NEWS DATA ANALYSIS

Guide

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Motivation

- Fake News is false information presented as news.
- Nowadays, Fake News is intentionally written to mislead readers.
- Fake News spreaded over media ecology (from newsprint to radio/television), and recently online news and social media.

The rapid spread of fake news has the potential for calamitous impacts on individual and society.

Applications

- Can stop fake news on social media.
- Detecting dishonest behaviour of retailers.
- Cannot manipulate elections by spreading fake news.

Problem Statement

The Prevalence of fake news has attracted increasing attention from researchers to politicians, our goal is to Build a solution that analyse news data i.e. fake news detection using granularity concept.

Objectives

- Detecting phony behaviour of news articles which can make an impact and maintain the social trust.
- Divide the mined attributes into respective defined granularity i.e. Coarse Grained(Topic, Sentence, Document level structures) and Fine Grained(Word Level Features).
- Apply Machine Learning techniques to analyse the result.

Literature Review

Authors	Paper Titles	Models Used	Features
Ning Cao et al. (2020)	A deceptive review detection framework	LDA-BP + TextCNN + SVM	Fine-grained and coarse-grained features
Ethan Fast, Bin Binbin Chen, Michael Bernstein(2016)	Empath: Understanding Topic Signals in Large-Scale Text	Empath,LIWC	Text classification, neural network training, 200 in-built features
Jae-Seung Shim et al (2019)	Document Summarization Technique on the Fake News Detection Model	PCA, SVM, Regression, Decision Tree	Lexrank to get 3 line summary.
Jing Li et. al (2020)	A Survey on Deep Learning for Named Entity Recognition	CNN, LSTM, encoder, Tag Decoder.	Traditional NER, Deep Learning NER with neural nets.

Literature Review

Authors	Paper Titles	Models Used	Features
Ritter et.al (2011)	Named Entity Recognition in Tweets:An Experimental Study	Named Entity Recognition.	Postagging, Shallow Parsers,LDA
Savelieva et.al (2020)	Abstractive Summarization of Spoken and Written Instructions with BERT	Text summarization	NLP,BERT,Neural Network.
Castelo et al. (2019).	A Topic-Agnostic Approach For Identifying Fake News Pages.	SVM, KNN, Random Forest	Morphological Features, Psychological Features, Readability Features, Web-Markup Features.
Kuai Xu et al. (2020)	Detecting Fake News Over Online Social Media via Domain Reputations and Content Understanding	LDA Topic Modelling	TF-IDF

Granularity Concepts

Fine Grained

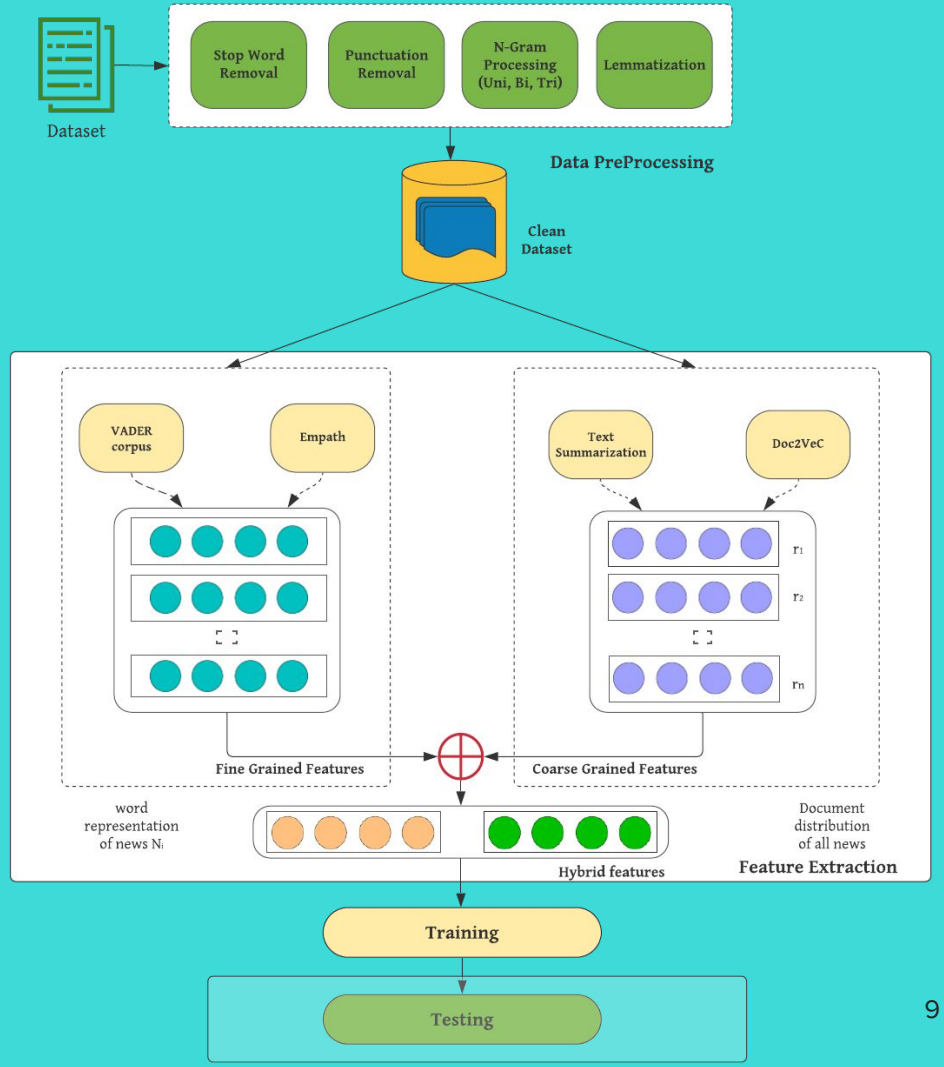
- The smallest possible meaningful content in a topic model can be a word which defines Fine Grained features.
- Eg. **Violence** is a attribute with seed words hurt, break, bleed, broken, etc.

