Human-in-the-loop Handling of Knowledge Drift

Andrea Bontempelli¹ * Fausto Giunchiglia¹,² Andrea Passerini¹ Stefano Teso¹
¹University of Trento, Italy, ²Jilin University, Changchun, China
name.surname@unitn.it

Abstract

We introduce and study knowledge drift (KD), a complex form of drift that occurs in hierarchical classification. Under KD the vocabulary of concepts, their individual distributions, and the is-a relations between them can all change over time. The main challenge is that, since the ground-truth concept hierarchy is unobserved, it is hard to tell apart different forms of KD. For instance, introducing a new is-a relation between two concepts might be confused with individual changes to those concepts, but it is far from equivalent. Failure to identify the right kind of KD compromises the concept hierarchy used by the classifier, leading to systematic prediction errors. Our key observation is that in many human-in-the-loop applications (like smart personal assistants) the user knows whether and what kind of drift occurred recently. Motivated by this, we introduce TRCKD, a novel approach that combines automated drift detection and adaptation with an interactive stage in which the user is asked to disambiguate between different kinds of KD. In addition, TRCKD implements a simple but effective knowledge-aware adaptation strategy. Our simulations show that often a handful of queries to the user are enough to substantially improve prediction performance on both synthetic and realistic data.

1 Introduction

We are concerned with human-in-the-loop applications of hierarchical classification under drift. In such applications, the concept hierarchy embedded into the predictor might become obsolete over time [28]. Smart personal assistants (PAs), for instance, often need to infer the location or social context of their user from sensor data (e.g., GPS coordinates, nearby Bluetooth devices), but the hierarchy of relevant places and people changes as the user’s life changes [9]. Another example is protein function prediction, in which annotations are structured according to the Gene Ontology, a resource that is regularly updated to incorporate the latest discoveries [11]. We refer to this as knowledge drift (KD).

Classifiers that fail to adapt to KD may output wrong, ambiguous, or irrelevant predictions. Standard approaches for learning under concept drift, however, are insufficient for handling KD [8]. Indeed, KD subsumes but is substantially more complex than concept drift, as it can affect the concept hierarchy itself: both concepts and is-a relations between them may appear, disappear, and change.

The main challenge is how to reliably distinguish between different kinds of KD. For instance, introducing an is-a relation between two concepts leaves a similar footprint on the data stream as changing their individual distributions. However, confusing one for the other entails acquiring spurious is-a relations and hence systematically mis-predicting future instances.

Our key observation is that, in our human-in-the-loop setting, the user can identify with little effort what kind of drift occurred, if any. Several examples are given below. Motivated by this observation, we design TRCKD (TRaCking Knowledge Drift), an approach that tackles KD by combining automated drift detection and adaptation with interactive drift disambiguation. At a high level, TRCKD detects possible KD by checking whether the distribution of current and past examples have diverged using the maximum mean discrepancy [10], and whenever it finds any drift it asks the user to identify what changed. In order to facilitate this step, TRCKD supplies the user with an initial guess and optionally with concrete examples in support of the guess. Moreover, TRCKD implements a simple but effective knowledge-aware adaptation strategy that we ground on top of k-NN-based multi-label classifiers [26]. Our experiments show that interactive drift disambiguation and knowledge-aware adaptation are key for good performance under KD, and that asking a handful of queries to the user is often enough to achieve substantial performance improvements.

Contributions: Summarizing, we:

1. Introduce knowledge drift and the related issue of drift disambiguation.
2. Design TRCKD, an approach to KD in human-in-the-loop applications that combines automated detection and adaptation with interactive disambiguation, and instantiate it on top of k-NN-based approaches to concept drift.
3. Show experimentally that, thanks to knowledge-aware adaptation guided by few user queries, TRCKD often outperforms its competitors on three data sets.

2 Preliminaries

We begin by introducing hierarchical classification under drift. Instances x belong to one or more concepts (aka

*Contact Author
performs well on future instances. The only possible forms of drift are concept drift, as it can affect the concept hierarchy itself. Four atomic types of drift to the hierarchy can be defined: concept addition, concept removal, relation addition, and relation removal. Concept addition refers to the appearance of new concepts and concept removal to the phasing out of obsolete concepts. Relation addition and relation removal, on the other hand, refer to changes in the structure of the hierarchy itself.

Example. Concepts like “Friend” and “Library” are essentially immutable, but the specific friends and libraries that matter to Ann (which are also concepts) can change over time, e.g., when Ann graduates or moves abroad. In particular: i) If Ann buys a vacation home, an unanticipated concept “Ann’s vacation home” appears in the ground-truth hierarchy (concept addition). Conversely, if Ann’s vacation home is sold, the corresponding concept is no longer meaningful and disappears (concept removal). ii) If Ann receives a promotion and her old boss Dave becomes her subordinate, then “Dave” moves from being a child of “Boss” (relation removal) to being a child of “Subordinate” (relation addition).

