A Novel Uncertainty Sampling Algorithm for Cost-sensitive Multiclass Active Learning

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Appier, November 24, 2016

Outline

- Problem Introduction
- Proposed Algorithm
- Experiments
- Conclusion

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Multiclass Classification (MCC)

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- learning from lots of labeled data
- example: animal recognition

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label	dog	cat	dog	rabbit	cat	rabbit

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labeling is expensive!

Active Learning for Multiclass Classification

Labeled pool

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Unlabeled pool

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Notation

- feature (image): $\mathbf{x} \in \mathbb{R}^d$
- label: $y \in \{c_1, c_2, ..., c_K\}$

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- labeled pool $\mathcal{D}_l = \{(\mathbf{x}^{(n)}, y^{(n)})\}_{n=1}^{N_l}$ and unlabeled pool $\mathcal{D}_u = \{\mathbf{x}^{(n)}\}_{n=1}^{N_u}$

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  - use **querying strategy** to query $\mathbf{x}_s$ in unlabeled pool $\mathcal{D}_u$ and get the label y_s

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  - learn a **classifier** $f^{(t)}$ from the current label pool $\mathcal{D}_l$
- improve the **performance** of $f^{(t)}$ with respect to **#queries**

Querying Strategies

Uncertainty sampling

- query most **uncertain** $\mathbf{x}$
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this work focuses on **uncertainty sampling**

Evaluation Criteria

Regular (Error rate)

actual \ predicted	healthy	cold	Zika
healthy	0	1	1
cold	1	0	1
Zika	1	1	0

- **same** misclassified penalties
- most common criterion

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Cost matrix

actual \ predicted	healthy	cold	Zika
healthy	0	10	50
cold	200	0	100
Zika	**1000**	800	0

- **different** misclassified penalties
- cost matrix $\mathbf{C}$
- $\mathbf{C}_{i,j}$: predict c_i as c_j

Cost-sensitive Active Learning Algorithms

Cost-sensitive algorithms

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	query strategy	classifier f
regular algorithms	by f, $\mathcal{D}_l$, and $\mathcal{D}_u$	learned from $\mathcal{D}_l$
cost-sensitive algorithms	by f, $\mathcal{D}_l$, $\mathcal{D}_u$, and $\mathbf{C}$	learned from $\mathcal{D}_l$ and $\mathbf{C}$

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Goal of our work

- **cost-sensitive uncertainty sampling algorithms**

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Goal of our work

- **cost-sensitive uncertainty sampling algorithms**

	regular	cost-sensitive
probabilistic uncertainty	well-studied	known [Chen et al., 2013]
non-probabilistic uncertainty	well-studied	ongoing (our work)

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Main tasks

- **query strategy**: non-probabilistic cost-sensitive uncertainty
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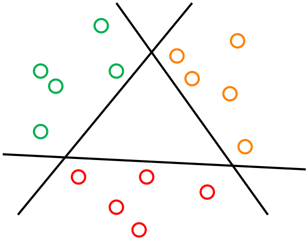

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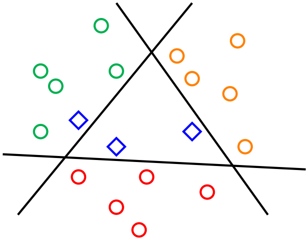
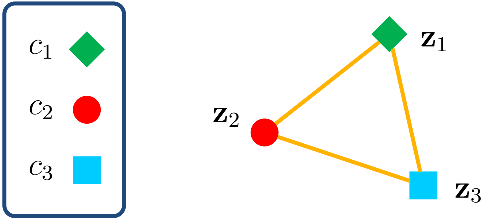


Embedding View for MCC (Training)



Training stage

- for classes $c_1, c_2, ..., c_K$, find K **hidden points** $\mathbf{z}_1, \mathbf{z}_2, ..., \mathbf{z}_K$ with **equal distances**

