Task Assignment in a Human-Autonomous Image Labeling System

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Outline

Summary

- We want to design a human-autonomous system which can efficiently and accurately classify a database of images.
  - We want to leverage computer vision technology, Brain-Computer Interface technology, and human agents.
  - We have to address who classifies which images and when.
  - We have to address how to combine the classifications from multiple agents for the same image.

Rapid Serial Visual Presentation (RSVP)

Ries and Larkin [2013]

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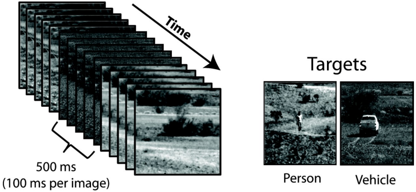
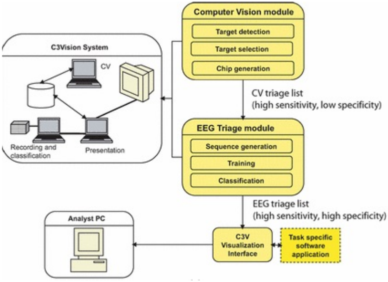


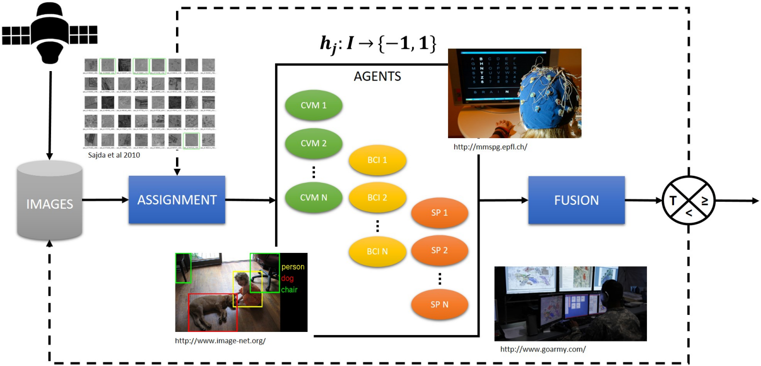
- Electroencephalogram (EEG) Brain-Computer Interface (BCI)
- Image presentation at high rate of speed (2-10 Hz)
- Visual oddball paradigm generates a neural signature

Cortically Coupled Computer Vision

Sajda *et al.* [2010]



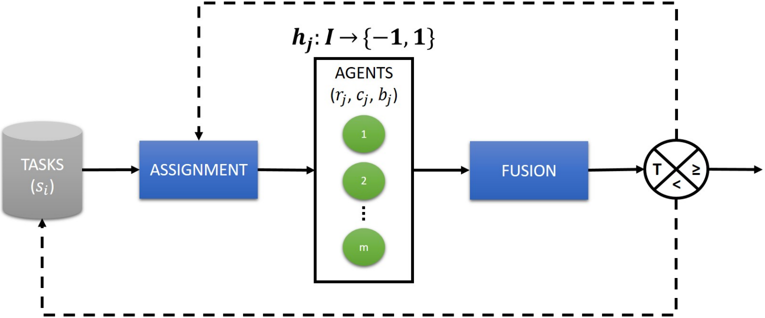
- Combine human understanding and computer speed to triage “interesting” images
- How to maximize the synergy? Triage in serial or parallel?
- Characterized serial triage


$h_j: I \rightarrow \{-1, 1\}$
AGENTS
CVM 1
CVM 2
CVM N
BCI 1
BCI 2
BCI N
SP 1
SP 2
SP N
IMAGES
ASSIGNMENT
FUSION
T
≥
<
Sajda et al 2010
http://mmspg.epfl.ch/
person
dog
chair
http://www.image-net.org/
http://www.goarmy.com/

Relevant Work

- "Repeated labeling using multiple noisy labelers," Ipeirotis *et al.* [2013]
  - When data collection is more expensive than noisy labeling, repeated labeling improves meta-label quality
- "Budget-optimal task allocation for reliable crowdsourcing systems," Karger *et al.* [2014]
  - Minimize task assignments to achieve target reliability with homogeneous agents and tasks
  - Random task assignment based on predetermined budget
  - Belief propagation algorithm for data fusion
- "Adaptive task assignment for crowdsourced classification," Ho *et al.* [2013]
  - Minimize task assignments to achieve target reliability with heterogeneous agents and tasks
  - Generalized assignment problem formulation
  - Exploration to learn agent reliability and task value

An Iterative Task Assignment System



Problem Statement

1. Assignment Problem – How to optimally assign homogeneous binary classification tasks amongst diverse agents?
2. Joint Classification Problem – How to dynamically combine multiple labels from noisy agents without supervised knowledge?

