## Importing the Libraries:

```
import pandas as pd
import gensim
from gensim import corpora, models
from gensim.models import CoherenceModel
import ast
from tqdm import tqdm
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud, STOPWORDS
import matplotlib.colors as mcolors
from nltk.corpus import stopwords
import itertools
```

# Loading the Pre-processed (Lemmatized) Data:

```
In [2]: lemmatized_text_data = pd.read_csv(r"C:\Users\Utkarsh\Desktop\Amazon_comments_processe
lemmatized_text_data = lemmatized_text_data.iloc[:, 1:]
lemmatized_text_data
```

	Project-Topic-Modeling V2							
	Business_outlook	CEO_approval	Recommend	Company_name	Stars	Title_Review		
['documer 'amazon', 'imp	['neutral']	['neutral']	['positive']	[ˈamazonˈ]	5.0	['good', 'impression', 'first', 'month']	0	
['4', 'day',	['neutral']	['neutral']	['neutral']	[ˈamazonˈ]	5.0	['intern']	1	
['great', 'balance', 'eı	['positive']	['positive']	['positive']	[ˈamazonˈ]	5.0	[ˈgoodˈ]	2	
['good', 'b 'flexible'	['positive']	['positive']	['positive']	['amazon']	5.0	['job', 'review']	3	
['fast', ' 'st 'culture',	['negative']	['negative']	['positive']	[ˈamazonˈ]	4.0	['growth', 'opportunity']	4	
							•••	
['ar 'won 'search	['positive']	['positive']	['positive']	[ˈamazonˈ]	5.0	['great', 'pay', 'onboarding']	9995	
[ 'company', 'find', 'a	['neutral']	['neutral']	['neutral']	[ˈamazonˈ]	5.0	[ˈgreatˈ, ˈcompˈ]	9996	
tean' 'great', 'e	['positive']	['positive']	['positive']	[ˈamazonˈ]	5.0	['far', 'good']	9997	
[ˈbe ˈexc ˈprc ˈsol	['negative']	['negative']	['negative']	['amazon']	2.0	['use', 'great', 'company']	9998	
['pro', 'com	['neutral']	['neutral']	['neutral']	[ˈamazonˈ]	1.0	['poor', 'management']	9999	
	10000 rows × 12 columns							
•								

```
df['current_employee'] = df['Employee_seniority'].apply(lambda x: 'current' in x).asty
df = df[['id', 'current_employee', 'Pros', 'Cons']]
df['Pros'] = df['Pros'].apply(ast.literal_eval)
df['Cons'] = df['Cons'].apply(ast.literal_eval)
df
```

C:\Users\Utkarsh\AppData\Local\Temp\ipykernel\_5604\1187017345.py:2: SettingWithCopyWa
rning:

A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row\_indexer,col\_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy

df['current\_employee'] = df['Employee\_seniority'].apply(lambda x: 'current' in x).a
stype(int)

Out[3]:

	id	current_employee	Pros	Cons
0	empReview_73247758	1	[documentation, amazon, super, important, poin	[need, understand, job, need, improve, good, d
1	empReview_73187609	0	[4, day, shifts, nice]	[long, hour, shift, make, feel, tire]
2	empReview_73188818	0	[great, work, balance, great, environment, loc	[workload, heavy, sometimes]
3	empReview_73190433	0	[good, benefit, flexible, time, shift, take, c	[good, organization, work, well, car, parking,
4	empReview_73197210	1	[fast, paced, start-up, culture, benefit]	[compensation, growth, prospect, development,
•••				
9995	empReview_71536795	1	[amazon, wonderful, search, site, find, anythi	[interview, process, long, worth, end]
9996	empReview_71537065	1	[great, company, easy, find, area, like]	[get, unlucky, team]
9997	empReview_71539933	1	[great, teamwork, great, work, environment, pe	[little, far, home]
9998	empReview_71882994	0	[become, excellent, problem, solver, use, data	[cut-throat, management, toxic, culture, unnec
9999	empReview_72354621	0	[pro, company]	[poor, pay, poor, management]