Coarse Grained

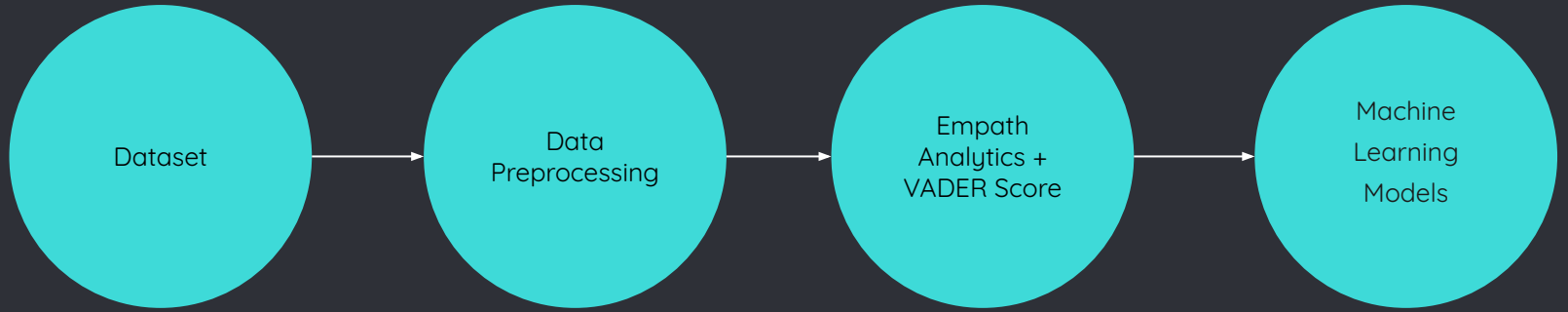
- Explicitly defined as overall data in the text which has a tendency to split enough.
- Eg. War is indeed painful. This sentence indirectly specifies **Violence**.

Proposed Framework

- ❑ Dataset Selection
- ❑ Dataset Preprocessing
- ❑ Granularity
- ❑ Train
- ❑ Predict
- ❑ Test

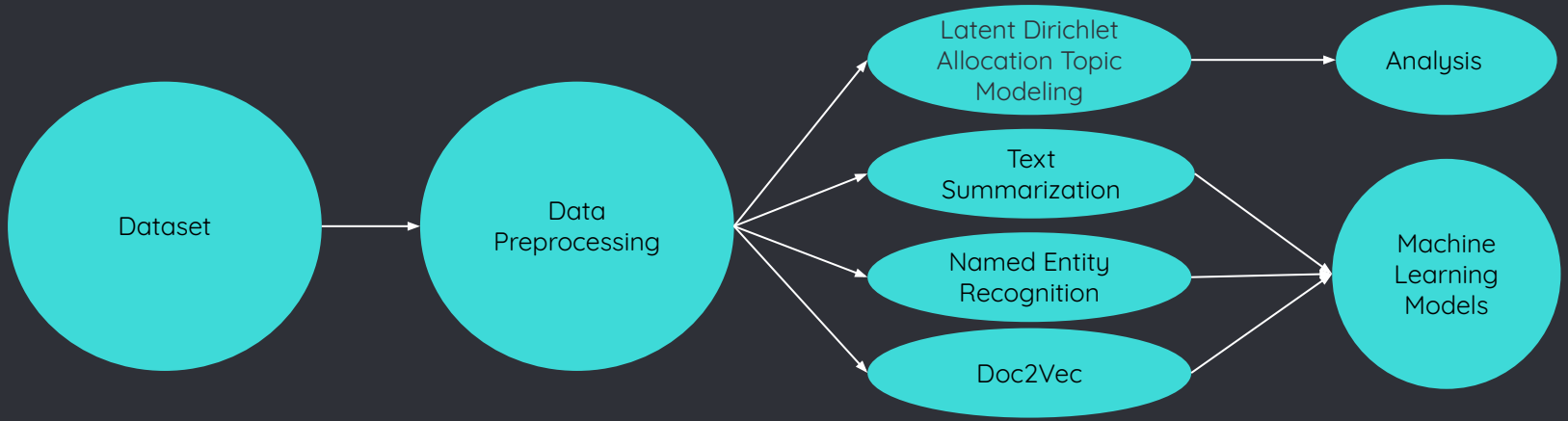


Solution Flow [Fine Grained]



