Unit 9: Inter-Annotator Agreement

Statistics for Linguists with R – A SIGIL Course

Designed by Stefan Evert[1] and Marco Baroni[2]

[1]Computational Corpus Linguistics Group
Friedrich-Alexander-Universität Erlangen-Nürnberg, Germany

[2]Center for Mind/Brain Sciences (CIMeC)
University of Trento, Italy

Outline

Outline

Introduction

Manually annotated data will be used for . . .

Introduction

Manually annotated data will be used for . . .

1. **Linguistic analysis**
   - Which factors determine a certain choice or interpretation?
   - Are there syntactic correlates of the container-content relation?

Introduction

Manually annotated data will be used for . . .

1. **Linguistic analysis**
   - Which factors determine a certain choice or interpretation?
   - Are there syntactic correlates of the container-content relation?
2. **Machine learning** (ML)
   - Automatic semantic annotation, e.g. for text mining
   - Extend WordNet with new entries & relations
   - Online semantic analysis in NLP pipeline (e.g. dialogue system)

Introduction

Manually annotated data will be used for . . .

1. **Linguistic analysis**
   - Which factors determine a certain choice or interpretation?
   - Are there syntactic correlates of the container-content relation?
2. **Machine learning** (ML)
   - Automatic semantic annotation, e.g. for text mining
   - Extend WordNet with new entries & relations
   - Online semantic analysis in NLP pipeline (e.g. dialogue system)

Crucial issue: **Are the annotations correct?**

☞ ML learns to make same mistakes as human annotator

☞ Inconclusive & misleading results from linguistic analysis

Validity vs. reliability

(terminology from Artstein & Poesio 2008)

- We are interested in the **validity** of the manual annotation
  - i.e. whether the annotated categories are **correct**

[1] The terms "annotator" and "coder" are used interchangeably in this talk.

Validity vs. reliability

(terminology from Artstein & Poesio 2008)

- We are interested in the **validity** of the manual annotation
  - i.e. whether the annotated categories are **correct**
- But there is no "ground truth"
  - Linguistic categories are determined by human judgement
  - Consequence: we cannot measure correctness directly

[1] The terms "annotator" and "coder" are used interchangeably in this talk.

Validity vs. reliability
(terminology from Artstein & Poesio 2008)

- We are interested in the **validity** of the manual annotation
  - i.e. whether the annotated categories are **correct**
- But there is no "ground truth"
  - Linguistic categories are determined by human judgement
  - Consequence: we cannot measure correctness directly
- Instead measure **reliability** of annotation
  - i.e. whether human coders[1] consistently make same decisions
  - Assumption: high reliability implies validity

[1] The terms "annotator" and "coder" are used interchangeably in this talk.

Validity vs. reliability
(terminology from Artstein & Poesio 2008)

- We are interested in the **validity** of the manual annotation
  - i.e. whether the annotated categories are **correct**
- But there is no "ground truth"
  - Linguistic categories are determined by human judgement
  - Consequence: we cannot measure correctness directly
- Instead measure **reliability** of annotation
  - i.e. whether human coders[1] consistently make same decisions
  - Assumption: high reliability implies validity
- How can reliability be determined?

[1] The terms "annotator" and "coder" are used interchangeably in this talk.

Inter-annotator agreement

- Multiple coders annotate same data (with same guidelines)
- Calculate **Inter-annotator agreement** (**IAA**)

Inter-annotator agreement

- Multiple coders annotate same data (with same guidelines)
- Calculate **Inter-annotator agreement** (**IAA**)

Sentence	A	B
Put tea in a heat-resistant jug and add the boiling water.	yes	yes
Where are the batteries kept in a phone?	no	yes
Vinegar's usefulness doesn't stop inside the house.	no	no
How do I recognize a room that contains radioactive materials?	yes	yes
A letterbox is a plastic, screw-top bottle that contains a small notebook and a unique rubber stamp.	yes	no

Inter-annotator agreement

- Multiple coders annotate same data (with same guidelines)
- Calculate **Inter-annotator agreement** (**IAA**)

Sentence	A	B	agree?
Put tea in a heat-resistant jug and add the boiling water.	yes	yes	✓
Where are the batteries kept in a phone?	no	yes	✗
Vinegar's usefulness doesn't stop inside the house.	no	no	✓
How do I recognize a room that contains radioactive materials?	yes	yes	✓
A letterbox is a plastic, screw-top bottle that contains a small notebook and a unique rubber stamp.	yes	no	✗

Inter-annotator agreement

- Multiple coders annotate same data (with same guidelines)
- Calculate **Inter-annotator agreement** (**IAA**)

Sentence	A	B	agree?
Put tea in a heat-resistant jug and add the boiling water.	yes	yes	✓
Where are the batteries kept in a phone?	no	yes	✗
Vinegar's usefulness doesn't stop inside the house.	no	no	✓
How do I recognize a room that contains radioactive materials?	yes	yes	✓
A letterbox is a plastic, screw-top bottle that contains a small notebook and a unique rubber stamp.	yes	no	✗

➥ Observed agreement between A and B is 60%

Easy & hard tasks

(Brants 2000 for German POS/syntax, Véronis 1998 for WSD)

Objective tasks

- Decision rules, linguistic tests
- Annotation guidelines with discussion of boundary cases
- POS tagging, syntactic annotation, segmentation, phonetic transcription, . . .

Easy & hard tasks

(Brants 2000 for German POS/syntax, Véronis 1998 for WSD)

Objective tasks

- Decision rules, linguistic tests
- Annotation guidelines with discussion of boundary cases
- POS tagging, syntactic annotation, segmentation, phonetic transcription, ...

Subjective tasks

- Based on speaker intuitions
- Short annotation instructions
- Lexical semantics (subjective interpretation!), discourse annotation & pragmatics, subjectivity analysis, ...

Easy & hard tasks

(Brants 2000 for German POS/syntax, Véronis 1998 for WSD)

Objective tasks

- Decision rules, linguistic tests
- Annotation guidelines with discussion of boundary cases
- POS tagging, syntactic annotation, segmentation, phonetic transcription, ...

