Ridit splines with applications to propensity weighting

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http://ideas.repec.org/s/boc/usug17.html
What are ridits?

- The distribution of a random variable $X$ can be specified by its Bross ridit function $R_X(\cdot)$, defined by the formula
  $$R_X(x) = \Pr(X < x) + \frac{1}{2}\Pr(X = x).$$
- So, ridits are like ranks, but expressed on a scale from 0 (below the bottom–ranking value) to 1 (above the top–ranking value).
- The word was chosen to be like logit and probit, as the prefix stands for “with respect to an identified distribution”.
- The Brockett–Levene ridit function $R^*_X(\cdot)$ is defined (on a scale from $-1$ to 1) as a difference between probabilities,
  $$R^*_X(x) = \Pr(X < x) - \Pr(X > x),$$
and should always be used to calculate the Bross ridit function
  $$R_X(x) = \frac{1}{2} [R^*_X(x) + 1],$$
avoiding the precision problems of adding tiny half–probabilities to huge probabilities.
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- The **Brockett–Levene ridit function**[1] $R^*_X(\cdot)$ is defined (on a 
  scale from $-1$ to 1) as a **difference** between probabilities,

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Computing ridits using the \texttt{wridit} package

- The SSC package \texttt{wridit} computes “folded” Brockett–Levene ridits or “unfolded” Bross ridits for a numeric Stata variable.
- These ridits may be on a reverse scale (using the \texttt{reverse} option) and/or on a percentage scale (using the \texttt{percent} option), as with the \texttt{ridit} module of Nick Cox’s \texttt{egenmore}.
- \textit{However,} \texttt{wridit} also allows weights, so the ridits can be with respect to the distribution of the variable in a \textbf{target population}.
- In particular, zero weights are allowed, so the user can define ridits for the zero–weighted observations with respect to the distribution of the variable in the nonzero–weighted observations.
- \textit{For instance,} in the \texttt{auto} data, we can define ridits of \texttt{length} with respect to the length distribution in US cars by zero–weighting non–US cars, or \textbf{vice versa}.
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- A **ridit spline** in a variable $X$ is a spline in the ridit–transformed variable $R_X(X)$.

- If the user has installed the SSC packages `bspline[3]` and `polyspline[4]` as well as `wridit`, then the user can compute an unrestricted **reference–spline basis** in the ridit of an $X$–variable.

- This spline basis will have the advantage that the corresponding parameters of a fitted model will be values of the ridit spline at a list of values on the ridit scale, ranging from 0 to 1 (such as 0, 0.25, 0.50, 0.75 and 1).

- These fitted parameters will be mean values of the outcome variable, corresponding to $X$–values equal to percentiles of $X$ (such as the minimum, median, maximum, and 25th and 75th percentiles).

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Example: Mileage and car length in the auto data

- We will demonstrate our methods in the auto data, with 1 observation for each of 74 car models.
- We will regress fuel efficiency in US/Imperial miles per gallon with respect to a ridit spline in car length in US/Imperial inches.
- We will use wridit to define the ridits of car length, and polyspline[4] to define an unrestricted cubic reference–spline basis in the ridits.
- We will then use rcentile[4] to estimate the percentiles corresponding to the reference ridits.
- We will then fit the regression model for fuel efficiency with respect to car length, with 1 parameter for each of 5 length percentiles (0, 25, 50, 75 and 100).
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Example: Mileage and car length in the `auto` data

- We will demonstrate our methods in the `auto` data, with 1 observation for each of 74 car models.
- We will regress fuel efficiency in US/Imperial miles per gallon with respect to a ridit spline in car length in US/Imperial inches.
- We will use `wridit` to define the ridits of car length, and `polyspline[4]` to define an unrestricted cubic reference–spline basis in the ridits.
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- Finally, we will plot the results.
Computing ridits using \texttt{wridit}

