## Lecture 25: Models for Matched Pairs

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## Matched Pairs

- We are going to conclude the semester examining models for repeated categorical data
- Repeated observations are common in longitudinal studies
- Since the data are matched on subject, they are often statistically dependent
- This dependence needs to be incorporated into our statistical models
- Our first example is when we have two repeated observations


## Example

- 1600 British citizens were surveyed on the Prime Minister's job performance
- Each citizen rated the Prime Minister as "approve" or "disapprove"
- Then, after 6 months, each citizen re-rates the Prime Minister
- A $(2 \times 2)$ table on the matched ratings is provided below

| First <br> Survey | Second Survey |  |  |
| ---: | ---: | ---: | ---: |
| Approve | Disapprove |  |  |
| Approve | 794 | 150 | 944 |
| Disapprove | 86 | 570 | 656 |
| Total | 880 | 720 | 1600 |

## Summary Measures

- One way we can begin to examine these data is to calculate the Odds Ratio

$$
\begin{aligned}
O R & =\frac{794.570}{86.150} \\
& =35.1
\end{aligned}
$$

- An OR of 35 indicates a strong association among opinions
- That is, the odds of approving after 6 months are over 35 times higher if a citizen approved initially
- Also, 1364 of the 1600 did not change opinion after 6 months
- 236 changed opinion
- We are interested in seeing whether or not the general opinion is changing over time


## Dependent Proportion

- Let $\pi_{a b}$ be the probability of outcome $a$ for the first observation and $b$ for the second
- For example, $\pi_{11}$ is the probability of approving at baseline and after 6 months still approving
- For a $(2 \times 2)$ table, the following table summarizes the true probabilities

| First | Second Survey |  |  |
| ---: | ---: | ---: | ---: |
| Survey | Approve | Disapprove |  |
| Approve | $\pi_{11}$ | $\pi_{12}$ | $\pi_{1+}$ |
| Disapprove | $\pi_{21}$ | $\pi_{22}$ | $\pi_{2+}$ |
| Total | $\pi_{+1}$ | $\pi_{+1}$ | $\pi_{++}=1$ |

## Marginal Homogeneity

- Marginal homogeneity occurs when

$$
\pi_{1+}=\pi_{+1}
$$

- Note, since

$$
\pi_{1+}-\pi_{+1}=0
$$

- Then

$$
\pi_{1+}-\pi_{+1}=\left(\pi_{11}+\pi_{12}\right)-\left(\pi_{11}+\pi_{21}\right)=\pi_{12}-\pi_{21}=0
$$

- Then,

$$
\begin{aligned}
\pi_{21}-\pi_{12} & =\left(\pi_{22}+\pi_{21}\right)-\left(\pi_{22}+\pi_{12}\right) \\
& =\pi_{2+}-\pi_{+2}
\end{aligned}
$$

- Thus, the marginal homogeneity models has the marginal column probabilities equaling the marginal row probabilities
- Or, the off diagonal probabilities are equal
- To develop a statistical test for this model, we will now consider the observed sample information
- let $n_{a b}$ be the count of subjects moving from $a$ to be $b$
- Then, in terms of the $(2 \times 2)$, the observed counts are

| First | Second Survey |  |  |
| ---: | ---: | ---: | ---: |
| Survey | Approve | Disapprove |  |
| Approve | $n_{11}$ | $n_{12}$ | $n_{1+}$ |
| Disapprove | $n_{21}$ | $n_{22}$ | $n_{2+}$ |
| Total | $n_{+1}$ | $n_{+1}$ | $n_{++}$ |

## Observed Proportions

- In terms of observed proportions

| First | Second Survey |  |  |
| ---: | ---: | ---: | ---: |
| Survey | Approve | Disapprove |  |
| Approve | $p_{11}$ | $p_{12}$ | $p_{1+}$ |
| Disapprove | $p_{21}$ | $p_{22}$ | $p_{2+}$ |
| Total | $p_{+1}$ | $p_{+1}$ | $p_{++}=1$ |

- where $p_{a b}=n_{a b} / n_{++}$
- Let $d=p_{+1}-p_{1+}=p_{2+}-p_{+2}$
- Note, $d$ is the difference of two dependent proportions
- If $p_{+1}$ and $p_{1+}$ were independent, then

$$
\begin{aligned}
\operatorname{var}(d) & =\operatorname{var}\left(p_{+1}-p_{1+}\right) \\
& =\operatorname{var}\left(p_{+1}\right)+\operatorname{var}\left(p_{1+}\right) \\
& =\frac{p_{+1}\left(1-p_{+1}\right)}{n_{+1}}+\frac{p_{1+}\left(1-p_{1+}\right)}{n_{1+}}
\end{aligned}
$$