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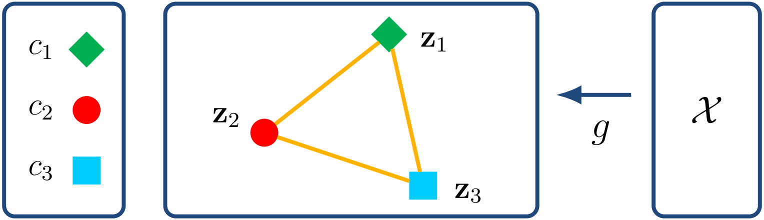

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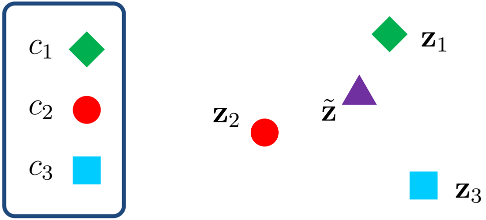

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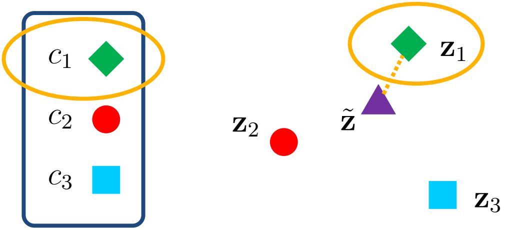

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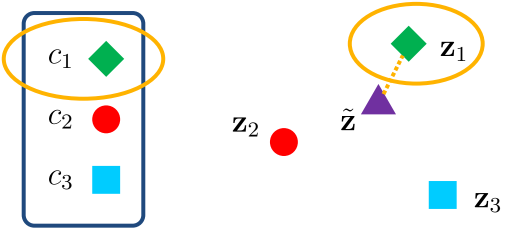

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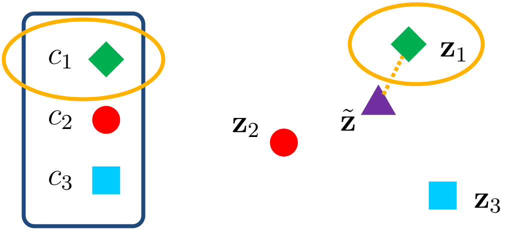
equivalent to one-versus-all scenario when g is linear

Cost Information



Embedding cost information

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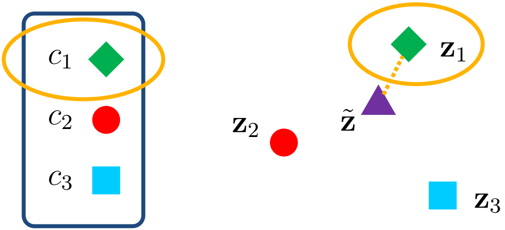
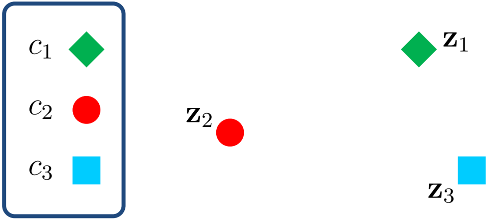


Embedding cost information

- get prediction by nearest neighbor (smallest distance)
- embed cost information in distance

Cost Embedding (Training)



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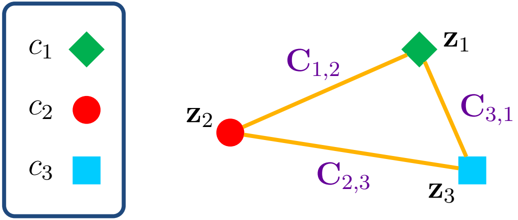

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- **higher (lower) cost $\mathrm{C}_{i,j} \Leftrightarrow$ larger (smaller) distance $d(\mathbf{z}_i, \mathbf{z}_j)$**
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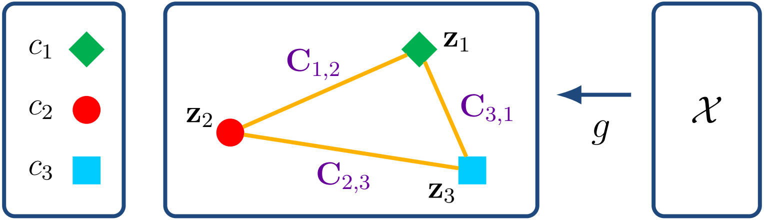

