

Some useful properties and formulas for random utility models with logit, nested logit, and ordered nested logit stochastic components

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January 8, 2010

Abstract

Within the framework of discrete choice Random Utility Models (RUM) with additive stochastic components, this note reviews existing results on closed-form expressions for several key functions: the distribution of the maximum utility, the expected maximum utility, the choice probabilities, and the selection function. The analysis considers three different specifications for the distribution of the stochastic component: i.i.d. type I extreme value distribution, nested extreme value distribution, and ordered generalized extreme value distribution.

1 Random Utility Models

Consider a discrete choice Random Utility Model (RUM) with additive stochastic component.

The optimal choice, a^* , is defined as:

$$a^* = \arg \max_{a \in \mathcal{A}} \{u_a + \varepsilon_a\} \quad (1)$$

where $\mathcal{A} = \{1, 2, \dots, J\}$ is the set of feasible choice alternatives, $\mathbf{u} = (u_1, u_2, \dots, u_J)$ is the vector with the deterministic component of the utility, and $\boldsymbol{\varepsilon} = (\varepsilon_1, \varepsilon_2, \dots, \varepsilon_J)$ is the vector with the stochastic component. The vector $\boldsymbol{\varepsilon}$ has a joint CDF $G(\cdot)$ that is continuous and strictly increasing with respect to the Lebesgue measure in the Euclidean space.

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This note derives closed-form expressions for the distribution of the maximum utility, $\max_{a \in \mathcal{A}} \{u_a + \varepsilon_a\}$, the expected maximum utility, $\mathbb{E}(\max_{a \in \mathcal{A}} \{u_a + \varepsilon_a\} | u)$, and the choice probabilities, $\Pr(a^* = a | \mathbf{u})$, under three different specifications for the distribution of the vector ε : (1) i.i.d. Type I Extreme Value distribution (MNL model); (2) nested Extreme Value distribution (NL model); and (3) Ordered Generalized Extreme Value distribution (OGEV model).

The following definitions and properties are used in the note.

Definition: A random variable X has a Double Exponential or Type I Extreme Value distribution with location parameter μ and dispersion parameter σ if its CDF is:

$$G(x) = \exp \left\{ - \exp \left(- \left[\frac{x - \mu}{\sigma} \right] \right) \right\} \quad (2)$$

for any $x \in (-\infty, +\infty)$. ■

Definition: Maximum utility. Let v^* be the random variable that represents the maximum utility: $v^* \equiv \max_{a \in \mathcal{A}} \{u_a + \varepsilon_a\}$. This maximum utility is a random variable because it depends on the vector of random variables ε . ■

Definition: McFadden's Social Surplus function. The social surplus function $S(\mathbf{u})$ is the expected value of the maximum utility conditional on the vector of constants \mathbf{u} : $S(\mathbf{u}) \equiv \mathbb{E}(\max_{a \in \mathcal{A}} \{u_a + \varepsilon_a\} | u)$. ■

Definition: Conditional choice probabilities (CCPs). The conditional choice probability $P(a | \mathbf{u})$ is the probability that alternative a is the optimal choice: $P(a | \mathbf{u}) \equiv \Pr(a^* = a | \mathbf{u})$. ■

Definition: Conditional choice expected utilities (CCEU). The conditional choice expected utility $e(a, \mathbf{u})$ is the expected value of utility $u_a + \varepsilon_a$ conditional on the vector \mathbf{u} and on the event that alternative a is the optimal choice: $e(a, \mathbf{u}) \equiv \mathbb{E}(u_a + \varepsilon_a | \mathbf{u}, a^* = a)$. ■

Definition: Selection function. The selection function $\lambda(a, \mathbf{u})$ is the expected value of the stochastic component of the utility, ε_a , conditional on the vector \mathbf{u} and on the event that alternative a is the optimal choice: $\lambda(a, \mathbf{u}) \equiv \mathbb{E}(\varepsilon_a | \mathbf{u}, a^* = a)$. ■

Williams-Daly-Zachary (WDZ) Theorem is an important property of discrete choice RUM with additive stochastic component. It is the discrete-choice version of Roy's Identity in consumer theory. I use this property in several parts of this note. I include here an enunciation of the Theorem and a simple proof.

