FAKE NEWS DETECTION USING NLP

TEAM MEMBER
KRISHNAN .T
KAVIYARASAN. R
KAVIYARASAN .S
LAKSHMANAN .P
KAVINESAN

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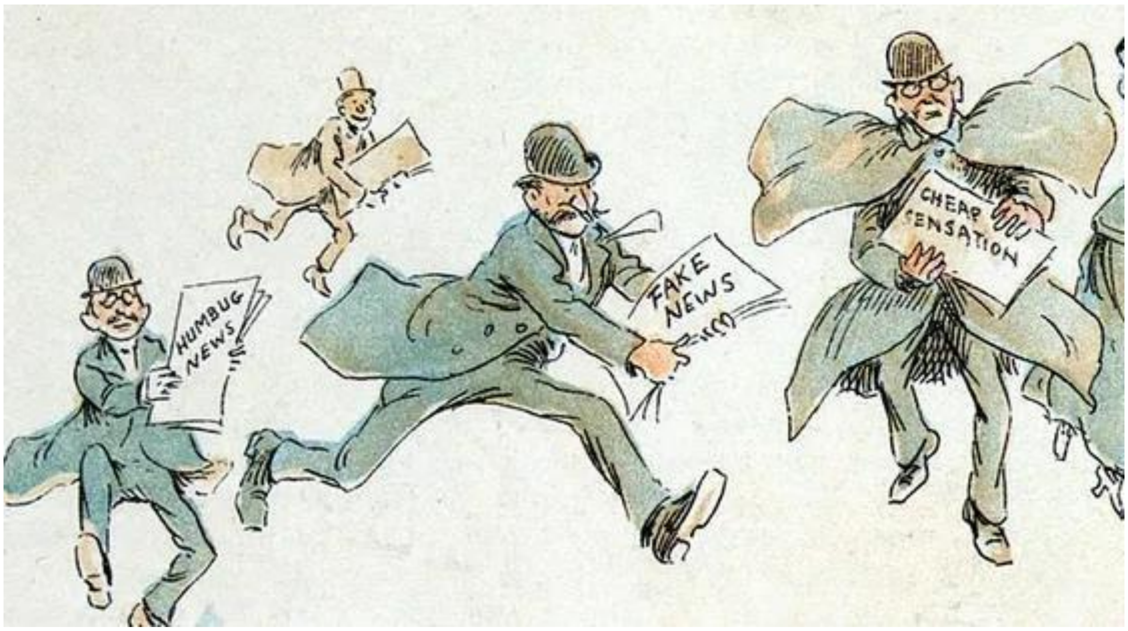


Phase 2: Innovation

Prepare seismic data, utilize python with scikitlearn or tensorflow to build regression model in fake news detection using nlp.

Our approach encompasses the following key steps:

- **Exploratory Data Analysis (EDA):** Gain insights into dataset characteristics and identify potential features for classification.

- **Text Preprocessing:** Prepare textual data for modeling through tokenization and removal of stopwords.

- **Model Development:** Utilize BERT-based classification models and fine-tune them on our dataset.

- **Model Evaluation:** Assess model performance using key metrics such as accuracy, precision, recall, and F1-score.

- **Interpretability:** Explore techniques to understand the model's decision-making process and identify important features.

- **Deployment:** Implement the trained model for automatic classification of news articles into fake or real categories.

Set Up

In this section, we'll guide you through the initial steps to prepare your **environment** for working with the **dataset** and building the **fake news detection model**. We will make the **required imports** and will also set some **constants & hyperparameters** which will be later used. [In1]

```
%pip install transformers datasets --quiet
```

```
Note: you may need to restart the kernel to use updated pack
ages
```

[In2]

```
# Imports for Dataset
import time import
numpy as np import
pandas as pd import
nltk
```

```
import string import tensorflow as
tf    from    nltk.corpus    import
stopwords
from sklearn.model_selection import train_test_split
nltk.download('stopwords')

# Data Visualization import
plotly.express as px

# Classification Model
from transformers import AutoTokenizer, TFAutoModelForSequen
ceClassification
# Model Training
from tensorflow.keras.optimizers import Adam from
tensorflow.keras.callbacks import ModelCheckpoint
```

```
/opt/conda/lib/python3.10/site-packages/scipy/__init__.py:146: UserWarning: A NumPy version >=
1.16.5 and <1.23.0 is required for this version of SciPy (detected version 1.23.5
warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
[nltk_data] Downloading package stopwords to /usr/share/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

In [3]:

```
  # Data set management
CLASS_NAMES = ["Fake", "Real"]
MAPPING_DICT = {
    "Fake":0,
    "Real":1
}
# Model Callbacks
model_name = "BERTFakeNewsDetector"
MODEL_CALLBACKS = [ModelCheckpoint(model_name, save_best_only=True)]
```

Data Loading & Pre-Processing

Now that we have **completed our setup**, it's time to **load our dataset**. In this section, we'll take a **closer look** at **the data**, perform **essential preprocessing steps**, and gain a **better understanding** of its **structure**. Let's delve into the **data loading and preprocessing** to set the stage for our **fake news detection journey.**

```
In [4]: fake_news_filepath = "/kaggle/input/fake-and-real-news-dataset/Fake.csv" real_news_filepath = "/kaggle/input/fake-and-real-news-dataset/True.csv"
```

```
In [5]: fake_df = pd.read_csv(fake_news_filepath) real_df = pd.read_csv(real_news_filepath)
```

```
In [6]: fake_df.head()
```

Out[6]:

	title	text	subject	date
0	Donald Trump Sends Out Embarrassing New Year'...	Donald Trump just couldn t wish all Americans ...	News	December 31, 2017
1	Drunk Bragging Trump Staffer Started Russian ...	House Intelligence Committee Chairman Devin Nu...	News	December 31, 2017
2	Sheriff David Clarke Becomes An Internet Joke...	On Friday, it was revealed that former Milwauk...	News	December 30, 2017
3	Trump Is So Obsessed He Even Has Obama's Name...	On Christmas day, Donald Trump announced that ...	News	December 29, 2017
4	Pope Francis Just Called Out Donald Trump Dur...	Pope Francis used his annual Christmas Day mes...	News	December 25, 2017

