Product Attribute Based Sentiment Analysis

By Yash Jain

Problem Statement

Problem :

- System should be able to identify and analyze different aspects (features) of a product mentioned in reviews and determine the sentiment associated with each aspect.

Example : Camera is good but battery have heating issue. **Rating :** 

Targeted Values :

Customer Sentiments & Insights are hidden in these reviews. To utilize the Power of NLP to grasp Aspect and Sentiment which could help Company to improve:

- Guest Shopping Experience.
- Product Quality
- Customer Service
- Delivery Service

Example:

- Camera is good but battery have heating issue.

- Got this (Delivery) product in just 2 days. Camera is good but battery have heating issue, But (customer service) People from Target helped me to resolve the issue.

Idea and inspiration:

Ironhill Bengaluru

Write a review

no 90/7 & 90, Sy, 8, Marathahalli - Sarjapur Outer Ring Rd, beside Radisson Blu, Bengaluru, Karnataka

4.6 ★★★★½ 19,891 reviews

People often mention

All | valet parking 104 | mocktails 95 | pool 33 | queue 32 | chicken tikka 24 | panna cotta 18 | seating capacity 17 | toffee pudding 16 | water body 13 | world series 12

Sort by

Most relevant | Newest | Highest | Lowest

Anitha Krishnamoorthy
2 reviews · 28 photos

★★★★★ a week ago NEW

This became an instant favorite of mine. The place was huge and spacious with a great ambience and good music. The best place to hangout with friends. The food was served on time and was absolutely delicious. My personal must-try dishes are … More

3

POCO M4 5G (Cool Blue, 64 GB)

4.2★ 84,196 Ratings & 5,981 Reviews

₹10,999 ~~₹15,999~~ 31% off

POCO M4 5G (Cool Blue, 64 GB) Reviews

Most Helpful

Overall | Camera | Battery | Display | Design | Performance

3.5

78% Positive feedback

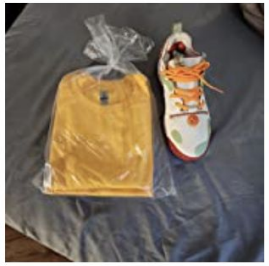
22% Negative feedback

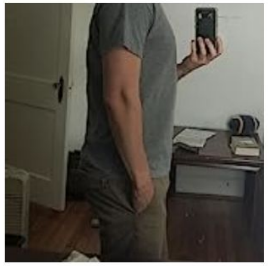
...Phone is good but back camera quality is too poor comparison in the catagory ,need to improve this .

Shailendra Mandloi Certified Buyer, Faridabad Jul, 2022

...Battery - 3.5/5

Reviews with images



See all customer images

Read reviews that mention

good quality | fit as expected | moisture wicking | safety green

cotton and polyester | true to size | fit perfectly | like a cotton

around the house | feel like | fit fine | dryblend | polyester and cotton

Top reviews

Google Travel Explore Things to do Flights Hotels Ho

Hotel Mayura Hoysala Mysuru

View list

Overview Prices Reviews Photos About

Search reviews

All | Food (190) | Transport (69) | Location (151) | Breakfast (92)

Property (369) | Bar (53) | Service (234) | Air Conditioning (43) | Amenities (62)

Cleanliness (126) | Bathroom (71) | Atmosphere (74) | Parking (29) | Sleep (35)

Family (32) | Safety (15) | Restaurant (17) | Wi-Fi (12) | Entertainment (11)

Accessibility (10) | Kitchen (6)

