

Benchmarking the Covariate Shift Robustness of Open-world Intent Classification Approaches

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Abstract

Task-oriented dialog systems deployed in real-world applications are often challenged by out-of-distribution queries. These systems should not only reliably detect utterances with unsupported intents (*semantic shift*), but also generalize to *covariate shift* (supported intents from unseen distributions). However, none of the existing benchmarks for open-world intent classification focus on the second aspect, thus only performing a partial evaluation of intent detection techniques. In this work, we propose two new datasets (CLINC14-COV and HWU12-COV) that include utterances useful for evaluating the robustness of open-world models to covariate shift. Along with the i.i.d. test set, both datasets contain a new cov-test set that, along with out-of-scope utterances, contains in-scope utterances sampled from different distributions not seen during training. This setting better mimics the challenges faced in real-world applications. Evaluating several open-world classifiers on the new datasets reveals that models that perform well on the test set struggle to generalize to the cov-test. Our datasets fill an important gap in the field, offering a more realistic evaluation scenario for intent classification in task-oriented dialog systems.

1 Introduction

Open-world classification has been extensively studied in both NLP and CV. Reliably refraining from prediction on samples from out-of-scope labels is of utmost value (Zhang et al., 2021), especially to ensure safety (e.g. autonomous driving) and high quality performance of ML models in production environments. Yang et al. (2021) term this as *semantic shift* detection.

With the advent of voice/text-based task-oriented dialog assistants, it is important to distinguish between supported and unsupported intents to ensure that the classifier does not return garbage when it is barraged with queries from intents it has not been trained on. Several state-of-the-art datasets have

been proposed to evaluate the performance of open-world classifiers for intent detection. For example, CLINC (Larson et al., 2019), ROSTD (Schuster et al., 2019; Gangal et al., 2020), HWU64 (Liu et al., 2021), etc.

However, to the best of our knowledge, none of the existing benchmarks for intent classification incorporate another fundamental aspect of inference in production. Not only should an open-world classifier reliably handle *semantic shift*, it should also generalize (or be robust) to inference-time *covariate shift* where $P_{train}(y|x) = P_{test}(y|x)$ but $P_{train}(x) \neq P_{test}(x)$ (Shimodaira, 2000; Moreno-Torres et al., 2012; Yang et al., 2021; Wang et al., 2022). In industrial settings, it is common practice for ML systems to be trained on some amount of synthetic data. In general, for most real-world applications the production distribution is often unknown. The classifier, however, is still expected to output correct predictions regardless of this potential shift from what it has observed during training.

In this work, we propose two new English (Bender, 2011) benchmarks, CLINC14-COV and HWU12-COV, that fill this gap by focusing on both semantic and covariate shift to evaluate the performance of intent classifiers. We leverage existing state-of-the-art intent classification datasets to specifically design a test set (cov-test) that, along with out-of-scope utterances, contains in-domain queries generated from a different distribution to the training set. The latter are collected by identifying *equivalence clusters* across different state-of-the-art intent classification datasets. Elements within an equivalence cluster contain intent classes that, despite being sourced from different datasets, share the same underlying intent. In total, CLINC14-COV cov-test contains 420 queries across 14 intents, while the cov-test split in HWU12-COV has 1080 queries across 12 intents.

We evaluate a range of open-world intent classifiers and out-of-scope detection techniques on our

#	Equivalence Clusters
1	rostd:alarm/set_alarm, hwu64:alarm_set, massive:alarm_set, clinc:alarm
2	rostd:alarm/cancel_alarm, hwu64:alarm_remove, massive:alarm_remove
3	rostd:alarm/show_alarms, hwu64:alarm_query, massive:alarm_query
4	rostd:weather/find, hwu64:weather_query, snips:GetWeather, massive:weather_query, clinc:weather
5	hwu64:calendar_query, massive:calendar_query, clinc:calendar
6	hwu64:cooking_recipe, massive:cooking_recipe, clinc:recipe
7	hwu64:datetime_query, massive:datetime_query, clinc:time, clinc:date
8	hwu64:general_repeat, massive:general_repeat, clinc:repeat
9	hwu64:qa_definition, massive:qa_definition, clinc:definition
10	hwu64:takeaway_order, massive:takeaway_order,, clinc:order
11	hwu64:transport_traffic, massive:transport_traffic, clinc:traffic
12	rostd:reminder/show_reminders, clinc:reminder
13	snips:PlayMusic, hwu64:play_music, massive:play_music, clinc:play_music
14	snips:BookRestaurant, clinc:restaurant_reservation
15	snips:AddToPlaylist, clinc:update_playlist
16	banking:declined_card_payment, clinc:card_declined

Table 1: Equivalence clusters ($\langle dataset:intent \rangle$). Elements within a cluster represent labels that, despite being from different source datasets, share the same underlying intent.