Generalized Assignment Problem (GAP)

Morales and Romeijn [2004]; Kundakcioglu and Alizamir [2008]

$$f(\mathbf{x}) = \min_{\mathbf{x}} \sum_{i=1}^{n} \sum_{j=1}^{m} -v_{ij}\mathbf{x}_{ij} \qquad (1)$$

1. $\sum_{i=1}^{n} c_{ij}\mathbf{x}_{ij} \leq b_j, \; j = 1, \ldots, m$
2. $\sum_{j=1}^{m} \mathbf{x}_{ij} = 1, \; i = 1, \ldots, n$
3. $\mathbf{x}_{ij} \in \{0, 1\}$
4. $v_{ij} = g(r_j, s_j) \geq 0$

- n – number of tasks
- m – number of agents
- $\mathbf{x}_{ij}$ – assignment of task i to agent j
- v_{ij} – assignment value of task i to agent j
- c_{ij} – assignment cost of task i to agent j
- b_j – budget for agent j
- r_j – reliability of agent j
- s_i – classification confidence of task i

Generalized Assignment Problem (GAP)

Morales and Romeijn [2004]; Kundakcioglu and Alizamir [2008]

The GAP is a *NP Hard* binary integer linear program with two primary classes of solution methods:

- Exact
  - Branch and Bound Algorithm*
  - Branch and Price Algorithm
- Heuristic
  - Relaxing integrality constraints
  - Lagrangian relaxation of constraints
  - Greedy methods*
  - Meta-heuristics

Branch and Bound Algorithm

Morales and Romeijn [2004]; Kundakcioglu and Alizamir [2008]

The branch and bound algorithm is an exact method which attempts to exhaustively search the feasible solution space. Equipped with an appropriate bounding heuristic, it can eliminate subspaces of the solution space from the search. It has three components:

1. Bounding function
   - Heuristic
2. Branching strategy
   - Serial
3. Searching Strategy
   - Best first
   - Depth first
   - Breadth first

x_{11}	1
x_{12}	0
x_{13}	1
	$\vdots$
x_{ij}	
	$\vdots$
x_{nm}	

Branch and Bound Algorithm

Morales and Romeijn [2004]; Kundakcioglu and Alizamir [2008]; Clausen [1999]

Data: $S \subset \{0,1\}^{m \times n}$, $g: \ S \to \mathbb{R}$
Result: $x_{opt} \in \{0,1\}^{m \times n}$
$I := \infty$; $LB(p_0) := g(p_0)$; $B := \{(p_0, LB(p_0))\}$;
while $B \neq \emptyset$ **do**
  Select $p \in B$; $B := B \backslash \{p\}$; branch on p for $1, \ldots, k$;
  for $i = 1, \ldots, k$ **do**
    $LB(p_i) := g(p_i)$;
    if $LB(p_i) < I$ **then**
      if $LB(p_i) = f(X)$ **then**
        $I = f(X)$; $x_{opt} = X$; go to end;
      else
        $B := B \cup \{(p_i, LB(p_i))\}$;
      end
    end
  end
end

Bounding Function: Lagrangian Relaxation

Morales and Romeijn [2004]; Fisher [2004]

We dualize the capacity constraints of our GAP

$$L(\lambda) = \min_{\mathbf{x}} \left(\sum_{i=1}^{n} \sum_{j=1}^{m} -v_{ij}\mathbf{x}_{ij} + \sum_{j=1}^{m} \lambda_j \sum_{i=1}^{n} (c_{ij}\mathbf{x}_{ij} - b_j) \right) \tag{2}$$

1. $\sum_{j=1}^{m} \mathbf{x}_{ij} = 1, \; i = 1, \ldots, n$
2. $\mathbf{x}_{ij} \in \{0, 1\}$
3. $\lambda_j \geq 0, \; j = 1, \ldots, m$

which satisfies the following inequality:

$$L(\lambda) \leq \min_{\mathbf{x}} f(\mathbf{x}) \tag{3}$$

Joint Classification Problem

Given m agents each making binary decisions on all n tasks, how do you infer the right decision?