Williams-Daly-Zachary (WDZ) Theorem. *For any choice alternative $a \in \mathcal{A}$, the CCP $P(a|\mathbf{u})$ can be obtained as the partial derivative of the surplus function $S(\mathbf{u})$ with respect to utility $u(a)$:*

$$P(a|\mathbf{u}) = \frac{\partial S(\mathbf{u})}{\partial u_a} \quad \blacksquare \quad (3)$$

Proof: By definition of $S(\mathbf{u})$, we have that:

$$\frac{\partial S(\mathbf{u})}{\partial u_a} = \frac{\partial}{\partial u_a} \int \max_{j \in \mathcal{A}} \{u_j + \varepsilon_j\} dG(\boldsymbol{\varepsilon}) \quad (4)$$

Given the conditions on the CDF of $\boldsymbol{\varepsilon}$, we can move the partial derivative inside the integral such that:

$$\begin{aligned} \frac{\partial S(\mathbf{u})}{\partial u_a} &= \int \frac{\partial \max_{j \in \mathcal{A}} \{u_j + \varepsilon_j\}}{\partial u_a} dG(\boldsymbol{\varepsilon}) \\ &= \int 1\{u_a + \varepsilon_a \geq u_j + \varepsilon_j, \forall j \in \mathcal{A}\} dG(\boldsymbol{\varepsilon}) \\ &= P(a|\mathbf{u}) \end{aligned} \quad (5)$$

where $1\{\cdot\}$ is the indicator function. \blacksquare

I also use the following Theorem to derive several results in this note.

Theorem CEV. *For any distribution of $\boldsymbol{\varepsilon}$, any value of the vector \mathbf{u} , and any choice alternative $a \in \mathcal{A}$, we have that:*

$$\mathbb{E}(\varepsilon_a \mid \mathbf{u}, a^* = a) = S(\mathbf{u}) - u_a \quad \blacksquare \quad (6)$$

Proof: First, I show that $e(a, \mathbf{u}) = S(\mathbf{u})$. Given that the random variable v^* represents

maximum utility, we have that the event $\{a^* = a\}$ implies the event $\{v^* = u_a + \varepsilon_a\}$. Thus,

$$\begin{aligned}
e(a, \mathbf{u}) &= \mathbb{E}(u_a + \varepsilon_a \mid \mathbf{u}, a^* = a) \\
&= \mathbb{E}(u_a + \varepsilon_a + v^* - v^* \mid \mathbf{u}, a^* = a) \\
&= \mathbb{E}(u_a + \varepsilon_a + v^* - v^* \mid \mathbf{u}, v^* = u_a + \varepsilon_a) \\
&= \mathbb{E}(v^* \mid \mathbf{u}) = S(\mathbf{u})
\end{aligned} \tag{7}$$

By definition, $e(a, \mathbf{u}) = u_a + \mathbb{E}(\varepsilon_a \mid u, a^* = a)$. Therefore, equation (7) implies that $\mathbb{E}(\varepsilon_a \mid \mathbf{u}, a^* = a) = S(\mathbf{u}) - u_a$. ■

2 Multinomial logit (MNL)

Suppose that the random variables in the vector ε are i.i.d. with Type I Extreme Value distribution with a location parameter $\mu = 0$ and unrestricted dispersion parameter σ . That is, for every alternative $a \in \mathcal{A}$, the CDF of ε_a is $G(\varepsilon_a) = \exp\{-\exp(-\frac{\varepsilon_a}{\sigma})\}$.

2.1 Distribution of the maximum utility

The maximum utility v^* is a random variable because it depends on the vector of random variables ε . By definition, the cumulative probability distribution of v^* is:

$$\begin{aligned}
F_{v^*}(v) &\equiv \Pr(v^* \leq v) = \prod_{a \in \mathcal{A}} \Pr(u_a + \varepsilon_a \leq v) \\
&= \prod_{a \in \mathcal{A}} \exp\left\{-\exp\left(-\frac{v - u_a}{\sigma}\right)\right\} \\
&= \exp\left\{-\exp\left(-\frac{v}{\sigma}\right) U\right\}
\end{aligned} \tag{8}$$

where $U \equiv \sum_{a \in \mathcal{A}} \exp\left(\frac{u_a}{\sigma}\right)$. We can also write this expression as:

$$F_{v^*}(v) = \exp\left\{-\exp\left(-\frac{v - \sigma \ln U}{\sigma}\right)\right\} \tag{9}$$

