Pricing and Marketing Risk Transfer in the Digital Era

Dr. Montserrat Guillen
Director of the Riskcenter
University of Barcelona

June 2015
The views expressed in the following material are the author’s and do not necessarily represent the views of the Global Association of Risk Professionals (GARP), its Membership or its Management.
1. Introduction

2. Marketing versus Pricing: should they ally?

3. Profit maximization

4. uplift R package

5. Conclusions
Basic concepts

- Risk transfer
- Expected loss & price calculation
- Expected profit (unknown). Value will be observed later
- Contract
- Even with default/claim, we must guarantee solvency
- ....and profitability
- Marketing pressure

Examples: consumer credit, investment project, insurance policy,..
Basic concepts

- Risk transfer
- Expected loss & price calculation
- Expected profit (unknown). Value will be observed later
- Contract
- Even with default/claim, we must guarantee solvency
  ....and profitability
- Marketing pressure

Examples: consumer credit, investment project, insurance policy,..
Basic concepts

- Risk transfer
- Expected loss & price calculation
- Expected profit (unknown). Value will be observed later
- Contract
- Even with default/claim, we must guarantee solvency
  ....and profitability
- Marketing pressure

Examples: consumer credit, investment project, insurance policy,..
Basic concepts

- Risk transfer
- Expected loss & price calculation
- Expected profit (unknown). Value will be observed later
- Contract
- Even with default/claim, we must guarantee solvency
- ....and profitability
- Marketing pressure

Examples: consumer credit, investment project, insurance policy,..
Basic concepts

- Risk transfer
- Expected loss & price calculation
- Expected profit (unknown). Value will be observed later
- Contract
- Even with default/claim, we must guarantee solvency
- ....and profitability
- Marketing pressure

Examples: consumer credit, investment project, insurance policy,..
Basic concepts

- Risk transfer
- Expected loss & price calculation
- Expected profit (unknown). Value will be observed later
- Contract
- Even with default/claim, we must guarantee solvency
- ....and profitability
- Marketing pressure

Examples: consumer credit, investment project, insurance policy,..
Basic concepts

- Risk transfer
- Expected loss & price calculation
- Expected profit (unknown). Value will be observed later
- Contract
- Even with default/claim, we must guarantee solvency
- ....and profitability
- Marketing pressure

Examples: consumer credit, investment project, insurance policy,..
Pricing, Retaining, Selling

✓ Pricing (calculating expected loss + margin + profits)
✓ Retaining (reducing lapse)
✓ Selling (offer additional products to existing customers)

Classical approach: Predictive modeling (Poisson/NegBin model, Gamma model, Logistic regression, Cox survival,...)

Observational data are available
But....do insurers/banks have historical information that can be understood as experimental data?
A simple example

Direct mail campaign in a bank (L=6256)
Proportion of purchase and non purchase in each treatment group

<table>
<thead>
<tr>
<th>Control</th>
<th>Promotion</th>
</tr>
</thead>
<tbody>
<tr>
<td>No purchase</td>
<td>85.17%</td>
</tr>
<tr>
<td>Purchase</td>
<td>14.83%</td>
</tr>
<tr>
<td></td>
<td>61.60%</td>
</tr>
<tr>
<td></td>
<td>38.40%</td>
</tr>
</tbody>
</table>

Average treatment effect (uplift)=23.57%
A simple example

Direct mail campaign in a bank (L=6256)

Proportion of purchase and non purchase in each treatment group

<table>
<thead>
<tr>
<th></th>
<th>Control</th>
<th>Promotion</th>
</tr>
</thead>
<tbody>
<tr>
<td>No purchase</td>
<td>85.17%</td>
<td>61.60%</td>
</tr>
<tr>
<td>Purchase</td>
<td>14.83%</td>
<td>38.40%</td>
</tr>
</tbody>
</table>

Average treatment effect (uplift) = 23.57%
A simple example

Direct mail campaign in a bank ($L=6256$)
Proportion of purchase and non purchase in each treatment group

<table>
<thead>
<tr>
<th></th>
<th>Control</th>
<th>Promotion</th>
</tr>
</thead>
<tbody>
<tr>
<td>No purchase</td>
<td>85.17%</td>
<td>61.60%</td>
</tr>
<tr>
<td>Purchase</td>
<td>14.83%</td>
<td>38.40%</td>
</tr>
</tbody>
</table>

Average treatment effect (uplift) = 23.57%

How can we implement this?

