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Minority Class Oriented Active Learning for Imbalanced Datasets

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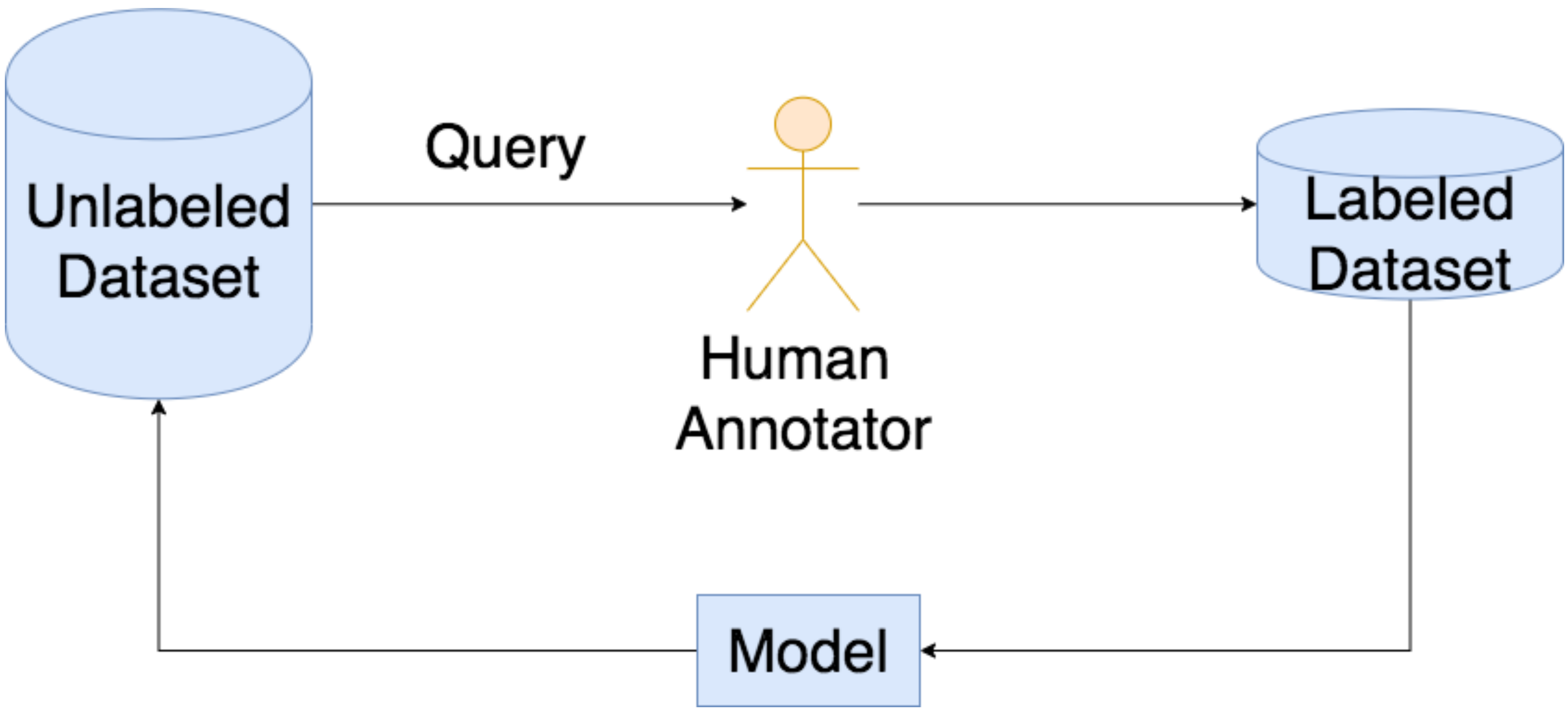
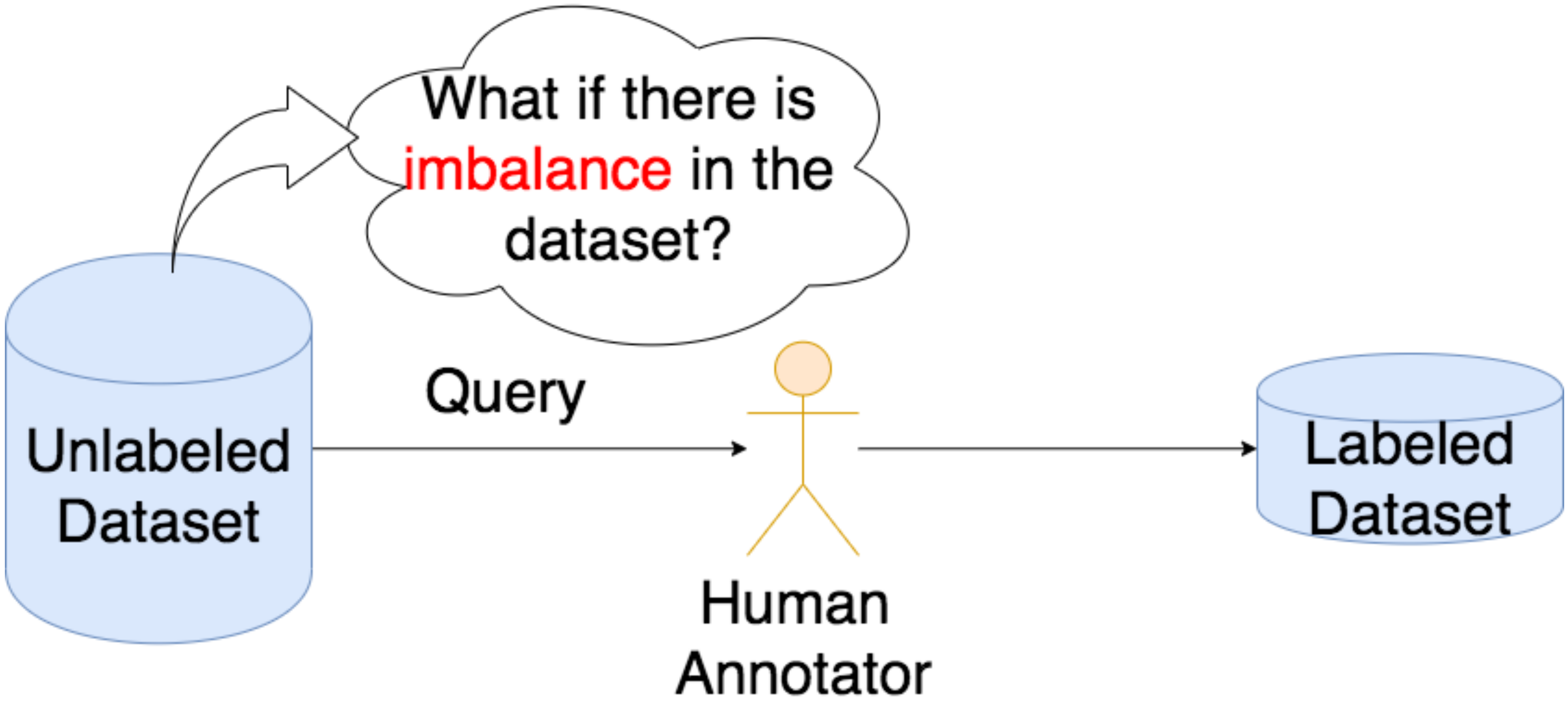
Iterative Active learning Cycle

