Learning Attitudes, Peer Assessment, and Gender in the context of a Social Constructionist Statistics Course

Introduction

- Within the context of ICT-based and math-related education, the academic community has shown great interest in the role and importance of social and individual constructivism (Von Glasersfeld (1987), Erick Smith (1999), Eggen and Kauchak (2001)) and its implementation in statistics education in particular (Nyaradzo Mvududu (2003))

Questions

- How do instructional strategies that support student knowledge construction address the needs of <u>all</u> students?
- Is it possible to introduce social interaction and knowledge construction in a statistics course with a large student population? (>100)
- What are the relationships between learning attitudes, gender, learning experience, and exam performance in such a constructivist course?

Course description

- Time Series Analysis:
  - Regression models of time series
  - ARIMA (Box-Jenkins) models:
    - Frequency and time domain
    - Seasonality, outliers, robustness issues
    - Simulation techniques
  - Granger causality & transfer function models
- Compulsory course in Master programme

Student Population

- #Active students = 137
- #Female students = 77
- #Male students = 60

ICT Learning Environment

- Online statistical software (http://www.wessa.net)
- Learning environment (http://www.moodle.org)
- Wordprocesor, Spreadsheet
- Online databases (http://www.belgostat.be)

Lectures

- 13 weeks (semester)
- Week 1: Introduction (explanation) + workshop assignment
- Week 2-12: Workshops + Peer Assessments
- Week 13: Final Exam (multiple choice)

Workshop cycle

- Day(t):
  - Workshop 1 assignment + explanation
- Day(t+7):
  - due date (Workshop 1: electronic submission in Moodle)
  - tutor explains about common mistakes + provides several solutions
  - Introduction for Workshop 2
- Day(t+14):
  - Deadline of Peer Assessment (about WS 1)
  - Due date (Workshop 2)
  - etc...

Peer Assessment

- Is a constructivist learning activity - not a real evaluation tool

  Final scores are computed as follows:

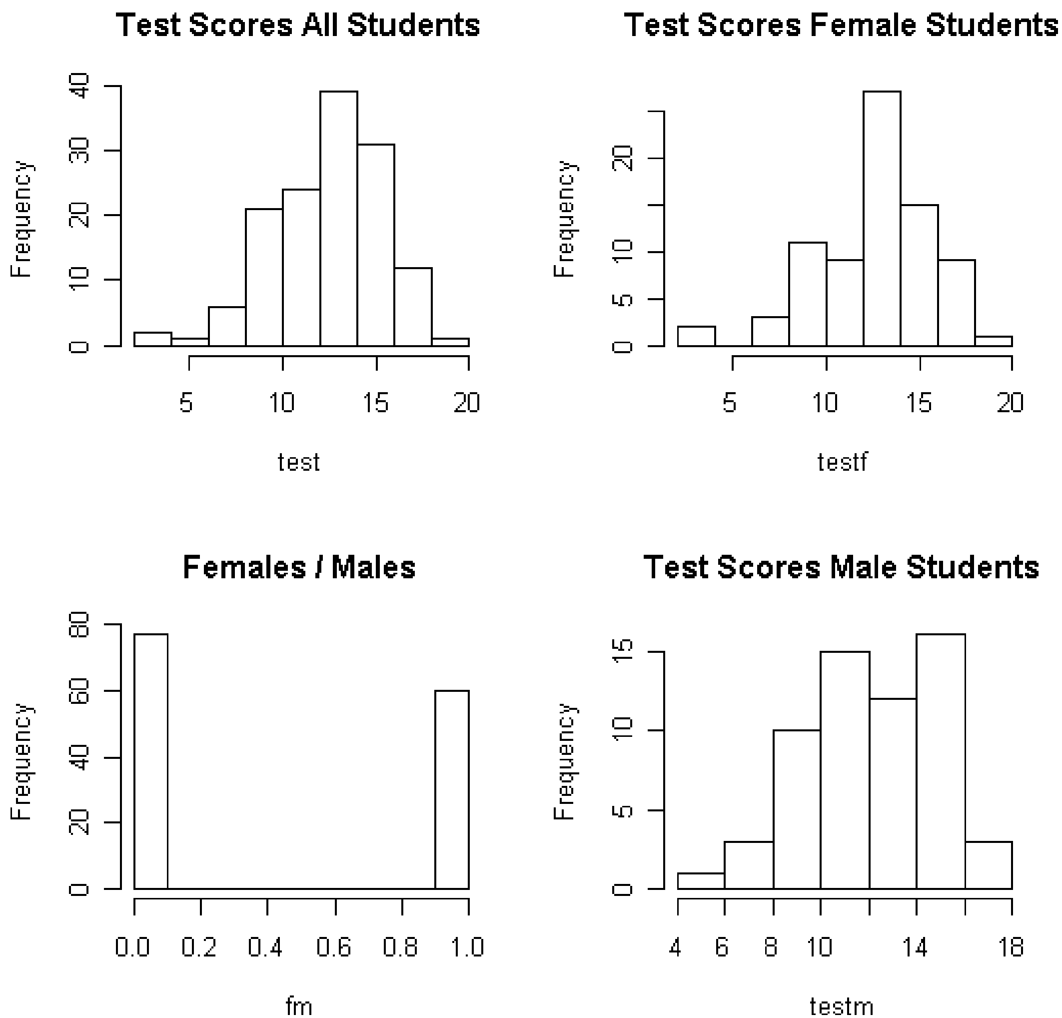
  Final Score = max[0.25*PAscore + 0.75*Examscore, Examscore]

- Is fully supported & managed by Moodle

Exam

- Multiple choice questions (Yes/No): students have the option to explain their answers
- Questions require the student to examine an appendix with computer output of statistical (time series) analysis. The appendix has about 20 pages.
- Duration 90 minutes
- Students were allowed to use their books, and workshop print-outs

Exam Scores (Test Scores)



Connected and Separate ways of knowing

- Separate:
  - Objective
  - Debate
  - Competitive
- Connected:
  - Empathy
  - Relationship
  - Collaboration

Attitudes Towards Thinking and Learning Survey (as implemented in Moodle) was used to measure connected/separate learning attitudes.