Wi-Fi

Mentioned in 12 Google reviews

67% unfavourable 8% positive

All reviews

D Domla Pass

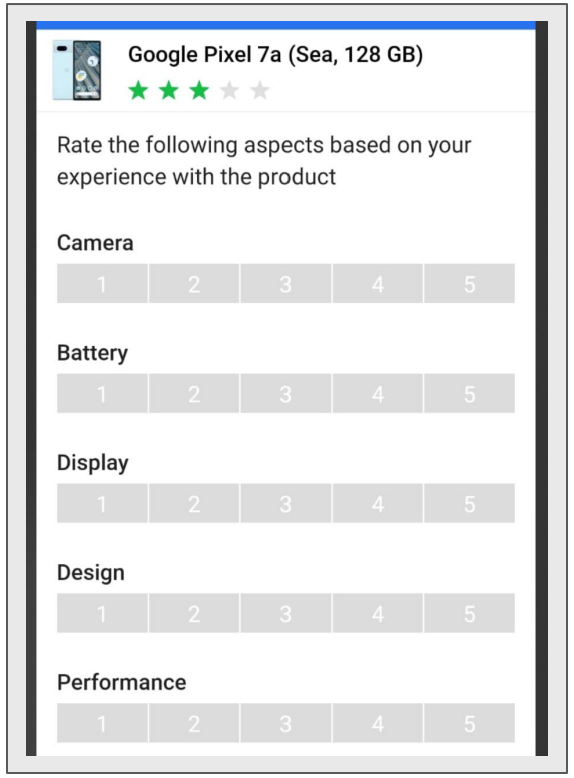
a week ago on Google

1/5

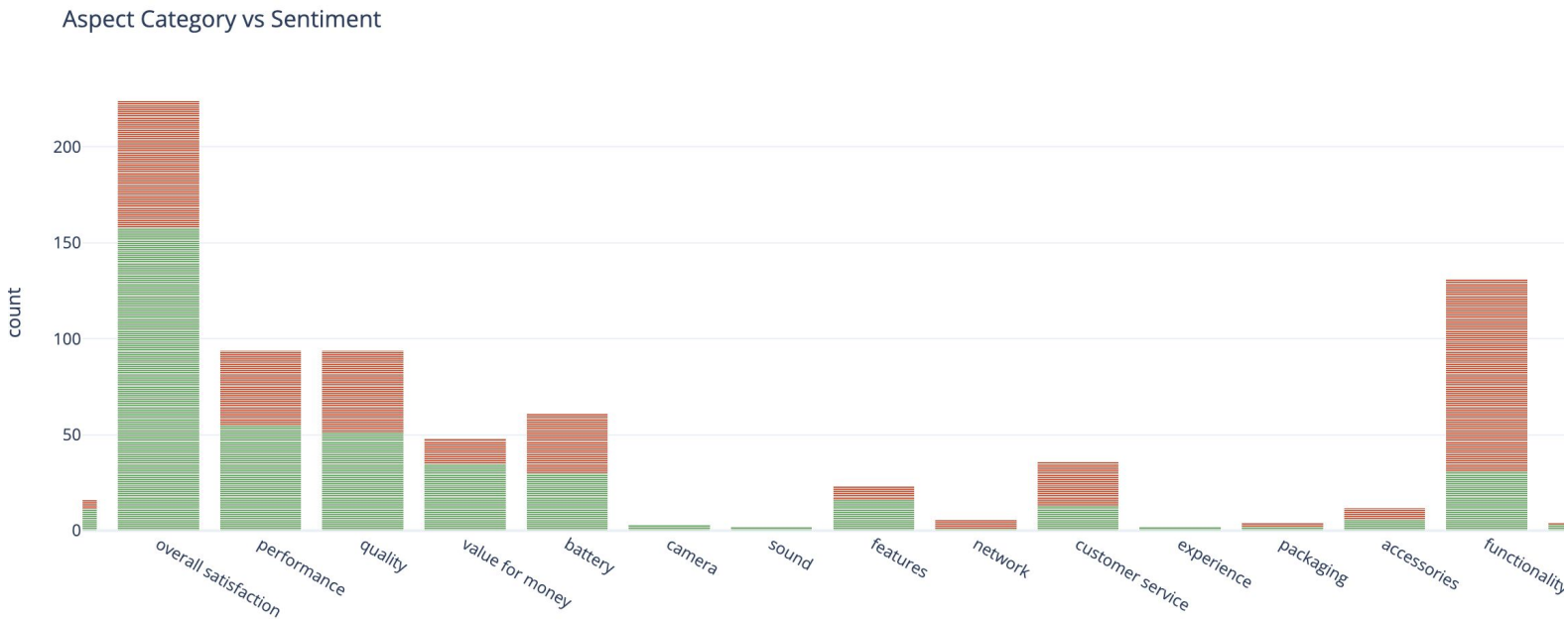
Aim and objective:

Our objective is to dynamically extract topics (aspects) from customer reviews and perform sentiment analysis, eliminating reliance on guest ratings and limited static aspects typical of traditional approaches.

Traditional Approach:



Advance Approach :

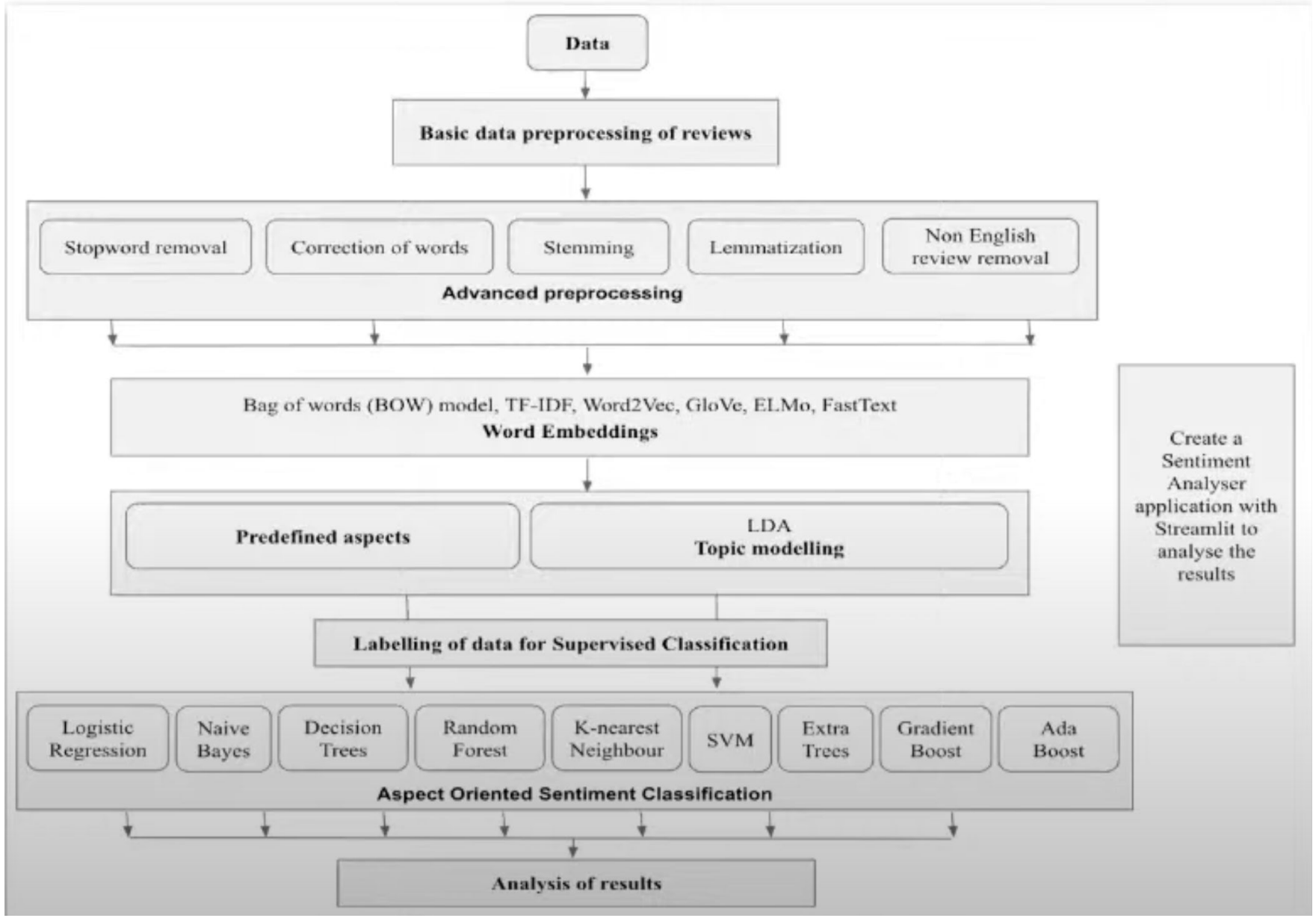


While determining aspects or product attributes for which guest ratings should be collected is relatively straightforward for mobile devices using traditional approaches, it becomes considerably more complicated when dealing with items such as washing machines, refrigerators, Playstations or other complex devices.