After loading the \texttt{auto} data, we use \texttt{wridit} to generate a new variable \texttt{lengthridit}, containing ridits (on a percentage scale) for the variable \texttt{length}:

\begin{verbatim}
. wridit length, percent generate(lengthridit);
. lab var lengthridit "Ridit (%) of Length (in.)";
. desc lengthridit, fu;
\end{verbatim}

\begin{verbatim}
storage display value
variable name type format label variable label
lengthridit double %10.0g Ridit (%) of Length (in.)
\end{verbatim}

\begin{verbatim}
. summ lengthridit;
\end{verbatim}

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>lengthridit</td>
<td>74</td>
<td>50</td>
<td>29.04986</td>
<td>.6756757</td>
<td>99.32432</td>
</tr>
</tbody>
</table>

Note that the Bross ridits (on a percentage scale) are \textit{strictly} bounded between 0 and 100 percent, and have a mean of \textit{exactly} 50 percent.
Computing a cubic ridit spine basis in length

We use the SSC package `polyspline`[4] to generate a basis of 5 cubic reference splines \( rs_1 \) to \( rs_5 \) in the ridit variable, corresponding to percentages of 0, 25, 50, 75 and 100, respectively:

```
. polyspline lengthridit, power(3) refpts(0(25)100) gene(rs_) labprefix(Percent@);
5 reference splines generated of degree: 3
```

```
. desc rs_*, fu;
```

<table>
<thead>
<tr>
<th>variable</th>
<th>storage</th>
<th>display</th>
<th>value label</th>
</tr>
</thead>
<tbody>
<tr>
<td>rs_1</td>
<td>float</td>
<td>%8.4f</td>
<td>Percent@00</td>
</tr>
<tr>
<td>rs_2</td>
<td>float</td>
<td>%8.4f</td>
<td>Percent@25</td>
</tr>
<tr>
<td>rs_3</td>
<td>float</td>
<td>%8.4f</td>
<td>Percent@50</td>
</tr>
<tr>
<td>rs_4</td>
<td>float</td>
<td>%8.4f</td>
<td>Percent@75</td>
</tr>
<tr>
<td>rs_5</td>
<td>float</td>
<td>%8.4f</td>
<td>Percent@100</td>
</tr>
</tbody>
</table>

Note that we have labelled them using the `labprefix()` option of `polyspline`.

Ridit splines with applications to propensity weighting
Percentiles corresponding to the 5 reference percentage ridits

To estimate the inverse ridits (also known as percentiles) corresponding to our 5 reference percentage ridits, we use the SSC package \texttt{rcentile}[4] to compute percentile car lengths in inches:

\begin{verbatim}
.rcentile length, centile(0(25)100) transf(asin);
Percentile(s) for variable: length
Mean sign transformation: Daniels’ arcsine
Valid observations: 74
95% confidence interval(s) for percentile(s)

Percent  Centile  Minimum  Maximum

 0         142  -9.0e+307   142
25        170    164      174
50       192.5    179      198
75        204    200      212
100       233    233  9.0e+307
\end{verbatim}

Percentiles 0 and 100 are estimated as the minimum and maximum lengths, respectively, with lower and upper confidence limits (respectively) equal to minus and plus infinity (respectively). \textit{However}, we are not really interested in confidence limits here, because...
Mean mileages corresponding to the 5 reference percentage ridits

... length is the $X$–variable, and we are really interested in the conditional means of the $Y$–variable mpg, corresponding to our 5 sample percentile lengths. We estimate these using `regress`:

```
. regress mpg rs_* , noconst vce(robust);
```

```
Linear regression
Number of obs = 74
F(5, 69) = 757.73
Prob > F = 0.0000
R-squared = 0.9778
Root MSE = 3.4072
```

|       | Robust | Coef. | Std. Err. | t     | P>|t| | [95% Conf. Interval] |
|-------|--------|-------|-----------|-------|-----|----------------------|
| rs_1  | 29.2563| 2.17573|           | 13.45 | 0.000| 24.91584 – 33.59677  |
| rs_2  | 25.66597| .9778877|           | 26.25 | 0.000| 23.71514 – 27.6168   |
| rs_3  | 19.43958| .6659589|           | 29.19 | 0.000| 18.11103 – 20.76813  |
| rs_4  | 18.01778| .5218036|           | 34.53 | 0.000| 16.97681 – 19.05875  |
| rs_5  | 12.68334| 1.043106|           | 12.16 | 0.000| 10.6024 – 14.76427   |

