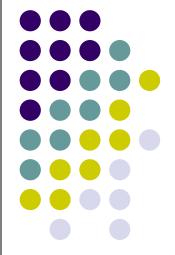
Generalized Agreement Statistics over Fixed Set of Experts

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Accenture Technology Labs

European Conference on Machine Learning Sep 07, 2011





Background and Settings

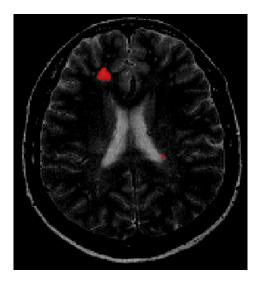
- Each instance in the data labeled by a fixed group of Raters
 - Expert Annotators, Opinion/Rating generators,...
- Multiple Classes (Nominal Scale)
- No ground truth labels

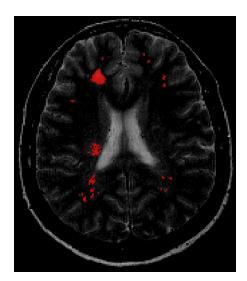
Many such scenarios

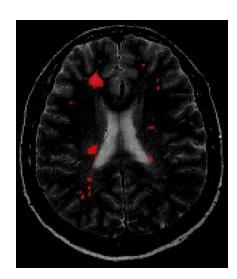


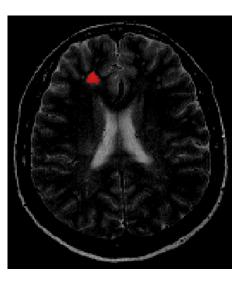
- Multiple experts' labels on multi-category examples
 - e.g., Human Intelligence Tasks (HITs)
- Medical Image Segmentation
 - e.g., Segmentation of lesion/tumor tissues from brain MRIs
- Applying ensemble methods for various tasks
 - e.g., multi-sensor radar systems for threat detection

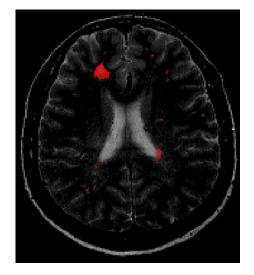
An Example













Another Example



5 Raters suggesting positions on stocks in portfolio

| Inst # | Rater 1 | Rater 2 Rater 3 | | Rater 4 | Rater 5 |
|--------|----------------------------------|----------------------------------|----------------------------------|---------|---------|
| 1 | Buy | Sell | Buy | Sell | Hold |
| 2 | Buy | Metaphysical/ Epistemological | Sell | Sell | Sell |
| 3 | Buy | Buy | Buy | Buy | Buy |
| 4 | Sell | Buy | Sell | Buy | Sell |
| 5 | Hold | Hold | Buy | Hold | Sell |
| 6 | Metaphysical/ Epistemological | Metaphysical/ Epistemological | Metaphysical/ Epistemological | Sell | Sell |
| 7 | Sell | Hold | Hold | Sell | Sell |

An example



| Inst # | Rater 1 | Rater 2 | Rater 3 | Rater 4 | Rater 5 |
|--------|---------|---------|---------|---------|---------|
| 1 | 1 | 2 | 1 | 2 | 3 |
| 2 | 1 | 4 | 2 | 2 | 2 |
| 3 | 1 | 1 | 1 | 1 | 1 |
| 4 | 2 | 1 | 2 | 1 | 2 |
| 5 | 3 | 3 | 1 | 3 | 2 |
| 6 | 4 | 4 | 4 | 2 | 2 |
| 7 | 2 | 3 | 3 | 2 | 2 |
| | | | | | |

Two Problems

| Inst # | Rater 1 | Rater 2 | Rater 3 | Rater 4 | Rater 5 |
|--------|---------|---------|---------|---------|---------|
| 1 | 1 | 2 | 1 | 2 | 3 |
| 2 | 1 | 4 | 2 | 2 | 2 |
| 3 | 1 | 1 | 1 | 1 | 1 |
| 4 | 2 | 1 | 2 | 1 | 2 |
| 5 | 3 | 3 | 1 | 3 | 2 |
| 6 | 4 | 4 | 4 | 2 | 2 |
| 7 | 2 | 3 | 3 | 2 | 2 |
| | | | | | |



