SYSU Lectures on the Theory of Aggregation Lecture 4: Collective Annotation

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[http://www.illc.uva.nl/~ulle/sysu-2014/]

Plan for Today

Aggregation methods can be used to support the *collective annotation* of data through crowdsourcing. This lecture wil be an introduction.

- Annotation and Crowdsourcing (in Linguistics and other fields)
- Formal Framework: Axiomatics of Collective Annotation
- Three Concrete Methods of Aggregation
- Results from Three Case Studies in Linguistics

In the final part of the lecture I will furthermore summarise what we have done this week, briefly mention some additional topics, and provide pointers for further reading.

U. Endriss and R. Fernández. Collective Annotation of Linguistic Resources: Basic Principles and a Formal Model. Proc. ACL-2013.

J. Kruger, U. Endriss, R. Fernández, and C. Qing. Axiomatic Analysis of Aggregation Methods for Collective Annotation. Proc. AAMAS-2014.

Annotation and Crowdsourcing

Disciplines such as computer vision and computational linguistics require large corpora of annotated data.

Examples from linguistics: grammaticality, word senses, speech acts People need corpora with *gold standard* annotations:

- set of *items* (e.g., text fragment with one utterance highlighted)
- assignment of a *category* to each item (e.g., it's a *question*)

Classical approach: ask a handful of experts (who hopefully agree).

Modern approach is to use *crowdsourcing* (e.g., Mechanical Turk) to collect annotations: fast, cheap, more judgments from more speakers.

<u>But:</u> how to *aggregate* individual annotations into a gold standard?

- some work using machine learning approaches
- dominant approach: for each item, adopt the *majority* choice

Using Social Choice Theory

Aggregating information from individuals is what *social choice theory* is all about. Example: aggregation of preferences in an election.

F: vector of individual preferences \mapsto election winner

F: vector of individual annotations \mapsto collective annotation

Research agenda:

- develop a variety of *aggregation methods* for collective annotation
- analyse those methods in a principled manner, as in SCT
- understand features specific to applications via *empirical studies*

Formal Framework

An annotation task has three components:

- $\bullet\,$ infinite set of agents N
- finite set of *items* J
- finite set of *categories* K

A *finite* subset of agents annotate some of the items with categories (one each), resulting in a *group annotation* $A \subseteq N \times J \times K$.

 $(i, j, k) \in A$ means that agent i annotates item j with category k.

An *aggregator* F is a mapping from group annotations to annotations:

$$F: 2_{<\omega}^{N \times J \times K} \to 2^{J \times K}$$

<u>Remark</u>: For |K| = 2, collective annotation is like binary aggregation (but without an integrity constraint), except that ballots can be *incomplete* (you don't have to answer all questions).

Notation

Because ballots are typically (highly) incomplete, it is convenient to change notation (and not to work with the usual profiles of ballots).

For a given group annotation $A \subseteq N \times J \times K$ and sets $N' \subseteq N$, $J' \subseteq J$, and $K' \subseteq K$, define *restrictions* like this:

$$A \upharpoonright N', J', K' := \{ (x, y, z) \in A \mid x \in N', y \in J', z \in K' \}$$

Also used in simplified form, e.g., $A \upharpoonright i = \{(x, y, z) \in A \mid x = i\}$.

Notation to *extract* relevant information from $A \subseteq N \times J \times K$:

$\operatorname{agt}(A)$:=	$\{i \mid (i,j,k) \in A\}$
$\operatorname{itm}(A)$:=	$\{j \mid (i,j,k) \in A\}$
$\operatorname{cat}(A)$:=	$\{k \mid (i, j, k) \in A\}$

Examples:

- $cat(A \upharpoonright i)$: set of categories used by agent i
- $itm(A \upharpoonright \{k_1, k_2\})$ set of items annotated with category k_1 or k_2

The Simple Plurality Rule

An example for an aggregator is the *simple plurality rule:*

 $SPR: A \mapsto \{(j, k^{\star}) \in J \times K \mid k^{\star} \in \underset{k \in \operatorname{cat}(A \upharpoonright j)}{\operatorname{argmax}} |A \upharpoonright j, k|\}$

That is, the SPR returns an annotation in which each item j is annotated with the category (or categories) chosen most often for j(and it returns the empty set if j has not been annotated at all).

Basic Axioms

Nontriviality. If at least one agent has annotated item j, then we should not leave j unannotated in the outcome:

 $|A \upharpoonright j| > 0$ should imply $|F(A) \upharpoonright j| > 0$

Groundedness. For the collective annotation of item j, never use a category that has not been used by at least one of the agents:

 $\operatorname{cat}(F(A)\restriction j)$ should be a subset of $\operatorname{cat}(A\restriction j)$

Independence

Using our special notation, we can give a very simple formulation of the usual independence axiom:

 $F(A) \upharpoonright j$ should be equal to $F(A \upharpoonright j)$

We call this *item-independence*, to stress that we never need to consider more than one item at a time to compute the collective annotation. Later, we will also mention *agent-independence*.