This expression shows that the maximum utility v^* is a double exponential random variable with dispersion parameter σ and location parameter $\sigma \ln U$. Therefore, the maximum of a vector of i.i.d. double exponential random variables is also a double exponential random

variable. This is the reason why this family of random variables is also called "extreme value". The density function of v^* is:

$$f_{v^*}(v) \equiv H'(v) = F_{v^*}(v) \frac{U}{\sigma} \exp\left(-\frac{v}{\sigma}\right) \quad (10)$$

2.2 Expected maximum utility

By definition, $S(\mathbf{u}) = \mathbb{E}(v^*|\mathbf{u})$. Therefore,

$$S(\mathbf{u}) = \int v^* h(v^*) dv^* = \int v^* \exp\left\{-\exp\left(-\frac{v^*}{\sigma}\right)U\right\} \frac{U}{\sigma} \exp\left(-\frac{v^*}{\sigma}\right) dv^* \quad (11)$$

Applying the change in variable $z = \exp(-v^*/\sigma)$, such that $v^* = -\sigma \ln(z)$, and $dv^* = -\sigma(dz/z)$, we have:

$$\begin{aligned} S(\mathbf{u}) &= \int_{+\infty}^0 -\sigma \ln(z) \exp\{-zU\} \frac{U}{\sigma} z \left(-\sigma \frac{dz}{z}\right) \\ &= -\sigma U \int_0^{+\infty} \ln(z) \exp\{-zU\} dz \end{aligned} \quad (12)$$

Using Laplace transformation we have that $\int_0^{+\infty} \ln(z) \exp\{-zU\} dz = \frac{\ln(U) + \gamma}{U}$, where γ is Euler's constant. Therefore, the expected maximum utility is:

$$S(\mathbf{u}) = \sigma U \left(\frac{\ln(U) + \gamma}{U}\right) = \sigma (\ln(U) + \gamma) \quad (13)$$

2.3 Choice probabilities

By Williams-Daly-Zachary (WDZ) theorem, the optimal choice probabilities can be obtained by differentiating the surplus function. Therefore, for the MNL model,

$$\begin{aligned} P(a|\mathbf{u}) &= \sigma \frac{\partial \ln(U)}{\partial u_a} = \sigma \frac{\partial U}{\partial u_a} \frac{1}{U} \\ &= \exp\left(\frac{u_a}{\sigma}\right) \frac{1}{U} = \frac{\exp(u_a/\sigma)}{\sum_{j \in \mathcal{A}} \exp(u_j/\sigma)} \end{aligned} \quad (14)$$

2.4 Conditional choice expected utilities

As shown in Theorem CEV, $\mathbb{E}(\varepsilon_a|\mathbf{u}, a^* = a) = S(\mathbf{u}) - u_a$. For the case of the i.i.d. double exponential ε we have that:

$$\mathbb{E}(\varepsilon_a|\mathbf{u}, a^* = a) = \sigma (\ln(U) + \gamma) - u_a \quad (15)$$

2.5 Relationship between selection function and CCPs

In some applications, we are interested in the selection function that relates the expected value $\mathbb{E}(\varepsilon_a|\mathbf{u}, a^* = a)$ with the conditional choice probabilities. From the expression for $P(a|\mathbf{u})$ in the MNL model, we have that $\ln P(a|\mathbf{u}) = u_a/\sigma - \ln U$, and therefore $\ln(U) = u_a/\sigma - \ln P_a$. Solving this expression in equation (15) we get:

$$\mathbb{E}(\varepsilon_a|\mathbf{u}, a^* = a) = \sigma (u_a/\sigma - \ln P(a|\mathbf{u}) + \gamma) - u_a = \sigma (\gamma - \ln P(a|\mathbf{u})) \quad (16)$$

3 Nested logit (NL)

Suppose that the random variables in the vector ε have the following joint CDF:

$$G(\varepsilon) = \exp \left\{ - \sum_{r=1}^R \left[\sum_{a \in \mathcal{A}_r} \exp \left(- \frac{\varepsilon_a}{\sigma_r} \right) \right]^{\frac{\sigma_r}{\delta}} \right\} \quad (17)$$

where $\{\mathcal{A}_1, \mathcal{A}_2, \dots, \mathcal{A}_R\}$ is a partition of \mathcal{A} , and $\delta, \sigma_1, \sigma_2, \dots, \sigma_R$ are positive parameters, with $\delta \leq 1$.

