

Information Relative Risk Aversion

Derivation of IRRA

Relative Risk Aversion (RRA) of the Coupled Logarithm utility function

First replicate Wikipedia page on Relative Risk Aversion

$$\text{In}[\ast] := \text{RRA}[c_ , q_] := -c \frac{D[q \ln[c, q], \{c, 2\}]}{D[q \ln[c, q], c]};$$

$$q \ln[c_ , q_] := \frac{c^{1-q} - 1}{1 - q};$$

$$\text{In}[\ast] := \text{FullSimplify}[\text{RRA}[c, q], 1 < q < 3]$$

$$\text{Out}[\ast] = q$$

Review the Information Relative Risk from the perspective of utility to double check aversion/tolerance direction. With straight line as utility function, risk averse has negative second derivative and risk tolerant has positive second derivative. For utility, use $\ln p$ rather than $-\ln p$.

$$\text{In}[\ast] := \text{IRRA}[p_ , \kappa_ , d_ , \alpha_] :=$$

$$-p \left(\frac{D\left[-\frac{1}{\alpha} \text{CoupledLogarithm}[p^{-\alpha}, \kappa, d], \{p, 2\}\right]}{D\left[-\frac{1}{\alpha} \text{CoupledLogarithm}[p^{-\alpha}, \kappa, d], p\right]} - \frac{D[\text{Log}[p], \{p, 2\}]}{D[\text{Log}[p], p]} \right);$$

$$\text{In}[\ast] := \text{FullSimplify}[\{\text{IRRA}[p, \kappa, d, \alpha], \text{IRRA}[p, \kappa, d, \alpha] /. \{\kappa \rightarrow q \text{ToCoupling}[q, \alpha, d]\}\},$$

$$\kappa > 0 \ \&\& \ \alpha > 0 \ \&\& \ d > 0 \ \&\& \ 0 < p < 1]$$

$$\text{Out}[\ast] = \left\{ \frac{\alpha \kappa}{1 + d \kappa}, \left\{ \begin{array}{ll} -1 + q & \frac{1-q}{d-d q+\alpha} \neq 0 \\ 0 & \text{True} \end{array} \right\} \right\}$$

Solve for Informational Relative Risk Aversion (IRRA) using the coupled surprisal in terms of the loss rather than the utility function. The variable p is inverted to make it a loss function. The sign of the IRRA equation does not change because the sign of both the second and the first derivative changed. The ratio is unchanged.

$$\text{In}[\ast] := \text{IRRA}[p_ , \kappa_ , d_ , \alpha_] :=$$

$$-p \left(\frac{D\left[\frac{1}{\alpha} \text{CoupledLogarithm}[p^{-\alpha}, \kappa, d], \{p, 2\}\right]}{D\left[\frac{1}{\alpha} \text{CoupledLogarithm}[p^{-\alpha}, \kappa, d], p\right]} - \frac{D[-\text{Log}[p], \{p, 2\}]}{D[-\text{Log}[p], p]} \right);$$

```
In[ ]:= FullSimplify[{IRRA[p, κ, d, α], IRRA[p, κ, d, α] /. {κ → qToCoupling[q, α, d]}},
  κ > 0 && α > 0 && d > 0 && 0 < p < 1]
```

$$\text{Out[]} = \left\{ \frac{\alpha \kappa}{1 + d \kappa}, \left\{ \begin{array}{ll} -1 + q \frac{1-q}{d-d q+\alpha} \neq 0 & \\ 0 & \text{True} \end{array} \right\} \right\}$$

Thus it is the positive κ values that have positive values of IRAA. The domain is $-0 < \kappa < \infty$.

Will use the expressions $r = r_a = -r_t$ to label relative risk aversion and relative risk tolerance.

