DSCC483.1.FALL2023ASE

Capstone Mini-Project

Kaggle Project: Classification of Tweets of Politicians from Northern Europe

Submitted By: Richa Yadav(32381047), Aradhya Mathur (32384567)

In [1]:
```
# importing important libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import nltk
import ast
import warnings
warnings.filterwarnings('ignore')
```

About the data

This dataset consists of all tweets posted by politicians of seven different Northern European countries: Belgium, Denmark, Iceland, Ireland, Netherlands, Norway, and Sweden. You will have:

- Tweets posted by politicians of seven Northern European countries mentioned above2
- Each country is associated with a different number of tweets. The test set consists of %20 of the tweets originating from each country (the remaining 80% is the training set).
- In total, there are 407,223 tweets in the training set (and 101,808 tweets in the test set). This makes a total of 509,031 tweets.

Kaggle Project – Data Dictionary The data has been provided in the assignment folder online (training_data.csv and test_data.csv). Open the CSV files and take a look at them before starting. Individual features (columns) of the dataset have been described below:

- hashtags: The list of hashtags included in the tweet
- full_text: The text of tweet (including emojis, htmls, hashtags)
- in_reply_to_screen_name: The Twitter screen name of the user the owner of the tweet is replying to (if any)
- country_user: Country of the owner of the tweet
- pol_spec_user: Political view of the owner of the tweet (found only on the training dataset)
- Id: An index number associated with tweets (found only on the test dataset)

In [2]:
```
# importing training dataset
train_data = pd.read_excel('training_data.xlsx')
pd.set_option('display.max_colwidth', None)
train_data.head()
```

Out[2]:

	hashtags	full_text	in_reply_to_screen_name	country_user	gen
0	feminist AskMeAnything	b'RT @swedennewyork: What does it mean to have a #feminist government? Join us on @reddit at 10 am (EST) Friday 3/23 for an #AskMeAnything se\xe2\x80\xa6'	NaN	sweden	
1	NaN	b'Jens Stoltenberg \xc3\xa5pnet virtuelle Rockheim i dag, sjekk det ut du ogs\xc3\xa5 http://bit.ly/1B6Nt5'	NaN	norway	
2	NaN	b'@Panenka_Bart Veel beterschap Bart en Loes! \xf0\x9f\xa5\xb0'	BartDerwael	belgium	
3	NaN	b'RT @CarlEmilLind: Tydelige S aftryk: \n\nPskykiatrien styrkes\n110% CO2 reduktion i 2050 \nPraktisk folkeskole + mesterl\xc3\xa6re\nAnnulationss\xc3\xb8gsm\xc3\xa5l\xe2\x80\xa6'	NaN	denmark	
4	NaN	b'\xf0\x9f\x98\x83 https://t.co/bpqoZ8Y4wm'	NaN	sweden	

In [3]:
```
# decoding UTF-8 encoded data
train_data['full_text'] = train_data['full_text'].map(lambda v: ast.literal_eval(v).decode())
train_data.head(5)
```

Out[3]:

	hashtags	full_text	in_reply_to_screen_name	country_user	gender_user	pol_spec_user
0	feminist AskMeAnything	RT @swedennewyork: What does it mean to have a #feminist government? Join us on @reddit at 10 am (EST) Friday 3/23 for an #AskMeAnything se...	NaN	sweden	Male	Left
1	NaN	Jens Stoltenberg åpnet virtuelle Rockheim i dag, sjekk det ut du også http://bit.ly/1B6Nt5	NaN	norway	Male	Left
2	NaN	@Panenka_Bart Veel beterschap Bart en Loes! 🥰	BartDerwael	belgium	Male	Left
3	NaN	RT @CarlEmilLind: Tydelige S aftryk: \n\nPskykiatrien styrkes\n110% CO2 reduktion i 2050 \nPraktisk folkeskole + mesterlære\nAnnulationssøgsmål...	NaN	denmark	Female	Left
4	NaN	😃 https://t.co/bpqoZ8Y4wm	NaN	sweden	Male	Left

Part I: Descriptive Analysis (20 points)

In this part of the analysis, you will be exploring some introductory NLP (natural language processing) techniques to better understand the data. Use the training dataset for the descriptive analysis.
[Important note: If you are an undergraduate student, please only answer the questions in Section A. If you are a graduate student, please answer Section A and Section B.]

Section A (20 points for undergraduate students, 10 points for graduate students): For all questions below, please use the training dataset.

a) Create a table that contains information on minimum, average, median, and maximum for the following: tweet length (#characters and #words) (text column), hashtag length (#characters and #words) (hashtags column)

In [4]:
```
# creating a new dataset with full_text and hashtags
text_hash = train_data[['full_text','hashtags']]
text_hash['full_text'] = text_hash['full_text'].astype("string")
text_hash['hashtags'] = text_hash['hashtags'].astype("string")
text_hash.head()
```

Out[4]:

	full_text	hashtags
0	RT @swedennewyork: What does it mean to have a #feminist government? Join us on @reddit at 10 am (EST) Friday 3/23 for an #AskMeAnything se...	feminist AskMeAnything
1	Jens Stoltenberg åpnet virtuelle Rockheim i dag, sjekk det ut du også http://bit.ly/1B6Nt5	<NA>
2	@Panenka_Bart Veel beterschap Bart en Loes! 😘	<NA>
3	RT @CarlEmilLind: Tydelige S aftryk: Pskykiatrien styrkes 110% CO2 reduktion i 2050 Praktisk folkeskole + mesterlære Annulationssøgsmål...	<NA>
4	😀 https://t.co/bpqoZ8Y4wm	<NA>

In [5]:
```
# tweet and hashtags - characters length
text_hash['text_char_len'] = text_hash['full_text'].str.len()
text_hash['hashtags_char_len'] = text_hash['hashtags'].str.len()
```

In [6]:
```
# tweet and hashtags - word length
text_hash['text_word_len'] = text_hash['full_text'].str.split().apply(len)
text_hash.loc[text_hash['hashtags'].notnull(), 'hashtags_word_len'] = text_hash.loc[text_hash['hashtags'
```

In [7]:
```
# Table with characters and word length
text_hash.head(5)
```

Out[7]:

	full_text	hashtags	text_char_len	hashtags_char_len	text_word_len	hashtags_word_len
0	RT @swedennewyork: What does it mean to have a #feminist government? Join us on @reddit at 10 am (EST) Friday 3/23 for an #AskMeAnything se...	feminist AskMeAnything	140	22	25	2.0
1	Jens Stoltenberg åpnet virtuelle Rockheim i dag, sjekk det ut du også http://bit.ly/1B6Nt5	<NA>	90	<NA>	13	NaN
2	@Panenka_Bart Veel beterschap Bart en Loes! 😘	<NA>	45	<NA>	7	NaN
3	RT @CarlEmilLind: Tydelige S aftryk: Pskykiatrien styrkes 110% CO2 reduktion i 2050 Praktisk folkeskole + mesterlære Annulationssøgsmål...	<NA>	139	<NA>	17	NaN
4	😀 https://t.co/bpqoZ8Y4wm	<NA>	25	<NA>	2	NaN

In [8]:
```
# table containing min, max, median and average for characters and word length
text_hash_describe = pd.DataFrame(text_hash.describe())
text_hash_describe
```

Out[8]:

	text_char_len	hashtags_char_len	text_word_len	hashtags_word_len
count	407223.0	127040.0	407223.000000	127040.000000
mean	140.31248	14.089948	20.284048	1.577724
std	63.191109	10.471846	10.144777	0.956729
min	1.0	1.0	1.000000	1.000000
25%	109.0	7.0	14.000000	1.000000
50%	140.0	11.0	19.000000	1.000000
75%	140.0	18.0	24.000000	2.000000
max	862.0	145.0	89.000000	16.000000

Inference

1) Text Character Length: Min: 1 ; Max: 862 ; Avg: 140.31 ; Median: 140 2) Hashtags Character Length: Min: 1 ; Max: 145 ; Avg: 14.09 ; Median: 11 3) Text Word Length: Min: 1 ; Max: 89 ; Avg: 20.28 ; Median: 19 4) Hashtags Word Length: Min: 1 ; Max: 16 ; Avg: 1.58 ; Median: 1

b) Find the top ten most commonly used hashtags (hashtags column) in each country. Then, create pie charts (one pie chart per country) which show the distribution of these ten most commonly used hashtags for each country. Do you observe any patterns? What are the meanings / interpretations of the hashtags you have identified?

In [9]:
```
# creating a new dataset with country_user, hashtags
# filtering null hashtags
user_hashtag = train_data[['country_user','hashtags']]
user_hashtag = user_hashtag[user_hashtag['hashtags'].notnull()]
# using str.split function to split hashtags into a list of hashtags
user_hashtag['hashtags'] = user_hashtag['hashtags'].str.split()
user_hashtag.head()
```

Out[9]:

	country_user	hashtags
0	sweden	[feminist, AskMeAnything]
9	norway	[Cyprus]
13	belgium	[anhienNealyse]
14	denmark	[IPAC, IPAC]
20	denmark	[sommerstævne]

In [10]:
```
# based on country - grouping hashtags
user_hashtag = user_hashtag.groupby('country_user').agg(sum)
user_hashtag.head()
```

Out[10]:

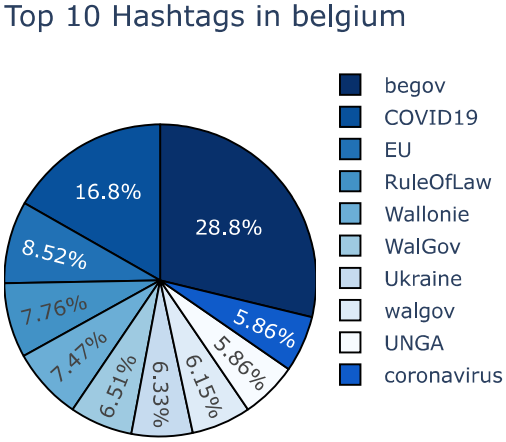
country_user	hashtags
belgium	[anhienNealyse, fordgenk, villapolitica, Begov, begrotingstekort, staatschuld, RuleOfLaw, Malta, Europe, Zeus, King, EuropeanUnion, culture, diversity, Greekmythology, thisiswhy, de1000km, ikbenWIJ, UE, Sahel, Marche, Vlareg, walgov, WallonieRelance, Houffalize, ProvLux, Brexit, LeSaviezVs, élection, terrorisme, sécurité, HateSpeech, Vienne, IDEVAW, Europe, SayNoStopVAW, orangetheworld, womensrightsarehumanrights, Kompassklub, grgent, haiku, EUelections2019, Hangout, Eerstelijnshervorming, zorg, eerstelijn, zorgvoorelkaar, IdéesPS, Leuven, Paris, RuleOfLaw, zwalm2012, oostende, geestelijkegezondheidszorg, Avanti, EnvoyeSpecial, CETA, ForMigration, EtudeSolidaris, civielebescherming, LGBTI, IDAHOT, glyphosate, Youtube, triebru15, walgov, nouveauCETA, BEmissionCHN, tvlnieuws, Vito, primeur, monaviscompte, Kluisbos, OCMW, climatechange, climate, EPhearings2019, productsafety, terrorisme, NATOPA, électricité, PS, naamkeuze, ouioui, COVID19, cancer, ONG, Selembao, Kinshasa, RDCongo, RDC, solidarité, SouthAfrica, Malta, uzbrussel, PVF, Hautekiet, Ebola, Congo, ItWasTime, ...]
denmark	[IPAC, IPAC, sommerstævne, dkpol, Finland, Sweden, NATO, refugee, dkiverden, dkpol, dagenskarikatur, comebackkids, energiewende, Afghanistan, ISAF, eudk, dkpol, uddpol, tårernesEuropa, EUbudget, dkpol, eupol, dkpol, TeamJunckerEU, dkpol, ValgflæskAlarm, dkpol, dktrp, dkpol, Politiken, Stoklund, dkpol, dkpol, dkforsvar, WeAreNATO, dr3valg, dkpol, dkgreen, fv15, G20, eudk, EUCO, dkpol, refugees, unhcr, offdig, digidk, dkpol, dkgreen, womenintech, dkpol, dkpol, dkpol, dkpol, dkpol, ForDanmark, WEURO2022, Energiewende2015, dkpol, danskebank, danskerhverv, dkpol, dkpol, dkgreen, elpriser, HRC32, FutureBuildings, dkpol, climate, Nyruphus, HelsingørKommmune, sdg2, dkpol, dkgreen, dkpol, UNGA, dkpol, innovation, dkinno, dkbiz, dkpol, voresnatur, dkgreen, dkpol, dkpol, stemja, dkpol, dkaid, LGBTI, ligestilling, dkpol, dkpol, dataetik, digitalisering, dkpol, dkpol, faglærttilfremtiden, dkpol, eud, dkpol, ...]
iceland	[Iceland, IcelandSecrets, hressandi, borgarstjórn, lífskjarasamningur, þeimtókstaðstöðvahjólatvinnulífsins, SmallStates, panamapapers, cashljós, tortólastjórnin, northernlights, winning, emisland, ForMin, NATO, WashingtonDC, solidarity, freetrade, trade, Brexit, StóruMálin, Léttir, afhjúpun, Íruglinu, nolafur, cashljós, ungjofn, WorldCup, Iceland, Huh, OneArctic, 12stig, emisland, isl, nýríkisstjórn, winning, Iceland, independence, sovereignty, kjósumbetralíf, Samtökiðnaðarins, Leitinaðsjálfinu, fjárlög, AskNordicAmbs, lowblow, NordicDayUSA, paskar2001, ReykjavikSummit, TheGoodDr, betriinnkaup, Schäuble, heforshe, artsweek, furðuland, samtökatvinnulífsins, vúhú, movienight, mömmutwitter, forseti2016, 200Forever, nrpol, nrsession, Töfftýpuráföstu, Iceland, AskNordicAmbs, NordicEquality, CSW65, forseti, 12stig, ARGICE, WorldCup, HUH, Stockholm, RealLiverpool, Arctic, Marine, Environment, Climate, Green, Islandia, BudaPESt, hib1816, Dýpt, nýársþankar, foreignpolicy, AskNordicAmbs, strakarnirokkar, Xiongan, ArcticGreenEnergy, Sinopec, Mótumframtíðinasaman, Iceland, ecofriendly, Iceland, Putin, Arkhangelsk, Arctic, Trade, eldhúsdagur, ARSMUN, ...]
ireland	[GE2020, OurRuralFuture, LeavingCertResults, EU, UN, 8thRef, ProudOfYou, TEN_E, FossilFree, OnTheRecordNT, MarRef, Ploughing2019, OurRuralFuture, ruralopportunity, Palestine, ICRC, MakeWayDay, Carrigaline, CBLive, galway, Covid19, ChildrensHospital, Limerick, Volunteerism, OurRuralFuture, EU, ge16, phabsaveslives, Wexford, Ukraine, Eurogroup, COVID19, GE2020, LookForward, Dáil, Seanad, 8Committee, ieinternetday, LE19, Recovery, Resilience, COVID19, RRF, trolleywatch, ParadisePapers, Repealthe8th, TBCTbridgethegap, DigitalStrategy, Kilbarrack, DebenhamsWorkersRally, Debenhams, Waiting4Years, AncientHistory, EuropeanElections2019, JobFairy, Derry, Ophelia, RTEtwip, SOTEU, nsp25, Covid, OurRuralFuture, EP2019, Brexit, TUI17, TonightVMTV, BuildBackBetter, radio, IMRO20, PlanetYouth, Budget21, housing, homelessireland, costrental, BREAKING, Covid19, Limerick, buseireann, MultilateralismMatters, EU4HumanRights, OurRuralFuture, RemoteWork, TransformYourWorkDay, SciFest2018, trialbymedia, RethinkingEconomics, TeamIvana, Limerick, InternationalWomensDay, StPatricksDay, DublinPride, YesEquality, vinb, biodiversityweek, COVID19, GreenNewDeal, LookForward, GE2020, REthinkEnergy, COVID19, ...]
netherlands	[women, families, communities, society, equality, equity, soil, EUSoil, 50jaarD66, Brexit, ReadingNow, COVID, Japan, Giacometti, Chadwick, FacingFear, Fundatie, Zwolle, Octopus2015, ArieSlob, carredebat, wifestival, Nutrition, UHC, UHCDay, InvestInNutrition, vrije, tarieven, specialisatie, fysiotherapie, D66Congres, Leeuwarden, kaasmarkt, fysiotherapeut, discon2017, bouw, wooncrisis, Buma, radio1debat, roverstrots, pochkapitalisme, climateneutralEU, methane, pensioenpotjes, WEF20, nutrition, people, planet, foodsystems, zorg, Rijksmuseum, Palau, UHC, politiek, D66, CoronaApp, nutrition, SUNGG19, GlastravanLoon, srilanka, lisabedankt, Dieselgate, D66, codegeel, lief, CoronaCrisis, COVID2019, zorghelden, vrijwilligers, sterkesamenleving, COVID19, Baantjer, volkskrant, WorldCitiesDay, apb2019, amsterdam, prinsengracht, EuropeTogether, DNB, KPN, resultaten, jaarcijfers, lerarentekort, D66, Delft, ajax, Eurovision, telegraafpremium, Highlightdelft, zzp, zzp, resilience, stunted, children, malnourished, poverty, humancapital, foodsystems, nutrition, ClimateChange, ...]

In [11]:
```
# Finding the top ten most commonly used hashtags (hashtags column) in each country separately.
hashtag_freq_dict = {}
user_hashtag = user_hashtag.reset_index()
for index, row in user_hashtag.iterrows():
    hashtag_freq_dict[row['country_user']] = nltk.FreqDist(row['hashtags']).most_common(10)
user_hashtag_df = pd.DataFrame(columns=['Country', 'Top 10 Hashtags'])
for country, top_hashtags in hashtag_freq_dict.items():
    user_hashtag_df = user_hashtag_df.append({'Country': country, 'Top 10 Hashtags': top_hashtags}, ignor
user_hashtag_df
```

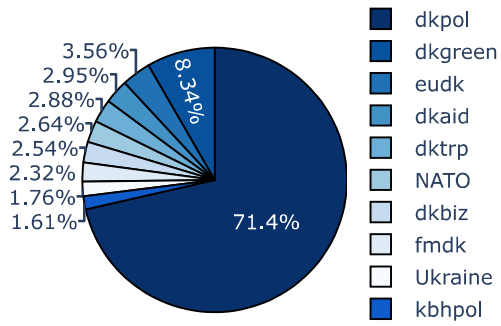
Out[11]:

	Country	Top 10 Hashtags
0	belgium	[(begov, 1291), (COVID19, 752), (EU, 382), (RuleOfLaw, 348), (Wallonie, 335), (WalGov, 292), (Ukraine, 284), (walgov, 276), (UNGA, 263), (coronavirus, 263)]
1	denmark	[(dkpol, 16090), (dkgreen, 1880), (eudk, 802), (dkaid, 664), (dktrp, 648), (NATO, 594), (dkbiz, 573), (fmdk, 523), (Ukraine, 397), (kbhpol, 363)]
2	iceland	[(Iceland, 97), (12stig, 42), (AskNordicAmbs, 37), (emisland, 33), (forseti, 30), (NordicUSAsummit, 25), (Nordic, 23), (NordicDayUSA, 21), (cashljós, 20), (kosningar, 20)]
3	ireland	[(COVID19, 541), (Brexit, 391), (Limerick, 350), (OurRuralFuture, 323), (Eurogroup, 231), (Ireland, 202), (GE2020, 199), (Ukraine, 190), (LE19, 156), (HumanRights, 147)]
4	netherlands	[(nutrition, 782), (D66, 273), (food, 149), (EUGreenDeal, 143), (NS, 134), (COVID19, 113), (Delft, 113), (SDGs, 113), (people, 107), (foodsystems, 101)]
5	norway	[(NATO, 779), (Cyprus, 310), (dax18, 214), (Ukraine, 194), (Norway, 182), (nrkdebatt, 162), (nrkvalg, 161), (likestilling, 155), (Russia, 141), (vaccineswork, 121)]
6	sweden	[(svpol, 1599), (fb, 707), (COVID19, 366), (GenerationEquality, 286), (klimat, 267), (bopol, 260), (MigrationEU, 212), (EU, 198), (pldebatt, 178), (föpol, 175)]

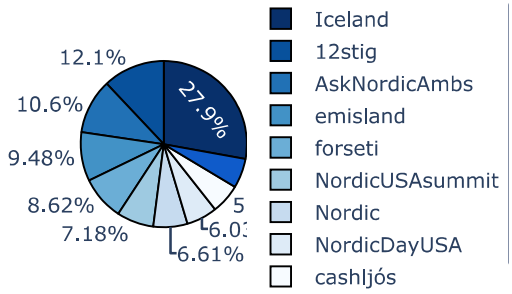
In [12]:
```
# Top 10 Hashtags for every country
custom_colors = px.colors.sequential.Blues_r[:10]
chart_width = 300
chart_height = 300
# iterating through the DataFrame and create a pie chart for each country
for index, row in user_hashtag_df.iterrows():
    country = row['Country']
    top_hashtags = row['Top 10 Hashtags']
    hashtags, counts = zip(*top_hashtags)

    pie_df = pd.DataFrame({'Hashtags': hashtags, 'Counts': counts})

    fig = px.pie(pie_df, names='Hashtags', values='Counts',
                 color_discrete_sequence=custom_colors)
    fig.update_layout(
        title=f'Top 10 Hashtags in {country}',
        title_x=0,
        margin=dict(l=0, r=0, b=0, t=40),
        legend=dict(x=1, y=1),
        width=chart_width,
        height=chart_height,
    )
    fig.update_traces(marker_line_color='black', marker_line_width=1)
    # ploting
    fig.show()
```