IMAGE

AGENT

$A_{ij} = \hat{y}_{ij}$	1	2	$\cdots$	i	$\cdots$	n
1	+1	+1	$\cdots$	+1	$\cdots$	+1
2	-1	X	$\cdots$	-1	$\cdots$	-1
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\cdots$	$\vdots$
j		-1	$\cdots$	+1	$\cdots$	X
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
m	-1	+1	$\cdots$	-1	$\cdots$	-1

Figure: Classification Outcomes, $\mathbf{A} = [\mathbf{a}_1 | \cdots | \mathbf{a}_m]^T$

$$\arg\min_{f} \sum_{i=1}^{n} \mathbb{P}(f(\hat{y}_{i1}, \ldots, \hat{y}_{im}) \neq y_i \tag{4}$$

1. $f : \{\hat{y}_{ij}\}_{j=1}^{m} \rightarrow \bar{y}_i$
2. $\hat{y}_{ij},\ \bar{y}_i,\ y_i \in \{-1, 1\}$

- $\hat{y}_{ij}$ – label for task i from agent j
- $\bar{y}_i$ – label for task i from fusion
- y_i – true label for task i

Joint Classification Approaches

Ipeirotis *et al.* [2013]; Parisi *et al.* [2014]

- Unsupervised
  - Majority vote
  - Mean
  - A priori knowledge
- Supervised
  - Linear Regression
  - Relative performance
- Semi-Supervised
  - Active/proactive Learning
  - Exploration-exploitation

Spectral Meta-Learner
Parisi *et al.* [2014]

Given the sample covariance matrix over the fully-classified classification outcomes, $\mathbf{A}_{FC} \subset \mathbf{A}$,

$$\hat{\mathbf{Q}} = \frac{1}{m-1}\sum_{j=1}^{m}(\mathbf{a}_j - \bar{\mathbf{a}})^T(\mathbf{a}_j - \bar{\mathbf{a}}),$$

it can be shown that

$$Q_{ij} = \lim_{n\to\infty}\hat{Q}_{ij} = \begin{cases} 1-\mu_j^2 & i=j \\ (1-b^2)(2\pi_i - 1)(2\pi_j - 1) & \text{o.w.} \end{cases}$$

where $b = \mathbb{P}(y_i = 1) - \mathbb{P}(y_i = -1)$ is the class imbalance and $\pi_i = \frac{\mathbb{P}(\bar{y}_i=1|y_i=1)+\mathbb{P}(\bar{y}_i=-1|y_i=-1)}{2}$ is the balanced accuracy.

Spectral Meta-Learner
Parisi *et al.* [2014]

This implies:

$$\mathbf{Q} \approx \lambda \mathbf{v}\mathbf{v}^T$$

and further that $v_j \propto (2\pi_j - 1)$!

This leads us to a maximum likelihood estimate for data fusion of multiple labels from noisy agents–the so-called Spectral Meta-Learner (SML):

$$\bar{y}_i^{MLE} = \text{sign}\left(\sum_{j=1}^{m} \hat{y}_{ij} v_j\right). \tag{5}$$

Resources

- Hardware
  - Dell Desktop Computer (100 GB RAM, 16 Processors, 3 GHz)
- Software
  - MATLAB
- Databases
  - Office Object Database – Translational Neuroscience Branch, Army Research Laboratories
  - Office Object Database RSVP Collection – Translational Neuroscience Branch, Army Research Laboratories

Validation and Testing

Validation

- On-line simulation of six agents of predetermined reliability and cost
- Compare against MATLAB integer programming application

Testing

- On-line simulation of two BCI agents and three computer vision agents
  - Actual results from experiments on Office Object Database
- Compare (speed and accuracy) against full-assignment off-line analysis

Schedule (with Milestones*)

- Preparation (- 15 OCT)
  - Project Proposal (15 OCT)*
- Late 1st Semester (15 OCT - 4 DEC)
  - Implement branch and bound algorithm (6 NOV)*
  - Implement greedy search algorithm
  - Compare performance of assignment algorithms
  - Mid-year Review (4 DEC)*
- Early 2nd Semester (25 JAN - 11 MAR)
  - Build agent classes
  - Integrate all components into a system (26 FEB)*
  - Validation (11 MAR)*
- Late 2nd Semester (21 MAR - 1 MAY)
  - Performance analysis
  - Testing (15 APR)*
  - Final Presentation and Results (6 MAY)*

Deliverables

- Software
  - Fusion module
  - Assignment module
  - Agent classes
  - Executive script
- Analysis
  - Performance analysis and implications for human-autonomous systems
  - Computational complexity of system

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