10000 rows × 4 columns

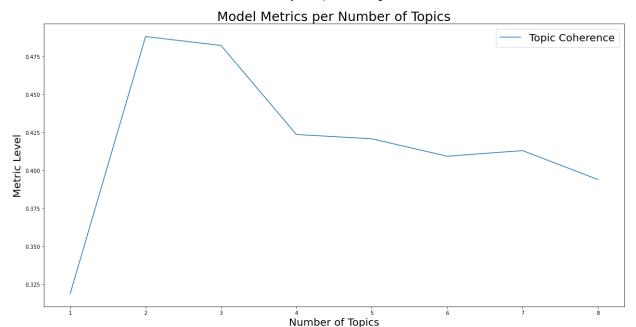
### Performing Topic Modelling on the Pros and Cons From Each Review:

#### Pros:

In this section we will evaluate the degree to which the words in the 'Pros' column are semantically related and form a coherent meaning.

We will do this by calculating the topic coherence score for different numbers of topics and choosing the one results in the highest score.

```
# Prepare Dictionary
In [4]:
        data_ready_pros = df['Pros'].tolist()
        id2word = corpora.Dictionary(data ready pros)
        corpus pros = [id2word.doc2bow(text) for text in data ready pros]
In [5]: # Building model
        num_topics = [i+1 for i in range(8)]
        num keywords = 20
        LDA models = {}
        LDA_topics = {}
        for i in tqdm(num topics):
            LDA models[i] = gensim.models.ldamodel.LdaModel(corpus=corpus pros,
                                                             id2word=id2word,
                                                             num topics=i,
                                                             update_every=1,
                                                             chunksize=10,
                                                             passes=20,
                                                             alpha='asymmetric',
                                                             random state=100)
            shown topics = LDA models[i].show topics(num topics=i,
                                                      num words=num keywords,
                                                      formatted=False)
            LDA_topics[i] = [[word[0] for word in topic[1]] for topic in shown_topics]
        100%
          | | | 8/8 [12:03<00:00, 90.44s/it]
In [6]:
        coherences = []
        for i in tqdm(num topics):
            coherences.append(gensim.models.CoherenceModel(model=LDA models[i], texts=data rea
        100%
          8/8 [01:12<00:00, 9.04s/it]
In [7]: # Visualizing results
        plt.figure(figsize=(20,10))
        ax = sns.lineplot(x=num_topics, y=coherences, label='Topic Coherence')
        ax.axes.set_title('Model Metrics per Number of Topics', fontsize=25)
        ax.set ylabel('Metric Level', fontsize=20)
        ax.set_xlabel('Number of Topics', fontsize=20)
        plt.legend(fontsize=20)
        plt.show()
```



```
In [8]:
        def format_topics_sentences(ldamodel, corpus, texts):
            sent topics df = pd.DataFrame()
            for i, row list in enumerate(ldamodel[corpus]):
                 row = row_list[0] if ldamodel.per_word_topics else row_list
                row = sorted(row, key=lambda x: (x[1]), reverse=True)
                # Get the Dominant topic, Perc Contribution and Keywords for each document
                for j, (topic_num, prop_topic) in enumerate(row):
                    if j == 0: # => dominant topic
                        wp = ldamodel.show topic(topic num)
                        topic_keywords = ", ".join([word for word, prop in wp])
                         sent topics df = sent topics df.append(pd.Series([int(topic num), rour
                    else:
                         break
            sent topics df.columns = ['Dominant Topic', 'Perc Contribution', 'Topic Keywords'
            # Add original text to the end of the output
            contents = pd.Series(texts)
            sent topics df = pd.concat([sent topics df, contents], axis=1)
            return(sent topics df)
```

```
In [9]: n_topics_pros = 2
  lda_model_pros = LDA_models[n_topics_pros]
```

```
In [10]: df_topic_pros_keywords = format_topics_sentences(ldamodel=lda_model_pros, corpus=corpu
# Format
df_dominant_topic = df_topic_pros_keywords.reset_index()
df_dominant_topic.columns = ['Review_ID', 'Dominant_Topic', 'Topic_Perc_Contrib', 'Key
```

```
In [11]: df_dominant_topic['Review_ID'] = df['id']
    df_dominant_topic.head(10)
```