2.2 Handling Knowledge Drift

Roughly speaking, handling concept drift involves two steps: detecting drift and adapting the model accordingly [8]. Timely detection and adaptation are a prerequisite for avoiding prediction mistakes, even more so in the hierarchical case, where a single misaligned concept can compromise the predictions of all related concepts.

Dealing with KD, however, requires the machine to maintain a copy of the (unobserved) ground-truth concept hierarchy and to update it based on the identified KD. Doing so involves one extra step: drift disambiguation. By this we mean identifying what concepts and relations were affected by drift and how. This step is critical, because different types of KD require different types of adaptation and failure to disambiguate KD can induce a mismatch between the ground-truth and the classifier’s hierarchies, leading to systematic, cascading prediction errors [16].

Solving disambiguation is far from trivial. To see this, consider relation addition. Like all other forms of KD, relation addition can only be identified by its effects on the data distribution. Specifically, adding a relation introduces a correlation between the concepts appearing in the relation. Naturally, the converse does not necessarily hold:

Example. Ann is on a work trip and sleeps in her hotel room by herself. Hence, the concepts “Sleeping” and “Alone” are highly correlated. Once Ann gets back home, she no longer sleeps alone and the correlation drops dramatically.
This shows that logically independent concepts can be highly correlated. Now, the machine has no sure way of telling apart relation addition from concept drift, and might react by adding a spurious relation to its concept hierarchy. It might take plenty of examples for the machine to correct its mistake, and reliable examples are usually scarce in non-stationary settings like ours. Relation removal works similarly.

Dealing with concept removal is also non-trivial: removing the \( i \)th concept implies not only that it cannot occur (and should not be predicted) ever again, but also that its child concepts are no longer attached to it. Treating concept removal as concept drift makes it hard to force the conditional distribution \( P(Y_i | X) \) exactly zero and, depending on the classifier being used, even doing so may not guarantee that the deleted concept is not predicted when one of its children is.\(^2\)

3 Handling Knowledge Drift with TRCKD

Our approach stems from the simple observation that in many human-in-the-loop scenarios the user can naturally disambiguate between different types of KD. Consider our running example: Ann is perfectly aware that the finals are tomorrow. Consider our running example: Ann is perfectly aware that the finals are tomorrow. She says she will study, and the machine updates its concept hierarchy accordingly. We discuss these three steps in turn.

Step 1: Detection. TRCKD builds on the multi-label two-window detector of Spyromitros-Xioufis et al. [26]. For every concept \( i \) in the machine’s hierarchy, TRCKD maintains two windows of examples:\(^3\) \( W_{\text{old}}^i \) holds the \( w \) most recent examples and is updated in each iteration, while \( W_{\text{cur}}^i \) holds the \( w \) reference (past) examples and is only updated when the \( i \)th concept drifts. Whenever this happens, the contents of \( W_{\text{old}}^i \) are replaced with those of \( W_{\text{cur}}^i \) and the latter is emptied. Predictions are made using a standard kNN rule using only the examples in the recent window. KD is detected whenever the measured difference between the distributions of the recent and past windows of at least one concept is larger than some threshold  \( \tau \).

TRCKD measures this difference using the \textit{maximum mean discrepancy} (MMD), a well-known discrepancy employed in hypothesis testing [10] and domain adaptation [30]. Letting  \( P \) and  \( Q \) be distributions over some space  \( \mathcal{X} \) and a user-defined kernel over  \( \mathcal{X} \), the MMD between  \( P \) and  \( Q \) relative to  \( k \) is:

\[
\text{MMD}(P, Q)^2 = \mathbb{E}[k(a, a')] - 2\mathbb{E}[k(a, b)] + \mathbb{E}[k(b, b')]
\]

where  \( a, a' \) are drawn i.i.d. from  \( P \) and  \( b, b' \) from  \( Q \). Estimating the MMD between  \( W_{\text{old}}^i \) and  \( W_{\text{cur}}^i \) requires to define a kernel between examples  \( z \). TRCKD achieves this by defining two separate kernels over instances and labels  \( k_X \) and  \( k_Y \) and then taking their tensor product [27]:

\[
k(z, z') = k((x, y), (x', y')) = k_X(x, x') \cdot k_Y(y, y').
\]

The choice of base kernels is application-specific. In our experiments, we employ a Gaussian kernel  \( k_X \) for the instances and a delta kernel  \( k_Y(y, y') = \mathbb{1}(y = y') \) for the labels.

The MMD has several advantages. First of all, if \( P \equiv Q \) then necessarily MMD(\( P, Q \)) = 0.\(^4\) Unlike other theoretically well-behaved discrepancies (like total variation distance and \( \text{A-distance} \) [14]), the MMD can be estimated efficiently (in linear or quadratic time, depending on the estimator) even for higher-dimensional data [19, 21, 10]. Just as importantly, in our experiments the MMD achieved better false detection rate than ME [13], a state-of-the-art discrepancy with better discrimination power on paper.

