video gaming classification

Improving the Craigslist User Experience

Team Unstrucata

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Team Unstrucata | Craigslist Video Gaming

Agenda

- background & problem statement
- our analytical approach
- 3 conclusion

background & problem statement

craigslist

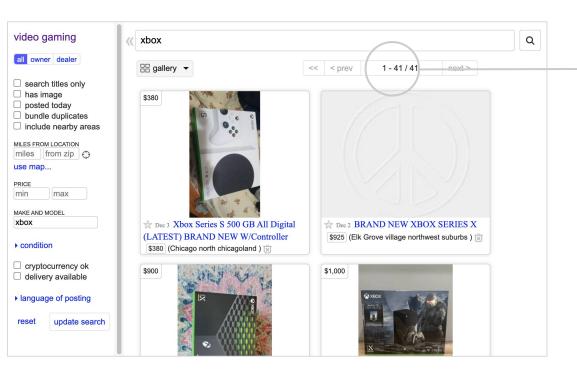
Finding what you need in the video game category can be...challenging.









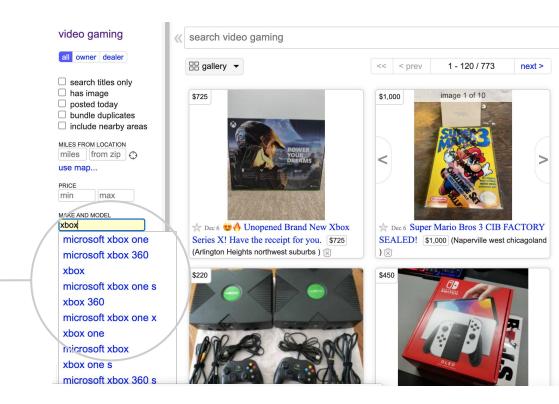


There are inconsistent filtering results.

This filter is showing that there are only **41** (when the general search shows **134**) xbox listings.

The search selection options are highly specific.

There are at least 5 different options if a user was looking for an xbox one.



Business Opportunity: Retention

The Video Gaming category does not generate revenue for craigslist.

By increasing customer satisfaction in the video gaming category with improved filters, we can increase the retention rate for the site overall, driving the company's revenue.

our analytical approach

Our Analytical Approach | Web Scraping

Cities | New York, Chicago, Miami, Washington DC, Los Angeles, and Philadelphia

posting_id	datetime	city	title	price	place	desc
						QR Code Link to This Post
7414934573	12/1/2021 8:4:	5 miami	Arcade Video Game Machine With Thousands Of Pre Loaded Retro Games	\$700	(Cutler Bay)	PRICE IS FIRM This is a real Multi Game Arcade packed with over 10,000 games. Perfect for a kids room, personal bar or man cave. Includes games for the following systems. - Arcade games - Atari 2600 - Atari 2000 - Atari 5200 - Atari 7800 - Atari Jaguar - Intellivision - Colecovision - Nintendo Entertainment system - Super Nintendo Entertainment System

Our Analytical Approach | Data Pre-Processing

title	price	place	desc
sony playstation five - ps5 NEW	\$850	(Fort Lauderdale)	QR Code Link to This Post
			Brand new sealed

title	price place	desc
sony playstation five - ps5 new	850 Fort Lauderdale	brand new sealed
battlefield 2042	50 Hollywood	like brand new also still in plastic and for ps5 ,ps4 and xbox. or
playstation 5 disc sealed	850 Hollywood	brand new sealed, only willing to meet at a gas station.