- However, since $p_{+1}$ and $p_{1+}$ are dependent, then we need to subtract out the covariance
- Thus

$$
\begin{aligned}
\operatorname{var}(d)= & \operatorname{var}\left(p_{+1}-p_{1+}\right)-2 \operatorname{cov}\left(p_{+1}, p_{1+}\right) \\
& \text { where } \operatorname{cov}\left(p_{+1}, p_{1+}\right) \text { equals } \\
& \left(p_{11} p_{22}-p_{12} p_{21}\right) / n
\end{aligned}
$$

- Therefore

$$
\operatorname{var}(\sqrt{n} d)=p_{+1}\left(1-p_{+1}\right)+p_{1+}\left(1-p_{1+}\right)-2\left(p_{11} p_{22}-p_{12} p_{21}\right)
$$

- After some algebra,

$$
\widehat{\operatorname{var}(d)}=\left[\left(p_{12}+p_{21}\right)-\left(p_{12}-p_{21}\right)^{2}\right] / n
$$

- This is the large sample (i.e., Wald or non-null) variance
- Thus, the test of marginal homogeneity is the same as testing

$$
H_{0}: d=0
$$

- Using

$$
z=\frac{d}{\sqrt{\operatorname{var}(d)}}
$$

## McNemar's Test

- Just as we have had all semester long, we could consider the variance under the null
- If $\pi_{12}-\pi_{21}$, then and alternative variance under the null is

$$
\operatorname{var}_{0}(d)=\frac{p_{12}+p_{21}}{n}=\frac{1 / n\left(n_{12}+n_{21}\right)}{n}=\frac{n_{12}+n_{21}}{n^{2}}
$$

- Then testing using the null standard error would yield

$$
\begin{aligned}
z_{0} & =\frac{p_{+1}-p_{1+}}{\sqrt{\operatorname{var}_{0}(d)}} \\
& =\frac{\left(n_{11}+n_{21}-n_{11}-n_{12}\right) / n}{\sqrt{\operatorname{var}_{0}(d)}} \\
& =\frac{n_{21}-n_{12}}{n \sqrt{\operatorname{var}_{0}(d)}} \\
& =\frac{n_{21}-n_{12}}{\left(n_{12}+n_{21}\right)^{1 / 2}}
\end{aligned}
$$

- McNemar's test is the square of $z_{0}$ and is distributed as chi-square with $1 d f$.


## Revisiting Example

- We have observed a strong association ( $\mathrm{OR}>35$ ), but does the marginal homogeneity model hold?

| First <br> Survey | Second Survey |  |  |
| ---: | ---: | ---: | ---: |
| Approve | Disapprove |  |  |
| Approve | 794 | 150 | 944 |
| Disapprove | 86 | 570 | 656 |
| Total | 880 | 720 | 1600 |

- For this data

$$
p_{1+}=944 / 1600=0.59
$$

and

$$
p_{+1}=880 / 1600=0.55
$$

## Difference in Dependent Proportions

- A large sample comparison of these proportions is

$$
d=0.55-0.59=-0.04
$$

- with standard error of

$$
\widehat{\operatorname{var}(d)}=\left[(150+86)-(150-86)^{2}\right] / 1600=0.000091188
$$

- Thus, a large sample confidence interval is

$$
-0.04 \pm 1.96 \sqrt{0.000091188}=(-0.06,-0.02)
$$

- Thus, the rating of the Prime Minister appears to have dropped between $2 \%$ and $6 \%$


## McNemar's

- McNemar's Test is

$$
z_{0}^{2}=\left[\frac{86-150}{(86+150)^{1 / 2}}\right]^{2}=(-4.17)^{2}=17.3559
$$

- Which is less than -1.96, so we have strong evidence to support a drop in rating


## Using SAS

```
data one;
    input pre post count;
    cards;
    1 1 794
    1 2 150
    2 1 86
    2 2 570
    ;
run;
proc freq;
    tables pre*post /agree;
    weight count;
run;
```