➥ IAA = 98.5% (POS tagging)
IAA ≈ 93.0% (syntax)

Subjective tasks

- Based on speaker intuitions
- Short annotation instructions
- Lexical semantics (subjective interpretation!), discourse annotation & pragmatics, subjectivity analysis, ...

[NB: error rates around 5% are considered acceptable for most purposes]

Easy & hard tasks

(Brants 2000 for German POS/syntax, Véronis 1998 for WSD)

Objective tasks

- Decision rules, linguistic tests
- Annotation guidelines with discussion of boundary cases
- POS tagging, syntactic annotation, segmentation, phonetic transcription, ...

➥ IAA = 98.5% (POS tagging)
IAA ≈ 93.0% (syntax)

Subjective tasks

- Based on speaker intuitions
- Short annotation instructions
- Lexical semantics (subjective interpretation!), discourse annotation & pragmatics, subjectivity analysis, ...

➥ IAA = $\frac{48}{70}$ = 68.6% (HW)
IAA ≈ 70% (word senses)

[NB: error rates around 5% are considered acceptable for most purposes]

☞ Is 70% agreement good enough?

Outline

Thought experiment 1

- Assume that A and B are lazy annotators, so they just marked sentences randomly as “yes” and “no”

  [or they enjoyed too much sun & Bordeaux wine yesterday]
- How much agreement would you expect?

Thought experiment 1

- Assume that A and B are lazy annotators, so they just marked sentences randomly as "yes" and "no"

  [or they enjoyed too much sun & Bordeaux wine yesterday]
- How much agreement would you expect?
- Annotator decisions are like coin tosses:

Thought experiment 1

- Assume that A and B are lazy annotators, so they just marked sentences randomly as “yes” and “no”

  [or they enjoyed too much sun & Bordeaux wine yesterday]
- How much agreement would you expect?

- Annotator decisions are like coin tosses:

  25% both coders randomly choose “yes” $(= 0.5 \cdot 0.5)$

Thought experiment 1

- Assume that A and B are lazy annotators, so they just marked sentences randomly as "yes" and "no"

  [or they enjoyed too much sun & Bordeaux wine yesterday]

- How much agreement would you expect?

- Annotator decisions are like coin tosses:

  25% both coders randomly choose "yes" ($= 0.5 \cdot 0.5$)

  25% both coders randomly choose "no" ($= 0.5 \cdot 0.5$)

Thought experiment 1

- Assume that A and B are lazy annotators, so they just marked sentences randomly as "yes" and "no"

  [or they enjoyed too much sun & Bordeaux wine yesterday]
- How much agreement would you expect?

- Annotator decisions are like coin tosses:

25%	both coders randomly choose "yes" $(= 0.5 \cdot 0.5)$
25%	both coders randomly choose "no" $(= 0.5 \cdot 0.5)$
50%	agreement purely by chance

Thought experiment 1

- Assume that A and B are lazy annotators, so they just marked sentences randomly as “yes” and “no”

  [or they enjoyed too much sun & Bordeaux wine yesterday]
- How much agreement would you expect?

- Annotator decisions are like coin tosses:

25%	both coders randomly choose “yes” $(= 0.5 \cdot 0.5)$
25%	both coders randomly choose “no” $(= 0.5 \cdot 0.5)$
50%	agreement purely by chance

➥ IAA = 70% is only mildly better than chance agreement

But 90% agreement is certainly a good result?

☞ i.e. it indicates high reliability

Thought experiment 2

- Assume A and B are lazy coders with a proactive approach
  - They believe that their task is to find as many examples of container-content pairs as possible to make us happy
  - So they mark 95% of sentences with "yes"
  - But individual choices are still random
- How much agreement would you expect now?

Thought experiment 2

- Assume A and B are lazy coders with a proactive approach
  - They believe that their task is to find as many examples of container-content pairs as possible to make us happy
  - So they mark 95% of sentences with “yes”
  - But individual choices are still random
- How much agreement would you expect now?
- Annotator decisions are like tosses of a biased coin:

Thought experiment 2

- Assume A and B are lazy coders with a proactive approach
  - They believe that their task is to find as many examples of container-content pairs as possible to make us happy
  - So they mark 95% of sentences with "yes"
  - But individual choices are still random
- How much agreement would you expect now?
- Annotator decisions are like tosses of a biased coin:

0.25%	both coders randomly choose "no" ($= .05 \cdot .05$)

Thought experiment 2

- Assume A and B are lazy coders with a proactive approach
  - They believe that their task is to find as many examples of container-content pairs as possible to make us happy
  - So they mark 95% of sentences with "yes"
  - But individual choices are still random
- How much agreement would you expect now?

- Annotator decisions are like tosses of a biased coin:

90.25%	both coders randomly choose "yes" $(= .95 \cdot .95)$
0.25%	both coders randomly choose "no" $(= .05 \cdot .05)$

Thought experiment 2

- Assume A and B are lazy coders with a proactive approach
  - They believe that their task is to find as many examples of container-content pairs as possible to make us happy
  - So they mark 95% of sentences with "yes"
  - But individual choices are still random
- How much agreement would you expect now?

- Annotator decisions are like tosses of a biased coin:

90.25%	both coders randomly choose "yes" ($= .95 \cdot .95$)
0.25%	both coders randomly choose "no" ($= .05 \cdot .05$)
90.50%	agreement purely by chance

Thought experiment 2

- Assume A and B are lazy coders with a proactive approach
  - They believe that their task is to find as many examples of container-content pairs as possible to make us happy
  - So they mark 95% of sentences with “yes”
  - But individual choices are still random
- How much agreement would you expect now?

