

# Context-Aware Drift Detection

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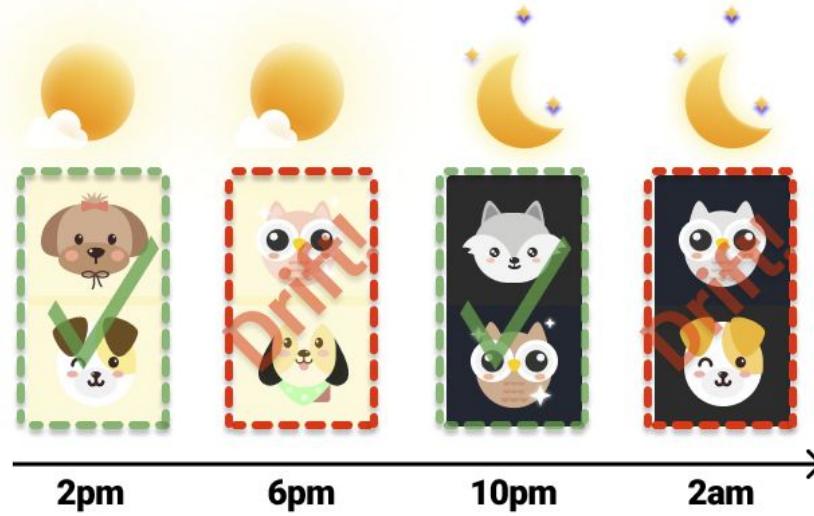


# Motivation

Training data



Deployment data



# Contextualised Samples

- Contextualised sample:

$$\{(s_i, c_i, z_i)\}_{i=1}^n$$

Diagram labels:  
context (arrow pointing to  $c_i$ )  
data (arrow pointing to  $s_i$ )  
set membership (ref=0, dep=1) (arrow pointing to  $z_i$ )

- Generative process:

$$Z \sim P_Z,$$

$$C \sim P_{C|Z},$$

$$S^0 \sim P_{S^0|C}, \quad S^1 \sim P_{S^1|C}$$

$$S = S^0(1 - Z) + S^1 Z.$$

# The Framework

- Null hypothesis:

$$h_0 : P_{S^0|C=c}(\cdot) = P_{S^1|C=c}(\cdot) \quad P_{C_1}\text{-a.e.}$$

- Test statistic:

ADiTT  
↙

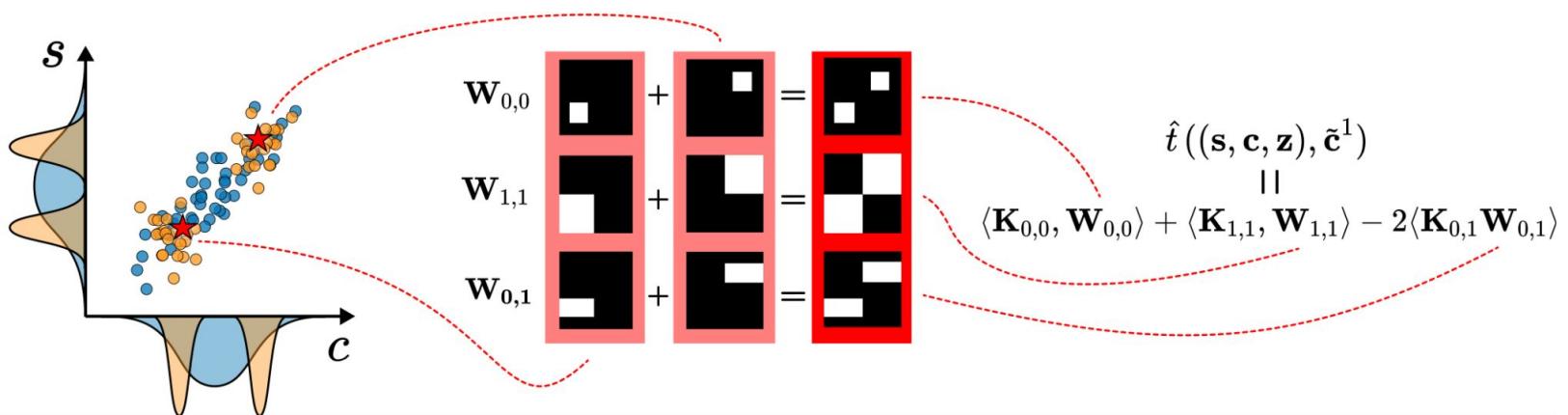
$$E[U_D(C)|Z=1] \quad \text{where} \quad U_D(c) = D(P_{S^0|C=c}, P_{S^1|C=c})$$

↗ CoDiTE

- p-value: conditional permutation test

# MMD-ADiTT

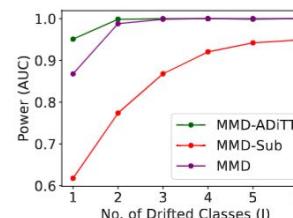
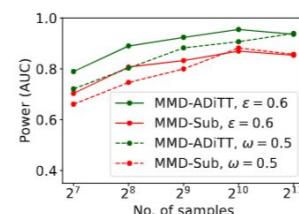
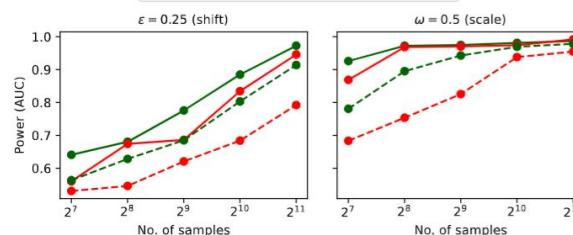
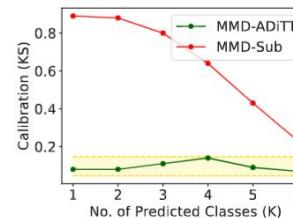
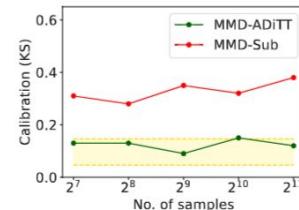
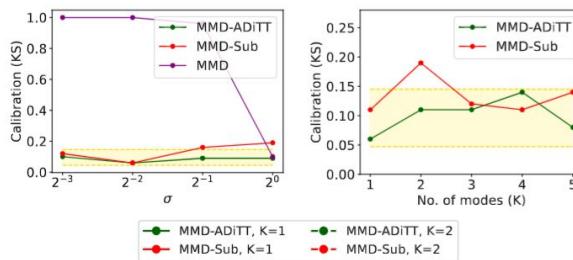
- MMD-based CoDiTE developed by Park et al. (ICML 2021)<sup>1</sup>.
- We introduce a corresponding ADiTT estimator



<sup>1</sup> Conditional distributional treatment effect with kernel conditional mean embeddings and u-statistic regression

# Further Applications and Results

- May alternatively wish to allow variation in:
  - Subpopulation prevalences
  - Model predictions
  - Model uncertainty



# Thanks for watching!



[github.com/SeldonIO/alibi-detect](https://github.com/SeldonIO/alibi-detect)