

SOCIAL MEDIA HANDS-ON SESSION

By Kathakoli Sengupta

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Today's Plan

- Social Media Survey Data Analysis
- Social Media Data Sentiment Analysis

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Social Media Survey Data Analysis

Social Media Data can be collected in form of Survey.

- Frequently asked Question:
 - Do you ever use [platform]? 1:Yes, 2:No, 99:No Answer
 - How often do you get news from [source]? 1:Often, 2:Sometimes, 3:Rarely, 4:Never
 - Age, Gender, Education are some participant details collected for analysis.
- Survey can be represented in .sav format.
 - It is the native data format for SPSS (Statistical Package for the Social Sciences), IBM's commercial statistics software.
 - It is like an Excel file but designed specifically for survey data.
 - It stores not just the numbers but also variable labels (what each column means), value labels (what each coded number represents, like 1 = Male, 2 = Female), and missing value definitions.
- PEW Datasets have survey data: <https://www.pewresearch.org/dataset/>

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Now let's explore Social Media Survey Data

- Registration Instructions:
 - Go to <https://www.pewresearch.org/profile/registration/>
 - Fill out Name, Email, Organization(use your university), Job Title(student), Click Submit.
 - Log in at <https://www.pewresearch.org/profile/> with the credentials created.
 - Search Wave150 (Direct Link: <https://www.pewresearch.org/dataset/american-trends-panel-wave-150/>).
- Download Wave 150 Dataset.

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Let's start Coding

- Steps of Social Media Survey Data Analysis
 - Loading and exploring the data.
 - Cleaning and Encoding the data.
 - Analysis
 - Plotting (for better understanding)
- Before we start
 - Take 5 mins and read the Readme.txt file given with your dataset for brief understanding of the dataset.
- Now, I will show you few analysis code and explain how I am using the data.
- Download the python file from https://drive.google.com/file/d/1_fpULYISsXgcekKcs-k0bzm_oWnxS8F0/view?usp=sharing and copy paste exactly the sections I am showing and run with me.
- Then, I will ask you to code some analysis from the same dataset.

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Loading and Exploring Data

- Importing Data

```
import os
print(os.getcwd())
os.chdir("")
SAV_FILE = "ATP W150.sav"
df, meta = pyreadstat.read_sav(SAV_FILE)
```

- Shape and columns

```
print(f"Dataset shape: {df.shape[0]} rows × {df.shape[1]} columns")
print(f"\n5column names:\n{list(df.columns[:5])}")
```

f "{ }": Whatever is present inside { }, that value will be printed instead of the string.

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Loading and Exploring Data

- Metadata
 - # meta.column_names → list of all variable names
 - # meta.column_labels → dict: variable name → description
 - # meta.variable_value_labels → dict: variable name → {code: label}
- Exploring columns

```
print(f"\nVariable label for SMUSE_a:")
idx = meta.column_names.index("SMUSE_a_W150")
print(meta.column_labels[idx])
print(f"\nValue labels for SMUSE_a:")
for code, label in meta.variable_value_labels["SMUSE_a_W150"].items():
    print(f" {code} = {label}")
```

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Data Details(Revealed from previous analysis)

Pew ATP datasets have TWO types of columns:

A. SURVEY QUESTIONS (specific to each wave):

These are the questions asked in this particular survey.

For Wave 150 (social media), the key variables are:

SMUSE_a through SMUSE_n – "Do you ever use [platform]?"

SMUSE_a	= Facebook	1=Yes, 2=No, 99=No answer
SMUSE_b	= YouTube	
SMUSE_c	= X (Twitter)	
SMUSE_d	= Instagram	
SMUSE_e	= Snapchat	
SMUSE_f	= WhatsApp	
SMUSE_g	= LinkedIn	
SMUSE_i	= TikTok	(note: no _h)
SMUSE_j	= Reddit	
SMUSE_l	= Nextdoor	(note: no _k)
SMUSE_m	= Rumble	
SMUSE_n	= Truth Social	