Connected/Separate Index

Equation 1 – Definition of Connected/Separate Index based on ATTLES

cs = [(connected scores average) – (separate scores average)] / (sum of all scores)

$$cs = \frac{\frac{1}{10}\left(\sum_{i=1}^{10} a_i - \sum_{i=11}^{20} a_i\right)}{\sum_{i=1}^{20} a_i}$$

- **a1-a10**: questions about connected learning attitudes on a 5-point Likert scale
- **a11-a20**: questions about separate learning attitudes on a 5-point Likert scale
- the Likert scale is coded as follows:
  - Strongly disagree = 1
  - Somewhat disagree = 2
  - Neither agree nor disagree = 3
  - Somewhat agree = 4
  - Strongly agree = 5

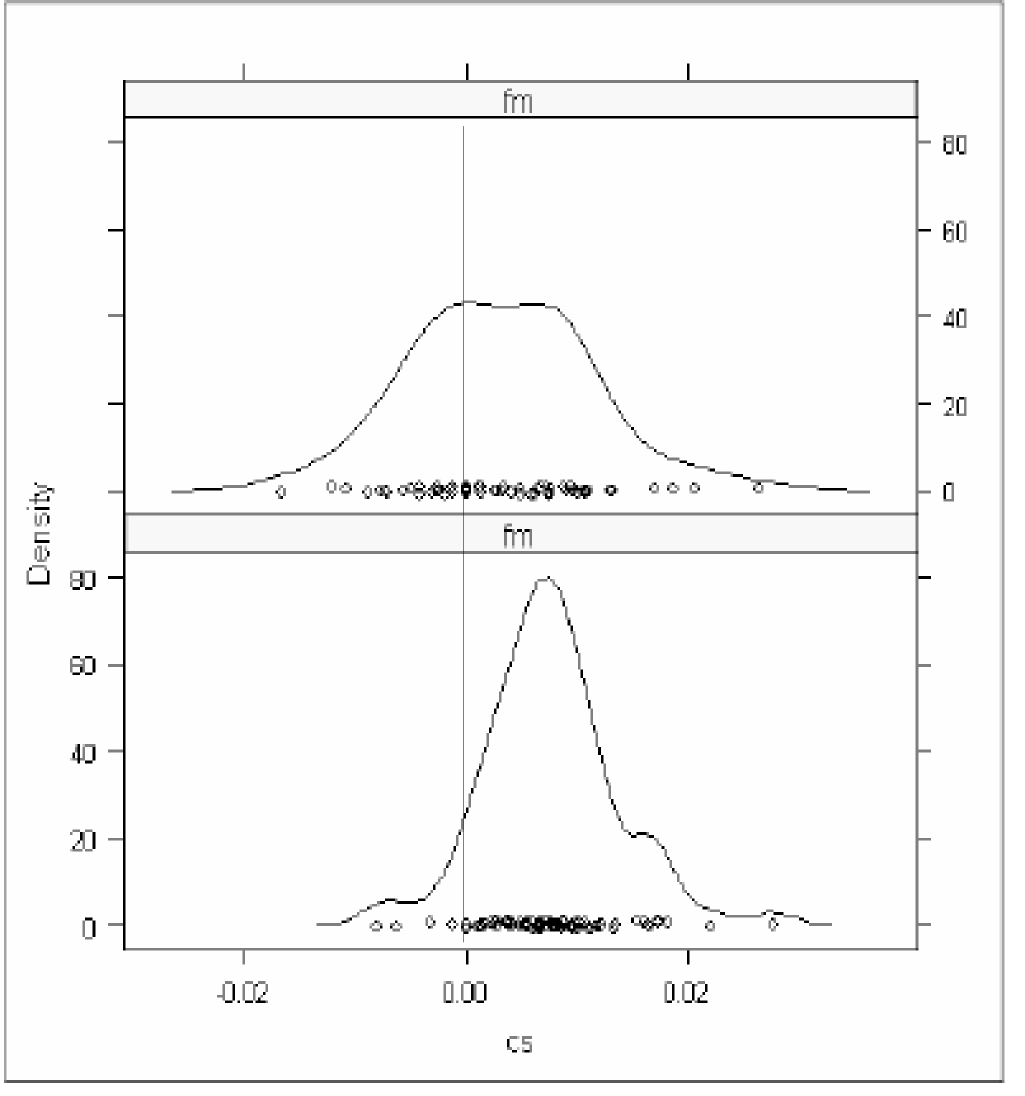
Table 3 - Attitudes to Thinking and Learning Survey (ATTLES)

Source: moodle.org, retrieved December 22, 2004

	Text of Question
a1	When I encounter people whose opinions seem alien to me, I make a deliberate effort to 'extend' myself into that person, to try to see how they could have those opinions.
a2	I can obtain insight into opinions that differ from mine through empathy.
a3	I tend to put myself in other people's shoes when discussing controversial issues, to see why they think the way they do.
a4	I'm more likely to try to understand someone else's opinion than to try to evaluate it.
a5	I try to think with people instead of against them.
a6	I feel that the best way for me to achieve my own identity is to interact with a variety of other people.
a7	I am always interested in knowing why people say and believe the things they do.
a8	I enjoy hearing the opinions of people who come from backgrounds different to mine - it helps me to understand how the same things can be seen in such different ways.
a9	The most important part of my education has been learning to understand people who are very different to me.
a10	I like to understand where other people are 'coming from', what experiences have led them to feel the way they do.
a11	I like playing devil's advocate - arguing the opposite of what someone is saying.
a12	It's important for me to remain as objective as possible when I analyze something.
a13	In evaluating what someone says, I focus on the quality of their argument, not on the person who's presenting it.
a14	I find that I can strengthen my own position through arguing with someone who disagrees with me.
a15	One could call my way of analysing things 'putting them on trial' because I am careful to consider all the evidence.
a16	I often find myself arguing with the authors of books that I read, trying to logically figure out why they're wrong.
a17	I have certain criteria I use in evaluating arguments.
a18	I try to point out weaknesses in other people's thinking to help them clarify their arguments.
a19	I value the use of logic and reason over the incorporation of my own concerns when solving problems.
a20	I spend time figuring out what's 'wrong' with things. For example, I'll look for something in a literary interpretation that isn't argued well enough.

