```
import pandas as pd
repo = "https://raw.githubusercontent.com/rcamwm/DATA301-project-data/main/"
```

```
from sklearn.ensemble import StackingRegressor
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import cross_val_score
from sklearn.neighbors import KNeighborsRegressor
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline
```

GDP Dataset

Description

The data shows the change in GDP from 1964 to 2021. We also had to clean the new data set with a larger time frame.

```
# Import GDP dataset and condense into new DataFrame
df_gdp = pd.read_csv(
    repo + "/GDP-Values-Worldwide.csv",
).drop(
    ['Country Code'],
    axis=1
).set_index("Country Name").transpose()

df_gdp.index.set_names("Date", inplace=True)
df_gdp.index = pd.to_datetime(df_gdp.index).year
df_gdp.head()
```

Country Name	Aruba	Africa Eastern and Southern	Afghanistan	Africa Western and Central	Angola	Albania	Andorra
Date							
1960	NaN	2.129059e+10	537777811.1	1.040414e+10	NaN	NaN	NaN
1961	NaN	2.180847e+10	548888895.6	1.112789e+10	NaN	NaN	NaN
1962	NaN	2.370702e+10	546666677.8	1.194319e+10	NaN	NaN	NaN
1963	NaN	2.821004e+10	751111191.1	1.267633e+10	NaN	NaN	NaN
1964	NaN	2.611879e+10	800000044.4	1.383837e+10	NaN	NaN	NaN

5 rows × 266 columns

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Historic NASDAQ Dataset

Description

The data shows the change in the NASDAQ's price from 1971 to roughly the present. We also had to clean the new data set with a larger time frame.

```
# Import NASDAQ dataset and set index to data
df_nasdaq = pd.read_csv(
    "https://fred.stlouisfed.org/graph/fredgraph.csv?bgcolor=%23e1e9f0&chart_type=l
    parse_dates=True
).dropna()
df_nasdaq.columns = ["Date", "NASDAQ Closing Price"]
df_nasdaq.set_index("Date", inplace=True)
df_nasdaq = df_nasdaq.loc[df_nasdaq["NASDAQ Closing Price"] != "."]
df_nasdaq.head()
```

Date	NASDAQ Closing Price
1971-02-05	100.00
1971-02-08	100.84
1971-02-09	100.76
1971-02-10	100.69
1971-02-11	101.45

```
def get_year_first_nasdaq(year):
  filtered = df_nasdaq[
      (df_nasdaq.index >= str(year)) & (df_nasdaq.index < str(year + 1))
  ]
  return float(filtered.iloc[0].values[0])
```

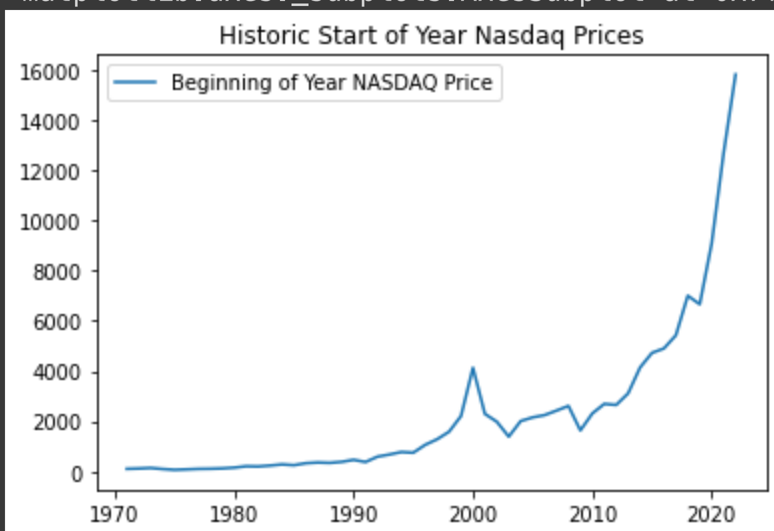
```
nasdaq_dates = pd.DatetimeIndex(df_nasdaq.index)
df_nasdaq_yearly = pd.DataFrame(
    index=range(nasdaq_dates[0].year, nasdaq_dates[-1].year + 1),
    columns=["Beginning of Year NASDAQ Price"],
    dtype="float64"
)
df_nasdaq_yearly["Beginning of Year NASDAQ Price"] = df_nasdaq_yearly.apply(
    lambda year: get_year_first_nasdaq(year.name),
    axis=1
```

```
    axis=1
)
df_nasdaq_yearly.head()
```

