

Combining Multiple Expert Systems using Combinatorial Fusion Analysis

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Outline

- (A) Information Fusion
- (B) Combinatorial Fusion Analysis
- (C) Multiple Expert Systems Applications
- (D) Remarks and Acknowledgement.



(A) Information Fusion

(A) Information Fusion

Pointers for IF:

- * Complexity: Multiple sensors, multiple sources, multiple systems.
- * Levels: Data fusion, Feature fusion, Decision fusion.
- * Computing, Informatics, and Analytics:

Data-Information-Knowledge-Wisdom-Enlightenment.

FAQ's for IF:

- * What: Combination of data or information from multiple sensors, sources, features, systems, cues, classifiers, or decisions.
- * Why: To improve the quality (better accuracy and higher effectiveness) of data, feature characteristics, decisions and actions.
- * When: To Fuse or Not To Fuse.
- * How: A diverse array of combination methods.



Crossing the Street



Figure Skating Judgment







Figure Skating Judgment

	J1	J2	J3	SC	D	J1	J2	J3	RC	С
d ₁	9.6	9.7	9.8	29.1	2	5	3	3	11	3
d ₂	9.8	9.2	9.9	28.9	3	3	8	2	13	4
d ₃	9.7	9.9	10	29.6	1	4	2	1	7	1
d ₄	9.5	9.3	9.7	28.5	6	6	7	4	17	7
d ₅	9.9	9.4	9.5	28.8	4	2	6	6	14	5
d ₆	9.4	9.6	9.6	28.6	5	7	4	5	16	6
d ₇	9.3	9.5	9.4	28.2	7	8	5	7	20	8
d ₈	10	10	7	27	8	1	1	8	10	2

Internet Search Strategy





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Internet Search Strategy



	ļ	ł	E	3	C Ra Corr	nk าb	D Score Comb			
d_1	1.00	1	0.80	2	1.5	1	0.90	1		
d ₂	0.40	7	1.00	1	4.0	4	0.70	3		
d ₃	0.70	4	0.35	5	4.5	5	0.525	5		
d ₄	0.90	2	0.60	3	2.5	2	0.75	2		
d ₅	0.80	3	0.40	4	3.5	3	0.60	4		
d ₆	0.60	5	0.25	7	6.0	6	0.425	6		
d ₇	0.20	9	0.30	6	7.5	8	0.25	8		
d ₈	0.50	6	0.20	8	7.0	7	0.35	7		
d ₉	0.30	8	0.10	10	9.0	9	0.20	9		
d ₁₀	0.10	10	0.15 9		9.5	10	0.125	10		



(B) Combinatorial Fusion Analysis (CFA) (1) Multiple Scoring Systems and RSC Functions (2) Applications (a) Science and Technology: Target Tracking and Computer Vision (b) Biomedical Informatics and Pharmacogenomics: Virtual Screening and Drug Discovery (c) Information Retrieval: **Biomedical Literature Collections** (d) Information Retrieval: Search Engine Optimization (e) On-line Learning (f) Classifier Ensemble



(1) Multiple Scoring Systems (MSS) and RSC Functions

Score function, rank function, and rank/score function of system A.

s(A)

 $s(A) \rightarrow r(A)$, sorting

 $s(A), r(A) \rightarrow f(A)$?

Score combination and rank combination

Scoring Systems A, B: Com_s(A,B) = C, Com_r(A,B) = D

- Performance evaluation (criteria)
- Diversity measure: Diversity between A and B, d(A, B), is equal to d(s(A), s(B)) or d(r(A), r(B)), or d(f(A), f(B))?
- Two main questions:
 - (1) When are P(C) or P(D) greater than or equal to P(A) and P(B)?

(2) When is P(D) greater or equal to P(C)?

Ref: Hsu, D.F., Chung, Y.S., and Kristal, B.S. Combinatorial fusion analysis: methods and practice of combining multiple scoring systems, in: H.H. Hsu (Ed.), Advanced Data Mining Technologies in Bioinformatics, Idea Group Inc., (2006), pp. 32-62.