- Annotator decisions are like tosses of a biased coin:

90.25%	both coders randomly choose “yes” ($= .95 \cdot .95$)
0.25%	both coders randomly choose “no” ($= .05 \cdot .05$)
90.50%	agreement purely by chance

➥ IAA $=$ 90% might be no more than chance agreement

Measuring inter-annotator agreement

(notation follows Artstein & Poesio 2008)

Agreement measures must be corrected for **chance agreement**!
(for computational linguistics: Carletta 1996)

Measuring inter-annotator agreement

(notation follows Artstein & Poesio 2008)

Agreement measures must be corrected for **chance agreement**!
(for computational linguistics: Carletta 1996)

Notation: A_o ... observed (or "percentage") agreement
A_e ... expected agreement by chance

Measuring inter-annotator agreement

(notation follows Artstein & Poesio 2008)

Agreement measures must be corrected for **chance agreement**!
(for computational linguistics: Carletta 1996)

Notation: A_o . . . observed (or "percentage") agreement
A_e . . . expected agreement by chance

General form of chance-corrected agreement measure R:

$$R = \frac{}{}$$

Measuring inter-annotator agreement

(notation follows Artstein & Poesio 2008)

Agreement measures must be corrected for **chance agreement**!
(for computational linguistics: Carletta 1996)

Notation: A_o . . . observed (or "percentage") agreement
A_e . . . expected agreement by chance

General form of chance-corrected agreement measure R:

$$R = \frac{A_o - A_e}{}$$

Measuring inter-annotator agreement

(notation follows Artstein & Poesio 2008)

Agreement measures must be corrected for **chance agreement**!
(for computational linguistics: Carletta 1996)

Notation: A_o ... observed (or "percentage") agreement
A_e ... expected agreement by chance

General form of chance-corrected agreement measure R:

$$R = \frac{A_o - A_e}{1 - A_e}$$

Measuring inter-annotator agreement

Some general properties of R:

Measuring inter-annotator agreement

Some general properties of R:

- Perfect agreement: $R = 1 = \dfrac{1 - A_e}{1 - A_e}$

Measuring inter-annotator agreement

Some general properties of R:

- Perfect agreement: $R = 1 = \dfrac{1 - A_e}{1 - A_e}$
- Chance agreement: $R = 0 = \dfrac{A_e - A_e}{1 - A_e}$

Measuring inter-annotator agreement

Some general properties of R:

- Perfect agreement: $R = 1 = \dfrac{1 - A_e}{1 - A_e}$
- Chance agreement: $R = 0 = \dfrac{A_e - A_e}{1 - A_e}$
- Perfect disagreement: $R = \dfrac{-A_e}{1 - A_e}$

Measuring inter-annotator agreement

Some general properties of R:

- Perfect agreement: $R = 1 = \frac{1 - A_e}{1 - A_e}$
- Chance agreement: $R = 0 = \frac{A_e - A_e}{1 - A_e}$
- Perfect disagreement: $R = \frac{-A_e}{1 - A_e}$

Various agreement measures depending on precise definition of A_e:

Measuring inter-annotator agreement

Some general properties of R:

- Perfect agreement: $R = 1 = \dfrac{1 - A_e}{1 - A_e}$
- Chance agreement: $R = 0 = \dfrac{A_e - A_e}{1 - A_e}$
- Perfect disagreement: $R = \dfrac{-A_e}{1 - A_e}$

Various agreement measures depending on precise definition of A_e:

- $R = S$ for random coin tosses (Bennett *et al.* 1954)

Measuring inter-annotator agreement

Some general properties of R:

- Perfect agreement: $R = 1 = \dfrac{1 - A_e}{1 - A_e}$
- Chance agreement: $R = 0 = \dfrac{A_e - A_e}{1 - A_e}$
- Perfect disagreement: $R = \dfrac{-A_e}{1 - A_e}$

Various agreement measures depending on precise definition of A_e:

- $R = S$ for random coin tosses (Bennett *et al.* 1954)
- $R = \pi$ for shared category distribution (Scott 1955)

Measuring inter-annotator agreement

Some general properties of R:

- Perfect agreement: $R = 1 = \frac{1 - A_e}{1 - A_e}$
- Chance agreement: $R = 0 = \frac{A_e - A_e}{1 - A_e}$
- Perfect disagreement: $R = \frac{-A_e}{1 - A_e}$

Various agreement measures depending on precise definition of A_e:

- $R = S$ for random coin tosses (Bennett *et al.* 1954)
- $R = \pi$ for shared category distribution (Scott 1955)
- $R = \kappa$ for individual category distributions (Cohen 1960)

Outline

Contingency tables for annotator agreement

	coder B		
coder A	yes	no	
yes	24	8	
no	14	24	

Contingency tables for annotator agreement

	coder B		
coder A	yes	no	
yes	24	8	
no	14	24	

Contingency tables for annotator agreement

coder A	coder B: yes	coder B: no	
yes	24	8	32
no	14	24	38

Contingency tables for annotator agreement

	coder B		
coder A	yes	no	
yes	24	8	32
no	14	24	38
	38	32	

Contingency tables for annotator agreement

	coder B		
coder A	yes	no	
yes	24	8	32
no	14	24	38
	38	32	70

Contingency tables for annotator agreement

coder A	coder B: yes	coder B: no	
yes	24	8	32
no	14	24	38
	38	32	70

coder A	coder B: yes	coder B: no	
yes	n_{11}	n_{12}	$n_{1\cdot}$
no	n_{21}	n_{22}	$n_{2\cdot}$
	$n_{\cdot 1}$	$n_{\cdot 2}$	N

Contingency tables for annotator agreement

coder A	coder B: yes	coder B: no	
yes	24	8	32
no	14	24	38
	38	32	70

coder A	coder B: yes	coder B: no	
yes	n_{11}	n_{12}	$n_{1\cdot}$
no	n_{21}	n_{22}	$n_{2\cdot}$
	$n_{\cdot 1}$	$n_{\cdot 2}$	N

coder A	coder B: yes	coder B: no	
yes	.343	.114	.457
no	.200	.343	.543
	.543	.457	1

coder A	coder B: yes	coder B: no	
yes	p_{11}	p_{12}	$p_{1\cdot}$
no	p_{21}	p_{22}	$p_{2\cdot}$
	$p_{\cdot 1}$	$p_{\cdot 2}$	p