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SOCIALNEWS2_a through _n – "Do you regularly get NEWS on [platform]?" Same platform mapping as SMUSE 1=Yes regularly get news, 2=No		
NEWSPLAT_a through _d – "How often do you get news from [source]?" NEWSPLAT_a = Television NEWSPLAT_b = Radio NEWSPLAT_c = Print NEWSPLAT_d = Digital device Values: 1=Often, 2=Sometimes, 3=Rarely, 4=Never		
B. DEMOGRAPHIC FRAME VARIABLES (same across all waves): These start with "F_" and contain demographics: F_AGECAT → Age group (1=18-29, 2=30-49, 3=50-64, 4=65+) F_GENDER → Gender (1=Man, 2=Woman, 3=Other) F_EDUCCAT → Education (1=College+, 2=Some college, 3=HS or less) F_RACETHNMOD → Race/ethnicity F_PARTY_FINAL → Party ID (1=Republican, 2=Democrat, 3=Independent, 4=Other) F_PARTYSUM_FINAL → Party with leaners (1=Rep/Lean Rep, 2=Dem/Lean Dem) F_INC_SDT1 → Family income bracket F_METRO → Metro area (1=Metropolitan, 2=Non-metropolitan) F_CREGION → Census region (1=NE, 2=MW, 3=South, 4=West) WEIGHT → Survey weight (ALWAYS USE THIS for representative results)		

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Cleaning and Encoding Data • Encoding platform usage into useful labels • Recode platform usage: 1=uses, 0=does not use • In the raw data: 1=Yes, 2=No, 99=No answer • We recode to binary: 1=Yes, 0=No (treating 99 as No) <pre>platform_map = { "SMUSE_a_W150": "Facebook", "SMUSE_b_W150": "YouTube", "SMUSE_c_W150": "X (Twitter)", "SMUSE_d_W150": "Instagram", "SMUSE_e_W150": "Snapchat", "SMUSE_f_W150": "WhatsApp", "SMUSE_g_W150": "LinkedIn", "SMUSE_i_W150": "TikTok", "SMUSE_j_W150": "Reddit", "SMUSE_l_W150": "Nextdoor", "SMUSE_m_W150": "Rumble", "SMUSE_n_W150": "Truth Social", }</pre> <pre>for var, name in platform_map.items(): if var in df.columns: # 1=Yes → 1, everything else → 0 df[f"uses_{name}"] = (df[var] == 1).astype(int) else: print(f" Warning: {var} not found in dataset (may be a different wave)")</pre>		

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Cleaning and Encoding Data

- Encoding news consumption into useful labels

```
news_map = {
    "SOCIALNEWS2_a_W150": "Facebook",
    "SOCIALNEWS2_b_W150": "YouTube",
    "SOCIALNEWS2_c_W150": "X (Twitter)",
    "SOCIALNEWS2_d_W150": "Instagram",
    "SOCIALNEWS2_e_W150": "Snapchat",
    "SOCIALNEWS2_f_W150": "WhatsApp",
    "SOCIALNEWS2_g_W150": "LinkedIn",
    "SOCIALNEWS2_i_W150": "TikTok",
    "SOCIALNEWS2_j_W150": "Reddit",
    "SOCIALNEWS2_l_W150": "Nextdoor",
    "SOCIALNEWS2_m_W150": "Rumble",
    "SOCIALNEWS2_n_W150": "Truth Social",
}

for var, name in news_map.items():
    if var in df.columns:
        df[f"news_{name}"] = (df[var] == 1).astype(int)
```

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Cleaning and Encoding Data

- Recode demographics into readable labels

```
age_labels = {1: "18-29", 2: "30-49", 3: "50-64", 4: "65+"}
df["age_group"] = df["F_AGE CAT"].map(age_labels)
```

```
gender_labels = {1: "Man", 2: "Woman", 3: "In some other way"}
df["gender"] = df["F_GENDER"].map(gender_labels)
```

```
edu_labels = {1: "College graduate+", 2: "Some College", 3: "H.S. graduate or less"}
df["education"] = df["F_EDUCCAT"].map(edu_labels)
```

```
party_labels = {1: "Rep/Lean Rep", 2: "Dem/Lean Dem"}
if "F_PARTYSUM_FINAL" in df.columns:
    df["party"] = df["F_PARTYSUM_FINAL"].map(party_labels)
```

```
metro_labels = {1: "Metropolitan", 2: "Non-metropolitan"}
if "F_METRO" in df.columns:
    df["metro"] = df["F_METRO"].map(metro_labels)
```

```
print("\nRecode complete")
print(f"Usable rows: {df['age_group'].notna().sum()}")
```

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Platform Adoption Rates (Analysis 1)

