Project Supply Chain -- First Data Exploration

Exploration of metadata (without Text Mining technics) Some ideas:

- Response rate, influence of brand or source, verified_purchase or not
  We took a look at verified purchases and how the reviewers rated differently
- Distribution of scores.
  We took a look at the distribution of scores in various scenarios
- Influence of the marketplace or the company on the distribution of notes (hypothesis testin could be used for this kind of analysis)
  We only have information about wether the reviewers were selected by the company or not, which we took a look at
- Information about the 10 most active users, with a small analysis on it (distribution of scores, response rate, company...).
  We looked at the 10 most active users

Goal 2 Analysis of text (and cleaning if necessary). You will need to complete the text mining module to be able to do this part. Some ideas :

- Analyze the punctuation according to the note
- Analyze the length of the text (nb character, nb words...) according to the note.
- Analyze the frequency of email addresses, links, phone numbers...
- Occurrence of words, wordcloud... We did a word cloud already to have an overview and saw that we need to improve on stop-words
- N-gram
- Occurrence of some words : delivery order, return order, delivery, SAV, customer service...

In [72]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import nltk
from nltk.tokenize import word_tokenize
from nltk.util import ngrams
from sklearn.feature_extraction.text import CountVectorizer
from wordcloud import WordCloud, STOPWORDS, ImageColorGenerator
nltk.download('stopwords')
nltk.download('punkt')

%matplotlib inline
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\Ling\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\Ling\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
```

In [2]:
```
import os
project_path = os.path.abspath(os.path.join(os.getcwd(), os.path.pardir, os.path.pardir)).replace('\\', '/')
project_path
```

Out[2]:
```
'D:/Ling/Study/AZ_DATASCIENCE_ACADEMY/project_supply_chain'
```

```
In [4]: data_hc = pd.read_csv(project_path + r"/data/amazon_reviews_us_Video_Games_v1_00.tsv", sep="\t", error_bad_lines=False)
        data_dc = pd.read_csv(project_path + r"/data/amazon_reviews_us_Digital_Video_Games_v1_00.tsv", sep="\t", error_bad_lines=False)
        data_raw = pd.concat([data_hc,data_dc], axis = 0)
```

```
C:\Users\Ling\AppData\Local\Temp\ipykernel_15072\667229618.py:1: FutureWarning: The error_bad_lines argument has been deprecated and will be removed in a future version. Use on_bad_li
nes in the future.


  data_hc = pd.read_csv(project_path + r"/data/amazon_reviews_us_Video_Games_v1_00.tsv", sep="\t", error_bad_lines=False)
b'Skipping line 20630: expected 15 fields, saw 22\nSkipping line 28172: expected 15 fields, saw 22\nSkipping line 54791: expected 15 fields, saw 22\n'
b'Skipping line 75419: expected 15 fields, saw 22\nSkipping line 104832: expected 15 fields, saw 22\n'
b'Skipping line 138464: expected 15 fields, saw 22\nSkipping line 194849: expected 15 fields, saw 22\n'
b'Skipping line 201568: expected 15 fields, saw 22\nSkipping line 242567: expected 15 fields, saw 22\n'
b'Skipping line 493585: expected 15 fields, saw 22\nSkipping line 502478: expected 15 fields, saw 22\n'
b'Skipping line 660750: expected 15 fields, saw 22\n'
C:\Users\Ling\AppData\Local\Temp\ipykernel_15072\667229618.py:2: FutureWarning: The error_bad_lines argument has been deprecated and will be removed in a future version. Use on_bad_li
nes in the future.


  data_dc = pd.read_csv(project_path + r"/data/amazon_reviews_us_Digital_Video_Games_v1_00.tsv", sep="\t", error_bad_lines=False)
```

explore data

```
In [5]: data_raw.shape
```

```
Out[5]: (1924992, 15)
```

```
In [6]: data_raw.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1924992 entries, 0 to 144723
Data columns (total 15 columns):
 #   Column             Dtype 
---  ------             ----- 
 0   marketplace        object
 1   customer_id        int64 
 2   review_id          object
 3   product_id         object
 4   product_parent     int64 
 5   product_title      object
 6   product_category   object
 7   star_rating        int64 
 8   helpful_votes      int64 
 9   total_votes        int64 
 10  vine               object
 11  verified_purchase  object
 12  review_headline    object
 13  review_body        object
 14  review_date        object
dtypes: int64(5), object(10)
memory usage: 235.0+ MB
```

In [7]:
```python
data_raw.head()
```

Out[7]:

	marketplace	customer_id	review_id	product_id	product_parent	product_title	product_category	star_rating	helpful_votes	total_votes	vine	verified_purchase	review_headline	review_body	review_date
0	US	12039526	RTIS3L2M1F5SM	B001CXYMFS	737716809	Thrustmaster T-Flight Hotas X Flight Stick	Video Games	5	0	0	N	Y	an amazing joystick. I especially love that yo...	Used this for Elite Dangerous on my mac, an am...	2015-08-31
1	US	9636577	R1ZV7R40OLHKD	B00M920ND6	569686175	Tonsee 6 buttons Wireless Optical Silent Gamin...	Video Games	5	0	0	N	Y	Definitely a silent mouse... Not a single clic...	Loved it, I didn't even realise it was a gami...	2015-08-31
2	US	2331478	R3BH071QLH8QMC	B0029CSOD2	98937668	Hidden Mysteries: Titanic Secrets of the Fatef...	Video Games	1	0	1	N	Y	One Star	poor quality work and not as it is advertised.	2015-08-31
3	US	52495923	R127K9NTSXA2YH	B00GOOSV98	23143350	GelTabz Performance Thumb Grips - PlayStation ...	Video Games	3	0	0	N	Y	good, but could be bettee	nice, but tend to slip away from stick in inte...	2015-08-31
4	US	14533949	R32ZWUXDJPW27Q	B00Y074JOM	821342511	Zero Suit Samus amiibo - Japan Import (Super S...	Video Games	4	0	0	N	Y	Great but flawed.	Great amiibo, great for collecting. Quality ma...	2015-08-31

In [10]:
```python
# check null data
print(data_raw.isnull().sum(axis = 0) / len(data) * 100)
```