Symmetry Axioms

Anonymity and the different kinds of neutrality axioms we have seen are really all just different sides of the same coin. To underline this fact, here we call all of them symmetry axioms:

- Agent-Symmetry: $F(\sigma(A)) = F(A)$ for all $\sigma : N \to N$
- *Item-Symmetry*: $F(\sigma(A)) = \sigma(F(A))$ for all $\sigma : J \to J$
- Category-Symmetry: $F(\sigma(A)) = \sigma(F(A))$ for all $\sigma: K \to K$

Here, $\sigma(A) = \{(\sigma(i), j, k) \mid (i, j, k) \in A\}$ for $\sigma: N \to N$, etc.

<u>Reminder</u>: annotation A, agents $i \in N$, items $j \in J$, categories $k \in K$

Monotonicity Axioms

Monotonicity. If a chosen category receives additional support, it should still be chosen:

$$k \in \operatorname{cat}(F(A) \upharpoonright j) \implies k \in \operatorname{cat}(F(A \cup (i, j, k)) \upharpoonright j)$$

Positive Responsiveness. In addition to monotonicity, additional support for a category should also break ties:

 $k \in \operatorname{cat}(F(A) \upharpoonright j) \And (i, j, k) \not \in A \ \Rightarrow \ \operatorname{cat}(F(A \cup (i, j, k)) \upharpoonright j) = \{k\}$

Characterisation of the SPR

A generalisation of *May's Theorem* to our model:

Theorem 1 An aggregator F is nontrivial, item-independent, agent-symmetric, category-symmetric, and positively responsive if and only if it is the simple plurality rule.

<u>Proof:</u> Omitted (but not difficult, using the same techniques we have previously used to prove May's Theorem and the characterisation result for quota rules in graph aggregation).

J. Kruger, U. Endriss, R. Fernández, and C. Qing. Axiomatic Analysis of Aggregation Methods for Collective Annotation. Proc. AAMAS-2014.

Weighted Plurality Rules

Many aggregation rules can be described as *weighted plurality rules*:

$$F_{wt}: A \mapsto \{(j, k^{\star}) \in J \times K \mid k^{\star} \in \operatorname*{argmax}_{k \in \operatorname{cat}(A \upharpoonright j)} \sum_{i \in \operatorname{agt}(A \upharpoonright j, k)\}} wt_A(i, j, k)\}$$

For a given group annotation A, wt maps triples (i, j, k) to weights:

$$wt: 2^{N \times J \times K}_{<\omega} \to (N \times J \times K \to \mathbb{R}^+_0)$$

In fact, *all* reasonable aggregation rules can be described this way:

Theorem 2 An aggregator is nontrivial and grounded if and only if it is a weighted plurality rule.

<u>Proof sketch</u>: The trick is to assign weight 1 to (i, j, k) for exactly one agent i choosing category k for item j in case k is the desired collective annotation for j, and to choose weight 0 in all other cases. \checkmark

J. Kruger, U. Endriss, R. Fernández, and C. Qing. Axiomatic Analysis of Aggregation Methods for Collective Annotation. Proc. AAMAS-2014.

Proposal 1: Bias-Correcting Rules

If an annotator appears to be *biased* towards a particular category, then we could try to correct for this bias during aggregation.

- $\operatorname{Freq}_i(k)$: relative frequency of annotator i choosing category k
- $\operatorname{Freq}(k)$: relative frequency of k across the full profile

 $\operatorname{Freq}_i(k) > \operatorname{Freq}(k)$ suggests that *i* is biased towards category *k*.

A *bias-correcting rule* tries to account for this by varying the weight given to k-annotations provided by annotator i:

- **Diff** (difference-based): $1 + \operatorname{Freq}(k) \operatorname{Freq}_i(k)$
- Rat (ratio-based): $\operatorname{Freq}_i(k) / \operatorname{Freq}_i(k)$
- Com (complement-based): $1 + 1 / |K| \operatorname{Freq}_i(k)$
- Inv (inverse-based): $1 / \operatorname{Freq}_i(k)$

For comparison: the simple plurality rule SPR always assigns weight 1.

Proposal 2: Greedy Consensus Rules

If there is *(near-)consensus* on an item, we should adopt that choice. And: we might want to classify annotators who disagree as *unreliable*. The *greedy consensus rule* **GreedyCR**^t (with *tolerance threshold* t) repeats two steps until all items are decided:

- (1) *Lock in* the majority decision for the item with the strongest majority not yet locked in.
- (2) *Eliminate* any annotator who disagrees with more than t decisions.