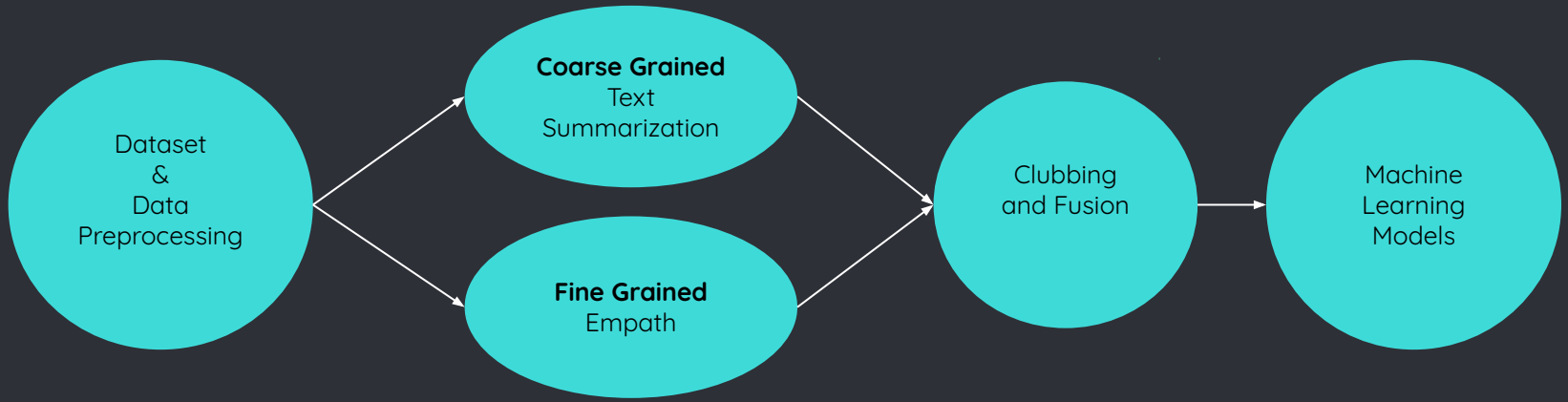
- The features of the dataset are title, text, subject, date, category.
- Lowercasing,
- Lemmatization,
- Stop-word removal.
- Missing Value Replacement.
- Text Reduction.
- Text Normalization.
- Tool for analyzing text across lexical categories.
- Classifies into around 200 attributes.
- sentiment score(VADER)
- Train models on various dataset discussed further.

Solution Flow [Coarse Grained]



- The features of the dataset are title, text, subject, date, category.
- Lowercasing,
- Lemmatization,
- Stop-word removal.
- Missing Value Replacement.
- Text Reduction.
- Text Normalization.
- Classifies sentences into topics.
- Each topic consists of pre-defined combination of words.
- Train models on various dataset discussed further.

Solution Flow [Fusion]



- The features of the dataset are title, text, subject, date, category.
- Lowercasing,
- Lemmatization,
- Stop-word removal, etc.

- Text Summarization with around 20 topics (CG) and Empath with around 200 features (FG).

- The features from fine grain and coarse grained are mixed.

- Train models on various dataset discussed further.

Algorithm Overview

Fine Grained

- Empath Analytics
- VADER score

Coarse Grained

- LDA Topic Modeling
- Text Summarization
- Named Entity Recognition
- Doc2Vec

Fusion

- Text Summarization (number of topics = [20]) + Empath Analytics

Dataset Analysis

- The Experimentation was carried out on three standard publicly available datasets.
  - Kaggle News Dataset
  - Covid19FN
  - Politifact

Dataset	Real	Fake	Total
Kaggle	4000	4000	8000
Covid19FN	1230	1591	2821
Politifact	374	514	888

Explainability

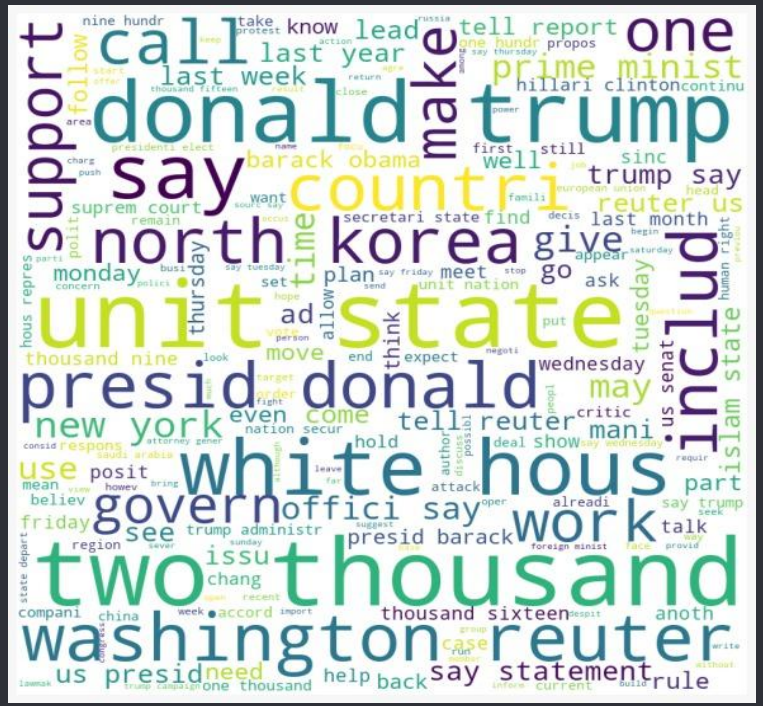
- Technique used to extract which features in the data are most important, how much does each feature effect the prediction.
- A single column of the validation data is randomly shuffled, leaving the target and all other columns in place, and the accuracy of predictions is then checked.
- A column on which model relied heavily for predictions is shuffled then accuracy suffers quite a lot.