```
marketplace          0.000000
customer_id          0.000000
review_id            0.000000
product_id           0.000000
product_parent       0.000000
product_title        0.000000
product_category     0.000000
star_rating          0.000000
helpful_votes        0.000000
total_votes          0.000000
vine                 0.000000
verified_purchase    0.000000
review_headline      0.001559
review_body          0.003169
review_date          0.001559
dtype: float64
```

In [62]:
```python
# drop missing data, since the amount of missing data is very low
data = data_raw.dropna(axis = 0)
```

check data quality and clean data

In [12]:
```python
# check duplicates
print(data["marketplace"].value_counts()) #Only data from us marketplace, so we can drop the row
print("number of duplicated customer ids = \n", len(data[data['customer_id'].duplicated() == True])) #most likely because customers ordered multiple items
print("number of duplicated review ids = \n", len(data[data['review_id'].duplicated() == True]))
#has to be 0 in order to ensure the ID is unique, i think we can drop this row as well in this case
#placeholder for code that shows if product_id, product_title and product_parent are fully correlated
print("product_category: \n", data["product_category"].value_counts())
print("star rating: \n", data["star_rating"].value_counts())
print("vines: \n",data["vine"].value_counts())
print("verified_purchases: \n",data["verified_purchase"].value_counts())
```