Variations are possible: any nondecreasing function from disagreements with locked-in decisions to annotator weight might be of interest.

Greedy consensus rules appar to be good at recognising *item difficulty*.

Proposal 3: Agreement-Based Rule

Suppose each item has a *true* category (its *gold standard*). If we knew it, we could compute each annotator i's *accuracy* acc_i .

If we knew acc_i , we could compute annotator *i*'s optimal weight w_i (using maximum likelihood estimation, under certain assumptions):

$$w_i = \log \frac{(|K| - 1) \cdot \operatorname{acc}_i}{1 - \operatorname{acc}_i}$$

But we don't know acc_i . However, we can try to *estimate* it as annotator *i*'s *agreement* agr_i with the plurality outcome:

$$\operatorname{agr}_i \ = \ \frac{|\{j \in J \mid i \text{ agrees with } \operatorname{SPR} \text{ on } j\}| + 0.5}{|\{j \in J \mid i \text{ annotates } j\}| + 1}$$

The agreement rule **Agr** thus uses weights $w'_i = \log \frac{(|K|-1) \cdot \operatorname{agr}_i}{1 - \operatorname{agr}_i}$.

Empirical Analysis

We have implemented our three types of aggregation rules and compared the results they produce to *existing gold standard* annotations for three tasks in computational linguistics:

- RTE: recognising textual entailment (2 categories)
- PSD: proposition sense disambiguation (3 categories)
- QDA: *question dialogue acts* (4 categories)

For RTE we used readily available crowdsourced annotations. For PSD and QDA we collected new crowdsourced datasets.

GreedyCR so far has only been implemented for the binary case.

Case Study 1: Recognising Textual Entailment

In RTE tasks you try to develop algorithms to decide whether a given piece of text entails a given hypothesis. Examples:

Text	Hypothesis	GS
Eyeing the huge market potential, currently led by Google, Yahoo took over search company Overture Services Inc last year.	Yahoo bought Overture.	1
The National Institute for Psychobiology in Israel was established in May 1971 as the Israel Center for Psychobiology.	Israel was established in May 1971.	0

We used a dataset collected by Snow et al. (2008):

- Gold standard: 800 items (T-H pairs) with an 'expert' annotation
- Crowdsourced data: 10 AMT annotations per item (164 people)

R. Snow, B. O'Connor, D. Jurafsky, and A.Y. Ng. Cheap and fast—but is it good? Evaluating non-expert annotations for natural language tasks. Proc. EMNLP-2008.

Example

An example where GreedyCR¹⁵ correctly overturns a 7-3 majority against the gold standard (0, i.e., T does *not* entail H):

- T: The debacle marked a new low in the erosion of the SPD's popularity, which began after Mr. Schröder's election in 1998.
- H: The SPD's popularity is growing.

The item ends up being the 631st to be considered:

ANNOTATOR	CHOICE	DISAGR'S	In/Out
AXBQF8RALCIGV	1	83	×
A14JQX7IFAICP0	1	34	×
A1Q4VUJBMY78YR	1	81	×
A18941IO2ZZWW6	1	148	×
AEX5NCH03LWSG	1	19	×
A3JEUXPU5NEHXR	0	2	\checkmark
A11GX90QFWDLMM	1	143	×
A14WWG6NKBDWGF	· 1	1	\checkmark
A2CJUR18C55EF4	0	2	\checkmark
AKTL5L2PJ2XCH	0	1	\checkmark

Case Study 2: Preposition Sense Disambiguation

The PSD task is about choosing the sense of the preposition "among" in a given sentence, out of three possible senses from the ODE:

- (1) situated more or less centrally in relation to several other things, e.g., *"There are flowers hidden among the roots of the trees."*
- (2) being a member or members of a larger set,
 e.g., "Snakes are among the animals most feared by man."
- (3) occurring in or shared by some members of a group or community, e.g., *"Members of the government bickered among themselves."*

We crowdsourced data for a corpus with an existing GS annotation:

- Gold standard: 150 items (sentences) from SemEval 2007
- Crowdsourced data: 10 AMT annotations per item (45 people)

K.C. Litkowski and O. Hargraves. SemEval-2007 Task 06: Word-Sense Disambiguation of Prepositions. *Proc. SemEval-2007*.