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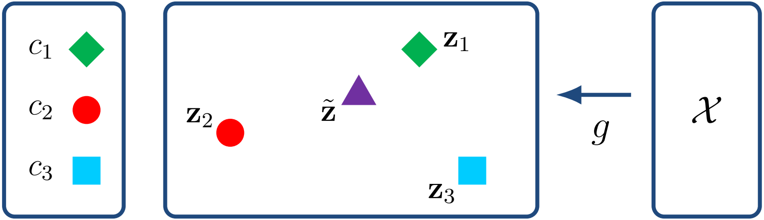

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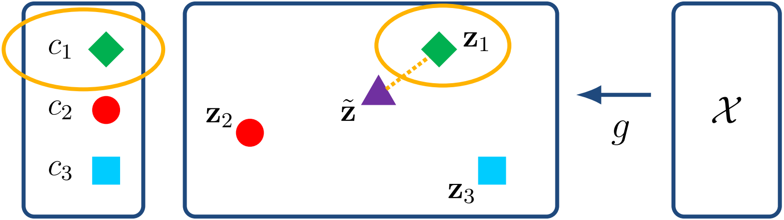

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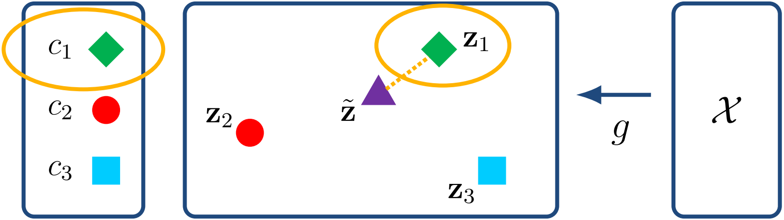

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how to preserve the **order** of the costs?

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- classic technique in manifold learning

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Goal of non-metric multidimensional scaling

- L objects $O_1, O_2, ..., O_L$
- symmetric dissimilarity matrix $\mathbf{\Delta}$: $\mathbf{\Delta}_{i,j}$ for dissimilarity of O_i and O_j

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asymmetric cost $\mathbf{C}$ ($\mathbf{C}_{i,j} \neq \mathbf{C}_{j,i}$) vs. **symmetric dissimilarity** $\boldsymbol{\Delta}$

Asymmetry of Cost Matrix

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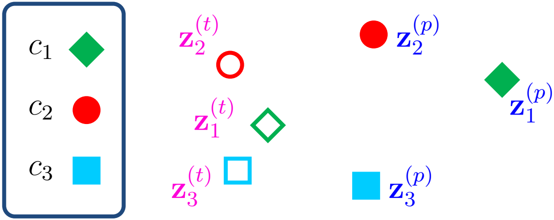
Two roles of classes

- two roles of class c_i: ground truth role and prediction role
- embed cost information in these two roles

Mirroring Trick



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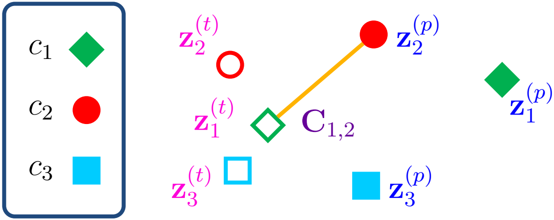

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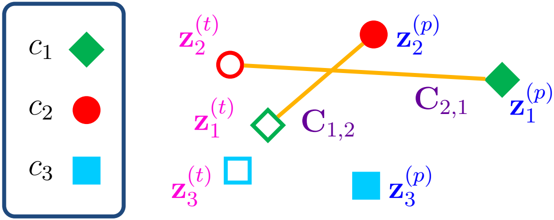

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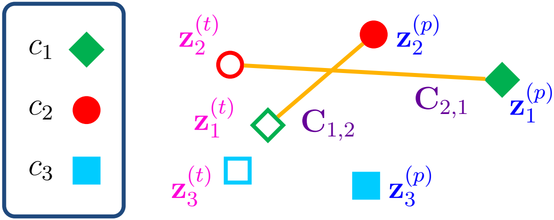