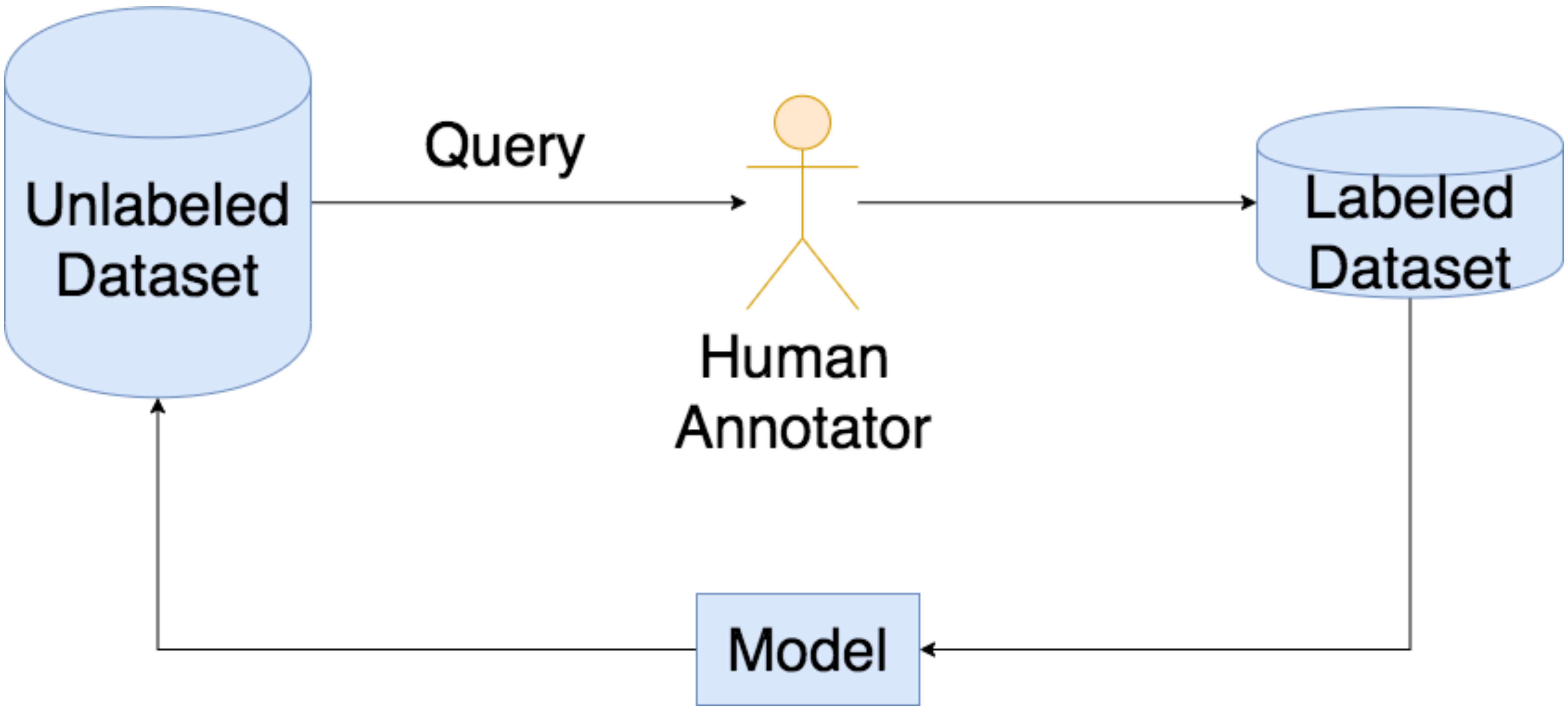


Context


What if there is imbalance in the dataset?
Unlabeled Dataset
Query
Human Annotator
Labeled Dataset

Motivation

Active learning as a way to make informative , diverse and balanced selection over unlabelled dataset.



Iterative Active learning Cycle

Selection criteria

Informativeness

1. Uncertainty based:
   - Least confidence
   - Margin sampling
   - Max entropy

2. Query-by-committee- multiple classifiers

3. Expected model change - loss gradient

Representativeness

1. Clustering based approaches

2. Farthest-first traversal

3. CoreSet

Proposed Method

Minority Class Oriented Sampling

1) Selecting samples predicted as minority class

Samples selected for a class:

$$\mathbb{D}_c^{U(k)} = \{\forall x \in \mathbb{D}_k^U, if\ P(c^1 = c|x)\}$$

Motivation:

if the sample is annotated as minority class :

help to mitigate imbalance

else if annotated as majority class :

help in decision boundary of minority class

2) Number of samples per class depends on imbalance and budget

For a given class (c), at iterative step (k):

Average number of class (μ_k) - Budget / number of classes.

Number of samples in class (c) - s_k^c;

$$m_k^c = \begin{cases} \mu_k - s_k^c, & \text{if } s_k^c < \mu_k \\ 0, & \text{otherwise} \end{cases}$$

3) Allows use of any other AF if imbalance is mitigated or if not enough minority class samples for found

Proposed Method

1) Certainty-oriented Minority Class Sampling

$$CMCS = arginvsort_{\forall x \in \mathbb{D}_c^{U(k)}} marg(x)$$

2) Uncertainty-oriented Minority Class Sampling

$$UMCS = argsort_{\forall x \in \mathbb{D}_c^{U(k)}} marg(x)$$

3)Diversity-oriented Minority Class Sampling

$$DMCS = core(\mathbb{D}_c^{U(k)}, \mathbb{D}_c^{L(k)})$$

Experimental setup

Dataset	Class	Images	Mean(μ)	Std(σ)	ir
FOOD-101	101	22956	227.28	180.31	0.793
CIFAR-100	100	17168	171.68	126.98	0.740
MIT-67	67	14281	213.15	168.16	0.789

TABLE I
DATASET STATISTICS. ir IS THE IMBALANCE RATIO.