Statistics for Table of pre by post

McNemar's Test

| Statistic (S) | 17.3559 |
| :--- | ---: |
| DF | 1 |
| Pr $>S$ | $<.0001$ |

## Small Sample $p$-value

- The null hypothesis of marginal homogeneity is

$$
H_{0}: \pi_{12}=\pi_{21}
$$

- Which is the same as

$$
\frac{\pi_{21}}{\pi_{21}+\pi_{12}}=0.5
$$

since

$$
\pi_{21}=0.5 \pi_{21}+0.5 \pi_{12}
$$

- Let $n^{*}=n_{21}+n_{12}$ (that is $n^{*}$ is the number of discordant (off diagonal pairs))
- Under $H_{0}, n_{21} \sim b\left(n^{*}, 0.5\right)$
- With $E\left(n_{21}\right)=0.5 n^{*}$
- That is, the discordant data should be equally distributed if marginal homogenous
- The exact $p$-value is the binomial tail probability.
- Recall, exact binomial inference is based on the "as extreme or more extreme" principle


## Example

- Consider the following made up example

|  | Rating 2 |  |  |
| ---: | :---: | :---: | :---: |
| Rating 1 | 1 | 2 |  |
| 1 | 35 | 12 | 47 |
| 2 | 3 | 40 | 43 |
|  | 38 | 52 | 90 |

- 90 subjects appears to be a large sample, but McNemar's is only based on discordant pairs
- For this example, we have $15(=12+3)$ pairs
- We should consider using an exact method based on the binomial


## Binomial PDF macro

## Recall our Binomial PDF macro

```
%macro mybinomialpdf(p,n);
```

dm "output" clear; dm "log" clear;
options nodate nocenter nonumber;
data myexample;
do i $=0$ to \&n;
prob $=\operatorname{PDF}\left({ }^{\prime} B I N O M I A L ', i, \& p, \& n\right) ;$
cdf = CDF ('BINOMIAL',i,\&p,\&n) ;
mlcdfprob = 1-cdf+prob;
output;
end;
label $i=$ "Number of $*$ Successes";
label prob $=$ "P(Y=y) ";
label cdf $=\quad$ "P(Y<=y)";
label m1cdfprob="P(Y>=y)";
run;
title "Binomial PDF for $N=\& n$ and $P=\& p$ ";
proc print noobs label split="*";
run;
\%mend mybinomialpdf;
\%mybinomialpdf(0.5,15); <-- null prob $=0.5$, n* $=15$

## Results

Binomial PDF for $N=15$ and $P=0.5$

Number of

$$
\text { Successes } \quad P(Y=y) \quad P(Y<=y) \quad P(Y>=y)
$$

| 0 | $0.00003 *$ | 0.00003 | 1.00000 |
| ---: | :--- | :--- | :--- |
| 1 | $0.00046 *$ | 0.00049 | 0.99997 |
| 2 | $0.00320 *$ | 0.00369 | 0.99951 |
| 3 | $0.01389 *$ | 0.01758 | 0.99631 |
| 4 | 0.04166 | 0.05923 | 0.98242 |
| 5 | 0.09164 | 0.15088 | 0.94077 |
| 6 | 0.15274 | 0.30362 | 0.84912 |
| 7 | 0.19638 | 0.50000 | 0.69638 |
| 8 | 0.19638 | 0.69638 | 0.50000 |
| 9 | 0.15274 | 0.84912 | 0.30362 |
| 10 | 0.09164 | 0.94077 | 0.15088 |
| 11 | 0.04166 | 0.98242 | 0.05923 |
| 12 | $0.01389 *$ | 0.99631 | 0.01758 |
| 13 | $0.00320 *$ | 0.99951 | 0.00369 |
| 14 | $0.00046 *$ | 0.99997 | 0.00049 |
| 15 | $0.00003 *$ | 1.00000 | 0.00003 |

* indicate as extreme or more extreme values

Exact P-value equals $P(Y \geq 12)+P(Y \leq 3)=0.01758+0.01758=0.03516$

## Using SAS the easy way

- Using a "new" (version 9+?) version of SAS, you can get the exact $p$-value directly from proc freq

```
data one;
        input rate1 rate2 count @@;
        cards;
        1 1 35 1 1 2 12 2 1 3 3 2 2 4 40
        ;
    run;
    proc freq data=one;
        weight count;
        tables rate1*rate2 / agree;
        exact mcnem;
    run;
```