Explainability

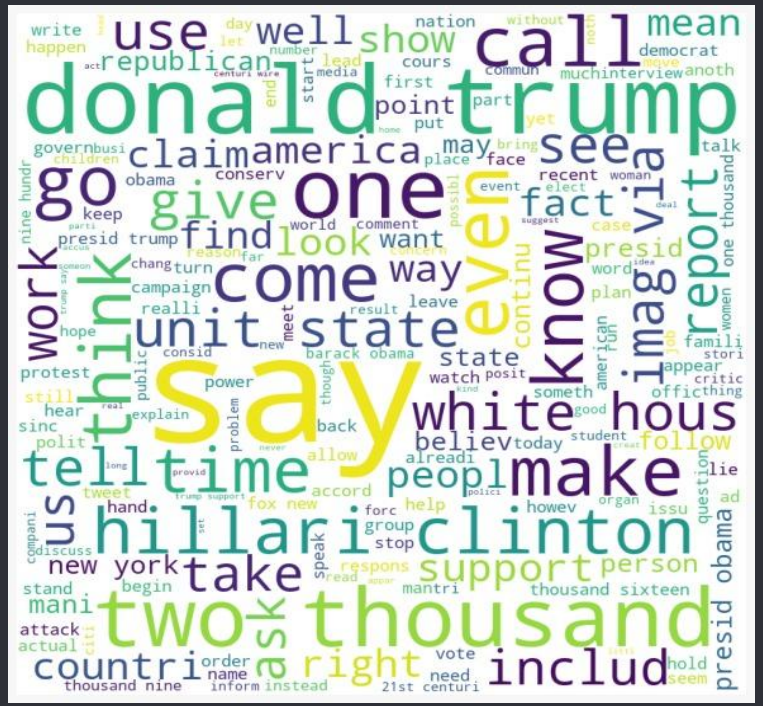
Weight	Feature
0.0893 ± 0.0052	['think', 'want', 'right', 'tweet', 'america']
0.0228 ± 0.0003	['post', 'facebook', 'covid', 'claim', 'social']
0.0225 ± 0.0042	messaging
0.0170 ± 0.0025	speaking
0.0137 ± 0.0025	['government', 'administration', 'unite', 'fund', 'company']
0.0054 ± 0.0028	['north', 'korea', 'trade', 'south', 'unite']
0.0045 ± 0.0011	['clinton', 'hillary', 'campaign', 'election', 'vote']
0.0039 ± 0.0006	['senate', 'vote', 'republican', 'republicans', 'democrats']
0.0025 ± 0.0012	swearing_terms
0.0020 ± 0.0016	giving
0.0020 ± 0.0007	['obama', 'barack', 'administration', 'years', 'claim']
0.0019 ± 0.0013	ridicule
0.0018 ± 0.0008	worship
0.0017 ± 0.0014	leader
0.0016 ± 0.0010	['video', 'police', 'claim', 'share', 'man']
0.0016 ± 0.0009	morning
0.0015 ± 0.0006	eating
0.0015 ± 0.0007	hate
0.0014 ± 0.0015	healing
0.0014 ± 0.0009	clothing

Explainability Of Top Features

Analysis Of Results [Fine Grained]

