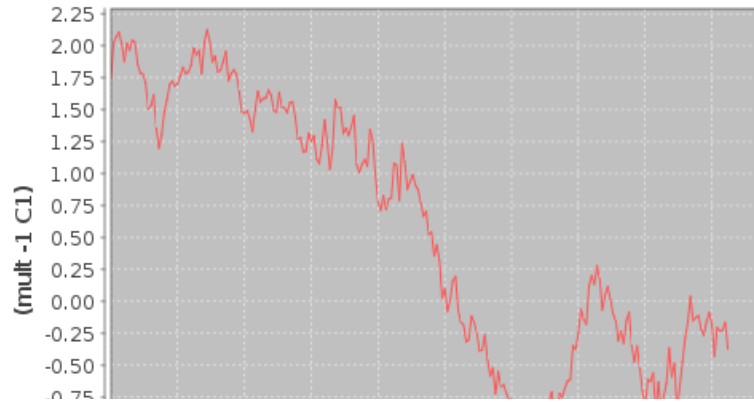


nikkei-adjclose-2010-1991.csv

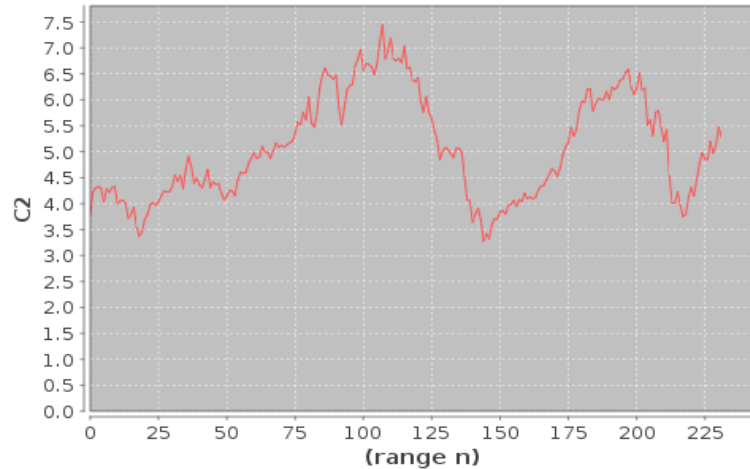


Components

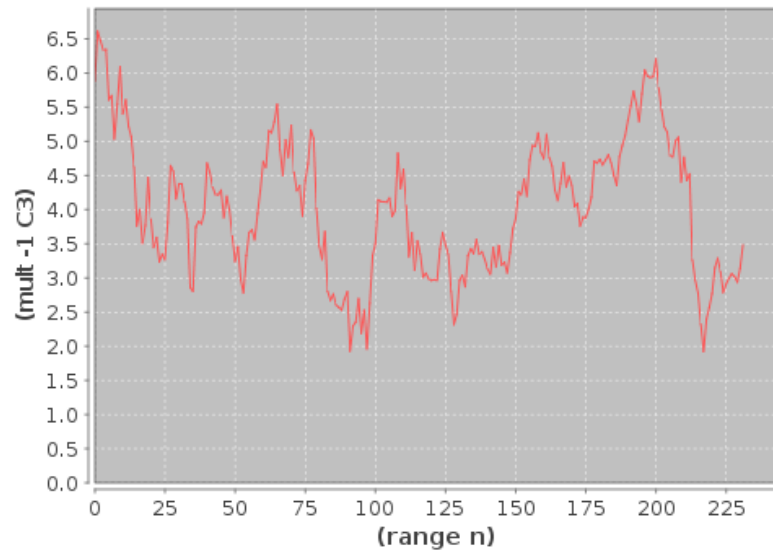
XY Plot



XY Plot

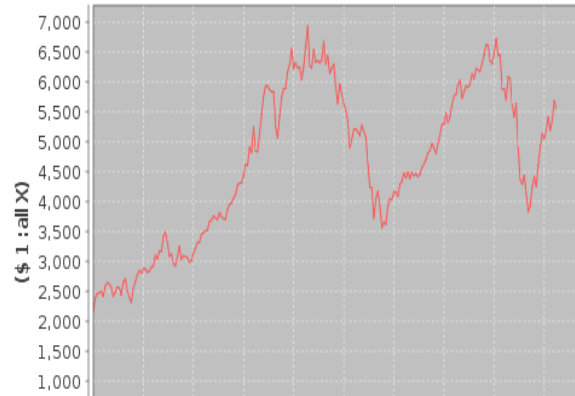


XY Plot

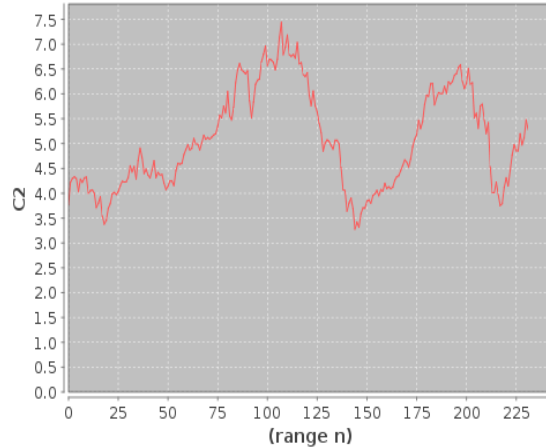


Comparison

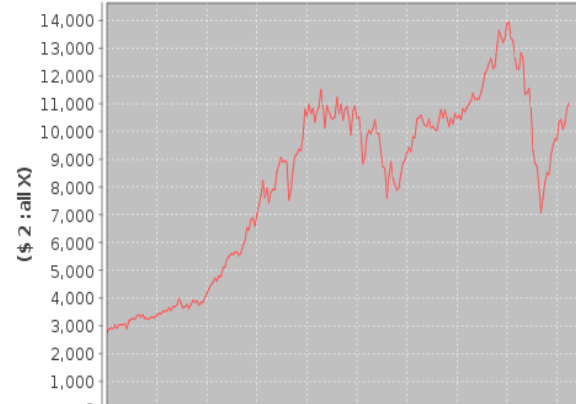
ftse-adjclose-2010-1991.csv



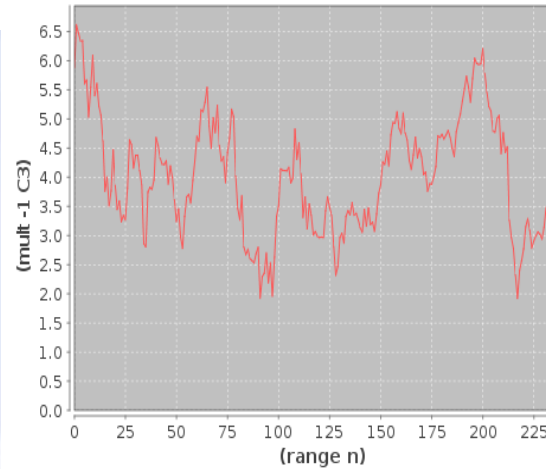
XY Plot



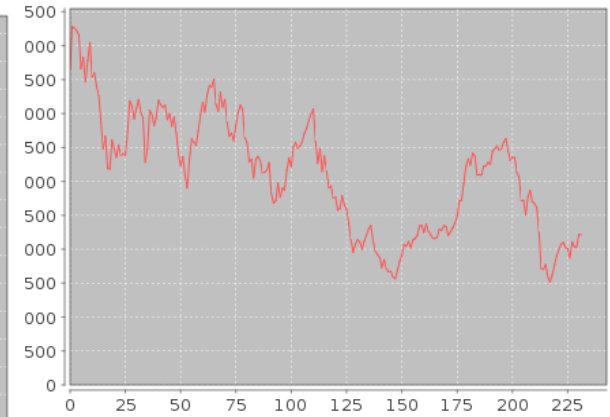
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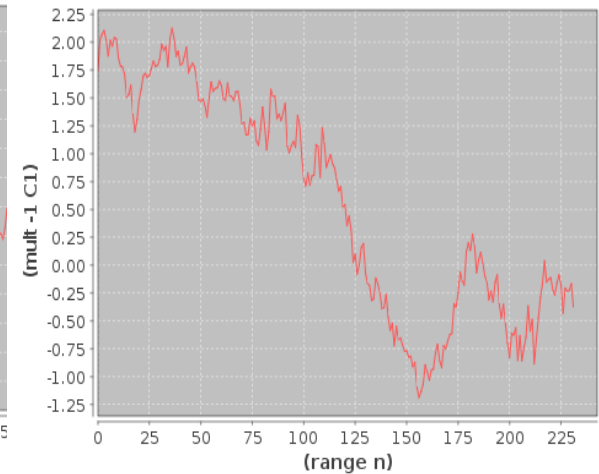
XY Plot



nikkei-adjclose-2010-1991.csv



XY Plot



Stock market indexes

- Not much can be concluded currently
 - Requires more domain/history knowledge
 - More tests need to be carried out
 - Maybe it shows the unpredictability of the stock market

Future work and conclusion

- ICA successfully implemented in Clojure in the simplest version
 - Satisfying result for finding few components
 - Need more experiments on different and larger data sets
 - Implement more contrast functions
 - Implement symmetric decorrelation

Questions?

Thank you