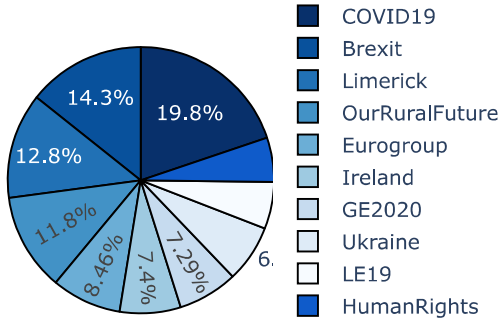
Top 10 Hashtags in denmark



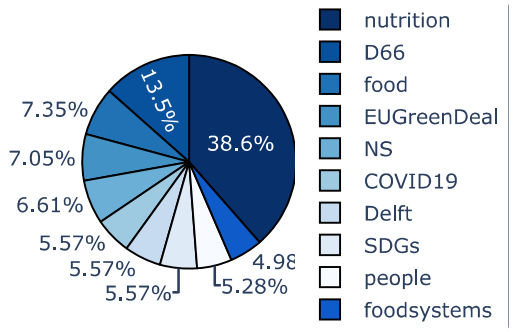
Top 10 Hashtags in iceland



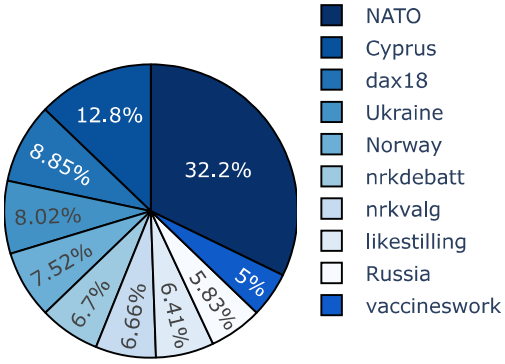
Top 10 Hashtags in ireland



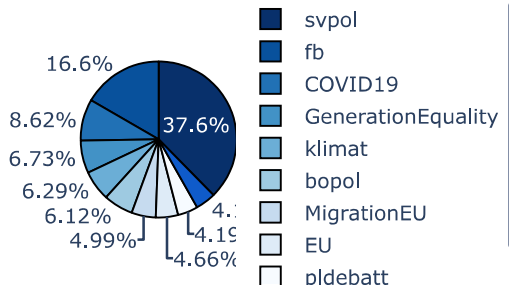
Top 10 Hashtags in netherlands



Top 10 Hashtags in norway



Top 10 Hashtags in sweden



Inferences:

1) Belgium and COVID-19 Focus: Belgium's top hashtags prominently feature COVID-19 related tags, with "COVID19" being one of the most frequently used hashtags. This suggests that discussions related to the pandemic are prevalent in Belgian social media discourse. 2) Denmark's Political Engagement: Denmark's hashtags reflect a strong engagement in political discussions with hashtags like "dkpol" (Danish politics) and "dkgreen" (Danish green initiatives) appearing as the most frequently used. This indicates active political participation and environmental awareness in Denmark. 3) Iceland's Cultural and Political Engagement:Iceland's hashtags include a mix of cultural references and political discussions, with hashtags like "Iceland," "12stig" (12 points, possibly related to Eurovision), and "AskNordicAmbs" (asking Nordic ambassadors) indicating diverse social media engagement. 4) Ireland and Brexit

Concerns: Ireland's hashtags prominently feature "Brexit," indicating the country's significant interest and concerns related to the United Kingdom's departure from the European Union. Additionally, "Limerick" suggests regional discussions. 5) Netherlands' Focus on Nutrition: The Netherlands' hashtags are centered around nutrition and sustainability, with "nutrition," "food," and "foodsystems" appearing among the top hashtags. This reflects a focus on healthy eating and sustainable food practices in the country. 6) Norway's International Engagement: Norway's hashtags include international topics such as "NATO," "Cyprus," and "Ukraine," indicating the country's engagement in global affairs. Additionally, hashtags related to gender equality ("likestilling") and vaccines ("vaccineswork") show a commitment to important social issues. 7) Sweden's Political Discourse: Sweden's top hashtags include "svpol" (Swedish politics) and "pldebatt" (planning debate), highlighting active political discourse and urban planning discussions. "COVID19" also appears, reflecting ongoing pandemic-related discussions.

c) Create a stacked bar chart (one stacked bar per country) that shows the percentage of political views associated with each country. [Create normalized bars to show percentages: minimum should be 0, maximum should be 1 (or 0% and 100%)]. Interpret your findings.

In [13]:
```
# creating a new dataset with country_user, pol_spec_user
country_pol = train_data[['country_user','pol_spec_user']]
country_pol['pol_spec_user'] = country_pol['pol_spec_user'].str.split()
# aggregating all political views - grouping based on country level
country_pol = country_pol.groupby('country_user').agg(sum)
country_pol = country_pol.reset_index()
country_pol.head()
```

Out[13]:

	country_user	pol_spec_user
0	belgium	[Left, Right, Center, Center, Center, Right, Left, Right, Right, Center, Left, Left, Right, Right, Right, Right, Right, Center, Right, Right, Center, Center, Left, Right, Right, Left, Right, Right, Center, Right, Right, Right, Right, Right, Center, Left, Left, Left, Right, Left, Right, Right, Right, Right, Center, Right, Center, Right, Right, Left, Center, Left, Left, Left, Center, Right, Left, Left, Center, Left, Right, Center, Center, Left, Left, Right, Left, Right, Right, Center, Right, Right, Center, Center, Center, Left, Right, Right, Left, Left, Right, Right, Right, Right, Center, Left, Left, Right, Center, Left, Right, Center, Right, Left, Right, Left, Left, Left, Center, Center, ...]
1	denmark	[Left, Left, Center, Center, Left, Left, Right, Left, Right, Right, Left, Center, Left, Right, Center, Left, Right, Center, Right, Left, Right, Right, Right, Center, Center, Left, Center, Left, Right, Center, Right, Right, Left, Right, Left, Center, Center, Center, Left, Left, Left, Right, Center, Left, Left, Center, Center, Left, Center, Left, Left, Left, Center, Center, Right, Left, Left, Right, Center, Center, Right, Center, Center, Center, Left, Right, Left, Right, Center, Right, Left, Right, Right, Left, Right, Left, Left, Left, Right, Right, Center, Center, Right, Left, Center, Center, Center, Right, Left, Right, Left, Right, Left, Left, Center, Center, Center, Left, Right, Left, Center, ...]
2	iceland	[Independent, Independent, Independent, Left, Left, Independent, Left, Right, Left, Left, Right, Left, Left, Independent, Left, Right, Left, Right, Left, Left, Left, Independent, Right, Right, Left, Right, Left, Center, Left, Left, Left, Left, Right, Independent, Left, Left, Right, Left, Independent, Left, Left, Left, Left, Left, Left, Right, Right, Left, Right, Left, Left, Left, Left, Left, Left, Left, Left, Right, Left, Left, Left, Independent, Right, Independent, Left, Right, Left, Left, Left, Right, Independent, Right, Left, Left, Independent, Left, Left, Right, Left, Left, Independent, Left, Left, Left, Right, Independent, Left, Right, Left, Left, Left, Left, Right, Left, Left, Left, Right, Left, Left, Left, Left, ...]
3	ireland	[Left, Left, Right, Right, Right, Left, Left, Center, Right, Left, Left, Right, Right, Right, Left, Right, Left, Center, Left, Left, Left, Left, Left, Left, Center, Center, Left, Right, Left, Right, Right, Right, Center, Right, Right, Left, Right, Right, Right, Right, Left, Left, Left, Left, Left, Left, Left, Right, Right, Center, Right, Right, Right, Right, Left, Left, Center, Left, Right, Right, Right, Right, Right, Right, Center, Left, Left, Center, Left, Left, Right, Right, Right, Center, Center, Left, Left, Center, Center, Left, Left, Left, Left, Center, Right, Right, Right, Right, Center, Left, Left, Right, Right, Left, Right, Right, Center, Right, Left, Left, Center, ...]
4	netherlands	[Center, Center, Center, Center, Center, Left, Center, Center, Left, Left, Center, Center, Center, Center, Left, Center, Center, Center, Center, Center, Center, Center, Left, Center, Center, Left, Center, Left, Center, Center, Left, Center, Left, Center, Center, Center, Center, Center, Center, Center, Left, Left, Right, Center, Left, Left, Left, Left, Center, Left, Left, Center, Center, Center, Center, Left, Center, Center, Left, Center, Center, Left, Left, Left, Center, Center, Left, Center, Center, Center, Center, Center, Center, Center, Center, Left, Center, Left, Center, Left, Center, Center, Center, Center, Center, Left, Center, Center, ...]

In [14]:
```
# initializing empty dictionary
polview_country_dict = {}
polviews = list(train_data['pol_spec_user'].unique())
for index, row in country_pol.iterrows():
    polviews_freq = nltk.FreqDist(row['pol_spec_user'])
    # 0-1 normalization
```

```
    total_pol_view_count = sum(polviews_freq.values())
    norm_polviews = {polview: count / total_pol_view_count for polview, count in polviews_freq.items()}
    # adding normalized values to the dictionary
    polview_country_dict[row['country_user']] = norm_polviews
polview_country_df = pd.DataFrame.from_dict(polview_country_dict, orient='index').fillna(0)
polview_country_df.index.name = 'Country'
polview_country_df
```

Out[14]:

Country	Left	Right	Center	Independent
belgium	0.338391	0.454943	0.206666	0.000000
denmark	0.411228	0.329448	0.259324	0.000000
iceland	0.582973	0.271697	0.000412	0.144919
ireland	0.424489	0.408122	0.167390	0.000000
netherlands	0.341769	0.038079	0.620151	0.000000
norway	0.527725	0.262127	0.210148	0.000000
sweden	0.483611	0.231019	0.285370	0.000000

In [15]:

```
# plot for Political Inclination Distribution by Country
custom_colors = ['#000004', '#011152', '#aac2f2', '#fafbff']

fig = px.bar(polview_country_df,
             labels={'index': 'Country', 'value': 'Normalized Count'},
             title='Political Inclination Distribution by Country',
             barmode='stack',
             color_discrete_sequence=custom_colors)

fig.update_layout(xaxis_title='Country', yaxis_title='Normalized Count',
                  legend_title='Political Views',
                  title_x=0.5)
fig.update_traces(marker_line_color='black', marker_line_width=1)
#plot
fig.show()
```

Inferences:

1. 'Left' Orientation: The 'Left' political orientation is prominent in multiple countries, including Denmark, Iceland, Norway, and Sweden, with proportions ranging from approximately 41% to 58%. This indicates a prevalent left-leaning political trend in these nations.

2. Significant 'Right' Leanings in Belgium and almost negligible in Netherlands : Belgium has highest proportions of individuals identifying as 'Right,' with percentages of approximately 45%. This suggests a substantial right-leaning population in Belgium, Whereas, in Netherlands only 3% individuals identify as 'Right'.

3. Strong 'Center' Orientation in the Netherlands: The Netherlands has a dominant 'Center' orientation, with around 62% of individuals aligning with centrist political ideologies.

4. Absence of 'Independent' Identifications: Across all the countries except Iceland, there are no reported identifications as 'Independent.' This suggests that the surveyed individuals in these countries do not align themselves with an independent or non-affiliated political stance, or it may indicate that the survey did not include an 'Independent' category.

d) Create a stacked bar chart that shows the distribution of genders by country. [Create normalized bars to show percentages: minimum should be 0, maximum should be 1 (or 0% and 100%)]. Interpret your findings.