- Platform Adoption Rates gives how widely each social media platform is used in your survey population i.e., the percentage of people who use each platform.

```
print("Platform Adoption Rates (Weighted)")
platforms_available = [name for var, name in
platform_map.items() if var in df.columns]
```

```
weight_col = "WEIGHT_W150"
```

```
if weight_col is not None:
    print(f"\nUsing survey weights: {weight_col}\n")
```

```
for name in platforms_available:
    col = f"uses_{name}"
    valid = df[col].notna() & df[weight_col].notna()
```

```
    weighted_pct = np.average(df.loc[valid, col],
weights=df.loc[valid, weight_col]) * 100
    unweighted_pct = df.loc[valid, col].mean() * 100
```

```
    print(f" {name:15s} Weighted:
{weighted_pct:.1f}% Unweighted: {unweighted_pct:.1f}%")
else:
```

```
    print("\nNo suitable weight column found.")
    print("Found:", [c for c in df.columns if "WEIGHT" in
c.upper()])
    print("Using unweighted means for now.\n")
```

```
for name in platforms_available:
    col = f"uses_{name}"
    pct = df[col].mean() * 100
    print(f" {name:15s} {pct:.1f}%")
```

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• Plotting

```
print("Generating Adoption Chart")
```

```
plt.rcParams.update({
    "figure.dpi": 120,
    "axes.spines.top": False,
    "axes.spines.right": False
})
```

```
COLORS = {
    "YouTube": "#FF0000", "Facebook": "#1877F2",
    "Instagram": "#E4405F",
    "TikTok": "#010101", "Snapchat": "#E8C700", "X
(Twitter)": "#1DA1F2",
    "LinkedIn": "#0A66C2", "Reddit": "#FF4500",
    "WhatsApp": "#25D366",
    "Pinterest": "#E60023", "Nextdoor": "#8ED500",
    "Rumble": "#85C742",
    "Truth Social": "#1A2B4A",
}
```

```
# Map column → platform name
col_to_name = {f"uses_{name}": name for name in
platforms_available}
use_cols = [f"uses_{name}" for name in
platforms_available]
```

```
# Compute adoption
adoption = df[use_cols].mean() * 100
adoption = adoption.rename(index=col_to_name)
adoption = adoption.sort_values(ascending=True)
```

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```
# Plot
fig, ax = plt.subplots(figsize=(10, 6))

bars = ax.barh(
    adoption.index,
    adoption.values,
    color=[COLORS.get(p, "#888") for p in adoption.index],
    edgecolor="white",
    linewidth=0.5
)

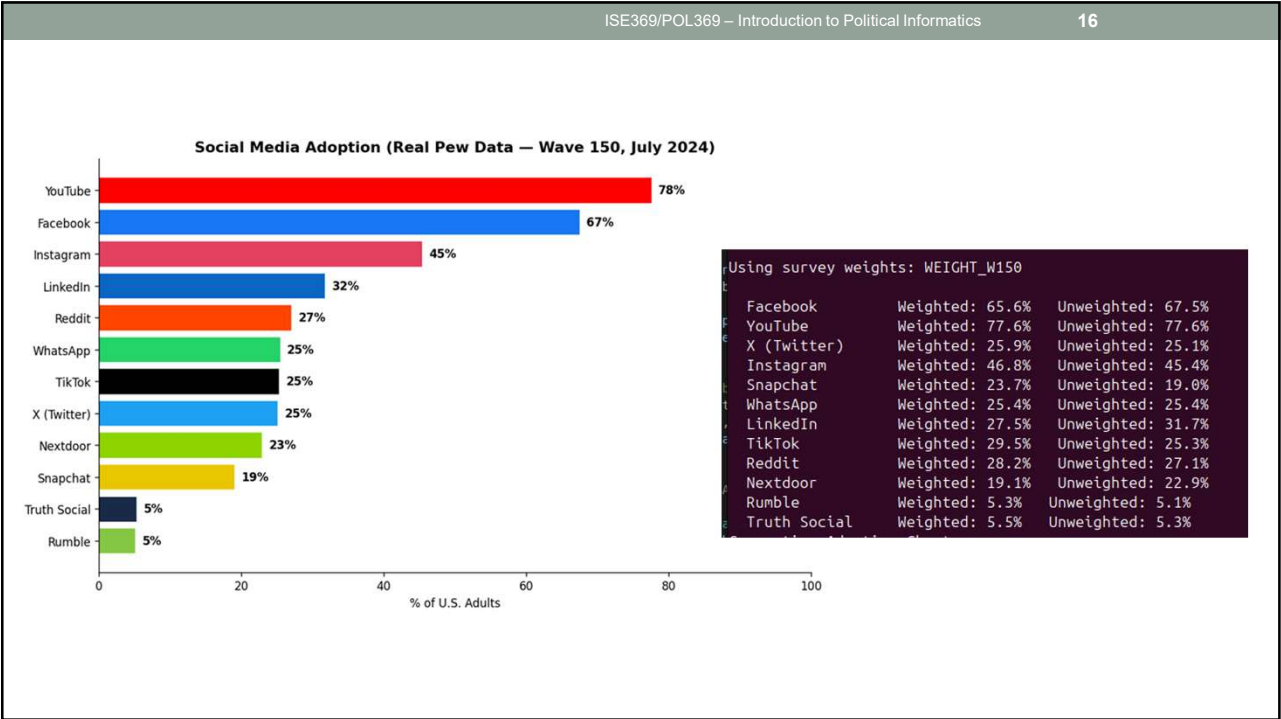
for bar, val in zip(bars, adoption.values):
    ax.text(bar.get_width() + 1,
            bar.get_y() + bar.get_height() / 2,
            f"{val:.0f}%",
            va="center",
            fontweight="bold",
            fontsize=10)

