The Thirty-First International Florida
Artificial Intelligence Research Society Conference (FLAIRS-31)

Consensus Mining — A Guided Group Decision Process for the German Coalition Negotiations

Klemens Schnattinger, Nadine Mueller, Heike Walterscheid

Baden-Wuerttemberg Cooperative State University Loerrach, Hangstrasse 46-50, 79539 Loerrach, Germany
{schnattinger,muellnad,walterscheid}@dhbw-loerrach.de

Abstract

The paper focuses on the applicability of a consensus mining model for group decision making. There seem to be no mechanism for translating different preferences of rational individuals or homogeneous preferences of groups into a coherent group preference that is not either itself irrational or dictatorial. Therefore, we are expanding the opinion mining architecture OMA, which brings opinions with weighted description logics into a ranking, to include incomplete fuzzy preference relations. In this work we will verify how feasible fuzzy modeling algorithms are in the German coalition negotiations in autumn 2017.

Introduction

In the autumn of 2017, after the Bundestag elections, the coalition negotiations took place between four parties, the so-called *experts*. These experts are the German Ecological Party "Grünen", the German Liberals "FDP" and the two Conservative Christian parties, "CDU" and "CSU". The manifestos of all parties contain five main policy fields relevant to negotiations: labor/social affairs, immigration affairs, national security/foreign affairs, taxation/financial issues and education. The policy fields were then ranked for each of the parties involved, with 1 being the highest and 5 the lowest preferred one. In a first attempt, experts were weighted equally as if they have reached the same number of votes. Thus, the weights must vary with heterogeneous percentages of votes.

As yet, the Opinion Mining Architecture OMA (Schnattinger and Walterscheid 2017) was only able to model preferences and rankings using weighted, but not to model a calculation of consensus as well. Thus, incomplete fuzzy preference relations (Herrera-Viedma et al. 2007) added into OMA are able to run the process of finding a consensus for group decision making. This means that the five policy fields considered in our example must equally divide the fuzzy interval [0,1].

In our political example, the decision-making process is modeled with three different assumptions to express preferences: On one hand the experts' preferences towards a certain political issue within a political field can vary between undetermined (indifference) and weighted (distinctive), respectively can vary between a cooperative or non-cooperative agenda. On the other hand, parties can stick tight to the issues within the political fields of their manifesto by calculating the allocative consequences to the governmental budget they might get access to. The different approaches tested are modeled to the following table:

Attitude / Party	undetermined	manifesto	budget driven	Model
CDU, CSU	X			1
FDP, Grünen		X		
"All"			X	2
"All"		X		3[1]

Table 1: Chosen models for example

Preliminaries

Opinion & Consensus Mining Architecture OMA

The first version of OMA (Schnattinger and Walterscheid 2017) based on traditional approaches of natural language processing, machine learning from texts (Sun, Luo, and Chen 2017) and basic ideas of the text understanding system SYNDIKATE (Hahn and Schnattinger 1998). The decision-making process uses weighted description logics to derive a posteriori preference relation over choices from a priori preference relations over attributes (Acar et al. 2017). OMA for consensus mining, consists of two main parts: *Opinion Mining* and *Consensus Mining*. In the first

[1] in model 3 also a weight reflecting the election results is incorporated

part relevant opinions from different sources, such as texts from newspapers or election programs are extracted. For this extraction standard techniques of natural language processing and machine learning are used. Next, the extracted opinions are stored into a *knowledge database* based on description logics (Baader et al. 2003). In the corresponding *TBox* domain specific rules, compliance etc. are given. The *ABox* is built up through the extracted (unweighted) opinions to weight these unweighted opinions and to calculate the possible consensus. The *ABox* and the *TBox* have to be transferred to the so-called *MBox* (methodology box), applying the mentioned techniques of *weighted description logics* and *fuzzy logics*. By applying the weighted description and fuzzy logic, the opinions considered are weighted and the consensus is calculated during negotiations in the *CBox* (Consensus box).

Consensus Model for Group Decision Making with Incomplete Fuzzy Preference Relations

The "Consensus Model for Group Decision Making with Incomplete Fuzzy Preference Relations" is a process which deals with the partly ambivalent task to find consensus among a group of experts while also incorporating the consistency of each of them.

The decision process is divided into four steps. Starting point for all calculations are the preference matrixes of each expert denoted as $P^m = (p_{ij})^m$ with n experts.