Contingency tables for annotator agreement

Contingency table of **proportions** $p_{ij} = \frac{n_{ij}}{N}$

coder A	coder B: yes	no	
yes	.343	.114	.457
no	.200	.343	.543
	.543	.457	1

coder A	coder B: yes	no	
yes	p_{11}	p_{12}	$p_{1\cdot}$
no	p_{21}	p_{22}	$p_{2\cdot}$
	$p_{\cdot 1}$	$p_{\cdot 2}$	p

Relevant information can be read off from contingency table:

Contingency tables for annotator agreement

Contingency table of **proportions** $p_{ij} = \frac{n_{ij}}{N}$

coder A	coder B yes	no	
yes	.343	.114	.457
no	.200	.343	.543
	.543	.457	1

coder A	coder B yes	no	
yes	p_{11}	p_{12}	$p_{1\cdot}$
no	p_{21}	p_{22}	$p_{2\cdot}$
	$p_{\cdot 1}$	$p_{\cdot 2}$	p

Relevant information can be read off from contingency table:

- Observed agreement $A_o = p_{11} + p_{22} = .686$

Contingency tables for annotator agreement

Contingency table of **proportions** $p_{ij} = \frac{n_{ij}}{N}$

coder A	coder B: yes	no	
yes	.343	.114	.457
no	.200	.343	.543
	.543	.457	1

coder A	coder B: yes	no	
yes	p_{11}	p_{12}	$p_{1\cdot}$
no	p_{21}	p_{22}	$p_{2\cdot}$
	$p_{\cdot 1}$	$p_{\cdot 2}$	p

Relevant information can be read off from contingency table:

- Observed agreement $A_o = p_{11} + p_{22} = .686$
- Category distribution for coder A: $p_{i\cdot} = p_{i1} + p_{i2}$

Contingency tables for annotator agreement

Contingency table of **proportions** $p_{ij} = \dfrac{n_{ij}}{N}$

coder A	coder B: yes	coder B: no	
yes	.343	.114	.457
no	.200	.343	.543
	.543	.457	1

coder A	coder B: yes	coder B: no	
yes	p_{11}	p_{12}	$p_{1\cdot}$
no	p_{21}	p_{22}	$p_{2\cdot}$
	$p_{\cdot 1}$	$p_{\cdot 2}$	p

Relevant information can be read off from contingency table:

- Observed agreement $A_o = p_{11} + p_{22} = .686$
- Category distribution for coder A: $p_{i\cdot} = p_{i1} + p_{i2}$
- Category distribution for coder B: $p_{\cdot j} = p_{1j} + p_{2j}$

Outline

Calculating the expected chance agreement

- How often are annotators expected to agree if they make random choices according to their category distributions?

coder A	coder B yes	no	
yes			.457
no			.543
	.543	.457	1

coder A	coder B yes	no	
yes			$p_{1\cdot}$
no			$p_{2\cdot}$
	$p_{\cdot 1}$	$p_{\cdot 2}$	p

Calculating the expected chance agreement

- How often are annotators expected to agree if they make random choices according to their category distributions?
- Decisions of annotators are independent ➜ multiply marginals

coder A	coder B: yes	no	
yes			.457
no			.543
	.543	.457	1

coder A	coder B: yes	no	
yes	$p_{1\cdot} \cdot p_{\cdot 1}$	$p_{1\cdot} \cdot p_{\cdot 2}$	$p_{1\cdot}$
no	$p_{2\cdot} \cdot p_{\cdot 1}$	$p_{2\cdot} \cdot p_{\cdot 2}$	$p_{2\cdot}$
	$p_{\cdot 1}$	$p_{\cdot 2}$	p

Calculating the expected chance agreement

- How often are annotators expected to agree if they make random choices according to their category distributions?
- Decisions of annotators are independent ➜ multiply marginals

	coder B		
coder A	yes	no	
yes	.248	.209	.457
no	.295	.248	.543
	.543	.457	1

	coder B		
coder A	yes	no	
yes	$p_{1\cdot} \cdot p_{\cdot 1}$	$p_{1\cdot} \cdot p_{\cdot 2}$	$p_{1\cdot}$
no	$p_{2\cdot} \cdot p_{\cdot 1}$	$p_{2\cdot} \cdot p_{\cdot 2}$	$p_{2\cdot}$
	$p_{\cdot 1}$	$p_{\cdot 2}$	p

Calculating the expected chance agreement

- How often are annotators expected to agree if they make random choices according to their category distributions?
- Decisions of annotators are independent ➜ multiply marginals

coder A	coder B yes	no	
yes	.248	.209	.457
no	.295	.248	.543
	.543	.457	1

coder A	coder B yes	no	
yes	$p_{1\cdot} \cdot p_{\cdot 1}$	$p_{1\cdot} \cdot p_{\cdot 2}$	$p_{1\cdot}$
no	$p_{2\cdot} \cdot p_{\cdot 1}$	$p_{2\cdot} \cdot p_{\cdot 2}$	$p_{2\cdot}$
	$p_{\cdot 1}$	$p_{\cdot 2}$	p

➥ Expected chance agreement:

$$A_e = p_{1\cdot} \cdot p_{\cdot 1} + p_{2\cdot} \cdot p_{\cdot 2} = 49.6\%$$

Sanity check: Is it plausible to assume that annotators always flip coins?

Sanity check: Is it plausible to assume that annotators always flip coins?

