

## Automated Research paper Categorization



### Problem Statement

Building an Automated Research paper categorizer using Machine Learning and Deep Learning techniques.

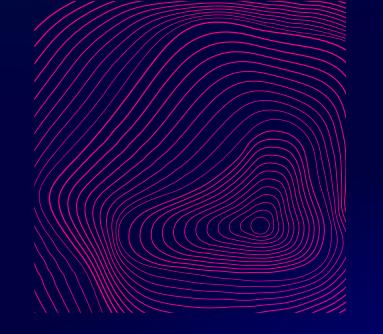
#### **DATASET DESCRIPTION:**

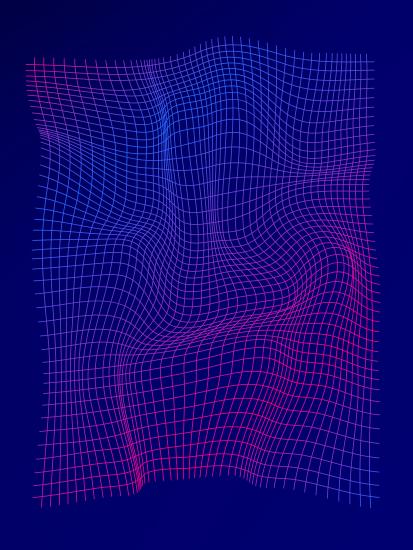
- The train and test datasets consist of multiple research papers.
- The features preset in the dataset are:
  - Title of research paper
  - Abstract of research paper
  - Categories to which the paper belongs to
  - Number of rows in train dataset is 51210
  - Number of rows in test dataset is 10974
  - Number of categories is 57



## A peak at the dataset

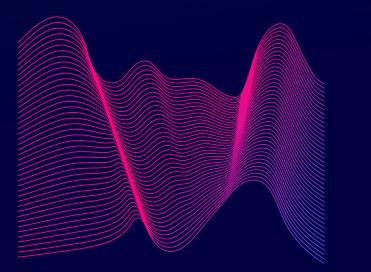
Title	Categories
Large deviations for Wishart processes	['math.PR']
Slicer Networks	['eess.IV', 'cs.AI', 'cs.CV']
New symmetry in nucleotide sequences	['q-bio.GN', 'q- bio.BM']
Modeling Credit Risk with Partial Information	['math.PR', 'q-fin.RM']
A Semantic Grid Oriented to E-Tourism	['cs.DC']