WHY IS ASPECT-BASED SENTIMENT ANALYSIS BETTER THAN TOPIC BASED SENTIMENT?

- While topic analysis only applies NER, aspect sentiment analysis employs both NER and semantic clustering.
- In this way, it automatically identifies key themes and topics in any data important to your organization and finds semantically similar words that can be grouped together to get an even more intricate comprehension of topics.
- For better understanding, Named Entity Recognition is a machine learning task that identifies named entities like *H&M, London, Kobe Bryant, Ferrari,* and such, in the collected data and classifies them into predetermined categories like company names, regional locations, names of people, brands, etc.

Methodology



- The Flowchart explains the step by step process followed in the research.
- It also includes the various models and methods used in each step for comparative study.

Biggest Challenge

- It’s basically an unsupervised learning Task because we do not have labelled data. We don’t have any labelled aspect and sentiment around that.
- We, first need that labelled data then only we could be able to train any machine learning model to make prediction on aspect and sentiment around it on any unseen new review.

Example:

Review: Camera is good but battery have heating issue.

Review Segmentation	Aspect	Sentiment
Camera is good	Camera	Positive
Battery have heating issue	Battery	Negative

Analysis - Preprocessing

- Splitting of review Paragraph into sentences
- Elimination of Non-English reviews from dataset.
- Removal of punctuation marks
- Removal of numeric data
- Stop words removal
- Spelling correction
- Convert sentences to lowercase
- Use POS Tagging to get rid of noisy data.
- Making sure not to remove negation words from sentence, otherwise context could be changed.
- Lemmatization

Example :

```
In [22]: preprocess_text_NA_SA("camera is not good . Major issue with charging as well")

Out[22]: ['camera not good', 'major issue charge']
```

Topic Modelling – LDA and Guided LDA

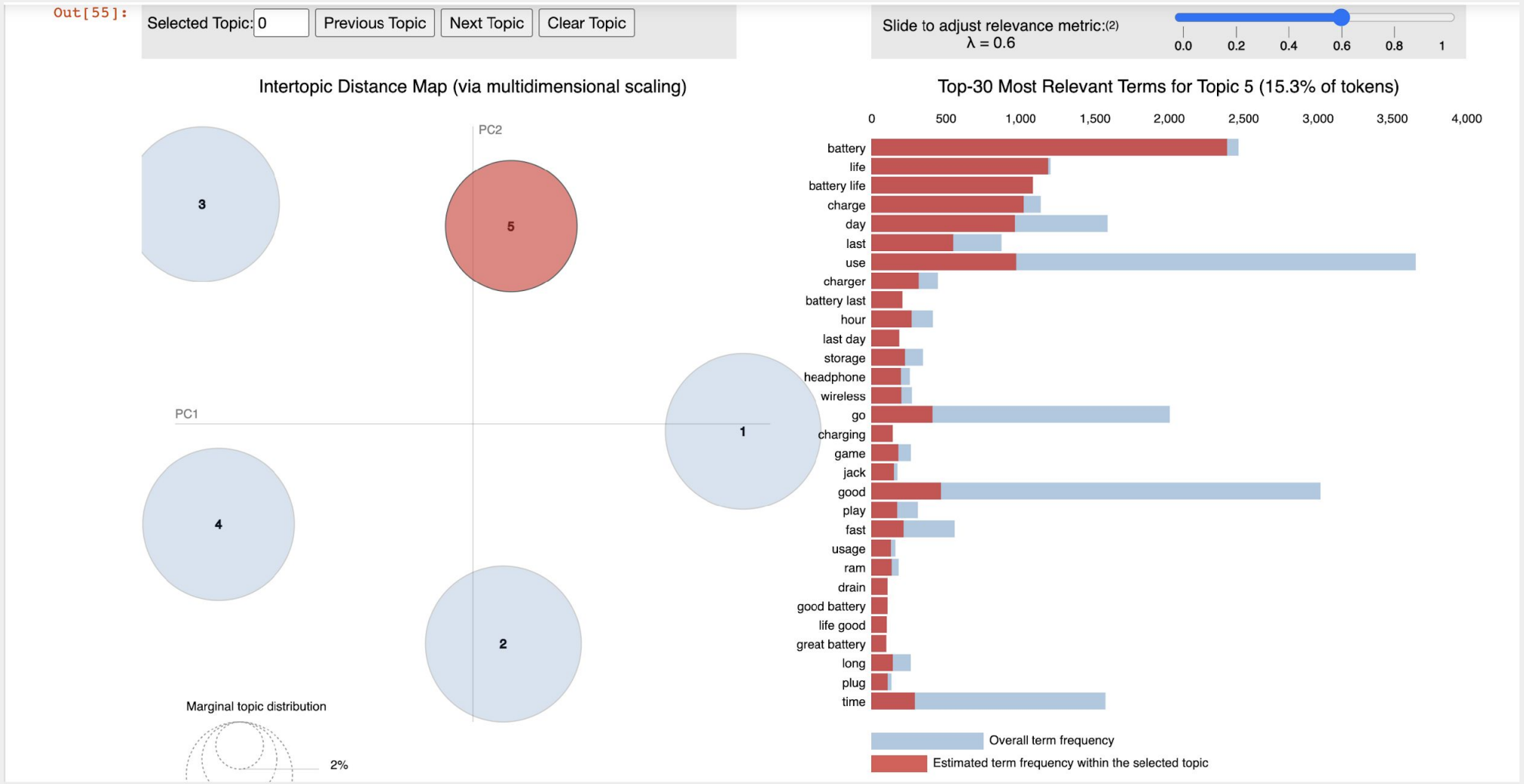
- Latent Dirichlet Allocation (LDA) is a popular topic modeling technique to extract topics from a given corpus. The term latent conveys something that exists but is not yet developed. In other words, latent means hidden or concealed.
- Now, the topics that we want to extract from the data are also "hidden topics". In our context, the Dirichlet model describes the pattern of the words that are repeating together, occurring frequently, and these words are similar to each other.