Simplification of Terms

```
In[ ]:= D[-1/α CoupledLogarithm[p^-α, κ, d], {p, 2}] // FullSimplify
```

$$\text{Out[]} = \left\{ \begin{array}{ll} -\frac{1}{p^2} & p^{-\alpha} \geq 0 \text{ \& } \kappa = 0 \\ -\frac{(p^{-\alpha})^{\frac{\kappa}{1+d\kappa}} (1+(d+\alpha)\kappa)}{(p+d p \kappa)^2} & p^{-\alpha} \geq 0 \text{ \& } \kappa \neq 0 \\ 0 & \text{True} \end{array} \right.$$

```
In[ ]:= D[-1/α CoupledLogarithm[p^-α, κ, d], {p, 1}] // FullSimplify
```

$$\text{Out[]} = \left\{ \begin{array}{ll} \frac{1}{p} & p^{-\alpha} \geq 0 \text{ \& } \kappa = 0 \\ \frac{(p^{-\alpha})^{\frac{\kappa}{1+d\kappa}}}{p+d p \kappa} & p^{-\alpha} \geq 0 \text{ \& } \kappa \neq 0 \\ 0 & \text{True} \end{array} \right.$$

```
In[ ]:= -1/α CoupledLogarithm[p^-α, 0, d] // FullSimplify
```

$$\text{Out[]} = -\frac{\text{Log}[p^{-\alpha}]}{\alpha} \text{ if } p^{-\alpha} \geq 0$$

Derivation of Decisive-Accuracy-Robustness Metric

From the Reduced Perplexity book chapter

$$P_r(\mathbf{p}^{(r)}, \mathbf{p}) = \left(\sum_{i=1}^N \left(\frac{p_i^{1-r}}{\sum_{j=1}^N p_j^{1-r}} \right) p_i^r \right)^{\frac{1}{r}} = \left(\sum_{i=1}^N p_i^{1-r} \right)^{\frac{-1}{r}} = P_{-r}(\mathbf{p}, \mathbf{p}). \quad (12.9)$$

Perhaps, I haven't fully absorbed the significance of this equation. The effect of weighting the generalized mean by the coupled probability is to change the sign of the generalized mean. If I apply the

generalized mean again, then the sign will reverse back.

However, the distinction with the assessment metric is that the equation is for the cross-entropy. For p - empirical distribution and q - quoted forecast, the equation is

$$\ln[\bullet] := \left(\sum_{i=1}^N \left(\frac{p_i^{1-r}}{\sum_{j=1}^N p_j^{1-r}} \right) q_i^r \right)^{\frac{1}{r}} = \left(\frac{1}{\sum_{j=1}^N p_j^{1-r}} \sum_{i=1}^N p_i \left(\frac{q_i}{p_i} \right)^r \right)^{\frac{1}{r}}$$

... Set : Tag Power in $\left(\sum_{i=1}^N \frac{p_i^{1-r} q_i^r}{\sum_{j=1}^N p_j^{1-r}} \right)^{\frac{1}{r}}$ is Protected.

$$\text{Out}[\bullet] := \left(\frac{\sum_{i=1}^N p_i \left(\frac{q_i}{p_i} \right)^r}{\sum_{j=1}^N p_j^{1-r}} \right)^{\frac{1}{r}}$$

The derivation of the DAR metric should focus on use of the inverse coupled logarithm.

Given $y = \frac{1}{\alpha} \text{CoupledLogarithm}[p^{-\alpha}, \kappa, d]$ as the coupled surprisal, the inverse of this to provide a probability is $(\text{CoupledExponential}[\alpha y, \kappa, d])^{\frac{-1}{\alpha}}$.

$$\ln[\bullet] := \text{FullSimplify} \left[\left(\text{CoupledExponential} \left[\text{FullSimplify} \left[\sum_{i=1}^N \frac{\alpha}{\alpha N} \text{CoupledLogarithm}[p^{-\alpha}, \kappa, d], \right. \right. \right. \right. \\ \left. \left. \left. 0 < p < 1 \ \&\& \ 0 < \alpha < \infty \ \&\& \ 0 < \kappa < \infty \ \&\& \ 0 < d < \infty \ \&\& \ N \in \text{Integers} \right], \right. \right. \\ \left. \left. \kappa, d \right] \right)^{\frac{-1}{\alpha}}, \left. 0 < p < 1 \ \&\& \ 0 < \alpha < \infty \ \&\& \ 0 < \kappa < \infty \ \&\& \ 0 < d < \infty \ \&\& \ N \in \text{Integers} \right]$$