Inter-expert agreement: Overall Agreement of the group

Two Problems

| | | Rater 5 | Rater 4 | Rater 3 | Rater 2 | Rater 1 | Inst # |
|--|------------------|-----------------------------|-----------------------------|-----------------------|-----------------------------|------------------------|----------------------------|
| | | 3 | 2 | 1 | 2 | 1 | 1 |
| | | 2 | 2 | 2 | 4 | 1 | 2 |
| Inter-expert agreement: | | 1 | 1 | 1 | 1 | 1 | 3 |
| Overall Agreement | | 2 | 1 | 2 | 1 | 2 | 4 |
| of the group | | 2 | 3 | 1 | 3 | 3 | 5 |
| | | 2 | 2 | 4 | 4 | 4 | 6 |
| | | | | | | | |
| | | 2 | 2 | 3 | 3 | 2 | 7 |
| | Classifier | 2 Rater 5 | 2 Rater 4 | 3 Rater 3 | 3 Rater 2 | 2 Rater 1 | 7 Inst # |
| | Classifier | | | | | | |
| | | Rater 5 | Rater 4 | Rater 3 | Rater 2 | Rater 1 | Inst # |
| Classifier Agreemer | 1 | Rater 5 3 | Rater 4 | Rater 3 1 | Rater 2 2 | Rater 1 1 | Inst # 1 |
| Classifier Agreemer Against the group | 1 4 | Rater 5 3 2 | Rater 4 2 2 | Rater 3 1 2 | Rater 2 2 4 | Rater 1 1 1 | Inst # 1 2 |
| | 1 4 1 | Rater 5 3 2 1 | Rater 4 2 2 1 | Rater 3 1 2 1 | Rater 2 2 4 1 | Rater 1 1 1 1 | Inst # 1 2 3 |
| | 1 4 1 2 | Rater 5 3 2 1 2 | Rater 4 2 2 1 1 | Rater 3 1 2 1 2 2 1 2 | Rater 2 2 4 1 1 | Rater 1 1 1 2 | Inst # 1 2 3 4 |

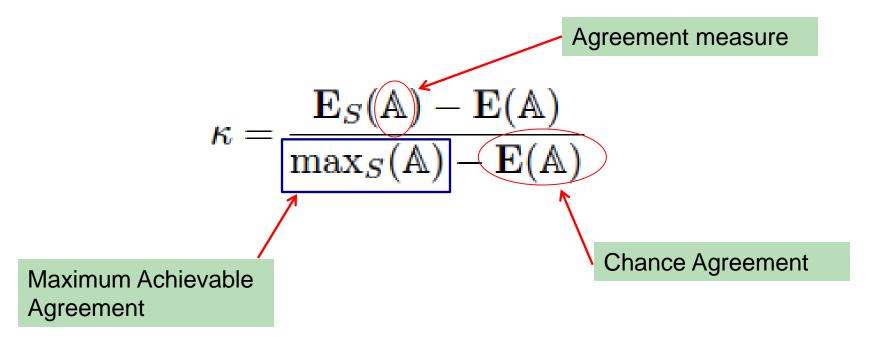


General Agreement Statistic

$$\kappa = \frac{\mathbf{E}_S(\mathbb{A}) - \mathbf{E}(\mathbb{A})}{\max_S(\mathbb{A}) - \mathbf{E}(\mathbb{A})}$$



General Agreement Statistic



Examples: Cohen's kappa, Fleiss Kappa, Scott's pi, ICC...

Modus operandi

- Define an agreement measure
- Derive expression for its expected value
- Define maximum achievable agreement
- Live happily ever after

Except...

this is easier said than done Model assumptions play a big role



Problem



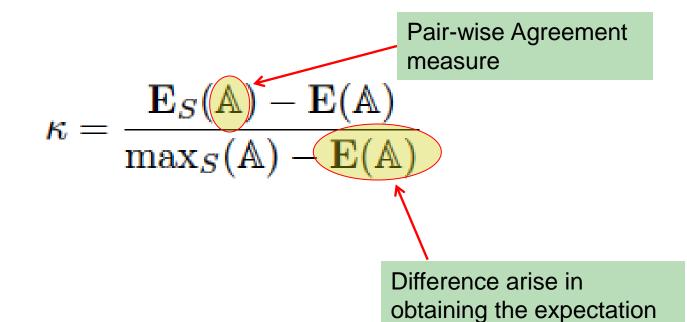
 To obtain general agreement measures over a fixed set of raters applicable in multi-class multi-rater case, accounting for coincidental concordances

