Active learning for online training in imbalanced data streams under cold start

arXiv: 2107.07724

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What is the smallest sample that we can label
to train a high performance model
in a system deployed for the first time?

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⇒ These conditions often hold for new clients in credit card fraud detection

Our Main Contributions:

An Active Learning **(AL) annotation strategy** for datasets with **orders of magnitude of class imbalance**, in a **cold start streaming** scenario.

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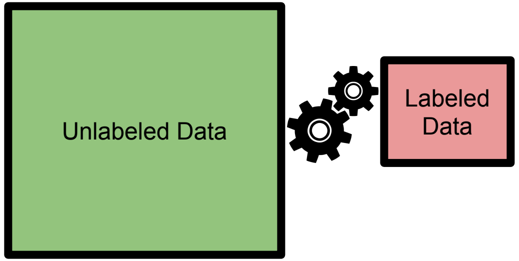
An **Outlier-based Discriminative** AL approach (**ODAL**) to be used as **warm-up** in a 3-stage sequence of AL policies.

An **empirical study** of policy sequences for **real world credit card fraud** datasets

Our Outlier-based Discriminative AL approach (ODAL)

Discriminative AL principle: Create a labeled pool distributed indistinguishably from unlabeled pool

1. Create auxiliary label to identify unlabeled pool
2. Train discriminative model



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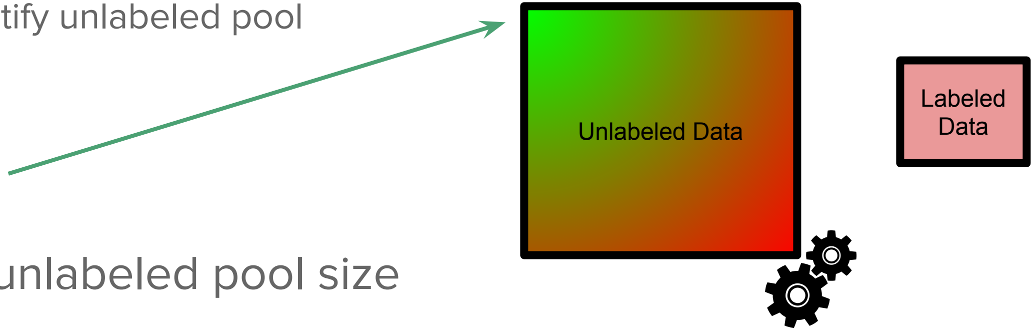

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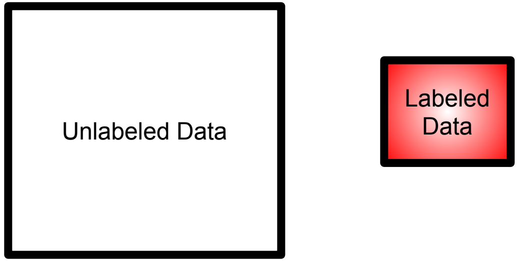

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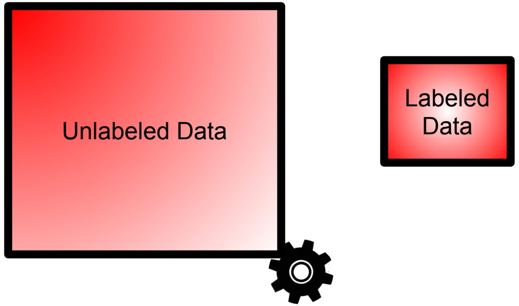

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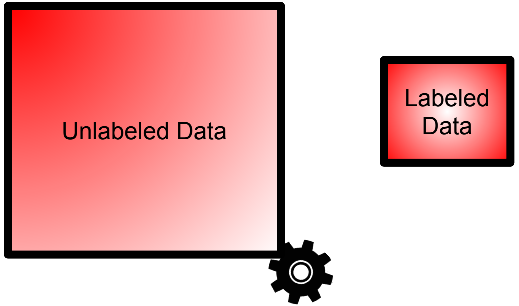