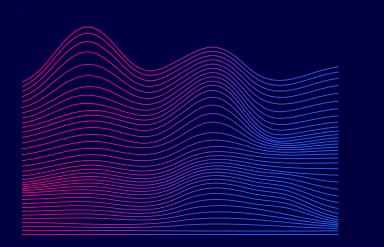




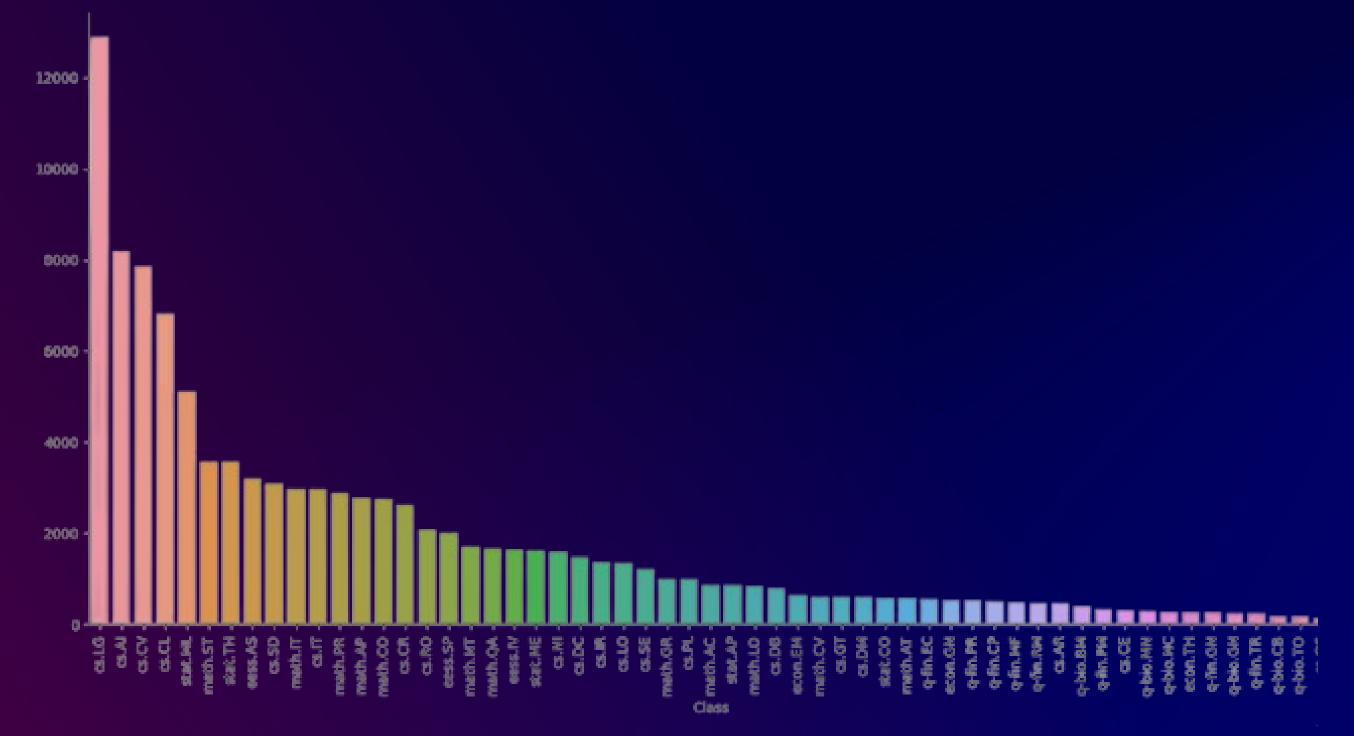


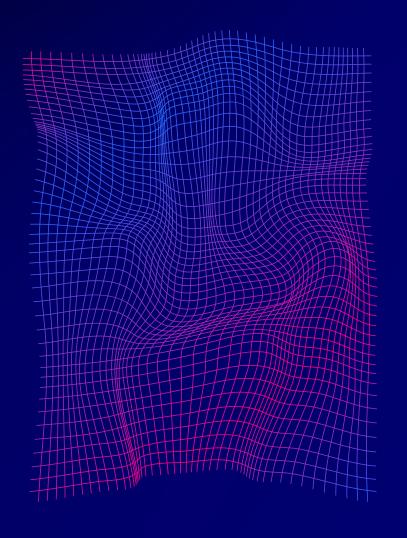
## Class Imbalance













## Data Preprocessing

- Class Weighting:
  - Assigned higher weights to minority classes during training to penalize misclassifications in these classes more heavily.
- Resampling:
  - Resampled the dataset to balance the class distribution. This involved randomly selecting samples from the majority class and creating synthetic samples for minority classes.



# Text Preprocessing Summary

1	Merged the 'Abstract' and the 'Title' columns into a column called 'Context' which is finally used for Prediction.
2	This was followed by decontraction of some word like won't ,can't to 'will not' and 'can not respectively'
3	We removed all the punctuation and stop word from the test.
4	Then we proceeded with stemming all the word to their root word . (Like 'Happier' to 'Happy', 'Programming' to 'Program' and so on)
5	Then we formed a vocabulary using all the word present in the text.
6	Finally each row in the dataset was converted into a vector where each word in text was replaced with its position number in the vocab



## Approaches

#### **DL** based approaches

#### **CNN and Bi-LSTM**

Gave a Public F1 score of 0.56

- Used an Embedding Layer
- Fed the embedding outputs to a 1D Conv layer
- Used a bidirectional LSTM layer followed by feeding it into a max pooling layer
- Feeded the outputs to subsequent dense layers
- Used an output layer with a sigmoid activation