- No need to make such strong assumptions
- Annotations of individual coders may well be systematic
- We only require that choices of A and B are **statistically independent**, i.e. no common ground for their decisions

Definition of the Kappa coefficient
(Cohen 1960)

Formal definition of the **Kappa** coefficient:

$$A_o = p_{11} + p_{22}$$

$$A_e = p_{1\cdot} \cdot p_{\cdot 1} + p_{2\cdot} \cdot p_{\cdot 2}$$

$$\kappa = \frac{A_o - A_e}{1 - A_e}$$

Definition of the Kappa coefficient
(Cohen 1960)

Formal definition of the **Kappa** coefficient:

$$A_o = p_{11} + p_{22}$$

$$A_e = p_{1\cdot} \cdot p_{\cdot 1} + p_{2\cdot} \cdot p_{\cdot 2}$$

$$\kappa = \frac{A_o - A_e}{1 - A_e}$$

In our example:

$$A_o = .343 + .343 = .686$$

$$A_e = .248 + .248 = .496$$

$$\kappa = \frac{.686 - .496}{1 - .496} = 0.376 \text{ !!}$$

Other agreement measures

(Scott 1955; Bennett *et al.* 1954)

1. π estimates a common category distribution $\bar{p}_i$
   - goal is to measure chance agreement between arbitrary coders, while κ focuses on a specific pair of coders

$$A_e = (\bar{p}_1)^2 + (\bar{p}_2)^2$$
$$\bar{p}_i = \frac{1}{2}(p_{i\cdot} + p_{\cdot i})$$

Other agreement measures

(Scott 1955; Bennett *et al.* 1954)

1. π estimates a common category distribution $\bar{p}_i$
   - goal is to measure chance agreement between arbitrary coders, while κ focuses on a specific pair of coders

$$A_e = (\bar{p}_1)^2 + (\bar{p}_2)^2$$
$$\bar{p}_i = \tfrac{1}{2}(p_{i\cdot} + p_{\cdot i})$$

2. S assumes that coders actually flip coins ...
   - i.e. equiprobable category distribution $\bar{p}_1 = \bar{p}_2 = \frac{1}{2}$

$$A_e = \frac{1}{2}$$

Other agreement measures

(Scott 1955; Bennett *et al.* 1954)

1. π estimates a common category distribution $\bar{p}_i$
   - goal is to measure chance agreement between arbitrary coders, while κ focuses on a specific pair of coders

$$A_e = (\bar{p}_1)^2 + (\bar{p}_2)^2$$

$$\bar{p}_i = \tfrac{1}{2}(p_{i\cdot} + p_{\cdot i})$$

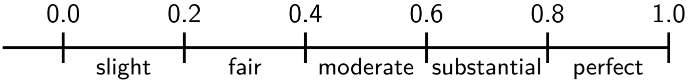
2. S assumes that coders actually flip coins …
   - i.e. equiprobable category distribution $\bar{p}_1 = \bar{p}_2 = \frac{1}{2}$

$$A_e = \frac{1}{2}$$

Much controversy whether π or κ is the more appropriate measure, but in practice they often lead to similar agreement values!

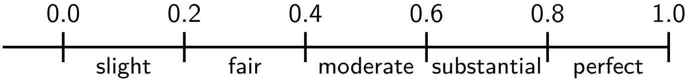
Scales for the interpretation of Kappa

- Landis & Koch (1977)

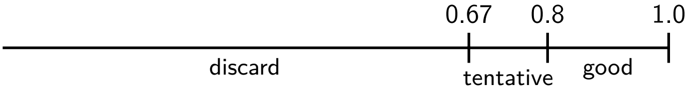


Scales for the interpretation of Kappa

- Landis & Koch (1977)

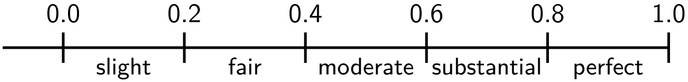


- Krippendorff (1980)

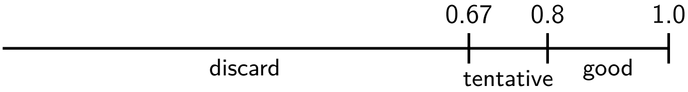


Scales for the interpretation of Kappa

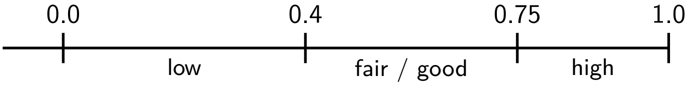
- Landis & Koch (1977)



- Krippendorff (1980)

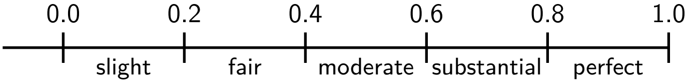


- Green (1997)

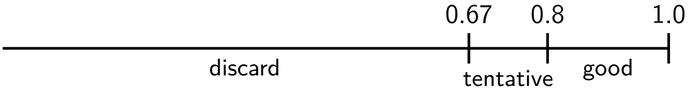


Scales for the interpretation of Kappa

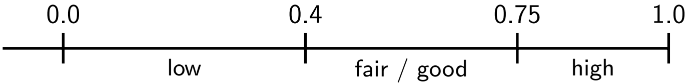
- Landis & Koch (1977)



- Krippendorff (1980)



- Green (1997)



- and many other suggestions . . .

Outline

An example from Di Eugenio & Glass (2004)

coder A	coder B yes	no	
yes	70	25	95
no	0	55	55
	70	80	150

An example from Di Eugenio & Glass (2004)

coder A	coder B: yes	no	
yes	70	25	95
no	0	55	55
	70	80	150

coder A	coder B: yes	no	
yes	.467	.167	.633
no	.000	.367	.367
	.467	.533	1

An example from Di Eugenio & Glass (2004)

coder A	coder B yes	coder B no	
yes	70	25	95
no	0	55	55
	70	80	150

coder A	coder B yes	coder B no	
yes	.467	.167	.633
no	.000	.367	.367
	.467	.533	1

- Cohen (1960): $A_o = .833$, $A_e = .491$, $\kappa = .672$

An example from Di Eugenio & Glass (2004)

coder A	coder B yes	no	
yes	70	25	95
no	0	55	55
	70	80	150

coder A	coder B yes	no	
yes	.467	.167	.633
no	.000	.367	.367
	.467	.533	1

- Cohen (1960): $A_o = .833$, $A_e = .491$, $\kappa = .672$
- Scott (1955): $A_o = .833$, $A_e = .505$, $\pi = .663$

An example from Di Eugenio & Glass (2004)

coder A	coder B yes	coder B no	
yes	70	25	95
no	0	55	55
	70	80	150

coder A	coder B yes	coder B no	
yes	.467	.167	.633
no	.000	.367	.367
	.467	.533	1

- Cohen (1960): $A_o = .833$, $A_e = .491$, $\kappa = .672$
- Scott (1955): $A_o = .833$, $A_e = .505$, $\pi = .663$
- ➥ Krippendorff (1980): data show tentative agreement according to κ, but should be discarded according to π

An example from Di Eugenio & Glass (2004)

coder A	coder B yes	coder B no	
yes	70	25	95
no	0	55	55
	70	80	150

coder A	coder B yes	coder B no	
yes	.467	.167	.633
no	.000	.367	.367
	.467	.533	1

- Cohen (1960): $A_o = .833$, $A_e = .491$, $\kappa = .672$
- Scott (1955): $A_o = .833$, $A_e = .505$, $\pi = .663$

➥ Krippendorff (1980): data show tentative agreement according to κ, but should be discarded according to π

☞ What do you think?