```
IN[7]:
```

Out[7]:

	title	text	subject	date
0	As U.S. budget fight looms, Republicans flip t...	WASHINGTON (Reuters) - The head of a conservat...	politicsNews	December 31, 2017
1	U.S. military to accept transgender recruits o...	WASHINGTON (Reuters) - Transgender people will...	politicsNews	December 29, 2017
2	Senior U.S. Republican senator: 'Let Mr. Muell...	WASHINGTON (Reuters) - The special counsel inv...	politicsNews	December 31, 2017
3	FBI Russia probe helped by Australian diplomat...	WASHINGTON (Reuters) - Trump campaign adviser ...	politicsNews	December 30, 2017
4	Trump wants Postal Service to charge 'much mor...	SEATTLE/WASHINGTON (Reuters) - President Donal...	politicsNews	December 29, 2017

```
real_df.head()
```

Taking a **brief glance** at the **dataset**, we observe **four primary features**: **title, text, subject, and date**. While **subject and title** may **not** be **our primary focus**, our attention is drawn to the **text and date fields**. These **two components** hold the key to **our analysis** and are **central to our efforts** in discerning **fake from real news**

Currently, we have **two seperate data frames** for the **real data and the fake data**. Let's combine them in a **single data frame**, which will make it easier to process the information.

.In [8]:

Out[9]:

	title	text	subject	date	Label
0	Donald Trump Sends Out Embarrassing New Year'...	Donald Trump just couldn t wish all Americans ...	News	December 31, 2017	Fake
1	Drunk Bragging Trump Staffer Started Russian ...	House Intelligence Committee Chairman Devin Nu...	News	December 31, 2017	Fake
2	Sheriff David Clarke Becomes An Internet Joke...	On Friday, it was revealed that former Milwauk...	News	December 30, 2017	Fake
3	Trump Is So Obsessed He Even Has Obama's Name...	On Christmas day, Donald Trump announced that ...	News	December 29, 2017	Fake
4	Pope Francis Just Called Out Donald Trump Dur...	Pope Francis used his annual Christmas Day mes...	News	December 25, 2017	Fake

```
#  Classification  Labels
real_df["Label"] = "Real"
fake_df["Label"] = "Fake"
```

In [9]: linkcode

```
df = pd.concat([fake_df, real_df])
df.reset_index() df.head()
```

In[10]:

```
print(f"Dataset Size: {len(df)}")
```

Dataset Size: 44898

Given the substantial size of this dataset, and considering the **limitations of memory resources**, we have opted to downsize the **dataset significantly**, capping it at **1,000 samples**.

In [11]:
linkcode

```
data = df.sample(1000).drop(columns=["title", "subject", "date"])
data.Label = data.Label.map(MAPPING_DICT) data.sample(10)
```

.

Out[11]:

	text	Label
5488	Donald Trump has not yet officially received t...	0
19114	Fun fact: While Trump press secretary Sean Spi...	0
4102	WASHINGTON (Reuters) - President Donald Trump'...	1
15382	BRUSSELS (Reuters) - Belgium s prime minister,...	1
1415	This morning President Trump called for a meet...	0
214	This article is uncensored and contains very o...	0
16894	PARIS (Reuters) - President Emmanuel Macron sa...	1
2648	White House press secretary of Alternative Fac...	0
5687	Ted Cruz, who chairs the Senate Judiciary Subc...	0
9865	(Reuters) - A federal judge on Tuesday approve...	1

The data presented above can be **valuable for visualization purposes**. However, when it comes to **model building and training**, we need a **streamlined version of the data**. Specifically, we can exclude the **title, subject, and date columns** as features for our model, focusing solely on the **essential text content**. Additionally, we'll need to convert the **categorical labels** into **numeric format** to facilitate **model training and evaluation.**

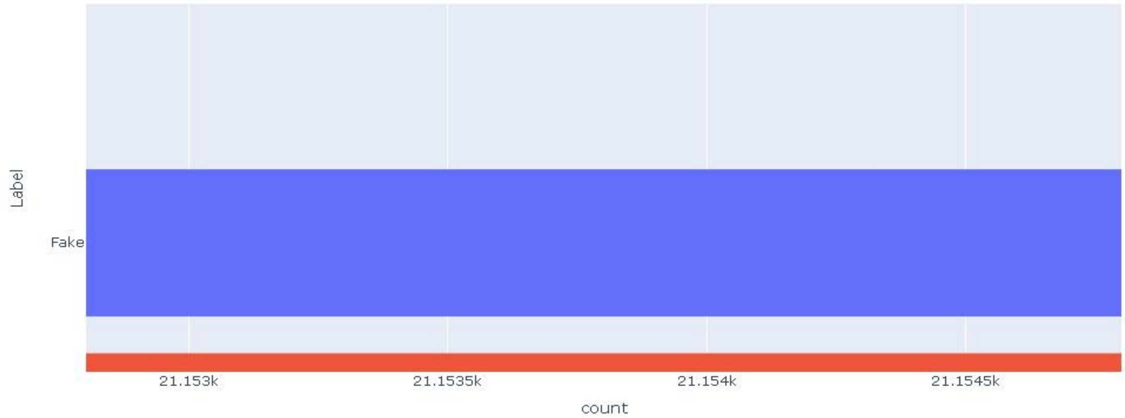
Data Visualization:

Before delving into the **classification task**, it's crucial to address **class imbalance**. This **initial analysis** is paramount because it can **significantly influence our model's performance**. Let's begin by assessing the **distribution of classes**, as this forms a **fundamental step** in our **model-building process**.

In [12]: linkcode