Step 2: Disambiguation. Upon detecting drift, TRCKD initiates interaction with the user. Interaction can be carried out through a simple UI akin to those used for designing ontologies [12, 1]. The interface shows (part of) the machine’s concept hierarchy and highlights the concepts that were identified by MMD. Notice that this visual description of the detected drift is unstructured, in that it does not have a window for negatives.

Algorithm 1 The TRCKD algorithm. Inputs:  \( S_1 \) is the initial data set, \( s := |S_1| \), \( w \) the window size, \( \tau \) a threshold. MMD is an empirical estimator of the MMD and  \( z_i := (x_i, y_i) \).

1: Fit initial classifier on  \( S_1 \)
2: \textbf{for} every concept  \( i \) in the machine’s hierarchy \textbf{do}
3: \hspace{1em} \( W_{\text{old}}^i \leftarrow \{z_s^i, \ldots, z_{s-w}^i\} \)
4: \textbf{for}  \( t = 1, 2, \ldots \) \textbf{do}
5: \hspace{2em} Receive new example  \( z_t \)
6: \hspace{2em} \textbf{for} every concept  \( i \) in the machine’s hierarchy \textbf{do}
7: \hspace{3em} \( W_{\text{cur}}^i \leftarrow \{z_{s+1}^i, z_{s-t+1}, \ldots, z_{s+t-w}^i\} \)
8: \hspace{2em} \textbf{if} \( \tau : \text{MMD}(W_{\text{cur}}^i, W_{\text{old}}^i) \geq \tau \) \textbf{then}
9: \hspace{3em} Illustrate detected KD to the user
10: \hspace{2em} \textbf{end if}
11: \hspace{2em} Adapt based on user’s KD description
12: \textbf{end for}
13: \hspace{1em} Adapt based on user’s KD description
14: \textbf{end for}
15: \textbf{end for}

\(^2\)The only “easy” case is concept addition, which is straightforward in our fully labeled setting and will not be considered further.

\(^3\)In hierarchical classification, most examples do not belong to most concepts. As in [26], TRCKD accounts for this by allocating 2/3 of each window for negatives.

\(^4\)If \( k \) is characteristic, the converse also holds [29].
not disambiguate between different forms of atomic KD. In our running example, the PA might highlight the concepts “Dave”, “Boss”, and “Subordinate”, thus enabling Ann to focus her recent promotion and identify related changes. Of course, the machine’s description of drift might be inaccurate or incomplete. For this reason, TRCKD asks the user to correct it using the graphical interface. Extra context can be supplied to the user by including a handful of examples that summarize how the concepts affected by KD have changed. Such examples can be selected from the past and current windows of those concepts using MMD witness functions [17].

If the machine’s drift description is accurate enough (which should typically be if the drift detector is tuned well) then the user’s job is simply to tell the machine whether the relations between the highlighted concepts have undergone drift and how. To this end, the user can deselect highlighted concepts and add or remove arrows in the DAG. This is not particularly cognitively demanding. If the machine’s description is not accurate, the user can still easily deselect wrongly highlighted concepts. This is already an improvement over no interaction. A sufficiently motivated and knowledgeable user has also the option of editing any drifting concepts or relations not detected by the machine. All of this extra information is useful for guiding knowledge-aware adaptation.

Step 3: Adaptation. Once it receives the user’s drift description, TRCKD adapts the machine’s hierarchy and the windows accordingly. In particular: i) For every instance of individual concept drift in the description, it empties the current window of the affected concept and transfers its contents to the past window. ii) For concept removal, the past and current windows of the affected are deleted and any is-a relations between the removed concept are deleted and its children are attached to the parent. iii) For relation addition, the positive examples belonging to the child concept are copied to the parent’s window and the latter is doubled in size to cope. iv) For relation removal, the positive examples belonging to the child concept are removed from the parent’s window and the latter is shrank accordingly. The child concept is also linked directly to its grandparent. This strategy applies immediately to kNN-based approaches and to other classifiers that support forgetting (i.e., removal of training examples). Our experiments show that this simple form of knowledge-aware adaptation strategies outperforms strategies based on adaptively forgetting obsolete examples [26, 23].

4 Experiments

We empirically address the following research questions:

Q1 Is knowledge-aware adaptation useful?
Q2 Does interacting with the user help adaptation?
Q3 Does TRCKD work in realistic, multi-drift settings?

The code for all experiments is at: https://gitlab.com/abonte/handling-knowledge-drift.