Traditional approaches

- Typically applicable for 2-rater binary classification case (E.g., Cohen's kappa)
- Generalizations assume a variable group and use marginalization argument (e.g, Fleiss kappa (Fleiss, 1971) statistic implemented in WEKA)
- **Claim:** Marginalization argument is unsuitable for the fixed experts' group case



Back to the agreement statistic



Traditional Approaches: Inter-expert Agreement



The Marginalization Argument:

Consider a simple 2 rater 2 class case

| Inst # | Rater 1 | Rater 2 |
|--------|---------|---------|
| 1 | 1 | 1 |
| 2 | 1 | 2 |
| 3 | 1 | 1 |
| 4 | 2 | 1 |
| 5 | 2 | 2 |
| 6 | 1 | 2 |
| 7 | 2 | 2 |

Agreement: 4/7 Probability of chance agreement over label 1:

> $Pr(Label=1| Random rater)^2$ = 7/14 * 7/14 = 0.25

Agreement = $\frac{4/7 - 0.5}{1 - 0.5} = 0.143$

Traditional Approaches: Inter-expert Agreement



The Marginalization Argument: **Consider another scenario**

| Inst # | Rater 1 | Rater 2 |
|--------|---------|---------|
| 1 | 1 | 2 |
| 2 | 1 | 2 |
| 3 | 1 | 2 |
| 4 | 1 | 2 |
| 5 | 2 | 1 |
| 6 | 2 | 1 |
| 7 | 2 | 1 |

Observed Agreement: 0

Probability of chance agreement over label-1:

 $Pr(Label=1| Random rater)^2$ = 7/14 * 7/14 = 0.25

Agreement =
$$\frac{0 - 0.5}{1 - 0.5}$$
 = -1

Traditional Approaches: Inter-expert Agreement



The Marginalization Argument: But this holds even when there is no evidence of a chance agreement

Observed Agreement: 0

| Inst # | Rater 1 | Rater 2 |
|--------|---------|---------|
| 1 | 1 | 2 |
| 2 | 1 | 2 |
| 3 | 1 | 2 |
| 4 | 1 | 2 |
| 5 | 1 | 2 |
| 6 | 1 | 2 |
| 7 | 1 | 2 |
| | | |

Probability of chance agreement over label-1:

 $Pr(Label=1| Random rater)^2$ = 7/14 * 7/14 = 0.25

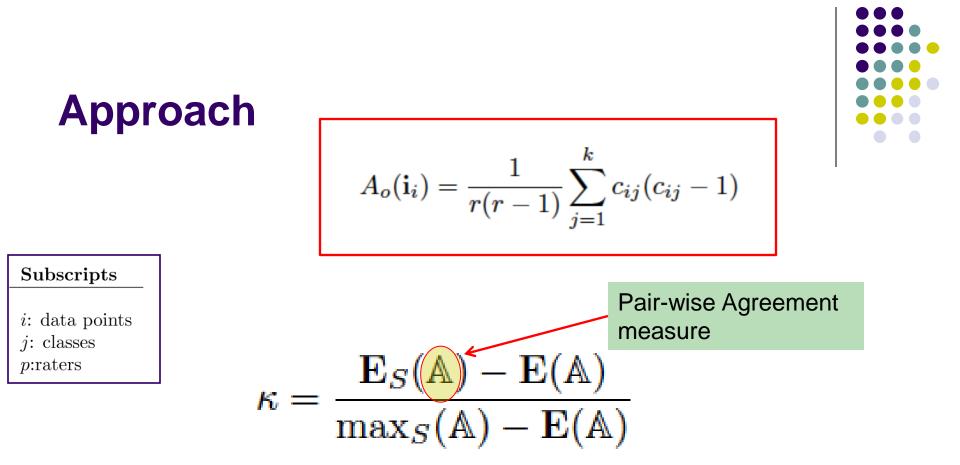
Agreement =
$$\frac{0 - 0.5}{1 - 0.5}$$
 = -1