ax.set_xlabel("% of U.S. Adults")
ax.set_title("Social Media Adoption (Real Pew Data — Wave 150, July 2024)",
            fontweight="bold", fontsize=13)
ax.set_xlim(0, 100)

plt.tight_layout()
plt.savefig("real_pew_chart1_adoption.png",
            bbox_inches="tight")
plt.close()

print("Saved: real_pew_chart1_adoption.png")
```

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Platform Usage by Age Group (Analysis 2)

- Which age groups use which platforms, and how much?
- Refer to the python code for plotting.

```
use_cols = [f'uses_{name}' for name in platforms_available]
age_table = df.groupby("age_group")[use_cols].mean() * 100

age_table.columns = platforms_available
print("\n", age_table.round(1).to_string())
```

	Facebook	YouTube	X (Twitter)	Instagram	Snapchat	WhatsApp	LinkedIn	TikTok	Reddit	Nextdoor	Rumble	Truth Social
age_group												
18-29	65.2	89.9	45.8	79.3	58.5	34.1	45.1	57.6	56.4	12.9	4.2	3.4
30-49	73.3	86.9	29.0	61.7	26.6	32.9	41.2	33.5	42.0	22.1	4.2	3.7
50-64	71.0	79.5	25.5	40.4	12.3	25.9	34.4	22.6	19.8	26.3	6.8	8.0
65+	59.3	61.6	13.7	20.8	3.4	14.1	14.9	7.8	7.3	24.5	5.0	5.3

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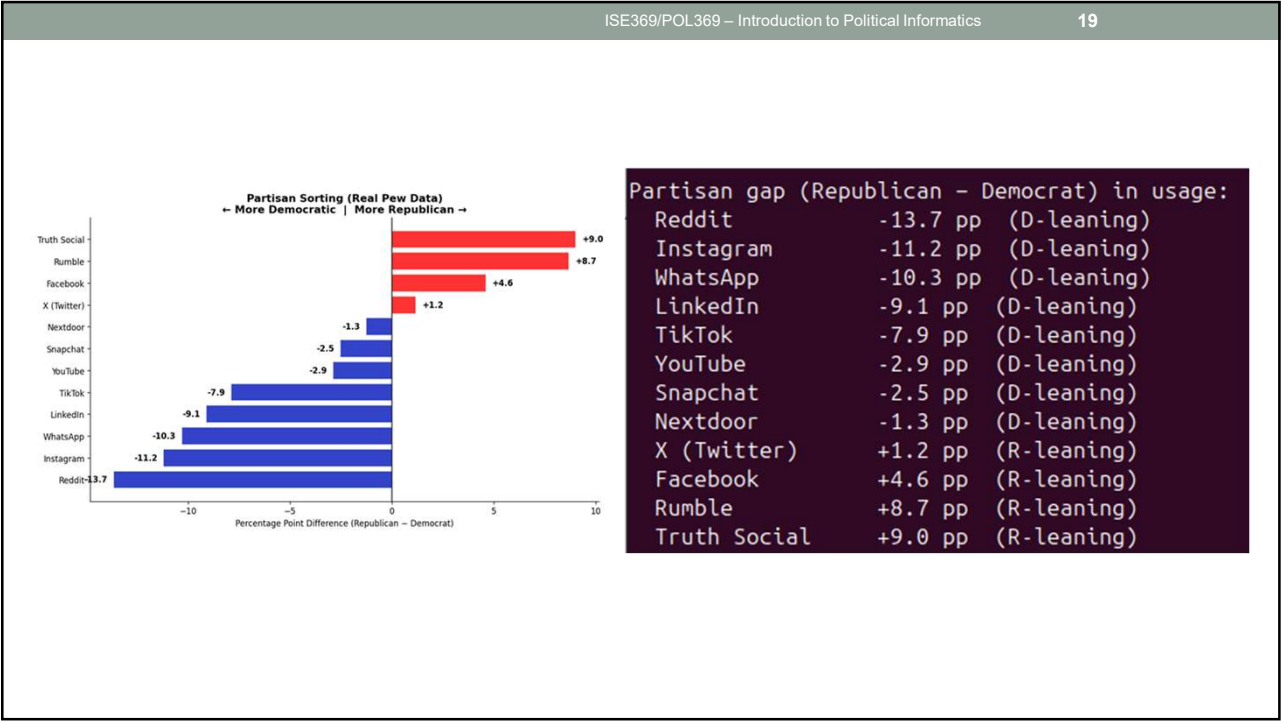
Partisan Platform Sorting(Analysis 3)

- How social media platform usage differs by political party?
- Refer to the python code for plotting.