Initial Budget- 500

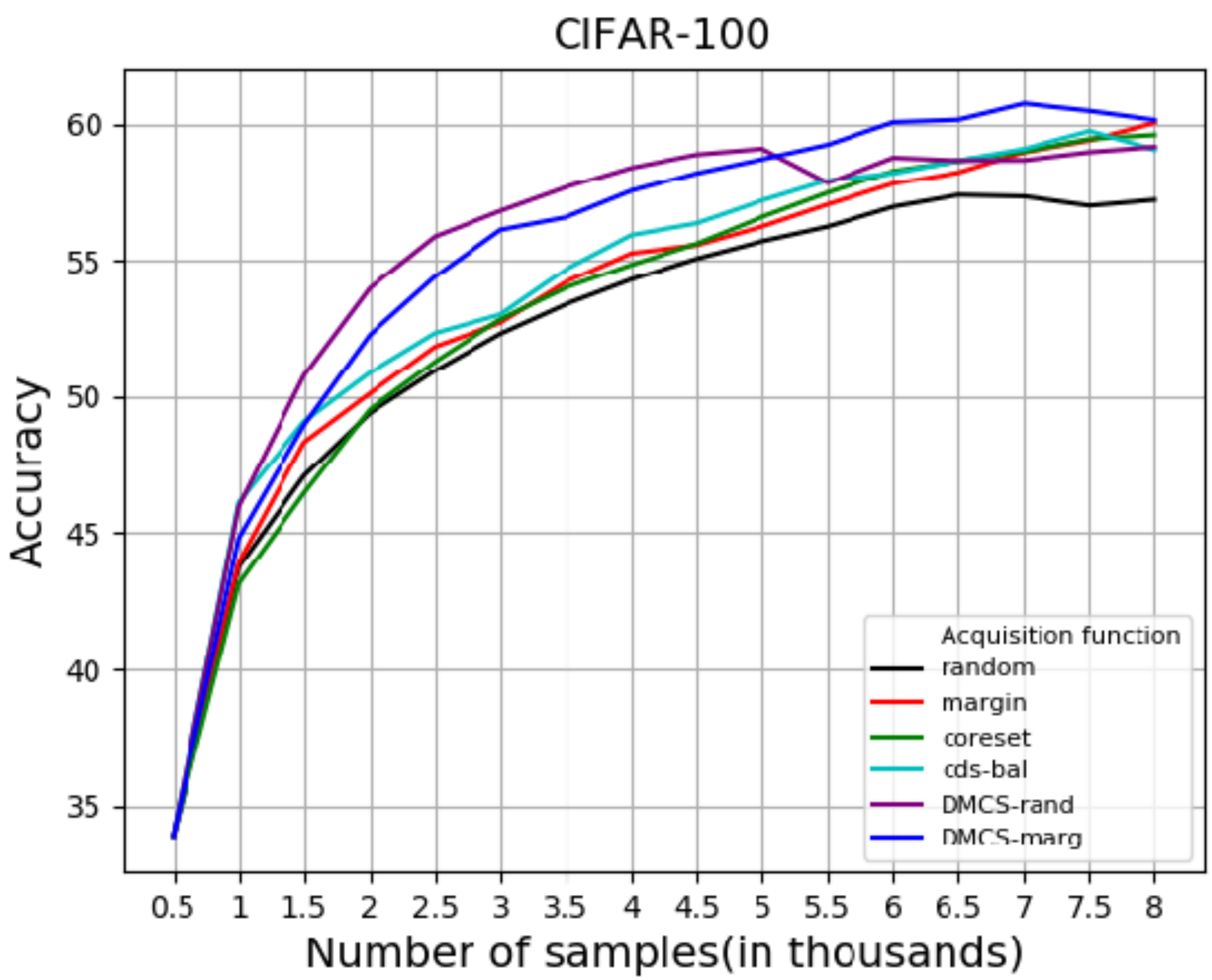
Iteration- 15, Total budget - 8000

Model- ResNet18

Training schemes

1. Fine-tuning ResNet18 with thresholding