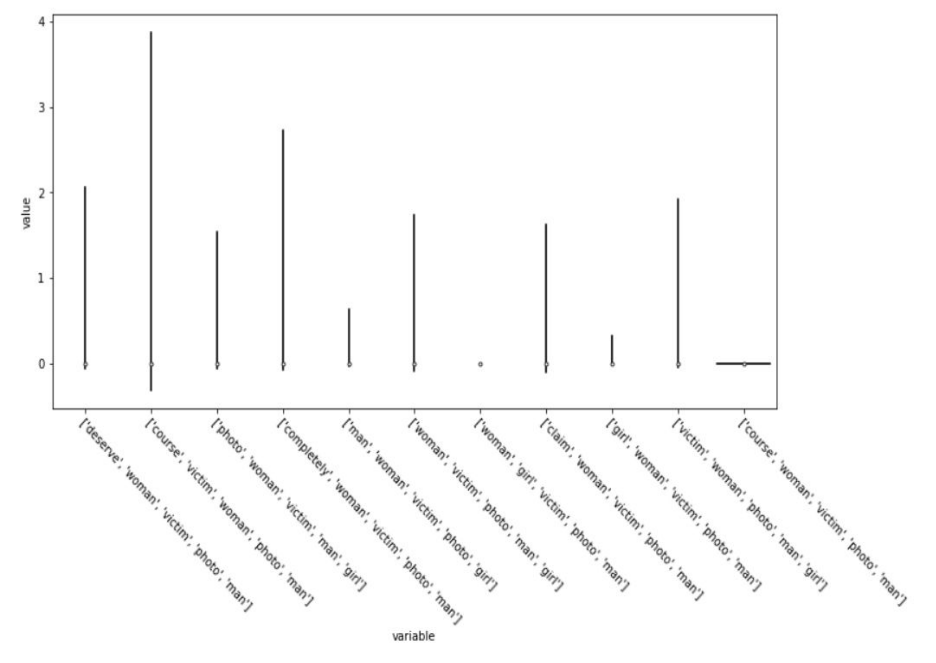


TRUE NEWS WORD CLOUD



FAKE NEWS WORD CLOUD

Analysis Of Results [Coarse Grained - TS]

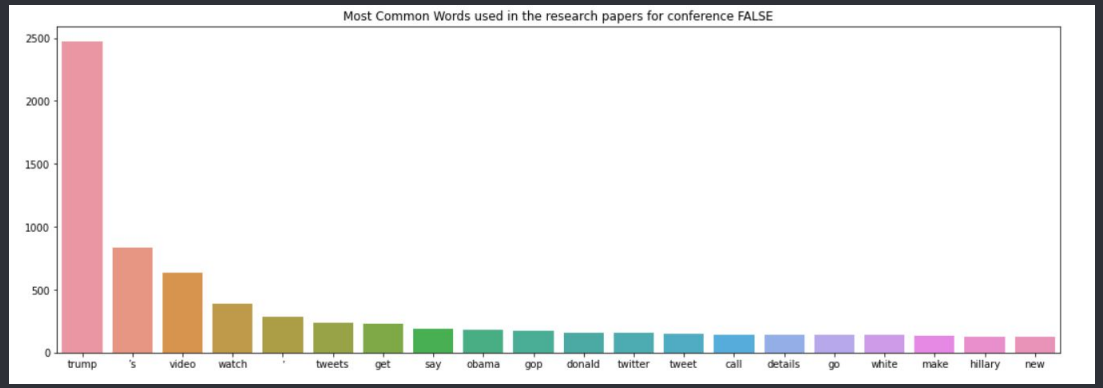


Text Summarization Topics

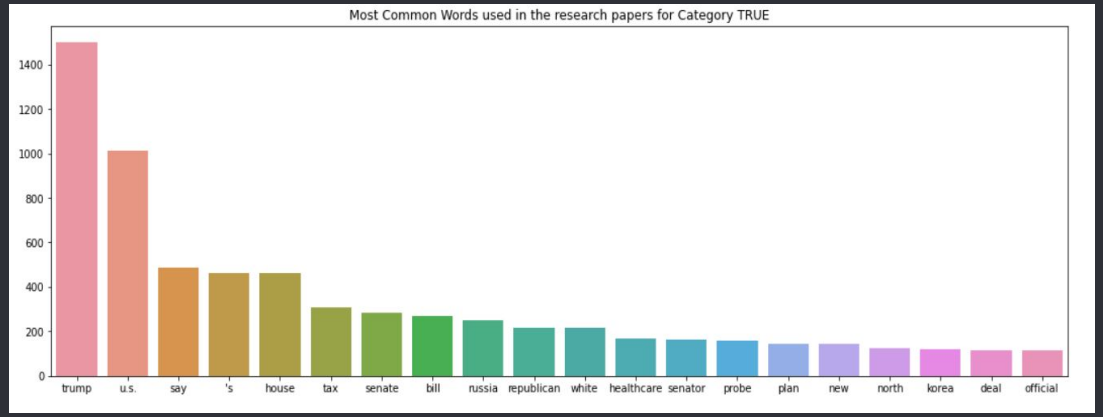
```
{0: ['women', 'know', 'right', 'don', 'going'],
 1: ['senate', 'republicans', 'vote', 'committee', 'senator'],
 2: ['russia', 'russian', 'intelligence', 'moscow', 'putin'],
 3: ['state', 'department', 'government', 'budget', 'federal'],
 4: ['tax', 'percent', 'reform', 'taxes', 'plan'],
 5: ['obamacare', 'insurance', 'healthcare', 'health', 'care'],
 6: ['realdonaldtrump', '2017', 'twitter', 'pic', 'com'],
 7: ['comey', 'fbi', 'investigation', 'director', 'james'],
 8: ['court', 'supreme', 'judge', 'case', 'justice'],
 9: ['ban', 'order', 'muslim', 'countries', 'united'],
 10: ['clinton', 'hillary', 'election', 'campaign', 'voters'],
 11: ['obama', 'barack', 'administration', 'years', 'rules'],
 12: ['trade', 'china', 'united', 'agreement', 'deal'],
 13: ['korea', 'north', 'nuclear', 'sanctions', 'china'],
 14: ['news', 'fox', 'media', 'fake', 'press']}
```

TS Topic Modeling

Analysis Of Results [Coarse Grained - NER]