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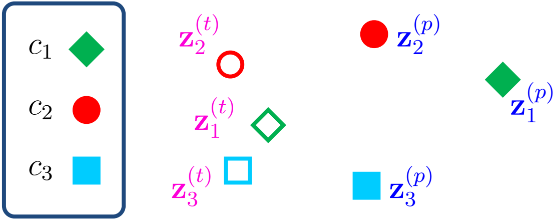
- $\mathbf{C}_{j,i} \Rightarrow$ cost when c_i is prediction and c_j is ground truth $\Rightarrow$ for $\mathbf{z}_i^{(p)}$ and $\mathbf{z}_j^{(t)}$
- cost information is embedded in **distance** between ground truth role $\mathbf{z}_i^{(t)}$ and prediction role $\mathbf{z}_i^{(p)}$

Mirroring Trick



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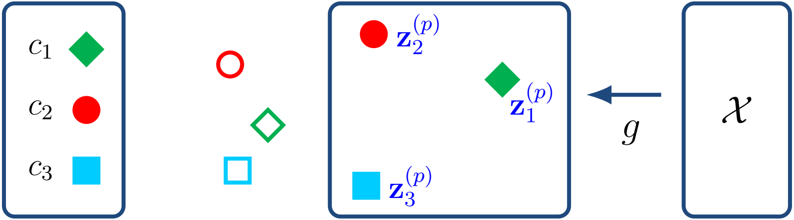

Training stage

- $\tilde{\mathbf{z}} = g(\mathbf{x})$ learned from $\{(\mathbf{x}^{(n)}, \mathbf{z}^{(n)})\}_{n=1}^{N} \Rightarrow$ prediction role
- learn **regressor** g from $\mathbf{z}_1^{(p)}, \mathbf{z}_2^{(p)}, \ldots, \mathbf{z}_K^{(p)}$

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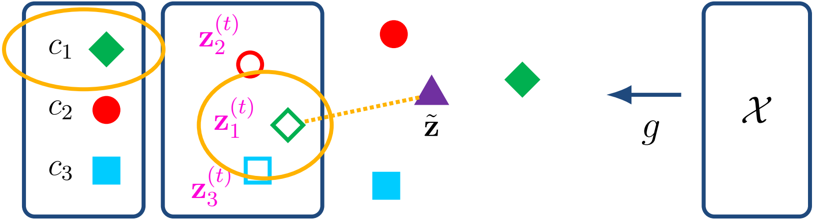

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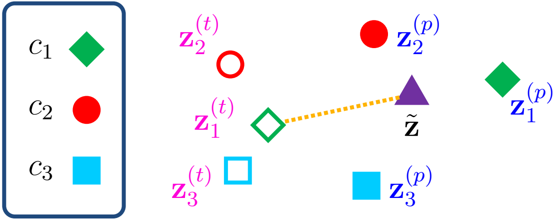
Predicting stage

- nearest hidden point of $\tilde{\mathbf{z}} \Rightarrow$ ground truth role
- find the **nearest hidden point** of $\tilde{\mathbf{z}}$ from $\mathbf{z}_1^{(t)}, \mathbf{z}_2^{(t)}, \ldots, \mathbf{z}_K^{(t)}$

Cost-sensitive Uncertainty



Cost-sensitive Uncertainty

- nearest hidden point with large distance $\Rightarrow$ uncertain prediction
- **cost-sensitive uncertainty**: distance between nearest hidden point and predicted hidden point $\tilde{\mathbf{z}}$

Active Learning with Cost Embedding (ALCE)

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- labeled pool $\mathcal{D}_l = \{(\mathbf{x}^{(n)}, y^{(n)})\}_{n=1}^{N_l}$, unlabeled pool $\mathcal{D}_u = \{\mathbf{x}^{(n)}\}_{n=1}^{N_u}$, and cost matrix $\mathbf{C}$