Not applicable in fixed rater scenario

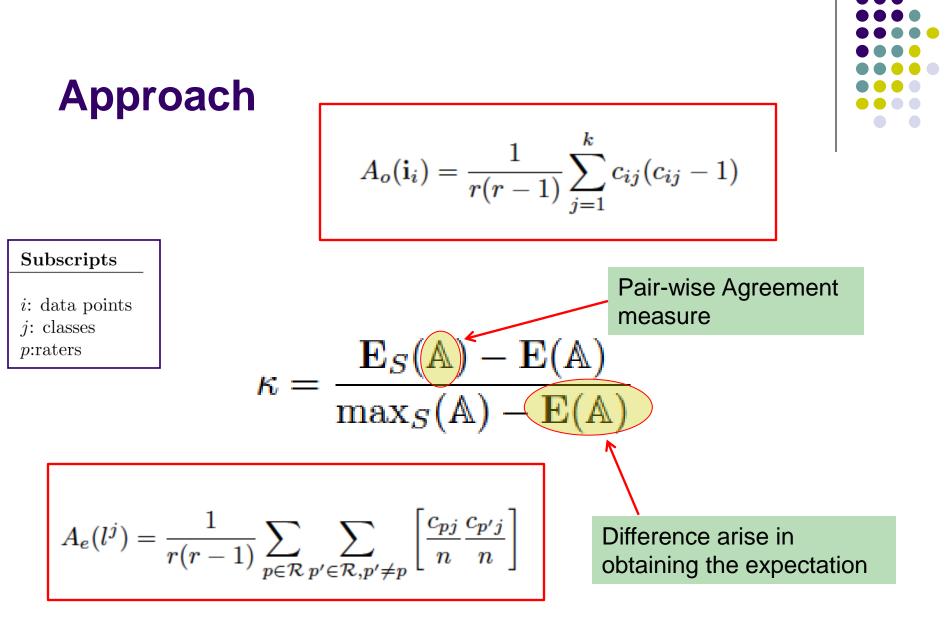
- Marginalization ignores rater correlation
- Ignores rater asymmetry
- Results in loose chance agreement estimates by optimistic estimation
- Hence, overly conservative agreement estimate

I: Inter-rater agreement over fixed set of raters

$$\kappa = \frac{\mathbf{E}_S(\mathbb{A}) - \mathbf{E}(\mathbb{A})}{\max_S(\mathbb{A}) - \mathbf{E}(\mathbb{A})}$$



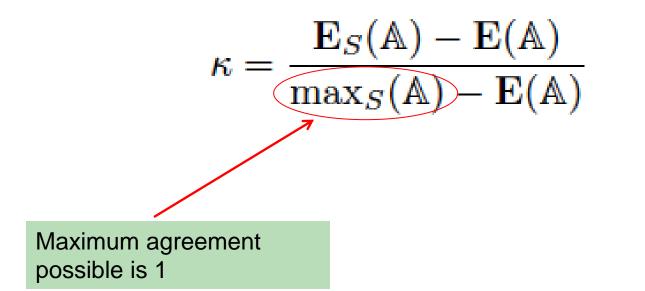
c_{ij} : No. of raters assigning point *i* to class *j*



 c_{ij} : No. of raters assigning point *i* to class *j* c_{pj} : No. of **data points** that rater *p* assigns to class *j*

Approach





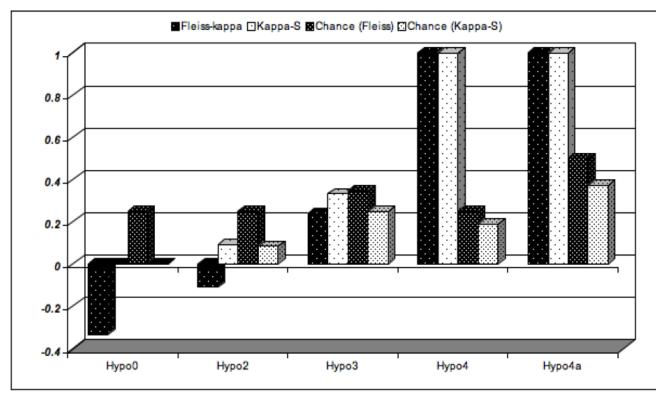
Inter-rater Agreement: Fixed rater scenario