datasets. Our experiments show that all methods perform relatively poorly on the new cov-test sets. In the full-setting, we find a drop in performance of more than 10 absolute F1 and Accuracy points from test to cov-test. We observe a smaller drop for few-shot classification suggesting that such a setting might lead to more robust intent classifiers. We also analyse the affect of covariate shift with and without semantic shift, and find that not only does the existence of both phenomena better mimic production scenarios, it also results in a more challenging setting for classifiers. Our results show that the current models are less reliable when exposed to queries with covariate shift, especially in the open-world setting. We hope that the new datasets will enable future work to fill this gap in the research and development of dialog systems.¹

2 Dataset

We introduce two new datasets that contain utterances to evaluate the robustness of intent-classifiers to both covariate shift and semantic shift.

2.1 In-Scope Data Collection

To collect in-scope utterances, we leverage the existing state-of-the-art intent-classification datasets

¹https://github.com/sopankhosla/cov_shift_intent_datasets

Dataset	TRAIN	VAL	TEST	COV-TEST
CLINC14-COV	1400	280 (100)	420 (1000)	420 (1000)
HWU12-COV	5055	815 (100)	1028 (1000)	1080 (1000)

Table 2: Data Statistics for our proposed benchmarks – #ID (#OOS) utterances in each split. COV-TEST depicts the newly introduced test set with covariate shift.

including HWU64 (Liu et al., 2021), MASSIVE (FitzGerald et al., 2022), CLINC (Larson et al., 2019), ROSTD (Schuster et al., 2019), SNIPS (Coucke et al., 2018), BANKING (Casanueva et al., 2020) as our starting points.

Equivalence Clusters. We manually go through the different intents and corresponding utterances in the above-mentioned datasets and define Equivalence Clusters (ECs) as clusters of labels across these datasets that represent similar underlying intents. Overall, we identify 16 such clusters (as shown in Table 1). The nature of these ECs gives rise to a natural covariate shift. Each element in the cluster comes from a different dataset and therefore can be safely assumed to be generated from a dissimilar underlying distribution (examples utterances shown in Table 3). We leverage this property to create our two new benchmarks.

CLINC14-COV. To collect this dataset, we consider the equivalence clusters that contain atleast one CLINC intent. We leverage the CLINC intents in 14 such clusters to build the in-domain training, development, and test set. Rest of the elements in those 14 clusters are used to populate the cov-test set. For example, from Cluster 1, *clinc:alarm* utterances are make up the train/dev/test; whereas utterances from *rostd:alarm/set_alarm*, *hwu64:alarm_set* are used for cov-test. Finally, to ensure balance among the in-domain classes in CLINC14-COV cov-test, we randomly sample 30 utterances for each intent.²

HWU12-COV. We first take the 12 ECs that contain a *hwu64* or *massive* intent. Then, we populate the train/dev/test/cov-test splits using the same procedure as discussed for CLINC14-COV. So, for Cluster 6, *hwu64/massive:cooking_recipe* are considered i.i.d., whereas *clinc:recipe* queries are added to the cov-test set. For cov-test, we randomly sample 90 utterances for each of the 12 intent classes.

2.2 Out-of-Scope Data Collection

We use the existing CLINC OOS samples as out-of-scope data for different splits of our benchmarks.

²i.i.d. test set also contains 30 utterances per intent class.

EC#	Utterance	Source Dataset : Label
1 (alarm_set)	tomorrow i would like an alarm for 9 tomorrow please add an alarm called "fitness" set an alarm for two hours from now please wake me up after 2 hours	clinc:alarm rostd:alarm/set_alarm hwu64:alarm_set rostd:alarm/set_alarm
4 (weather)	what will the weather be like in samoa at 6 pm Are we expecting snow this week? how does the weather feel should i take my raincoat with me now	snips:GetWeather rostd:weather/find clinc:weather hwu64:weather_query
13 (play_music)	play a song for me play my women of rock playlist please select the first song in my itunes library next play justin bieber's sorry	clinc:play_music snips:PlayMusic hwu64:play_music massive:play_music
16 (card_declined)	The payment for the card did not go through My card payment has been declined how come my credit card isn't working i could not buy food using my card when i was in vietnam	banking:declined_card_payment banking:declined_card_payment clinc:card_declined clinc:card_declined

Table 3: Example utterances from different equivalence clusters (EC).

OOS samples in CLINC test set are also used for the new cov-test. We refer the reader to [Larson et al. \(2019\)](#) for more details. Table 2 provides details on statistics for both benchmark datasets.

3 Benchmark Evaluation

We evaluate a range of open-world intent classification approaches on the new benchmarks.