```
US    1924871
Name: marketplace, dtype: int64
number of duplicated customer ids =
 798982
number of duplicated review ids =
 0
product_category:
 Video Games            1780154
Digital_Video_Games     144717
Name: product_category, dtype: int64
star rating:
 5    1103331
4     337771
1     216459
3     165032
2     102278
Name: star_rating, dtype: int64
vines:
 N    1920587
Y       4284
Name: vine, dtype: int64
verified_purchases:
 Y    1288358
N     636513
Name: verified_purchase, dtype: int64
```

In [63]:
```python
# drop the rows we do not need for this analysis or our model
to_drop = ["marketplace"] # we did not drop "review_id", "product_id", "product_parent" for now as they might
#still be usefull going forward
data = data.drop(to_drop, axis=1)
```

Reviews per product

In [38]:
```
reviews_per_product = data.groupby(["product_id"])["review_id"].nunique().reset_index(name="num_of_reviews").\
    sort_values(by=(['num_of_reviews']), ascending=False)
reviews_per_product.head()
```

Out[38]:

	product_id	num_of_reviews
56858	B00BGA9WK2	10317
36110	B002VBWIP6	5085
44335	B004RMK4BC	5039
50298	B007FTE2VW	3971
27498	B00178630A	3715

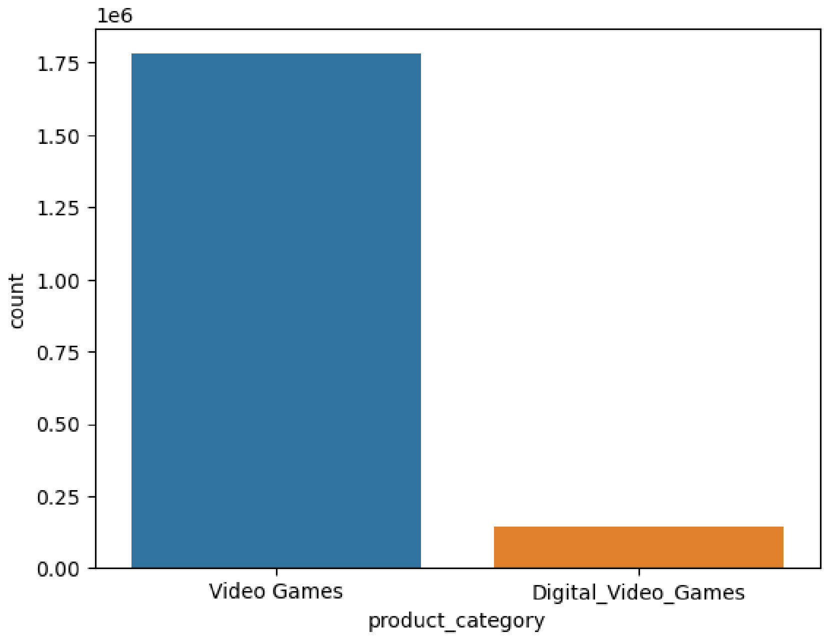
In [39]:
```
reviews_per_product["num_of_reviews"].quantile([0.01,0.1,0.25, 0.5,0.75,0.9,0.99])
```