In [16]:
```
# creating a new dataset with country_user, gender_user
gender_by_country = train_data[['country_user','gender_user']]
gender_by_country['gender_user'] = gender_by_country['gender_user'].str.split()
# aggregating genders - grouping based on country level
gender_by_country = gender_by_country.groupby('country_user').agg(sum)
gender_by_country = gender_by_country.reset_index()
gender_by_country.head()
```

Out[16]:

	country_user	gender_user
0	belgium	[Male, Male, Male, Male, Male, Female, Male, Male, Male, Male, Male, Male, Male, Male, Male, Male, Female, Male, Female, Male, Male, Male, Male, Male, Male, Male, Female, Male, Male, Male, Male, Male, Female, Male, Male, Male, Male, Male, Female, Male, Male, Male, Female, Male, Female, Male, Male, Male, Male, Male, Male, Male, Male, Male, Male, Male, Male, Male, Female, Male, Male, Male, Female, Male, Male, Male, Male, Male, Male, Female, Male, Male, Female, Female, Male, Male, Male, Male, Male, Male, Male, Female, Male, Female, Male, Male, Male, Male, Male, Male, Female, Male, Male, Male, Male, Male, ...]
1	denmark	[Female, Female, Male, Male, Male, Female, Female, Female, Female, Female, Female, Female, Male, Female, Male, Female, Male, Female, Male, Male, Male, Female, Male, Male, Male, Male, Male, Female, Female, Male, Female, Male, Female, Male, Male, Male, Male, Female, Male, Male, Female, Male, Male, Male, Female, Male, Male, Female, Male, Male, Female, Male, Female, Male, Male, Male, Male, Female, Male, Female, Female, Female, Male, Female, Male, Male, Female, Female, Male, Female, Female, Female, Female, Female, Male, Male, Male, Female, Female, Male, Male, Female, Male, Female, Female, Male, Female, Female, Male, Female, Female, Female, Male, Male, Male, Female, Female, Male, Female, Male, ...]
2	iceland	[Male, Male, Male, Female, Female, Male, Male, Male, Female, Male, Male, Female, Male, Male, Male, Male, Female, Male, Female, Female, Female, Male, Male, Male, Female, Male, Female, Male, Female, Female, Female, Male, Male, Male, Female, Male, Male, Male, Male, Female, Male, Female, Female, Female, Male, Male, Female, Male, Female, Female, Male, Female, Male, Male, Male, Male, Female, Female, Female, Male, Male, Male, Male, Male, Female, Female, Female, Male, Male, Male, Female, Female, Male, Male, Male, Male, Female, Female, Male, Female, Female, Male, Male, Male, Female, Male, Female, Female, Male, Male, Male, Female, Female, Female, Male, Female, Female, Female, Female, ...]
3	ireland	[Male, Male, Male, Male, Male, Female, Male, Male, Male, Male, Male, Male, Male, Male, Male, Male, Male, Male, Male, Male, Male, Male, Female, Male, Male, Male, Male, Female, Male, Male, Male, Male, Male, Male, Female, Female, Male, Male, Female, Female, Male, Male, Male, Male, Male, Male, Female, Male, Male, Female, Male, Female, Male, Male, Male, Male, Male, Female, Male, Male, Female, Male, Female, Male, Male, Male, Male, Female, Female, Male, Male, Female, Male, Male, Female, Male, Male, Male, Male, Male, Male, Male, Male, Male, Male, Male, Male, Male, Male, Female, Female, Male, Male, Female, Male, Male, Male, Male, Male, ...]
4	netherlands	[Female, Male, Female, Male, Male, Male, Male, Male, Male, Male, Male, Male, Female, Male, Male, Male, Male, Female, Male, Female, Female, Female, Male, Male, Male, Male, Male, Female, Female, Male, Male, Male, Male, Male, Male, Male, Male, Male, Female, Male, Male, Male, Male, Female, Male, Male, Male, Female, Male, Female, Male, Female, Male, Female, Female, Female, Male, Male, Male, Male, Male, Male, Female, Male, Male, Male, Male, Male, Male, Male, Female, Male, Female, Male, Female, Female, Male, Male, Female, ...]

In [17]:

```
import pandas as pd
import nltk
# initializing empty dictionary
gender_country_dict = {}
genders = list(train_data['gender_user'].unique())
for index, row in gender_by_country.iterrows():
    gender_freq = nltk.FreqDist(row['gender_user'])
    # 0-1 Normalization
    total_gender_count = sum(gender_freq.values())
    norm_genders = {gender: count / total_gender_count for gender, count in gender_freq.items()}
    # adding normalized values to the dictionary
    gender_country_dict[row['country_user']] = norm_genders
gender_country_df = pd.DataFrame.from_dict(gender_country_dict, orient='index').fillna(0)
gender_country_df.index.name = 'Country'
gender_country_df
```

Out[17]:

	Male	Female
Country		
belgium	0.818684	0.181316
denmark	0.605440	0.394560
iceland	0.543393	0.456607
ireland	0.788829	0.211171
netherlands	0.771152	0.228848
norway	0.685085	0.314915
sweden	0.431444	0.568556

In [18]:
```
# plot for Political Inclination Distribution by Gender
custom_colors = ['#000526', '#fafbff']
fig = px.bar(gender_country_df,
             labels={'index': 'Gender', 'value': 'Normalized Count'},
             title='Political Inclination Distribution by Gender',
             barmode='stack',
             color_discrete_sequence=custom_colors)
fig.update_layout(xaxis_title='Gender', yaxis_title='Normalized Count',
                  legend_title='Political Views',
                  title_x=0.5)
fig.update_traces(marker_line_color='black', marker_line_width=1)
# Plot
fig.show()
```

Inferences

1) In Belgium, the male proportion appears to dominate, as is the case in the Netherlands, Ireland, and Norway. 2) Sweden stands out with a female proportion of 0.568556%. 3) Belgium, Ireland, and the Netherlands exhibit roughly 18 to 22% female representation.

Section B (10 points for graduate students): Graduate students must also complete the following questions. For all questions below, please use the training dataset.

a) Write a 'text cleaner' function that does the following in the full_text column: (i) remove stopwords5, (ii) remove all words that are shorter than 3 characters, (iii) remove all links (starting with http), (iv) remove emojis, (v) remove punctuation. Attach the code you wrote to the lemmatizer.py file in the project folder. Run the lemmatizer function and create 'cleaned and lemmatized' version of text column. (You can name the new column as text_clean). After the cleaning, expand the table you have created in Section A) by calculating minimum, average, median, and maximum for the newly created text_clean column (#characters and #words). (5 points)

We are doing stemming, tokenize

In [19]:
```
from langdetect import detect
from nltk.stem import SnowballStemmer
stemmers = {
    'sv': SnowballStemmer('swedish'),
    'no': SnowballStemmer('norwegian'),
    'nl': SnowballStemmer('dutch'),
    'da': SnowballStemmer('danish'),
    'en': SnowballStemmer('english'),
    'fr': SnowballStemmer('french')
}

#function to detect language and apply the appropriate Snowball Stemmer
def stem_text(text):
    try:
        # detecting language of the text
        detected_language = detect(text)
        if detected_language in stemmers:
            stemmer = stemmers[detected_language]
            return ' '.join([stemmer.stem(word) for word in text.split()])
        else:
            return text
    except Exception as e:
        return text
```

In [20]:
```
#stemming
train_data['full_text'] = train_data['full_text'].apply(stem_text)
train_data.head()
```

Out[20]:

	hashtags	full_text	in_reply_to_screen_name	country_user	gender_user	pol_spec_user
0	feminist AskMeAnything	rt @swedennewyork: what doe it mean to have a #feminist government? join us on @reddit at 10 am (est) friday 3/23 for an #askmeanyth se...	NaN	sweden	Male	Left
1	NaN	jen stoltenberg åpn virtuell rockheim i dag, sjekk det ut du også http://bit.ly/1b6nt5	NaN	norway	Male	Left
2	NaN	@panenka_bart vel beterschap bart en loes! 😘	BartDerwael	belgium	Male	Left
3	NaN	rt @carlemillind: tyd s aftryk: pskykiatri styrk 110% co2 reduktion i 2050 praktisk folkeskol + mesterlær annulationssøgsmål...	NaN	denmark	Female	Left
4	NaN	😀 https://t.co/bpqoZ8Y4wm	NaN	sweden	Male	Left

In [21]:
```
# cleaning the full_texts and storing it in another column text_clean using lemmatizer.py
from lemmatizer import clean_text
train_data['text_clean'] = clean_text(train_data)
train_data.dropna(subset=['text_clean'], inplace=True)
train_data.head()
```

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

Out[21]:

	hashtags	full_text	in_reply_to_screen_name	country_user	gender_user	pol_spec_user	text_clea
0	feminist AskMeAnything	rt @swedennewyork: what doe it mean to have a #feminist government? join us on @reddit at 10 am (est) friday 3/23 for an #askmeanyth se...	NaN	sweden	Male	Left	swedennewyo doe mea femin government jo reddit est frid askmeany
1	NaN	jen stoltenberg åpn virtuell rockheim i dag, sjekk det ut du også http://bit.ly/1b6nt5	NaN	norway	Male	Left	jen stoltenbe apn virtu rockheim da sje
2	NaN	@panenka_bart vel beterschap bart en loes! 💘	BartDerwael	belgium	Male	Left	panenkabart v beterschap ba lo
3	NaN	rt @carlemillind: tyd s aftryk: pskykiatri styrk 110% co2 reduktion i 2050 praktisk folkeskol + mesterlær annulationssøgsmål...	NaN	denmark	Female	Left	carlemillind ty aftryk pskykia styrk co reduktio praktisk folkesk meste annulationssgsm
5	NaN	idag tog först spadtaget i kigali för biontech först vaccinfabrik i afrika. ämn för att producer vaccin i afrik för afrika. skall försörj helt med solenergi. grund ugur sahin på plat förstås. stolt över att eib finansier biontech utveckling av vaccin mot covid. https://t.co/qqxm6flvcm	NaN	sweden	Male	Left	idag tog for spadtaget kig biontech for vaccinfabrik afri amn produc vaccin afrik afri skall forsorj he solenergi grur ugur sahin pl forstas stolt e finansier biontec utveckling vacc cov

In [22]:
```
#tokenizing
from nltk.tokenize import word_tokenize
train_data['text_clean'] = train_data['text_clean'].astype(str)
train_data['text_clean_new'] = train_data['text_clean'].apply(lambda x: word_tokenize(x))
train_data.head()
```