	Beginning of Year NASDAQ Price
1971	100.00
1972	113.65
1973	134.63
1974	92.53
1975	60.70

```
df_nasdaq_yearly.plot(
    kind="line",
    title="Historic Start of Year Nasdaq Prices"
)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb5c9bc0eb0>
```



NASDAQ Prediction Model

Finding the countries whose GDP best predicts the NASDAQ.

```
from itertools import combinations

# Returns a list of all possible combinations of a list of features
def get_list_combinations(feature_list, r="All"):
    feature_count = len(feature_list) if r == "All" else r
    list_combinations = []
```

```
    list_combinations = []
    for n in range(feature_count + 1):
        list_combinations += list(combinations(feature_list, n))
    return list_combinations
```

```
def get_cv_average_error(features, prediction):
    pipeline = make_pipeline(
        StandardScaler(),
        LinearRegression()
    )
    cv_errs = -cross_val_score(
        pipeline,
        X=features,
        y=prediction,
        scoring="neg_mean_squared_error",
        cv=len(features)
    )
    return cv_errs.mean()
```

```
df_gdp_stocks = pd.merge(df_gdp, df_nasdaq_yearly, left_index=True, right_index=Tru
df_gdp_stocks.head()
```

	Aruba	Africa Eastern and Southern	Afghanistan	Africa Western and Central	Angola	Albania	Andorra
1971	NaN	4.947892e+10	1.831109e+09	2.083282e+10	NaN	NaN	8.940982e+07
1972	NaN	5.351484e+10	1.595555e+09	2.526495e+10	NaN	NaN	1.134082e+08
1973	NaN	6.960079e+10	1.733333e+09	3.127382e+10	NaN	NaN	1.508201e+08
1974	NaN	8.605778e+10	2.155555e+09	4.421448e+10	NaN	NaN	1.865587e+08
1975	NaN	9.164915e+10	2.366667e+09	5.144473e+10	NaN	NaN	2.201272e+08

5 rows × 267 columns

List of ten highest GDP countries according to https://en.wikipedia.org/wiki/List_of_countries_by_GDP_(nominal).

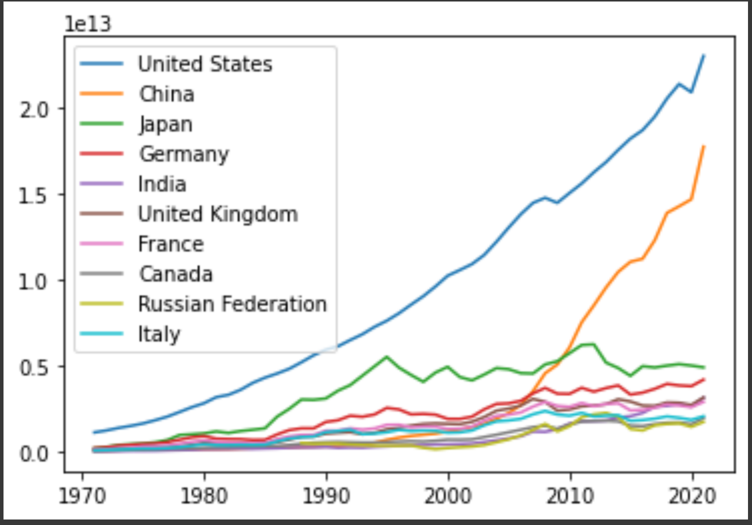
Ideally, we would have preferred to use all countries with available data to truly find the best results. But this was too computationally intensive, so we've limited the number of countries we'll be looking at.

```
top_10_gdps = [
```

```
    "United States",
    "China",
    "Japan",
    "Germany",
    "India",
    "United Kingdom",
    "France",
    "Canada",
    "Russian Federation",
    "Italy"
]
```

```
df_gdp_stocks[top_10_gdps].plot(
    kind="line"
)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fb5c781afd0>