```
if "party" in df.columns:
    party_table = df.groupby("party")[use_cols].mean() * 100
    party_table.columns = platforms_available

if "Rep/Lean Rep" in party_table.index and "Dem/Lean Dem" in party_table.index:
    gap = party_table.loc["Rep/Lean Rep"] - party_table.loc["Dem/Lean Dem"]
    print("\nPartisan gap (Rep - Dem):")
    for name, g in gap.sort_values().items():
        lean = "R-leaning" if g > 0 else "D-leaning"
        print(f" {name:15s} {g:+.1f} pp ({lean})")
```

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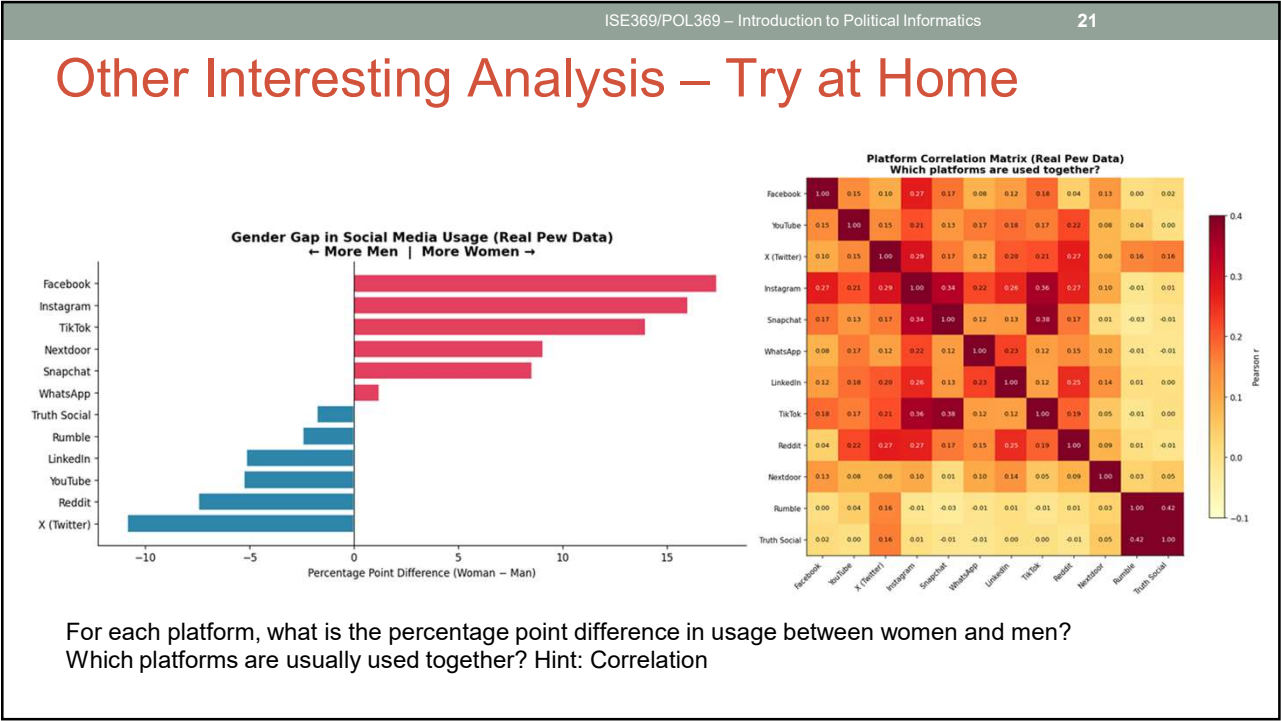
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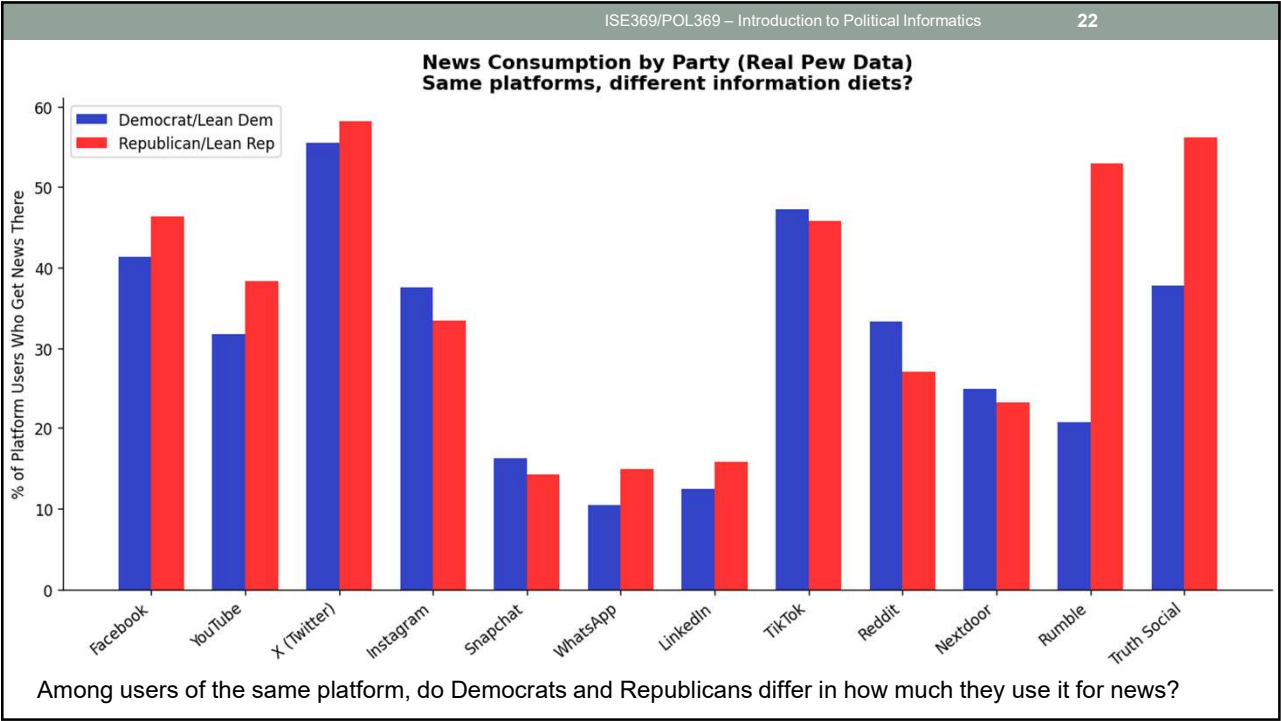
News Consumption Among Platform Users (Analysis 4) – Try this Yourself

- Among people who use a platform, how many actually use it to get news?
- Try to figure out some reasonable plot to show this analysis.

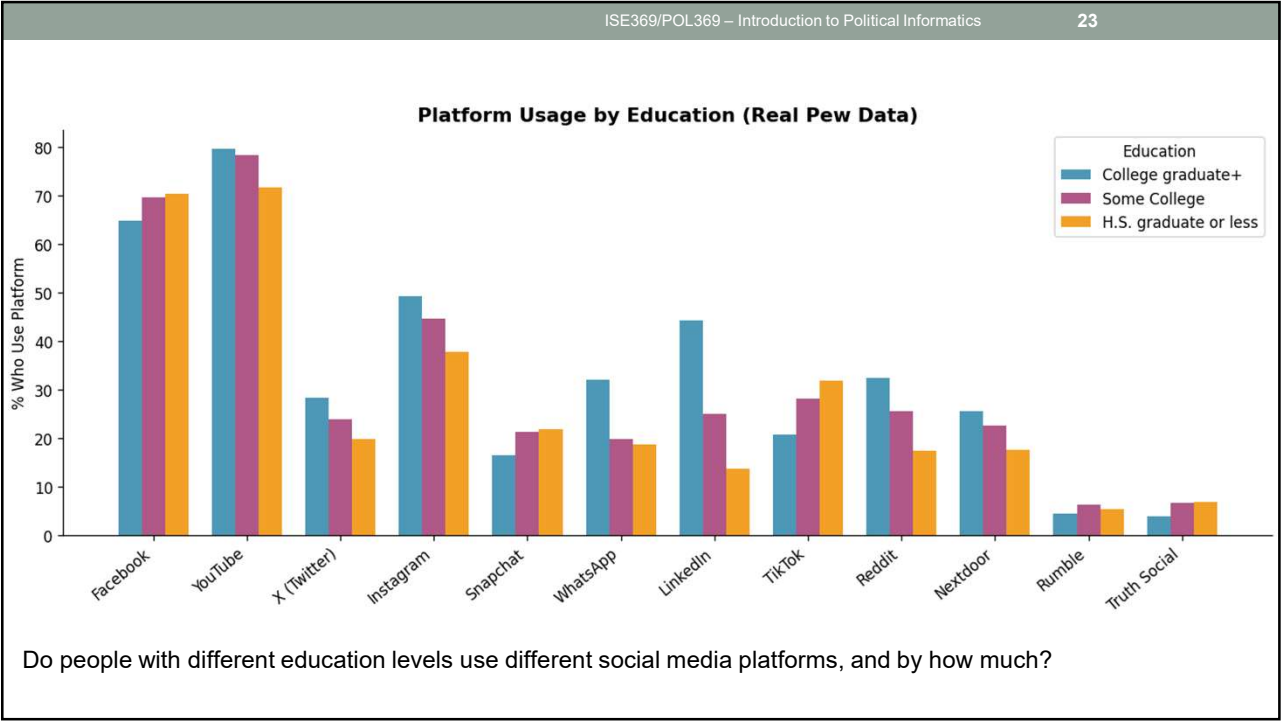
20



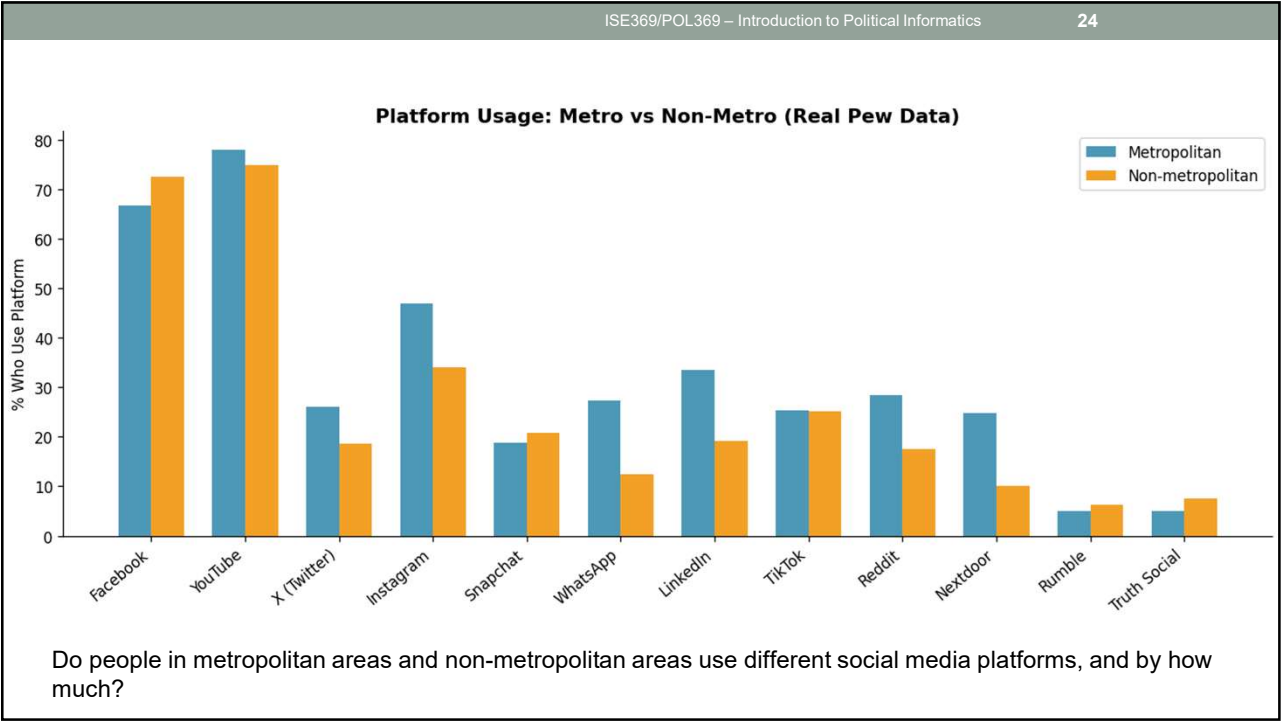