In [117]:
```
n_top_words = 20
topic_word = model.topic_word_
for i, topic_dist in enumerate(topic_word):
     topic_words = np.array(tf_feature_names)[np.argsort(topic_dist)][:-(n_top_words+1):-1]
     print('Topic {}: {}'.format(i, ' '.join(topic_words)))
```

```
Topic 0: camera good great screen quality price feature picture take nice use size well photo look go love feel display small
Topic 1: work sim call get card use version unlocked say service sim card carrier issue network new receive go buy try problem
Topic 2: battery life battery life charge day use last good get charger great time work hour month go battery last wireless come game
Topic 3: buy get new year good go price purchase use android update return time money one want love think upgrade review
Topic 4: screen use app work fingerprint time get case call go reader button issue thing make finger take try turn fingerprint reader
```

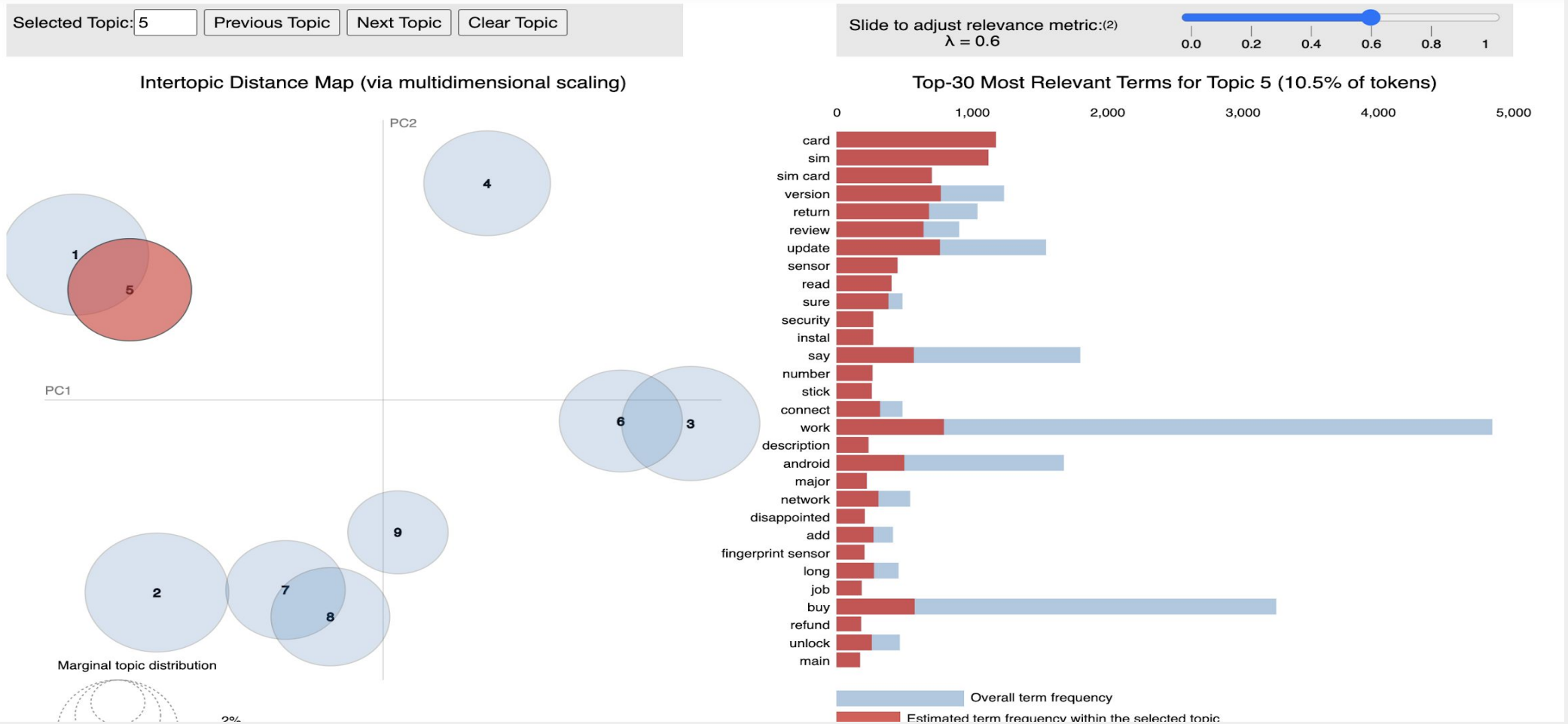
In [51]:
```
dics = {'topic 0': 'Camera/Display',
'topic 1':'simcard/Memory',
'topic 2':'Battery',
'topic 3':'Money',
'topic 4':'Features/Hardware'
}
```

No. of Topics in LDA



Why only 5??

Out[62]:



Assigning topic through Topic Vector

- LDA assumes that each document is a mixture of multiple topics, and each word in the document is generated from one of these topics.
- The topic vector for a given document is a probability distribution that assigns a probability to each topic in the model. The sum of the probabilities across all topics in the vector is equal to 1. The length of the topic vector is equal to the number of topics specified in the LDA model.
- For example, if we have a document with three topics, the topic vector might look like this:
- Topic Vector: [0.2, 0.5, 0.3]
- This means that in this document, Topic 1 has a probability of 0.2, Topic 2 has a probability of 0.5, and Topic 3 has a probability of 0.3.