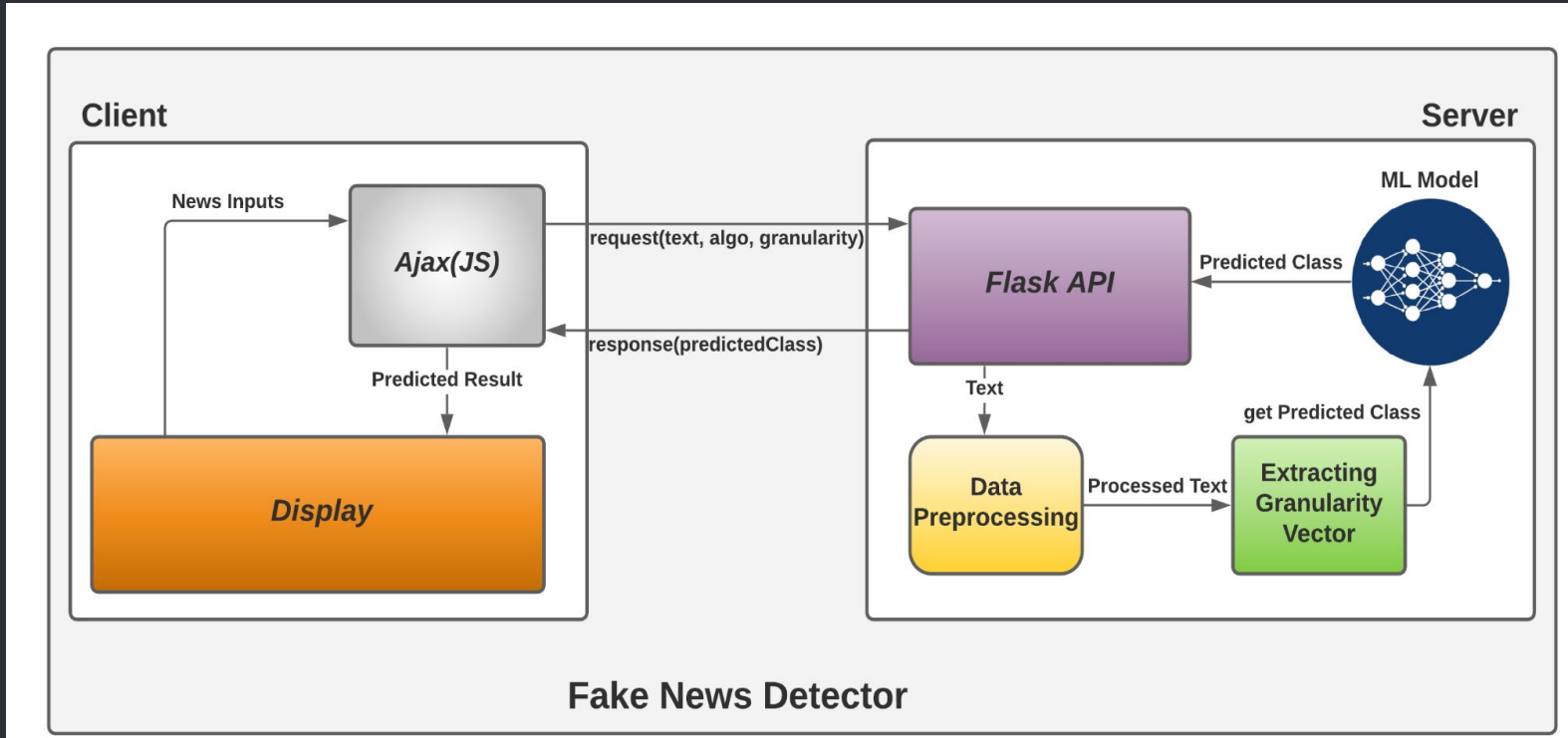


- NER False Words



- NER True Words

Web Flowchart

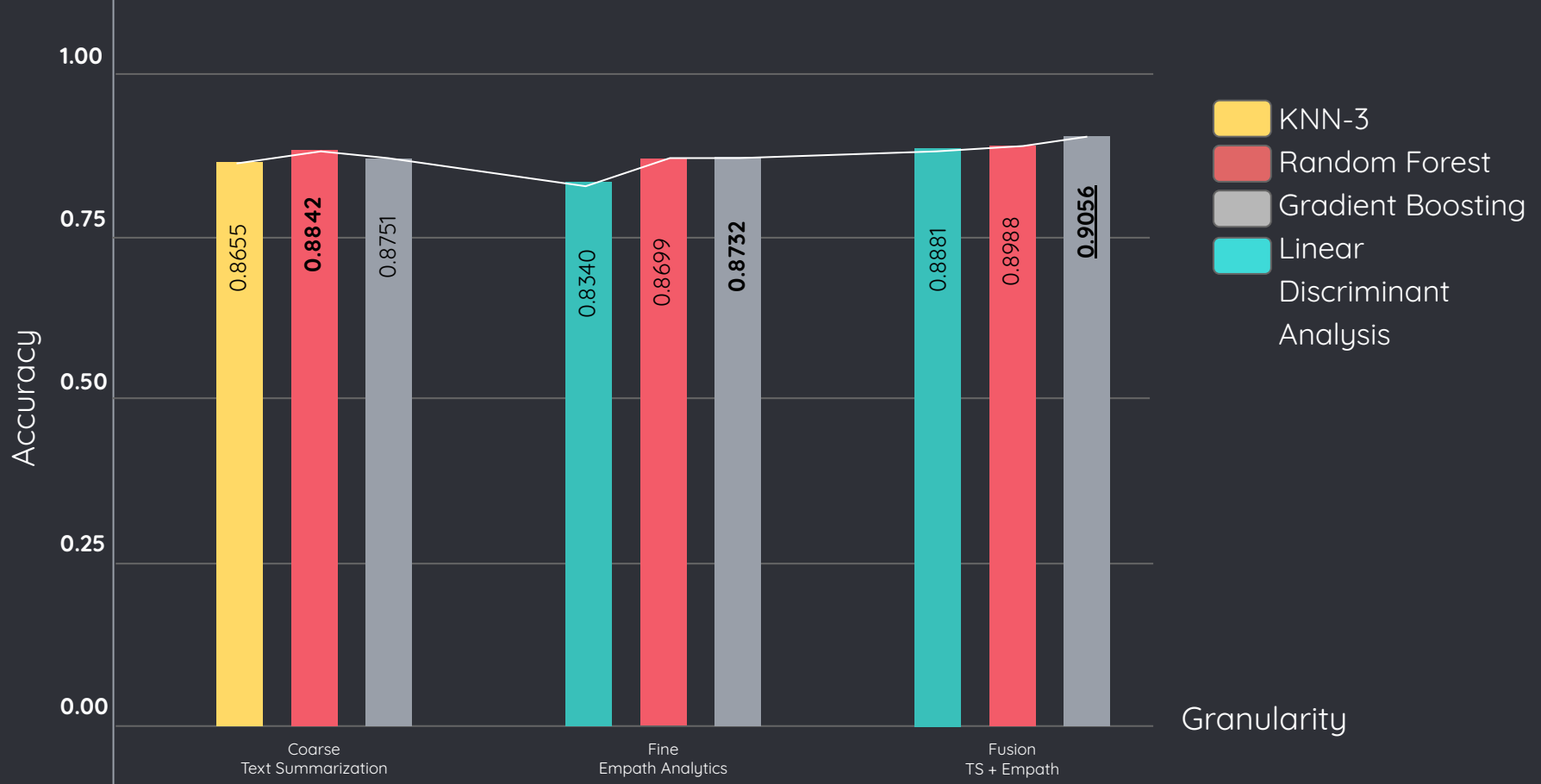


Simulation & Results

Model Type / Algorithm / ML-Models				Kaggle Dataset		Covid Dataset		PolitiFact	
				Accuracy	F1-Score	Accuracy	F1-Score	Accuracy	F1-Score
Coarse	*Doc2Vec*		Random Forest	0.5733	0.5159	0.7905	0.7906	0.7078	0.6804
			Logistic Regression	***0.9160***	***0.9154***	0.8047	0.8051	0.8127	0.8137
			Gradient Boosting	0.7926	0.7865	***0.8059***	***0.8006***	***0.7790***	***0.7805***
	Text Summarization	*Topic = 10*	KNN-3	0.8903	0.89	0.9004	0.91	0.7865	0.79
			Random Forest	**0.9056**	**0.91**	0.9218	0.92	***0.8464***	***0.85***
			Gradient Boosting	0.905	0.90	0.9194	0.92	*0.8464*	*0.85*
		Topic = 15	KNN-3	0.893	0.891	0.911	0.91	0.8089	0.81
			Random Forest	0.920	0.921	0.923	0.92	0.8576	0.86
			Gradient Boosting	***0.923***	***0.922***	***0.928***	***0.93***	***0.8614***	***0.86***
		Topic = 20	KNN-3	*0.8833*	*0.88*	*0.9102*	*0.91*	0.8352	0.84
			Random Forest	***0.9203***	***0.92***	***0.9445***	***0.94***	**0.8726**	**0.87**
			Gradient Boosting	*0.913*	*0.91*	*0.9397*	*0.94*	0.8576	0.86
		Topic = 25	KNN-3	*0.8563*	*0.86*	*0.8902*	*0.89*	0.8089	0.81