- Note the "exact" statement in proc freq


## Selected Results

```
Statistics for Table of rate1 by rate2
    McNemar's Test
\begin{tabular}{llr} 
Statistic (S) & 5.4000 \\
DF & 1 \\
Asymptotic \(\operatorname{Pr}>\quad S\) & 0.0201 \\
Exact & \(\operatorname{Pr}>=S\) & 0.0352
\end{tabular}
```

- The computed exact $p$-value matches our binomial pdf result
- There is some disagreement among the exact and chi-square based $p$-value, but the statistical conclusions are the same
- Just remember "large samples" for McNemar's test implies a large number of discordant pairs (and that the concordant pairs do not contribute to the test statistic)


## Marginal Homogeneity for $>2$ levels

- McNemar's Test is defined for a simple $2 \times 2$ table
- What if you have more than two levels in the classification?
- Consider a study in which 539 individuals where asked to what extent they agree with the notation that either their fellow church members or other friends encouraged them to exercise more
- The research question is to understand how the two different social support mechanisms (church v . other friends) may be contributing to increasing exercise in overweight individuals


## Data

|  | Outside Friend |  |  |  |  |
| ---: | :---: | :---: | :---: | :---: | :---: |
| Church Member | SA | A | D | SD | Total |
| SA | 47 | 20 | 2 | 2 | 71 |
| A | 39 | 139 | 32 | 3 | 213 |
| D | 24 | 87 | 106 | 7 | 224 |
| SD | 5 | 5 | 11 | 10 | 31 |
| Total | 115 | 251 | 151 | 22 | 539 |

- Like McNemar's, we are interested in testing

$$
\pi_{k+}=\pi_{+k} \quad \forall k
$$

- Or, in terms of cell probabilities

$$
\pi_{i j}=\pi_{j i} \quad \forall i, j
$$

- Hence, we are testing for symmetry of the probabilities above and below the concordant diagonal.
- which again translates into testing that the two marginal distributions are similar


## Using SAS

```
data two;
    input ch_rate fr_rate count @@;
    cards;
    1 1 1 47 1 2 2 20 1 3 3 2 1 1 4 4
    2}1143924 2 139 2 3 3 32 2 4 3
```



```
    4 1 5 5 4 2 5 4 4 3 11 4 4 10
    ;
run;
proc freq data=two;
    weight count;
    tables ch_rate* fr_rate / agree;
run;
```


## Selected Results

- The test results are:

```
    Test of Symmetry
Statistic (S) 52.8288
DF
    6
Pr>S <.0001
```

- However, interpreting the results, in this case, is easier if we collapse the categories
- This works since our data is ordinal and "agree" and "disagree" are easily understood (groupings of nominal levels may not make sense)

```
data twob;
    set two;
        if ch_rate > 2 then ch_rate2 = 2; else ch_rate2 = 1;
        if fr_rate > 2 then fr_rate2 = 2; else fr_rate2 = 1;
run;
proc freq data=twob;
        weight count;
        tables ch_rate2* fr_rate2 / agree;
run;
```

- Here, we are back to the regular McNemar's test


## Selected results

```
Statistics for Table of ch_rate2 by fr_rate2
    McNemar's Test
Statistic (S) 42.0250
DF 1
Pr > S <.0001
```

- 39 observations indicated that they agree church members are encouraging and disagreed that other friends are encouraging
- 121 observations indicated that they agree friends are encouraging and that church members are not
- Our results suggests that a respondent's belief is that friends are more likely to encourage increased exercise ( $p$-value $<0.0001$ )


## Measures of Agreement

- Suppose we have a double dichotomy formed by each of $n$ biostatisticians being rated by two raters on a dichotomous scale:

RATER 2


## Data



- In general,

$$
\begin{aligned}
& X=(\text { rating from rater } 1)=1 \text { or } 2 \\
& W=(\text { rating from rater } 2)=1 \text { or } 2
\end{aligned}
$$

- $\quad X$ and $W$ can take on the same possible values, say,

$$
\begin{aligned}
& 1=\text { 'positive rating'; } \\
& 2=\text { 'negative rating'. }
\end{aligned}
$$