4), topic\_keywords]), ignore\_index=True)

Out[11]:		Review_ID	Dominant_Topic	Topic_Perc_Contrib	Keywords	Text			
	0	empReview_73247758	1	0.8816	opportunity, learn, amazon, lot, growth, work,	[documentation, amazon, super, important, poin			
	1	empReview_73187609	0	0.9250	good, work, great, pay, benefit, time, job, en	[4, day, shifts, nice]			
	2	empReview_73188818	0	0.8313	good, work, great, pay, benefit, time, job, en	[great, work, balance, great, environment, loc			
	3	empReview_73190433	0	0.6971	good, work, great, pay, benefit, time, job, en	[good, benefit, flexible, time, shift, take, c			
	4	empReview_73197210	0	0.9292	good, work, great, pay, benefit, time, job, en	[fast, paced, start-up, culture, benefit]			
	5	empReview_73208298	1	0.7689	opportunity, learn, amazon, lot, growth, work,	[opportunity, grow, work, talented, people]			
	6	empReview_73149307	1	0.8495	opportunity, learn, amazon, lot, growth, work,	[lot, challenge, speak, data, great, leadership]			
	7	empReview_73146117	0	0.7682	good, work, great, pay, benefit, time, job, en	[good, pay, benefit, new, grad]			
	8	empReview_73105526	0	0.9354	good, work, great, pay, benefit, time, job, en	[pay, rate, good, accord, work]			
	9	empReview_73108472	0	0.7679	good, work, great, pay, benefit, time, job, en	[great, benefit, bonus, everything, available,			
In [13]:	<pre>stop_words = set(stopwords.words('english'))</pre>								
	<pre>cols = [color for name, color in mcolors.TABLEAU_COLORS.items()] # more colors: 'mcc</pre>								
	cl	wi he ma co	ckground_color: dth=2500, ight=1800, x_words=20, lormap='tab10'	='white',	s: cols[i],				
				a *args, **kwargs	s: cols[i],				

```
prefer_horizontal=1.0)

topics = lda_model_pros.show_topics(formatted=False)

fig, axes = plt.subplots(1, 2, figsize=(11,11), sharex=True, sharey=True)

for i, ax in enumerate(axes.flatten()):
    fig.add_subplot(ax)
    topic_words = dict(topics[i][1])
    cloud.generate_from_frequencies(topic_words, max_font_size=300)
    plt.gca().imshow(cloud)
    plt.gca().set_title('Topic ' + str(i), fontdict=dict(size=16))
    plt.gca().axis('off')

plt.subplots_adjust(wspace=0, hspace=0)
plt.axis('off')

plt.margins(x=0, y=0)
plt.tight_layout()
plt.show()
```



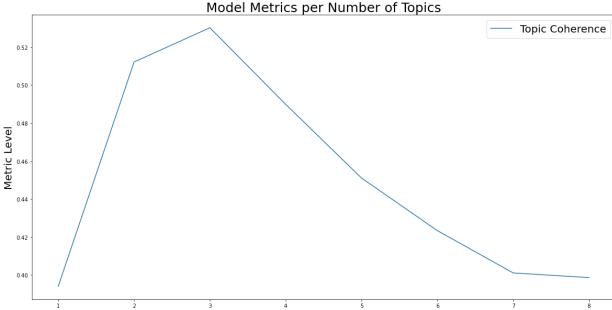
Our process resulted in two being the optimal number of topics for the 'Pros' column. One of the topics highlighted the pay grade and benefits as the pros of working at Amazon (Topic 0). The other topic highlighted the opportunity to learn and grow as the pros of working at Amazon (Topic 1).

#### Cons:

In this section we will evaluate the degree to which the words in the 'Cons' column are semantically related and form a coherent meaning.