In [53]:
```
columns_label = ['topic {}'.format(i) for i in range(5)]  # number of topics
topic_vector = pd.DataFrame(doc_topic, columns = columns_label)#dataframe of doc-topics
print(topic_vector.shape)
topic_vector.round(2).head(10)
```

```
(45306, 5)
```

Out[53]:

	topic 0	topic 1	topic 2	topic 3	topic 4
0	0.00	0.00	0.00	1.00	0.00
1	0.77	0.01	0.00	0.22	0.00
2	0.76	0.00	0.00	0.24	0.00
3	1.00	0.00	0.00	0.00	0.00
4	0.99	0.00	0.00	0.00	0.00
5	0.58	0.00	0.00	0.00	0.42
6	0.00	0.29	0.71	0.00	0.00
7	0.00	0.21	0.78	0.00	0.00
8	0.92	0.00	0.08	0.00	0.00
9	0.46	0.00	0.00	0.54	0.00

Sentiment Analysis

- VADER(Valence Aware Dictionary for Sentiment Reasoning) is an NLTK module that provides sentiment scores based on the words used. It is a rule-based sentiment analyzer in which the terms are generally labeled as per their semantic orientation as either positive or negative.

```
In [65]: x = sia.polarity_scores ('Camera is not good')

         df_Review_sentence.loc[df_Review_sentence.compound>0,'Sentiment']='Positive'
         df_Review_sentence.loc[df_Review_sentence.compound==0,'Sentiment']='Neutral'
         df_Review_sentence.loc[df_Review_sentence.compound<0,'Sentiment']='Negative'

Out[65]: {'neg': 0.445, 'neu': 0.555, 'pos': 0.0, 'compound': -0.3412}
```

Labelled Dataset

Review Example:

'The A54 is a excellent phone battery life is good phone functions very good. I will say there was issue with making calls on my head set with the phone locked spent several hours with Samsung and could not resolve. I after many hours was able to managed it I believe it is a issue between Google and Samsung.That said I really like the phone and the most important why I bought a Samsung of other phones is Samsung has committed to 4 years of Android updates and 5 years of security patches. That makes this in my thoughts with the quality of the phone and the update commitment the best phone on the market at this price. The pictures are also great Thank you’

Out[120]:

	index_column	Review_sentence	Sentiment	Aspect	Max_value
10	2	excellent battery life good function good	Positive	Battery	0.99
11	2	say issue make call head set lock spend severa...	Negative	simcard/Memory	0.97
12	2	many hour able manage believe issue say like i...	Positive	Money	0.99
13	2	make thought quality update good market price	Positive	Money	0.69
14	2	picture great thank	Positive	Camera/Display	0.99

Modelling

Embeddings:

Converted text to vector representation by trying different approaches.

- Word2vec.
- Tfidf
- Bow
- Glove

Algorithms:

- Svc
- KNN
- Adaboost
- Logistic regression
- Evaluation:

- **Aspect Classification** : Word2vec + Logistic Regresion.
  F1 Score= 0.85
- **Sentiment Classification** : Tfidf + Logistic Regression.
  F1 score = 0.84

Challenges

- **F1 score** : The F1 score is a commonly used metric for evaluating model performance. However, it may not always provide a true representation of the ground truth due to potential issues with mislabeled data. This can lead to the model learning from erroneous information during training, impacting the overall reliability of results.

[126]:

	index_column	Review_sentence	Sentiment	Aspect	Max_value
0	0	use amazon renew past week list new condition	Positive	Money	1.00
1	0	get price major difference	Neutral	Money	0.89
2	0	large screen resolution low text not look good	Negative	Camera/Display	0.99
3	0	camera good well get	Positive	Camera/Display	0.99
5	0	want good mid range good choice large battery ...	Positive	Camera/Display	0.96
6	0	want high end look renew price	Positive	Money	0.78

<- Wrong label in Training set

- **Handling Target 100 Classes** : The complexity of our task is magnified by the presence of 100 target classes. To address this, topic modeling would traditionally be required for each class to capture the varying aspects associated with them. However, this process can be time-consuming.

Challenges

- **Reviews Volume** :Gathering a substantial volume of reviews for each class can pose a significant challenge. Having comprehensive data is crucial for effective topic modeling, making the collection process time and resource-intensive.

- **Dealing with New Classes**: Additionally, the introduction of new products, such as the Apple Vision Pro, or the emergence of entirely new classes without any existing reviews present an additional obstacle that demands careful consideration and innovative strategies to progress effectively.

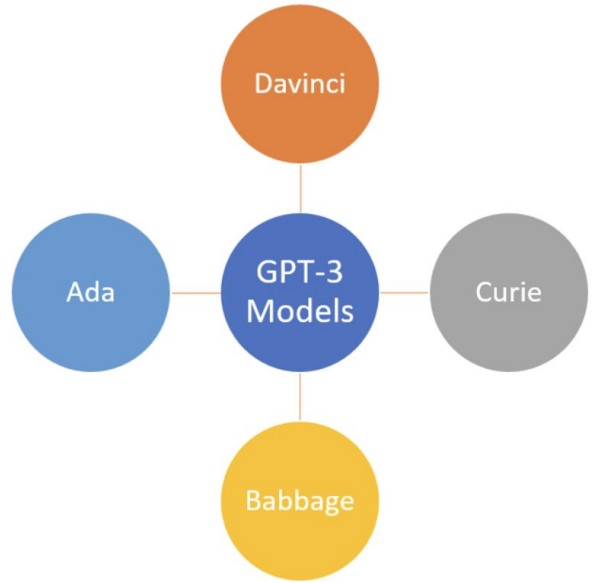
- **Restricting Aspect Analysis**: Moreover, restricting the number of aspects per class due to algorithmic limitations can hinder the comprehensive analysis and representation of product attributes and customer sentiments.

Solving Challenges: Large Language Models(LLMs)

- Large Language Models (LLMs) are foundational machine learning models that use deep learning algorithms to process and understand natural language. These models are trained on massive amounts of text data to learn patterns and entity relationships in the language.