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Sentiment Analysis on Social Media Data

- What is Sentiment Analysis?
It is simply the process of working out (statistically) whether a piece of text is positive, negative or neutral.
- Python Package Used:
<https://github.com/cjhutto/vaderSentiment>



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- VADER (Valence Aware Dictionary and sEntiment Reasoner) belongs to a type of sentiment analysis that is based on lexicons of sentiment-related words.
- Each of the words in the lexicon is rated as to whether it is positive or negative, and in many cases, *how* positive or negative.
- VADER analyses a piece of text to see if any of the words in the text are present in the lexicon. For example, the sentence "The food is good and the atmosphere is nice" has two words in the lexicon (good and nice) with ratings of 1.9 and 1.8 respectively.
- VADER produces four sentiment metrics from these word ratings.

Word	Sentiment rating
tragedy	-3.4
rejoiced	2.0
insane	-1.7
disaster	-3.1
great	3.1

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- The first three, positive, neutral and negative, represent the proportion of the text that falls into those categories. The example sentence was rated as 45% positive, 55% neutral and 0% negative.
- The final metric, the compound score, is the sum of all of the lexicon ratings (1.9 and 1.8 in this case) which have been standardised to range between -1 and 1. In this case, our example sentence has a rating of 0.69, which is pretty strongly positive.
- Vader can handle informal writing - multiple punctuation marks, acronyms and an emoticon by including these sorts of terms in its lexicon.

Sentiment metric	Value
Positive	0.45
Neutral	0.55
Negative	0.00
Compound	0.69

@Optus we moved legit two suburbs and u cut our internet off for 2 weeks??? Like wtf next time I'm switching like this is bs>:(

1:01 AM - 28 Apr 2016

1 0 0

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How to use Vader?

