Classifier Aggregation using Fuzzy Integral based on Interaction-Sensitive Fuzzy Measures

David Štěfka

28. March 2013

Martin Holeňa
1 Dynamic Classifier Systems

2 Aggregation Operators
   - Weighted Mean
   - Ordered Weighted Average
   - Choquet Integral
   - Sugeno Integral

3 Interaction-Sensitive Fuzzy Measures
   - I-ISFM
   - G-ISFM
   - MHM

4 Experiments
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4 Experiments
Classifier Combining

- classification – predict to which class a given pattern belongs
- classifier combining/aggregation/fusion/selection/…
  - create a team of classifiers and aggregate their predictions
  - better generalization properties
  - lower error rate
  - better robustness
  - less sensitive to overfitting
  - the resulting system behaves as a single classifier
  - no generally accepted unifying theory
  - how does it work? Bias/variance decomposition (variance is reduced), large margin classifiers (large margin $\rightarrow$ better generalization)
Classifier Team Design

- motivation: induce *diversity* to the team
- sampling from the training set (bagging, boosting)
- partitioning the feature space (divide&conquer, mixture of experts)
- using different combinations of features (multiple feature subset, attribute bagging)
- multi-model approaches (e.g., k-NN, neural net, decision tree, and SVM)
- changing parameters of a model (3-NN, 5-NN, 10-NN; neural net topology)
- output coding (error correcting output coding)
- hybrid methods (random forests)
Classification Confidence

- motivation: measure the degree of reliability of a prediction
  - static
    - global accuracy, precision, sensitivity, ...
  - dynamic
    - local accuracy
    - local match
    - methods based on d.o.c.
    - statistical methods - transduction
    - model-specific methods
Aggregation

- classifier selection (static/dynamic classifier selection, mixture of experts)
- crisp classifiers - voting, behavior knowledge space
- class ranking methods - Borda count
- soft classifiers - arithmetic approaches (mean, median, min, max), probabilistic approaches (product rule, Dempster-Shafer theory), fuzzy logic (fuzzy integral, decision templates)
- second level classifiers - stacking
Dynamic Classifier Systems

- framework of classifier combining with classification confidence
- \( S = (\mathcal{T}, \mathcal{K}, \mathcal{A}) \) – classifier system
- \( \mathcal{T} = (\phi_1, \ldots, \phi_r) \) – classifiers
- \( \mathcal{K} = (\kappa_{\phi_1}, \ldots, \kappa_{\phi_r}) \) – confidence measures
- \( \mathcal{A} \) – aggregator
- 3 types of classifier systems
  - confidence-free
  - static
  - dynamic
Types of classifier systems

(a) Confidence-free

(b) Static

(c) Dynamic
Classifier Aggregation

- prediction

\[ T(\vec{x}) = \begin{pmatrix} \phi_1(\vec{x}) \\ \phi_2(\vec{x}) \\ \vdots \\ \phi_r(\vec{x}) \end{pmatrix} = \begin{pmatrix} \gamma_{11}(\vec{x}) & \gamma_{12}(\vec{x}) & \cdots & \gamma_{1N}(\vec{x}) \\ \gamma_{21}(\vec{x}) & \gamma_{22}(\vec{x}) & \cdots & \gamma_{2N}(\vec{x}) \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{r1}(\vec{x}) & \gamma_{r2}(\vec{x}) & \cdots & \gamma_{rN}(\vec{x}) \end{pmatrix} \]

\[ \gamma_{ij}(\vec{x}) = \text{degree of classification to class } C_j \text{ given by } \phi_i \]

- confidence

\[ K(\vec{x}) = \begin{pmatrix} \kappa_{\phi_1}(\vec{x}) \\ \kappa_{\phi_2}(\vec{x}) \\ \vdots \\ \kappa_{\phi_r}(\vec{x}) \end{pmatrix} \]

\[ \kappa_{\phi_i}(\vec{x}) = \text{confidence of } \phi_i \text{ on } \vec{x} \]

- usually, aggregate \( j \)-th column of \( T(\vec{x}) \) by an aggregation operator, parametrized by \( K(\vec{x}) \)
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4. Experiments
Information Fusion