Competitors. We compared TRCKD against several alternatives: MW-kNN: the multi-window kNN approach of [26] designed specifically for multi-label problems. PAW-kNN: punitive adaptive window kNN, a state-of-the-art multi-label approach that employs a single window for all concepts and adapts by discarding examples responsible for prediction mistakes [23]. TRCKD$_{LLR}$: a fully-automated version of TRCKD that follows up MMD detection by performing drift disambiguation with a likelihood ratio test. This test detects a relation $y^j$ is-a $y^i$ iff $P(y^i|y^j) / P(y^i) \geq \beta$ with $\beta = \infty$. If the test detects relation addition/removal, TRCKD$_{LLR}$ applies the corresponding knowledge-aware adaptation strategy, otherwise it defaults to emptying the current window of the detected concept(s). kNN 1-window: kNN with a single window for all concepts that forgets old examples). kNN: regular kNN with no adaptation.

Data sets. We ran experiments on three data sets. HSTAGGER: a hierarchical version of STAGGER, a widely used synthetic data set of two-dimensional objects with three categorical attributes (shape, color, size) and labeled by drifting random formulas like “small and (green or red)” [24]. HSTAGGER has 3 attributes with 4 values each and labels instances using 5 different drifting random formulas chosen to have a reasonable pos./neg. ratio. The hierarchy is created by selecting two concepts as part of a third one that acts as parent concept. EMNIST: a data set of 28 × 28 handwritten digits and (uppercase, lowercase) letters [5]. We simulate hierarchical data by running multiple streams of EMNIST examples in parallel. The digits and letters are grouped in 5 concepts and structured as in HSTAGGER. Instances were embedded using a variational autoencoder [15]. 20NG: a data set of newsgroup posts categorized in twenty topics. The data set was converted to hierarchical classification by grouping different classes into super-topics (e.g., alt.atheism, soc.religion.christian and talk.religion.misc were grouped into a “religion” super-topic). The documents were embedded using a pre-trained Sentence-BERT model [22] and compressed to 100 features using PCA. The data sets are converted into streams by sequentially sampling random examples.

Experimental details All experiments were run on a machine with eight 2.8 GHz CPUs and 32 GiB RAM. Each experiment was run ten times by changing the random seed: 2 for selecting hyperparameters and 8 for evaluating performance. Our evaluation focuses on concept deletion, relation addition, and relation removal; plain concept drift is reported in the Supplementary Material. In the three cases, KD is injected into the stream by removing a random concept from the available ones, adding a random relation, and removing a random relation, respectively. KD starts after the competitors approximately reach their peak performance, namely after 100 iterations for HSTAGGER and EMNIST, and 170 for 20NG. Performance was measured in terms of micro $F_1$ score on a hold-out test set of

---

5This is the best possible value for $\beta$ as the ground-truth data is assumed to be always consistent with the ground-truth hierarchy.

6From archive.ics.uci.edu/ml/datasets/Twenty+Newsgroups
size 64 for HSTAGGER and 200 for EMNIST and 20NG) randomly selected before each run. All methods observed the same sequence of examples and drifts. The plots report standard error information. User replies were simulated by an oracle that always answers correctly to disambiguation queries.

**Hyperparameters** For TRCKD, the window size $w$ was fixed to 200 so to make it perform as well as standard $k$NN when no drift is present. MW-$k$NN and all variants of TRCKD use the same window size. To speed up detection, the MMD is computed on the 70 most recent examples only. Prior to each experiment, the threshold $\tau$ was selected from $\{0.4, 0.5\}$ to optimize $F_1$ on two independent runs. The ranges of $k$ differ between methods, the detailed values are reported in the Supplementary Material. For PAW-$k$NN, the penalty ratio was set to $p = 1$ as suggested by Roseberry et al. [23] and the minimum and maximum window sizes to 50 and 200 for consistency with TRCKD.

**Q1: Is knowledge-aware adaptation useful?** To evaluate the impact of our adaptation strategy, we remove unrelated effects due to spurious/delayed detection by telling all approaches exactly when KD occurs. We compare TRCKD$_{oracle}$ (i.e., TRCKD that knows exactly when drift occurs) to MW-$k$NN, PAW-$k$NN, $k$NN 1-window, regular $k$NN and TRCKD$_{forget}$ (TRCKD that adapts to all types of KD by forgetting old examples).

The results can be viewed in Figure 2. The plots show that TRCKD$_{oracle}$ is by far the best performing method on all data sets and for all forms of KD. In most cases the runner up is TRCKD$_{forget}$: while it performs similarly to TRCKD$_{oracle}$ for concept drift and removal (see the Supplementary Material; this is because our adaptation strategy boils down to forgetting in this simple setup), it does lag behind for relation addition and removal, showing a sizeable advantage for knowledge-aware adaptation. MW-$k$NN works reasonably well but suffers from relying on passive adaptation and does not always perform better than the two $k$NN baselines. PAW-$k$NN tends to underperform on EMNIST and 20NG, especially when KD affects the relations. These results validate knowledge-aware adaptation on all data sets and allows us to answer Q1 in the affirmative. For this reason, we will focus on knowledge aware adaptation in the following experiments.