More samples from the same annotators . . .

	coder B		
coder A	yes	no	
yes	70	25	95
no	0	55	55
	70	80	150

$A_0 = .833$

$\kappa = .672 \quad (A_e = .491)$

$\pi = .663 \quad (A_e = .505)$

More samples from the same annotators ...

coder A	coder B: yes	no	
yes	67	24	91
no	2	57	59
	69	81	150

$$A_0 = .827$$
$$\kappa = .659 \quad (A_e = .491)$$
$$\pi = .652 \quad (A_e = .502)$$

More samples from the same annotators . . .

	coder B		
coder A	yes	no	
yes	70	20	90
no	4	56	60
	74	76	150

$$A_0 = .840$$
$$\kappa = .681 \quad (A_e = .499)$$
$$\pi = .677 \quad (A_e = .504)$$

More samples from the same annotators ...

coder A	coder B yes	no	
yes	70	20	90
no	4	56	60
	74	76	150

$A_0 = .840$

$\kappa = .681 \quad (A_e = .499)$

$\pi = .677 \quad (A_e = .504)$

We are not interested in a particular sample, but rather want to know how often coders agree in general (for this task).

➥ **Sampling variation** of κ

[NB: A_e is *expected* chance agreement, not value in specific sample]

Outline

Kappa is a sample statistic $\hat{\kappa}$

	$+$	$-$
$+$	π_{11}	π_{12}
$-$	π_{21}	π_{22}

population

$$\alpha_o = \pi_{11} + \pi_{12}$$
$$\alpha_e = \pi_{1\cdot} \cdot \pi_{\cdot 1} + \pi_{2\cdot} \cdot \pi_{\cdot 2}$$
$$\kappa = \frac{\alpha_o - \alpha_e}{1 - \alpha_e}$$

	$+$	$-$
$+$	p_{11}	p_{12}
$-$	p_{21}	p_{22}

sample

$$A_o = p_{11} + p_{12}$$
$$A_e = p_{1\cdot} \cdot p_{\cdot 1} + p_{2\cdot} \cdot p_{\cdot 2}$$
$$\hat{\kappa} = \frac{A_o - A_e}{1 - A_e}$$

Sampling variation of $\hat{\kappa}$

(Fleiss *et al.* 1969; Krenn *et al.* 2004)

- Standard approach: show (or hope) that $\hat{\kappa}$ approximately follows Gaussian distribution if samples are large enough

Sampling variation of $\hat{\kappa}$

(Fleiss *et al.* 1969; Krenn *et al.* 2004)

- Standard approach: show (or hope) that $\hat{\kappa}$ approximately follows Gaussian distribution if samples are large enough
- Show (or hope) that $\hat{\kappa}$ is unbiased estimator: $\mathrm{E}[\hat{\kappa}] = \kappa$

Sampling variation of $\hat{\kappa}$

(Fleiss *et al.* 1969; Krenn *et al.* 2004)

- Standard approach: show (or hope) that $\hat{\kappa}$ approximately follows Gaussian distribution if samples are large enough
- Show (or hope) that $\hat{\kappa}$ is unbiased estimator: $\mathrm{E}[\hat{\kappa}] = \kappa$
- Compute standard deviation of $\hat{\kappa}$ (Fleiss *et al.* 1969: 325):

$$(\hat{\sigma}_{\hat{\kappa}})^2 = \frac{1}{N \cdot (1 - A_e)^4} \cdot \left(\sum_{i=1}^{2} p_{ii} \Big[(1 - A_e) - (p_{\cdot i} + p_{i \cdot})(1 - A_o) \Big]^2 + (1 - A_o)^2 \sum_{i \neq j} p_{ij} (p_{\cdot i} + p_{j \cdot})^2 - (A_o A_e - 2A_e + A_o)^2 \right)$$

Sampling variation of $\hat{\kappa}$

(Lee & Tu 1994; Boleda & Evert unfinished)

- Asymptotic 95% confidence interval:

$$\kappa \in \left[\hat{\kappa} - 1.96 \cdot \hat{\sigma}_{\hat{\kappa}},\ \hat{\kappa} + 1.96 \cdot \hat{\sigma}_{\hat{\kappa}}\right]$$

Sampling variation of $\hat{\kappa}$

(Lee & Tu 1994; Boleda & Evert unfinished)

- Asymptotic 95% confidence interval:

$$\kappa \in \left[\hat{\kappa} - 1.96 \cdot \hat{\sigma}_{\hat{\kappa}},\ \hat{\kappa} + 1.96 \cdot \hat{\sigma}_{\hat{\kappa}}\right]$$

- For the example from Di Eugenio & Glass (2004), we have

$$\kappa \in [0.562, 0.783] \quad \text{with} \quad \hat{\sigma}_{\hat{\kappa}} = .056$$

➥ comparison with threshold .067 is pointless!

Sampling variation of $\hat{\kappa}$

(Lee & Tu 1994; Boleda & Evert unfinished)

- Asymptotic 95% confidence interval:

$$\kappa \in \left[\hat{\kappa} - 1.96 \cdot \hat{\sigma}_{\hat{\kappa}},\ \hat{\kappa} + 1.96 \cdot \hat{\sigma}_{\hat{\kappa}}\right]$$

- For the example from Di Eugenio & Glass (2004), we have

$$\kappa \in \left[0.562, 0.783\right] \quad \text{with} \quad \hat{\sigma}_{\hat{\kappa}} = .056$$

➥ comparison with threshold .067 is pointless!