These estimates and confidence limits are expressed in miles per gallon, and in an alien–looking format. However . . .
Percentile lengths and mean mileages corresponding to the 5 reference percentage ridits

... if we collect the percentiles in an output dataset (or resultssset) using `xsvmat`, and collect the estimated mean mileages in a second resultssset using `parmest`, and reconstruct the `Percent` variable in the second resultssset using `factext`, and merge the 2 resultsssets by `Percent` to form a single resultssset in memory, then we can list the percents, percentile lengths, and conditional mean mileages as follows:

```
. list Percent Centile parm estimate min* max*, abbr(32);
```

<table>
<thead>
<tr>
<th>Percent</th>
<th>Centile</th>
<th>parm</th>
<th>estimate</th>
<th>min95</th>
<th>max95</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>142</td>
<td>rs_1</td>
<td>29.26</td>
<td>24.92</td>
<td>33.60</td>
</tr>
<tr>
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<td>12.68</td>
<td>10.60</td>
<td>14.76</td>
</tr>
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- These are the fitted parameters of the ridit–spline model for mileage.

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*Ridit splines with applications to propensity weighting*
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- In an observational study, a propensity score typically measures the odds of a subject being allocated to Treatment A instead of to Treatment B.
- It is typically computed using a logit regression model of treatment allocation with respect to a list of confounders.
- The propensity score can then be used to calculate propensity weights.
- These are used to standardize directly from the sampled population to a fantasy target population, with a real–world distribution of confounders (and therefore of the propensity score), but with no treatment–confounder association.
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- Unfortunately, once the propensity weights are calculated from the model, we may find that some of these weights are extremely large.
- These weights belong to subjects with an extremely atypical confounder profile for the treatment group (A or B) to which they were allocated in the real world.
- Such outlying weights may imply that the propensity weights do not do a very good job of balancing out the confounders, and/or that the variance of the estimated causal effect is inflated.
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- This example uses data from 2 British National Health Service databases, the Central Practice Research Datalink (CPRD) and the Hospital Episodes System (HES).
- We followed up 190,137 Type 2 diabetics in 490 English general practices, computing adverse event counts and 15 binary treatment indicators (9 prescribed drugs and 6 target achievements) for each of 10,135,062 patient-months.
- The aim was to assess the average treatment effect in the treated (ATET), defined as a treated-untreated difference in adverse event counts per 1,000 patient-years.
- We used a list of patient-month-specific confounders to define a primary propensity score and propensity weight for each of the 15 treatment indicators, and also a secondary propensity score and propensity weight, using a logit model of the treatment with respect to a ridit spline in the primary propensity score.
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Predictive power, balancing power and variance inflation checks

- To choose a propensity score for use in the final analysis, we used the methods of Newson (2016)[5].
- Predictive power was measured using the unweighted Somers’ $D$ of the propensity score with respect to the treatment indicator.
- Balancing power was measured using Somers’ $D$ of the propensity score with respect to the treatment indicator, weighted using the appropriate propensity weight.
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The left and right panels show them for primary and secondary propensity scores, respectively.

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- The propensity–weighted Somers’ $D$ values should be zero, if the weights standardize out the propensity–treatment association.
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Ridit splines with applications to propensity weighting

Graphs by Propensity method

<table>
<thead>
<tr>
<th>Primary</th>
<th>Secondary</th>
</tr>
</thead>
<tbody>
<tr>
<td>Metformin</td>
<td>Metformin</td>
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<tr>
<td>Sulphonylurea</td>
<td>Sulphonylurea</td>
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<tr>
<td>Insulin</td>
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<td>Glitoxin</td>
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<tr>
<td>Acarbose</td>
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<td>Medication review in previous 12 months</td>
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<td>QOF achievement for: DM003 (blood pressure)</td>
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Summary: Costs and benefits of propensity scores and weights

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References


This presentation, and the do–file producing the *auto* data examples, can be downloaded from the conference website at [http://ideas.repec.org/s/boc/usug17.html](http://ideas.repec.org/s/boc/usug17.html)

The packages used in this presentation can be downloaded from SSC, using the *ssc* command.