Unsupervised OOS Detection. The term unsupervised here refers to the absence of OOS samples during training. For this setup, we consider approaches that leverage a confidence-score to distinguish between in-domain and out-of-scope instances. Confidence scores can be calculated using logits like **Maximum Softmax Probability** ([Hendrycks et al., 2020](#); [Hsu et al., 2020](#)) or distance-based statistics like **Mahalanobis distance** and **Cosine similarity** ([Zhou et al., 2021](#)). In addition, we show results for **KNN-C** ([Zhou et al., 2022](#)) that uses cosine distance to arrive at a local outlier factor score, and **ADB** ([Zhang et al., 2021](#)) that learns adaptive spherical decision boundaries.

Pseudo k+1 OOS Detection strategies focus on generating synthetic out-of-scope samples. These synthetic samples are then included in the training regime of the open-world classifier in a k+1 multi-class classification setup, with k ID and 1 (pseudo) OOS classes. For our experiments, we consider recent algorithms like **ODIST** ([Shu et al., 2021](#)) and **DCLOOS** ([Zhan et al., 2021](#)) under this umbrella.

4 Experimental Setup

Evaluation Metrics. In line with [Shu et al. \(2017\)](#); [Lin and Xu \(2019\)](#); [Khosla and Gangadharaiah \(2022\)](#), we evaluate the performance of the

various approaches on accuracy (Acc) and macro F1-score on known classes ($F1_{In}$), open class ($F1_{Out}$), and all classes combined ($F1_{All}$).

Hyperparameters. For a fair comparison, we use the *bert-base-uncased* encoder from HuggingFace for classification with most of the default hyperparameters.³ We experiment with training batch sizes {32, 64, 128}. Model with batch size 64 performs the best across all datasets. The learning rate for ID classifier training is set to $2e-5$. For ADB, KNN-C, ODIST, and DCLOOS, we use the default hyperparameters in their released code.^{4,5}

Threshold Selection. For MSP, Maha, and Cosine we follow [Khosla and Gangadharaiah \(2022\)](#) and extract a random subset from the validation data (VAL-HOLD) for threshold selection. The in-domain classifier is not exposed to this random subset for development. For threshold tuning, we maximize $Acc_{in} + Recall_{out}$ on VAL-HOLD. For other methods, we follow their released source code.

5 Results and Analysis

Here, we present the results of our experiments.

Full Setting Open-world Classification. Table 4 shows the results on full setting open-world classification.⁶ The compared state-of-the-art methods see a significant drop in performance from i.i.d. test set to cov-test on both benchmark datasets.

On CLINC14-COV, the models consistently lose 8-12 Acc points, and 18-20 $F1_{All}$ points, a large

²Each result is an average of 10 runs with different seeds.

³<https://huggingface.co/bert-base-uncased>

⁴roberta-base results are present in the Appendix.

⁵All experiments are run on a Tesla V100 16GB GPU.

⁶We report the averaged scores on 10 random seeds and the std. dev. values for brevity.

Performance on TEST				COV-TEST				
$F1_{All}$	$F1_{In}$	$F1_{Out}$	Acc	$F1_{All}$	$F1_{In}$	$F1_{Out}$	Acc	
CLINC14-COV								
MSP	88.5	88.2	93.3	91.2	72.9	71.7	89.0	84.2
Cosine	91.4	91.0	96.1	94.4	71.6	70.2	90.8	86.0
Maha	92.4	92.1	96.7	95.2	73.2	71.9	91.4	86.9
ADB	89.1	88.7	94.2	92.1	71.9	70.9	85.8	80.6
KNN-C	92.5	92.2	96.6	95.2	71.2	69.8	91.0	86.3
ODIST	90.5	90.1	95.6	93.8	72.3	71.0	90.6	85.7
DCLOOS	92.5	92.2	97.0	95.7	59.7	57.6	89.3	83.2
HWU12-COV								
MSP	86.9	87.5	80.4	83.1	80.4	80.7	76.6	78.7
Cosine	92.0	92.1	90.4	90.6	85.4	85.3	86.6	86.6
Maha	92.3	92.4	90.8	91.1	84.5	84.3	86.6	86.5
ADB	88.8	89.1	85.3	86.6	84.7	84.9	82.6	83.7
KNN-C	92.1	92.3	89.8	90.3	84.0	83.9	85.7	85.7
ODIST	90.0	90.1	88.1	88.7	83.2	83.1	84.2	84.3
DCLOOS	93.6	93.7	92.9	93.0	80.5	80.1	85.2	84.1

Table 4: Full-setting open-world classification results. Although the compared state-of-the-art methods perform well on i.i.d. test, they struggle to generalize to the new cov-test.

part of which can be attributed to their poor performance on *in-domain* classes (F_{in}) on this set. On HWU12-COV, the drop is smaller yet still significant, with performance ($F1_{All}$, Acc) going down from low 90s to mid 80s. Similar to CLINC14-COV, we see large differences (around 10 points) between the $F1_{in}$ scores on test vs cov-test sets.