Out[22]:

	hashtags	full_text	in_reply_to_screen_name	country_user	gender_user	pol_spec_user	text_clea
0	feminist AskMeAnything	rt @swedennewyork: what doe it mean to have a #feminist government? join us on @reddit at 10 am (est) friday 3/23 for an #askmeanyth se...	NaN	sweden	Male	Left	swedennewyo doe mea femin government jo reddit est frid askmeany
1	NaN	jen stoltenberg åpn virtuell rockheim i dag, sjekk det ut du også http://bit.ly/1b6nt5	NaN	norway	Male	Left	jen stoltenbe apn virtu rockheim da sje
2	NaN	@panenka_bart vel beterschap bart en loes! 💘	BartDerwael	belgium	Male	Left	panenkabart v beterschap ba lo
3	NaN	rt @carlemillind: tyd s aftryk: pskykiatri styrk 110% co2 reduktion i 2050 praktisk folkeskol + mesterlær annulationssøgsmål...	NaN	denmark	Female	Left	carlemillind ty aftryk pskykia styrk co reduktio praktisk folkesk meste annulationssgsm
5	NaN	idag tog först spadtaget i kigali för biontech först vaccinfabrik i afrika. ämn för att producer vaccin i afrik för afrika. skall försörj helt med solenergi. grund ugur sahin på plat förstås. stolt över att eib finansier biontech utveckling av vaccin mot covid. https://t.co/qqxm6flvcm	NaN	sweden	Male	Left	idag tog fo spadtaget kig biontech fo vaccinfabrik afri amn produc vaccin afrik afri skall forsorj h solenergi gru ugur sahin pl forstas stolt e finansier biontec utveckling vacc cov

In [23]:
```
# calculating word and character length from text_clean
cleaned_text = train_data[['text_clean']]
cleaned_text['text_clean'] = cleaned_text['text_clean'].astype("string")
cleaned_text['text_clean_char_length'] = cleaned_text['text_clean'].str.len()
cleaned_text['text_clean_word_length'] = cleaned_text['text_clean'].str.split().apply(len)
cleaned_text.head()
```

Out[23]:

	text_clean	text_clean_char_length	text_clean_word_length
0	swedennewyork doe mean feminist government join reddit est friday askmeanyth	77	10
1	jen stoltenberg apn virtuell rockheim dag sjekk	48	7
2	panenkabart vel beterschap bart loes	37	5
3	carlemillind tyd aftryk pskykiatri styrk co reduktion praktisk folkeskol mesterlr annulationssgsmal	100	11
5	idag tog forst spadtaget kigali biontech forst vaccinfabrik afrika amn producer vaccin afrik afrika skall forsorj helt solenergi grund ugur sahin plat forstas stolt eib finansier biontech utveckling vaccin covid	212	30

In [24]:
```
# table containing min, max, median and average for characters and word length of clean text
cleaned_text = pd.DataFrame(cleaned_text.describe())
cleaned_text
```

Out[24]:

	text_clean_char_length	text_clean_word_length
count	404487.0	404487.000000
mean	84.739423	11.381476
std	39.68095	5.564959
min	1.0	0.000000
25%	60.0	8.000000
50%	84.0	11.000000
75%	100.0	13.000000
max	702.0	77.000000

In [25]:
```
# merging details of full_text and text_clean
expanded_table = text_hash_describe.join(cleaned_text)
expanded_table
```

Out[25]:

	text_char_len	hashtags_char_len	text_word_len	hashtags_word_len	text_clean_char_length	text_clean_word_length
count	407223.0	127040.0	407223.000000	127040.000000	404487.0	404487.000000
mean	140.31248	14.089948	20.284048	1.577724	84.739423	11.381476
std	63.191109	10.471846	10.144777	0.956729	39.68095	5.564959
min	1.0	1.0	1.000000	1.000000	1.0	0.000000
25%	109.0	7.0	14.000000	1.000000	60.0	8.000000
50%	140.0	11.0	19.000000	1.000000	84.0	11.000000
75%	140.0	18.0	24.000000	2.000000	100.0	13.000000
max	862.0	145.0	89.000000	16.000000	702.0	77.000000

Inference

The average character and word length has reduced drastically from around 140 and 20 respectively to almost 93 and 11 respectively, after cleaning the text.

b) Using the code in the following link6, perform LDA (i) and Non-negative Matrix Factorization (ii) for topic analysis. Please use the text_clean column you have created above. Set the number of clusters/topics to 10 (ten) and extract the topics in an unsupervised manner. Adjust any parameters as you see fit. Analyze the results. Compare the results of both models. Interpret your findings and add your findings to the report. (5 points)

In [26]:
```
from time import time
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.decomposition import NMF, LatentDirichletAllocation
from sklearn.datasets import fetch_20newsgroups
```

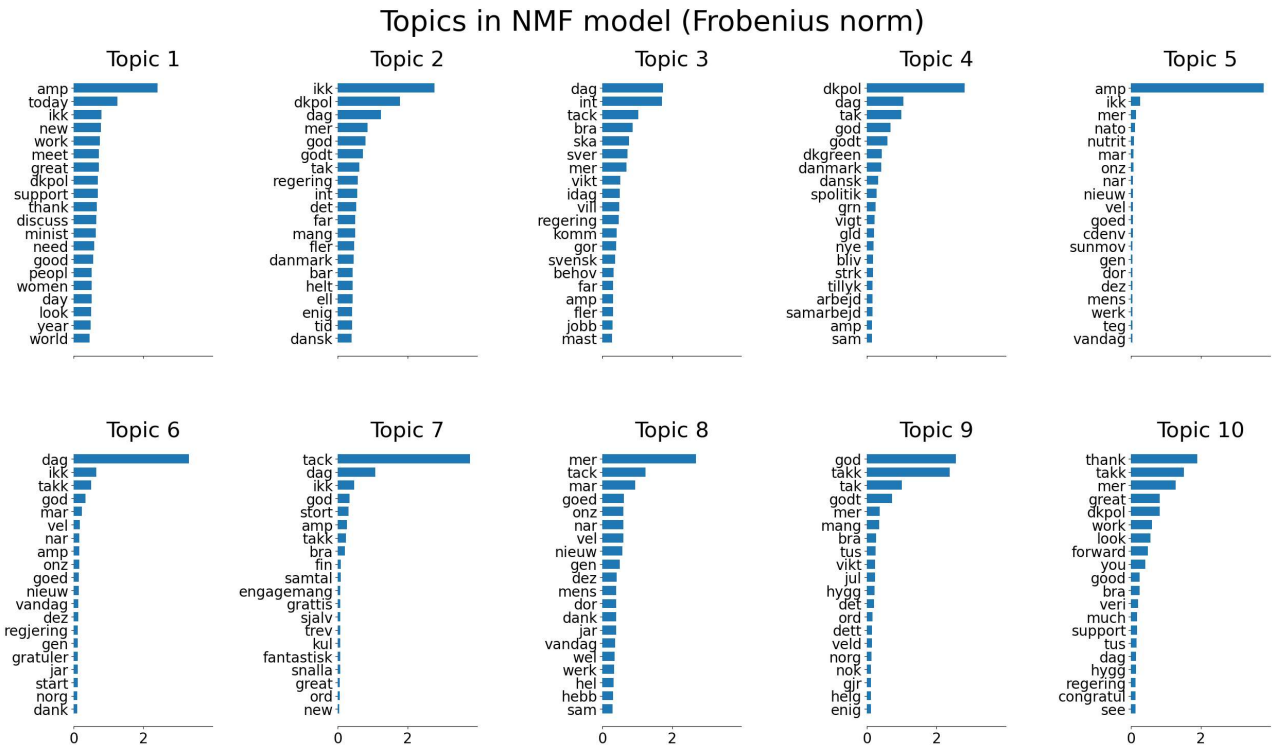
In [27]:
```
# initializations for Topic Modeling
n_samples = 404498
n_features = 100000
n_components = 10
n_top_words = 20
batch_size = 512
init = "nndsvda"
```

In [51]:
```
# creating data samples just like reference
data_samples = train_data['text_clean'].tolist()
data_samples = data_samples[:n_samples]
```

In [29]:
```
# ploting function for top 10 words
def plot_top_words(model, feature_names, n_top_words, title):
    fig, axes = plt.subplots(2, 5, figsize=(30, 15), sharex=True)
    axes = axes.flatten()
    for topic_idx, topic in enumerate(model.components_):
        top_features_ind = topic.argsort()[: -n_top_words - 1 : -1]
        top_features = [feature_names[i] for i in top_features_ind]
        weights = topic[top_features_ind]
        ax = axes[topic_idx]
        ax.barh(top_features, weights, height=0.7)
        ax.set_title(f"Topic {topic_idx +1}", fontdict={"fontsize": 30})
        ax.invert_yaxis()
        ax.tick_params(axis="both", which="major", labelsize=20)
        for i in "top right left".split():
            ax.spines[i].set_visible(False)
        fig.suptitle(title, fontsize=40)
    plt.subplots_adjust(top=0.90, bottom=0.05, wspace=0.90, hspace=0.3)
    plt.show()
```

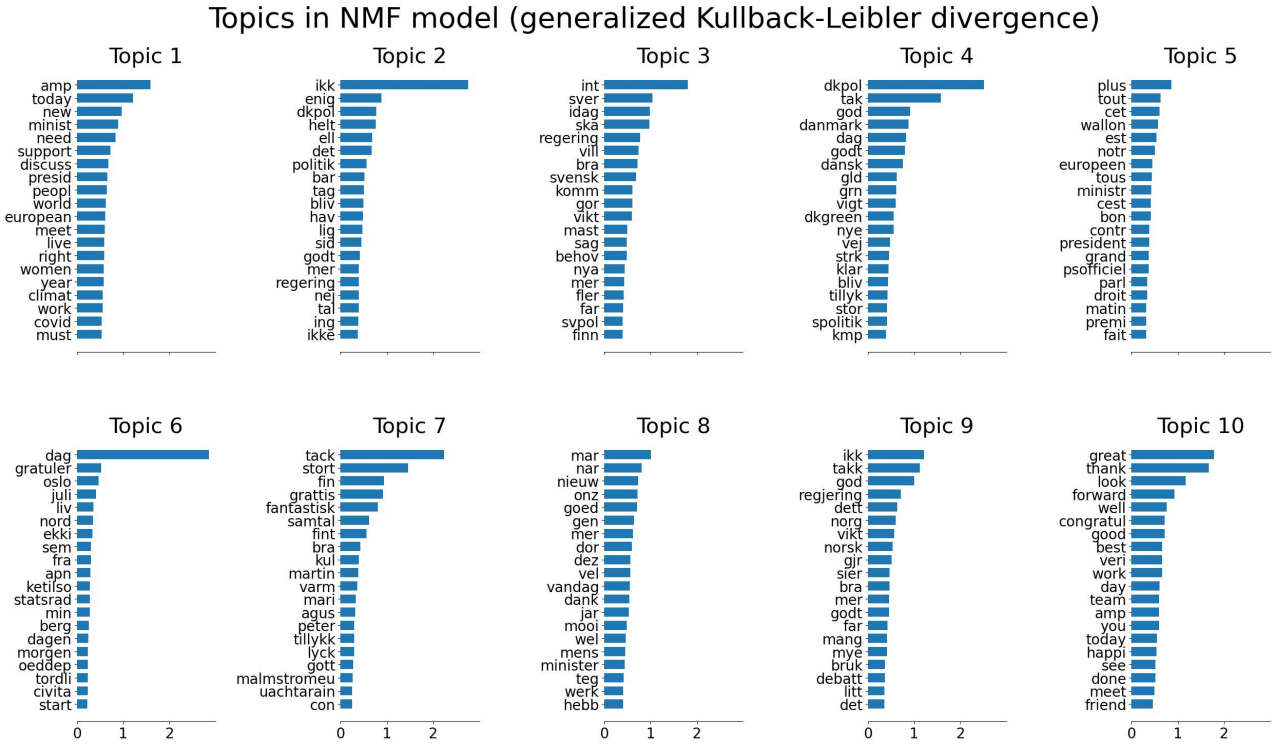
In [30]:
```
# using tf-idf features
print("Extracting tf-idf features for NMF...")
tfidf_vectorizer = TfidfVectorizer(
    max_df=0.95, min_df=2, max_features=n_features
)
t0 = time()
tfidf = tfidf_vectorizer.fit_transform(data_samples)
print("done in %0.3fs." % (time() - t0))
# fitting the NMF model (Frobenius norm).
print(
    "Fitting the NMF model (Frobenius norm) with tf-idf features, "
    "n_samples=%d and n_features=%d..." % (n_samples, n_features)
)
t0 = time()
nmf = NMF(
    n_components=n_components,
    random_state=1,
    init=init,
    beta_loss="frobenius",
    alpha_W=0.00005,
    alpha_H=0.00005,
    l1_ratio=1,
).fit(tfidf)
print("done in %0.3fs." % (time() - t0))
tfidf_feature_names = tfidf_vectorizer.get_feature_names_out()
plot_top_words(
    nmf, tfidf_feature_names, n_top_words, "Topics in NMF model (Frobenius norm)"
)
```

```
Extracting tf-idf features for NMF...
done in 5.718s.
Fitting the NMF model (Frobenius norm) with tf-idf features, n_samples=404498 and n_features=100000...
done in 54.501s.
```



