

Code for Alda Scale Mutual Information Analysis in *Asymmetrical Reliability of the Alda Score favours a Dichotomous Representation of Lithium Response*

Abraham Nunes (nunes@dal.ca), Thomas Trappenberg, and Martin Alda

Dalhousie University, Halifax, Nova Scotia, Canada

Analysis of Reliability of the Total Alda Score

Table 1 Summarizing the Average Total Scores Across the Sites

```
wd = "path/to/directory/here/";  
SetDirectory[wd];
```

In[4]:=

```
irrds = Import["S1_File.csv", "Dataset", HeaderLines->1];
```

In[5]:=

```

summary =Dataset[JoinAcross[Dataset[KeyValueMap[<|"Site"→#, "N Raters"→#2|>&,
    irrds[Counts, "Site"]]],
Dataset[KeyValueMap[<|
    "Site"→#1,"Case 1"→#2[[1]], "Case 2"→#2[[2]],
    "Case 3"→#2[[3]], "Case 4"→#2[[4]], "Case 5"→#2[[5]],
    "Case 6"→#2[[6]], "Case 7"→#2[[7]], "Case 8"→#2[[8]],
    "Case 9"→#2[[9]], "Case 10"→#2[[10]], "Case 11"→#2[[11]],
    "Case 12"→#2[[12]]|>&, irrds[GroupBy["site"],
    Round[N@Mean[#,0.1]&, Table["Case "<>ToString[i], {i, 12}]]]],
"Site"]];

summary = TextGrid[Flatten[
    Catenate[{{{Normal@Keys[summaryT]},{List@@@Normal@summary}}},1],
Frame→All]

```

Out[6]=

Site	N Rater s	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9	Case 10	Case 11	Case 12
Consensus	1	8.	9.	6.	7.	9.	3.	5.	9.	3.	9.	5.	1.
Centre 1	9	8.4	8.6	6.6	6.9	9.2	3.	3.9	8.8	3.1	9.1	4.7	1.2
Centre 2	4	7.8	8.2	6.2	7.	8.8	3.2	4.	8.5	2.2	8.5	3.2	1.8
Centre 3	2	9.	8.5	6.5	5.5	9.	4.	7.5	9.	5.	8.	4.5	4.5
Centre 4	2	8.5	7.5	6.	5.	8.5	1.5	6.	9.	3.5	8.5	4.	1.5
Centre 5	4	8.	8.2	4.8	6.5	8.5	2.	3.	8.5	1.	8.2	4.5	1.5
Centre 6	2	7.5	7.5	4.	6.5	8.	1.5	3.	9.	0.	7.	3.	0.5
Centre 7	3	7.7	9.	4.3	7.	5.7	4.	1.3	9.	0.7	7.3	4.	2.
Centre 8	2	7.5	8.5	7.5	7.	9.	5.	7.5	8.5	3.5	8.5	6.	3.5
Centre 9	2	8.5	8.5	6.	7.	9.	3.	3.5	8.5	1.5	9.	4.	1.
Centre 10	2	9.5	9.	4.	6.	9.	1.	1.	9.	1.5	9.	4.	3.
Centre 11	1	7.	9.	4.	6.	9.	2.	3.	8.	0.	7.	0.	2.
Centre 12	1	8.	8.	5.	8.	9.	5.	6.	9.	4.	9.	8.	1.
Centre 13	1	7.	9.	4.	8.	9.	3.	6.	9.	3.	9.	6.	1.
Centre 14	7	8.	8.7	5.3	5.9	8.3	2.7	2.4	9.1	2.	8.3	4.4	1.1
Centre 15	6	8.	8.2	6.	8.	9.	4.2	3.	9.	4.2	8.8	3.7	0.3
Centre 16	3	8.	8.3	5.3	6.3	8.7	2.	4.	9.	4.3	8.	4.7	0.7
Centre 17	4	7.5	9.	5.5	6.5	5.	2.5	4.	7.2	4.8	8.8	1.2	2.
Centre 18	3	7.7	8.7	6.7	5.3	9.7	5.	6.	8.7	1.3	9.	3.7	0.3

Analysis of the Reliability under Noise

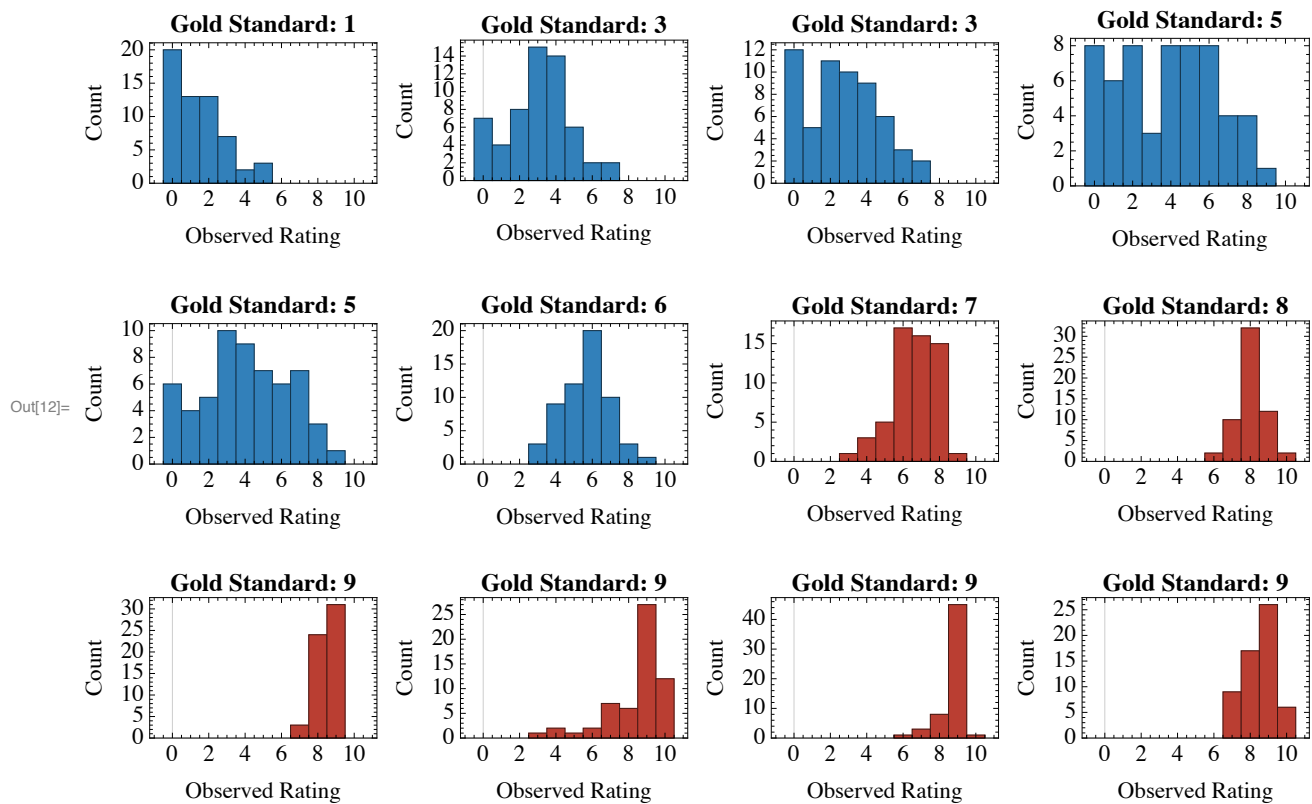
```
In[7]:= X = Transpose[List@@Normal@irrds[2;;, 4;;]);  
y = Flatten[List@@Normal@irrds[{1}, 4;;]);  
X = X[[Ordering[y]]];  
y = y[[Ordering[y]]];
```