3.1 Distribution of the Maximum Utility

Using the same approach as for the MNL model, we have:

$$\begin{aligned}
F_{v^*}(v) \equiv \Pr(v^* \leq v) &= \prod_{a \in \mathcal{A}} \Pr(u_a + \varepsilon_a \leq v, \forall a \in \mathcal{A}) \\
&= \prod_{a \in \mathcal{A}} \exp \left\{ - \sum_{r=1}^R \left[\sum_{a \in \mathcal{A}_r} \exp \left(- \frac{v - u_a}{\sigma_r} \right) \right]^{\frac{\sigma_r}{\delta}} \right\} \\
&= \exp \left\{ - \exp \left(- \frac{v}{\delta} \right) \sum_{r=1}^R \left[\sum_{a \in \mathcal{A}_r} \exp \left(\frac{u_a}{\sigma_r} \right) \right]^{\frac{\sigma_r}{\delta}} \right\} \\
&= \exp \left\{ - \exp \left(- \frac{v}{\delta} \right) U \right\}
\end{aligned} \tag{18}$$

where:

$$U \equiv \sum_{r=1}^R \left[\sum_{a \in \mathcal{A}_r} \exp \left(\frac{u_a}{\sigma_r} \right) \right]^{\frac{\sigma_r}{\delta}} = \sum_{r=1}^R U_r^{1/\delta} \tag{19}$$

and

$$U_r \equiv \left[\sum_{a \in \mathcal{A}_r} \exp \left(\frac{u_a}{\sigma_r} \right) \right]^{\sigma_r} \tag{20}$$

The density function of v^* is:

$$f_{v^*}(v) \equiv H'(v) = F_{v^*}(v) \frac{U}{\delta} \exp \left(- \frac{v}{\delta} \right) \tag{21}$$

3.2 Expected maximum utility

By definition, $S(\mathbf{u}) = \mathbb{E}(v^*)$. Therefore,

$$S(\mathbf{u}) = \int_{-\infty}^{+\infty} v^* h(v^*) dv^* = \int_{-\infty}^{+\infty} v^* \exp \left\{ - \exp \left(- \frac{v^*}{\delta} \right) U \right\} \frac{U}{\delta} \exp \left(- \frac{v^*}{\delta} \right) dv^* \tag{22}$$

Let's apply the following change in variable: $z = \exp(-v^*/\delta)$, such that $v^* = -\delta \ln(z)$, and $dv^* = -\delta(dz/z)$. Then,

$$S(\mathbf{u}) = \int_{+\infty}^0 -\delta \ln(z) \exp \{-z U\} \frac{U}{\delta} z \left(-\delta \frac{dz}{z} \right) = -\delta U \int_{+\infty}^0 \ln(z) \exp \{-z U\} dz \tag{23}$$

And using Laplace transformation:

$$S(\mathbf{u}) = \delta U \left(\frac{\ln(U) + \gamma}{U} \right) = \delta (\ln(U) + \gamma) \quad (24)$$

where γ is the Euler's constant.

3.3 Choice probabilities

By Williams-Daly-Zachary (WDZ) theorem, choice probabilities can be obtained differentiating the surplus function. For the NL model:

$$\begin{aligned} P(a|\mathbf{u}) &= \delta \frac{\partial \ln(U)}{\partial u_a} = \delta \frac{\partial U}{\partial u_a} \frac{1}{U} = \\ &= \delta \frac{\sigma_{ra}}{\delta} \left[\sum_{j \in A_{ra}} \exp\left(\frac{u_j}{\sigma_{ra}}\right) \right]^{\frac{\sigma_{ra}}{\delta} - 1} \frac{1}{\sigma_{ra}} \exp\left(\frac{u_a}{\sigma_{ra}}\right) \frac{1}{U} \\ &= \frac{\exp(u_a/\sigma_{ra})}{\sum_{j \in A_{ra}} \exp(u_j/\sigma_{ra})} \frac{\left[\sum_{j \in A_{ra}} \exp(u_j/\sigma_{ra}) \right]^{\frac{\sigma_{ra}}{\delta}}}{\sum_{r=1}^R \left[\sum_{j \in A_r} \exp(u_j/\sigma_r) \right]^{\frac{\sigma_r}{\delta}}} \end{aligned} \quad (25)$$

The first term is $q(a|r_a)$ (i.e., probability of choosing a given that we are in group A_{ra}), and the second term is $Q(r_a)$ (i.e., probability of selecting the group A_{ra}).