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1. Train an outlier detection algorithm on the labeled pool (small ⇒ fast training)
2. Score unlabeled pool
3. Select unlabeled instances that are outliers relative to the labeled pool

Experiments on credit card fraud datasets show:

Cold	*Warmup*	*Hot*	Bank 1	Bank 2	Payment Processor	Merchant	AVG
QueryAll	---	---	1.0	4.4	3.0	2.8	2.8
Random	ODAL	Unc. (entropy)	2.8	2.6	3.0	3.2	2.9
Random	ODAL	Unc. (epistemic)	3.4	1.6	4.8	3.4	3.3
Random	---	Unc. (entropy)	5.0	3.8	4.4	2.8	4.0
Random	---	ODAL	7.2	5.0	7.4	7.0	6.7
Random	ODAL	EMC	8.4	9.2	4.4	5.4	6.9
Random	---	EMC	10.4	10.4	4.2	5.4	7.6
Random	ODAL	Unc. (percentile)	4.4	6.2	10.8	9.4	7.7
OutlierDetect	---	---	8.0	7.2	7.6	8.6	7.9
Random	---	---	9.8	10.8	8.2	8.2	9.3
Random	ODAL	QBC	8.8	8.0	10.4	10.6	9.5
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Similar performance than optimistic baseline with only **2% to 10% of labels**.

Thank you

See paper for further details

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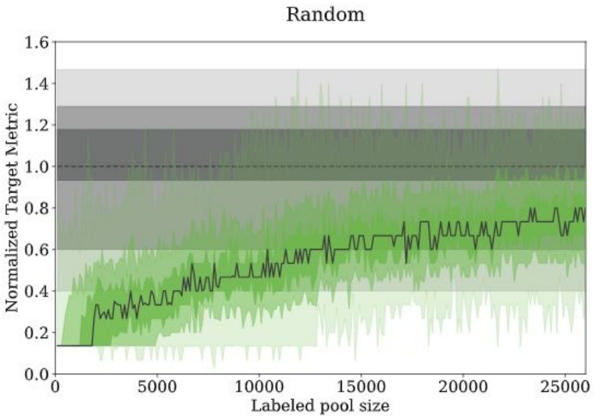

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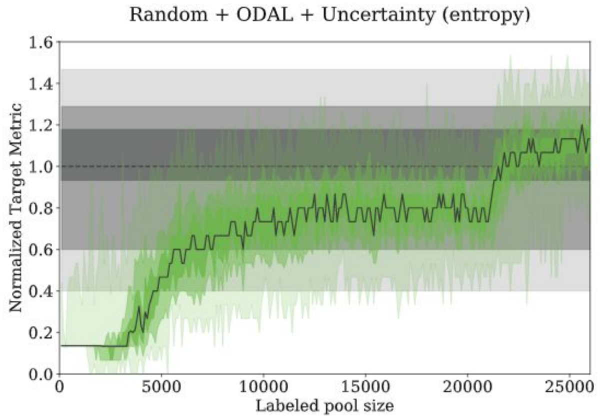

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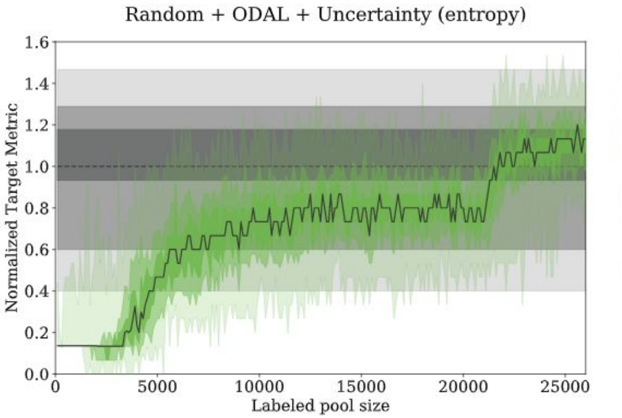

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