```
!pip install vaderSentiment

from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer

analyser = SentimentIntensityAnalyzer()

def print_sentiment_scores(sentence):
    snt = analyser.polarity_scores(sentence)
    print("{:-<40} {}".format(sentence, str(snt)))
```

Link: <https://drive.google.com/file/d/1WtmFodXlOLuDpf0O3om9aEA6VsiwRvb0/view?usp=sharing>

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Examples

```
print_sentiment_scores("I just got a call from my boss - does he realise it's Saturday?")

I just got a call from my boss - does he realise it's Saturday? {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}

print_sentiment_scores("I just got a call from my boss - does he realise it's Saturday? :(")

I just got a call from my boss - does he realise it's Saturday? :( {'neg': 0.172, 'neu': 0.828, 'pos': 0.0,
'compound': -0.4404} (Negative score from emoji)

print_sentiment_scores("I just got a call from my boss - does he realise it's Saturday? smh :(")

I just got a call from my boss - does he realise it's Saturday? smh :( {'neg': 0.271, 'neu': 0.729, 'pos': 0.0,
'compound': -0.6369} (Negative score increases from smh)

print_sentiment_scores("The food is good.")

The food is good.----- {'neg': 0.0, 'neu': 0.508, 'pos': 0.492, 'compound': 0.4404}
```

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```
print_sentiment_scores("The food is GOOD.")

The food is GOOD.----- {'neg': 0.0, 'neu': 0.452, 'pos': 0.548, 'compound': 0.5622} (Positive
score increases from capital letters.)

print_sentiment_scores("The food is GOOD!")

The food is GOOD!----- {'neg': 0.0, 'neu': 0.433, 'pos': 0.567, 'compound': 0.6027} (Positive
score increases from !.)

print_sentiment_scores("The food is really GOOD!")

The food is really GOOD!----- {'neg': 0.0, 'neu': 0.487, 'pos': 0.513, 'compound': 0.6391} (Compound
score increases from "really".)

print_sentiment_scores("The food is really GOOD! But the service is dreadful.")

The food is really GOOD! But the service is dreadful. {'neg': 0.284, 'neu': 0.548, 'pos': 0.169, 'compound': -
0.3977} (Negative score increases from "dreadful".)
```

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