Step 1: Computing Missing Information

Firstly, the preferences, which are not defined or unknown need to be estimated. The formula for these preferences bases on the additive transitivity, which implies additive reciprocity. Like this, all missing values are deduced from the existing ones. Since all values are defined, deduction becomes obsolete and thus is not described in detail.

Step 2: Computing Consistency Measure

Once all matrixes are fully staffed, for each expert a matrix with its estimated preference degrees is calculated:

$$cp_{ik} = \frac{\sum_{j=1;i\neq k\neq j}^{n} (cp_{ik})^{j1} + (cp_{ik})^{j2} + (cp_{ik})^{j3}}{3(n-2)}$$

where
$$(cp_{ik})^{j1} = p_{ij} + p_{jk} - 0.5$$
$$(cp_{ik})^{j2} = p_{jk} - p_{ji} + 0.5$$
$$(cp_{ik})^{j3} = p_{ij} - p_{kj} + 0.5$$

These values are within the interval $[-0.5,1.5]$. Normalized to the standard fuzzy interval they reflect the ideal consistent preference values. The error between a calculated resp. estimated and its real preference value results in

$$\varepsilon p_{ik} = \frac{2}{3} \cdot \left| cp_{ik} - p_{ik} \right|$$

The consistency level is $cl_{ik} = 1 - \varepsilon p_{ik}$ for each preference value, reflecting the distance of each expert to its ideal consistent matrix. The consistency measure associated to a specific attribute is the arithmetic mean over all preferences relating to this attribute. The overall consistency per expert is the arithmetic mean over all attributes. Using the same principle, the total measure of the consistency is determined.

Step 3: Computing Consensus Measure

To calculate a measure for the consensus the distances among each different pair of experts are firstly summed up and then averaged. As preparation for the feedback process, a collective fuzzy preference matrix is needed. To obtain the matrix an IOWA operator is used with the linguistic quantifier "most of" (Yager 2003).

Step 4: Feedback Process

After the measures are calculated, a feedback process with strong tendency to the consensus (0.75) is conducted. The threshold to fulfil is set to 0.85. In this process the below criteria are checked:

- All experts where the weighted consistency/consensus value (CCL) is above the threshold are flagged.
- For all these flagged experts the weighted consistency/consensus for each attribute is calculated. If the result is above the threshold, the attribute is flagged.
- For the flagged attributes, the weighted consistency/ consensus value for each preference is determined. If it is above the threshold it is flagged.

All flagged preference values and all values, set to unknown, are changed according to the feedback process. The newly calculated values are based on the individual consistency and the overall consensus preference matrix.

Model and Evaluate Data

Within the architecture, the data was structured and compressed and revealed within the different attitudes the following priorities:

electoral programs	labour/ social a.	immigr- ation a.	nat. sec./ for. a.	tax/fin- ancial. i.	educa- tion
CDU	3	5	1	2	4
CSU	3	4	1	1	3
FDP	5	4	2	1	3
Grünen	2	1	4	3	5

budget information	labour/ social a.	immigr- ation a.	nat. sec./ for. a.	tax/fin- ancial i.	educa- tion
CDU	2	4	2	3	4
CSU	2	5	2	5	3
FDP	3	5	2	5	1
Grünen	1	2	5	3	4

Due to the nature of the used ranks and their translation into fuzzy, the experts have a consistent set of preferences. Now, exemplary models 1 to 3 (table 1) will be applied.

Model 1

Above values are translated like stated in the introduction into fuzzy preferences. In accordance to their attitudes (table 1), for CDU/CSU all values are set to 0.5.

CDU/ CSU	labour/ social a.	immigr-ation a.	nat. sec./ for. a.	taxation/ financ. i.	educa-tion
labour/social a.	**empty**	0,50	0,50	0,50	0,50
immigration a.	0,50	**empty**	0,50	0,50	0,50
nat. sec./ for a.	0,50	0,50	**empty**	0,50	0,50
tax/financial i.	0,50	0,50	0,50	**empty**	0,50
education	0,50	0,50	0,50	0,50	**empty**

FDP	labour/ social a.	immigr-ation a.	nat. sec./ for. a.	taxation/ financ. i.	educa-tion
labour/social a.	**empty**	0,40	0,20	0,10	0,30
immigration a.	0,60	**empty**	0,30	0,20	0,40
nat. sec./ for a.	0,80	0,70	**empty**	0,40	0,60
tax/financial i.	0,90	0,80	0,60	**empty**	0,70
education	0,70	0,60	0,40	0,30	**empty**

