soc128d_notebook_4_visualizing_sentiment_and_more_using_the_empath

July 7, 2021

Sociology 128D: Mining Culture Through Text Data: Introduction to Social Data Science

1 Notebook 4: Visualizing Sentiment and More using the Empath Library

1.1 Sentiment Analysis and Dictionary Methods using `Empath`

Dictionary methods are among the most straightforward of methods for computational text analysis. A "dictionary" or "lexicon" in this sense is a list of words that we have decided in advance are related to a given topic, or "lexical category," like positive sentiment. To use these dictionaries, we count the words in a given document that are in that dictionary, often taking into account that longer documents aren't necessarily more positive or negative in a meaningful way by virtue of having more words. If we have a list of positive words and a list of negative words, and more words from the first list are in a document, we might say the document is positive. (Sentiment analysis is not restricted to dictionary methods, but that's where we'll start.)

In this notebook, we will learn to use dictionary methods for sentiment analysis and for more general exploration of topics in social media posts using `pandas`, `seaborn`, and Python's `Empath` library. You can read more about this library in the original paper here. Researchers commonly use paid sets of dictionaries like those available from LIWC, which we saw in the Paxton et al. (2020) reading for this week. However, the original paper behind `Empath` suggests that similar categories are correlated with LIWC. `Empath` offers 194 lexical categories in total–and it's free! Another benefit is the ease of creating custom dictionaries. To do this, you simply provide a set of seed words, and `Empath` will identify similar words to fill out the dictionary for you. (We'll talk more about how that works later.)

We will consider a few ways to use dictionary methods to analyze social processes. To do this, we're going to use a corpus of posts to Reddit's r/jobs message board between January 1 and December 31, 2020. Specifically, we will consider relationships like the following:

how and when people interact with social media (time of day, day of week)

how time relates to content and engagement (e.g., the number of replies or upvotes)

the relationship between content and engagement

`<li>relationships among different types of content (specifically, lexical categories, including`

More generally, we will consider how these relate to **social processes** and **social institutions**. For example, do users submit content to r/jobs less frequently during standard working hours, or perhaps take the weekends off from posting?

The standard work day and standard work week exert considerable influence on the organization of social life. It makes sense that people working a standard schedule might feel a bit buoyed on the weekend. But what about people who work different hours, or who aren't working? Young and Lim (2014) find that both working and unemployed individuals experience similar changes in subjective wellbeing throughout the course of the week. Both groups report greater wellbeing on weekends. Young and Lim argue that how people experience the rhythm of the week depends on the availability of other people as much as it does on just having time to do things (roughly speaking). That extends to the opportunities that exist based on formal and informal sanctions. Think about how opportunties are shaped by the day of the week. Places of business are often open later on weekends, for example. Now consider how our time-based expectations become entrenced and moralized. People who do shift work often get judged for having a drink after work when "after work" is early in the morning.

We might also use these data to ask questions like whether users writing about a certain topic also tend to write about another topic or set of topics, and we can come up with hypotheses for why we might observe certain associations.

First, we will import the libraries we need for the analyses we'll run.

[1]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import pingouin
import re
import seaborn as sns
import spacy
import time
import warnings

from empath import Empath
from scipy.stats import pearsonr

%matplotlib inline

warnings.filterwarnings("ignore") # comment out this line to see warnings

sns.set_theme(style="darkgrid")

# python -m spacy download en_core_web_sm
```

[2]:
```
def quick_r(x: str, y: str, df: pd.core.frame.DataFrame) -> str:
    """
    Returns (as a str) the Pearson's correlation coefficient
    with the p-value or asterisks for significant correlations
    *p<0.05, **p<0.01, ***p<0.001
```

```
    """
    tmp = df[[x, y]].dropna()
    r, pval = pearsonr(tmp[x], tmp[y])
    if pval < 0.001:
        r = f"{r:.2f}***"
    elif pval < 0.01:
        r = f"{r:.2f}**"
    elif pval < 0.05:
        r = f"{r:.2f}*"
    else:
        r = f"{r:.2f} (p = {pval:.2f})"
    return r
```

Next, we will load the corpus.

r/jobs provides the following description:

We aim to empower job seekers and employees through the promotion of their best interests, advice and encouragement.

Where is the corpus from? I pulled ~150 posts to Reddit's r/jobs community per day from pushshift.io's API for each day in 2020. Many thanks for the work they do to make data available! I have cleaned this corpus already. It includes 49,872 posts in total. The variables include the submission's score ("karma" or "upvotes"), the number of replies, the title of the submission, the text of the submission, and various markers of time. Specifically, I have included the date ("date") and separate variables for the day of the month (1-31), day of the week (as integers 0-6 and strings "Sunday" to "Monday"), day of the year (0-365, as it was a leap year!), week of the year, and the hour (0-23). Although Reddit allows for relative anonymity through the use of usernames/handles, I have provided an ID field ("author_id") in place of the username of the author.

```
[3]: df = pd.read_json("jobs_2020_clean_with_lex.json")
```

Let's take a quick look at the data. We'll get to an example post and some analyses of the content, but it's important to first have a sense of what the dataset is like overall.

```
[4]: df.head()
```

```
[4]:        id  author_id  score  num_comments  \
68263   0     114337      1            24
58753   1     455681      1             3
49469   2     711804      1             4
6681    3     971458      1             2
16847   4      90142      1             2

                                                   title  \
68263        I messed up an application for my dream job
58753  Hiring Managers, how common is it for an inter…
49469    Consulting agency - Sr. Associate role meaning?
6681                         How to get that interview in 2020
```

```
16847  How to be less nervous when talking on the pho…

                                                    selftext  \
68263  I found my dream job, its a social impact job …
58753  I nearly forgot to send a thank you email afte…
49469  Hello!\n\nI recently accepted a position as a …
6681   Hello, I'm a professional, and a Certified Res…
16847  Hi everyone!\n\nI landed a great job starting …

                                                        text       date  \
68263  I messed up an application for my dream job\n … 2020-12-15
58753  Hiring Managers, how common is it for an inter… 2020-10-16
49469  Consulting agency - Sr. Associate role meaning… 2020-08-27
6681   How to get that interview in 2020\n Hello, I'm… 2020-02-01
16847  How to be less nervous when talking on the pho… 2020-03-14

       dayofyear  hour  …  children  monster  ocean    giving contentment  \
68263        350     0  …  0.017857      0.0    0.0  0.053571         0.0
58753        290    22  …  0.000000      0.0    0.0  0.111111         0.0
49469        240    22  …  0.000000      0.0    0.0  0.034483         0.0
6681          32    15  …  0.000000      0.0    0.0  0.054545         0.0
16847         74    13  …  0.000000      0.0    0.0  0.044444         0.0

        writing rural  positive_emotion   musical  posts_that_day
68263  0.071429   0.0          0.000000  0.000000             180
58753  0.111111   0.0          0.000000  0.000000             172
49469  0.000000   0.0          0.000000  0.000000             188
6681   0.027273   0.0          0.000000  0.009091             181
16847  0.000000   0.0          0.066667  0.000000              90

[5 rows x 212 columns]
```

`.shape` provides the number of rows (posts) first, followed by the number of columns (variables)

[5]:
```
df.shape
```

[5]:
```
(49872, 212)
```

[6]:
```
print(f"{df.shape[0]:,} rows and {df.shape[1]} columns.")
```

```
49,872 rows and 212 columns.
```

1.2 Sample Posts

[7]:
```
sample = df.sample(3)
for _, row in sample.iterrows():
    print(row["text"], "\n\n")
```

Why would an employer call after rejecting a job applicant?
Hello,

So I applied for a job.

It is similar to the one I currently have but I had enough of the place I am working at and the new management. I don't mean to brag but I am excellent at what I do and my yearly employee review is always high. I have been working there for 7 years.

I have a problem that I suck at interviews.
I feel nervous and forget what I wanna say. So no employer will know how good I am till I actually work with them.

I did the interview. as usual, it was terrible . it seemed they weren't gonna take me. I was right and I got automated email few days ago that they found another candidate.

Only to have somebody leaving a voice mail from the other employer the very next day because they opened another position and they wanna talk to me about it.

2 issues:
1. I have a year left to get my degree , find a job and leave. I am not planning to stay at any either of them.
The degree is related to the work I am doing but I know they will not have a position ready for one of their employees because I saw ot happen to somebody else before.

So do i stay at my current job or go for the other one and start all over again?

2. I am worried because I think the other job will be worse than the one I have now. Why would they call me after not wanting ro take me in?
I think they are desperate and look for anyone to take in.

Any advise is appreciated

What kind of job title would this fall under?
Currently operating machinery in a factory and it is s-s-shit!

I'm after another job, and even if I don't end up there at first, I'd at least like to know what pathway I should take.

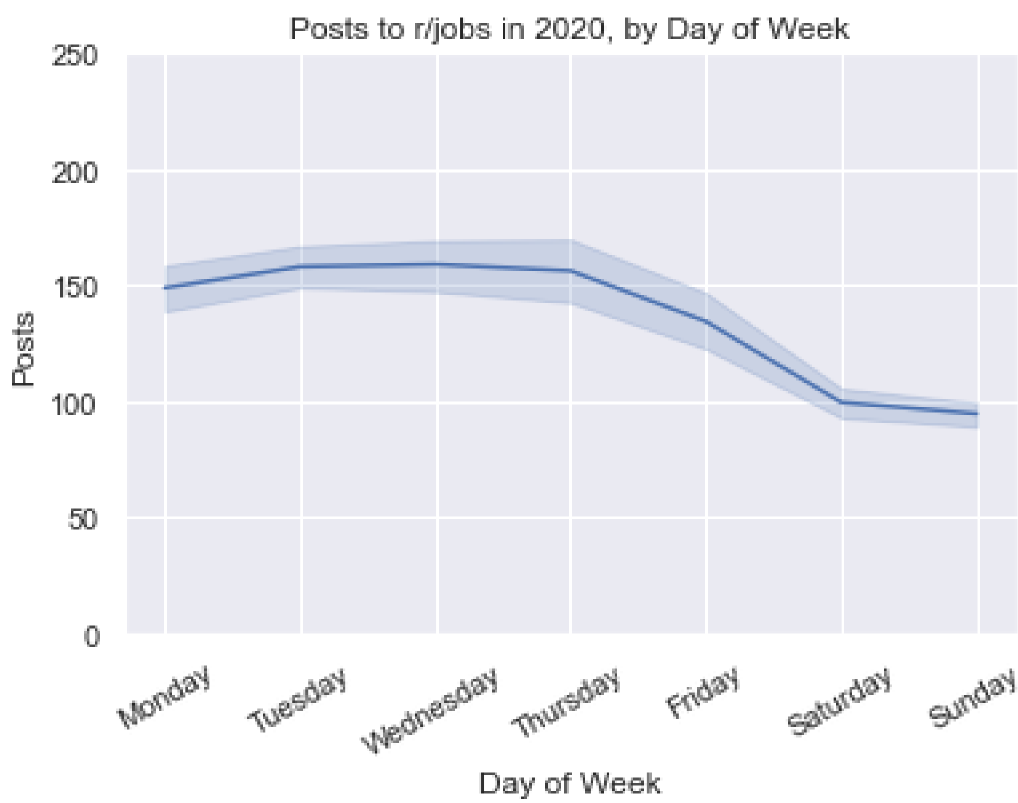
What kind of job would require someone to maintain physical servers/computers,

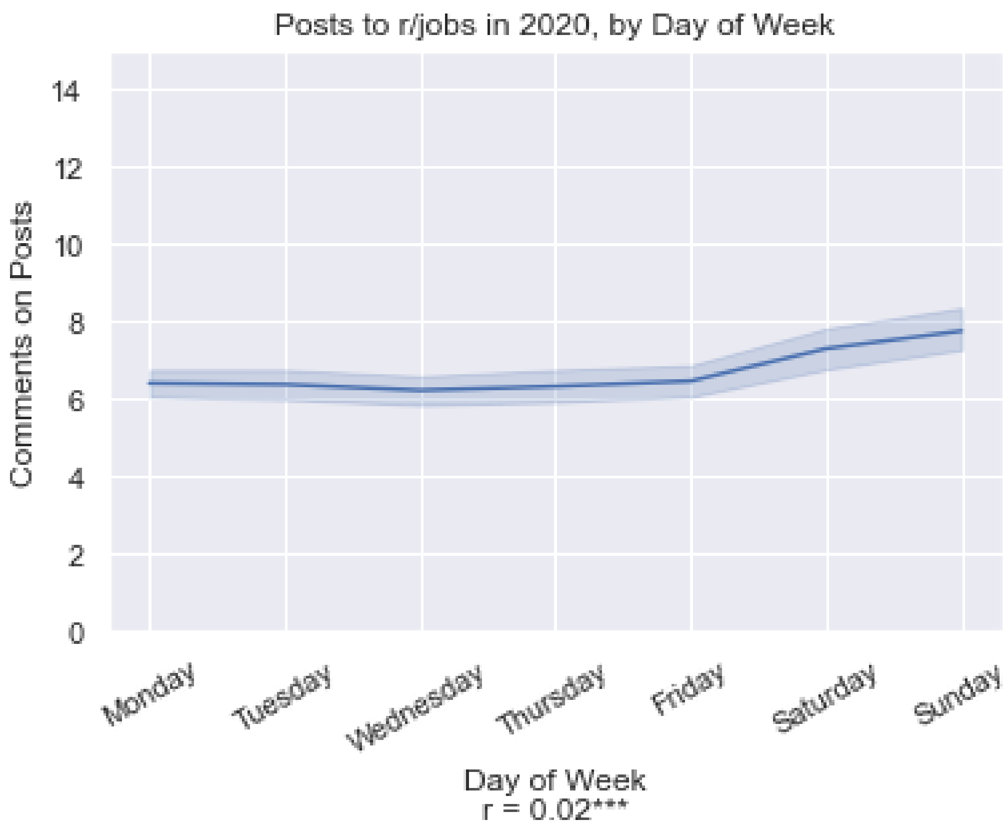
```
upgrade components, fix issues that arrise, cable management, network
configuration, etc.

I have no formal qualifications in that area but I am personally experienced in
doing those sorts of tasks on a small scale and in a personal capacity, so I
somewhat know what I'm going for.