Unsupervised vs Pseudo k+1 OOS Detection.

We also observe that the unsupervised open-world classification algorithms seem to suffer slightly smaller drops in $F1_{in}$ from test to cov-test as compared to their pseudo k+1 counterparts (Table 4). Although DCLOOS achieves a very high $F1$ on CLINC14-COV i.i.d. test ($F1_{in} = 92.2\%$, $F1_{All} = 92.5\%$), its performance on cov-test is substantially impacted ($F1_{in} = 57.6\%$, $F1_{All} = 59.7\%$). This holds true for HWU12-COV as well where DCLOOS scores the lowest $F1_{in}$, $F1_{All}$ on cov-test amongst all systems studied in this work. Compare this to unsupervised approaches like Cosine and Maha that achieve the highest $F1$ scores on cov-test while remaining competitive on i.i.d. test.

Few-shot Classification. Next, we study the impact of covariate-shift in the few-shot setting. Table 5 shows the results for 5, 10-shot classification.

Expectedly, the performance in the few-shot setting on i.i.d. test is lower than what was achieved in the full-setting. This difference is larger on HWU12-COV as compared to CLINC14-COV. It is interesting to see, however, that the drop in Acc and $F1$ from test to cov-test is lower than that in the full-setting. The gap is almost non-existent for HWU12-COV. This seems to indicate that the few-

Performance on TEST				COV-TEST				
$F1_{All}$	$F1_{In}$	$F1_{Out}$	Acc	$F1_{All}$	$F1_{In}$	$F1_{Out}$	Acc	
CLINC14-COV (5-Shot)								
MSP	79.7	79.1	88.0	84.3	65.8	64.4	85.0	78.6
Cosine	82.2	81.4	92.3	89.0	66.9	65.3	88.9	82.6
Maha	84.2	83.5	93.3	90.2	68.5	67.0	89.9	83.8
ADB	80.4	79.5	93.1	89.8	57.0	54.7	88.3	81.6
CLINC14-COV (10-Shot)								
MSP	83.6	83.0	91.3	88.1	70.0	68.7	87.8	82.1
Cosine	85.6	85.0	93.6	90.8	69.7	68.2	89.8	84.3
Maha	86.5	86.0	93.7	90.9	71.5	70.2	90.0	84.4
ADB	84.0	83.3	93.8	91.0	64.8	63.0	89.5	83.8
HWU12-COV (5-Shot)								
MSP	69.2	69.1	70.7	69.4	71.9	72.0	71.7	71.5
Cosine	70.7	70.4	74.4	71.9	72.5	72.3	74.9	73.1
Maha	73.8	73.1	81.8	77.1	73.7	73.1	81.1	77.2
ADB	63.8	62.8	76.7	70.7	59.4	58.0	75.7	69.9
HWU12-COV (10-Shot)								
MSP	77.3	77.4	75.6	76.3	80.0	80.2	76.5	78.2
Cosine	80.9	80.7	83.6	81.6	81.9	81.7	84.0	82.9
Maha	83.2	82.9	86.5	84.2	82.2	81.9	85.8	84.2
ADB	77.2	76.8	81.9	78.9	75.2	74.6	81.8	79.3

Table 5: Few-shot classification results for unsupervised open-world classification. The drop in performance from test to cov-test seems to be smaller than that observed in the full-setting. We note that this gap is almost non-existent on HWU12-COV.

shot setting might be more robust to covariate shift as the models do not overfit on the training data.

Covariate Shift in Open-world Setting. Finally, we also discuss the differential impact of covariate shift in the absence and presence of semantic shift.

On CLINC14-COV (Figure 1), Maha (seed 0) is extremely accurate in its predictions about the ID classes in the presence of semantic shift. But, it classifies some OOS samples incorrectly (Fig. 1 left). For covariate shift, we find that in the absence of any semantic shift, the model is robust enough for most intents (middle). However, when both phenomena occur together, as is the case in the newly proposed cov-test, model’s outputs go awry and it considers several of the ID samples to be OOS (right). For example, in the closed-world setting (no open-intent), the model only misclassifies 2 *date* samples from cov-test (middle). However, this number goes up to 24 when covariate shift is introduced in the open-world setting (right). This seems to be a result of the model’s reduced confidence on cov-set ID utterances, ultimately lowering their score below the OOS detection threshold. Open-world classification methods end up introducing tighter conceptual boundaries around each ID class as compared to their closed-world counterparts thus making it easier to confuse ID examples with covariate shift as OOS. We observe a similar trend for other methods, but exclude those results for brevity.