2. Cost-Sensitive SVM over pre-trained ResNet18 features

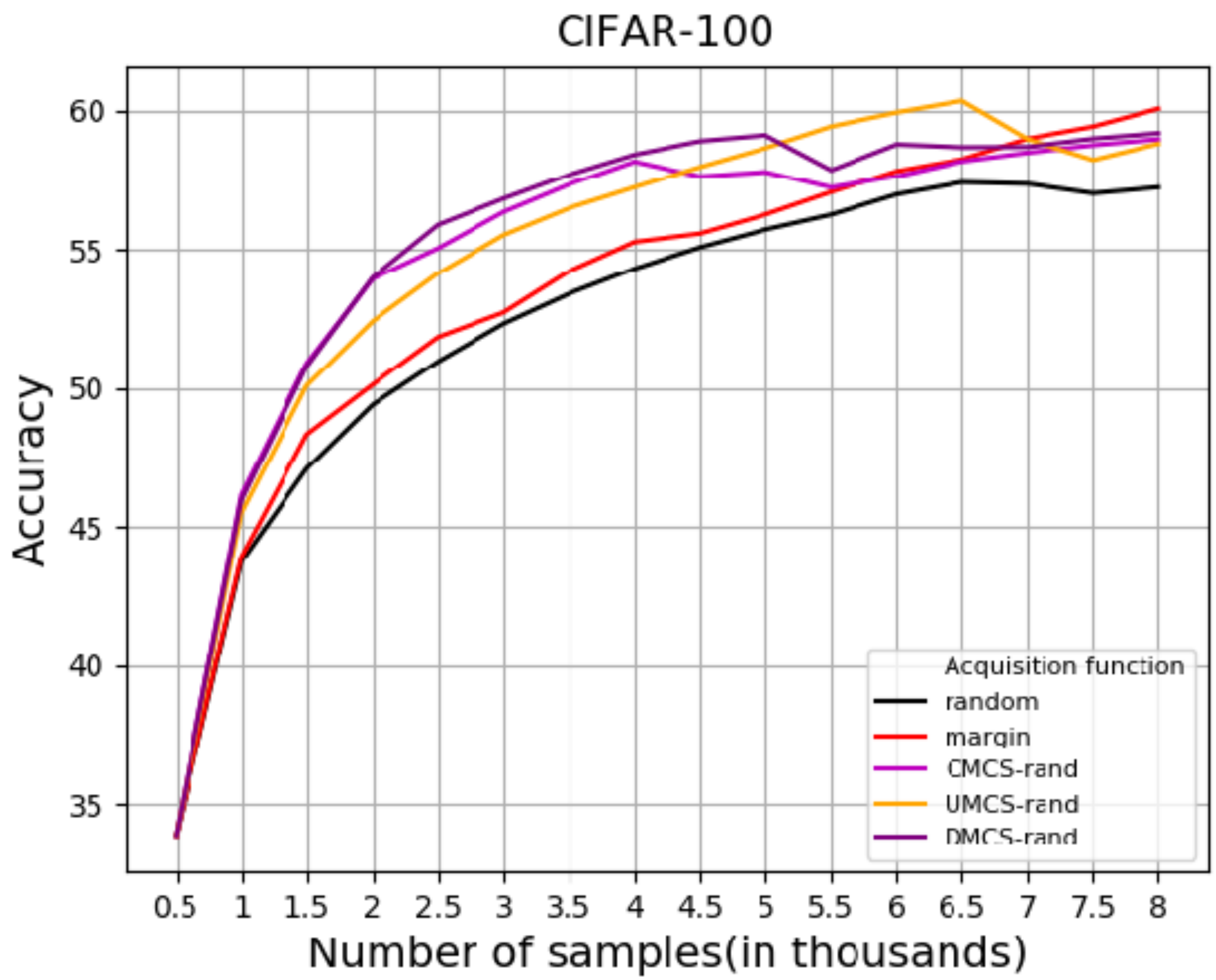
Results



Iterative active learning performance for baselines and for the proposed method DMCS