In[11]:=

```

RatingHistogram := Function[{X, y},
  Grid[
    ArrayReshape[
      Table[Histogram[
        X[[i]],
        PlotLabel->Style["Gold Standard: "<>ToString[y[[i]]], Black, Bold, 13,
        ChartStyle->ColorData[63][
          {1 y[[i]]≥7,
           2 True
        },
        PlotRange->{-1, 11}, Automatic,
        Frame->True, FrameStyle->Directive[Black, 12],
        FrameLabel->{"Observed Rating", "Count"},
        PlotTheme->"Scientific"],
        {i, Length@y}]], {3, 4}]]]
totalscorehistfig = RatingHistogram[X, y]
(*Export["total-score-hist-fig.pdf", totalscorehistfig, "AllowRasterization"→True];*)

```



Estimation of Conditional Distributions

Let $n_i^{(k)} \in \mathbb{N}_+$ denote the number of raters who assigned Alda score $i \in \mathcal{A}$, with $\mathcal{A} = \{0, 1, \dots, 10\}$, to an individual whose gold standard score is $k \in \mathcal{A}$. The vector of rating counts given gold standard

score k is $n^{(k)} = (n_i^{(k)})_{i \in \mathcal{A}}$. The probability of $n^{(k)}$ is multinomial with parameter vector $\theta^{(k)} = (\theta_i^{(k)})_{i \in \mathcal{A}}$, which is itself Dirichlet distributed $\theta^{(k)} \approx \text{Dir}(\theta \mid \alpha)$, where α are pseudocounts. The posterior of $\theta^{(k)}$ given $n^{(k)}$ and α is Dirichlet with parameters $\alpha' = \{\alpha_i + n_i^{(k)} - 1\}_{i=0}^{10}$. The MAP estimate of $\theta^{(k)}$ given α and $n^{(k)}$ can then easily be shown to equal

$$\hat{\theta}_\alpha(n^{(k)}) = \left\{ \frac{\alpha_i + n_i^{(k)} - 1}{\sum_{j=0}^{10} (\alpha_j + n_j^{(k)} - 1)} \right\}_{i=0}^{10}.$$

In the following analyses, we take $\hat{\theta}_\alpha(n^{(k)})$ to be the conditional distribution over scores $\mathcal{A}$ for any given rater when the gold standard score is k .

The thresholded Alda scores are defined as $\mathcal{T} = \{\mathbb{1}_{i \geq 7} : \forall i \in \mathcal{A}\}$, where $\mathbb{1}_x$ is an indicator function that evaluates to 1 if x is true, and 0 otherwise.

Letting $c_i^{(k)} = \mathbb{1}_{n_i^{(k)} \geq 7}$, $c_i^{(k)} \approx \text{Multinomial}(\phi^{(k)})$, and $\phi^{(k)} \approx \text{Dir}(\phi \mid \xi)$, then we can estimate conditional distributions $\hat{\phi}_\xi(c^{(k)})$ analogously to our process in the full score as follows:

$$\hat{\phi}_\xi(c^{(k)}) = \left\{ \frac{\xi_i + c_i^{(k)} - 1}{\sum_{j=0}^{10} (\xi_j + c_j^{(k)} - 1)} \right\}_{i=0}^{10}.$$

Let x_* denote a “true” (gold standard) Alda score in $\mathcal{A}$ and x_o be a single observed rating on that same domain. Given uniform priors on the true classes, $\forall_{k \in \mathcal{A}} p(x_* = k) = \frac{1}{11}$, the joint distribution over true and observed (x_o) full-scale ratings is

$$p(x_o, x_*) = p(x_o \mid x_*) p(x_*) = \{p(x_o = i \mid x_* = k) p(x_* = k)\}_{i=0,1,\dots,10}^{k=0,1,\dots,10} = \left\{ \frac{1}{11} \hat{\theta}_\alpha(n^{(k)}) \right\}_{k=0,1,\dots,10}.$$

Similarly for the binarized classes, we have a prior of $p(y_*) = \left\{ \frac{7}{11}, \frac{4}{11} \right\}$, and the joint distribution is thus

$$p(y_o, y_*) = p(y_o \mid y_*) p(y_*) = \{p(y_o = i \mid y_* = k) p(y_* = k)\}_{i=0,1}^{k=0,1} = \left\{ \frac{7}{11} \hat{\phi}_\xi(c^{(0)}), \frac{4}{11} \hat{\phi}_\xi(c^{(1)}) \right\}.$$

In[13]:=

```
DirMulEstimate[α_]:= Function[Q,
Module[{λ},
λ = Flatten@Table[
α[[i]] + { 0, Flatten[Position[
Tally[Q][[Flatten[Position[Tally[Q][[All, 1]], i]], 2]] True
{i, Length@α}];
λ/Total[λ]
]]
```