GPT- 3 OPENAI

- The GPT-3 models offer different levels of power and speed for various tasks related to understanding and generating natural language. Among these models, **Davinci** is the most capable, while **Ada** is the fastest. The following represents the four different GPT text models:

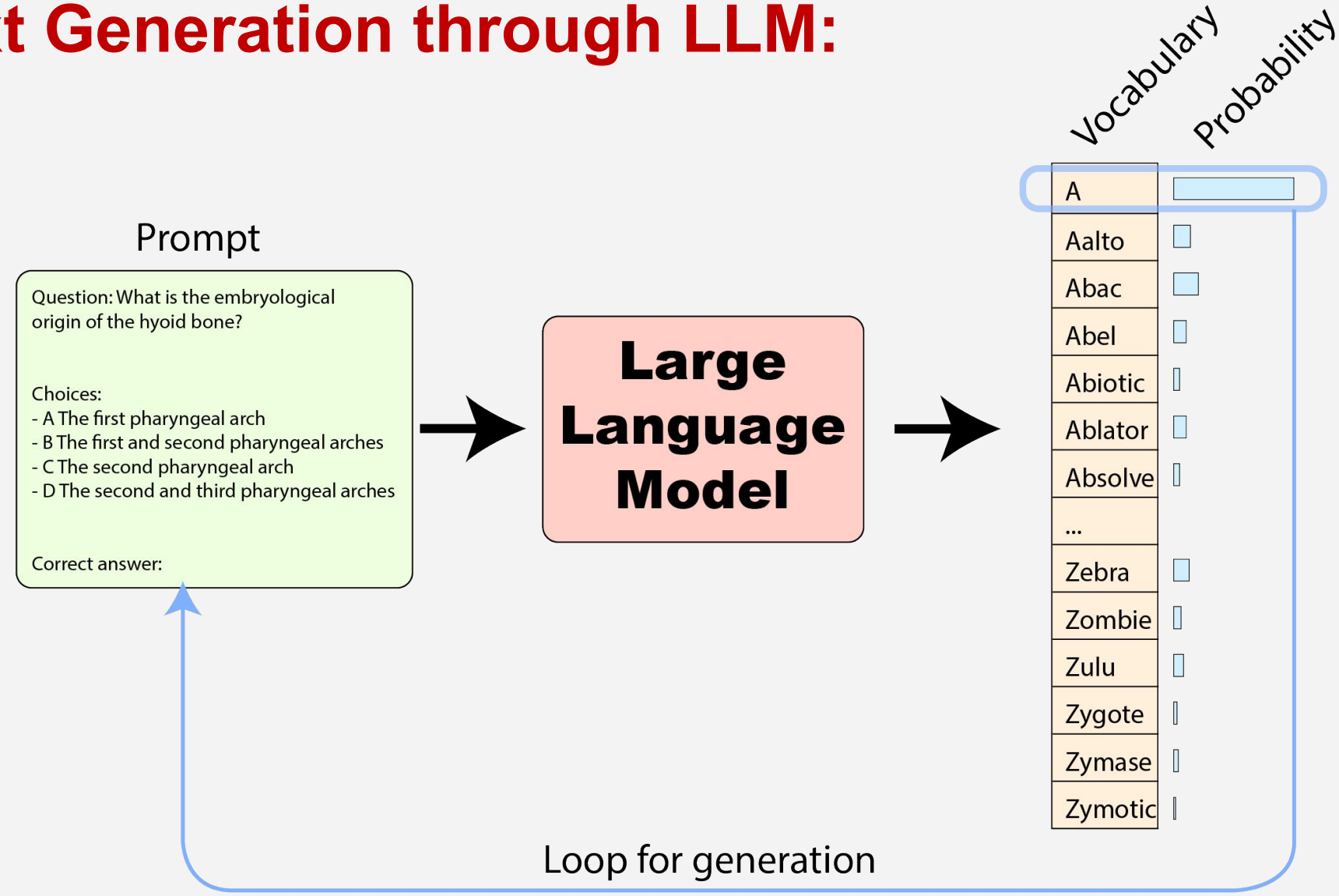


Prompt-based generation

We can generate labels for unlabeled data by constructing text templates called prompts, which will likely generate the label when we allow the language model to continue running. Prompts normally contain three components:

- A description of the task we want to perform
- Examples of the task being performed (also called in-context demonstrations)
- A new example we want to label

Text Generation through LLM:



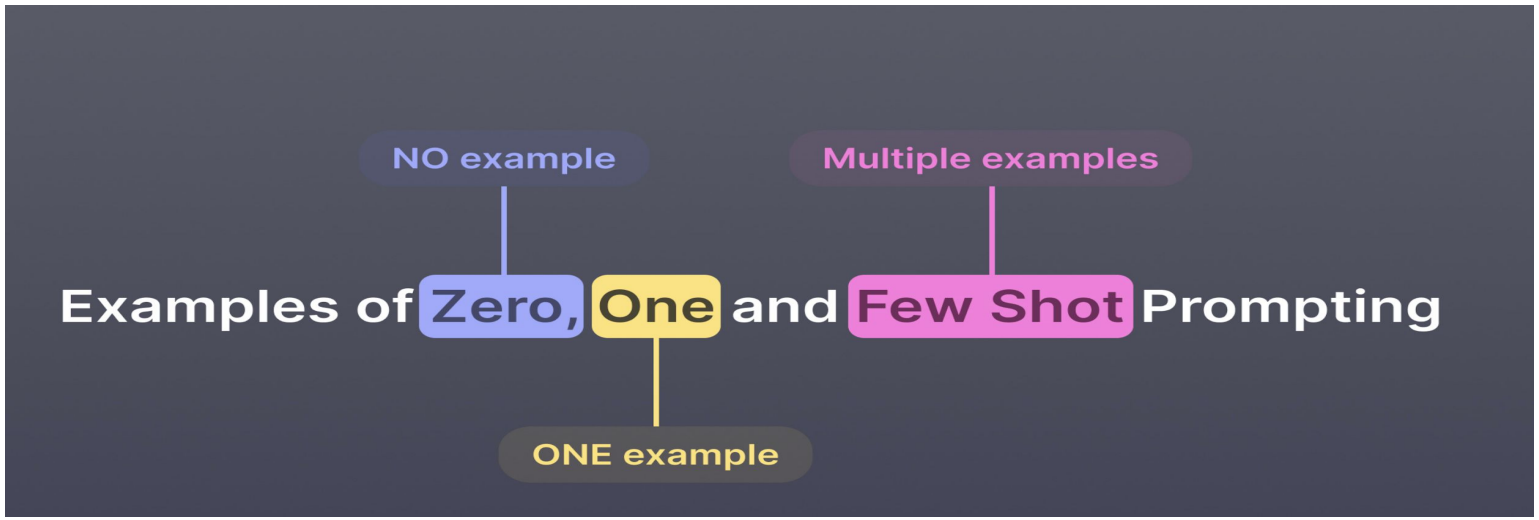
Zero shot vs Few shot Prompting

OpenAI : Show example

- Zero-shot prompting refers to a natural language processing (NLP) approach where a model is capable of performing a task without any task-specific training examples. The model can generalize and understand the task based on the provided prompt or instruction, even if it has never seen similar examples during its training

  .