The AL budget is 8000 and the number of iterations is 15

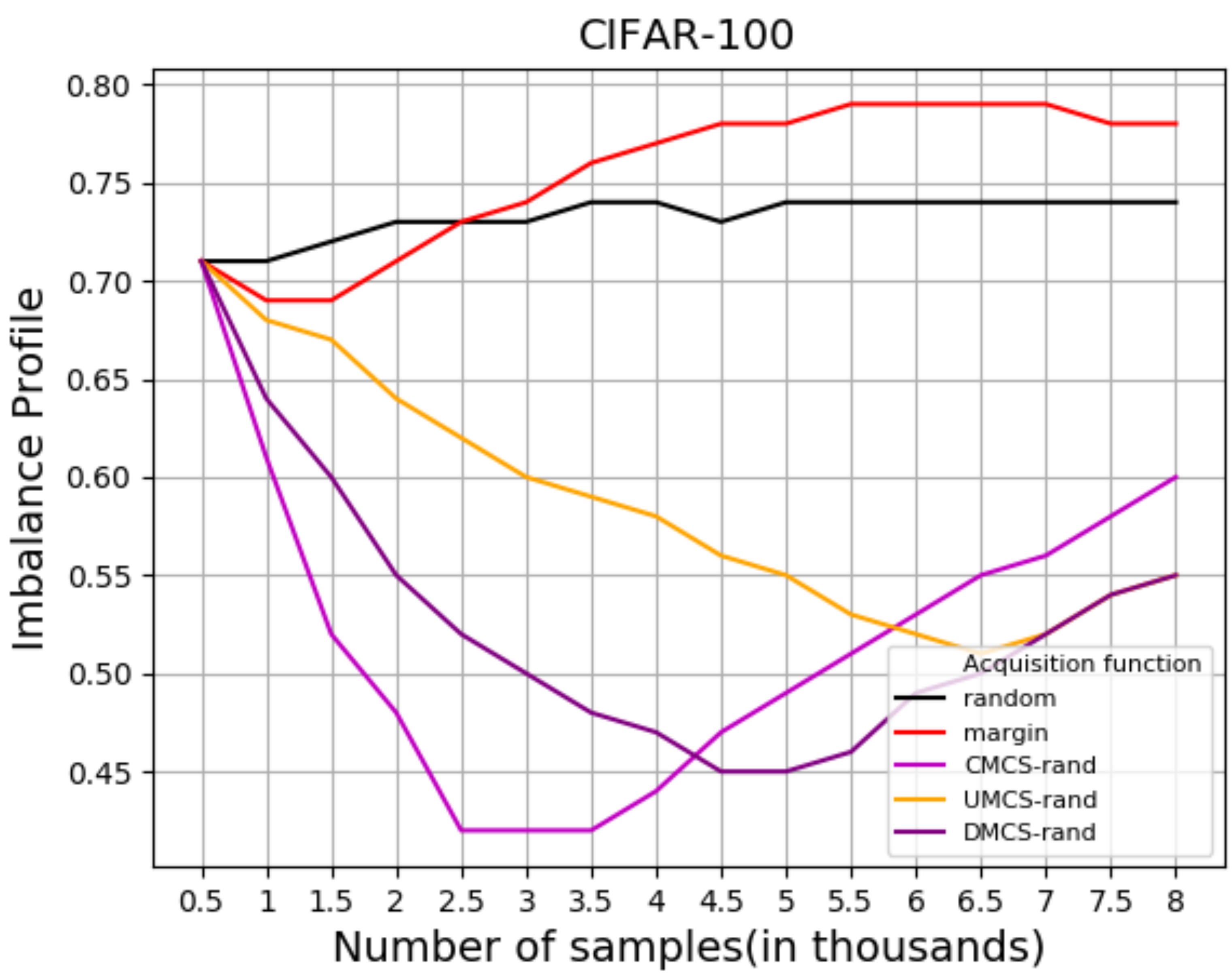
Results



Iterative active learning performance for baselines and three variants of the proposed method.

The AL budget is 8000 and the number of iterations is 15.