A degree saved my life! I was rejected from Tesco asda and primark? At
application stage
 Hey this just crossed my mind

But many years when I tried applying for my first jobs. I didn't get it

I applied to Tesco and primark and took their psychometric questionnaire and I
guess I kept failing
I didn't even get to one interview

I remember I applied for multiple posts
Like delivery, night shift

At this time I didn't have a degree
I can't imagine what I would have done in my life if I couldn't get a retail job

And when it came to getting a job in my field well it wasn't as hard as getting
one for Tesco or primark

What's the secret
```

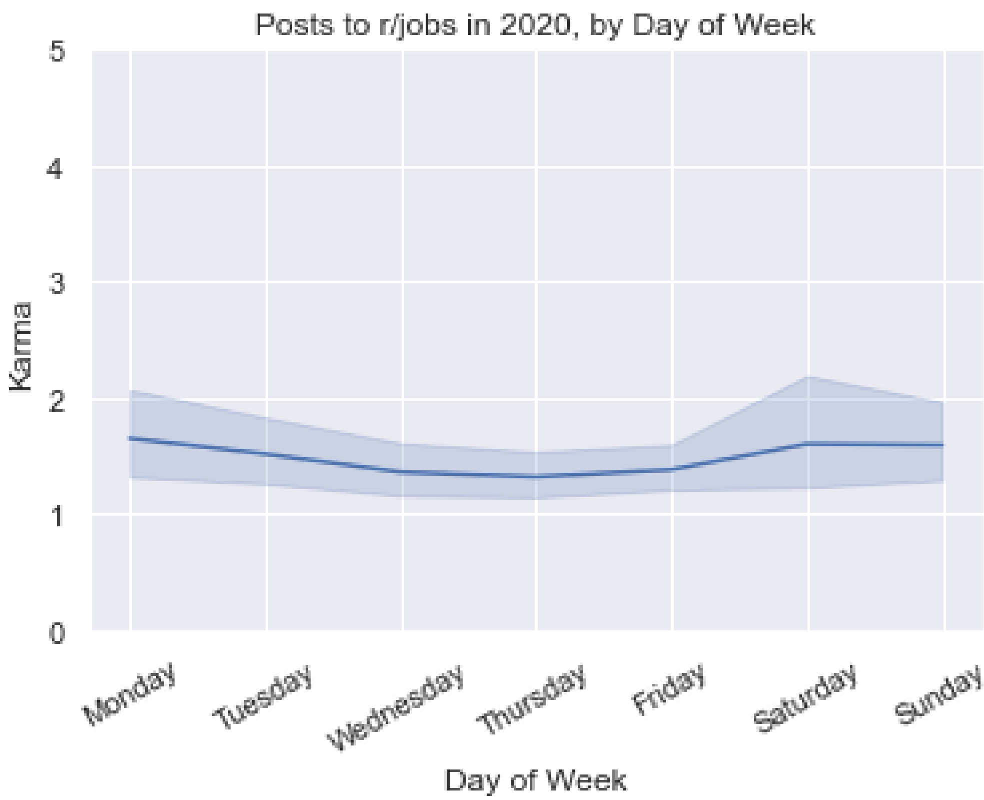
1.2.1 First, let's examine whether there seem to be general trends over the course of the week in the number of posts, the number of comments on posts, and how well posts do ("karma" or "upvotes").

[8]:
```python
daysofweek = ["Monday", "Tuesday", "Wednesday", "Thursday", "Friday",␣
 ↪"Saturday", "Sunday"]

sns.lineplot(x="dayofweek", y="posts_that_day", ci=95,
             data=df[["dayofweek", "date", "posts_that_day"]].groupby("date").
 ↪mean())
plt.title("Posts to r/jobs in 2020, by Day of Week")
plt.ylabel("Posts")
plt.ylim(0, 250)
plt.xticks(ticks=range(0,7), labels=daysofweek, rotation=30)
plt.xlabel("Day of Week")
plt.show()
```

```
plt.title("Posts to r/jobs in 2020, by Day of Week")
sns.lineplot(x="dayofweek", y="num_comments", data=df, ci=95) # sem
plt.ylabel("Comments on Posts")
plt.ylim(0, 15)
plt.xticks(ticks=range(0,7), labels=daysofweek, rotation=30)
plt.xlabel(f"Day of Week\nr = {quick_r('dayofweek', 'num_comments', df)}")
plt.show()

plt.title("Posts to r/jobs in 2020, by Day of Week")
sns.lineplot(x="dayofweek", y="score", data=df, ci=95) # sem
plt.ylabel("Karma")
plt.ylim(0, 5)
plt.xticks(ticks=range(0,7), labels=daysofweek, rotation=30)
plt.xlabel(f"Day of Week")
plt.show()
```

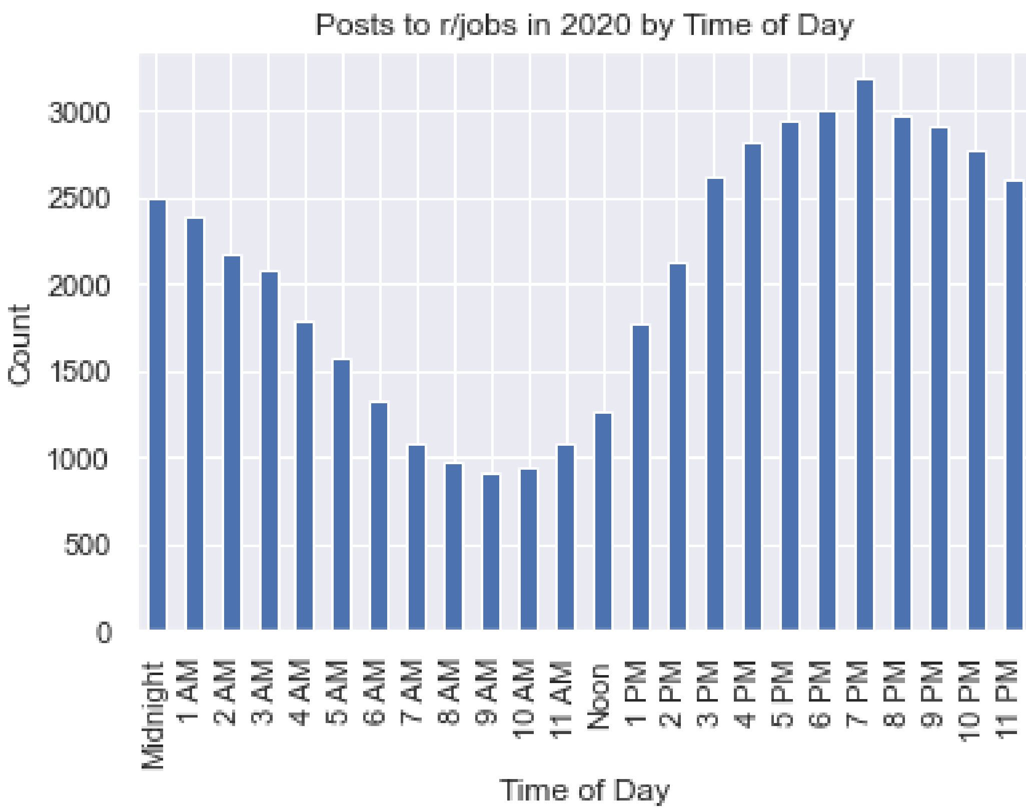



Posts to r/jobs in 2020, by Day of Week
Comments on Posts
14
12
10
8
6
4
2
0
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
Day of Week
r = 0.02***



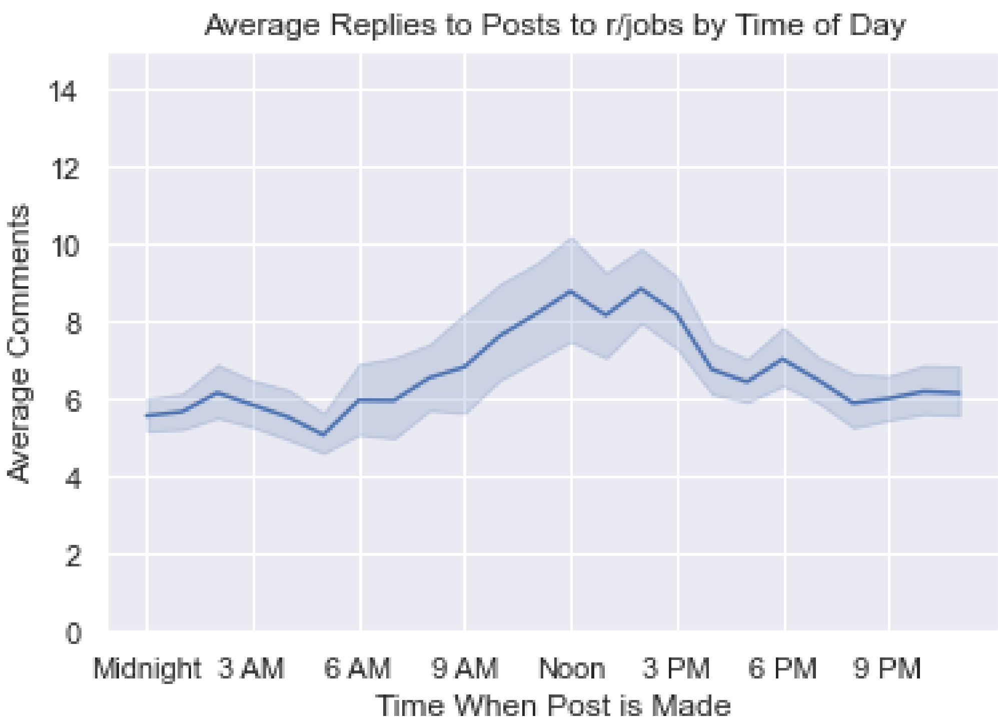
1.2.2 Now let's examine whether there is substantial variation over the course of the day.

[9]:
```
hours = ["Midnight"] + [f"{i} AM" for i in range(1,12)] + ["Noon"] + [f"{i-12}␣
↪PM" for i in range(13,24)]

df["hour"].value_counts().loc[list(range(24))].plot(kind="bar")
plt.xticks(ticks=list(range(24)), labels=hours)
plt.title("Posts to r/jobs in 2020 by Time of Day")
plt.ylabel("Count")
plt.xlabel("Time of Day")
plt.show()
```

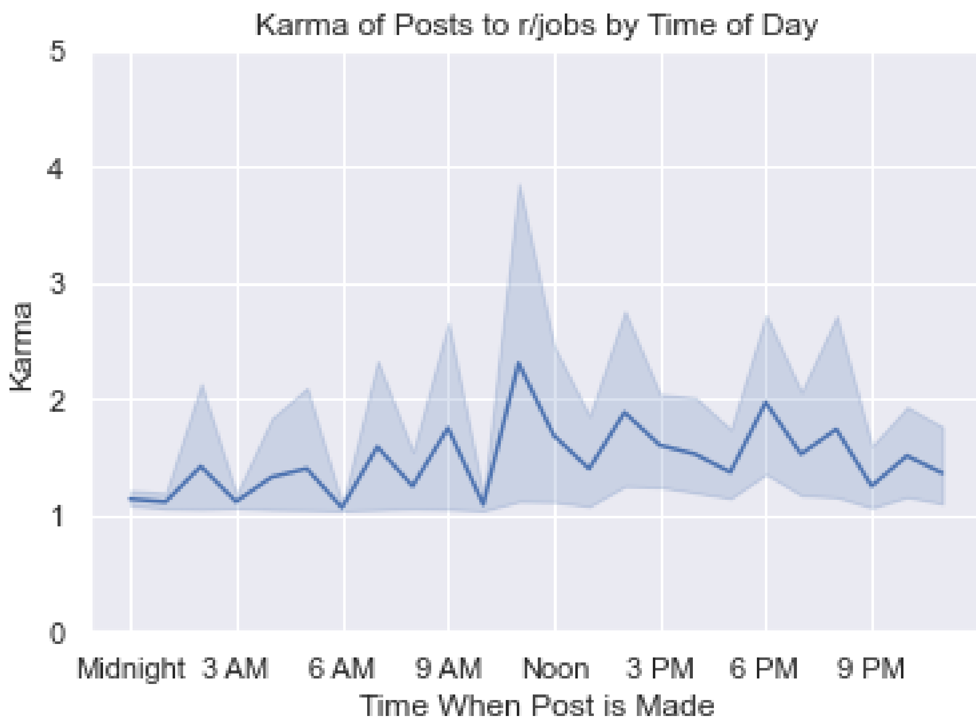


[10]:

```
hours = ["Midnight"] + [f"{i} AM" for i in range(1,12)] + ["Noon"] + [f"{i-12}␣
↪PM" for i in range(13,24)]

sns.lineplot(x="hour", y="num_comments", data=df, ci=95)
plt.title("Average Replies to Posts to r/jobs by Time of Day")
plt.xticks(ticks=range(0,24,3), labels=hours[::3])
plt.xlabel("Time When Post is Made")
plt.ylabel(f"Average Comments")
plt.ylim(0, 15)
plt.show()
```

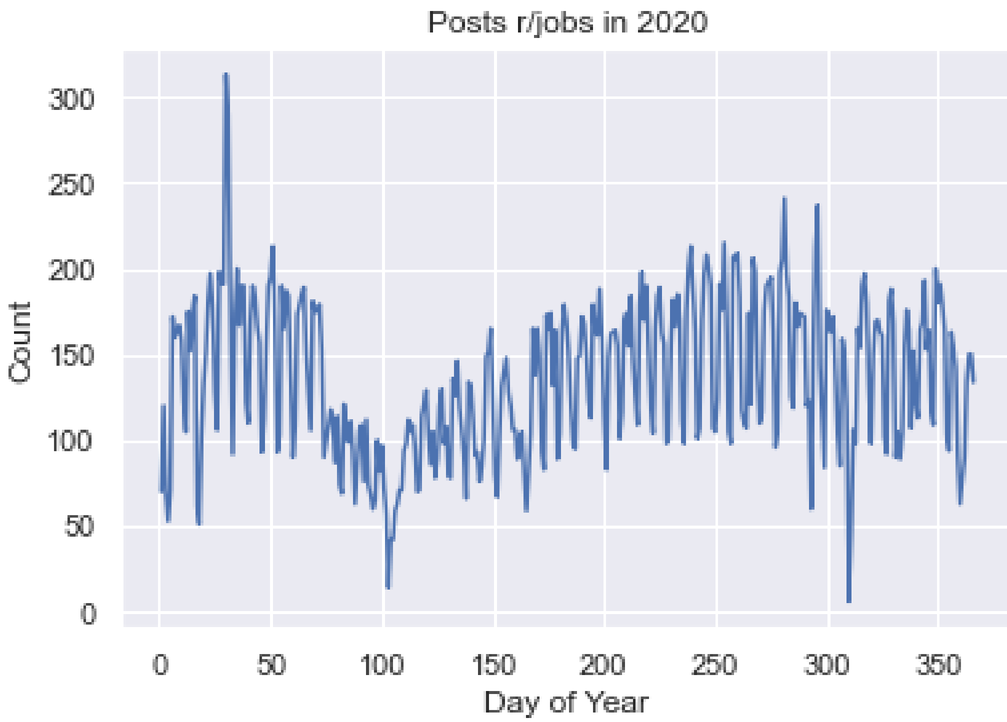