- Few-shot prompting is a similar NLP approach, but in this case, the model is provided with a limited number of task-specific training examples (usually a small dataset) to learn from. The model leverages this limited data to generalize and perform the task on new, unseen examples more accurately than zero-shot approaches



Few Examples:

index	segment	Aspect	Aspect Category	sentiment	review_id	Review
0	bought samsung s9 last july	purchase	purchase experience	positive	0	Bought Samsung S9 last July and the Phone is already dead. It says a brand NEW phone. Will not charge anymore. Contacted seller and said they cant do anything about it because warranty has expired. Phone is only 4 months and dead. Dont buy from this seller.
1	phone is already dead	phone	durability	negative	0	Bought Samsung S9 last July and the Phone is already dead. It says a brand NEW phone. Will not charge anymore. Contacted seller and said they cant do anything about it because warranty has expired. Phone is only 4 months and dead. Dont buy from this seller.
2	it says a brand new phone	phone	quality	negative	0	Bought Samsung S9 last July and the Phone is already dead. It says a brand NEW phone. Will not charge anymore. Contacted seller and said they cant do anything about it because warranty has expired. Phone is only 4 months and dead. Dont buy from this seller.
3	contacted seller and said they cant do anything about it because warranty has expired	warranty	customer service	negative	0	Bought Samsung S9 last July and the Phone is already dead. It says a brand NEW phone. Will not charge anymore. Contacted seller and said they cant do anything about it because warranty has expired. Phone is only 4 months and dead. Dont buy from this seller.
4	phone is only 4 months and dead	phone	durability	negative	0	Bought Samsung S9 last July and the Phone is already dead. It says a brand NEW phone. Will not charge anymore. Contacted seller and said they cant do anything about it because warranty has expired. Phone is only 4 months and dead. Dont buy from this seller.
5	dont buy from this seller	seller	purchase experience	negative	0	Bought Samsung S9 last July and the Phone is already dead. It says a brand NEW phone. Will not charge anymore. Contacted seller and said they cant do anything about it because warranty has expired. Phone is only 4 months and dead. Dont buy from this seller.

index	segment	Aspect	Aspect Category	sentiment	review_id	Review
967	i had to return with out using	return policy	customer service	neutral	290	I had to return with out using but I am giving it a good rate since my sister has had hers for quit awhile now and she loves it. She is the one who suggested it to me
968	i am giving it a good rate	product	overall satisfaction	positive	290	I had to return with out using but I am giving it a good rate since my sister has had hers for quit awhile now and she loves it. She is the one who suggested it to me
969	my sister has had hers for quit awhile now and she loves it	product	overall satisfaction	positive	290	I had to return with out using but I am giving it a good rate since my sister has had hers for quit awhile now and she loves it. She is the one who suggested it to me

index	segment	Aspect	Aspect Category	sentiment	review_id	Review
989	je l adore	product	overall satisfaction	positive	296	Je l adore je les même reçu 2 jours en avance
990	je les même reçu 2 jours en avance	delivery	delivery	positive	296	Je l adore je les même reçu 2 jours en avance

Overcoming Challenges of Phase 1:

- LLMs Adaptability to Prompt: LLMs eliminate the need for an extensive corpus of reviews for each class. Their capability to handle good prompts enables them to work with minimal data, making the process more efficient and resource-friendly.
- Eliminating Topic Modeling: By leveraging LLMs, we no longer require topic modeling for each class, streamlining the process and reducing the computational burden.
- Handling New Classes Seamlessly: LLMs can seamlessly handle new classes or products without requiring manual determination of aspects. Their ability to learn from context allows them to adapt to evolving scenarios effectively.
- Multilingual Support: LLMs excel in handling different languages like French, Spanish, and German. This allows for more extensive data collection and analysis, expanding the scope and accuracy of our results.
- Conclusion: Incorporating Large Language Models in our ML-based approach can overcome the challenges associated with handling numerous classes, volume of reviews, and the introduction of new products. By utilizing LLMs, we can streamline the process, enhance efficiency, and achieve more accurate results in our evaluation and analysis tasks.

Concerns of OpenAI:

- **Pricing/Pay per use:**

Model	Training	Usage
Ada	$0.0004 / 1K tokens	$0.0016 / 1K tokens
Babbage	$0.0006 / 1K tokens	$0.0024 / 1K tokens
Curie	$0.0030 / 1K tokens	$0.0120 / 1K tokens
Davinci	$0.0300 / 1K tokens	$0.1200 / 1K tokens

- **Data security:**

OpenAI retains API data for 30 days for abuse and misuse monitoring purposes. A limited number of authorized OpenAI employees, as well as specialized third-party contractors that are subject to confidentiality and security obligations, can access this data solely to investigate and verify suspected abuse.

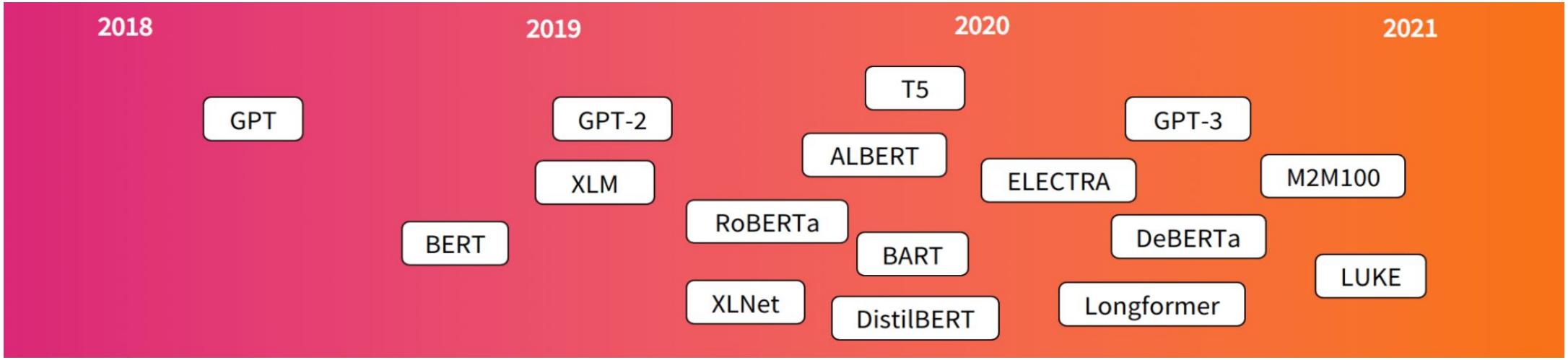
- **Microsoft open AI services (Microsoft) :**

Target does not have access to use Microsoft open AI services.