Compute the conditional distribution:

```
In[14]:= Q[α_:2] := {
  DirMulEstimate[Table[α, 11]][Table[Min[{Max[{X[[1]][[i]]-1, 0}], 10}], {i, Length@X[[
  DirMulEstimate[Table[α, 11]][X[[1]]],
  Mean[Table[DirMulEstimate[Table[α, 11]][X[[k]]], {k, 1, 3}]],
  Mean[Table[DirMulEstimate[Table[α, 11]][X[[k]]], {k, 2, 3}]],
  Mean[Table[DirMulEstimate[Table[α, 11]][X[[k]]], {k, 2, 5}]],
  Mean[Table[DirMulEstimate[Table[α, 11]][X[[k]]], {k, 4, 5}]],
  DirMulEstimate[Table[α, 11]][X[[6]]],
  DirMulEstimate[Table[α, 11]][X[[7]]],
  DirMulEstimate[Table[α, 11]][X[[8]]],
  Mean[Table[DirMulEstimate[Table[α, 11]][X[[k]]], {k, 9, 12}]],
  Mean[Table[DirMulEstimate[Table[α, 11]][X[[k]]+1], {k, 9, 12}]]
}
```

Thresholded Alda scores and joint distribution function:

```
In[15]:= ThresholdAlda[X_] := Table[{
  0 x<7
  1 True, {x, X}];
J[α_:2] := {
  7
  11 DirMulEstimate[Table[α, 2]][ThresholdAlda@Flatten@X[[;;6]]+1],
  4
  11 DirMulEstimate[Table[α, 2]][ThresholdAlda@Flatten@X[[7;;]]+1]
}
```

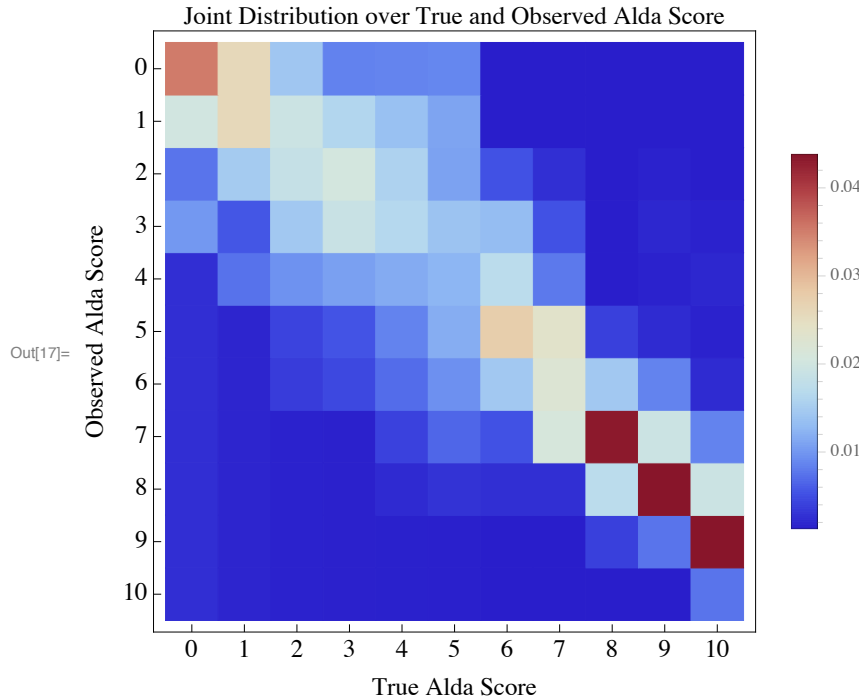
Joint Distribution over True and Observed Scores

```

In[17]:= jointdistribaldascorefig = ArrayPlot[Q[2]×Table[ $\frac{1}{11}$ , {i, 11}, {i, 11}],
PlotLabel→Style["Joint Distribution over True and Observed Alda Score", Black, 13],
PlotTheme→"Scientific",
ColorFunction→"ThermometerColors",
PlotLegends→Automatic,
Frame→True, FrameStyle→Directive[Black, 13],
FrameLabel→{"Observed Alda Score", "True Alda Score"},
FrameTicks→{{Range[11], Range[0, 10]}T, {Range[11], Range[0, 10]}T}, ImageSize→350]

(*Export["jointdistributionaldascore.png", jointdistribaldascorefig, ImageResolution→500,

```



We can compute the mutual information between the observed and gold standard Alda scores (continuous and thresholded) as follows:

$$\mathbb{I}_{\alpha}[x_o \parallel x_*] = \sum_{i \in \mathcal{A}} \sum_{j \in \mathcal{A}} p(x_o = i, x_* = j) \log \left[\frac{p(x_o = i, x_* = j)}{p(x_o = i) p(x_* = j)} \right],$$

and

$$\mathbb{I}_{\xi}[y_o \parallel y_*] = \sum_{i \in \mathcal{T}} \sum_{j \in \mathcal{T}} p(y_o = i, y_* = j) \log \left[\frac{p(y_o = i, y_* = j)}{p(y_o = i) p(y_* = j)} \right],$$

respectively. We maintain the hyperparameters α and ξ in the notation since they control the level of

uncertainty in the conditional distributions. Higher values of α and ξ yield conditional distributions $\hat{\theta}_\alpha(n^{(k)})$ and $\hat{\phi}_\xi(c^{(k)})$ with higher uncertainty (i.e they are noisier).

```
In[18]:= Pxy[α_] := (Q[α] × Table[ $\frac{1}{11}$ , {i, 11}, {i, 11}]);
Px[α_] := (Total@Pxy[α]);
Py[α_] := Total[Pxy[α]^T];
Jxy[α_] := J[α];
Jx[α_] := (Total@Jxy[α]);
Jy[α_] := Total[Jxy[α]^T];
```