Heterogeneity

Can we link this concept to maximizing profits?

Can we link this concept to maximizing profits and minimizing risks?
A simple example

Direct mail campaign in a bank (L=6256)
Proportion of purchase and non purchase in each treatment group

<table>
<thead>
<tr>
<th></th>
<th>Control</th>
<th>Promotion</th>
</tr>
</thead>
<tbody>
<tr>
<td>No purchase</td>
<td>85.17%</td>
<td>61.60%</td>
</tr>
<tr>
<td>Purchase</td>
<td>14.83%</td>
<td>38.40%</td>
</tr>
</tbody>
</table>

Average treatment effect (uplift) = 23.57%

How can we implement this?

Heterogeneity

Can we link this concept to maximizing profits?
Can we link this concept to maximizing profits and minimizing risks?
A simple example

Direct mail campaign in a bank (L=6256)

<table>
<thead>
<tr>
<th></th>
<th>Control</th>
<th>Promotion</th>
</tr>
</thead>
<tbody>
<tr>
<td>No purchase</td>
<td>85.17%</td>
<td>61.60%</td>
</tr>
<tr>
<td>Purchase</td>
<td>14.83%</td>
<td>38.40%</td>
</tr>
</tbody>
</table>

Average treatment effect (uplift) = 23.57%

How can we implement this?
Heterogeneity

Can we link this concept to maximizing profits?
Can we link this concept to maximizing profits and minimizing risks?
A simple example

Direct mail campaign in a bank (L=6256)
Proportion of purchase and non purchase in each treatment group

<table>
<thead>
<tr>
<th>Control</th>
<th>Promotion</th>
</tr>
</thead>
<tbody>
<tr>
<td>No purchase</td>
<td>85.17%</td>
</tr>
<tr>
<td>Purchase</td>
<td>14.83%</td>
</tr>
<tr>
<td></td>
<td>61.60%</td>
</tr>
<tr>
<td></td>
<td>38.40%</td>
</tr>
</tbody>
</table>

Average treatment effect (uplift) = 23.57%

How can we implement this?

Heterogeneity

Can we link this concept to maximizing profits?

Can we link this concept to maximizing profits and minimizing risks?
1. Introduction

2. Marketing versus Pricing: should they ally?

3. Profit maximization

4. uplift R package

5. Conclusions
Background

✓ The demand for insurance products: Hammond, Houston and Melander (1967); Ducker (1969); Mayers and Smith (1983); Doherty (1984); Babbel (1985); Showers and Shotick (1994); Ben-Arab, Brys and Schlesinger (1996); Gandolfi and Miners (1996)

✓ Customer satisfaction and loyalty: Crosby and Stephens (1987); Schlesinger and Schulenburg (1993); Wells and Stafford (1995); Stafford et al. (1998); Cooley (2002), Kuo, Tsai and Chen (2003); Bozzetto et al. (2004); Guillén, Nielsen and Pérez-Marín (2006)


✓ Cross-selling and multiple contracts: Bonato and Zweifel (2002); Guillén, Gustafsson, Hansen and Nielsen (2008), Thuring, Nielsen, Guillén and Bolancé (2014).

All approaches are based on causal/predictive modeling.
1. Introduction

2. Marketing versus Pricing: should they ally?

3. Profit maximization

4. uplift R package

5. Conclusions
Treatment-response: a new perspective


Model and notation

We assume price $P_{\ell m}^*$ charged to customer $\ell = 1, \ldots, L$ for a given contract in year $m = 1, \ldots, M$ is the sum of three components:

$$P_{\ell m}^* = C_{\ell m} + R_{\ell m} + B_{\ell m}, \quad \ell = 1, \ldots, L \quad m = \{1, \ldots, M\}$$

- a fair price ($C_{\ell m}$), resulting from an evaluation of the customer’s risk characteristics, that is, an estimation of expected claims compensation, default or expected loss severity;
- a premium loading ($R_{\ell m}$), capturing general costing, solvency requirements, managerial efficiency or caution; and, finally,
- a profit ($B_{\ell m}$), reflecting a minimum level of return to the shareholders/owners.
Model and notation