Alternatives: Hugging face open source LLM

[Hugging Face]

Apache License 2.0 or the MIT License. These licenses are open-source licenses that allow for commercial use, redistribution, modification, and sublicense of the models, subject to the terms and conditions specified in the license.



Advantages:

- **Enhanced Data Security:** Utilizing Open Source Hugging Face LLM eliminates the need for API services, ensuring complete data security throughout the natural language processing tasks.
- **Enterprise-Ready Licensing**: The platform can be employed for enterprise purposes, offering the flexibility and compatibility required for business applications.
- **Cost-Efficient Usage**: Unlike some alternatives, Open Source Hugging Face LLM does not involve pay-per-token usage, leading to more cost-effective and predictable resource management.

Comparing Opensource model with GPT-3.5(OpenAI)

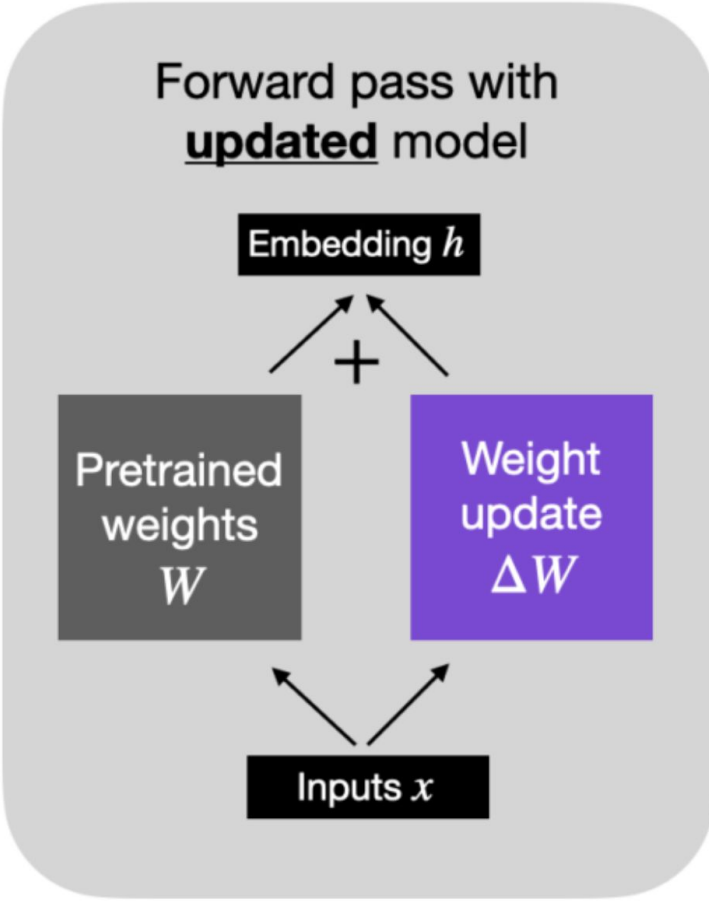
I hate this phone! Ads for apps frequently pop up. I have not downloaded any apps where I might have picked up malware that causes this and going into my settings hasn't enabled me to get rid of them.				
Segment	**Aspect**	**Aspect Category**	**sentiment**	**MODEL USED**
i hate this phone	phone	overall satisfaction	negative	
ads for apps frequently pop up	ads	ads	negative	GPT 3.5
i have not downloaded any apps where i might have picked up malware	malware	security	negative	
going into my settings hasn't enabled me to get rid of them	settings	functionality	negative	
Segment	**Aspect**	**Aspect Category**	**sentiment**	
I hate this phone!	phone	Overall satisfaction	negative	BLOOM
Ads for apps frequently pop up	Ads	Ads	negative	
I have not downloaded any apps	app	Overall satisfaction	neutral	
where I might have picked up malware	app	App download	neutral	
that causes this and going into my settings hasn't enabled me to get rid of	app	App download	negative	
that causes this and going into my settings hasn't enabled me to get rid of	settings	App download	neutral	
Segment	**Aspect**	**Aspect Category**	**sentiment**	
I hate this phone!	Phone	Overall satisfaction	negative	timdettmers/guanaco-33b-merged
Ads for apps frequently pop up	Ads	Ads	negative	
I have not downloaded any apps where I might have picked up malware tha	Malware	Security	negative	
going into my settings hasn't enabled me to get rid of them	Settings	Settings	negative	
Segment	**Aspect**	**Aspect Category**	**sentiment**	
i hate this phone	phone	overall satisfaction	negative	
ads for apps frequently pop up	ads	ads	negative	
i have not downloaded any apps	Compatibility	functionality	negative	openlm-research/open_llama_13b
where i might have picked up malware	security	security	negative	
that causes this	security	security	negative	
going into my settings hasn't enabled me to get rid of them	settings	Settings	negative	

PEFT: Parameter-Efficient Fine-Tuning

How to achieve similar performance like GPT-3?

- To attain comparable performance to GPT-3, PEFT (Pretraining with Extracted Feature-based Fine-Tuning) fine-tuning is recommended.

- The PEFT approach has shown promising results in enhancing the performance of language models on various downstream tasks by leveraging the knowledge captured during pretraining. By using this method, we can significantly improve the capabilities and performance of our language model, bringing it closer to the performance achieved by GPT-3. (https://huggingface.co/blog/peft)




AUTOMATIC DOOR
Thank You for Shopping Target
CAUTION STAND BACK