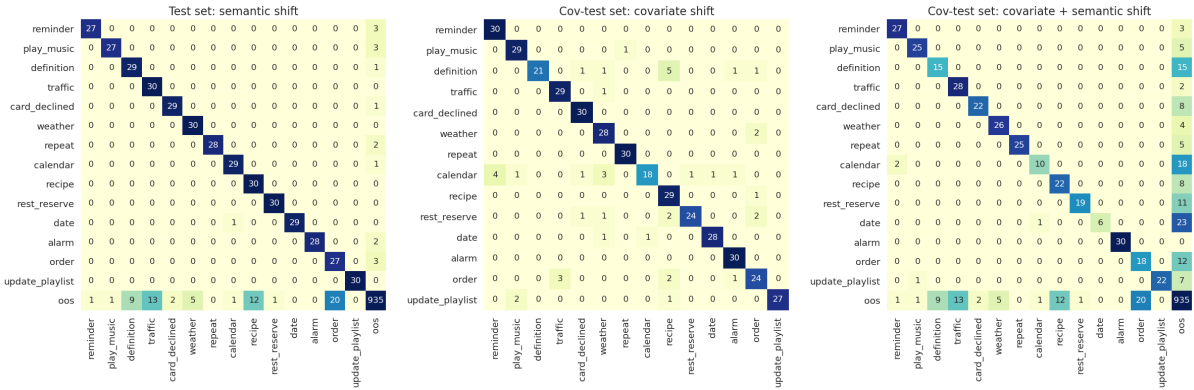


Figure 1: Confusion matrix for Maha (seed 0) on CLINC14-COV with and without covariate and semantic shifts. Covariate shift by itself (middle) does not seem to significantly affect classifier’s performance. However, when present along with semantic shift (right), often the case in real-world scenarios, it adversely affects the prediction accuracy (e.g. on intents like *date*, *calendar*).

6 Related Work

Intent Classification Corpora. There are several available state-of-the-art datasets to evaluate intent classification models (e.g. Larson et al. (2019); Lee et al. (2019); Liu et al. (2021), (Liu et al., 2021; Xu et al., 2015; Casanueva et al., 2020)). While some of these corpora also contain out-of-scope utterances in their test sets, none of them include non i.i.d. in-scope samples. Our new CLINC14-COV and HWU12-COV fill this gap by incorporating such samples in a new cov-test set to evaluate the robustness of intent classification models to both covariate shift and semantic shift.

Evaluating model robustness. Prior works have proposed datasets with adversarial examples to evaluate model robustness. Jia and Liang (2017) show that inserting text can confuse QA systems. Ribeiro et al. (2020) propose a behavioral checklist, an automated test data modification framework to probe model robustness on sentiment analysis and machine comprehension. Whereas, works like Peng et al. (2021); Krone et al. (2021) show that models trained on clean data often struggle to generalize to noisier inputs (e.g. spelling errors, speech disfluencies). In this work, we propose challenge sets that evaluate model robustness to covariate shift. These new benchmarks complement prior art by introducing a new dimension for probing robustness of open-world intent classification systems.

Larson et al. (2020) used crowdsourcing to generate paraphrases of test samples taboing the use of certain key words. They showed that models trained on the standard datasets struggled on these samples. Although similar in motivation, our benchmark creation approach differ from theirs. Instead of manual paraphrasing, we extract distribu-

tionally shifted examples from the equivalent intent classes in the existing state-of-the-art datasets.

Equivalence Clusters. Our notion of *equivalence clusters* is similar to the notion of *collisions* proposed concurrently in Larson and Leach (2022). They introduce the task of intent collision detection when updating the intent classification dataset to incorporate more intents, and show that model performance suffers if new data does not take colliding intents into consideration. On the other hand, we use semantically similar intents in our equivalence clusters to create a challenging test set that evaluates model robustness to covariate shift.

7 Conclusion

In this work, we propose two new benchmark datasets to evaluate open-world intent-classification techniques on their robustness to covariate shift. We leverage previously proposed intent-detection datasets to construct equivalence clusters whose elements represent intent labels that come from different datasets but refer to the same underlying intent class. The nature of these clusters results in a natural covariate shift, as utterances corresponding to each element can be assumed to be generated from a different distribution. These benchmarks test models in the presence of both semantic and covariate shift, a setting that better mimics the challenges faced in real-world production scenarios. We evaluate a range of state-of-the-art open-world classification techniques on our datasets and find that despite their superior performance on i.i.d. test data, they fail to generalize on the covariance test samples. We believe that our datasets and analysis will lead to developing more robust systems for task-oriented dialog.