```
[11]: hours = ["Midnight"] + [f"{i} AM" for i in range(1,12)] + ["Noon"] + [f"{i-12}␣
      ↪PM" for i in range(13,24)]

      sns.lineplot(x="hour", y="score", data=df)
      plt.title("Karma of Posts to r/jobs by Time of Day")
      plt.xticks(ticks=range(0,24,3), labels=hours[::3])
      plt.xlabel("Time When Post is Made")
      plt.ylabel("Karma")
      plt.ylim(0, 5)
      plt.show()
```

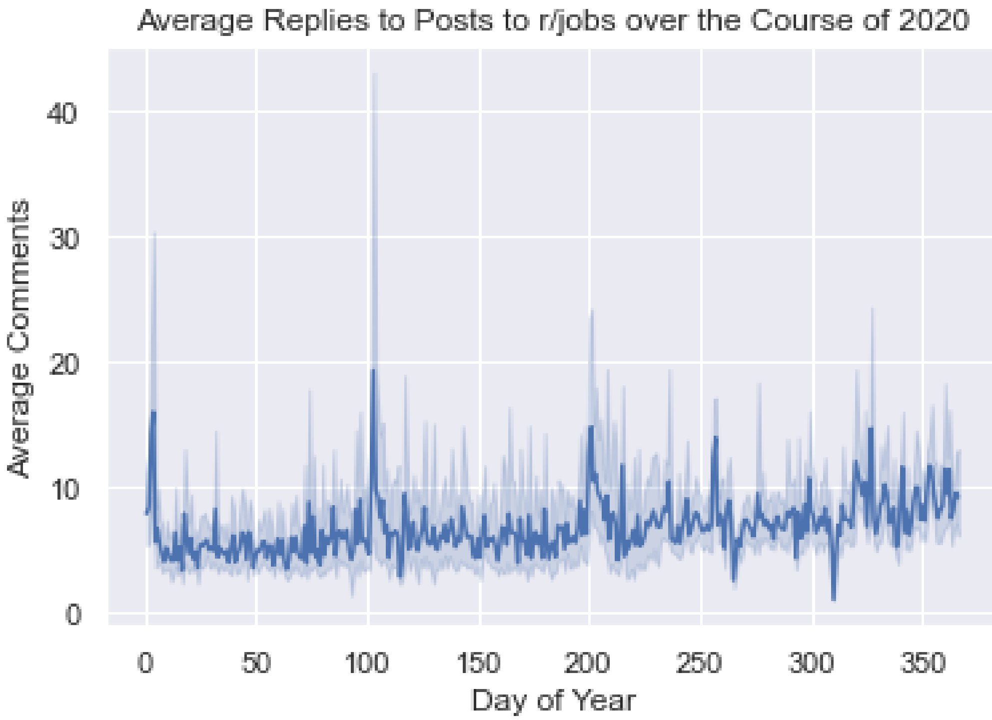


1.2.3 How about variation over the course of the year?

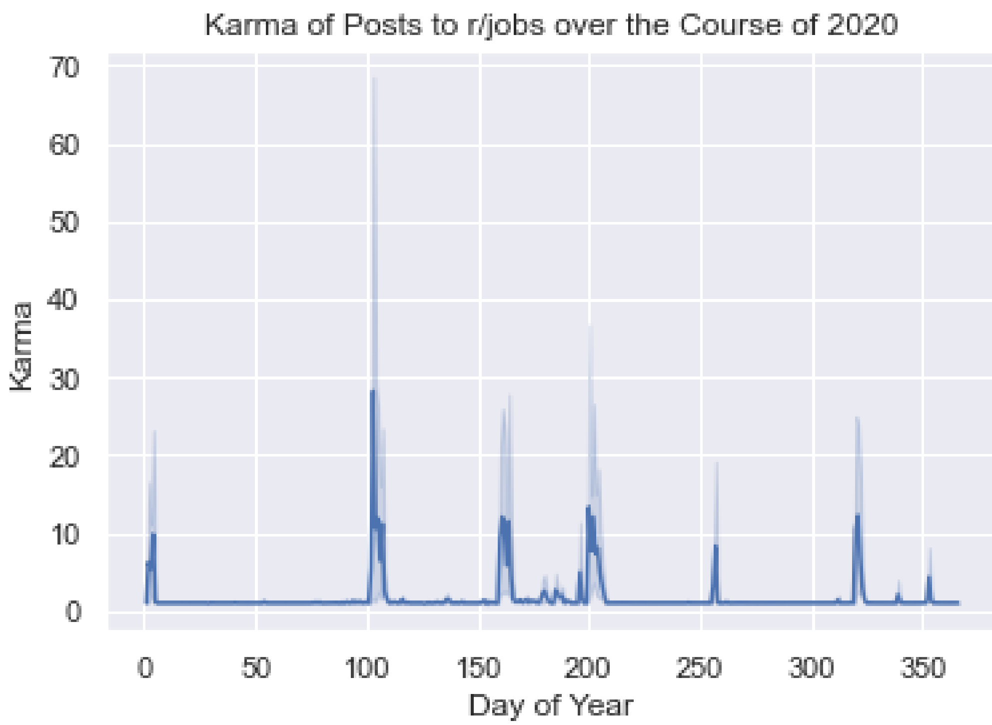
[12]:
```
df["dayofyear"].value_counts().loc[list(range(1,367))].plot(kind="line")
plt.title("Posts r/jobs in 2020")
plt.ylabel("Count")
plt.xlabel("Day of Year")
plt.show()
```



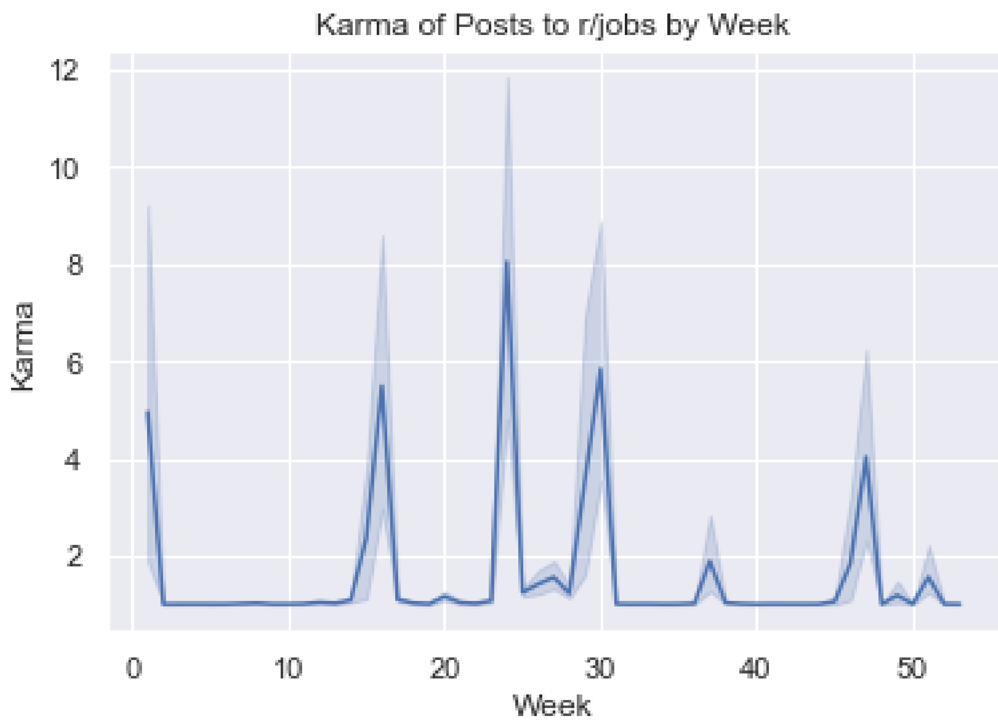
[13]:
```
sns.lineplot(x="dayofyear", y="num_comments", data=df, ci=95)
plt.title("Average Replies to Posts to r/jobs over the Course of 2020")
plt.xlabel("Day of Year")
plt.ylabel("Average Comments")
plt.show()
```



[14]:
```
sns.lineplot(x="dayofyear", y="score", data=df, ci=95)
plt.title("Karma of Posts to r/jobs over the Course of 2020")
plt.xlabel("Day of Year")
plt.ylabel("Karma")
plt.show()
```



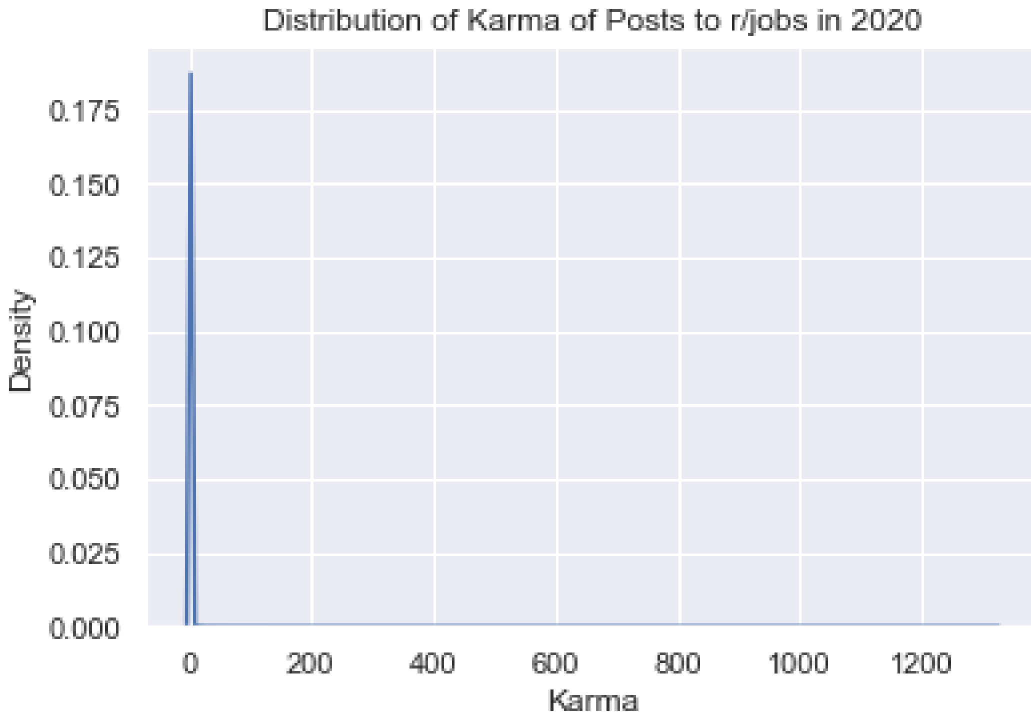
[15]:
```python
sns.lineplot(x="week", y="score", data=df, ci=95)
plt.title("Karma of Posts to r/jobs by Week")
plt.xlabel("Week")
plt.ylabel("Karma")
plt.show()
```



We see quite a bit variation with respect to time in these graphs. Based on these data, it looks like users most frequently post to r/jobs early in the week but take a break on the weekend, yet the average number of replies is higher on the weekend (perhaps due to the lack of new posts). Most posts are made in the afternoon of evening, peaking around 7 PM. The posts that earn the most karma and get the most replies are made around noon. There are days over the course of 2020 when there is a lot more activity. That could be an issue with the dataset, or there could be something sociologically interesting about those days.

Let's take a quick look at the distribution of scores and then dive into sentiment.

[16]:
```
sns.kdeplot("score", data = df)
plt.title("Distribution of Karma of Posts to r/jobs in 2020")
plt.xlabel("Karma")
plt.show()
```



This distribution highly skewed. Let's take a look at an outlier. We'll look for the post with the highest score.

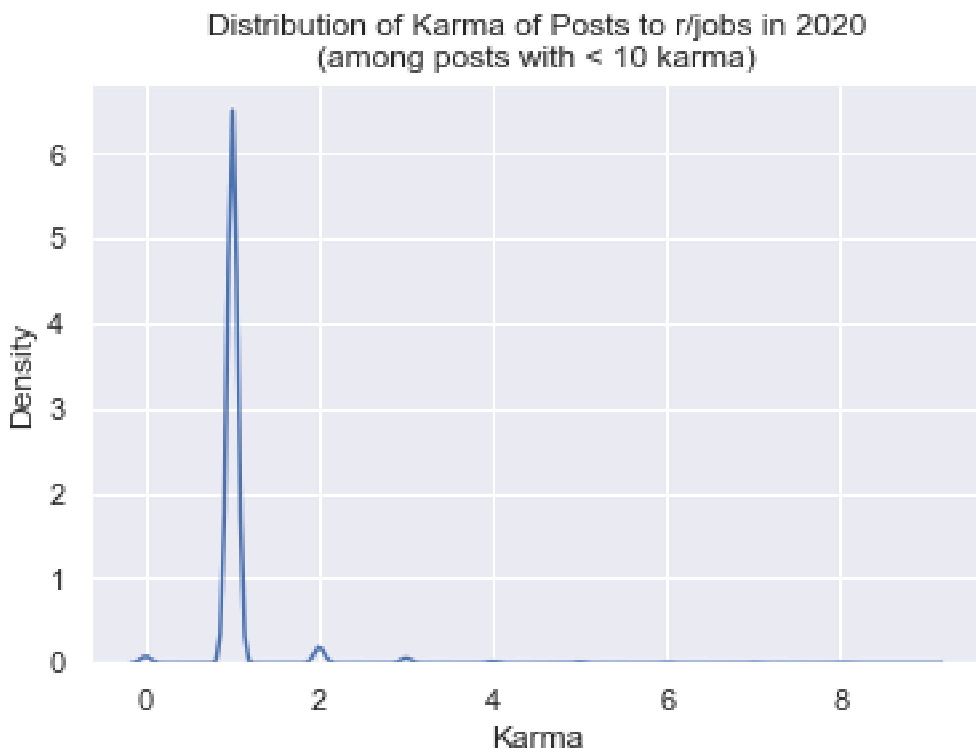
[17]:
```
print(df[df["score"]==df["score"].max()]["text"].values[0])
```

```
I was contacted by a recruiter. Gave a low ball salary at $80k. I declined just
because it was going to be a 1 hour+ commute, which is longer than my current 1
hour commute. Then he comes back with the real salary range is $100k-$120k.
Don't do this if you're a recruiter.
 I really did decline because of the commute. The low salary for the level of
work, responsibility, and liability was not an $80k job. Even $120k is the low
side. The job is in an economically depressed area and given the current job
market, I'm sure they think they'll find someone desperate to fill it.