```
gdp_country_errors = pd.Series(
    dtype='float64'
)
# Combinations limited to reduce computational time
country_groups = get_list_combinations(top_10_gdps, 3)
for country_group in country_groups[1:]:
  country_group_list = list(country_group)
  nan_filtered = df_gdp_stocks[
      country_group_list + ["Beginning of Year NASDAQ Price"]
  ].dropna()
  if not nan_filtered.empty:
    gdp_country_errors[str(country_group_list)] = get_cv_average_error(
        nan_filtered[country_group_list],
        nan_filtered["Beginning of Year NASDAQ Price"]
    )
```

```
best_country_features = gdp_country_errors.loc[
```

```
    gdp_country_errors == gdp_country_errors.min()
].index[0].strip("[']").split("', '")

best_country_features
```

```
['United States', 'China', 'Canada']
```

Finding the best k-value for k-nearest neighbors in predicting NASDAQ price based on GDP

```
def get_cv_error_for_k(features, prediction, k):
    pipeline = make_pipeline(
        StandardScaler(),
        KNeighborsRegressor(n_neighbors=k)
    )
    cv_errs = -cross_val_score(
        pipeline,
        X=features,
        y=prediction,
        scoring="neg_mean_squared_error",
        cv=len(features)
    )
    return cv_errs.mean()
```

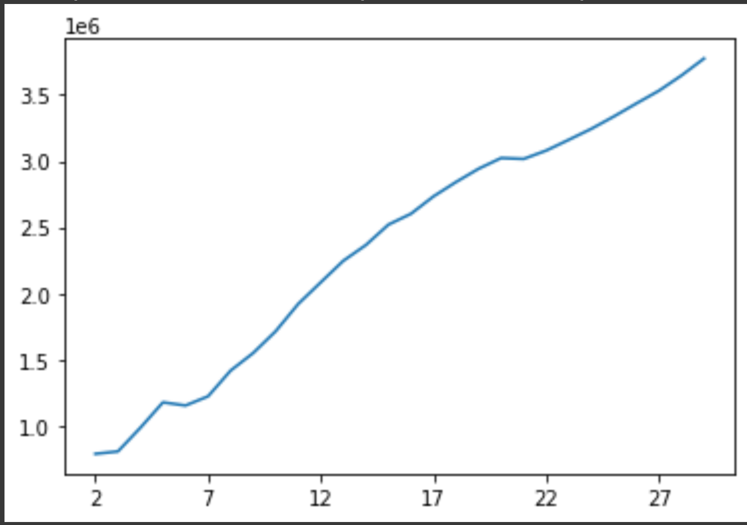
```
def get_best_k(features, prediction, max_k):
    k_errors = pd.Series(dtype='float64')
    for k in range(2, max_k):
        k_errors[str(k)] = get_cv_error_for_k(
            features,
            prediction,
            k
        )
    return int(k_errors.loc[
        k_errors == k_errors.min()
    ].index.values[0]), k_errors
```

```
best_fit_countries = df_gdp_stocks[
    best_country_features + ["Beginning of Year NASDAQ Price"]
].dropna()

k_return = get_best_k(
    best_fit_countries[best_country_features],
    best_fit_countries["Beginning of Year NASDAQ Price"],
    30
)
```

```
k_return[1].plot(kind="line")
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fb5c777b430>




```
best_k = k_return[0]
best_k
```

2

Create Stacked Model

```
def get_stacking_model(X, y, k):
    linear_model = LinearRegression()
    linear_model.fit(X=X, y=y)

    knn_model = make_pipeline(
        StandardScaler(),
        KNeighborsRegressor(n_neighbors=k)
    )
    knn_model.fit(X=X, y=y)

    stacking_model = StackingRegressor([
        ("linear", linear_model),
        ("knn", knn_model)],
        final_estimator=LinearRegression()
    )
    stacking_model.fit(X=X, y=y)
    return stacking_model
```

```
nasdaq_model = get_stacking_model(
    best_fit_countries[best_country_features],
    best_fit_countries["Beginning of Year NASDAQ Price"],
    best_k
```

```
)
```