3.4 Conditional choice expected utilities

As shown in general, $e(a, \mathbf{u}) = S(\mathbf{u})$. This implies that $\mathbb{E}(\varepsilon_a | u, a^* = a) = S(\mathbf{u}) - u_a$. Given that for the NL model $S(\mathbf{u}) = \delta (\ln U + \gamma)$ we have that:

$$\mathbb{E}(\varepsilon_a | u, a^* = a) = \delta \gamma + \delta \ln U - u_a \quad (26)$$

3.5 Relationship between selection function and CCPs

To write $\mathbb{E}(\varepsilon_a | u, a^* = a)$ in terms of choice probabilities, note that from the definition of $q(a|r_a)$ and $Q(r_a)$, we have that:

$$\ln q(a|r_a) = \frac{u_a - \ln U_{ra}}{\sigma_{ra}} \Rightarrow \ln U_{ra} = u_a - \sigma_{ra} \ln q(a|r_a) \quad (27)$$

and

$$\ln Q(r_a) = \frac{\ln U_{ra}}{\delta} - \ln U \Rightarrow \ln U = \frac{\ln U_{ra}}{\delta} - \ln Q(r_a) \quad (28)$$

Combining these expressions, we have that:

$$\ln U = \frac{u_a - \sigma_{ra} \ln q(a|r_a)}{\delta} - \ln Q(r_a) \quad (29)$$

Therefore,

$$\begin{aligned} e_a &= \delta\gamma + \delta \left(\frac{u_a - \sigma_{ra} \ln q(a|r_a)}{\delta} - \ln Q(r_a) \right) - u_a \\ &= \delta\gamma - \sigma_{ra} \ln q(a|r_a) - \delta \ln Q(r_a) \end{aligned}$$

4 Ordered GEV (OGEV)

Suppose that the random variables in the vector $\boldsymbol{\varepsilon}$ have the following joint CDF:

$$G(\boldsymbol{\varepsilon}) = \exp \left\{ - \sum_{r=1}^{J+M} \left[\sum_{a \in B_r} W_{r-a} \exp \left(- \frac{\varepsilon_a}{\sigma_r} \right) \right]^{\frac{\sigma_r}{\delta}} \right\} \quad (30)$$

where:

- M is a positive integer;
- $\{B_1, B_2, \dots, B_{J+M}\}$ are $J + M$ subsets of A , with the following definition:

$$B_r = \{a \in \mathcal{A} : r - M \leq a \leq r\} \quad (31)$$

For instance, if $A = \{1, 2, 3, 4, 5\}$ and $M = 2$, then $B_1 = \{1\}$, $B_2 = \{1, 2\}$, $B_3 = \{1, 2, 3\}$, $B_4 = \{2, 3, 4\}$, $B_5 = \{3, 4, 5\}$, $B_6 = \{4, 5\}$, and $B_7 = \{5\}$.

- δ , and $\sigma_1, \sigma_2, \dots, \sigma_{J+M}$ are positive parameters, with $\delta \leq 1$;
- W_0, W_1, \dots, W_M are constants (weights) such that: $W_m \geq 0$, and $\sum_{m=0}^M W_m = 1$.