The Rank Score Characteristic Function

D= set of classes, documents, forecasts, price ranges with |D| = n.
N= the set {1,2,...,n}
R= a set of real numbers

> f(i)=(s o r⁻¹) (i) =s (r⁻¹(i))

The RSC Function



Three RSC functions: f_A , f_B and f_C Cognitive Diversity between A and B = d(f_A , f_B)

The RSC Function

D	Score function s:D→R	Rank function r:D→N	RSC functi f:N→F	on R
d ₁	3	10	1	10
d_2	8.2	3	2	9.8
d ₃	7	4	3	8.2
d ₄	4.6	7	4	7
d ₅	4	8	5	5.4
d ₆	10	1	6	5
d ₇	9.8	2	7	4.6
d ₈	3.3	9	8	4
d ₉	1	12	9	3.3
d ₁₀	2.5	11	10	3
d ₁₁	5	6	11	2.5
d ₁₂	5.4	5	12	1

How do we compute the RSC function?

Sorting the score value by using its rank value as the key.



(2) Applications

(a) Science and Technology: Target Tracking and Computer Vision

We use three features:

- Color average normalized RGB color.
- Position location of the target region centroid
- Shape area of the target region.



Ref: Lyons, D.M., Hsu, D.F. Information Fusion 10(2): 124-136 (2009).





(a) Science and Technology: Target Tracking and Computer Vision

Experimental Results

Seq.	RU Score MSSD Avg.	I <mark>N2</mark> fusion MSSD Var.	RU Score and t using ground MSSD Avg.	N3 rank fusion truth to select MSSD Var.	RU Score and ran rank-score sel MSSD Avg.	N4 k fusion using function to ect MSSD Var.		
1	1537.22	694.47	1536.65	695.49	1536.9	694.24		
2	816.53	8732.13	723.13	3512.19	723.09	3511.41		
3	108.89	61.61	108.34	60.58	108.89	61.61		
4	23.14	2.39	23.04	2.30	23.14	2.39		
5	334.13	120.11	332.89	119.39	334.138	120.11		
6	96.40	119.22	66.9	12.91	67.28	13.38		
7	577.78	201.29	548.6	127.78	577.78	201.29		
8	538.35	605.84	500.9	57.91	534.3	602.85		
9	143.04	339.73	140.18	297.07	142.33	294.94		
10	260.24	86.65	252.17	84.99	258.64	85.94		
11	520.13	2991.17	440.98	2544.69	470.27	2791.62		
12	1188.81	745.01	1188.81	745.01	1188.81 745.01			

RUN4 is as good or better (highlighted in gray) than RUN2 in all cases
RUN4 is, predictably, not always as good as RUN3 ('best case').

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Note: Lower MSSD implies better tracking performance.



(b) Biomedical Informatics and Pharmacogenomics: Virtual Screening

The Performance of Thymidine Kinase (TK)



- •Combinations of different methods improve the performances
- •The combination of B and D works best on thymidine kinase (TK)

Ref: Yang et al. Journal of Chemical Information and Modeling. 45 (2005) 1134-1146.



(b) Biomedical Informatics and Pharmacogenomics: Virtual Screening The Performance of Dihydrofolate Reductase (DHFR)



- •Combinations of different methods improve the performances
- •The combination of B and D works best on dihydrofolate reductase (DHFR)



(b) Biomedical Informatics and Pharmacogenomics: Virtual Screening

The Performance of ER-Antagonist Receptor (ER)



- •Combinations of different methods improve the performances
- •The combination of B and D works best on ER-antagonist receptor (ER)



(b) Biomedical Informatics and Pharmacogenomics: Virtual Screening The Performance of ER-Agonist Receptor (ERA)



- •Combinations of different methods improve the performances
- •The combination of B and D works best on ER-agonist receptor (ERA)



(b) Biomedical Informatics and Pharmacogenomics: Virtual Screening





(c) Information Retrieval: Biomedical Literature Collections



Rank-Score Characteristic Graphs of Seven IR Models



(c) Information Retrieval: Biomedical Literature Collections



RSvar vs. Performance Ratio



(d) Information Retrieval: Search Engine Optimization



Ref: Hsu, D.F., Taksa, I. Information Retrieval 8(3) (2005) 449–480



(e) On-line Learning

GOAL: The goal is to learn a linear combination of the classifier predictions that maximizes the accuracy on future instances.

- * Sub-expert conversion
- * Hypothesis voting
- * Instance recycling

Ref: Mesterharm, C., Hsu, D.F. The 11th International Conference on Information Fusion, 2008. pp. 1117-1124



(e) On-line Learning



Mistake curves on majority learning problem with r = 10, k = 5, n = 20, and p = .05



(f) Classifier Ensemble

In regression, Krogh and Vedelsby (1995):

Ensemble generalization error: $E = \overline{E} - \overline{A}$ Weighted average of generalization errors($\overline{E} = \sum_{\alpha} w_{\alpha} E^{\alpha}$) Weighted average of ambiguities: ($\overline{A} = \sum_{\alpha} w_{\alpha} A^{\alpha}$)

In classification, Chung, Hsu, and Tang (2007): $\max\{\bar{P} - \bar{D}, p(\bar{P} + \bar{D}) + 1 - p\} \le P^{m} \le \min\{\bar{P} + \bar{D}, p(\bar{P} - \bar{D})\}$

Ref: Chung et al in Proceedings of 7th International Workshop on Multiple Classifier Systems (MCS2007), LNCS, Springer Verlag.