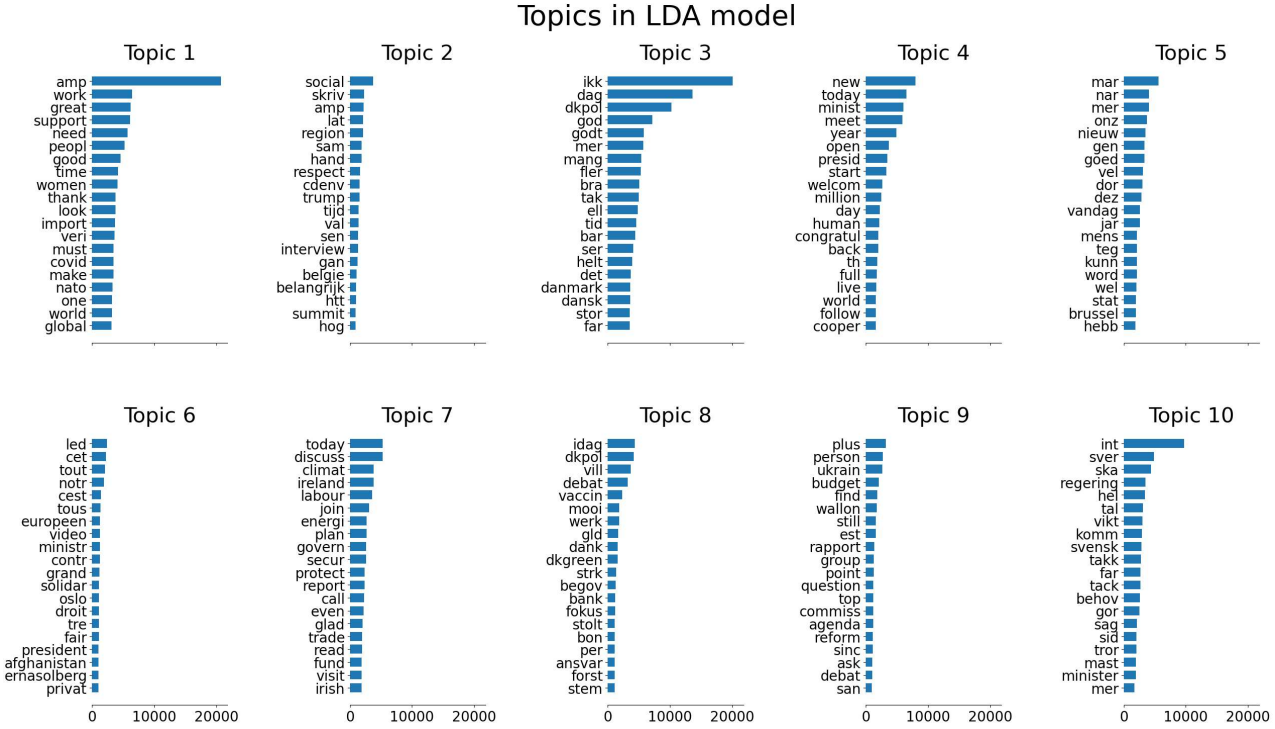
In [31]:
```
# fitting the NMF model (generalized Kullback-Leibler)
print(
    "\n" * 2,
    "Fitting the NMF model (generalized Kullback-Leibler "
    "divergence) with tf-idf features, n_samples=%d and n_features=%d..."
    % (n_samples, n_features),
)
t0 = time()
nmf = NMF(
    n_components=n_components,
    random_state=1,
    init=init,
    beta_loss="kullback-leibler",
    solver="mu",
    max_iter=1000,
    alpha_W=0.00005,
    alpha_H=0.00005,
    l1_ratio=0.5,
).fit(tfidf)
print("done in %0.3fs." % (time() - t0))
tfidf_feature_names = tfidf_vectorizer.get_feature_names_out()
plot_top_words(
    nmf,
    tfidf_feature_names,
    n_top_words,
    "Topics in NMF model (generalized Kullback-Leibler divergence)",
)
```

```
 Fitting the NMF model (generalized Kullback-Leibler divergence) with tf-idf features, n_samples=404498
and n_features=100000...
done in 111.920s.
```



In [32]:
```
# using tf (raw term count) features, fitting the LDA
print("Extracting tf features for LDA...")
tf_vectorizer = CountVectorizer(
    max_df=0.95, min_df=2, max_features=n_features
)
t0 = time()
tf = tf_vectorizer.fit_transform(data_samples)
print("done in %0.3fs." % (time() - t0))
print()
print(
    "\n" * 2,
    "Fitting LDA models with tf features, n_samples=%d and n_features=%d..."
    % (n_samples, n_features),
)
lda = LatentDirichletAllocation(
    n_components=n_components,
    max_iter=5,
    learning_method="online",
    learning_offset=50.0,
    random_state=0,
)
t0 = time()
lda.fit(tf)
print("done in %0.3fs." % (time() - t0))
tf_feature_names = tf_vectorizer.get_feature_names_out()
plot_top_words(lda, tf_feature_names, n_top_words, "Topics in LDA model")
```

```
Extracting tf features for LDA...
done in 6.090s.



 Fitting LDA models with tf features, n_samples=404498 and n_features=100000...
done in 1110.073s.
```



Inference

1) The NMF model, utilizing the Forbenius norm, exhibits a skewed distribution of words, where a significant proportion is concentrated among the top 3-4 words. However, this skewness is notably improved when we apply the LDA model, indicating that the LDA model effectively normalizes the data. Additionally, the NMF model with Kullback-Leibler divergence performs even better in normalizing the word distribution. 2) Comparing the scale of the plots, we observe that the NMF model employs a scale of (0, 2) to represent the frequency of the top 10 words, while the LDA model utilizes a scale of (0, 20000). This implies that the frequency of words within a single topic is much higher when the LDA model is employed, effectively covering a more extensive portion of the dataset. 3) However, it's worth noting that the advantage of using the LDA model comes at the expense of time. The LDA model takes more than 12 minutes to complete the topic modeling process, whereas the NMF model achieves the same results in just about a minute or two.

Part II: Model Creation and Prediction (50 points) Please do not post any of your code or solutions online. This part of the analysis needs to be submitted by the deadline (no late submission will be accepted). Please use the dataset provided to you. [We should be able to run your code with the original datasets and the additional external datasets you provide.] You cannot use any other Twitter data. You can use (non-Twitter) external datasets. For this part of the analysis, you will need to train a model that classifies the tweets in your training dataset according to 'pol_spec_user' labels7, report the Accuracy of your best model (i), and the confusion matrix (ii) that you will create. You will mainly be graded on the Accuracy of your model (more information provided below). Some guidelines (please also review the information shared through lectures):

Testing

In [33]:
```
# importing test dataset
test_data = pd.read_excel('test_data.xlsx')
test_data.head()
```

Out[33]:

	Id	hashtags	full_text	in_reply_to_screen_name	country_user	gender_user	pol_spec_use
0	0	EUAfrica	b'RT @eu_eeas: "Let me tell you that a big part of the world\'s future, and also its present, depends on Africa and #EUAfrica partnership" @Fe\xe2\x80\xa6'	NaN	belgium	Male	Na
1	1	COVID19	b'RT @stateofgreendk: "Although the #COVID19 pandemic overshadows our daily lives right now, we cannot forget the climate crisis. We must mak\xe2\x80\xa6'	NaN	denmark	Male	Na
2	2	NaN	b'@hjorvarhaflida // jebb - i\xc3\xb0a\xc3\xb0i \xc3\xa1 me\xc3\xb0an \xc3\xa9g bei\xc3\xb0 \xf0\x9f\xa4\x93 \xf0\x9f\x98\x84'	hjorvarhaflida	iceland	Female	Na
3	3	NaN	b'I ett l\xc3\xa4ge med pandemi, klimat, transport/vital teknik, ekonomi och s\xc3\xa4kerhetspolitiska konfliktzoner borde stor energi riktas mot att s\xc3\xa4kra svensk livsmedelsf\xc3\xb6rs\xc3\xb6rjning och energiproduktion! Liksom andra samh\xc3\xa4llsviktiga funktioner! @svt @sr_ekot Lugn och stabilitet kr\xc3\xa4vs.'	NaN	sweden	Female	Na
4	4	UNGA ChildrenNotSoldiers	b'RT @BelgiumMFA: \xf0\x9f\x93\x8d #UNGA\n\n\xf0\x9f\x92\xac "Every child deserves a safe childhood."\n\nFollow now live the #ChildrenNotSoldiers event with Queen Mathilde and\xe2\x80\xa6'	NaN	belgium	Male	Na

In [34]:
```
# decoding UTF-8 encoded data
test_data['full_text'] = test_data['full_text'].map(lambda v: ast.literal_eval(v).decode())
test_data.head(5)
```

Out[34]:

	Id	hashtags	full_text	in_reply_to_screen_name	country_user	gender_user	pol_spec_user
0	0	EUAfrica	RT @eu_eeas: "Let me tell you that a big part of the world's future, and also its present, depends on Africa and #EUAfrica partnership" @Fe...	NaN	belgium	Male	NaN
1	1	COVID19	RT @stateofgreendk: "Although the #COVID19 pandemic overshadows our daily lives right now, we cannot forget the climate crisis. We must mak...	NaN	denmark	Male	NaN
2	2	NaN	@hjorvarhaflida // jebb - iðaði á meðan ég beið 🤓😊	hjorvarhaflida	iceland	Female	NaN
3	3	NaN	I ett läge med pandemi, klimat, transport/vital teknik, ekonomi och säkerhetspolitiska konfliktzoner borde stor energi riktas mot att säkra svensk livsmedelsförsörjning och energiproduktion! Liksom andra samhällsviktiga funktioner! @svt @sr_ekot Lugn och stabilitet krävs.	NaN	sweden	Female	NaN
4	4	UNGA ChildrenNotSoldiers	RT @BelgiumMFA: 📍 #UNGA\n\n💬 "Every child deserves a safe childhood."\n\nFollow now live the #ChildrenNotSoldiers event with Queen Mathilde and...	NaN	belgium	Male	NaN