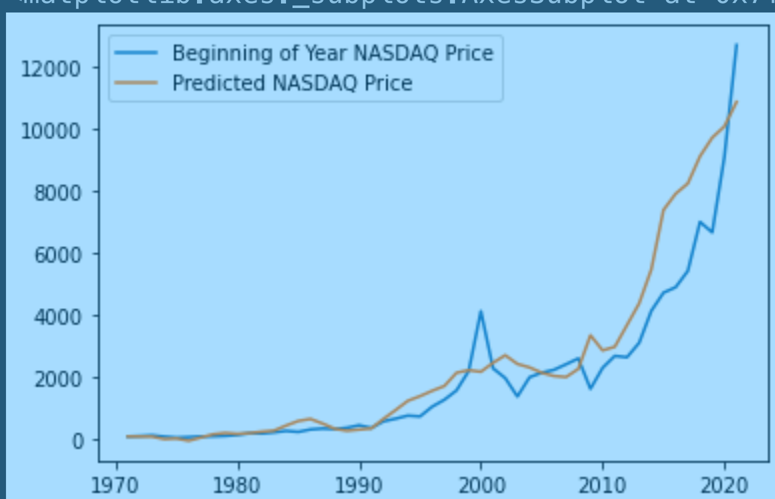
Model test

```
def get_prediction_for_year(year):
  if year in best_fit_countries.index:
    return nasdaq_model.predict(pd.DataFrame(best_fit_countries[best_country_featu
  else:
    return float("nan")
```

```
df_comparison = df_nasdaq_yearly
df_comparison = pd.merge( # Remove NaN rows
    best_fit_countries[[]], df_comparison, left_index=True, right_index=True
)
df_comparison["Predicted NASDAQ Price"] = nasdaq_model.predict(
    best_fit_countries[best_country_features]
)
```

```
df_comparison.plot(kind="line")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb5c7725a00>
```



Ethereum Prediction Model Based on NASDAQ

Recent NASDAQ and Ethereum datasets

```
# Import Ethereum dataset and set index to data
df_ethereum = pd.read_csv(
```

```
    repo + "ETH-USD-2.csv",
    index_col="Date",
    parse_dates=True
)

# Condense data into new DataFrame
df_ethereum_clean = df_ethereum[["Close"]].rename(
    columns={"Close":"Close ETH"}
)
df_ethereum_clean.head()
```

Date	Close ETH
2017-11-09	320.884003
2017-11-10	299.252991
2017-11-11	314.681000
2017-11-12	307.907990
2017-11-13	316.716003

```
# Import NASDAQ dataset and set index to data
df_nasdaq_recent = pd.read_csv(repo + "NASDAQ.csv",
    index_col="Date",
    parse_dates=True
)

# Condense data into new DataFrame
df_nasdaq_clean = df_nasdaq_recent[["Close/Last"]].rename(
    columns={"Close/Last":"Close NASDAQ"}
)
df_nasdaq_clean.head()
```

Date	Close NASDAQ
2022-11-11	11323.33
2022-11-10	11114.15
2022-11-09	10353.17
2022-11-08	10616.20
2022-11-07	10564.52

```
df_stocks_crypto = df_nasdaq_clean.join(
```

```
    df_ethereum_clean
).dropna()

df_stocks_crypto.head()
```

Date	Close NASDAQ	Close ETH
2022-11-11	11323.33	1287.221069
2022-11-10	11114.15	1299.464600
2022-11-09	10353.17	1100.169800
2022-11-08	10616.20	1332.835571
2022-11-07	10564.52	1568.591309

Model training

```
X = df_stocks_crypto[["Close NASDAQ"]]
y = df_stocks_crypto["Close ETH"]
k = get_best_k(X, y, 10)[0]
ethereum_model = get_stacking_model(X, y, k)
```