- \((X_1, \ldots, X_N)\) – information sources (sensors, experts, etc.)
- \((a_1, \ldots, a_N) \in D^N\) – outputs in domain \(D\), e.g. \(D = \mathbb{R}\)
- \(\mathbb{C} : D^N \rightarrow D\) – aggregation operator
- \(\mathbb{C}(a_1, \ldots, a_N)\) – aggregated value (consensus)
- arithmetic mean, weighted mean, median, minimum, maximum, ...
Desired Properties

- **unanimity**
  \[ \forall a : C(a, \ldots, a) = a \]

- **monotonicity**
  \[ \forall i : a_i \geq a_i' \Rightarrow C(a_1, \ldots, a_N) \geq C(a_1', \ldots, a_N') \]

- (unanimity) + (monotonicity) ⇒ internality
  \[ \min_i a_i \leq C(a_1, \ldots, a_N) \leq \max_i a_i \]

- **symmetry** (no source is distinguishable)
  \[ \forall \pi \in \Pi_{1,\ldots,N} : C(a_1, \ldots, a_N) = C(a_{\pi(1)}, \ldots, a_{\pi(N)}) \]

- **robustness** (influence of outliers) - arithmetic mean vs. median

- **applicability** – numeric / ordinal / nominal domains
Weighted Mean

\[ WM_p(a_1, \ldots, a_N) = \sum_i p_i a_i \]

- weighting vector: \( p = (p_1, \ldots, p_N) \in [0, 1]^N, \sum_i p_i = 1 \)
- \( p_i \) – importance (reliability) of \( i \)-th source
- properties
  - special case – arithmetic mean \( (p_i = 1/N) \)
  - not symmetric
  - dictatorship of the \( i \)-th source \( (p_i = 1, p_j = 0 \ j \neq i) \)
  - unbounded influence of outliers
Ordered Weighted Average (OWA)

- \( \text{OWA}_w(a_1, \ldots, a_N) = \sum_i w_i a_{<i>} \)
- weighting vector \( w \), (\( \cdot \)) indicating nondecreasing permutation, i.e. \( a_{<i>} \geq a_{<i-1>} \)
- \( w_i \) – importance of \( i \)-th largest output
- properties
  - can reduce (or ignore) extreme values, e.g. \( w = (0, 1/3, 1/3, 1/3, 0) \) – committee
  - special cases – minimum, maximum, median, arithmetic mean
  - symmetric
Fuzzy Measure

- \( \mu : \mathcal{P}(U) \rightarrow [0, 1] \) is called a fuzzy measure on \( U \) iff:
  1. (boundary condition) \( \mu(\emptyset) = 0, \mu(U) = 1 \)
  2. (monotonicity) \( A \subseteq B \Rightarrow \mu(A) \leq \mu(B) \)

- Generalization of additive measures (probability)
- Can model interaction between the elements
- Example: 3 subjects (math, physics, literature); \( \mu(\emptyset) = 0, \mu(M) = 0.45, \mu(P) = 0.45, \mu(L) = 0.3, \mu(M, L) = 0.9, \mu(P, L) = 0.9, \mu(M, P) = 0.5, \mu(M, P, L) = 1 \)
- Classifier aggregation: aggregate the integrand (predictions of the classifiers) with respect to the fuzzy measure (represents the confidence)
- No general definition of fuzzy integral; Choquet and Sugeno used most often
<table>
<thead>
<tr>
<th>i</th>
<th>support; $A_{&lt;i&gt;}$</th>
<th>d.o.c.-level; $f_{&lt;i&gt;}$</th>
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<tbody>
<tr>
<td>4</td>
<td>$\phi_3$</td>
<td>0.9</td>
<td>0.1</td>
</tr>
<tr>
<td>3</td>
<td>$\phi_3, \phi_4$</td>
<td>0.4</td>
<td>0.3</td>
</tr>
<tr>
<td>2</td>
<td>$\phi_1, \phi_3, \phi_4$</td>
<td>0.3</td>
<td>0.7</td>
</tr>
<tr>
<td>1</td>
<td>$\phi_1, \phi_2, \phi_3, \phi_4$</td>
<td>0.2</td>
<td>1</td>
</tr>
<tr>
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<td>0</td>
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</tbody>
</table>

$$\int_C f \, d\mu = \sum_{i=1}^{r} (f_{<i>} - f_{<i-1>}) \mu(A_{<i>})$$

$$= 0.5 \cdot 0.1 + 0.1 \cdot 0.3 + 0.1 \cdot 0.7 + 0.2 \cdot 1 = 0.35$$
Choquet Integral ctnd