- Neither margin is fixed by design, although the total number of subjects, $n$, usually is.
- Two raters 'agree' if the give a subject the same rating, i.e., the raters agree if they both rate subject $i$ as a ' 1 ' or they both rate subject $i$ as a ' 2 '.
- The simplest choice for a measure of agreement is the overall probability of agreement:

$$
\eta=p_{11}+p_{22}
$$

## CIATION

- For two raters, $X$ and $W$, to agree, they must fall in a diagonal of the $(2 \times 2)$ table.
- However, in general, for $X$ and $W$ to be associated, you should be able to predict one from the other.
- Consider the following $(2 \times 2)$ table

|  |  | Rater $2(W)$ |  |
| :---: | :---: | :---: | :---: |
|  |  | 1 | 2 |
|  | 1 | 0 | $\mathrm{p}_{12}$ |
| Rater 1 $(X)$ |  |  |  |
|  | 2 | $\mathrm{p}_{21}$ | 0 |

- For this table, the $O R=0,(\log (O R)=-\infty)$, which is perfect negative association: Given the rating from Rater 1, you can perfectly predict the rating of Rater 2, i.e., if $X=1$, then $W=2$. and if $X=2$, then $W=1$. Thus, the observations are highly associated.
- However, the raters completely disagree, and agreement is low. Using the above measure of agreement, it is 0 , i.e.,

$$
\eta=p_{11}+p_{22}=0
$$

## Another Measure

- Look at the previous measure of agreement,

$$
\eta=p_{11}+p_{22}
$$

We will see that this is not a great measure of agreement, because it tends to be too high, just by chance.

- If two raters independently rate the same subject, you would expect your measure of agreement to be 0 .
- By chance, if two raters independently rate the same subject,

$$
p_{j k}=p_{j+} p_{+k},
$$

and the measure of agreement $\eta$, is

$$
\eta=p_{1+} p_{+1}+p_{2+} p_{+2}>0
$$

- For example, suppose the probability of giving a positive rating (rating=1) is high:

$$
p_{1+}=p_{+1}=.9 \text { and thus } p_{2+}=p_{+2}=.1
$$

If the two raters are completely independent, still, by chance alone, the measure of agreement is high:

$$
\eta=.9^{2}+.1^{2}=.82
$$

- Thus, we need to scale this measure somehow; further, if the raters were independent, we would want a measure of agreement to be 0 .


## The Kappa Coefficient

- Cohen (1960) suggested the following measure, called 'Kappa',

$$
\begin{aligned}
\kappa & =\frac{\eta-\left(p_{1+} p_{+1}+p_{2+} p_{+2}\right)}{1-\left(p_{1+} p_{+1}+p_{2+} p_{+2}\right)} \\
& =\frac{\left(p_{11}+p_{22}\right)-\left(p_{1+} p_{+1}+p_{2+} p_{+2}\right)}{1-\left(p_{1+} p_{+1}+p_{2+} p_{+2}\right)}
\end{aligned}
$$

- Here, we have subtracted off the value $\eta$ under independence, so that, if the raters are independent, $\kappa=0$.
- Further, when agreement is perfect,

$$
\eta=p_{11}+p_{22}=1,
$$

which leads to the maximum value of the numerator,

$$
\begin{aligned}
& \max \left\{\left(p_{11}+p_{22}\right)-\left(p_{1+} p_{+1}+p_{2+} p_{+2}\right)\right\}= \\
& 1-\left(p_{1+} p_{+1}+p_{2+} p_{+2}\right)
\end{aligned}
$$

- The denominator of $\kappa$ is the maximum value of the numerator
- As such, the maximum value $\kappa$ can take is 1 :

$$
\kappa=\frac{\max \left\{\eta-\left(p_{1+} p_{+1}+p_{2+} p_{+2}\right)\right\}}{1-\left(p_{1+} p_{+1}+p_{2+} p_{+2}\right)}=1
$$

- However, $\kappa$ can also be negative when agreement is poor. Consider the following $(2 \times 2)$ table:

|  |  | Rater 2 |  |
| :---: | :---: | :---: | :---: |
|  |  | 1 | 2 |
|  | 1 | 0 | .5 |
| Rater 1 |  |  |  |
|  | 2 | .5 | 0 |

For this table,

$$
\begin{aligned}
\kappa & =\frac{\left(p_{11}+p_{22}\right)-\left(p_{1+} p_{+1}+p_{2+} p_{+2}\right)}{1-\left(p_{1+} p_{+1}+p_{2+} p_{+2}\right)} \\
& =\frac{0-\left(.5^{2}+.5^{2}\right)}{1-\left(.5^{2}+.5^{2}\right)}=-\frac{1}{3}
\end{aligned}
$$

## Example

- Suppose we have $n=107$ biostatisticians rated by two raters on a dichotomous scale:

RATER 2


- Just looking at the table, there appears to be high agreement, but is it greater than would be expected by chance?