Figure 2: Knowledge-aware versus other adaptation strategies. **Left to right:** Results for HSTAGGER, EMNIST, and 20NG. **Top row:** relation addition. **Bottom row:** relation removal. Plots for the other forms of KD can be found in the Supplementary Material.

Figure 3: Interactive versus fully automated drift disambiguation. **Left to right:** concept removal, relation addition, and relation removal. **Top:** HSTAGGER. **Bottom:** EMNIST. The results for 20NG can be found in the Supplementary Material due to space constraints.
Q2: Is interaction useful? To measure the impact of interaction, we compare four variants of TRCKD that differ in what information they elicit from the supervisor, namely: TRCKD, TRCKD_{LLR}, TRCKD_{oracle}, and TRCKD_{na} (like TRCKD except that instead of interacting with the user it assumes that all concepts detected as drifting by MMD have undergone individual concept drift and adapts by purging their current window). The results in Figure 3 are quite intuitive: TRCKD_{oracle} substantially outperforms all alternatives in all cases except for relation removal in 20NG. This shows that, if drift is detected correctly and timely, interactive disambiguation is extremely useful for guiding knowledge-aware adaptation and quickly aligning the model to the ground-truth. TRCKD tends to perform substantially better than the no-interaction baselines TRCKD_{LLR} and TRCKD_{na}, and if MMD detection works well it quickly reaches the performance of the oracle. This allows us to answer Q2 in the affirmative. If MMD underperforms (as in EMNIST), TRCKD does not get a chance to quickly interact with the user and shows no improvement. This could be fixed by better optimizing the choice of kernel and threshold used by MMD, perhaps by turning them into per-concept parameters. This is left to future work. Importantly, TRCKD interacts with the user 1.54 ± 0.78 times per run on average, showing that few interaction rounds are often enough to achieve a noticeable performance boost.

Q3: Does TRCKD work in multi-drift settings? We consider a realistic scenario with four sequential KD events, namely concept drift, relation addition, relation removal, and concept removal. The results in Figure 4 show that TRCKD tends to outperform all competitors except the oracle. The advantage is quite marked whenever the KD affects the concept hierarchy itself, up to +10% F1 for HSTAGGER and +5% for EMNIST. The plots mirror the advantages shown by TRCKD in the previous experiments and highlight that the benefits knowledge-aware adaptation and interaction carry over to more realistic settings. This allows us to answer Q3 in the affirmative. The lack of reactive adaptation penalizes MW-kNN and PAW-kNN, the latter especially on EMNIST.

5 Related Work

TRCKD is the first approach that considers KD in hierarchical classification and that explicitly tackles drift disambiguation. Indeed, existing work on concept drift focuses on the single-label [8] and multi-label [32] cases, while work on drift understanding is unconcerned with hierarchical classification [18]. TRCKD is also the first approach to tackle drift disambiguation by interacting with a human supervisor. Sliding windows were first employed for drift detection in [14]. This setup offers distribution-free guarantees on detection accuracy under mild assumptions. The idea of using examples in the windows for explanatory purposes was also discussed in [14]. The MMD, which TRCKD uses to compare present and past data, was leveraged in domain adaptation [30]. More recent two-sample tests, like ME [13], underperformed in our experiments.

Open world recognition is a streaming classification setting in which unanticipated classes appear over time [4, 2]. Open world recognition only deals with concept addition, and it is unconcerned with more general KD. Other recent work on interactive classification under concept addition [3] focuses on handling noisy labels rather than on adapting to drift.

Finally, in continual learning the machine must learn new concepts (or tasks) over time. The key difference is that our goal is to smartly forget obsolete information, whereas in continual learning the main issue is how to prevent the machine from forgetting previously acquired knowledge [20]. More generally, continual learning neglects other forms of KD altogether.

6 Conclusion

We introduced the problem of knowledge drift in hierarchical classification and proposed to partially offload drift disambiguation to a user. We introduced TRCKD, an approach for learning under KD that combines automated drift detection and adaptation, upgraded to hierarchical classifiers, with interactive drift disambiguation. Our results indicate that TRCKD outperforms fully automated approaches by asking just a few questions, even when detection performance is not ideal.

In future work, we plan to improve the interpretability of our interaction protocol by integrating ideas from explainable AI [6, 25], generalize TRCKD to active learning settings in which the labels must be explicitly queried and develop KD adaptation strategies for neural nets in continual learning.

7 Acknowledgments

The research of FG and AP has received funding from the European Union’s Horizon 2020 FET Proactive project “WeNet – The Internet of us”, grant agreement No 823783. The research of AB and ST has received funding from
the “DELPhi - DiscovEring Life Patterns” project funded by the MIUR Progetti di Ricerca di Rilevante Interesse Nazionale (PRIN) 2017 – DD n. 1062 del 31.05.2019.

References

[1] Gabor Angeli, Melvin Jose Johnson Premkumar, and Christopher D Manning. Leveraging linguistic structure for open domain information extraction. In *IJCNLP*, 2015.