- for additive measures, Choquet integral coincides with Lebesgue integral
- satisfies unanimity, monotonicity, internality (i.e., it is a proper aggregation operator)
- generalizes weighted mean, OWA, WOWA
### Sugeno Integral

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<td>1</td>
</tr>
<tr>
<td>0</td>
<td>$\phi_1, \phi_2, \phi_3, \phi_4$</td>
<td>0</td>
<td></td>
</tr>
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</table>

\[(S) \int f \, d\mu = \max_{i=1} \min(f_{<i>}, \mu(A_{<i>}))\]

\[= \max(0.1, 0.3, 0.3, 0.2) = 0.3\]
Sugeno Integral ctnd

- satisfies unanimity, monotonicity, internality (i.e., it is a proper aggregation operator)
- generalizes weighted minimum and maximum
Aggregation Operators - summary

- Arithmetic mean
- Weighted mean
- Minimum
- Median
- Maximum
- Weighted minimum
- Weighted maximum
- WOWA
- OWA
- Choquet integral
- Sugeno integral
- General fuzzy integral
- Weighted Mean
- Ordered Weighted Average
- Choquet Integral
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Fuzzy Integral

- aggregate the integrand w.r.t. fuzzy measure
- integrand \( \sim \) degrees of classification (d.o.c.) to \( C_j \) given by \( \phi_1, \ldots, \phi_r \)
- fuzzy measure \( \sim \) confidences of the individual classifiers
- integral \( \sim \) aggregated d.o.c. to class \( C_j \)
Fuzzy Measure

- $\mu : \mathcal{P}(X) \rightarrow [0, 1]$ is called a fuzzy measure on $X$ iff:
  1. (boundary condition) $\mu(\emptyset) = 0$, $\mu(X) = 1$
  2. (monotonicity) $A \subseteq B \Rightarrow \mu(A) \leq \mu(B)$

- generalization of additive measures (probability)
- can model interaction between the elements
  
  example: 3 subjects (math, physics, literature); $\mu(\emptyset) = 0$, $\mu(M) = 0.45$, $\mu(P) = 0.45$, $\mu(L) = 0.3$, $\mu(M, L) = 0.9$, $\mu(P, L) = 0.9$, $\mu(M, P) = 0.5$, $\mu(M, P, L) = 1$

- hard to define (needs $2^N - 2$ parameters)
- additive measures need only $N - 1$ parameters (for the singletons) - fuzzy densities $\mu(\phi_i)$
Common Fuzzy Measures

- **additive:** \( \mu(A \cup B) = \mu(A) + \mu(B) \) for disjoint \( A, B \)
  - correspond to probabilistic measures
- **symmetric:** \(|A| = |B| \Rightarrow \mu(A) = \mu(B)\)
  - \( \mu(A) \) depends only on the number of elements in \( A \)
  - leads to confidence-free aggregation
- \( \perp \)-decomposable: \( \mu(A \cup B) = \mu(A) \perp \mu(B) \) for disjoint \( A, B \)
  - special case: Sugeno \( \lambda \)-measure (used most often in classifier aggregation using FI); \( \mu(A \cup B) = \mu(A) + \mu(B) + \lambda \mu(A)\mu(B) \)
  - \( \mu(A \cup B) \) fully determined by \( \mu(A), \mu(B), \perp \)
- neither of these can model interactions between the classifiers
motivation: model the confidence of a set of classifiers, but take mutual classifier similarities ($\sim$ interactions) into account

- similar classifiers: small increase in the measure
- different classifiers: big increase in the measure

- diversity of the classifier team is taken into account in the aggregation process (not processed a priori)
- not limited to classifier aggregation only
Induced Interaction-Sensitive Fuzzy Measure (I-ISFM)