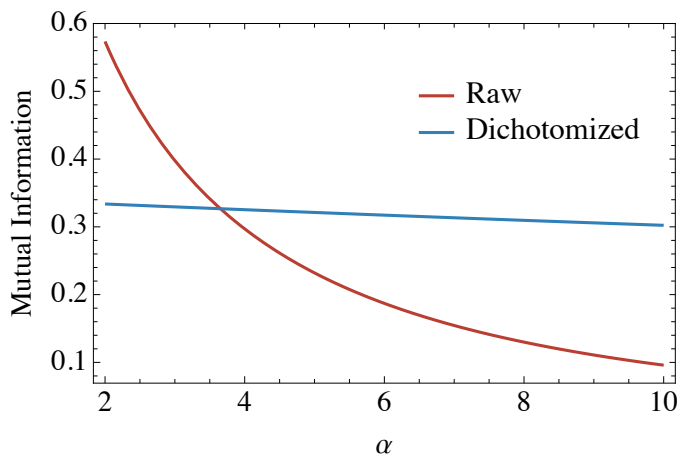
Letting $\xi = \frac{11}{2} \alpha$ in order to provide some equivalence between the priors, we can plot $\mathbb{I}_\alpha[x_o || x_*]$ and $\mathbb{I}_\xi[y_o || y_*]$ across increasing levels of uncertainty.

```
In[24]:= AldaMI[α_] := N@Total[Total[Pxy[α] Log[ $\frac{Pxy[α]}{Px[α] \otimes Py[α]}$ ]]]
DiscreteAldaMI[α_] := N@Total[Total[Jxy[α] Log[ $\frac{Jxy[α]}{Jx[α] \otimes Jy[α]}$ ]]]
```

In[26]:=

```
mitotalaldafig = Plot[
  {AldaMI[α], DiscreteAldaMI[α]}, {α, 2, 10},
  PlotStyle→63, Frame→True, FrameStyle→Directive[Black,15],
  FrameLabel→{"α", "Mutual Information"},
  PlotTheme→"Scientific",
  PlotLegends→Placed[{
    Style["Raw", Black, 16],
    Style["Dichotomized", Black, 16]},
    {0.75, 0.75}],
  ImageSize→350]
(*Export["~/Desktop/mutualinformationaldascores.png",
  mitotalaldafig,
  ImageResolution→500,
  "AllowRasterization"→True];*)
```

Out[26]=



We therefore note a whole set of conditions after approximately $\alpha = 3.5$ in which discretization is more informative than the continuous distribution.

But why is this the case? The plots below show that asymmetry may be the culprit.

In[27]:=

```
partA = GraphicsGrid[{{DiscretePlot3D[Pxy[0.0001][[i,j]],{i,1,11},{j,1,11}, ExtentSize→1
  PlotLabel→Style["Continuous Scale (α = 0)\nIα[xo||x*]="<>ToString[Round[Re@AldaMI[0.0001]
  PlotTheme→"Scientific", ColorFunction→"ThermometerColors", AxesLabel→{"x*", "xo", "p(xo,x
  AxesStyle→Directive[Black, 13]],
  DiscretePlot3D[Jxy[ $\frac{11}{2}$ ×0.0001][[i,j]],{i,1,2},{j,1,2}, ExtentSize→1/2,
  PlotLabel→Style["Discretized Scale (α = 0)\nIγ[yo||y*]="<>ToString[Round[DiscreteAldaMI[0
  PlotTheme→"Scientific", ColorFunction→"ThermometerColors", AxesLabel→{"y*", "yo", "p(yo,y
  AxesStyle→Directive[Black, 13],
  Ticks→{{1, 2}, {"Li(-)", "Li(+)"}}T, {{1, 2}, {"Li(-)", "Li(+)"}}T, Automatic]]}], ImageSize
```

```

partB = GraphicsGrid[{{DiscretePlot3D[Pxy[10][[i,j]],{i,1,11},{j,1,11}, ExtentSize→1/2,
PlotLabel→Style["Continuous Scale ( $\alpha = 10$ )\n $I_\alpha[x_o||x_*]=$ "<>ToString[Round[Re@AldaMI[10], 0
PlotTheme→"Scientific", ColorFunction→"ThermometerColors", AxesLabel→{"x_*", "x_o", "p(x_o,x
AxesStyle→Directive[Black, 13]],
DiscretePlot3D[Jxy[ $\frac{11}{2}\times 10$ ][[i,j]],{i,1,2},{j,1,2}, ExtentSize→1/2,
PlotLabel→Style["Discretized Scale ( $\alpha = 10$ )\n $I_\gamma[y_o||y_*]=$ "<>ToString[Round[DiscreteAldaMI[.
PlotTheme→"Scientific", ColorFunction→"ThermometerColors", AxesLabel→{"y_*", "y_o", "p(y_o,y
AxesStyle→Directive[Black, 13]],
Ticks→{{1, 2}, {"Li(-)", "Li(+)"}}T, {{1, 2}, {"Li(-)", "Li(+)"}}T, Automatic]]}}, ImageSize

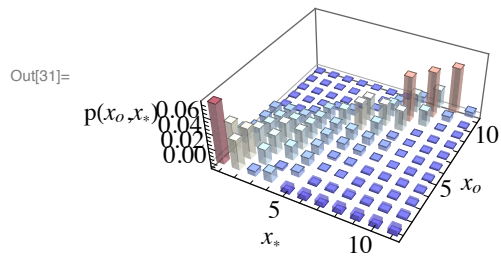
partC = GraphicsGrid[{{DiscretePlot3D[Pxy[100][[i,j]],{i,1,11},{j,1,11}, ExtentSize→1/2,
PlotLabel→Style["Continuous Scale ( $\alpha = 100$ )\n $I_\alpha[x_o||x_*]=$ "<>ToString[Round[Re@AldaMI[100],
PlotTheme→"Scientific", ColorFunction→"ThermometerColors", AxesLabel→{"x_*", "x_o", "p(x_o,x
AxesStyle→Directive[Black, 13]],
DiscretePlot3D[Jxy[ $\frac{11}{2}\times 100$ ][[i,j]],{i,1,2},{j,1,2}, ExtentSize→1/2,
PlotLabel→Style["Discretized Scale ( $\alpha = 100$ )\n $I_\gamma[y_o||y_*]=$ "<>ToString[Round[DiscreteAldaMI
PlotTheme→"Scientific", ColorFunction→"ThermometerColors", AxesLabel→{"y_*", "y_o", "p(y_o,y
AxesStyle→Directive[Black, 13]],
Ticks→{{1, 2}, {"Li(-)", "Li(+)"}}T, {{1, 2}, {"Li(-)", "Li(+)"}}T, Automatic]]}}, ImageSize

gridlab[x_] := Style[x, Black, Bold, 28, FontFamily→"Times New Roman"]
(*totalscoreasymmetrygrid = Grid[{
  gridlab[#]&@{"A", "B"},
  {partA, partB},
  gridlab[#]&@{"C", "D"},
  {partC, mitotalaldafig}}];
Export["totalscoreasymmetrygrid.pdf", totalscoreasymmetrygrid, "AllowRasterization"→True]

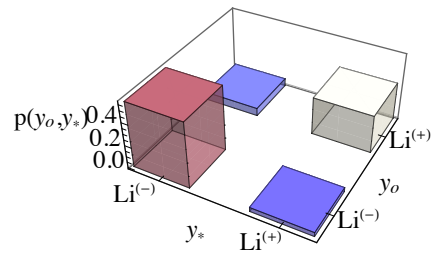
partA
partB
partC
mitotalaldafig