- **a1-a10**: questions about connected learning attitudes on a 5-point Likert scale
- **a11-a20**: questions about separate learning attitudes on a 5-point Likert scale
- the Likert scale is coded as follows:
  - Strongly disagree = 1
  - Somewhat disagree = 2
  - Neither agree nor disagree = 3
  - Somewhat agree = 4
  - Strongly agree = 5

Figure 3 – Density of the Connected/Separate Index for females (bottom) and males (top)



Gender and attitudes

- There seems to be a strong relationship between gender and learning attitude (X^2 test, sign. at 1% level)

Table 4 – Contingency table between Connected/Separate Categories and Gender

table(cors,fm)	Female (fm = 0)	Male (fm = 1)
Separate (cors = 0)	6	25
Connected (cors = 1)	67	34

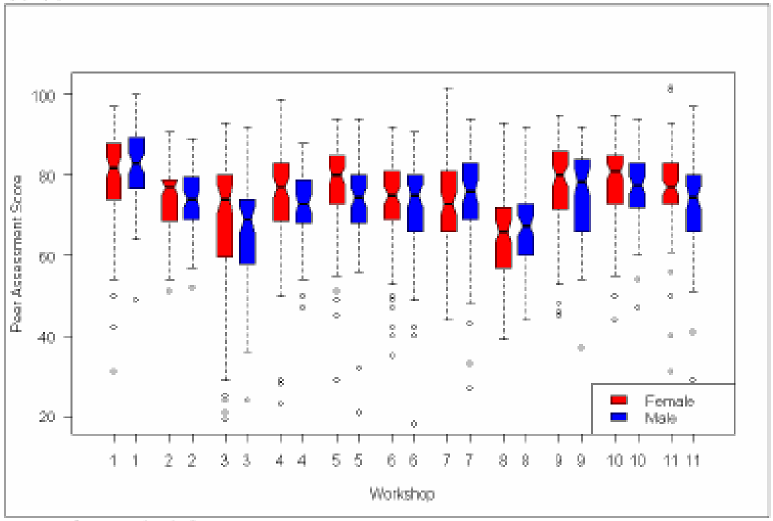
- Computation in R:
  table(cors,fm)
- **fm**: gender dummy (female=0 / male=1)
- **cors**: connected/separate attitude dummy (connected=1 / separate=0)

- Male students are connected or separate learners. Female students are almost always connected.

Peer Assessment

- PA score = w(1)S(r) + w(2)S(a)

Figure 4 – Notched Boxplots of Peer Assessment Scores by Workshop and Gender



- Computation in R:

```
wscat <- c(rep(1,137), rep(2,137), rep(3,137), rep(4,137), rep(5,137), rep(6,137),
rep(7,137), rep(8,137), rep(9,137), rep(10,137), rep(11,137))

boxplot(c(ws1f,ws2f,ws3f,ws4f,ws5f,ws6f,ws7f,ws8f,ws9f,ws10f,ws11f) ~ wscat, xlab =
"Workshop", ylab = "Peer Assessment Score",notch=TRUE,boxwex=0.28,at = 1:11-0.2, col
= "red")

boxplot(c(ws1m,ws2m,ws3m,ws4m,ws5m,ws6m,ws7m,ws8m,ws9m,ws10m,ws11m) ~ wscat,
xlab = "Workshop",ylab="Peer Assessment Score", notch = TRUE, boxwex = 0.28, at =
1:11+0.2, col="blue",add=TRUE)

legend("bottomright",c("Female","Male"),fill=c("red","blue"))
```

Test Score = f(early WS, late WS)

- Female students

Table 7 Learning Effect regressions for female students

Panel a

Variables	*Estimate*	*Std. Error*	*t value*	*p*
Intercept	3.828272	3.349986	1.143	0.25708
sumws1_3f	-0.017299	0.015629	-1.107	0.27220
sumws4_11f	0.022476	0.007152	3.143	0.00247

Residual standard error: 2.902 on 69 degrees of freedom
Multiple R-Squared: 0.1413, Adjusted R-squared: 0.1164
F-statistic: 5.679 on 2 and 69 DF, p-value: 0.00521
R code: summary(lm(formula = testf ~ sumws1_3f + sumws4_11f))

Panel b

Variables	*Estimate*	*Std. Error*	*t value*	*p*
Intercept	3.338390	3.349620	0.997	0.32247
sumws1_4f	-0.004331	0.012141	-0.357	0.72243
sumws5_11f	0.021549	0.008051	2.676	0.00932

Residual standard error: 2.89 on 68 degrees of freedom
Multiple R-Squared: 0.1327, Adjusted R-squared: 0.1072
F-statistic: 5.203 on 2 and 68 DF, p-value: 0.007893
R code: summary(lm(formula = testf ~ sumws1_4f + sumws5_11f))

Panel c

Variables	*Estimate*	*Std. Error*	*t value*	*p*
Intercept	3.276304	3.387478	0.967	0.3369
sumws1_5f	0.001882	0.010839	0.174	0.8626
sumws6_11f	0.020942	0.010179	2.057	0.0435

Residual standard error: 2.911 on 68 degrees of freedom
Multiple R-Squared: 0.12, Adjusted R-squared: 0.09416
F-statistic: 4.638 on 2 and 68 DF, p-value: 0.01293
R code: summary(lm(formula = testf ~ sumws1_5f + sumws6_11f))

- Male students

Table 8 Learning Effect regressions for male students

Panel a

Variables	*Estimate*	*Std. Error*	*t value*	*p*
Intercept	-0.799575	3.640383	-0.220	0.8270
sumws1_3m	0.041819	0.018424	2.270	0.0272
sumws4_11m	0.007355	0.003964	1.856	0.0690

Residual standard error: 2.576 on 54 degrees of freedom
Multiple R-Squared: 0.2291, Adjusted R-squared: 0.2005
F-statistic: 8.023 on 2 and 54 DF, p-value: 0.0008896
R code: summary(lm(formula = testm ~ sumws1_3m + sumws4_11m))

Panel b

Variables	*Estimate*	*Std. Error*	*t value*	*p*
Intercept	-5.096328	4.233751	-1.204	0.23404
sumws1_4m	0.044128	0.015311	2.882	0.00569
sumws5_11m	0.009536	0.005872	1.624	0.11033