#### **Bert transformer model**

Gave a Public F1 score of 0.61

- Used a pre-trained Bert model for multi-label classification
- Fine-tuned it on the train dataset

#### **Dense Neural Network**

Gave a Public F1 score of 0.65

- Used 3 dense layers with BatchNormalization and Dropout
- Used swish activation for initial layers with leaky relu for the last layer
- Used adam optimizer for model training



#### **ML** based approaches

#### **XGBoost Classifier**

Gave a Public F1 score of 0.54

- Used XGBoost with calibrated classifier CV
- Created a pipeline for each category using Tfidf
   Vectorizer and OnevsRestClassifier for multi-label
   classification

#### **Support Vector machine**

Gave a Public F1 score of 0.62

- Used SVM with calibrated classifier CV
- Created a pipeline for each category using Tfidf
   Vectorizer and OnevsRestClassifier for multi-label
   classification

## Final approach

#### **Dense Neural Network**

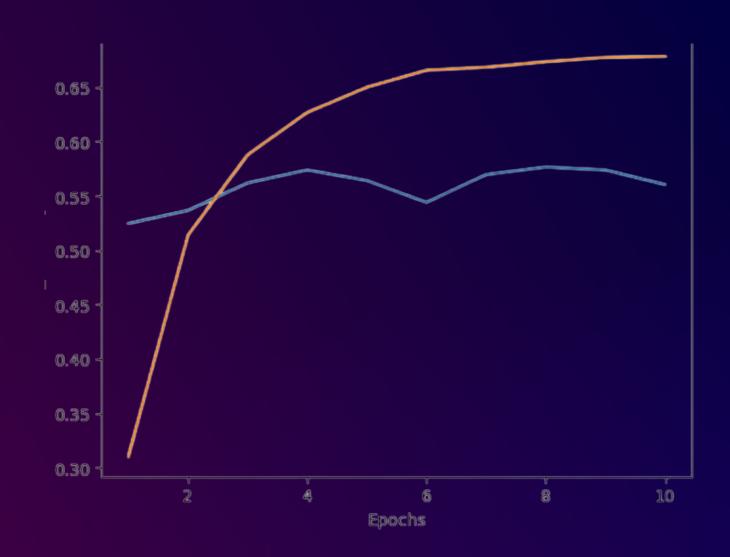
- 3 densely connected layers with 1024, 512, 256 and 128 units
- Swish activation function for the first three dense layers for its smooth, non-monotonic properties and leaky rely for the last dense layer and sigmoid activation for the output layer
- Used regularization techniques like dropout for each of the three layers (0.6, 0.5 and 0.2) and BatchNorm for each of the layers
- Used initializers like HeNormal, HeUniform and GlorotUniform for the final layer to maintain the scale of gradients
- Used Adam optimizer and binary crossentropy loss while training the model



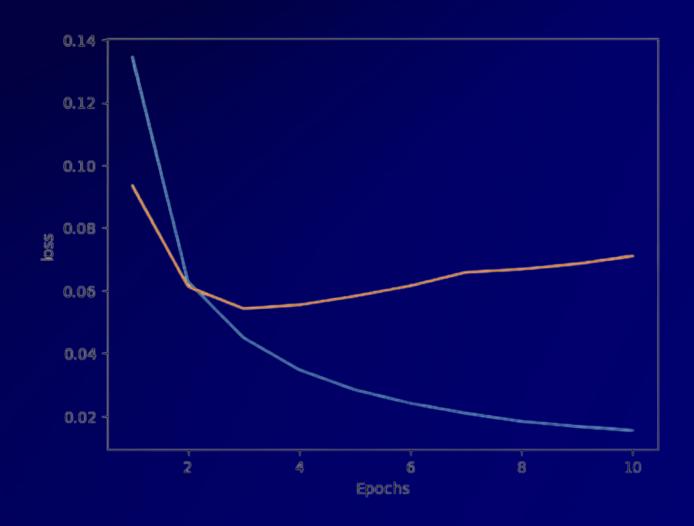
## Training Logs











Training loss vs Validation loss



## Thank You