```

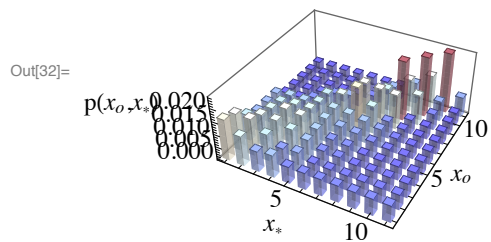
Continuous Scale ($\alpha = 0$)
 $\mathbb{I}_\alpha[x_o||x_*]=1.5$



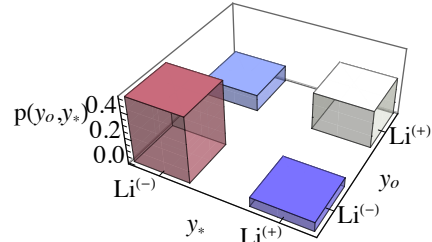
Discretized Scale ($\alpha = 0$)
 $\mathbb{I}_\gamma[y_o||y_*]=0.34$



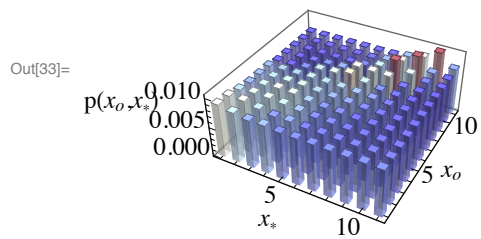
Continuous Scale ($\alpha = 10$)
 $\mathbb{I}_\alpha[x_o||x_*]=0.1$



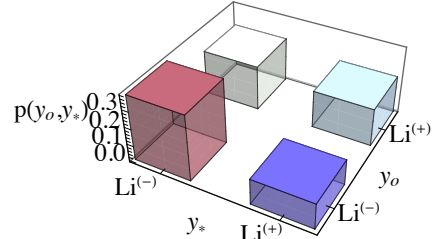
Discretized Scale ($\alpha = 10$)
 $\mathbb{I}_\gamma[y_o||y_*]=0.3$

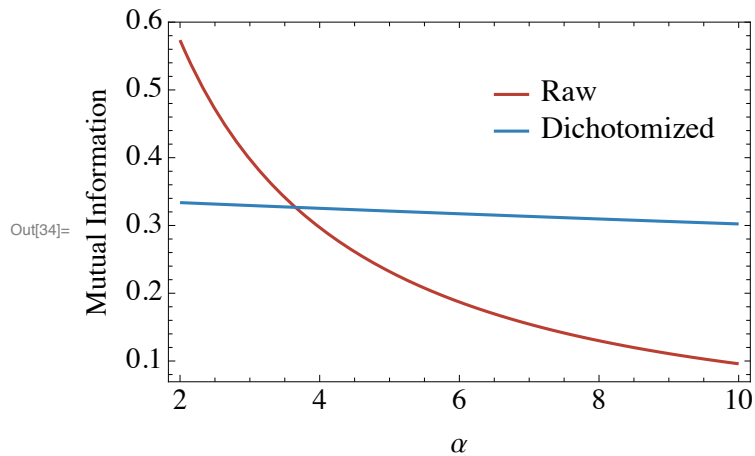


Continuous Scale ($\alpha = 100$)
 $\mathbb{I}_\alpha[x_o||x_*]=0.$



Discretized Scale ($\alpha = 100$)
 $\mathbb{I}_\gamma[y_o||y_*]=0.14$





Supplemental Analysis: Mutual Information of the Alda A-Score

Here we repeat the analyses done for the total score using only the Alda A-scores.

Summary Table

```
In[35]:= irrdsA = Import["S2_File.csv", "Dataset", HeaderLines→1];

In[36]:= summaryA = Dataset[JoinAcross[Dataset[KeyValueMap[<|"Site"→#, "N Raters"→#2|>&, irrdsA[Count
Dataset[KeyValueMap[<|
  "Site"→#1, "Case 1"→#2[[1]], "Case 2"→#2[[2]],
  "Case 3"→#2[[3]], "Case 4"→#2[[4]], "Case 5"→#2[[5]],
  "Case 6"→#2[[6]], "Case 7"→#2[[7]], "Case 8"→#2[[8]],
  "Case 9"→#2[[9]], "Case 10"→#2[[10]], "Case 11"→#2[[11]],
  "Case 12"→#2[[12]]|>&, irrdsA[GroupBy["site"], Round[N@Mean[#, 0.1]&, Table["Case "<>ToStr
"Site"]]]];
summaryA = TextGrid[Flatten[
  Catenate[{{{Normal@Keys[summaryA]}}, {List@@Normal@summaryA}}], 1],
Frame→All]
```