Residual standard error: 2.519 on 53 degrees of freedom
Multiple R-Squared: 0.2549, Adjusted R-squared: 0.2268
F-statistic: 9.068 on 2 and 53 DF, p-value: 0.0004102
R code: summary(lm(formula = testm ~ sumws1_4m + sumws5_11m))

Panel c

Variables	*Estimate*	*Std. Error*	*t value*	*p*
Intercept	-5.537171	4.570850	-1.211	0.23111
sumws1_5m	0.039480	0.014303	2.760	0.00791
sumws6_11m	0.008504	0.006656	1.278	0.20690

Residual standard error: 2.535 on 53 degrees of freedom
Multiple R-Squared: 0.2457, Adjusted R-squared: 0.2172
F-statistic: 8.632 on 2 and 53 DF, p-value: 0.0005687
R code: summary(lm(formula = testm ~ sumws1_5m + sumws6_11m))

Constructivist Learning Experience

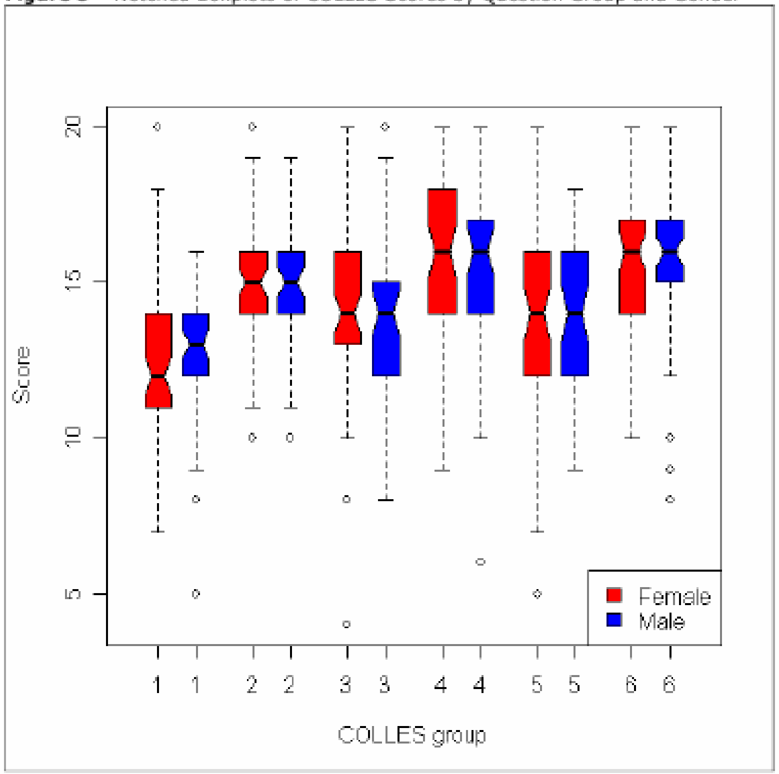
- Constructivist On-Line Learning Environment Survey (COLLES)

Table 5 - Constructivist On-Line Learning Environment Survey (COLLES)
Source: moodle.org, retrieved December 22, 2004

Question	***Text***
Group 1: Relevance and professional practice	
q1	my learning focuses on issues that interest me
q2	what I learn is important for my professional practice
q3	I learn how to improve my professional practice
q4	what I learn connects well with my professional practice
Group 2: Reflective Thinking	
q5	I think critically about how I learn
q6	I think critically about my own ideas
q7	I think critically about other students' ideas
q8	I think critically about ideas in the readings
Group 3: Interactivity (with respect to other students)	
q9	I explain my ideas to other students
q10	I ask other students to explain their ideas
q11	other students ask me to explain my ideas
q12	other students respond to my ideas
Group 4: Tutor Support	
q13	the tutor stimulates my thinking
q14	the tutor encourages me to participate
q15	the tutor models good discourse
q16	the tutor models critical self-reflection
Group 5: Peer Support	
q17	other students encourage my participation
q18	other students praise my contribution
q19	other students value my contribution
q20	other students empathize with my struggle to learn
Group 6: Interpretation (with respect to students and tutor)	
q21	I make good sense of other students' messages
q22	other students make good sense of my messages
q23	I make good sense of the tutor's messages
q24	the tutor makes good sense of my messages

- For every question a "preferred" and "actual" experience is scored on a 5-point scale
- the scale is coded as follows:
  - Almost never = 1
  - Seldom = 2
  - Sometimes = 3
  - Often = 4
  - Almost Always = 5

Figure 5 – Notched Boxplots of COLLES Scores by Question Group and Gender



- Computation in R:

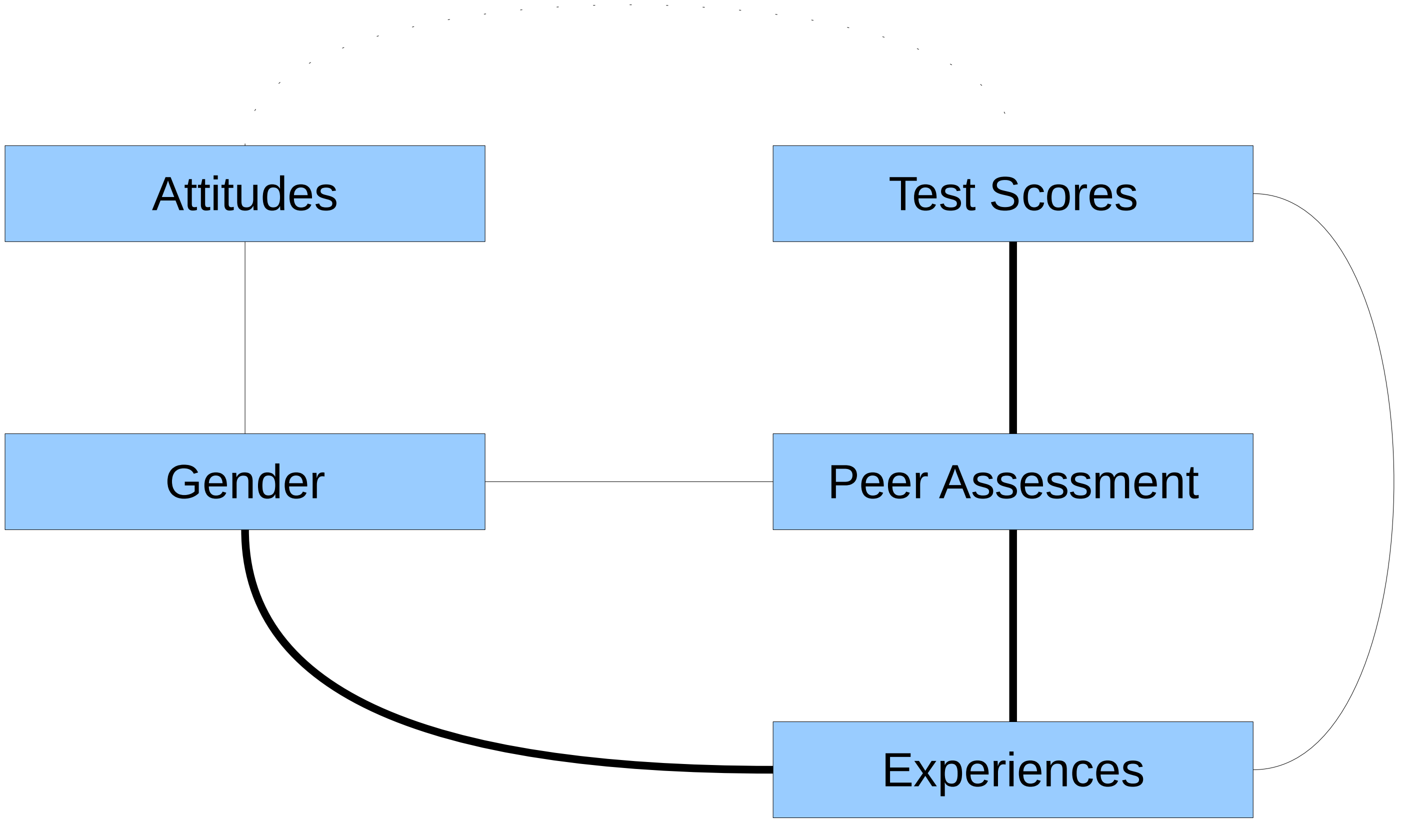
```
qcat <- c(rep(1,137),rep(2,137),rep(3,137),rep(4,137),rep(5,137),rep(6,137))

boxplot(c(q1f+q2f+q3f+q4f,q5f+q6f+q7f+q8f,q9f+q10f+q11f+q12f,q13f+q14f+q15
f+q16f,q17f+q18f+q19f+q20f,q21f+q22f+q23f+q24f) ~ qcat,xlab="COLLES
group",ylab="Score",notch=TRUE,boxwex=0.28,at=1:6-0.2,col="red")

boxplot(c(q1m+q2m+q3m+q4m,q5m+q6m+q7m+q8m,q9m+q10m+q11m+q12m,q13m+q14m+q15
m+q16m,q17m+q18m+q19m+q20m,q21m+q22m+q23m+q24m) ~ qcat,xlab="COLLES
group",ylab="Score",notch=TRUE,boxwex=0.28,at=1:6+0.2,col="blue",add=TRUE)

legend("bottomright",c("Female","Male"),fill=c("red","blue"))
```

Kendall's tau correlations

Table 9 – Summary of associations (Kendall's tau p-values ≤ 0.1)

variable	test		testf		testm		pass		passf		passm	
ws1	**0.00**		0.09		**0.00**				0.09			
ws2											0.08	
ws3	**0.01**				**0.01**				0.08			
ws4	**0.00**		**0.01**		**0.02**		**0.03**		0.09		0.08	
ws5	**0.00**		**0.01**		0.09		**0.00**		**0.00**			
ws6	**0.00**		**0.01**		**0.02**		**0.00**		**0.00**			
ws7	**0.03**				**0.04**							
ws8	**0.00**		**0.01**		**0.02**		**0.00**		**0.02**		0.07	
ws9	**0.00**		0.09		**0.05**		**0.05**					
ws10	**0.00**		**0.01**		**0.04**		**0.00**		**0.01**			
ws11	**0.00**		**0.01**									
sumws	**0.00**		**0.01**		**0.00**		**0.00**		**0.02**		0.08	
numws	**0.00**				**0.02**							
cs			**0.05**						**0.03**			
sumcs												
fm			nt		nt				nt		nt	
cors												
q01 | dq01												
q02 | dq02											**0.04**	
q03 | dq03												
q04 | dq04												
group1												
q05 | dq05		**0.01**			0.09	0.05						0.08
q06 | dq06		**0.05**			0.06	0.06		0.08			**0.03**	**0.00**
q07 | dq07	0.07						0.09					
q08 | dq08												
group2	**0.03**				**0.03**							
q09 | dq09	**0.01**	0.06	**0.04**	**0.05**	0.09							
q10 | dq10	0.08	**0.04**				0.08					0.08	0.08
q11 | dq11		0.07										
q12 | dq12												
group3	0.07											
q13 | dq13							0.08					
q14 | dq14							**0.00**	**0.01**	0.07		**0.00**	**0.01**
q15 | dq15		0.08					0.09	**0.04**			**0.03**	**0.01**
q16 | dq16	**0.01**	**0.01**		0.07	**0.01**	**0.05**	**0.05**					
group4	0.08				**0.02**		**0.01**				**0.02**	
q17 | dq17	0.06	**0.03**		0.09	0.07	0.07		**0.03**			**0.02**	**0.00**
q18 | dq18												0.10
q19 | dq19												
q20 | dq20												
group5											0.08	
q21 | dq21									0.09	0.06		
q22 | dq22									0.09	**0.02**		
q23 | dq23	**0.05**				**0.03**		0.08				**0.04**	
q24 | dq24											0.08	
group6					**0.01**						0.09	

Relationships



Problems

- Students are unable to reproduce results of peers. Therefore:
  - Collaboration & Peer Assessment is difficult (consumes a lot of time)
  - The educator only sees the output (there is no information about the learning process)
- Students are unable to reuse previously made computations. Improvements are only possible if they restart from scratch.