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Appendix

A Label Distribution

In Table A1, we show the label distribution for CLINC14-COV and HWU12-COV. The new cov-test sets contain a uniform distribution for each in-domain intent class, with the 30 and 90 new utterances per intent for CLINC14-COV and HWU12-COV respectively. Train, dev, and test splits for HWU12-COV are not balanced. Please note that this is a property of the original HWU64 corpus.

Dataset	Labels (#train, #dev, #test, #cov-test)
CLINC14-COV	reminder (100, 20, 30, 30), play_music (100, 20, 30, 30), definition (100, 20, 30, 30), traffic (100, 20, 30, 30), card_declined (100, 20, 30, 30), weather (100, 20, 30, 30), repeat (100, 20, 30, 30), calendar (100, 20, 30, 30), recipe (100, 20, 30, 30), restaurant_reserve (100, 20, 30, 30), date (100, 20, 30, 30), alarm (100, 20, 30, 30), order (100, 20, 30, 30), update_playlist (100, 20, 30, 30)
HWU12-COV	alarm_query (288, 36, 53, 90), cooking_recipe (361, 59, 91, 90), qa_definition (425, 71, 76, 90), alarm_remove (174, 24, 32, 90), weather_query (728, 143, 175, 90), play_music (794, 141, 195, 90), datetime_query (501, 81, 107, 90), transport_traffic (272, 38, 34, 90), calendar_query (724, 119, 145, 90), takeaway_order (290, 38, 41, 90), alarm_set (341, 47, 60, 90), general_repeat (157, 18, 19, 90)

Table A1: Label distribution: CLINC14-COV & HWU12-COV.

B Extended Results

The main paper shows results for open-intent classification methods built on top of *bert-base-uncased* encoder. Here, for completion, we also provide the scores achieved by methods which leverage *roberta-base* instead. Table A2 contains results for full-setting and 5,10-shot settings on both new benchmarks. Similar to the trends seen for *bert-base-uncased*, we find that there is a significant drop in F1 and Accuracy from test to cov-test in full setting. For $F1_{All}$ this gap is more than 15 absolute points on CLINC14-COV, and about 10 points on HWU12-COV. In the few-shot scenario, we note that this gap is smaller, and almost non-existent for HWU12-COV(5,10-Shot). Overall, roberta models yield slightly higher scores on both test and cov-test as compared to their bert counterparts.

C Confusion matrices

In Figures A1 and A2, we show the confusion matrices for Maha (seed 0) model on CLINC14 and HWU12 respectively. The four plots depict model’s

confusion in the presence and absence of covariate and semantic shift. We find that for both datasets, introducing both phenomena together results in the most difficult setting, with CLINC14-COV cov-test being harder than HWU12-COV cov-test.

Performance on TEST				COV-TEST				
	$F1_{All}$	$F1_{In}$	$F1_{Out}$	Acc	$F1_{All}$	$F1_{In}$	$F1_{Out}$	Acc
CLINC14-COV (Full)								
MSP	90.0	89.6	94.4	92.4	73.1	71.9	89.5	84.7
Energy	90.0	89.7	94.1	92.2	73.2	72.1	89.4	84.6
Cosine	92.5	92.3	96.2	94.6	73.2	71.9	90.6	86.0
Maha	92.5	92.2	96.2	94.6	73.3	72.1	90.5	85.7
ADB	88.8	88.5	93.2	91.0	73.4	72.5	85.7	80.8
CLINC14-COV (5-Shot)								
MSP	81.6	81.0	90.1	86.5	66.9	65.5	86.8	80.5
Energy	80.1	79.5	87.9	84.5	66.6	65.2	85.4	78.9
Cosine	86.8	86.2	94.3	91.8	71.5	70.1	90.8	85.6
Maha	87.6	87.1	95.1	92.7	70.9	69.4	91.3	85.9
ADB	86.1	85.5	94.5	92.0	66.9	65.2	90.0	84.5
CLINC14-COV (10-Shot)								
MSP	84.2	83.7	91.0	87.9	68.4	67.0	87.1	81.2
Energy	84.0	83.4	91.6	88.5	70.1	68.8	88.3	82.6
Cosine	88.7	88.3	95.0	92.8	71.7	70.4	90.6	85.6
Maha	89.0	88.5	95.0	92.9	72.6	71.3	90.8	85.9
ADB	86.0	85.6	92.5	89.7	70.8	69.5	88.4	83.0
HWU12-COV (Full)								
MSP	89.4	89.9	83.9	85.7	81.6	81.8	79.8	81.1
Energy	89.9	90.4	85.0	86.5	80.6	80.7	80.2	80.9
Cosine	93.4	93.5	92.3	92.2	83.5	83.2	87.2	86.6
Maha	93.8	93.8	92.9	92.8	82.8	82.5	87.1	86.3
ADB	89.5	89.8	86.8	87.9	84.4	84.5	84.1	84.7
HWU12-COV (5-Shot)								
MSP	73.3	73.5	71.8	72.6	73.5	73.6	71.5	72.5
Energy	72.9	73.3	68.3	71.5	73.9	74.3	69.3	72.3
Cosine	79.7	79.2	86.2	83.0	78.8	78.2	86.6	82.8
Maha	79.9	79.3	86.5	83.0	77.5	76.8	85.8	81.9
ADB	78.2	77.7	83.5	80.7	73.8	73.0	83.0	79.7
HWU12-COV (10-Shot)								
MSP	79.0	79.2	76.7	77.7	79.7	80.0	75.6	77.4
Energy	79.2	79.6	75.4	77.3	80.1	80.5	75.0	77.6
Cosine	84.8	84.6	87.0	85.6	83.7	83.5	86.8	85.6
Maha	85.3	85.1	88.2	86.6	83.2	82.9	87.3	85.4
ADB	82.4	82.3	83.9	82.6	81.2	80.9	83.8	83.0