## Using SAS

```
data one;
input rater1 rater2 count;
cards;
1 1 50
1 2 10
2 1 7
2 2 40
;
proc freq;
    table rater1*rater2 / agree;
weight count;
run;
/* SELECTED OUTPUT */
    Simple Kappa Coefficient
\begin{tabular}{lll} 
Kappa & 0.6797 & <--- Okay, what does this \\
ASE & 0.0711 & value mean? \\
95\% Lower Conf Limit & 0.5403 & \\
95\% Upper Conf Limit & 0.8190 &
\end{tabular}
Sample Size = 107
```


## Interpretation of Kappa

- Interpretation of Kappa is typically based on the guidelines by Landis and Koch (1977)
- The break the values into three categories
- $\kappa>0.75$ represents excellent agreement beyond chance
- $0.40 \leq \kappa \leq 0.75$ represents fair to good agreement beyond chance
- $\kappa<0.40$ represents poor agreement beyond chance


## Relationship of Kappa with McNemar's Test

- McNemar's (and the generalized test for symmetry) test the null hypothesis of marginal homogeneity
- If McNemar's test is statistically significant, the marginal probabilities differ
- Marginal probabilities differing suggests that the rows and columns are different
- If you want to test of the rows and columns are similar, you should consider Kappa
- In general, If Kappa is high, McNemar's is low and vise versa


## Agreement with more than 2 categories

- Diagnoses of $n=400$ biostatisticians by 2 raters:

|  |  | Psychot | Neurot | \|Organic | Total |
| :---: | :---: | :---: | :---: | :---: | :---: |
| R |  |  |  |  |  |
| a | Psychot | 75 | 1 | 4 | 80 |
| t |  |  |  |  |  |
| e | Neurot | 5 | 4 | 1 | 10 |
| r |  |  |  |  |  |
|  | Organic | 0 | 0 | 10 | 10 |
| 1 |  |  |  |  |  |
|  | Total | 80 | 5 | 15 | 400 |

## Weighted v. Unweighted Kappa

- If The ratings are ordinal, allowing for some tolerance in disagreement is feasible
- For example, If one rater strongly agrees and the other just agrees, it seems like we should account for the fact that both raters gave approximately the same rating
- One solution is to use the weighted $\kappa$ (Fliess, 1980) for a $K \times K$ table.
- Suppose that agreement weights, say $w_{j k}$, are assigned on rational grounds to the cells of the $(K \times K)$ table:
- 1. $w_{j j}=1$
- 2. $0 \leq w_{j k}<1$ for $j \neq k$.
- 3. $w_{j k}=w_{k j}$, (the two raters are considered symmetrically).
- Then, the 'weighted' proportion agreement is

$$
\eta_{w}=\sum_{j=1}^{K} \sum_{k=1}^{K} w_{j k} p_{j k}
$$

and

- The, the 'chance-expected' weighted proportion agreement is

$$
\eta_{c}=\sum_{j=1}^{K} \sum_{k=1}^{K} w_{j k} p_{j+} p_{+k}
$$

- Then, the WEIGHTED KAPPA is

$$
\kappa_{w}=\frac{\eta_{w}-\eta_{c}}{1-\eta_{c}} .
$$

- One choice for the weights is the 'simple weights':
- 1. $w_{j j}=1$
- 2. $w_{j k}=0$ for $j \neq k$.
so that we are measuring agreement along the diagonal. When $K=2$, this reduces to the $\kappa$ coefficient for a $(2 \times 2)$ table.
- Simple weights are appropriate if you are studying nominal ratings
- Another possibility is

$$
w_{j k}=1-\frac{|j-k|}{K-1},
$$

which gives observations further apart in table less weight; for the above example, with $K=3$,

$$
\begin{aligned}
& w_{12}=w_{21}=.5 \\
& w_{23}=w_{32}=.5 \\
& W_{13}=w_{31}=0
\end{aligned}
$$

and

$$
w_{11}=w_{22}=w_{33}=1
$$

- When $K=2$, this also reduces to the $\kappa$ coefficient for a $(2 \times 2)$ table.
- This style of weights is appropriate for ordinal ratings


## Example

Diagnoses in $n=400$ biostatisticians by 2 raters:


- Just looking at the table, there appears to be high agreement, but is it greater than would be expected by chance?