Solution (Future Research)

- Development of a Compendium Platform (funded by K.U.Leuven Association).

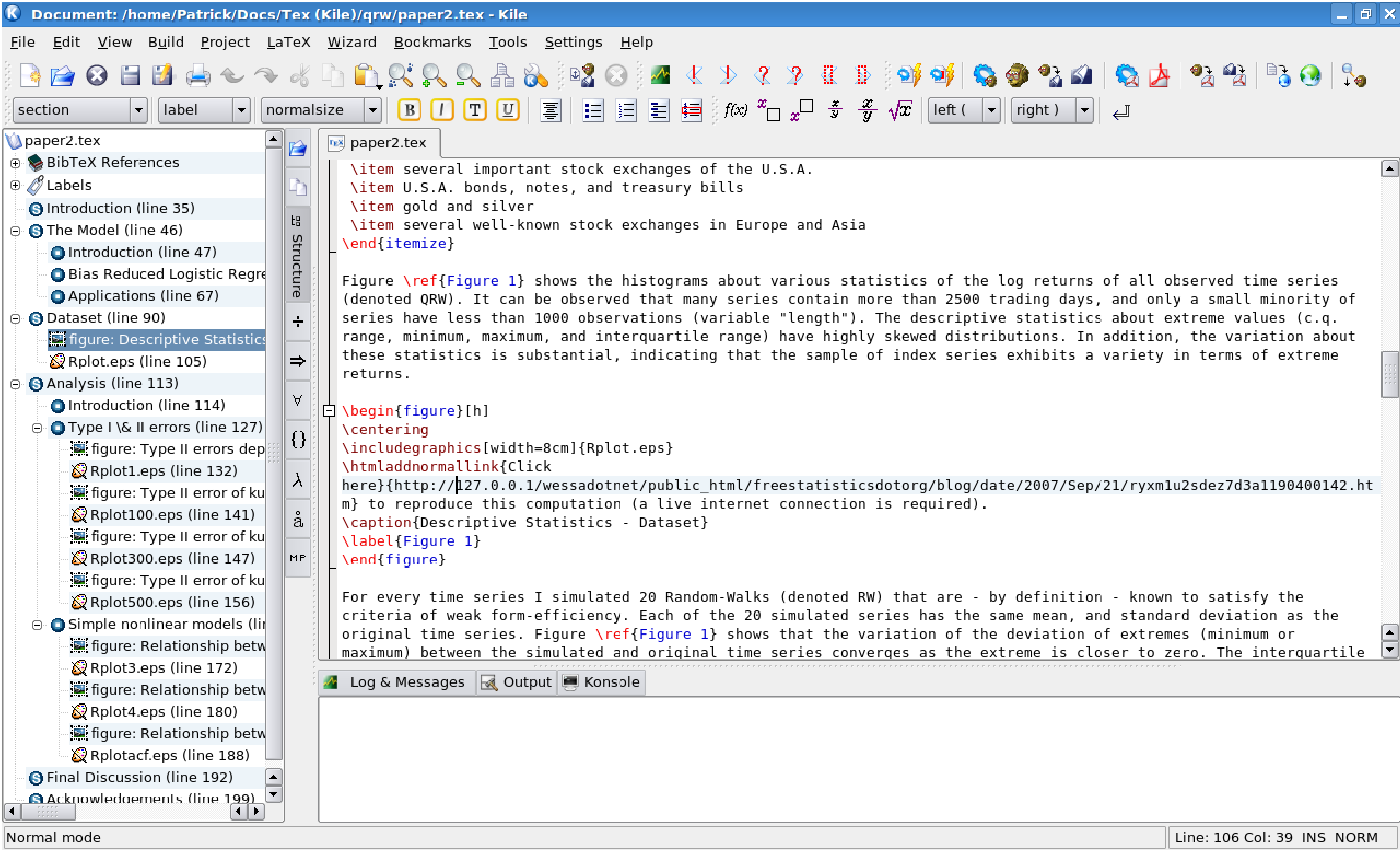
  It allows anyone with a internet connection to:

  - Do statistical computing (no installation!)
  - Archive computations for reference purposes
  - Communicate about computations
  - Reproduce computations
  - Reuse computations