I also know the job has been open for at least three weeks. I'm guessing that's
why they reached out to me widening their search radius.

I know business is business. But wtf? Trying to undercut someone's salary by
33%? That's just crooked robbery. Be careful right now. Know your worth. Know
your industry. Know the job market. There's scavengers out there.

Edit: lots of people asking - I'm an environmental scientist working in the
realm of Environment, Health, and Safety. The job was a small-mid size Midwest
town. I work in a large city. I have 15 years experience. When I started in this
```

```
industry, it was as a tech making $28k/yr. I have a B.S. Took lots of different
jobs, more responsibility, different companies.

And here I am. I will say, my path has not been normal, but it's not unheard of.
```

Let's zoom in and see what the distribution looks like without some of the posts in the long right tail.

[18]:
```
sns.kdeplot("score", data = df[df["score"] < 10])
plt.title("Distribution of Karma of Posts to r/jobs in 2020"
          "\n(among posts with < 10 karma)")
plt.xlabel("Karma")
plt.show()
```



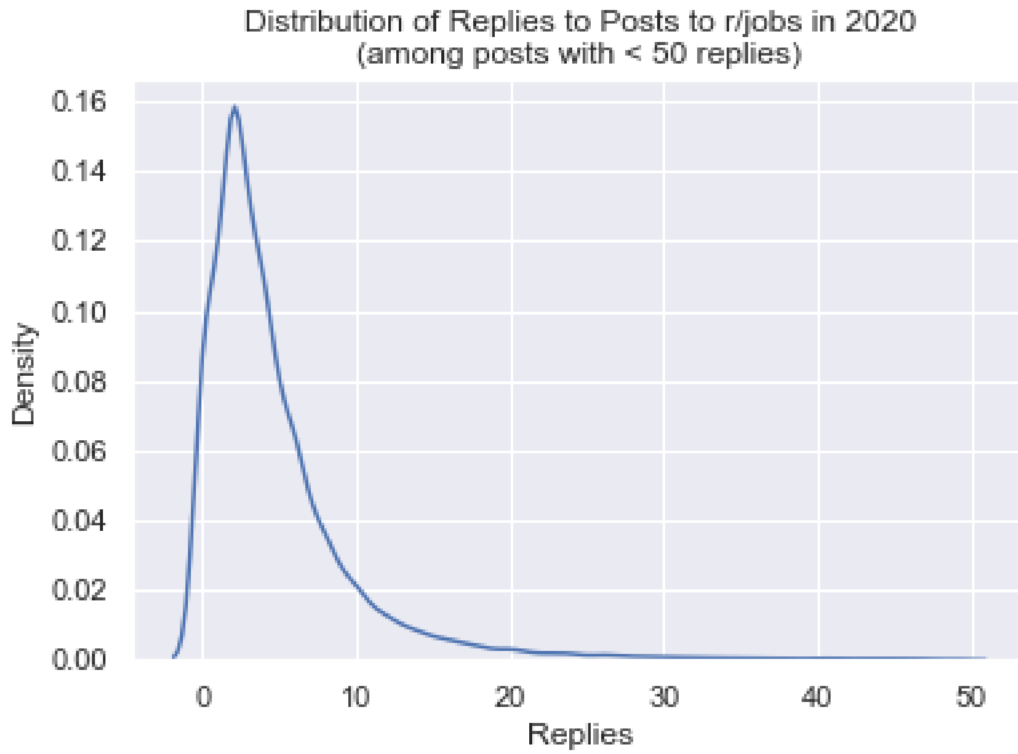
It seems like the data are clustered pretty tightly around 1 karma, which is where a post starts. Let's see how many posts have something other than 1 karma and look at the distribution of replies.

[19]:
```
df[df["score"]!=1].shape
```

[19]: (3032, 212)

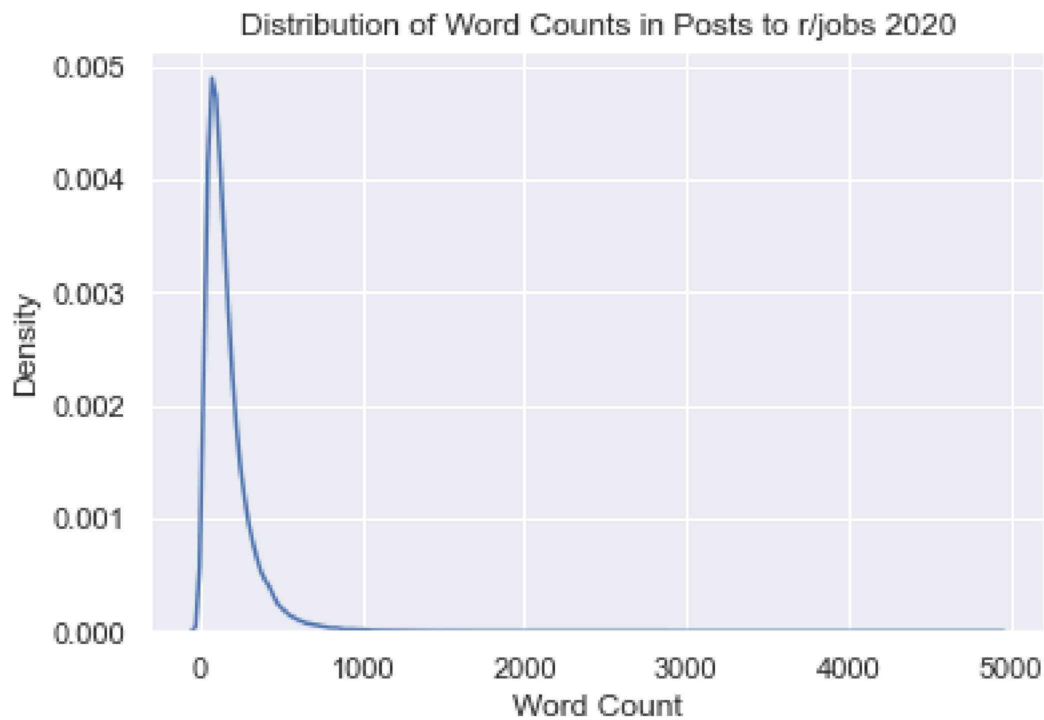
[20]:
```
sns.kdeplot("num_comments", data = df[df["num_comments"] < 50])
plt.title("Distribution of Replies to Posts to r/jobs in 2020"
          "\n(among posts with < 50 replies)")
```

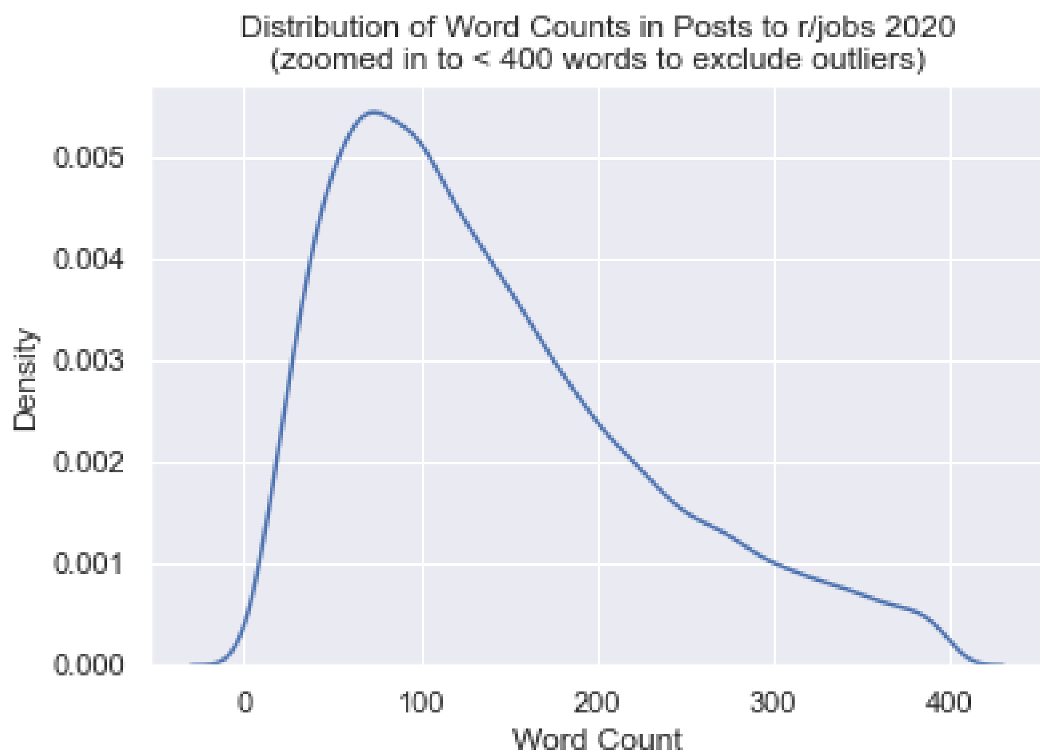
```
plt.xlabel("Replies")
plt.show()
```



We also know that people write posts of different lengths. The length of a post could be related to the score, to the topics someone discusses, or other factors.

[21]:
```
df["word_count"] = df["text"].apply(lambda x: len(x.split()))

sns.kdeplot(df["word_count"])
plt.title("Distribution of Word Counts in Posts to r/jobs 2020")
plt.xlabel("Word Count")
plt.show()

sns.kdeplot(df[df.word_count < 400]["word_count"])
plt.title("Distribution of Word Counts in Posts to r/jobs 2020"
         "\n(zoomed in to < 400 words to exclude outliers)")
plt.xlabel("Word Count")
plt.show()
```


Distribution of Word Counts in Posts to r/jobs 2020
Density
0.005
0.004
0.003
0.002
0.001
0.000
0
1000
2000
3000
4000
5000
Word Count


Distribution of Word Counts in Posts to r/jobs 2020
(zoomed in to < 400 words to exclude outliers)
Density
0.005
0.004
0.003
0.002
0.001
0.000
0
100
200
300
400
Word Count

[22]:
```
df[["score", "num_comments", "word_count"]].describe()
```

[22]:

	score	num_comments	word_count
count	49872.000000	49872.000000	49872.000000
mean	1.474515	6.581990	170.777530
std	12.838286	18.050039	156.728332
min	0.000000	0.000000	1.000000
25%	1.000000	2.000000	75.000000
50%	1.000000	3.000000	129.000000
75%	1.000000	6.000000	215.000000
max	1322.000000	673.000000	4903.000000

[23]:
```
df[["score", "num_comments", "word_count"]].rcorr()
```

[23]:

	score	num_comments	word_count
score	-	***	*
num_comments	0.32	-	***
word_count	0.01	0.025	-

[24]:
```
print(df[df["word_count"]<75].sample(1)["text"].values[0])
```

```
Question
 Has anyone ever worked for a Malloy car dealer in the northern VA area? Is it
as shitty as Glassdoor and Indeed say it is?
```

[68]:
```
print(df[df["word_count"]>215].sample(1)["text"].values[0])
```

```
how to get employee to be self-sufficient.
 i have a new employee (only employee) that i can't seem to motivate to do
things without being asked. it's frustrating because i feel like i have to
micromanage them.

we manufacture products as part of our services. i will usually ask them to do a
task such as 'cut these pieces for these people' . they will do this but then
won't naturally go into the next step of the process without me asking them to
five minutes later.

there are steps of the process that only i can do. so i would expect that while
i do these tasks they would start to prepare the next step. but they don't. they
stand there and do nothing until i ask them. at that point it would be the same
as me doing every task. i will usually wait a few minutes to give them an
opportunity before asking yhem to cut the next pieces. then they cut them and
stand again. so i have to stop and ask them to do the next step.

i'm not quite sure what i am missing here. i thought at first it was lack of
experience but it's been over a month.

is there another way for me to get them to work? is this me? are they just lazy?
i find that they do a lot of standing around while i work. in my downtime i try
```

```
to clean because things can always be done.

they are my only employee and are on a contract for two more months but at this
point i do not feel like hiring anyone. ever. again.
```

1.3 Using the Empath library

Now let's move on to analyzing posts using dictionary methods via the `Empath` library. We'll create the object `lexicon` that will analyze posts using 194 separate dictionaries, which range from positive or negative emotion to topics as diverse as optimism, terrorism, fashion, and eating.

[26]:
```
lexicon = Empath()
```

[27]:
```
# Number of categories
len(lexicon.cats.keys())
```

[27]:
```
194
```

Lexical categories Provided by Empath

achievement

affection

aggression

air_travel

alcohol

ancient

anger

animal

anonymity

anticipation

appearance

art

attractive

banking

beach

beauty

blue_collar_job

body

breaking

business

car

celebration

cheerfulness

childish

children

cleaning

clothing

cold

college

communication

competing

computer

confusion

contentment

cooking

crime

dance

death

deception

disappointment

disgust

dispute

divine

domestic_work

dominant_heirarchical

dominant_personality

driving

eating

economics

emotional

envy

exasperation

exercise

exotic

fabric

family

farming

fashion

fear

feminine

fight

fire

friends

fun

furniture

gain

giving

government

hate

healing

health

hearing

help

heroic

hiking

hipster

home

horror

hygiene

independence

injury

internet

irritability

journalism

joy

kill

law

leader

legend

leisure

liquid

listen

love

lust

magic

masculine

medical_emergency

medieval

meeting

messaging

military

money

monster

morning

movement

music

musical

negative_emotion

neglect

negotiate

nervousness

night

noise

occupation

ocean

office

optimism

order

pain

party

payment

pet

philosophy

phone

plant

play

politeness

politics

poor

positive_emotion

power

pride

prison

programming

rage

reading

real_estate

religion

restaurant

ridicule

royalty

rural

sadness

sailing

school

science

sexual

shame

shape_and_size

ship

shopping

sleep

smell

social_media

sound

speaking

sports

stealing

strength

suffering

superhero

surprise

swearing_terms

swimming

sympathy

technology

terrorism

timidity

tool

torment

tourism

toy

traveling

trust

ugliness

urban

vacation

valuable

vehicle

violence

war

warmth

water

weakness

wealthy

weapon

weather

wedding

white_collar_job

work

worship

writing

[28]:
```
df["text"] = df["text"].apply(str.lower) # lowercasing the text
```

[70]:
```
example = df.sample(1)
example_text = example["text"].values[0]
print(example_text)
```