4.1 Distribution of the Maximum Utility

$$\begin{aligned}
F_{v^*}(v) \equiv \Pr(v^* \leq v) &= \Pr(\varepsilon_a \leq v - u_a : \text{for any } a \in \mathcal{A}) \\
&= \exp \left\{ - \sum_{r=1}^{J+M} \left[\sum_{a \in B_r} W_{r-a} \exp \left(-\frac{v - u_a}{\sigma_r} \right) \right]^{\frac{\sigma_r}{\delta}} \right\} \\
&= \exp \left\{ - \exp \left(-\frac{v}{\delta} \right) \sum_{r=1}^{J+M} \left[\sum_{a \in B_r} W_{r-a} \exp \left(\frac{u_a}{\sigma_r} \right) \right]^{\frac{\sigma_r}{\delta}} \right\} \\
&= \exp \left\{ - \exp \left(-\frac{v}{\delta} \right) U \right\}
\end{aligned} \tag{32}$$

where:

$$U \equiv \sum_{r=1}^{J+M} \left[\sum_{a \in B_r} W_{r-a} \exp \left(\frac{u_a}{\sigma_r} \right) \right]^{\frac{\sigma_r}{\delta}} = \sum_{r=1}^{J+M} U_r^{1/\delta} \tag{33}$$

where $U_r \equiv \left[\sum_{a \in B_r} W_{r-a} \exp \left(\frac{u_a}{\sigma_r} \right) \right]^{\sigma_r}$. The density function of v^* is:

$$f_{v^*}(v) \equiv H'(v) = F_{v^*}(v) \frac{U}{\delta} \exp \left(-\frac{v}{\delta} \right) \tag{34}$$

4.2 Expected maximum utility

By definition, $S(\mathbf{u}) = \mathbb{E}(v^*|u)$. Therefore,

$$S(\mathbf{u}) = \int_{-\infty}^{+\infty} v^* h(v^*) dv^* = \int_{-\infty}^{+\infty} v^* \exp \left\{ - \exp \left(-\frac{v^*}{\delta} \right) U \right\} \frac{U}{\delta} \exp \left(-\frac{v^*}{\delta} \right) dv^* \tag{35}$$

Let's apply the following change in variable: $z = \exp(-v^*/\delta)$, such that $v^* = -\delta \ln(z)$, and $dv^* = -\delta(dz/z)$. Then,

$$S = \int_{+\infty}^0 -\delta \ln(z) \exp \{-z U\} \frac{U}{\delta} z \left(-\delta \frac{dz}{z} \right) = -\delta U \int_0^{+\infty} \ln(z) \exp \{-z U\} dz \tag{36}$$

And using Laplace transformation:

$$S = \delta U \left(\frac{\ln U + \gamma}{U} \right) = \delta (\ln U + \gamma) = \delta \gamma + \delta \ln \left[\sum_{r=1}^{J+M} \left[\sum_{a \in B_r} W_{r-a} \exp \left(\frac{u_a}{\sigma_r} \right) \right]^{\frac{\sigma_r}{\delta}} \right] \tag{37}$$

where γ is the Euler's constant.

4.3 Choice probabilities

By Williams-Daly-Zachary (WDZ) theorem, choice probabilities can be obtained differentiating the surplus function.

$$P(a|u) = \frac{1}{U} \sum_{r=a}^{a+M} \left[\sum_{j \in B_r} W_{r-j} \exp\left(\frac{u_j}{\sigma_r}\right) \right]^{\frac{\sigma_r}{\delta} - 1} W_{r-a} \exp\left(\frac{u_a}{\sigma_r}\right) = \sum_{r=a}^{a+M} q(a|r) Q(r) \quad (38)$$

where:

$$\begin{aligned} q(a|r) &= \frac{W_{r-a} \exp(u_a/\sigma_r)}{\sum_{j \in B_r} W_{r-j} \exp(u_j/\sigma_r)} = \frac{\exp(u_a/\sigma_r)}{\exp(\ln U_r/\sigma_r)} \\ Q(r) &= \frac{\exp(\ln U_r/\delta)}{\sum_{j=1}^{J+M} \exp(\ln U_j/\delta)} = \frac{\exp(\ln U_r/\delta)}{U} \end{aligned} \quad (39)$$

4.4 Conditional choice expected utilities

As shown in general, $e(a, \mathbf{u}) = S(\mathbf{u})$. This implies that $\mathbb{E}(\varepsilon_a | u, a^* = a) = S(\mathbf{u}) - u_a$. Given that for the OGEV model $S(\mathbf{u}) = \delta (\ln U + \gamma)$ we have that:

$$\mathbb{E}(\varepsilon_a | u, a^* = a) = \delta \gamma + \delta \ln U - u_a \quad (40)$$