Out[39]:
```
0.01      1.00
0.10      1.00
0.25      1.00
0.50      4.00
0.75     15.00
0.90     51.00
0.99    382.81
Name: num_of_reviews, dtype: float64
```

countplot of various data

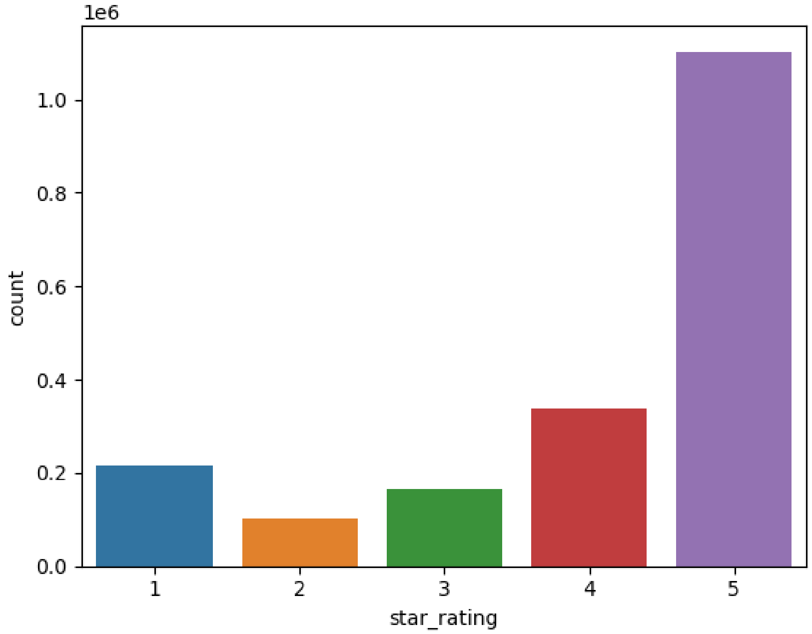
In [40]:
```
sns.countplot(x=data["product_category"])
```

Out[40]: <AxesSubplot: xlabel='product_category', ylabel='count'>



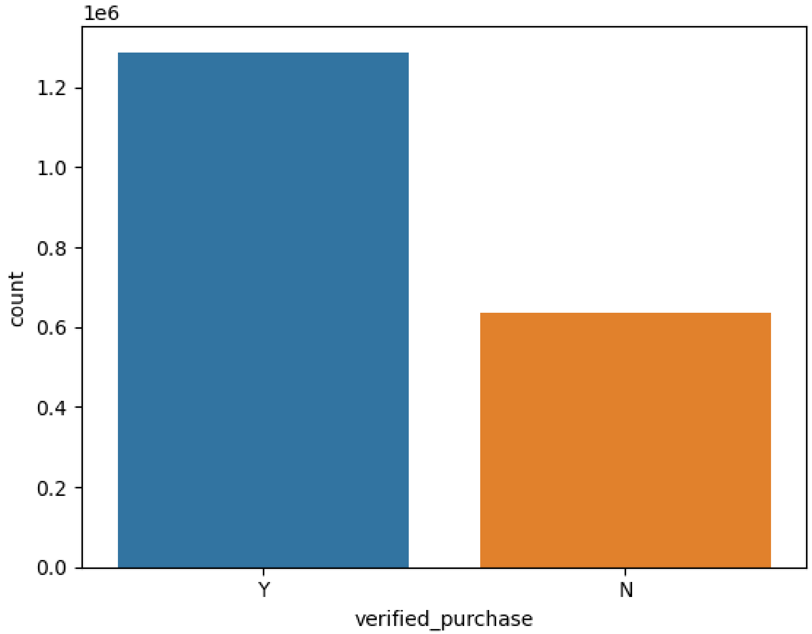
In [41]:
```
sns.countplot(x=data["star_rating"])
```

Out[41]: <AxesSubplot: xlabel='star_rating', ylabel='count'>



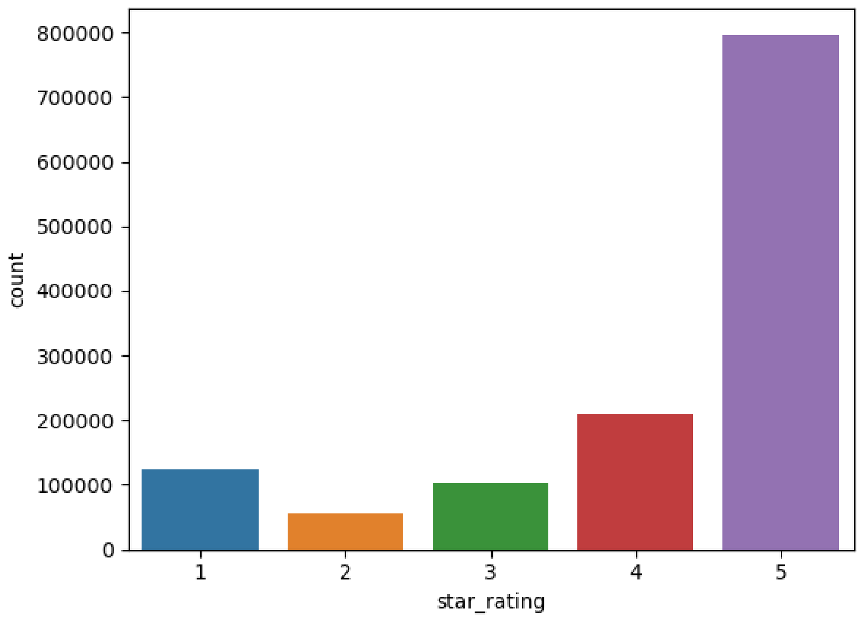
In [42]:
```
sns.countplot(x=data["verified_purchase"])
#there are a lot of non-verified purchases
#let's look at how the rating distribution of these reviews looks like compared to the verified ones
```

Out[42]: <AxesSubplot: xlabel='verified_purchase', ylabel='count'>



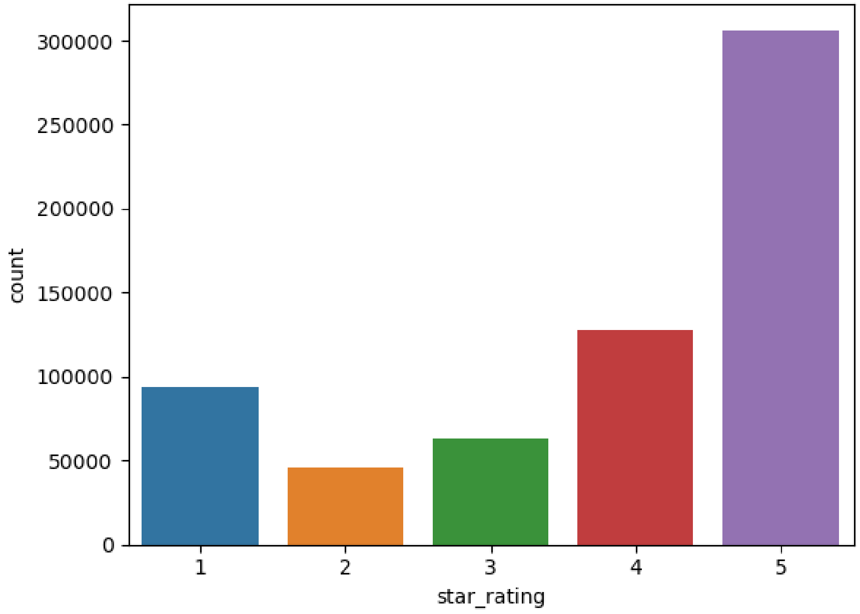
In [43]:
```
sns.countplot(x=data[data["verified_purchase"]=="Y"]["star_rating"])
```

Out[43]: <AxesSubplot: xlabel='star_rating', ylabel='count'>



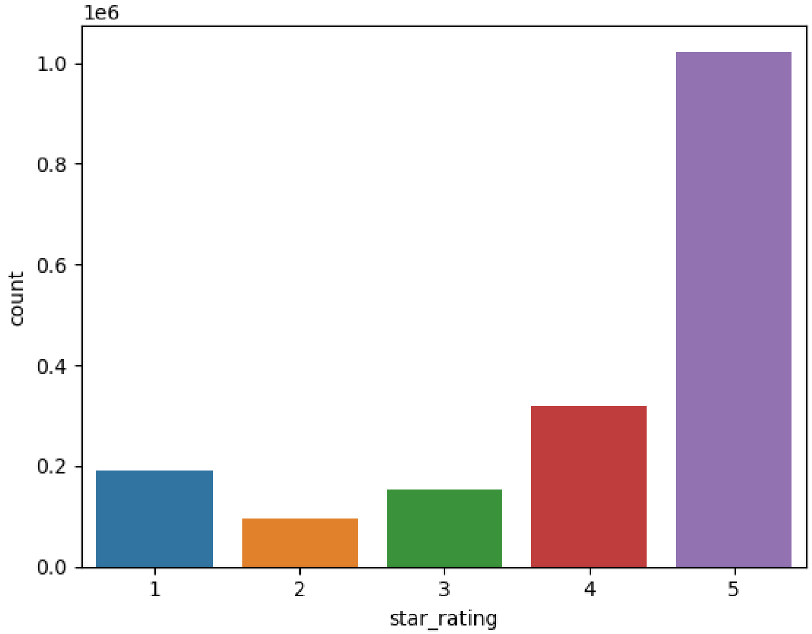
In [44]:
```
sns.countplot(x=data[data["verified_purchase"]=="N"]["star_rating"])
#there are a lot more lower ratings in comparison.
#It is possible that customers were so unhappy, that they created a 2nd account just to review the game negatively again