Out[37]=

Site	N Rater s	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9	Case 10	Case 11	Case 12
Consensus	1	9.	9.	7.	7.	10.	4.	7.	9.	5.	9.	6.	3.
Centre 1	9	9.1	8.6	7.3	7.1	9.9	4.4	6.9	9.	6.6	9.4	6.9	3.2
Centre 2	4	8.8	8.8	8.	7.2	9.5	5.2	7.8	8.5	5.8	8.8	6.	4.8
Centre 3	2	10.	9.5	6.5	6.5	10.	6.	8.5	9.	8.	8.	6.	7.5
Centre 4	2	9.	8.	6.	5.	9.	2.5	8.	9.	6.5	8.5	7.	2.5
Centre 5	4	9.	8.5	6.	6.5	9.5	3.	6.2	8.8	3.2	8.5	7.	3.
Centre 6	2	8.5	7.5	5.5	6.5	9.	3.5	7.	9.	3.5	8.	6.5	2.
Centre 7	3	9.	9.	6.3	7.	10.	6.	8.3	9.	6.7	8.3	8.	6.3
Centre 8	2	9.	8.5	8.	7.	10.	7.	9.5	10.	9.	5.5	8.5	7.5
Centre 9	2	9.5	8.5	8.	7.	10.	4.5	8.5	9.	7.	9.5	7.	3.
Centre 10	2	10.	9.	6.	6.	10.	2.5	7.	9.	6.5	9.	8.	7.
Centre 11	1	8.	9.	6.	7.	10.	4.	6.	8.	4.	8.	4.	4.
Centre 12	1	9.	8.	6.	8.	10.	7.	10.	9.	7.	9.	9.	3.
Centre 13	1	9.	9.	6.	8.	10.	5.	8.	9.	6.	9.	9.	3.
Centre 14	7	9.	8.9	7.	6.9	9.7	4.3	6.9	9.1	5.7	8.9	7.4	3.6
Centre 15	6	8.	8.2	7.	8.	9.	6.3	7.8	9.	7.2	9.	6.2	1.7
Centre 16	3	9.	8.3	7.3	6.7	10.	5.	8.3	9.	7.7	9.	7.	2.3
Centre 17	4	8.5	9.	6.8	7.	7.8	5.	6.2	9.	7.	9.5	5.	4.8
Centre 18	3	8.7	8.7	7.3	5.7	9.7	5.7	8.	8.7	4.7	9.	6.	3.3

```

In[38]:= X = Transpose[List@@@Normal@irrdsA[2;;;, 4;;;]];
y = Flatten[List@@@Normal@irrdsA[{1}, 4;;;]];
x = X[[Ordering[y]]];
y = y[[Ordering[y]]];

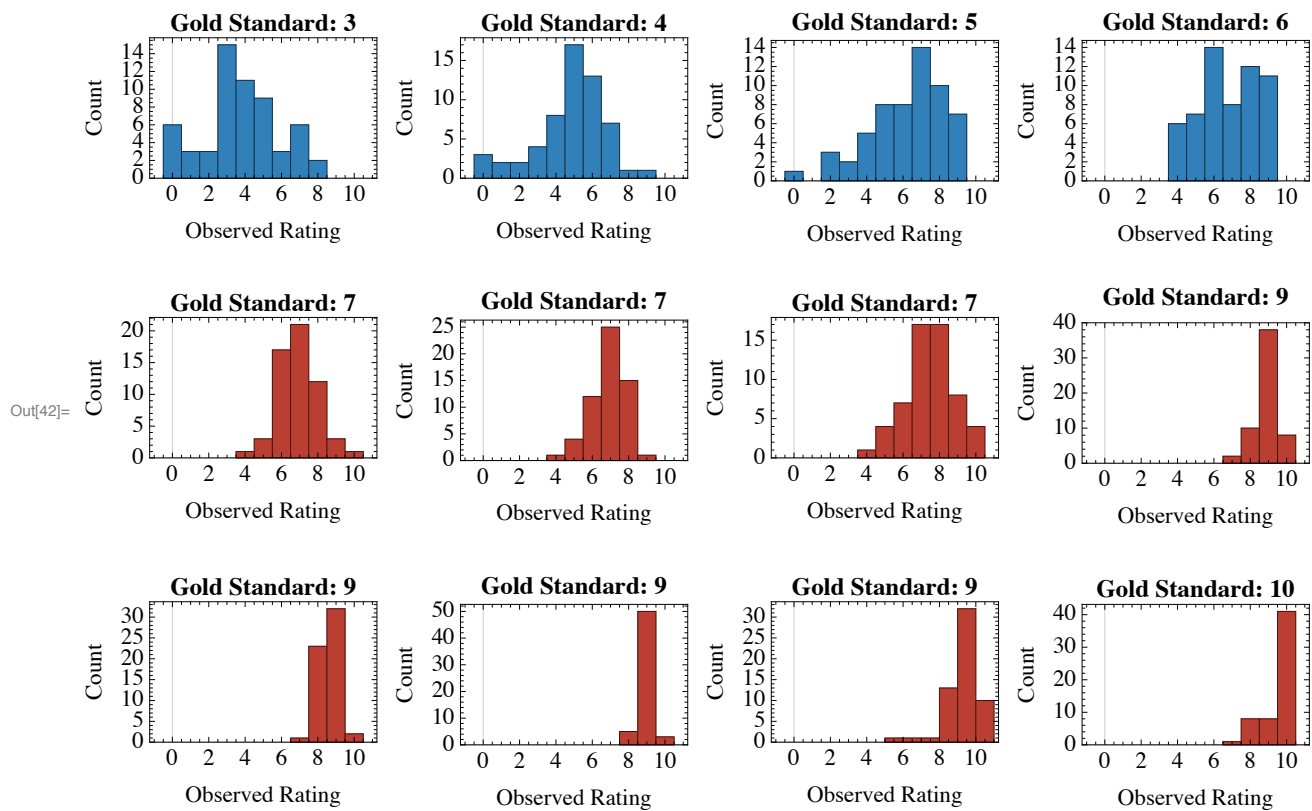
```

Plot the histograms

```

In[42]:= ascorehistfig = RatingHistogram[X, y]
(*Export["a-score-hist-fig.pdf", ascorehistfig, "AllowRasterization"→True];*)