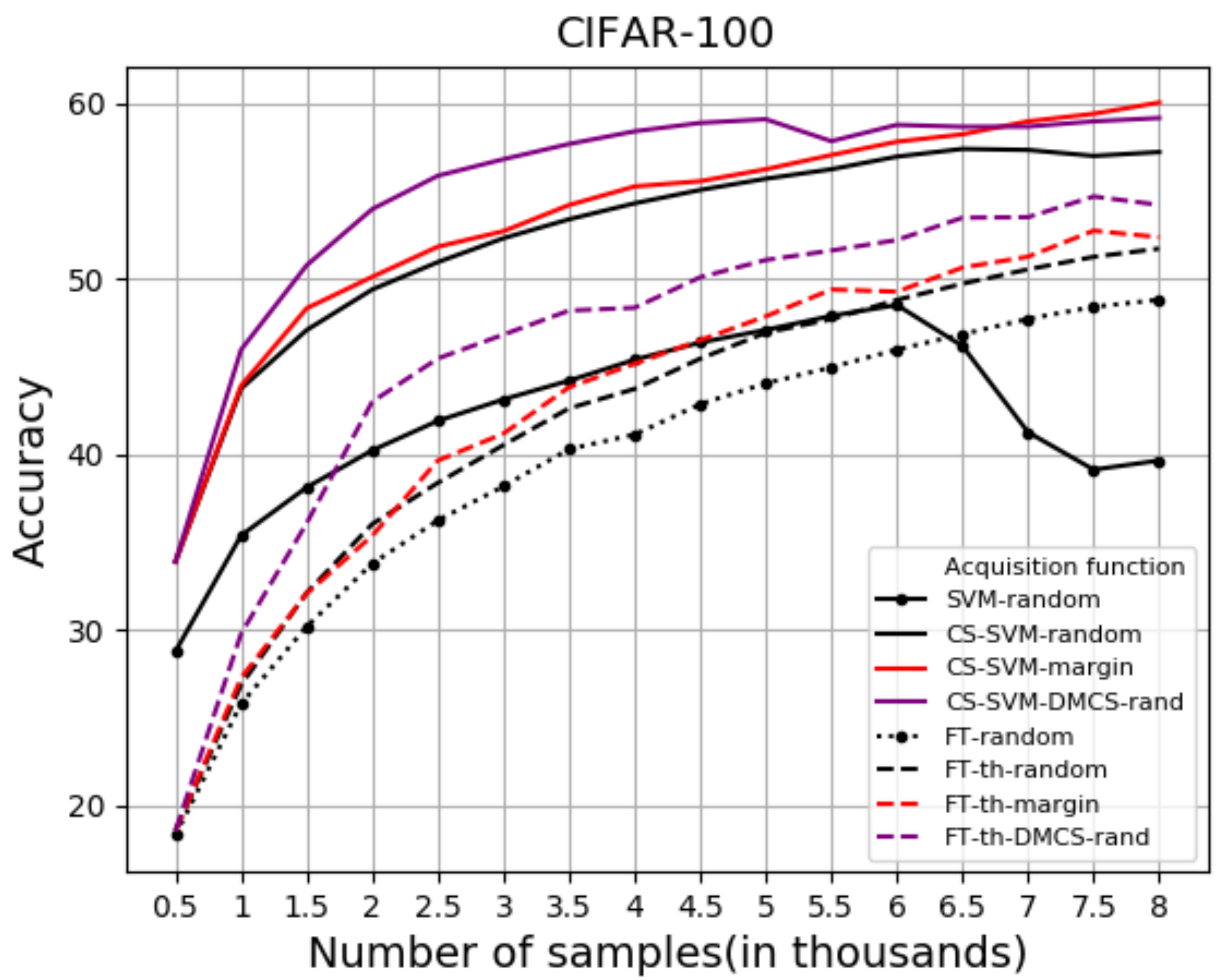
Results



Imbalance Profiles for baselines and three variants of the proposed method.

The AL budget is 8000 and the number of iterations is 15.

Results



Performance using CS-SVM and FT-th training schemes compared to SVM and FT.

- SVM training scheme outperforms FT
- Method work over the classical imbalance learning techniques

Discussion

- Imbalance needs to be treated at the time of sample selection
- Cost-Sensitive SVM over fixed representation acts as a good alternative to CNN-FT
- Certainty-oriented Minority Class Sampling provides best mitigation to imbalance, while diversity-oriented minority class sampling performs best overall

Perspectives

- Semi-supervised learning- label propagation from source to
- Domain adaptation/ Universality

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Thank you !

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