- We define renewal $D_{\ell m}$ as a binary variable which equals 1 if policy holder $\ell$ renews his policy in year $m$, and 0 otherwise.
- Renewal $D_{\ell m}$ depends on marketing actions.
- Renewal $D_{\ell m}$ depends on external competitors.
- Renewal ($D_{\ell m}$) and price ($P^*_{\ell m}$) are mutually dependent.
- If the price increases many customers will abandon the company, but if the price falls then renewal is more likely than lapsing while profits decrease.
Model and notation

\[
\begin{align*}
P^*_\ell m &= C_\ell m + R_\ell m + B_\ell m = (C_\ell m + R_\ell m)(1 + RC_\ell m) \\
&= P_\ell m(1 + RC_\ell m) \\
D_\ell m
\end{align*}
\]

\(RC_\ell m\) is the rate change or treatment for customer \(\ell\) in year \(m\).
There are $L$ customers in a portfolio and that they may hold more than one contract.

We indicate each type of risk transfer product by $j$, where $j = 1, \ldots, K$ and $K$ is the total number of possible contracts.

The company can control prices, so let us call denote by $Z_{\ell jmt}$ the binary indicator of action (price change) $t$ to be offered to customer $\ell$ in year $m$ for contract $j$ before renewal. There are $T$ possible treatments, $t = 1, \ldots, T$. 
Value: multi-product and multi-year

- The indicator $I_{\{D_{\ell jm}=1\}}$ equals one if customer $\ell$ holds product $j$ in year $m$, and 0 otherwise.
- Additionally, let $S_{\ell js}$ be the probability that customer $\ell$ renews $j$ in year $s$, namely $P(D_{\ell js} = 1)$ for $s = m, \ldots, M$.
- Let $B_{\ell jm}$ be the profit of contract $j$ from customer $\ell$ in year $m$, and $r$ is the interest discount factor. So the total value at $m$ is:

$$\sum_{\ell=1}^{L} \sum_{j=1}^{K} I_{\{D_{\ell jm}=1\}} B_{\ell jm} \sum_{s=m}^{M} S_{\ell js} r^{s-m}.$$
Profit: only one product and one year case

\[
\max_{Z_{\ell t} \forall \ell \forall t} \sum_{\ell=1}^{L} \sum_{t=1}^{T} Z_{\ell t} \left[ P_{\ell} (1 + R C_t) (1 - \hat{L} R_{\ell t}) (1 - \hat{r}_{\ell t}) \right]
\]

with restrictions:

\[
\sum_{t=1}^{T} Z_{\ell t} = 1, \quad Z_{\ell t} \in \{0, 1\}, \quad \sum_{\ell=1}^{L} \sum_{t=1}^{T} Z_{\ell t} \hat{r}_{\ell t} / L \leq \alpha
\]

where \( P_{\ell} \) is a baseline price paid by \( \ell, \ell = 1, 2, \ldots, L \), \( L \) is the total number of customers, \( R C_t \) is price change rate which is categorized in \( T \) ordered values, \( t = \{1 < 2 < \ldots < T \} \), \( \hat{L} R_{\ell t} \) is the loss ratio, namely, cost divided by price, \( \hat{r}_{\ell t} \) is the probability of lapse for customer \( \ell \) if price change \( t \) is applied \((Z_{\ell t} = 1)\) and \( \alpha \) is the maximum lapse rate that is allowed for this portfolio (so, \( 1 - \alpha \) is the minimum retention rate).
Empirical application: managers study personalized actions
Data considerations

1. The gold standard for measuring causal effects (i.e., effects attributable to treatments) is to obtain experimental data.

2. In the context of price-elasticity, this would involve randomizing customers to various rate change levels (the latter playing the role of the "treatments").

3. This condition rarely holds in practice, as usually rate changes are assigned to customers based on a risk-based pricing model. Thus, we end up with observational data (as opposed to experimental data).
Data considerations

1. The good news is that under certain data conditions (Rosenbaum and Rubin, 1983) it is still possible to obtain unbiased estimates of causal effect from observational data – that is, we can obtain unbiased estimates of price elasticities.