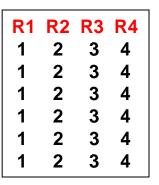
• Inter-rater agreement is:

$$\kappa_{S} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{k} c_{ij} \cdot (c_{ij} - 1) - \frac{1}{n} \sum_{j=1}^{k} \sum_{p \in \mathcal{R}} \sum_{p' \in \mathcal{R}, p' \neq p} [c_{pj} c_{p'j}]}{nr(r-1) \left[1 - \frac{1}{n^2 r(r-1)} \sum_{j=1}^{k} \sum_{p \in \mathcal{R}} \sum_{p' \in \mathcal{R}, p' \neq p} [c_{pj} c_{p'j}] \right]}$$

Simulations on synthetic data

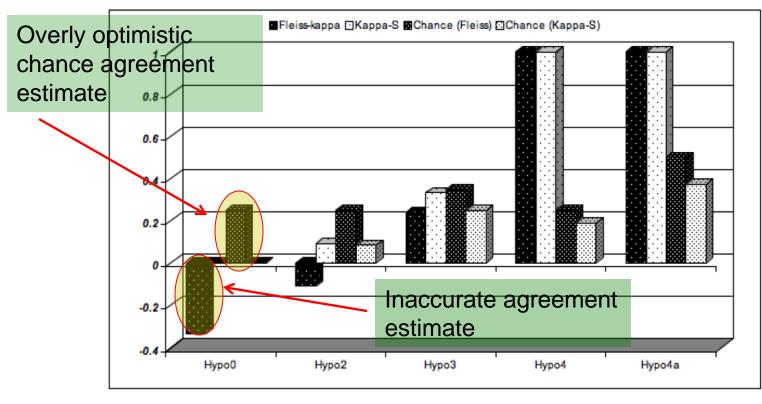


Setting: 200 data points, 4 raters, 4 classes Hypo0: All raters disagree on all points —

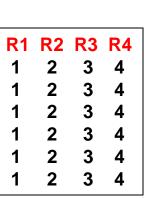




Simulations on synthetic data



Setting: 200 data points, 4 raters, 4 classes Hypo0: All raters disagree on all points —

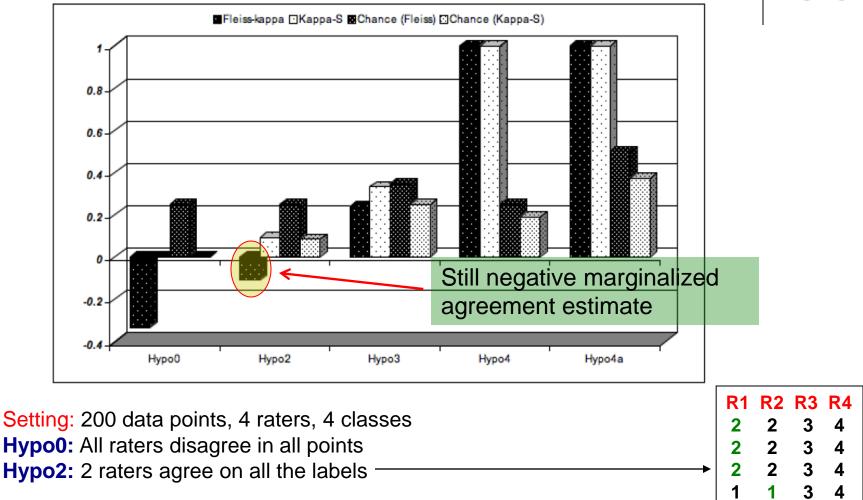




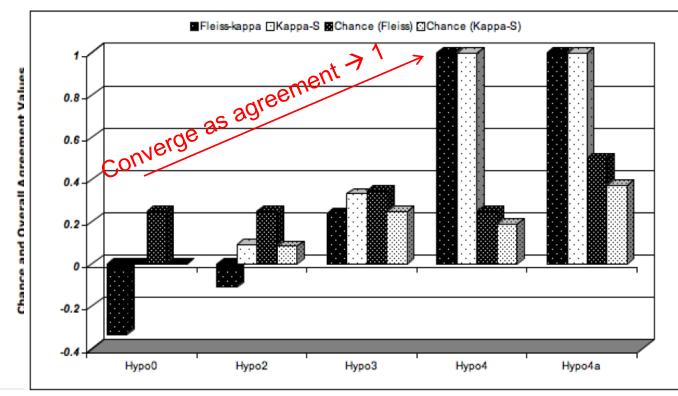


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Simulations on synthetic data