```
1 month at job and critiqued daily on how things are done
 i'm in my industry between 5-10 years and i started a new role in a sub
industry i'm not too familiar with. i have no problem getting feedback, but in
this one month there everything i do from the way i send an email to the way i
present something is incorrect and critiqued. every single day. i'm not sure
anymore if i'm a good fit for this company. how long do i give.it before looking
elsewhere or things to turn around?
```

[71]:
```
lexicon.analyze(example_text)
```

[71]:
```
{'help': 0.0,
 'office': 0.0,
 'dance': 0.0,
 'money': 0.0,
 'wedding': 0.0,
 'domestic_work': 1.0,
 'sleep': 0.0,
 'medical_emergency': 0.0,
 'cold': 0.0,
 'hate': 0.0,
 'cheerfulness': 0.0,
 'aggression': 0.0,
 'occupation': 1.0,
 'envy': 0.0,
```

'anticipation': 0.0,
'family': 0.0,
'vacation': 0.0,
'crime': 0.0,
'attractive': 1.0,
'masculine': 0.0,
'prison': 0.0,
'health': 0.0,
'pride': 0.0,
'dispute': 0.0,
'nervousness': 0.0,
'government': 0.0,
'weakness': 0.0,
'horror': 0.0,
'swearing_terms': 0.0,
'leisure': 0.0,
'suffering': 0.0,
'royalty': 0.0,
'wealthy': 0.0,
'tourism': 0.0,
'furniture': 0.0,
'school': 0.0,
'magic': 0.0,
'beach': 0.0,
'journalism': 0.0,
'morning': 0.0,
'banking': 2.0,
'social_media': 1.0,
'exercise': 0.0,
'night': 0.0,
'kill': 0.0,
'blue_collar_job': 1.0,
'art': 0.0,
'ridicule': 0.0,
'play': 0.0,
'computer': 1.0,
'college': 0.0,
'optimism': 0.0,
'stealing': 0.0,
'real_estate': 0.0,
'home': 0.0,
'divine': 0.0,
'sexual': 0.0,
'fear': 0.0,
'irritability': 0.0,
'superhero': 0.0,
'business': 2.0,

'driving': 0.0,
'pet': 0.0,
'childish': 0.0,
'cooking': 0.0,
'exasperation': 0.0,
'religion': 0.0,
'hipster': 1.0,
'internet': 1.0,
'surprise': 0.0,
'reading': 0.0,
'worship': 0.0,
'leader': 0.0,
'independence': 0.0,
'movement': 1.0,
'body': 0.0,
'noise': 0.0,
'eating': 0.0,
'medieval': 0.0,
'zest': 0.0,
'confusion': 0.0,
'water': 0.0,
'sports': 0.0,
'death': 0.0,
'healing': 0.0,
'legend': 0.0,
'heroic': 0.0,
'celebration': 1.0,
'restaurant': 0.0,
'violence': 0.0,
'programming': 1.0,
'dominant_heirarchical': 0.0,
'military': 0.0,
'neglect': 0.0,
'swimming': 0.0,
'exotic': 0.0,
'love': 0.0,
'hiking': 0.0,
'communication': 1.0,
'hearing': 0.0,
'order': 0.0,
'sympathy': 0.0,
'hygiene': 1.0,
'weather': 0.0,
'anonymity': 0.0,
'trust': 0.0,
'ancient': 0.0,
'deception': 0.0,

```
'fabric': 0.0,
'air_travel': 0.0,
'fight': 0.0,
'dominant_personality': 0.0,
'music': 0.0,
'vehicle': 0.0,
'politeness': 0.0,
'toy': 0.0,
'farming': 0.0,
'meeting': 1.0,
'war': 0.0,
'speaking': 0.0,
'listen': 0.0,
'urban': 0.0,
'shopping': 0.0,
'disgust': 0.0,
'fire': 0.0,
'tool': 0.0,
'phone': 0.0,
'gain': 2.0,
'sound': 0.0,
'injury': 0.0,
'sailing': 0.0,
'rage': 0.0,
'science': 0.0,
'work': 3.0,
'appearance': 0.0,
'valuable': 0.0,
'warmth': 0.0,
'youth': 0.0,
'sadness': 0.0,
'fun': 0.0,
'emotional': 0.0,
'joy': 0.0,
'affection': 0.0,
'traveling': 0.0,
'fashion': 0.0,
'ugliness': 0.0,
'lust': 0.0,
'shame': 0.0,
'torment': 0.0,
'economics': 3.0,
'anger': 0.0,
'politics': 0.0,
'ship': 0.0,
'clothing': 0.0,
'car': 0.0,
```

```
 'strength': 0.0,
 'technology': 0.0,
 'breaking': 0.0,
 'shape_and_size': 0.0,
 'power': 0.0,
 'white_collar_job': 1.0,
 'animal': 0.0,
 'party': 1.0,
 'terrorism': 0.0,
 'smell': 0.0,
 'disappointment': 0.0,
 'poor': 1.0,
 'plant': 0.0,
 'pain': 0.0,
 'beauty': 0.0,
 'timidity': 0.0,
 'philosophy': 0.0,
 'negotiate': 0.0,
 'negative_emotion': 0.0,
 'cleaning': 0.0,
 'messaging': 2.0,
 'competing': 0.0,
 'law': 0.0,
 'friends': 0.0,
 'payment': 0.0,
 'achievement': 0.0,
 'alcohol': 0.0,
 'liquid': 0.0,
 'feminine': 0.0,
 'weapon': 0.0,
 'children': 0.0,
 'monster': 0.0,
 'ocean': 0.0,
 'giving': 1.0,
 'contentment': 0.0,
 'writing': 1.0,
 'rural': 0.0,
 'positive_emotion': 0.0,
 'musical': 0.0,
 'stigma': 0.0,
 'YOURCATEGORYNAMEHERE': 0.0}
```

The output is a dictionary: each lexical category is a key and the score is the value. Let's define a function to print the output in a more manageable way. The function below finds all lexical categories where the score is nonzero for a given post, sorts them, and then print at most max_results results.

[72]:
```python
def analyze_post(post: str, normalize:bool=True, max_results=10):
    """
    Prints dictionaries and scores for nonzero scores
    """
    analysis = lexicon.analyze(post, normalize=normalize)
    nonzero = []
    for key, value in analysis.items():
        if value > 0.0:
            nonzero.append((key, value))
    nonzero = sorted(nonzero, key=lambda x: x[1], reverse=True)
    nonzero = nonzero[:min(max_results, len(nonzero))]
    for lex in nonzero:
        print(f"{lex[1]:.2f} {lex[0]}")
```

Normalizing is an important choice when using these methods. Compare the results below. Whether normalizing ultimately matters may depend on what we're trying to accomplish. For now, let's stick to normalizing. Posts vary a lot in length.

[73]:
```python
analyze_post(example_text, normalize=False)
```

```
3.00 work
3.00 economics
2.00 banking
2.00 business
2.00 gain
2.00 messaging
1.00 domestic_work
1.00 occupation
1.00 attractive
1.00 social_media
```

[75]:
```python
analyze_post(example_text, normalize=True)
```

```
0.03 work
0.03 economics
0.02 banking
0.02 business
0.02 gain
0.02 messaging
0.01 domestic_work
0.01 occupation
0.01 attractive
0.01 social_media
```

Preprocessing is also an important step for a lot of tasks. The code below loads a language model from `spacy`, disables some of its functionality (Named Entity Recognition) to make it run faster, and then preprocesses the sentence using the model. `nlp(example_text)` analyzes the string using the language model we have loaded, and it does things like part-of-speech tagging. We can also remove stopwords and lemmatize.

[34]:
```
# python -m spacy download en_core_web_sm

nlp = spacy.load("en_core_web_sm", disable=["ner"])
```

[76]:
```
prep_example_text = nlp(example_text)
prep_example_text = [word.lemma_ for word in prep_example_text if not word.
 ↪is_stop]
print(prep_example_text)
```

```
['1', 'month', 'job', 'critique', 'daily', 'thing', '\n ', 'industry', '5', '-',
'10', 'year', 'start', 'new', 'role', 'sub', 'industry', 'familiar', '.',
'problem', 'get', 'feedback', ',', 'month', 'way', 'send', 'email', 'way',
'present', 'incorrect', 'critique', '.', 'single', 'day', '.', 'sure',
'anymore', 'good', 'fit', 'company', '.', 'long', 'give.it', 'look', 'thing',
'turn', '?']
```

[77]:
```
analyze_post(prep_example_text, normalize=True)
```

```
0.07 business
0.07 work
0.07 economics
0.04 banking
0.04 gain
0.04 messaging
0.02 domestic_work
0.02 occupation
0.02 social_media
0.02 blue_collar_job
```

[78]:
```
lexicon.analyze(prep_example_text, normalize=True)["negative_emotion"]
```

[78]:
```
0.0
```

[79]:
```
# df.head()
```

The dataset has a variable ("preprocessed") with preprocessed versions of the posts and variables for each of the dictionaries provided by Empath.

1.3.1 Most and least positive and negative posts

Let's take a look at the most positive post according to the positive_sentiment lexicon:

[39]:
```
most_pos = df[df.positive_emotion==df.positive_emotion.max()]

display(most_pos[["score", "num_comments", "date"]])

print(most_pos["title"].values[0])
print(most_pos["selftext"].values[0])
```

```
       score  num_comments       date
```

```
47089      1            22 2020-08-14


I love my job
Hey I love my job
```

And the most negative post:

[40]:
```
most_pos = df[df.negative_emotion==df.negative_emotion.max()]

display(most_pos[["score", "num_comments", "date"]])

print(most_pos["title"].values[0])
print(most_pos["selftext"].values[0])
```

```
       score  num_comments       date
60111      1            11 2020-10-25


What's wrong
Why is it very hard get a job for me ?
```

What about the *least positive* or *least negative*? Unfortunately, these are going to be 0.0 and apply to a large portion of posts. Even if we standardize these, the lowest values will still be the posts that don't use relevant words, not necessarily words meaning the *opposite*. In fact, we'll often see that posts that use words related to one category use words related to the opposite. Positive and negative sentiment words are actually highly correlated according to this dictionary-based approach.

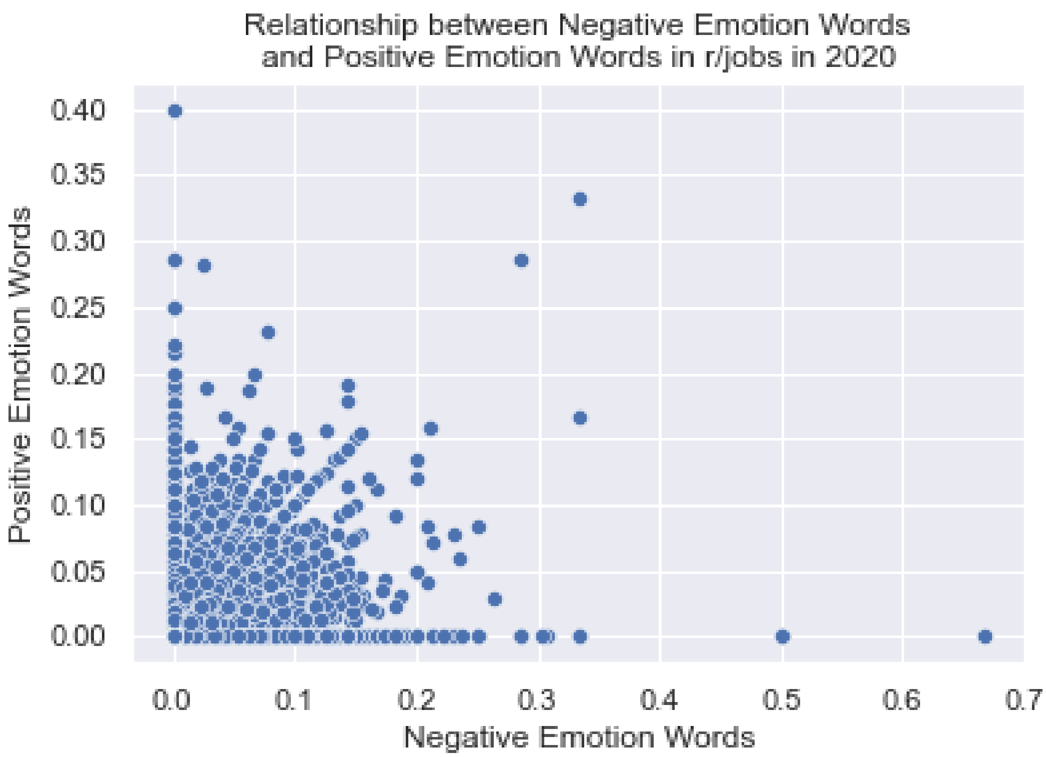
[41]:
```
print(f"Minimum for positive and negative emotion: {df.positive_emotion.min()}␣
↪and {df.negative_emotion.min()}")
```

```
Minimum for positive and negative emotion: 0.0 and 0.0
```

[42]:
```
print(f"Correlation between positive and negative emotion: r =␣
↪{quick_r('negative_emotion', 'positive_emotion', df)}")
```