[2] Abhijit Bendale and Terrance Boult. Towards open world recognition. In *CVPR*, 2015.

[3] Andrea Bontempelli, Stefano Teso, Fausto Giunchiglia, and Andrea Passerini. Learning in the wild with incremental skeptical gaussian processes. In *IJCAI*, 2020.

[4] TE Boult, S Cruz, AR Dhamija, M Gunther, J Hendrydoss, and WJ Scheirer. Learning and the unknown: Surveying steps toward open world recognition. In *AAAI*, 2019.

[5] Gregory Cohen, Saeed Afshar, Jonathan Tapson, and Andre Van Schaik. Emnist: Extending mnist to handwritten letters. In *IJCNN*, 2017.

[6] Jaka Demšar and Zoran Bosnič. Detecting concept drift in data streams using model explanation. *Expert Systems with Applications*, 2018.

[7] Jerome Friedman, Trevor Hastie, and Robert Tibshirani. Sparse inverse covariance estimation with the graphical lasso. *Biostatistics*, 2008.

[8] João Gama, Indré Žliobaitė, Albert Bifet, Mykola Pechenizkiy, and Abdelhamid Bouchachia. A survey on concept drift adaptation. In *PerCom*, 2017.

[9] Fausto Giunchiglia, Enrico Bignotti, and Mattia Zeni. Personal context modelling and annotation. In *PerCom*, 2017.

[10] Arthur Gretton, Karsten M Borgwardt, Malte J Rasch, Bernhard Schölkopf, and Alex Smola. A kernel two-sample test. *JMLR*, 2012.

[11] Matthew Jacobson, Adriana Estela Sedeño-Cortés, and Paul Pavlidis. Monitoring changes in the gene ontology and their impact on genomic data analysis. *GigaScience*, 2018.

[12] Ernesto Jiménez-Ruiz, Bernardo Cuenca Grau, Yujiao Zhou, and Ian Horrocks. Large-scale interactive ontology matching: Algorithms and implementation. In *ECAI*, 2012.

[13] Wittawat Jitkrittum, Zoltán Szabó, Kacper P Chwialkowski, and Arthur Gretton. Interpretable distribution features with maximum testing power. In *NeurIPS*, 2016.

[14] Daniel Kifer, Shai Ben-David, and Johannes Gehrke. Detecting change in data streams. In *VLDB*, 2004.

[15] Diederik P Kingma and Max Welling. Auto-encoding Variational Bayes. In *ICLR*’14, 2014.

[16] Daphne Koller and Nir Friedman. *Probabilistic graphical models: principles and techniques*. 2009.

[17] James R Lloyd and Zoubin Ghahramani. Statistical model criticism using kernel two sample tests. *Advances in Neural Information Processing Systems*, 2015.

[18] Jie Lu, Anjin Liu, Fan Dong, Feng Gu, Joao Gama, and Guangquan Zhang. Learning under concept drift: A review. *IEEE Transactions on Knowledge and Data Engineering*, 2018.

[19] Liam Paninski. Estimation of entropy and mutual information. *Neural computation*, 2003.

[20] German I Parisi, Ronald Kemker, Jose L Part, Christopher Kanan, and Stefan Wermter. Continual lifelong learning with neural networks: A review. *Neural Networks*, 2019.

[21] Fernando Pérez-Cruz. Estimation of information theoretic measures for continuous random variables. In *NeurIPS*, 2009.

[22] Nils Reimers and Iryna Gurevych. Sentence-bert: Sentence embeddings using siamese bert-networks. In *EMNLP-IJCNLP*, 2019.

[23] Martha Roseberry, Bartosz Krawczyk, and Alberto Cano. Multi-label punitive knn with self-adjusting memory for drifting data streams. *TKDD*, 2019.

[24] Jeffrey C Schlimmer and Richard H Granger. Incremental learning from noisy data. *Machine learning*, 1986.

[25] Patrick Schramowski et al. Making deep neural networks right for the right scientific reasons by interacting with their explanations. *Nat Mach Intell*, 2020.

[26] Eleftherios Spyromitros-Xioufis, Myra Spiliopoulou, Grigoris Tsoumakas, and Ioannis Vlahavas. Dealing with concept drift and class imbalance in multi-label stream classification. In *IJCAI*, 2011.

[27] Niranjan Srinivas, Andreas Krause, Sham Kakade, and Matthias Seeger. Gaussian process optimization in the bandit setting: no regret and experimental design. In *ICML*, 2010.

[28] Ljiljana Stojanovic, Alexander Maedche, Boris Motik, and Nenad Stojanovic. User-driven ontology evolution management. In *ICAW*, 2002.

[29] Zoltán Szabó and Bharath K Sriperrumbudur. Characteristic and universal tensor product kernels. *JMLR*, 2017.