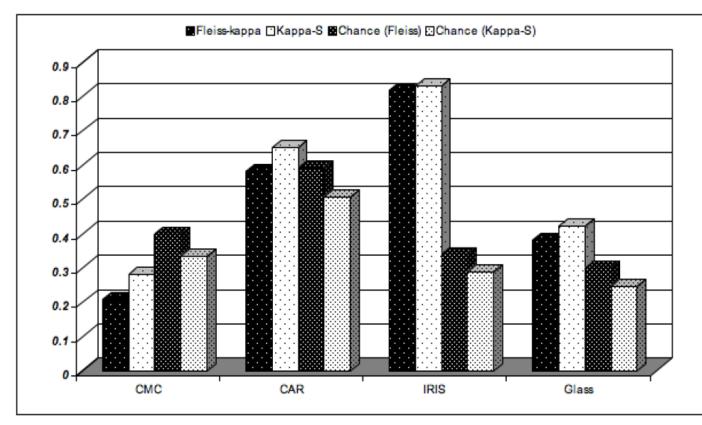
Simulations on synthetic data



Setting: 200 data points, 4 raters, 4 classes Hypo0: All raters disagree in all points Hypo2: 2 raters agree on all the labels Hypo 3: 3 raters agree Hypo4: All raters agree (50 points in each class) Hypo4a: All raters agree (100 points each in 2 classes)



Simulations on UCI data



Setting: 7 raters (6 classifiers + 1 true label), multiple classes

Both measures converges near unity but differs substantially on low or moderate agreement values



Inter-rater Agreement Conclusions: An upper bound on the variability



Theorem 1. Let κ_F and κ_S denote, respectively, the agreement statistics of Fleiss (1971) and that proposed in Equation 5 computed on a population (dataset) with large sample-size n where each of the sample has been assigned one of k labels by a fixed group of r experts. If $\sigma^2(\kappa)$ denotes the variance of κ then we have that:

$$\sigma^2(\kappa_S) \le \sigma^2(\kappa_F)$$

with equality satisfied when the experts emulate the pool.

II. Agreement of a classifier against a group: Two Traditional Approaches

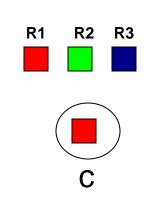


- Extension of marginalization argument
 - Recently appeared in Statistics literature: Vanbelle and Albert, (*stat. ner.* 2009)
- Consensus Based (more traditional)
 - Almost universally used in the machine learning/data mining community
 - E.g., medical image segmentation, tissue classification, recommendation systems, expert modeling scenarios (e.g. market analyst combination)

Marginalization Approach and Issues in Fixed experts setting

- Observed agreement: Proportion of raters with which the classifier agrees
 - Ignores qualitative agreement, may even ignore group dynamics

| Inst # | Rater 1 | Rater 2 | Rater 3 | Classifier |
|--------|---------|---------|---------|------------|
| 1 | 1 | 2 | 3 | 1 |
| 2 | 1 | 2 | 3 | 3 |
| 3 | 1 | 2 | 3 | 1 |
| 4 | 1 | 2 | 3 | 2 |
| 5 | 1 | 2 | 3 | 3 |
| 6 | 1 | 2 | 3 | 2 |
| 7 | 1 | 2 | 3 | 2 |



Marginalization Approach and Issues in Fixed experts setting

- Observed agreement: Proportion of raters with which the classifier agrees
 - Ignores qualitative agreement, may even ignore group dynamics

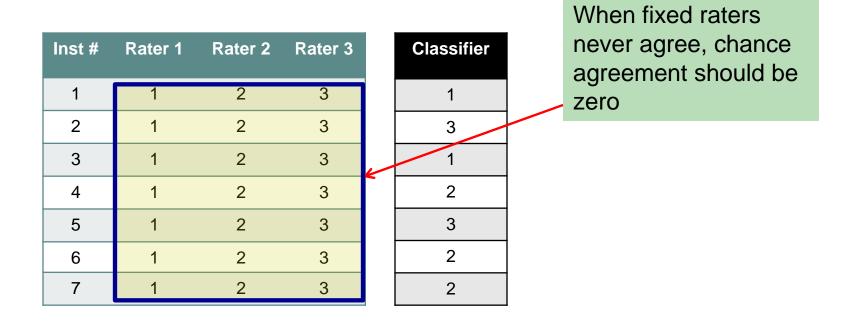
| Inst # | Rater 1 | Rater 2 | Rater 3 | Classifier | assignment gives same observed |
|--------|---------|---------|---------|------------|--------------------------------|
| 1 | 1 | 2 | 3 | | agreement |
| 2 | 1 | 2 | 3 | 3 | |
| 3 | 1 | 2 | 3 | 1 | |
| 4 | 1 | 2 | 3 | 2 🖌 | |
| 5 | 1 | 2 | 3 | 3 | |
| 6 | 1 | 2 | 3 | 2 | |
| 7 | 1 | 2 | 3 | 2 | |