In [35]:
```
#stemming
test_data['full_text'] = test_data['full_text'].apply(stem_text)
test_data.head()
```

Out[35]:

	Id	hashtags	full_text	in_reply_to_screen_name	country_user	gender_user	pol_spec_user
0	0	EUAfrica	rt @eu_eeas: "let me tell you that a big part of the world future, and also it present, depend on africa and #euafrica partnership" @fe...	NaN	belgium	Male	NaN
1	1	COVID19	rt @stateofgreendk: "although the #covid19 pandem overshadow our daili live right now, we cannot forget the climat crisis. we must mak...	NaN	denmark	Male	NaN
2	2	NaN	@hjorvarhaflida // jebb - iðaði á meðan ég beið 🤓😄	hjorvarhaflida	iceland	Female	NaN
3	3	NaN	i ett läg med pandemi, klimat, transport/vital teknik, ekonomi och säkerhetspolitisk konfliktzon bord stor energi rikt mot att säkr svensk livsmedelsförsörjning och energiproduktion! liksom andr samhällsvikt funktioner! @svt @sr_ekot lugn och stabilitet krävs.	NaN	sweden	Female	NaN
4	4	UNGA ChildrenNotSoldiers	rt @belgiummfa: 📍 #unga 💬 "everi child deserv a safe childhood." follow now live the #childrennotsoldi event with queen mathild and...	NaN	belgium	Male	NaN

In [36]:
```
#Lemmetizing
from lemmatizer import clean_text
test_data['text_clean'] = clean_text(test_data)
test_data.head()
```

Out[36]:

	Id	hashtags	full_text	in_reply_to_screen_name	country_user	gender_user	pol_spec_user	
0	0	EUAfrica	rt @eu_eeas: "let me tell you that a big part of the world future, and also it present, depend on africa and #euafrica partnership" @fe...	NaN	belgium	Male	NaN	eueeas part w prese afri p
1	1	COVID19	rt @stateofgreendk: "although the #covid19 pandem overshadow our daili live right now, we cannot forget the climat crisis. we must mak...	NaN	denmark	Male	NaN	state altho pandem o daili live cannot fo crisis
2	2	NaN	@hjorvarhaflida // jebb - iðaði á meðan ég beið 🤓 😄	hjorvarhaflida	iceland	Female	NaN	hjorvarh ia
3	3	NaN	i ett läg med pandemi, klimat, transport/vital teknik, ekonomi och säkerhetspolitisk konfliktzon bord stor energi rikt mot att säkr svensk livsmedelsförsörjning och energiproduktion! liksom andr samhällsvikt funktioner! @svt @sr_ekot lugn och stabilitet krävs.	NaN	sweden	Female	NaN	lag pand transport sakerh konfliktzor ener livsmedelsf energi li sa funktioner lugn stab
4	4	UNGA ChildrenNotSoldiers	rt @belgiummfa: 📍 #unga 💬 "everi child deserv a safe childhood." follow now live the #childrennotsoldi event with queen mathild and...	NaN	belgium	Male	NaN	belgiur everi cl safe childr event que

In [37]:
```
from nltk.tokenize import word_tokenize
test_data['text_clean'] = test_data['text_clean'].astype(str)
#tokenize the text in the 'text_clean' column
test_data['text_clean_new'] = test_data['text_clean'].apply(lambda x: word_tokenize(x))
test_data.head()
```

Out[37]:

	Id	hashtags	full_text	in_reply_to_screen_name	country_user	gender_user	pol_spec_user	
0	0	EUAfrica	rt @eu_eeas: "let me tell you that a big part of the world future, and also it present, depend on africa and #euafrica partnership" @fe...	NaN	belgium	Male	NaN	eueeas part w prese afri p
1	1	COVID19	rt @stateofgreendk: "although the #covid19 pandem overshadow our daili live right now, we cannot forget the climat crisis. we must mak...	NaN	denmark	Male	NaN	state altho pandem o daili live cannot fo crisis
2	2	NaN	@hjorvarhaflida // jebb - iðaði á meðan ég beið 🤓 😊	hjorvarhaflida	iceland	Female	NaN	hjorvarh ia
3	3	NaN	i ett läg med pandemi, klimat, transport/vital teknik, ekonomi och säkerhetspolitisk konfliktzon bord stor energi rikt mot att säkr svensk livsmedelsförsörjning och energiproduktion! liksom andr samhällsvikt funktioner! @svt @sr_ekot lugn och stabilitet krävs.	NaN	sweden	Female	NaN	lag pand transport sakerh konfliktzor ener livsmedelsf energi li sa funktioner lugn stab
4	4	UNGA ChildrenNotSoldiers	rt @belgiummfa: 📍 #unga 💬 "everi child deserv a safe childhood." follow now live the #childrennotsoldi event with queen mathild and...	NaN	belgium	Male	NaN	belgiur everi cl safe childr event que

Model

In [38]:
```
from sklearn.pipeline import Pipeline
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import SGDClassifier
import xgboost as xgb
from sklearn.preprocessing import LabelEncoder
from imblearn.over_sampling import RandomOverSampler
from sklearn.model_selection import train_test_split
import logging
logging.basicConfig(level=logging.INFO, format='%(asctime)s - %(levelname)s - %(message)s')
```

In [39]:
```
training_data = train_data
training_data.head()
```

Out[39]:

	hashtags	full_text	in_reply_to_screen_name	country_user	gender_user	pol_spec_user	text_clea
0	feminist AskMeAnything	rt @swedennewyork: what doe it mean to have a #feminist government? join us on @reddit at 10 am (est) friday 3/23 for an #askmeanyth se...	NaN	sweden	Male	Left	swedennewyo doe mea femin government jo reddit est frid askmeany
1	NaN	jen stoltenberg åpn virtuell rockheim i dag, sjekk det ut du også http://bit.ly/1b6nt5	NaN	norway	Male	Left	jen stoltenbe apn virtu rockheim da sje
2	NaN	@panenka_bart vel beterschap bart en loes! 💇	BartDerwael	belgium	Male	Left	panenkabart v beterschap ba lo
3	NaN	rt @carlemillind: tyd s aftryk: pskykiatri styrk 110% co2 reduktion i 2050 praktisk folkeskol + mesterlær annulationssøgsmål...	NaN	denmark	Female	Left	carlemillind ty aftryk pskykia styrk co reduktio praktisk folkesk meste annulationssgsm
5	NaN	idag tog först spadtaget i kigali för biontech först vaccinfabrik i afrika. ämn för att producer vaccin i afrik för afrika. skall försörj helt med solenergi. grund ugur sahin på plat förstås. stolt över att eib finansier biontech utveckling av vaccin mot covid. https://t.co/qqxm6flvcm	NaN	sweden	Male	Left	idag tog for spadtaget kig biontech for vaccinfabrik afri amn produc vaccin afrik afri skall forsorj he solenergi grur ugur sahin pl forstas stolt e finansier biontec utveckling vacc cov

In [40]:
```
testing_data = test_data
testing_data.head()
```

Out[40]:

	Id	hashtags	full_text	in_reply_to_screen_name	country_user	gender_user	pol_spec_user	
0	0	EUAfrica	rt @eu_eeas: "let me tell you that a big part of the world future, and also it present, depend on africa and #euafrica partnership" @fe...	NaN	belgium	Male	NaN	eueeas part w prese afri p
1	1	COVID19	rt @stateofgreendk: "although the #covid19 pandem overshadow our daili live right now, we cannot forget the climat crisis. we must mak...	NaN	denmark	Male	NaN	state altho pandem o daili live cannot fo crisis
2	2	NaN	@hjorvarhaflida // jebb - iðaði á meðan ég beið 🤓 😊	hjorvarhaflida	iceland	Female	NaN	hjorvarh ia
3	3	NaN	i ett läg med pandemi, klimat, transport/vital teknik, ekonomi och säkerhetspolitisk konfliktzon bord stor energi rikt mot att säkr svensk livsmedelsförsörjning och energiproduktion! liksom andr samhällsvikt funktioner! @svt @sr_ekot lugn och stabilitet krävs.	NaN	sweden	Female	NaN	lag pand transport sakerh konfliktzor ener livsmedelsf energi li sa funktioner lugn stab
4	4	UNGA ChildrenNotSoldiers	rt @belgiummfa: 📍 #unga 💬 "everi child deserv a safe childhood." follow now live the #childrennotsoldi event with queen mathild and...	NaN	belgium	Male	NaN	belgiur everi cl safe childr event que

In [41]:
```
from sklearn.impute import SimpleImputer
# imputing missing text_clean values
imputer = SimpleImputer(missing_values=np.nan, strategy='constant', fill_value='')
training_data['text_clean'] = imputer.fit_transform(training_data[['text_clean']])
testing_data['text_clean'] = imputer.transform(testing_data[['text_clean']])
```

In [42]:
```
# checking for NaN values in 'text_clean' column
nan_indices = testing_data[testing_data['text_clean'].isna()].index
if len(nan_indices) > 0:
    print("NaN values found in 'text_clean' column at indices:", nan_indices)
else:
    print("No NaN values found in 'text_clean' column.")
```

```
No NaN values found in 'text_clean' column.
```

In [43]:
```
# Built ensemble model using Naive Bayes, SVM, XGBoost
# For each country-gender group,  models are built. Then, we take vote for prediction.
country_gender_groups = []
accuracy_by_group = []
countries = training_data.country_user.unique().tolist()
countries.sort()
```

```
genders = training_data.gender_user.unique().tolist()
ensemble_validation = pd.DataFrame([])
ensemble_predictions = pd.DataFrame([])
```