```
Correlation between positive and negative emotion: r = 0.16***
```

[43]:
```
sns.scatterplot(x="negative_emotion", y="positive_emotion", data=df)
plt.xlabel("Negative Emotion Words")
plt.ylabel("Positive Emotion Words")
plt.title("Relationship between Negative Emotion Words\nand Positive Emotion␣
↪Words in r/jobs in 2020")
plt.show()
```



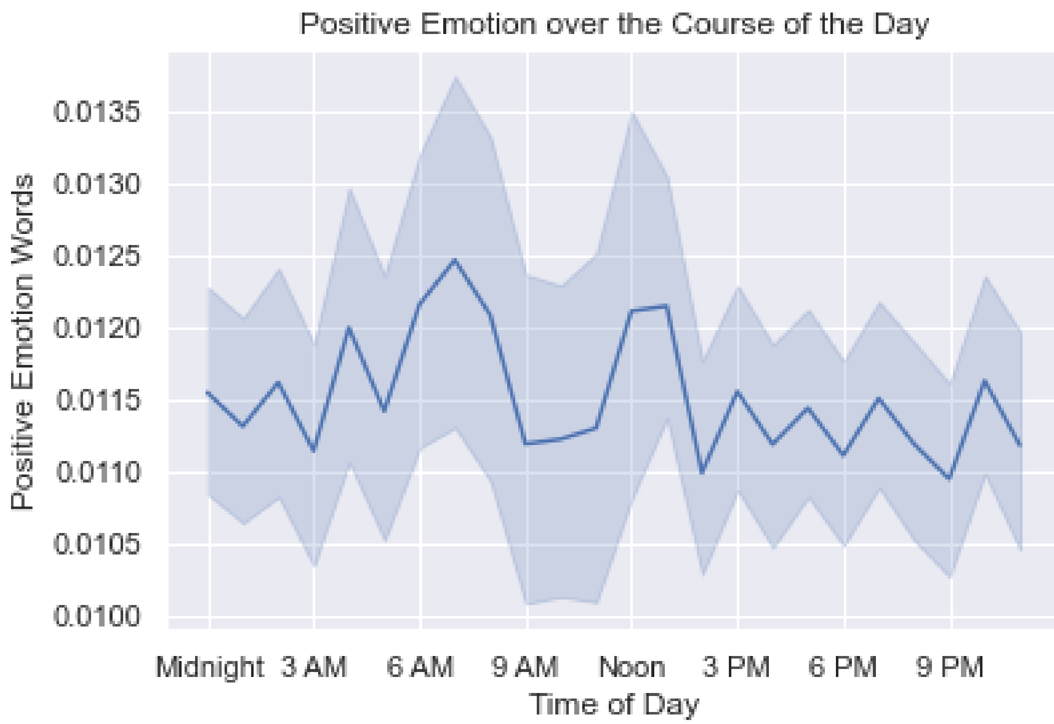
1.3.2 Temporal Trends in Sentiment

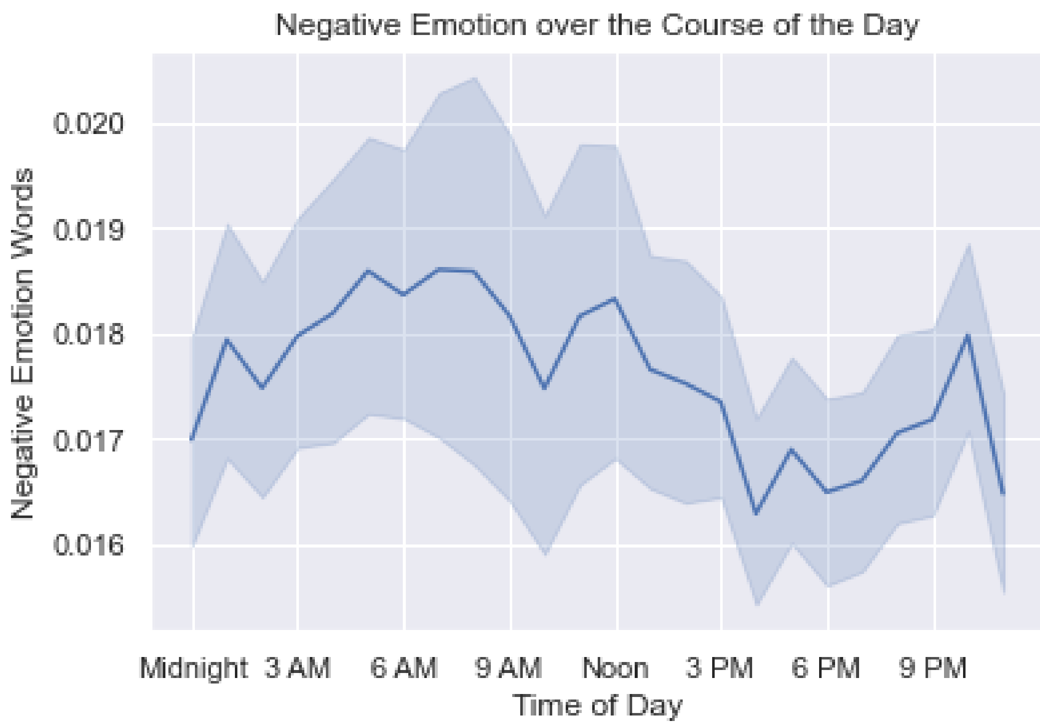
Do posts tend to relate to positive or negative sentiment to different degrees at different points in time? We'll plot these to find out and even check some of the correlations. Importantly, days and weeks are cyclical, so establishing a linear trend (as with a correlation coefficient) is unlikely. We might also expect seasonal effects over the course of the year if people are shorter on money at different times, if having money seems more important at different times (e.g., around specific holidays), or if people tend to lose their jobs more at certain times of year.

On the other hand, we're looking at 2020. There may be shifts in how much emotion words are used, on average, as the pandemic worsens. As a consequence, we may see linear trends over the course of the year.

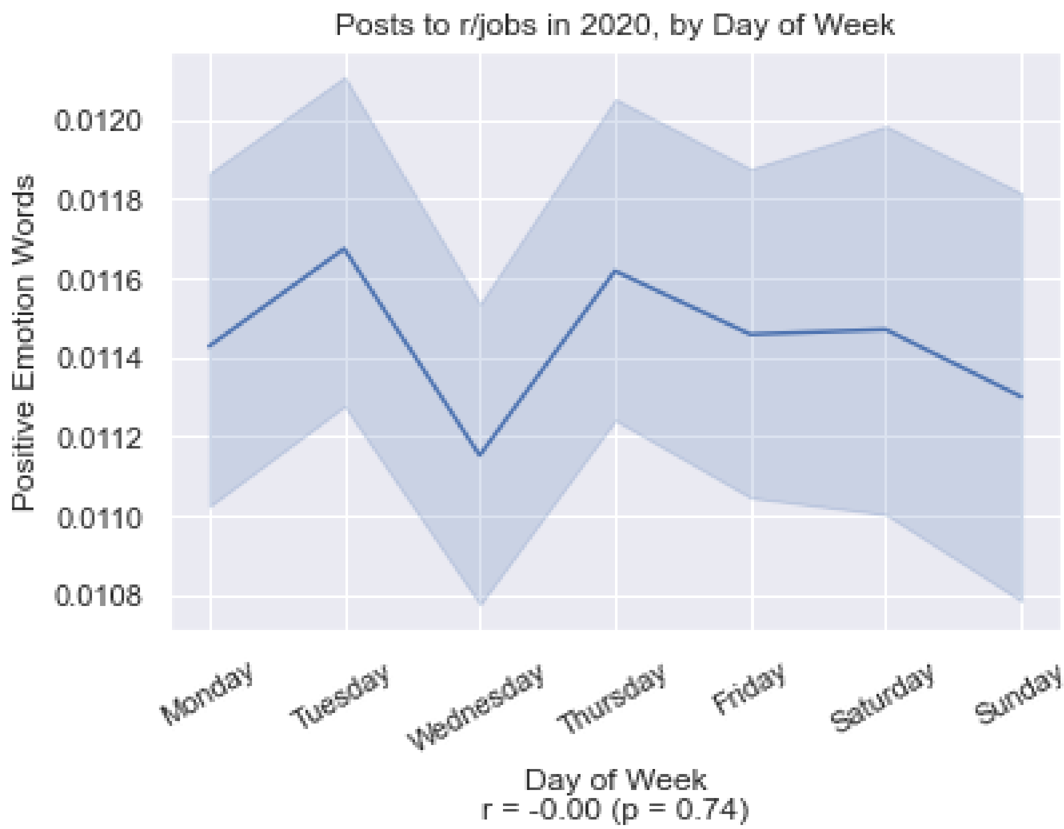
[44]:
```
sns.lineplot(x="hour", y="positive_emotion", data=df)
plt.title("Positive Emotion over the Course of the Day")
plt.ylabel("Positive Emotion Words")
plt.xlabel("Time of Day")
plt.xticks(ticks=range(0,24,3), labels=hours[::3])
plt.show()

sns.lineplot(x="hour", y="negative_emotion", data=df)
plt.title("Negative Emotion over the Course of the Day")
plt.ylabel("Negative Emotion Words")
```

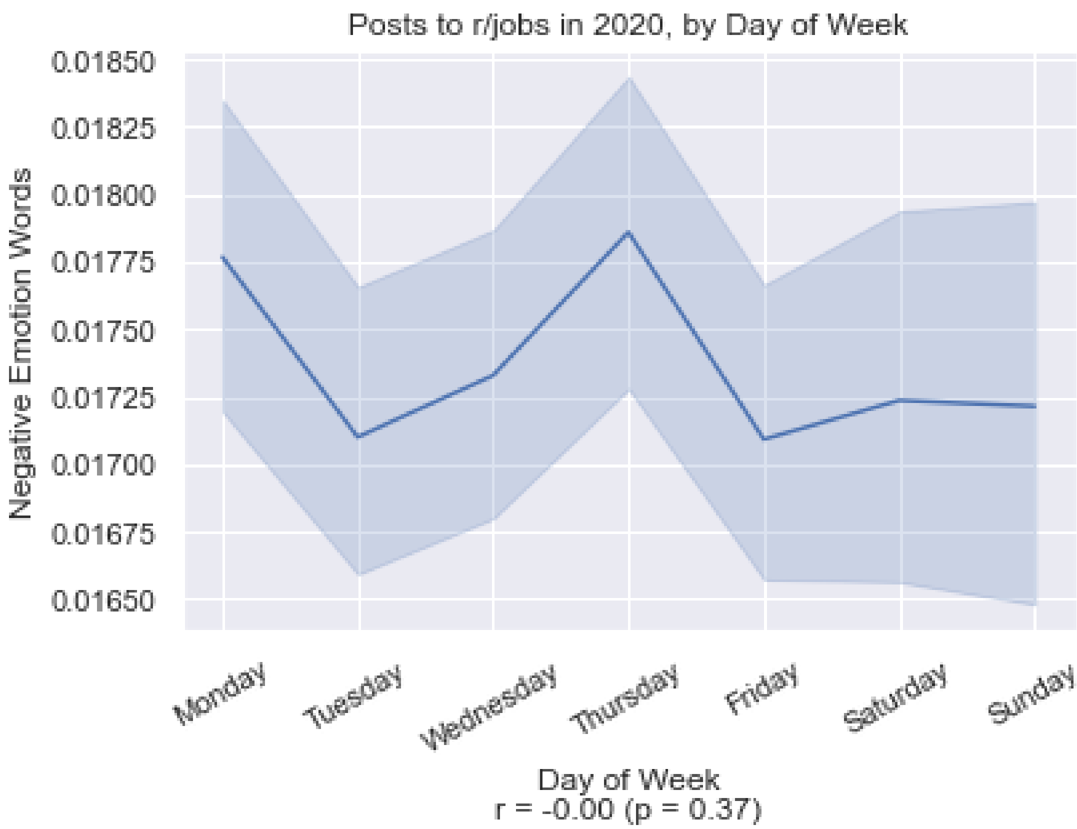
```
plt.xlabel("Time of Day")
plt.xticks(ticks=range(0,24,3), labels=hours[::3])
plt.show()
```





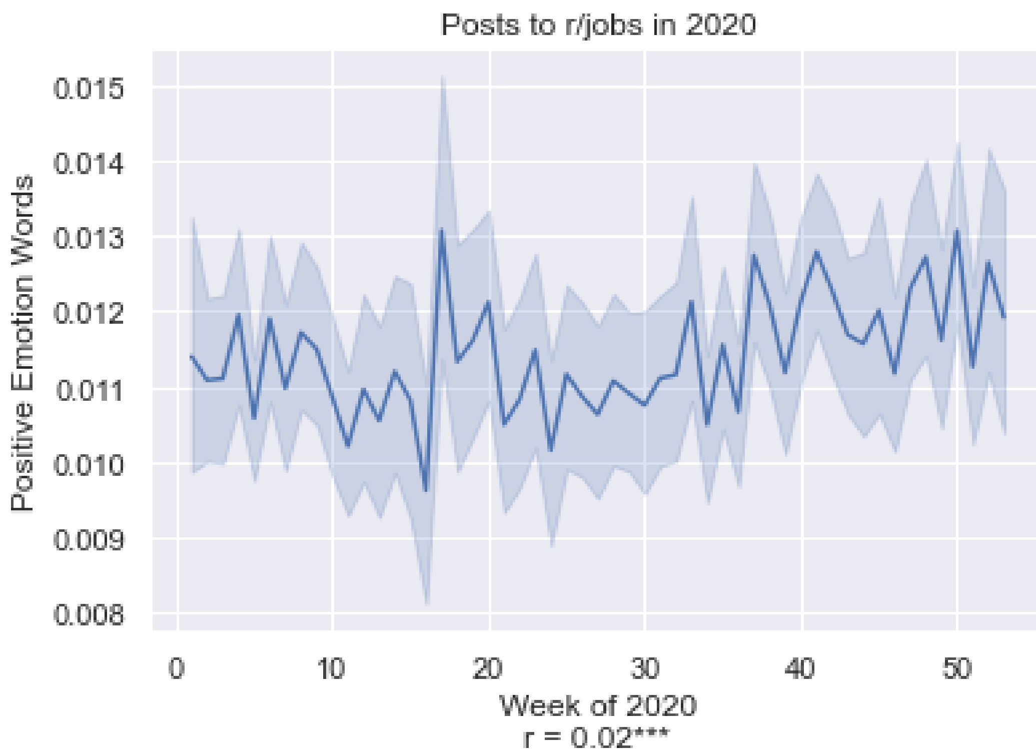
[45]:
```
plt.title("Posts to r/jobs in 2020, by Day of Week")
sns.lineplot(x="dayofweek", y="positive_emotion", data=df, ci=95) # sem
plt.ylabel("Positive Emotion Words")
plt.xticks(ticks=range(0,7), labels=daysofweek, rotation=30)
plt.xlabel(f"Day of Week\nr = {quick_r('dayofweek', 'positive_emotion', df)}")
plt.show()