```
class_dis = px.histogram(
data_frame = df,      y =
"Label",      color =
"Label",
    title = "Fake & Real Samples Distribution",
text_auto=True
    )
class_dis.update_layout(showlegend=False) class_dis.show()
```

FAKE & REAL SAMPLE DISTRIBUTION

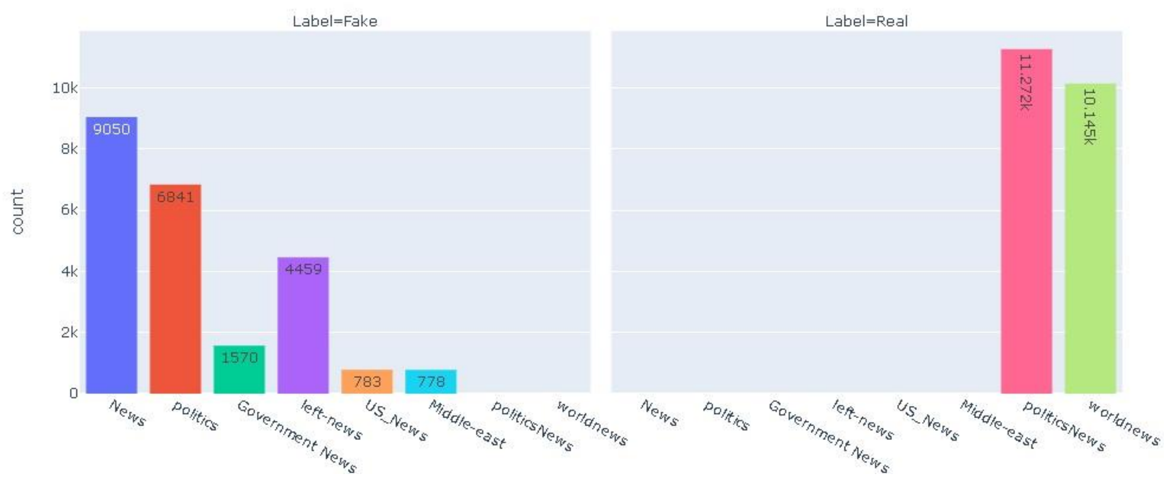


It's evident that there's a **slight class imbalance** in our dataset, with a **higher number of fake samples compared to real samples**. However, the imbalance is **relatively low**, with **approximately 23,000 samples** for **fake news** and **21,000 samples for real news**. (On original Data)

While this level of **class imbalance** is **not expected** to **significantly impact our model's performance**, we'll take a **precautionary approach** and use a **stratified split** to ensure a **balanced distribution** of classes in our **training and testing sets**. This will help us maintain **model stability and mitigate** any potential **bias introduced** by the **class distribution**.

```
IN[13]: subject_dis =
px.histogram(
data_frame = df,     x =
"subject",     color =
"subject",     facet_col =
"Label",
    title = "Fake & Real Subject Distribution",
text_auto=True
    )
subject_dis.update_layout(showlegend=False)
subject_dis.show()
```

FAKE & REAL SUBJECT DISTRIBUTION:



Indeed, the **distribution of subjects or categories** in our dataset poses a **significant challenge** for using the **'subject' column** as a **feature** for **our model**. It's clear that the **all of fake news articles fall** under various subjects such as **politics, government news, left news, US news, and the Middle East**, while **real news articles** are primarily categorized under **political news and**

world news. Utilizing the **'subject' column** as a feature could lead the model to **over-rely on this information**, potentially resulting in a **biased prediction** pattern where it **simply associates real news** with these **two subjects** and **makes guesses** based on that association.

Ideally, a **more balanced distribution** of **subjects between fake and real news** would have provided a **better learning environment** for the model. However, given the **dataset's inherent structure**, it's prudent to **exclude the 'subject' column** from our **feature set** and **focus on the textual content itself**. By doing so, we allow the model to **learn from the rich linguistic features** present in the text, enabling it to make **more nuanced and accurate predictions**.

IN[14]:

Out[15]:

	title	text	subject	date	Label
0	Donald Trump Sends Out Embarrassing New Year'...	Donald Trump just couldn t wish all Americans ...	News	2017-12-31	Fake
1	Drunk Bragging Trump Staffer Started Russian ...	House Intelligence Committee Chairman Devin Nu...	News	2017-12-31	Fake
2	Sheriff David Clarke Becomes An Internet Joke...	On Friday, it was revealed that former Milwauk...	News	2017-12-30	Fake
3	Trump Is So Obsessed He Even Has Obama's Name...	On Christmas day, Donald Trump announced that ...	News	2017-12-29	Fake
4	Pope Francis Just Called Out Donald Trump Dur...	Pope Francis used his annual Christmas Day mes...	News	2017-12-25	Fake

```
list(filter(lambda x: len(x)>20, df.date.unique()))
```

Out[14]:

```
['https://100percentfedup.com/served-roy-moore-vietnamletter-veteran-sets-record-straight-hono
rable-decent-respectable-patriotic-commander-soldier/',
 'https://100percentfedup.com/video-hillary-asked-about-trump-i-just-want-to-eat-some-pie/',
'https://100percentfedup.com/12-yr-old-black-conservative-whose-video-to-obama-went-viral-doyou-
really-love-america-receives-death-threats-from-left/',
 'https://fedup.wpengine.com/wp-content/uploads/2015/04/hillarystreetart.jpg',
 'https://fedup.wpengine.com/wp-content/uploads/2015/04/entitled.jpg',
 'MSNBC HOST Rudely Assumes Steel Worker Would Never Let His Son Follow in His Footsteps…He
Co uldn’t Be More Wrong [Video]']
```

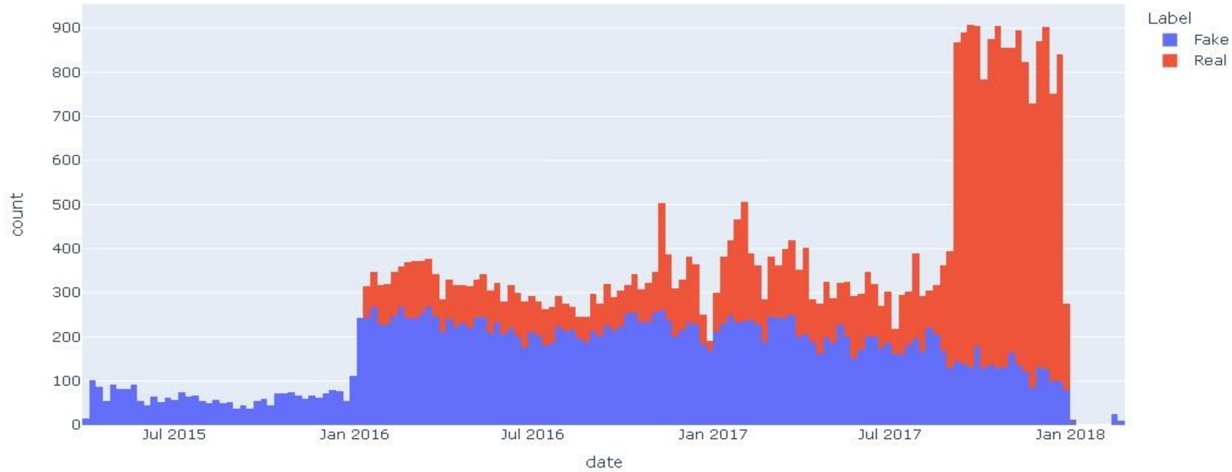
It does **seem unusual** to encounter **text and links** in a **date column**, especially in a **dataset** where one would expect the **'date' column to strictly contain date-related information**. Discovering such discrepancies highlights the **importance of data quality and integrity**. Anomalies like this can potentially **impact the accuracy and reliability of any analysis** or modeling conducted on the dataset.

In [15]:

```
df = df[df.date.map(lambda x: len(x)) <= 20]
df.date = pd.to_datetime(df.date, format="mixed")
df.head()
```

```
IN[16]: label_date_hist =
px.histogram(     data_frame =
df,     x = 'date',     color =
"Label",
)
```

```
label_date_hist.show()
```



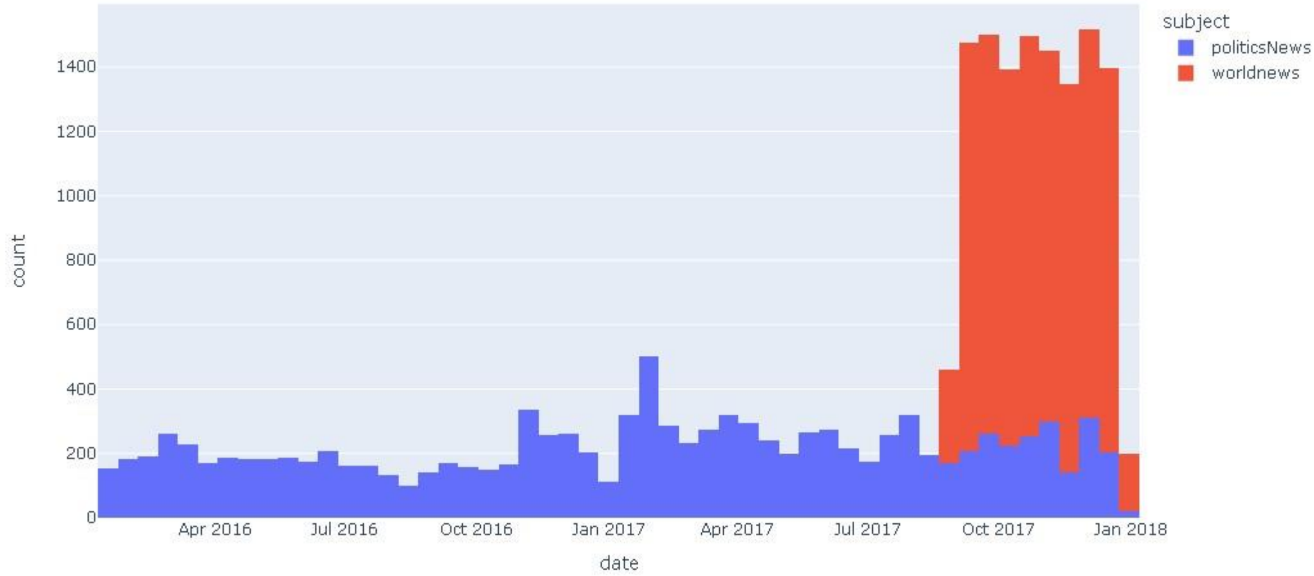
The **observed patterns** in **data collection over time** indeed **raise intriguing questions** about the **dynamics of fake and real news** in the dataset. As you've pointed out, there are **two potential explanations for this phenomenon**.

The first explanation suggests that **real news might be more prevalent** in **recent times**. This could be due to **various factors**, including **improved government measures** to combat **fake news or a shift in public perception** and **consumption of news**. In this scenario, the **data collection reflects a real-world trend** where genuine **news articles** are on the rise.

The **second explanation** is related to **data collection strategies**. Since the dataset doesn't **start collecting both fake and real news** from the **same date**, it's possible that there are **external factors influencing** the **data collection process**. For instance, the increase in the **total number of real news articles** in **2018 might** be due to a **deliberate effort to balance the class distribution** and **reduce class imbalance** issues in the dataset. This approach can help create a **more representative dataset for machine learning purposes.**

The histogram indeed provides valuable insights into the **temporal distribution of fake and real news articles**, showcasing a decrease in **fake news** and a **significant increase in real news** as we approach **2018**.

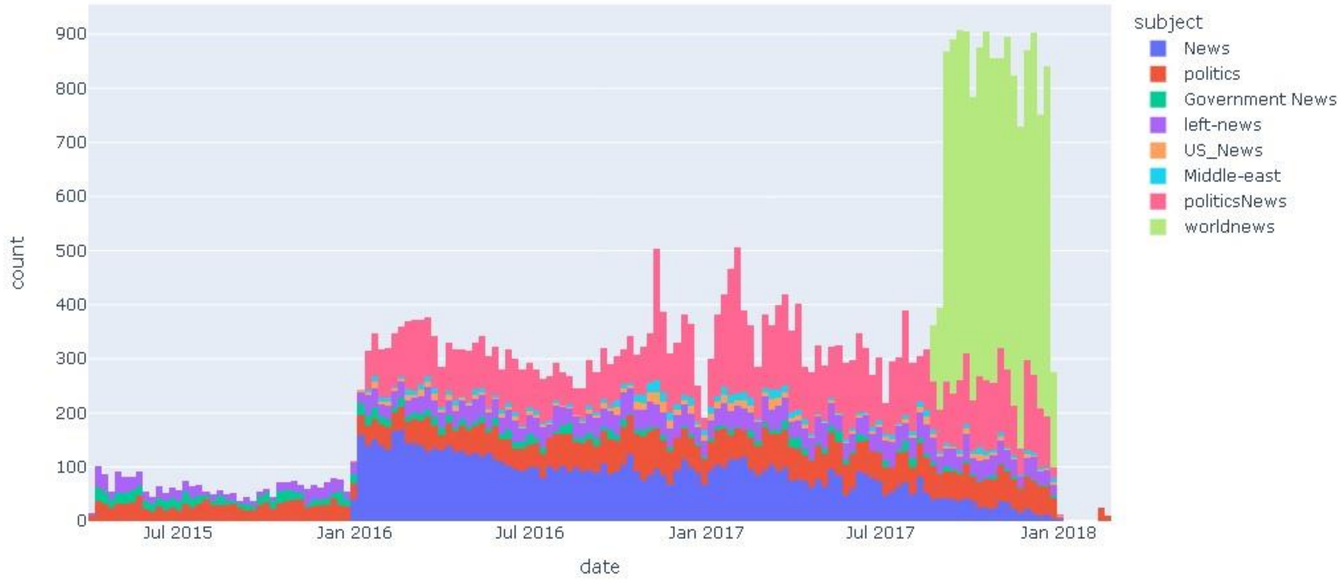
```
IN[17]: real_sub_hist =
px.histogram(
    data_frame = df[df.Label == "Real"],
x = 'date',     color = "subject",
)
real_sub_hist.show()
```



The observation that the spike in the **total number** of **real news articles** in recent years is **predominantly attributed to world news articles** collected starting in **August 2017** is an **interesting finding**.

It suggests that a **significant amount** of **world news** data, particularly from **August 2017 onwards**, was **incorporated into the dataset**. This clearly shows that the data is not collected in an **balanced manner**.