Any random label

Marginalization Approach and Issues in Fixed experts setting

- Chance Agreement: Extend the marginalized argument
 - Not informative when the raters are fixed, ignores raterspecific correlations





Consensus Approach and Issues

• Approach:

- Obtain a deterministic label for each instance if at least k >= r/2 raters agree
- Treat this label set as ground truth and use dice coefficient against classifier labels

• Issues:

- Threshold sensitive
- Establishing threshold can be non-trivial
- Tie breaking not clear
- Treats estimates as deterministic
- Ignores minority raters as well as rater correlation

Consensus approach fails in assessing classifier performance

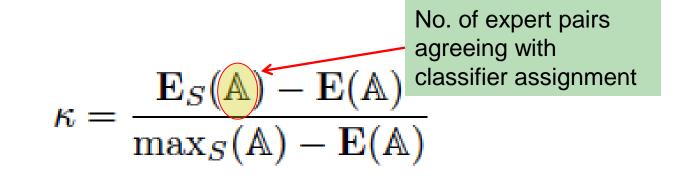
- Dice in addition to consensus
 - No chance correction
 - Ignores agreement with minority raters
 - Dependent on consensus (and not raters' estimates)
 - Applies to two class scenario
 - Can be less sensitive, potentially even misleading, to important label changes



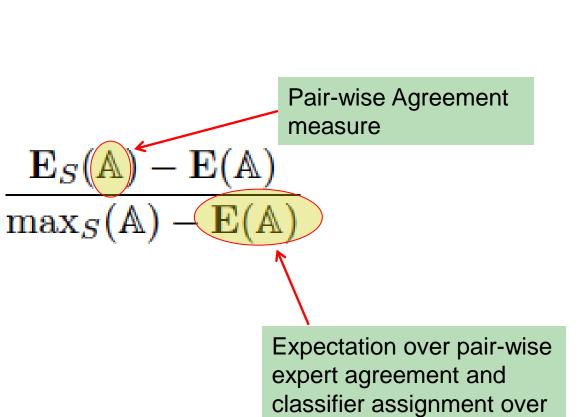
$$\kappa = \frac{\mathbf{E}_S(\mathbb{A}) - \mathbf{E}(\mathbb{A})}{\max_S(\mathbb{A}) - \mathbf{E}(\mathbb{A})}$$



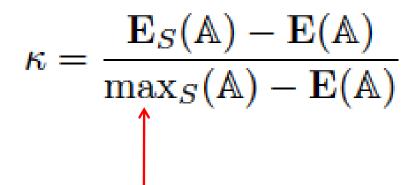


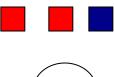


 $\kappa =$



all classes





Not necessarily 1, but upper bounded by the number of expert pairs agreeing



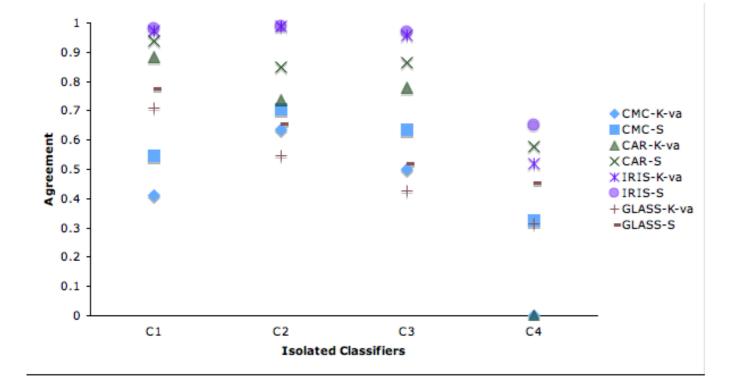
Agreement against Fixed Experts' group: The \mathcal{S} measure

$$S = \frac{\frac{1}{n} \sum_{i=1}^{n} \left[\sum_{j=1}^{k} \mathfrak{r}_{ij} A_o(\mathbf{i}_i, l^j) \right] - \sum_{j=1}^{k} \mathfrak{r}_j \cdot A_e(l^j)}{\frac{1}{n} \sum_{i=1}^{n} \max_j A_o(\mathbf{i}_i, l^j) - \sum_{j=1}^{k} \mathfrak{r}_j \cdot A_e(l^j)}$$