## Using SAS

```
data one;
input rater1 rater2 count;
cards;
1 1 75
1 2 1
1 3 4
2 1 5
2 2 4
2 3 1
3 1 0
3 2 0
3 3 10
;
proc freq;
    table rater1*rater2 / agree ;
weight count;
run;
```

```
/* SELECTED OUTPUT */
Kappa Statistics
\begin{tabular}{|c|c|c|c|c|}
\hline Statistic & Value & ASE & \multicolumn{2}{|l|}{95\% Confidence Limits} \\
\hline Simple Kappa & 0.6765 & 0.0877 & 0.5046 & 0.8484 \\
\hline Weighted Kappa & 0.7222 & 0.0843 & 0.5570 & 0.8874 \\
\hline
\end{tabular}
Sample Size = 100
```

- Which Kappa is to be reported?
- I would report the simple kappa since the classifications are nominal


## Revisiting Exercise Encouragement Example

- Recall our exercise example:

|  | Outside Friend |  |  |  |  |
| ---: | :---: | :---: | :---: | :---: | :---: |
| Church Member | SA | A | D | SD | Total |
| SA | 47 | 20 | 2 | 2 | 71 |
| A | 39 | 139 | 32 | 3 | 213 |
| D | 24 | 87 | 106 | 7 | 224 |
| SD | 5 | 5 | 11 | 10 | 31 |
| Total | 115 | 251 | 151 | 22 | 539 |

- Here, a weighted Kappa is feasible
- Although, this example isn't the typical kappa example (here, two ratings are given by the subject; usually, two independent raters give ratings about a single subject


## Selected Results

- From the same PROC FREQ statement specified previously, we also get the following output

> Kappa Statistics

| Statistic | Value | ASE | 5\% Conf | Limits |
| :---: | :---: | :---: | :---: | :---: |
| Simple Kappa | 0.3428 | 0.0313 | 0.2815 | 0.4041 |
| Weighted Kappa | 0.3942 | 0.0314 | 0.3326 | 0.4559 |

- Here, the weighted Kappa indicates "poor" agreement, but allowing form some disagreement (weighting) does improve the overall agreement
- Poor agreement should not be a surprise, since the test for symmetry suggested levels of support for exercise differed by type of person (church v. regular friend)


## SAS Notes

- SAS uses the scores assigned to each variable in the calculation of the sampling weights
- Linear transformations of scores yield the same weighted kappa
- Non linear transformations yield different weighted kappa scores
- The same slides pertaining to the selection of scores for ordinal measures of association apply to the selection of scores for weighted kappa


## Kappa Extensions

- If you have a stratification variable, you can calculate a stratum-specific kappa ( $\kappa_{w}$ )
- There is a "pooled" estimate of kappa that is calculated as

$$
\widehat{\kappa_{\text {pooled }}}=\frac{\sum_{w=1} \frac{\widehat{\kappa_{m}}}{\left.\frac{V_{m}(\kappa)}{\kappa_{m}}\right)}}{\sum_{w=1} \frac{1}{\overline{V_{m}\left(\widehat{\kappa_{m}}\right)}}}
$$

- and

$$
V_{m}\left(\widehat{\kappa_{m}}\right)=\frac{A+B-C}{n\left(1-p_{e}\right)^{2}}
$$

- where

$$
\begin{aligned}
A & =\sum_{i=1}^{k} \pi_{i j}\left[1-\left(\pi_{i+}+\pi_{+i}\right)(1-\widehat{\kappa})\right]^{2} \\
B & =(1-\widehat{\kappa})^{2} \sum \sum_{i \neq j} \pi_{i j}\left(\pi_{+i}+\pi_{j+}\right)^{2} \\
C & =\left[\widehat{\kappa}-p_{e}(1-\widehat{\kappa})\right]^{2} \\
p_{e} & =\sum_{i=1}^{k} \pi_{i+} \pi_{+i}
\end{aligned}
$$

## General Notes

- We have been concerned with "square tables"
- That is, the rows and columns have the same levels (descriptions and counts)
- Agreement, as measured by Kappa, is similar to a correlation and represents the amount of density on the main diagonal
- McNemar's measures marginal homogeneity...that is, does the proportion of a specific response change between responses.
- Since the two matched responses tend to be positively correlated, we gain precision (decrease the standard errors)
- That is, matched data design is more efficient and would require fewer subjects

