

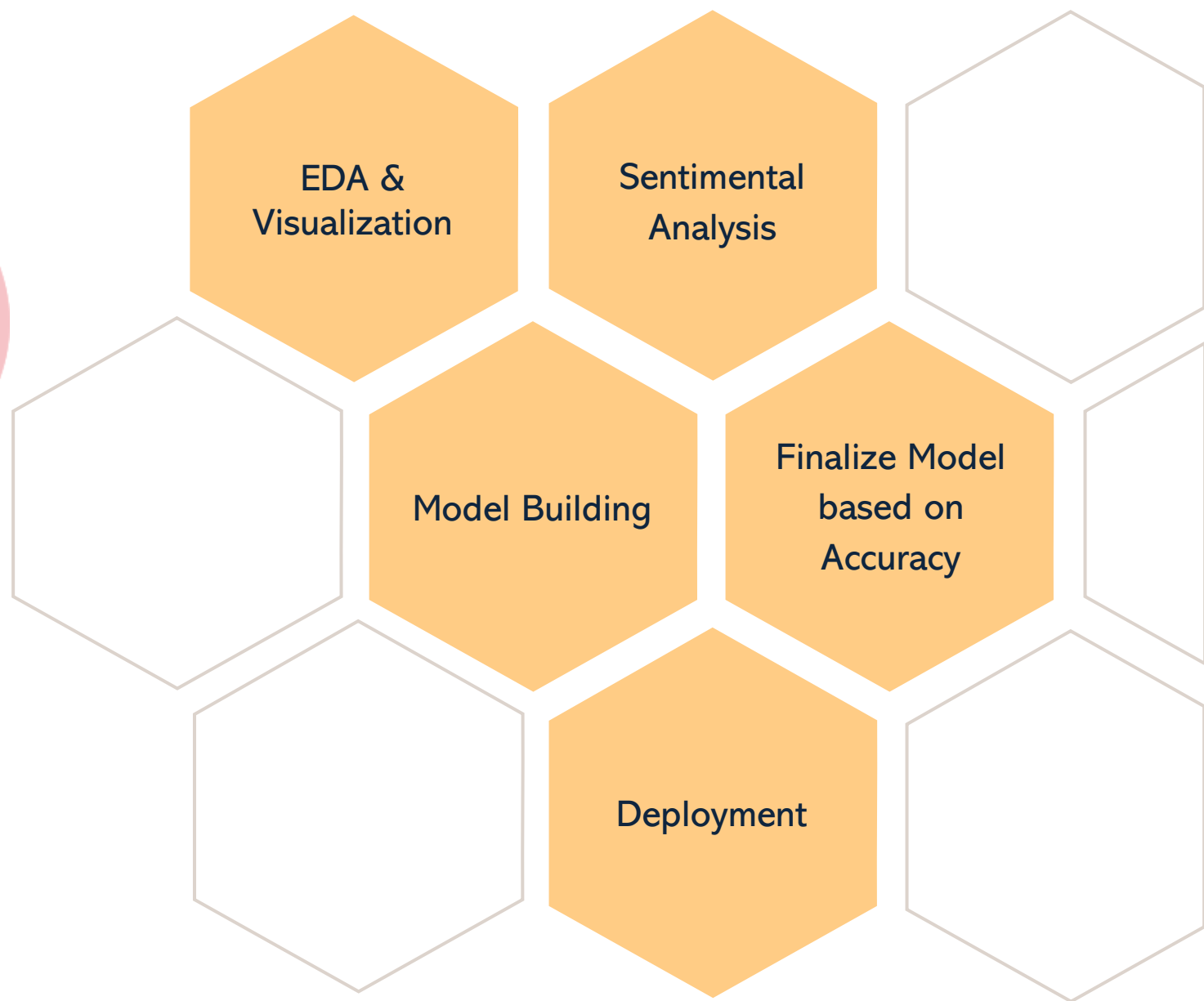
Amazon Sentimental Analysis

Classification Problem:

Daily Analysis of a product such as emotions, sentiment etc. using Amazon data

Text_ID | Product_Description | Product_Type | Sentiment

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EDA & VISUALIZATION

Product_Type	0	1	2	3	4	5	6	7	8	9	All
Sentiment											
0	0	0	2	1	0	0	2	0	1	105	111
1	4	5	69	49	0	36	84	43	65	44	399
2	1	1	15	10	0	6	16	8	6	3702	3765
3	47	53	379	240	19	171	563	276	122	219	2089
All	52	59	465	300	19	213	665	327	194	4070	6364

```
def review_cleaning(text):
    stop_words = stopwords.words('english')
    stop_words.extend(["sxsw", "@", "rt", "re", "w", "u", "m", "s", "sxswi", "mention", "link", "amp", "sx", "sw", "wi", "sxs",
                       "google", "app", "phone", "pad", "apple", "austin", "quot", "android", "ipad", "marissa", "mayer",
                       "social", "network", "store", "via", "popup", "called", "zlf", "zms", "quotmajorquot"])

    text = normalize("NFKD", text).encode("ascii", "ignore").decode("utf-8", "ignore") # Encoding & Decoding Data
    text = contractions.fix(text) #Contraction Replacement
    text = re.sub("\[.*?\]", "", text) #brackets
    text = re.sub("https?://\S+|www\.\S+", "", text) #links
    text = re.sub("<.*?>+", "", text) #characters
    text = re.sub("[%s]" % re.escape(string.punctuation), "", text) #punctuations
    text = re.sub("\n", "", text) #new line
    text = re.sub("\w*\d\w*", "", text) #numbers
    text = " ".join([s for s in re.split("([A-Z][a-z]+[^\A-Z]*)", text) if s]) #Split attached Uppercase words
    text = "".join("".join(s)[:2] for _, s in itertools.groupby(text)) #remove letter repeating twice in continuation
    text = str(text).lower() #Normalization
    text = " ".join(s for s in str(text).split() if s not in stop_words) #stopwords
    text = " ".join([w.lemmatize() for w in TextBlob(text).words]) #Lemmatizaion
    return text
```

SENTIMENTAL ANALYSIS

	mean	median
	Polarity_score	Polarity_score
Sentiment		
0	0.078659	0.000000
1	0.022575	0.000000
2	0.101766	0.000000
3	0.211351	0.136364

since sentiment 0 & 1 have very few reviews and polarity scores to a similar range, we combine both of them to balance the data

```
amazon["Sentiment"] = amazon["Sentiment"].replace(0,1)

labelencoder = LabelEncoder()

amazon["Sentiment"] = labelencoder.fit_transform(amazon["Sentiment"])
```

Negative

Neutral

Positive

		mean	median
		Polarity_score	Polarity_score
	Sentiment		
←	0	0.034782	0.000000
←	1	0.101766	0.000000
←	2	0.211351	0.136364

MODEL BUILDING

- X = TfidfVectors, Product_Type, Polarity_score
Shape = (6364, 7592)

- Y = Sentiment
Shape = (6364, 1)

- Trained Model using Various Classifiers like :
SVM, XG Boost, Ada Boost, KNN, Random Forest, Decision Tree,
Gradient Boosting

Accuracy	Sentiment	Classifier						GB
		SVM	XGBM	AB	KNN	RF	CART	
Precision	0	1.00	0.61	0.00	0.72	0.00	0.00	0.73
	1	0.92	0.92	0.92	0.91	0.60	0.60	0.92
	2	0.83	0.83	0.80	0.84	1.00	0.50	0.83
Recall	0	0.16	0.18	0.00	0.22	0.00	0.00	0.21
	1	0.98	0.98	0.98	0.98	1.00	1.00	0.98
	2	0.91	0.88	0.91	0.88	0.01	0.01	0.89
F1	0	0.28	0.28	0.00	0.33	0.00	0.00	0.32
	1	0.95	0.94	0.95	0.94	0.75	0.75	0.95
	2	0.86	0.85	0.85	0.86	0.01	0.01	0.86
Model Score		88.61%	87.82%	87.27%	88.37%	60.41%	60.33%	88.53%

[illegible]

FINAL MODEL BASED ON ACCURACY

Gradient Boosting Model returns the Highest Accuracy

```
model = GradientBoostingClassifier()
```

```
model.fit(X,Y)
```

```
dump(model, open("Amazon.sav", "wb"))
```

```
loaded_model = load(open('Amazon.sav', 'rb'))
```

```
result = loaded_model.score(X, Y)
```

89.3935%

		<u>Accuracy</u>			
Classification	Report -				
	precision	recall	f1-score	support	
0	0.73	0.21	0.32	106	
1	0.92	0.98	0.95	767	
2	0.83	0.89	0.86	400	
accuracy			0.89	1273	
macro avg	0.83	0.69	0.71	1273	
weighted avg	0.88	0.89	0.87	1273	

DEPLOYMENT

- Deployed model on Streamlit using command prompt
- Predict Button to Predict the Sentiment
- Download Button to save prediction as .csv file.

Sentiment Analysis of Amazon Reviews

Review

Worst Product

Product Type

5

User Input parameters

	Product_Description	Product_Type
0	Worst Product	5.0000

Predict

Sentiment

1

Download ↓



THANK YOU