Domain adaptation by proactive labeling

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Distribution drifts

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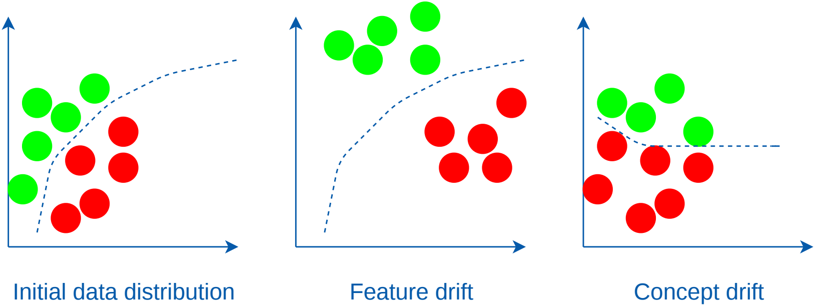

- Data and target variable distribution in real sources is not stationary.
- SentiRuEval2016.

- Initial labeled data and unlabeled data later – production setup.
- No prior knowledge if drifts present and about nature of drifts.
- Keep model perfomance $\sim$in-domain.
- Algorithm can call for labels for some of data.
- Labeling cost shoud be minimized.

Solution methods

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Online learning

- Incremental learning, learning new model over time, etc.
- Requires target variable for all examples.

Domain adaptation

- Optimal transport, SDAE, DANN, self-training, etc.
- ~~Concept drift~~.

Active learning

- Multiple re-training iterations.
- No knowledge of prior data.

Proposed method

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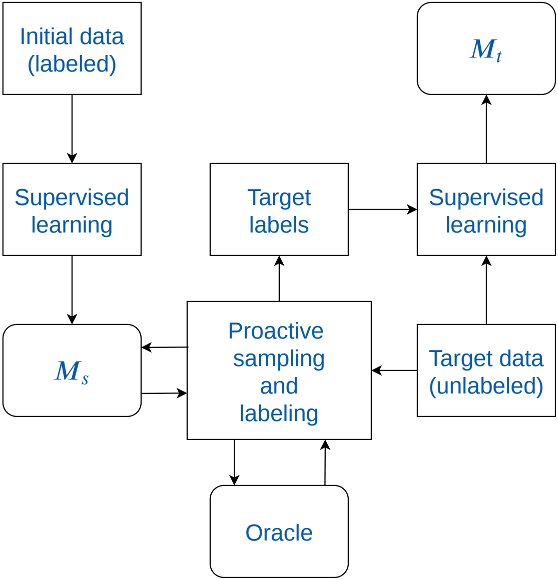
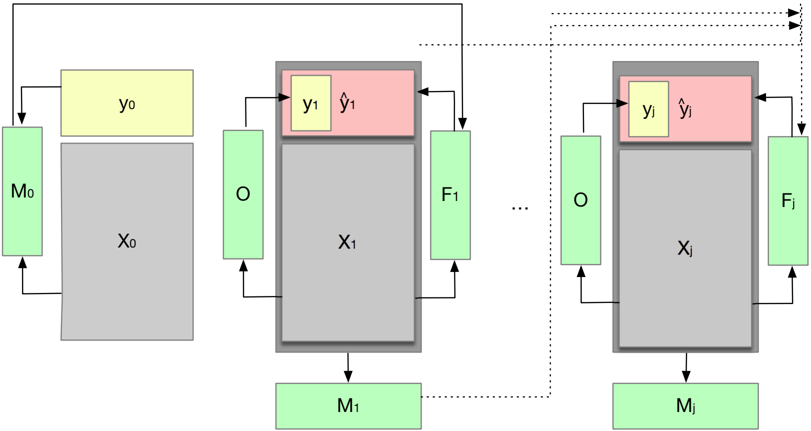


Proactive sampling and labeling

Here and further: binary classification example

- Adding example x to training set with probability $C = |0.5 - M_s(x)|$.
- If C > threshold, than label x with $round(M_s(x))$.
- Else label with oracle.

Making proposed algorithm online



Here: O – oracle, F – models from previous steps

Sampling and labeling algorith changes

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- Using every previously built model for labeling.
- Now C is mean confidence over all models.
- Label with oracle or models based on confidence and agreement.

Experiments

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- Amazon review.
- B – books ($\sim$ 9m.), E – electronics ($\sim$ 2m.), K – kitchen ($\sim$ 1m.)
- Fasttext + LSTM / tf-idf + logistic regression.
- Krishnapuram et al., “Online Domain Adaptation by Exploiting Labeled Features and Pro-active Learning” (further [1]).

Results 1

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Source	Target	Accuracy, [1]	Accuracy, with adaptation, LSTM	Accuracy, no adaptation, LSTM	Accuracy, with adaptation, log.reg.
B	E	78.4	**90.9 ± 0.2**	88.6 ± 0.1	87.5 ± 0.2
	K	78.6	**89.8 ± 0.4**	86.5 ± 0.2	86.6 ± 0.3
E	B	77.8	**90.1 ± 0.2**	87.0 ± 0.1	86.8 ± 0.2
	K	86.0	**90.2 ± 0.3**	89.1 ± 0.2	86.3 ± 0.3
K	E	70.1	**91.5 ± 0.3**	88.9 ± 0.1	85.5 ± 0.2
	B	73.2	**89.3 ± 0.1**	84.8 ± 0.1	84.7 ± 0.2

- Number of M_s labeled examples is 4 time greater than oracle labeled on avarage.
- Number of incorrectly labeled examples is 5 % of total labeled examples on avarage.

Results 2

Experiment	Accuracy	Cost
$B \to E$, $E \to K$	90.9 ± 0.2, 90.2 ± 0.3	34000, 52000
$B \to E \to K$	90.9 ± 0.2, 90.0 ± 0.3	34000, **8000**

- Further cost decrease is slower.
- Number of incorrectly labeled examples stays approximately the same.