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  - move $(\mathbf{x}_s, y_s)$ from unlabeled pool $\mathcal{D}_u$ to labeled pool $\mathcal{D}_l$
  - learn a **classifier** $f^{(t)}$ from the current label pool $\mathcal{D}_l$ by **cost embedding**

Outline

- Problem Introduction
- Proposed Algorithm
- Experiments
- Conclusion

Experiments

Settings

- 20 runs of experiments
- 60% data as training set and 40% data as testing set
- randomly select one instance of each class in the training set as the initial labeled pool $\mathcal{D}_l$
- $\mathbf{C}_{i,j}$ is uniformly sample from $\left[0, 2000\frac{|\{n:y^{(n)}=i\}|}{|\{n:y^{(n)}=j\}|}\right]$ [Beygelzimer et al., 2005]

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List of Experiments

- comparison with cost-insensitive algorithms
- comparison with cost-sensitive algorithms
- analysis of the dimension of embedded space

Comparison with Cost-insensitive Algorithms

- ID, HC, UC-D, UC-E: their querying strategies + kernel SVM
- ALCE-N: proposed querying strategy + kernel SVM
- ALCE: proposed querying strategy + cost embedding (kernel)

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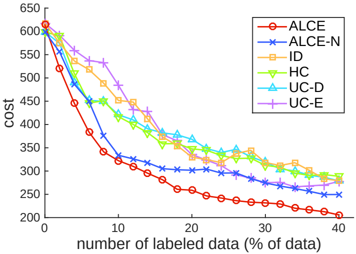
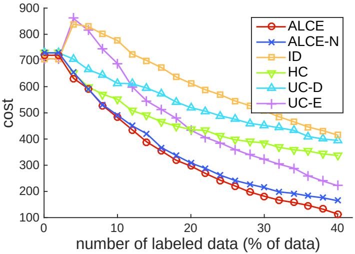


(a) vehicle



(b) vowel

- ALCE-N outperforms ID, HC, UC-D, UC-E ⇒ querying strategy is useful
- ALCE outperforms ALCE-N ⇒ cost embedding is useful

Comparison with Cost-sensitive Algorithms

- MEC, CWMM, DGS: probabilistic uncertainty + kernel classifier
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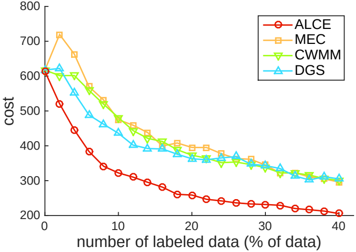

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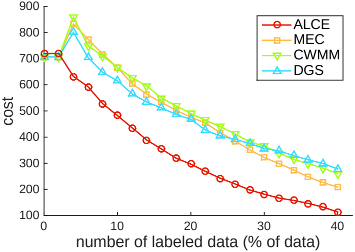
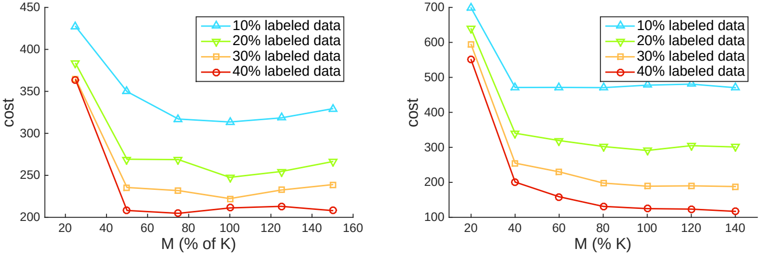


(b) vowel

- ALCE outperforms MEC, CWMM, DGS

Dimension of Embedded Space



(a) vehicle (b) vowel

- setting dimension of embedded space M as $60\%K$ is sufficient

Outline

Conclusion

- propose **active learning with cost embedding (ALCE)**
  - embedding view for cost-sensitive multiclass classification
  - embed cost information in distance by non-metric multidimensional scaling
  - mirroring trick for asymmetric cost matrix
  - define cost-sensitive uncertainty by distance
- **promising performance** of ALCE compared with state-of-the-art cost-sensitive active learning algorithms

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Thank you! Any question?