[30] Kun Zhang, Bernhard Schölkopf, Krikamol Muandet, and Zhiyun Wang. Domain adaptation under target and conditional shift. In *ICML*, 2013.
Additional Details

Hyperparameters. Table 1 reports the values used in each experiment.

| RQ       | Drift | τ  | TRCKD k | PAW-kNN k |
|----------|-------|----|----------|-----------|
|          |       |    |          |           |
| HSTAGGER |       |    |          |           |
| CD       | 0.04  | 3  | 3        |           |
| Q1 - Q2  |       |    |          |           |
| CR       | 0.04  | 11 | 3        |           |
| RA       | 0.04  | 11 | 3        |           |
| RR       | 0.04  | 11 | 3        |           |
| Q3       | All   | 0.04 | 11 | 3 |
| EMNIST   |       |    |          |           |
| CD       | 0.04  | 5  | 3        |           |
| Q1 - Q2  |       |    |          |           |
| CR       | 0.05  | 3  | 3        |           |
| RA       | 0.05  | 3  | 3        |           |
| RR       | 0.04  | 3  | 3        |           |
| Q3       | All   | 0.05 | 3  | 3 |
| 20NG     |       |    |          |           |
| CD       | 0.05  | 3  | 3        |           |
| Q1 - Q2  |       |    |          |           |
| CR       | 0.05  | 3  | 3        |           |
| RA       | 0.04  | 3  | 3        |           |
| RR       | 0.04  | 3  | 3        |           |
| Q3       | All   | 0.05 | 3  | 3 |

Table 1: Hyperparameter values.

The hyperparameters are: MMD threshold \( \tau \) used by TRCKD; number of neighbors \( k \) used by TRCKD and all competitors except PAW-kNN; and number of neighbors \( k \) used by PAW-kNN. Abbreviations: CD is concept drift, CR concept removal, RA relation addition, and RR relation removal. Before each experiment, the value of \( \tau \) and \( k \) are selected in two independent runs by optimizing \( F_1 \). The value of \( \tau \) is selected from \{0.4, 0.5\}; these values were frequently observed to indicate drift in our experiments. The value of \( k \) from \{3, 5, 11\} and it was chosen independently for TRCKD and its variants, including MW-kNN, and for PAW-kNN.

All other hyperparameters remain fixed across experiments. The window size of TRCKD was set to 200. The penalty ratio of PAW-kNN was set to \( p = 1 \) as in [23], while the minimum and maximum window sizes were set to \( m_{\text{min}} = 50 \) for HSTAGGER and EMNIST and 80 for 20NG data set and \( m_{\text{max}} = 200 \) respectively. To speed up detection, the MMD is only computed on the 70 most recent examples. This choice does not sacrifice reliability of detection.

The inference and training time is similar for all methods since they are all based on \( kNN \). One method requires 2 seconds for training on the new example and evaluating on test set at each iteration.

Data sets. Table 2 reports, for each of our three data sets, the number of examples sampled to generate the stream \( |S| \), the number of attributes \( d \) and their type, the number of concepts \( c \), as well as the following three measures of annotation density: the (average) number of positive labels per example \( LC \), the empirical probability that a label is positive \( LD \), and how many distinct combinations of positive categories (out of \( 2^c \)) are annotated in the data \( DL \). These metrics are taken from [31]. All instances in the data set belong to the root concept.

Metrics. The plots in the paper focus on the micro \( F_1 \) score, which consider the sparsity of the classes of our scenario. Letting \( \{(x_i, y_i) : i = 1, \ldots, n\} \) be the examples in the test set, \( y_i \) their predictions and \( y_i^* \) the \( j \)th element of \( y_i \), which is 1 if \( x_i \) belong to the \( j \)th concept and 0 otherwise, the micro \( F_1 \) is defined as follows:

\[
F_{1\text{-micro}} = \frac{2 \sum_{j=0}^{c} \sum_{i=1}^{n} y_i^j \hat{y}_i^j}{\sum_{j=0}^{c} \sum_{i=1}^{n} y_i^j + \sum_{j=0}^{c} \sum_{i=1}^{n} \hat{y}_i^j}
\]

The results showed in the following figures are averaged on 8 runs and for each of them the standard error is reported.

MMD Versus Mean Embeddings

In order to evaluate whether MMD is fit for dealing with KD, we implemented Mean Embeddings (ME), an state-of-the-art kernel-based discrepancy between distributions [13]. Importantly, the discrimination power of ME can be maximized on an independent training set with gradient ascent. In our experiment, we carried out this optimization on the pre-drift examples (i.e., on the first 100 examples in the stream for HSTAGGER and EMNIST and on the first 170 for 20NG). We also used the very same tensor product kernel for both MMD and ME and for ME we tuned the width of the Gaussian kernel \( k_x \) over instances along with the discrimination power of ME.