- Removed the dollar sign in price column
- Removed parentheses in place column
- Made the description column one line
- Lowered the title case

Our Analytical Approach | **Keyword Extraction**

Filter by Brand











Other

	Microsoft	Nintendo	Sony	Arcade	Meta	Other
0	0	2	0	4	0	0.5
1	0	0	3	0	0	0.5
2	1	0	2	0	0	0.5
3	0	0	1	0	0	0.5
4	2	0	0	0	0	0.5
	***	***				
3006	0	0	0	0	0	0.5
3007	0	0	0	0	0	0.5
3008	0	0	0	0	0	0.5
3009	0	0	0	0	0	0.5
3010	0	1	0	0	0	0.5

Our Analytical Approach | Model Building

Target Variable

Brand Classification

Input Variables

Review Texts

Models

Naive Bayes

Logistic Regression

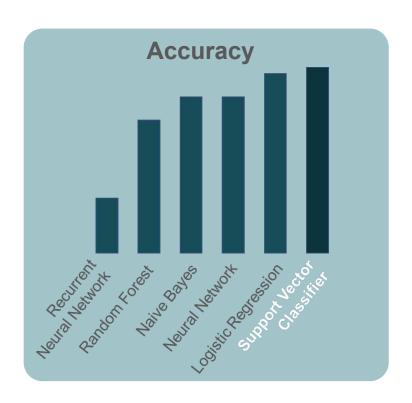
Random Forest

Support Vector Classification

Neural Network

Recurrent Neural Network

Our Analytical Approach | Validation



With our testing data,

SVC showed the highest accuracy with the score of **88.45**%

Logistic Regression | 84.99%

Neural Network | 74.24%

Naive Bayes | 73.97%

Random Forest | 63.75%

Recurrent Neural Network | 25.90%

Our Analytical Approach | Final Model

Final Model: SVC (Support Vector Classification) model.

Confusion Matrix

	Arcade	Meta	Microsoft	Nintendo	Other	Sony		
Arcade	43	0	0	1	1	1		
Meta	0	4	1	3	3	3		
Microsoft	0	0	147	0	4	6		
Nintendo	0	0	1	173	13	8		
Other	0	1	0	12	73	20		
Sony	1	0	1	1	6	226		
	Fa	False Positive						

False **Negative**

Faise Positive

conclusion

Conclusion | Impact: Information Gain

Our Model Craigslist Customer to extract information

Conclusion | Impact: Information Gain

	Manual Search Rate	Model Classification Rate	Information Gain
SONY	54%	96%	77% 👚
Nintendo	74%	89%	20% 👚
Microsoft	92%	94%	1.5% 👚
ARCADE	42%	93%	123% 👚
Meta	55%	29%	-48% 👢
Total	68%	92%	34% 🕇

Conclusion | Impact: Information Gain







Limitations

• The **amount of data we could scrape was limited** due to the Timeout Errors caused by Craigslist's servers.

 A filter-by-product classification was unrealistic without manually entering the target variable for each advertisement.

 Meta (Oculus) is an upcoming video gaming company, therefore the data for these products is sparse on Craigslist.

Looking Forward

- This feature could also be used within the "posting details" user interface for advertisers. It could automatically filter their listing into a brand category that would be confirmed by the advertiser.
- We recommend that Craigslist design and implement a filter-by-product option for customers. Customers could filter the Video Gaming Category for consoles, accessories, or video games.
- If Craigslist wished to continue computer-driven filtering, it could implement additional variables, like price, to best match the brand.

Thank you! Any questions?

GameCube lot bro - \$1,000 (Suburbs)

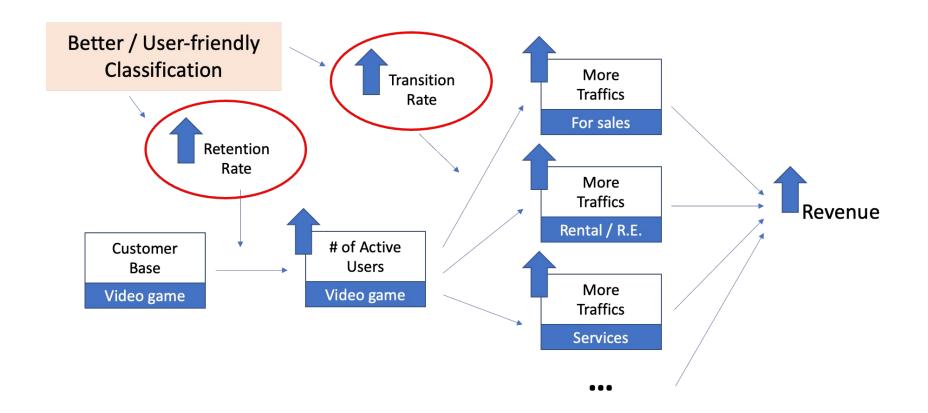
image 1 of 2



Lot of gamecube games . the Mario sunshine cases contain metroid prime echoes and the other is Luigi's mansion. The ereader cards are opened but complete in each pack. Don't low ball dude, I know what I got