plt.title("Posts to r/jobs in 2020, by Day of Week")
sns.lineplot(x="dayofweek", y="negative_emotion", data=df, ci=95) # sem
plt.ylabel("Negative Emotion Words")
plt.xticks(ticks=range(0,7), labels=daysofweek, rotation=30)
plt.xlabel(f"Day of Week\nr = {quick_r('dayofweek', 'negative_emotion', df)}")
plt.show()
```

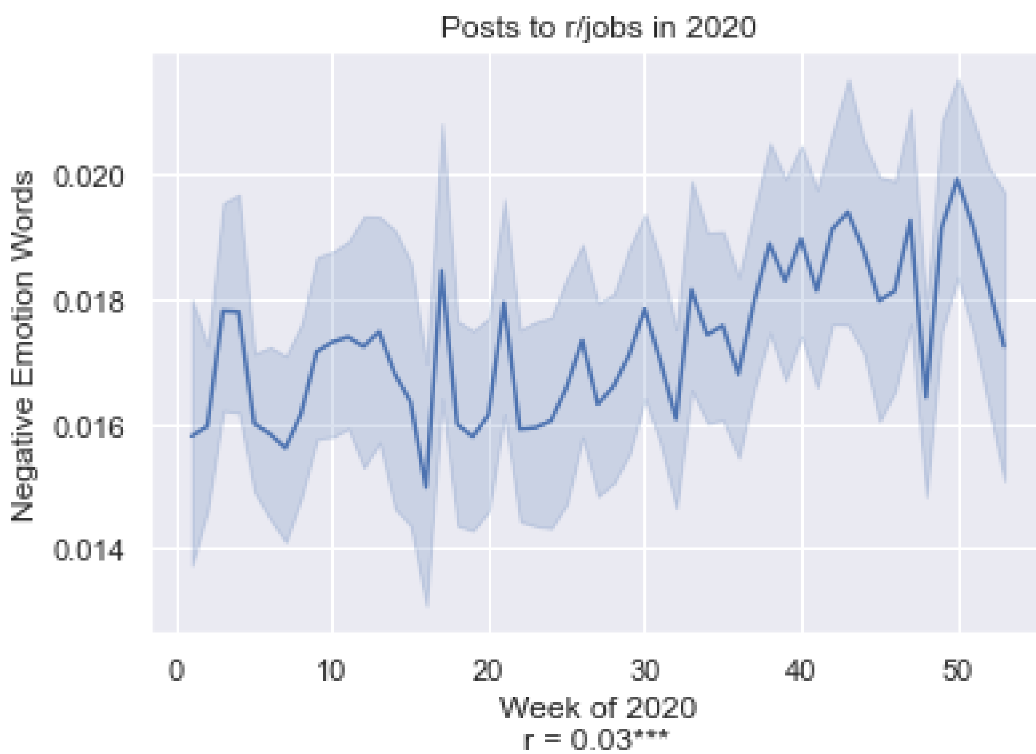

Posts to r/jobs in 2020, by Day of Week
Positive Emotion Words
0.0120
0.0118
0.0116
0.0114
0.0112
0.0110
0.0108
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
Day of Week
r = -0.00 (p = 0.74)



[46]:

```
plt.title("Posts to r/jobs in 2020")
sns.lineplot(x="week", y="positive_emotion", data=df, ci=95) # sem
plt.ylabel("Positive Emotion Words")
plt.xlabel(f"Week of 2020\nr = {quick_r('week', 'positive_emotion', df)}")
plt.show()

plt.title("Posts to r/jobs in 2020")
sns.lineplot(x="week", y="negative_emotion", data=df, ci=95) # sem
plt.ylabel("Negative Emotion Words")
plt.xlabel(f"Week of 2020\nr = {quick_r('week', 'negative_emotion', df)}")
plt.show()
```


Posts to r/jobs in 2020
Positive Emotion Words
0.015
0.014
0.013
0.012
0.011
0.010
0.009
0.008
0
10
20
30
40
50
Week of 2020
r = 0.02***


Posts to r/jobs in 2020
Negative Emotion Words
0.020
0.018
0.016
0.014
0
10
20
30
40
50
Week of 2020
r = 0.03***

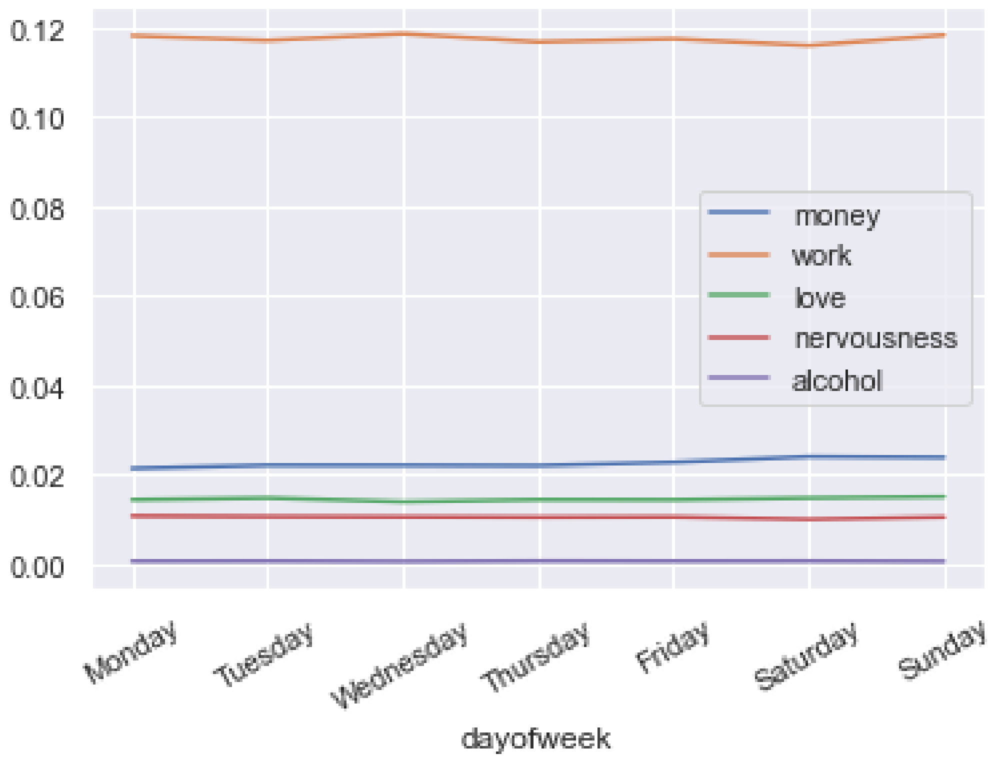
1.3.3 Standardizing Variables

Before we dive into the rest of our analyses, we are going to "standardize" the variables. If you have some background in statistics, this may be familiar: we subtract the mean of a variable from each value and divide by the standard deviation, which is the same as calculating a z-score. This sets the mean of the variable to zero and the standard deviation to one.

Standardizing variables offers two major advantages that are relevant to this class. First, sometimes variables are just difficult to interpret. Have you ever been asked whether you agree or disagree with a statement on a scale of 1-7 (or 1-5, or 0-100)? What would it mean to say that the difference between two groups is 0.24 on that 1-7 scale? Often, psychologists and others standardize variables so that differences have a more straightforward interpretation. This interpretation is that a difference is some fraction of a standard deviation. When analyzing the results of an experiment, a psychologist might say that the treatment has an effect on the outcome of 0.4 standard deviations. That's pretty opaque–but many people find it more intuitive than saying the effect is 0.24 out of seven.

The second and most immediately obvious advantage is that we can plot standardized variables at the same time. Examine the two plots below. The first plot includes unstandardized variables. If we were to look at any one of these variables, we may see more ups and downs, but the additional variables change the scale of the y-axis. This means we have zoomed out and the ups and downs are more difficult to see. (Whether the ups and downs matter is another question, and we'll talk more about this!)

[47]:
```
daysofweek = ["Monday", "Tuesday", "Wednesday", "Thursday", "Friday",␣
 ↪"Saturday", "Sunday"]

df[["dayofweek", "money", "work", "love", "nervousness", "alcohol"]].
 ↪groupby("dayofweek").mean(["money", "work", "love", "nervousness",␣
 ↪"alcohol"]).plot(kind="line")
plt.xticks(ticks=range(0,7), labels=daysofweek, rotation=30)
plt.show()
```



[48]:
```
df[["money", "work", "love", "nervousness", "alcohol"]].describe()
```

[48]:

	money	work	love	nervousness	alcohol
count	49868.000000	49868.000000	49868.000000	49868.000000	49868.000000
mean	0.022351	0.117543	0.014366	0.010392	0.000522
std	0.034592	0.065404	0.022281	0.019507	0.004473
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.074074	0.000000	0.000000	0.000000
50%	0.008333	0.110000	0.000000	0.000000	0.000000
75%	0.033333	0.151515	0.022727	0.015625	0.000000
max	0.500000	1.000000	0.400000	0.400000	0.200000

[49]:
```
def standardize(series):
    """
    Mean-centers a variable and divides by the standard deviation,
    resulting in a mean of zero and a standard deviation of one.
    This puts variables on the same scale and can make comparisons
    a bit easier to see.
    """
    if max(series) == 0.0:
        return series
    mu = np.mean(series.dropna())
```

```
    std = np.std(series.dropna(), ddof=1) + 1e-7
    series = [(val-mu)/std for val in series.values]
    return series
```

[50]:
```
start_time = time.time()

for cat in lexicon.cats.keys():
    df[cat] = standardize(df[cat])

print(time.time()-start_time)
```

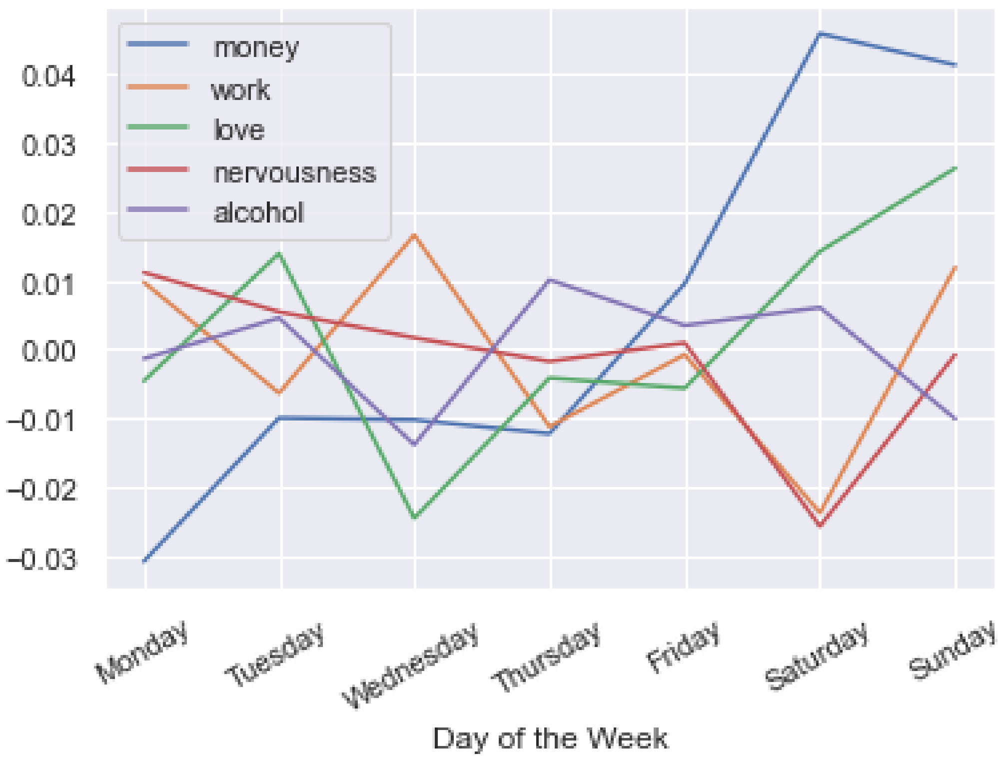
4.5554118156433105

[51]:
```
df[["money", "work", "love", "nervousness", "alcohol"]].describe()
```

[51]:

	money	work	love	nervousness	alcohol
count	4.986800e+04	4.986800e+04	4.986800e+04	4.986800e+04	4.986800e+04
mean	6.053534e-15	4.655312e-14	8.696701e-15	-1.701739e-15	1.040387e-15
std	9.999971e-01	9.999985e-01	9.999955e-01	9.999949e-01	9.999776e-01
min	-6.461376e-01	-1.797177e+00	-6.447591e-01	-5.327403e-01	-1.167443e-01
25%	-6.461376e-01	-6.646233e-01	-6.447591e-01	-5.327403e-01	-1.167443e-01
50%	-4.052366e-01	-1.153349e-01	-6.447591e-01	-5.327403e-01	-1.167443e-01
75%	3.174663e-01	5.194098e-01	3.752638e-01	2.682561e-01	-1.167443e-01
max	1.380792e+01	1.349229e+01	1.730764e+01	1.997277e+01	4.459379e+01

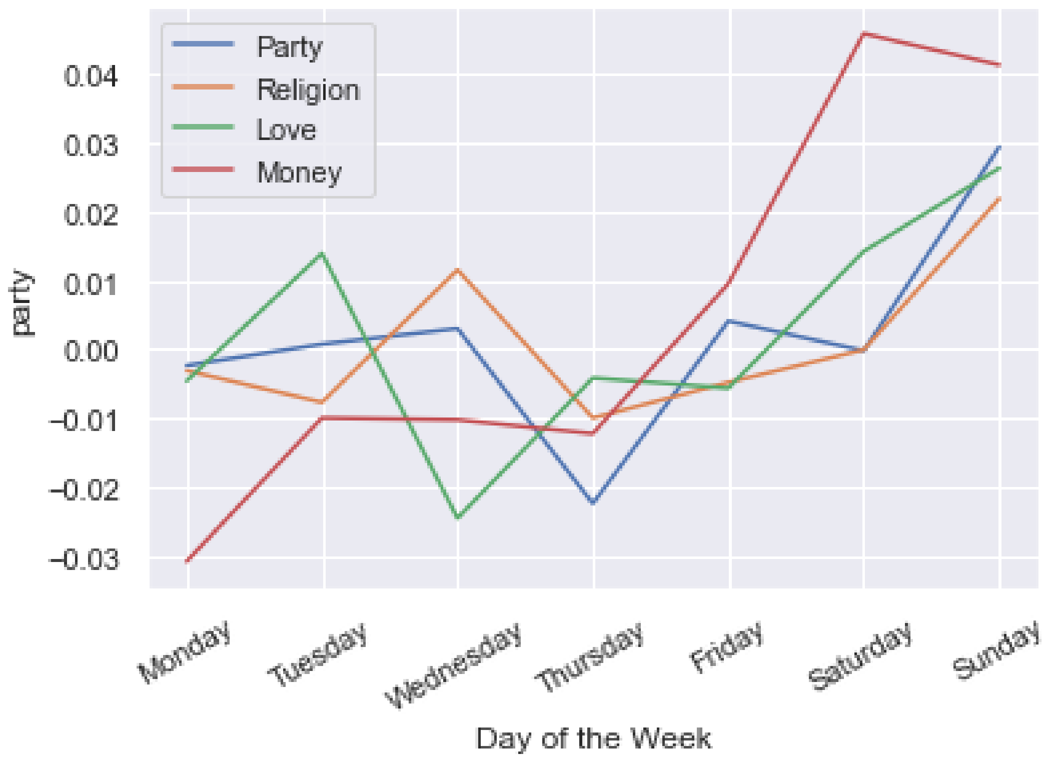
[52]:
```
daysofweek = ["Monday", "Tuesday", "Wednesday", "Thursday", "Friday",␣
 ↪"Saturday", "Sunday"]