```
IN[18]: subject_hist =
px.histogram(
    data_frame = df,
x = 'date',     color
= "subject",
)
subject_hist.show()
```



In our dataset, the **distinct spikes and variations** in **news distribution** become clearer upon **closer examination**. These fluctuations can be traced back to the **timing of data collection** for **different news categories**. Notably, **'World News'** articles were **predominantly collected in the year 2017**, while other categories were **documented as far back as 2015**. Additionally, the **'Political News' category** joined the dataset in **2016**. Understanding these **temporal dynamics** is crucial for our analysis, as it sheds light on the **composition and origins of the data**, offering a structured foundation for **further exploration and modeling**

Text Processing :

Before proceeding to the next steps, it's essential to apply preprocessing to our data. This includes converting the text to **lowercase**, **eliminating stopwords**, and **removing any punctuation marks.**

In [19]:

```
stop_words = set(stopwords.words('english')) def
text_processing(text):
    words = text.lower().split()
    filtered_words = [word for word in words if word not in stop_words]
    clean_text = ' '.join(filtered_words)
    clean_text = clean_text.translate(str.maketrans('', '', string.punctuation)).stri
p()
    return clean_text
```

In [20]:

```
X = data.text.apply(text_processing).to_numpy()
Y = data.Label.to_numpy().astype('float32').reshape(-1,1)

X_train, X_test, y_train, y_test = train_test_split(
X, Y,     train_size=0.9,
```

```
    test_size=0.1,
stratify=Y,
random_state=42
)

X_train, X_valid, y_train, y_valid = train_test_split(
    X_train, y_train,
train_size=0.9,
test_size=0.1,
stratify=y_train,
random_state=42 )
```

BERT Classification Model

BERT, or **Bidirectional Encoder Representations from Transformers**, is a **cutting-edge natural language processing (NLP) model** developed by **Google**. What sets **BERT** apart is its ability to **understand the context of words** in a sentence by considering both the words that come **before and after** them, allowing it to **grasp nuances**, **context**, and **meaning in language more effectively. BERT** has achieved **remarkable success** in various **NLP tasks**, including **text classification**, **sentiment analysis**, and **machine translation**, and it has become a **cornerstone** in the field of **AI** for **understanding and generating human language**.

Before proceeding with the loading of the **pre-trained BERT model**, a crucial step lies ahead: **tokenization** of our data. At present, our input data points remain in their **textual format**, necessitating their **transformation into tokens**. This **transformation** is essential to enable the **subsequent processing** of our data by the **BERT model.**

```
In [21]: linkcode
bert_name = "bert-base-uncased" tokenizer
= AutoTokenizer.from_pretrained(
bert_name,     padding = "max_length",
do_lower_case = True,
add_special_tokens = True,
)
X_train_encoded = tokenizer(
X_train.tolist(),     padding
```

```
Downloading (…)okenizer_config.json: 100% 28.0/28.0 [00:00<00:00, 2.06kB/s]

Downloading (…)lve/main/config.json: 100% 570/570 [00:00<00:00, 40.5kB/s]

Downloading (…)solve/main/vocab.txt: 100% 232k/232k [00:00<00:00, 5.50MB/s]

Downloading (…)/main/tokenizer.json: 100% 466k/466k [00:00<00:00, 25.5MB/s]
```

```
= True,     truncation =
True,     return_tensors =
"tf"
).input_ids

X_valid_encoded = tokenizer(
X_valid.tolist(),     padding
= True,     truncation =
True,     return_tensors =
"tf"
).input_ids

X_test_encoded = tokenizer(
X_test.tolist(),     padding
= True,     truncation =
True,     return_tensors =
"tf" ).input_ids
```

In [23]:

```
train_ds = tf.data.Dataset.from_tensor_slices((X_train_encoded, y_train)).shuffle(len
(X_train)).batch(8).prefetch(tf.data.AUTOTUNE)
valid_ds = tf.data.Dataset.from_tensor_slices((X_valid_encoded, y_valid)).shuffle(len
(X_valid)).batch(8).prefetch(tf.data.AUTOTUNE)
test_ds  = tf.data.Dataset.from_tensor_slices((X_test_encoded, y_test)).shuffle(len(X
_test)).batch(8).prefetch(tf.data.AUTOTUNE)
```

Fantastic! Our data is **now fully prepared** for **ingestion by our model**. It has been **successfully tokenized** from its **original textual format**, **enabling compatibility** with the **model's processing requirements**. Additionally, the **data** has been **organized** into **manageable data flows**, **optimizing efficiency**. The next step on our journey is to **load the model**.

In [24]:
linkcode

```
bert_model = TFAutoModelForSequenceClassification.from_pretrained(bert_name, num_labe
ls = 1)
```

```
Downloading model.safetensors: 100%
440M/440M [00:02<00:00, 223MB/s]
```

```
All PyTorch model weights were used when initializing TFBertForSequenceClassification
.

Some weights or buffers of the TF 2.0 model TFBertForSequenceClassification were not
initialized from the PyTorch model and are newly initialized: ['classifier.weight', '
classifier.bias']
You should probably TRAIN this model on a down-stream task to be able to use it for p
redictions and inference.
```

Training BERT

In this section, **our primary focus** will be on the **training** of the **BERT model**. In addition to **monitoring the loss**, we will assess the **model's performance** using **various metrics**, including the **F1 score**, **recall score**, and **precision score.**

In [25]:

.

In [25]:

```
bert_model.compile(
    optimizer = Adam(learning_rate = 1e-5),
metrics = [
        tf.keras.metrics.BinaryAccuracy(name="Accuracy"),
tf.keras.metrics.Precision(name="Precision"),
tf.keras.metrics.Recall(name="Recall"),
    ]
)

model_history = bert_model.fit(
train_ds,
    validation_data = valid_ds,
epochs = 5,     batch_size =
16,
    callbacks = MODEL_CALLBACKS
)

model_history = pd.DataFrame(model_history.history)
```

```
Epoch 1/5
102/102 [==============================] - 204s 1s/step - loss: 0.1709 - Accuracy: 0.
7617 - Precision: 0.7751 - Recall: 0.6818 - val_loss: 0.1052 - val_Accuracy: 0.8667 -
val_Precision: 0.7959 - val_Recall: 0.9512
Epoch 2/5
102/102 [==============================] - 151s 1s/step - loss: 0.0343 - Accuracy: 0.
9753 - Precision: 0.9758 - Recall: 0.9706 - val_loss: 0.0192 - val_Accuracy: 0.9667 -
val_Precision: 0.9524 - val_Recall: 0.9756
Epoch 3/5
102/102 [==============================] - 152s 1s/step - loss: 0.0079 - Accuracy: 0.
9988 - Precision: 1.0000 - Recall: 0.9973 - val_loss: 0.0048 - val_Accuracy: 1.0000 -
val_Precision: 1.0000 - val_Recall: 1.0000
Epoch 4/5
102/102 [==============================] - 109s 1s/step - loss: 0.0052 - Accuracy: 1.
0000 - Precision: 1.0000 - Recall: 1.0000 - val_loss: 0.0087 - val_Accuracy: 0.9778 -
val_Precision: 0.9535 - val_Recall: 1.0000
Epoch 5/5
102/102 [==============================] - 108s 1s/step - loss: 0.0043 - Accuracy: 1.
0000 - Precision: 1.0000 - Recall: 1.0000 - val_loss: 0.0075 - val_Accuracy: 0.9778 -
val_Precision: 0.9535 - val_Recall: 1.0000
```

In [26]:

```
# Save the mdoel
bert_model.save(model_name)
```

Learning Curve Visualization

Let's take a **visual journey** to explore how the **model embarked** on its **path to achieving** its **remarkable final performance.**

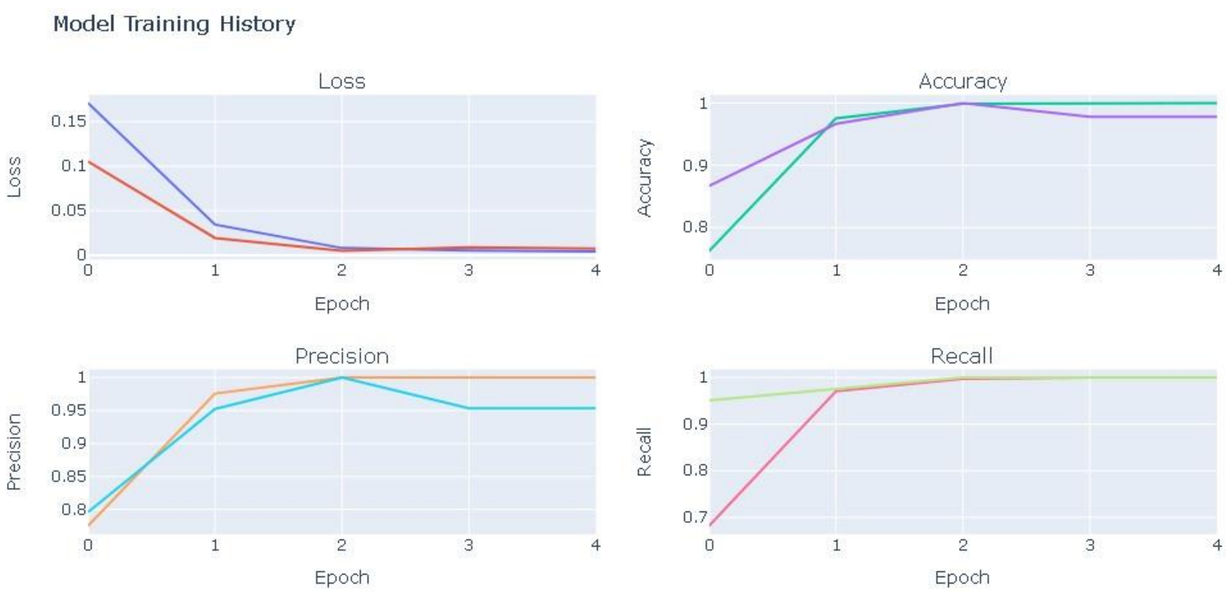
In [27]: linkcode