2. Two key concepts come into play here: propensity scores and matching algorithms.

3. These methods can be used to reconstruct a "sort of" randomized study from observational data.
Empirical application: the data

- \( L = 329,000 \) auto insurance policies from a major Canadian insurer that have been given a renewal offer from June-2010 to May-2012 consisting on a new rate either lower, equal or higher than the current rate.
- more than 60 pre-treatment covariates (characteristics of the policy, the vehicle and driver).
- the treatment is the rate change: percentage change in premium from the current to the new rate, categorized into 5 ordered values \( t = \{1 < 2 < \ldots < 5\} \).
- response variable: renewal outcome of the policy, measured 30 days after the effective date of the new policy term.
Empirical application: estimated lapse rate

![Graphs showing estimated lapse rate for different categories.](image-url)
Empirical application: summary

1. Calculate a price with a baseline strategy \((P_\ell)\)
2. Estimate lapse rate under different \(t\) strategies \((\hat{r}_{\ell t})\)
3. Use a particular price strategy \(t\) \((RC_t)\)
4. Find the expected loss-ratio \((\hat{LR}_{\ell t})\)
5. Maximize

\[
\begin{array}{c}
\text{Maximize} \\
\max_{Z_{\ell t}} \sum_{\ell=1}^{L} \sum_{t=1}^{T} \left[ P_\ell (1 + RC_t)(1 - \hat{LR}_{\ell t})(1 - \hat{r}_{\ell t}) \right]
\end{array}
\]

subject to a given overall retention level.
6. Decide the personalized price change for each customer \(\ell\)
7. Summarize retention level, expected profit and risk value.
Methodology

- $L$ customers, $\ell = 1, 2, \ldots, L$.
- vector of pre-treatment covariates $x_{\ell}$.
- ordered treatment variable $t$ (rate change levels), which takes values $t = \{1 < 2 < \ldots < T\}$ on a set $\mathcal{S}$.
- $Z_{\ell t}$ set of $T$ binary treatment indicators, $Z_{\ell t} = 1$ if subject $\ell$ received treatment $t$ (i.e. $RC_t$), and $Z_{\ell t} = 0$ otherwise.
- potential responses $r_{\ell t}$, renewal outcome that would be observed from policyholder $\ell$ if assigned to treatment $t$.
- observed response for subject $\ell$ is $R_{\ell} = \sum_{t \in \mathcal{S}} Z_{\ell t} r_{\ell t}$.
- Our interest is to estimate price elasticity, defined as the renewal outcomes that result and are caused by the price change interventions.
Methodology

Notation:

- \( X = \{X_1, \ldots, X_p\} \) a vector of predictor variables,
- \( D = \) binary response variable (1=renew, 0=lapse)
- \( t \) refers to the treatment \((t = 1)\) and control \((t = 0)\)
- \( L = \) a collection of observations \(\{(y_\ell, x_\ell, t_\ell); \ell = 1, \ldots, L\}\)
- **Uplift model** \( \hat{f}^{uplift}(x_\ell) = E(D_\ell| x_\ell; t_\ell = 1) - E(D_\ell| x_\ell; t_\ell = 0) \)
Uplift model: indirect estimation

There are two general approaches: indirect and direct estimation

- **Indirect uplift estimation:**
  - Build two separate models, one using the treatment \((t = 1)\) subset and another one using control data \((t = 0)\).
  - Predicted uplift is estimated by subtracting the class probabilities from the two models
    \[ P(Y = 1|x; t = 1) - P(Y = 1|x; t = 0) \]
  - Alternatively, a single model can be obtained including an interaction term for every predictor in \(X = \{X_1, ..., X_p\}\) and treatment \(t\).
  - This method does not work very well in practice, as the relevant predictors for the response are likely to be different from the relevant uplift predictors and the functional form of the predictors are likely to be different as well.
Uplift model: direct estimation

- Modeling uplift directly (pur contribution):
  - Requires modifying existing methods/algorithms or designing novel ones
  - Intuitively, tree-based algorithms are appropriate as they partition the input space into subgroups
  - Rzepakowski and Jaroszewicz (2011) and Radcliffe and Surry (2011) have proposed estimation algorithms
  - Our proposed algorithms: uplift Random Forests and causal conditional influence forests are implemented in R.
Methodology: uplift Random Forests

- In Guelman et al. (2012 and 2013) the proposed algorithm for modeling uplift directly is based on maximizing the distance in the class distributions between treatment and control groups.