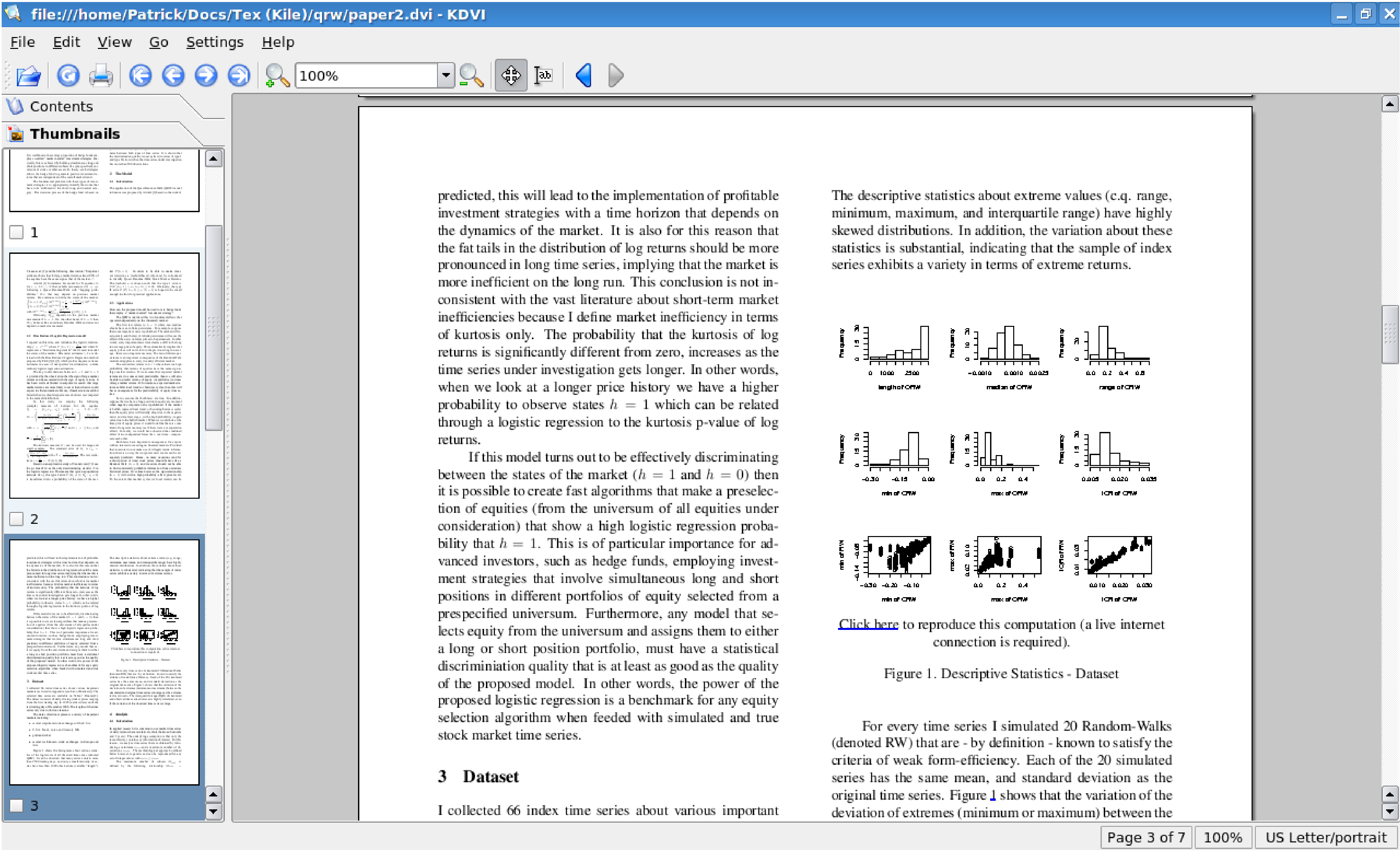
Compendium Platform

- A Compendium is an electronic collection of text, data, and software that allows the reader/user to replicate and reuse the science that is described.
- This system empowers users to:
  - Collaborate in scientific research
  - Evaluate learning processes
  - Disseminate research results

Demo (screenshots)



Demo (screenshots)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predicted, this will lead to the implementation of profitable investment strategies with a time horizon that depends on the dynamics of the market. It is also for this reason that the fat tails in the distribution of log returns should be more pronounced in long time series, implying that the market is more inefficient on the long run. This conclusion is not inconsistent with the vast literature about short-term market inefficiencies because I define market inefficiency in terms of kurtosis only. The probability that the kurtosis of log returns is significantly different from zero, increases as the time series under investigation gets longer. In other words, when we look at a longer price history we have a higher probability to observe states $h = 1$ which can be related through a logistic regression to the kurtosis p-value of log returns.

If this model turns out to be effectively discriminating between the states of the market ($h = 1$ and $h = 0$) then it is possible to create fast algorithms that make a preselection of equities (from the universum of all equities under consideration) that show a high logistic regression probability that $h = 1$. This is of particular importance for advanced investors, such as hedge funds, employing investment strategies that involve simultaneous long and short positions in different portfolios of equity selected from a prespecified universum. Furthermore, any model that selects equity from the universum and assigns them to either a long or short position portfolio, must have a statistical discriminiation quality that is at least as good as the quality of the proposed model. In other words, the power of the proposed logistic regression is a benchmark for any equity selection algorithm when feeded with simulated and true stock market time series.

3 Dataset

I collected 66 index time series about various important

The descriptive statistics about extreme values (c.q. range, minimum, maximum, and interquartile range) have highly skewed distributions. In addition, the variation about these statistics is substantial, indicating that the sample of index series exhibits a variety in terms of extreme returns.

Click here to reproduce this computation (a live internet connection is required).

Figure 1. Descriptive Statistics - Dataset

For every time series I simulated 20 Random-Walks (denoted RW) that are - by definition - known to satisfy the criteria of weak form-efficiency. Each of the 20 simulated series has the same mean, and standard deviation as the original time series. Figure 1 shows that the variation of the deviation of extremes (minimum or maximum) between the

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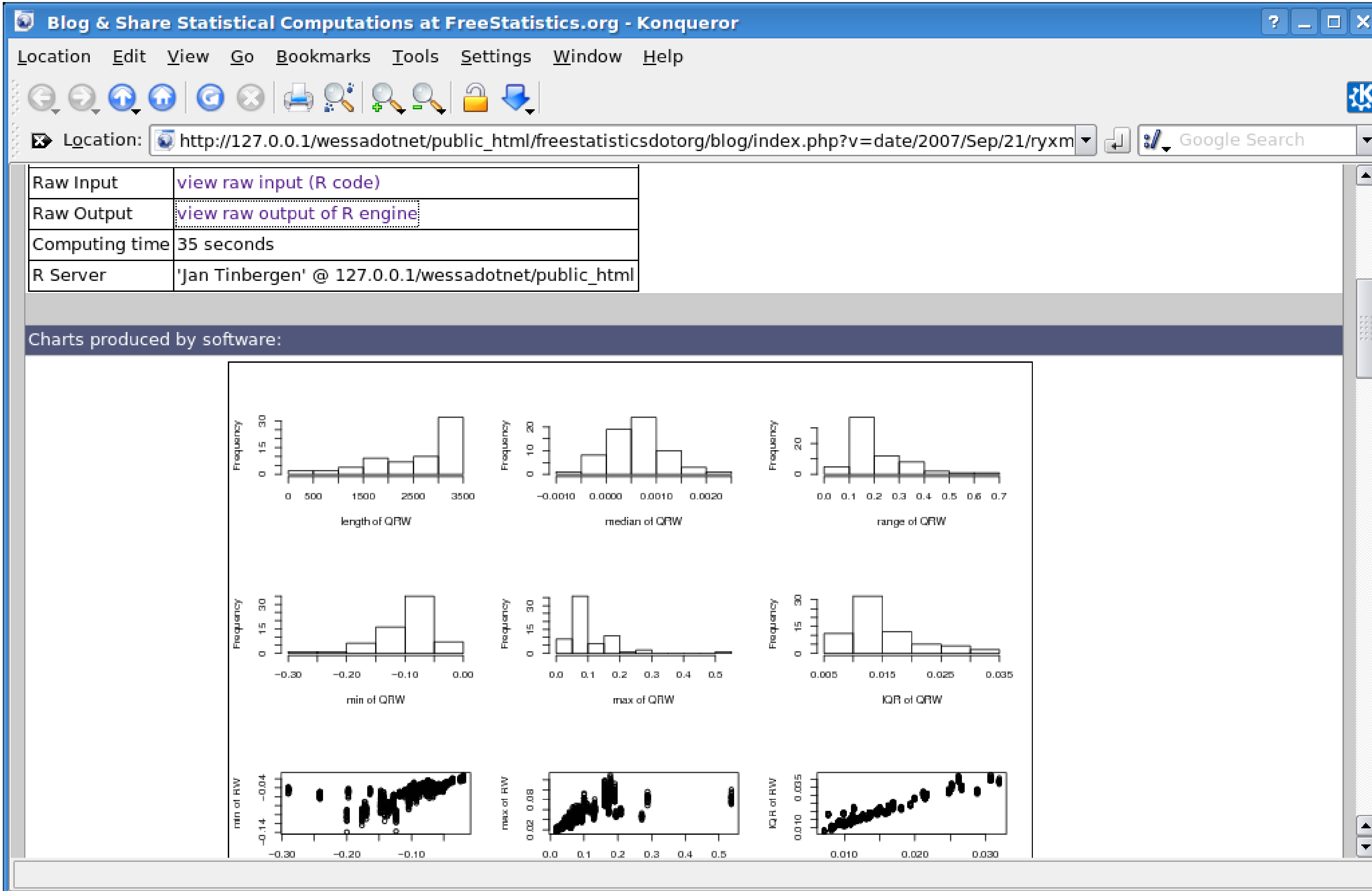
Demo (screenshots)