```

Out[44]: <AxesSubplot: xlabel='star_rating', ylabel='count'>



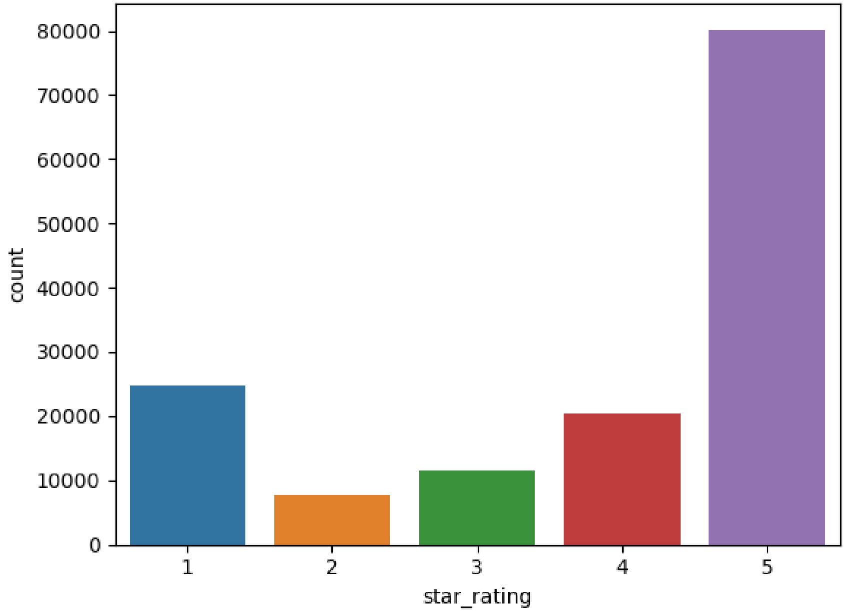
In [45]:
```
#there are definitely more hard-copy sales than digital sales, let's look at the ratings from the reviews for each one
sns.countplot(x=data[data["product_category"]=="Video Games"]["star_rating"])
```

Out[45]: `<AxesSubplot: xlabel='star_rating', ylabel='count'>`



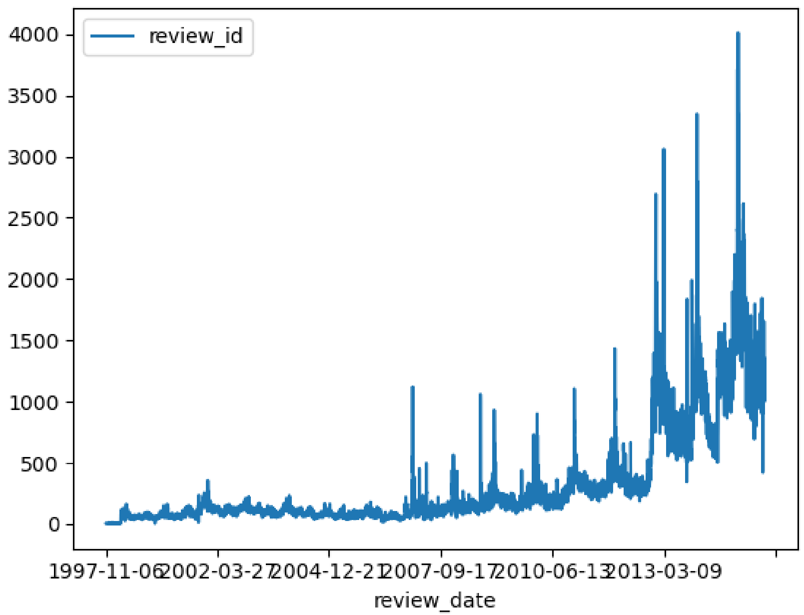
In [46]:
```
sns.countplot(x=data[data["product_category"]=="Digital_Video_Games"]["star_rating"])
#we can see from this simple analysis, that there are a lot more 1-star reviews for digital products
```

Out[46]: <AxesSubplot: xlabel='star_rating', ylabel='count'>



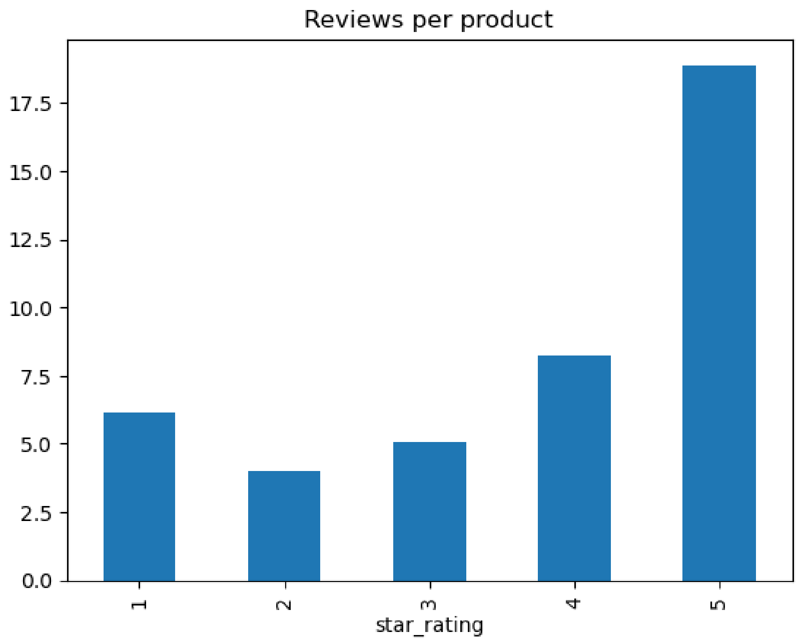
reviews over time

In [47]:
```
reviews_over_time = data.groupby("review_date").agg({"review_id":"count"}).plot(kind="line")
```



In [48]:
```
num_rev_prod_per_rating = data.groupby("star_rating").agg({"review_id":lambda x: x.nunique(), "product_id": lambda x: x.nunique()} )
num_rev_prod_per_rating["rev_per_prod"] = num_rev_prod_per_rating.apply(lambda x: x["review_id"] / x["product_id"], axis=1)
num_rev_prod_per_rating["rev_per_prod"].plot(kind="bar", title="Reviews per product")