Out[•] = p

$\ln[\circ] :=$

$$\text{FullSimplify}\left[\left(\text{CoupledExponential}\left[\right.\right.$$

$$\text{FullSimplify}\left[\sum_{i=1}^n \frac{\alpha}{\alpha n} \text{CoupledLogarithm}[p[i]^{-\alpha}, \kappa, d],\right.$$

$$0 < p < 1 \&\& 0 < \alpha < \infty \&\& 0 < \kappa < \infty \&\& 0 < d < \infty \&\& N \in \text{Integers}\left],\right.$$

$$\left.\left.\kappa, d\right]\right)^{-\frac{1}{\alpha}}, 0 < p < 1 \&\& 0 < \alpha < \infty \&\& 0 < \kappa < \infty \&\& 0 < d < \infty \&\& N \in \text{Integers}\left]$$

$$\text{Out}[\circ] = \text{If}\left[1 + \kappa \sum_{i=1}^n \frac{\text{If}\left[p[i]^{-\alpha} \geq 0, \text{If}\left[\kappa \neq 0, \frac{(p[i]^{-\alpha})^{\frac{\kappa}{1+d\kappa}} - 1}{\kappa}, \text{Log}[p[i]^{-\alpha}]\right], \text{Undefined}\right]}{n} > 0,\right.$$

$$\left.\text{If}\left[\kappa \neq 0, \left(1 + \kappa \sum_{i=1}^n \frac{\text{If}\left[p[i]^{-\alpha} \geq 0, \text{If}\left[\kappa \neq 0, \frac{(p[i]^{-\alpha})^{\frac{\kappa}{1+d\kappa}} - 1}{\kappa}, \text{Log}[p[i]^{-\alpha}]\right], \text{Undefined}\right]}{n}\right)^{\frac{1+d\kappa}{\kappa}},\right.$$

$$\left.\left.\text{Exp}\left[\sum_{i=1}^n \frac{\text{If}\left[p[i]^{-\alpha} \geq 0, \text{If}\left[\kappa \neq 0, \frac{(p[i]^{-\alpha})^{\frac{\kappa}{1+d\kappa}} - 1}{\kappa}, \text{Log}[p[i]^{-\alpha}]\right], \text{Undefined}\right]}{n}\right]\right],$$

$$\text{If}\left[\frac{1+d\kappa}{\kappa} > 0, 0, \infty\right]^{-1/\alpha}$$

$$\ln[\circ] := \text{FullSimplify}\left[\left(1 + \kappa \sum_{i=1}^n \frac{(p[i]^{-\alpha})^{\frac{\kappa}{1+d\kappa}} - 1}{n}\right)^{\frac{1+d\kappa}{-\alpha\kappa}}\right]$$

$$\text{Out}[\circ] = \left(1 + \kappa \sum_{i=1}^n \frac{-1 + (p[i]^{-\alpha})^{\frac{\kappa}{1+d\kappa}}}{n\kappa}\right)^{-\frac{1+d\kappa}{\alpha\kappa}}$$

$$\left(\frac{1}{n} \sum_{i=1}^n \left(p[i]^{-\frac{\alpha\kappa}{1+d\kappa}}\right)\right)^{-\frac{1+d\kappa}{\alpha\kappa}}$$

So, indeed the RAD metric uses $rt = \frac{-\alpha\kappa}{1+d\kappa}$ as the metric; thus it is based on the relative risk tolerance.