(f) Classifier Ensemble



Fig. 1. Bounds for majority voting accuracy. Here p = 3. The dashed and dotted lines are for $\bar{P} \in (\frac{\ell}{p}, \frac{\ell+1}{p})$, while the solid lines are for $\bar{P} \notin (\frac{\ell}{p}, \frac{\ell+1}{p})$. The bounds have different spans in \bar{D} since $\bar{D} \leq \min\{\bar{P}, 1-\bar{P}, \frac{\ell}{p}\}$.



(C) Multiple Expert Systems Applications

Ref: Tsai, R., Schweikert, C., Yu, S., Hsu, D.F. Combining Multiple Forecasting Experts for Corporate Revenue Using Combinatorial Fusion Analysis. Global Business & Technology Association's Thirteenth Annual International Conference (GBATA 2011), "Fulfilling the Worldwide Sustainability Challenge: Strategies, Innovations, and Perspectives for Forward Momentum in Turbulent Times", 2011, pp. 986-995.



Combining Multiple Forecasting Experts for Corporate Revenue Using Combinatorial Fusion Analysis



Actual: Actual end of quarter sales



Traditional Business Approach to Forecast Combination



Forecast Combination with MSS and CFA



Individual score functions for week 9

forecast	2154	1877	1901	2411	2154	1877	1901	2411
		Original	Score		N	ormalize	ed Score	;
buckets(di)	Е	ŋ	Η	С	E	G	Η	С
2503	19%	2%	2%	44%	23%	0%	0%	86%
2399	27%	5%	4%	49%	45%	5%	5%	100%
2294	36%	9%	8%	42%	71%	14%	15%	82%
2190	46%	16%	15%	36%	100%	28%	31%	65%
2086	43%	25%	26%	29%	<mark>91%</mark>	48%	53%	48%
1981	33%	37%	39%	24%	<mark>63%</mark>	73%	83%	34%
1877	25%	50%	47%	19%	38%	100%	100%	21%
1773	17%	37%	33%	14%	17%	73%	<mark>69%</mark>	9%
1669	12%	25%	21%	11%	0%	48%	42%	0%

Score functions constructed based on each unit's sales projection for week 9



Judge	E	G	Н	С
Sigma	405	313	283	603
mean	2154	1877	1901	2411

Combined mean = $\frac{\sum \frac{1}{\sigma_i^2} m_i}{\sum \frac{1}{\sigma_i^2}} = \overline{m}$

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Score and Rank Combinations

The score combination for *c* systems: $X_1, X_2, ..., X_c$:

$$s_{SC}(d_i) = \frac{1}{c} \sum_{j=1}^{c} s_{X_j}(d_i)$$

The rank combination for *c* systems: $X_1, X_2, ..., X_c$:

$$s_{RC}(d_i) = \frac{1}{c} \sum_{j=1}^{c} r_{X_j}(d_i)$$

.



Combination by Score

Rank Function of the Averaged Score Combination

buckets(di)	Е	G	Н	С	EG	EH	EC	GH	GC	HC	EGH	EGC	EHC	GHC	EGHC
2503	7	9	9	2	9	9	5	9	7	7	9	7	7	9	8
2399	5	8	8	1	7	7	3	8	3	3	8	6	6	7	7
2294	3	7	7	3	6	5	2	7	5	5	6	4	4	6	5
2190	1	6	6	4	4	4	1	6	6	6	4	1	1	5	4
2086	2	5	4	5	1	2	4	4	4	4	3	2	2	4	3
1981	4	2	2	6	3	1	6	2	2	2	2	3	3	2	2
1877	6	1	1	7	2	3	7	1	1	1	1	5	5	1	1
1773	8	2	3	8	5	6	8	3	8	8	5	8	8	3	6
1669	9	4	5	9	8	8	9	5	9	9	7	9	9	8	9
forecast	2190	1877	1877	2399	2086	1981	2190	1877	1877	1877	1877	2190	2190	1877	1877
performance	88%	96%	96%	77%	93%	98%	88%	96%	96%	96%	96%	88%	88%	96%	96%