#reviews per product by rating class, customers seem to review more often when they are happy
```

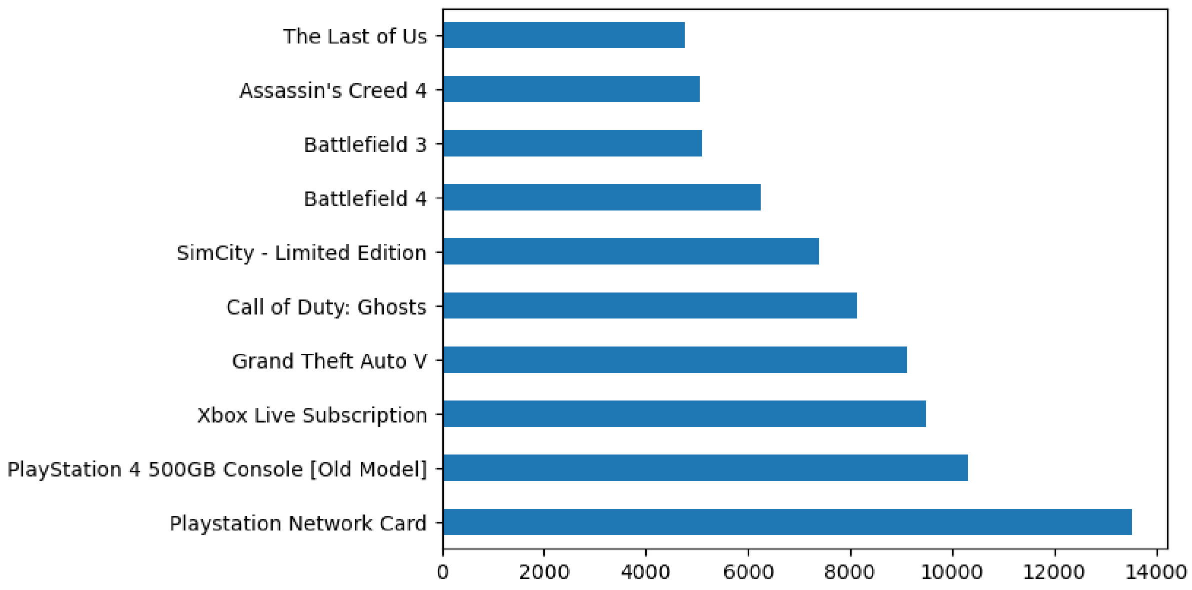
Out[48]: <AxesSubplot: title={'center': 'Reviews per product'}, xlabel='star_rating'>



10 most rated titles

In [49]:
```
data["product_title"].value_counts().head(10).plot(kind="barh")
```

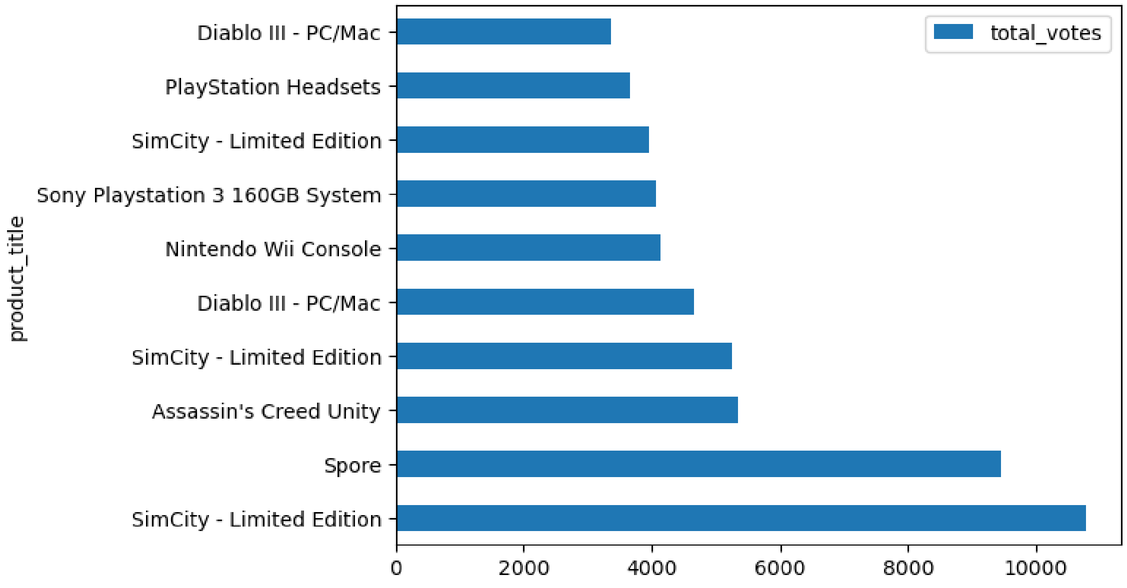
Out[49]: <AxesSubplot: >



Top 10 titles where the reviews recieved the most votes

In [50]:
```
data[["product_title", "total_votes"]].nlargest(10, ["total_votes"]).plot(x="product_title", y="total_votes", kind="barh")
```

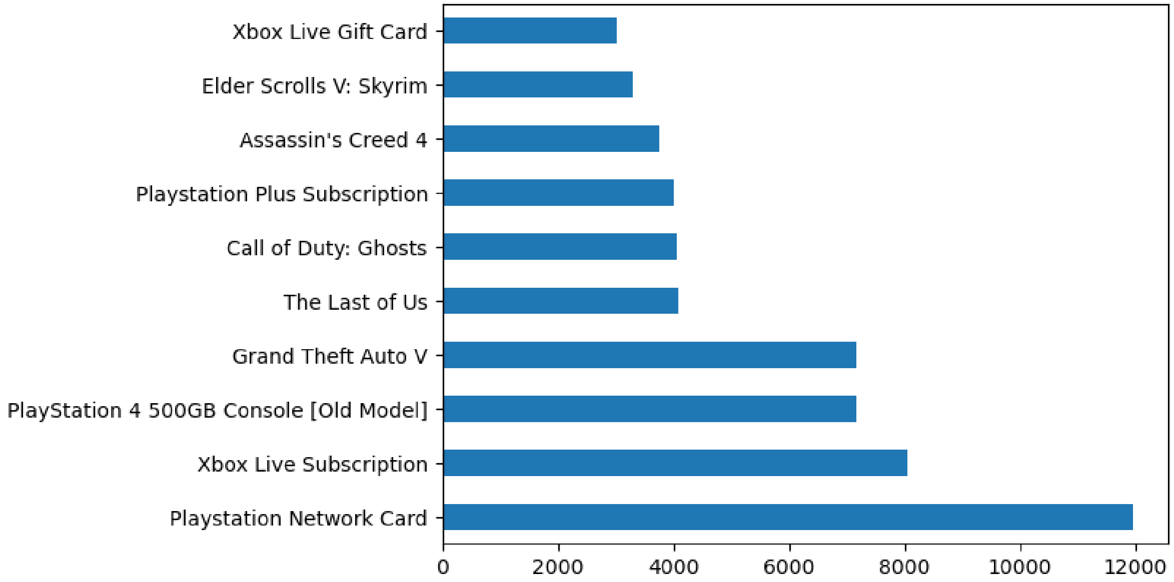
Out[50]: <AxesSubplot: ylabel='product_title'>



Top 10 titles have the most 5-star reviews

In [51]:
```
data[data["star_rating"] == 5]["product_title"].value_counts().head(10).plot(kind="barh")
```

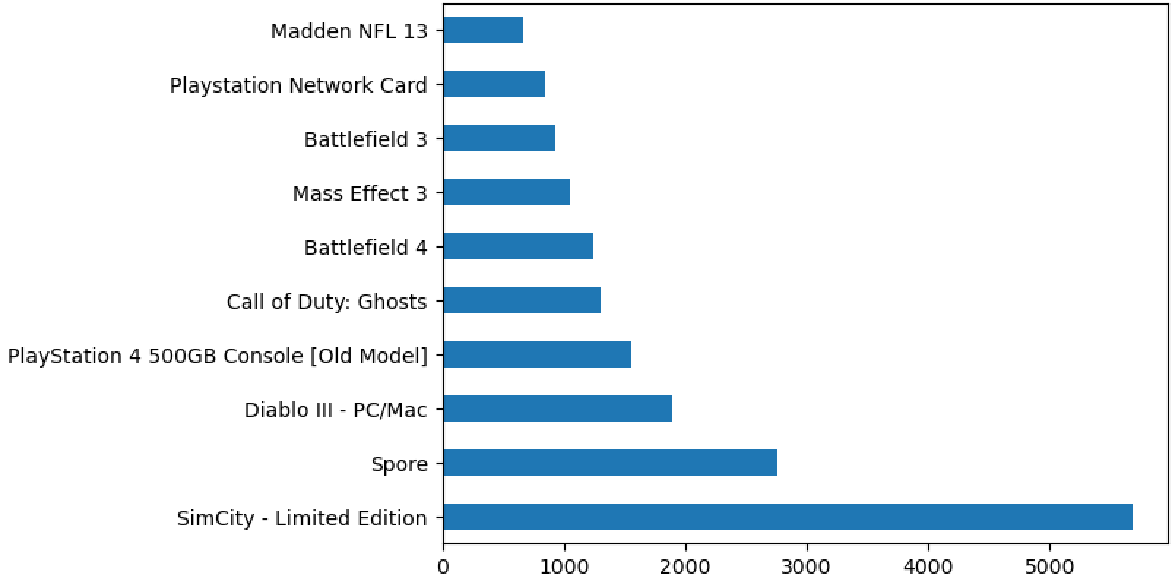
Out[51]: <AxesSubplot: >



Top 10 titles with the lowest rated reviews

In [52]:
```
data[data["star_rating"] == 1]["product_title"].value_counts().head(10).plot(kind="barh")
#that's where SimCity went, reviewers did not like this game at all
```

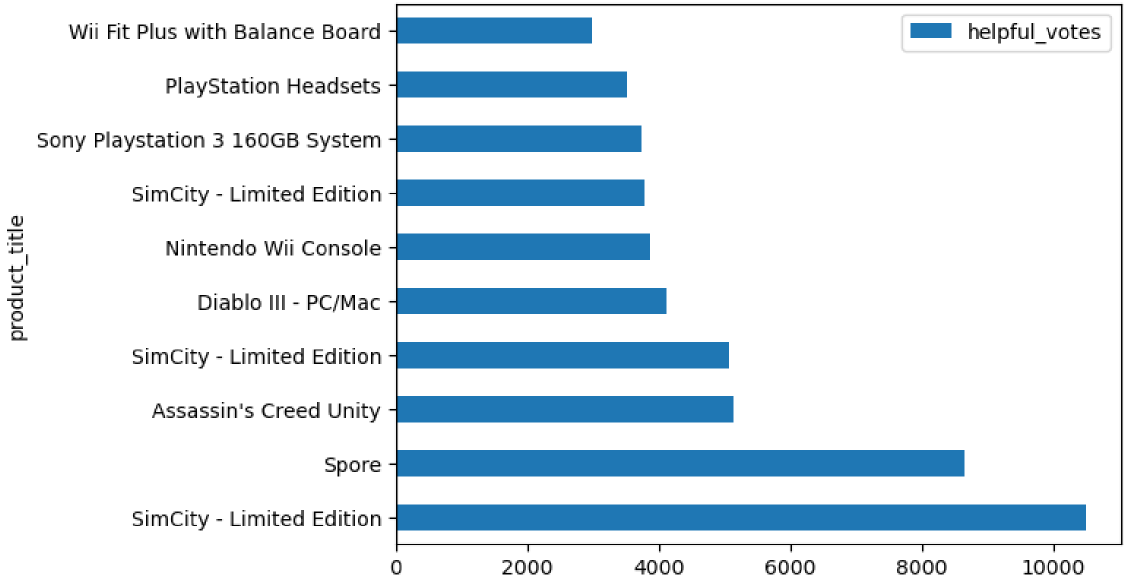
Out[52]: <AxesSubplot: >



Top 10 games with the most helpful reviews

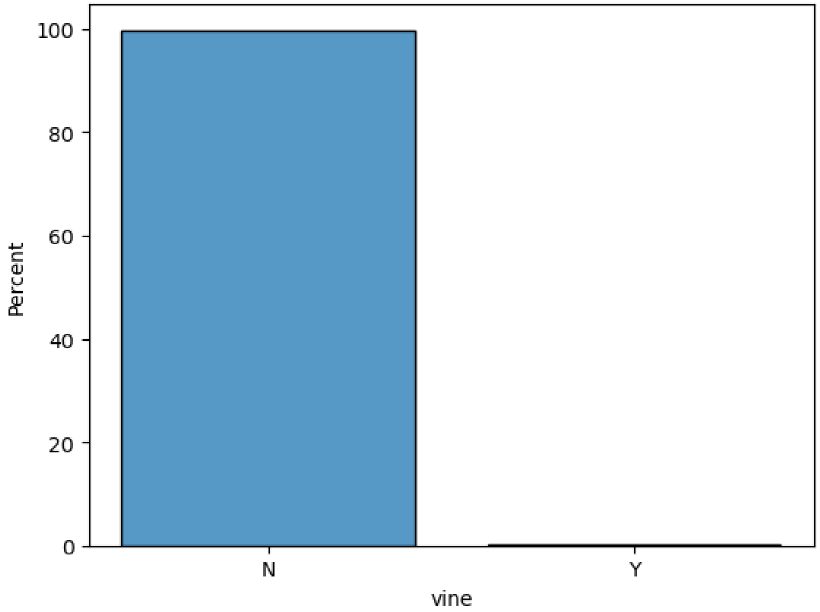
In [53]:
```