df[["dayofweek", "money", "work", "love", "nervousness", "alcohol"]].
 ↪groupby("dayofweek").mean(["money", "work", "love", "nervousness",␣
 ↪"alcohol"]).plot(kind="line")
plt.xticks(ticks=range(0,7), labels=daysofweek, rotation=30)
plt.xlabel("Day of the Week")
plt.show()
```



This plot is a mess, but we see a lot of change from day to day!

1.3.4 Do people talk about different things at different times?

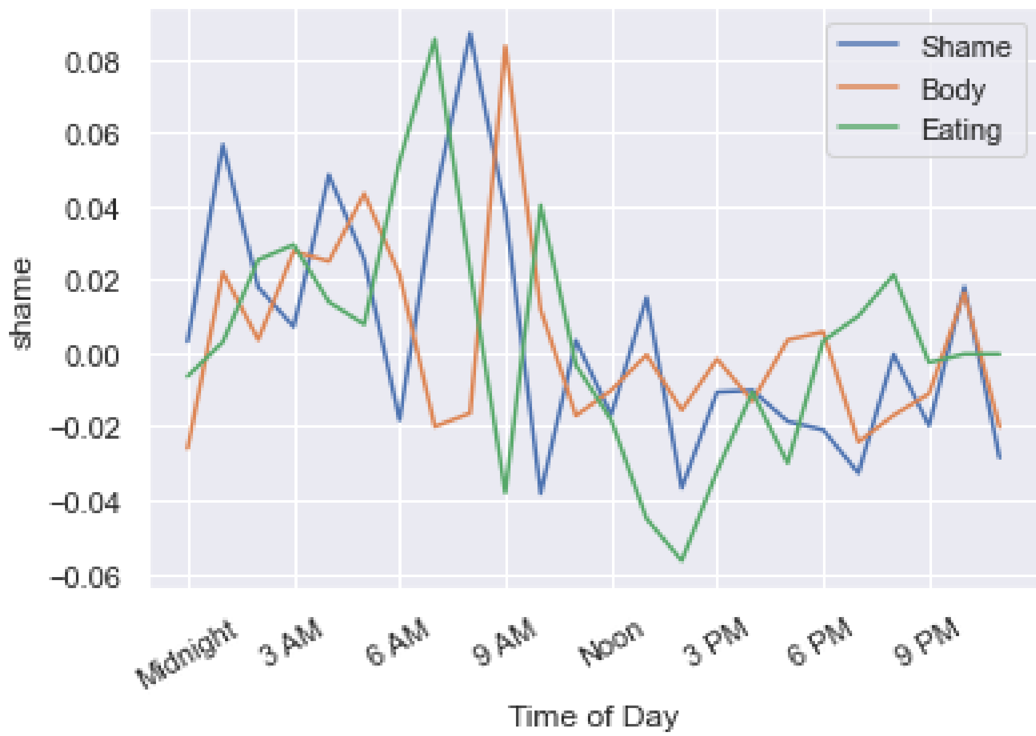
[53]:
```
daysofweek = ["Monday", "Tuesday", "Wednesday", "Thursday", "Friday",␣
↪"Saturday", "Sunday"]

vars_to_plot = ["party", "religion", "love", "money"]

plot_ci=None

for var in vars_to_plot:
    sns.lineplot(x="dayofweek", y=var, data=df, ci=plot_ci)
plt.xticks(ticks=range(0,7), labels=daysofweek, rotation=30)
plt.xlabel("Day of the Week")
plt.legend(labels=[v.capitalize() for v in vars_to_plot])
plt.show()
```



[54]:
```
df[["party", "religion", "love", "money"]].rcorr()
```

[54]:
```
           party religion    love money
party          -             ***   ***
religion   0.007        -
love      -0.038    0.003       -   ***
money     -0.026   -0.002  -0.025     -
```

[55]:
```
vars_to_plot = ["shame", "body", "eating"]

plot_ci=None

for var in vars_to_plot:
    sns.lineplot(x="hour", y=var, data=df, ci=plot_ci)
plt.xticks(ticks=range(0,24,3), labels=hours[::3], rotation=30)
plt.xlabel("Time of Day")
plt.legend(labels=[v.capitalize() for v in vars_to_plot])
plt.show()
```



[56]:
```
df[["shame", "body", "eating"]].rcorr()
```

[56]:
```
        shame   body eating
shame       -    ***
body    0.596      -    ***
eating  0.002  0.016      -
```

1.4 Exercises

First, pick a social problem you would like to explore using this corpus. In Exercise 1, you will create a dictionary for that topic in only three lines of code. You will use your dictionary for the remaining exercises.

`Empath` makes creating dictionaries for different lexical categories fairly straightforward on the surface. Beneath the surface, it uses some pretty powerful tools. We'll learn about these tools (such as word embeddings) later in the class. For now, all we need to know is that we can provide a small list of words related to our chosen topic and `Empath` will give us a longer list of related words. We can use that list as our lexicon.

For example, let's say we want to create a lexicon related to stigma. We can seed (start) our lexicon using a handful of words. Let's try these:

[57]:
```
stigma_words = ["stigma", "taboo", "avoid", "aversion", "stereotype", "trash"]
```

Now we can create our lexicon using the following line of code. The first part ("stigma") is what we are naming the category. The second part (stigma_words) is the list we created in the line above). The model="reddit" argument means we will find words that are related based on how language is (was) used in Reddit data when `Empath` was created. The alternatives are based on the New York Times and a collection of fiction.

Note: we will talk a LOT more about word embeddings and vector space models in the future, and you will learn how they are used to generate collections of words like the following. The TL;DR is that these tools assume words are "similar" if they are used in similar contexts. This assumption can make it easy to find synonyms, but sometimes tools based on this assumption will think *antonyms* are highly "similar" in this specific sense. These tools can also reflect social prejudices, which can make them useful for studying those issues (as we will later in the course) but may be a bit of a surprise. **Debiasing** word embeddings and other tools is also an active area of research, and we will discuss that more.

In other words, you may see examples of prejudice inherent to the language used on Reddit (or in fiction or the New York Times), but that doesn't mean that a word that shows up should be seen as part of the reality of your topic.

[58]:
```
lexicon.create_category("stigma", stigma_words, model="reddit", size=100)
```

```
["stigma", "negative_thing", "social_stigma", "taboo", "negative_stigma",
"aversion", "stigmas", "negative_connotations", "weird_idea",
"negative_connotation", "stereotype", "negative_association", "positive_thing",
"taboo", "stigmatized", "social_pressure", "bad_thing", "stigmatization",
"negative_associations", "whole_culture", "negative_attitudes", "fetishization",
"stereotypes", "negative_view", "social_taboo", "cultural_norm", "taboo",
"huge_stigma", "fetishizing", "stigmatize", "irrational_fear", "ironically",
"normal_thing", "certain_people", "stupid_stereotypes", "stigma",
"negative_stereotypes", "natural_thing", "obsession", "preconception",
"fetishize", "shunning", "negative_things", "serious_problem", "social_norm",
"skewed_view", "prudishness", "negative_aspects", "real_problem",
"ridiculous_notion", "stereotyping", "demeaning", "double_standard",
"real_issue", "negative_stereotype", "gay_culture", "disdain", "social_stigmas",
"typical_thing", "negative_perception", "good_thing", "phobia",
"knee_jerk_reaction", "inherently_bad_thing", "demonization", "perpetuates",
"serious_issue", "connotations", "trendy_thing", "implication", "distaste",
"victim_mentality", "associate", "double-standard", "just_a_thing", "dislike",
"common_thing", "shun", "insinuation", "phobic", "fetishism", "stigmatised",
"legitimate_thing", "legitimate_problem", "prejudice", "negative_context",
"taboo_subject", "common_response", "oversensitivity", "common_perception",
"negative_sense", "social_pressures", "mentality", "slut_shaming",
"cultural_stigma", "fixation"]
```

Also notice the n-grams connected by underscores (for example, "cultural_norm") and compound words (for example, "slut_shaming"). The corpus of posts from r/jobs only has unigrams and has no punctuation. We'll cover those issues more later on in the course. For now, that just means there are words in the lexicon that won't appear in any of the documents in this corpus.

That aside, this custom lexicon can now be used just like those we've already used. The line of code below will add a variable to our dataframe. Be sure to include the normalize=True argument when you create your own in Exercise 1! Alternatively, if you'd prefer to use the raw counts, you should use the raw counts for the other lexical categories as well, as we initially did toward the beginning of this notebook. If you opt to use raw counts, please provide your rationale.

[59]:
```
def score_category(s, category, normalize=True):
    """
    This function returns the score for a given document for a particular␣
↪category
    using Empath's dictionaries. The optional argument `normalize` defaults to␣
↪False.
    """
    res = lexicon.analyze(s, categories=[category], normalize=normalize)
    if res:
        return res[category]
    return 0.0


df["stigma"] = [score_category(s, "stigma", normalize=True) for s in␣
↪df["preprocessed"].values]
df["stigma"] = standardize(df["stigma"])
```

There you have it! We've created our own lexicon for the lexical category "stigma" in only three lines of code using Empath!

Now you will do the same.

1.4.1 Exercise 1

1. Create your custom lexicon by modifying the code below.

1.1 Replace "LISTOFWORDS" with whatever you like, but create a list of words to seed (start) your lexicon

[60]:
```
LISTOFWORDS = []
```

1.2 Now pick a name for your lexicon (replacing "YOURCATEGORYNAMEHERE") and replace LISTOFWORDS with your list. If you'd prefer, you can use the alternatives to Reddit-based word embeddings discussed above. You can also modify the size argument.

[61]:
```
lexicon.create_category("YOURCATEGORYNAMEHERE", LISTOFWORDS, model="reddit",␣
↪size=100)
```

```
[]
```

1.3 Replace the name with your chosen name and run this cell

[62]:
```
df["YOURCATEGORYNAMEHERE"] = [score_category(s, "YOURCATEGORYNAMEHERE",␣
↪normalize=True) for s in df["text"].values]
df["YOURCATEGORYNAMEHERE"] = standardize(df["YOURCATEGORYNAMEHERE"])
```

Exercise 2

Now you will use your lexicon to conduct a few analyses of your own. First, describe the topic you chose and a few hypotheses.

2.1 What topic did you choose, and what could it tell us about social processes and social institutions?

Your answer here

2.2 Is text data useful for studying your topic? (It's okay if you don't think it is!)

Your answer here

Exercise 3

Now let's think about how your topic might relate to social institutions like work, schooling, or others that might structure time use (that is, what people do at what times).

3.1 Come up with a hypothesis about when during the week redditors may be more or less likely to post about your topic to r/jobs. If you believe there's no reason to expect a relationship between the day of the week and writing about your topic, you may explain why instead. Clarify whether your hypothesis is causal or correlational (although we will not adequately *test* causal claims at this point). You may also describe potential confounding variables.

Your answer here

3.2 Create a plot showing variation in the frequency of posts about your topic to r/jobs over the course of the week. You may modify code from earlier in the notebook.

[63]:
```
# YOUR CODE HERE
```

3.3 Does this plot support your hypothesis? If you have a background in statistics or want to try something new, you may conduct and refer to formal hypothesis tests. If you believe there may be confounding variables, please describe them.

Your answer here

Exercise 4

4.1 Come up with a hypothesis about when during the *day* redditors may be more or less likely to post about your topic to r/jobs. If you believe there's no reason to expect a relationship between time of day and writing about your topic, you may explain why instead. Clarify whether your hypothesis is causal or correlational (although we will not adequately *test* causal claims at this point). You may also describe potential confounding variables.

Your answer here

4.2 Create a plot showing variation in the frequency of posts about your topic to r/jobs over the course of the day. You may modify code from earlier in the notebook.

[64]:
```
# YOUR CODE HERE
```

4.3 Does this plot support your hypothesis? If you have a background in statistics or want to try something new, you may conduct and refer to formal hypothesis tests. If you believe there may be confounding variables, please describe them.

Your answer here

Exercise 5

5.1 Come up with a hypothesis about whether a post's karma (upvotes, the "score" field in our dataset) would be related to the extent your topic is discussed. If you believe there is no reason to expect such a relationship, you may explain that instead. Clarify whether your hypothesis is causal or correlational (although we will not adequately *test* causal claims at this point). You may also describe potential confounding variables.

Your answer here

5.2 Create a plot showing the relationship between a post's score (df["score"]) and your topic. You may modify code from earlier in the notebook.

[65]:
```
# YOUR CODE HERE
```

5.3 Does this plot support your hypothesis? If you have a background in statistics or want to try something new, you may conduct and refer to formal hypothesis tests. If you believe there may be confounding variables, please describe them.

Your answer here

Exercise 6

6.1 Come up with a hypothesis about another lexical category that should be associated (positively or negatively) with your own category. Be sure to think about social practices. What is it about how people live that makes it likely they would (or would not) write about both your topic and this other topic in the same posts to r/jobs? Clarify whether your hypothesis is causal or correlational (although we will not adequately *test* causal claims at this point). You may also describe potential confounding variables.

Your answer here

6.2 Create a plot showing the relationship between your category and the category you chose. You may modify code from earlier in the notebook.

[66]:
```
# YOUR CODE HERE
```

6.3 Does this plot support your hypothesis? If you have a background in statistics or want to try something new, you may conduct and refer to formal hypothesis tests. If you believe there may be confounding variables, please describe them.

Your answer here