appendix

Retention



Web Scraping Code

```
for city in cities:
    print(city)
    base url = 'https://' + city + '.craigslist.org/search/vga'
    re = requests.get(base url, headers=headers)
    soup = bs4.BeautifulSoup(re.text)
   # find the total number of pages for the city
    count = int(soup.select('.totalcount')[0].getText())
    num pages = count // 120
   for page in range(num pages):
        base url = 'https://' + city + '.craigslist.org/search/vga?s=' + str(page*120)
        re = requests.get(base url, headers=headers)
        soup = bs4.BeautifulSoup(re.text)
        # only use HTML tags of tags that have the 'result-image' tag
        soup = soup.select('.result-image')
        # create a list of all the links on the page
        links = [x.attrs['href'] for x in soup]
        # loop through each listing on this page
        for link in links:
            posting re = requests.get(link)
            posting soup = bs4.BeautifulSoup(posting re.text)
```

Data Cleaning Code

```
newp = []
for p in allclean["price"]:
    newp.append(int(p.strip("$").replace(",", "")))
allclean["price"] = newp
descrip = []
for d in allclean["desc"]:
    des = ""
    for s in d.split("\n\n\n")[1].split("\n"):
        des += s
    descrip.append(des.lower())
allclean["desc"] = descrip
places = []
for p in allclean["place"]:
    places.append(p.strip(" (").strip(")"))
allclean["place"] = places
allclean["title"] = allclean["title"].str.lower()
```

```
brands = {"Microsoft": ["xbox", "microsoft", "360", "xbox one", " rig
import numpy as np
for brand in brands:
    allclean[brand] = np.repeat(0, 3011)
    for word in brands[brand]:
        allclean[brand] += allclean.title.str.contains(word)
        allclean[brand] += allclean.desc.str.contains(word)
allclean["Other"] = np.repeat(0.5, 3011)
allclean["Brand"] = allclean.iloc[:,-6:].idxmax(1)
allclean.to csv("allcleanwithbrand.csv")
allclean["Brand"].value counts()
Sony
             1012
Nintendo
              755
Microsoft
              643
Other
              380
Arcade
              177
Meta
Name: Brand, dtype: int64
```

Tokenization Code

```
import nltk
from nltk.corpus import stopwords
from sklearn.feature extraction.text import TfidfVectorizer
lemmatizer = nltk.stem.WordNetLemmatizer()
tokencomp = []
for review in list(training x):
    tokens = nltk.word tokenize(str(review).lower())
    lemmatized token = [lemmatizer.lemmatize(token) for token in tokens if token.isalnum()]
    tokencomp.append([token for token in lemmatized token if token not in stopwords.words('english')])
comp = []
for review in tokencomp:
    comp.append(" ".join(review))
vectorizer = TfidfVectorizer(ngram range = (1,2), min df = 2)
vectorizer.fit(comp)
train x = vectorizer.transform(training x)
test x = vectorizer.transform(testing x)
```

Model Code

Naive Bayes

```
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import accuracy_score
NBmodel = MultinomialNB()

NBmodel.fit(train_x, train_y)
y_pred_NB = NBmodel.predict(test_x)

acc_NB = accuracy_score(test_y, y_pred_NB)
print("Naive Bayes model Accuracy:: {:.2f}%".format(acc_NB*100))
```

Naive Bayes model Accuracy:: 73.97%

Logistic Model

```
from sklearn.linear_model import LogisticRegression
Logitmodel = LogisticRegression()

Logitmodel.fit(train_x, train_y)
y_pred_logit = Logitmodel.predict(test_x)

acc_logit = accuracy_score(test_y, y_pred_logit)
print("Logit model Accuracy:: {:.2f}%".format(acc_logit*100))
```