- at each step, classifier $\phi_{<i>}$ is added to a set of classifiers $(\phi_{<i+1>}, \ldots, \phi_{<r>})$
- increase of the measure is controlled by the similarity

\[
\mu(\emptyset) = 0 \\
\mu(A_{<r>}) = \mu(\{\phi_{<r>}\}) = \kappa_{<r>} \\
\mu(A_{<i>}) = \mu(\{\phi_{<i>}, \ldots, \phi_{<r>}\}) = \\
= \mu(A_{<i+1>}) + [1 - \max_{k=i+1}^{r} S(\phi_{<i>}, \phi_{<k>})] \kappa_{<i>}
\]

for $i = r - 1, \ldots, 1$,

- I-ISFM: $\mu$ normalized to $[0, 1]$
- theoretical weakness: tightly connected to the ordering $< \cdot >$ induced by $f$
Global Interaction-Sensitive Fuzzy Measure (G-ISFM)

- fuzzy measure on the whole universe; regardless of the integrand
- take the classifier confidences and transform them into new fuzzy densities
  \[ \mu(\phi_k) = \kappa_k \leadsto \tilde{\mu}(\phi_k) \]
- classifiers are sorted w.r.t. confidences \([\cdot]\)
- with decreasing confidence, the similarity to elements with higher confidence is taken into account
  \[ \tilde{\mu}(\phi[k]) = \kappa[k](1 - \max_{j=k+1}^{r} s[k,j]), \quad k = 1, \ldots, r \]
- use \(\tilde{\mu}(\phi[k])\) to build an additive measure
Modified Hüllermeier Measure (MHM)

- Cho-k-NN: use similarities of neighbors in k-NN classifier
- base measure \( \nu \) (e.g., additive, based on the confidences)
- use diversity of a set of classifiers to adjust the base measure

\[
div(A) = \frac{2}{|A|^2 - |A|} \sum_{u_i, u_j \in A; j < i} (1 - s_{i,j}) \in [0, 1]
\]

\[
rdiv(A) = \frac{2div(A)}{\max(1 - s_{i,j})} - 1 \in [-1, 1]
\]

\[
\mu_h(A) = \nu(A)(1 + \alpha rdiv(A)), \quad \alpha \geq 0
\]

- not necessarily monotone
  - enforce monotonicity using \( \mu_h(A) = \max_{B \subseteq A} \mu_h(B) \) is practically impossible
  - use the idea from I-ISFM: compute \( \mu_h \) only for the \( r \) values actually needed for the integration, i.e., sets \( A_{<i} \)
Example - similar classifiers

\[ T_{*,j}(\bar{x}) = [0.5, 0.4, 0.8]^T \]
\[ K(\bar{x}) = [0.3, 0.4, 0.6]^T \]
\[ (s_{i,j}) = \begin{pmatrix}
1 & 0.9 & 0.2 \\
0.9 & 1 & 0.2 \\
0.2 & 0.2 & 1
\end{pmatrix} \]

<table>
<thead>
<tr>
<th>i</th>
<th>support</th>
<th>d.o.c.-level</th>
<th>additive</th>
<th>Sugeno ( \lambda )</th>
<th>( \mu(A_{&lt;i&gt;}) )</th>
<th>I-ISFM</th>
<th>G-ISFM</th>
<th>MHM</th>
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<tr>
<td>3</td>
<td>( \phi_3 )</td>
<td>0.8</td>
<td>0.462</td>
<td>0.6</td>
<td>0.682</td>
<td>0.632</td>
<td>0.325</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>( \phi_1, \phi_3 )</td>
<td>0.5</td>
<td>0.693</td>
<td>0.791</td>
<td>0.955</td>
<td>0.663</td>
<td>0.977</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>( \phi_1, \phi_2, \phi_3 )</td>
<td>0.4</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td></td>
</tr>
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Example - similar classifiers

Similar classifiers

\[ T_{*,j}(\vec{x}) = [0.5, 0.4, 0.8]^T \]

\[ K(\vec{x}) = [0.3, 0.4, 0.6]^T \]

\[ (s_{i,j}) = \begin{pmatrix} 1 & 0.9 & 0.2 \\ 0.9 & 1 & 0.2 \\ 0.2 & 0.2 & 1 \end{pmatrix} \]
Example - dissimilar classifiers

\[ \mathcal{T}_{*,j}(\vec{x}) = [0.5, 0.4, 0.8]^T \]
\[ \mathcal{K}(\vec{x}) = [0.3, 0.4, 0.6]^T \]
\[ (s_{i,j}) = \begin{pmatrix} 1 & 0.3 & 0.2 \\ 0.3 & 1 & 0.2 \\ 0.2 & 0.2 & 1 \end{pmatrix} \]