Case Study 3: Question Dialogue Acts

The QDA task consists in selecting a *question dialogue act*, for a highlighted utterance in a dialogue fragment, out of four possibilities:

- (1) **Yes-No:** Questions with a standard form that could be answered with *yes* or *no*, e.g., *"Is that the only pet that you have?"*
- (2) Wh: Questions with a standard form that ask for specific information using wh-words, e.g., *"What kind of pet do you have?"*
- (3) **Declarative:** Questions with a statement-like form that nevertheless ask for an answer, e.g., *"You have how many pets."*
- (4) **Rhetorical:** Questions that do not need to be answered, but are asked only to make a point, e.g., *"If I had a pet, how could I work?"*

We crowdsourced data for a corpus with an existing GS annotation:

- Gold standard: 300 questions from the Switchboard Corpus
- Crowdsourced data: 10 AMT annotations per item (63 people)

D. Jurafsky, E. Shriberg, and D. Biasca. Switchboard SWBD-DAMSL: Shallow-Discourse-Function-Annotation Coders Manual. Univ. of Colorado Boulder, 1997.

Case Studies: Results

How well did we do? Observed *agreement* with the gold standard annotation (any ties are counted as instances of disagreement):

- Recognising Textual Entailment (two categories):
 - SPR: 85.6%
 - Best BCR's: Com 91.6%, Diff 91.5%
 - Agr: 93.3%
 - GreedyCR 0 : 86.6%, GreedyCR 15 : 92.5%
- Preposition Sense Disambiguation (three categories):
 - SPR: 81.3% [caveat: gold standard appears to have errors]
 - Best BCR: Rat 84%, Diff 83.3%
 - Agr: 82.7%
- Question Dialogue Acts (four categories):
 - SPR: 85.7%
 - Best BCR: Inv 87.7% [shared bias → agent-indep. rules better]
 - Agr: 86.7%

Summary: Collective Annotation

- Took inspiration from *social choice theory* to formulate model for aggregating expertise of speakers in *annotation projects*.
- Provided *axiomatic characterisation* of simple plurality rule and of family of all rules that can be decibed via weights.
- Proposed three families of *aggregation methods* that are more sophisticated than the standard plurality/majority rule, by accounting for the *reliability of individual annotators*.
- Empirical results show small but *robust improvements* over the simple plurality/majority rule (also requiring *fewer annotators*).

U. Endriss and R. Fernández. Collective Annotation of Linguistic Resources: Basic Principles and a Formal Model. Proc. ACL-2013.

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Theory of Aggregation: Review

Recall the topics of our four lectures on the theory of aggregation:

• Lecture 1: Preference and Judgment Aggregation

Concrete domains of aggregation. Standard material in social choice theory, including seminal results (Arrow's Theorem, May's Theorem).

• Lecture 2: Binary Aggregation with Integrity Constraints

Most abstract model discussed. IC can describe arbitrary set of rational outcomes. New perspective: language to describe rational outcomes.

• Lecture 3: Graph Aggregation

Useful intermediate level of abstraction. Focus on collective rationality. In-depth discussion of Arrow-like general impossibility theorem.

• Lecture 4: *Collective Annotation*

Focus on practical applications (in crowdsourcing) and on pragmatic aggregation rules for truth-tracking. New feature: incomplete profiles.

Other Topics

We have discussed *voting*, *preference aggregation*, and *judgment aggregation*, as well as *generalisations* of these standard frameworks.

Other import frameworks studied in social choice theory include:

- fair division
- two-sided matching

Methods

Problems of aggregation can be studied using a wide variety of different methods (and we have only seen some of them this week):

- *Philosophical* analysis (e.g., of axioms modelling fairness)
- *Characterisation* of aggregation rules: axiomatic method, truth-tracking (maximum likelihood estimation), distance-based rationalisation
- *Empirical* analysis of aggregation rules
- Logical modelling of aggregation problems, automated reasoning
- Compact *representation* (social choice and knowledge representation)
- Game-theoretical analysis (*strategic* manipulation and more)
- *Complexity* analysis of aggregation rules, *algorithm* design
- Information and communication requirements of aggregation rules

Of course, the above list is not exhaustive.

Last Slide

The website for this lecture series will remain online:

http://www.illc.uva.nl/~ulle/sysu-2014/

I teach a course on *computational social choice* in the Master of Logic programme at the ILLC in Amsterdam each year and the course website has a lot of additional material:

http://www.illc.uva.nl/~ulle/teaching/comsoc/

For general background reading, consider the references below.

W. Gaertner. A Primer in Social Choice Theory. Oxford University Press, 2006.

U. Endriss. Logic and Social Choice Theory. In A. Gupta and J. van Benthem (eds.), *Logic and Philosophy Today*, College Publications, 2011.

F. Brandt, V. Conitzer, and U. Endriss. Computational Social Choice. In G. Weiss (ed.), *Multiagent Systems*, MIT Press, 2013.