This results in:

Global Consistency Level	0,99729663
Global Consensus	0,81666667
CCL	0,86182416

In this scenario no feedback round is required. The overall consensus matrix is:

Global Consensus Matrix	labour/ social a.	immigr-ation a.	nat. sec./ for. a.	taxation/ financ. i.	educa-tion
labour/social a.	**empty**	0,49	0,43	0,41	0,46
immigration a.	0,51	**empty**	0,46	0,46	0,48
nat. sec./ for a.	0,57	0,54	**empty**	0,49	0,51
tax/financial i.	0,59	0,57	0,51	**empty**	0,54
education	0,54	0,52	0,49	0,46	**empty**

Conclusion for Model 1

No feedback round is necessary as the threshold is accomplished at once. This is because two experts take a very "neutral" position similar to the middle of the other two. Since the two represent half of the experts, the consensus clearly tends towards a strongly aligned preference matrix (the maximum distance between two preferences is less than 0.2). The overall ranking is:

Model 1 prio. (general)	labour/ social a.	immigr-ation a.	nat. sec./ for. a.	taxation/ financ. i.	educa-tion
CDU	unknown	unknown	unknown	unknown	unknown
CSU	unknown	unknown	unknown	unknown	unknown
FDP	5	4	2	1	3
Grünen	2	1	4	3	5
Overall ranks	**5**	**4**	**2**	**1**	**3**

Model 2

Within this model CDU and CSU have a clear position found in their electoral program. After steps 1 to 3 are done the result for the defined measures is:

Global Consistency Level	0,99237599
Global Consensus	0,77666667
CCL	0,830594

This is below the threshold. Therefore, a feedback round is necessary to reach enough overall consistency and consensus. All experts have to change preferences as all of them are below the threshold. Values in detail:

CDU	0,791145833	CSU	0,774791667
FDP	0,737792659	Grünen	0,764895833

The cells with a dark grey background and white letters mark the preferences, which the algorithm has to change for e.g. Grünen.

Grünen	labour/ social a.	immigr-ation a.	nat. sec./ for. a.	taxation/ financ. i.	educa-tion
labour/social a.	**empty**	0,72035	0,90	0,70	0,80
immigration a.	0,27975	**empty**	0,80	0,48972	0,70
nat. sec./ for a.	0,41591	0,58373	**empty**	0,61470	0,53208
tax/financial i.	0,27282	0,49534	0,70	**empty**	0,60
education	0,37791	0,54129	0,46791	0,57690	**empty**

To find a satisfying consensus, the Grünen must change 13 preferences, being the average amount each party has to modify. The overall measures are the following:

Global Consistency Level	0,96651638
Global Consensus	0,880376
CCL	0,90191109

The ranking after step 4 is:

Model 2 prio. (general)	labour/ social a.	immigr-ation a.	nat. sec./ for. a.	taxation/ financ. i.	educa-tion
CDU	2	4	2	3	4
CSU	2	5	2	5	3
FDP	3	5	2	5	1
Grünen	1	2	5	3	4
Ranks bef. FB	**1**	**5**	**2**	**4**	**3**
Ranks aft. FB	**2**	**5**	**1**	**4**	**3**

Conclusion for Model 2

A feedback round is necessary as the threshold value after step 3 has not been accomplished. This is because the preferences were too heterogeneous. In this situation, the consensus modeling reveals a forced ranking, although some parties cannot determine a stronger preference in advance (see CDU: labor and security). Also, the feedback process caused a slight change in the ranking (see rank 1 and 2).

Model 3 (An alternative Decision-Making Process)

One important fact has not been taken into account, when modeling the scenarios above. Each of the parties involved received a certain number of votes. Therefore, the party representing the most voters should also have the highest weight in reaching a consensus. To reflect these circumstances, the number of experts has to follow the same ratio as the results of the election.

As well one has to put into account the special ratio of one party (CSU) influenced by the pressure to win a federal state election in about one year or another party (FDP) making an effort to convey reliability. Their most weighted preferences (immigration and national security) very much contradict the position of the German Ecological Party (Grünen) in these political fields. Thus, the CSU's and FDP's willingness to give and take will be low. Since these political issues themselves (immigration and national security) are of high interest among all groups of voters, coalition agreements might not come about.