- Relative Entropy or Kullback-Leibler distance $KL$ between two probability mass functions $P_t(Y)$ and $P_c(Y)$ is given by

$$KL(P_t(Y) \| P_c(Y)) = \sum_{y \in Y} P_t(y) \log \frac{P_t(y)}{P_c(y)}$$
Methodology: illustration
Methodology: Causal Conditional Influence Forests

Algorithm 2: Causal conditional inference forests

1: for $b = 1$ to $B$ do
2: Draw a sample with replacement from the training observations $L$ such that $P(A=1) = P(A=0) = 1/2$
3: Grow a conditional causal inference tree $CCIT_b$ to the sampled data:
4: for each terminal node do
5: repeat
6: Select $n$ covariates at random from the $p$ covariates
7: Test the global null hypothesis of no interaction effect between the treatment $A$ and any of the $n$ covariates (i.e., $H_0 = \cap_{j=1}^{n} H_0^j$, where $H_0^j : E[W|X_j] = E[W]$) at a level of significance $\alpha$ based on a permutation test
8: if the null hypothesis $H_0$ cannot be rejected then
9: Stop
10: else
11: Select the $j^*$th covariate $X_{j^*}$ with the strongest interaction effect (i.e., the one with the smallest adjusted $P$ value)
12: Choose a partition $\Omega^*$ of the covariate $X_{j^*}$ in two disjoint sets $\mathcal{M} \subset X_{j^*}$ and $X_{j^*} \setminus \mathcal{M}$ based on the $G^2(\Omega)$ split criterion
13: end if
14: until a minimum node size $l_{min}$ is reached
15: end for
16: end for
17: Output the ensemble of causal conditional inference trees $CCIT_b$; $b = \{1, \ldots, B\}$

18: The predicted personalized treatment effect for a new data point $x$, is obtained by averaging the predictions of the individual trees in the ensemble: $\hat{\tau}(x) = \frac{1}{B} \sum_{b=1}^{B} CCIT_b(x)$
1. Introduction

2. Marketing versus Pricing: should they ally?

3. Profit maximization

4. uplift R package

5. Conclusions
An R programme package called uplift

uplift: Uplift Modeling

An integrated package for building and testing uplift models

Version: 0.3.5
Depends: R (≥ 3.0.0), Rtools, MASS, coin, tables, penalized
Published: 2014-03-17
Author: Leo Guelman
Maintainer: Leo Guelman <leo.guelman at gmail.com>
License: GPL-2 | GPL-3
NeedsCompilation: no
CRAN checks: uplift results

Downloads:

Reference manual: uplift.pdf
Package source: uplift_0.3.5.tar.gz
Windows binaries: r-devel: uplift_0.3.5.zip, r-release: uplift_0.3.5.zip, r-oldrel: uplift_0.3.5.zip
OS X Snow Leopard binaries: r-release: uplift_0.3.5.tar.gz, r-oldrel: uplift_0.3.5.tar.gz
OS X Mavericks binaries: r-release: uplift_0.3.5.tar.gz
Old sources: uplift archive
R implementation: The uplift package in CRAN

The highlights:

- Implements various functions for training personalized treatment learning models (a.k.a., uplift)
- Currently 5 estimation methods are implemented
  - Causal conditional inference forests (ccif)
  - Uplift random forests (upliftRF)
  - Modified covariate method (tian_transf)
  - Modified outcome method (rvtu)
  - Uplift k-nearest neighbor (upliftKNN)
- Exploratory Data Analysis (EDA) tools designed for PTE models
- Functions for evaluating performance of PTE models
- Profiling results of PTE models
- PTE Monte Carlo simulations
- Package in continuous development
A case study: Direct mail campaign

> treat.form <- ~ treatment + age + gender + withdrawals + deposit + credit_value + discounts + transactions + bank_logs + accruals + charges + cash_total + loan_payment + e_trans
> cb <- checkBalance(treat.form, data = bankDM.train)
> Model.form <- ~ response ~ trt(treatment) + age + gender + withdrawals + deposit + credit_value + discounts + transactions + bank_logs + accruals + charges + cash_total + loan_payment + e_trans
> niv_res <- niv(Model.form, B = 100, nbins = 4, data = bankDM.train)
> eda <- explore(Model.form, data = bankDM.train)
A case study: Direct mail campaign