In [44]:

```
for c in countries:
    for g in genders:
        print('Country: ', c)
        print('Gender: ', g)
        country_gender_groups.append(c+'_'+g)

        data = training_data[(training_data["country_user"] == c) &
                             (training_data["gender_user"] == g)]
        X = data.text_clean
        y = data.pol_spec_user
        # label encoding
        le = LabelEncoder()
        y = le.fit_transform(y)
        # class Balancing by RandomOverSampler
        ros = RandomOverSampler()
        rov_x, rov_y = ros.fit_resample(np.array(X).reshape(-1, 1),
                                        np.array(y).reshape(-1, 1));
        rov_os = pd.DataFrame(list(zip([x[0] for x in rov_x], rov_y)),
                              columns = ['text_clean', 'pol_spec_user']);

        rov_os.text_clean.fillna("", inplace = True)
        num_classes = len(rov_os['pol_spec_user'].unique())

        # final train set, we will divide it to train and valid in the following steps
        X = rov_os['text_clean'].values
        y = rov_os['pol_spec_user'].values
        X_train, X_val, y_train, y_val = train_test_split(X, y,
                                                          test_size=0.05,
                                                          random_state = 1)
        print("Naive Bayes..")
        nb = Pipeline([('vect', CountVectorizer()),
               ('tfidf', TfidfTransformer()),
               ('clf', MultinomialNB()),
              ])
        nb.fit(X_train, y_train)

        print("SGD..")
        sgd = Pipeline([('vect', CountVectorizer()),
                        ('tfidf', TfidfTransformer()),
                        ('clf', SGDClassifier(loss='hinge', penalty='l2',alpha=1e-6, random_state=3, max
                       ])
        sgd.fit(X_train, y_train)
        print("XGBoost..")
        if num_classes >2:
            xgclf = Pipeline([('vect', CountVectorizer()),
                    ('tfidf', TfidfTransformer()),
                    ('clf', xgb.XGBClassifier(random_state=7,num_class=num_classes,objective='multi:soft
                    ])
            xgclf.fit(X_train, y_train)
        else:
            xgclf = Pipeline([('vect', CountVectorizer()),
                    ('tfidf', TfidfTransformer()),
                    ('clf', xgb.XGBClassifier(random_state=7,objective='binary:logistic',learning_rate =
                    ])
            xgclf.fit(X_train, y_train)

        # validation data
        # ensembling
        nb_pred = nb.predict(X_val)
        sgd_pred = sgd.predict(X_val)
        xgclf_pred = xgclf.predict(X_val)

        result = pd.DataFrame({'nb_pred': nb_pred, 'sgd_pred': sgd_pred, 'xgclf_pred':xgclf_pred})
        result = result.mode(axis=1)
        y_pred = result[0]
```

```
        valid = pd.DataFrame({'actual': y_val, 'prediction': y_pred.to_numpy()})
        ensemble_validation = ensemble_validation._append(valid) # for confusion matrix to see ensemble r

        val_acc = accuracy_score(y_pred.to_numpy(), y_val)
        accuracy_by_group.append(val_acc)
        print('Accuracy: %s' % val_acc)
        print("_____________________________________________________________________________________

        # test data
        test_data = testing_data[(testing_data["country_user"] == c) &
                                 (testing_data["gender_user"] == g)]
        X_test = test_data.text_clean
        X_test.fillna("", inplace = True)

        # ensembling
        nb_pred = nb.predict(X_test)
        sgd_pred = sgd.predict(X_test)
        xgclf_pred = xgclf.predict(X_test)

        result = pd.DataFrame({'nb_pred': nb_pred, 'sgd_pred': sgd_pred, 'xgclf_pred':xgclf_pred})
        result = result.mode(axis=1)
        y_pred = result[0]

        result = pd.DataFrame({'Id': test_data.Id.to_numpy(), 'pol_spec_user': y_pred.to_numpy().astype(
        result["pol_spec_user_name"] = le.inverse_transform(result["pol_spec_user"])
        ensemble_predictions = ensemble_predictions._append(result)
```

```
Country:  belgium
Gender:  Male
Naive Bayes..
SGD..
XGBoost..
Accuracy: 0.8343871099326943
```

```
Country:  belgium
Gender:  Female
Naive Bayes..
SGD..
XGBoost..
Accuracy: 0.9095519864750634
```

```
Country:  denmark
Gender:  Male
Naive Bayes..
SGD..
XGBoost..
Accuracy: 0.790501852475581
```

```
Country:  denmark
Gender:  Female
Naive Bayes..
SGD..
XGBoost..
Accuracy: 0.851013672795851
```

```
Country:  iceland
Gender:  Male
Naive Bayes..
SGD..
XGBoost..
Accuracy: 0.9080459770114943
```

```
Country:  iceland
Gender:  Female
Naive Bayes..
SGD..
XGBoost..
Accuracy: 1.0
```

```
Country:  ireland
Gender:  Male
Naive Bayes..
SGD..
XGBoost..
Accuracy: 0.8567480423767849
```

```
Country:  ireland
Gender:  Female
Naive Bayes..
SGD..
XGBoost..
Accuracy: 0.9691912708600771
```

```
Country:  netherlands
Gender:  Male
Naive Bayes..
SGD..
XGBoost..
Accuracy: 0.9201044386422976
```

```
Country:  netherlands
Gender:  Female
Naive Bayes..
SGD..
XGBoost..
Accuracy: 0.9725776965265083
```

```
Country:  norway
```

```
Gender:  Male
Naive Bayes..
SGD..
XGBoost..
Accuracy: 0.8326715825297788
```

```
Country:  norway
Gender:  Female
Naive Bayes..
SGD..
XGBoost..
Accuracy: 0.922752808988764
```

```
Country:  sweden
Gender:  Male
Naive Bayes..
SGD..
XGBoost..
Accuracy: 0.9016786570743405
```

```
Country:  sweden
Gender:  Female
Naive Bayes..
SGD..
XGBoost..
Accuracy: 0.8570967741935483
```

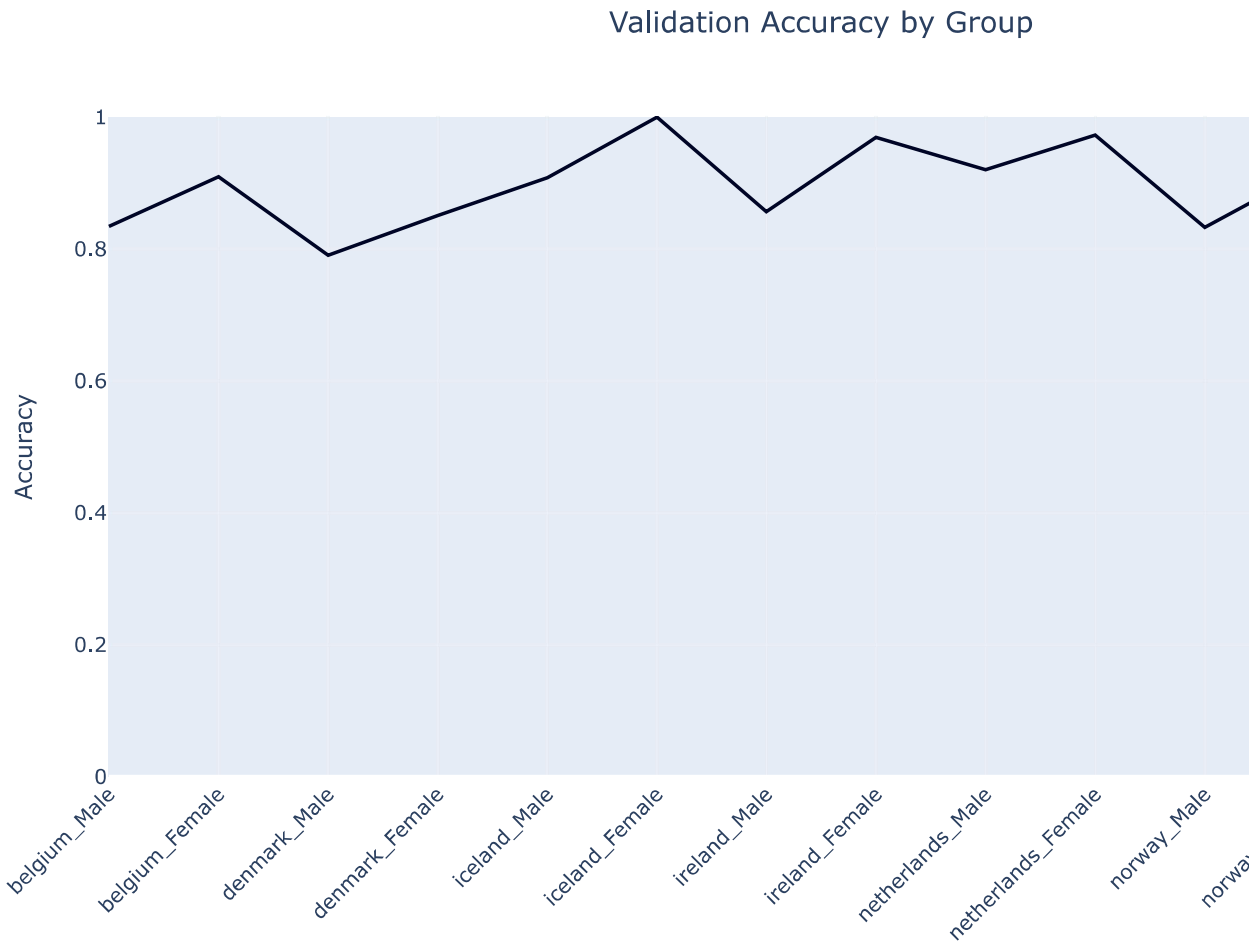
In [45]:
```
# validation accuracy dataframe
validation_accuracy_plot = pd.DataFrame({'Group_Country_Gender': country_gender_groups, 'Validation_Accu
validation_accuracy_plot
```

Out[45]:

	Group_Country_Gender	Validation_Accuracy
0	belgium_Male	0.834387
1	belgium_Female	0.909552
2	denmark_Male	0.790502
3	denmark_Female	0.851014
4	iceland_Male	0.908046
5	iceland_Female	1.000000
6	ireland_Male	0.856748
7	ireland_Female	0.969191
8	netherlands_Male	0.920104
9	netherlands_Female	0.972578
10	norway_Male	0.832672
11	norway_Female	0.922753
12	sweden_Male	0.901679
13	sweden_Female	0.857097

In [46]:
```
# plot for validation accuracy
fig = px.line(
    validation_accuracy_plot,
    x='Group_Country_Gender',
    y='Validation_Accuracy',
    title='Validation Accuracy by Group',
    labels={'Group_Country_Gender': 'Group (Country-Gender)', 'Validation_Accuracy': 'Validation Accuracy
    height=600,
    width=1000,
    line_shape='linear',  # You can customize the line shape as needed
    color_discrete_sequence=['#000526']  # Set the line color to '#fafbff'
```

```
)

fig.update_layout(
    xaxis_tickangle=-45,
    yaxis_range=[0, 1],
    xaxis_title=None,
    yaxis_title='Accuracy',
    font=dict(size=12),
    title_x=0.5
)
# line plot
fig.show()
```



In [47]:
```
# confusion matrix
print('Validation accuracy %s' % accuracy_score(ensemble_validation.prediction, ensemble_validation.actu
my_tags = list(training_data['pol_spec_user'].unique())
print(classification_report(ensemble_validation.actual, ensemble_validation.prediction,target_names=my_t
```

```
Validation accuracy 0.8654214059619465
              precision    recall  f1-score   support

        Left       0.84      0.92      0.88      9716
       Right       0.86      0.82      0.84      9557
      Center       0.89      0.86      0.87      9405
 Independent       0.90      0.85      0.87        71

    accuracy                           0.87     28749
   macro avg       0.87      0.86      0.87     28749
weighted avg       0.87      0.87      0.87     28749
```

In [48]:
```
# final result
ensemble_predictions_final = ensemble_predictions.sort_values('Id')
ensemble_predictions_final = ensemble_predictions_final.drop(columns=['pol_spec_user'])
ensemble_predictions_final = ensemble_predictions_final.rename(columns={'pol_spec_user_name': 'pol_spec_
ensemble_predictions_final.head()
```

Out[48]:

	Id	pol_spec_user
0	0	Right
0	1	Right
0	2	Left
0	3	Center
1	4	Right

In [49]:
```
# saving in csv format
ensemble_predictions_final.to_csv('kaggle_prediction_aradhya_richa_final.csv', header=True, index=False)
```