Plots of q-log and coupled log

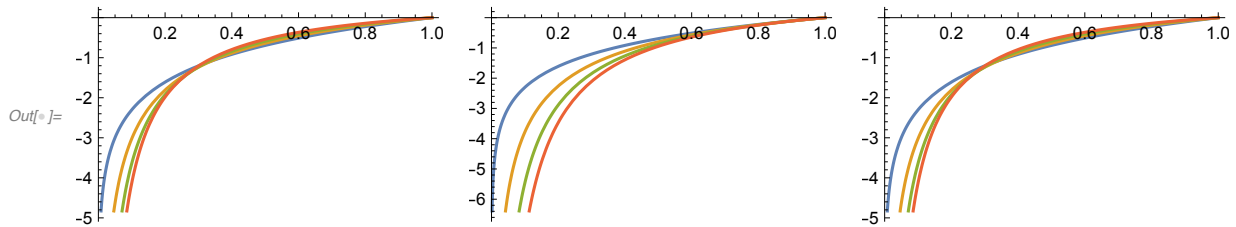
Plot of the coupled logarithm as a utility function shows more negative curvature as κ is more positive.

```
GraphicsGrid[{{Plot[Evaluate@
  
$$\left(\frac{-1}{\alpha} \text{CoupledLogarithm}[p^{-\alpha}, \#, d] \& /@ \{0, 0.25, .5, 0.75\} // . \{\alpha \rightarrow 2, d \rightarrow 1\}\right),$$

  {p, 0, 1}],
  (* Not the exact same function *)
  Plot[Evaluate@
    
$$(q \ln[p, \#] \& /@ \text{couplingToq}[\{10^{-6}, 0.25, .5, 0.75\}, \alpha, d] // . \{\alpha \rightarrow 2, d \rightarrow 1\}),$$

    {p, 0, 1}],
  Plot[Evaluate@
    
$$\left(\frac{1}{\alpha} \text{CoupledLogarithm}[p^{\alpha}, -\#, -d] \& /@ \{0, 0.25, .5, 0.75\} // . \{\alpha \rightarrow 2, d \rightarrow 1\}\right),$$

    {p, 0, 1}]
  ]}]
```

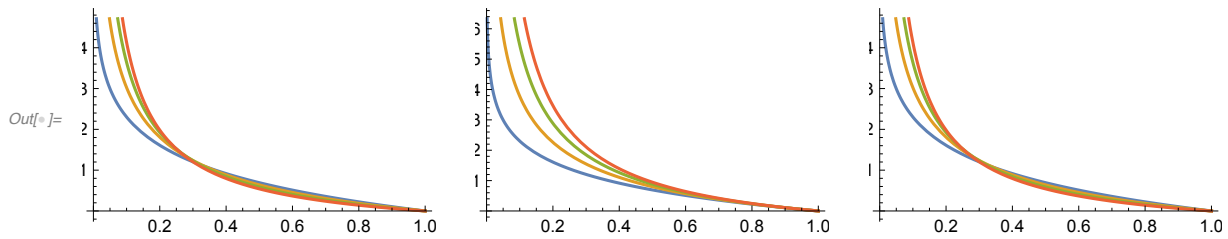


Plot the coupled-surprisal as the information loss function

```

In[ ]:= GraphicsGrid[{{Plot[Evaluate@
  (
     $\frac{1}{\alpha}$  CoupledLogarithm[p-α, #, d] & /@ {0, 0.25, .5, 0.75} /. {α → 2, d → 1}
  ),
  {p, 0, 1}],
Plot[Evaluate@
  (
    -qLn[p, #] & /@ couplingToq[{10-6, 0.25, .5, 0.75}, α, d] /. {α → 2, d → 1}
  ),
  {p, 0, 1}],
Plot[Evaluate@
  (
     $-\frac{1}{\alpha}$  CoupledLogarithm[pα, -#, -d] & /@ {0, 0.25, .5, 0.75} /. {α → 2, d → 1}
  ),
  {p, 0, 1}]}]}

```



Curious what the curves look like if alpha = 1

```

In[ ]:= GraphicsGrid[{{Plot[Evaluate@
  (
     $\frac{1}{\alpha}$  CoupledLogarithm[p-α, #, d] & /@ {0, 0.25, .5, 0.75} /. {α → 1, d → 1}
  ),
  {p, 0, 1}],
Plot[Evaluate@
  (
    -qLn[p, #] & /@ couplingToq[{10-6, 0.25, .5, 0.75}, α, d] /. {α → 1, d → 1}
  ),
  {p, 0, 1}],
Plot[Evaluate@
  (
     $-\frac{1}{\alpha}$  CoupledLogarithm[pα, -#, -d] & /@ {0, 0.25, .5, 0.75} /. {α → 1, d → 1}
  ),
  {p, 0, 1}]}]}

```