As the real interesting scenario above is the one, where every party sticks tight to its ideals, only model 3 will be calculated with these weighted expert opinions now. Therefore, we need to include the percentages of the Bundestag election, which were: CDU – 26,8%, FDP - 10,7%, Grünen – 8,9%, CSU – 6,2%. Considering the amount of votes each party achieved, we exemplary obtain the following situation: Giving CDU 5 experts, FDP and Grünen both 2 experts and CSU one experts will reflect about the percentages reached through the election. This results in:

Global Consistency Level	0,99825198
Global Consensus	0,84222222
CCL	0,88122966

The overall consensus matrix looks like:

Model 4 wie-ghted prio.	labour/ social a.	immigr-ation a.	nat. sec./ for. a.	taxation/ financ. i.	educa-tion
CDU	3	5	1	2	4
CSU	3	4	1	1	3
FDP	5	4	2	1	3
Grünen	2	1	4	3	5
Overall ranks	**3**	**5**	**1**	**2**	**4**

Now, the consensus was been achieved without a feedback loop and the overall ranking is the same than the one of the CDU. Manifold kinds of variables can lead to a result like. Thus, further work will be necessary.

Summary and Outlook

The different modeled situations showed that the "Consensus Model for Group Decision Making with Incomplete Fuzzy Preference Relations" works in real world situations and reveals different insights about the whole process. Future work will embed this process into the OMA architecture and combine it with different NLP and machine learning approaches, which enables an end-to-end opinion and consensus mining. Furthermore, we will integrate a type-1 OWA operator that works as an uncertain OWA operator to aggregate type-1 fuzzy sets with type-1 fuzzy weights, which then can be used among others to aggregate preferences in human decision making with linguistic weights (Zhou et al. 2008). Similarly, (Alonso et al. 2009) and (Wang 2010) expand the incomplete fuzzy preference relation with linguistic labels by a two-tuple fuzzy linguistic approach. Introducing linguistic features into the fuzzy OWA operator and implementing these augmented fuzzy operations will help us in OMA to extract the opinions in a much more accurate way.

Acknowledgements

Klemens and Heike are winners of the Dr. Karl Helmut Eberle Foundation's award on the study "Digitization and Knowledge Transformation". Nadine is supported by this foundation.

References

Acar, E., Fink, M., Meilicke, C., Thome, C., and Stuckenschmidt, H. 2017. Multi-attribute Decision Making with Weighted Description Logics, *IFCoLog: Journal of Logics and its Applications, 4*, pp. 1973-1995.

Alonso, S., Cabrerizo, F.J., Chiclana, F., and Herrera, F. 2009. Group Decision Making with Incomplete Fuzzy Linguistic Preference Relations, *International Journal of Intelligent Systems*, vol. 24, pp. 201-222.

Baader, F., McGuinness, D., Narci, D., and Patel-Schneider, P. 2003. *The Description Logic Handbook: Theory, Imlementation, and Applications*, Cambridge University Press.

Hahn, U. and Schnattinger, K. (1998) Towards Text Knowledge Engineering, AAAI'98 - Proc. 15th National Conference on Artificial Intelligence, 524-531.

Herrera-Viedma, E., Alonso, S., Chiclana, F., and Herrera, F. 2007. A Consensus Model for Group Decision Making Incomplete Fuzzy Preference Relations, *IEEE Transactions on Fuzzy Sytems*, pp. 863-877.

Schnattinger, K. and Walterscheid, H. 2017. Opinion Mining Meets Decision Making: Towards Opinion Engineering, IC3K17: Proc. 9th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management, 334-341.

Sun, S., Luo, C., and Chen, J. 2017. A Review of Natural Language Processing Techniques for Opinion Mining Systems, Volume 36, *Information Fusion*, pp. 10-25.

Wang, W.-P. 2010. A Fuzzy Linguistic Computing Approach to Supplier Evaluation, *Applied Mathematical Modelling*, vol. 34, pp. 3130-3141.

Yager, R. 2003. Induced aggregation operators, *Fuzzy Sets and Systems 137*, pp. 59-69.

Zhou, S.-M., Chiclana, F., John, R., and Garibaldi, J. 2008. Type-1 OWA operators for aggregating uncertain information with uncertain weights induced by type-2 linguistic quantifiers, *Fuzzy Sets and Systems*, vol. 159, pp. 3281-3296.