Despite being more powerful than MMD on paper, the ME did not perform as well in practice. In particular, ME turned out to be overly sensitive and had severe false detection issues. The changepoints detected by TRCKD +ME are illustrated as vertical dashed bars in Figure 5 for the case of HSTAGGER with sequential KD. In short, ME tends to detect three or four times as many drifts as MMD. This makes it inadequate for interacting with the user: indeed, querying the user too frequently is likely to rapidly make her lose interest in the interaction in practice.

[31] Min-Ling Zhang and Kun Zhang. Multi-label learning by exploiting label dependency. In Proceedings of the 16th ACM SIGKDD international conference on Knowledge discovery and data mining, 2010.

[32] Xiulin Zheng, Peipei Li, Zhe Chu, and Xuegang Hu. A survey on multi-label data stream classification. IEEE Access, 2019.
Comparison to Graphical Lasso

Given the similarity between drift disambiguation and structure learning for probabilistic graphical models [16], we evaluated a variant of TRCKD that uses graphical lasso to reconstruct the structure of the hierarchy from the most recent examples [7]. In particular, in each iteration a data set is built by combining the 70 most recent examples (analogously to what is done for MMD) for all concepts in the machine’s hierarchy. This data set set is fed to graphical lasso, which spits out an (sparse) undirected graph based on the empirical correlation between all the concepts. The directions of individual edges are set so to maximize the likelihood of the child implying the parent and edges are treated as is-a relations. The resulting directed graph replaces the machine’s concept hierarchy. The difference between the previous and current concept hierarchy is used to perform knowledge-aware adaptation.

A comparison between TRCKD + lasso and a baseline MW-kNN is reported in Figure 6. It turns out that for relation addition and removal, graphical lasso often fails to estimate the ground-truth concept hierarchy, leading to systematic prediction errors. Furthermore, it is quite unstable and often detects spurious changes to the hierarchy. The main issue is that – like other fully automated approaches for structure learning – graphical lasso does require substantial amounts of data to perform reliably, and this is simply not the case in our non-stationary setting. This makes structured learning-based approaches unsuitable for this setup.

Full Plots for Q1

Figures 7 report the $F_1$ score for all competitors on all data sets. The results are the same as in the main text: TRCKDoracle is by far the best performing method and the runner up is TRCKDforget, which lags behind when dealing with relation addition and removal. The MW-kNN baseline performs well but suffers from relying on passive adaptation. PAW-kNN tends to perform well for concept drift on HSTAGGER and EMNIST, but falls behind on 20NG and for all other forms of drift.

Full Plots for Q2

To measure the impact of interaction, we compare four variants of TRCKD that differ in what information they elicit from the supervisor: TRCKDoracle which knows exactly when and what kind of knowledge drift occurred; TRCKD, our proposed approach that combines MMD for detection and interactive identification; TRCKDoracle (no interaction) that trusts MMD for both detection and disambiguation, and uses forgetting for adaptation since MMD cannot distinguish between concept drift and relation addition/removal; TRCKDLLR: a fully-automated version of TRCKD that follows up MMD detection by performing drift disambiguation with a likelihood ratio test.

The results in terms of micro $F_1$ score are reported in Figure 8. The ideal baseline outperforms all alternatives in all cases. TRCKD performs as well or better than the less interactive variants in all cases. The concept drift case for 20NG (first column, last plot), the momentary decrease in the performance around iteration 240 is due to the fact that in most of the runs MMD detects the drift and TRCKD performs the adaptation around the same iteration.

| Data set     | $|S|$ | $d$ | Type | $c$ | $LC$ | $LD$ | $DL$ |
|--------------|-----|-----|------|-----|------|------|------|
| HSTAGGER     | 570 | 3   | cat. | 6   | 4.42 ± 0.16 | 0.63 ± 0.02 | 34.63 ± 11.89 |
| EMNIST       | 570 | 10  | cont.| 9   | 3.5 ± 0.04   | 0.44 ± 0.00   | 55.38 ± 5.57   |
| 20NG         | 570 | 100 | cont.| 6   | 2.19 ± 0.00  | 0.31 ± 0.00  | 8.5 ± 0.5    |

Table 2: Data sets statistics (mean ± std.). $|S|$: number of instances, $d$: number of attributes, type of features (categorical or continuous), $c$: number of labels, $LC$: label cardinality, $LD$: label density, $DL$: distinct label set. The metrics are averaged on 8 runs and refer to the experiment for Q3.
Figure 7: Comparison in terms of micro F\textsubscript{1} between TRCKD and standard forgetting strategies for kNN-based methods. Top to bottom: results for HSTAGGER, EMNIST, and 20NG. Left to right: concept drift, concept removal, relation addition, and relation removal.

Figure 8: Comparison in terms of micro F\textsubscript{1} between TRCKD and less interactive variants. Top to bottom: results for HSTAGGER, EMNIST and 20NG. Left to right: concept drift, concept removal, relation addition, and relation removal.