We will do this by once again calculating the topic coherence score for different numbers of topics and choosing the one results in the highest score.

```
# Prepare Dictionary
In [14]:
         data_ready_cons = df['Cons'].tolist()
          id2word = corpora.Dictionary(data ready cons)
          corpus cons = [id2word.doc2bow(text) for text in data ready cons]
In [15]:
         # Building model
         num_topics = [i+1 for i in range(8)]
         num keywords = 20
          LDA models = {}
          LDA_topics = {}
          for i in tqdm(num topics):
             LDA models[i] = gensim.models.ldamodel.LdaModel(corpus=corpus cons,
                                                              id2word=id2word,
                                                              num topics=i,
                                                              update_every=1,
                                                              chunksize=10,
                                                              passes=20,
                                                              alpha='asymmetric',
                                                              random state=100)
             shown topics = LDA models[i].show topics(num topics=i,
                                                       num words=num keywords,
                                                       formatted=False)
             LDA_topics[i] = [[word[0] for word in topic[1]] for topic in shown_topics]
         100%
           8/8 [14:31<00:00, 108.88s/it]
In [16]:
         coherences = []
         for i in tqdm(num topics):
             coherences.append(gensim.models.CoherenceModel(model=LDA models[i], texts=data rea
         100%
           8/8 [01:06<00:00, 8.37s/it]
In [17]: # Visualizing results
         plt.figure(figsize=(20,10))
          ax = sns.lineplot(x=num_topics, y=coherences, label='Topic Coherence')
          ax.axes.set_title('Model Metrics per Number of Topics', fontsize=25)
          ax.set ylabel('Metric Level', fontsize=20)
          ax.set_xlabel('Number of Topics', fontsize=20)
          plt.legend(fontsize=20)
          plt.show()
```



```
Number of Topics
          n \text{ topics cons} = 3
In [18]:
          lda model cons = LDA models[n topics cons]
         df topic cons keywords = format topics sentences(ldamodel=lda model cons, corpus=corpu
In [19]:
          # Format
          df dominant topic cons = df topic cons keywords.reset index()
          df_dominant_topic_cons.columns = ['Review_ID', 'Dominant_Topic', 'Topic_Perc_Contrib']
         C:\Users\Utkarsh\AppData\Local\Temp\ipykernel 5604\2700792715.py:13: FutureWarning: T
         he frame.append method is deprecated and will be removed from pandas in a future vers
         ion. Use pandas.concat instead.
           sent_topics_df = sent_topics_df.append(pd.Series([int(topic_num), round(prop_topic,
         4), topic_keywords]), ignore_index=True)
         C:\Users\Utkarsh\AppData\Local\Temp\ipykernel 5604\2700792715.py:13: FutureWarning: T
         he frame.append method is deprecated and will be removed from pandas in a future vers
         ion. Use pandas.concat instead.
            sent_topics_df = sent_topics_df.append(pd.Series([int(topic_num), round(prop_topic,
         4), topic keywords]), ignore index=True)
         df dominant topic cons['Review ID'] = df['id']
In [20]:
          df dominant topic cons.head(10)
```

3, 7:11 PM	Project-Topic-Modeling V2									
Out[20]:		Review_ID	Dominant_Topic	Topic_Perc_Contrib	Keywords	Text				
	0	empReview_73247758	2	0.6520	n't, con, job, manager, amazon, employee, like	[need, understand, job, need, improve, good, d				
	1	empReview_73187609	0	0.6398	work, hour, time, long, lot, day, shift, much,	[long, hour, shift, make, feel, tire]				
	2	empReview_73188818	0	0.8691	work, hour, time, long, lot, day, shift, much,	[workload, heavy, sometimes]				
	3	empReview_73190433	1	0.4363	get, bad, pay, balance, good, culture, life, t	[good, organization, work, well, car, parking,				
In [21]:	4	empReview_73197210	1	0.8770	get, bad, pay, balance, good, culture, life, t	[compensation, growth, prospect, development,				
	5	empReview_73208298	0	0.5003	work, hour, time, long, lot, day, shift, much,	[potential, layoff, fast, pace]				
	6	empReview_73149307	1	0.4016	get, bad, pay, balance, good, culture, life, t	[none, best, company, ever, glad, worked]				
	7	empReview_73146117	0	0.8953	work, hour, time, long, lot, day, shift, much,	[lot, work, high, stress]				
	8	empReview_73105526	0	0.4953	work, hour, time, long, lot, day, shift, much,	[much, stress, give, employee]				
	9	empReview_73108472	0	0.5310	work, hour, time, long, lot, day, shift, much,	[work, culture, negative, depend, location, li				
	<pre>cols = [color for name, color in mcolors.TABLEAU_COLORS.items()] # more colors: 'mcc cloud = WordCloud(stopwords=stop_words,</pre>									
	<pre>topics = lda_model_cons.show_topics(formatted=False)</pre>									