```
import plotly.graph_objs as go
from plotly.subplots import make_subplots

fig = make_subplots(rows=2, cols=2, subplot_titles=("Loss", "Accuracy", "Precision",
"Recall"))

# Add traces to subplots
fig.add_trace(go.Scatter(y=model_history['loss'], mode='lines', name='Training Loss')
, row=1, col=1)
fig.add_trace(go.Scatter(y=model_history['val_loss'], mode='lines', name='Validation
Loss'), row=1, col=1)

fig.add_trace(go.Scatter(y=model_history['Accuracy'], mode='lines', name='Training Ac
curacy'), row=1, col=2)
fig.add_trace(go.Scatter(y=model_history['val_Accuracy'], mode='lines', name='Validat
ion Accuracy'), row=1, col=2)

fig.add_trace(go.Scatter(y=model_history['Precision'], mode='lines', name='Training P
recision'), row=2, col=1)
fig.add_trace(go.Scatter(y=model_history['val_Precision'], mode='lines', name='Valida
tion Precision'), row=2, col=1)

fig.add_trace(go.Scatter(y=model_history['Recall'], mode='lines', name='Training Reca
ll'), row=2, col=2)
fig.add_trace(go.Scatter(y=model_history['val_Recall'], mode='lines', name='Validatio
n Recall'), row=2, col=2)

# Customize the layout
fig.update_layout(
    title='Model Training History',
    xaxis_title='Epoch',
yaxis_title='Metric Value',
showlegend=False,
)

# Update subplot axes labels
fig.update_xaxes(title_text='Epoch', row=1, col=1)
fig.update_xaxes(title_text='Epoch', row=1, col=2)
fig.update_xaxes(title_text='Epoch', row=2, col=1)
fig.update_xaxes(title_text='Epoch', row=2, col=2)
```

```
fig.update_yaxes(title_text='Loss', row=1, col=1)
fig.update_yaxes(title_text='Accuracy', row=1, col=2)
fig.update_yaxes(title_text='Precision', row=2, col=1)
fig.update_yaxes(title_text='Recall', row=2, col=2)

# Display the figure fig.show()
```

The power of a **pre-trained model** like **BERT** truly shines in its ability to **leverage vast amounts of prior knowledge** from a **large text corpus**. This **extensive understanding** of **text allows** it to **excel** in tasks such as **text classification**, like **distinguishing between fake and real news**. As we can witness, the **loss decreases almost to zero**, **precision and recall approach one**, and **accuracy soars**.

This level of **performance** is **truly remarkable**, especially considering the **dataset's size**. However, it's worth noting that **some memory constraints exist**; training on a **single GPU is impractical due to memory limitations**. This is why **I utilized two GPUs**, even though **only one is actively used**. The initialization process demands more than **30GB of memory**. Despite these **constraints**, **fine-tuning the BERT model** yields substantial **performance improvements**, making it a **powerful tool** in the realm of **natural language processing**



Test Performance Evaluation

Having evaluated our **model's performance** on both the **training and validation datasets**, it's crucial to now assess how well it **performs** on the **testing dataset**—a critical step in gauging its **real-world applicability and generalization capabilities.**

In [28]:

```
test_loss, test_acc, test_precision, test_recall = bert_model.evaluate(test_ds, verbo
se = 0)
print(f"Test Loss      : {test_loss}") print(f"Test
Accuracy   : {test_acc}") print(f"Test Precision :
{test_precision}")  print(f"Test  Recall        :
{test_recall}")  Test  Loss            :
0.0008588206837885082
Test Accuracy  : 1.0
```

```
Test Precision : 1.0
Test Recall    : 1.0
```

This model is **truly remarkable**, as it maintains its **exceptional performance** even when **tested on new, unseen data**. This level of consistency suggests that the **model possesses high accuracy** and is well-equipped to excel in **real-world scenarios**.

Model's Prediction Samples

Beyond the **numerical metrics**, it's beneficial to **examine the model's predictions directly**. This will provide us with a **visual insight** into the **accuracy and reliability** of the **model's classifications.**

In [29]:
```
def
predict_text(text, model):
    tokens = tokenizer(text, return_tensors = 'tf', padding="max_length", truncation=
True).input_ids
    return np.abs(np.round(model.predict(tokens, verbose = 0).logits))
```

In [30]:
```
for _ in range(5):     index =
np.random.randint(len(X_test))

    text = X_test[index]
true = y_test[index]
    model_pred = predict_text(text, model = bert_model)[0]

    print(f"ORGINAL TEXT:\n\n{text}\n\nTRUE: {CLASS_NAMES[int(true)]}\tPREDICTED: {CL
ASS_NAMES[int(model_pred)]}\n{'-'*100}\n")
```

```
ORGINAL TEXT:

washington reuters  president barack obama friday signed law meas
ure pledges greater efforts protect drugdependent newborns assist
parents comprehensive addiction recovery act also stresses drug t
reatment overdose prevention help stanch nation’s heroin opioid d
rug epidemic obama said statement 78 americans die opioid overdos
e every day noted legislation included modest steps address epide
mic “i deeply disappointed republicans failed provide real resour
ces seeking addiction treatment get care need” obama said “in fac
t blocked efforts democrats include 920 million treatment funding
” bill passed nearly unanimously house representatives senate eff
orts enforce provisions protect newborns help parents come respon
se reuters investigation last year titled “helpless  hooked” new
```

law requires federal government every state follow 2003 law routi
nely ignored law called states require hospitals social services
report track assist drugdependent newborns families reuters found
nine states following requirement children born addicted mothers
including many mothers taking prescribed methadone reported hospi
tals required law often medical workers feared involving child pr
otective services existing law requires cases reported social ser
vices reuters found efforts protect child help parents often limi
ted failures came cost reuters found 110 babies since 2010 died p
reventable circumstances sent home families illequipped care them
experts said far children likely died gone uncounted new law prom
ises nonpunitive approach includes “safe care plans” aimed keepin
g newborns home parents receive additional help “this step forwar
d vulnerable babies who due opioid dependency begin lives facing
enormous challenges” said senator bob casey pennsylvania ranking
democrat senate subcommittee children families “reuters’ initial
reporting shined light darkness enveloped far many lives much wor
k genuine step forward” representative john kline minnesota repub
lican chairs house committee education workforce initiated measur
e said track state actions “these reforms important part broader
efforts combat nation’s opioid epidemic provide vulnerable famili
es better chance brighter future” kline said statement 2013 lates
t year nationwide hospital reporting 27315 babies diagnosed newbo
rn drug withdrawal syndrome fivefold increase decade earlier reut
ers found one drugdependent baby born average every 19 minutes un
ited states suffer shaking crying feeding problems battle withdra
wal senator ron wyden oregon ranking democrat senate finance comm
ittee said broader addiction law “no half measure” without fundin
g wyden cosponsored measure setting aside money substance abuse t
reatment parents danger losing children passed house stalled sena
te jim greenwood former pennsylvania congressman championed 2003
law said deaths reuters revealed represent “a national disgrace g
laring failure federal state local level implement plans safe car
e infants” greenwood president washington dcbased biotechnology g
roup applauded new measure “to improve health safety babies famil
ies” stephen patrick assistant professor pediatrics vanderbilt un
iversity leading researcher condition said new law “good news” ad
ded “wish funding came it”

TRUE: Real PREDICTED: Real

ORGINAL TEXT:
washington
reuters us
government
could provide
80 billion aid
vi ctims
hurricane
harvey
fraction total
impact could
storm texas re
presentative
pete sessions
said thursday
“people think
federal go
vernment going
pay this fact
may 60 70 80
billion it’s 1
trillio n
impact”
sessions told
fox business
network
specify meant
impact damage
estimates
remain
preliminary

TRUE: Real PREDICTED: Real

ORGINAL TEXT:

donald trump arguably bizarre week history american presidency ca
reened outrage outrage lie lie lawless action lawless action span

five days starting firing fbi director james comey threw massive tantrum trumprussia collusion investigation well one respected am erican enough trump acting law journalist dan ratherrather took f acebook page rip trump shreds can begins talking long lived many presidencies lived including richard nixon moves extraordinary di sgrace donald trump presidency rather says partbut never seen wee k president nation behaved cavalier disregard norms institutions democracy seems like investigation expanding trump business deali ngs comparisons richard nixon plentiful days even seem untethered basic governance never seen many members political party rally ar ound incompetence intemperance inanitydan rather correct donald t rump makes richard nixon look like boy scout trump downright dang erous must restrained congress would jobs speak out act check pre sident supposed be hell happy check president obama even anything lawlessthis republican party putting partisan politics political futures good republic shameful must vote congress 2018mr rather t hank speaking truth power need voices like dark dire timesread en tire brilliant post belowfeatured image via kirk irwingetty image s siriusxm

TRUE: Fake PREDICTED: Fake

ORGINAL TEXT:
live wisconsin
want working
neighbors fund
existence may
need sta rt
peeing cup
prove
dependency
government
related
dependency
drug s
governor
wisconsin love
em hate em
kind leader

conservatives
lo ve making
public sector
unions pay
benefits
liberals hate
daring stand
powerful
organized
megadonors
democrat party
governor walke
r shake things
blue state
wisconsin
liberals gonna
happy gov scot
t walker
moving forward
effort drug
test food
stamp
recipients te
sting expected
begin little
year absent
action
lawmakers
federal
governmentwisc
onsin
republican
governor
submitted plan
state lawm
akers drug
testing
ablebodied
recipients
state food

share program
state
legislature
object within
120 days plan
go effect
though ta ke
least year
actual testing
beginthe
program
necessarily
massive effect
however walker
administration
estimated
october 220
food s tamp
recipients
statewide 03
ablebodied
adults would
test positiv e
first year
employers jobs
available need
skilled
workers pass d
rug test
walker said
statement rule
change means
people
battling
substance use
disorders able
get help need
get healthy
get back w
orkforce year

ago walker
asked
presidentelect
donald trump
incomi ng
administration
clear way
change food
stamp program
overseen st
ate largely
funded federal
taxpayers far
happened
walker
spokesma n
said monday
governor
believes state
proceed
without
federal act
ion position
authority
implement rule
spokesman tom
evenson saidt
he nowdeparted
appointees
president
barack obama
see way
january 2017
right trump
took white
house former
us official
charge repla
cement program
food stamps

said testing
would require
change fede
ral law law
clearly allow
it said kevin
concannon
undersecretary
federal food
nutrition
service within
us department
agriculture w
alker office
forwarded
request us
clear
consulted
legal counsels
law absolutely
allow it trump
administration
however may
see issu e
light journal
sentinel

TRUE: Fake PREDICTED: Fake

ORGINAL TEXT:

washington reuters us government could provide 80 billion aid vi
ctims hurricane harvey fraction total impact could storm texas re
presentative pete sessions said thursday “people think federal go
vernment going pay this fact may 60 70 80 billion it’s 1 trillio n
impact” sessions told fox business network specify meant impact damage
estimates remain preliminary

TRUE: Real PREDICTED: Real

Linkcode

Unquestionably, the **model's performance** stands as **nothing short** of an **aweinspiring marvel**, casting **aside any shadow of doubt** that might dare to linger around its **inferences**. Its predictions **unfailingly unveil** a **realm of unmatched**, staggering **accuracy**—a testament to its **sheer brilliance and prowess.**

Concluding this notebook, I welcome your valuable suggestions and comments. Please don't hesitate to pinpoint any specific aspects or areas for improvement. Thank you for accompanying us on this journey to the end.