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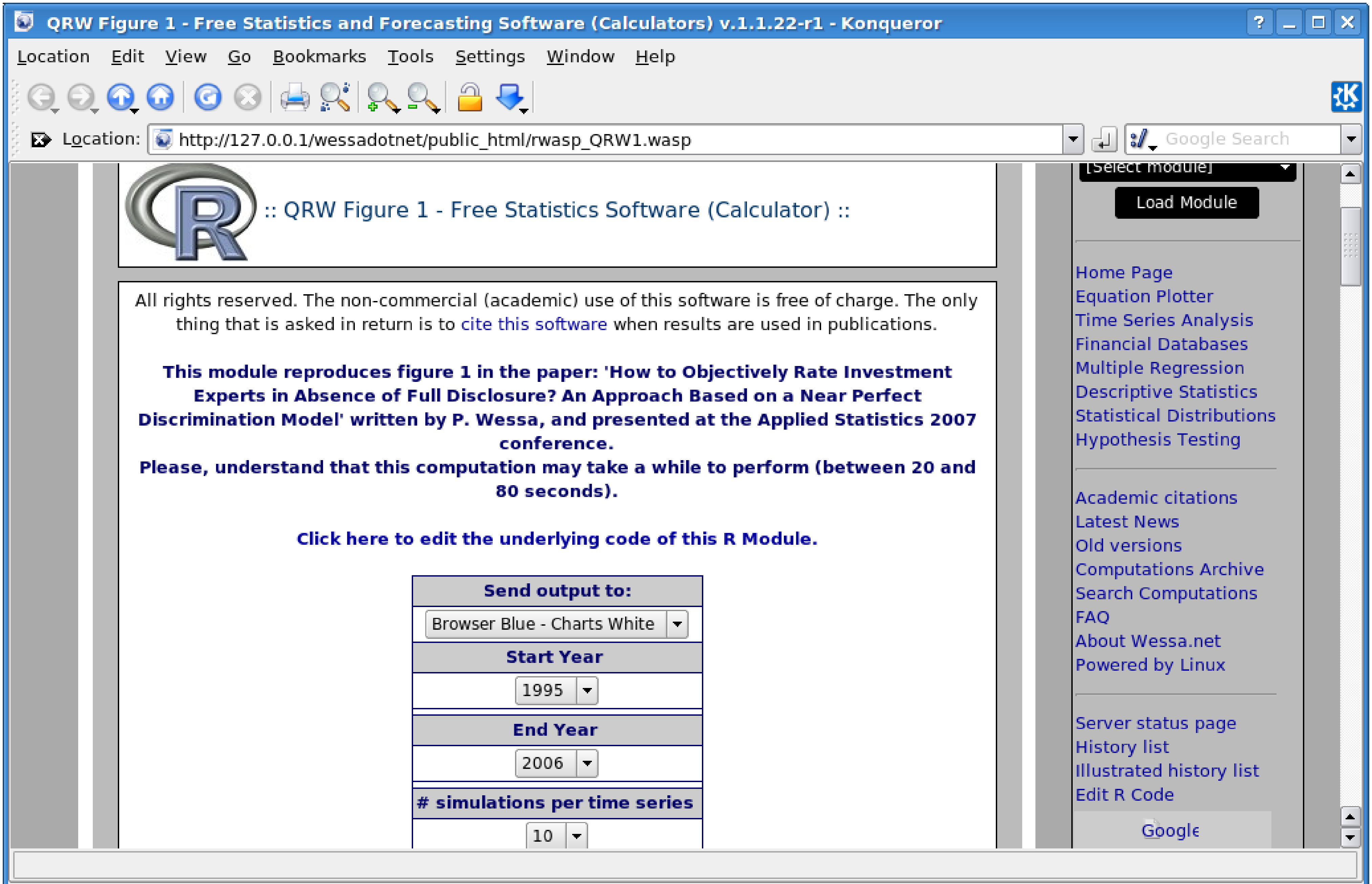

Invitation

- Feel free to contact us if you are interested to:
  - join in our research
  - test and use the Compendium Platform for the purpose of education or research
- Integration of tailor-made Compendia-based (constructivist) workshops in education
- Joint research:
  - Relationships between:
    - Learning Attitudes, Learning Experiences
    - Usability, and other ICT aspects
    - Test performance (measurable competences)
- International conference about the intersection of: ICT, Applied Statistics, and Education

Contact

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