- How accurate is the Gaussian approximation?
  - Simulation experiments indicate biased $\hat{\kappa}$, underestimation of $\hat{\sigma}_{\hat{\kappa}}$ and non-Gaussian distribution for skewed marginals
  - Confidence intervals are reasonable for larger samples

Sampling variation of $\hat{\kappa}$

(Lee & Tu 1994; Boleda & Evert unfinished)

- Asymptotic 95% confidence interval:

$$\kappa \in \left[\hat{\kappa} - 1.96 \cdot \hat{\sigma}_{\hat{\kappa}},\ \hat{\kappa} + 1.96 \cdot \hat{\sigma}_{\hat{\kappa}}\right]$$

- For the example from Di Eugenio & Glass (2004), we have

$$\kappa \in \left[0.562, 0.783\right] \quad \text{with} \quad \hat{\sigma}_{\hat{\kappa}} = .056$$

➥ comparison with threshold .067 is pointless!

- How accurate is the Gaussian approximation?
  - Simulation experiments indicate biased $\hat{\kappa}$, underestimation of $\hat{\sigma}_{\hat{\kappa}}$ and non-Gaussian distribution for skewed marginals
  - Confidence intervals are reasonable for larger samples
- Recent work on improved estimates (e.g. Lee & Tu 1994)

Outline

Extensions of Kappa: Multiple categories

- Straightforward extension to $C > 2$ categories
  ➜ $C \times C$ contingency table of proportions p_{ij}

Extensions of Kappa: Multiple categories

- Straightforward extension to $C > 2$ categories
  ➜ $C \times C$ contingency table of proportions p_{ij}
- Observed agreement: $A_o = \sum_{i=1}^{C} p_{ii}$

Extensions of Kappa: Multiple categories

- Straightforward extension to $C > 2$ categories
  ➜ $C \times C$ contingency table of proportions p_{ij}
- Observed agreement: $A_o = \sum_{i=1}^{C} p_{ii}$
- Expected agreement: $A_e = \sum_{i=1}^{C} p_{i\cdot} \cdot p_{\cdot i}$

Extensions of Kappa: Multiple categories

- Straightforward extension to $C > 2$ categories
  ➜ $C \times C$ contingency table of proportions p_{ij}
- Observed agreement: $A_o = \sum_{i=1}^{C} p_{ii}$
- Expected agreement: $A_e = \sum_{i=1}^{C} p_{i\cdot} \cdot p_{\cdot i}$
- Kappa: $\hat{\kappa} = \dfrac{A_o - A_e}{1 - A_e}$
- Equation for $\hat{\sigma}_{\hat{\kappa}}$ also extends to C categories

Extensions of Kappa: Multiple categories

- Straightforward extension to $C > 2$ categories
  ➜ $C \times C$ contingency table of proportions p_{ij}
- Observed agreement: $A_o = \sum_{i=1}^{C} p_{ii}$
- Expected agreement: $A_e = \sum_{i=1}^{C} p_{i\cdot} \cdot p_{\cdot i}$
- Kappa: $\hat{\kappa} = \dfrac{A_o - A_e}{1 - A_e}$
- Equation for $\hat{\sigma}_{\hat{\kappa}}$ also extends to C categories
- Drawback: $\hat{\kappa}$ only uses diagonal and marginals of table, discarding most information from the off-diagonal cells

Extensions of Kappa: Weighted Kappa

- For multiple categories, some disagreements may be more "serious" than others ➜ assign greater weight
- E.g. German PP-verb combinations (Krenn *et al.* 2004)
  1. figurative expressions (collocational)
  2. support-verb constructions (collocational)
  3. free combinations (non-collocational)

Extensions of Kappa: Weighted Kappa

- For multiple categories, some disagreements may be more "serious" than others ➜ assign greater weight
- E.g. German PP-verb combinations (Krenn *et al.* 2004)
  1. figurative expressions (collocational)
  2. support-verb constructions (collocational)
  3. free combinations (non-collocational)
- Rewrite $\hat{\kappa}$ in terms of expected/observed **disagreement**

Extensions of Kappa: Weighted Kappa

- For multiple categories, some disagreements may be more "serious" than others ➜ assign greater weight
- E.g. German PP-verb combinations (Krenn *et al.* 2004)
  1. figurative expressions (collocational)
  2. support-verb constructions (collocational)
  3. free combinations (non-collocational)
- Rewrite $\hat{\kappa}$ in terms of expected/observed **disagreement**

$$\hat{\kappa} = \frac{(1 - D_o) - (1 - D_e)}{1 - (1 - D_e)} = 1 - \frac{D_o}{D_e}$$

Extensions of Kappa: Weighted Kappa

- For multiple categories, some disagreements may be more "serious" than others ➜ assign greater weight
- E.g. German PP-verb combinations (Krenn *et al.* 2004)
  1. figurative expressions (collocational)
  2. support-verb constructions (collocational)
  3. free combinations (non-collocational)
- Rewrite $\hat{\kappa}$ in terms of expected/observed **disagreement**

$$\hat{\kappa} = \frac{(1 - D_o) - (1 - D_e)}{1 - (1 - D_e)} = 1 - \frac{D_o}{D_e}$$

$$D_o = 1 - A_o = \sum_{i \neq j} p_{ij}$$

Extensions of Kappa: Weighted Kappa

- For multiple categories, some disagreements may be more "serious" than others ➜ assign greater weight
- E.g. German PP-verb combinations (Krenn *et al.* 2004)
  1. figurative expressions (collocational)
  2. support-verb constructions (collocational)
  3. free combinations (non-collocational)
- Rewrite $\hat{\kappa}$ in terms of expected/observed **disagreement**

$$\hat{\kappa} = \frac{(1 - D_o) - (1 - D_e)}{1 - (1 - D_e)} = 1 - \frac{D_o}{D_e}$$

