Related Work

**Discussion and Implication**

Machine Learning catalog summarized from Empirical studies

Collected 22 code smells in total and linked them to four pipeline stages: Data Cleaning, Feature Engineering, Model Training, Model Evaluation.

16 smells are generic and 6 smells are API-specific smells. Generic smells occur no matter which library the user uses. On the other hand API-Specific smells depends on the specific library API design.

Possible Impacts of smells on application codes are : error-prone, less efficient, less re-producible, causing memory issues, less readable and less robust.

Most of the times data scientists would not have software Engineering background and are not up-to-date with the best practices from the software engineering field. So our catalog of smells mitigate this by providing guidelines during the development of machine learning applications.

Using Tensor Flow bugs, replication package replication package and found that many instances have already been deprecated because TensorFlow has upgraded to version 2. Hence, we expect that new API-specific code smells will appear with new versions and library features. In fact, our results showcase that most API related smells are only reported by grey literature in general instead of literature. We argue that collecting a catalog of code smells helps in promoting a continuous effort between practitioners and academics.

three smells can be considered temporary smells: Dataframe Conversion API Misused, Matrix Multiplication API Misused and Gradients Not Cleared before Backward Propagation.

Study focused on six python ML Libraries and frameworks.

**Implication to data scientists: -** ll