			Random Forest	*0.9193*	*0.92*	***0.9327***	***0.93***	***0.8614***	***0.86***
			Gradient Boosting	***0.9203***	***0.92***	*0.9327*	*0.93*	0.8389	0.84
		Topic = 30	KNN-3	*0.8593*	*0.86*	*0.8795*	*0.88*	0.7827	0.78
			Random Forest	***0.9176***	***0.92***	*0.9397*	*0.94*	0.8127	0.81
			Gradient Boosting	*0.9167*	*0.92*	***0.9421***	***0.94***	***0.8614***	***0.86***
	NER		Gradient Boosting	0.890	0.892	0.936	0.94	0.8775	0.88
			Random Forest	0.931	0.930	***0.952***	***0.95***	***0.9149***	***0.91***
			Linear SVM	***0.949***	***0.951***	0.947	0.95	0.8673	0.87
Fine	*Empath Analytics*		LDA	0.901	0.901	0.889	0.89	0.8277	0.83
			Random Forest	0.908	0.910	***0.923***	***0.92***	*0.8127*	*0.81*
			Gradient Boosting	***0.928***	***0.931***	0.921	0.92	**0.8726**	**0.87**
	Empath + VADER		LDA	0.9073	0.91	0.888	0.89	0.8127	0.81
			Random Forest	0.9086	0.91	***0.925***	***0.93***	*0.8314*	*0.83*
			Gradient Boosting	***0.9326***	***0.93***	0.921	0.92	**0.8764**	**0.88**
Fusion	*Text Summarization + Empath*		LDA	0.884	0.880	0.891	0.89	0.7902	0.79
			Random Forest	0.895	0.900	0.926	0.93	***0.8389***	***0.84***
			Gradient Boosting	***0.896***	***0.900***	***0.926***	***0.93***	0.8352	0.84