data[["product_title", "helpful_votes"]].nlargest(10, ["helpful_votes"]).plot(x="product_title", y="helpful_votes", kind="barh")
#Customers found reviews of SimCity the most helpful allthough the game also had a lot of bad reviews. this again shows that
#this title was highly controversial
```

Out[53]: <AxesSubplot: ylabel='product_title'>



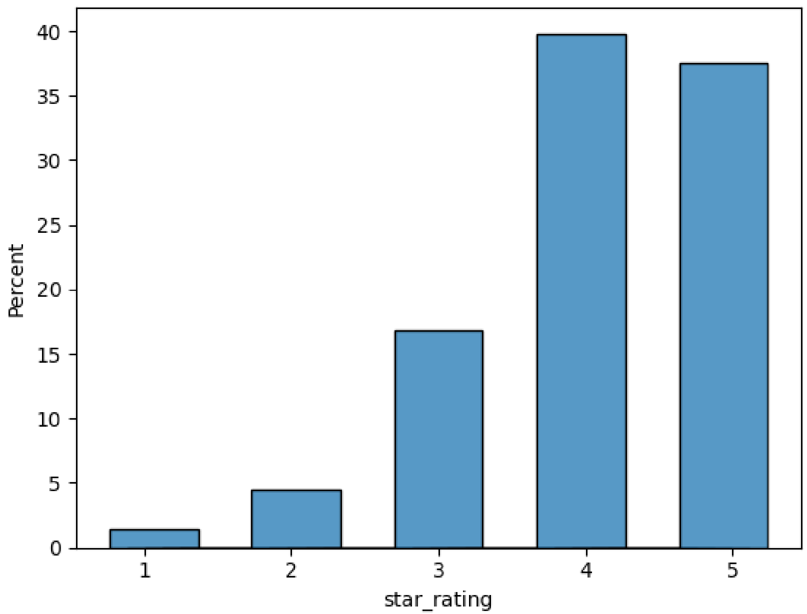
In [54]:
```
#now we will look at the distribution of vine reviews to non-vine reviews
sns.histplot(data, x="vine", stat="percent", multiple="dodge", shrink=0.8)
```

Out[54]: <AxesSubplot: xlabel='vine', ylabel='Percent'>



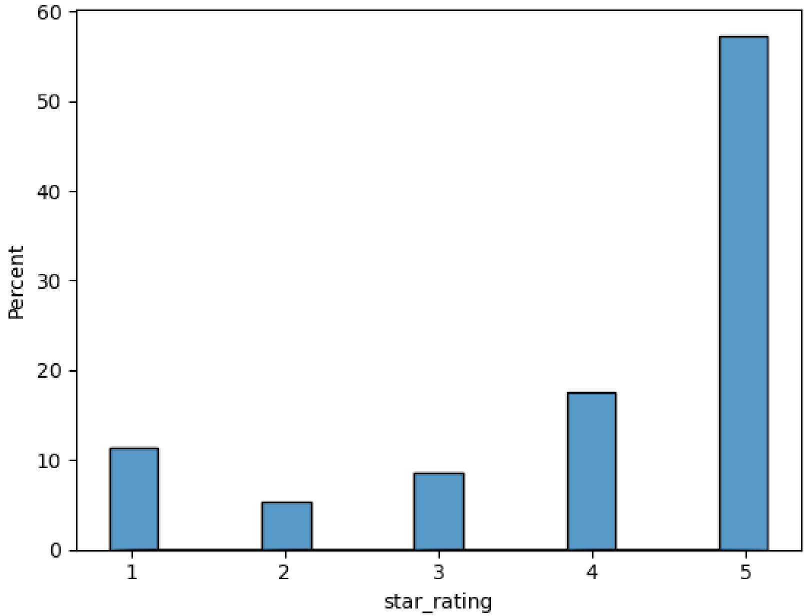
In [55]:
```
sns.histplot(data[data["vine"]=="Y"], x="star_rating", stat="percent", multiple="dodge", shrink=5)
```

Out[55]: <AxesSubplot: xlabel='star_rating', ylabel='Percent'>



In [56]:
```
sns.histplot(data[data["vine"]=="N"], x="star_rating", stat="percent", multiple="dodge", shrink=10)
#we can see that the vine reviews are more likely to give 3, 4 or 5 stars compared to the non-vine reviews
```

Out[56]: <AxesSubplot: xlabel='star_rating', ylabel='Percent'>



tokenization and stemming of review_body

In [57]:
```
from nltk.corpus import stopwords
stop_words = set(stopwords.words('english'))
from nltk.stem.snowball import EnglishStemmer
stemmer = EnglishStemmer()