```



```

In[43]:= Q[α_:2] := {
  DirMulEstimate[Table[α, 11]][Table[Min[{Max[{X[[1]][[i]]-1, 0}], 10}], {i, Length@X[[
  DirMulEstimate[Table[α, 11]][X[[1]]],
  DirMulEstimate[Table[α, 11]][X[[1]]],
  DirMulEstimate[Table[α, 11]][X[[1]]],
  DirMulEstimate[Table[α, 11]][X[[2]]],
  DirMulEstimate[Table[α, 11]][X[[3]]],
  DirMulEstimate[Table[α, 11]][X[[4]]],
  Mean[Table[DirMulEstimate[Table[α, 11]][X[[k]]], {k, 5, 7}]],
  (Mean[Table[DirMulEstimate[Table[α, 11]][X[[k]]], {k, 5, 7}]] +
    Mean[Table[DirMulEstimate[Table[α, 11]][X[[k]]], {k, 8, 11}]])/2,
  Mean[Table[DirMulEstimate[Table[α, 11]][X[[k]]], {k, 8, 11}]],
  DirMulEstimate[Table[α, 11]][X[[12]]]
}^T

```

Thresholded Alda scores and joint distribution function:

```

In[44]:= ThresholdAlda[X_] := Table[ $\begin{cases} 0 & x < 7 \\ 1 & \text{True} \end{cases}$ , {x, X}];

J[α_:2] := {
   $\frac{7}{11}$  DirMulEstimate[Table[α, 2]][ThresholdAlda@Flatten@X[;;6]]+1,
   $\frac{4}{11}$  DirMulEstimate[Table[α, 2]][ThresholdAlda@Flatten@X[[7;]]+1]
}

```

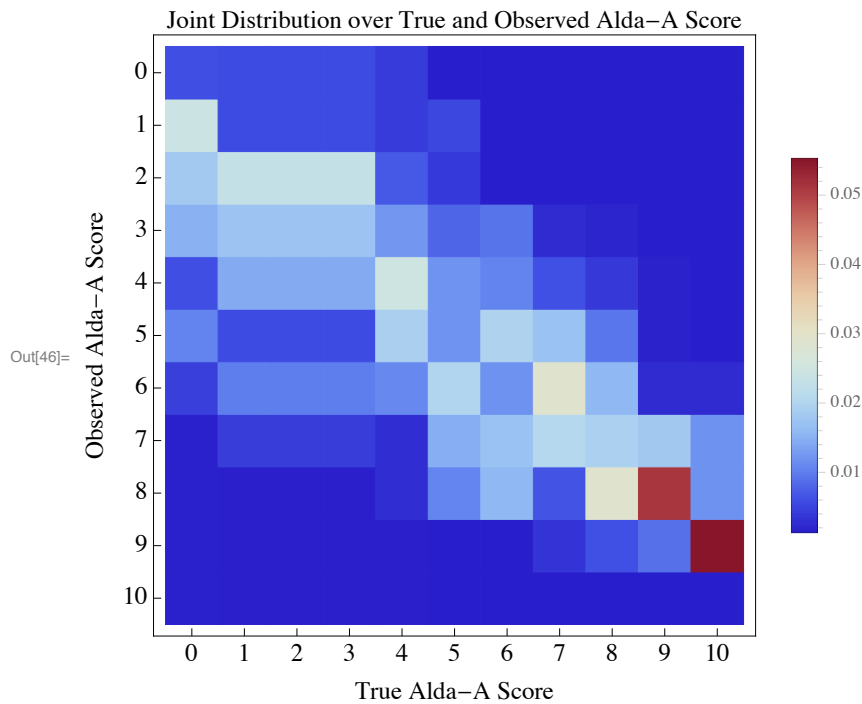
Joint Distribution over True and Observed Scores

```

In[46]:= jointdistribaldaScorefig = ArrayPlot[ $\left(Q[2] \times \text{Table}\left[\frac{1}{11}, \{i, 11\}, \{i, 11\}\right]\right)$ ,
  PlotLabel→Style["Joint Distribution over True and Observed Alda-A Score", Black, 13],
  PlotTheme→"Scientific",
  ColorFunction→"ThermometerColors",
  PlotLegends→Automatic,
  Frame→True, FrameStyle→Directive[Black, 13],
  FrameLabel→{"Observed Alda-A Score", "True Alda-A Score"},
  FrameTicks→{{Range[11], Range[0, 10]}T, {Range[11], Range[0, 10]}T}, ImageSize→350]

(*Export["jointdistributionaldascore.png", jointdistribaldaScorefig, ImageResolution→500

```



```

In[47]:= Pxy[α_] :=  $\left(Q[α] \times \text{Table}\left[\frac{1}{11}, \{i, 11\}, \{i, 11\}\right]\right)$ ;
Px[α_] := (Total@Pxy[α]);
Py[α_] := Total[Pxy[α]T];
Jxy[α_] := J[α];
Jx[α_] := (Total@Jxy[α]);
Jy[α_] := Total[Jxy[α]T];