Model Testing

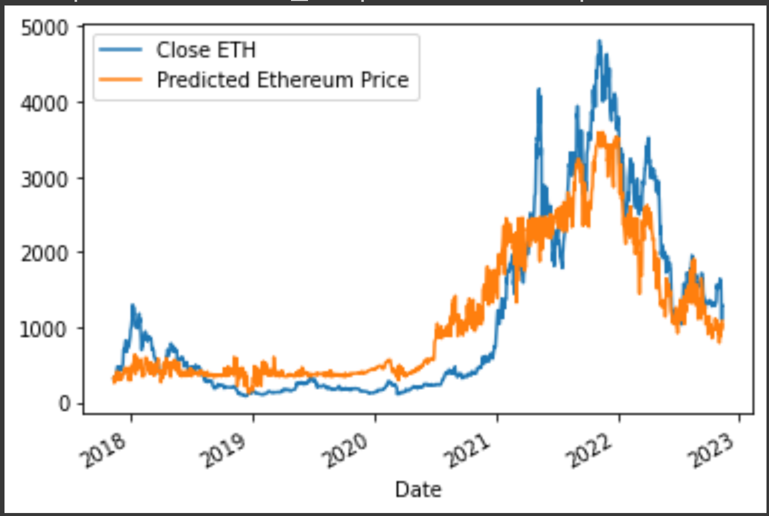
```
df_comparison_eth = df_ethereum_clean
df_comparison_eth = pd.merge( # Remove NaN rows
    df_stocks_crypto[["Close NASDAQ"]], df_comparison_eth, left_index=True, right_i
)
df_comparison_eth["Predicted Ethereum Price"] = ethereum_model.predict(
    df_stocks_crypto[["Close NASDAQ"]]
)
df_comparison_eth.head()
```

Date	Close NASDAQ	Close ETH	Predicted Ethereum Price
2022-11-11	11323.33	1287.221069	1085.097989
2022-11-10	11114.15	1299.464600	1006.909402
2022-11-09	10353.17	1100.169800	962.936030
2022-11-08	10616.20	1332.835571	1050.677519

2022-11-07	10564.52	1568.591309	958.253775

```
df_comparison_eth[["Close ETH", "Predicted Ethereum Price"]].plot(
    kind="line",
)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fb5c7bceee0>



All Together

The 3 countries whose GDP appears to affect the price of the NASDAQ the most are the US, China, and Canada.

According to The International Monetary Fund (https://www.imf.org/en/Publications/WEO/weo-database/2022/October/weo-report?c=512,914,612,171,614,311,213,911,314,193,122,912,313,419,513,316,913,124,339,638,514,218,963,616,223,516,918,748,618,624,522,622,156,626,628,228,924,233,632,636,634,238,662,960,423,935,128,611,321,243,248,469,253,642,643,939,734,644,819,172,132,646,648,915,134,652,174,328,258,656,654,336,263,268,532,944,176,534,536,429,433,178,436,136,343,158,439,916,664,826,542,967,443,917,544,941,446,666,668,672,946,137,546,674,676,548,556,678,181,867,682,684,273,868,921,948,943,686,688,518,728,836,558,138,196,278,692,694,962,142,449,564,565,283,853,288,293,566,964,182,359,453,968,922,714,862,135,716,456,722,942,718,724,576,936,961,813,726,199,733,184,524,361,362,364,732,366,144,146,463,528,923,738,578,537,742,866,369,744,186,925,869,746,926,466,112,111,298,927,846,299,582,487,474,754,698,&s=PPPGDP,&sy=2020&ey=2027&ssm=0&scsm=1&scc=0&ssd=1&ssc=0&sic=0&sort=country&ds=.&br=1) these three countries are predicted to have the following GDPs in 2023:

Canada: $2,353.876 billion
China: $32,529.230 billion
US: $26,185.210 billion

US: $26,185.210 billion

```
X_test = pd.DataFrame(index=["2023"], columns=["United States", "China", "Canada"])
X_test["United States"]["2023"] = 2.618521e+13
X_test["China"]["2023"] = 3.252923e+13
X_test["Canada"]["2023"] = 2.353876e+12
X_test.index = pd.to_datetime(X_test.index).year
```

```
nasdaq_2023 = pd.DataFrame(columns=["Close NASDAQ"])
nasdaq_2023["Close NASDAQ"] = nasdaq_model.predict(X_test)
ethereum_model.predict(nasdaq_2023)[0]
```

```
3814.968640114648
```