stop_words.update(["car", "work", "product", "install"])

def tokenization_and_stemming(text):
    tokens = []
    # exclude stop words and tokenize the document, generate a list of string
    for word in word_tokenize(text):
        if word.lower() not in stop_words:
            tokens.append(word.lower())

    filtered_tokens = []

    # filter out any tokens not containing letters (e.g., numeric tokens, raw punctuation)
    for token in tokens:
        if token.isalpha(): # filter out non alphabet words like emoji
            filtered_tokens.append(token)

    # stemming
    # Removes ing also in anything ...
    stems = [stemmer.stem(t) for t in filtered_tokens]
    return_string = " ".join(stems)

    return return_string
```

In [58]:
```
df_review_body = data.dropna(subset=['review_body'])
```

In [59]:
```
df_review_body["processed_reviews"] = df_review_body["review_body"].apply(lambda x: tokenization_and_stemming(x))
```

In [60]:
```
df_review_body.head()
```

Out[60]:

	customer_id	review_id	product_id	product_parent	product_title	product_category	star_rating	helpful_votes	total_votes	vine	verified_purchase	review_headline	review_body	review_date	processed_reviews
0	12039526	RTIS3L2M1F5SM	B001CXYMFS	737716809	Thrustmaster T-Flight Hotas X Flight Stick	Video Games	5	0	0	N	Y	an amazing joystick. I especially love that yo...	Used this for Elite Dangerous on my mac, an am...	2015-08-31	use elit danger mac amaz joystick especi love ...
1	9636577	R1ZV7R40OLHKD	B00M920ND6	569686175	Tonsee 6 buttons Wireless Optical Silent Gamin...	Video Games	5	0	0	N	Y	Definitely a silent mouse... Not a single clic...	Loved it, I didn't even realise it was a gami...	2015-08-31	love even realis game mous type silent mous se...
2	2331478	R3BH071QLH8QMC	B0029CSOD2	98937668	Hidden Mysteries: Titanic Secrets of the Fatef...	Video Games	1	0	1	N	Y	One Star	poor quality work and not as it is advertised.	2015-08-31	poor qualiti advertis
3	52495923	R127K9NTSXA2YH	B00GOOSV98	23143350	GelTabz Performance Thumb Grips - PlayStation ...	Video Games	3	0	0	N	Y	good, but could be bettee	nice, but tend to slip away from stick in inte...	2015-08-31	nice tend slip away stick intens hard press ga...
4	14533949	R32ZWUXDJPW27Q	B00Y074JOM	821342511	Zero Suit Samus amiibo - Japan Import (Super S...	Video Games	4	0	0	N	Y	Great but flawed.	Great amiibo, great for collecting. Quality ma...	2015-08-31	great amiibo great collect qualiti materi desi...

word cloud of processed_reviews

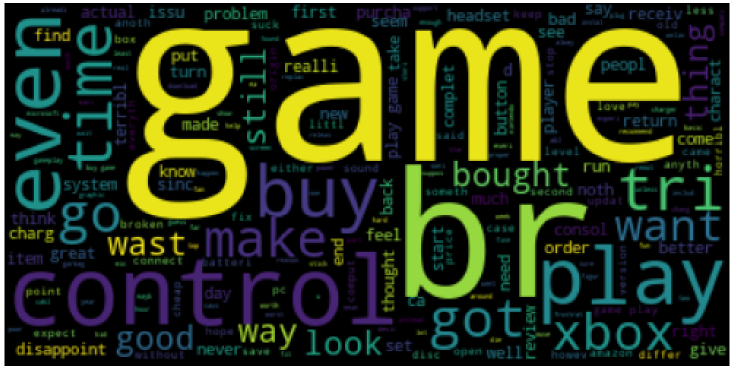
In [66]:
```
df_review_body.columns
```

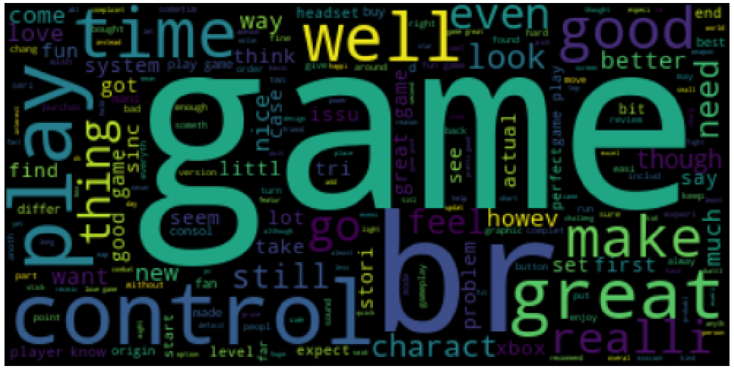
Out[66]:
```
Index(['customer_id', 'review_id', 'product_id', 'product_parent',
       'product_title', 'product_category', 'star_rating', 'helpful_votes',
       'total_votes', 'vine', 'verified_purchase', 'review_headline',
       'review_body', 'review_date', 'processed_reviews'],
      dtype='object')
```

In [67]:
```
df_processed_reviews = df_review_body.dropna(subset="processed_reviews")
processed_review_string = df_processed_reviews.groupby("star_rating").aggregate({"processed_reviews":lambda x: " \n ".join(x)})
```

In [74]:
```
def wc_for_rating(rating):
    wordcloud = WordCloud(collocations=True).generate(processed_review_string.loc[rating][0][1:5000000].replace("one", "").replace("use", "").replace(" br ", " ").replace("car", "").re
    # Display the generated image:
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.axis("off")
    plt.show()
```

In [75]:
```
wc_for_rating(1)
wc_for_rating(2)
wc_for_rating(3)
wc_for_rating(4)
wc_for_rating(5)
```





In [76]:
```
STOP -- end of code
```

```
  File "C:\Users\Ling\AppData\Local\Temp\ipykernel_15072\878011331.py", line 1
    STOP -- end of code
                ^
SyntaxError: invalid syntax
```

In [ ]:
```
```