fig, axes = plt.subplots(1, 3, figsize=(11,11), sharex=True, sharey=True)

```
localhost: 8888/nbconvert/html/Desktop/Project-Topic-Modeling~V2.ipynb?download=false
```

fig.add\_subplot(ax)

for i, ax in enumerate(axes.flatten()):

```
topic_words = dict(topics[i][1])
  cloud.generate_from_frequencies(topic_words, max_font_size=300)
  plt.gca().imshow(cloud)
  plt.gca().set_title('Topic ' + str(i), fontdict=dict(size=16))
  plt.gca().axis('off')

plt.subplots_adjust(wspace=0, hspace=0)
  plt.axis('off')
  plt.margins(x=0, y=0)
  plt.tight_layout()
  plt.show()
```



Our process resulted in three being the optimal number of topics for the 'Cons' column. One of the topics highlighted the long working times as the cons of working at Amazon (Topic 0). Another topic highlighted the bad culture and pay-grade as the cons of working at Amazon (Topic 1). The last topic highlighted managers and other fellow employees as the cons of working at Amazon (Topic 2).

### **Results:**

```
df pros cons = df[["id", "current employee"]]
In [22]:
         df_pros_cons["Pros_Dominant_Topic"] = df_dominant_topic["Dominant_Topic"]
          df pros cons["Pros Topic Perc Contrib"] = df dominant topic["Topic Perc Contrib"]
          df pros cons["Pros Keywords"] = df dominant topic["Keywords"]
          df pros cons["Cons Dominant Topic"] = df dominant topic cons["Dominant Topic"]
          df_pros_cons["Cons_Topic_Perc_Contrib"] = df_dominant_topic_cons["Topic_Perc_Contrib"]
          df pros cons["Cons Keywords"] = df dominant topic cons["Keywords"]
         df pros cons
         C:\Users\Utkarsh\AppData\Local\Temp\ipykernel 5604\977120469.py:3: SettingWithCopyWar
         ning:
         A value is trying to be set on a copy of a slice from a DataFrame.
         Try using .loc[row_indexer,col_indexer] = value instead
         See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
         er guide/indexing.html#returning-a-view-versus-a-copy
           df_pros_cons["Pros_Dominant_Topic"] = df_dominant_topic["Dominant_Topic"]
```