```

```
In[53]:= AldaMI[α_]:=N@Total[Total[Pxy[α] Log[ $\frac{Pxy[α]}{Px[α]⊗Py[α]}$ ]]]
DiscreteAldaMI[α_]:=N@Total[Total[Jxy[α] Log[ $\frac{Jxy[α]}{Jx[α]⊗Jy[α]}$ ]]]
```

```
In[55]:= miaaldafig = Plot[
  {AldaMI[α], DiscreteAldaMI[α]}, {α, 2, 10},
  PlotStyle→63, Frame→True, FrameStyle→Directive[Black,15],
  FrameLabel→{"α", "Mutual Information"},
  PlotTheme→"Scientific",
  PlotLegends→Placed[{
    Style["Raw", Black, 16],
    Style["Dichotomized", Black, 16]},
    {0.75, 0.75}],
  ImageSize→400];
(*Export["~/Desktop/mutualinformationaldascoresA.png",
  miaaldafig,
  ImageResolution→500,
  "AllowRasterization"→True];*)

partA = GraphicsGrid[{{DiscretePlot3D[Pxy[0.0001][[i,j]],{i,1,11}, {j,1,11}, ExtentSize→1
  PlotLabel→Style["Continuous Scale (α = 0)\nIα[xo||x*]="<>ToString[Round[Re@AldaMI[0.0001]
  PlotTheme→"Scientific", ColorFunction→"ThermometerColors", AxesLabel→{"x*", "xo", "p(xo,x
  AxesStyle→Directive[Black, 13]],
  DiscretePlot3D[Jxy[ $\frac{11}{2} \times 0.0001$ ][[i,j]],{i,1,2}, {j,1,2}, ExtentSize→1/2,
  PlotLabel→Style["Discretized Scale (α = 0)\nIγ[yo||y*]="<>ToString[Round[DiscreteAldaMI[0
  PlotTheme→"Scientific", ColorFunction→"ThermometerColors", AxesLabel→{"y*", "yo", "p(yo,y
  AxesStyle→Directive[Black, 13],
  Ticks→{{1, 2}, {"Li(-)", "Li(+)"}}T, {{1, 2}, {"Li(-)", "Li(+)"}}T, Automatic]]}}, ImageSize

partB = GraphicsGrid[{{DiscretePlot3D[Pxy[10][[i,j]],{i,1,11}, {j,1,11}, ExtentSize→1/2,
  PlotLabel→Style["Continuous Scale (α = 10)\nIα[xo||x*]="<>ToString[Round[Re@AldaMI[10], 0
  PlotTheme→"Scientific", ColorFunction→"ThermometerColors", AxesLabel→{"x*", "xo", "p(xo,x
  AxesStyle→Directive[Black, 13]],
  DiscretePlot3D[Jxy[ $\frac{11}{2} \times 10$ ][[i,j]],{i,1,2}, {j,1,2}, ExtentSize→1/2,
  PlotLabel→Style["Discretized Scale (α = 10)\nIγ[yo||y*]="<>ToString[Round[DiscreteAldaMI[.
  PlotTheme→"Scientific", ColorFunction→"ThermometerColors", AxesLabel→{"y*", "yo", "p(yo,y
  AxesStyle→Directive[Black, 13],
  Ticks→{{1, 2}, {"Li(-)", "Li(+)"}}T, {{1, 2}, {"Li(-)", "Li(+)"}}T, Automatic]]}}, ImageSize

partC = GraphicsGrid[{{DiscretePlot3D[Pxy[100][[i,j]],{i,1,11}, {j,1,11}, ExtentSize→1/2,
  PlotLabel→Style["Continuous Scale (α = 100)\nIα[xo||x*]="<>ToString[Round[Re@AldaMI[100],
  PlotTheme→"Scientific", ColorFunction→"ThermometerColors", AxesLabel→{"x*", "xo", "p(xo,x
```

```

AxesStyle→Directive[Black, 13]],
DiscretePlot3D[Jxy[ $\frac{11}{2} \times 100$ ][[i,j]],{i,1,2},{j,1,2}, ExtentSize→1/2,
PlotLabel→Style["Discretized Scale ( $\alpha = 100$ )\n $\mathbb{I}_\gamma[y_o||y_*]$ ="<>ToString[Round[DiscreteAldaMI
PlotTheme→"Scientific", ColorFunction→"ThermometerColors", AxesLabel→{"y*", "y_o", "p(y_o,y_o)"}],
AxesStyle→Directive[Black, 13],
Ticks→{{{1, 2}, {"Li(-)", "Li(+)"}}T, {{1, 2}, {"Li(-)", "Li(+)"}}T, Automatic]]}], ImageSize

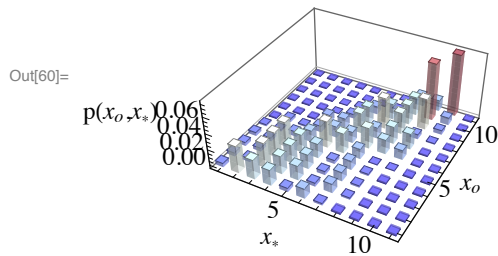
gridlab[x_] := Style[x, Black, Bold, 28, FontFamily→"Times New Roman"]
(*ascoreasymmetrygrid = Grid[{
  gridlab[#]&@{"A", "B"},
  {partA, partB},
  gridlab[#]&@{"C", "D"},
  {partC, miaaldafig}]]];
Export["ascoreasymmetrygrid.pdf", ascoreasymmetrygrid, "AllowRasterization"→True];*)

partA
partB
partC
miaaldafig

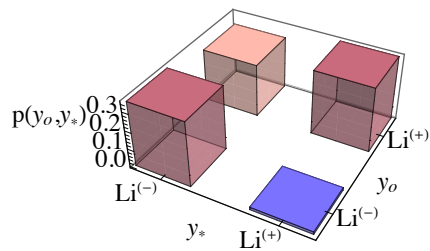
```

Continuous Scale ($\alpha = 0$)

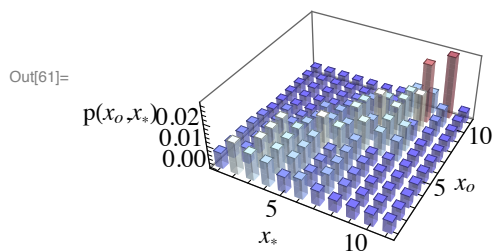
$$\mathbb{I}_\alpha[x_o||x_*]=1.41$$

Discretized Scale ($\alpha = 0$)

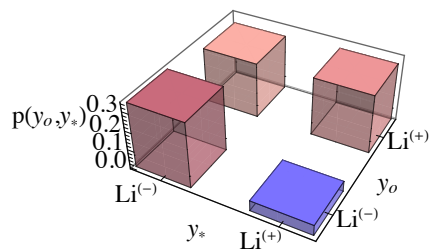
$$\mathbb{I}_\gamma[y_o||y_*]=0.47$$

Continuous Scale ($\alpha = 10$)

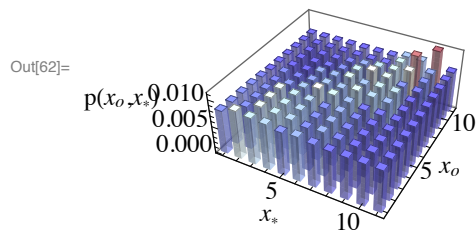
$$\mathbb{I}_\alpha[x_o||x_*]=0.11$$

Discretized Scale ($\alpha = 10$)

$$\mathbb{I}_\gamma[y_o||y_*]=0.43$$



Continuous Scale ($\alpha = 100$)
 $\mathbb{I}_\alpha[x_o||x_*]=0.$



Discretized Scale ($\alpha = 100$)
 $\mathbb{I}_\gamma[y_o||y_*]=0.26$