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<td>1</td>
<td>0.791</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td></td>
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</tr>
</tbody>
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Example - dissimilar classifiers

Dissimilar classifiers

\[ \mathcal{T}_{*,j}(\vec{x}) = [0.5, 0.4, 0.8]^T \]
\[ \mathcal{K}(\vec{x}) = [0.3, 0.4, 0.6]^T \]

\[ (s_{i,j}) = \begin{pmatrix} 1 & 0.3 & 0.2 \\ 0.3 & 1 & 0.2 \\ 0.2 & 0.2 & 1 \end{pmatrix} \]
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4 Experiments
Experiments

- compare non-interaction sensitive measures (additive, Sugeno $\lambda$-measure) to ISFM (I-ISFM, G-ISFM, MHM)
- 3 different classifier systems (Random Forest, k-NN ensemble, QDC ensemble)
- 23 datasets
- Choquet/Sugeno integral with Sugeno $\lambda$-measure and ISFM
- reference: single best, weighted mean ($\sim$ additive measure)
Experimental results

Number of datasets (out of 69), for which the aggregator obtained the best results among all aggregators.

- CI-ISFM-I
- CI-MHM
- CI-ISFM-G
- SI-ISFM-G
- SI-ISFM-I
- SI-MHM
- CI-lambda
- SB
- SI-lambda
- Wmean
## Experimental results

<table>
<thead>
<tr>
<th>↓ superior to →</th>
<th>SB</th>
<th>WMean</th>
<th>CI</th>
<th>SI</th>
<th>all</th>
</tr>
</thead>
<tbody>
<tr>
<td>(out of 69)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SB</td>
<td>-</td>
<td>32 (4)</td>
<td>19 (1)</td>
<td>9</td>
<td>18 (3)</td>
</tr>
<tr>
<td>WMean</td>
<td>37 (16)</td>
<td>-</td>
<td>15 (2)</td>
<td>5</td>
<td>15 (7)</td>
</tr>
<tr>
<td>CI-λ</td>
<td>50 (18)</td>
<td>54 (6)</td>
<td>-</td>
<td>9</td>
<td>20</td>
</tr>
<tr>
<td>CI-I-ISFM</td>
<td>60 (23)</td>
<td>64 (19)</td>
<td>60 (7)</td>
<td>-</td>
<td>45 (2)</td>
</tr>
<tr>
<td>CI-G-ISFM</td>
<td>61 (24)</td>
<td>54 (18)</td>
<td>49 (7)</td>
<td>24</td>
<td>-</td>
</tr>
<tr>
<td>CI-MHM</td>
<td>58 (24)</td>
<td>62 (17)</td>
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<td>43 (2)</td>
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<tr>
<td>SI-λ</td>
<td>51 (17)</td>
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<td>12</td>
<td>16</td>
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<td>39 (2)</td>
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<td>41 (5)</td>
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<td>21</td>
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<td>59 (13)</td>
<td>54 (6)</td>
<td>22</td>
<td>33 (2)</td>
</tr>
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Number of datasets (out of 69), on which aggregator i obtained better results than aggregator j, including significant improvements in parentheses.
Experimental results

- ISFMs generally outperform traditional fuzzy measures (often significantly)
- CI obtained better results than SI
- I-ISFM and MHM slightly superior to G-ISFM
Conclusions

- Dynamic classifier systems aggregated using fuzzy integral
- Traditional fuzzy measures (additive, symmetric, $\bot$-decomposable) do not take classifier similarities into account
- ISFM: use classifier similarities in the fuzzy measure to further improve the fuzzy integral-based aggregation
- Three novel fuzzy measures: I-ISFM, G-ISFM, MHM
- Diversity is processed directly in the aggregation
- Fast evaluation
- Not limited to classifier aggregation only
- Experimental results: ISFMs outperform traditional fuzzy measures
Dynamic Classifier Systems
Aggregation Operators
Interaction-Sensitive Fuzzy Measures
Experiments

Thank you for your attention

David Štefka
stefka@insophy.cz

Classifier Aggregation
using Fuzzy Integral based on
Interaction-Sensitive Fuzzy Measures