$$D_o = 1 - A_o = \sum_{i \neq j} p_{ij}$$

$$D_e = 1 - A_e = \sum_{i \neq j} p_{i\cdot} \cdot p_{\cdot j}$$

Extensions of Kappa: Weighted Kappa

- For multiple categories, some disagreements may be more "serious" than others ➜ assign greater weight
- E.g. German PP-verb combinations (Krenn *et al.* 2004)
  1. figurative expressions (collocational)
  2. support-verb constructions (collocational)
  3. free combinations (non-collocational)
- Rewrite $\hat{\kappa}$ in terms of expected/observed **disagreement**

$$\hat{\kappa} = \frac{(1 - D_o) - (1 - D_e)}{1 - (1 - D_e)} = 1 - \frac{D_o}{D_e}$$

$$D_o = 1 - A_o = \sum_{i \neq j} p_{ij} \rightsquigarrow \sum_{i \neq j} w_{ij} p_{ij}$$

$$D_e = 1 - A_e = \sum_{i \neq j} p_{i\cdot} \cdot p_{\cdot j} \rightsquigarrow \sum_{i \neq j} w_{ij} (p_{i\cdot} \cdot p_{\cdot j})$$

Extensions of Kappa: Multiple annotators

(Krenn *et al.* 2004)

- Naive strategy: compare each annotator against selected "expert", or consensus annotation after reconciliation phase

BK vs. NN	kappa value	homogeneity min	homogeneity max	interval size
7	.775	71.93%	82.22%	10.29
9	.747	68.65%	79.77%	11.12
10	.700	64.36%	75.85%	11.49
4	.696	64.09%	75.91%	11.82
1	.692	63.39%	75.91%	12.52
6	.671	61.05%	73.33%	12.28
5	.669	60.12%	72.75%	12.63
2	.639	56.14%	70.64%	14.50
11	.592	52.40%	65.65%	13.25
3	.520	51.70%	64.33%	12.63
8	.341	33.68%	49.71%	16.03
12	.265	17.00%	35.05%	18.05

Extensions of Kappa: Multiple annotators

- Better approach: compute $\hat{\kappa}$ for each possible pair of annotators, then report average and standard deviation

Extensions of Kappa: Multiple annotators

- Better approach: compute $\hat{\kappa}$ for each possible pair of annotators, then report average and standard deviation

- Extensions of agreement coefficients to multiple annotators are mathematical implementations of this basic idea (see Artstein & Poesio 2008 for details)

Extensions of Kappa: Multiple annotators

- Better approach: compute $\hat{\kappa}$ for each possible pair of annotators, then report average and standard deviation
- Extensions of agreement coefficients to multiple annotators are mathematical implementations of this basic idea (see Artstein & Poesio 2008 for details)
- If sufficiently many coders (= test subjects) are available, annotation can be analysed as psycholinguistic experiment
  - ANOVA, logistic regression, generalised linear models
  - correlations between annotators ➜ systematic disagreement

Outline

Different types of non-reliability

1. Random errors (slips)
   - Lead to chance agreement between annotators

Different types of non-reliability

1. Random errors (slips)
   - Lead to chance agreement between annotators
2. Different intuitions
   - Systematic disagreement

Different types of non-reliability

1. Random errors (slips)
    - Lead to chance agreement between annotators
2. Different intuitions
    - Systematic disagreement
3. Misinterpretation of tagging guidelines
    - May not result in disagreement ➜ not detected

Suggested reading & materials

Artstein & Poesio (2008)

Everyone should at least read this article.

R package `irr` (inter-rater reliability)

Lacks confidence intervals ➜ *to be included in* `corpora` *package.*

References I

Artstein, Ron and Poesio, Massimo (2008). Survey article: Inter-coder agreement for computational linguistics. *Computational Linguistics*, **34**(4), 555–596.

Bennett, E. M.; Alpert, R.; Goldstein, A. C. (1954). Communications through limited questioning. *Public Opinion Quarterly*, **18**(3), 303–308.

Brants, Thorsten (2000). Inter-annotator agreement for a German newspaper corpus. In *Proceedings of the Second International Conference on Language Resources and Evaluation (LREC 2000)*, Athens, Greece.

Carletta, Jean (1996). Assessing agreement on classification tasks: the kappa statistic. *Computational Linguistics*, **22**(2), 249–254.

Cohen, Jacob (1960). A coefficient of agreement for nominal scales. *Educational and Psychological Measurement*, **20**, 37–46.

Di Eugenio, Barbara and Glass, Michael (2004). The kappa statistic: A second look. *Computational Linguistics*, **30**(1), 95–101.

Fleiss, Joseph L.; Cohen, Jacob; Everitt, B. S. (1969). Large sample standard errors of kappa and weighted kappa. *Psychological Bulletin*, **72**(5), 323–327.

Green, Annette M. (1997). Kappa statistics for multiple raters using categorical classifications. In *Proceedings of the Twenty-Second Annual SAS Users Group International Conference (online)*, San Diego, CA.

References II

Krenn, Brigitte; Evert, Stefan; Zinsmeister, Heike (2004). Determining intercoder agreement for a collocation identification task. In *Proceedings of KONVENS 2004*, pages 89–96, Vienna, Austria.

Krippendorff, Klaus (1980). *Content Analysis: An Introduction to Its Methodology*. Sage Publications, Beverly Hills, CA.

Landis, J. Richard and Koch, Gary G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, **33**(1), 159–174.

Lee, J. Jack and Tu, Z. Nora (1994). A better confidence interval for kappa (κ) on measuring agreement between two raters with binary outcomes. *Journal of Computational and Graphical Statistics*, **3**(3), 301–321.

Scott, William A. (1955). Reliability of content analysis: The case of nominal scale coding. *Public Opinion Quarterly*, **19**(3), 321–325.

Véronis, Jean (1998). A study of polysemy judgements and inter-annotator agreement. In *Proceedings of SENSEVAL-1*, Herstmonceux Castle, Sussex, UK.