Table A2: Full-setting and few-shot classification results for unsupervised open-world classification (*roberta-base*).

D Example Predictions

In Table A3, we provide Maha (seed 2) model’s predictions on (atmost) five randomly sampled utterances from test and cov-test of CLINC14-COV. As shown, the utterances that are incorrectly classified for intent classes like *definition*, *alarm*, *card_declined*, *rest_reserve*, we do not find linguistic expressions that frequently occur in the correctly classified subset. For example, for *card_declined*, incorrectly classified queries consistently lack any explicit mention of "card". Similarly, for *definition*, most correctly classified utterances use words like "define", "mean" to depict their intent. Whereas, incorrect ones use phrases like "tell me". We observe that the linguistic differences between test and cov-test of *rest_reserve* are more subtle.

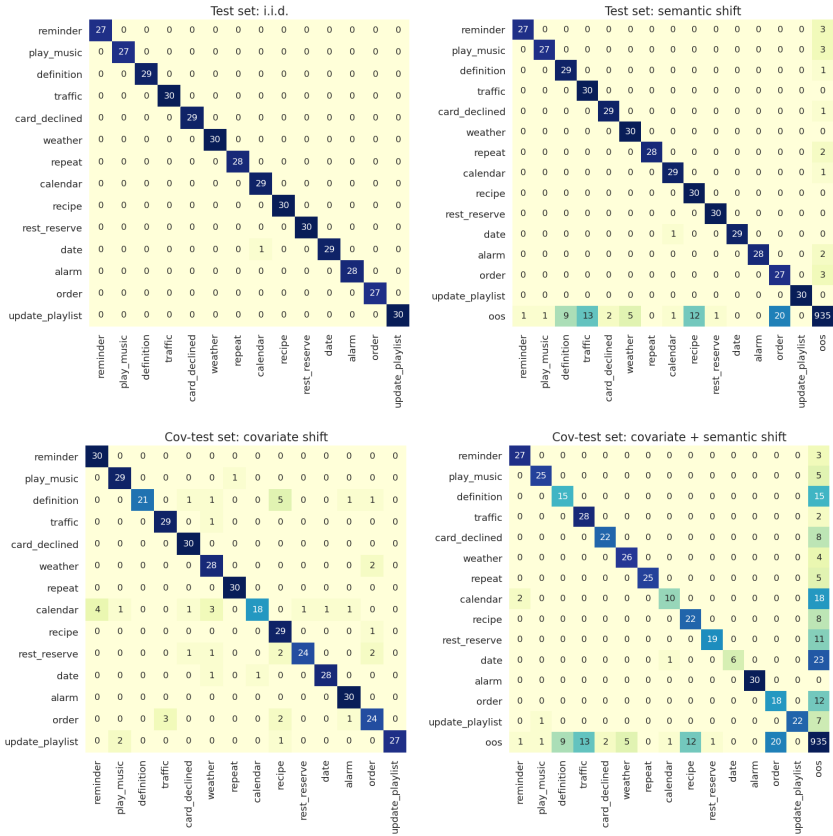


Figure A1: Confusion matrix for Maha (seed 0) on CLINC14-COV with and without covariate and semantic shifts. Covariate shift by itself (bottom left) does not significantly affect classifier’s performance. However, when present along with semantic shift (bottom right), often the case in real-world cases, it adversely affects the prediction accuracy (e.g. on intents like *order*, *calendar*).