Simulations & Results

Model Type Algorithm ML-Models			All Merged	
			Accuracy	**F1-Score**
Coarse	Text Summarization Topic = 20	KNN-3	0.8655	0.87
		Random Forest	**0.8842**	**0.88**
		Gradient Boosting	0.8751	0.88
Fine	Empath Analytics	LDA	0.8340	0.83
		Random Forest	*0.8699*	*0.87*
		Gradient Boosting	**0.8732**	**0.87**
Fusion	Text Summarization + Empath	LDA	0.8881	0.89
		Random Forest	0.8988	0.9
		Gradient Boosting	***0.9056***	***0.91***



Merged Dataset Analysis

Baseline Comparison

- We have list down the efficiency and approach we executed to attain the same.
- Fake and Real News Dataset(Kaggle) and Liar Dataset are used for the basis of comparison with referenced papers.

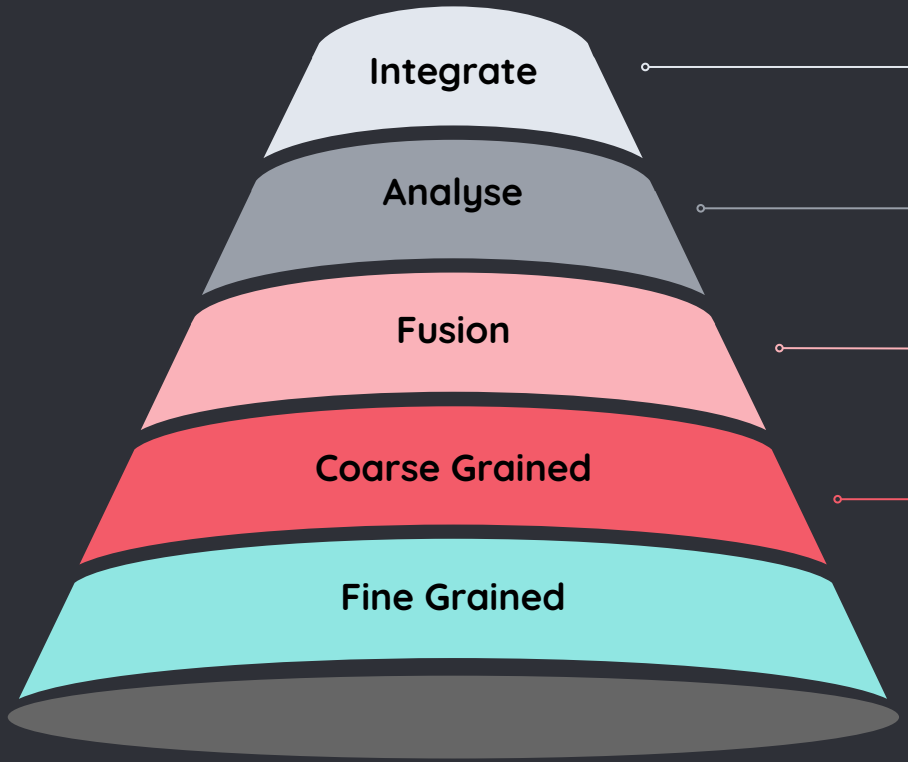
Dataset	Author	Author's Approach	Paper's Accuracy	Our Approach	Our Accuracy
Fake and Real News Dataset(Kaggle)	Ahmed, H. et. al.	n-gram features and the LSVM algorithm	87.0	Empath + Text Summarization fusion	***89.6***
Liar Dataset	Wang, W. Y. et. al.	SVM, Bi-LSTMs	26.1	Text Summarization + SVM	***55.6***

Conclusion

- Data Preprocessing was a core part along with feature extraction.
- We conclude granularity concepts and its implementations, ie. Fine Grain and Coarse Grain on textual news.
- Comprehensive experiments were designed and implemented based on three existing standard datasets.
- **Link to Report :-** Click here

Journal Name	Journal of Ambient Intelligence and Humanized Computing
Journal Link	https://www.springer.com/journal/12652/updates/18861560
Status	Under Review

Accomplished Future Works



Integrate with web application to make it real-time

Analyse On Different Datasets

Combine 2 Granularity Models

Detect Sentence Level Features

Detect Word Level Features

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Thanks!