Out[22]:		id	current_employee	Pros_Dominant_Topic	Pros_Topic_Perc_Contrib	Pros_Key		
	0	empReview_73247758	1	1	0.8816	oppor learn, ar lot, g		
	1	empReview_73187609	0	0	0.9250	good grea benefit jo		
	2	empReview_73188818	0	0	0.8313	good grea benefit jo		
	3	empReview_73190433	0	0	0.6971	good grea benefii jo		
	4	empReview_73197210	1	0	0.9292	good grea benefii jo		
	•••							
	9995	empReview_71536795	1	1	0.6897	oppor learn, ar lot, g		
	9996	empReview_71537065	1	1	0.6064	oppor learn, ar lot, g		
	9997	empReview_71539933	1	0	0.9658	good grea benefii jo		
	9998	empReview_71882994	0	1	0.9774	oppor learn, ar lot, g		
	9999	empReview_72354621	0	1	0.7427	oppor learn, ar lot, g		
4	10000	rowe v Q columns				•		
Tn [27]	# 6-	unt the number of	occumnences of a	ach unique valva		,		
In [27]:	<pre>pros_counts = df_pros_cons['Pros_Dominant_Topic'].value_counts() cons_counts = df_pros_cons['Cons_Dominant_Topic'].value_counts() # Print the result</pre>							
	print	("Occurrence of Pr	o Topics:")					

```
print(pros_counts)
         print("Occurrence of Con Topics:")
         print(cons_counts)
         Occurrence of Pro Topics:
              6220
         1
              3780
         Name: Pros Dominant Topic, dtype: int64
         Occurrence of Con Topics:
         0
              4652
         1
              2906
         2
              2442
         Name: Cons Dominant Topic, dtype: int64
In [28]:
         # Get all possible combinations of Pros Dominant Topic and Cons Dominant Topic
         combinations = list(itertools.product([0, 1], [0, 1, 2]))
         # Create a DataFrame to store the results
          result_df = pd.DataFrame({'Pros_Dominant_Topic': [], 'Cons_Dominant_Topic': [], 'count
         # Loop through the combinations and count the occurrences in the original DataFrame
          for combination in combinations:
             count = ((df_pros_cons['Pros_Dominant_Topic'] == combination[0]) & (df_pros_cons['
             result_df = result_df.append({'Pros_Dominant_Topic': combination[0], 'Cons_Dominant'
         # Print the result
         print(result_df)
            Pros_Dominant_Topic Cons_Dominant_Topic
                                                        count
         0
                             0.0
                                                  0.0 3375.0
         1
                                                  1.0 1544.0
                             0.0
         2
                             0.0
                                                  2.0 1301.0
         3
                             1.0
                                                  0.0 1277.0
         4
                                                  1.0 1362.0
                             1.0
         5
                             1.0
                                                  2.0 1141.0
```

```
C:\Users\Utkarsh\AppData\Local\Temp\ipykernel 5604\1291327798.py:10: FutureWarning: T
he frame.append method is deprecated and will be removed from pandas in a future vers
ion. Use pandas.concat instead.
  result_df = result_df.append({'Pros_Dominant_Topic': combination[0], 'Cons_Dominant
_Topic': combination[1], 'count': count}, ignore_index=True)
C:\Users\Utkarsh\AppData\Local\Temp\ipykernel_5604\1291327798.py:10: FutureWarning: T
he frame.append method is deprecated and will be removed from pandas in a future vers
ion. Use pandas.concat instead.
  result df = result df.append({'Pros Dominant Topic': combination[0], 'Cons Dominant
_Topic': combination[1], 'count': count}, ignore_index=True)
C:\Users\Utkarsh\AppData\Local\Temp\ipykernel 5604\1291327798.py:10: FutureWarning: T
he frame.append method is deprecated and will be removed from pandas in a future vers
ion. Use pandas.concat instead.
  result_df = result_df.append({'Pros_Dominant_Topic': combination[0], 'Cons_Dominant
Topic': combination[1], 'count': count}, ignore index=True)
C:\Users\Utkarsh\AppData\Local\Temp\ipykernel_5604\1291327798.py:10: FutureWarning: T
he frame.append method is deprecated and will be removed from pandas in a future vers
ion. Use pandas.concat instead.
  result df = result df.append({'Pros Dominant Topic': combination[0], 'Cons Dominant
Topic': combination[1], 'count': count}, ignore index=True)
C:\Users\Utkarsh\AppData\Local\Temp\ipykernel 5604\1291327798.py:10: FutureWarning: T
he frame.append method is deprecated and will be removed from pandas in a future vers
ion. Use pandas.concat instead.
  result df = result df.append({'Pros Dominant Topic': combination[0], 'Cons Dominant
_Topic': combination[1], 'count': count}, ignore_index=True)
C:\Users\Utkarsh\AppData\Local\Temp\ipykernel_5604\1291327798.py:10: FutureWarning: T
he frame.append method is deprecated and will be removed from pandas in a future vers
ion. Use pandas.concat instead.
  result df = result df.append({'Pros Dominant Topic': combination[0], 'Cons Dominant
_Topic': combination[1], 'count': count}, ignore_index=True)
```

From the results above, we can see that most employee reviews mention the pay grade and other benefits as the pros of working at Amazon. As for the cons of working at Amazon, most employee reviews mention the long working hours. In fact, approximately a third of the employee reviews point toward this combination of pros and cons. Reviews that focused on the opportunity to learn and grow as the pros of working at Amazon had a more even distribution of the cons topics, though the topic associated with the paygrade and company culture was the most frequent.

## **Exporting the Data:**

```
In [ ]: df_pros_cons.to_csv('employee_pros_cons_topic_modelling.csv', index=False)
```