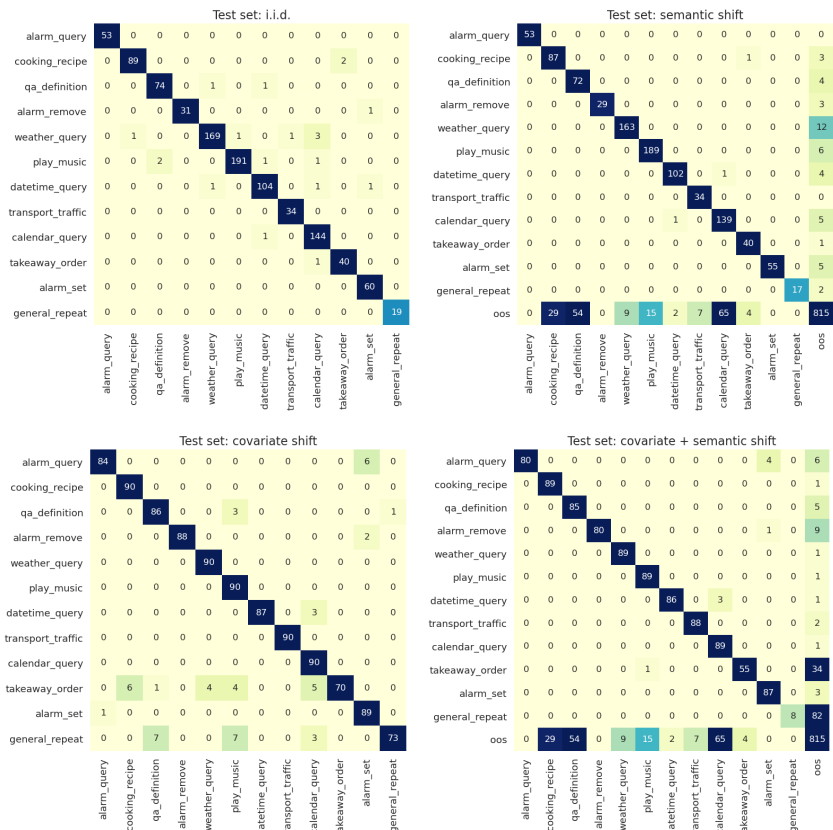


Figure A2: Confusion matrix for Maha (seed 0) on HWU12 with and without covariate and semantic shifts.

	TEST	COV-TEST
<i>definition</i>	what does amicable mean ✓ i'd like to know what bitcoin means ✓ what's the definition of remunerative ✓ define antebellum ✓ can you tell me what dendrofilous means ✓ i heard some woman say she was going to yerd me, what's that mean ✗	what are the definitions of orange ✓ what is photosynthesis ✓ spell and define oscillate ✓ define framework ✓ what is the definition of the word perpetual ✓ tell me all about hurricane ✗ what is computer ✗ tell me about morel mushrooms ✗ what is a mango ✗ give me the description about smartphone ✗
<i>alarm</i>	i need an alarm set now ✓ i'd love to set an alarm ✓ set the alarm now ✓ i would like to have an alarm set for me ✓ i need an alarm ✓ i need to up by noon ✗ can you wake me up at noon ✗	Reset the alarm for the beginning of the movie tonight ✓ set alarm for 8 am ✓ Set a daily alarm for 17h00 ✓ Set alarm for 6 am, Mon-Fri ✓ please ring the wake up alarm at eight am next saturday ✓
<i>card_declined</i>	why did i get rejected on my card ✓ why was my card not accepted ✓ i was in thailand and i could not use my card to buy snacks ✓ why was my card not working at target ✓ can you tell me why my card got declined ✓ how come i got declined ✗	My card was not accepted. ✓ Why has my card payment been declined? ✓ I couldn't pay with card in a shop ✓ I was trying to purchase something at the store today and my card has been declined. Why has this happened? ✓ My card payment did not complete. ✓ You have declined my payment. ✗ Why was my Payment declined ✗ Why are you declining my payment? Everything was fine. ✗ Why did it decline my payment? ✗ My latest payment was declined, I was told everything was back to working order. What happened? ✗
<i>rest_reserve</i>	i need a table for two at the havana at nine ✓ get me a table for five at itta bena at three ✓ could you reserve table for 3 at carlos jr under the name adam at 4 ✓ reserve table for 5 at red robin under the name sara at 3 ✓ are there any open reservations at outback tonight ✓	make a reservation in a popular sicilian bar place nearby for me only tomorrow ✓ book me a reservation for a party of 3 at a pub in northern mariana islands ✓ book a reservation for an oyster bar ✓ table for 8 at a popular food court ✓ i d like a table for midday at the unseen bean ✓ i want to book a restaurant for my father in law and i in buckner a year from now ✗ book a table for nine people in svalbard and jan mayen ✗ i want to book a jewish restaurant in gambia ✗ book a table at a fried chicken restaurant ✗ find a restaurant in fm that servec quiche ✗

Table A3: CLINC14-COV: Five random correctly and incorrectly classified examples (Maha; seed 2) across four intent classes in TEST and COV-TEST.