> # Causal conditional inference forests (ccif)
> set.seed(1)
> ccif_fit1 <- ccif(Model.form,
+ data = bankDM.train,
+ ntree = 1000,
+ split_method = "Int",
+ distribution = approximate (B=999),
+ verbose = TRUE)
> op <- par(mar = c(5, 10, 4, 2) + 0.1)
> varImportance(ccif_fit1, plotit = TRUE)
A case study: Direct mail campaign

```r
> ## Uplift random forests (upliftRF) > set.seed(1)
> upliftRF_fit1 <- upliftRF(Model.form, 
+   data = bankDM.train, 
+   ntree = 1000, 
+   interaction.depth = 3, 
+   split.method = "KL", 
+   msplit = 50, 
+   verbose = TRUE)
```
A case study: Direct mail campaign

```r
> ### Modified outcome method (mom)
> set.seed(1)
> bankDM.train.mom <- rvtu(Model.form, data = bankDM.train,
+ method = "undersample")
> Model.form.mom <- z ~ age+gender+withdrawals+deposit+credit_value
+ discounts+transactions
+ +bank_logs+accruals+charges+cash_total+loan_payment+e_trans
> glm.fit1 <- glm(Model.form.mom, data = bankDM.train.mom,
+ family = "binomial")
> ### Perform stepwise model selection by AIC
> glm.fit_step <- stepAIC(glm.fit1, direction = "backward", trace = 0)
```
A case study: Direct mail campaign

> ### Get predictions on test data
> pred_upliftRF < - predict(upliftRF_fit1, bankDM.test)
> pred_ccif < - predict(ccif_fit1, bankDM.test)
> pred_mom < - 2 * predict(glm.fit_step, bankDM.test) - 1
> ### Get uplift by decile
> ccif_perf < - performance(pred_ccif[, 1], pred_ccif[, 2],
+ bankDM.test$response, bankDM.test$treatment)
> upliftRF_perf < - performance(pred_upliftRF[, 1], pred_upliftRF[, 2],
+ bankDM.test$response, bankDM.test$treatment)
> mom_perf < - performance(pred_mom, rep(0, length(pred_mom)),
+ bankDM.test$response, bankDM.test$treatment)
> ### 1st to 3rd decile uplift
> Decile_3_perf < - data.frame(
+ ccif = (sum(ccif_perf[1:3, 4]) sum(ccif_perf[1:3, 2])) -
+ (sum(ccif_perf[1:3, 5]) sum(ccif_perf[1:3, 3])),
+ upliftRF = (sum(upliftRF_perf[1:3, 4]) sum(upliftRF_perf[1:3, 2])) -
+ (sum(upliftRF_perf[1:3, 5]) sum(upliftRF_perf[1:3, 3])),
+ mom = (sum(mom_perf[1:3, 4]) sum(mom_perf[1:3, 2])) -
+ (sum(mom_perf[1:3, 5]) sum(mom_perf[1:3, 3]))
+ )
A case study: Direct mail campaign

```r
> Decile_3_perf
  ccif upliftRF mom
  1 0.3673691 0.3590956 0.3571356
> ### qini-coefficient
> qini <- data.frame(ccif = qini(ccif_perf, plotit = FALSE)$Qini,
+ upliftRF = qini(upliftRF_perf, plotit = FALSE)$Qini,
+ mom = qini(mom_perf, plotit = FALSE)$Qini)
> qini
  ccif upliftRF mom
  1 0.02948474 0.03140241 0.02639283
```
1. Introduction

2. Marketing versus Pricing: should they ally?

3. Profit maximization

4. uplift R package

5. Conclusions
We have presented an approach to estimate price elasticity functions which allows for heterogeneous causal effects as a result of rate change interventions.

The model can assist managers in selecting an optimal rate change level for each customer for the purpose of maximizing the overall profits for the company.

Valuable insights can be gained by knowing the company current position of growth and profitability relative to the optimal values given by the efficient frontier.

The managerial decision is to determine in which direction the company should move towards the frontier, as each decision point places a different weight on each of these objectives.

Uplift models can anticipate the reaction to rate change interventions.
R resources for quantitative analysis in practice

This web is a source of examples for the analysis of data using R. We present many applications in finance and insurance. Some recent methods are also included. All examples contain downloadable data and R programs scripts. References to the methods and theoretical background are briefly outlined.

- Sampling methods
- Predictive modelling
  - Regression with categorical dependent variables
  - Survival analysis
  - Life tables and mortality models
- Non-parametric data analysis
  - Kernel density estimation
  - Transformed kernel density estimation
  - Non-parametric quantile estimation
- GlueVaR risk measures
- Performance measurement of pension strategies

New items are regularly added when they are ready and made available by UB riskcenter members and affiliates who wish to share them. Authors should be acknowledged and the source should be cited properly.

www.ub.edu/riskcenter/R