Logit model Accuracy:: 84.99%

Random Forest Model Accuracy: 63.75%

SVM model Accuracy: 88.45%

Random Forest

```
from sklearn.ensemble import RandomForestClassifier

RFmodel = RandomForestClassifier(n_estimators=50, max_depth=6, bootstrap=True, random_state=0)

RFmodel.fit(train_x, train_y)
y_pred_RF = RFmodel.predict(test_x)

acc_RF = accuracy_score(test_y, y_pred_RF)
print("Random Forest Model Accuracy: {:.2f}%".format(acc_RF*100))
```

SVC Model

```
from sklearn.svm import LinearSVC
SVMmodel = LinearSVC()

SVMmodel.fit(train_x, train_y)
y_pred_SVM = SVMmodel.predict(test_x)

acc_SVM = accuracy_score(test_y, y_pred_SVM)
print("SVM model Accuracy: {:.2f}%".format(acc_SVM*100))
```

Neural Network

```
from sklearn.neural network import MLPClassifier
DLmodel = MLPClassifier(solver='lbfgs', hidden layer sizes=(3,2), random state=1)
DLmodel.fit(train x, train y)
y pred DL= DLmodel.predict(test x)
acc DL = accuracy score(test y, y pred DL)
print("DL model Accuracy: {:.2f}%".format(acc DL*100))
DL model Accuracy: 74.24%
C:\Users\sthoy\anaconda3\lib\site-packages\sklearn\neural network\ multilayer perceptron.py:500: ConvergenceWarning: lbfgs fail
ed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
Increase the number of iterations (max iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
  self.n iter = check optimize result("lbfgs", opt res, self.max iter)
```

Recurring Neural Network

```
import numpy as np
docs x = []
docs train x = []
docs test x = []
for review in training x:
    docs x.append(nltk.word tokenize(str(review).lower()))
    docs train x.append(nltk.word tokenize(str(review).lower()))
for review in testing x:
    docs x.append(nltk.word tokenize(str(review).lower()))
    docs test x.append(nltk.word tokenize(str(review).lower()))
from collections import Counter
words = [j for i in docs x for j in i]
count words = Counter(words)
total words = len(words)
sorted words = count words.most common(total words)
vocab to int = {w: i+1 for i, (w,c) in enumerate(sorted words)}
text int = []
for i in docs train x:
    r = [vocab to int[w] for w in i]
    text int.append(r)
text test int = []
for i in docs test x:
    r = [vocab_to_int[w] for w in i]
    text test int.append(r)
```

```
from keras.preprocessing import sequence
from keras.models import Sequential
from keras.layers import Dense, Embedding, Flatten
from keras.layers import LSTM
max features = total words
maxlen = 250
batch size = 32
x train = sequence.pad sequences(text int, maxlen=maxlen)
x test = sequence.pad sequences(text test int, maxlen=maxlen)
encoded train = [0 if label == 'Sony' else 1 if label == "Nintendo" else 2 if label == "Microsoft" else 3 if label == "Arcade" els
encoded test = [0 if label == "Sony" else 1 if label == "Nintendo" else 2 if label == "Microsoft" else 3 if label == "Arcade" else
model = Sequential()
model.add(Embedding(max features, 20, input length=maxlen))
model.add(LSTM(100, dropout=0.10, recurrent dropout=0.10))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='categorical crossentropy', optimizer='adam', metrics=['accuracy'])
model.fit(x train.tolist(), encoded train, batch size=batch size, epochs=2, validation data=(x test.tolist(), encoded test))
```

Information Gain (Full Chart)

Brand	Man	ual	Classification		NaI	Classification	I
	Manually Typed	Total	Classfied Number(TP)	Total(Test)	Manual Rate	Classification Rate	Information Gain
Sony	549	1012	226	235	54%	96%	77.28%
Nintendo	558	755	173	195	74%	89%	20.04%
Microsoft	593	643	147	157	92%	94%	1.53%
Arcade	74	177	43	46	42%	93%	123.59%
Meta	24	44	4	14	55%	29%	-47.62%
Total	1798	2631	593	647	68%	92%	34.12%
Others excluded (Number of observations: 380)							