• **t** denotes an output of learning algorithm such that

 $\mathbf{r}_{ij} = 1$ if the classifier assigns label j to instance i $\mathbf{r}_{ij} = 0$ otherwise

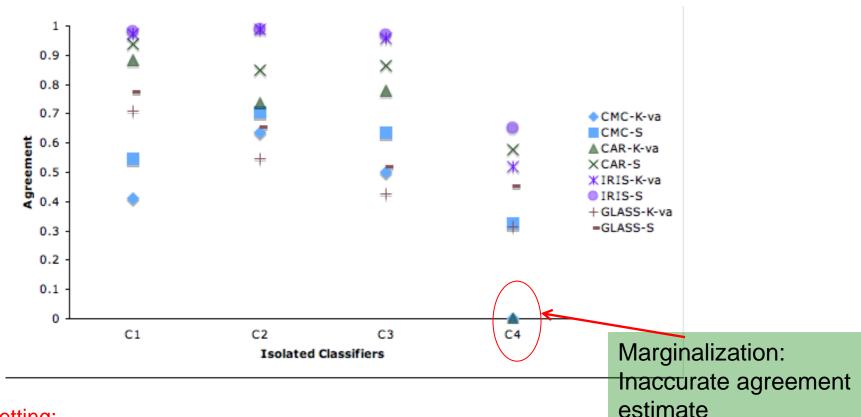
Agreement against silver standard: Illustration on UCI data



Setting: Expert labels: True labels + 2 classifiers with highest 10-fold cv accuracy



Agreement against silver standard: Illustration on UCI data

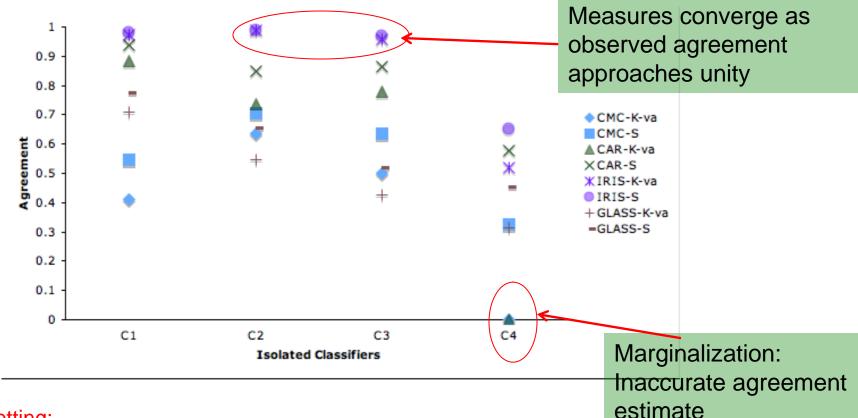


Setting:

Expert labels: True labels + 2 classifiers with highest 10-fold cv accuracy

Note C4 over CAR and CMC (K-va=0)

Agreement against silver standard: Illustration on UCI data



Setting:

Expert labels: True labels + 2 classifiers with highest 10-fold cv accuracy

```
Note C4 over CAR and CMC (K-va=0)
```

Measures converge close to unity

Conclusion



- We show that the marginalization argument is unsuitable when the experts' group is fixed
- We propose generalized metrics that
 - Apply to multi-class multi-rater scenario
 - Sensitive to changing rater agreement
 - Provide more meaningful estimates
- Variance behavior can be analytically established unlike dice/consensus
- Statistical hypothesis tests can be obtained



Importance of time travel

If you'd like to discuss details or know of more results and issues, please come to my poster **yesterday!**

Thank You



Now Available:

Evaluating Learning Algorithms A Classification Perspective

Nathalie Japkowicz • Mohak Shah