Score combination performance for week 9



С	Ε	G	Η	EC	EG	GH	GC	HC	EH	EGC	EHC	EGH	GHC	EGHC
77%	88%	96%	96%	88%	93%	96%	96%	96%	98%	88%	88%	96%	96%	96%



Combination by Rank

Rank Function of the Averaged Rank Combination

buckets(di)	Е	G	Η	С	EG	EH	EC	GH	GC	HC	EGH	EGC	EHC	GHC	EGHC
2503	7	9	9	2	9	9	5	9	8	8	9	8	7	9	9
2399	5	8	8	1	8	7	3	8	3	4	8	6	6	7	7
2294	3	7	7	3	6	5	3	7	7	6	6	4	4	7	5
2190	1	6	6	4	4	4	1	6	7	6	5	1	2	5	4
2086	2	5	4	5	4	2	4	5	7	4	3	3	2	4	3
1981	4	2	2	6	1	2	6	2	2	2	2	3	3	2	1
1877	6	1	1	7	4	4	7	1	2	2	2	6	6	1	2
1773	8	2	3	8	6	6	8	3	7	8	5	8	8	3	6
1669	9	4	5	9	8	8	9	5	9	9	7	9	9	8	9
forecast	2190	1877	1877	2399	1981	2033	2190	1877	1929	1929	1929	2190	2138	1877	1981
performance	88%	96%	96%	77%	98%	96%	88%	96%	99%	99%	99%	88%	90%	96%	98%



Rank combination performance for week 9



С	Ε	G	Η	EC	EH	GH	EG	GC	HC	EGC	EHC	GHC	EGH	EGHC
77%	88%	96%	96%	88%	96%	96%	98%	99%	99%	88%	90%	96%	99%	98%



Test results with four quarters, using Score Combination

Week	Ε	G	Η	С	EG	EH	EC	GH	GC	HC	EGH	EGC	EHC	GHC	EGHC
Q1 9	88%	96%	96%	77%	93%	98%	88%	96%	96%	96%	96%	88%	88%	96%	96%
Q2 9	97%	93%	93%	78%	98%	98%	97%	93%	93%	93%	93%	98%	98%	93%	93%
Q3 9	94%	94%	94%	86%	94%	94%	94%	94%	99%	94%	94%	94%	94%	94%	94%
Q4 9	93%	88%	88%	93%	88%	88%	93%	88%	88%	88%	88%	93%	93%	88%	88%
Average of week 9 performance	93%	93%	93%	84%	93%	95%	93%	93%	94%	93%	93%	93%	93%	93%	93%
Average Forecast Error	7%	7%	7%	16%	7%	5%	7%	7%	6%	7%	7%	7%	7%	7%	7%
Reduction of Error for the best single judge					-6%	-25%	2%	0%	-18%	0%	0%	-3%	-3%	0%	0%

Average Reduction of Error -5%



Test results with four quarters, using Rank Combination

	Week	Ε	G	Η	С	EG	EH	EC	GH	GC	HC	EGH	EGC	EHC	GHC	EGHC
Q1	9	88%	96%	96%	77%	98%	96%	88%	96%	99%	99%	99%	88%	90%	96%	98%
Q2	9	97%	93%	93%	78%	98%	96%	97%	93%	96%	93%	93%	99%	99%	93%	96%
Q3	9	94%	94%	94%	86%	94%	94%	94%	94%	97%	97%	94%	94%	94%	94%	94%
Q4	Q4 9			88%	93%	88%	88%	93%	88%	88%	88%	88%	90%	90%	88%	88%
Av	rerage of week 9 performance	93%	93%	93%	84%	95%	93%	93%	93%	95%	94%	94%	93%	94%	93%	94%
	7%	7%	7%	16%	5%	7%	7%	7%	5%	6%	6%	7%	6%	7%	6%	
Reducti					-25%	-7%	2%	0%	<u>-27%</u>	-18%	<u>-9%</u>	1%	-8%	0%	-17%	

Average Reduction of Error -10%



(D) Remarks



Forecasting Combination Remarks

- CFA application to sales forecasting is more robust because it takes advantage of the strengths and compensates for the weakness of different scoring functions
- Outperforms each individual judge as well as average performance for the quarter

Our Future Research

- Optimize the methodology
 - -- more judgers
 - -- more buckets
- Score function transformation and diversity
- Analyze historical data, acquire new data